Statistics for Linguists with R – a SIGIL course

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

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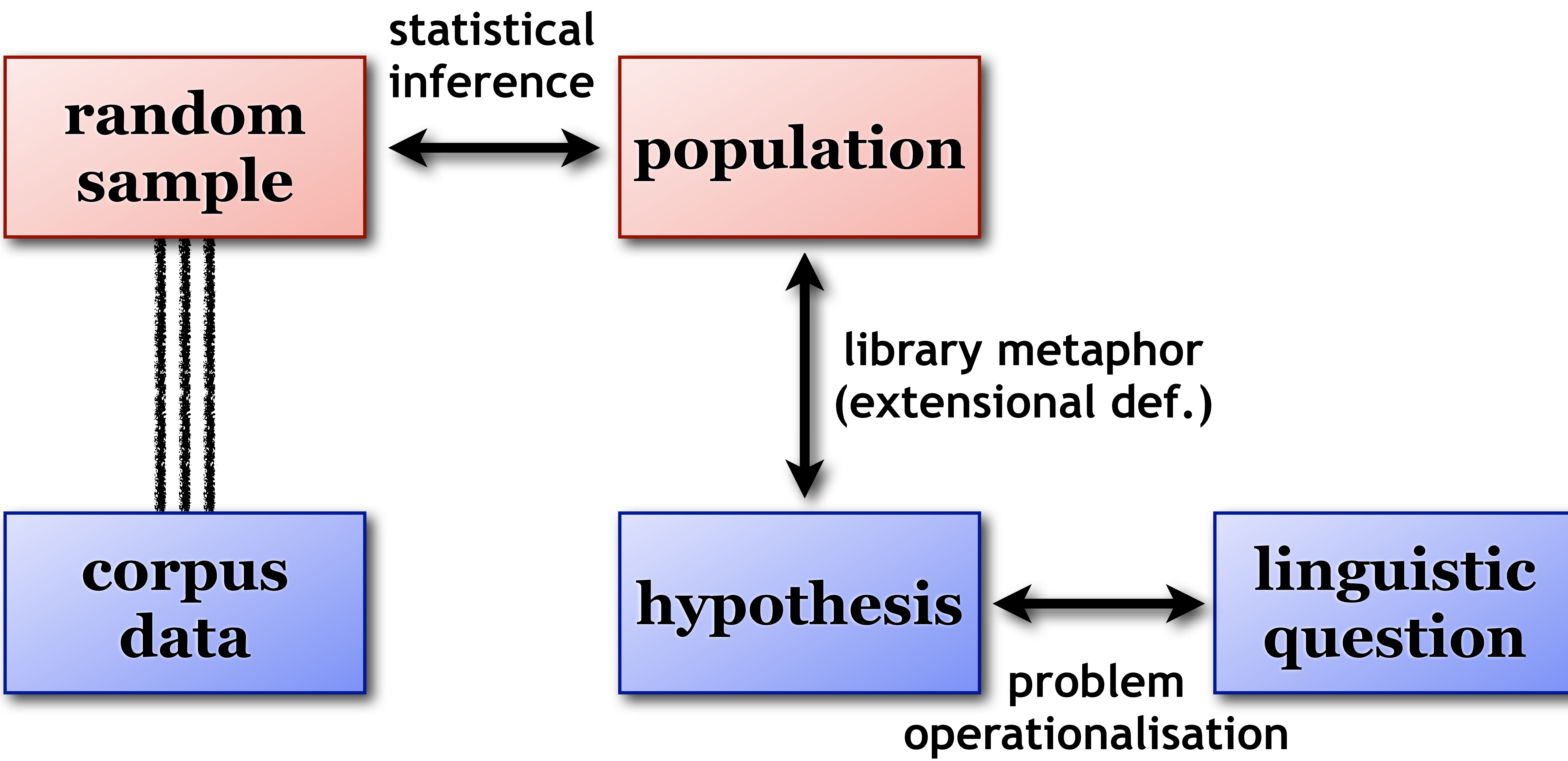
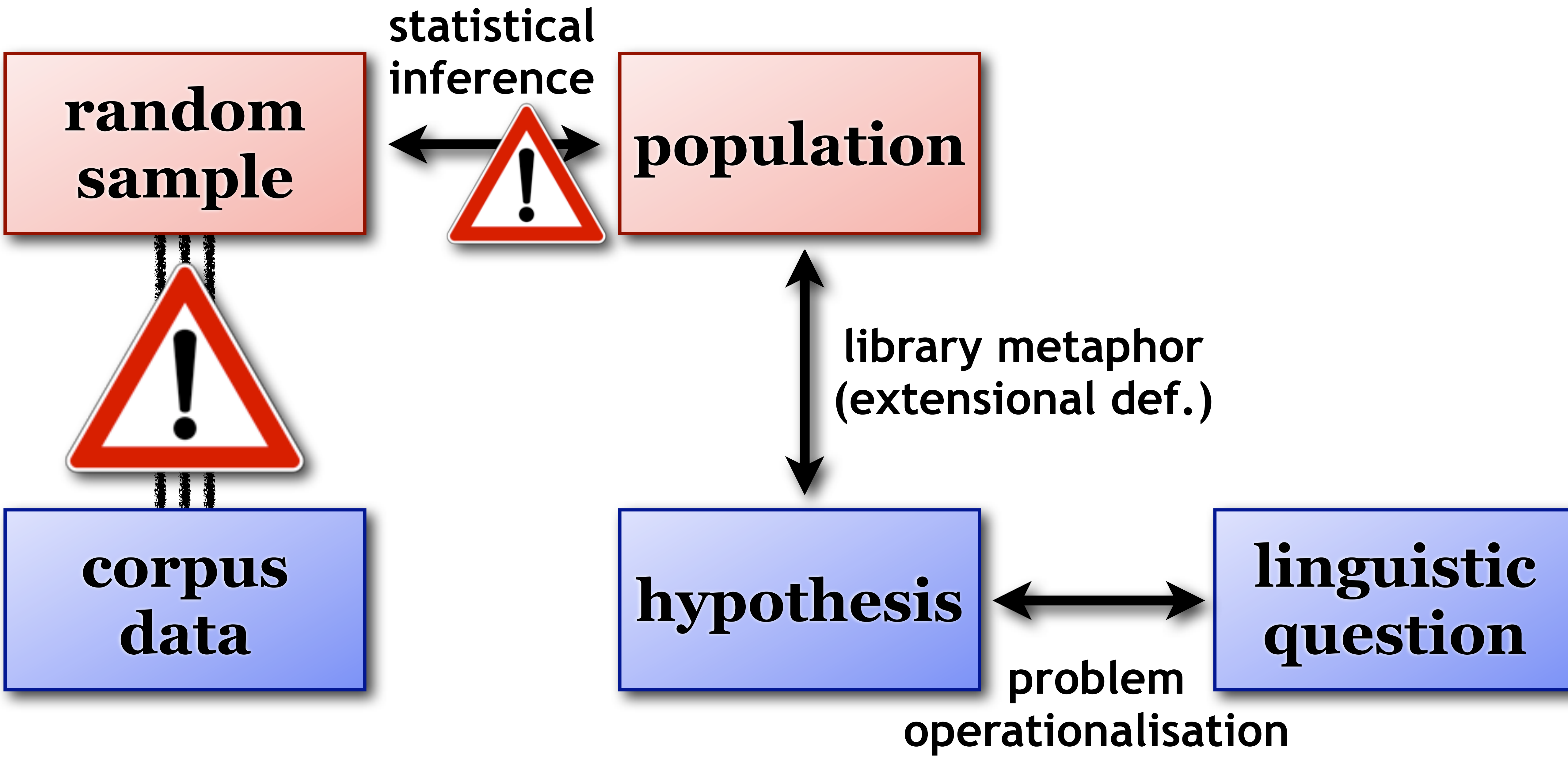
1

Introduction & Reminder

Problems with statistical inference



Problems with statistical inference



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    - e.g. manual samples of 100–500 items (as in our examples)
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    - 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

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  - e.g. **difference** of proportions, **relative risk** (ratio of proportions), **odds ratio**, logarithmic odds ratio, normalised X^2, …

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  - 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 $\boldsymbol{X^2}$, …
- 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

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  - 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*

Why a corpus isn’t a random sample

Corpora

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- 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 …

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- 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

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

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 $\pi = 25\%$ in the library
    - this is the null hypothesis H_0 that we will be testing

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    → overall proportion of $\pi = 25\%$ in the library
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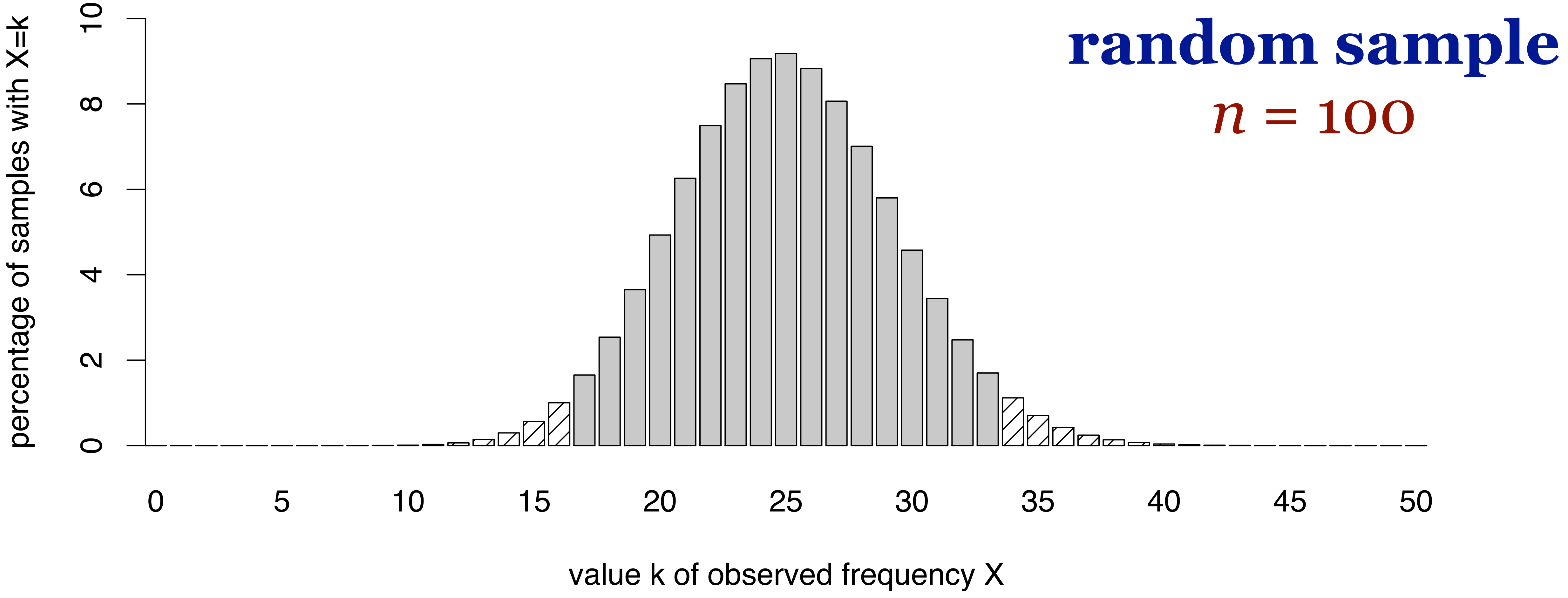
- Compare sampling variation for
  - random sample of 100 tokens from the library
  - two randomly selected books of 50 tokens each
    - book is assumed to be a random sample from its section


