

Quantitative text analysis: overview and fundamentals

Pablo Barberá

MY 459: Quantitative Text Analysis

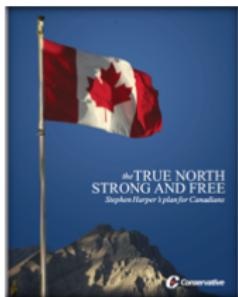
January 14, 2019

Course website: lse-my459.github.io

Text as data

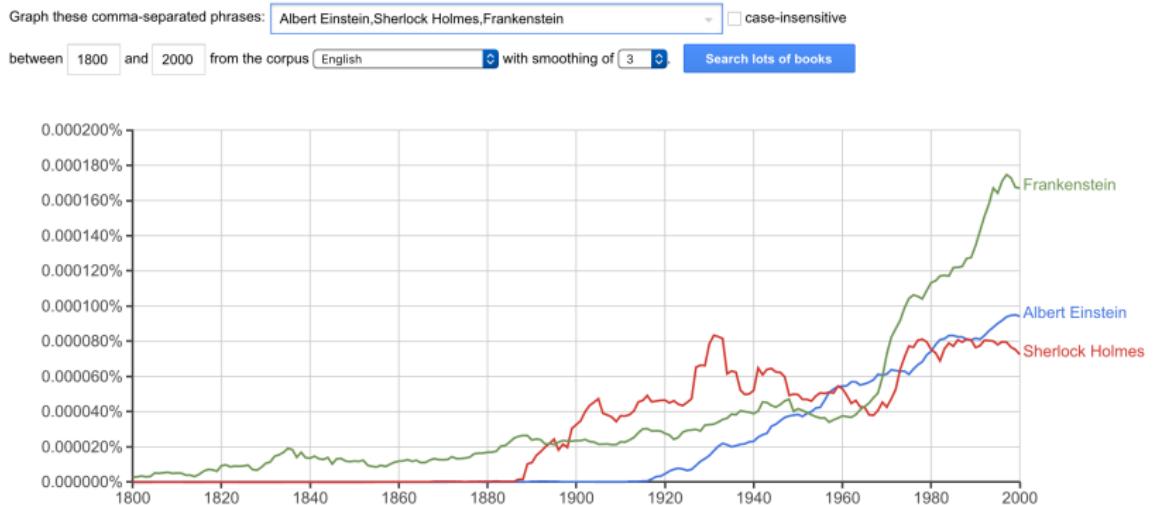


Text as data



Text as data

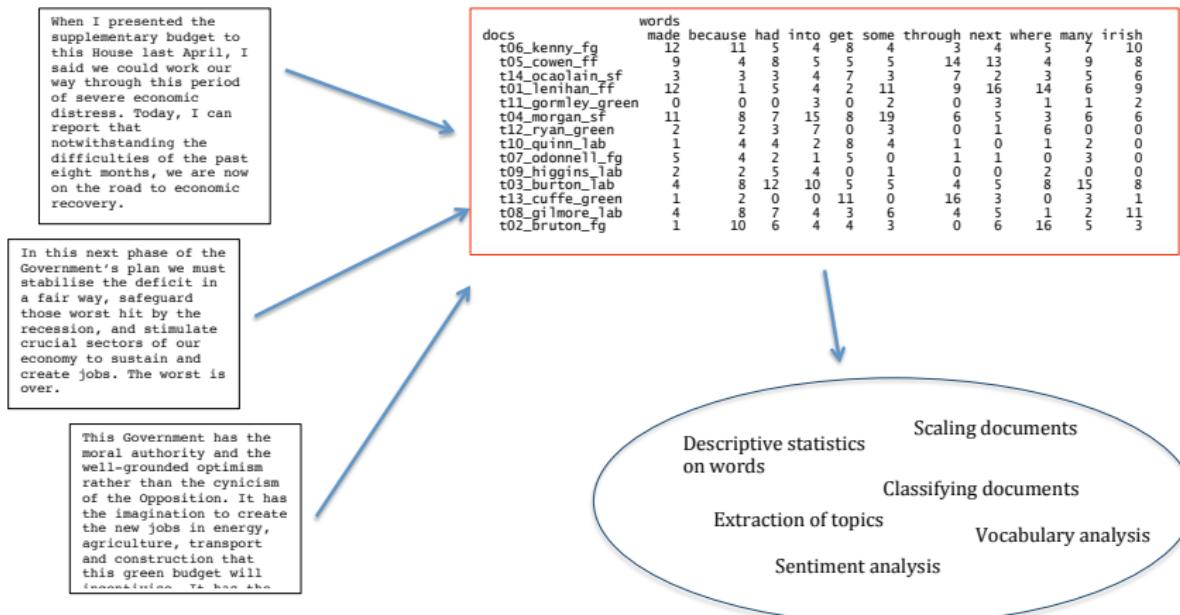
Google Books Ngram Viewer



Text as data



Basic QTA Process: Texts → Feature matrix → Analysis



Outline

- ▶ Motivation for this course
- ▶ Logistics
- ▶ Foundations
- ▶ Examples
- ▶ Key terms in quantitative text analysis
- ▶ Justifying a term/feature frequency approach
- ▶ Selecting texts / defining documents
- ▶ Selecting features

Targets

- ▶ Learning objectives
 - ▶ fundamentals of text analysis
 - ▶ availability and consequences of *choices*
 - ▶ practical ability to work with texts in R
 - ▶ issues of text for social science
- ▶ Prerequisites
 - ▶ linear algebra and quantitative methods (MY452 or equivalent regression analysis course)
 - ▶ familiarity with R and RStudio
 - ▶ (optional) ability to process text files in a programming language such as Python

Outline

- ▶ Motivation for this course
- ▶ Logistics
- ▶ Foundations
- ▶ Examples
- ▶ Key terms in quantitative text analysis
- ▶ Justifying a term/feature frequency approach
- ▶ Selecting texts / defining documents
- ▶ Selecting features

About me

- ▶ Assistant Professor in Computational Social Science at the Methodology Department, LSE
- ▶ Previously at the **University of Southern California**
- ▶ PhD in Politics, **New York University** (2015)
- ▶ Data Science Fellow at **NYU**, 2015–2016
- ▶ **My research:**
 - ▶ Social media and politics, comparative electoral behavior, political communication
 - ▶ Social network analysis, text as data methods
 - ▶ Author of R packages to analyze data from social media
- ▶ **Contact:**
 - ▶ P.Barbera@lse.ac.uk
 - ▶ www.pablobarbera.com
 - ▶ Office hours: Mondays 14:30-16:30 (COL 7.10) during the term (book through LSE for you)

Your turn!



