Abstract

In an online community, new words come and go: today’s *haha* may be replaced by tomorrow’s *lol*. Changes in online writing are usually studied as a social process, with innovations diffusing through a network of individuals in a speech community. But unlike other types of innovation, language change is shaped and constrained by the system in which it takes part. To investigate the links between social and structural factors in language change, we undertake a large-scale analysis of nonstandard word growth in the online community Reddit. We find that dissemination across many linguistic contexts is a sign of growth: words that appear in more linguistic contexts grow faster and survive longer. We also find that social dissemination likely plays a less important role in explaining word growth and decline than previously hypothesized.

1 Introduction

*Stop trying to make “fetch” happen! It’s not going to happen!* – Regina George (*Mean Girls*, 2005)

With the fast-paced and ephemeral nature of online discourse, language change in online writing is both prevalent (Andritsopoulos, 2011) and noticeable (Squires, 2010). In social media, new words emerge constantly to replace even basic expressions such as laughter: today’s *haha* is tomorrow’s *lol* (Tagliamonte and Denis, 2008). The reasons for such changes are various: adopting new words may be used to signal familiarity with the latest trends in a community (Bucholtz, 1999), they may represent the orthographic representation of an existing spoken vernacular (Eisenstein, 2015) or they may even result from an exogenous shock, such as the censorship of related terms (Chancellor et al., 2016). But while analysis of specific causes for change can offer insights, we must also address a more basic set of questions. Why do some nonstandard words, like *lol*, succeed and spread to new contexts, while others, like *fetch*, fail to catch on? Can a word’s growth be predicted from patterns of usage during its early days?

Language change in general, and lexical change in particular, can be treated like other social innovations, such as the spread of hyperlinks (Bakshy et al., 2011) or hashtags (Romero et al., 2011; Tsur and Rappoport, 2015). A key property for predicting the growth of a new practice is its dissemination: is it used by many people, and in many social contexts? High dissemination enables words to achieve greater exposure among social groups (Altmann et al., 2011) and may convince potential adopters that the word is positively evaluated.

But while language change shares some properties with other social innovations, it is also bound by the constraints of the language’s grammar (D’Arcy and Tagliamonte, 2015). New words and phrases rarely change the rules of the game but must instead find their place in a competitive ecosystem with finely-differentiated linguistic roles, or “niches” (MacWhinney, 1989). These structural properties may play a crucial role in determining whether a word will grow or decline. We therefore posit a structural analogue to social dissemination, which we call *linguistic dissemination*. Some
words become valid in a broad range of linguistic contexts, while others remain bound to a small number of fixed expressions. We compare the fates of such words to determine how linguistic and social dissemination each relate to word growth. The following hypotheses are evaluated:

- **H1:** Words with higher initial social dissemination are more likely to grow. Previous work has found conflicting effects of social dissemination on word growth: Garley and Hockenmaier (2012) report a negative correlation between dissemination and frequency change, while Altmann et al. (2011) report a positive correlation. Following the intuition that words require a large social base to succeed, we hypothesize a positive correlation between social dissemination and word growth.

- **H2:** Words with higher linguistic dissemination in the early phase of their history are more likely to grow. This follows from work in corpus linguistics showing that words and grammatical patterns with a higher diversity of collocations are more likely to be adopted (Ito and Tagliamonte, 2003; Partington, 1993).

- **H2a:** Words with higher linguistic dissemination are more likely to grow, even after controlling for social dissemination. This follows from the intuition that linguistic context and social context contribute differently to word growth.

We focus on the adoption of slang words in the popular online community Reddit between 2013 and 2016. To address H2 and H2a, we develop a novel metric for characterizing linguistic context diversity, by comparing the observed number of $n$-gram contexts to the number of contexts that would be predicted based on frequency alone. Our analysis of word growth and decline includes: (1) predicting frequency change of growth words (as in prior work); (2) causal inference of the influence of dissemination on probability of word growth; (3) binary prediction of future growth versus decline; and (4) survival analysis, to determine the factors that predict when a decline word’s popularity begins to “die.” Each of these analyses demonstrates that linguistic dissemination plays an important role in explaining the growth and decline of nonstandard words, perhaps more important than social dissemination.

