Measuring and Modeling Language Change

Jacob Eisenstein

Objectives

In this tutorial, you will learn about:

- the questions that can be asked of time-stamped text, across linguistics, social science, and the humanities;
- statistical methods for answering these questions, via **hands-on replications**;
- how to validate these methods;
- limitations of current NLP approaches, and prospects for doing better.

Outline

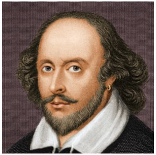
- Motivations and perspectives on language change
- Practical methods and case studies

  1. Word frequency
  2. Differences
  3. Word meaning
  4. Leaders and followers
  5. Cause and effect

- Next steps

Change as a constant

Full fathom five thy father lies; Of his bones are coral made.



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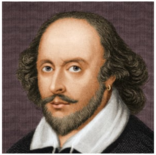
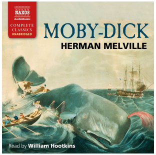


Aye, aye! it was that accursed white whale that razed me; made a poor pegging lubber of me for ever and a day!



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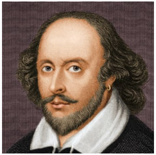

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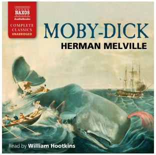
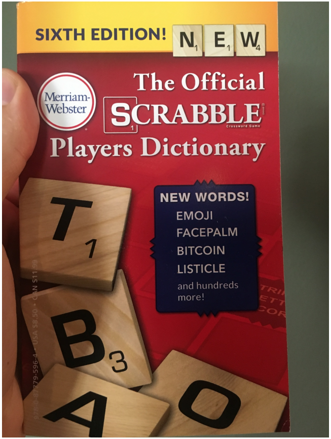


Now if you'll excuse me, I'm going to go on an overnight drunk, and in 10 days I'm going to set out to find the shark that ate my friend and destroy it.

Short term change



Even shorter term change

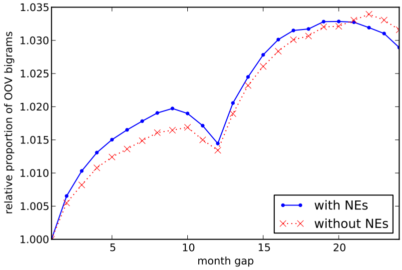
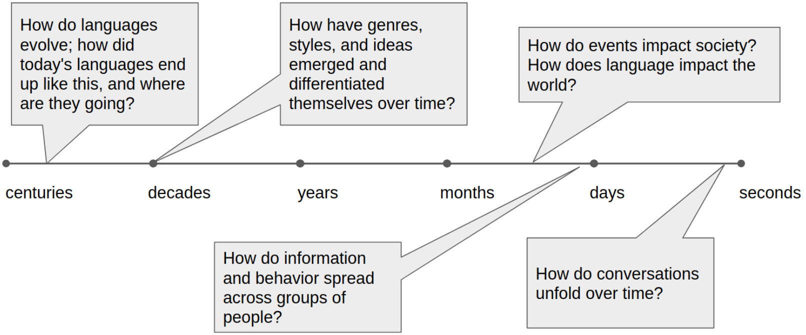


Figure: from Eisenstein (2013)

Some questions about language change



What changed?

Systemic change: what counts as grammatical / coherent / felicitous / appropriate in a language.

- full fathom five thy father lies
- historical linguistics and sociolinguistics

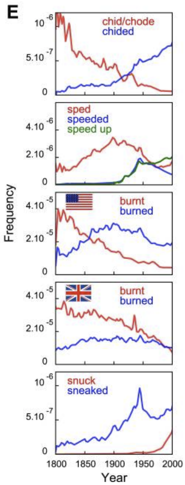


Figure: Michel et al. 2011

What changed?

Usage change: what people talk about.

- steam/electricity, horse/train
- digital humanities, computational social science, social computing

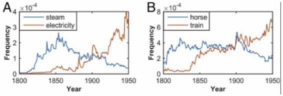


Figure: Lansdall-Welfare et al. 2017

Language change and sociolinguistics

Weinreich, Labov, and Herzog (1968) present five problems:

- **Constraints**: what changes are possible?
- **Transition**: how does a change propagate in a community of speakers?
- **Embedding**: what implications does a change have for the larger linguistic system?
- **Evaluation**: what is the social meaning of a particular change?
- **Actuation**: why this change, and why now?

Sources of information about language change

- **Corpora**: time-stamped ("diachronic") texts
- **Lexicons**: lists of word types or cognate sets
- **Simulation**: simple models and their ability to explain observed phenomena
- **Apparent time**: differences between individuals by age

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	Known Modern Languages			
Gloss†	Fijian	Pazeh	Melanau	Inabaknon
star	kalokalo§	mintol	biten	bitu'on
to hold	taura	maːraʔ	magem	kumkom
house	vale	xumaʔ	lebuʔ	ruma
bird	manumanu	aiam	manuk	manok
to cut, hack	tata	taːtatak	tutek	hadhad
at	e	-¶	gaʔ	-
what?	cava	ʔaxai	uaʔ inew	ay
this	oqo	ʔimini	itew	yayto
wind	cagi	varə	paŋay	bariyo

Figure: Bouchard-Côté et al. 2013

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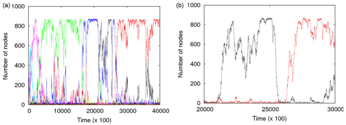

Figure: Fagyal et al. 2010

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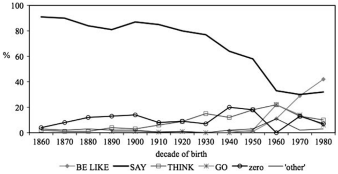

Figure: D'Arcy 2012

Language change beyond linguistics

- **Computational social science** (*text-as-data*)

  public attention, political communication, information diffusion, issue framing

- **Digital humanities** (*distant reading*)

  evolution of genres and writing styles, attitudes about race and gender, detection of influence

- **Human-computer interaction** (*social computing*)

  impact of social media on well-being, effects of policy changes on online communities, formation of social norms online

Secret agenda

Most of these fields are interested in **explanation**, not **prediction**.[1]

- Natural language processing can play an important role, by **operationalizing** variables of interest.
- But! Rigorously evaluating explanations is different and usually harder than evaluating predictions, and requires a different way of thinking.
- The tutorial includes several "case studies" to get you started.

[1] Shmueli 2010; Hofman, Sharma, and Watts 2017.

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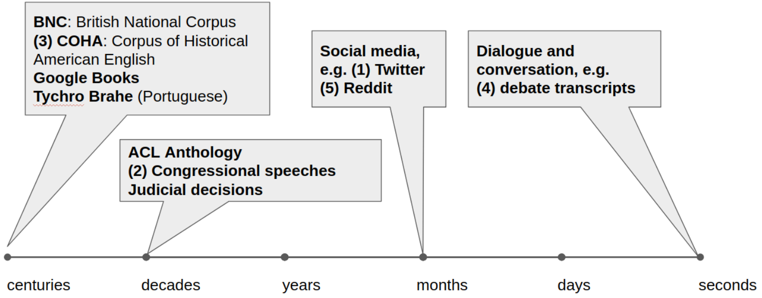
Case studies and data: a temporal view



