Computational Sociolinguistics

Social Networks, Social Media, Social Meanings

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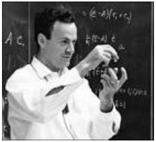
- People are adept at leveraging contextual clues to resolve ambiguity (Casasanto, 2008; Kehler & Rohde, 2013; Niedzielski, 1999).
  Can we build NLP software with the same ability?

Language across contexts

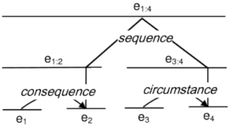
Visual

(Eisenstein et al., 2008a,b; Eisenstein, 2008)



Discourse

(Ji & Eisenstein, 2015; Bhatia et al., 2015; Ji et al., 2016)



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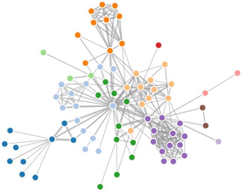

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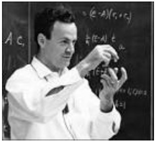

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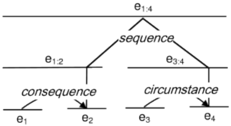

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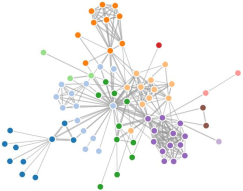

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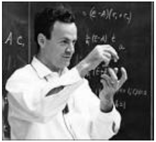

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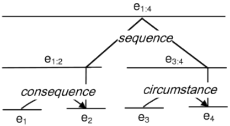

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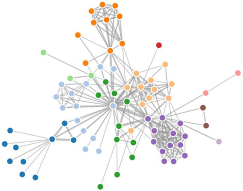

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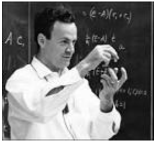

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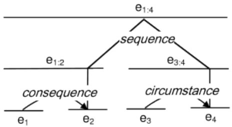

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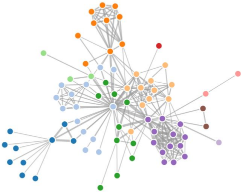

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(Krishnan & Eisenstein, 2015)
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Linguistic meaning

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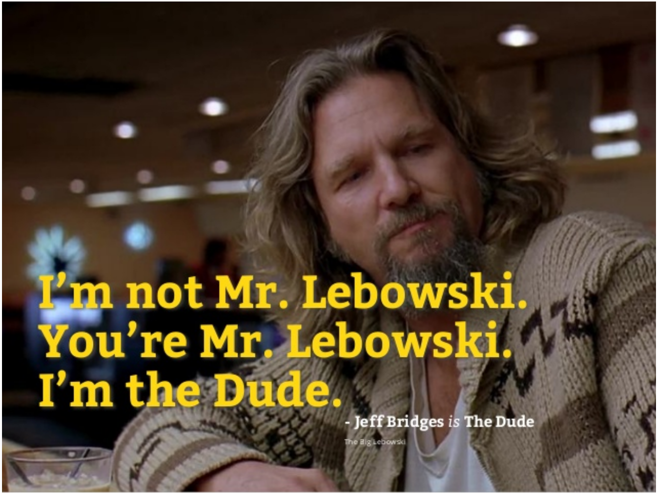


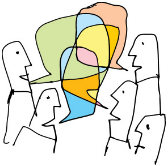
(Krishnan & Eisenstein, 2015)

Forms of address in a signed social network

- How does language reflect and reproduce social relationships?

- What relationships hold between nodes in a social network?

- Are there regular structures that emerge across signed networks?



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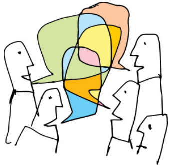

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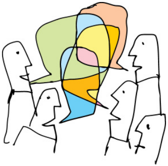

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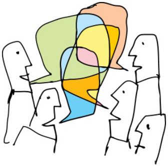
  Estimate a prior distribution over signed network structures.



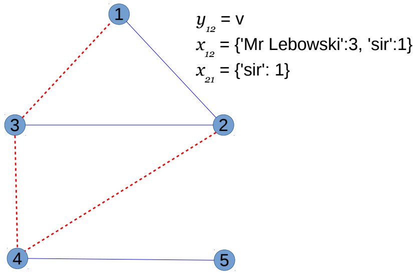
A generative model of networked content

- Undirected graph $G = \langle i, j \rangle$, $i < j$
- All edges have labels $y_{ij} \in \mathcal{Y}$
- Content vectors $\boldsymbol{x}_{i \rightarrow j}, \boldsymbol{x}_{i \leftarrow j} \in \mathbb{N}^V$, where V is the size of the vocabulary
- Each edge label indexes a distribution over text:

$$
\begin{aligned}
\boldsymbol{x}_{i \rightarrow j} \mid y_{ij} &\sim \text{Multinomial}(\boldsymbol{\theta}_{y_{ij}}) \\
\boldsymbol{x}_{i \leftarrow j} \mid y_{ij} &\sim \text{Multinomial}(\boldsymbol{\theta}_{y_{ij}}).
\end{aligned}
$$

Example

- At inference time, we observe x but not y.
- Inferring y gives a labeling over edges.
- Estimating θ gives the distribution over addresses for each edge type.



