At the Intersection of Language and Data Science

Kathleen McKeown
Department of Computer Science
Columbia University

NEW MEDIA FOR DATA SCIENCE

Develop the tools and talent to enhance communication and interactions within communities

Vision

- Generating presentations that connect
 - Events
 - Opinions
 - Personal accounts
 - Their impact on the world

Machine learning framework

Data (often labeled)

Extraction of "features" from text data

Prediction of output

Machine learning framework

Data (often labeled)

Extraction of "features" from text data

Prediction of output

What data is available for learning?

Machine learning framework

Data (often labeled)

Extraction of "features" from text data

Prediction of output

What features yield good predictions?

FACT News Wikipedia descriptions Personal narrative Social Media **Novels FICTION**

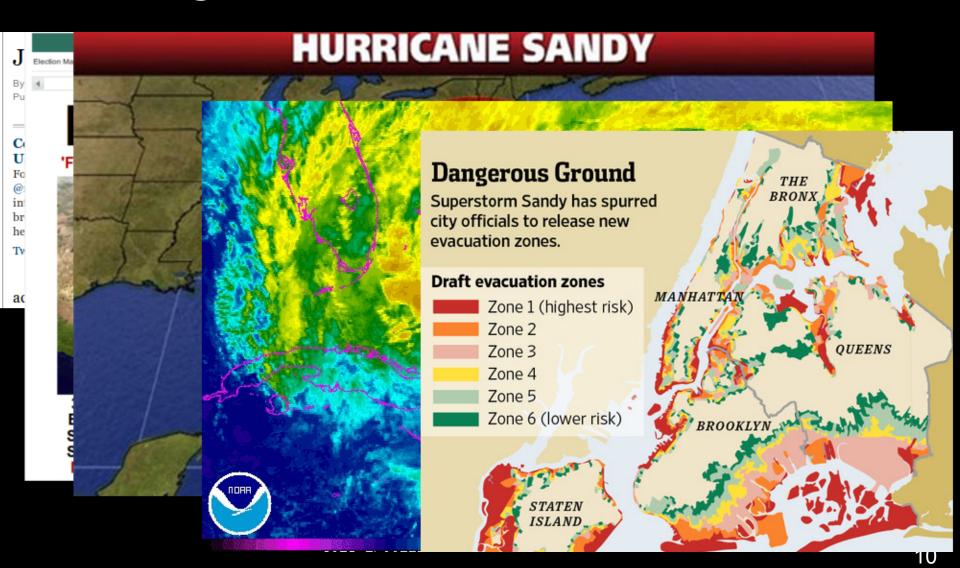


FACT News Wikipedia descriptions Personal narrative Social Media **Novels FICTION**





Problem: Identifying needs during disaster



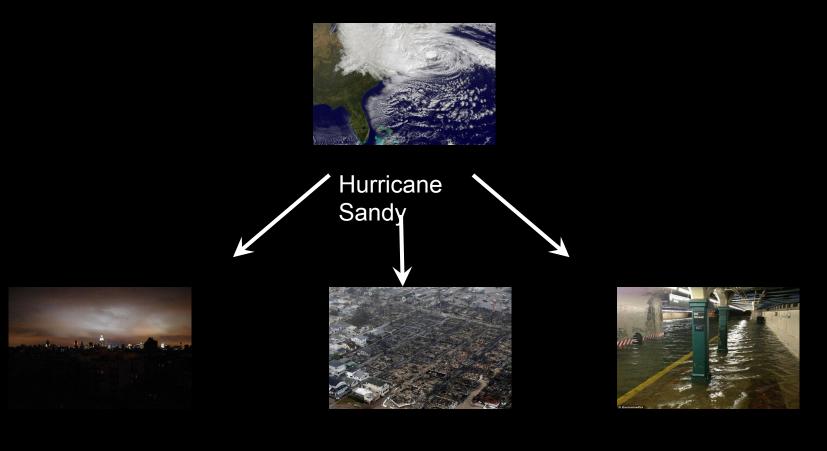
Monitor events over time

Input: streaming data

News, web pages

At every hour, what's new

Track events and SubEvents



Manhattan Blackout

Breezy Point fire

Public Transit Outage

Data from NIST: 2011 – 2013 Web Crawl, 11 categories











nbcdfw.com

local • news • classifieds

headlines: Rothko at the Modern ... city insists brown water safe to drink

The U.S. Pacific Tsunami Warning Center said there was a possibility of a local U.S. Pacific Tsunami Warning Center said there was a possibility of a local tsunami, within 100 or 200 miles of the epicenter, but they were not issuing an immediate warning for the broader region.

The magnitude-7.5 quake, about 20 miles deep, was centered off the town of Champerico.

People fled buildings in Guatemala City, in Mexico City and in the capital of the Mexican state of Chiapas, across the border from Guatemala.

Would you like to contribute to this story? Start a discussion.



nbcdfw.com

headlines: Rothko a

ny1.com

said 1

The U.S.

headlines: G train stuck forever ... weather on the 1's ... rats eat tourists

Pacific

there

A 7.4 magnitude earthquake struck off the coast of Guatemala Wednesday, the U.S. Geological Survey reported.

but th warni

within

The epicenter was 124 miles west southwest of Guatemala City.

The miles

Cham

People

in Me

Reuters reported that the quake could be felt as far away as Mexico City. There were no immediate reports of injury or damage.

Mexican state of Chiapas, across the border from Guatemala.

Would you like to contribute to this story? Start a discussion.



/ I			
	nbcd		
			kgw.com
headlines: Rothko at			local • news • classifieds
The U.S	headlines: fixy bike festival earthquake in Guatemala bridge renovation		
	CIIAT	EMALA CITY	The H.C. Coolegical

GUATEMALA CITY -- The U.S. Geological Survey says that a strong earthquake has hit off the Pacific coast of Guatemala, rocking the capital and shaking buildings as far away as Mexico City and El Salvador.

The U.S. Pacific Tsunami Warning Center said there was a possibility of a local tsunami, within 100 or 200 miles of the epicenter, but they were not issuing an immediate warning for the broader region.

