Stability in the temporal dynamics of word meanings

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Abstract

Words show complex dynamics of meaning change. In some cases, a word may acquire novel senses. In other cases, existing senses of a word may become obsolete. The rates at which words gain and lose senses may vary, but it is an open question which factors might account for this variation. Building on work in computational linguistics and cognitive science, we develop a computational approach that explores this question by leveraging word sense records from a large historical database of English. Our results suggest that polysemous words tend to gain and lose senses more than words with fewer senses, and that these effects are robust when word frequency and length are both controlled for. These results are consistent with recent findings on the mechanisms of emergent word meanings and they further suggest stability in the temporal dynamics of word meanings.

Keywords: lexicon; word meaning; sense gain; sense loss; polysemy; lexical evolution; stability

Introduction

Words are core components of the lexicon, but their meanings tend to change over time. For instance, a word might take on new senses (e.g., *crane* acquiring the sense of the construction device), while existing senses of a word might become obsolete (e.g., *awesome* losing the sense of 'inspiring awe'). Words develop senses at different rates. For example, words such as *mouse*, *run*, and *clear* have gained a variety of senses in the history of English, whereas words such as *antelope*, *waltz*, and *rainy* have developed fewer senses over time. Why do some words gain or lose senses more rapidly than others? We explore this question by examining temporal dynamics of word meanings in history.

Meaning change has been a topic of considerable interest in linguistics. Prior research has shown that historical changes in word meaning can take a variety of forms (Traugott & Dasher, 2001), such as narrowing or widening (Bréal, 1897; Bloomfield, 1933), metaphor (Sweetser, 1991), metonymy (Panther & Radden, 1999), and grammaticalization (Hopper & Traugott, 2003). Despite this rich literature, few attempts have been made in characterizing the temporal dynamics and stability of word meanings. Although similar questions have been explored in the evolution of word forms (Pagel, Atkinson, & Meade, 2007) and morphology (Lieberman, Michel, Jackson, Tang, & Nowak, 2007), comparably less work has been pursued in the area of meaning change. This difficulty arises in part due to the fact that meaning change is hard to quantify precisely and at a broad scale.

Recent work in computational linguistics has made progress toward these issues by taking a distributed approach to meaning change. In particular, Hamilton and colleagues (Hamilton, Leskovec, & Jurafsky, 2016) have quantified rates of semantic change by measuring differences in word (meaning) vectors over time, derived from word co-occurrence statistics in large historical text corpora. They discovered that rates of semantic change correlate negatively with word frequency but positively with polysemy, which they approximated by measuring how contextually diverse a word is in co-occurrence. They also found that the correlation with frequency is stronger than that with polysemy.

Follow-up work has challenged the validity of these findings on methodological grounds (Dubossarsky, Weinshall, & Grossman, 2017). Due to biases in the measure of semantic change and how frequency is represented by the word vectors, both the effects of frequency and polysemy were shown to be significantly reduced under random control sets. Furthermore, the polysemy measure used by Hamilton et al. (2016) shows a bias towards function words (e.g., *yet*, *always*), which overestimates the degrees of polysemy in these words. These methodological concerns suggest that alternative approaches may be needed for characterizing temporal properties of word meanings.

From a theoretical perspective, several questions remain open. First, independent research from cognitive science has suggested that semantic chaining is a key process in the historical emergence of word meanings (Lakoff, 1987; Bybee, Perkins, & Pagliuca, 1994; Malt, Sloman, Gennari, Shi, & Wang, 1999; Xu, Regier, & Malt, 2016; Ramiro, Srinivasan, Malt, & Xu, 2018). On this view, words tend to extend their meanings by linking an emerging sense to existing senses that are closely related, effectively forming a network of chain-like structures based on local neighborhood profiles. If this view is correct, we should predict words with many existing senses to develop more senses over time, because they potentially offer more points of attachment between existing and novel senses, in comparison to words with fewer senses. This rich-get-richer hypothesis is supported partly by previous work that models growth in semantic networks via preferential attachment (Steyvers & Tenenbaum, 2005). An empirical question that we investigate in the current work is whether similar dynamics would be present in the evolution of word senses over time. Perhaps even less understood are the dynamic properties of sense loss. One naïve prediction following the rich-get-richer hypothesis is that polysemous words should keep gaining senses. However, we do not expect this unbounded sense growth to be applicable for words at large, because a word form with an ever-increasing number of senses would ultimately become difficult to interpret (cf. Klein & Murphy, 2001). In contrast, we expect that a high rate of sense gain might be compensated by a high rate of sense loss, such that there is stability overall in the temporal dynamics of word meanings.

