Computational Political Science

Session 2

David Broska
Zeppelin University
February 9, 2021

Outline for today

1. **Course assignments**
    - Formative and summative
2. **Review of fundamentals**
    - Concepts and definitions
    - Bag of words
    - Roots of words
3. **Preprocessing**
    - Recipe
    - Complete example
4. **Descriptive statistics**
    - Term frequency
    - (Inverse) document frequency
    - Term frequency inverse document frequency
    - Lexical diversity
5. **Coding exercises**
    - Rmarkdown
    - Text analysis introduction

Assignments

Assignments

Formative

- The formative assignment does not count toward the final grade.
- Opportunity to practice the structure and questions of the summative assignments

Summative

- The *three* summative assignments weigh 10% respectively and amount to a total of 30% of the final grade.

Please send the `.Rmd` file and the compiled `.html` document to david.broska@zu.de before midnight on the due date.

Details on each assignment are given on the course page.

Course schedule

Session	Date	Topic	Assignment	Due date
1	Feb 02	Overview and key concepts	-	-
2	Feb 09	Preprocessing and descriptive statistics	Formative	Feb 22 23:59:59
3	Feb 16	Dictionary methods	-	-
4	Feb 23	Machine learning (for texts)	Summative 1	Mar 08 23:59:59
5	Mar 02	Supervised scaling models for texts	-	-
6	Mar 09	Unsupervised scaling models for texts	Summative 2	Mar 15 23:59:59
7	Mar 16	Similarity and clustering	-	-
8	Mar 23	Topic models	Summative 3	Apr 12 23:59:59
-	-	*Break*	-	-
9	Apr 13	Retrieving data from the web	-	-
10	Apr 20	Published applications	-	-
11	Apr 27	Project Presentations	-	-

