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„A visualization approach for analyzing social networks and triangulating them with psychological measures“

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Abstract

Social connections play an important role in the context of multiplayer video games, characteristics of players and teammates can impact their performance and actions. The goal of this work is to set up a novel toolkit that provides *League Of Legends* information as well as functionality to view, analyze and cluster them. The prepared data originates from different sources and includes in-game details, personal information including psychological measures and match statistics for over 600 players. Besides presenting numerical features and clustering results in plots, also player networks generated from match data can be viewed and analyzed. User feedback about usability, feature coverage and findings has been gained by the evaluation afterwards.

Kurzfassung

Soziale Interaktionen spielen eine wichtige Rolle im Kontext von Multiplayer-Videospielen, Charaktereigenschaften von Spieler*innen und deren Teamkolleg*innen können die Leistungen und Entscheidungen im Spiel beeinflussen. Das Ziel dieser Arbeit besteht darin, eine neuartige Anwendung aufzusetzen, welche *League Of Legends*-Datensätze sowie Funktionen, um diese darzustellen, zu analysieren und zu clustern bereitstellt. Die vorbereiteten Daten stammen aus verschiendenen Quellen und enthalten unter anderem Spiel- und Matchstatistiken sowie persönliche Informationen und psychologische Kenngrößen von über 600 Spieler*innen. Neben der visuellen Präsentation von numerischen Eigenschaften und Clusterergebnissen können auch Spieler*innen-Netzwerkgraphen, welche durch diverse Matchdaten erzeugt werden, angezeigt und analysiert werden. Nutzer*innen-Feedback über Benutzer*innenfreundlichkeit, Funktionsumfang und Erkenntnisse wurde im Anschluss durch die Evaluierung erlangt.

Contents

1 Introduction

Utilizing the large amounts of digitally available human-produced data, which grow faster than ever, has become an important part of our lives. With knowledge about different kinds of information and how they can be processed, combined or visualized, researchers are predestined to make interesting findings and correlations that may be beneficial for corporations, individuals or the environment. Thus, a variety of tools and frameworks has already been developed to handle both general and domain-specific research tasks [1]. Considering the ongoing digitalization, this is applicable to almost all domains and use cases.

With a remarkable grow in popularity, also multiplayer video games and their huge communities have become more anticipated to be analyzed over the past decades. The big number of active players and well-defined access to numerical game statistics that certain companies provide predestine the domain to be part of sophisticated research. By setting game data in relation to psychological aspects of players, the idea of this work follows the mentioned approach of establishing connections across different sources.

1.1 Target Audience

Targeting an audience with scientific psychological background, this project aims to allow the analysis of a larger user base for finding correlations in these fields. In succession, the findings can be used for assumptions about certain game behaviour indicating psychological and social characteristics or vice versa. Game developers can refine existing games or create new games based on this information to both maintain active players and gather new ones. Psychologists can utilize the results as well by recognizing positive effects from the game on people with certain personalities or mental health issues which may be applied eventually.

1.2 Information sources

The specific subdomains are built around the data used which contain information about players from the video game *League Of Legends (LOL)* [2]. Aside from having the biggest player base of all time [3], this game has been chosen also considering several other advantages that are further elaborated in Chapters 2 and 3.

Besides in-game details and match statistics from players, also psychological features gained from a survey [4] are included. In addition, by using the match data, ego-centered networks can be generated for each player which adds another layer of triangulation opportunities. As these different kinds of data are bound to the same profiles, they qualify for finding correlations between them by using visualization and analysis tools.

1.3 Research questions

The goal of this work is building a collection of tools to find answers to the following research questions:

- R1: How can the data be presented in a visually convenient way?
- R2: Which tools need to be provided for proper analysis?
- R3: How do the tools have to be integrated and connected in terms of usability?
- R4: Which correlations, dependencies and other relations can be found or derived between features of psychological, game statistics and player network provenance?

1.4 Approached solution

For answering these questions, research has been conducted in order to create a novel toolkit.

1.4.1 Backgrounds & related work

After the introduction, other work used for and related to this project is presented. Chapter 3 discusses the backgrounds of the data used by elaborating important game details, psychological attributes and gathered match information.

By utilizing different fundamental analysis methods, the project has been designed to be both accessible and useful when working with the underlying data introduced in Section 1.2. The application provides tables, plots, ego-centric network graphs and cluster methods to meet the expected scope of functionality for the discussed intent of use. Basic information about these features and their foundations are presented in Chapter 3 as well.

1.4.2 Implementation & evaluation

The software has been realized as a web application that can be used via any web browser on Desktop machines without installation. The used technologies include Flask [5], scikit-learn [6], vis-network [7] and plotly [8] with the application primarily being written in Python and JavaScript. All details of the approach for planning and implementing the solution are discussed later on in Chapter 4.

With the online evaluation of the solution that was done afterwards, important feedback about usability, scope and improvement suggestions could be gathered. In addition, details about how it has been used and what correlations the users were able to find were collected. While the research questions could have been answered without it in theory, the feedback contributed important insights to allow a more reflected discussion. The methods and results for the evaluation are presented in Chapter 5.

1.4.3 Discussion & conclusion

In the Discussion, the work is reflected in regard to the finished application and the user feedback from the evaluation. This includes discussing and answering the research questions introduced in Section 1.3 individually, followed by a closer look on limitations and future work of the project. The work finally wraps up with a Conclusion summarizing the results and findings gathered in the course of the discussion.

2 Related Work

The design and functionality of the visualization tool is based upon and influenced by prior research and related publications that are discussed in the following.

2.1 Psychology and Gaming

Investigating behavior in or emotions based on video games has already been part of scientific research for many years, dating back to articles in the 1980s that predominantly covered negative impacts like addiction and violent behavior [9]. In recent years, however, a large increase of interest in different psychological fields with relation to video games can be observed [10].

Findings and correlations gathered through these studies can then be utilized to improve psychological health implications as well as game quality and accessibility. The target audience defined in Section 1.1 also identifies with those benefits and has always been kept in mind when developing the application.

2.2 Ego-centric networks

In the process of gaining knowledge for this project, a scientific research paper about quantitative ego network analysis has been written in advance [11]. Although the content is based on a wider range of literature, two sources predominantly provided important state-of-the-art techniques to analyze and visualize ego-centric networks: *Social Network Analysis for Ego-Nets* by Crossley et al. [12] and *Egocentric Network Analysis* by Perry et al. [13]. Both of them are summarizing the most relevant information, features and tools in this domain.

Section 3.3 features some of this prior work with relevant information in regards to this project explained in detail; especially popular ego-centric network metrics and visualization approaches are utilized in different parts of the application.

2.2.1 Network analysis in the context of video games

A research approach proposed by Mora-Cantallops and Sicilia [14] makes use of networks built around *LOL* players. They show their potential in being a useful indicator for behavior in the game and found a negative correlation between social play and ranks of players. However, they only consider 1-level network structures with teammates and use no other data sources than match statistics gathered trough the Riot Games API [15]. Nevertheless, the paper delivers a good insight into ego network analysis in the context of psychology in multiplayer video games and has been used as an inspiration for this work. More literature related to *LOL* will be discussed in the next section.

Besides this article, the utilization of ego-centric networks in the context of video game research mostly remains an unexplored technique to this day. However, there are more general approaches to social interaction between players. [16] by Shen introduces a network perspective on gaming communities which aims to gain psychological insights by finding specific patterns. The results in this study show that there is a significant amount of players that prefer to play solo even though *EverQuest II* [17], the game discussed, is designed to support cooperative gameplay. By using the application, findings about social behaviour similar to this are expected to be made when looking at the network graphs.

2.3 League Of Legends (LOL)

Due to the easy access to detailed player behavior statistics during team matches, *LOL* became a popular game to analyze in research; the following publications are highly related to this work.

In 2020, Brühlmann et al. [4] published results of a self-assessment survey in which over 800 players participated, describing their feelings and emotions in relation to the game. The gathered data did not only help the authors finding four distinct motivational profiles but also served as information source for this work as they were kindly provided.

Being focused on motivation, Brühlmann et al. targeted a specific psychological field by analyzing survey and match data. On the other side, the application presented in this work is intended to cover more aspects of psychology and player behavior by providing more general tools as well as additional network statistics and visualization.

Eaton et al. are going in a different direction by analyzing explicit teams that have played more matches together and their cooperative play tactics. In particular, [18] addresses how participants sticking to specific roles within the team increases the overall group performance. In addition, they shortly raise a matter on important match measurements that, amongst others, found their way into this work as well.

2.4 Clustering

Another important part in this project are clustering techniques which are implemented for analyzing the player data that originate from different sources. A difficulty in finding the right algorithms to choose from is the unknown number of clusters and features used. In this matter, Rodriguez et al. [19] offer insights which have been helpful in determining the right set of techniques to implement. Detailed descriptions of the chosen techniques and algorithms that have been utilized in the clustering feature of the tool are presented in Section 3.4.

With *ClustVis*, a relatable tool offering similar functionality has been introduced by Metsalu and Vilo [20]. For visualizing clustering results, aside from heatmaps, Principal Component Analysis (PCA) is used to reduce the data to two-dimensional graphics. In contrary, this project follows the PCA approach as well, but differs in the number of resulting dimensions. Interactive 3D plots help to understand clusters even further and feature values can be viewed within box plots for each cluster individually. Also, t-distributed stochastic neighbor embedding (t-SNE) is provided as an alternative technique for dimensionality reduction (further discussed in Section 3.6).

3 Background

The work which has been done for creating and evaluating the visualization tool is based upon a composition of concepts and data from different types of domains. This section is about introducing and discussing those important fundamentals and their application fields. Furthermore, the motivation for their use in the tool is expressed.

3.1 Multiplayer online battle arena (MOBA) games

The data used in the project is consisting of player and match data from the video game *LOL* [2] which is one of the most popular representatives among the MOBA genre. The following sub-sections summarize the basic gameplay concepts, relations to scientific research and motivation for the application in the visualization tool.

3.1.1 Overview

Starting in the late 1990s, the first gameplay concepts that resemble key elements from the modern MOBA genre were introduced in terms of user-generated content for popular strategy games. As they have been refined over the next years, the player communities grew rapidly, and big videogame companies drove their attention on the genre [21].

A standalone commercial successor to the most popular amongst them, *Defense of the Ancients* (more often just referred to as *DotA*), turned out to be a huge success as well. *DotA 2* by Valve [22] and *LOL* by Riot Games [2] are two of the most well-known and commercially successful video games to this day, counting dozens of millions of active players and being subject of the biggest e-sports tournaments.

In a typical MOBA match, two teams play against each other on a map that resembles a natural landscape and architecture. Bases are placed at the two opposite ends of the map and destroying the one of the opponents marks the main target as it ends the game and determines the winning team. Lanes are paths that connect the two bases with each other, the terrain between them is usually also accessible for players and better known as jungle. The lanes feature more interaction between the teams, including team-assigned defense mechanisms, while jungles have more neutral objectives and obstacles that can help players gaining additional power or abilities throughout the match. All map geography and its elements are arranged in a way to provide fair and balanced gameplay (symmetrically where possible, see Figure 3.1).

Depending on the actual game, there are a lot of additional elements that increase the strategic aspects and replay value like a big roster of characters with individual strengths to choose from. Therefore, the next subsection will elaborate particular *LOL* mechanics

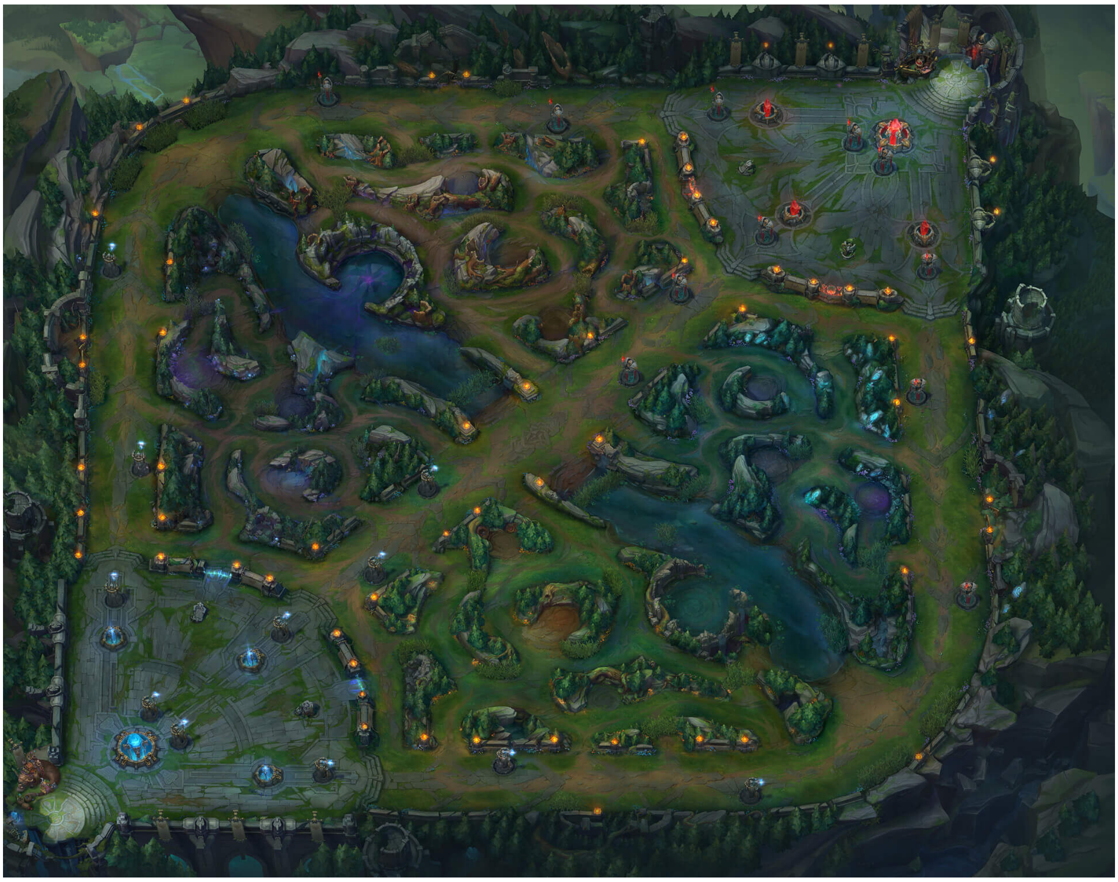


Figure 3.1: *Summoner's Rift* map from *LOL* (Image Source: [2])

and measures that will also be used later on for the data triangulation. It is worth mentioning that *DotA 2* and *LOL*, as well as other less popular MOBA games, use very similar concepts though.

3.1.2 League Of Legends (LOL)

LOL comes with a lot of mechanics and tactics that take time to understand and master [23]. Thus, the information provided in the following will only cover the basics as far as required to comprehend the metrics that are explained afterwards.

The game features over 150 playable characters which are called champions, each with their own strengths and abilities. Throughout a match, players can earn gold (and useful items as a result of spending it) or receive status upgrades by defeating enemy units or completing other objectives. Teams are supported by computer-operated minions and defense towers ("turrets") that are placed across the map.

Roles and collaboration within a team are important aspects that will, amongst other elements like player skill, determine the efficiency of chosen champions and tactics to optimize resources. Advanced and professional players can play in ranked mode which is a competitive equivalent to the classic game mode on the map Summoner's Rift with three lanes between the bases, the most popular and well-known way to play *LOL* (see Figure 3.1). Aside from this, the *All Random All Mid* mode with similar concepts takes place on the Howling Abyss map which only features one lane and faster-paced gameplay where matches only last about half as long. In both modes, teams consist of five players each.

New major versions with changes and improvements to the game are released every year and mark the start of a new season.

3.2 Data and measures

The 698 data records considered for analysis describe one specific player each. They include all statistics from their played *LOL* matches within the period of two weeks as well as psychological characteristics gathered through a survey. To build ego-centric networks (further discussed in 3.3) around these players, also data from other match participants, including their played matches to create a second level of depth, are featured in the dataset.

3.2.1 Psychological Measures

The groundwork for the psychological measures was done in a preceding cross-sectional study by Brühlmann et al. [4]. The survey takes several motivation measures that have been determined by Self-Determination Theory (SDT) concepts into consideration. The resulting motivational profiles are derived from correlating and analyzing game metrics and these psychological features which have been kindly provided for this work.

SDT compromises empirical methods to investigate how satisfied the basic psychological needs are [24]. The following questionnaires and scales were used to evaluate the measures that are also utilized in the visualization tool.