To test our proposals, we quantify rates of word meaning change by leveraging a large historical thesaurus. Different from corpus-based methods, our approach provides a way of measuring both sense gain and sense loss based on time-stamped sense records in the historical dictionary, independent of corpus-based frequencies. As we will show, this approach yields a more reliable measure of polysemy, and it allows us to both test how different factors account for rates of meaning change as well as our hypotheses about stability in word meanings.

Computational formulation

We first present a simple computational formulation that characterizes temporal rates of sense gain and loss, extending work by Hamilton et al. (2016). We then describe the condition under which temporal dynamics of word meanings would tend toward stability.

Modelling rates of sense gain and loss

We consider three variables that could influence rates of word sense gain and loss: word frequency (denoted by F), word length (denoted by L), and degree of polysemy (denoted by S). Frequency and degree of polysemy are both investigated in Hamilton et al. (2016), but not word length. We describe how we obtain values for these variables in the next section. We specify rate of sense gain ($s^{+}(w)$) for word w at time t in terms of a function $g(\cdot)$ that captures the joint influence of these variables:

$$\frac{ds^{+}(w)}{dt} \propto g(F_{t-1}, L, S_{t-1}) \tag{1}$$

We consider frequency and polysemy profiles at $t-1$ (or prior to the time of interest) because we are interested in how these variables at a given time point may predict rate of sense gain in the future. Word length does not vary over time and is fixed as L. Because the three variables are correlated (cf. Zipf, 1949), the critical question is which variable best predicts rates of word sense gain and loss when other variables are controlled for. To model rates of loss of senses for a word (denoted by $s^{-}(w)$), we use the same formulation:

$$\frac{ds^{-}(w)}{dt} \propto g'(F_{t-1}, L, S_{t-1}) \tag{2}$$

Following work by Hamilton et al. (2016), we assess the relative contributions of the three variables by specifying $g(\cdot)$ and $g'(\cdot)$ as linear mixed effect models with random intercepts on words (z^{w}), fixed effects per time point (with coefficient β_t), and an error term (ε_t^{w}) for noise:

$$\frac{ds^{+/-}(w)}{dt} \propto \beta_F \log(F_{t-1}) + \beta_L(L) + \beta_S \log(S_{t-1}) + \beta_t + z_w + \varepsilon_t^{w} \tag{3}$$

The β coefficients of the three variables represent the relative contributions toward predicting rates of word sense gain and loss, examined separately. If degree of polysemy is the key predictor, we expect its coefficient to be larger than that of the other variables in the historical evolution of word senses.

Condition of stable word sense dynamics

To explore the relationship between rates of sense gain and rates of sense loss, we define *net rate of sense change* by taking the difference between these rates. Let $r(w)_t^{+} = \frac{ds^{+}(w)}{dt}$ and $r(w)_t^{-} = \frac{ds^{-}(w)}{dt}$ be abbreviations of rates of sense gain and loss. We define net rate of sense change as the following:

$$r_t^{net} = r(w)_t^{+} - r(w)_t^{-} \tag{4}$$

If a word gains and loses senses at equal rates, we expect its net rate of sense change to be zero. It is possible that net rate of sense change may fluctuate across words, so we test the condition that the mean rate of sense change should be near zero over time, across words in a lexicon W of size $|W|$:

$$E[r_t^{net}] = \frac{1}{|W|} \sum_{w \in W} r_t^{net} \approx 0 \tag{5}$$

Equation 5 stipulates that the expected number of senses that flow in and out of words should be roughly balanced.