Review of fundamentals

Overview of text as data methods

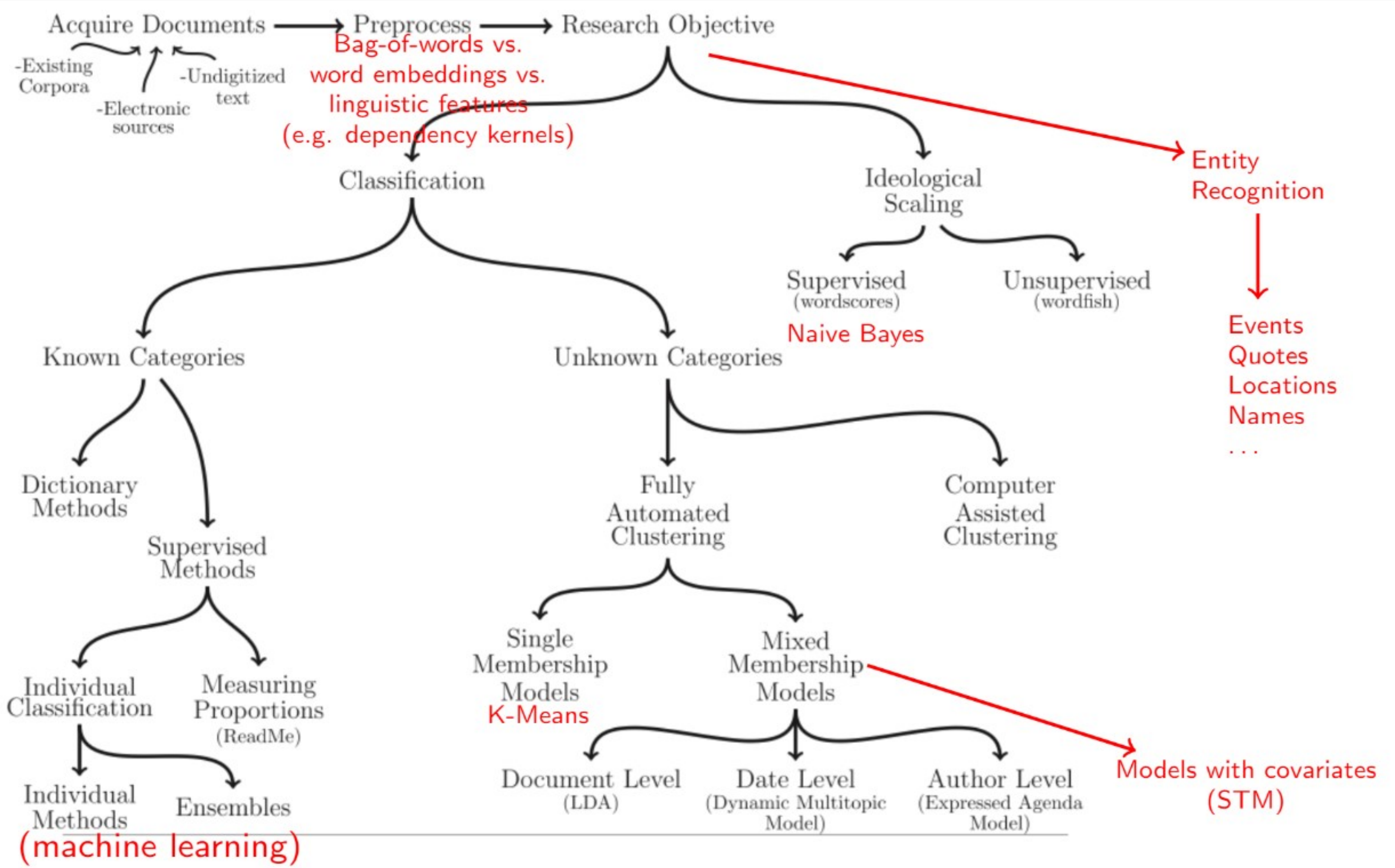


Fig. 1 in Grimmer and Stuart (2013)

Basic concepts (1)

Concept	Definition
(text) corpus	a large and structured set of texts for analysis
document	each of the texts of the corpus
types	for our purposes, a unique word
tokens	any word - so token count is total words

Example

> `[A corpus is a set of documents.]`
>
> `[This is the second document in the corpus.]`

is a corpus with 2 documents, where each document is a sentence.

The first document has 6 types and 7 tokens.

The second has 7 types and 8 tokens. (We ignore punctuation for now.)

Basic concepts (2)

