Statistical Analysis of Corpus Data with R

Hypothesis Testing for Corpus Frequency Data – The Library Metaphor

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A simple question

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- slightly more interesting version:
  Are there more passives in written English than in spoken English?

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➡ answers are based on the same frequency estimates

Back to our simple question

How many passives are there in English?

- American English style guide claims that
  - *"In an average English text, no more than 15% of the sentences are in passive voice. So use the passive sparingly, prefer sentences in active voice."*
  - http://www.ego4u.com/en/business-english/grammar/passive actually states that only 10% of English sentences are passives (as of June 2006)!
- We have doubts and want to verify this claim

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- Also applies to definition of sublanguage
  - dialect (Bostonian, Cockney), social group (teenagers), genre (advertising), domain (statistics), …

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- But does this allow quantitative statements?
  - we need something we can *count*
- Need **extensional** definition of language
  - i.e. language = body of utterances

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  “All utterances made by speakers of the language under appropriate conditions, plus all utterances they *could* have made”

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- Imagine a huge library with all the books written in a language, as well as all the hypothetical books that were never written

→ **library metaphor** (Evert 2006)

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  - So, how many passives *are* there in English?
  - **∞** … infinitely many, of course!
- Only **relative** frequencies can be meaningful

Relative frequency

- How many passives are there …

  … per million words?

  … per thousand sentences?

  … per hour of recorded speech?

  … per book?

- Are these measurements meaningful?

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- **Relative frequency** = **proportion** π

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- Many statistical methods are readily available

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- We want to take a random sample of these units

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  - repeat ***n*** times for **sample size *n***

Types vs. tokens

- Important distinction between types & tokens
  - we might find many copies of the “same” VP in our sample, e.g. *click this button* (software manual) or *includes dinner, bed and breakfast*
  - sample consists of occurrences of VPs, called **tokens**
    - each *token* in the language is selected at most once
  - distinct VPs are referred to as **types**
    - a sample might contain many instances of the same *type*
- Definition of types based on research question

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  - word type = dictionary entry (distinct word)
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- Example: passives
  - relevant VP types = active or passive (→ abstraction)
  - VP token = instance of VP in library texts

Types, tokens and proportions

- Proportions in terms of types & tokens
- Relative frequency of type v
  = proportion of tokens t_i that belong to this type

$$p = \frac{f(v)}{n}$$

frequency of type

sample size

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  - style guide → population proportion π = 15%
  - $p > \pi$ → reject claim of style guide?
- Take another sample, just to be sure
  - observe 13 passives → p = 13% = .13
  - $p < \pi$ → claim of style guide confirmed?

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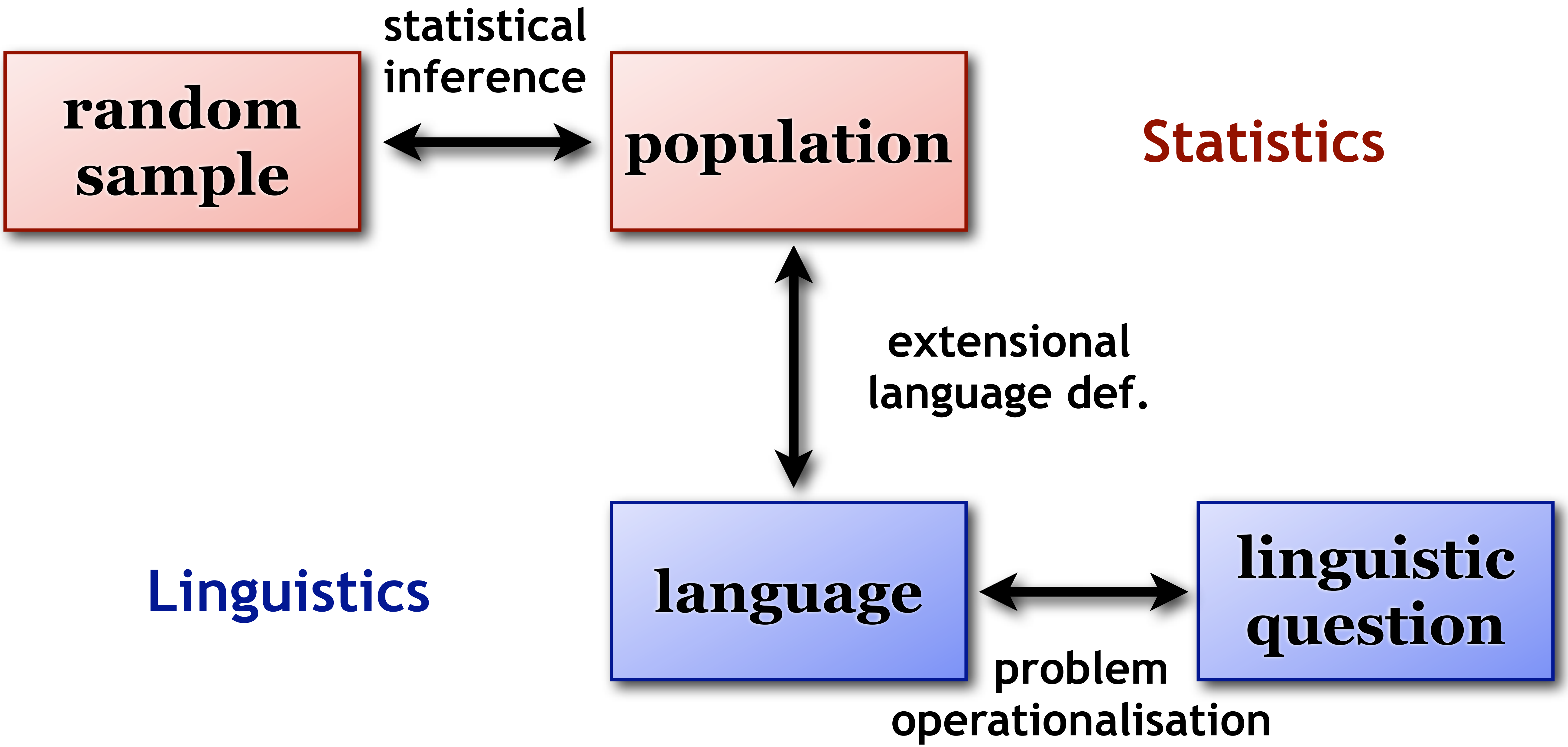
    → **sampling variation**

- The main purpose of statistical methods is to estimate & correct for sampling variation

  - that's all there is to statistics, really 

The role of statistics



Estimating sampling variation

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- Assume that the style guide's claim is correct
  - the **null hypothesis** H_o, which we aim to refute

$$H_0 : \pi = .15$$

  - we also refer to $\pi_o = .15$ as the **null proportion**

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$$H_0 : \pi = .15$$

  - we also refer to $\pi_o = .15$ as the **null proportion**
- Many corpus linguists set out to test H_o
  - each one draws a random sample of size $n = 100$
  - how many of the samples have the expected $k = 15$ passives, how many have $k = 19$, etc.?

Estimating sampling variation

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- We don't need an infinite number of monkeys (or corpus linguists) to answer these questions
  - randomly picking VPs from our metaphorical library is like drawing balls from an infinite urn
  - red ball = passive VP / white ball = active VP
  - H_0: assume proportion of red balls in urn is 15%

