# Quantitative text analysis: overview and fundamentals

Kenneth Benoit

Quants 3: Quantitative Text Analysis

Week 1: February 16, 2018

Course website: http://kenbenoit.net/quantitative-text-analysis-tcd-2018/

# Text as data

# Text as data


Kukuriku
koalicija
Plan
21


the TRUE NORTH
STRONG AND FREE
Stephen Harper's plan for Canadians
Conservative


Et retfærdigt
Danmark


ΕΚΛΟΓΙΚΗ ΔΙΑΚΗΡΥΞΗ
ΣΥΡΙΖΑ
ισχυρός
στη Βουλή
και στους αγώνες
Είναι στο χέρι μας!
ΣΥΡΙΖΑ
ΣΥΝΑΣΠΙΣΜΟΣ ΡΙΖΟΣΠΑΣΤΙΚΗΣ ΑΡΙΣΤΕΡΑΣ
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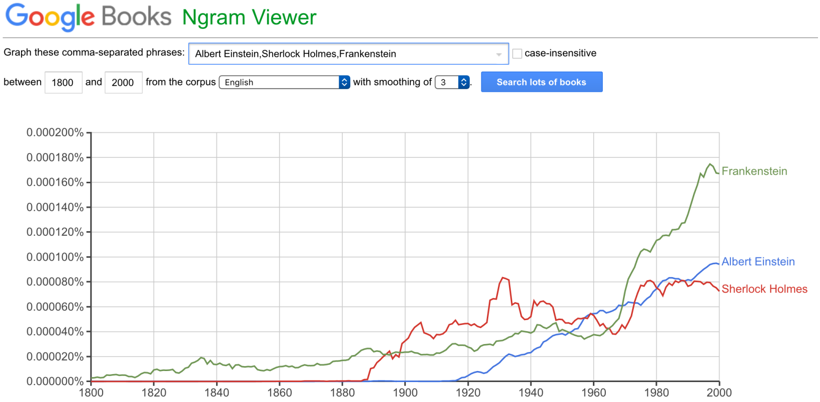
WIR HABEN DIE KRAFT
GEMEINSAM
FÜR UNSER LAND.
REGIERUNGSPROGRAMM 2009 – 2013
CDU CSU


Sozial und
Demokratisch.
Anpacken. Für Deutschland.
Das Regierungsprogramm der SPD
SPD

# Text as data


Google Books Ngram Viewer
Graph these comma-separated phrases:
Albert Einstein,Sherlock Holmes,Frankenstein
case-insensitive
between
1800
and
2000
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Search lots of books
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Frankenstein
Albert Einstein
Sherlock Holmes

# Text as data


facebook
XING
Gefällt mir
Instagram
twitter
LinkedIn
Pinterest
skype
flickr
YouTube

# Basic QTA Process: Texts → Feature matrix → Analysis

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.

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Scaling documents

Descriptive statistics on words

Classifying documents

Extraction of topics

Vocabulary analysis

Sentiment 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
  - availability and consequences of *choices*
  - practical ability to work with texts in `R`
  - issues of text for social science
- Whom this class is for
- Prerequisites
  - quantitative methods (Quant 2 or equivalent)
  - familiarity with R
  - ability to use a text editor
  - (optional) ability to process text files in a programming language such as Python

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# About me

- Professor of Quantitative Social Sciences, TCD (and at Dept of Methodology, LSE)
- **My research:**
  - Measuring policy positions of political actors
  - Models of party competition and government formation
  - creator of the **quanteda** R package(s) for text analysis
- **Contact:**
  - `mailto:kbenoit@tcd.ie`
  - `http://kenbenoit.net`
  - No office hours, but available for meetings by appointment after class each Friday

# Your turn!


1. Name?
2. Department, degree?
3. Research interests?
4. Previous experience with text analysis / R?
5. Why are you interested in this course?