Adding social theory

- So far, this is just a mixture model over dyads.
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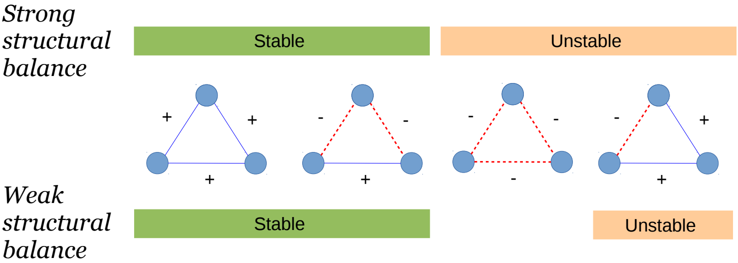
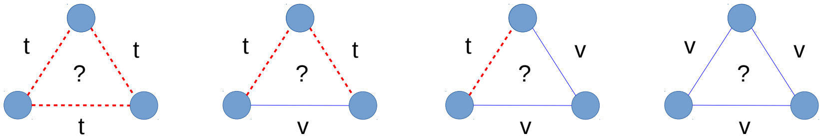
- But social theory may tell us that not all label configurations are equally likely.
- **Structural balance theory** describes networks of friend/enemy links, where signed triads may be stable or unstable:



Social theories with unknown parameters

- West et al (2014) incorporate structural balance theory by preferring stable triads.
- But what if the magnitude, and even the direction of the effect of each triad type is a priori unknown?



- We assume a triadic form, but make no assumptions about the specifics.

Social theory in a prior distribution

Assume the prior factors over dyads and triads.

$$P(\boldsymbol{y}; G, \boldsymbol{\eta}, \boldsymbol{\beta}) = \frac{1}{Z(\boldsymbol{\eta}, \boldsymbol{\beta}; G)} \times \exp \sum_{\langle i,j \rangle \in G} \boldsymbol{\eta} \cdot \boldsymbol{f}(y_{ij}, i, j, G)$$

$$\times \exp \sum_{\langle i,j,k \rangle \in \mathcal{T}(G)} \beta_{y_{ij}, y_{jk}, y_{ik}},$$

where,

- $Z(\boldsymbol{\eta}, \boldsymbol{\beta}; G)$ is a normalizing constant;
- $\boldsymbol{f}(y_{ij}, i, j, G)$ is a set of dyad features, with associated weights $\boldsymbol{\eta}$;
- $\mathcal{T}(G)$ is the set of triads in the graph G;
- $\beta_{y_{ij}, y_{jk}, y_{ik}}$ scores the stability of a triad type.

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Complete model specification

$$P(\boldsymbol{y}, \boldsymbol{x} \mid G; \Theta, \boldsymbol{\beta}, \boldsymbol{\eta}) = P(\boldsymbol{x} \mid \boldsymbol{y}; \Theta) P(\boldsymbol{y} \mid G; \boldsymbol{\beta}, \boldsymbol{\eta})$$

- The likelihood factors across dyads;
- The prior factors across dyads and triads.

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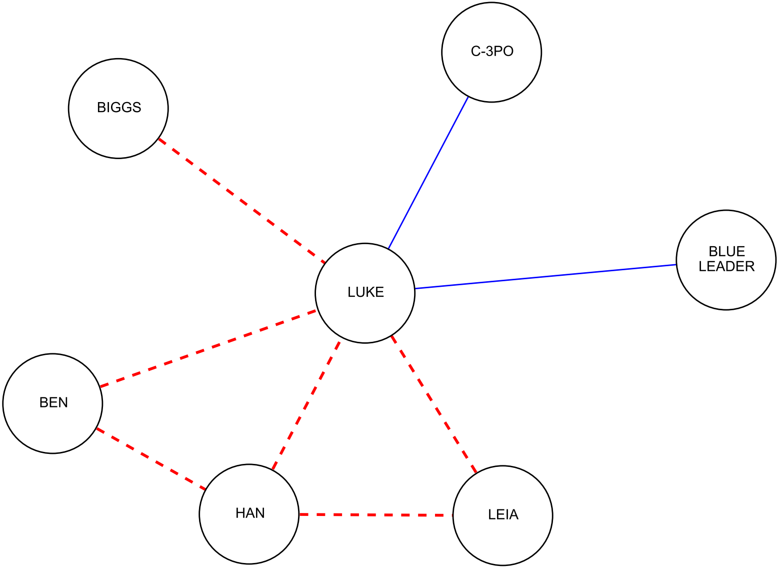
Application: a dataset of 617 movie scripts (Danescu-Niculescu-Mizil & Lee, 2011).