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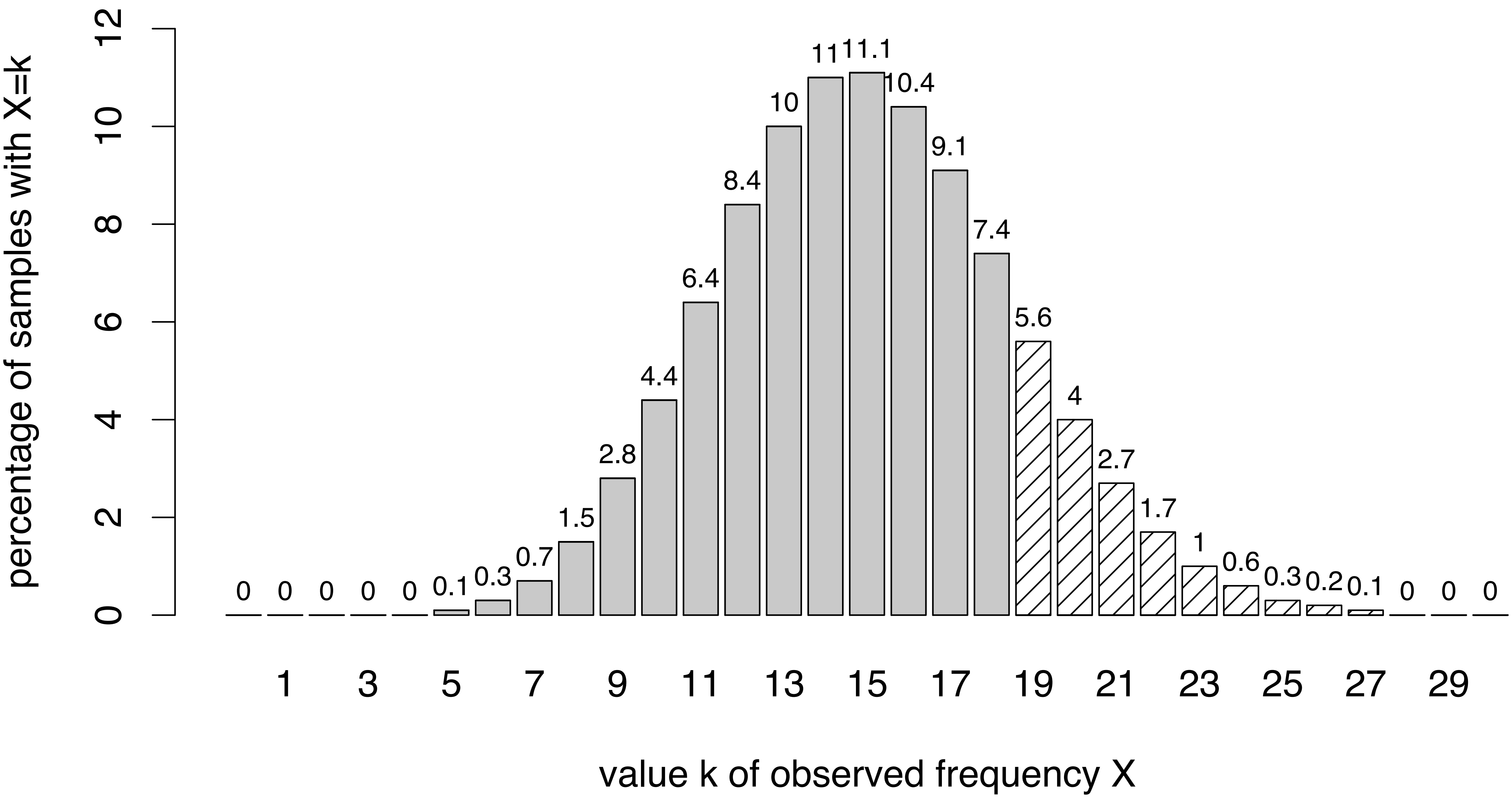
  - randomly picking VPs from our metaphorical library is like drawing balls from an infinite urn
  - red ball = passive VP / white ball = active VP
  - H_0: assume proportion of red balls in urn is 15%
- This leads to a **binomial distribution**

$$\Pr(\quad) = \qquad (\pi_0)\ (1-\pi_0)^{\ -}$$

Binomial sampling distribution



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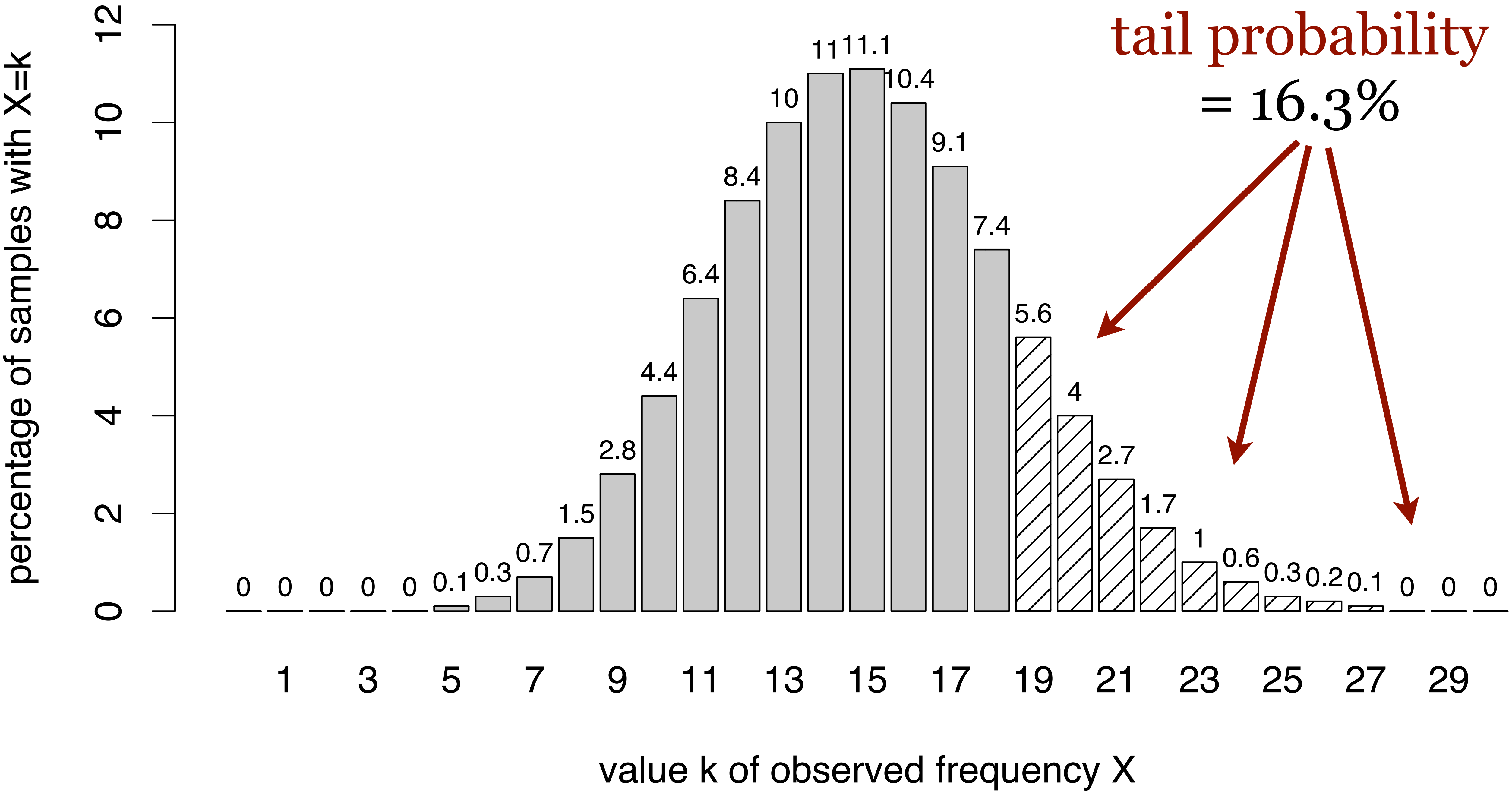

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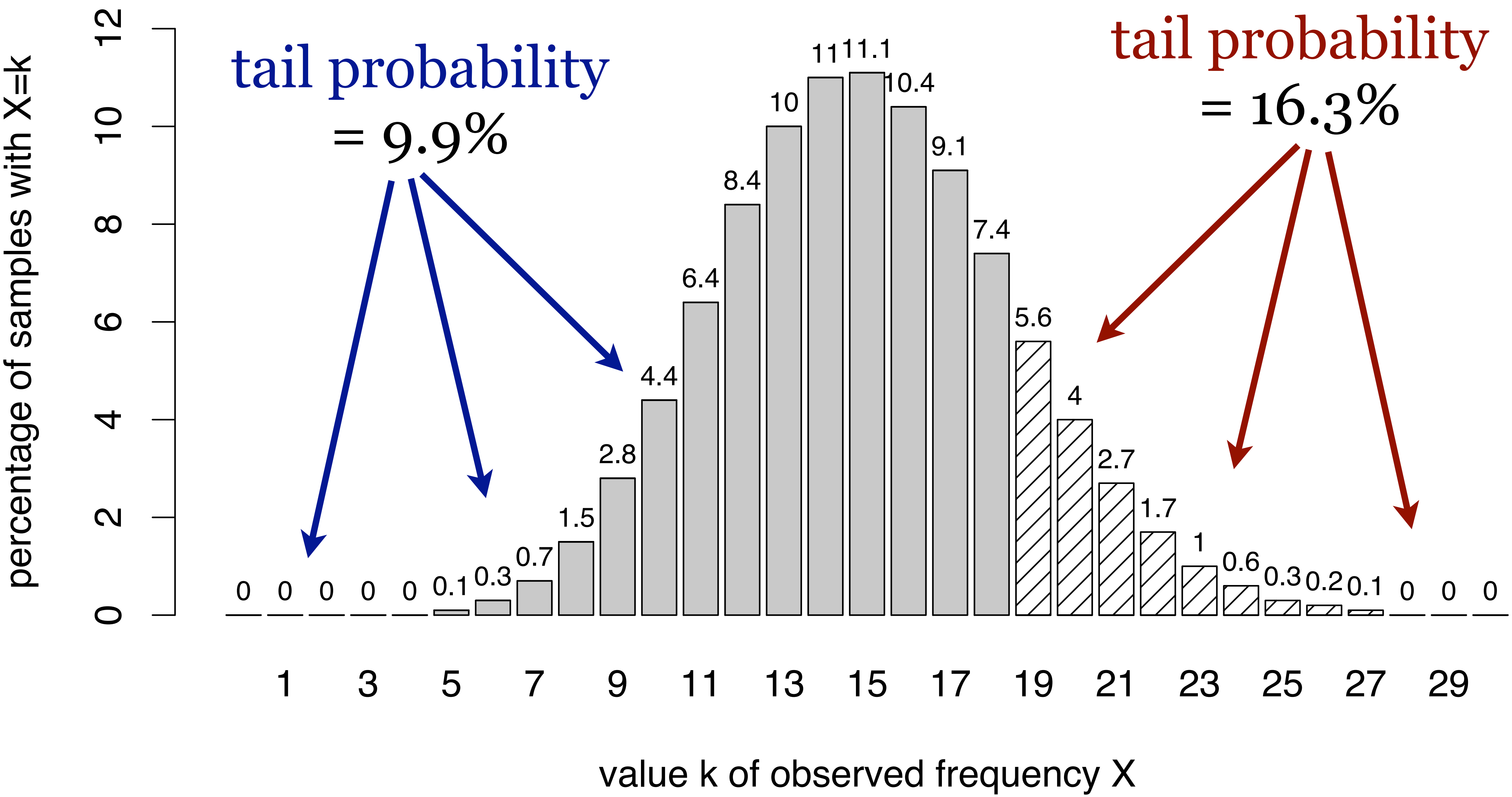

