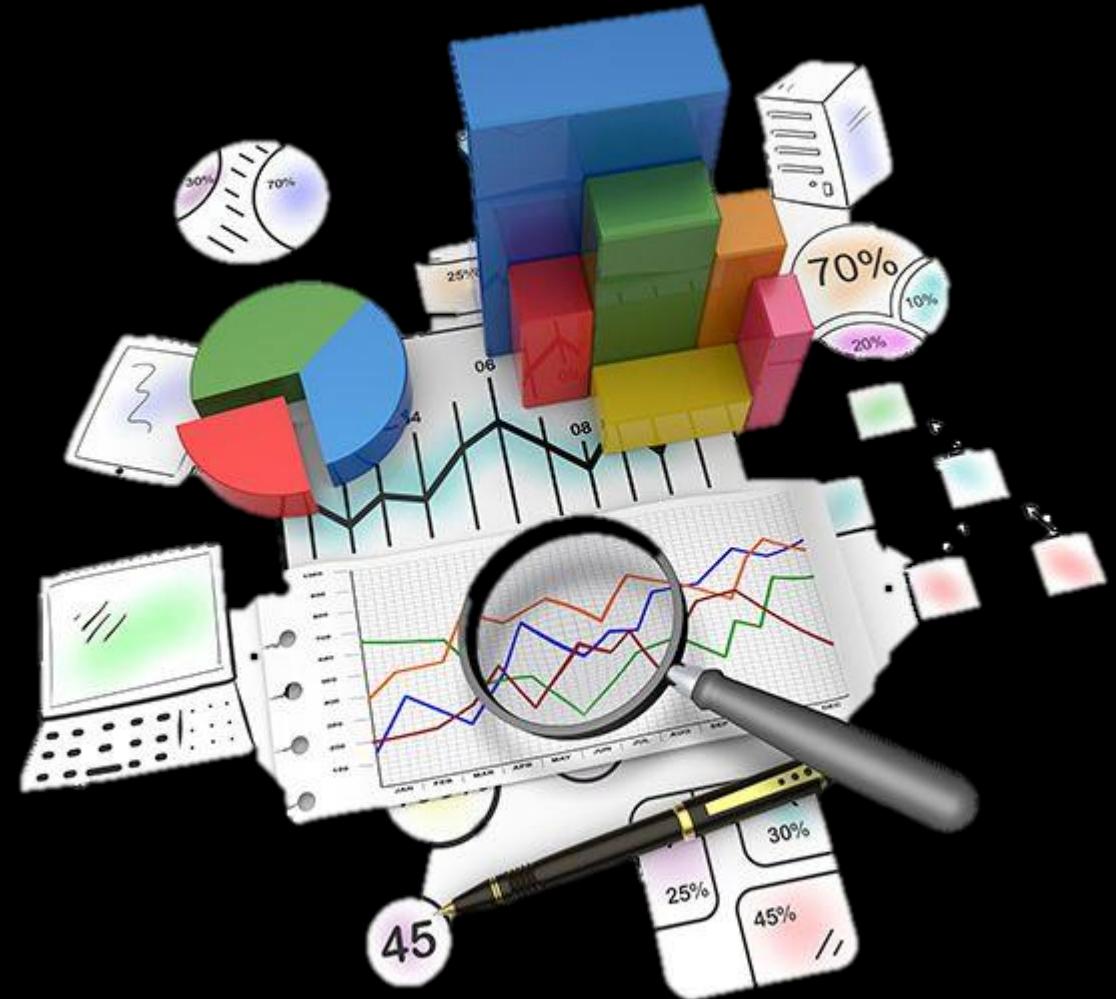


DATA ANALYSIS WITH PYTHON

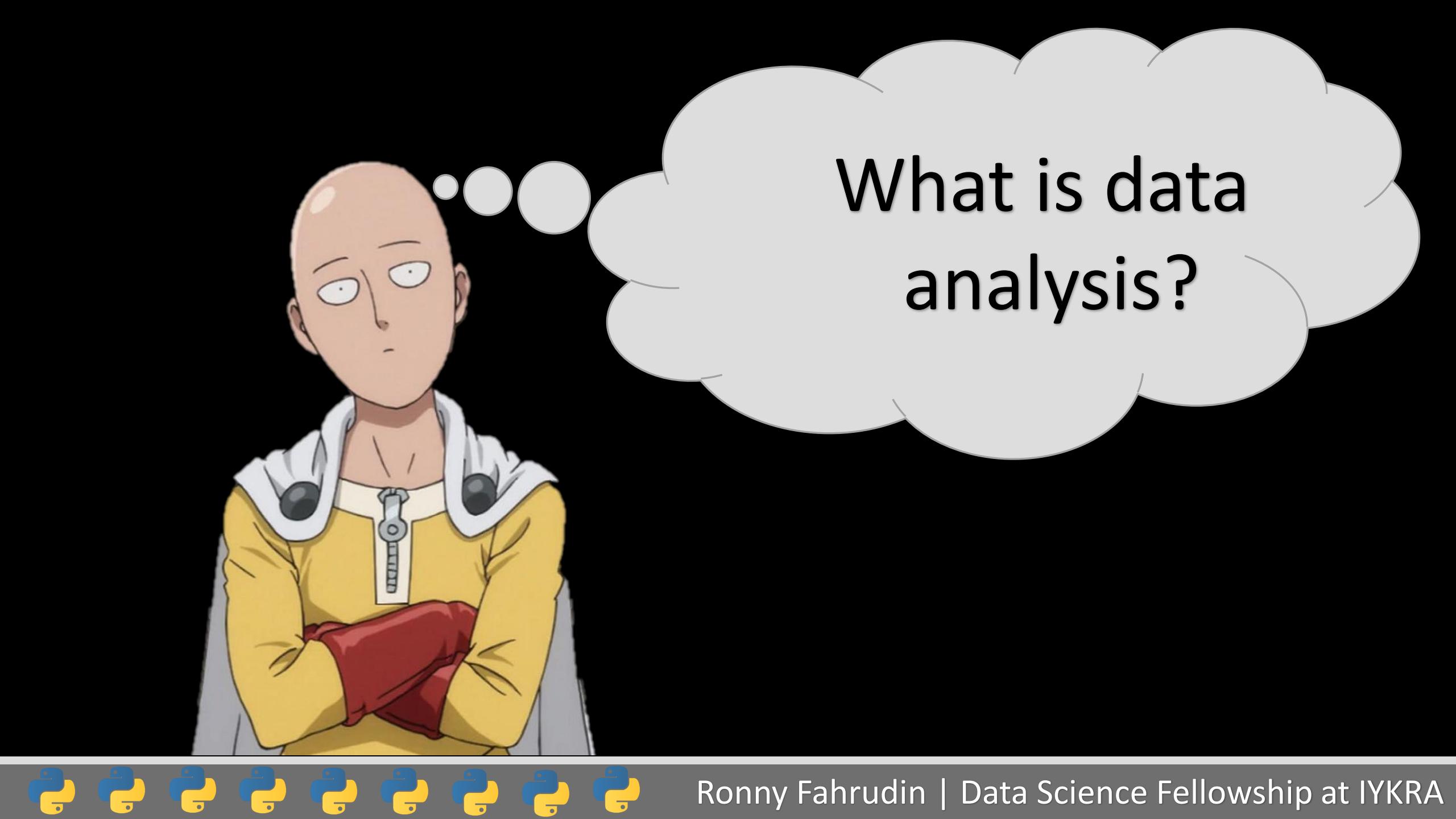


Ronny Fahrudin | Data Science Fellowship at IYKRA

OUTLINE

1. Data Analysis Definition
2. Reason Analyze Data with Python
3. How Analyze Data with Python
4. How visualize data with Python



A character from the anime One-Punch Man, Saitama, is shown from the waist up, standing against a black background. He has his signature bald head, white eyes, and a serious expression. He is wearing a yellow zip-up hoodie over a white t-shirt. His arms are crossed. To his right is a large, light gray thought bubble containing the text "What is data analysis?".

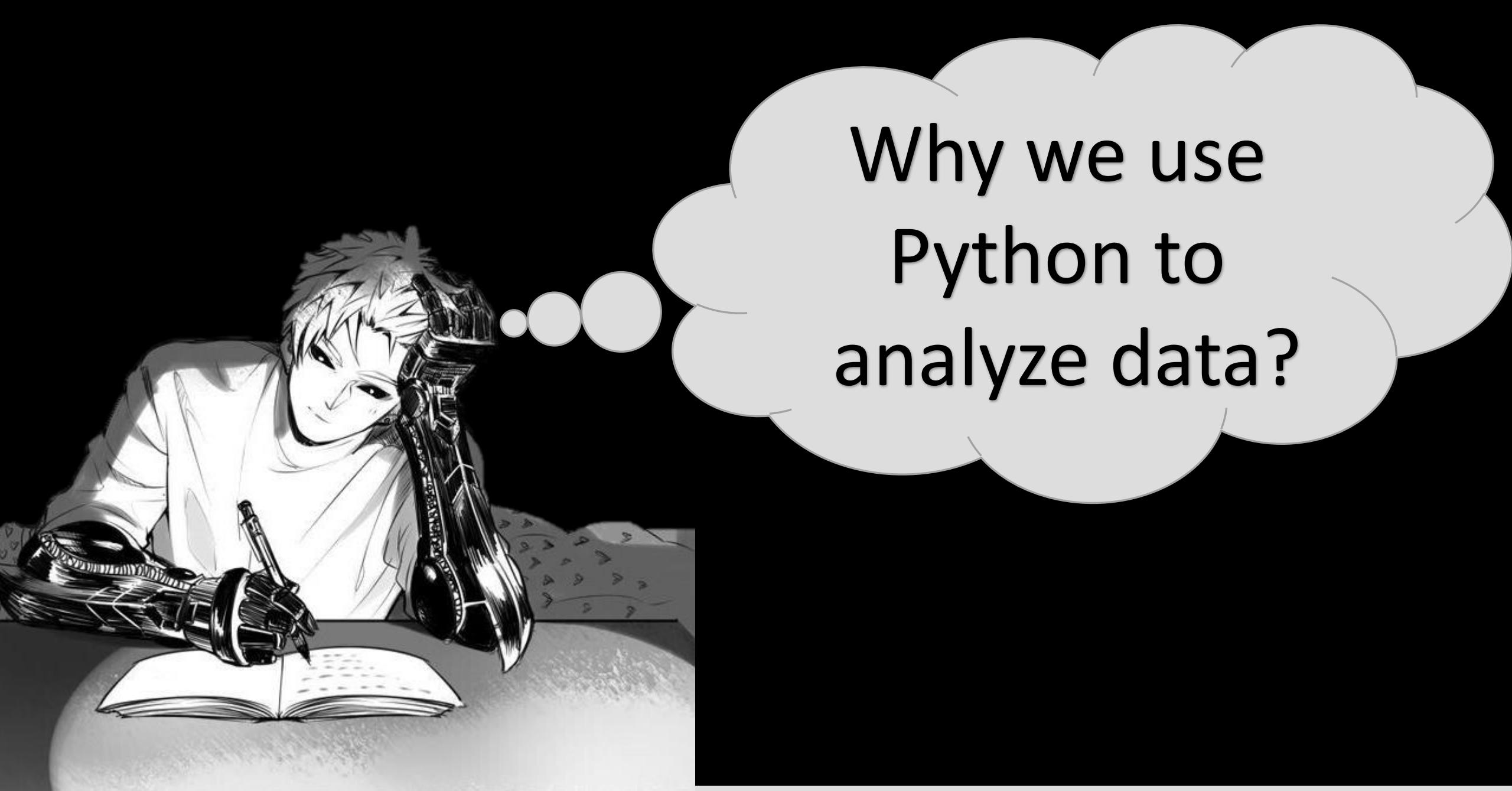
What is data
analysis?



Data analysis is defined as a process of cleaning, transforming, and modeling data to discover useful information for decision making.

The purpose of data analysis is to extract useful information from data and taking the decision based upon the data analysis





Why we use
Python to
analyze data?





1. Code would be easy for humans to read
2. Open source and has large library
3. Large community and easy to collaborate
4. Can correlate with others tools
5. Can to make visualization & graphics



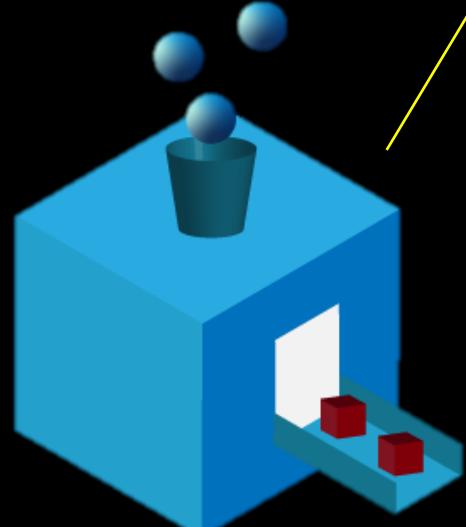
How to analyze data with Python?