2 Related Work

**Lexical change online** Language changes constantly, and one of the most notable forms of change is the adoption of new words (Metcalf, 2004), sometimes referred to as lexical entrenchment (Chesley and Baayen, 2010). New words may arise through the mutation of existing forms, including truncation (e.g., favorite to fave; Grieve et al., 2016) and blending (e.g., web+log to weblog to blog; Cook and Stevenson, 2010). The fast pace and interconnected nature of online communication is particularly conducive to new words, and social media provides a “birds-eye view” on the process of change (Androutsopoulos, 2011; Danescu-Niculescu-Mizil et al., 2013; Kershaw et al., 2016; Tsur and Rappoport, 2015). We use Reddit as an example online community to track the growth and decline of nonstandard words.

**Social dissemination** Language changes as a result of transmission across generations (Labov, 2007) as well as diffusion across individuals and social groups (Bucholtz, 1999). One way of quantifying the degree of social diffusion is a metric known as social dissemination, equal to the count of social units (e.g., speakers, communities) who have adopted a word, normalized by the expected count under a null model in which the word is used with equal frequency across the entire population. Altmann et al. (2011) use dissemination of words across forum users and forum threads to predict the words’ change in frequency. They find a robust positive correlation between frequency change and both kinds of social dissemination. In contrast, Garley and Hockenmaier (2012) use the same metric to predict the growth of English loanwords on German hip-hop forums and find that social dissemination is still a significant predictor but has less predictive power than expected. We seek to replicate these prior findings, test whether they hold even after accounting for context dissemination, and extend the definition of social dissemination beyond forum users and threads to include sub-communities.
Linguistic dissemination  In addition to social dissemination, it is important to consider a word’s linguistic context: does the word disseminate to multiple semantic contexts and find a unique “niche” (MacWhinney, 1989) or remain bound to a fixed phrase? Work in historical linguistics suggests that the distribution of a new word or construction across lexical contexts can signal future growth (Partington, 1993). Furthermore, variationist sociolinguistics work has highlighted the role of grammatical and lexical factors on the production of linguistic variants (Ito and Tagliamonte, 2003; Cacoullos and Walker, 2009), which can often provide more insight onto language change than social factors alone. Our study proposes a generalizable method of measuring the dissemination of a word across lexical contexts and jointly compares the social and linguistic dissemination as predictors of word growth and decline.

3 Data

Our study examines the adoption of words on social media, and we focus on Reddit as a source of language change. Reddit is a social content sharing site separated into distinct sub-communities or “subreddits” that center around particular topics (Gilbert, 2013). Reddit is a diverse and dynamic online platform, making it an ideal environment for research on language change (Kershaw et al., 2016). In addition, the division of discussion among communities provides an additional lens on social dissemination beyond users alone: for instance, a word disseminating to a popular subreddit may gain exposure to an unexpectedly wide audience.

We analyze a set of public Reddit comments posted between 1 June 2013 and 31 May 2016, totalling $T = 36$ months of data (comments are grouped by month). To reduce noise in the data, we filter all comments generated by known bots and spam users and filter all comments created in well-known non-English subreddits. We also filter all comments that had been deleted by the time of collection (1 October 2016). The final data collected is summarized in Table 1.

To normalize the text and avoid data sparsity, we replace all references to subreddits and users (marked by the convention r/subreddit and u/user) with r/SUB and u/USER tokens. Similarly, we replace all hyperlinks with a URL token. We also reduce all repeated character sequences to a maximum length of three (e.g., loooool to loool). Lastly, we limit our analysis to the top 100,000 words in the vocabulary and replace each occurrence of an OOV word with an UNK token.

