

## MATH-338 Midterm 2 Cheat Sheet

### THEORY

**Day 14:** probability density function is represented an integral with function  $f(x)$ . Our probability lies within the curve and is always 1. Density curve  $\rightarrow$  bell curve. Z-Score allows us to have a universal standard for density curves with different scales. They are directly proportional to the standard deviation and the delta from the mean of the graph.

**Day 15:** unimodal: one hump, bimodal: two humps. Mean is resistant whereas the mean is subject to change. Density curves decay to histograms (integral  $\rightarrow$  Reimann Sum). Whisker plots are an effective method to determine if a data set contains outliers (data points not belonging to the sample set)

**Day 16:** error: since there is some error while taking sample data, we do allow for some buffer. We also do not measure exact but to a tolerance which is influenced by the buffer above. The mean of the sampling distribution of the

### FORMULAS

- $\square = \text{width} \times \frac{1}{\text{width}}$  (finite curve)
- $Z = \frac{x-\mu}{\sigma}$  (z-score)
- $X \sim N(\mu, \sigma)$
- $\bar{X} \sim N(\mu, \frac{\sigma}{\sqrt{n}})$
- $t = \frac{\bar{X}-\mu}{\frac{s}{\sqrt{n}}}$
- $SEM = \frac{s}{\sqrt{n}}$

- $IQR = Q_3 - Q_1$
- $K = 1.5$
- Lower fence:  $Q_1 - K \times IQR$
- Upper fence:  $Q_3 + K \times IQR$

# Day 1

## Statistics

A set of tools for understanding data and making decisions/conclusions/predictions under uncertainty

### Randomness

- in the short term, we don't know what will happen (flipping a coin)
- in the long term, we know the **distribution** of possibilities (what outcomes are possible and how often they occur)
  - the crux of randomness
  - as the amount of times we get a random variable approaches infinity, the clearer/less random the variable becomes

### Two definitions of probability

- **proportion** of times an outcome occurs or would occur over infinitely many repetitions of a random action
  - Frequentist
  - math is a lot nicer
  - there is a fixed outcome but we don't know it
- a number quantifying our **belief** that an outcome can/will occur
  - Bayesian
  - 2000 times more intuitive and math is just as hard
  - random outcome (not fixed)

Both are calculus based

## Probability Model

Consists of two parts:

- sample space: list (set/list of all unique values) of all possibilities and must be well defined.
- probability of each outcome

### This in essence is a hash table

An **event** is an arbitrary set of 0 or more outcomes in a sample space

## Axioms of Probability

- axioms : something is so obvious it does not need to be proven
- For events A and B in the same sample space denoted as “S”:
  - The probability of event A, denoted as  $P(A)$  is a number between 0 and 1 (inclusive).
    - \*  $[0, 1]$  notation as well.
    - \* **NOTE:**  $P(A) = 0$  means A is “impossible” and  $P(A) = 1$  means A is guaranteed
  - $P(S) = 1$ 
    - \* **Some outcome is bound to happen**
  - If A and B are disjoint (there are no common outcomes. A is not in B AND B is not in A), then  $P(A \text{ or } B) = P(A) + P(B)$

### Simple rules that follows from the Axioms

- Compliment Rule: Define  $A^C = A$  compliment, that is  $A^C$  is the event “A does not occur”
  - $P(A^C) = 1 - P(A)$
  - The summation of all events that **do not** occur minus the overall probability (100%)
- General addition rule: Suppose events A and B have at least one common outcome
  - Define  $A \cap B$  to be the set of outcomes common to A & B
  - Define  $A \cup B$  to be the set of outcomes in A, or in B or in both A & B
    - \* Then  $(P(A \cup B)) = P(A) + P(B) - P(A \cap B)$
    - \* This is the same as this:

```
a = [1, 2, 3]
b = [2, 4, 5]
c = a + b
# c = [1, 2, 2, 3, 4, 5]
c = set(a+b)
# c = {1, 2, 3, 4, 5}
```

## Example

Random phenomenon: Draw 1 tile from a standard Scrabble bag of 100 tiles

- Sample space 1 (option one):
  - S = the 100 tiles in the bag
  - All tiles are equally likely to be drawn
  - $P(\text{draw particular tile}) = 1/100 \text{ or } 0.01 \text{ for all}$
- Sample space 2 (option two):
  - The 27 “letters” (26 letters and 1 blank)
- Let event C = “draw a letter in CAT”
- Let event D = “draw a letter in PET”

$$P(C) = P(C) + P(A) + P(T) = .02 + .09 + .06 = 0.17$$

$$P(D) = P(P) + P(E) + P(T) = 0.2 + 0.12 + 0.06 = 0.2$$

$$P(C^C) = P(\text{do not draw any of the letters in CAT}) = 1 - P(C) = 1 - .17 = .83 \quad P(C \cap D) =>$$

- =  $P(\text{letter in both CAT \& PET})$
- =  $P(T) = 0.06$

$$P(C \cup D) = P(\text{letter in CAT or PET or both words}) =>$$

- =  $P(C) + P(D) - P(C \cap D)$
- =  $0.17 + 0.2 - 0.06 = 0.31$

## Python Code Representation

```
#!/usr/bin/env python3.5

# probability can be calculated by using a hash table in conjunction with a set
# hash tables are used when there are two different letters with the same probability
# using a bare list would result in incorrect calculations of probability
# they would be treated as non unique instances
# in turn allowing for it to filter out needed objects
# this boils down to a set of unique hash tables and summing up their values

class hashabledict(dict):
    def __hash__(self):
        return hash(tuple(sorted(self.items())))
value_mapping = {
    "c": 0.02,
    "a": 0.09,
    "t": 0.06,
    "p": 0.02,
    "e": 0.12
}

def get_probability(*args):
    # s has extra new line for code to fit
    s = set((hashabledict({letter: value_mapping[letter]}))
            for argument in args for letter in argument))
    return sum([sum(dictionary.values()) for dictionary in s])

print(get_probability("cat", "pet"))
# this sometimes yields 0.3100000000000005 and 0.3099999999999994
# which is essentially the same number
```

## vim regex

```
# this replaces all caps in proper latex
:%s/cap/\$\\cap\$/g
```

# Outline

1. Recap of probability
2. Simulation
3. Random Variables

## Independent vs. Disjoint Events

- Independent events **can** happen at the same time, but knowing that event “A” occurred **does not** change  $P(B)$  and vice versa
- Disjoint events cannot happen at the same time.
  - Knowing that event “A” occurred changed  $P(B) = 0$  and vice versa
- If A and B are independent,  $P(A \cap B) = P(A) P(B)$
- If A and B are disjoint,  $P(A \cap B) = 0$

### Example One

- Draw a tile from a bag of 100 scrabble tiles
- Event C = “the tile is a C”
- Event A = “the tile is an A”

$$P(C) = .02$$

$$P(A) = .09$$

Events “C” and “A” are disjoint

Events “C” and “A” are not independent

### Example Two

Draw one tile and set it outside

Event C = “first tile is a C”

Event A = “second tile is a A”

Event C and A are not disjoint

Events “C” and “A” are not independent

### Sampling without replacement

### Example Three

Draw a tile, put it back in the bag and then draw another tile

Event C = “first tile is a C” Event A = “second tile is an A”

Event C and A are not disjoint Event C and A are independent

### Sampling with replacement

# Simulation

Trying to imitate in the real world where the outcome is uncertain but is random

- Specify our model for an uncertain situation/random event
- “Randomly” generate an outcome for the model
- Repeat step two many, many times

## Why simulate?

- Once we set up the model, the math maybe too difficult
- Situation may be unique, or we only have ability to observe it once, due to physical/financial limitations
- For fun and/or profit

Report assumptions of the model!

# Random Variables (RVs)

Random variable is a variable whose numerical values describe outcomes of a random event

Typically we map outcomes in our sample space denoted as “S” to numerical values of the random variable.

Discrete Random Variable : probability mass function (PMF) places positive probability at specific numbers on the number line

- Only specific numbers
- Example: all outcomes are real, positive numbers

Continuous Random Variable : probability density function (PDF)

- Places positive probability along a possibly infinite interval of the number line.

## Writing the PMF of a Discrete Random Variable

Each unique key value  $X=x$  is mapped to an non unique value  $P(X=x)$

```
example_hash_map = {  
    key: value  
}
```

A hash table is another way to represent data mapping.

- value represents a random variable
- key represents a “realization” of value

### Example One

We can find  $P(Y=0)$

Once we have observed the random event either  $y = 0$  or  $y \neq 0$

Let  $X$  = the point value of the chosen tile

```
map = {  
    0: 0.02,  
    1: 0.68,  
    2: 0.07,  
    3: 0.08,  
    4: 0.10,  
    5: 0.01,  
    8: 0.02,  
    10: 0.02  
}
```

Sum of values in map == 0

## Example Two

Use PMF & probability rules to find:

- $P(X \leq 3)$ 
  - $P(X = 0, 1, 2 \text{ or } 3)$
  - $P(X = 0) + P(X = 1) + P(X = 2) + P(X = 3)$
  - $= 0.85$
- $P(X > 1)$ 
  - $P(X = 2, 3, 4, 5, 8, \text{ or } 10)$
  - $1 - P(X \leq 1) = 1 - (X = 0 \text{ or } 1)$
  - $1 - [P(X = 0) + P(X = 1)] = 1 - [0.02 + 0.68] = 1 - .7 = 0.3$
- $P(X > 5)$ 
  - $P(X = \{0..5\})$
  - $0.04$
- $P(3 < X \leq 5)$ 
  - $0.11$
  - $P(X = 4, \text{ or } 5)$

## Expected Value (Mean) of a Random Variable

- Called expectation, mean, all the same thing
- On average, what value do we expect the random variable to be

Recall idea of “weighted average”

### Mean of a Probability Distribution

$\underline{\mu}$

Denotes the average of all events, which in turn gives us an expected value for a given function.

### Summation notation

$$\mu_x = \sum x \cdot p(x)$$

The mean equals the sum of all the values of  $x$  times their probabilities.

Figure 1: discrete random variable formula

Expected value is a linear operator (can take in sum and give back a result in the form of a sum of the applied operators)

### For random variables X and Y, and constant C

- $E[X+Y] = E[X] + E[Y]$
- $E[cX] = cE[X]$
- ^ where “c” is a constant applied

This implies, for X, Y and arbitrary constants a,b  $E[aX + bY] = aE[X] + bE[Y]$

Consequences:  $a = 1$  ,  $b = -1$

$$E[X - Y] = E[X] - E[Y]$$

$$\mu_{x-y} = \mu_x - \mu_y$$

# Day 3

## Outline

1. Expected value of the random variable
2. Variance and standard deviation of random variable
3. [If time allows]

### Expected values (mean)

Please refer to day\_two.pdf

### Law of Large Numbers

Suppose we have “N” independent and identically distributed (IID) realization of “X”.

That is, we observe our random event “N” times independently and record the value of “X”.

Then, as “N” increases, the sample mean of the “N” independent observations converges to  $\mu_x$

We can get arbitrarily close to  $\mu_x$  by simply observing values of “X” enough times.

## Variance of a Random Variable

Average squared deviance from mean (distance away from the middle)

# Variance Formula:

$$\sigma_x^2 = \sum [x^2 * P(x)] - \mu_x^2$$

Figure 1: variance formula

- Variance is non-negative
- Variance is not a linear operator

In general,  $\text{Var}(X+Y) \neq \text{Var}(X) + \text{Var}(Y)$

However, if X and Y are independent

$$\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y)$$

$$\text{Var}(cX) \neq c\text{Var}(X)$$

However!  $\rightarrow \text{Var}(cX) = C^2 \text{Var}(X)$

When X and Y are independent,

$$\text{Var}(aX+bY) = a^2\sigma_x^2 + b^2\sigma_y^2$$

## Standard Deviation of Random Variable

$$\sigma_x = \sqrt{\sigma_x}$$

Standard deviation is not linear

$$\sigma_{x+y} = \sqrt{\sigma_x + \sigma_y}$$

If X and Y are independent

$$\sigma_{cx} = |C|\sigma_x$$

## Adding a constant

Consider  $W = X + c$  (where  $c$  is an arbitrary constant)

$$\Sigma[W] = \Sigma[X+c] = \Sigma[X] + \Sigma[c]$$

$$\Sigma(W) = \Sigma(X) + c$$

$$\text{Var}(W) = \text{Var}(X+c)$$

$$= \text{Var}(X) + \text{Var}(c)$$

$$\text{Var}(c) = 0$$

$$\text{Var}(W) = \text{Var}(x)$$

$$\text{SD}(W) = \text{SD}(X)$$

## Example One

- Toss two fair coins.
- Let  $X$  be the number of heads observed
- Find the PMF, expected value, variance and standard deviation of  $X$ .

Each win is independent

$$P(\text{Heads}) = 1/2$$

Independence:  $P(A \cap B) = P(A) * P(B)$  0 heads: TT  $\Rightarrow P(\text{TT}) = P(T_1) * P(T_2) = 1/2 * 1/2 = 1/4$   
1 heads: HT TH 2 heads: HH

## Easy Way

1. Find the PMF and write as a table
2. Expand our table by adding columns
3. Add down each column

```
# key is X=x
# value is P(X=x)
# --> points to xP(X=x)
# ----> points to variance
map = {
    0: 0.25 --> 0 ----> 0.25
    1: 0.50 --> 0.5 ----> 0
    2: 0.25 --> 0.5 ----> 0.25
}
```

summation of  $P(X=x) = 1$

summation of  $xP(X=x)$   $\mu_x = 1$

summation of variance  $\sigma^2_x = 0.5$

summation of standard deviation of  $X \sim 0.7$

## Example Two

You enter a lottery in which there is a 1 in 1000 chance of winning. If you win, you get \$500 and if you don't you get nothing. Let  $Y$  be the amount of money you win.

Find the PMF, expected value, variance and standard deviation

```

map = {
    0: 0.999 -----> 0 ----> 0
    500: 0.001 ---> 0.5 --> 250 ---> 15.811
}
expected value: 0 and 500

```

## Example Two (With a twist)

You enter a lottery in which there is a 1 in 1000 chance of winning. If you win, you get \$500 and if you don't you get nothing Let Y be the amount of money you win.

Let V = amount of money you have after the lottery

Find the PMF, expected value, variance and standard deviation

$$\Sigma[V] = \Sigma[Y-1] = \Sigma[Y] - 1 = 0.5 - 1 = -0.5 \text{ Var}(V) = \text{Var}(Y-1) = \text{Var}(Y) = 249.75 \text{ SD}(V) = \text{SD}(Y) = 15.8$$

## Relationship Between Probability and Statistics

Let our random event be:

Pick one person at random and record some characteristics of the individual

The individual we record is the case or unit

The characteristics we record are called variables

The set of all cases of interest: population

# Day 4

## Outline

1. Statistical Terminology
2. Sampling Distributions

## Statistical Terminology

### Tidy Data

Each column represents a variable

Header row will contain the name of the variable

Each row represents a case

Each value goes in its own cell.

**Good form:** left most column contains label variable whose values are unique IDs for the cases

One row could represent:

- a patient
- a particular test for that patient
- all patients seen by a doctor

Merging datasets: you need to pair like data

### Data Dictionary

For each variable:

- name of the variable
- type of the variable
- units of measurement
- description

### Type of Variable

Numerical (Quantitative): int, float, double

Categorical (Qualitative): string, classes, char, software-specific variable type

Typically, we do not select only one case from the population. We instead select a subset of the population: sample. A sample will always exist in the real world.

## Statistical Terminology (Continued)

Variables vary between cases.

Statistics vary between samples

Parameters vary between populations.

## Frequentist Statistics

Parameters are constants, but we don't know their value.

Statistics are random variables that describe "randomly select a sample of some fixed size, record values of a variable for each case in the sample, and summarize the value".

### In this class

Numerical variables: we use  $\mu$  to represent population mean and  $\bar{X}$  to represent sample mean

Categorical variables: we use "p" to represent population proportion of outcome in a particular category.

We use  $\hat{p}$  to represent sample proportion of outcomes in a particular category.

