12. Special Topics

DS-GA 1015, Text as Data
Arthur Spirling

April 27, 2021

Where Are We?

Where Are We?

The Lost Realm of
Here was of old the Witch-realm of Angmar
Carn Dûm
Angmar
Ettenmoors
Fornost
Weather Hills
Weathertop (Amon Sûl)
RHUDAUR
Last Bridge
Bree
East-West Road
South Downs
THE SHIRE
Hobbiton
Sarn Ford
CARDOLAN
Mitheithel
Nîn-in-Eilph (Swanfleet)
Tharbad
Glanduin
MINHIRIATH
Baranduin
Harlond
Harlindon
Forlindon
Forlond
Gulf of Lhûn
Grey Havens
Mithlond
Blue Mountains
Tower Hills
Eryn Vorn
Lond Daer
ENEDWAITH
Gwathló (Greyflood)
Dunland
Isengard
North-South Road
Fords of Isen
(Isen)
Adorn
Angren
FANGORN
WESTFOLD
Helm's Deep
ERED NIMRAIS
Pinnath Gelin
Anfalas (Langstrand)
Andrast (Ras Morthil)
The Realm Of
MIDDLE EARTH
Miles
50
100
150
200

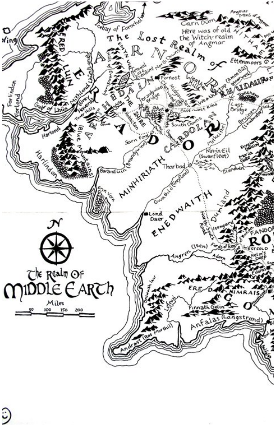
Where Are We?

We've covered the main ideas of text analysis: representing text,

Where Are We?

We've covered the main ideas of text analysis: representing text, supervised

Where Are We?



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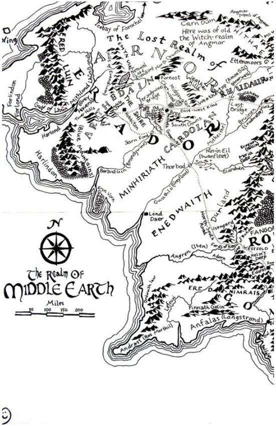

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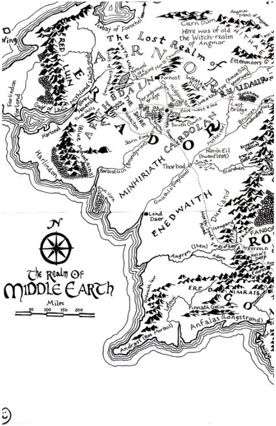

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We've covered the main ideas of text analysis: representing text, supervised and unsupervised learning.

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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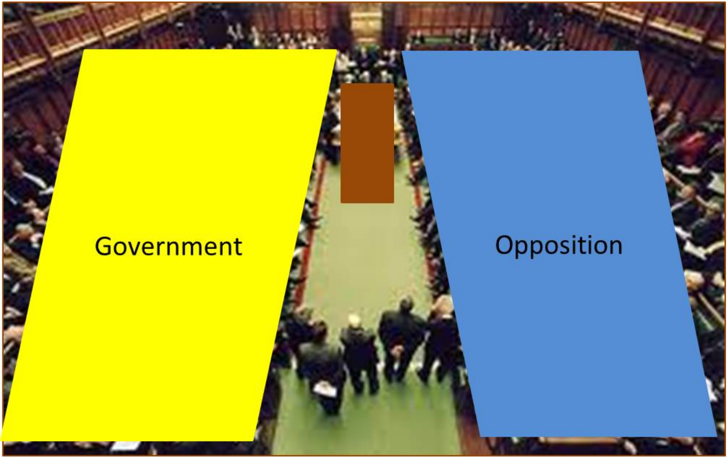
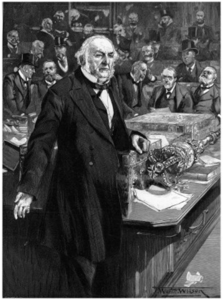
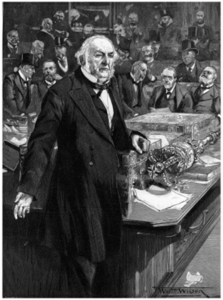