The magnitude-7.5 quake , about 20 miles deep, was centered off the town of Champerico.

People fled buildings in Guatemala City , in Mexico City and in the capital of...

story? Start a discu



nbcd ktla.com headlines: Rothko local • news • classifieds headlines: fixy bike festi The U.S. headlines: fire in south land ... earthquake in Guatemala ... accident on the 5 **GUATEMALA** said headlines: G tra Survey says tha Pacific TODAY'S BRIEF hit off the Pacifi A 7.4 ma there the coast the capital and withir • Greeks protesting austerity measures are as Mexico City U.S. Geold but th clashing with riot police in Athens. warni The U.S. Pacific The epic • The U.S. Geological Survey says that a southwest said there was a The strong earthquake has hit off the Pacific coast tsunami, withir miles of Guatemala, rocking the capital and epicenter, but th Reuters re Cham shaking buildings as far away as an immediate v felt as fa Mexico City and El Salvador. were no region. People damage. in Me • The election behind them, U.S. investors The magnitude-Mexican state of dumped stocks Wednesday and turned their deep, was cente border from Guaten focus to a world of problems - tax increases Champerico. and spending cuts that could stall the nation's Would you like to economic recovery and a deepening recession People fled buil story? Start a discu in Europe. Mexico City and



nbco

headlines: Rothko a

The U.S said t

warni

Pacific there A 7.4 ma withir the coast but the U.S. Geold

The epic southwest miles
Cham Reuters re

felt as fa People were no i in Me damage.

Mexican state of border from Guaten

Would you like t story? Start a discu headlines: fixy bike festive

GUATEMALA

Survey says tha hit off the Pacifi the capital and s as Mexico City a

The U.S. Pacific said there was a tsunami, within epicenter, but than immediate v region.

The magnitudedeep, was cente Champerico.

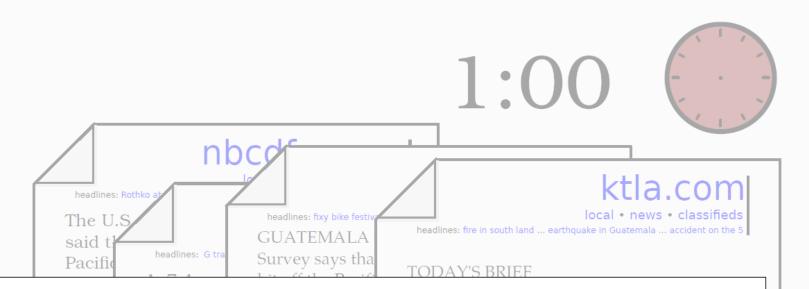
People fled buil Mexico City and ktla.com

local • news • classifieds

headlines: fire in south land ... earthquake in Guatemala ... accident on the 5

TODAY'S BRIEF

- Greeks protesting austerity measures are clashing with riot police in Athens.
- The U.S. Geological Survey says that a strong earthquake has hit off the Pacific coast of Guatemala, rocking the capital and shaking buildings as far away as Mexico City and El Salvador.
- The election behind them, U.S. investors dumped stocks Wednesday and turned their focus to a world of problems tax increases and spending cuts that could stall the nation's economic recovery and a deepening recession in Europe.



hour 1 updates

- The U.S. Geological Survey says that a strong earthquake has hit off the Pacific coast of Guatemala, rocking the capital and shaking buildings as far away as Mexico City and El Salvador.
- The magnitude-7.5 quake, about 20 miles deep, was centered off the town of Champerico.



Temporal Summarization Approach

At time **t**:

- 1. Predict salience for input sentences
 - Disaster-specific features for predicting salience
- 2. Remove redundant sentences
- 3. Cluster and select exemplar sentences for **t**
 - Incorporate salience prediction as a prior

Language Models (5-gram Kneser-Ney model)

- generic news corpus (10 years AP and NY Times articles)
- domain specific corpus (disaster related Wikipedia articles)

A domain specific language model scores sentences by how typical they are of the disaster type

Language Models (5-gram Kneser-Ney model)

- generic news corpus (10 years AP and NY Times articles)
- domain specific corpus (disaster related Wikipedia articles)

High Salience

Nicaragua's disaster management said it had issued a local tsunami alert.

Medium Salience

People streamed out of homes, schools and oce buildings as far north as Mexico City.

Low Salience

Language Models (5-gram Kneser-Ney model)

Geographic Features

- tag input with Named-Entity tagger
- get coordinates for locations and mean distance to event

High Salience

Nicaragua's disaster management said it had issued a local tsunami alert.

Medium Salience

People streamed out of homes, schools and oce buildings as far north as Mexico City.

Low Salience

Language Models (5-gram Kneser-Ney model)

Geographic Features

- tag input with Named-Entity tagger
- get coordinates for locations and mean distance to event

High Salience

Nicaragua's disaster management said it had issued a local tsunami alert.

Medium Salience

People streamed out of homes, schools and oce buildings as far north as Mexico City.

Low Salience

Language Models (5-gram Kneser-Ney model)

Geographic Features

Semantics

number of event type synonyms, hypernyms, and hyponyms

High Salience

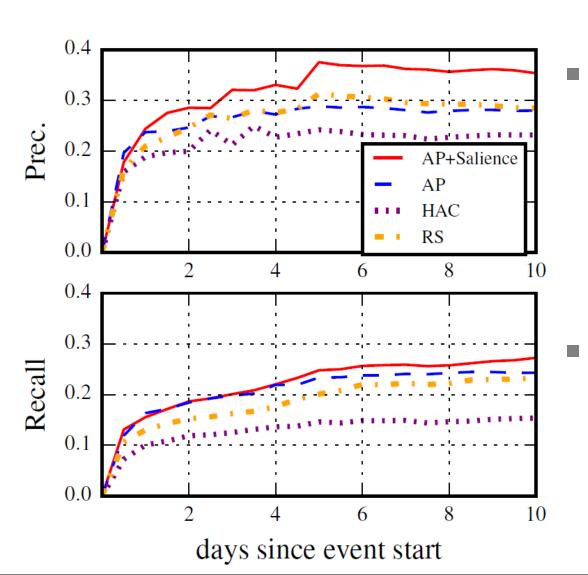
Nicaragua's disaster management said it had issued a local tsunami alert.

