Follow the Leader: Documents on the Leading Edge of Semantic Change
Get More Citations

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Abstract
Diachronic word embeddings offer remarkable insights into the evolution of language and provide a tool for quantifying sociocultural change. However, while this method identifies words that have semantically shifted, it studies them in isolation; it does not facilitate the discovery of documents that lead or lag with respect to specific semantic innovations. In this paper, we propose a method to quantify the degree of semantic progressiveness in each usage. These usages can be aggregated to obtain scores for each document. We analyze two large collections of documents, representing legal opinions and scientific articles. Documents that are predicted to be semantically progressive receive a larger number of citations, indicating that they are especially influential. Our work thus provides a new technique for identifying lexical semantic leaders and demonstrates a new link between early adoption and influence in a citation network.

1 Introduction
Languages are continuously evolving (Weinreich et al., 1968), with elements, such as words, repurposed to new meanings (Traugott and Dasher, 2001). Word embeddings can identify semantic changes by tracking shifts in each word’s distributional neighborhood (Kutuzov et al., 2018). However, these methods treat each word in isolation and do not indicate where change takes place: which documents or passages are at the leading edge of semantic change, and which lag behind?

The ability to identify documents in the vanguard of linguistic change would yield valuable insights into the life cycle of new ideas: for example, this capability could make it possible to identify and support innovation in science (Fortunato et al., 2018), and would provide new evidence about the social processes underlying linguistic and scholarly influence (Gerow et al., 2018). To address this goal, we propose a simple quantitative technique for identifying the leading examples of ongoing semantic changes. Our method builds directly on the embedding-based techniques for detecting changes, and takes the form of a likelihood ratio comparison between “older” and “newer” embedding models. Usages that are better aligned with the newer embedding model can be considered to be more semantically “progressive,” in the sense of reflecting newer word meanings.

Using large datasets of legal opinions and scientific research abstracts, we demonstrate that more semantically advanced usages are indeed associated with documents that are landmarks in their respective fields, such as prominent Supreme Court rulings, and foundational research papers. We further formalize these insights by demonstrating a novel relationship between semantic progressiveness and citation counts: in both domains, semantically progressive documents receive more citations, even after controlling for document content and a range of structural factors. To summarize the contributions of this paper:

• We identify markers of semantic change in scientific articles and legal opinions. Legal opinions have not previously been analyzed with respect to dynamic word embeddings, and have received little attention in NLP.
• We propose a novel method to score documents on their semantic progressiveness, thereby identifying documents on the vanguard of semantic change.
• We show that documents at the vanguard of semantic change tend to be more influential in citation networks.

2 Measuring Semantic Progressiveness
Diachronic word embeddings make it possible to measure lexical semantic change over time (e.g.,
Kulkarni et al., 2015; Hamilton et al., 2016a). In standard word embeddings, each word type is associated with a vector of real numbers, based on its distributional statistics (Turney and Pantel, 2010; Mikolov et al., 2013). In diachronic word embeddings, this vector is time-dependent, reflecting how a word’s meaning (and associated distributional statistics) can change over time. Building on diachronic word embeddings, our method is comprised of four steps: (1) learning diachronic embeddings of words; (2) identifying semantic innovations using their diachronic embeddings; and (3) scoring each usage by its position with respect to the semantic change; (4) aggregating these scores by document. We now describe each of these steps in detail.

2.1 Estimating Word Embeddings

Several methods to learn diachronic word embeddings have been proposed (e.g., Bamler and Mandt, 2017; Freermann and Lapata, 2016; Hamilton et al., 2016a; Rosenfeld and Erk, 2018). In this work, we use the method proposed by Hamilton et al. (2016a) as it is conceptually straightforward and offers flexibility in the choice of the embedding algorithm. The core of this approach is to fit embedding models to distinct time-slices of the corpora, and then align the resulting embeddings.

