12. Special Topics

DS-GA 1015, Text as Data
Arthur Spirling

April 30, 2019

Housekeeping

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3. No office hours today: but available for appointments via email.

Where Are We?

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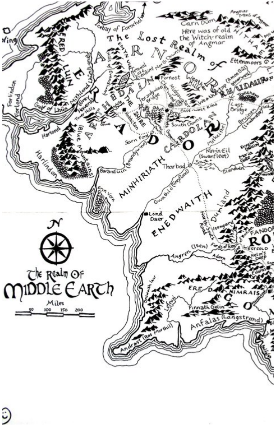

Carn Dûm
Here was of old the Witch-realm of Angmar
The Lost Realm of
ARNOR
Ettenmoors
Fornost
Weather Hills
RHUDAUR
Last Bridge
East-West Road
Bree
South Downs
THE SHIRE
Hobbiton
Sarn Ford
CARDOLAN
Mitheithel
Tharbad
Glanduin
MINHIRIATH
Lond Daer
ENEDWAITH
Dunland
Isengard
FANGORN
Angren
Adorn
Helm's Deep
NIMRAIS
Pinnath Gelin
Anfalas (Langstrand)
Forlindon
Forlond
Gulf of Lhûn
Harlond
Harlindon
Eryn Vorn
The Realm Of
MIDDLE EARTH
Miles

Where Are We?

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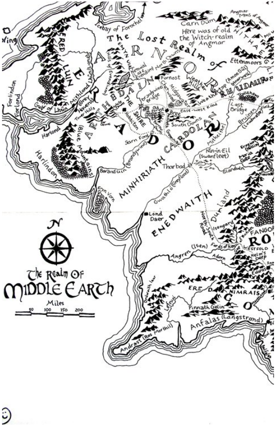

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Now look at some 'special topics' on debate, community behavior, bursts in streams, memes and spreading of stories/information.

Modeling Debate

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e.g. Westminster/Parliamentary systems: government-vs-opposition dynamic in which most debate takes place between one party vs the other(s).

Modern Arrangement

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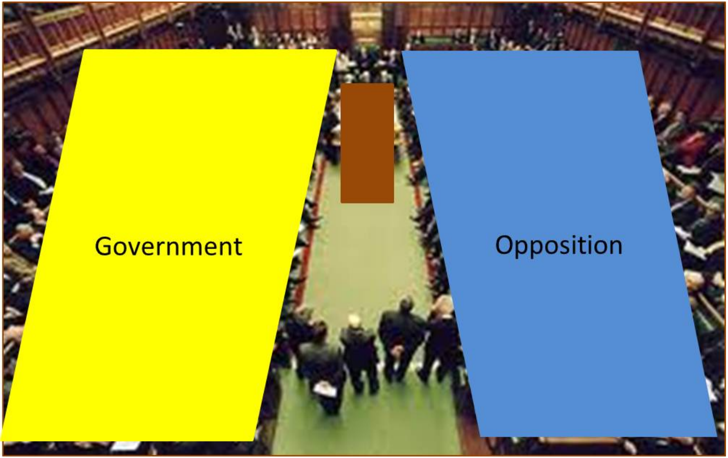
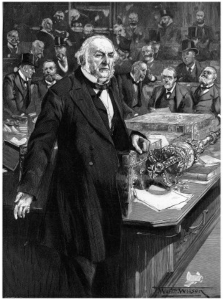
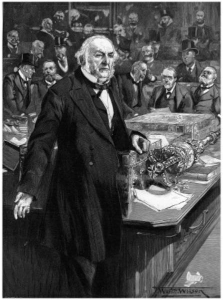


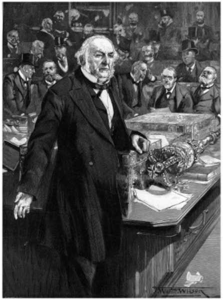
British Political Development

Theory is that between 1880–1902,





Theory is that between 1880–1902, ministers became more ‘responsive’ to (non-cabinet) MPs.