British Political Development

Theory is that between 1880–1902,





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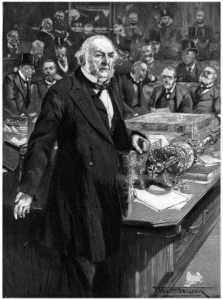

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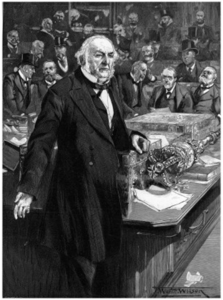

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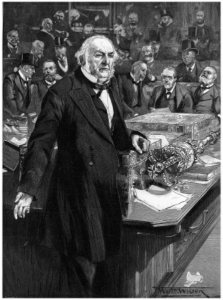

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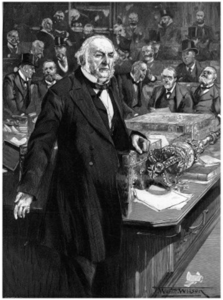

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→ *need to measure responsiveness*

Three Types of Actors

Three Types of Actors

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

G_M government minister

O

Three Types of Actors

G_B government backbencher

G_M government minister

O opposition member

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What we have

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Every speech made in parliament,
1803–today

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Every speech made in parliament, 1803–today

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

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1M+ digitized speech records:

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


```
- <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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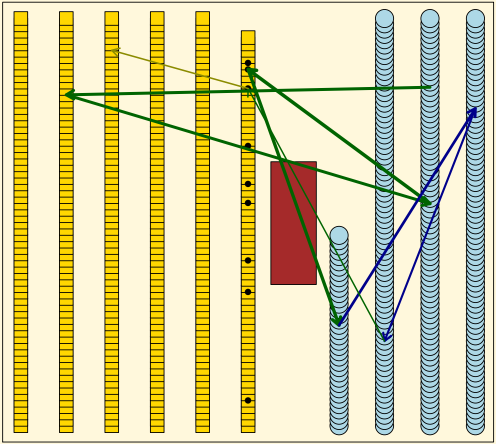
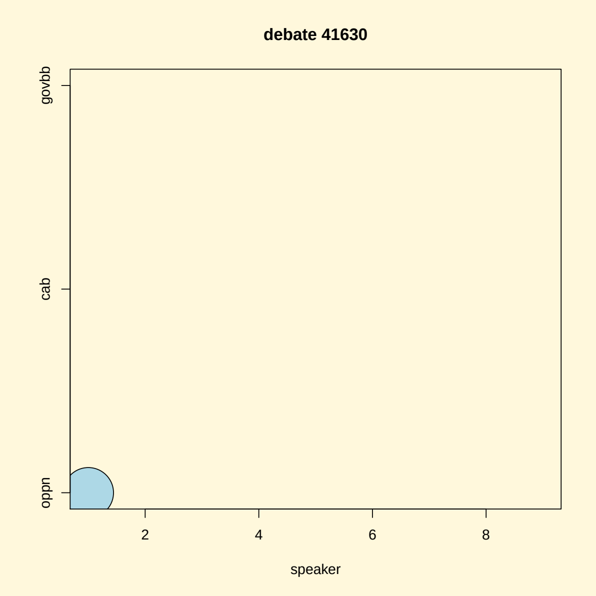
debate 41630




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

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

$L_{15} \rightarrow L_4$

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

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

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

Debate

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

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

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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$O_{15} \rightarrow O_{4} \rightarrow$

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

Debate

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

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

$$O_{15} \rightarrow O_4 \rightarrow G_{B\,6} \rightarrow O_2 \rightarrow G_{M\,5} \rightarrow O_2 \rightarrow O_{87} \rightarrow O_{31} \rightarrow G_{M\,5} \rightarrow G_{B\,13}$$

Debate

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

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$$O$$

Debate

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

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$$O \to$$

Debate

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$$O \rightarrow O$$

Debate

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

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$$O \rightarrow O \rightarrow$$

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$$O \rightarrow O \rightarrow G_B$$