1. Name?
2. MSc/PhD Programme?
3. Previous experience with R / GitHub / text analysis?

Course resources

- ▶ Course website: lse-my459.github.io
 - ▶ Class description
 - ▶ Course schedule
 - ▶ Slides from class
 - ▶ Readings list
 - ▶ Links to exercises and datasets
 - ▶ Submission links for homeworks
- ▶ Moodle page
 - ▶ Supporting materials
- ▶ Readings
 - ▶ Mainly articles
 - ▶ Complement content covered in lectures and seminars

Course schedule

- ▶ **Lectures:** Mondays 12:00-14:00 in 32.LG.03
- ▶ **Classes** only for weeks 2, 4, 7, 9, 11:
 1. Tuesdays 9:00-11:00 FAW.4.02
 2. Tuesdays 9:00-11:00 FAW.4.03
- ▶ No lectures or classes during Reading Week (week 6)

Week	Topic	Week	Topic
1	Overview and Fundamentals	7	Supervised Scaling Models for Texts
2	Descriptive statistical methods for text analysis	8	Unsupervised Models for Scaling Texts
3	Quantitative methods for comparing texts	9	Similarity and clustering methods
4	Automated dictionary methods	10	Topic models
5	Machine Learning for Texts	11	Working with Social Media
6	<i>Reading Week</i>		

Evaluation

- ▶ **Formative coursework:**

- ▶ Five problem sets, building upon content of lab sessions
- ▶ 60% of course grade
- ▶ Submitted via GitHub classroom (please create an account before first lab session)

- ▶ **Project:**

- ▶ Original analysis of texts using methods covered in class
- ▶ It can replicate or extend a published work
- ▶ 3,000 words (5,000 for MY559), due at the beginning of ST (May 3rd, 5pm)
- ▶ 40% of course grade

Assessment criteria

- ▶ **70–100:** Very Good to Excellent (Distinction).
 - ▶ Perceptive, focused use of a good depth of material with a critical edge. Original ideas or structure of argument.
- ▶ **60–69:** Good (Merit)
 - ▶ Perceptive understanding of the issues plus a coherent well-read and stylish treatment though lacking originality
- ▶ **50–59:** Satisfactory (Pass)
 - ▶ A “correct” answer based largely on lecture material. Little detail or originality but presented in adequate framework. Small factual errors allowed.
- ▶ **30–49:** Unsatisfactory (Fail)
- ▶ **0–29:** Unsatisfactory (Bad fail)
 - ▶ Based entirely on lecture material but unstructured and with increasing error component. Concepts are disordered or flawed. Poor presentation. Errors of concept and scope or poor in knowledge, structure and expression.

Outline

- ▶ Motivation for this course
- ▶ Logistics
- ▶ Foundations
- ▶ Examples
- ▶ Key terms in quantitative text analysis
- ▶ Justifying a term/feature frequency approach
- ▶ Selecting texts / defining documents
- ▶ Selecting features

Why quantitative text analysis?

Justin Grimmer's haystack metaphor: QTA improves reading

- ▶ Analyzing a straw of hay: understanding the meaning of a sentence
 - ▶ Humans are great! But computer struggle
- ▶ Organizing the haystack: describing, classifying, scaling texts
 - ▶ Humans struggle. But computers are great!
 - ▶ (What this course is about)

Principles of quantitative text analysis (Grimmer & Stewart, 2013)

1. All quantitative models are wrong – but some are useful
2. Quantitative methods for text amplify resources and augment humans
3. There is no globally best method for automated text analysis
4. Validate, validate, validate

Quantitative text analysis requires assumptions

1. Texts represent an observable implication of some underlying characteristic of interest
 - ▶ An attribute of the author
 - ▶ A sentiment or emotion
 - ▶ Salience of a political issue
2. Texts can be represented through extracting their *features*
 - ▶ most common is the **bag of words** assumption
 - ▶ many other possible definitions of “features” (e.g. word embeddings)
3. A **document-feature matrix** can be analyzed using quantitative methods to produce meaningful and valid estimates of the underlying characteristic of interest

When I presented the supplementary budget to this House last April, I said we could work our way through this period of severe economic distress. Today, I can report that notwithstanding the difficulties of the past eight months, we are now on the road to economic recovery.

In this next phase of the Government's plan we must stabilise the deficit in a fair way, safeguard those worst hit by the recession, and stimulate crucial sectors of our economy to sustain and create jobs. The worst is over.

This Government has the moral authority and the well-grounded optimism rather than the cynicism of the Opposition. It has the imagination to create the new jobs in energy, agriculture, transport and construction that this green budget will

docs	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_ft	9	4	8	5	5	5	14	13	4	9	8
t14_ocaoilain_sf	3	3	3	4	7	3	2	2	3	5	6
t01_leinenhan_ff	12	1	5	4	2	11	9	16	14	6	9
t04_morgan_sf	0	0	0	3	0	2	0	0	3	1	1
t11_gormley_green	11	8	7	15	8	19	6	5	3	6	6
t12_ryan_green	2	2	3	7	8	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

Scaling documents
Descriptive statistics
on words

Classifying documents

Extraction of topics

Vocabulary analysis

Sentiment analysis

Key feature of quantitative text analysis

1. Selecting texts: Defining the *corpus*
2. Conversion of texts into a common electronic format
3. Defining documents: deciding what will be the documentary unit of analysis

Key feature of quantitative text analysis (cont.)

4. Defining features. These can take a variety of forms, including tokens, equivalence classes of tokens (dictionaries), selected phrases, human-coded segments (of possibly variable length), linguistic features, and more.
5. Conversion of textual features into a quantitative matrix
6. A quantitative or statistical procedure to extract information from the quantitative matrix
7. Summary and interpretation of the quantitative results

