

Session 13

PMAP 8921: Data Visualization with R Andrew Young School of Policy Studies Summer 2022

Plan for today

Qualitative text-based data

Crash course in computational linguistics

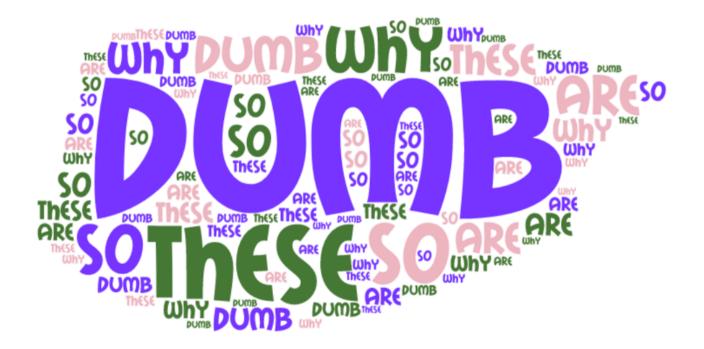
Qualitative text-based data

Free responses

N	0	P	
donate_likely	amount_donate	amount_keep	amount_why
Somewhat unlikely	0	100	I am poor
Somewhat unlikely	0	100	I really feel like I deserve to treat myself recently. I have been wo
Somewhat likely	10	90	I donate the amount that I usually would
Somewhat unlikely	0	100	i'm poor
Neither likely nor unlikely	10	90	It is not a cause that is very important to me. i have other things the
Extremely likely	29	71	I want to contribute to the cause, but also keep some of the mone
Somewhat likely	20	80	It's a reasonable amount of money for an individual to donate to ϵ
Extremely unlikely	0	100	I don't fully agree with their mission
Somewhat likely	10	90	I am pretty poor so I need to keep some for myself, but I also war
Extremely likely	5	95	I think it would be a good amount to give from the money I have ϵ
Neither likely nor unlikely	69	31	to help with their cause
Somewhat unlikely	0	100	My dad always told me to give until it hurts, and right now I am hu
Neither likely nor unlikely	0	100	I would rather keep the money for myself and find a charity that I
Extremely unlikely	0	100	I want the most for myself.
Neither likely nor unlikely	5	95	Can afford to give a little
Extremely unlikely	0	100	Because I would then have 100\$ more dollars.
Extremely unlikely	0	100	I'm a broke boi. If anyone need humanitarian aid, it's me.
Somewhat likely	10	90	I'm in a position where I would need the extra money, but I also w
Somewhat unlikely	90	10	I think it is a worthy cause and I think donating 90% of the amoun
Extremely likely	50	50	I feel splitting it 50/50 would be a fair deal. I get to help make a di
Extremely likely	20	80	I feel that my contribution is enough. I would gladly donate again
Somewhat likely	9	91	give a little
Somewhat likely	1	99	I like money
Somewhat unlikely	0	100	I do not really know what they will do with the money.

Typical free responses from a survey





Some cases are okay

What Happened

400

the result of a relentless barrage of political attacks and negative coverage But I also know that it was my job to try to break through all that noise and convince the American people to vote for me. I wasn't able to do it.

What Americans Have Heard or Read About Donald Trump What specifically do you recall reading, hearing or seeing about Donald Trump in the last day or two?



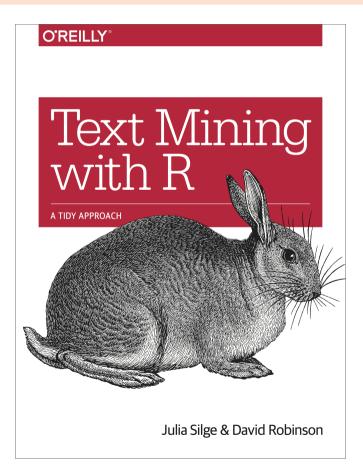
What Americans Have Heard or Read About Hillary Clinton What specifically do you recall reading, hearing or seeing about Hillary Clinton in the last day or two?



