

Sociolinguistic Structure Induction

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Sociolinguistic structure induction

Language is socially situated.

- ▶ Without the social dimension, we don't understand what language is for.

Social interactions are linguistically mediated.

- ▶ Without linguistic analysis, we don't understand what social (and political) interactions are about.

Sociolinguistic **structure** induction

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?

We need unified models of linguistic and social structure to capture emergent social meaning in communication.

Sociolinguistic structure **induction**

Supervised machine learning and inferential statistics are not up to the task.

- ▶ Social meanings are hard to annotate.
- ▶ Sociolinguistic research is driven by expert intuitions, but experts may have blind spots.

Sociolinguistic structure **induction**

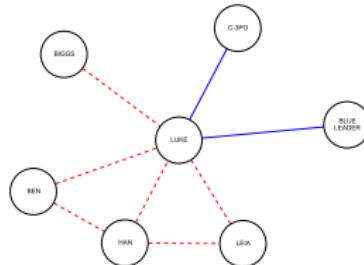
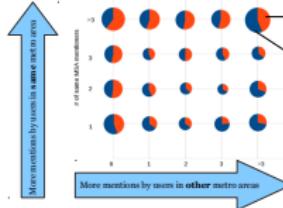
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Latent variable models can **induce** hidden structures that explain both linguistic data and increasingly rich social metadata.

- ▶ Ex: Relational Topic Model (Chang et al., 2010).
- ▶ How to better link these probabilistic models to social science theory?

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



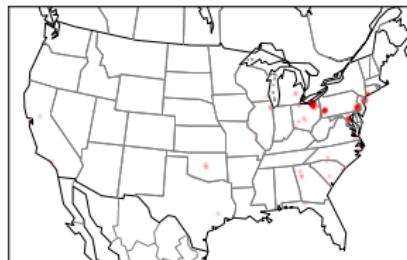
ard ("alright")



lbvs ("laughing but very serious")



ctfu ("cracking the fuck up")



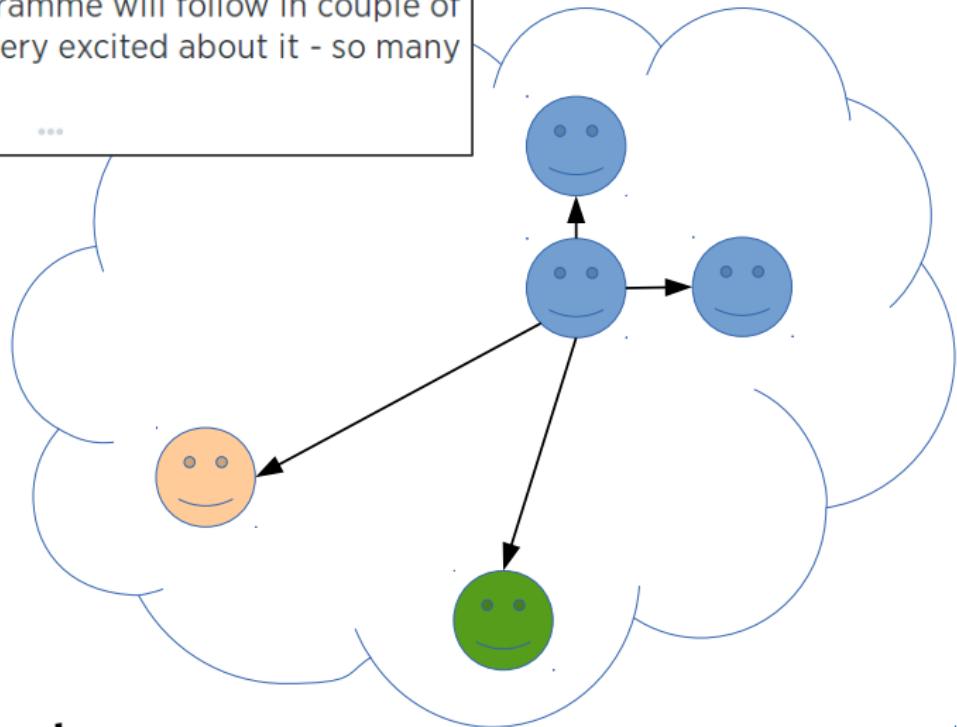
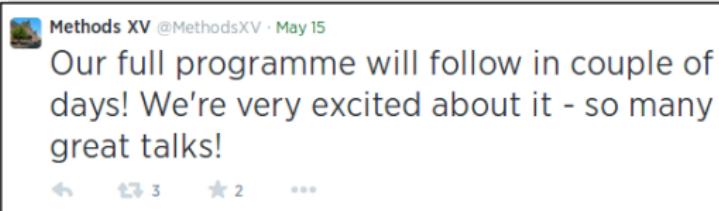
(Eisenstein et al., 2010, 2014)

A new geographical diversity?

What explains these geographical differences in online writing?

- ▶ Some of these differences are endogenous to writing (e.g., lbvs)
- ▶ 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.