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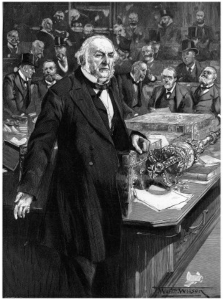

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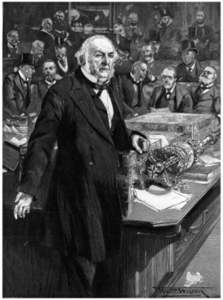

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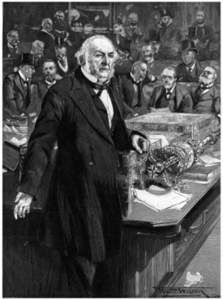

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Increase is ‘once-and-for-all’, not response to special circumstances

→ *need to measure responsiveness*

Three Types of Actors

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G_B

Three Types of Actors

G_B government backbencher

Three Types of Actors

G_B government backbencher

G_M

Three Types of Actors

G_B government backbencher

G_M government minister

Three Types of Actors

G_B government backbencher

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O

Three Types of Actors

G_B government backbencher

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What we have

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Every speech made in parliament,
1803–today

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Focus on period between 1832 (1st RA) and 1915 (4th RA)

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Problem: party not recorded (needed for Gov/Oppn assignment), lots of missingness/errors in terms of MP ids


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- <p id="S3V0094P0-00140">
  <member>SIR GEORGE GREY</member>
- <membercontribution>
    , in reply, stated that he had not as yet received any reply from the coroner of the
    district, to whom, as well as to the magistrates, he had written; neither had he
    received any communication from the magistrates tending to confirm the charges
    made against the owners of the colliery. He had, in consequence of the statement
    which had been made by the hon. Member for Finsbury respecting the accident,
    addressed a communication to the magistrates and coroner of the district, offering
    any assistance which could be given by the Home Office to forward the inquiry;
    and he had directed the magistrates to inquire rigidly into the means adopted for
    saving the lives of the persons who had been left in the pit, and to investigate the
    substance of the charges made against the proprietors of the colliery. He had just
    received a letter, dated the 6th of July, from the magistrates, in which they stated,
    that in consequence of the letter from the Home Office, they had directed their
    clerk to call a meeting of the magistrates, and that they had heard the statements
    of several parties upon the subjects alluded to in the communication. The result of
    the inquiry was, that they had come to an unanimous opinion as to cause of the
    accident. As that question, however, was still under the consideration of the
    coroner's inquest, he (Sir G. Grey) did not think it would be right for him to state
    the nature of their opinion until the verdict of the coroner's jury should have been
    ascertained. As to the question of the subsequent conduct of the owners of the
    colliery in preventing persons from descending into the pit to rescue those who
    might
  <image src="S3V0094P0I0035" />
  <col>49</col>
    have been left alive in it, the magistrates were convinced that no man left in the pit
    after the explosion could have been alive, and that every exertion that could have
    been made was made to get them out. That letter was signed by five magistrates.
    As he had before stated, he had received no letter from the coroner, whose
    investigation was still proceeding; but he would observe, that the gentleman who
    had been alluded to by the hon. Member for Fins-bury had had every opportunity
    during the inquest of examining and cross-examining any witnesses he chose.
    </membercontribution>
    </p>
- <p id="S3V0094P0-00141">
  <member>MR. DUNCOMBE</member>
  <membercontribution>expressed his astonishment at the hon. Member for Berwick
    denying the grounds for the statement which he had made. He had informed
    Gentlemen who was his authority. The man himself had been in London, and might
    have been examined in the lobby of the House by the hon. Member, had he chosen
    to satisfy himself upon the subject. And now he (Mr. Duncombe) was prepared to
    support the statement he had made. If the masters could have contradicted those
    statements, they had had opportunities of going before the coroner, whose inquiry
    had been adjourned from Thursday last to that very day. But he would state what
    one of the owners, Mr. Robert Lankester, had himself stated. Mr. Robert Lankester
    said the men were bricked up and could not escape.</membercontribution>
    </p>
    </section>
- <section>
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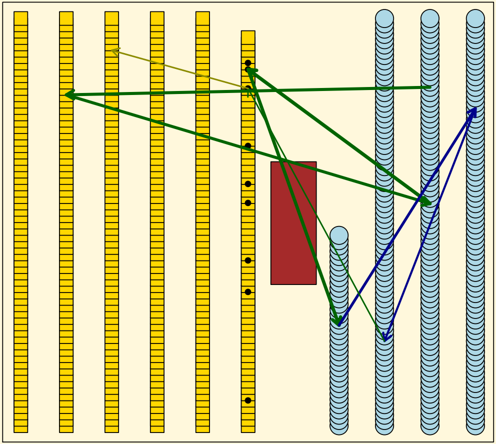
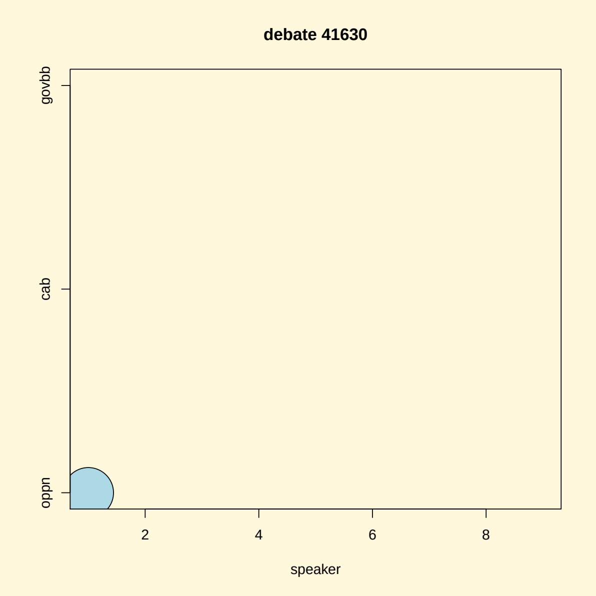
debate 41630




