Language Understanding in Social Context

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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

Credit to Dan Jurafsky in his CVPR'17 keynote talk

Language includes both
content and social information

NLP in Social Context

Ideational Semantics

⋮

Interpersonal Semantics

"Systemic Functional Linguistics":

Relations between language and its functions in social settings

by Michael Halliday

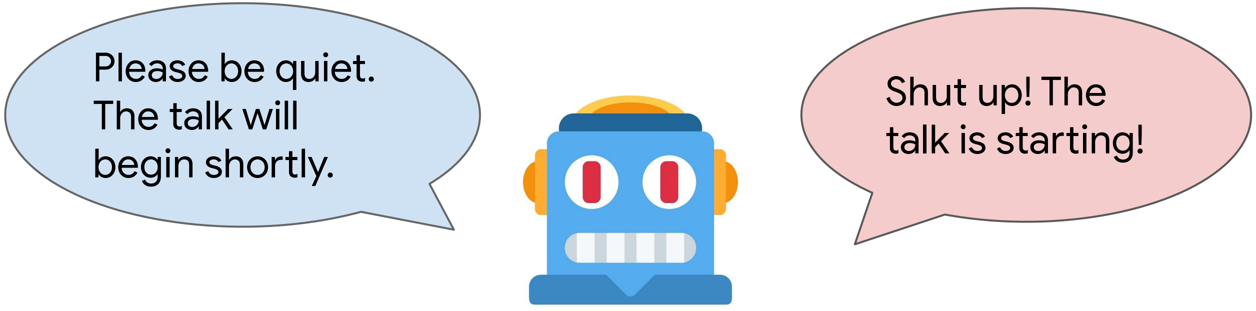
NLP in Social Context

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

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	Identification of social problems and construction of theories
NLP & ML	Formulation and measurement
HCI	Evaluation and intervention

Overview of This Talk

1. Model Persuasion in Language

2. Neutralize Subjectively Biased Text

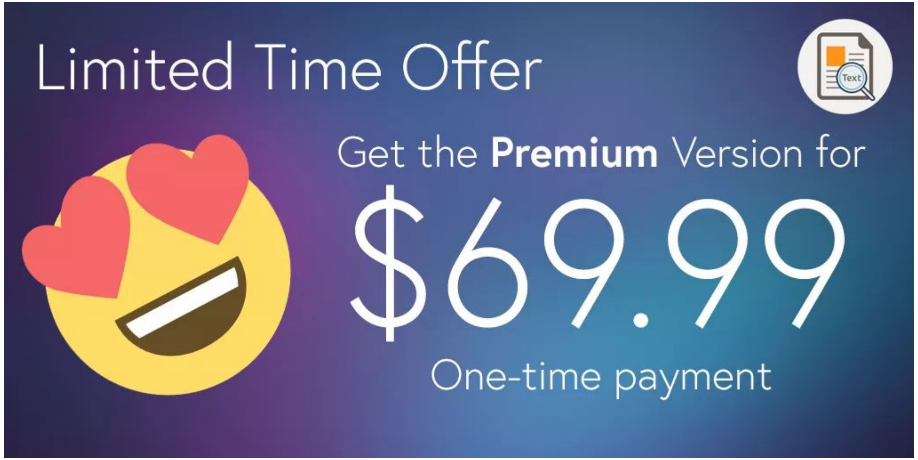
3. Langue and Social Roles in Online Health Communities

Overview of This Talk

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


Limited Time Offer
Text
Get the **Premium** Version for
$69.99
One-time payment


Tasty Flake Breakfast Cereal
Everyone is enjoying it!


Coca-Cola
open a Coke,
open happiness


iPhone 6
Bend it like Beckham

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 ▾

KIVA

loans that change lives

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

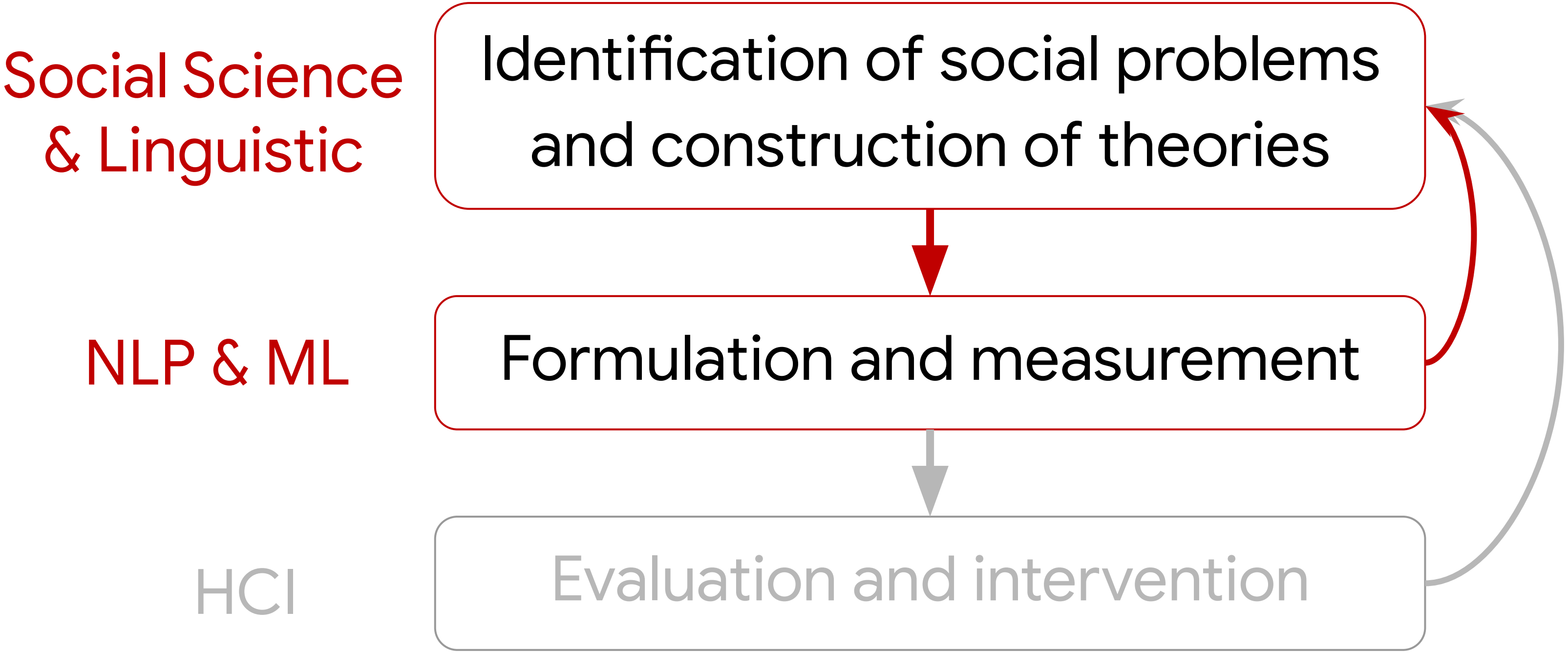
Argumentation

- ✓ 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



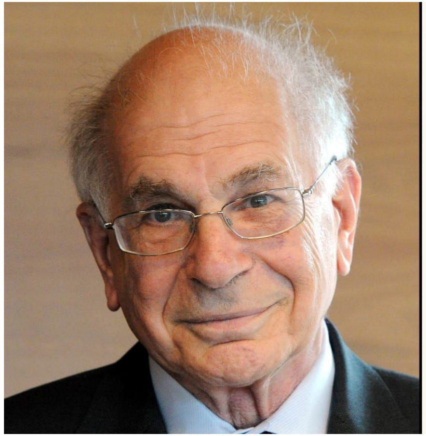
Kahneman: Thinking, Fast and Slow

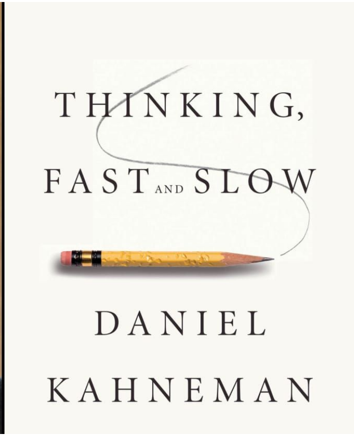
System 1: Think Fast

“Only a few left?”

“Experts recommended?”

“People who I like are using it?”





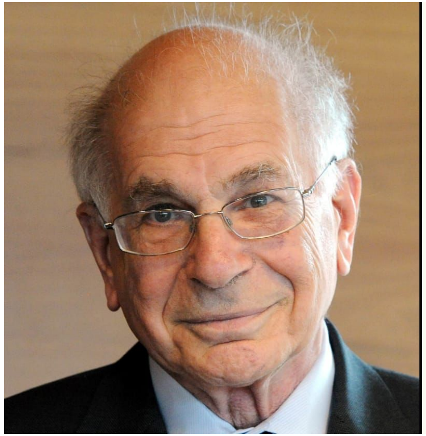
Kahneman: Thinking, Fast and Slow

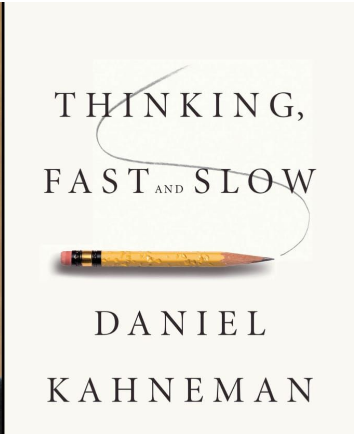
System 1: Think Fast

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

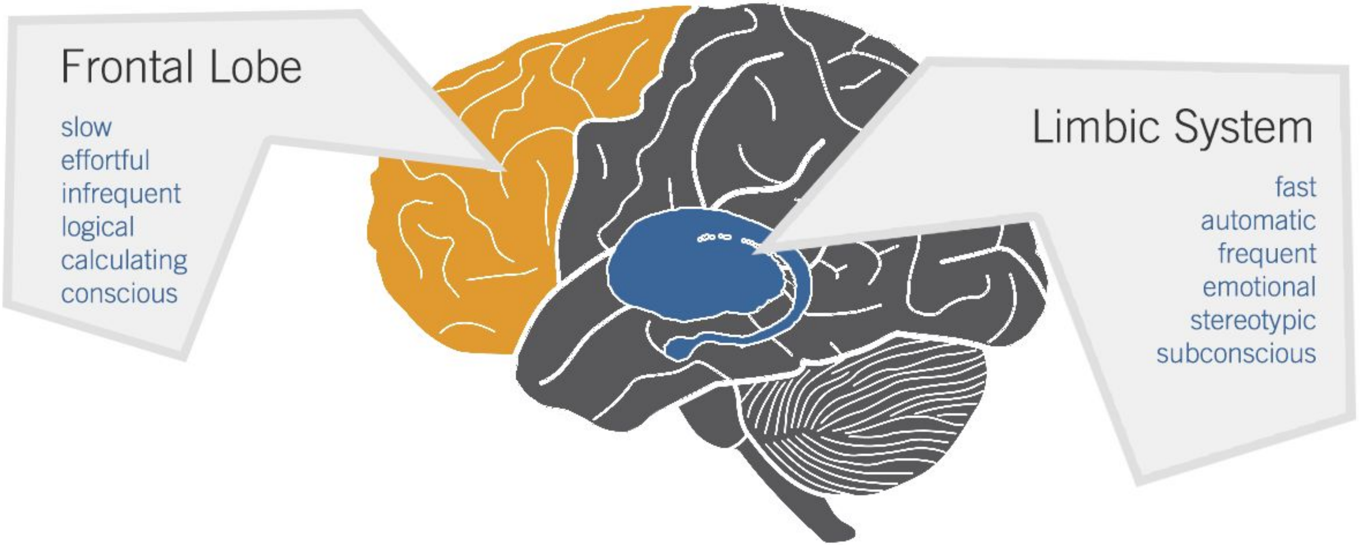


Image from http://www.centerline.net/blog/dual-process-theory-in-content-marketing-part-one/

