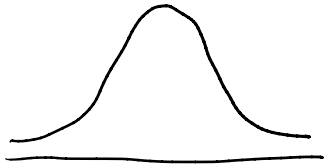
Lab #3

Cindy J. Pang

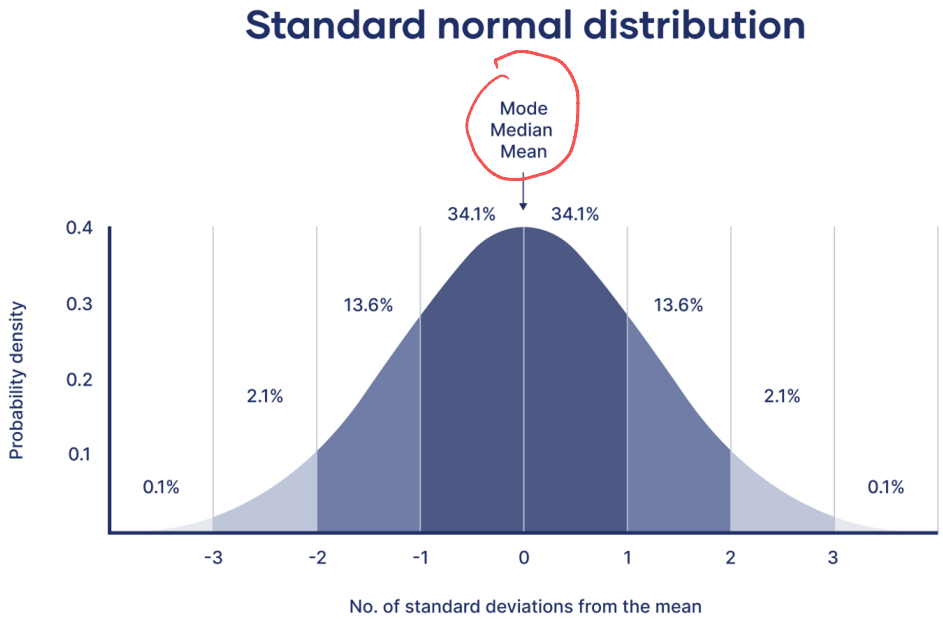
Lab 1B, MWF 12:00-12:50pm

Week 2 – August 14, 2024



1. Power Transformations and Assessing Normality

Normality



Usually, normally distributed data is the most ideal, It is well-understood and has many benefits:

- Easy to understand: mean as a central tendency and sd as a variance parameter
- Can be directly compared with other data
- Meet the assumptions of many statistical analysis.
- ….

Goal of a Power Transformation: To make skewed or non-normal data look normal.

But in many cases, our data is far from a normal distribution…

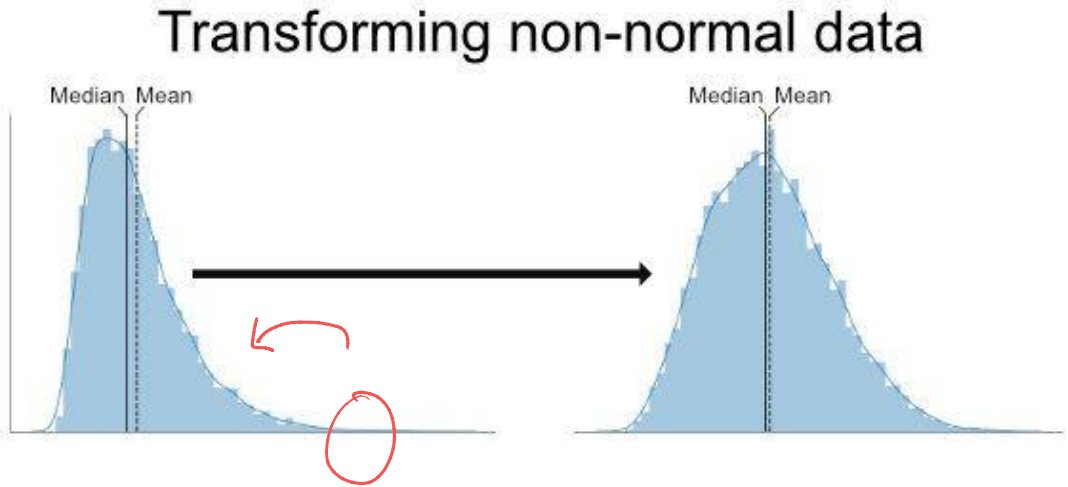
Slides Courtesy of Qingyuan Liu

Power Transformation

Data transformation can transform non-normal data to approximately normal distribution. Common transformations include the **logarithm, square root, and square**

Log-transformation Example:

- Log Transformation is usually used when the data is **positively skewed**, where data in the long tail is far away from the center
- Applying a logarithmic transformation compresses the range by **pulling in the extreme values more than the lower values,** which makes it more symmetric.



