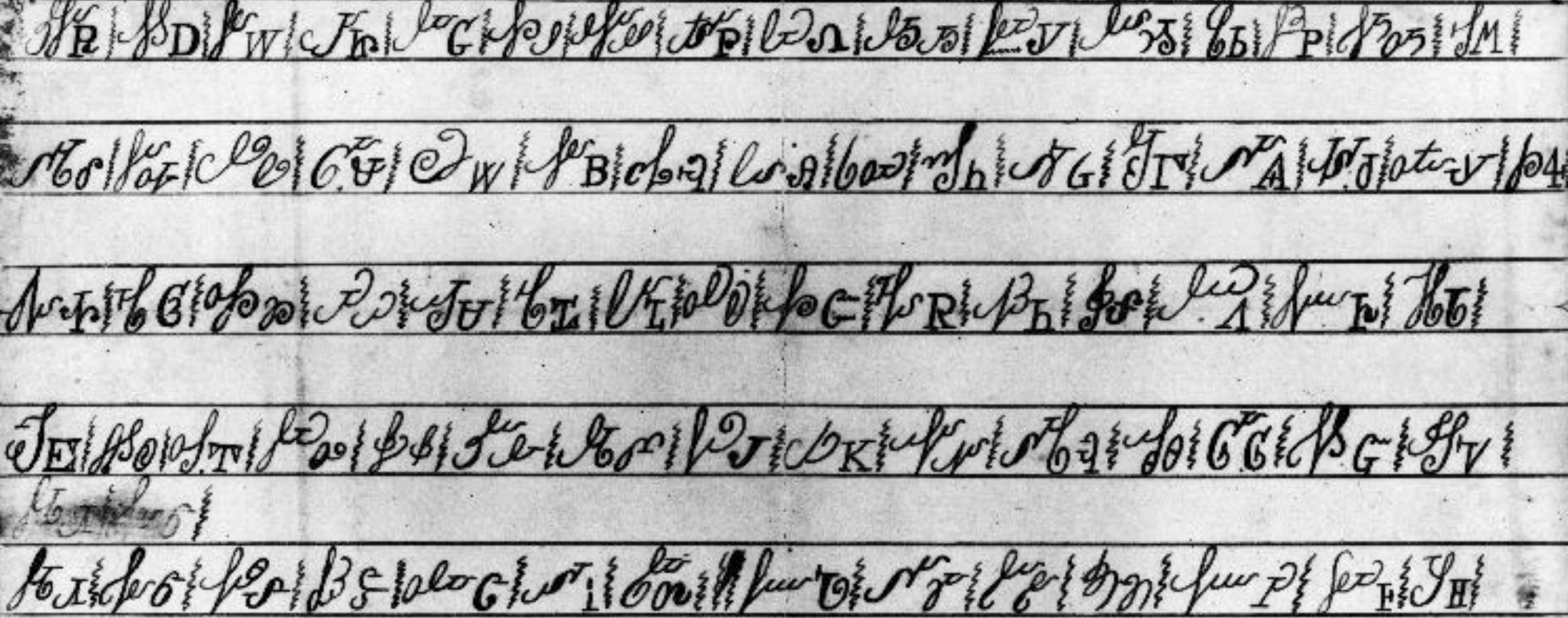




Natural Language Processing

Info 159/259

Lecture 25: Social NLP (April 23, 2020)

David Bamman, UC Berkeley

great



We are met on a great battle-field of that war.

Four score and seven years ago our fathers brought forth on this continent, a new nation, conceived in Liberty, and dedicated to the proposition that all men are created equal. Now we are engaged in a great civil war, testing whether that nation, or any nation so conceived and so dedicated, can long endure. **We are met on a great battle-field of that war.** We have come to dedicate a portion of that field, as a final resting place for those who here gave their lives that that nation might live. It is altogether fitting and proper that we should do this. But, in a larger sense, we can not dedicate -- we can not consecrate -- we can not hallow -- this ground. The brave men, living and dead, who struggled here, have consecrated it, far above our poor power to add or detract. The world will little note, nor long remember what we say here, but it can never forget what they did here. It is for us the living, rather, to be dedicated here to the unfinished work which they who fought here have thus far so nobly advanced. It is rather for us to be here dedicated to the great task remaining before us -- that from these honored dead we take increased devotion to that cause for which they gave the last full measure of devotion -- that we here highly resolve that these dead shall not have died in vain -- that this nation, under God, shall have a new birth of freedom -- and that government of the people, by the people, for the people, shall not perish from the earth.

Social NLP

- Social NLP covers a range of applications that analyze how language interacts with people in social settings.
- We leave behavioral **traces** in our interactions with others.
 - Tweets
 - Books
 - Emails
 - Audio transcripts

Twitter

Edit profile

David Bamman
@dbamman

Assistant Professor, School of Information, UC Berkeley. Natural language processing, machine learning, computational social science, digital humanities.

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📅 Joined October 2009

628 Following **2,863** Followers

Tweets Tweets & replies Media Likes

**David Bamman** @dbamman · 25m

Re-reading "Narrative Paths and Negotiation of Power in Birth Stories" (CSCW 2019) by [@maria_antoniak](#) [@dmimno](#) [@karen_ec_levy](#) to teach in my NLP class tomorrow, and I'm reminded what amazing work it is maria-antoniak.github.io/resources/2019...

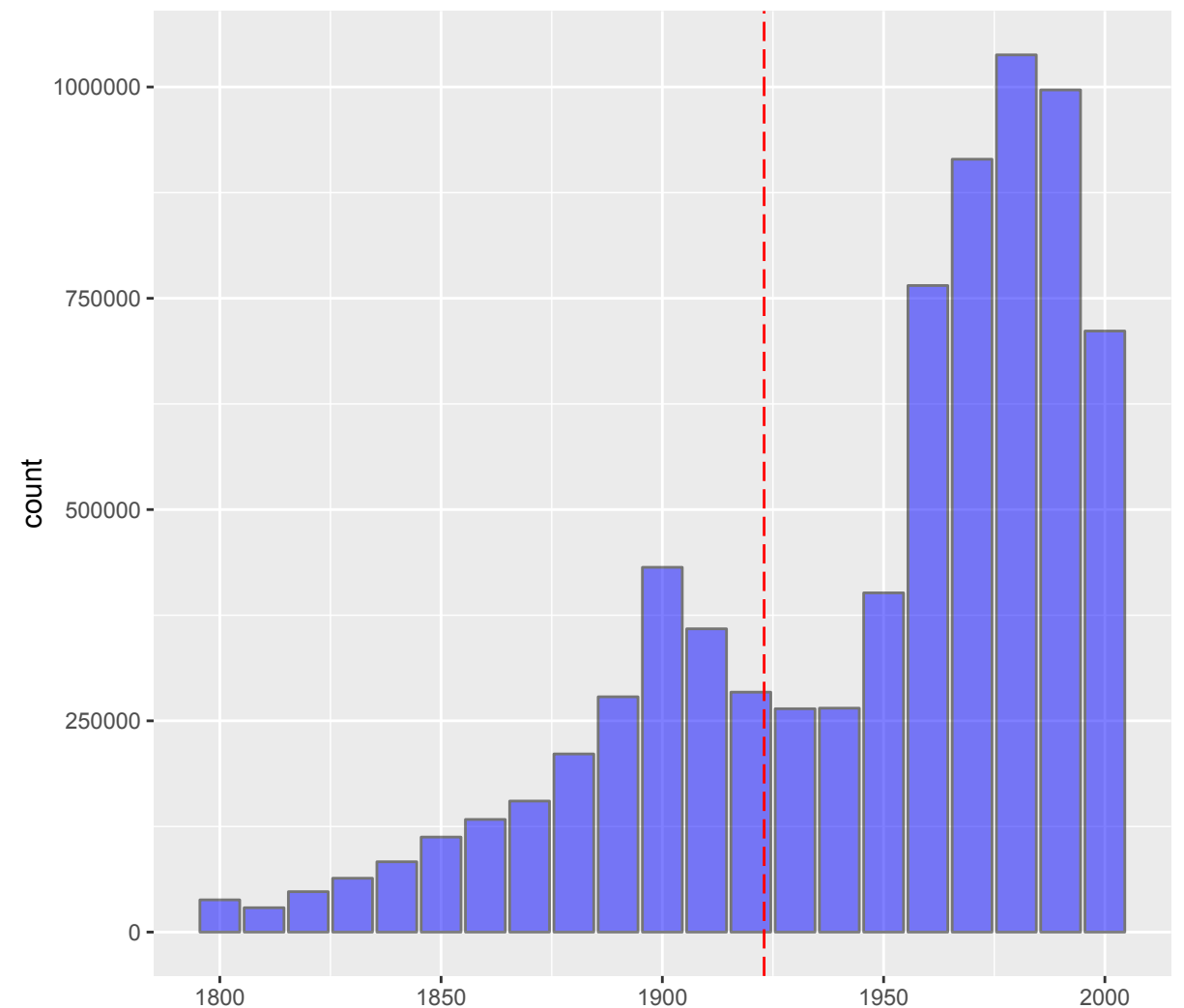
💬 1 ↻ ❤️ 10 📤 ⋮

↻ You Retweeted

**J. Stephen Downie** @profdownie · Apr 10

DH colleagues: The HathiTrust Research Center's Advanced Collaborative Support (ACS) program is a great way to do a deep analytic dive into the HT's fantastic corpus (over 6 billion pages!). Definitely worthy of checking out.

Data

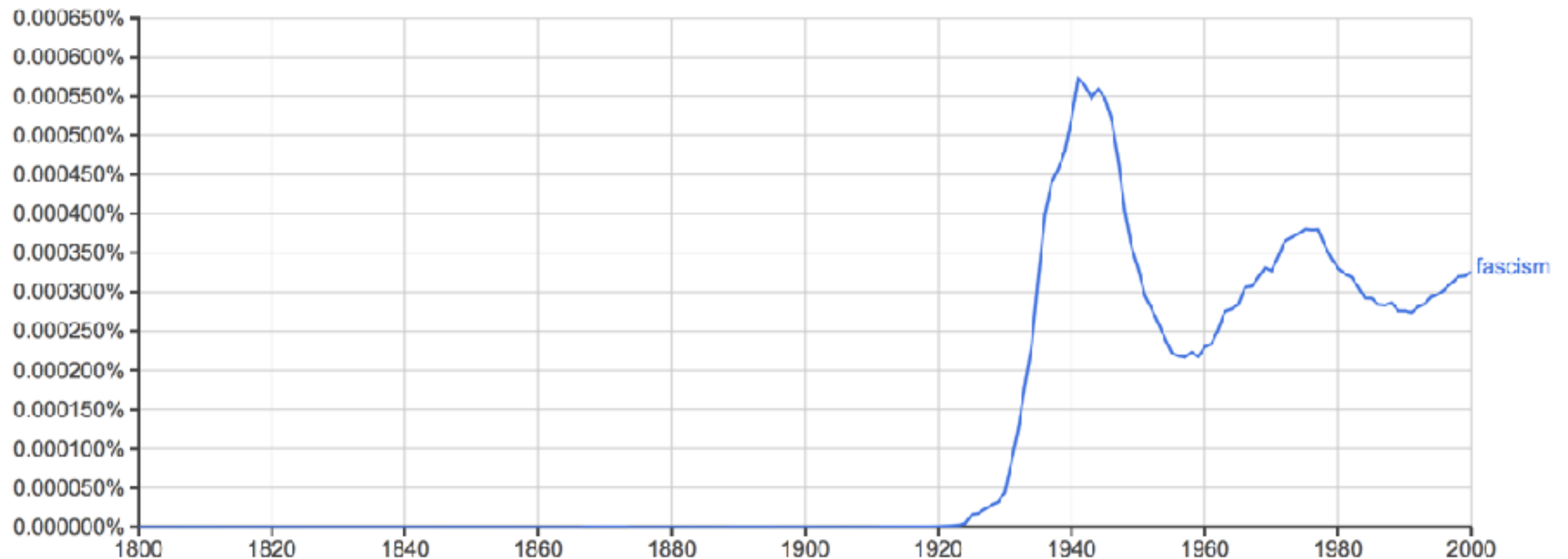


HathiTrust: 14.8M books; 5.7M in the public domain

Affordances

Large-scale analysis of culture

(*as recorded in published books, with university library accession policies)

