Day 1: The Elements of Textual Data

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Quantitative Analysis of Textual Data

September 23, 2014

Today's Basic Outline

- Building blocks/foundations of quantitative text analysis
- Justifying a term/feature frequency approach
- Selecting texts / defining documents
- Selecting features
- Weighting strategies for features
- Collocations

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.
```

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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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```
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 \ 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

Descriptive statistics on words

Scaling documents

Classifying documents

Extraction of topics

Vocabulary analysis

Sentiment analysis

This requires assumptions

- That texts represent an observable implication of some underlying characteristic of interest (usually an attribute of the author)
- That texts can be represented through extracting their *features*
  - most common is the bag of words assumption
  - many other possible definitions of "features"
- A document-feature matrix can be analyzed using quantitative methods to produce meaningful and valid estimates of the underlying characteristic of interest

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 doumentary 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

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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

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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
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Descriptive statistics on words

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Some key basic concepts

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

types: for our purposes, a unique word

tokens: any word – so token count is total words

- hapax legomena (or just *hapax*) are types that occur just once

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)

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

Some more key basic concepts

"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

readability provides estimates of the readability of a text based on word length, syllable length, etc.

complexity A word is considered "complex" if it contains three syllables or more

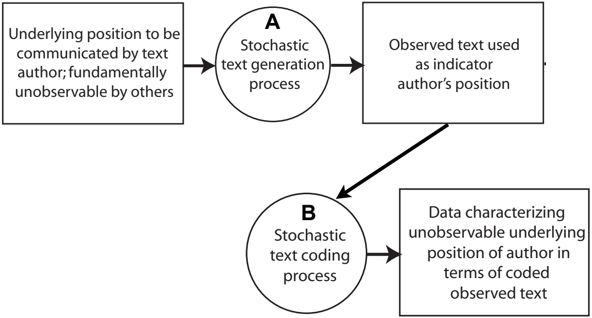
diversity (lexical diversity) A measure of how many types occur per fixed word rate (a normalized vocabulary measure)

Strategies for selecting units of textual analysis

- Words
- *n*-word sequences
- pages
- paragraphs
- Themes
- Natural units (a speech, a poem, a manifesto)
- Key: depends on the research design

Sample v. "population"

- Basic Idea: Observed text is a stochastic realization
- Systematic features shape most of observed verbal content
- Non-systematic, random features also shape verbal content



Implications of a stochastic view of text

- Observed text is not the only text that could have been generated
- Very different if you are trying to monitor something like hate speech, where what you actually say matters, not the value of your "expected statement"
- Means that having "all the text" is still not a "population"
- Suggests you could employ bootstrapping strategies to estimate uncertainty for sample statistics, even things like readability

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

Defining Features

- 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 1 8 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
- linguistic features: parts of speech

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, namely Apache's OpenNLP (and R package openNLP wrapper)

