

#### **Session 13**

PMAP 8921: Data Visualization with R Andrew Young School of Policy Studies Summer 2023

### **Plan for today**

### **Qualitative text-based data**

Crash course in computational linguistics

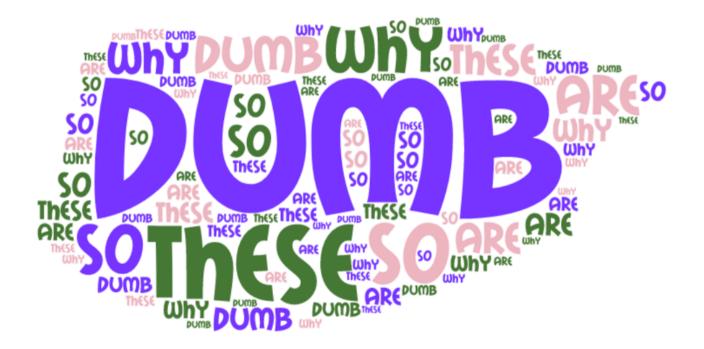
# Qualitative text-based data

### 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 $\epsilon$
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 $\epsilon$
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?



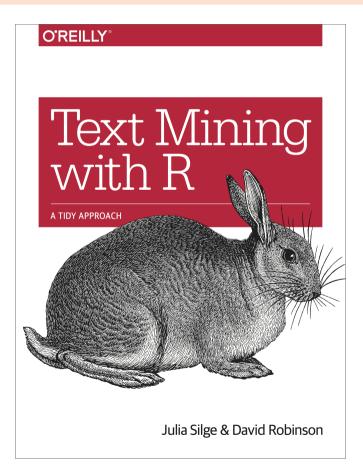
What Americans Have Heard or Read About Hillary Clinton What specifically do you recall reading, hearing or seeing about Hillary Clinton in the last day or two?