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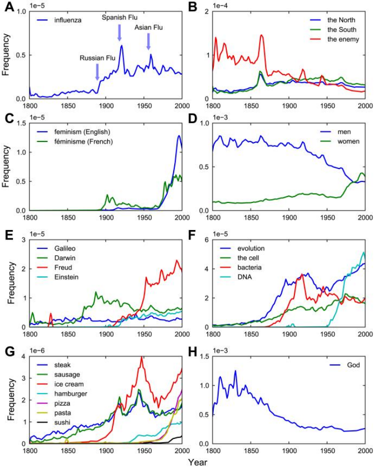
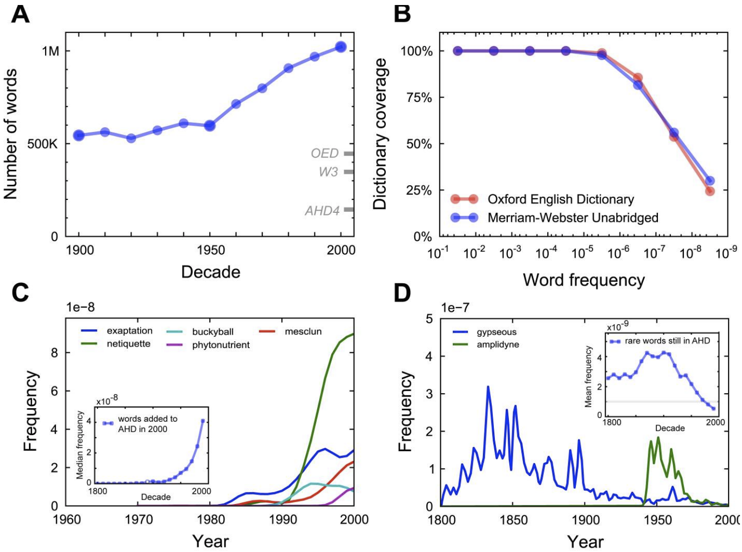
Big data and word frequency

Culturnomics: Quantitative analysis of culture using millions of digitized books (Michel et al. 2011)

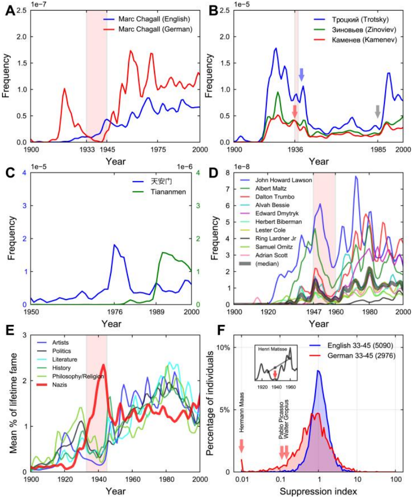
- 5M digitized books: "4% of all books ever published"
- 500B word tokens, 361B in English



Culturnomical lexicography



Culturnomical political science



Questions

Seems pretty easy! But research on frequency trajectories invites a number of questions:

- Which words? (what even is a word?)
- Which texts?
- What to count?
- Word frequencies and events have timestamps, but did one really cause the other?

Problemf recognifing characterf

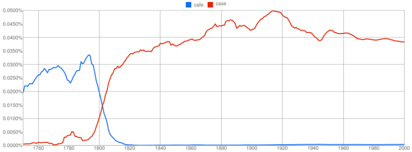


Figure: case vs cafe

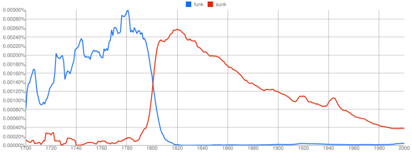
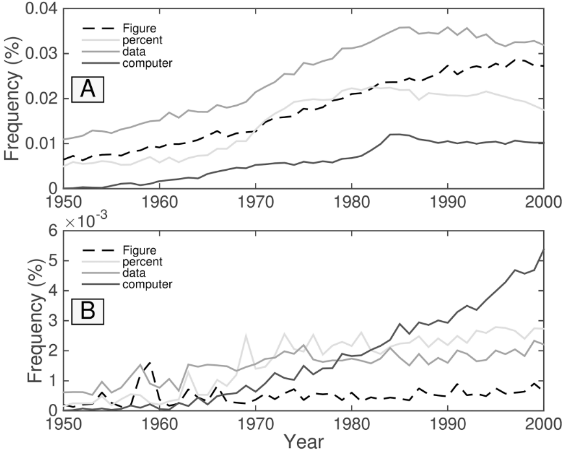


Figure: sunk vs funk

Liberman (2010) argues that OCR problems are a special case of a more general issue: Google Books' focus on strings.

Composition effects

Scientific articles occupy an increasing proportion of Google Books over time.[2]



[2]Pechenick, Danforth, and Dodds 2015.

Artisanal corpora

Corpus linguists have not produced datasets on the scale of Google books, but pay more attention to digitization and balance across genres and topics.

- Corpus of Historical American English (COHA; Davies 2012, 400M words)
- British National Corpus (BNC; Leech and Rayson 2014, 100M words)
- Global Web-based English Corpus (GlowBe; Davies and Fuchs 2015, 1.9B words)

Artisanal corpora

CHANGE TO VERTICAL CHART / CLICK TO SEE CONTEXT

SECTION	ALL	1810	1820	1830	1840	1850	1860	1870	1880	1890	1900	1910	1920	1930	1940	1950	1960	1970	1980	1990	2000
FREQ	586	0	1	1	1	0	28	1	14	13	17	22	43	46	50	20	21	24	91	97	96
WORDS (M)	405	1.2	6.9	13.8	16.0	16.5	17.1	18.6	20.3	20.6	22.1	22.7	25.7	24.6	24.3	24.5	24.0	23.8	25.3	27.9	29.6
PER MIL	1.45	0.00	0.14	0.07	0.06	0.00	1.64	0.05	0.69	0.63	0.77	0.97	1.68	1.87	2.05	0.81	0.88	1.01	3.59	3.47	3.25

SEE ALL YEARS AT ONCE

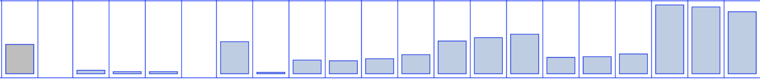


Figure: Frequency of funk in the Corpus of Historical American English (COHA)

A case study

Golder and Macy 2011: Diurnal and Seasonal Mood Varywith Work, Sleep, and Daylength Across Diverse Cultures

- Main question: how does mood shift across the day, week, and season?

  Prior work has “relied heavily on small homogeneous samples of American undergraduates who are not necessarily representative of the larger population”

- Text: positive and negative affect lexicons from LIWC[3]

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[3] Tausczik and Pennebaker 2010.

Replication time!

Launch the jupyter notebook and follow along:

```
jupyter-notebook HappierOnTheWeekend.ipynb
```

Validation and robustness

- Did population differences drive the results?

  "We removed between-individual differences by mean-centering the measures of PA and NA at the individual level"

- Does LIWC measure affect?

  "For all emotional expression words, LIWC's sensitivity and specificity values were 0.88 and 0.97[4]"

- Differences are driven by cultural norms of self-expression?

  "Because these norms are unlikely to be universal, the robust patterns we observed across diverse cultures give us confidence that affective expression is a reliable indicator . . ."

[4] Bantum and Owen 2009.

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The importance of difference

Many questions about time are questions about *difference*:

- Is political polarization increasing?
- Is polarization becoming more about identity groups than policy ideas?[5]
- Are gender roles becoming less stereotypical in fiction?
- Are NAACL and EMNLP becoming more or less similar?

[5] Iyengar, Sood, and Lelkes 2012.

Quantifying differences

What to measure:

- word frequencies;[6]
- latent topics[7]
- classifier accuracy.[8]

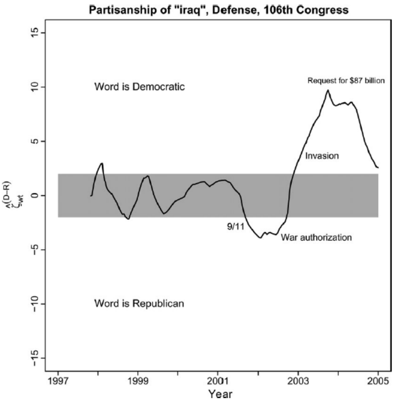
[6] Monroe, Colaresi, and Quinn 2008; Gentzkow, Shapiro, and Taddy 2016.

[7] Hall, Jurafsky, and Manning 2008; Tsur and Rappoport 2015; Barron et al. 2018.

[8] Peterson and Spirling 2018; Underwood, Bamman, and Lee 2018.

Frequencies: polarization of single words

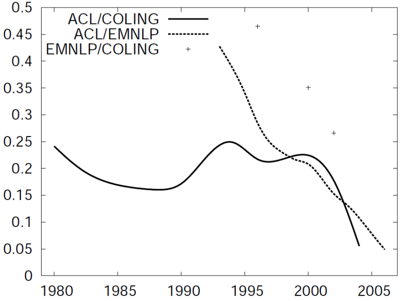
From Monroe, Colaresi, and Quinn (2008), “Fightin words”



We will replicate this figure!

