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An epistemological investigation into processes of dynamic constructions of useful knowledge for innovation"

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Constructing opportune knowledge

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by Erich Prem

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1 Introduction: knowledge for innovation

1.1 Innovation in the post-scientific society

Innovation is now a key term in public debates about science. It appears in research programmes, in research policy papers, and also in scientific journal articles and books. In fact, usage of the term has dramatically increased between the 1960s and 1970s. It is now often related to *knowledge* with the underlying idea of a causal connection between the two concepts: knowledge leads to innovation (Leydesdorff 2000, 2006; Anand et al. 2007, du Plessis 2007, Quintane et al. 2011). Whether this is the case or not, is not the subject of this thesis; the question underlying this dissertation is what are the changes and conditions induced in our conception of knowledge when it is primarily considered from the point of view of technological innovation?

Figure 1-1 Occurrence of the term "Innovation" in Google books in German in the period 1900-2000. Source: ngram[1]

This study takes inspiration from an article by Christopher T. Hill who claimed in 2007 that we are currently witnessing the emergence of a '*post-scientific society*'. Hill argues that a "*post-scientific society will have several key characteristics, the most important of which is that innovation leading to wealth generation and productivity growth will be based*

[1] https://books.google.com/ngrams/info Retrieved June 2017.

principally not on world-leadership in fundamental research in the natural sciences and engineering, but on world-leading mastery of the creative powers of, and the basic sciences of, individual human beings, their societies, and their cultures" (Hill 2007). Hill's argument is that from now on there will be much more emphasis on the speedy production of new products and services emerging from creatively putting together more or less existing buildings blocks of technology rather than from lengthy investigations in the basic sciences. This would be rather different from popular claims about the relation of science, technology, and innovation that strongly argue for the importance of the former for the latter. Note however, that the post-scientific era would certainly not be entirely un-scientific. It can be expected that the practical relevance of natural sciences would decrease, while we may witness an increased impact of social sciences, the arts, new business processes meeting consumer needs and demands.

Hill also claims a diminishing importance of engineering, for which there is little evidence, however. Obvious drivers of a post-scientific society today include globalization and a trend towards ever shortening product innovation cycles in global markets. As a result, there is a massive pressure on the *speed* and *cost* of development process in a broad range of industries today and there is currently no indication of an end to this trend. Already in 1994, Peter Drucker predicted a new economic order arising from a shift towards a knowledge-driven economy (Drucker 1994). Even if we put together only existing technology blocks, this would mean a demand for new and more efficient production processes which in turn will pose technological challenges.

Overall, these developments not only drive innovation from the need to speed up the development of products for the market, they have also led to innovation becoming a subject of research. The aim of such research is often not just an improved understanding of innovation processes, but also the acceleration of innovation in industry. The post-scientific society has the luxury of tapping into a vast amount of knowledge seemingly ready to be used. Indeed, every piece of knowledge adds to a combinatorial explosion of potential innovation pathways (cf. Schuster 2000). The challenge is to produce the right innovation at the right time – with an emphasis on *speed.*

1.2 The innovation neglect in epistemology

Apart from Hill’s article and claims, this inquiry is motivated by the apparent paradox that while the emphasis on knowledge for innovation is huge in today`s science, it is very small in epistemology. Moreover, in research policy today, an overwhelming proportion of public funding programmes is motivated with references to the key importance of knowledge for innovation, not only in the applied but also in the basic sciences. The precise nature of such knowledge, however, and its relation to furthering innovation is relatively little studied. Disciplines that have started to take a closer look at innovation-enabling knowledge are in the economic domain (e.g. Leydesdorff 2010) and, more recently, in the field of philosophy of technology (e.g. Ihde 1979, 1990). In business management (in particular in the field of knowledge management), the attention to knowledge arises from an interest to devise processes for the management and application of knowledge in order to innovate (e.g. Nonaka 1995, Quintane et al. 2011). In economics, the interest arises from the perspective of national economies where knowledge has become a decisive factor contributing to national productivity. In the philosophy of technology, the interest is in the kind of knowledge leading to technological artefacts, much in line with our intentions here. However, as we shall see below, this is still a relatively recent phenomenon and the question of how knowledge precisely leads to innovation was largely ignored for centuries.

There can be various reasons for this apparent paradox. It is possible that there simply is no problem, nothing needs to be further studied regarding the claim that knowledge and innovation are intimately linked. Perhaps it does not matter for knowledge whether it is put to use or not and whether it emerges more from theory or from practical experience? We will see later that this is not quite the case and some scholars and epistemologists (e.g. Scheler 1980, Banse & Wendt1986) have indeed pointed to differences in the character of knowledge that arises from different human intentions.

The apparent neglect of innovation in the history of epistemology could also relate to a sceptical attitude of philosophers and many researchers regarding the monetarization of knowledge. It is indeed much easier to find contemporary philosophical accounts arguing for the importance of *free and basic research* rather than those making a case for more *applied research and technology.* Even more generally, there is prominent philosophical criticism of instrumental reasoning said to inevitably lead to the domination of nature and to a reification and instrumentalisation of human beings (Horkheimer & Adorno 88).

A third reason may be the historic tradition in which purposeful interaction with the world has often been considered as a consequence of knowledge, but not as its source. Traditionally, knowledge and its use are separated (both in epistemology and in the theory of science). The source of knowledge was often largely regarded to be concerned with observation, description and prediction of the behaviour of nature – the classic paradigm of empiricism (Locke 1689). Of course, this observational stance started to change with empiricism making the case for the experiment and thus with goal-directed and carefully designed interaction with the world. Despite the human intervention in every experiment, this interaction was not usually put to the fore in philosophical analysis. Active interaction with the world appeared as a necessary condition to formulate rules about its characteristics, but the focus rarely was on this interaction itself. This intention was to become discredited as a "monstrous claim" (Blättler 2011) in forcefully asking and therefore torturing nature – Bacon's *natura vexata* (cf. Merchant 2008, p.741, Pesic 2014). In contrast to such views, radical constructivism emphasizes the role of action (and therefore, interaction) in order to gain primarily useful knowledge for maintaining the viability of organisms in close coupling with the world. While traditional empiricism emphasizes questioning nature, a primarily stimulus-based and mainly unidirectional conception, constructivism emphasizes continued interaction and viability which results in a much more dynamic view and concept.

Philosophers have proven sceptical about knowledge arising from the pursuit of innovation to the extent of even ridiculing it. Lissmann (2006) argues that illiterateness arises necessarily in a world that is massively interested in and focusing entirely on the capitalization of knowledge and that reduces literacy and education to only training. However, the innovation neglect is hardly explicitly argued for in epistemology and in fact does not appear justified: A possible shift towards a post-scientific society suggests that the future will bring even more emphasis on innovation and its knowledge. We are currently experiencing this process already. We therefore cannot ignore today's processes of innovation-driven knowledge production and have to ask what it means for our conception and understanding of knowledge. The question of knowledge and innovation is important not just in the realm of epistemology. It is of very practical impact, for example in the light of the underlying legal concepts of current funding rules, of scientific classification, of administering, funding, and understanding science. It simply reflects the modern renewed interest in knowledge, in science, in policies to further science, education, knowledge-based economies and societies.

For these reasons, this thesis aims to improve our understanding of knowledge as society shifts to an innovation society (cf. Drucker 1994, Hutter et al. 2015). It focuses on:

- the changes happening in processes of knowledge generation that are oriented by the pursuit of innovation
- a political, economic and social shift from science to innovation
- knowledge arising from technologically supported innovation and process
- technical knowledge as a consequence of the pursuit of research with clear action objectives in mind.

We will identify **the following main changes** induced by the shift to innovation:

1) a sub-conceptualization and de-individualisation of the conceptual knowledge base, i.e. its de-expertization (by means of automated knowledge discovery and collective epistemic processes)
2) a goal-oriented conceptualization following equivalence classes under an action-oriented learning function leading to anticipatory interaction models
3) social (economic) valuation and its prediction as a part of the knowledge processes
4) the rise of the importance of time in relation to knowledge

1.3 Objectives

The general motivation of this study is to improve our understanding of potential consequences of the current trend to emphasize innovation in processes that contribute to the creation of knowledge. This concerns not only science and research including development, but also research policy, and to some extent the management of research. The focus in this work is on the precise character of knowledge in the context of technological market innovations. In particular, we are interested in changes induced in the conception of knowledge as we put the emphasis on using knowledge in order to create novel products or services, for example based on new technologies or new research. Therefore, this dissertation examines models of processes of knowledge production in which this knowledge is created for purposeful action; because of its importance, a specific focus will be on the so-called linear model.

My specific research question is *to examine the extent to which a constructivist approach can mediate between a logotheoretical conception of knowledge and a technological conception of knowledge.* We use a framework from system science, namely from the area of anticipatory systems to describe and apply a biosemiotic and constructivist model of dynamic processes of constructing opportune knowledge. The model locates knowledge in a mediating position between observation and action and helps to clarify ontological consequences of the success-driven, functional construction of knowledge. In addition, it will help to identify fundamental shortcomings in the linear model of innovation. The model-based framework developed in this thesis can also improve our understanding of recent debates about the primacy of technology over science. The more general aim is to contribute to the current debate about technoscience and to discuss an innovation-oriented knowledge concept, and also to understand current innovation-driven epistemic technologies, and to discuss the relation of these concepts to the notion of utility as a central term in technology.

The objectives are clearly not to develop a complete theory of knowledge nor are we going to discuss all historic conceptualizations of knowledge in the light of innovation. But it is the aim to improve our understanding of knowledge affordances in technoscientific contexts that discuss innovation. In addition, we aim to improve the understanding of the linear model of innovation and that of technological research in general. This discussion will take us to general questions about knowledge and its validity, about timely knowledge and the role of knowledge technologies in society.

1.4 Methodology and target audience

The approach chosen in this dissertation is primarily constructivist. I will make use of an abstract constructivist model to clarify the consequences and implications from a system-theoretic perspective as knowledge is studied and developed for specific technical purpose.

From a methodological perspective, the main contribution of this study should arise from the effort to study knowledge, knowledge products, technology, and innovation from a range of disciplines and from the integration of the different perspectives.

The study should be of importance to experts in the field of research policies and support critical reflection of the sometimes-confusing language used today to discuss practical impact of science in society. Empirical contributions arise from studies on innovation technologies and also from the study of research programmes. As a research manager and innovation consultant, the author is particularly interested and experienced in current state-funded research and also in research policy and the narratives used to justify investments in research today.

This thesis draws from a range of disciplines. It is positioned at the intersection of epistemology, the theory of science, economics, systems theory, innovation management, innovation policy, technosciences and biosemantics. Although our motivation arises from the claims made in research management, we will argue along philosophical lines of thinking. In particular, we will examine exemplary positions developed in epistemology and put them in relation to innovation and knowledge.

1.5 Structure of the thesis

Unsurprisingly, this thesis starts with a closer look at the basic concepts, in particular of knowledge, innovation, and technology. As knowledge for innovation implies a market-based perspective, the concept of knowledge is put in the context of theories of the knowledge-based economy. Knowledge to realize new products and services is akin to technical knowledge and the chapter therefore also explores technical aspects and the way from knowledge in research to its application something called the linear model. It details how knowledge in basic science eventually leads to technical rules. Chapter 2 concludes with an overview of different functions of knowledge. This completes the first level of analysis, i.e. the shift from knowledge in basic science to goal-oriented knowledge in engineering. The second level of analysis examines today's technologically mediated knowledge production in Chapter 3. It discusses the technological acceleration of research and innovation by means of information and communication technologies and the underlying characteristics of IT-supported epistemic processes.

Chapter 4 takes a closer look at knowledge creation and utility. It examines this connection in four different historic epistemologies, namely positivism, Marxism, pragmatism, and constructivism. Chapter 5 presents a constructivist and biosemiotic model of action-based knowledge acquisition and a discussion of the impact on the characteristics of knowledge in such a model. There is a short path from the concept of utility to the notion of value. Chapter 6 therefore also discusses the value and relevance of knowledge. This is a topic of particular interest in the funding of knowledge production and for different funding frameworks. It should not be surprising that this also relates to the question of power and knowledge.

A claim of this thesis is that aspects of time have not received sufficient attention in epistemology to date. This is surprising since time is indeed a central concept in funding frameworks, but also in the practice of knowledge creation. Because of the importance of gaining knowledge in time, it is also covered in Chapter 6. Chapter 7 takes the notion of knowledge as a tool one step further and puts it in the context of phenomenological analysis and contemporary accounts in the philosophy of technology. In particular, it studies the relation of practical knowledge as a tool and ontology. It also puts knowledge-things in the context of the works of Heidegger and contemporary techno-scientific discourse such as the question of the causal relation between science and technology. The thesis concludes with a summary and pointers to limitations and open problems.

Figure 1-2 provides an overview of the structure of the discussion in this document. The aforementioned constructivist model will be a point of reference for the discussion and serves as a model for the process of technoscientific constructions of knowledge.

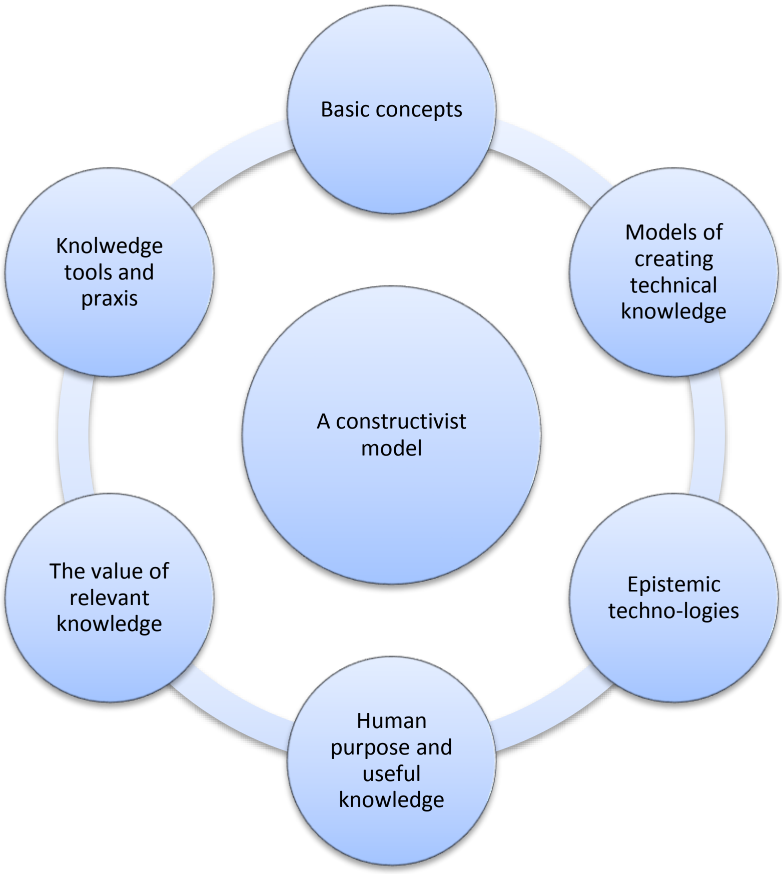

Figure 1-2 Aspects of knowledge and innovation discussed in this thesis. A constructivist model of opportune knowledge is the central concept for the study of epistemic processes and technologies, human purpose, value and relevance and knowledge tools.

2 The basic concept: from knowledge to innovation

2.1 The concept of knowledge

In this thesis, we investigate knowledge in an effort to generalize over a range of systems of which we commonly say that they *know*, such as animals, humans, enterprises, universities, science, the state etc. It is widely agreed today among philosophers that the nature and definition of knowledge is a matter of ongoing discussions; knowledge is an *"essentially contested"* concept (Adolf & Stehr 2014, p.12). In addition, our understanding of knowledge has dramatically changed in recent decades, for example with the advent of constructivism. For example, these changes have had major impact in theories of learning and teaching (Carter 2008). Also, the use of knowledge as a key concept in the explanation of phenomena has grown dramatically. It is nowadays not only important for epistemologists, but also for business managers, economists, computer scientists and experts from many other disciplines. In particular, knowledge has become a key concept in disciplines studying human behaviour from psychology to sociological studies.

Given this broad range of disciplines, it is hardly surprising that knowledge as an explanatory theoretical term has come to mean rather different things. Knowledge can be understood as something cognitive and belief-like that connotes wisdom and information; or it can help to explain action and is explained as resulting from interaction. These two aspects of knowledge need not be in contradiction as often something cognitive will facilitate action. Many theories however seem to put more emphasis on one aspect than the other as we shall discuss further below.

In this thesis, we will focus more on knowledge as something that arises from interaction with the world and facilitates interacting with the world. Such interaction includes playing a musical instrument, performing experiments in high-energy physics, or cooking a dish following a new recipe. It also includes reading a book, attending a class at school and taking a driving lesson. In line with the characterization of Adolf & Stehr (2014, p.22), knowledge is *"a generalized capacity to act"* and is used as *"a model for reality"*. In this study, we are less interested in whether such knowledge can be explicitly stated or is only tacit (Polanyi 1966).

Thereby, this investigation aims at a broad conception of knowledge that includes not only animals as knowing agents, and obviously humans, but also artificial systems such as firms, computers or robots. Indeed, modern conceptions of knowledge are extremely broad and range from its version in traditional epistemology where it is usually defined as *justified true belief* to the vast amount of knowledge said to be stored in libraries and, nowadays, in electronic form somewhere in digital systems worldwide. The former roots in Plato's discussion of knowledge in *Theaetetus* while the latter is more appropriately called *information,* cf. (Adolf & Stehr pp. 25-27). In the area of knowledge management, the DIKW pyramid was suggested to better delineate some knowledge-related terms. This pyramid puts (i) data before (ii) information which is the basis for (iii) knowledge eventually leading to (iv) wisdom (Ackoff 1989, Sharma 2008). It has been suggested that moving from (i) to (iv) adds connectedness and understanding (Belinnger et al. 2004) by first understanding relations (i)-(ii), then understanding patterns (ii)-(iii) and finally understanding principles (iii)-(iv). Belinnger et al. (ibid.) give the following example of a pattern: *"If the humidity is very high and the temperature drops substantially the atmosphere is often unlikely to be able to hold the moisture so it rains."* We will discuss in more detail below in Section 2.5 how such scientific knowledge relates to action.

In our effort to study different systems that are capable of knowing, it is necessary to use a broad characterization of knowledge, in particular we will understand knowledge as something that facilitates successful action and interaction with the world. Such knowledge is not concerned predominantly with the description of an image of reality and it is particularly not focused on argumentation for explaining states-of-belief. The classic notion of *justified true belief* in epistemology and analytic philosophy (Ichikawa & Steup 2017) mostly applies to human knowledge. In this thesis, however, the aim is to also discuss organizations, companies or scientific disciplines as knowledgeable. This is why the emphasis here is not so much on *justified* knowledge although we will come back to this important issue. A slightly softer version is *reliable belief* that acquires trustworthiness because of the process leading to the belief or because we trust the speaker, cf. (Zagzebski 2003, Craig 1990; Section 6.2.1)

There are very different types of knowledge. Those that will be most important in this document include the following:

- *Scientific knowledge*, in particular knowledge in natural science, but also in the humanities. This is knowledge acquired in scientific research and critically discussed in scientific discourse.
- *Technical knowledge*, in particular technical principles in order to achieve objectives by technical means. This includes knowledge produced in engineering in order to design artefacts for human problem-solving.
- *Knowledge as an image of reality expressed in symbolic form*, e.g. in language with the aim of describing, predicting and understanding the world.
- *Knowledge as something that enables action* in the world as mentioned above. This is knowledge that may or may not be linguistic. It includes knowledge acquired by organisations, animals or the state.

Throughout this thesis, we will be using "opportune" in the sense of practically useful for specific expected outcomes. *"Opportune knowledge"* will refer to practically useful knowledge in this sense.

Non-practical knowledge

This list seems to suggest that knowledge is mostly something practical, but as a term "knowledge" is used in a much broader sense. Sometimes knowledge is understood as education, i.e. it is attributed to people who are cultured, sophisticated, well-educated following a programme of human self-formation. Such knowledge is attributed exclusively to humans and it is related to cultural objectives, but also critical thinking, and general societal competencies. Although knowledge gained in education may without any doubt be useful in certain situations, precisely its use is usually not in the foreground, cf. (Barnett 1994). Paradoxically, an emphasis on useful knowledge in education is sometimes even considered detrimental in discussions that focus on knowledge and education. It is just not clear to what end and at what time knowledge acquired in education, during the formation of one's mind, actually becomes useful. Knowledge in education often plays a role as *reservoir* knowledge – or perhaps better – as an enabler of competencies. An often heard argument is that such knowledge should also equip the educated person with the capacity to question things, to argue, and to critically reflect. (Cf. the discussion on the controversy regarding operational versus academic competence in (Barnett 1994).) This type of knowledge has been called spiritual by Scheler (Scheler 1980, Good 1974, p.597). He famously distinguishes spiritual knowledge ("Erlösungwissen") carried forth in religion, cultural knowledge ("Bildungswissen") administered in philosophy, and knowledge of control ("Herrschaftswissen") targeted in positive science. In the context of bringing new solutions to the market, we will be mostly interested in knowledge of control.

An important aspect about knowledge of control is that it is not necessarily specific to *homo sapiens* (cf. Good 1974). Indeed, this is what makes this type of knowledge interesting in this thesis given that we consider a broad range of systems that are at least colloquially attributed knowledge. As early as 1974, Good points to cybernetic theories of knowledge, learning and epistemology that aim to explain "*the complex process of insight based on the model of the 'conditional reflex'"*, clearly an animal model of behaviour.

The analysis of practical knowledge

From the point of view of science and technology studies, the analysis of knowledge and science in the context of innovation that we perform in this thesis implies that we are to investigate science after its post-Kuhnian *practical turn* (Soler et al. 2014). Apart from the massive consequences of technology on science which we will revisit later, it is now often argued that scientific knowledge provides the basis for human technological activity. Therefore, much research is directed at the production of technoscientific knowledge that carries clarity about its potential use. In the research world today, research programmes are often instruments of research policy (Ihde & Selinger 2003, Aronowitz et al. 1996). These funding programmes specify specific programme objectives. As a consequence, much research work funded by such programmes is explicitly argued to be practical. In most cases this usefulness is not limited to an abstract understanding of phenomena or the use of research results in explanatory theories, i.e. basic research. More often, usefulness is argued with respect to societal impact, economic benefit or other policy objectives. Interestingly, these arguments concern knowledge targeted in research even *before* its creation. These claims are made in research proposals where it is argued at length as to why this specific knowledge will be useful and achieve "strong and durable" impact.

2.2 Innovation

Innovation is often defined as *a new idea brought to the market.* In economics and business management, the term is connected to Joseph Schumpeter's theory of creative destruction (Schumpeter 1943). Schumpeter, who studied and elaborated on Marxian economic theory, suggested that creative forces internal to economic entities constantly lead to new economic structures that also replace the old ones (ibid.) Innovation therefore should be regarded as the core driving force of an economic evolutionary process (ibid., pp. 81-84). Such a process strives to create growth from increasingly effective processes, improved products and business models. Improvements in the utilization of factors, and also improved products will often originate in technological improvements, i.e. they are related to knowledge and technology (Antonelli 2003). Innovation therefore is the main explanation for total factor productivity growth over extended periods of time in innovation economics (Antonelli 2003, p. 5).

Similar to knowledge, the conceptions and definitions of the notion of innovation vary considerably (Edison et al. 2013). Innovation is a term that has now also come to be used in a range of disciplines including philosophy, business management and economics. It is therefore not surprising that there are considerable differences in what precisely constitutes an innovation. Edison et al. (2013) list over 40 definitions of "innovation". Quintante et al. (2011) have pointed out that innovation has been studied with a focus on either the process or its outcome. They list about 30 publications that use either process- or outcome-based definitions of innovation with or without explicit reference to knowledge. An example for a more traditional, process-oriented view is: *"the technical, design, manufacturing, management and commercial activities involved in the marketing of a new (or improved) product or the first commercial use of a new (or improved) process or equipment"* (Terziovsky 2010). This contrasts with an outcome-oriented definition such as *"the first or early use of an idea by one of a set of organizations with similar goals"* (Daft 1978). Finally, examples of a knowledge- and outcome-oriented definition are *"a problem-solving process in which solutions to problems are discovered via search"* (Dosi 1988) or *"…innovation can be viewed as recombination of existing knowledge"* (Basalla 1988, Schumpeter 1939) or *"the creative application of knowledge to increase the set of techniques and products commercially available in the economy"* (Courvisanos 2007 p. 46).

The essential feature of innovation for our aims here is the fact that it refers to **novelty that is put to use** – usually by a customer buying a novel product or using a new service. In this sense, this definition combines features of novelty[2] and its application (Maranville 1992). It is an invention commercialized. When talking about innovation in this thesis, we usually refer to innovation as an outcome, i.e. new ideas, combinations, solutions or products and processes. The reason for using an innovation may be an underlying purpose or need. Interestingly, the innovation literature does not often explicitly refer to such purpose with which customers may use an innovation. Purposeful use is mostly implicitly assumed. The distinction from mere inventions is important in the academic discourse on innovation (see the clarification already published in the 50s, (Ruttan 1959)), but the focus in innovation research is often a user need or *pain* rather than purpose. This means, despite the fact that innovations require purposeful use, purpose itself is barely discussed in the innovation literature. The issue is, however, discussed in design-thinking and related discussions such as design-driven innovation (Verganti 2009). In the economic and management literature purpose often appears as user satisfaction or in aggregate form as market demand.

A strong focus in today's discussions of innovations lies on *technological innovation*. Such innovations may arise from novel technological capabilities, but more generally includes novel ideas for improved products, services, business processes and business models (Dodgson et al. 2008). Technology is often regarded as directly linked to knowledge, cf. the definition of technology in (Dodgson et al. 2008, p.2): *"Technology is a replicable artefact with practical application, and the knowledge that enables it to be developed and used. Technology is manifested in new products, processes, and systems, including the knowledge and capabilities needed to deliver functionality this reproducible."*

Therefore, in the innovation context, knowledge is regarded as an entity that facilitates creativity and technical realization, primarily in economic activity, i.e. knowledge that leads to new products and services. While not all economic success is based on new knowledge, a widely-communicated assumption today is that innovation and new knowledge are intimately related. (Quintante et al. 2011) refer to authors such as (Damanpour 1991) and (Van de Ven 1986) who conceptualize innovation without explicit reference to knowledge,

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[2] Merriam-webster.com, retrieved May 2017.

while (Galunic & Rodan 1998) and (Nonaka and Takeuchi 1995) are prominent speakers for the importance of knowledge in innovation. Finally, the feature that distinguishes innovation and invention is that the former has not only proven useful – in particular in business, but more recently also in the public sector; cf. (Dosi 1988) and (West & Farr 1990).

(Quinante et al. 2011) even propose to define innovation as the *"creation of new knowledge that is necessary to replicate the process leading to innovation outcomes."* In their definition, such knowledge must be (i) duplicable, (ii) new in the context, (iii) introduced in practice and (iv) demonstrated useful. Disregarding the circularity in this definition, the identification of an innovation with knowledge can be useful in contexts that study knowledge management processes for innovation. We propose to stick to a simpler view where the innovation refers to the new product or processes – and where the above characteristics of novelty, duplicability, practical context and usefulness all apply as well. This definition is aligned with *"[a]n invention which has reached market introduction in the case of a new product, or first use in a production process, in the case of a process innovation"* (Utterback, 1971, p. 77).

2.3 Knowledge for purposeful action: technical knowledge

Both the definition of innovation and the arguments for a knowledge-based economy suggest focusing on investigation of knowledge and innovation on knowledge that facilitates reaching objectives with specific means – either at the individual or economic level. This is usually termed "technology". Indeed, technological innovation is without doubt one of the central forces driving research and also science today (Stokes 1997). Engineers are at the forefront of delivering product innovations using new technology. Engineers are also involved in service innovations in close collaboration with marketing departments of their companies. The relation of knowledge to its eventual application is much more explicit in the field of technology than in other areas of science and research where this relation is not always clear. For example, the identification of the precise maximum force that can be applied to a silicon wafer before it is damaged, may facilitate the construction of a safe wafer transportation system in a straightforward way – although it does not strictly speaking provide information as to how such a system should be built.

Knowledge for purposeful action is usually called technical knowledge where it is understood as something that enables the solution of practical problems. For example, Banse & Wendt define technology (*"Technik"*) as the things and processes that humans create, use and reproduce in such a combination and form so that their properties effectuate (under certain conditions) in conformity with human objectives (Banse & Wendt 1986, p.12). The objects of technical science (i.e. technology) then are existing technical systems and their design and behaviour, components, materials, etc. (ibid., p. 15). Technical knowledge includes both assertions (statements) about systems and their properties, but also instructions about what to do. In line with other modern philosophers of technology, (Gaycken 2010) emphasizes that the development process in technology is not just simply *using* knowledge, but actually should be seen as *guiding* the search for a solution. Interim results during such a search process may after critical examination often result in the formulation of knowledge. The resulting process becomes circular and may often stop for pragmatic reasons, but not because a final or optimal solution has been found. Importantly, technical science is not just about the design of artefacts or only about technical principles. As Gaycken rightly points out, the interest in the technical science is *epistemic* as it targets knowledge (ibid., p.16), even if this sometimes includes "knowledge" about objects that do not yet exist, but will be constructed as a result of such anticipation and imagination (Ropohl 1997, p. 69).

Not all technical knowledge consists of application-oriented principles. (Lindemann 2004) lists four specific types of technical knowledge: (i) factual knowledge (know that), (ii) knowledge about relations (know why), (iii) action knowledge (know how), and (iv) knowledge about sources of knowledge (know where). Another conception of technical knowledge (Grunwald 2004) describes it as schemata for producing and using technology. The role of technical sciences then is to make such schemata accessible for various and new kinds of contexts. Finally, (Ropohl 2004) distinguishes technical know-how, knowledge of functional rules, knowledge of structural rules, knowledge of technological laws and eco-socio-technological knowledge about systems. In targeting innovations, the focus will be on technical know-how, but it is clear that the other types of knowledge are important for real-world success, e.g. concerning application contexts, economic aspects, regulatory frameworks, social acceptance etc.

To many philosophers outside the philosophy of technology it may come as a surprise that the references to the philosophy of technology are fairly recent. This is startling as one might naïvely assume that the question of what we mean by technical knowledge is either straightforward or has been long and exhaustively discussed, perhaps since Artistotle's work on practical or technical work, τέχνη and πρᾶξις. Although technical artefacts may be as old as mankind, the term *philosophy of technology* is only 150 years old (Nordmann 2008, p.9). As regards the specifics of technical knowledge, the disinterest of epistemologists in specifically technical knowledge may be traced back to Aristotle and perhaps Plato (Ihde 1979, pp. xviii ff.) Aristotle's basic distinction of causes acting in natural science from those relevant for creative activity (i.e. πρᾶξις or τέχνη) led scholars to study knowledge mostly in the natural science in an effort to unveil nature's principles. Technical knowledge on the other hand appeared much less fascinating as its source and principles are of human origin (Nordmann 2008, p. 34). In parallel to and driven by the appearance of a techno-scientific understanding of research, the sources of technical knowledge became much more interesting. This makes it necessary to take a closer look at the sources of technical knowledge as a basis for innovation.

2.4 Models of generating technical knowledge

2.4.1 Sources of technical knowledge

In their discussion of technology creation, (Banse & Wendt 1986, p. 33) identify three main factors for technical inventions: (i) natural law as the ever-present boundary condition, (ii) the state-of-technology and of society that points to what can be done in reality, and (iii) the (societal) goal. The question then arises how to acquire technical knowledge, i.e. how are we to arrive at the actions required in order to achieve selected objectives by technical means?

Two rather different approaches to this challenge are possible. The first one is to study actions and their effects directly and remember which actions led to desirable effects so as to reproduce these actions whenever we would like to reproduce the effects. This strategy would apply both when performing the actions or when imitating someone else who masters a technique to achieve the desired results. The second approach– based on science – would be to understand nature, predict its behaviour by studying causes and effects and then take actions leading to the intended effects through the application of the necessary causes. Obviously, the main difference between these two approaches is that one focuses on modelling components of nature, as well as causes and effects, while the other strategy makes no comparable effort and instead focuses on merely reproducing previously successful actions. For the sake of completeness, there is another strategy: we could just act randomly and hope to generate the right actions. Disregarding this last strategy, the differences between a modelling approach and reproducing actions are potentially small, if the connection between action and reaching a desirable state is immediate. But the longer the time lag between action and success, or for complex sequences of interaction, pure observation may become hugely challenging. This would make the scientific option – modelling actions and effects based on prediction of consequences – our primary choice. This way of looking at the creation of novel solutions to problems has come to form the basis of the so-called *linear model of innovation*.

2.4.2 Linear models: from knowledge to its application

In the context of innovation, the *linear model* is one of the earliest process models describing how, eventually, an invention leads to its success on the market. The precise historical origin of the model is not fully clear and it has developed at least partially in parallel in at least three distinct fields of scholarly research (Godin 2005). Firstly, a philosophical and to some extent political investigation into the difference and connection of pure and more applied research led to establishing a causal connection between basic and applied research. Godin identifies academic organizations lobbying for research funding as a main driver at this stage. Secondly, a macroeconomic interest in national statistics and in particular in the statistics of scientific knowledge production provided the basis of the famous definitions of basic and applied research etc. used in the Frascati manual (see also Section 6.5). And thirdly, also driven by management research and (micro-)economics, the subject was covered from the point of view of innovation as an objective of company management. Godin suggests that the first of these three steps served to connect pure (“basic”) research with applied research; the second step differentiated but also connected applied research and development; and finally, the third step provided the connection with production, diffusion, and the market. This means that rather different stake holders and scientific communities added to the linear model (Godin 2009):

- Natural scientists and academic associations emphasized their contribution to applied research and in this way argued for their share of research funds
- Economists brought forth the concept of development and presented it to policy makers to improve research policies
- Business schools from the perspective of RTD management and technology development

In short, there are good reasons why the different communities had an interest to emphasize their potential contribution to technology and innovation, i.e. to argue that their research is useful beyond just improving our understanding of the phenomena under question. The linear model is therefore nowadays commonly described as leading from basic research to applied research to development and then reaching the market in the form of produced and delivered goods and services:

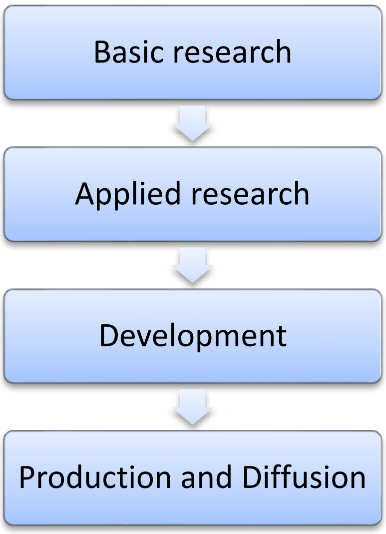

Figure 2-1 A prototypical (1st generation) linear model of innovation: knowledge developed in basic research eventually leads to new products through a process of applied research and product development, adapted from (Godin 2005, p.4). This version is a push-model as it "pushes" new research and technology to industry and on the market.

There can be no doubt today about how massively influential this view of science and technology development has become in policy making, but also far beyond in very different disciplines. The model has been termed a *"model of innovation", "a theory of knowledge production",* and perhaps to the surprise of epistemologists *"a theory of epistemology"* (Mahdjoubi 1997). Donald Stokes even called it *"a post-war paradigm for science policy"* (Stokes 1997). This means that the model appeals to scholars in epistemology, in business management, and in research policy at the same time. (Godin 2005) describes the parallel lines of reasoning in different research fields that all seek to make a causal connection between abstract, scientific knowledge with applied technical know-how and innovative, purposeful products.

Notably, the intentions in philosophy, business management, and economy may be quite different. The philosophical aspect lies in a justification for basic research as source of new products; the business aspect is to suggest guidelines for how to successfully create innovations, and in macroeconomic statistics and policy making the interest to discriminate potentially successful economic policies.

There are essentially two versions of the linear model: a push-model starting from the development of new knowledge including basic research and pull-models that argue for the importance of market demand. The pull-model is also sometimes termed a "*reverse linear model"* (Barbiere & Álvares 2016, p.5) and, according to Godin, was originally developed in direct opposition to the linear push model in the 1960s (Godin 2013).

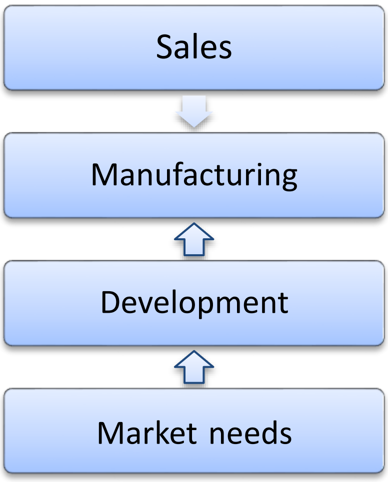

Figure 2-2 The pull-model of innovation: in contrast to the push-model, this version emphasizes the demand from the market as driving product development. The depicted version is Rothwell's variant of the diagram (Rothwell 1994), cf. (Godin 2013) or (Barbieri & Álvares 2016).

There is a broad range of versions of the pull model. The version of (Rothwell 1994, see Figure 2-2) only includes *"development"* before it connects to manufacturing. The version of Michael Martin maintains the sequence from *R&D* to *Production* and on to the market, but both *R&D* and *Marketing* receive input from *"expressed Market Need"* (Martin 1994. p.44). Another published version describes the sequence as "market research" -> "market need or requirement" -> "research and development prototypes" -> "marketing" -> "product sales" (Ryan 2013).

Godin explains in detail how the push-model disappeared from the literature – at least during a certain period in economics. This sudden disinterest was mostly driven by terminological issues with the term "demand" (need) that quite understandably created opposition from economists (Godin 2013).

More elaborate models of innovation in firms focus on more complex interactions between the agents, e.g. customers, research organizations, suppliers etc. Therefore, they contain more references to those actors, but also add more connections between the actors and the various steps in the model, see (Barbiere & Álvares 2016) for an overview. In total, (Rothwell 1994) describes five generations of innovation from technology push to system integration and networking. Similarly, (Barbiere & Álvares 2016) provide a scheme of five generations (and proposes a sixth).

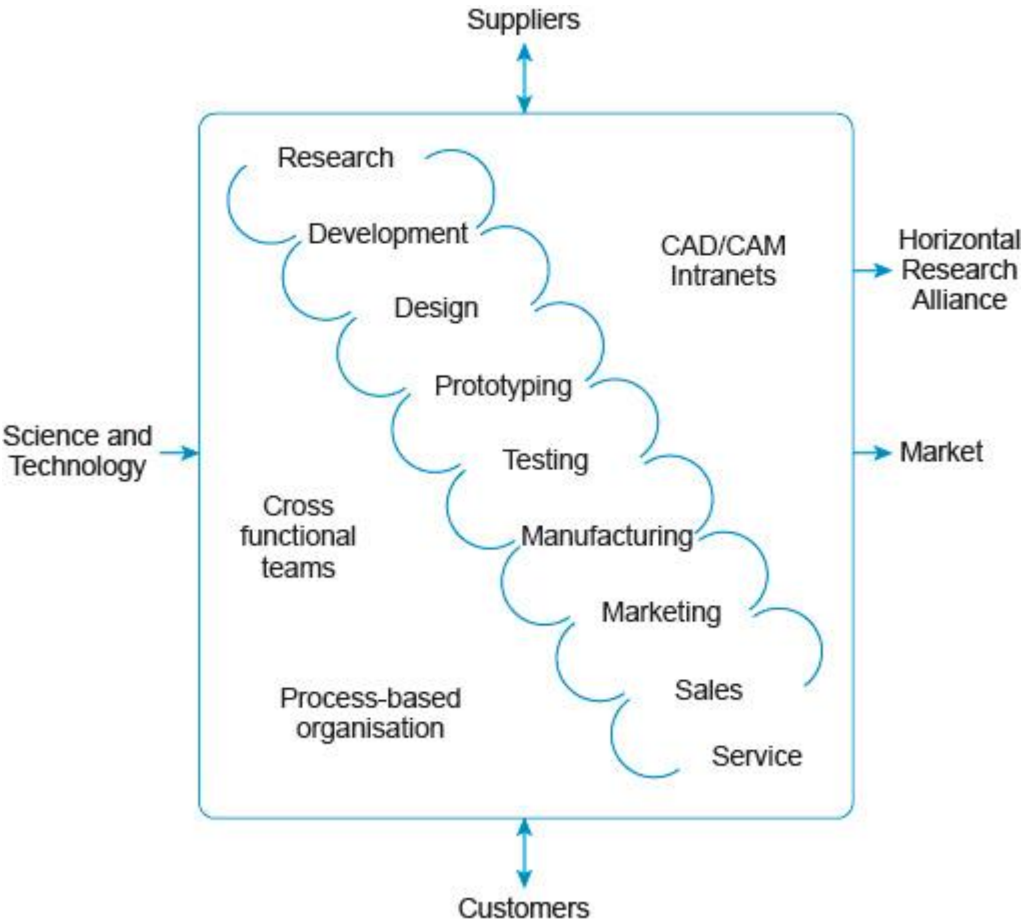

Figure 2-3 In the fourth-generation model of innovation (Dodgson & Gann 2008; source: http://www.open.edu), a linear path starting from research is still clearly visible. However, the model puts more emphasis on interactions with various actors and stakeholders such as academia, research, suppliers, customers etc. There are also first indications of what later become innovation technologies (CAD/CAM, Intranets).Reprinted with kind permission from Oxford University Press.

In such models, the connection with science and technology and the interaction with the market are both important interactions, but so is a strategic and technological integration with customers, suppliers, innovation communities and a broad range of networks. The innovation process itself is described as driven by an explicit innovation strategy and a dedicated high-level organisation and technological integration. A closer look at the fourth-generation model (Figure 2.3) reveals that there now seems to be a twofold linear path from science and technology to the market, namely left to right and more detailed within the box from research to service.

Dodgson & Gann (2007) added a sixth-generation model in which the linear aspects of the model, but also the integration with market and network partners are supported or even realized by means of information technology, cf. Chapter 3. Note however, that these connections are now bidirectional and therefore suggest that market needs have become important for science and technology.

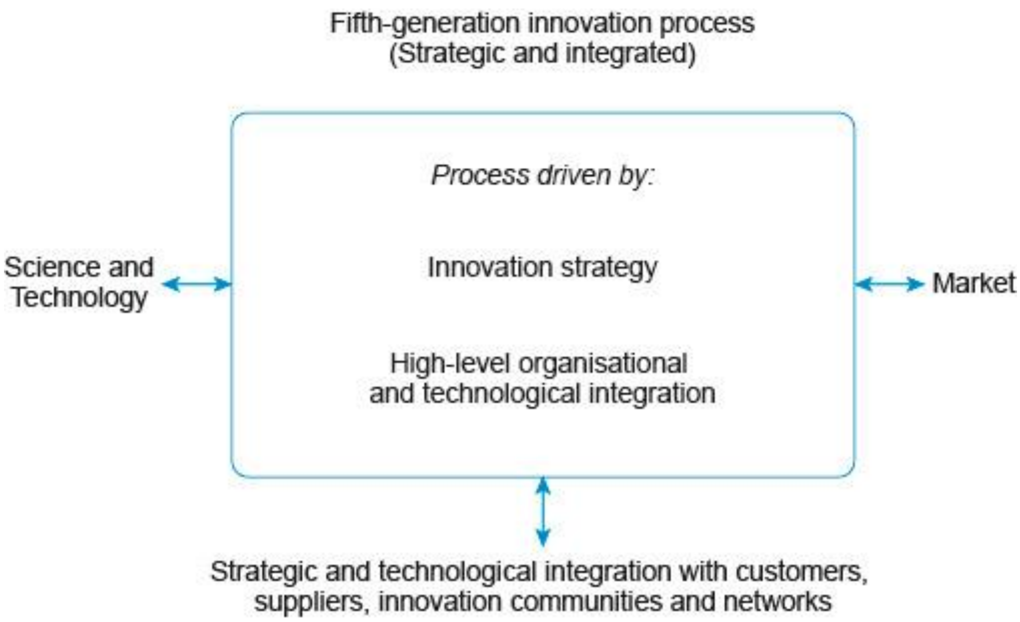

Figure 2-4 In Dodgons & Gannt's (2008) fifth-generation innovation process model, the linear structure is no longer explicitly depicted. Instead, the emphasis shifts to the integration with various actors and a more strategic view. Note however, that the model still suggests "Science and Technology" and "Market" as significant start/end points, albeit with bidirectional arrows. (Source: source: http://www.open.edu) Reprinted with kind permission from Oxford University Press.

In economic textbooks, the linear model (often in its simple first-generation form) still prevails (Zeilhofer 1995, p.101) in conjunction with the idea that basic research produces scientific knowledge that is not goal-oriented, at least not oriented towards any application of this knowledge. The following schematic (Figure 2-5) describes this point from the perspective of knowledge. Basic research produces scientific knowledge, such as models of natural systems, predictive theories and explanations of natural phenomena. Despite some confusion around the linear model, there is today broad agreement that basic science produces general knowledge, in particular an understanding of *"nature and its laws"* (Edgerton 2004). On this basis, a process of applied research results in technical knowledge and technology. This in turn – using a process called development and innovation results in knowledge about all details of the production process and its business side including market aspects.