Treatment of data

Historical thesaurus

We sourced data from the Historical Thesaurus of English (HTE) (Kay, Roberts, Samuels, Wotherspoon, & Alexander, 2017), a large digitized lexicon based on the *Oxford English Dictionary*. The version of the HTE we worked with includes approximately 800,000 dated word-sense records from Old English (around the year 1100) to the present day (up to the year 2000). Our analyses focused on records from the past 200 years of Modern English, from 1800 to 2000. We chose to work with this period because earlier records of the HTE can be relatively sparse, which might introduce biases in the analysis. Furthermore, this time period corresponds to that in the previous analyses by Hamilton et al. (2016), so it is useful for making comparisons with the corpus-based approach.

Word sets

Because the HTE database did not provide information on word frequency, we worked with two sets of common English words from two independent sources: 1) the 6,000 most frequent non-stop words (i.e., excluding extremely common function words such as *the*, *at*, and *on*) from the British National Corpus (BNC) (Kilgarriff, 1995) and 2) the 100,000 most common non-stop words from the Google Books English Fiction corpus (Davies, 2011) used in Hamilton et al. (2016), for which entries in the HTE are available ($n = 9778$).

Rates of sense gain and loss

For each word, we calculated its temporal rate of sense gain per decade by counting the number of novel senses that appeared during the 10 years (i.e., 20 data points from 1800 to 2000), based on the starting dates of word senses recorded in the HTE. Similarly, we calculated a word's rate of sense loss by counting the number of senses that become obsolete during those 10 years, based on the ending dates of word senses recorded in the HTE.

Word frequency and length

We estimated word frequencies over the past 200 years based on the Google Books N-gram corpus (Michel et al., 2011), provided by Hamilton et al. (2016). We took the orthographic length of a word as a proxy for word length by counting the number of letters.

Degree of polysemy

We defined degree of polysemy of a word at a given time t as the number of total non-obsolete senses (in the HTE) for that word up to t. To assess the reliability of our measure, we calculated rank correlation in polysemy for the year 2000 between these measures of polysemy and that from WordNet (Princeton University "About WordNet", 2010). The result indicates that our measure based on the HTE (Spearman $\rho = 0.40$, $p < 0.0001$) better correlates with WordNet than that from Hamilton et al. (2016) (Spearman $\rho = 0.26$, $p < 0.0001$). This difference is statistically significant under a two-sample bootstrap test with 10,000 samples (t = 926, p <0.0001). Table 1 shows the most polysemous words from the English Fiction Google corpus (Davies, 2011), retrieved from the HTE-based measure and the measure by Hamilton et al. (2016) separately. As observed, our measure does not produce a bias towards function words.

HTE database	*slip*, *shoot*, *point*, *take*, *round*, *set*, *fall*, *strike*, *out*, *run*
Hamilton et al. (2016)	*yet, always, even, little, called, also, sometimes, great, still, quite*

Table 1. Ten most polysemous words in the English Fiction corpus, retrieved from measures based on the HTE database and Hamilton et al. (2016).

Results

We present results from four analyses. First, we assess the explanatory power of the three variables described in accounting for rates of semantic change estimated from text corpora. This measure of rates does not distinguish between gain and loss of word senses, and we take the rate measurements directly from data made available by Hamilton et al. (2016). Next, we assess how well the same variables predict historical rates of sense gain and loss based on records from the HTE database, in two separate analyses that distinguish between sense gain and sense loss. In the final analysis, we assess whether the relationship between rates of sense gain and loss reflects a tendency toward stability in the lexicon.

Predicting corpus-based rates of semantic change

Following Hamilton et al. (2016), we performed linear mixed effect regression on our variables of interest (word frequency, polysemy, and length) against the rates of semantic change of individual words. (Hamilton et al. (2016) estimated these rates by measuring cosine distances between corpus-derived word vectors for consecutive decades, during the period of 1800-2000.) Figure 1 summarizes the coefficients of regression based on words in the English Fiction corpus, as used in Hamilton et al. (2016) (we obtained similar results based on words in the BNC corpus, as reported below).

Our results show that degree of polysemy is the strongest predictor of rates of semantic change when both word frequency and word length are controlled for. The positive correlation suggests that polysemous words tend to undergo more rapid semantic change than words with fewer senses. We also observed that word frequency is negatively correlated with rates of semantic change, as reported by Hamilton et al. (2016). However, this correlation is likely to be inflated, as shown by Dubossarsky et al. (2017).