Medium Salience

People streamed out of homes, schools and oce buildings as far north as Mexico City.

Low Salience

What Have We Learned?



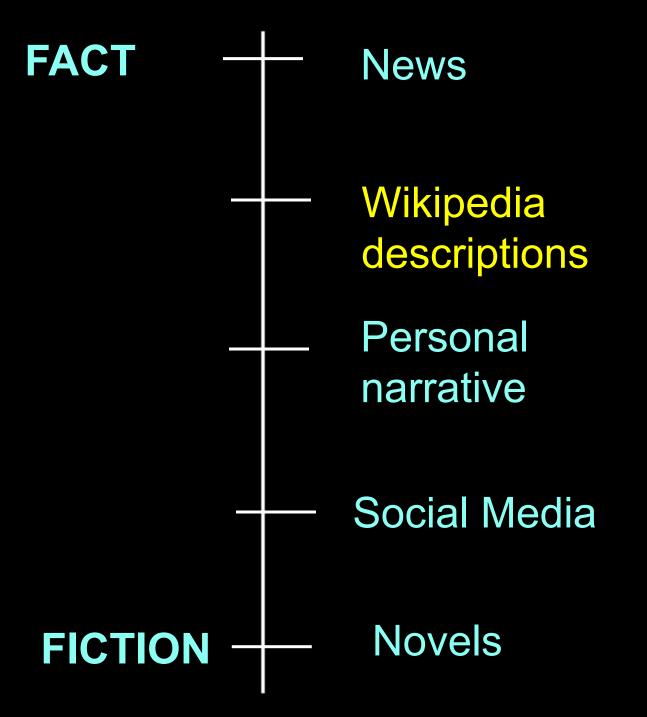
Salience predictions lead to high precision quickly

Salience predictions allow us to more quickly recover more information

What's next?

 Experimenting with neural nets for summarization updates

- Aiming for abstractive summarization
 - New sentences generated from phrases





WikipediA

The Free Encyclopedia

English

5 260 000+ articles

Español

1 289 000+ artículos

日本語

1 033 000+ 記事

Русский

1 346 000+ статей

Italiano

1 306 000+ voci



Deutsch

1 985 000+ Artikel

Français

1 801 000+ articles

Polski

1 187 000+ haseł

Português

939 000+ artigos

中文

904 000+ 條目

Input

Output



Towards a Public Data Infrastructure for a Large, Multilingual, Semantic Knowledge Graph















Formal language

Stylized format

Less varied content (for certain kinds of entries)



RDF Applications

Applications that generate descriptions of semantic web entities

- Biographies
- Company descriptions



RDF Applications

Biographies

Company descriptions

<typeOf> <Person>

<typeOf> <Company>

ofession>

<industry>

- Politicians
 - 311S
- Models

- Automotive
- Video games



RDF Applications

Core messages: messages built from rdf triples with instance entity as subject

- The [predicate] of [subject] is [object]
- [subject]'s [predicate] is [object]

- The location of Tessla is Palo Alto.





Mining paraphrasal templates from a domain corpus (Wikipedia)

Use taxonomy to find richly-typed paraphrasal templates

Find paraphrasal templates from nonparaphrase sentences



Sentences from the corpus

GM Taiwan was founded in August 1989

 In 1904, the company was established as Oscar Lear Automobile Company



Entities/dates identified

[GM Taiwan] was founded in [August 1989]

 In [1904], the company was established as [Oscar Lear Automobile Company]



Types replace entities/dates

Paraphrases:

- [company] was founded in [date]
- In [date], the company was established as [company]

Core Message:

The [start-date] of [company] was [date]

 Tesla Motors was founded by JB Straubel, Martin Eberhard and Elon Musk...Tesla Motors is a privately held company with approximately 6,000 employees. The product of Tesla Motors is Luxury vehicle. Tesla Motors' location is Palo Alto, California. In 2003, the company reorganized, adapting its current name, Tesla Motors. In May 2010, Toyota launched a collaboration with Tesla Motors to create electric vehicles. The "Tesla Factory" is an automobile manufacturing plant in Fremont, California, US, owned and operated by Tesla Motors.

 Tesla Motors was founded by JB Straubel, Martin Eberhard and Elon Musk...Tesla Motors is a privately held company with approximately 6,000 employees. The product of Tesla Motors is Luxury vehicle. Tesla Motors' location is Palo Alto, California. In 2003, the company reorganized, adapting its current name, Tesla Motors. In May 2010, Toyota launched a collaboration with Tesla Motors to create electric vehicles. The "Tesla Factory" is an automobile manufacturing plant in Fremont, California, US, owned and operated by Tesla Motors.



Hybrid Approach

Can we augment RDF triples with information drawn from the web?

 Summarization approach: Find all relevant sentences that match the entity and/or contain RDF triples on the web. Tesla Motors was founded by JB Straubel, Martin Eberhard and Elon Musk...Tesla Motors is a privately held company with approximately 6,000 employees. The product of Tesla Motors is Luxury vehicle. Tesla Motors' location is Palo Alto, California. In 2003, the company reorganized, adapting its current name, Tesla Motors. In May 2010, Toyota launched a collaboration with Tesla Motors to create electric vehicles. The "Tesla Factory" is an automobile manufacturing plant in Fremont, California, US, owned and operated by Tesla Motors.



Evaluation

100 texts generated from each application-domain combination, in 5 versions

- Full system
- No paraphrasal templates
- No hybrid and no components (baseline)

Annotators shown two texts, asked which is better (or equal)

On criteria:

- Content
- Ordering
- Style
- Overall





	Preference	Content	Ordering	Style	Overall
Baseline VS Full System	Baseline	20%	27%	24%	22%
	Equal	14%	11%	20%	14%
	Full System	66%	62%	56%	64%
	Winning difference	46%†	35% †	32% †	42% †

What have we learned?



