

# Natural Language Processing

Info 159/259

Lecture 23: NLP Applications & Beyond (April 22, 2024)

*Many slides & instruction ideas borrowed from:  
David Bamman, Sofia Serrano*

# Logistics

- Quiz 10: Due *tonight*
- AP3: Due this *Friday 4/26.*
- Final Deliverables: Due *Tuesday May 7*
  - INFO 159 NLP Subtopic Survey
  - INFO 259 NLP Project Report

# Info 259

## Project presentations

- 6:30-8:00pm Wednesday 4/24 (**last day of class**)
- Prepare a 5-minute presentation of your project to present to the class; be prepared to take questions from the audience.
- No recording will be released.

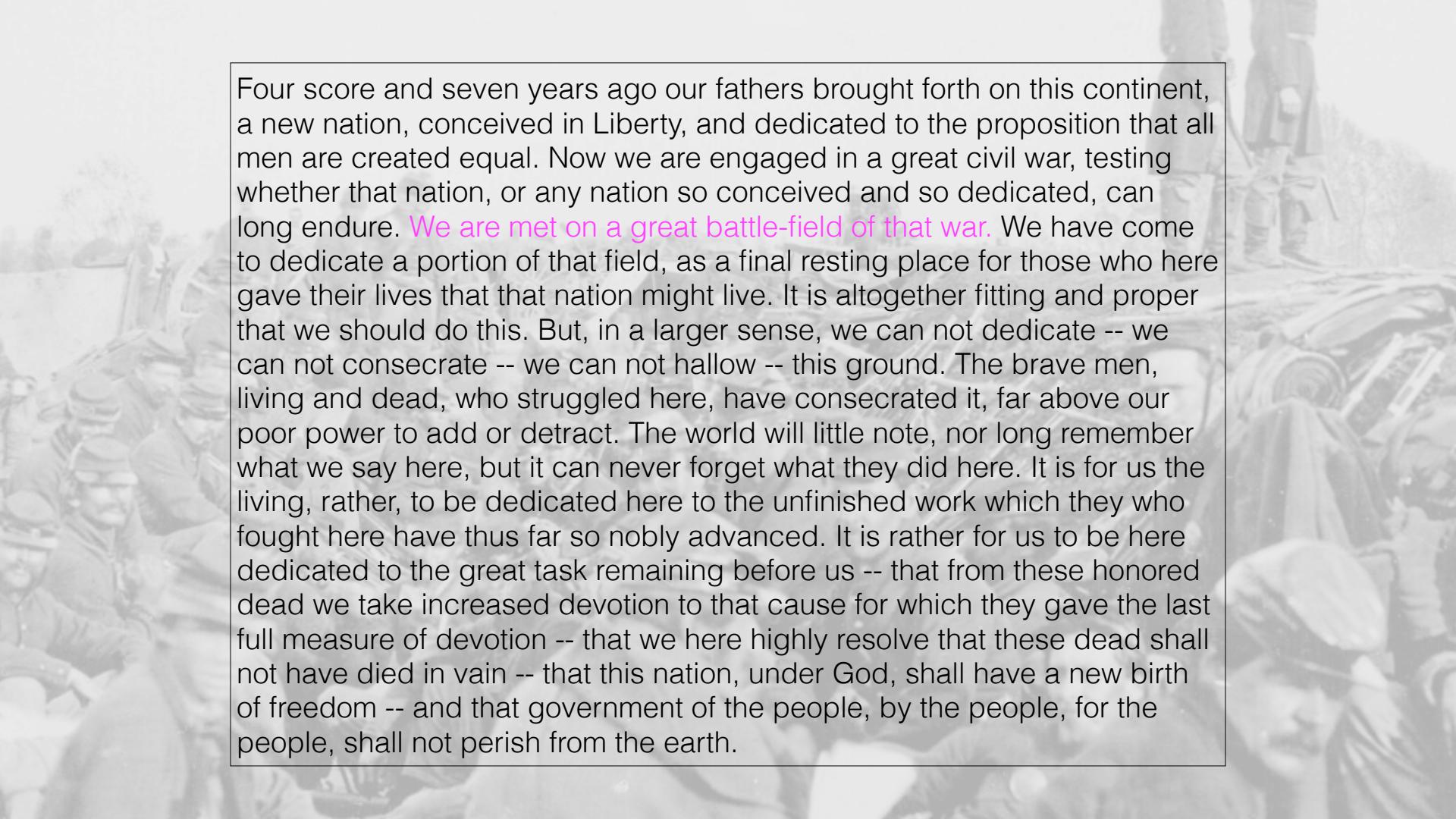
great

The diagram illustrates the binding of variables in a lambda expression. Three curved arrows point from the variables  $x$  and  $y$  in the first term to their respective occurrences in the sentence. The second term has no arrows pointing to it, indicating that the variable  $x$  is not bound there. The third term has two arrows pointing to its two occurrences of  $x$ .

