The basic reproductive ratio as a link between acquisition and change in phonotactics

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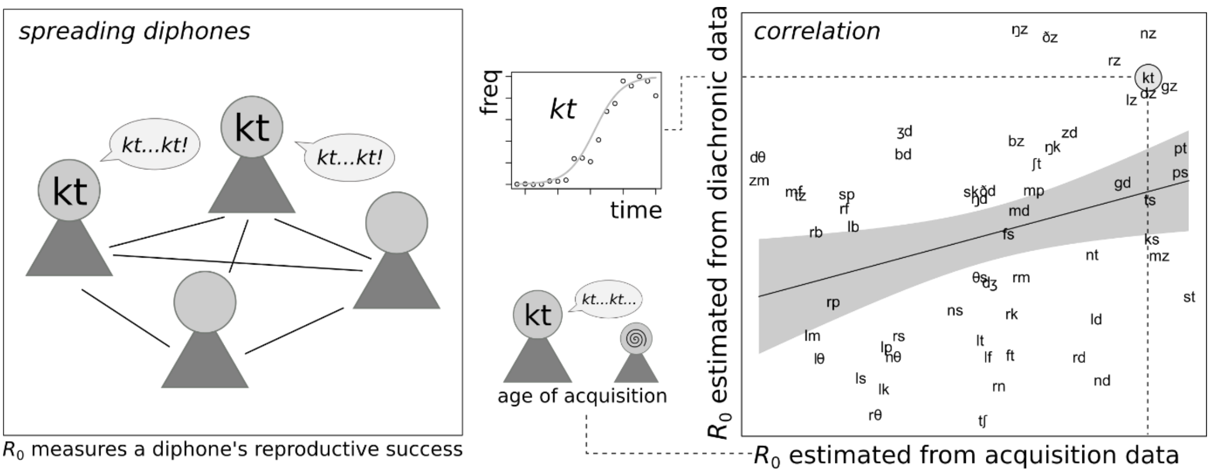
Abstract

Language acquisition and change are thought to be causally connected. We demonstrate a method for quantifying the strength of this connection in terms of the 'basic reproductive ratio' of linguistic constituents. It represents a standardized measure of reproductive success, which can be derived both from diachronic and from acquisition data. By analyzing English data, we show that the results of both types of derivation correlate, so that phonotactic acquisition indeed predicts phonotactic change, and *vice versa*. After drawing that general conclusion, we discuss the role of utterance frequency and show that the latter only exhibits destabilizing effects on late acquired items, which belong to phonotactic periphery. We conclude that – at least in the evolution of English phonotactics – acquisition serves conservation, while innovation is more likely to occur in adult speech and affects items that are less entrenched but comparably frequent.

Keywords: diachronic linguistics, language acquisition, reproductive success, basic reproductive ratio, phonotactics, dynamical systems



1 Introduction

Languages are systems of mental instructions that are shared by their speakers. They are instantiated in the mind-brains of many individuals and transmitted across generations through communicative interaction and language acquisition. For a constituent of linguistic knowledge to be successfully transmitted across generations, it needs to be used and expressed by adult speakers in such a way that new generations can acquire it successfully. Thus, the history of language constituents depends on language use and language acquisition and is likely to reflect constraints on both of them. This paper focusses on the relation between history and acquisition.

That language acquisition is crucial for language history is trivially true and generally acknowledged (Briscoe, 2008; Smith & Kirby, 2008). After all, constituents that are not acquired cannot survive. However, the matter is both more complex and more interesting than that. On the one hand, there is considerable disagreement about how much language acquisition contributes to linguistic change, and on the other hand, some correlations between acquisition and diachronic stability appear to be quite specific. For instance, Monaghan

(2014), demonstrates that the age at which a lexical item is acquired predicts the diachronic stability of its phonological form. The finding has inspired various attempts to account for it, but no consensus has been reached. On one interpretation, early acquisition is thought to cause diachronic stability: early acquired items become strongly entrenched, get to be used frequently, and are therefore more likely to be historically stable than items that are acquired later (MacNeilage & Davis, 2000; Monaghan, 2014). On another view, early acquisition and diachronic stability are thought to have common causes: items will both be acquired early and remain diachronically stable if they are easily produced, perceived, or memorized, for example.

This paper explores the relation between the diachronic stability of linguistic constituents and the age at which they are acquired. To determine how systematic that relation is, we introduce and test a rigorous quantitative model that relates patterns attested in historical language development to patterns attested in language acquisition. More specifically, we show how age-of-acquisition and diachronic stability can be related to each other in terms of a standardized measure of reproductive success, namely their 'basic reproductive ratio' (henceforth R_0) (Dietz, 1993; Heffernan, Smith, & Wahl, 2005). That measure (more on it below, see 2.1) has proved useful in the study of population-dynamics. We use a population dynamic model[1] that has already been applied to explain linguistic phenomena (Nowak, 2000; Nowak, Plotkin, & Jansen, 2000) and show in which way estimates of R_0 can be derived for linguistic constituents. Crucially, they can be derived both from age-of-acquisition data and from diachronic corpus evidence. By comparing the two estimates, one

[1] That model we use is similar to mathematical models of cultural and linguistic change (Cavalli-Sforza and Feldman (1981); Wang and Minett (2005); Niyogi (2006)) and equivalent to basic epidemiological models (Anderson and May (1991); see also Sperber (1985)).

can then put numbers on the relation between language acquisition and language history. Thus, the model provides a method for relating data of different origins mechanistically.

Empirically, our discussion is based on English word-final CC diphones (i.e. consonant clusters containing two segments). They are short, yet clearly structured linguistic constituents (Kuperman, Ernestus, & Baayen, 2008), and have had long and diverse histories. For instance, the word final cluster /nd/ as in English *land* is likely to have existed already more than 5000 years ago in Indo-European, the ancestor of English. It still thrives today. Many others, however, such as /gz/ or /vz/ as in English *legs* or *loves*, emerged much more recently, i.e. about 800 ago in the Middle English period. There are also considerable differences among the histories of individual clusters as far as their frequencies are concerned. Some of them, such as /xt/ – graphically still reflected in words like *knight* or *laughed* – have disappeared altogether.