A d ves there

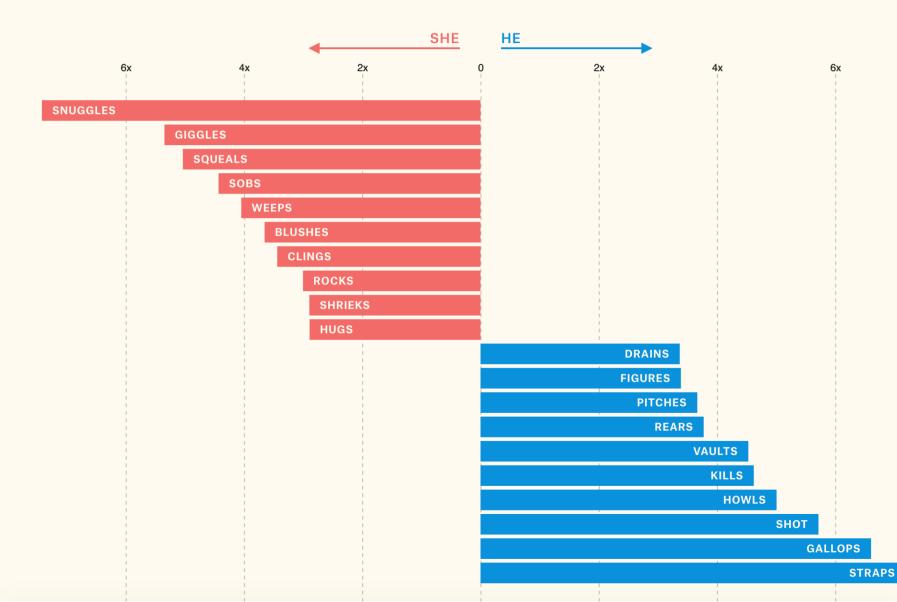
### Word clouds for grownups

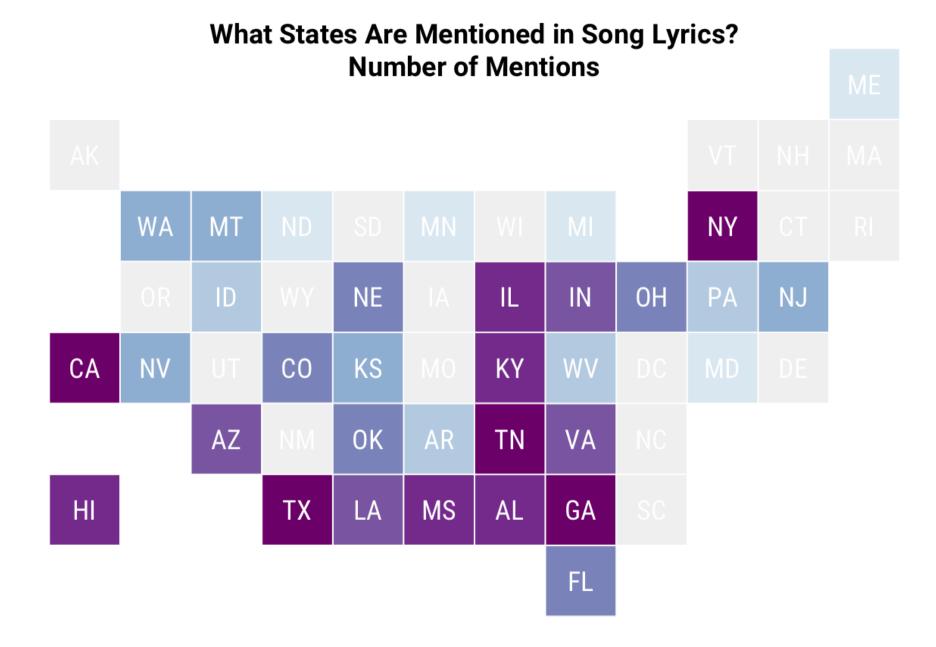
### **Count words, but in fancier ways**



#### The most used words for women vs. men

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





#### 9 / 34

# 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	A tibble: 6 ×	3			
C	chapter book				text
	<int> <chr></chr></int>				<chr></chr>
1	1 Harry	Potter and	the Philosopher's	Stone	"THE BOY WHO LIVED Mr. and Mrs. Dur…
2	2 Harry	Potter and	the Philosopher's	Stone	"THE VANISHING GLASS Nearly ten yea…
3	3 Harry	Potter and	the Philosopher's	Stone	"THE LETTERS FROM NO ONE The escape
4	4 Harry	Potter and	the Philosopher's	Stone	"THE KEEPER OF THE KEYS BOOM. They
5	5 Harry	Potter and	the Philosopher's	Stone	"DIAGON ALLEY Harry woke early the …
6	6 Harry	Potter and	the Philosopher's	Stone	"THE JOURNEY FROM PLATFORM NINE AND TH



### Split the text into even smaller parts

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

‡	ŧ	A tib	ole: 6 ×	3	
		word	chapter	book	
		<chr></chr>	<int></int>	<chr></chr>	
-	L	the	1	Harry	Potter
2	2	boy	1	Harry	Potter
	3	who	1	Harry	Potter
Ζ	1	lived	1	Harry	Potter
Ę	5	mr	1	Harry	Potter
6	5	and	1	Harrv	Potter

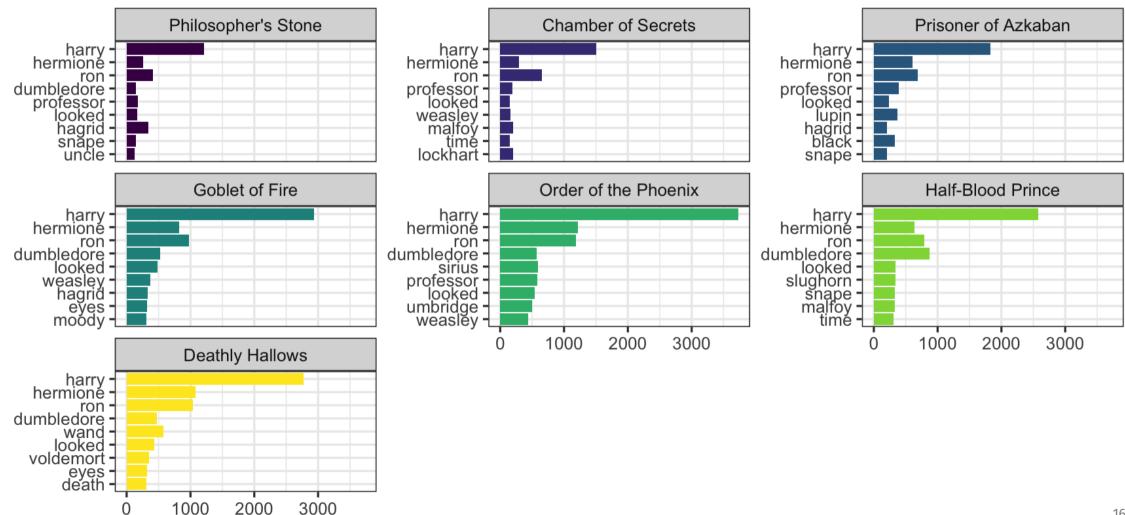
# A tibble:	6 × 3
bigram	chapter book
<chr></chr>	<int> <chr></chr></int>
1 the boy	1 Harry Potter
2 boy who	1 Harry Potter
3 who lived	1 Harry Potter
4 lived mr	1 Harry Potter
5 mr and	1 Harry Potter
6 and mrs	1 Harry Potter