# 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
  - (links to) Software tools and instructions for use
- Readings
  - Mainly articles
  - Read before class

# Course schedule

- **Lectures**: Fridays 09:00-12:00 in Arts 3020
- **No session Mar 1**
- **Exercises** Weeks 1 - 4

`http://kenbenoit.net/quantitative-text-analysis-tcd-2018/`

# Evaluation

- **Typical schedule**:
  - Lecture 90 mins
  - Break
  - Lecture 30-45 mins hr
  - Exercise review/overview
- **Assessment**:
  - 60% from four problem sets (15 pts each)
  - 40% from a final project

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# 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

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# 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

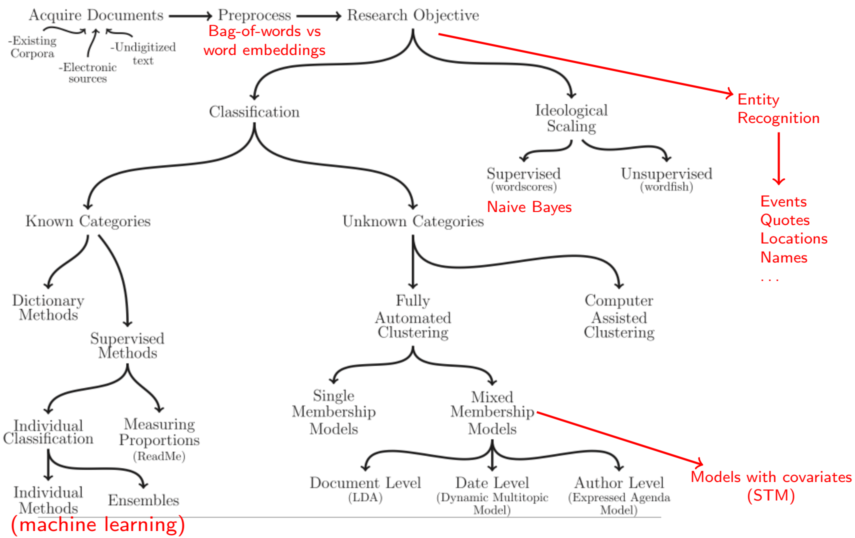


Fig. 1 in Grimmer and Stewart (2013)

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# Descriptive text analysis

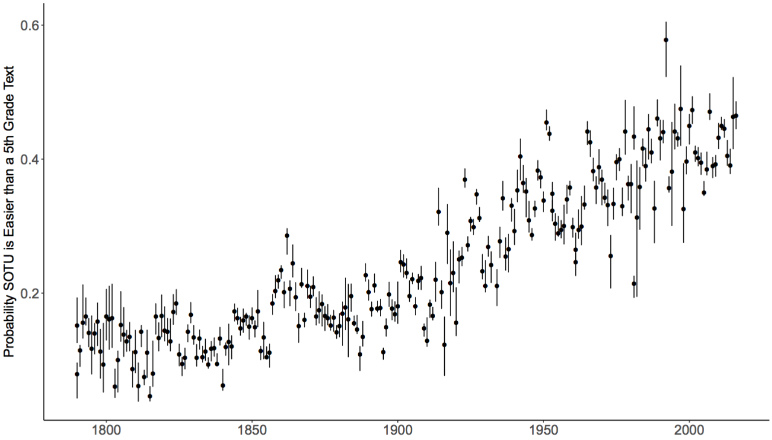
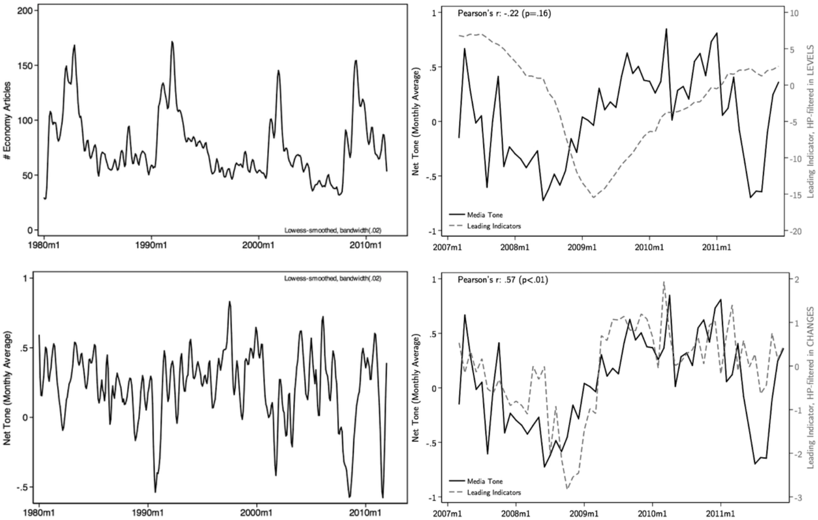



Figure 2: The probability that a State of the Union address is easier to understand than a fifth grade text baseline.