random sample
$n = 100$
percentage of samples with X=k
0
2
4
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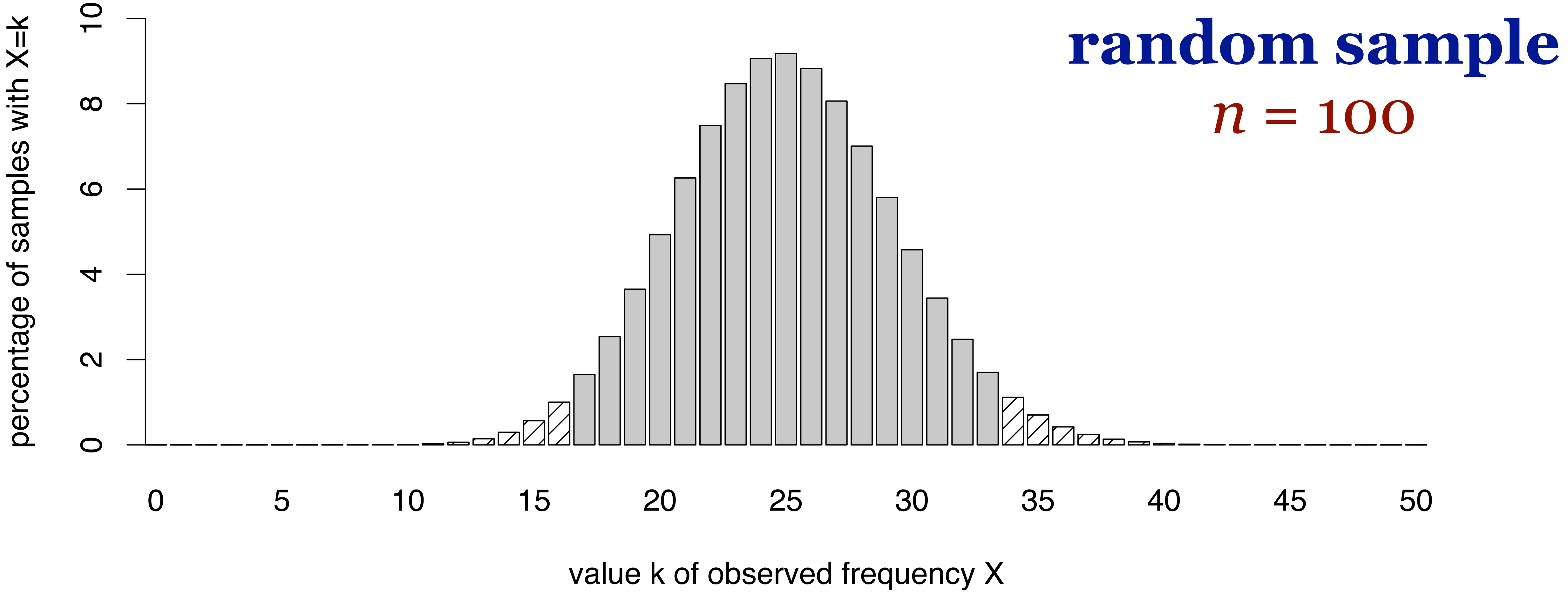
0 5 10 15 20 25 30 35 40 45 50
value k of observed frequency X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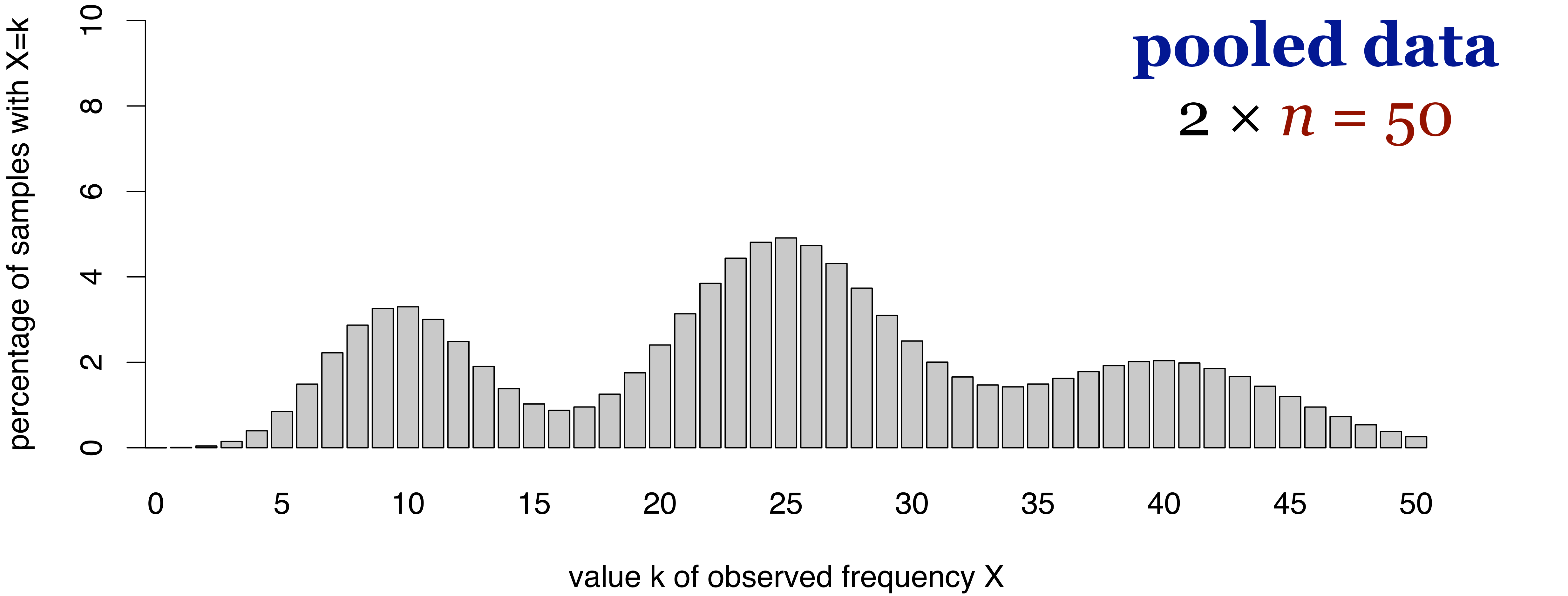
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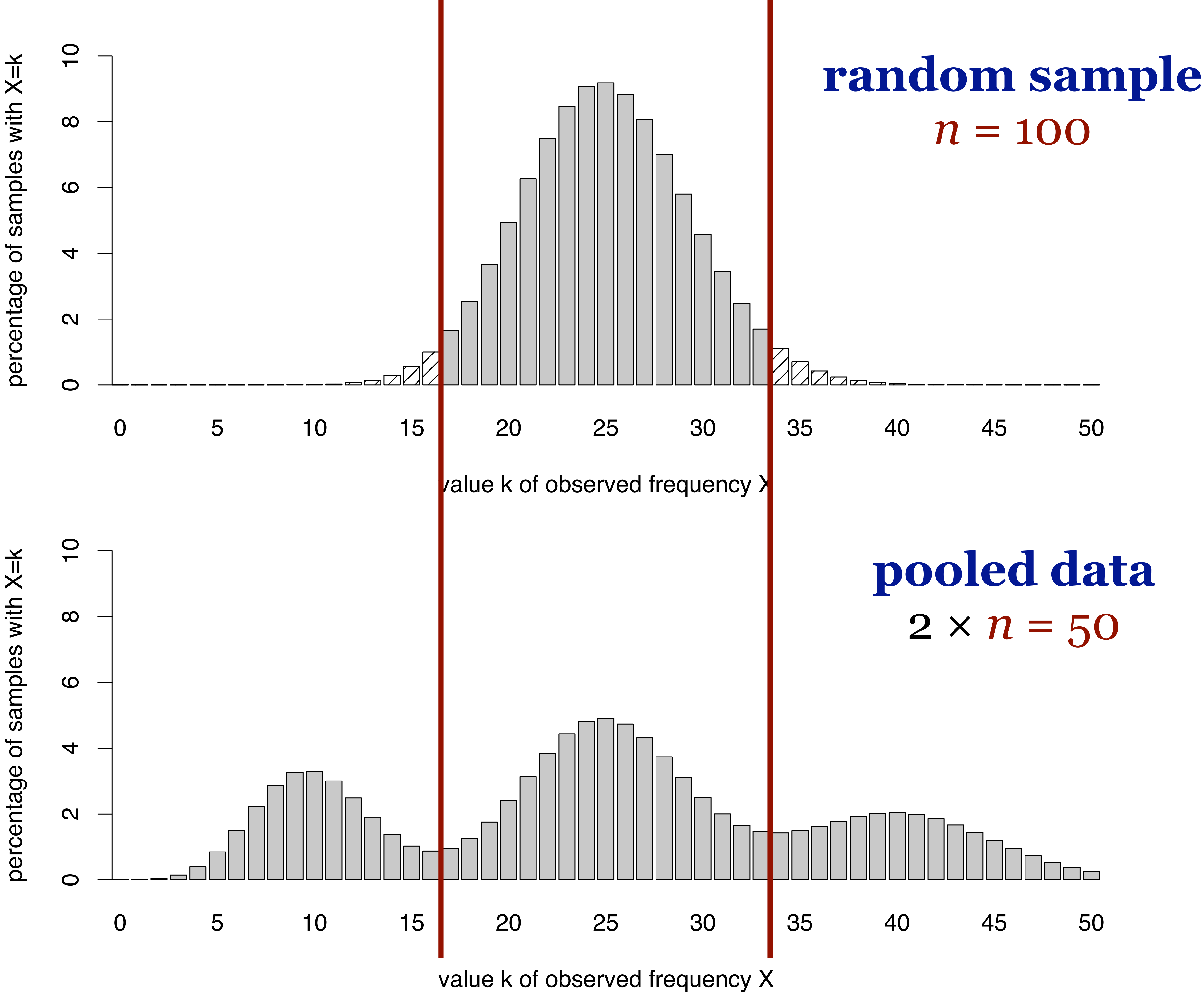
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  - 117 (!) occurrences in BNC, all in file HWX
  - very difficult to detect automatically
- Even worse for newspapers & Web corpora
  - see Evert (2004) for examples

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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

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  - repeat until the heap of sentences is gone
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- Pooled data from 2 (or more) boxes form a perfectly random sample of sentences from the original library!

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  - with respect to specific phenomenon of interest

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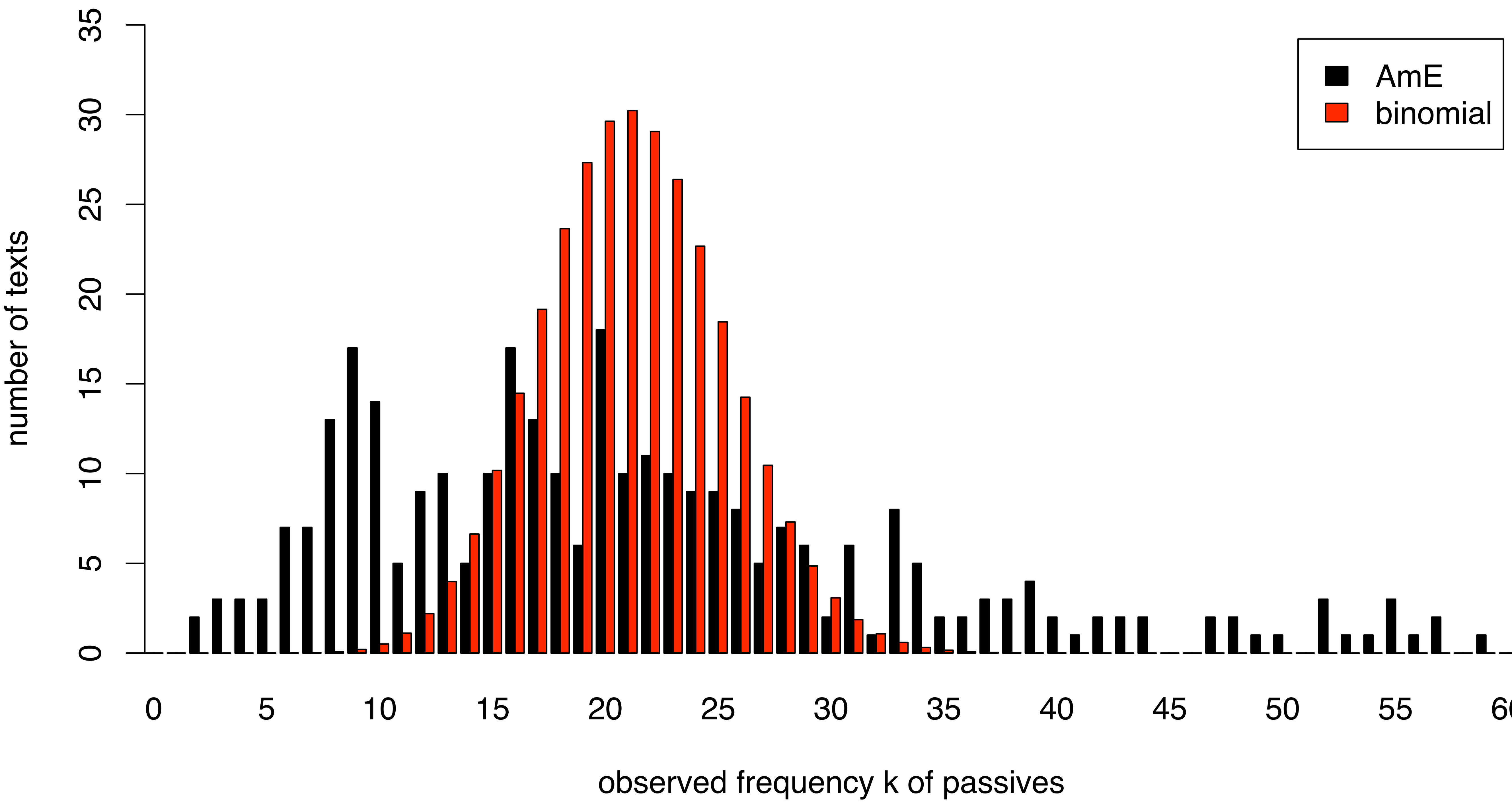
  - with respect to specific phenomenon of interest
- No we know how to measure non-randomness
  - find out if corpus texts are random samples
  - i.e., if they follow a binomial sampling distribution
  - ➡ tabulate observed frequencies across corpus texts