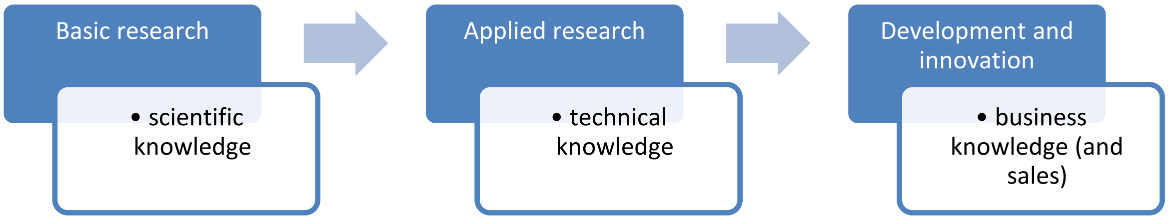

Figure 2-5 The sequence from scientific knowledge to business knowledge as implicitly proposed by the linear model.

Such a view, as Zeilhofer (ibid.) rightly argues, leads us to belief in a mono-causal explanation for technological change and it would severely limit the options for intervening in the linear process from basic science to innovation. The more complex models of innovation, however, emphasize that there are also other important sources of innovation – not just research and technology. We will return to the question of transforming one type of knowledge in the other in Section 2.5; first let us take a look at critics of the linear model.

2.4.3 Critics of the linear model

Both the linear model and the claim that technology is applied science have come under strong criticism in recent decades (most notable since the 1990s). This development emerged from at least three rather different perspectives: Historians of technology argue that science in general is clearly younger than technology. Epistemologists in the area of the philosophy of technology contend that the transformation from knowledge in basic science to technology is not a straightforward process. And thirdly it can be claimed that praxis and utility are ontologically prior to science. We shall revisit the last point towards the end in Chapter 7 and first take a look at the other arguments:

That technology is not in fact merely applied science is a recurring topic in contemporary philosophy of technology, for example in the works of Don Ihde in America and German philosophers of science such as Günther Ropohl, Hans Lenk and others. And more generally, the question of what precisely is the relation between technology and science is central to recent work in the philosophy of technology, e.g. (Ihde 1990). De Solla Price is particularly strict in his assessment of the role of science for technology when he says that *"[a]ll that seems clear is the inadequacy of the naive idea that somehow or other science can be 'applied' to make technology"* (De Solla Price 1984, p. 105). De Solla Price sees no use for the concept of "application" of basic science for technology in the history of science. He suggests that the statistical disaggregation of high-level research efforts into the three categories (basic research, applied research, development) are mainly artefacts of definitions *"rather than any illumination of the chain of action in which they are supposed to be linked"* (ibid.).

Ihde calls the idea that technology is applied science harbouring *"a latent ontological judgment, a judgment which I shall call the philosophic preference for 'platonism'"* (Ihde 1979, p. xviii). Don Ihde has called philosophical theories that put action in the centre of analysis and of theory *praxis philosophies* (Ihde 1979). For him, such theories embrace perception and embodiment (p. xix). As opposed to praxis philosophies, platonistic theories are less interested or even negate perception and embodiment (as "lower" capabilities) and focus on pure conceptuality (p. xix). Ihde describes how this contemptuousness for knowledge that is closer to sensory perception is already visible in Plato's cave: *"True knowledge is knowledge of the forms or ideas which are supposed to be free of all taint of embodiment. Functionally this scheme downgrades both perception and embodiment."* (Ihde 1979, p. xx)

Another central argument is that such a claim is simply historically wrong in that technology actually precedes science. However, the claim (e.g. Scharff 2006) that *"these facts are acknowledged by almost everyone not still suffering from the old reconstructionist orthodoxies"* may be wishful thinking given the enormous number of policy papers, research management documents, conference sessions etc. that suggest precisely that technology arises from the application of science. Even if Scharff argues that *"…for as long as there has been a desire to know, there has only been 'technoscience'…"* the arguments of policy makers – and of a large number of natural scientists – read differently. The truth is that the linear model (in fact its first-generation version of technology push) is hugely important today. The linear model is simple, but persistent. In research policy papers, it resists even massive criticism for its simplicity and in fact substantial doubts that it depicts any actual scientific processes. Edgerton (2004), who calls the model a *"model of* *innovation"*, claims that the academic literature in the 1990s used it mostly as *"something that was surpassed, criticized, to be moved beyond."* Note that the previously mentioned model of (Dodgson & Gann 2007) clearly contains a reference to the simple linear model – even if (Edgerton 2004) claims that no one actually believes in it. Godin (2005) provides another overview of the history of the linear model and calls it *"a political narrative"*. And indeed, it has been taken up in science and research policy even if it is today often accompanied by a disclaimer that science is not such a simple process. As an example, Tait & Williams (1999) describe a 'linear plus' model to overcome shortcomings arising from regulation that enforces a linear RTD policy approach. It is in fact credible that hardly any academic study argues in favour of the linear model as a plausible account of how innovations are actually produced in most cases. Most accounts today attribute the popularity of the linear model – at least in research policy – to Vannevar Bush's text entitled *"Science – the endless frontier"*. Suffice it to say at this point that – so goes the argument – the linear model supported the justification of funding for basic research as it would eventually lead to innovation. Edgerton (ibid.) emphasizes that Bush was focused on public funding of basic science rather than a model of science or innovation.

Scholars in economics, management and the philosophy of science have pointed out the oversimplification underlying the massively complex processes in transforming results of basic research into innovations. Arie Rip (1992, quoted from Edergton) summarizes: *"That technological innovation derives from scientific discovery, as it were in a linear sequence, is a myth, but a prevalent myth. As a myth it is tenacious because of its links to important legitimations of science as the horn of plenty, and of technology as the magic wand. The linear model has some truth in it, but it hides more than that it helps our understanding."*

The linear model usually depicts industrial research somewhere in-between application and basic research. Applied research is concerned with the development of applications. This suggests that in such research, fundamental knowledge from basic research would become somehow applied to real-world problems. However, as we shall argue below, such an application is not straightforward and of course this does not imply that *all* basic research leads to application. Vannevar Bush may be said to have used a *reservoir model of science* (Rip 1992) in which basic research first produces knowledge that can then be used off-the-shelve as need be. Summarizing, many scholars today believe that the linear model from basic research to applied research and innovation roots in and functions as a *political narrative* that is used in research policy and in particular in accounts fostering the funding of basic research. On the other hand, it would obviously be wrong to deny completely that applications can arise from the study of basic research. Frequently cited examples connect research in physics, e.g. in the area of semiconductors to innovations such as lasers and microelectronics.

Turning this perspective upside down, historians of science have pointed out that there is today a technological conception of science, e.g. Laudan (1995) and Koenig (1996), something that has been called "*technoscience"*. Not only has science become reliant on technology for its own advance, but *what constitutes advance in science* is now often considered to be technological progress which in turn is at least partially measured through innovation, i.e. as applications appreciated by the market. Merton (1938) (quoted after Etzkowitz & Leydesdorff 2000) argues that between 40% and 60% of 17th century discoveries originated in real-world problems in navigation, mining etc. This should be also in line with Edgerton's appeal: *"In studying science in industry we should start with the literature on industry, not academic science, and in particular from literature that is not driven by academic research model assumptions."* (Edgerton 2004, p.20)

In summary, there seems to be evidence for both versions of the linear model, i.e. the push- and the pull-variant. In particular, there is at least one exception where the connection between basic research and application becomes explicit: it is in the field of technical sciences where basic research results are most clearly directly related to applications. To make things appear even more complicated, scholars of the development of technology have pointed out that technologies may develop in complex trajectories that are non-linear and often culturally embedded. For example, Don Ihde uses the example of originally Indian prayer wheels adopted as windmills in the West and the mostly only local use of windmills in Iran and Afghanistan to shed light on the cultural embedding of technology in general and of technology transfer in particular (Ihde 1990, p. 127).

2.4.4 The call for technoscience: knowledge for power

The call for science to be essentially useful, in particular for technology and technological innovation is not exclusively modern. Without any doubt, Francis Bacon already realized how important knowledge was for practical purposes and that such technical knowledge is not the same as knowledge from pure science. In fact, large parts of Bacon's Novum Organum (e.g. 2/L) read like a plea for better technical research. In order see *"a real increase in the power of man"* all sorts of forces, energies, transformations, i.e. all sorts of actions must be studied together with their consequences.

"Although the roads to human power and to human knowledge lie close together and are nearly the same, nevertheless, on account of the pernicious and inveterate habit of dwelling on abstractions it is safer to begin and raise the sciences from those foundations which have relation to practice, and to let the active part itself be as the seal which prints and determines the contemplative counterpart. We must therefore consider, if a man wanted to generate and superinduce any nature upon a given body, what kind of rule or direction or guidance he would most wish for, and express the same in the simplest and least abstruse language. For instance, if a man wishes to superinduce upon silver that yellow color of gold or an increase of weight (observing the laws of matter), or transparency on an opaque stone, or tenacity on glass, or vegetation on some substance that is not vegetable — we must consider, I say, what kind of rule or guidance he would most desire. And in the first place, he will undoubtedly wish to be directed to something which will not deceive him in the result nor fail him in the trial. Secondly, he will wish for such a rule as shall not tie him down to certain means and particular modes of operation. For perhaps he may not have those means, nor be able conveniently to procure them. And if there be other means and other methods for producing the required nature (besides the one prescribed) these may perhaps be within his reach; and yet he shall be excluded by the narrowness of the rule, and get no good from them. Thirdly, he will desire something to be shown him, which is not as difficult as the thing proposed to be done, but comes nearer to practice." (Bacon, Nov.org., 2/IV)

Remarkably, Bacon implicitly looks for *"guidance"* and emphasizes its technical purpose (e.g. inducing features on material). This guidance apparently is primarily linguistic in nature; it should consist in *"rules"* that are formulated clearly. And thirdly, Bacon understands that the question of means to achieve the technical objectives deserves particular attention: While it is true that "[h]*uman knowledge and human power meet in one; for where the cause is not known the effect cannot be produced" (Bacon, Nov.Org., 1/III),* it does not follow that all knowledge has power,*"Ipsa scientia potentia est.", (Bacon,* *Med.Sac.).* Today, some philosophers and researchers (and policy makers) seem to simply forget that we may very well know about causes and still be unable to produce the effects. But that knowledge is not necessarily power is also identified by Adolf & Stehr (2014). They argue it is *"at best, potential power."* Bacon seems to recall this, however, and we will revisit this in more detail in Section 2.5.

In any case, it is deeply rooted in our current understanding that what is true may also be useful, a relation that Kaldeway sees originating in Bacon's philosophy in particular (2013, p. 22). We may take Bacon's aphorism not so much as a statement about knowledge, but as an imperative about the objectives or the purpose of science, in the words of Thomas Hobbes: *"The end or scope of philosophy is, that we may make use to our benefit of effects formerly seen ... for the commodity of human life ... The end of knowledge is power ... lastly, the scope of all speculation is the performing of some action, or thing to be done." (Hobbes, De Corp.)* In this short quote, Hobbes makes at least three different claims to which we will return several times. Firstly, Hobbes connects previous perceptions of effects with the opportunity to fulfil objectives. Secondly, there is Bacon's identification of knowledge with power. And thirdly, Hobbes suggests that the performance of action or job-to-be-done is the end of knowledge or cognition. We should keep this in mind as it is a curious forward reference to a position that will be much more prominently held in neo-constructivism.

Origins of power from knowledge

In his short article on technology and truth,[3] Hans Blumenberg (1953) provides a remarkable historical account of how an original ontological precedence of *φύσις* over *τέχνη* becomes reinterpreted as the domain where human power can rule. In the end, this leads to the modern primacy of how things should be over the ancient understanding of being. Blumenberg starts from the ancient tradition in which nature is entirely self-sufficient and *"true from within itself"* (p. 42). Although *φύσις* carries a character of becoming this becoming remains inaccessible for humans – it only becomes accessible and therefore the basis for our conceptual knowledge by means of *τέχνη*. (Dupré 1993, p. 23) describes how

[3] *Technik und Wahrheit.*

the fact that for Greek thinkers nature was itself mindful, provided the rational condition of possibility for science. However, this basis was not yet rationalistic in the sense of the human mind uncovering the rational basis of nature, instead it simply ensured a logical quality of nature's behaviour.

A small, but important reinterpretation happens in medieval times where nature in principle upholds its original character although all things natural now arise from divine creation. Most importantly the biblical story of creation provides a technical account in two ways. Nature arises from an intentional act of creation in the sense of *τέχνη*. Blumenberg explains how putting nature as a *factum*, i.e. something that is made, also results in interpreting truth from the viewpoint of creation and therefore becomes *adaequatio rei et intellectus* (1953, p. 43). Although now, ontologically, an engineering act of creation precedes nature, the human mind is still considered incapable of grasping its divine order. For Blumenberg, medieval nominalism provides the basis for the final step towards a technical understanding of knowledge. Truth becomes contextualised in economic concerns and turns into the result of labour. Descartes becomes instrumental in turning the old principle where *only he who creates could know (solus potest scire qui fecit)* (Blumenberg 1953, p. 45) around so that knowledge results in possession and more precisely in possessing power over the object of knowledge, for example in experiments. This turnaround has massive consequences, not least for technology. *"The only reason why technology can be applied science is because this science originates from a technical conception of being and truth."* (Blumenberg 1953, p. 45, my translation).

It is evident that such a conception is of central interest today in a society that focuses on making better use of is knowledge for innovation. This has even become the mission statement frequently issued with current research programmes. For example, EU commissioner Janez Potočnik and Günter Verheugen motivate the EC communication on knowledge transfer between research institutions and industry as follows: *"In today's global world, generating new knowledge and turning it into new products and services is crucial to maintain and enhance the EU's competitiveness. Even more so, it is a precondition for sustaining the 'European Way of Life'. Innovation and excellence will positively impact on our lives in very different ways: through improved medicines, more efficient and sustainable energy resources, and with new technological solutions to protect* *our environment or to guarantee the security of the citizens. Transforming the results of scientific research into new commercial products is, however, a complex process involving a broad range of actors. We need to ensure that researchers and industry work closely together and maximise the social and economic benefits of new ideas."* (EU 2007) In this appeal, Potočnik and Verheugen not only emphasize the direct link from new knowledge to novel products, they also make it *"crucial"* for our way of living (in Europe). Although they call for the creation of new knowledge, it is solely described as important due to its transformation into products. In this way, they define a programme of technoscience in which a complex and challenging transformation of new knowledge becomes the main task of science.

This assumed intimate relation of knowledge and innovation has become the subject of a wide range of policies, in particular but not limited to economic policies and science policy (Bell 1973, Ihde & Selinger 2003, Leydesdorff 2010). The assumption that modern economies are productively *knowledge-based* is often traced back to work by the OECD (OECDE 1996) and (Abramovitz & David 1996). In contrast to the earlier focus on knowledge work and the role of tacit knowledge, the OECD at that time diagnosed a change of the character of knowledge towards increasing codifiability of knowledge (Foray 2007, p.246). As early as 1973, Daniel Bell highlighted the importance of theoretical knowledge and its central role for the post-industrial society. He foregrounded the increasing share of GDP that is generated by economic activities within the knowledge field (e.g. information services, consulting, research etc.), cf. (Bell 1973).

The emphasis on *codified knowledge* is central to the triple helix model as proposed in (Etzkowitz & Leydesdorff 1995). It focuses on the three types of organisations central to a knowledge-based economy: university, industry, and government. The "triple helix" defines the operating space for these organisations and thus serves as an analytical framework for understanding the dynamics of institutional interactions in a knowledge-based society (Leydesdorff 2000, Leydesdorff & Etzkowitz 2000). Knowledge is formally exchanged at the interfaces of organisations participating in the knowledge-based economy. More recently, based on this triple helix model, (Ranga & Etzkowitz 2013) have described a framework for innovation policy in the knowledge society. It suggests the description of (i) components, (ii) relationships, (iii) and functions or processes and the specification of the

“Knowledge, Innovation and Consensus Spaces” in order to improve national or regional innovation systems; cf. (Prem 2016 b) for an application and critical review.

An important reason for the focus on *codified* knowledge is the intention of the authors of the triple helix concept to provide an endogenous explanation of innovation in economics. Such a theory would not only aim to explain the dynamics within one subdomain, for example the economic sphere based on economic selection mechanism. It would also strive to explain the dynamics of government interaction and novelty production. This is why the model has become influential and often referred in the context of innovation policy. The increasing application of information technology in science further contributes to an increase in and access to codified knowledge as will be studied in more detail in Section 3.

In the works of Leydesdorff (2010) and colleagues, knowledge becomes a *“social coordination mechanism”* (ibid., p. 374), a *“meaning that makes a difference”*. In this view, knowledge *“informs expectations in the present on the basis of previous operations of the system”.* This is an inherently anticipatory account of knowledge to which we will return below. For now, suffice it to say that in the triple helix model, knowing has the main function of providing *“science-based representations of possible futures”*.

Obviously, science is changing. As early as 2003, Nowotny and her colleagues pointed out a shifting research environment in which *pure* research is pressed to become more application-driven, more accountable, and oriented towards public policy objectives. (Nowotny et al. 2004) describe the following main changes in the research environment:

a) the steering of research priorities by programme research, e.g. the EU Framework Programme and national programmes
b) the commercialization of research, i.e. private funding of research and the new awareness of universities about the value of their intellectual property and
c) the accountability of science, i.e. the stronger emphasis on research management, evaluation, and quality assessment.

At least when looking at the concept of a linear model from the perspective of basic research, scholars argue that today there is a massive trend towards inter- and transdisciplinarity, contextualization, so-called “Mode-2” research (Gibbons et al. 1994, Nowotny et al. 2003). Gibbons, Nowotny and their colleagues characterize the old, “Mode-1” type of research as largely researcher-focused and researcher-driven intra-disciplinary production of knowledge whereas “Mode-2” research is pursued in awareness of its *application* context (Gibbons et al. 1994, p.4) and therefore in teams and in a collaborative effort between disciplines. Note that this may also include a range of effects that are less linear than what the model suggests. For example, we would expect stronger feedback loops from application-oriented research on basic research and stronger interactions between and with the different disciplines.

Mode-2 proceeds in sharp contrast to what Sandro Gaycken calls the meander of classical theory of science where science is portrayed as physicalizing and therefore isolating, particularizing (i.e. decontextualizing), but also deterministic, causal and reductionist. Latour locates such a decontextualized practice of modern science in Descartes’s argument for a res extensa in difference of res cogitans (Latour 2016, p.130). Contrary to this, Latour argues for *“cogitamus”* – a shared understanding of the world through science, perhaps much more in line with so-called mode-2 science. Even if post-modern science may have often gone beyond such physicalism, it is still a very import image of science, for example in science policy, but also in epistemology. Mode-2 is at least partially presented as a consequence of increasing technological perspectives on research and an increased interest in innovation, i.e. as a *techno-scientific* endeavour. On the other hand, Etzkowitz & Leydesdorff (2000) present us with an historical account that describes the now trendy Mode-2 science as an old model to which Mode-1 only followed later. Mode-1 is described by these authors as a *“construct…in order to justify autonomy for science”.* In this account, the physicist Henry Rowland plays a central role with his doctrine that *“if anyone with external interests tried to intervene, it would harm the conduct of science”* (Etzkowitz & Leydesdorff 2000, p.116).

In summary, there are massive calls for technoscience originating in rather different interests. As describe in Section 2.4, they may be science-internal and grounded in arguments for research funding; they arise from an implicit definition of usefulness of science; and they are founded on economic arguments both at the macroeconomic level and specific theories such as the triple-helix model. Before taking a closer look at contemporary ways to achieve such goal-oriented knowledge in practice, it is important to analyse in more detail how “basic knowledge” can be turned into technical know-how. The following section therefore takes a closer look at how knowledge work in technical science relates to knowledge in natural science in detail.

2.5 Knowledge work in technical science

An essential question when trying to understand any potential impact on knowledge as we move from basic research to innovation refers to the arrows in the linear model: what precisely flows from basic research to applied research and on to development; i.e. what do the arrows in the linear model really mean in addition to describing a temporal sequence? What is the kind of transformation that we can expect to happen to knowledge as we move from basic research to application, i.e. what is the transformation along the arrows of Figure 2-5? If knowledge becomes transformed or operated on, what then are the changes happening as we shift our interest from basic research to successful market application?

It can be expected that the envisaged transformation in the linear model (and in all accounts that argue for basic research as a basis for innovation) operates on knowledge in the form of regularities, for example natural law. It should result in answering how to achieve a desired objective. We are therefore looking for turning descriptive knowledge into technical knowledge. Despite its apparent importance, the conditions of transforming general scientific laws into technical principles have received relatively little attention in epistemology. Only fairly recently, in the realm of the philosophy of technology, is there a systematic and renewed interest in how this application actually works – both in practice and in theory. Investigations into the nature and characteristics of technical knowledge are a strong domain of a German school, e.g. in the works of (Banse & Wendt 1986, Banse & Friedrich 1996, Ropohl 1999).

Banse & Wendt (1986) describe the transformation of natural law to technical principles in detail. We take a closer although simplified look at the main aspects of this transformation. One caveat needs to be put in place here: the discussion is presented from a somewhat idealized perspective. It describes a necessarily simplified account of the transformation of basic research in technical knowledge. Today, the epistemology of technology and of other areas has progressed to what (Gaycken 2005, 24:25) calls “specialized epistemologies” for different areas of science and technology thereby giving up the ideal of one allencompassing theory of knowledge. But since said transformation remains a core argument in so many practical regulations of research, it deserves a detailed analysis.

The starting point for the discussion in (Banse & Wendt 1986) is the realisation that technical knowledge connects means with ends. Therefore, it always contains an element of prediction of means and also an element of planning. Such knowledge may be structural, e.g. in construction plans or action-oriented, e.g. in algorithms or recipes and is desirable for achieving objectives by means of artefacts that often do not yet exist.

We may thus describe the general technoscientific work, where actions help to generate a desirable end state (E_2) from an initial state (E_1) using specific means *(M)* under certain conditions *(B)*. As Banse and Wendt (ibid.) argue, such *anticipations* take the logical form

$$\left[B \Leftrightarrow \left(M \Rightarrow \left(E_1 \Rightarrow E_2 \right) \right) \right] \tag{1}$$

In technical construction or *application*, such rules factually become action directives that should be read as *"in order to achieve* (E_2)*, apply the necessary means (M), ensure the initial state (or input)* (E_1) *and check for valid boundary conditions (B)"*, or short:

$$!(B,\ M, E_1) \Rightarrow E_2 \tag{2}$$

Mathematically, this expression is rather unorthodox in expressing both a temporal action sequence *and* a relation. This innocent-looking form pinpoints the important characteristic of knowledge as it is converted from its logical form to technical knowledge: it becomes a goal-oriented action sequence; by now referring to an action, the expression is necessarily related to time and purpose.

This is more than logical sophistry. Lyotard reminds us that there is no legitimate reasoning from "The door is closed" to "Open the door!" Both statements depend on different rule sets with different "relevance" and "competence" (Lyotard 1986, p. 112). Reason as cognitive and theoretical thinking – albeit with predictive power – becomes separated from practical thinking. Consequently, it should not be surprising that significant efforts are required to put praxis back in reason.

From a logical perspective, Banse & Wendt describe this situation also as an epistemological problem. Their starting point is the description of basic research results in science (e.g. natural laws) that can be described in the following logical form:

$$_{g}\forall\, x\, [\, EB(x) \;\Leftrightarrow \big(A(x) \Longrightarrow^{p} B(x)\big)] \qquad (3)$$

Here, *g* indicates the degree of confirmation or inductive probability; this denotes the degree to which we believe in this law. *EB* are the boundary conditions that must be granted for the law to hold. Finally, *p* describes the statistical probability of the conclusion itself (which is not the same as the degree of confirmation *g*.) In the following, we assume that both *g* and *p* are 1, i.e. there is certainty about the conclusion described in the law:

This then facilitates the logical conclusion

$$\Big[\Big(EB(x) \Leftrightarrow \big(A(x) \Rightarrow B(x)\big)\Big) \wedge EB(x_i) \wedge \big(A(x_i)\big)\Big] \rightarrow B(x_i) \qquad (4)$$

This can be read as: *if* there is certainty about the connection between boundary conditions, the initial state and the resulting state of *x*, *and if there* is certainty that the boundary conditions, and the initial conditions really hold, *then* we may logically infer the final state *B(x).*

Epistemologically, this construct makes it possible to serve three different functions.

- First it explains, why there are *B(x),* i.e. it explains why there is B.
- Secondly, it allows to forecast from the existence of *EB(x)* and *A(x)* which *B(x)* will happen.
- Thirdly, and perhaps most importantly, it allows one to derive *what to do* if *B(x)* describes a desirable end state: namely, to make sure that *EB(x)* and *A(x)* hold.

The necessary steps to fulfil the desired objectives are therefore:

First, assume a set of goal conditions:

i. $Z = B(x_i)$

NB: we have not yet discussed the origin of these objectives. Obviously, when we talk about innovation, it will have to be assumed that there is a degree of novelty that lies in such goal conditions, for example to deliver a service yet unknown to the market.

Secondly, identify the relevant laws as above.

ii. $\left[\left(EB(x) \Leftrightarrow \left(A(x) \Rightarrow B(x)\right)\right) \wedge EB(x_i) \wedge \left(A(x_i)\right)\right] \rightarrow B(x_i)$

Thirdly, from these laws derive technical principles

iii. $(!\,EB(x_i) \wedge !\,A(x_i)) \Rightarrow Z$

(Here we simplify Banse & Wendt's five steps to just three.)

If we identify the boundary conditions *EB* with *B* in our previous formula, the E_1 with $A(x_i)$ and the E_2 with *Z* this results in a formula that

$$[\,B \Leftrightarrow \left(M \Rightarrow \left(E_1 \Rightarrow E_2\right)\right)] \qquad (5)$$

It should be striking to the reader that in the discussion of transforming laws into anticipations, we have somehow lost the technical means *M* that transform our input states to the desirable end state. This is, of course, not a coincidence, but describes the mere fact that natural law alone does not necessarily give us any information about *how* to realize the necessary conditions such that the desired end state can actually be reached. We may, for example, very well know that the moon will darken the sun in certain stellar positions. But this does not tell us anything about how to put the moon in such a position – and indeed making this happen at our will is impossible for us today.

Philosophers of technology, for example (Ropohl 1997), have pointed out how the transformation is not just the simple derivation of technical principles from knowledge in basic research, i.e. from predictive or explanatory knowledge to technical knowledge. Indeed, the linear model does not provide a sufficiently precise picture of knowledge in the context of technology development. As Ropohl argues, there is a *"…misleading reduction of technology to natural science…"* It is misleading for the following reasons (see also the discussion in Banse & Wendt). In particular, the engineer's epistemological effort is not just the mere *application* of natural law – a view that only started to change in the 70s of the last century (cf. Gaycken 2010) when technical science started to become interesting for a traditionally physical-minded theory of science.

Technical knowledge is not simply applied science

Let us have a closer look at the reasons why technical knowledge is in fact different (the first five are in line with arguments in Banse & Wendt):

1. The engineer knows what to do, but does not possess any details about how to do it or whether it can be done at all.
    - It is possible to set the values – at least partially – for the $A(x_i)$ or $EB(x_i)$, but not for all; e.g. a solar eclipse eludes our power to create it when desired.
    - Often, the objectives will be limited in the course of technical research to $B'(x_i) \subseteq B(x_i)$ (such as narrower boundary conditions (EB), fewer input cases (A) etc. In other words, engineers will narrow down the laws and put it in the concrete context of the application; they perform contextualisation work).
2. It is not necessarily clear how reliable a scientific law is in practice. Very often this concerns knowledge at the border of linearity (e.g. at what point is it necessary to move from linear behaviour of a rubber band to its non-linear tearing). In practice a lot of research in the technical sciences are experiments that aim to identify the precise boundary conditions in practical situations.
3. Similarly, it is often not clear, what is the probability of a law for the case of stochastic knowledge. This of course also hampers the applicability of the law in practice when a desirable end state should be reached with certainty.
4. In addition to problems of know-how stated above (#1), the derivation of goal-directed anticipation and technical principles from laws in basic research is not just deductive. There are multiple ways of realizing a given end condition: different means may achieve satisfactory outcomes. The derivation then means navigating a potentially very large search space that requires the application of heuristics to arrive at a satisfactory solution.
5. Usually, not all required laws are available for the engineer (yet).
6. Another potential problem for the engineer arises from the precise structure of knowledge, or better the concepts used in natural law. Of course, the concepts used

may depend on the aim with which the knowledge was first created. The concepts used in natural laws may primarily be useful for the purpose of description, explanation, and prediction, but they may not necessarily be at the right level for design and development. For example, a Turing machine provides a solid model of computation which is useful for solving problems in theoretical computer science. But whatever we may know about Turing machines, it is unlikely to support us in developing a word processing application.

This poses the question how the world becomes put into equivalence classes under our processes of knowledge construction and to what extent these conceptualizations are useful for both description and design. Physics usually starts with the intention to create a description that is maximally fine-grained, i.e. atomic (Kaneko & Tsuda 1996). In this way it would – theoretically – be able to reduce all other phenomena to this level of granularity. It is clear, however that this is not practical and today even chemistry is irreducible to physics for practical purposes, let alone economics (cf. Dupré 2010).

Furthermore, the following more practical points must be raised:

7. In engineering, fundamental laws become substantially simplified. Obviously, mechanical engineers do not use quantum physics in designing gear boxes. (Poser 1998)
8. Going beyond the previous point, technological laws are often just empirical generalizations. The engineer is often not interested in truth of natural laws, but interested in practical success. Such success may not require detailed knowledge about underlying causes or behaviours in all situations. (Ropohl 1997)
9. In addition to the above "functional" perspective (i.e. transforming natural laws to rules about how to yield a result for certain circumstances), there are also structural rules. These rules support the creation of novel realities (e.g. as plans or blueprints). This is a rather peculiar kind of knowledge not yet extensively studied in epistemology, cf. (Jonassen et al. 1993).

10. The search for technical principles happens in a knowledge space that may be huge already. There is little guidance on which knowledge may in fact lead to a technical solution and where to look.

11. Technical know-how includes a vast range of implicit or tacit knowledge such as practical skills gained through practice only. This may include bodily movements (Ihde 1979, 2001 p. 68 ff.), but also refers to more abstract design patterns, practical forms, planning structures, temporal sequences etc. Such knowledge needs to be acquired on the job without any role of theoretical knowledge in the basic sciences.

12. Philosophers of technology (e.g. Grunwald 2004) point out that engineers require a broad socio-technical understanding, for example regarding application contexts for their developments to be successful. Such knowledge needs to be contributed in design processes, but it cannot usually rely on formalized accounts of contexts. In fact, it may very well withstand aims to formalize it (cf. Dreyfus, p. 118). Technical knowledge therefore includes knowledge about activity contexts and about economic requirements, side effects (impacts, safety, resources, or even public opinion).

13. Contrary to the intuition that more knowledge makes engineering easier, there is the danger of an explosion of search space. It is counterintuitive but true that a larger choice of laws can obstruct finding relevant or right actions, as many more possible rules for reaching a (sub-) objective can potentially be used: the search space explodes with “too much” knowledge and makes it more difficult to find the means for producing the desired result.

All these reasons suggest that the work of engineers goes vastly beyond the mere transformation of natural law to technical principles. This is one of the reasons for (Grunwald 2004) to argue that knowledge in the technical sciences is *genuine* and not just an application of scientific knowledge. Unfortunately, the simplistic structure of the linear model entirely conceals the epistemological challenges that the engineer must solve. Calling the corresponding research activities of engineers “applied research” is *inappropriate terminology* as it suggests that existing research results would be simply taken and reshaped slightly. Rather, we may call such research “application-oriented” while acknowledging that this may mean large research programmes that will in turn generate massive new knowledge. Such activities will mostly take the shape of technical research activities in the sense that the goals of such research are often identified with technical objectives.

On the other hand, it is also clear that technical principles are *valid* only with respect to reaching objectives within a narrow framework of boundary conditions. While the validity of a technical principle may be hardly contestable (or vice versa easily demonstrable), it remains an important truth only for someone interested in reaching the corresponding objective in that particular context. In the end, knowledge simply has very different functions and ranges from helping us to understand nature to producing novel technological artefacts. Let us briefly summarize these functions of knowledge in the next section.

2.6 Functions of knowledge

In the different steps of the linear model, knowledge has very different *functions*: In “pure” (fundamental/basic) research, the function of knowledge appears to be firstly *epistemic*, satisfying the *need to know* and, secondly, providing the power to *predict*. Ian Hacking (1983, p. 51) describes theories as *“intellectual instruments for prediction, control, research and sheer enjoyment.”* The linear model, as we have seen, suggests such knowledge as the basis of a pyramid on which applied research builds to eventually result in economic and socially beneficial results – essentially as depicted in Figure 2-6.

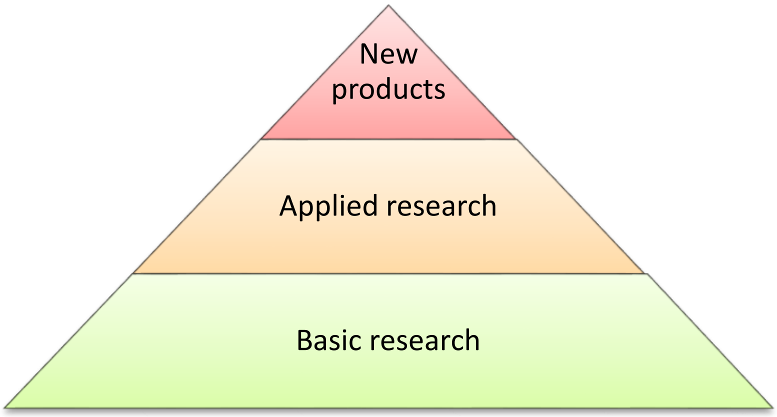

Figure 2-6 Basic research as the foundation for applied research and resulting new technology for novel products.

Note in addition, that pure prediction is usually not sufficient in basic research. It is important to be able to *explain*, to give reasons, to justify what will happen with reference to what was known before and what is currently known about the subject area. In the words of Bruno Latour: "*Stating the scientific rigor of a montage means to start the discussion, […] and not ending it. […] It means starting the work […] and not believing in accomplished facts." (Latour 2016, p. 168)* Such an effort is often in contradiction to purely statistical models, or at least pure statistics does not deliver the causal models that basic science also targets. Statistical models may have the power to predict phenomena from analysing data or to generate the right actions, but do not offer more than just a statistical correlation. This will be discussed in more detail in the context of epistemic technologies that generate statistical correlations in Chapter 3.

For Habermas (Habermas 1968) the point of science is precisely a form of prediction, but other scholars including C.S. Peirce have emphasized that there still remains a psychological component, a kind of satisfaction associated with knowledge and a sometimes even more discomforting feeling of doubt from knowing that we do not know, cf. (Schülein & Reitze 2002, p. 172). *"Doubt is an uneasy and dissatisfied state from which we struggle to free ourselves and pass into the state of belief; while the latter is a calm and satisfactory state which we do not wish to avoid, or to change to a belief in anything else." (Peirce, 1877, 5.372)* This unpleasantness drives us to arrive at a state of conviction: *"The irritation of doubt causes a struggle to attain a state of belief. I shall term this struggle inquiry, though it must be admitted that this is sometimes not a very apt designation."* (Peirce, 1877, 5.372) Moritz Schlick talks about a *"will to truth",* a leisure activity for the mind liberated from any practical considerations (1908, p. 155, cf. Kaldewey 2012). From the point of view of the history of philosophy, Dear describes natural philosophy as a largely contemplative act, something *"speculative because it was about* understanding *things, not* doing *things"* (Dear 2005, p. 394). Kaldeway reminds us that from Schlick to Polanyi and Luhmann an ancient semantic tradition becomes visible in which theory (as an essentially Aristotelian concept) is a self-sufficient cosmological discourse in combination with an epistemological discourse (Kaldeway 2012, p. 25). In such a view, anything practical belittles such contemplation, in particular practical, procedural (πρᾶξις) and technical (τέχνη) considerations are of comparatively small value. However, the different and largely differently motivated discourses of technical empowerment and of understanding nature *can* indeed be connected. It may be historically true that they have not developed in parallel, let alone in unification, but it is generally feasible to connect them (cf. Kaldeway 2012, p. 26; Dear 2005, p. 405).

The goal then would be to reach a state of conviction that allows it to develop – as Peirce calls it – *"habits of behaviour"* that help in reaching goals within the current circumstances. This suggests that science and research are means to overcome such doubts by offering practical orientation. This implicitly advocates two different functions of research: overcoming doubt as a personal feeling and offering practical orientation for the future, much like what has been termed *technical principles* above.

In "applied" research, the function of knowledge is already technical. It answers *how* we can achieve something. Although this may be grounded in scientific principles of nature, it does not necessarily have to be; it would in fact be more justified to call it grounded in function. The main criterion for the validity of applicable knowledge is a result, an output. Truth lies in what *really* works.

Similarly, in innovation, the function of knowledge is *the market-oriented production of goods or services* and perhaps even creativity in the discovery and design of yet undiscovered services (Maranville 1992). Such knowledge helps in selling products and services, or more precisely, to anticipate how to fulfil expected demands from the market.

Table 2-1 Overview of motivations and functions of knowledge, underlying questions, leading discipline and success criteria in basic research, in applied research, and in innovation.

	Pure research	**Applied research**	**Innovation**
Need	to know	to build	to sell
Underlying question	What?	How?	What for?
Leading discipline	Science	Engineering	Business management
Function of knowledge within the discipline	Understanding and prediction, and removal of doubt (Peirce)	Achievement of technical goals in practice	Facilitating the creation of marketable products and services
Success criterion	Prediction and publication	Functional fit, technical criteria	Commercial success

While there is a whole branch of philosophy (in fact two: theory of science and epistemology) that is concerned with the conditions that facilitate truth in pure science, there is little work on what are adequate conditions that make applied knowledge "true". There are of course general principles of scientific (or rather engineering) practice, but no comparable elaborate 'epistemology' of technical knowledge exists. There is epistemological work in the philosophy of technology that we have already mentioned (Ihde, Banse & Wendt), however, there is for example very little discussion about the validity criteria for technical propositions. This might be due to the fact that the application of the technical proposition is often considered its immediate verification: if the technical principle delivers its promise, then it was "correct". It is evident that this will pose a range of queries related to traditional epistemological questions, such as observability, verifiability, dispositional predicates etc. In addition, and perhaps more interestingly, the technical principle is substantially connected with an action or activity. This is why Gaycken (2010) argues that technical knowledge becomes manifest in action and is therefore bound to the actions taken by engineers. The resulting technical imperative is: in order to examine the technical principle, apply it! To be entirely fair, there are other criteria for technical knowledge such as situational invariance and trans-subjectivity, *"while realistic truth of the used theories is not an explicit criterion"* (Gaycken 2010, p.7).

There is a surprisingly rudimentary understanding of what application-oriented research really is about. In research policy papers, the emphasis given to application-oriented research is mostly from the point of view of *innovation* and therefore of technology development, starting perhaps with (Bush 1945), cf. (Godin 2005), (Godin 2013). However, for the engineer, there is little epistemological advice in terms of theory. In medical research, applied basic science has been introduced as something that applies basic knowledge to real world problems (Gibbs & Bendall 2014) – which poses the question as to whether knowledge in basic research is truly primary. The linear model presents knowledge from basic research as the basis in technology development and innovation and later stages of the development process build on top of that knowledge. Basic research comes first in a double sense: timewise and laying the foundation upon which further research efforts are to be built. For this reason, (Ropohl 1997) calls the linear model a cascading model.

More recently, philosophers of technology have started questioning the order of things in the linear model; most prominently perhaps Don Ihde. For decades, the focus in epistemology has been on natural science and in particular using physics as the role model for science in general. However, technology as we have seen is not just natural science which is then applied in a straightforward fashion. In fact, due to its massive use of measurement equipment, we could call science "applied technics", cf. (Gaycken 2010), (Ropohl 1997) who also refers to (Ihde 1990). As an example, we need not only consider the massive investments in huge measurement devices such as radio telescopes or cyclotrons. Just think of simple instruments such as thermometers and voltmeters which all, by their very nature help to first discover dimensions that are then discussed in science (Ihde 1990). While there is without doubt a scientific component in technical principles, there is also something about the practical way of interacting with nature and about the means for realizing functions that normally is not a component in purely predictive theories. We try to summarize this picture by means of Figure 2-7 that puts technology as the basis upon which science rests and develops. While it was not difficult to use "applied research" as a kind of middle term in Figure 2-6 above, this is less clear now. If technology is the basis of and primordial to basic science, how do we get from technological means and praxis to the kind of predictive models of science, i.e. what achieves the mediation at the position marked with (*) in Figure 2-7?

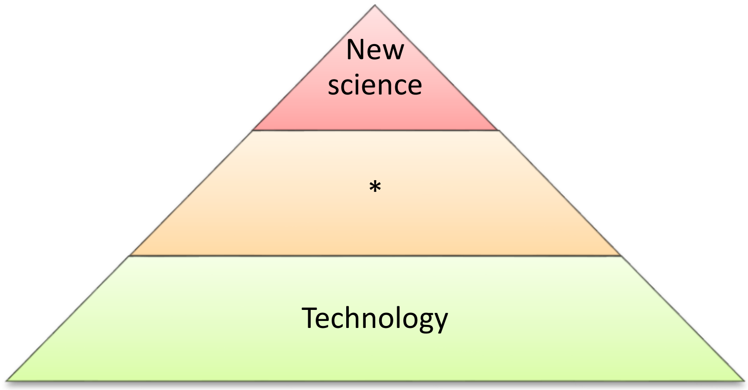

Figure 2-7 Technology as the basis of any scientific research. See text for further explanation.

This question may be one way of describing what has now become the basic dichotomy, in a quote from (Kaldeway 2013), where *"…science is characterized by a twofold objective: on the one hand, it is defined by the self-seeking striving for truth and knowledge; on the other hand, it has the practical benefit of the new knowledge in view."* Kaldeway limits this diagnosis to "modern science", but this Janus-headed feature has been surprisingly persistent over the centuries. Scholars have already traced this dichotomy not just to an ideology of pure research from the late 19th century, but it really roots in the very idea of science from its earliest beginnings: if we engage in the Aristotelian (and indeed Platonic) endeavour of unveiling nature, a task practically so religious that even the slightest hint of utility will necessarily have to appear inappropriate. Louis Dupré provides a clear and detailed account of how the emphasis on form drives an aesthetic vision of nature not only in ancient Greece, but is still visible in the Renaissance and even in later philosophies (Dupré 1993, p.20). As an illustrative example consider Lynn White (quoted by Don Ihde) who describes how clocks were not allowed inside the Hagia Sophia so as not to *"contaminate eternity with time"* (Lynn White 1971, p. 171). In the West, on the other hand, clocks spread to Latin Church towers. In parallel, nature's working was perceived as something that works with the precision of a mechanical clockwork (Ihde 1990, p. 61).

On the other hand, even for Aristotle and Plato the idea of truth was something practical as well; in the case of Artistotle this becomes clear in his discussion of the practical syllogism in *De Motu Animalium* where the conclusion may suggest an action (von Wright 1974). Still, it took the revolution of enlightenment to fully recognize knowledge from research as a tool for practical purpose – and perhaps even putting such purpose before mere understanding. Supporters of pure and basic research often not only make the case that knowledge emerging from it would in the long run lead to new and concrete societal benefits through innovation; a somewhat weaker position is that pure research and societal impact need not be contradictory. (Kaldeway, p. 17 quotes the German philosopher and former Minister of Culture, Nida-Rümelin, with *"the zest of use-free research does not have to be in contradiction with societal utility"*.) However, we have seen above in Section 2.5 that pure research at least does not necessarily provide the information possibly required for technical function. Moreover, systems that self-organize in the way described below in Chapter 3 at least may prove not to be extremely useful for conventional explanations in good conformity with existing theories. In this sense, they are perhaps not in contradiction, but they are definitely not completely in line with such theories because they are formulated entirely outside such theories and employ a different conceptual basis that may be very difficult to bring in line with what we already have come to know about a subject area.

The question that is touched here is rather fundamental. It comes down to whether function and technical purpose are mere external attributions of an otherwise purpose-free autonomous science (Kaldeway, Dear) or whether the two worlds of understanding and governing nature necessarily fall apart? And in addition, the question arises whether it is actually true that we cannot specify with precision (Kaldeway p.26) the *"amalgam of natural philosophy and instrumentality"* (Dear 2012, P. 40)? These questions are subject of current philosophical debates, but they have been alluded to for some decades, at least since Don Ihde's work in the late 1970s. Another perspective with which to look at this apparently fundamental dichotomy is to describe it as a historical shift from the old narrative of truth and basic science to a modern, even post-industrial (and perhaps post-scientific) focus on utility and therefore on technology. Lyotard describes giving up what he calls the great narrative in the 1980s: *"In the present society and culture, i.e. postindustrial society, postmodern culture, the question of the legitimation of knowledge arises in a different way. The great narrative has lost its credibility, whatever mode of unification is assigned to it: speculative narrative or narrative of emancipation. One can see in this decline of the narratives an effect of the revival of the techniques and technologies since the second world war, which has moved the heavyweight to the means of the action rather than to its ends; Or even those of the re-development of liberal, advanced capitalism, which, after its retreat under the protection of Keynesianism during the years 1930-1960, has advanced the communist alternative and upgraded the individual property of goods and services."* (Lyotard, 1986, p. 112) Here, Lyotard suggests that science as an activity of curiosity, as a result of astonishment, has died. There will be no more knowledge to understand and to see, but only knowledge for power (other than explanatory power). *The question, which is, explicitly or not, posed by the student oriented towards his career, the state, and the institution of higher education, is no longer true: Is that true? But: What is it for? In the context of the mercantilization of knowledge, this last question usually means: Is it sellable? And in the context of the increase of power: Is it efficient? [...] It is no longer competency according to other criteria, such as truth / falsity, the right / wrong, etc., and certainly not the low performativity in general.* (Lyotard 1986, p. 150)

This would replace education based on the externalization and retrievability of knowledge. As a consequence, research becomes de-personalized and commodified. The bio-inspired model which we will present in Section 5 will suggest that both understandings (or objectives) of science can in fact be unified at least from the perspective of an assumed external observer. The model may be rather unsatisfactory for lack of in-depth linguistic structure and ignorance about the intentions of analytical philosophy, but it helps to understand technical function and scientific explanation as two implementations of a more general scheme of anticipation and adaptation.