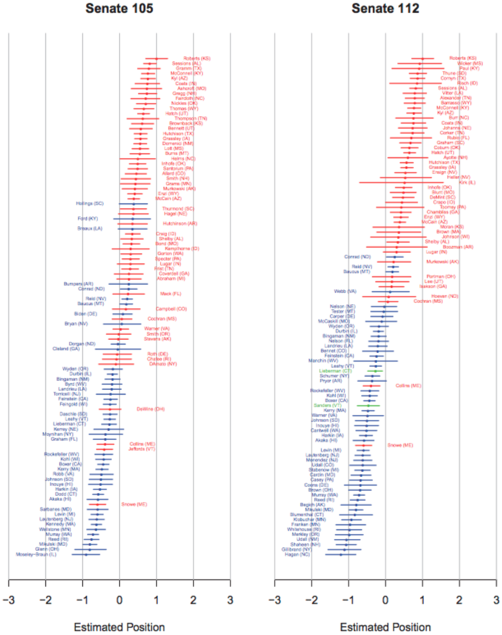
Benoit, Munger & Spirling (2017)

# 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)<br>linke, spd, partei, linken, pds, politik, kommunisten, parteien, grünen, punks<br>*the left, spd, party, the left, pds, politics, communists, parties, greens, punks* |
| Left topic 2: **Ideologies** (proportion = .26, average lr-scale value = 5.36)<br>kommunismus, links, sozialismus, lafontaine, rechts, aber, gysi, linkspartei, richtung, gleichmacherei<br>*communism, left, socialism, lafontaine, right, but, gysi, left party, direction, levelling* |
| Left topic 3: **Values** (proportion = .24, average lr-scale value = 4.06)<br>soziale, gerechtigkeit, demokratie, soziales, bürger, gleichheit, gleiche, freiheit, rechte, gleichberechtigung<br>*social, justice, democracy, social, citizen, equality, equal, freedom, rights, equal rights* |
| Left topic 4: **Policies** (proportion = .24, average lr-scale value =4.89)<br>sozial, menschen, leute, ddr, verbinde, kleinen, einstellung, umverteilung, sozialen, vertreten<br>*social, humans, people, ddr, associate, the little, attitude, redistribution, social, represent* |

| |
|---|
| Right topic 1: **Ideologies** (proportion = .27, average lr-scale value = 5.00)<br>konservativ, nationalsozialismus, rechtsradikal, radikal, ordnung, politik, nazi, recht, menschen, konservative<br>*conservative, national socialism, right-wing radicalism, radical, order, politics, nazi, right, people, conservatives* |
| Right topic 2: **Parties** (proportion = .25, average lr-scale value = 5.26)<br>npd, rechts, cdu, csu, rechten, parteien, leute, aber, verbinde, rechtsradikalen<br>*npd, right, cdu, csu, the right, parties, people, but, associate, right-wing radicalists* |
| Right topic 3: **Xenophobia** (proportion = .25, average lr-scale value = 4.55)<br>ausländerfeindlichkeit, gewalt, ausländer, demokratie, nationalismus, rechtsradikalismus, diktatur, national, intoleranz, faschismus<br>*xenophobia, violence, foreigners, democracy, nationalism, right-wing radicalism, dictatorship, national, intolerance, fascism* |
| Right topic 4: **Right-wing extremists** (proportion = .23, average lr-scale value = 4.90)<br>nazis, neonazis, rechtsradikale, rechte, radikale, radikalismus, partei, ausländerfeindlich, reich, nationale<br>*nazis, neonazis, right-wing radicalists, rightists, radicals, radicalism, party, xenophobia, rich, national* |

**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.

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

# Document classification into unknown categories

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

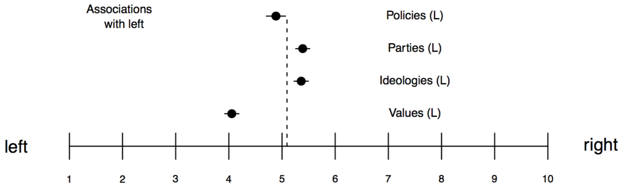
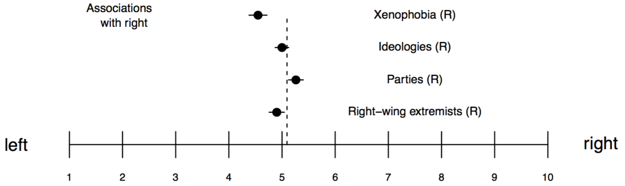


