Statistics for Linguists with R – a SIGIL course

Unit 8: Non-Randomness of Corpus Data & Generalised Linear Models

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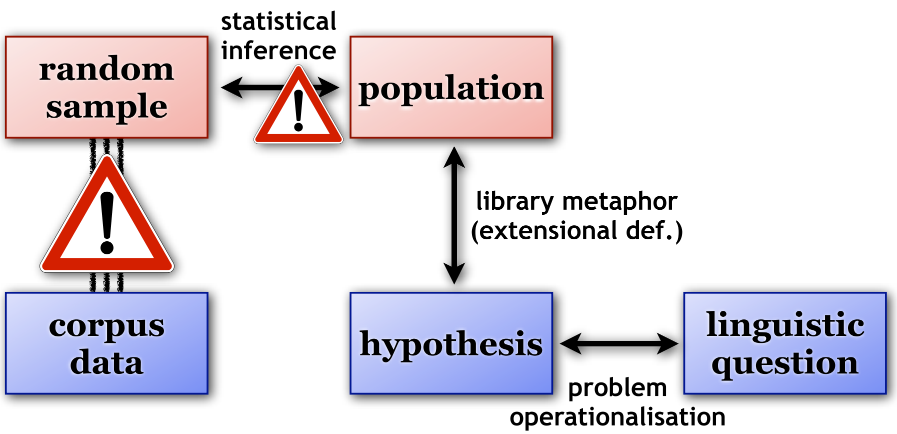
Introduction & Reminder

Problems with statistical inference



Mathematical problems: Significance

- 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^2 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

Mathematical problems: Effect size

- 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^2, …
- Confidence interval estimation
  - accurate & efficient estimation of confidence intervals for effect size is often very difficult
  - exact confidence intervals only available for odds ratio

Mathematical problems: 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

Mathematical problems: Multiple hypothesis tests

- Typical situation e.g. for collocation extraction
  - test whether word pair co-occurs 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. Unit 5 on word frequency distributions with *zipfR*

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Why a corpus isn't a random sample

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 10 million VPs for a BNC-sized sample at random
  - other studies will need tokens of different granularity (words, word pairs, sentences, even full texts)

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)
  - manually entered on punch cards

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

Unit of sampling

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

Unit of sampling

- Random sampling in the library metaphor
  - walk to a random shelf …
    … select a random book …
    … open it on a random page …
    … and pick a random sentence from the page
  - ➡ repeat n times for sample size n
- Corpus = random sample of books, not sentences!
  - we should only use 1 sentence from each book
  - ➡ sample size: n=500 (Brown) or n=4048 (BNC)

Pooling data

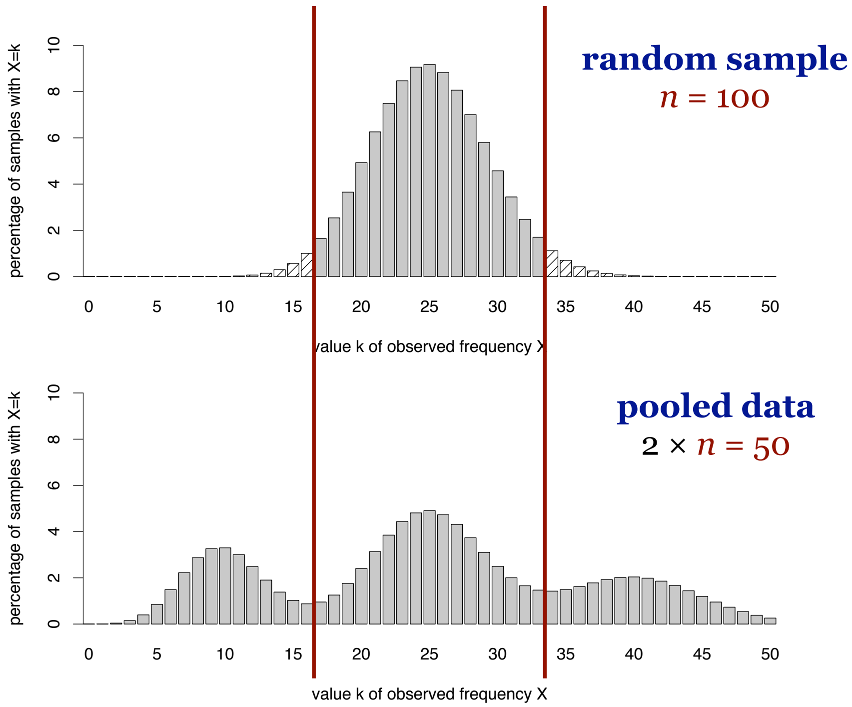
- In order to obtain larger samples, researchers usually **pool** all data from a corpus
  - i.e. they include all sentences from each book
- Do you see why this is wrong?