In summary, knowledge as a term is truly in the middle, ranging from basic to technical knowledge. It has undergone radical changes resulting in today's technoscientific focus and challenge to achieve a kind of mediation in the transformation from basic to applied science. Today, we are facing a mixed picture of knowledge for prediction and empowerment with a largely unclear relation. To add to this complexity, knowledge itself is often construed technically and as we shall see even technology is constructed technically. Let us therefore take a closer look at the contemporary construction of opportune knowledge, i.e. on the *automated construction of knowledgeable systems* for which we used to apply theories from basic science and research before we had computers.

3 Innovation and epistemic technologies

Before returning to the more philosophical question of knowledge and utility it is insightful to take a closer look at current developments in the practice of science, in particular in the creation of knowledge for technological innovation. Knowledge is now created by means of computer technologies while at the same time epistemic technologies are used to create desired system functionality based on learning. In fact, learning systems are now abundant. They are often based on observing input-output patterns – just in the way that we described it in Section 2.6.

3.1 Technological acceleration of research

The fact that we live in an information age, or perhaps better in an age of information technologies has become a truism as all aspects of human society have been penetrated by the widespread use of IT systems (Castells 1999). Science, research and innovation certainly are no exception to this trend. Today many labs are significantly computerized and routine experiments in a broad range of diverse areas, for example in medicine or biotechnology, are now performed or at least supported by lab robots or automatic analysis systems. Data is recorded somewhere in the cloud and may interpreted remotely by human experts or computer-supported systems. In addition, academics increasingly publish online and collaborate in electronically supported networks. They share software, data and other research infrastructure by means of information and communication technologies. These trends have now started to significantly change scientific practices, for example how to find project partners, perform peer evaluation, or collaborate in large teams, cf. Prem (2015).

The recent shift of interest in research policy towards innovation has reinforced efforts to *accelerate* scientific and innovation processes. This includes the use of information technologies (IT) in science, but also its use in innovation. This development is clearly visible in universities, academic research institutes, and private or state research organizations and in businesses, cf. (Prem et al. 2016, pp. 18-19; Pfeifenberger 2015). Drivers are the availability of low-cost broadband internet access and massive storage, new tools and platforms facilitating team collaboration and new sensors and techniques for data capture and analysis.

It would be naïve to assume that the way in which scientific knowledge develops bears no influence on that knowledge – either its form or its actual content. To the contrary, it is to be expected that the use of innovative technologies impacts the characteristics of the knowledge processes and thereby also knowledge itself.

First, the question arises of which steps of the scientific and innovation processes are most affected by new technologies. Secondly, the question is what the main effects of such a heavy shift towards IT-supported epistemic processes are for knowledge and knowledge processes – including those processes leading up to innovation. The following figure describes a simplified temporal sequence of steps in the practice of current research (Prem 2016, Prem 2016 et al.). It is simplified because in practice there may be feedback loops, steps can be missing or additional steps inserted.

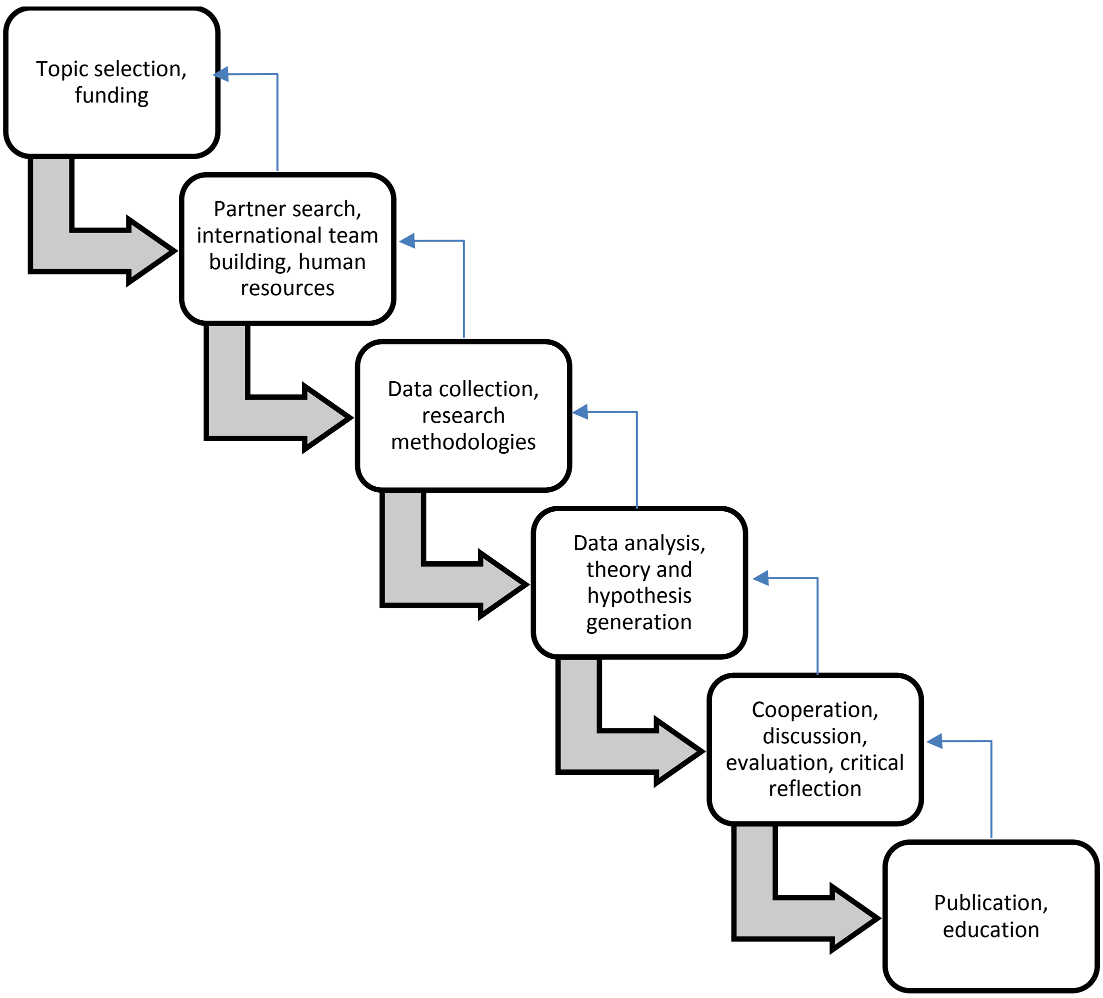

Figure 3-1 New and open scientific practices address every step in the (simplified) scientific research process (from: Prem 2016, adapted from Prem et al. 2016).

The following table describes the use of information technologies in each of these steps. It is evident that IT tools exist for each step, however the extent to which they are used in each process step is very different. It is perhaps fair to say that most tools are used today to collect, store and analyse data including the use of simulation models; there is also a strong trend towards electronic publishing of results including data and software; and IT-supported collaboration is on the rise. Some other aspects such as IT-enabled crowd funding of research or micro-harvesting of knowledge are in their infancy. Examples of mathematical proofs are described in (Nielssen 2011), perhaps the most famous example is the four-color theorem (Appel & Haken 1989).

Table 3-1 Examples of ICT use in science (Prem 2016; adapted from Prem et al. 2016)

Process step	**ICT use examples**
Topic selection, funding	Crowd funding of research, online problem data bases and open innovation systems
Partner search, team building, human resources	Research data bases; online information about projects, resources, research groups, research excellence
Data collection	Big data, new sensor systems, automated data collection from Internet-of-Things, laboratory robots, interaction with citizens
Data analysis and interpretation	Artificial Intelligence-based and statistical methods of knowledge discovery[4] (discovery science), data mining, interactive and visual data analysis; new computing infrastructure (cloud, distributed, and citizen computing), interaction with citizens (Citizen Science)

[4] The terminology for computer-supported scientific work is still very much evolving and ranges from scientific data mining to knowledge discovery, or even discovery science. The term "discovery science" is used to summarize application of machine learning and data mining to scientific data, cf. (Džeroski et al. 2016); "networked science" emphasizes the increased online interaction of scientists and researchers (cf. Nielsen 2012).

Cooperation, discussion, evaluation and critical reflection	New electronic forms of discussions[5], collection of micro-knowledge, interaction with citizens and artists, new metrics, reputation and recommender systems
Publication, education	Open access publication, open data (data re-use), open source software (software re-use), open methodology, collaborative writing, new media; impact factors, open educational resources
Other aspects	Open methodology (open notebook[6] science),

Three major current trends in computer-supported research *and innovation* are:

- Open digital publishing
- Networked collaboration and open practices
- Automated data collection and analysis

The massive use of online resources and tools for publishing of results is perhaps one of the most striking features of science in the 21st century. Although this trend started in the late 70s, it is now widely believed to fundamentally change many traditions that have prevailed in science for centuries, e.g. the way in which publications were reviewed and published based on a small number of peer assessments (e.g. Niemeyer 2017). Perhaps more importantly, the massive open publication of results is by far not only limited to research papers, but also includes data, software, videos, and all sorts of digital files (Nielsen 2012 p. 183 ff., Prem et al. 2016). There can be little doubt about the strong impact of digitization on scientific publishing. Digitization has changed the speed and formats of disseminating results of scientific work, but also how researchers interact with their peers, how they apply

[5] For example, the Polymath project is a lively forum for collaborating mathematicians, cf. http://polymathprojects.org

[6] Sanderson, K; Neylon, C (September 2008). "Data on display". Nature 455 (7211): 273. *doi*:*10.1038/455273a*

for funding and how they collaborate with other scientists (Mackenzie Owen 2007). It is also becoming an important asset in making research replicable, cf. Anderson et al. (2005).

It is perhaps fair to say that science often still happens very similar to the way it was done 200 years ago. On the other hand, there is a new generation of researchers emerging that makes massive use of online tools for communication and publishing, but also for collecting and analysing data etc. From the point of view of such a mostly younger generation we may indeed be witnessing the emergence of a new era of networked science (Nielssen 2011) where it becomes common for any researcher in nearly every field to engage with large numbers of creative individuals and often closely collaborate over digital networks. It is becoming clear also that these new tools for digital collaboration support shared epistemic processes in the formation of theories, the interpretation of data, the design of research projects and programmes and, more generally, scientific discourse. The various impacts of using IT systems are often at work simultaneously when producing knowledge with IT systems and when focusing on innovation. This means, there may be aspects of externalized knowledge, big data and deep learning in parallel with the composition of expert knowledge from various sources and a massive use of simulation etc. Simon describes how new tools are being used in such collective epistemic processes (Simon 2010) and which new socio-epistemological frameworks may prove useful.

3.2 Reasoning without reason

Automatically making sense of large amounts of data today is more than the marketing hype around Big Data. The availability of massive data and new methods for their analysis, in particular statistical machine learning algorithms, have led to the automated data analysis and construction of *knowledge* to an extent that was previously unthinkable (Temam 2016). As currently prominent examples, [7] just consider automatic driving and translation (Jordan & Mitchell 2015). In both areas massive progress regarding improvements in functional quality were achieved using statistical learning techniques that automatically extract properties from large data sets. Systems that are put in operation today by large companies

[7] Bernard Marr ranks smart cars and natural language processing among the top 10 use cases of machine learning today, in: Forbes (Sep 30, 2016),

such as Google, Baidu or OEM car manufacturers are no longer the child of linguistic research or rule-based knowledge-based systems. Although the old theories play a certain role, in particular in pre-processing and also in exception handling, a vast amount of mapping the relevant data on the desired output is nowadays handled by statistical pattern recognition machines (Sutskever et al. 2014, Lewis-Kraus 2016). Rather than using the old artificial intellgeince approach to translation that was based on linguistic research, Google successfully implemented a statistical algorithm that compares text written in different language versions. An older system based on phrase-based statistical machine translation worked without a great deal of analysis of grammar. Still, it was able to produce satisfactory translations for many users. In late 2016, Google redesigned its translate service with the aim to innovate and provide an even more improved quality service. Using statistical pattern recognition schemes (neural networks) and so-called deep-learning (Sutskever et al. 2014) it significantly improved its translation quality using a system that practically has no understanding of language, grammar, syntax etc. All it is capable of doing is associating word sequences in one language with word sequences in another. To be entirely precise, this is not all it does. It sometimes uses sub-word components and there are a few rules for special cases; see (Lewis-Kraus 2016) for an overview or (Wu et al. 2016) for details.

The example of Google's translate service is just one case where information technology can efficiently produce desired system behaviours based on information in large data bases. We have seen that this can be achieved by using novel IT tools, e.g. deep learning systems, that derive knowledge (in our sense of the word) from large data sets. Notably, the quality of the results has now reached new levels and there are examples where similar achievements would practically be impossible without this technology, i.e. such systems are starting to surpass systems based on traditional theories. At least, the technologies help to provide the desired services at relatively low cost and produce them in a very short time. This is the main reason why it has now become feasible to use systems that are designed to discover previously (and in truth often persistently) hidden meaning successfully in market applications.

Researchers knowledgeable in the history of artificial intelligence will be immediately reminded of the discussion after the advent of neural networks concerning symbolic representations versus sub-symbolic neural network representation, cf. (Peschl 1990), Bickhardt (1995). This discussion concerned aspects such as the proper form of theories of reasoning, logic, and cognition and in particular the degree to which sub-symbolic models can and should serve as explanatory constructs for theories of the mind. The resulting arguments over the degree to which symbolic representations, and consequently explanations are needed were intense and was referred to the "symbol wars" (Clark 1989, p. 49). Today, neural network models are perhaps less contested in general and mostly regarded as statistical systems that properly correlate inputs with outputs given the right data (often input/output pairs, but there are also unsupervised or simpler feedback models). Such systems result in models for which it is usually very difficult to produce human-like explanations as to why the system produces a specific output given an input. The models are simply based on mathematical-statistical techniques that do not facilitate symbolic explanations as they often lack internal structure and states that are easily identifiable in terms of the system's input. This is an important aspect, because the deep learning models, employed for example in Google translate or in algorithms that may help to guide autonomous cars, simply do not use and cannot easily provide concepts that are similar to what we may use in theoretical explanations that refer to a problem domain. Although we can always refer to properties of the data, the precise characteristics of the model and the learning technique that is used, the 'conceptual space' of these systems remains mostly shaped so as to produce the right output which may or may not include aspects of the input to the system. A large proportion of the discussions in the early 1990s already pointed to the fact that the knowledge accumulated in such learning systems is simply statistical in nature. The best explanation then to give someone who may be inquiring into the reasons as to why Google translate provides a specific translation is also statistical and refers to the data base. That is about as much of an explanation that can be given. Of course, these are perfectly causal and understandable explanations, but they are of a different kind than what explanations may achieve today. In a more traditional scientific theory, a model (rules) used to fill-in the missing parts between the data from observation and experiment. In the case of new statistical tools, this is replaced with interpolation, individual examples, and trust in other experts or even unknown individuals. This eliminates theory (Anderson 2008) – in the meaning of a set of explanations devised for a particular domain – from science. Understanding is no longer linguistically mediated, but reduced to delivering a techn(olog)ically mediated result or function.

The theory behind this is not new – nor are the discussions around how to interpret these developments in terms of the knowledge resulting from the learning process. In fact, a major part of the debate about symbolic versus sub-symbolic artificial intelligence concerns the differences between rule-based and conceptually symbolic approaches and inherently sub-symbolic neural networks. (See for example the criticisms of connectionism and the corresponding replies, e.g. McCarthy 1988, Pinker & Prince 1988.) These systems automatically derive desired functional behaviour based on statistical learning schemes but they usually lack any straightforward explanation of how they react to a specific input pattern. Their internal codes used for producing the correct outputs simply do not correspond to concepts that we may use in predictive and explanatory theories. Although there are techniques for analysing the resulting intermediary representation patterns, for example by visual inspection (Yosinski et al. 2015), these intermediary representations simply do not usually follow human categories. Therefore, the behaviour may be explainable in statistical terms. With some effort it is possible to identify salient features, for example based on input data, but a general rule-like explanation of the system behaviour is practically impossible. In fact, explaining recurrent neural networks (such as deep networks) trained with large amounts of data (such as in the case of Google translate) poses huge challenges. The important point is that since the statistical models are *only* selected (trained) to produce the right output, they typically have no connection to concepts that are used in other models for explanation or prediction.

An interesting point to note about deep learning and big data approaches is that we are often not knowledge-limited, but question-limited. It is not at all clear, given a large data set, what the interesting aspects of that data may be *beyond* the immediate objective of creating a working system. This is of course again due to the fact that with a lack of conceptual (symbolic) structure, there is not much we can reasonably study in terms of concepts that would require further explanation for or within that structure.

Regardless of these challenges, however, these systems are working very well in the sense that they result in proper functional systems. Google's new translation services are certainly far away from the translation quality offered by competent human translators, but they are quite good for many standard texts (Wu et al. 2016). In fact, they are often surprisingly good also when automatically translating non-standard texts, e.g. philosophy [8] or poetry. Similarly, there are now systems available that support automated driving which have no understanding of what is going on in the system's environment. They also use statistical techniques to acquire appropriate behaviour (cf. Burgard et al. 2016). Again, not much is new about these systems form a theoretical perspective – only their quality has improved to an extent which actually renders these new automated driving systems useful and in fact superior to the older systems that tried to automatically interpret by means of linguistically describable rules. Moreover, these systems appear to be the only way to achieve the desired quality (e.g. in the case of automatic driving) or sufficient quality at desired costs (in the case of automatic translation).[9] Other famous examples include the classification of images (Krizhevsky et al. 2012, Schroff 2015), language modelling, speech synthesis, information retrieval, audio and music processing (Deng & Yu 2014).

To be entirely fair, there were of course already applications of such techniques years ago, especially in pattern recognition, and also for control tasks. What is new is that such systems are successfully used for tasks that for a very long time were the domain of the application of traditional and explicitly formulated theories. Systems that used to be too difficult to program can now be trained to learn the desired output behaviour. They no longer require an intermediate conceptual layer or interpreter that would depend on human knowledge, cf. (Collobert et al. 2011). The new systems get the job done mostly without corresponding human pre-conceptualization and, moreover, they are simply trained on the job and deliver better results than systems based on centuries of linguistic research (Sutskever et al. 2014, LeCun et al. 2015). See (Ferrone & Zanzotto 2017) for a detailed discussion of symbolic representation in deep learning of natural language. While it is perhaps not surprising anymore that neural network based statistical machines are good at recognizing images, it is a surprise to many, how good they have become in a task that appears to be so fundamentally human, i.e. translation. And it may be particularly surprising to linguists that are used to rule-based translation systems based on linguistic knowledge. A possible reason

[8] I have used Google translate for a few quotes in this thesis.

[9] The issue of quality is not uncontested, however. Hatton and Giordani argue that error-free code is practicially impossible and that this poses significant challenges for the scientific method. (Hatton & Giordani 2012).

for discussing these successes in a thesis on opportune knowledge is that they simply do not require the vast amount of theoretical knowledge that has been piled up in the archives of science for decades, if not centuries. If in a few decades from now, this accumulated knowledge ever requires justification, we will have to find a purpose different from its potential application examples where, from now on, new statistical learning techniques are apparently more successful. In the light of the discussions of the **linear model we may as well say that it simply was disproved and shut down**: knowledge from the academic study of language in the field of linguistics is no longer required to deliver innovations in the field of translation. It has been replaced by a large amount of data and statistics – certainly also studied in basic research – but in domains very different from the application domains.

Here, let us pause for a moment to summarize the situation in view of the linear model of innovation. We have already seen that the knowledge in basic science, i.e. knowledge for prediction and explanation is not always easily transformed to technical principles (Section 2.5). This concerns the connection of the first two boxes in Figure 2-1 and in Figure 2-5. Reminding us of the problems with systems that produce functionality from data also means that the way back, i.e. from technical knowledge in those systems to prediction and explanation is blocked – or at least hugely difficult in practice (Figure 3-2).

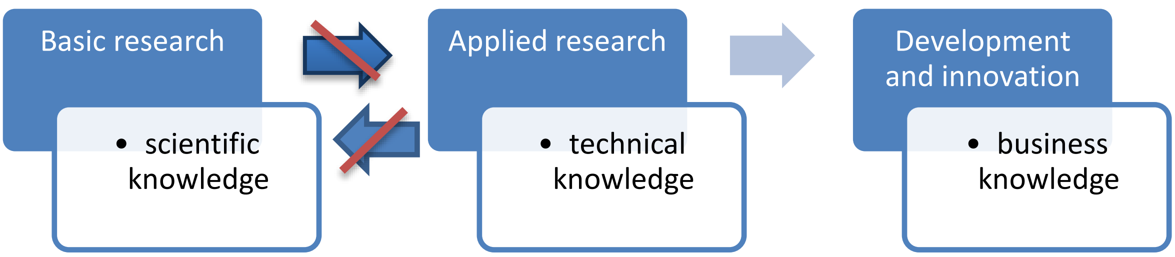

Figure 3-2 The way from explanatory and predictive knowledge to technical knowledge and back is hugely difficult due to different conceptual spaces used for prediction and explanation on the one side and the creation of function on the other. See text for explanation.

The more interesting question is perhaps, whether – in the longer run – these types of automated systems are going to change the *meaning of what we expect of an explanation*. It may be misleading to provide explanations for Google translations that refer to nouns, verbs, linguistic expressions and structures. They may still provide satisfactory insights for the linguistically minded, but simply do not describe the statistical nature of the mechanisms at work. In the future, we may very well be confronted with a situation where more and more rather difficult challenges are solved by statistical learning schemes, access to large data bases – this is the argument of (Anderson 2008) – or even conclusions drawn from the discussions of hundreds of experts or perhaps citizens. It is difficult to predict whether for those cases where such systems provide workable solutions, we will still be interested at all in individual, personal understanding or whether finding a workable answer from the system will simply be all we need.

From the point of an industry actor interested only in bringing working solutions to the market, the automatically constructed output patterns arising from the inputs from generalized past data may be often entirely sufficient. Anyone solely interested in innovation simply may not require explanations for a system as long as it works. Although it could add to the value of a system if explanations are available, many industry innovators do not require symbolic knowledge about the system's behaviour. More importantly, such innovators will not be interested in a system that can provide insightful explanations, but does not deliver the desired system behaviour; and vice versa if a deep learning model using large amounts of data produces proper system behaviour then that is all that may be required for successfully delivering the desired functionality. We may ask ourselves, how often we are entirely happy with a proper translation that an automatic system delivers rather than being interested in precisely why a certain phrase or word was translated. In many cases, delivering the functionality is simply enough.

The drastic increase in the application of IT tools that is clearly visible in science and engineering today is not exclusively due to new tools for data analysis and function approximation schemes. In fact, research policy makers and researcher are united in expecting more general benefits for science from the increased digitization of science. This means that beyond simple functionality, the increased use of digital IT tools has also become policy matter – both at a science-internal level (e.g. academic associations) and at the level of explicit policies for science and research (e.g. funding programmes), e.g. (Partha & David 1994, Brown 2012, García- Peñalvo et al. 2010, Stodden 2010, Nentwich & König 2013). We take a closer look at these expected benefits of digital science in the next section.

3.3 Promises and pitfalls of digitization in science

Science pursued with new ICT tools and in an open fashion not only promises to deliver solutions for currently unsolved application challenges. In going far beyond just useful applications, ICT use in science offers many and significant advantages. Some of the promises of open science and digital science that have been assessed in studies on these topics (Nielsen 2012, Salmi 2015, Prem et al. 2016) include:

- Wider diffusion of scientific knowledge, open for peers and the public: This is perhaps the most visible consequence of IT-accessible research publications. It has significantly impacted on the publication practices in science and research – although still not all publications are truly open and the impact is different in different fields (Tennant et al. 2016)
- Open publication, micro-publication of results as they become known including an increase in publishing more negative results: The publication of early results can lead to increased speed in access to relevant data for other research. In addition, information about negative results, e.g. unsuccessful experiments, can provide important information for other researchers and has often been argued for. In practice, there are however very few journals that would publish work on experiments that did not work (Nielsen 2012).
- Added reproducibility of research, increased transparency (e.g. access to experimental data): Researchers increasingly publish data from their experiments in open access data bases. Although this does not by itself facilitate the generation of the data, it helps to verify the analysis of the data and the theories that are built by means of such data.
- Added accountability and traceability (e.g. use of scientific work practices): within open science, there is a (small) trend towards *open methodology*. Detailed descriptions of experimental methods are rare in publications, for example because of page limits. Especially in biological sciences, many details of the research

methodology matter for added reproducibility of results. Increasingly, scientists can refer to online resources to describe software, tools, organisms, etc. in detail.[10]

- More efficient research, in particular where research work is automatized: laboratory robots, in particular in bioscience, have now become widespread and support automated analysis of large amounts of samples.
- Opening of research facilities, e.g. computing infrastructure – but also laboratories and other tools. The effects of digitization of science and research are not limited to only the digital world. There are also efforts to facilitate remote access to research infrastructures to perform experiments. A simple example are astronomical measurements that are highly computerized today. Telescopes offer measurements to researchers around the world.
- New types and forms of collaboration including facilitated inter- and transdisciplinary work, e.g. by easier access to results from other disciplines. (Nielsen 2012) describes the experiences with the online cooperation of mathematical experts including shaping of research questions, but of course also development and discussion of theories
- Improved interaction with society. Digitization and IT-supported networks are changing the involvement of citizens without formal scientific education. The term Citizen Science now refers to involving citizens in data collection, but also harvesting citizen expertise (Nielsen 2012). There have been initiatives to crowdsource computing resources (e.g. SETI[11]) or to enter in an open dialogue with citizens on science and research by means of computer-supported tools.

These are just a few applications and promises of *Open Digital Science.* Open Science has become a new buzzword in science and research policy. For research policy makers the increased utilization of IT in science promises the following advantages for science and also for society and policy, cf. (EU 2015, EC science 2.0, Salmi 2015).

[10] For example, the Resource Identification Portal supports research resource identification, discovery, and reuse: https://scicrunch.org/resources (accessed July 2017).

[11] SETI is a scientific experiment based UC Berkeley to use Internet-connected computers in the search for Extraterrestrial Intelligence: https://setiathome.berkeley.edu/ (accessed July 2017).

Table 3-2 Potential advantages (expectations) for science, society, and policy makers enabled by the shift to Open Digital Science.

Science	Society & Policy
Improved connection and exchange of scientific disciplines; facilitation of trans- and interdisciplinary work and discoveries	Easy access to results
Improved connection of basic research and societal interest	Participative science
Emergence of new disciplines	Support of lifelong learning etc.
More efficient, open practices	More trustworthy science
Improved traceability, transparency and accountability	Empower citizen access: understand and participate
More egalitarian science	Develop and monitor science
New symbiosis of science, society, and policy	Easier access for SME and industry

On the down side, there are of course challenges involved in using more information technology in science. This includes differences between disciplines as research in technical fields; formal disciplines and natural science are often more prone to digitization than work in the humanities, for example. True openness often remains difficult to implement, for example in the access to data and software. There are also challenges for quality control, career and funding issues or the open issue of how to ensure benefits for researchers that are truly open in all their research (Nielsen 2012, p. 175 ff.; Björk 2017). Open digital science also often faces a massive multi-stakeholder challenge where many different interests in science have to be taken into account.

Finally, and perhaps most importantly for our discussion here, there are significant pitfalls in the history of science where fields have become overly focused on the use of computers.

A well-known case is the story of Artificial Life (for an overview cf. Langton 1992). Fascinated with the patterns emerging from computer simulations of structures that evolved with some perceptual similarity of living structures, researchers discussed the potential meaning and implications of these models in conferences of Artificial Life at length. It was not always very clear what the real-world correlates of such computing models would be. In fact, many of the models were soon to be blamed for remaining just *metaphors*, but not simulations as they were not models of anything real (Rosen 1987, Rosen 1991, Louie 2009). The main issue is that the so-called simulations had no clear correspondence with anything real; similarly, the rules used for evolving the simulated artificial life form metaphors have no clear correlate in the real world. These artificial life computations result in short image sequences that can be easily interpreted as somehow corresponding to animal behaviour while there are clearly no animals to which they refer. The term “fact-free science" was coined by John Maynard Smith (Horgan 1995) to describe the problem that such science was a mathematical, perhaps aesthetic endeavour, but it could not as such establish its connection with real-world biology easily. See also (de Boer 2014), in particular concerning the (non-)relation to linguistics.

Obviously, the difference to models in natural science, e.g. physics, is that there should be a clear modelling relation. Such relations consist in mapping of entities of a formalism (or the computer simulation) to entities in the real world. The mapping is checked by means of observables implemented through measurement devices (Casti 1992). The use of simulations is of course commonplace in physics today. Physicists frequently evaluate law-like hypotheses based on simulations of formal models and checking the results of the simulation back with phenomena in the real world. In the case of automatic detection of rules, for example based on statistical techniques and large sets of data, there is no danger of generating just metaphors in principle. Such statistical models should always – in a precise mathematical sense – be models of the phenomenon represented in the data. However, it will still be necessary in many cases to evaluate the resulting model, test it with respect to new data, and assess its quality. There are two main differences to the Artificial Life case: firstly, the model is generated from real-world data; and secondly, the model is evaluated in comparison to the real world. This real-world connection is essential and substantially different from the mere appearance of the result as in the Artificial Life case.

Although this may seem trivial, there is an important lesson to be learned from the history of Artificial Life: knowledge – at least for acting in the real world – is best gained from interaction with the real world. Or in the words of Rodney Brooks, it is best to use *"*[t]*he world as its own model"* (Brooks 1991, p. 139).

3.4 Technological acceleration of innovation

In parallel to the increased use of information and communication technologies in science, IT tools have also penetrated the field of innovation (Rothwell 1994, Dodgson et al. 2005, Dodgson & Gann 2007). Although the first description of this phenomenon dates back at least to the early 1990s (Rothwell 1992), it can still be regarded a fairly new phenomenon for both practitioners and theorists in the field of innovation. In 1992, Rothwell focused on the support of knowledge flows that are required to manage the innovation processes. Today, information technology enters the innovation process at various points often with the overall intention to accelerate the process and to make it more reliable with respect to successful outcomes. The overarching goal, with which these tools are used, targets efficient innovation processes that are predominantly oriented at customer utility and market appreciation. Increasingly, information technologies also help in creatively composing existing technologies and picking from what has become today an international market of research offers (Prem 2013).

Information technology plays an increasing role for the communication with stakeholders in the innovation process, such as customers, partners, and researchers. In processes that are now termed "open innovation", the focus is on collecting both consumer needs but also possible solutions from broad audiences. Open innovation describes an explicit methodology for harvesting and joining the knowledge of individual entities (people or organisations) outside the boundaries of the innovating entity (Chesbrough 2003, Dodgson et al. 2006). Just as IT provides technology for opening scientific knowledge processes, IT also enables *"more open, distributed approaches to innovation"* (Dodgson & Gann 2007).

On the design side of the innovation process, there is today a massive usage of simulation to develop, refine and test customer experiences even before a physical product or a service is delivered. Innovation technologies (i.e. information technology application in the area of innovation) accelerate the construction, modification, and testing of designs. Simulation techniques including rapid virtual prototyping or visualization have become essential techniques for speeding up innovation (Bowie & Olsen 1994, Thomke & Hippel 2002). Although there is a theoretical risk of losing connection with reality when simulations and visualizations are used massively, there are only few reports that this poses much of a practical problem in reality. (Dodgson et al. 2005, Gann & Dodgson 2007) describe how new technologies facilitate *"thinking, playing, and doing"* and according to these authors thus lead to a new approach to the innovation process.

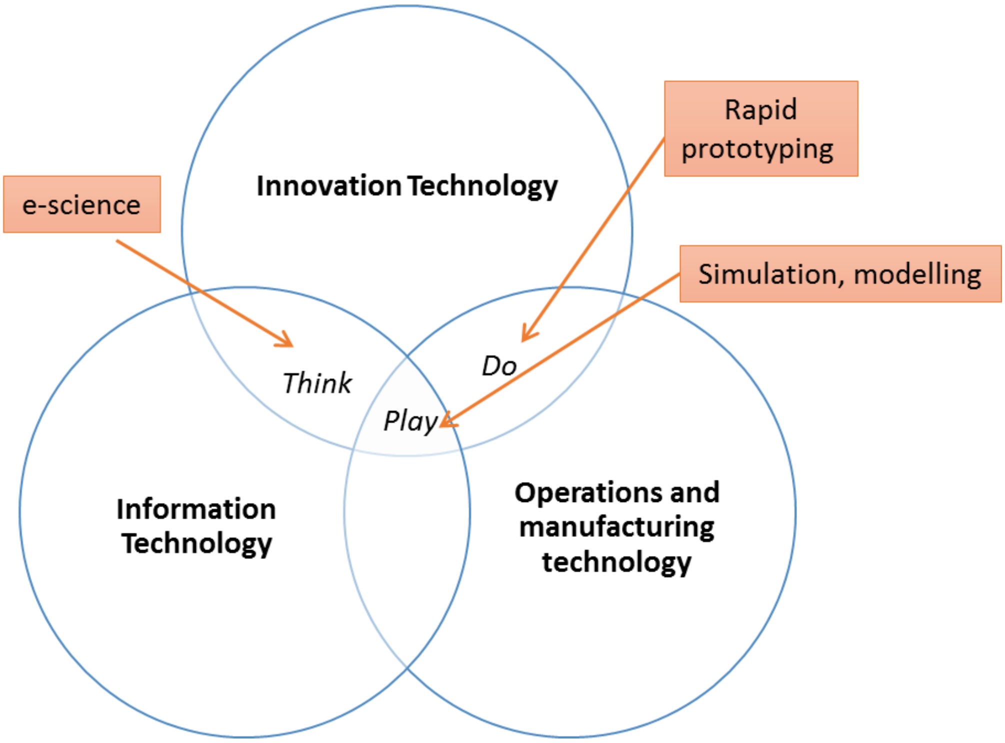

Figure 3-3 The interplay between IT, operations and manufacturing technology, and innovation technology, after (Gann & Dodgson 2007). See text for detailed description and terminological critique.

In particular, Dodgson and his colleagues argue that these technologies foster a process that is less divided into the discrete functions of the linear model, but instead facilitates a more playful approach in the sense of trial-and-error. Computer technology including in particular simulation facilitates such a novel approach because it eliminates risk and brings down the cost of trying out ideas for innovative products, e.g. using virtual reality or rapid prototyping. For Dodgson and Gann this playful construction or rapid prototyping *("Play")* lies at the heart of the new interaction between Innovation Technology, Information

Technology and Operations and Manufacturing Technology. The rapid transfer to production is facilitated by IT and Operations and Manufacturing Technology *("Do")*. The intersection of IT and Innovation Technology is described as *"Think"* and generally the place where e-science operates according to (Gann & Dodgson 2007). From today's perspective, their conceptual framework is confusing as Innovation Technologies largely consist in information technologies and may include technologies for rapid prototyping such as 3D printing or virtual reality and computer simulations, e.g. (Roozenburg & Eekels 1995). This means operations and manufacturing technologies have now massively blended with IT and their conceptual separation has become difficult.

From the point of view of innovation practice and its increased computerization it is more important to note that these technologies support a very practical approach to innovation today. Designers and engineers closely collaborate and scrutinize new ideas in simulations or physical models. They use networks of users and innovators to receive feedback and new ideas and they use short paths to computerized production processes that can quickly test innovative ideas also with respect to manufacturability.

As mentioned before, in bringing new solutions to the market, we are usually not so much interested in *explaining* how precisely a viable solution was found, but whether it meets customer expectation. In such dynamic, interactive, and IT-supported processes that may in addition often be open, the origin or source of an idea for a specific product feature becomes increasingly difficult to attribute. Such modern innovation processes are certainly not linear in any simple sense of the 1st generation linear model that suggests a mono-causal root for innovation in scientific knowledge. The ideas for changing (i.e. improving) products or services may come from many different sources including users, customers, or designers. IT-tools such as simulation and rapid prototyping offer a quick selection of preferred pathways to innovation, i.e. these tools tend to eliminate variants in the innovation process that are assessed as non-viable, for example because they do achieve the desired functionality, they are unsuited for the production process, too expensive, etc. It has even become possible today to exclude innovative product variants automatically based on such simulations (Dodgson et al. 2002, García 2005).

There is therefore a huge impact that Innovation Technology may have on innovation in parallel to the way in which new information technology impacts on all aspects of the scientific process. Then the basic question arises, what is the relation of knowledge and information technology tools in both innovation and science as we massively shift towards IT-facilitated processes? Is there a specific reason why information technology is such a powerful tool to operate both on the knowledge and the product or service level and what is the impact that we can expect on the structures on which it operates, for example on knowledge? In the next section it will become clear, that there are fundamental synergies between information technology and knowledge.

3.5 Synergies of knowledge and IT

Don Ihde makes a very interesting point about mathematics when he argues that modern science is now largely technologically embodied, in instruments and massively technical experimental set-ups; only mathematics has so far mostly remained outside this trend (Ihde 1990, p. 184). Ihde rightly proposes that the massive trend towards the use of computers even in mathematics (Ihde uses the example of visualizations) is beginning to change that. Indeed, we now see evidence of a computerized mathematics where computers become instruments in Ihde’s sense, i.e. embodiments of perception. Just as Ihde was proposing in 1990 (p. 185), computers now have revealed new mathematical phenomena (Nielsen 2012).

It remains to be argued that these new phenomena were actually previously unsuspected and therefore really are new. In addition, Ihde demands that these new embodiments work in parallel to the instrumental revelations now abundant in other scientific disciplines, which remains to be proven. In any case, the fact that science is increasingly pursued with IT tools, suggests that there are synergies of IT and digital science. The simplest connection obviously is the fact that information – as we have seen in the DIKW pyramid in Section 2.1– is a precursor to knowledge and also the subject of IT. But even beyond that, information and modern practices of science share many features:

Table 3-3 Prima facie similarities of information (communication) technology and digital science.

ICT	Digital Science
distributed	distributed
networked	networked
open	open
simulating	simulated
global	global
network effects	social networks
zero marginal cost	open access

These rather high-level similarities are not accidental. The reasons as to why knowledge and information technologies are intimately related lies in the similarity of information and knowledge. Information technologies have become a means for relaying knowledge, for accessing it and producing it in collaboration with others. Law-like characteristics of ICT important for its impact on knowledge processes are (i) the characteristics of group-forming networks; (ii) the zero marginal costs effect of software and information, (iii) the power of formal modelling and simulation. We may expect these characteristics also in digitally-driven science (Prem 2015).

The characteristics of growth of value in group-forming digital networks are now well established. For n users in a network, the network value is proportional to its $n^2 - n$ connections; this is known as Metcalfe's law (Shapiro & Varian 1999). Reed argues there is exponential growth of value with the number of users in networks with group formation, e.g. LinkedIn, Facebook, ResearchGate (Reed 1999). The main reason is that connections are not only made between single network users, but also between groups. This leads to a growth of connections – and value - proportionally to 2^n. This results in quite different network dynamics compared to non-group forming networks. Small numbers lead to a large potential for interaction between users and groups of users. This feature of information and communication networks is easily comparable to processes in science where scientists usually develop research in groups interested in similar or related subjects. As a linguistically mediated way of understanding the world, science benefits from this interaction in ways similar to the benefits of group-enabling digital networks. In other words, modern science is inherently networked and obviously benefits from these networks becoming increasingly digital.

(Nielsen 2012) already described that electronically mediated group discussions can facilitate harvesting of knowledge in synergistic fashion (cf. Simon 2010). This phenomenon is due to the large number of contributions and the selection and composition of contributions from individuals. Obviously, such processes have always played a role in science, but contemporary information technology facilitates them and has a strong potential to take it beyond what would be feasible with only traditional ways of collaboration. The examples in (Nielsen 2012) include the communication with new peers and the collation of a large number of micro-contributions that would never become published in traditional journals etc. In addition, the trends towards online publication and expert discussion forums will also facilitate interaction with citizens while at the same time collecting expertise from professionals to combine it that of laymen: *“[…] more and more laymen will be able to publish. While useless information may create a lot of noise, useful information is likely to be quickly selected by the crowd and its wisdom.”* (Prem 2015)

Secondly, the advent of digital information systems in combination with the internet has changed the economics of access to knowledge. As there are many freely available software tools today, the access to an enormous amount of information has become easy. That this access is often practically free roots deeply in the nature of the internet technology and of information goods and software. Both their delivery and production are practically free (Hess & Ostrom 2007). It has been argued for knowledge that it is a public good, because of the fact that it can be used without rivalry in consumption. Although access to scientific information stored in libraries has been often free for decades, it was not free in practice. In addition, much scientific knowledge in particular is not just the information contained in a research paper or book. It requires additional knowledge of backgrounds, practices, boundary conditions, and the access to tools to actually apply it. However, the advent of the internet now provides more such knowledge: there is access to software, to background data, even explanations about practices in the form of training tools or videos. In addition, high-quality software for large-scale interest-driven and interactive search supports both professionals and citizens to gain access to scientific knowledge. These features are changing the character of scientific knowledge – it turns the 'club good' into a more open good, free to find and use for anybody interested (Prem 2016).

Thirdly, computers are what is called "universal simulators". Although there are limits to simulation in both practice and theory (cf. Feynman 1982 and Section 3.3), simulation is closely linked with the very nature of abstract computational machines that manipulate numbers, but also symbol strings. This has resulted in an abundance of simulations of all types of systems, not just because computers are a commodity today and software is available for easy implementing it to visualize system simulations, processes, and the resulting calculations in understandable form. The visualizations have become so powerful that they have started to provide insights beyond what is possible with simple formulas. These insights are a kind of understanding that is in fact closely linked with *seeing* in the way that computers offer today (Breithaupt 2006).

These are just three examples of ways in which information technologies are changing scientific practices. These changes include some smaller steps – from a real paper to its digital form – and some much more fundamental ones such as citizen science, new computerized proofs, or the aforementioned potential change to explaining and understanding the world by means of computer simulations; or even to replacing explanation by statistical techniques. It remains to be seen whether the trend towards increased computerization will be equally strong in all scientific disciplines and all parts of the scientific community. However, the prevailing trends in technology (i.e. computer technology) suggest that we have barely scratched the surface of what will be possible in the near future. As an example, consider the recent advances in artificial intelligence, in simulation, mobile computing, etc. These trends will be further supported by societal trends such as the digital native scientist. A young generation of scientists may be expected to focus much more on digital interaction, publication, sharing and impacting on the world with perhaps less interest in a purely academic reception and career (Palfrey & Gasser 2008).

Further change arises from global megatrends that have the power to fundamentally change the basis of today's society, but also of the academic system. We may be witnessing another industrial revolution where the internet is becoming less of a scarce resource and where sharing may be rated higher than owning (Rifkin 2008). These trends are not IT-trends as such, but are massively IT-supported or mediated by IT. Sharing in science has already reached unprecedented levels and it is massively digital (but not just limited to the digital world). If a new generation of digital native scientists grows to live in a world where energy is freely available, research tools are abundant, largely automatic and free to use, the character of knowledge will massively change again.

Some of these changes have been identified in the discussions of post-modern philosophers, for example in the work of J.F. Lyotard. As mentioned already, externalized knowledge is a central concept in the Triple-Helix model (Leydesdorff 2010) and indeed in the OECD discussion (OECD 1996). These discussions first described how in a knowledge-based society, knowledge becomes *externalized*, for example in the form of electronically stored articles and patent knowledge. Already in the mid-eighties J.F. Lyotard predicted a computer-supported externalization of knowledge. There can be little doubt that this prediction has been correct. As we have seen, technology and in particular information and communication technology are changing the way how knowledge is constructed, how it is shared and tested and also used. But both externalization (as described in this section) and internalization (in the sense of automatic construction of knowledge, as described further below) play an important role as soon as knowledge for innovation is created through the use of computers.