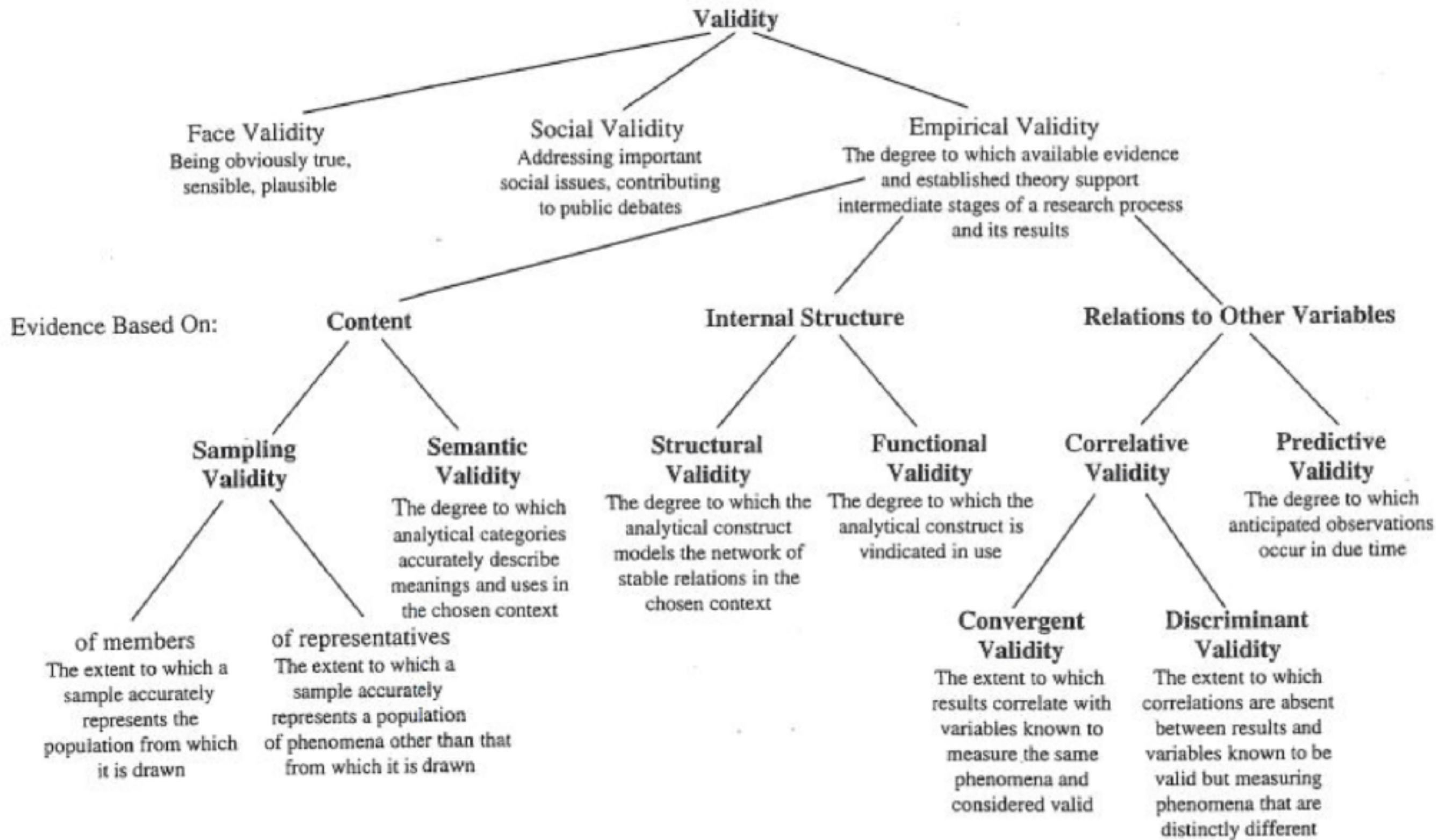


“Raw” data

- Social NLP often makes **claims** about the world using textual data.
- Data is not self-evident, neutral or objective
- Data is collected, stored, processed, mined, interpreted; each stage requires our **participation**.
- What is the **process** by which the data you have got to you?

Data Collection

- Data → Research Question
 - “Opportunistic data”
 - Research questions are shaped by what data you can find
- Research Question → Data
 - Research is driven by questions, find data to support answering it.



Social NLP

- What are the research questions that we can ask when applying NLP to text to answer **social** and **cultural** questions?
- How do we answer those research questions using methods we've learned about?
 - data
 - algorithms
 - evaluation

Social NLP

- Manifestations of **power** in text
- Inferring **social networks** from text
- Measuring **respect**
- Examining **gender bias** in novels
- Asking for a **favor**
- Discovering structure in **birth stories**

Power

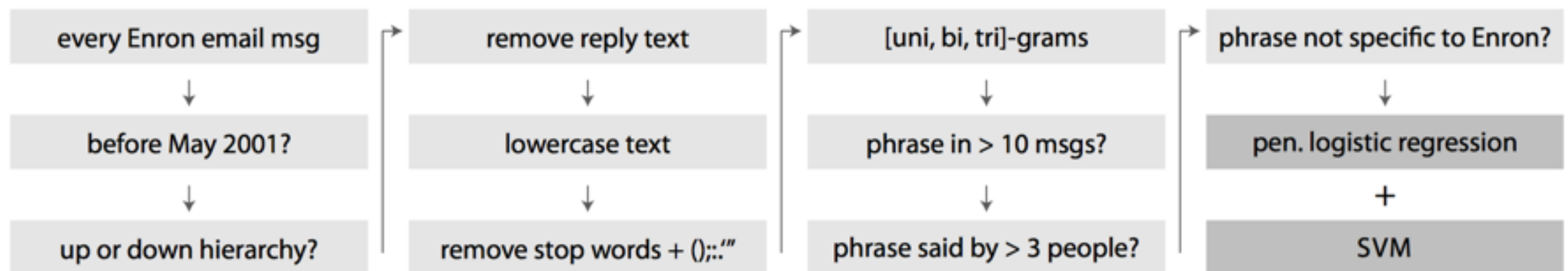
How is **power** manifested in language?

Power

- Text data: Enron emails
- Response: Enron org chart — for all pairs of entities in email (sender/recipients), who is higher on the org chart?

Power

- **Bag of words** representation of text + binary classification.



Gilbert 2012 ("Phrases that signal workplace hierarchy")

these predict message going up

not going up

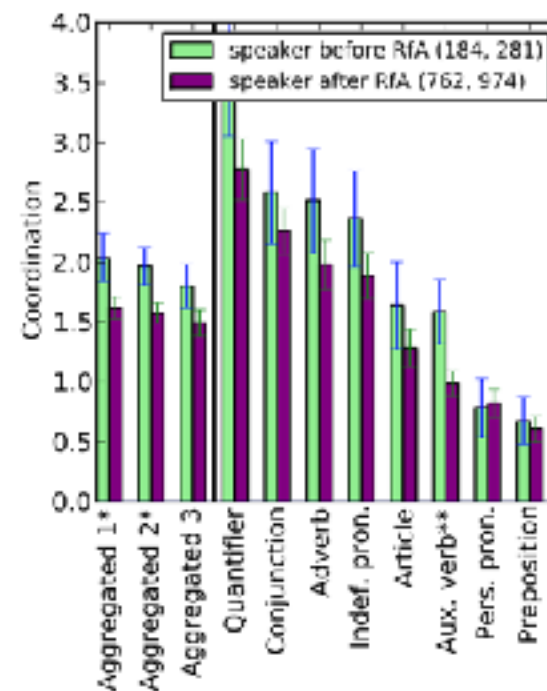
$\uparrow$ phrases	β	$\uparrow$ phrases	β	$\leftrightarrow\downarrow$ phrases	β	$\leftrightarrow\downarrow$ phrases	β
the ability to	6.76	attach	6.72	have you been	-8.46	to manage the	-6.66
I took	6.57	that we might	6.54	you gave	-6.64	let's discuss	-5.72
are available	6.52	the calendar	6.06	we are in	-5.44	publicly	-5.24
kitchen	5.72	can you get	5.72	title	-5.05	promotion	-5.02
thought you would	5.65	driving	5.61	need in	-4.80	good one	-4.62
, I'll be	5.51	thoughts on	5.51	opened	-4.57	determine the	-4.47
looks fine	5.50	shit	5.45	initiatives	-4.38	is difficult	-4.36
voicemail	5.43	we can talk	5.41	. I would	-4.34	man	-4.26
tremendous	5.27	it does	5.21	we will probably	-4.12	number we	-4.11
will you	5.17	involving	5.15	any comments	-4.06	contact you	-4.05
left a	5.07	the report	5.04	you said	-3.99	the problem is	-3.97
I put	4.90	please change	4.88	I left	-3.88	you did	-3.78
you ever	4.80	Issues I	4.76	can you help	-3.68	cool	-3.54
I'll give	4.69	Is really	4.65	send this	-3.47	your attention	-3.44
okay,	4.60	your review	4.56	whether we	-3.44	to think	-3.44
to send it	4.48	europe	4.45	the trade	-3.40	addition to the	-3.30
communications	4.38	weekend.	4.35	and I thought	-3.28	great thanks	-3.24
a message	4.35	have our	4.33	should include	-3.19	selected	-3.16
one I	4.28	interviews	4.28	please send	-3.14	ext	-3.13
can I get	4.28	you mean	4.26	existing	-3.06	and let me	-3.05
worksheet	4.15	haven't been	4.10	mondays	-3.02	security	-3.01
liked	4.07	me . 1	4.07	presentation on	-2.95	got the	-2.94
I gave you	3.95	tiger	3.94	let's talk	-2.94	get your	-2.88
credit will	3.88	change in	3.88	the items	-2.78	this week and	-2.77
you make	3.86	item	3.84	i hope you	-2.77	team that	-2.75
together and	3.82	a decision	3.82	did it	-2.75	a deal	-2.71
have presented	3.78	a discussion	3.74	test	-2.69	yours .	-2.68
think about	3.71	sounds good	3.65	be sure	-2.65	briefing	-2.60

Power

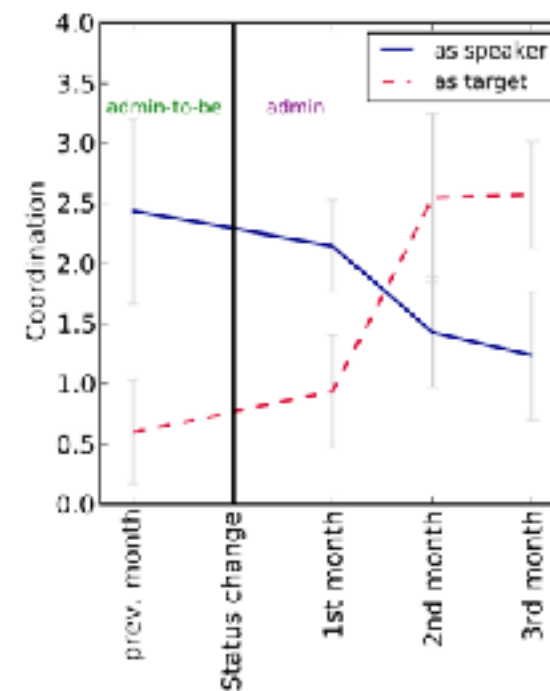
- Text data: Wikipedia discussions, SCOTUS arguments
- Response: Wikipedia admins/non-admins; SCOTUS justices/lawyers

Power

- LIWC representation of text + measurements of accommodation (adapting your speech to the language of your interlocutor)



(a) Supporting $\mathcal{P}'_{speaker}$



(b) Timed effect of status change ($\mathcal{P}$)

Networks

Can we learn a social network from mentions in text?