Pooling data

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

Pooling data

- Let us illustrate this with a simple example …
  - assume library with two sections of equal size
    - e.g. spoken and written language in a corpus
  - population proportions are 10% vs. 40%
    → overall proportion of π = 25% in the library
    - this is the null hypothesis H_0 that we will be testing
- 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



Duplicates

- Duplication = 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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Measuring non-randomness

A sample of random samples is a random sample

- Larger unit of sampling is not the original cause of non-randomness
  - if each text in a corpus is a genuinely random sample from the same population, then the pooled data also form a random sample
  - we can illustrate this with a thought experiment

The random library

- Suppose there's a vandal in the library
  - who cuts up all books into single sentences and leaves them in a big heap on the floor
  - the next morning, the librarian takes a handful of sentences from the heap, fills them into a book-sized box, and puts the box on one of the shelves
  - repeat until the heap of sentences is gone
  - ➡ library of random samples
- Pooled data from 2 (or more) boxes form a perfectly random sample of sentences from the original library!

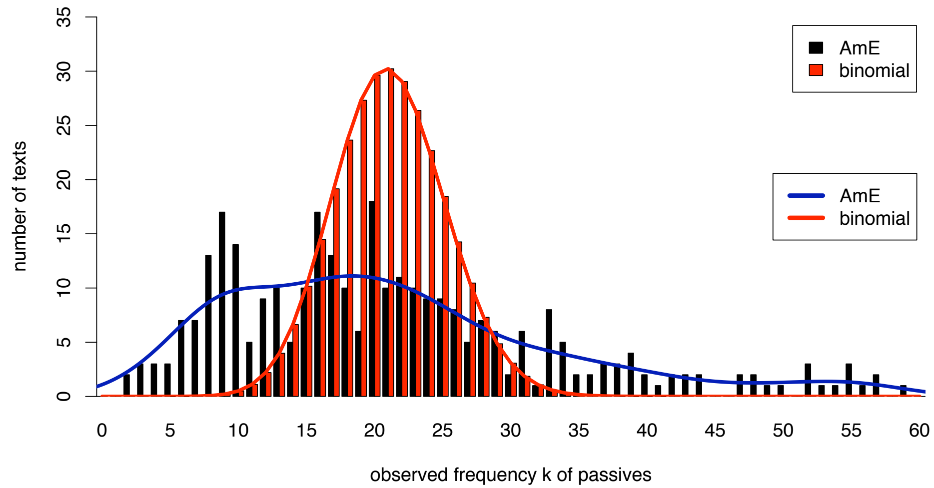
A sample of random samples is a random sample

- The true cause of non-randomness
  - discrepancy between unit of sampling and unit of measurement only leads to non-randomness if the sampling units (i.e. the corpus texts) are not random samples themselves (from same population)
  - with respect to specific phenomenon of interest
- No we know how to measure non-randomness
  - find out if corpus texts are random samples
  - i.e., if they follow a binomial sampling distribution
  - ➡ tabulate observed frequencies across corpus texts