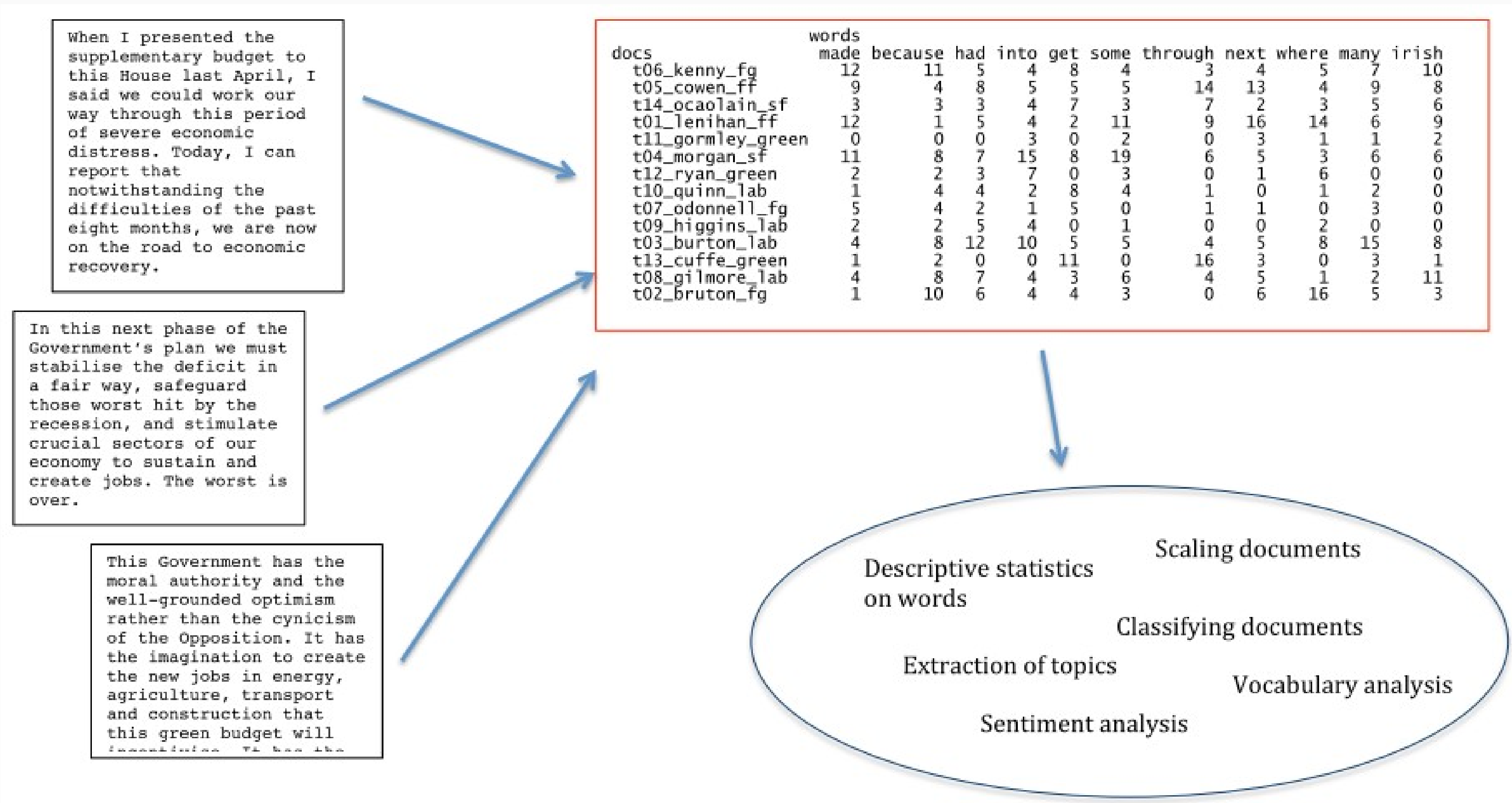
Concept	Definition
keys	such as dictionary entries, where the user defines a set of equivalence classes that group different word types (e.g. US, USA, U.S.)
stop words	words that are designated for exclusion from any analysis of a text
stems	words with suffixes removed
lemmas	canonical word form (the base form of a word that has the same meaning even when different suffixes or prefixes are attached)

Example

word	win	winning	wins	won	winner
stem	win	win	win	won	winner
lemma	win	win	win	win	win

QTA Workflow

Texts → Matrix → Analysis



docs	words made	because	had	into	get	some	through	next	where	many	irish
t06_kenny_fg	12	11	5	4	8	4	3	4	5	7	10
t05_cowen_ff	9	4	8	5	5	5	14	13	4	9	8
t14_ocaolain_sf	3	3	3	4	7	3	7	2	3	5	6
t01_lenihan_ff	12	1	5	4	2	11	9	16	14	6	9
t11_gormley_green	0	0	0	3	0	2	0	3	1	1	2
t04_morgan_sf	11	8	7	15	8	19	6	5	3	6	6
t12_ryan_green	2	2	3	7	0	3	0	1	6	0	0
t10_quinn_lab	1	4	4	2	8	4	1	0	1	2	0
t07_odonnell_fg	5	4	2	1	5	0	1	1	0	3	0
t09_higgins_lab	2	2	5	4	0	1	0	0	2	0	0
t03_burton_lab	4	8	12	10	5	5	4	5	8	15	8
t13_cuffe_green	1	2	0	0	11	0	16	3	0	3	1
t08_gilmore_lab	4	8	7	4	3	6	4	5	1	2	11
t02_bruton_fg	1	10	6	4	4	3	0	6	16	5	3

Bag of Words

QTA *assumes* that a document can be represented as a collection of words that could have occurred anywhere in the document.

→ Grammar and ordering or words are ignored.
→ Only word frequency is taken into account.