To assess whether the role of polysemy is dominant across time, we performed a paired t-test between polysemy and each of the alternative variables. The results indicate that the differences in regression coefficients are statistically significant (t = 25.8, $p < 0.0001$ (polysemy vs. frequency), t = 15.2, $p < 0.0001$ (polysemy vs. length) for words in the English Fiction corpus; t = 24.5, $p < 0.0001$ (polysemy vs. frequency), t = 16.2, $p < 0.0001$ (polysemy vs. length) for words in the BNC).

These initial analyses provide evidence that polysemy may be a key predictor of rates of meaning change—measured by text corpora, but they do not directly address the question of how the same variables account for gain and loss of word senses, respectively, which we address below.

Predicting rates of sense gain

We next assessed the explanatory powers of the three variables in accounting for historical rates of word sense gain, as computed from the HTE database. Following Equation 3, we performed linear mixed effect (LME) regression on these variables, jointly against rates of sense gain of individual words (i.e., $r(w)_t^+$) with random intercepts per word. For all LME regressions, we used the Python `statsmodels` package with restricted maximum likelihood estimation (REML) (Seabold & Perktold, 2010).

Figure 2(a) summarizes the regression coefficients on word frequency, word length, and degree of polysemy, based on words in the BNC corpus. The results indicate that degree of polysemy yielded the highest coefficients of regression among the three variables, confirming the hypothesis that words tend to gain senses in a rich-get-richer way. Table 2 further shows that degree of polysemy yielded coefficients an order of magnitude larger (in absolute value) than the other two variables.

We also observed that in both datasets, word frequency

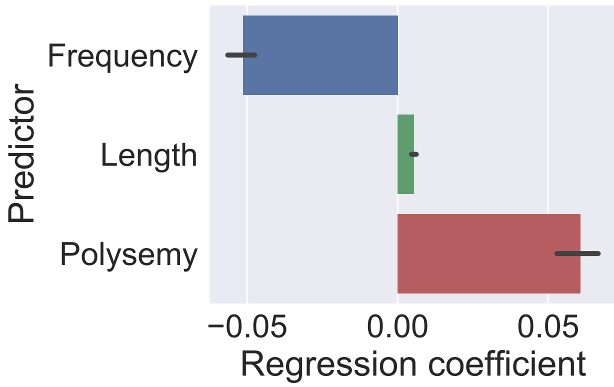


Figure 1. Summary of results on mixed effect regression of word frequency ($log(F_{t-1})$), word length (L), and number of senses for a word, or degree of polysemy ($log(S_{t-1})$), against rates of semantic change at time t, measured from the English Fiction corpus (cf. Hamilton et al. 2016). Error bars represent 95% confidence intervals across time points.

positively correlates with rate of sense gain (i.e., similar to degree of polysemy), while word length negatively correlates with rate of sense gain, suggesting that more frequent or shorter words tend to have higher rates of sense gain. However, these effects are substantially weaker than those observed with the variable of polysemy.

To further assess whether the predictive power of polysemy relative to the other variables is statistically significant, we performed paired t-tests among these variables across time. Table 3 shows that regression coefficients based on degree of polysemy are significantly different from those based on frequency or word length. Overall, these results suggest that degree of polysemy best accounts for rates of sense gain in English words, beyond word frequency and length.

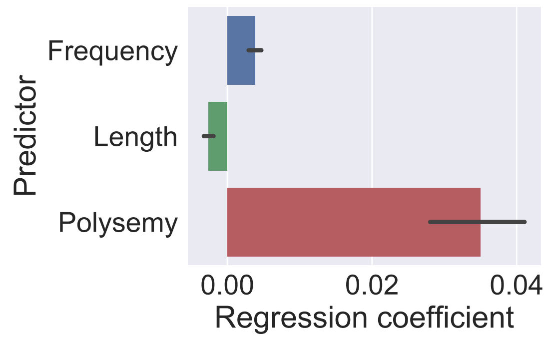
	$log(F_{t-1})$	L	$log(S_{t-1})$
BNC	+0.00382	-0.00259	**+0.0350**
Eng Fic	+0.000523	-0.00226	**+0.0215**

Table 2. Summary of mean coefficients of regression on the three variables of interest against rates of sense gain, for words in the BNC and Google Books English Fiction corpora.