## Example

A clinical trial compares two bladder cancer drugs:

- Drug A (Company's "new" drug)
- Drug B (Current best drug)

They recruit 200 subjects with bladder cancer and assign 100 to take Drug A and 100 to take Drug B

## Questions

- What is the case
- We can consider this study to have 2 "hypothetical" populations. What are they?
- What are the two samples from those hypothetical populations? (subset of a larger group/population)
- Name an outcome the drug company might be interested in. Is that outcome a numerical or categorical variable?
- What statistic might we use to summarize that outcome in a sample
- What is the corresponding parameter in the hypothetical population.

## Answers

- A case is one patient with bladder cancer
- Everyone on Drug A (all bladder cancer patients, if they took Drug A) and everyone on Drug B
- 100 people who took Drug A and 100 people who took Drug B
- How much more effective is Drug A compared to Drug B. This would yield a numerical value. (Reduction in tumor size, cancer remission/not in remission)
- Sample mean ( $\bar{X}$ ) tumor reduction. Sample proportion/sample percent of patients who are in remission.
- Population mean tumor reduction and population proportion in remission

## Sampling Distribution

These are things that do not have real world equivalences.

The probability distribution of a statistic is its sampling distribution

Distribution of a statistic over all possible samples of a given size from the sample population. **Must** specify size of sample.

To find a sampling distribution:

1. Simulation: approximate the sampling distribution by simulating samples.
2. Asymptotic behavior: as the number of samples  $\rightarrow \infty$ , what does the distribution look like?

## Properties of Sampling Distributions

Let  $X$  be the statistic we use to estimate a parameter  $\theta$  for a population.  $X$  is an unbiased estimator of  $\theta$  if  $\mu_x = \theta$ . Otherwise  $X$  is biased and the amount of **bias** is  $\mu_x - \theta$ .

The variability of  $X$  describes the amount by which individual realizations of  $X$  are “spread” about  $\mu_x$ .

We can summarize variability by variance, standard deviation, standard error, margin of error

# Day 5

## Outline

1. Sampling Distributions
2. Binomial Setting and Sampling Distribution

## Sampling Distributions

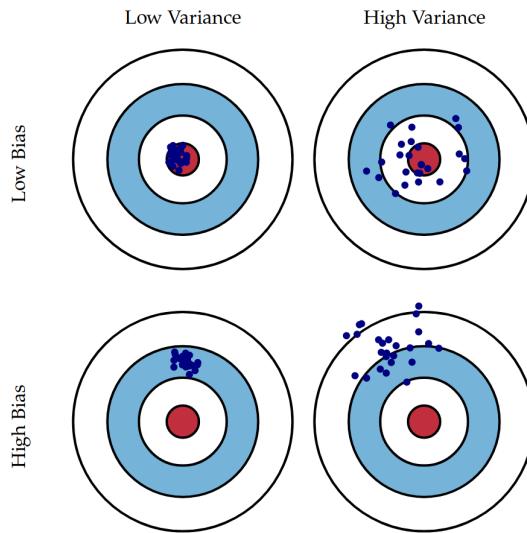


Fig. 1 Graphical illustration of bias and variance.

Figure 1: Illustration of bias and variance

Generally in science we have low bias and high variability.

## Joke

### A physicist, a biologist and a statistician go hunting:

They are hiding together in the bushes and they see a deer 70ft ahead of them. The physicist makes some calculations, aims and fires at the deer. His shot ends up 5ft to the left of the deer. The biologist analyzes the deer's movement, aims and fires. His shot ends up 5ft to the right of the deer. The statistician drops his rifle and happily shouts, "WE GOT IT!!"

In MATH-338, we assume our sample is generated using random sampling methods (simple random sampling)

- All samples of size  $N$  are equally likely

If we do not use good sampling methods:

- Probability distribution of sample changes → introduces bias

Sampling distribution depends on statistic & sample size

- For very large populations ( $\sim 20x$  sample size)
- Sampling distribution does NOT depend on population size

Variability of sampling size  $\downarrow$  as the sample size  $\uparrow$ .

---

Bias of sampling distribution << Bias introduced by bad sampling/study design

Variability of sampling distribution << Variability due to bad sampling/study design

## **Binomial (Probability) Distribution**

Describe the number of “success” in N trials in the binomial setting

### **Four Conditions**

Binary outcomes:

- All outcomes are classified either success or failure

Independent outcomes: (hand waved by good study design)

- The previous outcome does not influence the next outcome (flipping a coin, gender of a baby).

Number of outcomes = N

- Fixed sample size/number of trials
- Known in advance before any outcomes observed

Success is equally likely for each case/on each trial

- P = Probability of success = population probability of success
- the pass/fail rate of a class is 90/10, everyone is equally likely to fit these odds

### **Situations**

- N term is violated : World Series games. A minimum four games is played but there is no fixed amount of games played
- I term is violated : teams who play away games vs home games

## Binomial Random Variable

Let  $X = \text{count}(\text{number})$  of success in a set of  $N$  outcomes obtained in the binomial setting

$X$  has a PMF defined by:

$$P(X = x) = \binom{n}{x} P^x (1 - P)^{n-x}$$

- $n(x) = \frac{n!}{x!(n-x)!}$ 
  - Number of ways to get  $x$  success and  $n-x$  failures out of  $N$  trials
- probability of getting exactly  $x$  success
- Probability of getting  $n-x$  failures

Shorthand to:  $X \sim B(n, p)$

If you didn't understand them, an extreme simplification would be to say that you are repeating an activity with a chance of success  $p$ . Each repetition has the same chance of happening. This chance cannot be affected by the results of the other repetitions. You do this  $n$  times.  $X$  would represent the number of successes you got after doing  $n$  repetitions.

For example, if you toss a fair coin 10 times, the number of heads you will get is:

$$X \sim B(10, 0.5)$$

because you toss it 10 times, and each toss has a  $50\% = 0.5$  chance of being a head (because it is a fair coin).

Figure 2: Explanation

## Example One

Toss a fair coin 8 times and let  $X$  = number of heads

Is  $X$  a binomial random variable?

- B: ✓ success = heads
- I: ✓
- N: ✓  $n=8$
- S: ✓  $p=0.5$

$$X \sim B(8, 0.5)$$

## Mean and Variance of a Binomial Random Variable

Consider the Bernoulli random variable:

```
X = {  
    1: if outcome is success  
    0: if outcome is failure  
}
```

If p = probability of success, then:

$$\mu_x = 1 * P + 0(1 - P) = P$$

Binomial random variable is sum of N independent Bernoulli random variables

So if mean of binomial random variable =  $P + P + P \dots + P = nP$  (n number of times)

Variance of Bernoulli random variable =

$$(1 - P)^2 P + (0 - P)^2 (1 - P) = P(1 - P)$$

When X = 1 and X = 0 respectively ↑

$$\Sigma(X - \mu)^2 P(X = x) (1 - \mu)^2 P(X = 1)$$

Variance of binomial random variable =

$$P(1 - P) + P(1 - P) + \dots + P(1 - P) = nP(1 - P) \text{ (n number of times)}$$

Standard deviation if binomial random variable =  $\sqrt{nP(1 - P)}$

## **Example Two (Question)**

Sample of 2000 men get Gemfibrazil

Sample of 2000 men get some other drug (placebo)

It was assumed that 4% of men of the placebo group age get heart attacks (without drug intervention)

Looking at just placebo group:

- Define success, failure,  $N$ ,  $P$  in this binomial setting
- Find mean, variance, and standard deviation of number of heart attacks the placebo group would experience.

## **Example Two (Answers)**

**Formulas used from section: Mean and Variance of a Binomial Random Variable**

**1**

- Success is someone getting a heart attack
- Failure is someone not getting a heart attack
- 2000 is  $N$
- 0.04 is  $P$

**2**

- Mean: 80
- Variance: 76.8
- Standard deviation: 8.76356092

## Distribution of Sample Proportion

$$\hat{P} = \frac{X}{n}$$

We have no idea how to estimate the number of successes in a very large population

Proportions are restricted to  $[0, 1]$

Sample proportion and population proportion are on the same scale

$$E[\hat{P}] = E\left[\frac{X}{n*X}\right] = \frac{X}{n} * E[X]$$

If  $X \sim B(n, P)$  then  $E[X] = \mu_x = nP$

$$E[\hat{P}] = \frac{X}{n}(n - P) = P$$

$\hat{P}$  is an unbiased estimator of  $P$

$$\text{Variance}(\hat{P}) = V\left(\frac{1}{n} * X\right) = \left(\frac{1}{n}\right)^2 V(x)$$

If  $X \sim B(n, P)$  then  $V(x) = nP(1 - P)$

$$V(\hat{P}) = \left(\frac{1}{n}\right)^2 (nP(1 - P)) = \frac{P(1-P)}{n}$$

$$SD(\hat{P}) = \sqrt{\frac{P(1-P)}{n}}$$

## Probability Problems involving p hat

$\hat{P}$  does NOT have a binomial distribution

However we can convert  $X = n * \hat{P}$  and  $X$  has a binomial distribution

# Day 6

## Outline

1. Types of Studies
2. Design Experiments
3. Why studies go wrong

## Types of Studies

### Observational

We simply observe things and do not manipulate them



Figure 1: observing

### Experimental

Manipulate one or more explanatory variables and record response variables

Try to prove cause and effect

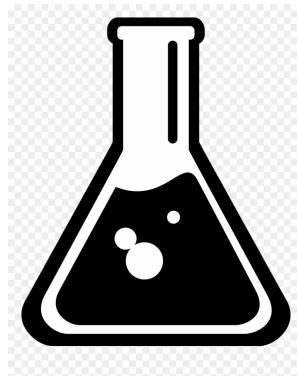


Figure 2: experimenting

## Design of Experiments: Terminology

Manipulated explanatory variables: **experimental variables, factors**

- Treat as a categorical variables
- Values are called levels of the factor

A set of conditions caused by combining levels of different factors: treatment

Recorded response variables: outcomes

### Example One

Experiment to compare two weight-loss drugs

Two separate factors

- Drug (A & B)
- Diet (Normal & Special)

Full factorial experiment: 4 treatments

- Drug A & normal diet
- Drug B & normal diet
- Drug A & special diet
- Drug B & special diet

### Example Two

Visitors to a website.

Two separate factors

- Placement of an ad (top/bottom)
- Background color (blue/red)

Full factorial experiment: 4 treatments

- Top & Blue
- Bottom & Blue
- Top & Red
- Bottom & Red

## Interacting Variables

Factors can be interacting variables effect of factor one on response changes depending on value on factor two.

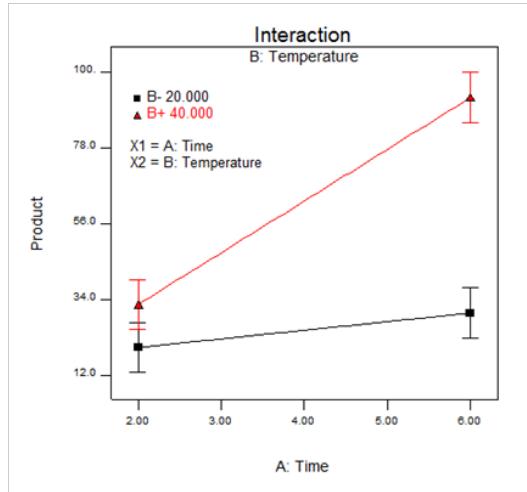


Figure 3: Interaction effect

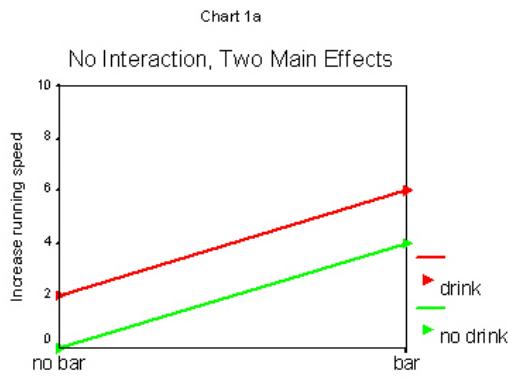


Figure 4: No interaction effect

## **Confounding Variable**

Two variables (factors or not manipulated explanatory variables) are confounding variables if their effects on response cannot be disentangled/distinguished.

Often but not always, confounding variables are related to each other.

Lurking variables are potential confounding variables that we ignore during study design.

**Formal definition:** In statistics, a confounder is a variable that influences both the dependent variable and independent variable, causing a spurious association. Confounding is a causal concept, and as such, cannot be described in terms of correlations or associations.

## **Examples**

- Age

## **Three Principles of Experimental Design**

### **Control**

Subjects on each treatment should be as “similar” as possible

“controlling” for effects of other variables than our experimental variable

### **Randomization**

Treatments should be randomly assigned to subjects

### **Replication/Repetition**

Other people can repeat your experiment on similar subjects and get similar results

We have enough subjects to “eliminate” variability issues

## Types of Experimental Designs

### Completely Random Design

Subjects assigned a treatment entirely at random

### Block Design

Non randomly divide our subjects into groups (“blocks”) based on potential confounding variables, then assign treatments within each block.

## Block Design (Example Diagram)

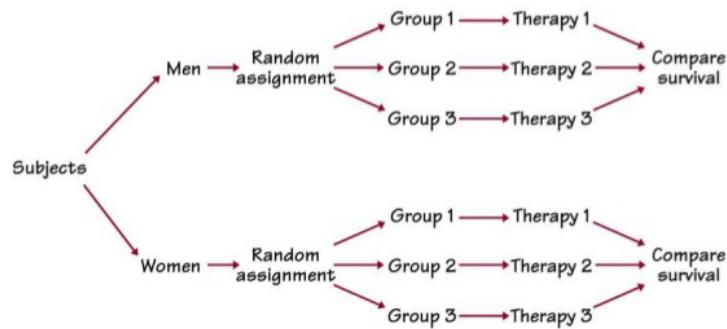


Figure 5: Block Design

### Matched Pairs Design (Paired Design)

Special case of block design with blocks size of two (only looking at one treatment with two levels)

## Matched Pair Design (example diagram - paired subjects)

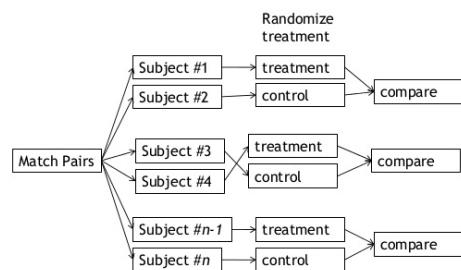


Figure 6: Matched Pair Design

## Repeated measures design

More than two levels

Idea: get you & someone as similar to you as possible.

Randomly assign you to one treatment and assign your “pair” to other treatment

Often, we have same subjects undergo all treatments or record response at multiple times.

These are matched pairs/repeated measures designs in which order of treatments is manipulated/randomized.

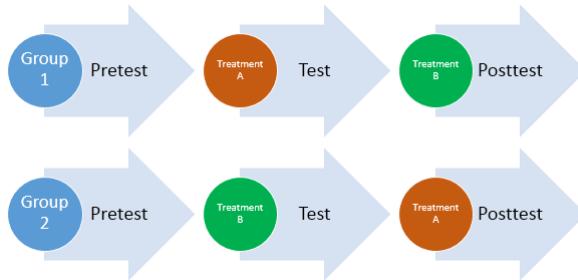


Figure 7: Repeated Measure Designs

One of the levels of treatment is control level

Group whose treatment entirely control levels = control group

In this class: one control group  $\geq 1$  "treatment group"

## Why Studies Go Wrong

1. You accidentally introduce a confounding variable
  - “Placebo effect”: Otherwise ineffective treatment “works” because people think it will
  - Effects due to people involved in experiment knowing who is in each group
  - Blinding/masking: not letting experimenters or subject know which group anyone is in
  - Double blind: neither subject nor experimenter know
2. Equipment failure/mistake in recording data
3. Hawthorne Effect
  - If people know they’re in the study they change their behavior
4. Subjects are not representative of the target population
  - Using rats for experiments where rats did not respond the way they needed to
5. Treatments are not representative of real world conditions

# Day 7

## Outline

1. Two-way tables and diagnostic testing
2. Conditional probability
3. Tree Diagrams
4. Bayes' Rule
5. Solving conditional probability problems

## Two-Way Table

Gender compared to handedness

		Handed	
		Left	Right
Female	7	46	53
	5	63	68
	12	109	121

Figure 1: Table Example

## Example

Helsinki Heart Study

2035 men in control group had 84 heart attacks 2046 men in special drug name group had 54 heart attacks

Referring to the table above, these are the correct mappings:

- Male: placebo
- Female: special drug
- Left: Heart attack
- Right: No heart attack

## Diagnostic Testing

Formal definition: an examination to identify an individual's specific areas of weakness and strength in order determine a condition, disease or illness.