	Preference	Content	Ordering	Style	Overall
Baseline VS Full System	Baseline	20%	27%	24%	22%
	Equal	14%	11%	20%	14%
	Full System	66%	62%	56%	64%
	Winning difference	46% †	35% †	32% †	42% †
No Paraphrases VS Full System	No Paraphrases	29%	33%	29%	30%
	Equal	31%	26%	28%	27%
	Full System	40%	41%	43%	43%
	Winning difference	11% †	8% †	14% †	13% †

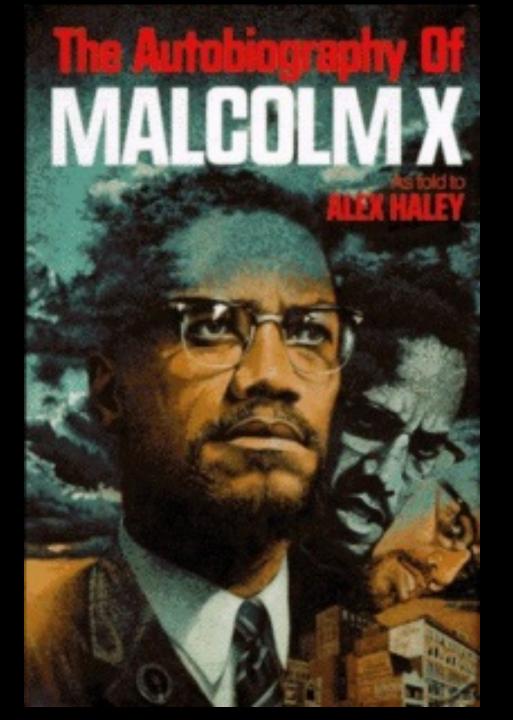
What's next?

Handling pronouns and other style questions

- Extending to other types of entities
- Developed similar approaches for explanation for machine learning

FACT News Wikipedia descriptions Personal narrative Social Media **Novels FICTION**









- Coherent telling of a story
- Compelling component

Monologue

Informal language

PERSONAL VIEWS





We were sitting down to a late dinner on Monday night when the storm was supposed to hit. It was incredibly windy but the rain really hadn't been that bad.



. . .

"By 10 p.m., the skies lit up in a purple and blue brilliance and the power started to go out here and there....That's when I noticed neighbors across the street running out of their homes and fire trucks racing down the block. I saw a trickle of steady water coming down the street on both sides and then water began pouring in through the creaks in the basement door, so my husband went to grab the pump. He went upstairs to get a tool and in those few seconds, ocean waves broke the steel door lock and flooded the basement 6 feet high in minutes."

We were sitting down to a late dinner on Monday night when the storm was supposed to hit. It was incredibly windy but the rain really had

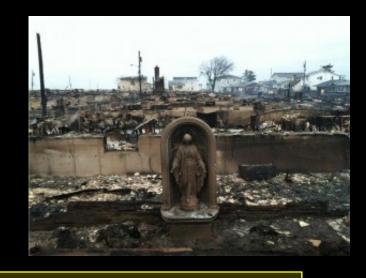
Background

• • •

"By 10 p.m., the skies lit up in a purple and blue brilliance and the power started to go out here and there....That's when I noticed neighbors across the street running out of their homes and fire trucks racing down the block. I saw a trickle of steady water coming down the street on both sides and then water began pouring in through the creaks in the basement door, so my husband went to grab the pump. He went upstairs to get a tool and in those few seconds, ocean waves broke the steel door lock and flooded the basement 6 feet high in minutes."

We were sitting down to a late dinner on Monday night when the storm was supposed to bit. It was incredibly windy Complicating in the been that bad.

action



"By 10 p.m., the skies lit up in a purple and blue brilliance and the power started to go out here and there....That's when I noticed neighbors across the street running out of their homes and fire trucks racing down the block. I saw a trickle of steady water coming down the street on both sides and then water began pouring in through the creaks in the basement door, so my husband went to grab the pump. He went upstairs to get a tool and in those few seconds, ocean waves broke the steel door lock and flooded the basement 6 feet high in minutes."

We were sitting down to a late dinner on Monday night when the storm was supposed to hit. It was incredibly windy but the rain really hadn't been that bad.



. . .

"By 10 p.m., the skies lit up in a purple and blue brilliance and the power started to go out here and there....That's when I noticed neighbors across the street running out of their homes

Reportable event

down the block. I saw a trickle of steady he street on both sides and then water bugh the creaks in the basement door, so my

nuspand went to grab the pump. He went upstairs to get a tool and in those few seconds, ocean waves broke the steel door lock and flooded the basement 6 feet high in minutes."



Identify the Reportable Event

Which sentence(s) convey the compelling event?

The reportable event could serve as a summary for "what is this story about?"

Data



- AskReddit subreddit: e.g., ``What's your creepiest real life story?"
 - **3000** stories
- Small amount manually labeled (seed)

 Large amount automatically labeled using distant supervision



Linguistic Theory

- Prince: stories about change
- Polanyi: turning point marked by change in formality, style, emphasis

 Labov: a change in verb tense often accompanies the MRE



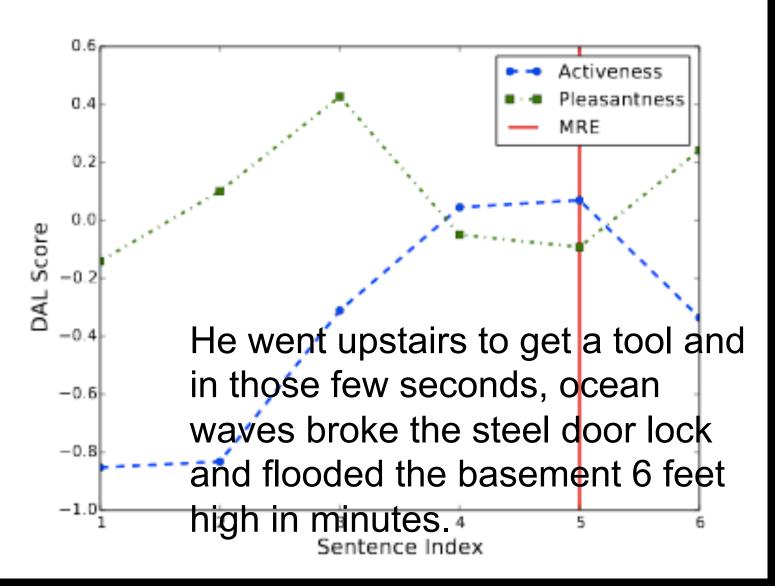
Sentence scores

- Syntactic: e.g., sentence length
- Semantic: similarity to surrounding sentences

Affect: pleasantness, activeness, imagery

Features: Change in Affect





What have we learned?