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

$\lambda x. \lambda y. \text{meet}(x, y)$      $\lambda x. \text{battlefield}(x)$      $\lambda x. \text{war}(x)$

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

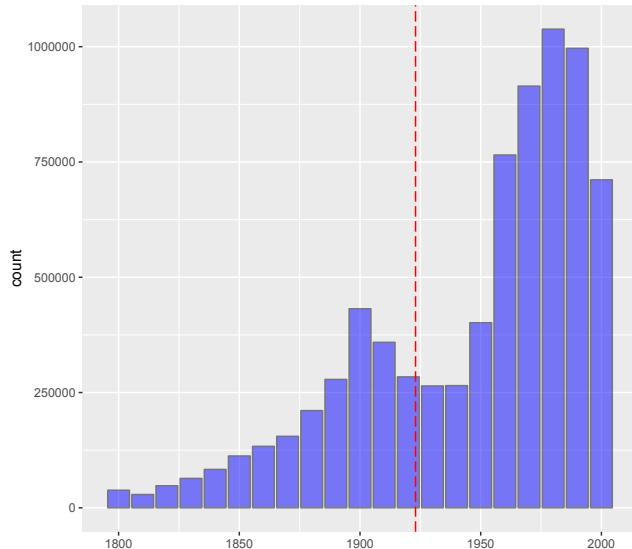


Four score and seven years ago our fathers brought forth on this continent, a new nation, conceived in Liberty, and dedicated to the proposition that all men are created equal. Now we are engaged in a great civil war, testing whether that nation, or any nation so conceived and so dedicated, can long 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.
  - Social media
  - Books
  - Emails
  - Audio transcripts

# Data

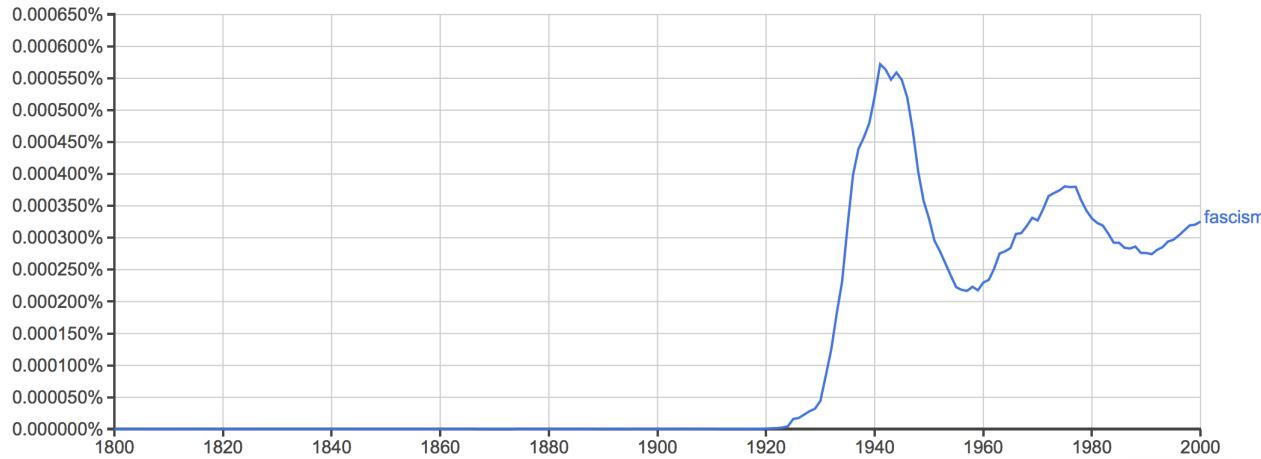


HathiTrust: 18.4M books

# Ngram viewer

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
- Measuring respect
- Examining gender bias in novels
- Discovering structure in birth stories

# Power

How is **power** manifested in language?

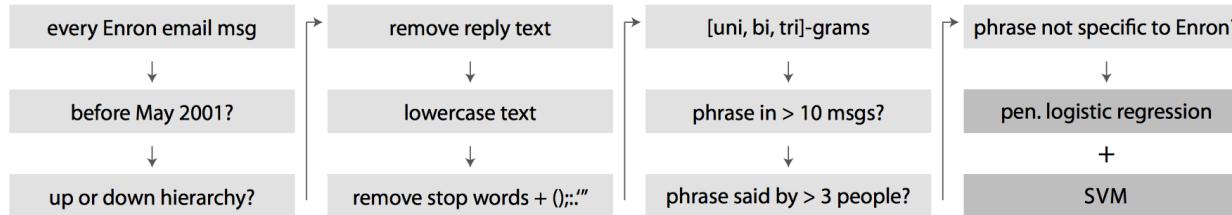
# Power

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

Gilbert 2012 ("Phrases that signal workplace hierarchy")

# Power

- Bag of words representation of text + binary classification.



