# ML Preprocessing / Feature Engineering

UTKARSH GAIKWAD

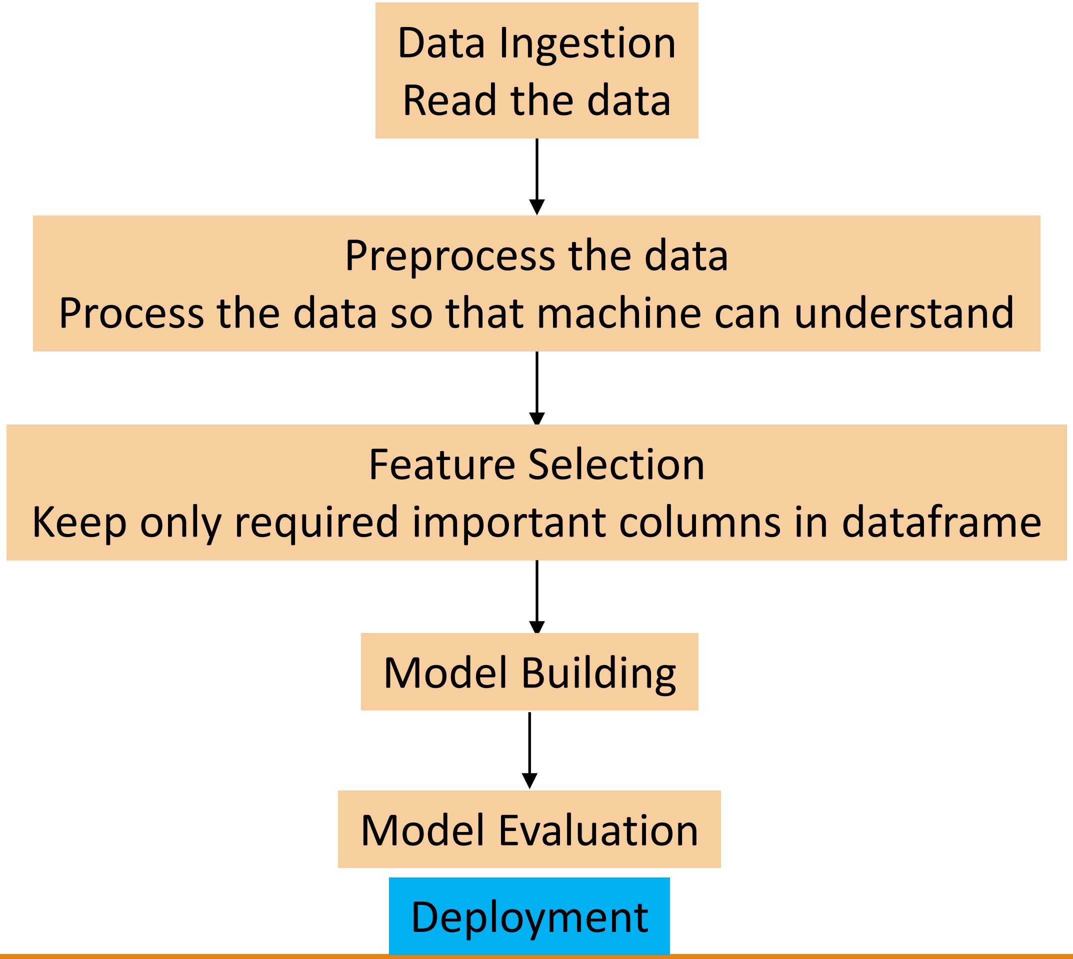
CLASS STARTING SHARP AT 4:05 PM

# Goal of Data Preprocessing

- Main Purpose of Data Preprocessing is to prepare the data for machine to understand

