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Advanced quantitative text analysis (2024W)

Petro Tolochko, Fabienne Lind

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Course objectives

- Getting to know procedures of automated text analysis
- Insight into practical challenges
- Critical reflection on the method and its results
- Inspiration for your own projects
- Make an informed decision about a suitable method for a given application scenario

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Contents (smaller changes possible)

Day	Session 1	Session 2	Session 3
1	Intro	Text representation	Feature Engineering
2	Concepts	Data	Dictionaries
3	Supervised machine learning	Unsupervised machine learning	Multilingual text analysis
4	Neural network models, transformers 1	Neural network models, transformers 2	Project talks

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Course philosophie

Topics are covered with

- Lecture style input
- Guided coded session

Interrupt us, ask all kinds of questions

Work on your own data, code, and projects

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About us

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- Research focus: Text complexity, social networks
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Your turn :)

- Name
- Affiliation? Background?
- Experience with content analysis, R & Python
- What are the expectations and wishes for the workshop and the workshop leaders?

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Course assessment

Participation in class (20%)

Final paper: application of one or several automated text analysis methods on a topic related to the PhD thesis or a topic of free choice (80%)

- Contents: short motivation, analysis (commented code), description and interpretation of results (about 10 pages)
- Format: Python or R Markdown
- Deadline: January 31st, 2025

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Receive feedback on your projects

Very informal opportunity to talk about your text analysis use case and (initial) design (plan)

- Research question, Data, Methods, Current struggles

And to receive some feedback (no grades, points, etc. just free brainstorming opportunity)

Can also be useful to get initial feedback for your final paper in this course.

When: Wednesday

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Course repository: GitHub

https://github.com/PeterTolochko/text-as-data-python

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Need a more general recap of content analysis?

Access online via library of University of Vienna

https://usearch.univie.ac.at

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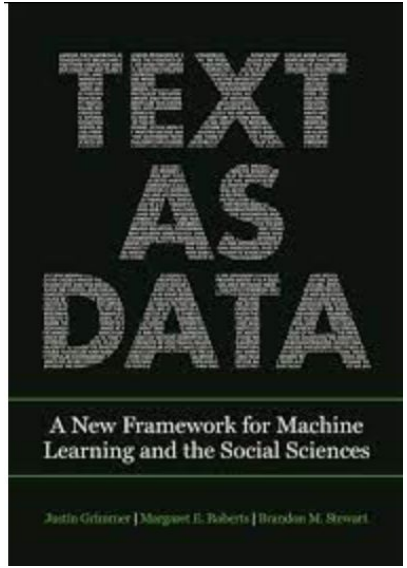
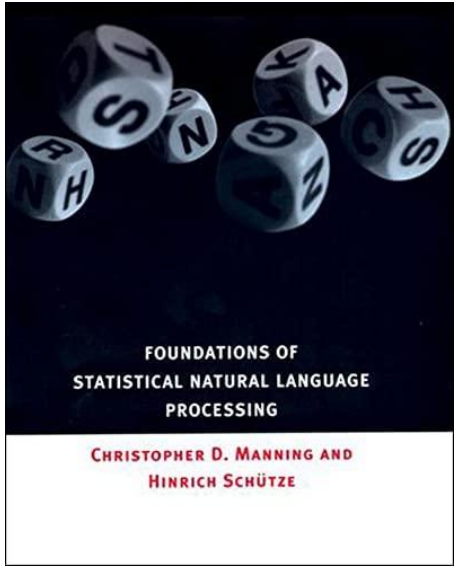
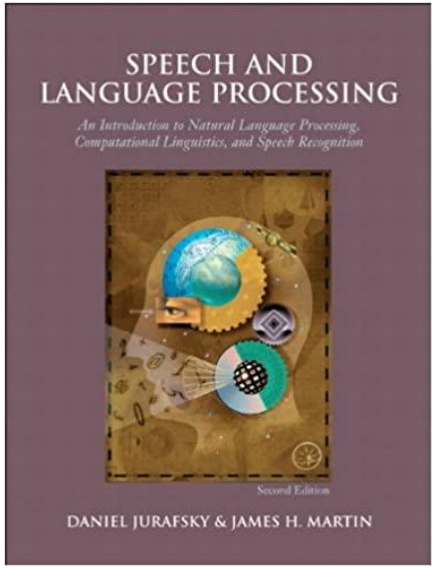
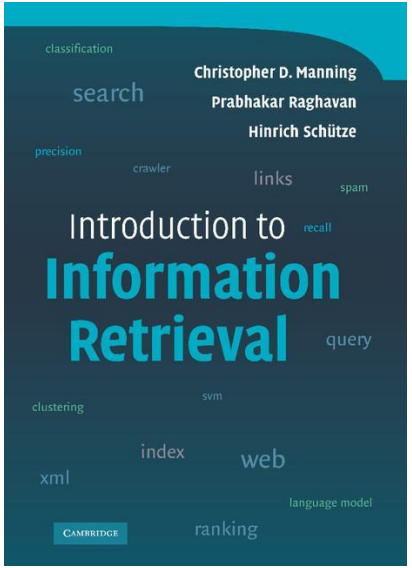
Resources









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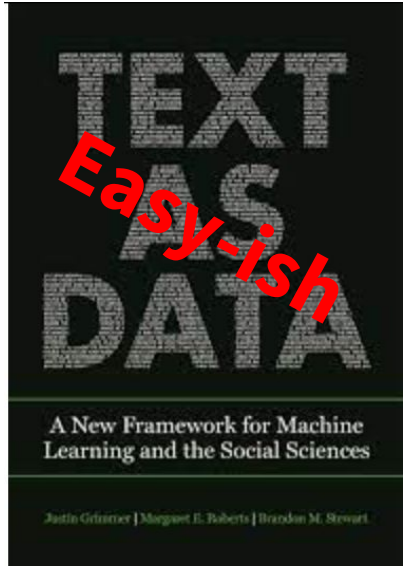
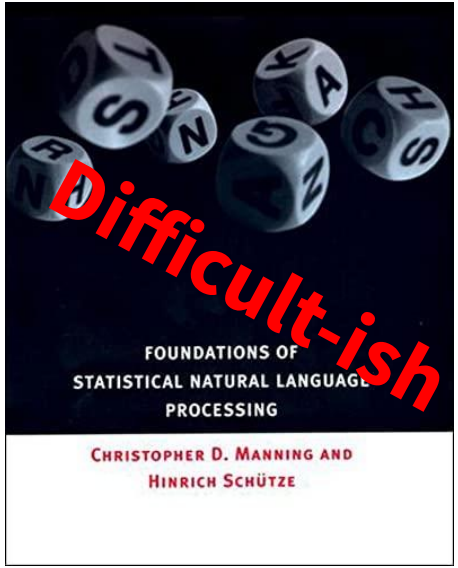
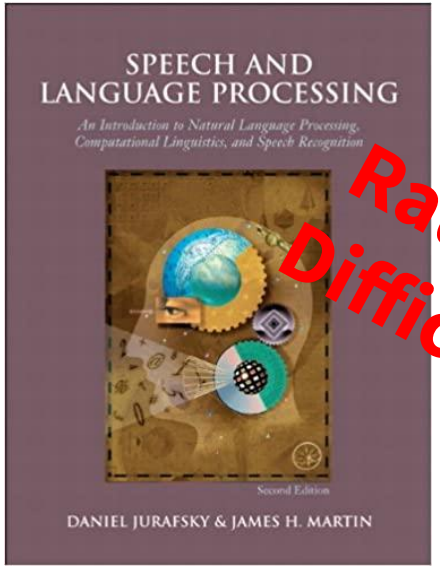
Resources



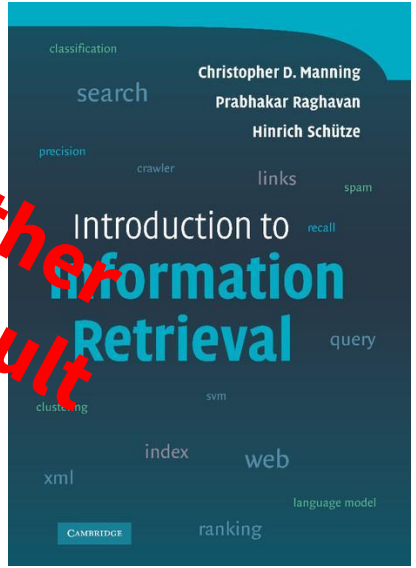
Easy-ish



Difficult-ish



Rather Difficult



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R and Python

- Both are free and open source
- Most things can be done in both languages
- Great online support ressources
- We love them bove :)