This externalization is not just limited to publication or information: "*One can be taken from there to a strong externalization of knowledge with respect to the "knower," at whatever point of the cognitive process he may be located.*" (Lyotard, 1986, p. 24) Here, Lyotard refers to the knowledge process as a chain and points out that externalization (i.e. computerisation, digitization) happens at each step in this process – very much in line with our diagnosis of changing practices in every step of the process of knowledge production. We may then expect that this changes the objectives of knowledge acquisition. It will move away from mere *education* and into the realm of a commodity good, or as Lyotard argues:

"The old principle, according to which the acquisition of knowledge is indissolubly connected with the formation of the mind and even of the person, decays more and more. The relationship of the suppliers and the users of cognition to it strives and will strive to

present itself in the form which characterizes the relationship between producers and consumers of goods to them: the value form. Knowledge is and will be created for its sale, and it will be consumed for its utilization in new production: in both cases, to be exchanged. It ceases to be its own purpose, it loses its 'utility'." (Lyotard, 1986, p. 24) Instead, knowledge gets a sale value based on its value on the market, cf. Chapter 6. In fact, at least from a research manager's perspective, Lyotard's description is hardly surprising as far as the sale value of knowledge is concerned. Perhaps a bit less evident is the kind of complete information that he also sees emerging already in 1986, but digital technologies certainly contribute massively to what Lyotard calls "postmodern knowledge" and "complete information": *"Now it is permissible to imagine the world of postmodern knowledge guided by a game of complete information, in the sense that here the data is in principle accessible to all experts: There is no scientific secret. In the case of equal competence, the increase in performativity - in the production of knowledge and no longer in its acquisition - ultimately depends on this "imagination", which either allows a new move to be performed, or to change the rules of the game change." (Lyotard, 1986, p. 152)*

New distribution of academic work

Another interesting aspect, already alluded to by (Nielsen 2012) is that the new IT tools lead to a *specialization* of researchers that are particularly trained in analysing data and developing statistical techniques and systems that make use of that data. This introduces massive changes to the traditional relationship of making observation and analysing data. The experimenter and the analyser of the data no longer is the same person: *"As more data is shared online, the traditional relationship between making observations and analysing data is changing"* (Nielsen 2012, p. 107). New emerging scientific fields such as bioinformatics, cheminformatics, astroinformatics etc. evidence this development. In addition, there is a trend towards new curricula in Data Science. Only a decade ago, a discipline that primarily studies the analysis of large data bases with statistical and AI tools to gain knowledge of a particular domain would usually not have been created outside of that domain; with the exception of supporting disciplines such as mathematics and statistics.

I have argued before that the changes emerging from a new generation of researchers may be more severe, and they are also related to information technology (Prem 2015): "*Radical change is likely to emerge from the new scientist and from economic and societal drivers. Although new scientific processes are facilitated by ICT they not just root in technology. They are linked to features of what it means to work scientifically. Visibility and speed, relevance and meaning are likely to be key drivers for the new scientists. They will be used to results being immediately available, to free computing resources provided on the internet and to making an impact in the real world – and not just in the academic world. They will not be shy to use 'quick and dirty' computing resources including software and data provided by large companies. The results of such highly dynamic experiments will have to stand practical tests including economic ones. This trend will not see the 'death of method', or the emergence of 'anything goes'. But it is likely to see a re-valuation of the impact of research and science and a larger degree of flexibility in methodology to answer burning questions in society, industry, and also within science and research. Some of the strict rules will go and be replaced with speed, convenience and immediate usefulness. In short, innovation and perhaps also public opinion will become a much bigger immediate driver for science and research."*

As we have argued before, tacit knowledge could traditionally not be easily externalized (Polanyi 1966). It still poses significant challenges, but modern IT is at least partially changing this (Prem 2016). I have described before that this leads to the opening of scientific clubs. In the future this may imply that much more scientific results are available to non-academically trained practitioners or to practitioners with a background in areas different from those new scientific results, e.g. managers.

Lyotard already predicted that new pressures on the academic profession of producers of knowledge may arise from this: *"However, what seems certain is that (...) the delegitimisation and the precedence of the performativity are ringing the tomb bells for the professor's era: he is not more competent to transmit the established knowledge than the memory networks, and he is not more competent to invent new moves than interdisciplinary research teams."* (Lyotard 1986, p. 156) Lyotard not only predicts the effects of externalised knowledge on the profession of knowledge production, he also bases it in the shift to performance criteria of science. From Lyotard's perspective in the 1980s, burying the academic profession may have been a massive exaggeration. More than 30 years later, Bruno Latour repeats this prediction with reference to modern IT services when he claims: *"The difference between a researcher and a search engine decreases every day."* (Latour 2016, p.16)

Lyotard and other authors are not particularly precise about the *form of knowledge* that such a connection between science and technology as a consequence of knowledge takes. Apart from the work in the philosophy of technology, the scholars working on the triple helix model suggest that publications and in particular patents may come closest to this connection. We have seen before that the transformation from basic research to technical knowledge is far from trivial. We also acknowledge that technology has existed long before the advent of any physical science. Thus, it is in fact not evident how "externalized" formal knowledge really supports innovation. Whether the facilitation of externalized knowledge is the most important feature of the trend towards the informatisation of science remains to be seen. The second massive trend that we are experiencing is a process of autonomous knowledge discovery or *internalization* of knowledge (to distinguish it from the effect of externalization). There is an important caveat to make, however, when discussing IT and formal systems in modern knowledge production for the non-formal world, which we discuss in the next section.

3.6 The instrument perspective

The advantages of digital data should not fool us into believing that everything scientists do is just finding explanations. We already mentioned how physicists spend enormous efforts in time and money on devising new experiments and on designing new measurement devices. Ian Hacking is to be praised for focusing on this part of the scientist's work (Hacking 1983). They create observables for reality which in principle cannot be replaced by any digital means. As much as it is great to have large amounts of data at hand, this data must facilitate what we would like to achieve with it. Even if we could compute anything we like – which we cannot – we still require the right information. We repeat from our study on digital science:

"In the future, scientists could work in a massively connected, electronic world with a range of computing resources and sensor networks at their disposition. Questions can be asked and answered in practically no time in interaction with citizens, artists, the industry and all other scientific disciplines. Computing time is abundant, energy is free and the software is so intelligent that it dynamically exploits all computing devices world-wide. [Anderson 08] has predicted the death of theory and argued it will be replaced by big data. Similarly, one might predict the death of research funding agencies – replaced by crowdfunding, the death of privacy – all data, programmes, and results immediately *go online; and the death of peer review – to be replaced by recommender and reputation systems. But all of this has to be met with great scepticism. As argued before, not all work of scientists will be replaced. The construction of observables and asking the right questions will remain a human creative endeavour. Indeed giving purpose to research is an essentially human activity."* (Prem 2015)

It is clear that technology plays a central role in the construction of observables to the extent that Gaycken in referring to Giere suggests that nothing proves the existence of electrons better than electron microscopes (Gaycken 2010 p.10), in particular their use and how they are dealt with create a "constructive realism" of electrons. The microscope then becomes a technological embodiment of knowledge constructs. Still, they do not point to "truths" about electrons, but are viable constructions. They are expensive, but useful embodiments of anticipations of interactions outcome.

Hacking (1983) devotes the second half of his book *Representing and Intervening* to the role of the experiment and in particular to the praxis of experimentation which despite of all the focus on empirical data had not received significant attention before. The focus until then was nearly entirely propositional and linguistic (Ihde, 1991 p.82). But as soon as we include experimentation in a theory of scientific discovery, the roles of interaction, of targeted experimentation, and also perception become more central. Both Hacking and Ihde are very critical of the neglect of the action side of the equation and thus also of the lack of describing technology as a condition of scientific knowledge.

In a similar line, Lenk focuses on Hacking's idea that theoretical entities are set by instruments and measuring devices that establish an epistemological relation to reality (Lenk, 2006, p. 258). For the case of electrons, electron rays used for other problems demonstrate that *"technologically mediated experimental activity allows for electrons to be hypothesized as 'real'; …"* (Lenk 2006, p. 258) This results in a realist-constructivist position as Lenk describes: *"…scientists are more or less successful constructive realists: they use technological instruments to intervene into reality and, despite their theoretical constructions, end up disseminating in the scientific community an experimentalist-realist interpretation of models in the sense of relative 'satisficing' (after H.A. Simon)."* (2006, p. 258-259). The notion of a satisficing model is quite remarkable as it is precisely what the constructivist/biosemiotics model of Chapter 5 suggests: it is another way of describing the fact that the system develops models that support its viability in the environment – and for such viability, satisfactory solutions are sufficient, they need not be optimal or "true".

Ihde (1979, p.23) in his early work focuses on how the use of instruments change human relation to the objects under study phenomenologically. *"To be known, a phenomenon must fall into the horizon of intentionality…"* And he also points out how instrument use inevitably reduces the phenomena under study. However, he also reminds us that reductions are useful for certain purposes. A pair of lovers speaking over the phone may still miss each other. Interviews performed over the phone may be mostly ok, although we still may miss some important information. But ordering pizza over the phone will in most cases be sufficiently successful. (p. 25)

This is to say that human purpose plays the essential role of deciding about the usefulness of the instruments. Similarly, human purpose should be central to the question of knowledge creation as we have identified the basic schism between explanatory and functional knowledge already. The question to what extent purpose was discussed in some selected epistemological theories is the subject of the next chapter.

4 Knowledge creation and human purpose

In systems employing epistemic technologies, such as the type of learning systems just discussed in Chapter 3, utility drives automatic knowledge creation quite differently from pure epistemic interests in the predictive models of basic research in natural science. Let us take a look at historically different accounts of this usefulness of created knowledge from the point of view of epistemological research.

4.1 Epistemological purposes of knowledge

Knowledge for innovation implies utility in a practical context. Bacon's position was already presented before (Section 2.4.4). In this section, we take a look at utility and the transcendental conditions for knowledge in a few more exemplar epistemologies, in particular as regards

- Knowledge for prediction (positivism)
- Knowledge for labour (Marx)
- Knowledge for practical understanding (pragmatism)
- Knowledge for survival (constructivism)

This choice is influenced by Habermas who in *Knowledge and Human Interests* [12] (Habermas 1968) investigates epistemological scientism. Habermas is particularly interested in Marx, Peirce, and Comte and their epistemological positions with an emphasis on creation and purpose of knowledge. To these positions, I add (neo-)constructivism which facilitates the study of knowledge the use and purpose of which is based on an explicit reference to a selector function.

These four positions vary substantially with respect to the main purpose they give to knowledge (see above), but also regarding the main level of analysis: Constructivism emphasizes the individuum and its relation to the environment. Similarly, positivism is

[12] German original title: *Erkenntnis und Interesse*

interested mostly in the cognitive abilities of the individuum (or even disregards the individual aspects completely when the focus is on mathematical prediction). Marx on the other hand is very much interested in labour as a societal coordination mechanism and also as an epistemic driving force (see below). Finally, for Peirce's pragmatism, linguistic coordination within a group is particularly important. I hasten to add that this can only be a simplification and high-level view. There are of course refined positions within these epistemologies that cross the strict boundaries suggested here. For example, communication within a group has been a topic in constructivism. However, the following Table 4-1 suggests that knowledge is viewed from rather different perspectives in these four well-developed epistemologies.

Table 4-1 Overview of the different, simplified perspectives on knowledge in four historic epistemological positions (positivism, Marxism, pragmatism and neo-constructivism).

	Positivism	***Marx***	***Pragmatism***	***Constructivism***
Purpose of knowledge	prediction	labour	understanding	survival
…at the level of…	individual	society	group	individual
Leading discipline	Mathematics	Economy	Linguistics	Biology

It is also possible to put these four aspects in a grid that distinguishes between an individual and societal dimension along the horizontal axis and a mostly logical (mathematical or linguistic) and praxis focus along the vertical axis:

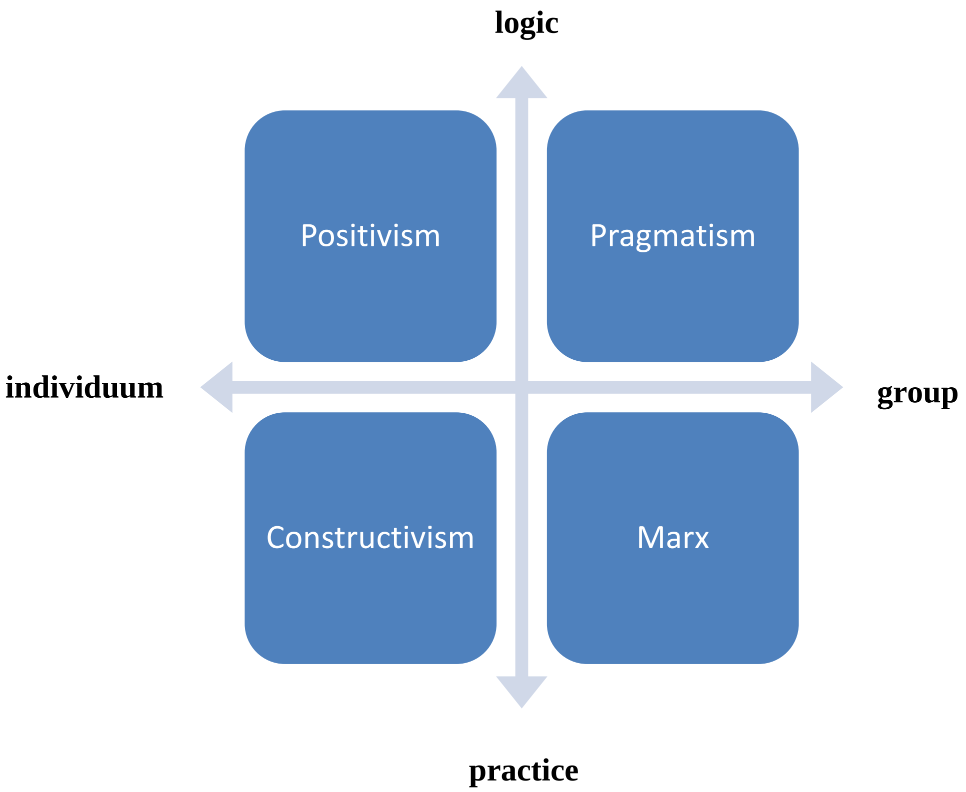

Figure 4-1 Four positions of epistemology put in a grid where the horizontal axis distinguishes individual from societal focus (left to right) and the vertical axis distinguishes logic-focused and practice-oriented positions (top to bottom).

Putting new knowledge to use has attracted relatively little explicit discussion in epistemology as the emphasis was on knowledge as representation, i.e. on mapping reality and on truth and later on methodologies for gaining truth. In total, both epistemology and the theory of science remained a hugely linguistic, concept-focused endeavour with little emphasis on the relation of knowledge and knowledge-based actions – or actions generating knowledge for that matter. I have to add that that this is, of course, a simplification and there have indeed been aspects of action in the discussion of even the most logically oriented philosophers. Kant for example, refers to the "activities of reason" when it comes to constructing the manifold of experiences into objects. However, such activity remains cognitive action that is little influenced by results of interactions with the environment.

It is clear that using knowledge has always been considered important and representatives of empiricism made a strong case for the usefulness of knowledge. But even here, using knowledge was not explicitly considered as a key component in knowledge generation and acquisition. It seems that the main emphasis for a large part of the discussion was on the usefulness of knowledge in order to understand and to predict. However, an explicit discourse on the connection from prediction to the usefulness of knowledge in action is historically far less prominent than, for example, the discussion of criteria to derive (true) knowledge as we shall see in the following examples.

In the following, we examine four prominent positions in the history of philosophy: the positivism of Comte or Mach, the epistemology of Marx, Peirce's pragmatism and (radical) constructivism with respect to their corresponding discussion of the *utility* of knowledge, cf. (Habermas 1968).

4.2 Positivism: Knowledge to predict

Perhaps the most succinct formulation concerning the practical usefulness of knowledge - based on predictive theories - is nowadays attributed to Auguste Comte who is frequently quoted with the words *"savoir pour prévoir, prévoir pour pouvoir"*. These may not be his words, however, because more precisely Comte argues: *"Thus the true positive spirit consists above all of seeing to predict, studying what is in order to conclude what will be according to the general dogma of the invariability of natural laws."* ("*Ainsi, le véritable esprit positif consiste surtout à voir Pour Prévoir, à étudier ce qui est afin d'en conclure ce qui sera, d'après le dogme général de l'invariabilité des lois naturelles",* Comte 1842, III, 15). Interestingly, this quote does not directly reflect today's interpretation that *power* follows *prediction*, i.e. "*prévoir pour pouvoir".* Today's version of the quote appears to have been formulated by the French philosopher and ethnologist Lucien Lévy-Bruhl (1931). Lévy-Bruhl actually proposes: *"'Knowing to foresee in order to be able': we regulate ourselves on this maxim without even thinking about it, as we are trained by our education to put our trust in science, and to enjoy safely the advantages that its applications provide us." ("» Savoir pour prévoir afin de pouvoir » : nous nous réglons sur cette maxime, sans même y penser, tant nous sommes dressés par notre éducation à mettre notre confiance en la science, et à profiter en toute sécurité des avantages que ses applications nous* *procurent.") (Levy-Bruhl, 1931)* Regardless of whether Comte actually intended to claim that *ability* follows from *prediction* or whether this is entirely due to Lévy-Bruhl, it is remarkable that no further arguments are given that one follows from the other. As we have seen in the discussion of technical knowledge, prediction is one thing, but ability to act is an entirely different matter altogether.

The motto attributed to Comte has also come to be known as *"See in order to predict, this is the motto of true science."* Habermas argues that this marks the end of epistemology and the starting point of theory of science as *"it puts an end to the question for the purpose of knowledge."* It is replaced with the results of modern science and reduced to its methods. Theory of science no longer studies the knowing subject, only science as a whole. *"The purpose of knowledge becomes irrational."* Habermas calls it a *"[…] naïve idea […] that knowledge describes reality."* (1968, p. 90). It is to be noted that Habermas here does not relate knowledge to action, only to utility. This is all the more surprising as, following Habermas, the positivist's interest in utility emerges from the condition of *technical* usability in Comte – in contrast to Comte's "void satisfaction of fruitless curiosity": If we only see to predict, knowledge becomes "identical with scientific knowledge" (Habermas, p. 103). Here Habermas also equals knowledge to predict with technical knowledge. But in reality, there are three different intentions that must be kept separate. First, there is *"fruitless curiosity"* that drives our intention to know, secondly there is the *power to predict* from scientific knowledge and thirdly, there may be *technical knowledge* that actually allows us to act. Again, there is at least a significant underestimation of the challenges involved in getting from prediction to technical principles (and perhaps initially driven by curiosity).

With a focus on only mapping facts and deriving futures, the *function* of knowledge remains rather unclear. In addition, however, the distinction of knowledge as a reaction to curiosity from knowledge that has a technical purpose may be much less clear-cut than Habermas would like to make us believe: in the end, such "fruitless" curiosity-driven knowledge also fulfils a purpose that we could call technical: such knowledge has the purpose to be used as a cure for burning curiosity, as a tool for explanation and understanding. The question *how to use positive knowledge for action* does not seem to have received a lot of attention in the work of the early positivists. The focus in the discussion is on validity of knowledge rather than its actual usability, for example in our daily efforts at work. This would be taken up only later in the considerations of Marx and his dialectic materialism.

Why was the problem of turning prediction into actionable knowledge not considered important for Comte? A simple explanation could be that in early stages of science this connection appeared straightforward, i.e. turning basic knowledge into technical principles may have been more direct when dealing with the laws of mechanics rather than with quantum physics. In order to create the desired effect, we simply repeat what we have previously observed. The assumption that prediction entails power assumes that we can in fact re-create what we have previously observed as leading to the predicted outcome. In this case, it is correct that seeing, prediction, and power operate along a temporal and logical axis. *"Science anticipates reality as epitome of potential technical products."* (Blumenberg 1953, p. 46) Where Blumenberg identifies *"hypotheses explaining phenomena"* with a potential *"instruction to create the phenomenon"* we hasten to add that this is only true if the hypothesis is already technical as for example in the experiment. The experimenter holds a position of power based on natural law. Paradoxically, what used to be nature's impenetrable hidden structure now provides the grounds for human use and mechanics. Peter Sloterdijk (2007, 29:00) reminds us that even mechanics as a word is related to artfulness and that a mechanism somehow is capable of artfully influencing nature. Natural science is knowledge of potential action for Blumenberg. Consequently, technology only instantiates what it means to be true within the programme of natural science. Mechanics then becomes the knowledge and science of finessing nature by means of a second nature, something he calls a kind of "counter-nature" ("Gegennatur"). So the whole *idea of a mechanism is the exertion of power over nature* – a position of great interest when using machines for labour and therefore also for Marx.

4.3 Marx: Knowledge for labour

In the works of Karl Marx scientific knowledge appears in the technological applications used to support the production process (Marx 1857) complementary to, or even contrasted with, the skills of the worker. For Marx, the originally manual production process becomes transformed from a laborious work process to a scientific process which subordinates the forces of nature to its service – very similar to Sloterdijk's diagnosis. Marx directly refers to a “*transformation”* process that is applied to natural law (i.e. chemical and mechanical law) in order to construct machines that replace or complement human workers: *“It is, on the one hand, the analysis and application of mechanical and chemical laws originating directly from science, which enable the machine to do the same work as the workers had done before.”* While the origin of science is clear, Marx does not devote much more attention to how precisely scientific laws enable machines, i.e. how mechanical and chemical laws become technical principles. The important aspect for Marx is that a natural process becomes transformed to an industrial one: *“It is no longer the worker, who inserts a modified natural object as an intermediary between the object and himself; But the natural process, which he transforms into an industrial one, he pushes as a means between himself and the inorganic nature he masters. He joins the production process, instead of being his main agent. In this transformation it is neither the direct work which man himself performs, nor the time which he works, but the appropriation of his own general productive power, his understanding of nature, and the mastery of it by his existence as a social body-in one word-the development of the social individual, which appears as the great pillar of production and wealth.” (Marx 1857, p.592)* Marx realizes that the efficiency of this machinery in the production process is of central importance and depends on the current state-of-the-art in both science and technology. [13]

Habermas criticizes Marx as overly focused on possible technical power over natural law when he discusses the human relation to nature. Marx focuses on the human relation to nature from the point of view of *knowledge of control* to gain control over societal life processes. For Habermas it is the invariant relation of the species to its environment which is the Kantian component in Marx: labour processes make up the eternal natural necessity of human life (Habermas 1968, p.39). But in contrast to Kant (or Fichte or Hegel), the connecting point is not logic, but economy. This also means a shift from epistemology to theory of society. From the perspective of a market economist, innovation always includes precisely such a societal component in the collective monetary valuation originating in the market place. For Habermas (ibid.) labour as it is discussed by Marx is an anthropological

[13] Interestingly, Marx also appears to be aware of the importance of technology for the development of science: *“The development of this science, especially of natural science, and with it all others, is itself again related to the development of material production.” (Ibid.)*

and epistemological category that has synthesis function. Labour creates the transcendental condition of potentially objective things in experience. As such humans are to be regarded primarily as tool-producing, working animals. For Habermas this implies that even sociology appears as knowledge of control. There is then a post-modern and indeed post-scientific tendency (Hill 2007) of humanities to knowledge of control.

In addition, Habermas rightly points to the important role of human bodily organisation to create identity in action (and not just from an original unity of apperception) (Habermas 1968 p. 49). Transcendental *synthesis* arises in the labour process in society. Production creates the frame in which both *creation and function of knowledge can be interpreted*. *“Transformation of the production process from the simple work process into a scientific process, which subordinates the natural forces to their service and makes them work in the service of human needs.” (Marx, quoted after Habermas, p.66.)* Although Marx investigates labour as a transcendental condition for knowledge indirectly reflecting purpose through the economic mirror of society, the relation of action to knowledge is not as immediate as in constructivism, because the focus is on labour and the society as a whole and not so much on the purpose-driven work of an individual.

Habermas connects this passage from Marx also to the development of technology as leading to replacing the whole operating process from the person. Progress in technology shows *“... how gradually all the achievements of the human organism, integrated in the functional circle of instrumental action, are transferred to the means of work; First the achievements of the executive organs, then those of the sense organs, the production of energy ..., and finally ... the brain.“ (Ibid., p.65).* This development is particularly important for Marx, because costs of production no longer depend solely on labour force, but also on the state-of-the-art in technology and science (ibid., p.67). Indeed, in economic theories technological state-of-the art is treated as an external variable to the theory describing labour productivity. Interestingly, however, markets are not directly and explicitly part of these considerations. Economy enters epistemological processes more indirectly via production and labour. Note that Habermas also uses the notion of the function circle, a concept that is today connected with Uexküll and theoretical biology and that we shall revisit in more detail below.

In summary, Habermas argues that the overall conception of Marx (ibid., p. 77) is based on synthesis through labour, productive work: theoretical-technical education through critical-revolutionary action, and conflict as the theoretical-practical relation between subject and object (nature). The proximity of knowledge and production is evident as is the focus on instrumental action. Finally, societal aspects arise from the view of labour and production as societal processes. An important remark of Habermas is the societal aspect, i.e. a shift away from *just* the individual cognitive agent. When we focus on innovation, society enters via the market in this epistemology. Marx and as we shall see, modern constructivism, bring action, knowledge use and creation of knowledge closer together than in positivism. But in the case of Marx, it is not yet the *use* of knowledge that directly creates it and as far as labour is concerned, the focus is on society as a whole and not the individual's actions.

Max Scheler reconsiders the relation of labour and knowledge from a rather different perspective. Paul Good in 1974 describes Scheler's position regarding knowledge as an ontological relation in that *knowing, man does not stay with himself, but enters in a relation to other being that remains unchanged.* And this is in contrast to *work* that always targets the *transformation* of material. *(Good 1974, p. 593.)*

4.4 Pragmatism

Following the pragmatic maxim of considering the practical effects of the objects of conception (Peirce 1878) implies focusing on thinking as an instrument. Consequently, it will often mean to consider utility of knowledge for our thinking, but also for action. This idea is central to pragmatism.

The function of truth of statements in pragmatism does not arise (as in Kant) from objective insight gained based on categories and the forms of intuition of reason. Rather, truth emerges from objective life contexts, however often with a strong orientation at logic, language and meaning (e.g. in the work of C.S.Peirce). The central idea is that concepts mainly consist in their conceivable relation to practical life, or in the words of William James: *"…if you follow the pragmatic method …[y]ou must bring out of each word its practical cash value, set it at work within the stream of your experience."* (James 1907, p.21.) James in particular emphasizes the difference of pragmatist truth to rationalist truth.

While the former is *"uncomfortable away from facts", the latter "is comfortable only in the presence of abstractions"* (ibd., p. 26). For pragmatists, there can be truths (in plural); it is possible to talk about their utility and the *"success with which they 'work'"* (ibid., p.27).

At the same time, Peircean pragmatism focuses on these concepts as rational meanings of words or expressions: *"[...] the theory that a conception, that is, the rational purport of a word or other expression, lies exclusively in its conceivable bearing upon the conduct of life."* (Peirce, 1905) It was mentioned before that Peirce regards doubt and the negative stimulus resulting from it as a major driver of something that could be called research. Although pragmatism puts strong emphasis on the utility of concepts, it is without doubt strongly focused on logic. Peirce even calls establishing an opinion the only goal of research (Peirce 1877, 5.374) and James even argues that *"...'truth' in our ideas and beliefs means the same thing that it means in science."* (James 1907, p.23) These ideas and opinions need to be determined by something that persists outside of us by something that is not influenced by our thought, i.e. by reality (Peirce 1877, 5.384). On the other hand, Peirce clearly refers to the effects of actions when he discusses doubt. Such doubt is not just a hesitation about what to do now, but more the anticipation of a hesitation about what to do at a later point in time (ibid., Footnote 22).

Habermas describes this methodologically as world constitution (logic of science). Research processes stabilize opinions, eliminate uncertainty and yield convictions that are no longer problematic. Reality becomes a concept based on a logic of science; it is neither Kant's conception of natural transcendence nor Comte's positivist world of facts. The validity of statements is bound to the methods of gaining consensus, and thus results in a linguistic-logical concept of truth (Habermas 1968, p. 126). Objectivity arises in symbolic communication *and* practical application. "*Prevailing convictions are universal statements about reality that [...] can be transformed in technical recommendations."* (ibid., p.154.)

A challenge arising from Peirce and from pragmatism more generally is the consideration of both logical and practical conceptions: Logical concepts stand the tests of using real objects. Truth therefore is only preliminary – in anticipation of imaginable effects and fixed with reference to the agreement of a universal communication group. We will see how important this notion of anticipation is for the notion of utility in constructivism. H.J. Schubert makes an effort to clarify the pragmatist position by means of an interaction circle

(Figure 4-2) in which inhibitions of usual actions drive us to experiment and find new, more legitimate concepts in our thinking which are then, again, put to use (Schubert 2010).

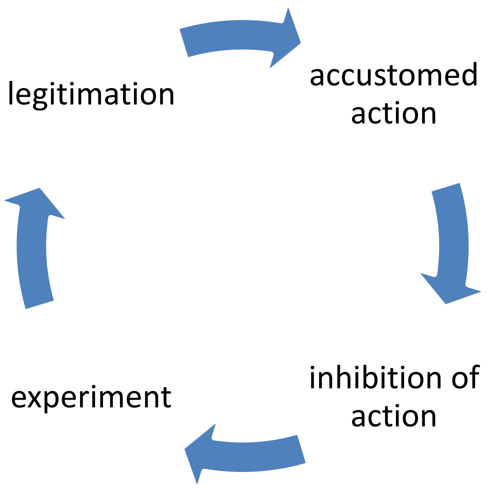

Figure 4-2 The pragmatic circle (after H.-J. Schubert, 2010, p. 45) starts with a problem that arises from the inhibition of a usual action that becomes the basis of an experiment. This results in newly legitimized concepts that become used in action until a new problem arises.

An important consideration in this circle is *"what would be better for us to believe"* (James 1907, p. 30) and James argues that eventually what is better for us to believe and what is true for us cannot be kept apart. Knowledge in such a pragmatist view then becomes shaped on the one hand in the interaction with reality in use and utility. But on the other hand, this knowledge is largely logical and conceptual, especially in the case of Peirce, and it is motivated by communication and reasoning. This is why (Schubert 2010) explains *"…we gain knowledge, when objects or facts create effects in situations of use…"* Internal consistence of beliefs in the sense that *"the greatest enemy of any one of our truths may be the rest of our truths"* (James 1907, p. 31) is a key element of pragmatism. Effectively, this implies the importance of justification and explanation, i.e. largely Aristotelian endeavours that are clearly visible in Peirce.

The intention with which Habermas mentions this aspect in the discussion of knowledge and utility is to pinpoint differences between humanities and natural science. His argument is that science only considers a tiny part of the whole context of life while the humanities necessarily focus on this whole. Empirical/analytical sciences are located within instrumental action and view reality from the point of view of technical availability. Hermeneutic sciences on the other hand are interested in communicative action and in inter-subjectivity of communication and in action under shared norms (Habermas, p. 221). Note however that there is of course hermeneutic knowledge: not everything will be negotiated from scratch. Such knowledge can be assigned a purpose: for example, enabling communication, and enabling understanding of the actions of others.

4.5 Constructivism

Another philosophical perspective that strongly emphasizes the active element in coming to know is constructivism. As early as 1710, the Neapolitan Giambattista Vico proclaimed that truth is what is constructed *"verum est ipsum factum"* (Vico 1710 p.15) and he thereby emphasized the role that the individual plays in an act of construction (Glasersfeld 1992). Today we interpret this as one of the earliest philosophical accounts of constructivism. Modern constructivism (sometimes called "neo-constructivism" to distinguish it from the work of Kant) is often traced back today to the work of Jean Piaget who is also said to have first introduced the term 'constructivist epistemology'. His focus on how humans make sense of the world – with a strong developmental but also genetic point of view – led him to emphasize the individual's construction of knowledge based on its interaction with the world (Piaget 1954, Glasersfeld 1987). It is not surprising then that his theories are milestones in the theory and practice of modern pedagogy.

From the focus on the individual's specific interpretation of experience emerged the idea of a "radical constructivism" (Glasersfeld 1984). With hindsight from three decades later, much of the arguments of radical constructivism seem to be in contrast to an objectivist, rationalist, and positivist theory of knowledge. Glasersfeld as one of constructivism's most prominent representative calls it *"farewell from objectivity"* (Glasersfeld 1996). In his view, whatever it is that we mean with knowledge, it cannot be the mapping of a world independent from our experience. The role of knowledge is not to reflect objective reality, but to enable us to act in our world and reach goals. The component of action is already present in Piaget, but it is even stronger in the work of Maturana & Varela (1984). As biologists, Maturana and Varela are aware of the continuous close interaction of a living entity with its environment and therefore they focus on action-based constructions that are oriented at what is possible and viable for the living system. In order to understand what is viable – judging from the results of an action – a living system necessarily has to act. (It is clear that the animal may not perceive causality, but only temporal consequences of its actions, cf. Glasersfeld 1997.)

One of modern constructivism's core contributions is indeed its focus on action (use, interaction, and structural coupling) as the source and at the same time the verification of knowledge. Action comes to the foreground, in fact it becomes *a condition of knowledge acquisition*. In constructivism, the emphasis is first on the construction of knowledge from action and interaction. Strictly speaking, Maturana and Varela describe knowledge as effective action (Maturana & Varela 1986, p. 35, p. 182). But action not only is the condition of knowledge acquisition, we also should treat knowledge as enabling action. With other artefacts (things) than knowledge, the stages of design, production, and use easily fall apart. In the constructivist perspective, knowledge creation and its use become inseparable which also explains the interest and influence of constructivist ideas in pedagogy. Of course, there is a caveat to make about linguistically mediated knowledge: it is possible, at least for humans, to learn to some extent from symbolic information. Constructivism certainly does not deny this, it only shifts the emphasis to what it considers primordial and also more important for beings that learn in non-linguistic ways such as animals.

Much philosophical debate has followed the publication of neo-constructivist positions in particular concerning the claim that knowledge has to fit with the environment and the system's requirements, but does not necessarily map reality. Knowledge that *"fits"* had not been extensively discussed by epistemologists before the advent of neo-constructivism. Traditionally, epistemologists were focused on the conditions of true knowledge understood as true statements about the world. The Stanford Encyclopedia (Steup 2016) states that *"[...] knowledge requires truth"* as well as belief and some kind of justification. The Internet Encyclopaedia of Philosophy[14] summarizes: *"We might say that the most typical*

[14] Online: www.iep.utm.edu/epistemo Accessed 6.7.2017

purpose of beliefs is to describe or capture the way things actually are; […] seeking a match between one's mind and the world.”

As we have seen above, turning such knowledge into relevant knowledge for action or even know-how is not trivial. It appears to have been mostly assumed by epistemologists without in fact considering the test for practical fit a valid source of objective knowledge. In the constructivist paradigm, useful knowledge to act should be true and justified as well. But it receives truth from the test in reality, from withstanding evaluation in action, and its justification arises from experience. In constructivism, the perhaps naïve purpose of knowledge and its ultimate goal is survival or “viability”. Indeed, as we shall see below, for the knowledge-constructing epistemic system, its world will always appear as full of potential for action simply because this is how it models the relation between itself and the environment.

This model is also strongly related to *interactivism* by Mark Bickhardt who in addition underlines the importance of temporal processes, for example in contrast to “snapshot models of perception” (Bickhard 2009). Surprisingly, there is little discussion about the notion of temporal aspects in radical constructivism. The focus, at least with Maturana & Varela is on “structural coupling” of system and environment, and on interaction – but temporal coupling is barely mentioned. Time is mostly discussed from the point of view and at the level of evolution, but a living system’s need to act and react in time to survive is not explicitly considered. Also, continuous processes of system-environment interaction received little attention in early versions of constructivism. A central notion for the ongoing interaction is “coupling”, but this coupling itself receives little detailed analysis, at least in (Marturana & Varela 1986). The notion of coupling is, however, important for explaining communication and social aspects in constructivism: Maturana & Varela discuss social phenomena based on a special form of structural coupling (3rd order coupling). Such coupling may occur in sexual reproduction or in stigmergic communication, e.g. between insects. In such a biological perspective, communication then becomes a mechanism for co-ordinated behaviours between members of a social community (Maturana & Varela 1986, p. 210). Language, e.g. in the form of speech or symbols of a written text is another way of co-ordinating behaviour among members of a social community (p. 226). The special feat of a symbolic language is its self-referential character, the basis of semantic auto-poiesis.

4.6 Knowledge use and purpose: a preliminary conclusion

Summarizing the discussion in this section, knowledge and its use, the utility of knowledge and its application have been issues in the works of Marx, Comte and Peirce in particular. However, the degree to which actions or interactions with the environment play a constitutive element in knowledge acquisition or construction varies greatly. The perspectives of the transcendental conditions are broad:

- For Comte, utility arises from the predictive power of knowledge.
- Marx focuses on societal production and labour as human nature, thus clearly emphasizing an action component in relation to knowledge.
- For Peirce both aspects, scientific justification and usefulness in action are important although the action is often discussed with an emphasis on linguistic interaction.
- Finally, in constructivism action and environmental interaction become more than just an application case for knowledge: viable actions and perception/action stability become *sources* of knowledge.

In summary, there is an increasing tendency in these different epistemologies of shifting the focus towards action and thereby moving from models *of* reality to models *for* reality. The really interesting aspect is the apparent paradox that models *of* reality in some way are insufficiently suitable *for* reality, in particular when we aim to construct technical artefacts. This is not just the problem of Section 2.5. The core methodological dispute in robotics in the 1990s concerns precisely the use of symbolic, predictive models as opposed to non-symbolic, interactivist models (Bickhard 2009). Again, it is as if epistemologists followed Rodney Brooks' insight that the world is its own best model (Brooks 1991, p. 139) for action – only that in a strict sense Brooks' early robots were practically model-free. But what is visible is a trend towards increasing interaction, increased proximity to reality and decreasing abstraction.

If we now compare these epistemologies with the discussion of ICT use in modern science and in particular with the tendency towards automated model construction, we realize that also there, systems aim at staying as close as possible to the data and abstracting only with respect to achieving the desired outcomes. These systems are certainly useful and when used in scientific contexts may be able to predict, but they achieve little in the way of explaining the phenomena. The systems *construct* models of data, but only of a very special type: the models are created *in order to* achieve the desired outcome such as translation or object recognition etc. They create models that *anticipate these outcomes* based on the desired input; something that appears very similar to constructivist epistemologies, as we shall see in the next section.

5 A constructivist model

In order to better understand the precise character of knowledge as we focus more on action and action outcome, it will be useful to use a simple system theoretic model of an autonomous system and its interaction with the environment. The following model is inspired by constructivism, but in the version that is presented below it is clearly connected to theoretical biology and ethology, in particular to the ethological concept of the function circle introduced by Uexküll (1909).

5.1 Knowledge from action for action

Uexküll was originally interested in how living systems perceive their environment with an emphasis on the subjective perspective and frame of reference of the individual being. In close proximity to concepts of radical constructivism, Uexküll focuses on the internal world of the animal. As a biologist, Uexküll also focuses on the interaction of the living being with its environment and categorically separates the system's actors from what might be called the points of contact or "carriers of an effect" (Prem 1997). The concept of the action circuit (Figure 5-1) is of central importance and has since become a central ethological concept, in particular as a fundamental behavioural schema in the explanation of animal behaviour, cf. (Brentari 2015, Tønnessen 2015). It has even been used as a design principle in robotics (Prem 1997, Prem 1998, Ziemke 2005).

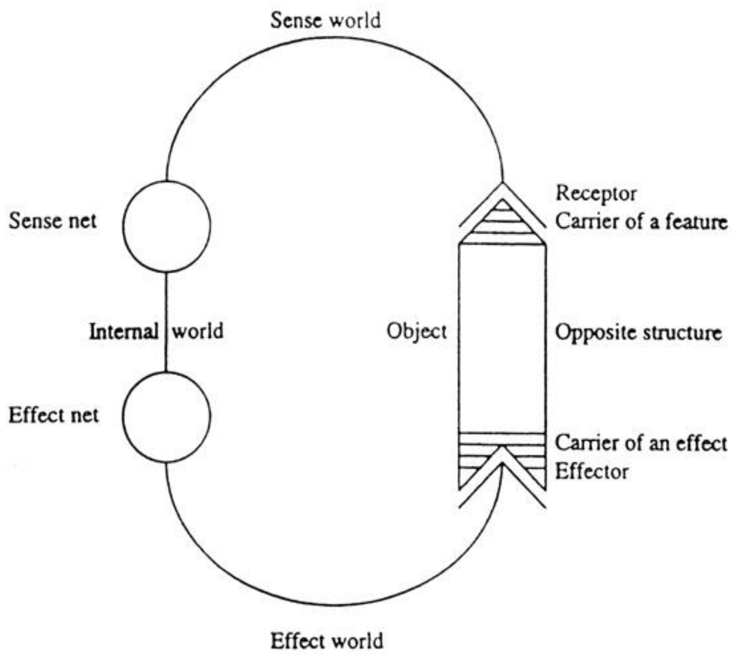

Figure 5-1 An action circle (Uexküll 1920)

Uexküll’s work clearly inspired a broad range of scholars (Kull 2001). In biology, for example, Rosen took up his ideas for the theoretical work on anticipatory systems. In addition, Kull describes Uexküll’s impact on philosophers such as Max Scheler, Ernst Cassirer, Merleau-Ponty Michel Foucault, Martin Heidegger and others. Uexküll also impacted on biosemiotics and biolinguistics (Augustyn 2009). Central to our interest here, his works were of importance to founders of neo-constructivism, e.g. Humberto Maturana. In relating internal world and environment through the concept of a living system’s interaction with the world, von Uexküll also can be regarded as a founder of biosemiotics. In this realm, (Bischof 1995) proposed a biosemiotics model and applies it to the action circuit example of Uexküll. The model originates in Bischof’s introduction to systems theory. The focus on control and in particular homeostasis conceptually puts it in the vicinity of cybernetic models, to which – unsurprisingly – Uexküll also contributed significantly (Lagerspetz 2001). While Bischof focuses on the (bio-)semantic interpretation of the example of tick behaviour, our interest will be more on the action and goal-directed interaction of the system.

The following figure depicts a system S that receives environmental stimuli *(α)* which are perceived as *s*. The system then generates reactions *r* to perceived stimuli in order to generate environmental effects ω.

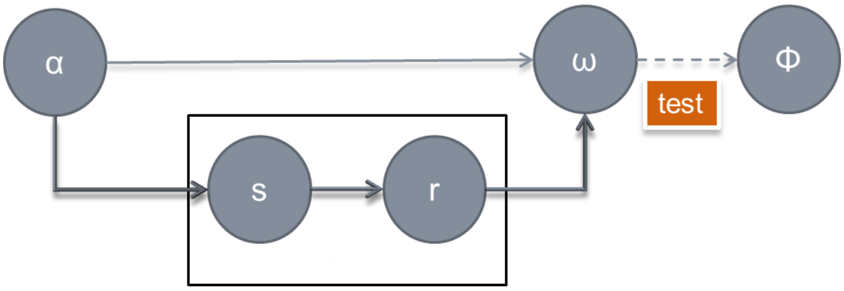

Figure 5-2 If S adapts to its environment Φ: S creates an anticipatory model of the world based on Φ (adapted from Bischof (1995). See text for description.

The selector Φ depicts an evaluation function that classifies the viability of actions. The evaluator operates on the level of the system, i.e. it evaluates the actions of the system and will select systems that choose viable actions in their environment. This is a very general approach to characterizing adaptive systems. The selector Φ is not characterized in terms of different types of learning systems, i.e. we are not interested in whether the system adapts based on chance, on supervised, self-supervised or unsupervised learning. The only important feature is that the system selects viable actions, i.e. actions that are positively evaluated by the selector. Obviously, the selector could be interpreted as survival for a biological system resulting in a selection of systems that are adapted to their environment.

In the example of Uexküll and Bischof, S may represent a tick. Ticks are capable of sensing the presence of mammals *(α)* through their sensory organs. By sensing butyric acid and temperature *(s)* ticks are able to trigger *(r)* the proper actions *(ω)* in order to feed on mammals within reach of the tick. Ticks have developed throughout evolution so that they are adapted to their environment, i.e. to the selective pressure that decides on survival of fit animals (Φ). Bischof uses the example to exemplify a semantic interpretation and the cognitive interpretation of the animal's cognitive states and reactions. Here we are more interested in the behaviour from the point of view of a system that acquires knowledge about its environment.

In order to use the example from the point of view of goal-directed and action-oriented knowledge, we take S to be a learning system and Φ represents a goal function (learning function). Over time, S should select actions *(ω)* that minimize the error provided by Φ. For this argument it is of no concern which kind of learning strategy the system uses as long as it eventually derives a strategy that minimizes the error. The system will then have learned – over time – a mapping from *s to r* that creates *"useful"* actions.

(Rosen 1985) has termed such systems anticipatory: the system appears to take an error minimizing action based on an input at that point in time, i.e. it will produce an error-minimizing action that seems to *anticipate* the response from the error function Φ at a later point in time. Obviously, there is a range of constraints under which this will work, most importantly the error function – or better reward function – and the environment will have to behave consistently over time, otherwise prediction becomes impossible. After some time, S will generate a model of the error function Φ and the system can then select error-minimizing actions based on its knowledge. "'*To know'"*, as von Glasersfeld says in the description of Piaget's contribution, *"does not involve acquiring a picture of the world around us. Instead it concerns the discovery of paths of action and of thought that are open to us, paths that are* viable *in the face of experience." (Glasersfeld 1997)*

The important point and reason to use such a constructivist scheme (or model) is that knowledge in this example is based on past experience and individual history. However, the knowledge is as much an internal model of the environment as it is an (internal) model of the selector function. It is also a model of the system's interaction with the environment. So, while the mapping of stimuli to reactions looks familiar and innocent, this mapping is based on the influence from rather different factors, namely the actions chosen (which in turn is based on the knowledge already accumulated including the interpretation of the environment); the environmental answer to the action, i.e. what happens in the environment as a consequence of the action; and of course the selector function.