		Positive test $T^+$	Negative test $T^-$	
Disease present $D^+$	True Positive (TP)	False Negative (FN)	Sensitivity (Sn)	
	False Positive (FP)	True Negative (TN)	Specificity (Sp)	
		Positive Predictive Value (PPV)	Negative Predictive Value (NPV)	
		$P[D^+   T^+]$ $TP / (TP+FP)$	$P[D^-   T^-]$ $TN / (TN+FN)$	

Figure 2: Diagnostic Testing Table

Machine Learning Terminology: we evaluate on a “training set” in which number if actual positive and actual negative is known in advance.

We compute:

- Sensitivity: proportion of actual positive classified correctly  $\frac{TP}{TP+FN}$ .
- Specificity: proportion of actual negative classified correctly  $\frac{TN}{TN+FP}$

These are both properties of our test/algorithim.

- Positive Predictive Value(PPV, precision): proportion of positive tests that were actually positive  $\frac{TP}{TP+FP}$
- Negative Predictive Value(NPV): proportion of negative tests that are actually negative  $\frac{TN}{TN+FN}$

Also depend on prevalence (base rate)  $\frac{\text{Actual positive}}{\text{Actual positive} + \text{Actual negative}}$

## Example

- 300 units
- 83% prevalence
- TP = 200
- FP = 10
- FN = 50
- TN = 40

Compute:

- Sensitivity:  $\frac{200}{200+50} = 80\%$
- Specificity:  $\frac{40}{40+10} = 80\%$
- PPV =  $\frac{200}{200+10} = 95.20\%$
- NPV =  $\frac{40}{40+50} = 44.4\%$

### In Class Example

- 300 units
- 3% prevalence
- TP = 8
- FP = 58
- FN = 2
- TN = 232

### Answers

- Sens:  $\frac{8}{10} = 80\%$
- Spec:  $\frac{232}{232+58} = 80\%$
- PPV:  $\frac{8}{8+58} = 12.1\%$
- NPV:  $\frac{232}{232+2} = 99.2\%$

## Conditional Probability

The conditional probability of event “B” given event “A”, denote denoted  $P(B|A)$ , is the probability of event “B”, looking only at outcomes in A.

$$P(B|A) = \frac{\text{number of outcomes in } A \cap B}{\text{number of outcomes in } A} \text{ when all outcomes are equally likely}$$

$$\text{More generally: } P(B|A) = \frac{P(A \cap B)}{P(A)} P(A) > 0$$

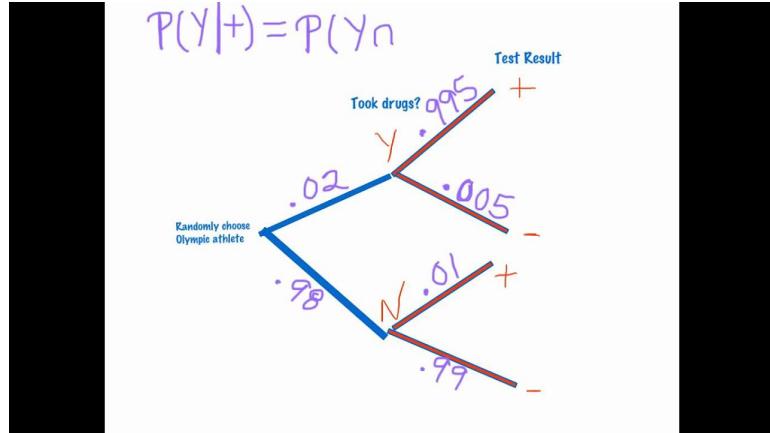


Figure 3: Conditional Probability Diagram

Independent events:  $P(A \cap B) = P(A) \times P(B)$

Conditional probability:  $P(A \cap B) = P(A) \times P(B|A)$

So: “A” and “B” are independent when  $P(B) = P(B|A)$  dependent when  $P(B) \neq P(B|A)$

### Example

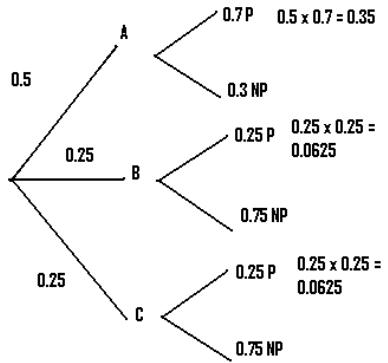
1. What is the probability that a randomly selected person in the control group had a heart attack?
2. What is the probability that a randomly selected heart attack victim was in the control group?

**Both of these are different questions**

$$1. P(\text{heart attack}|\text{control}) = \frac{84}{2035}$$

$$2. P(\text{control}|\text{heart attack}) = \frac{84}{140}$$

## Tree Diagram



- = branch

Each node represents an event.

Each branch represents probability of getting to next node, given that we got to previous node.

Ending node is the **terminal node**.

Splits in the branches must add up to one. Please refer to node “A” when it splits between “NP” and “P”.

## Notes on Probabilities

1. Probability of leaving a node is 1. The sum of probabilities on all branches exiting a node = 1.
2. Probability of getting to a terminal node is a product of probabilities along the branch path to it.
3. Probability of event “B” is sum of probabilities at all terminal nodes including “B”

# Day 8

## Outline

1. A History Lesson
2. Neyman-Pearson Hypothesis Testing

## History Lesson

### Major Players

- Karl Pearson
- Egon Pearson
- Jerzy Neyman
- Ronald Fisher

## TL;DR

This test will allow us to make preemptive decisions based on conditions presented before the study is conducted. These are the theoretical outcomes WITHOUT taking any sample data

## Neyman-Pearson Hypothesis Testing

### TL;DR version

1. Define a boundary used to inform a decision
2. Obtain data and see which side of the boundary it falls on
3. Make decision

### Example

We have a coin and it is weighted but we don't know if it's weighted to be 60% heads or 60% tails.

Define a parameter to describe the situation

Let  $P$  represent probability of getting heads ("population proportion of heads")

Define two competing "hypothesis" involving the parameter.

(heads)

- $H_0 : P = 0.6$  [null hypothesis: "nothing unexpected"]
- $H_1 : P = 0.4$  [alternative hypothesis: "something is happening, we should change our minds"]

Define a "critical region" based on our sample data

1. Define a test statistic  $T$  whose value can be computed from the sample data
2. Define the sampling distribution of  $T$  under  $H_0$  and  $H_1$
3. Based on the sampling distribution under  $H_0$ , define:
  - $\alpha = P(\text{we claim } H_1 \text{ is true} | H_0 \text{ is true})$  and find the region in the sampling distribution under  $H_0$  corresponding to that  $\alpha$  value.

4. If the observed value of  $T$  is in that region, conclude  $H_1$  is true. Otherwise, conclude  $H_0$  is true

Critical region: a range of values that corresponds to the rejection of the null hypothesis at some chosen probability level.

### Example

Our decision rule:

- If we get 4 or fewer heads in 10 flips: conclude  $H_1$  is true.
- If more than 4 heads in 10 flips: conclude  $H_0$  is true.

"Critical region": Let  $X = \text{number of heads in 10 flips}$

- $X \leq 4$

Recall:

Gender compared to handedness

		Handed	
		Left	Right
Female	7	46	53
	5	63	68
	12	109	121

Now apply this to Neyman-Pearson rules:

		Do not reject $H_0$	Reject $H_0$
$H_0$ is true	Correct Decision	Incorrect Decision: Type I error $\alpha$	
	Incorrect Decision: Type II error $\beta$	Correct Decision	

## Under N-P Rules

Type 1 Error is “worse” than Type 2 Error. However, if  $P(\text{Type 1 Error})$  is too low,  $P(\text{Type 2 Error})$  balloons.

$$\alpha = P(1) - P(\text{Concluded } H_1 \mid H_0 \text{ is true})$$

$$\beta = P(2) - P(\text{Concluded } H_0 \mid H_1 \text{ is true})$$

$$\text{Power of test} = 1 - \beta$$

$$\bullet = P(\text{concluded } H_1 \mid H_1 \text{ is true})$$

## Example [Continued from Above]

Let  $X = \text{number of heads in 10 flips}$

- Under  $H_0$ :  $X \sim B(10, 0.6)$
- Under  $H_1$ :  $X \sim B(10, 0.4)$

**For critical region  $X \leq 4$ :**

- $\alpha = P(X \leq 4 | p = 0.6) = 0.166$
- $\beta = P(X > 4 | p = 0.4) = 0.367$

$$\text{Power} = P(X \leq 4 | p = 0.4) = 0.633$$

Traditionally, set  $\alpha = 0.05$  or  $\alpha = 0.01$

- $\alpha$  refers to the probability of making a Type I Error.

**Find the critical region giving a Type 1 Error rate of at most  $\alpha$**

(Find  $x$  such that  $P(X \leq x | H_0 \text{ is true}) \leq \alpha$ )

$$P(x \leq 2 | H_0 \text{ is true}) = 0.0123$$

$$P(X \leq 3 | H_0 \text{ is true}) = 0.0548$$

Critical region corresponding to  $\alpha = 0.05$ :  $x \leq 2$

**What is  $\beta$  for this critical region?**

- $\beta = P(x > 2 | p = 0.4) = 0.833$

In most fields, we use power instead

$$\text{Power} = P(X \leq 2 | p = 0.4) = 0.167$$

## Rules of Thumb

1.  $\alpha < \beta$ . If  $\alpha \leq \beta$ , either decrease  $\alpha$  or switch  $H_0$  or  $H_1$
2. At your “given”  $\alpha$  value,  $\beta \leq 2$  or equivalently, power  $\geq 0.8$  (80% power). If power  $< 0.8$ , plan to collect more data!

Power must be at least 80 percent

## In Practice

1. The idea of “nothing weird happening” should give us the value of the parameter.
2. We define a clinically significant/practically significant difference in parameter values (“minimum effect size”)

## What we need at each step

1. To compute the critical region:
  - need  $\alpha$ ,  $H_0$  (value of P under  $H_0$ )
  - sampling distribution of test statistic under  $H_0$
2. To compute power:
  - need critical region,  $H_1$  (value of P under  $H_1$ )
  - sampling distribution of test statistic under  $H_1$

# **Day 9**

## **Outline**

1. Conditional probability example
2. Power analysis example

Please reference the attached sheets for full examples

## Conditional Probability Examples

### Example 1

In a lecture class of 150 students, 110 students are freshmen, 50 own a dog, and 25 are freshmen who own a dog. Suppose a student is selected at random.

### Tree Diagram Version

#### Root

- Freshman ( $\frac{110}{150}$ )
    - Own dog :  $\frac{25}{110}$  [Freshman AND own dog =  $(\frac{110}{150} \times \frac{25}{110} = \frac{1}{6})$ ]
    - No dog :  $\frac{85}{110}$  [Freshman AND no dog =  $(\frac{110}{150} \times \frac{85}{110} = \frac{17}{30})$ ]
  - Not Freshman ( $\frac{40}{150}$ )
    - Own dog :  $\frac{25}{40}$  [Not freshman AND own a dog =  $(\frac{40}{150} \times \frac{25}{40} = \frac{1}{6})$ ]
    - No dog :  $\frac{15}{40}$  [Not freshman AND not own a dog =  $(\frac{40}{150} \times \frac{15}{40} = \frac{1}{10})$ ]
- a. What is the probability of being a freshman, given that the student owns a dog?
- $P(\text{Freshman}|\text{Dog}) = \frac{P(\text{Freshman AND Dog})}{P(\text{Dog})} = \frac{\frac{25}{150}}{\frac{25}{150} + \frac{25}{150}} = \frac{25}{50} = \frac{1}{2}$
- b. What is the probability of owning a dog, given that the student is a freshman?
- $P(\text{Dog}|\text{Freshman}) = \frac{P(\text{Dog AND Freshman})}{P(\text{Freshman})} = \frac{\frac{25}{150}}{\frac{110}{150}} = \frac{25}{110} = \frac{5}{22}$
  - $P(\text{Freshman} \& \text{ Dog}) = P(\text{Freshman}) P(\text{Dog}|\text{Freshman})$
  - $P(\text{Freshman} \& \text{ Dog}) = P(\text{Freshman}) P(\text{Dog}) \leftarrow \text{Independence}$

### Table Diagram Version

	Freshman	Not Fresh.	Total
Dog	25	25	50
No Dog	85	15	100
Total	110	40	150

Figure 1: Freshman Table Example

## Power Analysis Examples

### Example 1

It is believed that about 10% of the population is left-handed. However, China has claimed that less than one percent of its students are left-handed. Suppose we are interested in evaluating whether there is something special about Chinese people, or whether the Chinese government is lying. Suppose further that we have devised a scientifically perfect test to measure a person's dominant hand. Would a random sample of 50 Chinese students be large enough to detect a population difference of 10% vs. 1%?

We want low  $\alpha$  and high power

- $H_0 : p = 0.1$  [Null]
- $H_1 : p = 0.01$  [Alternate]
- $N : 50$
- $\alpha : 0.05$ 
  - If  $\alpha$  is not given, please assume  $\alpha = 0.05$
- Define  $p$  = proportion of left handed students
- For midterm one, define  $X$  = number of (successes) left-handed students in our sample.
- Decision rule:
  - Critical region:  $X \leq x$
  - If  $X$  is in critical region, accept  $H_0$ , else accept  $H_1$ .
  - Only problem is we do not know what  $x$  is.
  - Defining our critical region to be  $X \leq 5$ 
    - \* Under the null hypothesis  $H_0$ ,  $X \sim B(50, 0.1)$ 
      - $P(X \leq 5|p = 0.1) = 0.616$
      - $P(\text{Type 1 Error}) = 0.616$
    - \* Under the alternative hypothesis  $H_1$ ,  $X \sim B(50, 0.01)$ 
      - $\beta = P(X > 5|p = 0.01) = 0$
      - Power =  $P(X \leq 5|p = 0.01) = 1$
  - Defining our critical region to be  $X \leq 1$ 
    - \* When  $p = 0.1$ 
      - 3.4% false positive
      - 96.6% true negative
      - $\alpha = 0.034$
    - \* When  $p = 0.01$ 
      - 91.1% true positive
      - 8.9% false negative
      - Power = 0.911
      - $\beta = 0.089$

## Example 2

Is this sample large enough to detect something → power rule!!!!!!

We want low  $\alpha$  and high power

- $H_0 : p = 0.26$  [Null]
- $H_1 : p = 0.52$  [Alternate]
- $N : 14$
- $\alpha : 0.05$ 
  - If  $\alpha$  is not given, please assume  $\alpha = 0.05$
- Define  $p = \%$  of patients progression free after 6 months

Using R:

- Critical region is  $X > 6$  or  $X \geq 6$
- `lower.tail = TRUE` includes  $\leq$
- `lower.tail = FALSE` includes  $>$
- When  $P = 0.26$ 
  - 4.7% false positive
  - 95.3% true negative
  - $\alpha = 0.047$
- When  $P = 0.52$ 
  - 66.2% true positive
  - 33.8% false negative
  - Power = 0.662
  - $\beta = 0.338$

# **Day 10**

## **Outline**

1. “Null Hypothesis Significance Testing”
2. When Null Hypothesis Significance Testing goes horribly wrong

# Null Hypothesis Significance Testing

## Recall

- identifying a parameter is not “too hard”
- identify its value under  $H_0$  is trivial
- However, identifying its value under  $H_a$  is difficult in practice
- Under N-P (Neyman-Pearson): define minimum effect size
- But often, we have no idea
- This is what we have been doing for the past 70 years and it does not require any subject knowledge. “It just works”. Will also allow us to get the P value.

