JOHNS HOPKINS
WHITING SCHOOL of ENGINEERING

Word Statistics

1/26/2026

Today (and next class)

- Word-level metrics, statistics, Bayesian Inference

- Exploratory text analysis
  - First approaches when working with a new data set – what can we do with minimal supervision? Minimal information about the data?

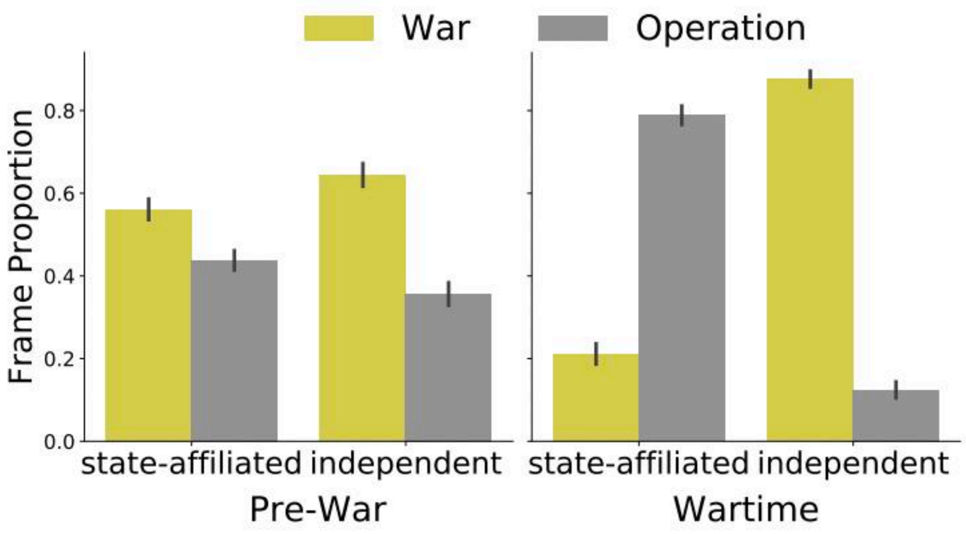
Monroe BL, Colaresi MP, Quinn KM. Fightin' Words: Lexical Feature Selection and Evaluation for Identifying the Content of Political Conflict. Political Analysis. 2008;16(4):372-403. doi:10.1093/pan/mpn018

Background

- One of the most fundamental analyses we may want to conduct is, how does word usage differ in different corpora?
  - How do AI policy discussions differ in the U.S. and Europe?
    - Maybe U.S. politicians use words like "innovation" while European politicians use words like "privacy" [fictional example]
  - How do Wikipedia articles about men and women differ?
    - Articles about women focus on family and relationships more than articles about men (Wagner et al. 2015) [fictional words: "family", "children", "married", "divorce"]
- "Entries in the burgeoning "text-as-data" movement are often accompanied by lists or visualizations of how word (or other lexical feature) usage differs across some pair or set of documents"

Example: Russia-Ukraine War

Example: State-affiliated outlets use "operation" over "war"



- We know to look for these terms because of laws passed in Russia, but what if we want to discover these differences?

"Challenges in Opinion Manipulation Detection: An Examination of Wartime Russian Media" Chan Young Park, Julia Mendelsohn, Anjalie Field, Yulia Tsvetkov (Findings of EMNLP, 2022)

Running Example: Congressional Record

- How does word usage differ in speeches made by Republican and Democratic members of congress?
  - "The question is not which of these terms are partisan and which are not, but which are the most partisan, on which side, and by how much." [Monroe et al. 2008]

