Socio-Digital Influence Networks from Language Analysis
(FA9550-14-1-0379)

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Trust and influence in socio-digital systems

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- **Social network analysis** captures structural phenomena like information diffusion and networked bargaining.
- **Natural language processing** captures meaning in communication: entities, topics, sentiment, argumentation, etc.

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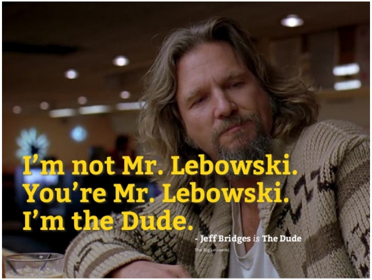
Social networks without language have no meaning; language without social context has no purpose.

Formality of address

- **Address terms** reflect social structure in language, indicating level of formality.
- Formality can be modeled as a **signed social network**.



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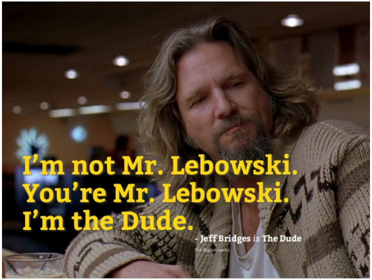

This research: model formality as a latent variable, unifying linguistic analysis with signed social networks.

Modeling formality of address

- What is the nature of the relationships between agents 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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  Estimate a likelihood distribution over address terms given formality.

A generative model of networked content

Basic notation:

- Undirected graph $G = \{\langle i, j \rangle\}$, $i < j$
- All edges $\langle i, j \rangle \in G$ have labels $y_{ij} \in \mathcal{Y}$
- Edges have **content** $\boldsymbol{x}_{i \rightarrow j}, \boldsymbol{x}_{i \leftarrow j} \in \mathbb{N}^V$, where V is the size of the vocabulary

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

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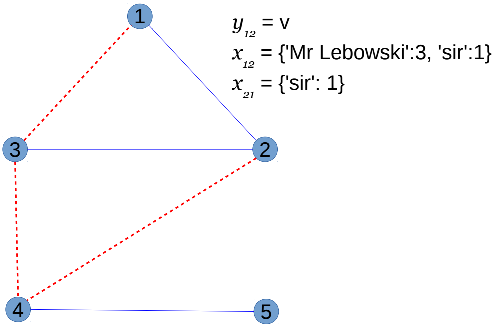
Example

At inference time, we observe x but not y.



Performing statistical inference over y gives a labeling over edges.

Likelihood

- The likelihood $P(x \mid y)$ captures how formality is expressed in language.
- Intuitively,

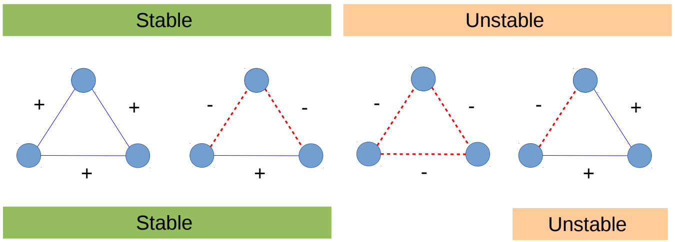
$$P(\text{dude} \mid y = \text{FORMAL}) < P(\text{dude} \mid y = \text{INFORMAL})$$
$$P(\text{sir} \mid y = \text{FORMAL}) > P(\text{sir} \mid y = \text{INFORMAL})$$

- These probabilities are expressed in the parameter $\boldsymbol{\theta}$, which is learned from data.
- We can generalize to directed signs by distinguishing $\boldsymbol{\theta}^{\rightarrow}_{y_{ij}}$ and $\boldsymbol{\theta}^{\leftarrow}_{y_{ij}}$.

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:

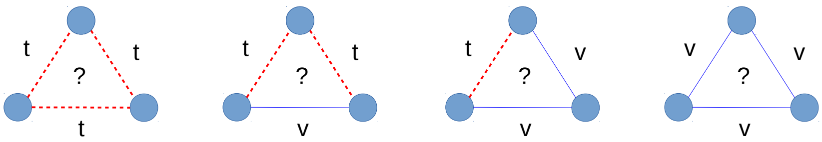
Strong structural balance



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.