**NHST:** just give the inequality in alternative hypothesis  $H_a$

Suppose  $H_0: \theta = \theta_0$

- $\theta \rightarrow$  arbitrary parameter
- $\theta_0 \rightarrow$  its value under  $H_0$

N-P:

- $H_1: \theta = \theta_1$
- $\theta_1 \rightarrow$  its value under  $H_1$

**NHST:** Choose from

- $H_a: \theta > \theta_0$ 
  - Theory says  $\theta$  should be bigger
  - One-tailed, one-sided hypothesis testing
    - \* One-tailed testing: The critical area of a distribution is either  $<$  or  $>$  a certain value but not both
- $H_a: \theta < \theta_0$ 
  - Theory says  $\theta$  should be smaller
  - One-tailed, one-sided hypothesis testing
- $H_a: \theta \neq \theta_0$ 
  - No idea what to expect or theory suggests arguments for both  $>$  AND  $<$
  - Two-tailed, two-sided hypothesis testing
    - \* Two-tailed the sample is greater than or less than a certain range of values:

**NOTE:** method of collecting data tells us what  $\theta$  is (what  $\theta_0$  is) and may suggest  $H_a$

When in doubt: use the  $H_a$  version with  $\neq$

## Next Step : Distribution

Define a test statistic whose value will be computed from sample data

**N-P:** Find its distribution under both  $H_0$  &  $H_1$

**NHST:** Find its distribution under  $H_0$  but we don't know its distribution under  $H_a$

## Next Step : Critical Region

Define a critical region of the test statistic such that if the observed value is in critical region, accept  $H_1$

**NHST:** Define a critical region such that if in critical region, reject  $H_0$ .

If not in critical region, fail to reject  $H_0$

## Example (Theory) : Jury

Start off assuming innocence ( $H_0$ ) [Null Hypothesis]

- Prosecution presents evidence (test statistic observed value)
- Jury decides if it enough evidence
  - Enough evidence (in critical region) → reject the assumption of innocence and declare guilty (reject  $H_0$  and accept  $H_a$ )
  - Not enough evidence (not in critical region) → fail to reject presumptions of innocence. He might still be guilty but the evidence is not damning enough to convince us otherwise. We fail to reject  $H_0$  or the Null Hypothesis

In NHST, define significance level (not  $\alpha$  but works like  $\alpha$ ). Here, the significance level is the probability of rejecting the null hypothesis which is generally the same value of  $\alpha$

This can go horribly wrong because power is not taken into account also, there is not a big enough sample size to correctly draw a conclusion.

## P-Value

A measure of the “strength” of the evidence against  $H_0$ . This is related to power?

### ALWAYS COMPUTED AFTER OBSERVATION

Official definition: probability of obtaining our observed value of the test statistic, or a value as or more favorable to  $H_a$ , if  $H_0$  is true.

- $P(X \geq x_{\text{observed}} \mid H_0 \text{ is true})$  when  $H_a: \theta > \theta_0$
- $P(X \leq x_{\text{observed}} \mid H_a: \theta < \theta_0)$

*Things go weird for two-tailed tests*

**Usually:**  $P(X \text{ is equally or less likely than } x_{\text{observed}} \mid H_0 \text{ is true})$  but sometimes we get one-tailed p-values

“How likely is it that I got this lucky or luckier?”

When P-Value  $\leq$  significance level

1.  $H_0$  is true and I got really lucky ← I will make a **Type I Error**
  - $H_0$  may in fact be false but you have circumstantial evidence to promote the notion that  $H_0$  is true
2.  $H_0$  is not true and  $H_a$ 
  - This is the ideal situation as we do not make any false assumptions about  $H_0$

Either way, I reject  $H_0$  and conclude  $H_a$  is true

When P-Value  $>$  significance level

1.  $H_0$  is true
2.  $H_0$  is not true, but we don't have “unlikely enough” evidence
  - In this case, we acquit an guilty man. Even though we damn well know he did it but the prosecution did not provide damning evidence to conclude that he is guilty.

Either way, we fail to reject  $H_0$  (make no conclusion so default to assumption  $H_0$  is true)

### Example (Book Exercise 8.20 [Application])

Study of children, program intended to increase consumption of whole grains. At end of program, sample of 86 children got a snack.

- 48 children chose whole grain
- 38 chose regular

Suppose that before program, children were equally likely to pick either snack. Do we have enough evidence to claim the program works as intended?

#### Step 1 (Identify Parameter of Interest)

Use it to write  $H_0$  and  $H_a$ .

- $p$  = Proportion of all children who choose whole grain (generalized results)
- $H_0 : p = 0.5$
- $H_a : p > 0.5$

#### Step 2 (Identify Test Statistic and its sampling distribution under $H_0$ )

Let  $X$  = number of success (number of children in sample choosing whole grain)

$$X \sim B(n = 86, p = 0.5)$$

#### Step 3 (Observe data and calculate value of test statistic)

$$X_{\text{observed}} = 48$$

#### Step 4 (Calculate EITHER the critical region or the P-Value)

P-Value is way easier to compute when you have software

```
binom.test(x = 48, n = 86, p = 0.5, alternative = "g")
```

From software: p-value = 0.166

#### Step 5 (Determine whether or not to reject $H_0$ )

5% is our cut-off. If the value is LESS than 5% then we **reject the Null Hypothesis**.

Since  $0.166 > 0.05$ , our results are likely enough under  $H_0$  therefore, we fail to reject  $H_0$

#### Step 6 (Write what “reject $H_0$ ” or “fail to reject $H_0$ ” means in context)

We do not have “statistically significant” evidence to claim that the program is working. It is reasonable to continue with the assumption that children are still equally likely to pick a healthy snack. **We failed to reject the notion that they will be more likely to pick a healthy snack.**

## When Null Hypothesis Significance Testing goes horribly wrong

1. Very small samples
2. Very large samples
  - Neyman-Pearson:  $p = 0.5$  vs  $p = 0.50001$
  - NHST:  $p = 0.5$  vs  $p > 0.5$
3. Significance level is not arbiter of importance (2 and 3 are practically the same)
4. Lots of tests
5. P-hacking

# Day 11

## Outline

1. Fisher's Significance Tests
2. Goodness of fit test

## Tl;DR

This model is concerned about the model used rather than actually trying to prove anything. If the initial hypothesis is rejected then we look into why it failed, rather than stopping at that conclusion.

## Midterm Exam 1

### Lecture

- ~ 60%
- 4 to 5 multi-part problems

Allowed: one-sided formula sheet (can be typed or printed)

### Lab

- ~ 40%
- 3 problems, 2 to 3 part problems

Allowed: textbook, notes, software help, anything on Titanium

# Fisher's Significance Testing

In Fisher's view, there is only one hypothesis. We see how well sample data "fit" that hypothesis.

In the strictest sense, the hypothesis includes all assumptions about the probability model used to obtain the sampling distribution of the test statistic.

Assumption are of two kinds:

1. Assumptions about parameters
2. Assumptions about data generation/collection

In practice, we refer to the hypothesis as the **null hypothesis** ( $H_0$ ).

Using the Null Hypothesis Significance Testing we write  $H_a$ : not  $H_0$

Where we see this:

- $\chi^2$  test (Chi-Squared)
  - ANOVA
- 

In Fisher's approach, we first specify our model

- Then: Specify sampling distribution of test statistic
- Then: Collect data and compute value of test statistic
- Then: Get P-Value

Recall: P-Value is probability of obtaining our data, or a result with a test statistic signalling equal or greater "distance" from  $H_0$ , if  $H_0$  is true.

Pure Fisher Philosophy: Stop here. P-Value represents "how well" data fit hypothesis.

- Very high P-Value: data fit suspiciously well
- Very low P-Value: data does not fit well at all

In practice: Fisher commands a personal significance level.

- Significance = "Signifying something"
- 

P-Value  $\leq$  significance level: our results are a meaningful difference from the model. We should investigate!

- Reject  $H_0$

P-Value  $>$  significance level: our results are consistent with the model. We did not prove it correct but the model is a reasonable approximation of reality.

- Fail to reject  $H_0$

In practice: we define one main assumption about the parameters to be the  $H_0$  that can get rejected.

# Goodness of Fit Testing

Most of the “classic” goodness of fit tests involve genetics.

## Example (Theory) : Mendel’s Pea Plants

Dihybrid cross for seed shape & seed color Mendel’s Laws: Should see a 9:3:3:1 ratio

Hypothesis:  $\frac{9}{16}$  round/yellow,  $\frac{3}{16}$  round/green,  $\frac{3}{16}$  wrinkled/yellow,  $\frac{1}{16}$  wrinkled/green

In practice:

$$H_0: P_{RY} = \frac{9}{16}, P_{RG} = \frac{3}{16}, P_{WY} = \frac{3}{16}, P_{WG} = \frac{1}{16}$$

---

We know the observed sample will probably not have those proportions.

We need a measure of “how far off” our sample is from what we expect. [ $\chi^2$  test statistic]

We define (Pearson) residuals for the different categories:

$$\text{Residual} = \frac{O-E}{\sqrt{E}}$$

- O : # of observed in sample
- E : # of expected in sample

$$\chi^2 = \sum \text{residual}^2 = \sum \frac{O-E}{\sqrt{E}}$$

Where  $\Sigma$  is all categories

---

Mendel observed:

- 315 RY
  - 108 RG
  - 101 WY
  - 32 WG
- 

Total: 556 seeds

---

What do we expect?

- $\frac{9}{16}(556) = 312.75$  RY
- $\frac{3}{16}(556) = 104.25$  RG
- $\frac{3}{16}(556) = 104.25$  WY
- $\frac{1}{16}(556) = 34.75$  WG

Pearson Residuals:

- RY :  $\frac{315-312.75}{\sqrt{312.75}} = 0.127$
- RG :  $\frac{108-104.25}{\sqrt{104.25}} = 0.367$
- WY :  $\frac{101-104.25}{\sqrt{104.25}} = -0.318$
- WG :  $\frac{32-34.75}{\sqrt{34.75}} = -0.467$

## Goodness of Fit Testing (Continued)

Contribution of a category  $\chi^2$  = square of its Pearson residual

In our example:

$$\chi^2 = (0.127)^2 + (0.367)^2 + (-0.318)^2 + (-0.467)^2 = 0.47$$

Our sample data is 0.47 “off” from what we expected.

$\chi$  is unit-less.

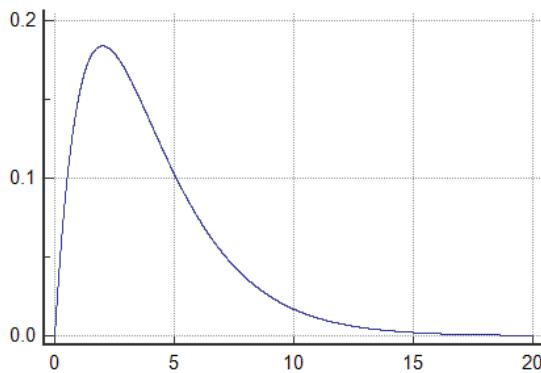
To compute the P-Value, we need a sampling distribution of  $\chi^2$

$$\text{P-Value} = P(\chi^2 \geq 0.47 \mid H_0 \text{ is true})$$

---

Approximate the sampling distribution 1 of 2 ways:

1. Under  $H_0$ ,  $\chi^2$  has approximately a  $\chi^2$  distribution with (# of categories - 1) degrees of freedom



- Strictly non-negative
- “Skewed right”

Software gives us approximate-value  $P(\chi^2 \geq 0.47) = 0.9254$

If P-Value is “really small”: reject  $H_0$  means “our proportions are not all correct” - we should investigate to find out which ones & why.

Mendel’s data was probably full crap, not on him but the guy collecting the peas.

2. Simulate very many samples of sizes  $n$ , under assumption of  $H_0$  is true, and compute  $\chi^2$  for each simulated sample

When we expected  $\geq 5$  in each category in our sample, both approaches give similar results.

When in any category we expect  $< 5$  counts, we use #2 above.

# Day 12

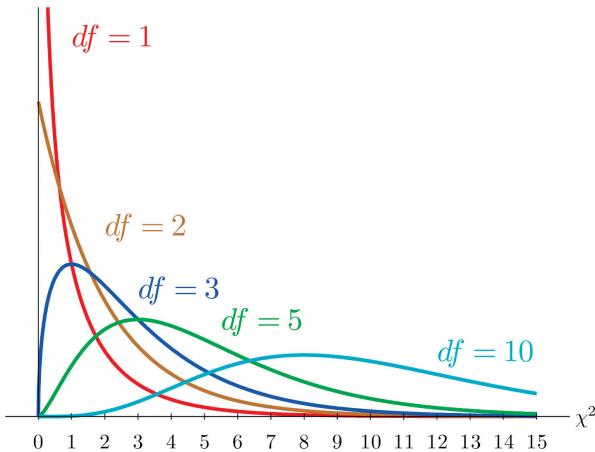
## Outline

1. Computing p-values with software using  $\chi^2$  distraction
2. Test of independence
3. Measures of association between two categorical variables

## Computing P-Value

Given  $\chi^2$

P-Value is always above or equal to degrees of freedom.



p \_\_\_\_

- interval values  $\rightarrow$  probability

q \_\_\_\_

- probability  $\rightarrow$  values

P-Values = probability of getting our data or data that “disagree” as much or more with our model, if model is correct.

```
arbitrary_val <- 4.8  
pchisq(arbitrary_val, df = 5, lower.tail = FALSE)
```

## Test of Independence

What I'm recording: two categorical variables

What I want to know: whether a suspected association between the variables will hold when generalized to the population.

## Test of Homogeneity

What I'm recording: 1 categorical variable in samples from multiple populations

What I want to know: Is the variable's distribution the same in all populations?

**Both tests use data summarised in two-way tables**

We use Fisher's significance testing approach.

Test of independence: we model assuming that the two variables are not actually associated

H<sub>0</sub>

- [Variable 1] does not affect [Variable 2]
  - [Variable 1] and [Variable 2] are independent/not associated/ not related

Testing of homogeneity: we model assuming the distribution is the same in every population

- H<sub>0</sub>: the distribution of [variable] is the same in [list of population]

More simply put: H<sub>a</sub>: not H<sub>0</sub>

In test of homogeneity, we consider “population” to be an explanatory variable & run a test of independence

Observed counts = number in sample of each cell of table.

### Example (Book Example 9.12)

	Low Salt	High Salt	Total
CVD			200
NO CVD			2215
Total	1169	1246	2415

Figure 1: Base Table

Estimated probability of Cardiovascular Disease(CVD) =  $\frac{200}{2415}$

If independent (according to chart):

- $P(\text{CVD} | \text{low salt}) = 1169 \times \frac{200}{2415} = 96.81$
- $P(\text{CVD} | \text{high salt}) = 1246 \times \frac{200}{2415} = 103.19$
- $P(\text{NO CVD} | \text{low salt}) = 1169 \times \frac{2215}{2415} = 1072.19$
- $P(\text{NO CVD} | \text{high salt}) = 1246 \times \frac{2215}{2415} = 1142.81$

## Pearson Residuals

$\frac{O-E}{\sqrt{E}}$  → for each cell

Contribution of a cell to  $\chi^2$ : residual<sup>2</sup> =  $\frac{(O-E)^2}{E}$

$$\chi^2 = \sum \frac{(O-E)^2}{E}$$

- $P(CVD | \text{low salt}) = \frac{88-96.81}{\sqrt{96.81}} = -0.895$
- $P(CVD | \text{high salt}) = \frac{112-103.19}{\sqrt{103.19}} = 0.867$
- $P(\text{NO CVD} | \text{low salt}) = \frac{1081-1072.19}{\sqrt{1072.19}} = 0.269$
- $P(\text{NO CVD} | \text{high salt}) = \frac{1134-1142.81}{\sqrt{1142.81}} = -0.261$

$$\chi^2 = (-0.895)^2 + (0.867)^2 + (0.269)^2 + (-0.261)^2 = 1.69$$

finish second chart from picture

## To get a P-Value

- Option 1: Our  $\chi^2_{\text{observed}}$  value comes from a  $\chi^2$  distribution with degrees of freedom. Find  $P(\chi^2 \geq \chi^2_{\text{observed}})$
- Option 2: Simulate a bunch of samples assuming independence, then find proportion of simulated  $\chi^2$  statistic  $\geq \chi^2_{\text{observed}}$

Fisher: df (degrees of freedom) =  $(r - 1)(c - 1)$

- r: rows
- c: columns

“Sample size assumptions” method (2) always works but different people can get different values.

Method 1 always gives some value, but that value can be inaccurate at small sample sizes.

When all expected counts  $\geq 5$ , use method 1.

When any expected count  $< 5$ , use method 2.

Alternate method when n is really small: Fisher's exact test

Condition on marginal totals being fixed, get a test statistic with hypergeometric distribution.

