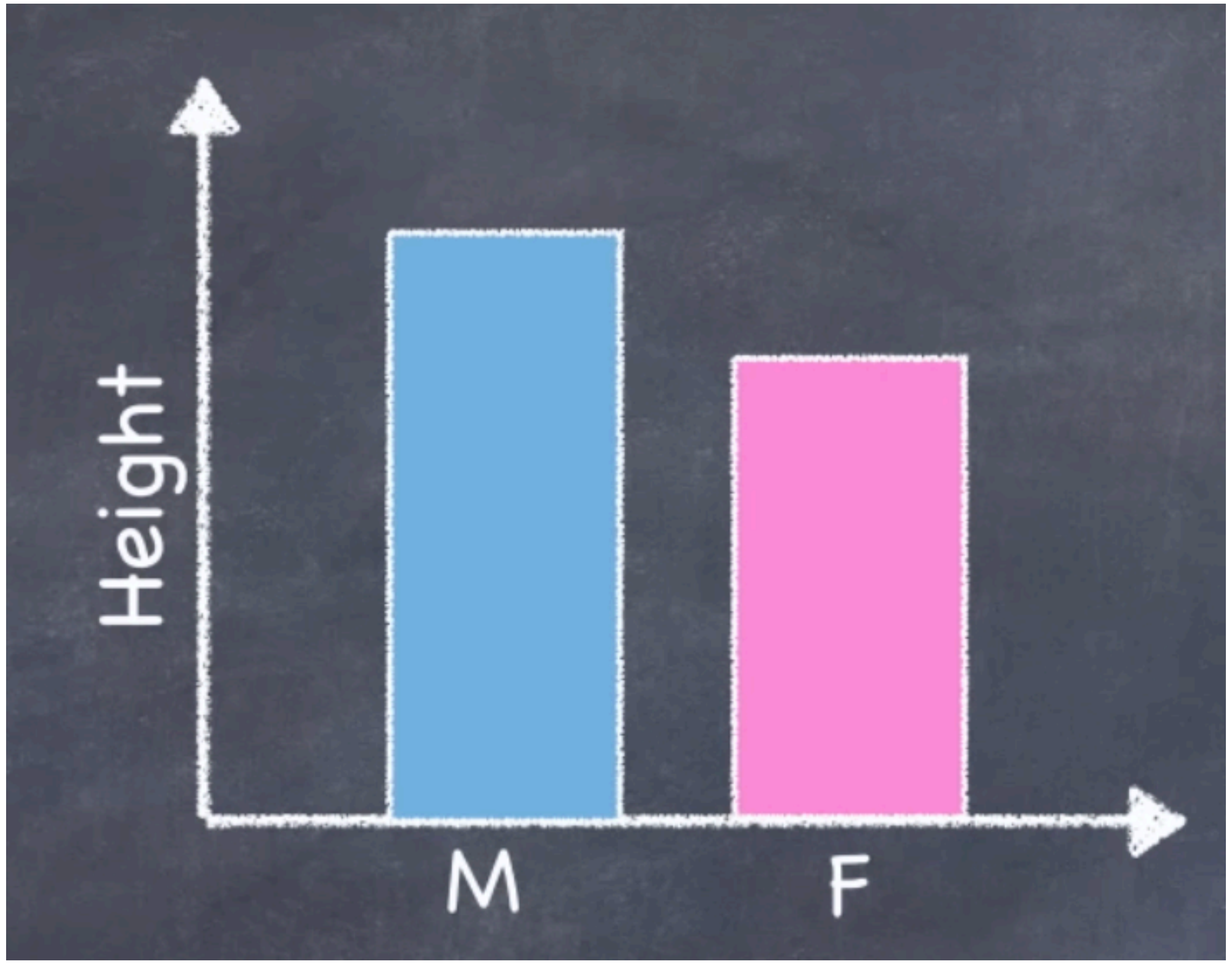
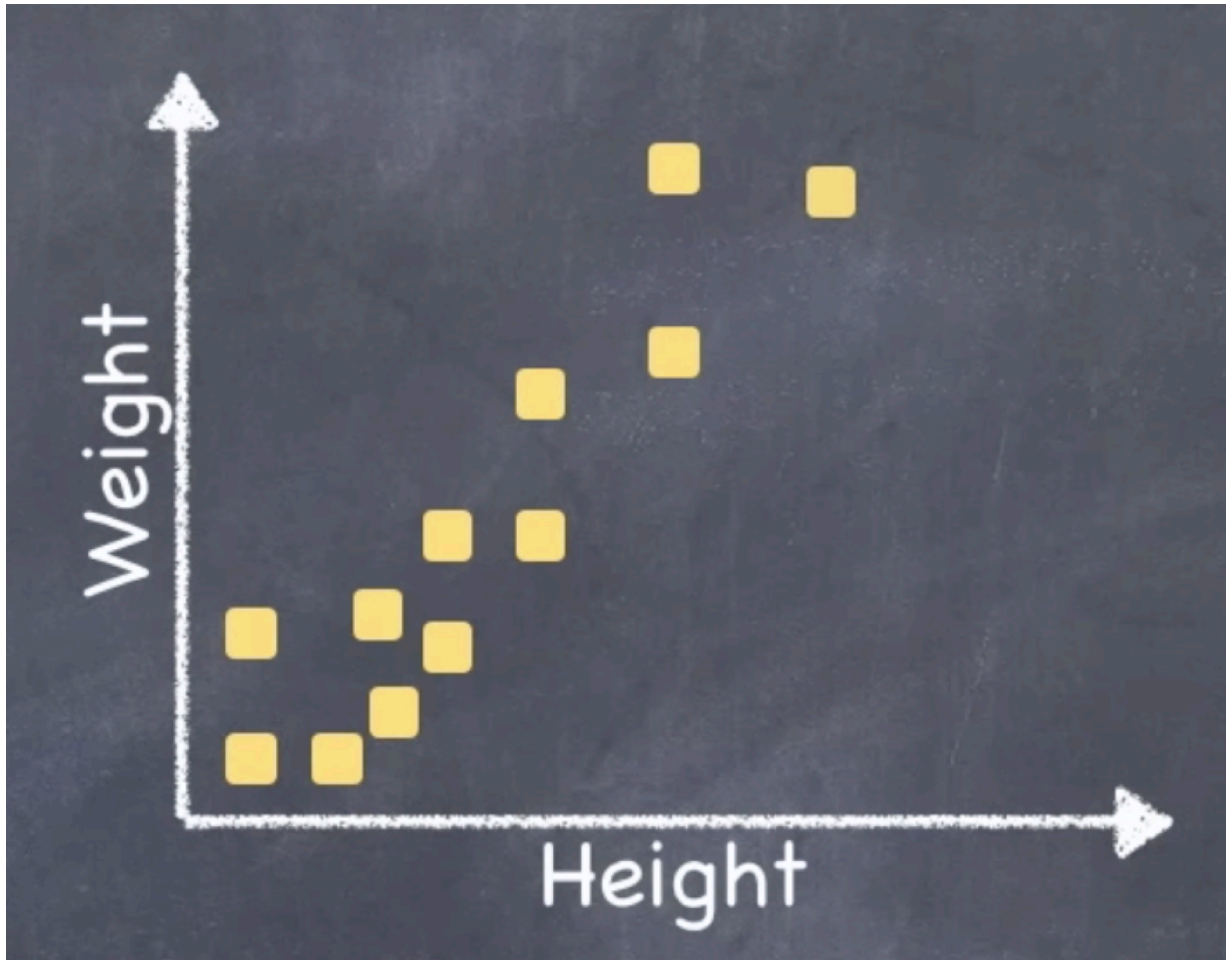
Statistical tests I