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

$$\left.\begin{array}{l}\text{Scarcity}\\\text{Emotion}\\\text{Identity}\\\text{Commitment}\end{array}\right\}\text{System 1: Heuristic Processing (think fast)}$$

(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

System 1: Heuristic Processing (think fast)

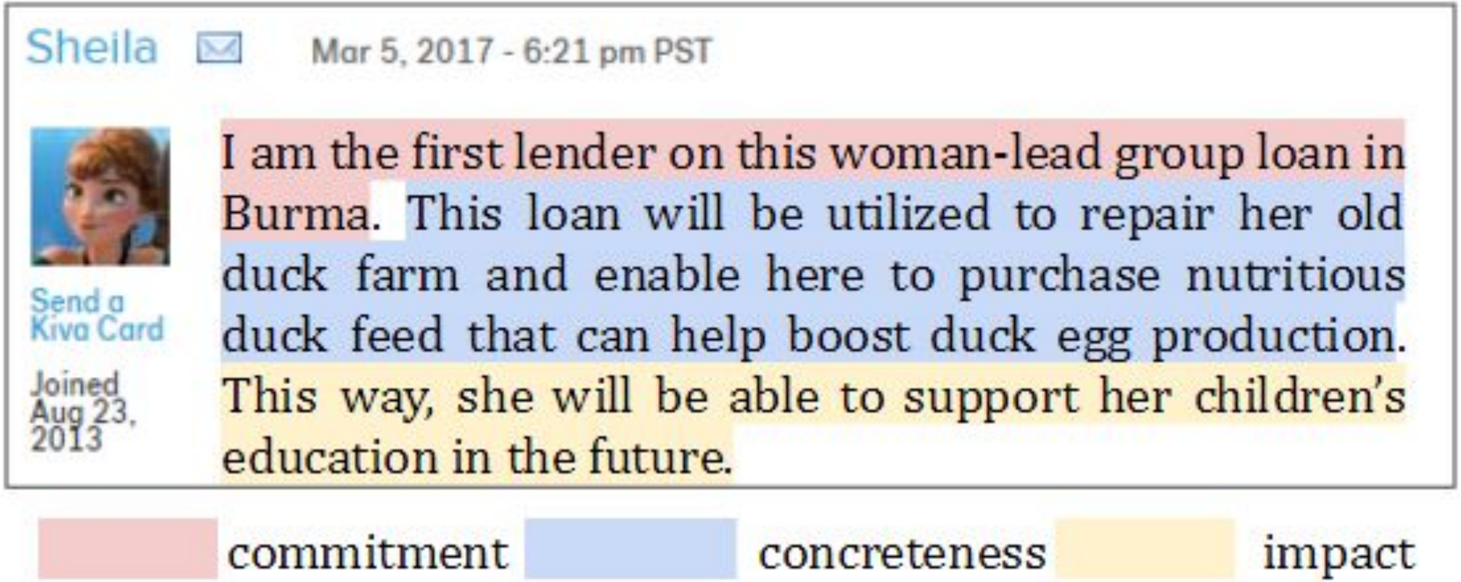
System 2: Systematic Processing (think slow)

(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

Send a Kiva Card

Joined Aug 23, 2013

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 here 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

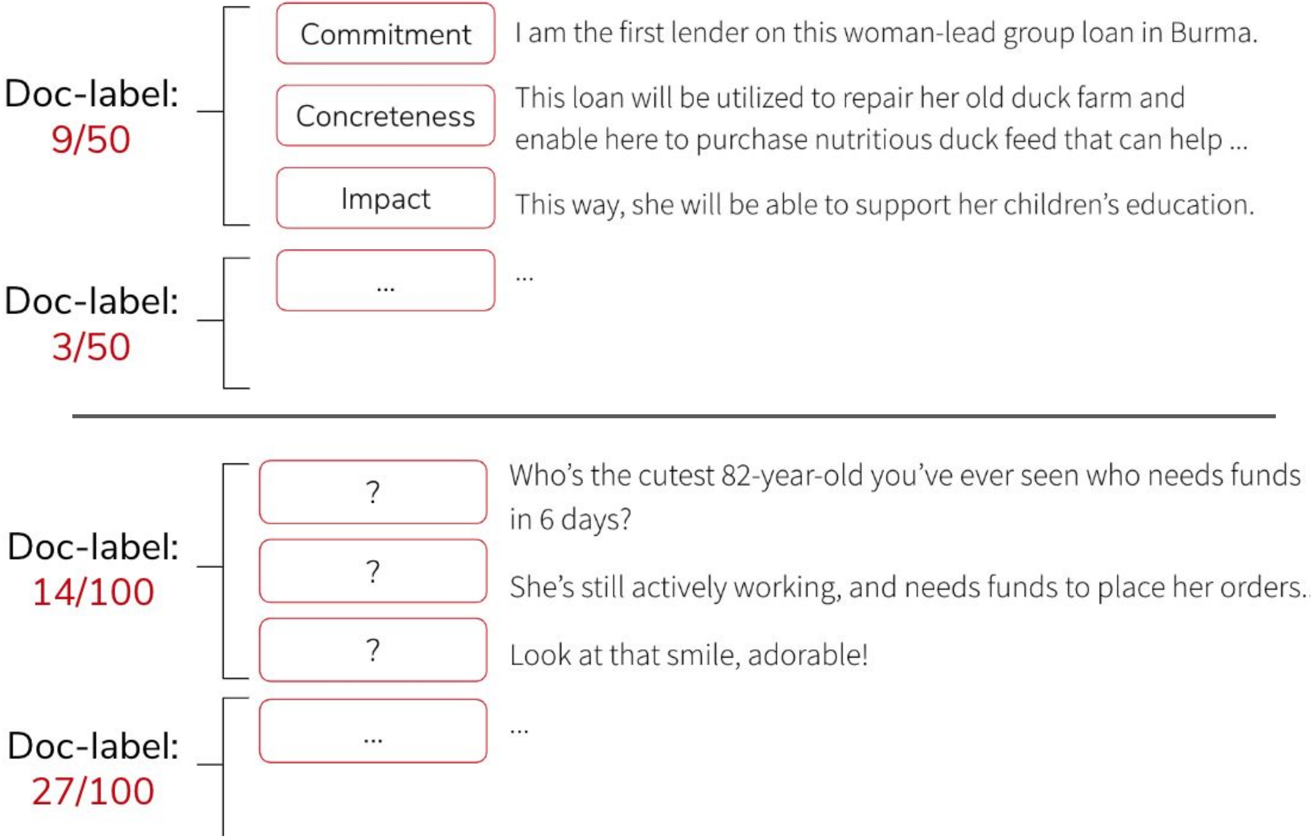
Limited Labeled Sentences

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 here 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!
...	...

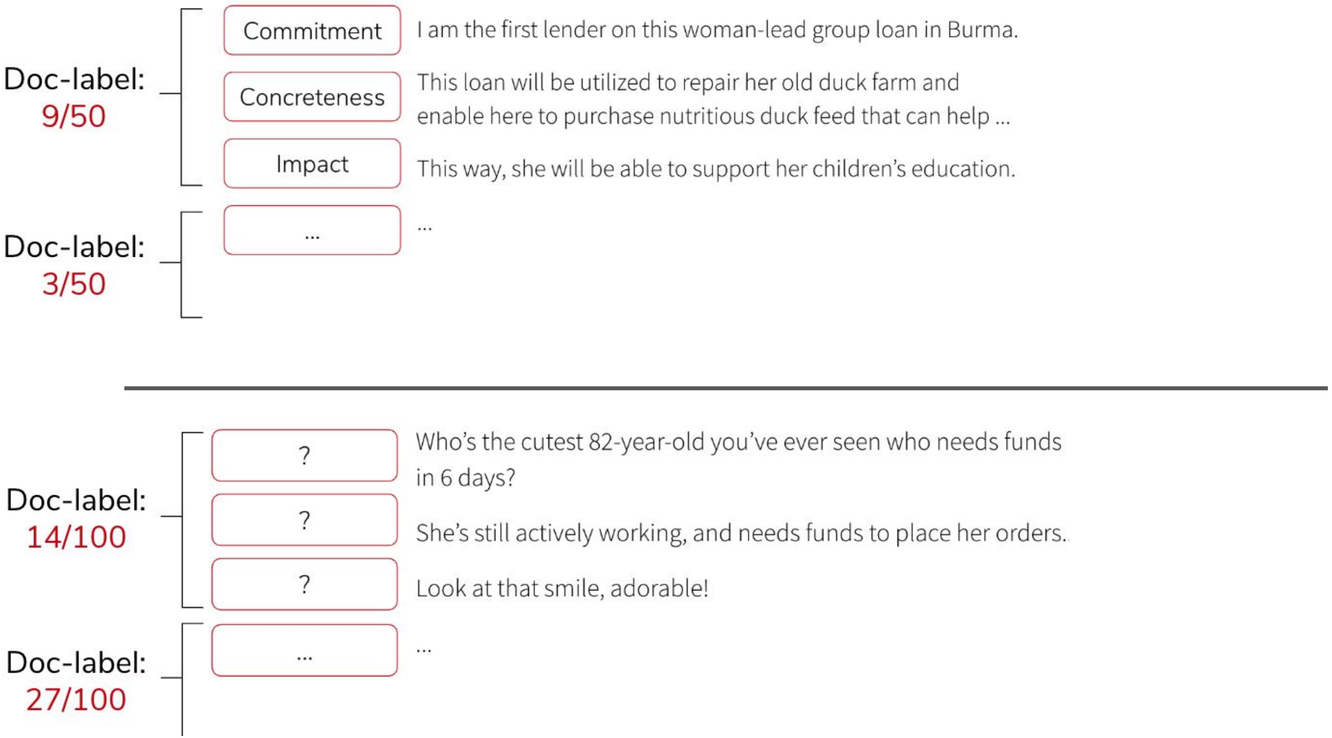
(Zhu, Lafferty, and Rosenfeld, 2003; Kingma et al., 2014; Chapelle, Scholkopf, Zien, 2006)


Doc-label:
9/50
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 here to purchase nutritious duck feed that can help ...
Impact
This way, she will be able to support her children's education.
Doc-label:
3/50
...
...
Doc-label:
14/100
?
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!
Doc-label:
27/100
...
...