Since (a) there is considerable diversity among the historical developments of final consonant clusters, and since (b) the ages at which they are acquired are similarly diverse, English consonant clusters are highly suitable for our purpose. They allow us to see clearly whether the reproductive ratios that population dynamic models derive from historical evidence and acquisition data actually correlate or not. We show that they do and interpret this as proof of the concept that models which derive R_0 for linguistic constituents are capable of relating language acquisition and language history in a meaningful way.

Thus – and although we are interested in the specific phenomena we investigate – our primary concern is in fact more general. In the context of testing the usefulness of population dynamic models for linguistic purposes, we address questions such as the following: (a) Does the age at which consonant clusters are acquired correlate with their historical stability? (b) Is there a single measure that relates these two properties? (c) What can be learnt from such measurements about causal relations between language acquisition and language history?

For (a) and (b), our study suggests positive answers: models developed in the study of evolutionary dynamics do indeed provide systematic and quantifiable correlations between the historical development of final clusters and the age at which are acquired. With regard to (c), we ask if the correlation between acquisition and diachronic stability differs between morpheme internal clusters (such as /mp/ in *lamp*) and morphologically produced ones (such as /gz/ in *eggs*), and whether the correlation between age-of-acquisition and historical stability is affected by utterance frequency. We show that the morphological status of clusters does not seem to matter much, but that the correlation between age-of-acquisition and historical stability is tighter among frequent than among rare clusters. Our results corroborate the view that phonological change may be more strongly driven by frequent use in adult speech (Bybee, 2007), and that early acquired core items are more resistant against frequency-driven effects like reduction, assimilation, or deletion. Thereby, our study contributes to the debate on the role which language acquisition plays in language change.

In terms of its general approach, our paper relates to a growing body of research that views culturally transmitted knowledge in evolutionary terms and models it accordingly (Cavalli-Sforza & Feldman, 1981; Dawkins, 1976; Henrich & Boyd, 2002; Newberry, Ahern, Clark, & Plotkin, 2017). It is also based on the view that the repeated learning events involved in cultural history can amplify and make visible cognitive biases that are too weak to be traceable in the behavior of individuals (Reali & Griffiths, 2009; Smith et al., 2017; Smith & Wonnacott, 2010).

We describe our modeling approach together with both ways of estimating the basic reproductive ratio in Section 2. After that, we introduce the statistical tools (3) which are used to empirically test our model against data from phonotactic acquisition and diachrony. The results of our analysis (4) are finally discussed in Sections 5 and 6, thereby particularly focusing on the effect of utterance frequency.

2 Data and methods

2.1 Standardizing reproductive success: basic reproductive ratio

Our analysis employs a modified version of the population dynamical model of linguistic spread proposed by Nowak and colleagues (Nowak, 2000; Nowak et al., 2000; Solé, 2011). For each linguistic constituent, i.e. in our case for each cluster, the model consists of two differential equations that track the growth of the number of 'users' U (speakers that know and use the cluster), and the number of 'learners' L that do not (yet) know or use it.

When users and learners meet, learners acquire the cluster at a rate $\alpha > 0$, whereby they become users (i.e. switch from class L to class U). Conversely, at a rate $\gamma = 1/G$, where $G > 0$ is linguistic generation time, users 'die' (i.e. are removed from class U) and learners are 'born' (i.e. added to class L). The respective rates of change thus read

$$\begin{aligned} \dot{L} &= -\alpha LU + \gamma U \\ \dot{U} &= \alpha LU - \gamma U \end{aligned}$$

where we set $L + U = 1$.[2]

The expected number of learners that acquire a cluster from a single user introduced into a population of learners is $R_0 = \alpha/\gamma$ (Hethcote, 1989). R_0 represents what has been labelled 'basic reproductive ratio' (Anderson & May, 1991; Nowak, 2000). It figures

[2] For $\gamma = 1$, the above system is exactly the model of word dynamics in Nowak (2000). In his model, α depends on the utterance frequency and learnability of a word, as well as on the number of informants a learner is exposed to (network density).

centrally in epidemiological research due to its straightforward properties: whenever it holds for a population (e.g. a subpopulation of infected individuals) that $R_0 > 1$, that population increases in size and spreads.

In our model, $R_0 > 1$ entails that the population of users approaches a stable equilibrium $\widehat{U} = 1 - \gamma/\alpha = 1 - 1/R_0$, so that $\hat{L} = 1/R_0$. If, on the other hand, $R_0 < 1$, the fraction of users approaches 0. The linguistic item vanishes.

R_0 represents a standardized measure of reproductive success that reflects the diachronic stability of linguistic items. Its greatest asset is that it can be derived from different types of data and that all derived estimates are situated on the same scale. Thus, estimates derived from different data types can be compared directly and without further transformation. In our paper, we exploit this for comparing the R_0 derived from diachronic frequency data to the R_0 derived from language-acquisition data. We show that such a comparison yields interesting perspectives on the relation between age of acquisition and historical stability.

2.2 Estimating reproductive success from diachronic growth

The model of linguistic spread outlined in the previous section can be reformulated in terms of a logistic equation (Hethcote, 1989; Solé, Corominas-Murtra, & Fortuny, 2010) with an intrinsic (potentially negative) growth rate $\rho = \alpha - \gamma$. Thus, if the linguistic generation time $G := 1/\gamma$ and the growth rate ρ are known, then α and $\alpha/\gamma = 1 + \rho G =: R_0^{\mathrm{GR}}$ can be determined. We approximate G, i.e. the average time it takes for new language learners to enter the population, by biological generation time, so that $G \cong 30$ years (Worden, 2008). This leaves the intrinsic growth rate ρ to be determined.

In order to estimate the intrinsic growth rates ρ of final CC clusters, we use logistic growth rates r_{lg} obtained from diachronic frequency data as a proxy (see also the discussion in section 5). For that purpose, we determine a trajectory of normalized token frequencies f from 1150 to 2012 for each word-final CC cluster. The token frequencies were retrieved from various historical and contemporary language databases and corpora (see Table 1, which also indicates who carried out the phonological interpretation). The collected data were divided into periods of 50 years, yielding 18 data points for each final CC cluster.

Table 1. Diachronic data covering the lineage from Early Middle English to Contemporary American English. Data were binned into periods of 50 years each (e.g. 1200 denoting 1200-1250 below). In the case of overlapping data sets (e.g. PPCMBE2 and COHA in the 19$^{\text{th}}$ century) weighted averages based on both corpus sizes were used to compute frequencies. Since we trace the American English lineage (COHA, COCA), phonological transcriptions for the late periods were taken from CMPD.