```
> s
Pierre Vinken, 61 years old, will join the board as a nonexecutive director Nov
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"        "./."
```

Strategies for feature selection

- 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, what I call a *thesaurus* (lots more on these on Day 4)

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, aint, 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, arent, 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, cmon, cs, came, can, cant, cannot, cant, cause, causes, certain, certainly, changes, clearly, co, com, come, comes, concerning, consequently, consider, considering, contain, containing, contains, corresponding, could, couldnt, course, currently, definitely, described, despite, did, didnt, different, do, does, doesnt, doing, dont, 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, hadnt, happens, hardly, has, hasnt, have, havent, having, he, hes, hello, help, hence, her, here, heres, hereafter, hereby, herein, hereupon, hers, herself, hi, him, himself, his, hither, hopefully, how, howbeit, however, id, ill, im, ive, ie, if, ignored, immediate, in, inasmuch, inc, indeed, indicate, indicated, indicates, inner, insofar, instead, into, inward, is, isnt, it, itd, itll, its, its, itself, just, keep, keeps, kept, know, knows, known, last, lately, later, latter, latterly, least, less, lest, let, lets, 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, shouldnt, since, six, so, some, somebody,

Weighting strategies for feature counting

- **term frequency** Some approaches trim very low-frequency words. Rationale: get rid of rare words that expand the feature matrix but matter little to substantive analysis
- **document frequency** Could eliminate words appearing in few documents
- **inverse document frequency** Conversely, could weight words more that appear in the most documents

Strategies for feature *weighting*: tf-idf

- $tf_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}}$
  where $n_{i,j}$ is number of occurences of term t_i in document d_j,
  k is total number of terms in document d_j
- $idf_i = \ln \frac{|D|}{|\{d_j : t_i \in d_j\}|}$
  where
  - $|D|$ is the total number of documents in the set
  - $|\{d_j : t_i \in d_j\}|$ is the number of documents where the term t_i appears (i.e. $n_{i,j} \neq 0$)
- $tf\text{-}idf_i = tf_{i,j} \cdot idf_i$

Computation of tf-idf: Example

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 *document frequency* is $100/40 = 2.5$, or $\ln(2.5) = 0.916$
- The *tf-idf* will then be $0.016 * 0.916 = 0.0147$
- If the word had only appeared in 15 of the 100 manifestos, then the *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 weighting schemes

- the SMART weighting scheme (Salton 1991, Salton et al): The first letter in each triplet specifies the term frequency component of the weighting, the second the document frequency component, and the third the form of normalization used (not shown). Example: *lnn* means log-weighted term frequency, no idf, no normalization

Term frequency		Document frequency	
n (natural)	$\mathrm{tf}_{t,d}$	n (no)	1
l (logarithm)	$1 + \log(\mathrm{tf}_{t,d})$	t (idf)	$\log \frac{N}{\mathrm{df}_t}$
a (augmented)	$0.5 + \frac{0.5 \times \mathrm{tf}_{t,d}}{\max_t(\mathrm{tf}_{t,d})}$	p (prob idf)	$\max\{0, \log \frac{N - \mathrm{df}_t}{\mathrm{df}_t}\}$
b (boolean)	$\begin{cases} 1 & \text{if } \mathrm{tf}_{t,d} > 0 \\ 0 & \text{otherwise} \end{cases}$		
L (log ave)	$\frac{1+\log(\mathrm{tf}_{t,d})}{1+\log(\mathrm{ave}_{t \in d}(\mathrm{tf}_{t,d}))}$		

- Note: Mostly used in information retrieval, although some use in machine learning

Stemming words

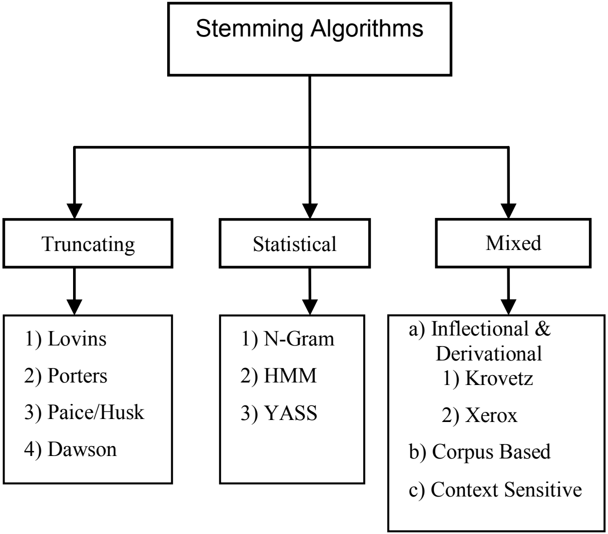
Lemmatization refers to the algorithmic process of converting words to their lemma forms.

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`

Varieties of stemming algorithms



Issues with stemming approaches

- The most common is proably 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 appraoches designed to overcome these limitations (good review in Jirvani article)
- Key for you is to be careful through inspection of morphological variants and their stemmed versions

Selecting more than words: collocations

collocations bigrams, or trigrams e.g. *capital gains tax*

how to detect: pairs occuring more than by chance, by measures of χ^2 or *mutual information* measures

example:

Summary Judgment	Silver Rudolph	Sheila Foster
prima facie	COLLECTED WORKS	Strict Scrutiny
Jim Crow	waiting lists	Trail Transp
stare decisis	Academic Freedom	Van Alstyne
Church Missouri	General Bldg	Writings Fehrenbacher
Gerhard Casper	Goodwin Liu	boot camp
Juan Williams	Kurland Gerhard	dated April
LANDMARK BRIEFS	Lee Appearance	extracurricular activities
Lutheran Church	Missouri Synod	financial aid
Narrowly Tailored	Planned Parenthood	scored sections

Table 5: Bigrams detected using the mutual information measure.

Word frequencies and their properties

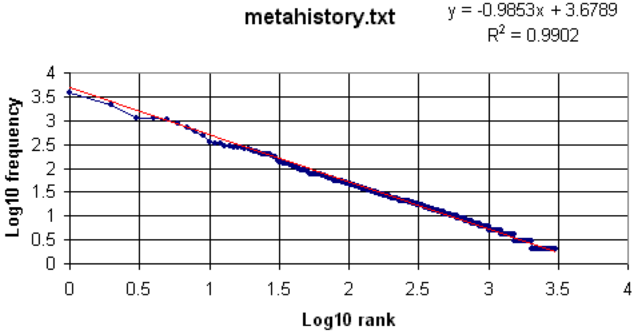
- Individual word usage tends to be associated with a particular degree of affect, position, etc. without regard to context of word usage
- Single tend to be the most informative, as *n*-grams are very rare
- Some approaches focus on occurrence of a word as a binary variable, irrespective of frequency: 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 nth 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

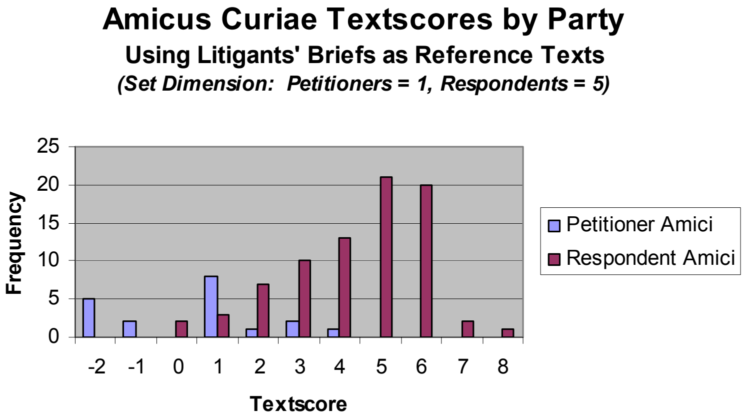
- Formulaically: if a word occurs f times and has a rank r in a list of frequencies, then for all words $f = \frac{a}{r^b}$ where a and b are constants and b is close to 1
- So if we log both sides, $\log(f) = \log(a) - b\log(r)$
- If we plot $\log(f)$ against $\log(r)$ then we should see a straight line with a slope of approximately -1.



Identifying collocations

- Does a given word occur next to another given word with a higher relative frequency than other words?
- If so, then it is a candidate for a collocation or "word bigram"
- We can detect these using χ^2 or likelihood ratio measures (Dunning paper)
- Implemented in quanteda as `collocations()`

Legal document scaling: "Wordscores"



(from Evans et. al. 2007)

Document classification: "Naive Bayes" classifier