debate 41630
govbb
cab
oppn
2
4
6
8
speaker

Debate

Debate

Use speech information—

Debate

Use speech information—'to and fro'

Debate

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

Debate

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L_{15}

Debate

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

$L_{15} \rightarrow$

Debate

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$L_{15} \rightarrow L_4$

Debate

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$L_{15} \rightarrow L_4 \rightarrow$

Debate

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

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

Debate

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$L_{15} \rightarrow L_{4} \rightarrow C_{6} \rightarrow$

Debate

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$L_{15} \rightarrow L_4 \rightarrow C_6 \rightarrow L_2 \rightarrow C_5 \rightarrow L_2 \rightarrow L_{87} \rightarrow I_{15} \rightarrow C_5 \rightarrow C_{13}$

Debate

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

$$L_{15} \to L_4 \to C_6 \to L_2 \to C_5 \to L_2 \to L_{87} \to I_{15} \to C_5 \to C_{13}$$

O_{15}

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$O_{15} \to O_4 \to G_{B6}$

Debate

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

$$L_{15} \to L_4 \to C_6 \to L_2 \to C_5 \to L_2 \to L_{87} \to I_{15} \to C_5 \to C_{13}$$

$$O_{15} \to O_4 \to G_{B6} \to O_2 \to G_{M5} \to O_2 \to O_{87} \to O_{31} \to G_{M5} \to G_{B13}$$

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$$O$$

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$$O \to O$$

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$O \to O \to$

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$$O \rightarrow O \rightarrow G_{B}$$

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$$\boxed{O \rightarrow O \rightarrow G_{B} \rightarrow O \rightarrow G_{M} \rightarrow O \rightarrow O \rightarrow O \rightarrow G_{M} \rightarrow G_{B}}$$

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$$\boxed{O \to O \to G_B \to O \to G_M \to O \to O \to O \to G_M \to G_B}$$

If. . .

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For given debate. . .

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For given debate. . .

Three states

If. . .

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Three states: ministers, government backbenchers, opposition

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For given debate. . .

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- Resulting Markov chain is discrete: i.e. only relevant information is identity of speaker (not 'how long' we have been in particular state)
- Resulting Markov chain is (time) homogenous: i.e. probability of moving from state i to j does not depend on t.

Then. . .

Then. . .

We can characterize chain with the set of transition probabilities

Then...