Statistical hypothesis testing

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- Statistical **hypothesis tests**
  - define a **rejection criterion** for refuting H_o
  - control the risk of false rejection (**type I error**) to a "socially acceptable level" (**significance level**)
  - **p-value** = risk of false rejection for observation
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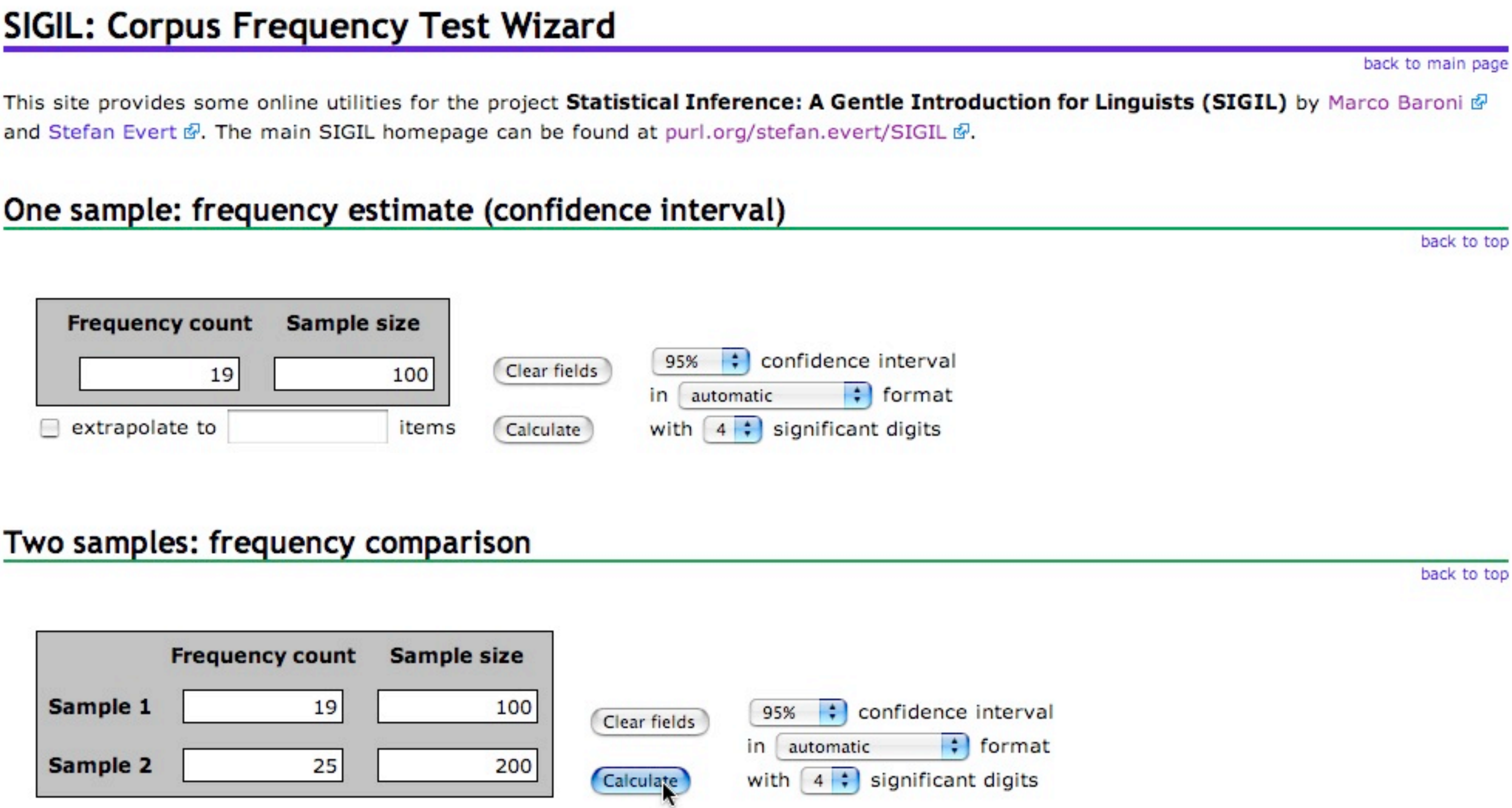
- Two-sided vs. one-sided tests
  - in general, two-sided tests should be preferred
  - one-sided test is plausible in our example

Hypothesis tests in practice



http://sigil.collocations.de/wizard.html

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- More options: statistical computing software
  - commercial solutions like SPSS, S-Plus, …
  - open-source software http://www.r-project.org/
  - we recommend R, of course,
    for the usual reasons

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  - **null hypothesis**: H_0: $\pi = \mathbf{15\%}$
- Using the `binom.test()` function:

```
> binom.test(19, 100, p=.15)  # two-sided
> binom.test(19, 100, p=.15,  # one-sided
    alternative="greater")
```

Binomial hypothesis test in R

```
> binom.test(19, 100, p=.15)

   Exact binomial test

data:  19 and 100

number of successes = 19, number of
trials = 100, p-value = 0.2623

alternative hypothesis: true probability of
success is not equal to 0.15

95 percent confidence interval:
 0.1184432 0.2806980

sample estimates:
probability of success
                  0.19
```

Binomial hypothesis test in R

```
> binom.test(19, 100, p=.15)$p.value
[1] 0.2622728

> binom.test(23, 100, p=.15)$p.value
[1] 0.03430725

> binom.test(190, 1000, p=.15)$p.value
[1] 0.0006356804
```

Power

Power

- Type II error = failure to reject incorrect H_o
  - the larger the discrepancy between H_o and the true situation, the more likely it will be rejected
  - e.g. if the true proportion of passives is $\pi = .25$, then most samples provide enough evidence to reject; but true $\pi = .16$ makes rejection very difficult
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  - a **powerful** test has a low type II error
- Basic insight: larger sample = more power
  - relative sampling variation becomes smaller
  - might become powerful enough to reject for $\pi = 15.1\%$

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- Parametric tests make stronger assumptions
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- Parametric tests are usually more powerful
  - strong assumptions allow less conservative estimate of sampling variation → less evidence needed against H_0

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- Conservative tests
    - put more weight on avoiding type I errors → weaker
    - most non-parametric methods are conservative

Confidence interval

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- But what if we do not have an obvious null hypothesis to start with?
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- But what if we do not have an obvious null hypothesis to start with?
  - this is typically the case in (computational) linguistics
- We can estimate the true population proportion from the sample data (relative frequency)
  - sampling variation → range of plausible values
  - such a **confidence interval** can be constructed by inverting hypothesis tests (e.g. binomial test)