User Motivation Inventory (UMI)

Needs are important indicators for mental health and tightly connected to motivation. In the *Self-Determination Continuum*, Ryan and Deci [24] present the different depending sources of motivation as regulatory styles (see Figure 3.2 for further details). They represent the psychological measures assessed by the UMI:

- Intrinsic Regulation (IMO)
- Integrated Regulation (INT)
- Identified Regulation (IDE)
- Introjected Regulation (INJ)
- External Regulation (EXT)

- Non-regulation (AMO)

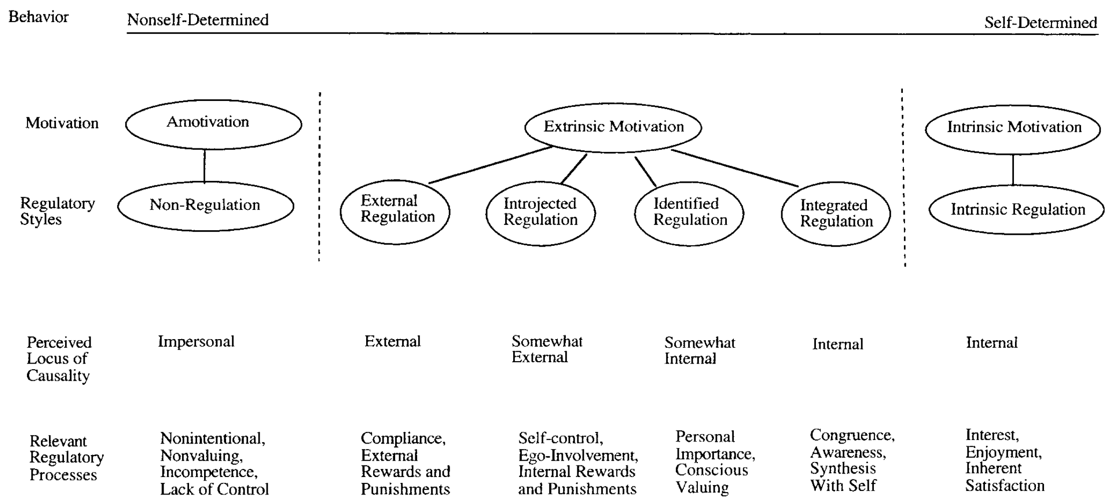


Figure 3.2: The Self-Determination Continuum showing types of motivation with their regulatory styles, loci of causality and corresponding processes (Image Source: [24])

Intrinsic Motivation Inventory (IMI)

The IMI questionnaire aims to evaluate subjective player experience on multiple different subscales where the following were utilized in the motivational profiling, with Interest-Enjoyment being considered as the self-report measure of intrinsic motivation. The pressure and tension measurement on the other side describes the negative impact [25].

- Interest-Enjoyment
- Pressure-Tension

Player Experience Need Satisfaction (PENS)

The PENS scale focuses on video games and utilizes the game play questionnaire introduced by Ryan et al. [26]. It targets a SDT core component, the satisfaction of basic psychological needs, namely:

- Relatedness
  - Scale that describes the need to be connected with other human beings
- Competence
  - Scale that describes the need for challenge

- Autonomy
  - Scale that describes the need of willingness

Achievement Goal Framework

The achievement goal framework as described by Elliot and McGregor [27] provides a questionnaire for calculating competence-related scores on four different subscales:

- Performance Approach
  - Motivation to perform better than others
- Performance Avoidance
  - Motivation to avoid being less performant than others
- Mastery Approach
  - Motivation to master certain tasks to improve knowledge
- Mastery Avoidance
  - Motivation to avoid subjectively difficult tasks and choose easier ones

Harmonious and Obsessive Passion

Another psychological feature considered is the kind of passion players have for *LOL*. Harmonious passion describes the autonomous decision to engage with a subject while obsessive passion hints at pressure induced by social acceptance matters or similar uncontrollable influence from internal or external sources [28].

Positive and Negative Affect Schedule (PANAS)

The PANAS scale introduced by Watson et al. [29] measures the positive and negative affect. These features do not directly contradict each other: A high positive affect indicates strong enthusiasm for a subject, a low one indolence. In comparison, a high negative affect more likely suggests distress with calm being predominant for low scores.

Vitality

The SDT vitality index gives an idea on the well-being of a player. The survey utilized the vitality scale by Ryan and Frederick [30].

3.2.2 Match information

Although the data from Brühlmann et al. [4] already contains information about the matches played by the survey participants, the provided details only served as a fraction of the data needed for this work. To perform proper social network analysis (further discussed in Section 3.3), also match information from the participant's teammates as well as the opponent's have been gathered via the Riot Games API [15] in advance as part of a university project.

Python scripts were utilized to identify the encrypted IDs from the survey data, gathering the player and match information via the API and linking them together. In a second step, the alters and their played matches were retrieved as well. Due to the exponential gain of data with increasing matches (and, in consequence, players), the queried data has been limited in terms of a predefined time frame which is close to the time of the conduction of the survey. The exact period dates to the two weeks between 2018-07-16 and 2018-07-31, gathering all match data within it took about half a year.

In contrary to the mentioned project, the text-formatted match information is directly processed and reduced instead of being transferred to a graph store first. This is due to a high error margin and reduced efficiency as not all details are considered in the end. In addition, the advantages of graph navigation can be neglected as the file hierarchy and naming conventions have been created with respect to easy-accessible keys.

Using this additional match data, the following *LOL* features that measure in-game performance and are popular amongst e-sports scores were derived from game statistics [31]. Some team-bound calculations for these features were adapted to reflect single player performance.

Single Match Statistics

These features are calculated per match. To be represented as a single player attribute, the mean of the match values has been calculated:

- Mean Kill/Death Assist Ratio: $\frac{\text{Player Kills + Player Assists}}{\text{Player Deaths}}$
- Mean Kill Participation: $\frac{\text{Player Kills + Player Assists}}{\text{Team Kills}}$
- Mean Team Damage Ratio: $\frac{\text{Player Damage}}{\text{Team Damage}}$
- Mean Team Gold Ratio: $\frac{\text{Player Gold}}{\text{Team Gold}}$
- Mean Combined Kills per Minute: $\frac{\text{Player Kills + Player Deaths}}{\text{Match Duration in minutes}}$

General Performance Statistics

The following features are statistics across several matches by default and do not need to be further processed for defining player attribute values:

- Kills per Win: $\frac{\text{Player Kills in won matches}}{\text{Number of won matches}}$
- Deaths per Loss: $\frac{\text{Player Deaths in lost matches}}{\text{Number of lost matches}}$
- Win Ratio: $\frac{\text{Number of won matches}}{\text{Number of all matches}}$

3.3 Ego networks

In the course of doing groundwork for the master thesis, a scientific paper covering state-of-the-art techniques and research for quantitative ego-centric network analysis and visualization has been created [11]. Relevant content covering fundamentals for this project is summarized and adapted in the following.

3.3.1 Characteristics

Networks in general represent graphs with nodes and connecting edges which may also have additional, non-structural information (labels) attached to them. For ego-centric network approaches, these fundamental building blocks play special contextual roles which will be described hereafter. Crossley et al. [12] offer a more detailed introduction to the structure (also including comparisons to other network types) in their book on ego net analysis.

Nodes

Nodes in a network are entities that can describe anything that is capable of having relations to the same or comparable kind of entity, reaching from human beings over ethnic groups over countries right up to organizations. In an ego net, there is exact one focal node, the **ego**. Any other present node must have a direct relation (tie) to ego and is considered as **alter**. In many cases, nodes (and especially the ego) are annotated with additional valued or categorical attributes like age, gender or educational level. Ego networks are always one-node networks, e.g. the node entity type is the same for all nodes.

Ties

The edges between nodes represent specific relations and are therefore called **ties**. Relations can be directional or bidirectional (reciprocal), f.e., a boss guiding his employees is directional as this does not happen in the opposite direction. On the other side, friendships or sexual relationships between people are by definition reciprocal ties. Also ties may contain additional information that characterizes or weights the corresponding edge and their semantics within the ego network. In addition to the obligatory ego-alter-ties, alter-alter ties between the ego's alters may also be present.

Categorical (Discrete) Attributes

Values for categorical attributes represent named or numbered labels from a finite, predefined set of classes. They can be further distinguished between nominal and ordinal data, with the latter ones having a defined order and therefore clearer relation between the values (f.e. grades in school). Nominal attributes, in contrary, do not follow any kind of order (f.e. movie genres or gender). Sarkar [32] provides a detailed introduction to categorical data in his blog.

Valued (Continuous) Attributes

While ordinal categorical attributes definitely draw nearer to valued attributes, the important difference is the continuity of their values, e.g. they are part of an indefinite set, even if only concrete values can be measured. Valued attributes are typically numerical values like age or length.

3.3.2 Measures

Tie Strength

Tie Strength is a single valued attribute built upon the available tie data using methods that reduces their initial dimension to a numerical value. This may include algorithms, weighted preferences or just omitting specific features.

Degree

The degree of a network describes its size which is defined by the number of alters. Crossley et al. [12] also link this measure to *Tie Central Tendency* and *Alter Central Tendency* and suggest to use statistical summaries (mean, median, etc.) for weighting alter relevance.

Density

Like degree, density is a general network measure that defines the "connectedness". For ego networks, the density is defined by the actual ties divided by the number of theoretically possible ties. Undirected ties are counted twice to achieve a resulting value in the range between zero and one.

Component Ratio

By removing the ego from the network, the network may split up from one component (the initial network) to multiple components (smaller, non-connected networks). For considering the size of the initial network, components are not just summed up but put in a relation to the number of alters, see Equation 3.1 where C is the number of components and N is the number of alters.

$$CR = \frac{C-1}{N-1} \tag{3.1}$$

Fragmentation Index

As Perry et al. [13] point out, the component ratio still does not consider component size. To overcome this issue, the concepts of density and component ratio are combined into one new measure, the fragmentation index (even though it does not consider the number of components directly anymore). As Equation 3.2 shows, the density value is calculated with reachable nodes r_{ij} instead of ties (multiple tie hops are are also considered) divided by the amount of possible alter-alter ties (N, again, denotes the number of alters) and subtracted from 1, e.g. the density value is indirectly proportional to the fragmentation value. A result of 0 indicates that all alters are somehow connected to each other while a result closer to 1 reflects a large number of isolates.

$$FI = 1 - \frac{\sum_{i \neq j} r_{ij}}{N(N-1)} \tag{3.2}$$

3.3.3 Visualization

As an important part of quantitative analysis, fundamental layout considerations to visualize ego-centric networks and their features are presented in the following.

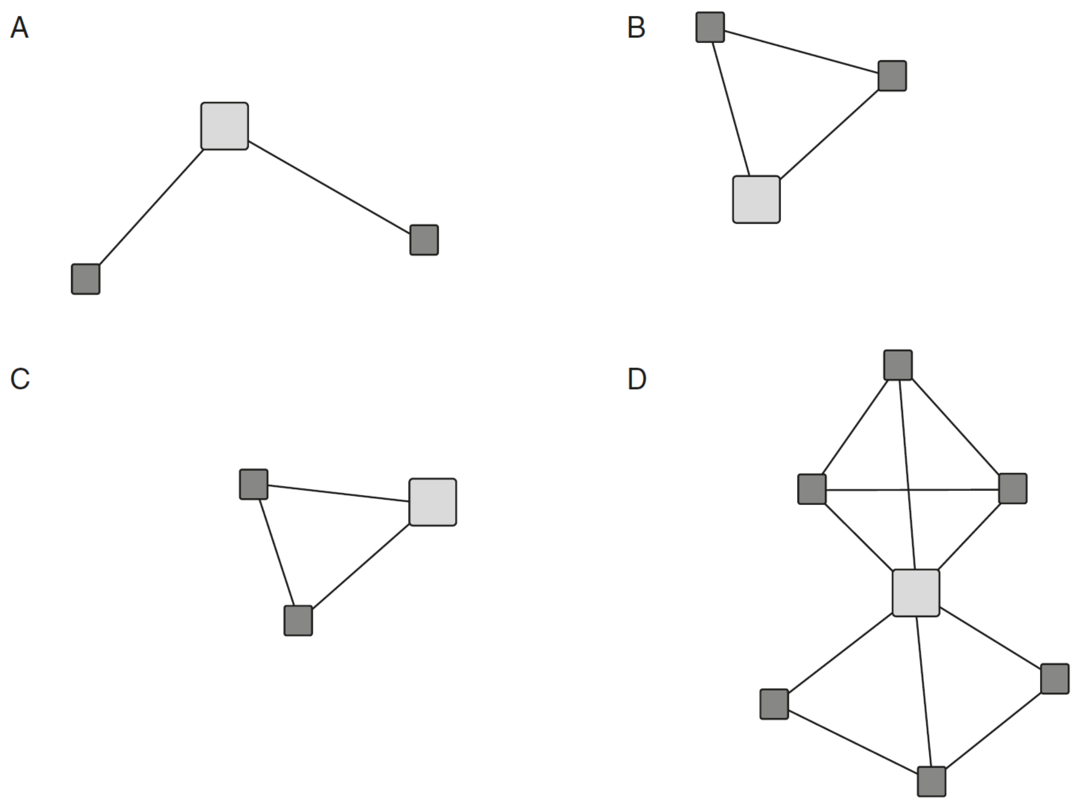


Figure 3.3: Simple ego nets without attributes (Image Source: [12] p. 18)

In Figure 3.3, four different small ego network graphs are pictured with the ego being a big light-grey square and alters being smaller, dark-grey squares. All ties are simple black straight lines connecting the according nodes. Without any further labeling, one can clearly distinguish between the actors and is able to capture the fundamental structure.

In addition to making the squares differ in size or colour, also shape variation (f.e. a circle instead of a square) can be used to identify members of a specific group. This may prove very helpful when trying to visualize alters with additional attributes or attached categories. Figure 3.4 extends the annotation potential even further and adds line-surrounded areas with corresponding labels.

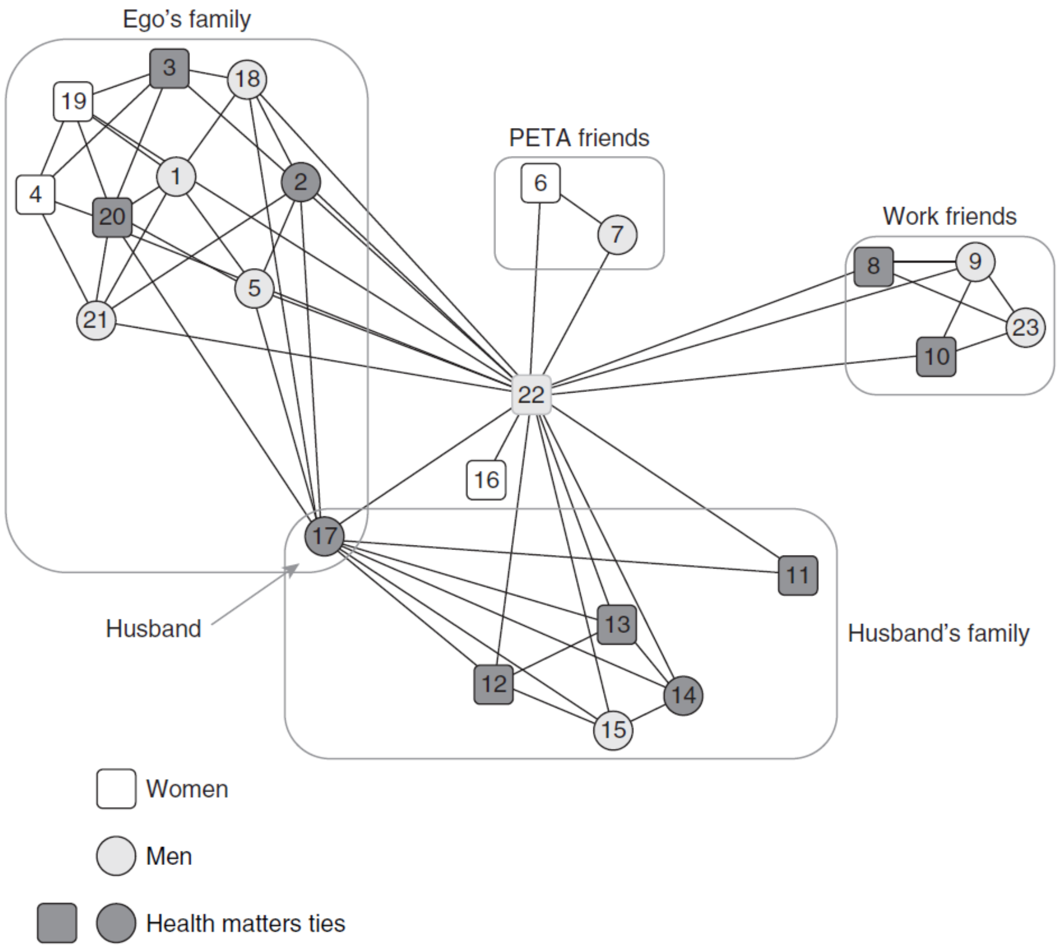


Figure 3.4: Ego net with several multidimensional alter attribute data (Image Source: [13] p. 134)

Also ties can be visually characterized by changing their color or thickness, representing relationship types (categories) and tie strength in best practice, respectively. Due to readability reasons, attribute-indicating lengths or other shapes than straight lines should not be considered though.

Finally, as already practiced for some measures in Section 3.3.2, the ego and its ties are omitted for further analysis sometimes. Hiding these parts of the network also for visualization will help recognizing isolated alters, components and bridges as seen in

Figure 3.5. It is the same network as from Figure 3.4, but without the ego node plotted.

