GBDi
Government Big Data Institute
สถาบันส่งเสริมการวิเคราะห์และบริหารข้อมูลขนาดใหญ่ภาครัฐ (สวข.)

depa

Exploratory Data Analysis (EDA) with Python

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Ph.D (Applied Mathematics), KMITL

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Technical Skill

- Programming: MATLAB, RStudio, C++, Python
- Data visualization: Power BI, Looker studio, Tableau

Experiences

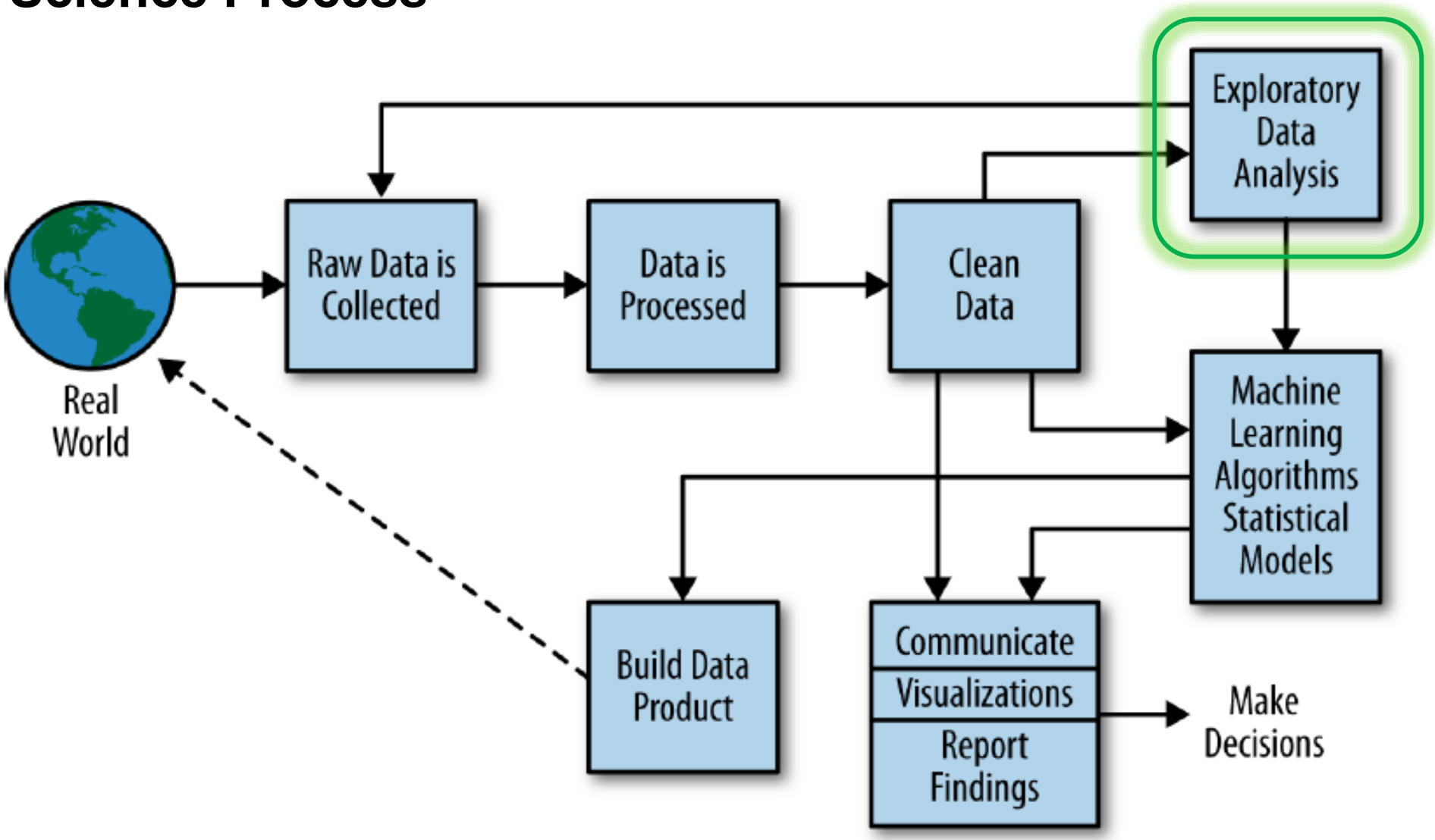
- Dashboard Development for Project
- Instructor and Teaching Assistant:

  Data Visualization - Data Science - Data Engineering - Data Governance and Data Catalog

Overview

- **Learning Outcome**
  - Understand the basic concepts of exploratory data analysis
  - Understand the role of statistics in data exploration
  - Choose appropriate data analysis techniques to explore and analyze data
- **Agenda**
  - Basic concepts of exploratory data analysis (EDA)
  - EDA techniques with Python

Data Science Process

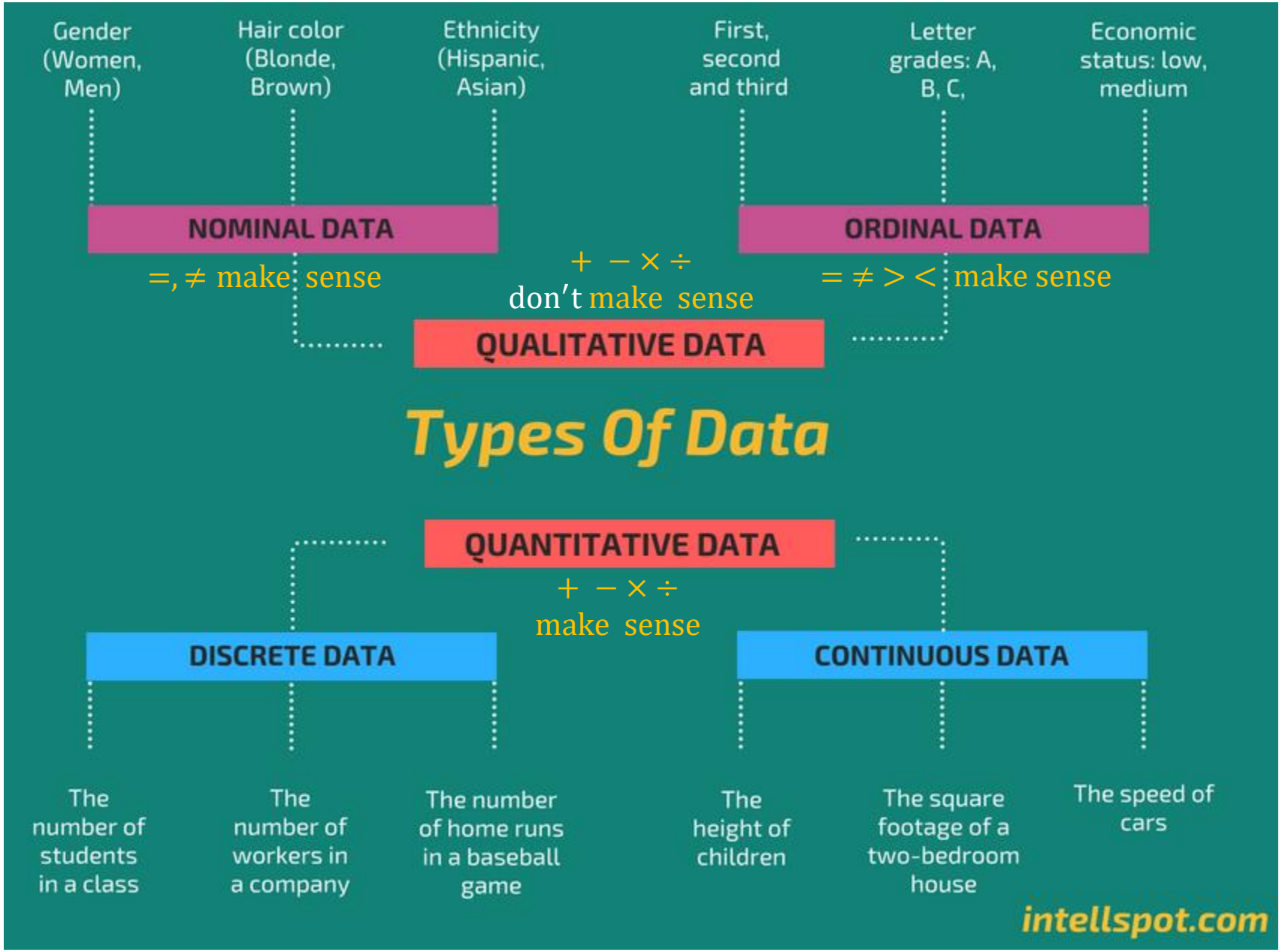


Exploratory Data Analysis (EDA)

- Exploratory data analysis or “**EDA**” is a critical step in analyzing the data
- The main reasons are
  - detection of mistakes, outliers or abnormalities
  - checking of assumptions
  - preliminary selection of appropriate models
  - determining relationships among the explanatory variables
  - assessing the direction and rough size of relationships between explanatory and outcome variables

Types of EDA

- **Graphical or Non-graphical**
  - **Non-graphical** methods usually involve with calculation of summary statistics
  - **Graphical** methods obviously summarize the data in a diagrammatic or pictorial way
- **Univariate or Multivariate**
  - **Univariate** methods look at one variable (column) at a time while
  - **Multivariate** methods look at two or more variables at a time


Gender (Women, Men)
Hair color (Blonde, Brown)
Ethnicity (Hispanic, Asian)
First, second and third
Letter grades: A, B, C,
Economic status: low, medium
NOMINAL DATA
ORDINAL DATA
=, ≠ make sense
+ − × ÷
don't make sense
= ≠ > < make sense
QUALITATIVE DATA
Types Of Data
QUANTITATIVE DATA
+ − × ÷
make sense
DISCRETE DATA
CONTINUOUS DATA
The number of students in a class
The number of workers in a company
The number of home runs in a baseball game
The height of children
The square footage of a two-bedroom house
The speed of cars
intellspot.com

Summary EDA Types

	UNIVARIATE	MUTIVARIATE
Graphical	**Quantitative Variable** • Histogram • Boxplots • Normal plot **Categorical Variable** • Bar Charts • Line Plot	**One Categorical and One Quantitative Variable** • Side-by-side Boxplots **Two or More Categorical Variables** • Grouped Bar Chart **Two or More Quantitative Variables** • Scatterplot • Correlation Heatmap
Non-Graphical	**Categorical Variable** • Tabular **Quantitative Variable** • Location (mean, median) • Spread (IQR, std dev, range) • Modality (mode) • Shape (skewness, kurtosis) • Outliers	**One Categorical and One Quantitative Variable** • Mean • Median • Range and Spread measures **Two or More Quantitative Variables** • Correlation • Covariance • Descriptive stat per

Univariate non-graphical EDA

Univariate non-graphical EDA

- This is to **measure certain characteristics** (e.g. age, gender, speed at a task, or response to a stimulus) of data of all subjects/records
- We should think of measurements as representations of a **“sample distribution”**, which in turn more or less representing the **“population distribution”**
- The goal is to **better understand the “sample distribution”** and **make some conclusion about the “population distribution”**

Univariate non-graphical EDA

Categorical data

- The characteristics of interest for a categorical variable are simply the range of values and the frequency (or relative frequency) of occurrence for each value.
- Therefore, the only useful univariate non-graphical techniques for categorical variables is some form of **tabulation of the frequencies**, usually along with calculation of the fraction (or percent) of data that falls in each category.

Univariate non-graphical EDA

Quantitative data

```
#ดูค่าทางสถิติพื้นฐาน
df.describe()
```

	Account length	Area code	Number vmail messages
count	667.000000	667.000000	667.000000
mean	102.841079	436.157421	8.407796
std	40.819480	41.783305	13.994480
min	1.000000	408.000000	0.000000
25%	76.000000	408.000000	0.000000
50%	102.000000	415.000000	0.000000
75%	128.000000	415.000000	20.000000
max	232.000000	510.000000	51.000000

Univariate non-graphical EDA

Categorical data

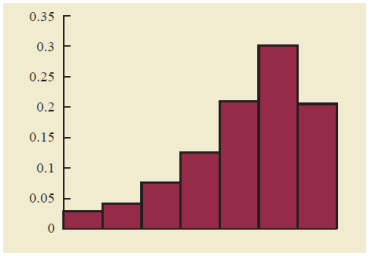
```
#ดูค่าทางสถิติพื้นฐานสำหรับข้อมูลที่เป็น object และ bool
df.describe(include=['object',bool])
```

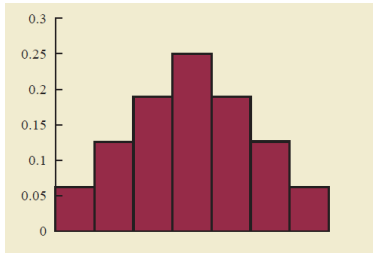
	State	International plan	Voice mail plan	Churn
count	667	667	667	667
unique	51	2	2	2
top	AZ	No	No	False
freq	19	614	478	572

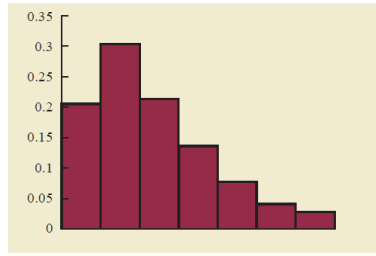
Univariate non-graphical EDA

Quantitative data

- Univariate EDA for a quantitative variable is a way to make preliminary assessments about the **population distribution** of the variable using the data of the observed sample.
- The **characteristics of the population distribution** of a quantitative variable are its
  - Center
  - Spread
  - Shape
  - Outliers

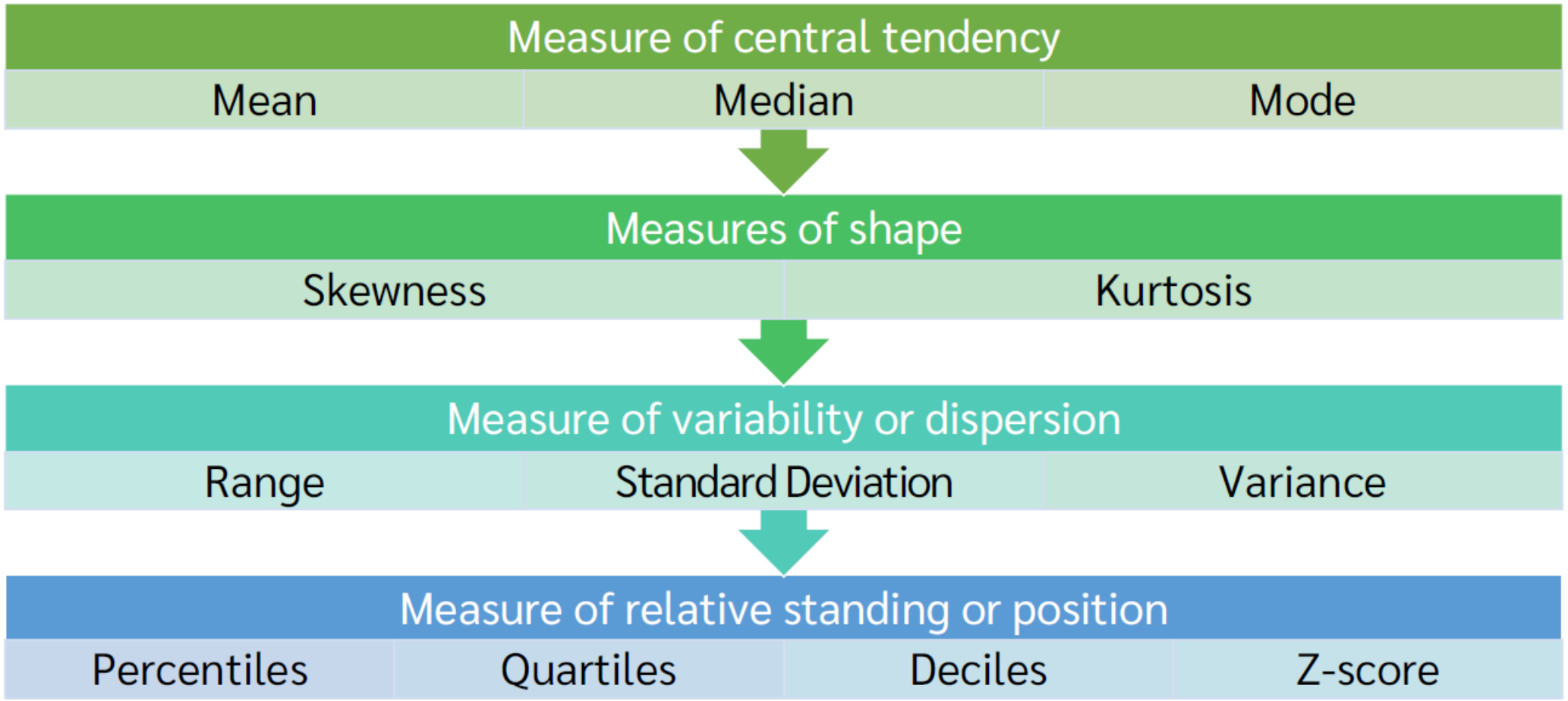






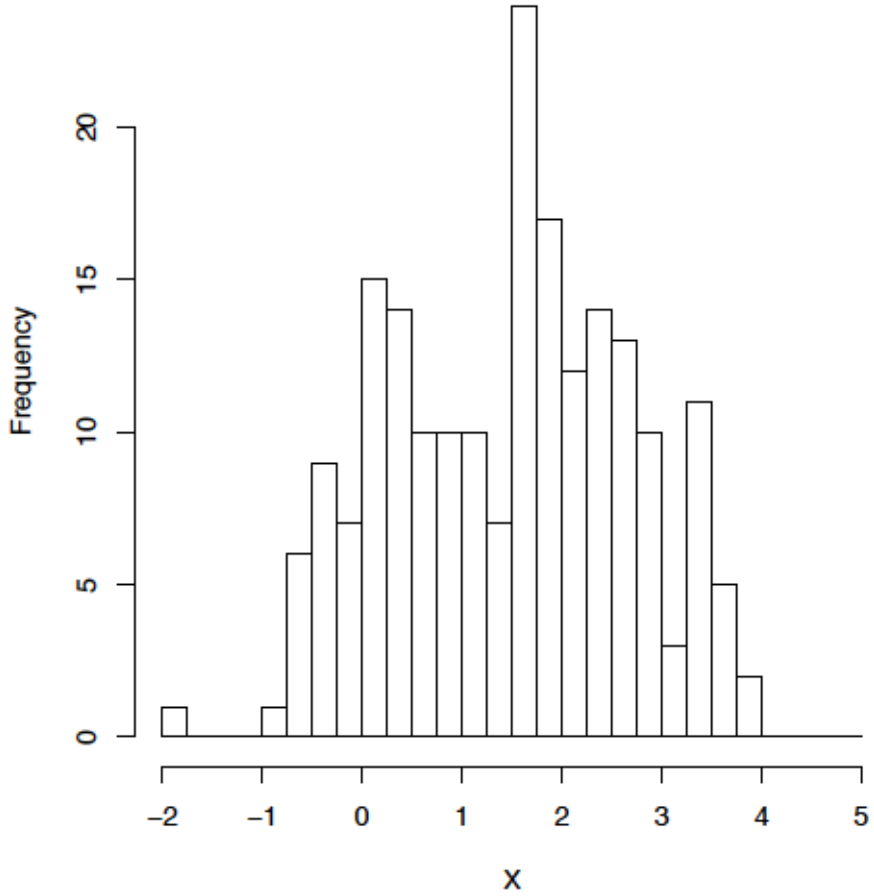
Univariate non-graphical EDA

Quantitative data



Univariate non-graphical EDA

Quantitative data



Central tendency
Spread
Skewness
Etc.

What can you see from this histogram?