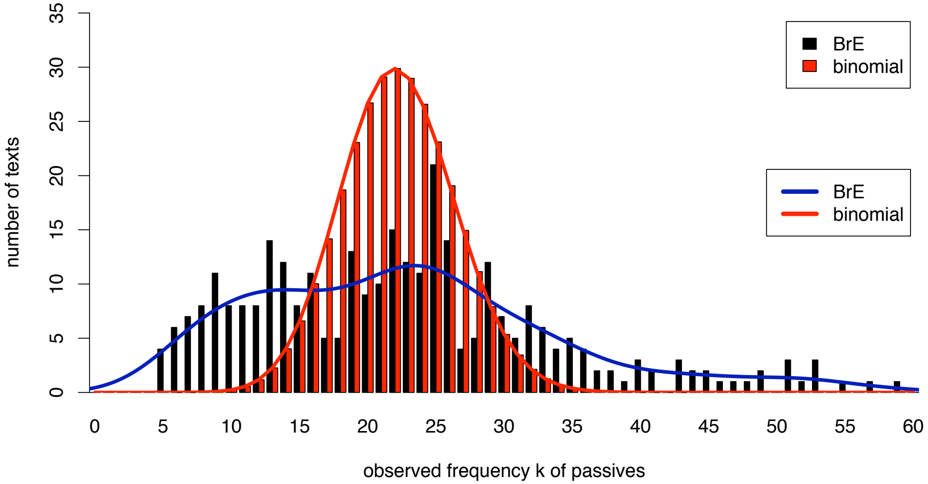
Measuring non-randomness

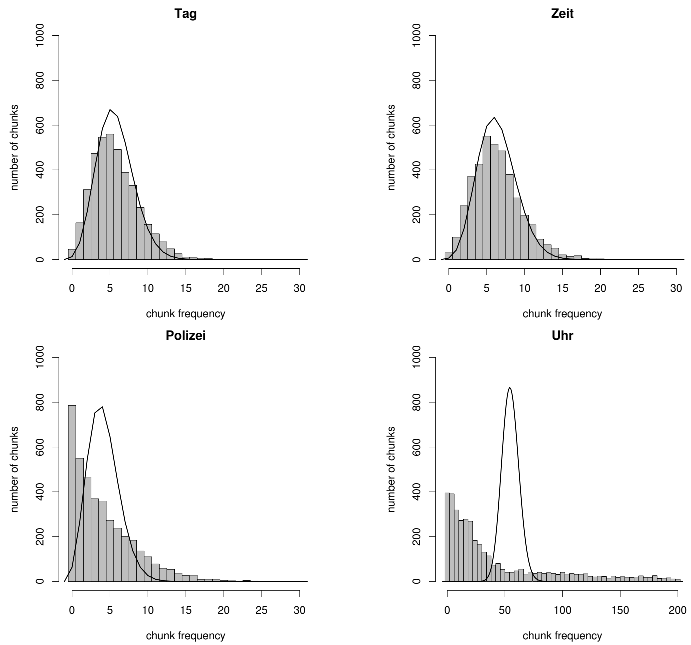
- Tabulate number of texts with *k* passives
  - illustrated for subsets of Brown/LOB (310 texts each)
  - meaningful because all texts have the same length
- Compare with binomial distribution
  - for population proportion $H_0 : \pi = 21.1\%$ (Brown) and $\pi = 22.2\%$ (LOB); approx. $n = 100$ sentences per text
  - estimated from full corpus → best possible fit
- Non-randomness → larger sampling variation

Passives in the Brown corpus



Passives in the LOB corpus





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

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Consequences

Consequences of non-randomness

- Accept that corpus is a **sample of texts**
  - data cannot be pooled into random sample of tokens
  - results in much smaller sample size ... (BNC: 4,048 texts rather than 6,023,627 sentences)
  - ... but more informative measurements (relative frequencies on interval rather than nominal scale)
- Use statistical techniques that account for the **overdispersion** of relative frequencies
  - Gaussian distribution allows us to estimate **spread** (variance) independently from **location**
  - Standard technique: **Student's t-test**

A case study: Passives in AmE and BrE

- Are there more passives in BrE than in AmE?
  - based on data from subsets of Brown and LOB
    - 9 categories: press reports, editorials, skills & hobbies, misc., learned, fiction, science fiction, adventure, romance
    - ca. 310 texts / 31,000 sentences / 720,000 words each
- Pooled data (random sample of sentences)
  - AmE: 6584 out of 31,173 sentences = 21.1%
  - BrE: 7091 out of 31,887 sentences = 22.2%
- Chi-squared test (→ pooled data, binomial) vs. t-test (→ sample of texts, Gaussian)

Let's do that in R …

```
# passive counts for each text in Brown and LOB corpus
> Passives <- read.delim("passives_by_text.tbl")

# display 10 random rows to get an idea of the table layout
> Passives[sample(nrow(Passives), 10), ]

# add relative frequency of passives in each file (as percentage)
> Passives <- transform(Passives,
    relfreq = 100 * passive / n_s)

# split into separate data frames for Brown and LOB texts
> Brown <- subset(Passives, lang=="AmE")
> LOB <- subset(Passives, lang=="BrE")
```


A case study: Passives in AmE and BrE

- Chi-squared test: **highly significant**
  - p-value: .00069 < .001
  - confidence interval for difference: 0.5% – 1.8%
  - large sample → large amount of evidence
- R code: pooled counts + proportions test

```
> passives.B <- sum(Brown$passive)
> n_s.B <- sum(Brown$n_s)
> passives.L <- sum(LOB$passive)
> n_s.L <- sum(LOB$n_s)

> prop.test(c(passives.L, passives.B),
            c(n_s.L, n_s.B))
```