I cannot understand raw data directly
Pre-process the data for me to understand

# Machine Learning Process



Data Ingestion
Read the data

Preprocess the data
Process the data so that machine can understand

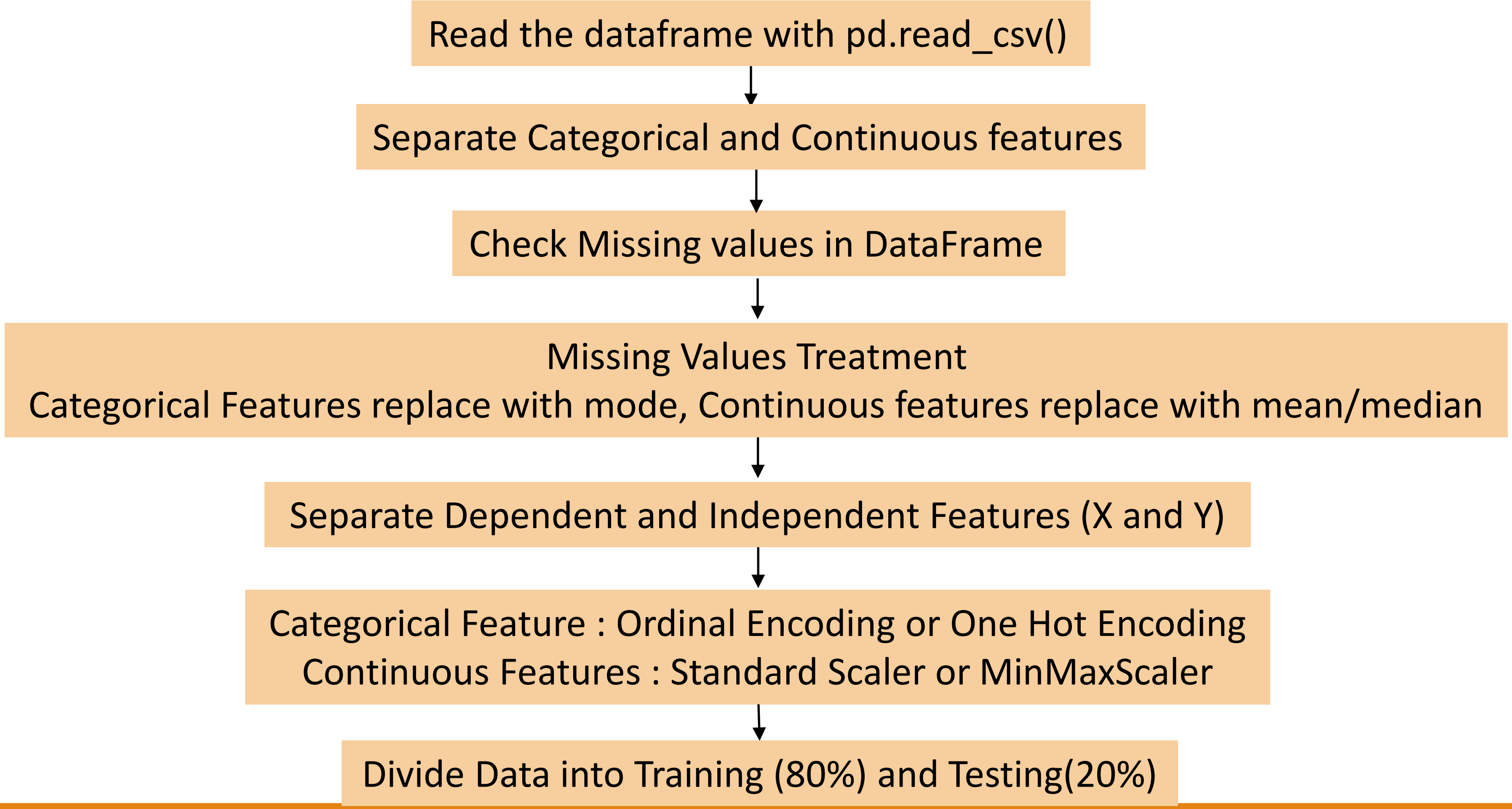
Feature Selection
Keep only required important columns in dataframe

Model Building

Model Evaluation

Deployment

# Basic Steps in creating a Data Preprocessing



Read the dataframe with pd.read_csv()

Separate Categorical and Continuous features

Check Missing values in DataFrame

Missing Values Treatment
Categorical Features replace with mode, Continuous features replace with mean/median