Broadcast



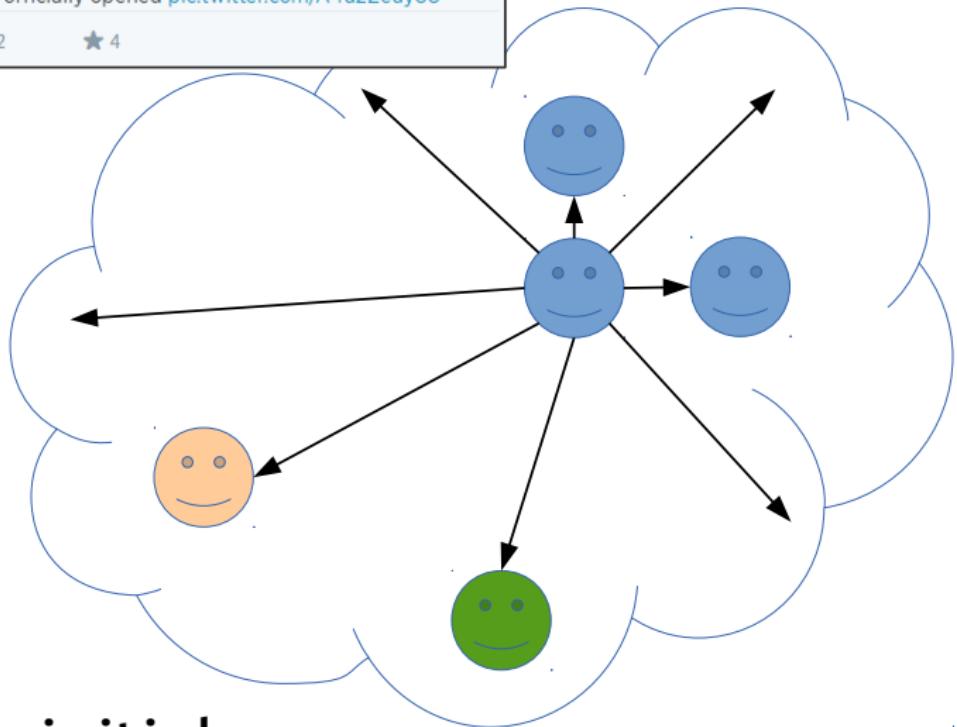
Methods XV @MethodsXV · Aug 11 · ... More

#methodsxv has officially opened pic.twitter.com/A4u2Zeuy8U



2

4



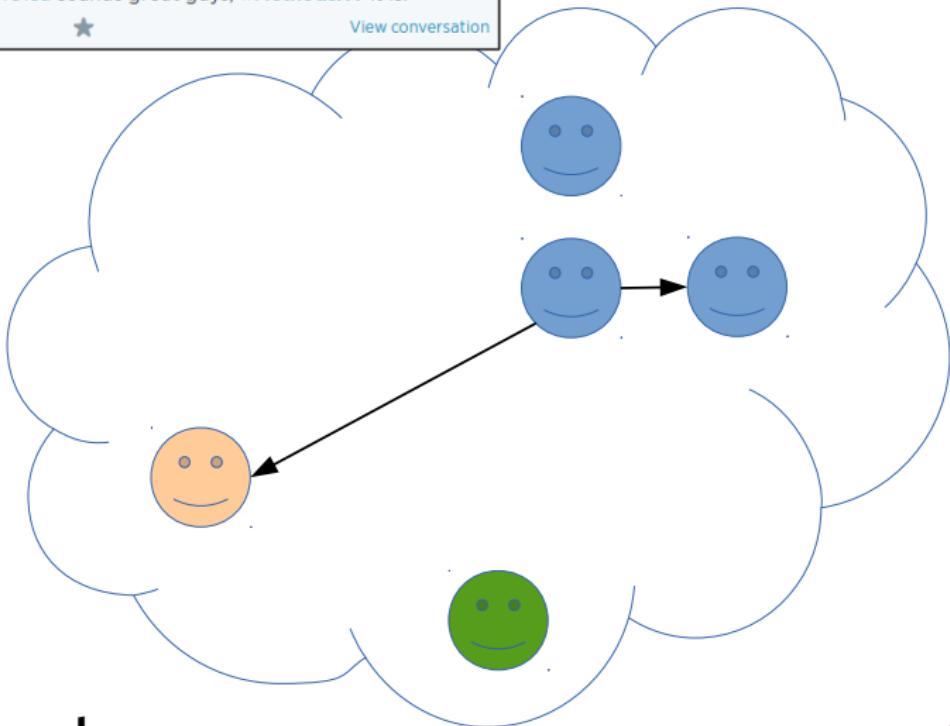
Hashtag-initial



Methods XV @MethodsXV · Aug 10 · ... More

@ajvYUL @wgi_pr3lea sounds great guys, #MethodsXV it is!

[View conversation](#)