A case study: Passives in AmE and BrE

- t-test: **not significant**
  - p-value: .1340 > .05 (t=1.50, df=619.96)
  - confidence interval for difference: -0.6% – +4.9%
  - H_0: same average relative frequency in AmE and BrE
- R code: apply `t.test()` function

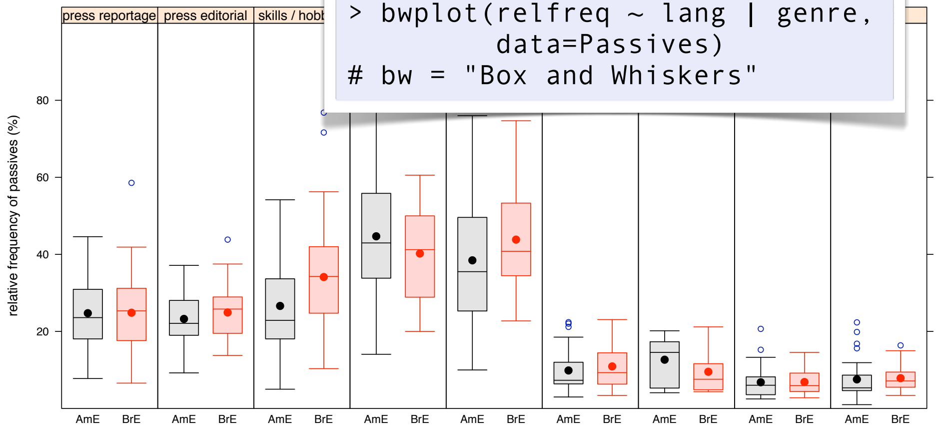
```
> t.test(LOB$relfreq, Brown$relfreq)

# alternative syntax: "formula" interface
> t.test(relfreq ~ lang, data=Passives)
```

What are we really testing?

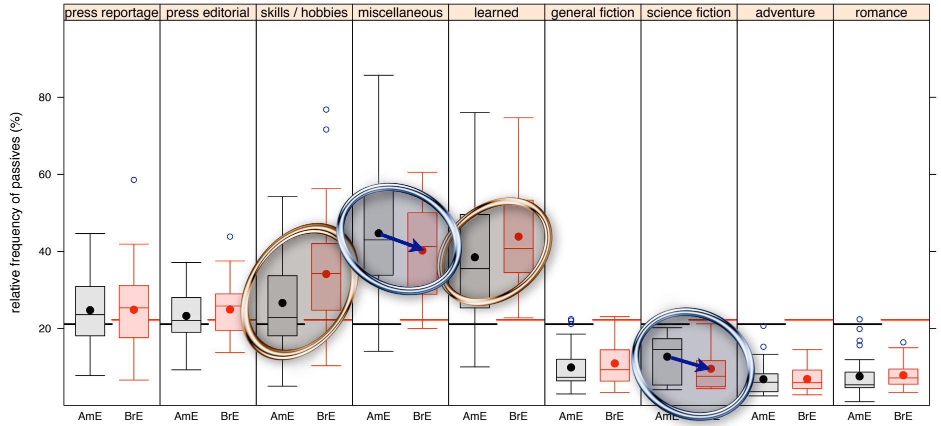
- Are population proportions meaningful?
  - corpus should be balanced and representative (broad coverage of genres, … in appropriate proportions)
  - average frequency depends on composition of corpus
  - e.g. 18% passives in written BrE / 4% in spoken BrE
- How many passives are there in English?
  - 50% written / 50% spoken: $\pi =$ 13.0%
  - 90% written / 10% spoken: $\pi =$ 16.6%
  - 20% written / 80% spoken: $\pi =$ 6.8%

Average relative frequency?

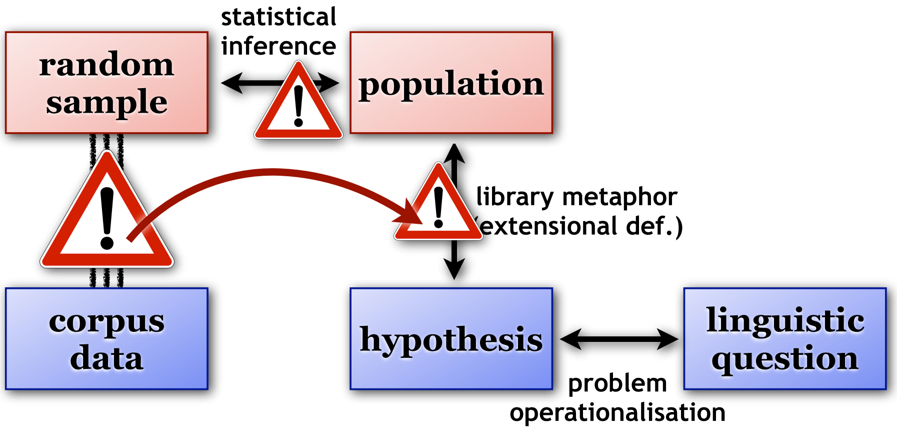



```
> library(lattice)
> bwplot(relfreq ~ lang | genre,
         data=Passives)
# bw = "Box and Whiskers"
```


Average relative frequency?



