Language Understanding in Social Context

Diyi Yang
School of Interactive Computing
Georgia Tech
We use **language** to accomplish various goals
Language Interaction Grows Exponentially

✓ between human and human
  ○ 2 billion monthly active Facebook users, 6000 tweets per sec

✓ between human and machines
  ○ 11 million Amazon Echo sold, Google Assistant on 400 million devices
The common misconception is that language has to do with *words* and what they mean.

It doesn’t.

It has to do with *people* and what *they* mean.

- Herbert H. Clark and Michael F. Schober, 1992
Language includes both **content** and **social** information
NLP in Social Context

“Systemic Functional Linguistics”: Relations between language and its functions in social settings

by Michael Halliday

Ideational Semantics

Interpersonal Semantics
NLP in Social Context

Interpersonal Semantics

Emotion, opinion, argument, humor, persuasion, attitude, subjectivity

“Systemic Functional Linguistics”, by Michael Halliday
NLP in Social Context

Interpersonal Semantics

Emotion, opinion, argument, humor, persuasion, attitude, subjectivity

“Systemic Functional Linguistics”, by Michael Halliday

Please be quiet. The talk will begin shortly.

Shut up! The talk is starting!
NLP in Social Context

Ideational Semantics

Social roles, influence, power, identity, structures, culture, ideology

Interpersonal Semantics

Emotion, opinion, argument, humor, persuasion, attitude, subjectivity

“Systemic Functional Linguistics”, by Michael Halliday
Research Methodology

Social Psychology & Linguistic

NLP & ML

HCI

Identification of social problems and construction of theories

Formulation and measurement

Evaluation and intervention
Overview of This Talk

1. Model Persuasion in Language
2. Neutralize Subjectively Biased Text
3. Langue and Social Roles in Online Health Communities
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1. Model Persuasion in Language
2. Neutralize Subjectively Biased Text
3. Langue and Social Roles in Online Health Communities
1. Modeling Persuasion in Language to Support Loans on Crowdfunding Platforms

Diyi Yang, Jiaao Chen, Zichao Yang, Dan Jurafsky, and Eduard Hovy. “Modeling Persuasive Strategies via Semi-supervised Neural Nets on Crowdfunding Platforms”. NAACL 2019
Loan Advocacy Requests on Crowdfunding Site

93% funded
Only 34 hours left!
$50 to go

Total loan: $775
Powered by 27 lenders

Lillyana Maria
Medellín, Colombia / Sewing

$25
What Makes Language Persuasive?

“I am the first lender on this woman-lead group loan in Burma. This loan will be utilized to repair her old duck farm and enable her to purchase nutritious duck feed that can help boost duck egg production. This way, she will be able to support her children’s education in the future.”

This request persuaded 3 out of 50 people to lend
Modeling Persuasion in Language

Q1: What are some widely used persuasive strategies?

Q2: How can we computationally model persuasion?

Q3: How do persuasive strategies affect request success?
Computational Argumentation & Persuasion

Argumentation

✓ Relational support structures and factual evidence to make claims (Zhang and Litman, 2015; Ghosh et al., 2016; Stab and Gurevych, 2017)

Persuasion

✓ Language cues that shape, reinforce and change people’s attitudes (Althoff et al., 2014; Pryzant et al., 2017; Yang and Kraut, 2018)
How to Computationally Model Persuasion

Social Science & Linguistic

Identification of social problems and construction of theories

Formulation and measurement

Evaluation and intervention

NLP & ML

HCI
Kahneman: Thinking, Fast and Slow

System 1: Think Fast

“Only a few left?”
“Experts recommended?”
“People who I like are using it?”
Kahneman: Thinking, Fast and Slow

System 1: Think Fast

System 2: Think Slow

“Are the facts correct?”

“Are the conclusions warranted?”
Dual Information Processing Theories (Shelly Chaiken. 1980)

S2: Think Slow
Systematic Processing

S1: Think Fast
Heuristic Processing

Frontal Lobe
- slow
- effortful
- infrequent
- logical
- calculating
- conscious

Limbic System
- fast
- automatic
- frequent
- emotional
- stereotypic
- subconscious

Image from http://www.centerline.net/blog/dual-process-theory-in-content-marketing-part-one/
Translating into Measurable Language Cues

**Scarcity** - people value an item more when it becomes rare or urgent

“This loan is going to expire in 35 minutes, please help!”