Bag of Words: Justification

Bag-of-words approach disregards grammar and word order and uses word frequencies as features.

- Context is *often* uninformative conditional on presence of words:
    - Individual word usage tends to be associated with a particular degree of affect, position, etc. without regard to context of word usage
- Single words tend to be the most informative, as co-occurrences of multiple words (n-grams) are rare
- Some approaches focus on occurrence of a word as a binary variable, irrespective of frequency: a binary outcome
- Other approaches use frequencies: Poisson, multinomial, and related distributions

Roots of words

- **Lemmatization** refers to the algorithmic process of converting words to their lemma forms.
- **Stemming** is the process for reducing inflected (or sometimes derived) words to their stem, base or root form.
  - Different from lemmatization in that stemmers operate on single words *without knowledge of the context*.

Both convert the morphological variants into stem or root terms

Why? Measure the same notion only once!

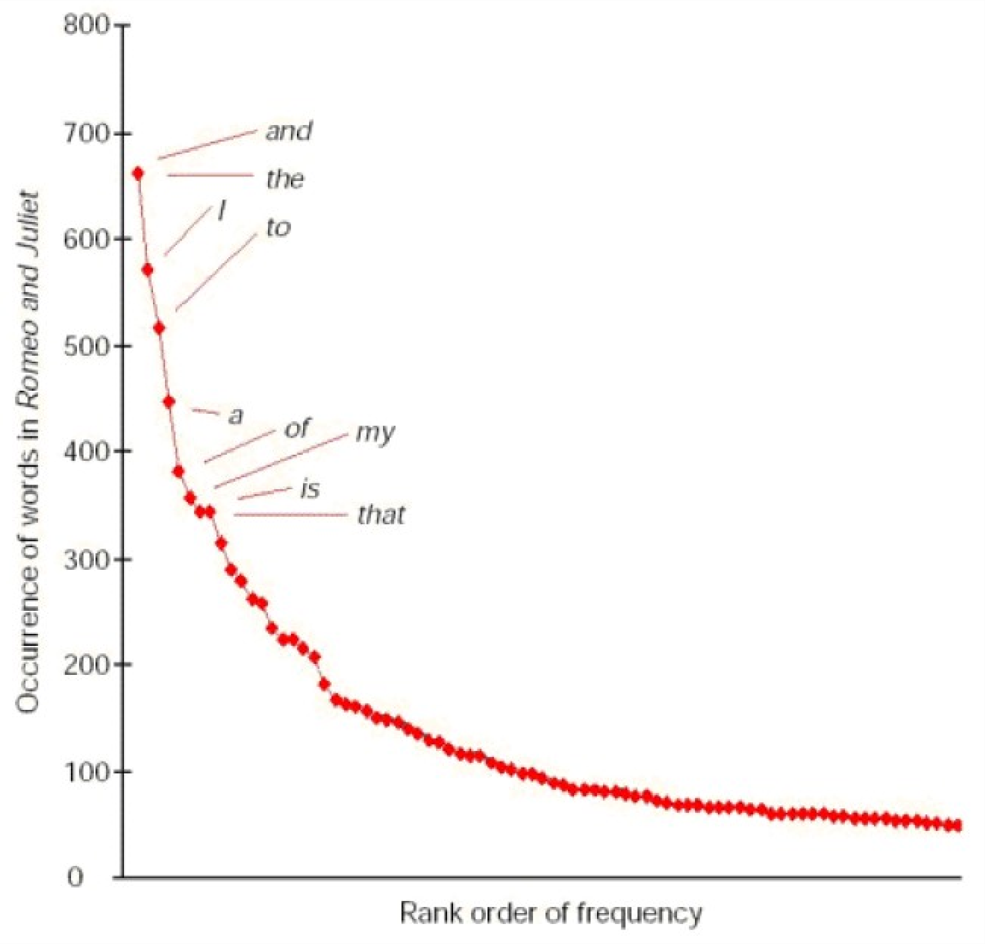
$\longrightarrow$ We reduce the feature space by collapsing different words into a stem
(e.g. "happier" and "happily" convey same meaning as "happy")