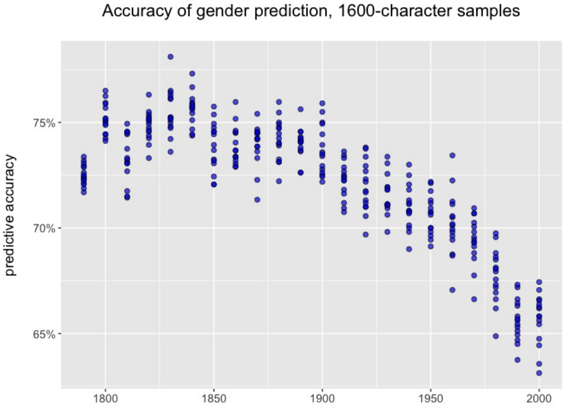
Topics: conferences over time

From Hall, Jurafsky, and Manning (2008)



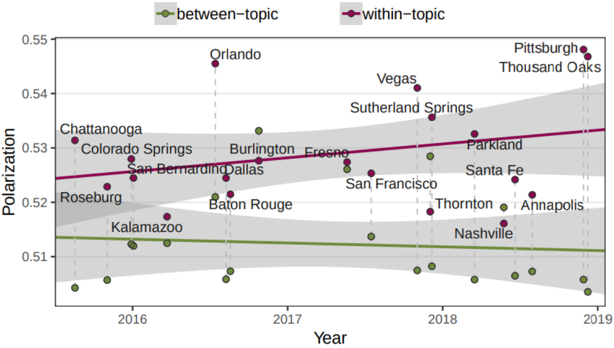
Classifiers: gender stability of fictional characters

From Underwood, Bamman, and Lee (2018)



Polarization between and within topics

Demszky et al. (2019) combine lexical and topic analysis to show how polarization about mass shootings is increasing.



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  powerful classifiers can relax IID assumption, but are computationally expensive and sensitive to dataset design

---

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Aggregation and variance

Main challenge in measuring differences over time in word frequencies is high variance:

> *The number of phrases a speaker could choose is large relative to the total amount of speech we observe, so many phrases are said mostly by one party or the other purely by chance.*
>
> *Naive estimators interpret such differences as evidence of partisanship, leading to a bias we show can be many orders of magnitude larger than the true signal in the data.*[9]

Monroe, Colaresi, and Quinn (2008): use MAP estimate of word frequency rates rather than empirical frequencies.

[9] *Gentzkow, Shapiro, and Taddy 2016.*

Replication time!

Replication: measuring and aggregating word-level partisanship in *Fightin Words*.

```
jupyter-notebook SameDifference.ipynb
```

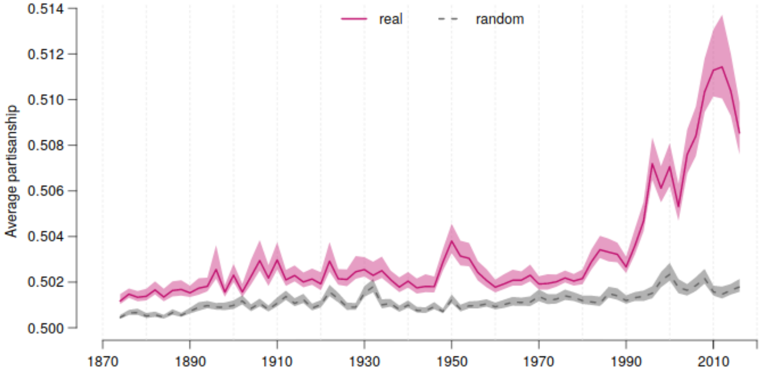
Partisanship by L1-regularized modeling

Gentzkow, Shapiro, and Taddy (2016):

- For each group g, estimate probabilities for each word j at time t,
$$q_{t,j}^{(g)} \propto \exp(\mu_{t,j} + \phi_{t,j}^{(g)}), \tag{1}$$
with $\phi_t^{(g)}$ optimized under L1 regularization.[10]
- They then compute partisanship as the expected per-word classification accuracy of a Naive Bayes classification model.

[10] Eisenstein, Ahmed, and Xing 2011; Taddy 2013.

Partisanship by L1: results[11]

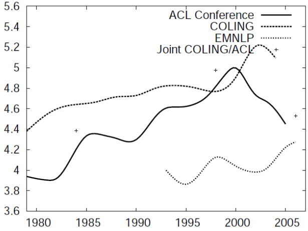


Confidence intervals require parametric bootstrap sampling, which we will discuss later.

[11] Gentzkow, Shapiro, and Taddy 2016.

Information theoretic measures of difference

Entropy: how concentrated is probability mass over words/topics, $H(p) = -\sum_j p_j \log p_j$.



In this figure,[12] p is defined over latent topics rather than words.[13]

[12] Hall, Jurafsky, and Manning 2008.

[13] See also Doyle and Frank (2015) on entropy of tweets over the course of a baseball game.

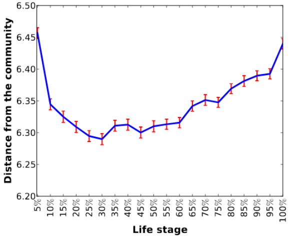
Individuals versus communities

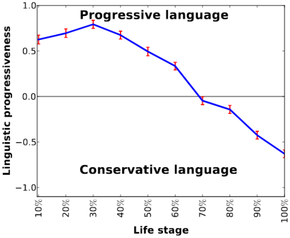
How similar is an individual's language to the community?

- Danescu-Niculescu-Mizil, West, et al. (2013) construct a "snapshot language model" for each month, and then compute the **cross-entropy**,

$$H(\boldsymbol{x}_{t,i}, \boldsymbol{q}_t) = -\frac{1}{N_{t,i}} \sum_j x_{t,i,j} \log q_{t,j}.$$

- *Progressiveness* is defined as the relative offset of the month that minimizes cross-entropy.





Information theoretic differences over time

- Kullback-Liebler (KL) divergence between p and q:

$$D_{\text{KL}}(p||q) = \sum_j p_j \log \frac{p_j}{q_j}, \tag{2}$$

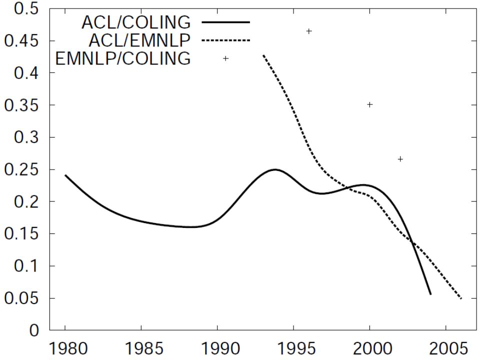
  also known as **relative entropy**.

- The Jensen-Shannon divergence is a symmetric measure based on KL-divergence,

$$\begin{aligned} D_{\text{JS}}(p||q) =& \frac{1}{2} D_{\text{KL}}(p||r) + \frac{1}{2} D_{\text{KL}}(q||r) & (3) \\ r =& \frac{1}{2} p + \frac{1}{2} q. & (4) \end{aligned}$$

Difference between conferences over time

Jensen-Shannon divegences between pairs of conferences, based on latent topic proportions:[14]



[14] Hall, Jurafsky, and Manning 2008.

The information theory of the French Revolution

Application to a dataset of 40K speeches from the *Archives Parliamentaires* (1787-1794):[15]

- "the celebrated radicals Robespierre and Pétion" diverged from the past and shaped the future;
- comments by technical specialists diverged from both past and future;
- the right wing was similar to both the past and future.

[15] Barron et al. 2018.

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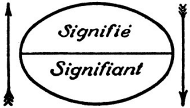
Change in the lexicon

Lexical innovation can happen on the level of new wordforms (signs) and new meanings (signifieds).



