Text

Session 14

PMAP 8551/4551: Data Visualization with R
Andrew Young School of Policy Studies
Fall 2025

Plan for today

Qualitative text-based data

Crash course in computational linguistics

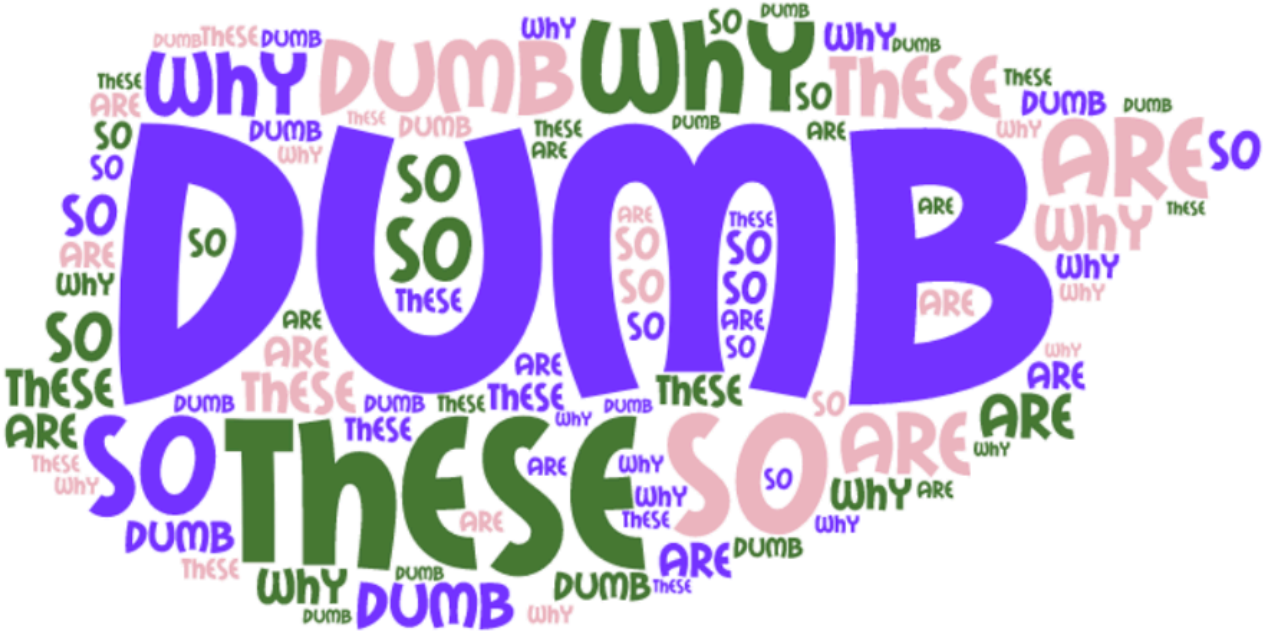
Qualitative text-based data

Free responses

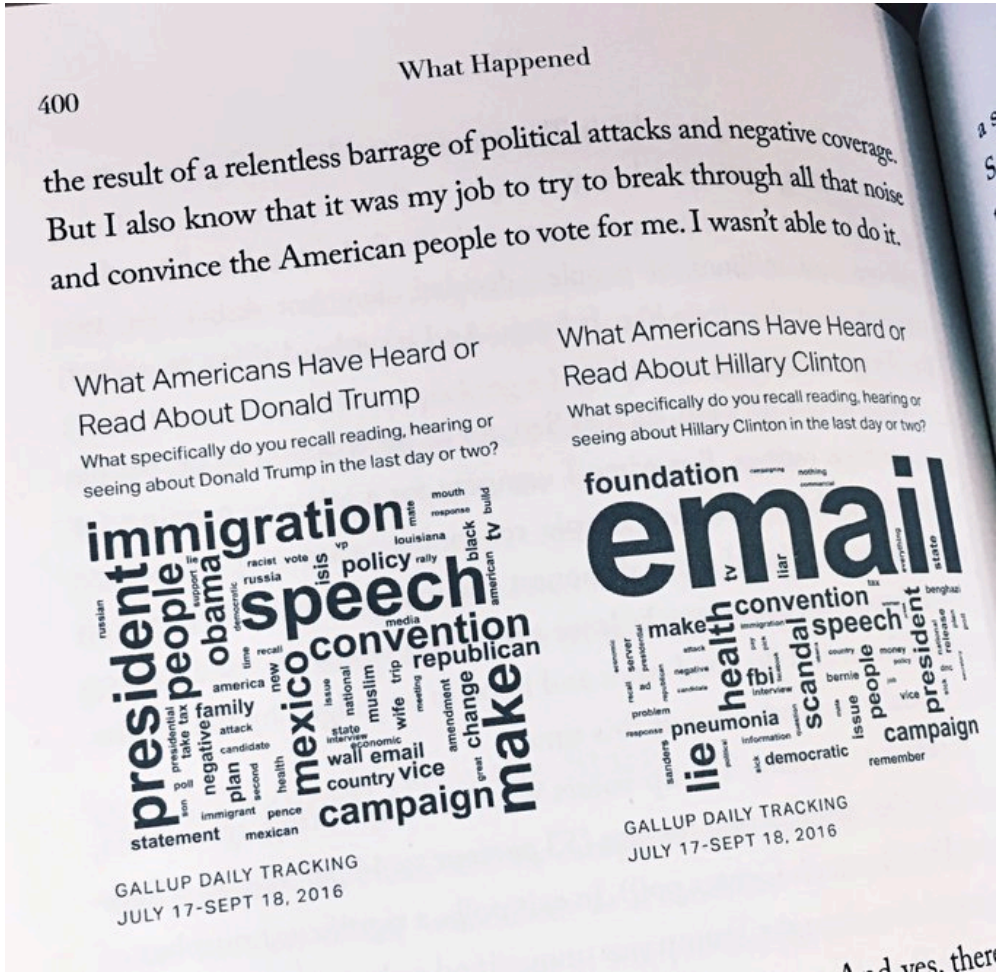
N	O	P	
donate_likely	amount_donate	amount_keep	amount_why
Somewhat unlikely	0	100	I am poor
Somewhat unlikely	0	100	I really feel like I deserve to treat myself recently. I have been wo
Somewhat likely	10	90	I donate the amount that I usually would
Somewhat unlikely	0	100	i'm poor
Neither likely nor unlikely	10	90	It is not a cause that is very important to me. i have other things t
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 a
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 a
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

y tho?