Change features are most effective

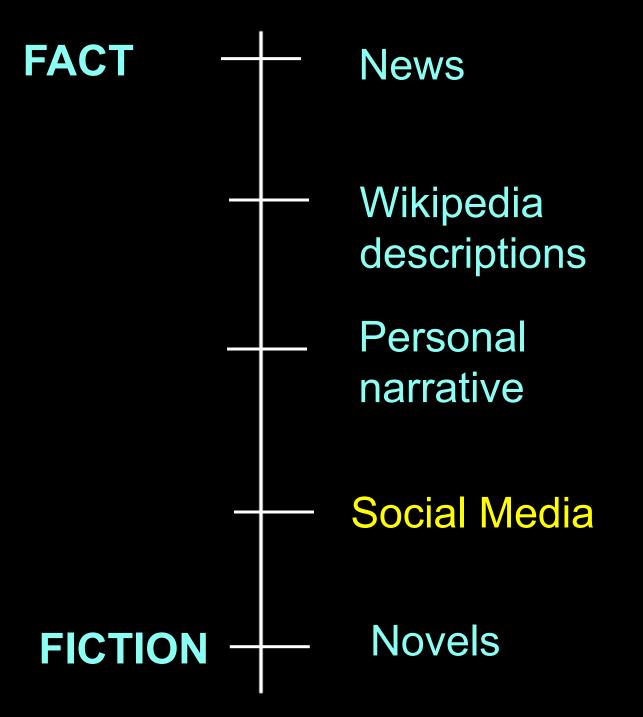
- How to use the data
 - Experimented with seed only (small), distant supervision (large but noisy) and self-training

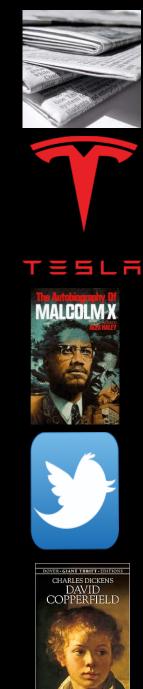
	Precision	Recall	F-measure
Seed only*	0.374	0.617	0.466
Dist. supervision*	0.398	0.745	0.519
Self-training*	0.478	0.946	0.635

What's next?

 Rewriting the extracted sentences for better summaries

 Browsing interface with summaries of different experiences





How is social media different

Informal

Slang.... Not the language of news!

Dialog

Each contribution short



Problem: The U.S. has the highest rate of firearm-related deaths when compared to other industrialized countries.

Violence particularly affects low-income, cities like Chicago, which had more than 3,000 shooting victims in 2015.



Gang Violence & Social Media





Can we automatically detect aggressive posts?





NO SURRENDER LIL B

@TyquanAssassin



Jst Brought A Crate Of Guns I'm on my way Thru Lamron shoot u n Whoeva nxt 2 u Nigga dats a And1

RETWEETS

LIKES

3

3













Approach



- Collaboration between social workers and natural language processing
- Annotation of tweets using "deep read" by social workers working with Chicago youth
 - Trigger events, triggered events, tone, meaning
- Used as labels for automatic prediction

Alert community outreach

Case Study



- Gakirah Barnes @TyquanAssassin
- Recently deceased gang member in Chicago
- ❖9 killings to her name until she was killed at the age of 17
- ***27,000 tweets from December 2011 to April 11,** 2014
- **❖~** 4,200 followers on Twitter

Themes That Emerge From Coding



Aggression

Insults, threats, bragging, hypervigilance, and challenges with authority.

Grief

Distress, sadness, loneliness, and death.

Other

General conversations between users, discussions about women, and tweets that represented happiness.

Qualitative Analysis

If We see a opp Fuck it We Gne smoke em 😈	Aggression (Threat)
Dnt get caught on Dat 800 block lame ass Lil niggas Betta take Dat Shyt on stony spot	Aggression (Insult)
Young niggas still getting shot babies still dying 🙏	Loss



Natural Language Tools

- Part of speech tagger
 - Supervised machine learning plus domain adaptation
 - Semantic clusters plus character ngrams
- Bilingual dictionary
 - Glossed tweets into standard American
 English and automatically aligned
 - "smoke" -> "kill"



Aggression/Loss Classifier

- Emotion lexicon
 - Scores words according to their affect

- Part-of-speech tags
- Bilingual lexicon

F-measure: 63%

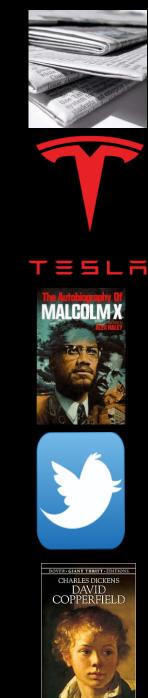
What have we learned?