3.1 Finding growth words

Our work seeks to study the growth of nonstandard words such as the acronym tbh (“to be honest”). To detect such words, we compute the Spearman correlation coefficient between the time steps $\{1...T\}$ and each word $w$’s frequency time series $f_{(1:T)}(w)$ (frequency normalized and log-transformed), for all words in the vocabulary. The Spearman correlation coefficient captures monotonic, gradual growth that characterizes the adoption of nonstandard words (Grieve et al., 2016; Kershaw et al., 2016).

The first set of words is filtered by a Spearman correlation coefficient above the $85^{th}$ percentile ($N = 15,017$). From this set of words, we identify

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1 Data downloaded from http://files.pushshift.io/reddit/comments/ (Accessed 1 October 2016).
2 The same list used in Tan and Lee (2015) available online: https://chenhaot.com/data/multi-community/README.txt (Accessed 1 October 2016).
3 We randomly sampled 100 posts from the top 500 subreddits and labelled a subreddit as non-English if fewer than 90% of its posts were identified by langid.py as English.
4 We restricted our search to the top 100,000 words because of the qualitative analysis required to identify nonstandard words. This reduces the risk of data sparsity but may exclude rare innovations.
1,125 words in set $G$ (“growth”) \(^5\) that are neither proper nouns (berniebot, killary, drumpf) nor standard words (election, voting), because the growth of these words may be due to exogenous influence rather than sociolinguistic factors. The judgment for “standard” was whether one of the words could plausibly be found in a newspaper article. This process was undertaken manually by one of the authors. In cases where it was unclear whether a word was standard or proper, the author inspected a sample of comments that included the word to determine its status. We validate this process by having two authors annotate the top 200 growth candidates for standard/proper versus nonstandard and computing the inter-annotator agreement (Cohen’s $\kappa = 0.79$).

3.2 Finding decline words

To determine what makes the growth words successful, we need a corresponding control set of decline words — words that are adopted and later abandoned. Although we do not know if these words were growing before the time period investigated, we can assume that their decline makes them a useful comparison for the growth words. We find such “decline words” by fitting two parametric models to the frequency time series.

**Piecewise linear** We fit a two-phase piecewise linear regression on each word’s frequency time series $f_{(1:T)}$, which splits the time series into $f_{(1:\hat{t})}$ and $f_{(\hat{t}+1:T)}$ where split point $\hat{t}$ is a free parameter. The goal is to select a split point $\hat{t}$ to minimize the sum of the squared error between observed frequency $f$ and predicted frequency $\hat{f}$:

$$\hat{f}(m_1, m_2, b, t) = \begin{cases} b + m_1 t & t \leq \hat{t} \\ b + m_1 \hat{t} + m_2 (t - \hat{t}) & t > \hat{t}, \end{cases}$$

(1)

where $b$ is the intercept, $m_1$ is the slope of the first phase, and $m_2$ is the slope of the second phase. Decline words $D_p$ (“piecewise decline”) display growth in the first phase ($m_1 > 0$), decline in the second phase ($m_2 < 0$), and a strong fit between observed and predicted data, indicated by $R^2(f, \hat{f})$ above the 85th percentile (36.1%); this filtering yields 14,995 candidates. An example decline word *wot* (re-spelling; “what”) and its piecewise fit are shown in the left panel of Figure 1.

**Logistic fit** To account for smoother growth-decline trajectories, we also fit the curve of a logistic distribution, which is a continuous unimodal distribution with support over the non-negative reals. We identify the set of candidates $D_l$ (“logistic decline”) as words with a strong fit to this distribution, as indicated by $R^2$ above the 99th percentile (82.4%), yielding 998 candidates. An example word *iifym* (acronym; “if it fits your macros”) is shown in the right panel of Figure 1. The logistic word set partially overlaps with the piecewise set, because some words’ frequency time series show a strong fit to both the piecewise function and the logistic distribution.

