Mapping the geographical diffusion of new words

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Abstract

Language in social media is rich with linguistic innovations, most strikingly in the new words and spellings that constantly enter the lexicon. Despite assertions about the power of social media to connect people across the world, we find that many of these neologisms are restricted to geographically compact areas. Even for words that become ubiquitous, their growth in popularity is often geographical, spreading from city to city. Thus, social media text offers a unique opportunity to study the diffusion of lexical change. In this paper, we show how an autoregressive model of word frequencies in social media can be used to induce a network of linguistic influence between American cities. By comparing the induced network with the geographical and demographic characteristics of each city, we can measure the factors that drive the spread of lexical innovation.

1 Introduction

As social communication is increasingly conducted through written language on computers and cellphones, writing must evolve to meet the needs of this less formal genre. Computer-mediated communication (CMC) has seen a wide range of linguistic innovation, including emoticons, abbreviations, expressive orthography such as lengthening [1], and entirely new words [2, 3, 4]. While these developments have been celebrated by some [5] and lamented by many others, they offer an intriguing new window on how language can change on the lexical level.

In principle social media can connect people across the world, but in practice social media connections tend to be quite local [6, 7]. Many social media neologisms are geographically local as well: our prior work has identified dozens of terms that are used only within narrow geographical areas [2]. Some of these terms were previously known from spoken language (for example, hella [8]), and others may refer to phonological language differences (the spelling suttin for something). But there are many terms that seem disconnected from spoken language variation — for example, differences that are only apparent in the written form, such as the spelling uu for you. This suggests that some geographically-specific terms have evolved through computer-mediated communication.

To study this evolution, we have gathered a large corpus of geotagged Twitter messages over the course of nearly two years, a time period which includes the introduction and spread of a number of new terms. Three examples are shown in Figure [1]

- The first term, bruh, is an alternative spelling of bro, short for brother. At the beginning of our sample it is popular in a few southeastern cities; it then spreads throughout the southeast, and finally to the west coast.
- The middle term, af, is an abbreviation for as fuck, as in I’m bored af. It is initially found in southern California, then jumps to the southeast, before gaining widespread popularity.
- The third term, -_--, is an emoticon. It is initially used in several east coast cities, then spreads to the west coast, and finally gains widespread popularity.
Clearly geography plays some role in each example — most notably in bruh, which may reference southeastern phonology. But each example also features long range “jumps” over huge parts of the country. What explains, say, the movement of af from southern California all the way to a cluster of cities around Atlanta?

This paper presents a quantitative model of the geographical spread of lexical innovations through social media. Using a novel corpus of millions of Twitter messages, we are able to trace the changing popularity of thousands of words. We build an autoregressive model that captures aggregate patterns of language change across 200 metropolitan areas in the United States. The coefficients of this model correspond to sender/receiver pairs of cities that are especially likely to transmit linguistic influence.

After inducing a network of cities linked by linguistic influence, we search for the underlying factors that explain the network’s structure. We show that while geographical proximity plays a strong role in shaping the network of linguistic influence, demographic homophily is at least equally important. Going beyond homophily, we identify asymmetric features that make individual cities more likely to send or receive lexical innovations.

2 Related work

This paper draws on several streams of related work, including sociolinguistics, theoretical models of language change, and network induction.

2.1 Sociolinguistic models of language change

Language change has been a central concern of sociolinguistics for several decades. This tradition includes a range of theoretical accounts of language change that provide a foundation for our work.

The wave model argues that linguistic innovations are spread through interactions over the course of an individual’s life, and that the movement of a linguistic innovation from one region to another depends on the density of interactions [9]. The simplest version of this theory supposes that the probability of contact between two individuals depends on their distance, so linguistic innovations should diffuse continuously through space.

The gravity model refines this view, arguing that the likelihood of contact between individuals from two cities depends on the size of the cities as well as their distance; thus, linguistic innovations should be expected to travel between large cities first [10]. Labov argues for a cascade model in which many linguistic innovations travel from the largest city to the next largest, and so on [11].
However, Nerbonne and Heeringa present a quantitative study of dialect differences in the Netherlands, finding little evidence that population size impacts diffusion of pronunciation differences [12].