What the model also explicates perhaps more clearly than other accounts is – in the words of (Adolf & Stehr 2014, p. 13) – that *"knowledge is always the knowledge of* someone *[...]*

knowing is some sort of personal participation*: knowing things, facts and rules means to 'appropriate' them in some manner, to include them in our field of orientation, competence and skills."* Similarly, compare (Glasersfeld & Varela 1997): *"Anything known is known by an experiencer.*") In this view, knowledge is more an activity than a state, at least is refers to potential purposeful activity. (Glasersfeld 1996, p. 2) explicitly refers to the *"activity of knowing"*.

I have pointed out in previous work that in this way, the system generates a representation of the environment that is characterized as much by the actions and Φ as it is shaped by the stimuli *(s)* (Prem 94). We expect that the system's knowledge is shaped in order to produce the right actions. If we further assume that the system is economic in the sense that it distinguishes mostly based on feedback received from Φ, then it will classify situations requiring similar actions in the same equivalence class. For such a system (just as for our tick), the world will appear solely in terms of the required actions and the expected selector, the sensory side will merely be used to differentiate useful actions. In fact, (just like the tick), the system may not even be capable to differentiate between situations that make no difference with respect to its actions. The world-view of such a system then becomes what (Susi & Ziemke 2005) called *"its own subjective universe".*

Knowledge in Bischof's biosemiotic model then is equivalent to the **anticipation of interaction outcomes**. Successful past interactions lead to the preferred selection of these interactions in the futures in similar situations; the system thus has created a **model for action**. From the point of view of our technical and goal-oriented discussion, the knowledge accumulated in the system becomes a type of knowledge that we might as well call *technical principles*. The system will develop the capability to apply actions in a goal-oriented fashion (namely to minimize the error function specified by the selector Φ). Knowledge becomes *a service,* as von Glasersfeld describes it: *"Instead of the supposed correspondence with an unfathomable reality, it is the service knowledge renders that can now be seen as its testable justification."* (von Glasersfeld 1996, p. 5)

Adolf and Stehr (2014, p.21) remind us that *"knowledge is virtually never uncontested"*. Note on the other hand, when knowledge is presented in the form of technical principles and used to build successful applications it is in fact hardly ever contested. Technically embodied knowledge convinces based on its performative demonstration of function. We shall see below that such a performative element is clearly also visible in the scientific experiment for which the previously commercial laboratory becomes the stage in modern science (below and later again in Section 6.6). But before returning to this performance element, there is the important point of function or purpose of the technical knowledge.

Opportune knowledge

In the biosemiotics model, knowledge arises from purpose – or in a broader sense from the selection function that creates and adapts the model, cf. (Rosen 1985). This approach solely focuses on purposeful knowledge. The truth conditions are given in the optimization and selection process. Indeed, they *are* the purpose in the sense that their fulfilment is all that counts. From this we may conclude that in adaptive systems, **there is practically no knowledge without purpose**. More specifically this means that we can always attribute the *purpose of anticipating an action according to a prediction that leads (and in the past led) to the selection of that knowledge*. In other words, the purpose of knowledge in such systems always is to minimize the error – regardless of what the specific shape of the selector is. And in this sense, knowledge that we act upon always anticipates successful interaction outcome. I am emphasizing this point here because it means in reverse that (at least for our constructivist system model) purpose-free knowledge is a myth. Also in this model, the primacy of technical knowledge over abstract, objectified knowledge is evident. And in addition, the way in which the model is constructed leads to an interpretation of the system's environment that is entirely based on action and interaction (assuming that the selector Φ rewards at least some form of activity and is not a degenerated reward function that leads to the selection of no action at all).

The role of action and instruments

It is surprising how relatively little attention the role of action and interaction still plays in modern philosophy of science. Despite of a renewed interest in experimentation in the school of "New Experimentalism", for example in the works of Don Ihde and Ian Hacking, the corresponding philosophical account is still *"in a rudimentary state for lack of a suitably* *comprehensive framework…"* (Crease 2006) Crease lists what such a framework should achieve: it should allow to describe the experiment as interest-driven, but also as event-driven and as a process of inquiry that *"... would need to show how experimentation is meaning-generating."* (Crease, p. 221) The original proposal of Crease is the concept of "performance" in the sense of conceiving, producing and witnessing material events such that the corresponding experience generates meaning, i.e. something in addition to just that experience. This is precisely what we see in the biosemiotics model. Unfortunately, also prominent philosophers such as Don Ihde *"... somewhat underestimate the 'action-impregnatedness' or 'activity-ladenness' of experimentation besides the instruments by tendentially overaccentuating 'perception'"* (Lenk 2006, p. 260). Lenk rightly points out that this also includes how knowledge is created in these interactions. He has argued many times how knowledge creation, interaction, but also interpretation go hand-in-hand.

The instruments mentioned by Lenk here require a word of explanation as our constructivist model does not explicitly refer to any instruments that the system may use in its actions and/or for perception. Such embodiment relations – to use Ihde's terminology (Ihde 1990, p. 40) – could be added to the model. In fact, the discussion of instruments in the sense of sensory organs and similarly effectors played a key role in von Uexküll's theories. However, while Ihde focuses his phenomenological discussion of technology in epistemic processes on instruments and on various types of body-instrument-world relations (Ihde 1990), our discussion really focuses on the knowledge constructs per se. In a sense the model is in a situation where the instruments are entirely transparent for the agent. Ihde draws a parallel between Heidegger's tool use (e.g. the hammer) and the use of eyeglasses as an instrument in the process of perception: just like hammers "disappear" when we are engaged in hammering, we are usually unaware of (clean) eyeglasses. But just like dysfunctional hammers, broken eyeglasses may become conspicuous. *"Then the meaning of eyeglasses changes from means to objects of experience."* (Ihde 1990, p. 48) We shall explore these aspects in more detail in Chapter 7. In addition, our model does not explicate the role of prior knowledge. That such knowledge influences perception is nothing new. In his work on the cultural embedding of technology, Ihde discusses how cultural knowledge plays a huge role in technology and in particular in the use and interpretation of measurement instruments (Ihde 1990, p. 43) against a techno-cultural background.

5.2 Predictive encoding

The biosemiotics model just presented here is consistent with recent discussion of *predictive encoding*, an explanatory Cognitive Science framework suggesting that brains are essentially prediction devices (Clark 2013 p.181) that constantly attempt to match sensory input with predictions. The theory of predictive encoding goes beyond just a neural theory of perception and action as Andy Clark also presents it as a unified theory of mind and action and in particular as a *“deeply unified account of perception and action”* (Clark 2013, p. 186). The theory builds on empirical results and explanatory frameworks of a range of authors including Helmhotz, McClelland, Hinton, Kawato etc., cf. (Clark 2013) for further references. The core idea is to understand neural activity as largely predictive in the sense that the brain uses Bayesian inference to derive from a goal state the actions necessary to reach the perceptions predicted for that goal. In the neuroscientific and epistemological discussion of predictive encoding (Clark 2013, de Bruin & Michael 2017), prior knowledge becomes massively important when neural systems are modelled as prediction error minimizers. The theory focuses on prior knowledge in the form of predictions, i.e. it is based on previous experience or information priors that facilitate the detection of unexpected events. An important characteristic of this framework is that it uses an efficient information flow where forward signals (from perception to higher neural levels) are mainly error-signals and downstream signals are predictions. This ultimately results in a situation where signals are not primarily related to just the inputs, but to their *“congruence with internal goals and predictions, calculated on the basis of previous input to the system.”* (Rauss et al 2011 p.1249, quoted after (Clark 2013)).

The important resemblance of neural predictive encoding with the biosemiotics constructivist model consists of the focus on action-oriented predictive models and processes. Although our model is not hierarchical and does focus on the prediction of sensory input, it clearly shares the focus on an interactivst and anticipatory perspective with the type of models that Clark argues for. In such models *“[p]erception, cognition, and action – if this unifying perspective proves correct – work closely together to minimize sensory prediction errors […]”* (Clarke 2013, p. 186). The characterisation that Clarke uses for predictive encoding, namely *"action-oriented predictive processing"* (ibid.) can also be used to characterize the biosemiotic model presented here. The difference between the two models lies in the specific prediction quality. While the biosemiotics model predicts interaction outcome, the predictive encoding scheme aims to minimize prediction error of inputs to improve recognition, learning, inference and action-selection (ibid, p.10). Another similarity lies in the fact that predictive encoding is strongly motivated and in synergy with situational and embodied approaches to cognition. Theories in accord with prediction error minimization need to take into account the body and its role for matching experience and prediction (de Bruin & Michael 2017). The importance of the body as the basis of the system's worldly interaction is also true for our model.

Although the core of the predictive encoding model presents itself at the neuronal level (i.e. the prediction of sensory inputs), Clarke easily expands it to multiple levels of abstractions and also time-scales (Clarke 2013, p. 195) to explain how we make our environment easier to predict, for example by colour-coding objects and to account for cultural phenomena such as patterned practices in language and music (Roepstorff et al. 2010). Perhaps surprisingly, the predictive encoding framework also seems to suggest that goals and rewards are less important than in many cognitive accounts; they become replaced with *"the more austere construct of predictions"* (Clarke 2013, p.200). And in particular, the predictive encoding approach suggests that we represent events in a way that they also carry significance. As we have seen, this is precisely what will happen in the biosemiotics model that creates a model of the interaction with the environment that is controlled by the system's interactions and the selector which it predicts.

5.3 Linguistic utility

While the biosemiotics model is perfectly in line with a conception of knowledge that Adolf & Stehr have called an effective model *for* reality (2014, p.23), it contrasts with more traditional conceptions that require knowledge *of* reality. In particular, the model does not require but also not facilitate a full symbolic account of causes and effects. All that is required for the system is a model that produces the desired effects, it knows-how, but does not know-that (cf. Ryle 1949). We may take this to be the construction of a purpose-specific representation of reality, thus clearly narrower than Giere's interpretation of science as the establishment of similarity relations between real systems and their models (Giere 1999).

What the model admittedly does not clearly explicate is, for example that it is also possible to know something just based on symbolic information (cf. Bernardo & Okagaki 1994, Adolf & Stehr 2014 p. 14). It is, however, possible to include this view in the model by taking that symbolic information to be a part of the environment. The model does not have to remain at the level of only "manual" (i.e. direct physical) interaction. The model can also be used to consider linguistic interaction as an activity with viable consequences in the speaker's environment, which in this case will mostly concern reactions from other speakers (or other systems understanding linguistic interaction). Very much in this line, (Matruana & Varela 1984) proposed to interpret *communication* as mutual triggering of co-ordinated behaviours within a group of agents. As a phenomenon, language in this view clearly resides within the realm of social behaviours, although Maturana and Varela make the valid point that linguistic behaviour is only a subset of communicative behaviour.

In order to exemplify the view of language in our model, let us take the simple example of stigmergic communication which was just mentioned. A (symbolic) sign in the environment of the system may be learned to stand-in for an action that is generated in the system. For example, an automated car may take a traffic sign to mean "turn left here". Similarly, a robot doll may learn to say "mama!" based on some sensor input in order to be rewarded with some kind of petting. These examples emphasize the character of symbolic interaction as a tool, not so much as pure reference (cf. Prem 1998). But the system can also acquire the meaning of purely referential terms. A robot might produce a different action in reaction to someone in its environment saying "Give me the book!" or "Give me the apple!" The system may learn to anticipate the successful interaction outcomes for both actions. It will perhaps have no knowledge about apples and books other than in which contexts they lead to success in action. The nucleus of the system's model facilitates pointing actions on the basis of adaptive model building. In such a view, the symbols used in language become anticipations of successful referral interaction outcomes. More generally, in the model, knowledge becomes the **anticipation of successful interaction outcome**. As we have seen, the selector is essential for the construction; models of reality are shaped depending on the objectives:

they decide which model is produced. Same environments can generate completely different constructions that are viable. Note that this is also what we already identified for the case of automated, statistical model construction in Section 3.2.

This effectively results in both a pragmatic and constructivist epistemology – two positions that have been argued to go nicely together. For example, (Ültanir 2012) discusses the similarities of Dewey's positions with constructivism. Dewey may be generally said to be positioned precisely between the two epistemologies (Hickman et al. 2009) in the sense that there may not be any approximation of a postulated reality, but life "works" as long as the system constructs the basis of viable actions. There is no direct contradiction between the constructivist aspects and the pragmatic "viability". In fact, such pragmatic constructivist actions may also include linguistic interactions. Strictly speaking, there are two types of functioning: a pragmatic (in the sense of Peirce) and a technical one (in terms of reaching the desired objectives). The connection between the two lies in the joint goals (as selected by Φ). If two such systems share goals, they may be able to understand each other in the sense that they acquire anticipations of successful interactions with each other. I have previously connected this to Wittgenstein's famous quote *"If the lion could speak, we would not understand him."* (Wittgenstein 1953, Prem 1995). As a simple example in our context here, a system may refer to the apple and a second, interacting system returns it. Then the best explanation for that apple in the interaction given our model is that it produces an interaction between the systems which is viable for both (one system taking the apple and giving it to the other). Researchers in Artificial Intelligence have implemented systems that are capable of doing just this; i.e. they learn to use symbols in order to refer to objects in pointing actions (Steels 2008, Steels & Hild 2012).

Admittedly, the main reason for discussing linguistic action in this thesis at all is the strong preference of traditional contemporary epistemology (and in fact epistemology since Plato) that it gives to abstract forms (Plato) or in other words on the definition of knowledge as justified true belief in contemporary analytical philosophy (Ichikawa & Steup 2017). For many philosophers, this definition is appropriate in that it provides insight as to why knowledge is more valuable than mere (true) belief. Consequently, there is today a large analytical discussion regarding the processes leading to such knowledge, the credit for an agent and (fairly recent) about what happens when we replace "knowledge" with "understanding" (Kvanig 2003). The discussion is particularly important from a scientific perspective because in science contexts, "true belief" is not enough. Scientific discourse is strongly centred on justification. Such justification may be methodological, evidence-based, logical (i.e. linguistic) – anything that undermines the suspicion that knowledge would just be accidental. Knowledge in science must be communicable and communicated, contestable and contested, defensible and defended.

It has been argued that the knowledge concept itself arises from a process (and perhaps an excess) of objectification (Craig 1990). Originally it may have had the function of identifying reliable informants (Pritchard & Turri 2014). Knowledge implies valuable sub-concepts such as *truth, justification, persistence, stability, safety* etc. Each of these can be valuable. Thus, a proper assessment of the value of knowledge depends on our precise choice and interpretation of any of these sub-concepts. In philosophy, the need to eliminate possibilities for error was then stretched to something rather far-fetched, i.e. absolute and eternal truth in correspondence of mind and world.

Justification, and therefore, truth in the sense of justified true belief, are *backwards-oriented in time,* at least in the theory of science. Justification concerns an argument about how we *came to believe*. Similarly, scientific truth often refers to *methodological conditions* ensuring reliability. An action and innovation-oriented conception, is intrinsically oriented towards the future. **It is true, if it will work.** Truth in relation to our model means the correctly anticipated interaction outcome. But even if we would like to stick to the definition of knowledge as "justified true belief", the constructivist model can still be used, at least in principle. In this case, knowledge remains the "anticipation of successful interaction outcome", only that in this case the *interaction* is linguistic as well, i.e. (i) there is real-world interaction (truth) and (ii) linguistic interaction (justification).

5.4 Novelty and the selector function

Up to this point in this thesis we have not systematically addressed the question of novelty that is ultimately linked to innovation in the sense of a new idea brought to the market. This includes new products, but also processes etc. So far, we have focused on the process of knowledge construction and on a model of an adaptive system. It was implicitly assumed that the knowledge built, for example in the constructivist model, is new for the system and is based on learning. We have already identified the importance of action in time and of adaptation in time. Novelty as a concept is also closely linked to the notion of time. In fact, in order to describe what is new in a system it is necessary that we are capable of providing a historic account as novelty always refers to a change with respect to a previous, older situation. Most accounts of learning or adaptation conceptualize it as something that happens within the system, i.e. something that is reflected in some change in internal parameters. System theorists rightly point out, however, that learning should be regarded as a change in the triadic relation of a system, its observer and its environment, the typical approach of Second Order Cybernetics (von Foerster 1974). Using our constructivist model as a basis, there are therefore three different sources of creating novel system-environment relations. Firstly, they can be system-internal; secondly, they can lie at the interface with the environment; and thirdly, they can be due to the selector.

i. The first and most commonly considered level is the acquisition of new knowledge in the sense that an internal rule or parameter is changed which leads to a novel behaviour. Such a new internal parameter was not part of the system's knowledge before the change. This can also be interpreted as exploring a part of the total state-space that perhaps was not seen yet or that did not produce the right outputs.

ii. Secondly, as already mentioned, there can be novelty in devising new ways of interacting with the world. This is the case of the construction of new observables and actions. In our model, it would mean that the system creates fundamentally new forms of interaction with the world.

iii. But thirdly, it is of course also possible to change the selector function and, for example, test the knowledge previously acquired given a new selector.

There are also cases where it makes sense to assume that the system itself influences the selector function. In the simple biological example, the selector will usually not greatly depend on individual knowledge, but we may construct cases where the system changes the environment so that ultimately different forms of the selector are created. As a simple example, consider a system that based on its knowledge builds a shelter to protect it from its harsh environment. The selector may not have changed in principle, but its description may now be easier taking into account the newly created shelter. In fact, it is a common strategy of living systems to select a part of the environment – where the selector may be less unforgiving than in other parts of the world. This self-selection of influence on the selector is particularly true for systems that are components of social systems so that their outputs influence the selector. For example, a political party may try to influence voting rules favourably to its advantage; i.e. it will try to change the selector so that it succeeds despite of few votes, for example. We will return to the questions of systems influencing their own selectors in the discussion of research funding and lobbying in Section 6.6.

5.5 Opportune knowledge in the constructivist model

The constructivist model presented in this section helps to clarify some important characteristics of opportune knowledge, i.e. of knowledge useful for action:

- The selector operates on the *results of the actions*, i.e. it is entirely activity-based.
- Knowledge for successful action depends on and is influenced by its *usefulness* for generating these actions.
- The constructivist model contains an internal, *anticipatory model* of the system-environment interaction. We call this *knowledge* with respect to the constructivist model.[15]
- The constructivist model does not include specifics of how knowledge is created, i.e. there is no specific choice of learning algorithm or similar. We *only require a selection based* on the outcome of the interaction.
- By adapting various interpretations for the system, its environmental interaction and the selector, the constructivist model can be applied to a range of different situations, i.e. from living systems to learning organizations etc.

In terms of the central research question of this thesis, the model demonstrates key impacts on the characteristics of opportune knowledge:

[15] When speaking of a model here, we will mostly mean the whole constructivist model and not its internal knowledge-model. In the few cases where we refer to this model, we call it the "internal model", or similar.

- In a constructivist model, the *objectives of action-generating knowledge* come to the foreground. The *internal model* will be mostly shaped by these objectives, i.e. formed based on the selection of the selection mechanism.
- The model emphasizes *the importance of time* in general and in particular, the need to act in time, gain knowledge in time, and use timely concepts (Section 6.4).
- In terms of the mediation between explanatory or purely predictive accounts and technical knowledge, the model shows that such mediation is difficult to achieve *unless* the explanatory and predictive account becomes a selector. We have discussed the challenge to arrive from predictive knowledge at technical knowledge and, vice versa, the change to arrive from statistically constructed technical function at explanatory knowledge.

A threefold structure results from the different levels in the model as (i) components of the action-generating mechanisms ("concept space"), (ii) adaptation, learning or synthesis in order to crate the action that is anticipated to be positively selected and (iii) the selector as evaluating that function.

If we emphasize the technical aspect of the model, we see that (ii) corresponds to the technical knowledge; (iii) defines the resulting functionality of the system; and the conceptual structure (i) depends on how precisely the system structures its environment.

From a more conventional perspective, for example along the lines of the linear model, the generative epistemological process for creating a market innovation would usually be as follows:

i. A scientific process of prediction, explanation, and legitimization developing an underlying conceptual space;
ii. a technical process to define, develop, and implement proper functionality
iii. a selection process based on societal relevance, for example through utility measured as monetary value

The difference between (i) and (ii) is small for knowledge that is easily transformed from mere causal explanations to purposeful application.

Another way of looking at these processes of the model is to understand it as a model of how to get from *"what?"* to *"how?"* to *"what for?",* which obviously are the steps of the linear model in (Table 2-1). The question "*what?"* (i) concerns the ontological question of which concepts there are in the internal model of the system. The functional side is the point of generating the right actions, the *"how?"*-side of things (ii). And finally, (iii) the overall function emerges from the choice of selector.

This ternary structure also means that the resulting system holistically develops its competences with respect to the selector, but not with respect to any other purpose. This is quite important as we may interpret this as the kind of concretization or contextualisation that was already mentioned in Section 2.5. The technical knowledge in the system is limited to generating just the selected functionality. In practice, this will be a rather limited application domain (although sufficient as regards system viability). However, it then remains a completely open question as to whether and how the acquired knowledge could be used for other selectors. This means, we cannot easily use acquired knowledge in different contexts as it will be entirely specific to the system-environment interaction and the selector.

In addition, the question arises whether we can generalize the knowledge in the system. This concerns the question if there is an approach to systematic de-contextualization and generalization in order to broaden the knowledge in the system? However, the model does not provide a straightforward answer to this. It is always already a model of concretely contextualized, selector-specific action knowledge.

The one part of our model that has received relatively little attention so far is the selector, i.e. the question of *"what for?"* This concerns not just purpose, but also relevance and value of knowledge as we shall discuss further below.

6 Relevant knowledge and value

The autonomous agent modelled in the last chapter constructs *opportune* or appropriate knowledge, because the selector selects knowledge that leads to viable actions. But it is easy to see that the model selector also will tend to facilitate the construction of *relevant* knowledge. The agent may occasionally still predict and generate actions that have no influence on the selector, i.e. that are all similarly viable actions. But it needs to select actions that the selector evaluates positively as well and it will definitely not select actions that are not viable. The selector will exclude changes in the knowledge base that lead to non-viable actions. In this sense, the model supports the construction of relevant knowledge and knowledge that is *valuable* from the point of view of the agent. Generally, the question how to gain relevant and valuable knowledge is hugely important for any system that generates knowledge-based actions. In this chapter, we therefore take a close look at relevant knowledge and knowledge that can be regarded valuable. One reason among others will be that knowledge is available when you need it, i.e. in time for viable action. We will conclude this chapter with a connection to the effort that it takes to discover relevant knowledge, the funding of research and the value of knowledge for policy.

6.1 Relevant knowledge

Epistemology studies conditions and sources of knowledge, its structure and limits (Steup 2016). Therefore, theory of science and epistemology focus on truth from a methodological perspective and often from the point of transcendental conditions for the cognizing agent. An important question that is not typically discussed – at least not systematically – is the *relevance* of knowledge. The philosophy of science is engaged in analysing science, in particular its aims, concepts, and methods (Salmon et al. 1992, p.1). However, neither are there widely discussed and accepted methods to achieve relevant knowledge, nor do we have in-depth theories about which knowledge is relevant for a chosen individual or a collective. However, it is clear that not all knowledge is equally relevant. There are of course discussions about the relevance of individual claims, but a *general* account of which knowledge is more relevant than other knowledge is difficult to find.

At first sight, there can of course be valid, but irrelevant knowledge. We may want to attribute value to knowledge, if it leads to the desired result or similarly, if it has a measurable value (e.g. a monetarily quantifiable, economic value), if it is productive (in the sense of recursive definition of value, see below) or if it is socially relevant. Before studying these conceptions of value in more detail, consider the following assertions which can all be assumed to be generally true:

(1) In certain semiconductors, excited electrons can relax by emitting light instead of producing heat. (Al-Azzawi 2006)

(2) Every planar map is four-colourable. (Appel & Haken 1989)

(3) The picture that appears to be showing Marilyn Monroe with eleven toes really shows a clot of sand.[16]

(4) There is a used underground ticket in the bin on the platform.

We would perhaps only be willing to pay for learning with some certainty whether the first two sentences are true – although it is possible to design contexts that make all these sentences interesting to know. We could be willing, for example, to pay a higher price for a picture that shows Marilyn Monroe with her original 11th toe and knowledge about the used ticket might become valuable if we urgently need paper. From an economic perspective, however, the first statement has proven to be highly interesting as laying the foundation of the LED lighting industry. Notably, the statement only asserts the phenomenon, alas it says nothing about how to build a working, robust light source. The other three statements may be considered what has been called "reservoir" knowledge before. It may become important in certain contexts. However, from the point of view of innovation, the interest is in knowledge that is relevant and will be used and thus carries some kind of value for the *user*.

The question of value is important in order to determine whether or not to invest in the production of knowledge. In this sense market success becomes a condition of synthesis:

[16] The puzzled reader is referred to the famous picture and an assertion that Marilyn Monroe only had ten toes here: http://www.marilynmonroepages.com/6toes/ (Accessed July 2017)

the person applying the final service or product participates in the decision whether it will be worth bothering about the underlying technology and the necessary knowledge. This poses the question for the *use value of knowledge*.

6.2 The use value of knowledge

6.2.1 Meno value

Apart from a general appreciation of knowledge as useful in principle and therefore valuable, more elaborate discussions of the value of knowledge are an ongoing topic in current epistemology (Brendel 2013). A major focus of the discussion in contemporary epistemology is the so-called *Meno* problem as originally posed by Socrates. This is the question why knowledge is more valuable than belief or more elaborate concepts such as justified true belief (Pritchard & Turri 2014, Kvanig 2003, Pritchard et al. 2010). However, this focus has also been questioned, e.g. by (Goldman & Olsson 2009). In particular Goldman and Olsson suggest that knowing simply means to "believe truly" and discuss it in the context of the traditional discourse on justified true belief. In any case, the more traditional *Meno*-related discourse is focused mostly on the creation of knowledge side of the problem, e.g. in reliabilist accounts such as (Zagzebski 2003, Kvanig 2003), but not usually on the instrumental use or application value of knowledge. This reliabilist account focuses on the processes that first create knowledge and argues that true beliefs arising from reliable processes should be more valuable than just beliefs. However, the now common argument against this approach is that many products are considered valuable disregarding the process that created them, e.g. a cup of coffee. An interesting proposal to rescue reliabilism has been made by Michael Brady who approaches the problem from evaluation in the sense that *"to be valuable is to be a fitting or appropriate object of positive evaluation attitudes"* (Brady 2006, p. 91). This reduces the problem to the question why knowledge is worthy of positive evaluation.

The distinction of knowledge and beliefs is not easy in our biosemiotics model; however, it is still instructive to consider this problem here: for the system in our model, we have assumed that there is a selector capable of distinguishing viable from non-viable agent-environment interactions. This in turn results in knowledge (in the form of a model) that predicts viable actions. This means that the selector shapes and *evaluates* the system's actions. This value arises from use.

6.2.2 Use value

Value can mean a range of different things. In economics, it usually refers to a measure of the benefit provided by a good or service, for example arising from a subjective value judgment based on the importance that some individual attributes on a good or service for achieving desired ends (Luwig von Mises 1940). In psychology (Scriven 1999), value relates to merit (or quality), worth (economic value) and significance (or importance) (cf. Prem 2014). While merit may be regarded a historic dimension, significance and worth are related and carry a forward-looking dimension. In ethics, value also denotes significance and importance, in particular in determining what actions are best to do or to avoid. In economics, the value of knowledge is usually discussed in the theory of the enterprise and/or of company valuation with respect to intellectual property rights (Bontisa et al. 1999, Crevoisier 2015). The importance – and valuation – of knowledge has significantly changed in recent decades with the advent of information and communication technologies and new emerging market conditions such as electronic markets (Picot & Fiedler 2000).

The economic value of knowledge may arise from very different sources, for example:

- Its application
- Its appreciation
- Its exchange

The *application value* of knowledge is the worth emerging from *using* it in actions. It is easy to think of this in an economic context: a proper valuation of knowing the correct numbers of a forthcoming lottery would be the price money for that lottery.

The *appreciation value* is the value attributed to knowledge that is not put to use directly. It may, for example, be a valuation of reservoir knowledge that may eventually become valuable. This could also include knowledge appreciated for other reasons, for example because it overcomes Peirce's psychological state of unrest. Brendel argues that such *final* valuation of knowledge is more related to understanding than to just knowing. It may therefore require a whole system of knowledge to really appreciate it (Brendel 2013, p.161).

Finally, the *exchange value* of knowledge is economic by nature and emerges from the scarcity of a good and its appreciation. It appears logical to assume that the exchange value can in principle be reduced to the application value. However, there may be exceptions in the case of final valuations (cf. Brendel). In any case, knowledge can be traded to some extent, not just in the form of research data or studies, but also in education or, for example, in artistic training.

Privatization of public goods and the Marxist conception of value

There is an important link from the tradability of knowledge to its scarcity. Today, factual trading of knowledge happens for example by means of patents and licensing rights. While knowledge may in principle be reproducible and non-rival in consumption, its scarcity is created with the help of regulatory environments such as intellectual property rights. Marxists argue that the exchange value of knowledge is bound to the practical ability to limit its free distribution, for example by means of patents, intellectual property rights or licenses and contracts, cf. (Gorz 2004, Lohoff 2007). The value of such knowledge does not arise from its natural scarcity, but from institutional or factual access limitations.

This is particularly true of digital information goods including, for example, software. As briefly alluded to, software shares the non-rivalry in consumption with knowledge (Prem 2016). For Marxist economists, results from information work (software, knowledge) are not (private) goods, but privatized universal goods (Gorz 2004). In other words, digital information goods (and formal knowledge) are not produced by independent private work, but arise from privatized universal work. Thus, such goods do not constitute Marxist value. Note that for Marxists, *value represents a specific societal relationship* – and only work of independent private producers takes the form of value relation. (Formal) knowledge as such is unproductive – unless it is put to use. In an information economy, value is generated when knowledge is put to use. But formal knowledge can become productive (e.g. as software for production process control) and save much more work than what its production costs. In this way, it reduces the exchange value of products and as Rifkin has argued leads to an economy of abundance (Rifkin 2008, 2014).

Therefore, cognitive capitalism is different from simple capitalism. For Marxists, knowledge arises mostly from a collective, unpaid activity that is self-produced and founded in general intelligence. Therefore, it does not have exchange value. Formal knowledge potentially is also free, because it can be reproduced and distributed at nearly no cost and would be accessible for nearly everybody. Science – as a productive force independent of labour – is put in the service of capital and it acts through the machine as an alien force, as the force of the machine. Techno-scientific knowledge therefore as control and repression of live work under the machining not only operates on the side of the capital, it is the capital's means for oppressing added work. The owner of this knowledge, the engineers, are explicitly and ideologically positioned on the side of the capital owner. This brings us to the question of how much is it really worth, i.e. what is the value of knowledge (in a non-Meno sense)?

6.2.3 Valuating knowledge

Focusing on the individual's perspective, there are two obvious criteria to quantify the value of knowledge and to decide accordingly, how much this individual may be willing to invest in its production:

1. Economic return
2. Philosophical criticism and social relevance including political decision

As regards economic return, higher relevance of knowledge implies higher economic value. This is the usual value as it may become expressed in the price of a patent. Note however that patent prices do not necessarily reflect just its use-related value, e.g. as parts of company IP portfolios (Kamiyama et al. 2006). The application value *v* today will usually be higher for earlier turnovers, i.e. we can assume a value that is depreciated over time (where *i* represents the rate of depreciation):

$$\mathrm{v\ (k)} = \frac{\mathrm{return(k)}}{(1+\mathrm{i})^{\mathrm{t}}}$$

In addition, knowledge may not directly return any value; i.e. may have to defer the value of a piece of knowledge to a later stage where we can assign value. Instead of such kind of knowledge being immediately valuable, it may be a “step in the right direction” and prove valuable only at a later stage and at a later point in time (deferred application value). In this situation, we would value knowledge because of its productivity for other, eventually valuable knowledge:

$$v(k) \sim \text{productivity}(k)$$

This means that we are dealing with a recursive calculation of worth. However, at a certain point this process must come to an end in valuable knowledge. Productivity per se, without ever resulting in valuable knowledge, should not be regarded valuable. Otherwise, we may be rewarding very productive, but completely wrong theories or also huge bodies of knowledge that remain irrelevant. This means that producing knowledge that will never be used should not even be called “reservoir” knowledge, or rather, what is worth storing in a reservoir can only be known with certainty if what is stored is needed or used. It is important to note that later insight may change the value assessment dramatically. Previously irrelevant knowledge may sometimes become relevant with a new discovery and, quite often, knowledge becomes irrelevant. As an example for the former, consider the massive increase in importance of number theory after the advent of cryptographic machines. While number theory certainly has always been a tool for mathematicians to some extent, it suddenly saw a massive surge of applications, interest, and growth with the advent of asymmetric computer cryptography. As an example of once relevant knowledge that practically no longer is of any value we may consider the rules of medieval bookkeeping.

In the narrower context of scientific knowledge, a particularly long-term perspective and an appreciation of how knowledge may eventually be used in the future is required. A practical example actually used in research management today is the notion of *oriented basic research: “Oriented basic research is research carried out with the expectation that it will produce a broad base of knowledge likely to form the background to the solution of recognised or expected current or future problems or possibilities.”* This is the OECD definition (OECD 2002). It clearly accepts that the results from oriented basic research do not produce value immediately – its value lies in the expected, eventual generation of *“solutions of recognised or expected current or future problems”*.

Today, the economic return of research investments has become of obvious and explicit importance. As briefly stated before, applied research should not cost more than its expected revenue in economic terms. Lyotard proposes that in post-modernity, the economic return becomes a primary motivation for knowledge by first connecting profit and technology and later science and technology: "*It is more the desire for enrichment than for knowledge, which first imposes the imperative to the techniques of the improvement of the achievements and the realization of the yields. The "organic" connection between technology and profit precedes its connection with science. In contemporary knowledge, techniques are only gaining in importance through the spirit of generalized performativity."* However, even Lyotard concedes that *"[e]ven today, the subordination of the progress of knowledge among those of the technological investment is not immediate."* (Lyotard, 1986, p. 132) Interestingly, this does not leave us with a very clear picture. Although for Lyotard, the "organic" connection of technology and profit seems clear, he also concedes that the technological investment is not yet the only determinant; there are of course more options to valuate knowledge.

Valuation at production costs

A rather different method for assigning value to knowledge is to simply calculate its production costs. In times of wide-spread public funding for bottom-up or top-down (programme) research, the price of knowledge is often known. For example, knowledge about the potential damage that the parasitic fly philornis downsi creates for the darwin finch[17] comes with a price tag of € 353,144.40. Production costs are a frequent way to valuate public sector costs in public finance. This is the price that society as a whole – at least in democratically governed countries – is willing to pay for finding out that particular knowledge. We could even go as far as measuring the price of a TV show including its broadcast time for knowledge that attracts large audiences, but remains otherwise

[17] *Der Einfluss eines exotischen Parasiten auf Darwinfinken*. FWF project nr. P26556, Austrian Research Promotion Fund, March 2013, Vienna.

economically unattractive. Such costs can serve as a proxy for production costs of knowledge as well.

In our simple biosemiotic model, the sources of worth and appreciation must exist in relation to the user of knowledge. The value of knowledge is implicitly given through the selector function. It can be assessed quantitatively, if the selector allows a quantification, e.g. an error-value. It can also be more qualitative, e.g. in the case of a biological system it may simply take the binary value of success or failure (e.g. for the tick in the feeding context). In this case, value is related entirely to the success (or quality) in the application. The environmental evaluation function (i.e. the selector) determines the value of the resulting action and therefore the knowledge leading to that action.

Socially valuable knowledge

Regardless of economic value, we may appreciate that knowledge simply satisfies a human demand for answers without being able to immediately attribute economic value. For example, the question as to whether there are or are not exoplanets is at first sight without economic impact. As already outlined, such knowledge may still be valued economically, e.g. at production costs or through willingness-to-pay. Again, the funding of such research appears legitimate, if the public's willingness to pay equals or is higher than its production costs.

Proxys of such appreciation are democratic decisions about funding programmes. Scientists may argue at this point that funding decisions in science are hardly ever entirely democratic. In fact, most funding is nowadays based on the appreciation of peers. This does not change the argument that we may take the funding amount as a proxy for the value of knowledge. In fact, several evaluation systems of academic research include the amount of funding that a researcher has acquired over a certain period as an important quality criterion in research assessment exercises and many academic researchers, in particular in Anglo-American countries, are not shy to advertise the amount of funding they won in competitive research grants in their CVs and on their homepages.

At this point it is important to add that we are in no way *proposing* to evaluate research in the way described here. The aim of this exercise is to clarify what happens to knowledge and to knowledge production if we focus on the perspective of economically relevant knowledge. Let us therefore look at the biosemiotics model of action-relevant knowledge from the point of view of use value and the selector function.

6.3 The system value of knowledge

The model was originally introduced from a biological perspective. But following the discussion we have just given, we may as well use it for a much broader clarification of action in knowledge-systems with feedback from their environment, i.e. we now return to our original aim of studying knowledge in a broad range of systems such as living systems, firms, robots or economies.

For the case of living systems, the basic viability is biological. The feedback received at the individual level ultimately is survival, but of course in a less simplistic scenario there may be a much richer feedback function. We have seen already how the systems under this feedback become knowledge-based predictors of the selector function. The world according to such a system is a model for action in reality, it thereby becomes a model anticipating positive feedback on actions from the environment. In addition, the model is generated through action.

It is important to note that in biological reality, the selector operates on genetic pools and much *action-enabling knowledge* consists in the structure of the living system rather than in what it may learn during lifetime. In the tick example, the tick does not literally learn to recognize butyric acid as a predictor of an opportunity to satisfy its thirst. Ticks simply evolved this way. Still, the physical shape and body of the animal also represents an anticipation of proper interaction with its environment – at least as far as past generations of its ancestors have experienced it. The importance of this point is one of the central arguments of the embodied approach to Artificial Intelligence. Its advocates argue that the physical interaction with the world solves numerous problems that other non-embodied approaches have. In particular, the use of highly specialized sensors and actuators facilitates viable interaction with the world much better than the use of very general sensors that require complex, non-physical software-based interpretation. (Brooks 1991).

Let us now change the system for another knowledge-based entity, e.g. a company. The successful company will generally act in the market based on its anticipations of the future, e.g. (Araújo & Gava 2012). Successful companies will have developed knowledge – based on the past – that facilitates rewards in economic terms from the environment. In the field of evolutionary economics, the main three functional mechanisms have been described as the markets working as selectors, the institutional structures as control systems, and the technological innovation as sources of variation, c.f. (Etzkowitz & Leydesdorff 2000). This is very close to the model that we are using here. Knowledge-based firms have developed a model for appropriate action in their environment.

We can even extend the model to scientific knowledge in the sense that the adaptive system may be a scientist publishing a paper. These publications can be regarded her interactions with the academic environment. The paper will be written so as to be positively selected in that environment and in the long run, the scientist will develop a model for proper publication actions so as to get funded or cited or promoted in the future.

Our admittedly simple constructivist model can also serve to explain the funding actions of research policy makers. The research policy maker (e.g. at the level of a minister of research) will have to take actions that make sure he remains popular with his electorate or constituency. Obviously – as in all the other cases – this is a strong simplification of all the processes going on within such systems and, hopefully, research policy makers will select their actions not *solely* optimizing feedback from voters. In fact, the environmental selector is much more complicated in this case as the researchers to be funded or the industry perhaps also pay an important role as selectors of the researcher’s future.

The following Figure 6-1 and Table 6-1 summarizes our proposed view of an action-based and anticipatory conception of knowledge in various systems.

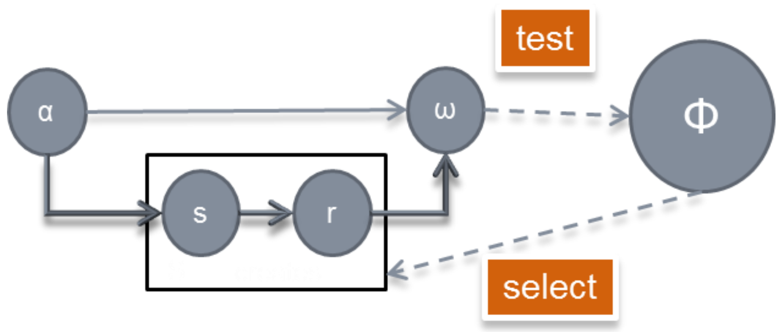

Figure 6-1 The constructivist model as described in Sections 5 and 6.
The selector Φ operates on the system based on evaluating the system's environmental interaction.
See text in Sections 5 and 6 and the description of Figure 5-2 for further detail.

Taking a look at this model from a more general system perspective, this means that possible selectors are biological success (survival), economic success (market sales, operating costs and also innovation) or scientific success (publication) or political success (election). Depending on the knowledge-based system under study, the system will develop knowledge that anticipates *actions for the corresponding viabilities*.

Stretching the model a bit further, the knowledge created in the system will have to be in line with rather different conditions for such knowledge to be present or valid. We could simply call this *truth criteria* and they may be *survival* for biology, *sales* for economy and so on. This means that an action-enabling piece of knowledge in the animal will be valid if it facilitates biological viability; etc. An emphasis on just innovation, i.e. on bringing a new products to the market, is likely to foster a technical, value-based concept of knowledge that primarily focuses on economic value. However, knowledge in this case may not necessarily be driven by explanatory power or understanding. All that may matter in order to create novel applications may be its utility in producing increased market sales.

Table 6-1 Possible interpretations of viability, domain of the selection operator, and selector of knowledge for different systems.

Viability	**Domain of selection operator**	**Selector (example)**
Φ1: biological	environmental action	survival
Φ2: economic	sales, costs	return on investment, innovation
Φ3: political	public perception	election
Φ4: scientific-internal	publication	citation factor

We can consider rather arbitrary viabilities: historic, sports-related, logical, religious. They all imply different truth conditions. The decisive factor is that they share an environment – or a community that constitutes the corresponding truth conditions and that these conditions follow from the environmental selector. If the emphasis is on economic viability, the values of a globalized consumer society will be put in the fore. This is how truth is constituted and how societal circumstances are reflected in knowledge.

Ontology and conceptualization

Following the discussion of our model, viability is central for the constitution of knowledge. Utility thus is as important as is the “world”. The error-minimizing strategy in the system generates models that are capable of producing the right actions, i.e. the state-space is put into equivalence classes under the optimization function. It is, at least theoretically, unimportant whether the inputs are in any way similar. What matters most is the production of the desired outputs, or more precisely viable actions. In more general words: the world becomes categorized so that the desired actions are taken. From an ontological stance, i.e. from the point of view of the system, *the world is represented in terms of these actions*. It is not the inputs which are important, but how the inputs can be used in order to generate the right outputs. The system’s ontology then becomes a mirror of its interaction with the world and of its objectives, but not necessarily of the world as perceived by others.

The constructivist model evidently focuses on action and therefore implicitly also includes a notion of time at several levels. This timeliness emerges as another key criterion for the constitution of knowledge. This will be studied in more detail in the next section.

6.4 Value and time

As soon as *action* enters the picture, so does *time*. Time has arisen at several points in our discussion before. It was mentioned when we discussed value because of the depreciation (over time) of knowledge that may only become relevant at a later point in time; it obviously plays a role in the action concept due to actions happening in time; finally, it is a central component in discussing the anticipatory nature of knowledge, i.e. predicting something now in order to maximize positive feedback at a later point in time.

The Austrian economic school explained that human behaviour has a purpose. Humans are separated from this purpose through time. As humans value time less than the purpose or goal, they strive to reach that goal investing their time in purposeful action. Both Eugen Böhm von Bawerk and Ludwig von Mises take such differences in valuation as the origin of interest (Hülmann 2002, Herbener 2011). But these different valuations with respect to time are not limited to humans. In particular, they also apply to companies which usually prefer payments earlier rather than later. Most entities that are interested in knowledge in order to act, require that such action takes place within given time limits. Or in Gorbatchov's eternal words in 1989: *"Those who are late will be is punished by life itself."* This is obvious for the world of biology, but it also – and perhaps more prominently in relation to science and research – holds true for companies aiming to remain competitive. With product cycles becoming shorter and shorter, time-to-innovate is of central importance and therefore knowledge for purposeful action **should be valid, valuable and available in time.**

Validity does not necessarily have to be conceived as a separate condition: it could be subsumed under valuable. We can, for example, assume that invalid knowledge simply is assigned zero value (or perhaps even negative value). An interesting point is the question of whether knowledge could be available *too early*. This problem can arise if there are costs associated with storing, finding, or accessing such knowledge in particular.

The bio-semiotic constructivist model presented above facilitates a discussion of time in the type of goal-oriented systems that may use knowledge to act and where actions that come too late may lead to non-viable systems, i.e. systems that are de-selected by the environment so that only systems remain that have predictive knowledge about successful actions. For the case of artificial intelligent agents, the pressure to act in time was long neglected before the case was made for situated and embodied agents (Brooks 1991, Bereiter 1997, Robbins & Ayded 2008).