Issues with stemming approaches

- The most common is probably the Porter stemmer
- But this set of rules gets many stems wrong, e.g.
    - policy and police considered (wrongly) equivalent
- Other corpus-based, statistical, and mixed approaches designed to overcome these limitations
- It is key to be careful through inspection of morphological variants and their stemmed versions
- Sometimes not appropriate! e.g. Schofield and Minmo (2016) find that "stemmers produce no meaningful improvement in likelihood and coherence (of topic models) and in fact can degrade topic stability"

Zipf Distribution of Word Frequency

Where are the most informative words on this plot?



How might we address the problem of highly weighted non-informative tokens?

Word frequency: Zipf's Law

Zipf's law

Given some corpus of natural language utterances, the frequency of any word is inversely proportional to its rank in the frequency table.

Basic idea

Word frequency follows a power distribution; "of" and "the" make up 10% of all occurrences and "aardvark" hardly ever occurs.

The simplest case of Zipf’s law is a function of the type $\frac{1}{\text{frequency}}$.

Given a set of Zipfian distributed frequencies, sorted from most common to least common, the second most common frequency will occur $\frac{1}{2}$ as often as the first. The third most common frequency will occur $\frac{1}{3}$ as often as the first. The nth most common frequency will occur $\frac{1}{n}$ as often as the first.

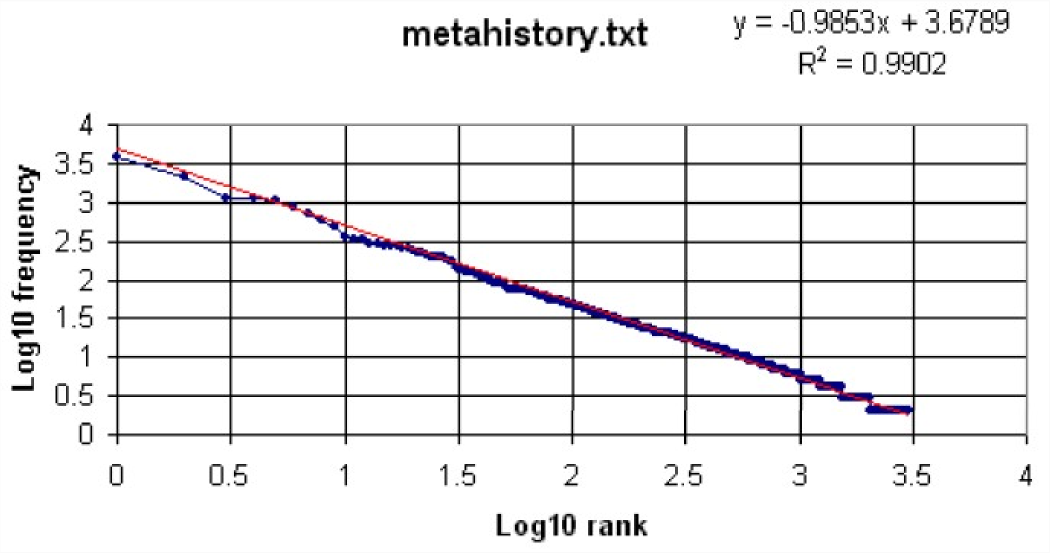
Besides: this law also holds for measures such as the population of global cities.

Word frequency: Zipf's Law

Formulaically: if a word occurs f times and has a rank r in a list of frequencies, then for all words $f = \frac{a}{r^b}$ where a and b are constants and b is close to 1. So if we $\log$ both sides,

$$\begin{aligned}\log(f) =& \log(\frac{a}{r^b}) \\ =& \log(a) - \log(r^b) \\ =& \log(a) - b \times \log(r)\end{aligned}$$

If we plot $\log(f)$ against $\log(r)$ then we should see a straight line with a slope of approximately -1.