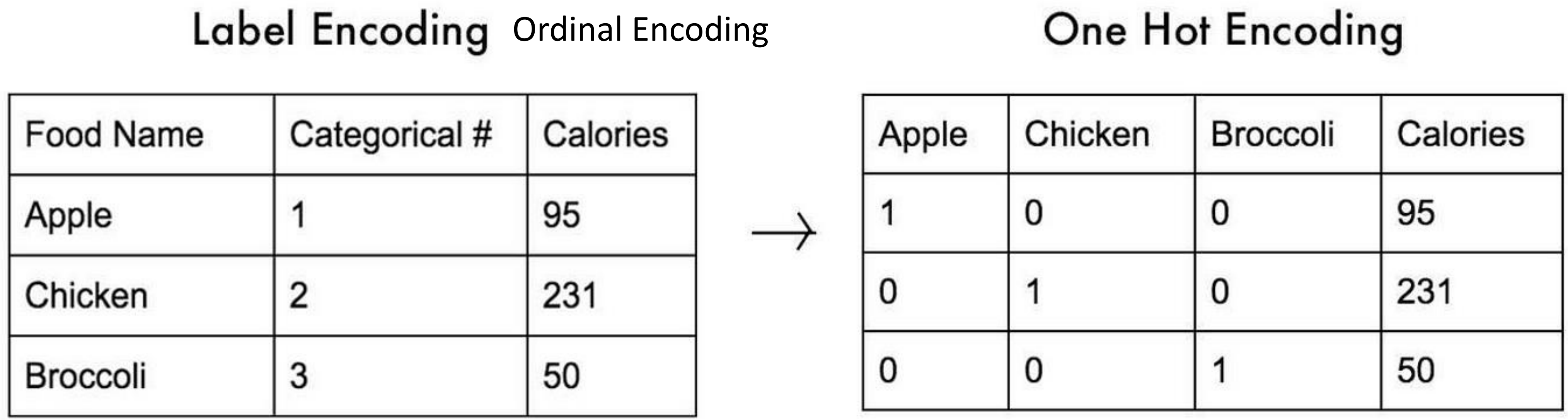
Separate Dependent and Independent Features (X and Y)

Categorical Feature : Ordinal Encoding or One Hot Encoding
Continuous Features : Standard Scaler or MinMaxScaler

Divide Data into Training (80%) and Testing(20%)

# Machine does not understand text directly

Because machine does not understand Text directly we can use 2 approaches to convert categorical features to Numeric data : Label Encoding or One Hot Encoding



Label Encoding

Ordinal Encoding

| Food Name | Categorical # | Calories |
|---|---|---|
| Apple | 1 | 95 |
| Chicken | 2 | 231 |
| Broccoli | 3 | 50 |

→

One Hot Encoding

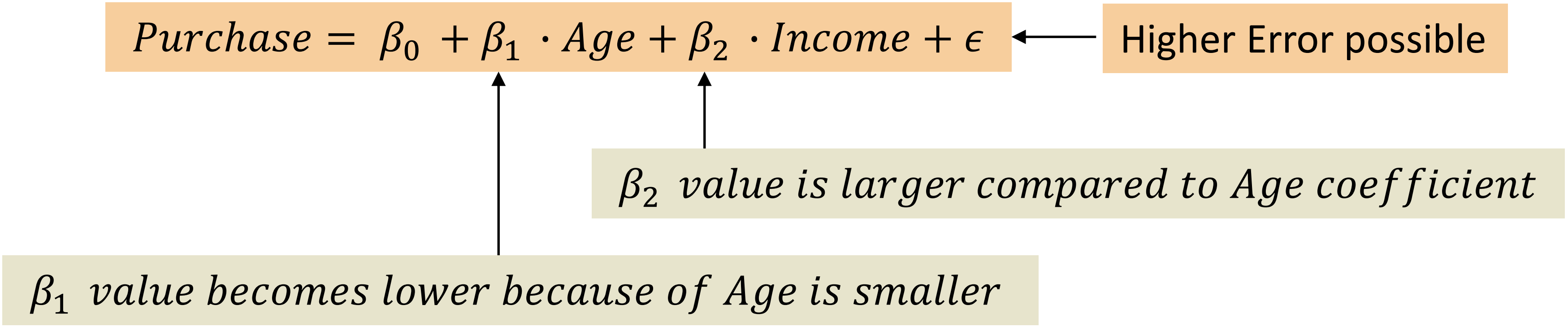
| Apple | Chicken | Broccoli | Calories |
|---|---|---|---|
| 1 | 0 | 0 | 95 |
| 0 | 1 | 0 | 231 |
| 0 | 0 | 1 | 50 |

S, M, L, XL ,….