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



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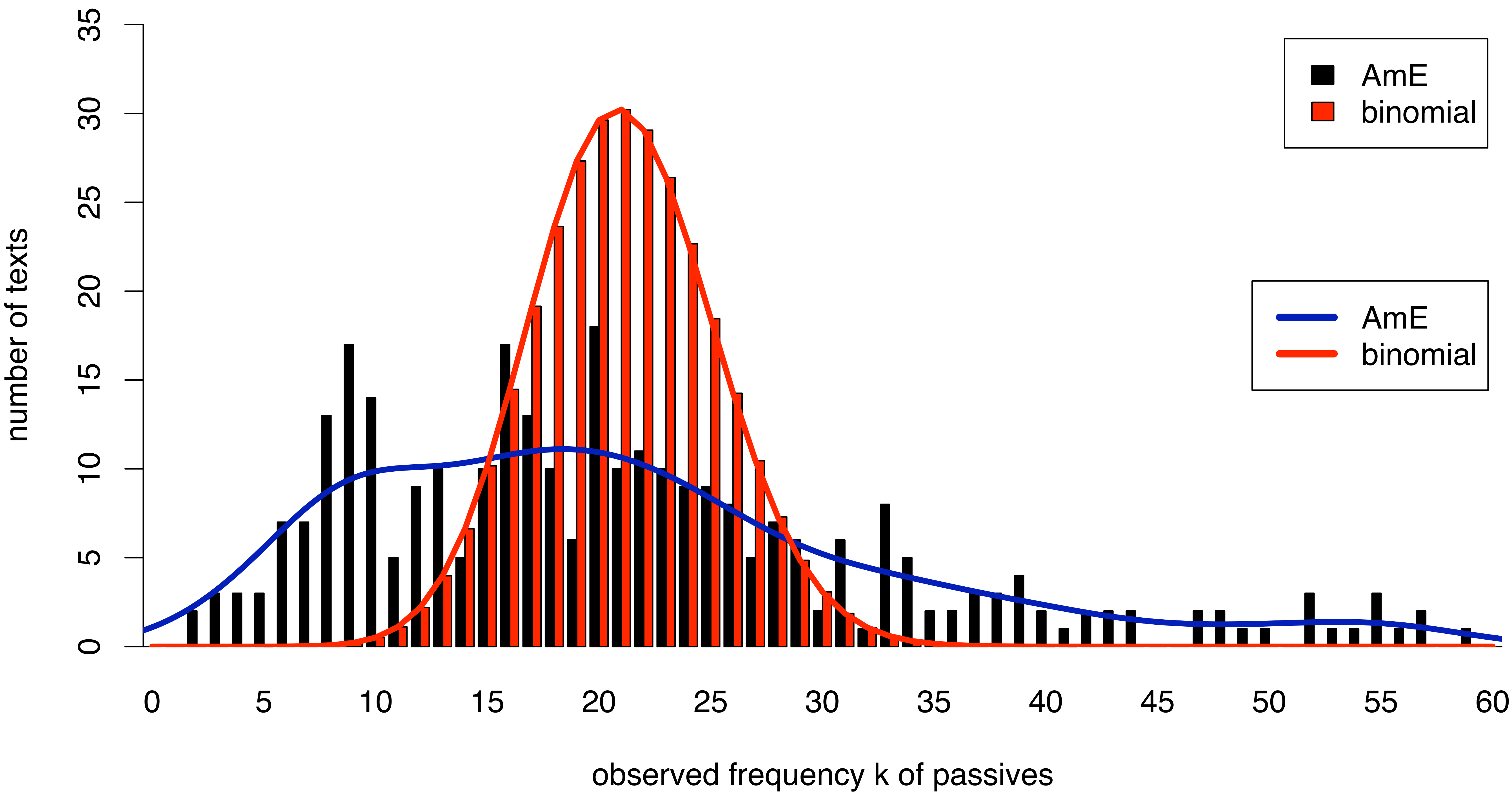
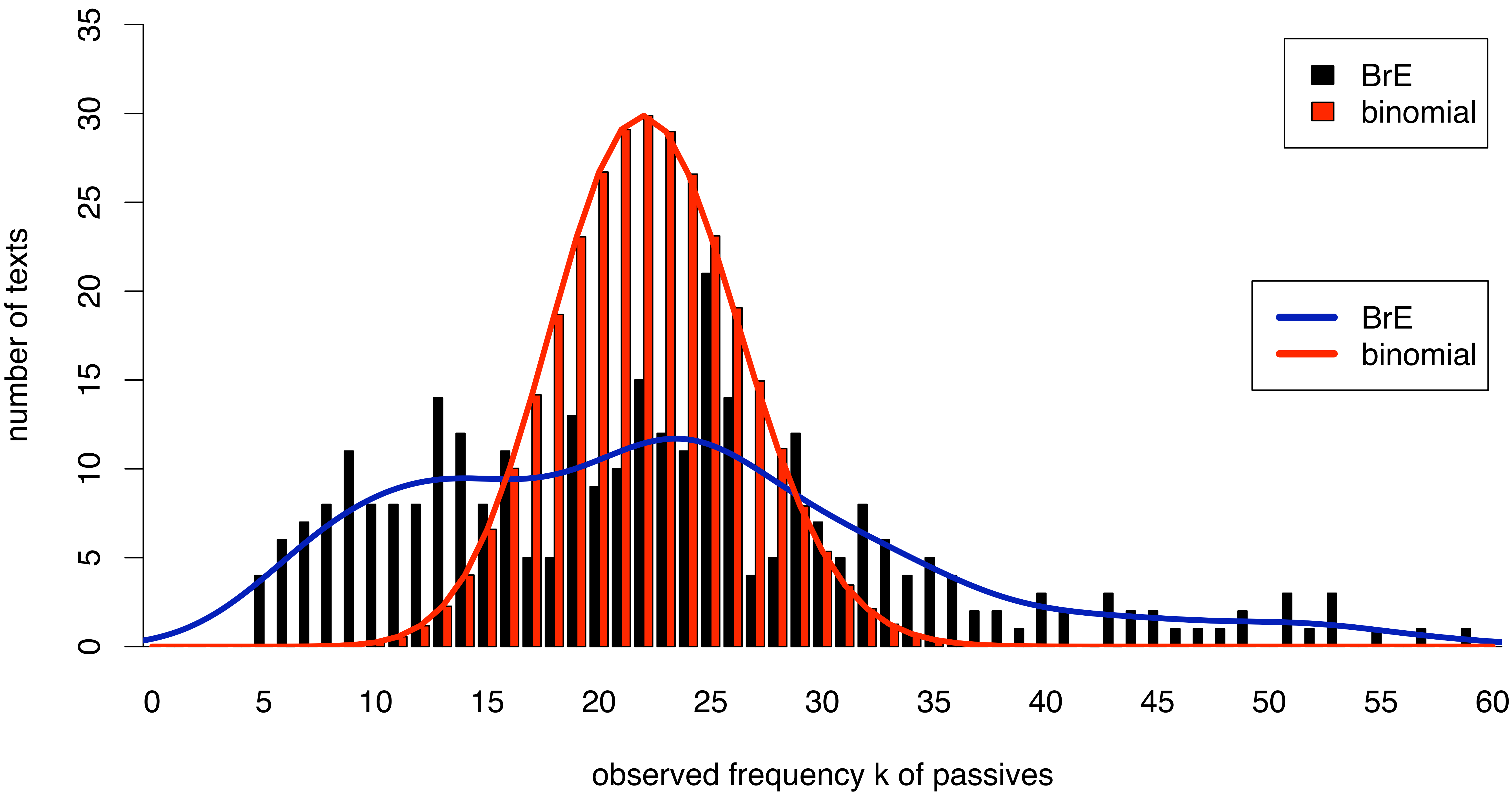
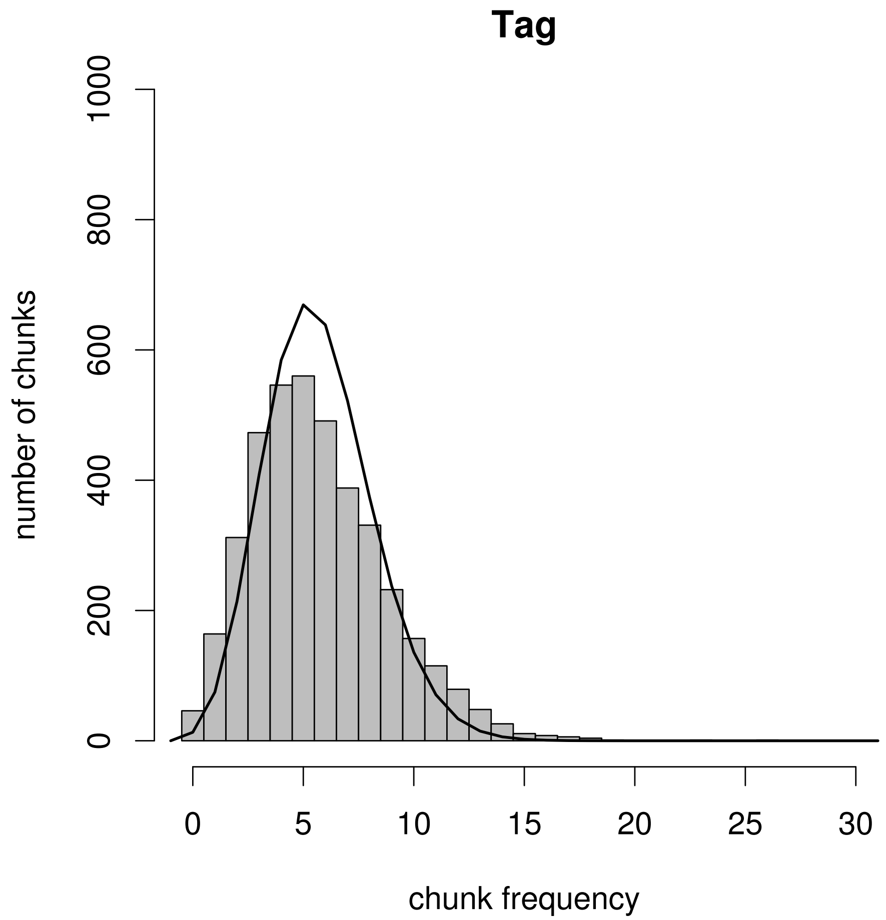
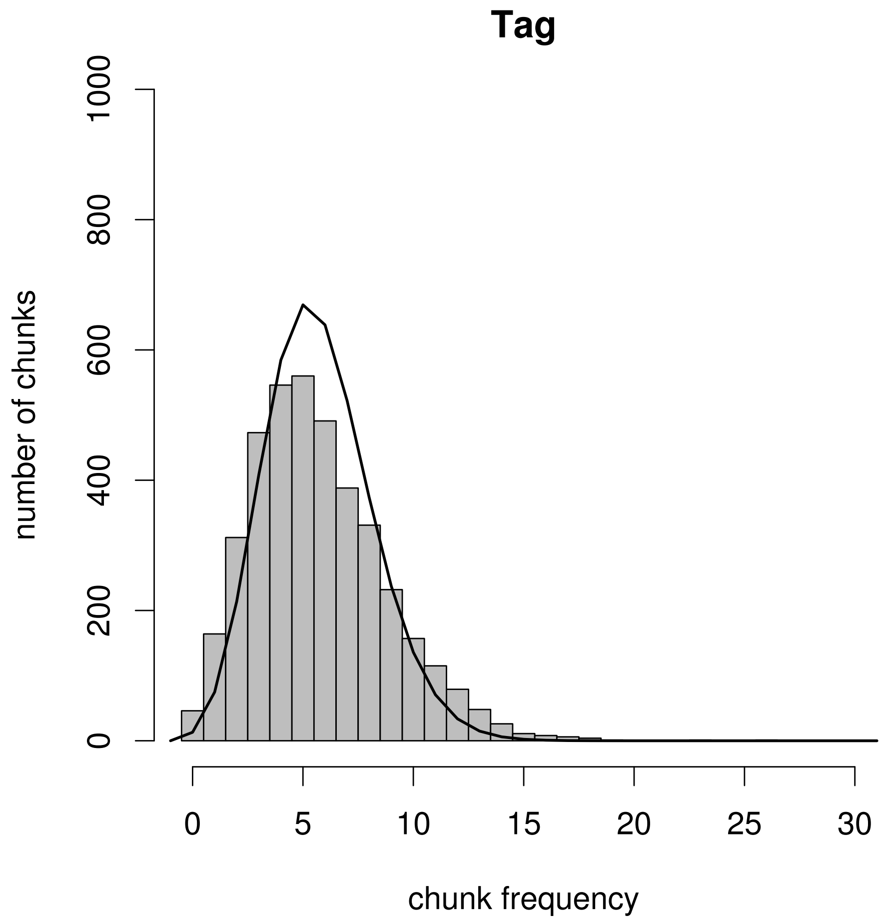


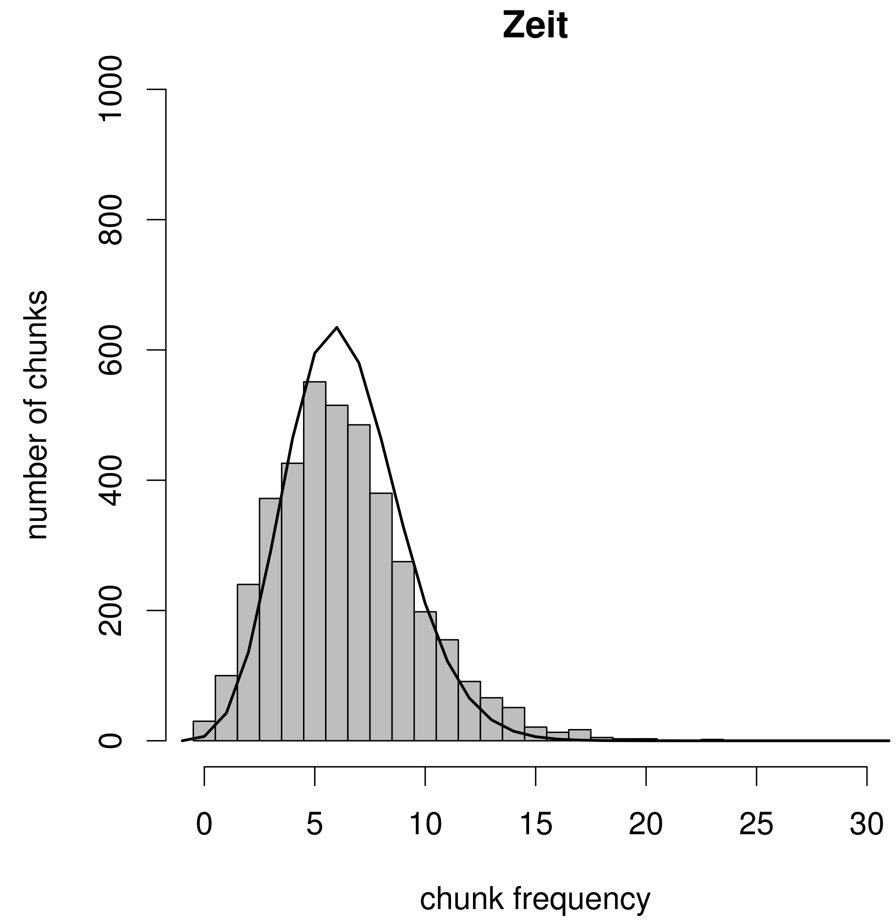
Passives in the LOB corpus





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





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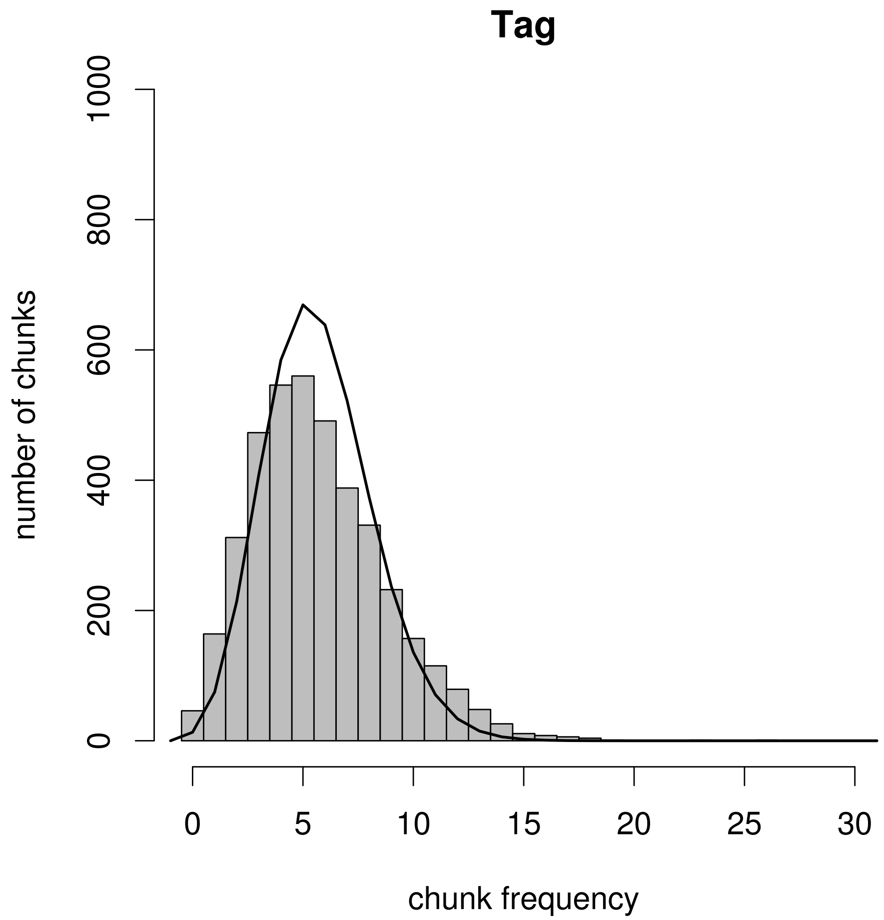