**Cultural factors** surely play an important role in both the diffusion of, and resistance to, language change. Many words and phrases have entered the standard English lexicon from dialects associated with minority groups: for example, *cool*, *rip off*, and *uptight* all derive from African American English [13]. Conversely, Gordon finds evidence that minority groups in the US resist regional sound changes associated with White speakers [14]. Political boundaries also come into play: Boberg demonstrates that the US-Canada border separating Detroit and Windsor complicates the spread of sound changes [15]. While our research does not distinguish the language choices of speakers within a given area, gender and local social networks can have a profound effect on the adoption of sound changes associated with a nearby city [16].

Methodologically, traditional sociolinguistics usually focuses on a small number of carefully chosen linguistic variables, particularly phonology [10][11]. Because such changes typically take place over decades, change is usually measured in *apparent time*, by comparing language patterns across age groups. Social media data lend a complementary perspective, allowing the study of language change by aggregating across thousands of lexical variables, without manual variable selection. (Nerbonne has shown how to build dialect maps while aggregating across regional pronunciation differences of many words [17], but this approach requires identifying matched words across each dialect.) Because language in social media changes rapidly, it is possible to observe change directly in real time, thus avoiding confounding factors associated with other social differences in the language of different age groups.

### 2.2 Theoretical models of language change

A number of abstract models have been proposed for language change, including dynamical systems [18], Nash equilibria [19], Bayesian learners [20], agent-based simulations [21], and population genetics [22], among others. In general, such research is concerned with demonstrating that a proposed theoretical framework can account for observed phenomena, such as the geographical distribution of linguistic features and their rate of adoption over time. In contrast, this paper fits a relatively simple model to a large corpus of real data. The integration of more complex modeling machinery seems an interesting direction for future work.

### 2.3 Identifying networks from temporal data

From a technical perspective, this work can be seen as an instance of network induction. Prior work in this area has focused on inducing a network of connections from a cascade of “infection” events. For example, Gomez-Rodriguez et al. reconstruct networks based on cascades of events [23], such as the use of a URL on a blog [24] or the appearance of a short textual phrase [25]. We share the goal of reconstructing a latent network from observed data, but face an additional challenge in that our data do not contain discrete infection events. Instead we have changing word counts over time; our model must decide whether a change in word frequency is merely noise, or whether it reflects the spread of language change through an underlying network.

### 3 Data

This study is performed on a new dataset of social media text, gathered from the public “Gardenhose” feed offered by the microblog site Twitter (approximately 10% of all public posts). The dataset has been acquired by continuously pulling data from June 2009 to May 2011, resulting in a total of 494,865 individuals and roughly 44 million messages. In this study, we consider a subsample of 86 weeks, from December 2009 to May 2011.

We considered only messages that contain geolocation metadata, which is optionally included by smartphone clients. We locate the latitude and longitude coordinates to a Zipcode Tabulation Area (ZCTA) [1] and use only messages from the continental USA. We use some content filtering to focus on conversational messages, excluding all retweets (both as identified in the official Twitter API,
as well as messages whose text includes the token “RT”), and also exclude messages that contain a URL. Grouping tweets by author, we retain only authors who have between 10 and 1000 messages over this timeframe. Each Twitter message includes a timestamp. We aggregate messages into seven-day intervals, which facilitates computation and removes any day-of-week effects.

The United States Office of Management and Budget defines a set of Metropolitan Statistical Areas (MSAs), which are not legal administrative divisions, but rather, geographical regions centered around a single urban core [26]. We consider the 200 most populous MSAs, and place each author in the MSA whose center is nearest to the author’s geographical location (averaged among their messages). The most populous MSA is centered on New York City (population 19 million); the 200th most populous is Burlington, VT (population 208,000).