	BNC		English Fiction	
	β_S vs. β_F	β_S vs. β_L	β_S vs. β_F	β_S vs. β_L
t-stat	9.05	11.0	11.0	12.4

Table 3. Results of paired t-tests on the difference between regression coefficients for word frequency, β_F, word length, β_L, and degree of polysemy, β_S. For all cases $p < 0.0001$.

(a) Sense gain



(b) Sense loss

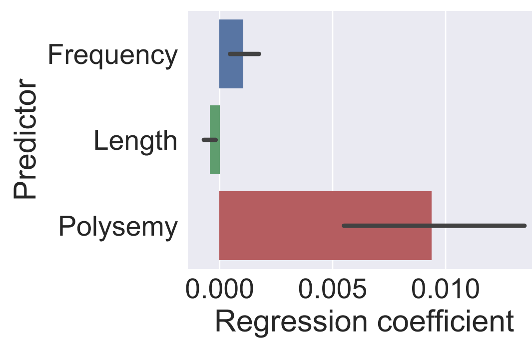


Figure 2. Summary of results on mixed effect regression against rates of sense gain and loss. (a) Regression coefficients of word frequency ($log(F_{t-1})$), word length (L), and degree of polysemy ($log(S_{t-1})$) on predicting rates of sense gain at time t of individual English words in the BNC word set. (b) Regression coefficients on predicting rates of sense loss of words in the BNC word set. Error bars represent 95% confidence intervals across time points.

Predicting rates of sense loss

To assess how the three variables account for rates in the loss of word senses obtained from the HTE database, we performed the same mixed regression analysis.

Although degree of polysemy appears to be the strongest predictor for rates of sense gain, it is possible that it might not be equally predictive in the case of sense loss. However, Figure 2(b) indicates that similar to the case of sense gain, polysemy outperforms the other two variables in accounting for rates of sense loss. In particular, the average regression coefficients based on polysemy are still substantially larger in absolute value than those based on word frequency or length (as summarized in Table 4). Table 5 further shows that such differences are statistically significant in paired t-tests across time, just as what we found in the case of sense gain.

Taken together, our results show that more polysemous words tend to gain and lose senses at higher rates than words with fewer senses despite variation in word frequency and length. These results extend the findings by Hamilton et al. (2016) by suggesting how these linguistic variables might influence the separate processes of word sense gain and loss, and how degree of polysemy of a word is the best predictor among the variables examined.

	$log(F_{t-1})$	L	$log(S_{t-1})$
BNC	+0.00105	-0.000428	**+0.00937**
Eng Fic	+0.000218	-0.000326	**+0.00569**

Table 4. Summary of mean coefficients of regression on the three variables of interest against rates of sense loss, for words in the BNC and Google Books English Fiction corpora.

	BNC		English Fiction	
	β_S vs. β_F	β_S vs. β_L	β_S vs. β_F	β_S vs. β_L
t-stat	3.83	4.56	4.46	4.91

Table 5. Summary of paired t-tests on regression coefficients of word frequency, β_F, word length, β_L, and degree of polysemy, β_S, against rates of sense loss, over time. For all cases $p < 0.0001$.

Evidence for stability

In the final analysis, we assessed how the processes of sense gain and loss may be related, particularly whether words tend to gain and lose senses at roughly equal rates.

Following Equation 4, we computed the net rate of sense change for words in the lexicon. This measure is an indicator of semantic stability: if this value is near-zero over time, it suggests that sense gain and loss tend to balance each other out; if the value shows a clear upward or downward trend over time, it indicates that the stability criterion that we have stipulated might not be met.