- Changes in a corpus may be driven by new real-world events and entities (e.g., email, tablet).
- Linguistic "fashions" involve new signs for existing meanings (lol).
- Existing signs can be repurposed to new meanings (hot, actually): "linguistic drifts" versus "cultural shifts"[16]

Changes can reverberate throughout the lexical system.[17]

[16] Traugott and Dasher 2001; Hamilton, Leskovec, and Jurafsky 2016a.

[17] Pierrehumbert 2010.

Meaning change in distributional semantics

Distributional representations of word meaning have a very long history in NLP:[18]

- latent semantic analysis
- Brown clusters
- word2vec

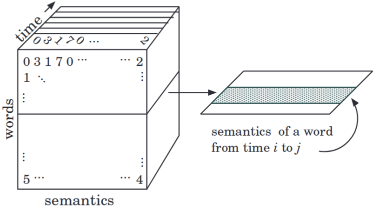


Figure: Jurgens and Stevens (2009)

Hypothesis: if the meaning of word w is summarized by a distributional representation $\boldsymbol{u}_w$, then changes in meaning should be reflected in $\boldsymbol{u}_w$.

[18]Deerwester et al. 1990; Brown et al. 1992; Mikolov, Sutskever, et al. 2013.

Word embeddings and lexical semantics

For our purposes a **word embedding** has two properties:

- it is a fixed-length vector that is computed from the set of contexts in which a word appears;
- if words i and j are semantically similar, then the vector correlation is large:[19]

$$\text{corr}_{i,j} = \frac{\boldsymbol{u}_i \cdot \boldsymbol{u}_j}{||\boldsymbol{u}_i|| \times ||\boldsymbol{u}_j||}. \tag{5}$$

As a corollary, a change in a word's embedding implies a change in meaning.

[19] This property seems to hold at a coarse level (Mikolov, Yih, and Zweig 2013) but important questions remain (Antoniak and Mimno 2018; Wendlandt, Kummerfeld, and Mihalcea 2018).

Anecdotal evidence

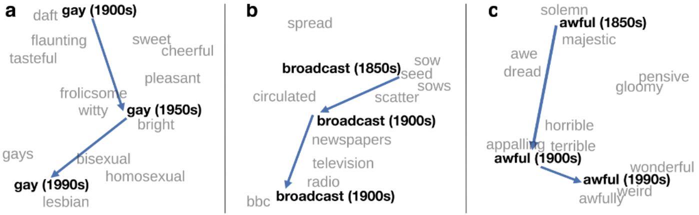


Figure: Figure from Hamilton, Leskovec, and Jurafsky (2016). For a closely related idea using raw word-context counts, see Gulordava and Baroni (2011); for an early clustering-based approach, see Wijaya and Yeniterzi (2011)

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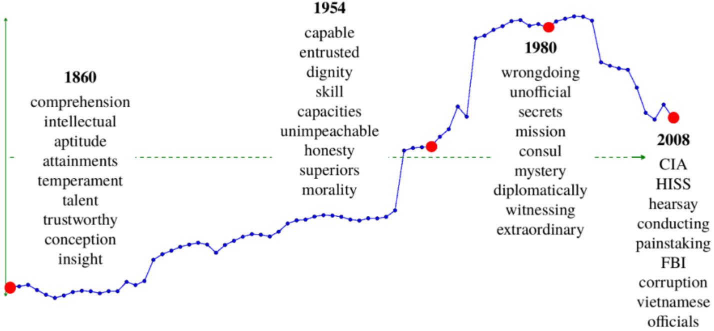

(b) INTELLIGENCE in U.S. Senate speeches (1858–2009)

Figure: Figure from Rudolph and Blei (2018)

Research timeline

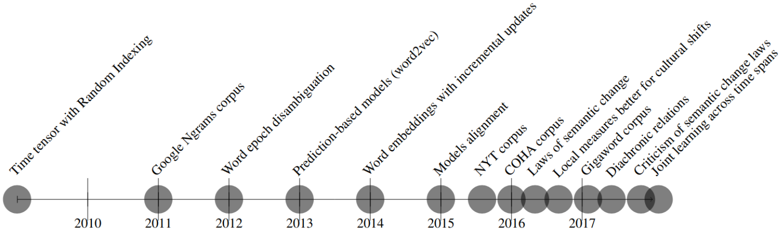

Figure: Kutuzov et al. 2018

Lots of work in this area!

- We will focus on a few relatively simple techniques.
- For much more, there are several recent surveys.[20].

[20]Kutuzov et al. 2018; Tahmasebi, Borin, and Jatowt 2018; Tang 2018.

Detecting changes in meaning

General recipe:

1. Estimate temporal word embeddings, $\boldsymbol{u}_i^{(t)}$.
2. Aggregate embeddings into a single score, $\{\boldsymbol{u}_i^{(t)}\}_{t=1}^{T} \mapsto \psi_i$.
3. Evaluate against a small list of known semantic changes in English.[21]

[21] Hamilton, Leskovec, and Jurafsky 2016b.

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Estimating temporal word embeddings

Most papers divide the corpus into "epochs", and estimate embeddings separately in each epoch.[22]

- The embeddings must be *aligned* to be comparable.
- The epochs should be similar in size and composition.

There are a few models that operate over the entire corpus:

- Bayesian priors:[23] $\boldsymbol{u}_i^{(t)} \sim f(\boldsymbol{u}_i^{(t-1)})$.
- Refinement by feedforward network:[24] $\boldsymbol{u}_i^{(t)} = g(t, \overline{\boldsymbol{u}}_i)$.

---

[22] e.g., Kulkarni et al. 2015; Hamilton, Leskovec, and Jurafsky 2016b.

[23] Bamler and Mandt 2017; Rudolph and Blei 2018.

[24] Rosenfeld and Erk 2018.

Procrustes alignment of word embeddings

- Cross-epoch embeddings may be superficially different but fundamentally the same – just permute the columns!
- To align word embeddings across epochs, we solve the orthogonal Procrustes problem,

$$\min_{\Omega^\top \Omega = \mathbb{I}} ||\Omega A - B||_F,$$

where $||M||_F$ is defined as $\sqrt{\sum_i \sum_j m_{i,j}^2}$.
- The solution is obtained by singular value decomposition,

$$\begin{aligned} U\Sigma V^\top =& \mathrm{SVD}(BA^\top) \\ \Omega =& UV^\top. \end{aligned}$$

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Aggregating word embedding differences

Hamilton, Leskovec, and Jurafsky (2016) distinguish *global* and *local* metrics for embedding differences over time:

- **Global**: compare $\boldsymbol{u}_i^{(t)}$ and $\boldsymbol{u}_i^{(t')}$ (after projection), e.g.,

$$\psi_{t,i}^{(G)} = 1 - \cos(\boldsymbol{u}_i^{(t)}, \boldsymbol{u}_i^{(t+\delta)}) \tag{6}$$

- **Local**:[25]
  1. identify nearest neighbors of i at times t and t';
  2. compute similarity to each of these neighbors, arrange as vector $\boldsymbol{s}^{(t)}$;
  3. compute $\psi_{t,i}^{(L)} = 1 - \cos(\boldsymbol{s}^{(t)}, \boldsymbol{s}^{(t')})$.

---

[25] See Kulkarni et al. (2015) for an alternative neighbor-based approach.

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Validation

Hamilton, Leskovec, and Jurafsky (2016): 28 word pairs, distinguish whether they are moving together or apart.

Word	Moving towards	Moving away	Shift start	Source
gay	homosexual, lesbian	happy, showy	ca 1920	(Kulkarni et al., 2014)
fatal	illness, lethal	fate, inevitable	<1800	(Jatowt and Duh, 2014)
awful	disgusting, mess	impressive, majestic	<1800	(Simpson et al., 1989)
nice	pleasant, lovely	refined, dainty	ca 1900	(Wijaya and Yeniterzi, 2011)
broadcast	transmit, radio	scatter, seed	ca 1920	(Jeffers and Lehiste, 1979)
monitor	display, screen	—	ca 1930	(Simpson et al., 1989)
record	tape, album	—	ca 1920	(Kulkarni et al., 2014)
guy	fellow, man	—	ca 1850	(Wijaya and Yeniterzi, 2011)
call	phone, message	—	ca 1890	(Simpson et al., 1989)

[26] Mihalcea and Nastase 2012; Popescu and Strapparava 2015.