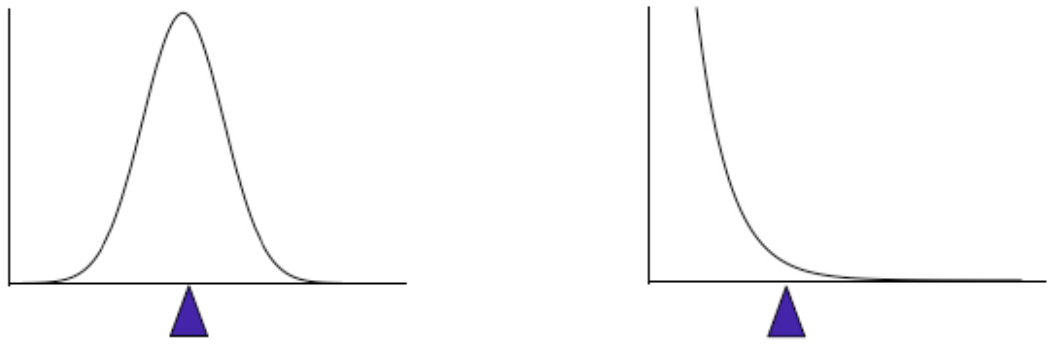
Central tendency (Middle Value)

Mean

1. The Mean

To calculate the average $\overline{x}$ of a set of observations, add their value and divide by the number of observations:

$$\overline{x} = \frac{x_1 + x_2 + x_3 + \ldots + x_n}{n} = \frac{1}{n}\sum_{i=1}^{n} x_i$$



Central tendency

Median

- **Median** – the exact middle value

- **Calculation**:
  - If there are an odd number of observations, find the middle value

  - If there are an even number of observations, find the middle two values and average them

- **Example**

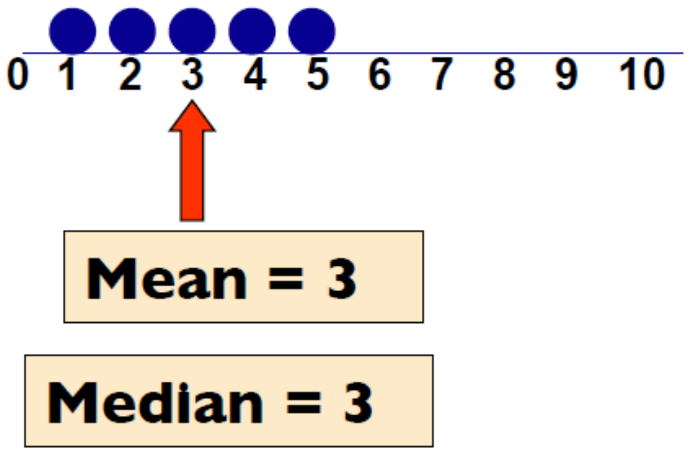
  Some data:
  Age of participants: 17 19 21 22 23 23 23 38

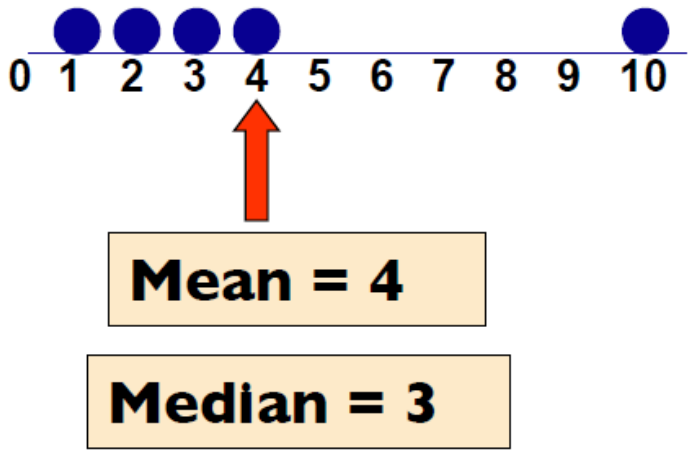
  Median = (22+23)/2 = 22.5

Central tendency

Which location measure is the best?

- Mean is best for symmetric distributions without outliers
- Median is useful for skewed distributions or data with outliers





Scale: Variance Standard measurement of Spread

- Average of squared deviations of values from the mean

$$\hat{\sigma}^2 = \frac{\sum_{i}^{n} (x_i - \bar{x})^2}{n-1}$$

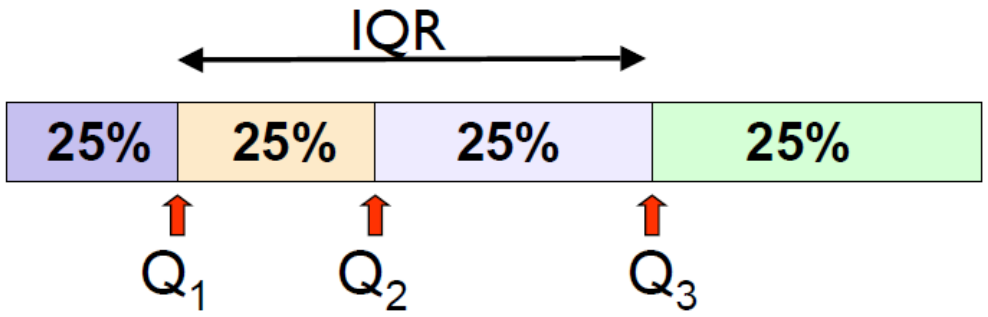
Scale: Standard deviation

$$\hat{\sigma} = \sqrt{\frac{\sum_{i}^{n}(x_i - \bar{x})^2}{n-1}}$$

For Normally distributed data, approximately 95% of the values lie within 2 SD of the mean.

1. Score (in the units that are meaningful)
2. Mean
3. Each score's deviation from the mean
4. Square that deviation
5. Sum all the squared deviations (Sum of Squares)
6. Divide by n-1
7. Square root – now the value is in the units we started with!!!

Scale: Quartiles and IQR

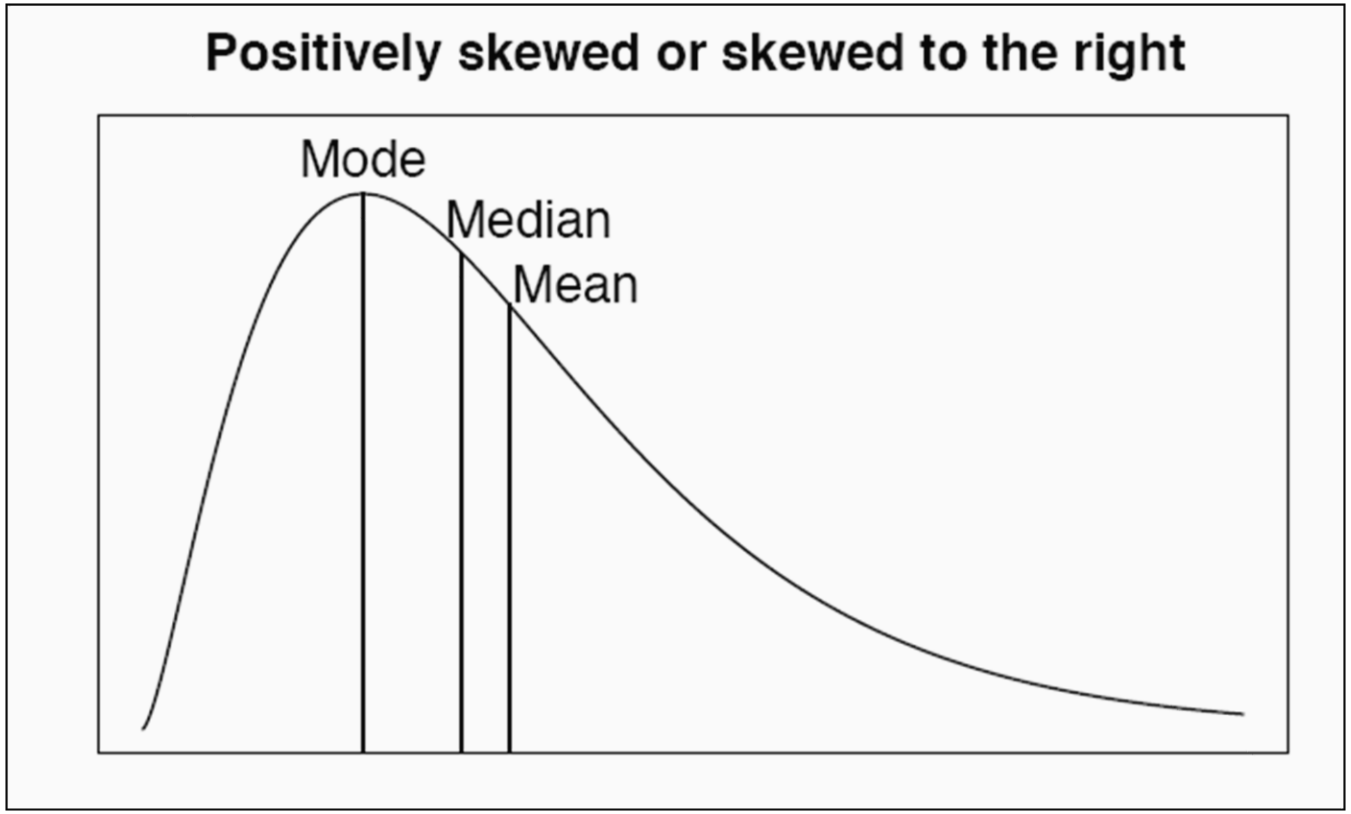


- The first quartile, Q_1, is the value for which 25% of the observations are smaller and 75% are larger
- Q_2 is the same as the median (50% are smaller, 50% are larger)
- Only 25% of the observations are greater than the third quartile

Skewness

Positively skewed

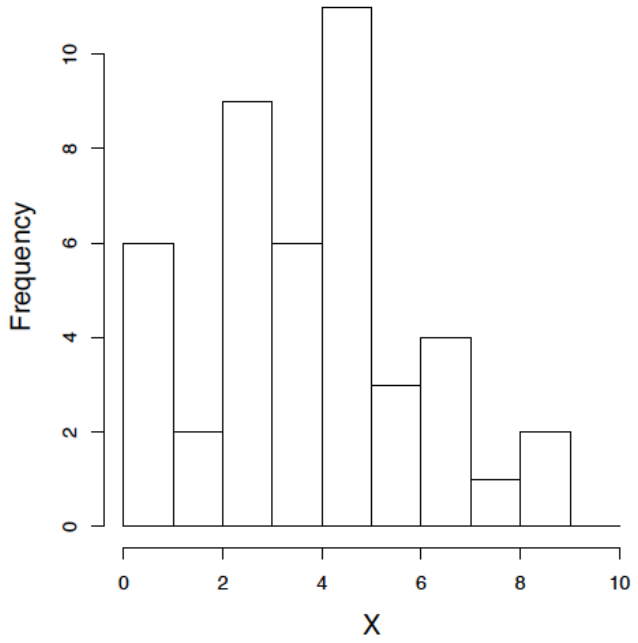
- Longer tail in the high value
- Mean > Median > Mode



Univariate Graphical EDA

Univariate Graphical EDA

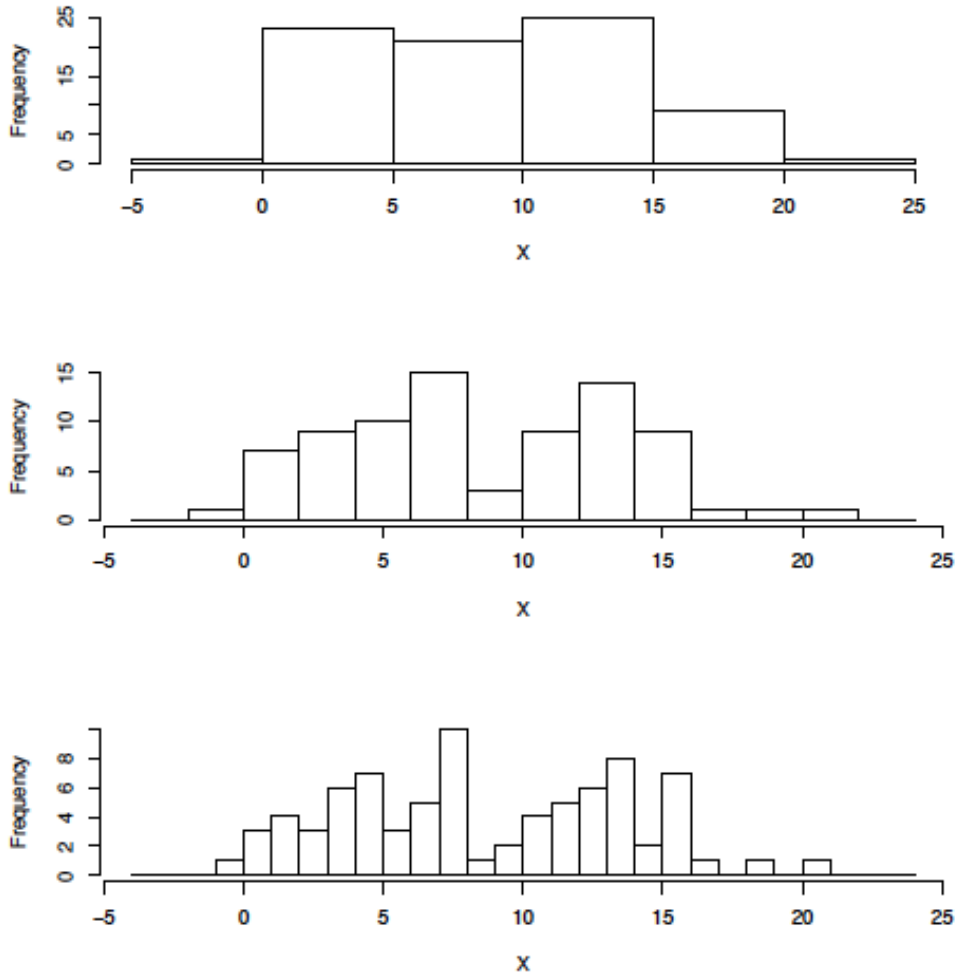
Histogram



- **Histogram** is a graphical representation of the **distribution of numerical data**
- It provides a view of data **density** and the **shape** of data distribution
- To construct a histogram, the first step is to
  - bin the range of values
  - count how many values fall into each interval
- The **bins** are usually specified as consecutive, non-overlapping intervals of a variable.
- The bins (intervals) must be adjacent and are usually equal size.

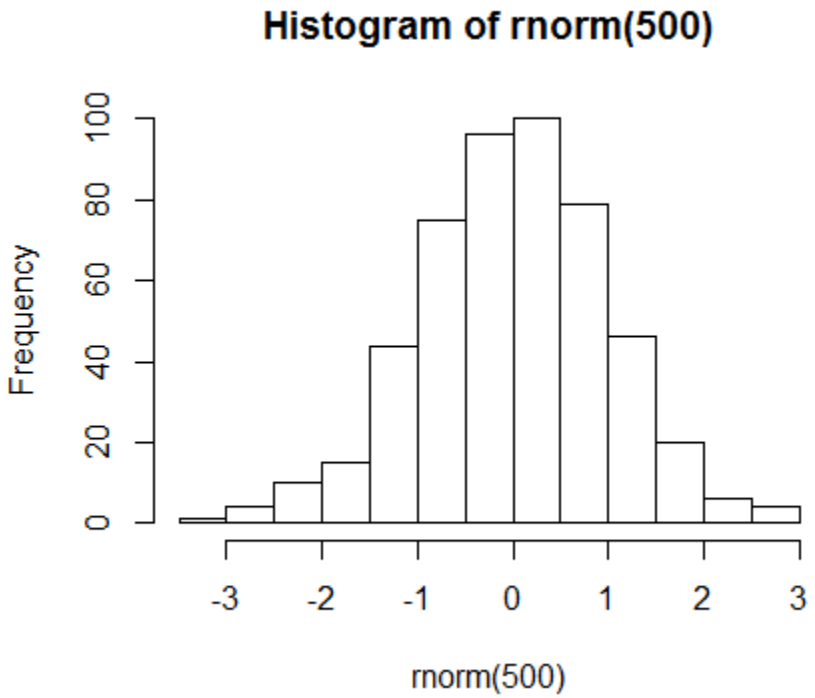
Univariate Graphical EDA

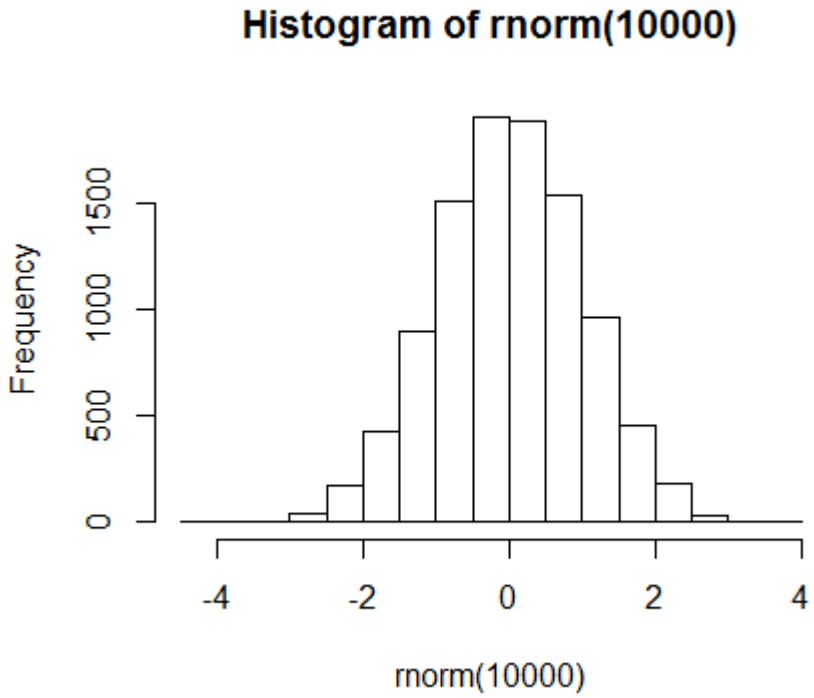
Effects of Histogram Bin



Univariate Graphical EDA

Effects of Number of Samples





Univariate Graphical EDA

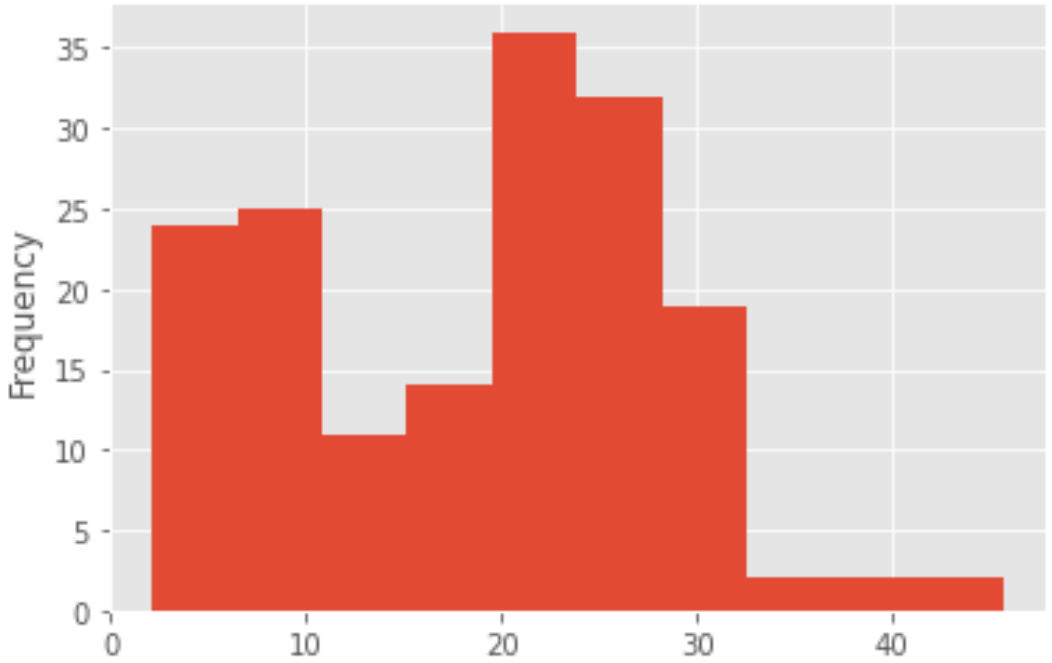
Histogram in Python

- Histogram
  - plot() method

```
Country
Afghanistan              4.5
Albania                 22.3
Algeria                 26.6
Angola                   6.8
Antigua and Barbuda     19.1
Argentina               28.5
Armenia                 20.9
Australia               30.4
Austria                 21.9
Azerbaijan              19.9
Name: Obesity, dtype: float64
```

```
# An easy way to create the histogram.
df_fat['Obesity'].plot.hist()
```

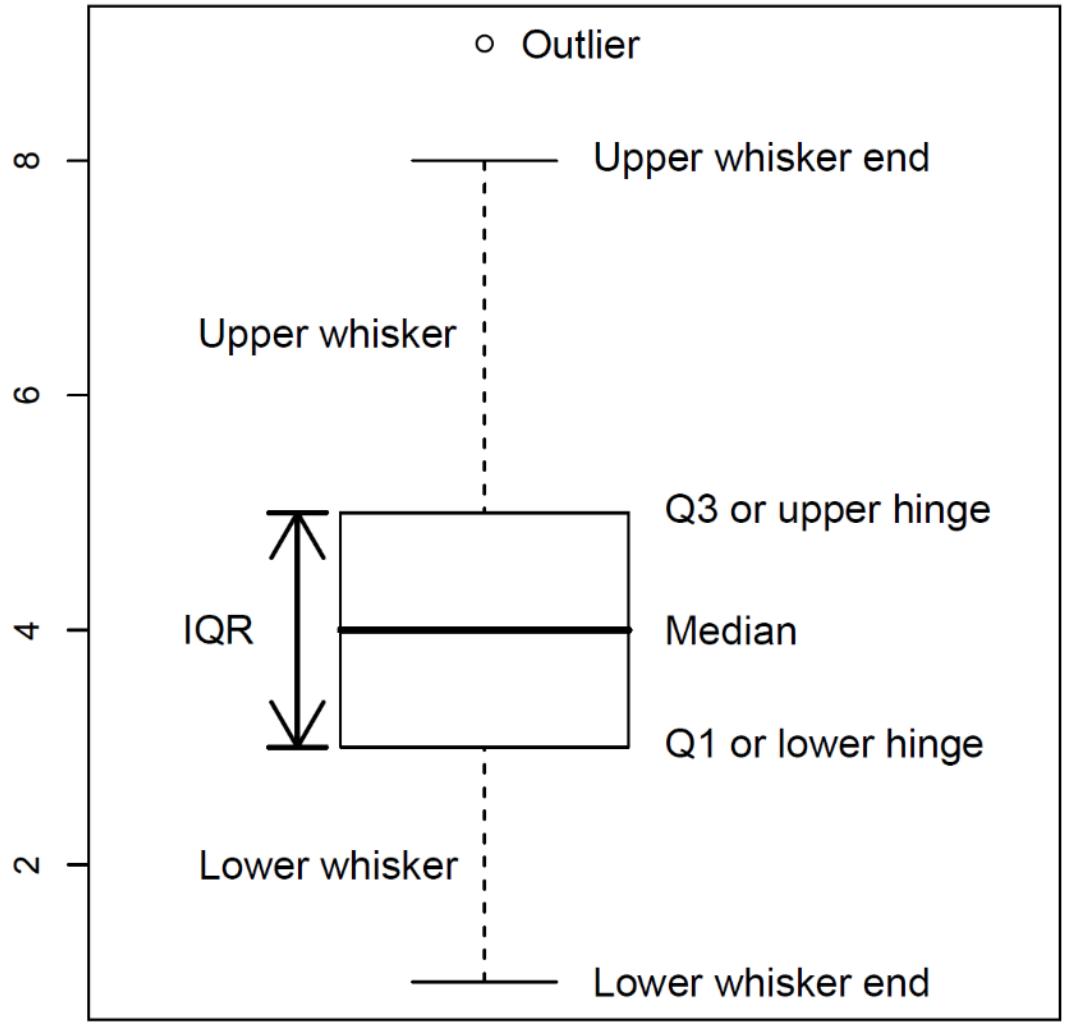
```
<AxesSubplot:ylabel='Frequency'>
```