Confidence interval

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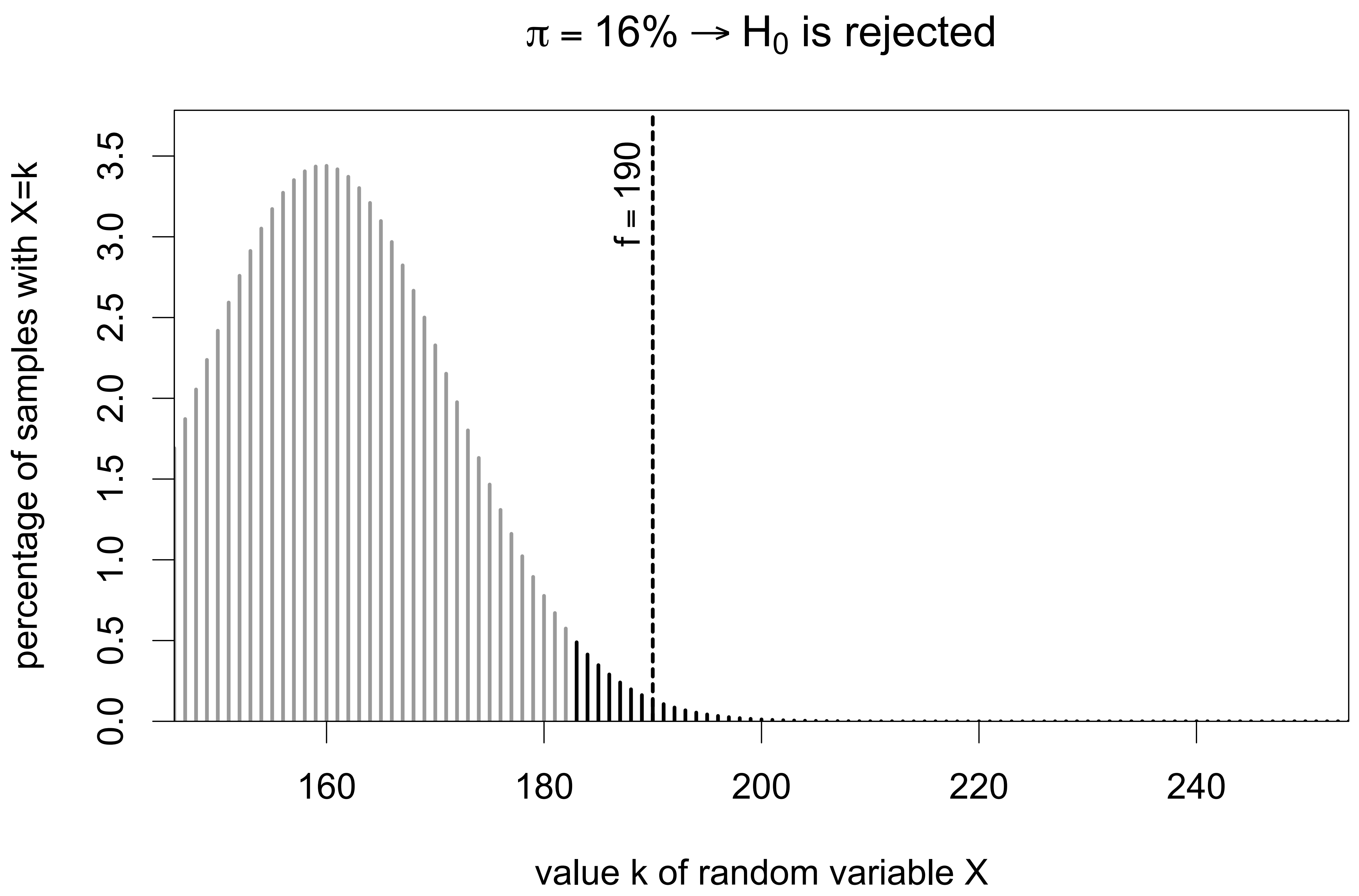

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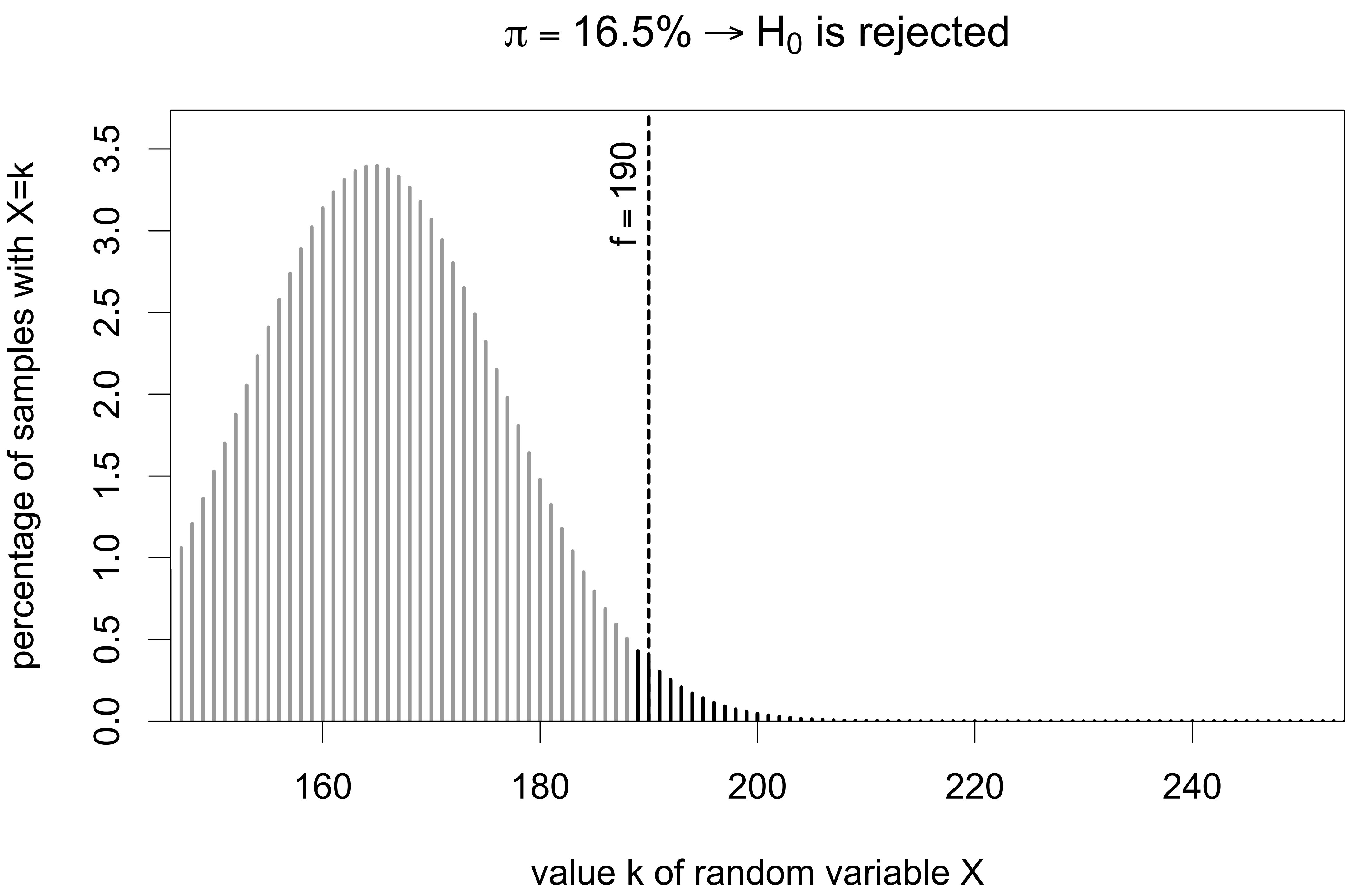

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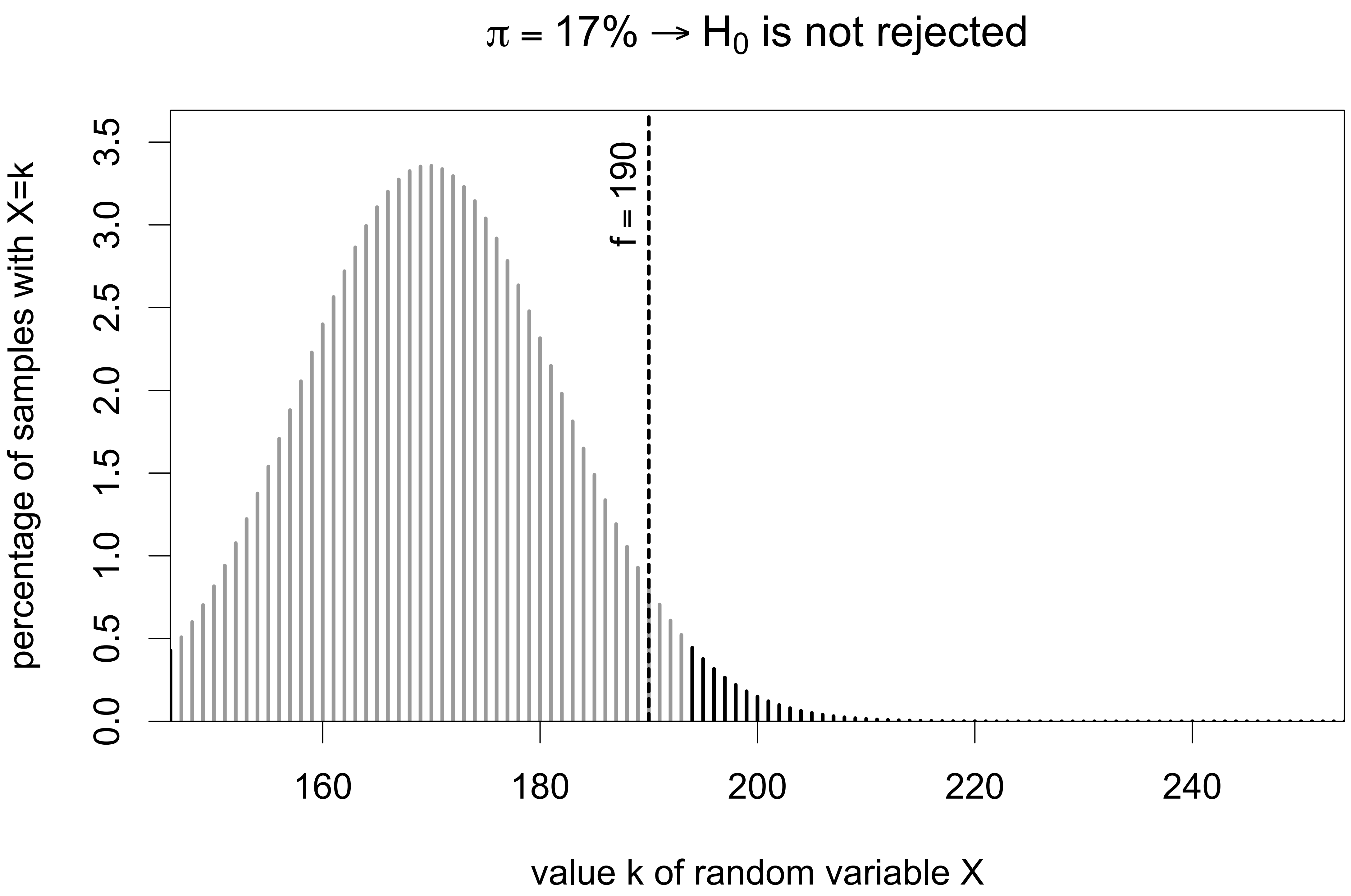