A d ves there

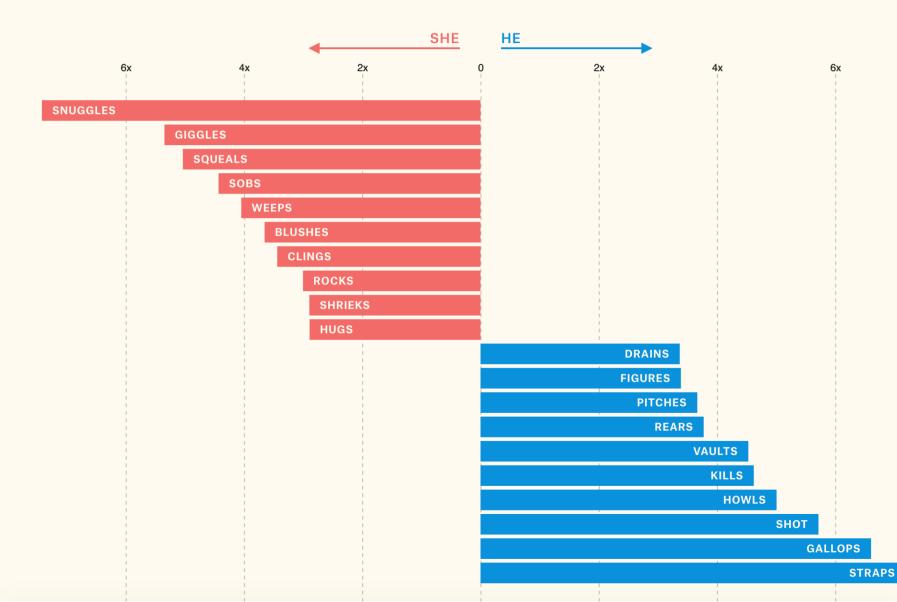
Word clouds for grownups

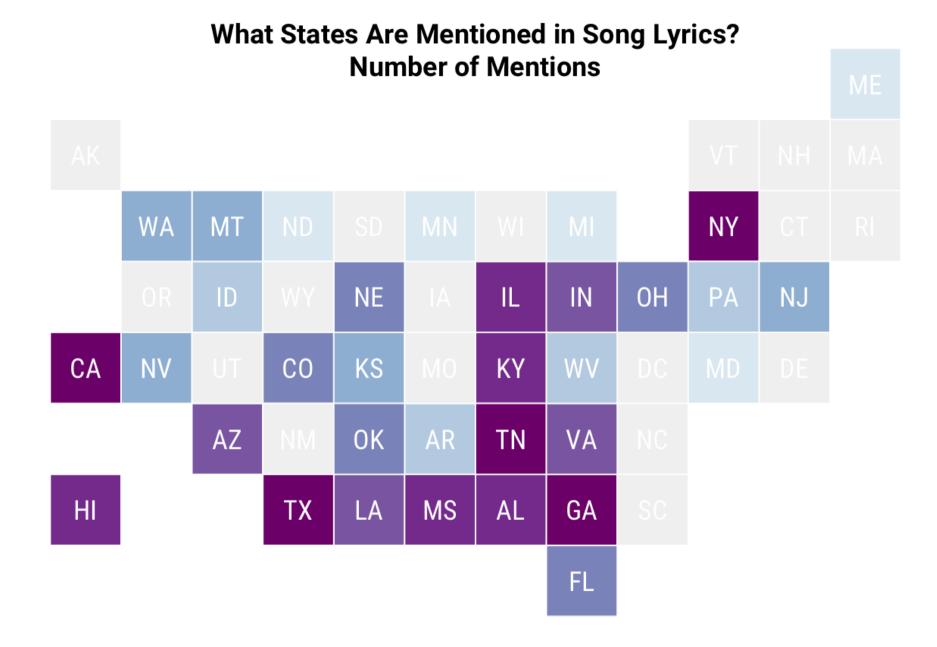
Count words, but in fancier ways



The most used words for women vs. men

Likelihood that certain words appear after "she" vs. "he" in screen direction.