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Motivations to use R and RStudio

- Great for visualization and statistical analysis
- Popular in the social science community
- A full programming language and thus a good start to pick up other programming languages

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Motivations to use Python

- Speed, simple syntax
- General-purpose programming language, not limited to the data science community
- Certain text analysis approaches (e.g., deep learning) are more accessible in Python

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Some R Ressources

- R for Data Science https://r4ds.had.co.nz/
- Tidy Modeling with R. https://www.tmwr.org/
- Big book of R. Database of R resources. https://www.bigbookofr.com/

Twitter accounts: @WeAreRLadies

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Some Python Ressources

- Learn Python for Everybody: https://www.youtube.com/watch?v=8DvywoWv6fI
- Data Analysis with Python: https://www.youtube.com/watch?v=GPVsHOlRBBI
- VanderPlas, J. (2016). Python Data Science Handbook: Essential Tools https://github.com/jakevdp/PythonDataScienceHandbook

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R and Python Ressources for Text Analysis

- Atteveldt, W., Trilling, D., & Arcila, C. (2021). Computational Analysis of Communication. Wiley-Blackwell.
  - URL: http://cssbook.net
  - Code examples for R and Python

- NLP Course: https://huggingface.co/learn/nlp-course/chapter0/1

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Today

13:00-14:30	Intro
14:30-14:45	Coffee Break
14:45-16:00	Text representation
16:00-16:30	Coffee Break
16:30-18:00	Feature Engineering

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Text as Data

Day 1 Session 1

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Parteiprogramm der Freiheitlichen Partei Österreichs (FPÖ)

Beschlossen vom Bundesparteitag der Freiheitlichen Partei Österreichs am 18. Juni 2011 in Graz

FPÖ DIE SOZIALE HEIMATPARTEI

Österreich zuerst

Freiheit, Sicherheit, Frieden und Wohlergehen für Österreich und seine Bevölkerung sind die Leitlinien und der Maßstab für unser Handeln als soziale, leistungsorientierte und österreichpatriotische politische Kraft.

Unsere Verwurzelung in der reichen Geschichte und in unseren Traditionen ist untrennbar verbunden mit der Verantwortung, die daraus für die aktive Gestaltung der Zukunft für kommende Generationen erwächst.

Wir bekennen uns zu unserem Heimatland Österreich als Teil der deutschen Sprach- und Kulturgemeinschaft, zu unseren heimischen Volksgruppen sowie zu einem Europa der freien Völker und Vaterländer.

Wir bekennen uns zu Freiheit und Verantwortung des Einzelnen und der Gemeinschaft, zur Demokratie, zum freiheitlichen Rechtsstaat, zu den Prinzipien der Marktwirtschaft und der sozialen Gerechtigkeit.

Wir bekennen uns zum Selbstbestimmungsrecht Österreichs sowie zur Bewahrung und Verteidigung unseres in unserer Tradition und unserer geschichtlichen Entwicklung gewachsenen Menschen- und Gesellschaftsbildes.

Parteiprogramm: PDF Download

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Motivations to analyse text

- Huge volumes of digital available information
- These data can be useful to perform research on media contents, communicators, effects, and user interactions
- Explain, understand, predict feelings, attitudes and behaviour of individuals, groups, societies

Barberá, P., & Steinert-Threlkeld, Z. C. (2020). How to use social media data for political science research. *The SAGE handbook of research methods in political science and international relations*, *2*, 404-423.

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Motivations to analyse text automatically

- Reading all the texts in a large corpus takes time
- Reliability issues

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Discourse patterns

Research Question: What are users of anti-vaccinations Facebook pages talking about?

- **Approach:** topic modelling

Topic	Top 10 terms within topic
Topic 1: Activism	Sick, signed, shared, petition, AMA, stomach, count, Tylenol, likes, sickening, signing, signatures, sadly, twisted, perfect, petitions, commented, legit, provaxers, flue, object, exactly, counting, repeal, referendum
Topic 2: Governance	Missed, homeopathy, double, terrible, placebo, figures, Abbott, midwife, style, shocked, hiding, tony, amen, midwives, Sweden, transparency, max, Denmark, meningococcal, plot, speed, tall, triple, saline, prozac
Topic 3: Media, censorship, and 'cover up'	News, link, gates, surprised, shedding, Canada, fake, click, India, china, button, strange, rotavirus, blocked, ads, chart, edgy, pushers, thread, fox, Reply, Disney, Melinda, unlike, horrific
Topic 4: Vaccination as genocide	Land, jail, crime, Nazi, Germany, experiment, crimes, tyranny, assault, criminals, prison, Hitler, murdered, mafia, Washington, flag, amendment, discrimination, powers, democracy, Nuremberg, owned, genocide, suicide, experiments
Topic 5: Zika Virus and Gates Foundation	Disturbing, jenny, finally, three, brazil, Florida, accident, shocking West, Texas, looks, error, McCarthy, brown, microcephaly, mosquitoes, hoax, privacy, poisonous, precious, absolutely, rats, spears, horror, messed
Topic 6: Moral transgressions	Poison, follow, evil, sue, total, sounds, pure, lying, gene, fire, eugenics, greed, dirty, greedy, recall, suit, roll, bastards, violation, gross, unethical, abortions, bullies, pays, madness
Topic 7: Vaccine injury	Sad, horrible, glad, omg, shame, heartbreaking, tragic, terrible, incredibly, tragedy, liked, frightening, wth, terribly, frustrating, shameful, unfortunate, sadly, shell, ugh, Shill, outrageous, unreal, definitely, guard
Topic 8: Junk topic	Man, word, Gardasil, corruption, brilliant, speaks, google, careful, cholesterol, acceptable, wise, greed, episode, English, England, causation, dream, indeed, usual, bird, everywhere, king, arrogant, perspective, abusive
Topic 9: Food as medicine	Oil, coconut, sunscreen, butter, coffee, dentist, eggs, soda, tap, vit, raw, Cannabis, burn, bottled, honey, olive, green, silver, tea, fish, taste, corn, fillings, cook, apple
Topic 10: Chemtrails and Agriscience	Stupid, smart, Monsanto, idiot, dumb, chemical, fucking, brainwashed, uneducated, stupidity, plain, damn, ban, chemtrails, kidding, fix, everywhere, depopulation, morons, Russian, roulette, fools, moron, talks, ass

Smith, N., & Graham, T. (2019). Mapping the anti-vaccination movement on Facebook. *Information, Communication & Society*, *22*(9), 1310-1327.

Effects of social media communication

Research Question: How prevalent is each frame in NGOs' tweets?

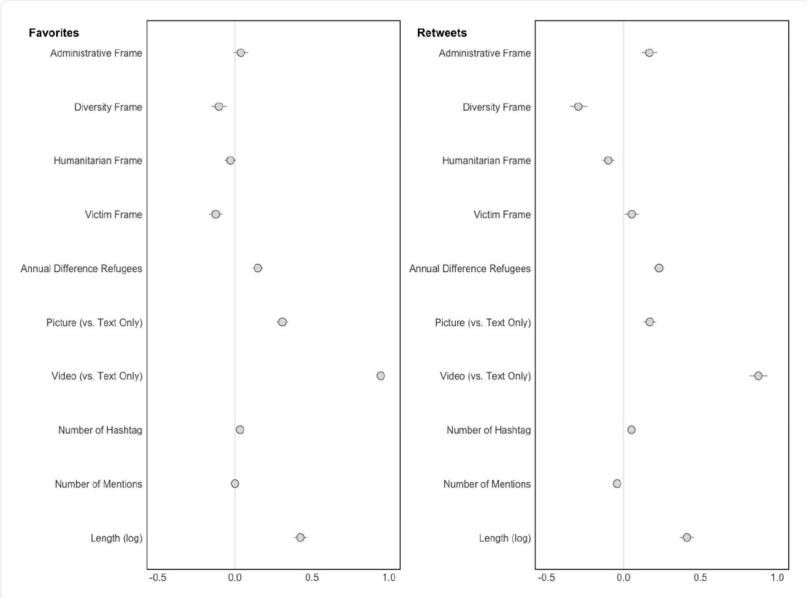
- **Approach:** Dictionary

Table 3. Frame frequencies in Twitter communication of top 10 humanitarian NGOs.