For each MSA we compute demographic attributes using information from the 2000 U.S. Census [2]. We consider the following demographic attributes: % White; % African American; % Hispanic; % urban; % renters; median log income. Rather than using the aggregate demographics across the entire MSA, we correct for the fact that Twitter users are not an unbiased sample from the MSA. We identify the finer-grained Zip Code Tabulation Areas (ZCTA) from which each individual posts Twitter messages most frequently. The MSA demographics are then computed as the weighted average of the demographics of the relevant ZCTAs. Of course, Twitter users may not be a representative sample of their ZCTAs, but these finer-grained units are specifically drawn to be demographically homogeneous, so on balance this should give a more accurate approximation of the demographics of the individuals in the dataset. For the first author’s home city of Atlanta, the unweighted MSA statistics are 55% White, 32% Black, 10% Hispanic; our weighted estimate is 53% White, 40% Black, and 6% Hispanic. In the Pittsburgh MSA, the unweighted statistics are 90% White and 8% Black; our weighted estimate is 84% White and 12% Black. This coheres with our earlier finding that American Twitter users inhabit zipcodes with higher-than-average African American populations [3], and matches survey data showing a high rate of adoption for Twitter among African American populations [27, 28].

We consider the 10,000 most frequent words (no hashtags or usernames were included), and further require that each word must be used more than five times in one week within a single metropolitan area. The second filtering step — which reduces the vocabulary to 1,818 words — prefers words that attain short-term popularity within a single region, as compared to words that are used infrequently but uniformly across space and time. Text was tokenized using the twokenize.py script, which is designed to be robust to social media phenomena that confuse other tokenizers, such as emoticons [29]. We normalized repetition of the same character two or more times to just two (e.g. sooooo → soo).

4 Autoregressive model of language change

We model language change as a simple dynamical system. For each word \( i \), in region \( r \) during week \( t \), we count the number of individuals who use \( i \) as \( c_{i,r,t} \), and the total number of individuals who have posted any text at all as \( s_{r,t} \). Our model assumes that \( c_{i,r,t} \) follows a binomial distribution: 
\[
c_{i,r,t} \sim \text{Binomial}(s_{r,t}, \theta_{i,r,t})
\]
where \( \theta_{i,r,t} \) is the expected likelihood of each individual using the word \( i \) during the week \( t \) in region \( r \). We treat \( \theta_{i,r,t} \) as the result of applying a logistic transformation to four pieces of information: the background log frequency of the word, \( \nu_i \); a temporal-regional effect quantifying the general activation of region \( r \) at time \( t \), \( \tau_{r,t} \); a global temporal effect for word \( i \), \( \eta_i \); and a regional-temporal activation for word \( i \), \( \eta_{i,r,t} \). To summarize, 
\[
\theta_{i,r,t} = \sigma(\nu_i + \tau_{r,t} + \eta_i + \eta_{i,r,t})
\]
where \( \sigma(x) = e^x/(1+e^x) \).

Only the variables \( \eta_{i,r,t} \) capture geographically-specific changes in word frequency over time. We perform statistical inference over these variables, conditioned on the observed counts \( c \) and \( s \), using a vector autoregression (VAR) model. The general form can be written as \( \eta_{t} \sim f(\eta_{t-1}, \ldots, \eta_{t-\ell}) \), assuming Markov independence after a fixed lag of \( \ell \). The function \( f \) can model dependencies both between pairs of words and across regions, but in this paper we consider a restricted form of \( f \): autoregressive dependencies are assumed to be linear and first-order Markov; a single set of autoregressive coefficients is shared across all words; cross-word dependencies are otherwise

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3 This part of the data was prepared before the 2010 Census information was released; we believe it is sufficient for developing our model and data analysis method, but plan to update it in future work.

https://github.com/brendano/tweetmotif
Table 1: Summary of mathematical notation. The index \( i \) indicates words, \( r \) indicates regions (MSAs), and \( t \) indicates time (weeks).