Cleaning



Pandas



Transform

Visualization



Matplotlib, Seaborn,
Folium, plotly



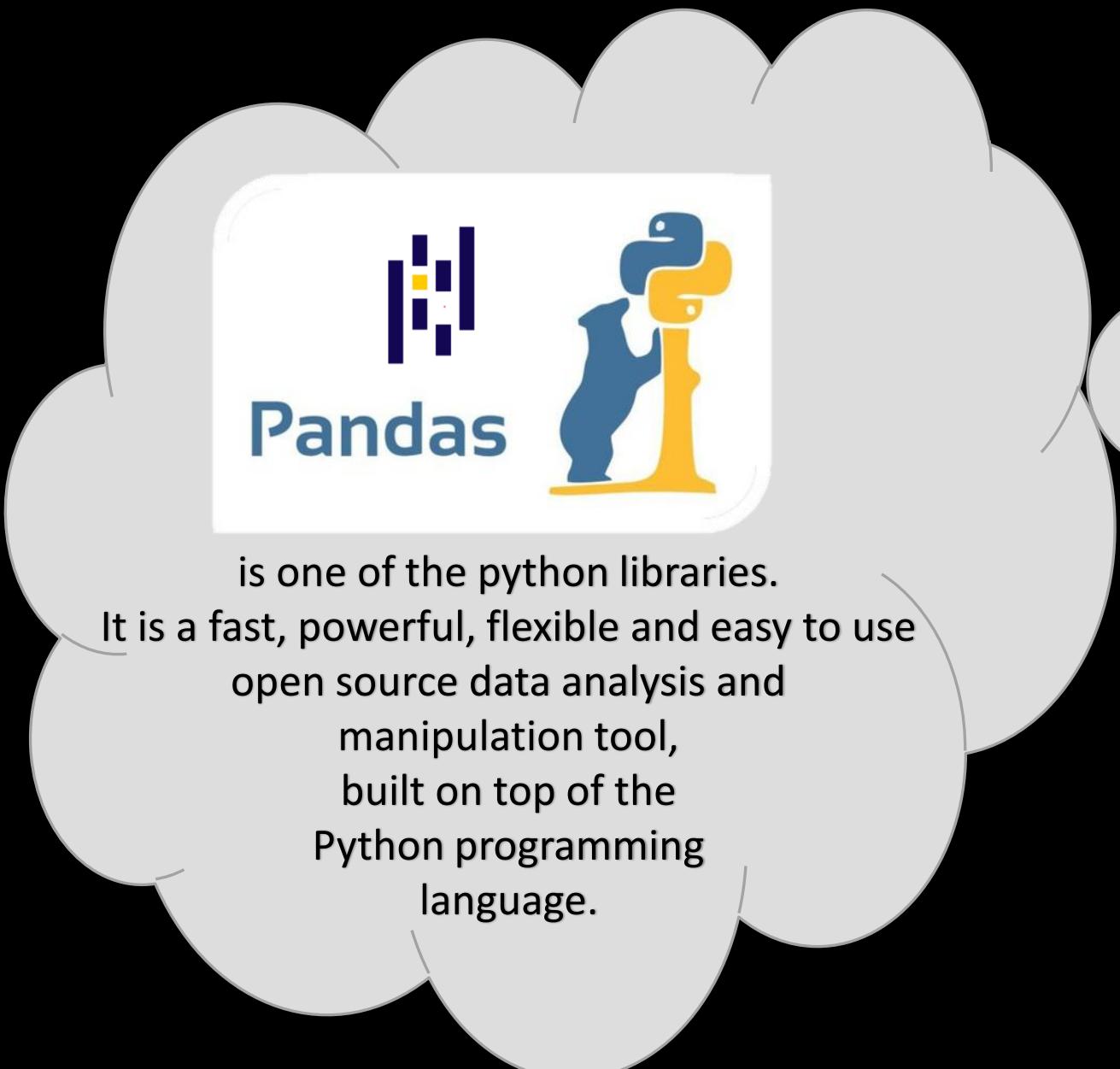
What is pandas?

Is this pandas?



Or is this?







Why Pandas is so
powerful?



Because

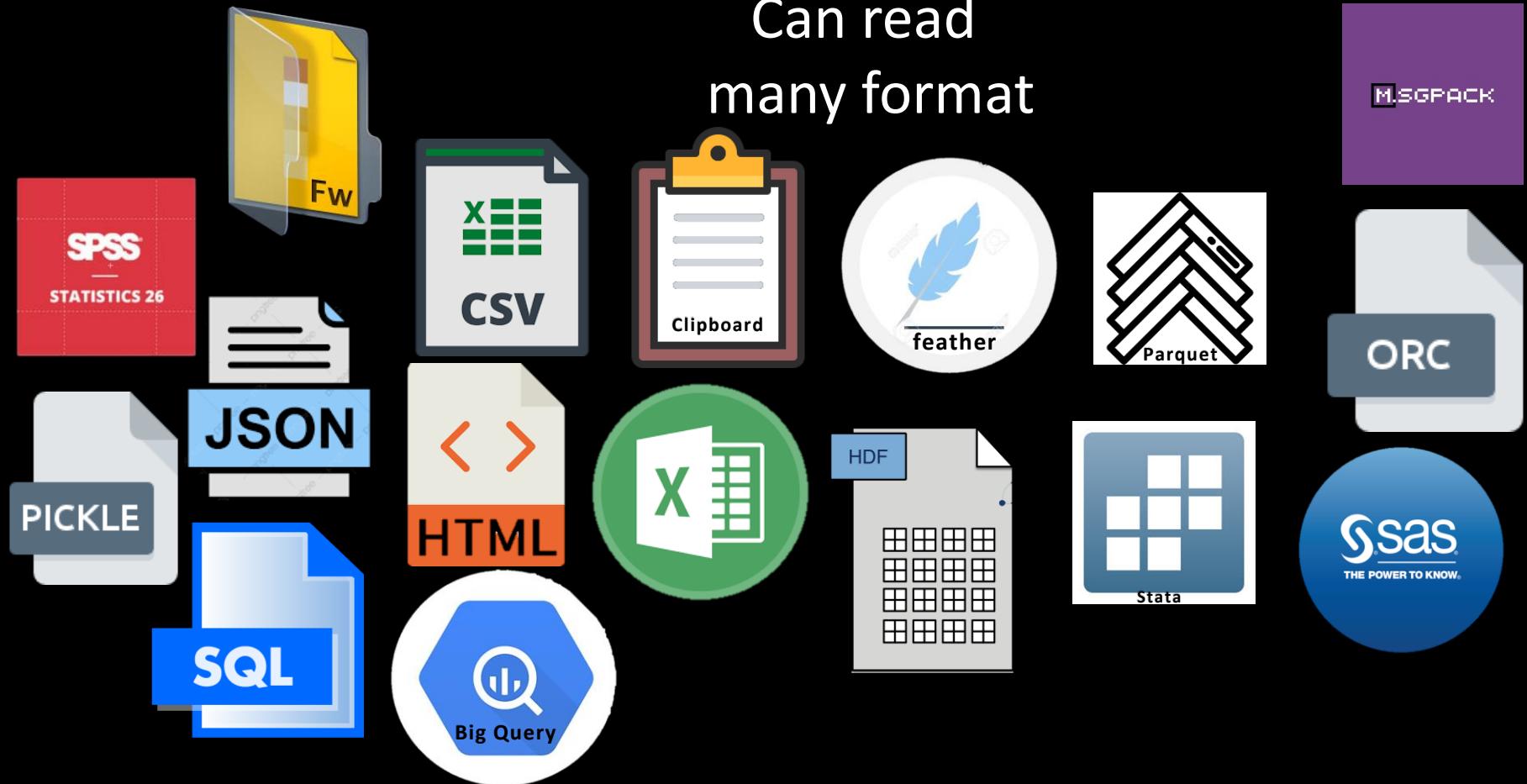


1. Built on top of Numpy package, hikes its performance.
2. Customized indexing for Data Frames
3. Tools for loading data into in memory data objects from different file formats
4. Data alignment and effective handling of missing data
5. Reshaping of the dataset is possible
6. Slicing, indexing, and sub setting of large data sets
7. Deletion or insertion of columns
8. Group by data for aggregation and transformations
9. High-performance merging and joining of data
10. Time series functionality





Can read
many format



How to read data in pandas?

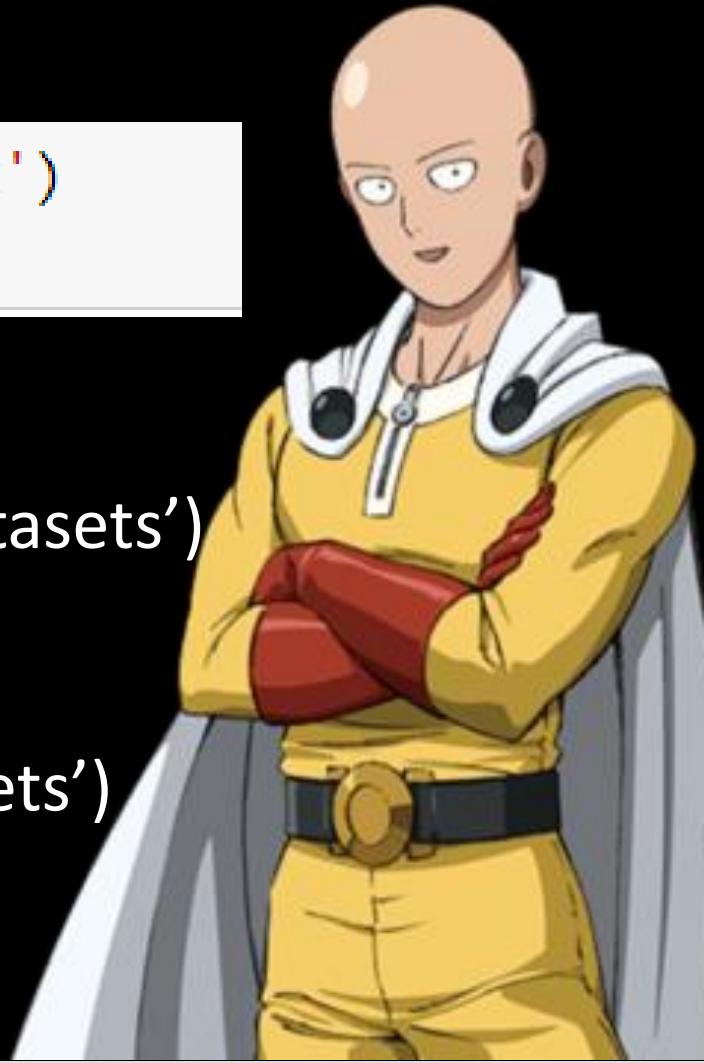
```
dc_ritz = pd.read_excel('data_dictionary_Ritz_jager.xlsx')
ritz_jager = pd.read_csv('Ritz_Jager_Data.csv')
```

To read excel

```
pd.read_excel('this your path data sets and your name datasets')
```

To read csv

```
pd.read_csv('this your path data sets and your name datasets')
```



In Pandas there is dataframe

Index

	company	agent	country_origin	children
0	NaN	NaN	PRT	0.0
1	NaN	NaN	PRT	0.0
2	NaN	NaN	GBR	0.0
3	NaN	304.0	GBR	0.0
4	NaN	240.0	GBR	0.0
...
119385	NaN	394.0	BEL	0.0
119386	NaN	9.0	FRA	0.0
119387	NaN	9.0	DEU	0.0
119388	NaN	89.0	GBR	0.0
119389	NaN	9.0	DEU	0.0
119390 rows x 4 columns				

dataframe

Columns/feature

Rows/records

	agent
0	NaN
1	NaN
2	NaN
3	304.0
4	240.0
...	...
119385	394.0
119386	9.0
119387	9.0
119388	89.0
119389	9.0

