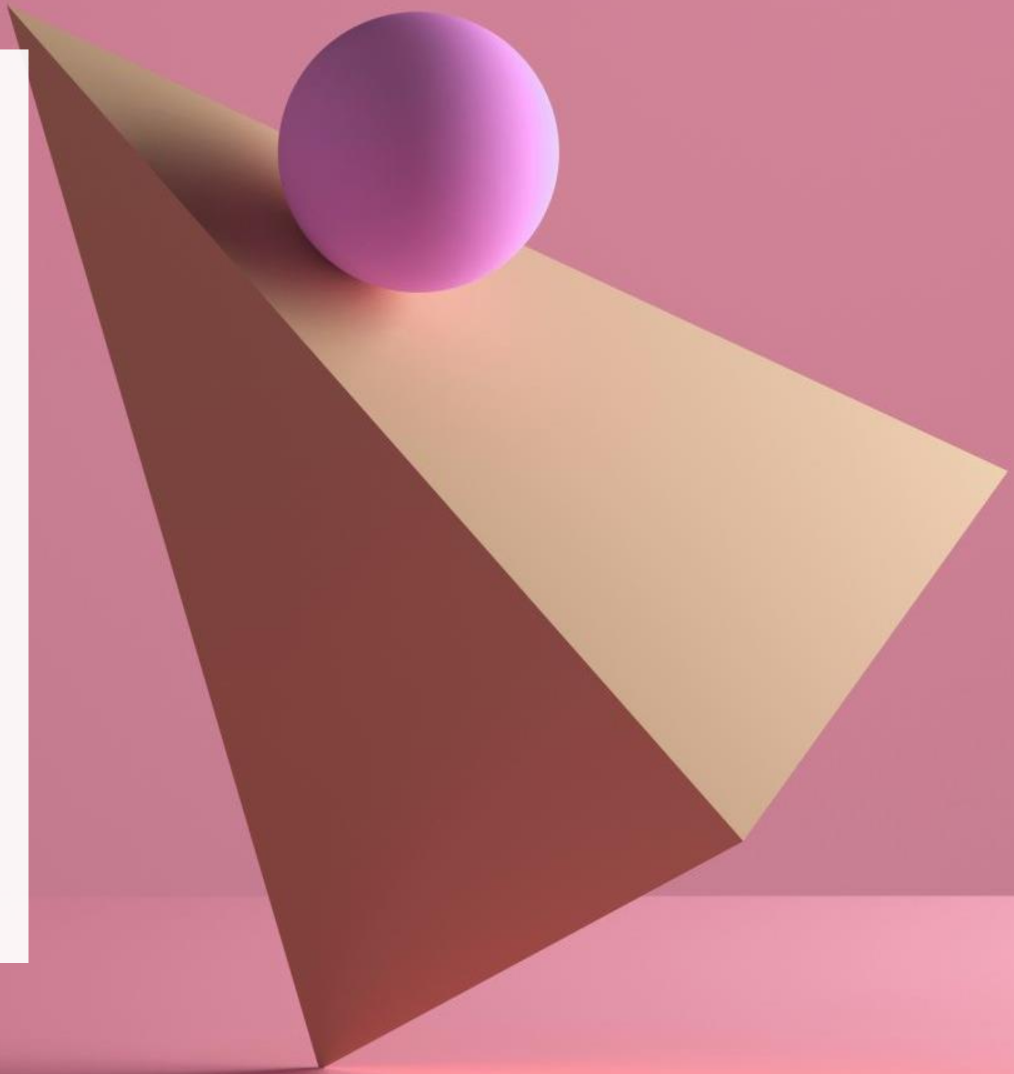
Behavioral Research: Statistical Methods

INTRODUCTION

WHY DO STATISTICS?



