Sociolinguistic Structure Induction

Jacob Eisenstein
@jacobeisenstein

Georgia Institute of Technology

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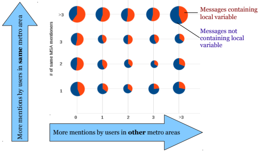
Linguistics and social network analysis both wrestle with understanding **emergent structure**.

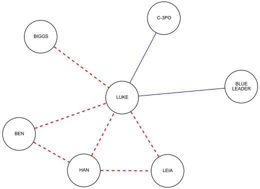
- Linguistics: how does meaning arise from individual linguistic features?
- Social networks: how do macro-level social phenomena arise from individual dyads?

Premise: Jointly modeling linguistic and social structures will help us capture the emergence of social meaning in communication.

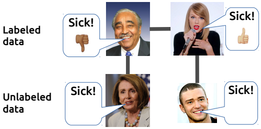
Overview



1. Language standards and innovation in social media networks



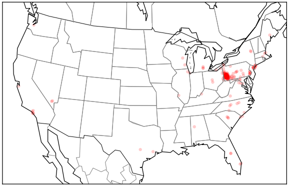
2. Linguistic signals of interpersonal relationships



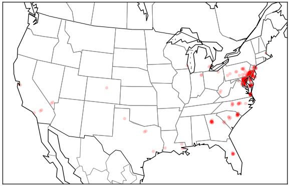
3. Social communities for more robust NLP

Language standards and innovation in social media networks

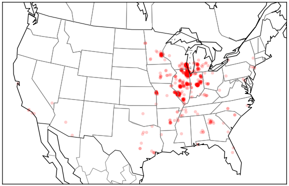
Audience-modulated variation in online social media. Pavalanathan & Eisenstein (2015) yinz



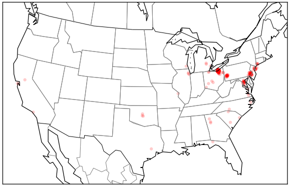
ard ("alright")



lbvs ("laughing but very serious")



ctfu ("cracking the fuck up")



(Eisenstein et al., 2010, 2014)

A new geographical diversity?

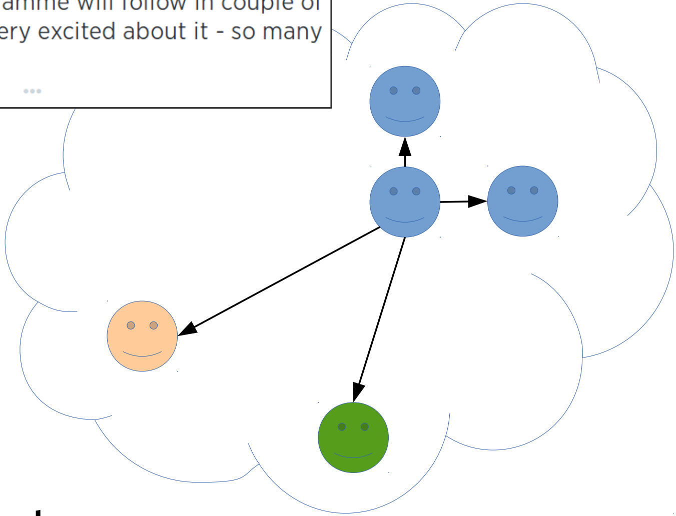
What explains these geographical differences in online writing?

- These are not just variables from speech!
- Are the users of these words aware that they are geographically specific?
- Will these differences eventually "wash out"?
- Modeling usage **in context** can shed light on the social function of linguistic variables.