Gilbert 2012 ("Phrases that signal workplace hierarchy")

these predict message going up

$\uparrow$ phrases	$\beta$	$\uparrow$ phrases	$\beta$
the ability to	6.76	attach	6.72
I took	6.57	that we might	6.54
are available	6.52	the calendar	6.06
kitchen	5.72	can you get	5.72
thought you would	5.65	driving	5.61
, I'll be	5.51	thoughts on	5.51
looks fine	5.50	shit	5.45
voicemail	5.43	we can talk	5.41
tremendous	5.27	it does	5.21
will you	5.17	involving	5.15
left a	5.07	the report	5.04
I put	4.90	please change	4.88
you ever	4.80	issues I	4.76
I'll give	4.69	is really	4.65
okay,	4.60	your review	4.56
to send it	4.48	europe	4.45
communications	4.38	weekend .	4.35
a message	4.35	have our	4.33
one I	4.28	interviews	4.28
can I get	4.28	you mean	4.26
worksheet	4.15	haven't been	4.10
liked	4.07	me . 1	4.07
I gave you	3.95	tiger	3.94
credit will	3.88	change in	3.88
you make	3.86	item	3.84
together and	3.82	a decision	3.82
have presented	3.78	a discussion	3.74
think about	3.71	sounds good	3.65

not going up

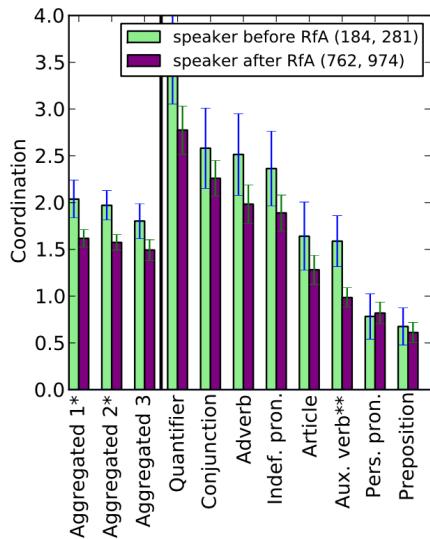
$\leftrightarrow\downarrow$ phrases	$\beta$	$\leftrightarrow\downarrow$ phrases	$\beta$
have you been	-8.46	to manage the	-6.66
you gave	-6.64	let's discuss	-5.72
we are in	-5.44	publicly	-5.24
title	-5.05	promotion	-5.02
need in	-4.80	good one	-4.62
opened	-4.57	determine the	-4.47
initiatives	-4.38	is difficult	-4.36
. I would	-4.34	man	-4.26
we will probably	-4.12	number we	-4.11
any comments	-4.06	contact you	-4.05
you said	-3.99	the problem is	-3.97
I left	-3.88	you did	-3.78
can you help	-3.68	cool	-3.54
send this	-3.47	your attention	-3.44
whether we	-3.44	to think	-3.44
the trade	-3.40	addition to the	-3.30
and I thought	-3.28	great thanks	-3.24
should include	-3.19	selected	-3.16
please send	-3.14	ext	-3.13
existing	-3.06	and let me	-3.05
mondays	-3.02	security	-3.01
presentation on	-2.95	got the	-2.94
let's talk	-2.94	get your	-2.88
the items	-2.78	this week and	-2.77
i hope you	-2.77	team that	-2.75
did it	-2.75	a deal	-2.71
test	-2.69	yours .	-2.68
be sure	-2.65	briefing	-2.60

# Power

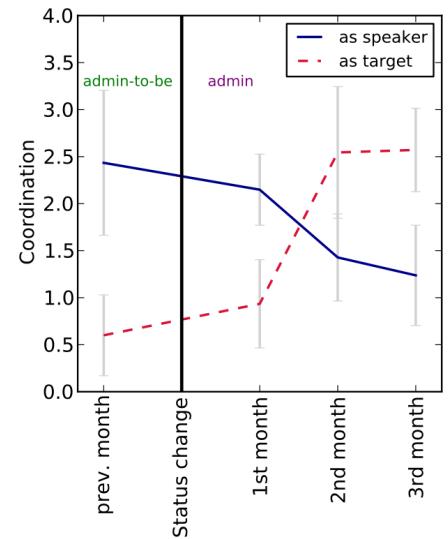
- Text data: Wikipedia discussions, SCOTUS arguments
- Response: Wikipedia admins/non-admins; SCOTUS justices/lawyers