<table>
<tr><th>Sources for frequencies</th><th>Covered periods</th><th>Phonological interpretation</th></tr>
<tr><td>PPCME2 (Kroch & Taylor, 2000)</td><td>1150,1200,…,1450</td><td rowspan="2">[Authors]</td></tr>
<tr><td>PPCEME (Kroch, Santorini, & Delfs, 2004)</td><td>1500,1550,…,1700</td></tr>
<tr><td>PPCMBE2 (Kroch, Santorini, & Diertani, 2016)</td><td>1700,1750,…,1900</td><td rowspan="3">CMPD (Carnegie Mellon Speech Group, 2014)</td></tr>
<tr><td>COHA (Davies, 2010)</td><td>1800,1850,…,1950</td></tr>
<tr><td>COCA (Davies, 2008)</td><td>2000</td></tr>
</table>

We chose 1150 to 2012 as our observation period because word final CC clusters were rare before (i.e. in Old English). The vast majority of them was only first produced by schwa loss in final syllables, which started roughly at this time (Minkova, 1991). Note that although the phonological process of schwa loss affected word final sequences quite uniformly in the early Middle English period, the different cluster types it produced developed relatively independently of each other after schwa loss was completed (in the 15th century). This reflects the post-medieval influx of loans ending in CC clusters as well as phonological processes other than schwa loss – for instance final devoicing – that produced new clusters. For most of the observation period the dynamics of the individual cluster types can thus be considered as relatively independent from each other.

The derived trajectories were normalized to the unit interval with respect to their maximum values, and subsequently fit to a logistic model given by $f(t) = 1/(1 + \exp(-r_{\mathrm{lg}}(t - t_0)))$, where t_0 was set at the middle of the observation period. Non-linear least-squares regression was used to estimate r_{lg} for each cluster. The quality of this estimate depends on the actual shape of the empirical trajectory. Since the model presupposes (positively or negatively) unidirectional development, r_{lg} estimates can be unreliable for clusters who show (inverse) U-shaped developments. Therefore, we also computed Spearman's Rho ($\mathrm{P_{sp}}$) for each cluster. We excluded clusters for which $|\mathrm{P_{sp}}|$ scored below the threshold of 0.1, to rule out clearly non-monotonous developments.[3] This also eliminated clusters that occurred only sporadically in a few periods. Finally, we did not consider final

[3] We are grateful to an anonymous reviewer for addressing the issue of non-monotonous patterns. The employed threshold $|\mathrm{P_{sp}}| > 0.1$ is relatively mild, as we wanted to keep our data set reasonably large. It excludes only trajectories that are strongly non- monotonous. The qualitative results of this paper still apply up to a threshold of $|\mathrm{P_{sp}}| \sim 0.3$.

cluster types that are absent in Present Day English such as /mb/ in *limb* because there are no data on the age at which they are acquired. Thus, a total of 58 final CC types entered our analysis (Table A1 in the appendix). For the purpose of illustration, Figure 1 shows logistic models for nine different cluster types: for instance, /kt/ exhibits a sigmoid increase in frequency (i.e. $r_{\text{lg}} > 0$ and $R_0^{\text{GR}} > 1$), while /rn/ becomes less frequent ($r_{\text{lg}} < 0$ and $R_0^{\text{GR}} < 1$).

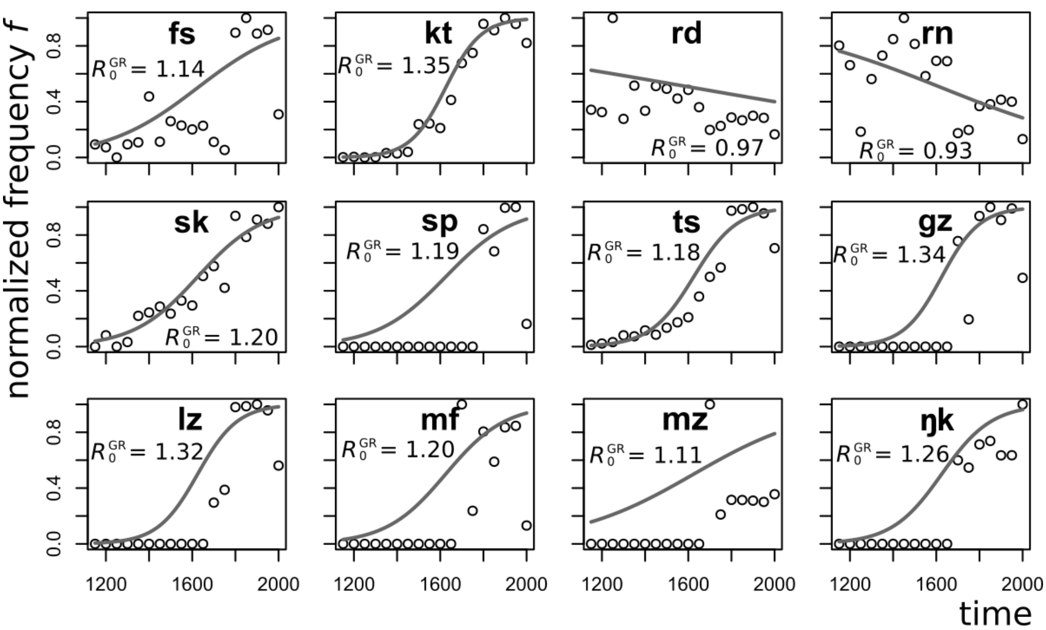


Figure 1. Logistic growth curves for a set of English word-final CC-clusters. All clusters show a non-trivial monotonous development (decreasing or increasing). The graphs were selected in order to represent a large variety of diachronic patterns. In some cases (e.g. /sk/, /ts/, /sk/) trajectories fit the logistic pattern remarkably well. In other cases (e.g. /rn/, /fs/, /sp/) they don’t. Some clusters feature extremely low frequencies in early periods.