Formally, assume a finite vocabulary \( V \), and two corpora, \( W^{\text{(old)}} \) and \( W^{\text{(new)}} \), where each corpus is a set of sequences of tokens, \( W = \{(w_{1,1}, w_{1,2}, \ldots, w_{1,T_1})\}_{i=1}^{N} \), and each \( w_{i,t} \in V \). For each corpus, we estimate a set of word embeddings on the single vocabulary \( V \). Following Hamilton et al. (2016a), we estimate skipgram embeddings (Mikolov et al., 2013), in which the goal is to predict context words \( w_{t'} \) conditioned on a target word \( w_t \).

While the mathematical details of skipgram word embeddings are well known, they are crucial to our method for situating individual usages of words with respect to ongoing semantic changes. For this reason, we present a brief review. Omitting the document index \( i \), the skipgram objective is based on the probability,

\[
P(w_{t'} | w_t) \propto \exp \left( \mathbf{v}_{w_{t'}} \cdot \mathbf{u}_{w_t} \right).
\]

Normalizing this probability requires summing over all possible \( w_{t'} \), which is computationally expensive. Typically the skipgram estimation problem is solved by negative sampling (Mikolov et al., 2013), but this does not yield properly normalized probabilities. We therefore turn instead to noise-contrastive estimation (Gutmann and Hyvärinen, 2010), which makes it possible to estimate the probability in Equation 1 without computing the normalization term (Mnih and Kavukcuoglu, 2013).

Suppose that the observed data is augmented with a set of “noise” examples \( \{(\tilde{w}, w_{t'})\} \), where each \( \tilde{w} \) is sampled from a unigram noise distribution \( P_n \). Further assume that there are \( k \) noise examples for every real example. An alternative prediction task is to decide whether each example is from the real data \( (D = 1) \) or from the noise \((D = 0)\). The cross entropy for this task is,

\[
J = \sum_{t} \log \Pr(D = 1 | w_t, w_{t'}) \\
+ \sum_{j=1}^{k} \log \Pr(D = 0 | w_t, \tilde{w}^{(j)})
\]

where each \( \tilde{w}^{(j)} \) is drawn from \( P_n \).

Now let us define the probability,

\[
\Pr(D = 1 | w_t, w_{t'}) = \frac{P(w_{t'} | w_t)}{P(w_{t'} | w_t) + kP_n(w_{t'})}
\]

\[
= \sigma \left( \mathbf{v}_{w_{t'}} \cdot \mathbf{u}_{w_t} - Z(w_t) - \log(kP_n(w_{t'})) \right)
\]

(4)

(5)

where the log-normalization term \( Z(w_t) = \log \sum_{w'} \exp \mathbf{v}_{w'} \cdot \mathbf{u}_{w_t} \) can be dropped because the NCE objective is approximately “self-normalizing” when \( P_n \) has positive support over all \( w \in V \) (Mnih and Kavukcuoglu, 2013). We then maximize Equation 2 by gradient descent, which yields embeddings that are asymptotically equivalent to the optimizers of Equation 1 (Gutmann and Hyvärinen, 2010). Noise-contrastive estimation is closely related to the negative sampling objective typically employed in skipgram word embeddings, but of the two, only NCE-based embeddings can be interpreted probabilistically (Dyer, 2014), as required by our approach.

The skipgram model is not identifiable: any permutation of the dimensions of the input and output embeddings will yield the same result. To reconcile the input embeddings between the corpora \( W^{\text{(old)}} \) and \( W^{\text{(new)}} \), we follow Hamilton et al. (2016a) and apply the Procrustes method (Gower et al., 2004) to identify an orthogonal projection.
Q that minimizes the Frobenius norm \[ ||QU^{(\text{old})} - U^{(\text{new})}||_F \], where \[ ||X||_F = \sqrt{\sum_{i,j} x_{i,j}^2} \].