Common English stop words

a, able, about, across, after, all, almost, also, am, among, an, and, any, are, as, at, be, because, been, but, by, can, cannot, could, dear, did, do, does, either, else, ever, every, for, from, get, got, had, has, have, he, her, hers, him, his, how, however, I, if, in, into, is, it, its, just, least, let, like, likely, may, me, might, most, must, my, neither, no, nor, not, of, off, often, on, only, or, other, our, own, rather, said, say, says, she, should, since, so, some, than, that, the, their, them, then, there, these, they, this, tis, to, too, twas, us, wants, was, we, were, what, when, where, which, while, who, whom, why, will, with, would, yet, you, your

Data sources

Where to obtain textual data? Some tips...

- Existing datasets, e.g.
  - UCD's EuroParl project
  - Hansard Archive of parliamentary debates in UK
  - Media archives for newspaper articles, TV transcripts and other texts at LexisNexis, ProQuest, Factiva, etc.
  - Academic articles (JSTOR Data for Research)
  - Open-ended responses to survey questions
- Collect your own data:
  - From social media (Twitter, FB) and blogs
  - Scraping other websites
- Digitize your own text data using optical character recognition (OCR) software
  - Options: Tesseract (open-source), Abbyy FineReader

Preprocessing

A potential recipe for preprocessing

1. Remove capitalization and punctuation
2. Segment into words, characters, morphemes
3. Discard order ("Bag of Words" Assumption)
4. Discard stop words
5. Create equivalence class: stem, lemmatize, or synonym
6. Discard less useful features
7. Other reduction, specialization

A complete example

"Political power grows out of the barrel of a gun"- Mao

Compound Words/Collocations: [political], [power], [grows], [out], [of] [the], [barrel of a gun]

→ An analyst may want to combine words into a single term that can be analyzed.

Stopword Removal: [political], [power], [grows], [out], [~~of~~] [~~the~~], [barrel of a gun]

→ Removing terms that are not related to what the author is studying from the text.

Stemming: [polit~~ical~~], [power], [grow~~s~~], [out], [barrel of a gun]

→ Takes the ends off conjugated verbs or plural nouns, leaving just the ”stem.”

A complete example

Imagine we have a second document in addition to the Mao quote, "**the political science students study politics**", which tokenizes as follows.

Document #1: [polit], [power], [grow], [out], [barrel of a gun]
Document #2: [polit], [scien], [student], [studi], [polit]

Finally, we can turn tokens and documents into a "document-term matrix."

$$\begin{array}{c} \\ \\ \end{array}\begin{array}{c} \begin{array}{ccc} \phantom{\text{barrel of a gun}} & \text{Doc 1} & \text{Doc 2} \end{array} \\ \begin{bmatrix} \text{power} & 1 & 0 \\ \text{grow} & 1 & 0 \\ \text{out} & 1 & 0 \\ \text{barrel of a gun} & 1 & 0 \\ \text{student} & 0 & 1 \\ \text{studi} & 0 & 1 \\ \text{polit} & 1 & 2 \\ \text{scien} & 0 & 1 \end{bmatrix} \end{array}$$

Descriptive statistics

Weighting strategies

term frequency

Frequency is clearly useful; if sugar appears a lot near apricot, that's useful information. But overly frequent words like "the", "it", or "they" are not very informative about content.

We need a function that resolves this frequency paradox! ($\longrightarrow$ tf-idf)

document frequency

Depending on the research question one could weight words more that appear in few documents or vice versa

tf-idf

a combination of term frequency and inverse document frequency, common method for feature weighting

Term frequency (tf)

Idea: A term t is more important if it occurs more frequently in a document d

Term frequency (raw count)

$$\mathrm{tf}_{i,j} = n_{i,j}$$

where $n_{i,j}$ is the number of occurrences of term t_i in document d_j

Relative term frequency

$$\mathrm{tf}_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}}$$

where $n_{i,j}$ is the number of occurrences of term t_i in document d_j, k is the total number of terms in document d_j

Note: tf-idf uses the relative term frequency

Inverse document frequency (idf)

Idea: A term is more discriminative if it occurs only in fewer documents.

$$\mathrm{idf}_i = \log(\frac{N}{\mathrm{df}_i})$$

N is the total number of documents in the collection

df_i is the number of documents in the collection that contain the word i

Words like ”the” or ”and” have a very low idf.

