## CMPT 733 – Big Data Programming II

# Statistics (I)

Instructor

Course website

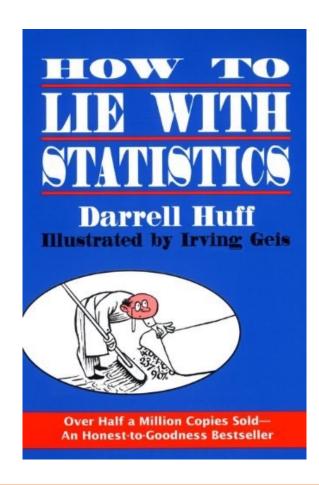
Slides by

Steven Bergner

https://sfu-db.github.io/bigdata-cmpt733/

Jiannan Wang & Steven Bergner

# Why Should You Care?



# There are three kinds of lies: lies, damned lies, and statistics

1.	The Sample with the Built-in Bias	<u>13</u>
2.	The Well-Chosen Average	29
3.	The Little Figures That Are Not There	39
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10	How to Talk Back to a Statistic	12.4

# Simpson's paradox

## Is UC Berkeley gender biased?

	Applicants	Admitted
Men	8442	44%
Women	4321	35%



# Simpson's paradox

#### Is UC Berkeley gender biased?

Donortmont	Ме	n	Wom	nen
Department	Applicants	Admitted	Applicants	Admitted
Α	825	62%	108	82%
В	560	63%	25	68%
С	325	37%	593	34%
D	417	33%	375	35%
E	191	28%	393	24%
F	373	6%	341	7%



Women tended to apply to competitive departments with low rates of admission

## **Outline**

Statistical Thinking

**Descriptive Statistics** 

Inferential Statistics

### **Outline**

#### Statistical Thinking

Descriptive Statistics

Inferential Statistics

# Statistical Thinking

1. Data is just a sample

2. You goal is to infer a population

3. Think about how to go "backwards" from the sample to the population

# **Example 1. Image Classification**

Is it a dog or a cat?



Dataset: 1000 images collected

from the Web

# Without Statistical Thinking

Treat the 1000 images as the population

- > Train a model on the data
- > Evaluate a model on the same data
- > Model accuracy: 95%

# With Statistical Thinking

#### What is the population?

All the images in the Web

#### What is your dataset?

A sample of 1000 images drawn from the Web

#### What should you do?

- Split the dataset into a training dataset and a test dataset
- Train the model on the training dataset
- Evaluate the model on the test dataset

# **Example 2. Poll Prediction**

#### Who will win the election?



Dataset: A survey of 100 people

# Without Statistical Thinking

Treat the 100 people as the population

- > Count the number of people who wants to vote for Hillary, e.g., 52
- > Count the number of people who wants to vote for Trump, e.g., 48
- > Hillary will win the election

# With Statistical Thinking

#### What is the population?

All the people who will vote in the election day

#### What is your dataset?

A sample of 1000 people before the election day

#### Analysis result

Hillary: 52% ±3%

Trump: 48% ± 2%

<u>Assumption:</u> People have not changed their votes since the time of the poll

## Summary

#### Statistical Thinking

- Sample, Population and Their Connection
- With vs. Without Statistical Thinking

Descriptive Statistics

Inferential Statistics

## **Outline**

Statistical Thinking

**Descriptive Statistics** 

Inferential Statistics

# Descriptive vs. Inferential Statistics

#### Descriptive Statistics: e.g., Median

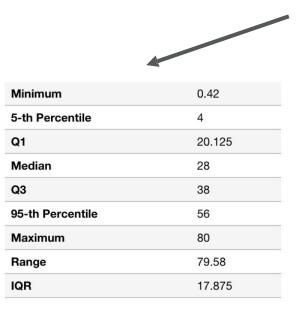
- Why? Aim to understand the data
- How? Data summarization, data visualization, etc.