**Combined set** We combine the sets $D_p$ and $D_l$ to produce a set of decline word candidates ($N = 15,665$). Next, we filter this combined set to exclude standard words and proper nouns, yielding a total of 533 decline words in set $\mathcal{D}$. Each word is

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\(^5\)Word lists to be released upon publication.
| Predictor | Low dissemination | High dissemination |
|-----------|------------------|--------------------|
| $D^L$    | ah, ooc, yeah, yikes, yup | aka, combos, ingame, ish, spamming |
| $D^U$    | crit, har, ooc, trans, vaping | asap, chill, pops, shitting, whoops |
| $D^S$    | atk, crit, ooc, vaping, winrate | btw, dang, info, sub, whoops |
| $D^T$    | crit, har, ooc, pvp, trans | ah, btw, dang, fwiw, whoops |

Table 2: Examples of growth words with high and low dissemination values.

Table 3: Examples of nonstandard words in all word sets: growth ($\mathcal{G}$), logistic decline ($\mathcal{D}_l$) and piecewise decline ($\mathcal{D}_p$).

We provide examples of both growth and decline words in Table 3. The growth words show several notable acronyms (lmao, tbh), while the decline words show more variety including clippings (atty, “atomizer”) and compounds (nparent, “narcissistic parent”). The time series for these words are visualized in the appendix (Figure 8).

4 Predictors

We now outline the predictors used to measure the degree of social and linguistic dissemination in the growth and decline words.

4.1 Social dissemination

We consider several versions of the dissemination metric proposed by Altmann et al. (2011) to measure the degree to which a word occupies a specific social niche. Low dissemination implies that a word occupies a limited niche, while a high dissemination implies wide-scale social acceptance. We compute the dissemination of words across a particular social variable (user, thread, and subreddit) as follows. To compute user dissemination $D^U$ for word $w$ at time $t$, we first compute the number of individual users who used word $w$ at time $t$, written $U_t^{(w)}$. We then compare this with the expectation $\tilde{U}_t^{(w)}$ under a model in which word frequency is identical across all users. The user dissemination is the log ratio,

$$\log \frac{U_t^{(w)}}{\tilde{U}_t^{(w)}} = \log U_t^{(w)} - \log \tilde{U}_t^{(w)}. \quad (2)$$

We compute the expected count $\tilde{U}_t^{(w)}$ using the same equation as Altmann et al. (2011),

$$\tilde{U}_t^{(w)} = \sum_{u \in U_t} (1 - e^{-f_t^{(w)} m_t^u}), \quad (3)$$

where $m_t^u$ equals the total number of words contributed by user $u$ in month $t$ and $U_t$ is the set of all users active in month $t$. This corresponds to a model in which each token from a user has identical likelihood $f_t^{(w)}$ of being word $w$. In this way, we compute dissemination for all users ($D^U$), subreddits ($D^S$) and threads ($D^T$) for each month $t \in \{1\ldots T\}$.

Examples of words with high and low average social dissemination are shown in Table 2. Highly disseminated words among users include the acronym asap, a widely accepted form of as soon as possible, while low-dissemination words among subreddits include crit (“critical hit”), which is restricted to users interested in video games. Similarly, $D^T$ approximates the spread of a word among discussion threads, which is relevant to words such as pvp (“player versus player”), an acronym restricted to video game threads.
4.2 Linguistic dissemination

Linguistic dissemination captures the diversity of linguistic contexts in which a word appears, as measured by unique n-gram counts. We compute the log count of unique trigram contexts for all words \(C^3\) using all possible trigram positions: in the sentence “that’s cool af haha”, ‘af’ appears in three unique trigrams, ‘that’s cool af’, ‘cool af haha’, ‘af haha’.

