ABI Summer 2021 Introduction to Statistics

Guest Session 2

Javier Cabrera*, Volha Tryputsen** & Davit Sargsyan**

July 7, 2021



Know Your Tools

- What are the research questions you are trying to answer?
- What data do you need to answer them?
- Can you design an experiment that will provide you with the data? Think about the experimental design long and hard!
- What are the right tools, i.e., appropriate statistical techniques that can help you answer the questions?
- Do you understand the statistical methods well enough to be confident with your inference? Things to consider:
 - Distributions
 - Missing data
 - Outliers







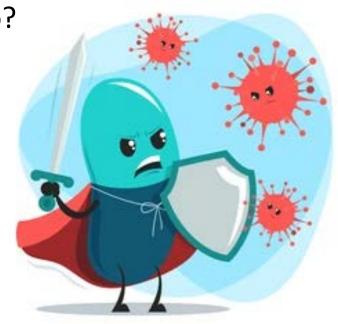
Research Questions

Ultimately, we are developing a drug that can cure or manage a disease

Is my drug better than the standard treatment or placebo?

Depending on a therapeutic area, these can be:

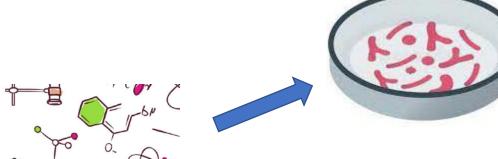
- Can the drug reduce or eliminate cancer (oncology)
- Can the drug reduce inflammation (immunology)
- Can the drug help reduce weight, correct blood pressure, help damaged heart, regulate insulin (cardio-vascular and metabolism)
- ➤ Can the drug eliminate harmful bacteria and viruses and prevent new infections (infectious diseases and vaccines)

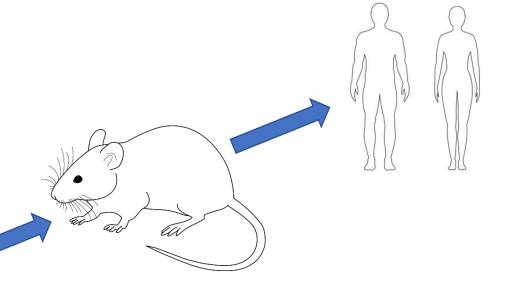




Animal Models in Drug Development

- Before a drug is tested in humans, it needs to be tested in cells and animals
- Cells, tissues or computer simulations are not complex enough (yet) to fully understand biological processes and interactions





 Animal models are used to test compound toxicity, model PK/PD, understand drug-drug interactions, and many more



Know Your Tools

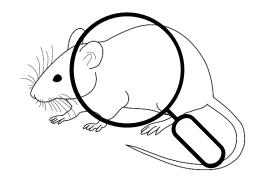
- What are the research questions you are trying to answer?
- What data do you need to answer them?
- Can you design an experiment that will provide you with the data? Think about the experimental design long and hard!
- What are the right tools, i.e., appropriate statistical techniques that can help you answer the questions?
- Do you understand the statistical methods well enough to be confident with your inference? Things to consider:
 - Distributions
 - Missing data
 - Outliers







Study Endpoints

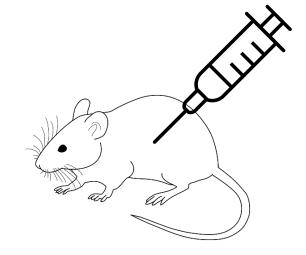


Endpoints that can be observed directly:

- Survival rate and time
- > Tumor volume
- Body weight change
- Skin inflammation
- Bacterial count

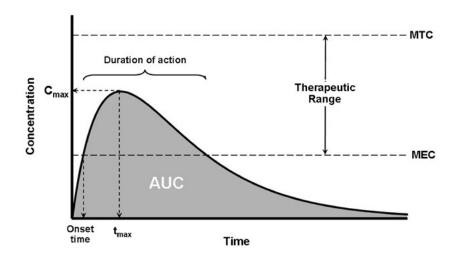
Biomarkers from blood or tissue

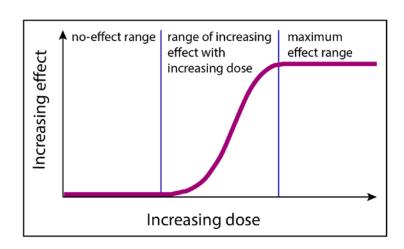
- Protein concentration (Western blot, proteomics)
- Gene expression (microarrays, qPCR, RNA- and DNA-seq, DNA methylation and acetylation)
- Cell counting (flow cytometry)





Pharmacokinetic/Pharmacodynamics (PK/PD)





Pharmacokinetic: what a body does to a drug

- Drug concentration in blood or urine over time
- Estimate large number of parameters: total drug exposure (AUC), distribution volume, drug elimination half-life, maximum concentration, renal clearance, etc.

Pharmacodynamics: what a drug does to a body

- Estimate dose-response or exposure-response relationship
- Calculate parameters: top and bottom asymptotes, slope, EC50/IC50, etc.