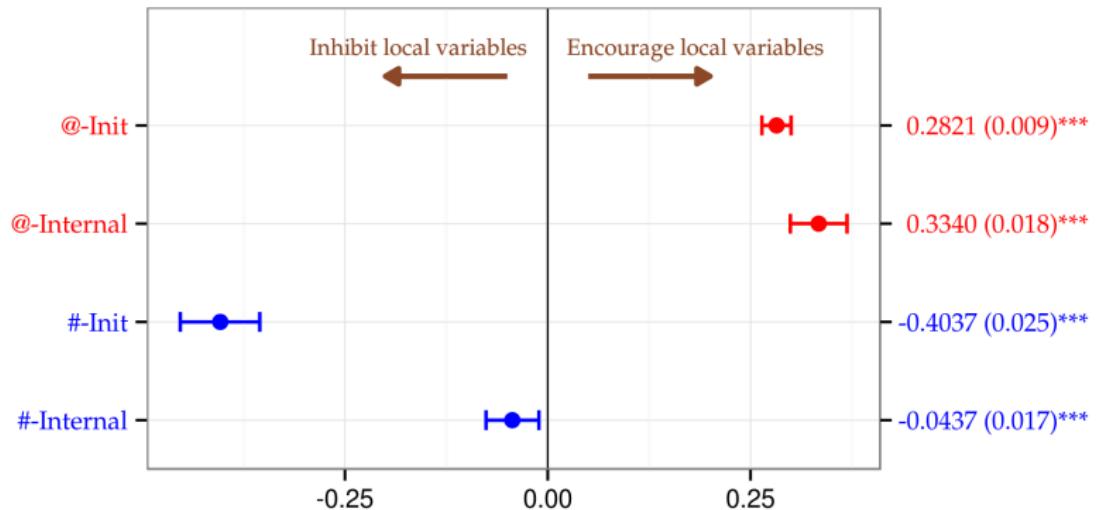


Addressed

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 ;
 - ▶ nobody outside metro m .

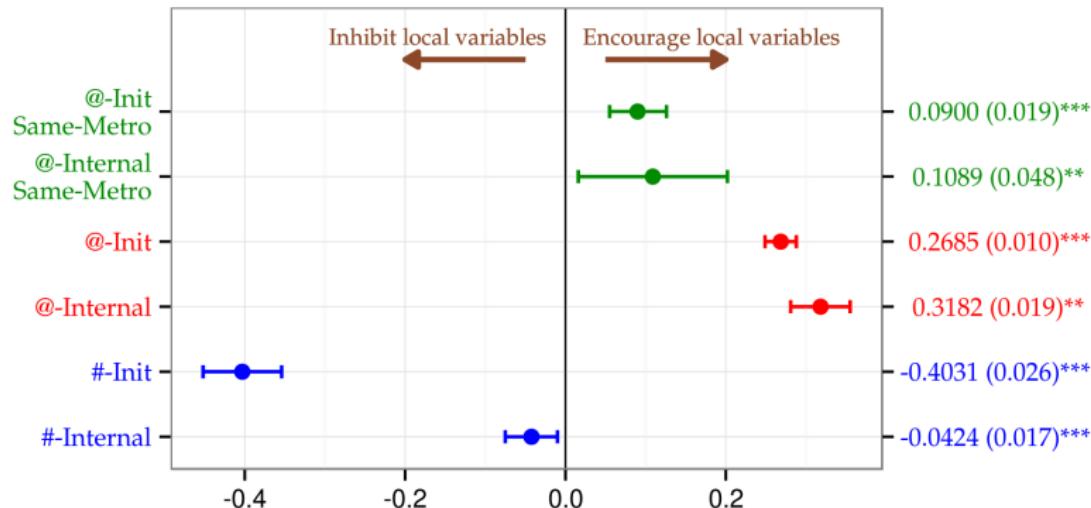
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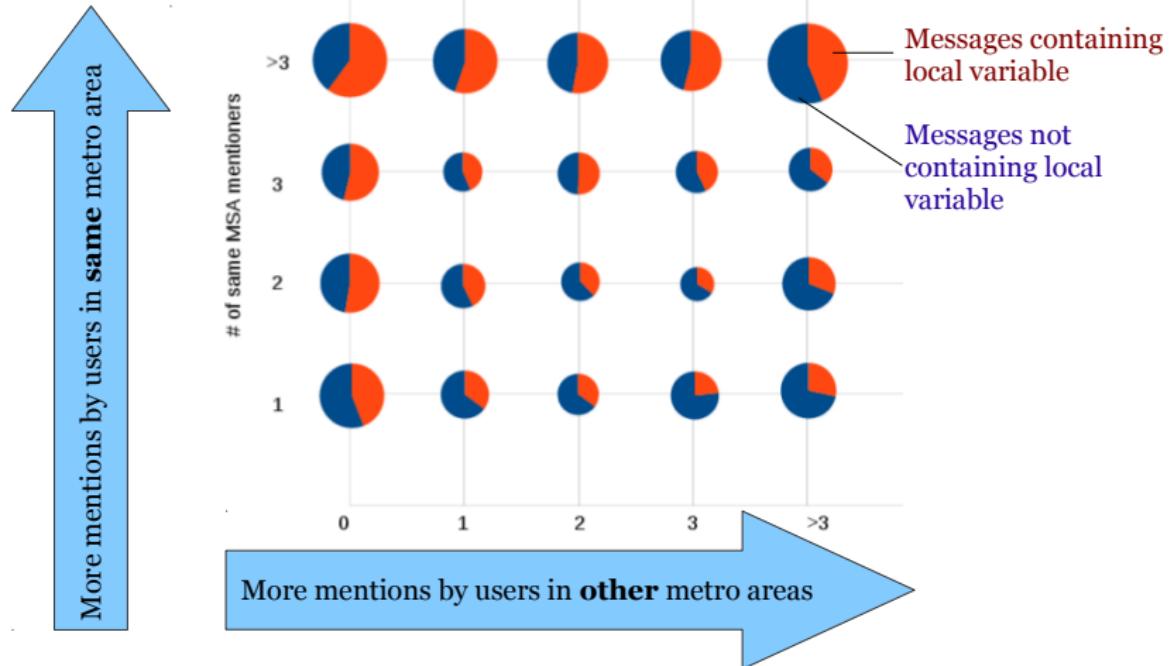
The social network lets us impute the locations of unknown users from the 1-2% of users who reveal their GPS! (Sadilek et al., 2012)

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Local ties make non-standard language even more likely.