Frame	Frequency (percent)
Administrative frame	2301 (11.78)
Diversity frame	2028 (10.39)
Humanitarian frame	4411 (22.59)
Victim frame	3075 (15.75)

Note. $N = 19{,}528$. Part of the sample did not contain any of the four frames measured.

- **Research Question:** What reactions to the frames provoque?

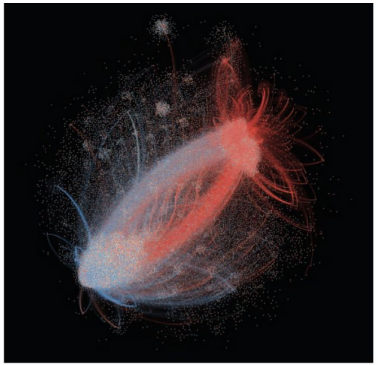


Dimitrova, D., Heidenreich, T., & Georgiev, T. A. (2022). The relationship between humanitarian NGO communication and user engagement on Twitter. *New Media & Society*, 14614448221088970.

Data selection for Network Analysis

Data selection requirement: Which of the 12 defined topics was mentioned in which tweet?

- **Approach:** Dictionary



2012 Presidential Election

Dark red = conservative
dark blue = liberal

2013 Super Bowl

Barbera et al., 2015, Fig. 3

Barberá, P., Jost, J. T., Nagler, J., Tucker, J. A., & Bonneau, R. (2015). Tweeting from left to right: Is online political communication more than an echo chamber?. *Psychological science*, *26*(10), 1531-1542.

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Purpose of obtaining measures for a large number of texts

- Filter options
  - If measurements are available for a large number of texts, other filtering options are possible. E.g.; linkage studies combination with media usage data
- Evidence-based policy making
  - Making the opinion of populations visible, holding politicians accountable

González-Bailón, 2013

The end of manual coding?

- Augmenting not replacing (Grimmer & Steward, 2013)
- Human input for quality control:
  - select, monitor, and test on the level of data, inputs, process, outputs

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Potential applications scenarios

- Discover new concepts
- Measure contents of large naturally occurring text collections
  - As standalone interest (descriptive interests)
  - As input for another interest (inference interests)
- Explore the texts that survey participants type into open answer questions
- Etc.

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Exercise: challenges when working with large corpora

- Let’s brainstorm together
- What are potential challenges when working with large text corpora?

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Some major challenges when working with large corpora

Big data, big bias?

The end of theory?

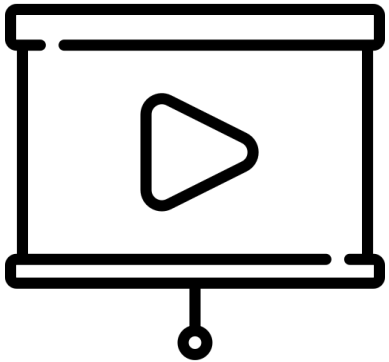
Generalizing from online to offline behavior

Ethical concerns

Barbera, 2021; González-Bailón, 2013

Exercise: First text analysis project idea

- Let’s form groups
- Jointly discuss about initial text analysis projects ideas
  - You can talk about project ideas that you already have or about areas in your discipline where large text quantities play a role



by Freepik - Flaticon

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Text Representation

Day 1 Session 1

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What is text?

- Data
- *Unstructured*
- *Multidimensional (Highly)*

In general, difficult to work with (if you're not human)

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What is text?

- So, how do we make computers process our language?

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From Text to Structure

- We need to “structure” the text before we perform analyses
- Different ways to ***represent*** text so that computers “understand”
- Different ways to ***model*** text so that both (we and computer) “understand”
    - Different research questions
    - Different ways to think about what text is

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Two approaches to text representation

- Discrete text representation
- Distributed text representation

Document-Term Matrix

$$X = \begin{bmatrix} 1 & 1 & \dots & 0 \\ 2 & 1 & \dots & 0 \\ \dots & \dots & \dots & \\ 2 & 0 & \dots & 3 \end{bmatrix}$$

X = N * K matrix
N = number of ***documents***
K = number of ***terms***/***features***

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Example

Corpus (Collection of texts)

Document 1: “John loves ice-cream”
Document 2: “John loves oranges”
Document 3: “Marry hates ice-cream”

N? K?

	Terms					
Docs	icecream	john	loves	oranges	hates	marry
1	1	1	1	0	0	0
2	0	1	1	1	0	0
3	1	0	0	0	1	1

N = 3
K = 6

X = 3 * 6 matrix

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Types & Tokens

Types: unique words in a text

Tokens: all words in the text

Types and tokens in our example corpus?

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Types & Tokens

Types: unique words in a text

Tokens: all words in the text

Types and tokens in our example corpus?

6 types (unique words) / *9 tokens* (total length of the corpus)

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Bag-of-Words representation

Representation of text as a bag of words

- Collection of words
- Ordering is unimportant
- Each text is represented as a ***count*** of words contained in it

	Terms					
Docs	icecream	john	loves	oranges	hates	marry
1	1	1	1	0	0	0
2	0	1	1	1	0	0
3	1	0	0	0	1	1

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Multinomial Model of Language

You can think of a text as a draw from a Multinomial distribution

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Binomial

$$\binom{n}{k} p^k (1-p)^{n-k}$$

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Binomial

n = number of events
k = number of successes

$$\binom{n}{k} p^k (1-p)^{n-k}$$

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Multinomial

$$\frac{n!}{x_1!...x_k!}p_1^{x_1}...p_k^{x_k}$$

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Multinomial

$$\frac{n!}{x_1!...x_k!}p_1^{x_1}...p_k^{x_k}$$

n = text length
k = size of vocabulary
p = probability of a word

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Example Texts

Text_1 = "banana banana banana banana chocolate"

Text_3 = "chocolate chocolate chocolate banana fudge"

Text_2 = "banana banana"

Text_4 = "icecream icecream fudge ice-cream"

Text_5 = "fudge fudge fudge"

Text_6 = "ice-cream ice-cream fudge fudge"

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Example Texts

Text_1 = "banana banana banana banana chocolate"

Text_3 = "chocolate chocolate chocolate banana fudge"

Text_2 = "banana banana"

John

Text_4 = "icecream icecream fudge ice-cream"

Text_5 = "fudge fudge fudge"

Text_6 = "ice-cream ice-cream fudge fudge"

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Example Texts

Text_1 = "banana banana banana banana chocolate"
Text_3 = "chocolate chocolate chocolate banana fudge"
Text_2 = "banana banana"

John

Text_4 = "icecream icecream fudge ice-cream"
Text_5 = "fudge fudge fudge"
Text_6 = "ice-cream ice-cream fudge fudge"

Marry

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Document-Term Matrix

banana	chocolate	fudge	icecream
4	1	0	0
2	0	0	0
1	3	1	0
0	0	1	3
0	0	3	0
0	0	2	2

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Document-Term Matrix

banana	chocolate	fudge	icecream
7	4	1	0

John rates

banana	chocolate	fudge	icecream
1	3	7	5

Marry rates

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John Language Model

Document-Term Matrix

banana	chocolate	fudge	icecream
7	4	1	0

John rates

banana	chocolate	fudge	icecream
1	3	7	5

Marry rates

Marry Language Model

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New Texts

new_text_1 = "ice-cream fudge fudge"

new_text_2 = "chocolate chocolate banana banana"

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New Texts

new_text_1 = "ice-cream fudge fudge"

new_text_2 = "chocolate chocolate banana banana"

What's the probability that they have been generated by John or Marry?

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New Texts

banana	chocolate	fudge	icecream
0	0	2	1
2	2	0	0

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Probability Spoken by John

new_text_1 = "ice-cream fudge fudge"

$$Pr(b = 0, ch = 0, f = 2, i = 1) = \frac{3!}{0!0!2!1!} 0.583^0 \times 0.333^0 \times 0.08^2 \times 0^1 = 0$$

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Probability Spoken by John

new_text_2 = "chocolate chocolate banana banana"

$$Pr(b = 2, ch = 2, f = 0, i = 0) = \frac{4!}{2!2!0!0!} 0.583^2 \times 0.333^2 \times 0.08^0 \times 0^0 = 0.23$$

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Probability Spoken by Marry

new_text_1 = "ice-cream fudge fudge"

P = 0.18

new_text_2 = "chocolate chocolate banana banana"

P = 0.0008

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Vector Space Representation

Representation of texts as ***vectors*** in a multidimensional ***space***

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Multidimensional?