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Caution: Zero Values in Power Transformation

log(0) = VND

=LN(D36)

C	D	E	F	G	
UARE	ORIGINAL	SQUARE ROOT	LOGS	RECIPROCAL ROOT	RE
324	18	4.242640687	2.890372	0.23570226	0
289	17	4.123105626	2.833213	0.242535625	0
196	14	3.741657387	2.639057	0.267261242	0
441	21	4.582575695	3.044522	0.21821789	0
441	21	4.582575695	3.044522	0.21821789	0
441	21	4.582575695	3.044522	0.21821789	0
0	0	0	=LN(D36)	#DIV/0!	
196	14	3.741657387	2.639057	0.267261242	0
841	29	5.385164807	3.367296	0.185695338	0

- Many power transformation, such as log, is not applicable if the data contains 0's!
- It is important to check your original and transformed data to make sure there is no error produced

Log(0) = UNDEFINED
1/0 = UNDEFINED

CUBE	SQUARE	ORIGINAL	SQUARE ROOT	LOGS	RECIPROCAL ROOT	RECIPROCAL	RECIPROCAL SQUARE	RECIPROCAL CUBE
5832	324	18	4.242640687	2.890372	0.23570226	0.055555556	0.00308642	0.000171468
4913	289	17	4.123105626	2.833213	0.242535625	0.058823529	0.003460208	0.000203542
2744	196	14	3.741657387	2.639057	0.267261242	0.071428571	0.005102041	0.000364431
9261	441	21	4.582575695	3.044522	0.21821789	0.047619048	0.002267574	0.00010798
9261	441	21	4.582575695	3.044522	0.21821789	0.047619048	0.002267574	0.00010798
9261	441	21	4.582575695	3.044522	0.21821789	0.047619048	0.002267574	0.00010798
0	0	0	0	#NUM!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!
2744	196	14	3.741657387	2.639057	0.267261242	0.071428571	0.005102041	0.000364431
24389	841	29	5.385164807	3.367296	0.185695338	0.034482759	0.001189061	4.10021E-05
24389	841	29	5.385164807	3.367296	0.185695338	0.034482759	0.001189061	4.10021E-05

Slides Courtesy of Qingyuan Liu

Solutions for error messages in transformed data

- One way to omit the error: **IF()** combined with **ISNUMBER()** inside summary functions

  =SUM(IF(ISNUMBER(A1:A10), A1:A10))

  =PERCENTILE(IF(ISNUMBER(A1:A10), A1:A10), 0.25)

-In this case, IF() **evaluates whether the value is a valid number** for each value one by one, return True or False

-If True, this data is included, if false, it is not. The error message “#NUM!” is not a valid number, thus it will not be included in the summary functions

- For average(), you can also use **AVERAGEIFS()** instead:

  =AVERAGEIFS(A1:A10, "<>#DIV/0!")