Agenda

Syllabus and related questions

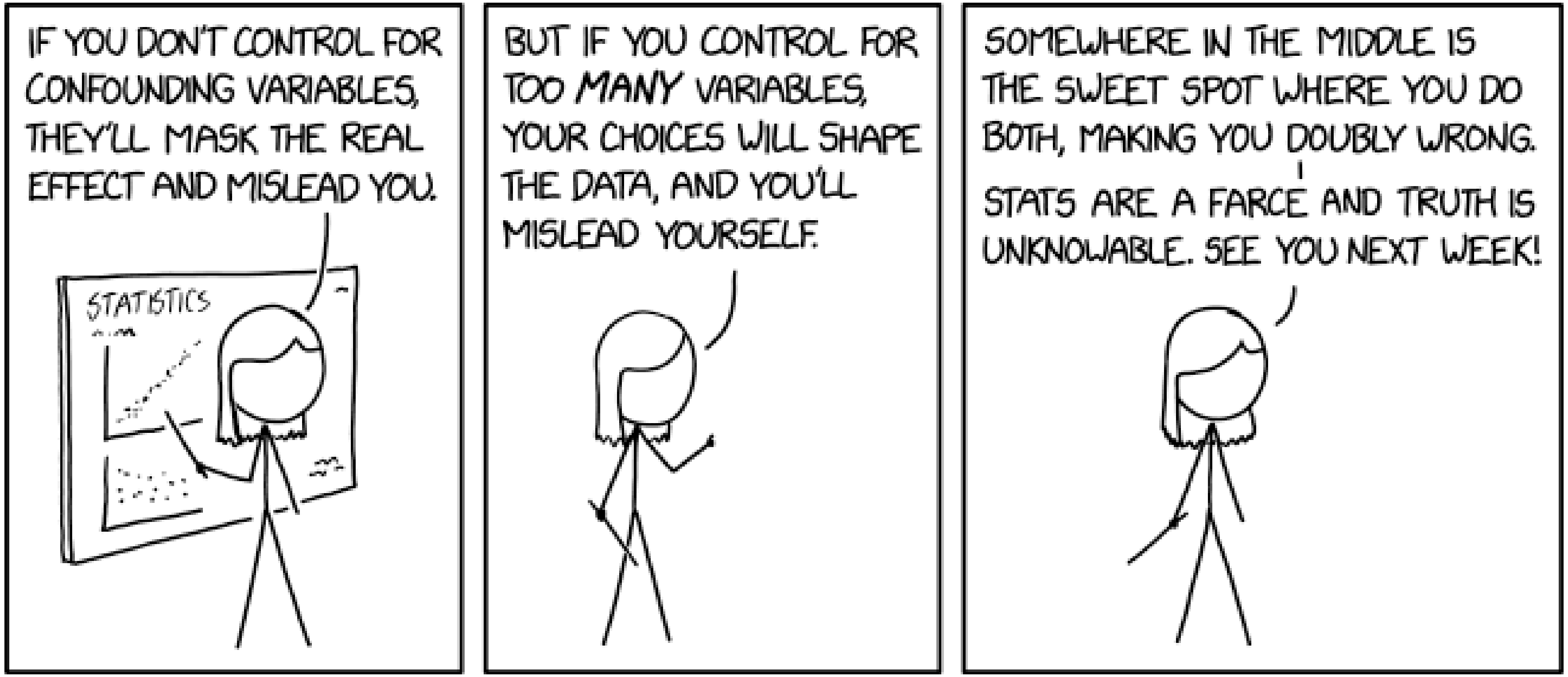
Syllabus

- Please read carefully!
- Uploaded on Moodle.
- Some big changes this semester due to the high enrollment.

Question about coding language

The reference textbook for the course uses R. Many of our problem and practice sets will include R code snippets. So you will need a laptop with R and RStudio installed.

You can however use any language of your choice (MATLAB, Python, etc) to complete your assignments and projects.



Why do statistics?