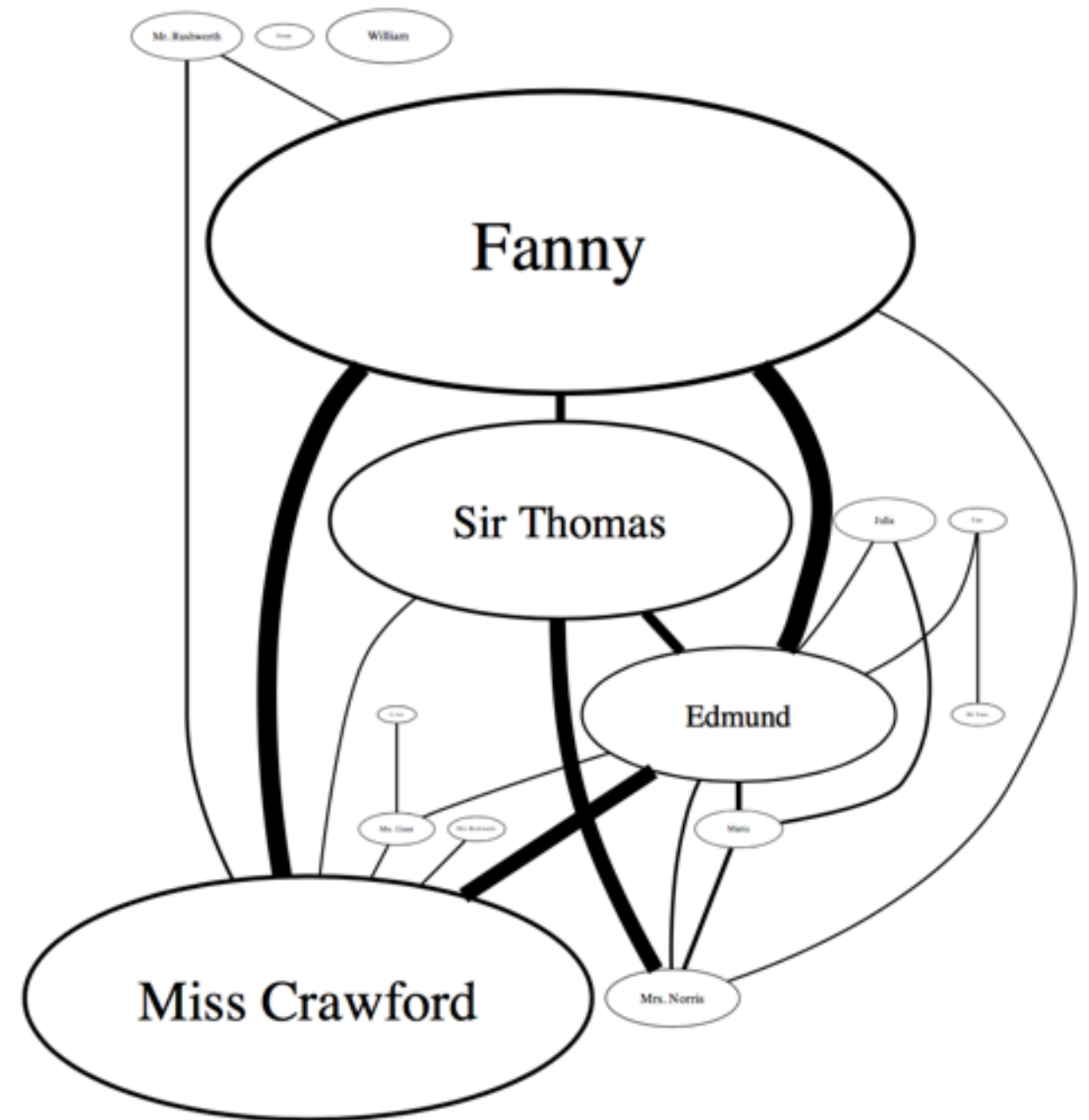
Networks

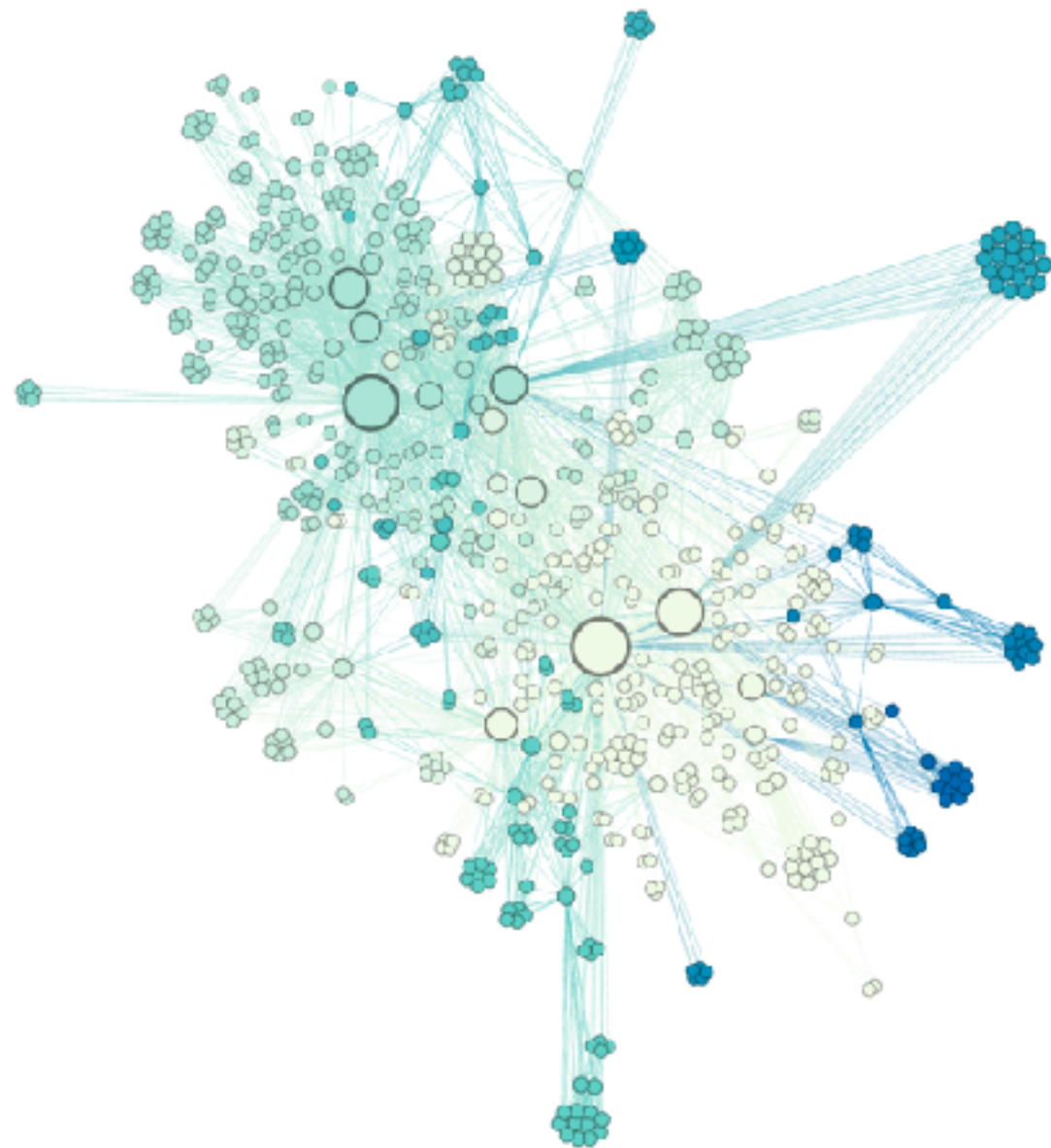
- Data: 60 novels from Project Gutenberg
- Conversational network:
 - Characters are in the same place at the same time
 - Characters take turns speaking
 - The characters are mutually aware of each other and each character's speech is mutually intended for the other to hear.

Networks

- Alias clustering: Tom, Tom Sawyer, Mr. Saywer = TOM SAWYER)
- Quoted speech attribution (“Yes,” said TOM SAWYER)
- Network construction
 - Divide book into 10-paragraph sections, count number of sections with two characters
 - Count occurrences of one character mentioning another in dialogue

Networks

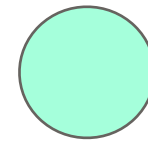
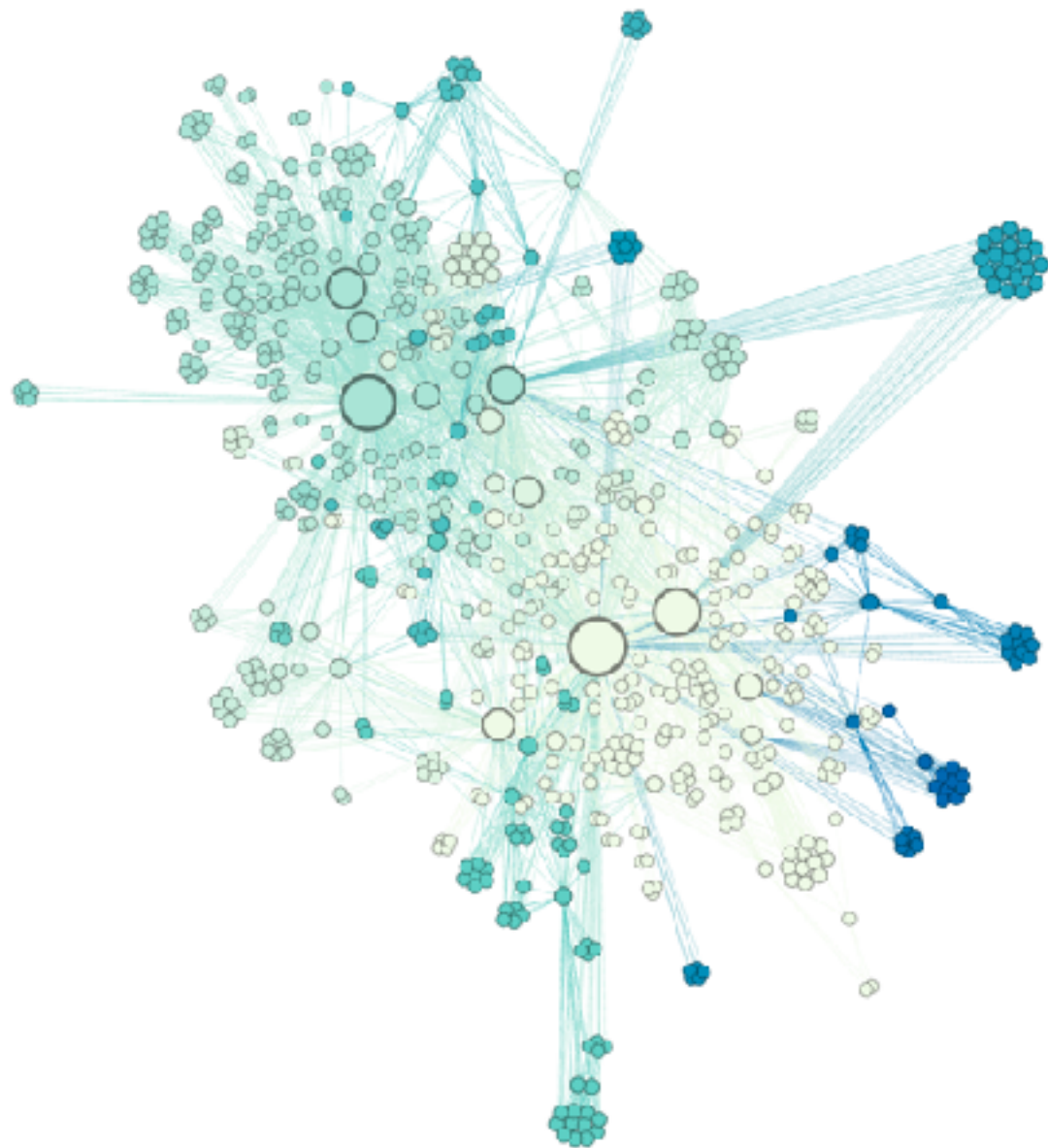




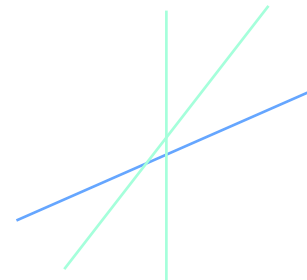
How does information
propagate through
implicit social networks?