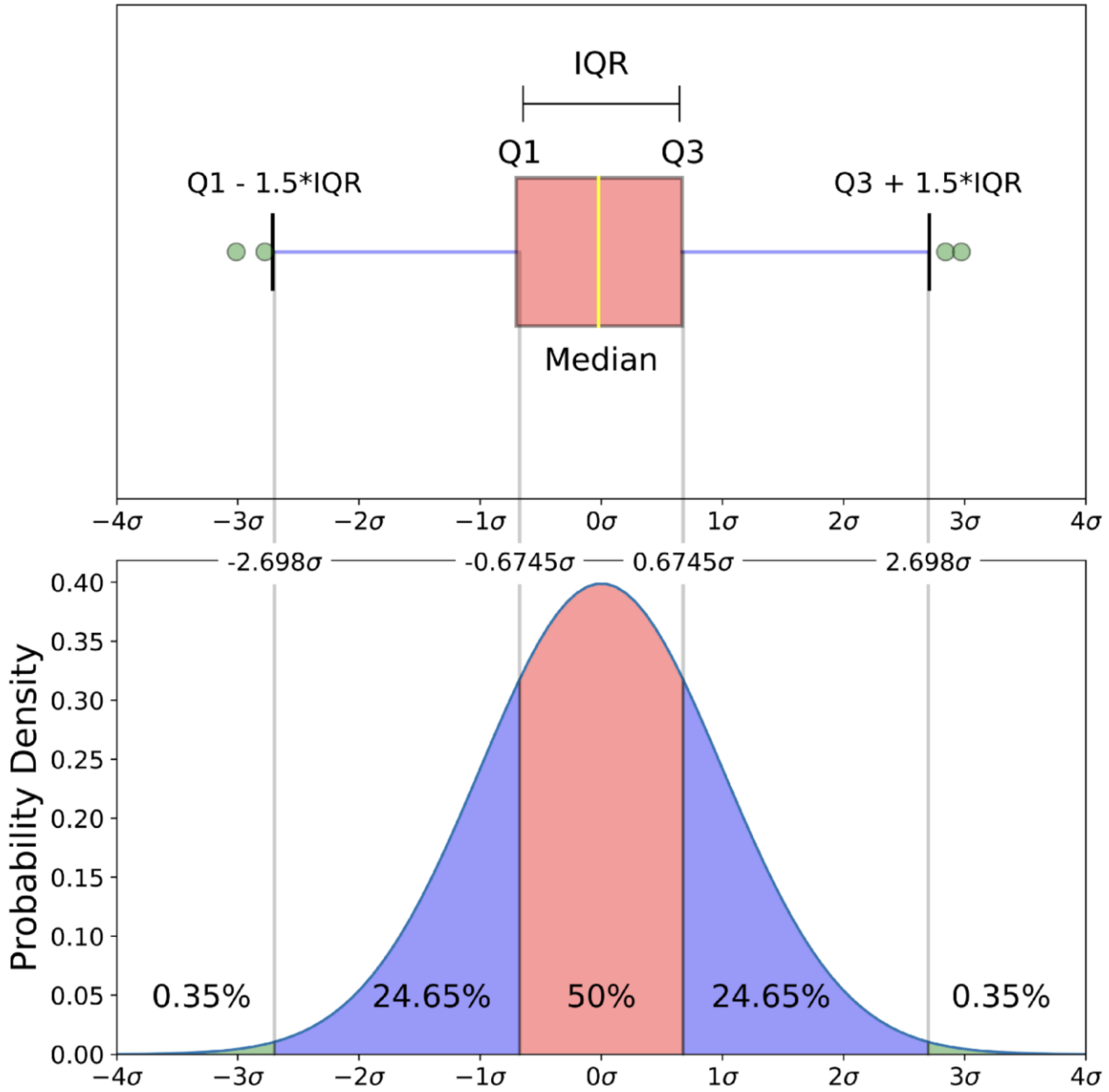


Univariate Graphical EDA

Boxplot

- The box in boxplot represents the middle 50% of the data
- The middle line indicates median
- Whiskers can be designated as either
  - Max/Min
  - Outlier boundaries
    - Upper = Q3 + 1.5*IQR
    - Lower = Q1 – 1.5*IQR



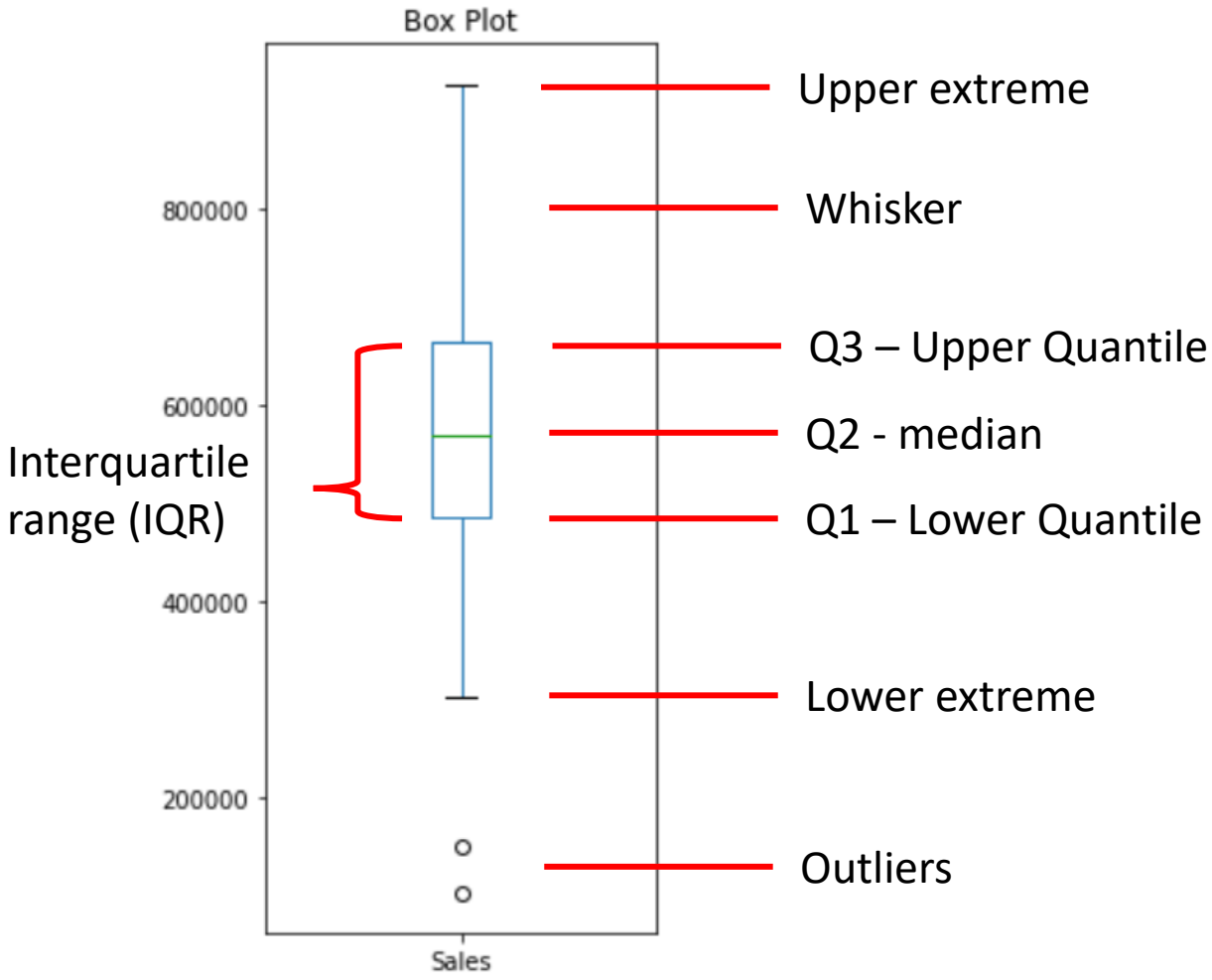

IQR
Q1
Q3
Q1 - 1.5*IQR
Q3 + 1.5*IQR
Median
−4σ
−3σ
−2σ
−1σ
0σ
1σ
2σ
3σ
4σ
-2.698σ
-0.6745σ
0.6745σ
2.698σ
Probability Density
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0.35%
24.65%
50%
24.65%
0.35%

Univariate Graphical EDA

Boxplot in Python

- Box Plots with matplotlib library

```
#We only take the variable sales.
df_oper_sales = df_operations.loc[:,'Sales']

df_oper_sales.plot(kind='box', figsize=(3,7))
plt.title('Box Plot')
plt.show()
```



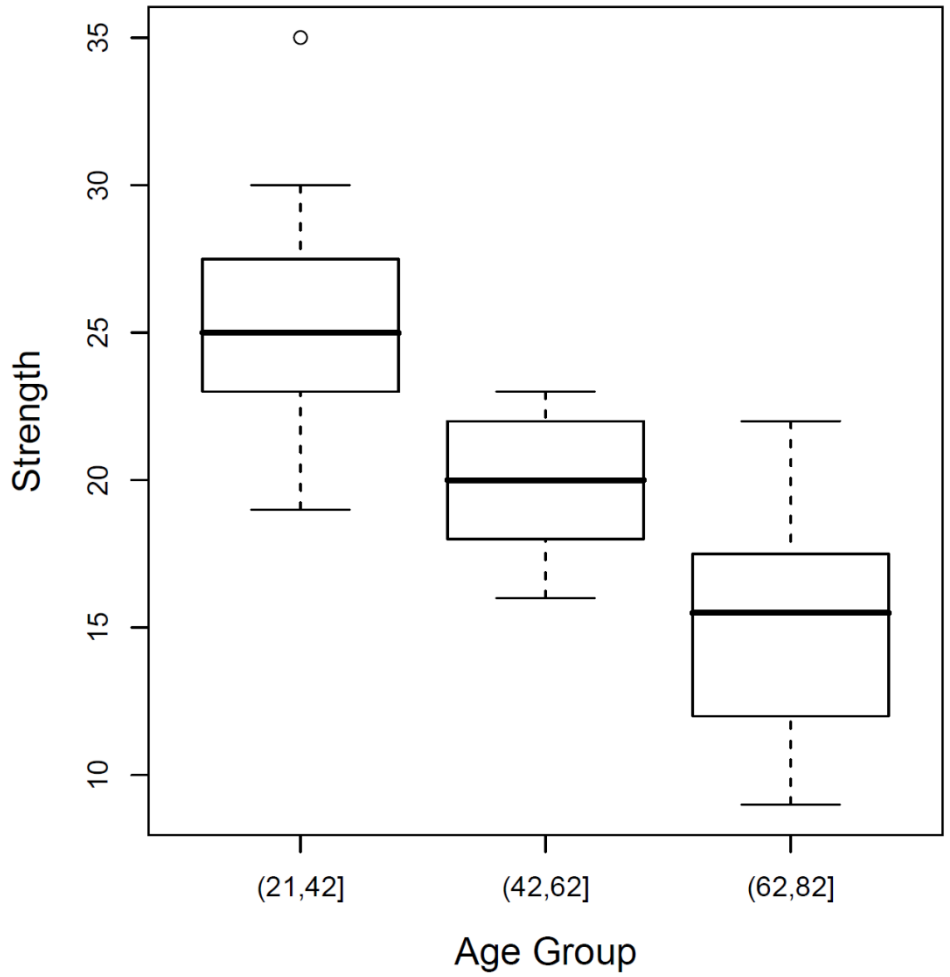
Multivariate Graphical EDA

Multivariate Non-Graphical EDA

- Multivariate non-graphical EDA techniques show the **relationship between two or more variables** in the form of either **cross-tabular** or **statistics**

Multivariate Graphical EDA

side-by-side boxplot

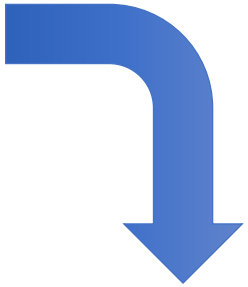


Side-by-side boxplots are good for examining the relationship between a categorical variable and a quantitative variable.

Multivariate Non-Graphical EDA

Cross-Tabulation

Subject ID	Age Group	Sex
GW	young	F
JA	middle	F
TJ	young	M
JMA	young	M
JMO	middle	F
JQA	old	F
AJ	old	F
MVB	young	M
WHH	old	F
JT	young	F
JKP	middle	M



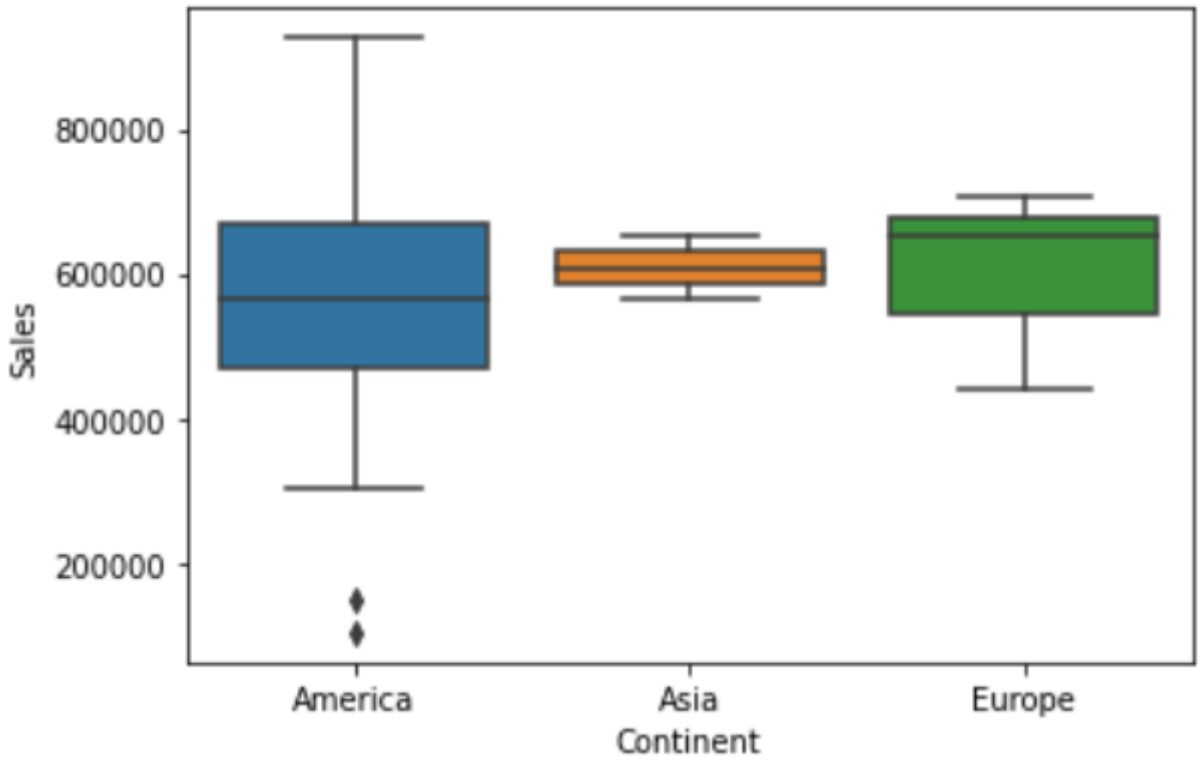
Age Group / Sex	Female	Male	Total
young	2	3	5
middle	2	1	3
old	3	0	3
Total	7	4	11

Multivariate Graphical EDA

side-by-side boxplot in Python

- Box Plots with seaborn library

```
sns.boxplot(x="Continent", y="Sales", data=df_operations)
```

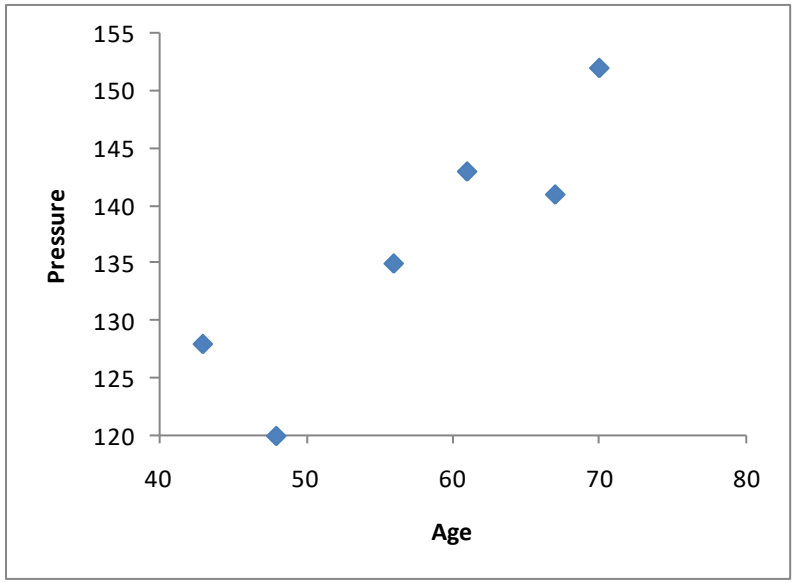


Multivariate Graphical EDA

Scatter plot

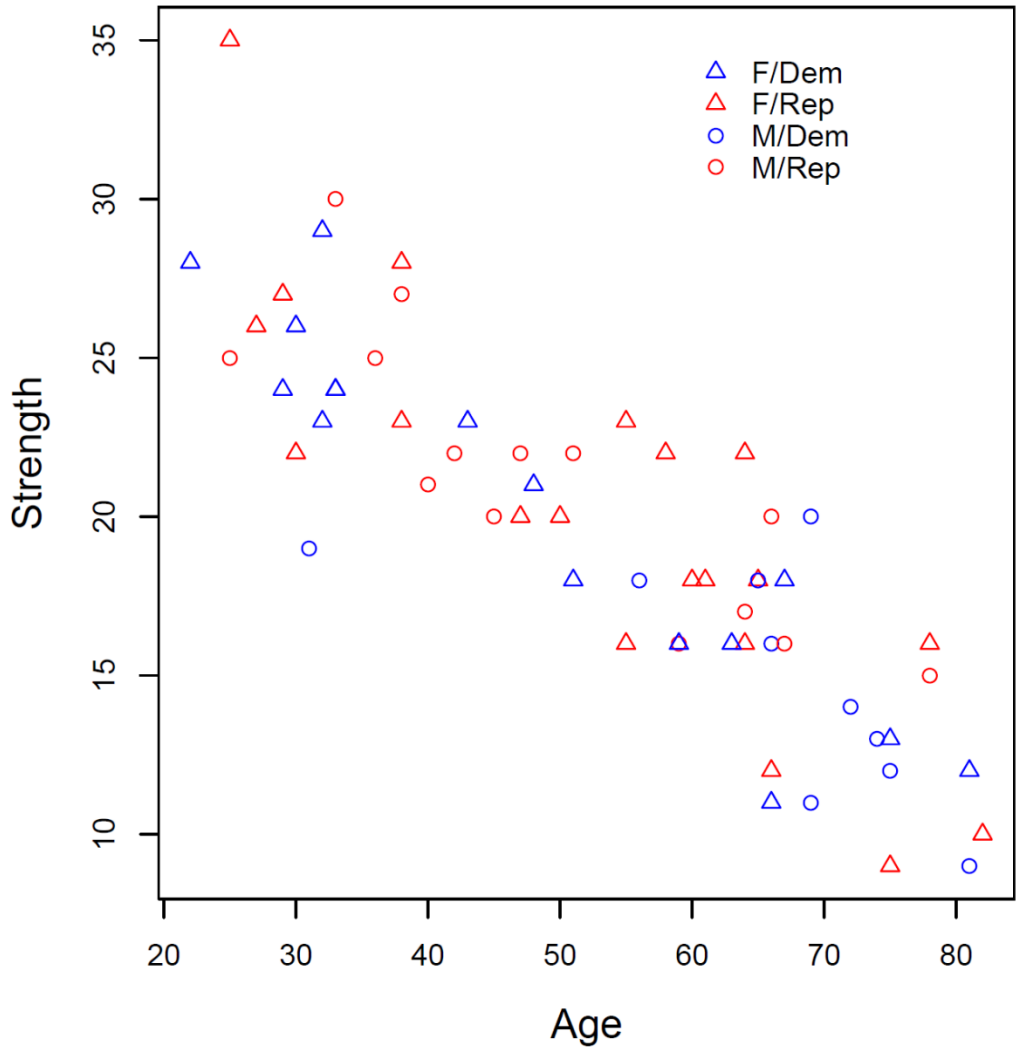
- A **scatter plot** is a graph of the ordered pairs (x,y) of numbers consisting of the **independent variable** x and the **dependent variable** y.