Why NCE? One potential downside of NCE is that its embeddings depend on the random initialization, unlike deterministic techniques such as singular value decomposition (Levy and Goldberg, 2014). As a result, the list of near neighbors can change across multiple runs (Hellrich and Hahn, 2014). Nonetheless, we chose NCE because the resulting embeddings outperformed alternatives on intrinsic word similarity benchmarks (Luong et al., 2013). Our robustness checks indicated that the method identified similar sets of semantic innovations across multiple runs.

2.2 Discovering Semantic Innovations

After estimating the diachronic embeddings for each word, the next step is to identify semantic innovations: words that have shifted in meaning. One possibility would be to directly measure differences between the embeddings \( u^{(\text{old})} \) and \( u^{(\text{new})} \), but this can be unreliable because the density of embedding space is not guaranteed to be uniform. We therefore follow the local second-order approach proposed by Hamilton et al. (2016b). First, for each word we form the union of the sets of a word’s near-neighbors \((n = 50)\) in the “old” and “new” periods. Next, we compute the similarity of the word’s embedding to the embeddings for members of this set, for both the “old” and “new” embeddings. This yields a pair of vectors of similarities, each reflecting the word’s position in a local neighborhood. The degree of change in a word’s position is the distance between these two vectors.

2.3 Situating Usages with Respect to Semantic Change

Given a set of semantic innovations \( S \subset \mathcal{V} \), our main methodological innovation is to situate usage with respect to semantic changes. Each usage of an innovation \( w^* \in S \) can be analyzed using the likelihood function underlying the skip-gram objective, and scored by the ratio of the log-likelihoods under the embedding models associated with \( \mathcal{W}^{(\text{old})} \) and \( \mathcal{W}^{(\text{new})} \). Specifically, we compute the sum,

\[
    r_{w^*,i} = \sum_{t: w_i,t = w^*} \sum_{j \geq -k}^{j \leq k} \sum_{j \neq 0} \log \frac{P^{(\text{new})}(u_{i,t+j} \mid w^*)}{P^{(\text{old})}(u_{i,t+j} \mid w^*)}.
\]

Substituting the form of probability from Equation 1 and simplifying further, the log-likelihood ratio reduces to:

\[
    r_{w^*,i} = \sum_{t: w_i,t = w^*} \sum_{j \geq -k}^{j \leq k} v_{w^*,i}^{(\text{new})} \cdot u_{w^*,i}^{(\text{new})} - Z_{w^*}^{(\text{new})} - v_{w^*,i}^{(\text{old})} \cdot u_{w^*,i}^{(\text{old})} + Z_{w^*}^{(\text{old})},
\]

where \( Z_{w^*} \) is the log normalization term, \( \log \sum_{w'} \exp(v_{w'} \cdot u_{w^*}) \). This metric intuitively favors documents that use \( w^* \) in contexts that align with the new embeddings \( u^{(\text{new})} \) and \( v^{(\text{new})} \).

2.4 Aggregating to Document Scores

Given a set of innovations \( S \subset \mathcal{V} \), for each document \( i \) we obtain a set of scores \( \{r_{i,w^*} : w^* \in S\} \). The score for document \( i \) is the maximum over the set of innovations, \( m_i = \max_{w^* \in S} r_{i,w^*} \). This quantifies the maximal extent to which the document’s lexical semantics match that of the more contemporary embedding model, \((U^{(\text{new})}, V^{(\text{new})})\). We then standardize against other documents published in the same year, by computing the \( z \)-score, \( z_i = \frac{m_i - \mu}{\sigma} \), where \( \mu \) is the mean score \( m \) for documents published in the same year, and \( \sigma \) is the standard deviation. Documents with a positive \( z \)-score have lexical semantics that better match the contemporary embedding model than other documents written at the same time, and can thus be said to be semantically progressive.

