# Day 2: The Elements of Textual Data

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# Day 2 Basic Outline

- Building blocks/foundations of quantitative text analysis
- Justifying a term/feature frequency approach
- Selecting texts
- Selecting features
- Practical issues working with texts
- Demonstrations
- Examples

# THE ELEMENTS OF TEXTUAL DATA

# 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) |

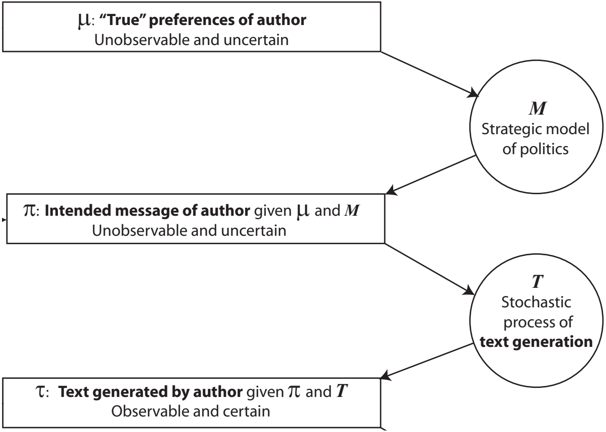
# DEFINING “DOCUMENTS”

# 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

# Random versus “Constructed” Sampling

- Based on a study by Riffe, Aust and Lacy (1993), who compared sampling from newspaper articles randomly versus “constructed”
- Either randomly sample 7 consecutive days, or between 2–4 consecutive weeks, and compare to “known” quantities
- Study showed that constructed sampling is much more efficient
- Why? Because cyclic variation in newspaper content occurs according to the day of the week – not every day contains equal proportions of different content

# SELECTING FEATURES

# 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
- purposive selection Use of a dictionary of words or phrases
- deliberate disregard Use of "stop words": words excluded because they represent linguistic connectors of no substantive content

# 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,

# 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

# Stemming words

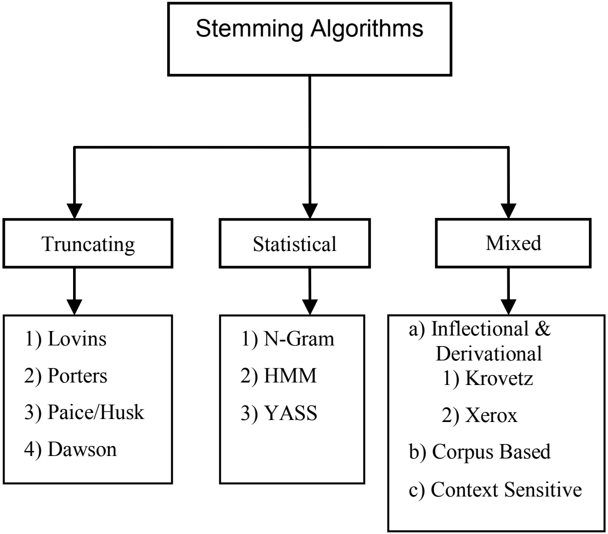
**Lemmatization** refers to the algorithmic process of converting words to their lemma forms.

**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 $\chi^2$ 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.

# COUNTING FEATURES

# Word frequencies and their properties

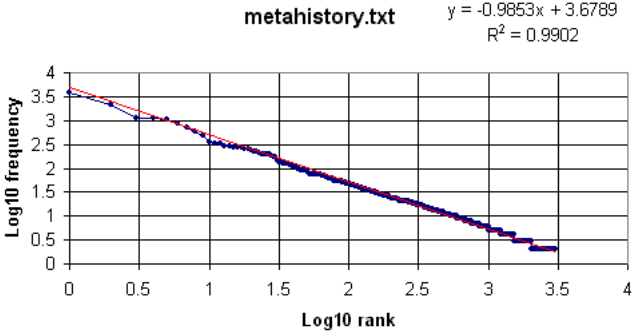
- Individual word usage tends to be associated with a particular degree of affect, position, etc. without regard to context of word usage
- Atomic words have been found to be far more informative than *n*-grams in this regard (Benoit and Laver 2003, Midwest paper)
- Some approaches focus on occurrence of a word as a binary variable, irrespective of frequency: a binary outcome (e.g. Hopkins and King 2008)
- Other approaches use frequencies: Poisson, multinomial, and related distributions (e.g. Laver, Benoit and Garry 2003)

# 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.



# 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

# Word concordances on popular web sites

- Amazon word statistics example http://www.amazon.com/Innovative-Comparative-Methods-Policy-Analysis/dp/0387288287/ref=sr_1_1?ie=UTF8&s=books&qid=1249293340&sr=8-1

- New York Times inaugural address example: http://www.nytimes.com/interactive/2009/01/17/washington/20090117_ADDRESSES.html

# PRACTICAL ISSUES WORKING WITH TEXT

# Practical issues working with texts

**File formats** How the electronic text is formatted

**Conversion** Converting files from one format to another

**Pre-analysis text processing** Considering inflected forms as equivalent, through lemmatization and/or stemming

**dropping infrequent words** as they may not be informative

**stop lists** for most frequent words

# Practical issues working with texts

- Formats
- Encodings
- Managing meta-data
  - document-level meta-data (aka document "variables")
  - corpus-level meta-data