Semi-supervised Setting w/ Document Supervision

Labeled Docs
+
Limited Labeled Sentences

Labeled Docs
+
Extra Unlabeled Sentences



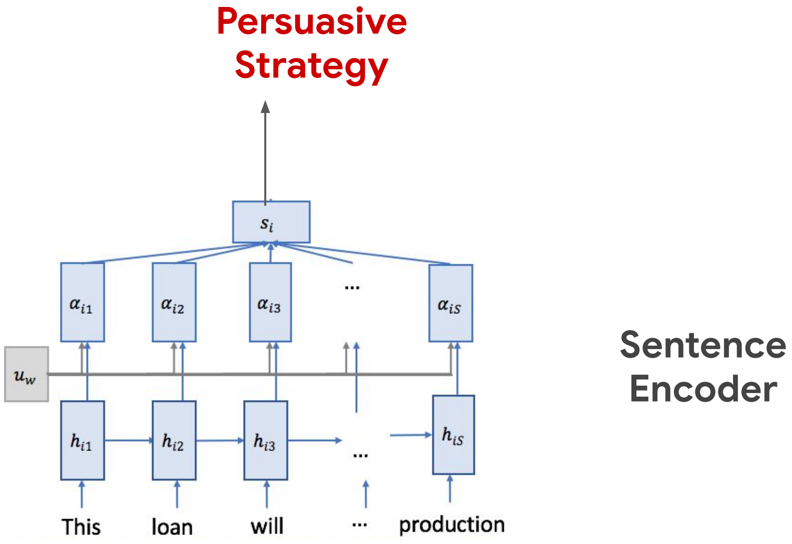
(Obquab et al, 2015; Pinheiro and Collobert, 2015)

Semi-supervised Net

Sentence encoder with attention

Persuasion prediction via softmax

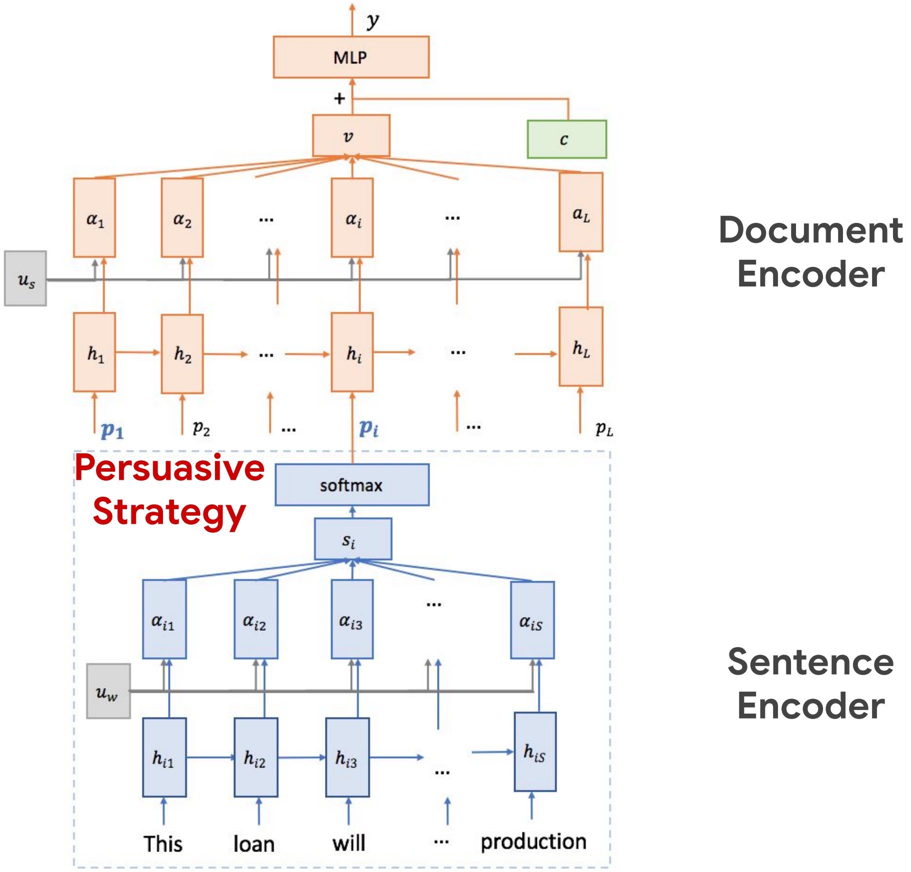
$$p_i = softmax(W_v \cdot s_i + b_v)$$



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

Semi-supervised Net

Document encoder



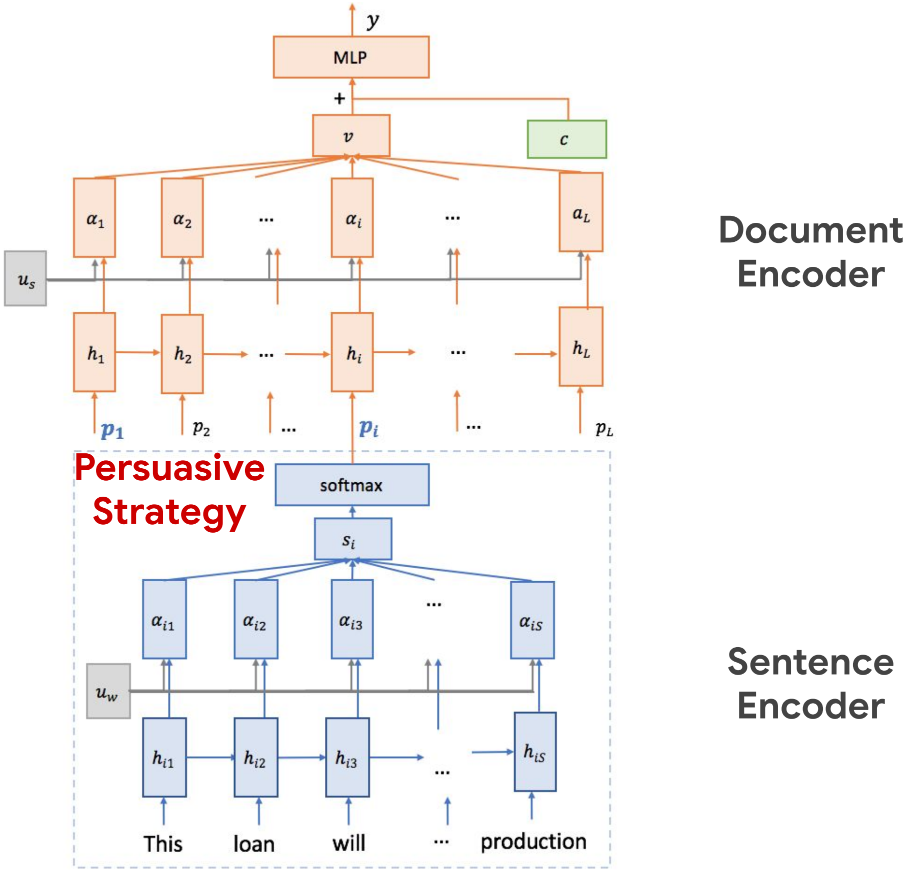
(Bahdanau et al., 2014; Yang et al., 2016)

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

Model	Sentence-Level		Doc-Level
	Accuracy	F1	RMSE
Sentence Only (SVM)	0.34	0.17	
Sentence Only (GRU)	0.51	0.47	

Results on Predicting Persuasion Strategies

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	Accuracy	F1	RMSE
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Supervised Sentence + Doc (Hierarchical Net)	0.48	0.43	1.15

Results on Predicting Persuasion Strategies

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Sentence Only (GRU)	0.51	0.47	
Supervised Sentence + Doc (Hierarchical Net)	0.48	0.43	1.15
Semi-supervised Sentence + Doc (Semi + Hierarchical Attention Net)	**0.57**	**0.52**	1.04

https://github.com/GT-SALT/Persuasion_Strategy

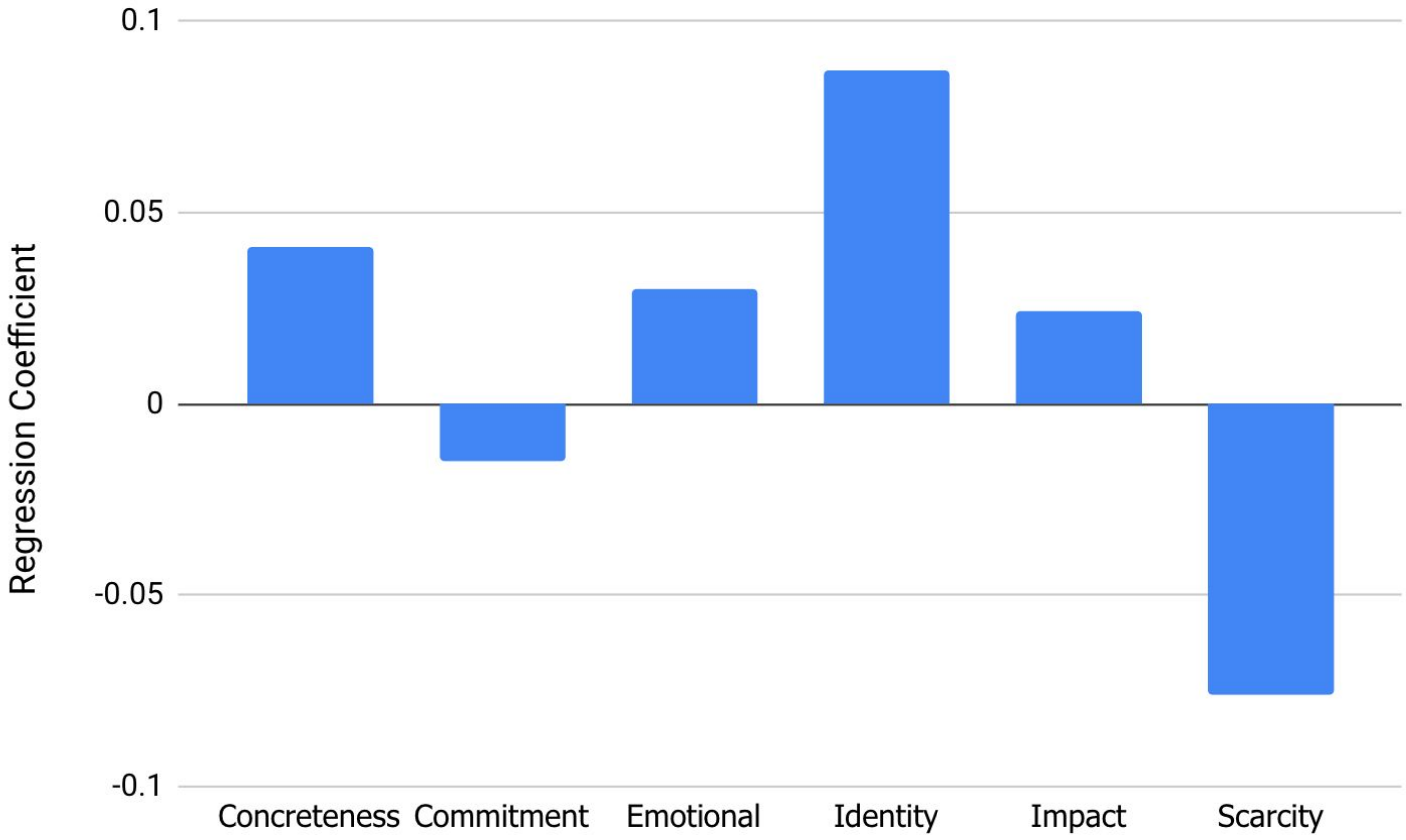
Representative Lexicon for Persuasive Strategies

