12. Special Topics (flipped)

DS-GA 1015, Text as Data
Arthur Spirling

April 27, 2021

Housekeeping

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3. Lecture next week is flipped only.

Debate

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Use speech information—

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Use speech information—'to and fro'— to measure how responsive front bench is to legislature

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L_{15}

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$L_{15} \rightarrow L_4$

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$L_{15} \to L_4 \to C_6$

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where m_{ij} is probability of a move from speaker of identity i to speaker of identity j

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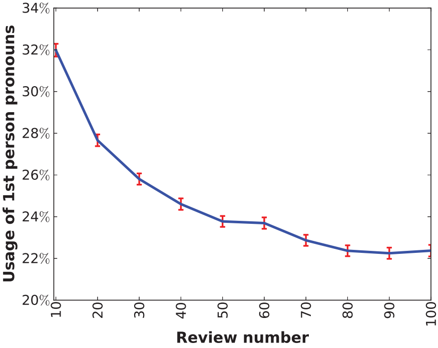
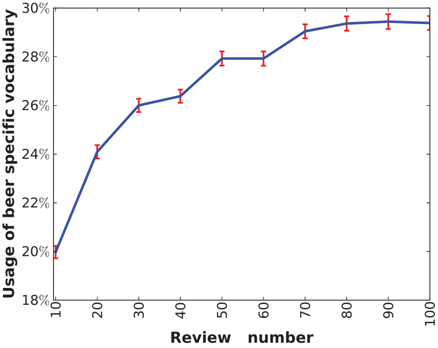


(a) First person sing. pronouns



(b) Beer specific vocabulary

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1. men or women?

2. people who are happy or people who are depressed?

3. extraverts or introverts?

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In principle, s could be estimated, but typically set to 2.

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3. How do models of the burstiness of words differ from 'topic models'? Which would you use to study changing subjects of debate over time? Which would you use to study conceptual change?

BTW, Twitter trends

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Trends are determined by an algorithm and, by default, are tailored for you based on who you follow, your interests, and your location. This algorithm identifies topics that are popular now, rather than topics that have been popular for a while or on a daily basis, to help you discover the hottest emerging topics of discussion on Twitter.

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Twitter seems to hand-curate also (unsurprisingly)

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Authors gather $\sim$ 750M election tweets, and use dictionary and non-dictionary approaches.

Find no evidence of sustained increase: “[W]hile key campaign events and policy announcements produced brief spikes in hateful language, these bursts quickly dissipated”

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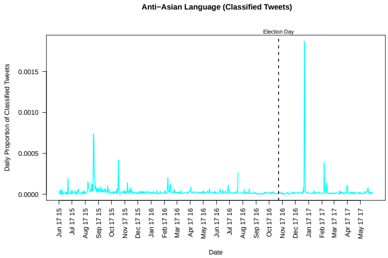
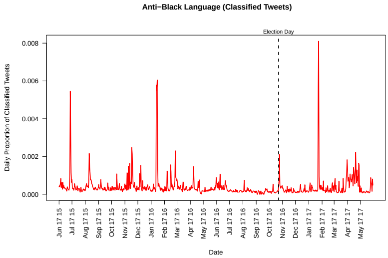
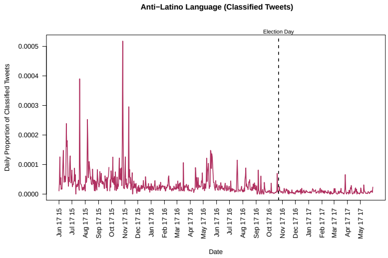
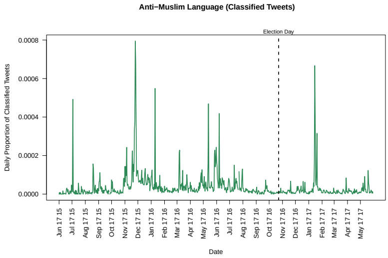
Anti-Asian, Anti-Black, Anti-Latino, Anti-Muslim tweets









Recap: “Meme-tracking and the Dynamics of the News Cycle”

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What is a meme for these authors?