Sims and Bamman (2020), "Information Propagation in Literary Social Networks"

Great Expectations

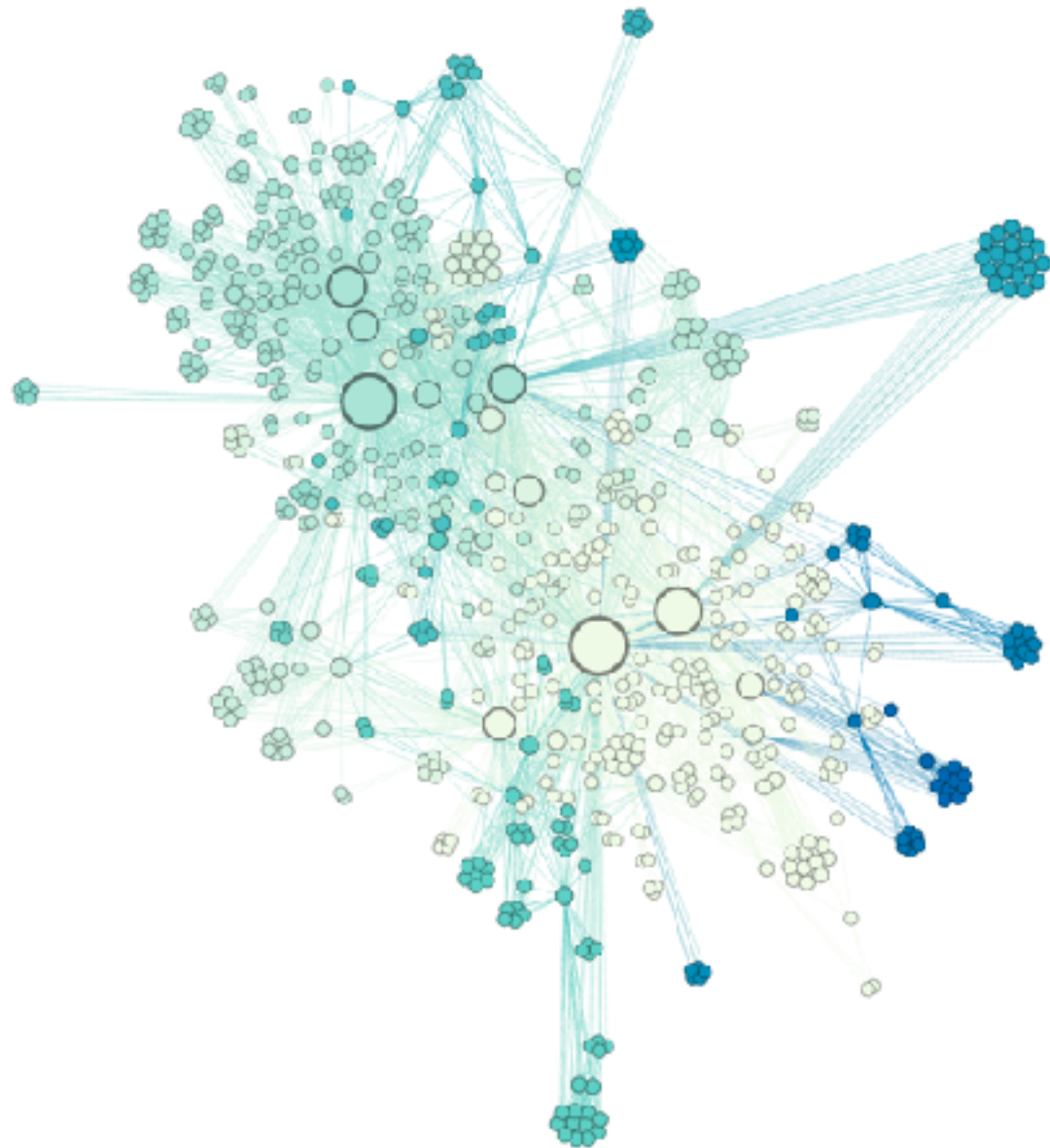


= Character



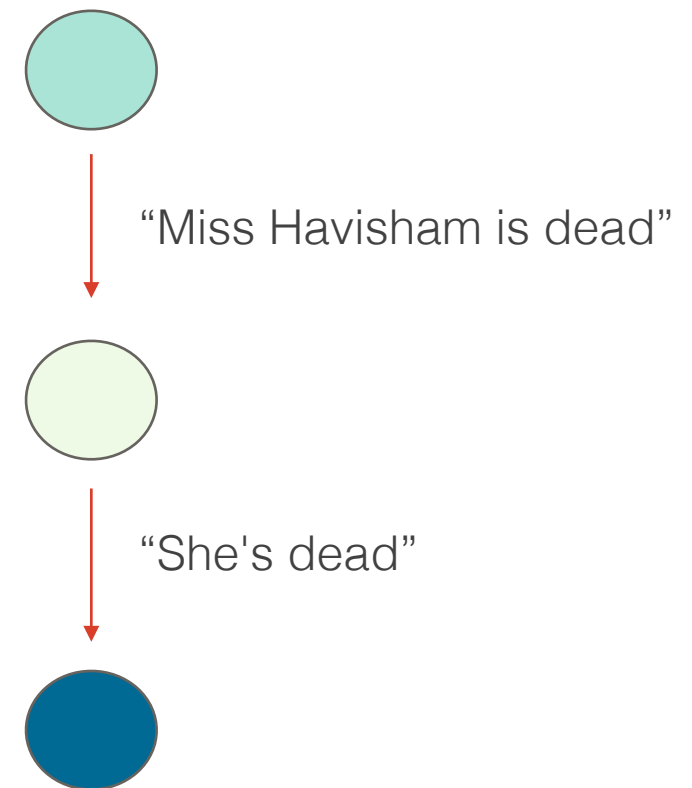
= Conversational
Interaction

Great Expectations



Information = Quoted Speech
e.g.,
“Miss Havisham is dead”

Propagation = Repetition of information
across a character triad



Research question

What are the structural properties of **information-propagating** nodes in fiction?

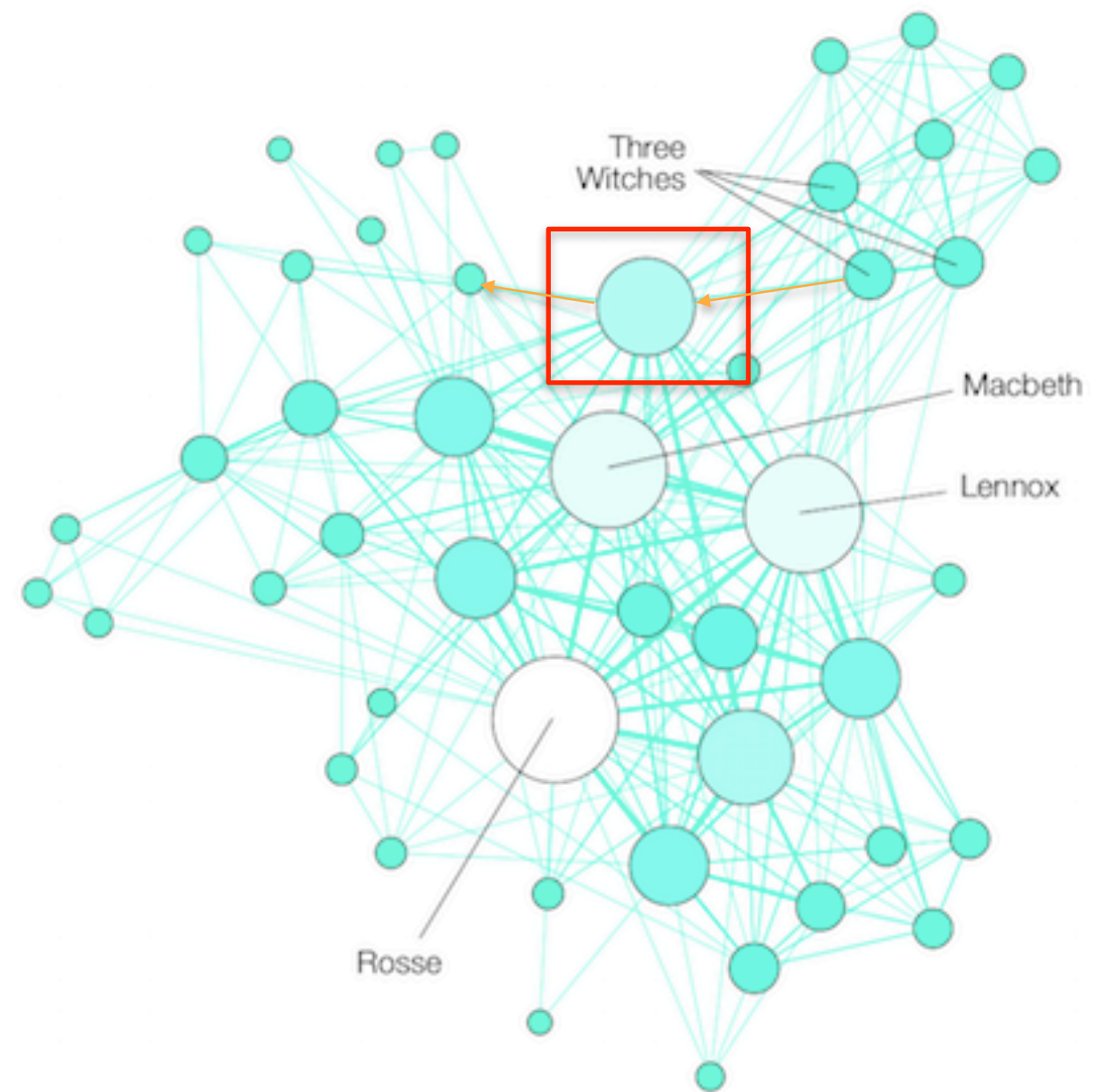
- “Gossip” among close friends, family, etc.: nodes that circulate information among densely-connected strong ties.
- **Information bridges**: nodes that pass information between otherwise disconnected communities.

- “Gossip” among close friends, family, etc.: nodes that circulate information among densely-connected strong ties.



Macbeth

- Information bridges: nodes that pass information between otherwise disconnected communities.



Macbeth

NLP Pipeline

What are the structural properties of **information-propagating** nodes in fiction?