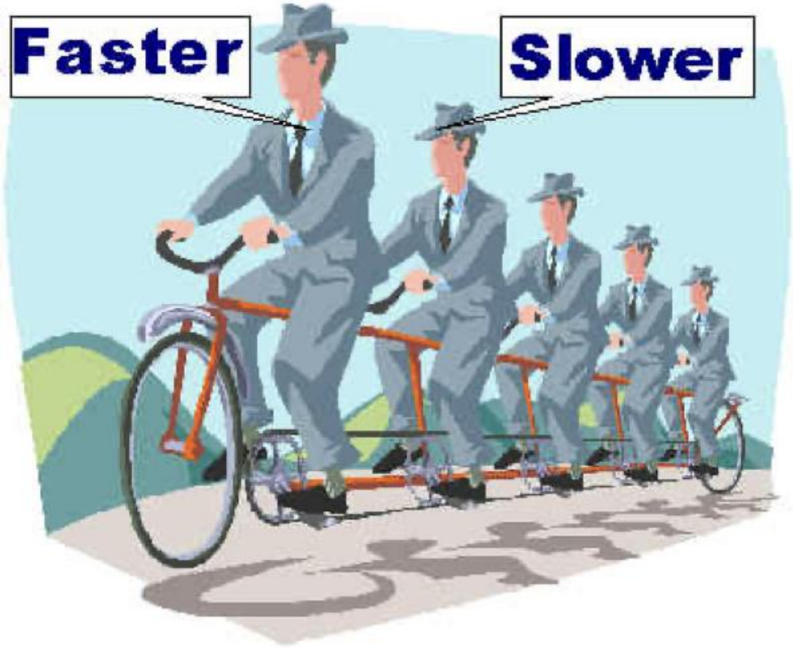
Why do statistics, why not use common sense?

My mom: drink milk with turmeric, it will cure you of sore throat. I have experienced this, 3 days of drinking it and my sore throat is gone. My friends have also experienced it.

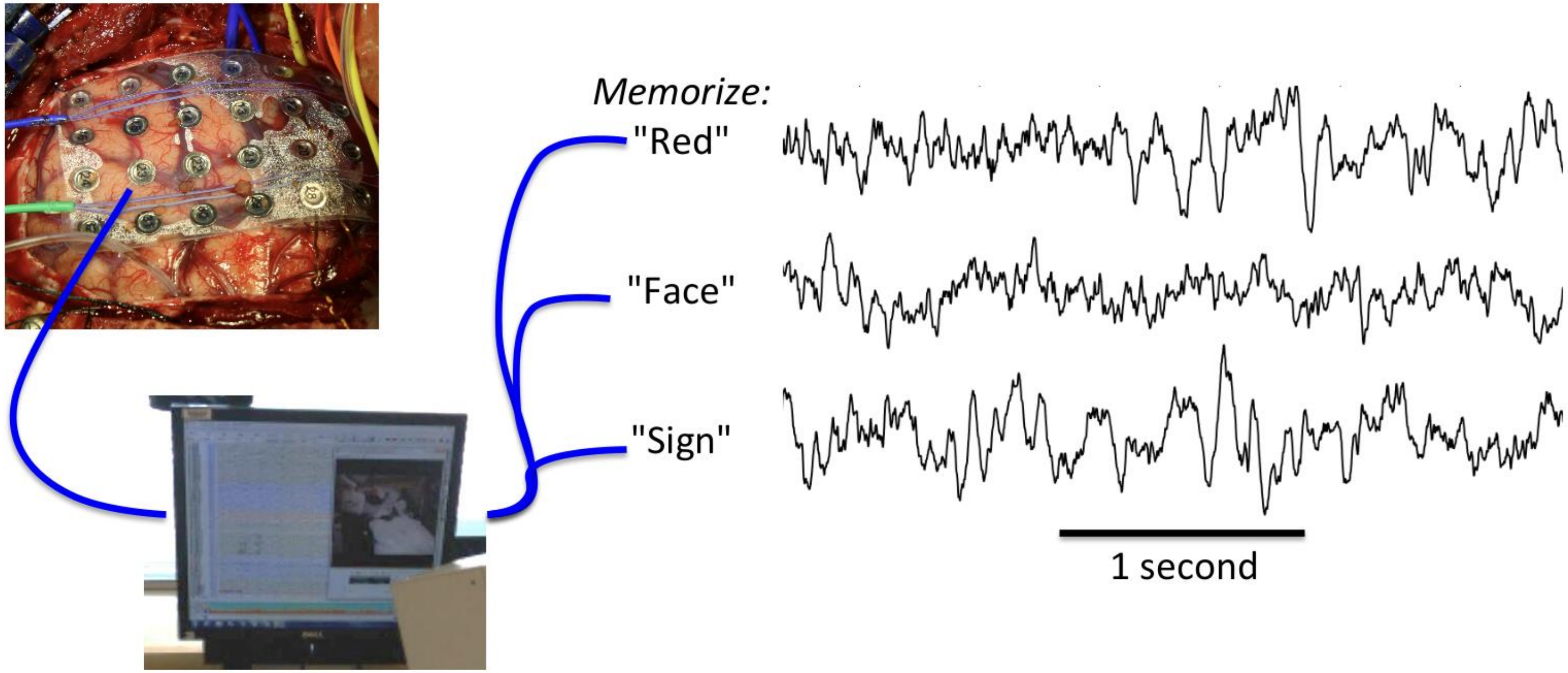
You might have encountered many such claims, especially during the early days of COVID. There is also currently a proliferation of pseudoscientific thinking in India. An education in basic statistics and research design will hopefully help you see through some of the issues with such claims.