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

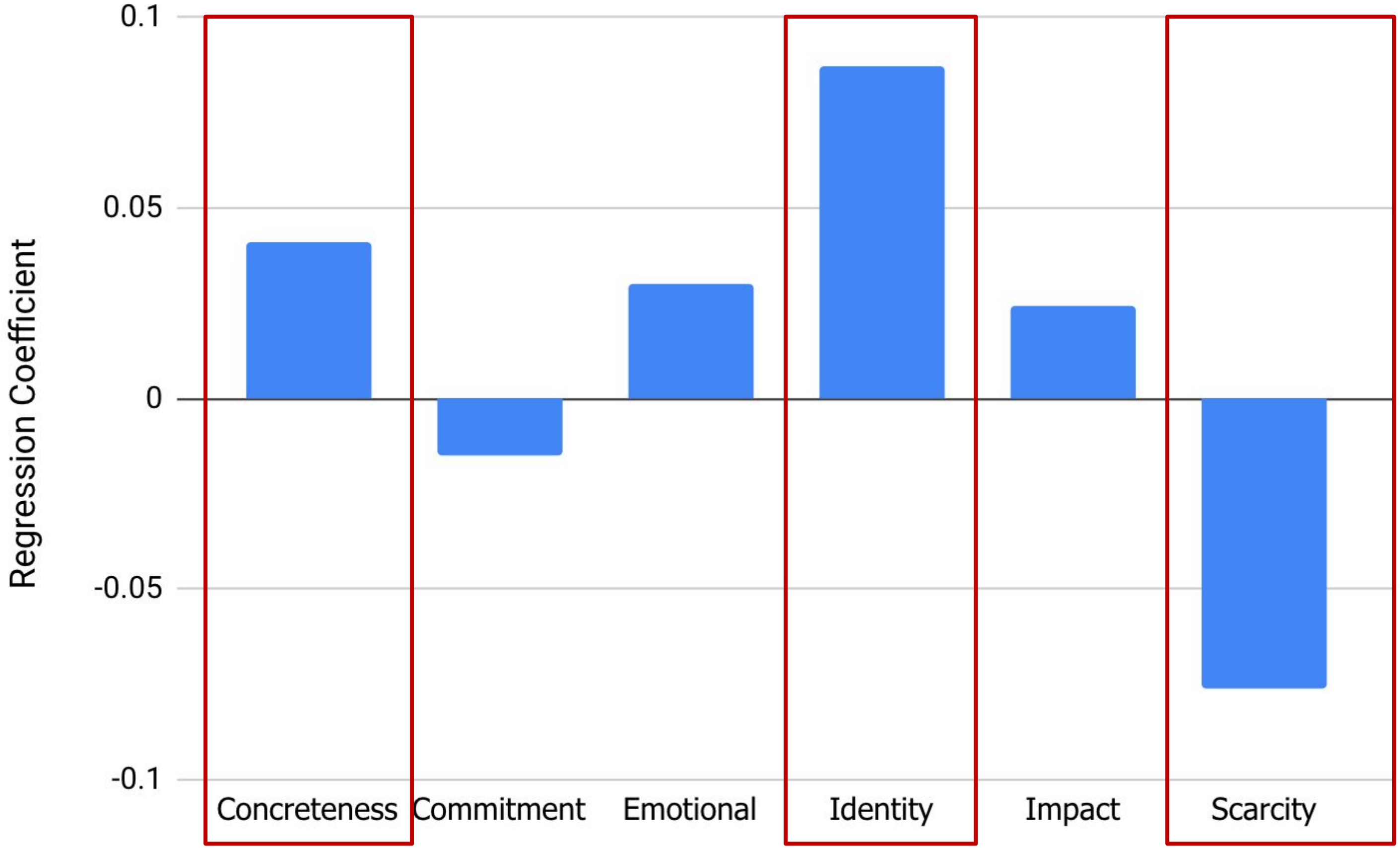
Modeling Persuasion in Language

- ✓ 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

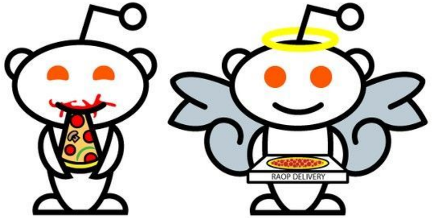


Identity and Concreteness Matter, Not Scarcity



Generalizing Model to Random Acts of Pizza

Random Acts of Pizza on Reddit (r/RAOP)



50

[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!

submitted 2 days ago by OriginalWF **Small Fish (15)**

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!

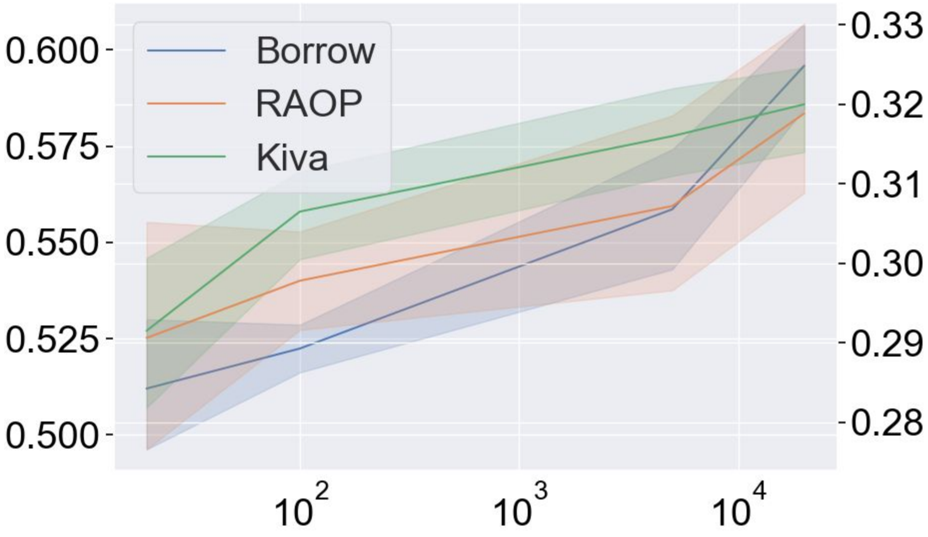
2 comments share save hide report

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

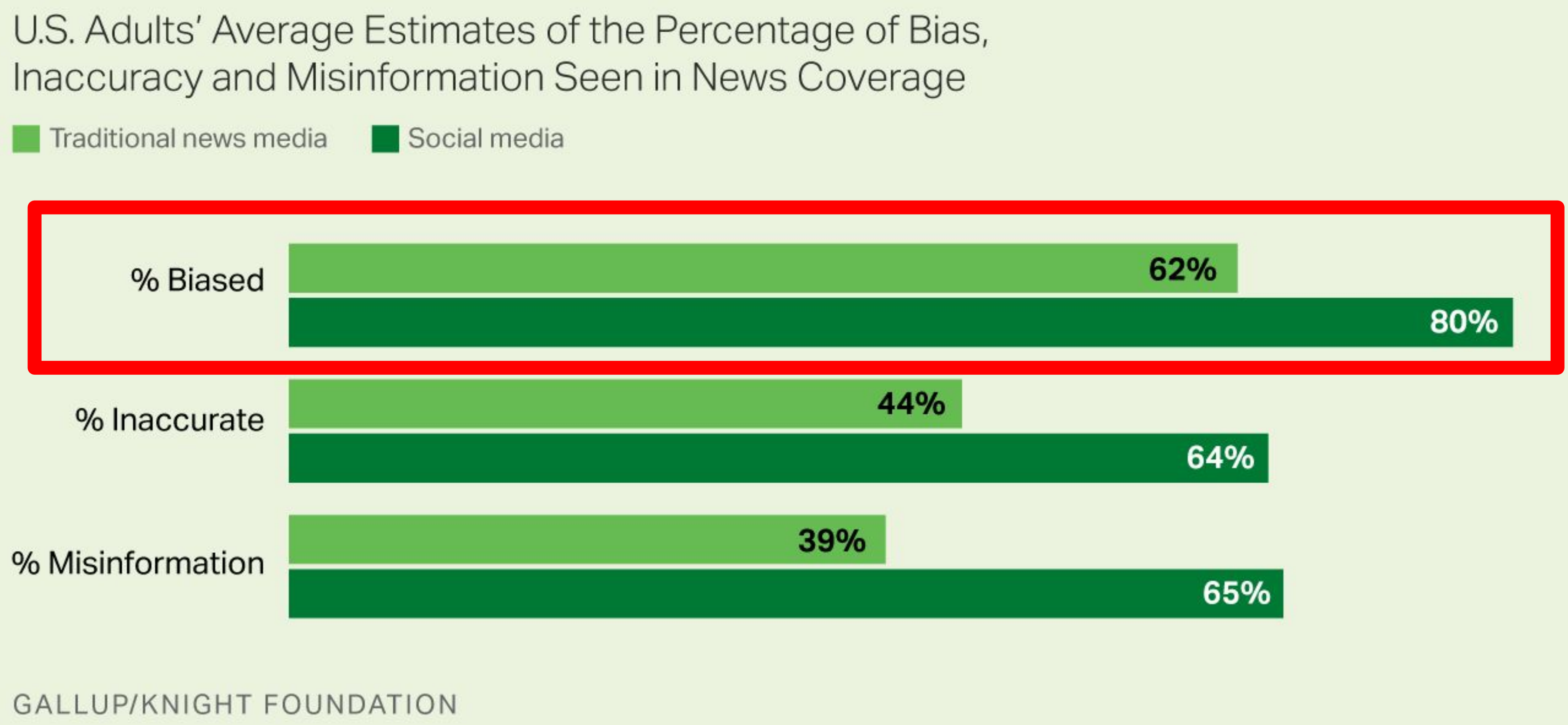
Reid Pryzant, Richard Diehl Martinez, Nathan Dass, Sadao Kurohashi, Dan Jurafsky, Diyi Yang. Automatically Neutralizing Subjective Bias in Text. AAAI 2020.