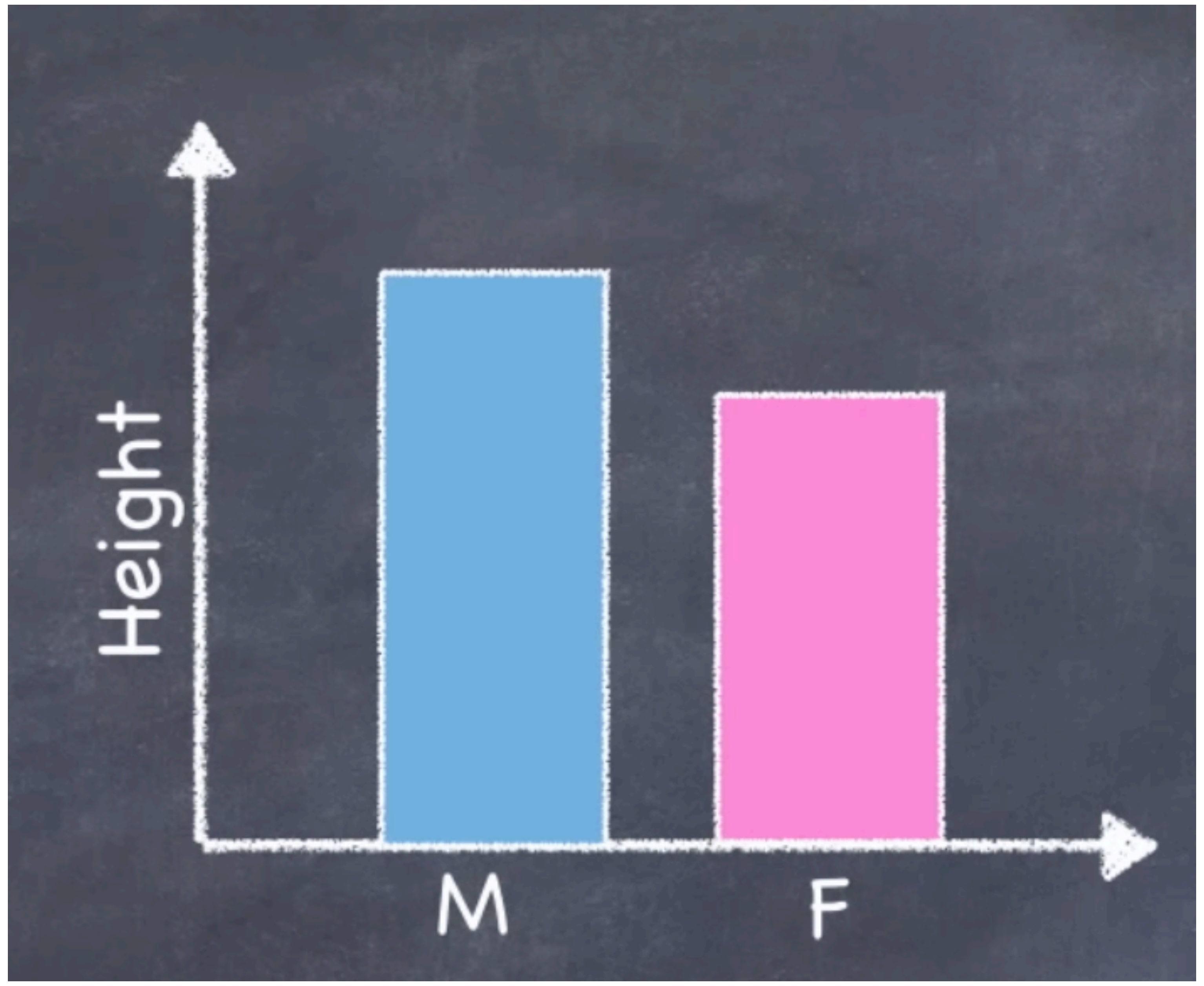
Rachel Warnock

22.04.2025


Height
M
F


Weight
Height

Objectives



Compare the means of 2 groups → z-test

→ t-test

Compare 2+ groups → ANOVA

You do **not** need to remember all the details of these statistical tests, you just need to **get the gist**

The most important thing to ask, is what test is most appropriate for my data?

Statistical hypothesis testing

1. Define your research question / hypothesis

2. Define your statistical hypothesis (null & alternative)

3. Find an appropriate test & sampling distribution

4. Choose the type I error rate

Statistical hypothesis testing

5. Collect the data

6. Calculate test statistics

7. State the **statistical** conclusion

8. Interpret your results

Comparing 2 means — *z*-test or *t*-test

We often want to know if the average value of some variable is different (or higher or lower) than some specific value or between two groups

The *z*-test — the most useless of all statistical tests

Almost never applied in real life (because it relies on a known standard deviation)

It's useful as a stepping stone to understanding the *t*-test

A simple z-test

You might ask, are students from geology scoring higher than the average student in statistics?

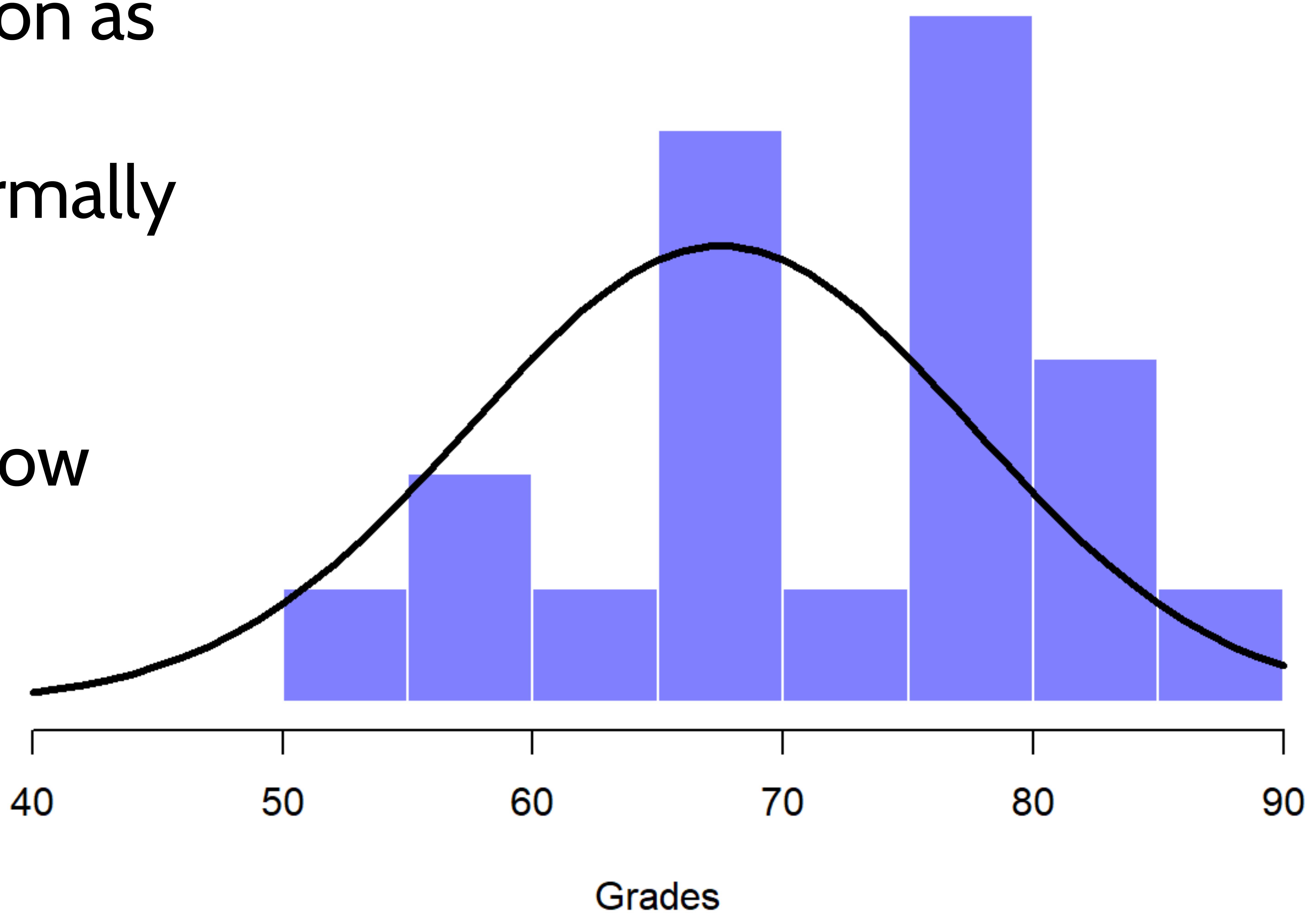
mean average grade = 67.5 and s.d. = 9.5

geology students mean = 73.2, N = 20

Assumptions

- The same standard deviation as the rest of the class
- The student grades are normally distributed

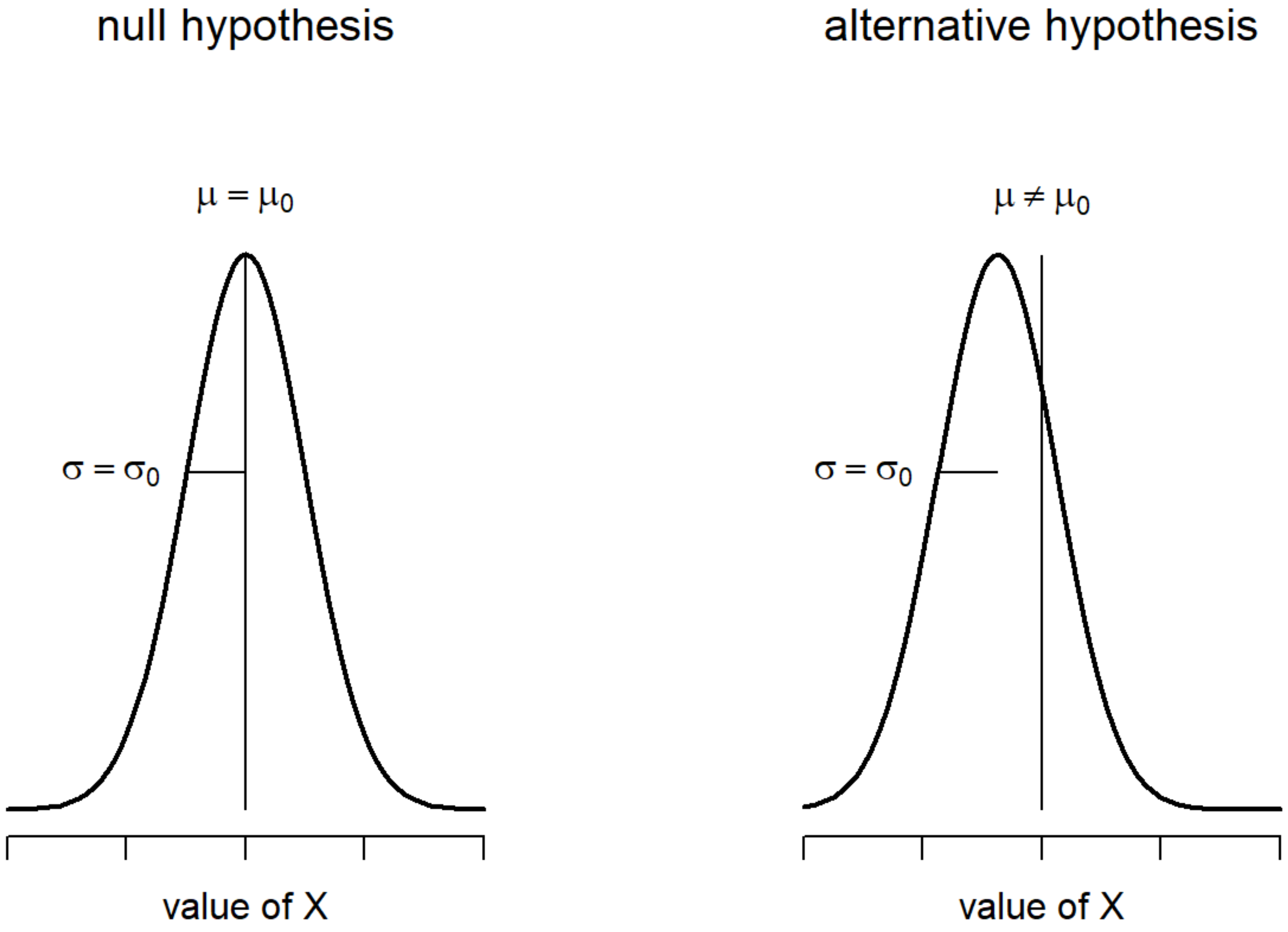
(In reality we usually don't know either of these things)