Problems with statistical inference



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Rethinking corpus frequencies

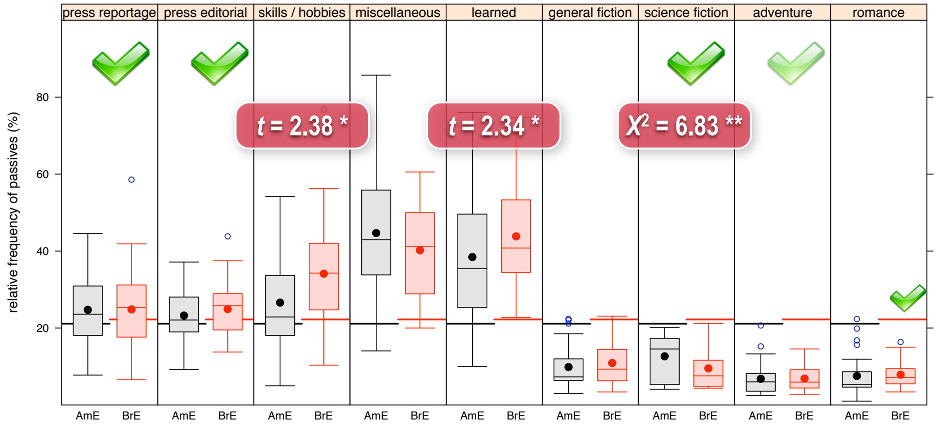
Studying variation in language

- It seems absurd now to measure & compare relative frequencies in "language" (= library)
  - proportion π depends more on composition of library than on properties of the language itself
- Quantitative corpus analysis has to account for the variation of relative frequencies between individual texts (cf. Gries 2006)
  - research question → one factor behind this variation

Studying variation in language

- Approach 1: restrict study to sublanguage in order to eliminate non-randomness
  - data from this sublanguage (= single section in library) can be pooled into large random sample
- Approach 2: goal of quantitative corpus analysis is to explain variation between texts in terms of
  - random sampling (of tokens within text)
  - stylistic variation: genre, author, domain, register, …
  - subject matter of text → term clustering effects
  - differences between language varieties ← **research question**

Eliminating non-randomness



Explaining variation

- Statisticians explain variation with the help of **linear models** (and other statistical models)
  - linear models predict response ("dependent variable") from one or more factors ("independent variables")
  - simplest model: linear combination of factors
- Linear model for passives in AmE and BrE:

overall average "intercept"

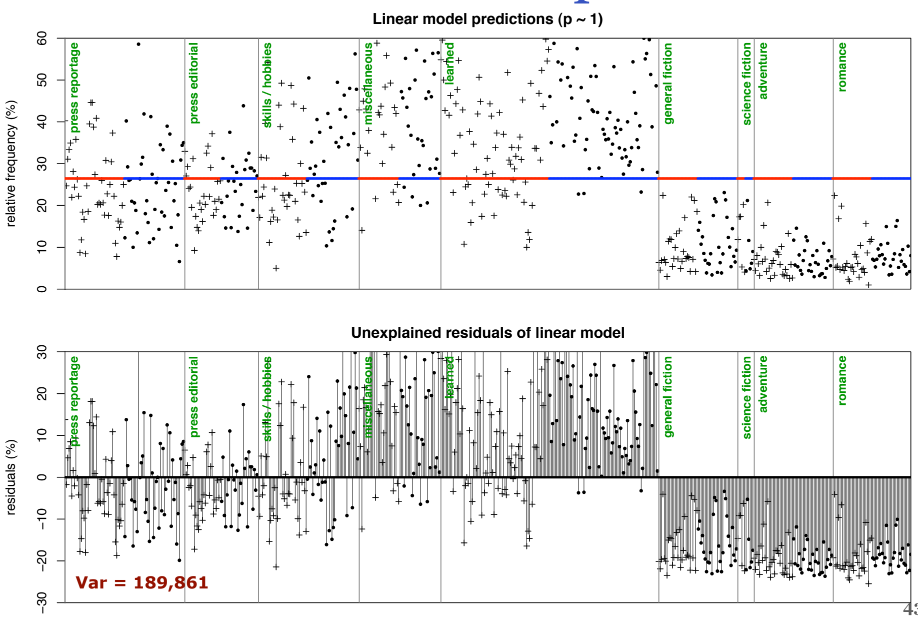
unexplained "residuals" + sampling variation