Overview of text as data methods

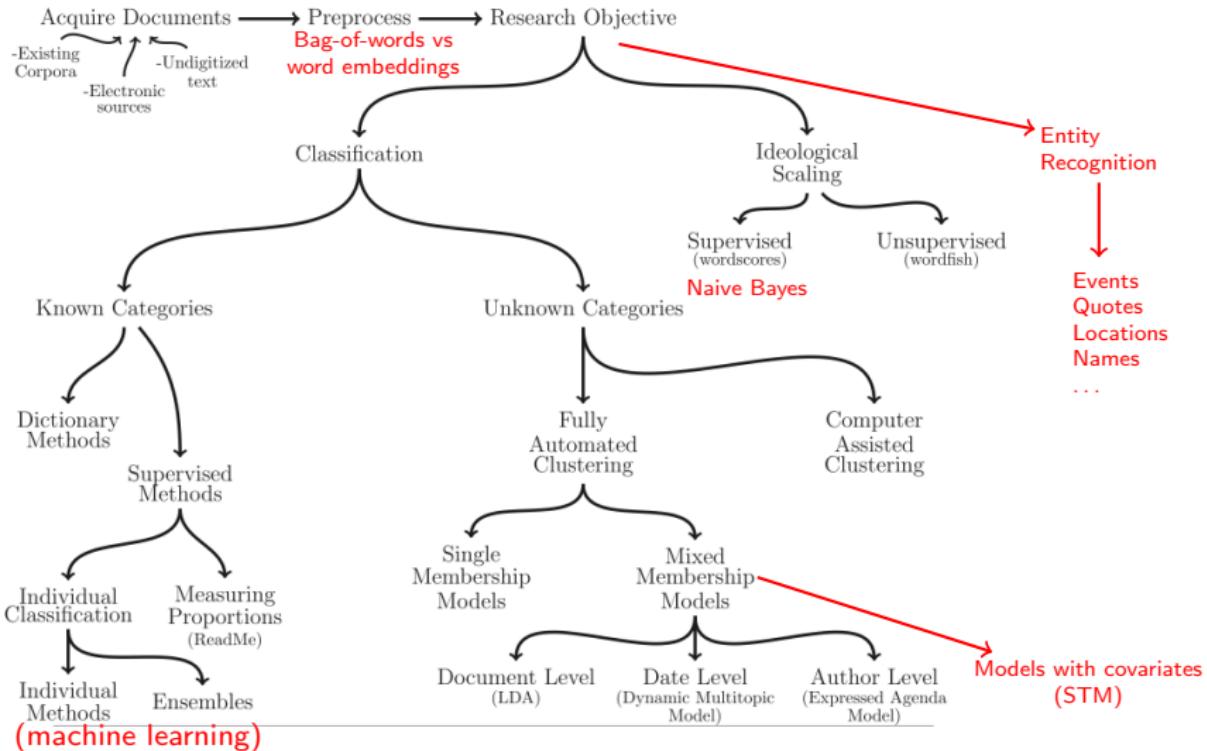


Fig. 1 in Grimmer and Stewart (2013)

Outline

- ▶ Motivation for this course
- ▶ Logistics
- ▶ Foundations
- ▶ Examples
- ▶ Key terms in quantitative text analysis
- ▶ Justifying a term/feature frequency approach
- ▶ Selecting texts / defining documents
- ▶ Selecting features

Descriptive text analysis

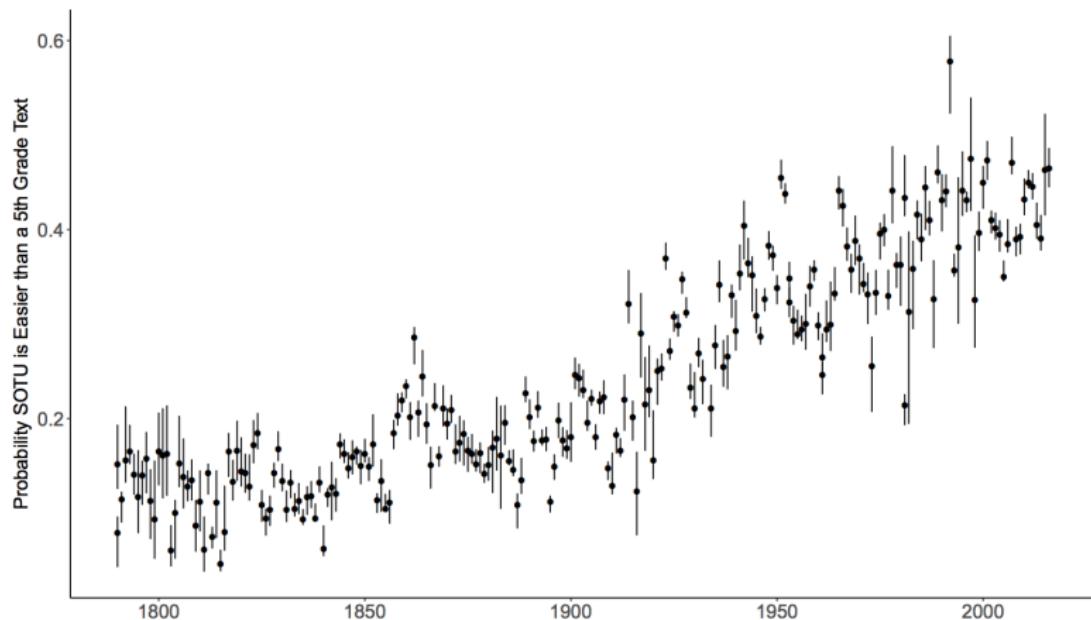
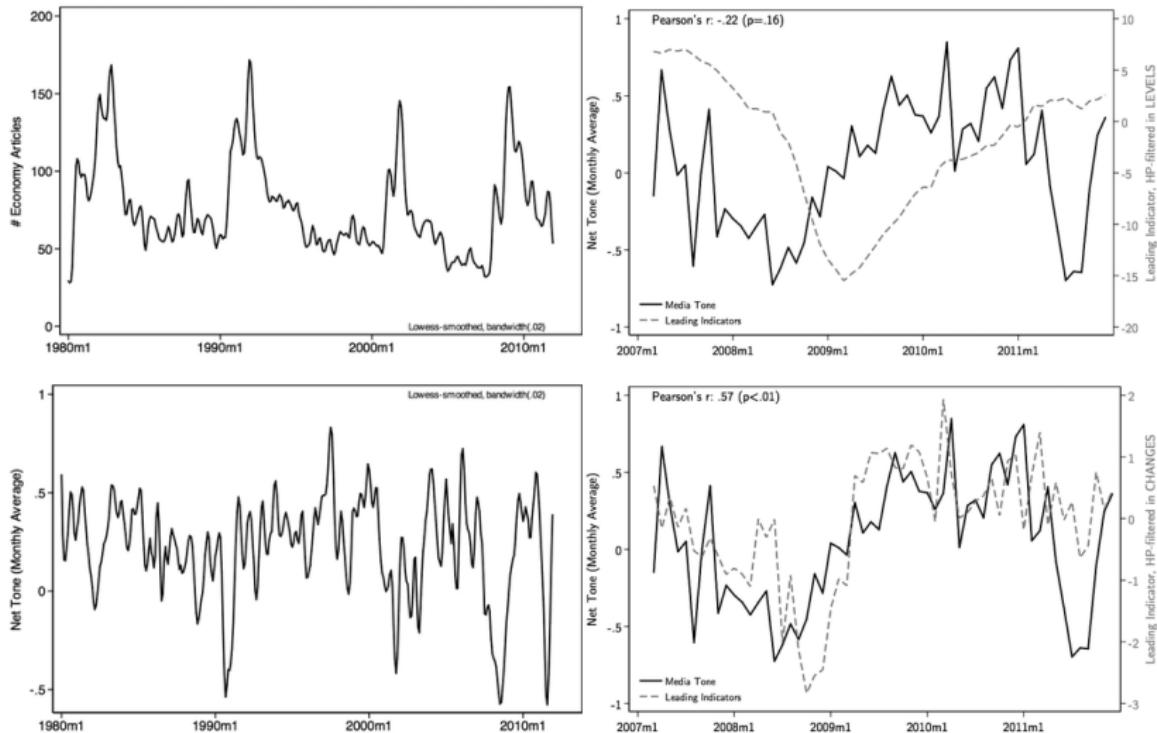


Figure 2: The probability that a State of the Union address is easier to understand than a fifth grade text baseline.