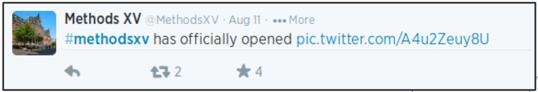
Methods XV @MethodsXV · May 15

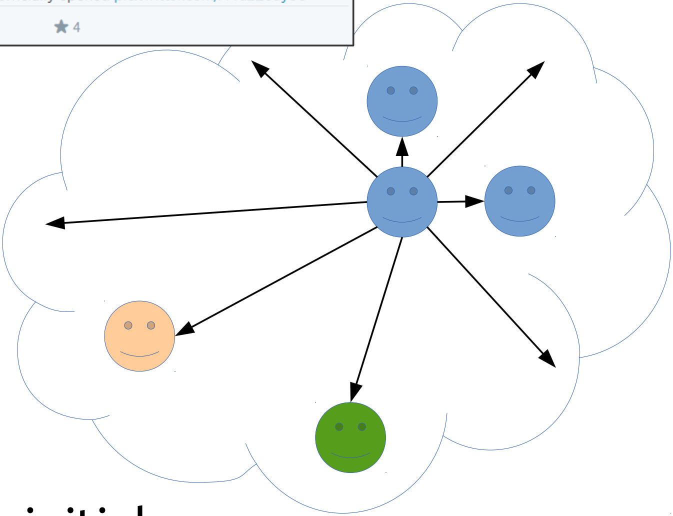
Our full programme will follow in couple of days! We're very excited about it - so many great talks!

3 2

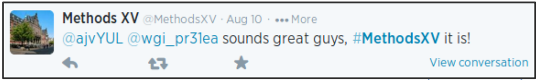


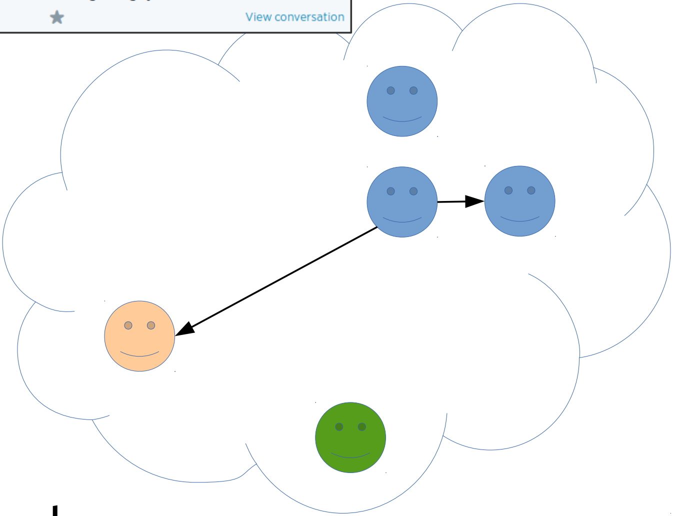
Broadcast





Hashtag-initial


Methods XV @MethodsXV · Aug 10 · ••• More
@ajvYUL @wgi_pr31ea sounds great guys, #MethodsXV it is!
View conversation

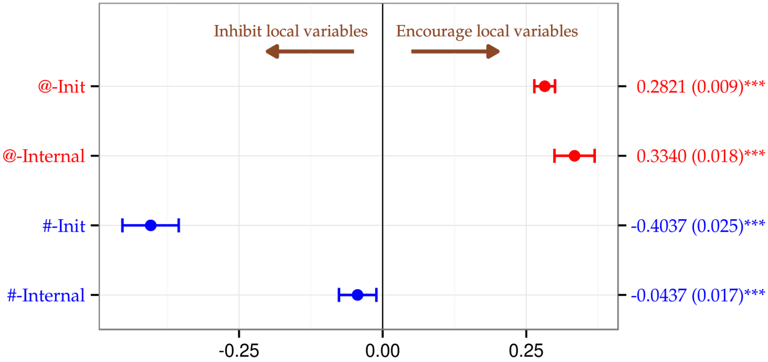


Addressed

Logistic regression

- **Dependent variable**: does the tweet contain a non-standard, geographically-specific word (e.g., lbvs, hella, jawn)
- **Predictors**
  - **Message type**: broadcast, addressed, #-initial
  - **Controls**: message length, author statistics

Small audience → less standard language



Distinguishing local ties

To distinguish **local** audiences:

- Use GPS metadata to identify author locations
- Associate metro m with user u if u is @-mentioned by:
  - at least three users within metro m;
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The social network lets us impute the locations of unknown users from the 1-2% of users who reveal their GPS! (Sadilek et al., 2012)