2.3 Estimating reproductive success from age of acquisition

Next, we derived R_0 estimates from language acquisition data. Here, our derivation follows Dietz (1993). The population of linguistic agents is once again split into a fraction L of 'learners' and a fraction U of 'users' for each linguistic item. AoA denotes the age of acquisition of that item and LE denotes the life expectancy of an individual. Under the assumption of a roughly rectangular age structure (Dietz 1993), at equilibrium $\mathrm{LE}/\mathrm{AoA} = (\hat{L} + \hat{U})/\hat{L} = R_0 =: R_0^{\mathrm{AoA}}$. It is therefore sufficient to estimate AoA, as long as LE is known. For the sake of simplicity, we assume a constant life-expectancy of $\mathrm{LE} \cong 60$ years (Lancaster, 1990: 8).[4]

Our estimates for the AoAs of 58 final clusters are based on Kuperman et al.'s (2012) AoA ratings for 30,000 English words. These ratings were collected in a broad crowdsourcing study among speakers of American English and correlate highly with ratings obtained under laboratory conditions (see also Monaghan 2014). The AoA of a cluster type was operationalized as the mean of the AoA ratings of the three earliest-acquired word-forms containing it. Averaging over the first three acquired items containing a cluster yields a more robust measure of its AoA than considering only the very earliest word containing it. Since we treat CC clusters as linguistic constituents in their own right (and not just as properties of words), we consider their acquisition to require exposure to more than a single word containing them. Nevertheless, we operationalize the AoA of a cluster as a point estimate that

[4] Note that the results presented in Section 4 are qualitatively robust with respect to altering life expectancy since R_0^{AoA} scales linearly with LE. Nevertheless, incorporating time dependent LE would represent an interesting but substantially more complex extension of our method.

divides the life of a speaker into a period before and a period after acquisition of that cluster (i.e. the transition date from L to U).[5]

Word-forms in which final CC clusters result from morphological operations (such as /gz/ in the plural *egg+s*) received the AoA rating of the base forms contained the data set (e.g. *egg*). There are two reasons why this is likely to yield plausible estimates. First, the lowest AoA rating in our data is 2.74, and the majority of English inflectional morphology is acquired during between 2.25 to 3.75 years (Brown, 1973). Furthermore, it has been shown that in languages which are morphologically poor (such as English as opposed to Polish) there is no significant difference between the ages at which morphologically produced and morpheme-internal clusters are acquired (Korecky-Kröll et al., 2014, p. 48). Transcriptions were once again taken from CMPD.

2.4 Utterance frequency

Frequency has often been argued to affect the diachronic stability of linguistic items (Bybee 2007). Thus, Pagel et al. (2007) show that the rate of phonological change in the lexicon can be predicted from the frequency of word use. At the same time, frequent words are acquired earlier than rare ones (Kuperman et al. 2012). This suggests that frequency increases reproductive success. On the other hand, utterance frequency has also been shown to drive phonological erosion. Frequent words are also comparably expectable and therefore more tolerant of reduction (Bybee & Hopper 2001; Diessel 2007). Thus, it is unclear if frequency should increase or decrease the diachronic stability of CC clusters.

[5] This operationalization of AoA is most compatible with the underlying population dynamical model. We found that the exact operationalization of AoA is crucial to the comparison of the two derived R_0 estimates. AoA ratings for clusters that are derived from the AoAs of all words containing it get implausibly high because some of those words are inevitably acquired extremely late and unlikely to play any role in the acquisition of a cluster.

In order to investigate that issue, our study takes frequency into consideration as an additional factor. Since cluster-specific utterance frequencies fluctuate during the observation period, we first extracted per million normalized token frequencies for all cluster types in every single period of 50 years. In addition, we computed average token frequencies for each cluster type across all 18 periods, denoted as $\langle \mathsf{frequency} \rangle$ in order to obtain a more compact summary measure (see Table A1 in the appendix).

2.5 Morphology

While syntax or pragmatics have little immediate influence on word internal phonotactics, morphology affects it strongly. Thus, many word-final CC clusters result from morphological operations (Dressler, Dziubalska-Kołaczyk, & Pestal, 2010; Hay & Baayen, 2005). As far as the acquisition of morpheme-internal phonotactics is concerned, however, we do not expect morphology to contribute much (see 2.3). In our observation period, English syntheticity (i.e. the amount of morphological operations) underwent a non-uniform development which exhibits a U-shaped curve, as demonstrated by Szmrecsanyi (2012). Thus, the interaction of morphology and the diachronic dynamics of word-final phonotactics is a priori not so clear. In order to account for morphological effects in our analysis, we classified final CC types as (a) (exclusively) morphologically produced (and 'illegal' within morphemes, e.g. /md/ in *seemed*), (b) (exclusively) morpheme internal ('legal', /lp/ in *help*), or (c) both ('mixed', /nd/ in *hand* and *planned*).

3 Calculation

To explore the relative impact and the interaction of the different factors, we employed linear models (LM) and generalized additive models (GAM, Wood, 2006a). First, z-normalized estimates of R_0^{GR} (the reproductive ratio derived from diachronic growth data) and R_0^{AoA} (the reproductive ratio derived from age-of-acquisition data) entered a LM as dependent and independent variables (Model 1a). No transformation (e.g. log) was needed for either variable. The effect of morphology (‘illegal’; ‘mixed’; ‘legal’; the latter as default) was analyzed by adding a linear interaction term to the previous model (Model 1b).

Analyzing the interaction of frequency with the derived R_0 measures is more complicated because it involves time as an additional factor. Initially (Model 2), normalized (i.e. z-transformed) log-transformed average frequency, $\langle\mathrm{frequency}\rangle$, was integrated as an interacting variable into a GAM, in which R_0^{AoA} figures as predictor and R_0^{GR} as dependent variable. The interaction between R_0^{AoA} and logged $\langle\mathrm{frequency}\rangle$ was modeled by means of a tensor-product term (Wood, 2006b). The effects of logged $\langle\mathrm{frequency}\rangle$ on R_0^{GR} and R_0^{AoA} were then evaluated in two separate GAMs (Model 3a and 3b, respectively). In both of them, logged $\langle\mathrm{frequency}\rangle$ figures as predictor (smooth term). Finally, the interaction of time and logged frequency – both affecting R_0^{GR} and R_0^{AoA} respectively –, was modeled as a tensor product term in two additional GAMs (model 4a and 4b, respectively).[6]

4 Results

The direct comparison of the two estimates of R_0 (model 1a, Fig. 2) reveals a non-trivial linear relationship between the two variables (standardized coefficient $\beta_{\mathrm{AoA}} = 0.31 \pm 0.13 SE$ at $p = 0.016$). Adding morphology (model 1b) does not reveal a statistically significant interaction and decreases the explanatory power of the model ($\beta_{\mathrm{AoA}} = 0.20 \pm$

[6] All models based on Gaussian distribution with identity link. The number of knots in smooth terms was deliberately kept low in order to detect monotone and easy to interpret (but still possibly nonlinear) relationships.