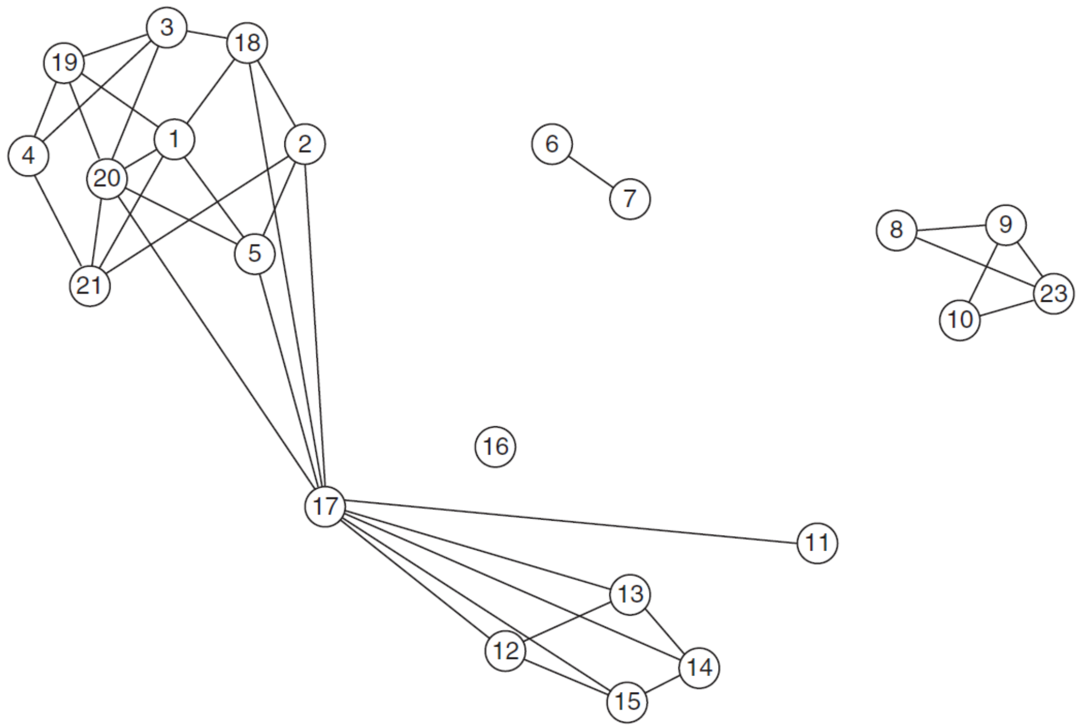


Figure 3.5: Ego net without ego and ego-alter ties (Source: [13] p. 136)

3.4 Clustering methods

Clustering techniques aim to classify data records by labelling them, e.g., associate them with certain other records and building a group (cluster) together with them. The tool uses different approaches to cluster the player features. Furthermore, other data processing methods are utilized for preparing the clustering input or the visual output. In the following, the corresponding algorithms are presented and explained.

3.4.1 K-Means

The k-Means algorithm is one of the most commonly used clustering techniques and shows its strengths in simplicity and speed [33]. It has been proven useful on datasets with groups of similar size and small variance between datapoints. As the name suggests, k-Means expects the number of resulting clusters to be specified.

Algorithm

Although the k-Means operational steps sometimes get altered, Llyod's algorithm is generally the one that is associated with it. It consists of three steps:

- Initialization: Choose k initial data points that have the same dimension as the data records. They do not have to match points from the dataset but using samples from it is a common method for the initialization. These points are called the centroids.
- Assignment: The inertia or within-cluster sum-of-squares criterion is calculated for each data record-centroid pair. As the algorithm aims to minimize this squared Euclidean distance measure, a data record is then assigned to the centroid where inertia is the lowest.
- Update: Find the mean for each cluster and use it as the new centroid for that cluster

The second and third steps are looped until convergence (centroids do not change their position anymore) or a certain threshold is reached.

Limitations

Despite being popular, k-Means comes with some limitations that will make other clustering algorithms perform better for certain datasets:

- Convergence is often reached at local minima and depends heavily on the initial positions of the centroids. Running the algorithm multiple times with different initialization therefore leads to different results, a high number of outlier points (noise) will interfere in addition to this.
- If the number of clusters is unknown in advance, it can be difficult to determine the optimal k to choose. Elbow plots provide a remedy to this problem as they indicate the value to pick visually by presenting a curve that shows the percent of explained variance as a function of k.
- Irregular shaped clusters will most probably not be detected and high-dimensional data records are difficult to handle due to the Euclidean distance measure used.

3.4.2 DBSCAN

DBSCAN is short for *Density-Based Spatial Clustering of Applications with Noise* and therefore suits better for irregular shaped clusters than the centroid-based k-Means algorithm [34]. While the number of clusters does not need to be specified in advance, DBSCAN expects two other parameters as an input: the minimum of neighbored data records of a point (including that point) in a cluster as well as the maximum distance between them to count as neighbors. The used distance measure for this algorithm can vary but is generally defined as ε which holds a floating-point number.

Algorithm

DBSCAN starts by choosing a random data record and immediately marks it as visited so it will not be evaluated another time. Afterwards, the neighborhood is searched for the number of data points within the range of ε. The examination stops if the specified minimum of points is not reached which results in the data record being tagged as noise; afterwards, the next random unvisited data record is looked at. If the minimum threshold is satisfied, the neighbors will be traversed to expand the cluster in the next step.

If a neighbor is already tagged as noise, it is identified as a border point which does not have enough neighbors to extend the cluster. For unvisited points, the neighborhood must be evaluated again and, if the threshold is reached, the new points are added to the group of points that is currently iterated through. Either way, the point examined will be added to the current cluster and the procedure is repeated until all points, including newly added points in the neighborhood, are traversed.

After the expanding step is done, the algorithm looks for new unvisited data points that are not related to this cluster and repeats the whole process, eventually forming new clusters. During the traversal of the neighborhood, also data points that are already assigned to another cluster may be encountered, making these common border points that will not be relabeled. Thus, the algorithm is not entirely deterministic, but still very robust and nearly independent of the order the points are looked at.

3.4.3 OPTICS Clustering

Ordering Points To Identify the Clustering Structure (OPTICS) is a density-based clustering algorithm as well but extends its functionality to detect clusters that have different density [35]. It also expects the minimum number of data record neighbors within a cluster, however, in contrary to DBSCAN, without also counting the examined point. The distance parameter ε is optional here as this value can vary now for each cluster. However, a maximum distance can be defined to reduce runtime.

Algorithm

Starting from a random data record which's reachability distance will be set to infinite, all unprocessed points within the ε range will be counted to see if the specified minimum of neighbors is reached. The data point will be marked as processed and its reachability distance will be added to an ordered list. If there are enough neighbors, the minimum radius to reach this number of other points is calculated and set as a core distance for the initial point. The points within this radius will be updated with the core distance as their reachability distance while other observed points will be assigned the actual distance between it and the initial point as reachability distance.

Unprocessed points are kept in a queue where they will be ordered by their reachability distances. After one point is processed, the algorithm takes the first entry from that queue (which should has the lowest reachability distance available) and repeats the steps from the beginning, ignoring processed points. When checking neighborhoods, many unprocessed points may have already been assigned a reachability distance before – this will only be updated if the newly calculated value is lower than the stored one.

When every point is processed, the ordered list of reachability distances and their points will be analyzed to label the clusters by recognizing different levels of density.

3.4.4 Spectral Clustering

Spectral Clustering adds additional steps with more options to choose from than the algorithms mentioned in the preceding subsections [36]. The idea is to convert the dataset to an adjacency matrix that reflects a connected graph. From that matrix, a Laplace matrix can then be built and used to extract an eigenvector. Afterwards, the values within it are clustered using a known method like k-Means.

3.5 Data Scaling

Scalers prepare datasets by rescaling its values to pre-defined ranges which can be better interpreted by the clustering algorithms.

3.5.1 Standardization

Assuming the datapoints in the original dataset are gaussian-distributed, standardization centers the values so that their mean equals 0 with standard deviation being 1. Equation 3.3 shows how the new value for a record is calculated. x is the original value, μ notes the mean value for that dataset and σ is the standard deviation.

$$z = \frac{x - \mu}{\sigma} \tag{3.3}$$

3.5.2 Normalization

Normalization aims to convert datapoints to numbers on a range from 0 to 1 where the minimum and maximum of the given dataset is located at these scale borders. In the corresponding Equation 3.4, the x_{min} and x_{max} values refer to the lowest and highest value in the dataset, respectively.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{3.4}$$

3.6 Dimensionality Recuction

Having multi-dimensional datasets, the difficulty of visualizing and clustering them increases with the number of dimensions, e.g. features from the data records included. To overcome the issue, this number can be reduced by either using selection (filtering) techniques like regression analysis or one of the following projection methods.

3.6.1 Principal Component Analysis (PCA)

With PCA [37], multivariate data are translated into orthogonal principal components that contain weighted information of the original features, maximizing the explained variance.

3.6.2 t-distributed stochastic neighbor embedding (t-SNE)

The t-SNE method projects all datapoints to a lower-dimensional space using similarities between points assuming an ideal normal distribution for each point [38]. The points in the new space are reassigned in single steps at a time using their t-distributed similarities, aiming to match the normal-distributed similarities of the data in the original space.

4 Approach

This chapter provides details about the planning and implementation phase of the project which includes the approaches to create, use and evaluate the visualization tool.

4.1 Scope

For defining the scope of the tool, the title of this thesis

> A visualization approach for analyzing social networks and triangulating them with psychological measures

as well as the research questions introduced in Chapter 1 will be inspected in detail by decomposing them into the following components, also considering the used dataset discussed in Section 3.2.

4.1.1 User knowledge

The goal is to provide an easy-to-use set of functions within a graphical interface for domain experts to view and analyze social network data as well as comparing and clustering it with additional data from another source. The users are expected to have extensive prior knowledge in social network analysis and clustering techniques. With regard to the underlying dataset, additional knowledge in MOBA games and psychological measures is also anticipated to a certain extent.

4.1.2 Social networks

The social networks derived from the used dataset are ego-centric networks with players that participated in the study [4] conducted by Brühlmann et al. as ego. Teammates and opponents of these players within a two-week period act as alters which have their own additional alters in a second level. Section 3.3 introduces the basic concepts which are important for this work while their contribution value is discussed in the following.

Selection of measures

As mentioned in Section 3.3, work on the current state of quantitative social network analysis has been conducted prior to this project; however, not all the measures covered are present in this project and explained in Section 3.3.2. In particular, measurements related to structural holes, ego-alter similarity and diversity have been skipped by intention.

The choice for using this subset of measures has been made taking the following factors related to the dataset into consideration:

- No structure-relevant categories or labels suitable for similarity and diversity measures are attached to the data
- Structural hole measures lack expressiveness in networks with smaller, tightly interconnected structures like the player relationships in 5-vs-5 matches

With these filters in place, the measures discussed in Section 3.3.2 remain and are set to be calculated for all egos.

Structure visualization

With respect to the visualization layout basics introduced in Section 3.3.3, it is important to distinguish between the following features:

- Nodes
  - Ego
  - Alters
- Ties
  - Played in same team
  - Played in opponent team
  - Number of matches played together

Applying the visualization techniques discussed in Section 3.3.3 to the given data, nodes only need to differ by one visual feature while ties must use at least two properties to show their characteristics immediately: Blue ties connect players that played in the same team, red ties denote opposing player relationships within matches. If more matches were played together, the tie strength has an increased value represented by the thickness of the edge. Ego and alters differ in their node size with the ego being the bigger one. In rare cases, study participants appear as alters in other ego networks. These players are presented as slightly bigger nodes than normal alters and can also be recognized by having their anonymous ID instead of their user name attached as label. Figure 4.1 shows examples with certain features turned on and off.

4.1.3 Triangulation of data

In the context of this work, triangulation can be defined as establishing relations, dependencies or other connections between data properties that are collected from different sources. Displaying the values and network structures next to each other may be enough to detect such connections manually and therefore fits into the scope of the project.

However, the use of clustering methods can automate and accelerate this process by grouping data according to their numerous features. By refining algorithm parameters or the selection of features computed, users are potentially faster in finding relations and thus getting meaningful results. Sections 3.4 and 3.5 introduce well-known techniques that are provided within the tool to work with the data.

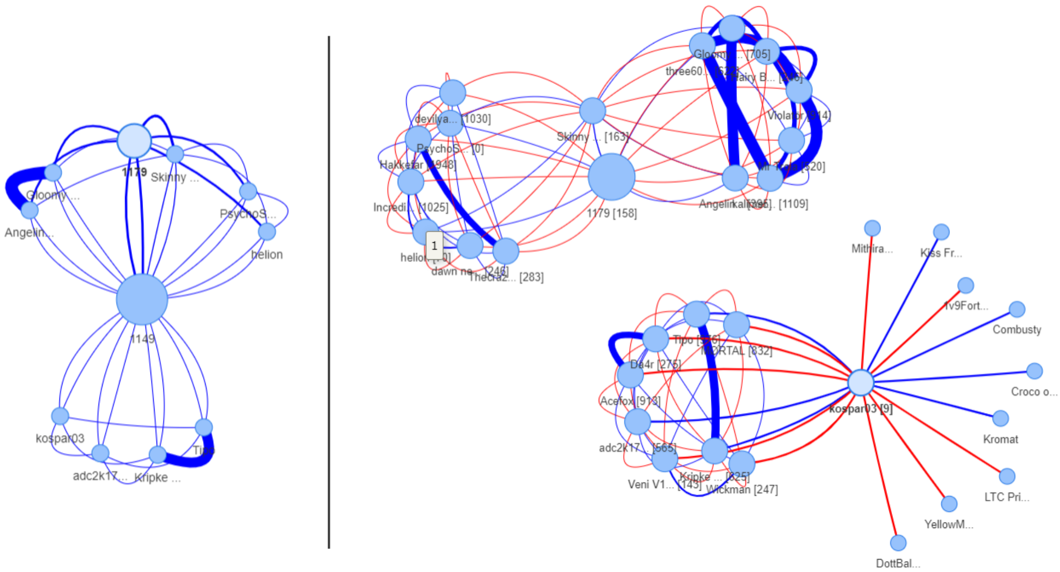


Figure 4.1: Both graphs are built around the same player. In the left structure, only teammates are displayed. In the right structure, the ego is removed. In addition, the latter one contains a second level; the numbers in alter brackets denote how much additional alters they have, with the option to expand such a node like visualized at the bottom right. The known alter with the anonymous ID 1179 can also be seen in both visualizations as slightly bigger nodes.

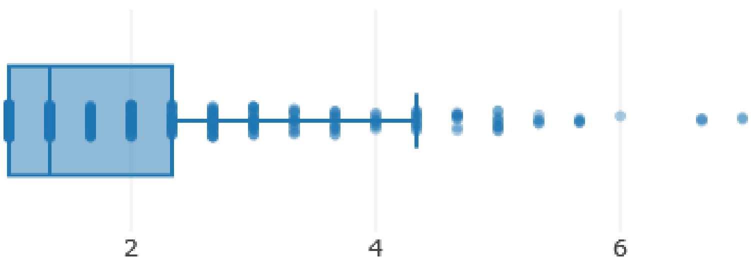


Figure 4.2: Exported PNG of the External Regulation (EXT) feature statistics box plot

4.1.4 Visualization of data and results

Apart from visualizing the network structures, plain feature values are displayed in categorized and easily readable manner as well, giving an option to compare specific players to each other. Furthermore, numerical attributes are also presented in an overview of the value distribution amongst all study participants. Box plots are a proper way to achieve this, as they do not only show the values on an axis but also highlight statistically important properties (see Figure 4.2).

Results from triangulated data (see 4.1.3) also become easier understandable when shown in a graphic. As the number of possible features far exceeds three – the maximum of dimensions expressible in a displayed coordinate system – a dimensionality reduction technique must be used to present all the cluster-labeled data points within the 3D space (see Figure 4.3). Additionally, feature-based box plots as described above showing only data points within each cluster can be displayed on demand to help determine connections between attributes.

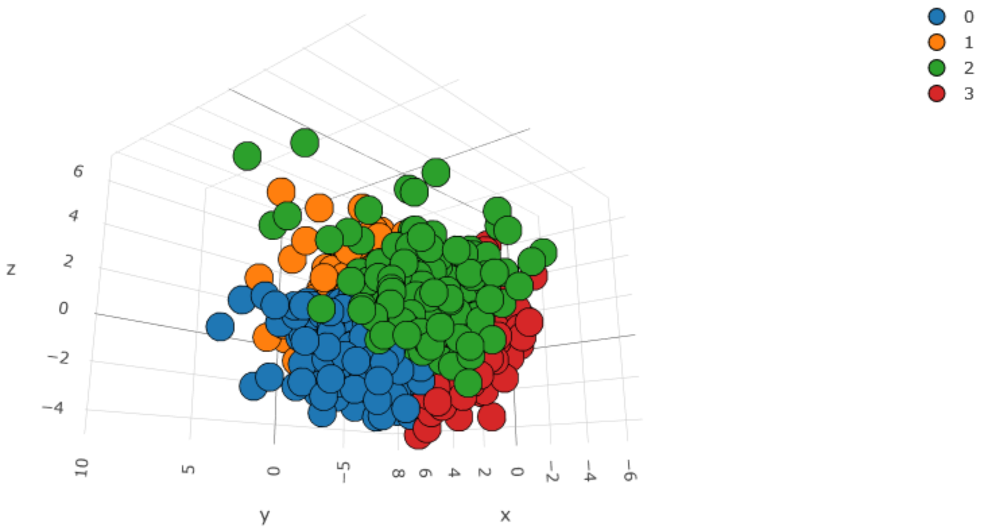


Figure 4.3: Exported PNG of a 3D cluster plot (k-Means clustering) with each color representing a cluster label

4.2 Navigation & actions

With the scope in place, this section addresses the concrete interactions the user is able to have and the segmentation of features on different subareas that can be navigated to within the tool. Alongside a general navigation option, also context-sensitive links between pages are available for certain cases which are described below (also see Figure 4.4).