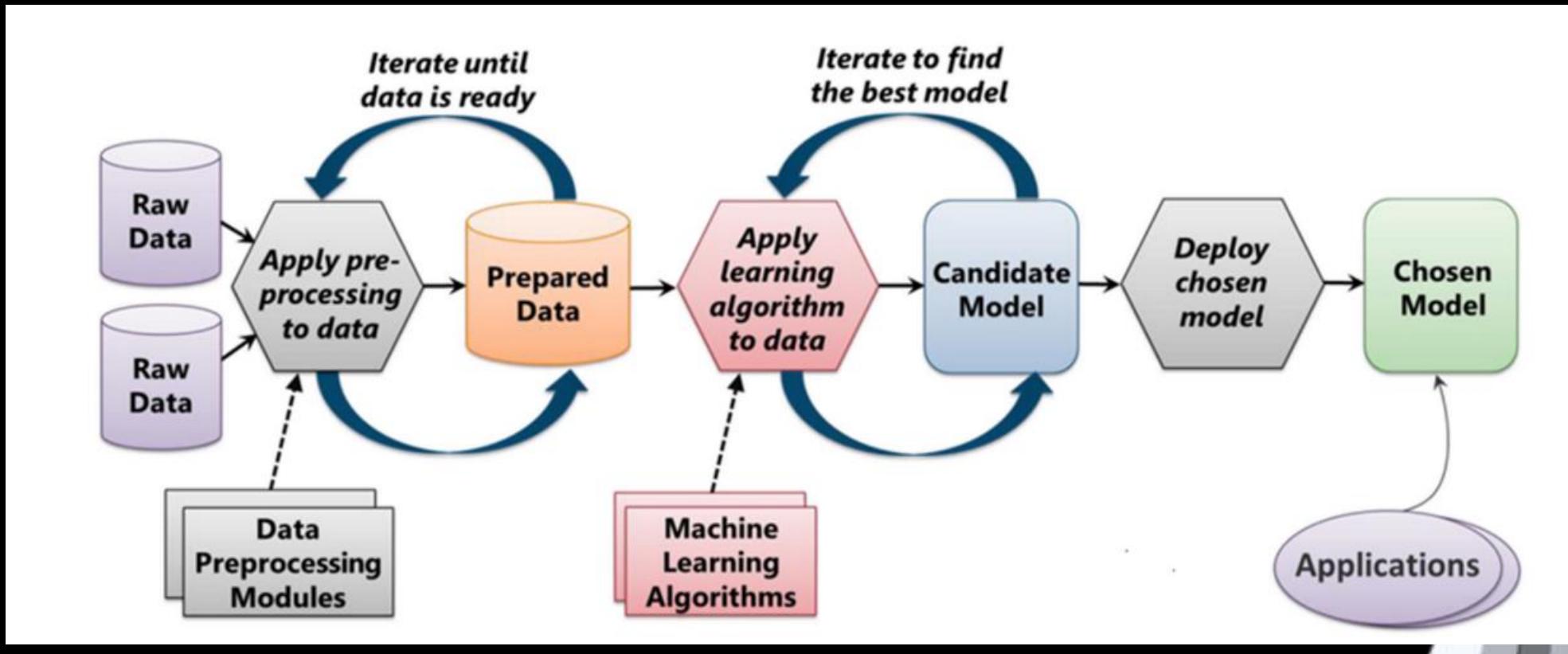
series



Basic Data Manipulation with

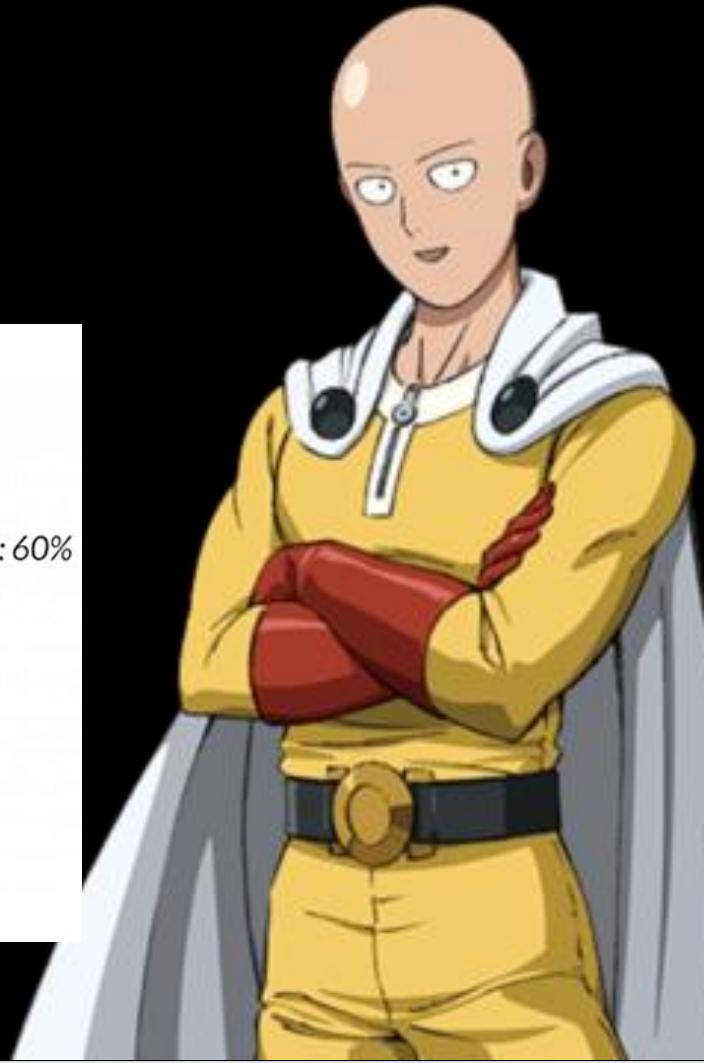
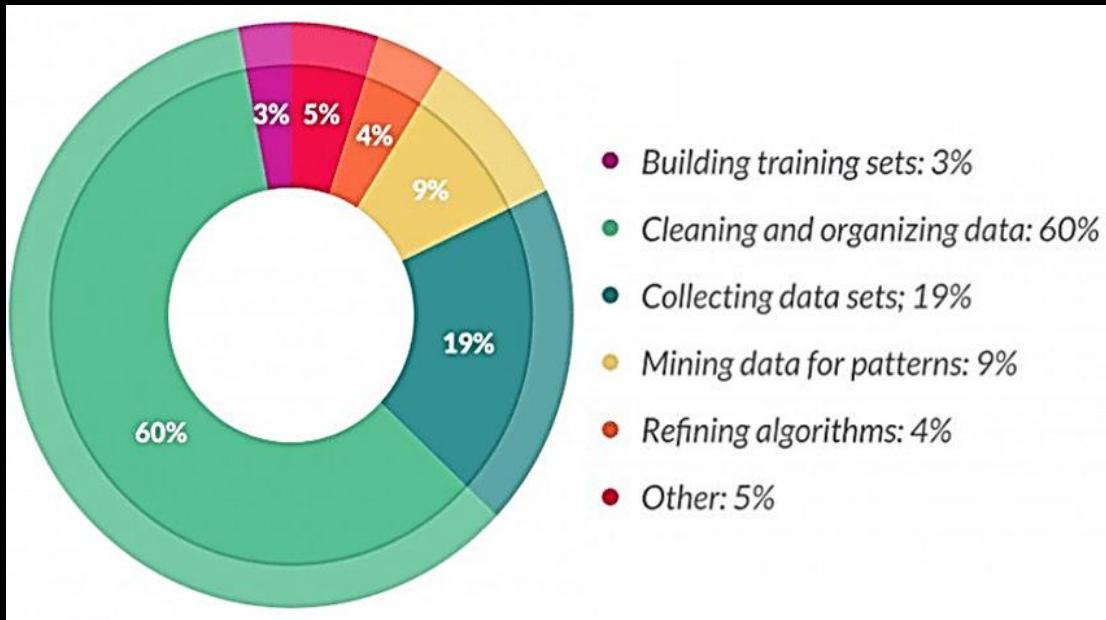


Why required required to preprocessing the data?



Preprocessing Datasets

The first step in your data science or machine learning workflow is cleaning data. Without clean data you'll be having a much harder time seeing the actual important parts in your exploration. According to Crowd flower, data scientist spend 60%.



Data manipulation with pandas

1. Selecting
2. Filtering
3. Deleting
4. Sorting



Data Selection

Selection by Columns

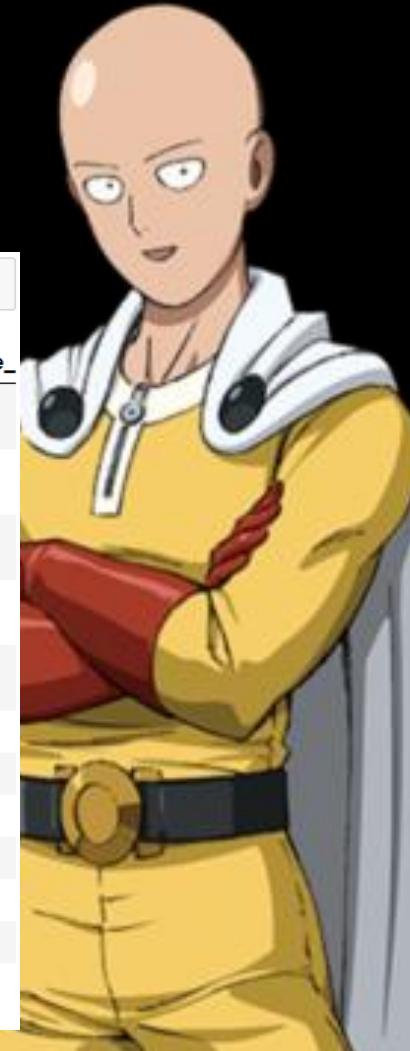
ritz_jager[['agent','agent','children']]			
	agent	agent	children
0	9.0	9.0	0.0
1	9.0	9.0	0.0
2	9.0	9.0	0.0
3	304.0	304.0	0.0
4	240.0	240.0	0.0
...
119385	394.0	394.0	0.0
119386	9.0	9.0	0.0
119387	9.0	9.0	0.0
119388	89.0	89.0	0.0
119389	9.0	9.0	0.0

119390 rows × 3 columns

Selection by Rows

ritz_jager.iloc[::2]					
	hotel_type	is_canceled	lead_time	arrival_date_year	arrival_date_month
0	Resort Hotel	0	342	2015	July
2	Resort Hotel	0	7	2015	July
4	Resort Hotel	0	14	2015	July
6	Resort Hotel	0	0	2015	July
8	Resort Hotel	1	85	2015	July
...
119380	City Hotel	0	44	2017	August
119382	City Hotel	0	135	2017	August
119384	City Hotel	0	21	2017	August
119386	City Hotel	0	102	2017	August
119388	City Hotel	0	109	2017	August

59695 rows × 32 columns



Data Selection

Selection .loc

```
ritz_jager.loc[1,['agent','agent','country_origin','children']]  
agent      9  
agent      9  
country_origin    PRT  
children     0  
Name: 1, dtype: object
```

Selection .iloc

ritz_jager.iloc[::2]					
	hotel_type	is_canceled	lead_time	arrival_date_year	arrival_date_month
0	Resort Hotel	0	342	2015	July
2	Resort Hotel	0	7	2015	July
4	Resort Hotel	0	14	2015	July
6	Resort Hotel	0	0	2015	July
8	Resort Hotel	1	85	2015	July
...
119380	City Hotel	0	44	2017	August
119382	City Hotel	0	135	2017	August
119384	City Hotel	0	21	2017	August
119386	City Hotel	0	102	2017	August
119388	City Hotel	0	109	2017	August
59695 rows × 32 columns					



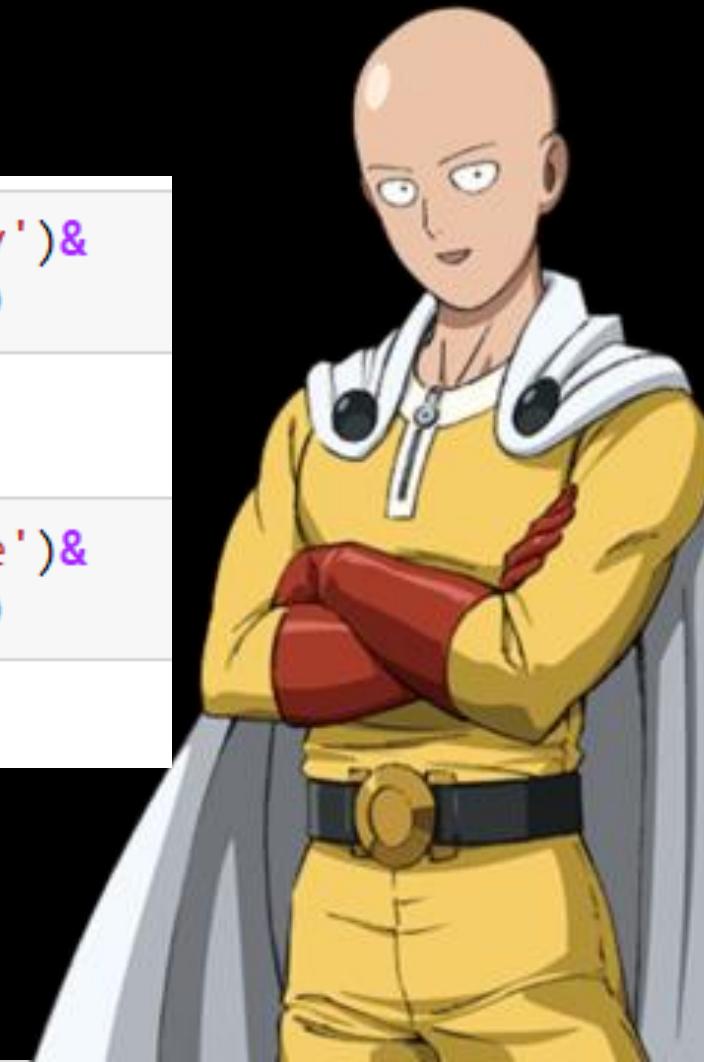
Data Filtering

```
len(ritz_jager[(ritz_jager['arrival_date_month']=='July')&  
                (ritz_jager['stays_in_week_nights']>3)])
```

3838

```
len(ritz_jager[(ritz_jager['arrival_date_month']=='June')&  
                (ritz_jager['stays_in_week_nights']>4)])
```

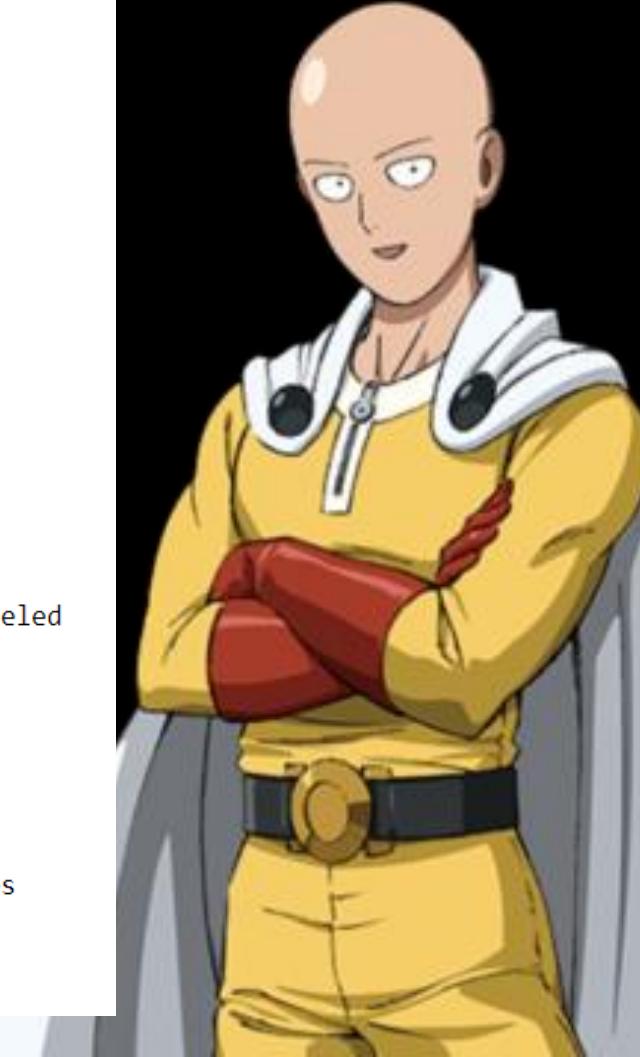
1678



Data Deletion

```
# 1. drop company column  
ritz_jager = ritz_jager.drop('company', axis = 1)
```

```
agent  
children  
reservation_status_date  
market_segment  
is_canceled  
lead_time  
arrival_date_year  
arrival_date_month  
arrival_date_week_number  
arrival_date_day_of_month  
stays_in_weekend_nights  
stays_in_week_nights  
adults  
babies  
meal_type  
country_origin  
distribution_channel  
reservation_status  
is_repeated_guest  
previous_cancellations  
previous_bookings_not_canceled  
reserved_room_type  
assigned_room_type  
booking_changes  
deposit_type  
days_in_waiting_list  
customer_type  
adr  
required_car_parking_spaces  
total_of_special_requests  
hotel_type  
dtype: int64
```