# 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** ( $\mathcal{P}$ )

# Respect

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

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

# 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**.

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

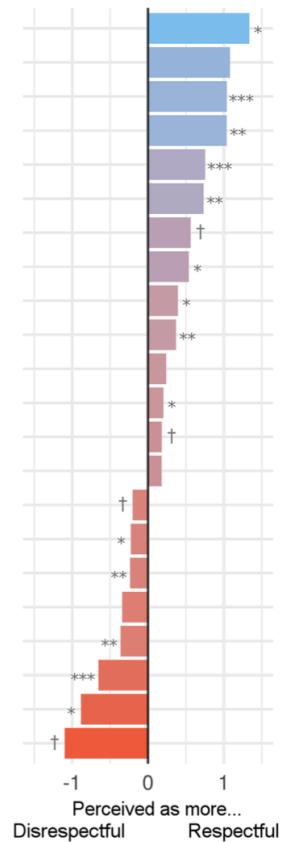
Feature Name	Implementation
Adverbial "Just"	"Just" occurs in a dependency arc as the head of an advmod relation
Apologizing	Lexicon: "sorry", "oops", "woops", "excuse me", "forgive me", "apologies", "apologize", "my bad", "my fault"
Ask for Agency	Lexicon: "do me a favor", "let me", "allow me", "can 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)"

Hedges	All words in the "Tentat" LIWC lexicon
Impersonal Pronoun	All words in the "Impron" 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 Inquierer, matching on word lemmas
Positive Words	All words in the "Positiv" category in the Harvard General Inquierer, 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"

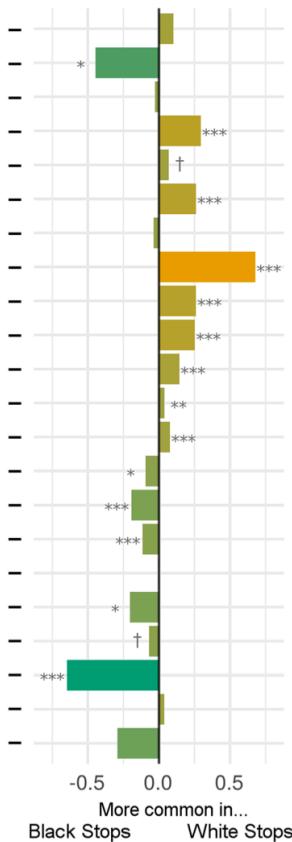
# Respect

EXAMPLE	RESPECT SCORE
<p>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?</p> <p>↑ ↑ ↑ DISFLUENCY NEGATIVE WORD DISFLUENCY</p>	-1.07
<p>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.</p> <p>↑ ↓ ↓ "HANDS ON THE WHEEL"</p>	-0.51
<p>APOLOGY INTRODUCTION LAST NAME Sorry to stop you. My name's Officer [name] with the Police Department.</p>	0.84
<p>FORMAL TITLE SAFETY PLEASE There you go, ma'am. Drive safe, please.</p>	1.21
<p>ADVERBIAL "JUST" FILLED PAUSE REASSURANCE It just says that, uh, you've fixed it. No problem. Thank you very much, sir.</p> <p>↑ ↑ ↑ GRATITUDE FORMAL TITLE</p>	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

Home News Journals Topics Careers

Science Science Advances Science Immunology Science Robotics Science Signaling Science Translational Medicine

SHARE REPORT

Semantics derived automatically from language corpora contain human-like biases

Aylin Caliskan<sup>1,\*</sup>, Joanna J. Bryson<sup>1,2,†</sup>, Arvind Narayanan<sup>1,2</sup>

\* See all authors and affiliations

13 Science 14 April 2017: Vol. 356 no. 6333 pp. 383-386 DOI: 10.1126/science.aad4230

Peer Reviewed by our peers

Article Figures & Data Info & Metrics eLetters PDF

- 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 bending down and punching under the bed with 0.53 so she needed breath to punctuate the punches with. She ~~resuscitated~~ 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. What *is* that truck?" "I don't know what."