It is possible to distinguish three different levels where time and value are intrinsically coupled:

- *Action in time:* the system, for example a biological entity, acts in time. If its actions are not adequately timed, it may die.
- *Gaining knowledge in time:* if knowledge is essential for action, it needs to be discovered within a certain time limit. In contrast to a papal expert commission, an army corps may have to quickly gather intelligence so as not to perish.
- *Predictive character of knowledge:* the model components, i.e. the equivalence classes generated in order to produce the right actions also carry an implicit element of time. The knowledge has anticipatory character, this knowledge *is* the predicted (technical, economic, scientific) success of interaction. The knowledge in the model has been structured under past actions, i.e. created on the basis of the right actions and thus came to represent a prediction. In addition, the feedback from the actions needs to arrive in time. We have seen previously (Section 6.3) that the world becomes categorized in a way that is more driven by the objectives of the system than its inputs, but the same can be said about the timing of this behaviour. The model will also be structured in a way that is driven by the timing of the actions, i.e. the knowledge components will implicitly also represent appropriate timing.

To make this last point clearer, it may be instructive to think about an appropriate model for predicting whether lifting a beer glass will create a viable action. Such a model may contain the notion of a full glass to distinguish successful from unsuccessful interactions. The property of being full carries an element of time in relation to glasses that is key in such a classification of the world to predict successful drinking outcomes.

The following table provides a summary of these levels.

Table 6-2 The various levels of time in epistemic processes of active systems

Level	**Valuable activity**
Knowledge (application) time	Generate properly time action
Epistemic time	Gain knowledge in time for use
Ontological time	Conceptualize the world as timely

In the constructivist model, time therefore also appears on three levels:

i. Action in time: the mapping from inputs to generating actions must happen in time or else the integrity of the system may come under threat. This creates a primacy of action.

ii. Knowledge in time: (consecutive application of) Φ implicitly decides about how much time there is to develop proper knowledge in S.

iii. The anticipatory character of knowledge, i.e. the knowledge to produce actions based on inputs anticipates a positive selection by the selector function Φ. In other words, all knowledge is anticipatory that was created in order to select viable actions. Such knowledge is always predictive, as a minimum it predicts how to minimize the error with respect to the selector function Φ.

It should be clear now that goal-direction of knowledge implies that time needs to be considered. In our model, the anticipation requires a notion of time. Indeed, *there are two time scales in the model*: one in which the model operates and is evaluated, and a second level where the selection operates. This results in an adapted model that selects proper actions based on anticipating *now* what will happen *later*. As briefly mentioned, such models have been called anticipatory models in theoretical biology (Rosen 1985, 1991). They are an important argument about the system-theoretic properties of living systems and they have also strongly influenced economic theories, in particular the triple-helix model (cf. Leydesdorff 2005, Nadin 2012).

Time and relevance in epistemology

Time is not a traditional epistemological or epistemic category. This does not mean that time has not been discussed at all by epistemologists: quite to the contrary, time as a perceptual and cognitive category has puzzled philosophers from Augustine to Kant. But the need for living systems to act in time, to cognize and understand in time for action did not impact much on epistemology. It is not even found much in the epistemology of constructivists such as Humberto and Maturana. A notable exception is the recent work of (Williamson 2000, p.101) who regards knowledge as superior to mere true belief because *"…it better facilitates action at a temporal distance."* A possible reason for time being largely disregarded lies in the conception of truth as something permanent and absolute. Epistemology was mostly concerned with stable truth not a concept of sufficient truths for a period of time that is more relevant for living systems.

Even scholars who agree that knowledge should be regarded an ability to be guided by the facts (Hyman 2010, p. 19) are not explicitly referring to the need to act under the pressure of time, cf. (Duncan & Turri 2014). This pressure to act in time, however, is clearly systematically present in constructivism, even if it is not explicitly discussed. The very notion of *viability* may be interpreted as replacing a permanent notion of truth with action-enabling knowledge that suffices to survive (i.e. something facilitating action). Indeed, it is difficult to see how traditional epistemology could arrive at an understanding of truth conditions that is just *good enough* or how a theory of science could develop methods for finding truth that stop when *sufficiently good* truth has emerged.

In any case, relevance and timeliness are central aspects in today's epistemic processes and in particular in engineering – and they are practically, i.e. methodologically unsolved. There are some general strategic methods and there may be criteria for stopping research, but there is no broadly applicable methodology comparable to the methods available for systematic scientific research today.

In practice, precisely such strategies for finding knowledge under pressure of time have become hugely relevant for industry and often simply consist in the discontinuation of research programmes. As a practical example from the business world, we may again refer to Google's research on its translation service. Until 2015, Google actually worked on a technology that delivered reasonable, but not very good results. With the advent of the work on the previously mentioned bidirectional neural architectures, RTD managers at Google recognized that the approach taken had to change completely. Within a very short time frame, large teams were told to give up on the methods that were under development until that point in time and to switch to the new, more promising approach (Lewis-Kraus 2016). While the example seems trivial in the case of Google, it is in fact not common in academic research. It is a huge practical challenge to reorient large teams of researchers at universities in order to accelerate knowledge discovery. And the reason is not simply organisational or related to work contracts in the public sector. It also lies in the fact that academic research rarely experiences the same kind of market pressure that induces the need to respond as quickly as a large industry player.

We may interpret this movement towards speed as a facet of the post-modern condition of research that Lyotard identified in the late 70s of the last century, namely that science has given up its grand narratives and replaced *truth* with *performativity* (Lyotard 1986). From post-modernity, there is a direct path to Hill's post-scientific society (Hill 2007) via innovation. As innovation becomes more important, efficiency and success become more important which in turn emphasizes timely production of knowledge and purpose-driven, useful knowledge. A potential way to address this issue is, as Hill rightly suggested, the recombination of existing knowledge (or research that leads to results quickly) rather than lengthy investigations of a more basic nature. Knowledge to satisfy curiosity, to respond to amazement, wonder and unfounded metaphysics becomes irrelevant. We will return to this point in discussing Lyotard again below.

6.5 Frascati time and value

We can now take another look at the linear model of innovation from the perspective of time and the pressure to quickly develop solutions for markets. In the description of the linear model above, it was mentioned in passing that the sequence of steps is considered hierarchical in two different ways: it is a *logical hierarchy* because knowledge from basic research is considered to lay the foundation on top of which other layers of more applied research are built, but it is also – and perhaps more frequently – considered *a sequence in* *time:* first comes basic research and only thereafter is there a place for applied research (i.e. application-oriented research). In fact, this is more than just a claim often heard by researchers in basic science. It has become a *definition* of basic research. This definition can be found in one of the practically most important documents of research policy today, in particular in Europe: the so-called Frascati manual (OECD 2002). This document is of central importance as it lays the foundation of how to measure scientific research activities of all kinds. Originally devised as a guideline for statistical purposes, it has quickly turned into a *definition* of what should be counted as basic research, as applied research or as various kind of development activities, e.g. experimental development, cf. (Godin 2005). The book is no longer just a tool for statisticians used to generate metrical comparisons between OECD countries, it has in fact become central to a variety of policy processes including science and research regulation. Its definitions are used in legal texts for research-related tax incentives or such laws may simply refer to the Frascati manual. For example, the Austrian tax law gives incentives for research, lists definitions in close proximity to those from the manual and the Frascati manual is referred in further explanations from the ministry; similarly, current European Union regulations frequently refer to or use the Frascati manual.

Interestingly for our discussion in this section, time is the implicitly defining feature to differentiate between different types of research in the Frascati manual. The definition of basic research, applied research, experimental development and serial production makes use of the idea of time-to-market in the underlying epistemic processes. The Frascati Manual defines basic research as follows:

"*Basic research is experimental or theoretical work undertaken primarily to acquire new knowledge of the underlying foundation of phenomena and observable facts, without any particular application or use in view."*

Taken literally, this definition implies that any research that has a particular application or use in view cannot be basic. It then becomes *applied research:*

"Applied research is also original investigation undertaken in order to acquire new knowledge. It is, however, directed primarily towards a specific practical aim or objective." (OECD 2002)

The underlying *aim* of the definitions in the Frascati Manual is to make sure that effort (time and money) is required to move from basic research closer to innovation so that public intervention (i.e. public funding of research) does not distort markets too much. Here, the assumption is that the markets are less distorted when the application is *"not in sight"* or – due to the necessary time and efforts to be spent – costly and uncertain. Most public funding schemes therefore provide higher funding rates for basic research than for industrial or applied research. This principle is now also a basic rule in the regulatory environment of RTD policies, e.g. in EU competition law.

The aspect of time-to-market as a differentiating feature also underlies the notion of *technology readiness levels* or TRLs. The TRL concept originated at NASA to estimate the readiness of a technology for astronautics (Mankins 1995) and now are also used by the European Space Agency. Increasingly, it is being adopted in research programmes as a measure and classification of prediction horizons for marketable results or innovations. For example, the European Framework Programme for Research indicates targeted TRL levels for certain calls.

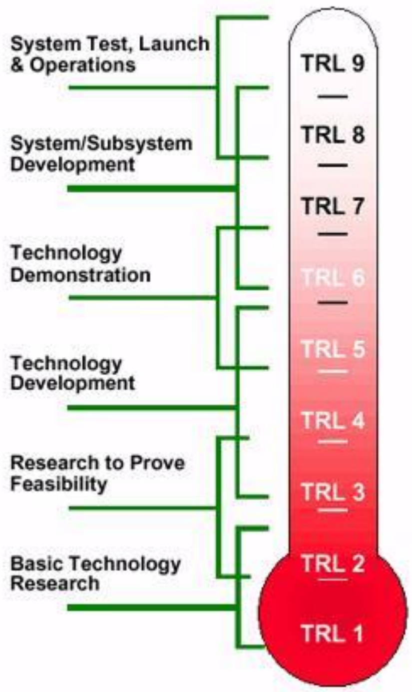

Figure 6-2 TRL levels from Basic Research (TRL 1) to Systems Test (TRL 9). (Source: NASA, Wikipedia, http://as.nasa.gov/aboutus/trl-introduction.html archived: https://commons.wikimedia.org/w/index.php?curid=17884292)

It is difficult to resist the temptation to compare the Frascati definitions and the more fine-grained technology readiness levels to the linear model. Although the purpose of the Frascati manual originally was national statistics and the TRL levels were a means to classify technologies for space flight, they both breathe the spirit of the linear model. At least, the TRL-model supports an understanding of how difficult it may be to actually derive working systems from basic technology research. But the whole set-up is inspired by the idea of basic research coming first and being *practically* useless. While *"useless"* may be taken as an entirely negative description, it may also indicate that modern conceptions of basic science agree in that no precise purpose is evident and needs to emerge from a mostly science-internal autonomous discourse. (See the discussion in Kaldeway 2012, p.20). Note that the TRL levels are strictly speaking already starting from *"Basic Technology Research",* i.e. a conceptual mix of basic research and technology.

Frascati Time Critique

The Frascati-based understanding of basic and applied research is now prevailing in many practical contexts regulating the life of academic and industrial researchers. It has severe practical implications as it provides the basis for funding rates, RTD contracts, research programmes and policies. But the basic concepts used in the manual are certainly contestable.

First, it is not at all evident that in today's "mode-2" research world, there is a lot of research *without an application in view* at all (Etzkowitz & Leydesdorff, 2000). How much research is there really that is not driven by use considerations? Even some most fundamental research projects consider the long-term functionality of the considered research ideas and models. Paradoxically, because of the success of the linear model, even basic research nowadays is often justified with reference to potential applications (Mahdjoubi 1997 p.3). This is not to say that the arguments would be straightforward from making the case for basic research to the development of new applications, but the arguments very often suggest that such a connection can be made. For example, Dan Kleppner says *"[...] basic science is the best thing that mankind pursues—not so much because it leads to new applications* *but because it leads to new understanding...”* But this sentence is preceded by the assertion that *“[w]ith basic research, you don’t begin to recognize the applications until the discoveries are in hand”* (Karagianis 2014) and this indeed suggests a connection, even if it is not made very clear what it really is.

Secondly, if the criterion for basic research is that no application is in view, can there be any basic research in the technical sciences then? Research in the technical sciences implies a purpose and objective, be it only in the long term. A potentially useful example in this line is the European Commission’s FET programme (EC 2017) with its aim to create technologies of a ground-breaking nature. The research in this programme has often very clear applications in mind, but really starts with very basic investigations that include research in quantum physics or genetics. This question is not just philosophically interesting. Whether or not a specific project is applied or basic research determines the allowable rate of public funding and therefore is of very practical relevance for researchers.

Thirdly, it is also necessary to critically examine whether the basic/applied distinction supports the underlying aim of non-distortion of markets. It is fairly easy to think of examples where research results in basic research may have direct impact on the market. Consider for example research in number theory: a new result in the area of asymmetric functions may be turned into a new cryptographic algorithm with very little time and effort. Also, it is of course possible that funding today distorts the markets in 10 years from now. In fact, some scholars have pointed to precisely this problem (Kealey 2010).

In summary, the definitions of the Frascati manual are highly questionable following our analysis. They are quite imprecise, in particular for technology; it is highly questionable whether they serve the economic purpose of avoiding market distortion by public funding of research, and they arise from an underlying concept of the linear model that should simply be outdated.

An inquiry into changes to the concept of knowledge in the post-scientific society should also take a look at the conditions of producing such knowledge including covering the costs of knowledge discovery. The obvious connection is *value* as a measure for the *appreciation* of knowledge that may contribute to innovation.

6.6 Funding valuable knowledge

Let us take a brief look at the history of financing the production of knowledge. Throughout the history of science and philosophy, who decides on research funding and thereby on which questions should be asked and in particular answered? In ancient Greece, philosophy including the philosophy of nature is largely depicted today as an individual endeavour. Let us assume that many Greek philosophers were either financially autonomous because of a noble family background or simply had no money at all - and did not care. In such a case, scientific research is entirely funded by the individual researcher. The philosopher alone decides what is interesting and how to best arrive at true and valuable knowledge. He also decides how much time to devote to this task. In addition, there was state-funded research with precise objectives as well very early in the history of science, for example with the purpose of military defence. The Roman army in fact regularly employed architects and engineers for the purpose of constructing and improving defence infrastructure including weapons. Ihde describes the example of military innovation or more generally research proposed by Leonardo da Vinci (Ihde 1990, p. 195). This example clearly shows the potential power of knowledge as Leonardo argues that he knows *“how to build very light, strong bridges, made to be easily transported so as to follow and at times escape the enemy…”* and other similarly useful things and if necessary, i.e. where his knowledge is not yet sufficient, that he *“will invent catapults, mangonels, traps …”* (Ihde 1990, p. 196 quoting from Cianchi 1988).

The power to be right

In medieval times, much production of knowledge was also funded by the church and often organised in combination with scholarly teaching. The practice of state-funded research really took off from the 17th century. There soon was funding for research from the state and being a scientist started to become a profession. Interestingly, there has always been a strong element of self-governance in the decision-making and quality control. The state could formulate its interest in science, for example in competitions to devise novel machines or methods for navigation, and also in funding decisions. But most interesting, the states started a systematic production of knowledge and thereby of truth: *“At the end of the* *discourse Descartes demanded loans for laboratories. The problem was thus posed: The apparatuses, which optimize the performance of the human body for the purpose of proving the evidence, demand a subsidy of expenditure. So no proof, no verification of statements and no truth without money. The scientific language games will become games of the rich, where the richest has the greatest chance to be right. An equation between wealth, efficiency and truth stands out.*" (Lyotard, 1986, p. 131) As a side remark, also (Latour 2016, p.168 ff) suggests that the very idea of scientific rigor means (in the broadest sense of the word) to invite in a laboratory so that it becomes possible to witnesses the outcome of an experiment.

The emphasis on the laboratory is particularly interesting in Descarte's reference because the laboratory emerges from an endeavour that was originally economic by nature, cf. Latour (2016, pp. 112): *"The laboratory originally derives from the craftsman's workshop. In medicine, biology, physics, architecture, optics and the design of weapons the craftsman always precedes the engineer […] The situation is only turned around in the late 19th century and only for some occupations."* What we would call research infrastructure then actually was largely privately funded equipment probably mostly bought or built in order to make profit, not as equipment devoted primarily to uncover truth. Moreover, Latour makes the case that in parallel to craftsmanship the art of thinking developed into cognitive technologies. (p.113), thus transforming normal brains into the brains of scholars. The laboratory as such results from a factor combination where the workshop of the craftsman provides the infrastructure, i.e. technology in the form of apparatus, with cognitive technology (p.116). *"But it is true that performativity, by extending the capacity of proof, extends that of being right: the technical criterion of truth, which is massively introduced into scientific knowledge, does not remain without influence on the criterion of truth."* (Lyotard, 1986, p. 136)

Lyotard may be simplifying the situation rather too much in his account when he equals financial power with the power to be right. But it is undeniable that modern scientific proof often requires a costly infrastructure or massive personnel resources. Suddenly, the state became supporter of research and thereby of a profession of experts for truth in nature (and other fields of science and research). Don Ihde has described at length how the use of instruments not only improves proximity to the phenomena of interest, but also focuses attention and thus limits the scope of the investigated phenomena. Technology not just facilitates truths – it also determines the conditions of these truths: No proof can be produced without enormously thinning the phenomena under investigation. Boyle not only accepts simplifying phenomena, but also to create new phenomena artificially (e.g. vacuum).

Ihde also refers to Latour's emphasis of the role of the laboratory as the location where technoscience materializes in experimental praxis, cf. (Ihde 1991, p. 129). A range of authors (Ihde 1990, De Solla Price 1984) noted that the Renaissance period "researcher" was often more interested in the performance effects or spectacle of an experiment. But this performative element prepared the pathway for the experimental proof and its eye-witness account of natural phenomena in the laboratory. Interestingly, (Coeckelbergh 2017) points us to a performative element also for the area of innovation.

Today, research and technology policy makers in modern democracies make funding decisions based on a political decision making process. The political discourse emerges from the academic research community, industry lobbies, policy opinion etc. It has become a bureaucratic, vastly expertocratic, technocratic, and oligarchic process in the sense that research funding decisions are often made by peers based on complex regulatory frameworks and evaluated by third parties such as research management consultants and research and science evaluation professionals. Philip Kitcher (quoted after Kaldewey 2012) suggests that science should aim at *"significant truths"* and *"truths that matter"*. In the interpretation of Kaldeway (p. 21) this does not just mean the kind of relevant research mentioned before in our discussion of relevant knowledge (Section 6.1). It means that scientific or academic autonomy is only limited up to the point of a democratic or otherwise legitimate research agenda that suits the needs of mankind. The important caveat to make – from the point of view of a research manager's experience – is that this is precisely what we currently find at large in public research programmes. And the degree to which such programmes are factually democratic is arguable. Top-down research programmes have become the playing field of RTD lobbyists, both from within the academic and private research arena and from industry. Latour puts his emphasis on the equation between wealth and truth where the richest are more likely to be right. But perhaps more importantly, today's complex research management processes have become methods of discourse management in which usually a relatively small community is involved that determines focus and scope of the discussions, cf. Section 6.7.

Lyotard describes the private and public financing of private, industrial research and of public research in order to improve the chances for profitable innovation. This is the other side of the power to prove and to be right. It is the point is where research turns into money for being capable of doing things, for its performativity. His arguments also remind us of the linear model, but it is now turned in a self-sustaining cycle: *"With the end of the eighteenth century, at the time of the first industrial revolution, the reversal was discovered: no technology without wealth but no wealth without technology. A* technical *disposition requires an investment; But because it optimizes the performance to which it is applied, it can thus optimize the added value that comes from this better performance. It is sufficient that this added value is realized, that is, the product of the service is sold. And the system can be closed as follows: part of the proceeds from this sale is absorbed by the research fund, which is designed to improve performance. Precisely at this moment, science becomes a productive force, that is, a moment in the circulation of capital."* (Lyotard, 1986, p. 132) Here, Lyotard describes something that has become central to our contemporary discourse in research policy, in particular as regards the question of technical knowledge or, more generally, technoscience. Of course, this narrative is mostly economic today.

A new policy discourse

The technology and innovation policy in many countries explicitly targets improvements of a country's competitiveness by means of targeted strategies for science, technology and innovation. In particular, a growing share of public R&D spending is now allocated to the business sector, policy tools such as tax breaks incentivize business R&D and there is an increasing interest in the ties between public and private research (OECD 2016, pp. 161 ff.)

Modern policy processes for research and technology systematically include RTDI stakeholders, i.e. academics but also industry researchers. Large lobby groups support RTDI policy makers with arguments such as past success stories and research roadmaps to further motivate public spending on industrially relevant research topics and other research policy measures. An illustrative example at the European level are the so-called *Technology Platforms;* these are large stakeholder associations that jointly define research roadmaps for

European RTDI programmes such as the Framework Programme for Research (EC 2013). These stakeholders systematically influence the policies not only at European level, but also in the member states. Large national research programmes are in fact initiated to support industry in their research and development activities. These programmes are often thematically focused, for example in the area of bio- or nanotechnology, information and communication technologies, manufacturing, transportation and energy technologies to name just the most prominent examples. In most cases the programmes are much more narrowly focused than this list would suggest. They may, for example, focus on just Internet-of-Things technologies instead of all areas of information technology or be limited to specific sectors.[18]

In addition, market relevance is now an important criterion in many research initiatives that are relatively close to more academic interest. A prominent European example is the aforementioned *Future and Emerging Technologies Programme* of the European Commission. It is designed to support *"early-stages of the science and technology research and innovation around new ideas towards radically new future technologies"* (EC 2017). Its evaluation includes an assessment of the expected impact on technological outcomes, on industrial leadership, and more generally on impact beyond the research world (EC 2017 p.16).

Such a direct connection is not always visible in purely scientific research programmes. In fact, they are practically absent from evaluation criteria of basic research funds, e.g. Austria's FWF fund in the general programme. Still, in public (and also professional) discourses about science, many arguments for a specific project or specific research activities refer to economic and technological reasons, see for example (Gruss 2009, Powell 2017). There are few scientists who would argue exclusively with "pure knowledge" or "education". Quite to the contrary, even fields that are difficult to connect with applications argue with potential utility of knowledge. Prominent examples in this area are mathematics and physics who are united in their claim to laying the foundations of modern computing technologies. It is argued, for example that Kurt Gödel's mathematical theories about

[18] An example in Austria are the FFG programmes "IKT der Zukunft" and "Produktion der Zukunft" targeting information technologies and production technologies respectively, but they also focus to a certain extent on sectors such as energy or production, cf. https://www.ffg.at (July 2017).

computability provide the basic theory behind today's computer programs. Other contemporary examples of these arguments include current research in quantum physics targeting the eventual development of quantum computers and quantum cryptography. This work, for example, can be said to be grounded in the basic research work of Erwin Schrödinger (University of Vienna 2017).

These arguments – and the fact that they seem to be required – are evidence for the massive change towards the post-modern techno-scientific narrative that discontinued the earlier primary focus on knowledge per se. In the words of Lyotard: *"The state and / or the company give up the narrative of the idealistic or humanistic legitimation to justify the new mission: in the discourse of the silent partners of today, the only creditworthy commitment is the power (puissance). You do not buy scholars, technicians and apparatuses to learn the truth, but to expand the power."* (Lyotard, 1986, p. 135)

Self-steering power of industry lobbying

It is not difficult to be critical of the practice of research funding today in which lobbying plays a huge role. This lobbying may not always be that of industry, it is certainly also taking place from various interest groups in the academic world as well. There is today little option for the policy maker interested in supporting researchers in a top-down, i.e. goal-oriented fashion: they will have to involve researchers or peers not only in order to decide on research funding at project level, but also on the level of whole research programmes. This creates a tendency for more knowledgeable groups to remain in a more powerful position to also guide future funding decisions. It may also create a situation of self-fulfilling predictions about the importance of a research subject, i.e. a field is said to be interesting, receives more funding, increases in size (projects, people, and professors), produces more results and questions and thus becomes more important.

Similarly, industry may create research lines that – once created – acquire inertia. They do not just disappear once they were generated as they now may have produced institutes, funding lines, lobby groups etc. In contrast to Lyotard's view, however, this tendency is not limited to technical knowledge. It is a consequence of a self-steering process where knowledge becomes selected that in turn receives power in future funding decisions. This is precisely the kind of self-selection (i.e. the case where the system influences the selector operating on itself) that we have mentioned for the constructivist model in Section 5.4.

Let us discuss this last aspect in the light of our constructivist model. As already indicated, economic return, political decision and even philosophical appreciation are cases where the selector will be influenced by the output generated, i.e. in these cases it can be argued that the outputs adds to a knowledge base that in turn changes the selector function. This creates a dependency of the selector on the system so that for example in social systems the situation thus becomes heavily recursive. Let's turn to the authors of the triple helix model again: *"[T]he driving force of the interactions can be specified as the expectation of profits. 'Profit' may mean different things to the various actors involved. ... Note that analytically the drivers are no longer conceptualized as ex ante causes, but in terms of expectations that can be evaluated only ex post"* (Etzkowitz & Leydesdorff 2000).

There is, of course, an important difference in the degree to which such influence is of practical relevance. The selector will not usually strongly depend on just a single expert's views. But this changes when considering, for example, smaller fields of science and technology that indeed strongly depend on the views and publications of just a few experts. And in such cases, we may observe self-steering phenomena that are indeed of practical relevance in science, in research funding or science and technology policy.

6.7 Power to the powerful

That knowledge is of interest to politics is evident; but this interest originates not just in a predominantly technological power over nature or other micro- or macro-economic processes. In addition, from the policy perspective knowledge itself establishes control of the production of truth. In other words, it is a medium of and for social control. *"Knowledge constitutes* a basis *for power. Knowledge excludes."* (Adolf & Stehr, 2014, p. 41)

We have already seen how Marx puts knowledge at the side of the capital where it becomes technical knowledge: *"The accumulation of knowledge and fortune, the general productive forces of the social brain, is thus absorbed in labor against the capital, and therefore appears as a property of capital, more precisely of capital fixe, as far as it enters the* *production process as the actual means of production. Machinery thus appears as the most adequate form of the capital fixe"* (Marx 1857) But more important than the technical implications are the social aspects that Marx and Lyotard (as before: Lyotard, 1986, p. 132) allude to: it is the fact that knowledge and wealth are accumulated and in turn facilitate the production of wealth. Foucault takes this idea one step further when he says *"It is more likely to be assumed that the power produces knowledge [...]; That power and knowledge are directly interrelated; That there is no power relationship without a corresponding field of knowledge being constituted, and no knowledge that does not at the same time presuppose and establish power relations."* (Foucault 1976, p. 39 ff.) This obviously creates another circle in which knowledge not only leads to technical power or the power to be right, but also where the knowledge creates power relations; Foucault:*"These power / knowledge relationships are therefore not to be analyzed from a cognitive subject, which is free and unfree in relation to the system of power. Rather, it must be taken into account that the knowing subject, the object to be recognized and the modes of knowledge form the effects of those fundamental power / knowledge complexes and their historical transformations."* (Foucault 1976, p. 39 ff.)

Following Foucault, it would be a shortcoming to discuss the changes in the knowledge concept and the corresponding discourse about the production of knowledge in science and research exclusively from the point of economic exploitation and technological power. This change in discourse is only one face of a larger politicization where scientists and engineers locate themselves on the side of the politician. The economic argument is but one example. Latour refers to the famous case of longitude (Latour 2016, p.124). In her now famous account of the naval problem of finding longitude, (Sobel 1995) provides insights into the political motivation and process for funding solutions to the problem. While the problem as such was known for a long time in principle, it only attracted the interest of the English parliament and its politicians when trade was at stake. Policy makers only decided to initiate a research competition when economic success (and indeed the outcome of war) depended on it.

Engineering political power

Latour (2016, p.23 and 1990, p.49) makes the case for the political power shift towards technology through public experiment. He uses the report of Plutarch and the example of Archimedes' demonstration of the enormous physical power suddenly available to an old man through the use of a lever (what Latour calls a reversal of power). This experiment also signifies the translation of a geometrical assertion in a technical dispositive, it makes way for a shift from geometry to geopolitics (i.e. war).

The basic dichotomy between scientists' technical arguments and their interest in rather non-technical knowledge is also described by (Latour 2016, p.24). Archimedes advertises the *usefulness* of his knowledge in the *political* discourse using the argument of power. Science and politics share objectives – at least in the arguments of Archimedes and the political goals of Hieron. *"Science become interesting or not interesting to the extent in which they will be able to relate to other streams of actions, […] keeping their promises and becoming recognised as the main cause of the […] ensemble"* (Latour 2016 p.31). However, in the end Archimedes is not fundamentally interested in the actual delivery of technology. After all, he remains a true scientist following its very own (i.e. science-internal) rules (Latour 2016, pp. 29-30).

(Latour 2016, p.48) argues that there are two kinds of discourses happening: one discourse argues for a relation of science to society, the other negates it. Latour thinks both are true, albeit not at precisely the same time. Whether a technique functions or not decides its socio-technical presence or whether it completely disappears in the course of action. And also, the social importance given to technology (or not) decides the extent to which it can be applied. We will revisit this in Section 7.3.

To summarize, power as the impure objective of scientific knowledge – as opposed to pure science – is not only limited to economic utility and instrumental action. Ropohl (1991, p.12) reminds us that "magic" – an etymological relative of 'machine' and the German 'Macht' (power) – used to be in charge of removing resistance from both nature and society and to realize what we desire, be it rain, fertility, or affection. This desire for power seems to be a human universal, but it also brings fear of failure (Ropohl op.cit.) which connects to

Peirce's uncomfortable feeling of doubt, in which case both science and technology would ultimately be rooted in fear – indeed a rather negative perspective. We have seen here that power is not *just* the power arising from sheer technical capability. In addition, it is political power where the scientist positions himself or herself on the side of the politician, and it becomes the power to be right as in the performance of technically enabled laboratory instruments.

7 Knowledge tools and praxis

At several points in our discussion of knowledge and its use we have touched upon the question of the linear model and its temporal and logical sequence from basic research to innovation while others identify technology as the basis for science. We asked how opportune knowledge and technical power arise in epistemic processes and used a constructivist model to explain the impact of a selector on the type of knowledge in such models. Now there are two main reasons to put our constructivist investigation of knowledge for technological innovation in the context of phenomenological analysis. The first reason is the similarity of the ontological conception that arises from the constructivist model to Heidegger's account of tool use and more generally technology. The other is the question of the relation of praxis and technology which is central to contemporary streams in the philosophy of technology, e.g. in the work of Don Ihde, and which directly addresses the issues raised above.

7.1 Tool-based ontologies

The biosemiotic constructivist model demonstrates how an adaptive agent develops knowledge about its environment that facilitates actions. In addition to this epistemological function, it helps to clarify the ontology of such an agent. We have pointed out several times in this thesis how in the constructivist model, a selector shapes the world of the knowledgeable agent by means of an anticipatory (internal) model of its interaction with the world. From such a point of view, the world around the knowing agent is shaped based on the consequences of the (anticipated) interaction. This implies that the resulting ontology for the agent is entirely purposeful; in fact, *the system perceives its environment as a set of affordances* where *objectives and actions* are directly linked. In terms of the tick example, the world for the tick consists of its potential to act upon it. Indeed, the tick most likely has no other way of discovering the world. What comes into being (i.e. what is selected by the selector) based on the adaptation is what facilitates positively evaluated interaction outcomes.

In the simple world of the tick everything worth noticing in the world always already appears as purposeful. This may not be always the case for humans; for example, for the innovator to whom the world may at one point appear as an opportunity for business while at other times this potential is ignored. The river may at one point in time appear as a potential to produce energy, and at other times it may remain mostly unconsciously perceived when we are engaged in leisurely running along its banks. Even the tick may disregard the opportunity provided by warm-blooded animals in the context of mating. Such a distinction between different types of engagement is not possible in our simple model. Despite of the simplicity in the model, it helps to explain how in principle an all-purposeful ontology may arise in the first place and how it relates to opportune knowledge and as we shall discuss below to tool-use.

Our analysis of the constructivist model as an agent that perceives its world in affordance is strikingly similar to Martin Heidegger's conception of tools and human tool use in *Being and Time* (Heidegger 1927) and later in his analysis of technology (Heidegger 1953). This connection of an (artificial) agent with Heidegger's tool use is not completely new. There have been various discussions of his ontological analysis in the context of robotics in particular. In such a preliminary investigation, I discussed first ideas for how Heidegger's phenomenological analysis facilitates understanding a robot's perspective of the world (Prem 1997b). The main point is the kind of immediate interaction with everyday objects that Heidegger describes in *Being and Time.* Consider for example how humans engage with pens or hammers for writing and with hammers for hammering usually without any abstract cognizing or detached deliberation. In their work on object perception and tool using agents, (Susi & Ziemke 2005) analyse how subjects perceive tools and their use. They also investigate the positions of Uexküll and Heidegger and describe how subject/object relations become interdependent in tool-using situations. Heidegger's views have become particularly important in the realm of engineering, in particular of embodied Artificial Intelligence and robotics, as an answer to the kind of massive challenges that a purely rationalistic approach to dealing with everyday situations faces, cf. (Brooks 1991, Dreyfus 1991). The discussion in the 1990s focused massively on the difficulties anybody faces who tries to describe – with language or using abstract propositional frameworks – everyday practices of humans including, for example their seemingly straightforward way of using tools. In particularly in the 1990s there was a huge perceived discrepancy between the ease with which humans recognize and deal with tools and the clumsy, slow, and often faulty way in which robots could do similar things. Heidegger's ontology provided at least a theoretical answer to these challenges in that he insists on a primacy of tool use – even before we start describing tools, purposes, usages etc. Using tools, i.e. the praxis of engaging in a tool-based interaction with the world for Heidegger is clearly ontologically prior to a rational, detached analysis of the world. On the other hand, the kind of explanatory and symbolic models already described in Section 5, were understood and used as (ontologically) fundamental and this in turn created massive practical problems when trying to add affordances and functionalities in a later step, as (Dreyfus 1991) noted. Dreyfus – although not an engineer – rightly blames the need for adding function and affordance at a later step to structures that were not originally created for that purpose. Our constructivist model also suggests that knowledge gained in interaction need not in any way be related to knowledge for explanation; precisely what we have also seen in the analysis of (Banse & Wendt 1986) in Section 2.5.

In our everyday activities, humans are immersed in a network of tools that are "*ready-to-hand"* ("Zuhandenheit") to use Heidegger's terminology. There are qualitatively different relations to entities differentiating whether they are just used as they are *ready-to-hand* or whether they are just occurrent, *present-at-hand* ("Vorhandenheit") for us to be studied, for example in scientific discourse. Our everyday activities flow from one engagement with tools to another without ever giving it much thought. In the 1990s – and to a large extent also today – it is not easy to see how an artificial system could do the same: How is it possible that systems come to know how to use tools, how to seemingly float from one activity to the other; how to acquire and the apply the rich knowledge that humans seem to have about hammers, nails, wood, soap, dirt, water etc.? This is even more puzzling given that in using it, the tool itself often becomes transparent in action. Basically, the tool disappears as long as it functions properly, as long as it is in conformity with expected behaviour. This suggests that humans have somehow acquired knowledge about this expected behaviour; that there is knowledge about the *anticipated successful interaction* and the outcome of such interaction in using tools. Obviously, one way to acquire this knowledge is from using tools and remembering anticipated results including perception and action during hammering; but also, outcomes and sequences of useful interactions. This strongly suggests a connection to anticipated properties of using tools as we have already presented in the theory of predictive encoding (Section 5.2). But another way of looking at this phenomenon is that the things in our environment ontologically arise from tool use, or as in our constructivist model, from looking at the world already in terms of *anticipations of successful interaction outcomes*. When the objects around us are primarily shaped based on their usefulness for our actions, it is not difficult to see how they lend themselves to the activities for which they predict success. At least in the example of the tick, it is easy to understand how warm-blooded and butyric acid emitting objects afford biting for the tick with the anticipated interaction outcome of feeding. The obvious price that the tick (at least in the model) pays is that it cannot refer to deer or people based on its ontology; it only knows about things to be bitten with satisfaction.

Primacy of praxis

We have not said anything here about how the tick learns about the world, i.e. about the way in which this knowledge becomes shaped. The model does not include a specification of the precise processes or – in the case of artificial systems – algorithms that create the kind of tool-structure and knowledge just described. In the case of the tick, we may assume that this knowledge (if we want to call it that at all) has arisen from thousands of years of interaction and selection that shaped sensors and effectors of the tick, but also its nervous system. This is a strength of the model as it does not rely on a specific method of adaptation. The precise kind of genetic mutation or learning is unimportant as long as the *selector in the model operates on action outcomes* of the tick. This alone suffices to result in the type of anticipation that lets the world appear as a huge potential to satisfactorily act upon it; i.e. that lets the world be *ready-to-hand*. While the case for the tick may be relatively clear, can we also draw conclusions at the level of other knowledgeable systems?

Perhaps the most prominent representative of a philosophy of technology that insists on the primacy of praxis is Don Ihde. His work strongly focuses on the work of Martin Heidegger and his account of praxis, in particular in relation to tool use, and on the ontological primacy that Heidegger (in the account of Ihde, e.g. 1979, p. xxi) gives to technology over science. Don Ihde (1990, p. 32 ff.) refers to Heidegger's example of a hammer to clarify how tool-use exemplifies the fact that in hammering, we do not usually experience the hammer so much, but actually the world as we are engaged in hammering. Ihde describes the three outstanding results of Heidegger's phenomenological analysis as (i) context-dependence, (ii) reference to a network of other things (nails, floor, etc.), and (iii) how tools *"become the means, not the object of the experience"* (Ihde 1990, p. 32 ff.) According to (Waelbers 2011), the postphenomenological aspect of Ihde's work, i.e. what it adds to the phenomenological understanding of humans as *"constantly experiencing the (phenomena of the) world while realizing their own existence"* (Waelbers 2011, p. 77), is his focus on technological mediation of the relation of Being and world. For post-phenomenologists the aspect of technological mediation is important as technology arises from a praxis of instrument use. Our analysis here, however, lays the path to such a post-phenomenological understanding with a specific focus on instruments; it already roots in purposeful tool-use.

Ihde explains how Heidegger's unreadyness-to-hand lets a piece of equipment first "appear" as a thing in the conventional (Ancient Greek pragmata) sense (Ihde 1979, p.123). Interestingly, knowledge is quite similar in this sense: it appears mostly when it is lacking. (We will return to this point in Section 7.2.) Ihde points out (Ihde 1979, p. 120) that the connections existing in tool-use, the whole structure of *practical* knowledge that is rather distinct from theoretical knowledge, is rooted in praxis, i.e. in practical dealing with the world. Already in *Technics and Praxis*, Don Ihde (1979, p.109) suggests that Heidegger's tool analysis of *Being and Time* inverts the sequence from science to technology: Heidegger's ontological analysis not only suggests a *primacy of praxis*, Heidegger also replaces Husserlian intentionality with a "praxical base" (Ihde 1979, p.117). This means to replace the theoretical-cognitive stance with a view that first focuses on practical (and instrumental – in the double sense of using instruments and for a purpose) interaction with the world: *"The kind of dealing which is closes to us is […] not a bare perceptual cognition, but rather that kind of concern which manipulates things and puts them to use; and this has its own kind of 'knowledge'[…]"* (Heidegger *Being and Time*, 95, quoted from Ihde 1979, p. 118).

Ihde argues that there is a certain paradox in Heidegger's description of tool use in that the tool disappears in use which somehow conceals *"the very context in which the equipment occurs"* (Ihde 1979 p. 122). This aspect of *negativity* (ibd.) becomes clear when the tool breaks down (*unreadiness-to-hand*) and the equipmental context re-appears (resulting in *presence-at-hand*). It is remarkable and indeed something of a paradox in Heidegger's work that un-usability is discovered in use efforts and thus within the *"circumspection of the dealing in which we use it"* (Heidegger *Being and Time*, 102, quoted after Ihde 1979 p.122). Ihde summarizes the key features of Heidegger's account of technology: *"(a) world is revealed* through *the equipmental context; (b) the equipmental context is the condition of the possibility of specific 'tools' being what they are; (c) noetically, engagement of the environment through readiness-to-hand reveals existential intentionality as* concern *[...], and (d) concern takes account of the context [...]"* (Ihde 1979, p.126-127). But Heidegger's phenomenological analysis in his later work on technology goes a step further as we shall discuss below.

Knowledge and Ge-stell

There is another level at which we can interpret the all-purposeful ontology arising in our constructivist model of the adaptive agent. In his philosophy of technology, Martin Heidegger famously uses the example of the Rhine River to demonstrate how modern technology challenges nature to reveal its usefulness: hydropower challenges the Rhine for its water pressure. Heidegger's criticism of modern technology (Heidegger 1953) is founded on the claim that such processes of *challenging-forth* result in an attitude where anything becomes *standing-reserve* ("Bestand") – not just an object or a thing merely encountered in our everyday dwelling in the world. Heidegger calls this challenging claim that gathers mankind to hold nature as standing in reserve "Ge-stell" or *enframing*. *"Enframing means the gathering together of that setting-upon that sets upon man, i.e., challenges him forth, to reveal the real, in the mode of ordering, as standing-reserve."* (Heidegger 1977) Technology lets the world stand-reserve for just about any human purpose. *"The revealing that rules in modern technology is a challenging, which puts to nature the unreasonable demand that it supply energy which can be extracted and stored as such."* (Heidegger 1953, quoted after Ihde 1979, p. 108)

However, following the argument of Steinschaden (2015, p.78), Heidegger's critique of a primarily technical view of being does not explicate *why* various actions, views of the world etc. result in a technical way of all being. Our version of the biosemiotic model suggests the primacy of the instrumental character of all knowledge that is developed in order to facilitate action. Just as technology sets all being to realize possible purposes, all knowledge is now seen as a means to possible ends. Knowledge *only* appears as something that can be used for a purpose. This is not a particularly difficult view; even spiritual knowledge that we mentioned in the introduction may easily be understood as purposeful. The important point is that in our constructivist model it follows simply from the way the selector operates on acting agents and thereby how it selects knowledgeable agents. The selection process results in purposeful knowledge and in a situation where everything may be taken as potentially useful for reward-maximizing i.e. anticipatory action. I suggest interpreting this as taking anything there is as standing-reserve. The biosemiotic agent intrinsically responds to something akin to enframing. Heidegger largely bsaes this enframing in early Greek philosophy and the focus on providing justifying arguments (λόγον διδόναι) in discourse (Steinschaden 2015, p. 72). This challenges argumentation and reasoning in a way that is very similar to technology as it connotes causality, consequence, and (potential) purpose. From the point of view of our analysis, we can only agree insofar as the chain of arguments, the *λόγον διδόναι* that Heidegger refers to, is a means for being right in argumentation. But as we have pointed out several times, pure description and even pure prediction are in principle insufficient for the kind of technical problem solving that Steinschaden alludes to.

One of the problems that Heidegger points us to is that in such an account nature impoverishes and becomes stripped from many of its characteristics (Steinschaden 2015, p.78). Among the many relations and relata that things may have, only those that fulfil purposes remain. Lastly, as Luckner says (2015, p.19), human existence is reduced to that of the *"technician, the problem solver…the producers of his conditions of existence"*. Contrary to what Luckner emphasizes about things – that they carry *various* meanings entangled in a network of references (Steinschaden, ibd.) – enframing makes them replaceable with anything that fulfils the identified purpose. Ihde suggests that Heidegger's *Question Concerning Technology* demonstrates how this enframing also results in technology that is now taken to dominate nature (Ihde 1979, p.109), e.g. in the case of the river Rhine that stands reserve for energy demand and that inherits this demand from the power station.

In his later lecture on the question concerning technology, Heidegger returns to his diagnosis of technology as enframing when he says that *"physics, indeed already as pure theory, sets nature up as a coherence of forces calculable in advance".* (Heidegger quoted after Ihde 1979, p.111) This makes the connection to nature as standing-reserve as Ihde has argued in detail. From today's perspective, it is a consequence of the modern turn towards an efficient programme of natural science that gives rise to a purpose-driven ontology. The smallest sub-atomic particle becomes something that should be there and be it only as the imagined entity facilitating the construction of complex measurement and experimental devices (cf. Blumenberg and Ihde, op.cit.). It is also noteworthy that Heidegger already clearly refers to the instrumental nature of physics and its dependence upon technical progress in their construction (Heidegger 1953, 295). Ihde calls this the technological embodiment of science (Ihde 1979, p. 110). It should be noted, however, that Ihde really focuses to a large extent on measurement devices and not so much on the aspect of interaction.