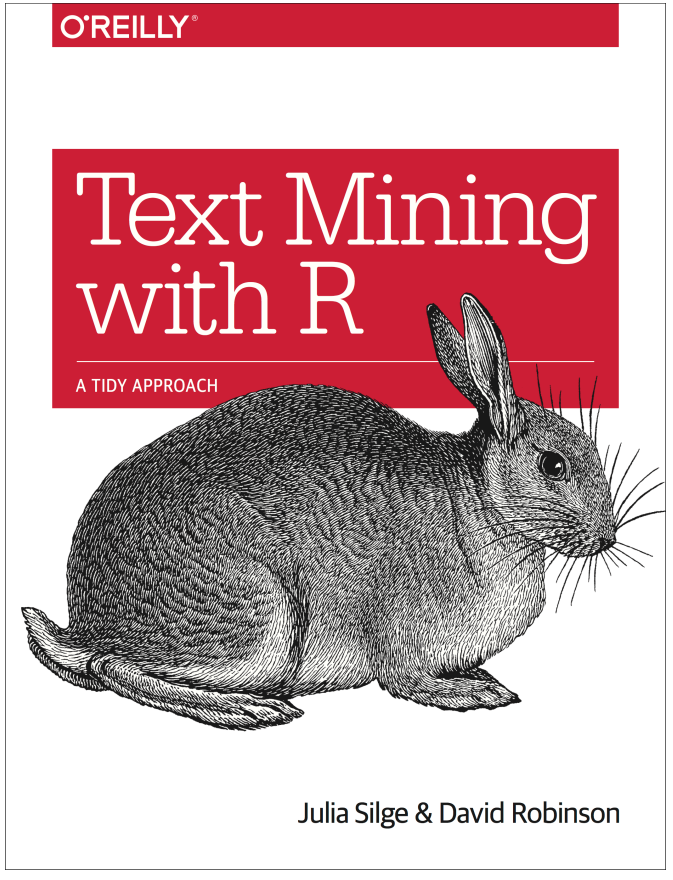


Some cases are okay



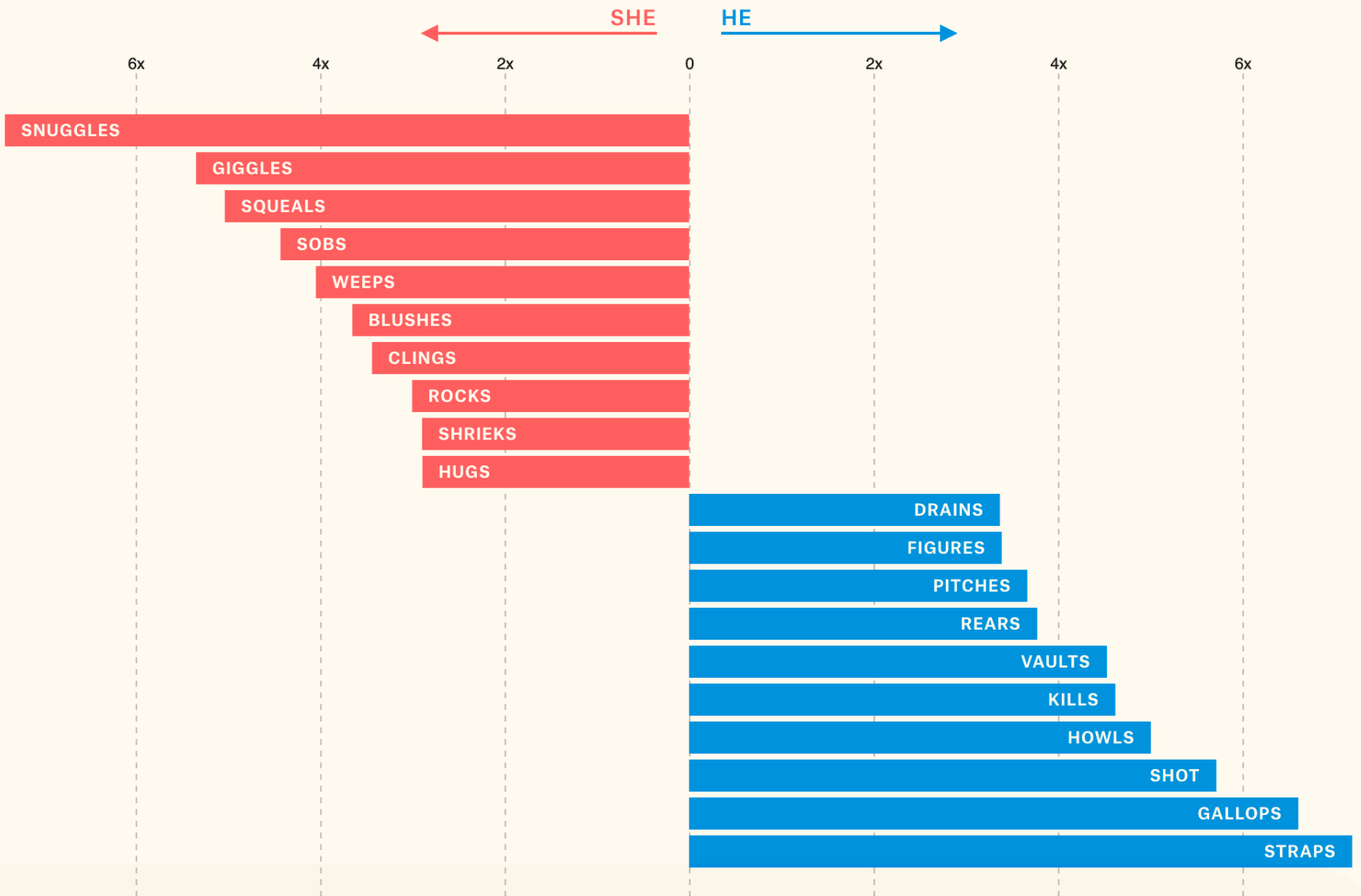
Word clouds for grownups

Count words, but in fancier ways

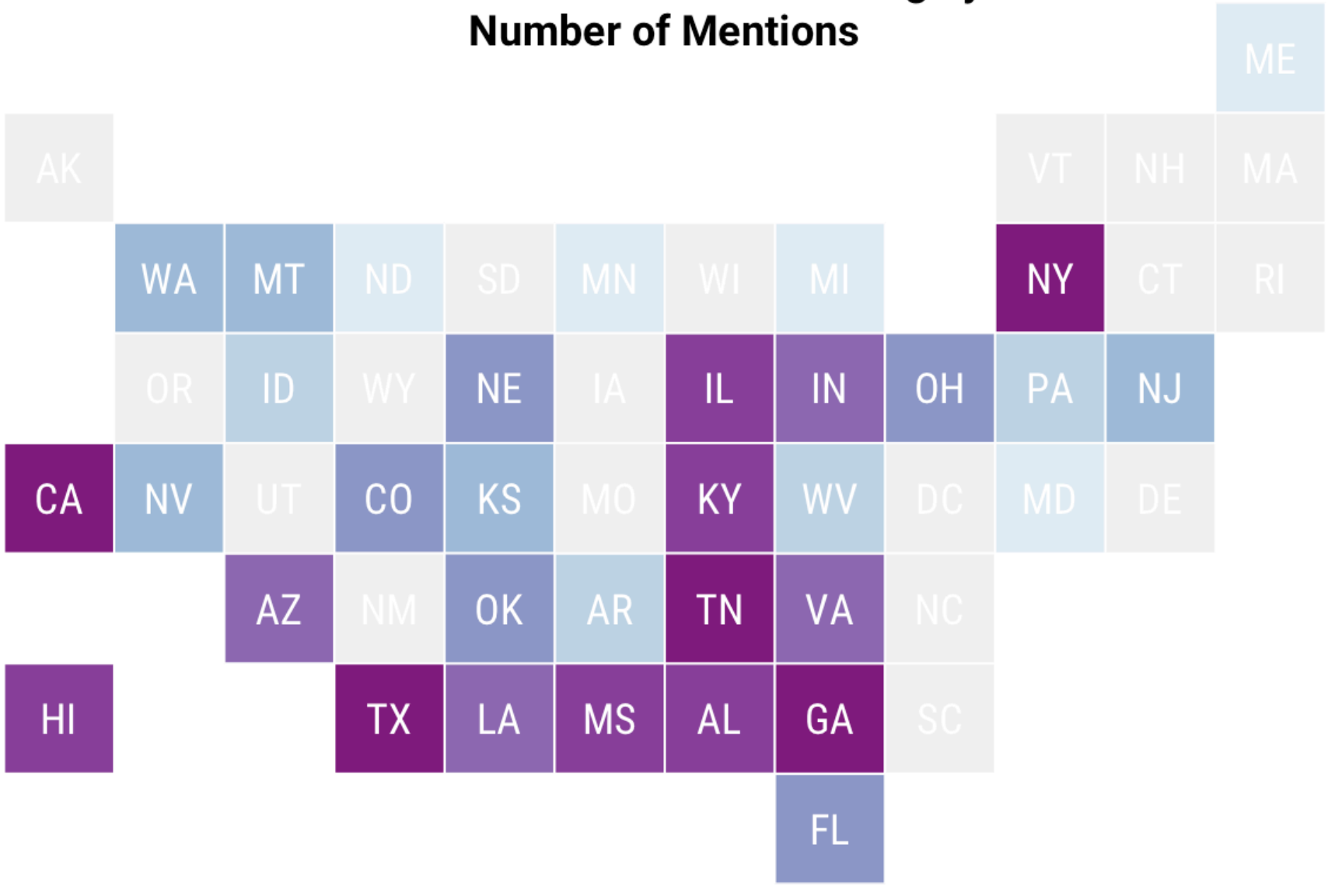


The most used words for women vs. men

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



What States Are Mentioned in Song Lyrics?
Number of Mentions



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...

Tidy text

One row for each text element

Can be chapter, page, verse, etc.