Strategies for feature weighting: tf-idf

Relative term frequency

$$\mathrm{tf}_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}}$$

where $n_{i,j}$ is the number of occurrences of term t_i in document d_j, k is the total number of terms in document d_j

Inverse document frequency

$$\mathrm{idf}_i = \log(\frac{N}{\mathrm{df}_i})$$

N is the total number of documents in the collection. df_i is the number of documents in the collection that contain the word i

Term frequency inverse document frequency

$$\text{tf-idf}_i = \mathrm{tf}_{i,j} \times \mathrm{idf}_i$$

Computing tf-idf: Example

We have 100 political party manifestos, each with 1000 words.

The first document contains 16 instances of the word “environment”.

40 of the manifestos contain the word “environment”.

- The term frequency is $16/1000 = 0.016$
- The inverse document frequency is $100/40 = 2.5$, or $\ln(2.5) = 0.916$
- The tf-idf will then be $0.016 \times 0.916 = 0.0147$
- If the word "environment" had only appeared in 15 of the 100 manifestos, then its tf-idf would be 0.0304 (three times higher).
- A high weight in tf-idf is reached by a high term frequency (in the given document) and a low document frequency of the term in the whole collection of documents; **hence the weights hence tend to filter out common terms**

Other quantities for describing texts

Length

in characters, words, lines, sentences, paragraphs, pages, sections, chapters, etc.

Readability statistics

Use a combination of syllables and sentence length to indicate “readability” in terms of complexity

Vocabulary diversity

(At its simplest) involves measuring a type-to-token ratio (TTR) where unique words are types and the total words are tokens

Vocabulary diversity and corpus length

In natural language text, the rate at which new types appear is very high at first, but diminishes with added tokens