Data Sorting

```
s = ritz_jager[['arrival_date_month','is_canceled']][ok]
s.groupby('arrival_date_month').count().reset_index().sort_values('is_canceled',ascending = False)
```

	arrival_date_month	is_canceled
1	August	8638
5	July	7919
8	May	7114
10	October	6914
7	March	6645
0	April	6565
6	June	6404
11	September	6392
3	February	5372
9	November	4672
2	December	4409
4	January	4122



Advanced Data Manipulation With Pandas

- 1.Pivoting
- 2.Crosstab
- 3.Binning
- 4.Categorical Encoding



Pivoting

pivot table is a table of statistics that summarizes the data of a more extensive table. in practical terms, a pivot table calculates a statistics on breakdown of values. for the first column, it displays values as rows and for the second columns as columns

```
data = ritz_jager[ritz_jager['market_segment'] == 'Online TA']
pd.pivot_table(data, index = ['customer_type','country_origin'],
               values='adr', aggfunc='mean').head(10)
```

		adr
customer_type	country_origin	
Contract	AGO	124.818571
	ARG	77.210000
	AUS	113.633333
	AUT	106.863000
	AZE	112.500000
	BEL	112.400357
	BGR	112.500000
	BLR	107.166667
	BRA	99.140000
	CHE	104.769500



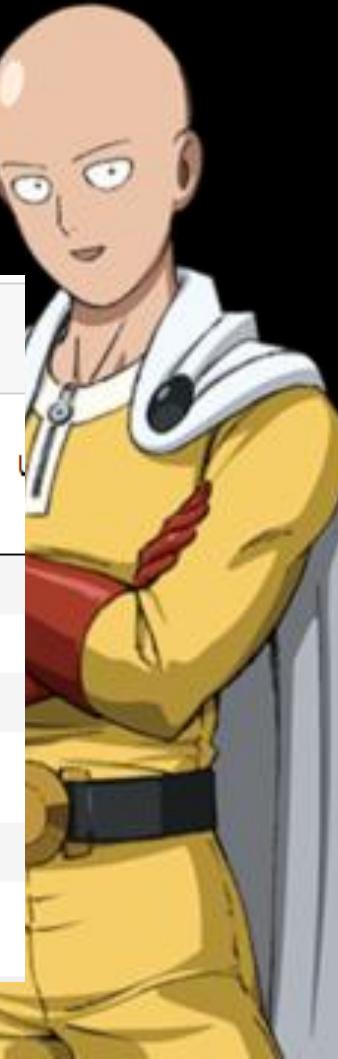
Crosstab

Compute a simple cross-tabulation of two or more factors. By default computes a frequency table of the factors

```
#crosstab  
pd.crosstab(data.customer_type, data.country_origin, margins=True)
```

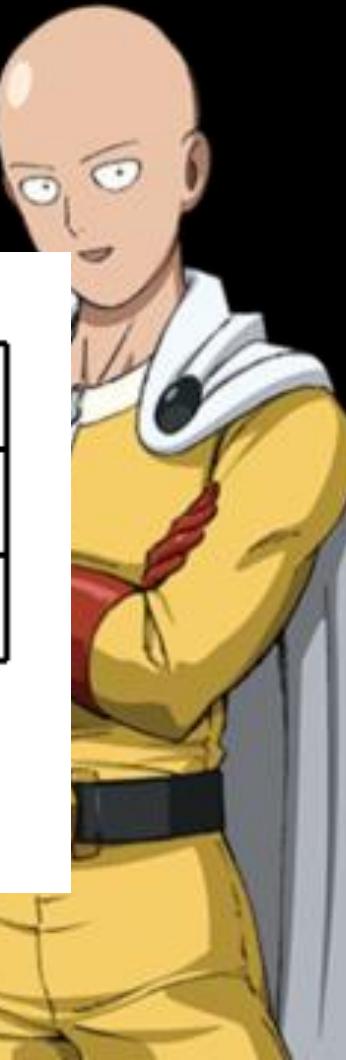
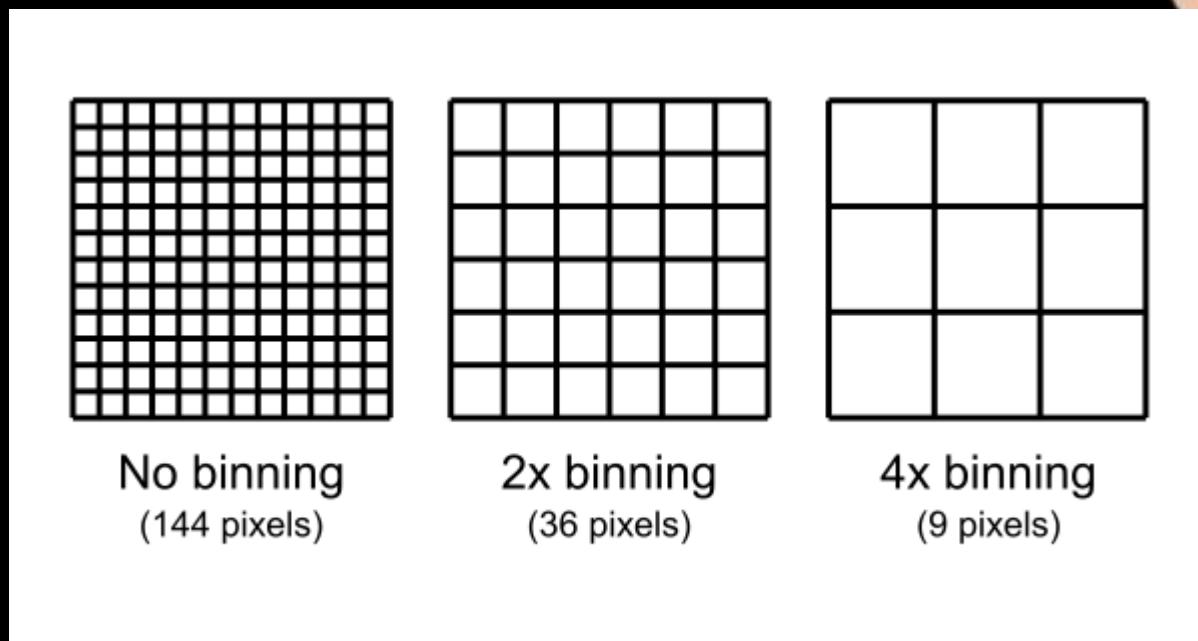
country_origin	ABW	AGO	AIA	ALB	AND	ARE	ARG	ARM	ASM	ATA	... customer_type	URY	USA	UZB
Contract	0	7	0	0	0	0	1	0	0	0	...	0	17	0
Group	0	0	0	0	0	0	1	0	0	0	...	0	7	0
Transient	2	196	1	3	6	46	142	4	1	1	...	24	1355	0
Transient-Party	0	1	0	2	0	1	10	0	0	0	...	0	58	0
All	2	204	1	5	6	47	154	4	1	1	...	24	1437	0

5 rows × 167 columns



Binning

1. When dealing with continuous numeric data, it is often helpful to bin the data into multiple buckets for further analysis



Categorical Encoding

We doing encoding so that machine learning can understanding the data.

If we have ordinal data we have to label encoding with numeric data.

If we have nominal data we have to one hot encoding.



Data Cleansing

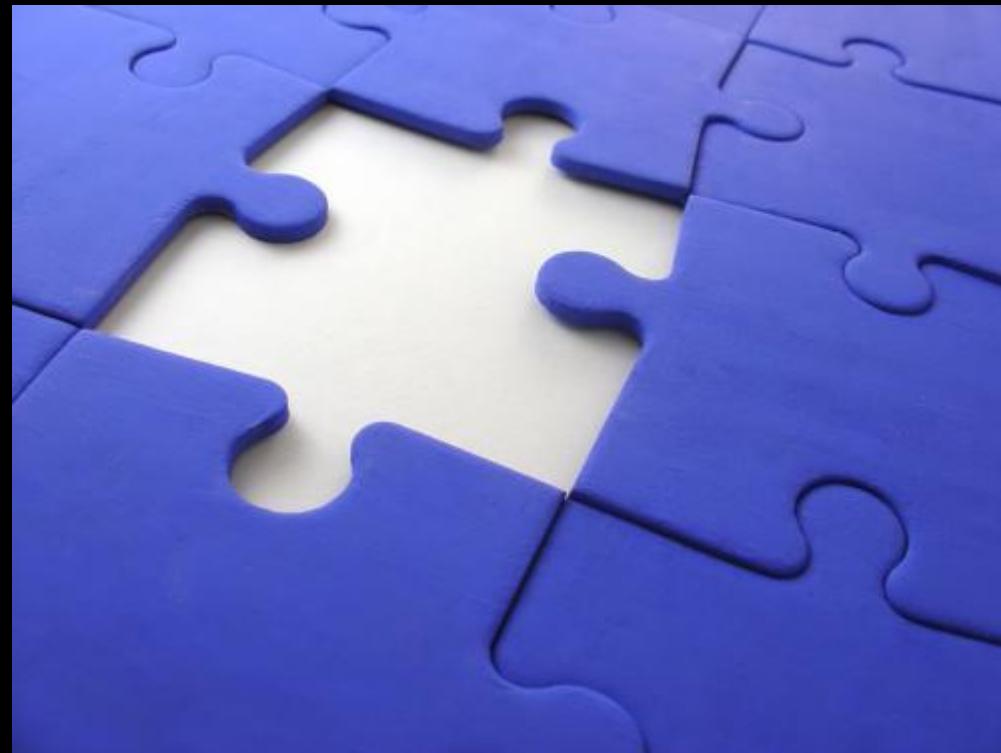
1. Missing Values Checking and handling
2. Duplicates Checking
3. Anomaly and Outlier Detection
4. Data Type Checking
5. Data Type Correction
6. Feature Extraction



Missing Values Checking and Handling

Why missing value exist?

1. Missed data
2. Deleted
3. Corrupt
4. Mismatch row and column
5. real value not available



Cleaning & Transform Data



1. Importing library and datasets

Import Data

```
# import Lybrary
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

data = pd.read_csv('data.csv')
```



Cleaning & Transform Data



2. Shape, head, tail data

```
print(data.shape)
data.head()
```

(205, 26)

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...	engine-size	fuel-system	bore	stroke	compression-ratio	horsepo
0	3	?	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	2.68	9.0	
1	3	?	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	2.68	9.0	
2	1	?	alfa-romero	gas	std	two	hatchback	rwd	front	94.5	...	152	mpfi	2.68	3.47	9.0	
3	2	164	audi	gas	std	four	sedan	fwd	front	99.8	...	109	mpfi	3.19	3.4	10.0	
4	2	164	audi	gas	std	four	sedan	4wd	front	99.4	...	136	mpfi	3.19	3.4	8.0	

5 rows × 26 columns

```
< >
```

```
data.tail()
```

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...	engine-size	fuel-system	bore	stroke	compression-ratio	horsepower
200	-1	95	volvo	gas	std	four	sedan	rwd	front	109.1	...	141	mpfi	3.78	3.15	9.5	11
201	-1	95	volvo	gas	turbo	four	sedan	rwd	front	109.1	...	141	mpfi	3.78	3.15	8.7	16
202	-1	95	volvo	gas	std	four	sedan	rwd	front	109.1	...	173	mpfi	3.58	2.87	8.8	13
203	-1	95	volvo	diesel	turbo	four	sedan	rwd	front	109.1	...	145	idi	3.01	3.4	23.0	10
204	-1	95	volvo	gas	turbo	four	sedan	rwd	front	109.1	...	141	mpfi	3.78	3.15	9.5	11