$0.23SE$; $\beta_{\text{AoA}\times\text{mixed}} = -0.04 \pm 0.33SE$; $\beta_{\text{AoA}\times\text{illegal}} = 0.48 \pm 0.37SE$).[7] Thus, we can assume the discovered correlation to hold irrespective of morphological status.

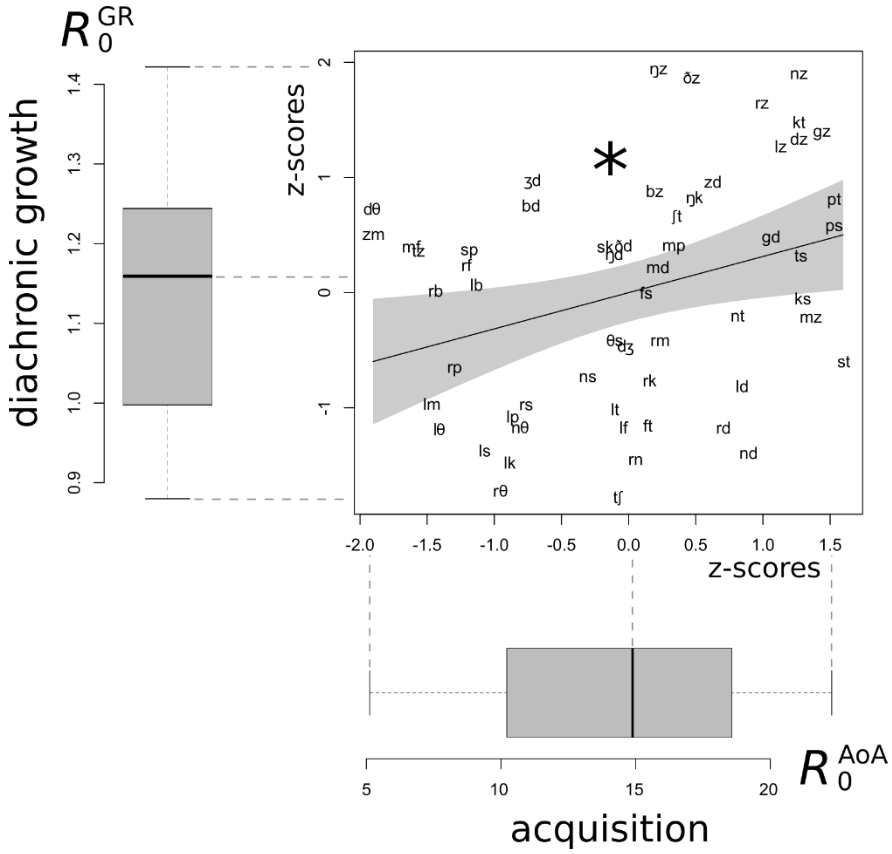


Figure 2. Linear relationship between normalized estimates of R_0^{GR} (vertical axis) and R_0^{AoA} (horizontal axis) (model 1; $p < 0.05$). Gray areas denote 95% confidence regions. Boxplots next to the vertical and horizontal axis indicate the distribution of R_0^{GR} and R_0^{AoA}, respectively. Scores derived from acquisition data are considerably higher than scores estimated from diachronic data.

[7] Model 1a: $R^2(\text{adj}) = 0.08$, $F = 6.13$, $p = 0.016$, $AIC = 163.56$; model 1b: $R^2(\text{adj}) = 0.10$, $F = 3.05$, $p = 0.04$, $AIC = 164.5$; model 2: $R^2(\text{adj}) = 0.11$, 16.5% explained deviance; model 3a: $R^2(\text{adj}) = 0.05$, 7.00% explained deviance; model 3b: $R^2(\text{adj}) = 0.36$, 37.5% explained deviance; model 4a: $R^2(\text{adj}) = 0.20$, 20.7% explained deviance; model 4b: $R^2(\text{adj}) = 0.33$, 34.1% explained deviance.

Model 2 (Fig. 3a, right) reveals that the relationship between R_0^{GR} and R_0^{AoA}, established in model 1, is much tighter for frequent clusters (e.g. /ns/ as in *hence* vs. /st/ as in *best*) than for infrequent ones, where it is approximately constant (/rp/ as in *harp* vs. /lk/ as in *milk*; interaction term: $df = 4.33, F = 4.76, p < 0.001$). Another way of looking at Fig. 3a is this: in the phonotactic core inventory (i.e. among early acquired clusters), frequency does not affect diachronic stability, while in the phonotactic periphery (among late acquired clusters), frequency reduces it significantly (Fig 3a, left).

In model 3a (Fig. 3b), $\langle\text{frequency}\rangle$ correlates negatively with R_0^{GR} (smooth term: $df = 1, F = 4.20, p = 0.045$; linear effect $\beta = -0.24$, $\mathrm{CI}_{0.95} = (-0.50, -0.01)$). Thus, clusters that have been relatively abundant in the history of English have not become more frequent.[8] In contrast, model 3b (Fig. 3b) shows that R_0^{AoA} positively correlates with average frequency (smooth term: $df = 1, F = 33.57, p < 0.001$; linear effect $\beta = 0.61$, $\mathrm{CI}_{0.95} = (0.42, 0.75)$). Frequent CC clusters are acquired significantly earlier than rare ones. Model 4a (Fig. 3c) shows that frequency and R_0^{GR} were inversely related in the beginning of the observation period but not during more recent periods. The relationship between frequency and R_0^{AoA} (model 4b, Fig. 3c) was slightly negative in the early part of the observation period but evolved towards a strongly positive interaction later on (interaction term: $df = 4.6$, $F = 81.8, p < 0.001$).

[8] Model 3a was additionally fit to all clusters with $R_0^{\mathrm{AoA}} > 1$ ('core' items) and $R_0^{\mathrm{AoA}} < -1$ ('periphery' items), respectively, in order to make the effect of frequency more clearly visible. Core items: smooth term at $df = 1, F = 0.58, p = 0.47$ ($n = 12, R^2(\mathrm{adj}) = -0.04$, 5.47% explained deviance). Periphery items: significantly decreasing smooth term at $df = 3.06, F = 25.3, p < 0.001$ ($n = 12, R^2(\mathrm{adj}) = 0.90$, 92.5% explained deviance).