Subject	Age x	Pressure y
A	43	128
B	48	120
C	56	135
D	61	143
E	67	141
F	70	152



Multivariate Graphical EDA

Scatter plot with categorical data



- **One or two** additional **categorical variables** can be accommodated on the scatterplot
- Encoding the additional information in the **symbol type** and/or **color.**
- Here, colors code political party and gender

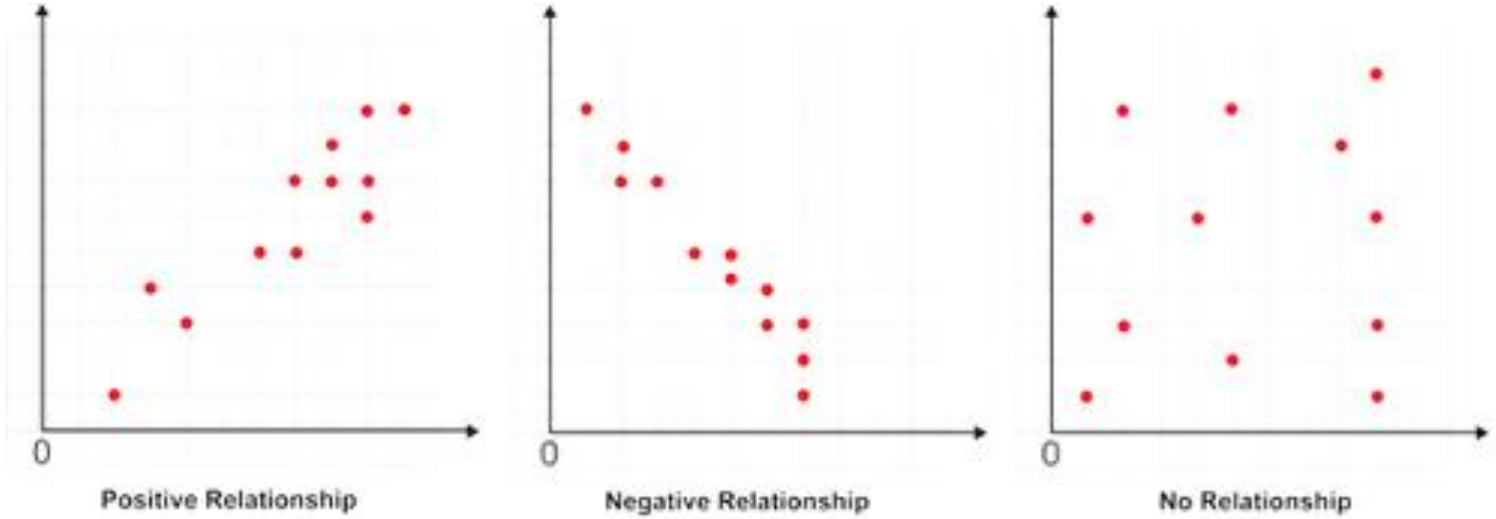
Relationship Between Variable

The study of the relationship between variable

Subject ID	Age	Strength	Age-50	Str-19	product
GW	38	20	-12	+1	-12
JA	62	15	+12	-4	-48
TJ	22	30	-28	+11	-308
JMA	38	21	-12	+2	-24
JMO	45	18	-5	-1	+5
JQA	69	12	+19	-7	-133
AJ	75	14	+25	-5	-125
MVB	38	28	-12	+9	-108
WHH	80	9	+30	-10	-300
JT	32	22	-18	+3	-54
JKP	51	20	+1	+1	+1
Total			0	0	-1106

Positive and negative relationship

- Simple relationships can also be positive or negative
- A **positive relationship** exists when both variables increase or decrease at the same time.
- In a **negative relationship**, as one variable increases, the other variable decreases, and vice versa.



Correlation Analysis

- Pearson's Correlation Coefficient.

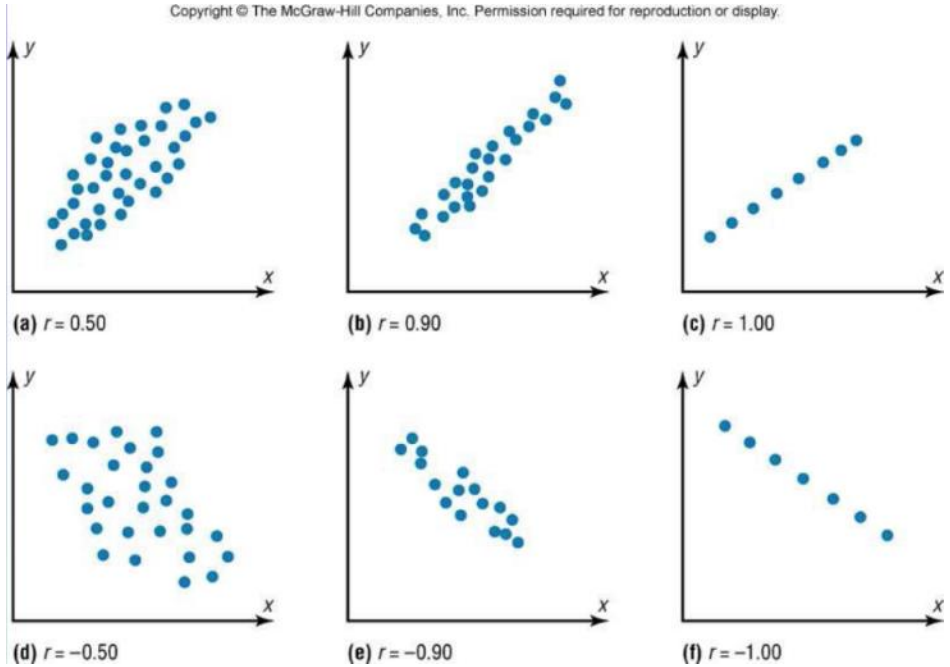
$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}$$

$$r = \frac{(20 * 4213.468) - (190.3998 * 361.6)}{\sqrt{[(20 * 2501.446) - 190.3998^2][(20 * 8568.5) - 361.6^2]}}$$

$$r = \frac{559552262.4}{23654.85706} = 0.651908$$

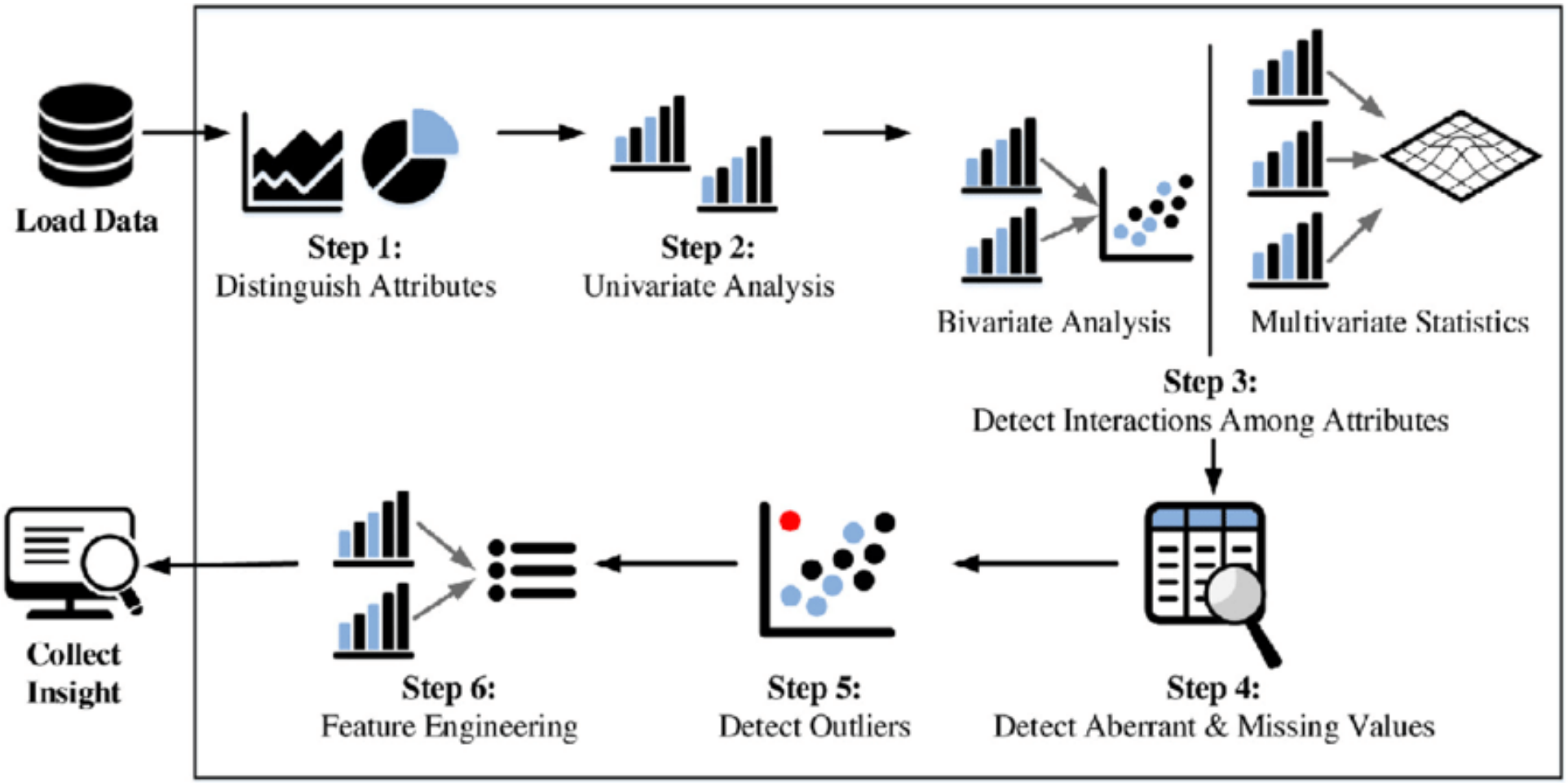
Meat	Obesity			
x	y	xy	x^2	y^2
6.1244	4.5	27.5598	37.50828	20.25
8.7428	22.3	194.9644	76.43655	497.29
3.8961	26.6	103.6363	15.1796	707.56
11.0268	6.8	74.98224	121.5903	46.24
14.3202	19.1	273.5158	205.0681	364.81
19.2693	28.5	549.1751	371.3059	812.25
10.8165	20.9	226.0649	116.9967	436.81
11.6002	30.4	352.6461	134.5646	924.16
8.1099	21.9	177.6068	65.77048	479.61
11.9993	19.9	238.7861	143.9832	396.01
17.4941	32.1	561.5606	306.0435	1030.41
1.8407	3.4	6.25838	3.388176	11.56
13.1382	24.8	325.8274	172.6123	615.04
11.5636	26.6	307.5918	133.7168	707.56
5.6817	24.5	139.2017	32.28171	600.25
10.3435	22.4	231.6944	106.988	501.76
3.2849	8.2	26.93618	10.79057	67.24
21.1476	18.7	395.4601	447.221	349.69
190.3998	361.6	4213.468	2501.446	8568.5

Correlation coefficient and scatter plot



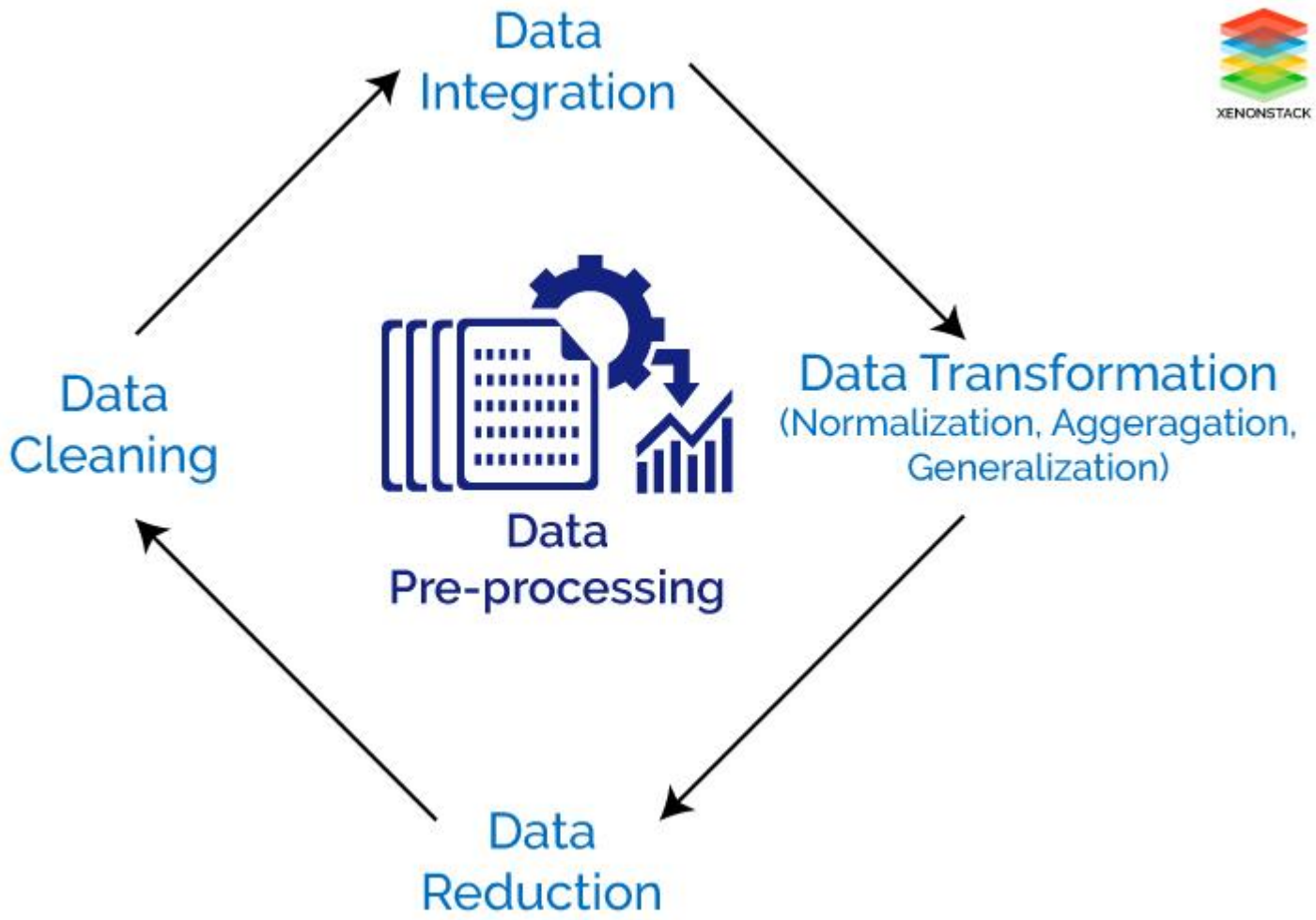
- The range of the correlation coefficient is from -1 to 1.
- If there is a strong positive linear relationship between the variables, the value of *r* will be close to 1.
- If there is a strong negative linear relationship, the value of *r* will be close to -1.
- When there is no linear relationship between the variables or only a weak one, the value of *r* will be close to 0

EDA Process Overview



Data Preparation

- Data Exploration
- Data Cleaning
  - missing data
  - noisy data, outliers
  - duplication
- Data Integration
- Data Transformation
  - Normalization
  - Aggregation
  - Generalization



Data format

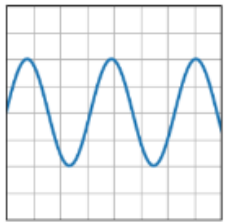
- Data from either experiments or operations are generally collected in databases (e.g. spreadsheet)
- One row per record and one column for each identifiers, outcome variables, and explanatory variables
- Each column contains the **numerical value** of a particular quantitative variable or the levels for a **categorical variable**

matplotlib

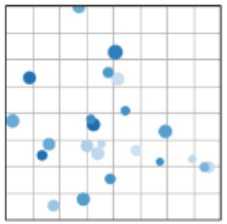
- Create publication quality plots.
- Make interactive figures that can zoom, pan, update.
- Customize visual style and layout.
- Export to many file formats.
- Embed in JupyterLab and Graphical User Interfaces.
- Use a rich array of third-party packages built on Matplotlib.

Basic

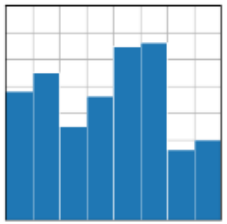
Basic plot types, usually y versus x.



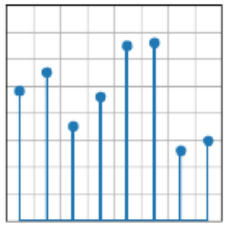
plot(x, y)



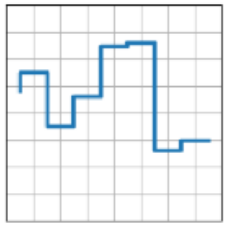
scatter(x, y)



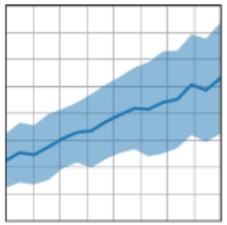
bar(x, height)



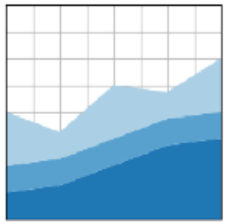
stem(x, y)



step(x, y)



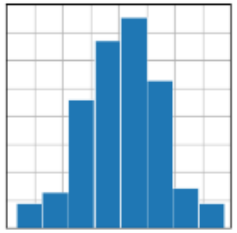
fill_between(x, y1, y2)



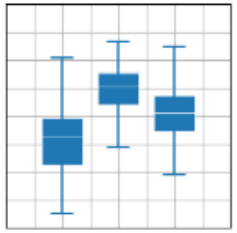
stackplot(x, y)

Statistics plots

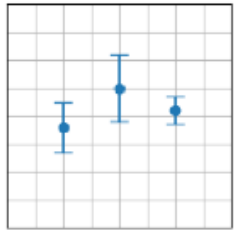
Plots for statistical analysis.



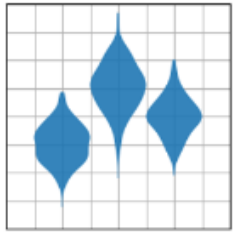
hist(x)



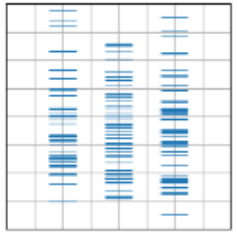
boxplot(X)



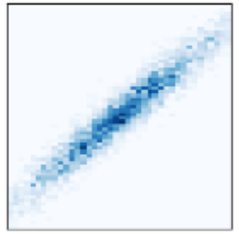
errorbar(x, y, yerr, xerr)



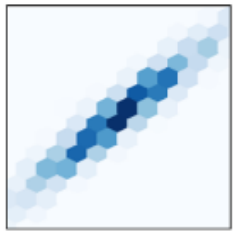
violinplot(D)



eventplot(D)



hist2d(x, y)

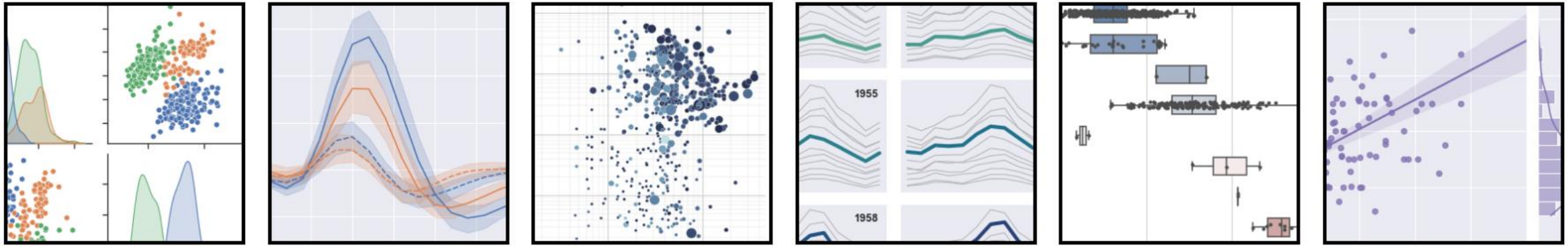


hexbin(x, y, C)

pie(x)

seaborn

- Seaborn is a Python data visualization library based on matplotlib.
- It provides a high-level interface for drawing attractive and informative statistical graphics



Data Exploration

Load Data

- โหลดข้อมูลเข้าสู่โปรแกรม Python โดยใช้ Pandas ซึ่งเป็นไลบรารีที่ช่วยในการจัดการข้อมูลและการวิเคราะห์ข้อมูลในรูปแบบตาราง (DataFrame)

python Copy code

```python
import pandas as pd

# โหลดข้อมูลจากไฟล์ CSV
data = pd.read_csv('data.csv')
```

Data Exploration

python Copy code

```python
# แสดงตัวอย่างข้อมูลหัวตาราง
data.head()

# แสดงข้อมูลเกี่ยวกับตาราง
data.info()

# สรุปสถิติเบื้องต้นของข้อมูล
data.describe()
```