Know Your Tools

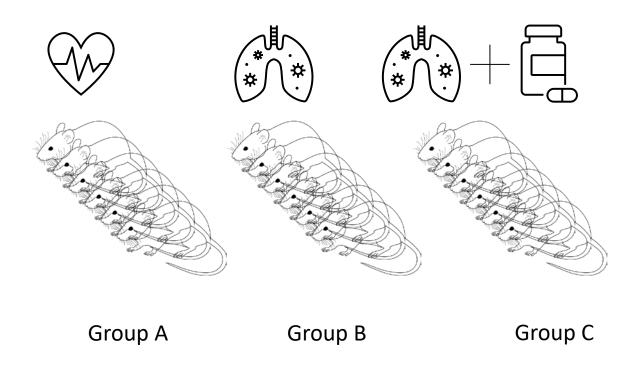
- What are the research questions you are trying to answer?
- What data do you need to answer them?
- Can you design an experiment that will provide you with the data? Think about the experimental design long and hard!
- What are the right tools, i.e., appropriate statistical techniques that can help you answer the questions?
- Do you understand the statistical methods well enough to be confident with your inference? Things to consider:
 - Distributions
 - Missing data
 - Outliers







Basics of Animal Study Design



Is my drug working?

- What is the range of values for my endpoints in healthy animals? Use naïve animals as controls (**Group A**)
- Are they sufficiently different in sick animals? Use sick untreated animals as negative controls (**Group B**).
- Can the drug prevent or reverse the effect of the disease? Use the drug in sick animals (treatment group, **Group C**)



Study Design Considerations

- ➤ What questions do we need to answer with the study? The research hypotheses must be negatable!
- What are the primary, i.e., the most important endpoints of the study?
- What is the criteria for success? Minimum difference in primary endpoints that is biologically meaningful.
- How much variability we expect? Use published data and previous experiments.
- How many control and treatment groups do we need?
- How many animals do we need that, given all of the above, we have a good chance to show statistically significant results?
- ➤ What variables and experimental conditions can we control for?



Know Your Tools

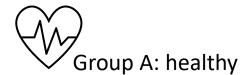
- What are the research questions you are trying to answer?
- What data do you need to answer them?
- Can you design an experiment that will provide you with the data? Think about the experimental design long and hard!
- What are the right tools, i.e., appropriate statistical techniques that can help you answer the questions?
- Do you understand the statistical methods well enough to be confident with your inference? Things to consider:
 - Distributions
 - Missing data
 - Outliers