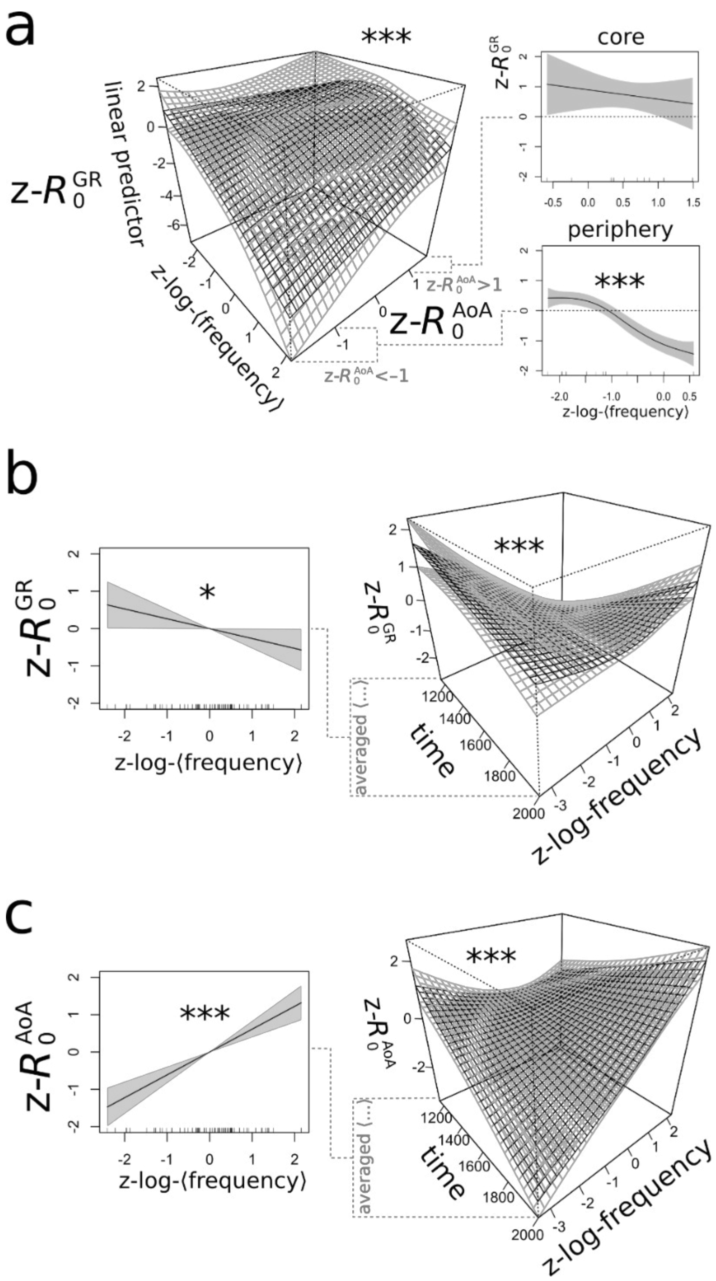


Figure 3. (a) Left: The effect of cross-temporally averaged frequency, ⟨frequency⟩, on the relationship between R_0^{GR} and R_0^{AoA} (z-scores; ⟨frequency⟩ log-transformed; model 2). The positive relationship becomes stronger as ⟨frequency⟩ increases and vanishes in low-frequency items. Right: ⟨frequency⟩ decreases R_0^{GR} significantly when looking at periphery

items (z- $R_0^{\mathrm{AoA}} < -1$) but not in the core inventory (z- $R_0^{\mathrm{AoA}} > 1$) (model 3a with restricted data set). (b) Left: $\langle \mathrm{frequency} \rangle$ decreases R_0^{GR} (model 3a). Right: Frequency (log- and z-transformed) computed for each period of 50 years separately and related with R_0^{GR} and time (model 4a). (c) Left: Same as in (b) with R_0^{GR} replaced by R_0^{AoA}, which correlates positively with $\langle \mathrm{frequency} \rangle$ (model 3b). Right: Over the past 800 years, a strongly positive relationship between frequency and R_0^{AoA} established itself (model 4b). Recall that R_0^{AoA} is based on contemporary AoA estimates.

5 Discussion

We have shown that a simple population-dynamical model of linguistic spread derives correlating estimates of reproductive success from age-of-acquisition data on the one hand, and from diachronic corpus data on the other. At least for English final CC clusters, this means that the basic reproductive ratio[9] R_0 qualifies as a standardized measure of reproductive success which allows to the relate AoA with diachronic growth. It has a clear linguistic interpretation and permits the direct comparison of data of various origins (Heffernan et al., 2005).

The correlation between the estimates derived from acquisition data and diachronic evidence supports the widely shared view that age of acquisition and diachronic stability are causally linked. Concurring with Monaghan (2014), our study suggests that what is acquired early is diachronically more stable (and *vice versa*). Interestingly, however, the tightness of this relationship increases with the frequency of CC clusters. This means that frequent

[9] Defined as the expected number of learners that acquire an item from a single user.

clusters are not simply acquired before rare ones, but that the historical stability of a cluster can be more confidently predicted from the age at which it is acquired when that cluster is frequent. Among rare clusters the correlation is not as tight. At the same time, these results show that late acquired items from the phonotactic periphery suffer most from frequency driven effects such as assimilation, reduction, or deletion. In that respect, they differ strongly from early acquired – and highly entrenched – core items. Thus, the notion than utterance frequency reduces historical stability still applies (e.g. via erosion in adult speech; Bybee, 2007), but we have demonstrated it to be restricted to the periphery.

The correlation between frequency and R_0 estimated from AoA is not surprising. It reflects the way in which the (linguistic version of the) basic reproductive ratio is derived. According to Nowak (2000), R_0 depends on (a) the ease with which a linguistic item is learnt and memorized, (b) utterance frequency, and (c) the density of the speaker network. Thus, our results highlight the importance learnability for the successful replication of phonotactic items ([Authors]; Croft, 2000; Smith & Kirby, 2008). In that sense, age of acquisition seems to reflect linguistic and cognitive constraints on the production and the perception of clusters, and on their role in further cognitive processing. These constraints may act on articulatory and perceptual properties of clusters, such as (differences in) the manner or the place of their articulation (Berent, Steriade, Lennertz, & Vaknin, 2007; Mesgarani, Cheung, Johnson, & Chang, 2014), or on their semiotic functionality (such as boundary signaling, see McQueen, 1998, Dressler et al., 2010).