Propagation



“The wicked witch is dead”

Propagation



“You’ll never guess what happened to the wicked witch... she’s dead”

Propagation



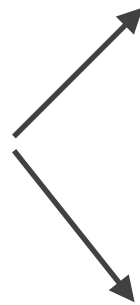
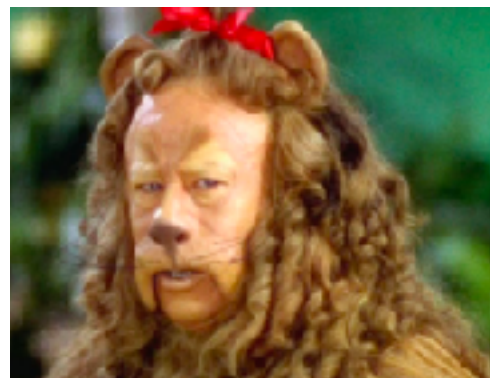
“You’ll never guess what happened to the wicked witch... she’s dead”

Propagation

A Node



B Nodes



Propagation

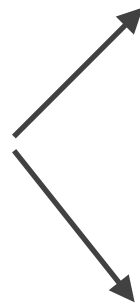
A Node



B Nodes



C Node



Propagation

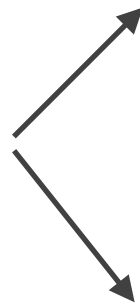
A Node



B Nodes



C Node

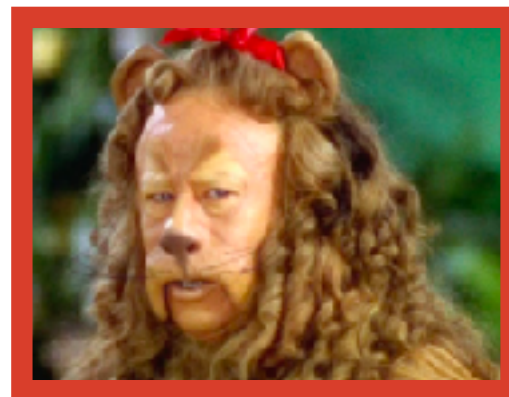


Propagation

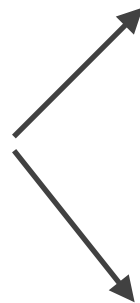
A Node



B Nodes

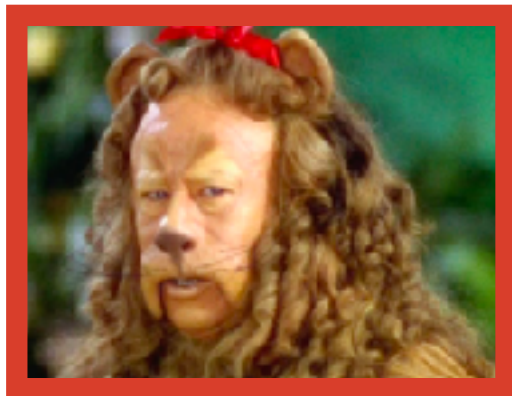


C Node



Network Measures

B Nodes



- Betweenness Centrality
 - Effective Size
 - Efficiency
-
- Degree Centrality
 - Average Neighbor Degree
 - Number of Triangles

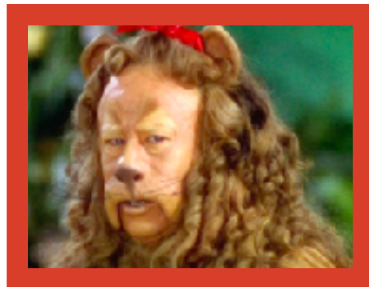
Information bridges

Modeling

B Nodes



x 3200



x 3200

- Use logistic regression to identify which node measures are meaningful
- Contextualize results to determine the network dynamics that are most integral to information propagation in literary fiction

Feature Coefficients

Graph Measure	Model Coefficient	P-value < .01
Effective Size	11.6	*
Efficiency	3.8	*
Betweenness Centrality	2.3	*
Degree Centrality	-0.4	
Triangles	-6.2	*
Average Neighbor Degree	-9.5	*

Respect

- Data: transcripts of 981 OPD traffic stops (everyday interactions)
- Response: race

Respect

- Present one dialogue turn (police/driver) to be rated by people for respect (4-point Likert scale). High IAA.
- Build a predictive model mapping text to respect.

Feature Name	Implementation
Adverbial "Just"	"Just" occurs in a dependency arc as the head of an advmod relation
Apologizing	Lexicon: "sorry", "oops", "woops", "excuse me", "forgive me", "apologies", "apologize", "my bad", "my fault"
Ask for Agency	Lexicon: "do me a favor", "let me", "allow me", "can i", "should i", "may i", "might i", "could i"
Bald Command	The first word in a sentence is a bare verb with part-of-speech tag VB ("look", "give", "wait" etc.) but is not one of "be", "do", "have", "thank", "please", "hang".
Colloquialism	Regular expression capturing "y'all", "ain't" and words ending in "in'" such as "walkin'", "talkin'", etc., as marked by transcribers
Conditional	Lexicon: "if"
Disfluency	Word fragment ("Well I thi-") as indicated by transcribers
Filled Pauses	Lexicon: "um", "uh"
First Names	Top 1000 most common first names from the 1990 US Census, where first letter is capitalized in transcript
Formal Titles	Lexicon: "sir", "ma'am", "maam", "mister", "mr*", "ms*", "madam", "miss", "gentleman", "lady"
For Me	Lexicon: "for me"
For You	Lexicon: "for you"
Give Agency	Lexicon: "let you", "allow you", "you can", "you may", "you could"
Gratitude	Lexicon: "thank", "thanks", "appreciate"
Goodbye	Lexicon: "goodbye", "bye", "see you later"
Hands on the Wheel	Regular expression capturing cases like "keep your hands on the wheel" and "leave your hands where I can see them": "hands? ([,?!:;]+)?(wheel see)"

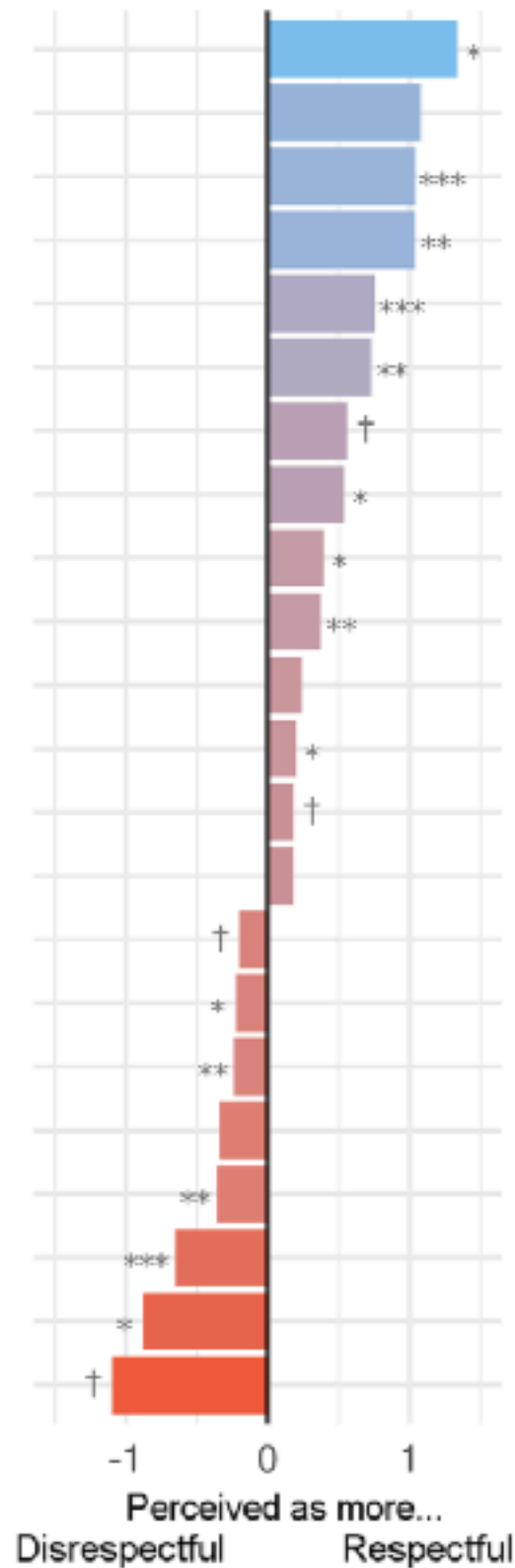
Voigt et al. 2017, "Language from police body camera footage shows racial disparities in officer respect"

Hedges	All words in the "Tentat" LIWC lexicon
Impersonal Pronoun	All words in the "Imppron" LIWC lexicon
Informal Titles	Lexicon: "dude*", "bro*", "boss", "bud", "buddy", "champ", "man", "guy*", "guy", "brotha", "sista", "son", "sonny", "chief"
Introductions	Regular expression capturing cases like "I'm Officer [name] from the OPD" and "How's it going?": "((i my name).+officer officer.+(oakland opd)) ((hi hello hey good afternoon good morning good evening how are you doing how 's it going))"
Last Names	Top 5000 most common last names from the 1990 US Census, where first letter is capitalized in transcript
Linguistic Negation	All words in the "Negate" LIWC lexicon
Negative Words	All words in the "Negativ" category in the Harvard General Inquirer, matching on word lemmas
Positive Words	All words in the "Positiv" category in the Harvard General Inquirer, matching on word lemmas
Please	Lexicon: "please"
Questions	Occurrence of a question mark
Reassurance	Lexicon: "'s okay", "n't worry", "no big deal", "no problem", "no worries", "'s fine", "you 're good", "is fine", "is okay"
Safety	Regular expression for all words beginning with the prefix "safe", such as "safe", "safety", "safely"
Swear Words	All words in the "Swear" LIWC lexicon
Tag Question	Regular expression capturing cases like "..., right?" and "..., don't you?": ", (((all right right okay yeah please you know)(sir ma'am miss son)?) ((are is do can have will won't) (n't)?(i me she us we you he they them))) [?]"
The Reason for the Stop	Lexicon: "reason", "stop* you", "pull* you", "why i", "why we", "explain", "so you understand"
Time Minimizing	Regular expression capturing cases like "in a minute" and "let's get this done quick": "(a one a few) (minute min second sec moment)s? this[+,.?!]+quick right back"

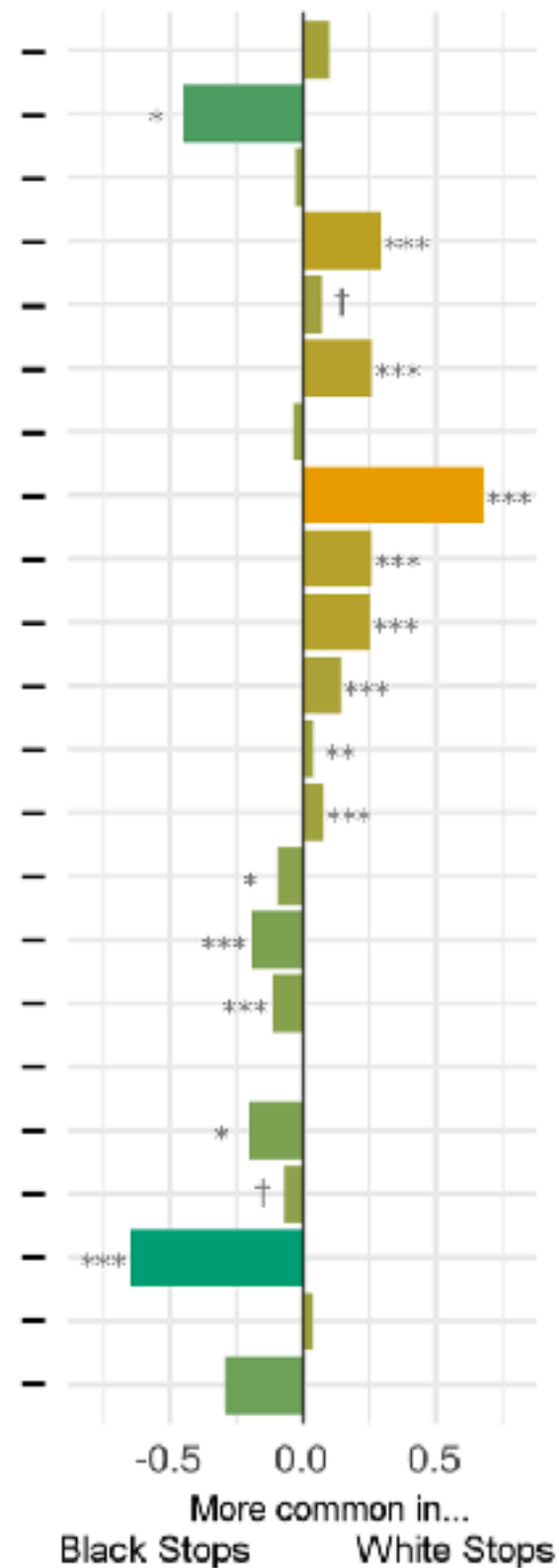
Respect

EXAMPLE	RESPECT SCORE
FIRST NAME ASK FOR AGENCY QUESTIONS [name], can I see that driver's license again? It- it's showing suspended. Is that- that's you? DISFLUENCY NEGATIVE WORD DISFLUENCY	-1.07
INFORMAL TITLE ASK FOR AGENCY ADVERBIAL "JUST" All right, my man. Do me a favor. Just keep your hands on the steering wheel real quick. "HANDS ON THE WHEEL"	-0.51
APOLOGY INTRODUCTION LAST NAME Sorry to stop you. My name's Officer [name] with the Police Department.	0.84
FORMAL TITLE SAFETY PLEASE There you go, ma'am. Drive safe, please.	1.21
ADVERBIAL "JUST" FILLED PAUSE REASSURANCE It just says that, uh, you've fixed it. No problem. Thank you very much, sir. GRATITUDE FORMAL TITLE	2.07

Respect Model Coefficients



Log Odds Ratio by Race



Respect

- Higher respect to white drivers, older drivers, when a citation is issued.
- Lower respect when a search is conducted.