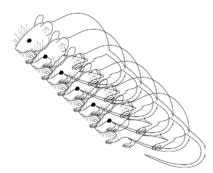


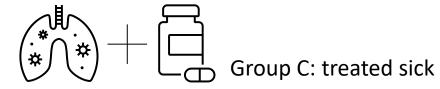
Comparing groups

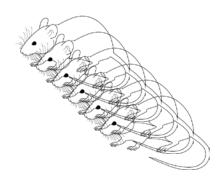




Group B: sick

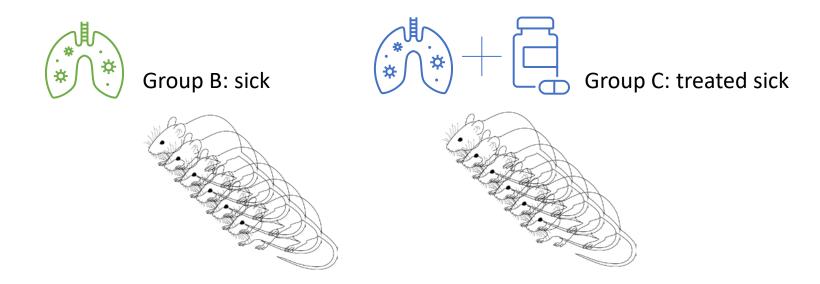






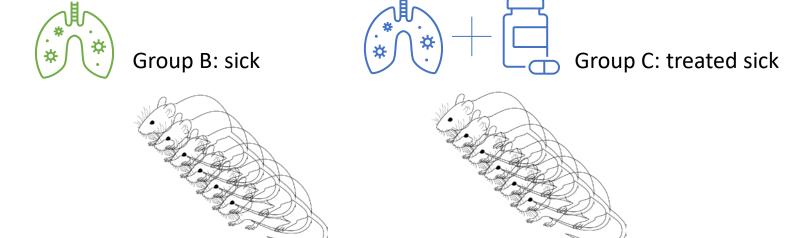


1. Comparing 2 groups





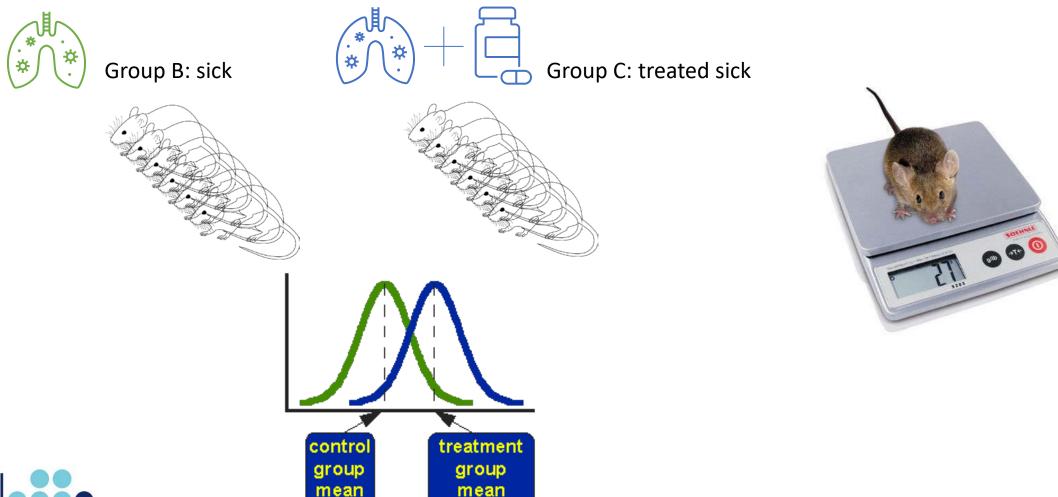
Mouse weight





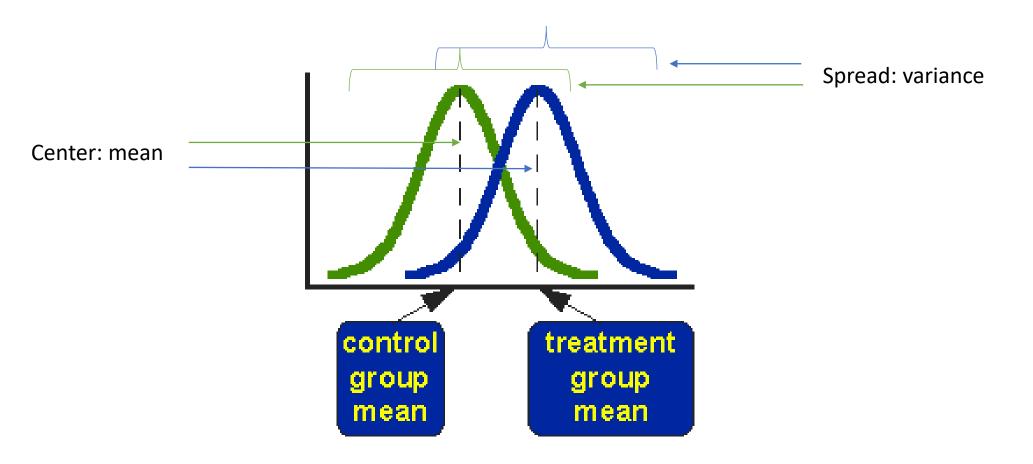


Weight distributions



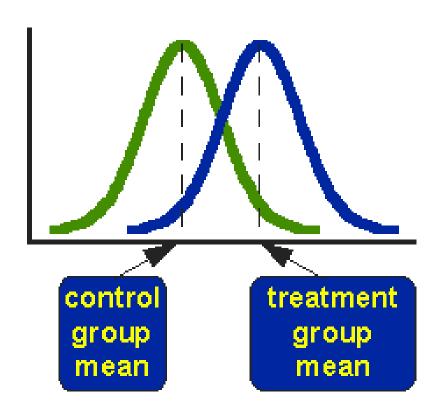


Weight distribution's center and spread





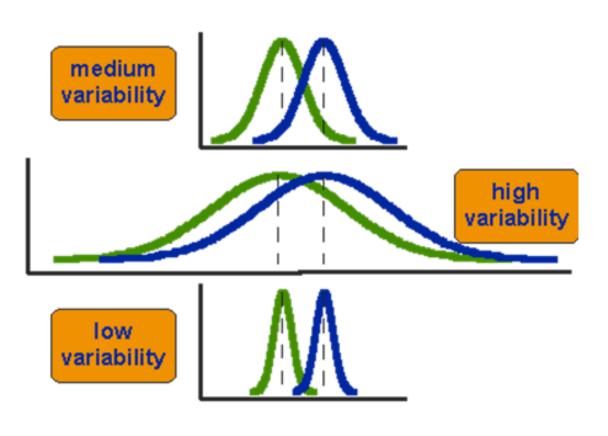
Comparing 2 means



Question: Are mean weights in control are treated groups statistically different?



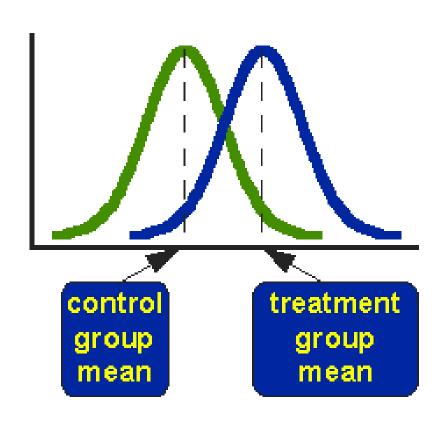
Difference between means - 3 scenarios



- 1. The difference between the means is the same in all three.
- 2. The two groups appear most different or distinct in the bottom or low-variability case.
- 3. When we are looking at the differences between weights for 2 groups, we must judge the difference between their means relative to variability!