- Position on a map:
  - **X** = Longitude **Y** = Latitude
- Position in a real world:
  - **X** = Longitude **Y** = Latitude **Z** = Height
- Point in time and space
  - **X** = Longitude **Y** = Latitude **Z** = Height **T** = Time

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Multidimensional?

Number of dimensions is the ***number of data points*** needed to describe an object in space

- ***Coordinates*** in the context of ***geographical position***
- ***Words*** in the context of position of text within a ***linguistic space***

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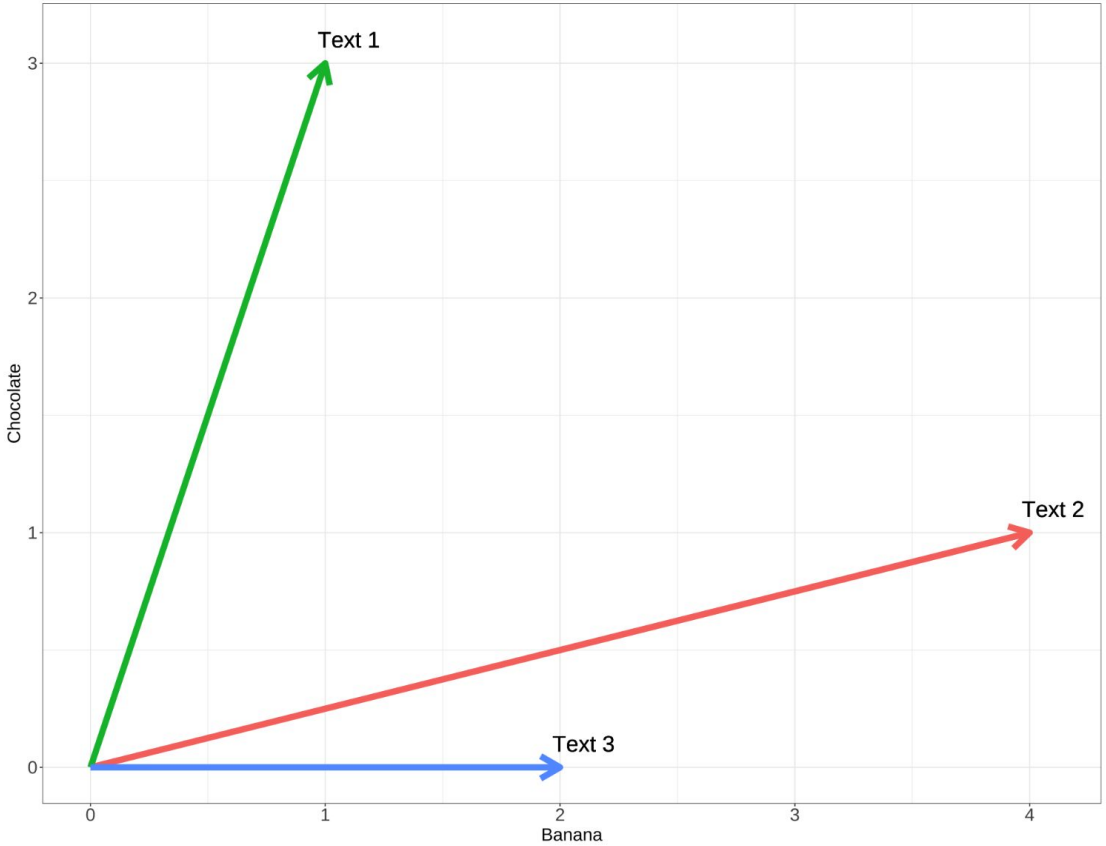
Two-dimensional space

