COGS138: Neural Data Science

Lecture 9

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http://casimpkinsjr.radiantdolphinpress.com/pages/cogs138_sp23

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(Based on a course created by Prof. Bradley Voytek)

Plan for today

- Announcements
- Assignment 2 overview due tonight at midnight!
- Review Last time
- More on Data, Visualization, and outlier detection
- Statistical data analysis, Part 1
- Group projects introduction

Announcements

- A2 due **Friday 5/5**
- Reading 2 Released on canvas and in web site password protected area soon, lecture quiz due next Tuesday 5/9 R2 quiz
- Group formation check canvas for empty groups, please self-sign up
- Previous project review released when we get the groups together (this week)
- Podcasts added to webpage along with several links to readings

Last time

Course links

Website	http://casimpkinsjr.radiantdolphinpress.com/pages/ cogs138_sp23	Main face of the course and everything will be linked from here. Lectures, Readings, Handouts, Files, links
GitHub	https://github.com/drsimpkins-teaching	files/data, additional materials & final projects
datahub	https://datahub.ucsd.edu	assignment submission
Piazza	https://piazza.com/ucsd/spring2023/ cogs138_sp23_a00/home (course code on canvas home page)	questions, discussion, and regrade requests
Canvas	https://canvas.ucsd.edu/courses/44897	grades, lecture videos
Anonymous Feedback	Will be able to submit via google form	If I ever offend you, use an example you are uncomfortable with, or to provide general feedback. Please remain constructive and polite

A quick overview of one possible data cleaning process example

- 1. View your data (EDA) commands ('print()', 'dataFrame.head()', 'dataFrame.shape')
- 2. Compute the missing proportions of data (NANs etc)
- 3. View each column data type, format, content
- 4. Check for trailing white spaces in text, eliminate characters that are irrelevant (punctuation, symbols, etc)
- 5. Explore if any columns need to be split or combined
- 6.Check uniqueness of values (sanity check)

Visualization of neural data

- https://mne.tools/stable/auto_tutorials/evoked/
 20_visualize_evoked.html
- https://mne.tools/stable/auto_tutorials/inverse/
 70_eeg_mri_coords.html#sphx-glr-auto-tutorials-inverse-70-eeg-mri-coords-py

To the notebook overview

Visualization

Tools:

- seaborn generating plots
- pandas wrangling data
- matplotlib fine-tuning plots