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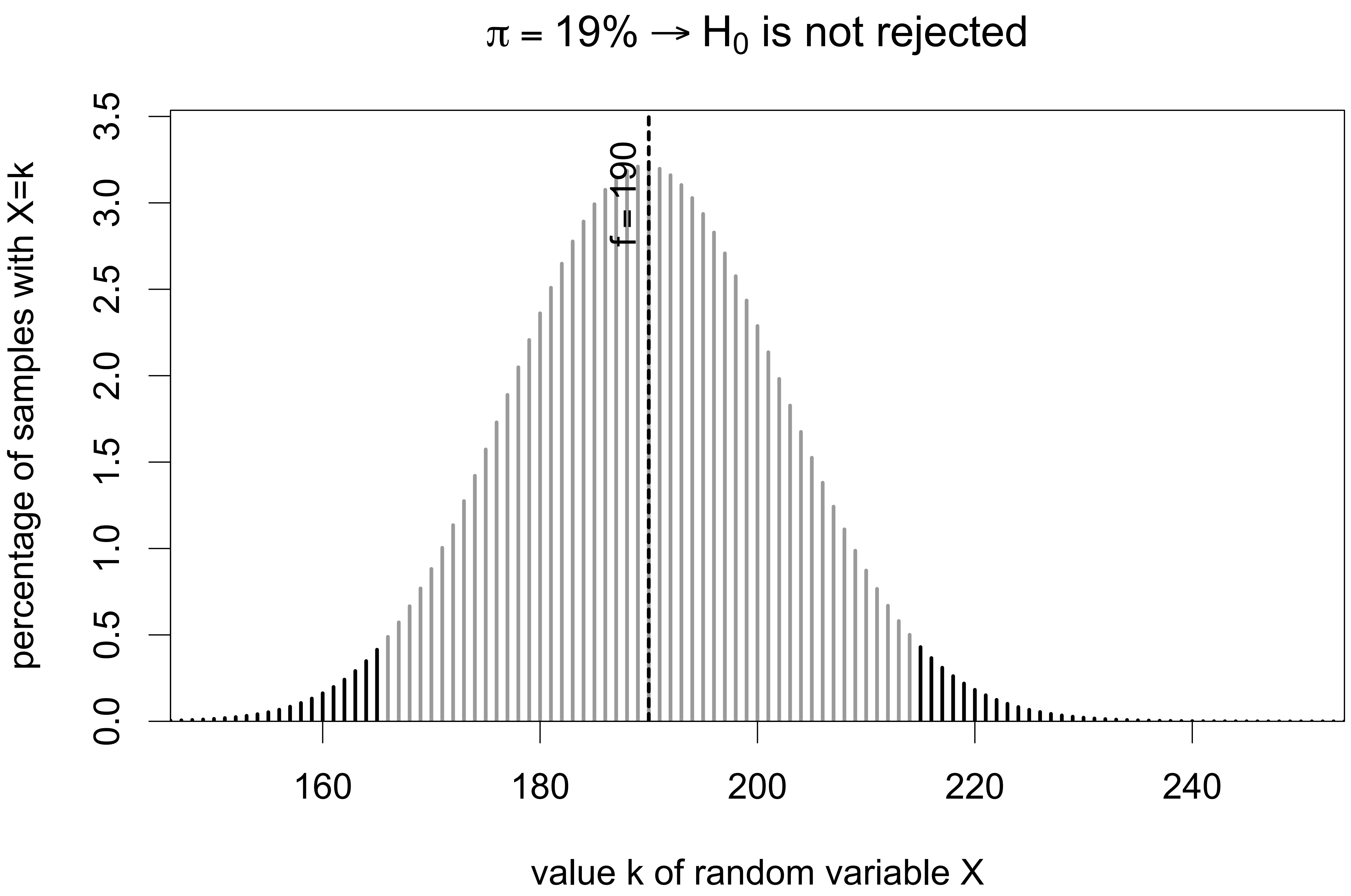

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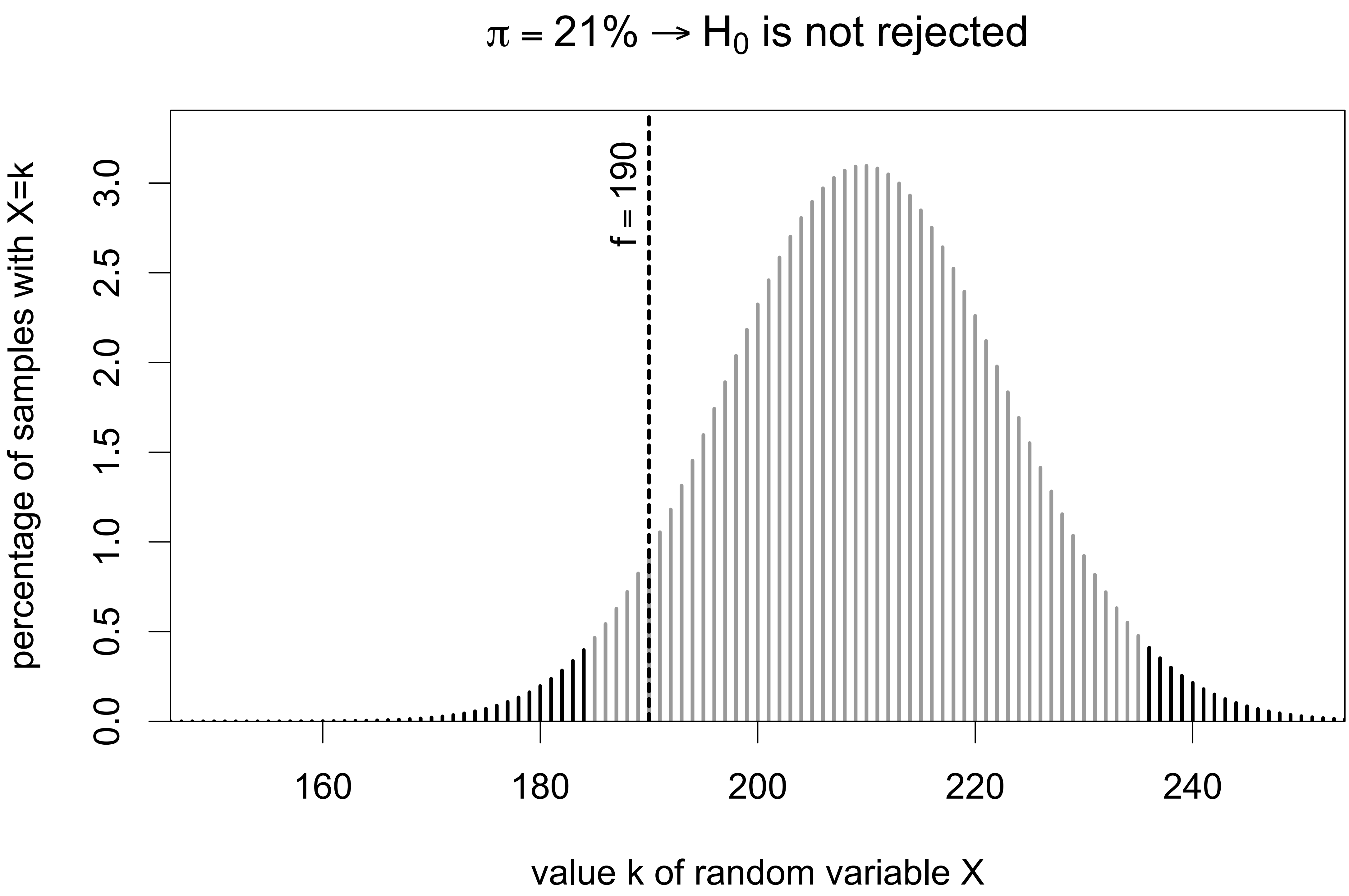
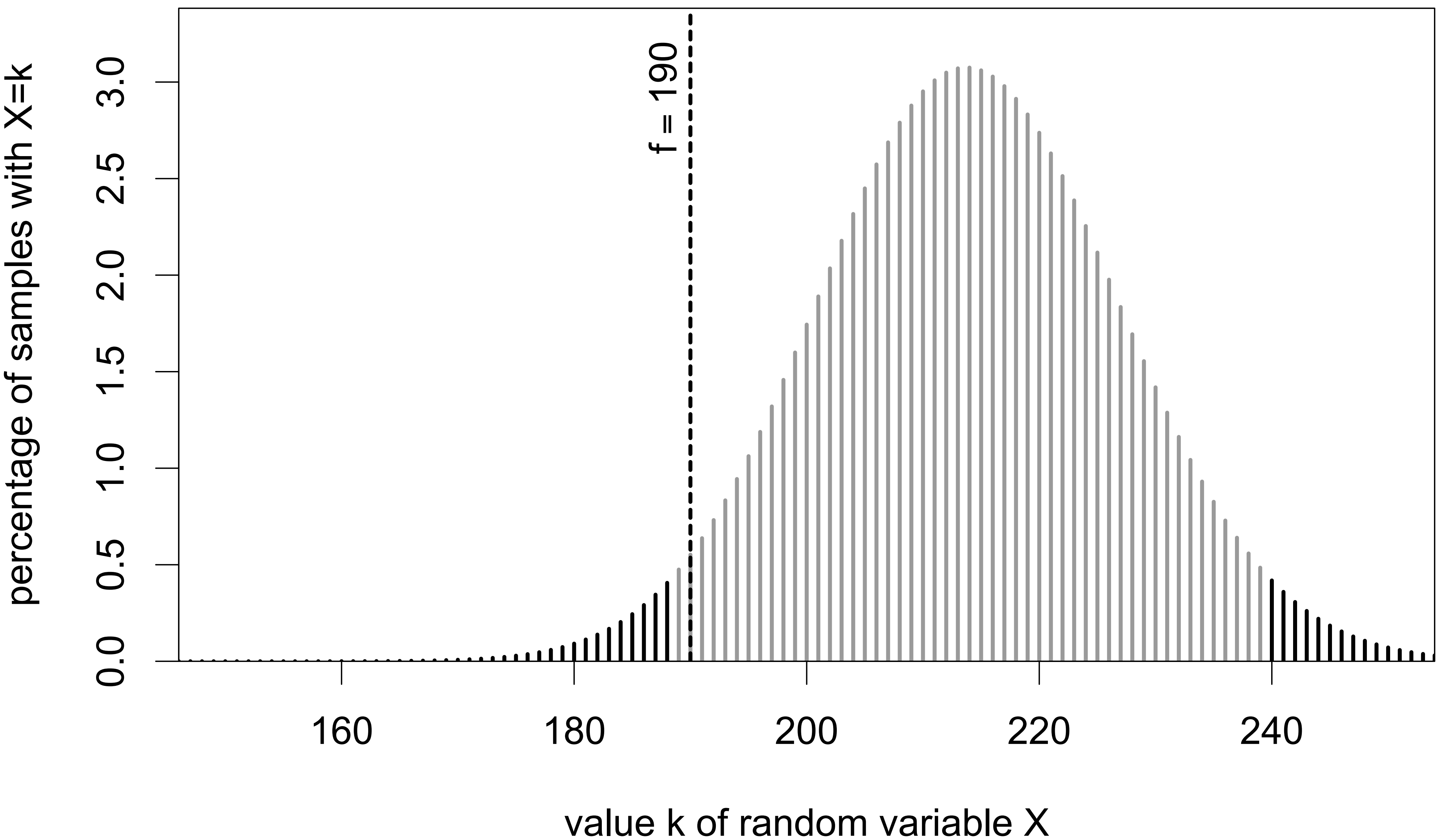