$$p_i = \beta_0 + \beta_1(\text{genre}) + \beta_2(\text{AmE/BrE}) + \epsilon_i$$

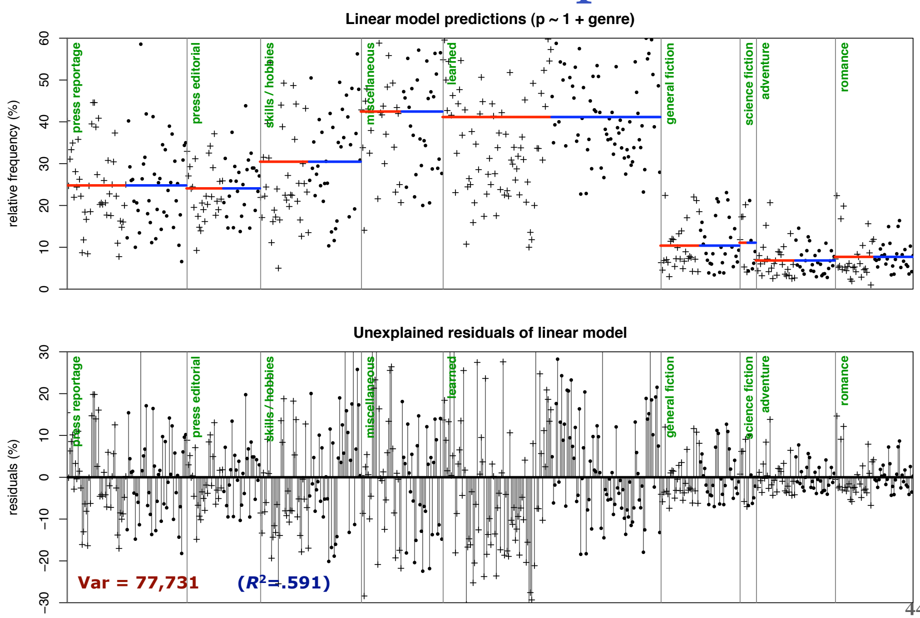
relative frequency in text i

I'm just an ANOVA …

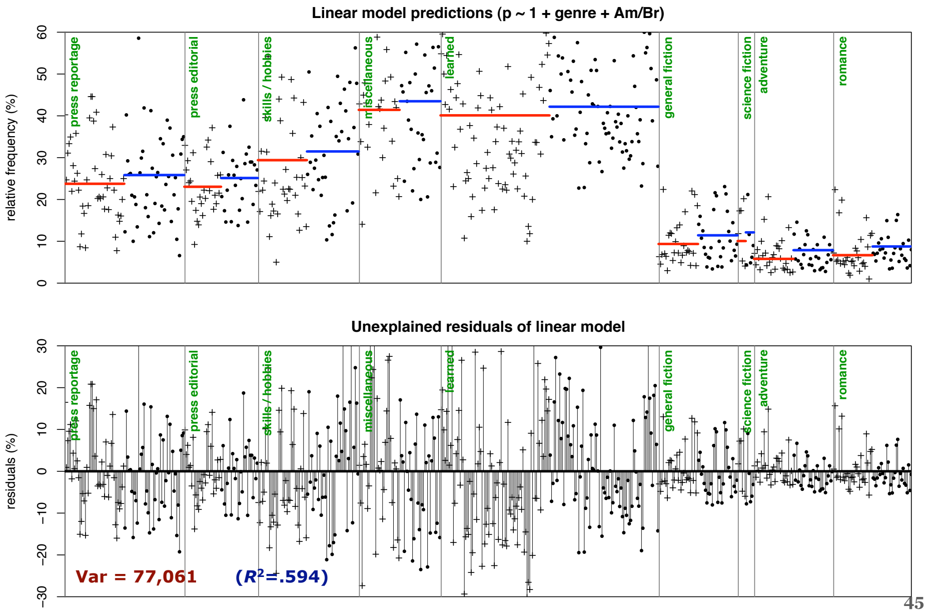
Linear model for passives



Linear model for passives



Linear model for passives



Linear model for passives

- Goodness-of-fit (analysis of variance)
  - total variance (sum of squares): 189,861
  - explained by genre***: 112,113 (= 59.0%)
  - explained by AmE/BrE*: 687 (= 0.4%)
  - unexplained (residuals): 77,061 (= 40.6%)
- Is variance explained well enough?
  - binomial sampling variation: ca. 10,200 (= 5.4%)