Data type

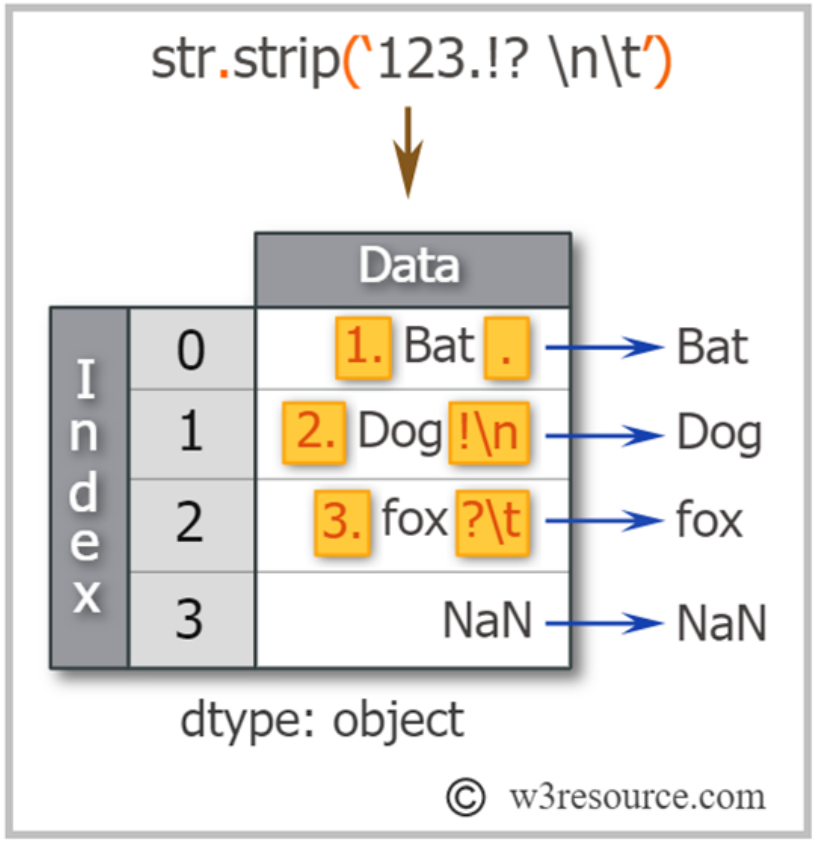
Datatype	Example	Python data type
Text data	First name, last name, address ...	`str`
Integers	# Subscribers, # products sold ...	`int`
Decimals	Temperature, $ exchange rates ...	`float`
Binary	Is married, new customer, yes/no, ...	`bool`
Dates	Order dates, ship dates ...	`datetime`
Categories	Marriage status, gender ...	`category`

Strings to integers

```
   SalesOrderID Revenue
0             0  39545$
1             1  31465$
2             2  13426$
```

```
Sale_data.dtypes
```

```
SalesOrderID     int64
Revenue         object
dtype: object
```



Split

```
  prefix     name     surname              name_full
0    mr.      xxx         yyy            mr. xxx yyy
1    ms.     abcd     efghijk       ms. abcd efghijk
2   miss   dfhjdj   fhdfhdhdf  miss dfhjdj fhdfhdhdf
```

```
#Split
mydata["name_full"].str.split(expand=True)
```

	0	1	2
0	mr.	xxx	yyy
1	ms.	abcd	efghijk
2	miss	dfhjdj	fhdfhdhdf

Replace

```
   prefix    name    surname
0     นส.     xxx        yyy
1  นางสาว    abcd    efghijk
2     นส.  dfhjdj  fhdfhdhdf
```

```
mydata['prefix']=mydata['prefix'].str.replace("นส.","นางสาว")
mydata['name']=mydata['name'].str.replace("f","_")
mydata['surname']=mydata['surname'].str.replace("f","_")
print(mydata)
```

```
   prefix    name    surname
0  นางสาว     xxx        yyy
1  นางสาว    abcd    e_ghijk
2  นางสาว  d_hjdj  _hd_hdhd_
```

Change type

```
   sex    name    surname
0    1     xxx        yyy
1    2    abcd     efghijk
2    1  dfhjdj   fhdfhdhdf
```

```
mydata['sex'].describe()
```

```
count    3.000000
mean     1.333333
std      0.577350
min      1.000000
25%      1.000000
50%      1.000000
75%      1.500000
max      2.000000
Name: sex, dtype: float64
```

```
# Convert to categorical
mydata['sex'] = mydata['sex'].astype('category')
mydata['sex'].describe()
```

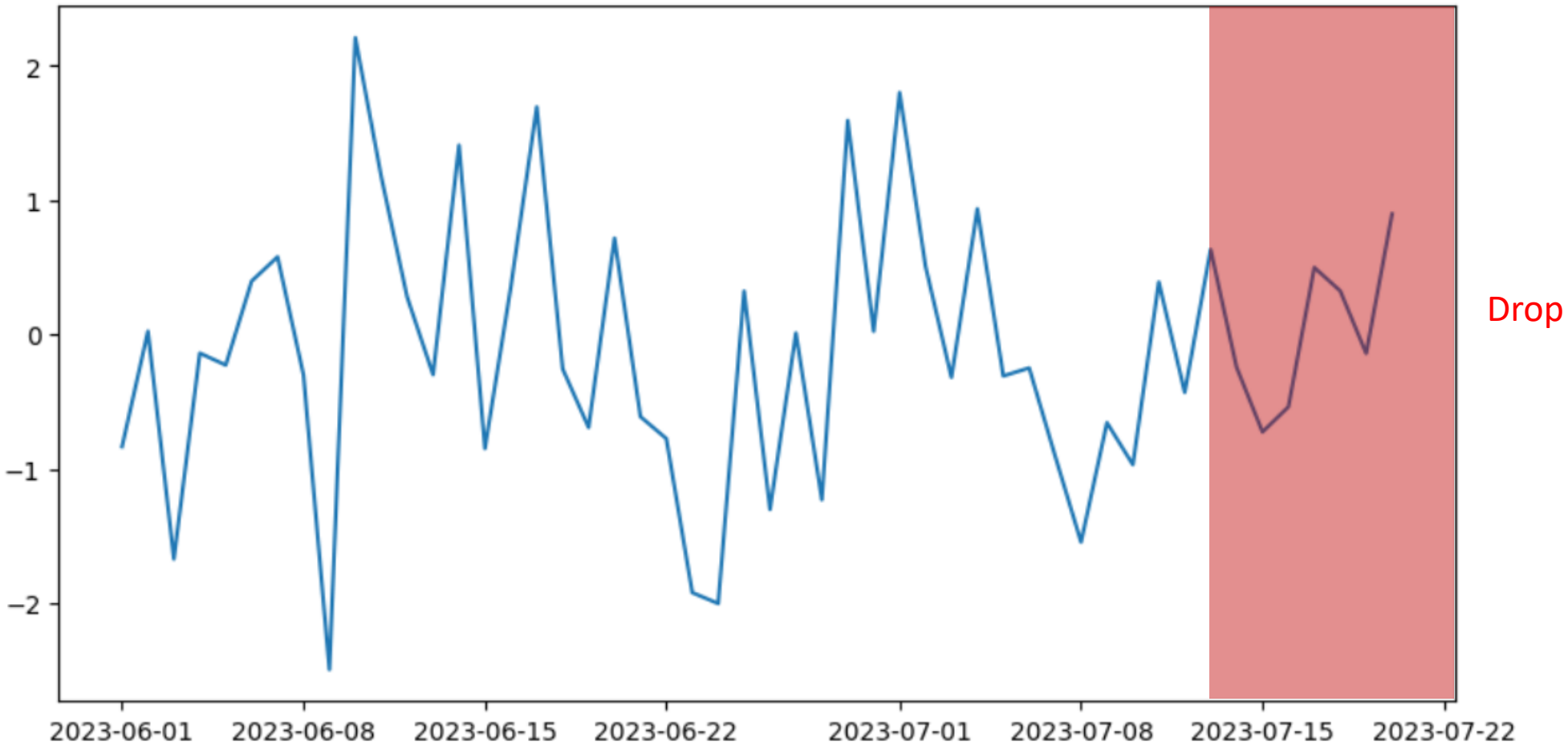
```
count     3
unique    2
top       1
freq      2
Name: sex, dtype: int64
```

```
mydata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3 entries, 0 to 2
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   sex      3 non-null      category
 1   name     3 non-null      object
 2   surname  3 non-null      object
dtypes: category(1), object(2)
```

Date Range Problem

```
plt.figure(figsize=(10,5))
plt.plot(df['date'],df['x']);
```



Drop

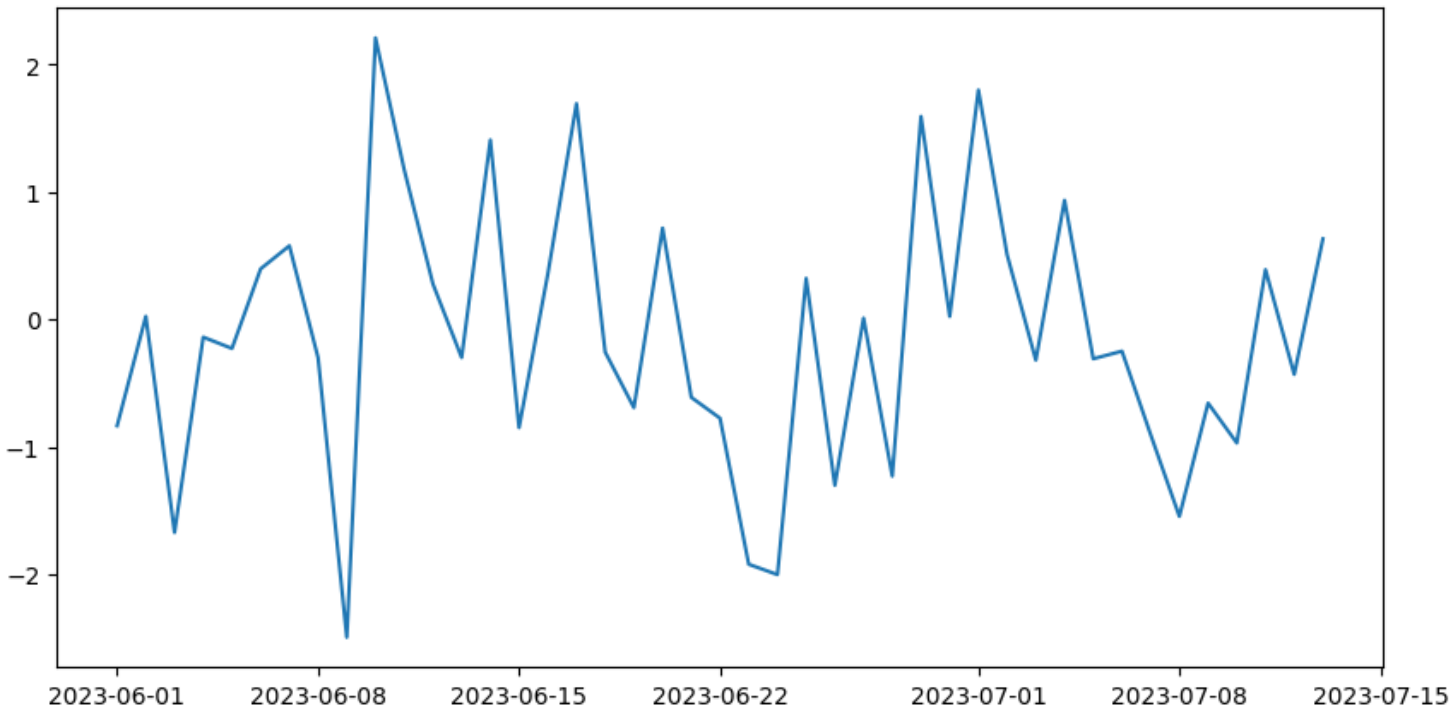
Date Range Problem

```
import datetime as dt
today_date = pd.Timestamp('today')
print(today_date)
```

```
2023-07-13 02:28:30.460829
```

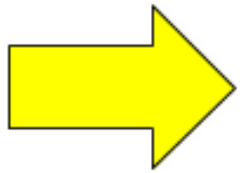
```
# Drop values using filtering
df2 = df[df['date'] < today_date]
```

```
plt.figure(figsize=(10,5))
plt.plot(df2['date'],df2['x']);
```



Categorical Data

Color
Red
Red
Yellow
Green
Yellow



Red	Yellow	Green
1	0	0
1	0	0
0	1	0
0	0	1

Data Cleaning

Data Cleaning

python Copy code

```python
# ตรวจสอบข้อมูลที่หายไป
data.isnull().sum()

# ลบข้อมูลที่หายไป
data = data.dropna()

# ตรวจสอบและลบข้อมูลที่ซ้ำกัน
data.duplicated().sum()
data = data.drop_duplicates()
```

Missing data

Occurs when no data value is stored for a variable in an observation

Can be represented as `NA` , `nan` , `0` , `.` ...

Technical error

Human error

Breast Cancer Wisconsin Data Set

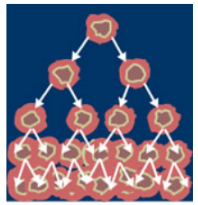
- University of Wisconsin Hospitals Madison, Wisconsin, USA
- https://archive.ics.uci.edu/ml/datasets/breast+cancer+wisconsin+(original)
- Features are computed from a digitized image of a fine needle aspirate (FNA) of a breast mass. They describe characteristics of the cell nuclei present in the image.

UCI Machine Learning Repository
Center for Machine Learning and Intelligent Systems

Breast Cancer Wisconsin (Original) Data Set

Download: Data Folder, Data Set Description

Abstract: Original Wisconsin Breast Cancer Database



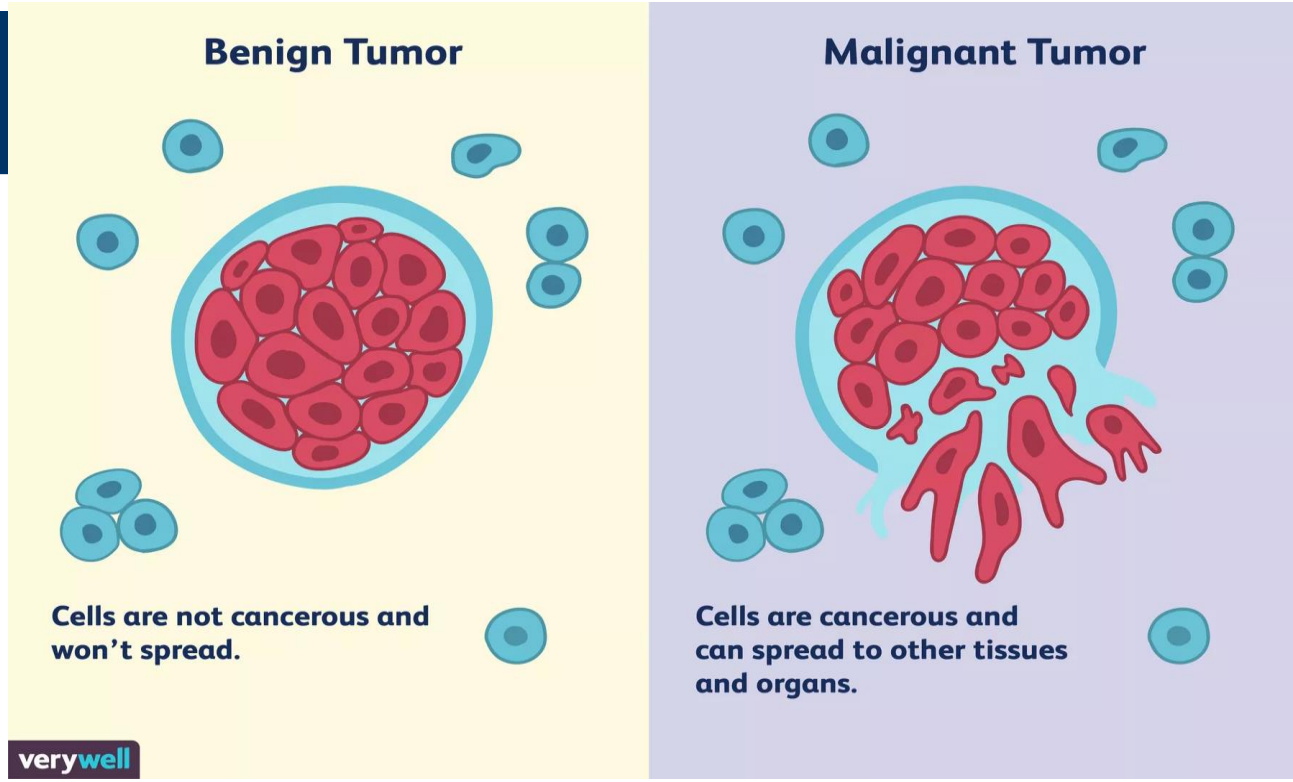
Data Set Characteristics:	Multivariate	**Number of Instances:**	699	**Area:**	Life
Attribute Characteristics:	Integer	**Number of Attributes:**	10	**Date Donated**	1992-07-15
Associated Tasks:	Classification	**Missing Values?**	Yes	**Number of Web Hits:**	502764

Source:

Creator:

Dr. WIlliam H. Wolberg (physician)
University of Wisconsin Hospitals
Madison, Wisconsin, USA

Donor:



Breast Cancer Wisconsin Data Example

```
#load Data "breast_cancer_data.csv"
mydata = pd.read_csv('breast_cancer_data.csv')
print(mydata)
```

```
     patient_id  clump_thickness  ...      class  doctor_name
0       1000025              5.0  ...     benign      Dr. Doe
1       1002945              5.0  ...     benign    Dr. Smith
2       1015425              3.0  ...     benign      Dr. Lee
3       1016277              6.0  ...     benign    Dr. Smith
4       1017023              4.0  ...     benign     Dr. Wong
..          ...              ...  ...        ...          ...
694      776715              3.0  ...     benign      Dr. Lee
695      841769              2.0  ...     benign    Dr. Smith
696      888820              5.0  ...  malignant      Dr. Lee
697      897471              4.0  ...  malignant      Dr. Lee
698      897471              4.0  ...  malignant     Dr. Wong

[699 rows x 12 columns]
```

```
mydata.info()
```

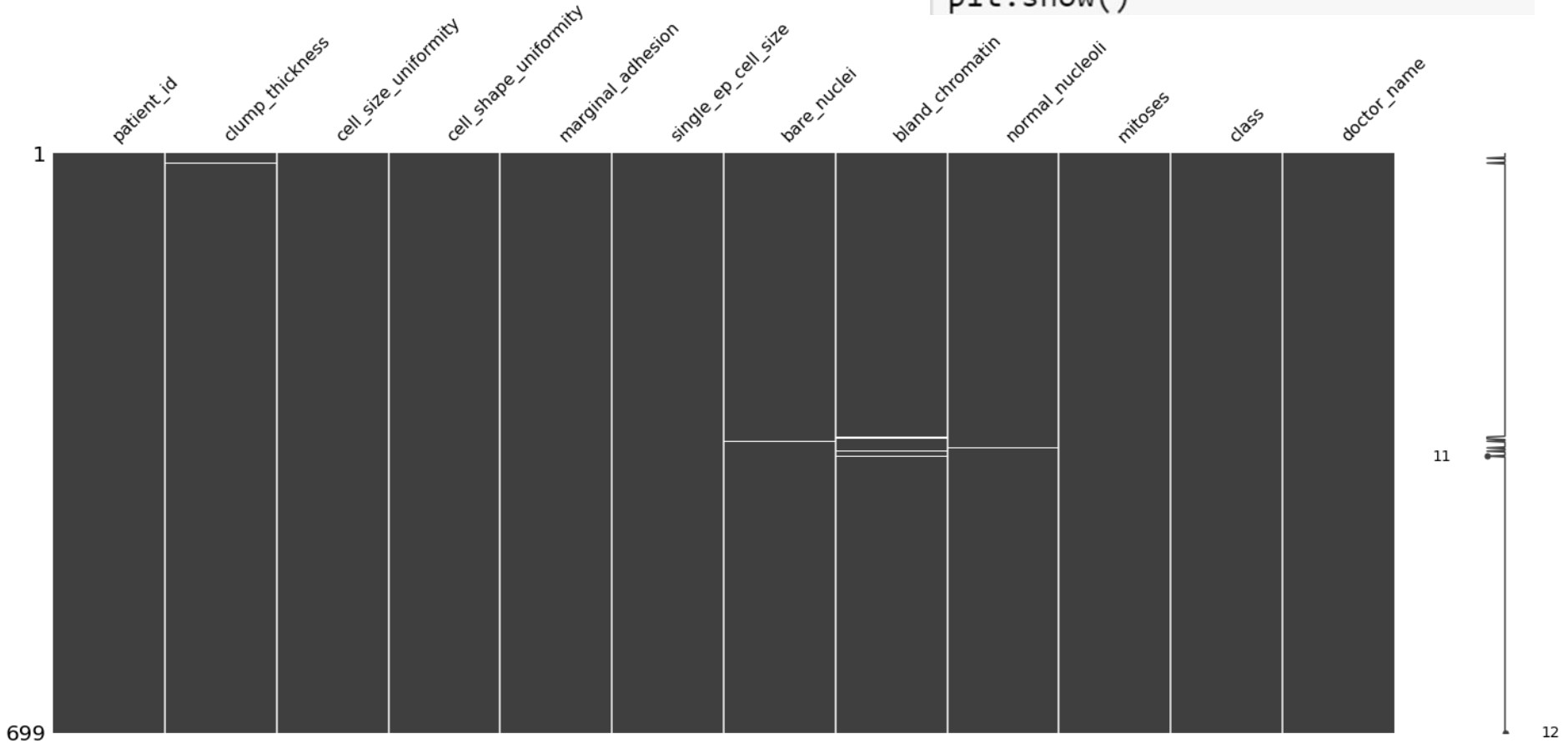
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 699 entries, 0 to 698
Data columns (total 12 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   patient_id              699 non-null    int64
 1   clump_thickness         698 non-null    float64
 2   cell_size_uniformity    698 non-null    float64
 3   cell_shape_uniformity   699 non-null    int64
 4   marginal_adhesion       699 non-null    int64
 5   single_ep_cell_size     699 non-null    int64
 6   bare_nuclei             697 non-null    object
 7   bland_chromatin         695 non-null    float64
 8   normal_nucleoli         698 non-null    float64
 9   mitoses                 699 non-null    int64
 10  class                   699 non-null    object
 11  doctor_name             699 non-null    object
dtypes: float64(4), int64(5), object(3)
```

Breast Cancer Wisconsin Data Example