### **Stop words**

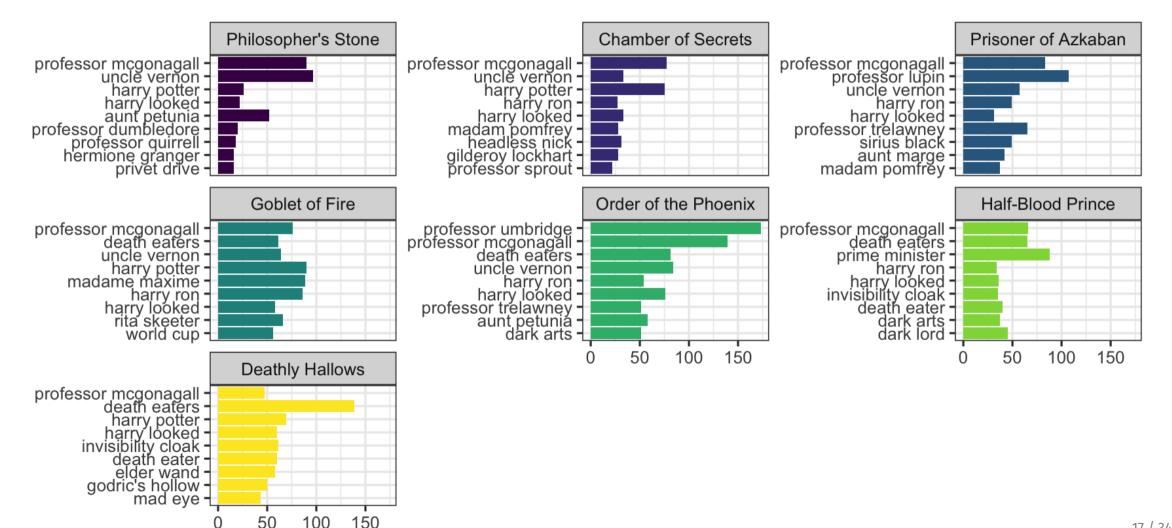
### Common words that we can generally ignore