The unique log number of trigram contexts is strongly correlated with log word frequency \(\rho(C^3, f) = 0.904\). We therefore adjust this statistic by comparing with its expected value \(\tilde{C}\), similar to controlling for expected value in social dissemination. At each timestep \(t\), we fit a linear regression between log-frequency and log-unique ngram counts, and then compute the residual \(D^L\) between the observed log count of unique trigrams and its expectation, \(C_t(w) - \tilde{C}_t(w)\).

The expected log-count \(\tilde{C}_t(w)\) is predicted by a linear regression from log-frequency. This follows from the observation that the relationship between word frequency and contexts follows a roughly log-log relationship, similar to Heaps’ law (Egghe, 2007). The residual \(D^L\), or linguistic dissemination, identifies words with a higher or lower number of lexical contexts than expected.

Examples of growth words with high and low linguistic dissemination are shown in Table 2. High dissemination words include flexible acronyms (aka) and modifiers that can apply to a variety of contexts (ish). Words with low linguistic dissemination include words that are often used in sentence initial or final position (yikes).

Grammatical aspects of linguistic dissemination

To confirm the grammatical aspects captured by linguistic dissemination, we visualize the distribution of \(D^L\) values across words grouped by part of speech tags. These tags were obtained automatically from the CMU Twitter Part-of-Speech tagger (Gimpel et al., 2011).\(^6\) As shown in Figure 2, interjections have lower linguistic dissemination because they can appear throughout the sentence, often near open-class words such as nouns and verbs. But while these differences are real and in some cases substantial (one-way ANOVA between part-of-speech groups: \(F = 822.6, p < 0.0001\)), robustness checks in § 5.3 show that the role of linguistic dissemination in explaining word growth goes beyond part-of-speech category.

5 Results

The hypotheses about social and linguistic dissemination are tested under four analyses: correlation against frequency change in growth words; causal inference on probability of word growth; binary prediction of word growth; and survival analysis of decline words.

5.1 Correlating frequency change

We can first test the relative importance of the linguistic and social context on word growth by correlating the metrics with frequency change \((\Delta f_t = f_t - f_{t-k})\) across all growth words. This replicates the methodology in prior work by Altmann et al. (2011) and Garley and Hockenmaier (2012). Focusing on long-term change with \(k = 12\) (one year) and \(k = 24\) (two years), we compute the proportion of variance in frequency change explained by the covariates using a relative importance regression (Kruskal, 1987).

The results of the regression are shown in Table 4, and all predictors have nonzero relative importance according to a bootstrap method (Tonidand-
Table 4: Percent of variance explained in frequency change, computed over all growth words \( G \). The number of observations \( N \) is equal to 30,600 for \( k = 12 \) and \( N = 15,300 \) for \( k = 24 \).

| \( f_{t-12} \) | 10.8% | [10.2%, 11.5%] |
| --- | --- | --- |
| \( D_{L-12} \) | 0.584% | [0.461%, 0.777%] |
| \( D_{U-12} \) | 0.307% | [0.251%, 0.398%] |
| \( D_{S-12} \) | 0.120% | [0.0852%, 0.191%] |
| \( D_{T-12} \) | 0.246% | [0.171%, 0.379%] |
| \( f_{t-24} \) | 21.4% | [20.4%, 22.4%] |
| \( D_{L-24} \) | 1.29% | [1.05%, 1.64%] |
| \( D_{U-24} \) | 0.400% | [0.346%, 0.493%] |
| \( D_{S-24} \) | 0.287% | [0.201%, 0.392%] |
| \( D_{T-24} \) | 0.272% | [0.226%, 0.380%] |

The method for estimating the average dose response operates as follows.\(^8\) For clarity, the following terminology is used: \( Z \) for treatment variable, \( X \) for covariates, \( Y \) for outcome.

1. A linear model is fit to estimate the treatment from the covariates,

\[
Z_i \mid X_i \sim \mathcal{N}(\beta^T X_i, \sigma^2).
\] (4)

The output of this estimation procedure is a vector of weights \( \hat{\beta} \) and a variance \( \hat{\sigma}^2 \).