It is interesting that there is no simple positive correlation between R_0 estimated from historical data and utterance frequency. That would have been expected given the way in which Nowak (2000) defines the basic reproductive ratio. It would also have been expected from previous empirical findings, e.g. by Pagel et al. (2007) or Lieberman et al.

(2007). In fact, taking frequency averaged over the entire observation period into account the opposite seems to be the case, very much in line with the view that high utterance frequency decreases an item's phonological stability (Bybee, 2007, 2010; Diessel, 2007). So why do our data not reveal such a correlation? First, as discussed above, the effect of frequency on the relationship between both R_0 estimates show that frequency affects diachronic stability negatively among late acquired items, but does not do so among early acquired items. Since Pagel et al. (2007) focused exclusively on core vocabulary (200 lexical core items), which is acquired early, they would not have seen the destabilizing effects of frequency on late acquired items. Lieberman et al. (2007) analyze the loss of 177 irregular verbal forms and find that their stability is positively correlated with frequency. The divergence between their result and ours is noteworthy. We suspect that it reflects that the frequencies employed in Lieberman et al. (2007) were derived from contemporary data (CELEX) rather than historically layered sources: in the slice representing most recent periods in Figure 2b (right), a negative interaction between stability and frequency is not visible either. We think that averaged frequencies, which cover the entire observation period, provide a more robust picture.[10]

Alternatively, there might be fundamental differences between phonotactics and the lexical domain. In the sublexical domain, the destabilizing effect of frequency might be stronger than in the lexical domain, because for the recognition of lexical items listeners can rely on the syntactic, semantic and pragmatic context, and may therefore recognize them even in phonetically reduced forms (Ernestus, 2014). In this regard, cluster perception is supported at best by morphological cues and benefits much less from linguistic redundancy. Therefore,

[10] We would like to thank an anonymous reviewer for raising this issue.

weakly entrenched phonotactic items may be more vulnerable to the destabilizing effects of frequency than weakly entrenched lexical items.

In summary, it appears that linguistic entrenchment is a function of both age of acquisition and frequency rather than just the latter (Ellis, 2012; Schmid, 2016). If we operationalize entrenchment by means of diachronic stability (because of the conserving function of routinization) then our analysis suggests that the relative age at which an items is acquired plays a key role in linguistic entrenchment. One straightforward mechanistic explanation is this: an item that happens to be acquired early has more time for being routinized than an item that is acquired late. Crucially, this holds irrespectively of how frequent an item is. Another mechanism discussed by Monaghan (2014: 533), applies to the lexical domain and involves higher plasticity of the cognitive system at early ages. Lexical items that are acquired early (for whatever reason) are more easily entrenched because the cognitive system is still more flexible. This, then, should also apply to complex processes of cognitive planning, articulation and perception relevant in the sublexical domain (Cholin, Dell, & Levelt, 2011; Levelt & Wheeldon, 1994).[11]

Finally, the comparison between the reproductive ratios derived from our two data sets, sheds light on the question how much acquisition contributes to language change. To see this, note that the ratios derived from AoA data are considerably larger than the ones derived

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[11] According to Nowak (2000), there is a third factor that influences the spread of items, namely network density. It is reflected in the number of users to which a learner is exposed. Thus, changes in the number of communicative contacts could cause socially motivated change in phonotactics (Trudgill (2001)), because R_0 decreases as the social network gets sparse. This relates to studies about the relationship between social structure and linguistic evolution (e.g. Wichmann, Stauffer, Schulze, and Holman (2008); Nettle (2012)), but based on the data that we analyzed in this study we cannot add to this discussion at this point.

from diachronic data (Fig. 2, boxplots). While that difference may partly be an artefact of our method[12], it may also be revealing. Thus, it might plausibly be interpreted as reflecting the different contributions which first-language learners and proficient speakers make to the actuation of linguistic change (Bybee, 2010; Croft, 2000). Since age-of-acquisition data predict greater diachronic stability than is derivable from actual diachronic evidence, this potentially suggests that language use by adults may play a more important role in causing linguistic innovation than language acquisition by new generations of children (Diessel, 2012). Of course, further research is still needed to corroborate this suspicion, but the methods we have demonstrated in this paper may help to make the question addressable in quantitative terms.

[12] To some extent, the difference may reflect the way in which R_0^{GR} has been estimated, because linguistic tokens and speakers represent two different dimensions in the first place. We suppose our token-frequency based proxy r_{lg} to represent a lower bound for the intrinsic growth rate ρ in the population-dynamical model. This is because the spread of an item in a population of tokens involves both its spread through a population of speakers (i.e. ρ), and its spread through the linguistic system and the lexicon (Kroch (1989); Croft (2000); Denison (2003); Wang and Minett (2005); Blythe and Croft (2012)). The two dimensions are hard to disentangle on the basis of the limited number of historical texts available. Only quantitative empirical and computational approaches that incorporate both dimensions can shed more light on this issue.

As to R_0^{AoA}, one possible reason why it might be overestimated is that our measure of AoA is based on lexical acquisition. Of course, the first form of a word that a child uses may not be the one containing the relevant cluster, nor will a child's first productions of what is a cluster in the target form always be accurate. Moreover, considering only AoA for estimating R_0 neglects the possibility that clusters, once acquired, may disappear again in adult speech – not only through language attrition and articulatory loss (see Seliger and Vago (1991); Ballard, Robin, Woodworth, and Zimba (2001); Torre and Barlow (2009)), but also through natural phonological backgrounding and deletion processes. If the proportion of individuals abandoning a particular cluster is underestimated, this will result in R_0^{AoA} being overestimated.

6 Outlook

Although our case study has been restricted to a very specific set of phonotactic constituents and to a single language, namely English, there is no *a priori* reason why our approach should not work in other domains (e.g. modeling the spread of single phonemes or words), and for other languages. The two operationalizations of R_0, however, require (a) diachronic data that cover the complete histories of constituents (ideally from the period of their first emergence), as well as (b) corresponding acquisition data. As so often, English enjoys a privileged status in this regard. A large number of historical sources have been digitized, and also research on acquisition has produced a large amount of data. Testing the methods described in this study against other languages is likely to face difficulties, although it would of course be important. At least on the lexical level, however, the prospects are not so bad. For core-vocabulary items in 25 languages a set of AoA ratings has been compiled by Łuniewska et al. (2016), and diachronic resources such as the Google Books Ngram Corpus, currently featuring eight languages, may serve as good starting points.