# 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

patient  
Sally kisses him

poss  
He used his paintbrush

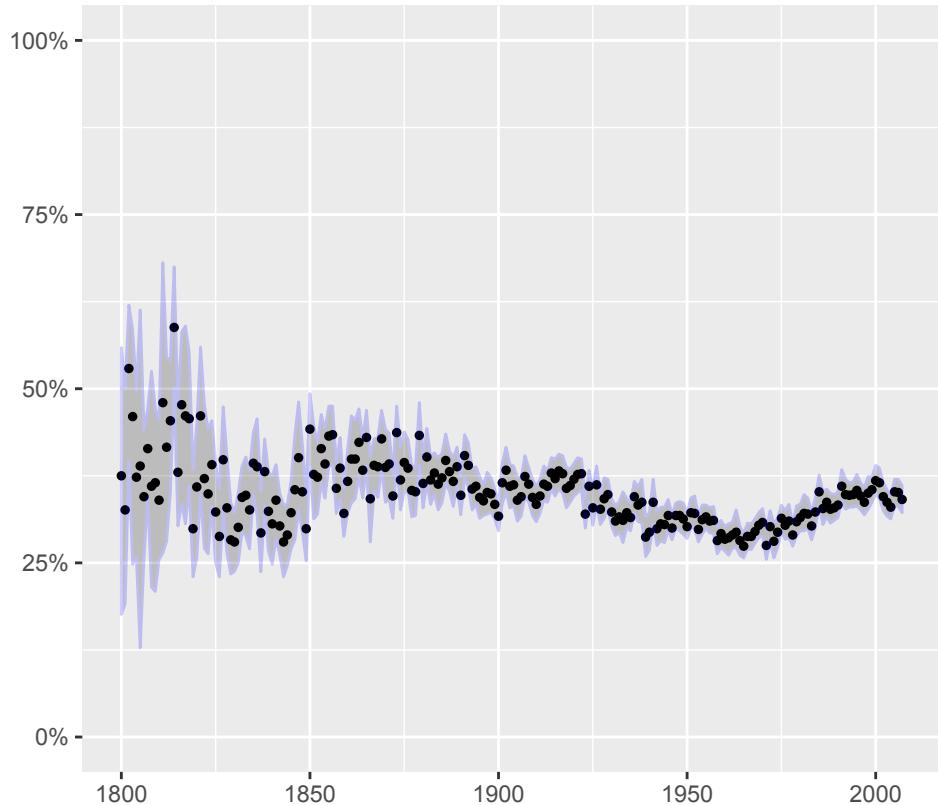
pred  
He's a rascal

# Data

- 104,000 narratives from the HathiTrust Digital Library ([www.hathitrust.org](http://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?



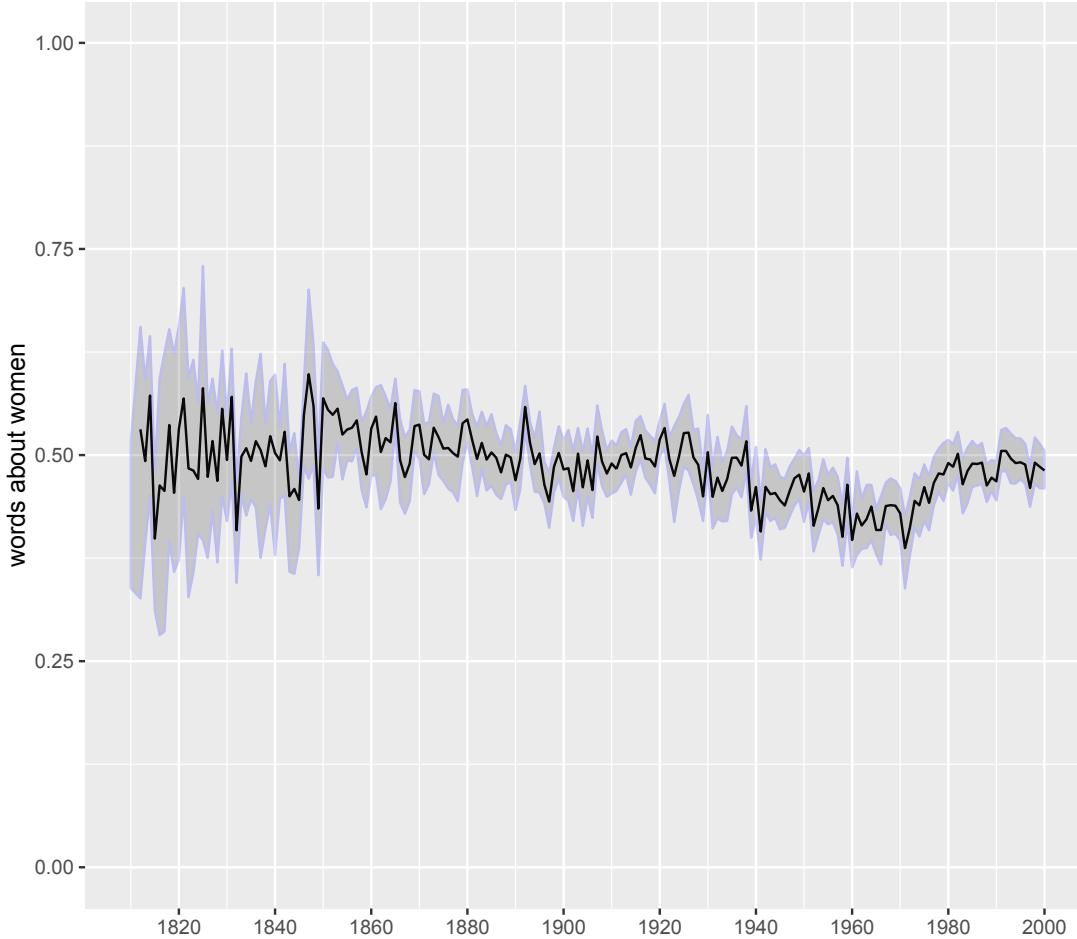
Words about women, as a function of all characterization