Local audience → less standard language



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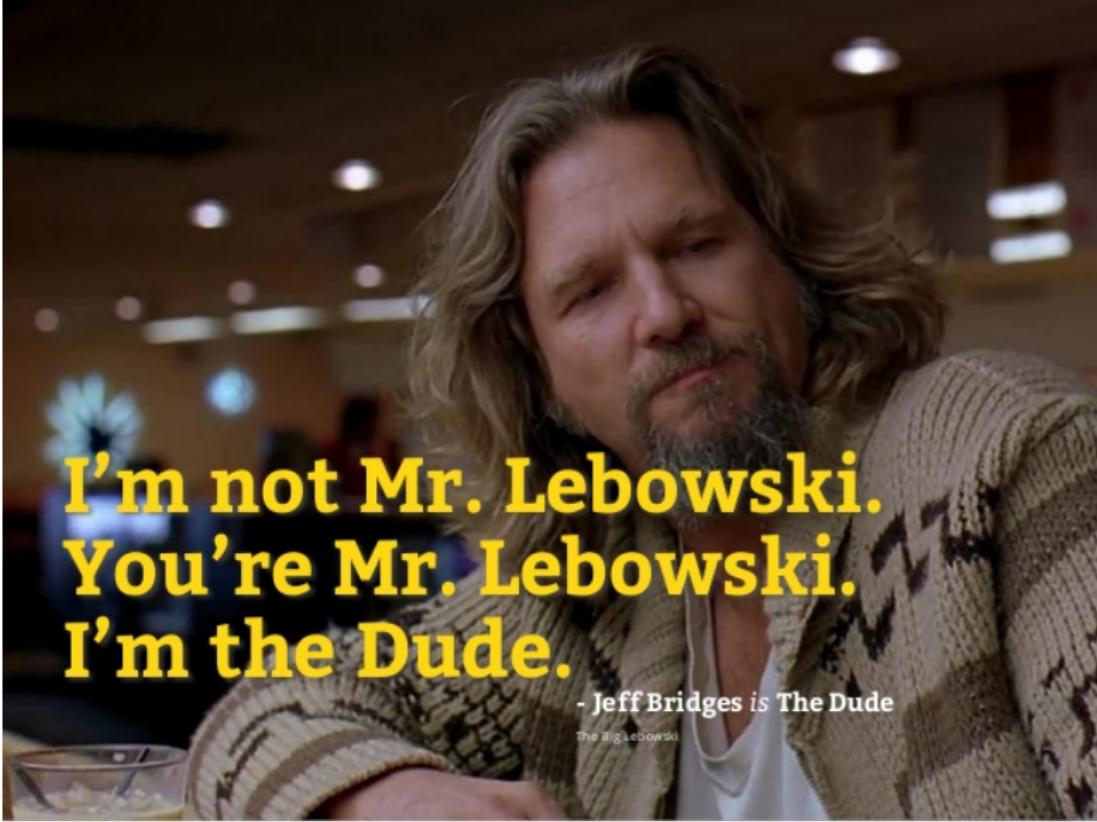
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Linguistic Signals of Social Relationships



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

A close-up portrait of Jeff Bridges as The Dude. He has long, wavy, light brown hair and a full, dark beard. He is wearing a patterned, cable-knit cardigan over a white t-shirt. He is looking slightly to his left with a neutral or slightly weary expression. The background is dark and out of focus, showing some lights and what might be a bar or restaurant interior.

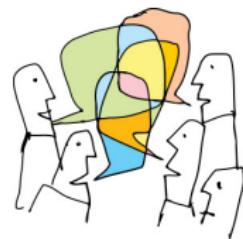
**I'm not Mr. Lebowski.
You're Mr. Lebowski.
I'm the Dude.**

- 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?
- ▶ How does language reflect and reproduce social relationships?



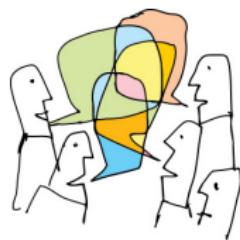
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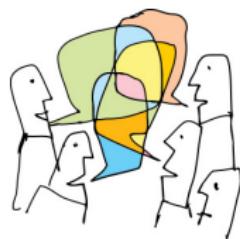
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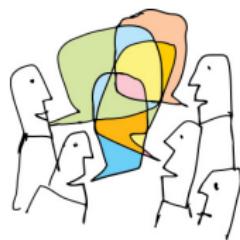
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- ▶ How does language reflect and reproduce social relationships?

We estimate a likelihood distribution over address terms given formality.

A generative model of networked content

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

$$x_{i \rightarrow j} \mid y_{ij} \sim \text{Multinomial}(\theta_{y_{ij}}^\rightarrow)$$
$$x_{j \leftarrow i} \mid y_{ij} \sim \text{Multinomial}(\theta_{y_{ij}}^\leftarrow).$$

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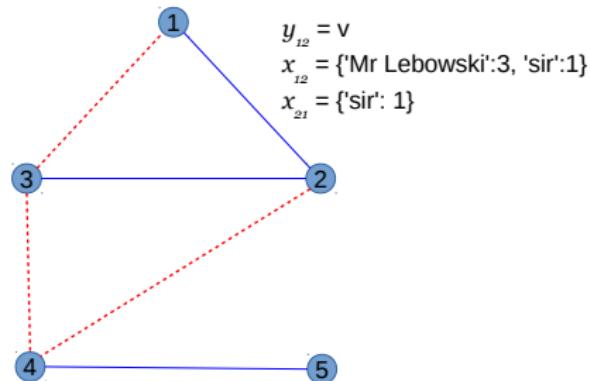
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- ▶ We add the constraint $\theta_{y_{ij}}^{\rightarrow} = \theta_{y_{ij}}^{\leftarrow} = \theta_{y_{ij}}$;
without it, we can generalize to directed signs.