(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



American Views: Trust, Media and Democracy

What Makes One Headline Biased and Another Neutral?

?

Can Suggest Less Biased Alternatives to Text?

?

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, but not subjectivity bias
anti-semitic trope

John McCain exposed as an agent of the Rothschilds

↓

John McCain described as an agent of the Rothschilds

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

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*

based on

Epistemological bias

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

which its promoters hope

Demographic bias

✓ *A lead programmer usually spends* ***his career****...*

their careers

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.

Fifteenth United States Army: Difference between revisions

From Wikipedia, the free encyclopedia

Browse history interactively

Revision as of 14:05, 27 November 2008 (edit) GraemeLeggett (talk I contribs) *(→Early formation: ref)* ← Previous edit	**Revision as of 16:02, 29 December 2008 (edit) (undo)** 142.177.31.185 (talk) *("the legendary Gen. Patton" seems juuust a bit POV)* Next edit →
Line 26:	**Line 26:**
}}	}}
− 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 **the legendary Gen.** [[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	+ 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 **General** [[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]], or ETO. The

A Large Scale Wikipedia Neutrality Corpus

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

Text with subjective bias	Corresponding neutral point of view
Kathy Kirby, 1960's **blonde singing legend**	Kathy Kirby, 1960's **singer**
Go is **the deepest** game in the world	Go is **one of the deepest game** in the world
The authors' **expose** on nutrition studies	The authors' **statements** on nutrition studies
Marriage is a **holy union** of individuals	Marriage is a **personal union** of individuals

Method 1: Concurrent

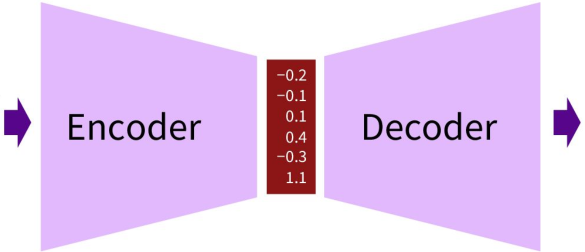
Seq2seq (with copy mechanism (See et al. 2017))

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.



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Method 1: Concurrent

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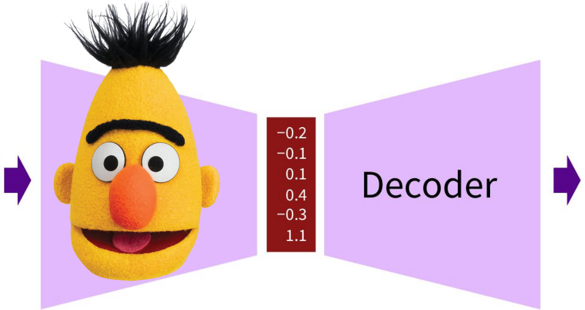

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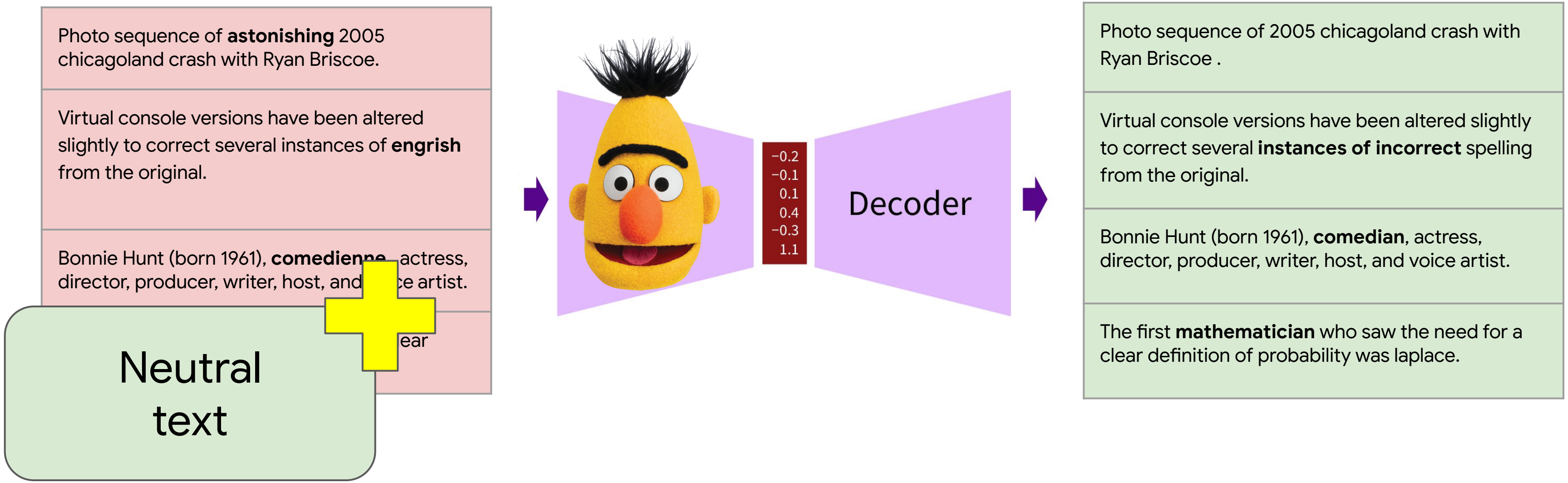
Method 1: Concurrent

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



Method 1: Concurrent

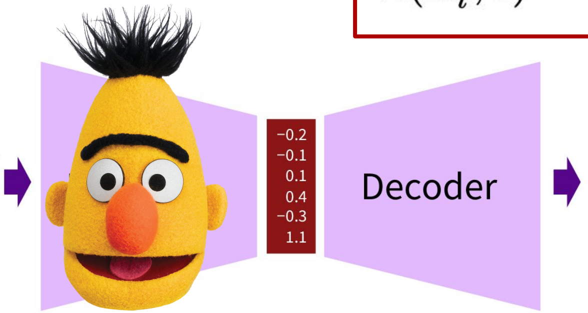
Seq2seq (with copy mechanism (See et al. 2017))
+ Bert
+ Pretraining on the unbiased corpus
+ Token-weighted loss function

$$\mathcal{L}(s,t) = -\sum_{i=1}^{m} \boxed{\lambda(w_i^t, s)} \log p(w_i^t | s, w_{<i}^t) + c$$

$$\lambda(w_i^t, s) = \begin{cases} \alpha & : w_i^t \notin s \\ 1 & : \text{otherwise} \end{cases}$$

