Quantitative text analysis: Word Embeddings

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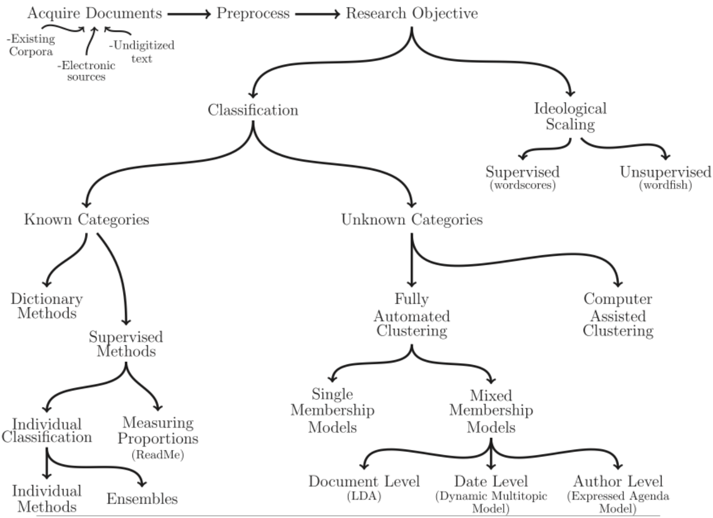
MY 459: Quantitative Text Analysis

March 11, 2019

Course website: lse-my459.github.io

1. Overview and Fundamentals
2. Descriptive Statistical Methods for Text Analysis
3. Automated Dictionary Methods
4. Machine Learning for Texts
5. Supervised Scaling Models for Texts
6. *Reading Week*
7. Unsupervised Models for Scaling Texts
8. Similarity and Clustering Methods
9. Topic models
10. Word embeddings
11. Working with Social Media

Overview of text as data methods



Outline

- Extensions of LDA
- Word embeddings:
  - Overview
  - Applications
  - Bias
  - Embeddings demo
- Encoding issues

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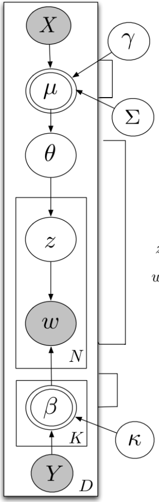
Extensions of LDA

1. Structural topic model (Roberts et al, 2014, AJPS)
2. Dynamic topic model (Blei and Lafferty, 2006, ICML; Quinn et al, 2010, AJPS)
3. Hierarchical topic model (Griffiths and Tenembaun, 2004, NIPS; Grimmer, 2010, PA)

Why?

- Substantive reasons: incorporate specific elements of DGP into estimation
- Statistical reasons: structure can lead to better topics.

Structural topic model



Topic Prevalence:

$$
\begin{aligned}
\mu_{d,k} &= X_d \gamma_k \\
\gamma_k &\sim \mathcal{N}(0, \sigma_k^2) \\
\sigma_k^2 &\sim \text{Gamma}(s^\gamma, r^\gamma)
\end{aligned}
$$

Language Model:

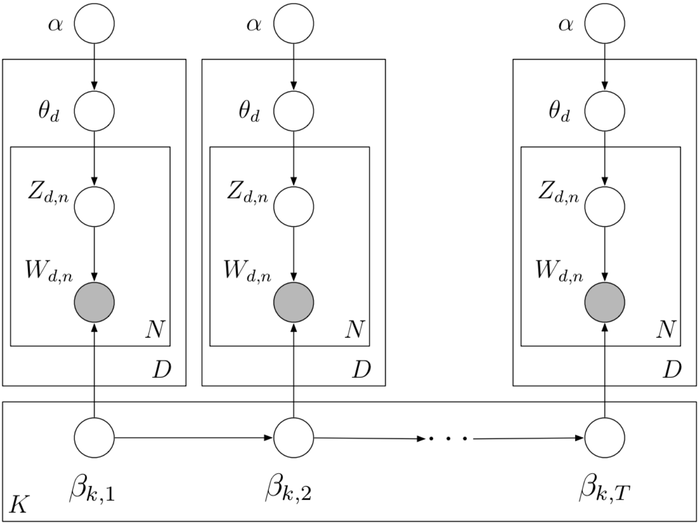
$$
\begin{aligned}
\theta_d &\sim \text{LogisticNormal}(\mu_d, \Sigma) \\
z_{d,n} &\sim \text{Mult}(\theta_d) \\
w_{d,n} &\sim \text{Mult}(\beta_d^{k=z_{d,n}})
\end{aligned}
$$