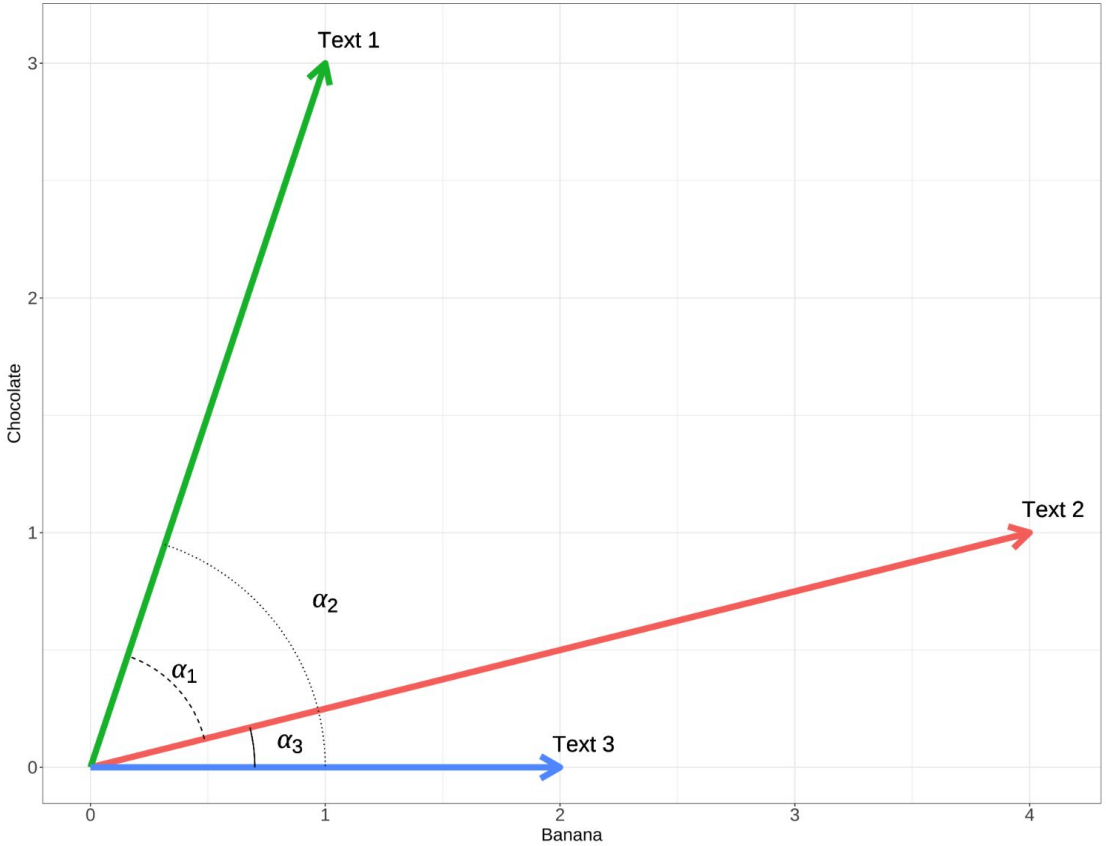
vocabulary = {“banana”, “chocolate”}

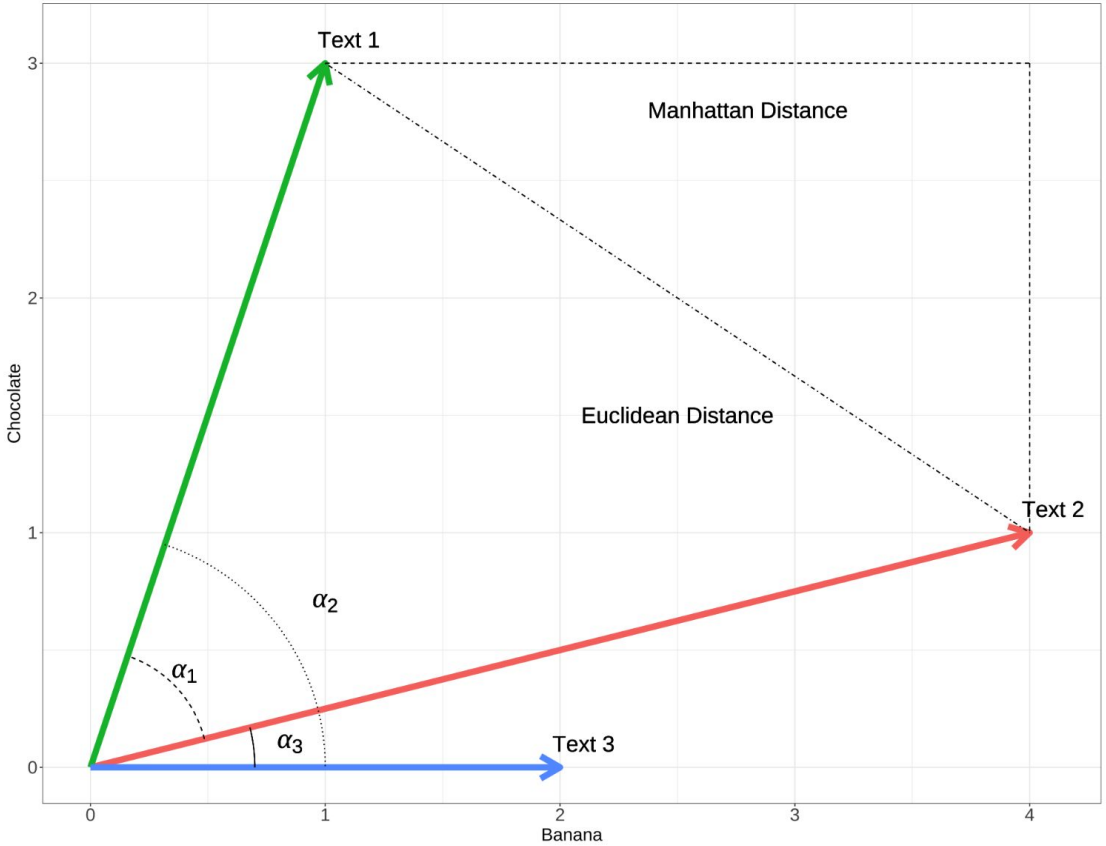
Text 1 = “chocolate, chocolate, chocolate, banana”

Text 2 = “banana, banana, banana, banana, chocolate”

Text 3 = “banana, banana”


Text 1
Text 2
Text 3
Chocolate
Banana
0
1
2
3
4


Text 1
Text 2
Text 3
α_1
α_2
α_3
Chocolate
Banana
0
1
2
3
4


Text 1
Manhattan Distance
Euclidean Distance
Text 2
α_2
α_1
α_3
Text 3
Chocolate
Banana
0
1
2
3
4

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Multidimensional?

Estimated ~1,022,000 words in English language

~ 1,022,000-dimensional space


[adult swim]

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Same math, though

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Discrete representation

Summary: Each word is considered unique & independent from each other

Main advantages:

- Simple representation that is easy to understand, implement and interpret

Main disadvantage:

- For corpora with large corpora, memory constraints
- Positional information of the word is not captured
- Semantics is not captured

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Distributed representation

- aims to capture the semantic meaning and contextual information of words or sentences
- the information about a word is distributed along the vector it is represented as

- The fundamental concept that forms the basis for distributed representation = **the distributional hypothesis**

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Distributional Hypothesis / Word Embeddings

The new thing kids do…

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Distributional Hypothesis / Word Embeddings

The new thing kids do… at least since ‘57…

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Distributional Hypothesis

- difference of meaning correlates with difference of distribution (Harris, 1954)
- In most cases, the meaning of a word is its use (Wittgenstein, 1953)
- A word is characterized by the company it keeps (Firth, 1957)
- Words which are similar in meaning occur in similar contexts (Rubenstein & Goodenough, 1965)
- Words with similar meanings will occur with similar neighbors if enough text material is available (Schütze & Pedersen, 1995)
- Or: words that are used in similar ways, surrounded by similar words, are likely to have similar semantic meanings.

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Distributional Hypothesis / Word Embeddings

Each word is *embedded* in an n-dimensional vector space (typically, 300 dimensions)

Neural network that “learns” the context of a word by looking at the words *around* it