Crash course in computational linguistics

Core concepts and techniques

Tokens, lemmas, and parts of speech

Sentiment analysis

tf-idf

Topics and LDA

Fingerprinting

Regular text

THE BOY WHO LIVED Mr. and Mrs. Dursley, of number four, Privet Drive, were proud to say that they were perfectly normal, thank you very much. They were the last people you'd expect to be involved in anything strange or mysterious, because they just didn't hold with such nonsense. Mr. Dursley was the director of a firm called Grunnings, which made drills. He was a big, beefy man with hardly any neck, although he did have a very large mustache. Mrs. Dursley was thin and blonde and had nearly twice the usual amount of neck, which came in very useful as she spent so much of her time craning over garden fences, spying on the neighbors. The Dursleys had a small son called Dudley and in their opinion there was no finer boy anywhere. The Dursleys had everything they wanted, but they also had a secret, and their greatest fear was that somebody would discover it. They didn't think they could bear it if anyone found out about the Potters. Mrs. Potter was Mrs. Dursley's sister, but they hadn't met for several years; in fact, Mrs. Dursley pretended she didn't have a sister, because her sister and her good-for-nothing husband were as unDursleyish as it was possible to be. The Dursleys shuddered to think what the neighbors would say if the Potters a...



One row for each text element

Can be chapter, page, verse, etc.

# A	tibble: 6 ×	3				
С	hapter book				text	
	<int> <chr></chr></int>				<chr></chr>	
1	1 Harry	Potter and	the Philosophe	r's Stone	"THE BOY WHO LIVED Mr. and	Mrs. Dur…
2	2 Harry	Potter and	the Philosophe	r's Stone	"THE VANISHING GLASS Nearly	/ ten yea…
3	3 Harry	Potter and	the Philosophe	r's Stone	"THE LETTERS FROM NO ONE TH	ne escape
4	4 Harry	Potter and	the Philosophe	r's Stone	"THE KEEPER OF THE KEYS BOO	M. They …
5	5 Harry	Potter and	the Philosophe	r's Stone	"DIAGON ALLEY Harry woke ea	arly the …
6	6 Harry	Potter and	the Philosophe	r's Stone	"THE JOURNEY FROM PLATFORM NI	NE AND TH



Split the text into even smaller parts

Paragraph, line, verse, sentence, n-gram, word, letter, etc.

#	A tibl	ole: 6 ×	3	
	word	chapter	book	
	<chr></chr>	<int></int>	<chr></chr>	
1	the	1	Harry	Potter
2	boy	1	Harry	Potter
3	who	1	Harry	Potter
4	lived	1	Harry	Potter
5	mr	1	Harry	Potter
6	and	1	Harrv	Potter

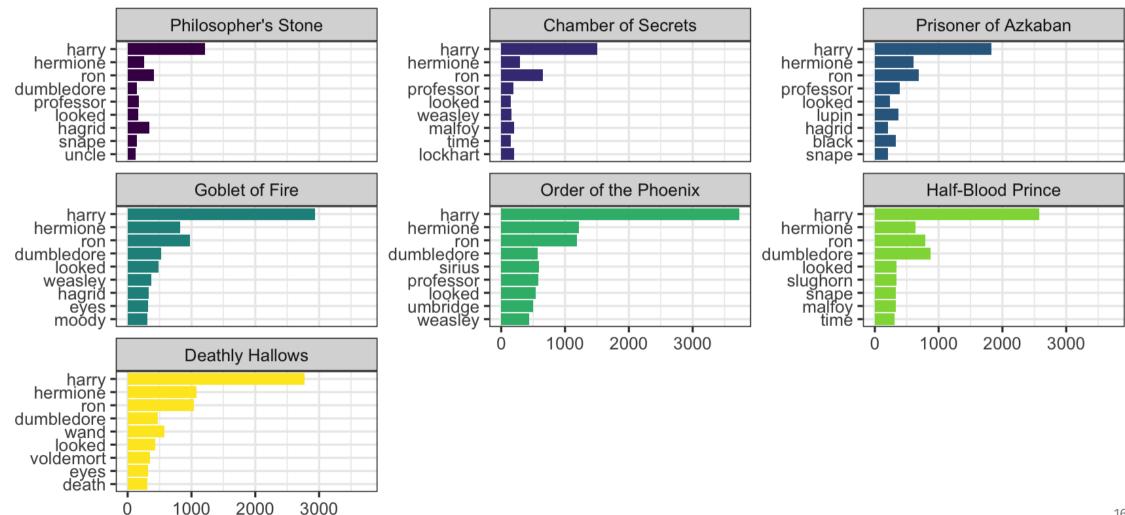
# A tibble:	6 × 3	
bigram	chapter bo	ook
<chr></chr>	<int> <c< td=""><td>:hr></td></c<></int>	:hr>
1 the boy	1 Ha	arry Potter
2 boy who	1 Ha	arry Potter
3 who lived	1 Ha	arry Potter
4 lived mr	1 Ha	arry Potter
5 mr and	1 Ha	arry Potter
6 and mrs	1 Ha	arry Potter

