

Statistical analysis in R

MiCM Fall Workshop Series (2022)
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McGill

MiCM McGill initiative in
Computational Medicine

Prerequisites

- Have R and RStudio (or equivalent) installed
- Understand basics of R and RStudio
 - Terminal, console, script editor, environment windows
- Please feel free to ask questions
 - Even if it is “what does this word mean?”

Libraries

- `install.packages("medicaldata")`
- `install.packages("scatterplot3d")`
- `install.packages("ggplot2")`
- `install.packages("tidyverse")`

Online content

- shorturl.at/gkprL
- https://github.com/diazale/intro_to_r_stats

Core concepts

- R objects and variable types
- Hypothesis testing and analysis of variance (ANOVA)
- Linear regression
- Learn how ***and why*** to use statistical methods

Goals

- Learn core concepts in R and statistical analyses
- “Bread and butter” tools
 - The most commonly used methods
- Basics of quality and interpretable analysis
- Build up to univariate multiple linear regression

Generate + understand this

Call:

```
lm(formula = number12m ~ baseline + treatment + age + sex, data = medicaldata::polyps)
```

Residuals:

Min	1Q	Median	3Q	Max
-20.202	-10.251	-3.595	7.657	23.272

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	51.83751	13.06029	3.969	0.00123	**
baseline	0.05931	0.05441	1.090	0.29289	
treatmentsulindac	-26.53350	7.10892	-3.732	0.00200	**
age	-0.70497	0.47822	-1.474	0.16112	
sexmale	-1.37836	8.19318	-0.168	0.86865	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 15.23 on 15 degrees of freedom

(2 observations deleted due to missingness)

Multiple R-squared: 0.579, Adjusted R-squared: 0.4667

F-statistic: 5.157 on 4 and 15 DF, p-value: 0.008127

Breakdown

- I. R concepts (30 minutes + 15 minutes exercise)
- II. Hypothesis tests (45 minutes + 15 minutes exercise)
- III. Break (20 minutes)
- IV. ANOVA + Regression (Remaining time)
 - Overview with slides, in-depth with R Markdown

Structure

- Slides provide overview of concepts
- Some theory to explain math and statistics
 - Try to follow along, but this isn't a math-stats course
- Most work will be in R Markdown files
- Will give you example code to follow along
- Exercises with empty code cells provided

Data types and structures

**“Computers are like Old
Testament gods;
lots of rules and no mercy.”**

–Joseph Campbell

R concepts

- R will do whatever you tell it to do
- You must understand what you are telling it to do
- Do not fish for numbers!
- Learn what you're using and how to get what you need
- Use the `?` command
 - e.g. `?lm` gives the documentation for `lm`
 - `??` will search R documentation instead

R variable types

- Variable types
 - Important ones: Boolean, Numeric, Character, Factor
- Boolean (Logical): {TRUE/FALSE}, {T/F}, {1/0}
- Numeric: Integers, real numbers (“double”)
- Character: Strings of text
- Factor: Categorical, Indicator, Boolean

Pitfalls to avoid

- Some characters have special meanings. **DO NOT USE THEM.**
 - c, g, t, C, D, F, I, T
- R often imports data as factors — check to make sure!
 - Object structure: `str()` command
 - Variable type: `typeof()` command
 - Class type: `class()` command
- Be careful coding categories as numbers
 - Make sure they are factors and not numeric

R objects

- Vectors: `c()`
 - Only one variable type (e.g. all numeric)
- Lists: `list()`
 - Can have multiple variable types
- Matrices
 - Multi-dimensional array of one variable type
- Data frames
 - Subtly different from tibbles

R objects

- Convert between types with `as.[type]`

```
x <- c(1, 0, 1)
```

```
typeof(x)
```

```
x <- as.logical(x)
```

```
typeof(x)
```


Data frames

- Data is usually stored in a **data frame**
- Observations are rows, variables are columns
- Created with `as.data.frame()`
 - Many functions import external data as data frames
 - Useful functions:
`names()`, `colnames()`, `rownames()`, `subset()`
- Conversion functions still apply

Data frames

- Examine with `str()`
- Subset with `[,]` or `subset()`
- Lots of ways to manipulate them, you can get clever
- Beyond the scope of this workshop
- For now, our data is already in good shape

\$ and summary()

- Use `summary()` to retrieve summaries of results
 - e.g. ANOVA, regression
- Use `$` to retrieve parts of R objects
 - e.g. t-test, data frame columns

Hypothesis testing

Overview

- You want to compare data
- Are sets of data different?
 - How “different” are they? “Kinda” different? “Very” different?
 - Test statistics are a formal way of asking this
- We consider two types of tests:
 - t-test
 - ANalysis Of VAriance (ANOVA)