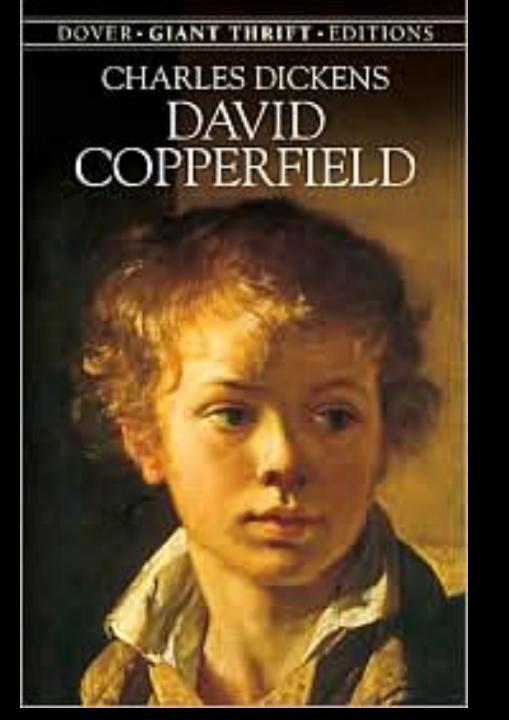
Need collaboration to make progress

Context essential to annotation

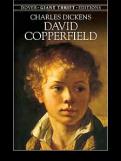
Next steps: generating explanation of prediction

FACT News Wikipedia descriptions Personal narrative Social Media **Novels FICTION**





Novels



It was broad day—eight or nine o'clock; the storm raging, in lieu of the batteries; and someone knocking and calling at my door.

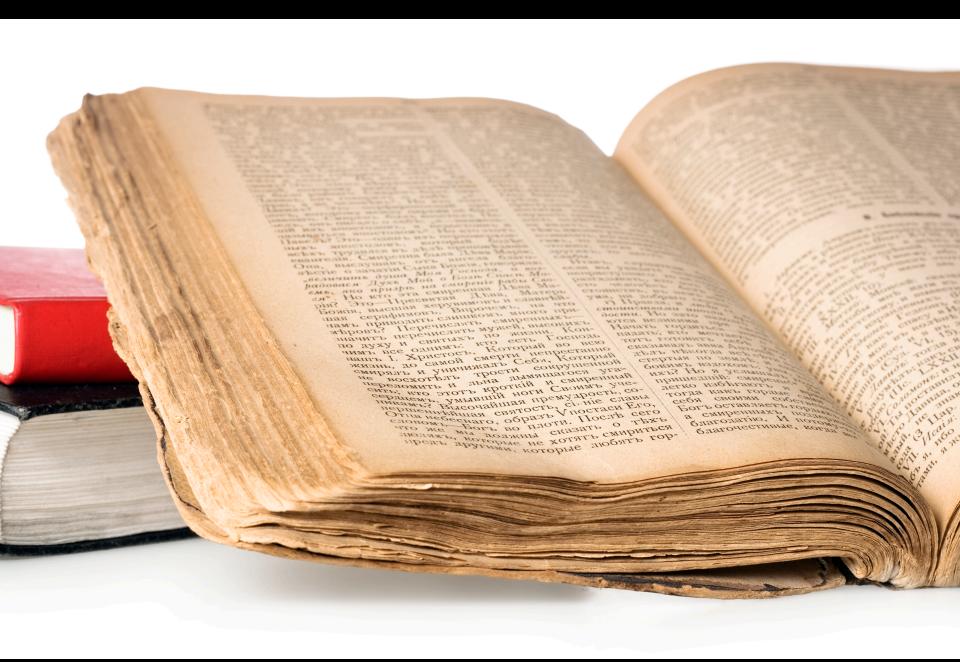
'What is the matter?' I cried.

'A wreck! Close by!'

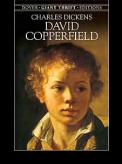
I sprung out of bed, and asked, what wreck?

'A schooner, from Spain or Portugal, laden with fruit and wine. Make haste, sir, if you want to see her! ...'

Dickens, David Copperfield

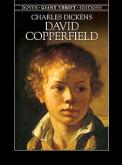


Computer Science and Comparative Literature



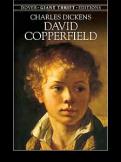
- Provide evidence for or against literary theory
- Social network extraction from literature
 - Corpus of 19th Century British literature
 - Network based on conversation
- Method based on quoted speech
 - Identify who talks to whom
 - Extract graph features that evaluate hypotheses

Hypothesis #1



- Larger conversational networks (with more people) tend to be less connected
 - Franco Moretti: : at 10 or 20 characters, possible to include "distant and openly hostile groups"
 - Terry Eagleton: in a large community, "most of our encounters consist of seeing rather than speaking, glimpsing each other as objects rather than conversing as fellow subjects"
- Can we show empirically that conversational networks with fewer people are more closely connected?





- Nodes = people who said something
 - Quote attribution with 83% accuracy
- Edges = people who are talking to each other
 - Quote adjacency used as heuristic for detecting conversations
 - Edge weight set to share of detected conversation
 - 95% precision, 51% recall





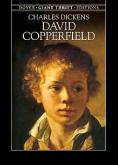
- As the number of named characters increases, we expect:
 - Same or less total speech
 - Weak yes: Normalized number of quotes flat at r=.16
 - Less lopsided distribution of quotes among speakers
 - Yes: Share of quotes by top 3 speakers decreases at r=-.61





- As the number of named characters increases, we expect:
 - Lower density (fewer conversational partners as percentage of population)
 - No: Increases at r=.30. Larger networks are more connected
 - Same or fewer cliques
 - No: 3-clique rate increases at r=.38. Larger networks form cliques more often





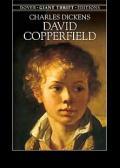
- As the number of speakers increases, we expect:
 - Less overall dialogue ("glimpsing rather than speaking")
 - No: Increases at .50. Larger networks are more talkative
 - Lower density
 - No: Increases at .49. In larger networks, people know more of their neighbors