.small-code[

```
[38;5;246m# A tibble: 6 × 3 [39m
  chapter book                                                  text
    [3m [38;5;246m<int> [39m [23m  [3m [38;5;246m<chr> [39m [23m
[38;5;250m1 [39m       1 Harry Potter and the Philosopher's Stone
[38;5;250m2 [39m       2 Harry Potter and the Philosopher's Stone
[38;5;250m3 [39m       3 Harry Potter and the Philosopher's Stone
[38;5;250m4 [39m       4 Harry Potter and the Philosopher's Stone
```

Tokens

Split the text into even smaller parts

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

.pull-left.small-code[

```
[38;5;246m# A tibble: 6 × 3 [39m
  word  chapter book
   [3m [38;5;246m<chr> [39m [23m    [3m [38;5;246m<int> [39m [23m  [3
[38;5;250m1 [39m the          1 Harry Potter...
[38;5;250m2 [39m boy          1 Harry Potter...
[38;5;250m3 [39m who          1 Harry Potter...
[38;5;250m4 [39m lived        1 Harry Potter...
```

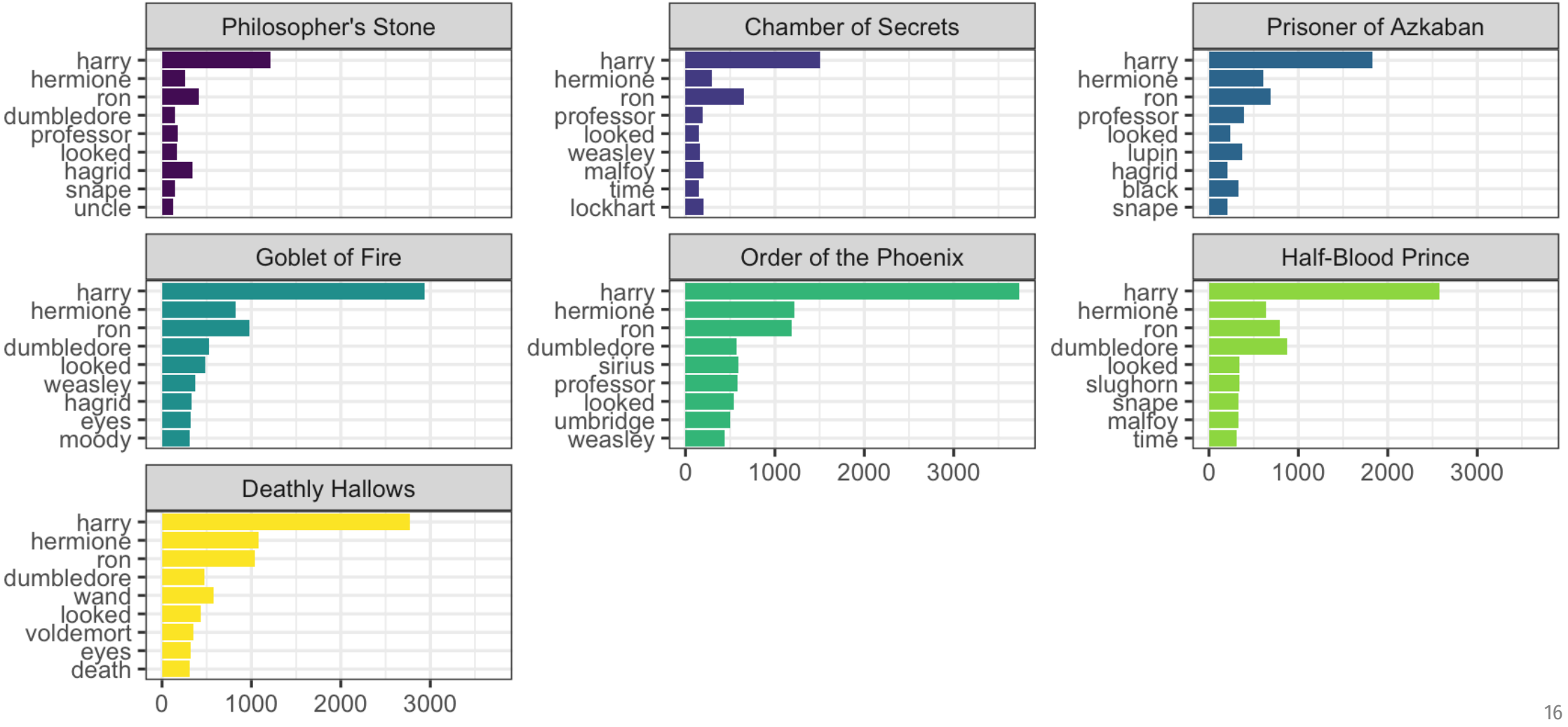
Stop words

Common words that we can generally ignore

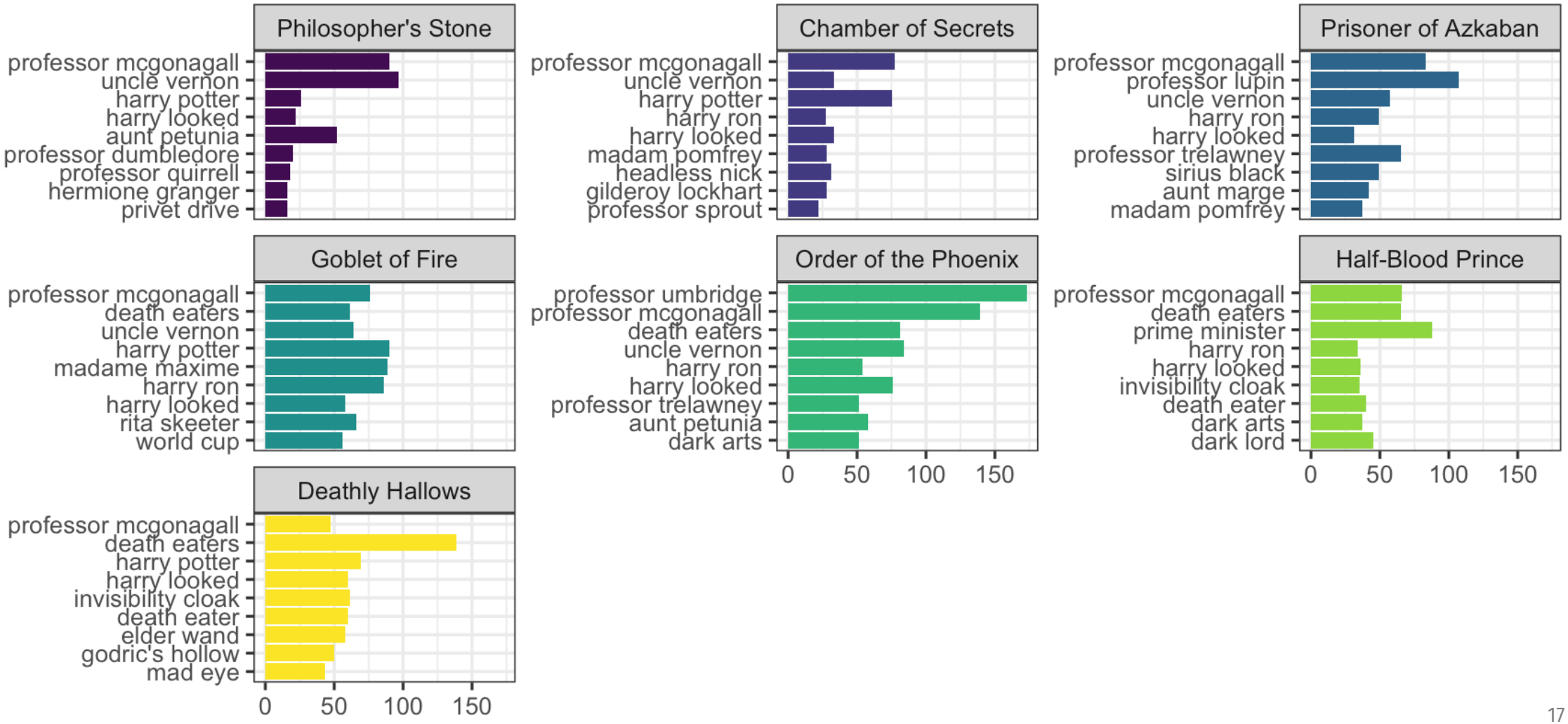
.center.small-code[

```
[38;5;246m# A tibble: 1,149 × 2 [39m
  word        lexicon
   [3m [38;5;246m<chr> [39m [23m        [3m [38;5;246m<chr> [39m [23
[38;5;250m 1 [39m a           SMART
[38;5;250m 2 [39m a's         SMART
[38;5;250m 3 [39m able        SMART
[38;5;250m 4 [39m about       SMART
[38;5;250m 5 [39m above       SMART
```