Comparing 2 Groups' Means: t-Test



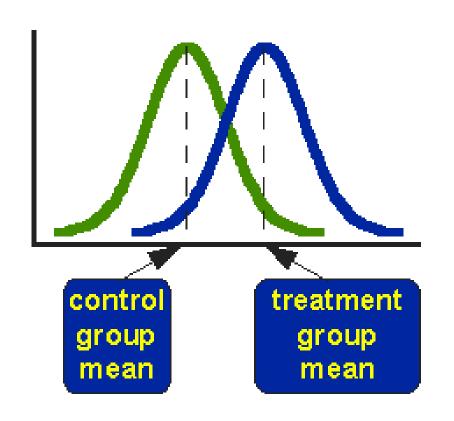
$$\frac{signal}{noise} = \frac{difference\ between\ two\ means}{groups\ variance} =$$

$$\frac{\overline{X_T} - \overline{X_C}}{SE(\overline{X_T} - \overline{X_C})} = \frac{\overline{X_T} - \overline{X_C}}{\sqrt{\frac{\operatorname{var}_T}{n_T} + \frac{\operatorname{var}_C}{n_C}}} = t - value$$



$$ext{SE}(ar{X}_T - ar{X}_C) = \sqrt{rac{ ext{var}_T}{n_T} + rac{ ext{var}_C}{n_C}}$$

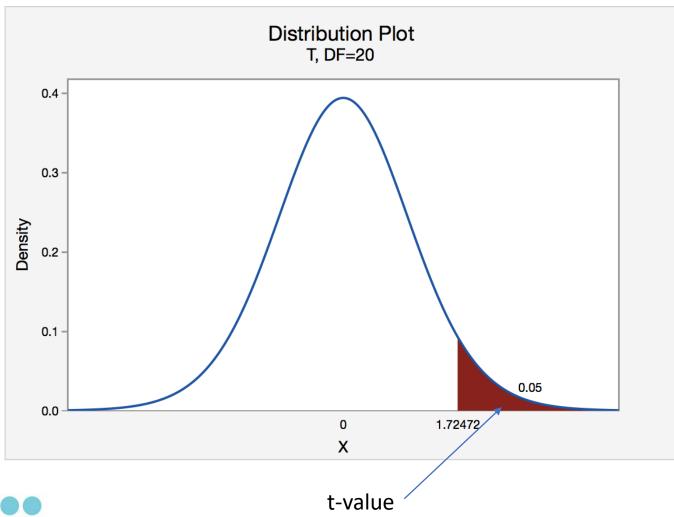
Comparing 2 Groups' Means: t-Test



$$\frac{signal}{noise} = \frac{difference\ between\ two\ means}{groups\ variance} = \frac{\overline{X_T} - \overline{X_C}}{SE(\overline{X_T} - \overline{X_C})} = \frac{\bar{X}_T - \bar{X}_C}{\sqrt{\frac{\mathrm{var}_T}{n_T} + \frac{\mathrm{var}_C}{n_C}}} = t - value$$
 number of animals in treated and control groups



Comparing 2 Groups' Means: t-Test

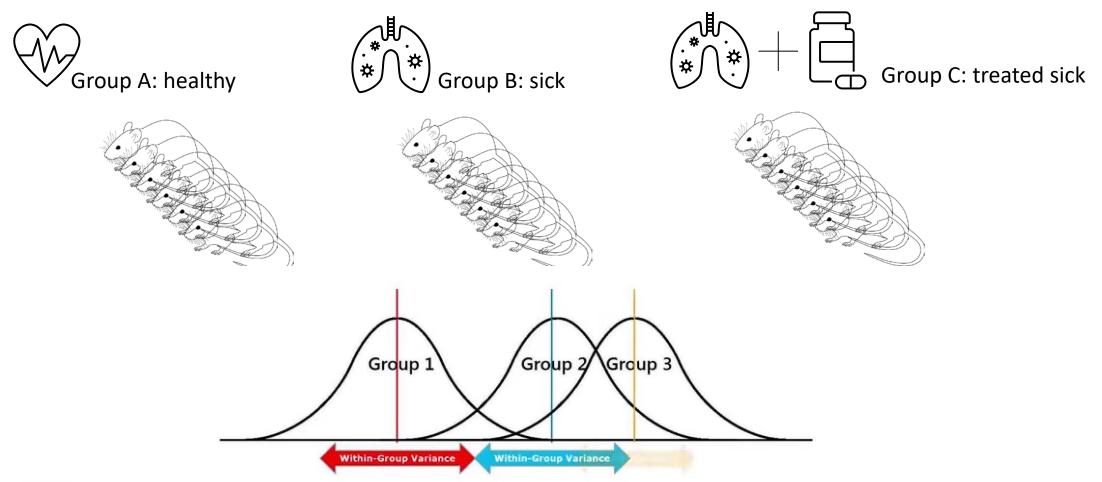


- Compute the t-value.
- To test the significance, you need to set a significant level alpha (usually alpha = 0.05). This means that 5% of time you would find a statistically significant difference between the means even if there was none (i.e., by "chance").
- You also need to determine the degrees of freedom (df) for the test = the sum of the mice in both groups minus 2.
- Given the alpha level, the df, and the tvalue, you can determine whether the tvalue is large enough to be significant.