(Cialdini, 1987; Chiaken, 1980)
Translating into Measurable Language Cues

Scarcity

Emotion - messages full of emotional valence make people care

“The picture of widow Bunisia holding her baby in front of her meager home brings tears to my eyes.”

(Cialdini, 1987; Chiaken, 1980)
Translating into Measurable Language Cues

Scarcity

Emotion

Identity - people like their group/identity more over others

“For those of you in our team who love bread, here is a loan about bakery”

(Cialdini, 1987; Chiaken, 1980)
Translating into Measurable Language Cues

Scarcity
Emotion
Identity
Commitment – we like to convince others we made the correct choice

“We loaned to her already!”

(Cialdini, 1987; Chiaken, 1980)
Translating into Measurable Language Cues

Scarcity
Emotion
Identity
Commitment

System 1: Heuristic Processing (think fast)

(Cialdini, 1987; Chiaken, 1980)
Translating into Measurable Language Cues

Scarcity
Emotion
Identity
Commitment

**Concreteness** - providing concrete facts or evidence

“She wishes to have a septic tank and toilet, and is 51% raised and needs $125”
Translating into Measurable Language Cues

Scarcity
Emotion
Identity
Commitment
Concreteness

**Impact** - emphasizing the importance or bigger impact

“she can provide better education for her daughter”
Translating into Measurable Language Cues

Scarcity
Emotion
Identity
Commitment
Concreteness
Impact

(Cialdini, 1987; Chiaken, 1980)
Modeling Persuasion in Language

✓ Q1: Operationalized a set of persuasion strategies

➢ Q2: How can we computationally model persuasion?
To Predict Persuasive Strategies w/ Limited Data

Sheila  Mar 5, 2017 - 6:21 pm PST

I am the first lender on this woman-lead group loan in Burma. This loan will be utilized to repair her old duck farm and enable her to purchase nutritious duck feed that can help boost duck egg production. This way, she will be able to support her children’s education in the future.

commitment concreteness impact
To Predict Persuasive Strategies w/ Doc Supervision

How to design models for semi-supervised learning with document supervision?

➢ Document labels (global): # people convinced by a request
➢ Sentence labels (local): persuasive strategy (partially labeled)
Classical Semi-supervised Setting

Limited Labeled Sentences

Commitment
I am the first lender on this woman-lead group loan in Burma.

Concreteness
This loan will be utilized to repair her old duck farm and enable her to purchase nutritious duck feed that can help ...

Impact
This way, she will be able to support her children’s education.

Extra Unlabeled Sentence

? Who’s the cutest 82-year-old you’ve ever seen who needs funds in 6 days?

? She’s still actively working, and needs funds to place her orders...

? Look at that smile, adorable!

... ...

(Zhu, Lafferty, and Rosenfeld, 2003; Kingma et al., 2014; Chapelle, Scholkopf, Zien, 2006)
Commitment

I am the first lender on this woman-lead group loan in Burma.

Concreteness

This loan will be utilized to repair her old duck farm and enable her to purchase nutritious duck feed that can help...

Impact

This way, she will be able to support her children’s education.

Who’s the cutest 82-year-old you’ve ever seen who needs funds in 6 days?

She’s still actively working, and needs funds to place her orders.

Look at that smile, adorable!

...
Semi-supervised Setting w/ Document Supervision

Labeled Docs + Limited Labeled Sentences

Labeled Docs + Extra Unlabeled Sentences

(Obquab et al, 2015; Pinheiro and Collobert, 2015)
Semi-supervised Net

**Sentence encoder** with attention

Persuasion prediction via softmax

\[ p_i = \text{softmax} (W_v \cdot s_i + b_v) \]

(Bahdanau et al., 2014; Yang et al., 2016)
Semi-supervised Net

Document encoder

(Bahdanau et al., 2014; Yang et al., 2016)
Semi-supervised Net

Document encoder

Semi-supervised objective

\[ l = \gamma \sum_{d} (y_d - \bar{y}_d)^2 - \beta \sum(-g_i \log p_i) \]

(Bahdanau et al., 2014; Yang et al., 2016)
Dataset Construction

- 42K advocacy messages with document level labels
- 3K sentences annotated with persuasion strategies via Amazon Mechanical Turk
Results on Predicting Persuasion Strategies