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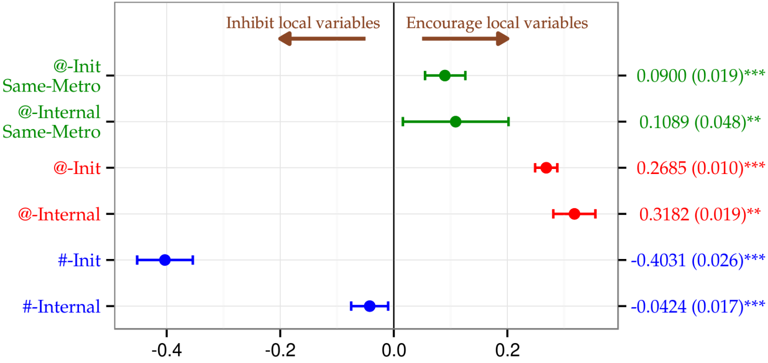
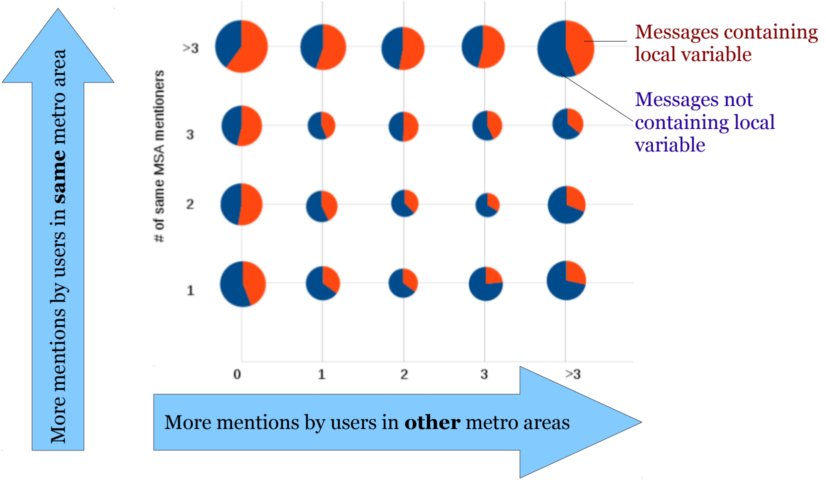


Local ties make non-standard language even more likely.

Local audience → less standard language



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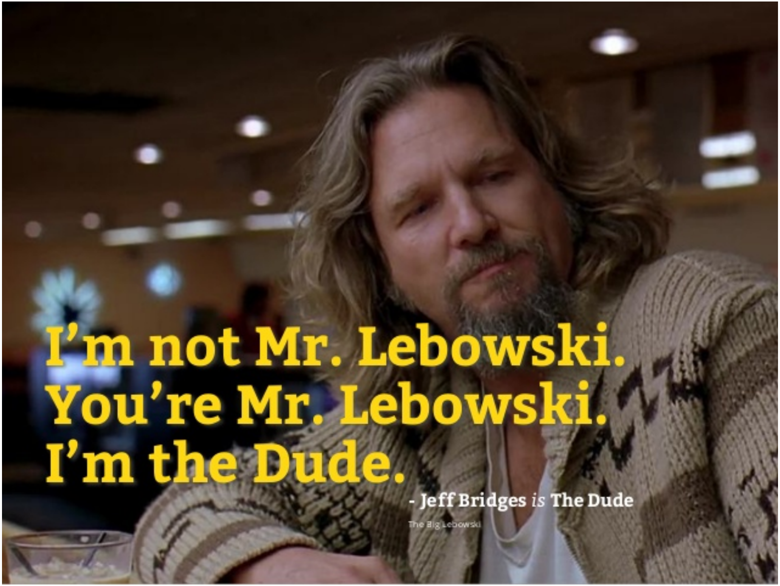
Linguistic Signals of Social Relationships

You're Mr. Lebowski, I'm the Dude: Inducing Address Term Formality in Signed Social Networks
Krishnan & Eisenstein (2015).


I'm not Mr. Lebowski.
You're Mr. Lebowski.
I'm the Dude.
- Jeff Bridges *is* The Dude
The Big Lebowski

Modeling formality of address

- What is the nature of the relationships between actors in a social network?
- Are there regular structures that emerge across signed networks?
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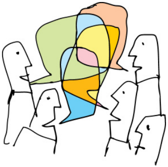

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- How does language reflect and reproduce social relationships?

  We estimate a likelihood distribution over address terms given formality.