Statistical significance

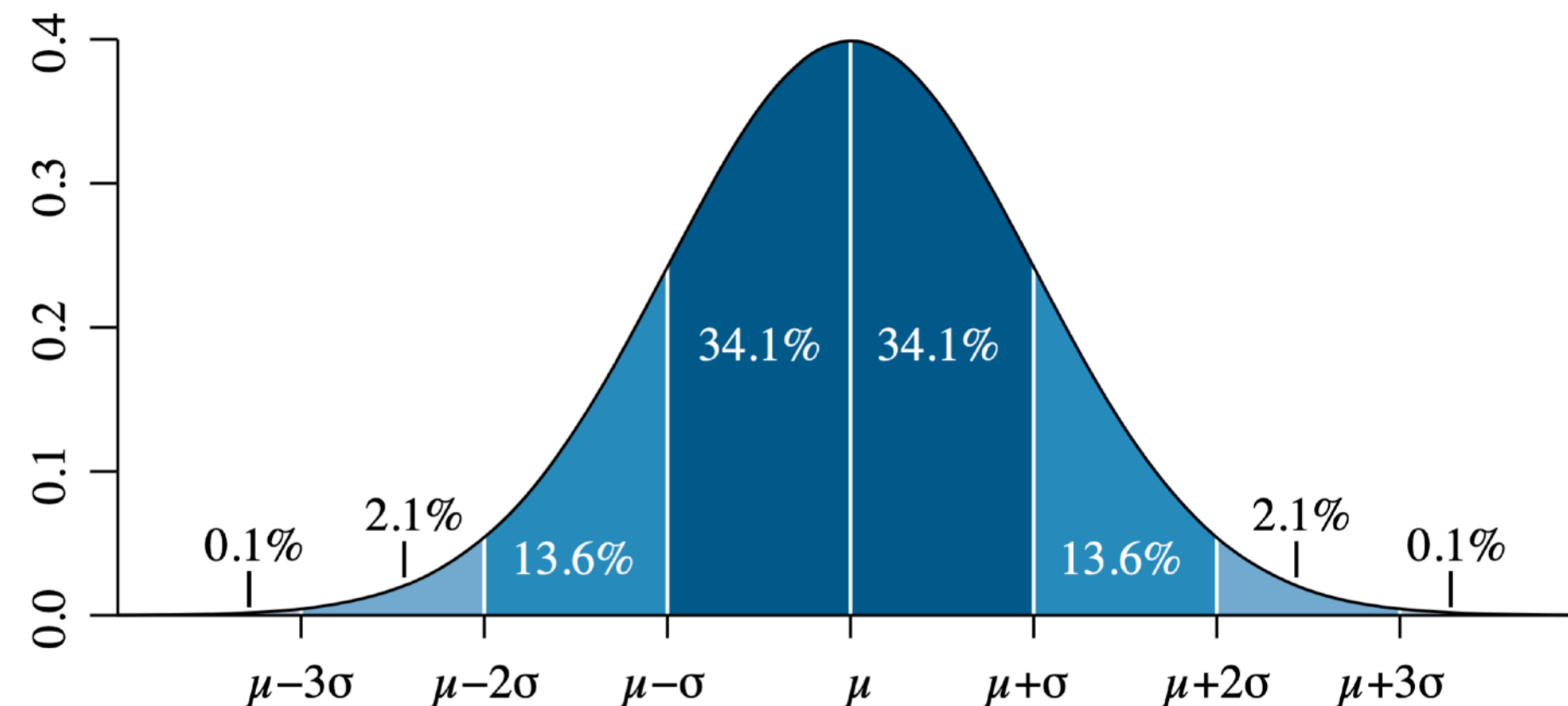
- “This measurement is unlikely to have happened by chance”
- Does **not** mean any of the following:
 - Logically sound
 - Scientifically meaningful
 - Causally linked
- All statistical tests and methods are just fancy calculations
- You, the scientist, make the decisions and interpretations
- **Never choose a test based on whether it gives a smaller p-value**

Quick math-stats review

- Random variables are defined by their distributions
- Distributions defined by PDFs (probability density functions)*
- We look at:
 - Normal
 - t-distribution
 - Chi-squared (sort of, as an intermediate)
 - F-distribution