What are our hypotheses? 🤔

- Research
- Statistical (null and alternative)

The hypotheses for a one-sided or two-sided *z*-test



If the null hypothesis is true then the **sampling distribution** of the mean can be written as:

$$\bar{X} \sim \mathrm{Normal}(\mu_0, \mathrm{SE}(\bar{X}))$$

i.e., **comes from a distribution with the same mean & SD**

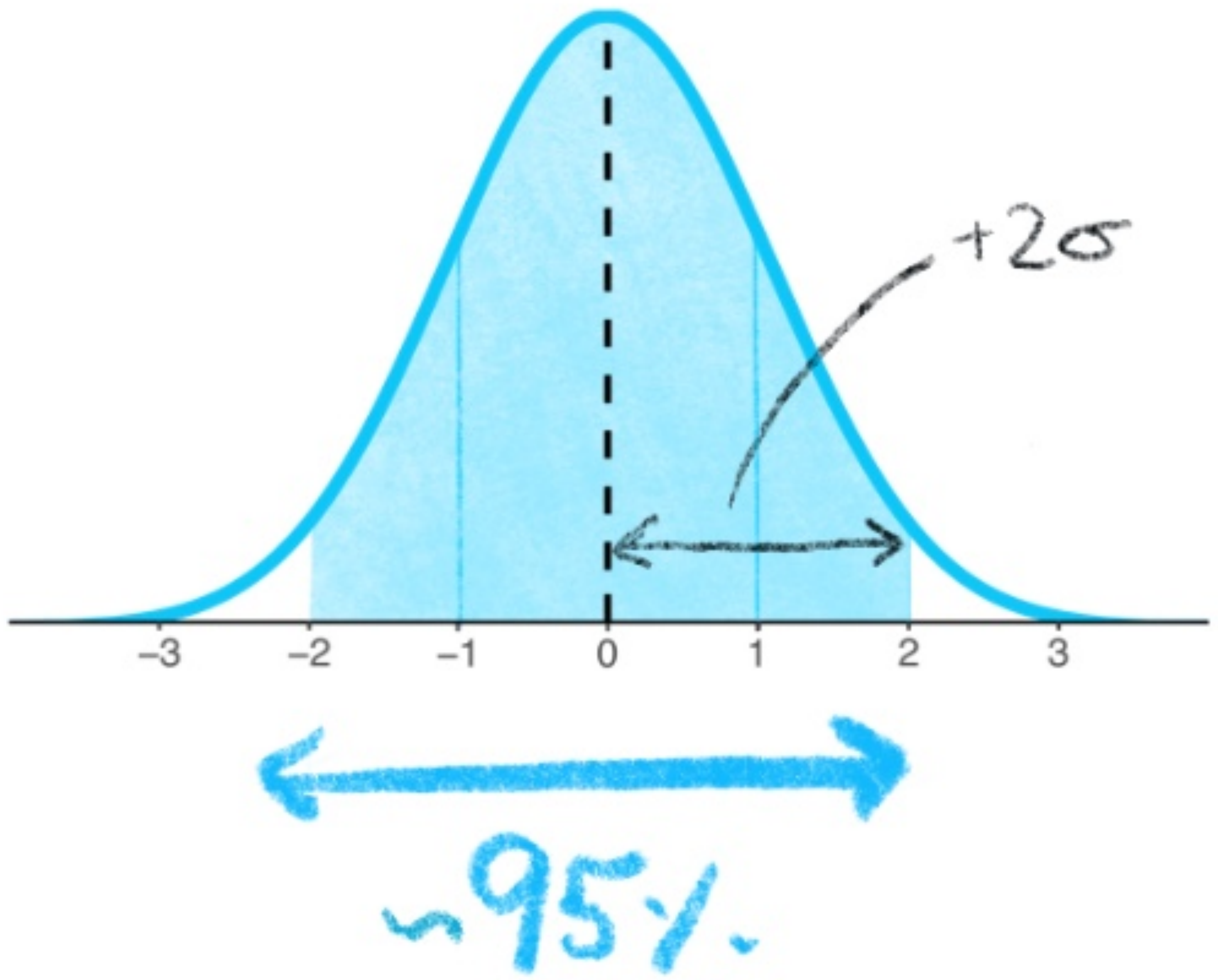
We focus on **the difference between the means**

If $\mu - \mu_0$ equals or is very close to zero, this indicates support for the null hypothesis

If $\mu - \mu_0$ is a long way away from zero, then it's less likely that we'd accept the null hypothesis

How far from zero should it be for us to reject H_0?

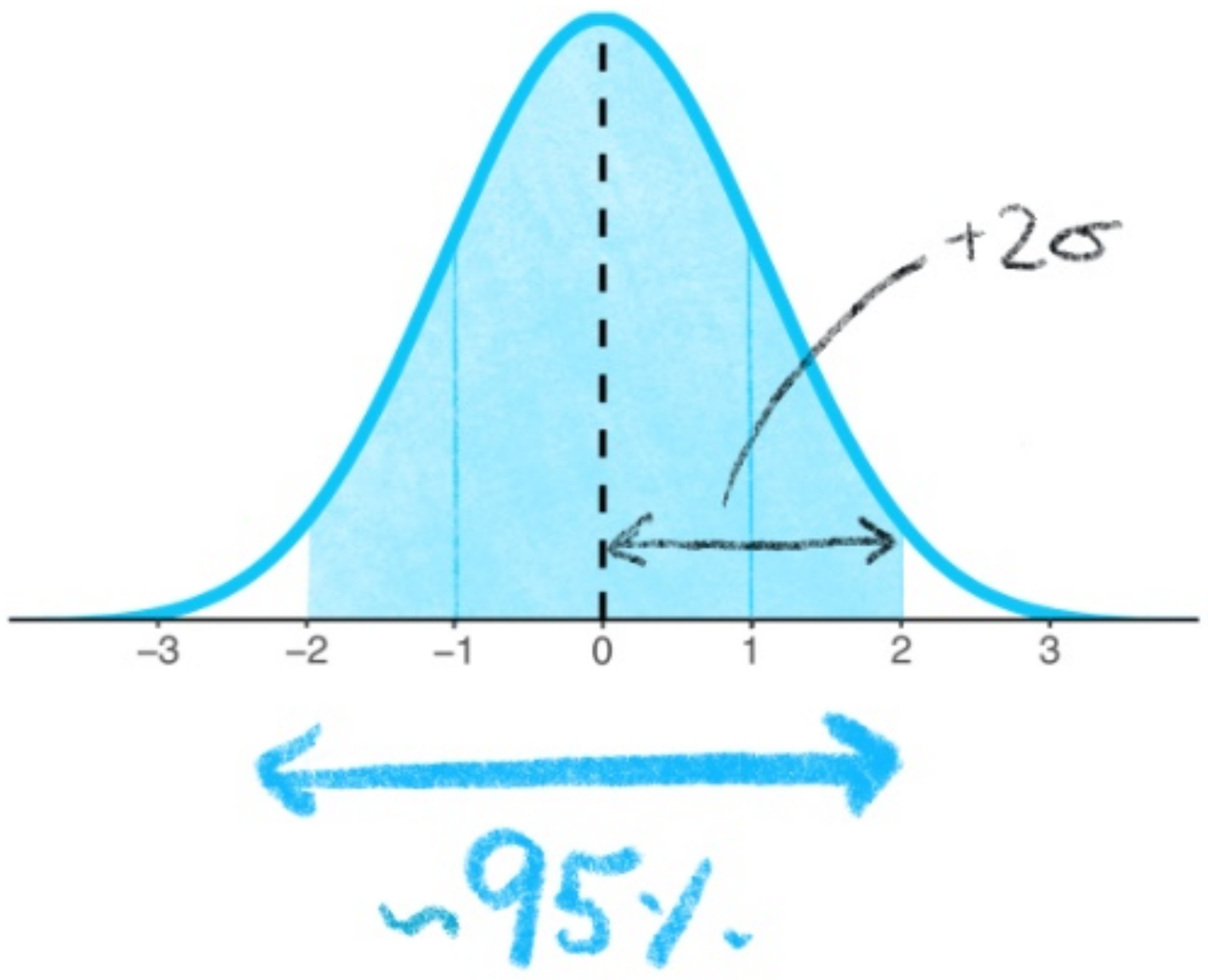
Standard scores, also know as z-scores



= number of standard deviations the sample mean is away in the test distribution

$$\text{standard score} = \frac{\text{raw score} - \text{mean}}{\text{standard deviation}}$$