<table>
<thead>
<tr>
<th>Model</th>
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<th>Doc-Level</th>
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<tr>
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<td>Accuracy</td>
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</tr>
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<td>Sentence Only (SVM)</td>
<td>0.34</td>
<td>0.17</td>
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<td>Sentence Only (GRU)</td>
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## Results on Predicting Persuasion Strategies

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<td>0.52</td>
</tr>
<tr>
<td>(Semi + Hierarchical Attention Net)</td>
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</tr>
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[https://github.com/GT-SALT/Persuasion_Strategy](https://github.com/GT-SALT/Persuasion_Strategy)
## Representative Lexicon for Persuasive Strategies

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Lexicon with higher attentional weight</th>
</tr>
</thead>
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<tr>
<td>Commitment</td>
<td>Joined, lenders, lend, loan, join, loaned, made, lent</td>
</tr>
<tr>
<td>Concreteness</td>
<td>Women, married, old, heads, year-old, sells, years, business</td>
</tr>
<tr>
<td>Emotion</td>
<td>Hard, thank, better, grief, great, maybe, help, please, happy</td>
</tr>
<tr>
<td>Identity</td>
<td>Captain, promotion, form, spirits, members, team</td>
</tr>
<tr>
<td>Impact</td>
<td>Improve, new, better, use, products, more, order, use</td>
</tr>
<tr>
<td>Scarcity</td>
<td>Minutes, left, now, soon, expire, go, hours, days, number</td>
</tr>
</tbody>
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Modeling Persuasion in Language

✓ Q1: Operationalized a set of persuasion strategies

✓ Q2: Predicted persuasive strategies via semi-supervised nets with document supervision

➢ Q3: How does persuasion influence request success?
To Explain the Influence of Persuasion Strategies
Identity and Concreteness Matter, Not Scarcity
Generalizing Model to Random Acts of Pizza

Random Acts of Pizza on Reddit (r/RAOP)

[REQUEST] I battled through a cold, took 4 exams and gave 2 presentations all in 1 week. I just found out I have all A's because of my hard work!

My wife and I have been sick for the past week while working and taking care of our daughter. I just found out that I passed all my exams and I have straight A's in all my classes, which is a first for my entire college career. I want to celebrate but we just payed rent, which means we don't have the ability to go out.

If anyone could help with a pizza, I'd appreciate it a bunch!
Top Effective Strategies on /r/RAOP:
Emotion, Scarcity, Concreteness
Modeling Persuasion in Language

✓ Q1: Operationalized a set of persuasion strategies
✓ Q2: Predicted persuasive strategies via semi-supervised nets with document supervision
✓ Q3: Showed persuasive strategies differently correlate with request success
Similar Trend on More Diverse Datasets

Latent variable model to disentangle **content** and **persuasion strategies** in good-faith requests

(ongoing work)
Overview of This Talk

1. Model Persuasion in Language

2. Neutralize Subjectively Biased Text

3. Language and Social Roles in Online Health Communities
2. Neutralizing Biased Text


(Slides credit to Reid Pryzant)
Stanford, Kyoto & Georgia Tech Model ‘Neutralizes’ Biased Language

While AI is delivering unprecedented progress and convenience, the increasing implementation of AI technologies has also triggered ... 

🔗 medium.com
U.S. Adults’ Average Estimates of the Percentage of Bias, Inaccuracy and Misinformation Seen in News Coverage

Traditional news media  Social media

- % Biased: 62% (Traditional)  80% (Social)
- % Inaccurate: 44% (Traditional)  64% (Social)
- % Misinformation: 39% (Traditional)  65% (Social)

GALLUP/KNIGHT FOUNDATION

American Views: Trust, Media and Democracy
What Makes One Headline Biased and Another Neutral?

John McCain Exposed As An Agent Of The Rothschilds

John McCain accused of accepting improper donations from Rothschilds
Can Suggest Less Biased Alternatives to Text?

John McCain Exposed As An Agent Of The Rothschilds

The Rothschilds have been secretly funneling money to the US Senator and former presidential runner, John McCain, to influence his policies.

John McCain
McCain accused of accepting improper donations from Rothschilds
Subjectivity bias

This is bias via *inappropriate subjectivity*:

✓ attitudes
✓ presuppositions
✓ casting doubt
John McCain exposed as an agent of the Rothschilds

John McCain described as an agent of the Rothschilds

biased via
1. “exposed”
2. “agent of the rothschilds”

biased via
1. “exposed”
2. “agent of the rothschilds”
**subjectivity bias**

presupposes John is an agent

biased via

1. “exposed”
2. “agent of the rothschilds”

biased via

1. “exposed”
2. “agent of the rothschilds”

biased, but not subjectivity bias anti-semitic trope
Three Types of Subjectivity Bias

Framing bias
✓ Most of the gameplay is *pilfered from* ddr

Epistemological bias
✓ Developing a new downtown *will bring back* our arts.