*actually defined by many things, including PDFs, beyond scope of today

Normal distribution



Credit: Wikipedia

$$X \sim \mathcal{N}(\mu, \sigma^2)$$

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(\mu - x)^2}{2\sigma^2}}$$

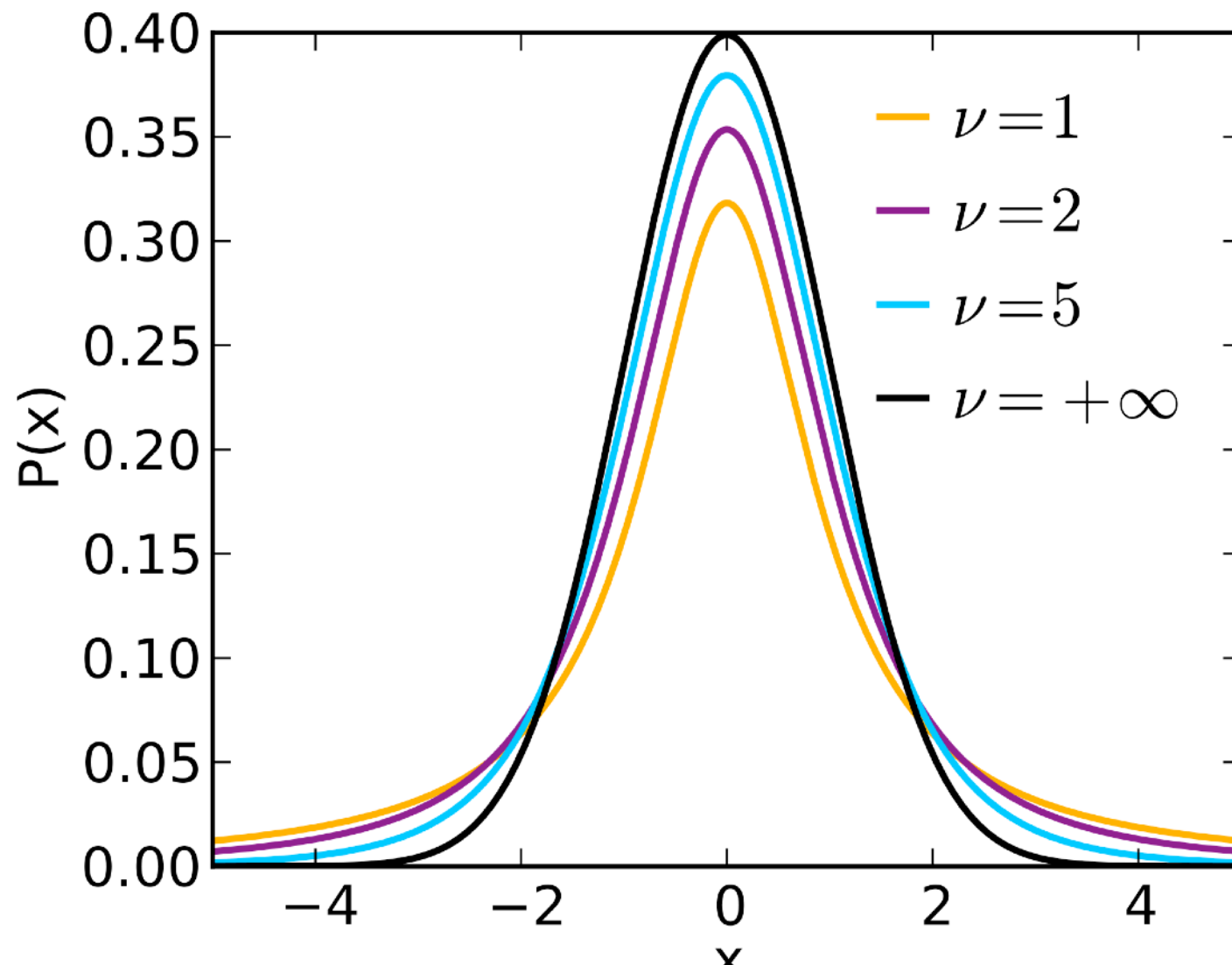
Normal distribution

- Extremely common, also called the Gaussian distribution
- Known for its bell curve
- Lots of nice properties
- Central Limit Theorem
 - For many distributions, their normalized sum is Normal
- Can be standardized to a $N(0,1)$

Properties of the Normal

- Still Normal when
 - Subtracting a constant, dividing by a non-zero constant
- Standardization:
 - Subtract the mean, divide by standard deviation
 - If $X \sim N(\mu, \sigma^2)$ then $\frac{X - \mu}{\sigma} \sim N(0, 1)$
- If $X \sim N(0, 1)$ then $X^2 \sim \chi_1^2$ (Chi-squared with 1 d.f.)
- If $X_i \stackrel{\text{i.i.d.}}{\sim} N(0, 1)$ then $\sum_{i=1}^n (X_i)^2 \sim \chi_n^2$

t-distribution



- Defined by degrees of freedom

$$f(t) = \frac{\Gamma(\frac{\nu+1}{2})}{\sqrt{\nu\pi} \Gamma(\frac{\nu}{2})} \left(1 + \frac{t^2}{\nu}\right)^{-(\nu+1)/2}$$