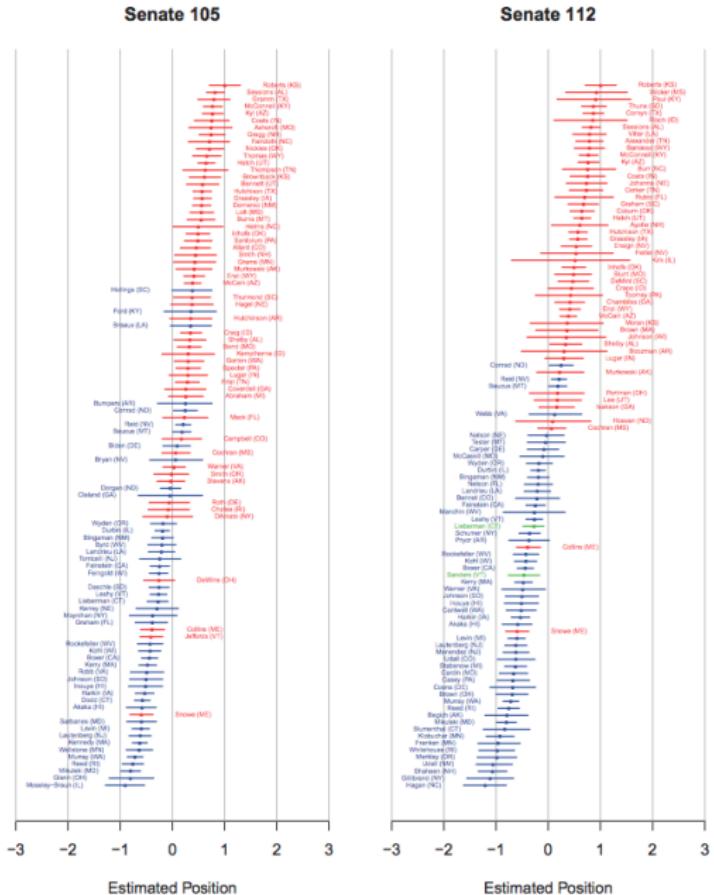
Benoit, Munger & Spirling (2017)

Document classification into known categories



Soroka et al, *American Journal of Political Science*, 2015.

Ideological scaling (Lauderdale & Herzog, PA 2016)



Document classification into unknown categories

Bauer, Barberá *et al*, *Political Behavior*, 2016.

- ▶ Data: General Social Survey (2008) in Germany
- ▶ Responses to questions: *Would you please tell me what you associate with the term “left”? and would you please tell me what you associate with the term “right”?*
- ▶ Open-ended questions minimize priming and potential interviewer effects
- ▶ Automated text analysis to discover unknown categories and classify responses

Document classification into unknown categories

Table 1: Top scoring words associated with each topic, and English translations)

Left topic 1: Parties (proportion = .26, average lr-scale value = 5.38) linke, spd, partei, linken, pds, politik, kommunisten, parteien, grünen, punks <i>the left, spd, party, the left, pds, politics, communists, parties, greens, punks</i>
Left topic 2: Ideologies (proportion = .26, average lr-scale value = 5.36) kommunismus, links, sozialismus, lafontaine, rechts, aber, gysi, linkspartei, richtung, gleichmacherei <i>communism, left, socialism, lafontaine, right, but, gysi, left party, direction, levelling</i>
Left topic 3: Values (proportion = .24, average lr-scale value = 4.06) soziale, gerechtigkeit, demokratie, soziales, bürger, gleichheit, gleiche, freiheit, rechte, gleichberechtigung <i>social, justice, democracy, social, citizen, equality, equal, freedom, rights, equal rights</i>
Left topic 4: Policies (proportion = .24, average lr-scale value = 4.89) sozial, menschen, leute, ddr, verbinde, kleinen, einstellung, umverteilung, sozialen, vertreten <i>social, humans, people, ddr, associate, the little, attitude, redistribution, social, represent</i>
Right topic 1: Ideologies (proportion = .27, average lr-scale value = 5.00) konservativ, nationalsozialismus, rechtsradikal, radikal, ordnung, politik, nazi, recht, menschen, konservative <i>conservative, national socialism, right-wing radicalism, radical, order, politics, nazi, right, people, conservatives</i>
Right topic 2: Parties (proportion = .25, average lr-scale value = 5.26) npd, rechts, cdu, csu, rechten, parteien, leute, aber, verbinde, rechtsradikalen <i>npd, right, cdu, csu, the right, parties, people, but, associate, right-wing radicals</i>
Right topic 3: Xenophobia (proportion = .25, average lr-scale value = 4.55) ausländerfeindlichkeit, gewalt, ausländer, demokratie, nationalismus, rechtsradikalismus, diktatur, national, intoleranz, faschismus <i>xenophobia, violence, foreigners, democracy, nationalism, right-wing radicalism, dictatorship, national, intolerance, fascism</i>
Right topic 4: Right-wing extremists (proportion = .23, average lr-scale value = 4.90) nazis, neonazis, rechtsradikale, rechte, radikale, radikalismus, partei, ausländerfeindlich, reich, nationale <i>nazis, neonazis, right-wing radicalists, rightists, radicals, radicalism, party, xenophobia, rich, national</i>

Note: "proportion" indicates the average estimated probability that any given response is assigned to a topic. "average lr-scale value" is the mean position on the left-right scale (from 0 to 10) of individuals whose highest probability belongs to that particular topic.