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- Precision-based evaluations: are the changes that the model identifies meaningful?
- Predictive evaluations: given a passage, when was it written?[26]

[26] Mihalcea and Nastase 2012; Popescu and Strapparava 2015.

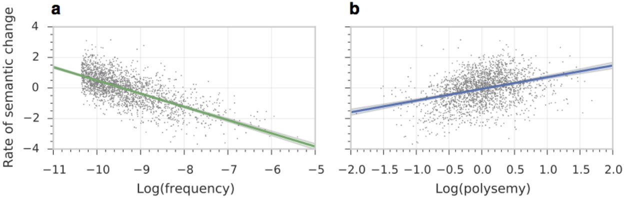
Replication time!

Replication: measuring and aggregating semantic change.[27]

```
jupyter-notebook DirtyLaundering.ipynb
```

[27] Data from Hamilton (2016), who is hereby nominated for the replicability hall of fame.

Laws of semantic change



Hamilton, Leskovec, and Jurafsky (2016):

- **Conformity**: frequently-used words are more stable.
- **Innovation**: polysemous words change more quickly.

Eger and Mehler (2016):

- **Linearity**: self-similarity decays linearly over time.

Robustness check

Dubossarsky, Weinshall, and Grossman (2017): randomly shuffle timestamps, see if these laws still hold.

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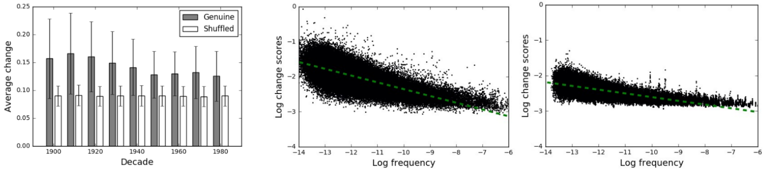


- Original data: $r = -0.748$, shuffled data: $r = -0.747$
- Similar findings for polysemy.
- These results are for SVD-based word embeddings, not tested for skipgrams.

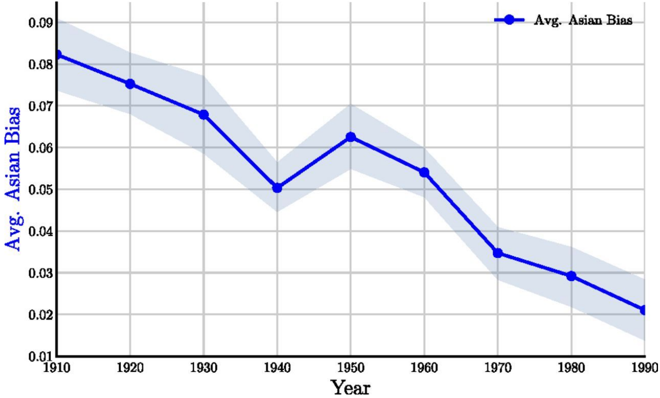
Diachronic word embeddings and bias

Garg et al. (2018): words whose embeddings are more similar to the embeddings of Asian-American last names than White-American last names, based on COHA embeddings.

1910	1950	1990
Irresponsible	Disorganized	Inhibited
Envious	Outrageous	Passive
Barbaric	Pompous	Dissolute
Aggressive	Unstable	Haughty
Transparent	Effeminate	Complacent
Monstrous	Unprincipled	Forceful
Hateful	Venomous	Fixed
Cruel	Disobedient	Active
Greedy	Predatory	Sensitive
Bizarre	Boisterous	Hearty

Diachronic word embeddings and bias

Garg et al. (2018): similarity between Asian-American name embeddings (COHA) and a lexicon of words characterizing "outsiders."



Outline

- Motivations and perspectives on language change
- Practical methods and case studies

1. Word frequency	Are you happier on the weekend?
2. Differences	Is polarization on the rise?
3. **Word meaning**	When did peers apply pressure?
4. Leaders and followers	Who is shaping the debate?
5. Cause and effect	Should we feed the trolls?

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Language change and sociolinguistics

Weinreich, Labov, and Herzog (1968) present five problems:

- **Constraints**: what changes are possible?
- **Transition**: how does a change propagate in a community of speakers?
- **Embedding**: what implications does a change have for the larger linguistic system?
- **Evaluation**: what is the social meaning of a particular change?
- **Actuation**: why this change, and why now?

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Who leads? Who follows? Who resists?

Language change on the social network: nodes

- Language change is transmitted across a social network of individuals.
- The likelihood of a speaker to adopt a change, and their success at propagating a change, depends on their position in the network.[28]

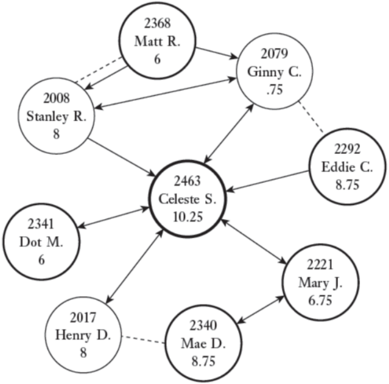

Figure: Labov (2001)

[28]Labov 2001; Milroy 1991.

Language change on the social network: dyads

- The transmission of an innovation between two individuals requires a communication channel and a social evaluation.
- Diachronic text data makes it possible to reconstruct the latent network of linguistic influence.

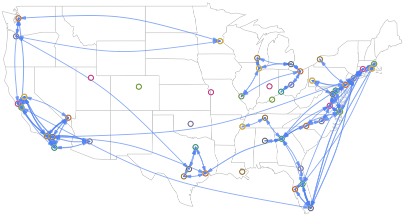

Figure: Eisenstein, O'Connor, et al. (2014)

Language change on the social network: attributes

- Social connections and status are shaped by attributes such as race, class, and gender.
- Diachronic language data can help to unpack the social meaning of such attribute through their influence on language change.

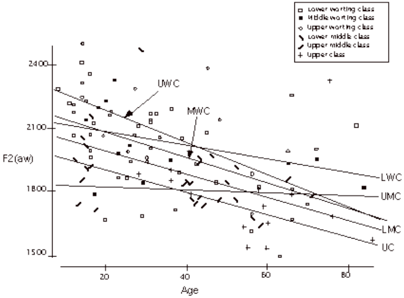

Figure: Labov (2001)

Leadership and influence across time scales

- **Decades**: systemic change in phonology and syntax[29]
- **Years**: usage change in subcommunities such as scientific research articles[30]
- **Months**: adoption of conventions and styles, e.g., in social media[31]
- **Days**: spread of news stories and memes[32]
- **Minutes**: linguistic accommodation[33] and topic control[34]

---

[29] Labov 2001.

[30] e.g., Gerow et al. 2018.

[31] e.g., Kooti et al. 2012; Eisenstein, O'Connor, et al. 2014; Goel et al. 2016; Del Tredici and Fernández 2018; Stewart and Eisenstein 2018.

[32] e.g., Leskovec, Backstrom, and Kleinberg 2009.

[33] Danescu-Niculescu-Mizil and Lee 2011.

[34] Nguyen et al. 2014.