#	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
#	i 1,139 mor	e rows

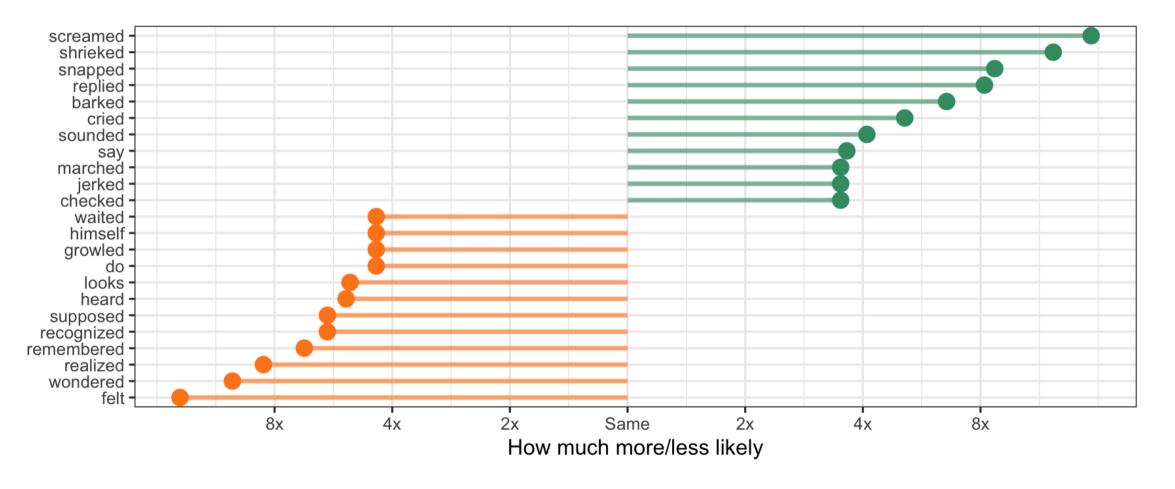
### Token frequency: words



### **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
# i	40 mor	re rows	5								

#### These use the Penn part of speech tags

### Parts of speech frequency

#### Verbs

# A	tibble	e: 1,5	57 ×	2
	lemma	n		
	<chr></chr>	<dbl></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		
<b># i</b>	i 1,547	more	rows	

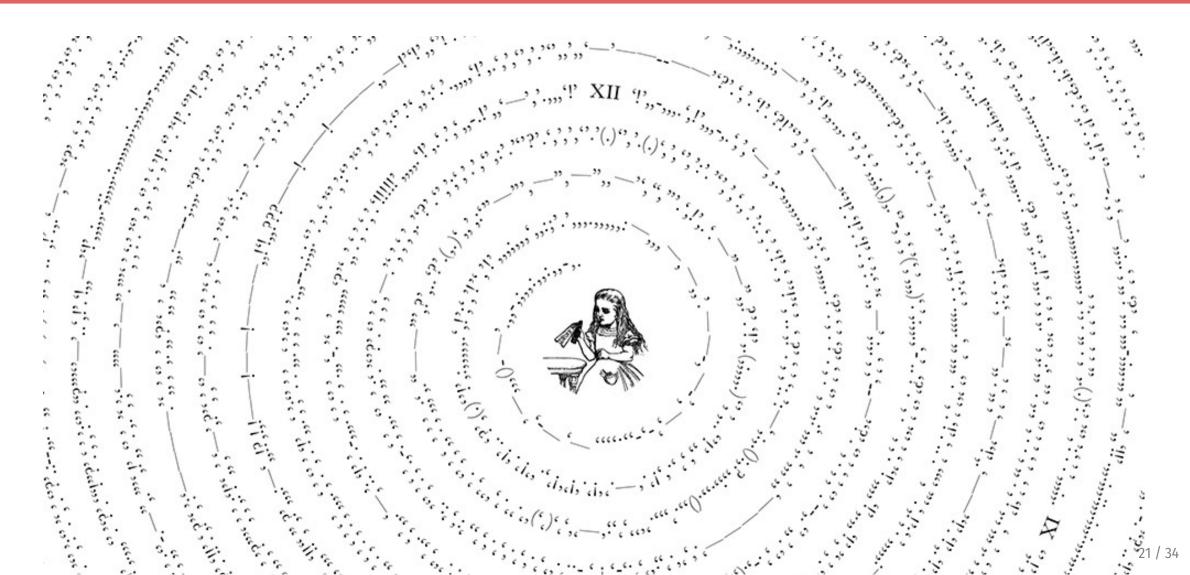
#### Nouns

# A tibble: 2	$2,852 \times 2$
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 Dumbledore	e 144
8 time	138
9 Dudley	136
10 uncle	122
# i 2,842 mor	re rows

