Intro to Basic understanding of the data using Python **Credits** - Image from Internet Why Python for DA? • Python is very easy to get started. • Python is a good fit since it has all the requirements available for Data Analysis and Data Science. Get more from less. • The community of Python is so large that you can find anything easily. Note - Check google trends for comaprison. • Before clicking the below link, please sign-in your google account on web. • Link → https://trends.google.com/trends/explore?cat=1227&q=%2Fm%2F05z1_, %2Fm%2F0212jm, %2Fm%2F0j3djl7 " But when it comes to speed compatibility, Python is slower. " • Link → https://juliacomputing.com/blog/2020/06/fast-csv/ **Data Analysis vs Data Science Data** Visualization Cleaning Collection **Storage Analysis** Credits - Image from Internet **Data Analyst's role** As a Data Analyst, we often need to do the following things - Data Collection Data Cleaning · Data Organaising Data Managing · Identify the goal of the problem statement · Finding insights in order achieve the goal **Questions like -**WHY HOW WHEN **Data Scientist's role** Data Science is story telling process with the valid insights acquired from data to information. Thus helping to take decisions. • Design Data Models · Create or use Algorithms · Predict the future outcomes with accuracy · Make decisions from the conclusions More information - https://www.northeastern.edu/graduate/blog/what-does-a-data-scientist-do/ Note - Data Scientist with anlaytical skills is a Blessing upon the blessed. In []: **Practise problem** 1. Collect data from online using Pandas. 2. Check if data cleaning is necessary. - yes → Clean the data no → Proceed 3. Identify the relationship between data varaibles. Apply Correlation Plot the relationship Data Source → http://wiki.stat.ucla.edu/socr/index.php/SOCR_Data_Dinov_020108_HeightsWeights In []: 1. Collect data from online Pandas is python library mainly used for data analysis. 2. It is similar to doing analysis on Excel but just we write code here. 3. It is one of the best open source libraries avalibale for doing data manipulation and data wrangling. More information → https://pandas.pydata.org/ In [1]: import pandas as pd read html() extracts all the tables from the html page. In [2]: data_source = 'http://wiki.stat.ucla.edu/socr/index.php/SOCR_Data_Dinov_020108_HeightsWeights' data = pd.read_html(data_source) type(data) In [3]: Out[3]: list len(data) In [4]: Out[4]: 3 # data[0] In [5]: In [6]: # data[1] # data[2] In [8]: df = data[1]df.head() Out[8]: Height(Inches) Weight(Pounds) Index 0 65.78 112.99 1 2 71.52 136.49 3 69.40 153.03 68.22 142.34 3 4 67.79 144.30 In []: In []: 2. Check if data cleaning is necessary Data Cleaning is one of the important aspects in both Data Analysis and Data Science roles. It is one of the procedural steps where a data analyst or data scientist spends most of their time. More information → https://en.wikipedia.org/wiki/Data_cleansing PS: Do not data cleaning for granted. a. Check for any NaN values \rightarrow Missing values In [9]: df.isna() Out[9]: Index Height(Inches) Weight(Pounds) 0 False False False 1 False False False 2 False False False 3 False False False 4 False False False **195** False False False 196 False False False False 197 False False 198 False False False False 199 False False 200 rows × 3 columns • Since the dataset is sort of big, we cannot see all the values. Infact we cannot comprehend the actual missing values from the • In order to get the actual values (indices), the below function can be used. In [10]: # check if there is any missing data def check_for_nan(dframe): dframe → pandas data frame object returns `nan_places` a dictionary of column names and the `nan_indices` nan frame = dframe.isna() d cols = dframe.columns nan_places = {} for col in d cols: col_lvals = nan_frame[col].to_list() nan_indices = [index for index, val in enumerate(col_lvals) if val == True] if nan_indices: nan_places[col] = nan_indices else: nan_places[col] = None return nan_places In [11]: check_for_nan(dframe=df) Out[11]: {'Index': None, 'Height(Inches)': None, 'Weight(Pounds)': None} Above result is clear, every column has non-nan values. Hence we can proceed with further steps. b. Check for the datatypes from each column df.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 200 entries, 0 to 199 Data columns (total 3 columns): Column Non-Null Count Dtype 0 Index 200 non-null int64 Height(Inches) 200 non-null float64 Weight (Pounds) 200 non-null float64 dtypes: float64(2), int64(1)memory usage: 4.8 KB Seems like every column has a unique data type. If at all there is then it is required to purify the data - make sure all the values are of same type. c. Overall description of the data frame In [13]: df.describe() Out[13]: Index Height(Inches) Weight(Pounds) count 200.000000 200.000000 200.000000 mean 100.500000 67.949800 127.221950 11.960959 57.879185 1.940363 std 1.000000 63.430000 97.900000 min 50.750000 66.522500 119.895000 25% 100.500000 67.935000 127.875000 50% 136.097500 