Credit: Wikipedia

Deriving the t-test

- Details are mathematically dense, this is a very brief summary

- Sample of n identically independently distributed (i.i.d.) values $X_i \sim N(\mu, \sigma^2)$

CORE ASSUMPTION

- We don't know the true values of μ or σ
- Test hypothesis about μ using the sample mean \bar{X}
- Estimate σ as $\hat{\sigma}$

- Our test statistic is $t = \frac{Z}{s} = \frac{\bar{X} - \mu}{\hat{\sigma}/\sqrt{n}}$, which follows a **t-distribution**

- t-distribution is defined by **degrees of freedom**. We have **$n - 1$ (or $\nu - 1$)**

Deriving the t-test

- We want to test whether $\mu = \mu_0$ for some value μ_0 (**Null hypothesis**)
- Often assume $\mu_0 = 0$ and test this assumption
 - This comes up in regression!

- This test statistic is
$$t = \frac{Z}{s} = \frac{\bar{X} - 0}{\hat{\sigma}/\sqrt{n}} = \frac{\bar{X}}{\hat{\sigma}/\sqrt{n}}$$

- What is the probability that we get this statistic?
- This is the ***p-value***

Assumptions of t-test

- Observations are independent
 - Don't use the same observation in two groups
- No massive outliers
 - Look at your data!
- Data are approximately normal
- Groups should have approximately equal variances
 - Welch's t-test is used if this assumption is violated

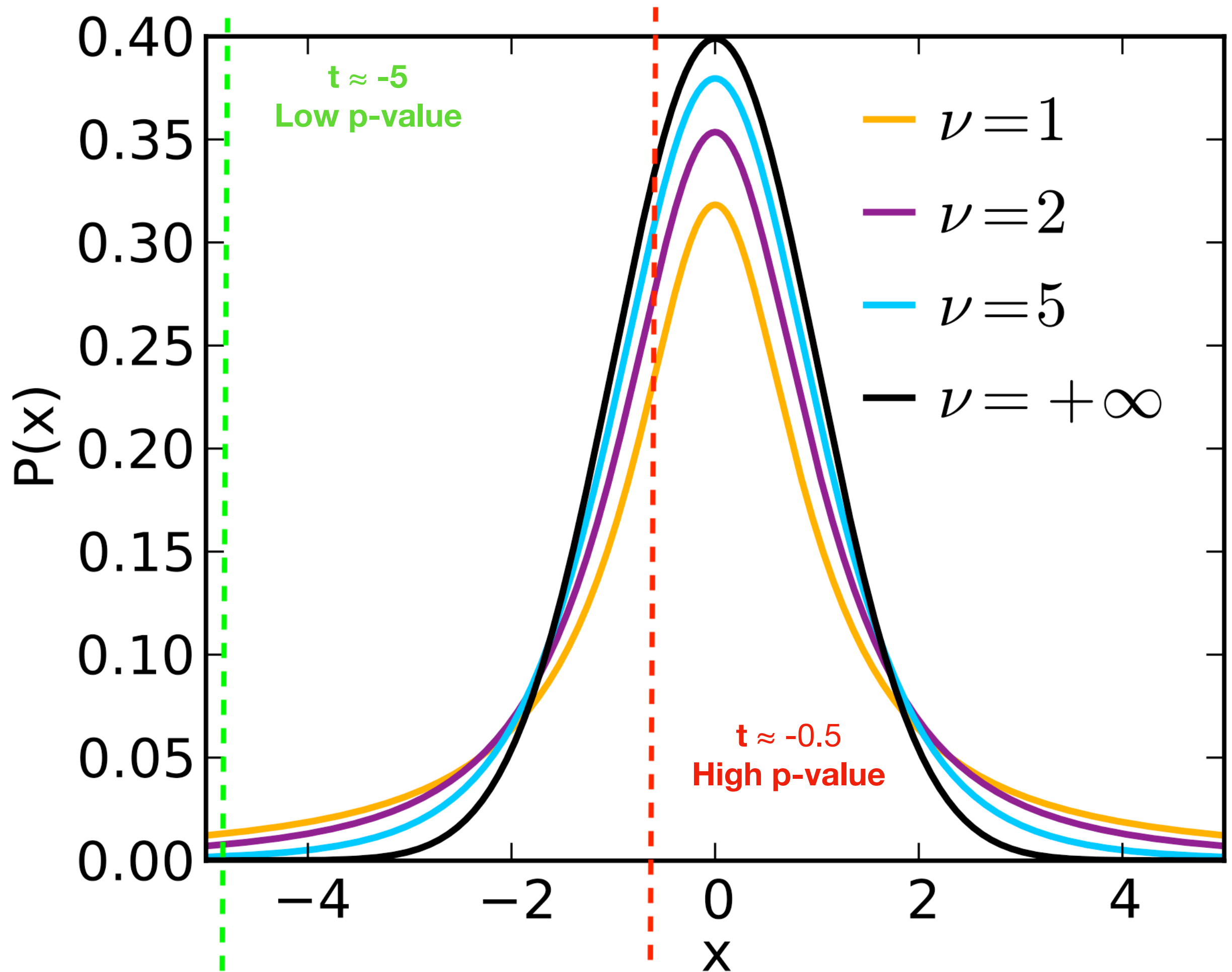
Two-sample t-test

- Test whether two population means are the same
 - Instead of testing whether one mean is a specific value
 - e.g. do two populations have the same mean height?
- Similar derivation