Demographic bias
✓ A lead programmer usually spends *his career*...
Neutralizing Subjectivity Bias

Framing bias
✓ Most of the gameplay is pilfered from ddr

Epistemological bias
✓ Developing a new downtown will bring back our arts.

Demographic bias
✓ A lead programmer usually spends his career...
This follows NPOV Policy on Wikipedia

All encyclopedic content on Wikipedia must be written from a **neutral point of view** (**NPOV**), which means representing fairly, proportionately, and, as far as possible, without editorial bias, all of the significant **views** that have been **published by reliable sources** on a topic.
The "Fifteenth United States Army" was the last [[field army]] to see service in northwest Europe during [[World War II]] and was the final command of [[George S. Patton]]. The Fifteenth Army served two separate missions while assigned to the area. During the later stages of World War II its mission was training and rehabilitating units and acting as a defensive line against counterattacks. After the war its mission was to carry out occupation duties and to gather historical information related to the [[European Theater of Operations]].
A Large Scale Wikipedia Neutrality Corpus

The first parallel corpus of biased language, with 180,000 sentence pairs

<table>
<thead>
<tr>
<th>Text with subjective bias</th>
<th>Corresponding neutral point of view</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kathy Kirby, 1960’s <strong>blonde singing legend</strong></td>
<td>Kathy Kirby, 1960’s <strong>singer</strong></td>
</tr>
<tr>
<td>Go is <strong>the deepest</strong> game in the world</td>
<td>Go is <strong>one of the deepest game</strong> in the world</td>
</tr>
<tr>
<td>The authors’ <strong>expose</strong> on nutrition studies</td>
<td>The authors’ <strong>statements</strong> on nutrition studies</td>
</tr>
<tr>
<td>Marriage is a <strong>holy union</strong> of individuals</td>
<td>Marriage is a <strong>personal union</strong> of individuals</td>
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Method 1: Concurrent

(Seq2seq (with copy mechanism (See et al. 2017) )

Photo sequence of astonishing 2005 chicagoland crash with Ryan Briscoe.

Virtual console versions have been altered slightly to correct several instances of *engrish* from the original.

Bonnie Hunt (born 1961), comedienne, actress, director, producer, writer, host, and voice artist.

The first man who saw the need for a clear definition of probability was Laplace.

Photo sequence of 2005 chicagoland crash with Ryan Briscoe.

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Method 1: Concurrent

**Seq2seq** (with copy mechanism (See et al. 2017)) + Bert

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Bonnie Hunt (born 1961), **comedian**, actress, director, producer, writer, host, and voice artist.

The first **mathematician** who saw the need for a clear definition of probability was Laplace.
Method 1: Concurrent

**Seq2seq** (with copy mechanism (See et al. 2017))
+ Bert
+ **Pretraining** (as denoising autoencoder) on the unbiased corpus!

Photo sequence of astonishing 2005 chicagoland crash with Ryan Briscoe.

Virtual console versions have been altered slightly to correct several instances of *english* from the original.

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Method 1: Concurrent

**Seq2seq** (with copy mechanism (See et al. 2017))
+ Bert
+ **Pretraining** on the unbiased corpus
+ Token-weighted loss function

\[
\mathcal{L}(s, t) = - \sum_{i=1}^{m} \lambda(w_i^t, s) \log p(w_i^t | s, w_{<i}^t) + c
\]
\[
\lambda(w_i^t, s) = \begin{cases} 
\alpha : w_i^t \notin s \\
1 : \text{otherwise}
\end{cases}
\]

The first **man** who saw the need for a clear definition of probability was Laplace.
Method 2: Modular

Give the source to
1. an encoder
2. a **tagger** that predicts possibly biased words
Method 2: Modular

Use the tagger’s predictions to mix in a “change this word!” embedding

The first **man** who saw...
Method 2: Modular

Then decode as normal

The first mathematician who saw...
Method 2: Modular

Use the same pretraining + weighted loss

The first mathematician who saw...