Confidence interval

$\pi = 21.4\% \rightarrow H_0$ is not rejected



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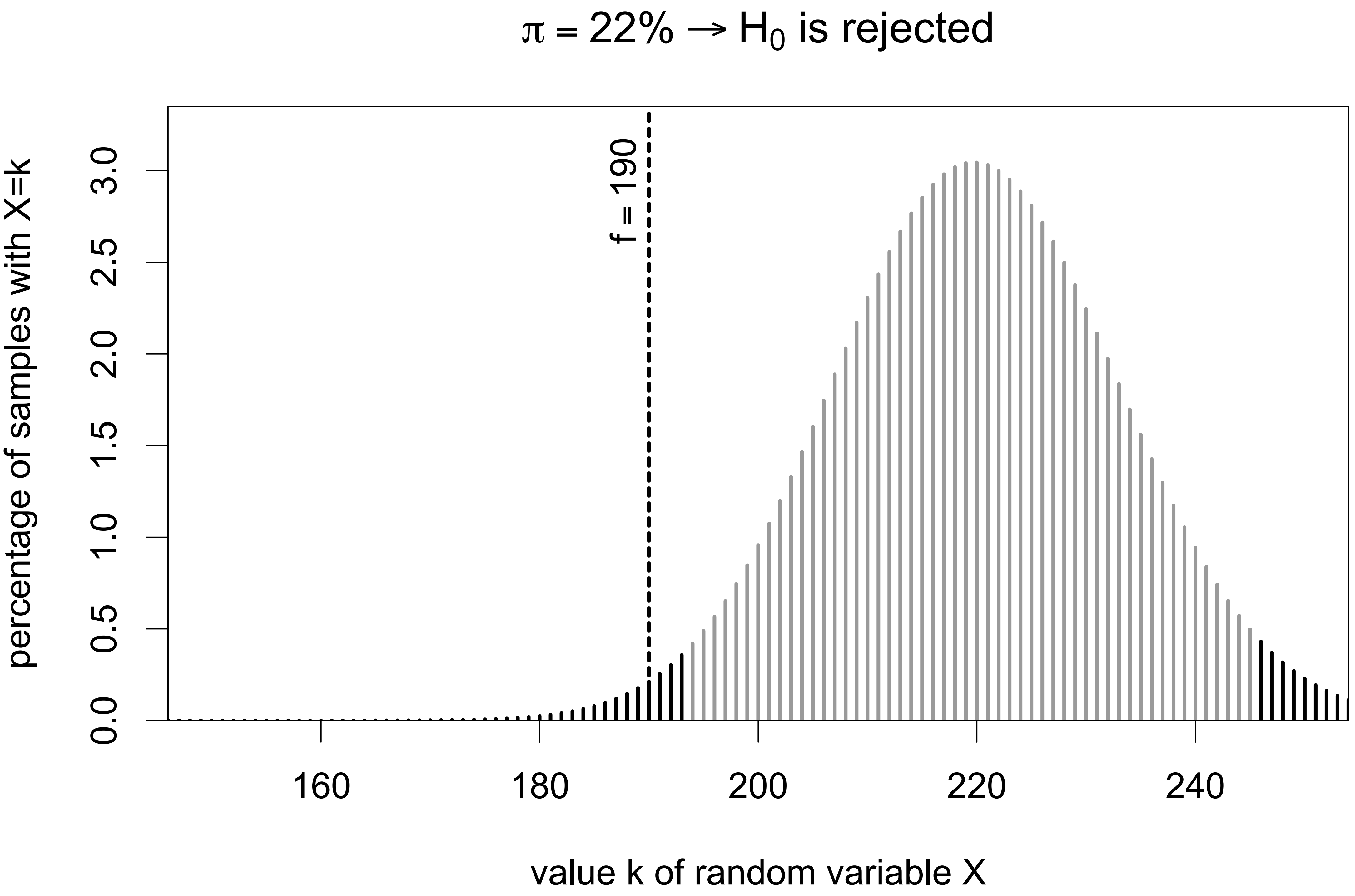

