STA260 Consulting Project

Word Semantic Shift in Early Modern English

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Outline

Introduction and Background

Word Semantic changes over time

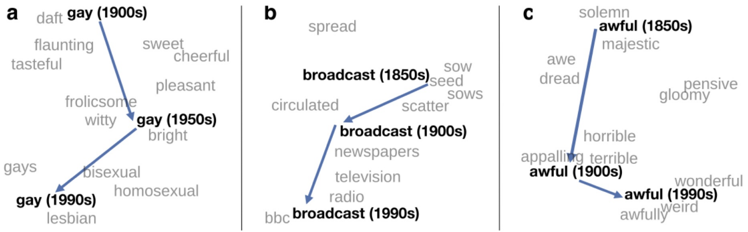


Figure 1: Examples of semantic change

Introduction and background

Two quantitative laws of semantic changes

- the *law of conformity*: The rate of semantic change scales with an inverse power-law of word frequency;
- the *law of innovation*: Independent of frequency, words that are more polysemous have higher rates of semantic changes

Object

EEBO-TCP Dataset

The *Early English Books Online TCP* (EEBO-TCP) is a corpus consisting of 60000 transcriptions from 1470 to 1700.

- large range in document length
- reprints
- transcription errors

Goal

Verify the validity of the two laws in EEBO datasets

Data preprocessing

Solve the undesirable properties in EEBO Datasets

- large range of document length: Separating datasets to equal number of words according to the print time.
- reprints: Compare the author set, title and main text of each pair of books to determine pairs of duplicate/reprinting books. We delete the earlier book in all such pairs.
- transcription errors: Delete all the non-ASCII character.

Word Embedding Methods

PPMI matrix

Positive Pointwise Mutual Information (PPMI) is a characteristic that can be used to represent the correlation of two words. The word vectors correspond to the rows of the matrix $\mathsf{M}^{\mathrm{PPMI}} \in \mathsf{R}^{|V| \times |V_c|}$ with entries given by

$$\mathsf{M}_{i,j}^{\mathrm{PPMI}} = \max\left\{\log\left(\frac{\hat{p}\left(w_i, c_j\right)}{\hat{p}(w)\hat{p}\left(c_j\right)}\right) - \alpha, 0\right\} \tag{1}$$

where $\alpha > 0$ is a negative prior which provides the smoothing bias, and the $\hat{p}$ corresponds to the smoothed empirical probabilities of word (co-)occurrences within fixed-size sliding windows of text.

Word Embedding Methods

SVD of the PPMI matrix

SVD embeddings correspond to low-dimensional approximations of the PPMI embeddings learned via singular value decomposition. The vector embedding for word wi is given by

$$\mathsf{w}_i^{\mathrm{SVD}} = (\mathsf{U}\Sigma^{\gamma})_i$$

where $\mathsf{M}^{\mathrm{PPMI}} = \mathsf{U}\Sigma \boldsymbol{V}^{\top}$ is the truncated singular value decomposition of $\mathsf{M}^{\mathrm{PPMI}}$ and $\gamma \in [0, 1]$ is an eigenvalue weighting parameter. Setting $\gamma < 1$ has been shown to dramatically improve embedding qualities.

Word Embedding Methods

word2vec

Example: *'I like to eat apple'*

- Skip-gram (SG): Uses the target word to predict the context word within fixed-size sliding windows of text. It actually builds a one-layer neural networks.
- Negative Sampling: Only consider a subset of the '0' output in the one-hot representation which highly decrease the dimension of the weights that need to be updated each time, reducing the calculation burden.
- Skip-gram with negative sampling (SGNS): Combine these two.

word2vec

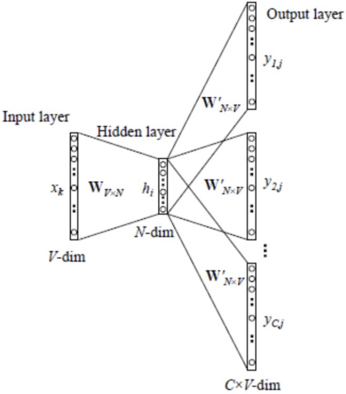


Figure 2: Skip-gram method

Quantifying characteristics

Quantifying polysemy

We measure a word's contextual diversity, and thus polysemy, by examining its neighborhood in an empirical co-occurrence network. The polysemy of a word is defined as the reciprocal of its local clustering coefficient within this network:

$$d\left(w_i\right) = 1 / \frac{\sum_{c_i, c_j \in N_{\mathrm{PPMI}}\left(w_i\right)} \mathbb{I}\left\{\mathrm{PPMI}\left(c_i, c_j\right) > 0\right\}}{\left|N_{\mathrm{PPMI}}\left(w_i\right)\right| \left(\left|N_{\mathrm{PPMI}}\left(w_i\right)\right| - 1\right)} \tag{2}$$

where $N_{\mathrm{PPMI}}\left(w_i\right) = \left\{w_j : \mathrm{PPMI}\left(w_i, w_j\right) > 0\right\}$.