A generative model of networked content

- Undirected graph $G = \langle i, j \rangle$, $i < j$

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- Each edge label has **two** associated distributions, so that:

$$\boldsymbol{x}_{i \rightarrow j} \mid y_{ij} \sim \text{Multinomial}(\boldsymbol{\theta}^{\rightarrow}_{y_{ij}})$$
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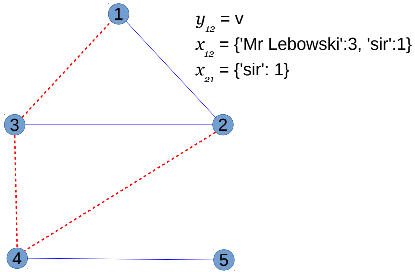
- We add the constraint $\boldsymbol{\theta}^{\to}_{y_{ij}} = \boldsymbol{\theta}^{\leftarrow}_{y_{ij}} = \boldsymbol{\theta}_{y_{ij}}$; without it, we can generalize to directed signs.

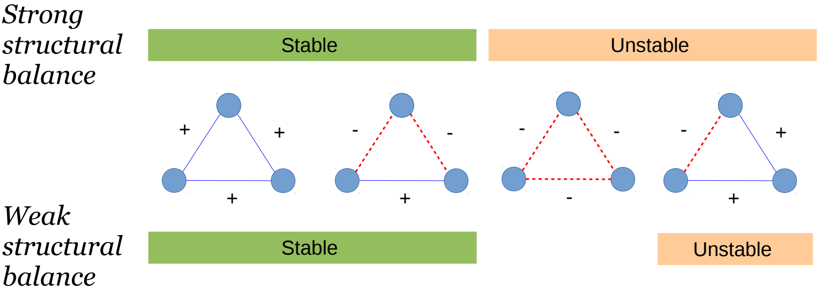
Example

- 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.



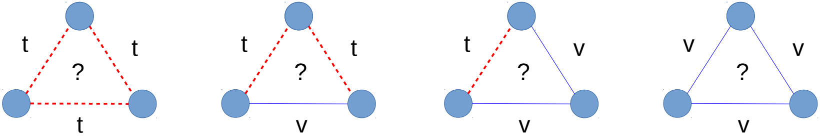
Adding social theory

- So far, this is just a mixture model over dyads.
- But social theory may tell us that not all label configurations are equally likely.
- Ex: **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.

$$P(\boldsymbol{y}; G, \boldsymbol{\eta}, \boldsymbol{\beta}) = \frac{1}{Z(\boldsymbol{\eta}, \boldsymbol{\beta}; G)} \times \exp \sum_{\langle i,j \rangle \in G} \boldsymbol{\eta}^\top \boldsymbol{f}(y_{ij}, i, j, G)$$
$$\times \exp \sum_{\langle i,j,k \rangle \in \mathcal{T}(G)} \beta_{y_{ij}, y_{jk}, y_{ik}},$$

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;
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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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Bayesian inference answers several questions:

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Intractability of Inference

- The normalizing constant z requires summing across all labelings.

  The number of labelings is $\mathcal{O}(\#|\mathcal{Y}|^N)$.

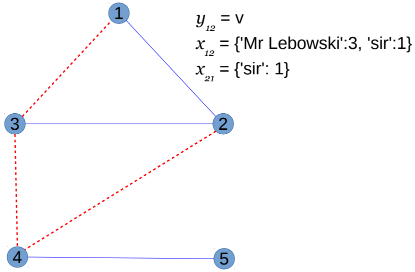
- West et al (2014) show that optimizing an objective over dyads and triads is NP-hard.

  Even exact posterior decoding of $\boldsymbol{y}$ is not tractable, given point estimates for parameters $\boldsymbol{\theta}$, $\boldsymbol{\eta}$, and $\boldsymbol{\beta}$.

- We therefore apply a variational approximation.
  - We make point estimates of the parameters $\boldsymbol{\theta}$, $\boldsymbol{\eta}$, and $\boldsymbol{\beta}$ (empirical Bayes).
  - We represent uncertainty over $\boldsymbol{y}$ through a factorized distribution $Q(\boldsymbol{y}) = \prod_{\langle i,j \rangle \in G} q_{ij}(\boldsymbol{y}_{ij})$.

Let's do it!

- The Cornell Movie Dialogue corpus offers 300K conversational turns between 10K dyads, in 617 movies.
- All we need are the address terms...
- But no such resource appears to exist!



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.

