#### The role of statistics

#### Statistical Analysis of Corpus Data with R The Limitations of Random Sampling Models for Corpus Data

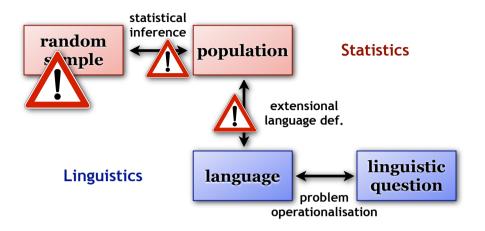
Marco Baroni<sup>1</sup> & Stefan Evert<sup>2</sup> http://purl.org/stefan.evert/SIGIL

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#### Problem 1: Extensional language definition

- ◆ Are population proportions meaningful?
  - data from the BNC suggests ca. 9% of passive VPs in written English, little more than 2% in spoken English
  - note the difference from the 15% mentioned before!
- ♦ How much written language is there in English?
  - if we give equal weight to written and spoken English, proportion of passives is 5.5%
  - if we assume that English is 90% written language (as the BNC compilers did), the proportion is 8.3%
  - if it's mostly spoken (80%), proportion is only 3.4%



Problem 2: Statistical inference

- ◆ Inherent problems of particular hypothesis tests and their application to corpus data
  - $X^2$  overestimates significance if any of the expected frequencies are low (Dunning 1993)
    - various rules of thumb: multiple E < 5, one E < 1
    - especially highly skewed tables in collocation extraction
  - G<sup>2</sup> overestimates significance for small samples (well-known in statistics, e.g. Agresti 2002)
    - e.g. manual samples of 100-500 items (as in our examples)
    - often ignored because of its success in computational linguistics
  - Fisher is conservative & computationally expensive
    - also numerical problems, e.g. in R version 1.x

#### Problem 2: Statistical inference

- ◆ Effect size for frequency comparison
  - not clear which measure of effect size is appropriate
  - e.g. difference of proportions, relative risk (ratio of proportions), odds ratio, logarithmic odds ratio, normalised X<sup>2</sup>, ...
- ◆ Confidence interval estimation
  - accurate & efficient estimation of confidence intervals for effect size is often very difficult
  - exact confidence intervals only available for odds ratio

#### Problem 3: Multiple hypothesis tests

- ◆ Typical situation e.g. for collocation extraction
  - test whether word pair cooccurs significantly more often than expected by chance
  - hypothesis test controls risk of type I error if applied to a single candidate selected *a priori*
  - but usually candidates selected a posteriori from data
     → many "unreported" tests for candidates with f = 0!
  - large number of such word pairs according to **Zipf's** law results in substantial number of type I errors
  - can be quantified with LNRE models (Evert 2004), cf. session on word frequency distributions with *zipfR*

## Problem 3: Multiple hypothesis tests

- ◆ Each individual hypothesis test controls risk of type I error ... but if you carry out thousands of tests, some of them *have* to be false rejections
  - recommended reading: *Why most published research findings are false* (Ioannidis 2005)
  - a monkeys-with-typewriters scenario

#### Corpora

- ◆ Theoretical sampling procedure is impractical
  - it would be very tedious if you had to take a random sample from a library, especially a hypothetical one, every time you want to test some hypothesis
- ◆ Use pre-compiled sample: a **corpus** 
  - but this is not a random sample of tokens!
  - would be prohibitively expensive to collect
     million VPs for a BNC-sized sample at random
  - other studies will need tokens of different granularity (words, word pairs, sentences, even full texts)

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#### The Brown corpus

- ◆ First large-scale electronic corpus
  - compiled in 1964 at Brown University (RI)
- ◆ 500 samples of approx. 2,000 words each
  - sampled from edited AmE published in 1961
  - from 15 domains (imaginative & informative prose)

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• manually entered on punch cards

## Problem 4: Coverage & representativeness

- ◆ Coverage: does corpus include all material that falls under our extensional language definition?
  - some genres problematic for legal or practical reasons (e.g. private letters, conversation, printed books)
  - opportunistic data collection for large corpora: newspapers, parliamentary debates, Web as corpus
- ◆ Representativeness: different genres, speakers, etc. included in appropriate proportion?
  - you may not agree with 10% of spoken English in BNC
  - can be corrected for if problem is known and sufficiently detailed meta-information is available

#### The British National Corpus

- ◆ 100 M words of modern British English
  - compiled mainly for lexicographic purposes: Brown-type corpora (such as LOB) are too small
  - both written (90%) and spoken (10%) English
  - XML edition (version 3) published in 2007
- ◆ 4048 samples from 25 to 428,300 words
  - 13 documents < 100 words, 51 > 100,000 words
  - some documents are collections (e.g. e-mail messages)
  - rich metadata available for each document

#### Problem 5: Non-randomness







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#### Unit of sampling

- ♦ Key problem: unit of sampling (text or fragment) ≠ unit of measurement (e.g. VP)
  - recall sampling procedure in library metaphor ...