P-Value =  $P(\chi^2 \geq 1.69)$  from  $\chi^2$  distribution with 1 degree of freedom = 0.193

Not on test but may show up in context:

### 3 “Measures of association” between categorical variables

1. Difference in proportions

- Population:  $P_1 - P_2$
- Samples:  $\hat{P}_1 - \hat{P}_2$

2. Relative risk (RR)

- Population :  $\frac{P_1}{P_2}$

## **Day 13 (Review Session)**

### **Problem Solving Methodology**

1. What problems look like
2. What info to look for
3. How to solve them

## Independent vs. Disjoint

### Are A and B Disjoint

Looks like: define two events

Looking for:

- $P(A)$
- $P(B)$
- $P(A \cap B)$

Check: Is  $P(A \cap B) = 0$

If yes  $\rightarrow$  disjoint

If no  $\rightarrow$  not disjoint

### Are A and B independent

Looking for:

- $P(A)$
- $P(B)$
- $P(A \cap B)$

Find ONE OF the following comparisons:

Is  $P(A \cap B) = P(A)P(B)$

If yes  $\rightarrow$  independent

If no  $\rightarrow$  dependent

Is  $P(B | A) = P(B)?$

- $P(B|A) = \frac{P(A \cap B)}{P(A)}$

### Event vs Probability

- **Event:** an actual thing that could happen or not
  - Example: the dog will go to the right place
- **Probability:** a number between 0-1 assigned to the “chance” of an event
  - Example: The dog has a 50% chance of going to the right bowl

### Example

Problem: 3 lights, independently red/green

If red  $\rightarrow$  2 minutes

10 minutes to get to work

All green  $\rightarrow$  8 minutes

$$P(A) = 0.6 \quad P(B) = 0.4 \quad P(C) = 0.9$$

A  $\rightarrow$  Light 1 is red B  $\rightarrow$  Light 2 is red C  $\rightarrow$  Light 3 is red

Goal: Find the probability of not being late to work

Employee is not late if:

- all green
- one light is red

$$P(\text{not late}) = P(\text{all green}) + P(\text{one red})$$

all green =  $\{(A^c, B^c, C^c)\}$  he hits no red lights

one red =  $\{(A, B^c, C^c), (A^c, B, C^c), (A^c, B^c, C)\}$  he hits at most one light

$$\text{all green} = P(\{(A^c, B^c, C^c)\})$$

$$= P(A^c)P(B^c)P(C^c)$$

$$= (0.4)(0.6)(0.1)$$

$$= 0.024$$

*finish from picture*

## Conditional Probability/Bayes' Rule

Given: two conditional probabilities/proportions  $P(B|A), P(B|A^c)$

One unconditional probability/proportions (prevalence/base rate)  $P(A)$

Goal: Find a different conditional probability  $P(A|B)$

$$P(A|B) = \frac{P \cap B}{P(B)}$$

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## Day 14

## Continuous Random Variables

Can take any real number ( $\mathbb{R}$ ) value within any given interval.

We cannot use a probability mass function so we will instead use a probability **density** function (PDF) denoted as  $f(x)$

### Properties

- The probability of being in an interval  $(a, b]$  is:

$$\int_a^b f(x)dx = \int_{-\infty}^b f(x) - \int_{-\infty}^a f(x)dx$$

– This is considered the area under the curve between a and b

- $P(X = x) = 0 \forall x$ 
  - $P(X \leq x) = P(X < x)$
  - $P(X \geq x) = P(X > x)$

$f(x)$  is displayed graphically as a density curve

### Properties of $f(x)$

- $\forall x \in \mathbb{R}, f(x) \geq 0$ 
  - Density never goes below x-axis
- $\int_{-\infty}^{\infty} f(x)dx = 1$

Mean of continuous random variable:  $\mu_x = \int_{-\infty}^{\infty} x \times f(x)dx$

Variance of continuous random variable is  $\sigma^2 = \int_{-\infty}^{\infty} (X - \mu_x)^2 f(x)dx$

## Uniform Random Variable

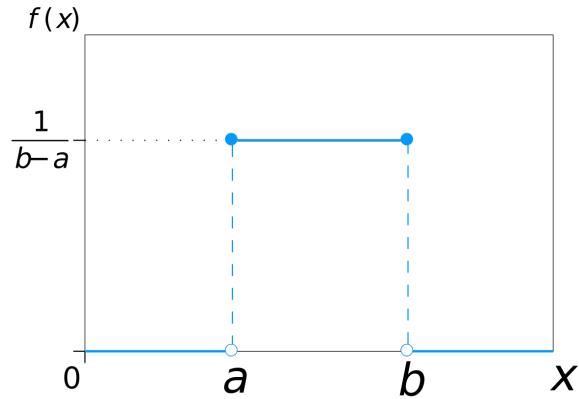


Figure 1: Graphical Representation

$$X \sim U(a, b)$$

**Example : Standard Uniform Random Variable**

$$X \sim U(0, 1)$$

**Find**

- $P(X \geq 0.3)$
- $P(X = 0.3)$
- $P(0.3 < X \leq 1.3)$
- $P(0.2 \leq X \leq 0.7 \text{ or } 0.7 \leq X \leq 0.9)$
- $P(X \text{ is not in the interval } (0.4, 0.7))$

**Answers**

- $\square = (0.7) \times (1) = 0.7$
- $\square = 0$ 
  - The probability of being exactly on a point in the infinite sum will \*\*always\*\* be 0.
- $\square = (0.7) \times (1) = 0.7$ 
  - Do not keep shading when there is no density curve, meaning it is a hard stop at  $X = 1$
- $\square = ((0.25 - 0.2) \times \frac{1}{0.25-0.2}) + ((0.91 - 0.7) \times \frac{1}{0.91-0.7}) = 0.25$
- $\square = 0.4 + 0.3 = 0.7$

## Normal Random Variable

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

Density curve is also a “bell curve”

Empirical (68-95-99.7) Rule

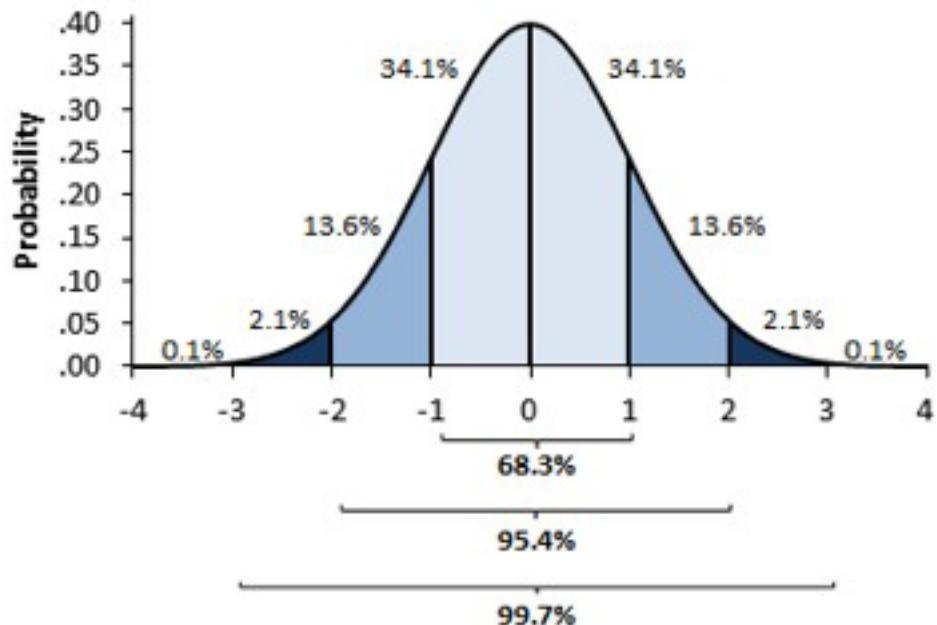


Figure 2: Bell Curve

$$X \sim N(\mu, \sigma)$$

## Standardization

It may be useful to standardize distributions to compare 2 variables with same density curve shape but different scales. For normal distributions  $X \sim N(\mu, \sigma)$ , we convert to Z-Scores  $Z \sim N(0, 1)$

$$Z = \frac{x - \mu}{\sigma} = \frac{\text{value} - \text{mean of distribution}}{\text{standard deviation}}$$

$$P(Z \leq z) = P(X \leq x)$$

“Cumulative proportion”/“Cumulative probability”

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# Day 15

## Z-Score Example

Two tests of “English” ability

- NAEP Reading Test
- SAT verbal

Suppose a student scored 320 on NAEP & 650 SAT

Which test did he do better on?

$NAEP \sim N(288, 38)$

$SAT \sim N(500, 120)$

### Convert to Z-Scores

NAEP:

$$Z = \frac{\text{value} - \text{mean}}{\text{standard deviation}} = \frac{320 - 288}{38} = 0.842$$

Student scored 0.842 standard deviation above average

SAT:

$$Z = \frac{\text{value} - \text{mean}}{\text{standard deviation}} = \frac{650 - 500}{120} = 1.25$$

Student scored 1.25 standard deviation above average

### R-Code

```
pnorm(320, mean = 288, sd = 38)
[1] 0.8001355
```

Cumulative proportion of 0.800 (80%) which means 80<sup>th</sup> percentile.

```
pnorm(650, mean = 500, sd = 120)
[1] 0.8943502
```

Cumulative proportion of 0.8943502 which means 89<sup>th</sup> percentile.

# Water bottle example

## Questions

- Why does it continue to overfill
  - How much does it actually pour → average
- Why does Dr. Wynne have such terrible reaction speed?
  - Reaction speed → average
- Does the water fill at the same rate
  - Average rate for one pour
  - → average over several attempts

Expected value =  $\mu$  = expected amount filled

$\bar{X}$  = average amount filled in a sample of pours “sample mean”.

Variability: how variable are the individual values. (range)

- $\sigma$  = Standard Deviation
- $\sigma^2$  = Variance
- $S$  = Sample Standard Deviation
- $S^2$  = Sample Variance

Bias: Center: - on average, are we where we expected to be? (mean, median, mode)

## Shape

Shape: where “average” is compared to “most likely”

- How “consistent” the values are given variability

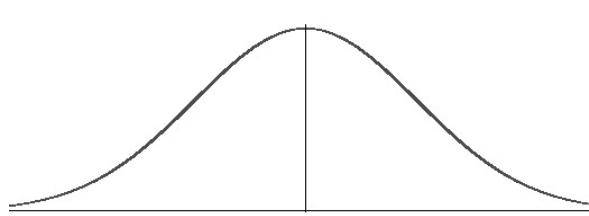


Figure 1: Unimodal Distribution

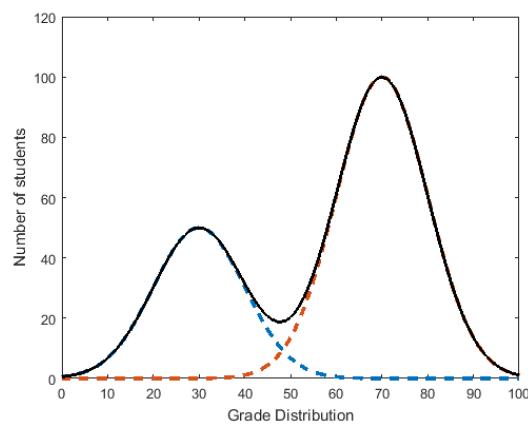


Figure 2: Bimodal Distribution

The median is resistant, the mean is subject to more change.

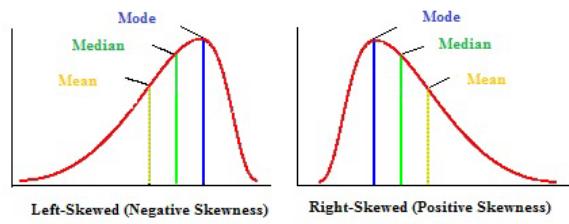


Figure 3: Left and Right Skewed Graphs

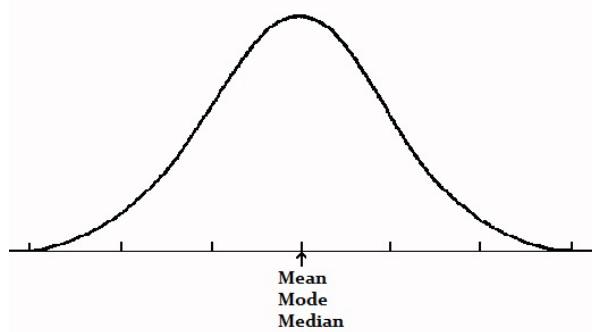


Figure 4: Symmetric Graph

Approximating a Density Curve: Histogram

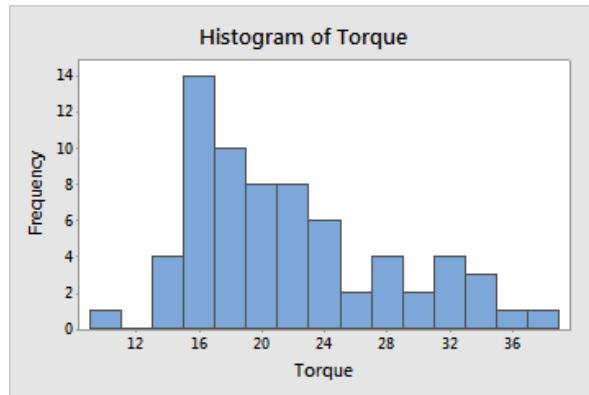


Figure 5: Histogram

- “bins”: intervals on the x-axis
- Choice of bins is very important
  - Endpoints of bins
  - Center & Width
- Riemann Integral of an unknown density curve

# Outliers

Points that doesn't fit with everything else

## Attempting to determine outliers

- Plot your data & look for points that don't belong
- ↑ best way
- Investigate why they're different

## Box-Plots

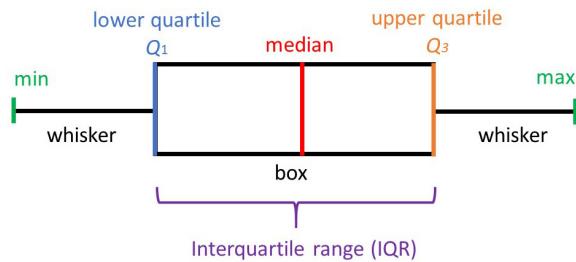


Figure 6: Box Plot

## Rule of Thumb

- Step 1: Get five number summary (min,  $Q_1$ , medium( $Q_2$ ),  $Q_3$ , max)
- Step 2: Compute  $IQR = \text{range middle } 50\% \text{ of data}$ 
  - $IQR = Q_3 - Q_1$
- Step 3: Compute “fences”
  - Lower fence:  $Q_1 - K \times IQR$
  - Upper fence:  $Q_3 + K \times IQR$

Anything outside the fences is an outlier.

By convention,  $k = 1.5$

## Example : Senator Ages

Five number summary:

- Min = 39
- $Q_1 = 55.5$
- Median = 63
- $Q_3 = 69$
- Max = 85

$$IQR = 69 - 55.5 = 13.5$$

$$\text{Lower fence: } 55.5 - (1.5)(13.5) = 35.25 \quad \text{Upper fence: } 69 + (1.5)(13.5) = 89.25$$

In this data set we have no outliers because our data falls between the fences.

## Numerical Variable Connection to Random Variables

### Recall for random variable X

$$E(A + Bx) = a + b \times E(x)$$

$$Var(A + Bx) = b^2 \times Var(x)$$

$$SD(A + Bx) = |b| \times sd(x)$$

### Recall for random variable X and Y

$$E(Ax + By) = aE(x) + bE(y)$$

$$Var(Ax + By) = A^2 \times var(x) + B^2 var(y)$$

$$SD(Ax + By) = \sqrt{A^2 \times var(x) + B^2 \times var(y)}$$

All of these rules hold for numerical variables too

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## Day 16

# Error and Variability

Rounding variability: error due to precision of our machine/scale/etc.