400,000
Method 1: Concurrent

**PROS**
- Straightforward
- Easy to use

**CONS**
- Opaque
- Uncontrollable

Method 2: Modular

**PROS**
- Controllable
- Interpretable

**CONS**
- Complicated
- Harder to train
In-Domain Results (train on wiki, test on wiki)

<table>
<thead>
<tr>
<th>Method</th>
<th>BLEU</th>
<th>Accuracy</th>
<th>Fluency</th>
<th>Meaning</th>
<th>Bias</th>
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<tbody>
<tr>
<td>Source Copy</td>
<td>91.33</td>
<td>0.00</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Detector (always delete biased word)</td>
<td>92.43*</td>
<td>38.19*</td>
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**Fluency**: how much more fluent is the output compared to the source?
⇒ higher is better

**Meaning**: how well does the output preserve the meaning of the source?
⇒ higher is better

**Bias**: how much more biased is the output compared to the source?
⇒ Lower is better
# In-Domain Results (train on wiki, test on wiki)

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<td>Base</td>
<td>89.13</td>
<td>24.01</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>+ loss</td>
<td>90.32*</td>
<td>24.10</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>+ loss + pretrain</td>
<td>92.89*</td>
<td>34.76*</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>+ loss + pretrain + detector (MODULAR)</td>
<td>93.52*</td>
<td>46.80*</td>
<td>-0.078</td>
<td>0.996</td>
<td>-0.467</td>
</tr>
<tr>
<td>+ loss + pretrain + BERT (CONCURRENT)</td>
<td><strong>93.94</strong></td>
<td><strong>45.87</strong></td>
<td><strong>0.132</strong></td>
<td><strong>0.758</strong></td>
<td><strong>-0.423</strong></td>
</tr>
<tr>
<td>Target copy</td>
<td>100.0</td>
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<td>-0.077</td>
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</tbody>
</table>
Test on **Political Books**

<table>
<thead>
<tr>
<th></th>
<th>The Ideological Books Corpus</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>Activists have filed a lawsuit...</td>
</tr>
<tr>
<td>Modular</td>
<td>Critics of it have filed a lawsuit ...</td>
</tr>
<tr>
<td>Concurrent</td>
<td>Critics have filed a lawsuit ...</td>
</tr>
</tbody>
</table>

![Bar graph comparing fluency and bias for Modular and Concurrent versions.](image)
<table>
<thead>
<tr>
<th></th>
<th>News Headlines</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Original</strong></td>
<td>Zuckerberg <em>claims</em> Facebook can...</td>
</tr>
<tr>
<td><strong>Modular</strong></td>
<td>Zuckerberg <em>stated</em> Facebook can...</td>
</tr>
<tr>
<td><strong>Concurrent</strong></td>
<td>Zuckerberg <em>says</em> Facebook can...</td>
</tr>
</tbody>
</table>

![Fluency vs Bias Chart]

- **Fluency**
- **Bias**

- Modular: -0.2
- Concurrent: -0.6
Test on **Campaign Speeches**

<table>
<thead>
<tr>
<th></th>
<th>Campaign speeches</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Original</strong></td>
<td>This includes <em>amazing</em> Americans like...</td>
</tr>
<tr>
<td><strong>Modular</strong></td>
<td>This includes Americans like...</td>
</tr>
<tr>
<td><strong>Concurrent</strong></td>
<td>This includes <em>some</em> Americans like...</td>
</tr>
</tbody>
</table>

![Graph showing fluency and bias comparison between Modular and Concurrent speech styles.](chart.png)
Overview of This Talk

1. Model Persuasion in Language
2. Neutralize Subjectively Biased Text
3. Language and Social Roles in Online Health Communities
3. Modeling Social Roles to Support Patient Communication in Online Health Communities


Cancer Survivor Network - An Online Cancer Support Group

Cancer Survivors Network

CSN Login Username Password Go Forgot username or password?

CSN Home

Discussion boards
- Log in to post new content in the forum.
Cancer Survivor Network – An Online Cancer Support Group

Cancer Survivors Network

13-year data since 2005

66K users

140K threads and 1.3M replies
I was diagnosed with Invasive Ductal Carcinoma grade 2. I'm told I will need chemo. I don't understand. Any words of that will help me wrap my head around this nightmare?

Since you are a triple positive they can put you on hormones and the chance of recurrence is low. Listen to your chemo nurse ...