Topical Content:

$$
\begin{aligned}
\beta_{d,v}^k &\propto \exp(m_v + \kappa_v^{\cdot,k} + \kappa_v^{y,\cdot} + \kappa_v^{y,k}) \\
\kappa_v^{y,k} &\sim \text{Laplace}(0, \tau_v^{y,k}) \\
\tau_v^{y,k} &\sim \text{Gamma}(s^\kappa, r^\kappa)
\end{aligned}
$$

- **Prevalence**: Prior on the mixture over topics is now document-specific, and can be a function of covariates (documents with similar covariates will tend to be about the same topics)
- **Content**: distribution over words is now document-specific and can be a function of covariates (documents with similar covariates will tend to use similar words to refer to the same topic)

Dynamic topic model



Source: Blei, "Modeling Science"

Dynamic topic model

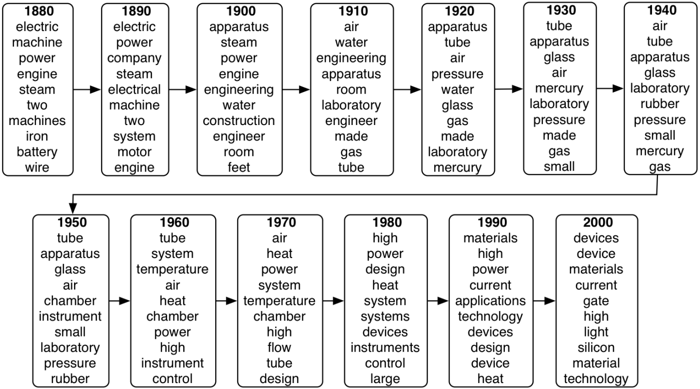


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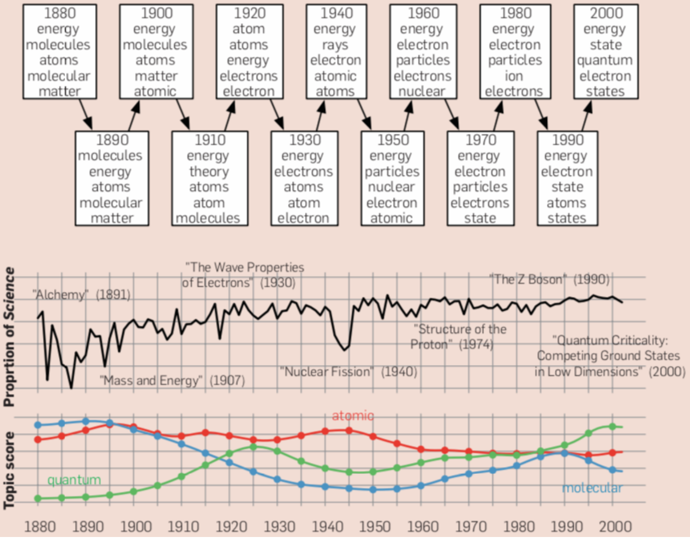
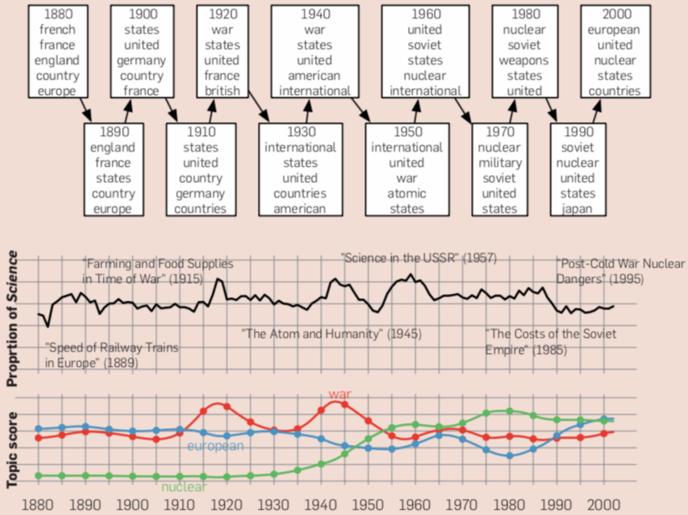
Figure 5. Two topics from a dynamic topic model. This model was fit to *Science* from 1880 to 2002. We have illustrated the top words at each decade.