Calculating the z-score



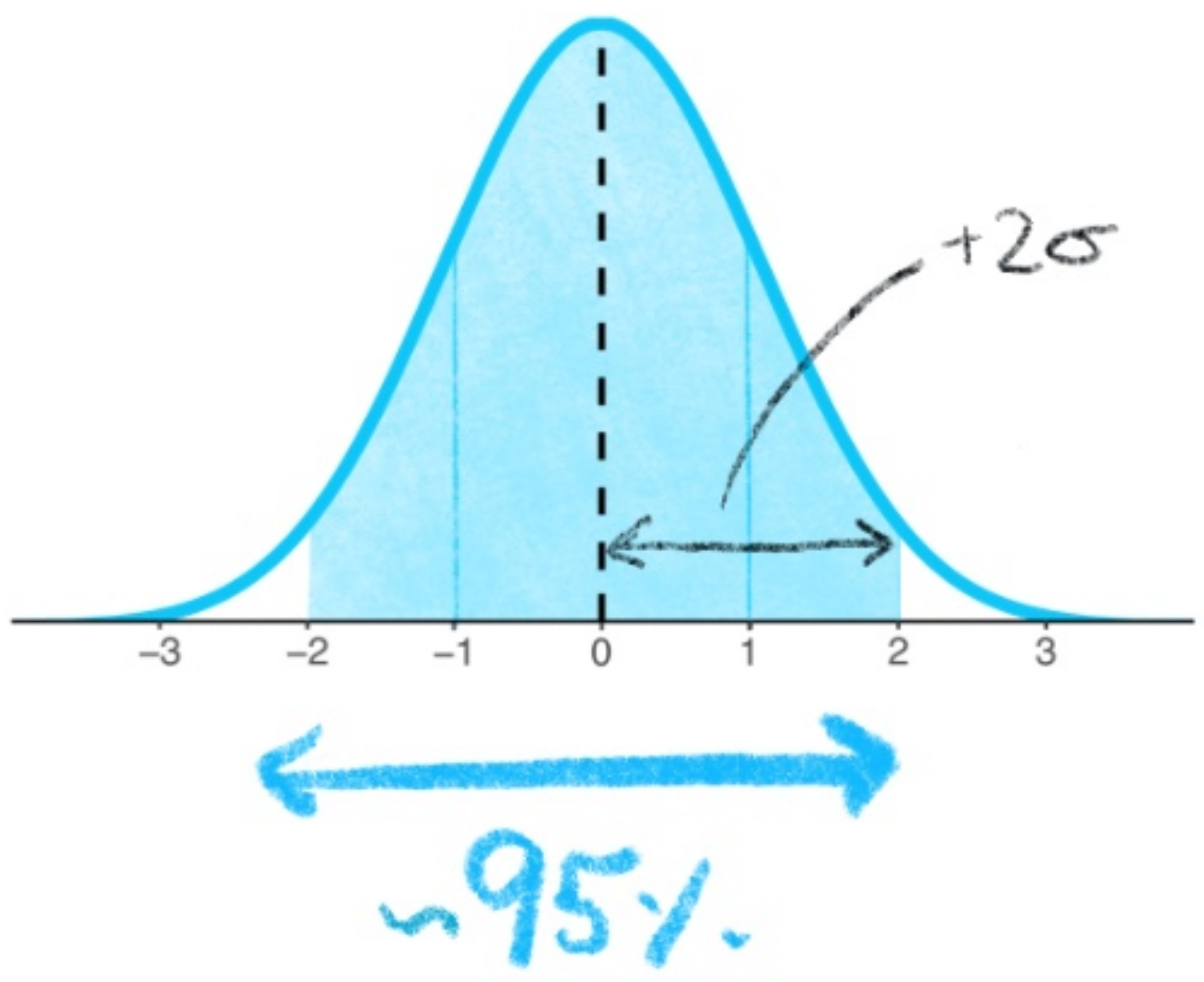
$$z_{\bar{X}} = \frac{\bar{X} - \mu_0}{\mathrm{SE}(\bar{X})}$$

OR

$$z_{\bar{X}} = \frac{\bar{X} - \mu_0}{\sigma / \sqrt{N}}$$

You don't need to remember the formulas! Only here for reference

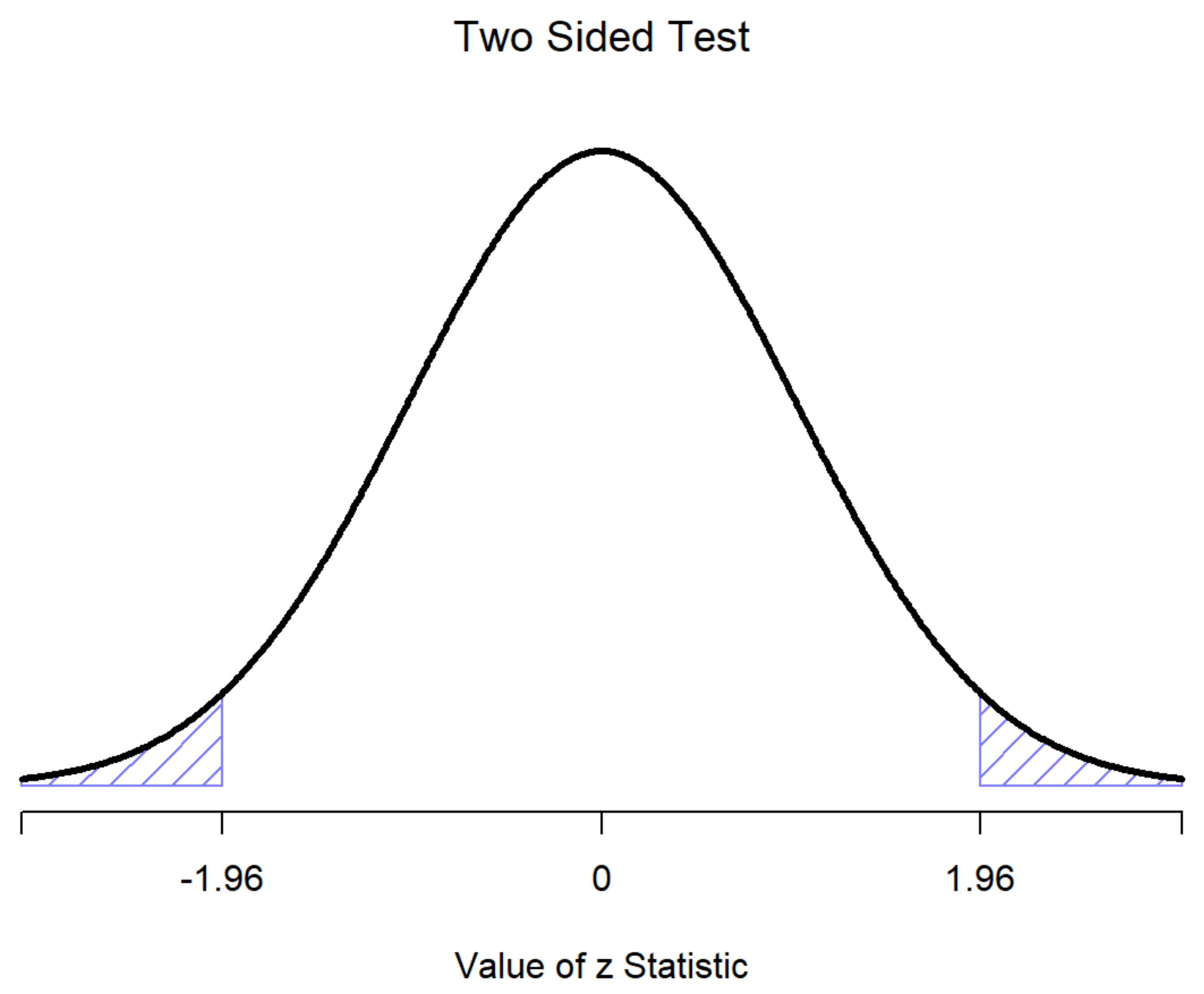
Calculating the z-score

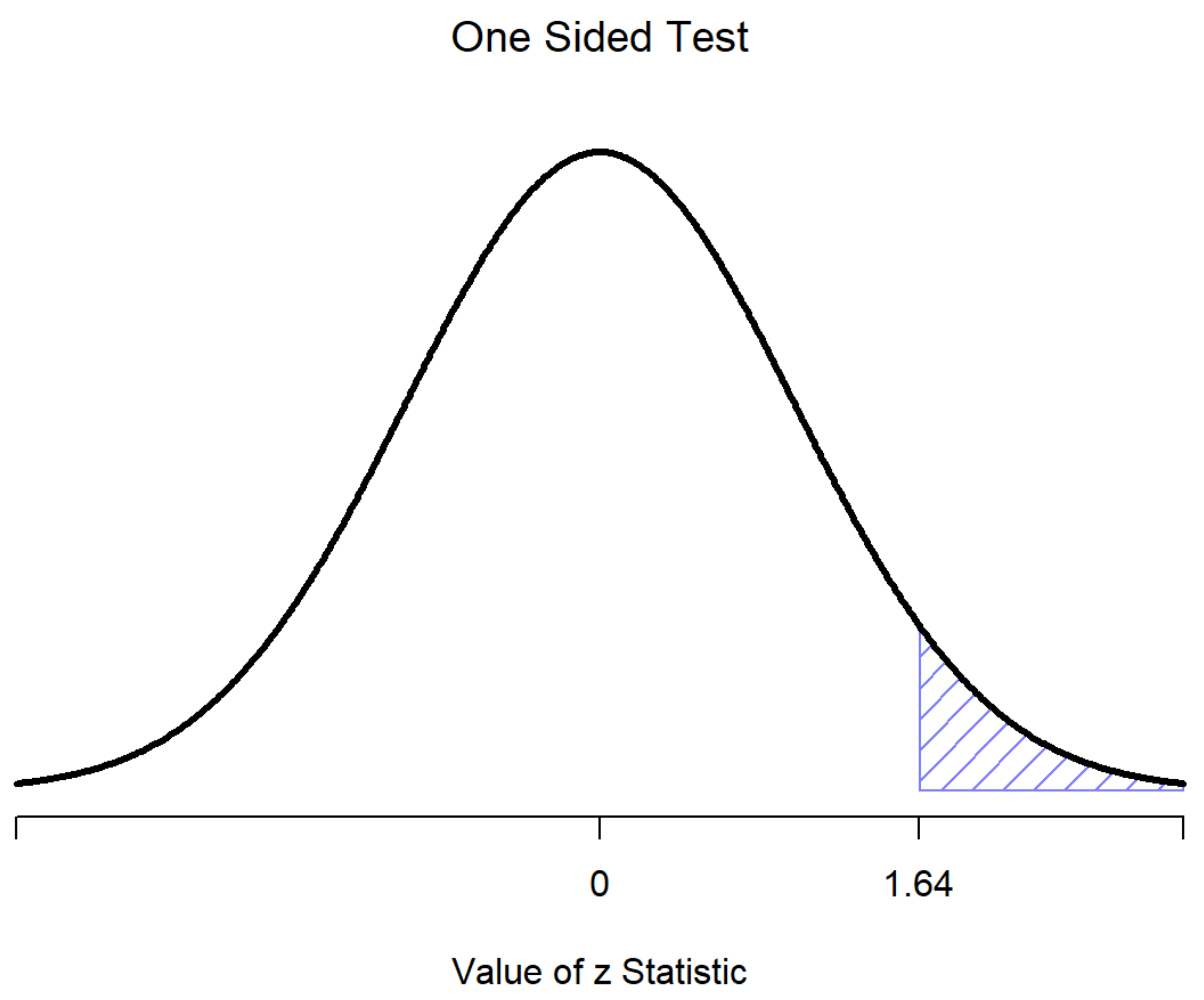


The z-statistic is equal to the number of standard deviation that separates the observed sample mean μ from the population mean μ_0, according to the null hypothesis.