Quantifying semantic change

Embedding alignment

We use orthogonal Procrustes to align the learned low-dimensional embeddings across the consecutive time points.
Defining $\mathrm{W}^{(t)} \in \mathbb{R}^{d\times|\mathcal{V}|}$ as the matrix of word embeddings learned at year t, we align across time-periods while preserving cosine similarities by optimizing:

$$\mathrm{R}^{(t)} = \arg\min_{\mathrm{Q}^\top\mathrm{Q}=\mathrm{I}} \left\| \mathrm{Q}\mathrm{W}^{(t)} - \mathrm{W}^{(t+1)} \right\|_F$$

with $\mathrm{R}^{(t)} \in \mathbb{R}^{d\times d}$. The solution corresponds to the best rotational alignment and can be obtained efficiently using an application of SVD.

Quantifying semantic change

Quantifying semantic change

The measurements of a word's rate of semantic change is defined as:

$$\Delta^{(t)}(w_i) = \cos - \text{dist}\left(\mathrm{w}_i^{(t)}, \mathrm{w}_i^{(t+1)}\right) = 1 - \frac{\mathrm{w}_i^{(t)} \cdot \mathrm{w}_i^{(t+1)}}{\|\mathrm{w}_i^{(t)}\| \|\mathrm{w}_i^{(t+1)}\|} \quad (3)$$

depends on its frequency, $f^{(t)}(w_i)$ and a measure of its polysemy, $d^{(t)}(w_i)$

$\Delta^{(t)}(w_i)$ is log-transformed and normalized and referred as $\tilde{\Delta}^{(t)}(w_i)$, which is the response we consider.

Linear Mixed Model

Linear Mixed Model

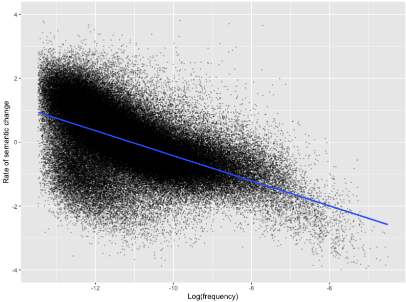
$$\tilde{\Delta}^{(t)}(w_i) = \beta_f \log\left(f^{(t)}(w_i)\right) + \beta_d \log\left(d^{(t)}(w_i)\right) + \beta_t + z_{w_i} + \epsilon_{w_i}^{(t)} \quad \forall w_i \in \mathcal{V}, t \in \{t_0, \ldots, t_n\} \tag{4}$$

where $\beta_f, \beta_d,$ and β_t correspond to the fixed effects for logarithm of frequency, logarithm of polysemy and the decade t, respectively. $z_{w_i} \sim \mathcal{N}(0, \sigma_{w_i})$ is the random intercept for word w_i and $\epsilon_{w_i}^{(t)} \in \mathcal{N}(0, \sigma)$ is an error term.

Then we can study the relationship between rates of semantic change and word frequency/polysemy depending on the values of β_f, β_d.

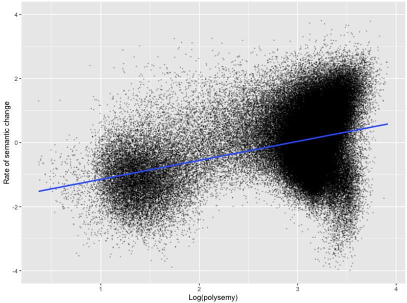
Law of conformity: Frequently used words change at slower rates

- the logarithm of a word's frequency, $\log(f(w_i))$, has a significant and substantial negative effect on rates of semantic change.
- rates of semantic change are proportional to a negative power (β_f) of frequency, i.e., $\Delta(w_i) \propto f(w_i)^{\beta_f}$ with $\beta_f = -0.4365$ and p-value$< 2 \times 10^{-16}$



Law of innovation: Polysemous words change at faster rates

- the logarithm of the polysemy score exhibits a strong positive effect on rates of semantic change.
- As with frequency, the relation takes the form of a power law $\Delta(w_i) \propto d(w_i)^{\beta_d}$ with $\beta_d = 0.6993$ and p-value$< 2 \times 10^{-16}$



Conclusions

- for EEBO corpus, rates of semantic change obey a scaling relation of the form $\Delta(w_i) \propto f(w_i)^{\beta_f} \times d(w_i)^{\beta_d}$ with $\beta_f = -0.4365 < 0$ and $\beta_d = 0.6993 > 0$.
- frequent words change at slower rates while polysemous words change faster, and that both these relations scale as power laws, which confirms that the laws of conformity and innovation [Hamilton et al., 2016] are true for EEBO corpus.

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Contribution

- Doudou Zhou: Construct the PPMI matrices, train the embeddings using SVD and compute the rotation matrices.
- Yi Han: Train the SGNS word2vec model and get the word-context matrices.
- Yishan Huang: Data cleaning and pre-processing.
- Wancheng Cai: Summarize all word embedding results for the final linear mixed model.
- Yidong Zhou: Run linear mixed model and analyze the result.

All the team members contribute equally to the final report and presentation slides.

Bibliography

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Diachronic word embeddings reveal statistical laws of semantic change.
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