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In particular:

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$$\begin{array}{cc} & \begin{array}{ccc} G_M & G_B & O \end{array} \\ \begin{array}{c} G_M \\ G_B \\ O \end{array} & \begin{pmatrix} m_{MM} & m_{MB} & m_{MO} \\ m_{BM} & m_{BB} & m_{BO} \\ m_{OM} & m_{OB} & m_{OO} \end{pmatrix} \end{array}$$

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

Partner Exercise

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1. Suppose that the weather {good, bad} evolves according to a Markov chain. In particular:

$$\begin{array}{cc} & \begin{array}{cc} G & B \end{array} \\ \begin{array}{c} G \\ B \end{array} & \begin{pmatrix} 0.8 & 0.2 \\ 0.6 & 0.4 \end{pmatrix} \end{array}.$$

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Task

Task

Must estimate m_{ij}

Task

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MLE is well known, and available,

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$\rightarrow$ Predicted probabilities are then (estimates of) transition probabilities

Rearranging Data

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S_1	S_2	S_3	S_4	S_5	S_6	S_7

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	S_1		S_2		S_3		S_4		S_5		S_6		S_7
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x	x_1	x_2	x_3	x_4	x_5	x_6
	O	O	G_B	O	G_M	G_M

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	O		O		G_B		O		G_M		G_M		
y			y_1		y_2		y_3		y_4		y_5		y_6
			O		G_B		O		G_M		G_M		G_B

Results

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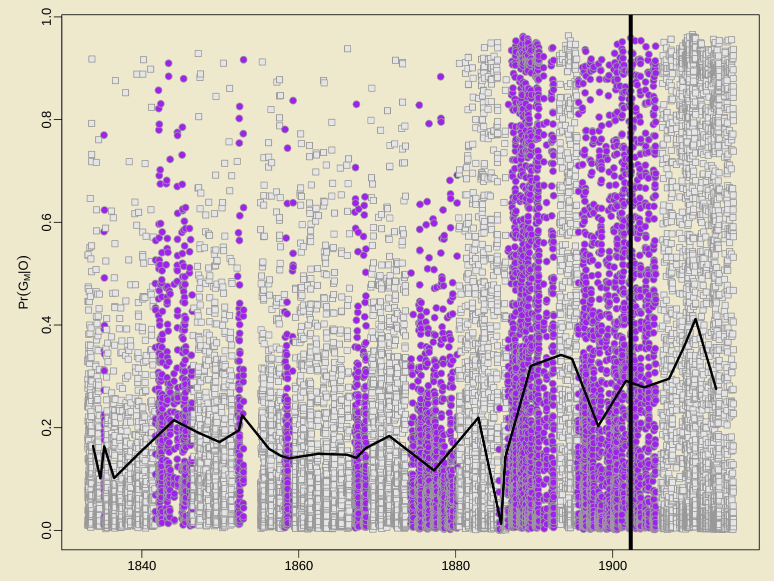

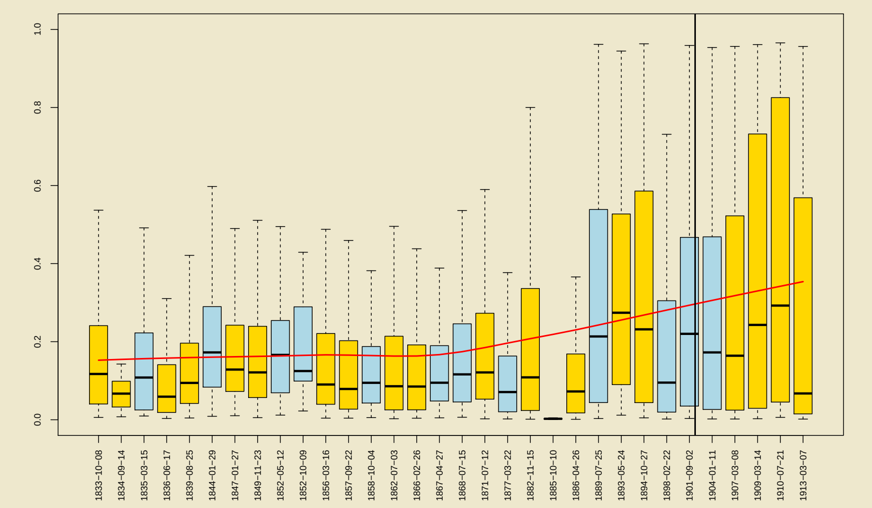

0.0
0.2
0.4
0.6
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1.0
1833−10−08
1834−09−14
1835−03−15
1836−06−17
1839−08−25
1844−01−29
1847−01−27
1849−11−23
1852−05−12
1852−10−09
1856−03−16
1857−09−22
1858−10−04
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1871−07−12
1877−03−22
1882−11−15
1885−10−10
1886−04−26
1889−07−25
1893−05−24
1894−10−27
1898−02−22
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1904−01−11
1907−03−08
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Well, early on, users adopt norms of community—until 'linguistic adolescence'—after which they cease to respond to community changes.

and results allow them to predict how long user will stay in community from early posts!

