Week 4 Video Lecture Notes

A. Learning Outcomes and Key Terms - for categorical data analysis

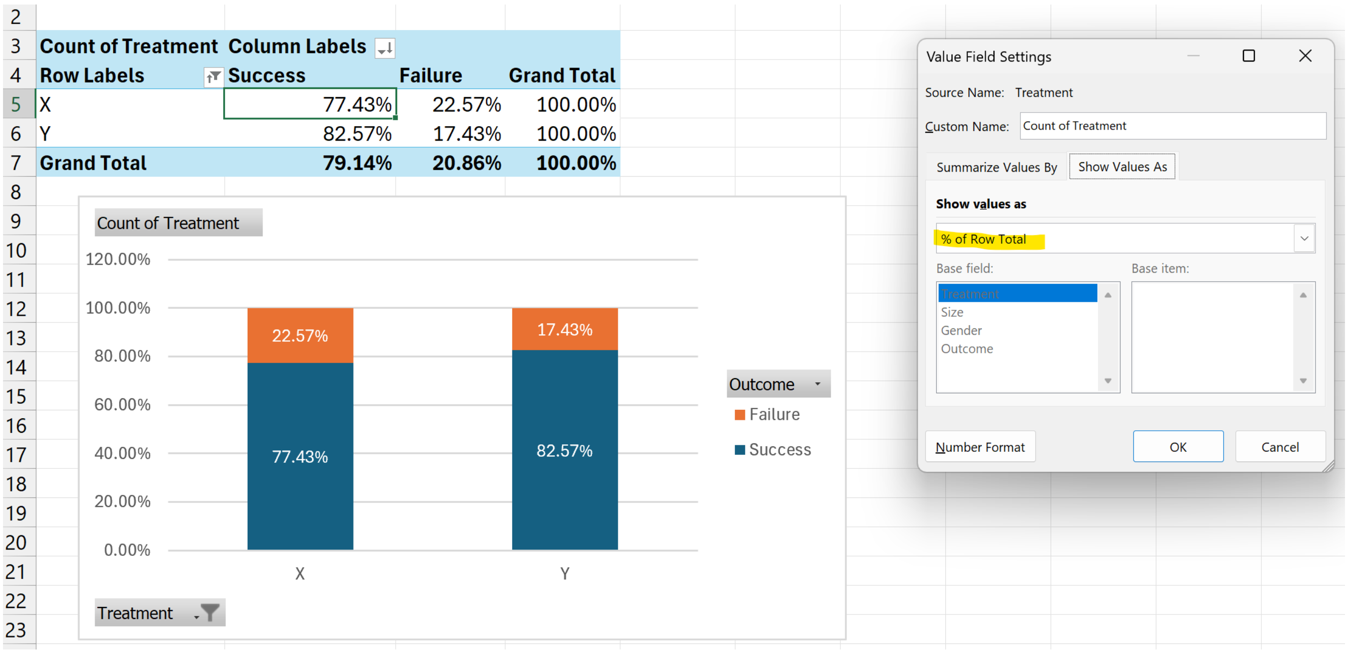
- Simpson's paradox
- define and identify potential confounding variables in studies

Recap
Gone through *a few cycles* of the PPDAC

- Are the treatments helping? *Yes, as there is a high success rate in general.*
- Which treatment is better? *Treatment Y is positively associated with success* (i.e. Treatment Y is better than Treatment X)
- Anything else? $\implies$ Should we continue sending patients to get Treatment Y in this case?
  - few more variables like gender and kidney stone size were ignored in this case

Should ask oneself of the type on visualizations to do.

- Binary Categorical + Association $\implies$ use stacked bar plots (i.e. PivotChart feature on excel)



B. Simpson's Paradox

> *def:* The phenomenon when a trend appears in the **majority** of several groups of data, but disappears or reverses when the groups are combined

- the two variables in the study of question are no longer associated (i.e. $rate\,(A|B) = rate\,(A|NB)$)
- when you aggregate all the results, the trend says one thing; whereas when we subdivide the results into sub-groups, the trend says something very different.

When exploring a particular (usually dependent) variable, we use *(a) simple plots* and *(b) summary stats* to discover interesting trends.

1. Identification

- not considering other (categorical) variables that may affect conclusion
  - Examples

- for **large stones**, `rate(Success | X) > rate(Success | Y)` (i.e. `rate(A | B) > rate(A | NB)`) $\implies \therefore$ for large kidney stones, treatment X is much better
- in every single age bucket, being in Italy means a higher chance of survival from COVID than in China, yet overall it is the opposite (i.e. being in China means one has a higher chance of survival than Italy) -- because there are much more older people who have gotten COVID as compared with China

Use of a sliced bar graph to compare three categorical variables and determine association `rate(A | B) = rate(A | NB)` ???

Causes of the paradox

- the sample size for one particular group is very different as compared to another.

Able to conclude that we should give treatment X in all cases since we have found out that it has a positive association with success for both big and small stones (regardless of stone size).

2. Analyzing Simpson's Paradox using Slicing

- allows us to take into account a third or fourth variable
    - Treatment X has been used predominantly to treat large kidney stones, with a lower success rate because they are harder to treat, thus making it seem like it performs worse than Treatment Y.
    - Treatment Y has been used to treat **more patients** with small stones, thus yielding a higher rate of success for this category

Example 2.4.4 (Analysing 3 categorical variables using a table.) Let us put the two tables in Example 2.4.2 for both the large and small kidney stones together into one unified table.

	Large stones			Small stones			Total (Large+Small)		
	Succ.	Total trt.	R(succ.) in %	Succ.	Total trt.	R(succ.) in %	Succ.	Total trt.	R(succ.) in %
X	381	**526**	**72.4%**	161	**174**	**92.5%**	542	700	77.4%
Y	55	80	68.8%	234	270	86.7%	289	350	**82.6%**

- after identifying Simpson's paradox $\implies$ this implies that there is definitely a confounding variable associated with the other two variables under investigation.

C. Confounders

> *def:* A confounding variable (or **confounder**) is a variable that is **associated to both the two other variables** that we are investigating.

- as long the variable(s) is associated in some way to the main variables under investigation, we call these confounders
- cases of wasting time by filling in surveys with background questions (age, gender etc.)
    - researchers might not be sure if they can determine if a variable is a confounder or not
    - by collecting more info or other variables, the researchers can associate variables and determine if there might be presence of confounders
- use the symmetry rule or graphical comparison to show association between confounder and dependent/independent variable

Controlling confounders

1. Use of **slicing** to control confounders
2. Collection of *more* background data / variables that might be confounders (not entirely feasible and costly)
    1. Require researchers to collect info beyond research questions
3. **Randomized assignment** (proportional allocation based on other variables)

1. might be difficult and unethical to force patients on undergoing specific treatment type $\implies$ observational study

Cons of Non-randomized studies

1. Unsure if all confounders are controlled
2. Limited conclusion
3. Evidence of association, *but not* causation.