3 Data

We empirically validate our approach on two document collections: documents representing legal opinions in federal courts of the United States of America (Lerman et al., 2017),\(^1\) and the DBLP collection of computer science abstracts (Ley, 2002).\(^2\) These datasets were chosen because they include timestamps as well as citation information, making it possible to link semantic innovation with influence in a citation network.

\(^1\)https://www.courtlistener.com/
\(^2\)https://dblp.uni-trier.de/
Legal opinions. A legal opinion is a document written by a judge or a judicial panel that summarizes their decision and all relevant facts about a court case. We obtained all legal opinions by using the bulk API of a publicly available service. These opinions span over 400 courts, multiple centuries and have a broad jurisdictional coverage.

Scientific abstracts. The abstracts from DBLP were obtained from ArnetMiner, a service that has released multiple versions of this data with the latest papers since 2010 (Tang et al., 2008; Sinha et al., 2015). We chose the latest version (v10) from their collection.

Metadata. Both datasets feature common metadata, including the year in which the document was published, the number of citations the document has received and the number of references to other documents in the citation network. A descriptive summary of the complete collection is given in Table 1.

4 Identifying semantic innovations

We now describe the steps taken to create a list of semantic innovations in these datasets. These innovations are then used to score every document for its progressiveness.

4.1 Preprocessing

For the legal documents, we stripped out HTML and used only the text. The scientific abstracts were available in plain text, but required filtering to identify English-language documents, which we performed using langid.py (Lui and Baldwin, 2012). In both collections, we converted the text to lowercase before proceeding, and employed spaCy for tokenization.

4.2 Estimating Word Embeddings

For both document collections, the first (oldest) 500,000 documents were used to learn the early embeddings (matrices $V^{(old)}$ and $U^{(old)}$); the most recent 500,000 documents were used to learn the later embeddings (matrices $V^{(new)}$ and $U^{(new)}$). Embeddings were estimated using a public tensorflow implementation. We ignored tokens with frequency below a predetermined threshold: 5 for the abstracts and 10 for the larger dataset of legal opinions. The maximum size of the context window was set to 10 tokens. The number of negative samples was set to 100. The NCE objective was optimized for 50 epochs and the size of the embeddings for each word was set to $d = 300$ dimensions. While most of the hyperparameters were set to the default values, the size of the embeddings was selected by evaluating on word similarity benchmarks (Luong et al., 2013).

4.3 Postprocessing

After estimating the embeddings, semantic innovations were identified using the technique from § 2.2. The number of nearest neighbors used for the computation of the metric was set to 50.

Names. In the case of legal opinions, names (e.g., of plaintiffs, defendants, and judges) pose a real difficulty in identifying genuine candidates of semantic innovations. Although names can be part of semantic innovations (e.g. Nash equilibrium or Miranda rights), names often change their distributional statistics due to real-world events rather than semantic change. To overcome this problem, we use two heuristics. We first label a small set of terms if they are names of people, organizations or places, and train a feed-forward neural network to map the embeddings of each word to the label. This method identifies terms that are distributionally similar to terms that are labeled as names. Second, we tag a randomly-selected 10% of the documents for their part of speech and obtain a distribution over parts-of-speech for each word type, using the pre-trained tagger provided by spaCy. If a term is either (a) labelled as a name using the first heuristic or, (b) tagged as a proper noun more than 90% of the time, then it is likely to be a name and is therefore discarded from the candidates of semantic innovations.

Abbreviations. In the dataset of scientific abstracts, the mention of names is rare, but abbreviations pose a similar challenge. We identify abbreviations using a similar heuristic procedure as described above: a term was judged as a likely abbreviation if it was used in all capital (majuscule) letters at least 90% of the time. However, as abbreviations can transition to the status of more typical words (e.g., laser), we chose to discard only those abbreviations which are used fewer than 25 times in both the early and the later set of abstracts.
After applying all the steps mentioned above, we inspected the top words for both legal opinions and computer science abstracts and manually removed names and abbreviations that were not caught by these heuristics, as well as tokenization errors. For each dataset, we retain a list of 1000 words each as candidate semantic innovations.