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#### Pooling data

- ◆ In order to obtain larger samples, researchers usually **pool** all data from a corpus
  - i.e. they include all VPs from each book
- ◆ Do you see why this is wrong?

#### Unit of sampling

- ◆ Random sampling in the library metaphor
  - walk to a random shelf ... ... pick a random book ...
    - ... open a random page ...
    - ... and choose a random VP from the page
- ◆ A corpus is a random sample of books, not VPs!
  - we should only pick 1 VP from each document
  - sample size: n = 500 (Brown) or n = 4048 (BNC)

#### Pooling data

- ♦ Books aren't random samples themselves
  - each book contains relatively homogeneous material
  - much larger differences between books
- ◆ Therefore, pooled data isn't a random sample from the library
  - for each randomly selected VP, we co-select a substantial amount of very similar material
- ◆ Consequence: sampling variation increased

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#### Pooling data

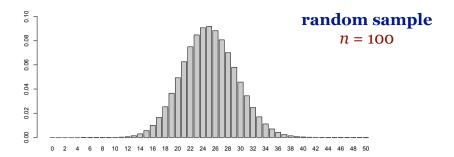
- ◆ Let us illustrate this with a simple example ...
  - assume library with two sections of equal size
  - population proportions are 10% vs. 40%
     → overall proportion of 25% in the library
- ◆ Compare sampling variation for
  - random sample of 100 tokens from the library
  - two randomly selected books of 50 tokens each
    - book is assumed to be a random sample from its section

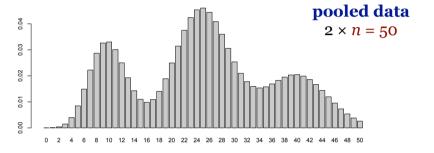
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## Problem 5A: Duplicates

- ◆ Duplicates = extreme form of non-randomness
  - Did you know the British National Corpus contains duplicates of entire texts (under different names)?
- ◆ Duplicates can appear at any level
  - The use of keys to move between fields is fully described in Section 2 and summarised in Appendix A
  - 117 (!) occurrences in BNC, all in file HWX
  - very difficult to detect automatically
- ◆ Even worse for newspapers & Web corpora
  - see Evert (2004) for examples





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## Problem 5B: (Lexical) specialisation

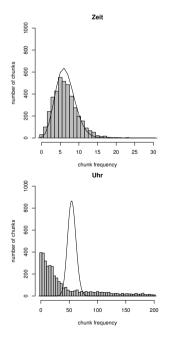
- ◆ Illustrated by data pooling example
  - true population proportions usually different in distinct sections of the library (e.g. spoken vs. written English, different genres, registers, domains, ...)
  - if you pick just a few books, it is likely that some sections will be seriously over-represented
- ◆ Specialisation increases sampling variation
  - even if each book is a random sample from its section!

# Problem 5B: Lexical specialisation

- ◆ Particularly serious (and well-known) problem for lexical phenomena (words, collocations, ...)
- ◆ Specialisation wrt. domain and topic
  - a book about a football team will use an entirely different vocabulary than a statistics textbook or a romantic novel
  - usually not enough meta-information about topics available to split corpus into homogeneous sections
- ◆ See e.g. Baayen (1996)

# number of churks. Samuel of thurks and the samuel of thurks. Samuel

chunk frequency



Data from Frankfurter Rundschau corpus, divided into 10,000 equally-sized chunks

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#### Problem 5C: Term clustering

- ◆ If a "content" word occurs once in a document, it is very likely to occur again
  - The chance of two Noriegas is closer to p/2 than p<sup>2</sup> (Church 2000; also Church & Gale 1995, Katz 1996)
  - i.e. documents are *not* random samples
- ◆ Two complementary effects:
  - specialisation = non-randomness <u>between</u> documents
  - term clustering = non-randomness within documents



#### Cave canem!

- ◆ Treat statistical methods based on random sampling assumptions with great caution!
  - doesn't mean statistical analysis should be discarded
  - random variation is a lower bound on true variability
- Can still be useful for the analysis of corpus data, but may also give very misleading answers
- ♦ Always look at your data!
  - R helps you to know & understand what you're doing (unlike online wizards and many commercial tools)

### Thank you for following this course!

Stefan & Marco

#### Alternative (better?) methods

- ◆ Empirical approach → t-test & ANOVA
  - based on relative frequencies in documents
- Explaining variation with linear models
- ◆ Generalised linear models
  - binomial/Poisson family for low-frequency data
  - negative binomial family to account for term clustering (= Poisson mixtures, Church & Gale 1995)

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