Are there differences in the depiction of men and women in fiction?

Gender bias



WIKIPEDIA
The Free Encyclopedia



- 15% of Wikipedia biographies are of women
- Women's biographies are 2.58x more likely to mention divorce, 1.57x more likely to mention marriage [Bamman and Smith 2015]
- Word embeddings encode cultural bias implicit in natural language usage [Caliskan et al. 2017; Bolukbasi et al. 2016]

Measurement

This is fundamentally a problem of **measurement**:
how do we design an algorithmic instrument that can
transform an entire novel into a quantity expressing
the depiction of gender?

“TOM!” No answer. “TOM!” No answer. “What's gone with that boy, I wonder? You TOM!” No answer. The old lady pulled her spectacles down and looked over them about the room; then she put them up and looked out under them. She seldom or never looked *through* them for so small a thing as a boy; they were her state pair, the pride of her heart, and were built for “style,” not service--she could have seen through a pair of stove-lids just as well. She looked perplexed for a moment, and then said, not fiercely, but still loud enough for the furniture to hear: “Well, I lay if I get hold of you I'll--” She did not finish, for by this time she was on her knees and punching under the bed with the broom, and not breathing to punctuate the punches with. She resurrected nothing but the cat. “I never did see the beat of that boy!” She went to the open door and stood in it and looked out among the tomato vines and “jimpson” weeds that constituted the garden. No Tom. So she lifted up her voice at an angle calculated for distance and shouted: “Y-o-u-u TOM!” There was a slight noise behind her and she turned just in time to seize a small boy by the slack of his roundabout and arrest his flight. “There! I might 'a' thought of that closet. What you been doing in there?” “Nothing.” “Nothing! Look at your hands. And look at your mouth.

0.53

Measurement

Measurement here is dependent on character. We'll infer the characters in a novel and measure:

- the amount of “screen time” they get
- what those characters do.
- [dialogue, number of characters, etc.]



Becky Thatcher



Aunt Polly



Huckleberry Finn



Tom Sawyer

Character Depiction

Typed dependency information
anchored on each character

Tom Sawyer		N
agent	paints, runs, ...	137
patient	kisses, saw ...	41
poss	paintbrush, ...	30
pred	rascal, boy, ...	8
total		216

agent
Tom Sawyer paints the fence

A curved arrow points from the word 'paints' to the name 'Tom Sawyer'. The word 'agent' is written in pink above the arrow.

patient
Sally kisses him

A curved arrow points from the word 'kisses' to the pronoun 'him'. The word 'patient' is written in pink above the arrow.

poss
He used his paintbrush

A curved arrow points from the word 'used' to the possessive pronoun 'his'. The word 'poss' is written in pink above the arrow.

pred
He's a rascal

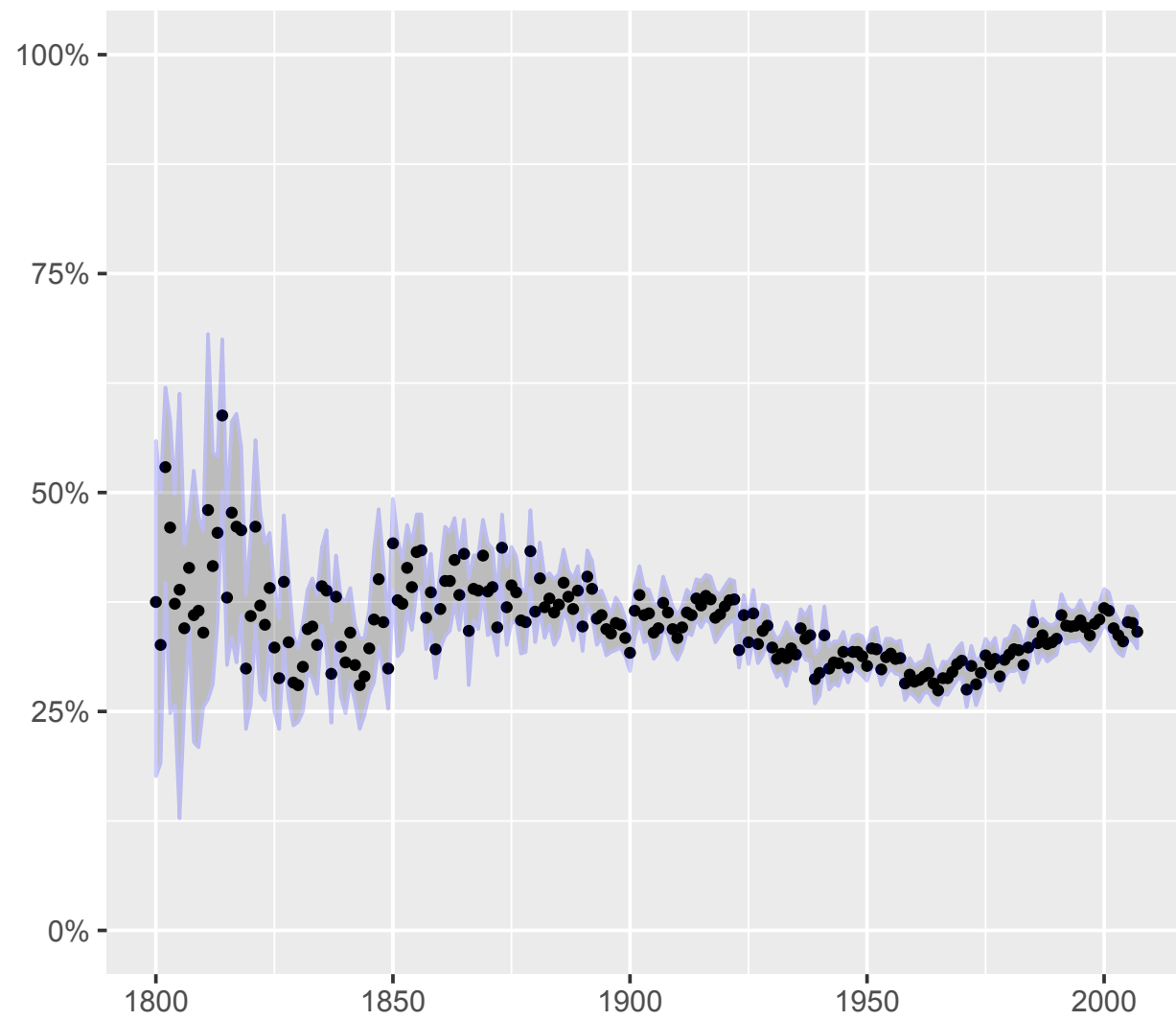
A curved arrow points from the verb 'is' (part of 'He's') to the noun 'rascal'. The word 'pred' is written in pink above the arrow.

Data

- 104,000 narratives from the HathiTrust Digital Library (www.hathitrust.org), published between 1703-2009.
- OCR'd from page scans.
- Subject each narrative to an NLP pipeline to extract entity data.
- 10,000 narratives from the Chicago Corpus, published between 1880-1989

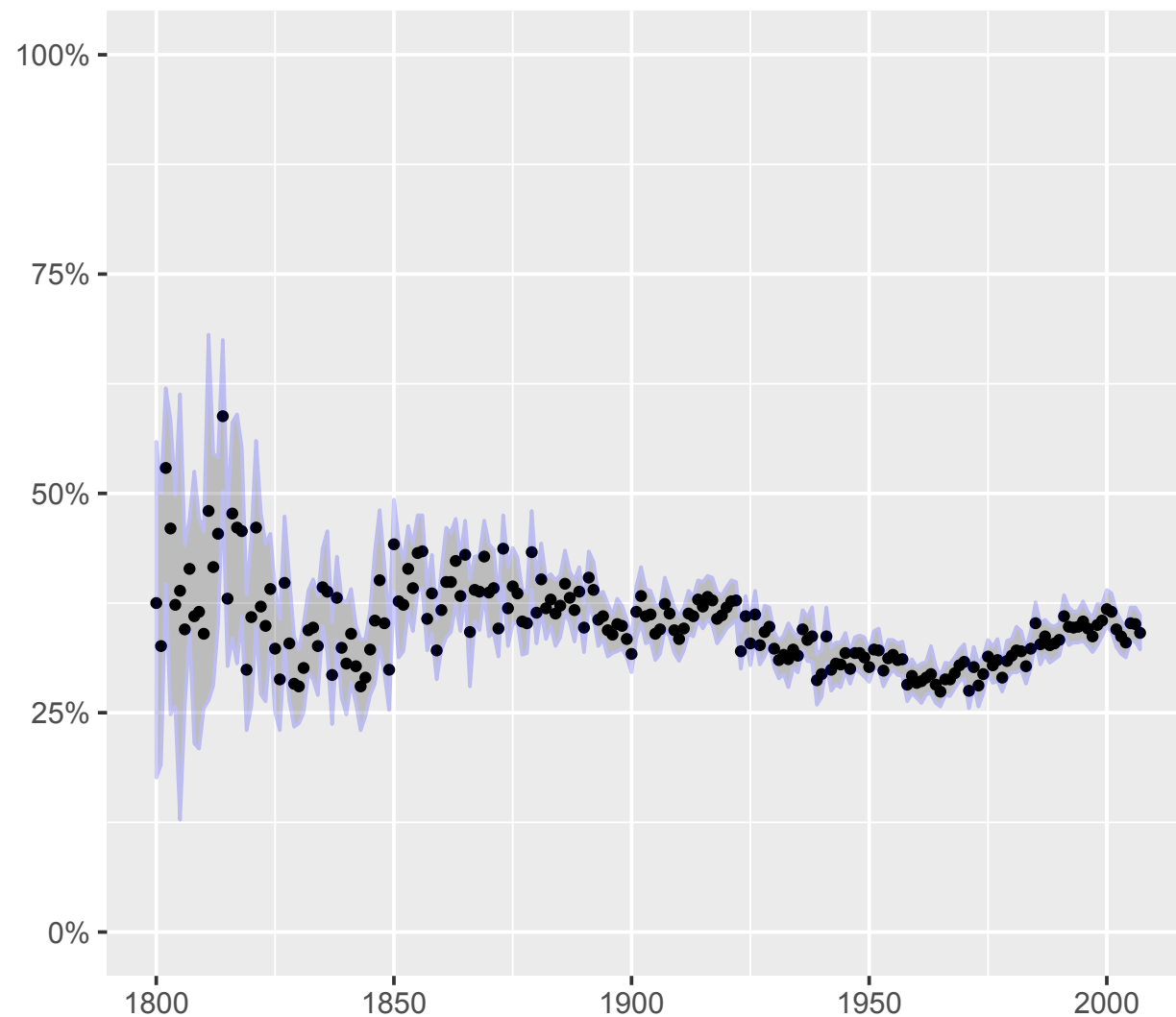


Are there differences in the attention given to men and women in fiction?