Stop words

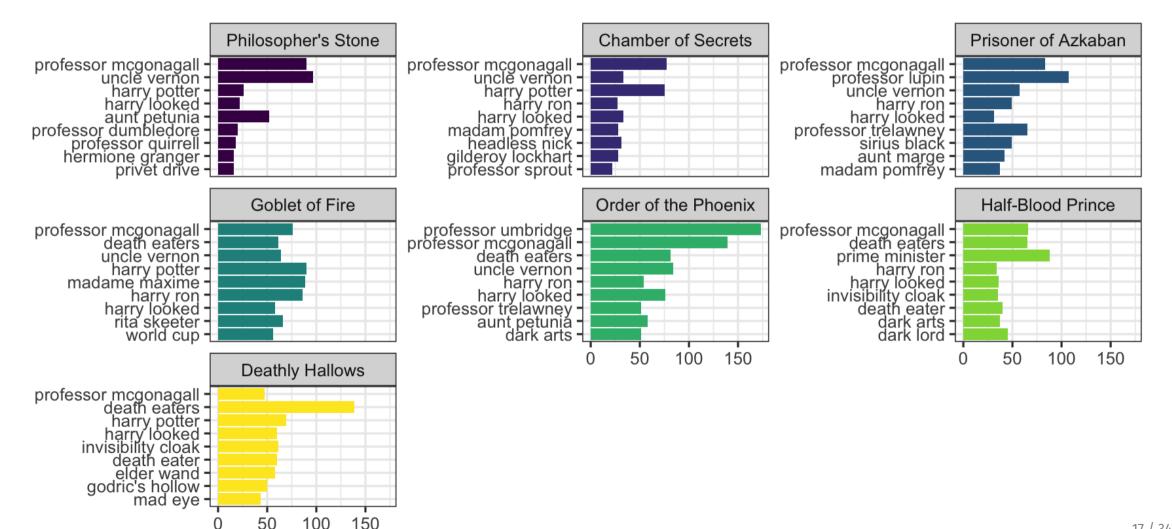
Common words that we can generally ignore

#	A tibble: 1,	149 × 2
	word	lexicon
	<chr></chr>	<chr></chr>
1	а	SMART
2	a's	SMART
3	able	SMART
4	about	SMART
5	above	SMART
6	according	SMART
7	accordingly	SMART
8	across	SMART
9	actually	SMART
10	after	SMART
#	with 1,139 r	more rows

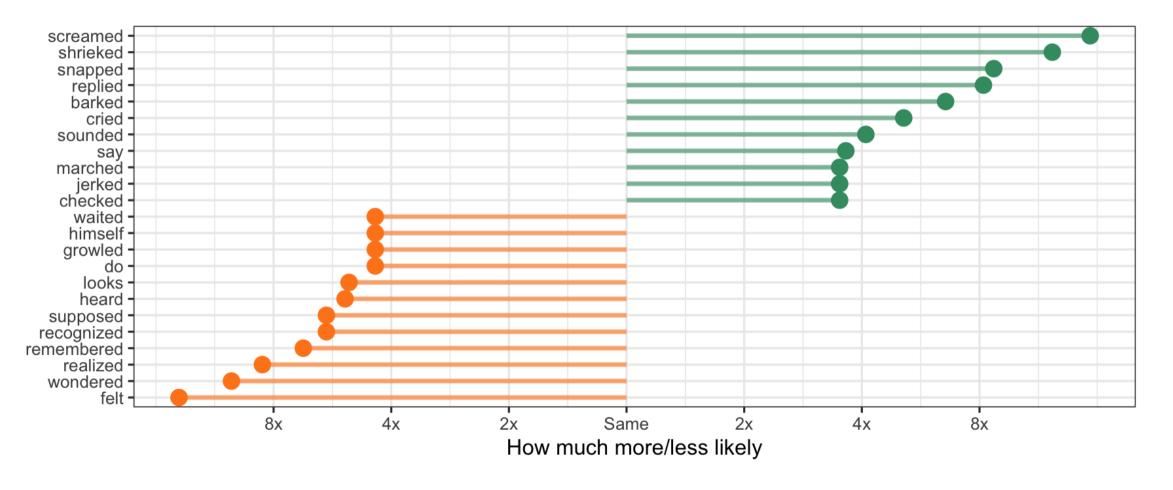
Token frequency: words



Token frequency: n-grams



Token frequency: n-gram ratios



🕒 More 'she' 🔶 More 'he'