\[
\begin{align*}
\eta_{i,r,t} & \quad \text{count of individuals who use word } i \text{ in region } r \text{ at time } t \\
s_{r,t} & \quad \text{count of individuals who post messages in region } r \text{ at time } t \\
\theta_{i,r,t} & \quad \text{estimated probability of using word } i \text{ in region } r \text{ at time } t \\
\nu_i & \quad \text{overall log-frequency of word } i \\
\tau_{r,t} & \quad \text{general activation of region } r \text{ at time } t \\
\eta_{i,t} & \quad \text{global activation of word } i \text{ at time } t \\
\eta_{i,r,t} & \quad \text{activation of word } i \text{ at time } t \text{ in region } r \\
\eta_{i,r,t}^* & \quad \text{vertical concatenation of each } \eta_{i,r,t} \text{ and } \eta_{i,s,t}, \text{ a vector of size } R + 1 \\
\sigma(\cdot) & \quad \text{the logistic function, } \sigma(x) = e^x / (1 + e^x) \\
\mathbf{A} & \quad \text{autoregressive coefficients (size } R \times R) \\
\mathbf{\Gamma} & \quad \text{variance of the autoregressive process (size } R \times R) \\
\zeta_{i,r,t} & \quad \text{parameter of the Taylor approximation to the logistic binomial likelihood} \\
m_{i,r,t} & \quad \text{Gaussian pseudo-emission in the Kalman smoother} \\
\Sigma_{i,r,t}^2 & \quad \text{emission variance in the Kalman smoother} \\
\omega_{i,r,t}^{(k)} & \quad \text{weight of particle } k \text{ in the forward pass of the sequential Monte Carlo algorithm}
\end{align*}
\]

4.1 Sequential Monte Carlo estimation of word activations

To obtain smoothed estimates of \( \eta \), we apply a sequential Monte Carlo (SMC) smoothing algorithm known as Forward Filtering Backward Sampling (FFBS) \cite{douc2007}. The algorithm appends a backward pass to any SMC filter that produces a set of particles and weights \( \{ \eta_{i,r,t}^{(k)}, \omega_{i,r,t}^{(k)} \}_{1 \leq k \leq K} \). Our forward pass is a standard bootstrap filter \cite{ Internacional 2004}: by setting the proposal distribution \( q(\eta_{i,r,t} | \eta_{i,r,t-1}) \) equal to the transition distribution \( P(\eta_{i,r,t} | \eta_{i,r,t-1}; \mathbf{A}, \mathbf{\Gamma}) \), the forward particle weights are equal to the recursive product of the emission likelihoods,

\[
\omega_{i,r,t}^{(k)} = \omega_{i,r,t-1}^{(k)} \text{Binomial}(c_{i,r,t}; s_{r,t}, \sigma(\nu_i + \tau_{r,t} + h_{r,t}, \eta_{i,r,t}^{(k)})). 
\] (2)

We experimented with more complex SMC algorithms, including resampling, annealing, and more accurate proposal distributions, but none consistently achieved higher likelihood than the straightforward bootstrap filter.

FFBS converts the filtered estimates \( P(\eta_{i,r,t} | c_{i,r,1:T}, s_{r,1:T}) \) to a smoothed estimate \( P(\eta_{i,r,t} | c_{i,r,1:T}, s_{r,1:T}) \) by resampling the forward particles in a backward pass. In this pass, at each time \( t \), we select particle \( \eta_{i,r,t}^{(k)} \) with probability proportional to \( \omega_{i,r,t}^{(k)} P(\eta_{i,r,t+1} | \eta_{i,r,t}) \), which is the filtering weight multiplied by the transition probability. When we reach \( t = 1 \), we have obtained an unweighted draw from the distribution \( P(\eta_{i,r,1:T} | c_{i,r,1:T}, s_{r,1:T}; \mathbf{A}, \mathbf{\Gamma}, \nu, \tau) \). We can use these draws to estimate the distribution of any arbitrary function of \( \eta \).
4.2 Estimation of system dynamics parameters

The parameter $\Gamma$ controls the variance of the latent state, and the diagonal elements of $A$ control the amount of autocorrelation within each region. The maximum likelihood settings of these parameters are closely tied to the latent state $\eta$. For this reason, we estimate these parameters using an expectation-maximization algorithm, iterating between maximum-likelihood estimation of $\Gamma$ and diag($A$) and computation of a variational bound on $P(\eta_i | c_i, s; \Gamma, A)$. We run the sequential Monte Carlo procedure described above only after converging to a local optimum for $\Gamma$ and diag($A$). This combination of variational and Monte Carlo inference offers advantages of both: variational inference gives speed and guaranteed convergence for parameter estimation, while Monte Carlo inference allows the computation of confidence intervals around arbitrary functions of the latent variables $\eta$. Similar hybrid approaches have been proposed in the prior literature [32].