1880 french france england country europe
1890 england france states country europe
1900 states united germany country france
1910 states united country germany countries
1920 war states united france british
1930 international states united countries american
1940 war states united american international
1950 international united war atomic states
1960 united soviet states nuclear international
1970 nuclear military soviet united states
1980 nuclear soviet weapons states united
1990 soviet nuclear united states japan
2000 european united nuclear states countries
"Farming and Food Supplies in Time of War" (1915)
"Science in the USSR" (1957)
"Post-Cold War Nuclear Dangers" (1995)
"The Atom and Humanity" (1945)
"The Costs of the Soviet Empire" (1985)
"Speed of Railway Trains in Europe" (1889)
Proprtion of Science
war
european
nuclear
Topic score
1880 1890 1900 1910 1920 1930 1940 1950 1960 1970 1980 1990 2000

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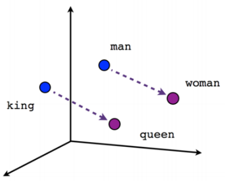
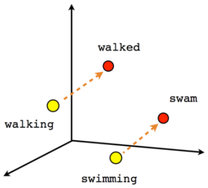
  - Distributional hypothesis: words that appear in the same context share semantic meaning
- Operations with vectors are also meaningful

Word embeddings example

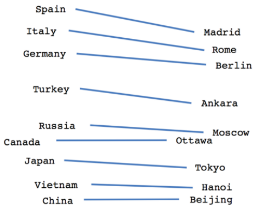
word	D_1	D_2	D_3	...	D_N
man	0.46	0.67	0.05	...	...
woman	0.46	-0.89	-0.08	...	...
king	0.79	0.96	0.02	...	...
queen	0.80	-0.58	-0.14	...	...



Male-Female



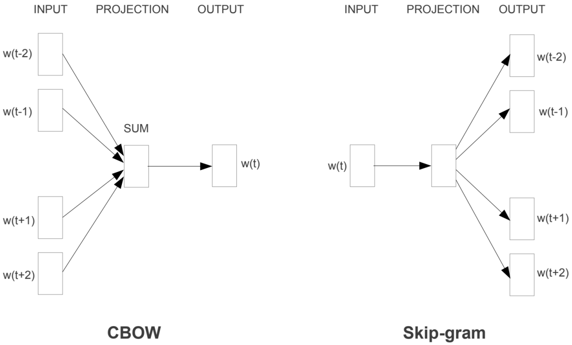
Verb tense



Country-Capital

word2vec (Mikolov 2013)

- Statistical method to efficiently learn word embeddings from a corpus, developed by Google engineer
- Most popular, in part because pre-trained vectors are available
- Two models to learn word embeddings:



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Application: Pomeroy et al 2018