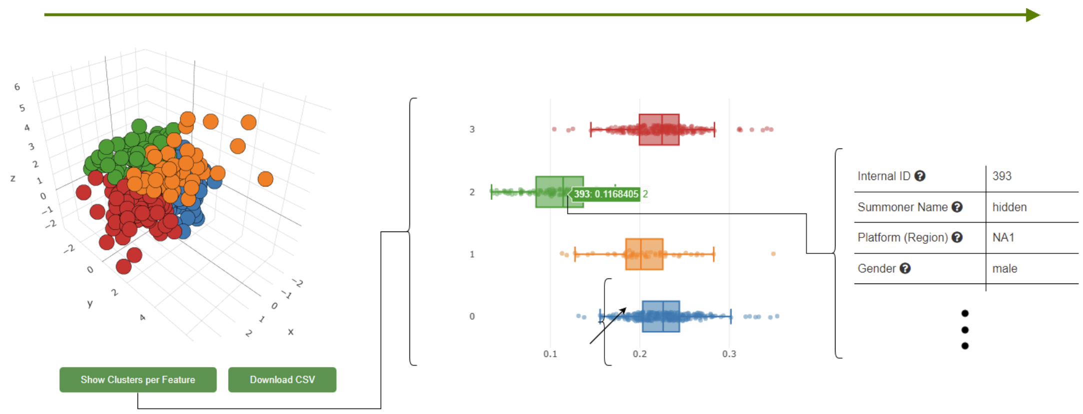


Figure 4.4: Navigation between subsections trough context-sensitive links

4.2.1 Player details

This place allows users to choose one or multiple players to show their attached details, including the features and measures from all sources. As the social networks also build around these players, the ego net visualizations are accessible from here, giving customizable parameters that cover the range of layout options discussed in Section 3.3.3:

- Include or exclude the ego from the visualization
- Include or exclude the second level of nodes (alters of alters)
- Show all nodes or hide player nodes the ego played either against or within a team

4.2.2 Clustering

All clustering-related actions belong to this section; here the user can choose between different operations to conduct and select the features to be considered for it. For each operation, additional parameters may be specified. Other options which use best-practice default values are non-configurable for simplicity reasons.

- Elbow Plot
- k-Means Clustering
  - k can be chosen by the user and specifies the number of clusters to be created. The elbow plot helps to find a good value for this parameter.
  - For the number of initialization attempts, a default of 10 is used
  - The maximum of iterations is set to 300

- DBSCAN Clustering
  - ε specifies the range (maximum distance) to neighbors and can be entered by the user.
  - The *minPts* parameter is dynamically set to the number of features used, increased by one.
- OPTICS Clustering
  - The user can define the minimum number of samples within a cluster
  - The optional ε parameter is set to infinite (default) as no performance issues are occurring in this environment
- Spectral Clustering
  - n can be chosen by the user and specifies the number of clusters to be created (dimension of the projection subspace)

In addition, the scalers introduced in Section 3.5 can be used for preprocessing the data and one of the two dimensionality reduction techniques explained in Section 3.6 must be selected for rendering the 3D plots when doing clustering operations.

With clusters computed, the user can export the results (data with cluster labels) as a CSV file or navigate to the statistics page to show the data distribution per cluster for every feature.

4.2.3 Statistics

Navigating directly to this area, the box plots explained in Section 4.1.4, one per feature, are presented. When being redirected from the Clustering page for showing cluster-dependent statistics, the number of plots is multiplied by the number of clusters and the data points are split up accordingly. In addition, hovering over a datapoint reveals the ID of the associated player and clicking on it will navigate the user to the Player details page showing the related information.

The user also can export and download all shown plots as PNGs within a ZIP-compressed folder.

4.3 Platform and technologies

With all the functionality defined, the approach for implementing it is left to discuss in this section.

4.3.1 Platform

Considering the target audience explained above, the users expected to work with this tool will presumably prefer working on computers with keyboard and mouse over working on mobile devices with touchscreen input. While all common operating systems greatly support native applications, the idea of developing a web-based solution brings forward certain advantages.

Web applications operate within internet browsers which are already natively developed for almost every web-connected device. This makes the implementation of the app itself independent of the underlying operating systems as long as common browser compatibility is ensured. Another benefit that especially end users will appreciate is that no installation or disk space is required to run the tool which keeps their environment cleaner.

Taking these conveniences in combination with the massive advancements in web development that already brought forward many sophisticated web applications into account, browsers have been chosen to serve as a platform for this tool. However, the target devices focused on are still computers, thus touch inputs and responsive design for devices with smaller screen sizes are given less attention.

4.3.2 Technologies

For developing an application of this scope, including large amounts of stored data and computational effort, a plain frontend using only HTML and JavaScript is not sufficient. However, there is a wide range of web development frameworks utilizing different programming languages available. Despite Python being already used for gathering and preparing the data, it is known widely for its efficiency in data processing and analysis mainly through its sophisticated scikit-learn module [6]. This makes the language predestined to be used for this tool.

With visualization being another major part of this project, the technologies used for implementing it also have to be discussed in this section. Although creating graphical representations of the data can be done in several ways in the backend, frontend JavaScript libraries presumably can do it in a more flexible and efficient way. The main advantage of client-side rendering is the range of potential user interactions within the browser, triggering events that, f.e., alter viewed data and perspectives or redirect to other pages by clicking on datapoints. Also, transferred payloads from the server do not need to be complex or even in binary format.

Considering these two decisions, the backend solution will utilize Python as a programming language and its sophisticated web framework module Flask [5] for the webserver. In addition, the sklearn module will be used for doing clustering operations. Since Flask does allow any kind of additional client-side code, the JavaScript libraries vis-network [7] and plotly [8] can be incorporated to cover visualization functionality.

4.4 Visual design

This section focuses on the user experience aspects, including the usage and visual appearance of the application as well as user interface (UI) design decisions for the different areas and features discussed earlier in this chapter.

4.4.1 General application layout

Having chosen the Python Flask framework for implementing the visualization tool, the general layout is based on a pre-built, modern looking example application [39] that has been modified and enhanced with non-relevant parts being removed. Also, the incorporation of the Flask framework has been inspired by a project previously made for a tutorial [40]. The predominant mix of colors used consists of white and a darker green, the secondary color red is mainly utilized in evaluation-related areas.

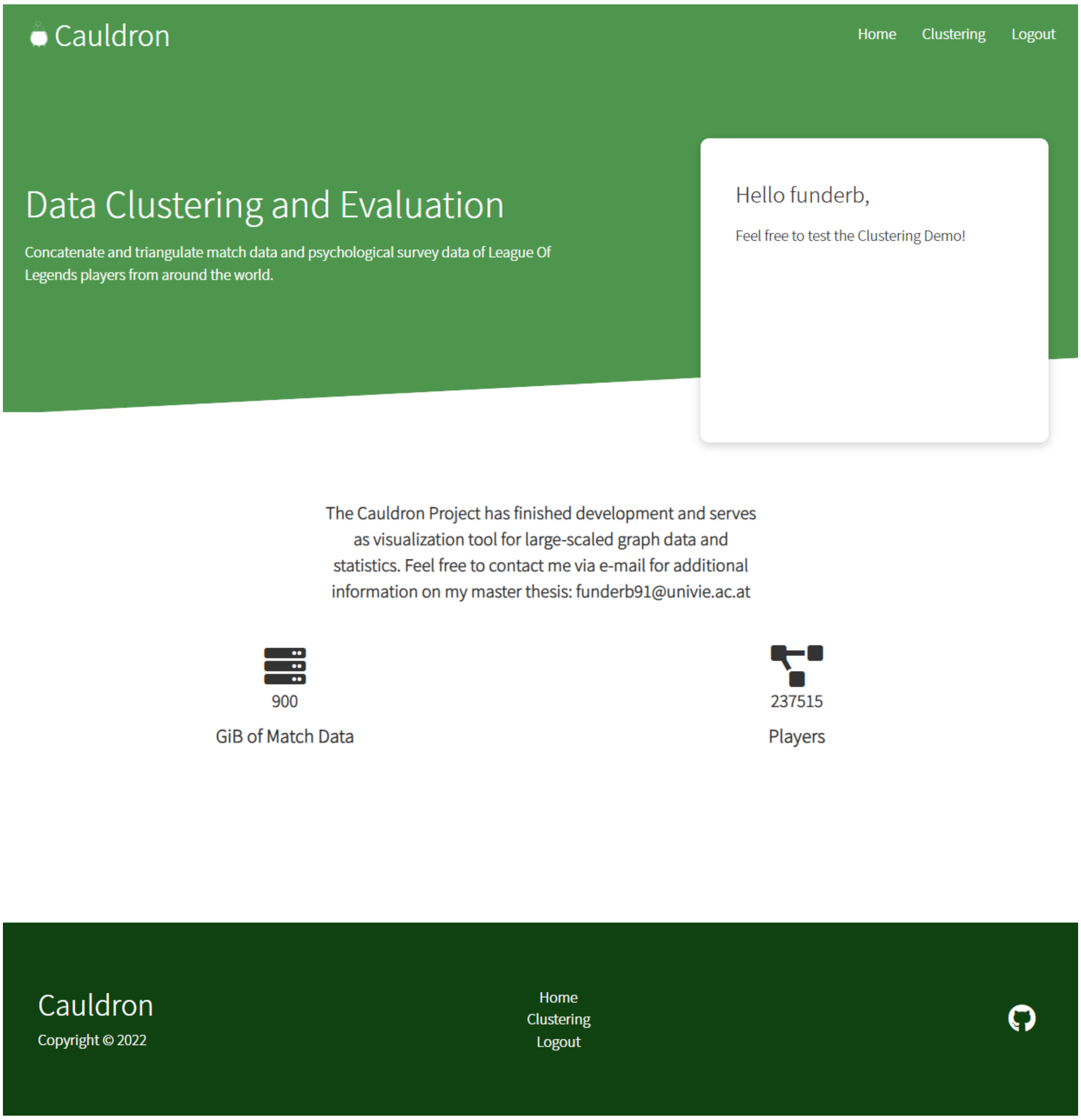


Figure 4.5: Home and landing page of the Cauldron web application

Due to the experimental nature of the application's features, the tool has been given the name Cauldron which is always displayed on the left in the navigation bar on the top of the website, links to different pages reside on the right. On the bottom, another bar with page navigation and a link to the GitHub project is present.

When implementing the result fields in the corresponding bar for the sixth evaluation task, the drop-down checkbox implementation by John Graham [41] has been adapted for the project.

4.4.2 Homepage

The homepage features a short description of the project as well as a login form for authentication which is required for using the tool. During the evaluation phase, a link for starting the evaluation was included as well. When logged in, an additional link for logging out is displayed in the navigation bars (see Figure 4.5).

4.4.3 Clustering page

The clustering page contains the actual functionalities of the visualization tool and is separated into the three areas discussed in Section 4.2. They reside in separate tabs that can be switched to either directly or via references between them. Initially, when navigating to the clustering page, the user is prompted to select a tab.

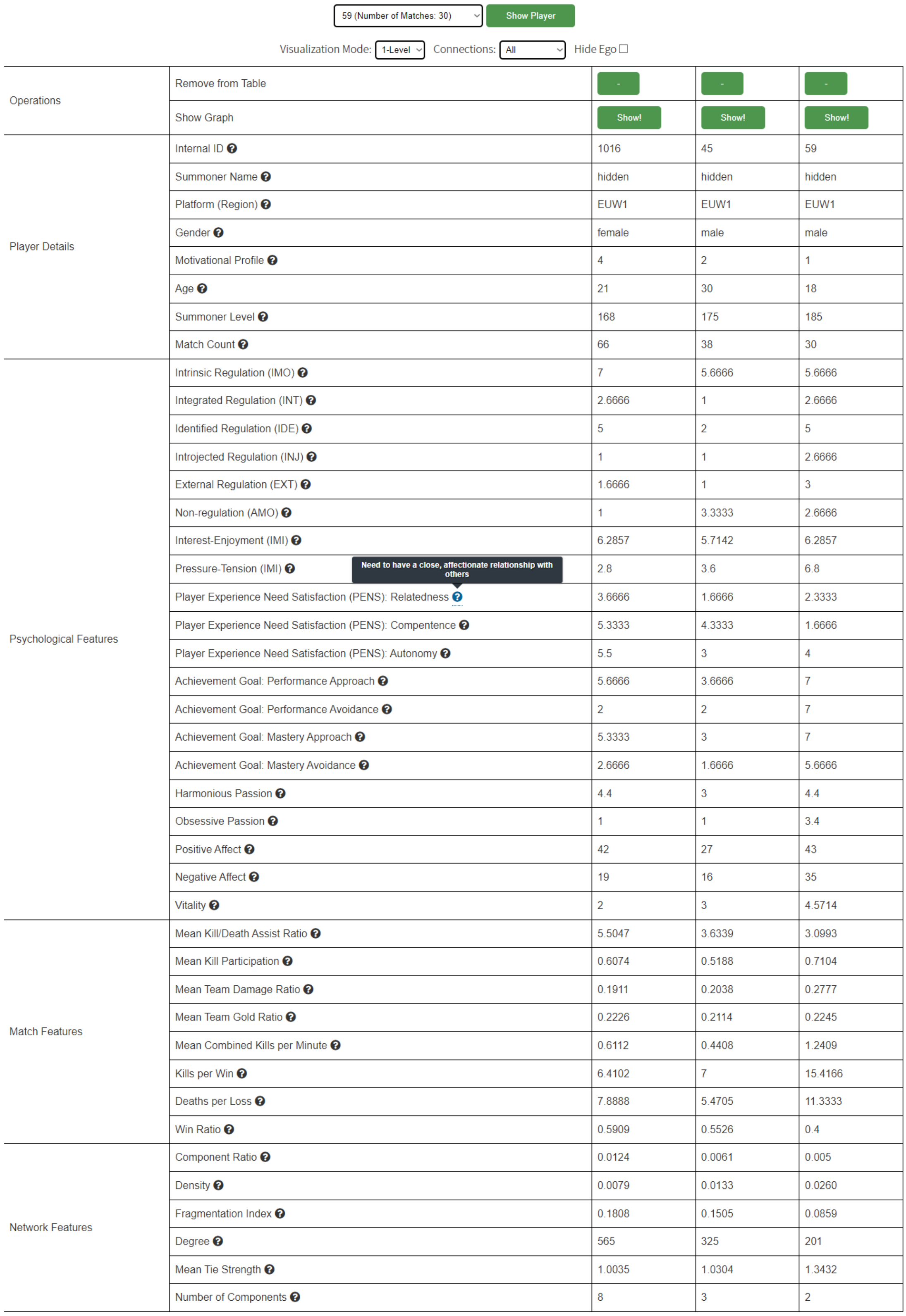
Player details

On the top of the section, the user can select a player from a drop-down menu with all source players sorted by their internal ID. Alongside the ID, the labels show the number of matches included with each player. When clicking on the *Show Player* button, the details of the selected player will be added as a column in the table below which contains values for all stored features. The dynamic table has different sections which separate the features by their categories, namely network measurements, match statistics, psychological survey results and general details retrieved from the user account and survey.

In addition, a fifth section at the top of the table is used for displaying clickable buttons to allow operations with the player of the corresponding column. The user can either remove it from the table or show its network graph in a pop-up using the configuration set below the player selection. This configuration allows to display either one level or two levels of alters, optionally hiding connections of a specific type (teammates/opponents) or the ego and its connections. The single features in the table have question mark icons attached to them which provide additional explanations as tooltip pop-overs when hovering over them with the mouse cursor. Figure 4.6 shows the Player details page, Figure 4.7 the pop-up with a network graph.