Acknowledgements: This work has been supported by FWF (grant no. P27592-G18).

Appendix

Table A1. Derived scores for each English type of final CC cluster used in empirical analysis: logistic growth rate r_{lg} (2.2); goodness-of-fit measure $\mathrm{P_{sp}}$ (2.2); basic reproductive ratio estimated from logistic growth R_0^{GR} (2.2); age-of-acquisition AoA (2.3); basic reproductive ratio estimated from AoA R_0^{AoA} (2.3); total per million normalized frequency across all periods $\Sigma = 18 \times \langle \text{frequency} \rangle$ (2.4); average frequency across all periods $\langle \text{frequency} \rangle$; morphological status (2.5).

cluster	AoA	R_0^{AoA}	r_{lg}	$\mathrm{P_{sp}}$	R_0^{GR}	Σ	⟨frequency⟩	morph
bd	5.51	10.88	0.0083	0.86	1.25	2875.39	159.74	illegal
bz	3.9	15.38	0.0089	0.83	1.27	3577.02	198.72	illegal
d	4.23	14.18	0.0066	0.76	1.2	1035.56	57.53	illegal
d	11.7	5.13	0.0081	0.77	1.24	182.59	10.14	mixed
dz	2.91	20.64	0.0111	0.83	1.33	16066.49	892.58	illegal
dʒ	4.17	14.38	0.0024	0.86	1.07	17120.47	951.14	legal
z	3.6	16.67	0.0137	0.86	1.41	624.26	34.68	illegal
fs	3.98	15.08	0.0046	0.7	1.14	4236.11	235.34	illegal
ft	3.96	15.14	-0.001	-0.16	0.97	18692.94	1038.5	mixed
gd	3.06	19.63	0.0069	0.8	1.21	2462.6	136.81	illegal
gz	2.79	21.48	0.0113	0.83	1.34	5024.83	279.16	illegal
ks	2.89	20.79	0.0044	0.86	1.13	47399.45	2633.3	mixed
kt	2.91	20.64	0.0118	0.93	1.35	33376.3	1854.24	mixed
lb	6.74	8.9	0.0049	0.75	1.15	156.01	8.67	legal
ld	3.23	18.58	0.0007	0.47	1.02	127823.96	7101.33	mixed
lf	4.21	14.25	-0.0011	-0.27	0.97	21867.05	1214.84	legal
lk	5.94	10.11	-0.0025	-0.84	0.92	10516.45	584.25	legal
lm	8.26	7.27	-0.0001	0.12	1	4858.57	269.92	legal
lp	5.87	10.22	-0.0007	-0.16	0.98	4273.8	237.43	legal
ls	6.53	9.19	-0.002	-0.56	0.94	25955.21	1441.96	mixed
lt	4.3	13.94	-0.0003	0.12	0.99	18907.59	1050.42	mixed
l	7.92	7.57	-0.0011	-0.64	0.97	8198.53	455.47	legal
lz	3	19.98	0.0108	0.84	1.32	40839.21	2268.85	illegal
md	3.87	15.5	0.0057	0.81	1.17	12894.59	716.37	illegal
mf	9.21	6.51	0.0066	0.86	1.2	581.9	32.33	legal
mp	3.73	16.09	0.0065	0.66	1.19	4675.2	259.73	legal
mz	2.85	21.08	0.0035	0.81	1.11	22968.2	1276.01	illegal
nd	3.19	18.81	-0.0021	-0.35	0.94	623823.11	34656.84	mixed
d	4.33	13.86	0.0062	0.84	1.19	1339.24	74.4	illegal
k	3.58	16.78	0.0086	0.86	1.26	10257.91	569.88	legal
ns	4.63	12.95	0.001	0.21	1.03	94903.51	5272.42	legal
nt	3.26	18.4	0.0036	0.97	1.11	133291.44	7405.08	mixed
n	5.7	10.52	-0.0011	-0.8	0.97	6894.34	383.02	mixed
nz	2.91	20.64	0.0138	0.83	1.41	71827.44	3990.41	illegal
z	3.88	15.48	0.0141	0.84	1.42	12585.83	699.21	illegal
ps	2.74	21.92	0.0073	0.94	1.22	16989.12	943.84	mixed
pt	2.74	21.92	0.0085	0.95	1.25	15427.24	857.07	mixed

rb	8.1	7.41	0.0047	0.71	1.14	773.34	42.96	legal
rd	3.35	17.89	-0.0011	-0.59	0.97	115745.44	6430.3	mixed
rf	7.04	8.53	0.0058	0.79	1.17	402.81	22.38	legal
rk	3.95	15.2	0.0009	0.27	1.03	11891.15	660.62	legal
rm	3.85	15.58	0.0025	0.89	1.08	9209.52	511.64	legal
rn	4.08	14.69	-0.0025	-0.54	0.93	23164.88	1286.94	legal
rp	7.41	8.09	0.0013	0.29	1.04	1957.53	108.75	legal
rs	5.61	10.7	-0.0002	-0.28	1	51490.02	2860.56	legal
r	6.13	9.78	-0.0037	-0.91	0.89	20723.15	1151.29	mixed
rz	3.11	19.29	0.0125	0.83	1.38	23445.87	1302.55	illegal
sk	4.42	13.58	0.0065	0.96	1.2	4500.53	250.03	legal
sp	6.95	8.63	0.0063	0.76	1.19	860.12	47.78	legal
st	2.69	22.28	0.0017	0.75	1.05	164960.88	9164.49	mixed
t	3.73	16.09	0.0078	0.95	1.24	14280.96	793.39	illegal
ts	2.9	20.71	0.0062	0.92	1.18	71384.23	3965.79	mixed
t	4.24	14.16	-0.004	-0.6	0.88	96962.87	5386.83	legal
s	4.32	13.9	0.0026	0.4	1.08	62.73	3.49	illegal
tz	8.85	6.78	0.0064	0.76	1.19	90.09	5	illegal
zd	3.43	17.51	0.0093	0.94	1.28	22371.96	1242.89	illegal
ʒd	5.51	10.9	0.0093	0.92	1.28	6219.11	345.51	illegal
zm	11.66	5.14	0.007	0.74	1.21	152.89	8.49	legal

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