If it is, you can conclude that the difference between the means for the two groups is different.



Comparing More Than 2 Groups' Means with ANOVA





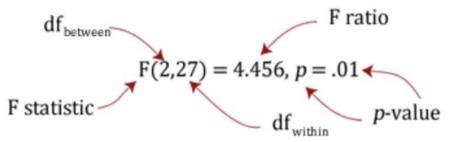
- •Null: All group means are equal.
- •Alternative: Not all group means are equal.

Comparing More Than 2 Groups' Means with ANOVA

Source	SS	df	MS	F	Sig.
Between	SS _b	k-1	MS _b	MS _b /MS _w	p value
Within	SS_W	N-k	MS_W		
Total	$SS_b + SS_w$	N-1			

Source	SS	df	MS F	Sig.
Between	91.476	2	45.733 4.467	.021
Within	276.400	27	10.237	
Total	367.867	29		





Comparing More Than 2 Groups' Means with ANOVA and post hoc

The ANOVA test tells you whether you have an overall difference between your groups, but it does not tell you which specific groups differed – post hoc tests do.

Because post hoc tests are run to confirm where the differences occurred between groups, they should only be run when you have a shown an overall statistically significant difference in group means.

Post-hoc tests:

- Tukey's honestly significant difference (HSD) post hoc test for all pair-wise comparison -
- **Dunnett's test** for all treatment to control comparisons



Group Assignment

Group 1	Group 2	Group 3	Group 4	Group 5
Gisane (R)	Arabo (R)	Susie (R)	Tamara (R)	Mher (R)
Arvin	Nerses	Ashkhen	Vardan	Vika
Satenik	Liana	Anush (R)	Hripsime	Nelli



The Royal Guinea Pig Problem



- Once upon a time there were King and Queen
- They had a favorite pet Peppa the Guinea Pig
- And life was great until one day...



The Royal Guinea Pig Problem



- Once upon a time there were King and Queen
- They had a favorite pet Peppa the Guinea Pig
- And life was great until one day... Peppa became very ill



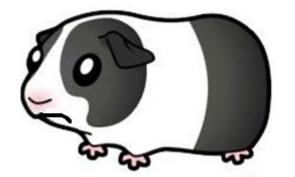
The Royal Guinea Pig Problem

➤ The Guinea pig lost appetite and began losing weight. It even stopped eating its favorite treat - carrot



- Available resources:
- Castle basement full of mice and rats
- 2 types of diet: regular grass or carrot-rich
- > 3 natural compounds to use as treatments

- You are commissioned to find a cure for Peppa – and get half of the Kingdom
- > Or else...



Peppa's Information

Age: 5 years 2 months; Sex: Female, Skin Color: Pink;

Favorite snack: carrots

	Last Week	This Week
Diet	Grass and Carrots	Grass
Weight	550g	423g
Food Intake	128g/day	105g/day



Now, Lets Design the Experiment!

Research Question(s):

- Diagnose Peppa first! You noticed inflammation in the guts.
- 2. Does the treatment make a difference?
- 3. Is diet affecting weight?

Endpoints:

- 1. Body weight
- 2. Food intake
- 3. Activity



Define success:

- 1. Significant difference between sick and treated mice body weight
- 2. No significant body weight change from the baseline weight

Study design:

- 5 Treatment groups: Naïve, negative control (harsh chemical to make mice sick), 3 treatments (all sick animals). We will not consider combinations
- 2. Diet: grass only vs crass + carrots

Data analysis and visualization:

- 1. t-Test: Naïve vs. Negative control to see if the inflammation made the animals sick
- 2. ANOVA + pairwise comparison: what treatment9s) work?
- 3. Dot plots, histograms, boxplots

Reporting:

Explain your results clearly to a non-scientists (aka King and Queen)



Homework (Due Next Tuesday)



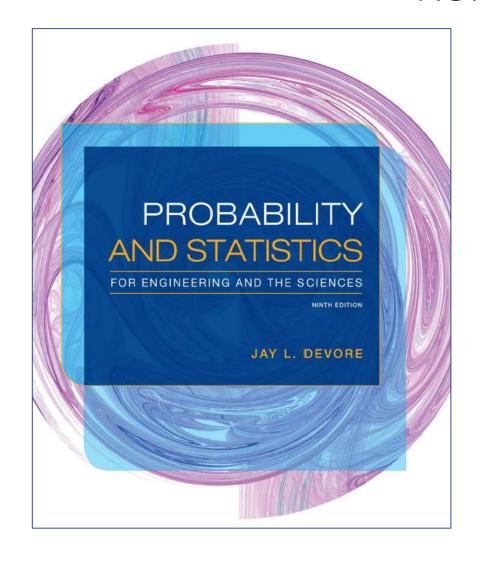
- Clone our GitHub
 https://github.com/sargdavid/abi statistics
- Find the data file in the "data" folder
- Visualize the data (dot plot, histogram, boxplot)
- Data analysis (t-Test, ANOVA with pair-wise comparisons)
- Report the results: what is the best treatment available, and how confident you are that it will work. Hint: take into account the patient's preferences
- Report limitations of your study