Clustering

The selection of possible features to include for the clustering operation are displayed on the top, each representing a checkbox-label pair with the checkbox selection indicating



Operations	Remove from Table	-	-	-
	Show Graph	Show!	Show!	Show!
Player Details	Internal ID	1016	45	59
	Summoner Name	hidden	hidden	hidden
	Platform (Region)	EUW1	EUW1	EUW1
	Gender	female	male	male
	Motivational Profile	4	2	1
	Age	21	30	18
	Summoner Level	168	175	185
	Match Count	66	38	30
Psychological Features	Intrinsic Regulation (IMO)	7	5.6666	5.6666
	Integrated Regulation (INT)	2.6666	1	2.6666
	Identified Regulation (IDE)	5	2	5
	Introjected Regulation (INJ)	1	1	2.6666
	External Regulation (EXT)	1.6666	1	3
	Non-regulation (AMO)	1	3.3333	2.6666
	Interest-Enjoyment (IMI)	6.2857	5.7142	6.2857
	Pressure-Tension (IMI) Need to have a close, affectionate relationship with others	2.8	3.6	6.8
	Player Experience Need Satisfaction (PENS): Relatedness	3.6666	1.6666	2.3333
	Player Experience Need Satisfaction (PENS): Compentence	5.3333	4.3333	1.6666
	Player Experience Need Satisfaction (PENS): Autonomy	5.5	3	4
	Achievement Goal: Performance Approach	5.6666	3.6666	7
	Achievement Goal: Performance Avoidance	2	2	7
	Achievement Goal: Mastery Approach	5.3333	3	7
	Achievement Goal: Mastery Avoidance	2.6666	1.6666	5.6666
	Harmonious Passion	4.4	3	4.4
	Obsessive Passion	1	1	3.4
	Positive Affect	42	27	43
	Negative Affect	19	16	35
	Vitality	2	3	4.5714
Match Features	Mean Kill/Death Assist Ratio	5.5047	3.6339	3.0993
	Mean Kill Participation	0.6074	0.5188	0.7104
	Mean Team Damage Ratio	0.1911	0.2038	0.2777
	Mean Team Gold Ratio	0.2226	0.2114	0.2245
	Mean Combined Kills per Minute	0.6112	0.4408	1.2409
	Kills per Win	6.4102	7	15.4166
	Deaths per Loss	7.8888	5.4705	11.3333
	Win Ratio	0.5909	0.5526	0.4
Network Features	Component Ratio	0.0124	0.0061	0.005
	Density	0.0079	0.0133	0.0260
	Fragmentation Index	0.1808	0.1505	0.0859
	Degree	565	325	201
	Mean Tie Strength	1.0035	1.0304	1.3432
	Number of Components	8	3	2

Figure 4.6: Player details page of the Cauldron web application

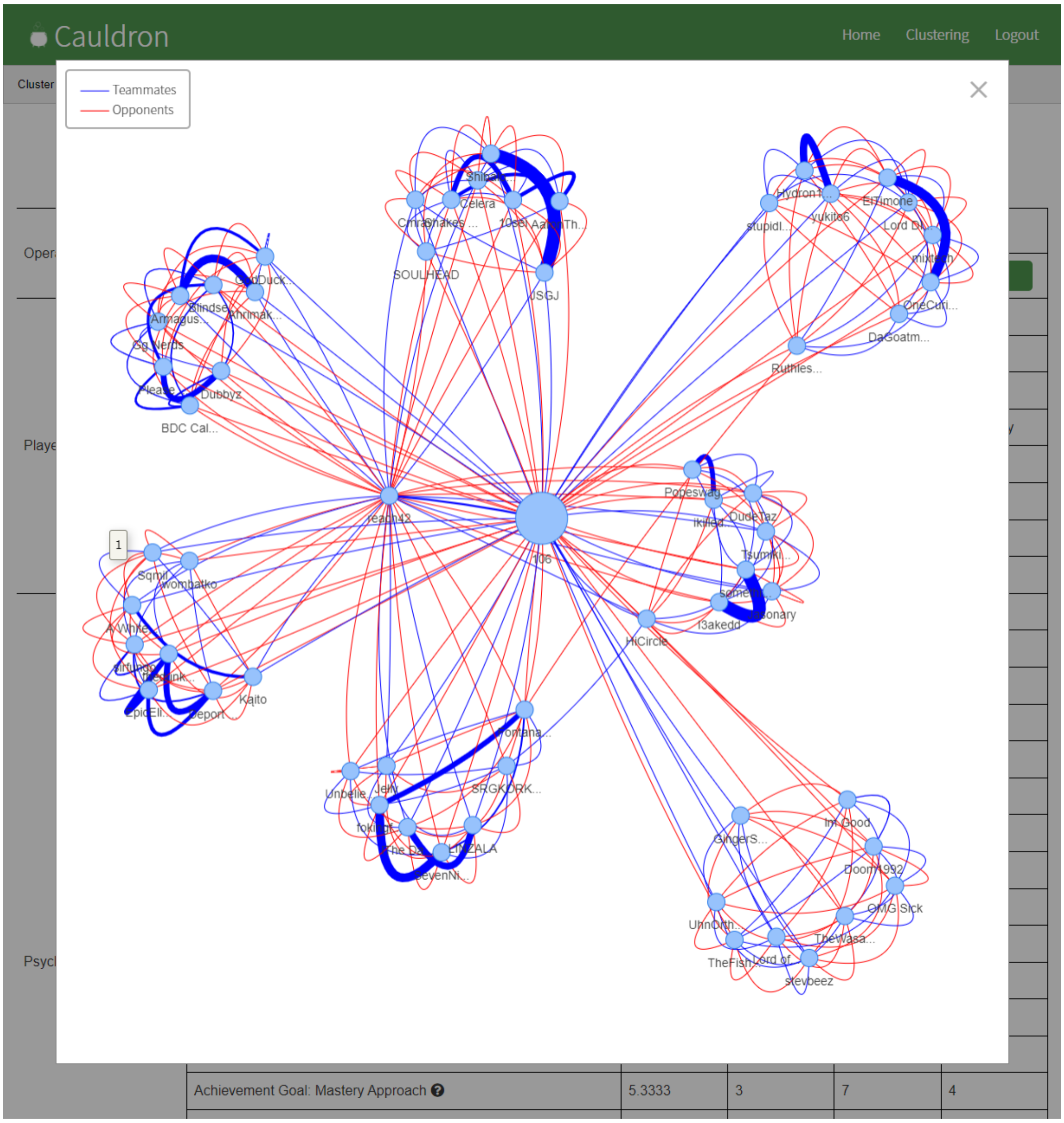


Figure 4.7: Network graph pop-up in player details page of the Cauldron web application

the use of the according feature. Just like in the player details section, they are separated again by their categories, omitting the general details which are mostly categorical and have no relevance for the purpose of clustering. Additional buttons let the player select or deselect all features at once.

Below the features, the operation to be conducted can be chosen in a drop-down menu. Depending on the selection, additional configuration parameters are shown and may be set. They include preprocessing and dimensionality reduction techniques as well as input

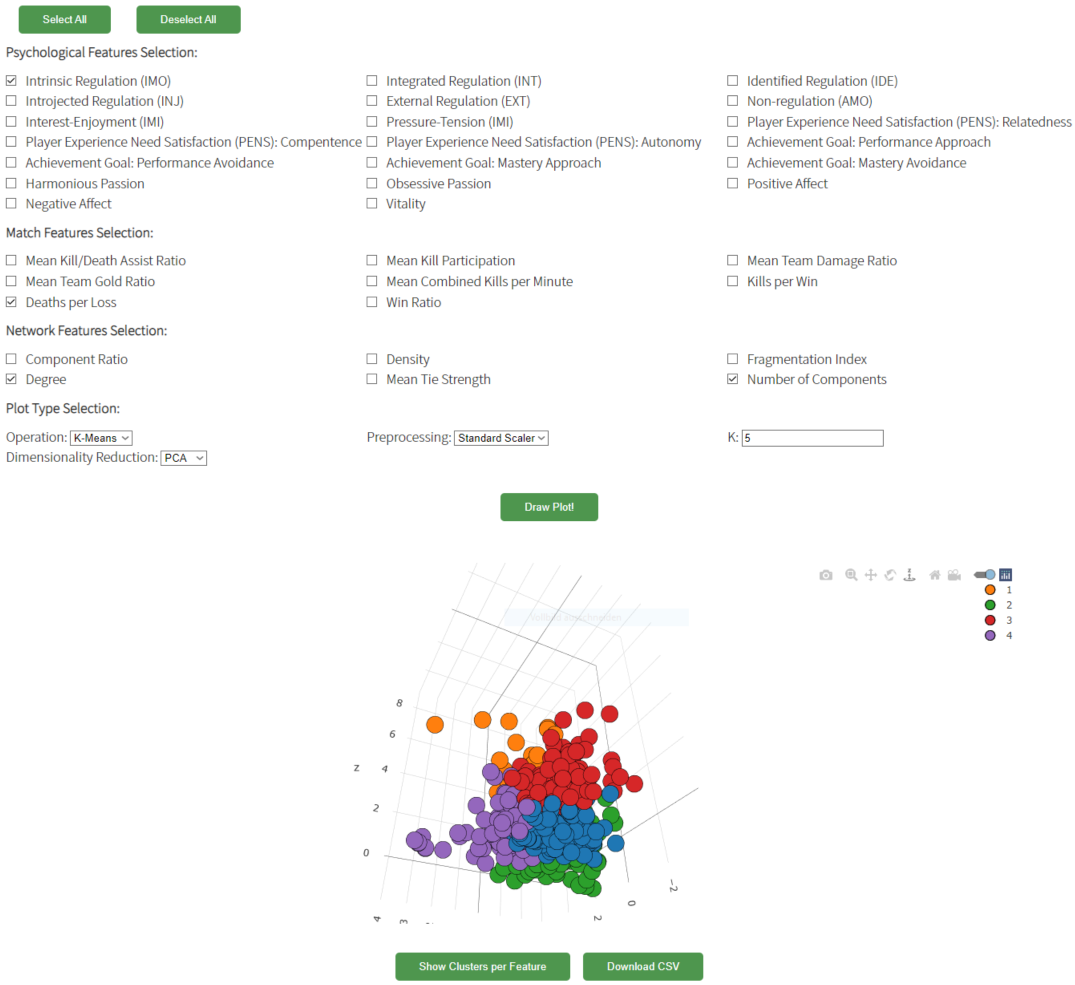


Figure 4.8: Clustering page of the Cauldron web application

parameters for the clustering operations. When a clustering operation is performed, two buttons beneath the resulting plot, which allow the user to show the clusters per feature in the Statistics section or download the clustering results as CSV file, are displayed (see Figure 4.8).

Statistics

Having all features that are available for clustering, each of them is also represented as a box plot that contains all data points which refer to the corresponding feature values of the players. At the bottom of the section, users can download a ZIP archive containing all visible plots as PNG files (see Figure 4.9).

Figure 4.9: Statistics page of the Cauldron web application

When navigating from the clustering section's *Show Clusters per Feature* button, each of the plots is split up in multiple, vertically arranged box plots which only contain the data points that are assigned to a specific cluster each (see Figure 4.10).

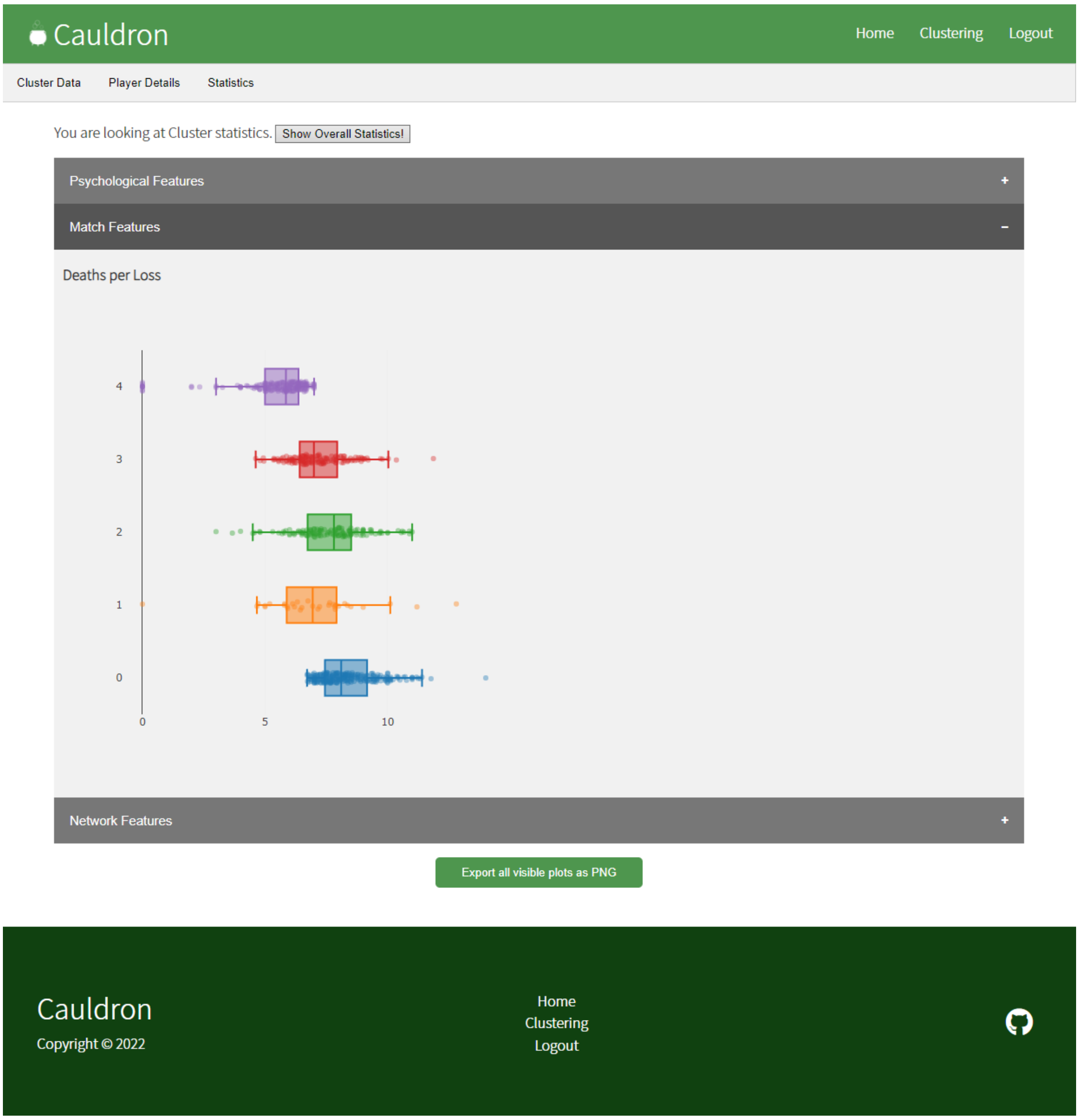


Figure 4.10: Statistics page of the Cauldron web application showing cluster-separated features

4.4.4 Evaluation

By following the *Start Evaluation* link (either through a reference on the website or shared messages and posts), a page with general information about the project and the evaluation modalities is displayed as shown in Figure 4.11. The text contains disclaimers about the usage of the data that will be gathered, contact information and the expected time that will be spent on it. By pressing the button to get started, a user object will be created in the backend database with an ID that will be referred to by collected evaluation information. Afterwards, a short introduction to the tool and its features is presented along with a small guide on how the tasks part of the evaluation is meant to be done.

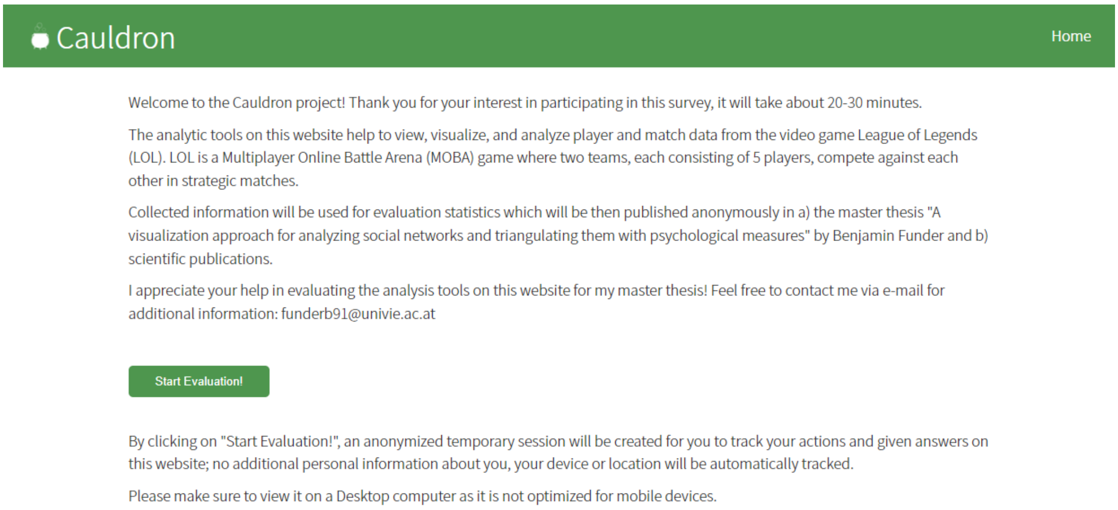


Figure 4.11: Introduction and disclaimers before starting the evaluation

For each task, the user will then see the description first and is redirected to the clustering page when clicking the Continue button (see Figure 4.12). Above the bottom taskbar, an extra section, the evaluation bar, is displayed in contrast red color. In there, task-specific values (solutions and findings) need to be entered before continuing to the next task by pressing the dark red button next to it. Additionally, the evaluation bar shows a short description of the current task on the left with a tooltip icon that will display the full description as seen on the page before.