## 5 Innovations and Innovators

### Semantic changes.
A few prominent semantic innovations are listed in Table 2. The innovations in the legal opinions corpus we discover span multiple domains, including financial (e.g. laundering, which earlier exclusively meant washing), socio-political (e.g. noncitizens, which was earlier closer to tribals or indians but has now moved closer in meaning to immigrants), medical (e.g. fertilization, which was first used in the context of agriculture, but now increasingly refers to human reproduction) and technological (e.g. web, which now refers almost exclusively to the internet). Our analysis also independently discovers semantic changes in words like cellular and asylum, which have previously been identified as semantic changes in other corpora (Kulkarni et al., 2015; Hamilton et al., 2016a,b).

In the scientific domain, a common source of semantic innovation is through the use of abbreviations (recall that the filtering steps in the previous section exclude only rare abbreviations). Examples include nfc, which earlier meant “neuro-fuzzy controllers” but lately refers to “near-field communication”; ux, which was used as a short form for unix, but is now increasingly used to mean “user experience”; and ssd, which previously stood for “sum-of-squared difference”, but of late additionally means “solid state drives.” Another common source of semantic innovations is the creative naming of technological components. Examples include cloud, which now refers to services offered through the internet in comparison to its mainstream meaning; spark, which was earlier popularly used to mean ignition, but has lately been referred to the popular mapreduce framework; and android, which referred to robots with human appearances, but now commonly refers to the popular operating system from Google.

### Leading documents.
Two examples of legal opinions at the leading edge of change according to our metrics are Planned Parenthood vs Casey (505 U.S. 833) and United States v. Talmadge G. Rauhoff, (7th Cir. 1975). The landmark 1992 opinion in Planned Parenthood vs Casey was identified by our method as leading a change with several semantically progressive terms like fertilization, provider and viability mentioned in the document. The term fertilization had previously been used in the context of agriculture, but this decision was an early example of an increasingly common alternative usage in connection with reproductive rights:

- ... two-week gestational increments from fertilization to full term ...
- ... before she uses a post-fertilization contraceptive.

Similarly, the United States v. Talmadge G.
Rauhoff, (7th Cir. 1975) scores highly on our measure and was one of the first to use laundering to refer to illegal transfer of money:

- ... $15,000 as part of the ‘laundering’ process...
- ...first step in the successful laundering of the funds...

The first mention of the term was quoted, which may indicate a metaphorical intent.

In the scientific domain, the seminal paper on the Android operating system is rated as a semantically progressive document (Shabtai et al., 2010). At that time, the conventional meaning of the term android was an interactive robot (e.g. …interaction using an android that has human-like appearance…), but Shabtai et al. used the now-prevalent meaning as a mobile operating system (e.g. …the android framework…). Figure 1 shows the evolution of the semantic innovations which approximately aligns with the leading documents that our method discovered.

### 6 Innovation and Influence

While the examples in the previous section are suggestive of the validity of our method for identifying innovations and innovators, additional validation is necessary. Lacking large-scale manual annotations for the semantic progressiveness of legal opinions or scientific abstracts, we instead measure influence, as quantified by citations. Specifically, we investigate the hypothesis that more citations will accrue to documents that our metrics judge to be semantically progressive.

#### 6.1 Univariate analysis

Figure 2 shows the number of citations for each quartile of our progressiveness measure, indicating a steady increase in both datasets. This figure excludes documents that do not include any of the terms identified as having changing semantics. We also exclude documents predating 1980, which skew the population with a few landmark examples with vast citation counts; these documents are included in the multivariate analysis that follows.