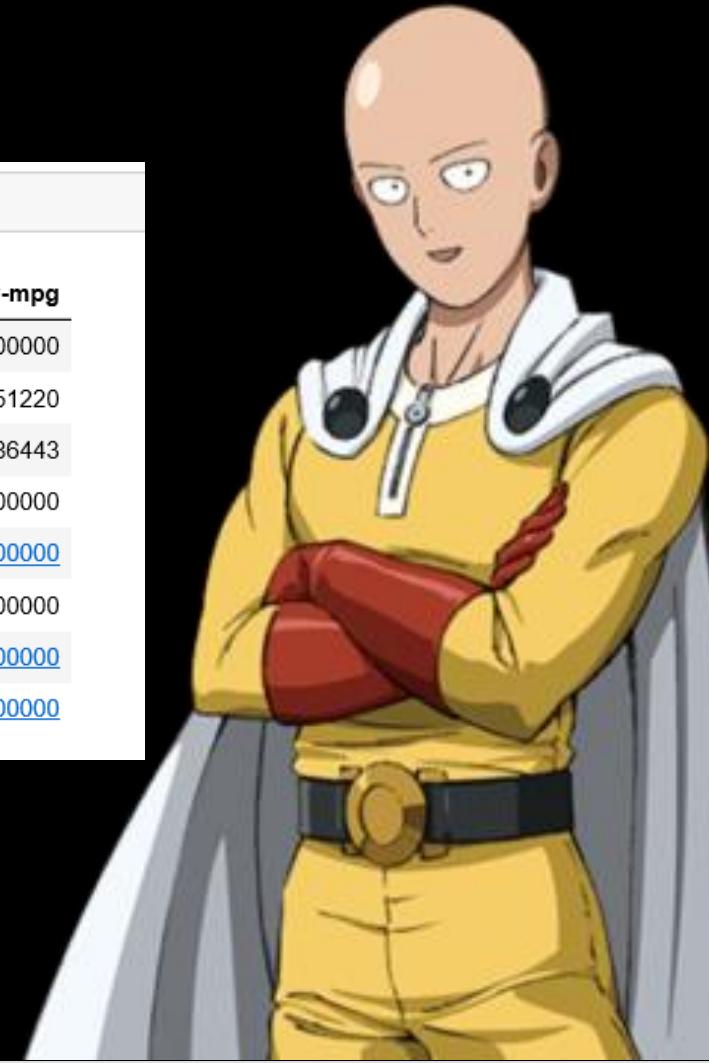
Cleaning & Transform Data



3. Describe data

```
data.describe()
```

	symboling	wheel-base	length	width	height	curb-weight	engine-size	compression-ratio	city-mpg	highway-mpg
count	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000
mean	0.834146	98.756585	174.049268	65.907805	53.724878	2555.565854	126.907317	10.142537	25.219512	30.751220
std	1.245307	6.021776	12.337289	2.145204	2.443522	520.680204	41.642693	3.972040	6.542142	6.886443
min	-2.000000	86.600000	141.100000	60.300000	47.800000	1488.000000	61.000000	7.000000	13.000000	16.000000
25%	0.000000	94.500000	166.300000	64.100000	52.000000	2145.000000	97.000000	8.600000	19.000000	25.000000
50%	1.000000	97.000000	173.200000	65.500000	54.100000	2414.000000	120.000000	9.000000	24.000000	30.000000
75%	2.000000	102.400000	183.100000	66.900000	55.500000	2935.000000	141.000000	9.400000	30.000000	34.000000
max	3.000000	120.900000	208.100000	72.300000	59.800000	4066.000000	326.000000	23.000000	49.000000	54.000000



Cleaning & Transform Data



4. See data types

data.dtypes	
symboling	int64
normalized-losses	object
make	object
fuel-type	object
aspiration	object
num-of-doors	object
body-style	object
drive-wheels	object
engine-location	object
wheel-base	float64
length	float64
width	float64
height	float64
curb-weight	int64
engine-type	object
num-of-cylinders	object
engine-size	int64
fuel-system	object
bore	object
stroke	object
compression-ratio	float64
horsepower	object
peak-rpm	object
city-mpg	int64
highway-mpg	int64
price	object
dtype: object	



Cleaning & Transform Data



5. Fixing '?' values and see missing values

```
#identify missing value
data.replace('?', np.NaN, inplace = True)
data.isnull().sum().sort_values(ascending = False)

normalized-losses      41
price                  4
stroke                 4
bore                   4
peak-rpm                2
horsepower              2
num-of-doors             2
length                  0
make                     0
fuel-type                 0
aspiration                 0
body-style                 0
drive-wheels                 0
engine-location                 0
wheel-base                 0
height                     0
width                     0
highway-mpg                 0
curb-weight                 0
engine-type                 0
num-of-cylinders                 0
engine-size                 0
fuel-system                 0
compression-ratio                 0
city-mpg                     0
symboling                     0
dtype: int64
```

Find
anomaly data



Cleaning & Transform Data

6. See percentage missing values

In column **num-of-doors**

We can fix it with mode.

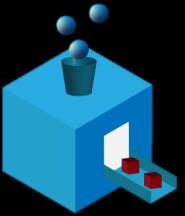
Because that's column is categorical data.

But the other missing values are numerical.

We have to check the Distribution.

```
#percentage missing values  
data.isnull().sum().sort_values(ascending = False)/len(data)
```

normalized-losses	0.200000
price	0.019512
stroke	0.019512
bore	0.019512
peak-rpm	0.009756
horsepower	0.009756
num-of-doors	0.009756
length	0.000000
make	0.000000
fuel-type	0.000000
aspiration	0.000000
body-style	0.000000
drive-wheels	0.000000
engine-location	0.000000
wheel-base	0.000000
height	0.000000
width	0.000000
highway-mpg	0.000000
curb-weight	0.000000
engine-type	0.000000
num-of-cylinders	0.000000
engine-size	0.000000
fuel-system	0.000000
compression-ratio	0.000000
city-mpg	0.000000
symboling	0.000000



Cleaning & Transform Data



7. Handle missing value

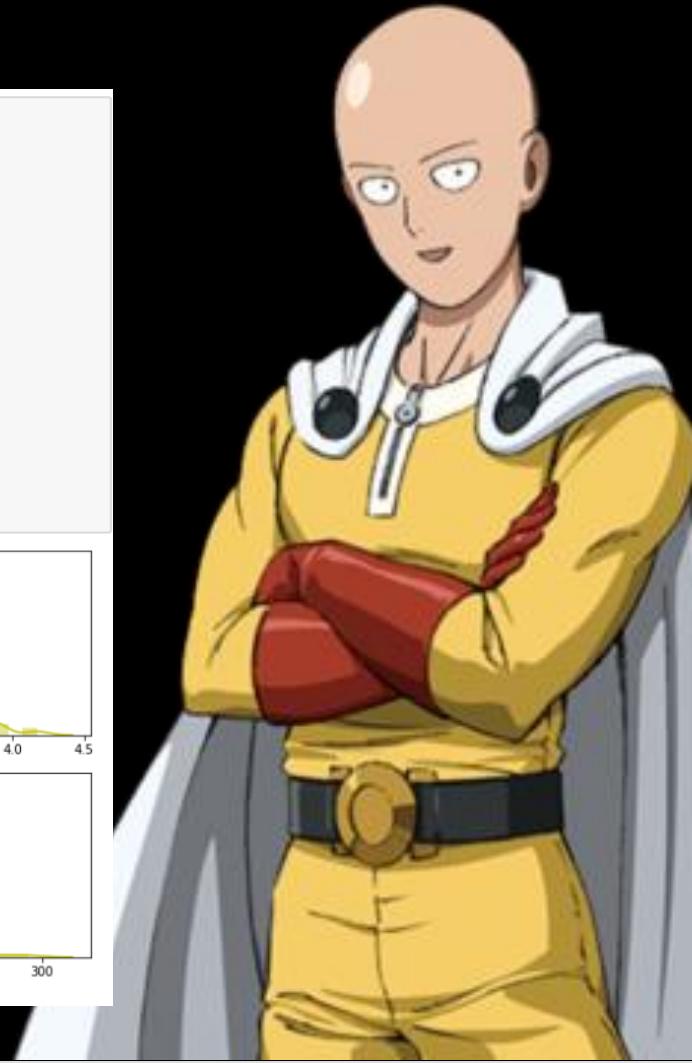
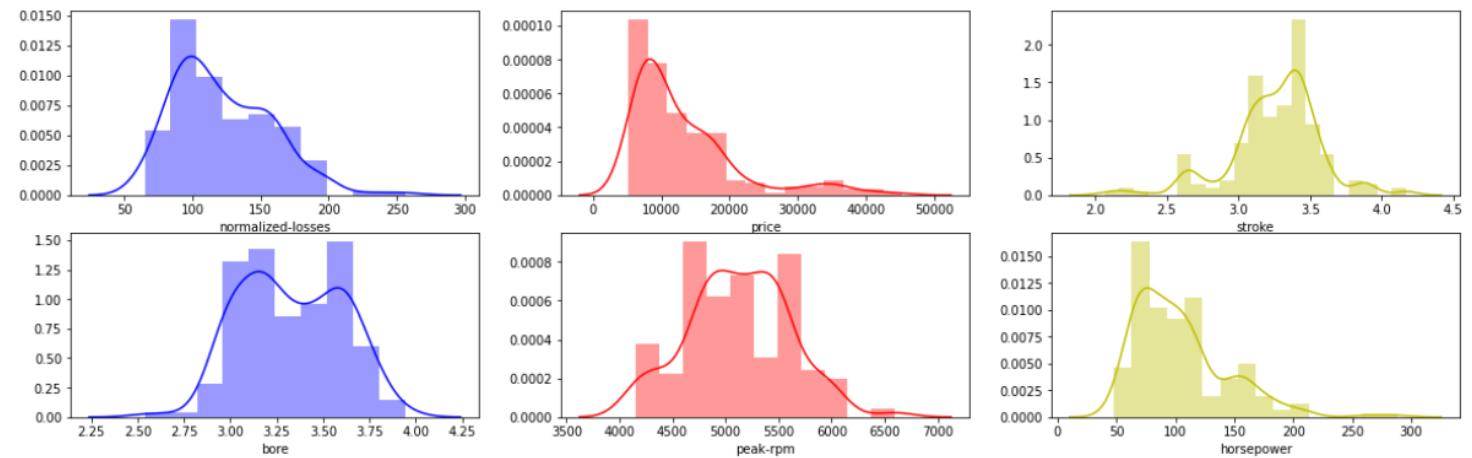
In all column we can fillna with median. Because all graph show a tendency skew left and right. There is no perfect normal, So the representative value

is **median** from each column

```
nl = data['normalized-losses']
price = data['price']
stroke = data['stroke']
bore = data['bore']
peak_rpm = data['peak-rpm']
horse= data['horsepower']

f, axes = plt.subplots(2,3, figsize = (20, 6))# ,sharex = True, sharey=True)
sns.distplot(nl,color = 'b', ax = axes[0,0])
sns.distplot(price,color = 'r', ax = axes[0,1])
sns.distplot(stroke,color = 'y', ax = axes[0,2])
sns.distplot(bore,color = 'b',ax = axes[1,0])
sns.distplot(peak_rpm,color = 'r', ax = axes[1,1])
sns.distplot(horse,color = 'y', ax = axes[1,2])

plt.show()
```



Cleaning & Transform Data

8. Handling Missing Value

```
data['num-of-doors'].value_counts()  
  
four    114  
two     89  
Name: num-of-doors, dtype: int64
```

In columns num-of-doors

Fillna with value:

“four”

Because it's a mode.

```
# replace with median in NaN  
data= data.fillna(data.median())  
data['num-of-doors'] = data['num-of-doors'].fillna('four')  
data.isnull().sum().sort_values(ascending = False)  
  
price          0  
highway-mpg    0  
normalized-losses 0  
make           0  
fuel-type       0  
aspiration      0  
num-of-doors    0  
body-style       0  
drive-wheels    0  
engine-location  0  
wheel-base       0  
length          0  
width           0  
height          0  
curb-weight      0  
engine-type      0  
num-of-cylinders 0  
engine-size      0  
fuel-system       0  
bore             0  
stroke           0  
compression-ratio 0  
horsepower        0  
peak-rpm          0  
city-mpg          0  
symboling         0  
dtype: int64
```

All clean



Convert data types to datetime

```
# convert datetime
from datetime import datetime
ritz_jager['date_reservation_status'] = pd.to_datetime(ritz_jager['reservation_status_date'],format = '%d/%m/%Y')
```

```
adr          float64
required_car_parking_spaces   int64
total_of_special_requests     int64
reservation_status            object
reservation_status_date       object
dtype: object
```

```
adr          float64
required_car_parking_spaces   int64
total_of_special_requests     int64
reservation_status            object
reservation_status_date       object
date_reservation_status       datetime64[ns]
dtype: object
```



How to make data visualization with Python?