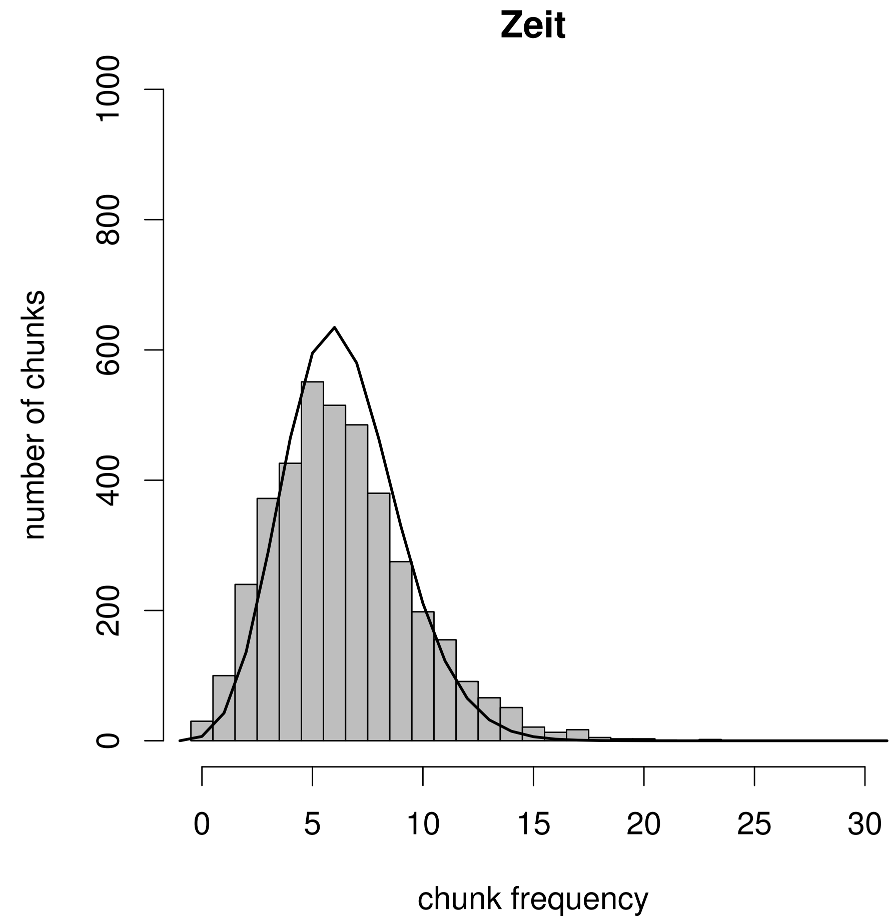

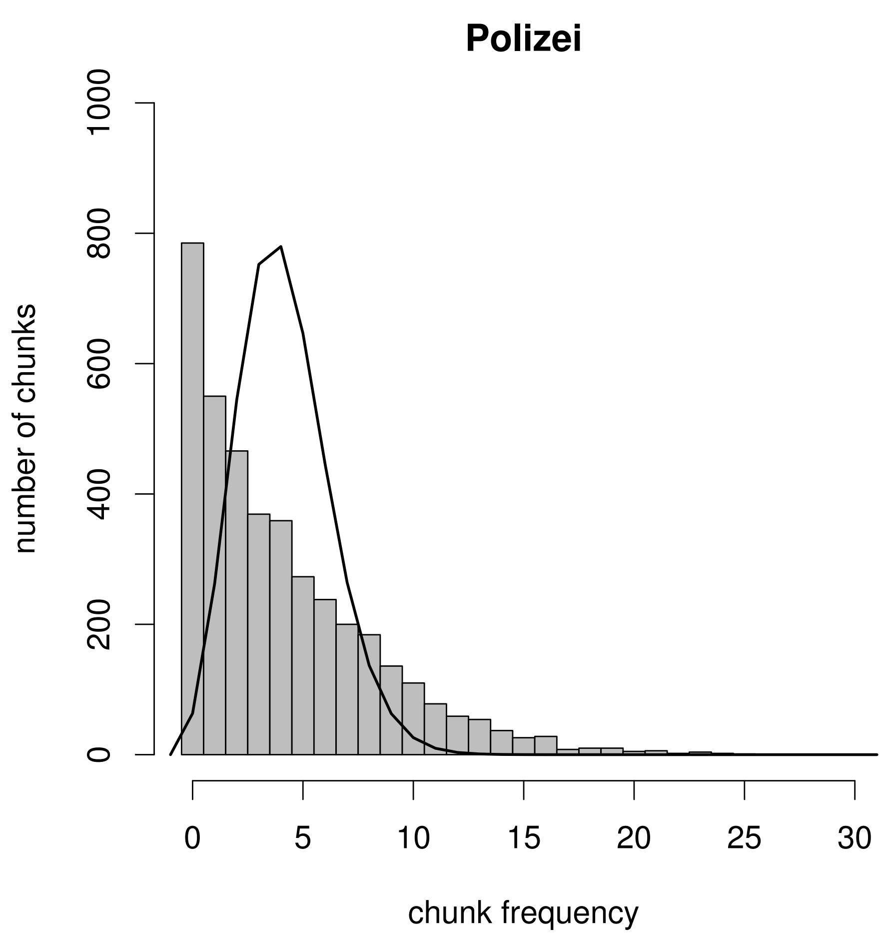

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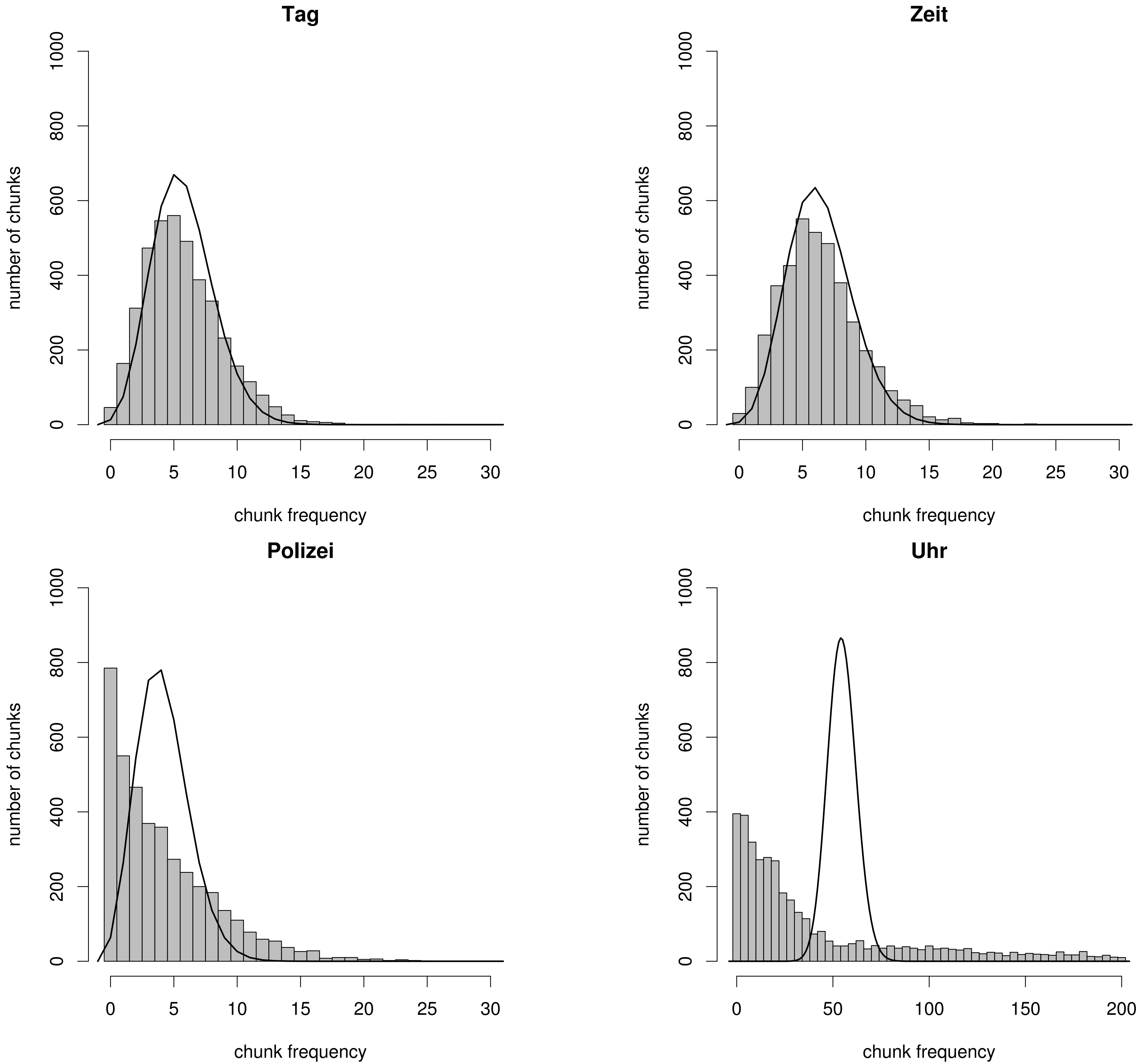

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  - data cannot be pooled into random sample of tokens
  - results in much smaller sample size …
    (BNC: 4,048 texts rather than 6,023,627 sentences)
  - … but more informative measurements (relative frequencies on interval rather than nominal scale)

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    (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

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  - based on data from subsets of Brown and LOB
    - 9 categories: press reports, editorials, skills & hobbies, misc., learned, fiction, science fiction, adventure, romance
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- 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")
```

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- Chi-squared test: **highly significant**
  - p-value: .00069 < .001
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- 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))
```

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- 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

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  - 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)
```


STOP

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  - 90% written / 10% spoken: $\pi =$ 16.6%

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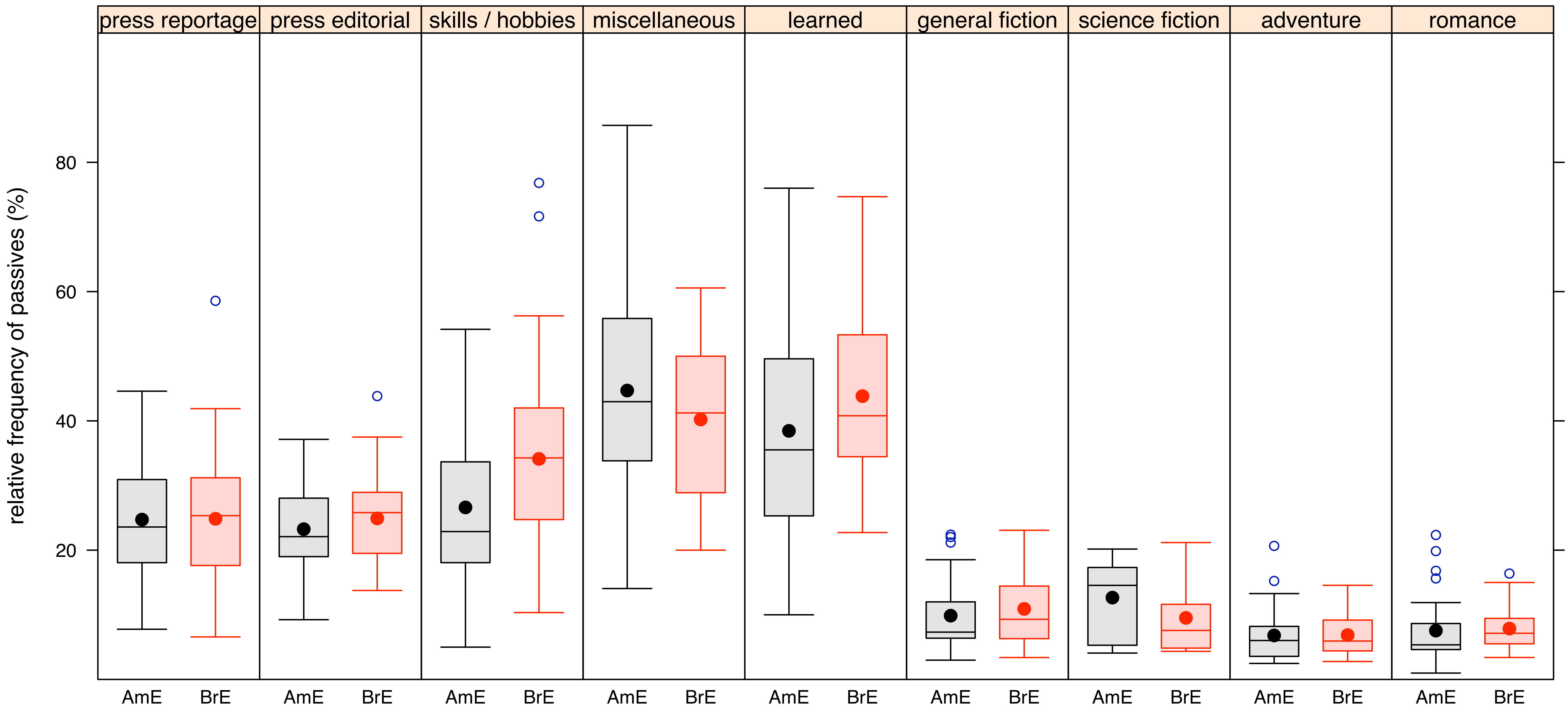
  - 90% written / 10% spoken: $\pi =$ 16.6%
  - 20% written / 80% spoken: $\pi =$ 6.8%

Average relative frequency?



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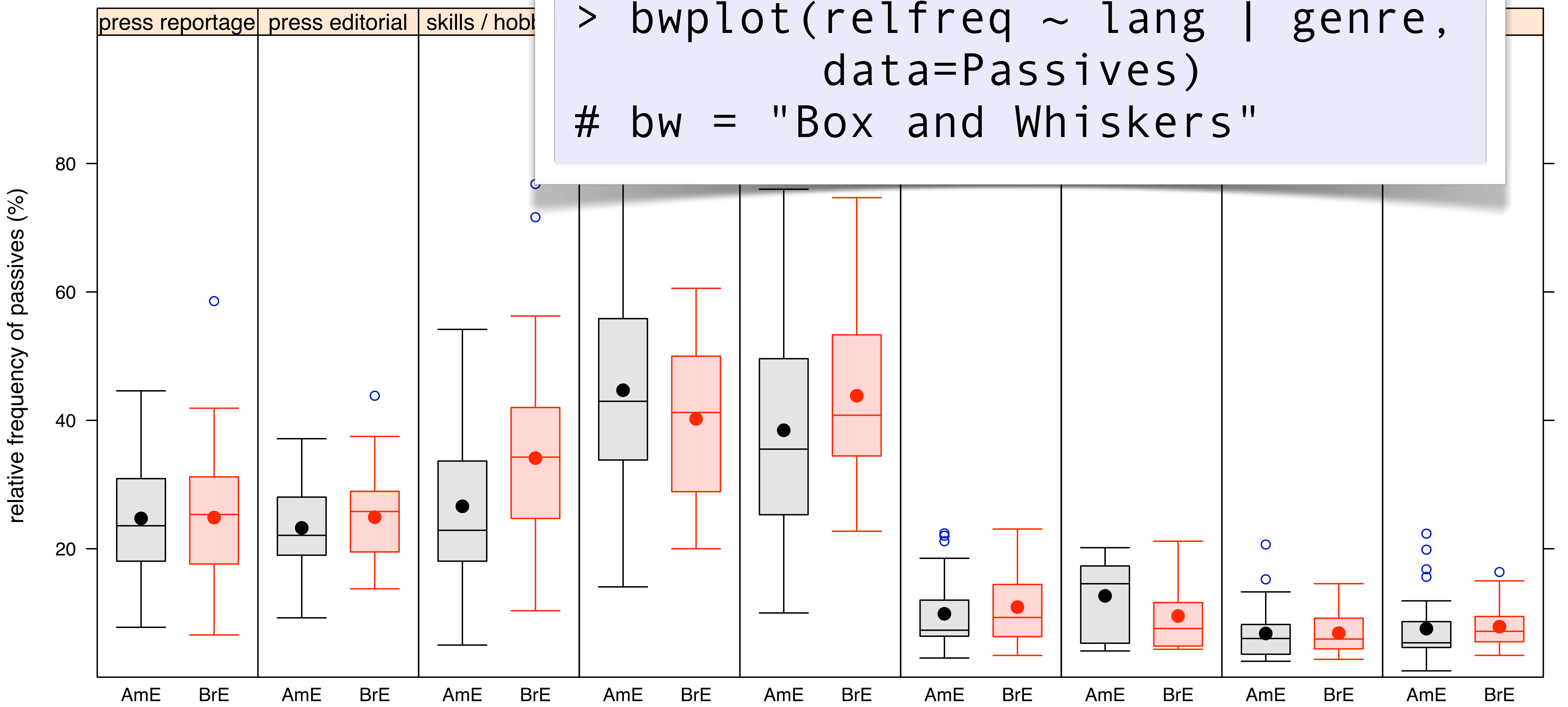