Debate

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

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

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

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

If. . .

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For given debate. . .

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For given debate. . .

Three states

If. . .

For given debate. . .

Three states: ministers, government backbenchers, opposition

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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. . .

We can characterize chain with the set of transition probabilities

In particular:

Then. . .

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In particular:

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

Then...

We can characterize chain with the set of transition probabilities

In particular:

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

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

Task

Task

Must estimate m_{ij}

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MLE is well known, and available,

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$\rightarrow$ set up as multinomial logit with random effects

$$\exp(\boldsymbol{X}\boldsymbol{\beta} + \mathbf{Zu} + \mathbf{e})$$

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

Rearranging Data

Rearranging Data

S_1	S_2	S_3	S_4	S_5	S_6	S_7

Rearranging Data

	S_1		S_2		S_3		S_4		S_5		S_6		S_7
d_2	O	$\rightarrow$	O	$\rightarrow$	G_B	$\rightarrow$	O	$\rightarrow$	G_M	$\rightarrow$	G_M	$\rightarrow$	G_B

Rearranging Data

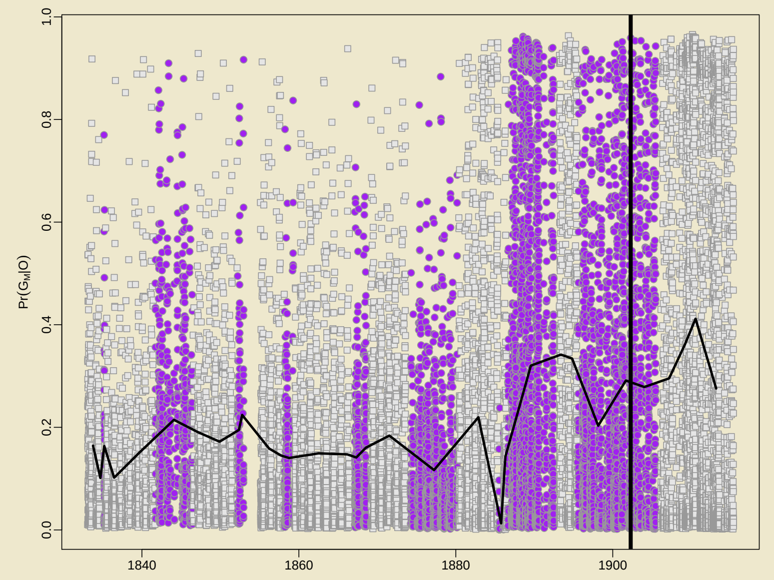
	S_1		S_2		S_3		S_4		S_5		S_6		S_7