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:

*Strong
structural
balance*

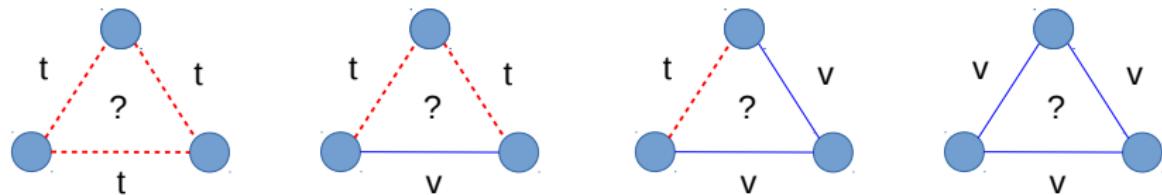


*Weak
structural
balance*



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.

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

where,

- ▶ $Z(\boldsymbol{\eta}, \boldsymbol{\beta}; G)$ is a normalizing constant;
- ▶ $\mathbf{f}(y_{ij}, i, j, G)$ 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

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

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

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Bayesian inference answers several questions:

1. What is the label (formality) of each dyad?
2. How is formality expressed in language?
3. Are there structural regularities across networks?

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Intractability of Inference

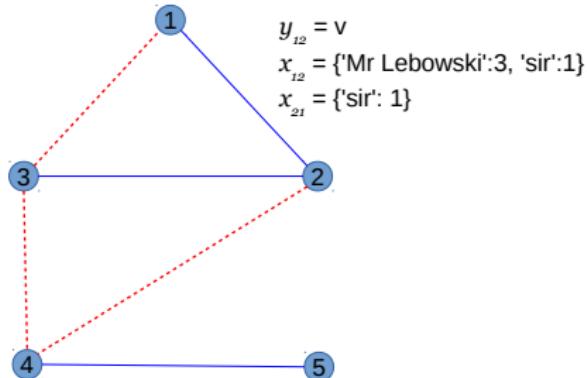
- ▶ The normalizing constant z requires summing across all labelings.

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 y is not tractable, given point estimates for parameters θ , η , and β .
- ▶ We therefore apply a variational approximation.
 - ▶ We make point estimates of the parameters θ , η , and β (empirical Bayes).
 - ▶ We represent uncertainty over y through a factorized distribution $Q(y) = \prod_{\langle i,j \rangle \in G} q_{ij}(y_{ij})$.

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.