We Visualize data with Matplotlib and Seaborn or folium to map visualization

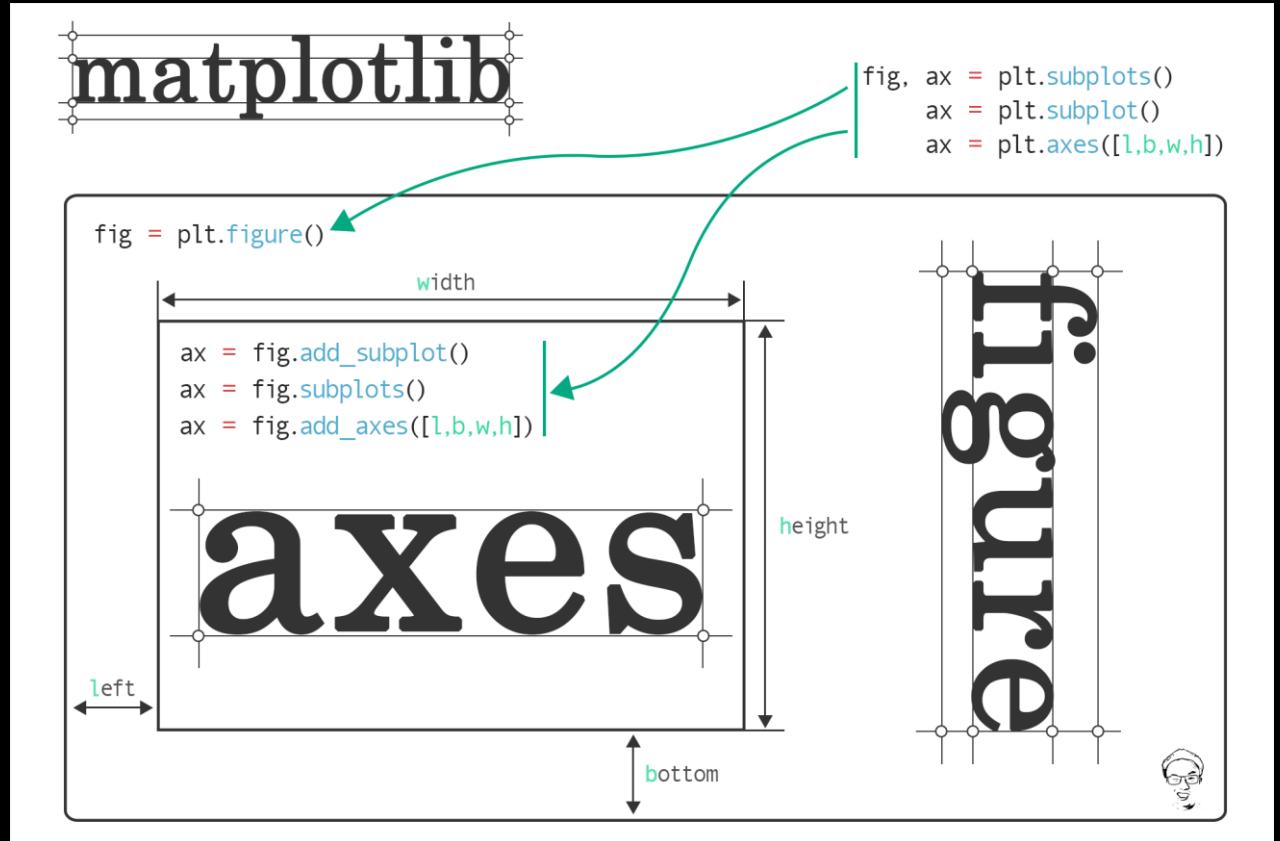


folium

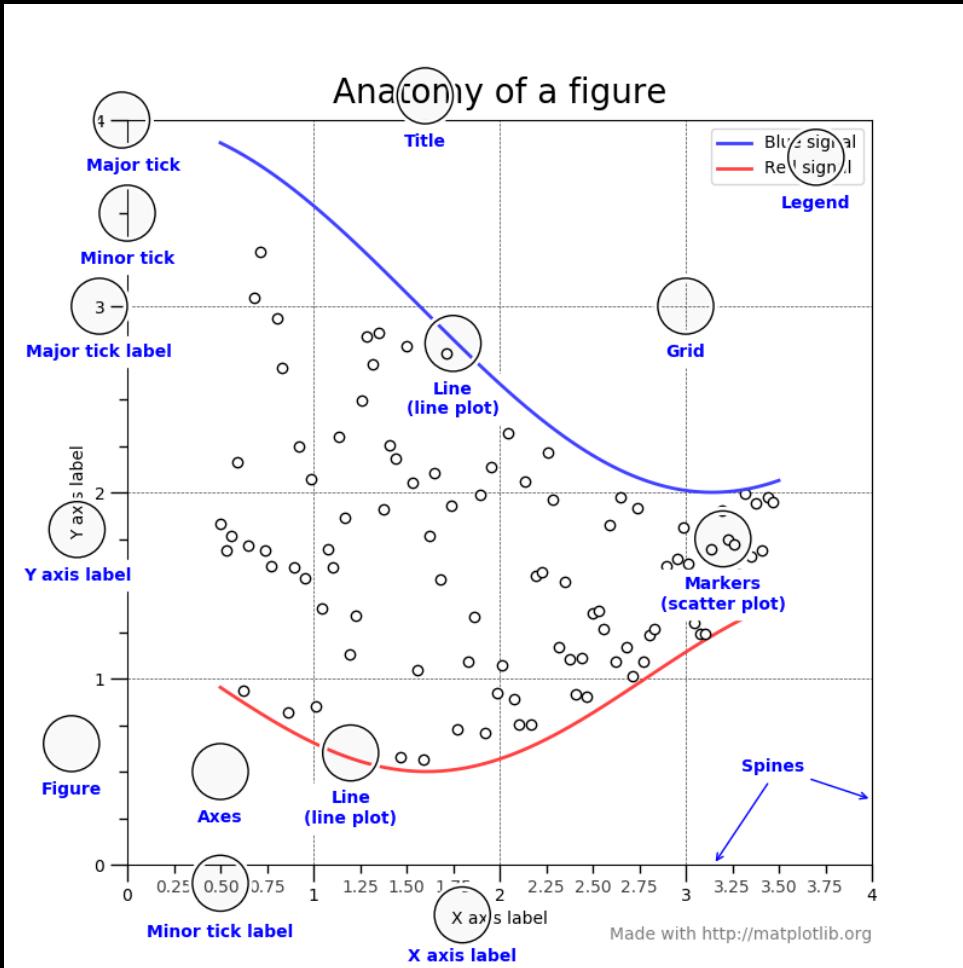




Parts of Visualization in Python



Anatomy of a figure



Kinds of Data Visualization

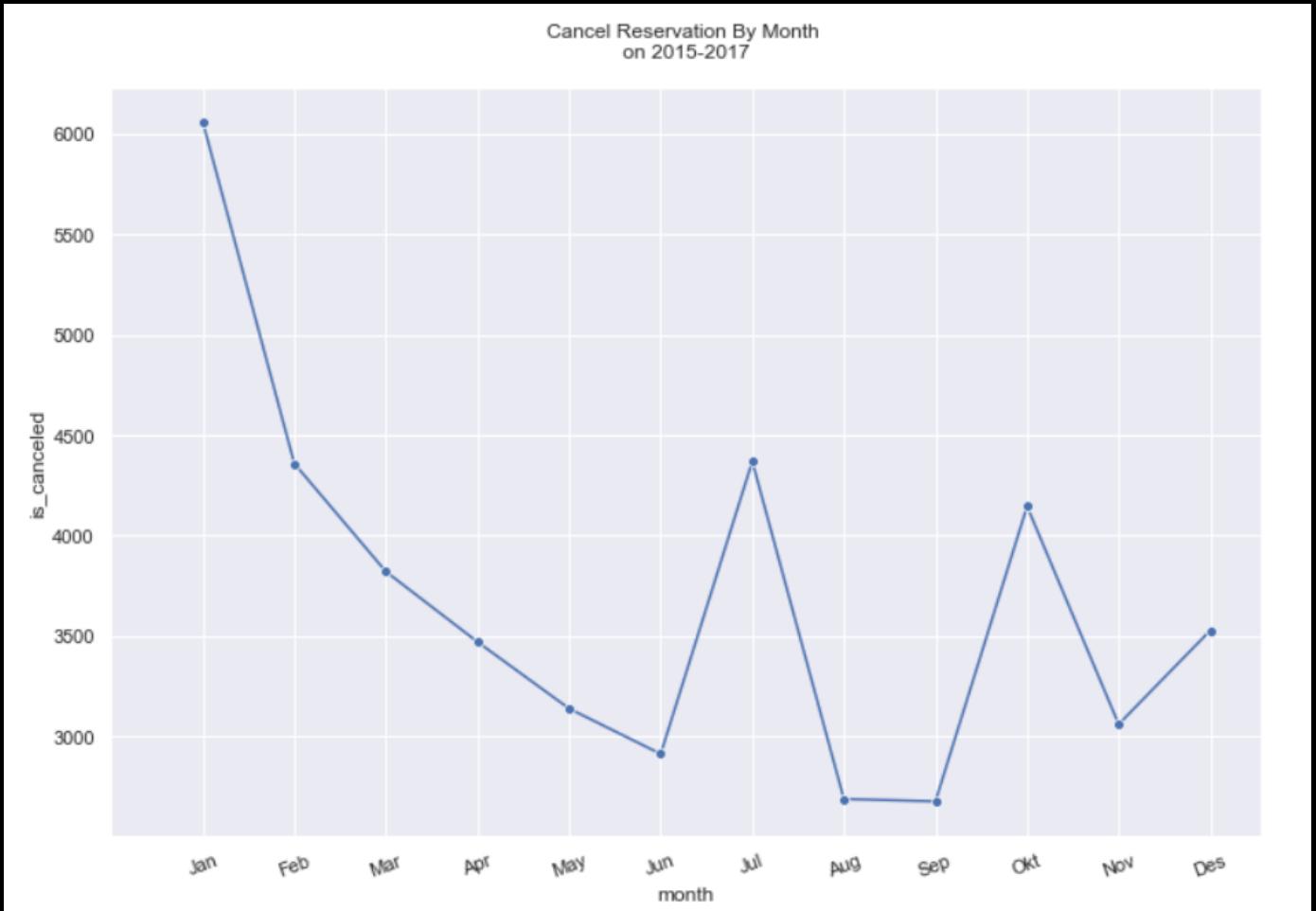
1. Line Chart
2. Bar chart
3. Histogram chart
4. Boxplot
5. Pie Chart
6. Heatmap
7. Scatter Plot



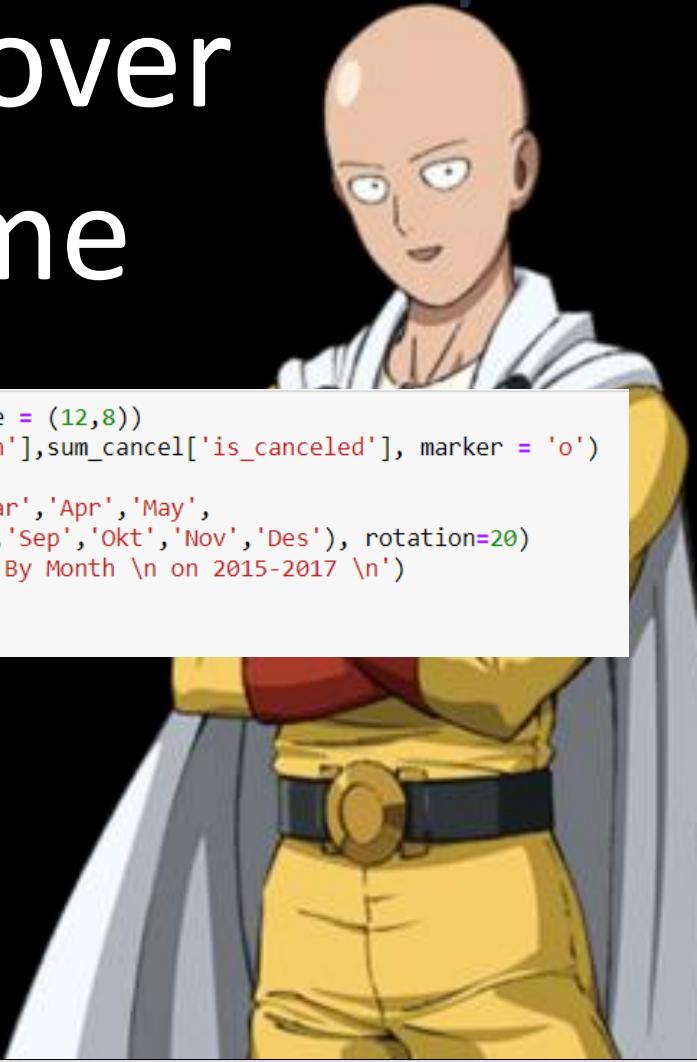


Line Graph

See over
time

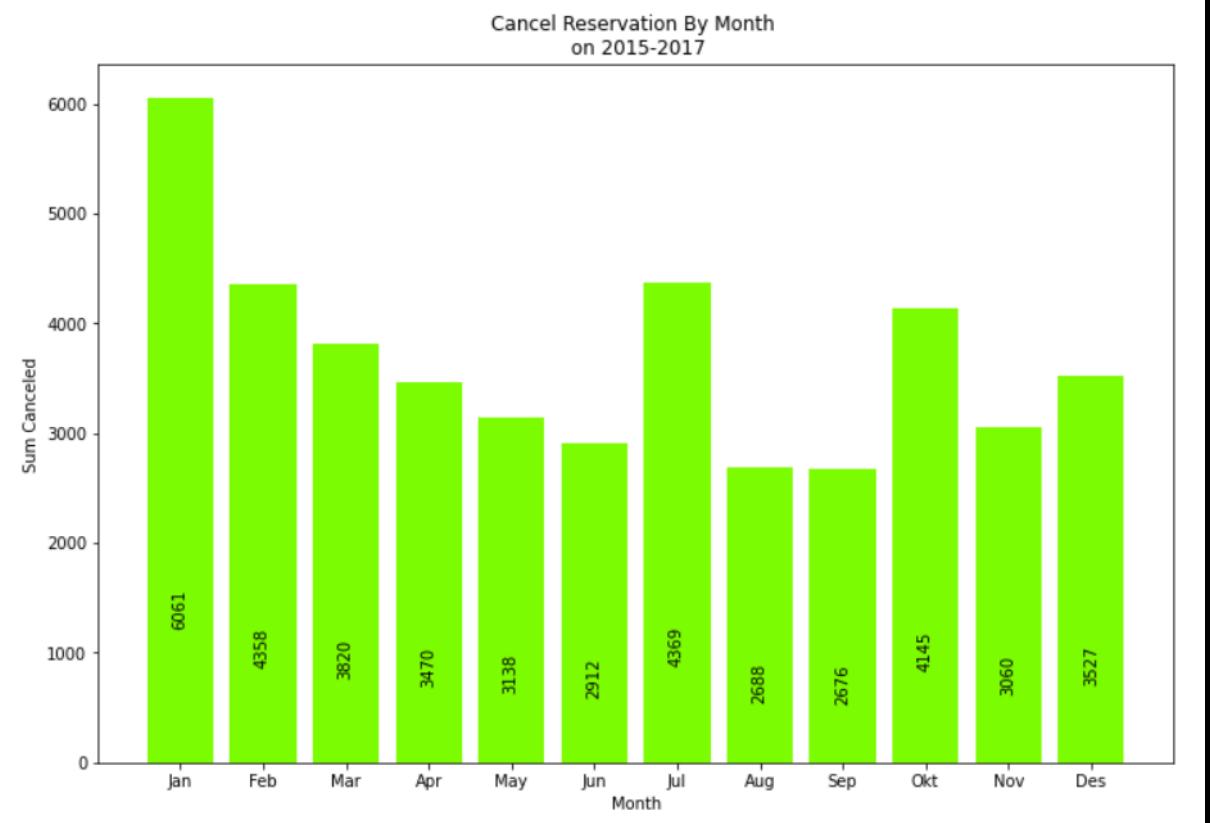


```
ax, fig = plt.subplots(figsize = (12,8))
sns.lineplot(sum_cancel['month'],sum_cancel['is_canceled'], marker = 'o')
plt.xticks(np.arange(13),
           ('','Jan','Feb','Mar','Apr','May',
            'Jun','Jul','Aug','Sep','Okt','Nov','Des'), rotation=20)
plt.title('Cancel Reservation By Month \n on 2015-2017 \n')
sns.set()
plt.show()
```