- $t = \frac{\bar{X}_1 - \bar{X}_2}{s}$, where s is a very long formula for s.e.

Using the t-test

- Software does most of the work for us, thank god
- We calculate t (our **t-statistic** or **test statistic**)
- What is the probability that we get this number?
- We find the area under the curve of the distribution
- The probability we get is the **p-value**
- If $p < \text{threshold}$, we say it is “significant”
- A common threshold is 0.05



Interpreting the t-test

- **Remember your hypothesis!**
- Usually one of two:
 - The mean is equal to [some value]
 - The means of two populations are the same
- Can test if mean is bigger/smaller than [some value]
 - This is the one-tailed test
- A low p-value means the hypothesis is unlikely
- We **reject the null hypothesis**

Statistical significance

- Big t-statistic will give small p-value

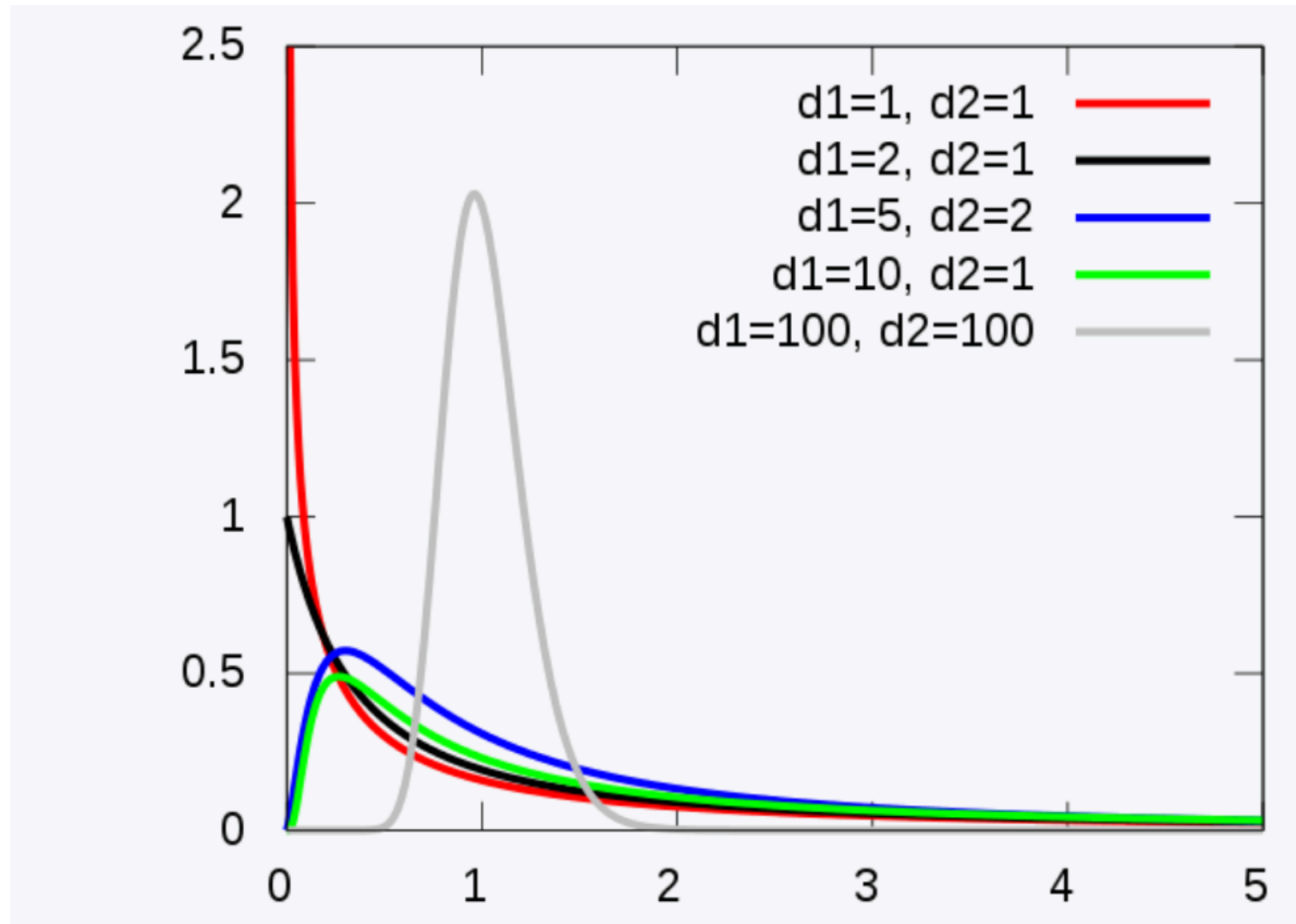
- Recall: $t = \frac{Z}{s} = \frac{\bar{X} - \mu_0}{\hat{\sigma}/\sqrt{n}}$

