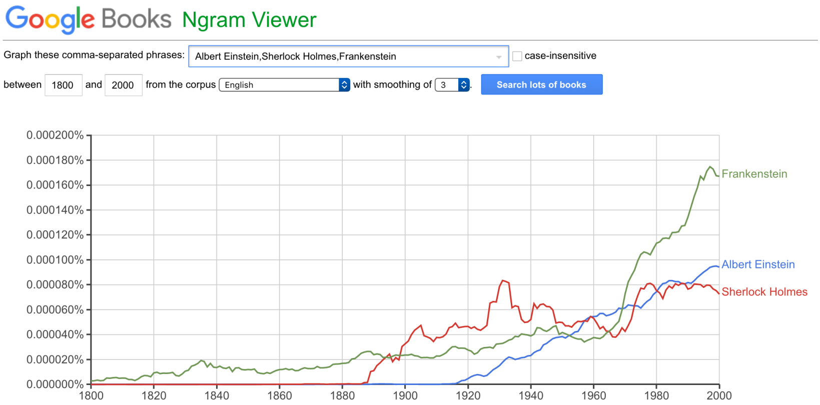
Text as data



Google Books Ngram Viewer
Graph these comma-separated phrases: Albert Einstein,Sherlock Holmes,Frankenstein
case-insensitive
between 1800 and 2000 from the corpus English with smoothing of 3.
Search lots of books
0.000200%
0.000180%
0.000160%
0.000140%
0.000120%
0.000100%
0.000080%
0.000060%
0.000040%
0.000020%
0.000000%
1800
1820
1840
1860
1880
1900
1920
1940
1960
1980
2000
Frankenstein
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Text as data


facebook
XING
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Basic QTA Process: Texts → Feature matrix → Analysis

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Descriptive statistics on words

Scaling documents

Classifying documents

Extraction of topics

Vocabulary analysis

Sentiment analysis

Outline

- 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

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4. Validate, validate, validate

Quantitative text analysis requires assumptions

1. Texts represent an observable implication of some underlying characteristic of interest

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   - 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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1. Selecting texts: Defining the *corpus*

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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.

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7. Summary and interpretation of the quantitative results

Descriptive text analysis

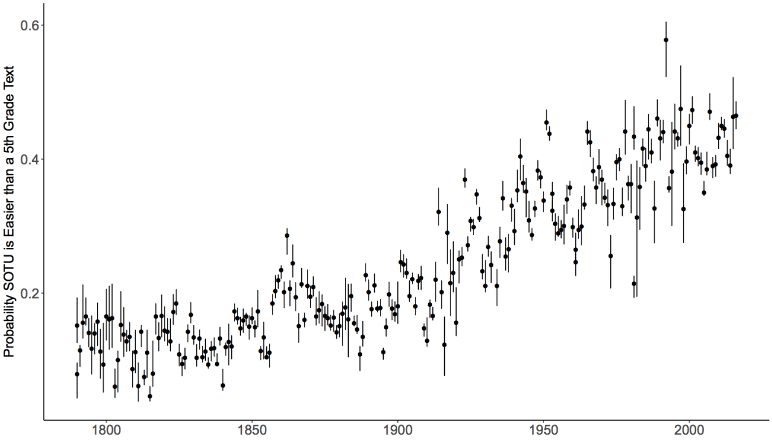
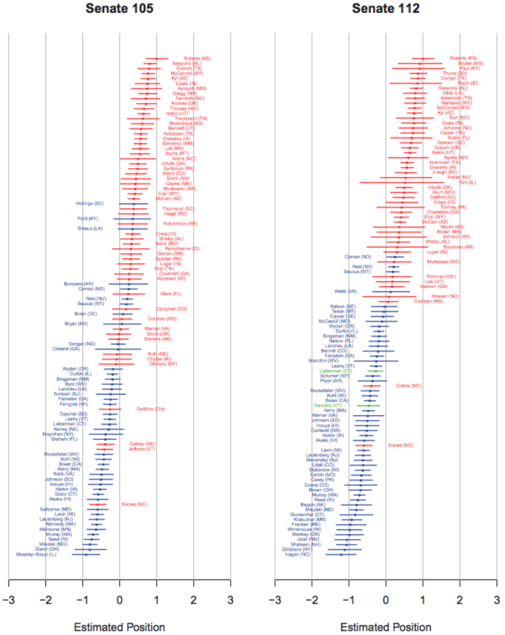


Figure 2: The probability that a State of the Union address is easier to understand than a fifth grade text baseline.

Benoit, Munger & Spirling (2017)

Ideological scaling (Lauderdale & Herzog, PA 2016)



Document classification into unknown categories

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

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

Right topic 1: **Ideologies** (proportion = .27, average lr-scale value = 5.00) konservativ, nationalsozialismus, rechtsradikal, radikal, ordnung, politik, nazi, recht, menschen, konservative *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) npd, rechts, cdu, csu, rechten, parteien, leute, aber, verbinde, rechtsradikalen *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) ausländerfeindlichkeit, gewalt, ausländer, demokratie, nationalismus, rechtsradikalismus, diktatur, national, intoleranz, faschismus *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) nazis, neonazis, rechtsradikale, rechte, radikale, radikalismus, partei, ausländerfeindlich, reich, nationale *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.

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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.)

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stems words with suffixes removed (using set of rules)

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

Basic QTA adopts a bag-of-words approach

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From words to numbers:

1. Preprocess text:

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   “This is the second document in the corpus.”

Bag-of-words approach

From words to numbers:

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Bag-of-words approach

From words to numbers:

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Bag-of-words approach

From words to numbers:

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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)

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2. 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

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- Some approaches focus on occurrence of a word as a binary variable, irrespective of frequency: a binary outcome

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

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  Saunauntensitzer

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- 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
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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

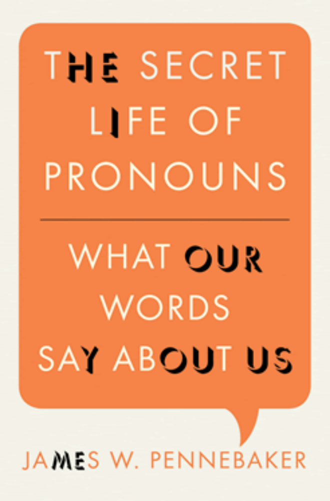
A more comprehensive list of stop words

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

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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”)

Wrapping up...

Big questions we answered today:

- Quantitative Text Analysis: why?
- Key terms: document, corpus, feature, document feature matrix, type, token
- How to select features? Bag-of-words, stemming, stopwords, part-of-speech tagging