Document classification into unknown categories

Fig. 6: Left-right scale means for different subsamples of associations with left (dashed = sample mean, bars = 95% Cis)

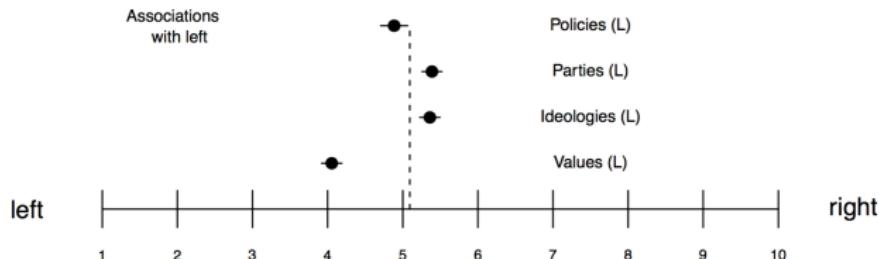
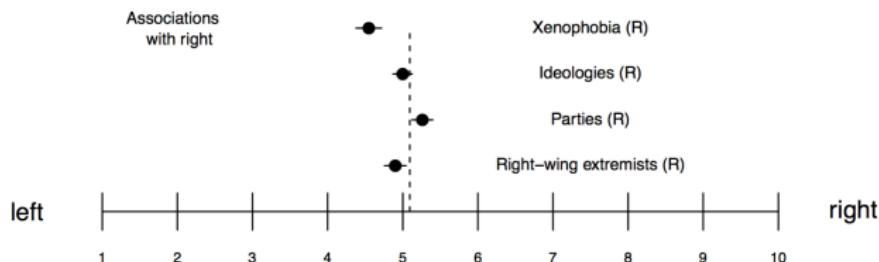
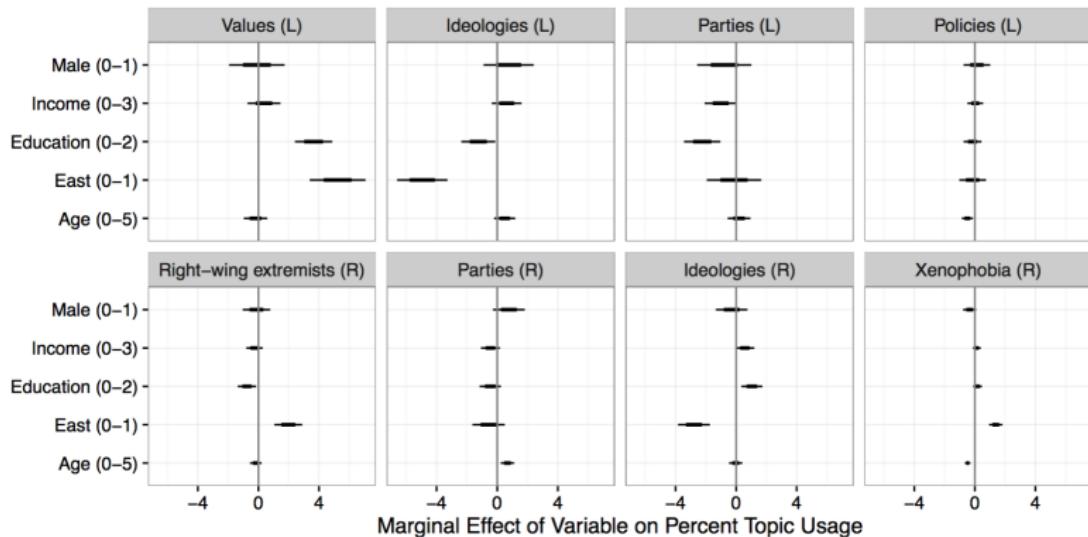


Fig. 7: Left-right scale means for different subsamples of associations with right (dashed = sample mean, bars = 95% Cis)



Document classification into unknown categories

Fig. 9: Systematic relationship between associations with “left” and “right” and characteristics of respondents



Note: Each line indicates a 95% confidence interval (and 66% confidence interval in darker color) for the coefficient of eight different regressions of topic usage (in a scale from 0 to 100) at the respondent level on seven individual-level characteristics. The line on the bottom right corner (second row, second plot), for example, shows that individual a one-category change in age is associated with around one percentage point increase in the probability that the individual associated “right” with political parties.

Bauer, Barberá *et al*, *Political Behavior*, 2016.

Document classification into unknown categories

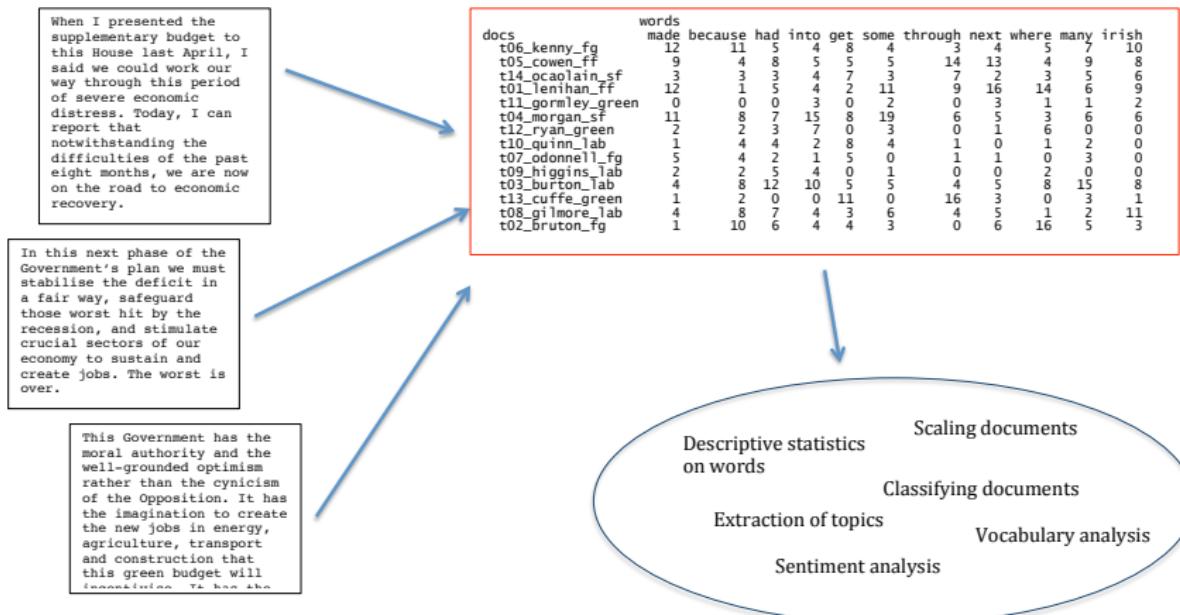
What political issues do U.S. legislators emphasize on Twitter?

- ▶ Data: 651,116 tweets sent by US legislators from January 2013 to December 2014.
- ▶ Unit of analysis: tweets aggregated by day, party, and chamber
- ▶ 2,920 documents = $730 \text{ days} \times 2 \text{ chambers} \times 2 \text{ parties}$
- ▶ Automated text analysis to discover unknown categories and classify responses
- ▶ Validation: <http://j.mp/lda-congress-demo>

Outline

- ▶ Motivation for this course
- ▶ Logistics
- ▶ Foundations
- ▶ Examples
- ▶ Key terms in quantitative text analysis
- ▶ Justifying a term/feature frequency approach
- ▶ Selecting texts / defining documents
- ▶ Selecting features

Basic QTA Process: Texts → Feature matrix → Analysis



Some key basic concepts

(text) corpus a large and structured set of texts for analysis

document each of the units of the corpus

types for our purposes, a unique word

tokens any word – so token count is total words

e.g. 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.)