#### 6.2 Multivariate analysis

There are many factors that drive citation counts, such as age, length, and content (Fowler et al., 2007; Van Opijneni, 2012). Some of these factors may be correlated with semantic progressiveness, confounding the analysis: for example, older documents have more chances to be cited, but are unlikely to lead a semantic change that would be captured by our metrics. To control for these additional predictors, we formulate the problem as a multivariate regression. The dependent variable is the number of citations, and the predictors include our measure of semantic progressiveness, as well as a set of controls. As the number of citations is a count variable, we fit a Poisson regression model. In cases of overdispersion (high variance), negative binomial regression is preferred to Poisson regression (Greene, 2003). However, the Cameron-Trivedi test (Cameron and Trivedi, 1990) did not detect overdispersion in our data.
6.2.1 Regression models

To assess the relevance of semantic progressiveness, we compare against two baseline models, which include covariates that capture structural information about each document: the number of outgoing references that a document makes; its age; its length, operationalized as the number of unique types; and the number of authors for the document (available only for scientific articles). The baseline also incorporates a lightweight model of document content, to account for the fact that some topics may get cited more than others. Specifically, we fit a bag-of-words regression model on a small subset of documents (similar to Yogatama et al., 2011), and use its prediction as a covariate in the multivariate regression. This baseline is referred to as M1.

The second baseline, M2, includes all the covariates from M1, and an additional covariate for the number of unique semantic innovations present in the document. This is aimed to tease out the effect of the presence of words with changing semantics from the extent to which the document employs the more contemporary meaning, as captured by our measure of semantic progressiveness.

To test the effect of semantic progressiveness, we create two experimental models, M3 and M4, which use the z-scores described in § 2.4. In M3, the z-score is included as a raw value; in M4 it is binned into quartiles. Note that for M4, the bottom quartile (Q1) receives a coefficient of zero by default, so that the model is not underdetermined.

We compare these models by goodness-of-fit, which is a standard technique from quantitative social science (Greene, 2003). We compute the log-likelihood for each model; under the null hypothesis that the more complex model is no better than the baseline, the log-likelihood ratio has a χ² distribution with degrees of freedom equal to the number of parameters in the more expressive model. If the observed log-likelihood ratio is unlikely to arise under this distribution, then we can reject the null hypothesis. This approach is similar in spirit to the Akaike Information Criterion (AIC), which also penalizes the log-likelihood by the number of parameters.

6.2.2 Results

The regressions reveal a strong relationship between semantic progressiveness and citation count. For the scientific abstracts (Table 3), M3 and M4 obtain a significantly better fit than M1 (χ²(2) = 137767, p ≈ 0 and χ²(4) = 250479, p ≈ 0 respectively). M3 and M4 also obtain a significantly better fit than M2 (χ²(1) = 130176, p ≈ 0 and χ²(3) = 242889, p ≈ 0 respectively), indicating again that semantic progressiveness of the document is highly predictive of the number of incoming citations, even after controlling for several covariates.

The story is similar for the legal opinions in Table 4, with only minor differences. Both M3 and M4 significantly improve the goodness of fit over the baseline M1 (χ²(2) = 8352, p ≈ 0 and χ²(4) = 7164 respectively) and the baseline M2 (χ²(1) = 3758, p ≈ 0 and χ²(3) = 2571 respectively), indicating again that semantic progressiveness of the document is highly predictive of the number of incoming citations, even after controlling for several covariates.
Table 4: Poisson regression analysis of citations to legal documents. Each column indicates a model, each row indicates a predictor, and each cell contains the coefficient and, in parentheses, its standard error.