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

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;
- $\beta_{y_{ij}, y_{jk}, y_{ik}}$ scores the stability of a triad type.

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Complete model specification

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Bayesian inference answers several questions:

1. What is the label (formality) of each dyad?
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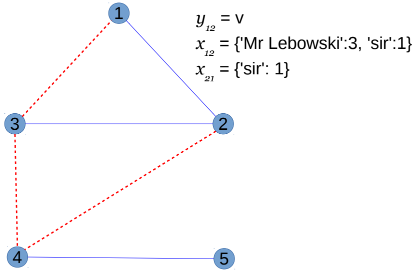
Let's do it!

- 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**

- Surprisingly little prior work on these problems!

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 address 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
B-ADDR	0.800	483
I-ADDR	0.58	53
L-ADDR	0.813	535
U-ADDR	0.987	1864
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 the lexicon (e.g., You're **Mr. Lebowski**)
- Any element in the placeholder name lexicon, if tagged as the unique element in an address span (e.g., Thanks, **dude**)

Dyad feature: Adamic-Adar metric 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.

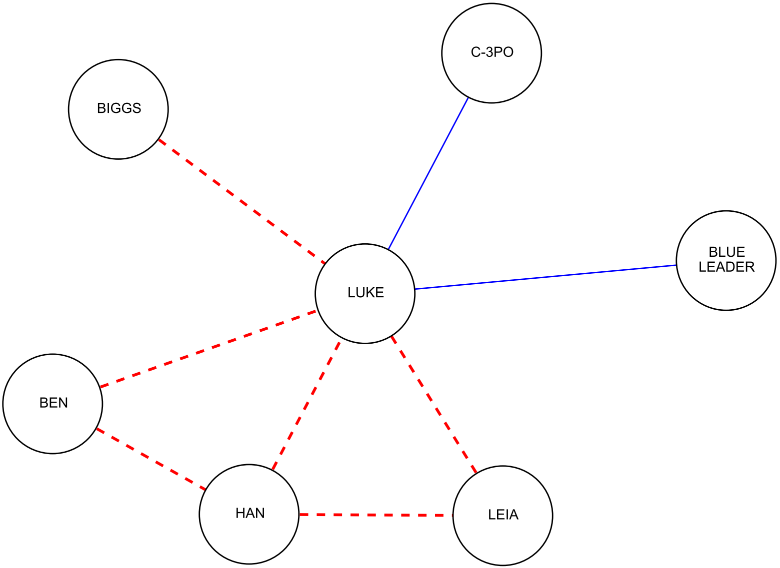
Cluster coherence

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

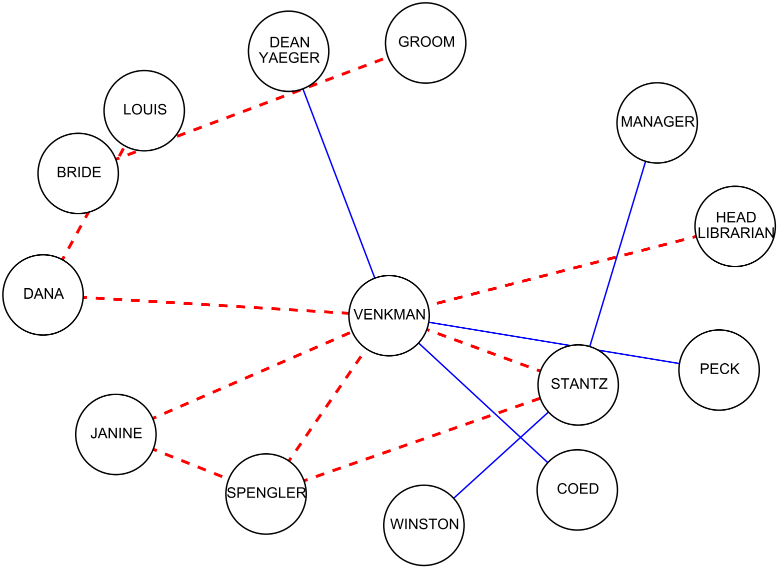
On an intrusion task

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

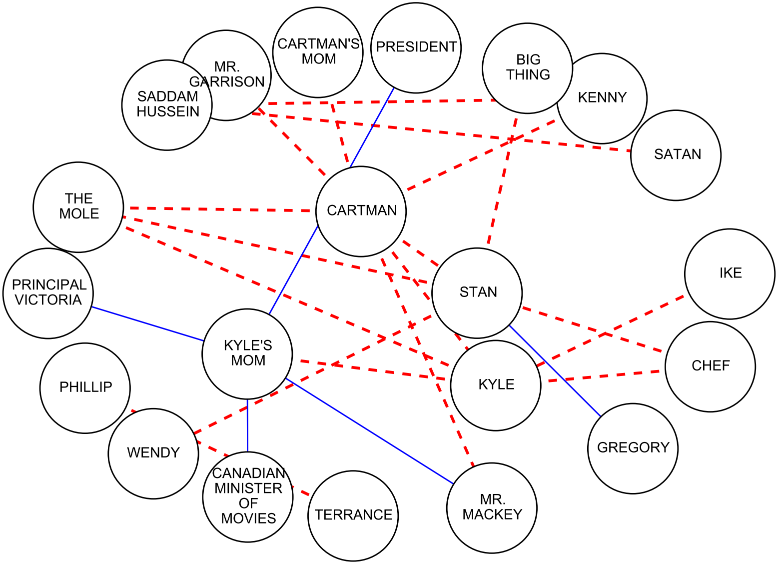
Star Wars



Ghostbusters



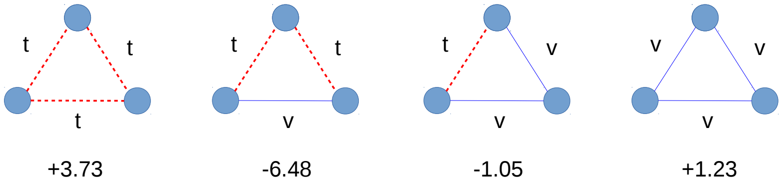
South Park



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

Network features

- Structural balance theory **stipulates** which triads are stable and unstable.
- In contrast, we are able to induce triadic stability as a parameter of the model:



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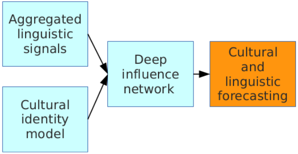
Publications, Awards, Patents, or Transitions Attributed to the Grant