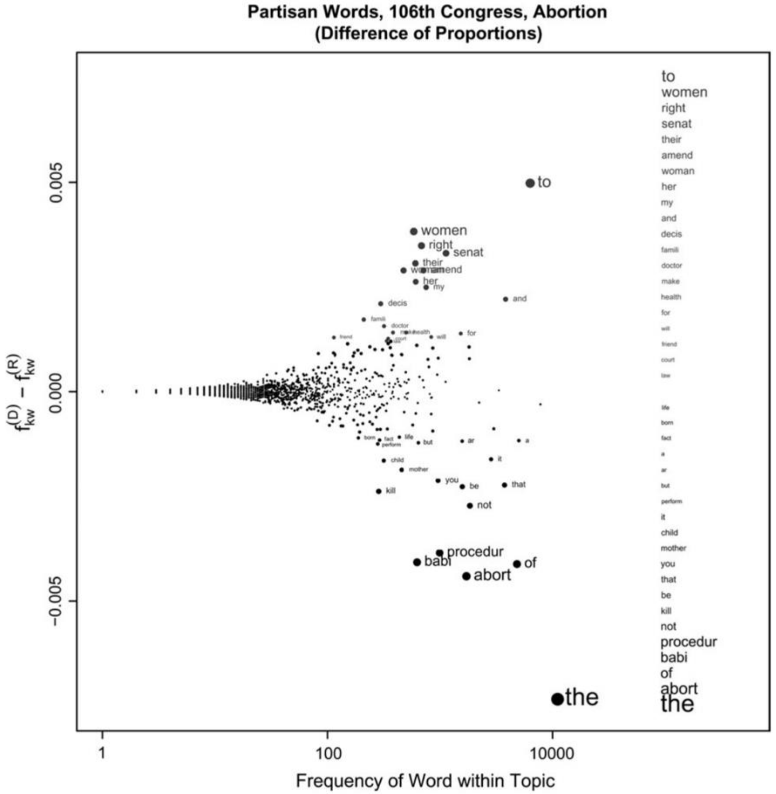
Data credits:

- The corpus was originally constructed in plaintext format by Gentzkow, Shapiro, and Taddy (2018) (repository for full download, license).
- Preprocessed by Rodriguez and Spirling (2021) (code, R data file): remove non-alphabetic characters, lowercase, and remove words of length 2 or less, then filter to Congressional sessions 111-114 (Jan 2009 - Jan 2017) and to speakers with party labels D and R.
- Converted plaintext and csv files and subsampled by *Sandeep Soni* *and* *Connor Gilroy* (code)

Some initial ideas: proportion of words

- Which words have the highest frequency in statements by Democrats?
  - “the”, “and”, “that”, "this”, “for", “have”, “are”, “not”

- Which words have the highest frequency in statements be Republicans?
  - “the”, “and”, “that”, ”for”, “this", “have”, “are”, “our”



Some initial ideas: Odds ratio

- Odds ratio: $O_w^{(i)} = \frac{f_w}{1-f_w}$, where f_w is the proportion of word *w* in corpus subset *i*
- Odds ratio between two groups: $\theta_w^{(i-j)} = \frac{O_w^i}{O_j^w}$
- Log-odds ratio: $\log(O_w^i) - \log(O_j^w)$ → is symmetrical

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Some initial ideas: Odds ratio

- Odds ratio: $O_w^{(i)} = \frac{f_w}{1 - f_w}$

- Odds ratio between two groups: $\theta_w^{(i-j)} = \frac{O_w^i}{O_j^w}$

Becomes infinite/undefined if words only exist in one corpus

- Log-odds ratio: $\log(O_w^i) - \log(O_j^w)$

Odds ratio in Congressional data

Word	Odds-Ratio	Frequency in Republican Speech	Frequency in Democratic Speech
idahoans	-5.46	211	1
fairtax	-4.99	131	1
cdh	-4.75	103	1
isna	-4.71	99	1
zinser	4.96	1	161
gaspee	4.74	1	128
vermonters	4.59	5	555
corinthian	4.57	2	218

Some initial ideas: Odds ratio

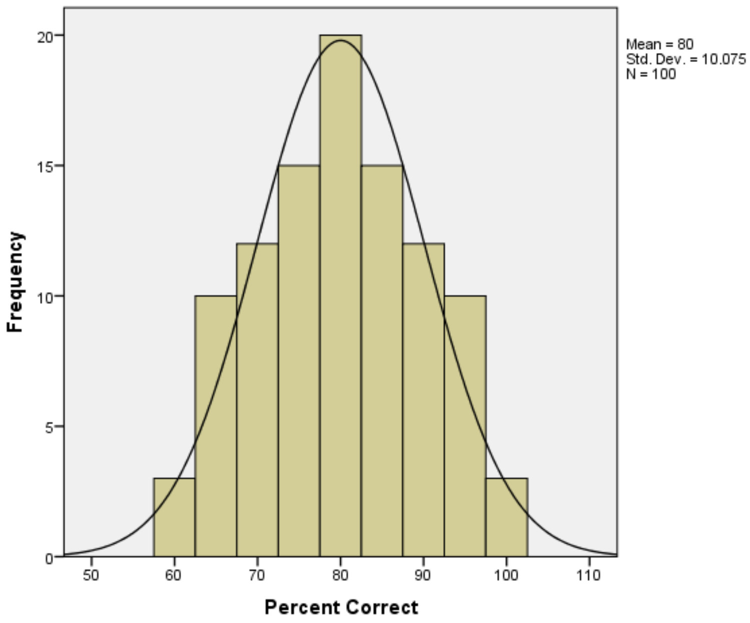
- Odds ratio: $O_w^{(i)} = \frac{f_w}{1 - f_w}$
- Odds ratio between two groups: $\theta_w^{(i-j)} = \frac{O_w^i}{O_j^w}$
- Log-odds ratio: $\log(O_w^i) - \log(O_j^w)$