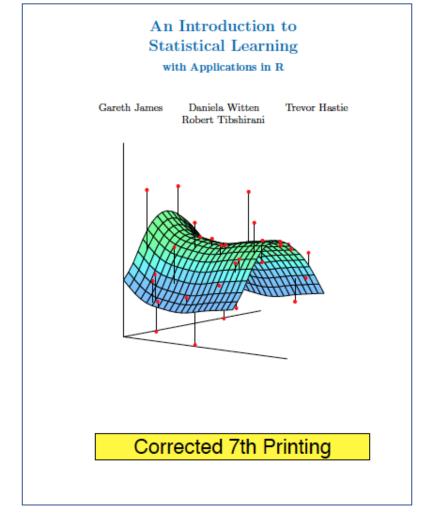


Questions



References





https://www.statlearning.com/



Topics in Statistics Level I

2 Probability

Introduction 52

- 2.1 Sample Spaces and Events 53
- 2.2 Axioms, Interpretations, and Properties of Probability 58
- 2.3 Counting Techniques 66
- 2.4 Conditional Probability 75

4 Continuous Random Variables and Probability Distributions

Introduction 141

- 4.1 Probability Density Functions 142
- 4.2 Cumulative Distribution Functions and Expected Values 147
- 4.3 The Normal Distribution 156
- 4.4 The Exponential and Gamma Distributions 170
- 4.5 Other Continuous Distributions 177
- 4.6 Probability Plots 184

Joint Probability Distributions and Random Samples

Introduction 198

- 5.1 Jointly Distributed Random Variables 199
- 5.2 Expected Values, Covariance, and Correlation 213
- 5.3 Statistics and Their Distributions 220
- 5.4 The Distribution of the Sample Mean 230

6 Point Estimation

Introduction 247

- 6.1 Some General Concepts of Point Estimation 248
- 6.2 Methods of Point Estimation 264

7 Statistical Intervals Based on a Single Sample

Introduction 276

- 7.1 Basic Properties of Confidence Intervals 277
- 7.2 Large-Sample Confidence Intervals for a Population Mean and Proportion 285

8 Tests of Hypotheses Based on a Single Sample

Introduction 310

- 8.1 Hypotheses and Test Procedures 311
- 8.2 z Tests for Hypotheses about a Population Mean 326
- 8.3 The One-Sample t Test 335
- 8.4 Tests Concerning a Population Proportion 346

9 Inferences Based on Two Samples

Introduction 361

- 9.1 z Tests and Confidence Intervals for a Difference Between Two Population Means 362
- 9.2 The Two-Sample t Test and Confidence Interval 374
- 9.3 Analysis of Paired Data 382
- 9.4 Inferences Concerning a Difference Between Population Proportions 391

Topics in Statistics Level II

10 The Analysis of Variance

Introduction 409

- 10.1 Single-Factor ANOVA 410
- 10.2 Multiple Comparisons in ANOVA 420
- 10.3 More on Single-Factor ANOVA 426

11 Multifactor Analysis of Variance

Introduction 437

- 11.1 Two-Factor ANOVA with $K_{II} = 1$ 438
- 11.2 Two-Factor ANOVA with K_s > 1 451
- 11.3 Three-Factor ANOVA 460
- 11.4 2^p Factorial Experiments 469

12 Simple Linear Regression and Correlation

Introduction 487

- 12.1 The Simple Linear Regression Model 488
- 12.2 Estimating Model Parameters 496
- 12.3 Inferences About the Slope Parameter β_1 510
- 12.4 Inferences Concerning μ_Y . _{x*} and the Prediction of Future Y Values 519
- 12.5 Correlation 527

13 Nonlinear and Multiple Regression

Introduction 542

- 13.1 Assessing Model Adequacy 543
- 13.2 Regression with Transformed Variables 550
- 13.3 Polynomial Regression 562
- 13.4 Multiple Regression Analysis 572

15 Distribution-Free Procedures

Introduction 652

- 15.1 The Wilcoxon Signed-Rank Test 653
- 15.2 The Wilcoxon Rank-Sum Test 661
- 15.3 Distribution-Free Confidence Intervals 667
- 15.4 Distribution-Free ANOVA 671

Topics in Statistics Level III

An Introduction to Statistical Learning

with Applications in R

1 Introduction > \(\) 2 Statistical Learning > 3 Linear Regression 4 Classification > 5 Resampling Methods > A 6 Linear Model Selection and Regularization 7 Moving Beyond Linearity > 3 Tree-Based Methods > 9 Support Vector Machines > \(\) 10 Unsupervised Learning Index

Probability: Central Limit Theorem and Bayes' Theorem

The Central Limit Theorem (CLT)

Let X_1, X_2, \ldots, X_n be a random sample from a distribution with mean μ and variance σ^2 . Then if n is sufficiently large, \overline{X} has approximately a normal distribution with $\mu_{\overline{X}} = \mu$ and $\sigma_{\overline{X}}^2 = \sigma^2/n$, and T_o also has approximately a normal distribution with $\mu_{T_o} = n\mu$, $\sigma_{T_o}^2 = n\sigma^2$. The larger the value of n, the better the approximation.