Slides Courtesy of Qingyuan Liu

check for normality by inspection

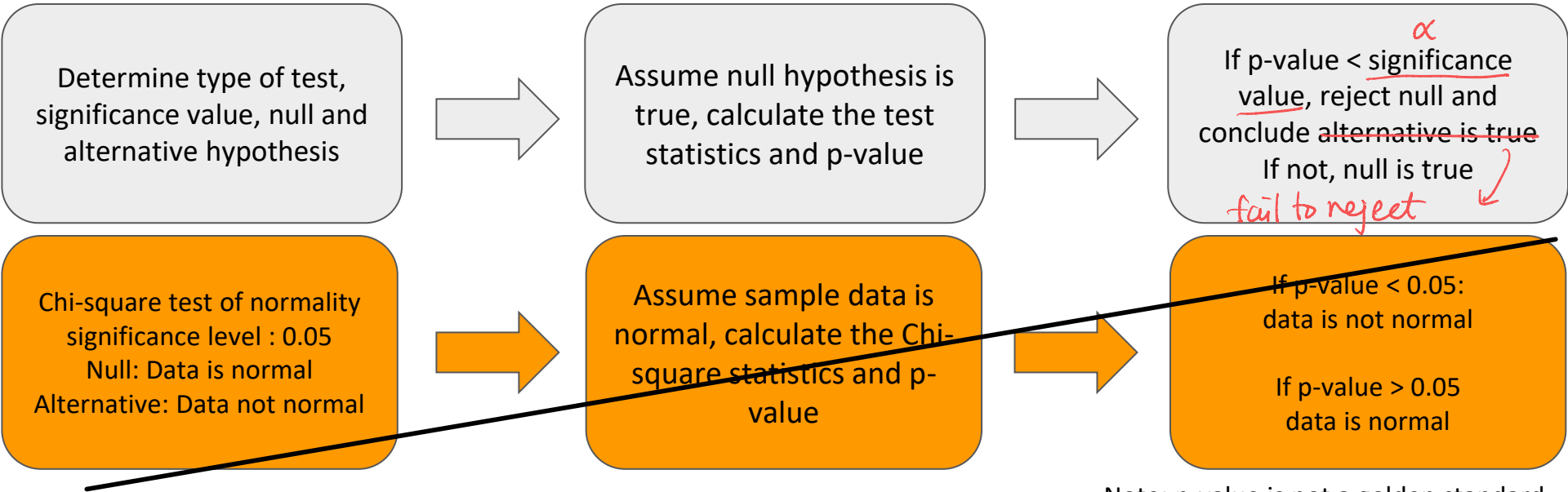
Normality Test - Hypothesis Testing

The mechanism of normality test is beyond the scope, this diagram is just a simple illustration of a general hypothesis testing, you will learn more in the later lectures.

$p < \alpha \Rightarrow$ reject H_0

$p > \alpha \Rightarrow$ fail to reject

IMPORTANT: HOW TO INTERPRET P-VALUE



Note: p-value is not a golden standard, the test result could be misleading

Slides Courtesy of Qingyuan Liu

Competency

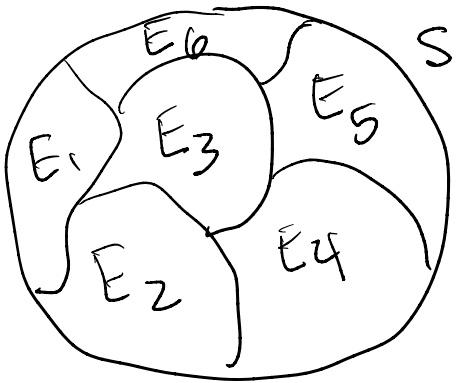
2. Union and Intersection

Recall: Axioms of Probability

Let E = event, $P(\cdot)$ = "Probability of $\cdot$"

- 1. $0 \leq P(E) \leq 1$

- 2. $E_1, E_2, \ldots, E_N$ are all possible events from a given statistical experiment, then $P(E_1) + \ldots + P(E_N) = 1$ ← all probabilities add to 1



$$P(S) = P(E_1 + E_2 + \ldots + E_N)$$
$$= P(E_1) + \ldots + P(E_N)$$
$$= 1$$

"or" "and"

Union (∪) vs. Intersection (∩)

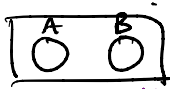
$P(A \cup B) = A \text{ or } B$

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

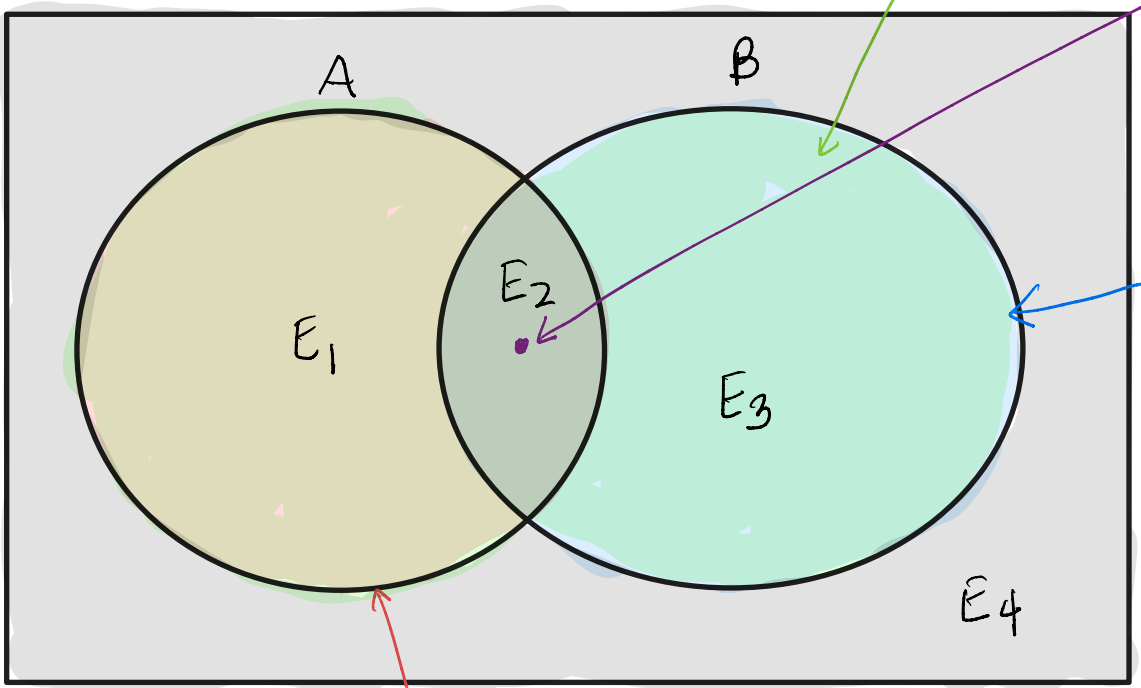
$P(A \cap B) = P(A \text{ and } B)$

where "∩" means "and" or "intersection."