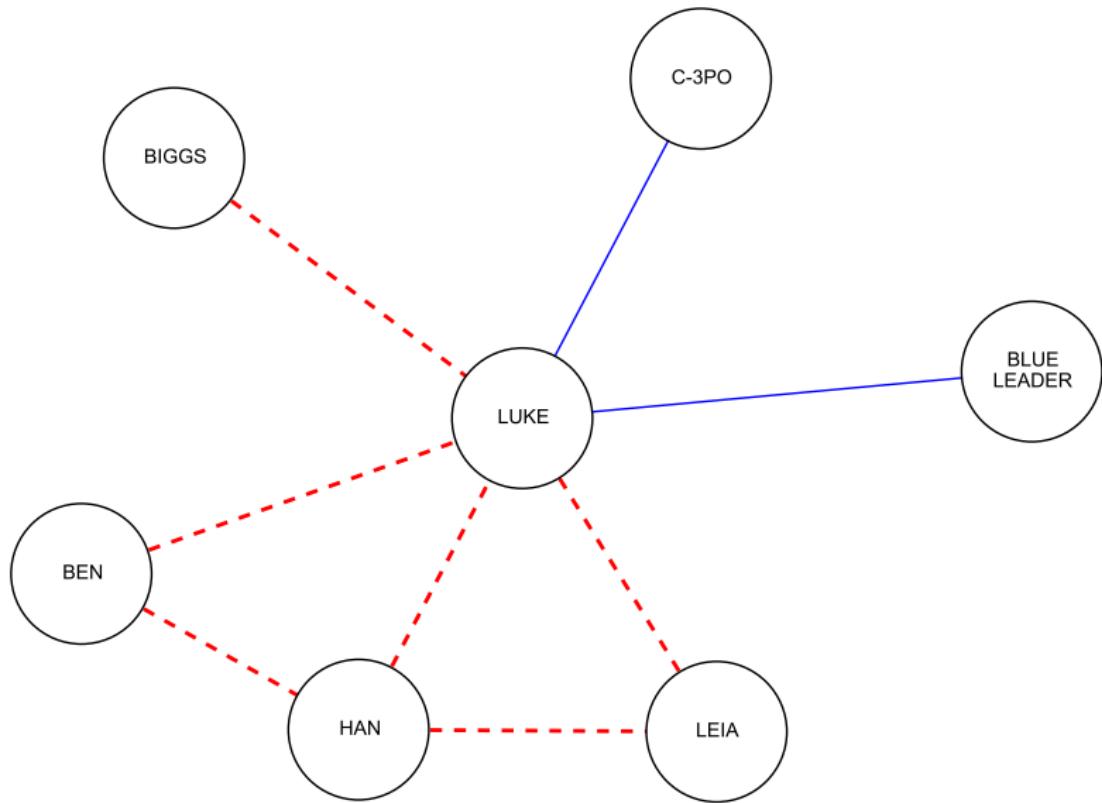
Cluster coherence

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

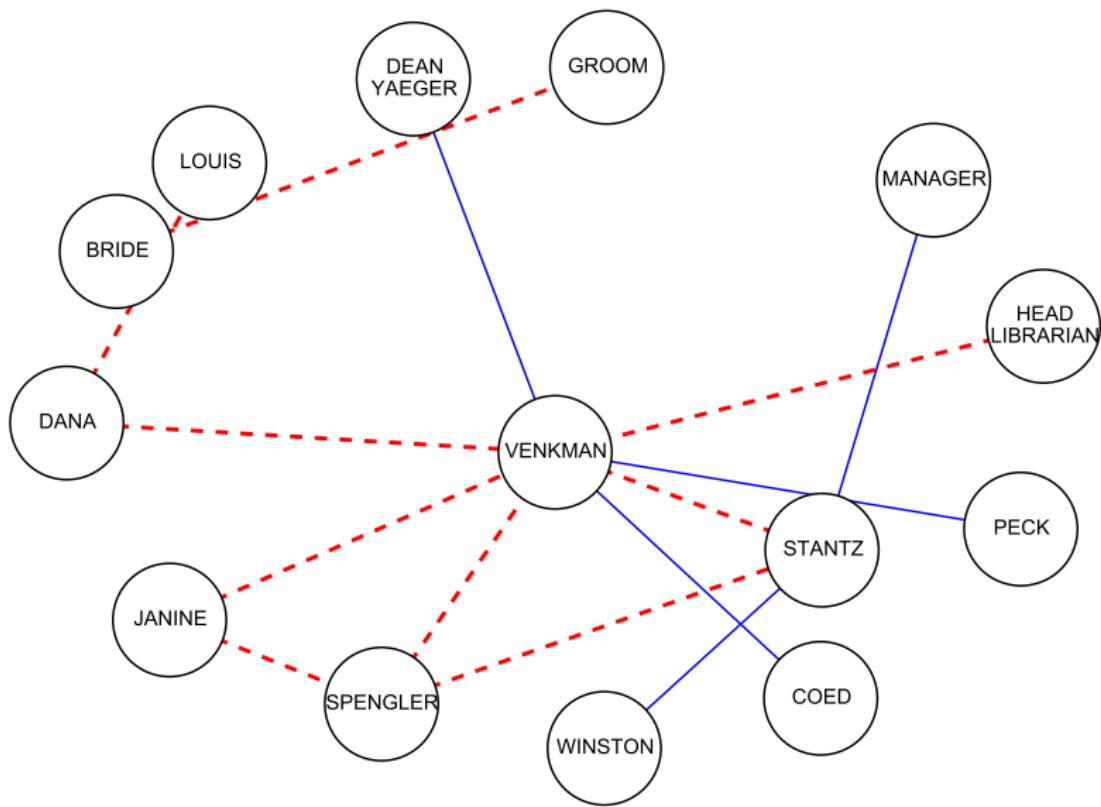
On an intrusion task

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

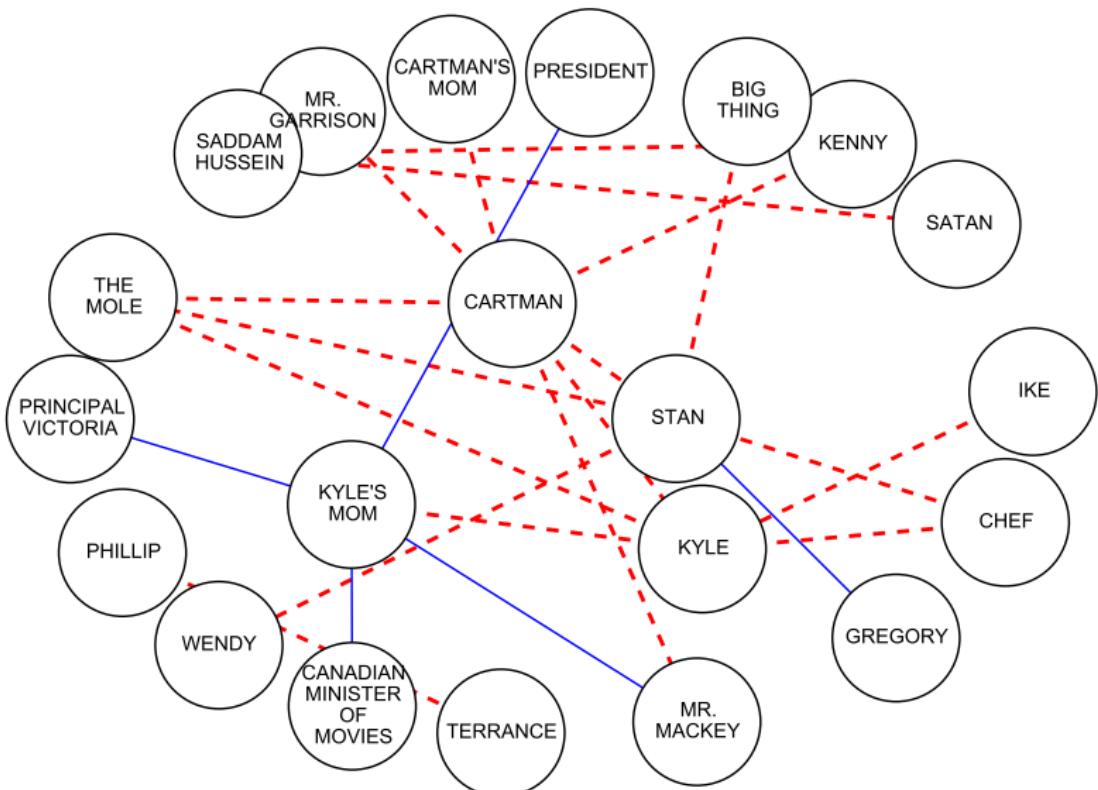
Star Wars



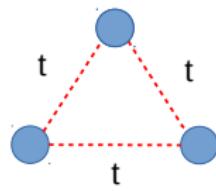
Ghostbusters



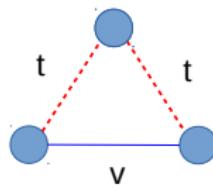
South Park



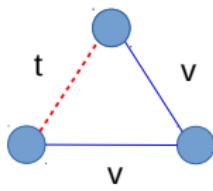
Network features



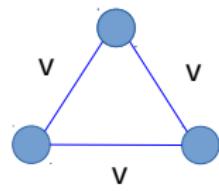
+3.73



-6.48



-1.05



+1.23

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.”

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“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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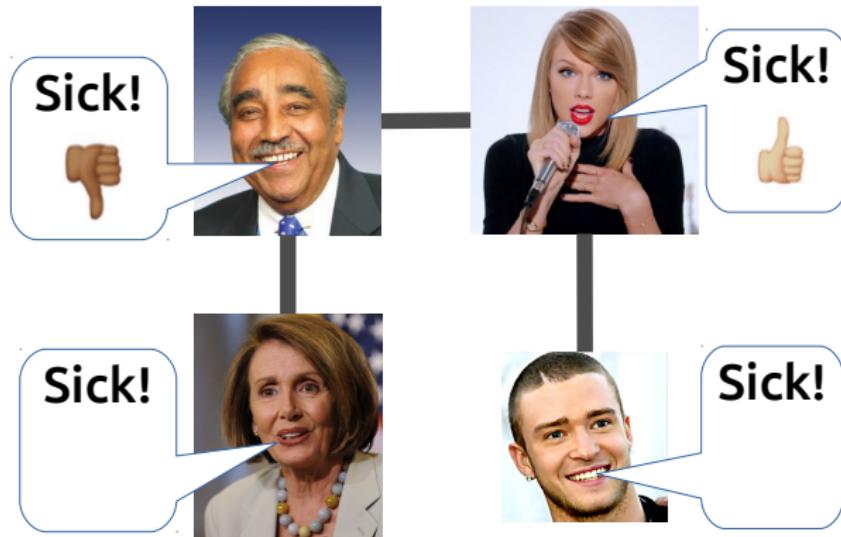
Homophily: neighbors have similar properties.

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



Homophily to the rescue?

Labeled
data



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

The SemEval Social Network

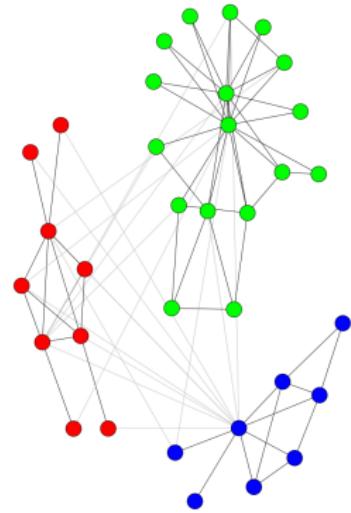