```
> library(lattice)

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

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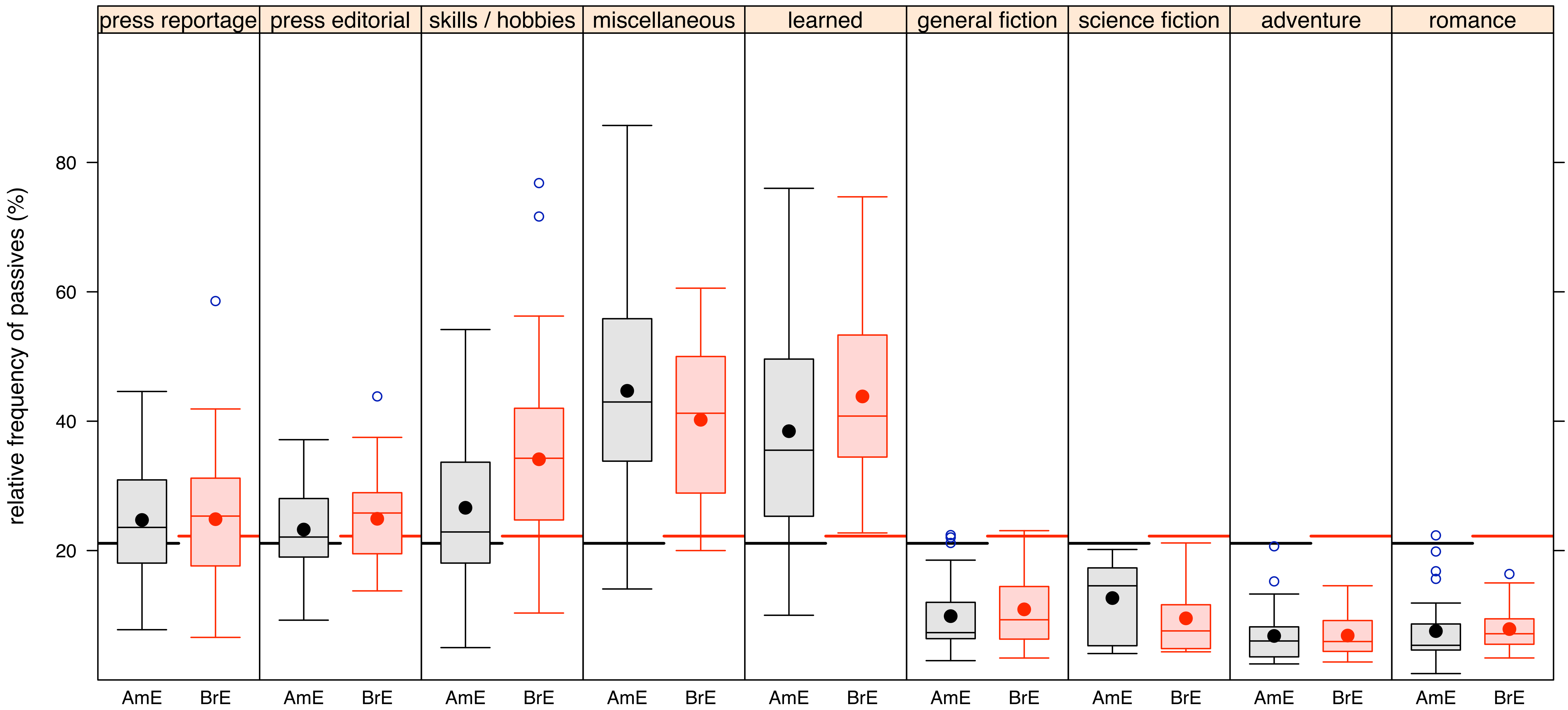

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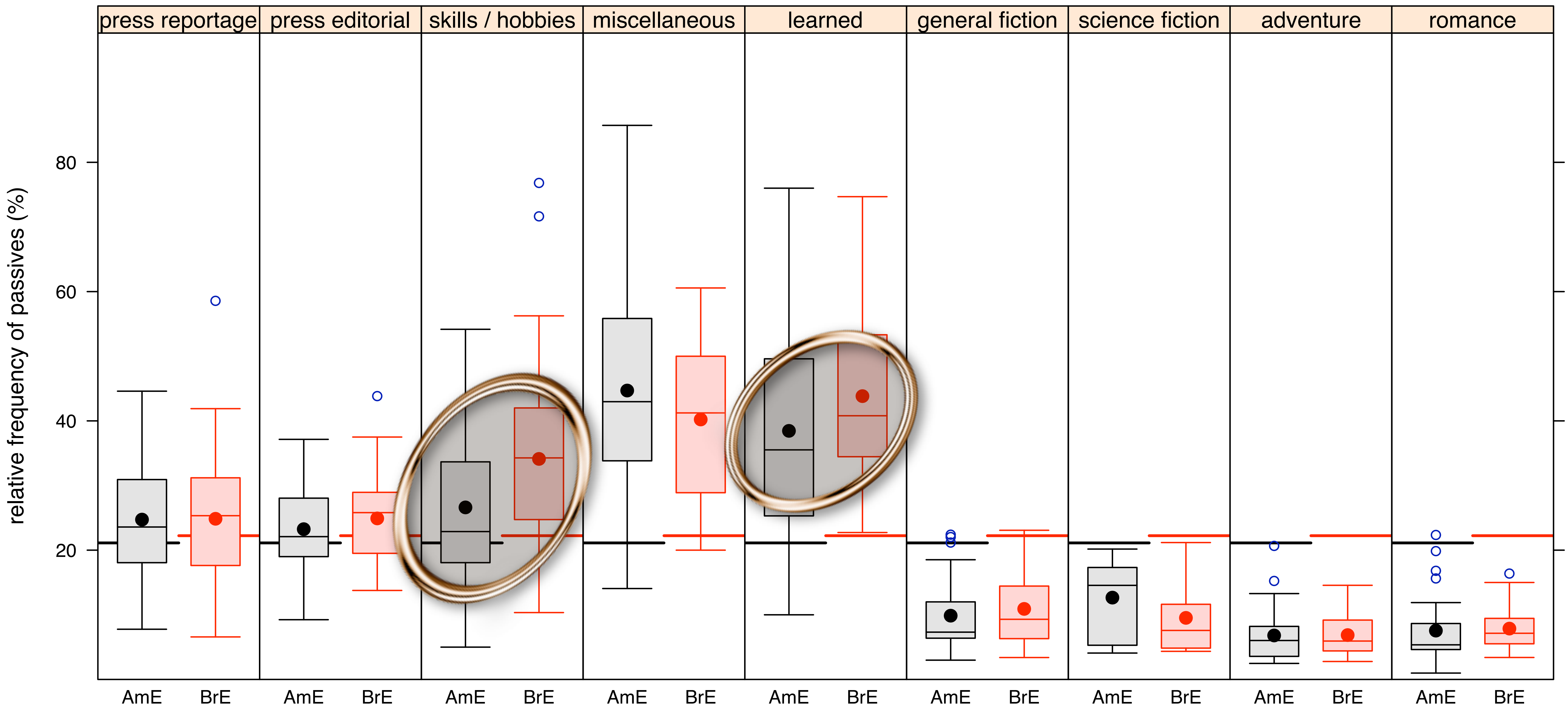

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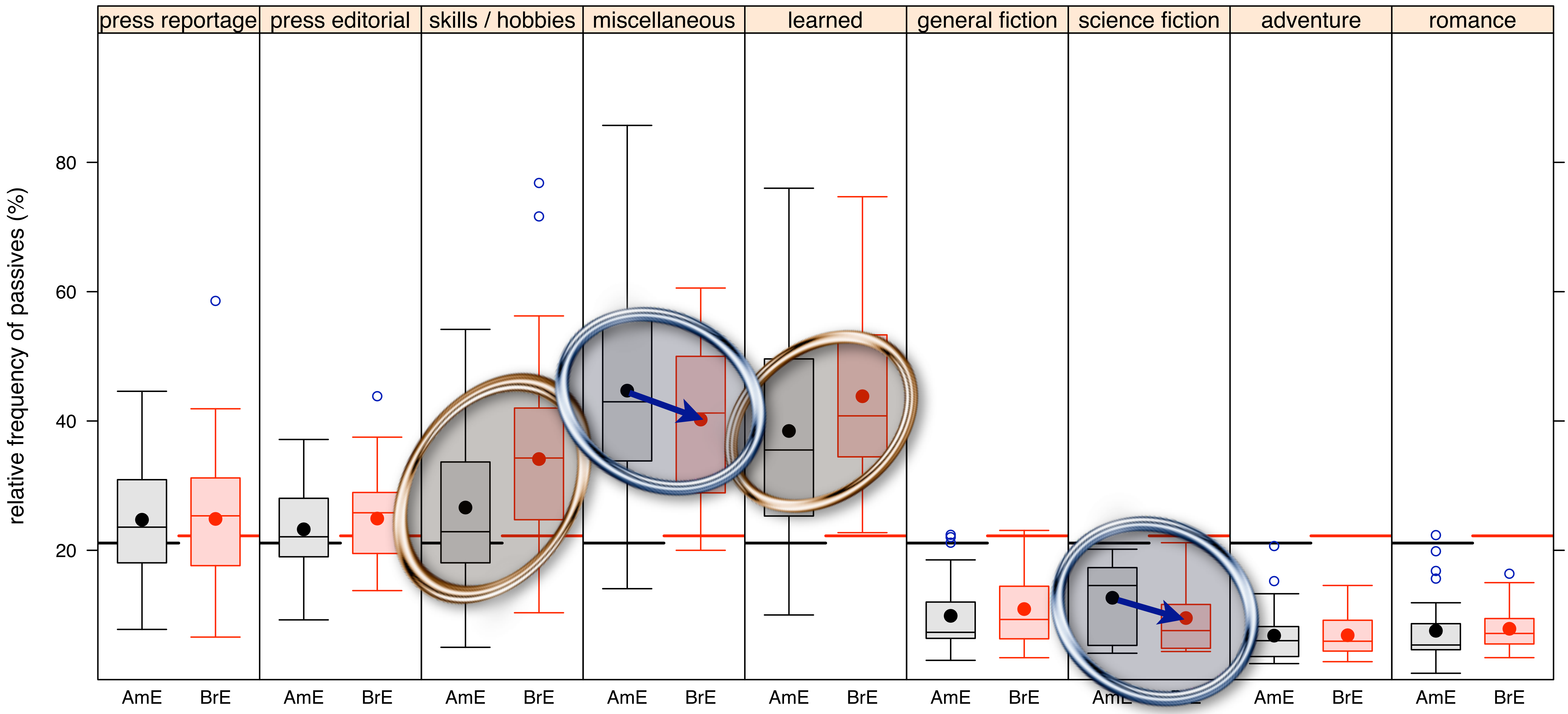