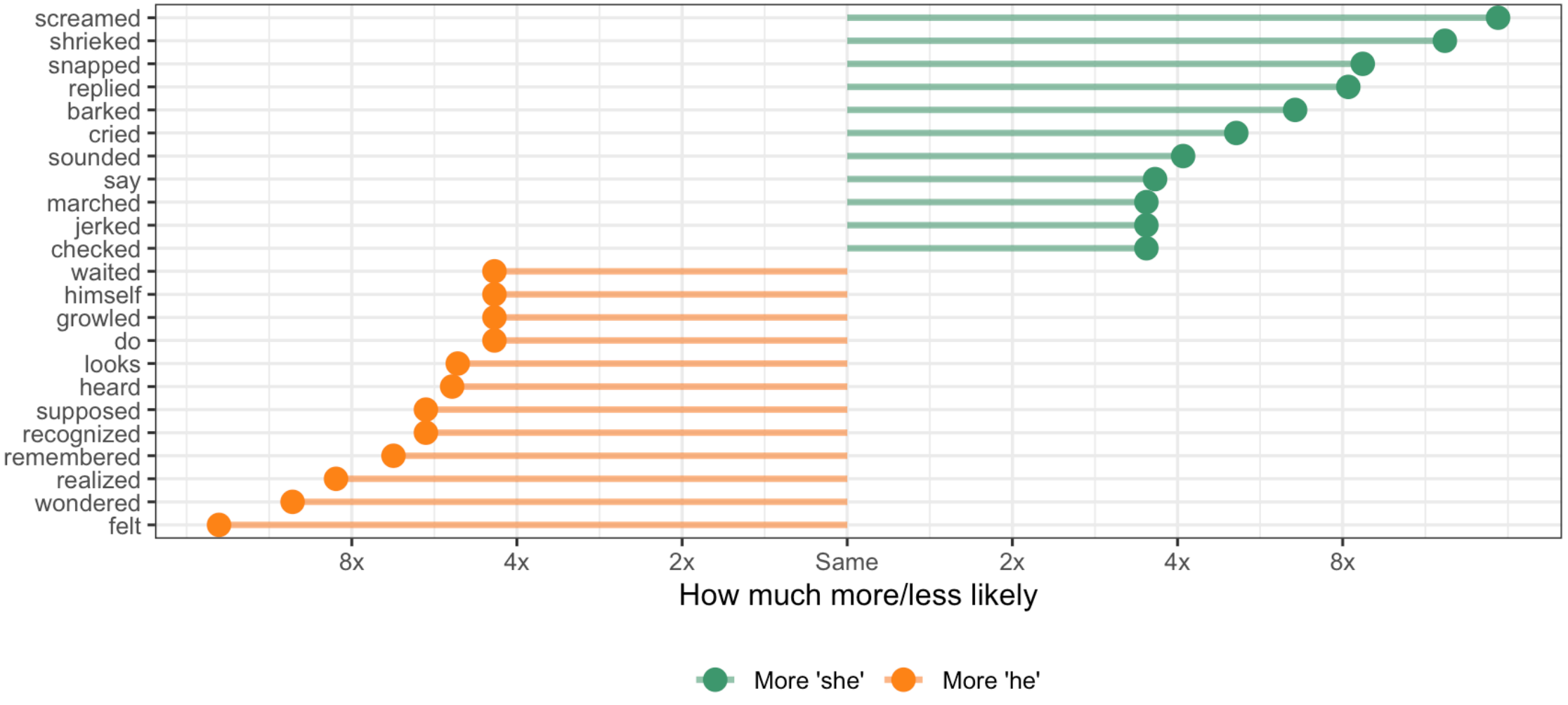
Token frequency: words



Token frequency: n-grams



Token frequency: n-gram ratios



Parts of speech

.small-code[

```
[38;5;246m# A tibble: 50 × 11 [39m
   doc_id   sid   tid token   token_with_ws lemma   upos  xpos  f
     [3m [38;5;246m<dbl> [39m [23m  [3m [38;5;246m<dbl> [39m [23m  [3
[38;5;250m 1 [39m      1     1      1 THE      THE            the
[38;5;250m 2 [39m      1     1      2 BOY      BOY            Boy
[38;5;250m 3 [39m      1     1      3 WHO      WHO            who
[38;5;250m 4 [39m      1     1      4 LIVED    LIVED          live
[38;5;250m 5 [39m      1     1      5 Mr.      Mr.            Mr.
[38;5;250m 6 [39m      1     1      6 and      and            and
[38;5;250m 7 [39m      1     1      7 Mrs.     Mrs.           Mrs.
```

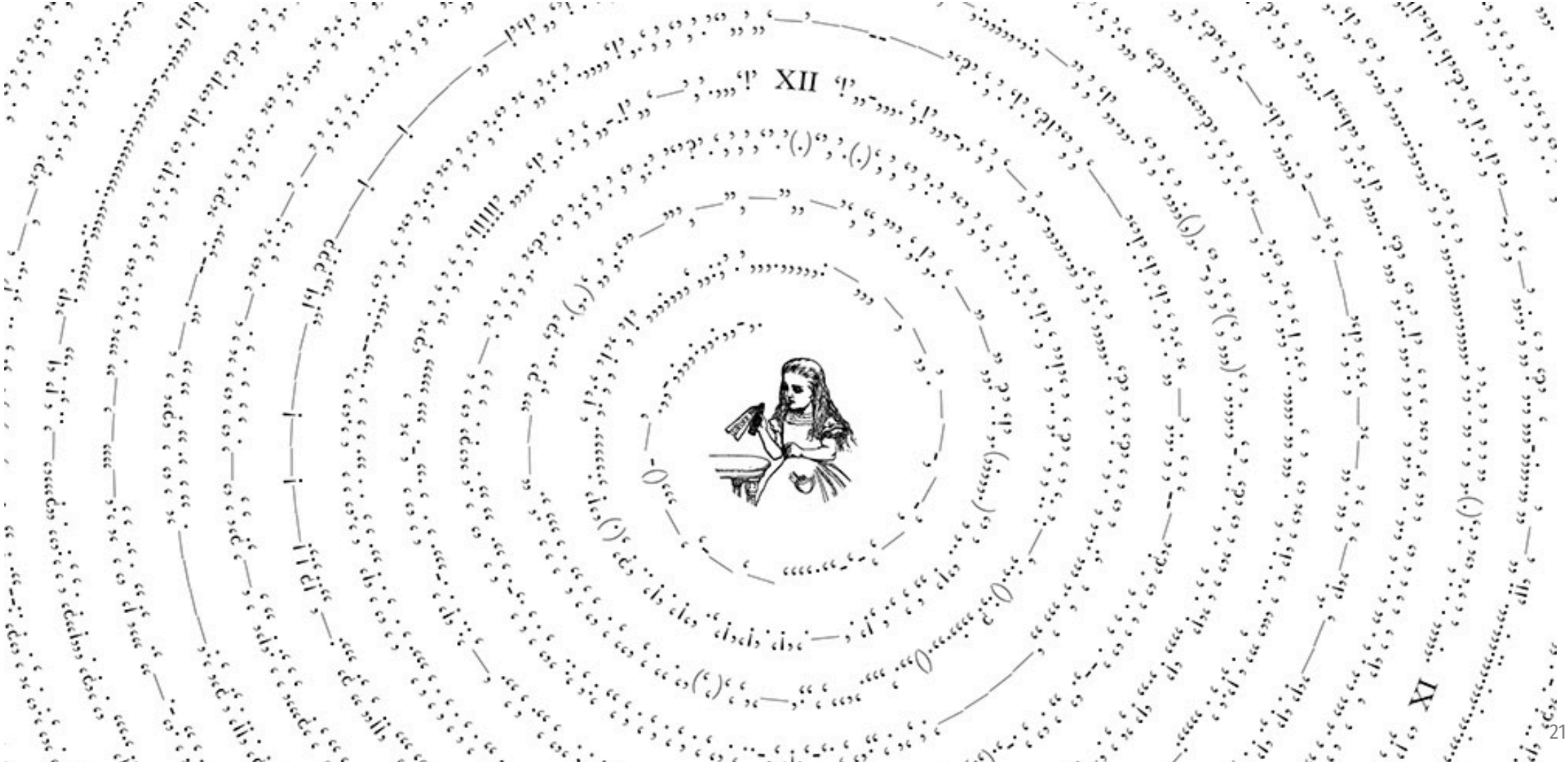
Parts of speech frequency

.pull-left-3.small-code[

Verbs

```
[38;5;246m# A tibble: 1,557 × 2 [39m
   lemma      n
    [3m [38;5;246m<chr> [39m [23m  [3m [38;5;246m<dbl> [39m [23m
[38;5;250m 1 [39m say      920
[38;5;250m 2 [39m get      440
[38;5;250m 3 [39m have     417
[38;5;250m 4 [39m go       384
[38;5;250m 5 [39m look     380
[38;5;250m 6 [39m be       310
```