- ▶ SemEval 2013-2015 is a standard benchmark for Twitter Sentiment Analysis (Nakov et al., 2013; Rosenthal et al., 2015).
- ▶ Follower network statistics:

	# 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 expanded	Fast-Greedy	19	0.1549
		5	0.2102
original expanded	Multi-Level	19	0.1462
		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.

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

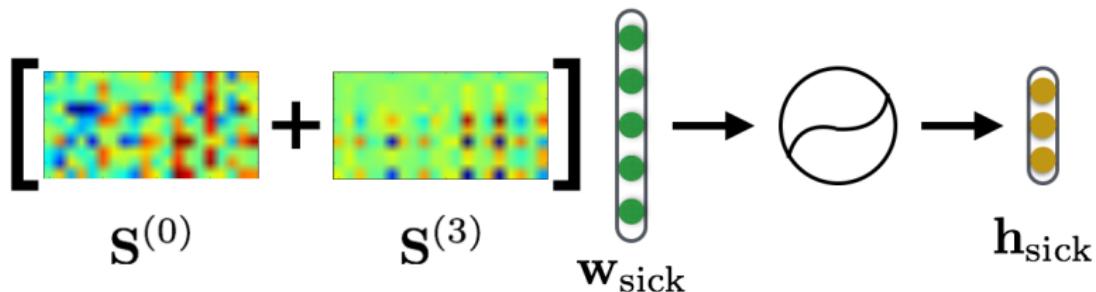
where

- ▶ \mathbf{x}_j is the pre-trained embedding of word j
- ▶ \mathbf{S} is a discriminatively learned task-specific projection matrix
- ▶ \mathbf{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 ,

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



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

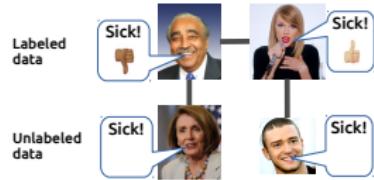
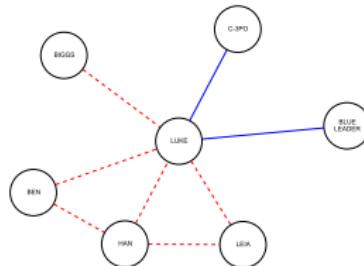
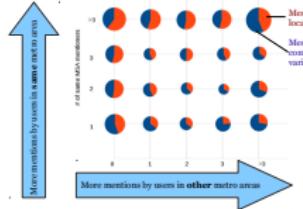
Results

Communities	T2013	T2014	T2015	Avg
<i>Prior work</i>				
None	72.0	72.7	65.2	70.0
<i>Our methods</i>				
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.