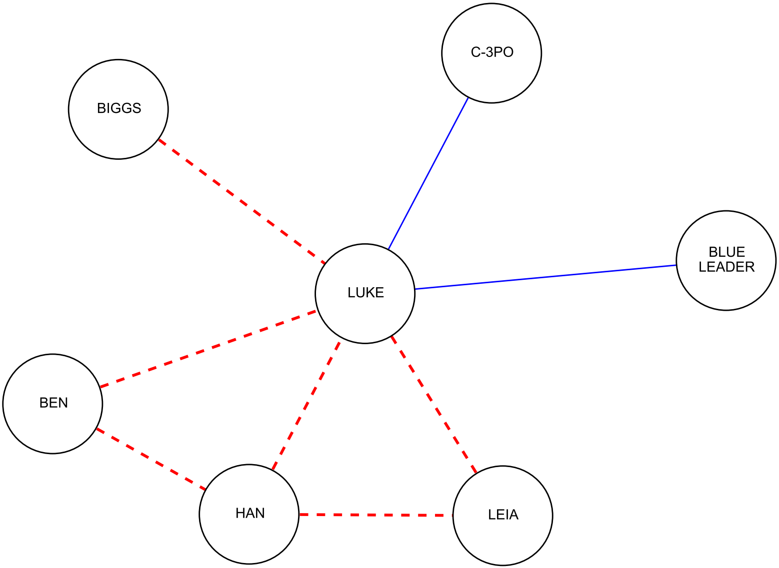
Cluster coherence

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

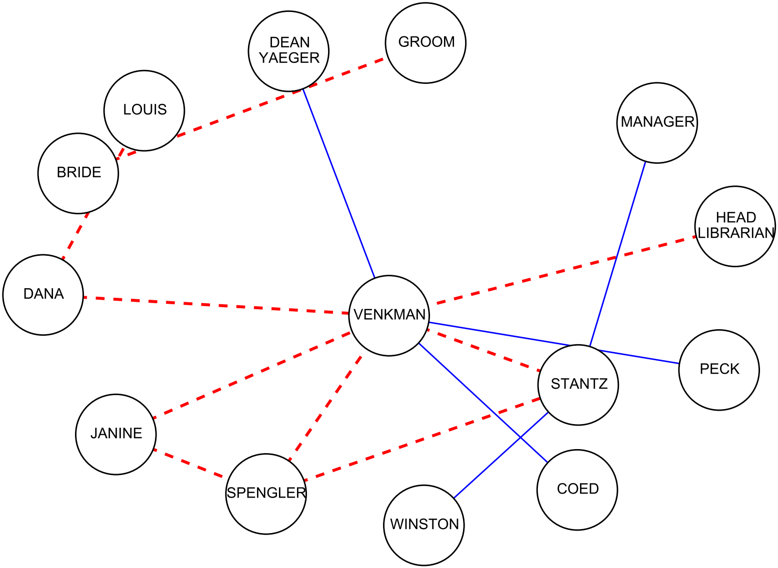
On an intrusion task

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

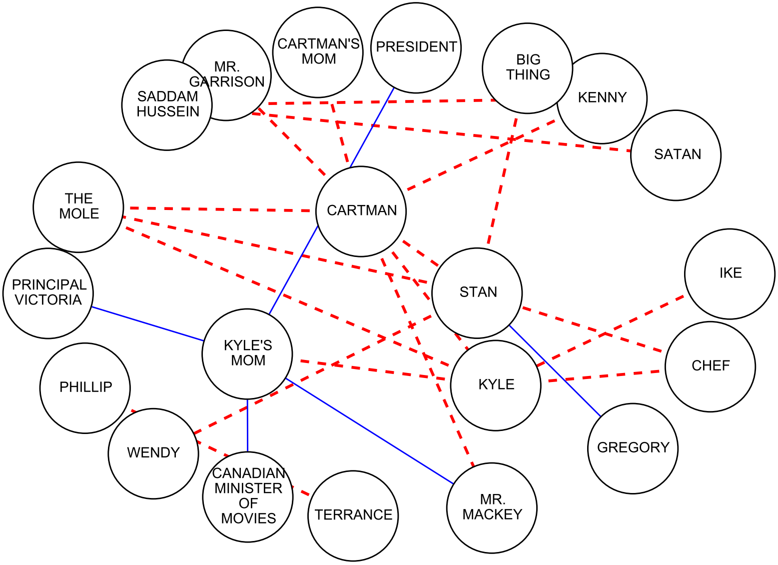
Star Wars



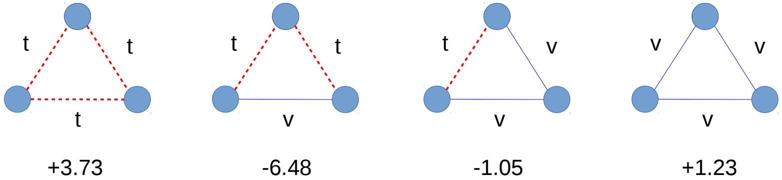
Ghostbusters



South Park


MR. GARRISON
CARTMAN'S MOM
PRESIDENT
BIG THING
KENNY
SADDAM HUSSEIN
SATAN
THE MOLE
CARTMAN
IKE
PRINCIPAL VICTORIA
STAN
KYLE'S MOM
CHEF
KYLE
PHILLIP
GREGORY
WENDY
CANADIAN MINISTER OF MOVIES
TERRANCE
MR. MACKEY

Network features



Social Networks for Better NLP

Putting Things in Context: Community-specific Embedding Projections for Sentiment Analysis.

Yang & Eisenstein (2015)

Words mean different things to different people

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

Words mean different things to different people

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

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

As author sets become increasingly diverse, variation is increasingly a problem for NLP.

Language diversity and social attributes

Language variation is everywhere.
What can we do about it?

- Hovy (2015): author demographics (age, gender) improves text classification.
- What if we don't have the author demographics?