Artsy stuff

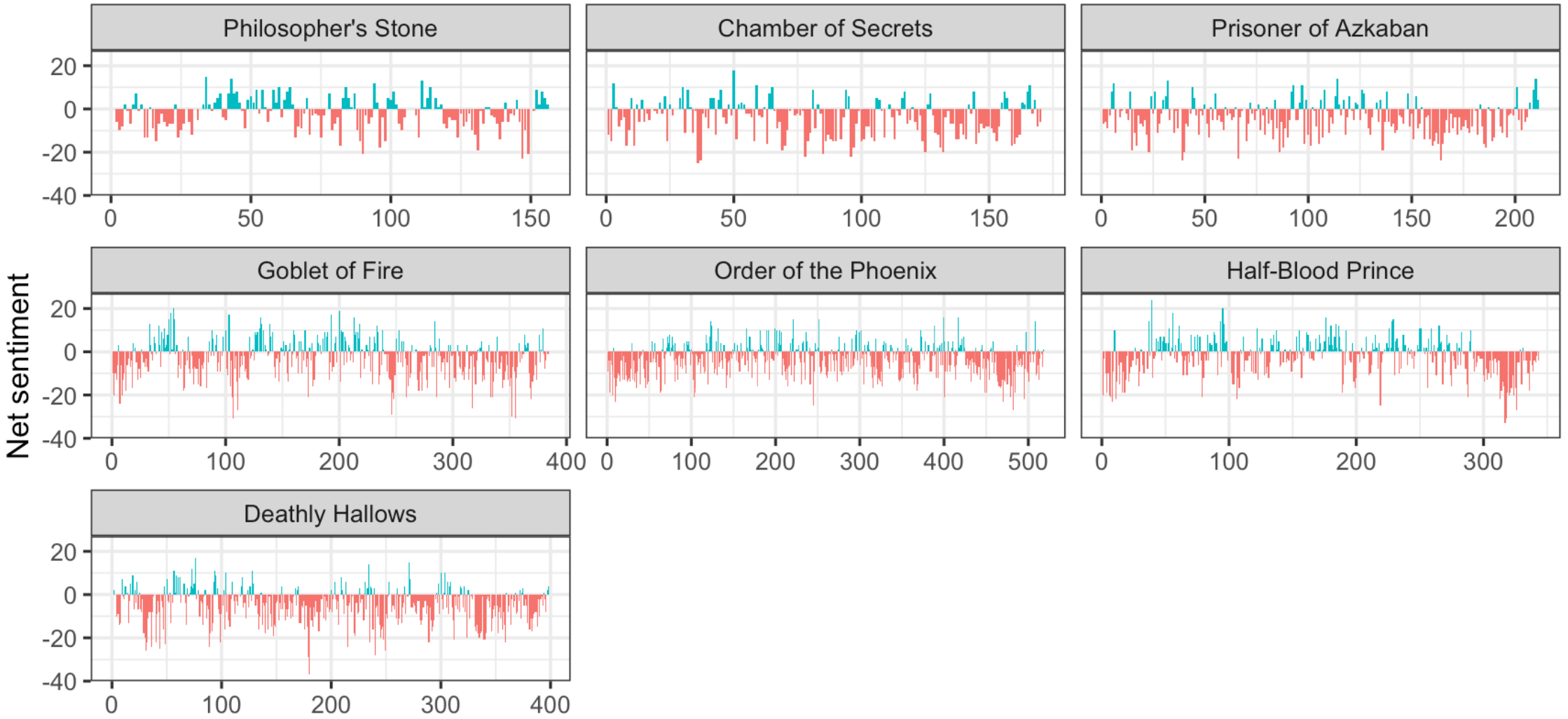


Sentiment analysis

.pull-left-3.small-code[

```
get_sentiments("bing")
```

```
[38;5;246m# A tibble: 6,786 × 2 [39m
   word          sentiment
    [3m [38;5;246m<chr> [39m [23m          [3m [38;5;246m<chr> [39m [23
[38;5;250m 1 [39m 2-faces     negative
[38;5;250m 2 [39m abnormal    negative
[38;5;250m 3 [39m abolish     negative
[38;5;250m 4 [39m abominable  negative
[38;5;250m 5 [39m abominably  negative
```


Philosopher's Stone
Chamber of Secrets
Prisoner of Azkaban
Goblet of Fire
Order of the Phoenix
Half-Blood Prince
Deathly Hallows
Net sentiment
20
0
-20
-40
0
50
100
150
200
300
400
500

tf-idf

Term frequency-inverse document frequency

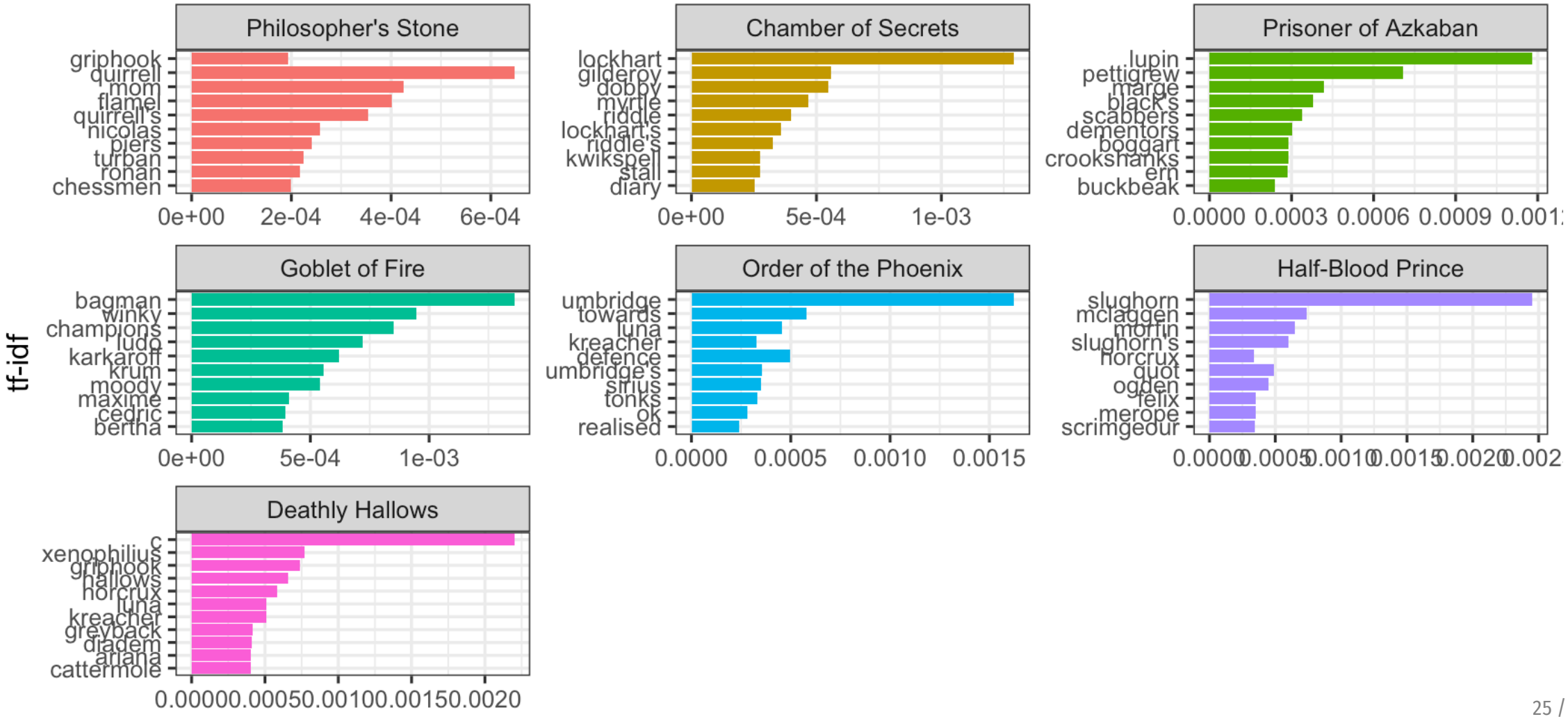
How important a term is compared to the rest of the documents