An enframing of tools

It is, of course, no coincidence that the tool-based ontology in our model also leads us to Heidegger's concept of the enframing ("Ge-stell"). Although these two frameworks emerged at different points in Heidegger's work, they are strongly related and for some actually only two sides of the same problem. Don Ihde calls the tool analysis in Heidegger's early work "isomorphic" to the analysis in *The Question Concerning Technology* (Ihde 1979, p. 121), although technology is not explicitly addressed in *Being and Time*. Ihde suggests that the praxis-related (i.e. practical) dimension of the tool-analysis corresponds to the condition of the possibility for technology (ibid.), in particular Ihde argues that Heidegger's later and more explicit philosophy of technology was anticipated already in *Being and Time* in the primacy of the *ready-to-hand*. The connection between the two perspectives is not difficult to make: Heidegger criticizes what Ihde has called the anthropological-instrumental definition of technology (Ihde 1979, p. 106) as correct but insufficient and instead investigates the conditions of possibility of technology: *"Technology, as Heidegger sees it, is not only ontic, but ontological." (Ihde 1979, p.106)* In other words, while it is factually correct that technology consists of technical tools and functioning, technology for Heidegger is a mode of revealing or as Ihde calls it *a mode of* *truth. "...what is decisive in* techne *does not lie at all in making and manipulating nor in the using of means, but rather in the revealing mentioned before. [...] Technology is therefore no mere means, Technology is a way of revealing."* (Heideger 1953, quoted after Ihde 1979, p. 106). However, technology is not just a mode of revealing in the sense of a simple analysis or understanding. Much more than that, *"[r]evealing is a coming to presence within a framework."* (Ihde 1979, p. 108). Ihde calls this framework, i.e. Heidegger's enframing *(Ge-stell)* a *"civilizational variant into which humans have moved [...] of being a call or claim upon humans for some necessary response; and it has a telos or destiny as a direction of development."* (Ihde 1979, p. 107)

That such a view may as well emerge from our constructivist model should not be entirely surprising. Blumenberg already argued in 1952 that a primarily *technical* supposition (Blumenberg 1952, p. 46) that creates *truth by anticipation* leads to Kant's focus on reason that only understands what it first created. In our model, because of its technical character, knowledge always appears goal-oriented (for action), although these goals themselves may not always have technical or constructive character (e.g. argumentation).

It is Heidegger who connects technology with poiesis (through techné) (Heidegger 1953); for Heidegger, technology is something poietic, but also something where knowledge is at work. *"What Heidegger discerns as the emergence of technology as a mode of revealing is not simply postscientific. Its roots lie deep within our (and others) histories."* (Ihde, 1991 p. 59) Where Heidegger (1955, p.18) refers to technology, it is possible to replace technology with knowledge where knowledge then turns into entities in our environment to which Heidegger's existential-ontological analysis can be applied. Consequently, using the terminology and translation of Dreyfus (1991, p. 84), knowledge-things may exhibit *availableness (Unzuhandenheit), unavailableness (Unzuhandenheit), occurrentness (Vorhandenheit) and pure occurentness (Bloß-Vorhandenheit).* As long as we simply cope applying our knowledge, such knowledge is available or ready-to-hand. Where our smooth coping with the world based on knowledge breaks down for a moment, but may be continued, we may enter in a transitional state of acknowledging this deficit and recognize the lack of knowing. Once decontextualized, knowledge can be recontextualized in formal accounts and theories, thus becoming *occurrent.* And when treated abstractly, such as in this thesis or in other studies that investigate knowledge in the abstract and without recontextualizing, it is a purely occurrent entity.

Multiple purpose from one piece of knowledge

Our simple model does not easily help us to understand that knowledge may of be good for more than just a single purpose. Knowledge sometimes results from complex objectives such as identification and naming and publishing and testing etc. and we may find it difficult to construct a selector that achieves all this at the same time.

Similarly, it is not straightforward to determine whether and to what extent some identified piece of knowledge is useful for a given purpose, if this is not how it first was created. In fact, this is often what engineering research needs to discover in its course of study and based on creative ideas for potential application. Today, knowledge is generally produced not only with the goal to meet only specific objectives, for example to arrive at a previously specified innovation. Quite to the contrary, programmes of policy makers suggest that knowledge be used for innovation of which we do not net yet know what it might be precisely. It is the *potential application* or the *potential innovation* for which knowledge is produced, not a specific innovation. This reminds us of the previously mentioned reservoir view of knowledge which is produced without really knowing what it might be good for. Here, every piece of knowledge is examined to eventually become a means to realize a potential goal. Knowledge also stands-reserve. Similarly, in our model, every action appears to fulfil a technical objective, namely generation of an action in order to be positively evaluated by the selector.

7.2 Knowledge-Things

Clearly, the constructivist analysis in this thesis focuses on knowledge as an enabler of action. However, this does not strictly mean it needs to remain only at the level of an internal structure; things can come to represent knowledge – or at least, information. We have referred to accounts that describe knowledge as a subject of economic processes already in the introduction. In these aforementioned contexts of the knowledge-based economy, in particular in the triple-helix models, knowledge often refers to externalised knowledge, formalised in a research paper or in a patent. Although we may prefer to call this information (as mentioned in section 2.1), for example for lack of a knowing agent, it is insightful to consider knowledge as a *thing*. Here we are not referring to conventional things, but to the kind of existential-ontological *things* that Heidegger describes.

It is possible to extend Heidegger's analysis of technology as enframing and apply it to knowledge. When Heidegger suggests that humans today regard everything that exists as a tool, as means to ends this is in fact very similar to the idea of reservoir knowledge. Such knowledge may not yet be useful, but it carries the potential to be an answer to a latent use. In this sense, knowledge is part of the same enframing – it is viewed as something that can be used, just like other things in our surrounding. In this section, we focus on the idea of knowledge being a thing in line with the phenomenological analysis that we just presented. This analysis follows Andreas Luckner who recently published an account of Heidegger's discussion of things in the light of the philosophy of technology (Luckner 2015). In the following, we apply this analysis to knowledge, i.e. we explicitly focus on understanding knowledge as a thing in Heidegger's phenomenological analysis.

Luckner distinguishes three main views of things in the work of Heidegger – from its first discussion in *Being and Time* to its characterization as a work of art (Luckner 2008, 2015). (i) In *Being and Time* the characterisation of things is primarily negative. They emerge from tool use in situations where tools break down; when they cease to function as expected. This is the point when we stop using them without being aware of them; when they first come into being for us. In the previous section, it was mentioned that Heidegger's notion of *unreadyness-to-hand* first lets a piece of equipment occur as a thing (Ihde 1979, p.123). Similarly, for knowledge, it may first occur to us when it is unavailable. Luckner talks about the thing being an un-tool ("Unzeuge") or "tool-zombies". They only come to life when they re-enter their whole of meaningful reference (Luckner 2015, p. 21).

(ii) The second characterisation of things emerges from Heidegger's work on the *Origin of the Work of Art.* Artworks have an element of autonomy; in contrast to tools they do not depend on their successful use. Apart from their determination as pure things (i) in their formal-existential structure (ibid.) they also possess something discrete, independent, autonomous from them being tools. And the clearest way to see this is in the case of the work of art (Prem 2017).

(iii) Thirdly, in his late work, Heidegger gives another account of things in *Das Ding* where it is characterized as the focal point of world relations. Luckner argued that special human attention is required to recognize things and their relations, a special kind of philosophical thinking, *"das andenkende Denken"* (Heidegger 1949, p. 174).

Let us now apply this framework to *knowledge* as a special kind of thing:

i. Just as tools become recognized most when they do not work, knowledge – in particular from a techno-scientific perspective – receives special attention when and where it is unavailable. Knowledge becomes important in situations where our normal foundations of actions become dysfunctional and we view knowledge from a perspective of deficit. In such an understanding, knowledge implies *not-(yet)-being-able-to*, in particular from a technical position and for the innovation-minded. Here, knowledge is entirely regarded from a purpose-driven perspective, not just from ways of using it, but already from its *potential* use. Knowledge does not present itself where it is seamlessly used; only when it becomes unavailable does it receive its specific characteristic as a thing.

   Even where it has already been created, i.e. where it already achieves a purpose, it additionally appears as a potential answer to more, eventually realizable purposes that may still await definition and discovery.

   Clearly, in modern discussions about turning results of basic research into innovation, i.e. in thinking along the lines of the traditional linear model, knowledge to predict and to explain still suffers an apparent deficit: it is not yet knowledge that enables action or empowerment; it is just occurrent knowledge not yet put to use.

ii. In sharp contrast to knowledge-things as readily available or unavailable tools we may, however, consider self-contained knowledge-things that we bring forth with claims of truth – but not with claims of power or potentiality. Such knowledge-things will remain independent and stand for themselves, similar to works of art. Here, knowledge is different from its mere fulfilment of purpose. Like works of art they may afford an emotional stance – much in the line of Peirce's feeling about the state of not-knowing.

Such knowledge-things refer to a truth claim, but also to their way of coming into being, e.g. as being scientific. This is in clear contrast to knowledge as a tool where the way it was first created disappears once such knowledge becomes *available.* For this reason, these knowledge-things are unlikely to disappear, even when used.

iii. Knowledge-things may also be understood as a focus of world-relation; these knowledge-things may be embedded in a contextual whole. Such things assemble the world in the sense where Luckner refers to the Germanic *thing* as the assembly. We shall not further investigate this here, but mention that Latour talks about things as assembly or *"assemblage"* and something that brings agents together (Barla 2015, p. 105.)

Verbeek describe Heidegger's account of things very similar to Luckner when he says: *"Heidegger assigned to useful objects a place midway between pure things and artworks. A useful thing is not a pure thing, for it has to be made just as does the artwork. But neither is it artwork, for it must be* used *in order to be present as useful. In its use it withdraws from our attention – again, in contrast to the artwork, which imposes itself on us and whose presence we linger over – though it should be noted that [...] a useful object never completely withdraws, as Heidegger thought, but can evoke a certain measure of engagement with itself."* (Verbeek 2003, p. 210-211) In this sense, we may assign knowledge precisely such a place between *"pure things"* and artworks. Where it is useful in the form of opportune knowledge, it does not present itself to our attention. And where it is like art it stands out as something created, but not yet useful, such as knowledge from basic inquiries into nature.

In Section 6.2.1, we briefly discussed recent reliabilist theories and their focus on the processes that make knowledge something reliable. Although our model does not facilitate any explanation of such a process, the obvious connection of reliability and Heidegger's account of tools is usefulness. Usefulness is closely linked to reliability and *"[a]ccording to Heidegger…reliability is the way of being equipment."* (Verbeek 2003, p. 85) This – as

Verbeek points out – is a more positive turn to Heidegger's account of tools that basically remain concealed unless in situations where they are broken.

7.3 Knowledge-things are not neutral

If knowledge itself becomes a tool and thus a component of technology, this poses the question about what our relation as humans to such knowledge-things is. Today the claim that "technology is not neutral" has become a well-known motto in some arts initiatives.[19] However, technology is still often considered to be precisely "neutral" while its significance arises from its use (Ihde 1990, p. 128). This view is hard to maintain based on phenomenological analysis of technologies and Ihde calls it a "disembodied abstraction" (Ihde 1990, p. 128). Even technological ruins, for example Austria's only and never used atomic power plant, are indications of an at least perceived "usefulness" (ibid.). For Steinschaden, technical tools create a specific attitude in our dealing with them (Steinschaden 2015, p. 69). This is the reason why the essence of technology is deeper than and not completely grasped at the level of tools and purposes.

For example, Peter-Paul Verbeek reminds us of Jaspers' description, how modern machines *"reduces human beings and their material environment to their functioning"* (Verbeek 2003, p.21) The work of Jaspers (e.g. Jaspers 1951) particularly points to the ways in which modern technology and in particular mass production changes human existence in terms of changing the characteristics of labour and resulting in standardized functional products that have value only with respect to their function (Verbeek, p. 23).

In his discussion of Heidegger's philosophy of technology Steinschaden (2015, p. 71) points out that *"[t]he means do not behave neutrally against the objects to be processed and their users, but demand that we take a specific attitude towards the things."* Consequently, our way of handling them changes our relation to them. This also applies to knowledge as a technical tool: when knowledge becomes a tool, it demands a specific attitude. This goes

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[19] *Technology is not neutral* was the title of a touring exhibition project curated by Gordana Novakovic, Anna Dumitriu and Irini Papadimitriou in 2016. https://www.watermans.org.uk/new-media-arts-archive/technology-is-not-neutral/ (Accessed July 2017)

beyond just regarding knowledge as power or the potential to act or the possibility to be right. In paraphrasing Heidegger (1955), we could say that the power hidden in techno-scientific knowledge determines the human relation to everything that is.

If both, human tool use and scientific inquiry are essentially challenging and part of the enframing, the interesting question arises what then is the difference. The abstract nature identified in physics is essentially decontextualized from most human interests. Nature is reduced to its response to our inquisitive interaction in experimentation, compare also the discussion in (Ihde 1979, p.124). Heidegger's account of this difference appears to be somewhat romanticizing: *"The botanist's plants are not the flowers of the hedgerow."* (Heidegger 1927, 100). He refers to the wood as a forest of timber and anticipates (Ihde, ibid.) standing-reserve.

Ihde criticizes the change in tone from Heidegger's discussion of tools to his account of technology (Ihde 1979, p.127). Where the former is mostly positively connected, the latter is considered critical. However, the distinction is already visible in *Being and Time*. The main difference appears to be an essentially human engagement versus a not-so-essential, perhaps economic activity. Steinschaden (2015, p. 66) argues historically that the prevalence of Fordism, the industrial version of Taylorism, in the first half of the 20th century ultimately motivated Heidegger's account and critique of technology.

Ihde has rightly identified that the Heideggerian model suggests a non-neutrality of science that still may be underestimated today. While the non-neutrality of technology is perhaps more widely accepted because of clearly visible negative effects of technology, science often considers precisely its "staring-at" as largely neutral, perhaps because it is decontextualized. However, the instrumentalizing perspective of science first announced in Heidegger's analysis is clearly not completely neutral. It may already be partially economic or technical, but at least it is driven by an explanatory intention.

Verbeek rightly criticizes a transcendental tendency in phenomenological analysis of technology that focuses entirely on conditions of possibility of the material environment but does not sufficiently study current technologies. Verbeek (2003, p. 30) asks us to *"look forward to what technological artefacts themselves make possible, and what this means for human existence"*. (Ihde 1979 p. 129) summarizes the difference between art and science (in Heidegger) in that *"[a]rt is essentially anti-reductive in its imaginative fecundity. Its 'worlds' are essentially endless."* Ihde thereby suggests that art produces at least the potential for a proliferation of possibilities, while Heidegger warns about technology's tendency towards a reduction of possibilities.

If in this sense and direction, it is possible to regard *knowledge as a work of art,* it may open the door to this proliferation of options rather than limiting our attitude to it to only its potential application.

7.4 Technology before science?

There have been several recurring topics in our study of knowledge for innovation. Apart from the issues of *anticipation* and *selection (adaptation),* the two central perspectives were *doing* and *knowing,* their relation, how they condition each other and in the last sections which comes first. Perhaps the most problematic point is their connection, i.e. the way in which doing and knowing facilitate each other. While we have already discussed to some extent the role of action for knowledge, there is also the aspect of technology versus science; i.e. which comes first. This concerns the arrows in the linear model: does pure knowledge first enable goal-oriented technology or is there a founding role of technology for pure knowledge? From our model, the question seems difficult to decide: on the one hand the model requires action for the selector to operate: there can be no knowledge without testing the consequences of the actions it enables. On the other, knowledge appears as the only facilitator of action in the model. Note however that the knowledge in the model is per se related to action. It is (unless for the exceptional cases of "explanation" and "doing physics") not the type of explanatory and purely predictive knowledge that the linear model refers to; *it is always already technical* in the sense that it will produce action, it *anticipates viable actions* generating positive action outcomes. But if we assume (as in the linear model) that there is an important role of pure science in the creation of technology (despite of the difference mentioned in Section 2.5), then the opposite question must be asked as well: does science depend on technology and praxis?

The topic of the creative relation of the kind of explanatory knowledge arising in basic science and technical knowledge is of current interest, in particular from the point of view of post-phenomenology. There is a whole set of arguments in the recent post-phenomenological philosophy of technology that argues for the primacy of technology over science. Some of the more important ones are the following; note that points (i), (ii) and (v) were already covered in this section, for a brief discussion of the others see below:

(i) Heidegger's argument about the ontological primacy of a technical stance in science.
(ii) Don Ihde's focus on technology as the enabler and indeed source of scientific information, e.g. in measurement and experimental devices.
(iii) Kuhn's practical turn that suggests the importance of scientific practice and scientific communities.
(iv) The historic argument that many technological developments predate their scientific understanding.
(v) To these more discussed aspects, we may add our own analysis from constructivism where anticipatory representations are inherently technical (the subject of Sections 5 and this section).

As we have seen, Ihde argues that for Heidegger the origin of modern science ontologically is modern technology and, moreover, physics is a tool of technology in the sense of the way in which the natural sciences "reveal" the world. There are basically two arguments that support such a characterization: Firstly, there is the technological way of revealing natural phenomena based on using instruments, but secondly there is the abstraction present in physics' mathematical theories which is also predominantly technological (Ihde 1990, p.135).

Ihde (1990) and De Solla Price (1984) have pointed out how developments in technology are the *origin* of new scientific information and should not primarily be regarded as the testing of hypotheses. Kuhn's paradigmatic paradigm shifts (Kuhn 1962) are then less based in victories of one set of ideas or theories over another, but predated by technological changes (improvements) that support new information to what Price terms "artificial revelation" (Price 1984, p. 106). Both authors, Ihde and Price, also emphasize the tendency of science to focus on the theoretical (and indeed mathematical) over the material conditions of knowledge arising from experiments. Given the massive theoretical scaffolding of theories such as quantum theory in physics, this focus clearly persists today. Ihde calls science a *"conceptual tool of technological culture"* (Ihde 1990, p. 202). This identification emerges from a hermeneutical approach that demythologizes the science/technology relation. The demythologization particularly refers to the exaggerations and myths about science to which for Ihde science education also vastly contributed. *"What can be called the Old philosophy of science tended to interpret science in a noncontextual way, focusing almost solely upon its logical, propositional, and rational procedures."* (Ihde 1990, p. 204) As a consequence, science had to appear as ahistorical and acultural. While nowadays we are beginning to appreciate science as a *"situated, a contexted phenomenon"* (ibid.) From the analysis in this thesis, we may want to add that it is now also functional, timely, and in a fundamental sense technical.

At the same time, Ihde demonstrates how the issue of objectivity in science remains contested and that for defenders of a more traditional understanding of science nothing else but the *"progress of civilization"* is at stake if we were to give up *"objectivity, truth, and science"* and in particular a presumed concept of universal and objective truth (Ihde 1990, pp. 205-206). I believe that this position lies also at the root of putting science before technology or more generally the linear model of innovation. As Ihde suggests (Ihde 1990, p.212), Kuhn may have remained largely within more traditional and idealized philosophies of science, but at least he shifted the attention to more practical (in the sense of praxis) and indeed social aspects of science.

Another strand revising our interpretation of science and technology is the historian's view that technological improvement has often preceded scientific insight. More than 30 years ago, (Laudan 1984, p.10) described two attacks on the thesis that technology is applied science. Empirically many historians identify long periods *"where the major advances in the development of technology where the major advances owed little or nothing to science".* And the examples range from the steam engine to the use of water power, the manufacturing of clocks etc. While these are more historical examples, the second argument is based on 20th century studies that also *"demonstrate that the connection between science and technology even in the modern period is much more complex and tenuous than suggested by the popular image of technology as applied science".* Laudan reminds us that Edwin Layton (1974) suggested using the *"classic Aristotelian definition of technology as 'systematic knowledge of the useful arts'"* (Laudan 1984, p. 10). And these useful arts do not necessarily require knowledge of basic physics or other sciences, but rather suggest more practical know-how.

Constant (1984, p. 29) identified *"community and tradition"* as the main boundary condition and source of (mostly incremental) technological progress. Very often, high-tech comes in readily identifiable communities with a few major leaders. In 1984, Constant's example were Turbojet engines or aircraft industries, today we may quote smartphones and computers. Such communities of practice show strong intra-community linkages, while the inter-community linkages are usually much weaker (ibid.) Constant (1984, p. 31) also argues that in such communities in particular, science has a special forecasting function, in particular of predicting the *limits* of current technologies. Paradoxically, while we have seen in this thesis how difficult it is to move from basic research to technical knowledge, there is a role for the kind of predictive models in science to inform technology about its limits.

Still, there are enormous differences between scientific and engineering practices in research. While both may publish a lot, and both should have a genuine interest in precision, repeatability, impartiality etc., engineers are not usually interested in scholarly writing (Constant 1984 p.32). Apart from other important differences regarding hierarchy in technical structures and decomposability, Layton pointed out the difference between communities interested in "doing" and "knowing", i.e. engineers and scientists (Layton 1974). Hottois argued that the difference in the interests in these communities becomes clearly visible in today's contrasting juxtaposition of an old, primary logotheoretical, contemplative and verbal science with another whose core consists in effectiveness (i.e. technoscience). The latter is often mathematically oriented, critical of linguistic and literary knowledge. It also establishes an active relation to nature. Operating efficacy, combination of knowledge and power are practical signs of objectivity and of the underlying realism, i.e. Bacon's power from knowledge (Hottois 2015).

Revisiting the linear model

Let us collect results from our analysis to analyse its impact on the linear model. This is not an exercise to save or improve the model, rather it should clarify some of its major shortcomings. Although science may still provide an important basis for technology, we have seen in this section, how science itself is practically and technologically conditioned. Redrawing this as an expansion of Figure 2-5 results in the following version of the linear push-model of innovation (Figure 7-1):

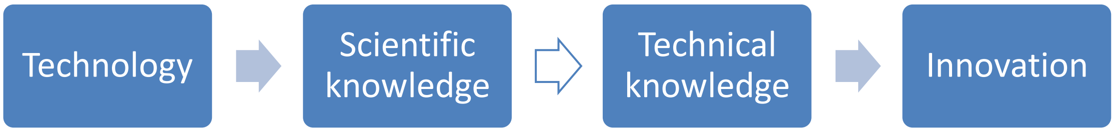

Figure 7-1 As a simple correction to the linear model of innovation, technology is added as a primordial enabler of scientific knowledge that may create technical knowledge which in turn leads to applications.

We have also discussed at length the trouble with deriving technical knowledge from scientific knowledge in Section 2.5. Note that technology plays a double role here as both a result and an enabler of science. To the extent that technology arises from scientific knowledge and to the extent that such technology in turn serves to identify scientific inputs, this results in the circle depicted in Figure 7-2:

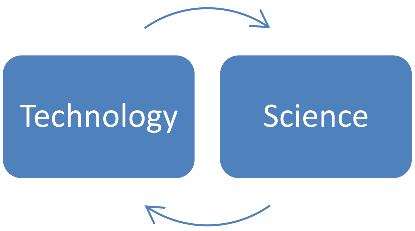

Figure 7-2 Technology and science condition each other: instrumental input from technology provides science with data that in turn results in novel technologies.

In addition, Don Ihde (Ihde 1979, p. xxiii ff.) has emphasized how science depends on technology as the primary cause in a sequence of changes that ultimately impact on society (Figure 7-3). Basically, this is just the old linear model with the added understanding that innovation impacts on society (for example through commercialized invention) and that technology is a precursor to scientific knowledge.

Figure 7-3 Following Ihde, technology provides the instruments for science that produces results impacting on society. (Note that we might want to add applied research or technology development between science and society.)

However, as we have discussed, Ihde proposes an inversion of this sequence and studies this inversion focusing strongly on how technology and technical praxis impact on science. In addition, the question arises to what extent technologies depend on society. We did not explicitly address this question from the point of view of society, but we refer to the recent reception of the work of Deleuze and Guattari that Hubatsche summarizes as *"The social always comes before the technical."* (Hubatschke 2015, p. 185).

In fact, for the case where the constructivist model is regarded as a model of the creation of technical knowledge following a market-oriented selector, it is quite clear that society indeed influences technology. Volker Gerhardt (2015, p.152) analysed for innovation and the World Wide Web that technology becomes recognized in its role of cultural endowment. Similarly, it needs to be acknowledged how innovation and technology have become founders of contemporary knowledge. In combination with the arguments above about technology being before science, this would then lead to the situation depicted in Figure 7-4:

Figure 7-4 In this view, the social comes before the technical, and scientific progress depends on progress in technology.

Figure 7-5To make things even more complicated, we have seen in Section 3, how technology also may be used to arrive at the development of technical knowledge (Figure 7-5) to create innovative products and services, e.g. automated translation services. And strictly, we also have to add how IT in the shape of innovation technologies directly impacts on innovation.

Figure 7-5 Technology, in particular information technology directly generates technically applicable knowledge that results in market innovation, but it also impacts directly on innovation (Sections 3.1, 3.2, 3.4).

Figure 7-5

To avoid oversimplification, it should be clear that this last picture does not describe all aspects that may as well be important. For example, we leave out the question of how Information Technology first came into existence (no arrows into the first box). Also, Figure 7-5 does not describe the source of the data that we use for training the systems (no domain knowledge enters the second box) and there is no clearly described market push here (no arrow from the market side of things to the technical knowledge).

We can now try to put these rather different diagrams into a single scheme. The result is shown in Figure 7-6.

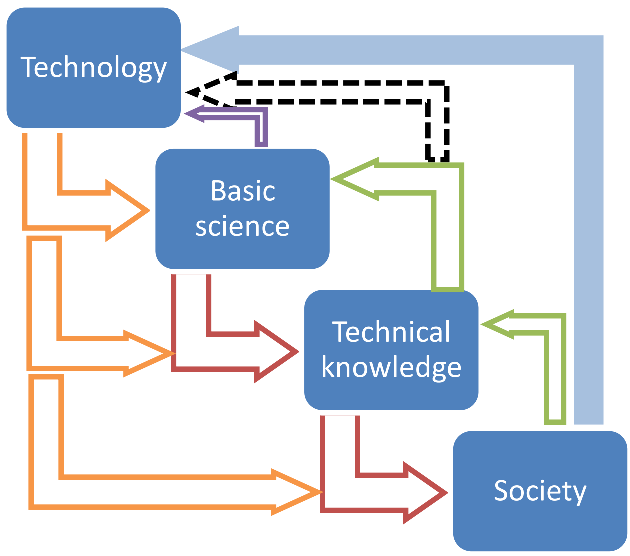

Figure 7-6 The expanded model of generative processes of opportune (technical) knowledge. Red arrows are from the 1st generation version of the linear model; orange arrows are based on

technological primacy for basic science, and its role for the construction of technical knowledge as well as its impact on society (above); the blue arrow stands for the impact of society on technology (this section). The green arrows are taken from the pull-model version of the linear model; and the impact from improved technical knowledge (black dotted arrow) on technology may be expected, but was not discussed here. Finally, the purple arrow results from Figure 7-2 (above).

The situation described in Figure 7-6 is hugely complex; in fact, in mathematical terms this has now turned into a complete graph with all the connections between all the nodes. In addition, technology appears twice in this picture: as a source of all other processes, but also as their target – at least before it impacts on society. This is no coincidence. So-called applied research and its goal-achieving technical knowledge is put in the focus of research processes; but not because of its role in the linear model, instead it forms the basis of the epistemic connection between purpose and power. Technical knowledge is: it becomes a middle term that negotiates demands, willingness -to-pay, and viabilities.

The scheme also poses an important question about the relation of science and society. Although it is clear that both depend on each other, it is not easy to see how much science depends on technology that results from society – and to what extent science results in changes that impact on society. Deleuze and Guattari suggest replacing questions about how machines follow from simple tools (Hubatschke 2015, p. 185; Deleuze & Guttari 1977, p. 517) with the question which societal machine generates the occurrence of technical machines. We take this suggestion seriously and ask within our context, which societal conditions generate a general knowledge creation machine such as Google translate? The answer brings us back to the diagnosis from the introduction: it is a situation in which a quick market success is required and where there is no need or use for explanation or prediction. In addition, it is a condition where information technologies are pervasive and first create the opportunity for in turn creating a knowledge creation machine.

8 Conclusion

This thesis presented an investigation into the creation of opportune, or useful, knowledge. It investigated changes induced in our notion of knowledge as science and society put more and more focus on innovation. The result may be called a technologistic and action-theoretic constructivist epistemology (Lenk 2004, p.76). Let me summarize the main results, *cum grano salis* as follows:

Using a constructivist model of knowledge creation, we located the origin of technical knowledge processes neither directly in observation nor in prediction in the classical physicalist sense. Instead, we recognize the importance of action (i.e. praxis), instruments (inputs), and in particular in the objectives. These objectives can be represented in a selector function that determines viable systems in a constructivist framework. The selector operates on the outcomes of system-environment interactions that an internal model selects. In this way, objectives are an ontologically formative source of technical knowledge; the practical knowledge arising from interaction facilitates successful interaction. In such a view, technical knowledge becomes the prediction of successful interaction outcomes while at the same time producing these actions.

We have also seen, how the emphasis on purposeful knowledge changes the character of knowledge and the epistemic processes that create this knowledge in just about every aspect: It changes epistemic processes, fosters externalisation – but also *internalisation* in the sense of functionality without delivering at the same time understandable explanation or abstract prediction. It leads to an emphasis on timeliness thereby undermining longevity of knowledge in favour of speedy development and application of knowledge.

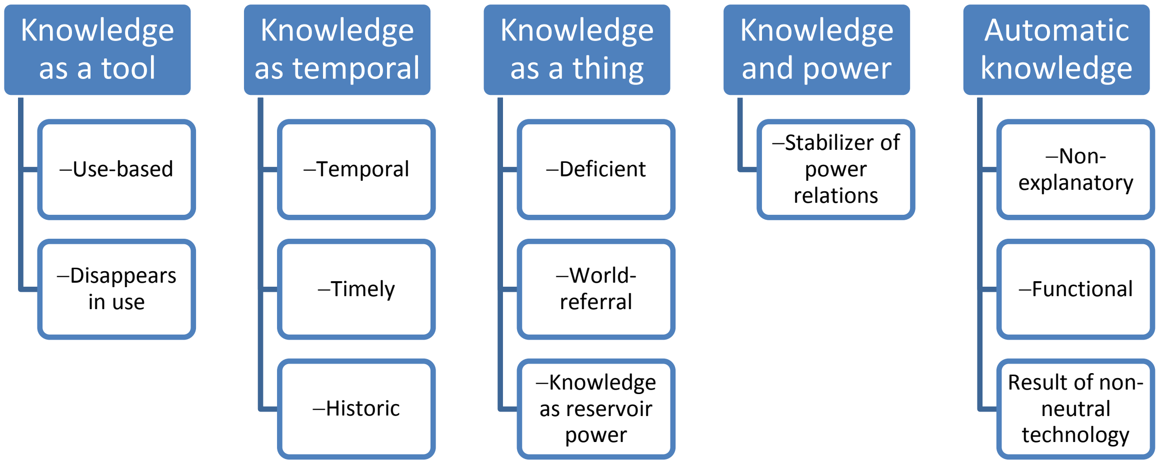

Figure 8-1 Overview of various characteristics of opportune knowledge arising from using a constructivist model and a purpose-based interaction framework. See text for summary.

The functional account of knowledge presented here supports Ihde's analysis of a primacy of technology before science. Our ontological analysis of the constructivist model supports a view for the system that is nearly exclusively use- and outcome-driven and at the same time carries a time-dimension. As a consequence, the world for this system appears full of potential to act. The model explains, how a complete functional orientation implies examining the entire environment (and the interaction with this environment) with respect to its affordances. It suggests that this kind of enframing results from the very emphasis on the selection process that is in turn based on action. Opportune knowledge is not only reservoir power, but in addition demands to be examined for further potential purposes.

An existential-ontological analysis of knowledge-things, i.e. regarding knowledge as similar to things, suggests that opportune knowledge can be regarded a tool that disappears in use and re-appears when it is deficient. Knowledge may also be regarded a thing that focuses references to a whole world of other knowledge; such knowledge need not be grounded in function alone, but convey meaning similar to a work of art.

Opportune knowledge creates specific power relations; in particular, it creates a tendency to increase the power to be right through its performative character in action. Additionally, it lends itself to the creation of feedback loops and self-selection so as to give power to the powerful.

Limitations and open problems

At several points, it was made clear that the constructivist model is a strong simplification. In fact, the model will not even create much knowledge for purists of Meno-valued epistemologies. On the other hand, despite of the simplicity of the model, it could clarify a range of issues that have massive practical implications and impact on science and technology today, such as the definitions in the Frascati manual, the ideas underlying a linear model of innovation or its variants, and pinpoint some aspects that require further analysis such as time and relevance.

The linear model, as a model of innovation or even a theory of epistemology (Section 2.4.2) is unlikely to disappear any time soon. However, an improved understanding of the relation of basic science and the technical sciences requires to recognize the shortcomings of the current view. A potential path towards an improved understanding must start with the acknowledgement of the inherent differences in technical knowledge versus explanatory or predictive knowledge. This will primarily remain a task of philosophers of technology.

On the other hand, traditional main-stream epistemology will also remain important because innovation and the interests of the market may also be driven by superstition, pseudo-knowledge or wrong believes. They may not, strictly speaking, work; but be successful in the market and therefore create pseudo-technical knowledge. This is an issue we have not addressed at all. Take for example the magnetic bracelet to improve your golf swing. It certainly was an innovation at one point in time. The bracelet and the homeopathic medication do not *really* work, but it may be possible to sell them. They are actually not fulfilling the function they claim to achieve. However, if their function is reformulated as "confirming people's believe it works", they actually behave as promised. In such cases, given our model, we can only hope that in the long run, success lies in what really works. While the technical principle should still remain an important criterion distinguishing knowledge from superstition, it may prove difficult in practice. For example, homeopathy presents such a massive construction of theoretical "knowledge" that it has become difficult to prove it wrong.

There is a strong sense in the scientific community that regarding knowledge just as a tool is dangerous because of a tendency to commercialize science completely. However, this commercialization and functionalization is massively present already as I have argued along the likes of Lyotard and Latour. Danger does not lie in our tendency to regard everything as a tool. This tendency is at work whenever we learn, whenever we pursue goals. We may even go as far as Sloterdijk (op.cit.) who suggests that all we are as humans, we are because of our prosthetic situation; i.e. a situation in which we use technology as prostheses for our body. But does this imply that only technology counts? Perhaps even more apocalyptic, Gilbert Hottois asks whether technoscience is a programme to reach through omniscience a divine status of almightiness? Or do we humans need the contingency of becoming where nothing is predetermined or predicted as a condition of liberty, creativity, and hope for an unlimited open future (Hottois 2015)?

Hottois answers with a compromise proposal: *"The creative exploration of the question of man must be at the same time symbolic (hermeneutic, discursive) and operative, technical-physical."* (Hottois 2015, translated by Google)

References

M. Abramovitz, P. David (1996) Technological change, intangible investments and growth in the knowledge-based economy: the US historical experience. In: D. Foray, B.A. Lundvall (eds.) *Employment and Growth in the Knowledge-based Economy*, OECD, Paris.

R.L. Ackoff (1989) From Data to Wisdom, in: Journal of Applied Systems Analysis, Vol. 16.

Marian Adolf, Nico Stehr (2014) *Knowledge*. Routledge, UK.

Abdul Al-Azzawi (2006) *Light and Optics.* CRC Press, Taylor & Francis, Boca Raton, FL.

N. Anand, H. K. Gardner, T. Morris. (2007) Knowledge-based Innovation: Emergence and Embedding of New Practice Areas in Management Consulting Firms. In: Academy of Management Journal 50, no. 2, April 2007.

Richard G. Anderson, William H. Greene, B.D. McCullough, H.D. Vinod (2005) The role of data & program code archives in the future of economic research. Working Paper 2005-014C, Federal Reserve Bank of St. Louis, St. Louis, MO. https://research.stlouisfed.org/wp/2005/2005-014.pdf

C. Anderson (2008) The end of theory: the data deluge makes the scientific method obsolete. Wired Magazine, 16:07.

Cristiano Antonelli (2003) *The Economics of Innovation, New Technologies, and Structural Change.* Routledge, London, UK.

Kenneth Appel, Wolfgang Haken (1989) Every planar map is four-colorable. *Contemporary Mathematics,* Bd. 98, American Mathematical Society, Providence, RI.

Leonardo Araújo, Rogério Gava (2012) *Proactive Companies. How to Anticipate Market Changes.* Palgrave Macmillan, Basingstoke, UK.

Stanley Aronowitz, Barbara Martinsons, Michael Menser, Jennifer Rich (eds.) (1996) *Technoscience and Cyberculture.* Routledge, New York.

Prisca Augustyn (2009) Uexküll, Peirce, and other affinities between biosemiotics and biolinguistics. *Biosemiotics*, Vol. 2 (1), pp. 1-17.

Francis Bacon (1597) *Meditationes sacrae*.

Francis Bacon (1620) *Novum organon*. Quotes in this text are based on the standard translation of J. Spedding, R.L. Ellis, D.D.Heath in *The Works* (vol. VIII), Taggard & Thompson, Boston (1863).

Josef Barla (2015) "Ihr wortlos Lied, vielstimmig scheinbar eins". Die Frage nach dem Politischen in Bruno Latours Technikphilosophie. In: Mona Singer (ed.) *Technik & Politik*. Löcker, Wien, pp. 88-115.

Bart de Boer (2014) Modelling and language evolution: beyond fact-free science. In: Physics of Life Reviews, Vol. 11 (2), pp. 307-308.

Gerhard Banse, Helge Wendt (1986) *Erkenntnismethoden in den Technikwissenschaften*. (Knowledge methods in the technical sciences.) VEB Verlag Technik Berlin.

Gerhard Banse, Käthe Friedrich (1996). *Technik zwischen Erkenntnis und Gestaltung*. Philosophische Sichten auf Technikwissenschaften und technisches Handeln. Berlin.

José Carlos Barbieri, Antonio Carlos Teixeira Álvares (2016) Sixth generation innovation model: description of a success model. *RAI Revista de Administração e Inovação* 13, pp. 116–127.

G. Basalla (1988) *The Evolution of Technology*. Cambridge University Press, Cambridge, MA.

Ronald Barnett (1994) *The Limits of Competence: Knowledge, Higher Education and Society*. Open University Press, PA.

Daniel Bell (1973) *The Coming of the Post-Industrial Society. New York: Basic Books.*

Gene Bellinger, Durval Castro, Anthony Mills (2004) *Data, information, knowledge and wisdom*. Systems Thinking. http://www.systems-thinking.org/index.htm, http://www.systems-thinking.org/dikw/dikw.htm

Carl Bereiter (1997) How to Overcome It. In: David Kirshner, James A. Whitson (eds.) *Situated Cognition. Social, Semiotic, and Psychological Perspectives.* Lawrence Erlbaum Assocaites, Mahwah, NJ, pp. 281ff.

Allan B.I. Bernardo, Lynn Okagaki (1994) Roles of symbolic knowledge and problem-information context in solving word problems. *Journal of Educational Psychology*, Vol. 86 (2), pp. 212-220.

Mark. H. Bickhardt, L. Terveen (1995) *Foundational Issues in Artificial Intelligence and Cognitive Science: Impass and Solution.* Elsevier Scientific.

Mark H. Bickhardt (2009) Interactivism: A manifesto. In: New Ideas in Psyhology, 27, pp. 85-89.

Christine Blätter (2011) Nietzsche und die Experimentalisierung des Lebens. In Helmut Heit, Günter Abel, Marco Brusotti (Eds.) *Nietzsches Wissenschaftsphilosophie*, de Gruyter 2011, pp. 455-464.

Norbert Bischof (1995) *Struktur und Bedeutung*. (Structure and Meaning.) Eine Einführung in die Systemtheorie. (Structure and Meaning. An introduction to system theory.) Verlag Hans Huber, Bern.

Bo-Christer Björk (2017) Open access to scientific articles: a review of benefits and challenges. *Internal and Emergeny Medicine*, Vol. 12 (2), pp. 247-253.

Hans Blumenberg (2015) *Schriften zur Technik.* (Writings in technology.) Suhrkamp.

Hans Blumenberg, Technik und Wahrheit (Technology and truth). First published 1953. In: (Blumenberg 2015), p. 42-50.

Nick Bontisa, Nicola C. Dragonettib, Kristine Jacobsenc, Göran Roosc (1999) The knowledge toolbox: A review of the tools available to measure and manage intangible resources. *European Management Journal*, Vol. 17 (4), pp. 391-402.

Jack E. Bowie, Arthur J. Olsen (1994) *Data Visualization in Molecuar Science*: Tool for insight and innovation. Addison-Wesley Longman, Boston, MA.

Michael S. Brady (2006) Appropriate attitudes and the value problem. *American Philosophical Quarterly*, Vol. 43, pp. 91-99.

Holger Breithaupt (2006) Seeing is understanding. EMBO reports, Vol. 7 (5), 467-470. DOI 10.1038/sj.embor.7400695

Elke Brendel (2013) *Wissen*. (Knowledge.) Walter de Gruyter, Berlin.

Carlo Brentari (2015) Influences and interpretations of the work of Uexküll. In: C. Brentari (ed.) *Jakob von Uexküll.* Volume 9 of the series Biosemiotics, Springer, Dordrecht, pp. 175-231.

Rodney A. Brooks (1991) Intelligence without representation. In: Artificial Intelligence, 47, pp. 139-159.

Susan A. Brown (2012) Seeing Web 2.0 in context: A study of academic perceptions. *The internet and higher education.* Vol. 15 (1), pp. 50-57.

Leon de Bruin, John Michael (2017) Prediction error minimization: Implications for Embodied Cognition and the Extended Mind Hypothesis. *Brain and Cognition*, Vol. 112, p. 58-63.

Vannevar Bush (1945) *Science, the Endless Frontier: a Report to the President.* US Government Printing Office, Washington, D.C. https://www.nsf.gov/about/history/vbush1945.htm

Wolfram Burgard, Uwe Franke, Markus Enzweiler, Mohan Trivedi (eds.) (2016) *The Mobile Revolution – Machine Intelligence for Autonomous Vehicles.* Dagstuhl Seminar 15462, Dagstuhl Reports Vol. 5 (11), Dagstuhl, DE.

Timothy L. Carter (2008) Millennial expectations, constructivist theory, and changes in a teacher preparation course. SRATE Journal, Winter 2008-2009, Vol. 18 (1), pp. 25-31.

Manuel Castells (1999) *The Information Age.* Volumes 1-3. Wiley-Blackwell, Oxford, UK; 2nd edition 2010, Blackwell, Oxford, UK.

John L. Casti (1992) *Reality Rules: Picturing the World in Mathematics.* John Wiley & Sons, New York, NY.

H. Chesbrough (2003) *Open Innovation: The New Imperative for Creating and Profiting from Technology*. Harvard Business School Press, Cambridge, MA.

Marco Cianchi (1988) *Leonardo da Vinci's Machines.* Becocci Editore, Italy.

Andy Clark (1989) Connectionism and the multiplicity of mind. *Artificial Intelligence Review*, Vol. 3, pp. 49-65.

Andy Clark (2013) Whatever next? Predictive brains, situated agents, and the future of cognitive science. *Behavioral and Brain Sciences*, Vol. 36 (3), pp. 181-204. DOI: https://doi.org/10.1017/S0140525X12000477.

Mark Coeckelbergh (2017) The art, poetics, and grammar of technological innovation as practice, process, and performance. *AI and Society*, pp. 1-10. doi:10.1007/s00146-017-0714-7

Ronan Collobert, Jason Weston, Léon Bottou, Michael Karlen, Koray Kavucuoglu, Pavel Kuska (2011) Natural language processing (almost) from scratch. *Journal of Machine Learning Research* 12 (August), pp. 2493-2537.

Auguste Comte (1842) *Discours sur l'esprit positif.*

Edward W. Constant II (1984) Communities and hierarchies: Structure in the practice of science and Technology. In: (Laudan 1984), pp. 27-46.

Jerry Courvisanos (2007) The ontology of innovation: human agency in the pursuit of novelty. *History of Economics Review*, Vol. 45 (1), pp. 41-59.

Edward Craig (1990) *Knowledge and the State of Nature: An Essay in Conceptual Synthesis*, Clarendon Press, Oxford.

Robert P. Crease (2006) From workbench to cyberstage. In (Selinger 2006), pp. 221-245.

Olivier Crevoisier (2015) The economic value of knowledge. *Regional Studies*, 1-13. DOI: 10.1080/00343404.2015.1070234

R.L. Daft (1978) A dual-core model of organizational innovation. In: Academy of Management Journal, Vol. 21, pp. 193-210.

F. Damanpour (1991) Organizational innovation: A meta-analysis of effects of determinants and moderators. In: Academy of Management Journal, Vol. 34, pp. 555-590.

Peter Dear (2005) What is the history of science the history of?: Early modern roots of the ideology of modern science. In: Isis Vol. 96 (3), pp. 390-404.

Gilles Deleuze, Félix Guattari (1977) *Anti-Ödipus. Kapitalismus und Schizophrenie I.* Suhrkamp, Frankfurt am Main, DE.

Li Deng, Dong Yu (2014) *Deep Learning: Methods and Applications.* Now Publishers, Hanover, MA.

Mark Dodgson, David Gann, Ammon Salter (2002) The intensification of innovation. *International Journal of Innovation Management*, Vol. 6 (1), pp. 53-83. https://doi.org/10.1142/S1363919602000495

Mark Dodgson, David Gann, Ammon Salter (2005) *Think, Play, Do: Technology, Innovation and Organization.* Oxford University Press, Oxford, UK.

Mark Dodgson, David Gann, Ammon Salter (2006) The role of technology in the shift towards open innovation: the case of Procter & Gamble. In: R&D Management, Vol. 36 (3), pp. 333-346.

Mark Dodgson, David Gann (2007). Innovation Technology: How new technologies are changing the way we innovate. NESTA.

Mark Dodgson, David Gann, Ammon Salter (2008) *The Management of Technological Innovation*, Oxford University Press, Oxford, UK.

G. Dosi (1988) Sources, procedures, and microeconomic effects of innovation. In: Journal of Economic Literature, Vol. 26, pp. 1120-1171.

Louis Dupré, *Passage to Modernity.* Yale University Press, New Haven, CT, 1993.

Hubert L. Dreyfus (1991) *Being-in-the world.* MIT Press, Cambridge, MA.

Peter F. Drucker (1994) The age of social transformation. *Atlantic Monthly*, Vol. 274 (5), November 1994, pp. 53-80.