Becomes infinite if words only exist in one corpus

Becomes dominated by obscure words

Model-driven approach

- Clear that simple methods aren't going to work
- General statistical modeling approach:
  - Given a collection of data
    - Assume you generated this data from some model
    - Estimate model parameters
- Example:
  - Assume you gathered data by sampling from a normal distribution
  - Estimate mean and stdev



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Model-driven approach

- High-level idea:
  - First model the word usage in the full collection of documents
  - Then investigate how subgroup-specific word usage diverges from that in the full collection of documents

- Incorporate a *prior*
  - Background estimate of how often a word is used in this type of document

Bag-of-words (BOW) assumption

- ”the state of healthcare in this country is…”
- We ignore ordering of words and assume that we can represent the document collection as a “bag of words”
- [We’ve already been doing this implicitly]

country state the

in this

healthcare

is of

Terminology

- **y** = vector of term counts in the corpus

101	**60**	**10**	**…**	**11**	**231**
country	**state**	**healthcare**	**…**	**employment**	**the**

- n = number of terms in the corpus
- n = 101 + 60 + 10 … + 11 + 231

Terminology

Define:

- $\mathbf{y}$ = vector of term counts in the corpus
- n = number of terms in the corpus
- $\boldsymbol{\pi}$ = unknown distribution the vocabulary

- **Assume:**
  - $\mathbf{y} \sim$ Multinomial(n, $\boldsymbol{\pi}$)
  - Intuition: we got **y** by repeatedly sampling from a bag. $\boldsymbol{\pi}$ describes how many of each word is in the bag