The 5% critical regions for the z-test are always the same

desired α level	two-sided test	one-sided test
.1	1.644854	1.281552
.05	1.959964	1.644854
.01	2.575829	2.326348
.001	3.290527	3.090232





A simple z-test

You might ask, are students from geology scoring higher than the average student in statistics?

mean average grade = 67.5 and s.d. = 9.5

geology students mean = 73.2, N = 20

desired α level	two-sided test	one-sided test
.1	1.644854	1.281552
.05	1.959964	1.644854
.01	2.575829	2.326348
.001	3.290527	3.090232

With a mean grade of 73.2 in the sample of geology students, and assuming a true standard deviation is 9.5, we get z = 2.26

What is p?

Assumptions of the *z*-test

Randomness

Normality

Independence

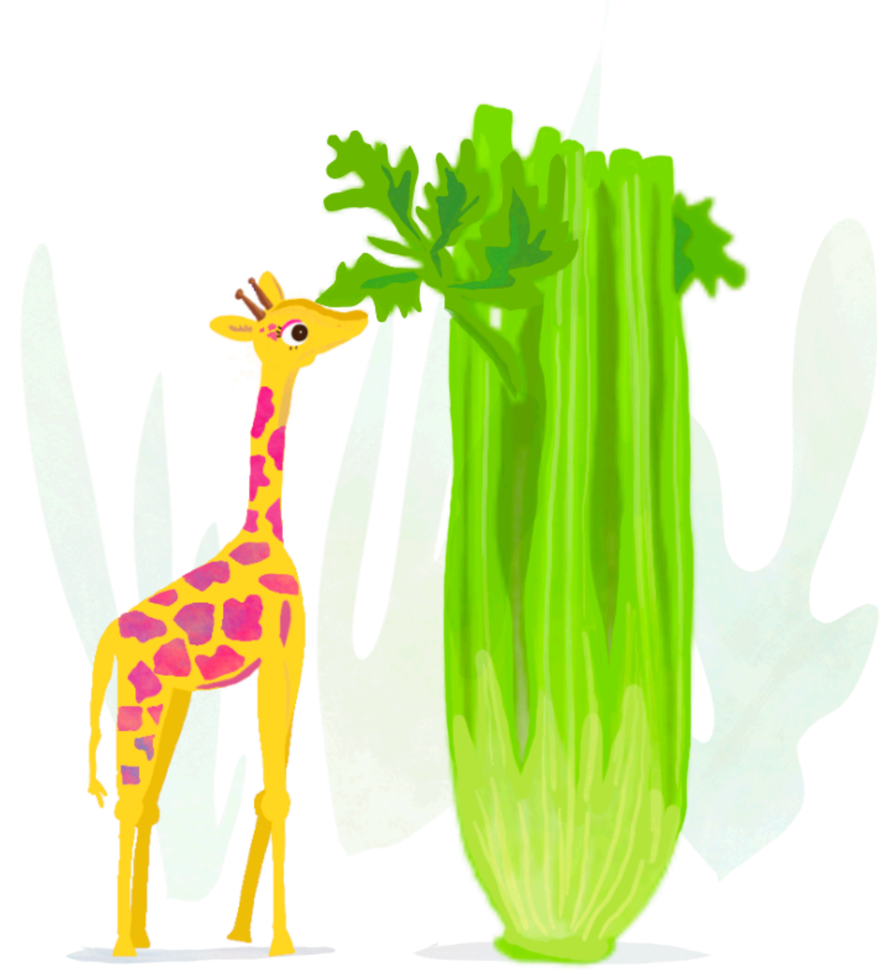
Known standard deviation

From *z*-test to *t*-test

Suppose we don't know the true standard deviation?

We only know the **estimated** standard deviation

See Teacup Giraffes for more on the normal distribution

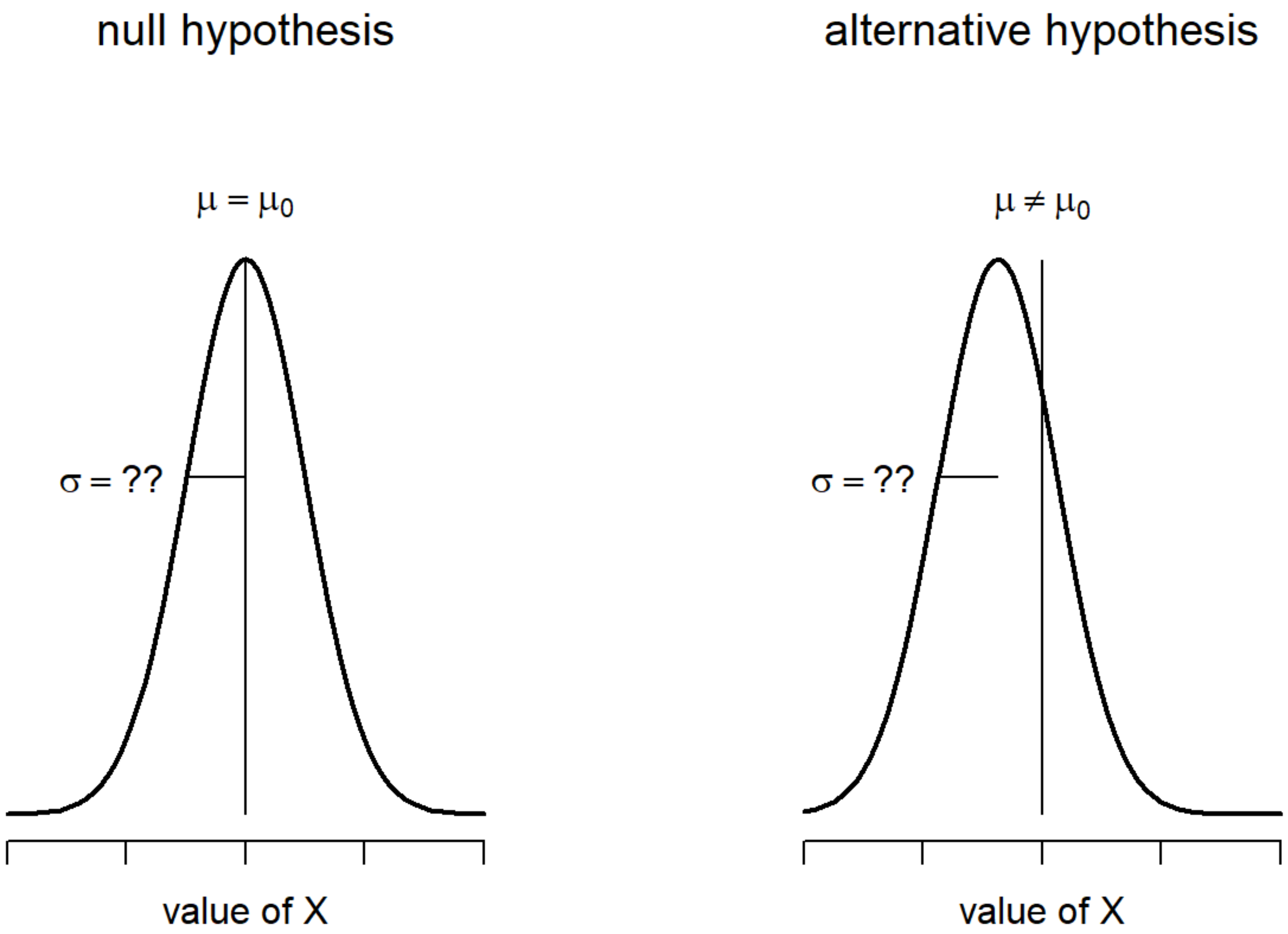


From *z*-test to *t*-test

We *could* use the estimated s.d. but this wouldn't be strictly appropriate

What if the estimate is incorrect?

In the previous example, if the s.d. changes from 9 to 11, the results become non-significant


null hypothesis
alternative hypothesis
μ = μ0
μ ≠ μ0
σ = ??
σ = ??
value of X
value of X

The one-sample *t*-test

To accommodate the fact we don't know the s.d, we need to change the sampling distribution

The t-test statistic is very similar.