Human-beings

- Complexity
- Variability
- Reactivity



Brains



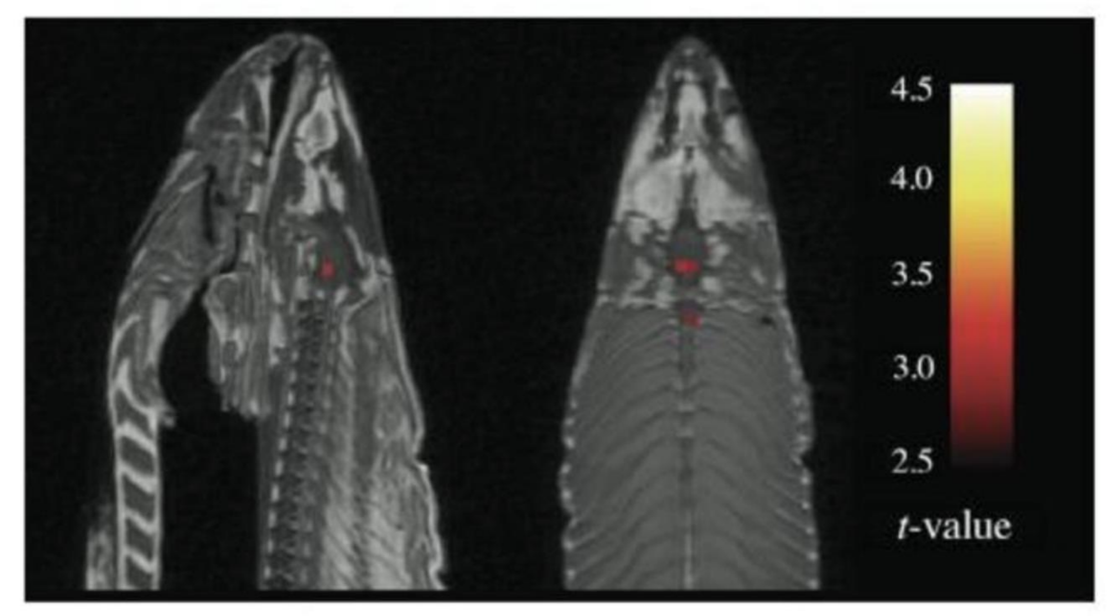
Related statistical pitfalls

Replication Crisis

Reproducibility Crisis

Reviewed by Psychology Today Staff

The replication crisis in psychology refers to concerns about the credibility of findings in psychological science. The term, which originated in the early 2010s, denotes that findings in behavioral science often cannot be replicated: Researchers do not obtain results comparable to the original, peer-reviewed study when repeating that study using similar procedures. For this reason, many scientists question the accuracy of published findings and now call for increased scrutiny of research practices in psychology.