$$tf = \frac{n_{\text{term}}}{n_{\text{terms in document}}}$$

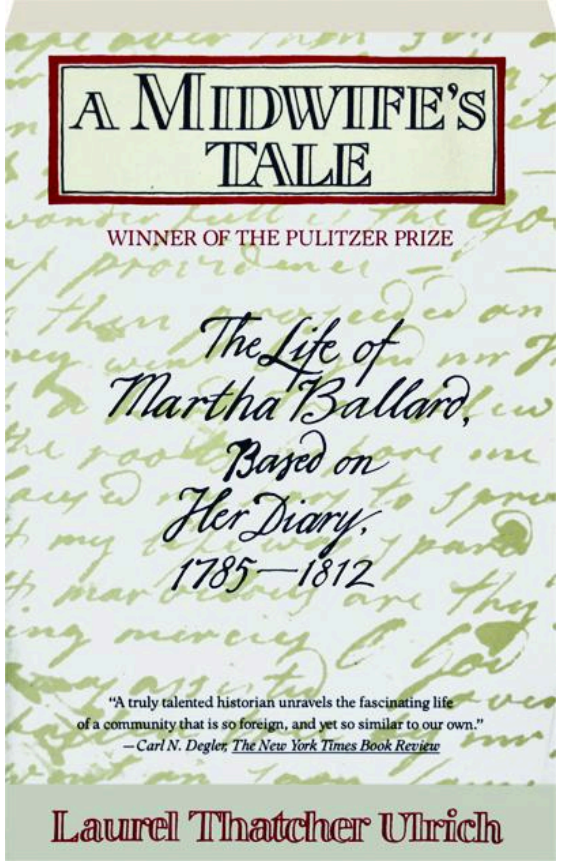
$$idf(\text{term}) = \ln\left(\frac{n_{\text{documents}}}{n_{\text{documents containing term}}}\right)$$

$$tf\text{-}idf(\text{term}) = tf(\text{term}) \times idf(\text{term})$$

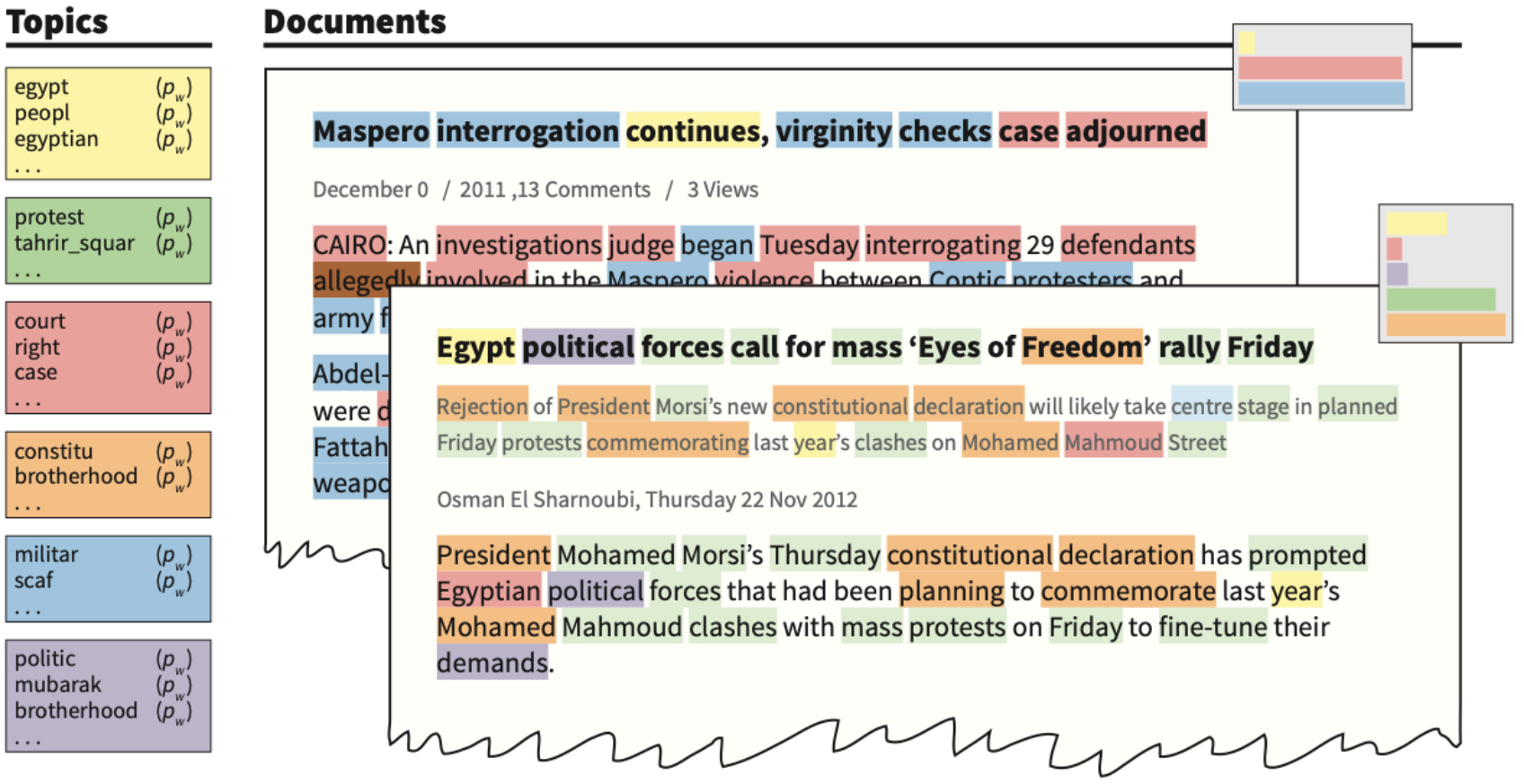
tf-idf


Philosopher's Stone
griphook
quirrell
mom
flamel
quirrell's
nicolas
piers
turban
ronan
chessmen
0e+00
2e-04
4e-04
6e-04
Chamber of Secrets
lockhart
gilderoy
dobby
myrtle
riddle
lockhart's
riddle's
kwikspell
stall
diary
0e+00
5e-04
1e-03
Prisoner of Azkaban
lupin
pettigrew
marge
black's
scabbers
dementors
boggart
crookshanks
ern
buckbeak
0.0000
0.0003
0.0006
0.0009
Goblet of Fire
bagman
winky
champions
ludo
karkaroff
krum
moody
maxime
cedric
bertha
0e+00
5e-04
1e-03
Order of the Phoenix
umbridge
towards
luna
kreacher
defence
umbridge's
sirius
tonks
ok
realised
0.0000
0.0005
0.0010
0.0015
Half-Blood Prince
slughorn
mclaggen
moffin
slughorn's
horcrux
quot
ogden
felix
merope
scrimgeour
0.0000
0.0005
0.0010
0.0015
0.0020
Deathly Hallows
c
xenophilius
griphook
hallows
horcrux
luna
kreacher
greyback
diadem
ariana
cattermole
0.0000
0.0005
0.0010
0.0015
0.0020
tf-idf

Topic modeling



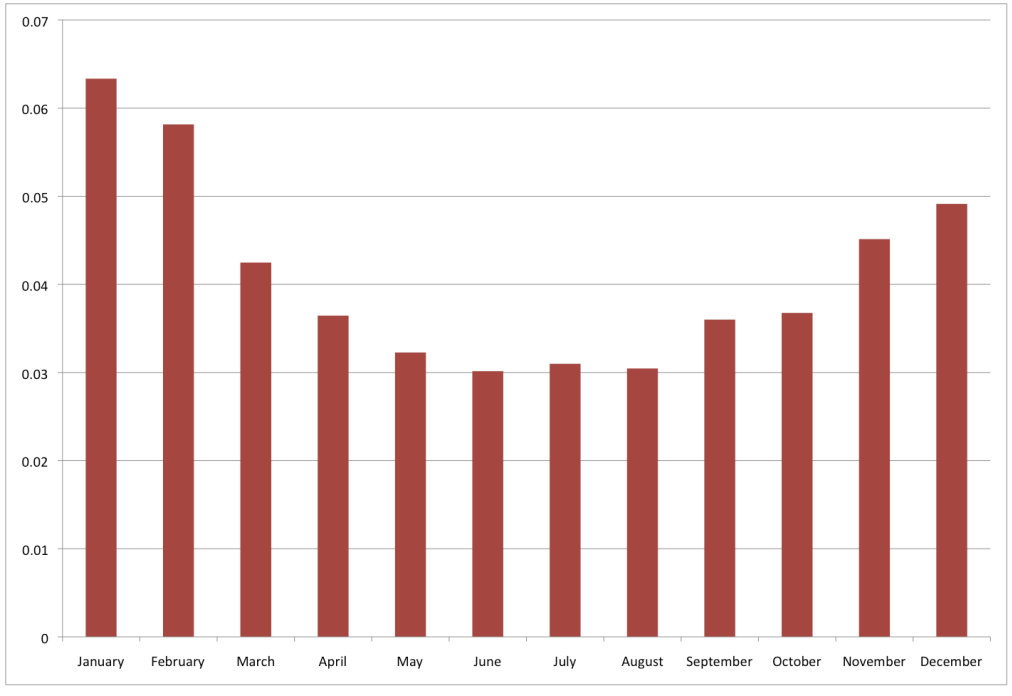
Latent Dirichlet Allocation (LDA)