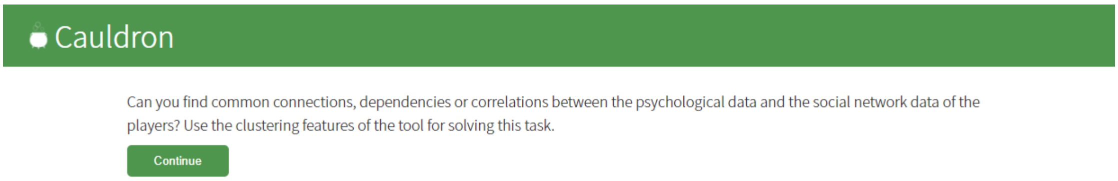


Figure 4.12: Page showing the description of the next task

The tasks part is followed by the survey part which consists of Likert scales, free text fields and radio button groups on four different pages, each with separate intent as described in Section 5.1.2. The different layouts of evaluation-related implementations for tasks, open questions and Likert scales are shown in Figures 4.13, 4.14 and 4.15, respectively.

Figure 4.13: Player details page of the Cauldron web application during an evaluation

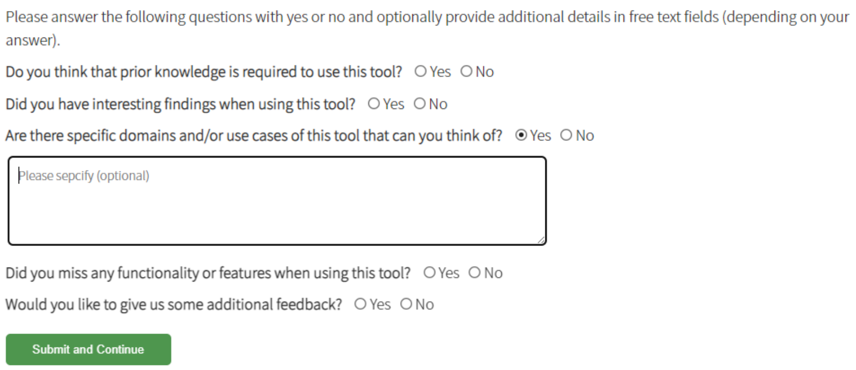


Figure 4.14: Evaluation survey page of the Cauldron web application showing open questions

For the assessment of this tool, please fill out the following questionnaire. The questionnaire consists of pairs of contrasting attributes that may apply to the tool. The circles between the attributes represent gradations between the opposites. You can express your agreement with the attributes by ticking the circle that most closely reflects your impression.

Please decide spontaneously. Don't think too long about your decision to make sure that you convey your original impression. Sometimes you may not be completely sure about your agreement with a particular attribute or you may find that the attribute does not apply completely to the particular product. Nevertheless, please tick a circle in every line. It is your personal opinion that counts. Please remember: there is no wrong or right answer!

Please assess the product now by ticking one circle per line.

	1	2	3	4	5	6	7	
annoying	○	○	○	○	○	○	○	enjoyable
not understandable	○	○	○	○	○	○	○	understandable
creative	○	○	○	○	○	○	○	dull
easy to learn	○	○	○	○	○	○	○	difficult to learn
valuable	○	○	○	○	○	○	○	inferior
boring	○	○	○	○	○	○	○	exciting
not interesting	○	○	○	○	○	○	○	interesting
unpredictable	○	○	○	○	○	○	○	predictable
fast	○	○	○	○	○	○	○	slow
inventive	○	○	○	○	○	○	○	conventional
obstructive	○	○	○	○	○	○	○	supportive
good	○	○	○	○	○	○	○	bad
complicated	○	○	○	○	○	○	○	easy
unlikable	○	○	○	○	○	○	○	pleasing
usual	○	○	○	○	○	○	○	leading edge
unpleasant	○	○	○	○	○	○	○	pleasant
secure	○	○	○	○	○	○	○	not secure
motivating	○	○	○	○	○	○	○	demotivating
meets expectations	○	○	○	○	○	○	○	does not meet expectations
inefficient	○	○	○	○	○	○	○	efficient
clear	○	○	○	○	○	○	○	confusing
impractical	○	○	○	○	○	○	○	practical
organized	○	○	○	○	○	○	○	cluttered
attractive	○	○	○	○	○	○	○	unattractive
friendly	○	○	○	○	○	○	○	unfriendly
conservative	○	○	○	○	○	○	○	innovative

Submit and Continue

Figure 4.15: Evaluation survey page of the Cauldron web application showing Likert scales

4.5 Code

This section addresses the structure of the application source code as well as implementation details regarding major features[1]. The tool was written in Python, JavaScript, HTML/Django and CSS using Microsoft Visual Studio Code as an Integrated Development Environment (IDE).

4.5.1 Structure

All functional code is designed as a Python module named *website* and resides in the same-called directory. Together with files needed for running the website, including the required modules, a script for local execution and a *Web Server Gateway Interface* (WSGI) configuration for servers, the files are wrapped within a superordinate folder called *app* that sits in the root directory of the project. *tasks*, another folder in the root directory, holds three Python scripts that are used for static data processing and an INI configuration file containing important data paths and terminology. Other root files include the GitHub configuration, a README text file and a Docker file for creating an image to run the application in a Docker container.

The Python module containing the website logic is separated into five subdirectories:

- Service
  - Python methods for processing and preparing data used in the different areas of the clustering page
- Blueprints
  - Flask blueprint files for defining URL paths and rendering webpages
- Templates
  - HTML Django templates with inline Python code rendered by Flask
- Static
  - Client-side code files written in JavaScript and CSS as well as image files for icons displayed on the website
- Constants
  - INI configuration files that contain human-readable terminology and descriptions for internally used variable names

In addition, a Python initialization file for setting up the application, an INI configuration file for declaring data paths and database access keys and a SQLAlchemy database user model reside in the main directory.

[1] The source code (without configuration files containing sensitive information) is available at `https://github.com/funderos/Cauldron`

4.5.2 Data management

As discussed in Section 3.2.2, the text-formatted match information was reduced and prepared to be used with the tool. Using two Python scripts within the *tasks* folder, the CSV-formatted results from the psychological survey and relevant features, including match and network statistics, were summarized in Python objects and stored in Pickle files. Depending on the match count for a player, the process of iterating through all its alters could take from a few seconds until a few hours. The resulting summarized files as well as dictionaries containing important key-value pairs that are also created by the scripts are used in the application afterwards.

During the evaluation phase, additional Pickle files containing Python dictionaries were created for each participant and updated with logs and user-provided information from the evaluation process. They contain every request to the server for that participant with the full URL including query parameters, the payload if present and a timestamp. This way, not only the task and survey fields are persisted locally, but also additional information about how tasks were approached and how much time was spent on them.

A third script processes the collected evaluation information. The results are collected and stored in a Microsoft Excel spreadsheet (XLSX) containing separate sheets for each evaluation user as well as a feedback overview. In addition, LaTeX-formatted tables and box plot graphics for use within these tables are generated and exported as plain text and PNG files, respectively. They are utilized in Chapter 5.

The files are stored in a regular file system. For both the application and the scripts, the paths to files and directories are configured in INI configuration files.

4.5.3 Visualization management

All graphics within the clustering page are interactive and created via JavaScript on the client side while the clustering itself is handled in the backend. Therefore, all transmitted network traffic is text only and relatively small of size.[2] For the statistics and clustering sections, the plotly.js library is utilized, the network graph visualizations use vis.js.

4.5.4 User management

Users need to authenticate themselves to use the clustering page which contains all the visualization and analysis functionality. With a valid username and password combination, they can login on the homepage and logout via a link in the navigation bar menu. There is no registration functionality on the website itself, but credentials can be read in from the configuration file and saved when triggering the workflow by visiting a specific URL. Evaluation participants are stored as users as well, however, they have a flag identifying them as such.

[2]The elbow plot generation was done using a matplotlib function on the backend and sent as SVG payload to the client side. Since this operation does not work when running the application in a docker container which was done after the evaluation phase, the function was later adapted to use the plotly.js frontend library as well with only transmitting data points via the REST API.

All users are stored within a SQLAlchemy database which's location is defined in the configuration file. If a user is inactive for 60 minutes, the session will become invalid.

4.6 Hosting & deployment

When building the web application, it was running locally on demand and could not be accessed from outside the local network. For internal presentations and during the evaluation phase, a WSGI service was running on a private server that could be accessed over the World Wide Web via a provided Uniform Resource Locator (URL). Since March 2022, the project is kindly hosted on a server of Johannes Kepler University Linz for permanent public access. As part of this deployment, the Dockerfile for creating a docker image has been added to the project.

5 Evaluation

The evaluation phase of the project started on the 9th of November, 2021 and ended on the 13th of December, 2021. During that period, the website has been hosted on a private server with evaluation functionality enabled. Due to contact restrictions caused by the COVID-19 pandemic, the survey has been done entirely online with links to the website shared on different platforms and sent to potentially interested individuals.

The benefits of evaluating the web tool are versatile as the feedback aims to provide a wider range of opinions on the following aspects:

- Scope and coverage
- Target audience
- Usability and experience
- Proper functionality
- Findings and insights

5.1 Method

To measure these criteria properly, an evaluation mode within the website extends the functionality discussed in Chapter 4 by accepting additional inputs explicitly marked as information that will be saved anonymously for evaluation purposes.

The evaluation mode consists of two main parts, namely tasks and surveys, which are done sequentially and split up in different subcomponents:

5.1.1 Evaluation Tasks

In the context of this work, tasks are different challenges the user should be able to tackle using the website's features. Each task requires entering the results found before proceeding to the next step of the evaluation pipeline.

While some tasks have explicit solutions and show whether the user understands the navigation on the website as well as the use of its features properly, other ones are requesting findings and results by looking at and interpreting computed and visualized data. In addition, the requests to the server and the time spent for a task are also logged.

To cover all functionality of the website, the six tasks described in Table 5.1 have been defined for evaluating the tool. The goals behind choosing them are discussed in the following.

Task Number	Task Description	Expected Solution(s)
Task 1	View the provided tools in the different tabs and feel free to play around. Try to understand what they are for and how they can be used.	-
Task 2	Try to find out the Identified Regulation (IDE) value as well as the age of the player with ID 1273.	Age: 19, IDE: 2
Task 3	One player has got an exceptional high mean tie strength. Find out how many matches this player participated in are included in the used dataset.	Match Count: 241
Task 4	Can you find common connections, dependencies or correlations between the psychological data and the social network data of the players? Use the clustering features of the tool for solving this task.	-
Task 5	View the network graph of the player with the ID 1149. Can you spot some features and derive information about that player's play style or social connections based on the given numerical features?	-
Task 6	Which player features do you think are most important for clustering? Which can be easily omitted or may even distort a meaningful result? Which clustering method works best for you?	-

Table 5.1: Table containing the descriptions and explicit solutions (if applicable) for Tasks 1-6

Task Goals

Task 1: Familiarization The first task aims at getting the evaluation participant used to the navigation and available actions provided on the website. For proceeding, no input of results is therefore expected here.

Task 2: Get the age and IDE of the player with ID 1273 The first challenge is kept easy by intention and should confirm whether the user has understood the purpose of the different sections. Getting static features like age and IDE of a player is done by navigating to the Player details section, selecting the given ID and looking at the details. The two requested values have to be provided before moving on to the next step.

Task 3: Get the match count from player with high mean tie strength This is another task with an explicit value being requested. However, getting to this static feature cannot be simply done within the Player details section as the ID of the player with a high mean tie strength is not known. The intended way of solving is navigating to the Statistics section and looking at the box plots to find the plot for high mean tie strength. As there is only one clear outlier, the user can click on it which will trigger a redirect action to the Player details section, showing the details including the match count. Alternatively, the ID can be directly read from the box plot scale and selected manually afterwards for showing the details.

Task 4: Cluster data and find correlations The first prompt with an open answer addresses the Clustering section and its capabilities. Specifically in this case, the user should look out for correlations between the psychological data and the ego network features of players by making use of the different clustering options and looking at the results.

Task 5: View the network graph of the player with ID 1149 to derive playing habits Task 5 requires an individual solution to be submitted in the form of free text as well, however, focuses on the network graph visualization feature and its visualization options found in the Player details section. Participants are asked to display the network of a specific player with the given ID and derive conclusions regarding the play style or social connections.

Task 6: Find useful clustering feature combinations In the last task, the Clustering section should be utilized again to determine the most important and the most neglectable features to take into consideration for clustering, as well as the most efficient clustering method. Trying different features and clustering combinations, the user may identify which variables are dependent on each other and which are not, as well as how much each of them influences the results.

For finishing this section of the evaluation and proceeding to the next step by completing the task, there are three lists with selectable elements in them – one for selecting the important features, one for selecting the neglectable features and the third one for choosing the algorithm that worked best.

5.1.2 Evaluation Survey

The survey component aims to determine the overall impression of the participants. It is incorporated into the evaluation process on the website but does not require the use of the tool itself anymore.

The mandatory usability and user experience questionnaires used are a compact way of collecting all the feedback necessary for proper evaluation, especially considering the expected knowledge gap between the target audience and participant backgrounds. With a big focus on usability, the response also helps to understand how self-explanatory the tool is and whether certain explanations or guidance are missing.

Additional free text feedback and basic details about the participants are included in the survey as well and further discussed alongside the questionnaires in the following.

User Experience Questionnaire (UEQ)

The UEQ aims to maximize the usability coverage of a software product and became a popular measurement for user experience that has been proven reliable throughout several studies. The simplicity of the questionnaire also ensures fast execution and is suitable for online evaluation [42][43].

The questionnaire has 26 different items, each consisting of a pair of perception features that have opposite meaning and are separated by a seven-point Likert scale. Participants have to choose the value which describes their experience best within this range. Half the features range from positive to negative, the other half vice versa and the order of the items can be randomized.

There are six main scales the 26 items are assigned to:

- Attractiveness
  - Annoying – Enjoyable
  - Good – Bad
  - Unlikable – Pleasing
  - Unpleasant – Pleasant
  - Attractive – Unattractive
  - Friendly - Unfriendly
- Perspicuity
  - Not understandable – Understandable
  - Easy to learn – Difficult to learn
  - Complicated – Easy
  - Clear – Confusing
- Efficiency
  - Fast – Slow
  - Inefficient – Efficient
  - Impractical – Practical
  - Organized – Cluttered
- Dependability
  - Unpredictable – Predictable
  - Obstructive – Supportive
  - Secure – Not secure
  - Meets expectations – Does not meet expectations
- Stimulation
  - Valuable – Inferior
  - Boring – Exciting
  - Not interesting – Interesting
  - Motivating – Demotivating

- Novelty
  - Creative – Dull
  - Inventive – Conventional
  - Usual – Leading Edge
  - Conservative – Innovative

System Usability Scale (SUS)

A similar approach with 5-point Likert scales is the SUS which focuses on the usability including training, need for support and complexity. In contrast to the UEQ, statements instead of features are rated and it is less comprehensive with 10 items [44].

- I think that I would like to use this system frequently.
- I found the system unnecessarily complex.
- I thought the system was easy to use.
- I think that I would need the support of a technical person to be able to use this system.
- I found various functions in this system were well integrated.
- I thought there was too much inconsistency in this system.
- I would imagine that most people would learn to use this system very quickly.
- I found the system very cumbersome (awkward) to use.
- I felt very confident using the system.
- I needed to learn a lot of things before I could get going with this system.

Lewis did a comprehensive study about the development and validation of the SUS and strongly recommend its use in research [45]. For the evaluation of this tool, the term *system* has been replaced by *tool* to fit the environment.

Open Questions

The six open questions are written specifically for this tool and allow to give open text feedback on several topics:

- Do you think that prior knowledge is required to use this tool? Which knowledge is required?
- Did you have interesting findings when using this tool? Which findings did you have?

- Are there specific domains and/or use cases of this tool that can you think of? Please specify.
- Did you miss any functionality or features when using this tool? Please specify.
- Would you like to give us some additional feedback? Please specify.

The questions have to be answered with no or yes and are expected to be further specified if choosing the latter one (although users can leave the according free text fields empty).

Participant details

In this section, the participants may provide their age and gender as well as giving information about their prior experience in certain topics using 5-point Likert scales. The domains (listed alongside the self-reported values in Table 5.2) have been chosen with regard to expert knowledge people have in the target audience (see Section 1.1 and 4.1.1). Knowing the relation between the experience and other evaluation feedback, the overall results are expected to be more expressive.

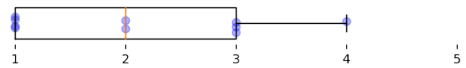
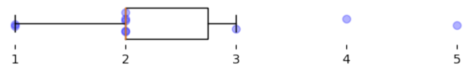
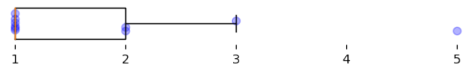
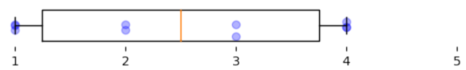
Data Mining	No knowledge		Expert
Data Analytics	No knowledge		Expert
Social Network Analysis	No knowledge		Expert
Player Communities in video games	No knowledge		Expert
League Of Legends	No knowledge		Expert

Table 5.2: Table containing the self-reported knowledge

5.2 Result overview

The total number of participants aggregates to 40 of whom 10 finished the evaluation and therefore provided a complete result data record. For the assessment of the survey data, only those complete records were taken into consideration. The age of the participants ranges from 23 to 33 with the average being 29.2. 70% are male, 20% female and 10% preferred to not disclose their gender. The distribution of experience presented as box plots can be observed in Table 5.2.