d_2	O	$\rightarrow$	O	$\rightarrow$	G_B	$\rightarrow$	O	$\rightarrow$	G_M	$\rightarrow$	G_M	$\rightarrow$	G_B

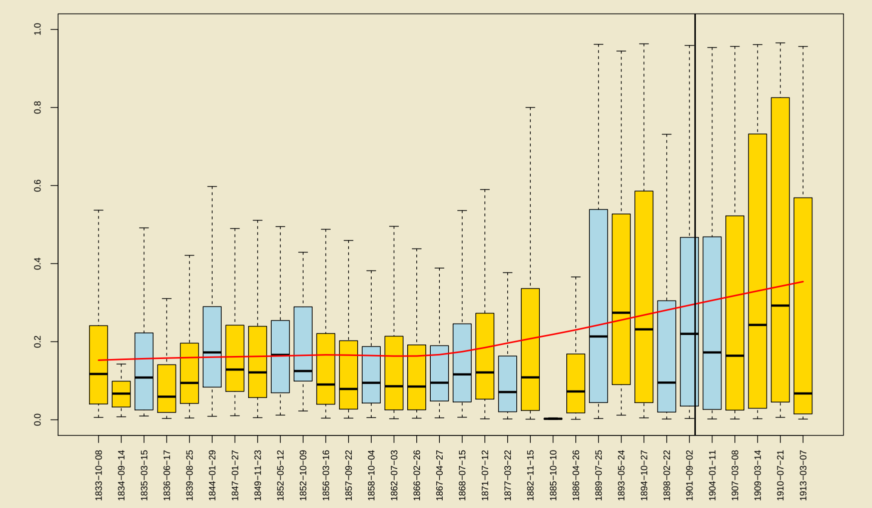
x	x_1	x_2	x_3	x_4	x_5	x_6
	O	O	G_B	O	G_M	G_M

	S_1	S_2	S_3	S_4	S_5	S_6	S_7
d_2	$O \rightarrow$	$O \rightarrow$	$G_B \rightarrow$	$O \rightarrow$	$G_M \rightarrow$	$G_M \rightarrow$	G_B
x	x_1: O	x_2: O	x_3: G_B	x_4: O	x_5: G_M	x_6: G_M	
y		y_1: O	y_2: G_B	y_3: O	y_4: G_M	y_5: G_M	y_6: G_B

Results

Results





0.0
0.2
0.4
0.6
0.8
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
1862−07−03
1866−02−26
1867−04−27
1868−07−15
1871−07−12
1877−03−22
1882−11−15
1885−10−10
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1889−07−25
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1894−10−27
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1904−01−11
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1909−03−14
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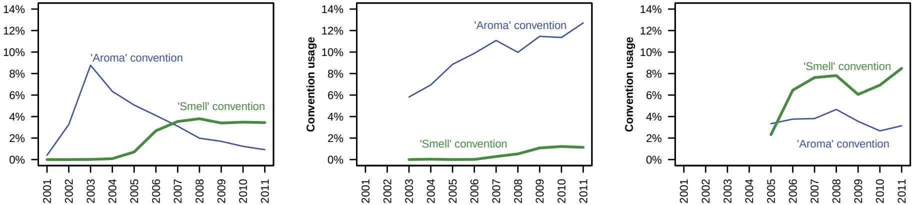

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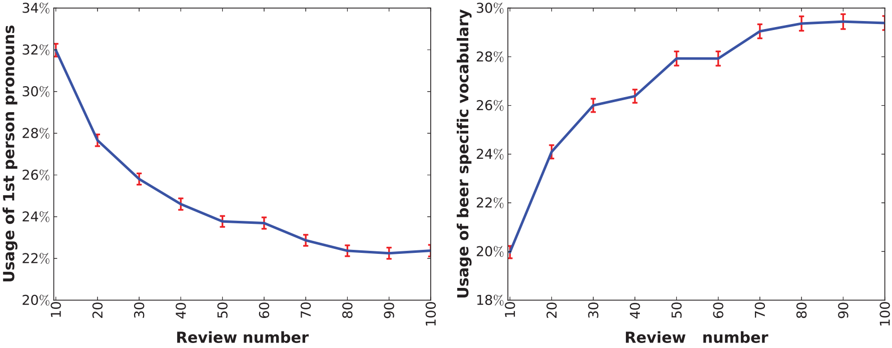

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word	burst
gentlemen	1790–1800
british	1809–1814
slaves	1859–1863
japanese	1942–1945
health	1992–1994
help	1998–

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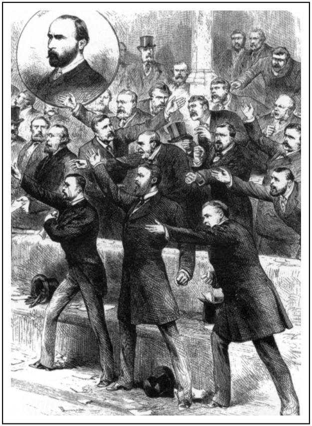

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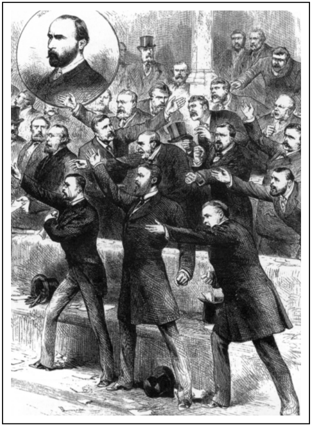

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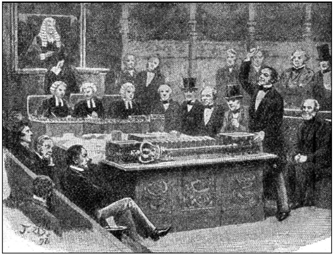

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		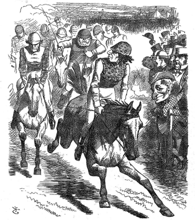 THE DERBY, 1867. DIZZY WINS WITH "REFORM BILL." MR. PUNCH. "DON'T BE TOO SURE; WAIT TILL HE'S WEIGHED."	 THE RIVALS.