| Predictors | M1       | M2       | M3       | M4       |
|------------|----------|----------|----------|----------|
| Constant   | 1.614    | 1.421    | 1.476    | 1.168    |
|            | (0.003)  | (0.004)  | (0.004)  | (0.006)  |
| Outdegree  | 0.022    | 0.020    | 0.021    | 0.020    |
|            | (0.000)  | (0.000)  | (0.000)  | (0.000)  |
| Age        | 0.009    | 0.011    | 0.010    | 0.010    |
|            | (0.000)  | (0.000)  | (0.000)  | (0.000)  |
| Length     | 0.000    | -0.000   | -0.000   | -0.000   |
|            | (0.000)  | (0.000)  | (0.000)  | (0.000)  |
| BoWs       | -0.000   | -0.000   | -0.000   | -0.000   |
|            | (0.000)  | (0.000)  | (0.000)  | (0.000)  |
| # Innovs   | 0.054    | 0.045    | 0.042    |
|            | (0.001)  | (0.001)  | (0.001)  |
| Prog.      | 0.094    |          |          |
|            | (0.001)  |          |          |
| Prog. Q2   |          | 0.384    |
|            |          | (0.007)  |
| Prog. Q3   |          | 0.382    |
|            |          | (0.007)  |
| Prog. Q4   |          | 0.470    |
|            |          | (0.007)  |
| Log Lik.   | -415195  | -410601  | -406843  | -408031  |

Table 4: Poisson regression analysis of citations to legal documents. Each column indicates a model, each row indicates a predictor, and each cell contains the coefficient and, in parentheses, its standard error.

7 Related Work

Although language change has been a topic of great general interest, early computational work typically focused on tracking the frequency of lexical items, rather than their meaning (e.g., Michel et al., 2011; Danescu-Niculescu-Mizil et al., 2013; Eisenstein et al., 2014). More recently, several methods have been proposed to learn diachronic word embeddings as a means to track language change at a finer semantic level (Wijaya and Yeniterzi, 2011; Kim et al., 2014; Kulkarni et al., 2015; Frermann and Lapata, 2016; Bamler and Mandt, 2017; Rosenfeld and Erk, 2018; Yao et al., 2018). Applications of such methods have shown to identify language and socio-cultural changes over time (Garg et al., 2018; Hamilton et al., 2016a), and two recent surveys review the existing research on diachronic language change through word embeddings (Kutuzov et al., 2018; Tahmasebi et al., 2018). However, despite the success of such methods in discovering semantic changes, they do not trivially generalize to identify the documents at the forefront of semantic change. Our work specifically addresses this gap.

Another body of work has used topic modeling to study changes over time (Blei and Lafferty, 2006; Wang and McCallum, 2006; Mimno, 2012). Of particular relevance is the use of topical changes in scientific literature to discover documents with the most scholarly impact (Gerrish and Blei, 2010; Hall et al., 2008). We argue that these approaches are complementary. While topic models provide a macro-level view of the concerns and interests of a set of writers, word embeddings provide a more fine-grained perspective by demonstrating shifts in meaning of individual terms. Topic models are centered at the document level, and so make it easy to identify innovators; our work extends this capability to embedding-based analysis of semantic change.

The number of citations a document receives has long been used as a proxy for the impact and influence of scientific articles (Fortunato et al., 2018), legal opinions (Fowler et al., 2007), as well as researchers and scientific trends (Borner et al., 2004). Dynamic models capturing the mechanics of attention have been modestly successful in predicting long-term scientific impact (Wang et al., 2013). Other models accounting for changing language have been used to identify important new topics (Borner et al., 2004) or to estimate the influence of papers on one another (Dietz et al., 2007).

8 Conclusion

This paper shows how to identify the leading examples of semantic change, by leveraging the models underlying diachronic word embeddings. This enables us to test the hypothesis that semantically progressive documents — that is, documents that use words in ways that reflect a change in progress — tend to receive more citations. This technique has potential applicability in the digital humanities, computational social science, and scientometrics (the study of science itself; see Van Raan, 1997). In future work, we are interested to assess how semantically progressive documents are received by their audiences, and to explore semantic change as a site of linguistic contestation. For example, recent work has linked diachronic word embeddings to gender and ethnic stereotypes in large-scale datasets of books (Garg et al., 2018). Our method could link author and audience covariates with the documents that led and trailed changes in these stereotypical associations, providing new insight on these historical trends.
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