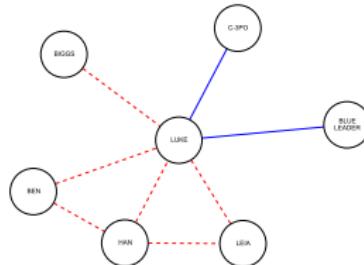
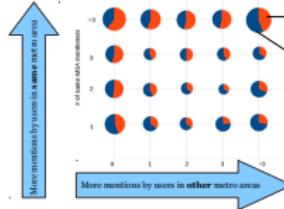
What's next?

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.

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References I

- Al Zamal, F., Liu, W., & Ruths, D. (2012). Homophily and latent attribute inference: Inferring latent attributes of Twitter users from neighbors. In *Proceedings of the International Conference on Web and Social Media (ICWSM)*, (pp. 387–390)., Menlo Park, California. AAAI Publications.
- Astudillo, R. F., Amir, S., Lin, W., Silva, M., & Trancoso, I. (2015). Learning word representations from scarce and noisy data with embedding sub-spaces. In *Proceedings of the Association for Computational Linguistics (ACL)*, Beijing, China.
- Bryden, J., Funk, S., & Jansen, V. (2013). Word usage mirrors community structure in the online social network twitter. *EPJ Data Science*, 2(1).
- Chang, J., Blei, D. M., et al. (2010). Hierarchical relational models for document networks. *The Annals of Applied Statistics*, 4(1), 124–150.
- danah boyd (2006). Friends, friendsters, and top 8: Writing community into being on social network sites. *First Monday*, 11(12).
- Eisenstein, J., O'Connor, B., Smith, N. A., & Xing, E. P. (2010). A latent variable model for geographic lexical variation. In *Proceedings of Empirical Methods for Natural Language Processing (EMNLP)*, (pp. 1277–1287)., Stroudsburg, Pennsylvania. Association for Computational Linguistics.
- Eisenstein, J., O'Connor, B., Smith, N. A., & Xing, E. P. (2014). Diffusion of lexical change in social media. *PLoS ONE*, 9.
- Hovy, D. (2015). Demographic factors improve classification performance. In *Proceedings of the Association for Computational Linguistics (ACL)*, (pp. 752–762)., Beijing, China.
- Huberman, B., Romero, D. M., & Wu, F. (2008). Social networks that matter: Twitter under the microscope. *First Monday*, 14(1).
- Krishnan, V. & Eisenstein, J. (2015). "You're Mr. Lebowski, I'm The Dude": Inducing address term formality in signed social networks. In *Proceedings of the North American Chapter of the Association for Computational Linguistics (NAACL)*.
- Nakov, P., Kozareva, Z., Ritter, A., Rosenthal, S., Stoyanov, V., & Wilson, T. (2013). Semeval-2013 task 2: Sentiment analysis in twitter. In *Proceedings of the 7th International Workshop on Semantic Evaluation, SemEval*.

References II

- Pavalanathan, U. & Eisenstein, J. (2015). Audience-modulated variation in online social media. *American Speech*, 90(2).
- Rosenthal, S., Nakov, P., Kiritchenko, S., Mohammad, S. M., Ritter, A., & Stoyanov, V. (2015). SemEval-2015 task 10: Sentiment analysis in twitter. In *Proceedings of the 9th International Workshop on Semantic Evaluation, SemEval*.
- Sadilek, A., Kautz, H., & Bigham, J. P. (2012). Finding your friends and following them to where you are. In *Proceedings of the fifth ACM international conference on Web search and data mining*, (pp. 723–732). ACM.
- Thelwall, M. (2009). Homophily in MySpace. *J. Am. Soc. Inf. Sci.*, 60(2), 219–231.
- Yang, Y. & Eisenstein, J. (2015). Putting things in context: Community-specific embedding projections for sentiment analysis. *CoRR*, abs/1511.06052.

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.

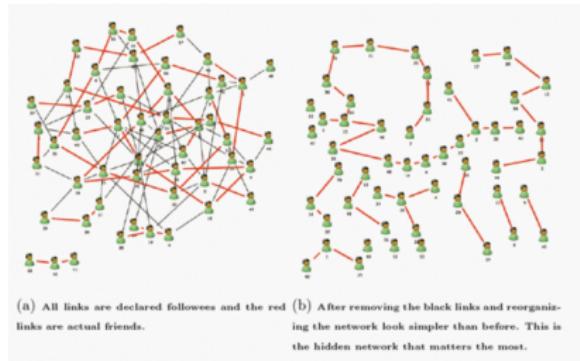
Behavioral network Inferred from conversational interactions, such as replies or mentions.



(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.



(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
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