Word2Vec (Mikolov, 2013) – one of the most famous methodologies, developed by Google engineer

```
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  1.1739  , -0.40348 ,  3.2028  ,  0.75381 , -2.7179  , -1.3587  ,
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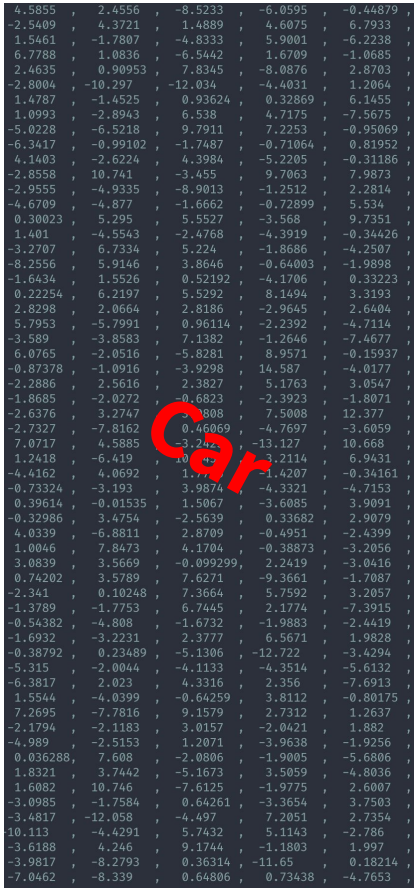
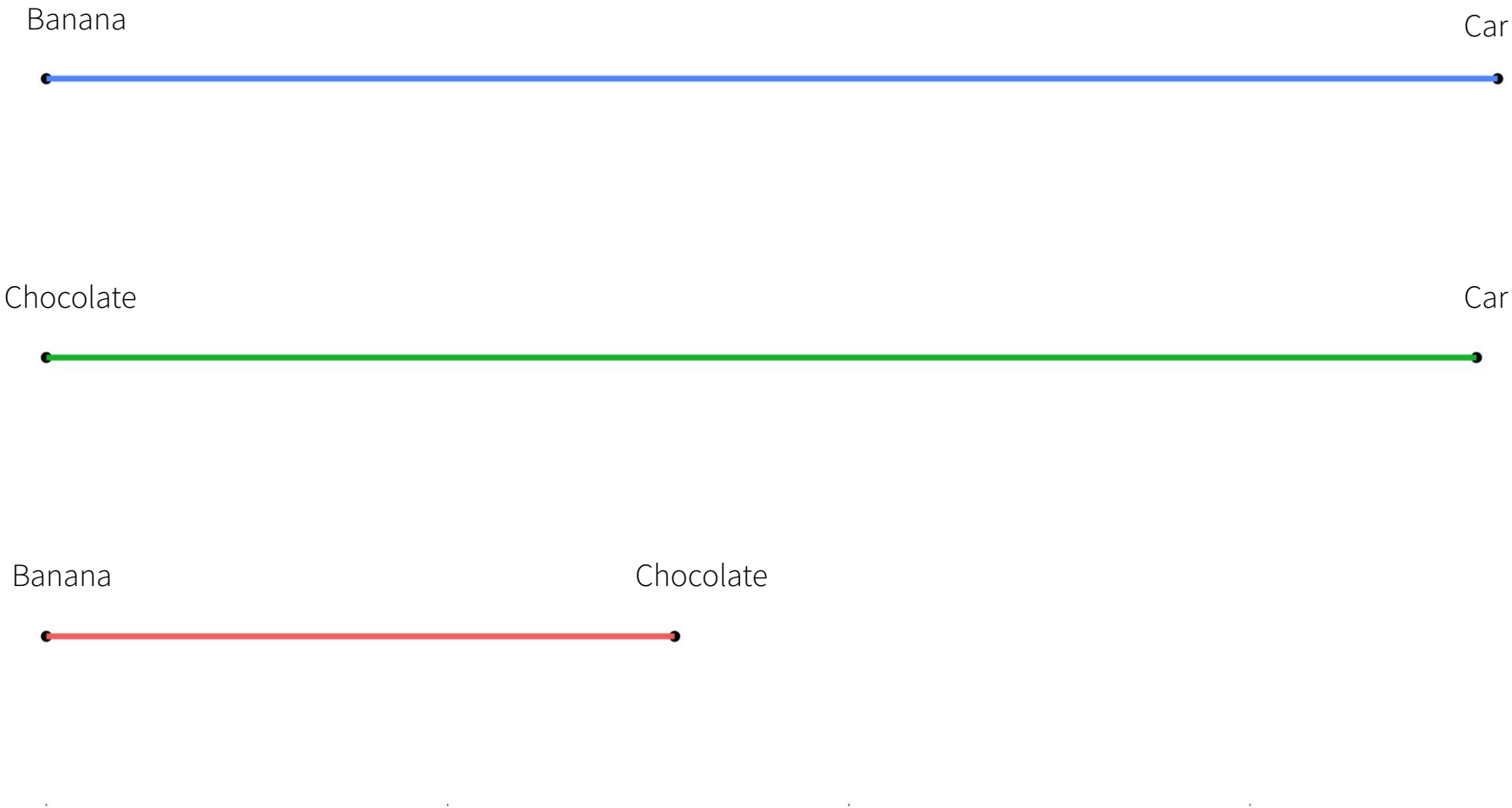
Banana


Chocolate


Car


Banana
Car
Chocolate
Car
Banana
Chocolate

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Summary: text representation

Text representations are powerful algorithms

- Just by themselves: Useful for understanding & exploring the corpus (e.g., word frequencies)
- Even more so in combination with other procedures such as document classification, topic modeling, named entity recognition, etc.

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More on text representation later in the week

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Text Processing / Feature Engineering

Day 1 Session 3

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Features?

Features are characteristics or attributes of the data that are used for analysis or processing

- In a survey (e.g., age, frequency of a certain behaviour)
- In automated text analysis (e.g., text length, word frequencies)

Feature engineering is the process of selecting, transforming, or creating new features from raw data

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Text Preprocessing

- Texts are ***highly*** dimensional
- When possible, it is nice to reduce this dimensionality and to focus on the features that are informative for a specific analysis
- Ideally, without losing too much information

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Danny & Spirling, 2018

- Punctuation
- Numbers
- Lowercasing
- Stemming
- Stop-words
- N-grams
- Removal of words by frequency

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Punctuation / Numbers / Lowercasing

- Fairly straightforward
- Often we don’t care about punctuation and/or numbers – so, might be better to remove them
- We probably do care about the letter case
  - But to what extent?
  - Reduction in dimensions might be worth the reduction in accuracy
  - Can you think of examples when we do /don’t care about the case?
    - “rose” (the flower), and “Rose” the proper name

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Stemming

- A ***stem*** is the part of the word responsible for lexical meaning
- A stem is invariable part of the word under inflection
- “wait” is a stem of:
  - “waiting”
  - “waited”
  - “waits”
- Can be useful to reduce the vocabulary but can also introduce noise: what are the stems of these examples?: “college students partying”, and “political parties”

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Lemmatization

- A ***lemma*** is the base / “original” part of the word
- Lemmatization takes into account the part of speech (POS) of a word to determine its lemma.
- Also useful for dimension reduction

Consider the following 2 examples:

1. Word: "Running" , Lemma: "Run"
2. Word: "Better" Lemma: "Good"

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More examples

Word: "Caring" Stem: ? Lemma: ?

Word: "Ducks" Stem: ? Lemma: ?

What is the stem? What is the lemma?

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More examples

Word: "Caring" Stem: "Car" Lemma: "Care"

Word: "Ducks" Stem: "Duck" Lemma: "Duck"

What is the stem? What is the lemma?

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Stop Words

- Words that are filtered out before the analysis begins
- Could be any type of words that you do not want in the analysis
- Usually, function words are used as stop words (*FORESHADOWING*…)
  - “The”
  - “Is”
  - “I”
  - “That”
  - etc.
- Domain-specific words are also often excluded from the analysis
- E.g., “Global Warming” in the corpus of texts about Global Warming

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N-grams

- So far, we've only looked at "unigrams" – individual words
- Texts can be broken down into any n-gram sequences

- "I love ice-cream and bananas"
  - "I" "love" "ice-cream" "and" "bananas"