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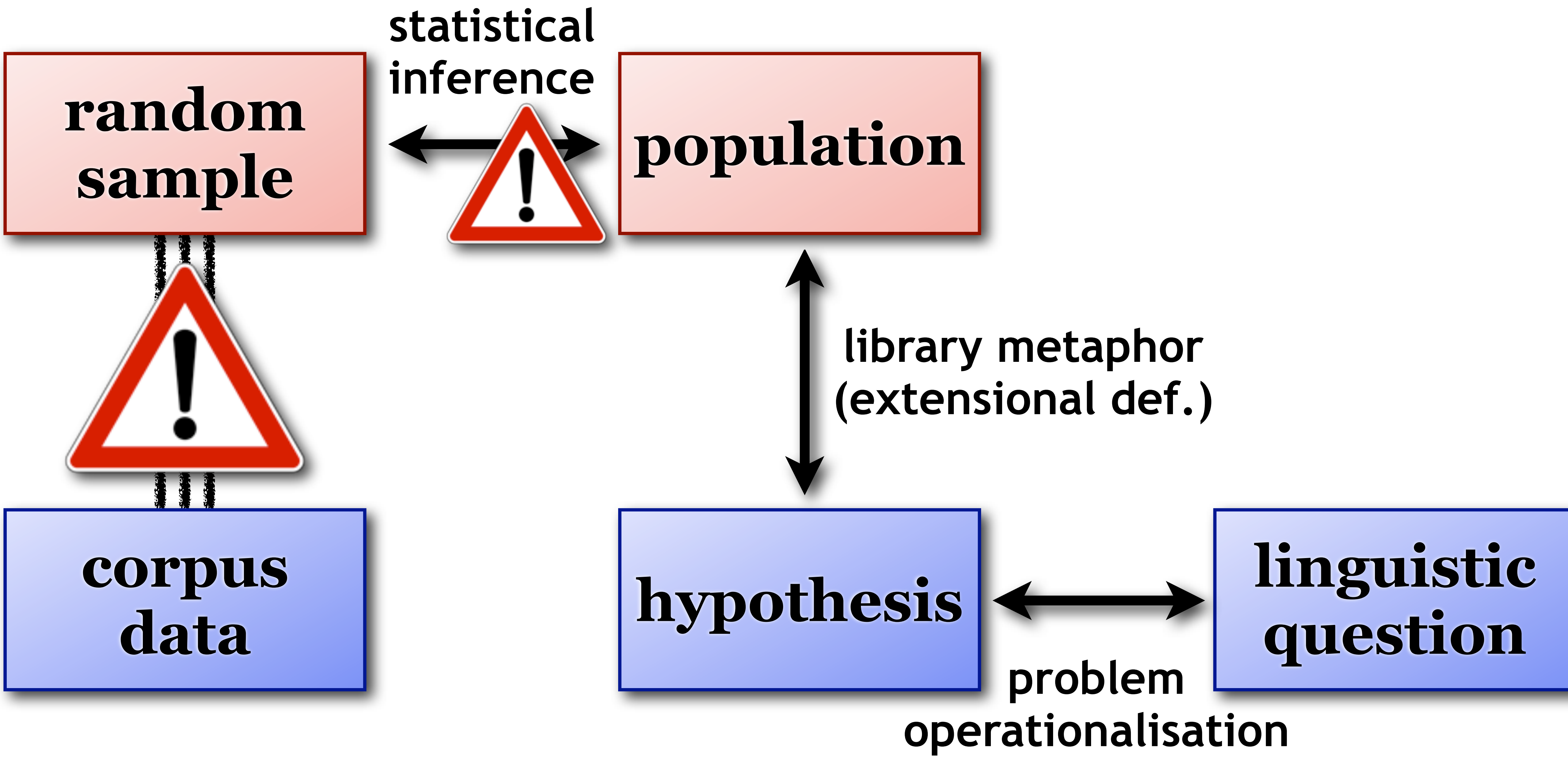
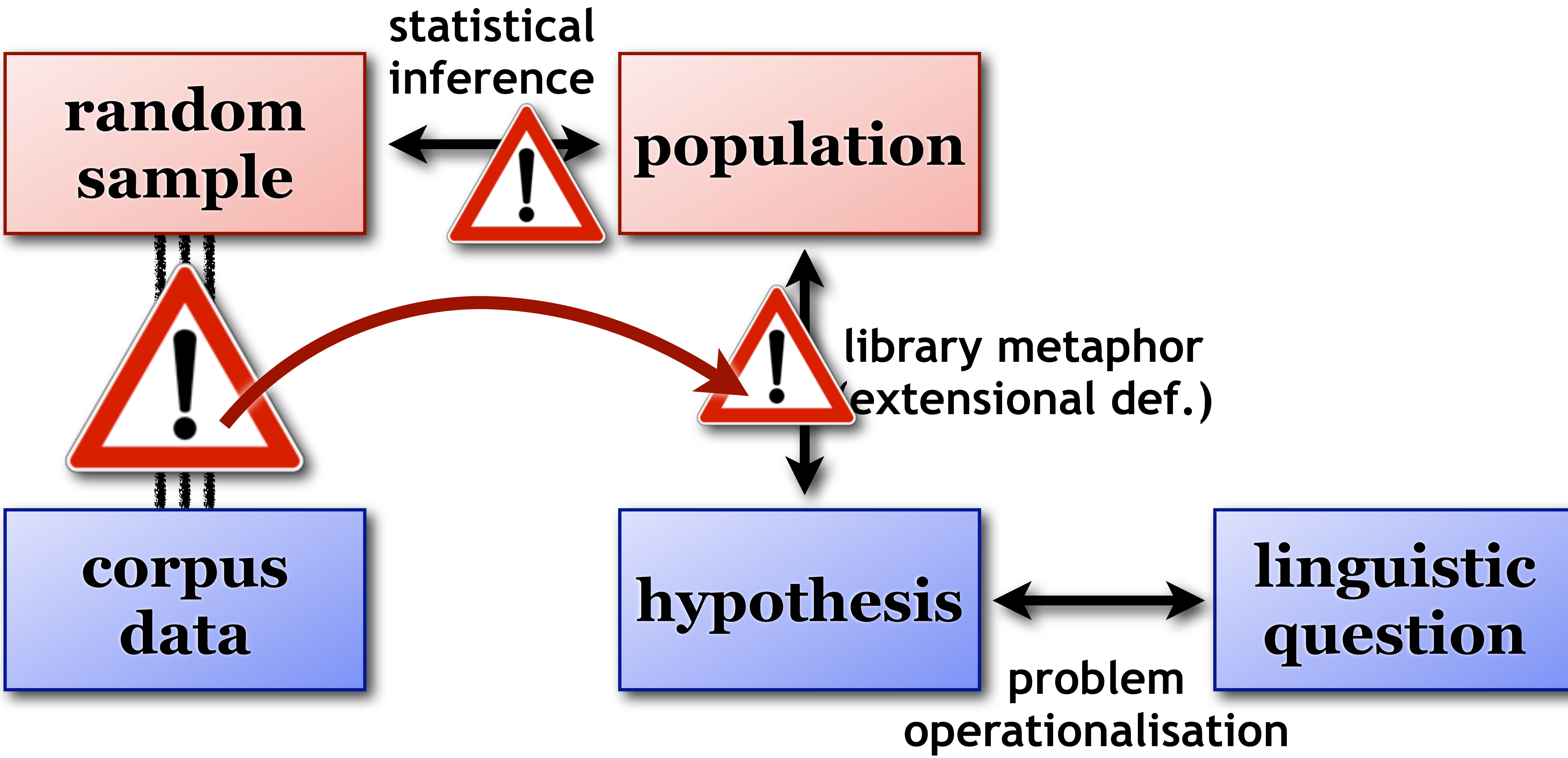


Problems with statistical inference



5

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

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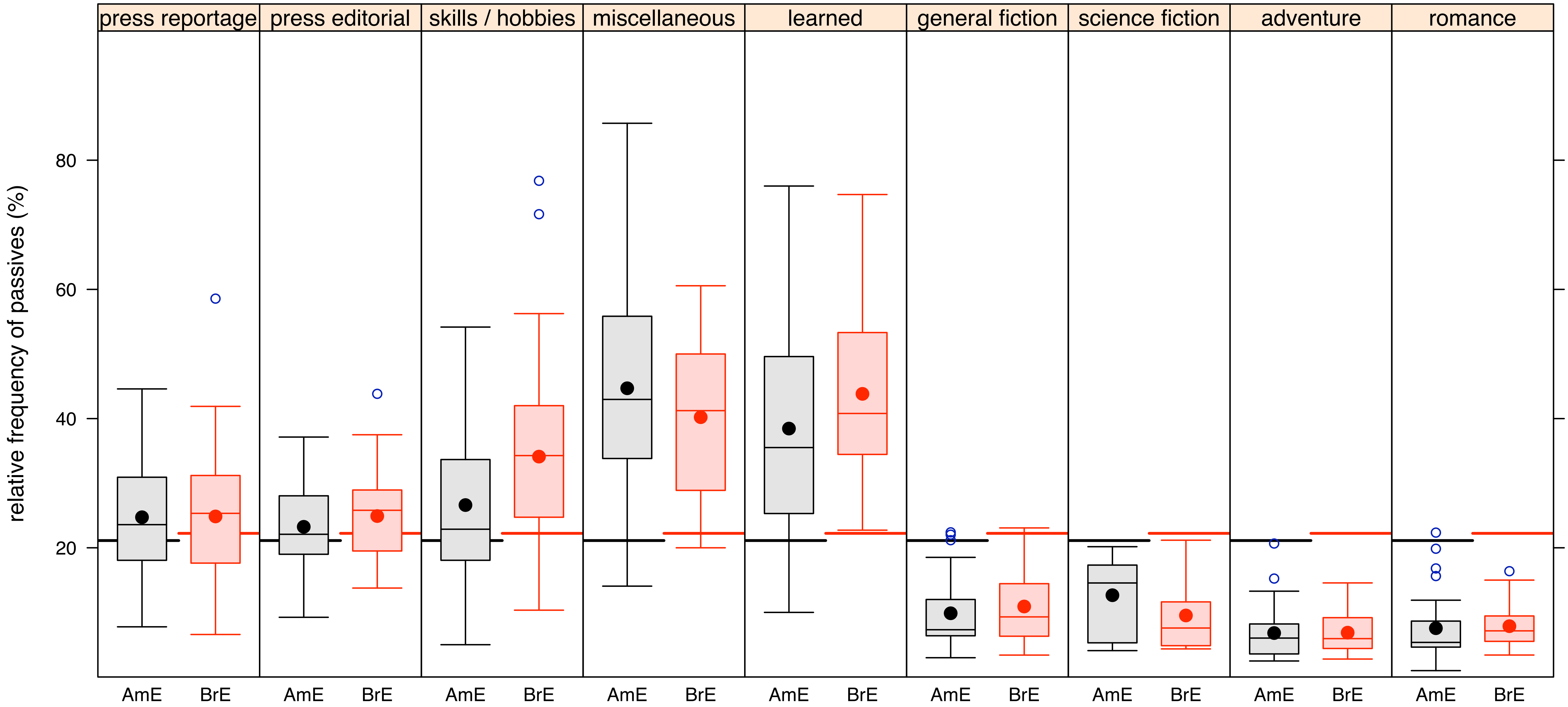
  - data from this sublanguage (= single section in library) can be pooled into large random sample
- Approach 2: goal of quantitative corpus analysis is to explain variation between texts in terms of
  - random sampling (of tokens within text)
  - stylistic variation: genre, author, domain, register,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

Eliminating non-randomness



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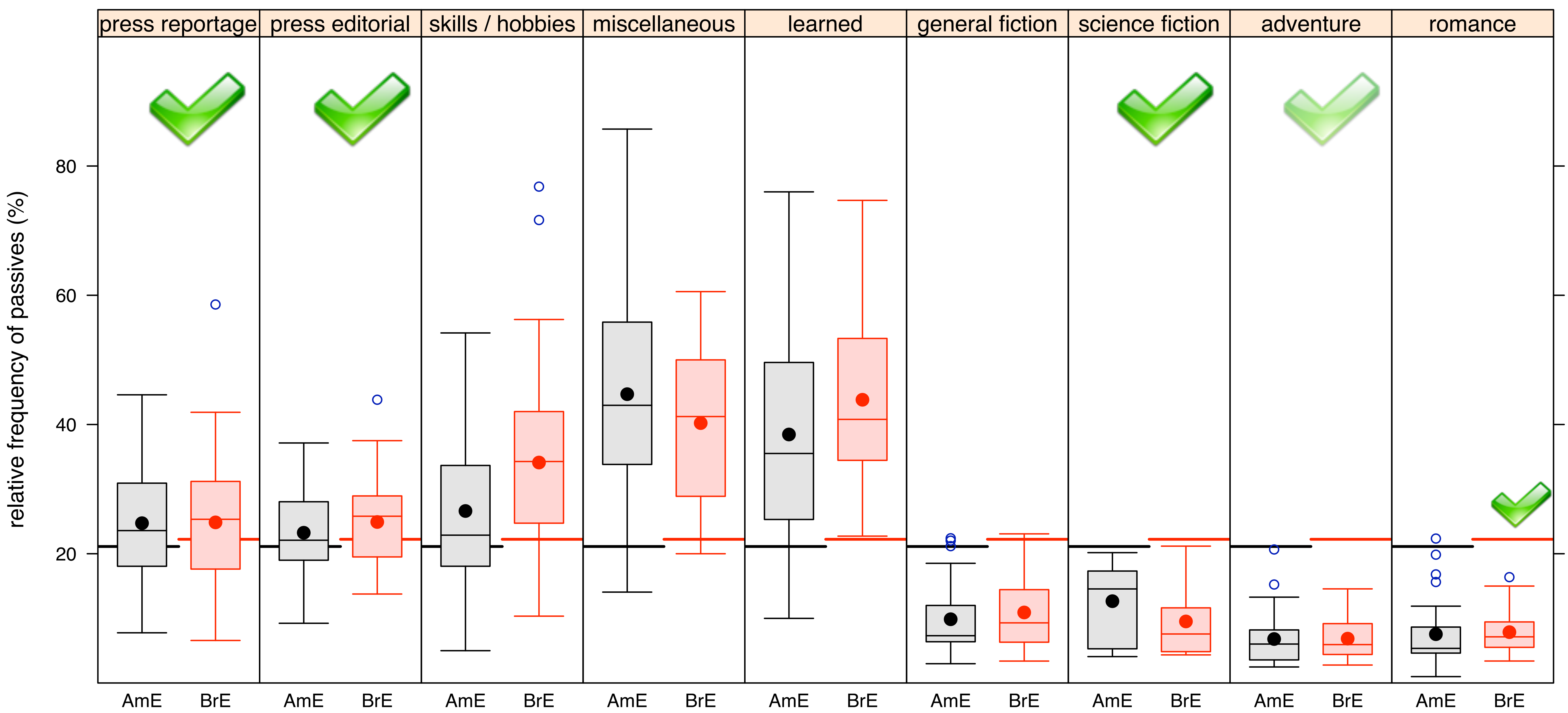