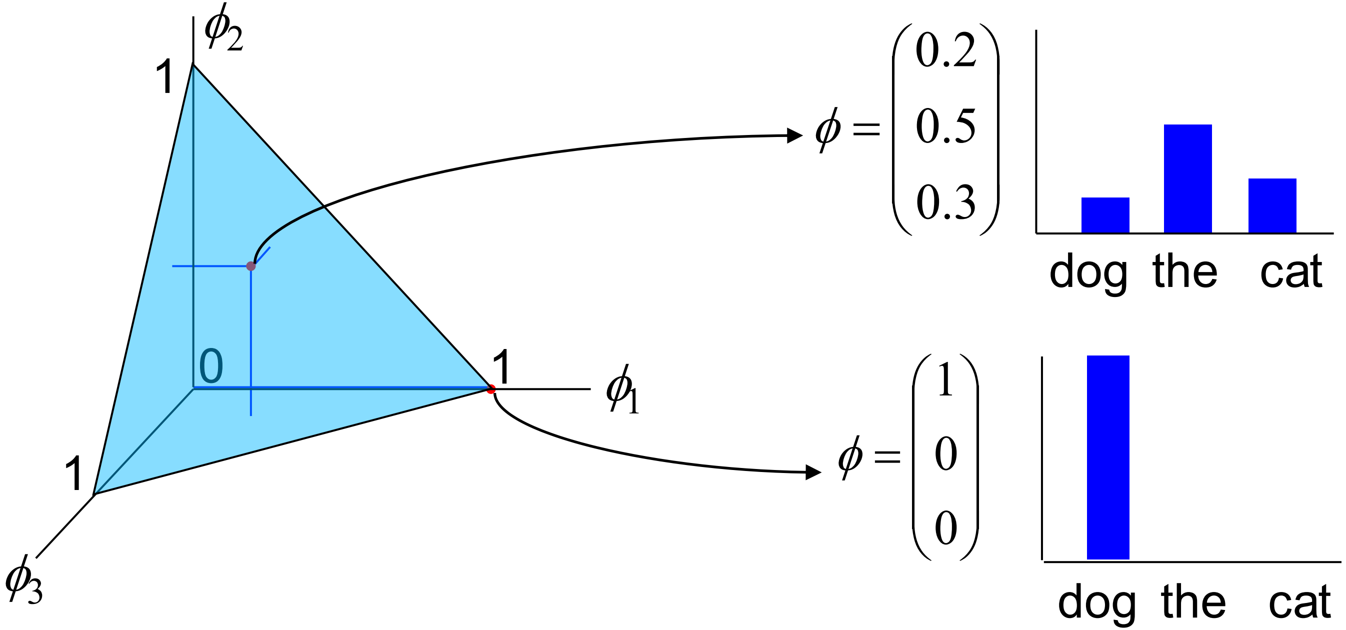
Impose *Dirichlet Prior* on π

$$\boldsymbol{\pi} \sim \text{Dirichlet}(\boldsymbol{\alpha})$$

$$\boldsymbol{y}^{(i)} \sim \text{Multinomial}(n^{(i)}, \boldsymbol{\pi}^{(i)}) \qquad \boldsymbol{y}^{(j)} \sim \text{Multinomial}(n^{(j)}, \boldsymbol{\pi}^{(j)})$$

What is a Dirichlet distribution?

- We can plot multinomial probability distributions
- Shape we get is a *simplex*

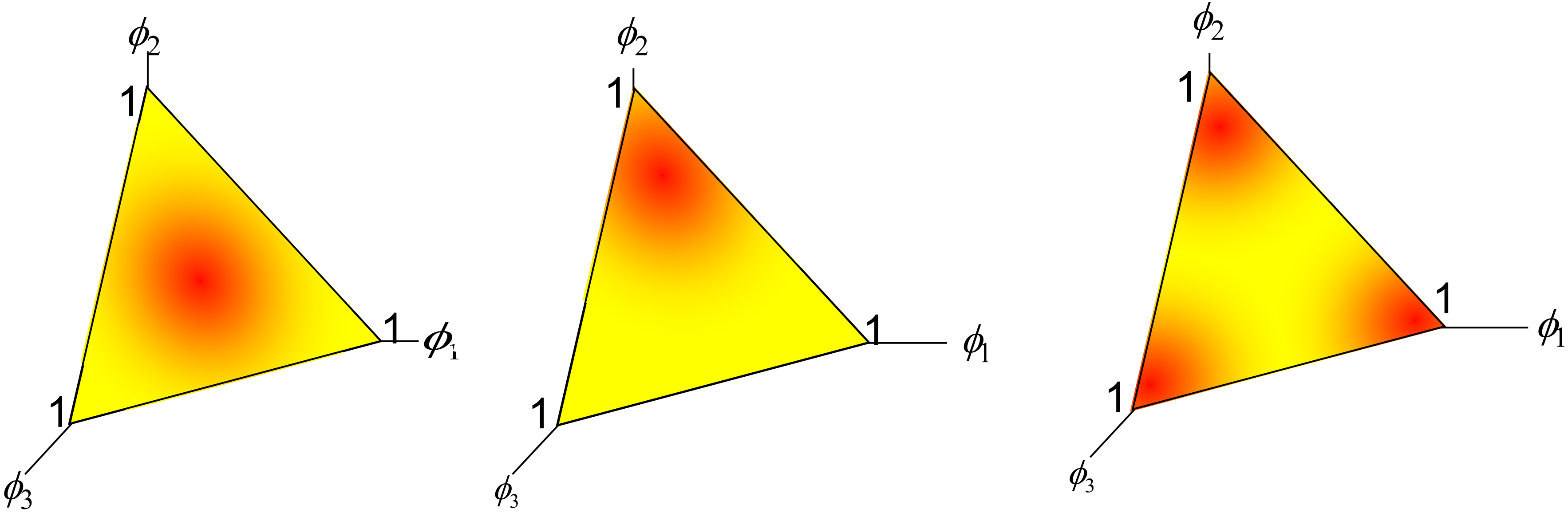


$$\sum_i \phi_i = 1$$

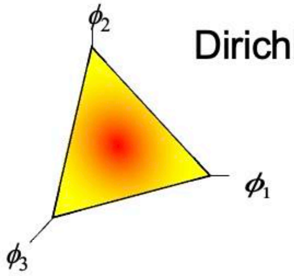
$$\sum_i \phi_i = 1$$

What is a Dirichlet distribution?