  - "I love" "love ice-cream" "ice-cream and" "and bananas"
  - 3-grams?

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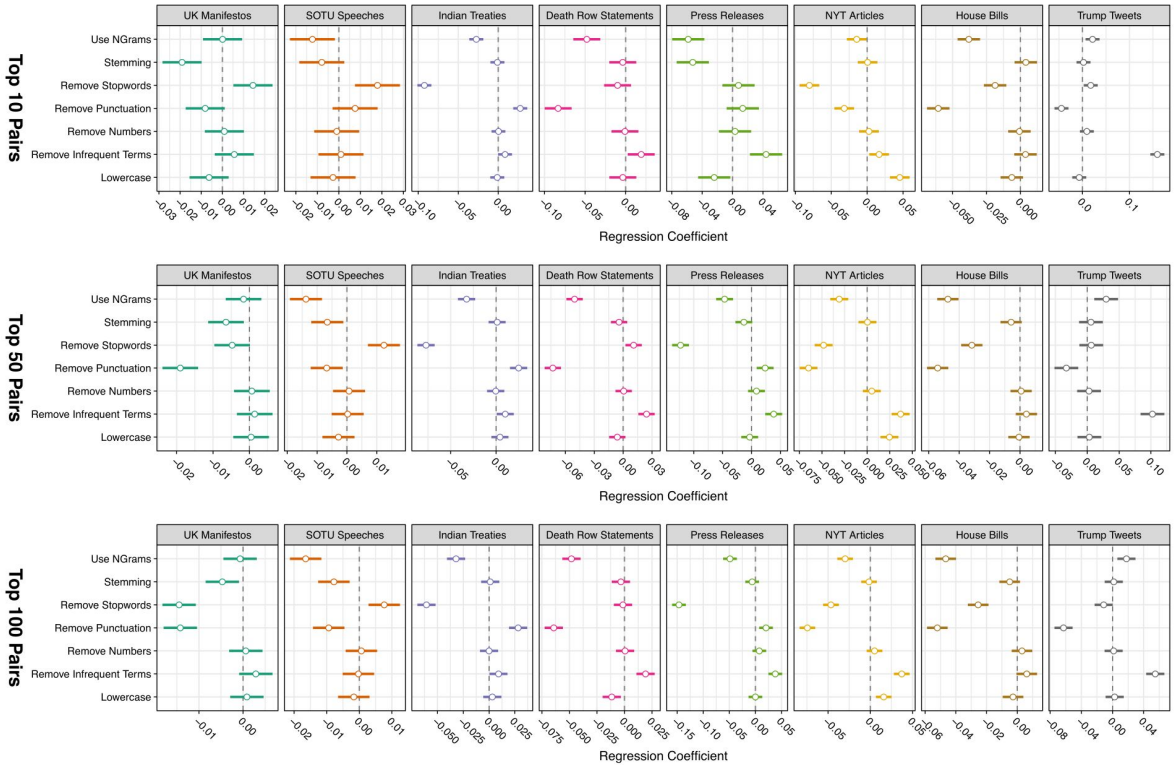
Removal of terms by frequency

- Further removal of dimensionality can be achieved by removing either very frequent or very infrequent terms
- If they are very frequent, they probably don’t carry much discriminating information for our analysis (think stopwords)
- If they are very infrequent, they probably carry a lot of discriminating information, but very low statistical power



Danny & Spirling, 2018

Figure 5. Regression results depicting the effects of each of the seven preprocessing steps on the `preText` score for that preprocessing combination.

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Best practises

- Use theory to choose potential preprocessing/feature selection steps
- Inspect the data and consider its domain and the specific task you want to do
- Try several specifications and report them all not just the result closest to your expectation

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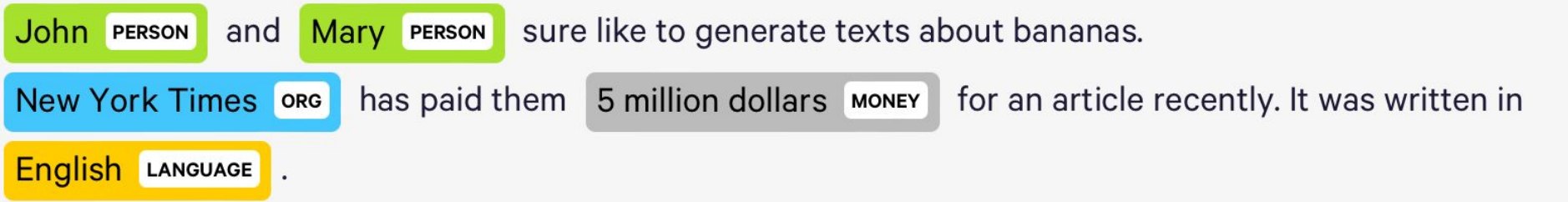
Named Entity Recognition

Named entities are specific words or phrases that refer to real-world entities, such as persons, organizations, locations, dates, quantities

Goal of named entity recognition: identifying and classifying these named entities within a given text



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Named Entity Recognition

How does this work: dictionary methods, RNNs neural networks , etc.

Overview: Balluff et al. (2024)

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Named Entity example

"Apple."

1. Sentence 1: "I ate an apple." In this sentence, "Apple" refers to a common noun, representing the fruit. It does not refer to a specific named entity.
2. Sentence 2: "I work at Apple." In this sentence, "Apple" refers to a proper noun and represents the company "Apple Inc." Here, it is a named entity representing an organization.

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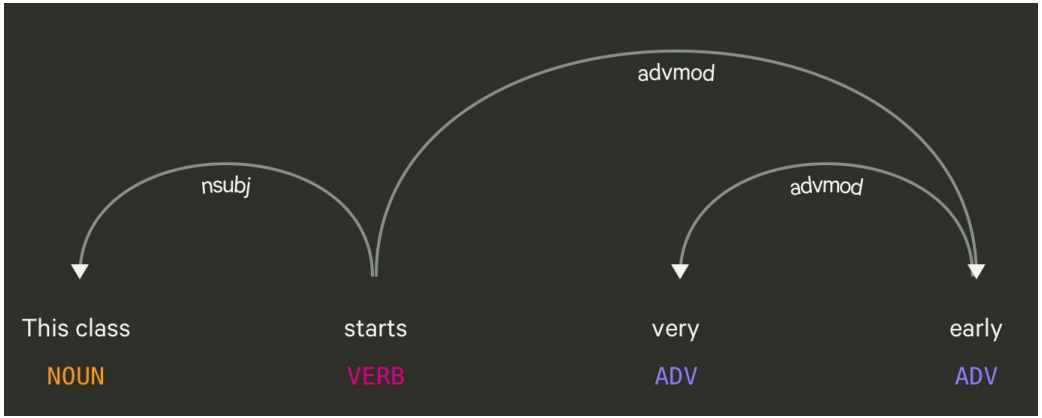
Part of Speech Tagging (POS Tagging)

Parts of speech (POS) refer to the grammatical categories into which words can be grouped based on their syntactic and semantic roles in a sentence

Goal: identify the syntactic role of each word in the sentence, such as whether it is a noun, verb, adjective, adverb, pronoun, etc.



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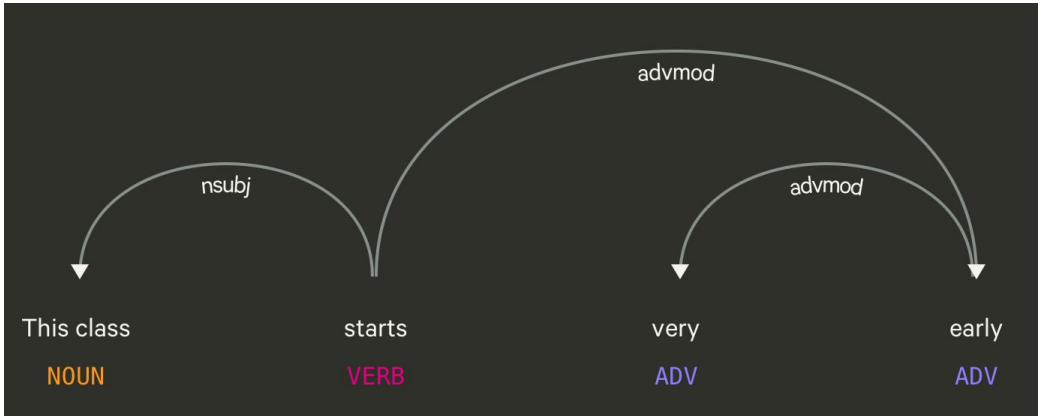
Part of Speech Tagging (POS Tagging)

How does this work?

Models (e.g., (RNNs) are trained on labeled datasets containing sentences with their corresponding POS tags to learn the patterns and associations between words and their respective POS categories



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POS Example

Input: "The cat is sitting on the mat."

POS Tags:

- The/DT (Determiner)
- cat/NN (Noun)
- is/VBZ (Verb)
- sitting/VBG (Verb, Gerund or Present Participle)
- on/IN (Preposition)
- the/DT (Determiner)
- mat/NN (Noun)

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Tf-idf

We can do more than just ***count*** words

We can transform these counts

Use some sort of a weight in order to transform

Term frequency inverse document frequency in one form of weighting

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Term Frequency

$$tf(t,d) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}}$$

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Term Frequency Frequency

$$tf(t,d) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}}$$

Inverse Document

$$idf = log \frac{N}{n_j}$$

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Term Frequency

$$tf(t,d) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}}$$

Inverse Document Frequency

$$idf = log\frac{N}{n_j}$$

Number of Documents

Number of Documents where the term *j* appears

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tfidf

$$W_{ij} \times log\frac{N}{n_j}$$

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What?

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What?

- ***Exactly!***