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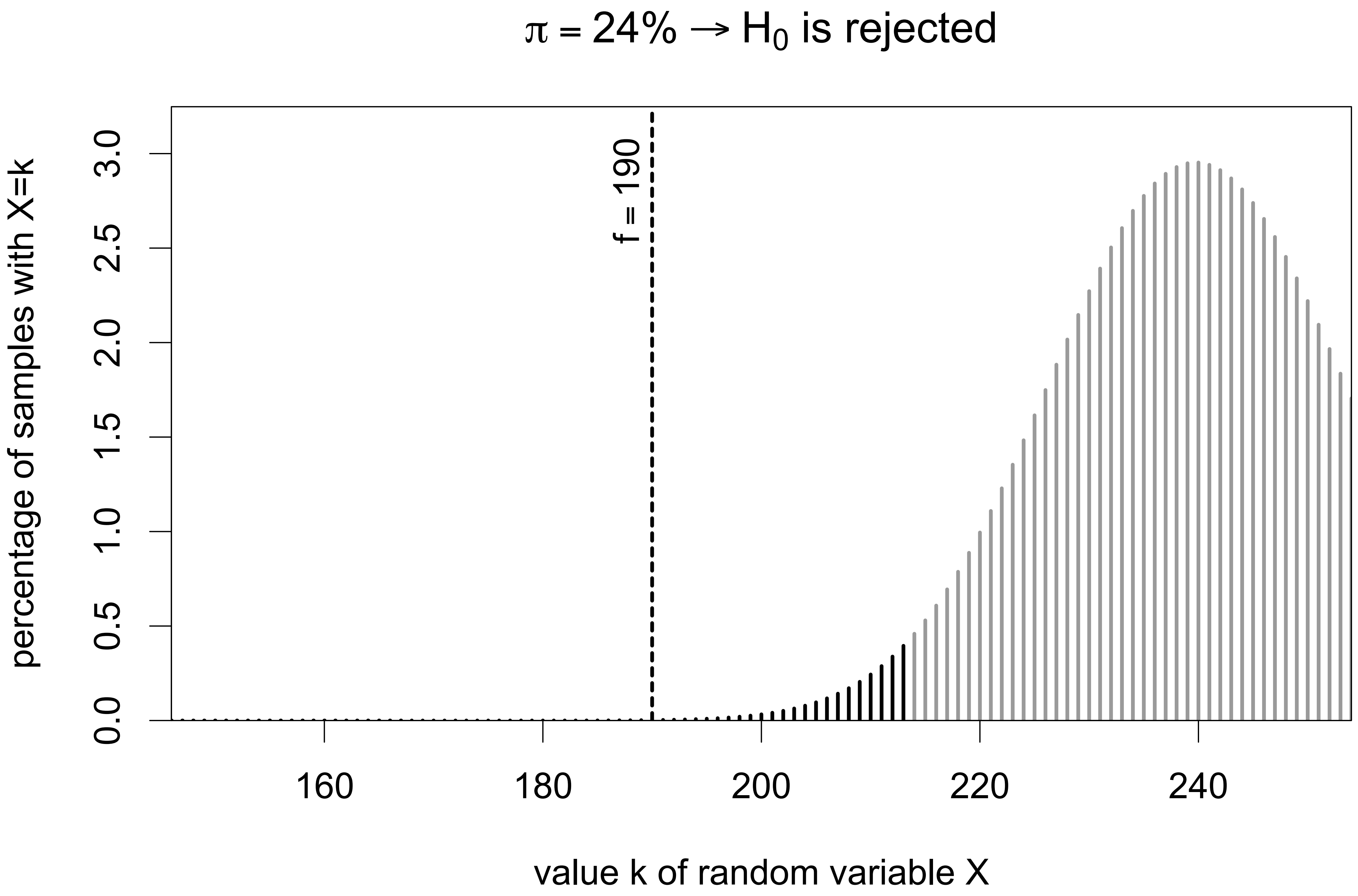

Confidence intervals

- Confidence interval = range of plausible values for true population proportion
- Size of confidence interval depends on sample size and the significance level of the test

	$n = 100$ $k = 19$	$n = 1{,}000$ $k = 190$	$n = 10{,}000$ $k = 1{,}900$
$\alpha = .05$	11.8% ... 28.1%	16.6% ... 21.6%	18.2% ... 19.8%
$\alpha = .01$	10.1% ... 31.0%	15.9% ... 22.4%	18.0% ... 20.0%
$\alpha = .001$	8.3% ... 34.5%	15.1% ... 23.4%	17.7% ... 20.3%

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  - omit H_0 if only interested in confidence interval
- Significance level of underlying hypothesis test is controlled by `conf.level` parameter
  - expressed as confidence, e.g. `conf.level=.95` for significance level $\alpha = .05$, i.e. 95% confidence
- Can also compute one-sided confidence interval
  - controlled by `alternative` parameter
  - two-sided confidence intervals strongly recommended

Confidence intervals in R

```
> binom.test(190, 1000, conf.level=.99)

   Exact binomial test

data:  190 and 1000

number of successes = 190, number of
trials = 1000, p-value < 2.2e-16

alternative hypothesis: true probability of
success is not equal to 0.5

99 percent confidence interval:
 0.1590920 0.2239133

sample estimates:
probability of success
                  0.19
```

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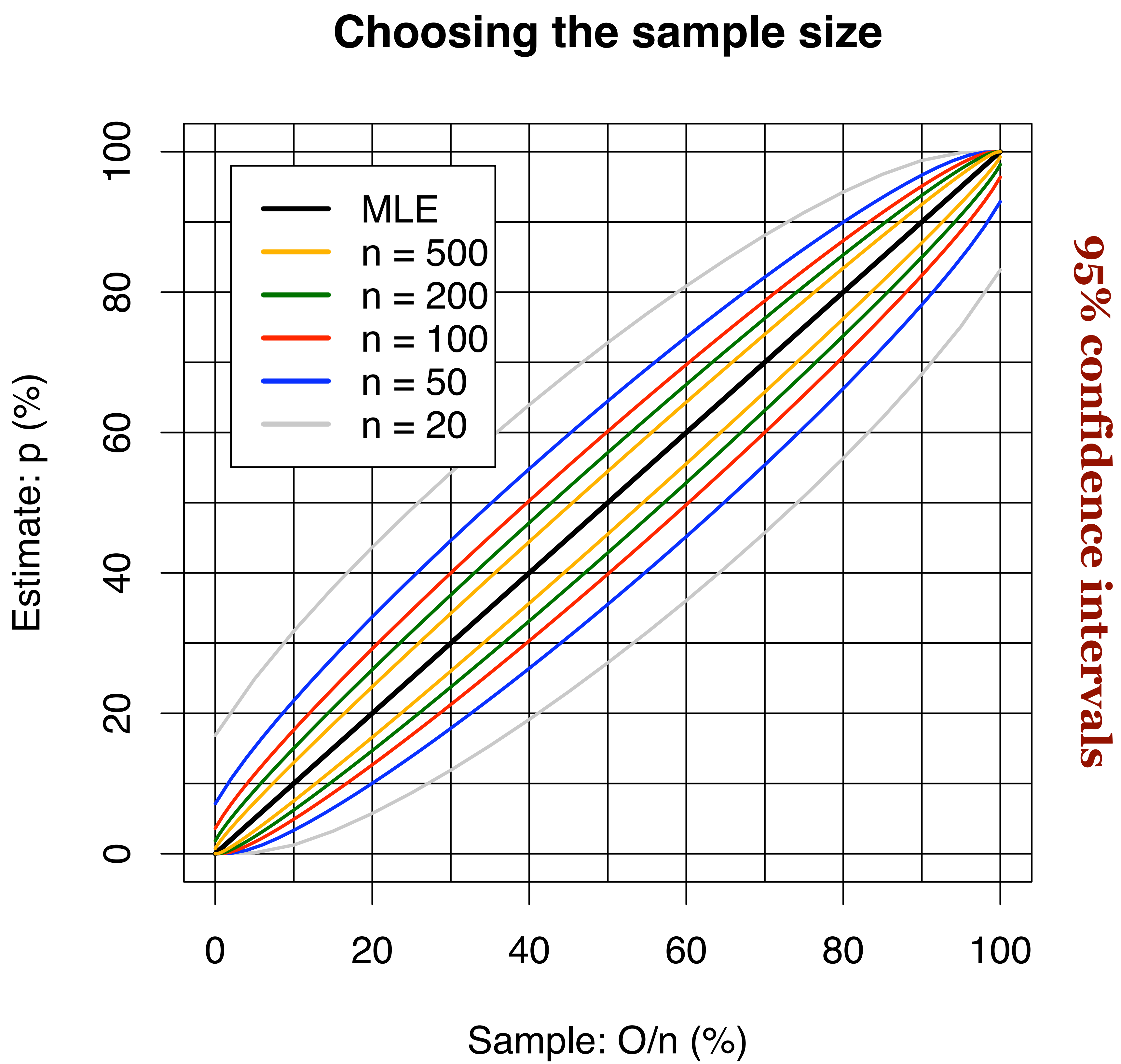