Plotting

- quantitative data
- categorical data
- Customizing visualizations

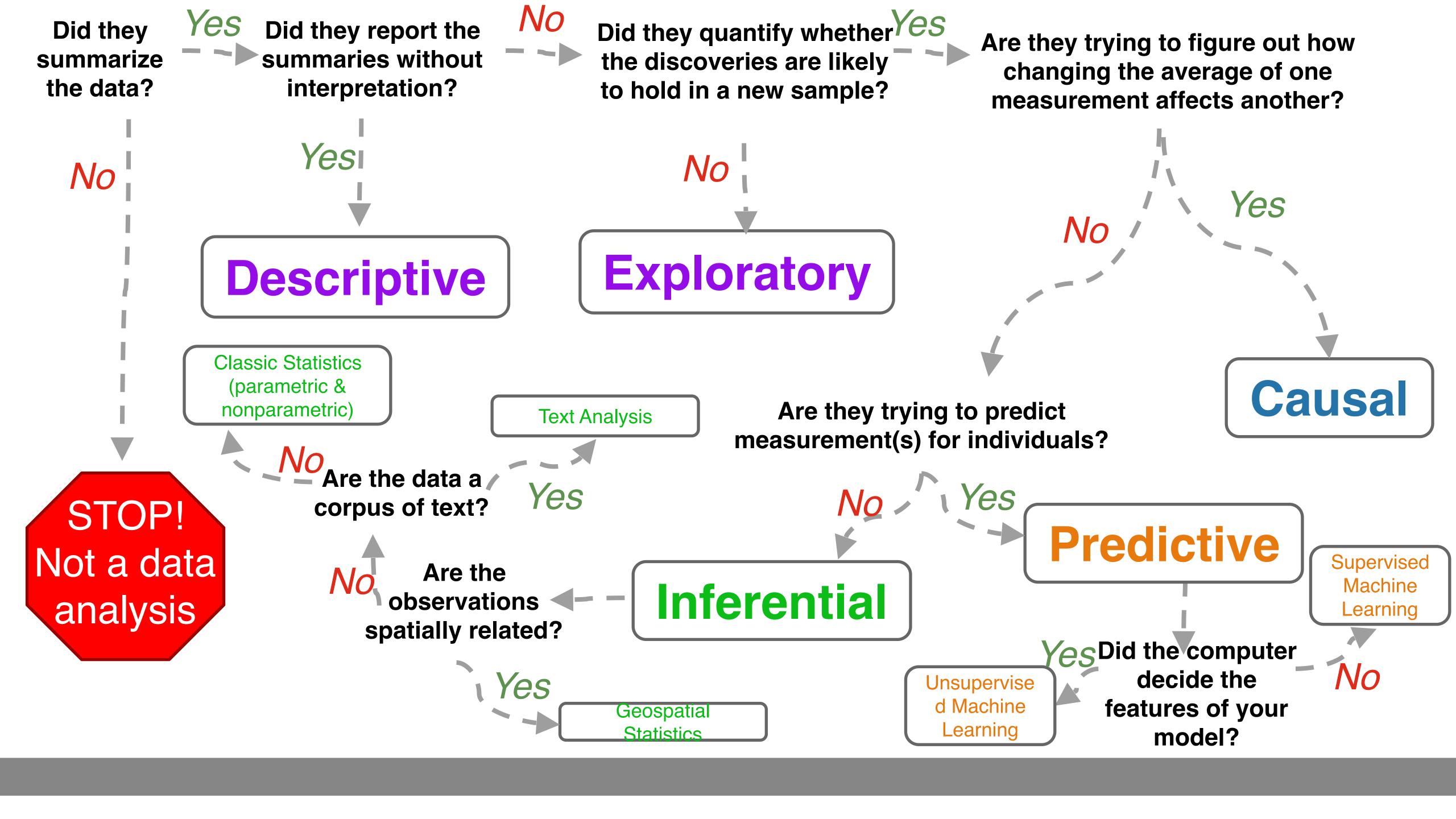
On to today...

"Data science is the process of formulating a quantitative question that can be answered with data, collecting and cleaning the data, analyzing the data, and communicating the answer to the question to a relevant audience."

To do this, you have to look at, describe, and explore the data

Summary: Analytical Approaches

- 1. Descriptive (and Exploratory) Data Analysis are the first step(s)
- 2. Inference establishes relationships
 - a. Classic Statistics
 - b. Geospatial Analysis
 - c. Text Analysis
- 3. Machine Learning is for prediction
 - a. Supervised
 - b. Unsupervised
- 4. Experiments best way to establish the likelihood of causality
 - a. Remember you *cannot* establish causality with computational methods only correlations along with statistical beliefs



Statistical Data Analysis

- There are various definitions
- "Statistics" the science of gathering data and discovering patterns
- "the science that deals with the collection, classification, analysis, and interpretation of numerical facts or data" [dictionary.com]

What are the 2 types of statistics?

What are the 2 types of statistics?