The variational bound on $P(\eta_i | c_i, s; \Gamma, A)$ is obtained from a Gaussian approximation to the Binomial emission distribution. This enables the computation of the joint density by a Kalman smoother, a two-pass procedure for computing smoothed estimates of a latent state variable given Gaussian emission and transition distributions. For each $\eta_{i,r,t}$, we take a second-order Taylor approximation to the emission distribution at the point $\zeta_{i,r,t}$. This yields a Gaussian approximation,

$$\text{Binomial}(c_{i,r,t} | s_{r,t}, \sigma(\nu_i + \tau_{r,t} + \eta_{i,s,t} + \eta_{i,r,t})) \approx \text{Normal}(m_{i,r,t} | \eta_{i,r,t}, \Sigma_{i,r,t}^2),$$

where the parameters $m$ and $\Sigma^2$ depend on a Taylor approximation parameter $\zeta_{i,r,t},$

$$\Sigma_{i,r,t}^2 = (s_{r,t}\sigma(\zeta_{i,r,t})(1 - \sigma(\zeta_{i,r,t})))^{-1}$$

$$m_{i,r,t} = s_{r,t}(c_{i,r,t} - \eta_{i,s,t} + \zeta_{i,r,t} + \tau_{r,t} - \nu_i)$$

Intuitively, the emission parameter $m$ depends on the gap between the observed counts $c$ and the expected counts $s\sigma(\zeta)$. We initialize $\zeta_{i,r,t}$ to the relative frequency estimate $\sigma^{-1}(\frac{c_{i,r,t}}{s_{r,t}})$, and then iteratively update it to improve the quality of the approximation.

During initialization, the parameters $\nu_i$ (overall word log-frequency) and $\tau_{r,t}$ (global activation in region $r$ at time $t$) are fixed to their maximum-likelihood point estimates, assuming $\eta_{i,r,t} = \eta_{i,s,t} = 0$. The global word popularity $\nu_i$ is a latent variable; we perform inference by including it in the latent state of the Kalman smoother. The final state equations are:

$$\eta_{i,t} \sim \text{Normal}(A\eta_{i,t-1}, \Gamma)$$

$$m_{i,t} \sim \text{Normal}(H\eta_{i,t}, \Sigma_{i,t}^2),$$

where the matrix $A$ is diagonal and the matrix $H$ is a vertical concatenation of all row vectors $h_r$ (equivalently, it is a horizontal concatenation of the identity matrix with a column vector of 1s). As we now have Gaussian equations for both the emissions and transitions, we can apply a standard Kalman smoother (we use an optimized version of the Bayes Net Toolbox for Matlab [33]). The EM algorithm arrives at local optima of the data likelihood for the emission variance $\Gamma$ and the auto-covariance on the diagonal of $A$.

Figure 2 shows the estimates of $\eta$ for the word *ctfu* (cracking the fuck up) in five metropolitan areas. The strong dotted lines show the 95% confidence intervals of the Kalman smoother; each of 100
Figure 3: $A_{m,n}$ estimates for all $(m,n)$, showing intervals $\mu_m, n \pm 3.12 \sigma_{m,n}$. **Left:** Both self-effects and cross-region effects are shown (excluding two having $z > 500$). **Right:** only cross-region effects.

FFBS samples is shown as a light dotted line. The right panel shows the estimated term frequencies with lines, and the empirical frequencies with circles. The term was used only in Cleveland (among these cities) at the beginning of the dataset, but eventually became popular in Philadelphia, Pittsburgh, and Erie (Pennsylvania). The wider confidence intervals for Erie reflect greater uncertainty due to the smaller overall counts for this city.

4.3 Estimating cross-region effects

The maximum-likelihood estimate for the system coefficients is ordinary least squares,

$$A = \left( \eta_1^{T-1} \eta_1^{T-1} \right)^{-1} \eta_2^{T-1} \eta_1^{T-1}$$

The regression includes a bias term. We experimented with ridge regression for regularization (penalizing the squared Frobenius norm of $A$), comparing regularization coefficients by cross-validation within the time series. We found that regularization can improve the likelihood on held-out data when computing $A$ for individual words, but when words are aggregated, regularization yields no improvement.