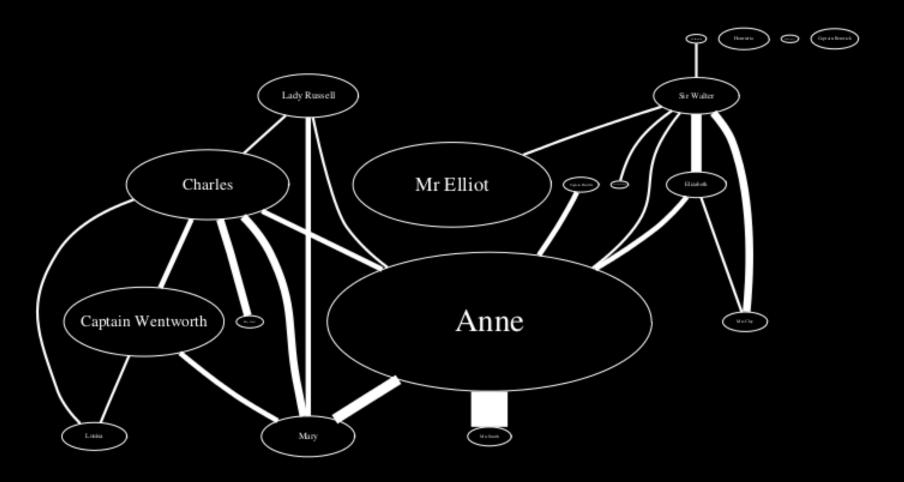
Alternate Explanation

- DOVER-GIANT THRUST-EDITIONS
 CHARLES DICKENS
 DAVID
 COPPERFIELD
- Text perspective dominates network shape
 - 3rd person tellings: Significant increases in
 - Normalized number of quotes (p<.05)
 - Average degree (p<.005)</p>
 - Graph density (p<.05)</p>
 - Rate of 3-cliques (p<.005)</p>
 - ...With no significant difference in number of characters or speakers
 - Hypothesis: First-person narrators not privy to other characters' conversations with each other

3rd Person Narrative

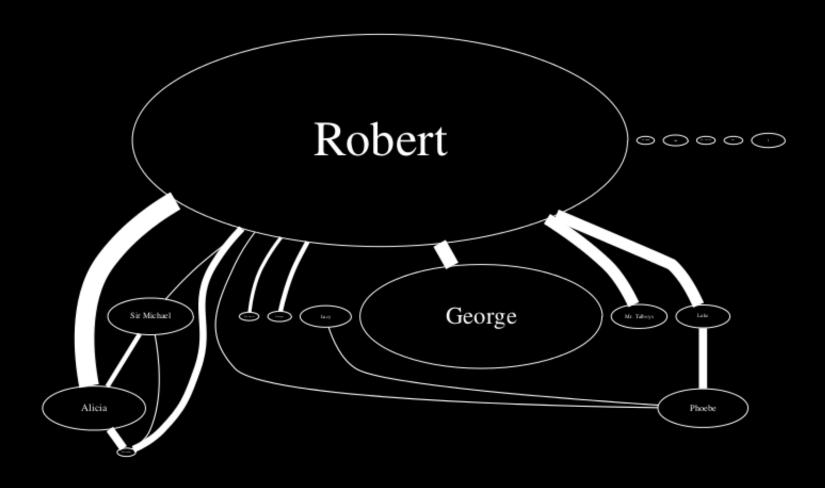
(Austen, Persuasion)



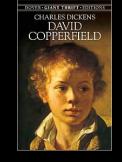


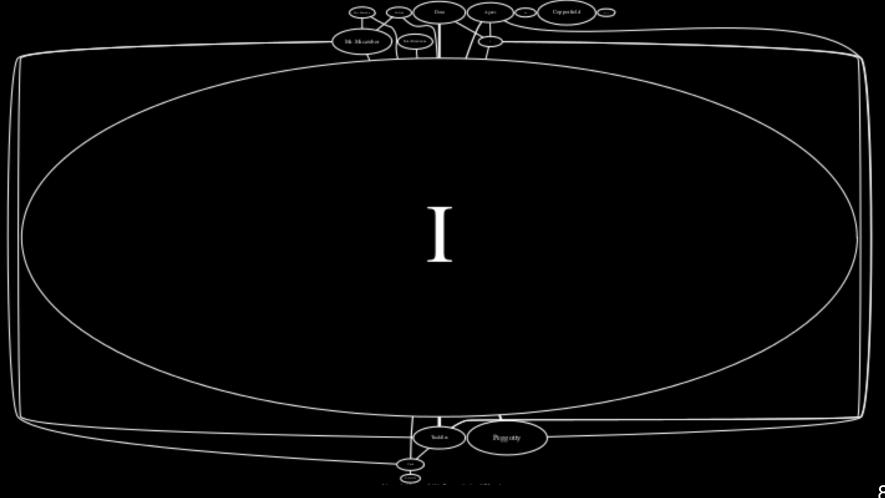
"Close 3rd" Narrative (Braddon, Lady Audley's Secret)





1st Person Narrative (Dickens, David Copperfield)