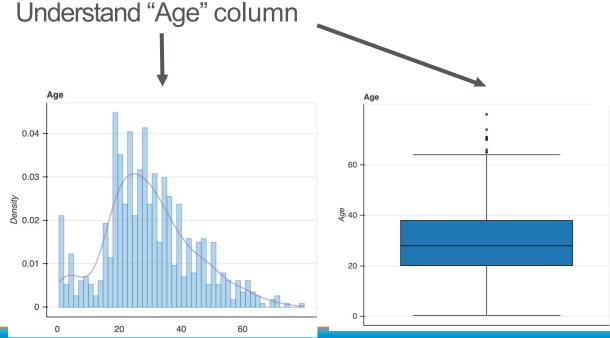
## Inferential Statistics: e.g., A/B Testing

- Why? Aim to use the data (i.e., sample) to learn about a population
- How? Estimation, confidence intervals, hypotheses testing, etc.

# Exploratory Data Analysis (EDA)

Understand data and discover insights via data visualization, data summarization, etc.

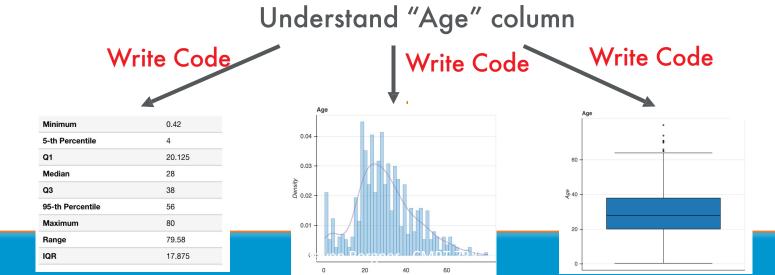




# Current EDA Solutions in Python

#### Solution 1: Pandas + Matplotlib

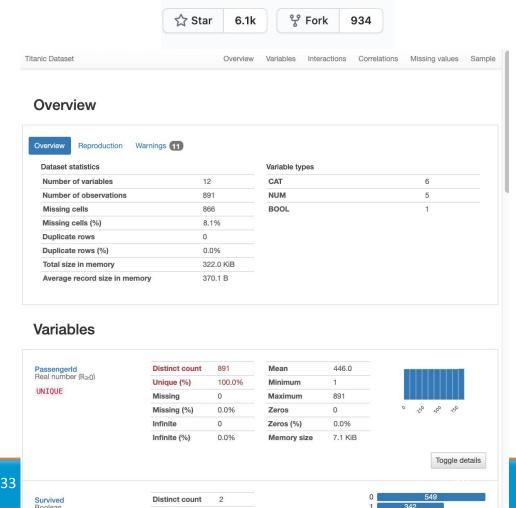
- R Hard to Use
  - <u>Beginner:</u> Need to know how to write plotting code
  - Expert: Need to write lengthy and repetitive code



# Current EDA Solutions in Python

- Solution 2: Pandas-profiling
- ® Slow
- R Hard to Customize

profile = ProfileReport(df, title="Pandas Profiling Report")



# DataPrep.EDA Design Goals

<b>EDA</b> Solutions	Easy to Use	Interactive Speed	Easy to Customize
1. Pandas + Matplotlib		( <u>(</u> )	©
2. Pandas-profiling	©		
3. DataPrep.EDA	©	0	©

# Key Idea

#### Task-Centric API Design

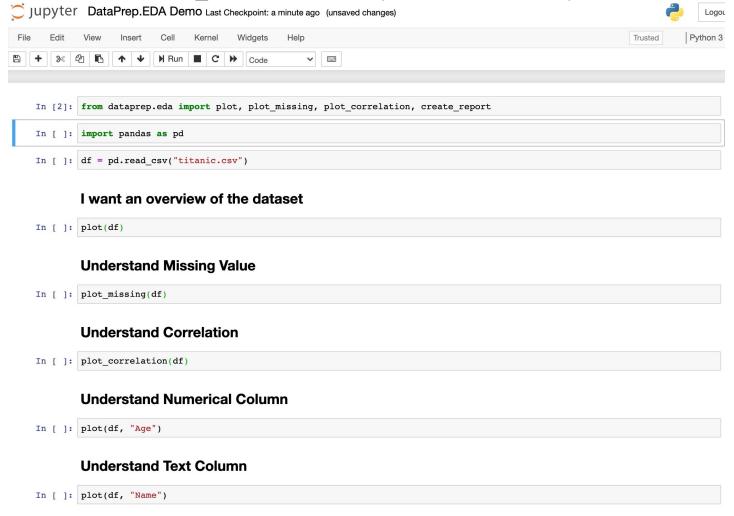
- Declarative
- Support both coarse-grained and fine-grained EDA tasks