```
# Get summary of missingness
mydata.isna().sum()
```

```
patient_id                0
clump_thickness           1
cell_size_uniformity      1
cell_shape_uniformity     0
marginal_adhesion         0
single_ep_cell_size       0
bare_nuclei               2
bland_chromatin           4
normal_nucleoli           1
mitoses                   0
class                     0
doctor_name               0
dtype: int64
```

```
import missingno as msno
import matplotlib.pyplot as plt
# Visualize missingness
msno.matrix(mydata)
plt.show()
```



How to deal with missing data?

Simple approaches:

1. Drop missing data
2. Impute with statistical measures (mean, median, mode..)

More complex approaches:

1. Imputing using an algorithmic approach
2. Impute with machine learning models

Drop missing values

```
# Drop missing values
mydata_dropped = mydata.dropna(subset = ['bland_chromatin'])
mydata_dropped.shape
```

```
(695, 12)
```

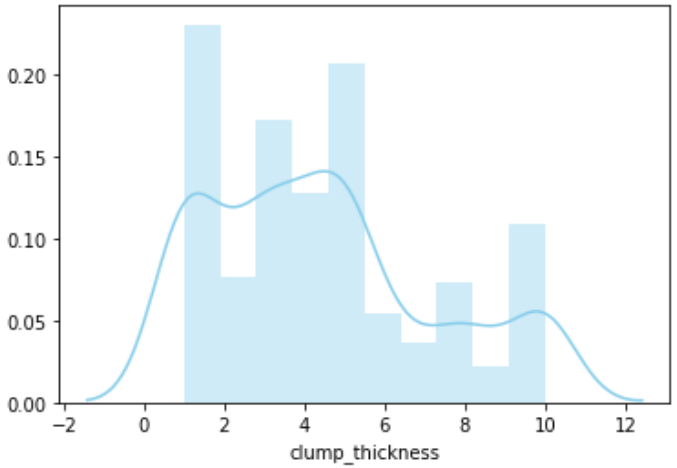
```
mydata.shape
```

```
(699, 12)
```

```
mydata_dropped.isna().sum()
```

```
patient_id                0
clump_thickness           1
cell_size_uniformity      1
cell_shape_uniformity     0
marginal_adhesion         0
single_ep_cell_size       0
bare_nuclei               2
bland_chromatin           0
normal_nucleoli           1
mitoses                   0
class                     0
doctor_name               0
dtype: int64
```

Replacing with statistical measures




```
#Replacing with statistical measures
clump_thickness_mene = mydata_dropped['clump_thickness'].mean()
mydata_imputed = mydata_dropped.fillna({'clump_thickness': clump_thickness_mene})
mydata_imputed.isna().sum()
```

```
patient_id              0
clump_thickness         0
cell_size_uniformity    1
cell_shape_uniformity   0
marginal_adhesion       0
single_ep_cell_size     0
bare_nuclei             2
bland_chromatin         0
normal_nucleoli         1
mitoses                 0
class                   0
doctor_name             0
dtype: int64
```

Fill gaps forward

```
In [944]: df
Out[944]:
        one       two     three
a  0.059117  1.138469 -2.400634
b       NaN       NaN       NaN
c -0.280853  0.025653 -1.386071
d       NaN       NaN       NaN
e  0.863937  0.252462  1.500571
f  1.053202 -2.338595 -0.374279
g       NaN       NaN       NaN
h -2.359958 -1.157886 -0.551865
```

```
In [945]: df.fillna(method='pad')
Out[945]:
        one       two     three
a  0.059117  1.138469 -2.400634
b  0.059117  1.138469 -2.400634
c -0.280853  0.025653 -1.386071
d -0.280853  0.025653 -1.386071
e  0.863937  0.252462  1.500571
f  1.053202 -2.338595 -0.374279
g  1.053202 -2.338595 -0.374279
h -2.359958 -1.157886 -0.551865
```

Duplicate Problem

All columns have the same values

first_name	last_name	address	height	weight
Justin	Saddlemyer	Boulevard du Jardin Botanique 3, Bruxelles	193 cm	87 kg
Justin	Saddlemyer	Boulevard du Jardin Botanique 3, Bruxelles	193 cm	87 kg

What are duplicate values?

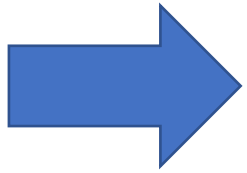
Most columns have the same values

first_name	last_name	address	height	weight
Justin	Saddlemyer	Boulevard du Jardin Botanique 3, Bruxelles	193 cm	87 kg
Justin	Saddlemyer	Boulevard du Jardin Botanique 3, Bruxelles	***194 cm***	87 kg

How to find duplicate values?

```
#แปลงให้เป็นตัวพิมพ์เล็กให้หมด
mydata['name']=mydata['name'].str.lower()
mydata['surname']=mydata['surname'].str.lower()
mydata.sort_values(by = 'name')
```

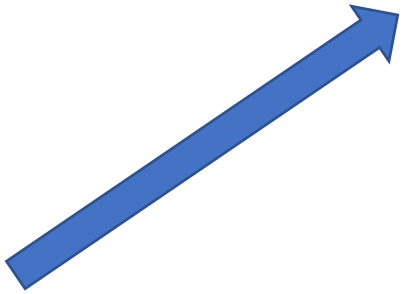
	name	surname	weight
4	Xxx	Xxxx	49
5	ZZZ	ZZZZ	70
3	aaa	aaaa	55
0	xxx	xxxx	50
1	yyy	xxxx	60
2	zzz	zzzz	70



	name	surname	weight
3	aaa	aaaa	55
0	xxx	xxxx	50
4	xxx	xxxx	49
1	yyy	xxxx	60
2	zzz	zzzz	70
5	zzz	zzzz	70

How to find duplicate values?

	name	surname	weight
3	aaa	aaaa	55
0	xxx	xxxx	50
4	xxx	xxxx	49
1	yyy	xxxx	60
2	zzz	zzzz	70
5	zzz	zzzz	70



```
# Get duplicate rows
duplicates = mydata.duplicated()
mydata[duplicates].sort_values(by = 'name')
```

	name	surname	weight
5	zzz	zzzz	70

How to find duplicate values?

```
#subset : List of column names to check for duplication.
#keep : Whether to keep xrst ( 'first' ), last ( 'last' ) or all ( False )
column_names = ['name','surname']
duplicates = mydata.duplicated(subset = column_names, keep = False)
mydata[duplicates].sort_values(by = 'name')
```

	name	surname	weight
3	aaa	aaaa	55
0	xxx	xxxx	50
4	xxx	xxxx	49
1	yyy	xxxx	60
2	zzz	zzzz	70
5	zzz	zzzz	70

	name	surname	weight
0	xxx	xxxx	50
4	xxx	xxxx	49
2	zzz	zzzz	70
5	zzz	zzzz	70

How to treat duplicate values?

	name	surname	weight
3	aaa	aaaa	55
0	xxx	xxxx	50
4	xxx	xxxx	49
1	yyy	xxxx	60
2	zzz	zzzz	70
5	zzz	zzzz	70

```
# Drop duplicates
#subset : List of column names to check for duplication
#keep : Whether to keep ×rst ( 'first' ), last ( 'last'
#inplace : Drop duplicated rows directly inside DataFra
mydata2=mydata.drop_duplicates()
mydata2.sort_values(by = 'name')
```

	name	surname	weight
3	aaa	aaaa	55
0	xxx	xxxx	50
4	xxx	xxxx	49
1	yyy	xxxx	60
2	zzz	zzzz	70

How to treat duplicate values?

```
column_names = ['name','surname']
mydata2=mydata.drop_duplicates(subset = column_names, keep = 'first')
mydata2.sort_values(by = 'name')
```

	name	surname	weight
3	aaa	aaaa	55
0	xxx	xxxx	50
4	xxx	xxxx	49
1	yyy	xxxx	60
2	zzz	zzzz	70
5	zzz	zzzz	70

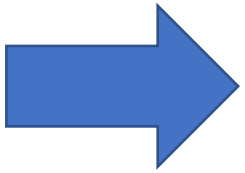
	name	surname	weight
3	aaa	aaaa	55
0	xxx	xxxx	50
1	yyy	xxxx	60
2	zzz	zzzz	70

Group by column names and produce statistical summaries

```
# Group by column names and produce statistical summaries
column_names = ['name','surname']
summaries = {'weight': 'mean'}
mydata2 = mydata.groupby(by = column_names).agg(summaries).reset_index()
mydata2.sort_values(by = 'name')
```

	name	surname	weight
3	aaa	aaaa	55
0	xxx	xxxx	50
4	xxx	xxxx	49
1	yyy	xxxx	60
2	zzz	zzzz	70
5	zzz	zzzz	70

mean

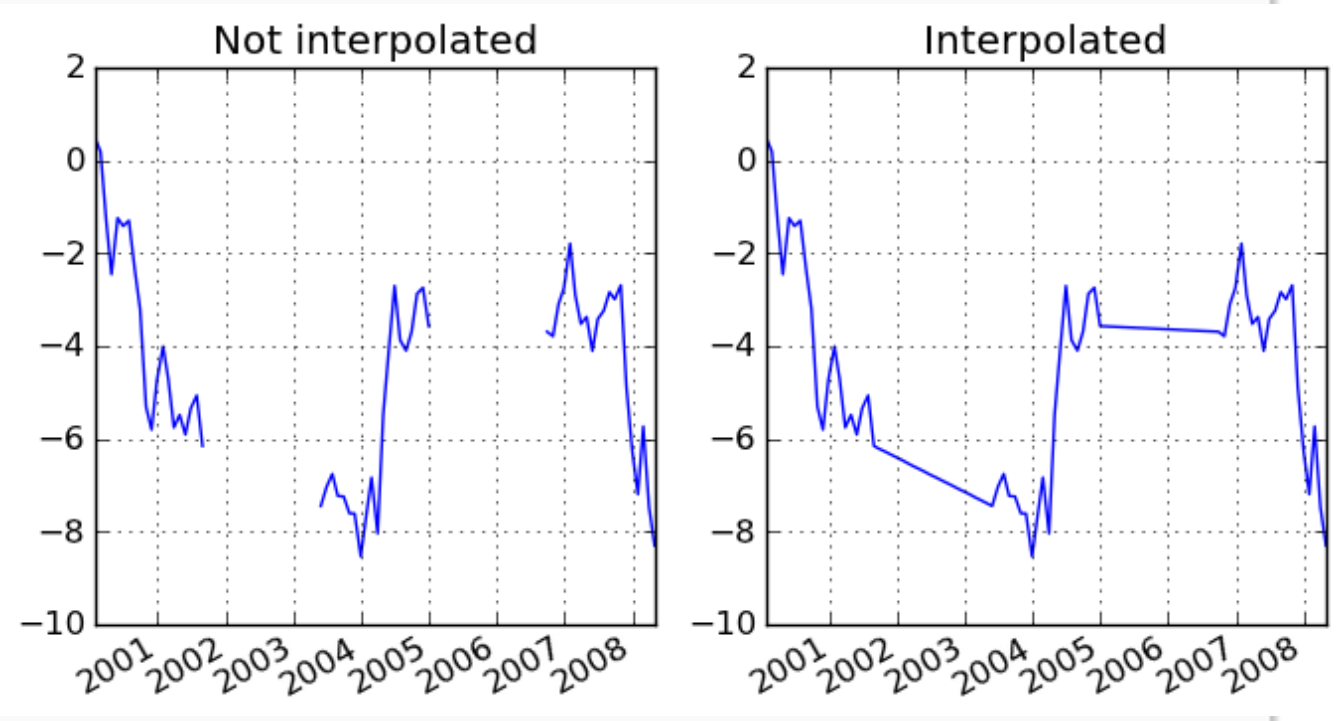


	name	surname	weight
0	aaa	aaaa	55.0
1	xxx	xxxx	49.5
2	yyy	xxxx	60.0
3	zzz	zzzz	70.0

Interpolate

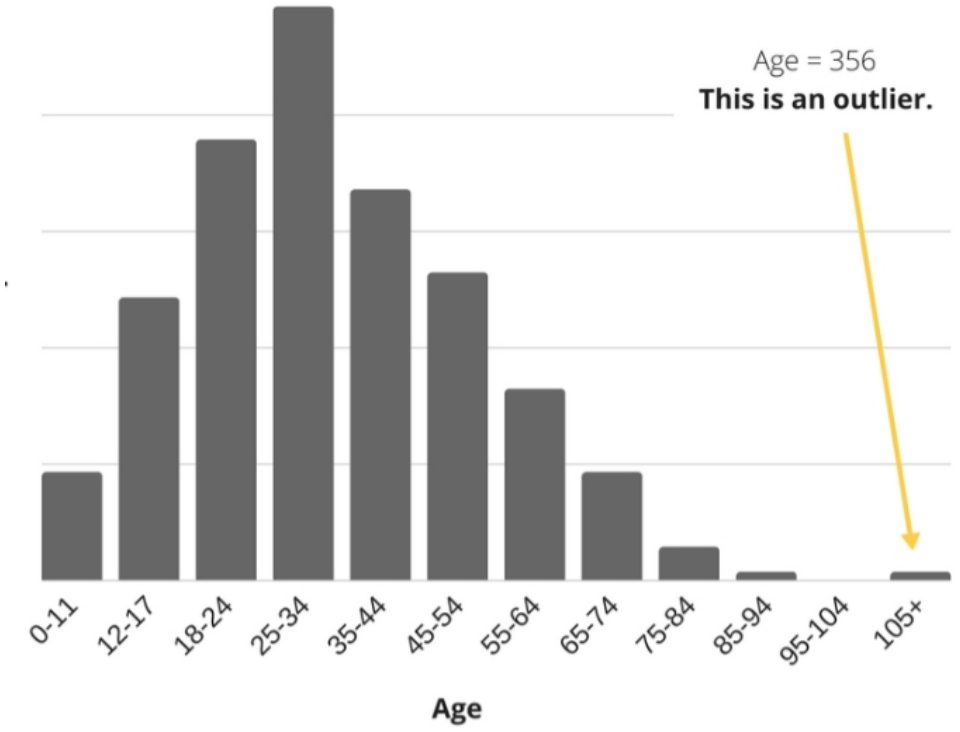
Filling in `NaN` in a `Series` via linear interpolation.

```
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s
0    0.0
1    1.0
2    NaN
3    3.0
dtype: float64
>>> s.interpolate()
0    0.0
1    1.0
2    2.0
3    3.0
dtype: float64
```



Dealing with outlier

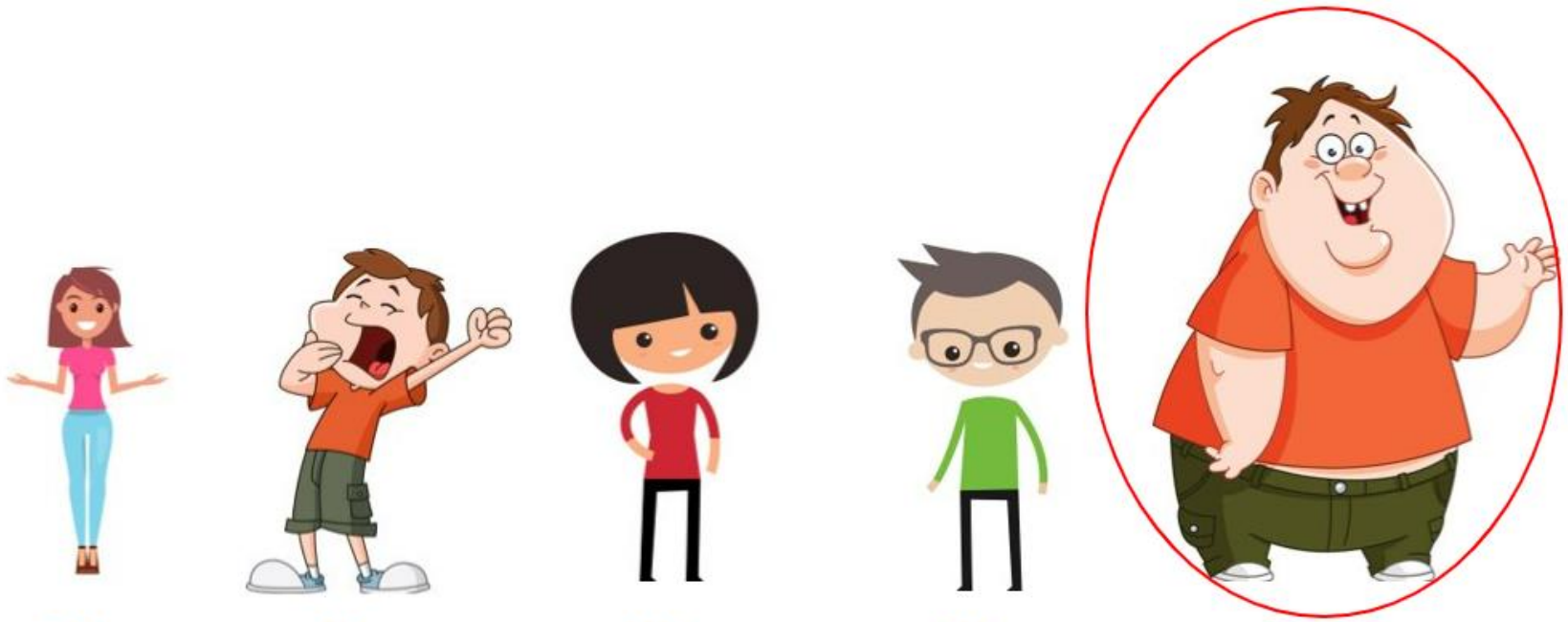
- **Outlier** is an observation in a given dataset that lies far from the rest of the observations.



Dealing with outlier

- **Affect of outlier data**

Average weight of first 4 kids = (30 + 35 + 40 + 50)/4 = 38.75 kg
Average weight of all kids = (30 + 35 + 40 + 50 + 300)/5 = 91 kg



Data Analysis

python

Copy code

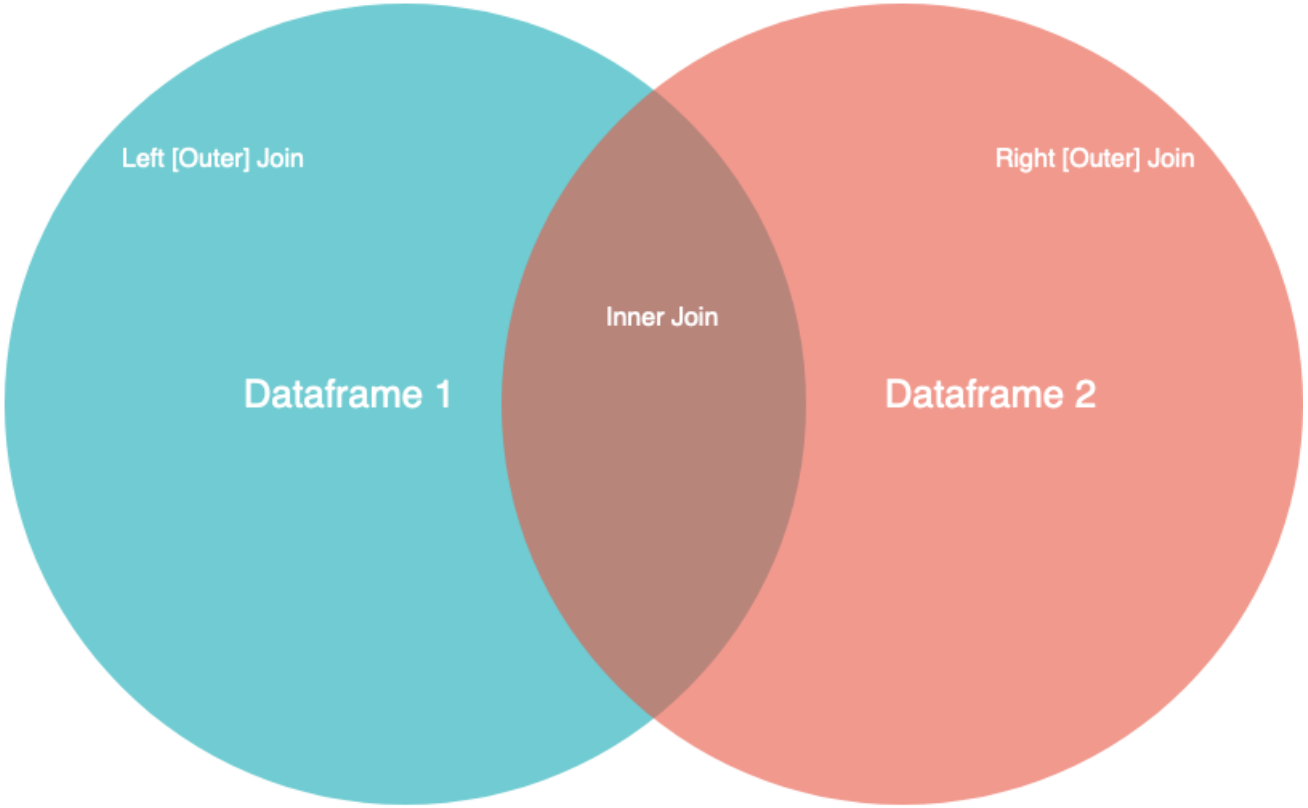
```python
import matplotlib.pyplot as plt
import seaborn as sns