Parts of speech

# A	tibble	e: 50 >	< 11								
	doc_id	sid	tid	token	token_with_ws	lemma	upos	xpos	feats	tid_source	relation
	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>	<chr></chr>	<chr></chr>	<chr></chr>	<chr></chr>	<chr></chr>	<chr></chr>	<dbl></dbl>	<chr></chr>
1	1	1	1	THE	THE	the	DET	DT	Defin…	2	det
2	1	1	2	BOY	BOY	Воу	NOUN	NN	Numbe	18	nsubj
3	1	1	3	WHO	WHO	who	PRON	WP	PronT	4	nsubj
4	1	1	4	LIVED	LIVED	live	VERB	VBD	Mood=	2	acl:rel…
5	1	1	5	Mr.	Mr.	Mr.	PROPN	NNP	Numbe	4	xcomp
6	1	1	6	and	and	and	CCONJ	CC	<na></na>	7	сс
7	1	1	7	Mrs.	Mrs.	Mrs.	PROPN	NNP	Numbe	5	conj
8	1	1	8	Dursley	Dursley	Dursley	PROPN	NNP	Numbe	7	flat
9	1	1	9	,	,	,	PUNCT	,	<na></na>	5	punct
10	1	1	10	of	of	of	ADP	IN	<na></na>	11	case
#	with 4	10 more	e rows								

These use the Penn part of speech tags

Parts of speech frequency

Verbs

A tibble: 1,557 × 2 lemma n <chr> <dbl> 1 say 920 2 get 440 3 have 417 4 go 384 5 look 380 6 be 310 7 know 310 8 see 303 9 think 230 10 do 227 # ... with 1,547 more rows

Nouns

# A tibble:	2,852 × 2
lemma	n
<chr></chr>	<dbl></dbl>
1 Harry	1315
2 Ron	423
3 Hagrid	258
4 Professor	167
5 Snape	154
6 Hermione	153
7 Dumbledor	e 144
8 time	138
9 Dudley	136
10 uncle	122
# with 2,84	42 more rows