- **Descriptive** Summarizing the characteristics of data
- Inferential Modeling, making 'inferences' from data

Descriptive statistics

- Summarizing the characteristics of data
 - Central tendency ("center") mean, median, mode
 - Variability ("dispersion") variance, standard deviation
 - Frequency distribution ("occurrence within data") counts
- Charts, plots, probability distribution shapes

Inferential statistics

- "Modeling" or making 'inferences' from the data
- Taking data from samples and making predictions about populations
- 2 types
 - Estimating parameters
 - Hypothesis tests

Estimating parameters

Parametric data (data consisting of parameters)

Hypothesis testing

• Non-parametric data (no parameters)

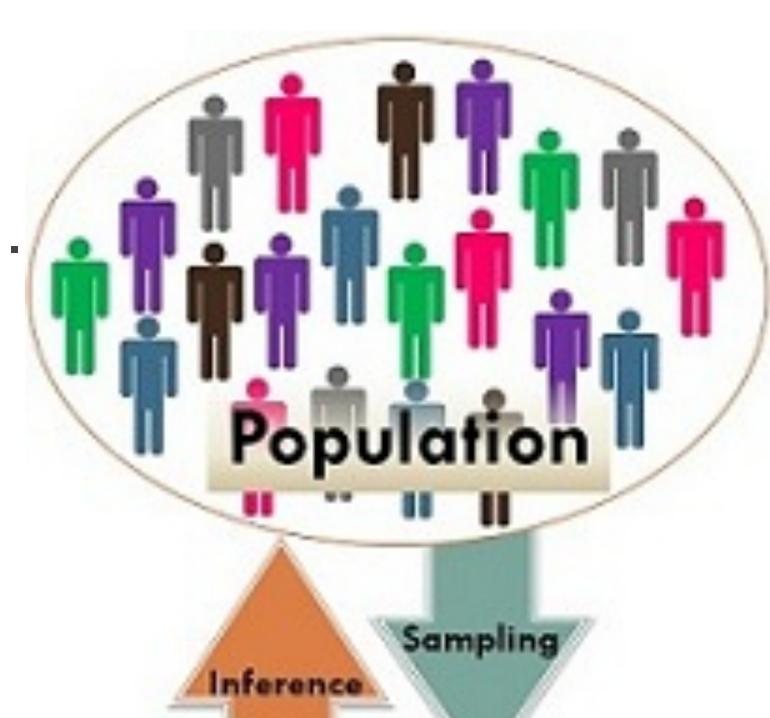
Statistic

"A quantity computed from a sample"

Source: dictionary.com

Populations & Samples

We want to learn something about this...



Sample

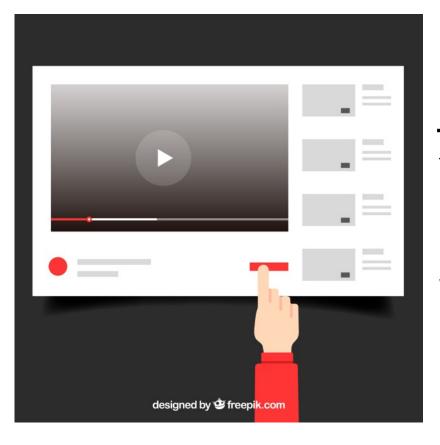
Our <u>population</u>: *all*Neurons in the motor cortex

Our <u>sample</u>: LFP ~ 1-10k neurons

....but we can only actually collect data from this

statistic

"A quantity computed from a sample"



For our YouTube analysis, we could take a random sample of comments from YouTube and calculate the following statistic: the number of positive and the number of negative words in each review.

Source: dictionary.com

Best sampling practices:

- Always think about what your population is
- Collect data from a sample that is representative of your population
- If you have no choice but to work with a dataset that is not collected randomly and is biased, be careful not to generalize your results to the entire population



You'd want to be sure you sample randomly across *all* YouTube comments, making sure not to get more comments from one genre over another, or one location over another, etc.