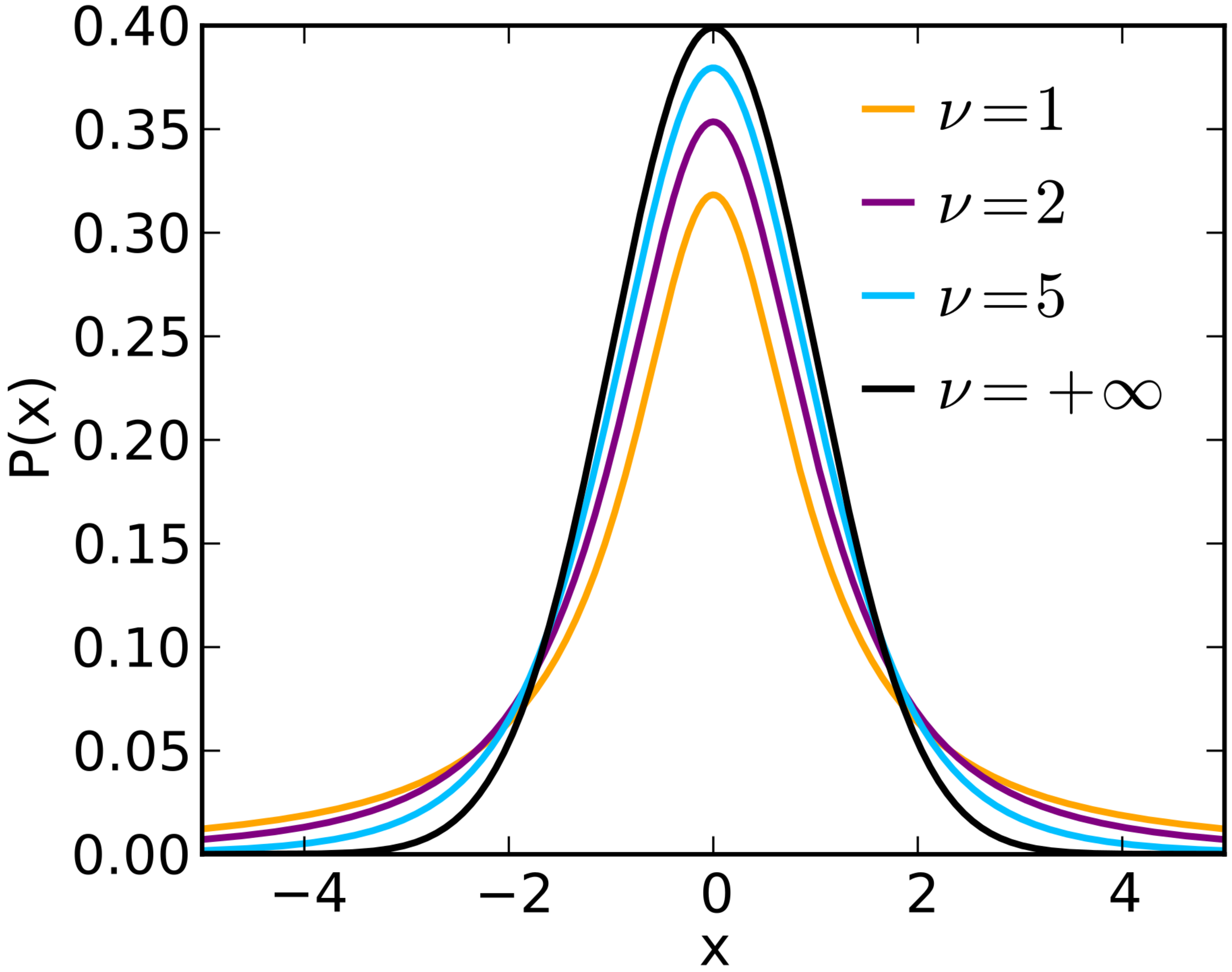
The first diff. is that we use the est. s.d.

$$t = \frac{\bar{X} - \mu}{\hat{\sigma}/\sqrt{N}}$$

If the estimate has been constructed from *N* observations, then the sampling distribution becomes a ***t*-distribution** with *N* - 1 degrees of freedom

From here we can obtain a *p*-value for the *t*-distribution

The one-sample *t*-test



Very similar to the normal distribution, but with "heavier" tails

As d.f. (*v*) gets larger, the t-distribution converges on the normal distribution

Assumptions of the one sample *t*-test

Randomness

Normality

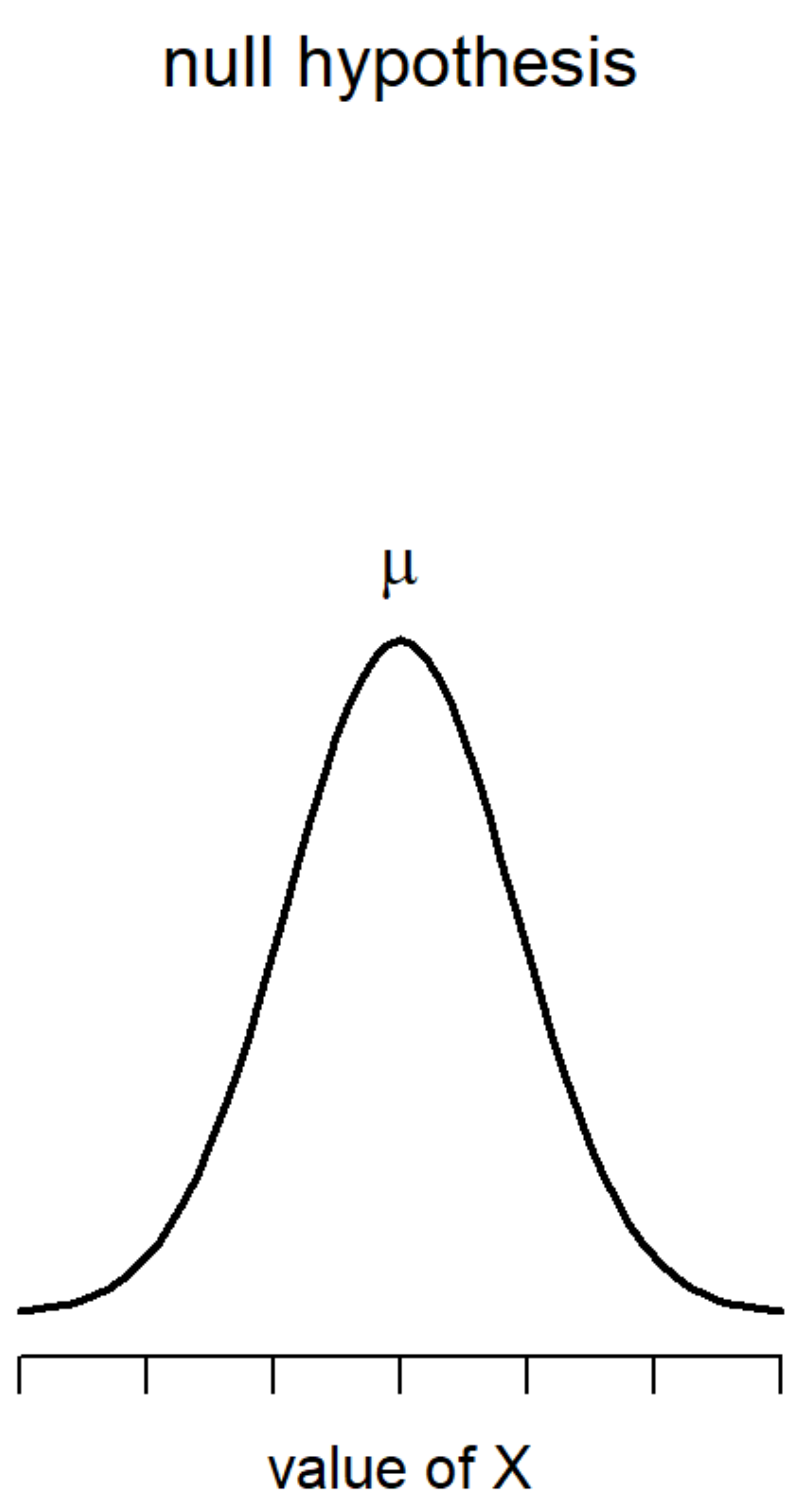
Independence

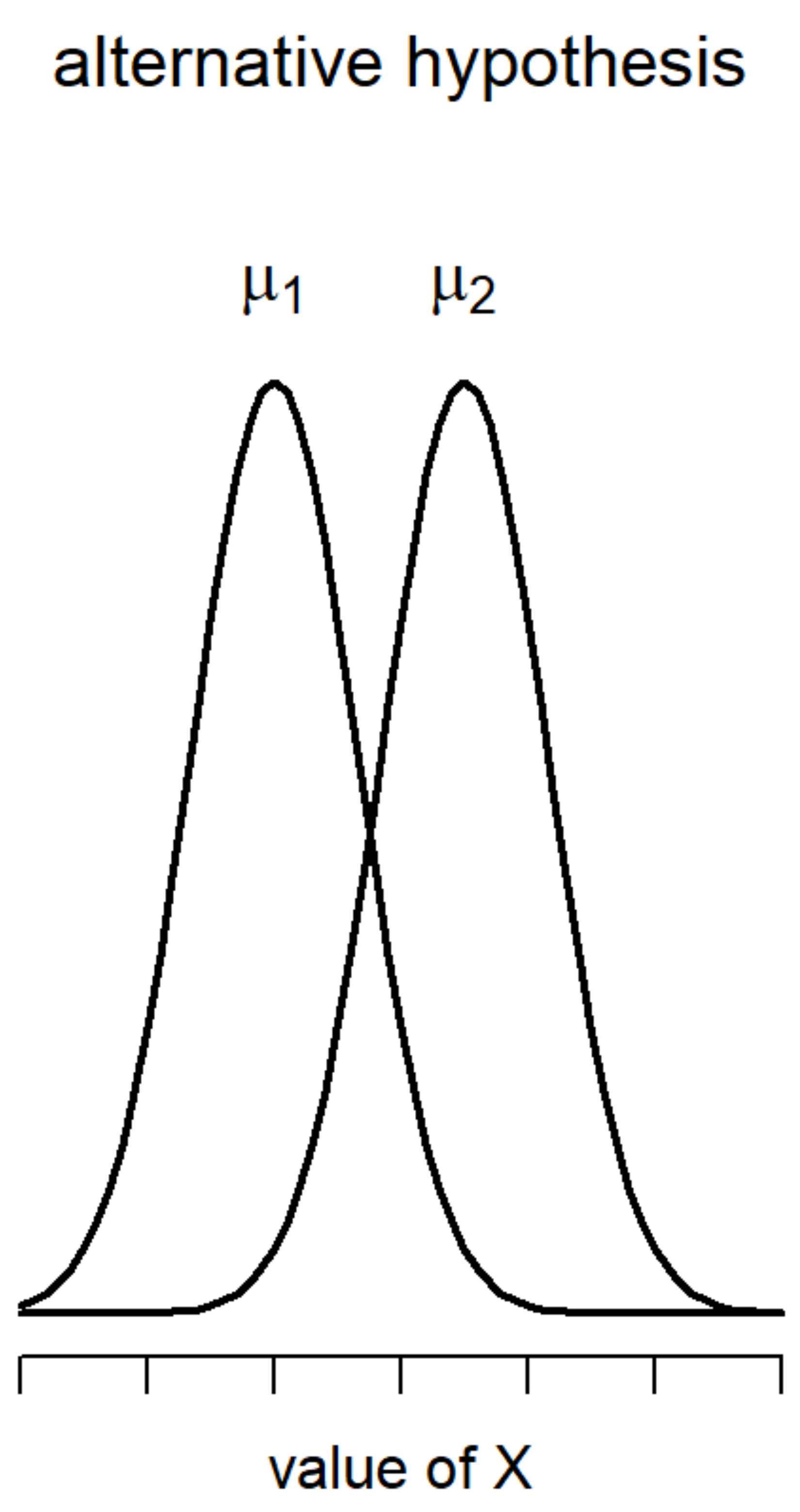
There are many varieties of *t*-test that get round some of these assumptions

The one-sample *t*-test compares the mean of a single sample to some pre-defined value, to test whether the sample mean is significantly greater or less than that value

The independent samples *t*-test compares the mean of a given group to the mean of another group

The independent-samples *t*-test





If the null is true we expect the difference between the means = 0.