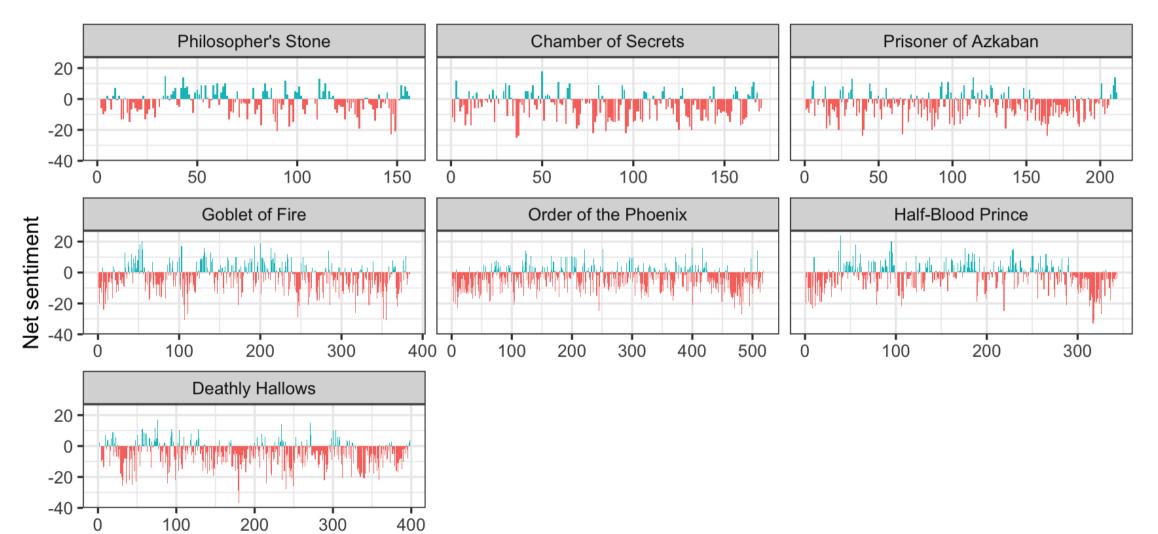
Adjectives & adverbs

# A tibbl	.e: 1,240	x	2
lemma	n		
<chr></chr>	<dbl></dbl>		
1 back	223		
2 so	215		
3 just	180		
4 when	178		
5 very	171		
6 now	166		
7 then	165		
8 all	147		
9 how	136		
10 there	123		
# with	1,230 mo	re	rows



Sentiment analysis

<pre>get_sentiments("bing"</pre>) get_sentiments("afinn")	<pre>get_sentiments("nrc")</pre>
# A tibble: 6,786 × 2	# A tibble: 2,477 × 2	# A tibble: 13,872 × 2
word sentime	nt word value	word sentiment
<chr> <chr></chr></chr>	<chr> <dbl></dbl></chr>	<chr> <chr></chr></chr>
1 2-faces negativ	e 1 abandon – 2	1 abacus trust
2 abnormal negativ	e 2 abandoned -2	2 abandon fear
3 abolish negativ	e 3 abandons -2	3 abandon negative
4 abominable negativ	e 4 abducted -2	4 abandon sadness
5 abominably negativ	e 5 abduction -2	5 abandoned anger
6 abominate negativ	e 6 abductions -2	6 abandoned fear
7 abomination negativ	e 7 abhor -3	7 abandoned negative
8 abort negativ	e 8 abhorred -3	8 abandoned sadness
9 aborted negativ		9 abandonment anger
10 aborts negativ	e 10 abhors -3	10 abandonment fear
# with 6,776 more ro	ws # … with 2,467 more rows	# … with 13,862 more rows