Bar Plot



To Compare

```
ax, fig = plt.subplots(figsize = (12,8))
bar_plots = plt.bar(sum_cancel['month'],sum_cancel['is_canceled'],
                     color = 'lawngreen', tick_label = ['Jan','Feb','Mar','Apr',
                     'May','Jun','Jul','Aug',
                     'Sep','Okt','Nov','Des'])

plt.xticks(sum_cancel['month'])
plt.title('Cancel Reservation By Month \n on 2015-2017')
plt.xlabel('Month')
def autolabel(rects):
    for idx,rect in enumerate(bar_plots):
        height = rect.get_height()
        plt.text(rect.get_x() + rect.get_width()/2., 0.2*height,
                 sum_cancel['is_canceled'][idx],
                 ha='center', va='bottom', rotation=90)
autolabel(bar_plots)
plt.ylabel('Sum Canceled')
plt.show()
```



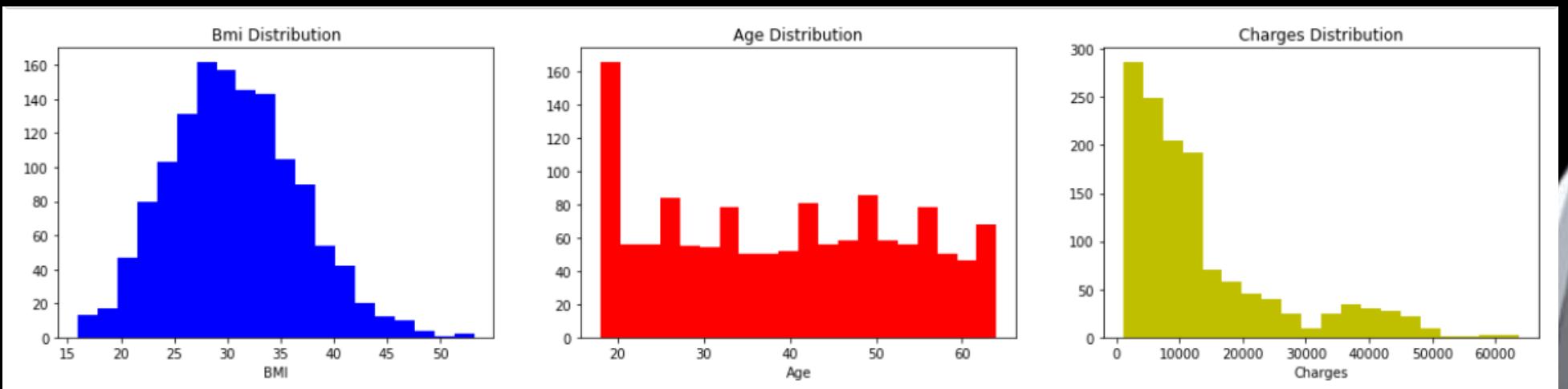
Histogram Plot



```
bmi = insurance['bmi']
age = insurance['age']
charges = insurance['charges']
fig, ax = plt.subplots(ncols = 3, figsize = (20, 4))
ax[0].hist(bmi,color = 'b',bins = 20)
ax[1].hist(age,color = 'r', bins = 20)
ax[2].hist(charges,color = 'y',bins = 20)
ax[0].set_title('Bmi Distribution')
ax[1].set_title('Age Distribution')
ax[2].set_title('Charges Distribution')
ax[0].set_xlabel('BMI')
ax[1].set_xlabel('Age')
ax[2].set_xlabel('Charges')

plt.show()
```

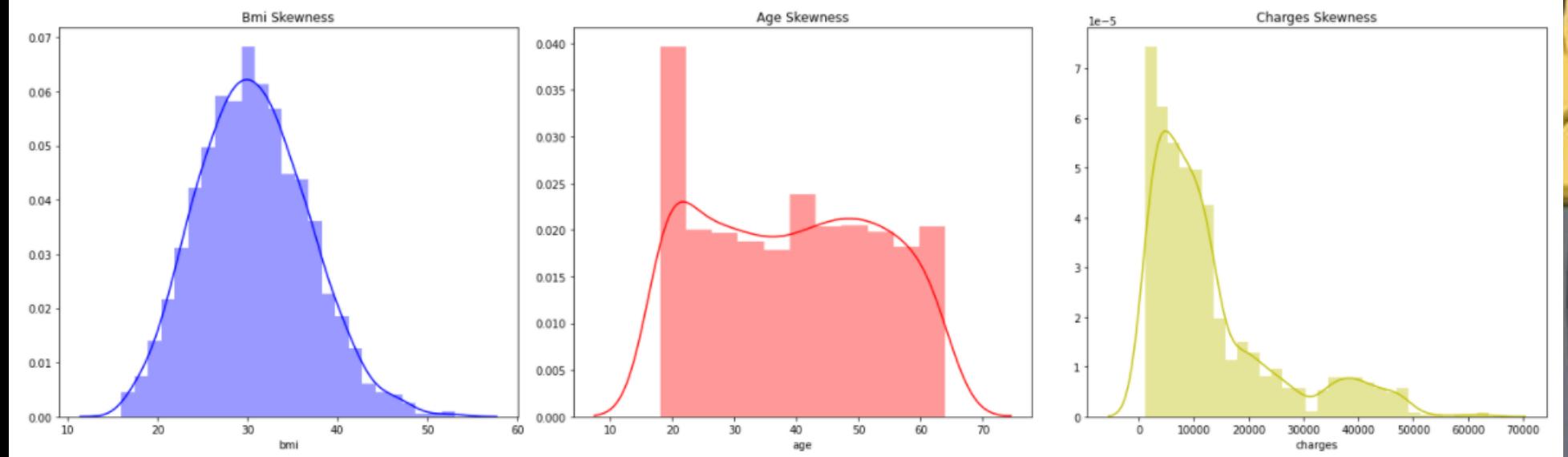
See distribution





Seeing Skew Plot

```
f, axes = plt.subplots(1,3, figsize = (20, 6))
#sns.despine(left=True)
sns.distplot(insurance['bmi'], color = 'b',ax = axes[0])
sns.distplot(insurance['age'], color = 'r', ax = axes[1])
sns.distplot(insurance['charges'], color = 'y',ax = axes[2])
#plt.setp(axes, yticks=[])
axes[0].set_title('Bmi Skewness')
axes[1].set_title('Age Skewness')
axes[2].set_title('Charges Skewness')
plt.tight_layout()
print(f"score skewness bmi: {skew(insurance['bmi'])}")
print(f"score skewness age: {skew(insurance['age'])}")
print(f"score skewness charges: {skew(insurance['charges'])}")
```

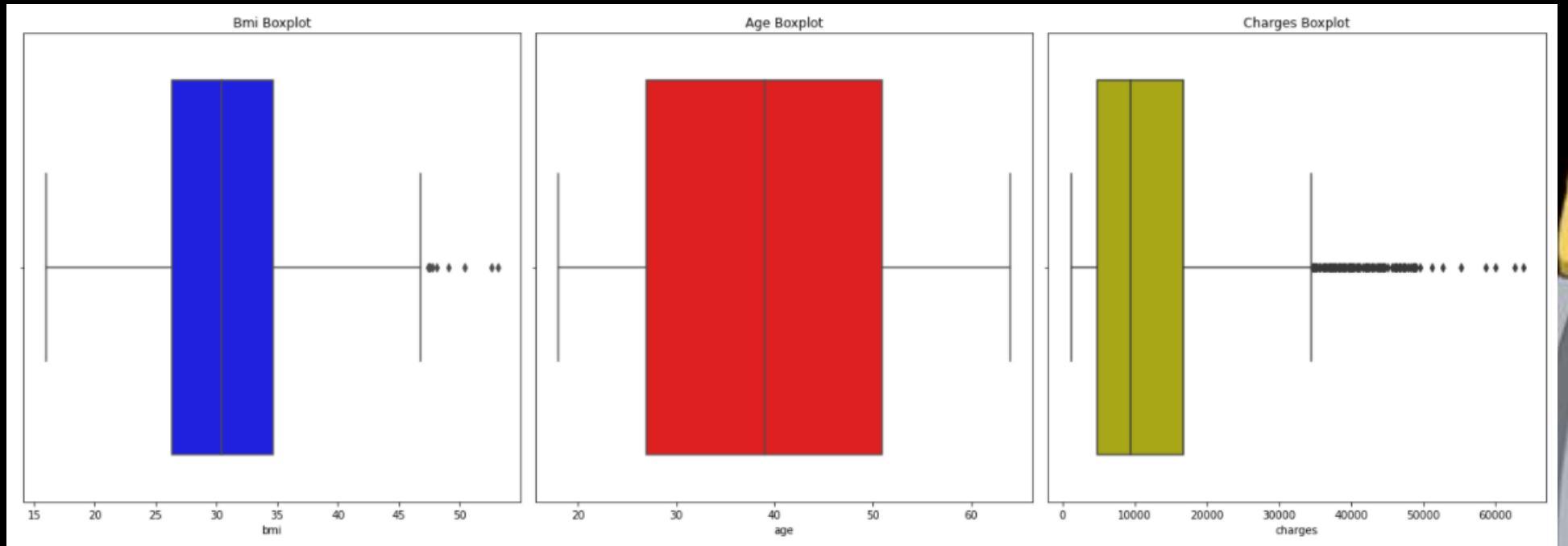




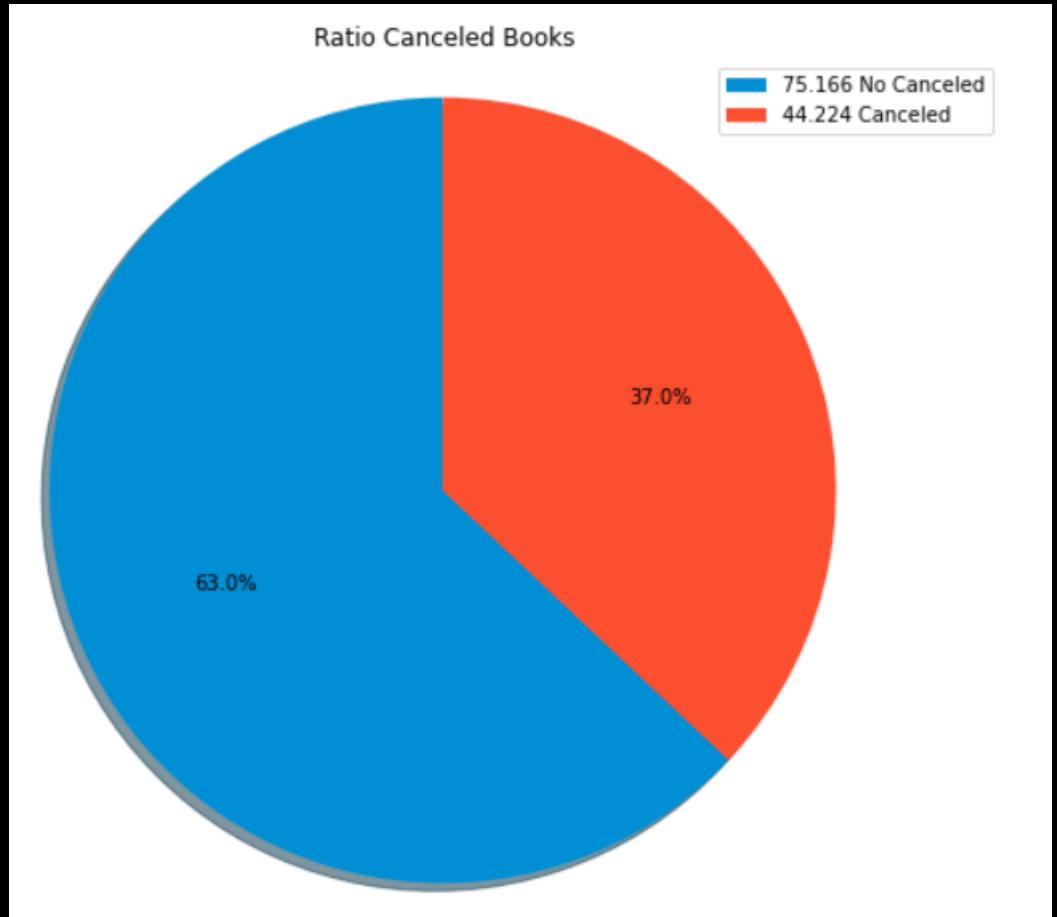
Box Plot Chart

```
f, axes = plt.subplots(1,3, figsize = (20, 7))
sns.despine(left=True)
sns.boxplot(insurance['bmi'], color = 'b', ax = axes[0])
sns.boxplot(insurance['age'], color = 'r', ax = axes[1])
sns.boxplot(insurance['charges'], color = 'y', ax = axes[2])
axes[0].set_title('Bmi Boxplot')
axes[1].set_title('Age Boxplot')
axes[2].set_title('Charges Boxplot')
plt.setp(axes, yticks=[])
plt.tight_layout()
```