Linear models in R

```
# linear model "formula": response ~ explanatory factors
# (here, only main effects without genre/language interaction)
> LM <- lm(relfreq ~ genre + lang, data=Passives)

# analysis of variance shows which factors are significant
> anova(LM)      # see ?anova.lm for details

# individual coefficients + standard errors
> summary(LM)
> confint(LM)    # corresponding confidence intervals

# interaction term improves model fit, but is not quite significant
> LM <- lm(relfreq ~ genre + lang + genre:lang,
           data=Passives)
> anova(LM)
```


Linear model for passives

- F-tests show significant effects of genre ($p < 10^{-15}$) and AmE / BrE ($p = .0198$)
- 95% confidence intervals for effect sizes:
  - AmE / BrE: 0.3% … 3.8%
  - genre = learned 13.4% … 19.3%
    - compared to "press reportage" genre as baseline
  - genre = romance −20.8% … −13.4%
  - genre = …

Linear models in R

```
# more intuitive than coefficients: model predictions for each
# genre and language variety; based on "dummy" data frame with
# all possible genre/language combinations (ordered by genre)
> Predictions <- unique(
    Passives[, c("genre", "lang")])
> Predictions <- Predictions[
    order(Predictions$genre, Predictions$lang), ]

# predicted average relative frequency of passives in each category
> transform(Predictions,
    predicted=predict(LM, newdata=Predictions))

# confidence and prediction intervals
> cbind(Predictions, predict(LM,
    newdata=Predictions, interval="confidence"))
> cbind(Predictions, predict(LM,
    newdata=Predictions, interval="prediction"))
```



```
> par(mfrow=c(2,2))
> plot(LM)
> par(mfrow=c(1,1))
```

Linear models are not appropriate!

Why linear models are not appropriate for frequency data

- Binomial sampling variation not accounted for
- Normality assumption (error terms)
  - Gaussian approximation inaccurate for low-frequency data (with non-zero probability for negative counts!)
- Homoscedasticity (equal variances of errors)
  - variance of binomial sampling variation depends on population proportion and sample size
  - different sample sizes (texts in Brown/LOB: 40 – 250 sentences; huge differences in BNC)
- Predictions not restricted to range 0% – 100%

Generalised linear models

- **Generalised linear models** (**GLM**)
  - account for binomial sampling variation of observed frequencies and different sample sizes
  - allow non-linear relationship between explanatory factors and predicted relative frequency (π_i)

$$f_i \sim B(n_i, \pi_i)$$ binomial sampling ("family")

$$\pi_i = \frac{1}{1 + e^{-\theta_i}}$$ "link" function

linear predictor $$\theta_i = \beta_0 + \beta_1(\text{genre}) + \beta_2(\text{AmE/BrE})$$

GLM for passives

- Goodness-of-fit (analysis of deviance)
  - total deviance ("unlikelihood"): 13,265
  - explained by genre***: 8,275 (= 62.4%)
  - explained by AmE/BrE***: 36 (= 0.3%)
  - unexplained (residual deviance): 4,953 (= 37.3%)
  - binomial sampling variation: ≈ 1,000 (= 7.5%)
- Interpretation of confidence intervals difficult

GLM in R

(note the extra options needed!)

```
# for GLM with binomial family, responses are paris of
# passive / active counts (fk, nk−fk) = "successes" / "failures"
> response.matrix <- cbind(Passives$passive,
    Passives$n_s - Passives$passive)

# genre * lang is shorthand for main effects + all interactions
> GLM <- glm(response.matrix ~ genre * lang,
             family="binomial", data=Passives)

# individual coefficients + standard errors
> anova(GLM, test="Chisq")  # interaction significant now

> summary(GLM)  # even more difficult to interpret than for LM
> confint(GLM)

# diagnostics plot ( ; separate multiple commands in single line)
> par(mfrow=c(2,2)); plot(GLM); par(mfrow=c(1,1))
```

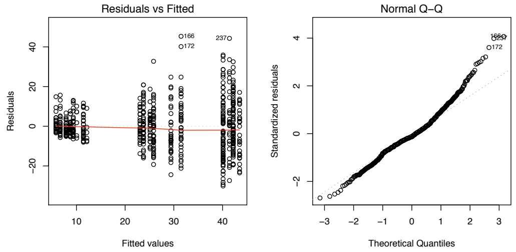

GLM in R

(note the extra options needed!)