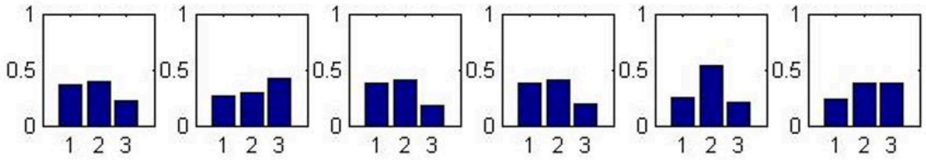
- A Dirichlet distribution is a distribution over multinomial distributions ϕ *in the simplex*



Example draws from a Dirichlet distribution over the 3-simplex



Dirichlet(5,5,5) [higher alpha – more dense]



slide thanks to Nigel Crook/Jason Eisner

Impose *Dirichlet Prior* on π

$$\boldsymbol{\pi} \sim \text{Dirichlet}(\boldsymbol{\alpha})$$

$$\boldsymbol{y}^{(i)} \sim \text{Multinomial}(n^{(i)}, \boldsymbol{\pi}^{(i)}) \qquad \boldsymbol{y}^{(j)} \sim \text{Multinomial}(n^{(j)}, \boldsymbol{\pi}^{(j)})$$

Impose *Dirichlet Prior* on π

$\boldsymbol{\pi} \sim \text{Dirichlet}(\boldsymbol{\alpha})$

Frequency of a term in the *entire* corpus

321	**176**	**53**	**…**	**54**	**543**
country	**state**	**healthcare**	**…**	**employment**	**the**

Impose *Dirichlet Prior* on π

$$\boldsymbol{\pi} \sim \text{Dirichlet}(\boldsymbol{\alpha})$$

$\boldsymbol{y}^{(i)} \sim \text{Multinomial}(n^{(i)}, \boldsymbol{\pi}^{(i)})$ $\boldsymbol{y}^{(j)} \sim \text{Multinomial}(n^{(j)}, \boldsymbol{\pi}^{(j)})$

$y^{(i)}$ can be word frequencies for Democrat Speech
$y^{(j)}$ can be word frequencies for Republican Speech

Both are assumed to have the same prior – frequency in general congressional speech

Generative Story

1. Draw $\boldsymbol{\pi}^{(i)} \sim$ Dirichlet($\boldsymbol{\alpha}$)
2. For $n^{(i)}$ steps:
   1. Draw $w \sim$ Multinomial($\boldsymbol{\pi}^{(i)}$)

For each subset of our corpus,

- $y^{(i)}, n^{(i)}$ and $\boldsymbol{\alpha}$ are observed in the data (where $y^{(i)}$ contains counts of w)
- $\boldsymbol{\pi}^{(i)}$ is what we need to estimate

Another aside about distributions

- Prior distribution: P($\boldsymbol{\pi}$)
- Posterior distribution: P($\boldsymbol{\pi}$ | w)

- When the posterior distribution is in the same family as the prior distribution, they are called **conjugate distributions**

- The Dirichlet distribution is a **conjugate prior** of the multinomial distribution

- [For our purposes, we often chose a Dirichlet prior for a multinomial distribution because it makes inference easier]

Point estimate of π

$$\hat{\pi}_w^{(i)} = \frac{y_w^{(i)} + \alpha_w}{n^{(i)} + \alpha_0}$$

→ Point estimate of $\pi, where\ \alpha_0 = \sum \alpha_w$

Intuitive interpretation: imagine we saw α_0 additional words and α_w were w

Johns Hopkins Whiting School of Engineering

Point estimate of π

$$\hat{\pi}_w^{(i)} = \frac{y_w^{(i)} + \alpha_w}{n^{(i)} + \alpha_0}$$

→ Point estimate of $\pi, where\ \alpha_0 = \sum \alpha_w$

$$\hat{\delta}_w^{(i-j)} = \log(\frac{\pi_w^{(i)}}{1-\pi_w^{(i)}}) - \log(\frac{\pi_w^{(j)}}{1-\pi_w^{(j)}})$$