- Introduced in 1972 by a computer scientist (Spärck Jones, 1972)
- No theoretical justification
- Apart from “it seems to work…”

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What?

- ***Exactly!***
- Introduced in 1972 by a computer scientist (Spärck Jones, 1972)
- No theoretical justification
- Apart from “it seems to work…”

- And *sometimes* it does

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Log Odds / Log Odds Ratio

$$\log O_w^i = \log \frac{f_w^i}{1 - f_w^i}$$

$$\log \frac{O_w^i}{O_w^j} = \log \frac{f_w^i}{1 - f_w^i} / \frac{f_w^j}{1 - f_w^j} = \log \frac{f_w^i}{1 - f_w^i} - log \frac{f_w^j}{1 - f_w^j}$$

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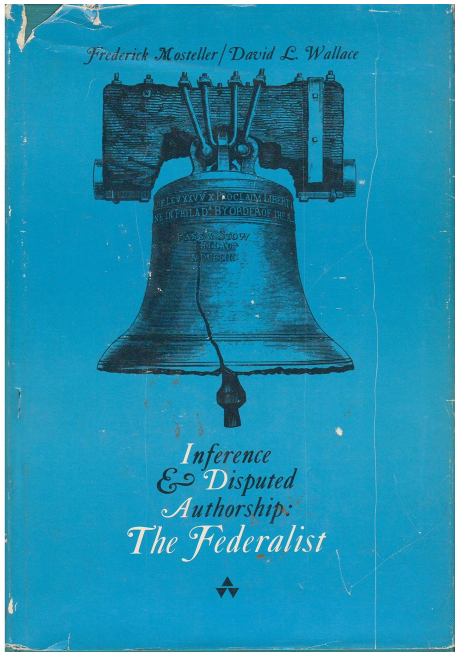
Inference and Disputed Authorship: The Federalist



Mosteller & Wallace, 1963

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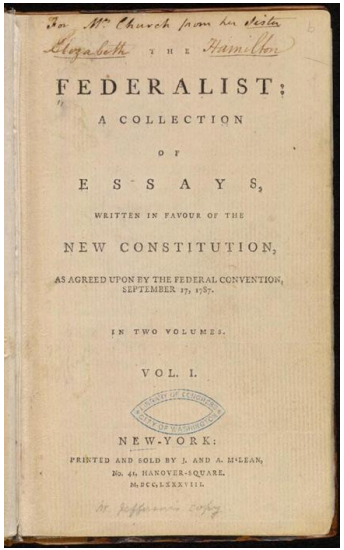
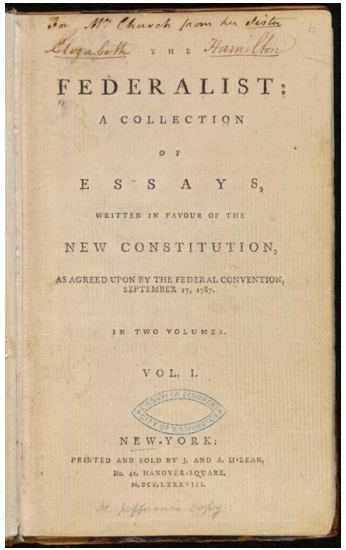
One of the first (if not the first) text-as-data study



One of the first (if not the first) text analysis study


For Mrs Church from her Sister
Elizabeth THE Hamilton

FEDERALIST:

A COLLECTION

OF

ESSAYS,

WRITTEN IN FAVOUR OF THE

NEW CONSTITUTION,

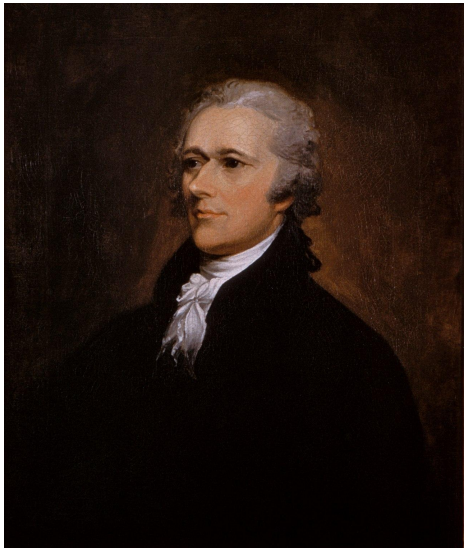
AS AGREED UPON BY THE FEDERAL CONVENTION,
SEPTEMBER 17, 1787.

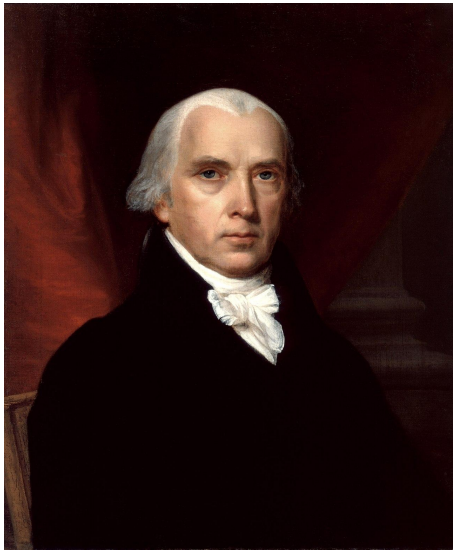
IN TWO VOLUMES.

VOL. I.

NEW-YORK:

PRINTED AND SOLD BY J. AND A. M'LEAN,
No. 41, HANOVER-SQUARE.
M,DCC,LXXXVIII.





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Who wrote them?

- 71 of the essays have a fairly certain authorship
- 12 are disputed
- Big historical debate as to how to ascribe authorship

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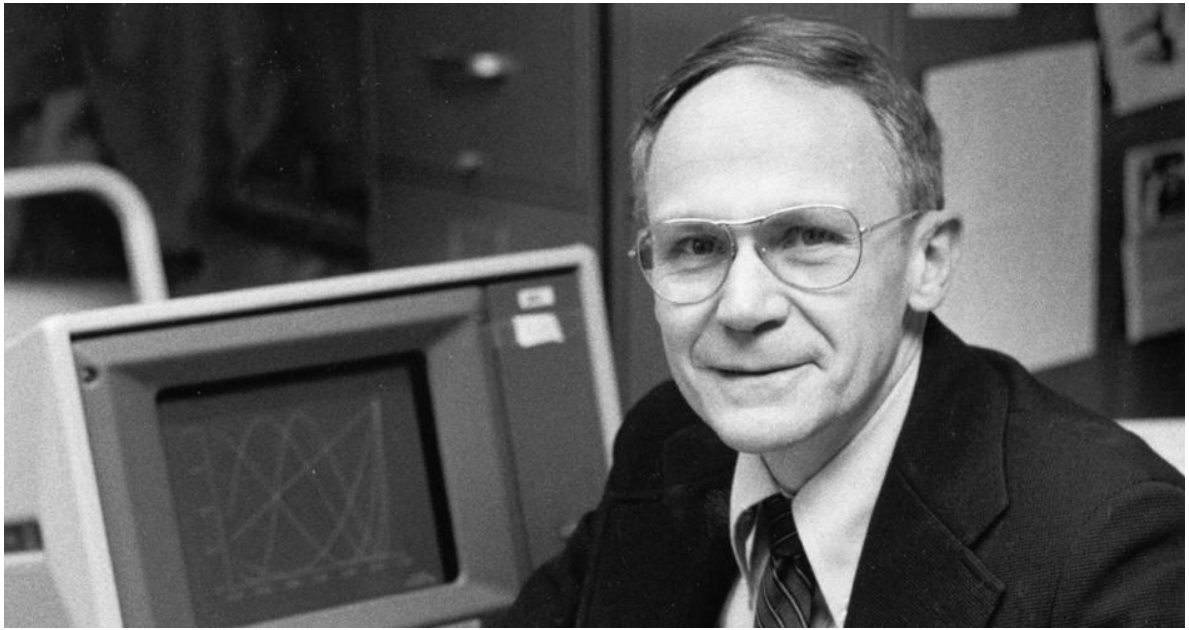

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Computer-assisted text analysis!

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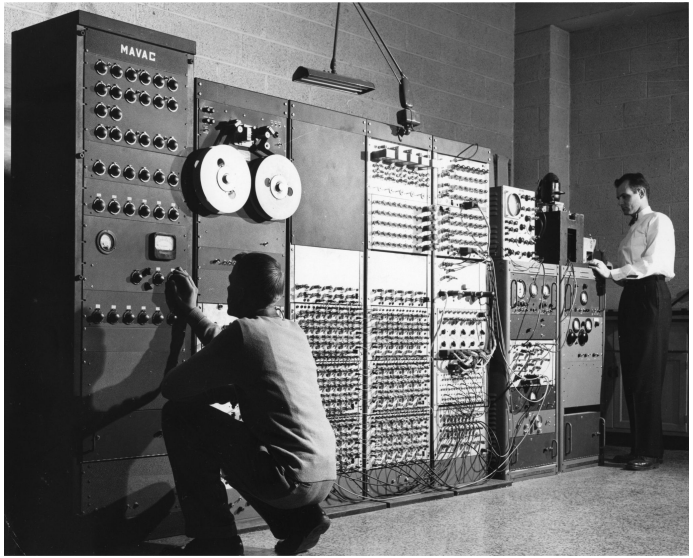
Computer-assisted text analysis…?



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Dimension Reduction

Remove all the stop-words!

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Dimension Reduction

Remove all the stop-words!

Still, too many words…

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Dimension Reduction

Remove all the stop-words!

Still, too many words…

Remove ***all*** words, ***but*** the stop-words

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Dimension Reduction

Remove all the stop-words!

Still, too many words…

Remove ***all*** words, ***but*** the stop-words

Maybe there is information in them?

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Simplified example from Grimmer et al., 2022

- Focus on:
  - “Man”
  - “By”
  - “Upon”
- The rates with which the authors use these words may indicate authorship

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Word Rates

	man	by	upon
Hamilton	102	859	374
Madison	17	474	7
Jay	0	82	1

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Word Proportions

	man	by	upon
Hamilton	.076	.643	.28
Madison	.034	.952	.014
Jay	0	.988	.012

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Multinomial Language Models

Word Proportions

	man	by	upon
Hamilton	.076	.643	.28
Madison	.034	.952	.014
Jay	0	.988	.012

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Disputed Paper

	man	by	upon
Disputed	2	15	0

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Disputed Paper

$$p(D|H) = \frac{17!}{2!15!0!}(.076)^2 \times (.643)^{15} \times (.28)^0$$

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Disputed Paper

Total Words

Raw Rates from text

$$p(D|H) = \frac{17!}{2!15!0!}(.076)^2 \times (.643)^{15} \times (.28)^0$$

Hamilton Rates

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Calculate Jay and Madison yourself

$$p(D|H) = \frac{17!}{2!15!0!}(.076)^2 \times (.643)^{15} \times (.28)^0 = .001$$

$$p(D|J) = \frac{17!}{2!15!0!}(0)^2 \times (.988)^{15} \times (.012)^0 = 0$$

$$p(D|M) = \frac{17!}{2!15!0!}(.034)^2 \times (.952)^{15} \times (.014)^0 = .076$$

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Federalist Vector Space Model

In the markdown file…