If a statistic T is some linear combination of RV's Then for large samples T / SE(T) is approximately normally distributed regardless of the population of the data. This is the fundamental theorem of all statistics.

Bayes' Theorem

Let $A_1, A_2,..., A_k$ be a collection of k mutually exclusive and exhaustive events with *prior* probabilities $P(A_i)$ (i = 1,...,k). Then for any other event B for which P(B) > 0, the *posterior* probability of A_i given that B has occurred is

$$P(A_j|B) = \frac{P(A_j \cap B)}{P(B)} = \frac{P(B|A_j)P(A_j)}{\sum_{i=1}^k P(B|A_i) \cdot P(A_i)} \quad j = 1, ..., k$$
 (2.6)

Suppose that we assume a model for the Data based on some parameter-s θ , P(Data $|\theta$) And suppose we give a prior distribution to θ , P(θ). P(θ) represents our prior believe before collecting the data and then we collect the data Data.

Then Bayes theorem gives us the posterior distribution of θ given the observe Data $P(\theta \mid Data)$ incorporating the observed data to the distribution of θ .

Q 1:

A is a disease: Prostate Cancer {A1, A2}

A1: Healthy A2: Prostate cancer

B is a genotype variable, it has 3 possible values

{B1, B2, B3}

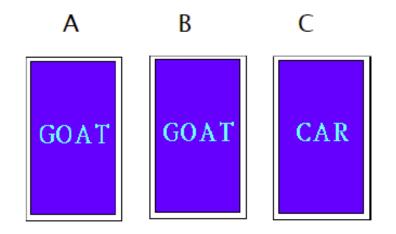
The following tables give the conditional probabilities of A and of B|A

	Prob(Bj Ai)	
Genotype	A1: Healthy	A2: Prostate C.
B1	0.2	0.8
B2	0.4	0.1
B3	0.4	0.1
Total	1	1
Disease	A1: Healthy	A2: Prostate C.
Prob	0.8	0.2

The Data: For each patient we measure the genotype either B1, B2 or B3.
Calculate the posterior distribution of A (prostate cancer) given a genotype Bj.

Q 2:

Goat game (a TV Game): Behind three closed doors, one has a car, and two have a goat.



- a. Player chooses one door, say door C
- b. Game host shows a goat behind a door, say door A
- c. There are two closed doors left B, C. The player is asked if he would like to switch.

Question: Is it better to switch (S) or not to switch (S^c)?

The Two-Sample t Test and t-Confidence Interval

Pooled t-Interval Procedure

Purpose To find a confidence interval for the difference between two population means, μ_1 and μ_2

Assumptions

- 1. Simple random samples
- 2. Independent samples
- 3. Normal populations or large samples
- 4. Equal population standard deviations

Step 1 For a confidence level of $1 - \alpha$, use Table IV to find $t_{\alpha/2}$ with $df = n_1 + n_2 - 2$.

Step 2 The endpoints of the confidence interval for $\mu_1 - \mu_2$ are

$$(\bar{x}_1 - \bar{x}_2) \pm t_{\alpha/2} \cdot s_p \sqrt{(1/n_1) + (1/n_2)},$$

where s_p is the pooled sample standard deviation.

Step 3 Interpret the confidence interval.

Note: The confidence interval is exact for normal populations and is approximately correct for large samples from nonnormal populations.

Pooled t-Test

Purpose To perform a hypothesis test to compare two population means, μ_1 and μ_2

Assumptions

- 1. Simple random samples
- 2. Independent samples
- 3. Normal populations or large samples
- Equal population standard deviations

Step 1 The null hypothesis is H_0 : $\mu_1 = \mu_2$, and the alternative hypothesis is

$$H_a$$
: $\mu_1 \neq \mu_2$ or H_a : $\mu_1 < \mu_2$ or H_a : $\mu_1 > \mu_2$ (Right tailed)

- Step 2 Decide on the significance level, α .
- **Step 3** Compute the value of the test statistic

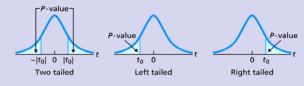
$$t = \frac{\bar{x}_1 - \bar{x}_2}{s_p \sqrt{(1/n_1) + (1/n_2)}},$$

where

$$s_{\rm p} = \sqrt{\frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}}.$$

Denote the value of the test statistic t_0 .

Step 4 The *t*-statistic has $df = n_1 + n_2 - 2$. Use Table IV to estimate the *P*-value, or obtain it exactly by using technology.



Step 5 If $P \le \alpha$, reject H_0 ; otherwise, do not reject H_0 .