Estimating influence from diachronic data

- Goal is to estimate parameters $\alpha_{i \to j}$ for all i, j in population $\mathcal{I}$.
- Given covariates $\{\boldsymbol{x}_i\}_{i \in \mathcal{I}}$, we may set $\alpha_{i \to j} = f(\boldsymbol{x}_i, \boldsymbol{x}_j)$.
- Observed data:
  - **Time series**: counts or proportions $\boldsymbol{y}_{t,i}$ at each $t = (1, 2, \ldots, T)$.
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Dynamical systems

A latent variable time series model:

$$\boldsymbol{z}_{t,i} \sim f\left(\sum_{j \in \mathcal{I}} \alpha_{j \to i} \boldsymbol{z}_{t-1,j}\right) \tag{7}$$

$$\boldsymbol{y}_{t,i} \sim g(\boldsymbol{z}_{t,i}). \tag{8}$$

Lots of interesting special cases:

- **Kalman filter/smoother**: f and g are affine+Gaussian
- **Generalized Kalman**: f and g are affine+other[35]
- **Dynamic topic model**: g is a topic model, f models changes in topic *proportions*[36] or *content*[37]

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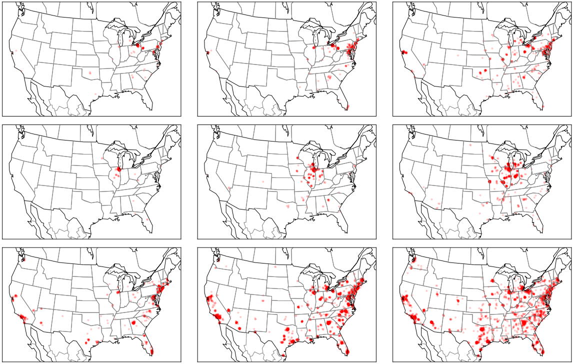
City-to-city influence from Twitter data[38]

Thousands of words have changing frequencies.



ctfu

lbvs

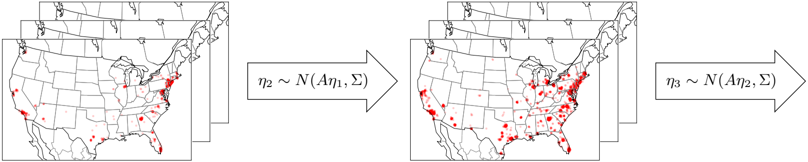
-_-

- Each spatiotemporal trajectory is idiosyncratic.
- What's the aggregate picture?

[38] Eisenstein, O'Connor, et al. 2014.

Language change as an autoregressive process

Raw data: counts for thousands of words, binned into 200 metro areas and 165 weeks.

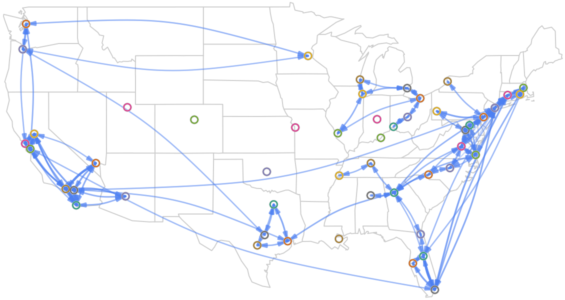


$$\begin{aligned} c_{\text{ctfu},1} &\sim \text{Binomial}(f(\eta_{\text{ctfu},1}), N_1) \\ c_{\text{hella},1} &\sim \text{Binomial}(f(\eta_{\text{hella},1}), N_1) \\ &\ldots \end{aligned}$$

$$\begin{aligned} c_{\text{ctfu},2} &\sim \text{Binomial}(f(\eta_{\text{ctfu},2}), N_2) \\ c_{\text{hella},2} &\sim \text{Binomial}(f(\eta_{\text{hella},2}), N_2) \\ &\ldots \end{aligned}$$

- The dynamics matrix A encodes city-to-city linguistic influence.
- It can be estimated by Monte Carlo Estimation Maximization

Aggregated city-to-city influence



Weights on demographic features can then be estimated by regressing the city-to-city parameters $\alpha_{i \to j}$ on city-level covariates such as population, race, wealth, and age.

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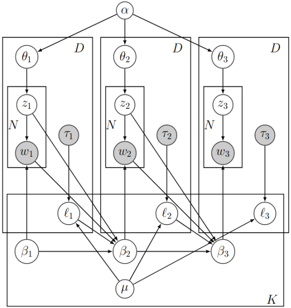
Influence on scientific topics[39]

Each document has:

- a bag-of-words generated from a latent topic model;
- an influence parameter, which is a function of its covariates.

Topics

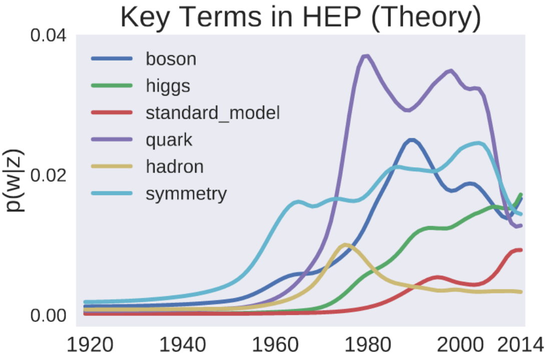
- are smoothly evolving vectors, $\boldsymbol{\beta}_{t,k} \in \mathbb{R}^V$, where
- each $\boldsymbol{\beta}_{t,k}$ depends on $\boldsymbol{\beta}_{t-1,k}$ and the words used in influential documents at $t-1$.



[39] Gerow et al. 2018.

Evolution of a scientific topic[40]

From a topic model of physics research papers:



[40] Gerow et al. 2018.

Attribution of leadership to authors[41]

From a topic model of the ACL anthology:

Parsing & Grammar	Information Retrieval
tree	document
grammar	term
node	query
structure	text
feature	topic
language	retrieval
figure	collection
form	result
constituent	information
set	sentence

Parsing & Grammar		Information Retrieval	
Parameter	**Value in $\hat{\mu}_k$**	**Parameter**	**Value in $\hat{\mu}_k$**
Gerald Gazdar	0.00013	Donna Harman	0.00017
Robert C. Berwick	0.00012	G. Vladutz	0.00014
Monique Rolbert	0.00012	Gerard Salton	0.00013
J. N. Verastegui-Carvajal	0.00011	Jade Goldstein	0.00012
C. Raymond Perrault	0.00001	Chris Buckley	0.00011
Jan Landsbergen	0.00009	David D. Lewis	0.00011
James Kilbury	0.00008	Tomek Strzalkowski	0.00010
Luis Damas	0.00008	K. L. Kwok	0.00009
R. C. Bainbridge	0.00008	John Broglio	0.00009
C. S. Mellish	0.00008	Andy Lauriston	0.00007

[41] Gerow et al. 2018.

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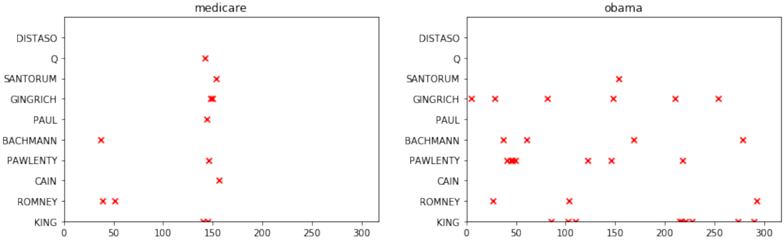
Event cascade data

From a 2012 Republican Presidential Primary debate:



How can we discern leaders, followers, and resisters from this type of data?

The Poisson Process probability model

- Consider a set of event times, $\{t_n\}_{n=1}^{N}$.
- The number of events in any interval $(t_1, t_2]$ can be modeled as a draw from a Poisson distribution:

$$n(t_1, t_2) \sim \text{Poisson}(\mu_{t_1,t_2}) \tag{9}$$

$$\mu_{t_1,t_2} = \int_{t_1}^{t_2} \lambda(\tau) d\tau, \tag{10}$$

  where $\lambda(\tau)$ is an **intensity function**.
- This is a very general framework for modeling sequences of events. Let's explore a special case that is appropriate for our research questions.[42]

[42] For more on temporal point processes, see the 2018 ICML tutorial by Gomez-Rodriguez and Valera (2018).

The Hawkes Process

A Hawkes Process is a **self-exciting** Poisson process,[43] in which the intensity function depends on the previous events,

$$\lambda(\tau) = \lambda_0 + \alpha \sum_{t_n < \tau} \kappa(\tau - t_n), \tag{11}$$

where,

- the sum is over all events before time τ;
- $\kappa : \mathbb{R}_+ \to \mathbb{R}_+$ is a kernel decay function, typically monotonically decreasing in the temporal gap $\tau - t_n$, e.g. $\kappa(\delta t) = \beta \exp(-\delta t / \gamma)$.[44]
- $\alpha \in \mathbb{R}$ is a scalar excitement parameter.

---

[43] Hawkes 1971.