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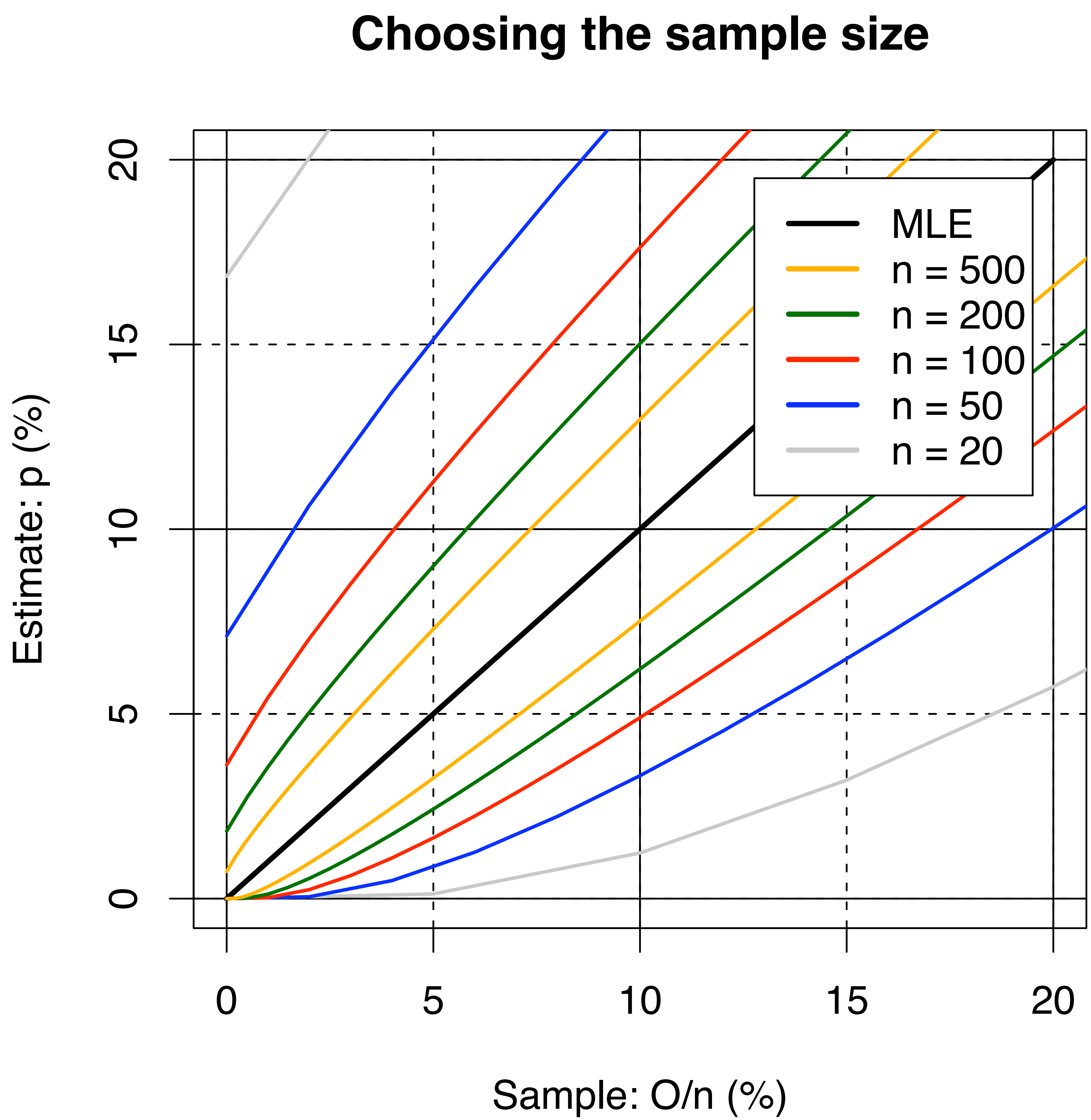

95% confidence intervals

Using R to choose sample size

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  - requires calculation of large number of hypothetical confidence intervals
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  - `binom.test()` is both inconvenient and inefficient
- The `corpora` package has a vectorized function

```
> library(corpora)  # install from CRAN
> prop.cint(190, 1000, conf.level=.99)
> ?prop.cint  # “conf. intervals for proportions”
```

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- Compare observed frequencies in two samples

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- Chi-squared X^2, likelihood ratio G^2, Fisher's test
  - based on same principles as binomial test

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- Frequency comparison in practice
  - all relevant tests can be performed in R
  - easier (for non-techies) with **online wizards**

Frequency comparison in R

- Frequency comparison with `prop.test()`
  - easy to use: specify counts k_i and sample sizes n_i
  - uses chi-squared test "behind the scenes"
  - also computes confidence interval for difference of population proportions
- E.g. for 19 passives out of 100 vs. 25 out of 200

```
> prop.test(c(19,25), c(100,200))
```

  - parameters `conf.level` and `alternative` can be used in the familiar way

Frequency comparison in R

```
> prop.test(c(19,25), c(100,200))

   2-sample test for equality of proportions with
continuity correction

data:  c(19, 25) out of c(100, 200)

X-squared = 1.7611, df = 1, p-value = 0.1845

alternative hypothesis: two.sided

95 percent confidence interval:
 -0.03201426  0.16201426

sample estimates:
prop 1 prop 2
 0.190  0.125
```

Frequency comparison in R

- Can also carry out chi-squared (`chisq.test`) and Fisher's exact test (`fisher.test`)
  - requires full contingency table as 2×2 matrix
  - NB: likelihood ratio test not in standard library
- Table for 19 out of 100 vs. 25 out of 200

```
> ct <- cbind(c(19,81),
              c(25,175))

> chisq.test(ct)

> fisher.test(ct)
```

19	**25**
81	**175**

Some fine print

- Convenient `cont.table` function for building continency tables in `corpora` package

```
> library(corpora)
> ct <- cont.table(19, 100, 25, 200)
```

- Difference of proportions no always suitable as **measure of effect size**
  - especially if proportions can have different magnitudes (e.g. for lexical frequency data)
  - more intuitive: ratio of proportions (**relative risk**)
  - Conf. int. for similar **odds ratio** from Fisher's test

A case study: passives

- As a case study, we will compare the frequency of passives in Brown (AmE) and LOB (BrE)
  - pooled data
  - separately for each genre category

- Data files provided in CSV format
  - **`passives.brown.csv`** & **`passives.lob.csv`**
  - `cat` = genre category, `passive` = number of passives, `n_w` = number of word, `n_s` = number of sentences, `name` = description of genre category

Preparing the data

```
> Brown <- read.csv("passives.brown.csv")
> LOB <- read.csv("passives.lob.csv")

> Brown          # take a first look at the data tables
> LOB

# pooled data for entire corpus = column sums (col. 2 … 4)
> Brown.all <- colSums(Brown[, 2:4])
> LOB.all <- colSums(LOB[, 2:4])
```

Frequency tests for pooled data

```
> ct <- cbind(c(10123, 49576-10123),  # Brown
              c(10934, 49742-10934))  # LOB
> ct          # contingency table for chi-squared / Fisher
> fisher.test(ct)

# proportions test provides more interpretable effect size
> prop.test(c(10123, 10934), c(49576, 49742))

# we could in principle do the same for all 15 genres ...
```

Automation: user functions

```
# user function do.test() executes proportions test for samples
# k1/n1 and k2/n2, and summarizes relevant results in compact form
> do.test <- function (k1, n1, k2, n2) {
    # res contains results of proportions test (list = data structure)
    res <- prop.test(c(k1, k2), c(n1, n2))
    # data frames are a nice way to display summary tables
    fmt <- data.frame(p=res$p.value,
      lower=res$conf.int[1], upper=res$conf.int[2])
    fmt  # return value of function = last expression
}
> do.test(10123, 49576, 10934, 49742)  # pooled data
> do.test(146, 975, 134, 947)          # humour genre
```

A nicer user function

```
# extract relevant information directly from data frames
> do.test(Brown$passive[15], Brown$n_s[15],
          LOB$passive[15], LOB$n_s[15])

# nicer version of user function with genre category labels
> do.test <- function (k1, n1, k2, n2, cat="") {
   res <- prop.test(c(k1, k2), c(n1, n2))
   fmt <- data.frame(p=res$p.value,
     lower=res$conf.int[1], upper=res$conf.int[2])
   rownames(fmt) <- cat  # add genre as row label
   fmt
}

> do.test(Brown$passive[15], Brown$n_s[15],
          LOB$passive[15], LOB$n_s[15],
          cat=Brown$cat[15])
```

Automation: the `for` loop

```
# our code relies on same ordering of genre categories!
> all(Brown$cat == LOB$cat)

# carry out tests for all genres with a simple for loop
> for (i in 1:15) {
   res <- do.test(Brown$passive[i], Brown$n_s[i],
                  LOB$passive[i], LOB$n_s[i],
                  cat=Brown$cat[i]))
   print(res)
}

# it would be nice to collect all these results in a single overview
# table; for this, we need a little bit of R wizardry ...
```

Collecting rows

```
# lapply collects results from iteration steps in a list
> result.list <- lapply(1:15, function (i) {
   do.test(Brown$passive[i], Brown$n_s[i],
           LOB$passive[i], LOB$n_s[i],
           cat=Brown$name[i])
})

> result <- do.call(rbind, result.list)
# think of this as an idiom that you just have to remember ...

> round(result, 5)    # easier to read after rounding
```

It's your turn now …

- Questions:
  - Which differences are significant?
  - Are the effect sizes linguistically relevant?

- Homework:
  - Extend `do.test()` such that the two sample proportions are included in the summary table.
  - Do you need to modify any of the other code as well?

Further reading

- Baroni, Marco and Evert, Stefan (2008, in press). Statistical methods for corpus exploitation. In A. Lüdeling and M. Kytö (eds.), *Corpus Linguistics. An International Handbook*, chapter 38. Mouton de Gruyter, Berlin.
  - an extended and more detailed version of this talk
- Evert, Stefan (2006). How random is a corpus? The library metaphor. *Zeitschrift für Anglistik und Amerikanistik*, **54**(2), 177–190.
  - introduces library metaphor for statistical tests on corpus data
- Agresti, Alan (2002). *Categorical Data Analysis*. John Wiley & Sons, Hoboken, 2nd edition.
  - mathematical details on frequency tests and frequency comparison