Cluster coherence

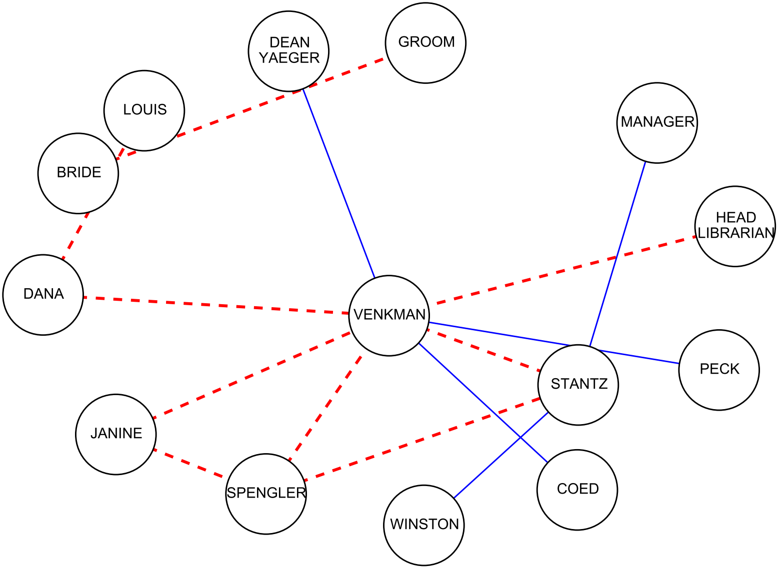
V-cluster	T-cluster
sir	FIRSTNAME
mr+LASTNAME	man
mr+FIRSTNAME	baby
mr	honey
miss+LASTNAME	darling
son	sweetheart
mister+FIRSTNAME	buddy
mrs	sweetie

- Raters found the intruder term in 73% of cases for the full model (M4).
- ... versus 52% in the text-only model (M1).

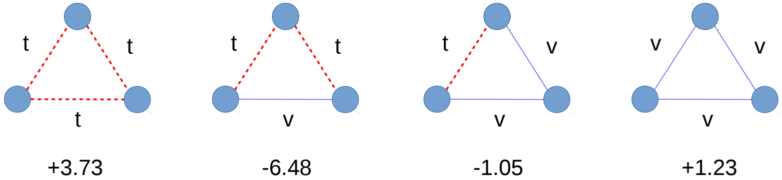
Star Wars



Ghostbusters



Network features



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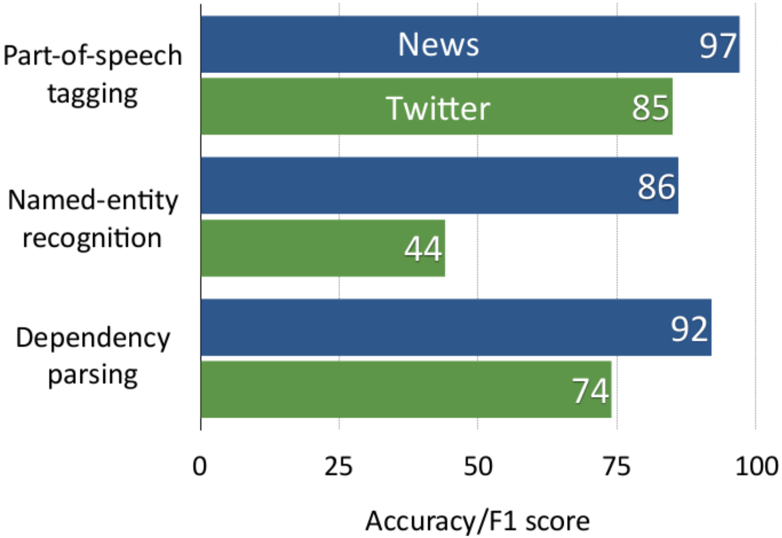

(Gimpel et al., 2011; Ritter et al., 2011; Foster et al., 2011)

NLP without social context

Eisenstein (2013): social media has forced NLP to confront the challenge of missing social context.