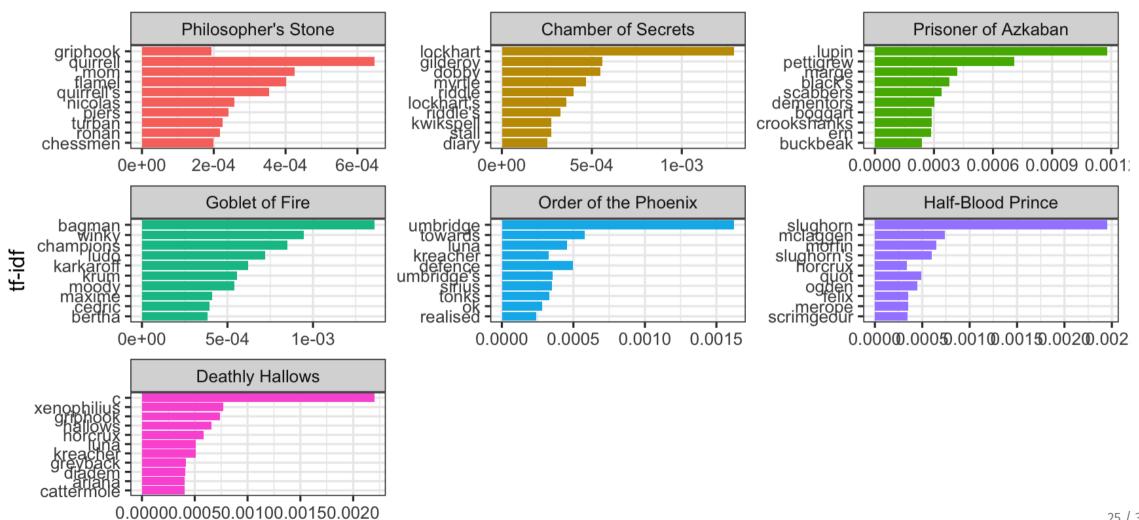


Term frequency-inverse document frequency

How important a term is compared to the rest of the documents

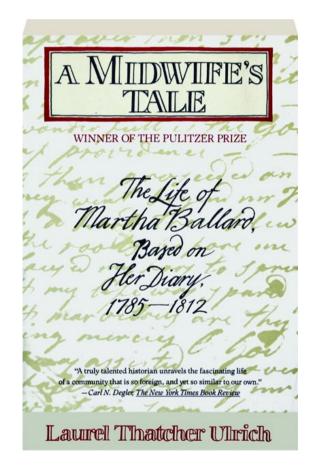
$$egin{aligned} tf &= rac{n_{ ext{term}}}{n_{ ext{terms in document}}} \ idf(ext{term}) &= \ln\left(rac{n_{ ext{documents}}}{n_{ ext{documents containing term}}}
ight) \ tf\-idf(ext{term}) &= tf(ext{term}) imes idf(ext{term}) \end{aligned}$$

tf-idf

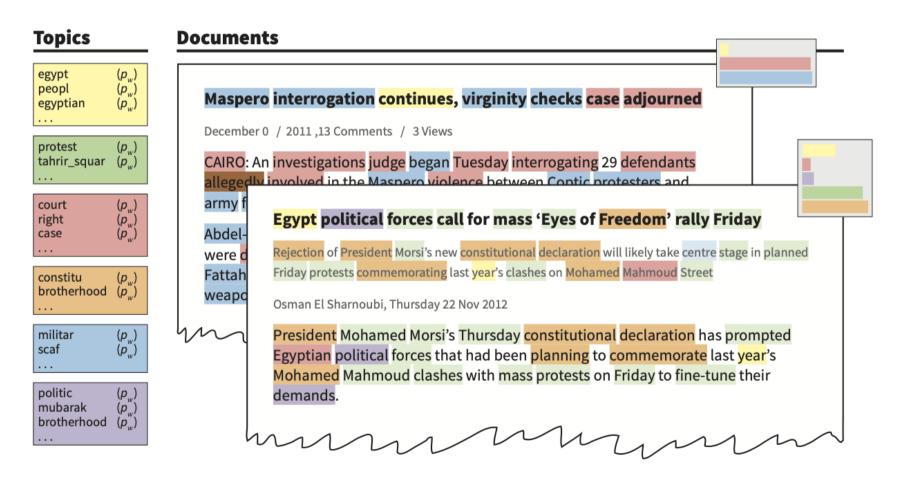


Topic modeling





Latent Dirichlet Allocation (LDA)

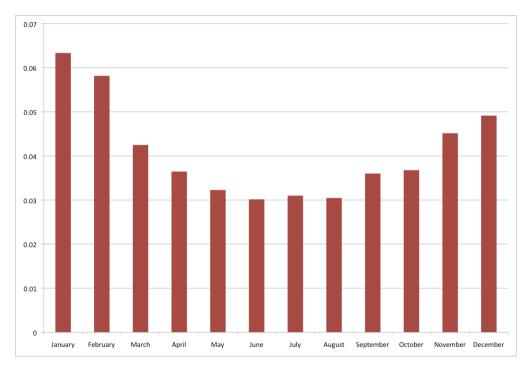


Clusters of related words

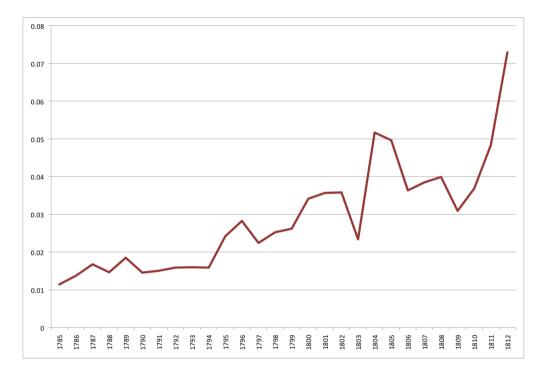
Topic label Topic words

Midwifery	birth safe morn receivd calld left cleverly pm labour
Church	meeting attended afternoon reverend worship
Death	day yesterday informd morn years death expired
Gardening	gardin sett worked clear beens corn warm planted
Shopping	lb made brot bot tea butter sugar carried
Illness	unwell sick gave dr rainy easier care head neighbor