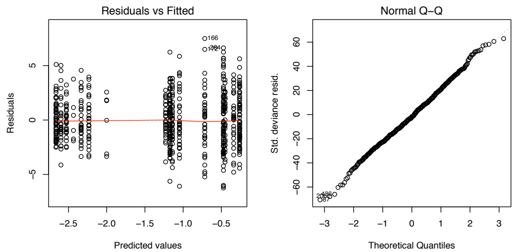
```
# predictions for each genre and language variety
> transform(Predictions, predicted = 100 *
    predict(GLM, type="response",
    newdata=Predictions))

# calculate confidence intervals from standard errors
> res <- predict(GLM, type="response",
                 newdata=Predictions, se.fit=TRUE)
> transform(Predictions,
            predicted=100*res$fit,
            lwr=100*(res$fit - 1.96*res$se.fit),
            upr=100*(res$fit + 1.96*res$se.fit))

# we can't compute prediction intervals for new texts — why?
```


Model diagnostics comparison

Linear Model



Generalised Linear Model



Still no satisfactory explanation for observed variation in frequency of passives between texts!

Take-home messages

- Don't trust statistic(ian)s blindly
  - You know how complex language really is!
  - linguists and statisticians should work together
- No excuse to avoid significance testing
  - good reasons to believe that binomial sampling distribution is a lower bound on variation in language
- Needed: large corpora with rich metadata
  - study & "explain" variation with statistical models
  - full data need to be available (not Web interfaces!)

References (1)

- Agresti, Alan (2002). *Categorical Data Analysis.* John Wiley & Sons, Hoboken, 2nd edition.
- Baayen, R. Harald (1996). The effect of lexical specialization on the growth curve of the vocabulary. *Computational Linguistics*, **22**(4), 455–480.
- Baroni, Marco and Evert, Stefan (2008). Statistical methods for corpus exploitation. In A. Lüdeling and M. Kytö (eds.), *Corpus Linguistics. An International Handbook*, chapter 38. Mouton de Gruyter, Berlin.
- Church, Kenneth W. (2000). Empirical estimates of adaptation: The chance of two Noriegas is closer to $p/2$ than p^2. In *Proceedings of COLING 2000*, pages 173–179, Saarbrücken, Germany.
- Church, Kenneth W. and Gale, William A. (1995). Poisson mixtures. *Journal of Natural Language Engineering*, **1**, 163–190.
- Dunning, Ted E. (1993). Accurate methods for the statistics of surprise and coincidence. *Computational Linguistics*, **19**(1), 61–74.

References (2)

- Evert, Stefan (2004). *The Statistics of Word Cooccurrences: Word Pairs and Collocations.* Dissertation, Institut für maschinelle Sprachverarbeitung, University of Stuttgart. Published in 2005, URN urn:nbn:de:bsz:93-opus-23714.
- Evert, Stefan (2006). How random is a corpus? The library metaphor. *Zeitschrift für Anglistik und Amerikanistik*, **54**(2), 177–190.
- Gries, Stefan Th. (2006). Exploring variability within and between corpora: some methodological considerations. *Corpora*, **1**(2), 109–151.
- Gries, Stefan Th. (2008). Dispersions and adjusted frequencies in corpora. *International Journal of Corpus Linguistics*, **13**(4), 403–437.
- Ioannidis, John P. A. (2005). Why most published research findings are false. *PLoS Medicine*, **2**(8), 696–701.

References (3)

- Katz, Slava M. (1996). Distribution of content words and phrases in text and language modelling. *Natural Language Engineering*, **2**(2), 15–59.
- Kilgarriff, Adam (2005). Language is never, ever, ever, random. *Corpus Linguistics and Linguistic Theory*, **1**(2), 263–276.
- Rayson, Paul; Berridge, Damon; Francis, Brian (2004). Extending the Cochran rule for the comparison of word frequencies between corpora. In *Proceedings of the 7èmes Journées Internationales d'Analyse Statistique des Données Textuelles* (JADT 2004), pages 926–936, Louvain-la-Neuve, Belgium.
- McEnery, Tony and Wilson, Andrew (2001). *Corpus Linguistics*. Edinburgh University Press, 2nd edition.
- Rietveld, Toni; van Hout, Roeland; Ernestus, Mirjam (2004). Pitfalls in corpus research. *Computers and the Humanities*, **38**, 343–362.