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@SheaSerrano

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an absolutely perfect response by the warriors

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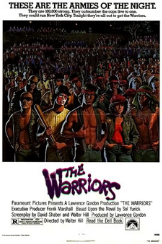
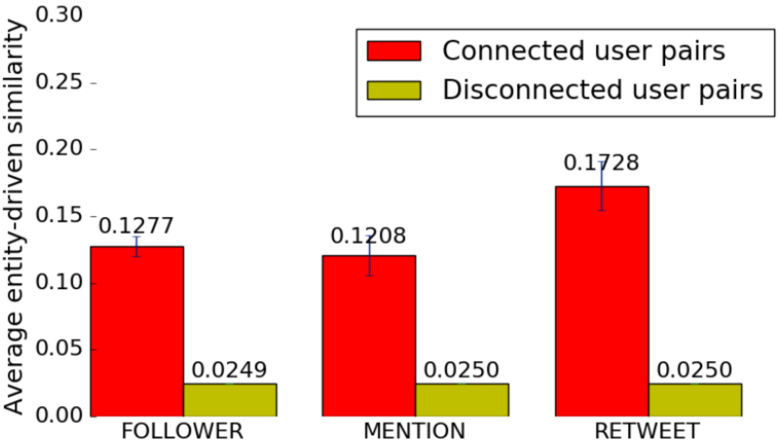


GOLDEN STATE WARRIORS

Finding tacit context in the social network

- Social media texts lack context, because it is implicit between the writer and the reader.
- **Homophily**: socially connected individuals tend to share traits.

Assortativity of entity references



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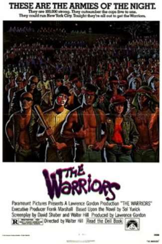

/r/NBA
@NBA_Reddit

Lana Berry
@Lana

Michael Lee
@MrMichaelLee

Shea Serrano
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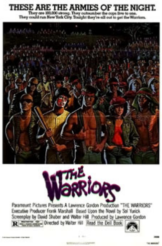

GOLDEN STATE WARRIORS

/r/NBA
@NBA_Reddit

Lana Berry
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Michael Lee
@MrMichaelLee

The return of Clutch Dirk Nowitzki is one of the more exciting, unexpected developments in an already bonkers NBA season

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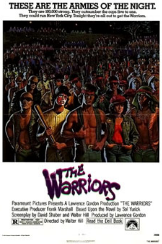
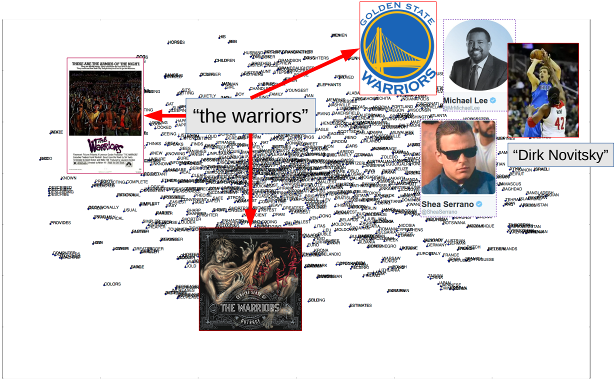


GOLDEN STATE WARRIORS

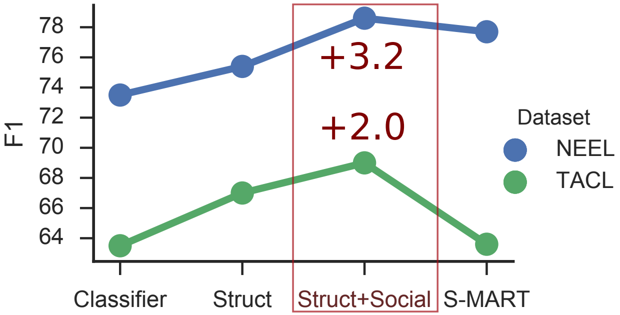
Projecting into a joint semantic space

We project embeddings for entities, words, and authors into a shared semantic space.



Inner products in this space indicate compatibility.

Results



- Structure prediction improves accuracy.
- Social context yields further improvements.
- S-MART is the prior state-of-the-art (Yang & Chang, 2015).

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Language variation

"I would like to believe he's **sick** rather than just mean and evil."

Language variation

"I would like to believe he's **sick** rather than just mean and evil."

"You could've been getting down to this **sick** beat."

(Yang & Eisenstein, 2017)

Personalization by ensemble

- Goal: personalized conditional likelihood, $P(y \mid \boldsymbol{x}, a)$, where $\boldsymbol{x}$ is the text and a is the author.