Examples of bad sampling:

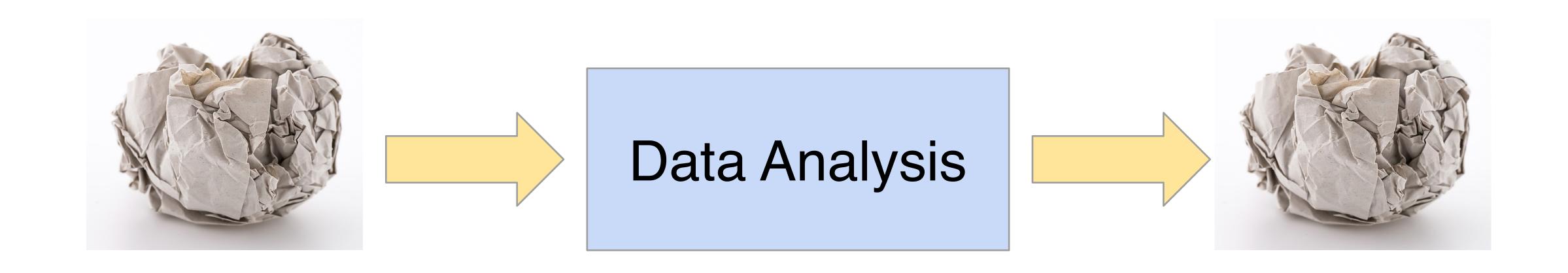
- Surveying subscribers of a Marvel movie magazine for research on Americans' attitudes toward DC movies
- Randomly sampling Facebook users for what TV shows people like



To understand *all* YouTube comments, you wouldn't just want to sample from one YouTube channel, or videos in a single language.

It's *always* worth spending time at the <u>beginning</u> of a project to determine whether or not the data you have are garbage. Be certain they are actually able to help you answer the question you're interested in.

GIGO: Garbage In. Garbage Out.





For survey data I collect from you all, which of the following best describes the population I could generalize findings back to.