Words about women, as a function of all characterization

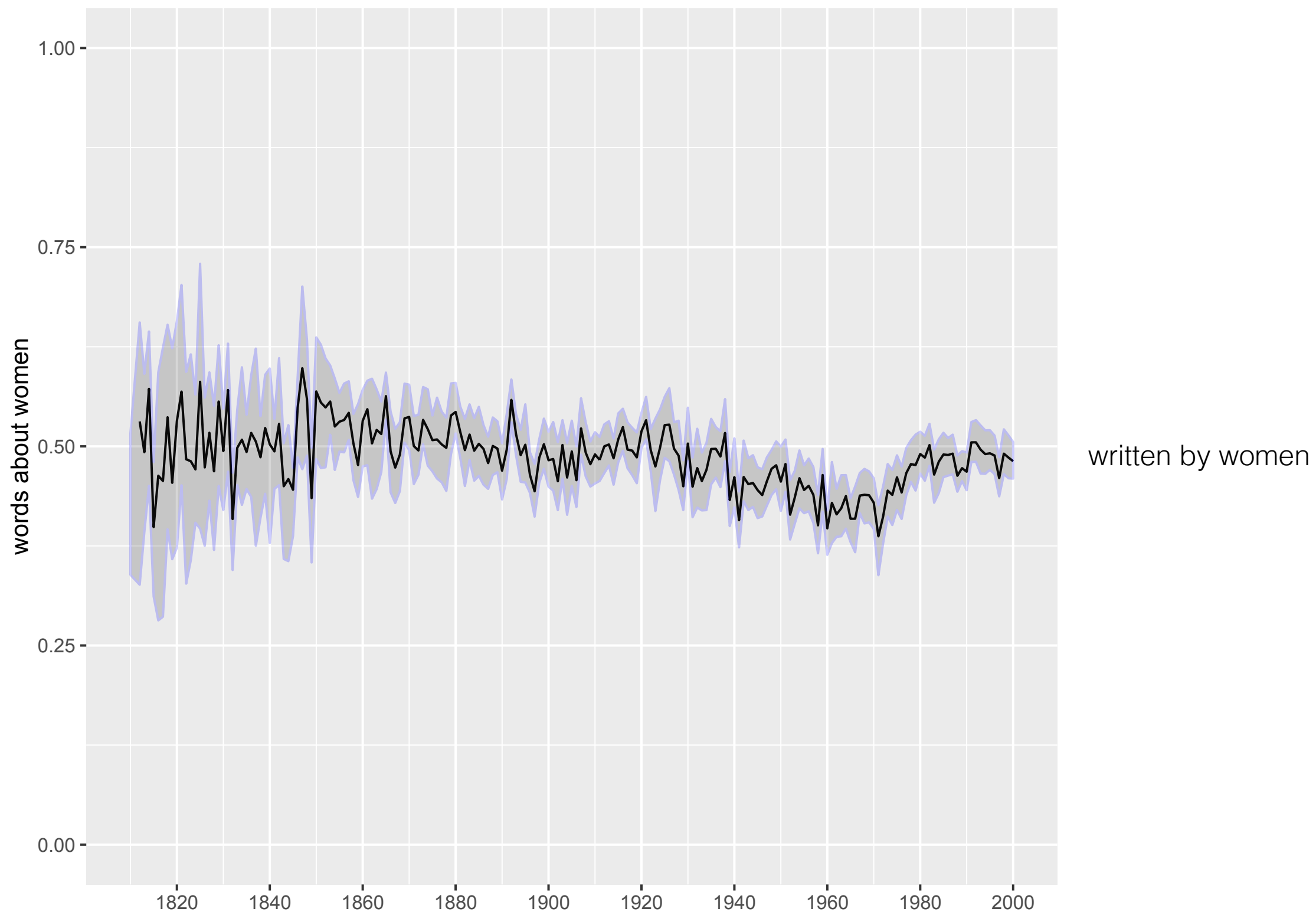
$$\frac{C(a, g = \text{female})}{C(a, g = \text{female}) + C(a, g = \text{male})}$$

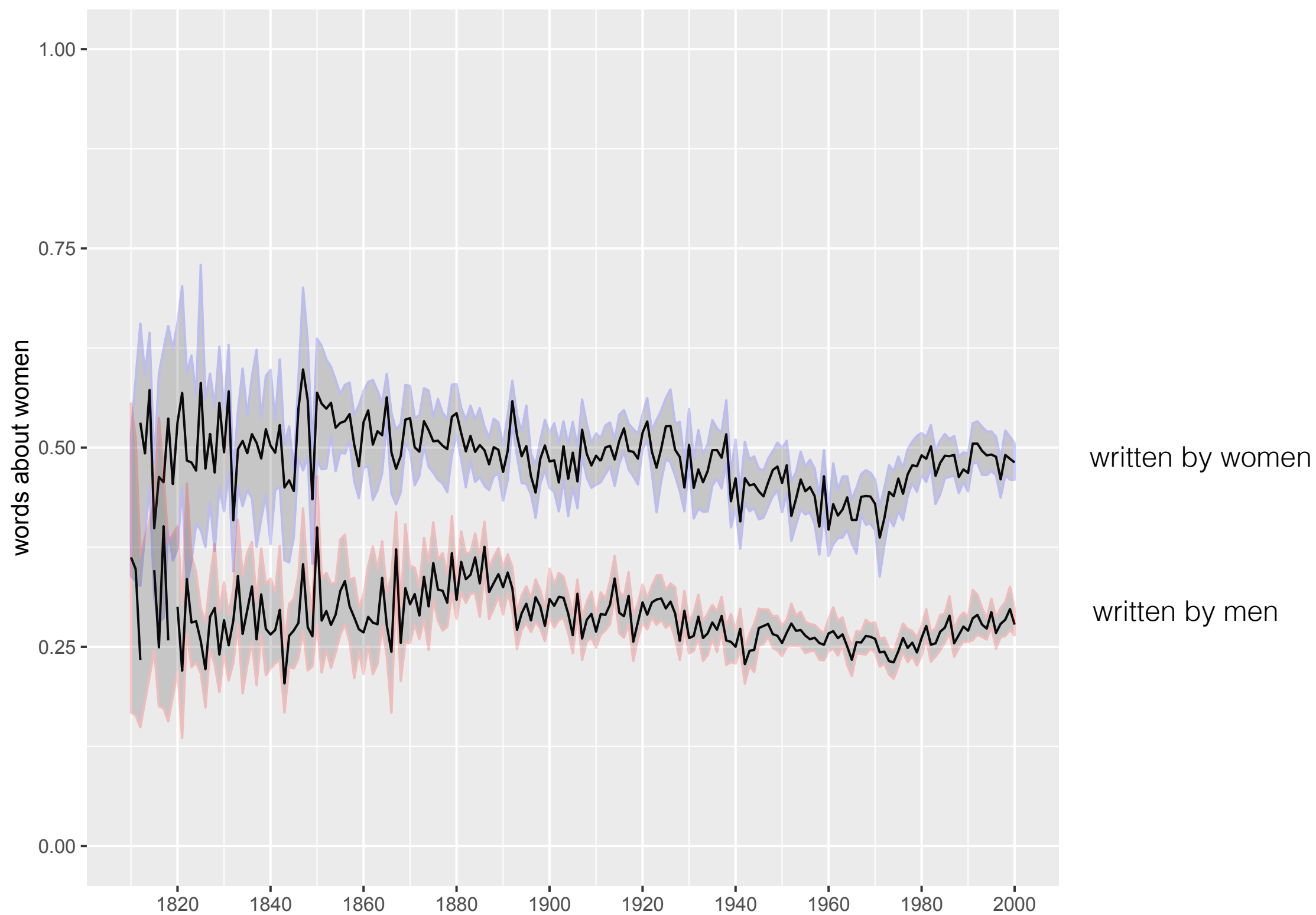


Words about women, as a function of all characterization

Tuchman and Fortin (2012), *Edging Women Out: Victorian Novelists and Social Change*

- “Before 1840 at least half of all novelists were women; by 1917 most high-culture novelists were men.”
 - Early 19th c. fiction was not yet high-status career; after 1840, increasingly brought status
 - Terms of publisher’s contracts became disadvantageous to women
 - Careers others than “novelist” were opening up to women







RANDOM ACTS OF PIZZA | READ THE RULES BEFORE POSTING.

HOT

NEW

RISING

CONTROVERSIAL

TOP

WIKI

- Data: Random acts of pizza (subreddit)
- Response: Is a request successful in getting a pizza?

Althoff et al. (2014), "How to Ask for a Favor: A Case Study on the Success of Altruistic Requests"

Favors

- Representation of text:
 - Temporal features of post/author
 - Politeness
 - Evidentiality (image link in text)
 - Reciprocity (“pay it forward”, “return the favor”)
 - Sentiment
 - Length
 - Status (reddit karma points)
 - “Money”, “Job” “Student”, “Family”, “Craving” topics

Coefficient	Estimate	SE
Intercept	−2.02 ^{***}	0.14
Community Age (Decile)	−0.13 ^{***}	0.01
First Half of Month (Binary)	0.22 ^{**}	0.08
Gratitude (Binary)	0.27 ^{**}	0.08
Including Image (Binary)	0.81 ^{***}	0.17
Reciprocity (Binary)	0.32 ^{**}	0.10
Strong Positive Sentiment (Binary)	0.14	0.08
Strong Negative Sentiment (Binary)	−0.07	0.08
Length (in 100 Words)	0.30 ^{***}	0.05
Karma (Decile)	0.13 ^{***}	0.02
Posted in RAOP before (Binary)	1.34 ^{***}	0.16
Narrative Craving (Binary)	−0.34 ^{***}	0.09
Narrative Family (Binary)	0.22 [*]	0.09
Narrative Job (Binary)	0.26 ^{**}	0.09
Narrative Money (Binary)	0.19 ^{**}	0.08
Narrative Student (Binary)	0.09	0.09

^{***} $p < 0.001$, ^{**} $p < 0.01$, ^{*} $p < 0.05$

Features	ROC AUC
Random Baseline	0.500
Unigram Baseline	0.621 ^{***}
Bigram Baseline	0.618 ^{***}
Trigram Baseline	0.618 ^{***}
Text Features	0.625 ^{***}
Social Features	0.576 ^{***}
Temporal Features	0.579 ^{***}
Temporal + Social	0.638 ^{***}
Temporal + Social + Text	0.669^{***}
Temporal + Social + Text + Unigram	0.672^{***}

Social NLP

- Many different methods from NLP
 - Text-based classification, regression, sequence labeling (e.g., NER)
- Representation is important:
 - Bag of words
 - Features derived from parts of speech, syntax
- When testing theories, interpretable models are important.

Social NLP

Text also provides a lens into **exploratory analysis** of social and cultural phenomena

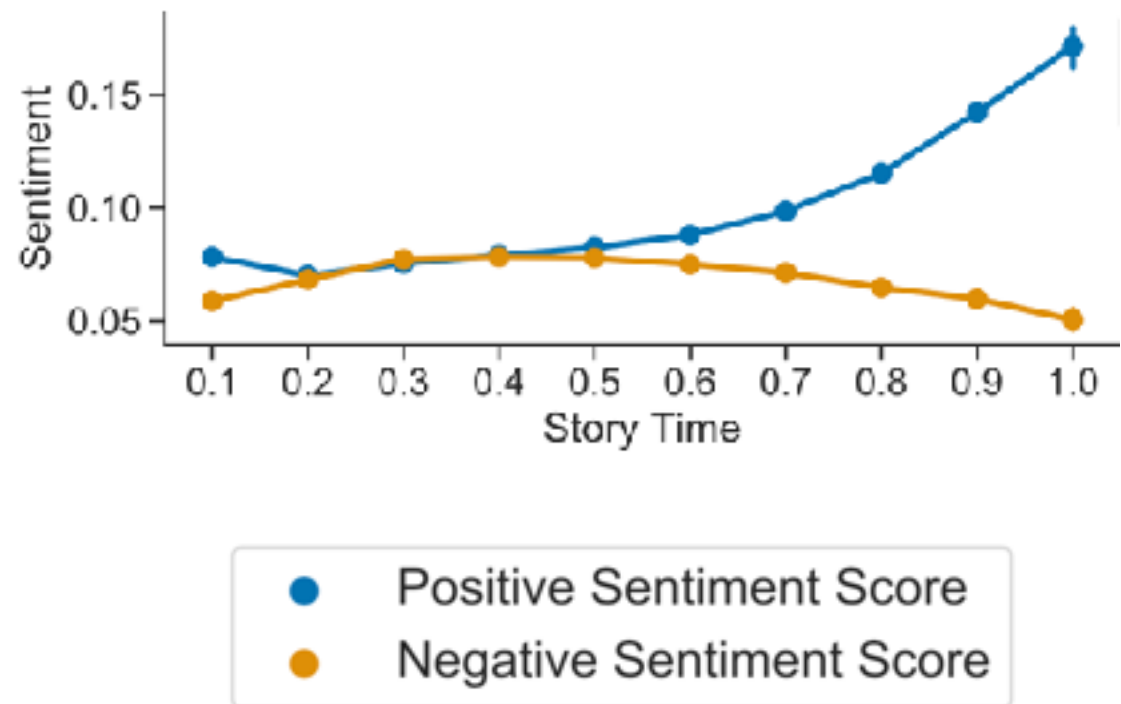
What is the structure of birth stories?