[44] This function can be much more expressive! (Du et al. 2015; Mei and Eisner 2017)

Multivariate Hawkes Processes

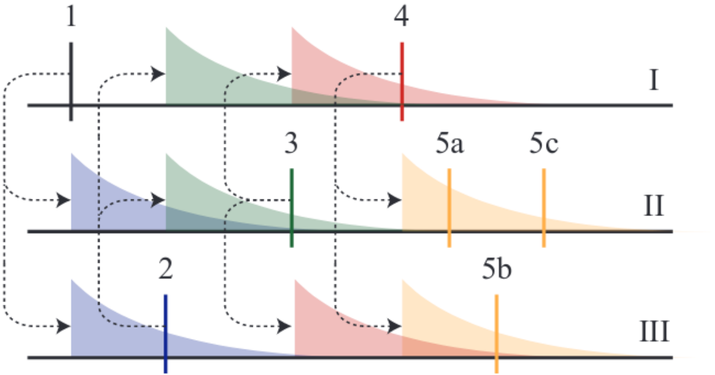
In a multivariate Hawkes Process, each event is marked with a **source** s_n, and each source exerts a different level of excitement on its neighbors:

$$\lambda_i(\tau) = \lambda_{i,0} + \sum_{t_n < \tau} \alpha_{s_n \rightarrow i} \kappa(\tau - t_n), \tag{12}$$

where

- $\lambda_i(\tau)$ is the excitement function for individual i;
- $\alpha_{s_n \rightarrow i}$ quantifies how much events from s_n tend to excite events in i.

A multivariate Hawkes Process[45]



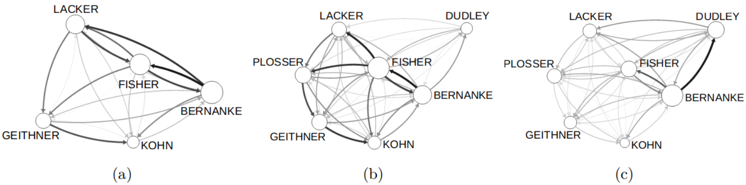
[45] Linderman and Adams 2014.

Notebook time!

Notebook: leaders and followers in the 2012 Republican Presidential Primary debates.

```
jupyter-notebook FollowTheLeader.ipynb
```

Point process models of language change[49]



- Accommodation and influence in multiparty dialogues[46]
- Spread of new words over the Twitter social network[47]
- Variable temporal kernels for different types of events in social media[48]

---

[46] Blundell, Beck, and Heller 2012; Guo et al. 2015.

[47] Goel et al. 2016.

[48] Du et al. 2015.

[49] Figure from Guo et al. (2015)

Outline

- Motivations and perspectives on language change
- Practical methods and case studies

1. Word frequency	Are you happier on the weekend?
2. Differences	Is polarization on the rise?
3. Word meaning	When did peers apply pressure?
4. **Leaders and followers**	Who is shaping the debate?
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Explanations and causes

- Did the restaurant close because of the bad reviews?
- Did the DARPA program cause people to change their research agendas?[50]
- Did the introduction of emojis cause people to use fewer emoticons?[51]
- Did the lobbying group's "model legislation" cause the bill to be written differently?[52]
- Did censorship cause people to change spelling?[53]

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[50] Gerow et al. 2018.

[51] Pavalanathan and Eisenstein 2016.

[52] Burgess et al. 2016.

[53] Wang, Juffermans, and Du 2016; Stewart, Chancellor, et al. 2017.

The Randomized Controlled Trial (RCT)

The "gold standard" of causal inference.[54]

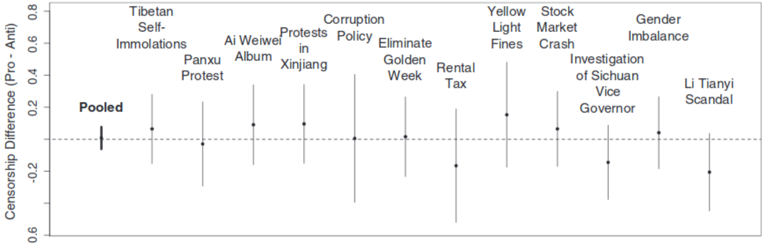
- Does the **treatment** affect the **outcome**?
  The challenge is that each unit (e.g., patient) is either treated or not; we do not observe the counterfactual.
- Solution: ensure treatment and **control** groups are similar on average, by assigning the treatment randomly.[55]
- **Average Treatment Effect**: difference in average outcome between the treatment and control groups.

[54] Rosenbaum 2017.

[55] Further assumptions: treatment of one unit does not affect outcome for another; all treatments are identical.

Example: Censorship in Chinese social media

- **Treatment**: whether the post is pro- or anti-government
- **Outcome**: whether the post is censored
- Many potential **confounds**: previous history of the author, their social network, the platform...
- Therefore King, Pan, and Roberts (2014) randomly assigned posts to (fake) user accounts.



Problems with RCTs

- **Impossible**: we cannot randomly assign legislation to be treated with lobbying.
- **Expensive**: King, Pan, and Roberts (2014) had to hire a team to write 1200 unique social media posts.
- **Unethical**:[56] it would be wrong to randomly assign bad reviews to restaurants.
- **Not representative**: RCTs typically rely on participants who are often drawn from pools that are notoriously different from the larger population.

[56] see also Kramer, Guillory, and Hancock 2014; Verma 2014.

Causation from observation

Impossible in general, but acceptable under some conditions.
A non-exhaustive list of approaches:

- **Matching**: try to enumerate all covariates, select treatment and control groups to be balanced.[57]
- **Natural experiments**: identify some exogeneous factor that affects probability of treatment but is assigned at random (e.g., the weather).[58]
- **Interrupted time series**: compare outcome before and after the treatment, correcting for temporal trends.[59]

---

[57] e.g., De Choudhury et al. 2016; Pavalanathan and Eisenstein 2016.

[58] e.g., Coviello et al. 2014.

[59] Bernal, Cummins, and Gasparrini 2017.

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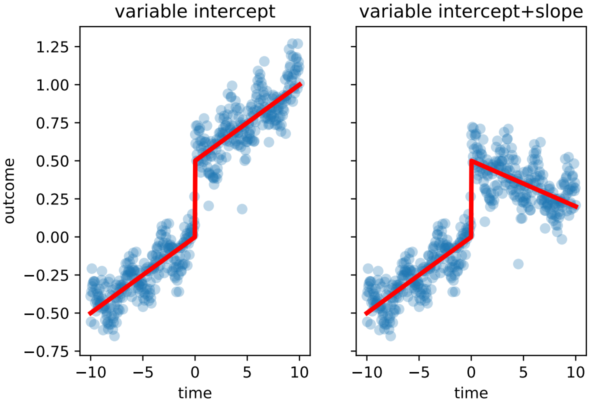
Interrupted time series schematics



Variable intercept model as segmented regression

$$y_{t,i} \sim f(\boldsymbol{\beta} \cdot \boldsymbol{x}_{t,i} + \gamma\delta(t > \tau)), \tag{13}$$

where,

- f is a probability function;
- $y_{t,i}$ is the outcome for individual i at time t;
- $\boldsymbol{x}_{t,i}$ is a vector of covariates, including t;
- $\boldsymbol{\beta}$ is a vector of parameters;
- $\delta(t > \tau)$ indicates if t is in the post-treatment period;
- γ quantifies the causal impact of the treatment on the intercept.

Variable intercept+slope model

$$y_{t,i} \sim f(\boldsymbol{\beta} \cdot \boldsymbol{x}_{t,i} + \gamma\delta(t > \tau) + \omega\delta(t > \tau)t), \qquad (14)$$

where,

- ω quantifies the causal impact of the treatment on the slope;
- all other terms are the same as in the variable intercept model.

Assumptions

If $\gamma < 0$, can we conclude that the treatment causes the outcome to decrease? Some assumptions are needed:

- **Ignorability**: there is no latent covariate that is associated with both the treatment and the outcome.

  For example, suppose Reddit's decision to censor hate speech coincided with a widespread internet outage. This concern can be alleviated by adding a control group.