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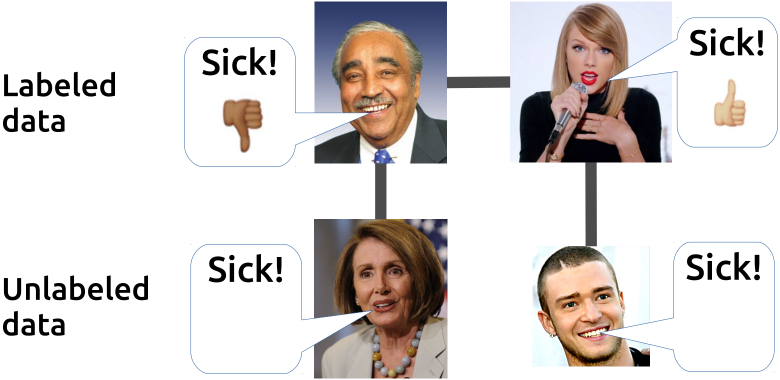
Homophily: neighbors have similar properties.

- Demographics (Thelwall, 2009; Al Zamal et al., 2012)
- Language (Bryden et al., 2013)

Homophily to the rescue?



Social network structure can help us identify which meaning is likely, even in unlabeled instances.

The SemEval Social Network

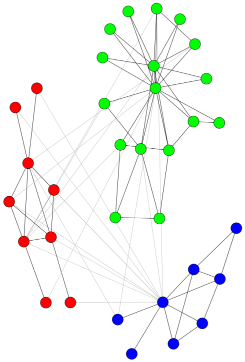
- SemEval 2013-2015 is a standard benchmark for Twitter Sentiment Analysis (Nakov et al., 2013; Rosenthal et al., 2015).
- Follower network statistics:

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

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

From Homophily to Modularity

- Reasoning about lexical semantics in a social network of 10^4 nodes is hard!
- Solution: summarize the network by clustering nodes into social network communities.
- **Modularity**: nodes in the same community tend to have similar properties.



Linguistic Modularity in SemEval

Network	Algorithm	# Communities	$Q^{(L)}$
original	Fast-Greedy	19	0.1549
expanded		5	0.2102
original	Multi-Level	19	0.1462
expanded		7	0.2526

Table: Linguistic modularities on the SemEval data

- Social network communities use similar words...
- But does meaning also cluster on a social network?