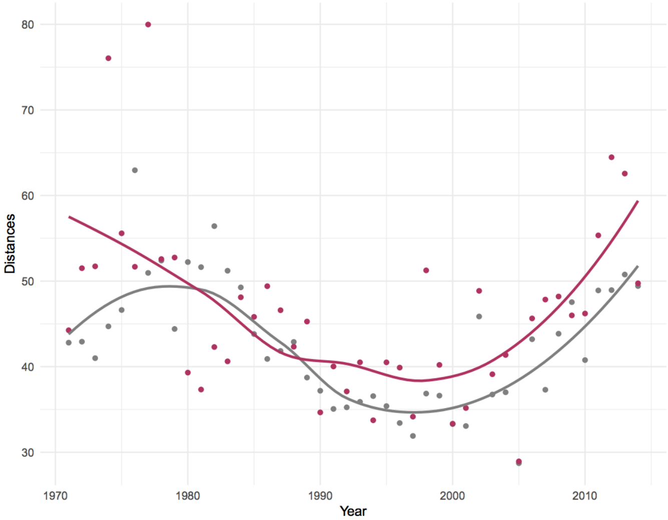
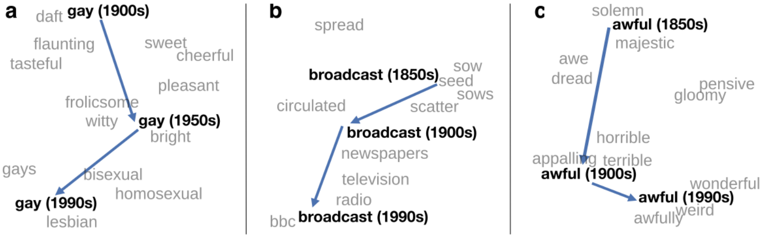


Figure 4: *Distances by core countries*. Plot of Euclidian distances between US and Russia (gray), and US and China (maroon).

Application: semantic shifts

Using word embeddings to visualize changes in word meaning:



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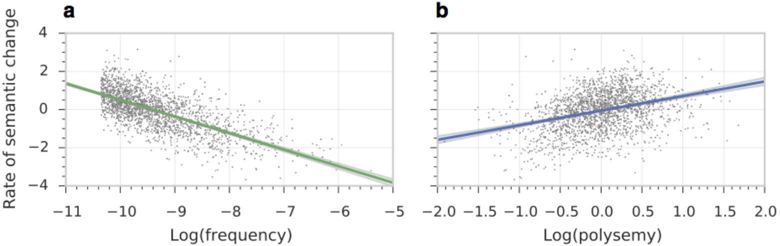

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Application: dictionary expansion

Using word embeddings to expand dictionaries (e.g. incivility)

```
> distance(file_name = "FBvec.bin",
+          search_word = "libtard",
+          num = 10)
Entered word or sentence: libtard

Word: libtard  Position in vocabulary: 5753
          word              dist
1          lib 0.798957586288452
2        lefty 0.771853387355804
3      libturd 0.762575328350067
4    teabagger 0.744283258914948
5     teabilly 0.715277075767517
6      liberal 0.709996342658997
7       retard 0.690707504749298
8      dumbass 0.690422177314758
9         rwnj 0.684058785438538
10 republitard 0.678197801113129
```

```
> distance(file_name = "FBvec.bin",
+          search_word = "idiot",
+          num = 10)
Entered word or sentence: idiot

Word: idiot  Position in vocabulary: 646
        word              dist
1   imbecile 0.867565214633942
2    asshole 0.848560094833374
3      moron 0.781079053878784
4     asshat 0.772150039672852
5     a-hole 0.765781462192535
6      ahole 0.760824918746948
7    asswipe 0.742586553096771
8  ignoramus 0.735219776630402
9   arsehole 0.732272684574127
10     idoit 0.720151424407959
```

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Bias in word embeddings

Semantic relationships in embeddings space capture stereotypes:

- Neutral example: man – woman $\approx$ king – queen
- Biased example: man – woman $\approx$ computer programmer – homemaker

Gender stereotype *she-he* analogies.

sewing-carpentry	register-nurse-physician	housewife-shopkeeper
nurse-surgeon	interior designer-architect	softball-baseball
blond-burly	feminism-conservatism	cosmetics-pharmaceuticals
giggle-chuckle	vocalist-guitarist	petite-lanky
sassy-snappy	diva-superstar	charming-affable
volleyball-football	cupcakes-pizzas	hairdresser-barber

Gender appropriate *she-he* analogies.

queen-king	sister-brother	mother-father
waitress-waiter	ovarian cancer-prostate cancer	convent-monastery

Source: Bolukbasi et al, 2016. arXiv:1607.06520
See also Garg et al, 2018 PNAS and Caliskan et al, 2017 Science.

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- UTF-8 (part of Unicode standard) is most popular scheme and used on many websites.