Word set	Examples
$\mathcal{G}$	*idk, lmao, shitpost, tbh, tho*
$\mathcal{D}_l$	*atty, eyebleach, iifym, obeasts, trashy*
$\mathcal{D}_p$	*brojob, nparent, rekd, terpers, wot*

Table 2: Examples of nonstandard words in all word sets: growth ($\mathcal{G}$), logistic decline ($\mathcal{D}_l$) and piecewise decline ($\mathcal{D}_p$).

	Clipping	Compound	Respelling	Other	Total
$\mathcal{G}$	198 (17.7%)	334 (29.8%)	83 (7.4%)	505 (45.1%)	1,120
$\mathcal{D}$	53 (10.0%)	100 (18.9%)	108 (20.4%)	269 (50.8%)	530

Table 3: Word formation category counts in growth ($\mathcal{G}$) and decline ($\mathcal{D}$) word sets.

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 85^{th} percentile (36.1%); this filtering yields 14,995 candidates.

Logistic fit To account for smoother growth-decline trajectories, we also fit the growth curve to a logistic distribution, which is a continuous unimodal distribution with support over the non-negative reals. We identify the set of candidates $\mathcal{D}_l$ ("logistic decline") as words with a strong fit to this distribution, as indicated by R^2 above the 99^{th} percentile (82.4%), yielding 998 candidates. 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 $\mathcal{D}_p$ and $\mathcal{D}_l$ 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 530 decline words in set $\mathcal{D}$. Each word is assigned a split point $\hat{t}$ based on the estimated time of switch between the growth phase and the decline phase, which is the split point $\hat{t}$ for piecewise decline words and the center of the logistic distribution $\hat{\mu}$ for the logistic decline words.

Examples of both growth and decline words are shown in Table 2. The growth words include several acronyms (*tbh*, "to be honest"; *lmao*, "laughing my ass off"), while the decline words include clippings (*atty*, "atomizer"), respellings (*rekd*, "wrecked"; *wot*, "what") and compounds (*nparent*, "narcissistic parent").

We also provide a distribution of the words across word generation categories in Table 3, including compounds and clippings in similar proportions to prior work (Kulkarni and Wang, 2018). Because the growth and decline words exhibit similar proportions of category counts, we do not expect that this will be a significant confound in differentiating growth from decline.

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 rely on the dissemination metric proposed by Altmann et al. (2011) to measure the degree to which a word occupies a specific social niche (e.g., low dissemination implies limited niche). 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,

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

Following Altmann et al. (2011), the expected count $\tilde{U}_t^{(w)}$ is computed as,

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

where $m_t^{(u)}$ equals the total number of words contributed by user u in month t, and $\mathcal{U}_t$ 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 $t \in \{1...T\}$.

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