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

Neutral Text

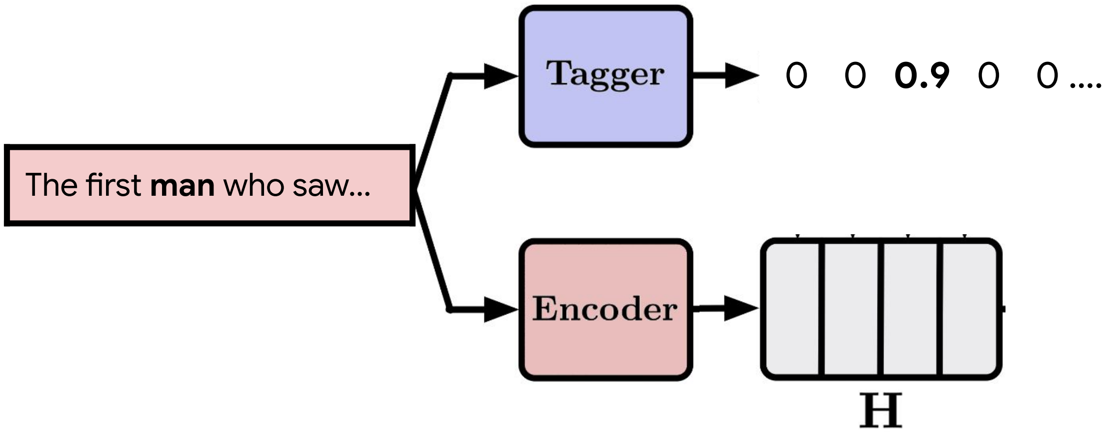


Loss weight (lambda):	1.0	1.0	1.5	1.0
Token	The	first	**mathematician**	who

Method 2: Modular

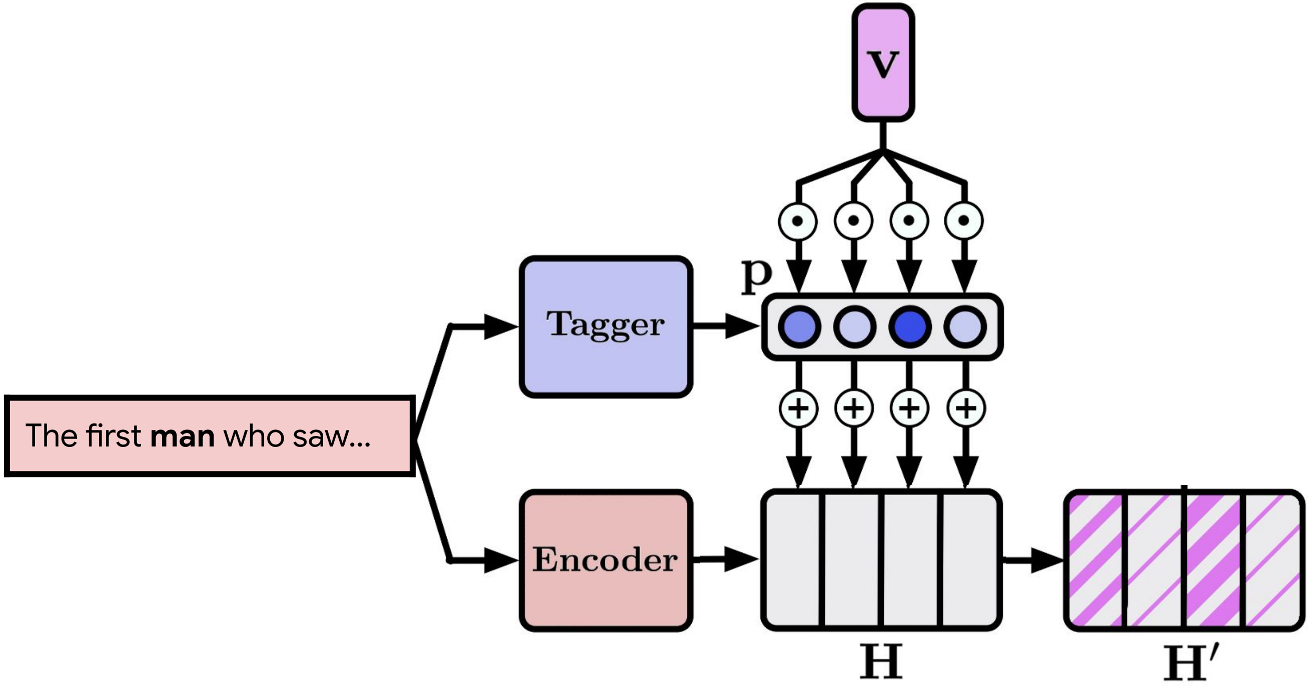
Give the source to

1. an encoder
2. a **tagger** that predicts possibly biased words



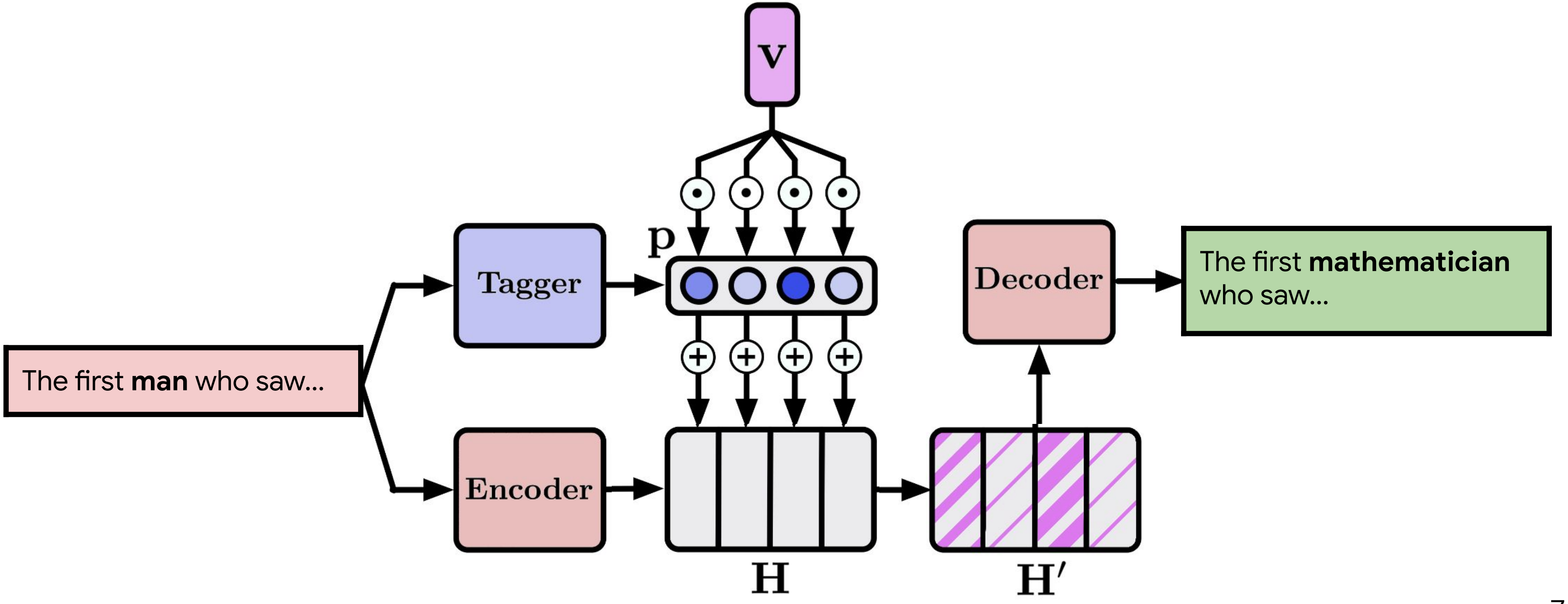
Method 2: Modular

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



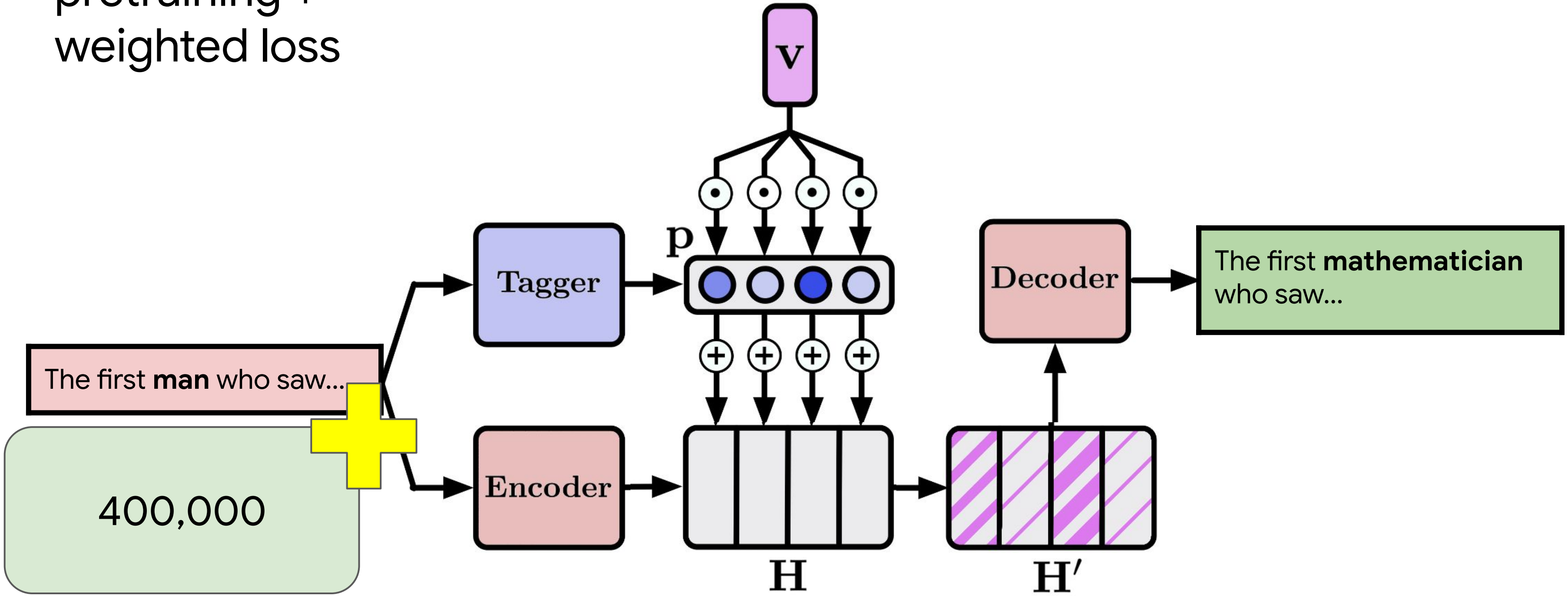
Method 2: Modular

Then decode as normal



Method 2: Modular

Use the same pretraining + weighted loss



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**)

Method	BLEU	Accuracy	Fluency	Meaning	Bias
Source Copy	91.33	0.00	-	-	-
Detector (always delete biased word)	92.43*	38.19*	-0.253	1.108	-0.324
Detector (predict substitution from biased word)	92.51	36.57*	-0.233	1.139	-0.327
Delete Retrieve (ST) (Li et al. 2018)	88.46*	14.50*	-0.209	1.294	-0.456
Back Translation (ST) (Prabhumoye et al. 2018)	84.95*	9.92*	-0.359	1.126	-0.390
Transformer (MT) (Vaswani et al. 2017)	86.40*	24.34*	-0.259	0.905	-0.458
Seq2Seq (MT) (Luong, Pham, and Manning 2015)	89.03*	23.93	-0.423	1.294	-0.436

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**)

Method	BLEU	Accuracy	Fluency	Meaning	Bias
Source Copy	91.33	0.00	-	-	-
Detector (always delete biased word)	92.43*	38.19*	-0.253	1.108	-0.324
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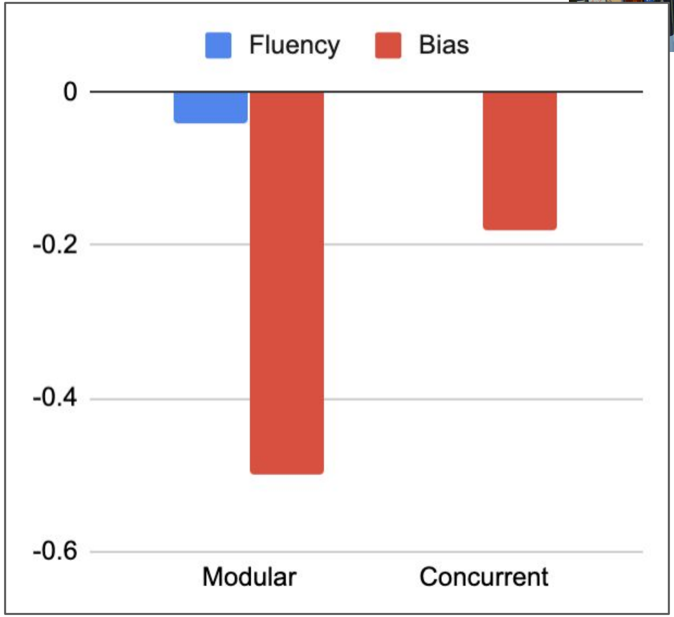
Seq2Seq (MT) (Luong, Pham, and Manning 2015)	89.03*	23.93	-0.423	1.294	-0.436
Base	89.13	24.01	-	-	-
+ *loss*	90.32*	24.10	-	-	-
+ *loss* + *pretrain*	92.89*	34.76*	-	-	-
+ *loss* + *pretrain* + *detector* (MODULAR)	93.52*	**46.80***	-0.078	0.996	**-0.467**
+ *loss* + *pretrain* + *BERT* (CONCURRENT)	**93.94**	45.87	**0.132**	**0.758**	-0.423
Target copy	100.0	100.0	-0.077	1.128	-0.551

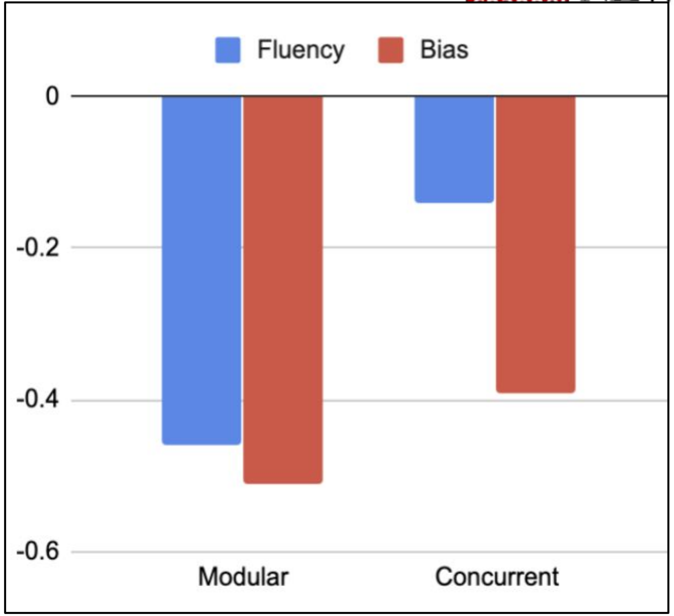
Test on **Political Books**

	The Ideological Books Corpus
Original	Activists have filed a lawsuit...
Modular	Critics of it have filed a lawsuit ...
Concurrent	Critics have filed a lawsuit ...