#### Example

- plot(df): "I want to see an overview of the dataset"
- <u>plot\_missing(df)</u>: "I want to understand the missing values of the dataset"
- plot(df, x): "I want to understand the column x"
- plot(df, x, y): "I want to understand the relationship between x and y"

•

# DataPrep.EDA (Demo)



# **Correlation Analysis**

#### Correlation

It is a measure of relationship between two variables

#### Why is correlation analysis useful?

- For understanding data better
- For making predictions better

# Case Study: How to do correlation analysis

Height and weight are correlated

1	height	weight	age	male
2	151.765	47.8256065	63	1
3	139.7	36.4858065	63	0
4	136.525	31.864838	65	0
5	156.845	53.0419145	41	1
6	145.415	41.276872	51	0
7	163.83	62.992589	35	1
8	149.225	38.2434755	32	Θ

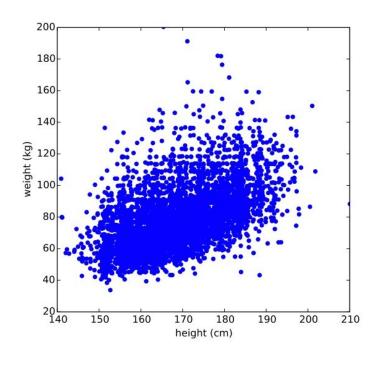
Source: Think Stats -- Exploratory Data Analysis in Python

## Idea 1. Visualization

## **Scatter Plot**

1	height	weight	age	male
2	151.765	47.8256065	63	1
3	139.7	36.4858065	63	0
4	136.525	31.864838	65	0
5	156.845	53.0419145	41	1
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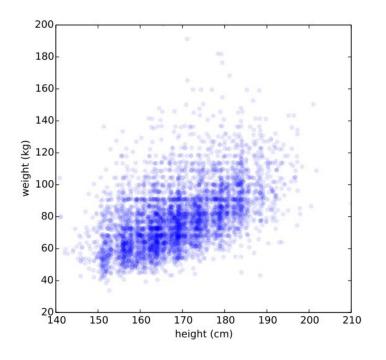




# Scatter Plot (with transparency)

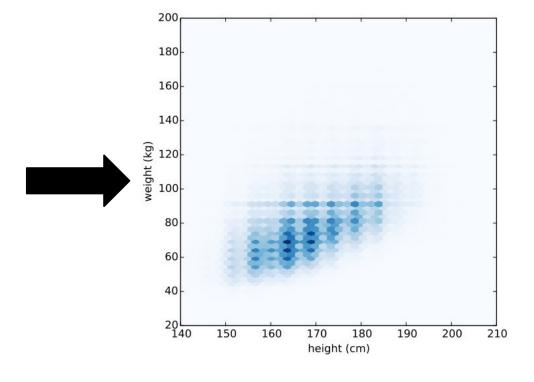
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## **Hexbin Plot**

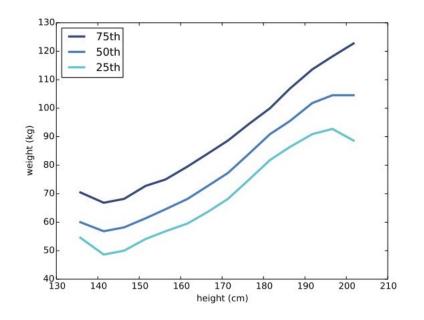
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8	149.225	38.2434755	32	0



# Characterizing relationships

1	height	weight	age	male
2	151.765	47.8256065	63	1
3	139.7	36.4858065	63	0
4	136.525	31.864838	65	0
5	156.845	53.0419145	41	1
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## Idea 2. Correlation Coefficient