- What makes t big?
 - Big numerator ($\bar{X} - \mu_0$); and/or Small denominator (big n)
- Huge sample sizes (big n) will give small p-values
- May be more interested in effect size (numerator)

ANOVA

F-distribution

- Defined by two degrees of freedom



$$f(x; d_1, d_2) = \frac{\sqrt{\frac{(d_1 x)^{d_1} d_2^{d_2}}{(d_1 x + d_2)^{d_1 + d_2}}}}{x B\left(\frac{d_1}{2}, \frac{d_2}{2}\right)}$$

Credit: Wikipedia

F-statistic

- Similar to t-statistic
- Follows Snedecor's F-distribution
- If $S_1 \sim \chi_a^2, S_2 \sim \chi_b^2$ then $\frac{S_1/a}{S_2/b} \sim F_{a,b}$
- The ratio of two Chi-squareds follows the F-distribution
- Null hypothesis: multiple means are all equal
- Rejection means: At least one group is different

F-statistic interpretation

- Null hypothesis: All groups are equal
- Logical opposite of this is:
 - **Not** all groups are equal
 - **At least one** group is not equal
 - Could have one group different
 - Could have all groups different
 - Could have anything in between

What do we check?

- Look at your data
- Look at your data
 - It's the quickest and easiest way
- Pairwise comparisons with correction factor
 - Tukey's HSD (`TukeyHSD()` in R)
 - Pairwise t-tests with Bonferroni correction

Motivation

- ANOVA generalizes the t-test by partitioning the variance
- We want to test the means of 3+ groups