Next, we compute confidence estimates for $A$. We compute $A^{(k)}$ for each sampled sequence $\eta^{(k)}$, summing over all words. We can then compute Monte Carlo-based confidence intervals around each entry $A_{m,n}$, by fitting a Gaussian to the samples: $\mu_{m,n} = \frac{1}{K} \sum_k A^{(k)}_{m,n}$ and $\sigma^2_{m,n} = \frac{1}{K} \sum_k (A^{(k)}_{m,n} - \mu_{m,n})^2$. To identify coefficients that are very likely to be non-zero, we compute Wald tests using $z$-scores $z_{m,n} = \mu_{m,n} / \sigma_{m,n}$. We apply the Benjamini-Hochberg False Discovery Rate correction for multiple hypothesis tests [34], computing a one-tailed $z$-score threshold $\bar{z}$ such that the total proportion of false positives will be less than .01. This test finds a $\bar{z}$ such that

$$FDR = 0.01 = \frac{\mathbb{E}[\# \{ \text{that pass under null hypothesis} \}]}{\# \{ \text{that pass empirically} \}} = \frac{200(199)(1 - \Phi(\bar{z}))}{\# \{ z_{m,n} > \bar{z} \}}$$

Coefficients that pass this threshold can be confidently considered to indicate cross-regional influence in the autoregressive model.

5 Analysis

We apply this method to the Twitter data described in Section 3. In practice, we initialize each $\eta_i$ to smoothed relative-frequency estimates, and run the EM-Kalman procedure for 100 steps or until convergence. We then draw 100 samples of $\eta_i$ from the FFBS smoother. These samples are used to compute confidence intervals around the autoregression coefficients $A$. When aggregating across all words, the total number of significant $(m,n)$ interactions is 3544, out of 39,800 possible, with $z$-score threshold of 3.12. Figure 3 visually depicts these estimates; the FDR of 0.01 indicates that the blue points occur 100 times more often than they would by chance.

Figure 4 shows high-confidence, high-influence links among the 50 largest metropolitan statistical areas in the United States. For more precise inspection, Figure 5 shows, for each city, all high-
confidence influence links to and from all other cities (also called ego networks). The role of geographical proximity is apparent: there are dense connections within regions such as the northeast, midwest, and west coast, and relatively few cross-country connections.

By analyzing the properties of pairs of cities with significant influence, we can identify the geographic and demographic drivers of linguistic influence. First, we consider the ways in which similarity and proximity between regions causes them to share linguistic influence. Then we consider the asymmetric properties that cause some regions to be linguistically influential.

### 5.1 Symmetric properties of linguistic influence

To assess symmetric properties of linguistic influence, we compare pairs of MSAs linked by non-zero autoregressive coefficients, versus randomly-selected pairs of MSAs. Specifically, we compute the empirical distribution over senders and receivers (how often each city fills each role), and we sample pairs from these distributions. The baseline thus includes the same distribution of MSAs as the experimental condition, but randomizes the associations. Even if our model were predisposed to detect influence among certain types of MSAs (for example, large or dense cities), that would not bias this analysis, since the aggregate makeup of the linked and non-linked pairs is identical.

Table 2 shows the similarities between pairs of cities that are linguistically linked (line 1) or selected randomly (line 2). Cities indicated as linked by our model are more geographically proximal than randomly-selected cities, and are more demographically similar on every measured dimension. All effects are significant at $p < 0.05$; the percentage of renters just misses the threshold for $p < 0.01$.

Because demographic attributes correlate with each other and with geography, it is possible that some of these homophily effects are spurious. To disentangle these factors, we perform a multiple regression. We choose a classification framework, treating each linked city pair as a positive example, and randomly selected non-linked pairs as negative examples. Logistic regression is used to assign weights to each of several independent variables: product of populations, geographical...
Figure 5: Ego networks for each of the 50 largest MSAs. Unlike Figure 4, all incoming and outgoing links are included (having z-score > 3.12). A blue link between cities indicates there is both an incoming and outgoing edge; green indicates outgoing-only; orange indicates incoming-only. Maps are ordered by population size. Official MSA names include up to three city names to describe the area; we truncate to the first.
Table 3: Logistic regression to predict linked pairs of MSAs

(a) Logistic regression coefficients predicting influence links between MSAs. Bold typeface indicates statistical significance at \( p < .01 \).