A Undergraduates

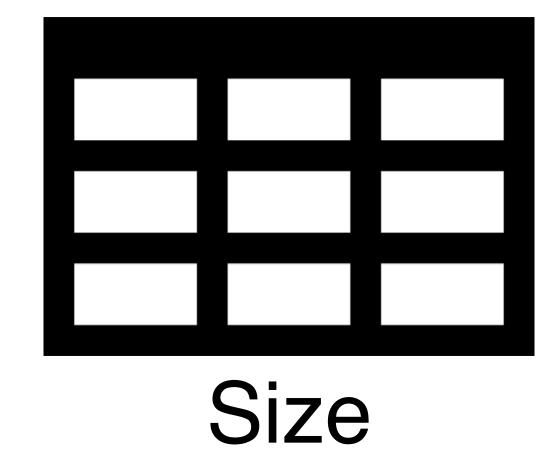
B Undergraduates in the US

C Undergraduates at UCSD

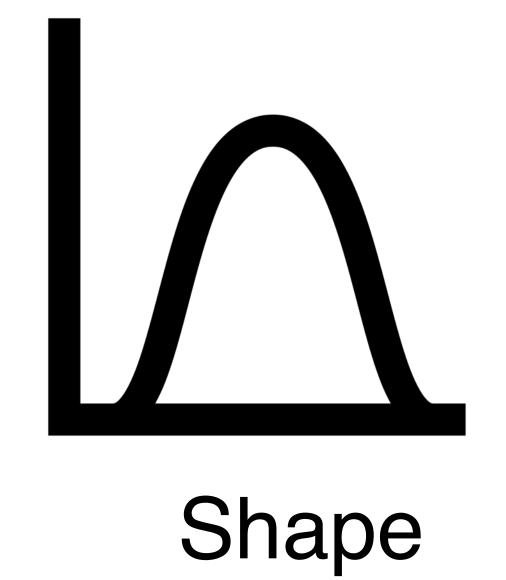
D Students aged 18-25

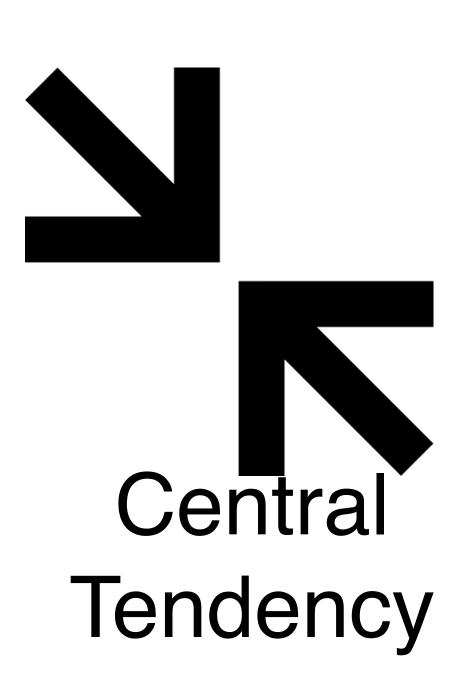
E UCSD COGS138 students

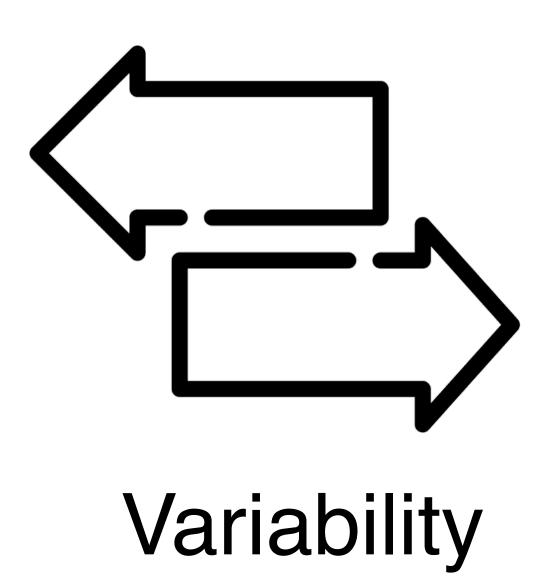
Descriptive Analysis



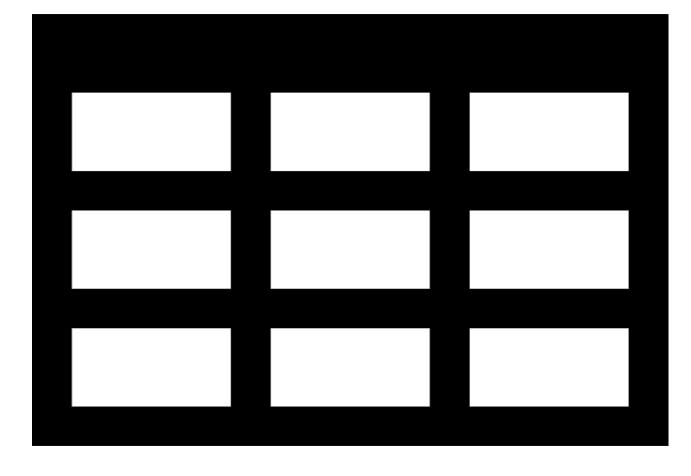












Size

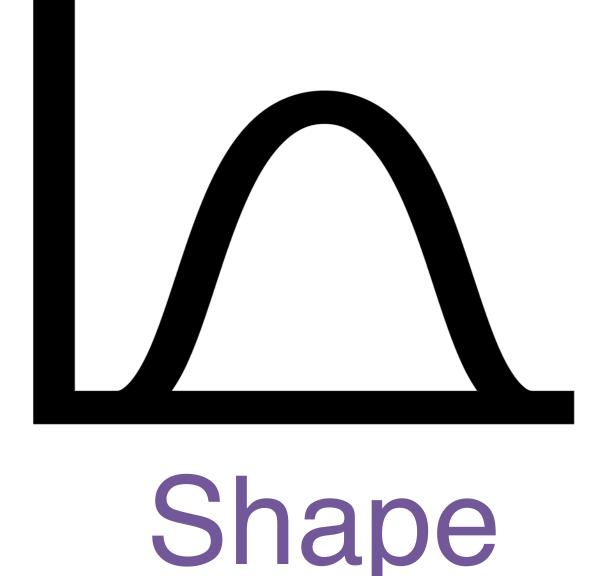
How many <u>observations</u> (rows) and <u>variables</u> (columns) you have is an important first step. You should always be aware of the size of your dataset.