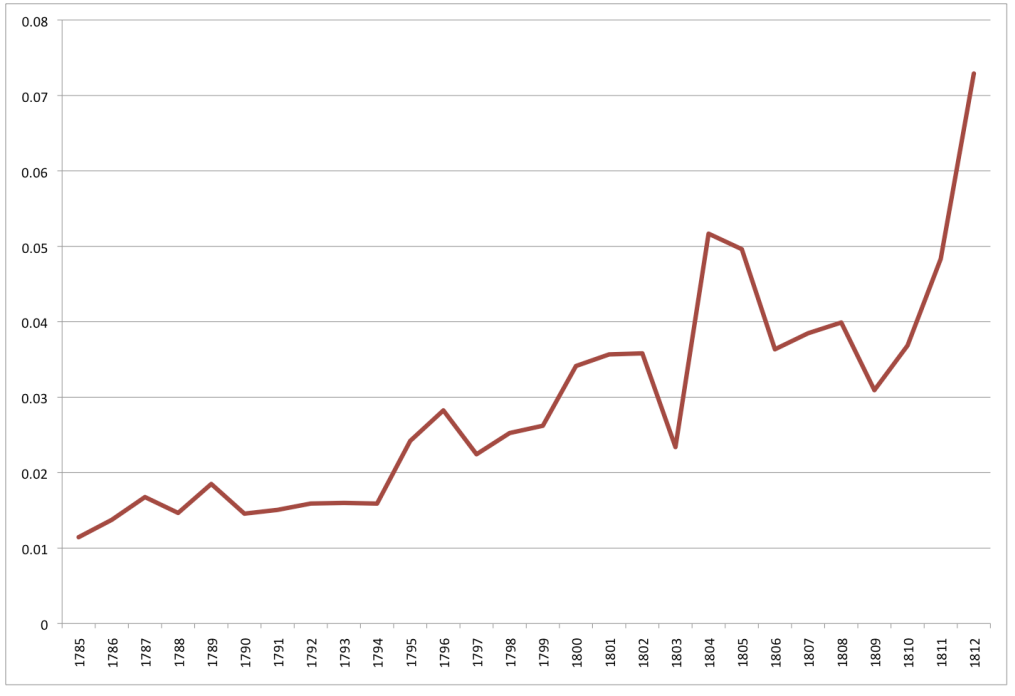
Clusters of related words

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

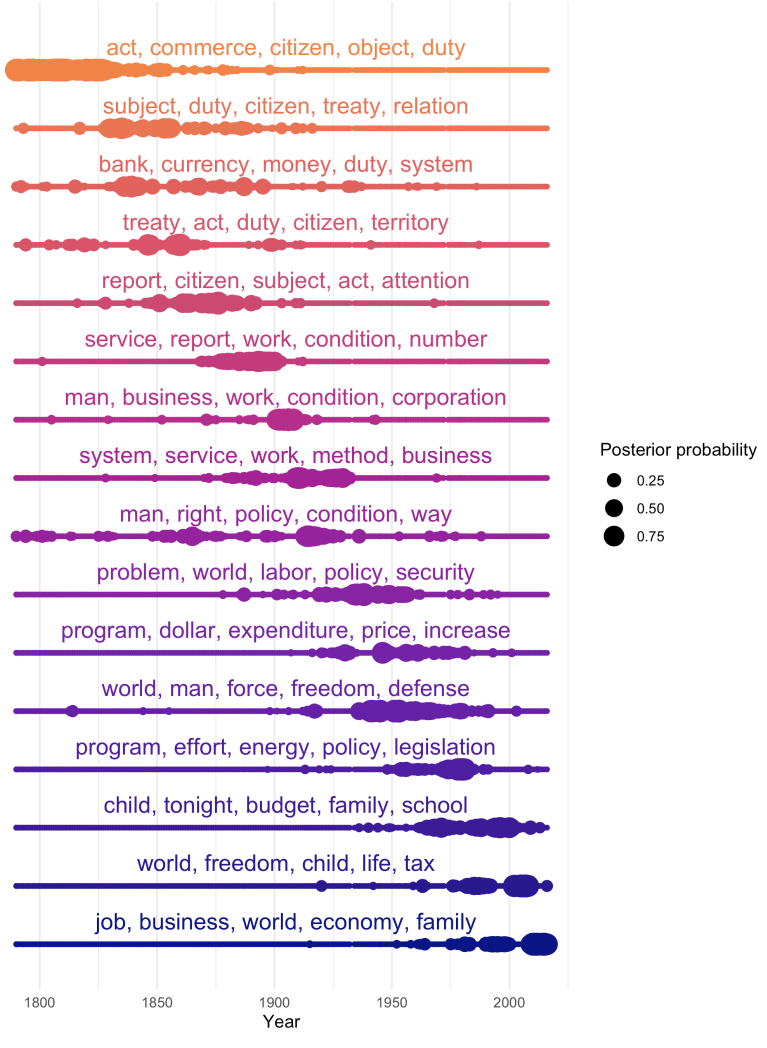


Cold weather topic by month



Emotion topic over time

State of the Union addresses



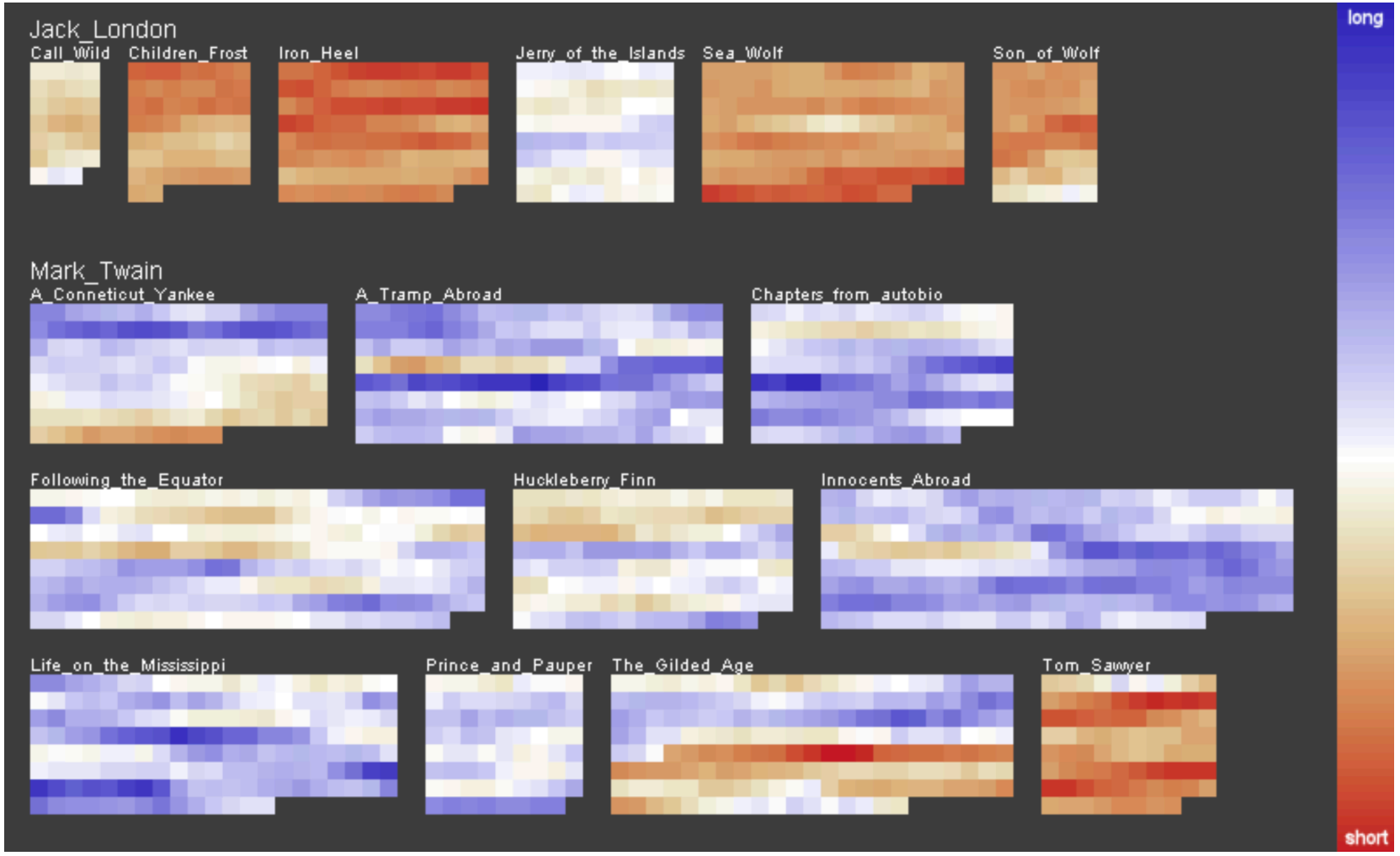