IgNobel Prize in Neuroscience: The dead salmon study

Human biases

Belief bias

We tend to be swayed by the "believability" of the conclusion even when we are trying to deduce the conclusion from certain premises in a logical fashion (I.e., assuming the premises are true, is the conclusion valid?).

Believable conclusion and valid argument

- No cigarettes are inexpensive (Premise 1)
- Some addictive things are inexpensive (Premise 2)
- Therefore, some addictive things are not cigarettes (Conclusion)

Unbelievable conclusion but valid argument

- No addictive things are inexpensive (Premise 1)
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Believable conclusion but invalid argument

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Unbelievable conclusion and invalid argument

- No cigarettes are inexpensive (Premise 1)
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- Therefore, some cigarettes are not addictive (Conclusion)

	conlusion feels true	conclusion feels false
argument is valid	92% say “valid”	–
argument is invalid	–	8% say “valid”

Evans, Barston, & Pollard (1983)

when the structure of the argument was in line with pre-existing beliefs and biases

	conlusion feels true	conclusion feels false
argument is valid	92% say “valid”	**46% say “valid”**
argument is invalid	**92% say “valid”**	8% say “valid”

Evans, Barston, & Pollard (1983)

when the structure of the argument contradicted pre-existing beliefs and biases

Can we improve our chances of being correct from 60% to 90+%?

Probably.

With the use of good statistical methods (and importantly, good research design)

Simpson's paradox

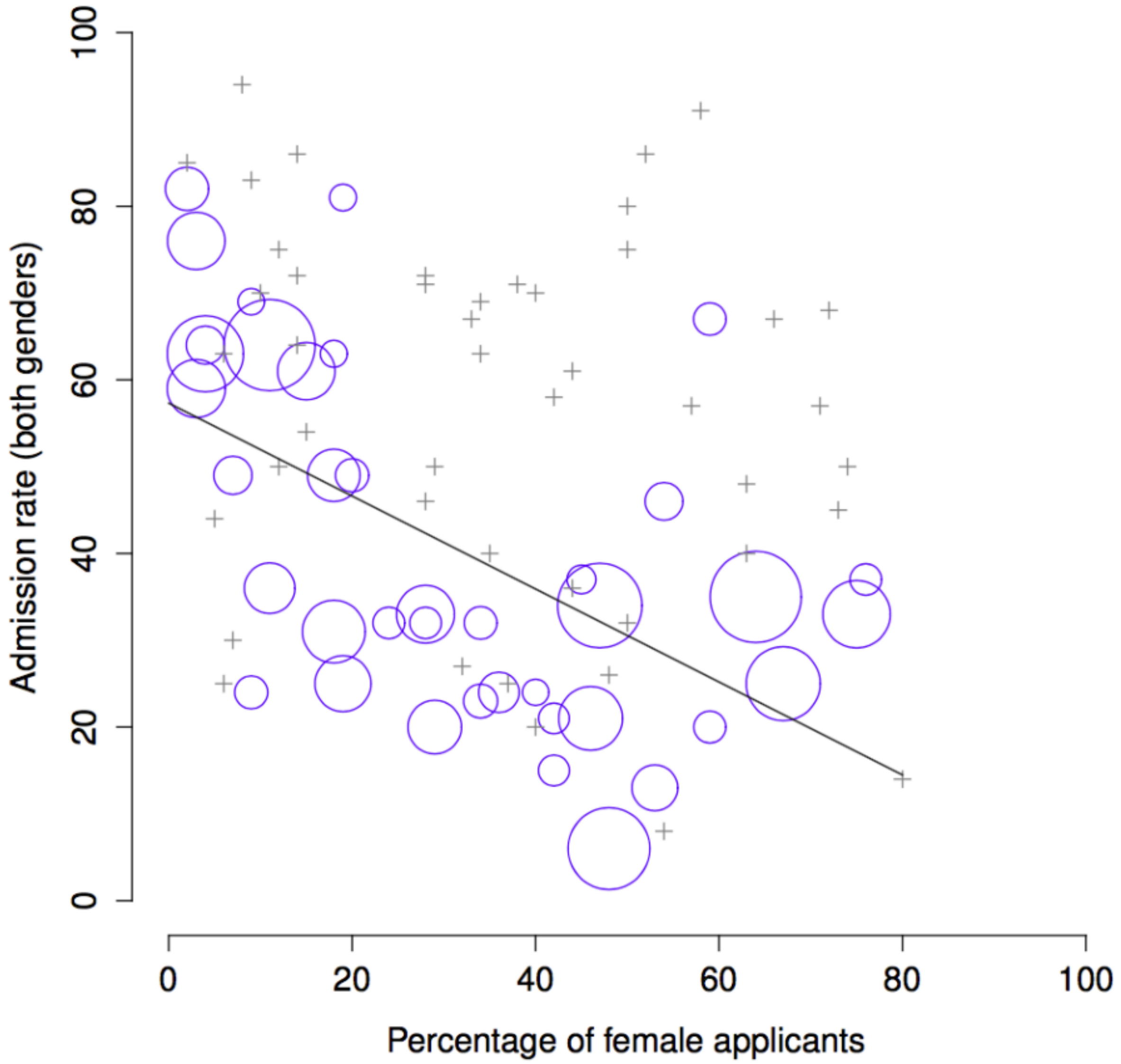
	Number of applicants	Percent admitted
Males	8442	44%
Females	4321	35%