Why are they hard to track?

Authors find peak and decay of memes is symmetric: what does this suggest?

McCain: “The fundamentals of our economy are strong”

Length	Qoute text	Vo
7	the fundamentals of our economy are strong	365
7	the fundamentals of the economy are strong	988
6	fundamentals of our economy are strong	645
6	fundamentals of the economy are strong	557
41	if john mccain hadn't said that the fundamentals of our economy are strong on the day of one of our nation's worst financial crises the claim that he invented the blackberry would have been the most preposterous thing said all week	224
4	fundamentals of the economy	172
7	the fundamentals of the economy are sound	119
18	i promise you we will never put america in this position again we will clean up wall street	83
7	the fundamentals of our economy are sound	81
4	clean up wall street	78
12	our economy i think still the fundamentals of our economy are strong	75
6	fundamentals of the economy are sound	72
27	the fundamentals of our economy are strong but these are very very difficult times and i promise you we will never put america in this position again	68
5	the economy is in crisis	66
6	these are very very difficult times	63

Top 50 threads in 2008/9

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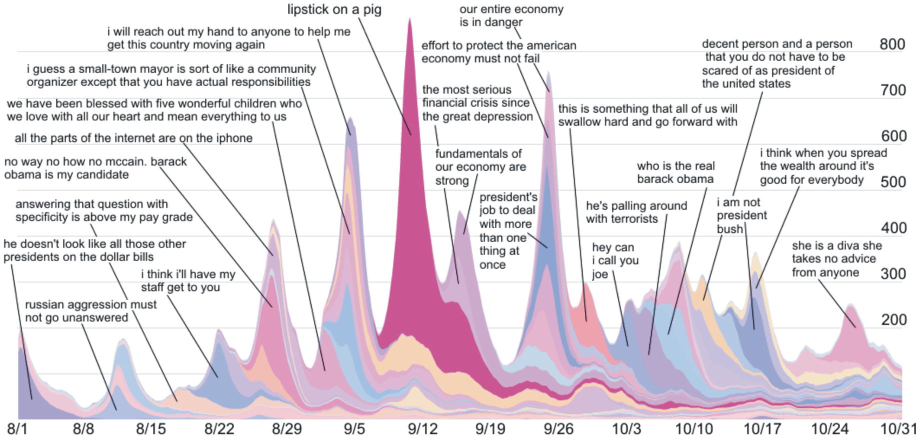

Quotus: Bias

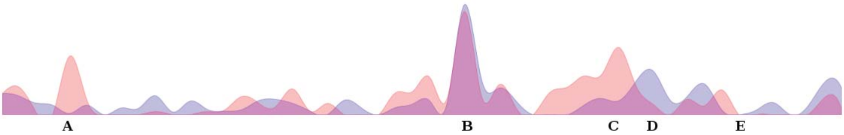

Figure 1: Volume of quotations for each word from a fragment of the 2010 State of the Union Address split by political leaning: conservative outlets shown in red and liberal outlets shown in blue. Quotes from the marked positions are reproduced in Table 1 and shown in the QUOTUS visualization in Figure 2.

Position	Quote from the 2010 State of the Union Address
A	And in the last year, hundreds of al Qaeda's fighters and affiliates, including many senior leaders, have been captured or killed—far more than in 2008.
B	I will work with Congress and our military to finally repeal the law that denies gay Americans the right to serve the country they love because of who they are. It's the right thing to do.
C	Each time lobbyists game the system or politicians tear each other down instead of lifting this country up, we lose faith. The more that TV pundits reduce serious debates to silly arguments, big issues into sound bites, our citizens turn away.
D	Democracy in a nation of 300 million people can be noisy and messy and complicated. And when you try to do big things and make big changes, it stirs passions and controversy. That's just how it is.
E	But I wake up every day knowing that they are nothing compared to the setbacks that families all across this country have faced this year.