In the following sections, the findings are presented and, in part, visualized. The results are separated by the evaluation methods introduced in Section 5.1.

5.3 Task results

For the tasks the users were asked to carry out, all individual requests within the website were logged. Table 5.3 shows box plots containing the number of requests for each task as well as the calculated average value for the time spent accordingly. This indicates how much time and effort the participants devoted themselves to solving the tasks. In addition to this, the content of the individual requests and the path they form reveal their navigation behaviour and is considered as well when discussing the given answers and their expressiveness in the next chapter.

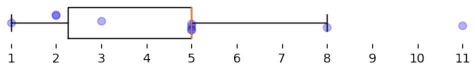
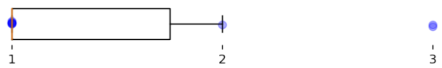
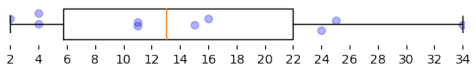
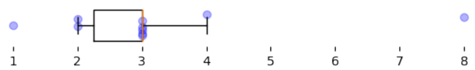
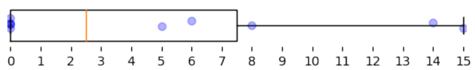
Task Number	**Number of requests**	**⌀ Completion time**
Task 1		151.08 seconds
Task 2		60.05 seconds
Task 3		293.33 seconds
Task 4		550.83 seconds
Task 5		311.04 seconds
Task 6		248.7 seconds

Table 5.3: Table containing the number of requests and the mean completion time for Tasks 1-6

5.3.1 Navigation task performance

While Task 1 does not require any solution at all, Task 2 and 3 are designed to evaluate the navigation performance as the user is prompted to provide explicit values tied to certain player data. Table 5.4 contains the percentages of users that provided the correct solutions for these tasks.

The overall performance for the second task aggregates to 90% while the third, more difficult task was only answered correctly in 70% of the cases.

Task Number	Requested attribute	% solved
Task 2	Age	80
Task 2	IDE	100
Task 3	Match Count	70

Table 5.4: Table containing the percentages of correct answers given for each task with a predefined solution

5.3.2 Findings task performance

The next two tasks were about findings participants had using the clustering and graph visualization features. As open text answers were prompted here, the results are presented in the following. The manually summarized expressions contain the essence of the feedback participants provided for each task, e.g., differently worded, but semantically similar statements were pooled together.

70% of the participants were not able to find correlations using the clustering feature, partly while stating that they did not understand resulting plots or the use of the feature. The negative feedback about navigation and missing information is summarized in Section 5.4.2. The other 30% claimed that they were able to see connections using the tool, stating the following explicitly (each statement occurred only once):

- Correlation between Harmonious Passion and Degree/Number of components
- Proportionality between Kills per Win and Positive Affect
- Indirect proportionality between Achievement Goal and Combined Kills per minute

For the fifth task, only 10% stated to have found nothing while the other participants made assumptions by looking at the network graph or the numerical features of the requested player, namely (Numbers in brackets denote occurrences):

- Solo player with automatically matched teammates (based on having different teammates except for a single common one) (4)
- Rarely plays the game (based on other players/opponents who have more alters) (3)
- Above-average social (based on PENS/Relatedness) (1)
- High interest and enjoyment (1)
- Defensive playstyle (based on damage and kill participation) (1)
- Alters from disjunct separate pools in regards of density (1)

#	**(Sub-)Set of selected features**
5	Kills per Win
3	Kills per Win, Player Experience Need Satisfaction (PENS): Autonomy Interest-Enjoyment (IMI)	Player Experience Need Satisfaction (PENS): Competence	Player Experience Need Satisfaction (PENS): Autonomy	Win Ratio
2	Player Experience Need Satisfaction (PENS): Autonomy, Kills per Win, Player Experience Need Satisfaction (PENS): Relatedness, Player Experience Need Satisfaction (PENS): Competence Achievement Goal: Mastery Approach, Interest-Enjoyment (IMI), Achievement Goal: Performance Approach	Player Experience Need Satisfaction (PENS): Autonomy, Player Experience Need Satisfaction (PENS): Relatedness, Player Experience Need Satisfaction (PENS): Competence	Kills per Win, Player Experience Need Satisfaction (PENS): Relatedness, Player Experience Need Satisfaction (PENS): Competence	Kills per Win, Player Experience Need Satisfaction (PENS): Relatedness, Player Experience Need Satisfaction (PENS): Autonomy	Player Experience Need Satisfaction (PENS): Autonomy, Kills per Win, Player Experience Need Satisfaction (PENS): Competence	Mean Team Damage Ratio, Mean Kill Participation, Win Ratio Interest-Enjoyment (IMI), Achievement Goal: Performance Approach	Achievement Goal: Mastery Approach, Interest-Enjoyment (IMI)	Achievement Goal: Mastery Approach, Achievement Goal: Performance Approach	Player Experience Need Satisfaction (PENS): Relatedness, Player Experience Need Satisfaction (PENS): Competence	Player Experience Need Satisfaction (PENS): Relatedness, Player Experience Need Satisfaction (PENS): Autonomy	Kills per Win, Player Experience Need Satisfaction (PENS): Relatedness	Player Experience Need Satisfaction (PENS): Autonomy, Player Experience Need Satisfaction (PENS): Competence	Kills per Win, Player Experience Need Satisfaction (PENS): Competence	Mean Team Damage Ratio, Mean Kill Participation	Mean Kill Participation, Win Ratio	Mean Team Damage Ratio, Win Ratio	Kills per Win, Win Ratio	Kills per Win, Interest-Enjoyment (IMI)	Kills per Win, Deaths per Loss	Kills per Win, Degree Mean Tie Strength	Achievement Goal: Performance Approach	Achievement Goal: Mastery Approach	Player Experience Need Satisfaction (PENS): Relatedness	Mean Kill Participation	Mean Team Damage Ratio	Deaths per Loss	Degree	Density

Table 5.5: Table containing the preferred (sub-)sets of features that have been given in Task 6, grouped by their occurrence counts and sorted by the size of the set (# = occurrence count for the sets of selected features in the according row)

5.3.3 Effectiveness task performance

The 6th and last task aimed to further investigate the different clustering techniques and the selection of features to use with it for finding well-working configurations. 30% of the participants did not state important or neglectable features, table 5.5 shows how often certain groups of features were marked as relevant. The most popular algorithm for the use cases within this evaluation is k-Means as 60% chose it as their preferred one, followed by OPTICS and Spectral Clustering with 20% each.

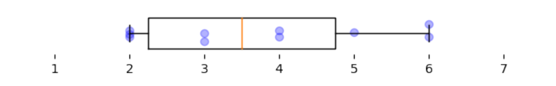
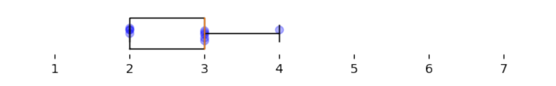
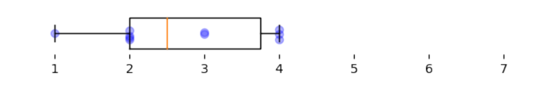
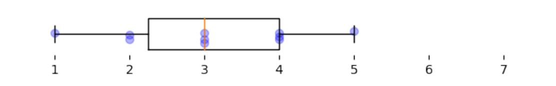
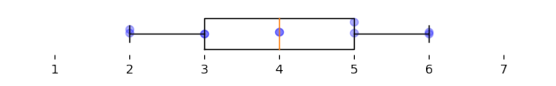
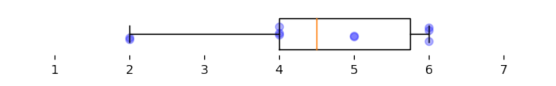
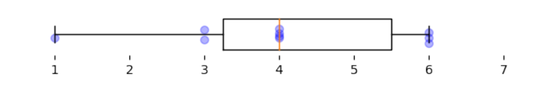
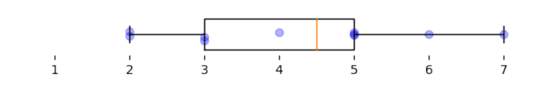
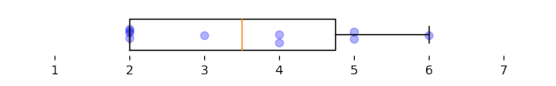
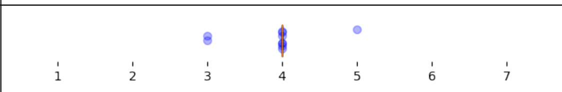
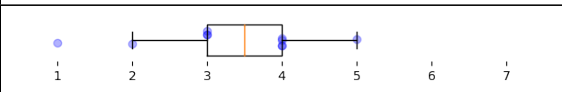
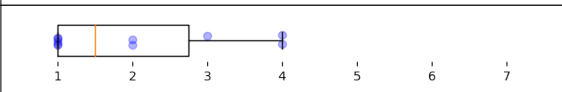
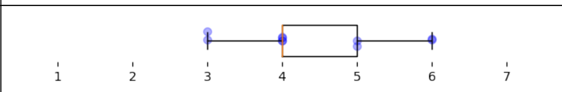
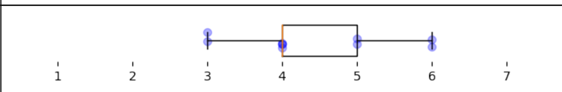
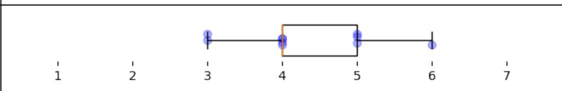
Except for the fragmentation index, all features in sets marked as irrelevant, which are listed below, have been named only once within the evaluation:

- Win Ratio
- Component Ratio, Density, Fragmentation Index, Degree
- Intrinsic Regulation (IMO), Integrated Regulation (INT), Identified Regulation (IDE), Introjected Regulation (INJ), External Regulation (EXT), Non-regulation (AMO), Interest-Enjoyment (IMI), Pressure-Tension (IMI)
- Mean Tie Strength, Number of Components
- Harmonious Passion, Obsessive Passion
- Fragmentation Index (2)
- Mean Combined Kills per Minute, Kills per Win, Deaths per Loss

5.4 Survey results

5.4.1 Likert scales

The results of the UEQ and the SUS show how the participants felt and thought of the website in general, rating different statements and properties on Likert scales ranging from 1 to 5 and 1 to 7. The user feedback is presented as box plots in Tables 5.6 and 5.7 for UEQ and SUS, respectively.

annoying		enjoyable
not understandable		understandable
creative		dull
easy to learn		difficult to learn
valuable		inferior
boring		exciting
not interesting		interesting
unpredictable		predictable
fast		slow
inventive		conventional
obstructive		supportive
good		bad
complicated		easy
unlikable		pleasing
usual		leading edge
unpleasant		pleasant

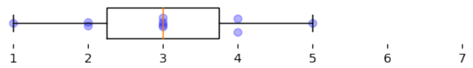
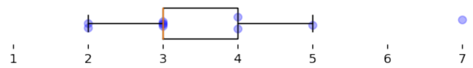
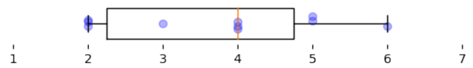
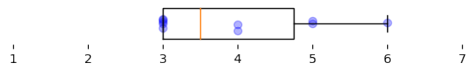
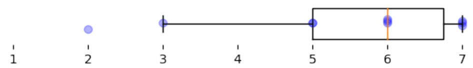
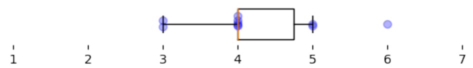
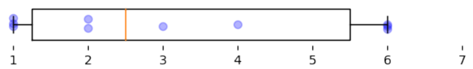
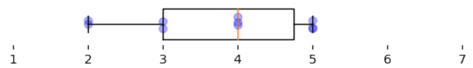
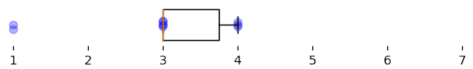
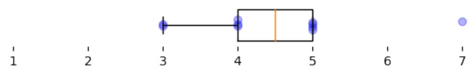
secure		not secure
motivating		demotivating
meets expectations		does not meet expectations
inefficient		efficient
clear		confusing
impractical		practical
organized		cluttered
attractive		unattractive
friendly		unfriendly
conservative		innovative

Table 5.6: Table containing the feedback from the UEQ

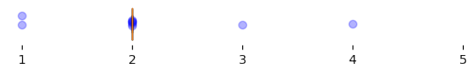
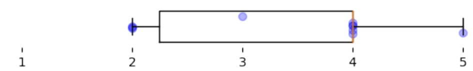
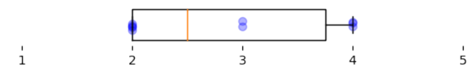
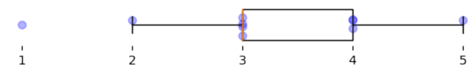
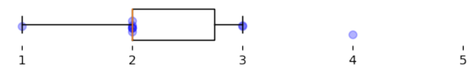
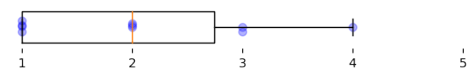
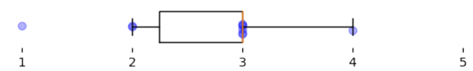
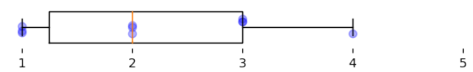
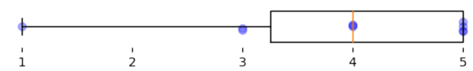
I think that I would like to use the tool frequently.	Strongly Disagree		Strongly Agree
I found the tool unnecessarily complex.	Strongly Disagree		Strongly Agree
I thought the tool was easy to use.	Strongly Disagree		Strongly Agree
I think that I would need the support of a technical person to be able to use the tool.	Strongly Disagree		Strongly Agree
I found the various functions in the tool were well integrated.	Strongly Disagree		Strongly Agree
I thought there was too much inconsistency in the tool.	Strongly Disagree		Strongly Agree
I would imagine that most people would learn to use the tool very quickly.	Strongly Disagree		Strongly Agree
I found the tool very cumbersome (awkward) to use.	Strongly Disagree		Strongly Agree
I felt very confident using the tool.	Strongly Disagree		Strongly Agree
I needed to learn a lot of things before I could get going with the tool.	Strongly Disagree		Strongly Agree

Table 5.7: Table containing the feedback from the SUS

5.4.2 Open feedback

In the third section of the survey, users were asked if they want to give additional feedback on certain topics. As mentioned in Section 5.1.2, providing the feedback was entirely optional, even when participants affirmed the corresponding question. Like the task results based on open text (presented in Section 5.3.2), the following summarized expressions contain the essence from statements within the according survey parts.

Prior Knowledge

All participants agreed that prior knowledge is required for using the tool. The following domains have been specified in particular:

- Statistics and box plots (4)
- Clustering and 3D cluster plots (2)
- Social Networks (2)
- Psychology and related features used (5)
- LOL and player attributes (5)
- E-Sports (1)

User findings

30% of the users claimed to have interesting findings during the evaluation. For this matter, however, only one participant used the opportunity to specify his positive answer by mentioning that the players are really young.

Domains and use cases

One half of the participants could think of domains and use cases where the tool may be utilized while the following examples have been specified explicitly:

- Finding correlations between mental and social factors on player performance/win rate (2)
- HR Data Clustering (1)
- Social Networks (1)

Missing features

For evaluating how complete the set of features for this tool is, users were asked if they are missing certain functionality. Again, half of the users voted yes and specified the following aspects:

- Axis descriptions for plots (2)
- Selected Champion (player attribute) (1)
- Search for players by attributes (1)
- Accessible documentation or a help tool (1)

General feedback

Finally, participants were asked to give any additional feedback they have in mind. 40% provided their opinion here, however, the summary below also contains parts of other free text submissions that contained more information than the corresponding fields were intended for. Repeated statements from the same participant in different fields were counted only once.

- Unclear meaning of plots (and their axes) (5)
- Unclear meaning of player attributes (3)
- Unclear meaning of ego network graph edges (2)
- No explanations for clustering methods and their parameters (2)
- No tutorial (2)
- Complex interface (1)
- Evaluation bar at the bottom not fixed (1)
- Likert scales do not always reach from positive to negative association (1)
- Explanations for Statistics features are obsolete (1)
- Clustering sometimes loads infinitely (1)
- Easy understandable UI (1)

6 Discussion

In the discussion, the experience and knowledge gathered by using the tool is further elaborated with a strong focus on feedback from evaluation participants. Also, personal expectations are reviewed with regard to the status of the finalized project. Each of the following four sections relates to one of the research questions introduced in Section 1.3.

6.1 R1: Data visualization

Although the different sources of data and clustering results are presented in various ways, primarily the player network graphs and their customization options set the tool apart from similar approaches in comparable domains. The structures in both small and big communities are interesting to analyze and compare, as smaller assumptions can be easily derived by just looking at them. Evaluation participants endorse this with interesting findings in the course of solving the fifth task (see Sections 5.3.2 and 6.4).