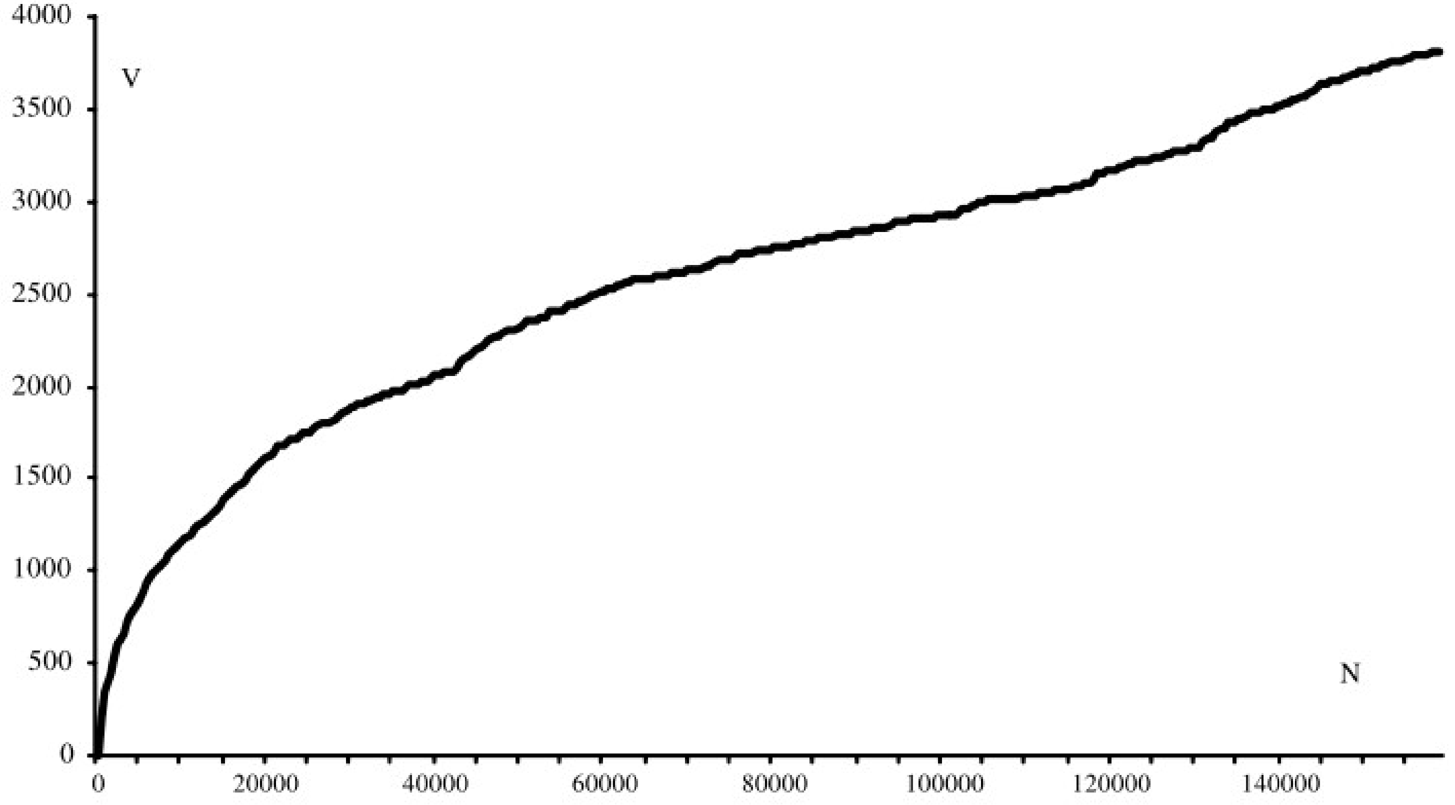


Fig. 1. Chart of vocabulary growth in the tragedies of Racine (chronological order, 500 token intervals).

Lexical diversity: Type to token

Type to token ratio (TTR)*

$$\frac{\text{total types}}{\text{total tokens}}$$

Guiraud

$$\frac{\text{total types}}{\sqrt{\text{total tokens}}}$$

D (Malvern et al 2004)

Randomly sample a fixed number of tokens and count those

MTLD

"the mean length of sequential word strings in a text that maintain a given TTR value" (McCarthy and Jarvis 2010), e.g. fixes the TTR at 0.72 and counts the length of the text required to achieve it

*Reminder: Loosely speaking, unique words are types and tokens are words

Descriptive table about texts

Whenever you write a report:

Provide the reader with a *description* of the data on which your conclusions are based!

Speaker	Party	Tokens	Types
Brian Cowen	FF	5,842	1,466
Brian Lenihan	FF	7,737	1,644
Ciaran Cuffe	Green	1,141	421
John Gormley (Edited)	Green	919	361
John Gormley (Full)	Green	2,998	868
Eamon Ryan	Green	1,513	481
Richard Bruton	FG	4,043	947
Enda Kenny	FG	3,863	1,055
Kieran ODonnell	FG	2,054	609
Joan Burton	LAB	5,728	1,471
Eamon Gilmore	LAB	3,780	1,082
Michael Higgins	LAB	1,139	437
Ruairi Quinn	LAB	1,182	413
Arthur Morgan	SF	6,448	1,452
Caoimhghin O'Caolain	SF	3,629	1,035
All Texts		49,019	4,840
Min		919	361
Max		7,737	1,644
Median		3,704	991

Readability indices

Flesch Reading Ease Index

$$206.835 - 1.015\left(\frac{\text{total words}}{\text{total sentences}}\right) - 84.6\left(\frac{\text{total syllables}}{\text{total words}}\right)$$

Interpretation: 0-30: university level; 60-70: understandable by 13-15 year olds; and 90-100 easily understood by an 11-year old student

Flesch-Kincaid Readability Index

$$0.39\left(\frac{\text{total words}}{\text{total sentences}}\right) + 11.8\left(\frac{\text{total syllables}}{\text{total words}}\right) - 15.59$$

Interpretation: Rescales to the US educational grade levels (1-12)

Coding exercises