Nonlinear Subspace Embeddings (NLSE)

We build on NLSE (Astudillo et al., 2015), which learns a task-specific projection of word embeddings for sentiment analysis.

$$\boldsymbol{h}_j = \text{Sigmoid}(\mathbf{S}\boldsymbol{x}_j), \tag{1}$$

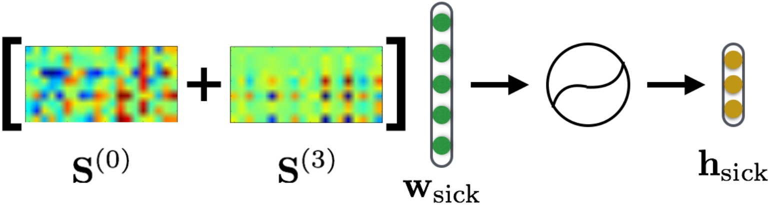
where

- $\boldsymbol{x}_j$ is the pre-trained embedding of word j
- $\mathbf{S}$ is a discriminatively learned task-specific projection matrix
- $\boldsymbol{h}_j$ is the projected embedding
- To project multiple words, Astudillo et al. (2015) just add up the embeddings.

Adding Community Structure

For a node i in community c_i,

$$\boldsymbol{h}_j = \text{Sigmoid}\left(\left[\mathbf{S}^{(0)} + \mathbf{S}^{(c_i)}\right] \boldsymbol{w}_j\right), \qquad (2)$$



We can also detect multiple community structures, and add separate projections for each.

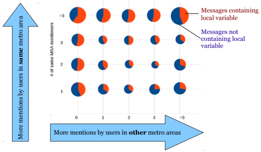
Results

Communities	T2013	T2014	T2015	Avg
Prior work				
None	72.0	72.7	65.2	70.0
Our methods				
Fast-Greedy	72.0	73.7	65.6	70.4
Multi-Level	72.1	**73.8***	**66.1***	**70.7**

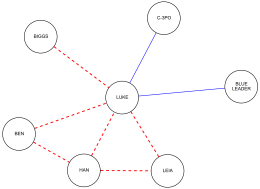
Table: Average F1 score on the SemEval test sets. Results are marked with * if they are significant better than pooled NLSE at $p < 0.05$.

Running NLSE separately in each community is substantially worse.

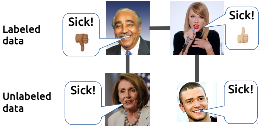
Overview



1. Language standards and innovation in social media networks



2. Linguistic signals of interpersonal relationships



3. Social communities for more robust NLP

Thanks to support from the National Science Foundation, the Air Force Office of Scientific Research, and the National Institutes for Health.

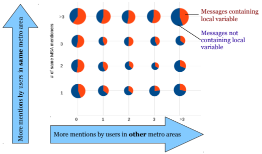
What's next?

Beyond and inside the lexicon Tracing syntactic and orthographic markers of linguistic style and social dynamics.

From style to content What do your stylistic decisions reveal about what you believe?

From macro to micro Tracking the spread of language change through individual linguistic decisions.

Overview



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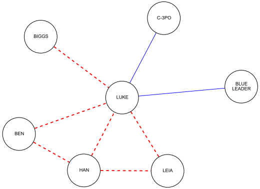

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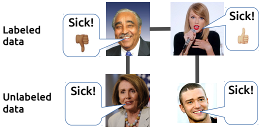

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Social networks in social media

Social media platforms offer a number of forms of metadata that capture social networks.

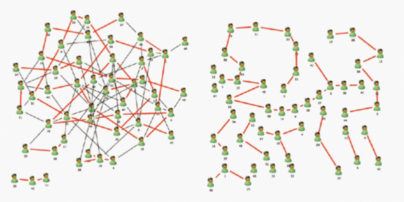
Articulated network
: Explicitly-defined connections; undirected in Facebook, directed in Twitter.

Behavioral network
: Inferred from conversational interactions, such as replies or mentions.

(danah boyd, 2006)

Social networks on Twitter

- Twitter users often follow 1000s of other users.
- Mention networks are smaller, and arguably more socially meaningful.
- Twitter query rate limiting makes mention network much easier to obtain.



(a) All links are declared followees and the red links are actual friends. (b) After removing the black links and reorganizing the network look simpler than before. This is the hidden network that matters the most.

(Huberman et al., 2008)

Community-specific Meanings

	Most distinct words
C1	brighter blessings celebrate shine brightest blessing gbu glowing celebrating hwaiting
C2	*mistakes stfu ass shutup bitch #ohwell retard regret dgaf idgaf*
C3	enjoyin #stillkidrauhl funny brighter happiest catchy sweeter jealous relaxing smartest