- V. Krishnan and J. Eisenstein. “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), 2015. **Best student paper award!**
- U. Pavalanathan and J. Eisenstein. “Audience-modulated variation in online social media.” American Speech, (in press), 2015.
- Presentation at the NIPS 2014 Workshop on Social Network Analysis
- Invited talk at the NIPS 2014 Workshop on Modern Machine Learning and Natural Language Processing
- Invited keynote at the NAACL 2015 Workshop on Natural Language Processing for Social Media

Project Summary

Research Objectives:



Induce actionable patterns of social power and influence from socio-digital information traces, forecasting future changes in language and culture..

Technical Approach:

• Mine cultural artifacts and socio-digital information sources for linguistic signals and social behavioral traces.
• Invent machine learning techniques for **structure induction** to find latent structures that concisely explain both modalities.
• Apply longitudinal and causal analysis to identify how sociocultural influence spreads over these structures, yielding actionable predictions.

Key Findings:

• It is possible to combine theories of signed social networks with linguistic information in a joint probabilistic model, inducing a latent network of social relationships between actors.
• **Address terms** naturally cluster into social network edge types, and an unsupervised model can closely match human intuitions.
• Social media users predictably modulate their writing styles depending on the size and nature of the audience that they wish to address.

Benefits to the wider academic or DoD community:

1. New mathematical models for combining text and social network structures.
2. New algorithms for performing approximate inference in these models.
3. Substantive insights on social organization and its realization in natural language.

Project Start Date: October 2014

Project End Date: September 2017