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

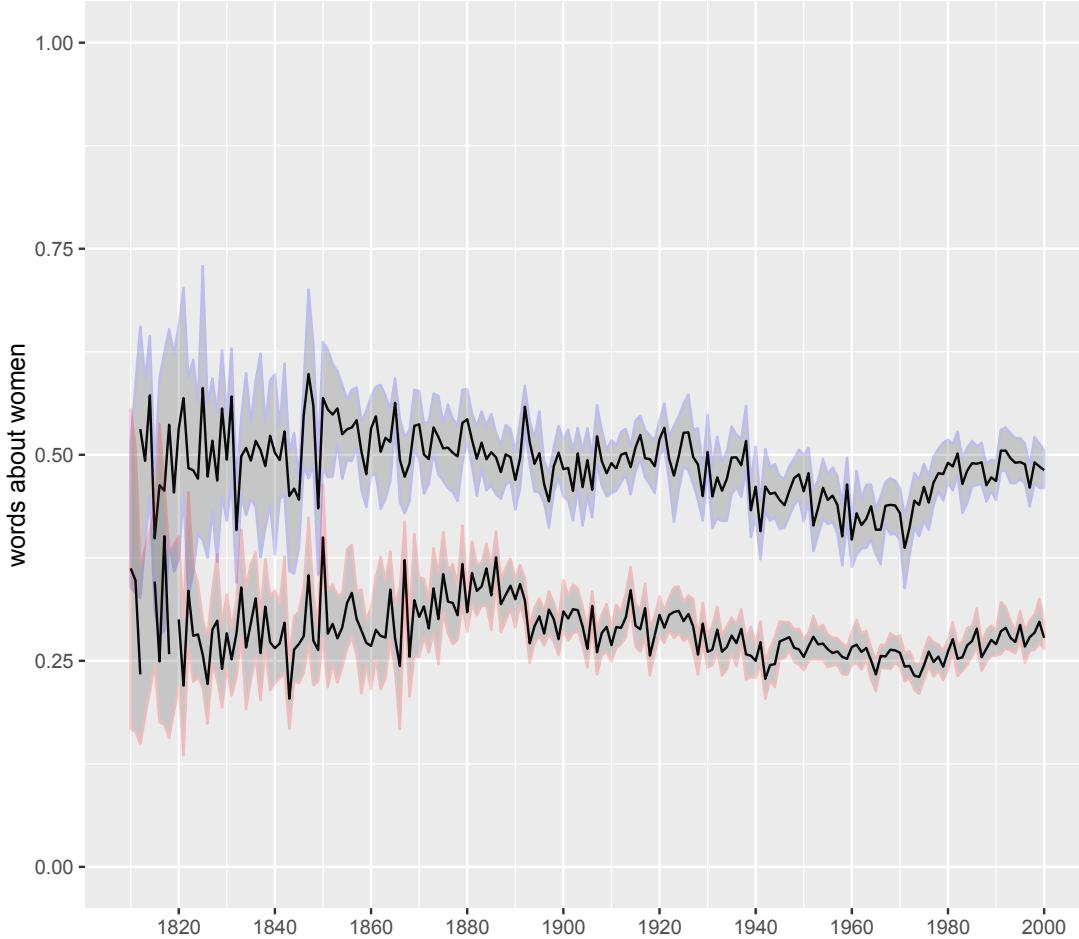


Tuchman and Fortin (2012), *Edging Women Out: Victorian Novelists and Social Change*

- “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



written by women



# 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?

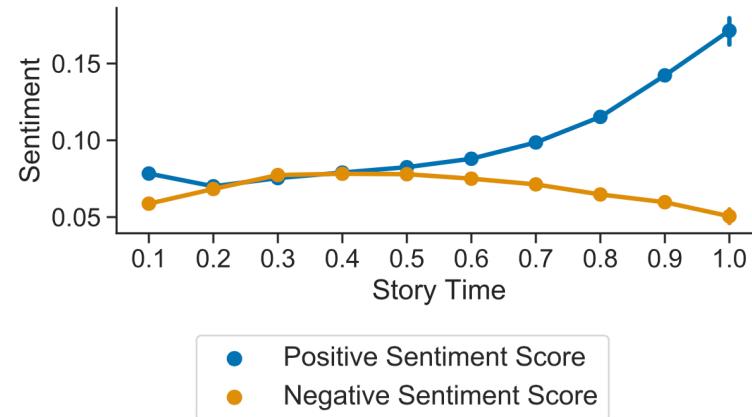
# Birth stories

- 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

Antoniak et al. (2019), “Narrative Paths and Negotiation of Power in Birth Stories,” CSCW