See outlier



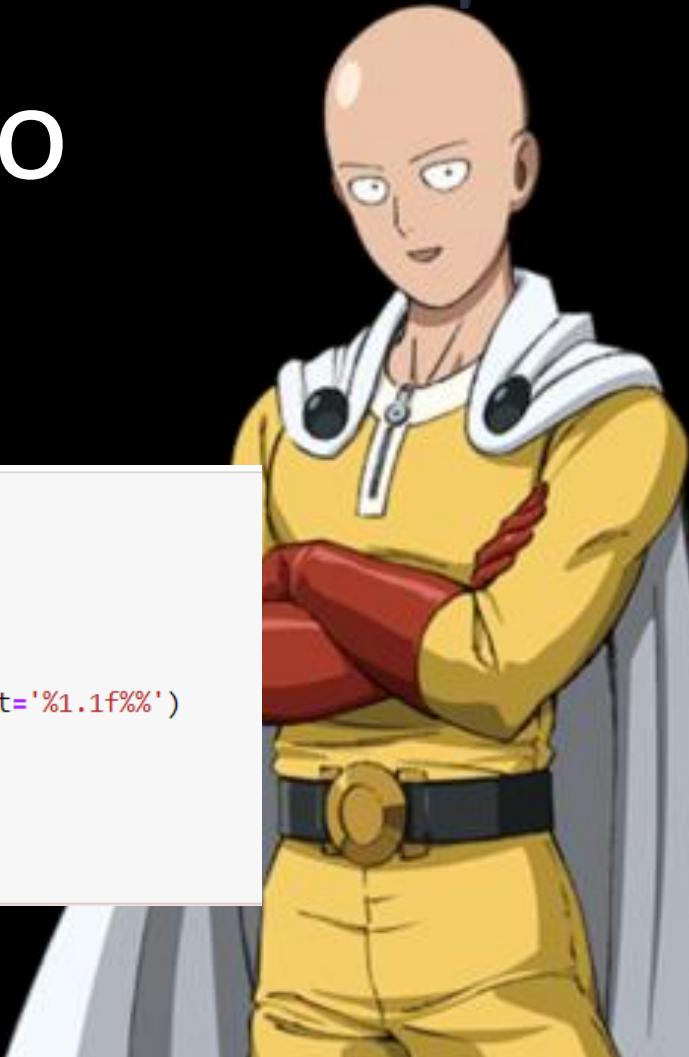
Pie Chart



See Ratio

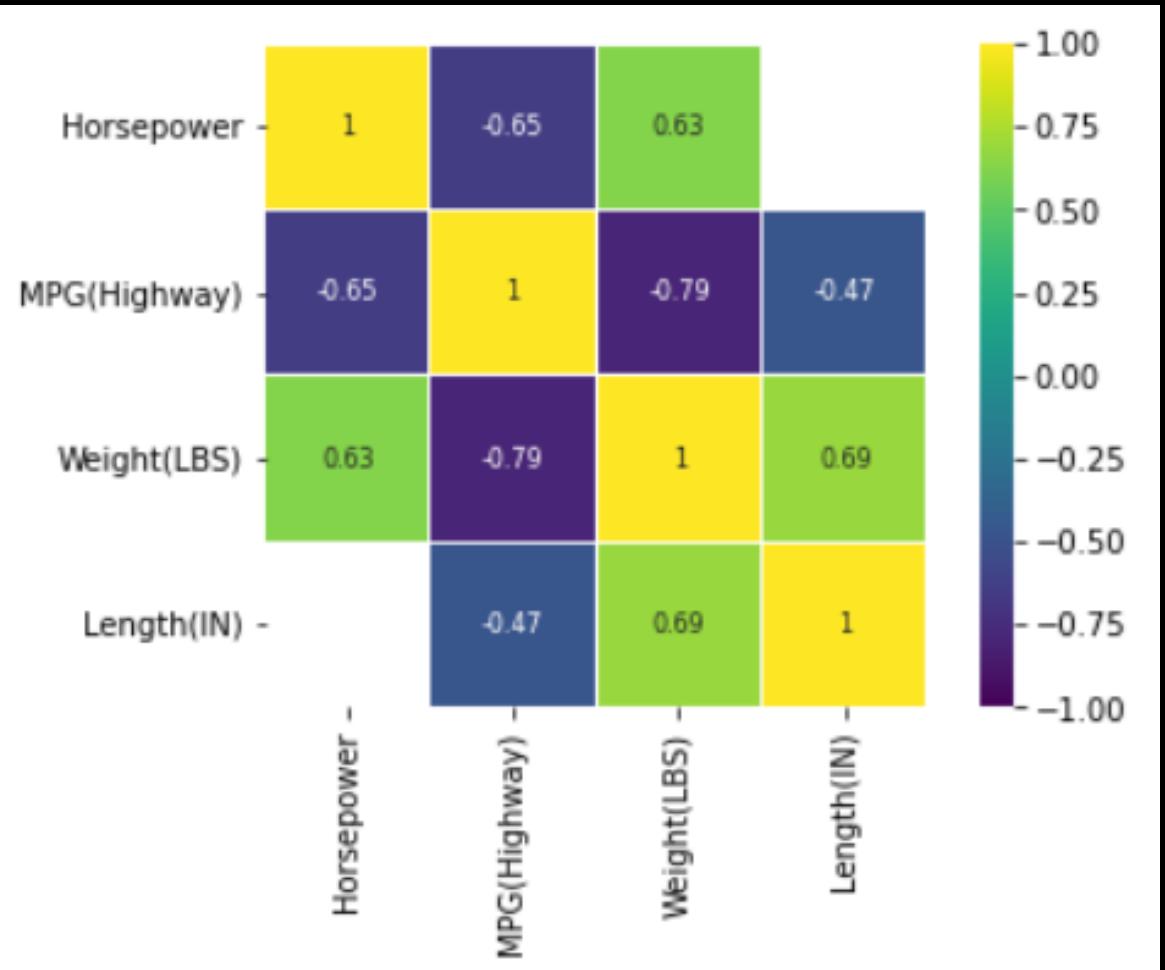
```
fig, ax = plt.subplots(figsize = (10,8))
colors = ['#008fd5', '#fc4f30']
sizes = s[:] # your data
recipe = ["75.166 No Canceled",
          "44.224 Canceled"]
plt.pie(sizes, colors=colors, shadow=True,
        startangle=90, autopct='%1.1f%%')

plt.title('Ratio Canceled Books')
plt.legend(labels = recipe, loc="upper right")
plt.axis('equal')
plt.show()
```





Heatmap Chart



To
Composition

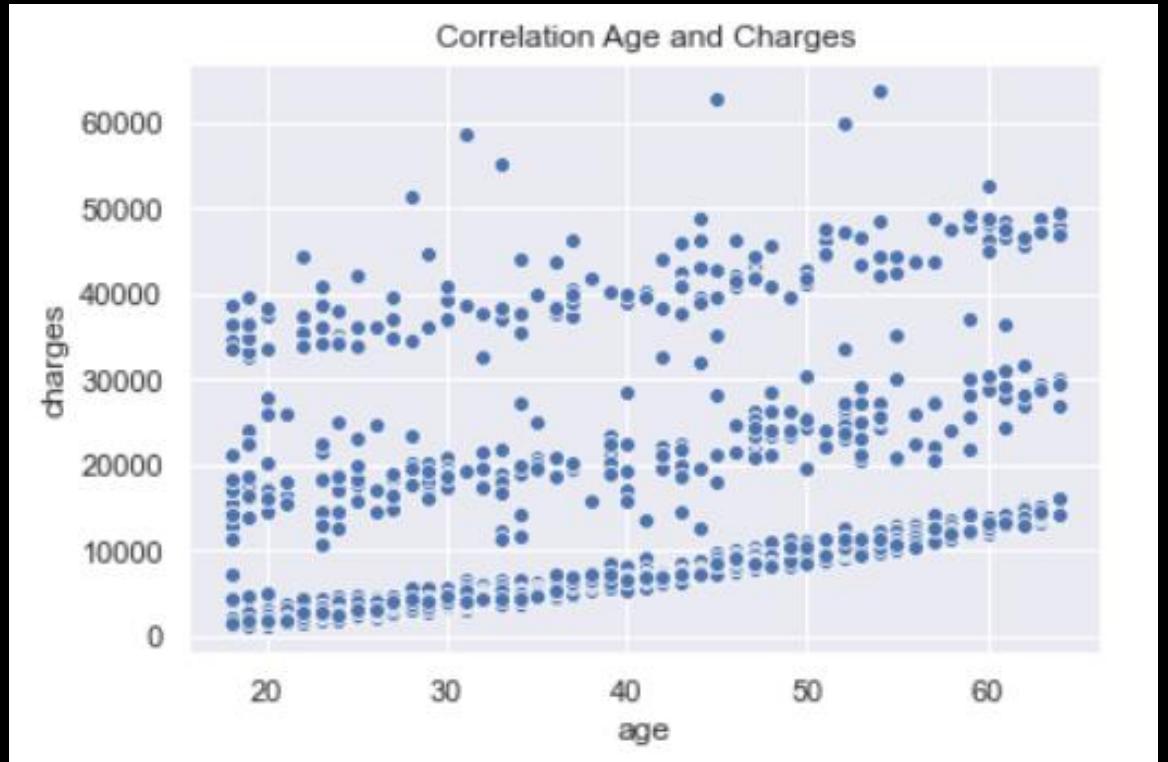
```
fig, axes = plt.subplots(figsize = (6,4))
corr = cars_num.drop('MPG(City)', axis = 1).corr()
sns.heatmap(corr[(corr >= 0.5) | (corr <= -0.4)], cmap = 'viridis',
            vmax = 1.0, vmin = -1.0, linewidths=0.1,
            annot=True, annot_kws={"size":8}, square=True);
```



Scatter Plot



```
f, axes = plt.subplots()  
sns.scatterplot(insurance['age'],insurance['charges'])  
axes.set_title('Correlation Age and Charges')  
sns.set()
```



To See
Correlation



Basic Map Chart



```
import folium
def generateBaseMap(default_location=[-7.8682695, 120.33345], default_zoom_start=4):
    base_map = folium.Map(location=default_location,
                          control_scale=True,
                          zoom_start=default_zoom_start)
    return base_map
base_map=generateBaseMap()
base_map
```



Covid Map Chart

```
# positive mapping
base_map=generateBaseMap()
for i in range(0, len(df_global)):
    folium.Circle(location=[df_global.iloc[i]['latitude'], df_global.iloc[i]['longitude']],
                  radius=float(df_global.iloc[i]['sembuh']),#the bigger the positive, the bigger the circle
                  #popup = df_global.iloc[i], #so that the information appears when clicked
                  color='crimson'#with color
                  fill=True, #the circle inside also has a color
                  fill_color = 'crimson').add_to(base_map)
for i in range(0, len(df_global)):
    folium.Circle(location=[df_global.iloc[i]['latitude'], df_global.iloc[i]['longitude']],
                  radius=float(df_global.iloc[i]['positif']),
                  #popup = df_global.iloc[i],
                  color='yellow',
                  fill=True,
                  fill_color = 'yellow').add_to(base_map)
# Circle = making bullets a number of countries because of using len (df_global)
base_map
```





Exploratory Data Analysis

INFOGRAPHICS

Data
Your main contents

Sorted
Understand relationships and every small details

Arranged
Have a distribution plan, be creative & narrative

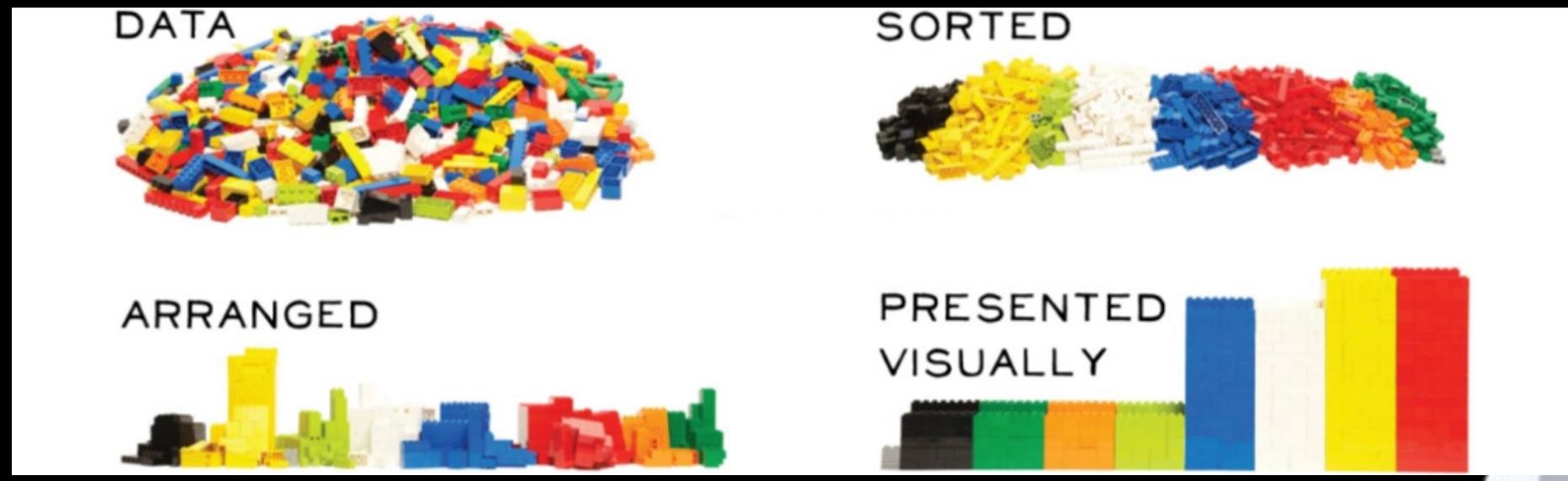
Presented Visually
Make the impact, there are free tools available





Exploratory Data Analysis

EDA is process of studying and investigating to find anomalies, patterns, with statistical processes.





Why we have to apply EDA?



Data Scientist



Ensure the integrity
of your
gathered data and
performed analysis

Remember
concept GIGO





3 Parts of EDA

1. Cleansing
2. Defining questions
3. Visualizations



Source

1. <https://www.guru99.com/what-is-data-analysis.html>
2. <http://www.data-analysis-in-python.org/#:~:text=Python%20is%20an%20increasingly%20popular,have%20accumulated%20over%20the%20years.>
3. <https://seaborn.pydata.org/>
4. <https://matplotlib.org/>
5. https://pandas.pydata.org/pandas-docs/stable/getting_started/index.html



Thank You



Ronny Fahrudin | Data Science Fellowship at IYKRA