But how close?

Test statistic is:

$t = (\mu - \mu_0) / SD$

The independent-samples *t*-test

For the variance, we calculate a "pooled" estimate by taking a weighted average of the variance estimates for each sample

The weight assigned to each sample is equal to the number of observations in that sample, minus 1

$$s = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}} \longrightarrow$$

$$\begin{aligned} w_1 &= N_1 - 1 \\ w_2 &= N_2 - 1 \end{aligned}$$

$$\hat{\sigma}_p = \sqrt{\frac{w_1 \hat{\sigma}_1{}^2 + w_2 \hat{\sigma}_2{}^2}{w_1 + w_2}}$$

The independent-samples *t*-test

Compared to the one sample *t*-test:

$$t = \frac{\bar{X} - \mu}{\hat{\sigma}/\sqrt{N}} \longrightarrow t = \frac{\bar{X}_1 - \bar{X}_2}{\mathrm{SE}(\bar{X}_1 - \bar{X}_2)}$$

Again, from here we can obtain a *p*-value for the *t*-distribution

Assumptions of the <u>independent</u> samples *t*-test

Randomness

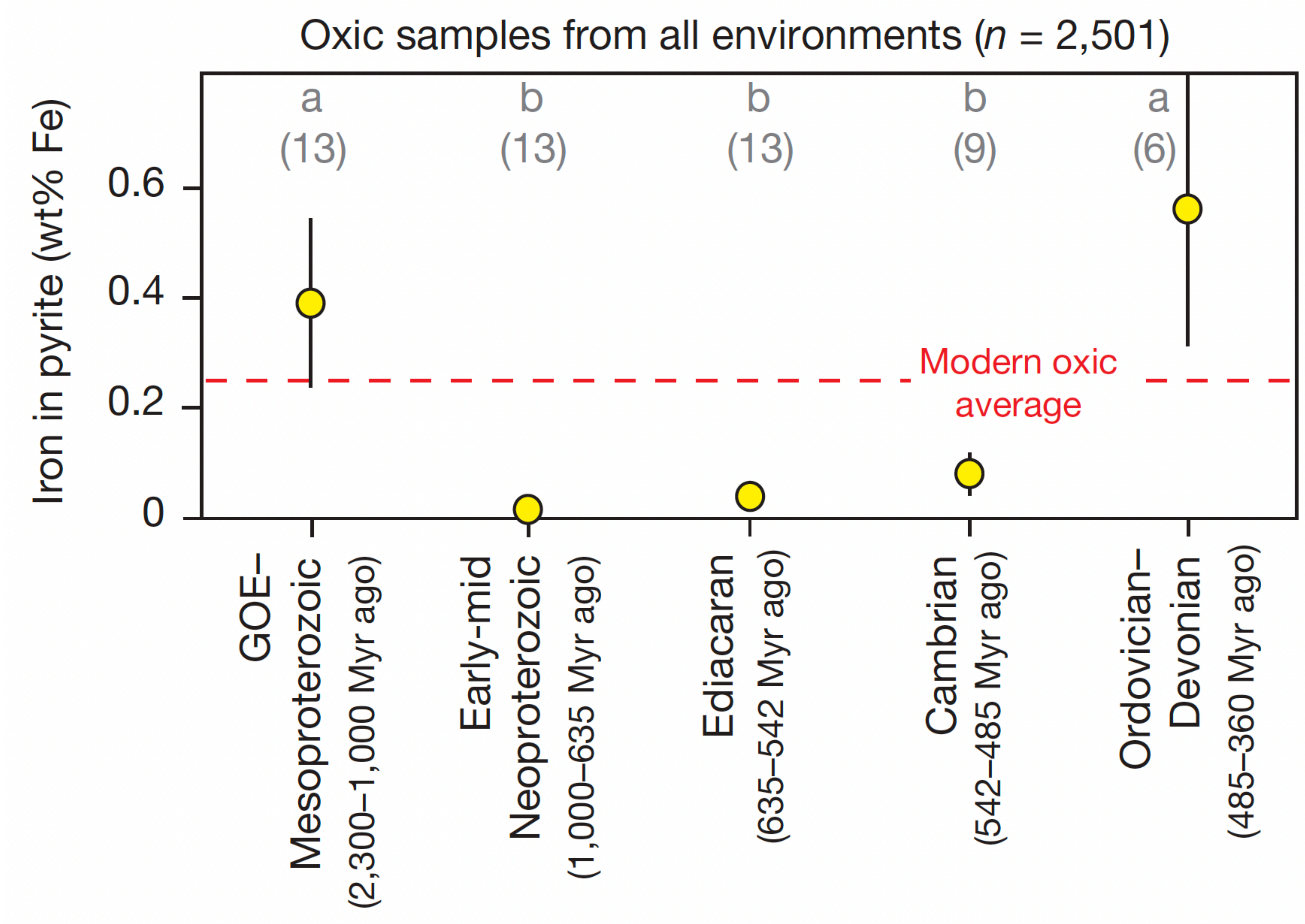
Normality

Independence (between groups)

Homogeneity of variance (the s. d. is the same between both groups)

One-way ANOVA (analysis of variances)

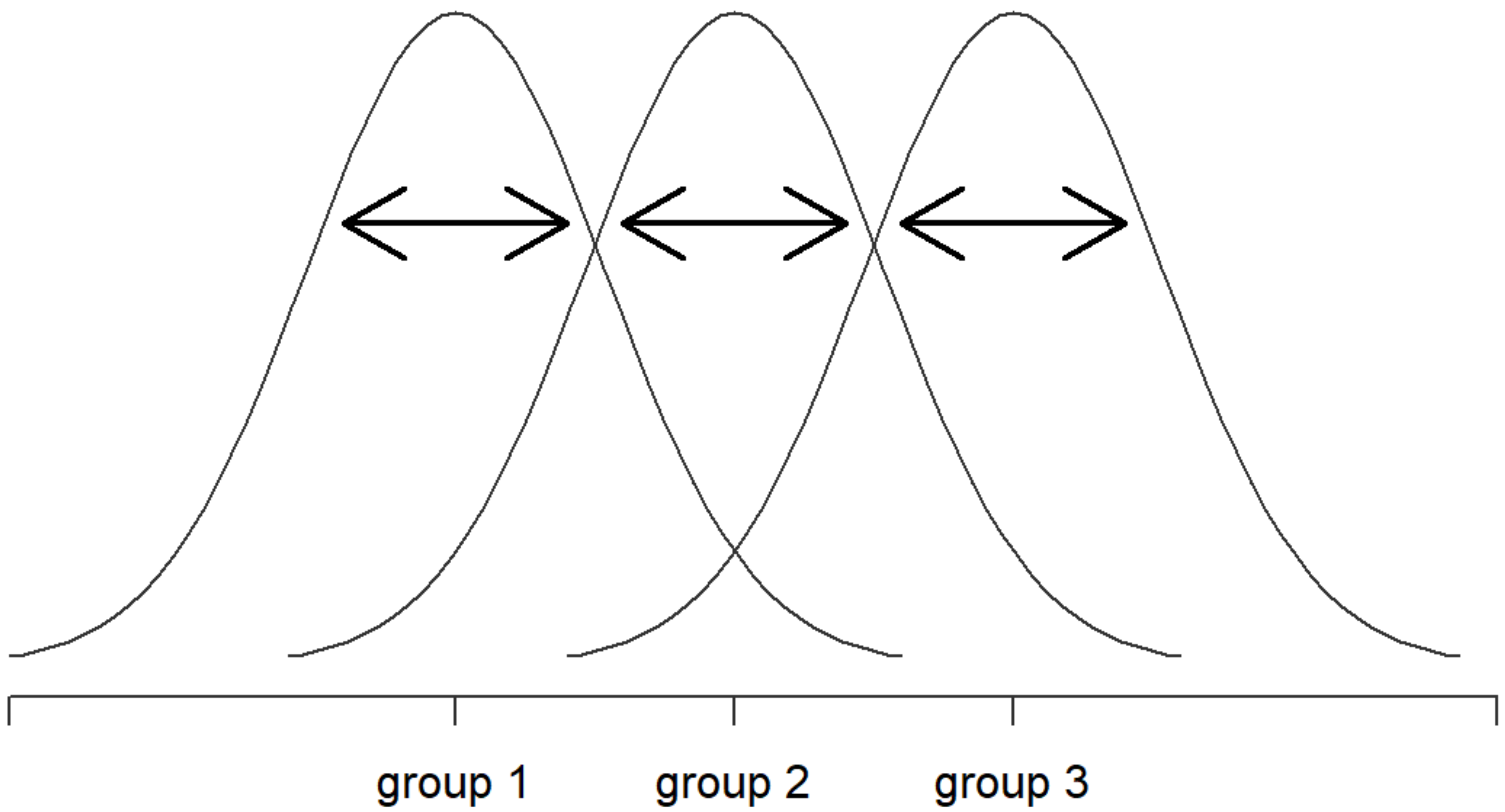
What if you want to compare more than 2 groups?