Birth stories

- Text data: 2,847 birth stories from r/BabyBumps — “narratives of individual experiences giving birth, often in great medical and emotional detail”
- Methods:
 - Topic modeling (clustering tokens in documents into coherent “topics”)
 - Sentiment analysis
 - Connotation frames of power

Birth stories

- Dictionary-based sentiment analysis with VADER lexicon (Hutto and Gilbert 2014)



Topic Models

- A probabilistic model for discovering hidden “topics” or “themes” (groups of terms that tend to occur together) in documents.
- Unsupervised (find *interesting structure* in the data)

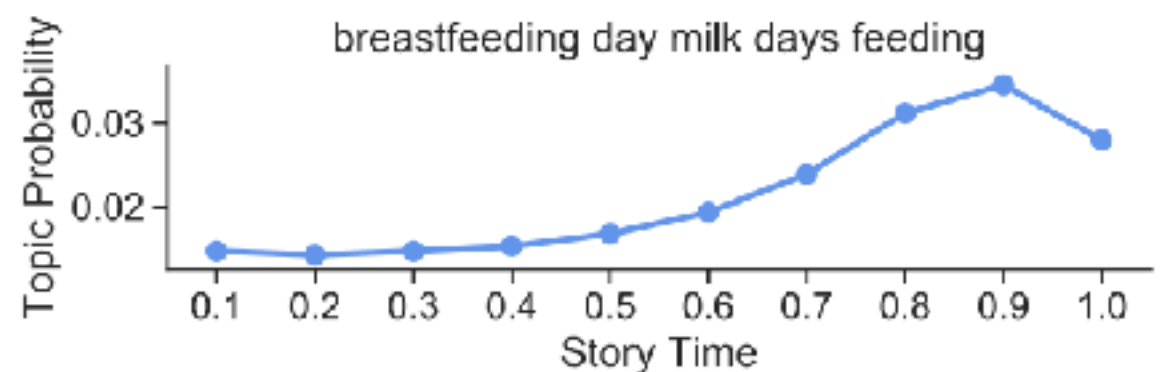
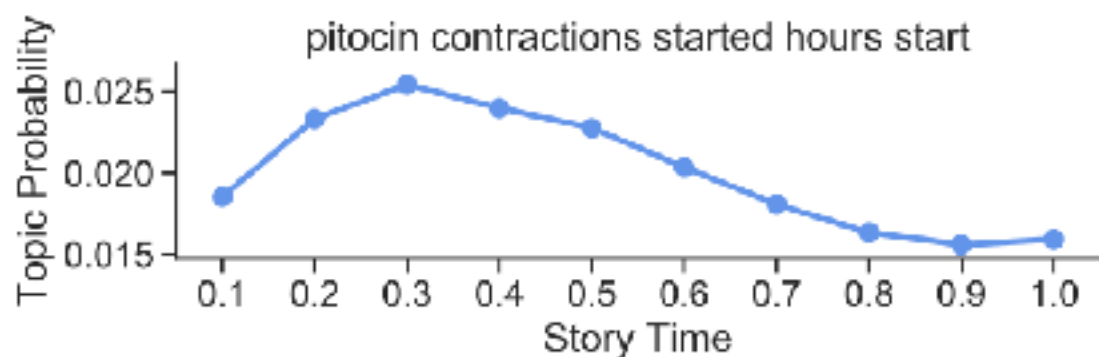
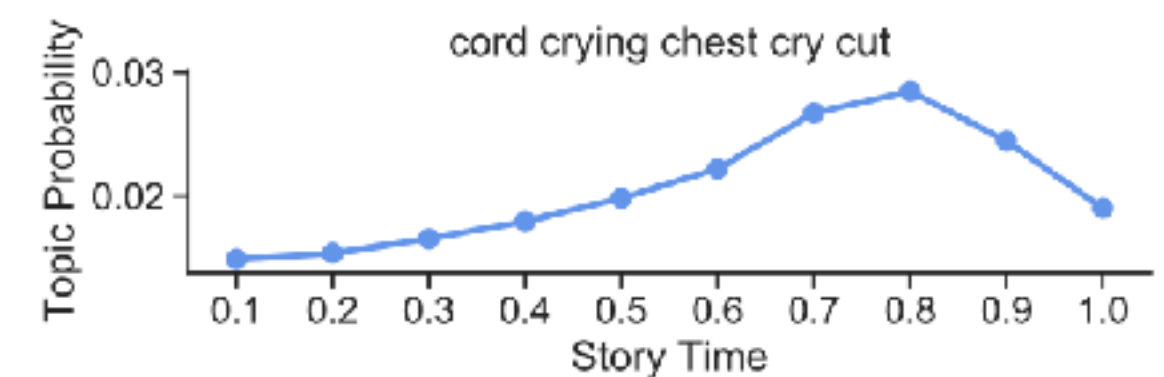
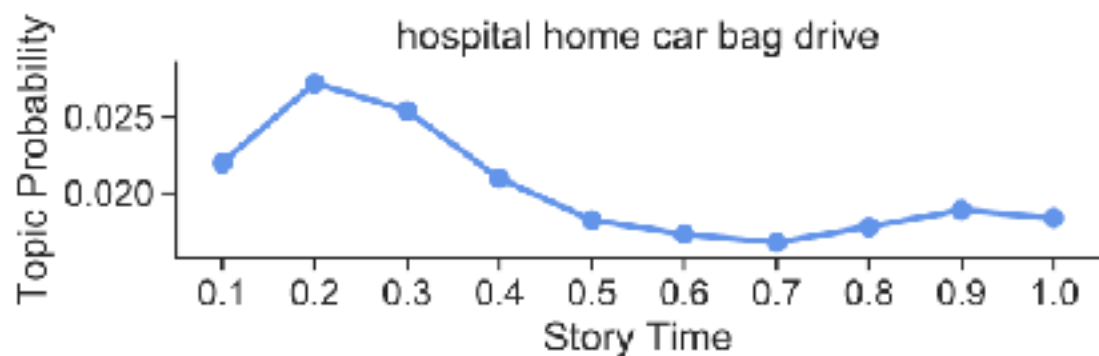
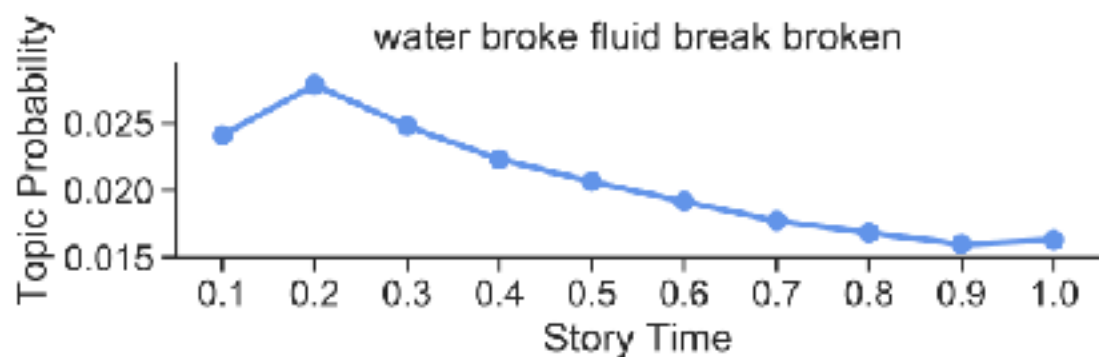
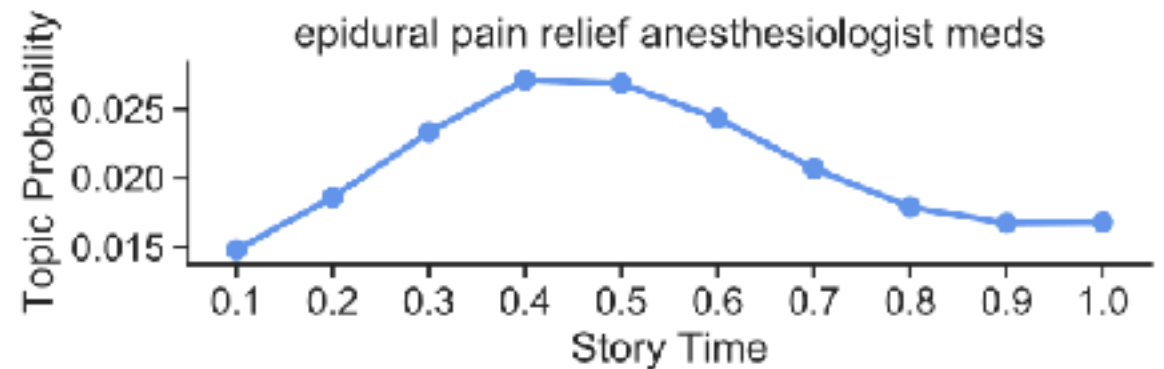
Topic Models

- **Input:** set of documents, number of clusters to learn.
- **Output:**
 - topics
 - topic ratio in each document
 - topic distribution for each word in doc

{album, band, music}	{government, party, election}	{game, team, player}
album	government	game
band	party	team
music	election	player
song	state	win
release	political	play
{god, call, give}	{company, market, business}	{math, number, function}
god	company	math
call	market	number
give	business	function
man	year	code
time	product	set
{city, large, area}	{math, energy, light}	{law, state, case}
city	math	law
large	energy	state
area	light	case
station	field	court
include	star	legal

Topic modeling

- Run Latent Dirichlet Allocation (LDA) on training birth stories, each divided into 100-word chunks
- 50 topics
- Divide each story into 10 chunks, plot aggregate topic distribution over narrative time.



Personas

Persona	N-Grams	Total Mentions	Stories Containing Mentions	Average Mentions per Story
AUTHOR	I, me, myself	210,795	2,846	74.0
We	we, us, ourselves	24,757	2,764	8.7
BABY	baby, son, daughter	14,309	2,668	5.0
DOCTOR	doctor, dr, doc, ob, obgyn, gynecologist, physician	10,025	2,262	3.5
PARTNER	partner, husband, wife	8,998	2,006	3.2
NURSE	nurse	7,080	2,012	2.5
MIDWIFE	midwife	4,069	886	1.4
FAMILY	mom, dad, mother, father, brother, sister	3,490	1,365	1.2
ANESTHESIOLOGIST	anesthesiologist	1,398	876	0.5
DOULA	doula	896	256	0.3

Table 5. Personas identified in the birth stories collection and the n-grams used to classify the personas.

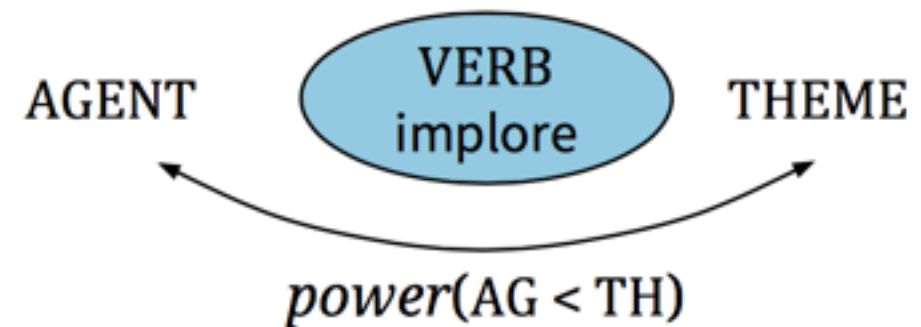
- Dictionary-based method to group word types into “personas” — e.g., partner, husband, wife →

PARTNER

Power frames

- Verbs imply power differential between their agent/theme

He **implored** the tribunal to show mercy.



$power(AG < TH)$



$power(AG > TH)$



Power frames

- The only time I got upset was when the nurse accused me of not feeding my child.
- The doctor broke my water.

Birth stories

- The author is framed as having the **least power** (except for the baby).
- Clinicians are framed as having high power

