Modeling Influence in Text Corpora

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Identifying influential documents

Identifying *influential* documents is a pervasive challenge for many researchers

- Historiography
- Academic research
- Much of Bibliometrics

There are many specific application areas

- News articles
- Legal opinions
- Scientific impact
- Transcriptions of radio content and orations

Predicting and understanding citations

Often citations provide useful information.

Existing research often aims to predict citation counts using a discriminative classifier and specific features, e.g.:

- Document length
- Citations to first author
- Citations to last author
- Key words
- Journal

Or some analyses focus on the citation level:

- Using topics to predict citation influence [3]
- Understanding the influence of blogs [4]
- Relational topic Models [2]

Our goal

1. Our *goal* is to predict the influence of documents without additional information such as citations, i.e. using *just their words*.
2. Our *intuition* is that influential documents change the language of their fields (i.e., their topics).
3. We define influence to be item 2: influential documents change the language of their topics.

Modeling documents with changing topics

There are a number of approaches to modeling changing topics

- Topics over time [6]
- Dynamic Topic Models [1]
- Dynamic Mixture Models [7]

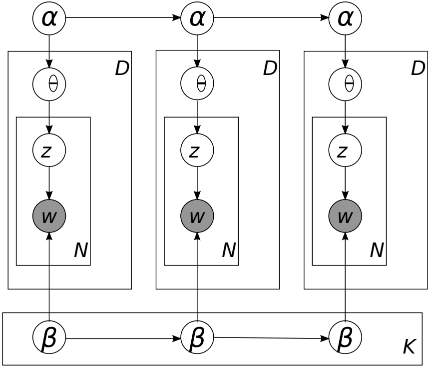
We chose to extend the Dynamic Topic Model.

The Dynamic Topic Model

Assumes topics drift in a Markov chain:

$\beta_t \sim \mathcal{N}(\beta_{t-1}, \sigma^2)$

$D_t \sim \mathrm{LDA}(\alpha_t, \beta_t)$

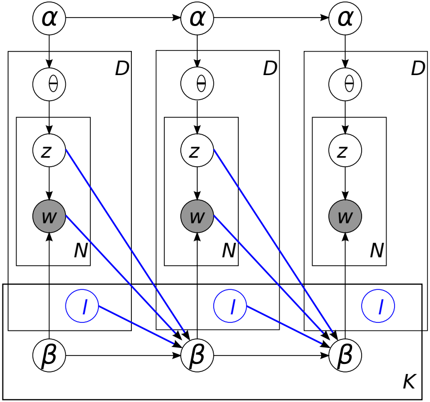


The Document Influence Model

Assumes each document has a weight which affects topic drift...

$l_{d,k} \sim \mathcal{N}(0, \sigma_l^2)$

$\beta_t \sim \mathcal{N}(\beta_{t-1} + \mathrm{Inf}(l_{t-1}, z_{t-1}, w_{t-1}), \sigma^2)$

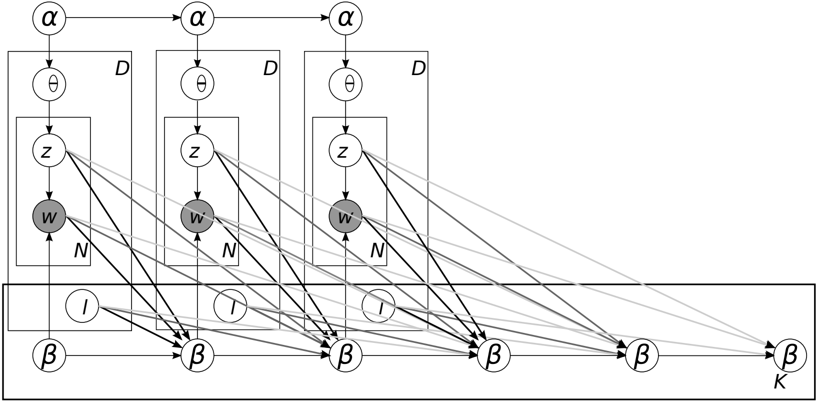


The Document Influence Model

... with documents having potential influence in the distant future.

$l_{d,k} \sim \mathcal{N}(0, \sigma_l^2)$

$\beta_t \sim \mathcal{N}(\beta_{t-1} + \mathrm{Inf}(l_{s<t}, z_{s<t}, w_{s<t}), \sigma^2)$

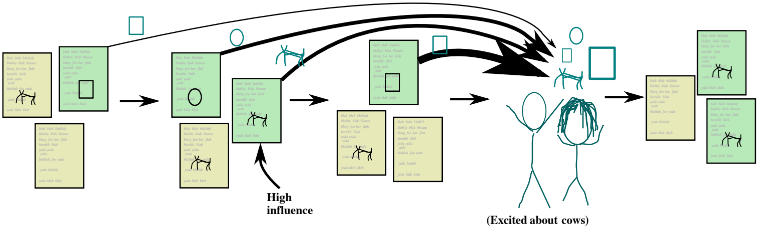


The DIM influence function

Markov step: $\beta_{t,k} \sim \mathcal{N}(\beta_{t-1,k} + Inf(t,k), \sigma^2 I)$,