John Dupré (2010) It is not possible to reduce biological explanations to explanations in chemistry and/or physics. In: F.J. Ayala, R.Arp (eds.) *Contemporary Debates in Philosophy of Biology*. Wiley-Blackwell, Chichester, UK, pp. 32-48.

Sašo Džeroski, Dragi Kocev, Pančе Panov (2016) Editorial: Special issue on discovery science. *Machine Learn*ing 105 (1), pp. 1-2. Doi:10.1007/s10994-016-5589-1

EC (2013) *Strategy for European Technology Platforms: ETP 2020.* Commission staff working document. European Commission, SWD (2013) 272 final, Brussels.

EC (2017) *Horizon 2020 Work Programme 2016-2017, 2. Future and Emerging Technologies.* European Commission, C(2017) 2468 of 24 April 2017, Brussels. https://ec.europa.eu/research/participants/data/ref/h2020/wp/2016_2017/main/h2020-wp1617-fet_en.pdf

David Edgerton (2004) 'The linear model' did not exist: Reflections on the history and historiography of science and research in industry in the twentieth century. In: Karl Grandin and Nina Wormbs (eds), The Science–Industry Nexus: History, Policy, Implications. (New York: Watson, 2004) https://workspace.imperial.ac.uk/historyofscience/Public/files/edgerton_linear_model_did_not_exist.pdf

Edison, H., Ali, N.B., & Torkar, R. (2013). Towards innovation measurement in the software industry. Journal of Systems and Software 86(5), 1390-1407. http://www.torkar.se/resources/jss-edisonNT13.pdf

Etzkowitz, H., & Leydesdorff, L. (1995). The Triple Helix: University-industry-government relations: A laboratory for knowledge based economic development. EASST Review, 14, 14–19.

Henry Etzkowitz, Loet Leydesdorff (2000) The dynamics of innovation: from National Systems and ''Mode 2'' to a Triple Helix of university–industry–government relations. In: Research Policy, 29, pp. 109–123.

EU (2007) Improving knowledge transfer between research institutions and industry across Europe. Communication from the Commission, EUR 22836 EN COM(2007)182.

EU (2015) Council conclusions on open, data-intensive and networked research as a driver for faster and wider innovation. Council of the European Union, 9360/15, Brussels, 29 May.

EC (science 2.0) Science 2.0: Science in Transition. Background document, public consultation. https://ec.europa.eu/research/consultations/science-2.0/background.pdf

Lorenzo Ferrone, Fabio Massimo Zanzotto (2017) Symbolic, distributed, and distributional representations for natural language processing in the era of deep learning: a survey. *ArXiv.* CoRR abs/1702.00764.

Richard Feynman (1982) *Simulating physics with computers.* Int. J. Theor. Physics, Vol. 21 (6/7)

Heinz von Foerster (ed.) (1974) (1995) Cybernetics of cybernetics: Or, the control of control and the communication of communication (2nd ed.). Minneapolis, MN.

Michel Foucault (1976) *Überwachen und Strafen. Die Geburt des Gefängnisses*. (Discipline and punish.) Suhrkamp, Frankfurt am Main, DE, 9th edition 2008.

Dominique Foray (2007) Tacit and codified knowledge. In: Horst Hanusch, Andreas Pyka (eds.) *Elgar Companion to Neo-Schumpeterian Economics.* Elgar, Cheltenham, UK.

Galunic, C. and Rodan, S. (1998) Resource recombination in the firm: Knowledge, structures and the potential for Schumpeterian innovation. In: Strategic Management Journal, Vol.19, pp.1193-1201.

Rosanna García (2005) Use of agent-based modeling in innovation/new product development research. *Product Innovation Management*, Vol. 22 (5), pp. 380-398.

Francisco J. García- Peñalvo, Carlos García de Figuerola, José A. Merlo, (2010) Open knowledge: challenges and facts. *Online Information Review*, Vol. 34 Issue: 4, pp. 520-539. https://doi.org/10.1108/14684521011072963

Sandroy Gaycken (2005) *Was ist technisches Wissen?* Talk at the 22nd Chaos Communication Congress, December 27-30, 2005, Berlin. https://www.youtube.com/watch?v=nxnn2_MxsYk&t=1297s

Sandro Gaycken (2010) *Was ist technisches Wissen?* Denken im Dienste des Handelns (Reihe Technikphilosophie, Bd. 19). Münster, London: LIT.

Volker Gerhardt (2015) Die digitale Innovation. (Digital innovation.) In: Gamm et al. (2105), pp.151-170.

Michael Gibbons, Camille Limoges, Helga Nowotny, Simon Schwartzman, Peter Scott, Martin Trow (1994) The New Production of Knowledge: The dynamics of science and research in contemporary societies, Sage, London, UK.

James Gibbs, Stephen Bendall (2014) Applied basic science. In: Gavin Bowyer, Andrew Cole (eds.) *Selected References in Trauma and Orthopaedics.* Springer Verlag, London, UK, pp. 341-363.

Ronald N. Giere (1999) *Science without Laws.* University of Chicago Press, Chicago, IL.

Ernst von Glasersfeld (1984) An introduction to radical constructivism. In: Paul Watzlawick (ed.) (1984) The Invented Reality. Norton, New York.

Ernst von Glasersfeld, Francisco Varela (1985) Problems of knowledge and cognizing organisms. In: Aprendizagem/Desenvolvimento 2 (6), pp. 17-23. (Also in: Methodologia, 1, 1987, 29-45.)

Ernst von Glasersfeld (1996) Farewell to objectivity. In: Systems Research, 13(3), pp. 279-286.

Ernst von Glasersfeld (1992) Aspects of Constructivism: Vico, Berkeley, Piaget. Published in Italian Aspetti del costruttivismo: Vico, Berkeley, Piaget. In: M. Ceruti (ed.) *Evoluzione e conoscenza*. Lubrina, Bergamo, IT, pp. 421–432. Reprinted: Glasersfeld E. von (2007) Aspects of constructivism. Vico, Berkeley, Piaget. In E. v. Glasersfeld, *Key works in radical constructivism.* Sense, Rotterdam, NL, pp. 91–99.

Ernst von Glasersfeld (1997) Anticipation in the constructivist theory of cognition. In: CASYS’97 International Conference on Computing Anticipatory Systems Liège, August 11–15, 1997. Published in D.M.Dubois (Ed.) Computing anticipatory systems (1998), American Institute of Physics, Woodbury, NY, pp.38–47.

Benoit Godin (2005) The linear model of innovation: the historical construction of an analytical framework. Project on the History and Sociology of S&T statistics. Working paper No. 30. http://www.csiic.ca/PDF/Godin_30.pdf

Benoit Godin (2013) Pushes and Pulls: the Hi(story) of the Demand Pull Model of Innovation. Project on the Intellectual History of Innovation, Working Paper No. 13, Montreal, Canada. http://www.csiic.ca/PDF/Demand-pull.pdf

Alvin I. Goldman, Erik J. Olsson (2009) Reliabilism and the value of knolwedge. In: A. Haddock, A Millar, D.H. Pritchard *Epistemic Value.* Oxford University Press, UK, pp. 19-41.

Paul Good (1974) Wissen und Bildung: in der Sicht des Phänomenologen Max Scheler. In: Schweizer Monatshefte: Zeitschrift für Politik, Wirtschaft, Kultur. Bd. 54 (1974-1975). http://dx.doi.org/10.5169/seals-162992

André Gorz (2004) *Wissen, Wert und Kapital. Zur Kritik der Wissensökonomie.* Rotpunktverlag, Berlin.

Gerhard Grimm, Petra Gehring, Christoph Hubig, Andreas Kaminski, Alfred Nordmann (Eds.) (2015) *Ding und System.* Jahrbuch Technikphilosophie, diaphanes, Zürich.

Peter Gruss (2009) Basic research ist he key driver of innovation. *Max Planck Research*, Special Issue, Max-Planck-Gesellschaft, München, DE, pp. 6-9. https://www.mpg.de/799746/W000_Viewpoint_006-009.pdf

Armin Grunwald (2004) Wissenschaftstheoretische Perspektiven auf die Technikwissenschaften. In: Gerhard Banse, Günther Ropohl: Wissenskonzepte für die Ingenieurspraxis, Düsseldorf: VDI (VDI-Report 35)

Jürgen Habermas (1968) *Erkenntnis und Interesse*. (Knowledge and human interests). Suhrkamp, Frankfurt am Main.

Ian Hacking (1983) *Representing and intervening*. Introductory topics in the philosophy of natural science. Cambridge University Press, Cambridge, MA.

Leslie Hatton, Adrian Giordani (2012) Does computation threaten the scientific method? Online: https://sciencenode.org/feature/does-computation-threaten-scientific-method.php accessed June 2017.

Martin Heidegger (1927) *Sein und Zeit. (Being and Time.)* Niemeyer, Tübingen, 1927.

Martin Heidegger (1949) Das Ding. (The Thing.) In: *Vorträge und Aufsätze.* G. Neske, Pfullingen (1954).

Martin Heidegger (1955) *Gelassenheit.* 2nd Ed., Karl Alber, Freiburg, 2015.

Martin Heidegger (1953) Die Frage nach der Technik. In: *Vorträge und Aufsätze.* G.Neske, Pfullingen (1954).

Martin Heidegger (1977) The question concerning technology. In: David Farrel Krell (Ed.) *Basic Writings.* Harper & Row.

Jeffrey M. Herbener (ed.) (2011) *The Pure Time-Preference Theory of Interest.* Ludwig von Mises Institute, Auburn, AL. Online: https://mises.org/system/tdf/The%20Pure%20Time-Preference%20Theory%20of%20Interest_2.pdf?file=1&type=document

C. Hess, E. Ostrum (2007) *Understanding knowledge as a commons – from theory to practice.* MIT, Cambridge, USA.

Larry A. Hickman, Stefan Neubert, Kersten Reich (eds). *John Dewey Between Pragmatism and Constructivism.* Fordham University Press, NY.

Christopher T. Hill (2007) The post-scientific society. In: Issues in science and Technology. Vol. XXIV (1), Fall 2007. http://issues.org/24-1/c_hill/

Thomas Hobbes (1655) De Corpore, Part I, Chapter I (On Phylosophy). In Thomas Hobbes, The English Works of Thomas Hobbes of Malmesbury..., Volume I, p. 7. From the Latin edition: Thomas Hobbes, Opera philosophica..., Volume 1, p. 6.

John Horgan (1995) From complexity to perplexity. In: Scientific American, p. 107.

Max Horkheimer, Theodor W. Adorno (1988) *Dialektik der Aufklärung*. (Originally: Eclipse of Reason, 1947). Fischer, Frankfurt am Main.

Gilbert Hottois (2015) Technoscience et sagesse? In: Grimm et al. (2015), pp.189-206.

Christoph Hubatsche, Maschinelle Revolte. Skizzen einer Technikphilosophie in Anschluss an Deleuze und Guatarri. In (Singer 2015), pp. 167-192.

Jörg Guido Hülmann (2002) A Theory of Interest. *The Quarterly Journal of Austrian Economics* Vol. 5 (4), Winter 2002, pp. 77–110.

Michael Hutter, Hubert Knoblauch, Werner Rammert, Arnold Windeler (2015) Innovation society today: the reflexive creation of novelty. *Historical Social Research*, Vol. 40, Nr. 3 (153), pp. 30-47.

John Hyman (2010) The road to Larissa. *Ratio*, Vol. 23, pp. 393-414.

Jonathan Jenkins Ichikawa, Matthias Steup (2017) The analysis of knowledge. In: Edward N. Zalta (ed.) *The Stanford Encyclopedia of Philosophy*, Spring 2017 Edition. https:plato.stanford.edu /archives/spr2017/entries/knowledge-analysis/

Michael I. Jordan, Tom M. Mitchell (2015) Machine learning: trends, perspectives, and prospects. *Science* Vol. 349, (6245), pp. 255-260. DOI: 10.1126/science.aaa8415

Don Ihde (1979) *Technics and Praxis. Reidel, Dordrecht.*

Don Ihde (1990) *Technology and the Lifeworld:* From Garden to Earth. Indiana University Press.

Don Ihde (1991) *Instrumental Realism.* Indiana University Press, Bloomington, IN.

Don Ihde (2001) *Bodies in Technology*. University of Minnesota Press, Minneapolis, MN.

Don Ihde, Evan Selinger (eds.) (2003) *Chasing Technoscience*. Matrix for materiality. Indiana University Press, Bloomington.

William James (1907) *Pragmatism.* Dover, NY, 1995.

K. Jaspers (1951) *Man in the Modern Age.* Routledge & Kegan Paul, London.

David H. Jonassen, Katherine Beissner, Michael Yacci (1993) *Structural Knowledge.* Lawrence Erlbaum Ass., Hillsdale, NJ.

David Kaldewey (2012) *Wahrheit und Nützlichkeit*. (Truth and utility.) Transcript, Bielefeld, DE.

Shigeki Kamiyama, Jerry Sheehan, Catalina Martinez (2006) Valuation and exploitation of intellectual property. STI Working Paper 2006/5 *OECD Publishing, Paris.*

Kunihiko Kaneko, Ichiro Tsuda (1996) *Complex Systems: Chaos and Beyond.* Springer Verlag, Berlin.

Liz Karagianis (2014) The brilliance of basic research. *Spectrum*, Spring 2014, MIT, Cambridge, MA. Online at: http://spectrum.mit.edu/spring-2014/the-brilliance-of-basic-research/

Terrence Kealey (2010) *Sex, science and profits*. Random House, NY.

Wolfgang Koenig (1996) Science-Based Industry or Industry Based Science? Electrical Engineering in Germany before World War 1. In: Technology and Culture, vol. 37, pp. 70–101.

Krizhevsky, Alex, Sutskever, Ilya, and Hinton, Geoff. (2012) Imagenet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems,* Vol. 25, pp. 1106–1114.

Thomas S. Kuhn (1962) *The Structure of Scientific Revolutions.* University of Chicago Press, Chicago, IL.

Kalevi Kull (2001) Jakob von Uexküll: An introduction. In: Semiotica 134 (1/4), pp. 1–59.

Jonathan L. Kvanig (2003) *The Value of Knowledge and the Pursuit of Understanding.* Cambridge University Press, NY.

Karl Y.H. Lagerspetz (2001) Jakob von Uexküll and the origins of cybernetics. In: Semiotica. Bd. 2001, 134, pp. 643–651.

Bruno Latour (1990) The force and reason of experiment. In: H.E. Legrand (Ed.) *Experimental Inquiries.* Kluwer Academic, Dordrecht, pp.49-80.

Bruno Latour (2010) *Cogitamus*. (Cogitamus. Six lettres sur les humanités scientifiques. La Découverte, Paris) Edition Unseld, Suhrkamp, Berlin, 2016.

Christopher G. Langton (Ed.) (1992) *Artifical Life*. MIT Press, Cambridge MA.

Rachel Laudan (ed.) (1984) *The Nature of Technological Knowledge: Are Models of Scientific Change Relevant?* D. Reidel, Dordrecht, NL.

Rachel Laudan (1995) Natural Alliance or forced marriage—changing relations between the histories of science and technology. In: Technology and Culture, vol. 36, pp 17-28.

Edwin T. Layton Jr. (1974) Technology as knowledge. *Technology and Culture,* Vol. 15 (1), pp. 31-41.

Yann LeCun, Yoshua Bengio, Geoffrey Hinton (2015) Deep learning. *Nature* Vol. 521, pp. 436-444.

Hans Lenk (2002) Zur technologie- und handlungsorientierten Wissenschaftstheorie. In: Günter Abel, Hans-Jürgen Engfer, Christoph Hübig (Eds.) *Neuzeitliches Denken.* (Modern-age thinking.) Walter de Gruyter, Berlin, pp.67-82.

Hans Lenk (2006) Toward a practice-oriented methodology and philosophy of technoscience. In: Selinger (2006), pp. 257-263.

Gideon Lewis-Kraus (2016) The great A.I. awakening. In: The New York Times Magazine, December 14, 2016, New York. http://www.nytimes.com/2016/12/14/magazine/the-great-ai-awakening.html?_r=0

Lucien Lévy-Bruhl (1931) Le surnaturel et la nature dans la mentalité primitive. Online: http://classiques.uqac.ca/classiques/levy_bruhl/surnaturel/surnaturel_intro.html

Loet Leydesdorff (2000) The triple helix: an evolutionary model of innovation. In: Research Policy, Vol. 29 (2), p. 243.

Loet Leydesdorff, Henry Etzkowitz (2000) The dynamics of innovation: from national systems and "mode-2" to a triple helix of university-industry-government relations. In: Research Policy 29, pp. 109-123.

Loet Leydesdorff (2005) Anticipatory Systems and the Processing of Meaning: a Simulation Study Inspired by Luhmann's Theory of Social Systems. In: Journal of Artificial Societies and Social Simulation, Vol. 8 (2). http://jasss.soc.surrey.ac.uk/8/2/7.html

Loet Leydesdorff (2006) The Knowledge-Based Economy: Modeled, Measured, Simulated. Universal Publishers, Boca Raton (FL), USA. http://www.bookpump.com/upb/pdf-b/1129378b.pdf

Loet Leydesdorff (2010) The knowledge-based economy and the triple helix model. In: Annual Review of Information Science and Technology, Vol. 44, pp. 367-417. http://www.leydesdorff.net/arist09/

Konrad Paul Liessmann (2006) *Theorie der Unbildung*. (Theory of illiterateness.) Zsolnay, Wien.

Udo Lindemann (2004) *Methodische Entwicklung technischer Produkte*. (Methodic development of technical products.) Springer, Berlin

John Locke (1689) *An Essay Concerning Human Understanding.* 1st Ed. Thomas Bassett, England; A.C.Fraser (Ed.), 1894, Clarendon Press, Oxford.

Ernst Lohoff (2007) Der Wert des Wissens. (The value of knowledge.) *Krisis,* 31.

A H. Louie (2009) *More Than Life Itself.* Ontos Verlag, Frankfurt, DE.

Andreas Luckner (2008) *Heidegger und das Denken der Technik. (Heidegger and the Thinking of Technology.)* Transcript Verlag, Bielefeld, DE.

Andreas Luckner (2015) Ding und Bestand. In: Grimm et al. (2015), pp.15-31.

Jean-Francois Lyotard (1986) *Das postmoderne Wissen.* (Postmodern knowledge.) Böhlau, Wien.

John Mackenzie Owen (2007) *The Scientific Article in the Age of Digitization*. Springer.

Darius Mahdjoubi (1997) The linear model of technological innovation. [online] https://www.ischool.utexas.edu/~darius/04-Linear%20Model.pdf

Karl Marx (1857) Grundrisse der Kritik der politischen Ökonomie (Rohentwurf) (Basics of the critique of political economy.) 1857-58, first published 1939/41, Berlin/DDR 1953, new edition MEW 42, 47-768 (1983) und MEGA II.1-2, 49-747.

Steven Maranville (1992) Entrepreneurship in the business curriculum. *Journal of Education for Business.* Vol. 68 (1), pp. 27-31.

Humberto R. Maturana, Francisco J. Varela. Der Baum der Erkenntnis (1984) (El arból del conocimiento) Goldmann, München.

R.K. Merton (1938) *Science, Technology and Society in Seventeenth Century England*. Sainte Catherine Press, Bruges.

R.K. Merton (1942) Science and technology in a democratic order. In: Journal of Legal and Political Sociology, 1, p. 115-126.

Mihai Nadin (2012) Who speaks in favor of an inquiry into anticipatory processes? In Rosen (1985, 2nd Ed. 2012), pp. xv-lv.

John C. Mankins (1995) *Technology readiness levels: A white paper*. NASA, Office of Space Access and Technology, Advanced Concepts Office. http://www.hq.nasa.gov/office/codeq/trl/trl.pdf

Michael J.C. Martin (1994) *Managing Innovation and Entrepreneurship in Technology-based Firms.* Wiley, NY.

J. McCarthy (1988) Epistemological challenges for connectionism. In: Behavioral and Brain Sciences, 11 (44).

Carolyn Merchant (2008) The violence of impediments. *Isis,* 2008, Vol. 99, pp. 731-760.

Ludwig von Mises (1940) *Human Action. A Treatise on Economics. (*Scholars Edition, Ludwig von Mises Institute, Auburn, Alabama).

Michael Nentwich, René König (2013) Academia goes Facebook? The potential of social network sites in the scholarly realm. In: Sönke Bartling, Sascha Friesike (eds.) *Opening Science,* Springer, New York, NY, pp. 107-124.

Michael Nielsen (2012) *Reinventing Discovery:* the new era of networked science. Princeton University Press.

Kyle E. Niemeyer (2017) Open science and the future university researcher. Online: https://orcid.org/0000-0003-4425-7097 DOI: 10.17605/OSF.IO/2XZXH

Nonaka, I. and Takeuchi, H. (1995) *The Knowledge Creating Company:* How Japanese companies create the dynamics of innovation. Oxford University Press, New York.

Alfred Nordmann (2008) *Technikphilosophie:* zur Einführung. (Philosophy of technology). Junius, Hamburg.

Helga Nowotny, Peter Scott, Michael Gibbons (2003) Mode-2 revisited: The new production of knowledge. In: Minerva. 41, pp. 179–194.

OECD (1996) The Knowledge-Based Economy. OCDE / GD (96) 102. https://www.oecd.org/sti/sci-tech/1913021.pdf

OECD (2002) Frascati Manual 2002. Proposed standard practice for surveys on research and experimental development: the measurement of scientific and technological activities. OECD, Paris.

OECD (2016) *Science, Technology, and Innovation Outlook 2016.* OECD Publishing, Paris, http://dx.doi.org/10.1787/sti_in_outlook-2016-en

J. Palfrey, U. Gasser (2008) *Born digital: the first generation of digital natives.* Basic books, New York

Dasgupta Partha, Paul A. Davies (1994) Toward a new economics of science. *Research Policy*, Vol. 23 (5), pp. 487-521.

Charles Sanders Peirce (1877) Die Festlegung einer Überzeugung (The fixation of belief. In: *Popular Science Monthly,* 12, pp. 1–15.) In: Philosophie des Pragmatismus, Reclam, Stuttgart.

Charles Sanders Peirce (1878) How to make our ideas clear, *Popular Science Monthly*, Vol. 12, pp. 286–302.

Markus Peschl (1990) *Cognitive Modelling.* Springer Fachmedien, Wiesbaden.

Peter Pesic (2014) Turning the tables on Bacon: computer-assisted Baconian philology. *Early Modern Literary Studies,* Vol. 17 (1). https://extra.shu.ac.uk/emls/journal/index.php/emls/article/view/34

H. Pfeifenberger (2015) Evolution of Open Science in Europe and he Helmholtz Association. http://epic.awi.de/39044/1/2015-09-24-RDA-PaNSIG-OA-Pfeiffenberger.pdf

Piaget (1954) *The Construction of Reality in the Child*. Routledge, UK.

Arnold Picot, Marina Fiedler (2000) Der Wert des Wissens. (The value of knowledge.) In: M. Boos, N. Goldschmidt (eds.) Wissenswert!) Ökonomische Perspektiven der Wissensgesellschaft, pp. 15-37.

Steven Pinker, Alan Prince (1988) On language and connectionism: Analysis of a parallel distributed processing model of language acquisition. In: S. Pinker, J. Mehler (Eds.) Connections and Symbols. MIT Press, Cambridge, MA, pp. 73-193.

Marina du Plessis (2007) The role of knowledge management in innovation. Journal of knowledge management, 11(4), 20-29.

Michael Polanyi (1966) *The Tacit Dimension.* University of Chicago Press.

Hans Poser (1998) On structural differences between science and engineering. In: Techné, Winter 1998 (4:2).

Erich Prem (1994) *Symbol Grounding*. Die Bedeutung der Verankerung von Symbolen in reichhaltiger sensorischer Erfahrung mittels neuronaler Netzwerke. Dissertation, University of Vienna.

Erich Prem (1995) Understanding complex systems: What can the speaking lion tell us? In: L. Steels (ed.) *The Biology and Technology of Intelligent Autonomous Agents.* Springer, Berlin, pp. 459-474.

Erich Prem (1997) Epistemic autonomy in models of living systems. *Proceedings of the Fourth European Conference on Artificial Life*, pp. 2-9.

Erich Prem (1997b) The world according to a humanoid robot. In Beneder M.(ed.), *robots@aec.at*, Oldenbourg, Muenchen/Wien, pp. 17-27. Also available at: http://www.ofai.at/cgi-bin/tr-online?number+97-19

Erich Prem (1998) Semiosis in Embodied Autonomous Systems, Proc. of IEEE International Symposium on Intelligent Control, IEEE, Piscataway, NJ, pp.724-729.

Erich Prem (2013) Technologien der Innovation (Innovation Technologies), APA Science, Austrian Press Agency, 18.11.2013. http://science.apa.at/rubrik/kultur_und_gesellschaft/Technologien_der_Innovation/SCI_20131118_SCI39911359215588358

Erich Prem (2014) Evaluation as the construction of policy narratives. In: fteval Journal for Research and Technology Policy Evaluation, No. 39, Vienna.

Erich Prem (2015) ICT and science 2.0: technology-mediated trends and characteristics of new scientific practices. In: Proc. 15th Int. Conf. on Knowledge Technologies and Data-Driven Business, ACM.

Erich Prem (2016) From open science to open clubs: the power of digital tools. In: Proceedings of the 15th Annual STS Conference, Graz, Austria. https://conference.aau.at/event/46/material/paper/1.pdf

Erich Prem (2016 b) Triple helix concepts application to a regional ICT innovation system. In: Proc. of the ISPIM Innovation Summit, 4-7 December, Kuala Lumpur. ISPIM, www.ispim.org

Erich Prem, Fermin Serrano Santz, Martina Lindorfer, Dietmar Lampert, Jörg Irran (2016) Open Digital Science. Final study report for the European Commission. http://ec.europa.eu/newsroom/dae/document.cfm?doc_id=16018 (Accessed July 2017)

Erich Prem (2017) Truths emerging from leading-edge art/science/technology interaction. *Leonardo* Just Accepted MS. *doi: 10.1162/LEON_a_0147*

Derek de Solla Price (1984) Notes towards and philosophy of the science/technology interaction. In: Rachel Laudran (Ed.) *The Nature of Technological Knowledge: Are Models of Scientific Change Relevant?* D. Reidel Publishing Co., Dordrecht, pp. 106-107.

Alvin Powell (2017) The false choice of basic vs. applied research. *Harvard University*, January 3, 2017, https://www.seas.harvard.edu/news/2017/01/false-choice-of-basic-vs-applied-research, accessed July 2017.

Duncan Pritchard, Alan Millar, Adrian Haddock (2010) *The Nature and Value of Knowledge.* Oxford University Press, UK.

Duncan Pritchard, John Turri (2014) The value of knowledge. In: N. Zalta (ed.) *The Stanford Enyclopedia of Philosophy*, Spring 2014 Edition. https://plato.stanford.edu/archives/spr2014/entries/knowledge-value/

Eric Quintane, R. Mitch Casselman, B. Sebastian Reiche, Petra A. Nylund (2011) Innovation as a knowledge- based outcome. In: Journal of Knowledge Management, Vol. 15 (6), pp. 928 - 947

M. Ranga, H. Etzkowitz (2013) Triple Helix Systems: An Analytical Framework for Innovation Policy and Practice in the Knowledge Society, Industry and Higher Education 27 (4), pp. 237-262, Special Issue "Innovation policy as a concept for developing economies: renewed perspectives on the Triple Helix system"

K. Rauss, S. Schwartz, G. Pourtois (2011) Top-down effects on early visual processing in humans: A predictive coding framework. *Neuroscience and Biobehavioral Reviews*, Vol. 35 (5), pp.1237–1253.

Jeremy Rifkin (2008) The third industrial revolution. In: Engineering & Technology, Vol. 3 (7), 26-27.

Jeremy Rifkin (2014) *The Zero Marginal Cost Society*. Palgrave Mcmillan, Basingstoke, UK.

David P. Reed (1999) That sneaky exponential. In: *Context*, Spring 1999.
Online at: http://www.reed.com/dpr/locus/gfn/reedslaw.html

Arie Rip (1992) Science and Technology as Dancing Partners. In: Peter Kroes and Martijn Bakker, Technological Development and Science in the Industrial Age: New perspectives on the Science-Technology Relationship (London: Kluwer), p. 233.

Philip Robbins, Murat Aydede (2008) *The Cambridge Handbook of Situated Cognition.* Cambridge University Press, New York, NY.

Andreas Roepstorff, Jörg Niewöhner, Stefan Beck (2010) Enculturing brains through patterned practices. *Neural Networks*, Vol. 23 (8-9), pp. 1051-1059.

Günther Ropohl (1991) Die Maschinenmetapher. In: Technikgeschichte, Bd. 58, Nr.1.

Günther Ropohl (1997) Knolwedge types in technology. In: International Journal of Technology and Design Education 7: 65-72. Kluwer Academic Publishers, NL.

Günther Ropohl (1999) *Allgemeine Technologie*. Eine Systemtheorie der Technik. Carl Hanser Verlag.

Günther Ropohl (2004) Was tun Ingenieure und was müssen sie dazu wissen? - Versuch einer Systematik In: Gerhard Banse, Günther Ropohl: Wissenskonzepte für die Ingenieurspraxis, Düsseldorf: VDI 2004 (VDI-Report 35)

Robert Rosen (1985) *Anticipatory Systems*. Philosophical, mathematical, and methodological foundations. Pergamon Press, Oxford, UK. Second edition: Springer, New York, 2012.

Robert Rosen (1987) On the scope of syntactics in mathematics and science: the machine metaphor. In: *Proc. of Workshop on Brain Research, Artificial Intelligence and Cognitive Science*, Abisko, SE. (Reprinted in: J.L. Casti, A.Karjqvist (eds.), *Real Brains, Artificial Minds.* Elsevier Science, NY, pp. 1-23).

Robert Rosen (1991) *Life Itself*. A comprehensive inquiry in the nature, origin and fabrication of life. Columbia University Press, NY.

Roy Rothwell (1992) Successful industrial innovation: Critical factors for the 1990s. *R&D Management*, 22 (3), pp. 221-239.

Roy Rothwell (1994) Towards the Fifth-generation Innovation Process, *International Marketing Review*, Vol.11 (1), pp. 7-31.

Norbert F.M. Roozenburg, Johannes Eekels. (1995) Product design: fundamentals and methods. Vol. 2. Wiley, Chicester.

Vernon W. Ruttan (1959) Usher and Schumpeter on invention, innovation, and technological change. *The Quarterly Journal of Economics.*Vol. 73 (4), November 1959, pp. 596-606.

V.Ryan (2013) What is market pull? World Association of Technology Teachers. Online: http://www.technologystudent.com/prddes1/marketpull1.html

Gilbert Ryle (1949) *The Concept of Mind*. New York, Penrose, 2000.

Jamil Salmi (2015) *Study on Open Science*. European Commission, DG Research and Innovation, ER 27390 EN. Online: https://ec.europa.eu/research/innovation-union/pdf/expert-groups/rise/study_on_open_science-impact_implications_and_policy_options-salmi_072015.pdf

Merrilee H. Salmon et al. (1992) *Introduction to the Philosophy of Science.* Prentice-Hall, Englewood Cliffs, NJ.

Robert C. Scharff (2006) Ihde's Albatross. In (Selinger 2006), pp. 131-144.

Max Scheler (1980) *Problems of a sociology of knowledge.* Routledge & Kegan Paul, London, UK. (*Die Wissensformen und die Gesellschaft*, 1924.)

Moritz Schlick (1908) *Lebensweisheit. Versuch einer Glückseligkeitslehre*. (Wisdom of Life.) Becksche Verlagsbuchhandlung, Munich.

Florian Schroff, Dmitry Kalenichenko, James Philbin (2015) A unified embedding for face recognition and clustering. *ArXiv e-prints*, https://arxiv.org/abs/1503.03832

Hans-Joachim Schubert et al. (2010) *Pragmatismums:* zur Einführung. Junius, Hamburg.

Joseph A. Schumpeter (1939) *Business Cycles.* McGraw-Hill, New York, NY.

Joseph A. Schumpeter (1943). Capitalism, Socialism, and Democracy (6 ed.). Routledge. pp. 81–84. ISBN 0-415-10762-8.

Johann August Schülein, Simon Reitze (2002) *Wissenschaftstheorie für Einsteiger*. WUV, Wien.

Peter Schuster (2000) Taming combinatorial explosion. In: *PNAS,* July 5 2000, Vol. 97 (14), pp.7678-7680).

Michael Scriven (1999) The nature of evaluation. ERIC/AE Digest Series EDO-TM-99-06, University of Maryland, College Park, US. http://ericae.net/digests/tm9906.pdf

Evan Selinger (Ed.) (2006= *Postphenomenology : A critical companion to Ihde.* State University of New York Press.

Carl Shapiro, Hal R. Varian (1999) *Information rules.* Harvard Business Press.

Nikhil Sharma (2008) The origin of the data information knowledge wisdom hierarchy. https://www.researchgate.net/publication/292335202_The_Origin_of_Data_Information_Knowledge_Wisdom_DIKW_Hierarchy

Judith Simon (2010) *Knowing Together:* A social epistemology for socio-technical epistemic systems. Dissertation, University of Vienna, Austria. http://othes.univie.ac.at/10285/1/2010-04-19_0547816.pdf

Mona Singer (Ed.) (2015), *Technik & Politik (Technology and politics).* Löcker, Wien.

Peter Sloterdijk (2007) Der Mensch als homo technologicus. Talk at the NanoConvention07, Bern, Switzerland, (last accessed July 2017). https://www.youtube.com/watch?v=-mVZbx0y6DA&index=30&list=WL

Léna Soler, Sjoerd Zwart, Michael Lynch, and Vincent Israel-Jost (eds.) (2014), *Science after the Practice Turn in the Philosophy, History, and Social Studies of Science*. Routledge, London, UK.

Dava Sobel (1995) *Longitude.* Walker Books, New York, NY.

Luc Steels (2008) The symbol grounding problem has been solved. So what's next. In: Manuel de Vega, Arthur M. Glenberg, Arthur C. Graesser (eds.) *Smbols and Embodiment: Debates on Meaning and Cognition.* Oxford University Press, Oxford, UK, pp. 223-244.

Luc Steels, Manfred Hild (eds) (2012) *Language Grounding in Robots.* Springer, New York, NY.

Fabian Steinschaden (2015) Heidegger und das Denken der Technik. In: Mona Singer (Ed.) *Technik & Politik.* Löcker, Wien, Austria.

Matthias Steup (2016) Epistemology. In: E.N. Zalta (ed.) *The Stanford Encyclopedia of Philosophy.* Fall 2016 Edition. https://plato.stanford.edu/archives/fall2016/entries/epistemology/

Victoria Stodden (2010) Open science: policy implications for the evolving phenomenon of user-led scientific innovation. *Journal of Science Communication,* Vol. 9 (1), pp. 1-8.

Donald Stokes (1997) *Pasteur's Quadrant*: Basic science and technological innovation. Brookings, Washington DC.

Tarja Susi, Tom Ziemke (2005) On the subject of objects: four views on object perception. *Triple C*, Vol. 3 (2), pp. 6-19.

Ilya Sutskever, Oriol Vinyals, Quoc V. Le (2014) Sequence to sequence learning with neural networks. In: arXiv:1409.3215 https://arxiv.org/abs/1409.3215

Joyce Tait, Robin Williams (1999) Policy approaches to research and development: foresight, framework and competitiveness. In: Science and Public Policy, 26 (2), pp. 101-112. https://doi/10.3152/147154399781782536

Olivier Temam (2016) Enabling future progress in machine-learning. *Proc. of the 2016 IEEE Symposium on VLSI Circuits.* DOI: 10.1109/VLSIC.2016.7573457

Jonathan P. Tennant, Francois Waldner, Damein C. Jacques, Paoloa Masuzzo, Lauren B. Collister, Chris H.J. Hartgerink, The academic, economic and societal impacts of Open Access: an evidence-based review. *F1000Research,* 5:632, DOI: 10.12688/f1000research.8460.1

Stefan Thomke, Eric von Hippel (2002) Customers as innovators: a new way to create value. In: Harvard Business Review, April, pp. 5-11.

Mile Terziovsky (2010) Innovation practice and its performance implications in small and medium enterprises (SMEs) in the manufacturing sector: a resource-based view. In: Strategic Management Journal, Vol. 31, pp. 892-902.

Morten Tønnessen (2015) The relevance of Uexküll's Umwelt theory today. In: C. Brentari (ed.) *Jakob von Uexküll.* Springer, Dordrecht, pp. 1-20.

Jakob von Uexküll (1909) *Umwelt und Innenwelt der Tiere*. Springer, Berlin.

Jakob von Uexküll (1920) *Theoretische Biologie*. Suhrkamp, Frankfurt am Main, 1973.

Emel Ültanir (2012) An epistemological glance at the constructivist approach: constructivist learning in Dewey, Piaget, and Montessori. *International Journal of Instruction,* Vol. 5 (2), pp. 195-212.

University of Vienna (2017) *Innovation durch Grundlagenforschung.* (Innovation from basic research.) Vienna. https://phaidra.univie.ac.at/view/o:467088

J.M. Utterback (1971) The process of technological innovation within the firm. *Academy of Management Journal*, Vol. 14, pp. 75-88.

Roberto Veganti (2009) *Design-driven Innovation.* Harvard Business Press, Boston, MA.

Andrew H. Van de Ven (1986) Central problems in the management of innovation. *Management Science*, Vol. 32, pp. 590-607.

Peter-Paul Verbeek (2003) *What Things Do.* Pennsylvania State University Press.

Giambattista Vico (1710) *De Antiquissima Italorum Sapientia.* Stamperia de'Classici Latini, Naples (1858). Online: http://www.ispf-lab.cnr.it/system/files/ispf_lab/documenti/opere_deantiquissima.pdf

Katinka Waelbers (2011) Doing Good with Technologies: Taking Responsibility for the Social Role of Emerging Technologies, Springer, New York, NY, p. 77.

Michael A. West, James L. Farr (1990) Innovation at work. In: West, M.A. and Farr, J.L. (Eds.), Innovation and Creativity at Work: Psychological and Organizational Strategies. Wiley, Chichester, UK, pp. 3-14.

Lynn Whyte Jr. (1971) Cultural climates and technological advance in the Middle Ages. In: Viator 2, p. 171.

Timothy Williamson (2000) *Knowledge and its Limits.* Oxford University Press, Oxford, UK.

Ludwig Wittgenstein (1953) *Philosophische Untersuchungen. (Philosophical Investiations.)* Suhrkamp, Frankfurt/Main, Werkausgabe Bd. 1, 1986.

Georg Henrik von Wright (1974) *Erklären und Verstehen. (Explaining and Understanding.)* Athenäum, Frankfurt 1974, pp. 93-12.

Yonghui Wu, Mike Schuster, Zhifeng Chen et al. (2016) Google's neural machine translation system: Bridging the gap between human and machine translation. In: arXiv:1609.08144 https://arxiv.org/abs/1609.08144

Jason Yosinski, Jeff Clune, Anh Ngyuen, Thomas Fuchs, Hod Lipson (2015) Understanding neural networks through deep visualization. In: *Deep Learning Workshop, 31st Int.Conf. on Machine Learning,* Lille, France.

Linda T. Zagzebski (2003) Intellectual motivation and the good of truth. In: M. DePaul, LT. Zagzebski (eds) *Intellectual Virtue: Perspectives from Ethics and Epistemology*. Oxford University Press, Oxford, UK.

Markus Zeilhofer (1995) *Technikfolgenpolitik*. Zur Gestaltbarkeit des technischen Wandels. (Technological impact politics.) Westdeutscher Verlag, Opladen.

Tom Ziemke (2005) Ziemke, T. (2005). Cybernetics and embodied cognition: On the construction of realities in organisms and robots. *Kybernetes*, 34 (1/2), pp. 118-128.

Abstract

Knowledge-based innovation as the success of a technical or organisational novelty based on scientific knowledge currently lies at the centre of a range of arguments and programmes in science and technology policy. The aim of this dissertation is a fundamental critical philosophical reflection of knowledge in the light of innovation. The main subject of this investigation is the process of constructing opportune knowledge: how do our concepts of knowledge and knowledge creation change if innovation is at the heart of the knowledge creation process? A present change to these processes that is relevant for the praxis of innovation are new epistemic methods and innovation technologies. These methods for the automated production of knowledge-based functional systems illustrate the current trend towards increased efficiency and universal function orientation while frequently neglecting explanatory power.

Traditionally, use and usability of knowledge were central themes for only few philosophers, for example, Marx, the pragmatists and in constructivism. However, applicable knowledge and knowledge to innovate play a central role in the current science policy discourse. This discourse is still characterized by the linear model, although many authors believe to have it unmasked as a political narrative. In the technical sciences, the focus is on orientation towards purpose. Therefore, the various stages of the linear model can be readily analysed with the help of an epistemology of technology, which helps to clarify the relationship between knowledge processes in natural science and purpose-oriented technology development. In the linear model, knowledge has a central position: it intercedes between the performances of scientific insight and technical function.

This intercession and the strong orientation towards function in the context of goal-directed action can be explained using a constructivist model of knowledge processes. Such a model can help to intercede between descriptive-logotheoretical conceptions of science and techno-scientific conceptions of knowledge. It interprets knowledge as the anticipation of successful environmental interaction under the pressure to act and can also be expanded in the direction of linguistic interaction and a more traditional concept of knowledge. The central tool-character of knowledge in this model facilitates the connection of a constructivist epistemology and existential-ontological analysis that also forms the basis of

new work in the philosophy of technology. Apart from the primacy of praxis, this also facilitates an explanation of the current challenging of knowledge with respect to its technical goal. Therefore, this dissertation addresses the pragmatic-political aspects in the discourse of transferring scientific results to innovation, but also the practical knowledge work of the technology scientist and different historical epistemological positions in view of constructing opportune knowledge.

Zusammenfassung

Wissensbasierte Innovation als Durchsetzung einer technischen oder organisatorischen Neuerung auf der Basis wissenschaftlichen Wissens steht derzeit im Mittelpunkt zahlreicher Argumente und Programme der Wissenschafts- und Technologiepolitik. Ziel der Dissertation ist eine prinzipielle kritische philosophische Reflexion von Erkenntnis im Lichte von Innovation. Hauptgegenstand dieser Untersuchung ist der Prozess der Konstruktion nützlichen Wissens, vor allem der Frage, wie sich unsere Begriffe von Wissen und der Wissenserzeugung verändern, wenn Innovation im Mittelpunkt des Wissensgenerierungsprozesses steht. Eine aktuelle und für die Innovationspraxis relevante Veränderung dieser Prozesse stellen neue epistemische Verfahren und Innovationstechnologien dar. Diese Verfahren zur automatischen Produktion wissensbasierter funktionaler Systeme verdeutlichen die aktuelle Bewegung in Richtung Effizienzsteigerung und durchgängiger Funktionsorientierung und ihren häufigen Verzicht auf die Erbringung von Erklärungsleistungen.

Traditionell waren Verwendung und Verwendbarkeit des generierten Wissens nur bei wenigen Philosophen ein zentrales Thema, zum Beispiel bei Marx, den Pragmatisten und im Konstruktivismus. Verwendbares Wissen und Wissen um zu innovieren spielen aber die zentrale Rolle im gegenwärtigen wissenschaftspolitischen Diskurs. Dieser wird immer noch von einem linearen Modell der Innovation geprägt, obwohl viele Autoren dieses als politisches Narrativ enttarnt glauben. In den technischen Wissenschaften steht die Zweckorientierung des Wissens im Mittelpunkt. Die verschiedenen Stadien im linearen Modell lassen sich daher gut mittels einer Epistemologie der Technikwissenschaften analysieren, die den Zusammenhang zwischen naturgesetzlicher Erkenntnis der Grundlagenforschung und zweckorientierter Technologieentwicklung klären hilft. Im linearen Modell nimmt traditionell wissenschaftliches Wissen eine zentrale Position ein: es vermittelt zwischen wissenschaftlicher Erkenntnisleistung und technischer Funktion.

Diese Vermittlungsleistung und die starke Funktionsorientierung im Kontext zielgerichteten Handelns lassen sich anhand eines konstruktivistischen Modells der Erkenntnis erläutern. Ein solches Modell kann helfen, zwischen beschreibend-logotheoretischer Wissenschaftskonzeption und technikwissenschaftlicher Konzeption der

Erkenntnis zu vermitteln. Es versteht Wissen als Antizipation erfolgreicher Umweltinteraktionen unter Handlungsdruck und kann in Richtung sprachlicher Interaktion und eines traditionellen Wissensbegriffs erweitert werden. Der zentrale Werkzeugcharakter von Wissen in diesem Modell erlaubt schließlich auch eine Verbindung von konstruktivistischer Epistemologie und existenzialontologischer Analyse, die auch die Grundlage neuer Arbeiten der Technikphilosophie bildet. Neben dem Primat der Praxis lässt sich auf diese Weise auch das aktuelle Stellen jeglichen Wissens auf seinen technischen Zweck hin erklären. In dieser Dissertation werden daher auch die pragmatisch-politischen Aspekte im Diskurs der Überführung wissenschaftlicher Resultate zu Innovationen berührt, sowie die praktische Erkenntnisarbeit des Technikwissenschafters und unterschiedliche historische erkenntnistheoretische Positionen im Blick auf Konstruktionen nützliches Wissen.