Track topics over time

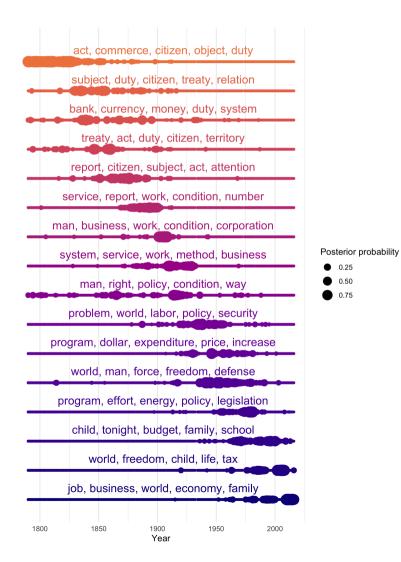


Cold weather topic by month



Emotion topic over time

State of the Union addresses



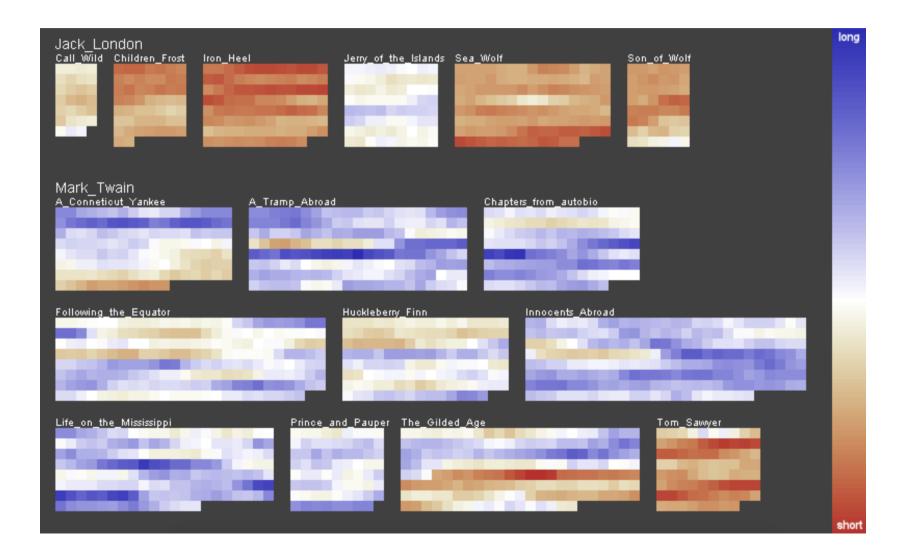
Fingerprinting

Analyze richness or uniqueness of a document

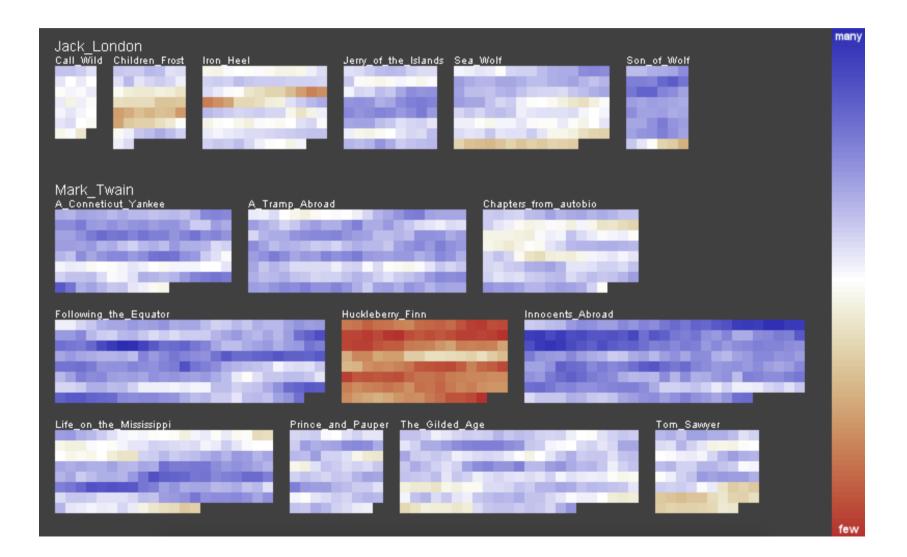
Punctuation patterns, vocabulary choices, sentence length

Hapax legomenon

Sentence length



Hapax legomena



Verse length