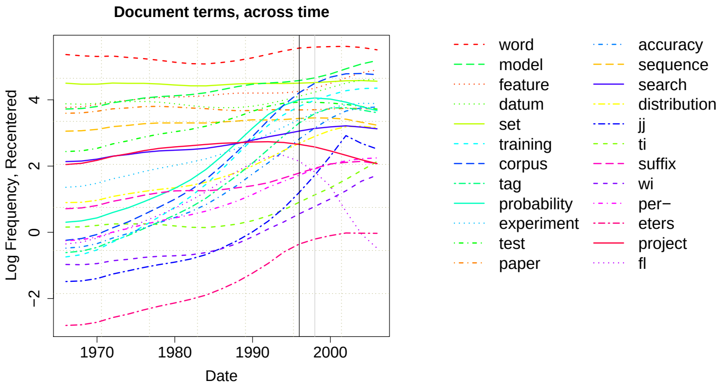
$Inf(s,k) := \exp(-\beta_{s-1,k}) \circ \sum_{i=0}^{s-1} r(s-1-i)([z_i]_k \circ \mathbf{W}_i) l_{i,k}$,

- $r(j)$ is the fraction of a document's influence after j years (called the influence envelope), and
- $[z]_k$ is the indicator describing whether term z is in topic k.
- $\exp(-\beta_{s-1,k})$ is a correction term to make sure our units are correct for log-space drift.



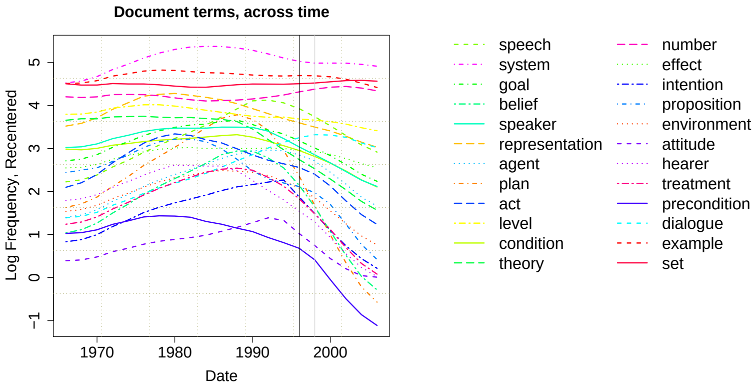
A Closer Look

A Maximum Entropy Model for Part-of-Speech Tagging



A Closer Look

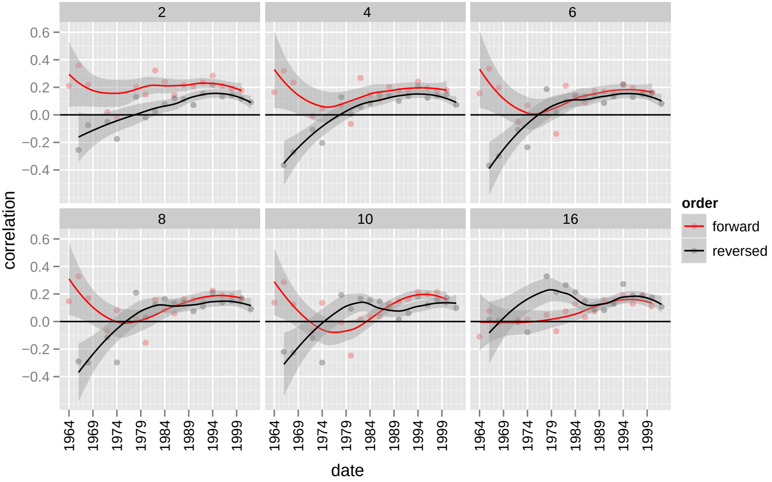
An Ascription-Based Approach to Speech Acts



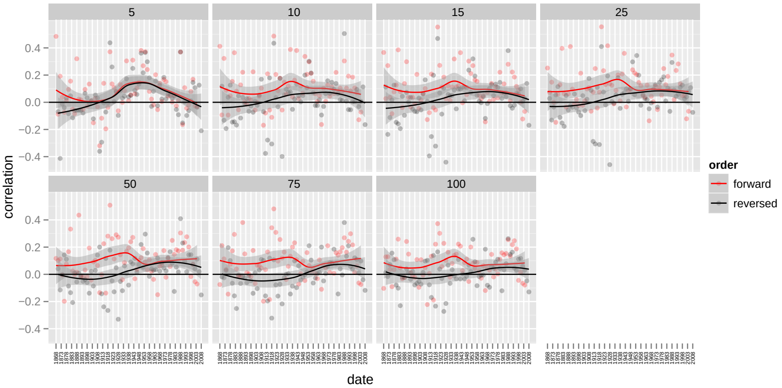
Experiments

- Procedure
  - Derive influence values from corpus
  - Compute correlation with citation counts
- Corpora
  - The *ACL Anthology*
  - *Nature*
- Evaluation with citations
  - ACL Anthology Network [5]
  - Google Scholar