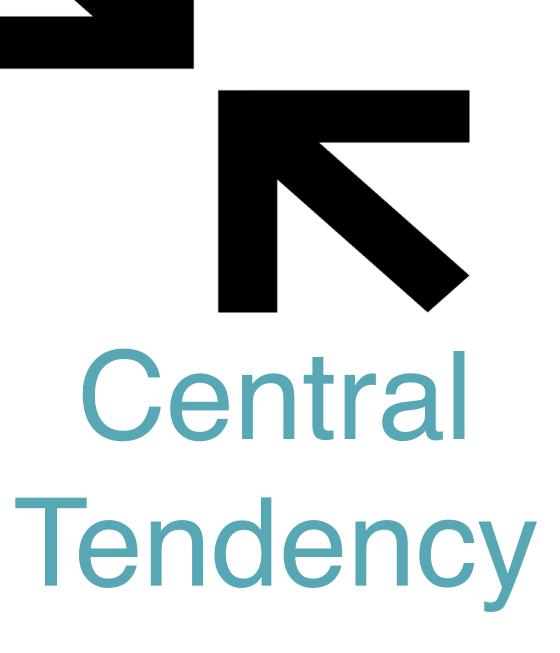
It's critical to know how many observations have missing data for variables of interest in your data. Knowing *why* their missing is also important.





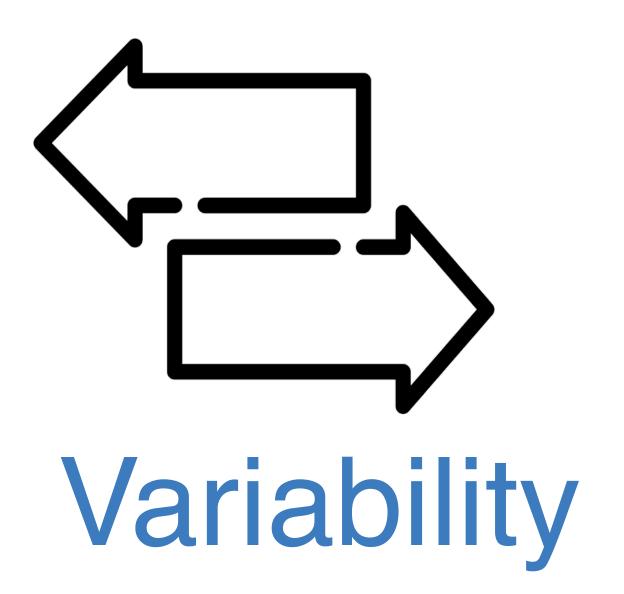
It's critical to know the distribution of the variables in your dataset. Certain statistical approaches can only be used with certain distributions.

Descriptive



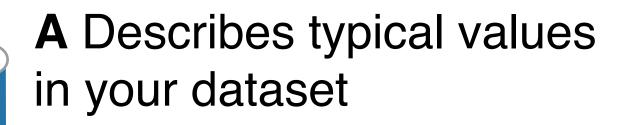
Knowing the mean, median, and/or mode can help you get an idea of what a typical value is for your variable(s) of interest





The central tendency tells you part of the story. The variability in the values in your observation helps fill in the rest.

Which of the following is NOT something accomplished by a descriptive analysis?





B Determines the size of your dataset

C Establishes causal relationships between variables

D Identifies missing data

E Determines how variable values in your dataset are

Descriptive Statistics & Summary

- •We look for the summary, the relevant features of the data to the study
- ·Use statistics to express them

Descriptive Analyses are often included as "Table 1" in academic * Plus-minus values are means ±SD. † Race was self-reported. † Total thickness at the fovea includes