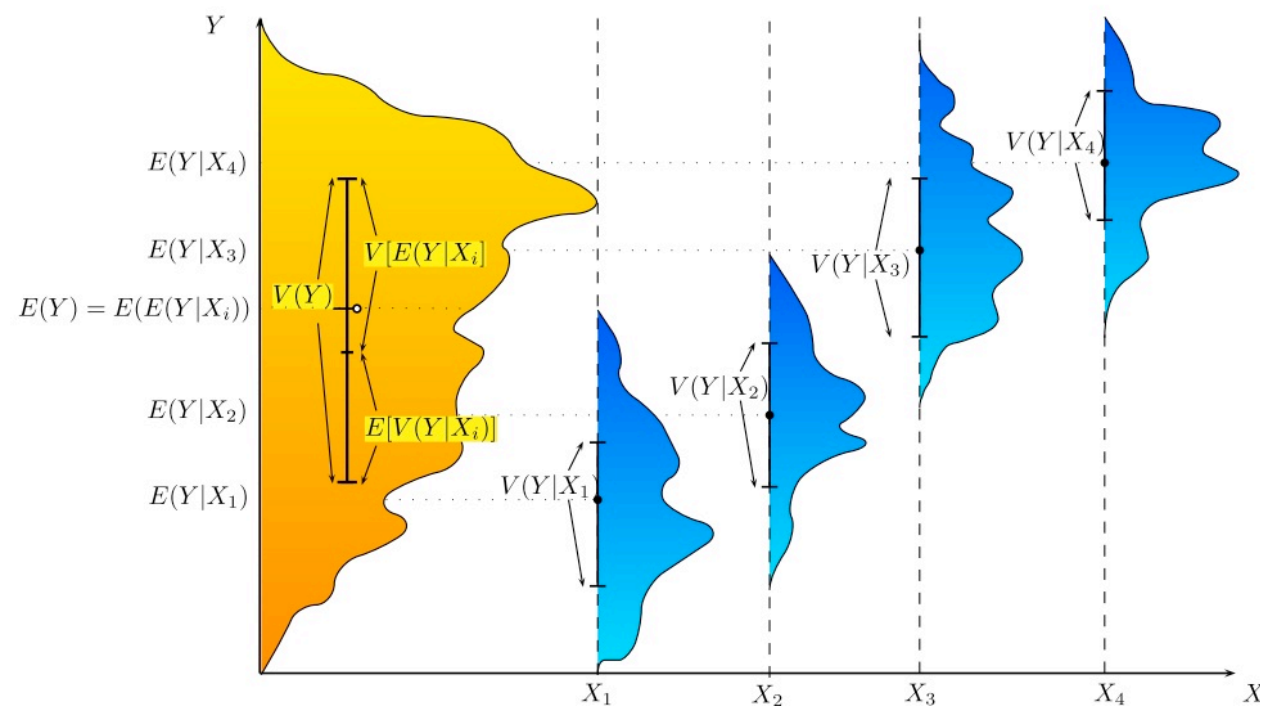


Figure 1: ANOVA : Fair fit

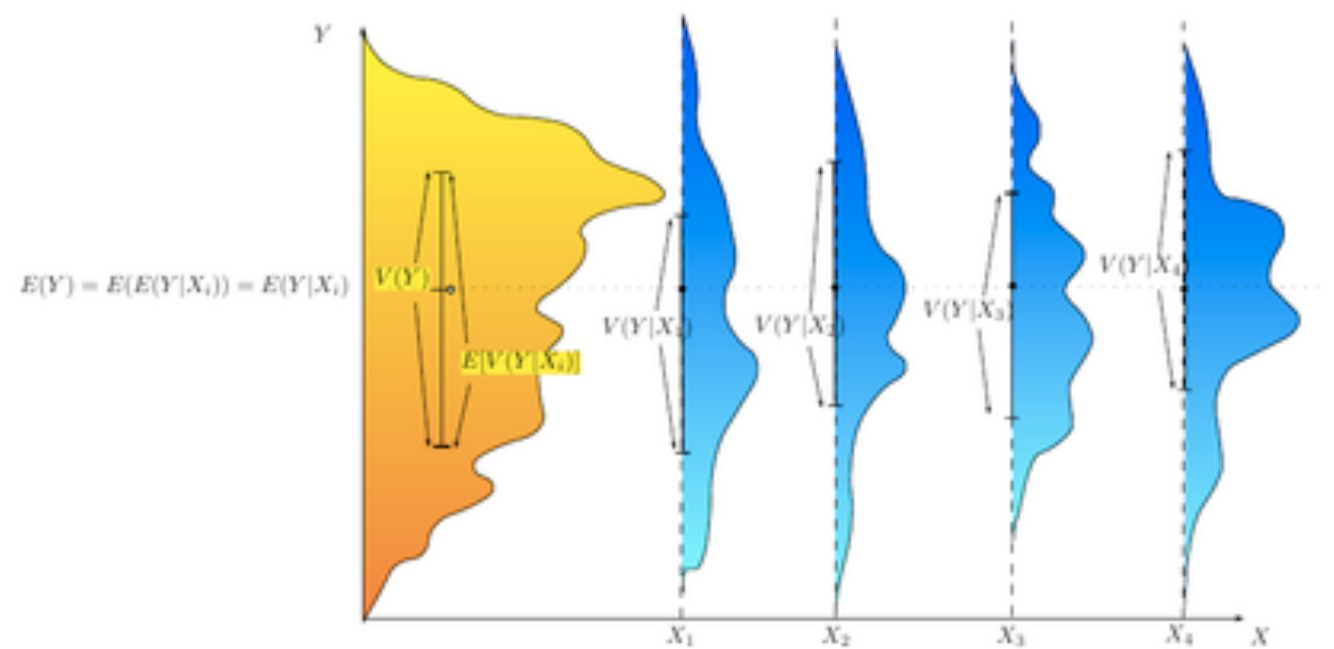


Figure 2: ANOVA : No fit

Credit: Wikipedia article for ANOVA

Motivation

- Interested in the relationship between variables
- Categories and continuous (factors and numerics)
- Examples:
 - Differences between population centres
 - Differences between treatment types
 - Differences between diets

Formulation

- $y_{ij} = \mu + \tau_j + \epsilon_{ij}, \epsilon_{ij} \sim N(0, \sigma^2)$
- Observations $i=1 \dots I$, treatments (groups) $j=1, \dots, J$
 - Total mean μ
- How much does a measurement vary by group?
 - What is the effect of τ_j ?
- $H_0 : \tau_1 = \dots = \tau_J = 0$ vs. $H_A : \tau_i \neq \tau_j$ for some $(i, j), i \neq j$
 - All treatments are equal vs at least one treatment is not

Formulation

- Equivalent formulation:

$$y_{ij} = \mu_j + \epsilon_{ij}, \epsilon_{ij} \sim N(0, \sigma^2)$$

- How much variation is in our data?

$$SST = \sum_{i=1}^n (y_i - \bar{y})^2$$

(sum of squares, total)

$$= SS(Model) + SS(Residuals)$$

$$= SS(Treatments) + SS(Errors)$$

- How much variation explained by our treatments/model?