Figure 3 provides support for the first view. We observed that the net rates of sense change are roughly constant and close to zero over time in the BNC dataset (with similar results for the English Fiction dataset). We verified this observation quantitatively by fitting the net rates of sense change against time via linear regression. The coefficient of the slope term did not show statistical significance ($p = 0.40$ (BNC); $p = 0.26$ (English Fiction data)), indicating that there is minimal temporal trend in the data. We also found the mean net rate of sense change across time to be 0.02 (with standard deviation of 0.01), which indicates that words gain only 0.02 senses (i.e., very close to zero) per 20 years, on average. Furthermore, we correlated rates of sense gain vs. rates of sense loss across words and found a significant positive correlation between the two variables (Pearson $r = 0.455$, $p < 0.0001$ (BNC); Pearson $r = 0.46$, $p < 0.0001$ (English Fiction)). These results suggest that not only do words gain senses in a rich-get-richer way and lose senses in a rich-get-poorer way, but they also do so by balancing the amount of sense gain with the amount of sense loss (hence keeping the net influx of senses in words relatively stable).

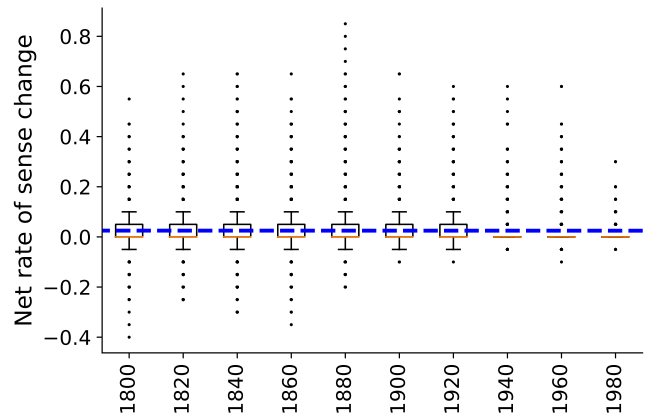


Figure 3. Net rate of sense change in words from the BNC corpus over the recent 200 years, binned by 20-year intervals. Boxplots were constructed with 95% confidence intervals across words. Dots represent outlier words. Dashed line represents the fit from a linear regression.

Taken together, our findings provide support for the view that although words vary in their rates of sense gain and loss (see Table 6 for words that show the highest rates of sense gain and loss), the dynamics of sense gain and loss tend to be relatively stable over time.

Discussion

The fluidity of word meaning raises the fundamental question of why certain words show rapid historical growth and loss in meaning, while others are more semantically stable. We have presented a computational treatment of this problem, leveraging a rich historical thesaurus. We reached two main findings. First, words gain senses in a rich-get-richer way after controlling for the variables of word frequency and length. Our result shows that polysemous words tend to attract emerging senses, more so than words with fewer senses. This finding is consistent with the view that words grow senses in chained mechanisms (Xu et al., 2016; Ramiro et al., 2018), where we expect more fully fledged sense networks to develop more connective points for developing novel senses. We also showed that rich-get-richer sense growth is countered by similar dynamics in sense loss, such that the amount of sense gain roughly equals the amount of sense loss in words in the English lexicon. These findings provide evidence for stability in the temporal dynamics of word meanings.

Our work opens up several directions for future research. A natural question is whether our findings on semantic change in the English lexicon would hold for other languages, particularly those outside the Indo-European family. Answers to

Highest rate of sense gain	*run* (+83), *roll* (+64), *ring* (+63), *strip* (+62), *line* (+61), *shoot* (+60), *slip* (+59), *break* (+59), *swing* (+59), *pull* (+58)
Highest rate of sense loss	*cast* (-26), *upon* (-25), *turn* (-23), *cross* (-18), *cut* (-18), *tail* (-18), *top* (-18), *put* (-17), *fat* (-17), *close* (-16)

Table 6. Ten words that show the highest rates of sense gain and loss, respectively, between the period of 1800 to 2000, from the BNC corpus. Numbers in parentheses indicate the total counts in sense change, with signs indicating directions of change.

this question would help to assess the generality of our proposal, but they do rely on rich lexical resources comparable to those in English that might not be readily available. Another outstanding issue is why certain senses of a word become obsolete over time, while others do not. Finally, it would be instructive to explore how factors beyond linguistic variables examined here (e.g., those due to cultural or social changes) have influenced the temporal dynamics of word meanings. Our current research serves as a starting point towards these open questions in lexical evolution.

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