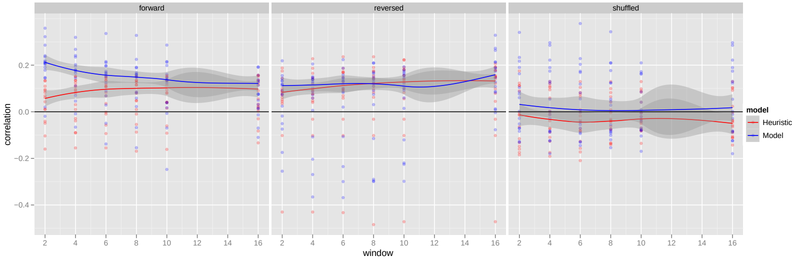
Experiments - ACL



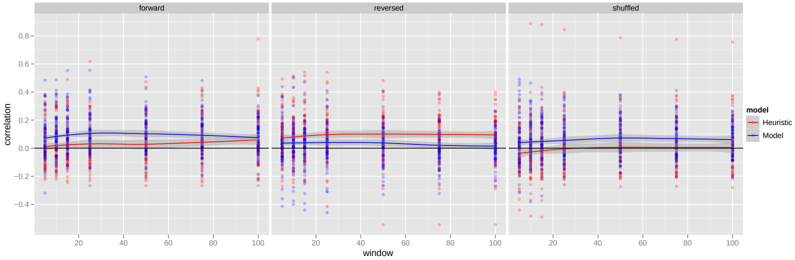
Experiments - Nature



Experiments - ACL validation



Experiments - Nature validation



Summary

- Document Influence Model
- Inference
- Evaluation
- Significance of baseline

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Motivation for $\exp(-\beta)$ coefficient in $Inf(t, l, z, w)$

$$
\begin{aligned}
& \exp(\beta_t) = \exp(\beta_{t-1}) + Inf_t \\
\iff \quad & 1 = \exp(\beta_{t-1} - \beta_t) + \exp(-\beta_t) Inf_t \\
\iff \quad & 1 - \exp(-\beta_t) Inf_t = \exp(\beta_{t-1} - \beta_t) \\
\iff \quad & \log(1 - \exp(-\beta_t) Inf_t) = \beta_{t-1} - \beta_t \\
\iff \quad & \beta_t = \beta_{t-1} - \log(1 - \exp(-\beta_t) Inf_t)
\end{aligned}
\tag{1}
$$

Note that when $\exp(-\beta_t) Inf_t$ is small, we have $\beta_t \approx \beta_{t-1} + \exp(-\beta_t) Inf_t$.

Regularized linear regression for $\tilde{l}$ updates

$$g(s,q) := \Lambda_{\exp(-\tilde{m}_{q,k}+\tilde{V}_{q,k}/2)}(\mathbf{W}_{s,k} \circ \phi_{s,k}) \tag{2}$$

$$h(s,q) := ((\mathbf{W}_{s,k} \circ \phi_{s,k})^T \Lambda_{\exp(-2\tilde{m}_q+2\tilde{V}_q)+\exp(-2\tilde{m}_q+\tilde{V}_q)}(\mathbf{W}_{s,k} \circ \phi_{s,k}) \tag{3}$$

$$+\Lambda_{(\mathbf{W}_{s,k}\circ\mathbf{W}_{s,k}\circ(\phi_{s,k}-\phi_{s,k}\circ\phi_{s,k}))^T(\exp(-2\tilde{m}_q+2\tilde{V}_q)+\exp(-2\tilde{m}_q+\tilde{V}_q))}\big) \tag{4}$$

$$\tilde{l}_{t,k} \leftarrow \left(\frac{\sigma^2}{\sigma_d^2} I + \left(\sum_{i=t}^{T-1} r(i-t)^2 h(t,i)\right)\right)^{-1}$$
$$\left(\sum_{i=t}^{T-1} r(i-t) g(t,i)^T (\tilde{m}_{i+1,k} - \tilde{m}_{i,k} + \tilde{V}_{i,k} - \sum_{j=0\ldots i, j\neq t} r(i-j) g(j,i) \tilde{l}_{j,k})\right) \tag{5}$$

Inference

We use structured variational inference, as in the DTM.

- Nonconjugacy makes sampling methods more difficult.
- Document-level variational parameters as in LDA.
- Models $\hat{\beta}$ variational parameters as observations of a Markov chain. By the symmetry of the Gaussian, we can use backward-forward Kalman updates for these parameters.
- Update for $\hat{l}_{d,k}$ is regularized linear regression.

The DIM generative model

For time $t = 1, \ldots, T$:

- For topic $k = 1, \ldots, K$:
  Draw natural parameters
  $\beta_{t,k} | \beta_{t-1,k}, \mathbf{z}_{s<t}, l_{s<t} \sim \mathcal{N}(\beta_{t-1,k} + Inf(t,k), \sigma^2 I)$
- For each document d_t:
  - Generate document d_t using traditional LDA with parameters α_t and β_t.
  - For topic $k = 1, \ldots, K$, draw document weight $l_{d,k} \sim \mathcal{N}(\mathbf{0}, \sigma_d^2 I)$;