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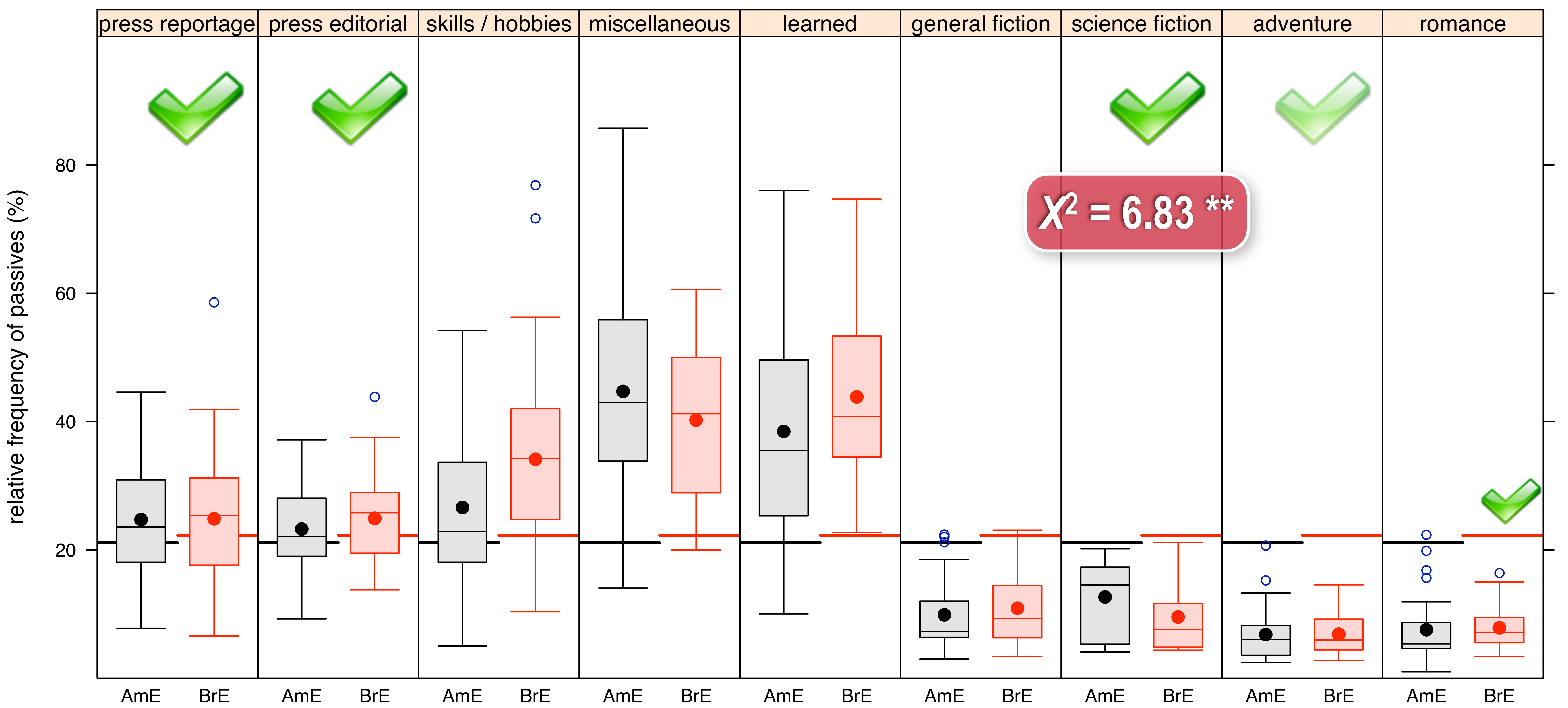

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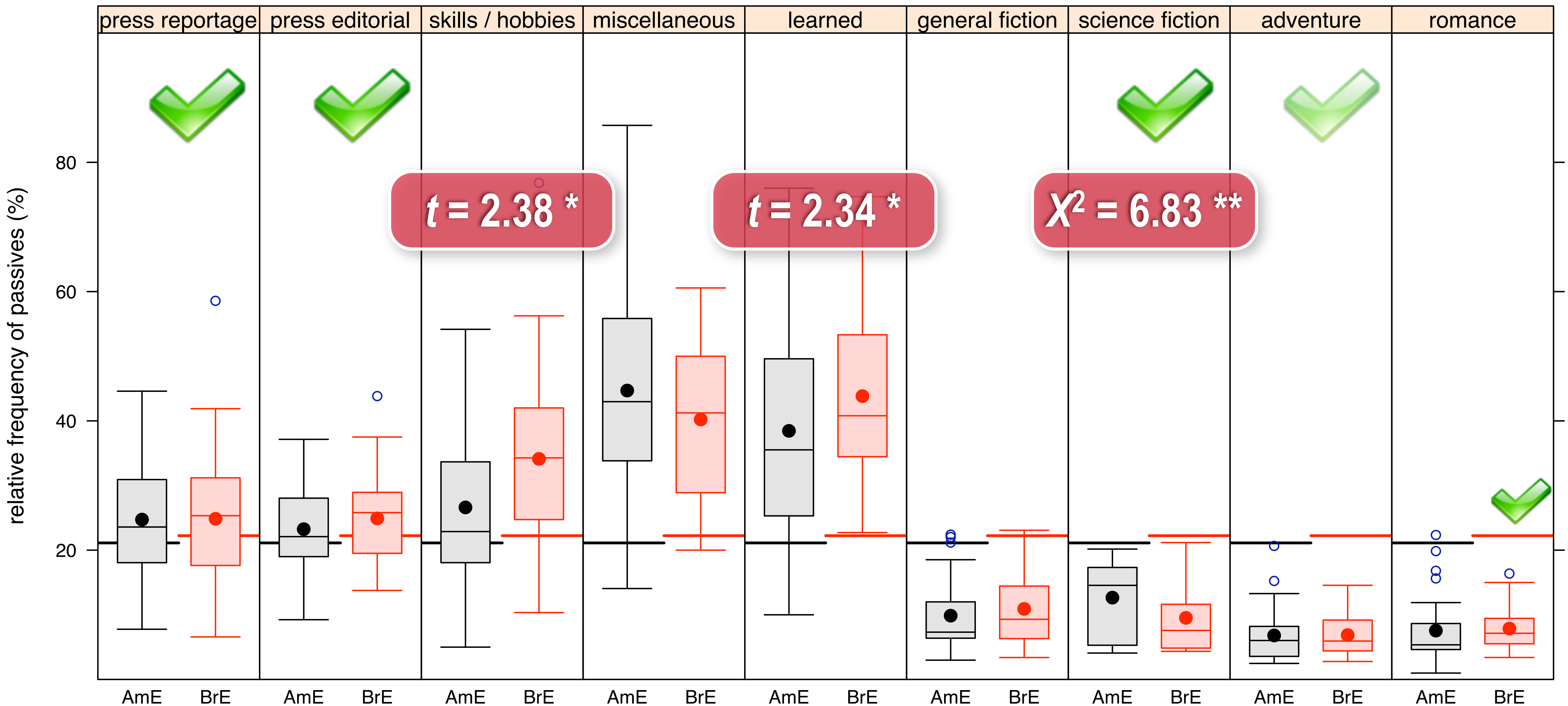

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overall average "intercept"

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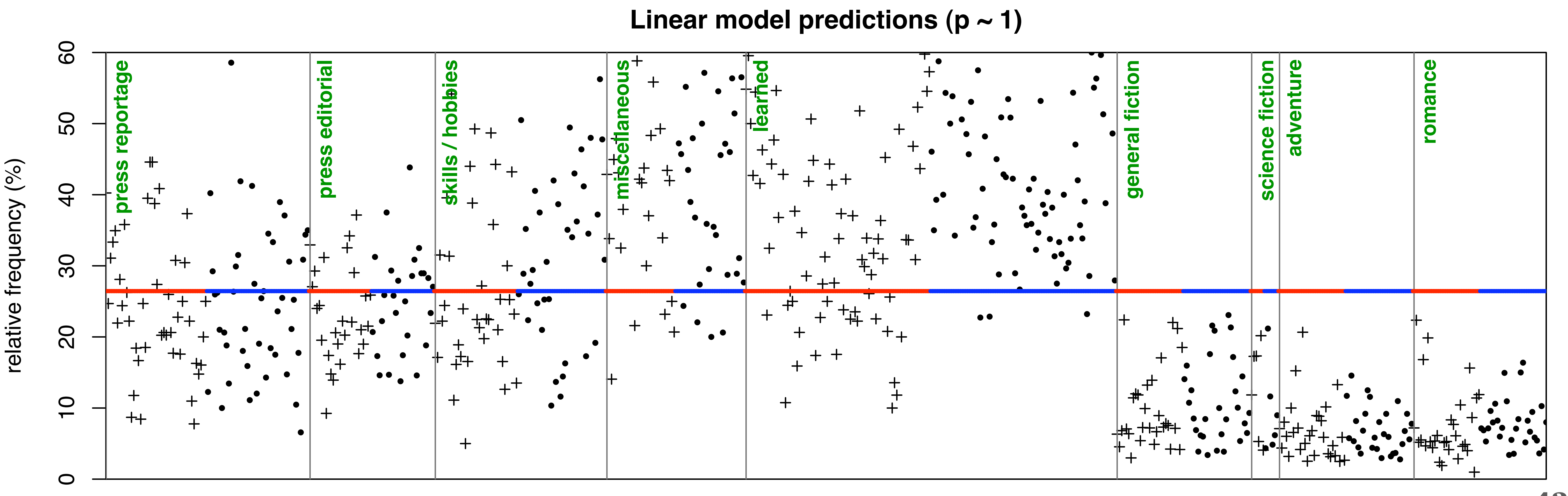
I'm just an ANOVA …

Linear model for passives



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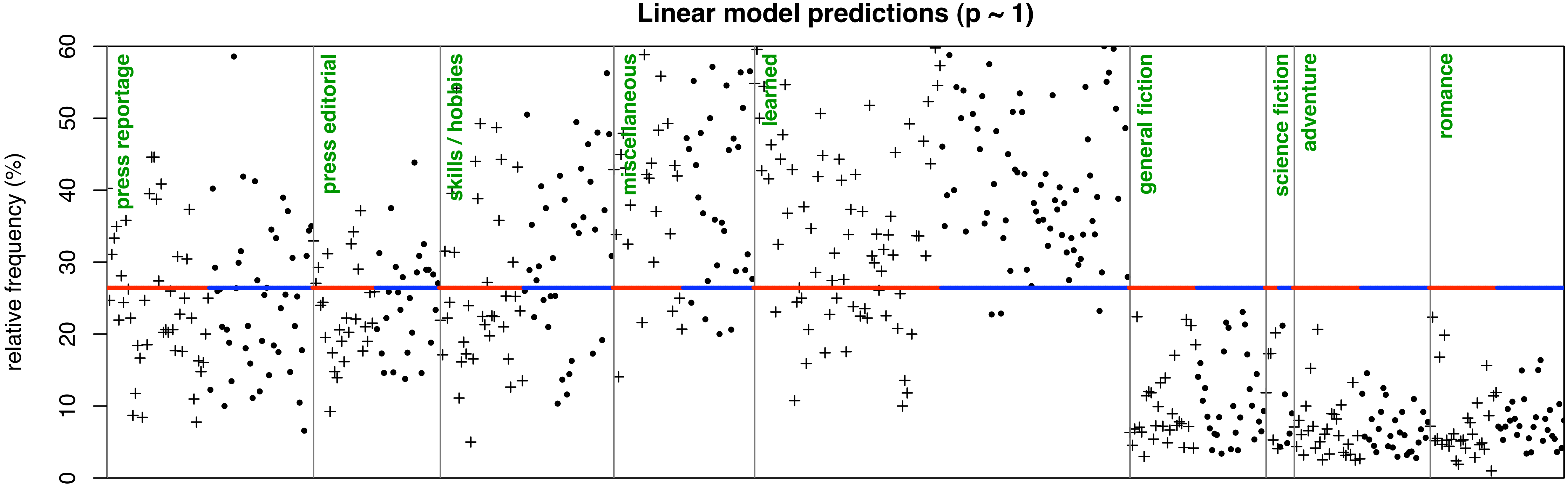