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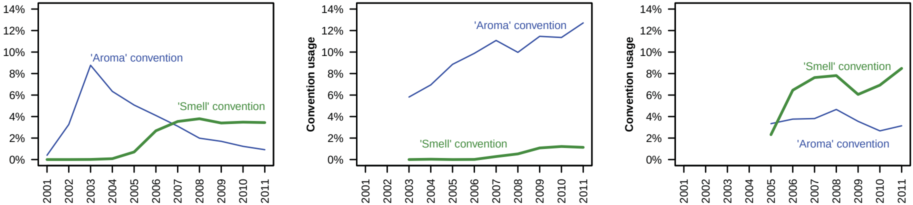

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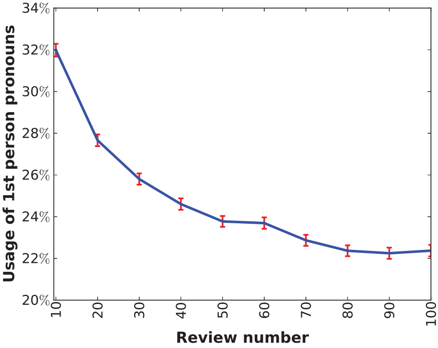
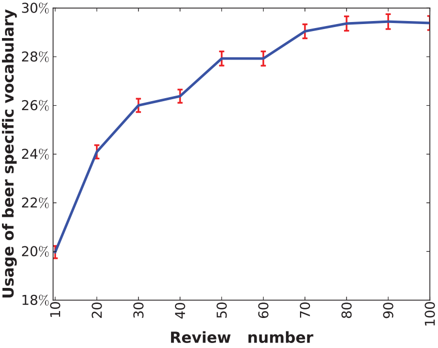


(a) First person sing. pronouns



(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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word	burst
gentlemen	1790–1800
british	1809–1814
slaves	1859–1863
japanese	1942–1945
health	1992–1994
help	1998–

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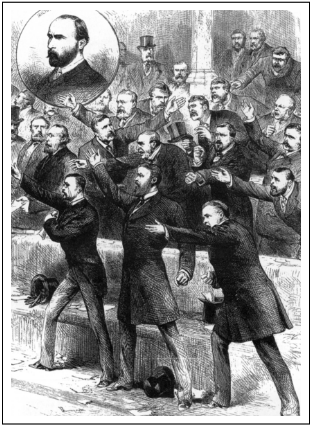

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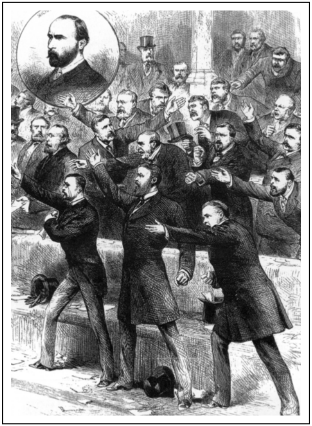

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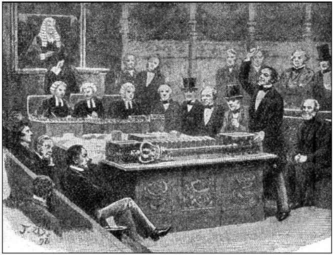

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$\Leftrightarrow$ this is an infinite state hidden Markov model.

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		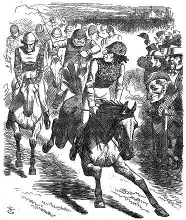 THE DERBY, 1867. DIZZY WINS WITH "REFORM BILL." MR. PUNCH. "DON'T BE TOO SURE; WAIT TILL HE'S WEIGHED."	 THE RIVALS.