$$H_0 \quad : \quad \text{it is true that } \mu_P = \mu_A = \mu_J$$

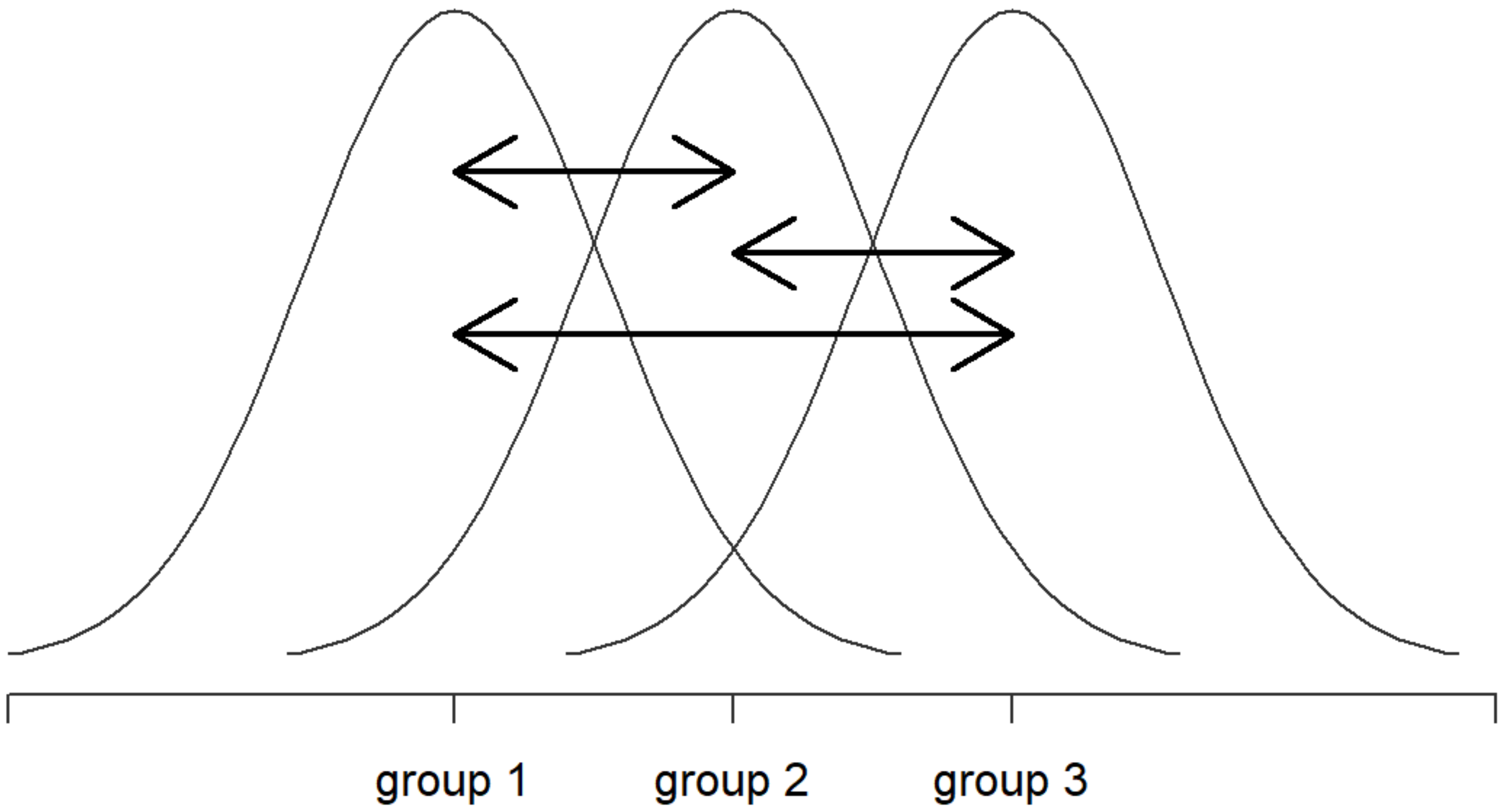
$$H_1 \quad : \quad \text{it is *not* true that } \mu_P = \mu_A = \mu_J$$

Within group variation (SS_w)



Between group variation (SS_b)

i.e., the differences between group means



Total group variation (SS_{tot})

SS_{tot} is the sum of variation within groups (SS_w) plus variation between groups (SS_b)

$SS_{tot} = SS_w + SS_b$

If the null hypothesis is true, **we expect all the sample means to be similar** and SS_b to be small, with $SS_{tot} = SS_w$

From sums of squares to the *F*-test via the *F* ratio

df1 = no. of groups - 1
df2 = no. of obs. - groups

We calculate the "degrees of freedom" associated with the SS_b and SS_w values

$$\begin{aligned} \mathrm{df}_b &= G - 1 \\ \mathrm{df}_w &= N - G \end{aligned}$$

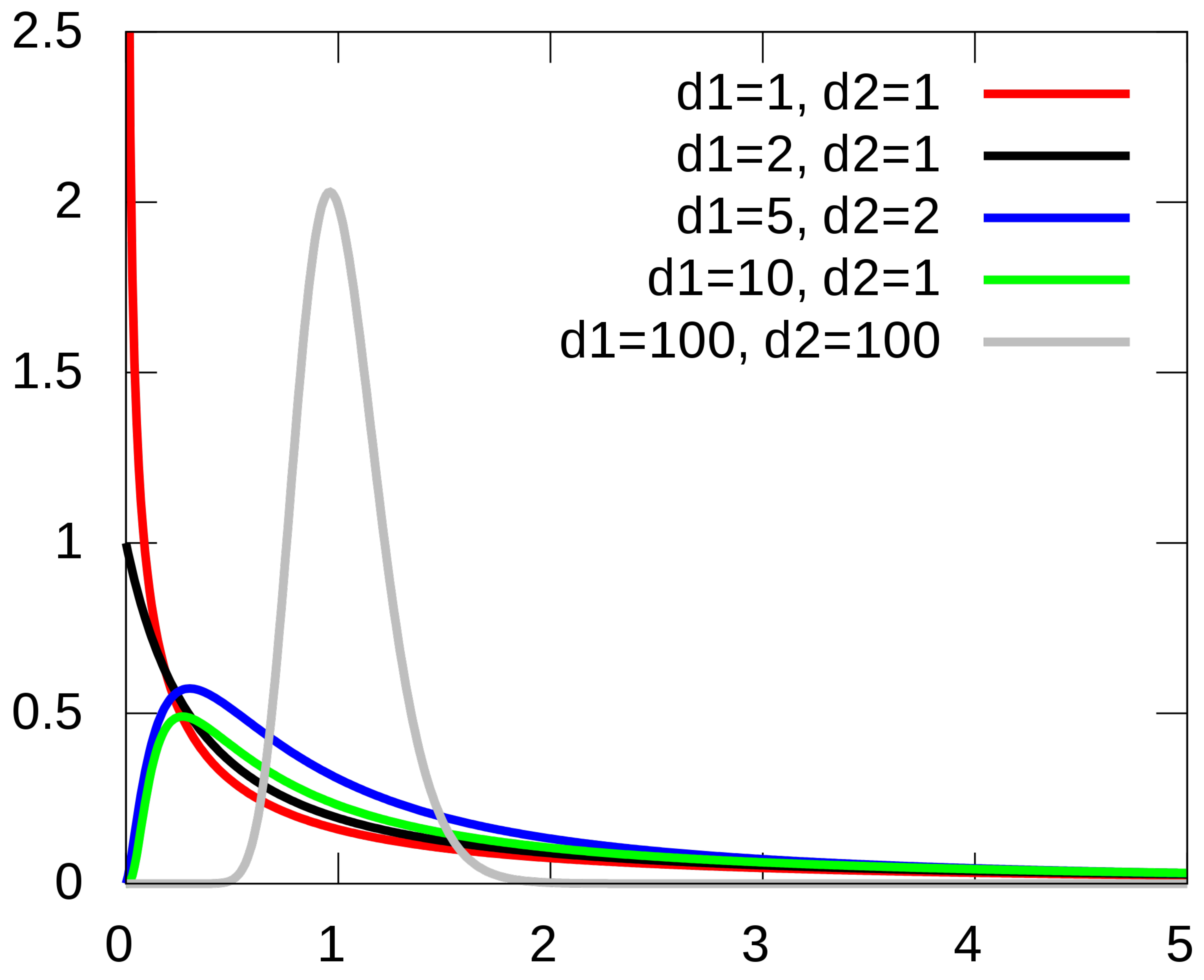
Next we calculate a "mean squares" value, by dividing by the degrees of freedom

$$\begin{aligned} \mathrm{MS}_b &= \frac{\mathrm{SS}_b}{\mathrm{df}_b} \\ \mathrm{MS}_w &= \frac{\mathrm{SS}_w}{\mathrm{df}_w} \end{aligned} \longrightarrow F = \frac{\mathrm{MS}_b}{\mathrm{MS}_w}$$

The gist behind the *F* statistic

The intuition behind the *F* statistic: larger values of *F* indicate the between-groups variation is large, relative to the within-groups variation

The larger the value of *F*, the more evidence we have against the null hypothesis



post hoc ANOVA test → Tukey-Kramer

Steel Dwass

equivalent to a one-sample *t*-test, non-parametric → Wilcoxon test

equivalent to ANOVA, non-parametric → Kruskal-Wallis

Further info

Video: ANOVA (Analysis of variance) simply explained

Video: ANOVA: One-way analysis of variance

ANOVA in R - A Complete Step-by-Step Guide

Two-way ANOVA - Examples and when to use it