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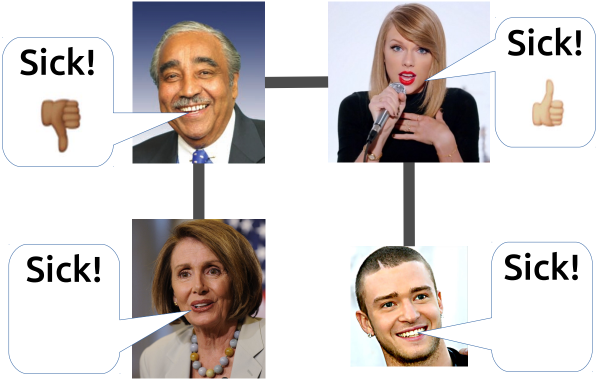
- Problem: We have labeled examples for only a few authors.

Homophily to the rescue?

Labeled data

Unlabeled data



Homophily again: are language styles assortative on the social network?

Evidence for linguistic homophily

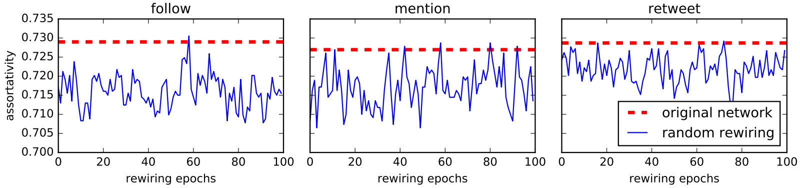
Pilot study: is classifier accuracy **assortative** on the Twitter social network?

$$\text{assort}(G) = \frac{1}{\#|G|} \sum_{(i,j) \in G} \delta(y_i = \hat{y}_i)\delta(y_j = \hat{y}_j) + \delta(y_i \neq \hat{y}_i)\delta(y_j \neq \hat{y}_j)$$

Evidence for linguistic homophily

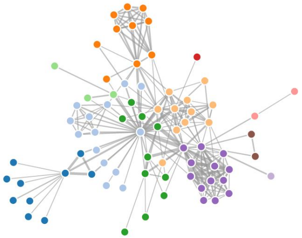
Pilot study: is classifier accuracy **assortative** on the Twitter social network?

$$\text{assort}(G) = \frac{1}{\#|G|} \sum_{(i,j)\in G} \delta(y_i = \hat{y}_i)\delta(y_j = \hat{y}_j) + \delta(y_i \neq \hat{y}_i)\delta(y_j \neq \hat{y}_j)$$



Network-driven personalization

- For each author, estimate a **node embedding** $\boldsymbol{e}_a$ (Tang et al., 2015).
- Nodes who share neighbors get similar embeddings.



$$\boldsymbol{\pi}_a = \mathrm{SoftMax}(f(\boldsymbol{e}_a))$$

$$P(y \mid \boldsymbol{x}, a) = \sum_{k=1}^{K} P_k(y \mid \boldsymbol{x}) \pi_a(k)$$

The SemEval social network

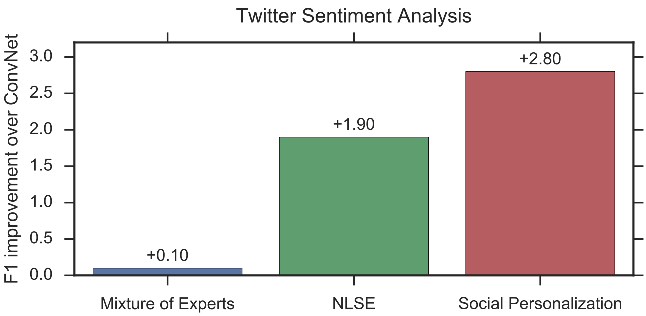
SemEval 2013-2015 is a standard benchmark for Twitter Sentiment Analysis.
(Nakov et al., 2013; Rosenthal et al., 2015).

	# Author	# Relations	# Isolates
original	14,087	40,110	3,633
expanded	17,417	1,050,369	689

Table: Follower network statistics

We “densify” the social network by adding individuals who are followed by at least 100 SemEval authors.

Results



Improvements over ConvNet baseline:

- +2.8% on Twitter Sentiment Analysis
- +2.7% on Ciao Product Reviews

NLSE is prior state-of-the-art (Astudillo et al., 2015).