2. The generalized propensity score (GPS) is the likelihood of observing the treatment given the covariates, \( P(Z_i \mid X_i) \). It is computed from the parameters estimated in the previous step:

\[
\hat{R}_i = \frac{1}{\sqrt{2\pi \hat{\sigma}^2}} \exp(-\frac{(Z_i - \hat{\beta}^T X_i)^2}{2\hat{\sigma}^2}).
\] (5)

3. A logistic model is fit to predict the outcome \( Y_i \) using the treatment \( Z_i \) and the GPS \( \hat{R}_i \):

\[
\hat{Y}_i = \text{Logistic}(\hat{\alpha}_0 + \hat{\alpha}_1 Z_i + \hat{\alpha}_2 \hat{R}_i).
\] (6)

Hirano and Imbens (2005) show that by incorporating the GPS into this predictive model over the outcome, it is possible to isolate the causal effect of the treatment from the other covariates.

\(^8\)The procedure is implemented in the causaldrf package in R: https://cran.r-project.org/package=causaldrf
4. The range of treatments is divided into levels (quantiles). The average dose response for a given treatment level $s_z$ is the mean estimated outcome for all instances at that treatment level,

$$\hat{\mu}(s_z) = \frac{1}{|s_z|} \sum_{z_i \in s_z} \hat{Y}_i.$$  \hspace{1cm} (7)

The average dose response function is then plotted for all treatment levels.

For treatment, we consider each dissemination metric separately. For each treatment variable, we consider all other dissemination metrics as covariates, as well as the overall frequency: e.g., for treatment variable $D_L$, the covariates are set to $[f, D_U, D_S, D_T]$. We bootstrap the above process 100 times to produce confidence intervals. To balance the outcome classes, we sample an equal number of growth and decline words for each bootstrap iteration.

The average dose response function curves in Figure 3 show that using linguistic dissemination ($D_L$) as the treatment variable produces the most dramatic increase in word growth probability. For linguistic dissemination, the lowest treatment quantiles (0%-10%) yields a growth probability below 40% (significantly less than chance), as compared to the highest treatment quantiles (90-100%) which yields a growth probability nearly at 70% (significantly greater than chance). This supports the hypothesis that linguistic dissemination is predictive of growth, even after controlling for the frequency and the other dissemination metrics. Subreddit dissemination also shows a slight increase in probability of word growth, up to 60% in the highest treatment quantile. The dose response functions for the other metrics are flatter, with the growth probability not significantly exceeding the chance rate of 50% even at the highest levels of user dissemination ($D_U$) and thread dissemination ($D_T$).

### 5.3 Predicting growth

We now turn to prediction to determine the utility of the different dissemination metrics: using the first $k$ months of data, can we predict whether a word will grow or decline?

We use logistic regression with 10-fold cross-validation over four different feature sets: frequency-only ($f$), frequency plus linguistic dissemination ($f + L$), frequency plus social dissemination ($f + S$) and all features ($f + L + S$). Each fold is balanced for classes so that the baseline
accuracy is 50%. The results in Figure 4 show that linguistic dissemination provides more predictive power than social dissemination. The accuracy score is consistently higher for the models with linguistic dissemination than for the frequency-only and social dissemination models. However, the scores converge as the training data size increases, which suggests that the frequency-only model learns to detect the decline word “trajectory” and the linguistic dissemination models do not gain extra information with more training data.

Robustness checks Considering the uneven distribution of linguistic dissemination across part-of-speech groups (see Figure 2), the prediction results may be explained by an imbalance of POS tags between the growth and decline words. This issue is addressed through two robustness checks: within-group comparison and prediction.