if $P(A \cap B) = \emptyset$ they never intersect!



call that "mutually exclusive"



$P(B)$

$P(A)$

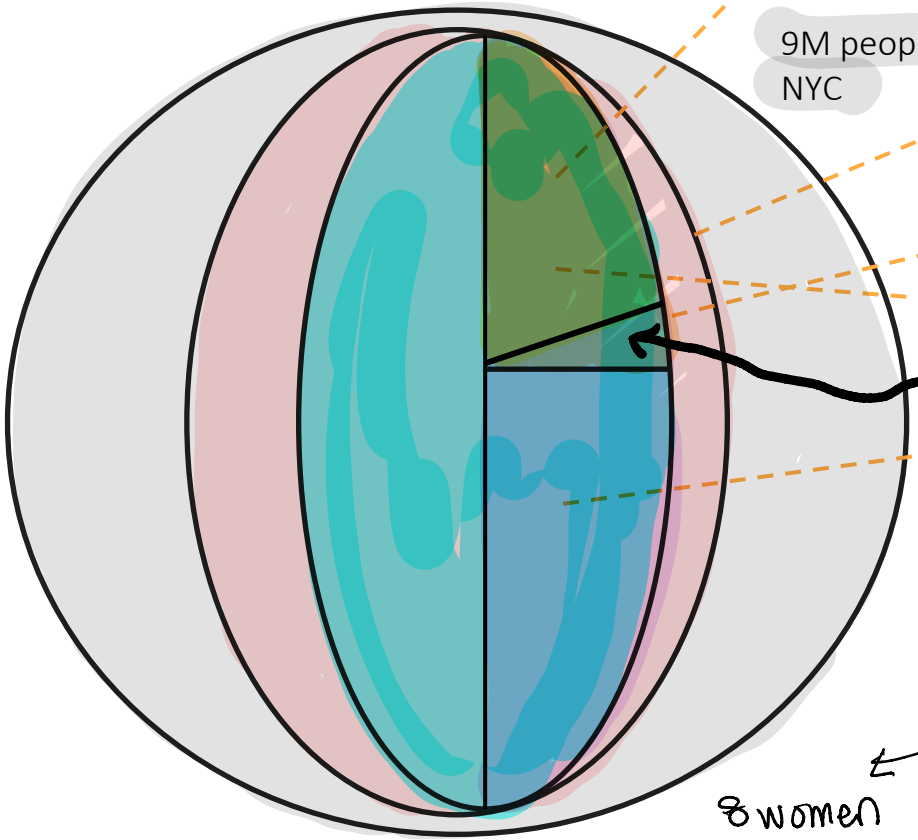
$1 - P(A \cup B)$?

$= 1 - [E_1 + E_2 + E_3]$

$= E_4$

Example: Ted Mosby

Personal Qualities ⊆ Not in relationships ⊆ Women ⊆ NYC



Personal Qualities

9M people in NYC

4.5 M women

482k +/- 5 years

8 women

Ex-girlfriends and relatives, lesbians

Not in relationships

What is the **Union** of what Ted is looking for?

NYC people

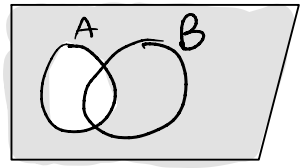
What is the **Intersection** of what Ted is looking for?

NYC + Woman + Age Range + Not Relationship + Personal Qualities + Available

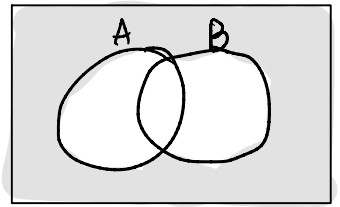
8 women

Complements

- Denoted like E^c or A^c with the "c" subscript. When you see the "c" you can read it like "not E" or "not A"
- Other ways you may see this notation: $\bar{E}$, $\neg E$ (common in math)
  - They all mean the same thing (not E)
- Examples:
  - A^c



  - $(A \cup B)^c$



Competency Assessment (part A)

The □'s are ∩ "intersections"

So you need to label areas

1. $A \cap B$
2. $A \cap B^c$
3. $A^c \cap B$
4. $A^c \cap B^c$