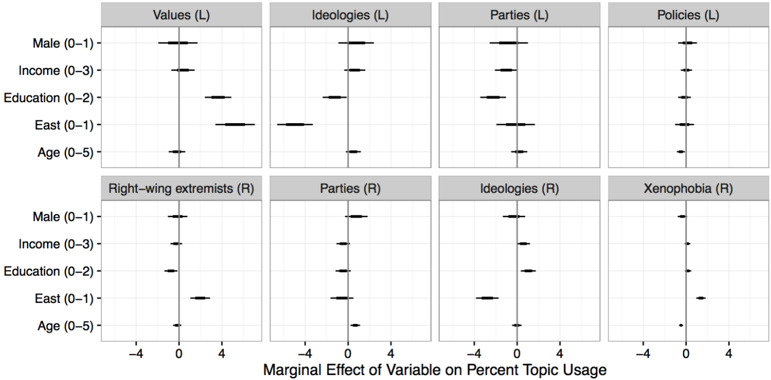

Fig. 7: Left-right scale means for different subsamples of associations with **right** (dashed = sample mean, bars = 95% Cis)




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

# 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 days $\times$ 2 chambers $\times$ 2 parties
- Automated text analysis to discover unknown categories and classify responses
- Validation: http://j.mp/lda-congress-demo

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# Basic QTA Process: Texts → Feature matrix → Analysis

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# 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

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# Basic QTA adopts a bag-of-words approach

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# 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 document~~s~~"
   "second document corpus" [corpus, set, document, corpus set, set document]
   [second, document, corpus, second document, document corpus]

# Bag-of-words approach

1. Document-feature matrix:
   - **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 |
|---|---|---|---|---|---|---|
| Document 1 | 1 | 1 | 1 | 1 | ... | |
| Document 2 | 1 | 0 | 1 | 0 | ... | |
| ... | | | | | | |
| Document $n$ | 0 | 1 | 1 | 0 | ... | |

# 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?

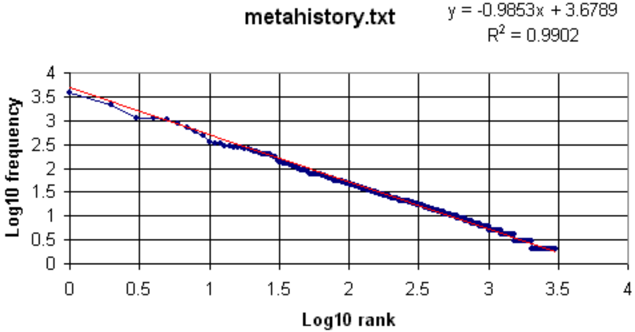
- *Context is often uninformative*, conditional on presence of words:
  - Individual word usage tends to be associated with a particular degree of affect, position, etc. without regard to context of word usage
- Single words tend to be the most informative, as co-occurrences of multiple words (*n*-grams)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

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# 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 *there* |
| 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 | *to* |
| 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.)

```
> library("spacyr")
> txt <- "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."
> spacy_parse(txt)
doc_id sentence_id token_id       token       lemma   pos       entity
1   text1          1        1      Pierre      pierre PROPN     PERSON_B
2   text1          1        2      Vinken      vinken PROPN     PERSON_I
3   text1          1        3           ,           , PUNCT
4   text1          1        4          61          61   NUM       DATE_B
5   text1          1        5       years        year  NOUN       DATE_I
6   text1          1        6         old         old   ADJ       DATE_I
7   text1          1        7           ,           , PUNCT
8   text1          1        8        will        will  VERB
9   text1          1        9        join        join  VERB
10  text1          1       10         the         the   DET
11  text1          1       11       board       board  NOUN
12  text1          1       12          as          as   ADP
13  text1          1       13           a           a   DET
14  text1          1       14 nonexecutive nonexecutive   ADJ
15  text1          1       15   \n          \n          SPACE
16  text1          1       16    director    director  NOUN
17  text1          1       17        Nov.        nov. PROPN       DATE_B
18  text1          1       18          29          29   NUM       DATE_I
19  text1          1       19           .           . PUNCT
```