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Validating II: given words are bursty, at right time

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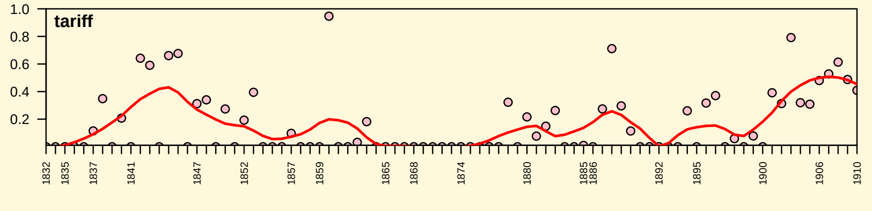

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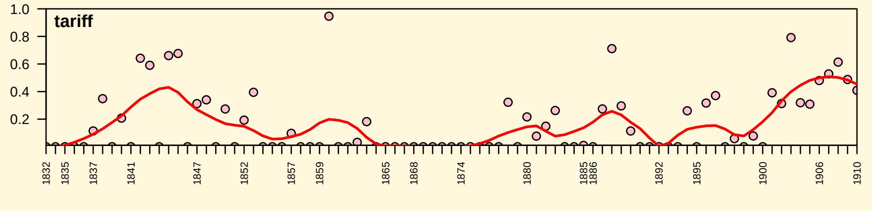

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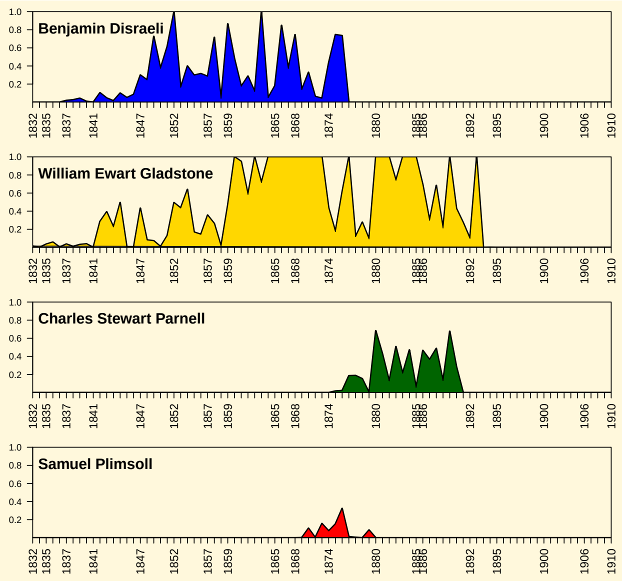

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then partition the graph back to a 'meme' of closely related (defined technically) phrases that can be followed through the news media as a thread

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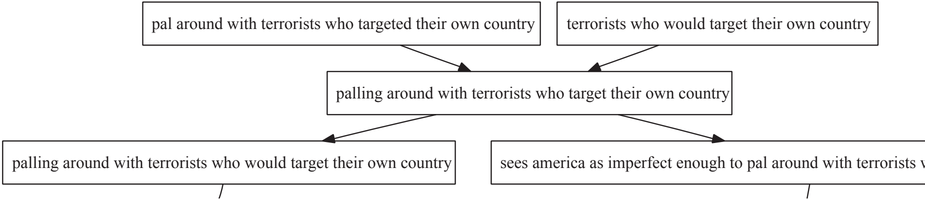
"Our opponent is someone who sees America, it seems, as being so imperfect, imperfect enough that he's palling around with terrorists who would target their own country."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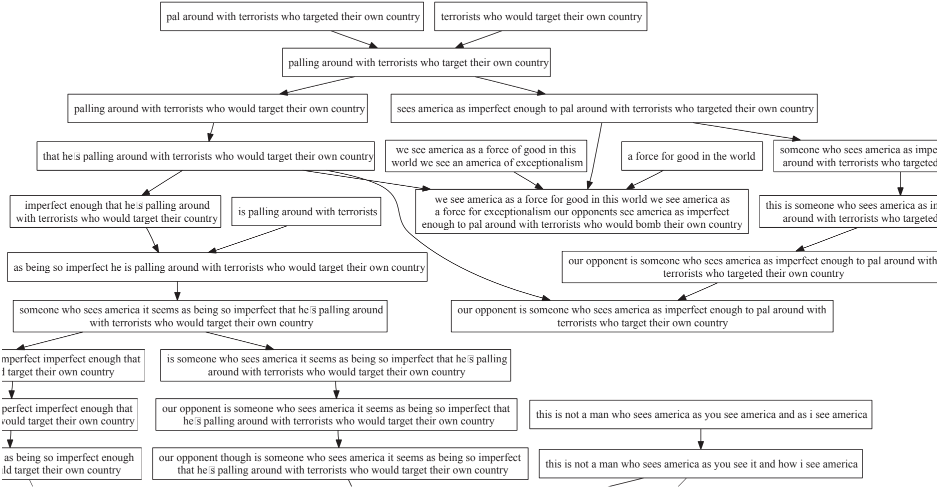
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perfect imperfect enough that vould target their own country
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this is not a man who sees america as you see america and as i see america
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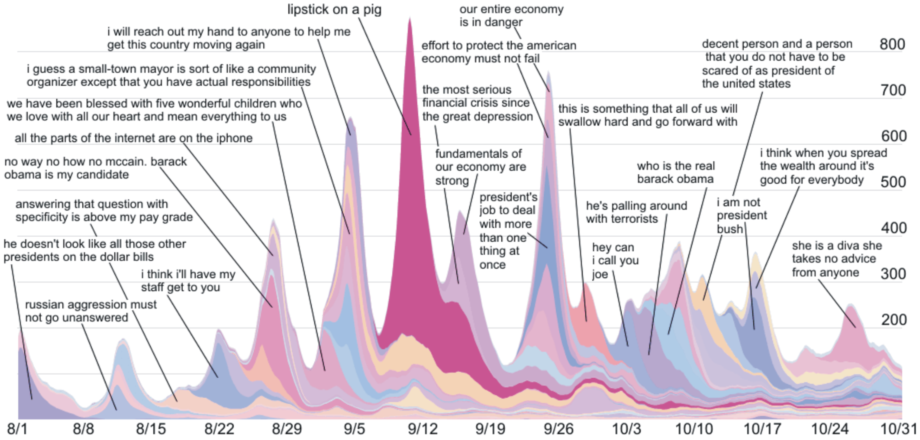

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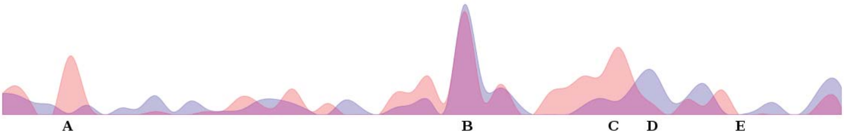

Figure 1: Volume of quotations for each word from a fragment of the 2010 State of the Union Address split by political leaning: conservative outlets shown in red and liberal outlets shown in blue. Quotes from the marked positions are reproduced in Table 1 and shown in the QUOTUS visualization in Figure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