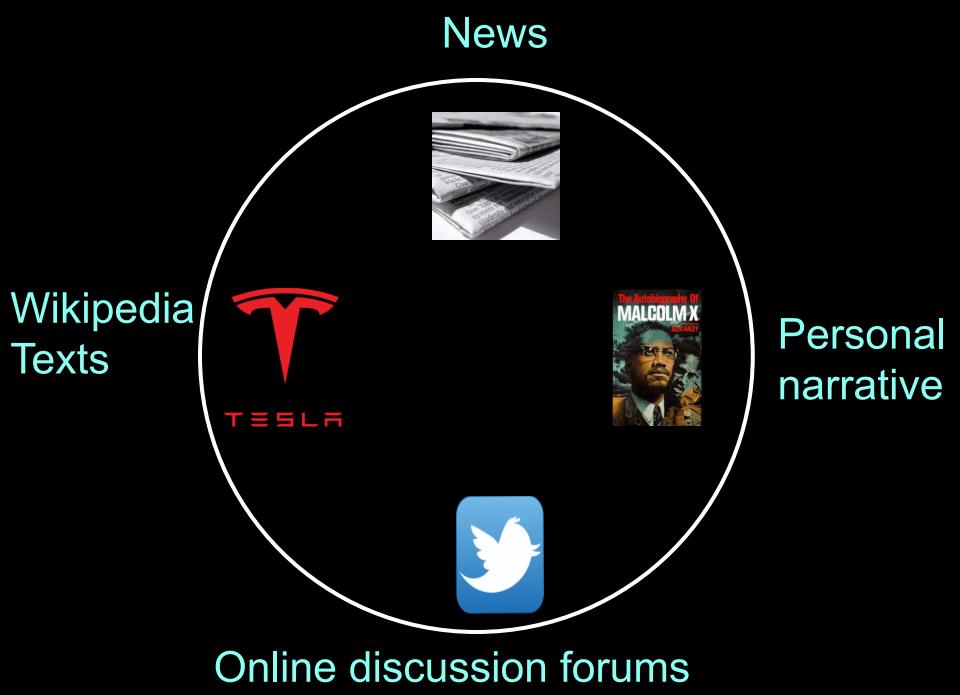


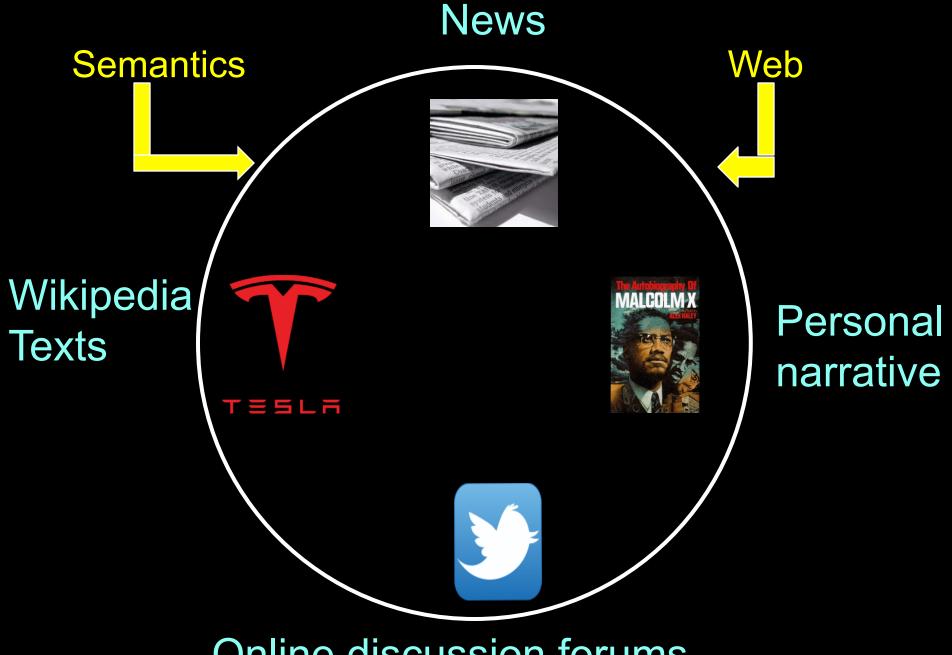
What have We Learned?

 High-precision conversational networks can be extracted from literature

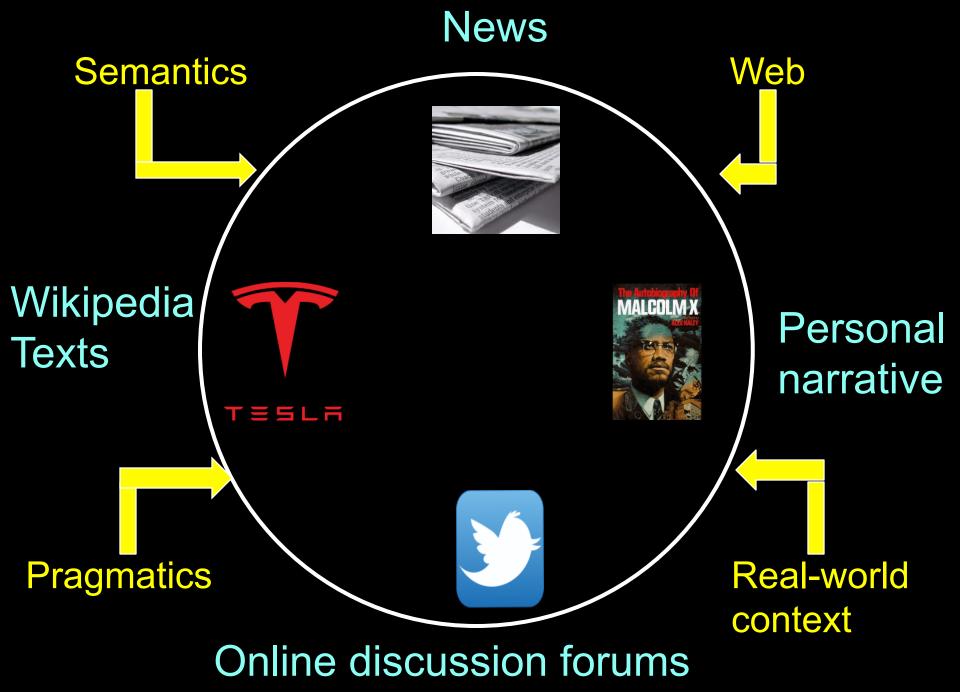
Time is right for exploring analysis of fiction

What might we have overlooked? Working now on detection of scene changes





Online discussion forums



Current PhD Students



Or Biran



Noura Farra



Chris Hidey



Chris Kedzie



Jessica Ouyang



Melody Ju





Fei-Tzin Lee Elsbeth Turcan

Past Students



















Regina Barzilay

Sasha Blair- Andrea Goldensohn Danyluk

Galina
Datskovsky
Moerdler

Pablo Duboue

Michael Elhadad

Noemie Elhadad

David Elson

David Evans



















Elena Filatova

Pascale Fung

Michael Galley

Vasileios H Hatzivassiloglou

Hongyan ou Jing

Min Yen Kan

Ani Nenkova

Shimei Pan

Cecile Paris



















Kristen Parton

Dragomir Radev

Jacques Robin







Eric Siegel

Frank Smadja

Ursula Wolz



Weiyun Ma



Yves Petinot



Sara Rosenthal



Kapil Thadani

Thank You!

The research presented here has been supported in part by DARPA and NSF.