First, we compare the distribution of linguistic dissemination values between growth and decline words, grouped by the most common POS tags. Each decline word is matched with a growth word based on similar mean frequency in the first \( k = 12 \) months, and their mean linguistic dissemination values during that time period are compared, grouped within POS tag groups. The differences in Figure 5 show that across all POS tags, the growth words show a tendency toward higher linguistic dissemination with significant \((p < 0.05)\) differences in the interjections and verbs.

Next, the POS tags are used in the same binary prediction task as before, in two different models: (1) as sole features, (2) as additional features in the frequency-only model, each with one month of data \((k = 1)\). The linguistic dissemination model significantly outperforms both models (mean accuracy of 50.6% and 54.8% respectively), which suggests that the difference in linguistic dissemination between the growth and decline words is not explained by a difference in the POS distribution.

5.4 Survival analysis of decline words

We now focus on the factors that precede a word’s decline phase, which can be viewed as the beginning of “word death” (Drouin and Dury, 2009) for many of these terms — though some may emerge again later. We use the decline words as “uncensored” data, words with an observed death date, and the growth words as “censored” data, words with an unobserved death date. The distribution of survivors is shown in Figure 6, which shows that most of the decline words begin to decline before the year mark \((t = 12)\).

Predicting the time until a word’s decline can be framed as survival analysis (Klein and Moeschberger, 2005), in which a word is said to “survive” until the beginning of its decline phase at split point \( \hat{t} \). In the Cox proportional hazards model (Cox, 1972), the hazard of death at each time \( t \), written \( \lambda(t) \), is modeled as a linear function of
some predictors $X$,

$$\lambda_i(t) = \lambda_0(t) \exp(\beta \cdot x_i), \quad (8)$$

where $x_i$ is the vector of predictors for word $i$, and $\beta$ is the vector of coefficients. Each cell $x_{i,j}$ is set to the mean value of predictor $j$ for word $i$ over the training period $t = \{1..k\}$ where $k = 3$. We use frequency, social dissemination and linguistic dissemination as predictors in a Cox regression model.\(^9\)

The estimated coefficients from the regression are shown in Table 5. We find a negative coefficient for linguistic dissemination ($\beta = -0.330, p < 0.001$), which mirrors the results from the previous prediction task: higher $D^L$ correlates with a lower hazard of word death, and therefore a higher likelihood of survival. We also find that higher subreddit dissemination has a weak but insignificant correlation with a lower likelihood of word death ($\beta = -0.156, p > 0.05$). Both of these results mirror the finding from the causal inference analysis, that higher linguistic and subreddit dissemination lead to higher probability of growth.

The role of each factor is tested by comparing the goodness-of-fit for Cox regression models using different feature sets: frequency ($f$), frequency plus linguistic dissemination ($f + L$), frequency plus social dissemination ($f + S$) and all factors ($f + L + S$). The results in Table 6 demonstrate that the model with dissemination and the model with linguistic diversity each have significantly better-than-null fits (lower deviance than null model). However, the all-factor model ($f + L + S$) does not have a significantly lower deviance than the linguistic dissemination model ($f + L$) ($\chi^2 = 4.6, p = 0.80$), therefore adding social dissemination does not significantly improve the model fit. This points to the especially important role of linguistic dissemination in predicting the word growth, as compared with social dissemination.

To compare the predictive performance of the separate Cox models, we compute their concordance scores using 10-fold cross-validation.\(^10\) As shown in Figure 7, the model incorporating linguistic dissemination ($f + L$) consistently achieves higher concordance than the baseline frequency-only model ($f$), ($t = 4.29, p < 0.001$) and the model with all predictors $f + L + S$ outperforms the model with social dissemination $f + S$ ($t = 4.64, p < 0.001$).

### 6 Discussion

All four quantitative analyses find a strong role for linguistic dissemination as a positive predictor in the nonstandard word growth: it was the strongest predictor of year-to-year frequency changes in growth words, the best differentiator of growth and decline words in causal and predictive tasks, and the most effective warning sign that a word is about to decline. Overall, H2 and its stronger form, H2a, are well supported by these analyses. Linguistic dissemination can be related to theories such as the FUDGE factors (Chesley and Baayen, 2010; Cook, 2010).