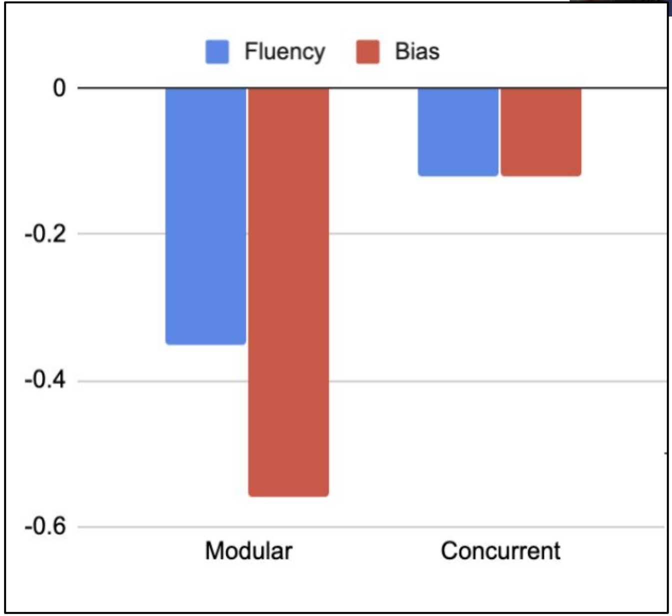
Test on **News Headlines**

	News Headlines
Original	Zuckerberg claims Facebook can...
Modular	Zuckerberg stated Facebook can...
Concurrent	Zuckerberg says Facebook can...



Test on **Campaign Speeches**

	Campaign speeches
Original	This includes amazing Americans like...
Modular	This includes Americans like...
Concurrent	This includes some Americans like...



Overview of This Talk

1. Model Persuasion in Language

2. Neutralize Subjectively Biased Text

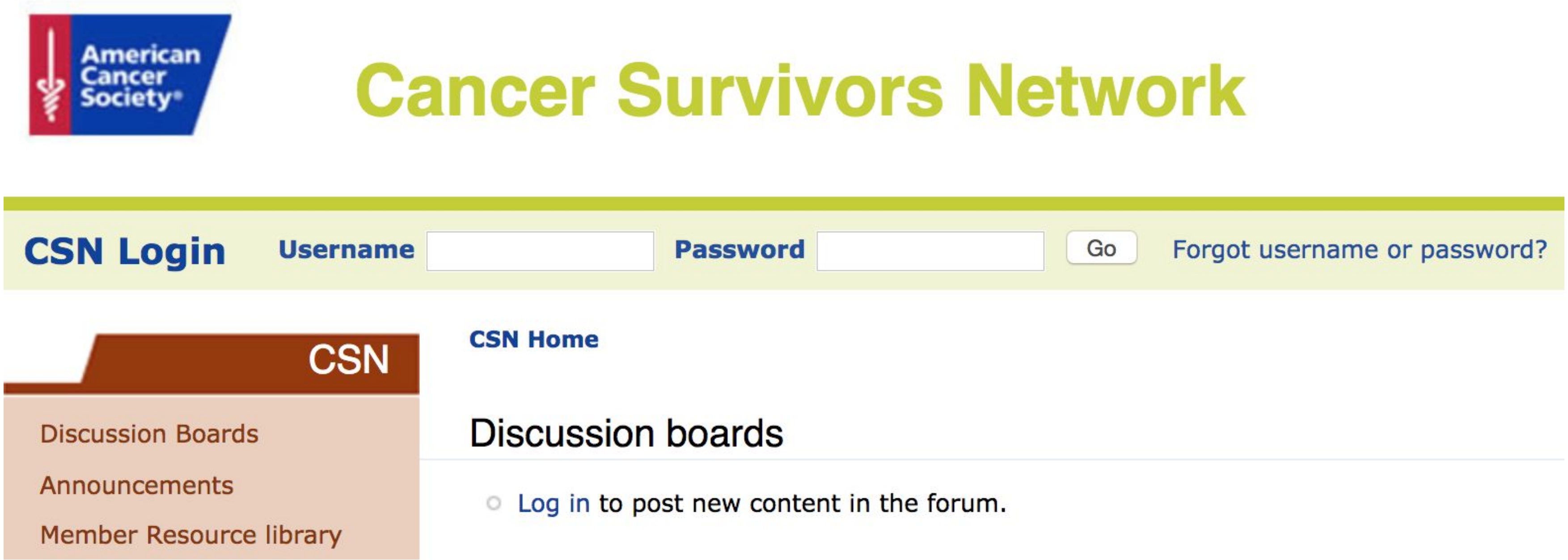
3. **Language and Social Roles in Online Health Communities**

3. Modeling Social Roles to Support Patient Communication in Online Health Communities

Diyi Yang, Robert Kraut, Tenbroeck Smith, Elijah Mayfield, and Dan Jurafsky. *Seekers, Providers, Welcomers, and Storytellers*: Modeling Social Roles in Online Health Communities. CHI, 2019. Best paper honorable mention

Diyi Yang, Zheng Yao, Joseph Seering, and Robert Kraut. The Channel Matters: Self-disclosure, Reciprocity and Social Support in Online Cancer Support Groups. CHI, 2019. Best paper honorable mention

Cancer Survivor Network - An Online Cancer Support Group



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

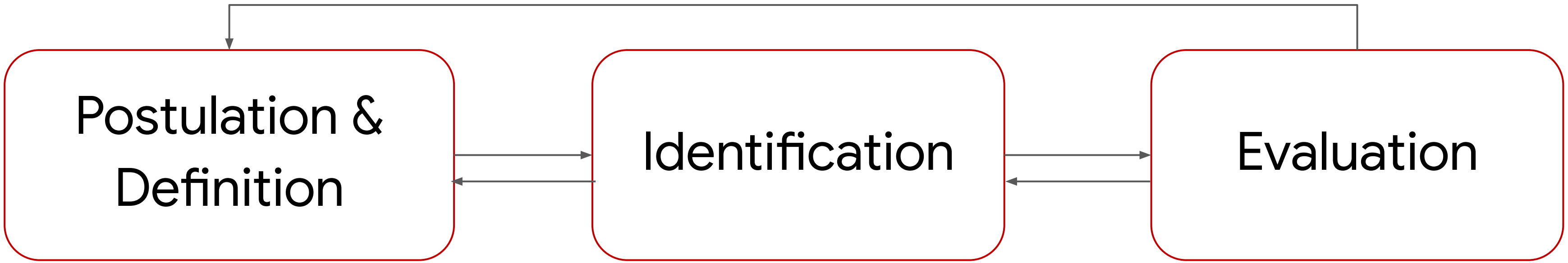
"The role concept centers upon behaviors that are characteristic of persons in a context."
— Bruce J Biddle 1979

"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

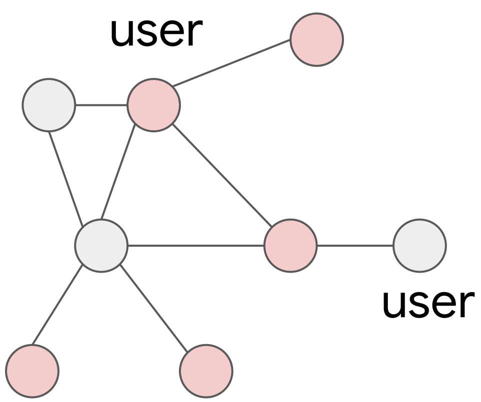
A repeated cycle of role postulation, definition, identification and evaluation.

— *A version of the Scientific Method*



Postulation & Definition: The Facet of Interaction

Network-based Measures



user-user reply network

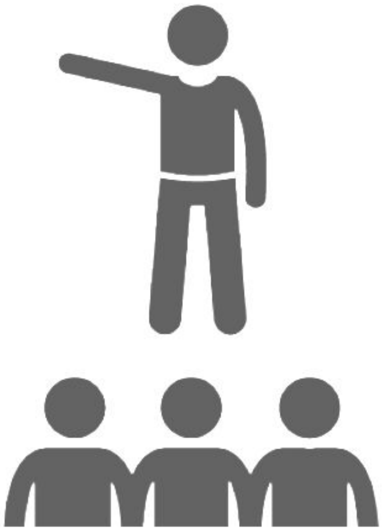
Content-based Measures

- ✓ # 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

Postulation & Definition: The Facet of Goal

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

Informational Support

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

Emotional Support

Automatic Measurement of the Facet of Goal

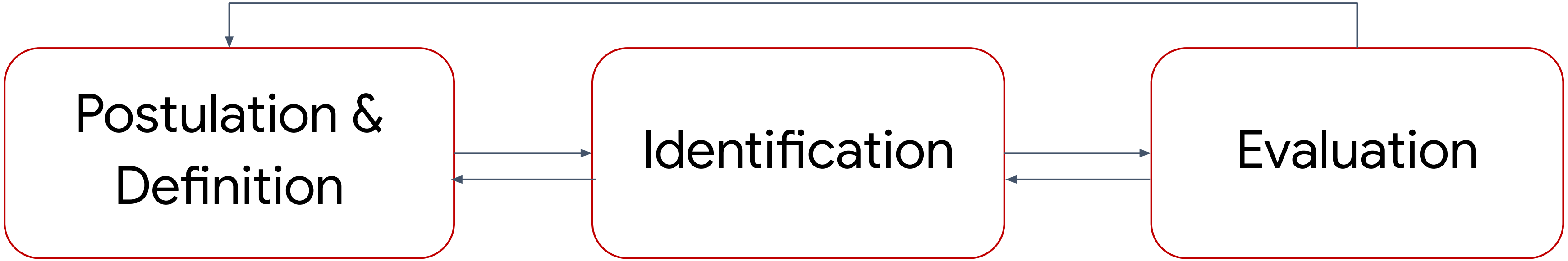
1. Seek emo support (r=0.64)
2. Provide emo support (r=0.75)
3. Provide empathy (r=0.72)
4. Provide appreciation (r=0.67)
5. Provide encouragement (r=0.64)

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



The facets of interaction, goal, context

Gaussian mixture models

Modeling Social Roles via Mixture Model

Intuition: a user is a mixture of different social roles

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

- ✓ User X is represented by the aforementioned features
- ✓ Select the number of roles K quantitatively and qualitatively