Formulation

ANOVA table for fixed model, single factor, fully randomized experiment

Source of variation	Sums of squares	Sums of squares	Degrees of freedom	Mean square	F
	Explanatory SS	Computational SS	DF	MS	
Treatments	$\sum_{Treatments} I_j (m_j - m)^2$	$\sum_j \frac{(\sum_i y_{ij})^2}{I_j} - \frac{(\sum_j \sum_i y_{ij})^2}{I}$	$J - 1$	$\frac{SS_{Treatment}}{DF_{Treatment}}$	$\frac{MS_{Treatment}}{MS_{Error}}$
Error	$\sum_{Treatments} (I_j - 1) s_j^2$	$\sum_j \sum_i y_{ij}^2 - \sum_j \frac{(\sum_i y_{ij})^2}{I_j}$	$I - J$	$\frac{SS_{Error}}{DF_{Error}}$	
Total	$\sum_{Observations} (y_{ij} - m)^2$	$\sum_j \sum_i y_{ij}^2 - \frac{(\sum_j \sum_i y_{ij})^2}{I}$	$I - 1$		

MS_{Error} is the estimate of variance corresponding to σ^2 of the model.

Credit: Wikipedia article for one-way ANOVA

- Degrees of freedom are (J-1), (N-J)
- Ratio of (variance between groups) to (variance within groups)
- If there is high variance between groups, we get a low p-value
- R does all the calculations via `aov()`

Extensions

- Two-way ANOVA (interactions)
- Three-way ANOVA
- Blocking (grouping, confounding, etc)
- Experimental design in general

Linear regression

Formulation

- We have two continuous variables
- Want to measure their relationship, assume it's linear
- Draw a line of best fit between them

Remember from high school: $y = mx + b$

What if we had y and x and needed to estimate m, b ?

- We would also need to account for error in estimates


Motivation

- Simple but powerful concept: line of best fit
- Measure relationship between variables
- Simplest form: correlation between continuous variables
 - Simple single linear regression
- Very powerful, robust, flexible tool
- Can predict (extrapolate) and infer (interpolate)

Assumptions

- Outcome is **continuous** and a **linear combination of predictors**
 - Predictors must not be perfectly correlated
- Errors are $\epsilon_i \stackrel{\text{i.i.d.}}{\sim} N(0, \sigma^2)$. For every observation i the error is:
 - **Normally distributed**
 - **Mean zero**
 - **Homoskedastic** (same variance as other observations)
 - **Independent** (not correlated)
- Patterns in your errors are **very bad** and **should be examined!!!!**

Mathematical form

- $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_p x_p + \epsilon, \epsilon \sim N(0, \sigma^2)$  (linear model)
- Outcome (y) is a linear combination of measurements (x)
 - Values of y and x are **known**
- Related to each other by intercept (β_0) and slopes (β_j)
 - Not known, so we **estimate** them
- Errors are **random**, on average **zero**, with **same variance**
 - **On average**, model won't over/underestimate (mean zero, unbiased)
 - Errors do not grow/shrink with data (constant variance)

Connecting concepts

- $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_p x_p + \epsilon, \epsilon \sim N(0, \sigma^2)$

- ANOVA is a special case of linear regression

- Categorical variables rather than continuous

- t-tests are used to test individual slopes in regression

$$H_0 : \beta_j = 0 \text{ vs } H_A : \beta_j \neq 0$$

- F-tests are used to test all slopes in regression

$$H_0 : \beta_1 = \dots = \beta_p = 0 \text{ vs } H_A : \beta_j \neq 0 \text{ for some } j$$

- Confidence intervals are built around normal variables

Connecting concepts

Call: 
lm(formula = number12m ~ baseline + treatment + age + sex, data = medicaldata::polyps)

Residuals:

Min	1Q	Median	3Q	Max
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categorical data

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
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t-statistics

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 15.23 on 15 degrees of freedom
(2 observations deleted due to missingness)

Multiple R-squared: 0.579, Adjusted R-squared: 0.4667
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**variance explained +
F-statistics**

Extensions

- Interaction effects
 - Outcomes depend on interactions of (e.g.) age*sex
- What if we have other types of data?
 - Multivariate regression (multiple, correlated outcomes)
 - Logistic regression (Binary outcomes like lived/died)
 - Multinomial regression (Count data)
 - ARIMA (Time series—data correlated over time)

Importance

- Regression is a bedrock of modern science
- Understand that software is a calculator
- You are ultimately responsible for interpretation
 - Statistics will guide your decision-making

Resources

- Introduction to regression modeling (Bovas Abraham and Johannes Ledolter, 2006)
 - More mathematical but fairly concise
- Wikipedia pretty reliable for equations, summaries
- University lecture notes and course topics:
 - Regression
 - Experimental design