#### **Adjectives & adverbs**

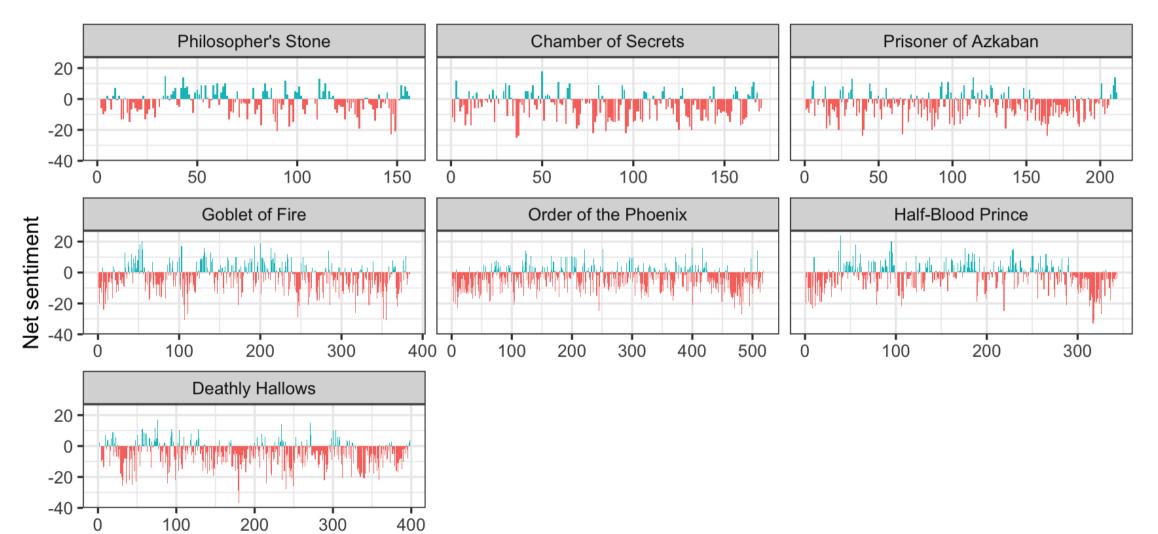
# A tibble	e: 1,2	40 ×	2
lemma	n		
<chr> &lt;</chr>	<dbl></dbl>		
1 back	223		
2 so	215		
3 just	180		
4 when	178		
5 very	171		
6 now	166		
7 then	165		
8 all	147		
9 how	136		
10 there	123		
# i 1,230	more	rows	

# Artsy stuff



### Sentiment analysis

get_sentiments	s("bing")	get_senti	ments( <mark>"afinn</mark> ")	get_sentiment	s("nrc")
# A tibble: 6,	786 × 2	# A tibble	: 2,477 × 2	# A tibble: 13	,872 × 2
word	sentiment	word	value	word	sentiment
<chr></chr>	<chr></chr>	<chr></chr>	<dbl></dbl>	<chr></chr>	<chr></chr>
1 2-faces	negative	1 abandon	-2	1 abacus	trust
2 abnormal	negative	2 abandon	ed –2	2 abandon	fear
3 abolish	negative	3 abandon	s –2	3 abandon	negative
4 abominable	negative	4 abducte	d –2	4 abandon	sadness
5 abominably	negative	5 abducti	on –2	5 abandoned	anger
6 abominate	negative	6 abducti	ons -2	6 abandoned	fear
7 abomination	negative	7 abhor	-3	7 abandoned	negative
8 abort	negative	8 abhorre	d –3	8 abandoned	sadness
9 aborted	negative	9 abhorre	nt -3	9 abandonment	anger
10 aborts	negative	10 abhors	-3	10 abandonment	fear
# i 6,776 more	rows	# i 2,467	more rows	# i 13,862 mor	e rows