Some more key basic concepts

stems words with suffixes removed (using set of rules)

lemmas canonical word form (the base form of a word that has the same meaning even when different suffixes or prefixes are attached)

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

keys such as dictionary entries, where the user defines a set of equivalence classes that group different word types

“key” words Words selected because of special attributes, meanings, or rates of occurrence

stop words Words that are designated for exclusion from any analysis of a text

Outline

- ▶ Motivation for this course
- ▶ Logistics
- ▶ Foundations
- ▶ Examples
- ▶ Key terms in quantitative text analysis
- ▶ Justifying a term/feature frequency approach
- ▶ Selecting texts / defining documents
- ▶ Selecting features

Basic QTA adopts a bag-of-words approach

When I presented the supplementary budget to this House last April, I said we could work our way through this period of severe economic distress. Today, I can report that notwithstanding the difficulties of the past eight months, we are now on the road to economic recovery.

In this next phase of the Government's plan we must stabilise the deficit in a fair way, safeguard those worst hit by the recession, and stimulate crucial sectors of our economy to sustain and create jobs. The worst is over.

This Government has the moral authority and the well-grounded optimism rather than the cynicism of the Opposition. It has the imagination to create the new jobs in energy, agriculture, transport and construction that this green budget will

docs	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_ocaplain_sf	3	3	3	4	7	3	7	2	3	5	6
t01_leinhan_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	2	0	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

Descriptive statistics
on words

Scaling documents

Classifying documents

Extraction of topics

Vocabulary analysis

Sentiment analysis

Bag-of-words approach

From words to numbers:

1. Preprocess text: lowercase, remove stopwords and punctuation, stem, tokenize into unigrams and bigrams (bag-of-words assumption)

"A corpus is a set of documents."

"This is the second document in the corpus." "a corpus is a set of documents."

"this is the second document in the corpus." "a corpus is a set of documents."

"this is the second document in the corpus." "corpus set documents"

"second document corpus" [corpus, set, document, corpus set, set document]

[second, document, corpus, second document, document corpus]

2. Document-feature matrix:

- \mathbf{W} : matrix of N documents by M unique n-grams
- w_{im} = number of times m -th n-gram appears in i -th document.

corpus
set
document
corpus set
⋮
 M n-grams

Bag-of-words approach

QTA often disregards grammar and word order and uses word frequencies as features.

Why? What are the main advantages and limitations of this assumption?

Word frequencies and their properties

Bag-of-words approach disregards grammar and word order and uses word frequencies as features. [Why?](#)

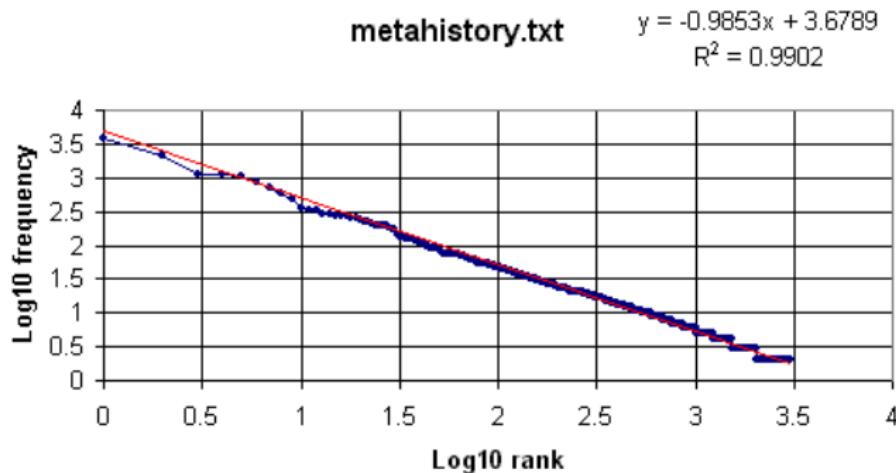
- ▶ *Context is often uninformative*, conditional on presence of words:
 - ▶ Individual word usage tends to be associated with a particular degree of affect, position, etc. without regard to context of word usage
- ▶ Single words tend to be the most informative, as co-occurrences of multiple words (n -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

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.
- ▶ The simplest case of Zipf's law is a “ $1/f$ function”. Given a set of Zipfian distributed frequencies, sorted from most common to least common, the second most common frequency will occur $1/2$ as often as the first. The third most common frequency will occur $1/3$ as often as the first. The n th most common frequency will occur $1/n$ as often as the first.
- ▶ In the English language, the probability of encountering the the most common word is given roughly by $P(r) = 0.1/r$ for up to 1000 or so
- ▶ The assumption is that words and phrases mentioned most often are those reflecting important concerns in every communication

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



Outline

- ▶ Motivation for this course
- ▶ Logistics
- ▶ Foundations
- ▶ Examples
- ▶ Key terms in quantitative text analysis
- ▶ Justifying a term/feature frequency approach
- ▶ Selecting texts / defining documents
- ▶ Selecting features

Strategies for selecting units of textual analysis

What can the **document** be?

- ▶ Words
- ▶ n -word sequences
- ▶ Sentences
- ▶ Pages
- ▶ Paragraphs
- ▶ Natural units (a speech, a poem, a manifesto)
- ▶ Aggregation of units (e.g. all speeches by party and year)
- ▶ Key: **depends on the research design**
- ▶ Frequent trade-off between cost and accuracy

Sampling strategies for selecting texts

- ▶ Difference between a **sample** and a **population**
- ▶ *May not be feasible* to perform any sampling
- ▶ *May not be necessary* to perform any sampling
- ▶ Be wary of sampling that is a feature of the social system:
“social bookkeeping”
- ▶ Different types of sampling vary from random to purposive
 - ▶ random sampling
 - ▶ non-random sampling
- ▶ Key is to make sure that what is being analyzed is a valid representation of the phenomenon as a whole – a question of **research design**

Outline

- ▶ Motivation for this course
- ▶ Logistics
- ▶ Foundations
- ▶ Examples
- ▶ Key terms in quantitative text analysis
- ▶ Justifying a term/feature frequency approach
- ▶ Selecting texts / defining documents
- ▶ **Selecting features**

Defining Features

- ▶ characters
- ▶ words
- ▶ word stems or lemmas: this is a form of defining *equivalence classes* for word features
- ▶ word segments, especially for languages using compound words, such as German, e.g.
Rindfleischetikettierungsberwachungsaufgabenbertragungsgesetz
(the law concerning the delegation of duties for the supervision of cattle marking and the labelling of beef)
Saunauntensitzer

Defining Features (cont.)