Variable sentiment words

	More positive	More negative
1	banging loss fever broken fucking	dear like god yeah wow
2	chilling cold ill sick suck	satisfy trust wealth strong lmao
3	ass damn piss bitch shit	talent honestly voting win clever
4	insane bawling fever weird cry	lmao super lol haha hahaha
5	ruin silly bad boring dreadful	*lovatics* wish *beliebers arianators kendall*

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4	insane bawling fever weird cry	**lmao** super **lol** haha hahaha
5	ruin silly bad boring dreadful	**lovatics** wish **beliebers ari-anators** kendall

Linking language and social context

(Krishnan & Eisenstein, 2015)
(Eisenstein et al., 2014; Goel et al., 2016)

Linguistic meaning

Social phenomena

(Yang et al., 2016; Yang & Eisenstein, 2017)

Linking language and social context

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(Eisenstein et al., 2014; Goel et al., 2016)

Linguistic meaning

Social phenomena

(Yang et al., 2016; Yang & Eisenstein, 2017)

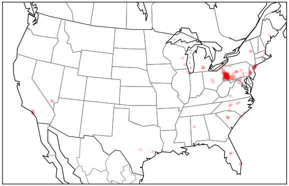
Language as social scientific evidence

- Propagating neologisms like lovatics and lmao requires:
  1. **Exposure**
  2. **Decision** to adopt (Rogers, 1962).

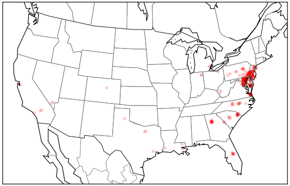
- By tracking the spread of these words, it is possible to reconstruct "deep networks" of social affinity and influence. (Eisenstein et al., 2014; Goel et al., 2016).

The important of place

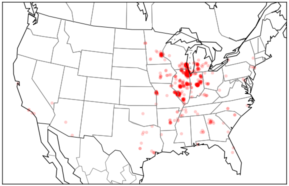
yinz



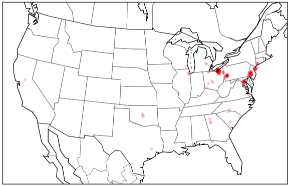
ard ("alright")



lbvs ("laughing but very serious")

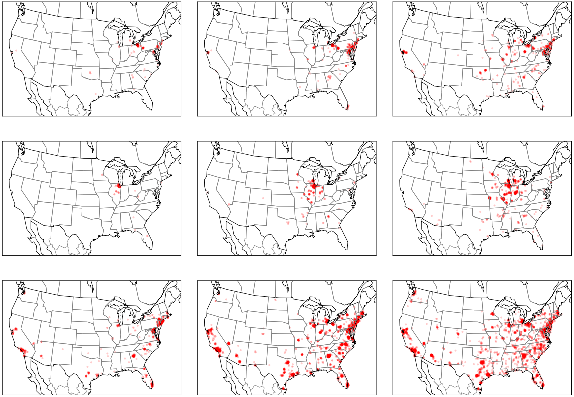


ctfu ("cracking the fuck up")



(Eisenstein et al., 2010, 2014)

An aggregate model of lexical diffusion



ctfu

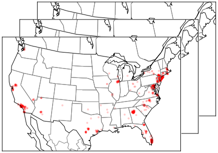
lbvs

-__-

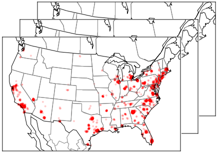
- Thousands of words have changing frequencies.
- Each spatiotemporal trajectory is idiosyncratic.
- What's the aggregate picture?

Language change as an autoregressive process

Word counts are binned into 200 metro areas and 165 weeks.



$$\eta_2 \sim N(A\eta_1, \Sigma)$$



$$\eta_3 \sim N(A\eta_2, \Sigma)$$

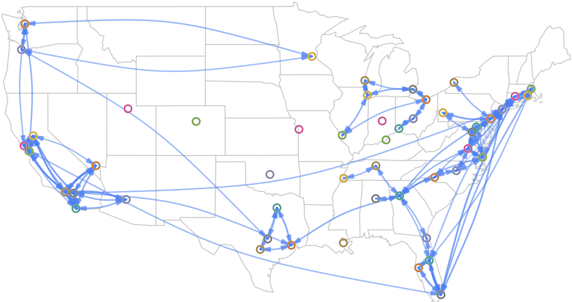
$$\begin{aligned} c_{\text{ctfu},1} &\sim \text{Binomial}(f(\eta_{\text{ctfu},1}), N_1) \\ c_{\text{hella},1} &\sim \text{Binomial}(f(\eta_{\text{hella},1}), N_1) \\ &\dots \end{aligned}$$

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

Estimating parameters of this autoregressive process reveals geographic pathways of diffusion across thousands of words (Eisenstein et al., 2014).

Aggregating city-to-city influence

Highly-confident pathways of diffusion
(from autoregressive parameter A).



Is geography the whole story?

Possible roles for demographics

- **Assortativity**: similar cities evolve together.
- **Influence**: certain types of cities tend to lead, others follow.

