Day 2: Textual Data, Sampling, and Working with Texts

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Some key basic concepts

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

word frequency refers to the number of times that words occur in a text or in a *corpus* of texts

concordance a(n alphabetical) list of the principal words used in a text, with their immediate contexts

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

Some 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

Word frequency as an indicator of substantive content

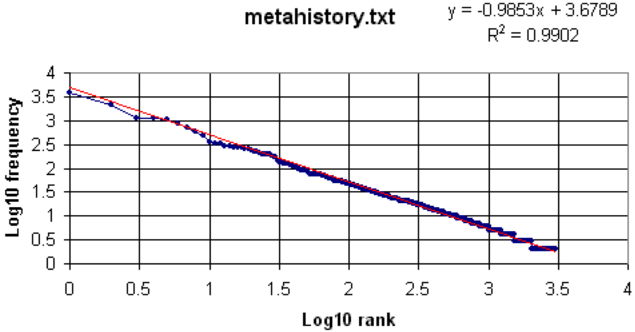
- Individual word usage tends to be associated with a particular degree of affect, position, etc. without regard to context of word usage
- Atomic words have been found to be far more informative than *n*-grams in this regard (Benoit and Laver 2003, Midwest paper)
- Some approaches focus on occurrence 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 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.



Word frequency continued

- Some approaches trim low-frequency words or words that are non-discriminating among texts
- Frequently this is based on a measure of word frequency known as *tf-idf*: term frequency-inverse document frequency
- Rationale behind filtering out words based on frequency
  - Substantive: Non-discriminating words (articles, conjunctions, pronouns, etc.) are non-informative
  - Practical: Non-discriminating words may strain computational abilities of particular statistical or computational techniques, esp. those requiring word frequency matrix analysis
  - Substantive: Low-frequency words may simply not be worth bothering about

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

Computation of 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".

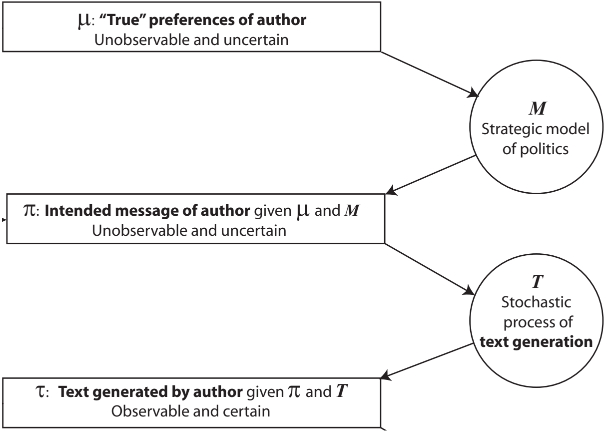
- The *term frequency* is $16/1000 = 0.016$
- The *document frequency* is $100/40 = 2.5$, or $\ln(2.5) = 0.916$
- The *tf-idf* will then be $0.016 * 0.916 = 0.0147$
- If the word had only appeared in 15 of the 100 manifestos, then the *tf-idf* would be 0.0304 (three times higher).
- A high weight in 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

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



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

Word frequency examples

- Variations use vocabulary diversity analysis (e.g. Labbé et. al. 2004)

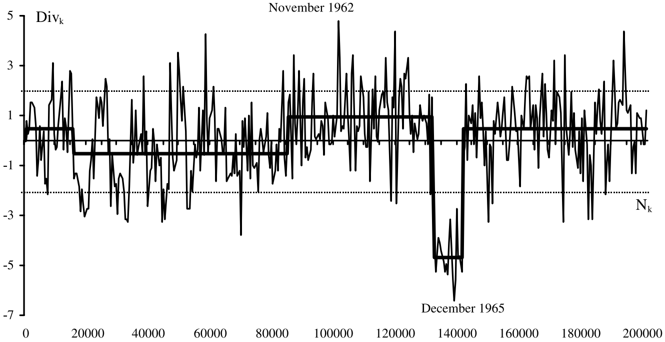
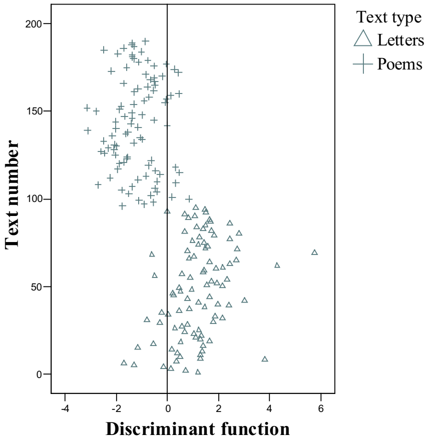


Fig. 8. Evolution of vocabulary diversity in General de Gaulle's broadcast speeches (June 1958–April 1969).

Examples continued

- Word *length* (defined as number of syllables) can be indicative of genre, if not necessarily authorship (Kelih et. al. 2004)



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
- *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.

- reducing infrequent words
- "stop lists" for most frequent words

"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,

Practical issues working with texts

Dataset generation
: How to convert text files into "datasets"

MaxQDA/Wordstat take care of this step for us, along with stemming etc.

"Collocations": bigrams, or trigrams e.g. *capital gains tax*

Software preview

- QDAMiner/Wordstat
- MaxQDA
- Jfreq
- Yoshikoder
- Stata and Wordscores library
- R and `austin` library
- Other programs