Preparing the data has been done beforehand for all players, as the translation can take – depending on the number of matches – more time to finish. The exponential growth also shows in rendering the graphs in terms of visual complexity and loading times. Bigger graphs can be hard to analyze and second level networks in the corresponding display mode are collapsed by default with respect to this. Also, when graph structures with more than 200 nodes are to be drawn, a confirmation dialog will arise to notify the user that loading will take more time and may impact the browser performance if they continue. The decision to display the number of played matches next to each player ID in the drop-down menu is heavily influenced by this challenging aspect as well.

Another visualization of data within the tool, besides having player details in text form, are the box plots for viewing the distribution of numerical values for each player per feature. The individual clustering results are presented in three-dimensional scatter plots with the axes representing compound attributes built from all selected features by the dimensionality reduction techniques.

6.2 R2: Features

While the statistics, player details and network graphs present the underlying data in different ways, clustering algorithms help finding correlations between features with computational effort. The results can be viewed as dimensionality reduced 3D plots and feature statistics per cluster or exported as CSV-formatted file for further processing.

One user reported a bug where clustering data leads to an infinite loading loop. By looking into according requests, this happens, if less than three features are selected to include for clustering as the dimensionality reduction techniques are not working properly then. This case has not been considered when implementing and testing the solution; other than that, no bugs or faulty results were mentioned by evaluation participants.

6.3 R3: Usability

Both the questionnaires and the written feedback indicate a bad usability of the tool. The main point of criticism concerns bad or lacking explanations for the features as well as for plotted data. Looking at the request paths evaluation participants took, especially the graph visualization options were not easy to find or use, thus, navigation issues probably occurred as well.

The answers given in the SUS scored a total of 42,25 (out of 100 possible) points, following the official guidelines for calculation [44]. In the UEQ, the Perspicuity scale also performed poorly while other user experience features like attractiveness and novelty achieved moderate (but not exceptionally high) results. Besides Figure 6.1, where the results are visualized, the official UEQ analysis sheet [43] provides many additional statistics and diagrams.

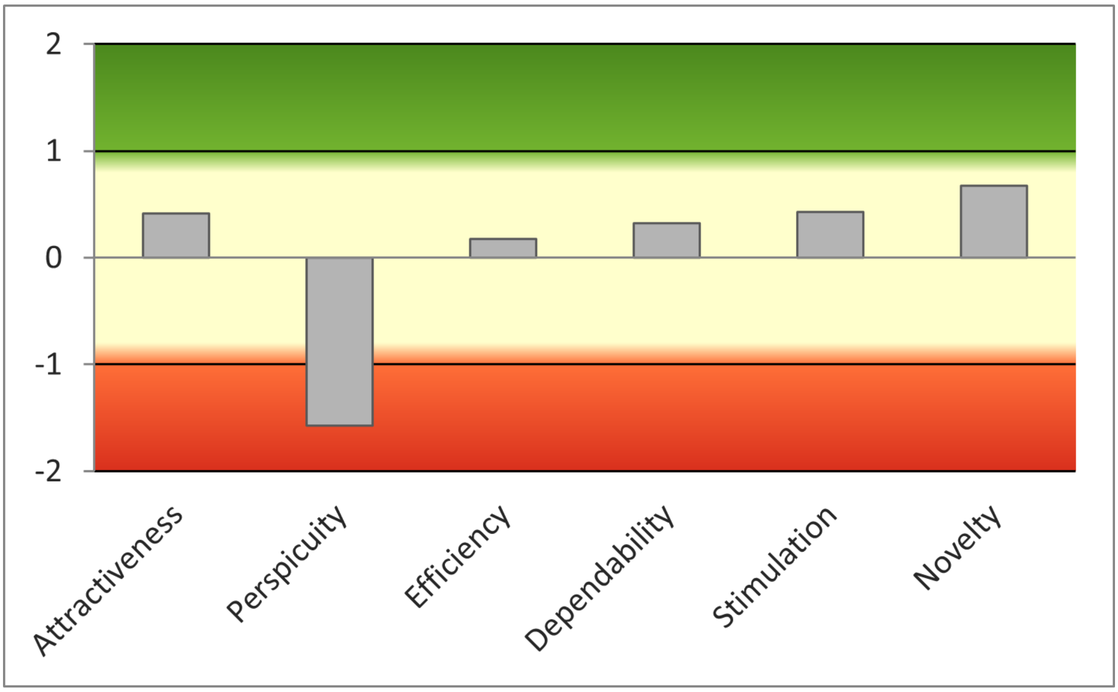


Figure 6.1: Diagram showing the mean values for each scale, generated by the UEQ Data Analysis Excel sheet [43]

6.4 R4: Data coherences

Evaluation participants have been given tasks to utilize the cluster and graph visualization functionalities of the tool in order to derive more general information about a player or detect coherences within and across different data sources. The results listed in Section 5.3.2 show that 30-90% (depending on the feature used) of the users were able to find correlations between psychological features and game/network statistics. Also, by solely looking at the graph or singular psychological scores of a player, they were able to create a small profile (with two findings being in common, namely that a specific player seems to have randomly matched players as teammates and rarely plays the game). This shows that certain attributes or network graphs can help understanding player behaviour more easily or even making it self-explanatory. However, according to the individual request paths, people especially seemed to struggle with using the graph visualization feature and its options.

In the last task of the evaluation, the most expedient clustering type as well as features that are especially relevant or irrelevant to include could be specified. Besides having k-Means as their favorite algorithm, the match statistic *Kills per Win* is the most popular feature with being chosen 50% of the time. However, in clustering applications, not necessarily single characteristics but the right combination of them is the essential key for getting good results [46]. Based on this, the layout of Table 5.5 has been chosen, where the item subsets are ordered by their size within the separation of occurrences.

The four-item subset that has been mentioned twice sticks out here, but in general, the results from Task 6 are lacking expressiveness due to the low number (10) of eligible participants and, according to the clustering requests, questionable derivations (also see Section 6.5). When asked for general findings made in the open feedback section, only one of the approving participants further specified his answer by mentioning that *LOL* players are very young.

6.5 Limitations

6.5.1 Evaluation participation

After filtering out records from participants that did not finish the evaluation, only ten datasets of survey data could be used. Consequently, the resulting scores for the UEQ and SUS questionnaires may lack in expressiveness. In addition, due to low prior knowledge or difficulties in using certain features, given answers for tasks probably have suffered because the tool could not be used properly.

Another limitation is that most participants presumably do not belong to the target audience of the project. Although many of them stated to have prior knowledge in some of the relevant domains (see Table 5.2), more experts (especially with equal knowledge in multiple categories) participating would have led to more meaningful results. The lack of understanding core clustering concepts is reflected in the navigation behavior as well as in the written feedback.

The low participation rate can be attributable to the potentially unsuitable period that has been chosen. During the winter and a few weeks before Christmas, people may have been too stressed out to gain motivation for doing the whole evaluation which took up to 30 minutes to complete. In addition, after nearly two years of the COVID-19 pandemic, there has been another lockdown in the country of Austria where the evaluation was primarily promoted.

6.5.2 Hard data structure dependencies

The data used in this project have very specific structures that are probably unique outside of their sources. Although preparation is done outside of application code, the tool still features hardcoded parts in the frontend that have to be rewritten to allow automatized handling of data from different sources; f.e. other psychological features or play statistics from other video games that are structured differently.

6.5.3 Extent of feature customization and pool of attributes

Most of the features provided with the tool come with a few parametrization options. However, although not mentioned explicitly in evaluation feedback, there may be demand for additional parameters and visualizations that cannot be done in the current state of the website from domain experts.

The provided attributes chosen to cluster *LOL* players could be modified and extended as well. The initial datasets contain additional information that may be relevant in other use cases. However, getting all descriptive information (without using it for clustering) for a specific player can be done easily by using the unique identifiers the corresponding records are tagged with.

6.6 Future Work

While the scope of the project has met the proposed requirements, the mentioned limitations clearly show that there is room to expand it further. Aside from the usability aspect that has been criticized by evaluation participants, the tool could feature more clustering methods and parametrization options. Also, additional customization options for visualizing and exporting data as well as clustering results could be beneficial for research. In further consequence, the user account management could be expanded to save or bookmark certain results or visualizations.

With respect to the open feedback (as listed in Section 5.4.2), the following concrete ideas may be implemented:

- Updated, more expressive feature descriptions
- 3D plot axes labels with corresponding feature composition details
- Search and filter options for players

- A help page explaining details about the tool functionality
- More intuitive navigation and separation of functionality
- Fixing the evaluation bar on the bottom during task solving in evaluation mode
- Prevent using less than three features for clustering

7 Conclusion

Except for minor technology changes in comparison to the master thesis proposal, the planning and implementation of the project could be realized without major inconveniences. The research topic which entitles this work is successfully met by creating the website and its features.

The evaluation results show mixed feedback. Especially the strong dependence on prior knowledge in multiple topics and lacking usability have been criticized while the functionality and scope itself did not receive negative comments from the survey participants. Considering this fact, as well as other suggestions given by them, a broader introduction to the topic and more detailed explanations of the features attached to players would have resulted in a better understanding. Also, the way the page navigation and the clustering methods work assume an expert user with prior experience.

By analyzing the different features and ego network graphs attached to players, users were able to derive assumptions about their playstyle. In addition, they found coherences using the clustering feature, indicating dependencies between psychological features and the player network or match details.

Bibliography

[1] M. Sh Levin. Combinatorial clustering: Literature review, methods, examples. *Journal of communications technology and electronics*, 60(12):1403–1428, 2015.

[2] Inc. Riot Games. League of legends website. `https://www.leagueoflegends.com/`. Accessed: 2022-03-25.

[3] ActivePlayer.io Game Statistics Authority. Most played games. `https://activeplayer.io/most-played-games/`. Accessed: 2022-12-08.

[4] Florian Brühlmann, Philipp Baumgartner, Günter Wallner, Simone Kriglstein, and Elisa D. Mekler. Motivational profiling of league of legends players. *Frontiers in Psychology*, 11, 2020.

[5] Pallets. Flask website. `https://palletsprojects.com/p/flask/`. Accessed: 2022-07-21.

[6] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.

[7] vis.js community. vis-network website. `https://visjs.github.io/vis-network/docs/network/`. Accessed: 2022-07-21.

[8] Plotly Technologies Inc. Collaborative data science. `https://plot.ly`, 2015. Accessed: 2022-07-21.

[9] Karen E. Dill and Jody C. Dill. Video game violence: A review of the empirical literature. *Aggression and Violent Behavior*, 3(4):407–428, 1998.

[10] Celia Hodent. *The psychology of video games.* The psychology of everything. Routledge, Taylor and Francis Group, !c 2021., London, 2021.

[11] Benjamin Funder. Quantitative analysis and visualization of ego networks. 2020. 053049 SE Master Seminar, University of Vienna.

[12] Nick Crossley, Elisa Bellotti, Gemma Edwards, Johan Koskinen, Mark Tranmer, and Martin G Everett. *Social network Analysis for Ego-Nets.* Sage Publications Ltd, United Kingdom, August 2015.

[13] Brea L. Perry, Bernice A. Pescosolido, and Stephen P. Borgatti. *Egocentric Network Analysis: Foundations, Methods, and Models*. Structural Analysis in the Social Sciences. Cambridge University Press, 2018.

[14] Marçal Mora-Cantallops and Miguel Ángel Sicilia. Player-centric networks in league of legends. *Social Networks*, 55:149–159, 2018.

[15] Inc. Riot Games. Riot developer portal. `https://developer.riotgames.com/`. Accessed: 2022-08-22.

[16] Cuihua Shen. Network patterns and social architecture in massively multiplayer online games: Mapping the social world of everquest ii. *New Media & Society*, 16(4):672–691, 2014.

[17] Daybreak Game Company LLC. Everquest 2 website. `https://www.everquest2.com/`. Accessed: 2022-09-15.

[18] Joshua A. Eaton, David J. Mendonça, and Matthew-Donald D. Sangster. Attack, damage and carry: Role familiarity and team performance in league of legends. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 62(1):130–134, 2018.

[19] Mayra Z. Rodriguez, Cesar H. Comin, Dalcimar Casanova, Odemir M. Bruno, Diego R. Amancio, Luciano da F. Costa, and Francisco A. Rodrigues. Clustering algorithms: A comparative approach. *PLOS ONE*, 14(1):1–34, 01 2019.

[20] Tauno Metsalu and Jaak Vilo. Clustvis: a web tool for visualizing clustering of multivariate data using principal component analysis and heatmap. *Nucleic acids research*, 43(W1):W566–W570, 2015.

[21] Marçal Mora-Cantallops and Miguel Ángel Sicilia. Moba games: A literature review. *Entertainment Computing*, 26:128–138, 2018.

[22] Valve Corporation. Dota 2 website. `https://www.dota2.com/home`. Accessed: 2022-03-25.

[23] Inc. Riot Games. How to play - league of legends website. `https://www.leagueoflegends.com/en-gb/how-to-play/`. Accessed: 2022-03-25.

[24] Richard M Ryan and Edward L Deci. Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *The American psychologist*, 55(1):68–78, 2000.

[25] Center for Self-Determination Theory. Intrinsic motivation inventory (imi). `https://selfdeterminationtheory.org/intrinsic-motivation-inventory/`. Accessed: 2022-03-25.

[26] Richard M Ryan, C Scott Rigby, and Andrew Przybylski. The motivational pull of video games: A self-determination theory approach. *Motivation and emotion*, 30(4):344–360, 2006.

[27] A. J. Elliot and H. A. McGregor. A 2 x 2 achievement goal framework. *Journal of personality and social psychology*, 80(3):501–519, 2001.

[28] Robert J Vallerand, Céline Blanchard, Geneviève A Mageau, Richard Koestner, Catherine Ratelle, Maude Léonard, Marylène Gagné, and Josée Marsolais. Les passions de l'Âme: On obsessive and harmonious passion. *Journal of personality and social psychology*, 85(4):756–767, 2003.

[29] David Watson, Lee Anna Clark, and Auke Tellegen. Development and validation of brief measures of positive and negative affect: The panas scales. *Journal of personality and social psychology*, 54(6):1063–1070, 1988.

[30] Richard M. Ryan and Christina Frederick. On energy, personality, and health: Subjective vitality as a dynamic reflection of well-being. *Journal of Personality*, 65(3):529–565, 1997.

[31] Inc. Esports One. Stats 101: Popular league of legends stats. `https://esportsone.com/stats-101-league-of-legends/`. Accessed: 2022-08-13.

[32] Dipanjan Sarkar. Categorical data, Jan 2018. `https://towardsdatascience.com/understanding-feature-engineering-part-2-categorical-data-f54324193e63`, Date of last access: 2020-11-26.

[33] J. B. MacQueen. Some methods for classification and analysis of multivariate observations. In L. M. Le Cam and J. Neyman, editors, *Proc. of the fifth Berkeley Symposium on Mathematical Statistics and Probability*, volume 1, pages 281–297. University of California Press, 1967.

[34] Martin Ester, Hans-Peter Kriegel, Jörg Sander, and Xiaowei Xu. A density-based algorithm for discovering clusters in large spatial databases with noise. In *Proceedings of the Second International Conference on Knowledge Discovery and Data Mining*, KDD'96, page 226–231. AAAI Press, 1996.

[35] Mihael Ankerst, Markus M. Breunig, Hans-Peter Kriegel, and Jörg Sander. Optics: ordering points to identify the clustering structure. *SIGMOD record*, 28(2):49–60, 1999.

[36] Ulrike Luxburg. A tutorial on spectral clustering. *Statistics and Computing*, 17:395–416, 01 2004.

[37] Ian T Jolliffe. *Principal component analysis.* Springer series in statistics. Springer, New York, NY [u.a.], 1986.

[38] L.J.P van der Maaten and G.E Hinton. Visualizing high-dimensional data using t-sne. *Journal of machine learning research*, 9(nov):2579–2605, 2008.

[39] bradtraversy. Lokuri website github page. `https://github.com/bradtraversy/loruki-website`. Accessed: 2022-07-21.

[40] techwithtim. Flask web app tutorial github page. `https://github.com/techwithtim/Flask-Web-App-Tutorial`. Accessed: 2022-07-21.

[41] John Graham. Dropdown checkboxes codepen project. `https://codepen.io/RobotsPlay/pen/pyNLdL`. Accessed: 2022-07-21.

[42] Bettina Laugwitz, Theo Held, and Martin Schrepp. Construction and evaluation of a user experience questionnaire. In *HCI and Usability for Education and Work*, Lecture Notes in Computer Science, pages 63–76. Springer Berlin Heidelberg, Berlin, Heidelberg, 2008.

[43] Martin Schrepp, Andreas Hinderks, and Jorg Thomaschewski. Construction of a benchmark for the user experience questionnaire (ueq). *International journal of interactive multimedia and artificial intelligence*, 4(4):40, 2017.

[44] John Brooke. Sus: A quick and dirty usability scale. *Usability Eval. Ind.*, 189, 11 1995.

[45] James R. Lewis. The system usability scale: Past, present, and future. *International journal of human-computer interaction*, 34(7):577–590, 2018.

[46] Rui Xu and Don Wunsch. *Clustering*, volume 10 of *IEEE Press Series on Computational Intelligence*. Wiley-IEEE Press, Hoboken, 1. aufl. edition, 2008.