- 1) Never measure exact, only to some tolerance
  - $\rightarrow$  typically rounding error  $\sim (E, -E)$

Example: weight is 150 pounds - reality  $\rightarrow 150 \pm U(-0.5, 0, 5)$

- 2) When making repeated measurements of something, there will be some natural variability, due to many small sources of error. Usually (as long as errors are on the same scale), we can make measurement error of  $\sim N(0, \sigma)$
- 3) Sampling error: error due to only having a sample from the population. Estimate a population mean  $\mu$  based on a sample mean:

$$\bar{X} = \frac{1}{n} \sum_{i=1}^n x_i$$

What is the distribution of  $\bar{X}$  over all possible samples = sampling distribution of  $\bar{x}$  which is the sampling mean

Consider simple random sample from a given population, the values  $x_1 \rightarrow x_n$  values of some numerical variables. We assume the  $x_i$ 's are independent and identically distributed random variables.

With theoretical/population mean  $\mu$  and standard deviation  $\sigma$ , then  $\bar{X} = \frac{1}{n} \rightarrow (X_1 + X_2 + \dots + X_n)$  is considered a linear combination.

$$E(\bar{X}) = E\left(\frac{1}{n} \times (X_1 + X_2 + \dots + X_n)\right) = \frac{1}{n}(E(x_1) + E(x_2) + \dots + E(x_n))$$

$$E(\bar{X}) = n\mu \times \frac{1}{n} = \mu$$

## Important Facts

- The mean of the sampling distribution of  $\bar{X}$  is equal to the population mean  $\mu$

$$\begin{aligned} (Var \bar{X}) &= var\left(\frac{1}{n} \times (x_1 + x_2 + \dots + x_n)\right) \\ &= \left(\frac{1}{n}\right)^2 \times [var(x_1 + x_2 + \dots + x_n)] \\ &= \left(\frac{1}{n}\right)^2 \times [var(x_1) + var(x_2) + \dots + var(x_n)] \end{aligned}$$

- The variance of sampling distribution of  $\bar{X}$  is smaller than the population variance by a factor of  $n$ . The standard deviation is smaller by a factor of  $\sqrt{n}$ . Consider a normally distributed population. Theorem: any linear combination of normal random variables is also normally distributed.

$$\bar{X} \sim N\left(\mu, \frac{\sigma}{\sqrt{n}}\right)$$

# Central Limit Theorem

For a simple random sample (ASRS) of size  $n$  from a population with finite mean  $\mu$  and finite standard deviation  $\sigma$ :

When  $n$  is “large enough”,  $\bar{x}$  is approximately  $\sim N(\mu, \frac{\sigma}{\sqrt{n}})$

What does “large enough” depend on?

- How good the approximation needs to be (robust procedures-approximation just needs to be OK)
- Shape of population distribution
  - Higher skew requires larger  $n$
  - Outliers in sample suggest larger  $n$  is needed

Consider a normally distributed population.

$\bar{X}$  is a linear combination of random variables  $X_i \sim N(\mu, \sigma)$

## Example

You take a sample size of 64 from a population normally distributed with mean of 82 and standard deviation of 24.

- a) Find the sampling distribution of the sample mean  $\bar{X}$
- b) Middle 95% of values of  $x$  are expected to be in what interval.
- c) Middle 95% of sample means  $\bar{X}$  are expected to be in what interval?

## Answers

- a)  $\bar{X} \sim N(82, \frac{24}{\sqrt{64}}) \sim N(82, 3)$
- b)  $(34, 130)$
- c)  $E[\bar{x}] = \mu = 82$ ,  $SD[\bar{x}] = \frac{\sigma}{\sqrt{n}} = \frac{24}{\sqrt{64}} = 3$   
 $\mu + 2SD[\bar{x}] = 82 + 6 = 88$   
 $\mu - 2SD[\bar{x}] = 82 - 6 = 76$

The range between 76 and 88

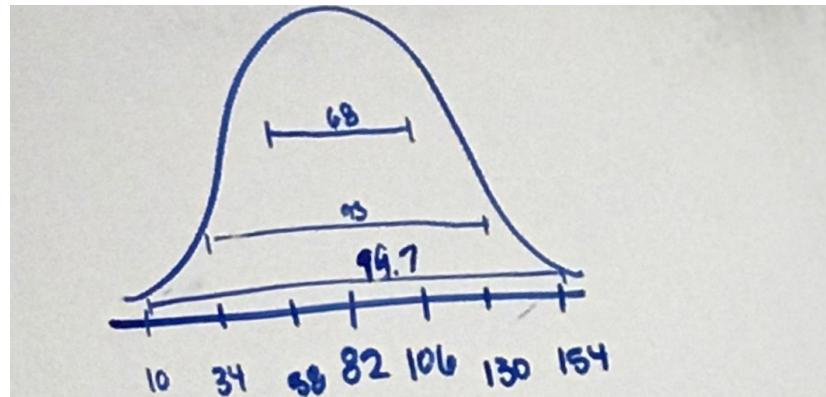


Figure 1: Curve

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## Day 17

This material is not on the exam but will tie into different concepts that will be present

# Review

## Neyman-Pearson Hypothesis Testing

Step 1: Define a parameter and its value under  $H_0$  &  $H_1$

Step 2: Define a test statistic and its sampling distributions under the two hypothesis.

Step 3: Define our alpha level ( $\alpha$ ) which is  $P(\text{Type 1 Error})$ . This translates to  $P(\text{accept } H_1 \mid H_0 \text{ is true})$ . Use it to compute a critical region.

Step 4: Collect sample data and compute observed value of test statistic.

Step 5: If value in critical region, then accept  $H_1$ . If value not in critical region, then accept  $H_0$ .

## What changes now?

We are using stand in variables for instead of using categories. This is still using the NPHT framework but uses numerical data.

Step 1: Parameter is  $\mu$  = population mean. Now we are talking about numerical data now, not categorical data.

- $H_0 = \mu = \mu_0$
- $H_1 = \mu = \mu_1$
- This value of  $\mu$  is cc

Step 2: Statistic  $\bar{X}$  = sample mean. Assuming Central Limit Theorem holds, we will have an approximately normal sampling distribution and will be centered at  $\mu_0$  under the null and  $\mu_1$  under the alternative hypothesis.

- $H_0, \bar{X} \sim N(\mu_0, \frac{\sigma}{\sqrt{n}})$
- $H_1, \bar{X} \sim N(\mu_1, \frac{\sigma}{\sqrt{n}})$

## Sonnet Example

For an old author, sonnets are known to contain an average of 8.9 “new” words, with a standard deviation of 2.5 words. New meaning that they are unique to each of the sonnet and are not used in the others.

A new set of 6 sonnets has been discovered and authorship has been disputed. The sonnets contain an average of 10.2 “new” words. Suppose we believe a different author would use on average 10.9 “new” words.

Using  $\alpha = 0.05$ , what should we conclude about the authorship of the new sonnets?

### Response

Parameter:  $\mu$  = population mean which in this context will be the number of “new” words

- Under  $H_0: \mu = 8.9$   
– Step 2:  $\bar{X} \sim N(8.9, \frac{2.5}{\sqrt{6}})$
- Under  $H_1: \mu = 10.9$   
– Step 2:  $\bar{X} \sim N(10.9, \frac{2.5}{\sqrt{6}})$
- Here we are stating that it is worse to give credit to someone who didn’t write the sonnets.
- We then accept the null hypothesis because the value is not in the critical region of 10.58. This means the original author wrote the sonnets.
- The way we set up the problem will affect the conclusion we come to.

### R-Code

```
alpha <- 0.05
mu <- 8.9
sigma_from_sample <- 2.5/sqrt(6)

qnorm(alpha, mu, sigma_from_sample, lower.tail = FALSE)
```

## Neyman-Pearson Power Analysis

Step 1: Define a parameter and its value under  $H_0$  &  $H_1$

Step 2: Define a test statistic and its sampling distributions under the two hypothesis.

Step 3: Define our alpha level ( $\alpha$ ) which is  $P(\text{Type 1 Error})$ . This translates to  $P(\text{accept } H_1 \mid H_0 \text{ is true})$ . Use it to compute a critical region.

Step 4: Compute our power =  $P(\text{test statistic in critical region} \mid H_1 \text{ is true})$

Step 5: [OPTIONAL] Compare power to 80% and/or compute  $\beta$  to  $\alpha < \beta \leq 0.2$

### Sonnet Example with Power Analysis

For an old author, sonnets are known to contain an average of 8.9 “new” words, with a standard deviation of 2.5 words. New meaning that they are unique to each of the sonnet and are not used in the others.

A new set of 6 sonnets has been discovered and authorship has been disputed. The sonnets contain an average of 10.2 “new” words. Suppose we believe a different author would use on average 10.9 “new” words.

Using  $\alpha = 0.05$ , what is the power of our test to detect the “new” author?

You are trying to compute a probability here so this R code will suffice

### R-Code

```
alpha <- 0.05
old_mu <- 8.9
mu <- 10.9
sigma_from_sample <- 2.5/sqrt(6)

critical_value <- qnorm(alpha, old_mu, sigma_from_sample, lower.tail = FALSE)
pnorm(critical_value, mu, sigma_from_sample, lower.tail = FALSE)
[1] 0.6235198
```

## NHST Framework

- Step 1: Define a parameter and its value under  $H_0$
- Step 2: Define an interval representing an inequality (under  $H_0$ , parameter in that interval)
- Step 3: Define a test statistic and its sampling distribution under  $H_0$
- Step 4: Collect data and compute the observed value of the test statistic.
- Step 5: Compute the P-Value which is  $P(\text{observe a test statistic as or more favorable to } H_1 \mid H_0 \text{ is true})$
- $P(\text{test statistic} \geq \text{observed value})$  OR
  - $P(\text{test statistic} \leq \text{observed value})$  OR
  - $P(\text{test statistic "further" from parameter value compared to observed value})$

Find either of the three listed above ↑ and double the smaller one.

- Step 6: We define our significance level.

If

- $P\text{-Value} \leq \text{significance level} \implies \text{reject } H_0 \text{ & accept } H_1$
- $P\text{-Value} > \text{significance level} \implies \text{fail to reject } H_0$

### Sonnet Example with NHST

For an old author, sonnets are known to contain an average of 8.9 “new” words, with a standard deviation of 2.5 words. New meaning that they are unique to each of the sonnet and are not used in the others.

A new set of 6 sonnets has been discovered and authorship has been disputed. The sonnets contain an average of 10.2 “new” words. Suppose we believe a different author would use on average 10.9 “new” words.

Theory suggest a different author would use more “new” words.

What should we conclude about authorship at the 5% significance level?

Parameter:  $\mu$  = population mean number of new words

- $H_0 : \mu = 8.9$
- $H_1 : \mu > 8.9$ 
  - can only be  $>, <, \neq$

We assume the new author is going to have more words than the original author.

$$\bar{X} \sim N(8.9, \frac{2.5}{\sqrt{6}})$$

### R-Code

```
x_bar <- 10.2
mu <- 8.9
sigma_from_sample <- 2.5/sqrt(6)

pnorm(x_bar, mu, sigma_from_sample, lower.tail = FALSE)
[1] 0.1013787
```

Since the outcome is 10 percent, we fail to reject the null hypothesis. We need to default back onto the original assumption. We do not have any definitive truth to accept the null hypothesis but since we have nothing else to fall back onto be need to say its likely to still be true.

## Two-sided Tests

Use this when theory does not definitively give an “alternative”.

For Neyman-Pearson tests: critical region is half in left tail and half in right tail of sampling distribution under  $H_0$ .

This means that our power will decrease ( $\downarrow$ ).

For NHST: Find the “one-sided” p-value & double it.

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## Day 18

# Historical Motivation for T-Statistics

## Example : Best Beer

### Questions

- What type of barely is best?
  - How much barely can be produced?
  - How high quality is the barely?

Combine the two questions proposed into one variable → value per acre. We know there is variation in this variable. Different farms have variable soil, temperature, etc.

We need to know the average value per acre.

$$\bar{X} \sim N(\mu, \frac{\sigma}{\sqrt{n}})$$

Problem is that we don't know  $\mu$  nor  $\sigma$

We can hand-waive this by saying:

- For sufficiently large samples we can replace population standard deviation  $\sigma$  with sample standard deviation  $s$  and our probability calculations are not too far off.

Our sample size is 4 farms, which is not enough.

For small samples, there is a lot variability in  $S$ . We need to take this variation into account.

### Conclusions being Published

- Released in 1908 under the pseudonym Student who's real name is W.S. Gosset
- “Conclusions are not strictly applicable to populations known to be normally distributed; yet it appears probable that the deviation from normality must be very extreme to lead to serious error.”

Fisher was the only person who really cared about this report. This allowed Fisher for coming up with a better way. Most problems solved by statistics have been solved by beer and eugenics.

$$t = \frac{\bar{X} - \mu}{\frac{s}{\sqrt{n}}}$$

## Definitions

### Standard Error of the Mean (SEM)

The estimated standard deviation of the sampling distribution of  $\bar{X}$ , calculated as  $\frac{s}{\sqrt{n}}$ . More generally, the standard error of the statistic is the estimated (from sample data) standard deviation of its sampling distribution. As  $n \uparrow$ , SEM  $\downarrow$

### One-Sample t Statistic:

$$t = \frac{\bar{X} - \mu}{\frac{s}{\sqrt{n}}}$$

Has a (student's) t-distribution

With  $n - 1$  degrees of freedom, supposing a simple random sample of size  $n$  drawn from a population  $\sim N(\mu, \sigma)$  where ( $\mu$  known,  $\sigma$  unknown). When population is not normal, procedures using t-distribution are still roughly accurate (unless clear skew/outlier issues). At high degrees of freedom,  $t(n - 1)$  is indistinguishable from  $N(0, 1)$  visually. It gets more rounded and less peaked at the top.

## R Code

- pt: values → probability
- qt: probability → values

## Example

Suppose you have a simple random sample of 16, one-bedroom apartments for renting in a neighborhood. The sample mean rent price is \$1280 per month and sample standard deviation is \$180 per month.

### Computational

- What is the SEM?
- What would the distribution of a t-statistic based on this sample?
- What else would you need to know/assume to calculate t-statistic?

### Theoretical

- If you took a simple random sample of 25 apartments instead, would you express SEM to be larger or smaller? Why?
- Is it guaranteed?

### Response

#### Computation

- $\frac{s}{\sqrt{n}} = \frac{180}{\sqrt{16}} = 45$
- Degrees of freedom:  $n - 1 = 16 - 1 = 15 \rightarrow t(df = 15) \rightarrow t(15)$
- $\mu$

#### Theoretical

- The SEM will go  $\downarrow$  because there is less variability.
- No because if  $s > 225 \implies \frac{s}{\sqrt{n}} > 45$

## One-Sample T-Statistic

$$H_0 : \mu = \mu_0$$

$$t = \frac{\bar{X} - \mu_0}{\frac{s}{\sqrt{n}}}$$

$\uparrow$  under the null hypothesis ( $H_0$ ). If  $t_{\text{observed}}$  is in critical region: accept  $H_1: \mu = \mu_1$ . Else accept  $H_0: \mu = \mu_0$  Also, under  $H_0$ ,  $t \sim t(n-1)$

$$t_{\text{observed}} = \frac{\bar{x}_{\text{observed}} - \mu_0}{\frac{s_{\text{observed}}}{\sqrt{n}}}$$

## Neyman-Pearson Framework

Critical Region: on the t-scale

- $t \geq t^*$
- $t \leq -t^*$

$$t \geq \frac{\bar{X} - \mu_0}{\frac{s}{\sqrt{n}}}$$

## Two-Sided Test

$$|t| \geq t^{**}$$

If  $t_{\text{observed}}$  is in critical region: accept  $H_1: \mu = \mu_1$ . Else accept  $H_0: \mu = \mu_0$

$$t_{\text{observed}} = \frac{\bar{x}_{\text{observed}} - \mu_0}{\frac{s_0}{\sqrt{n}}}$$

## NHST

- $H_a: \mu > \mu_0$
- OR :  $\mu < \mu_0$
- OR :  $\mu \neq \mu_0$

## P-Value

- $P(t \geq t_{\text{observed}})$
- $P(t \leq t_{\text{observed}})$
- $P(|t| \geq |t_{\text{observed}}|)$ 
  - Find one-sided p-value and double it

## Distributions we Should Know

- $N(\mu, \sigma)$
- $B(n, P)$
- $U(a, b)$  OR  $V(a, b)$ , can't tell
- $\chi^2(df)$
- $t(df)$

## External Links

- [Two Tailed Test Article](#)

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## Day 19

## One-Sample T-Test Examples

Please see attached PDF for example procedures

### Review

$$H_0: \mu = \mu_0$$

T-Statistic:

$$t = \frac{\bar{x} - \mu}{\frac{s}{\sqrt{n}}}$$

$$t \sim t(n - 1)$$

## Example 1 : Budwiser

ABV: Alcohol By Volume

February 2013, a lawsuit claimed actual ABV content in Budwiser was 4.7% but Budwiser advertised ABV of 5%.