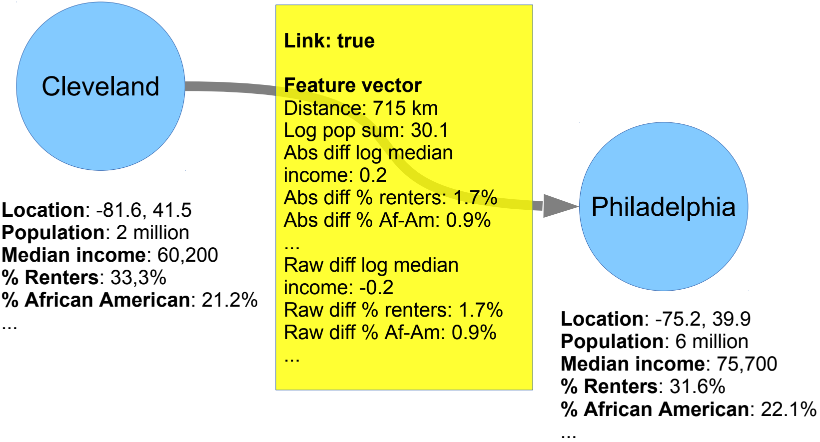
Possible roles for demographics

- **Assortativity**: similar cities evolve together.
- **Influence**: certain types of cities tend to lead, others follow.

- 2010 US Census gives detailed demographics for each city.
- Are there types of demographic relationships that are especially frequent among linked cities?

Location: -81.6, 41.5
Population: 2 million
Median income: 60,200
% Renters: 33,3%
% African American: 21.2%
...

Location: -75.2, 39.9
Population: 6 million
Median income: 75,700
% Renters: 31.6%
% African American: 22.1%
...


Cleveland
Location: -81.6, 41.5
Population: 2 million
Median income: 60,200
% Renters: 33,3%
% African American: 21.2%
...
Link: true
Feature vector
Distance: 715 km
Log pop sum: 30.1
Abs diff log median income: 0.2
Abs diff % renters: 1.7%
Abs diff % Af-Am: 0.9%
...
Raw diff log median income: -0.2
Raw diff % renters: 1.7%
Raw diff % Af-Am: 0.9%
...
Philadelphia
Location: -75.2, 39.9
Population: 6 million
Median income: 75,700
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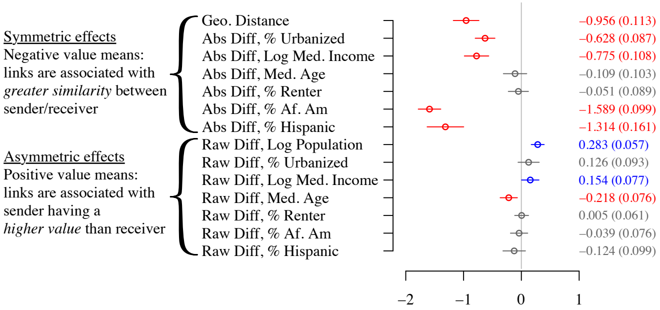
...

Regression coefficients



- Assortativity by race (of cities!) even more important than geography.
- Asymmetric effects are weaker, but bigger, younger metros tend to lead.

Summary and some next steps

- **Social context** plays a crucial role in disambiguating language, enabling robust text processing in domains like social media.

- Text offers a new window on social phenomena such as **cultural affinity and influence**.

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Summary and some next steps

- **Social context** plays a crucial role in disambiguating language, enabling robust text processing in domains like social media.

  Towards socially-scoped information extraction and semantic parsing?

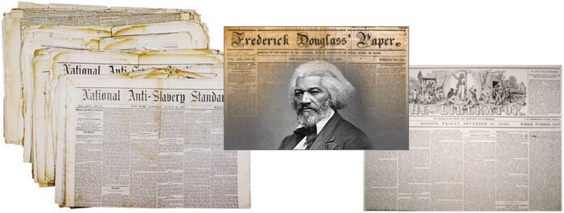
- Text offers a new window on social phenomena such as **cultural affinity and influence**.

  How can we move computational social science beyond the bag-of-words?

Computational social science beyond bag of words

Proposal: model the transmission of **meaning** and **argumentation** in historical social networks

- Peldszus & Stede (2013) propose formal models of argumentation structure.
- We plan to automatically parse argumentation in historical anti-slavery newspapers.
- How did the argumentation around the abolition of slavery evolve in the period before the US civil war?



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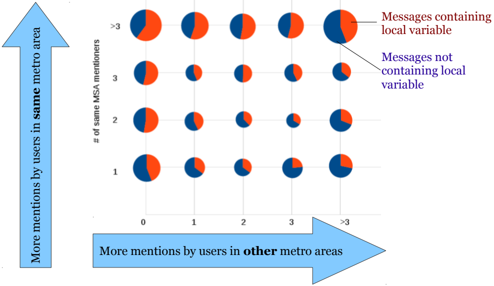
Why is geography so important?