It gives me faith that you can have cancer and live a full life. Sorry to hear. God bless you. Stay strong please!

This conversation has been paraphrased.
28% of Internet users have used online support group for medical information (Fox 2009)
Modeling Social Roles to Better Support Patient

- Receive Timely Help
- Match with Support Providers
- Connect with Similar Peers
Modeling Social Roles on CSN

1. How to identify social roles that people occupy

2. How do roles influence members’ participation?
Five Facets Social Role Framework

A cluster of interaction patterns regulated by expectations adopted by people in a context to achieve specific goals

“The role concept centers upon behaviors that are characteristic of persons in a context.” — Bruce J Biddle 1979

“A social role is a comprehensive pattern of behavior and attitudes, constituting a strategy for coping with a recurrent set of situations” — Ralph H Turner 1990
Generic Methodology for Role Identification

A repeated cycle of role postulation, definition, identification and evaluation.

"A version of the Scientific Method"
Postulation & Definition: The Facet of Interaction

**Network-based Measures**

- User-user reply network

**Content-based Measures**

- # seek request, # comments
- Emotional aspects: anger, sadness
- Social concerns: friend, family, social
- Religious orientation: religious, death
- Self-focus: I, you, he/she
- Topics modeling
Postulation & Definition: The Facet of Context

Differentiate behaviors in two contexts on CSN:

✓ Public
✓ Private

Discussion Boards
Private Chats
Since you are a triple positive they can put you on hormones and the chance of recurrence is low. Listen to your chemo nurse ...

It gives me faith that you can have cancer and live a full life. Sorry to hear that. God bless you. Please stay strong!

Informational Support

Emotional Support
Automatic Measurement of the Facet of Goal

1. Seek emo support \( (r=0.64) \)
2. Provide emo support \( (r=0.75) \)
3. Provide empathy \( (r=0.72) \)
4. Provide appreciation \( (r=0.67) \)
5. Provide encouragement \( (r=0.64) \)
6. Seek info support \( (r=0.73) \)
7. Provide info support \( (r=0.79) \)

Reasonable correlations between model predictions and human judgements

Regression models trained on human-annotated data (Yang et al., 2017), with features from LIWC and word embeddings
Role Identification Methodology

Postulation & Definition

The facets of interaction, goal, context

Identification

Gaussian mixture models

Evaluation
Modeling Social Roles via Mixture Model

Intuition: a user is a mixture of different social roles

\[ p(x) = \sum_{k=1}^{K} \pi_k \cdot \mathcal{N}(x | \mu_k, \Sigma_k), \quad \sum_k \pi_k = 1 \]

✓ User X is represented by the aforementioned features
✓ Select the number of roles K quantitatively and qualitatively
## Roles Identified by Our Model (trained on 66K users)

<table>
<thead>
<tr>
<th>Emotional Support Provider</th>
</tr>
</thead>
<tbody>
<tr>
<td>Newcomer Welcomer</td>
</tr>
<tr>
<td>Informational Support Provider</td>
</tr>
<tr>
<td>Story Sharer</td>
</tr>
<tr>
<td>Informational Support Seeker</td>
</tr>
<tr>
<td>Private Communicator</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Private Support Provider</th>
</tr>
</thead>
<tbody>
<tr>
<td>All-round Expert</td>
</tr>
<tr>
<td>Newcomer Member</td>
</tr>
<tr>
<td>Knowledge Promoter</td>
</tr>
<tr>
<td>Private Networker</td>
</tr>
</tbody>
</table>
### Example Roles Identified by Our Model

<table>
<thead>
<tr>
<th>Role Name</th>
<th>%</th>
<th>Typical Behaviors Listed in Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Emotional Support Provider</td>
<td>33.3</td>
<td>Provide emo support, appreciation, empathy, encouragement &amp; empathy, info support, # subforums a user participated</td>
</tr>
<tr>
<td>Welcomer</td>
<td>15.9</td>
<td>Out-degree in forum, # replies, % of talk to newcomers, provide encouragement &amp; empathy</td>
</tr>
<tr>
<td>Informational Support Provider</td>
<td>13.3</td>
<td>Provide info support, empathy in the forum, use words related to symptoms, anxiety, and drugs related words</td>
</tr>
<tr>
<td>Story Sharer</td>
<td>10.2</td>
<td>Initialize threads, positive and negative self-disclose, seek emo support, negative self-disclosure, seek info support</td>
</tr>
<tr>
<td>Informational Support Seeker</td>
<td>8.9</td>
<td>Initialize threads, seek info support, negative self-disclosure, seek emo support, use words related to disease and symptoms</td>
</tr>
</tbody>
</table>
Role Identification Methodology

1. Quantitative measures
2. Qualitative measures
3. Survey role holders
4. Downstream applications
Role Evaluation: Qualitative Measures

Work with 6 moderators on CSN to assess the derived roles

“It seems very comprehensive and there are so many different examples, so I feel like it is covered very well with your different roles and labels.”