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Find that more conservative outlets tend to favor quotes that display negative sentiment (depressing!), more negation (controversial topics), more conservative topics of interest (e.g. troops rather than health care)

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Questions and Answers

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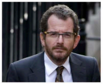
What do you say is permissible and **what do** you say is impermissible on this issue [of boundaries for privacy]?

J.K. Rowling, phone hacking victim

… it is not normal for anyone, famous or not famous, for their address to be known to millions of newspaper readers or users of the Internet. So **that is where I would draw the line**. …

Mr. Jay, lead counsel



… I paraphrase: he [the bin-man] turned up with sackfuls of Elton [John]'s documents, including the bank statements. **Did you have any qualms** about that, Mr Morgan?

Piers Morgan, tabloid editor

Yes, slightly. I mean, it clearly is, you know, a strange thing to be doing. … **Did I think he was doing anything illegal?** No. **Did I think it was on the cusp of unethical?** Yes.

… **Would you agree** that the magnitude of legal risk to a company is merely a function of the magnitude of **ethical misbehaviour** within a company?

Rupert Murdoch, tabloid owner

No. Clearly it may be. Serious breaches of the law are certainly unethical, but I think **I can think of other unethical things** which I would call unethical and extremely serious, but -- **which are not criminal**.

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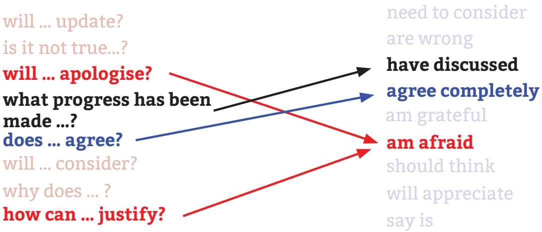
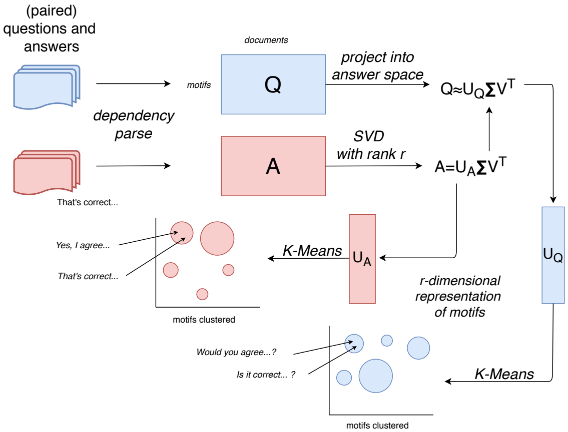


Map Questions into Answer Space



Zhang et al "Asking Too Much", 2018

Types of Questions that Prime Ministers face. . .

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Types of Questions that Prime Ministers face...

0. Issue update
1. Shared concerns
2. Narrow factual
3. Prompt for comment
4. Agreement
5. Self promotion
6. Concede & accept
7. Condemnatory

Zhang et al "Asking Too Much", 2018

Types of Questions that Prime Ministers face. . .

0. Issue update

Will you update us on Afghanistan?

1. Shared concerns

2. Narrow factual

What funding will be given to the College of Dentistry?

3. Prompt for comment
4. Agreement
5. Self promotion
6. Concede & accept
7. Condemnatory

Zhang et al "Asking Too Much", 2018

Types of Questions that Prime Ministers face...

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6. **Concede & accept**
7. **Condemnatory**

Will you accept that [Brexit] will undermine our security?

Will you apologise for leading us into the Iraq disaster?

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Looks at respondent types in Leveson:

Utterance type	Victim (compared to media, police, govt.)
Receive deferential question	**More** likely
Receive leading question	*Less* likely
Receive formal or hypothetical question	*Less* likely
Give evasive answer	*Less* likely