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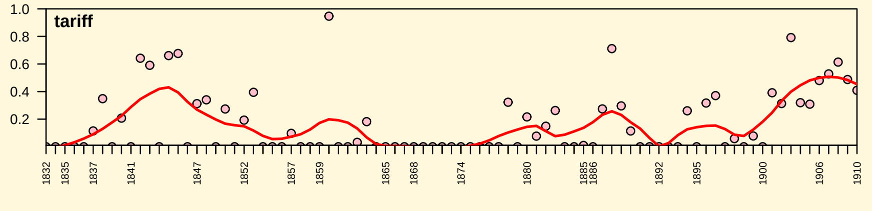

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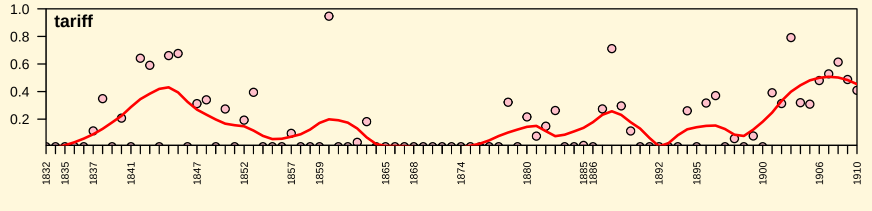

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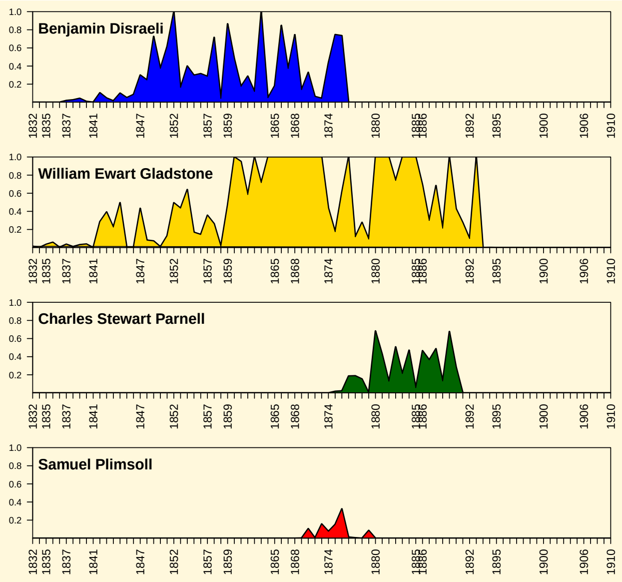

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then partition the graph back to a 'meme' of closely related (defined technically) phrases that can be followed through the news media as a thread