150.250000 69.202500 75% max 200.000000 73.900000 158.960000 d. Some visualization to explore more about the data We can use pandas plotting functions like plot() to explore about the data visually. • plot() can show the following plots - line → line plot (default) bar → vertical bar plot ■ **barh** → horizontal bar plot hist → histogram box → boxplot ■ **kde** → Kernel Density Estimation plot density → same as 'kde' area → area plot pie → pie plot scatter → scatter plot hexbin → hexbin plot. Ugly plot example In [14]: df.plot() Out[14]: <AxesSubplot:> 200 Index Height(Inches) 175 Weight(Pounds) 150 125 75 50 25 100 125 150 175 200 The above is the plot of all the data variables. This is not something we should do. Plotting without unimportant data variables - excluded Index In [15]: df[['Height(Inches)', 'Weight(Pounds)']].plot() Out[15]: <AxesSubplot:> 160 Height(Inches) Weight(Pounds) 140 120 100 80 60 200 The above is the plot of both Heights and Weights from the data frame df. In [16]: df.plot(x='Index', y='Height(Inches)', kind='scatter') Out[16]: <AxesSubplot:xlabel='Index', ylabel='Height(Inches)'> 74 72 66 64 125 25 50 100 150 175 200 Index The above is the scatter plot of Index and Heights data variables from the data frame df. df.plot(x='Index', y='Weight(Pounds)', kind='scatter') Out[17]: <AxesSubplot:xlabel='Index', ylabel='Weight(Pounds)'> 160 150 140 130 Weight 120 110 100 100 175 200 Index The above is the scatter plot of Index and Weights data variables from the data frame df. In []: 3. Relationship between data variables **Correlation** - one of the statistical measurements applied to find out if any two variables are linrealy related. If one varibles is increasing, then other variable also increases. Vice versa. For example • If income of an employee increases then the household expenses increase. • If income of an employee decreases then the household expenses decrease. • Scatter plot is really helpful to find the relationship between two variables. With this, it can be easily noticed the linear trend as well. b. Plot the relationship In [18]: df.plot(x='Height(Inches)', y='Weight(Pounds)', kind='scatter') Out[18]: <AxesSubplot:xlabel='Height(Inches)', ylabel='Weight(Pounds)'> 160 150 130 120 110 100 68 Height(Inches) From the above plot, we can see that when <code>Heights</code> increase, then <code>Weights</code> also increased. What if we interchange the values? In [19]: df.plot(y='Height(Inches)', x='Weight(Pounds)', kind='scatter') Out[19]: <AxesSubplot:xlabel='Weight(Pounds)', ylabel='Height(Inches)'> 74 72 70 66 130 Weight(Pounds) a. Find the Correlation Correlation value ranges from -1 to 1. • If the calculated correlation value is -■ -1, then it is perfectly negative correlation ■ 1, then it is perfectly **positive correlation** < -1, then it means that error in the correlation measurement • > 1, then it means that **error** in the correlation measurement More information \rightarrow <u>https://www.investopedia.com/terms/c/correlationcoefficient.asp</u> df.corr() In [20]: Out[20]: Index Height(Inches) Weight(Pounds) Index 1.000000 -0.094260 -0.128882 Height(Inches) -0.094260 1.000000 0.556865 Weight(Pounds) -0.128882 0.556865 1.000000 In [21]: relation = df.corr() relation.style.background gradient(cmap='viridis r') Out[21]: Index Height(Inches) Weight(Pounds) -0.094260 -0.128882 1.000000 0.556865 Height(Inches) -0.094260 1.000000 Weight(Pounds) -0.128882 0.556865 1.000000 **Correlation plots** based on the correlation value obtained. → https://en.wikipedia.org/wiki/Correlation and dependence#/media/File:Correlation examples2.svg Well, the above results are obtained for the data which was already stored. But, what about Streaming data? **Streaming data** - that data that is continuously generated by different sources is called streaming data. • For example - Tesla Self-driving Car generates the data continuously. One tesla car generates 11 TB and 152 TB data per day. Big data problem ■ More information → https://www.tuxera.com/blog/autonomous-and-adas-test-cars-produce-over-11-tb-of-data-per-day/ In []:

 $\textbf{Case Study} \rightarrow \textbf{Activity}$ 1. Select any one of these or you can find your own topic of interest not specifically from below.

- Study to analyse peoples' habits on YouTube platform • Study to analyse the changes occurred in peoples' life due to Demonotization
- Study to analyse the students' overall development due to online education 2. Create a google form where you can have a set of questions and answer options. • Have atleast 8 to 10 questions
- 3. Collect the data from your friends, families etc (by sharing the link).

Note - To learn how to create google forms (Questionnaires) and collect the data,

• The data will be stored in your drive (in a spreasheet) 4. Once the data is collected -

• Create your own data variables from the questions • Try to basic analysis like processing and visualization

 $\bullet \ \ \text{please watch this video} \rightarrow \underline{\text{https://www.youtube.com/watch?v=vQw2jDlylDU}}$