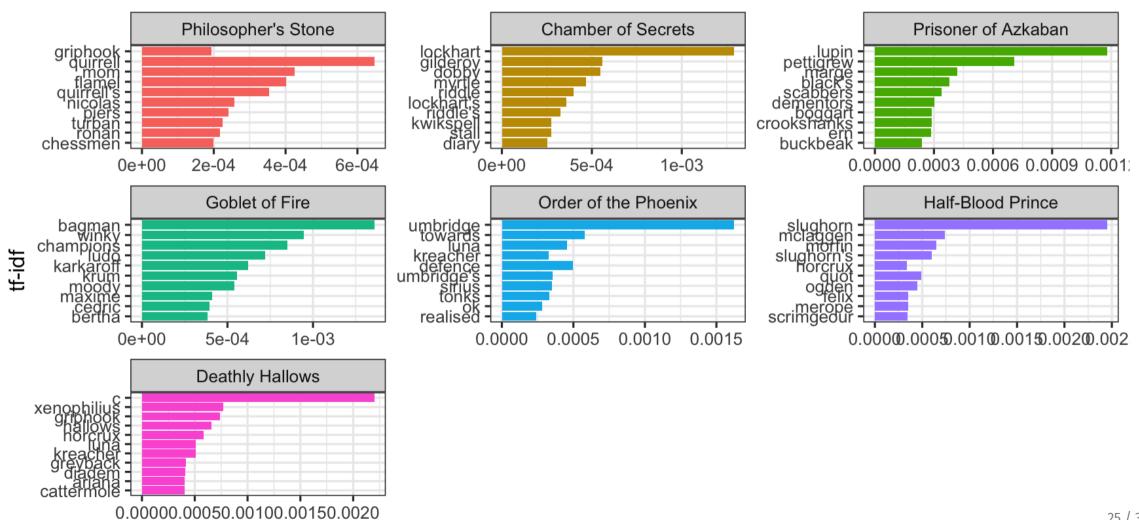


### **Term frequency-inverse document frequency**

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

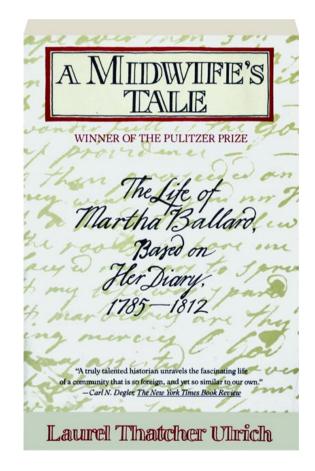
$$egin{aligned} tf &= rac{n_{ ext{term}}}{n_{ ext{terms in document}}} \ idf( ext{term}) &= \ln\left(rac{n_{ ext{documents}}}{n_{ ext{documents containing term}}}
ight) \ tf\text{-}idf( ext{term}) &= tf( ext{term}) imes idf( ext{term}) \end{aligned}$$