Characteristic	Ranibizumab Monthly (N=301)	Bevacizumab Monthly (N = 286)	Ranibizumab as Needed (N=298)	Bevacizumal as Needed (N=300)
Age — no. (%)	(11-302)	(11-200)	(11-250)	(11-200)
50–59 yr	2 (0.7)	1 (0.3)	6 (2.0)	2 (0.7)
60–69 yr	33 (11.0)	28 (9.8)	31 (10.4)	34 (11.3)
70–79 yr	102 (33.9)	84 (29.4)	115 (38.6)	103 (34.3)
80–89 yr	142 (47.2)	150 (52.4)	126 (42.3)	142 (47.3)
≥90 yr	22 (7.3)	23 (8.0)	20 (6.7)	19 (6.3)
Mean — yr	79.2±7.4	80.1±7.3	78.4±7.8	79.3±7.6
Sex — no. (%)				
Female	183 (60.8)	180 (62.9)	185 (62.1)	184 (61.3)
Male	118 (39.2)	106 (37.1)	113 (37.9)	116 (38.7)
Race — no. (%)†	()	()	()	
White	297 (98.7)	281 (98.3)	296 (99.3)	294 (98.0)
Other	4 (1.3)	5 (1.7)	2 (0.7)	6 (2.0)
History of myocardial infarction — no. (%)	34 (11.3)	40 (14.0)	30 (10.1)	36 (12.0)
History of stroke — no. (%)	14 (4.7)	18 (6.3)	22 (7.4)	16 (5.3)
History of transient ischemic attack — no. (%)	12 (4.0)	25 (8.7)	12 (4.0)	19 (6.3)
Blood pressure — mm Hg		, ,		
Systolic	134±18	135±19	136±17	135±17
Diastolic	75±10	75±10	76±9	75±10
Visual-acuity score and Snellen equivalent				
68–82 letters, 20/25–40 — no. (%)	111 (36.9)	94 (32.9)	116 (38.9)	103 (34.3)
53–67 letters, 20/50–80 — no. (%)	98 (32.6)	118 (41.3)	108 (36.2)	119 (39.7)
38–52 letters, 20/100–160 — no. (%)	67 (22.3)	53 (18.5)	58 (19.5)	58 (19.3)
23–37 letters, 20/200–320 — no. (%)	25 (8.3)	21 (7.3)	16 (5.4)	20 (6.7)
Mean score	60.1±14.3	60.2±13.1	61.5±13.2	60.4±13.4
Total thickness at fovea — μ m‡	458±184	463±196	458±193	461±175
Retinal thickness plus subfoveal-fluid thickness at fovea — μ m	251±122	254±121	247±122	252±115
Foveal center involvement — no. (%)				
Choroidal neovascularization	176 (58.5)	153 (53.5)	176 (59.1)	183 (61.0)
Fluid	85 (28.2)	81 (28.3)	77 (25.8)	72 (24.0)
Hemorrhage	20 (6.6)	24 (8.4)	24 (8.1)	25 (8.3)
Other	18 (6.0)	20 (7.0)	15 (5.0)	18 (6.0)
No choroidal neovascularization or not possible to grade	2 (0.7)	8 (2.8)	6 (2.0)	2 (0.7)

Descriptive

[†] Total thickness at the fovea includes the retina, subretinal fluid, choroidal neovascularization, and retinal pigment epi-

Descriptive

170
IZU

Zooming in on
this we see
variables
stratified by
Age, Sex, and
Race

	aracteristics of the Patients.*				
Characteristic		Ranibizumab Monthly (N = 301)	Bevacizumab Monthly (N = 286)	Ranibizumab as Needed (N=298)	Bevacizumab as Needed (N=300)
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Other

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^{*} Plus-minus values are means ±SD.

[†] Race was self-reported.

[‡] Total thickness at the fovea includes the retina, subretinal fluid, choroidal neovascularization, and retinal pigment epithelial elevation.

Descriptive Statistics & Summary

Calculating descriptive statistics, understanding what they tell you about your data, and reporting them are critical steps in every analysis.

Exploratory

Exploratory: The goal is to find unknown relationships between the variables you have measured in your data set. Exploratory analysis is open ended and designed to verify expected or find unexpected relationships between measurements.