|                     | estimate | s.e. | \( t \)-value |
|---------------------|----------|------|---------------|
| intercept           | -0.0601  | 0.0287| -2.10         |
| product of populations | 0.393    | 0.048 | 8.22          |
| distance            | -0.870   | 0.033 | -26.1         |
| abs. diff. % White  | -0.214   | 0.040 | -5.39         |
| abs. diff. % Af. Am.| -0.693   | 0.042 | -16.7         |
| abs. diff. % Hispanic| -0.140   | 0.030 | -4.63         |
| abs. diff. % urban  | -0.170   | 0.030 | -5.76         |
| abs. diff. % renters| -0.0314  | 0.0304| -1.04         |
| abs. diff. log income | 0.0458  | 0.0301| 1.52          |

(b) Accuracy of predicting influence links, with ablated feature sets.

| feature set          | accuracy | gap |
|----------------------|----------|-----|
| all Features         | 72.3     |     |
| -population          | 71.6     | 0.7 |
| -geography           | 67.6     | 4.7 |
| -demographics        | 66.9     | 5.4 |

Table 4: Differences in demographic attributes between senders and receivers of lexical influence. Bold typeface indicates statistical significance at \( p < .01 \).

|                  | Log pop. difference | % White difference | % Af. Am difference | % Hispanic difference | % Urban difference | % Renters difference | Log income difference |
|------------------|---------------------|--------------------|---------------------|-----------------------|-------------------|----------------------|----------------------|
| estimate         | 0.968               | -0.0858            | 0.0703              | 0.0094                | 0.0612            | 0.0231               | 0.0546               |
| s.e.             | 0.0543              | 0.0065             | 0.0063              | 0.0098                | 0.0054            | 0.0041               | 0.0113               |
| \( z \)-score    | 17.8                | -13.2              | 11.1                | 0.950                 | 11.3              | 5.67                 | 4.82                 |

5.2 Asymmetric properties of linguistic influence

Next we evaluate asymmetric properties of linguistic influence. The goal is to identify the features that make metropolitan areas more likely to send rather than receive lexical influence. Places that possess many of these characteristics are likely to have originated or at least popularized many of the neologisms observed in social media text. We consider the characteristics of the 466 pairs of MSAs in which influence is detected in only one direction.

Table 4 shows the average difference in population and demographic attributes between the sender and receiver cities in each of the 466 asymmetric pairs. Senders have significantly higher populations, more African Americans, fewer Whites, more renters, greater income, and are more urban (\( p < 0.01 \) in all cases). Because demographic attributes and population levels are correlated, we again turn to logistic regression to try to identify the unique contributing factors. In this case, the classification problem is to identify the sender in each asymmetric pair. As before, all features are standardized. The feature weights from training on the full dataset are shown in Table 5. Only the coefficients for population size and percentage of African Americans are statistically significant. In 5-fold cross-validation, this classifier achieves 82\% accuracy (population alone achieves 78\% accuracy; without the population feature, accuracy is 77\%).
6 Conclusions

This paper presents an aggregate analysis of the changing frequencies of thousands of words in social media text, over the course of roughly one and a half years. From these changing word counts, we are able to reconstruct a network of linguistic influence; by cross-referencing this network with census data, we identify the geographic and demographic factors that govern the shape of this network.

We find strong roles for both geography and demographics, but the role of demographics is especially remarkable given that our analysis is centered on metropolitan statistical areas. MSAs are by definition geographically homogeneous, but they are heterogeneous along every demographic attribute. Nonetheless, demographically-similar cities are significantly more likely to share linguistic influence. Among demographic attributes, racial homophily seems to play the strongest role, although we caution that demographic properties such as socioeconomic class are more difficult to assess from census statistics.

At the level of individual language users, demographics may play a stronger role than geography, as has been asserted in the case of African American English [14]. Further research is necessary to assess how the geographical diffusion of lexical innovation is modulated by demographic variation within each geographical area. A second direction for future research is to relax the assumption that word activations evolve independently. Many innovative words reflect abstract orthographic patterns — for example, the spelling *bruh* employs a transcription of a particular pronunciation for *bro*, and this transcription pattern may be applied to other words that have similar pronunciation. A latent variable model could identify sets of words with similar shape features and spatiotemporal characteristics, while jointly identifying a set of influence matrices.

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