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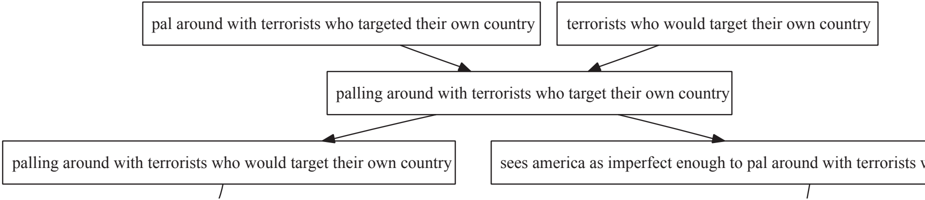
"Our opponent is someone who sees America, it seems, as being so imperfect, imperfect enough that he's palling around with terrorists who would target their own country."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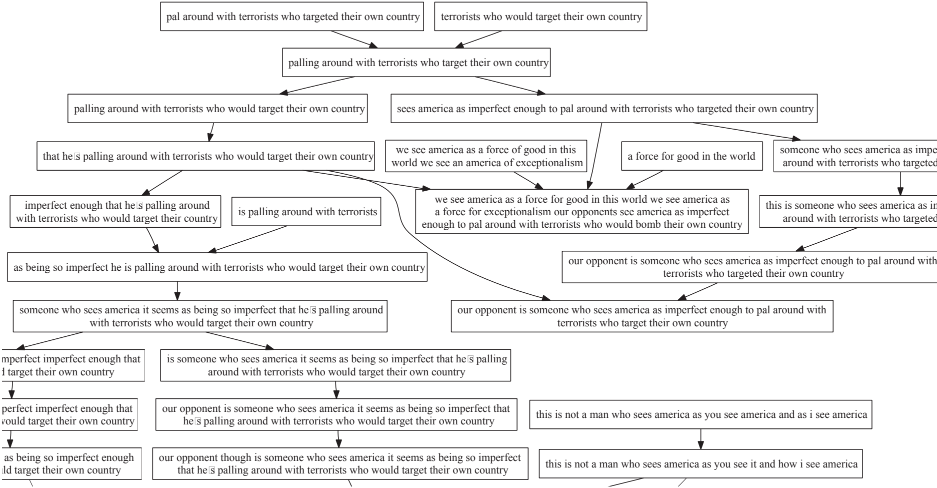
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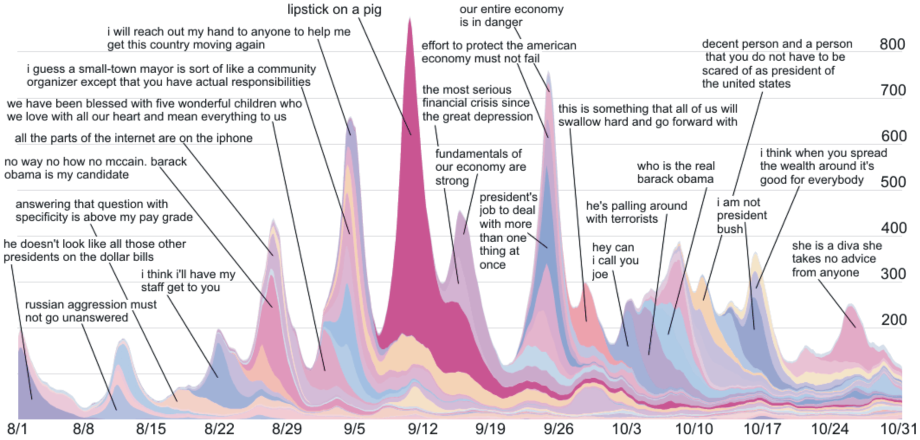

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Prima Facie evidence of bias

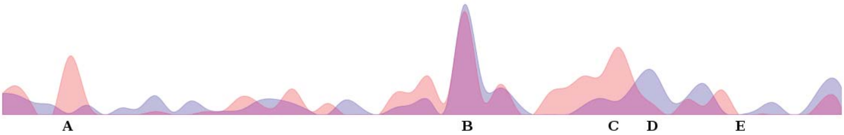

Figure 1: Volume of quotations for each word from a fragment of the 2010 State of the Union Address split by political leaning: conservative outlets shown in red and liberal outlets shown in blue. Quotes from the marked positions are reproduced in Table 1 and shown in the QUOTUS visualization in Figure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

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First dimension of bias	
High	The principle that people of all faiths are welcome in this country, and will not be treated differently by their government, is essential to who we are.
	The United States is not, and will never be, at war with Islam. In fact, our partnership with the Muslim world is critical.
	At a time when our discourse has become so sharply polarized [...] it's important for us to pause for a moment and make sure that we are talking with each other in a way that heals, not a way that wounds.
Low	Tonight, we are turning the east room into a bona fide country music hall.
	You guys get two presidents for one, which is a pretty good deal.
	Now, nothing wrong with an art history degree—I love art history.

Second dimension of bias	
High	Those of you who are watching certain news channels, on which I'm not very popular, and you see folks waving tea bags around...
	If we don't work even harder than we did in 2008, then we're going to have a government that tells the American people, "you're on your own."
	By the way, if you've got health insurance, you're not getting hit by a tax.
Middle	Congress passed a temporary fix. A band-aid. But these cuts are scheduled to keep falling across other parts of the government that provide vital services for the American people.
	Keep in mind, nobody is asking them to raise income tax rates. All we're asking is for them to consider closing tax loopholes and deductions.
	The truth is, you could figure out on the back of an envelope how to get this done. The question is one of political will.
Low	By the end of the next year, all U.S. troops will be out of Iraq.
	We come together here in Copenhagen because climate change poses a grave and growing danger to our people.
	Wow, we must come together to end this war successfully.