- ▶ “word” sequences, especially when inter-word delimiters (usually white space) are not commonly used, as in Chinese

莎拉波娃现在居住在美国东南部的佛罗里达。今年 4 月
9 日，莎拉波娃在美国第一大城市纽约度过了 18 岁生
日。生日派对上，莎拉波娃露出了甜美的微笑。

- ▶ linguistic features, such as parts of speech
- ▶ (if qualitative coding is used) coded or annotated text segments
- ▶ word embeddings (more on this later in the course)

Parts of speech

- ▶ the Penn “Treebank” is the standard scheme for tagging POS

Number	Tag	Description
1.	CC	Coordinating conjunction
2.	CD	Cardinal number
3.	DT	Determiner
4.	EX	Existential <i>there</i>
5.	FW	Foreign word
6.	IN	Preposition or subordinating conjunction
7.	JJ	Adjective
8.	JJR	Adjective, comparative
9.	JJS	Adjective, superlative
10.	LS	List item marker
11.	MD	Modal
12.	NN	Noun, singular or mass
13.	NNS	Noun, plural
14.	NNP	Proper noun, singular
15.	NNPS	Proper noun, plural
16.	PDT	Predeterminer
17.	POS	Possessive ending
18.	PRP	Personal pronoun
19.	PRP\$	Possessive pronoun
20.	RB	Adverb
21.	RBR	Adverb, comparative
22.	RBS	Adverb, superlative
23.	RP	Particle
24.	SYM	Symbol
25.	TO	<i>to</i>
26.	UH	Interjection
27.	VB	Verb, base form
28.	VBD	Verb, past tense
29.	VBG	Verb, gerund or present participle
30.	VBN	Verb, past participle
31.	VBP	Verb, non-3rd person singular present
32.	VBZ	Verb, 3rd person singular present
33.	WDT	Wh-determiner
34.	WP	Wh-pronoun
35.	WP\$	Possessive wh-pronoun
36.	WRB	Wh-adverb

Parts of speech (cont.)

- ▶ several open-source projects make it possible to tag POS in text, such as Apache's OpenNLP (and R package openNLP wrapper) or TreeTagger

```
> s
Pierre Vinken, 61 years old, will join the board as a nonexecutive director
Nov. 29. Mr. Vinken is chairman of Elsevier N.V., the Dutch publishing
group.
> sprintf("%s/%s", s[a3w], tags)
[1] "Pierre/NNP"      "Vinken/NNP"      ",/,"          "61/CD"
[5] "years/NNS"       "old/JJ"        ",/,"          "will/MD"
[9] "join/VB"         "the/DT"        "board/NN"      "as/IN"
[13] "a/DT"            "nonexecutive/JJ" "director/NN"   "Nov./NNP"
[17] "29/CD"           "./."          "Mr./NNP"      "Vinken/NNP"
[21] "is/VBZ"          "chairman/NN"    "of/IN"        "Elsevier/NNP"
[25] "N.V./NNP"        ",/,"          "the/DT"       "Dutch/JJ"
[29] "publishing/NN"   "group/NN"      "./."
```

Parts of speech (cont.)

Example: Creating an index of editorialization of journalists' and media outlets' political news coverage.

Proportion of tweets that: (1) mention a major party or candidate, (2) include at least one adjective.

Table 2.4 Determinants of editorialisation and popularity of news accounts on twitter (OLS regressions)

	DV = Editorialisation		DV = Popularity	
	Model 1	Model 2	Model 3	Model 4
Type: journalist	5.10*** (1.13)	4.32*** (1.26)	2.70*** (0.22)	2.49*** (0.30)
Tweets about Europe (%)	-0.03+ (0.02)	-0.03+ (0.02)	0.01*** (0.002)	0.01*** (0.002)
Editorialisation Index			0.02*** (0.004)	0.02*** (0.004)
(Intercept)	7.58** (2.59)	7.94** (2.47)	-4.03*** (0.40)	-3.92*** (0.41)
Country fixed effects	YES	YES	YES	YES
Outlet fixed effects	YES	YES	YES	YES
R ²	0.12	0.12	0.71	0.71
Adj. R ²	0.08	0.08	0.70	0.70
Num. obs.	2662	2662	2662	2662
RMSE	7.63	7.63	1.08	1.08

Strategies for feature selection

How to choose which features to include?

- ▶ All? Computationally inefficient, and rare words are generally uninformative

Potential criteria to select features (“trim” the DFM):

- ▶ document frequency: How many documents in which a term appears
- ▶ term frequency: How many times does the term appear in the corpus
- ▶ deliberate disregard: Use of “stop words” – words excluded because they represent linguistic connectors of no substantive content
- ▶ purposive selection: Use of a *dictionary* of words or phrases
- ▶ declared equivalency classes: Non-exclusive synonyms, also known as *thesaurus* (more on this later)