#### Covariance

# Covariance is a measure of the tendency of two variables to vary together.

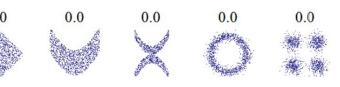
$$\operatorname{cov}(X,Y) = \operatorname{E}\left[(X - \operatorname{E}[X])(Y - \operatorname{E}[Y])\right]$$

$$cov(X,Y) = E[XY] - E[X]E[Y]$$

Hard to interpret 113 kilogram-centimeters

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## Pearson's correlation



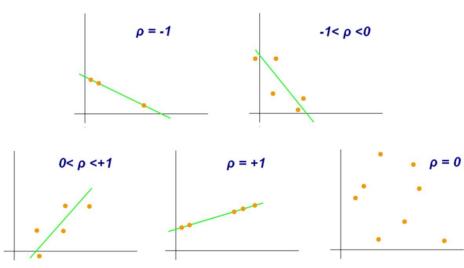
What about non-linear relationship?

# Pearson's correlation is a measure of the linear relationship between two variables

$$ho_{X,Y} = rac{\mathrm{cov}(X,Y)}{\sigma_X \sigma_Y}$$

#### Easy to Interpret

- $[-1, 0) \rightarrow \text{Negative Correlated}$
- $(0,+1] \rightarrow$  Positive Correlated
- o -1 or +1 → Perfectly Correlated



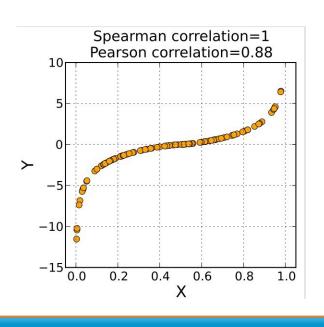
# Spearman's rank correlation

Spearman's rank correlation is a measure of monotonic relationship between two variables

$$r_s = 
ho_{\mathrm{r}_X,\mathrm{r}_Y} = rac{\mathrm{cov}(\mathrm{r}_X,\mathrm{r}_Y)}{\sigma_{\mathrm{r}_X}\sigma_{\mathrm{r}_Y}}$$

#### Advantages

- Mitigate the effect of outliers
- Mitigate the effect of skewed distributions



# Summary

#### Statistical Thinking

#### **Descriptive Statistics**

- Descriptive vs. Inferential Statistics
- Exploratory Data Analysis with DataPrep
- Correlation Analysis

Inferential Statistics

### **Outline**

Statistical Thinking

**Descriptive Statistics** 

Inferential Statistics

Estimation

# Estimation

#### Problem statement

Estimate a numerical value associated with a population

#### Examples

- Estimate the percentage of the people in the US who will vote for Biden
- Estimate the median annual income of all households in the US

# Example: Median Annual Income

How to estimate the median annual income of all households in the US?

- Randomly select 10,000 households from the US
- Report their median annual income: 50,000USD

BUT, we need to report something like

50,000 ±500 USD

#### **A Naïve Solution**

- Randomly select 10,000 households from the US
- Report their median annual income

Repeat this process for 100 times

50,000 49,600 50,200 ... 49,200

You have to survey 1,000,000 million households in total!

# A Smart Solution: Bootstrapping

Key Idea: Resampling

Sample with replacement from the original data sample

Population: 1, 1, 8, 2, ... 3, 3

Sample: 3, 8, 1, 8, 3

Resample: 8, 3, 3, 3, 1

# A Smart Solution: Bootstrapping

- Randomly select 10,000 households from the US
- Draw a resample from the 10,000 households
- Report the median annual income of the resample

Repeat this process for 100 times

You do NOT need to survey any new household. ©

# Notes on Bootstrapping

• Start with a large random sample (at least 30)

•Replicate the resampling procedure as many times as possible (more than 1000 times)

Does not work for min/max

## Conclusion

#### Statistical Thinking

- Sample, Population and Their Connection
- With vs. Without Statistical Thinking

#### **Descriptive Statistics**

- Descriptive vs. Inferential Statistics
- EDA with DataPrep.eda
- Correlation Analysis

#### Inferential Statistics

Estimation and Bootstrapping