Suppose 3 independent labs test Budwiser beer ABV content.

Recall: measurement error is assumed normally distributed

Assume: measurements are unbiased

**read these as percents but treat as whole numbers**

$$H_0: \mu = 5$$

$$H_1: \mu = 4.7$$

$$\alpha = 0.05$$

Find the critical region:

$$t = \frac{\bar{x} - 5}{\frac{s}{\sqrt{3}}}$$

Under  $H_0 \implies t \sim t(2)$

There are two degrees of freedom.

Critical Region:  $t \leq -2.92$

If  $t_{\text{observed}} \leq -2.92$ , accept  $H_1$  claiming the beer is watered down.

If  $t_{\text{observed}} > -2.92$ , accept  $H_0$  claiming the beer is not watered down.

Lab Measurements:

$$\bar{x} = 4.927$$

$$s = 0.032$$

$$t_{\text{observed}} = \frac{4.977 - 5}{\frac{0.032}{\sqrt{3}}} = -1.257$$

`qt(0.05, 2, lower.tail = TRUE)`

Since  $-1.257 > -2.92$ , we accept  $H_0 \implies$  beer is not watered down.

## Power Analysis

Is a sample of 3 labs big enough to detect  $\mu = 4.7$ ?

## Special Case: Matched Pairs (Paired) t-Test

When it's used: matched-pairs experiment case-control observation study **or** any other situation where we have a numerical response variable recorded on the same subjects under two different conditions/on pairs of subjects

Commonly seen: before and after treatment studies.

We do inference on the paired differences

E.G) after - before

$\mu_d$  denotes the population mean of paired differences

$\bar{x}_d$  denotes the sample mean of paired differences

$s_d$  denotes the sample standard deviation of paired differences

$n$  denotes the number of paired differences

$$t = \frac{\bar{x}_d - \mu_d}{\frac{s_d}{\sqrt{n}}}$$

Very common:

$H_0: \mu_d = 0$

→ no difference between conditions

$H_a: \mu_d \neq 0$

→ difference between conditions

## Example : Book Exercise 7.10

Comparing taste of hash browns in deep fryer (oil) vs air fryer (no oil)

Five experts rate taste of hash browns made in each fryer

Expert	Oil Rating	No Oil Rating
1	78	75
2	84	85
3	62	67
4	73	75
5	63	66

Figure 1: Hash Brown Expert Analysis

Is there a difference in taste between oil and no-oil hash browns?

$$H_0: \mu_d = 0$$

$$H_a: \mu_d \neq 0$$

No oil - oil

Expert	Oil Rating	No Oil Rating	Diff
1	78	75	-3
2	84	85	1
3	62	67	5
4	73	75	2
5	63	66	3

Figure 2: Hash Brown Expert Analysis (Difference)

$$\bar{x}_d = 1.6$$

$$s_d = 2.966$$

$$t_{\text{observed}} = \frac{1.6 - 0}{\frac{2.966}{\sqrt{5}}} = 1.96$$

$$t_{\text{observed}} \sim t(4)$$

$$P(t \geq 1.96 \mid H_0 \text{ is true}) = 0.061$$

$$\text{p-value} = 2(0.061) = 0.122$$

Compare the p-value to the significance level, which by default is 0.05

If p-value  $\leq$  significance level, we reject  $H_0$  & accept  $H_a$  conclude there is a taste difference.

If p-value  $>$  significance level, we fail to reject  $H_0$  cannot claim there is a difference.

If  $H_a: \mu_d = 0 \rightarrow$  no-oil taste better than oil taste. This is because our difference were no\_oil - oil.

Then:  $t_{\text{observed}} = 1.96$

$$\text{p-value} = P(t \geq 1.96 \mid H_0 \text{ is true}) = 0.061$$

If  $H_a$ :  $\mu_d < 0$ , with no oil taste worse than oil taste.

$t = 1.96$

p-value =  $P(t \leq 1.96 \mid H_0 \text{ is true}) = 0.939$

## **Example : Case of Beer**

$$H_0 = \mu = 5 \quad H_a = \mu < 5$$

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## Day 20

## Two Independent Samples t-Test

When it's used: randomized with unrelated treatments & control groups **OR** observational study with comparing two unrelated groups.

Very common: compute mean if everyone got “new” treatment to mean if everyone got “control” treatment. Example; two groups, one smoking and the other group not smoking.

Data looks like: one numerical response variable measured in two **independent groups**

## Example

Figure 1: Numbers to numbers

Lung Cap		Group
#		Smoker
#		Smoker
#		Smoker
#		No smoker

Figure 2: Numbers to groups

# Theory & Concepts

Let  $\mu_1$  = population mean in group 1.  $\mu_2$  = population mean in group 2.

Example:  $\mu_1$  = population mean cholesterol level if everyone got new drug.  $\mu_2$  = population mean cholesterol level if everyone current drug.

We want to do inference on  $\mu_1 - \mu_2$ , the difference of population means.

Recall:

$$t = \frac{\text{STATISTIC - PARAMETER}}{\text{STANDARD ERROR}}$$

$$t = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{\text{STANDARD ERROR}}$$

Now we have two sample, so we have:

- $\bar{x}_1$
- $S_1$
- $n_1$
- $\bar{x}_2$
- $S_2$
- $n_2$

By CLT,

$$\bar{X}_1 \sim N(\mu_1, \frac{\sigma_1}{\sqrt{n_1}})$$

$$\bar{X}_2 \sim N(\mu_2, \frac{\sigma_2}{\sqrt{n_2}})$$

$$\bar{X}_1 - \bar{X}_2 \sim N(\mu_1 - \mu_2, \sqrt{\frac{(\sigma_1)^2}{n_1} + \frac{(\sigma_2)^2}{n_2}})$$

$$Var(\bar{X}_1 - \bar{X}_2) = Var(\bar{X}_1) + Var(\bar{X}_2)$$

$$(\sigma_1)^2 + (\sigma_2)^2$$

Serious problem: we need to estimate two standard deviations!

**Solution 1 : Assume  $\sigma_1 = \sigma_2$**

Estimate using pooled standard deviation  $S_p$

$$\sqrt{\text{weighted average of variance}}$$

this is not needed

**Satterthwaite Approximation**

$$t \sim t(df)$$

Where **df** is calculated by Satterthwaite approximation.

In general, df is NOT an integer

## Welch's t-Test

Almost always,  $H_0$ :

- $\mu_1 - \mu_2 = 0$
- $(\mu_1 = \mu_2)$

Under  $H_0$ ,

$$t = \frac{(\bar{x}_1 - \bar{x}_2)}{\sqrt{\frac{(s_1)^2}{n_1} + \frac{(s_2)^2}{n_2}}}$$

Almost always: use a two-sided test

Alternative hypothesis: difference between treatment & control.

**Neyman-Pearson:**

$H_1$ :

- $\mu_1 - \mu_2 = \Delta$
- $\Delta$  = desired effects size in original units
- Two sided critical region:

Compute  $t_{\text{observed}}$

Accept  $H_1$  if  $t_{\text{observed}}$  in critical region. Else accept  $H_0$ .

## NHST Approach

$H_a: \mu_1 - \mu_2 \neq 0$

**NOTE:** can use  $\mu_1 - \mu_2 > 0$  or  $\mu_1 - \mu_2 < 0$  but be very careful

Under  $H_0$ :

$$t = \frac{(\bar{x}_1 - \bar{x}_2)}{\sqrt{\frac{(s_1)^2}{n_1} + \frac{(s_2)^2}{n_2}}} \sim t(K)$$

**K is given by software**

Two-sided p-value =  $P(|t| \geq |t_{\text{observed}}| \mid H_0 \text{ is true})$

If p-value  $\leq$  significance level, reject  $H_0$  & accept  $H_a$ . Else fail to reject  $H_0$ .

## Example

Study comparing fat consumption of early vs late eaters. We want to know whether there is a difference in fat consumption.

Use NHST approach

- $H_0: \mu_1 - \mu_2 = 0$
- $H_a: \mu_1 - \mu_2 \neq 0$

Let  $\mu_1$  = population mean fat consumption in early eaters

Let  $\mu_2$  = population mean fat consumption in later eaters

## Data

Early eaters (n=202)

- $\bar{x} = 23.1g$
- $S = 12.5g$

Late eaters (n=200)

- $\bar{x} = 21.4g$
- $S = 8.2g$

$\mu_1 - \mu_2 > 0 \implies$  always above

$\mu_1 - \mu_2 < 0 \implies$  always below

Under  $H_0$ :

$$t = \frac{(\bar{x}_1 - \bar{x}_2)}{\sqrt{\frac{(s_1)^2}{n_1} + \frac{(s_2)^2}{n_2}}}$$

The answer is about 1.614.

Satterthwaite approximation gives df = 347.41

`pt(1.614, df = 347.41, lower.tail = FALSE)`

p-value =  $2(0.054) = 0.108$

At 5% significance level, we fail to reject  $H_0$  because  $0.108 > 0.05$ . We failed to find a statistically significant difference in fat consumption.

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## Day 21

# ANOVA → Analysis of VAriance

## Why ANOVA?

We want to compare the means of more than two populations and our previous methods of analysis have been limiting.

Example: we want to compare three samples to see if a difference exists somewhere between those groups. Each of them have their own sampling distributions and other characteristics.

Question to ask yourself: Do all three of these means come from a common population.

This type of test takes in  $n$  amount of distributions and then distributes them along a unifying curve. We can then see where those distributions lie on the bigger distribution.

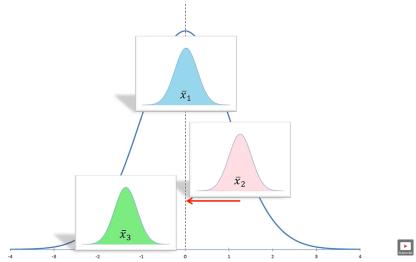


Figure 1: ANOVA Distribution Close to Mean

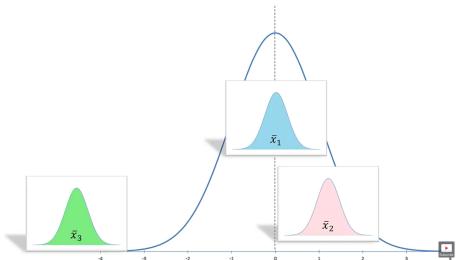


Figure 2: ANOVA Distribution Far from Mean

Mean is in a different location relative to the overall mean of the populations. This might conclude that it is not apart of the common population.

Null Hypothesis:  $H_0 : \mu_1 = \mu_2 = \mu_3$

⇒ All the samples come from the same population. We are not asking if they are EXACTLY equal. We are asking if each mean likely came from the larger overall population. Variability AMONG/BETWEEN the sample means ( $\bar{x}_i$ )

## Comparing Analysis Methodology

The problem with running the individual tests on each respective sampling distribution, we run into some issues:

- All three t-tests have  $\alpha = 0.05 \therefore$  the all compound
  - This makes the confidence of decrease to  $0.95 \times 0.95 \times 0.95 = 0.857$
  - Recall that this is the confidence level or  $\beta$
- Our new  $\alpha$  value need to reflect as such:  $\alpha = 1 - 0.857 = 0.143$

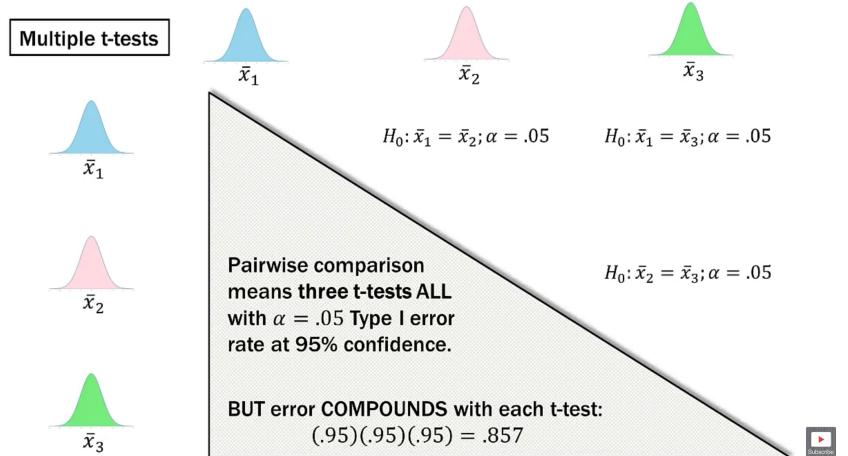


Figure 3: Multiple t-Test Chart

This is why we do not do this, the error rate goes ↑.

## Variability Ratio

ANOVA: Analysis of Variance is *variability ratio*.

This can be seen in the following figure:

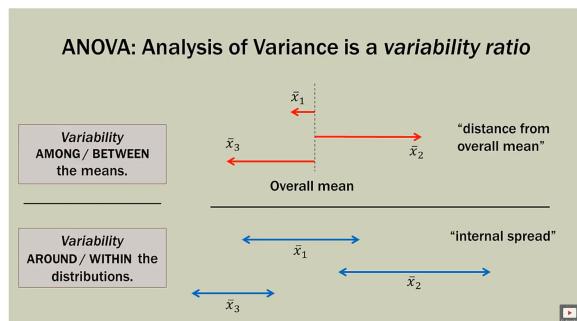


Figure 4: Variability Ratio Visual Example

Variance Between  
Variance Within

**THE** classic Fisher test.

Model:  $y \sim N(\mu, \sigma)$

- $\mu$  and  $\sigma$  are unknown.
- $\mu$  may not be the same for all data points
- $\sigma$  is assumed same for all data points

In one-way ANOVA:

- Data: one numerical response variable  $y$  and one categorical explanatory variable whose values are the “groups”.
- We need  $\geq 2$  groups

Example situations where we use it:

- Compare control group to  $> 1$  treatment group
- Observational study comparing 3 or more groups/populations

## Use cases

- Between-group effects: variation due to changes in  $\mu$
- Within-group effects: variation due to individual differences

## Notation

- $\bar{y}$  = grand mean or the mean of all data in the whole sample.
- $N$  = total sample size
- $I$  = number of groups
- $\bar{y}_i$  = sample mean in group  $i$
- $s_i$  = sample standard deviation in group  $i$
- $n_i$  = sample size in group  $i$
- $y_{ij}$  = value of  $y$  for the  $j^{\text{th}}$  case in group  $i$ .

## Hypothesis Testing

$H_0: \mu_1 = \mu_2 = \dots = \mu_I$

- All the population means are equal  $\implies$  no effect of group on response.
- Under  $H_0$ ,  $y_{ij} \sim N(\mu, \sigma)$
- Also:  $\bar{y}_i \sim N(\mu, \frac{\sigma}{\sqrt{n_i}})$
- $\mu, \sigma$  are fixed but unknown

$H_a:$  not  $H_0$  [not really necessary because this is Fisher framework]

- $\implies$  effect of group on response

### Implicit Assumptions of Model

- Normal population distribution
- $\sigma$  is the same for all groups [not as critical]
  - robust to violations of this assumption as long as the largest  $s_i < 2 \times$  smallest  $s_i$

Under  $H_0$ :

- $F \sim F(DFG, DFE)$
- Think of  $F$  like  $\chi^2$
- $t$  and  $F$  are linked
- $N(0, 1)$  and  $\chi^2$  are linked
- If p-value  $\leq$  significance level, reject  $H_0$  and claim the population means are not all equal
- Do posthoc procedures to figure out which measure different & how different they are.
- If p-value  $>$  significance level, we fail to reject the hypothesis we did not prove a difference /an effect.

ANOVA tests **CANNOT** determine/make conclusions about all populations means ( $\forall$ ), only at least one element in the set ( $\mu \in \forall$ )

Suppose a horticulturist measures the aboveground height growth rate of four different ornamental shrub species grown in a greenhouse. The shrubs were grown from a random sample of seeds, and they were all grown in the same soil mixture and in the same size pot. To ensure that any slight differences in the environmental conditions throughout the greenhouse are not confounded with species, she randomizes the location of the pots throughout the greenhouse. The table contains a summary of her data.