→ Log-odds ratio with π instead of frequencies

$$\hat{\delta}_w^{(i-j)} = \log(\frac{y_w^{(i)}+\alpha_w}{n^{(i)}+ \alpha_0 -y_w^{(i)}-\alpha_w}) - \log(\frac{y_w^{(j)}+\alpha_w}{n^{(j)}+ \alpha_0 -y_w^{(j)}-\alpha_w})$$

Congressional data with Dirichlet prior

Word	δ (rounded)	**Frequency in Republican Speech**	**Frequency in Democratic Speech**
idahoans	-0.7321	210	0
fairtax	-0.7321	130	0
cdh	-0.7321	102	0
isna	-0.7321	98	0
zinser	0.6542	0	160
gaspee	0.6542	0	127
vania	0.6542	0	105
fiveminute	0.6542	0	95

We don’t have to drop zero counts anymore, but this isn’t that much better than before!

We could impose a stronger prior?

Variance

- Report *z-score:* point estimate divided by variance
  - Lower-frequency words have higher variance

With some assumptions, we can estimate:

$$\sigma^2(\hat{\delta}_w^{(i-j)}) \approx \frac{1}{y_w^{(i)} + \alpha_w^{(i)}} + \frac{1}{y_w^{(j)} + \alpha_w^{(j)}}$$

And use as our final score:

$$\frac{\delta_w^{(i-j)}}{\sqrt{\sigma^2(\delta_w^{(i-j)})}}$$

Odds ratio in Congressional data

Top Republican Words	Score	Top Democrat Words	Score
spending	-66.26	republican	56.63
obamacare	-59.90	wealthiest	40.78
government	-47.92	rhode	39.43
going	-45.33	women	38.16
that	-44.58	pollution	33.66
trillion	-43.43	republicans	32.86
taxes	-42.39	gun	32.45
you	-40.85	investments	32.22
administration	-39.07	families	31.93
debt	-38.92	violence	30.88

New Example: Narrative framing in restaurant reviews

- As online reviews have become commonplace, they offer an opportunity to study consumer behavior
- How do consumers frame positive and negative sentiment online?
- Data:
  - 900,000 Yelp restaurant reviews from 9 cities: Boston, Chicago, Los Angeles, New York, Philadelphia, San Francisco, and Washington D.C
  - Corpus subsets:
    - "i" = one star reviews
    - "j" = 5 star reviews
    - Prior: entire review corpus

Jurafsky, Dan, et al. "Narrative framing of consumer sentiment in online restaurant reviews." First Monday (2014)

New Example: Narrative framing in restaurant reviews

Table 2: Top 50 words associated with one–star reviews by the Monroe, *et al.* (2008) method.	
Linguistic class	**Words in class**
Negative sentiment	worst, rude, terrible, horrible, bad, awful, disgusting, bland, tasteless, gross, mediocre, overpriced, worse, poor
Linguistic negation	no, not
First person plural pronouns	we, us, our
Third person pronouns	she, he, her, him
Past tense verbs	was, were, asked, told, said, did, charged, waited, left, took
Narrative sequencers	after, then
Common nouns	manager, waitress, waiter, customer, customers, attitude, waste, poisoning, money, bill, minutes
Irrealis modals	would, should
Infinitives and complementizers	to, that

"In summary, one–star reviews were overwhelmingly focused on narrating experiences of trauma rather than discussing food, both portraying the author as a victim and using first person plural to express solace in community."

Jurafsky, Dan, et al. "Narrative framing of consumer sentiment in online restaurant reviews." First Monday (2014)

More serious example: Racial differences CPS services

- Words used in caseworker notes about families referred to child protective services
- Compare words used in notes about about Black families vs. white families

Black-assoc.	Score	White-assoc.	Score
Referrals			
she	52.19	he	54.64
belt	47.37	heroin	41.87
her	45.39	PGF	36.08
BM	37.90	treatment	36.16
bus	30.95	anxiety	34.25
shelter	25.11	using	27.45
whooped	23.96	therapist	26.05
Cases			
school	56.80	F	130.67
housing	42.01	parents	59.26
informed	37.76	drug	37.65
pass	35.75	methadone	36.55

Field, Anjalie, et al. "Examining risks of racial biases in NLP tools for child protective services." FAccT. 2023.