Department	Applicants	Percent admitted	Applicants	Percent admitted
A	825	62%	108	82%
B	560	63%	25	68%
C	325	37%	593	34%
D	417	33%	375	35%
E	191	28%	393	24%
F	272	6%	341	7%

Counter-intuitive but of practical relevance

The overall rate of admission was lower for females than males but in individual departments, it was the opposite!!

The textbook says this is a rare example, but this is actually quite applicable in many scenarios where instead of departments in this example, you have data from different human subjects. These subjects do slightly different things but you try to make a conclusion about the whole population with some average measure. What the average tells you in some cases may be misleading. We need to have strong foundations in statistics to be aware of such cases.



Data visualization

Data interpretation

Once you do the statistics, it is time to interpret the results of your analysis

Is there gender bias in admissions?

Based on the departmental data?

Based on what criteria? This now is where you bring your theories to bear upon the data. For example, does the theory care about systemic issues that make females apply less frequently to say the engineering departments (explaining why the total number of applicants are distributed differently across the departments for males and females)?

Statistics in everyday life

WE SEE CLAIMS EVERY DAY IN THE MEDIA USING STATISTICS

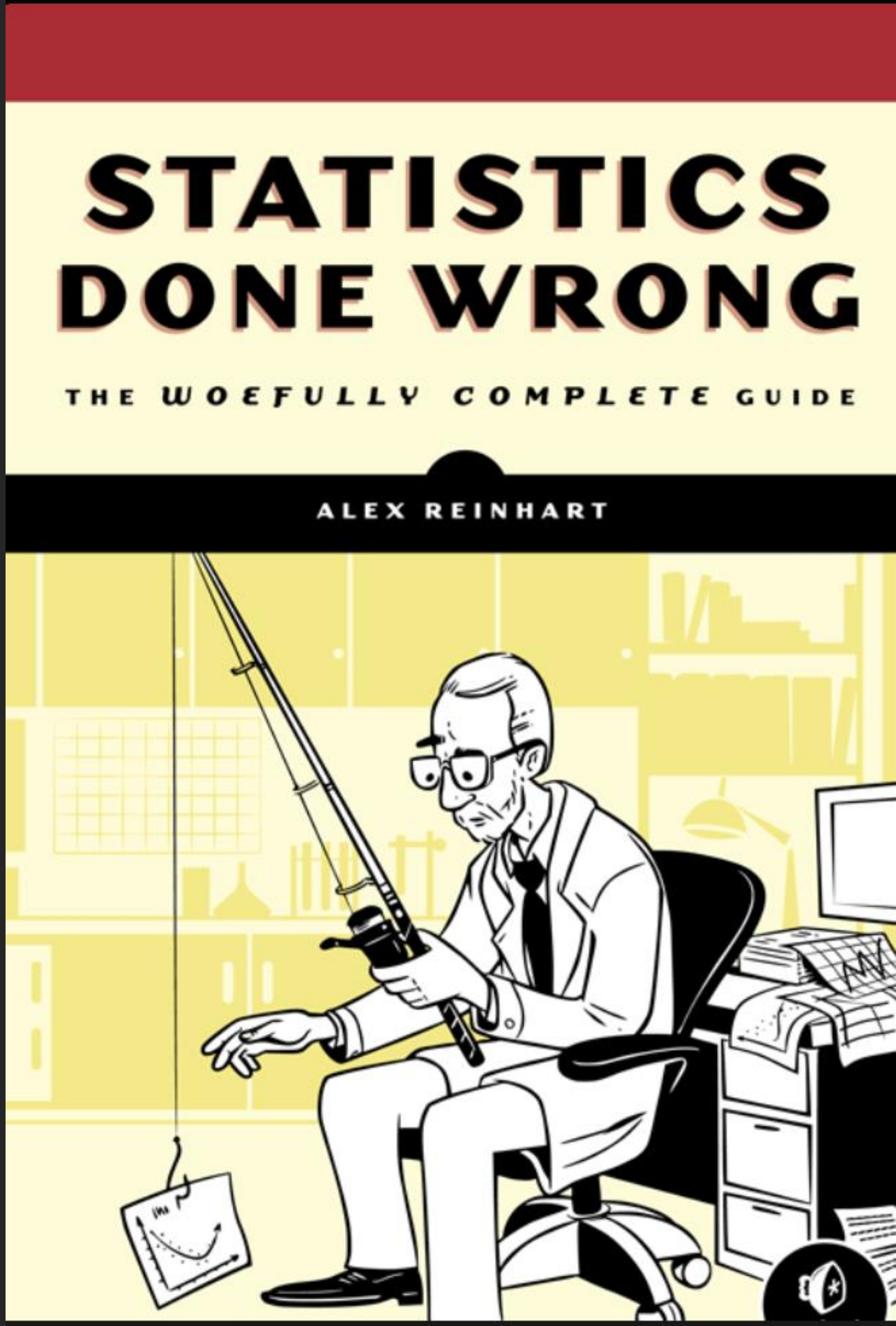
OFTEN, REPORTERS MAKE FUNDAMENTAL ERRORS WHEN THEY REPORT NUMBERS (E.G. NOT TAKING INTO ACCOUNT BASE RATES)

Some pitfalls

Misinterpreting p values

Misinterpreting confidence intervals (I estimate the mean height of boys in this class to be 5'7" with a 95% CI of [5'3", 5'11"])

Base rate fallacy (a lack of understanding of Bayesian probability)



The base rate fallacy

Let's say you or your relative/friend gets a positive mammogram result.

How likely is it that they have cancer?

Some relevant info (premises)

0.8% of all women who get mammograms have breast cancer

In 90% of these women with breast cancer, a mammogram will correctly detect it (defined as the **statistical power**)

However 7% of women without cancer will get a false positive mammogram

How likely is it that a positive test indicates cancer?

Imagine 1000 tests

8 of them have cancer

7/8 of them will get a positive mammogram (due to the 90% power of this test)

992 with no breast cancer

7% false positive = ~70 women incorrectly told they have breast cancer

Now, how many total positive mammograms do we have?? 70 + 7 = 77

Only 7 of them actually have breast cancer.

(7/77)x100 = 9%.