- **Correct specification**: the functional form of the regression model is correct.
- **No autocorrelation**: $y_{t,i}$ depends only on the covariates and treatment, and not on $y_{t'<t,i}$. Autocorrelation can usually be tested for and removed.

Replication time!

Replication: does banning hate speech forums reduce the overall amount of hate speech on Reddit?[60]

```
jupyter-notebook DontFeedTheTrolls.ipynb
```

[60] Chandrasekharan et al. 2018.

Granger causation

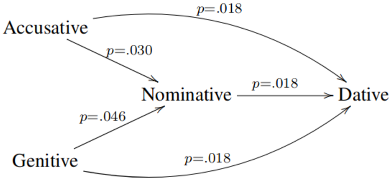
Granger causation is assessed by comparing two predictors of each element in a time series y_t:

1. the previous history $\boldsymbol{y}_{1:t-1}$;
2. the previous histories $\boldsymbol{x}_{1:t-1}, \boldsymbol{y}_{1:t-1}$.

- The time series $\boldsymbol{x}$ **Granger-causes** $\boldsymbol{y}$ if prediction 2 is significantly more accurate.
- Warning: it is possible to have Granger causation without "real" causation.

Granger causation of function shifts in case

Prototype embeddings of case groups in Icelandic predict changes in the embeddings of other case groups:[61]



This finding, which is based on an annotated corpus of nearly 1000 years of Icelandic, suggests that while the Icelandic case paradigms have not changed, their **functions** have undergone a gradual chain shift.

[61] Moscoso del Prado Martin and Brendel 2016.

Text as cause, text as consequence

Many possible roles for text in causal inference[62]:

- outcome (e.g., hate speech in Reddit);
- treatment (e.g., pro- or anti-government stance in Chinese social media);[63]
- deconfounding;[64]
- correcting for missing data and measurement error.[65]

Watch this space!

---

[62] Egami et al. 2018.

[63] see also Landeiro and Culotta 2018.

[64] Roberts, Stewart, and Nielsen 2018; Mozer et al. 2018; Veitch, Sridhar, and Blei 2019.

[65] Wood-Doughty, Shpitser, and Dredze 2018.

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- **Next steps**

Broadening the scope

- Beyond English[66]
- Beyond the lexicon
- New collaborative models

[66] Hamilton, Leskovec, and Jurafsky 2016b; Moscoso del Prado Martin and Brendel 2016; Garley and Hockenmaier 2012.

Contrasting lexical and phonological change

Phonological change:

- measured by decades and centuries;
- (usually thought of as) acquired from peers and caretakers during early childhood;
- tightly interconnected system.

Lexical change:

- usually measured by months and years;
- acquired socially into adulthood;
- structural aspects are less clear.[67]

[67] but see Pierrehumbert 2010; Stewart and Eisenstein 2018.

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Is this one mechanism or two? What can students of these two phenomena teach each other?

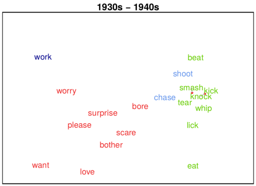
[67] but see Pierrehumbert 2010; Stewart and Eisenstein 2018.

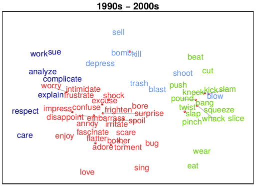
Challenges for future work

1. Elaborate the connection between lexical change and other forms of systemic language change.

Measuring syntactic change: specific constructions

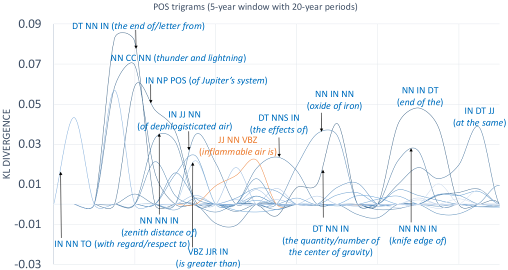
- Perek (2014):
  V the hell out of NP
  - snakes scare the hell out of me
  - you drove the hell out of it
- Increasing productivity throughout the 20th century, with new cases tending to occur in denser parts of embedding space.
- Identifying this construction requires part-of-speech tagging and lemmatization (Schmid 1995).





Measuring syntactic change: POS trigrams

Degaetano-Ortlieb and Teich (2018): KL-divergence of POS trigrams decreases over time in scientific writing.

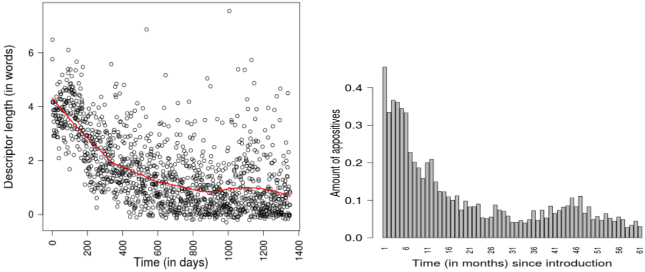


- "Grammatical consolidation" follows lexical expansion.
- Again, automated POS tagging required.[68]

[68] Schmid 1995; Baron and Rayson 2008.

Forms of referring expressions over entity lifespans

Staliūnaitė et al. (2018): referring expressions reflect information status of entities.



Uses CoreNLP for constituency parsing and coreference.[69]

[69] Manning et al. 2014.

How good is syntactic analysis on historical text?

We can assume some transfer loss when moving trained systems to historical text, but how much?

- There is not much evidence about this, as almost all labeled data is from the 20th century.
- **English**: Penn Parsed Corpus of Historical English: great resource, but idiosyncratic tagset and purchasing model.
- **Portuguese**: Tycho Brahe corpus uses a single annotation system over several centuries.[70]

Yang and Eisenstein (2015):
POS error rate doubles for older texts.

The concern: are syntactic effects real, or are they an artifact of changes in tagger performance?

---

[70] Galves and Faria 2010.

Challenges for future work

1. Elaborate the connection between lexical change and other forms of systemic language change.

Challenges for future work

1. Elaborate the connection between lexical change and other forms of systemic language change.
2. Make NLP systems more robust to language change, without labeling thousands of documents.

Construct validity challenges

Construct validity is not just a problem for syntax!

- We want to use diachronic corpora to make claims, e.g., about changing ideas, beliefs, agendas, etc.
- Some of these constructs will be visible to the tools we have (which are mostly lexical), some won't.
- In many historical corpora, digitization creates its own measurement artifacts.[71]
- Extant statistical methodology is designed to quantify uncertainty due to finite samples, not variable measurement error.

[71] e.g., Soni, Klein, and Eisenstein 2019, at this year's LaTeCH.

Challenges for future work

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Challenges for future work

1. Elaborate the connection between lexical change and other forms of systemic language change.
2. Make NLP systems more robust to language change, without labeling thousands of documents.
3. Better account for errors, especially when those errors are unevenly distributed over time.

Toward new collaborative models

- Many text mining tools are becoming "commoditized."
- There are good reasons for practitioners to prefer standard tools (like LDA and LIWC) over bespoke solutions.
- Yet there remains a need for computationally-augmented access to large-scale corpora **in human terms**:

lexicons, POS patterns, dependency subtrees, . . .

Challenges for future work

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Challenges for future work

1. Elaborate the connection between lexical change and other forms of systemic language change.
2. Make NLP systems more robust to language change, without labeling thousands of documents.
3. Better account for errors, especially when those errors are unevenly distributed over time.
4. Allow non-specialists to tell NLP systems what they want without labeling thousands of examples.

Thank you!

Thank you!

- **Students** and **Collaborators**: **Sandeep Soni and Ian Stewart**, Eshwar Chandrasekharan, Munmun De Choudhury, Fernando Diaz, Lauren F. Klein, Eric Gilbert, Rahul Goel, Naman Goyal, Adam Glynn, Xiaochuang Han, Brendan O'Connor, John Paparrizos, Umashanthi Pavalanathan, Noah A. Smith, Hanna Wallach, Eric Xing, Yi Yang.
- **Sponsors**: National Endowment for the Humanities, National Science Foundation, National Institutes for Health, Air Force Office of Scientific Research, Google.

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