Alternate Approach: Pointwise-mutual information

- Probability/Information theory measure of association
- Common formulation: measure how often two events, x and y occur, compare with what we would expect if they were independent

$$PMI(x,y) = log \frac{p(x,y)}{p(x)p(y)}$$

How often we observe x and y together ($p(x,y)$)

How often we expect x and y to co-occur, if they each occur independently ($p(x)p(y)$)

Alternate Approach: Pointwise-mutual information

- Compute the co-occurrence between a word *w* and a label *i*

$$PMI(w,i) = log\frac{p(w,i)}{p(w)p(i)}$$

Probability of w and i co-occurring

Probability of w occurring

Probability of i occurring

Computing PMI

$$PMI(w,i) = log\frac{p(w,i)}{p(w)p(i)} = log\frac{p(w|i)p(i)}{p(w)p(i)} = log\frac{p(w|i)}{p(w)}$$

	country	state	healthcare	…	employment	the	Total
Republican	321	176	15	…	54	500	10233
Democratic	100	31	53	…	20	543	12231
Total	421	207	68	…	74	1043	22464

$$PMI(Republican, employment) = log\frac{\left(\frac{54}{22464}\right)}{\left(\frac{74}{22464}\right)\left(\frac{10233}{22464}\right)}$$

Alternate Approach: Pointwise-mutual information

- Compute the co-occurrence between a word *w* and a label *i*

$$PMI(w,i) = log\frac{p(w,i)}{p(w)p(i)}$$

$p(w,i)$: Number of times w occurs in i-labeled documents / number of total words

$p(w)$: Proportion of w

$p(i)$: Proportion of i-labeled terms

Alternate Approach: Pointwise-mutual information

- Common to use *Positive Pointwise mutual information (PPMI)*
  - Set PMI to 0 wherever it is negative

- Still run into problems with over-emphasizing rare words:
  - There are some fixes for this, including smoothing

- PMI scores are used frequently

Example of PMI: Gender Bias on Wikipedia

- [Only include words that occur in at least 1% of biographies]
- Women: actress (15.9%), women’s (8.8%), female (5.6%), **her husband** (4.1%), women (5.3%), first woman (1.9%), film actress (1.6%), her mother (1.8%), woman (4.4%), **nee** (3.6%), feminist (1%), miss (1.9%), model (3.3%), girls (1.5%) and singer (6.5%).

- Men: played (14.2%), footballer who (3.0%), football (4.5%), league (5.9%), john (7.9%), major league (1.8%), football league (1.6%), college football (1.5%), son (7%), football player (2.2%), footballer (2%), served (11.7%), william (4.6%), national football (2%) and professional footballer (1%).

Eduardo Graells-Garrido, Mounia Lalmas, and Filippo Menczer. 2015. First women, second sex: Gender bias in Wikipedia. In Proc. of Hypertext & Social Media. ACM, New York, 165–174.

Additional Applications

- PPMI and variants of odds ratio are commonly used as *features* in other NLP tasks (not just for word statistics on their own)
  - Represent a document using one of these metrics instead of using word counts
  - Document vectors can be used for similarity metrics, e.g. clustering or information retrieval

	country	**state**	**healthcare**	**…**	**employment**	**the**
Republican	321	176	15	…	54	500
Democratic	100	31	53	…	20	543

Today's takeaways

- Counting words can be surprisingly hard!
- Key ideas behind two popular methods for examining word statistics:
  - Log-odds with a Dirichlet prior ("Fightin' Words")
  - Pointwise mutual information scores
- Examples of applications and understanding of when these methods are useful

Some takeaways from the course goals from

- Range of places people are interested in applying concepts from this course: public health, economics, cognitive science, environmental science
- Mix of background in NLP
- Topics of interest: misinformation, bias/inequality, validation, LLMs

Reminders

- Course website: http://nlp-css-601-672.cs.jhu.edu/sp2026/
- Join class Piazza
- Fill out course goals survey (linked on slides from last class)

References

- Jurafsky and Martin, 2022, Sec 6.6
    - https://web.stanford.edu/~jurafsky/slp3/ed3book_jan122022.pdf
- Monroe BL, Colaresi MP, Quinn KM. Fightin' Words: Lexical Feature Selection and Evaluation for Identifying the Content of Political Conflict. *Political Analysis*. 2008;16(4):372-403. doi:10.1093/pan/mpn018

End