### tf-idf

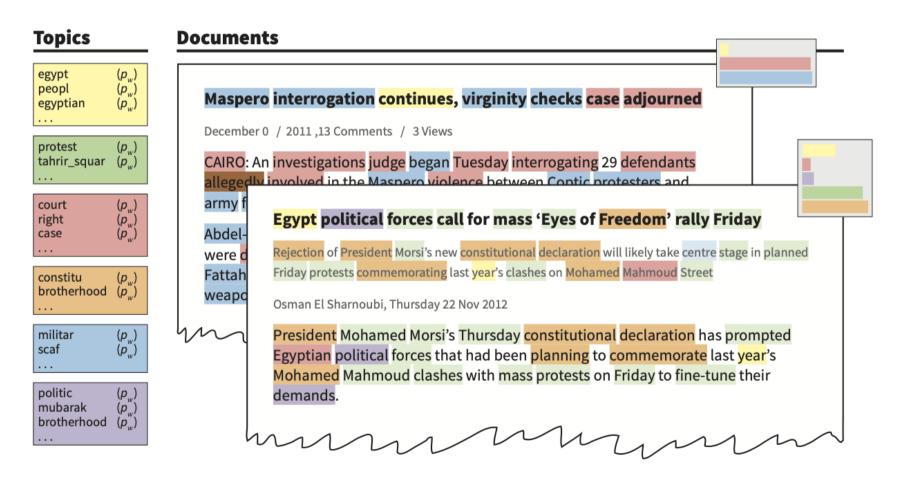


# **Topic modeling**





# Latent Dirichlet Allocation (LDA)

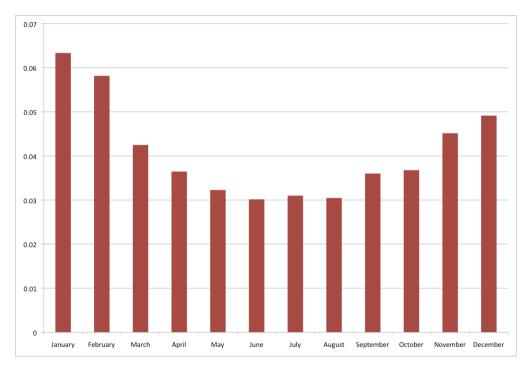


### **Clusters of related words**

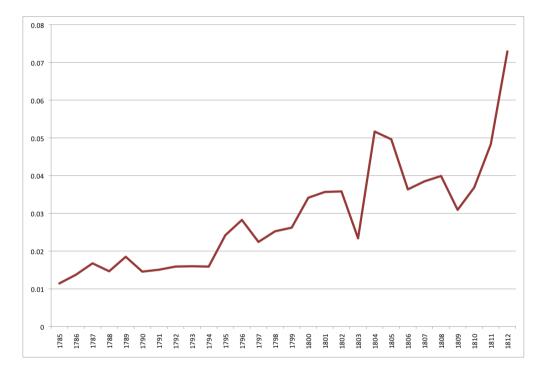
### **Topic label Topic words**

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

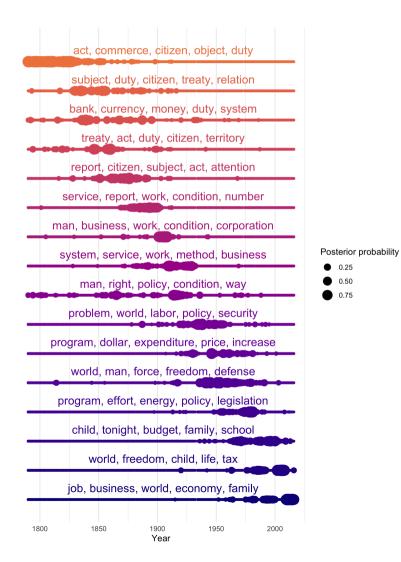


Cold weather topic by month



Emotion topic over time

### State of the Union addresses



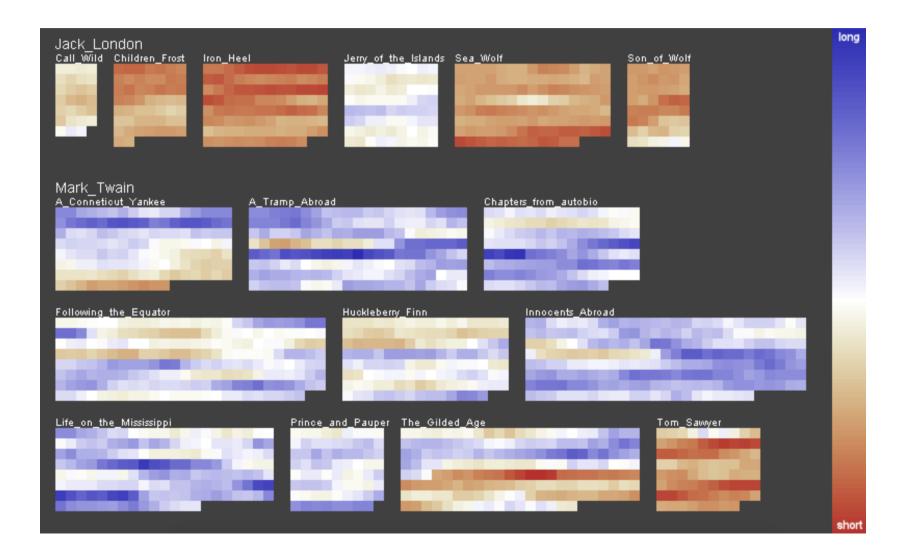
# Fingerprinting

Analyze richness or uniqueness of a document

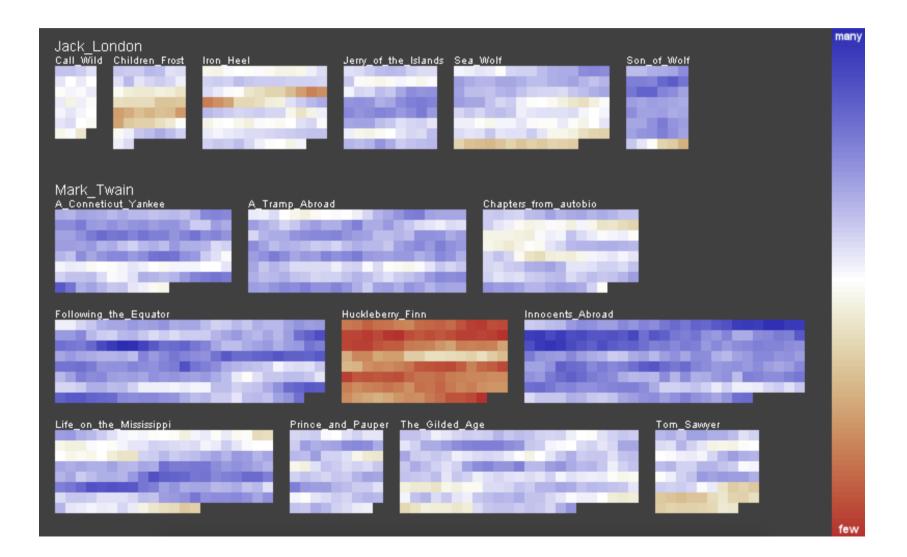
Punctuation patterns, vocabulary choices, sentence length

Hapax legomenon

### Sentence length



## Hapax legomena



### Verse length