# 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

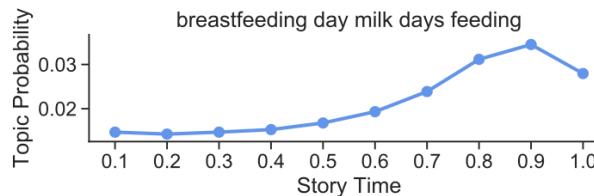
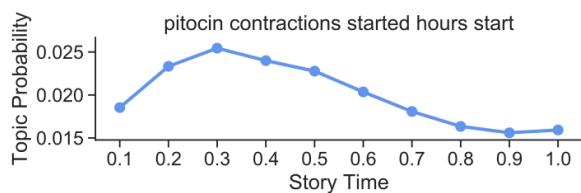
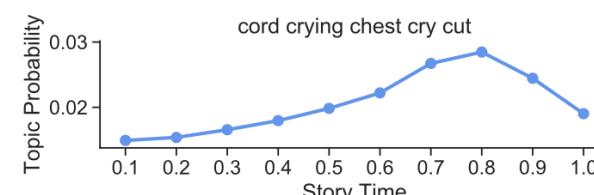
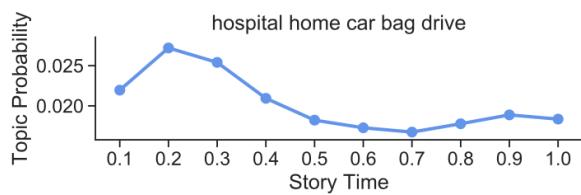
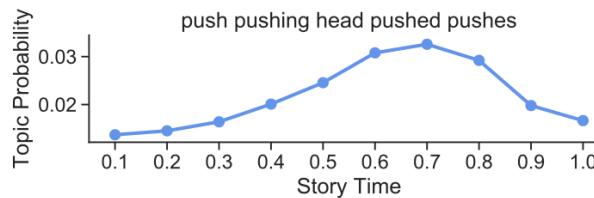
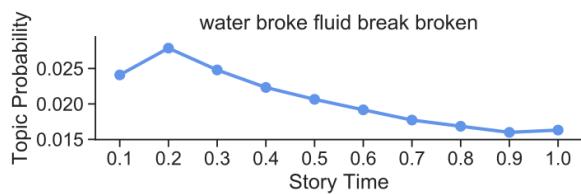
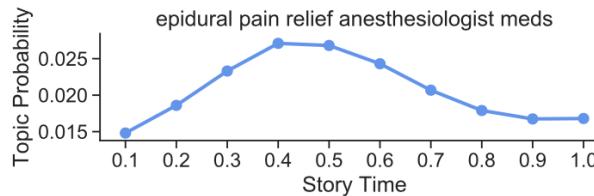
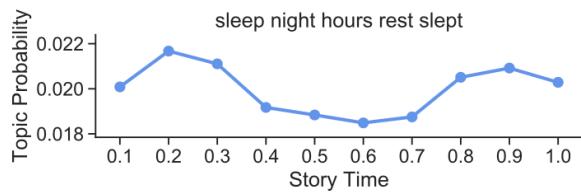
{god, call, give}	{company, market, business}	{math, number, function}
god	company	math
call	market	number
give	business	function
man	year	code
time	product	set

{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

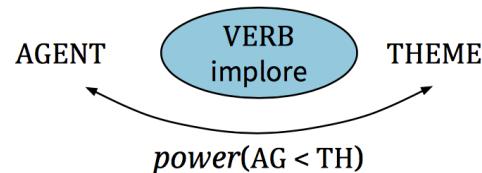
Table 5. Personas identified in the birth stories collection and the n-grams used to classify the personas.