Pavalanathan & Eisenstein (2015): People are more likely to use non-standard words when addressing audiences that are

1. small
2. local



Some other results on language change

- Goel et al. (2016): neologisms are best transmitted through strong ties.
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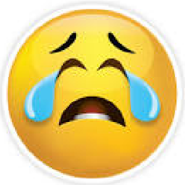

(but emojis raise a bunch of new interesting research questions ☺)

Related work

Signed social networks Hassan et al. (2012) and West et al. (2014) induce signs from sentiment analysis;

Formality of address Faruqui & Padó (2011) project formality from German into English;

Power in language Several researchers link linguistic features to annotations of power relations (Bramsen et al., 2011; Prabhakaran et al., 2012; Danescu-Niculescu-Mizil et al., 2012).

Key difference: we assume no labels, just text on a social network.

Forms of address

Names such as Barack, Barack Hussein Obama.

Titles such as Ms., Dr., Private, Reverend.
Titles can be used for address either by preceding a name (e.g., Colonel Kurtz), or in isolation (e.g., Yes, Colonel.).

Placeholder names such as dude, bro, brother, sweetie, cousin, and asshole.
These terms can be used for address only in isolation.

Subtasks

- Build a vocabulary of titles.
- Build a vocabulary of placeholder names.
- Distinguish address **tokens**:

  His/O name/O is/O **Lebowski/O** *?/O*
  That's/O your/O name/O, **Dude/ADDR**

- There is surprisingly little prior work on these problems, including lexicons.

Automatic address annotations

Text:	You	're	Mr.	Lebowski	.
POS:	PRP	VBP	NNP	NNP	.
Address:	O	O	B-ADDR	L-ADDR	O

1. Look for character names (mined from rotten tomatoes).
2. Identify NNP tag sequences including those names.
3. Automatically label those sequences as entity spans.

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Address tagger: features

Feature	Description
Lexical	The word to be tagged, and its two predecessors and successors, $w_{i-2:i+2}$
POS	The part-of-speech of the token to be tagged, and its neighbors
Case	The case of the word to be tagged, and its neighbors.
Constituency parse	First non-NNP ancestor node of the word w_i in the constituent parse tree, and all leaf node siblings in the tree.
Dependency	All dependency relations involving w_i.
Location	Distance of w_i from the start and the end of the sentence or turn.
Punctuation	All punctuation symbols occurring before and after w_i.
Second person pronoun	All forms of the second person pronoun within the sentence.

Address tagger: accuracy

Class	F-measure	Total Instances
I-ADDR	0.58	53
B-ADDR	0.800	483
U-ADDR	0.987	1864
L-ADDR	0.813	535
O-ADDR	0.993	35975

Lexicon induction: titles

- Run the tagger, find terms that frequently appear at the beginning of address spans containing the character's name.
- We then manually filter out 17 of 34 candidates, obtaining:

agent, aunt, captain, colonel, commander, cousin, deputy, detective, dr, herr, inspector, judge, lord, master, mayor, miss, mister, miz, monsieur, mr, mrs, ms, professor, queen, reverend, sergeant, uncle

Lexicon induction: placeholder names

- Remove the CURRENT-WORD feature from the tagger model, then find terms that are frequently tagged as the unique element in an address span.
- After manually filter out 41 of 96 candidates, we obtain:

asshole, babe, baby, boss, boy, bro, bud, buddy, cocksucker, convict, cousin, cowboy, cunt, dad, darling, dear, detective, doll, dude, dummy, father, fella, gal, ho, hon, honey, kid, lad, lady, lover, ma, madam, madame, man, mate, mister, mon, moron, motherfucker, pal, papa, partner, peanut, pet, pilgrim, pop, president, punk, shithead, sir, sire, son, sonny, sport, sucker, sugar, sweetheart, sweetie, tiger

Feature vector construction

Content features

- Addressee name, including any title in lexicon
  You're **Mr. Lebowski** → MR. LASTNAME
- Any element in the placeholder name lexicon, if tagged as the unique element in address span
  Thanks, dude → DUDE

Dyad feature: Adamic-Adar metric (normalized mutual friends) for each dyad

Model comparison

	Text	Dyad Feature	Signed triads	Predictive Log-likelihood
M1	✓			
M2	✓		✓	
M3	✓	✓		
M4	✓	✓	✓	

Model comparison

	Text	Dyad Feature	Signed triads	Predictive Log-likelihood
M1	✓			-2133.28
M2	✓		✓	-2018.21
M3	✓	✓		-1884.02
M4	✓	✓	✓	-1582.43

Predictive likelihood is evaluated on held-out address terms for a 10% test fold.