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

- ▶ But no list should be considered universal

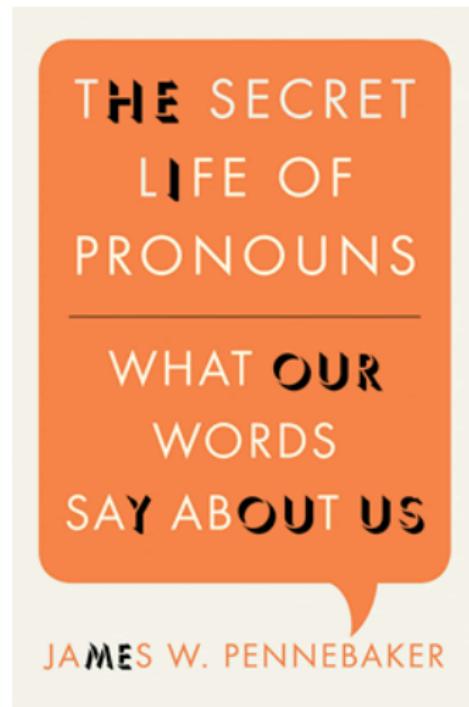
A more comprehensive list of stop words

as, able, about, above, according, accordingly, across, actually, after, afterwards, again, against, ain't, all, allow, allows, almost, alone, along, already, also, although, always, am, among, amongst, an, and, another, any, anybody, anyhow, anyone, anything, anyway, anyways, anywhere, apart, appear, appreciate, appropriate, are, aren't, around, as, aside, ask, asking, associated, at, available, away, awfully, be, became, because, become, becomes, becoming, been, before, beforehand, behind, being, believe, below, beside, besides, best, better, between, beyond, both, brief, but, by, c'mon, c's, came, can, can't, cannot, cant, cause, causes, certain, certainly, changes, clearly, co, com, come, comes, concerning, consequently, consider, considering, contain, containing, contains, corresponding, could, couldn't, course, currently, definitely, described, despite, did, didn't, different, do, does, doesn't, doing, don't, done, down, downwards, during, each, edu, eg, eight, either, else, elsewhere, enough, entirely, especially, et, etc, even, ever, every, everybody, everyone, everything, everywhere, ex, exactly, example, except, far, few, fifth, first, five, followed, following, follows, for, former, formerly, forth, four, from, further, furthermore, get, gets, getting, given, gives, go, goes, going, gone, got, gotten, greetings, had, hadn't, happens, hardly, has, hasn't, have, haven't, having, he, he's, hello, help, hence, her, here, here's, hereafter, hereby, herein, hereupon, hers, herself, hi, him, himself, his, hither, hopefully, how, howbeit, however, i'd, i'll, i'm, i've, ie, if, ignored, immediate, in, inasmuch, inc, indeed, indicate, indicated, indicates, inner, insofar, instead, into, inward, is, isn't, it, it'd, it'll, it's, its, itself, just, keep, keeps, kept, know, knows, known, last, lately, later, latter, latterly, least, less, lest, let, let's, like, liked, likely, little, look, looking, looks, ltd, mainly, many, may, maybe, me, mean, meanwhile, merely, might, more, moreover, most, mostly, much, must, my, myself, name, namely, nd, near, nearly, necessary, need, needs, neither, never, nevertheless, new, next, nine, no, nobody, non, none, noone, nor, normally, not, nothing, novel, now, nowhere, obviously, of, off, often, oh, ok, okay, old, on, once, one, ones, only, onto, or, other, others, otherwise, ought, our, ours, ourselves, out, outside, over, overall, own, particular, particularly, per, perhaps, placed, please, plus, possible, presumably, probably, provides, que, quite, qv, rather, rd, re, really, reasonably, regarding, regardless, regards, relatively, respectively, right, said, same, saw, say, saying, says, second, secondly, see, seeing, seem, seemed, seeming, seems, seen, self, selves, sensible, sent, serious, seriously, seven, several, shall, she, should, shouldn't, since, six, so, some, somebody, somehow, someone, something, sometime, sometimes, somewhat, somewhere, soon, sorry, specified, specify, specifying, still, sub, such, sup, sure, t's, take, taken, tell, tends, th, than, thank, thanks, thanx, that, that's, thats, the, their, theirs, them, themselves, then, thence, there, there's, thereafter, thereby, therefore, therein, theres, thereupon, these, they, they'd, they'll, they're, they've, think, third, this, thorough, thoroughly, those, though, three, through, throughout, thru, thus, to, together, too, took, toward, towards, tried, tries, truly, try, trying, twice, two, un, under, unfortunately, unless, unlikely, until, unto, up, upon, us, use, used, useful, uses, using, usually, value, various, very, via, viz, vs, want, wants, was, wasn't, way, we, we'd, we'll, we're, we've, welcome, well, went, were, weren't, what, what's, whatever, when, whence, whenever, where, where's, whereafter, whereas, whereby, wherein, whereupon, wherever, whether, which, while, whither, who, who's, whoever, whole, whom, whose, why, will, willing, wish, with, within, without, won't, wonder, would, would, wouldn't, yes, yet, you, you'd, you'll, you're, you've, your, yours, yourself, yourselves, zero

Stopwords

Are there cases in which we would want to keep stopwords? Or should we always exclude them from our analysis?

Stopwords sometimes can be informative!



But sometimes we want to add/remove our own new stopwords
(e.g. female pronouns, legislative terms, directional terms)

Stemming words

Lemmatization refers to the algorithmic process of converting words to their lemma forms.

stemming 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.

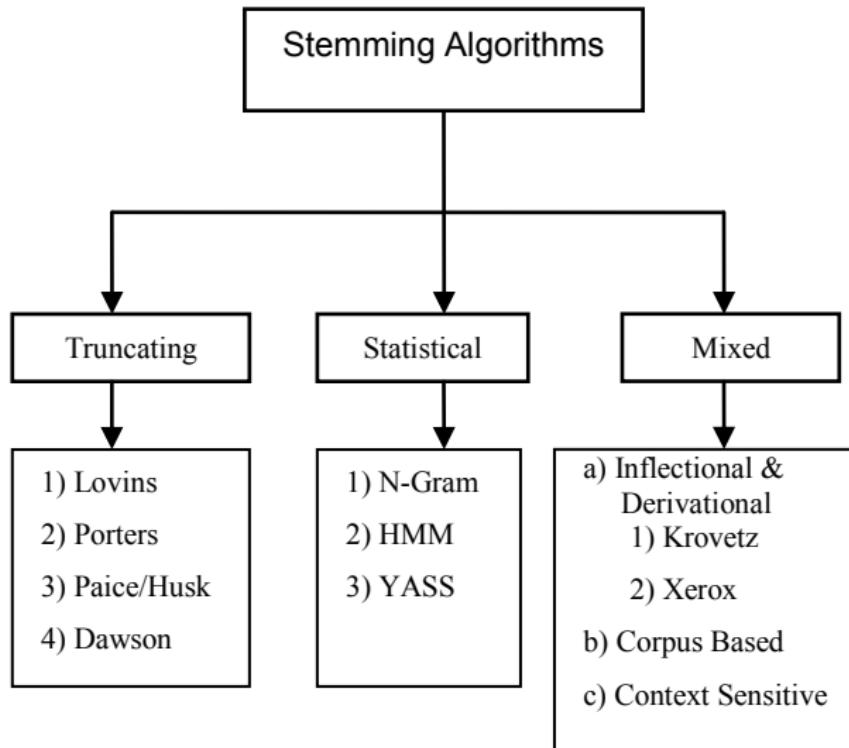
both convert the morphological variants into stem or root terms

example: **produc** from

production, producer, produce, produces,
produced

Why? Reduce feature space by collapsing different words into a stem (e.g. “happier” and “happily” convey same meaning as “happy”)

Varieties of stemming algorithms



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
 - ▶ general becomes gener, iteration becomes iter
- ▶ Other corpus-based, statistical, and mixed approaches designed to overcome these limitations
- ▶ Key for you is to be careful through inspection of morphological variants and their stemmed versions
- ▶ Sometimes not appropriate! e.g. Schofield and Minno (2016) find that “stemmers produce no meaningful improvement in likelihood and coherence (of topic models) and in fact can degrade topic stability”

Where to obtain textual data?

Some tips...

- ▶ Existing datasets, e.g.
 - ▶ UCD's EuroParl project
 - ▶ Hansard Archive of parliamentary debates in UK
 - ▶ Media archives (newspaper articles, TV transcripts...) at LexisNexis, ProQuest, Factiva...
 - ▶ 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 OCR (optical character recognition) software
 - ▶ Options: Tesseract (open-source), Abbyy FineReader

Where to obtain textual data?

What type of textual data have you worked with?
What data would you be interested in collecting?

Wrapping up...

Big questions we answered today:

- ▶ Quantitative Text Analysis: why?
- ▶ Key terms: document, corpus, feature, document feature matrix, type, token
- ▶ How to select the unit of analysis (i.e. documents)?
- ▶ How to select features? Bag-of-words, stemming, stopwords, part-of-speech tagging

Before next class

- ▶ Do readings for today and next class
- ▶ Create a GitHub account