The identified roles were comprehensive
Role Evaluation: Qualitative Measures

Work with 6 moderators on CSN to assess the derived roles

“The one that I think did not emerge is the policeman, these people complain to moderators when some people are doing things wrong.”

Model failed to capture the “defenders”
Role Evaluation: Qualitative Measures

Work with 6 moderators on CSN to assess the derived roles

“there are not a lot of them, but they kind of stick in your memories since they are telling others what to do.”

Model failed to capture the “defenders”
Modeling Social Roles on CSN

1. What roles do people occupy?
A mixture model that identifies 11 functioning roles

2. How do roles influence members’ participation?
Roles People Enact Change with Time on CSN

Among those who stay on CSN for at least 12 months:

✓ Support seekers and story sharer decline with tenure
Roles People Enact Change with Time on CSN

Among those who stay on CSN for at least 12 months:

✓ Support seekers and story sharer decline with tenure
✓ Support providers increase with tenure
I initially stayed because information was important, but over time, I found talking with people who had similar experiences is more helpful.
From Roles Seeking Sources to Ones Offering Help

12 interviews of users on Cancer Survivor Network

I’m now looking for helping people who are seeking for advice.
Modeling Social Roles on CSN

1. What roles do people occupy?
A mixture model that identifies 11 functioning roles

2. How do roles influence members’ participation?
Members frequently change roles from ones that seek resources to ones offering help
Automated Intervention to Improve Interaction

- Provide Timely Help
- Match with Support Providers
- Connect with Similar Peers
Our Deployed Recommender System* on CSN

* Feature-based matrix factorization (Yang et al., 2014a; Yang et al., 2014b; Yang et al., 2014c)
Our Deployed Recommender System* on CSN

* Feature-based matrix factorization (Yang et al., 2014a; Yang et al., 2014b; Yang et al., 2014c)
Over 11,000 people have signed up and are using our intervention on Cancer Survivor Network since 2018

https://csn.cancer.org/forum
Recommendation Increase Reading outside Favorite Forum

<table>
<thead>
<tr>
<th>Recommender Setting</th>
<th>Displayed</th>
<th>Hits</th>
<th>Hit Ratio (%)</th>
<th>Improvement over control</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recommend recent threads in favorite forum</td>
<td>6718</td>
<td>150</td>
<td>2.23</td>
<td></td>
</tr>
<tr>
<td>Recommend based on history &amp; restricted to favorite forum</td>
<td>7002</td>
<td>138</td>
<td>1.97 (ns)</td>
<td>-3%</td>
</tr>
<tr>
<td>Recommend based on history</td>
<td>6615</td>
<td>238</td>
<td>3.60 ***</td>
<td>+61%</td>
</tr>
</tbody>
</table>

Recommendations based on history and user roles are ongoing
“Here are some newcomers you might want to say hi ”

“Here are some information experts you could reach out to”
Summary of This Talk

1. Model Persuasion in Language
2. Neutralize Subjectively Biased Text
3. Language and Social Roles in Online Health Communities
Other Work

- Persuasion (Yang et al., NAACL 2019)
- Humor (Yang et al., EMNLP 2015)
- Confusion (Yang et al., L@S 2015)
- Edit intent on Wikipedia (Yang et al., EMNLP 2017)

- Social roles (Yang et al., ACL 2015)
- Social support (Yang et al., CHI 2017)
- Mental health & well-being (Yang et al., CHI 2019)

- Ideational Semantics
- Interpersonal Semantics
Language includes both **Content** and **Social** information
Socially Aware Language Technologies

- Language use in social context
  - Persuasion, bias, argumentation, formality, disfluency

- Socially low-resourced settings
  - Social contexts have very limited labeled data
  - How to harness the advances of unsupervised training

- NLP + X
  - Mental health and well-being
  - Education domain
Thank You!

Language Understanding in Social Context

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