Exploratory



Exploratory Data Analysis (EDA) detective work answering the question: "What can the data tell us?"

Why EDA?

Exploratory

- Understand data properties
- Discover Patterns
- Generate & Frame Hypothesis
- Suggest modeling strategies
- Check assumptions (sanity checks)
- Communicate results (present the data)

....and if you don't, you'll regret it

Exploratory

The dataset

You





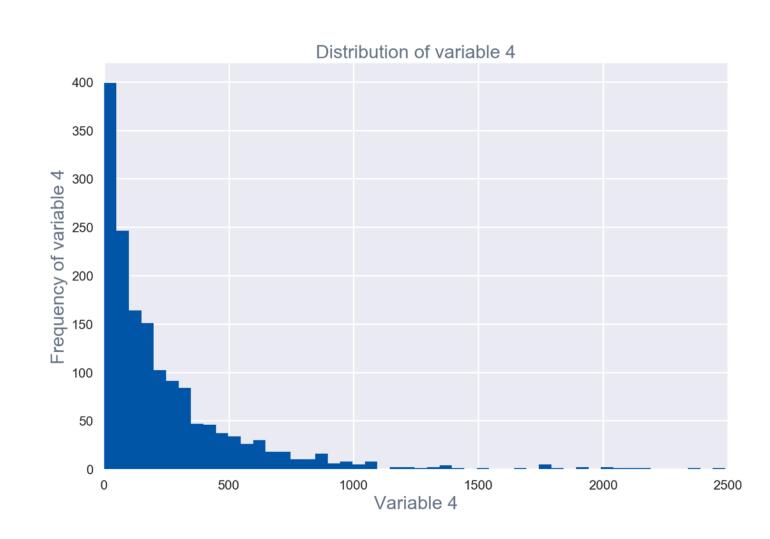
The general principles of exploratory analysis:

- Look for missing values
- Look for outlier values
- Calculate numerical summaries
- Generate plots to explore relationships
- Use tables to explore relationships
- If necessary, transform variables

EDA Approaches to "Get a Feel for the Data"

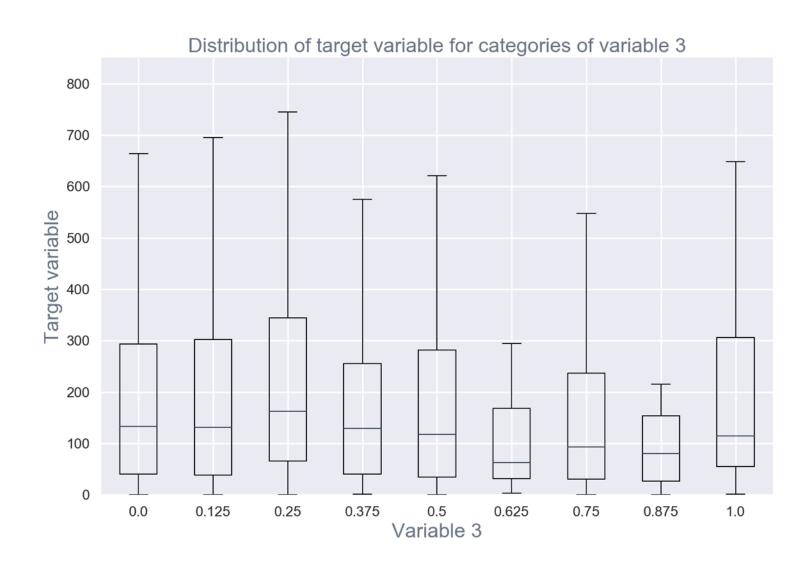
Understanding the relationship between variables in your dataset

Exploratory





understanding a single variable i.e.: histogram, densityplot, barplot



<u>Bivariate</u>

understanding relationship between 2 variables

i.e.: boxplot, scatterplot, grouped barplot, boxplot



Dimensionality Reduction

projecting high-D data into a lower-D space

i.e.: PCA, ICA, Clustering