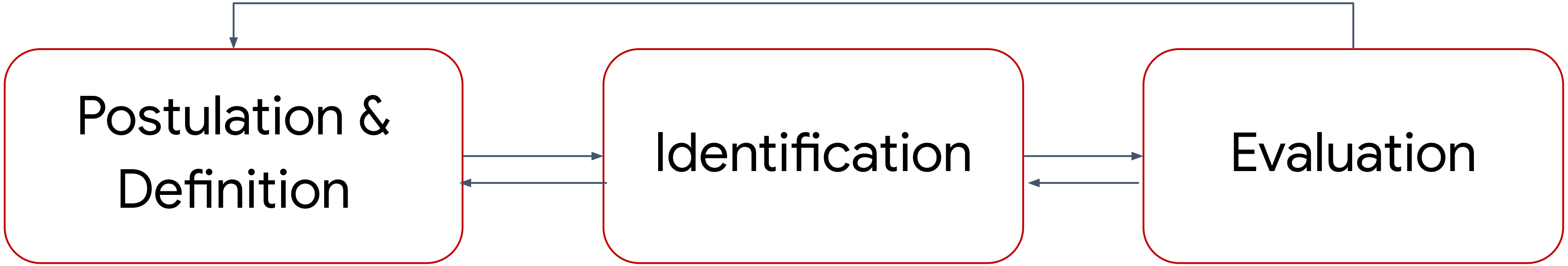
Roles Identified by Our Model (trained on 66K users)

Emotional Support Provider	Private Support Provider
Newcomer Welcomer	All-round Expert
Informational Support Provider	Newcomer Member
Story Sharer	Knowledge Promoter
Informational Support Seeker	Private Networker
Private Communicator	

Example Roles Identified by Our Model

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

Role Identification Methodology



The facets of interaction, goal, context

Gaussian mixture models

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"*

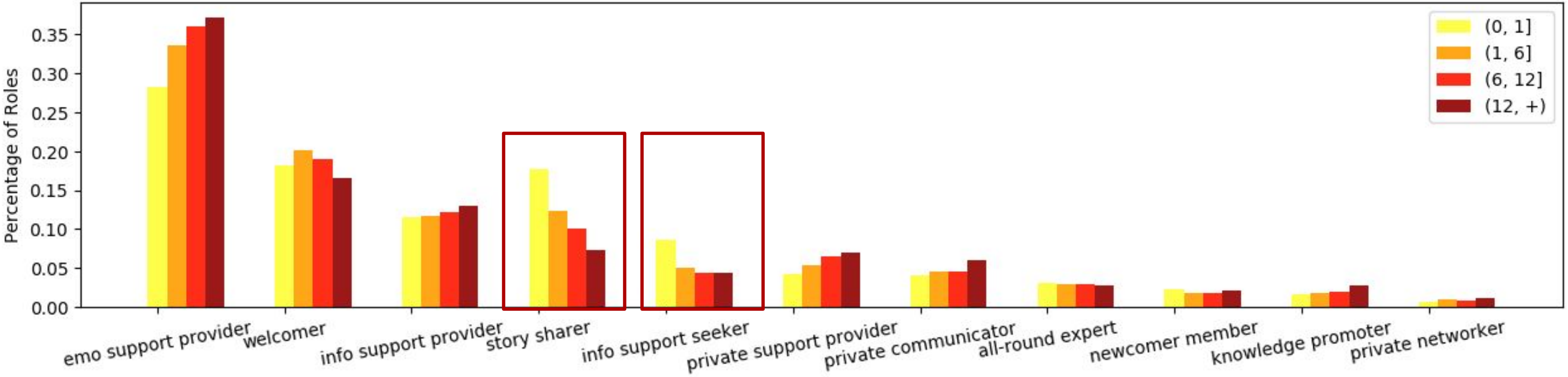
Modeling Social Roles on CSN

1. What roles do people occupy?

A mixture model that identifies 11 functioning roles

2. How do roles influence members' participation?

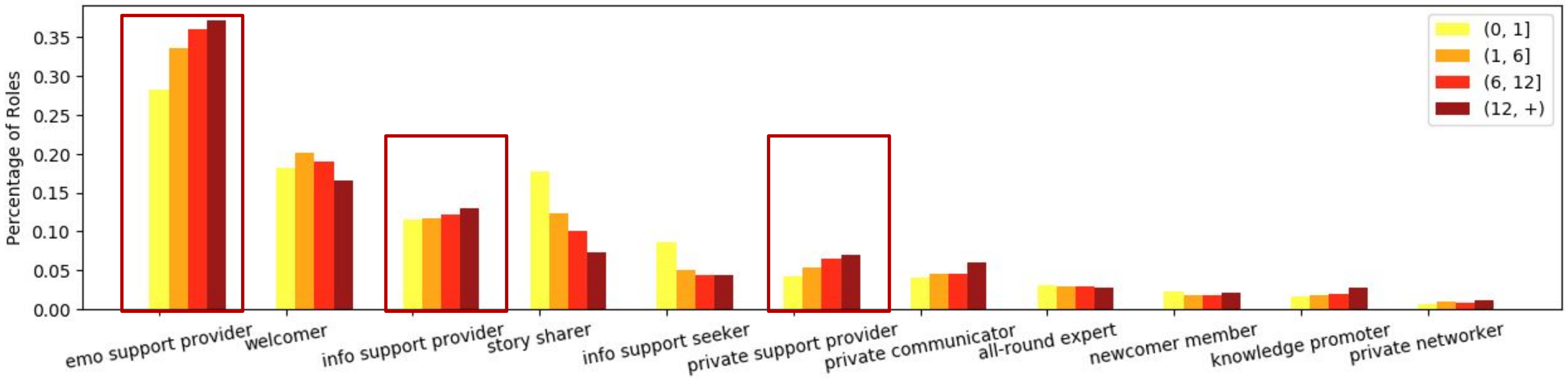
Roles People Enact Change with Time on CSN



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

From Roles Seeking Sources to Ones Offering Help

12 interviews of users on Cancer Survivor Network

*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 changes roles from ones that seek resources to ones offering help

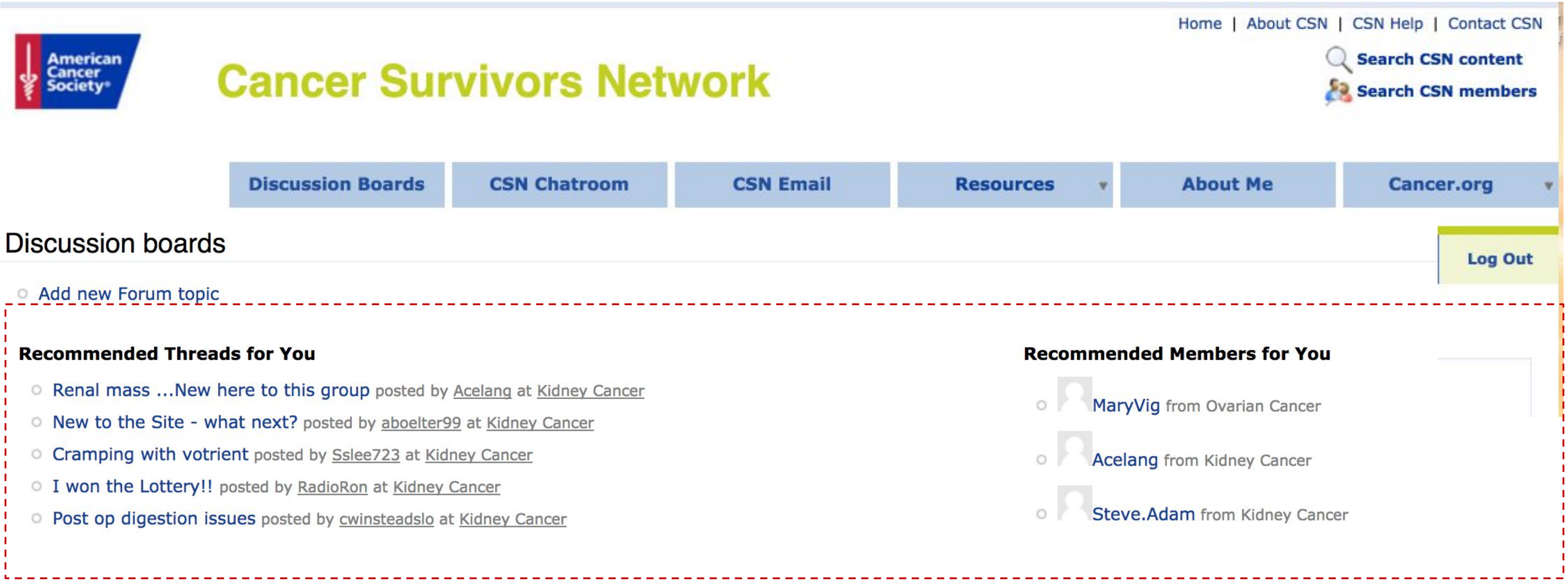
Automated Intervention to Improve Interaction

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

Add to favorites | Manage your favorites

Renal mass ...New here to this group

Acelang

Posts: 19

Joined: Apr 2017

Apr 18, 2017 - 8:46 pm

Hi I'm new here but very no nervous about findings on a CT scan I had done in the er .. a 5 cm renal mass was found along with enlarged lymph nodes my concern is 6 month prior this tumor was 2.6cm I don't see a doctor until next week but I'm worried because I have a lump in my side and back ...Have night sweats fatigue and back and stabbing pains in my stomach where the lump is

How relevant is this thread to you?:

☆☆☆☆☆

Your rating: None

Add new comment   1083 reads   Report as Inappropriate

icemantoo

Thats a lot of growth

Apr 18, 2017 - 9:14 pm

Ace,

Do what you have to do to get this taken care of asap. It is either very aggressive or was measured 2 different ways like Ultrasound and CT. It shoild have been addressed at 2.6 cm as that is too large for watch and wait. At 5 cm a surgery only result is still very possable and if so you would need no further tratments other than scans.

You might be interested in...

right kidney mass???
atos posted at Kidney Cancer

Renal Cell Cancer
gerard posted at Kidney Cancer

Help eliminate cancer
drrhorho posted at Kidney Cancer

20 Year Old with Kidney Cancer
veg4you posted at Kidney Cancer

HELP! JUST DIAGNOSED WITH RENAL CANCER! NEED A FRIEND TO TALK TOO!
TOM659 posted at Kidney Cancer

* Feature-based matrix factorization (Yang et al., 2014a; Yang et al., 2014b; Yang et al., 2014c)

People (newcomers & oldtimers) On CSN Use Our Intervention

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

Recommender Setting (Result till May, 2018)	Displayed	Hits	Hit Ratio (%)	Improvement over control
Recommend recent threads in favorite forum	6718	150	2.23	
Recommend based on history & restricted to favorite forum	7002	138	1.97 (ns)	-3%
Recommend based on history	6615	238	3.60 ***	+61%

Recommendations based on history and user roles are ongoing

Explain Recommendation via Social Roles

“ 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

Ideational Semantics

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

Interpersonal Semantics

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)

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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Twitter @Diyi_Yang