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\(^9\)Cox regression implemented in the lifelines package in Python: https://lifelines.readthedocs.io/en/latest/.

\(^10\)The concordance score for a Cox regression model represents the accuracy of predicting the order of word death, such that a score of 0.5 reflects a random order of death times while a score of 1.0 reflects a perfect order of death times.
2010; Metcalf, 2004), in which a word’s growth depends on a combination of frequency (F), unobtrusiveness (U), diversity of users and situations (D), generation of other forms and meanings (G), and endurance (E). Linguistic dissemination provides an example of “diversity of situation,” because words with a higher linguistic dissemination occur in more diverse lexical situations.

Regarding H1, we generally found a positive role for social dissemination as well, although these results were not consistent across all social dissemination predictions. Furthermore, the social dissemination features were relatively ineffective in the survival analysis. Taken together, these findings are somewhat aligned with the conclusion from Garley and Hockenmaier (2012), who argued that social dissemination is less predictive of word adoption than Altmann et al. (2011) originally suggested. One possible explanation is the inclusion of word categories such as proper nouns in the analysis of Altmann et al. (2011); it is plausible that the dissemination of such terms relies on social dynamics more than the dissemination of nonstandard terms. Another explanation is the focus of Garley and Hockenmaier (2012) on loanwords rather than native words, because loanwords could be more socially salient thanks to their obvious difference from native words (Poplack et al., 1988).

Limitations One limitation in the study was the exclusion of orthographic and morphological features such as affixation, which has been noted as a predictor of word growth (Kershaw et al., 2016). This was an intentional decision to focus on the effect of dissemination, but further study should compare the relative importance of these different factors, possibly under the FUDGE framework (e.g., affixation represents Generation of other forms). In addition, the study omitted borrowings, unlike prior work in word adoption that has focused on borrowings (Chesley and Baayen, 2010; Garley and Hockenmaier, 2012). Our early language-filtering steps eliminated most non-English words from the vocabulary, although it would have been interesting to examine loanword use in English-language posts. Lastly, our study was limited by the focus on individual words rather than phrases (e.g., *like a boss*) which may show similar correlation between dissemination, growth and decline (Bybee, 2006).

Future work We approximate linguistic dissemination using trigram counts, because they are easy to compute and they generalize across word categories. In future work, a more sophisticated approach might estimate linguistic dissemination with syntactic features such as appearance across different phrase heads (Kroch, 1989; Ito and Tagliamonte, 2003) or across nouns of different semantic classes (D’Arcy and Tagliamonte, 2015). However, the poor performance of automatic parsers on social media data (Eisenstein, 2013; Blodgett et al., 2016) and the limits of manual annotation may render this typical analysis difficult or impossible. Future work should also investigate the possibility of more semantically-aware definitions of linguistic dissemination. The existence of semantic “neighbors” occurring in similar contexts (e.g., the influence of standard intensifier *very* on nonstandard intensifier *af*) may prevent a new word from reaching widespread popularity.

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The growth and decline trajectories of the best-fitting words from each word set ($G, D_l, D_p$; from Table 3) are shown in Figure 8. The growth words (a) have a clear monotonic growth trajectory, and the decline words (b,c) all follow a similar trajectory of growth up to a peak followed by gradual decline.

**Appendix**

The growth and decline trajectories of the best-fitting words from each word set ($G, D_l, D_p$; from Table 3) are shown in Figure 8. The growth words (a) have a clear monotonic growth trajectory, and the decline words (b,c) all follow a similar trajectory of growth up to a peak followed by gradual decline.
Figure 8: Frequency time series for words from the (a) growth, (b) logistic decline and (c) piecewise decline word sets.