# แสดงการกระจายข้อมูล
sns.scatterplot(x='column1', y='column2', data=data)

# แสดงการแจกแจงความถี่ของข้อมูล
sns.histplot(data['column3'])

# แสดงแผนภูมิแท่ง
sns.barplot(x='category', y='count', data=data)

# แสดงแผนภูมิกล่อง (box plot)
sns.boxplot(x='category', y='value', data=data)
```

Data Integration

Combine Data with Merge and Join

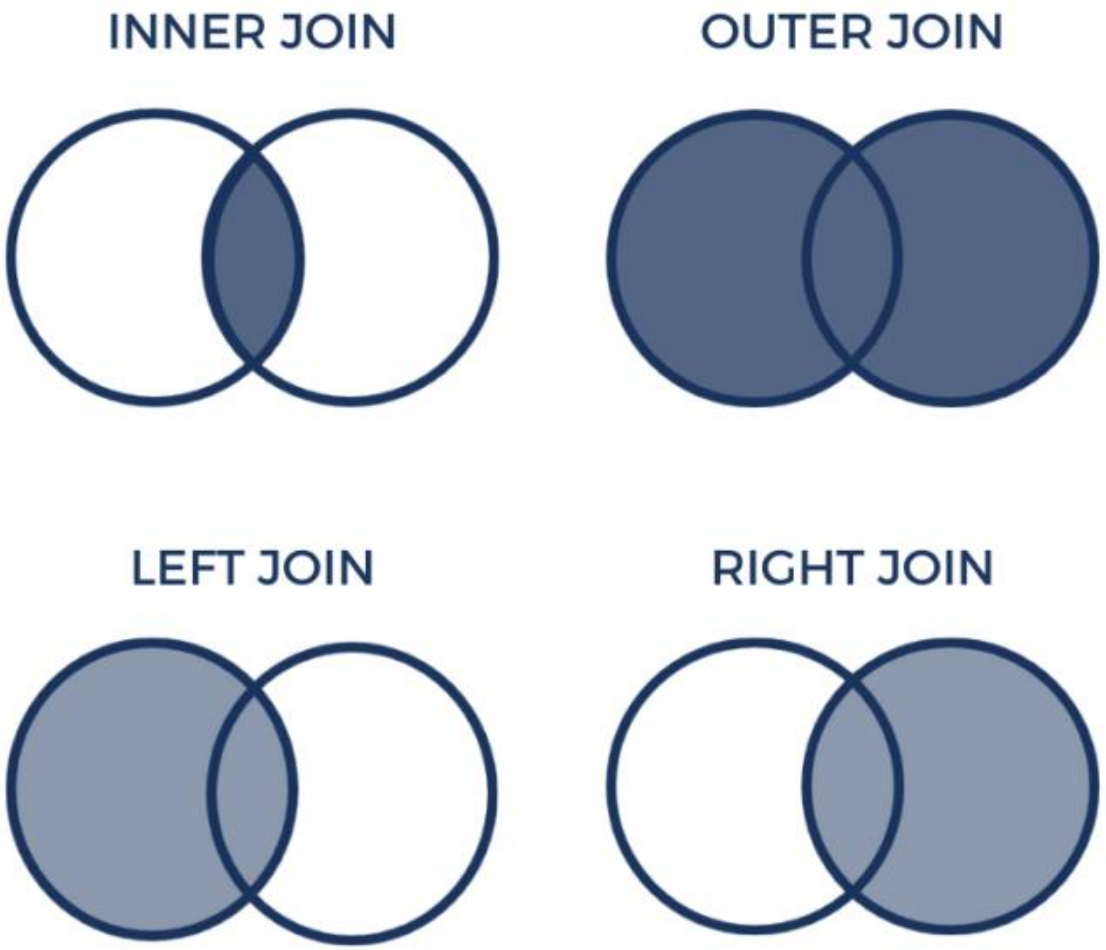
- Both join and merge can be used to **combines two dataframes** but the
- **Concat** method combines two dataframes **on the basis of their indexes**
- **Merge** method is more versatile and **allows us to specify columns** beside the index to join on for both dataframes.

Combine Data



Outer Join

Join Methods



Concat

	A	B
001	1	-3
002	2	-2
003	3	-1

+

	A	B
004	-6	0

```
pd.concat([x, y], axis=0)
```

	A	B
001	1	-3
002	2	-2
003	3	-1
004	-6	0

	A	B
001	1	-3
002	2	-2
003	3	-1

+

	C
001	-1.0
002	0.0
003	1.0

```
pd.concat([x, w], axis=1)
```

	A	B	C
001	1	-3	-1.0
002	2	-2	0.0
003	3	-1	1.0

Merge

	ID	Value A
0	PY101	-35
1	PY243	23
2	PY132	36

+

	ID	Value B
0	PY132	List
1	PY155	Tuple
2	PY101	Array

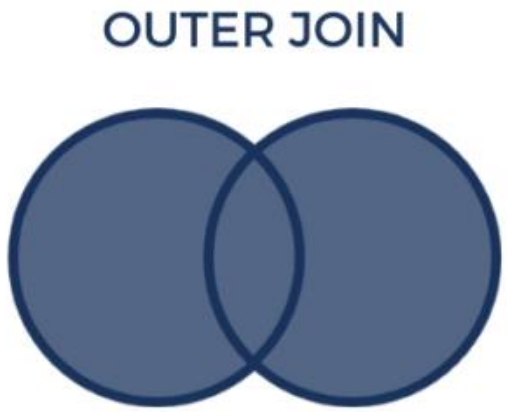
	ID	Value A	Value B
0	PY101	-35	Array
1	PY132	36	List

Merge

	ID	Value A
0	PY101	-35
1	PY243	23
2	PY132	36

+

	ID	Value B
0	PY132	List
1	PY155	Tuple
2	PY101	Array



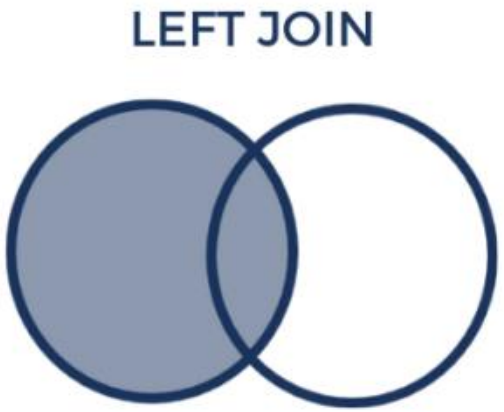
	ID	Value A	Value B
0	PY101	-35.0	Array
1	PY243	23.0	NaN
2	PY132	36.0	List
3	PY155	NaN	Tuple

Merge

	ID	Value A
0	PY101	-35
1	PY243	23
2	PY132	36

+

	ID	Value B
0	PY132	List
1	PY155	Tuple
2	PY101	Array



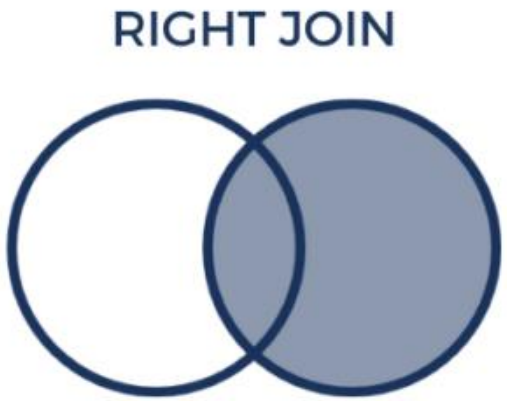
	ID	Value A	Value B
0	PY101	-35	Array
1	PY243	23	NaN
2	PY132	36	List

Merge

	ID	Value A
0	PY101	-35
1	PY243	23
2	PY132	36

+

	ID	Value B
0	PY132	List
1	PY155	Tuple
2	PY101	Array



	ID	Value A	Value B
0	PY132	36.0	List
1	PY155	NaN	Tuple
2	PY101	-35.0	Array

Merge

	ID	Value A
0	PY101	-35
1	PY243	23
2	PY132	36

+

	ID	Value B
0	PY132	List
1	PY155	Tuple
2	PY101	Array

```
x.merge(y, on='ID', how='   ')
```

inner

	ID	Value A	Value B
0	PY101	-35	Array
1	PY132	36	List

outer

	ID	Value A	Value B
0	PY101	-35.0	Array
1	PY243	23.0	NaN
2	PY132	36.0	List
3	PY155	NaN	Tuple

left

	ID	Value A	Value B
0	PY101	-35	Array
1	PY243	23	NaN
2	PY132	36	List

right

	ID	Value A	Value B
0	PY132	36.0	List
1	PY155	NaN	Tuple
2	PY101	-35.0	Array

Merge and Join in Python

1) สร้าง DataFrame 2 ตาราง ที่มีลักษณะดังต่อไปนี้ ชื่อ df_left และ df_right ตามลำดับ

left_df

	A	B
0	a	1
1	b	2

right_df

	A	C
0	c	3
1	d	4

2) ใช้ฟังก์ชัน concat และ merge ในการรวมตารางข้อมูล

Link Colab

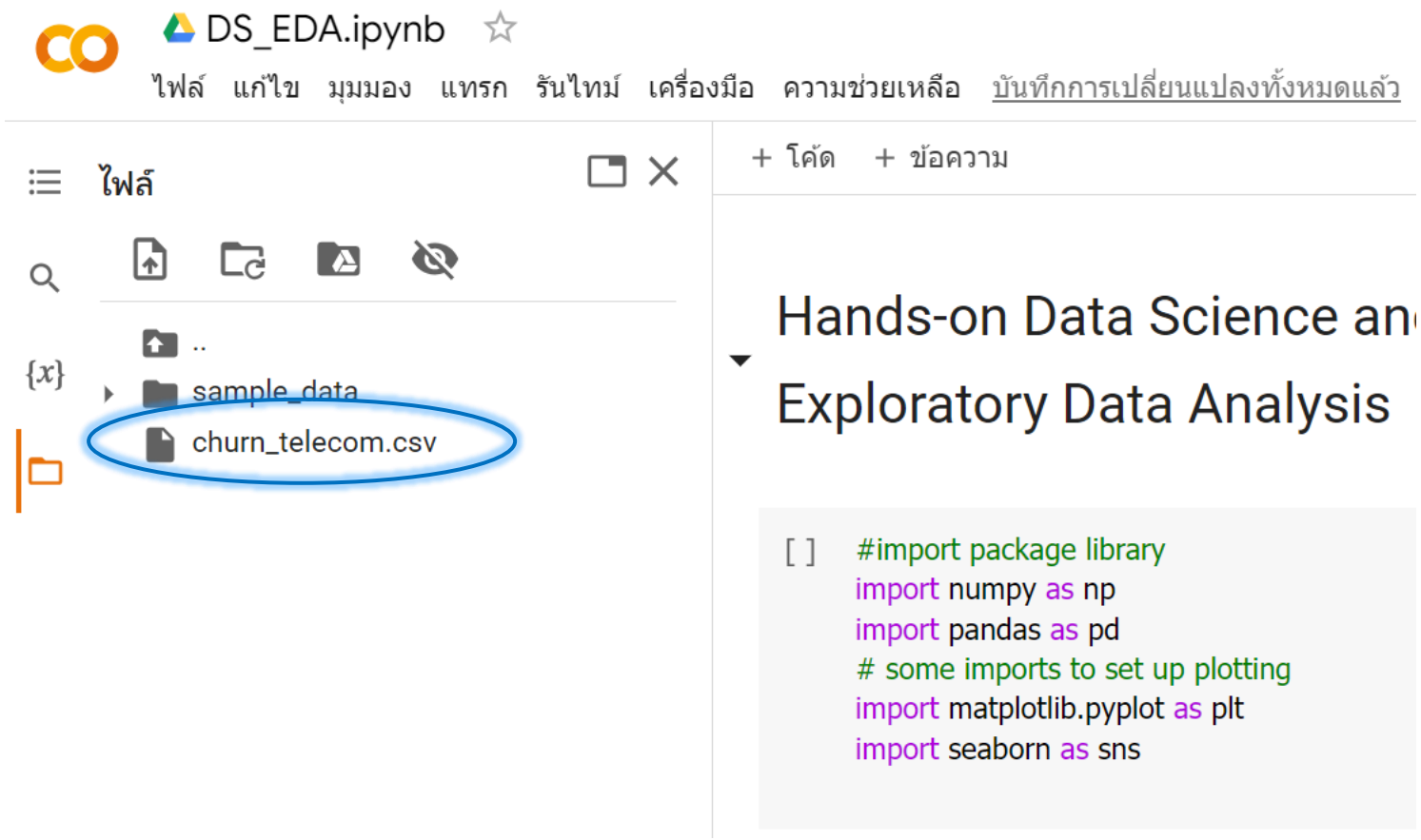
LAB 1

Example: Churn_Telecom

```
# import package library
import numpy as np
import pandas as pd

# some imports to set up plotting
import matplotlib.pyplot as plt
import seaborn as sns
```

Link Colab

Example: Churn_Telecom




```
df=pd.read_csv('churn_telecom.csv')
```

Example: Churn_Telecom

```
#ดูตัวอย่างข้อมูล 5 แถวแรก
df.head()
```

	State	Account length	Area code	International plan	Voice mail plan	Number vmail messages	Total day minutes	Total day calls	Total day charge
0	LA	117	408	No	No	0	184.5	97	31.37
1	IN	65	415	No	No	0	129.1	137	21.95
2	NY	161	415	No	No	0	332.9	67	56.59
3	SC	111	415	No	No	0	110.4	103	18.77
4	HI	49	510	No	No	0	119.3	117	20.28

Example: Churn_Telecom

```
#สุ่มข้อมูลมา 3 แถว
df.sample(3)
```

	State	Account length	Area code	International plan	Voice mail plan	Number vmail messages	Total day minutes	Total day calls	Total day charge	Total eve minutes	Total eve calls	Total eve charge
95	IN	78	415	No	No	0	208.9	119	35.51	252.4	132	21.45
530	HI	171	510	No	No	0	189.8	122	32.27	173.7	85	14.76
531	DE	90	415	No	No	0	198.5	124	33.75	266.6	100	22.66

Example: Churn_Telecom

```
#ดูรายละเอียดข้อมูล
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 667 entries, 0 to 666
Data columns (total 20 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   State                   667 non-null    object
 1   Account length          667 non-null    int64
 2   Area code               667 non-null    int64
 3   International plan      667 non-null    object
 4   Voice mail plan         667 non-null    object
 5   Number vmail messages   667 non-null    int64
 6   Total day minutes       667 non-null    float64
 7   Total day calls         667 non-null    int64
 8   Total day charge        667 non-null    float64
 9   Total eve minutes       667 non-null    float64
 10  Total eve calls         667 non-null    int64
 11  Total eve charge        667 non-null    float64
 12  Total night minutes     667 non-null    float64
 13  Total night calls       667 non-null    int64
```

Example: Churn_Telecom

```
#ดูค่าทางสถิติพื้นฐาน
df.describe()
```

	Account length	Area code	Number vmail messages	Total day minutes	Total day calls	Total day charge	Total eve minutes	Total eve calls
count	667.000000	667.000000	667.000000	667.000000	667.000000	667.000000	667.000000	667.000000
mean	102.841079	436.157421	8.407796	180.948126	100.937031	30.761769	203.355322	100.476762
std	40.819480	41.783305	13.994480	55.508628	20.396790	9.436463	49.719268	18.948262
min	1.000000	408.000000	0.000000	25.900000	30.000000	4.400000	48.100000	37.000000
25%	76.000000	408.000000	0.000000	146.250000	87.500000	24.860000	171.050000	88.000000
50%	102.000000	415.000000	0.000000	178.300000	101.000000	30.310000	203.700000	101.000000
75%	128.000000	415.000000	20.000000	220.700000	115.000000	37.520000	236.450000	113.000000
max	232.000000	510.000000	51.000000	334.300000	165.000000	56.830000	361.800000	168.000000

Example: Churn_Telecom

```
#ดูค่าทางสถิติพื้นฐานสำหรับข้อมูลที่เป็น object และ bool
df.describe(include=['object',bool])
```

	State	International plan	Voice mail plan	Churn
count	667	667	667	667
unique	51	2	2	2
top	AZ	No	No	False
freq	19	614	478	572

Example: Churn_Telecom

```
#นับจำนวนข้อมูล Churn ในแต่ละค่า
df['Churn'].value_counts()
```

```
False    572
True      95
Name: Churn, dtype: int64
```

```
df['International plan'].value_counts()
```

```
No     614
Yes     53
Name: International plan, dtype: int64
```

Example: Churn_Telecom

```
#Summary tables
pd.crosstab(df['Churn'], df['International plan'])
```

International plan	No	Yes
Churn		
False	538	34
True	76	19

Example: Churn_Telecom

```
#นับค่า Null
df.isnull().sum()
```

```
State                     0
Account length            0
Area code                 0
International plan        0
Voice mail plan           0
Number vmail messages     0
Total day minutes         0
Total day calls           0
Total day charge          0
Total eve minutes         0
Total eve calls           0
Total eve charge          0
Total night minutes       0
Total night calls         0
Total night charge        0
Total intl minutes        0
Total intl calls          0
Total intl charge         0
Customer service calls    0
Churn                     0
dtype: int64
```

Example: Churn_Telecom

```
#pivot table
df.pivot_table(['Total day calls', 'Total eve calls',
                'Total night calls'], 'Area code'], aggfunc='mean')
```

Area code	Total day calls	Total eve calls	Total night calls
408	99.390533	100.680473	100.952663
415	101.928783	100.074184	99.023739
510	100.484472	101.105590	101.515528

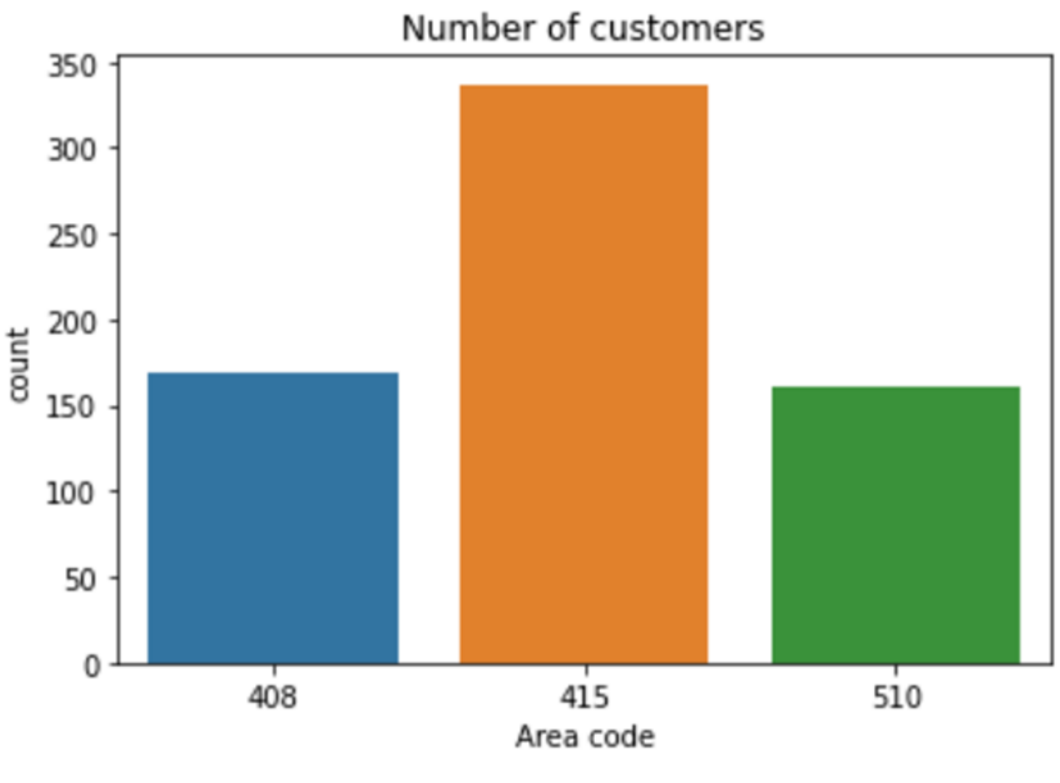
Example: Churn_Telecom