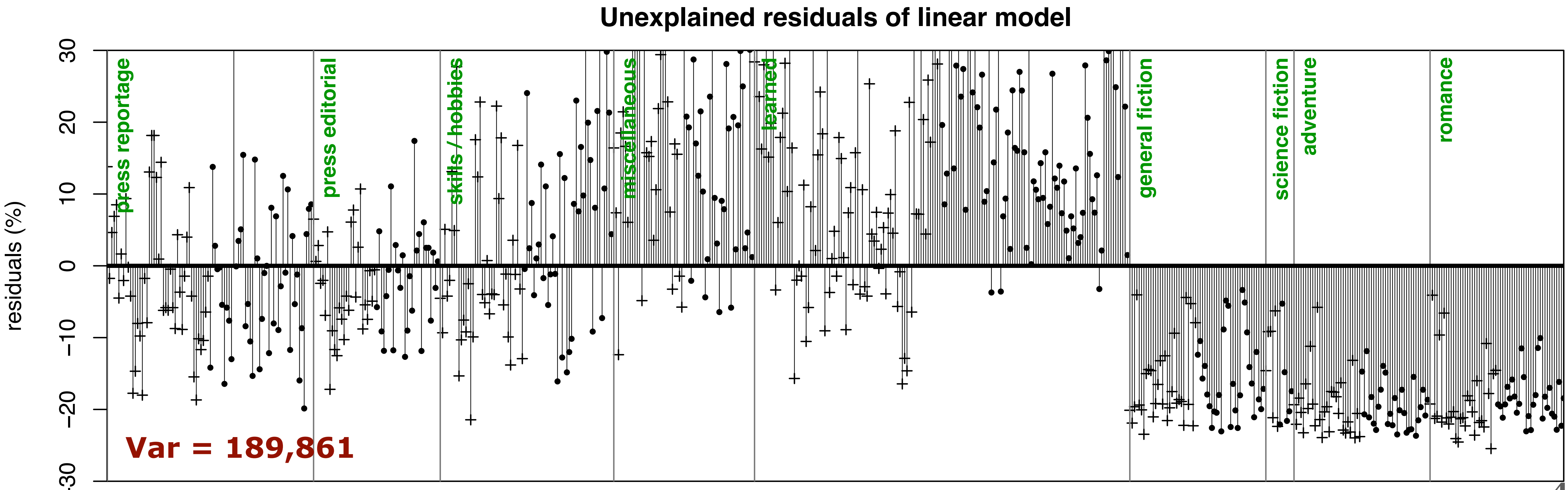

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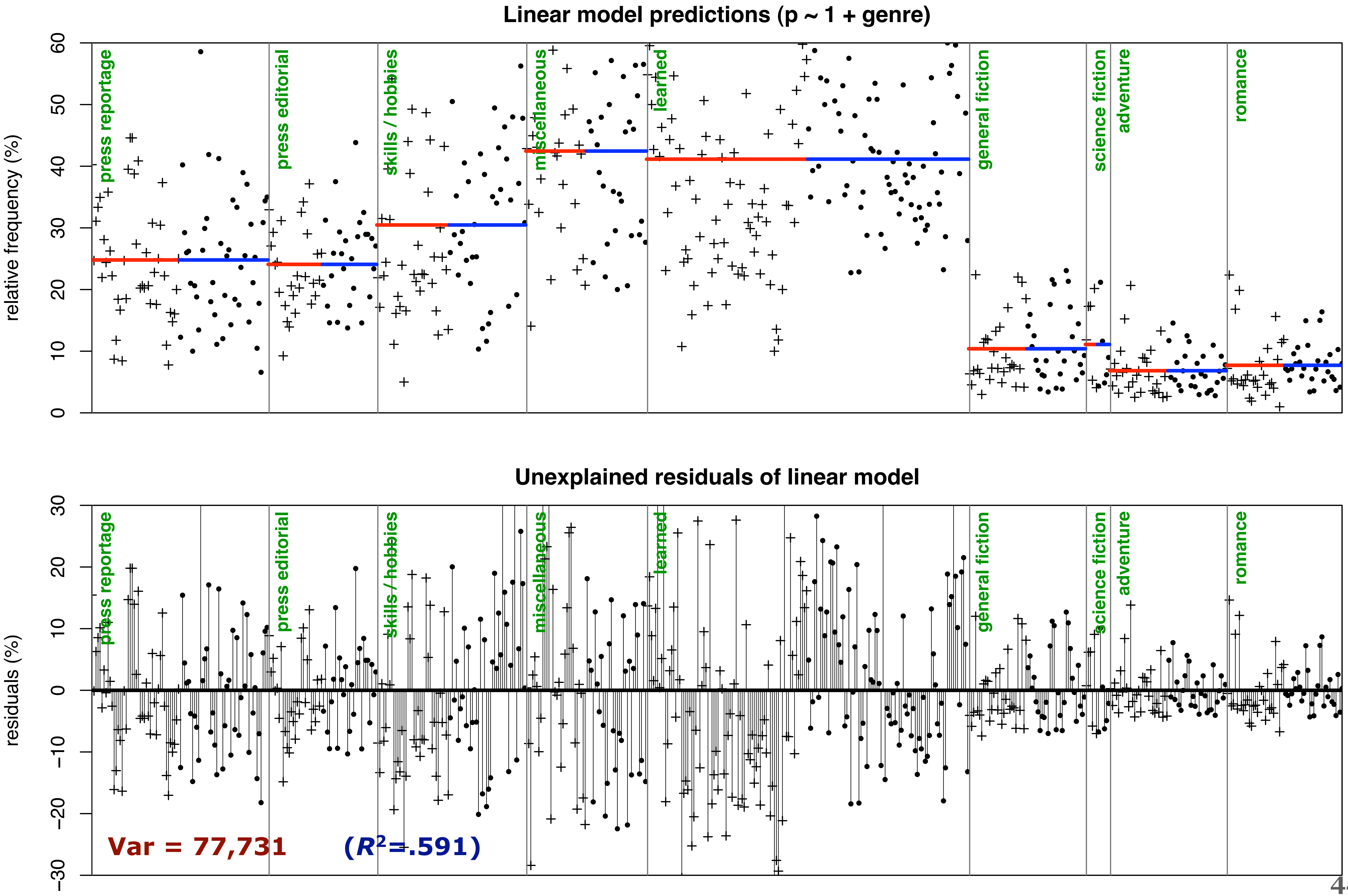

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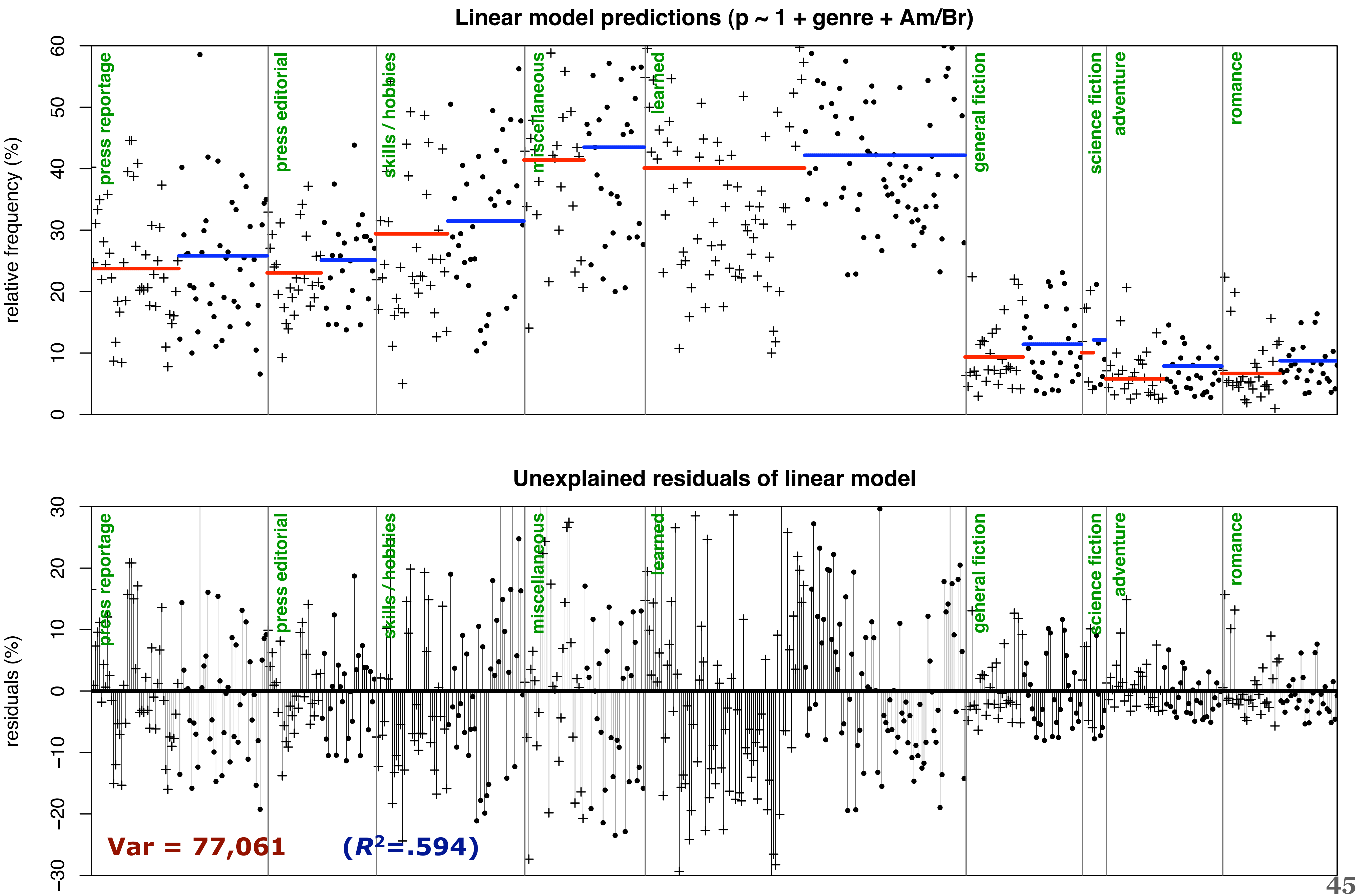

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- Is variance explained well enough?
  - binomial sampling variation: ca. 10,200 (= 5.4%)

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"))
```

Linear models are not appropriate!

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

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Why linear models are not appropriate for frequency data

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  - 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**)
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binomial sampling
("family")

$$f_i \sim B(n_i, \pi_i)$$

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

"link" function

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

linear predictor

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  - 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 (f_k, n_k–f_k) = "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))
```

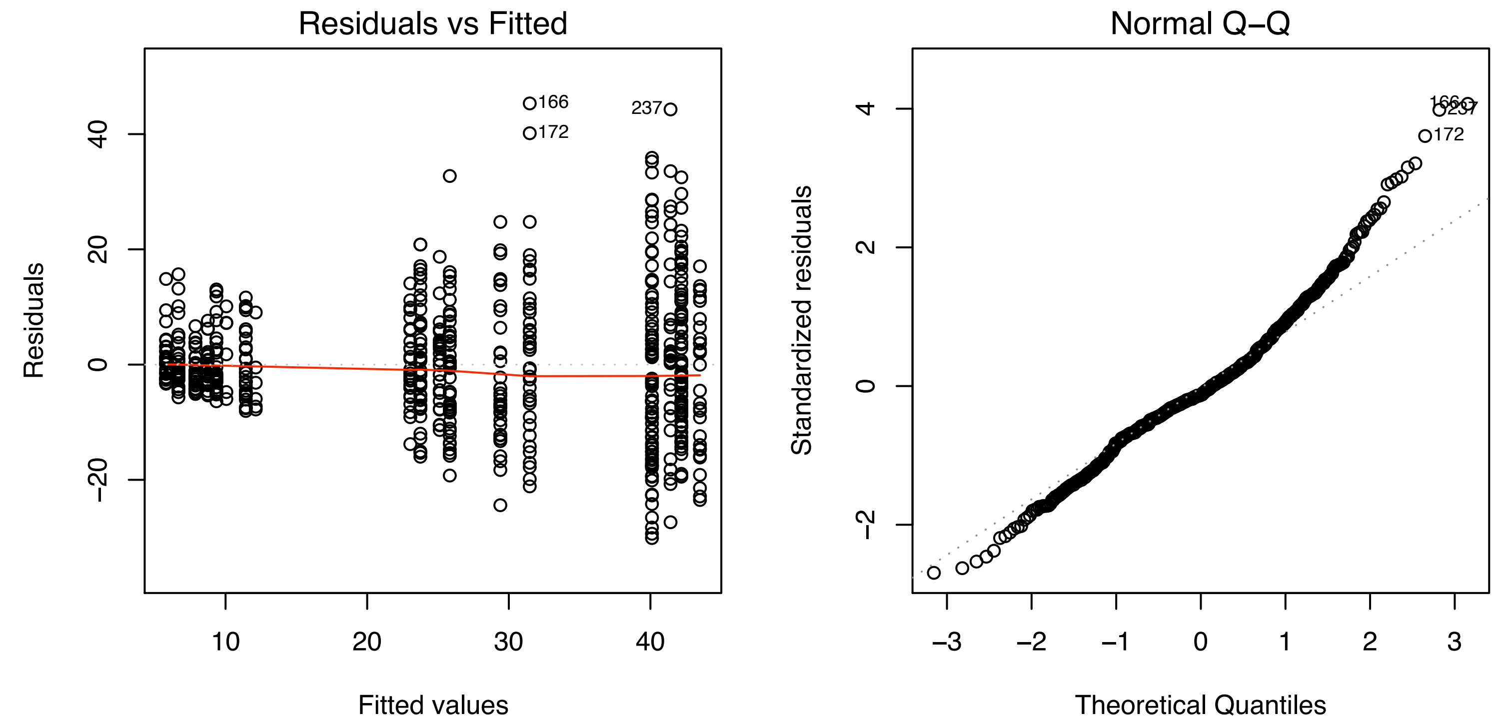
GLM in R

(note the extra options needed!)

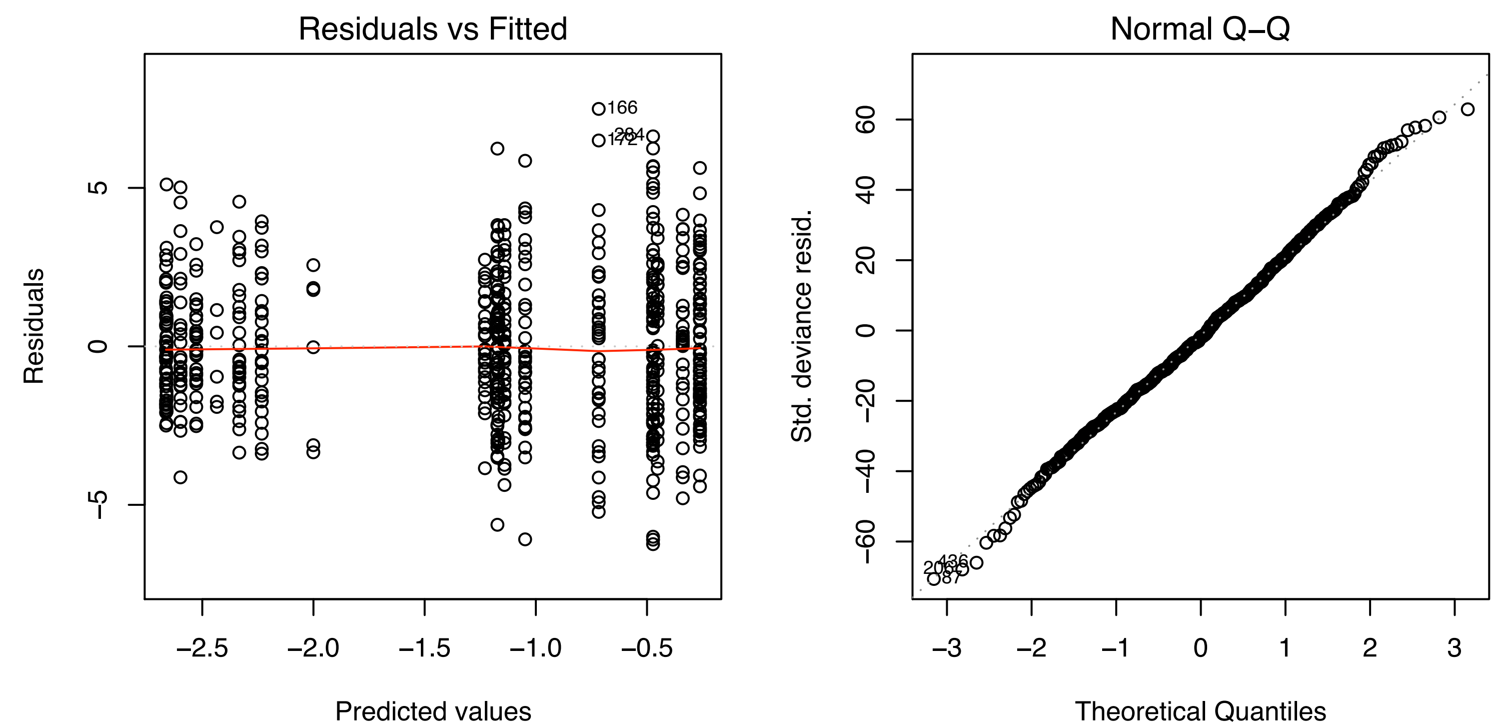
```
# predictions for each genre and language variety
> transform(Predictions, predicted = 100 *
    predict(GLM, type="response",
    newdata=Predictions))

# 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!)

THANK

YOU

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.