Single-Factor ANOVA

- The relevant hypotheses are
- H_0 : $\mu_1 = \mu_2 = \dots = \mu_l$ (POPULATION MEANS ARE EQUAL)
- versus
- H_a : at least two the of the μ_i 's are different
- If I = 4, H_0 is true only if all four μ_i 's are identical. H_a would be true, for example, if

$$\mu_1 = \mu_2 \neq \mu_3 = \mu_4$$
, if $\mu_1 = \mu_3 = \mu_4 \neq \mu_2$,

or if all four μ_i 's differ from one another.

- Assumptions
 - Samples are independent
 - Populations are Normal
 - POPULATION VARIANCES ARE EQUAL

The Test Statistic

Mean square for treatments is given by

$$MSTr = \frac{J}{I-1} [(\overline{X}_{1.} - \overline{X}..)^{2} + (\overline{X}_{2.} - \overline{X}..)^{2} + \dots + (\overline{X}_{I.} - \overline{X}..)^{2}]$$
$$= \frac{J}{I-1} \sum_{i} (\overline{X}_{i.} - \overline{X}..)^{2}$$

and mean square for error is

$$MSE = \frac{S_1^2 + S_2^2 + \dots + S_I^2}{I}$$

The test statistic for single-factor ANOVA is F = MSTr/MSE.

Theorem

Let F = MSTr/MSE be the test statistic in a single-factor ANOVA problem involving I populations or treatments with a random sample of J observations from each one. When H_0 is true and the basic assumptions of this section are satisfied, F has an F distribution with $\nu_1 = I - 1$ and $\nu_2 = I(J - 1)$. Because a larger f is more contradictory to H_0 than a smaller f, the test is upper-tailed:

$$P$$
-value = $P(F \ge f \text{ when } H_0 \text{ is true})$
= area under the $F_{I-1,I(I-1)}$ curve to the right of f

Statistical software will provide an exact *P*-value. Refer to Section 9.5 for a description of how our book's table of *F* critical values, Table A.9, can be used to obtain an upper or lower bound (or both) on the *P*-value.

Multiple Comparisons in ANOVA

- Several of the most frequently used procedures are based on the following central idea.
- First calculate a confidence interval for each pairwise difference $\mu_i \mu_j$ with i < j. Thus if l = 4. the six required CIs would be for $\mu_1 \mu_2$ (but not also for $\mu_2 \mu_1$), $\mu_1 \mu_3$, $\mu_1 \mu_4$, $\mu_2 \mu_3$, $\mu_2 \mu_4$, and $\mu_3 \mu_4$.
- Then if the interval for $\mu_1 \mu_2$ does not include 0, conclude that μ_1 and μ_2 differ significantly from one another; if the interval does include 0, the two μ 's are judged not significantly different.

Tukey's Procedure (the *T* Method)

With probability
$$1-\alpha$$
,
$$\overline{X}_{i\cdot} - \overline{X}_{j\cdot} - Q_{\alpha,I,I(J-1)} \sqrt{\text{MSE}/J} \leq \mu_i - \mu_j$$

$$\leq \overline{X}_{i\cdot} - \overline{X}_{j\cdot} + Q_{\alpha,I,I(J-1)} \sqrt{\text{MSE}/J} \quad (10.4)$$
 for every i and j ($i = 1, ..., I$ and $j = 1, ..., I$) with $i < j$.

2^p Factorial Experiments

• If an experimenter wishes to study simultaneously the effect of p different factors on a response variable and the factors have $I_1, I_2, ..., I_p$ levels, respectively, then a complete experiment requires at least $I_1 \cdot I_2, ..., I_p$ observations.

In such situations, the experimenter can often perform a "screening experiment" with each factor at only two levels to obtain preliminary information about factor effects.

An experiment in which there are p factors, each at two levels, is referred to as a 2^p factorial experiment.

2³ Experiments

As in Section 11.3, we let X_{ijkl} and X_{ijkl} refer to the observation from the Ith replication, with factors A, B, and C at levels i, j, and k, respectively. The model for this situation is

$$X_{ijkl} = \mu + \alpha_i + \beta_j + \delta_k + \gamma_{ij}^{AB} + \gamma_{ik}^{AC} + \gamma_{jk}^{BC} + \gamma_{ijk} + \epsilon_{ijkl}$$

for i = 1, 2; j = 1, 2; k = 1, 2; l = 1, ..., n. The \in_{ijkl} 's are assumed independent, normally distributed, with mean 0 and variance σ^2 .

Because there are only two levels of each factor, the side conditions on the parameters of (11.14) that uniquely specify the model are simply stated:

$$\alpha_1 + \alpha_2 = 0, \dots, \gamma_{11}^{AB} + \gamma_{21}^{AB} = 0, \gamma_{12}^{AB} + \gamma_{22}^{AB} = 0,$$

 $\gamma_{11}^{AB} + \gamma_{12}^{AB} = 0, \gamma_{21}^{AB} + \gamma_{22}^{AB} = 0,$

and the like.

These conditions imply that there is only one functionally independent parameter of each type (for each main effect and interaction).