```
#ลบคอลัมน์ State
df.drop(columns= ['State'], inplace=True)
df.columns
```

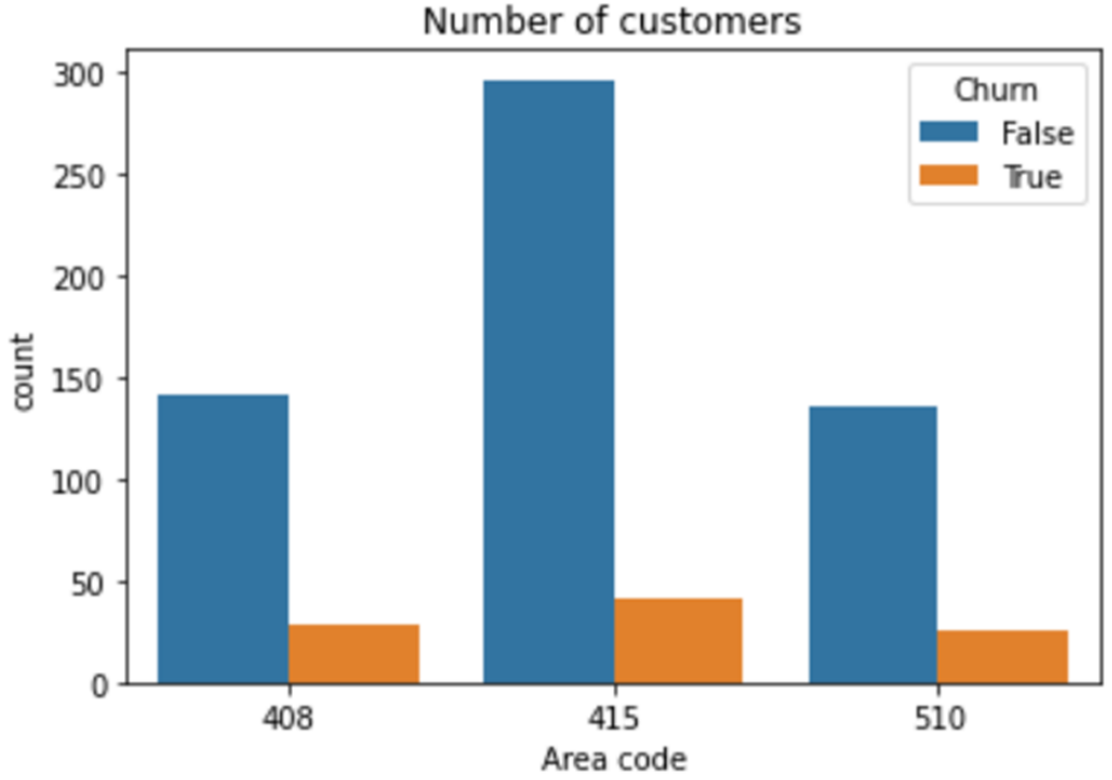
```
Index(['Account length', 'Area code', 'International plan', 'Voice mail plan',
       'Number vmail messages', 'Total day minutes', 'Total day calls',
       'Total day charge', 'Total eve minutes', 'Total eve calls',
       'Total eve charge', 'Total night minutes', 'Total night calls',
       'Total night charge', 'Total intl minutes', 'Total intl calls',
       'Total intl charge', 'Customer service calls', 'Churn'],
      dtype='object')
```

Data Visualization: Bar Plot

```
sns.countplot(x="Area code", data=df);
plt.title('Number of customers');
```

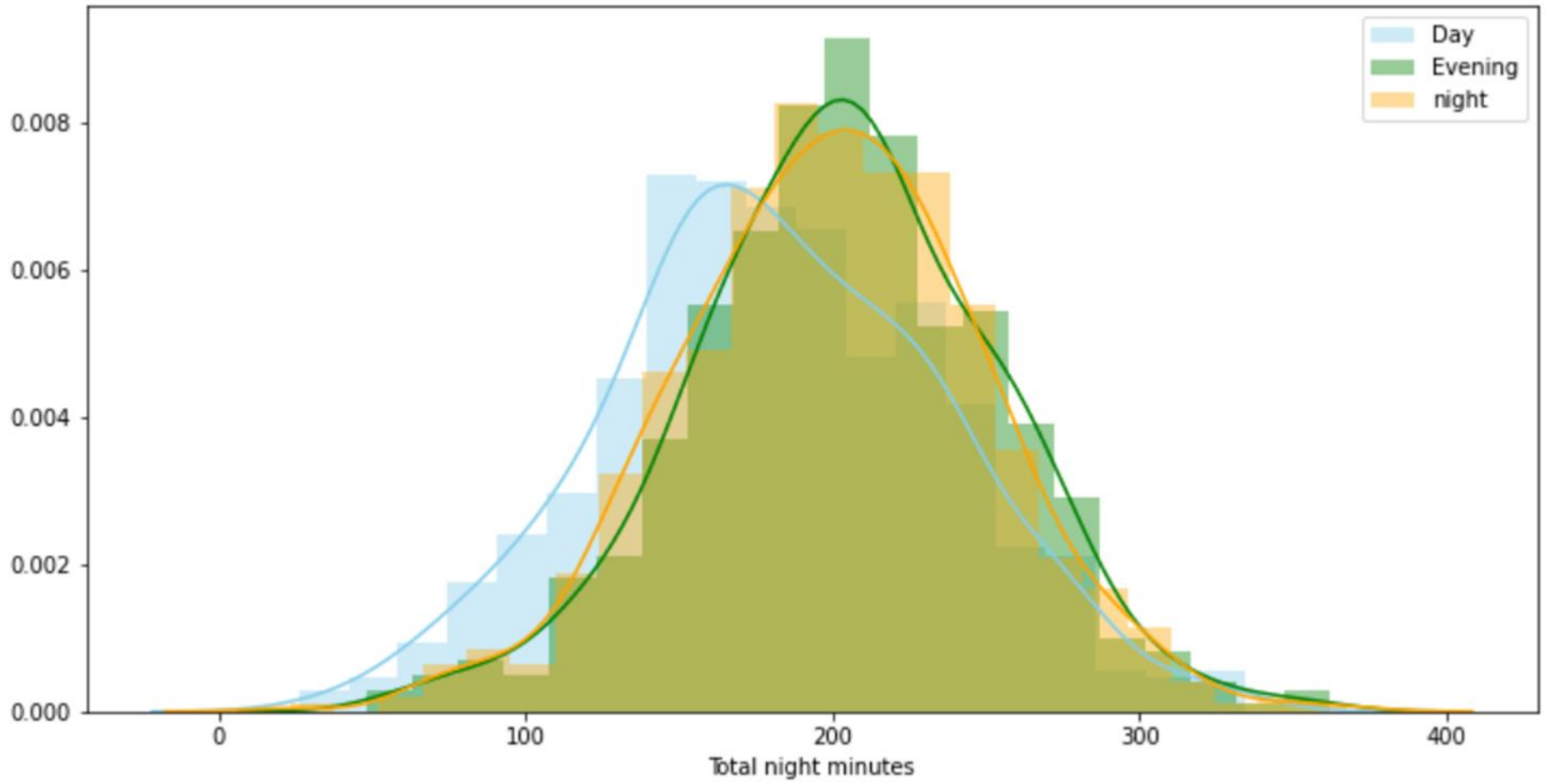



```
sns.countplot(x="Area code", hue='Churn', data=df);
plt.title('Number of customers');
```

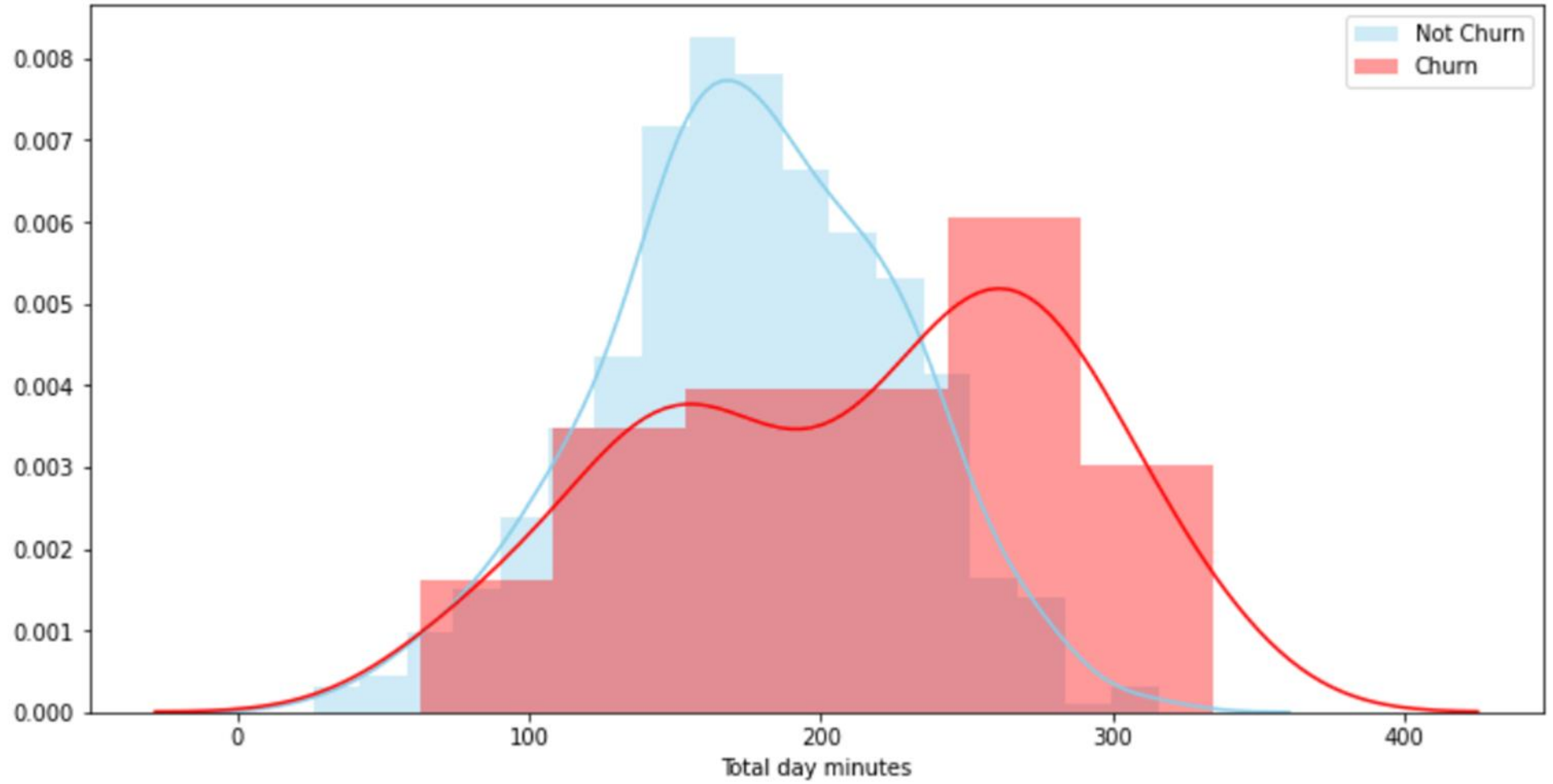


Distribution

```
#เปรียบเทียบจำนวนนาทีการโทรในช่วงกลางวัน ตอนเย็น และกลางคืน
plt.figure(figsize=(12,6))
sns.distplot( df["Total day minutes"] , color="skyblue",label="Day")
sns.distplot( df["Total eve minutes"] , color="green",label="Evening")
sns.distplot( df["Total night minutes"] , color="orange",label="night")
plt.legend();
```



```
#Distribution of Total day minutes, comparing churn and not churn
plt.figure(figsize=(12,6))
sns.distplot( df_not_churn["Total day minutes"] , color="skyblue",label="Not Churn")
sns.distplot( df_churn["Total day minutes"] , color="red",label="Churn")
plt.legend();
```



Data Transformation

Data Scaling and Normalization

- Scaling vs. Normalization: What's the difference?
  - in **scaling**, you're changing the ***range*** of your data, while
  - in **normalization**, you're changing the ***shape of the distribution*** of your data

Data Scaling

- Data Scaling Methods.
  - Simple Feature Scaling

$$x_{new} = \frac{x_{current}}{x_{maximum}}$$

  - Min-Max Scaling

$$x_{new} = \frac{x_{current} - x_{minimum}}{x_{maximum} - x_{minimum}} \qquad 0 \leq x_{new} \leq 1$$

  - Standard or Z-score Scaling

$$x_{new} = \frac{x_{current} - Mean}{Standard\ Deviation} \qquad -3 \leq x_{new} \leq 3$$

Data Scaling

- It consists of putting the data in a **similar range** to be able to compare them.

	No	Employee ID	First Name	Last Name	Age	Worked years	Salary	Status	Grade
0	1	1000001	John	Denver	23	1	500	Single	Elementary
1	2	1000002	Peter	Hank	30	3	900	Married	High School
2	3	1000003	Jack	Sullivan	27	2	900	Married	High School
3	4	1000004	Marco	Aurelio	40	8	1500	Married	Master Degree
4	5	1000005	Claudia	Perez	35	5	1300	Single	Master Degree
5	6	1000006	Sally	Royal	19	1	1400	Single	Graduate
6	7	1000007	Peter	Miller	33	4	600	Married	Graduate
7	8	1000008	Susan	Gordon	35	10	2000	Married	Master Degree

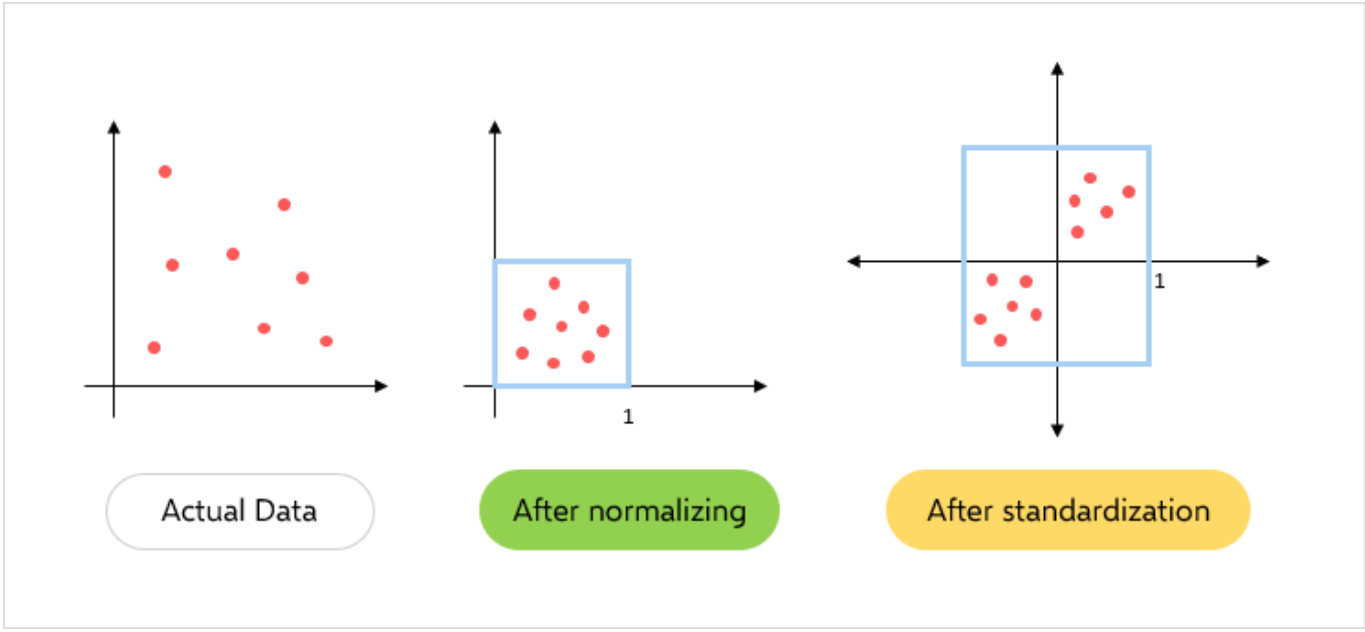
Data Scaling

Standardisation

	Age	Salary
0	0.758874	7.494733e-01
1	-1.711504	-1.438178e+00
2	-1.275555	-8.912655e-01
3	-0.113024	-2.532004e-01
4	0.177609	6.632192e-16
5	-0.548973	-5.266569e-01
6	0.000000	-1.073570e+00
7	1.340140	1.387538e+00
8	1.630773	1.752147e+00
9	-0.258340	2.937125e-01

Max-Min Normalization

	Age	Salary
0	0.739130	0.685714
1	0.000000	0.000000
2	0.130435	0.171429
3	0.478261	0.371429
4	0.565217	0.450794
5	0.347826	0.285714
6	0.512077	0.114286
7	0.913043	0.885714
8	1.000000	1.000000
9	0.434783	0.542857

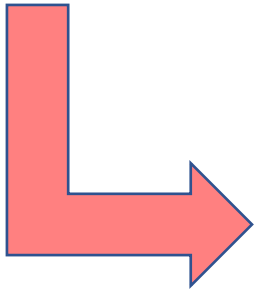


Data Scaling

- Applying Simple Feature Scaling method in Python.

```
df_employees[['Age','Worked years','Salary']].head()
```

	Age	Worked years	Salary
0	23	1	500
1	30	3	900
2	27	2	900
3	40	8	1500
4	35	5	1300



```
df_norm1 = df_employees

df_norm1["Age"] = df_norm1["Age"] / df_norm1["Age"].max()
df_norm1["Worked years"] = df_norm1["Worked years"] / df_norm1["Worked years"].max()
df_norm1["Salary"] = df_norm1["Salary"] / df_norm1["Salary"].max()

df_norm1[['Age','Worked years','Salary']].head()
```

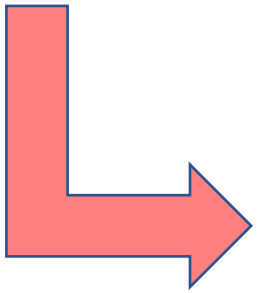
	Age	Worked years	Salary
0	0.575	0.1	0.25
1	0.750	0.3	0.45
2	0.675	0.2	0.45
3	1.000	0.8	0.75
4	0.875	0.5	0.65

Data Scaling

- Applying Min-Max method in Python.

```
df_employees[['Age','Worked years','Salary']].head()
```

	Age	Worked years	Salary
0	23	1	500
1	30	3	900
2	27	2	900
3	40	8	1500
4	35	5	1300



```
df_norm2 = df_employees

df_norm2["Age"] = (df_norm2["Age"] - df_norm2["Age"].min()) / (df_norm2["Age"].max() - df_norm2["Age"].min())
df_norm2["Worked years"] = (df_norm2["Worked years"] - df_norm2["Worked years"].min()) / (df_norm2["Worked years"].max() - df_norm2["Worked years"].min())
df_norm2["Salary"] = (df_norm2["Salary"] - df_norm2["Salary"].min()) / (df_norm2["Salary"].max() - df_norm2["Salary"].min())

df_norm2[['Age','Worked years','Salary']].head()
```

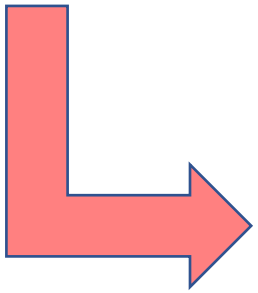
	Age	Worked years	Salary
0	0.190476	0.000000	0.000000
1	0.523810	0.222222	0.266667
2	0.380952	0.111111	0.266667
3	1.000000	0.777778	0.666667
4	0.761905	0.444444	0.533333

Data Scaling

- Applying Z-score method in Python.

```
df_employees[['Age','Worked years','Salary']].head()
```

	Age	Worked years	Salary
0	23	1	500
1	30	3	900
2	27	2	900
3	40	8	1500
4	35	5	1300



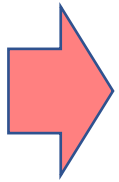
```
df_norm3 = df_employees

df_norm3["Age"] = (df_norm3["Age"] - df_norm3["Age"].mean()) / df_norm3["Age"].std()
df_norm3["Worked years"] = (df_norm3["Worked years"] - df_norm3["Worked years"].mean()) / df_norm3["Worked years"].std()
df_norm3["Salary"] = (df_norm3["Salary"] - df_norm3["Salary"].mean()) / df_norm3["Salary"].std()

df_norm3[['Age','Worked years','Salary']].head()
```

	Age	Worked years	Salary
0	-1.044119	-0.989598	-1.264654
1	-0.036004	-0.380615	-0.471146
2	-0.468053	-0.685106	-0.471146
3	1.404160	1.141844	0.719117
4	0.684078	0.228369	0.322363

Grouping Numerical Data into Classes

- Grouping the data into classes.
- Sales have a range that goes from 100,000 to a little more than 900,000

Sales
150000
651750
563750
706250
640375
519375
870375
926250
676250
103750
567925



Classes	Classes Range
Low	0 - 299,999
Medium	300,000 - 599,999
High	600,000 - 999,999

Grouping into Classes

- Grouping with Python.

```
my_class = np.linspace(min(df_test["Sales"]), max(df_test["Sales"]), 4)
group_names = ["Low","Medium","High"]

df_test["Sales Category"] = pd.cut(df_test["Sales"], my_class, labels = group_names, include_lowest = True)

df_test[['Sales','Sales Category']].head()
```

	Sales	Sales Category
0	150000.0	Low
2	563750.0	Medium
3	706250.0	High
4	553509.0	Medium
5	519375.0	Medium

Converting Categorical Variables to Numeric Variables

- Converting categorical variables to numeric variables.
- get_dummies()

```
df_dummies = pd.get_dummies(df_test['Payment Type'])
df_test2 = pd.concat([df_test, df_dummies], axis = 1, sort = False)

df_test2.head()
```

Customer	Customer Type	Payment Type	Purchases	Sales	Refunds	Country	Continent	Purchases in thousands	Sales in thousands	Refunds in thousands	Sales Category	Cash	Credit Card	Transfer
10000	Person	Cash	120000.0	150000.0	240	Canada	America	120.0	150.000	0.240	Low	1	0	0
10002	Company	Credit Card	451000.0	563750.0	902	Mexico	America	451.0	563.750	0.902	Medium	0	1	0
10003	Company	Transfer	565000.0	706250.0	1130	Spain	Europe	565.0	706.250	1.130	High	0	0	1
10004	Person	Transfer	512300.0	553509.0	1024	Argentina	America	512.3	553.509	1.024	Medium	0	0	1
10005	Person	Transfer	415500.0	519375.0	0	Canada	America	415.5	519.375	0.000	Medium	0	0	1

LAB 2

Link Colab

Workshop

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