# Parts of speech (cont.)

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 20 | text1 | 1 | 20 | | | SPACE | |
| 21 | text1 | 2 | 1 | Mr. | mr. | PROPN | |
| 22 | text1 | 2 | 2 | Vinken | vinken | PROPN | PERSON_B |
| 23 | text1 | 2 | 3 | is | be | VERB | |
| 24 | text1 | 2 | 4 | chairman | chairman | NOUN | |
| 25 | text1 | 2 | 5 | of | of | ADP | |
| 26 | text1 | 2 | 6 | Elsevier | elsevier | PROPN | ORG_B |
| 27 | text1 | 2 | 7 | N.V. | n.v. | PROPN | ORG_I |
| 28 | text1 | 2 | 8 | , | , | PUNCT | |
| 29 | text1 | 2 | 9 | \n | \n | SPACE | WORK_OF_ART_B |
| 30 | text1 | 2 | 10 | the | the | DET | WORK_OF_ART_I |
| 31 | text1 | 2 | 11 | Dutch | dutch | ADJ | NORP_B |
| 32 | text1 | 2 | 12 | publishing | publishing | NOUN | |
| 33 | text1 | 2 | 13 | group | group | NOUN | |
| 34 | text1 | 2 | 14 | . | . | PUNCT | |

# 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*** | 4.32*** | 2.70*** | 2.49*** |
| | (1.13) | (1.26) | (0.22) | (0.30) |
| Tweets about Europe (%) | −0.03+ | −0.03+ | 0.01*** | 0.01*** |
| | (0.02) | (0.02) | (0.002) | (0.002) |
| Editorialisation Index | | | 0.02*** | 0.02*** |
| | | | (0.004) | (0.004) |
| (Intercept) | 7.58** | 7.94** | −4.03*** | −3.92*** |
| | (2.59) | (2.47) | (0.40) | (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 |

Barberá, Vaccari, Valeriani (2016) [control variables ommitted]

# 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

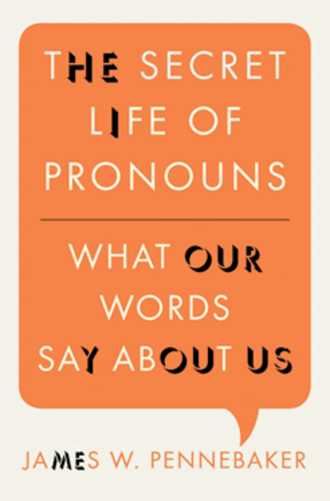
# A more comprehensive list of stop words

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.

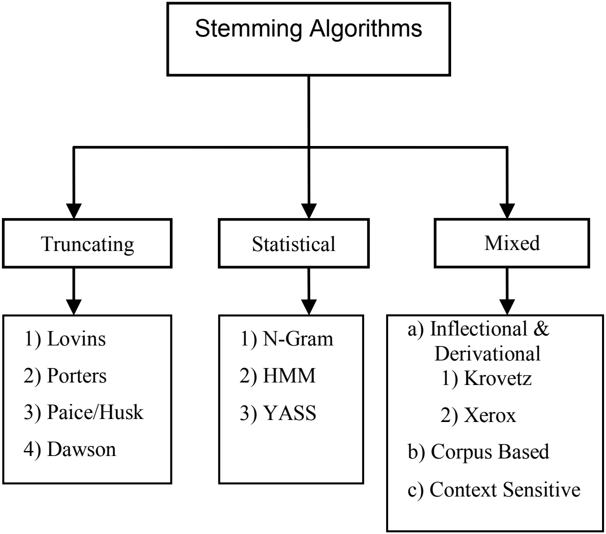
**stemming** the process for reducing inflected (or sometimes derived) words to their stem, base or root form. Different from *lemmatization* in that stemmers operate on single words without knowledge of the context.

**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 Minmo (2016) find that "stemmers produce no meaningful improvement in likelihood and coherence (of topic models) and in fact can degrade topic stability"

# Stemming v. lemmas

```
> library("quanteda")
> tokens(txt) %>% tokens_wordstem()
tokens from 1 document.
text1 :
[1] "Pierr"     "Vinken"    ","          "61"         "year"       "old"        ","
[9] "join"      "the"       "board"      "as"         "a"          "nonexecut" "di
[17] "."         "29"        "."          "Mr"         "."          "Vinken"     "i
[25] "of"        "Elsevier"  "N.V"        "."          ","          "the"        "D
[33] "group"     "."

sp$lemma
[1] "pierre"       "vinken"       ","              "61"              "year"
[7] ","            "will"         "join"           "the"             "board"
[13] "a"            "nonexecutive" "\n           "   "director"        "nov."
[19] "."            " "            "mr."            "vinken"          "be"
[25] "of"           "elsevier"     "n.v."           ","               "\n           "
[31] "dutch"        "publishing"   "group"          "."
```

# 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
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- 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"

# 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