Population	Population description	Sample size	Sample mean	Sample standard deviation
1	Species 1	$n_1 = 20$	$\bar{x}_1 = 13.749 \text{ cm/year}$	$s_1 = 2.160 \text{ cm/year}$
2	Species 2	$n_2 = 20$	$\bar{x}_2 = 16.619 \text{ cm/year}$	$s_2 = 4.284 \text{ cm/year}$
3	Species 3	$n_3 = 20$	$\bar{x}_3 = 13.608 \text{ cm/year}$	$s_3 = 3.396 \text{ cm/year}$
4	Species 4	$n_4 = 20$	$\bar{x}_4 = 12.769 \text{ cm/year}$	$s_4 = 2.683 \text{ cm/year}$

The growth rate distributions of each sample are approximately normal, and the data do not contain outliers. The horticulturist uses a one-way analysis of variance (ANOVA) at a significance level of  $\alpha = 0.01$  to test if the mean growth rates of all four species are equal. Her results are shown in the table.

Source of variation	SS	df	MS	f	P-value	f-critical
Between groups	169.057	3	56.352	5.398	0.002	4.050
Within groups	793.330	76	10.439			
Total	962.386	79				

Figure 5: ANOVA Example Problem

### Homework Example

- $k = 4$
- $n = 20$
- $\alpha = 0.01$
- P-Value = 0.002
- $H_0$ : the shrubs are in the same species ( $\mu_1 = \mu_2 = \mu_3 = \mu_4$ )
- $H_1$ : the shrubs are not in the same species ( $\mu_1 \neq \mu_2 \neq \mu_3 \neq \mu_4$ )

The decision to reject the null hypothesis at a significance level of  $\alpha = 0.01$ . There is sufficient evidence to conclude that at least one of the population means different from at least one other population mean.

## Computing an F-Statistic

$df_1 = \text{Between} \implies k - 1$

$df_2 = \text{Within} \implies n - k$

- n: total number of elements in the sample
- k: number of populations

$$F = \frac{\text{Between}}{\text{Within}}$$

## Example [Made Up]

Four groups:

1.  $n_1 = 15$
2.  $n_2 = 20$
3.  $n_3 = 15$
4.  $n_4 = 25$

$\uparrow$  F-Stat,  $\downarrow$  p-value

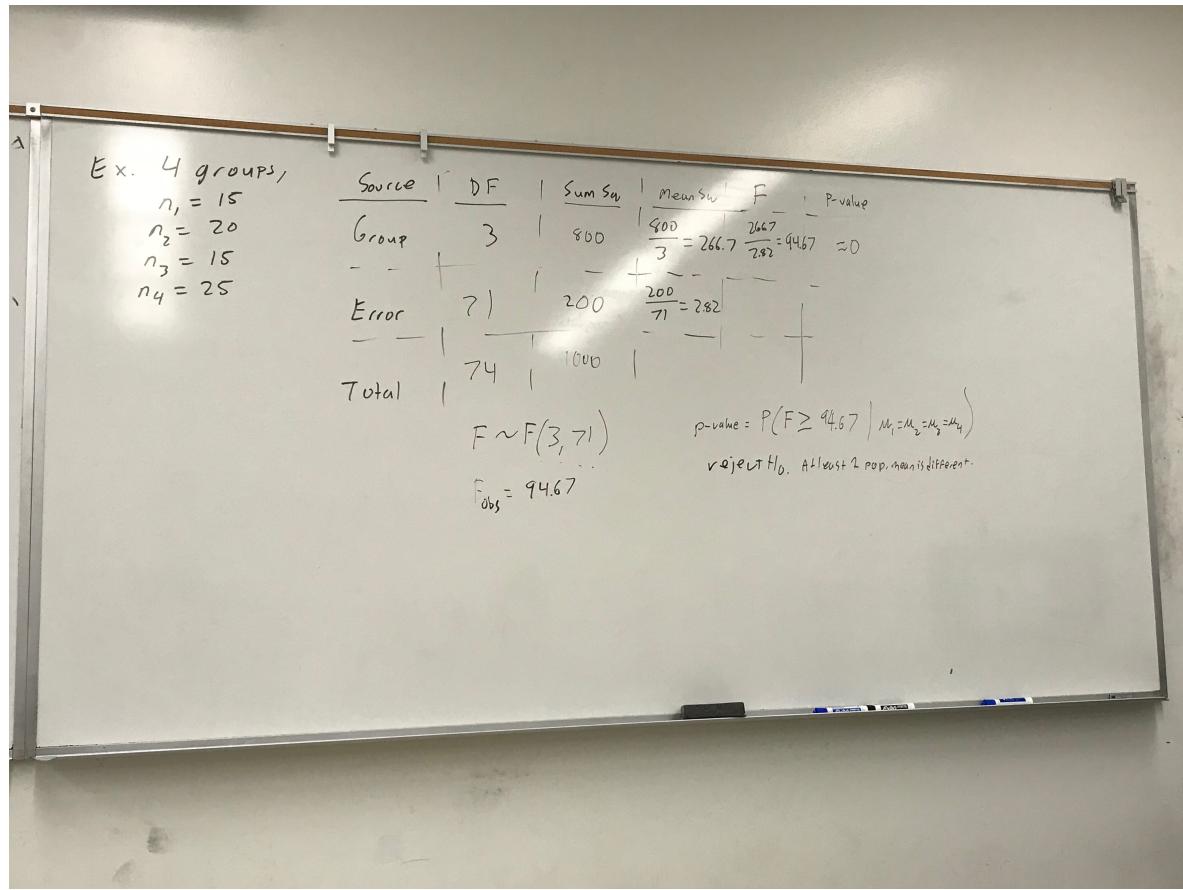


Figure 6: Example Worked in Class

## External Links

- ANOVA YouTube Lecture

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# Day 22

Test is next Thursday 11/21.

## Confidence Intervals

Neyman-Pearson Ideas:

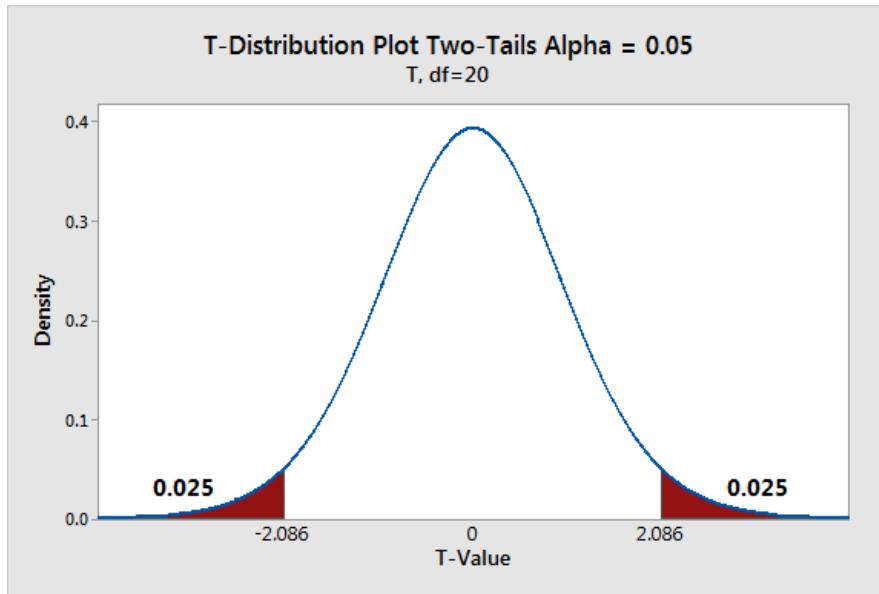


Figure 1: Two Sided Test

If  $t_{\text{observed}}$  is anywhere in the area  $1 - \alpha = C$ , we accept  $H_0$ .

One-sample t-Test: For what values of  $\mu_0$  will we accept  $H_0: \mu = \mu_0$ ?

$$-t^{**} < t_{\text{observed}} < t^{**}$$

$$-t^{**} < \frac{\bar{x}_{\text{observed}} - \mu_0}{\frac{s_{\text{observed}}}{\sqrt{n}}}$$

Any value of  $\mu$  between

$$\bar{x}_{\text{observed}} - t^{**} \times \frac{s_{\text{observed}}}{\sqrt{n}}$$

and

$$\bar{x}_{\text{observed}} + t^{**} \times \frac{s_{\text{observed}}}{\sqrt{n}}$$

We will accept.

The interval  $(\bar{x}_{\text{observed}} - t^{**} \times \frac{s_{\text{observed}}}{\sqrt{n}}, \bar{x}_{\text{observed}} + t^{**} \times \frac{s_{\text{observed}}}{\sqrt{n}})$ , represents the range of values within which we reasonably would believe  $\mu$  to be. This interval is called a confidence interval for  $\mu$ .

In many situations, we either don't know what  $\mu_0$  should be or don't care to make a decision - just want to estimate  $\mu$ .

## How confident are we?

We define confidence level as the proportion of samples for which we would accept  $H_0: \mu = \mu_0$  when  $H_0$  is true.

So confidence level  $C = 1 - \alpha \leftarrow$  depends on  $H_0$  is true.

- $\uparrow \alpha \implies \downarrow C$
- $\downarrow \alpha \implies \uparrow C$

## Problem

We don't know  $\mu_0$ !

Confidence is in our estimate of  $\mu$ .

If  $\mu$  is in our interval - “good” sample, correctly accept  $H_0$  If  $\mu$  is not in our interval - “bad” sample, make a Type 1 Error

We always assume we got a “good” sample.

## Affecting Width

What affects the width of the confidence interval?

$$\bar{x} \pm t^{**} \times \frac{s}{\sqrt{n}}$$

- $\bar{x}$ : center
- $t^{**}$ : comes from  $t(df)$  and is also dependent on  $\alpha$ 
  - $df \uparrow, t^{**} \downarrow, \text{width} \downarrow$
  - $\alpha \uparrow, t^{**} \downarrow, \text{width} \downarrow$
  - $C \uparrow, t^{**} \uparrow, \text{width} \uparrow$
- n: sample size  $\uparrow, \text{width} \downarrow$
- s: sample standard deviation  $\uparrow, \text{width} \uparrow$

## Example

Suppose we take a simple random sample of 8 college students and ask how much time they spend per week watching broadcast TV. In the sample,  $\bar{x} = 14.5$  hrs/week and  $s = 14.884$  hrs/week. Use this information to estimate with 95% confidence the population mean time college students spend watching TV per week.

Is this data symmetric?

- This data is **not** because the sample standard deviation is quite large.

## Solution

Step 1: Assume this is a good sample. So for any value in  $\mu$  in:

$$y = mx + b$$

Step 2: Plug in for  $\bar{x}, s, n$

$$y = ax^2 + bx + c$$

Step 3: Find  $t^{**}$

$$df = 7, C = 0.95 \implies \alpha = 0.05$$

```
qt(0.025, df = 7, lower.tail = FALSE)
[1] 2.305
```

$$\frac{\alpha}{2} = 0.025 \implies t^{**}$$

Step 4:

$$\begin{aligned} &= (14.5 - 23.05\left(\frac{14.854}{\sqrt{8}}\right), 14.5 + 23.05\left(\frac{14.854}{\sqrt{8}}\right)) \\ &= (2.08, 26.92) \end{aligned}$$

## Tying Example Back into Theory [Interpretation]

We are 95% confident (in our estimate) that the population mean (number of hours per week) is between 2.08 and 26.92.

## Other Frameworks

### Matched Pairs

$$- t_{\text{observed}} = \frac{\bar{x}_d - \mu_d}{\frac{s_d}{\sqrt{n}}}$$

- Confidence Interval for  $\mu_d$ :

$$\bar{x}_d \pm t^{**} \times \frac{s_d}{\sqrt{n}}$$
$$(\bar{x}_d - t^{**} \times \frac{s_d}{\sqrt{n}}, \bar{x}_d + t^{**} \times \frac{s_d}{\sqrt{n}})$$

### Two-Sample

## Terms

Point Estimate: statistic whose value is our “best guess” as to the value of a parameter

- $\bar{x}, \bar{x}_d, \bar{x}_1 - \bar{x}_2, etc$

Margin of Error: how much to add/subtract to create an interval estimate we are C% confident in:

t critical value  $\times$  standard error [for two sided N-P test]

## Example : Book Exercise 7.71

202 “early” eaters [Population 1]

- $\bar{x} = 23.1$  grams of fat
- $s = 12.5$  grams

200 “late” eaters [Population 2]

- $\bar{x} = 21.4$  grams of fat
- $s = 8.2$  grams

Estimate with 95% confidence the difference in population mean fat consumption.  $(\mu_1 - \mu_2)$ :  $(-0.4, 3.8)$

We are 95% confident in our estimate that the difference in population mean fat consumption between early & late eaters is between -0.4 and 3.8 grams.

Suppose  $H_0: \mu_1 - \mu_2 = 0$ .  $H_1: \mu_1 - \mu_2 = \Delta$

Can I accept  $H_0$  [in Neyman-Pearson Framework] using this sample.

- Yes because  $-0.4 < 0 < 3.8$

Can I reject  $H_0: \mu_1 - \mu_2 = 0$  [NHST] in favor of  $H_a: \mu_1 - \mu_2 \neq 0$ ? (Using  $\alpha = 0.05$ )

- No because  $-0.4 < 0 < 3.8$

Based on our sample:

1.  $\mu_1$  and  $\mu_2$  could be =
2.  $\mu_1$  could be as much as 3.8 bigger than  $\mu_2$
3.  $\mu_1$  could be as much as 0.4 smaller than  $\mu_2$

## Interpretations

We are 95% confident in our estimate that, on average (in the population), early eaters consume between 0.4 grams less & 3.8 grams more fat compared to late eaters.

↑ SAME THING ↓

$\mu_1$  = population mean late eaters,  $\mu_2$  = population mean early eater  $(-3.8, 0.4)$

## Hypothetical Scenarios

Suppose both bounds are positive:

$$\mu_{\text{early}} - \mu_{\text{late}} \implies \text{CI: } (0.4, 3.8)$$

Only possibility:  $\mu_{\text{early}} > \mu_{\text{late}}$

We are 95% confident in our estimate that, on average (in the population), early eaters consume between 0.4 grams more and 3.8 grams more than late eaters

Suppose both bounds are negative:

....

insert chart from picture

### NOTE:

We can always always perform hypothesis testing by constructing a confidence interval with confidence level

$$C = 1 - \alpha$$

and seeing if the null value is in the confidence interval!

Prefer confidence interval over hypothesis testing:

- Additional information!
- Confidence interval screws up in the interpretation are much less costly than hypothesis testing screws ups.

Generally only use hypothesis for Fisher-type tests ( $\chi^2$ , ANOVA)

$$H_0: \mu_1 = \mu_2 = \mu_3$$

Reject  $H_0$ : at least 1  $\mu$  is different.

→ *Estimate*:

- $\mu_1 - \mu_2$
- $\mu_1 - \mu_3$
- $\mu_2 - \mu_3$

Knowing at least one of the differences exists.

# Distributions We Should Know

- Binomial:  $B(n, P)$ 
  - n = sample size
  - p = probability of success
  - going to be on the exam NO  
`pbinom()`  
`qbinom()`
- $\chi^2$ :  $\chi^2(df)$ 
  - df = k - 1 or  $(r - 1)(c - 1)$
  - going to be one the exam NO  
`pchisq()`  
`qchisq()`
- $\square$  Uniform:  $U(a, b)$ 
  - a = min
  - b = max
  - going to be one the exam YES
  - seen in Lecture 13 (ONLY for continuous random variable)  
`punif()`  
`qunif()`

---
- Normal:  $N(\mu, \sigma)$ 
  - $\mu$  = population mean
  - $\sigma$  = population standard deviation
  - going to be one the exam YES
  - Lecture 13 (continuous random variable) and Lecture 15 (sampling distribution of  $\bar{x}$ )  
`pnorm()`  
`qnorm()`
- t:  $t(df)$ 
  - df = n - 1 or computed via software
  - going to be one the exam YES

---

## Things that can be asked

- Boxplots
- Histograms
- Mean Inference → One and Two Populations
  - t-Test  
`t.test()`
    - Power Analysis  
`power.t.test()`
    - ANOVA & Post-Hoc  
`aov()`  
`TukeyHSD()`