Fingerprinting

Analyze richness or uniqueness of a document

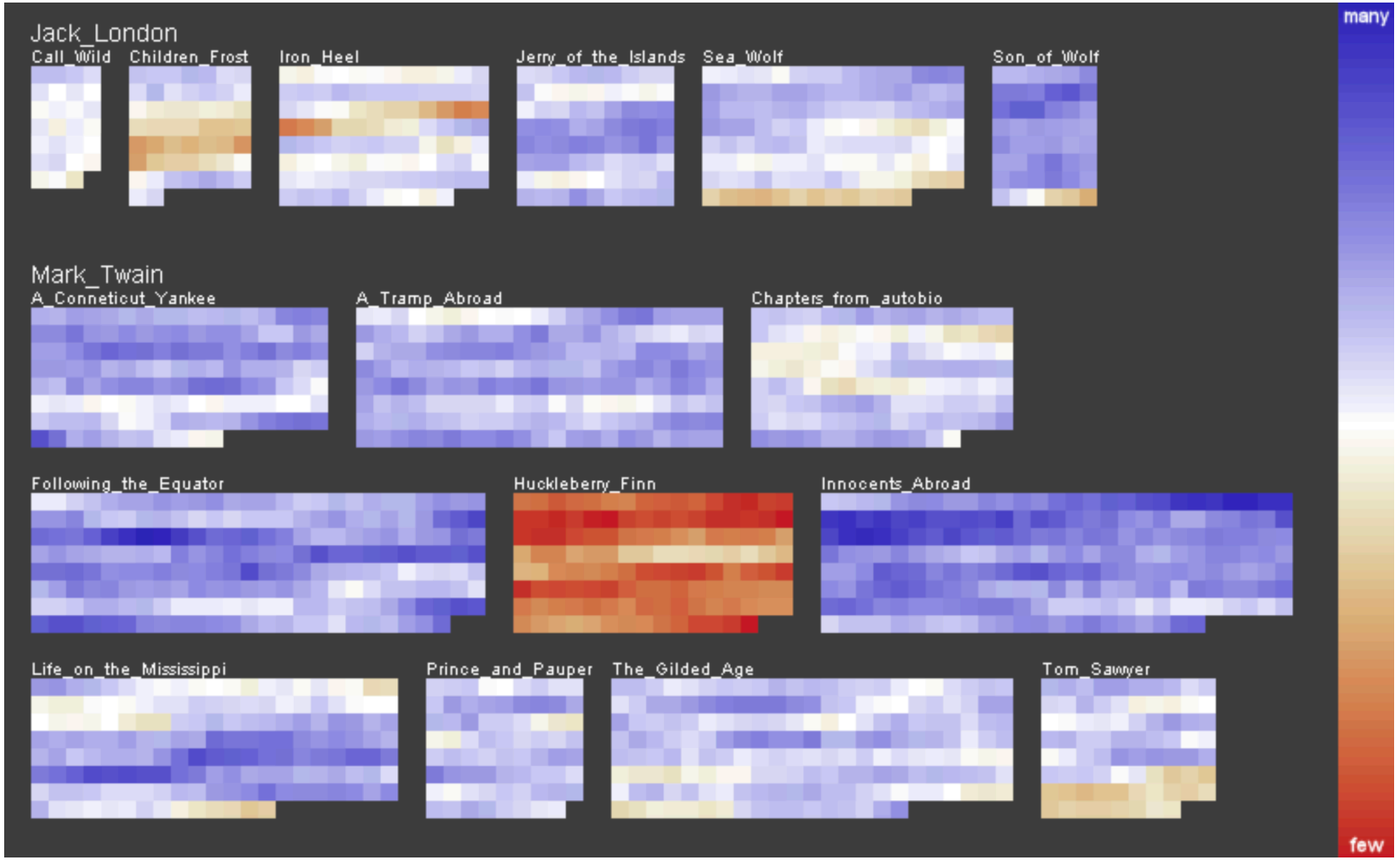
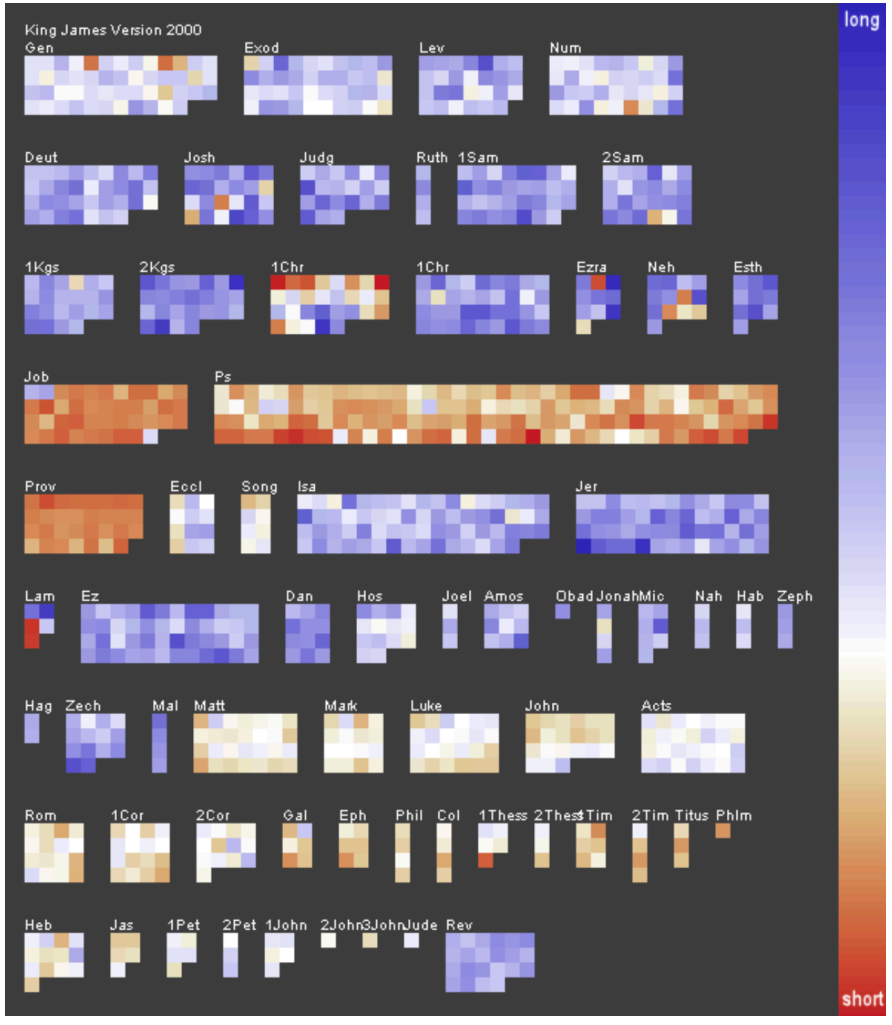
Punctuation patterns, vocabulary choices, sentence length

Hapax legomenon

Sentence length



Hapax legomena



Verse length