- 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)*

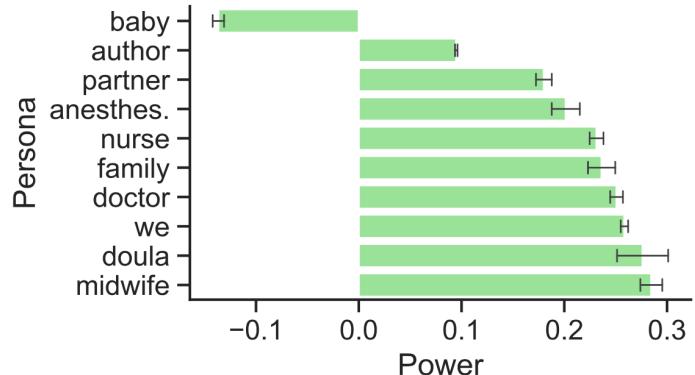


# Power frames

- 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



# Question?

# Our NLP Journey

INFO 159/259 NLP		
Home	Jan. 17: <a href="#">Introduction</a>	Browse NLP-progress
Policies	Jan. 22: <a href="#">Words, Embeddings</a>	SLP Ch 6
Projects	Jan. 24: <a href="#">Text Classification 1: Logistic Regression</a>	SLP Ch 5
Schedule	Jan. 29: <a href="#">Text Classification 2: Feed-forward, Convolutional Neural Networks</a>	SLP Ch 7.1-7.6, NNLP Ch 13.
Staff	Jan. 31: <a href="#">Text Classification 3: Attention &amp; Transformers</a>	SLP Ch 10
	Feb. 5: <a href="#">Corpora &amp; Annotation</a>	NLA Ch 6
	Feb. 7: <a href="#">Language Modeling 1: Ngram and Log Linear Models</a>	SLP Ch 3
	Feb. 12: <a href="#">Language Modeling 2: Contextual Embeddings</a>	SLP Ch 10
	Feb. 14: <a href="#">Language Modeling 3: BERT, GPT, Prompting</a>	Xie and Min 2022
	Feb. 19: <a href="#">Presidents' Day (No Class)</a>	
	Feb. 21: <a href="#">Exam 1</a>	
	Feb. 26: <a href="#">Statistical Sequence Labeling</a>	SLP Ch 8
	Feb. 28: <a href="#">Neural Sequence Labeling</a>	SLP Ch 9.3-9.6
	Mar. 4: <a href="#">Syntax &amp; CFG Parsing</a>	SLP Ch 17
	Mar. 6: <a href="#">Dependency Parsing</a>	SLP Ch 18
	Mar. 11: <a href="#">Semantic Role Labeling</a>	SLP Ch 24
	Mar. 13: <a href="#">Wordnet, WSD, Supersenses</a>	SLP Ch 23
	Mar. 18: <a href="#">Coreference Resolution</a>	SLP Ch 26
	Mar. 20: <a href="#">Exam 2</a>	
	Mar. 25: <a href="#">Spring Break</a>	
	Mar. 27: <a href="#">Spring Break</a>	
	Apr. 1: <a href="#">Information Extraction</a>	SLP Ch 19
	Apr. 3: <a href="#">Question Answering</a>	SLP Ch 14
	Apr. 8: <a href="#">Machine Translation</a>	SLP Ch 13
	Apr. 10: <a href="#">Text Generation: Dialogue</a>	SLP Ch 15
	Apr. 15: <a href="#">Ethics &amp; Safety in NLP+Guest Lec:Olya Gurevich</a>	Bender et al., 2021
	Apr. 17: <a href="#">NLP For Low Resource Languages</a>	Hedderich et al., 2021
	Apr. 22: More NLP Applications and Conclusion	Talk by Dan Klein:Are LLMs the Beginning or End of NLP?
	Apr. 24: <a href="#">Final Project Presentations</a>	

# Recurring Themes

- Challenge of NLP: Ambiguity, Evaluation, Data, Low Resource
- Supervised ML in NLP: Counts/Normalize, Loglinear models (LR), Neural Models
- Data (existing corpora, annotation and your AP)
- NLP Foundations: Syntax, Semantics, Discourse
- NLP Applications

# Things we didn't get to cover

- Discourse and Pragmatics
- Speech Processing
- Unsupervised methods (e.g. topic modeling)
- Some applications: NL Inference, Summarization
- “Deeper” coverage of neural networks

# Beyond This Course

- CS 288: NLP ([Fall 2023 page](#))
- INFO 256: Applied NLP ([Fall 2023 page](#))
- Many Seminar/Focused courses:
  - Social NLP ([Summer 2024](#))
  - Language Agents in Interaction ([Spring 2024](#))

# NLP Research@Berkeley

- Prof. Marti Hearst (iSchool/CS)
- Prof. David Bamman (iSchool)
- Prof Dan Klein (CS)
- Prof Alane Suhr (CS)
- Prof. Gopala Krishna Anumanchipalli (CS)
- Prof. Gasper Begus (Linguistics)
- Prof. John DeNero (CS)

# Beyond Berkeley

- [NLP Highlights](#) podcast
- [SLP Book](#) (Jurafsky & Martin)
- [ACL Anthology](#) & ACL Conferences
- Search on [semanticscholar.com](#)
- NLP Industry

# Reminders

- Wednesday 4/24: Come & see/support your peers in INFO 259
- Please evaluate us: <https://course-evaluations.berkeley.edu/>

# Thank you!

- And plz keep in touch!
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  - <https://www.linkedin.com/in/behrangmohit/>