So the probability that given a positive mammogram, someone actually has breast cancer = 0.09 or 9%

Bayes' rule

Bayes' Theorem

We can turn the process above into an equation, which is Bayes' Theorem. It lets you take the test results and correct for the "skew" introduced by false positives. You get the real chance of having the event. Here's the equation:

$$\Pr(\mathrm{H}|\mathrm{E}) = \frac{\Pr(\mathrm{E}|\mathrm{H})\Pr(\mathrm{H})}{\Pr(\mathrm{E}|\mathrm{H})\Pr(\mathrm{H}) + \Pr(\mathrm{E}|\text{not H})\Pr(\text{not H})}$$

The chance evidence is real (supports a hypothesis)
is the chance of a true positive among
all positives (true or false)

Bayes' rule

P(cancer|positive test) = P(positive test|cancer) * P(cancer)/P(positive test)

What we know:

1. P(positive test|not cancer) = 0.07 (false positive probability)
2. P(cancer) = 0.8% = 0.008
3. P(positive test|cancer) = 0.9

P(positive test) = 77/1000 = 0.077 (from the last slide)

The other way to calculate P(positive test) = P(positive test|cancer)*P(cancer) + P(positive test|not cancer) * P(not cancer) = 0.9*0.008 + 0.07*0.992 = 0.07664 ~= 0.077

P(cancer|positive test) = 0.9 *0.008/0.077 = 0.09

P(cancer) = base rate

P(positive test|not cancer = false positive probability

Many fail to give the right answer

2/3rds of doctors fail this test

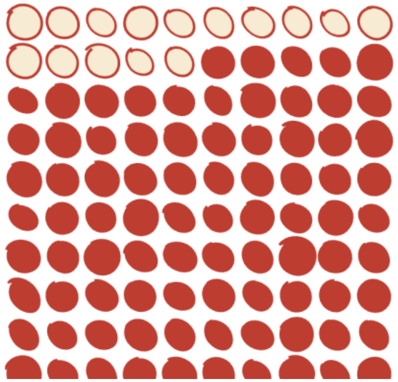
1/3rds of statistics and methodology instructors like myself and statistics students.

Just from recent news:

The New York Times

When They Warn of Rare Disorders, These Prenatal Tests Are Usually Wrong

Some of the tests look for missing snippets of chromosomes. For every 15 times they correctly find a problem ...



Genetic counselors who have dealt with false positives say some doctors may not understand how poorly the tests work. And even when caregivers do correctly interpret the information, patients may still be inclined to believe the confident-sounding results sheets.

When Cloey Canida, 25, got a positive result from Roche's Harmony test in September, the result sheet seemed clear: It said her daughter had a "greater than 99/100" probability of being born with Patau syndrome, a condition that babies often do not survive beyond a week.

"I wish that we would have been informed of the false positive rate before I agreed to the test," she said. "I was given zero information about that."

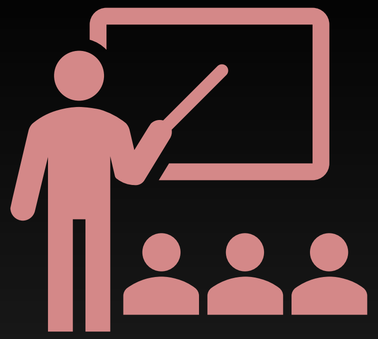
Basic knowledge of statistics and probability can help you in everyday life as well

You read a story in the newspaper about a certain group of people (with certain attributes: religion, caste, etc) and how prone they are to violence based on some numbers. Knowledge of basic statistical and probabilistic pitfalls can help you evaluate these claims better.

You read a story about COVID-19 and Omicron, and the probability of getting seriously sick based on hospital admission numbers. You know about confounding variables, you know about base rates, etc – evaluate the claims calmly and logically.

False positives, false negatives, etc in statistics for psychology

We as researchers too conduct tests. Every test has some chance of a false positive, false negative, etc. To make inferences from the data, we need to compute numbers. There are many statistical tools available to do this.



This will be a major topic of this course.

15 min homework

PLEASE READ CHAPTER 1: HTTPS://LEARNINGSTATISTICSWITHR.COM/BOOK/WHY-DO-WE-LEARN-STATISTICS.HTML