A+ , B+ , AB-,

# Need for Scaling of continuous data

| Age | Income | Purchase |
|---|---|---|
| 25 | 50,000 | 1,000 |
| 30 | 60,000 | 2,000 |
| 35 | 70,000 | 3,000 |
| 40 | 125,000 | 4,000 |
| 45 | 150,000 | 5,000 |



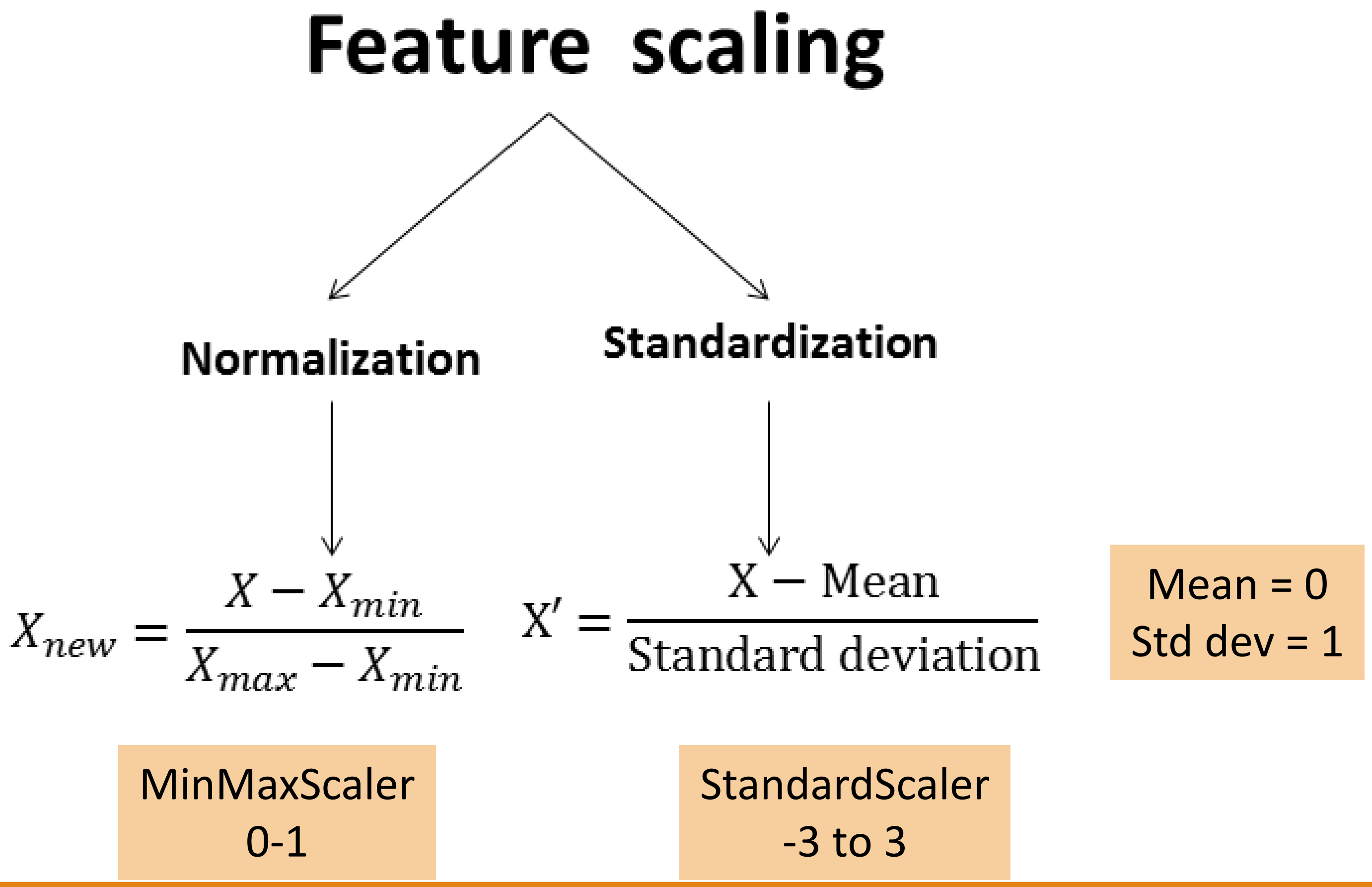
$$Purchase = \beta_0 + \beta_1 \cdot Age + \beta_2 \cdot Income + \epsilon$$

Higher Error possible

$\beta_2$ *value is larger compared to Age coefficient*

$\beta_1$ *value becomes lower because of Age is smaller*

# 2 methods to bring down data in same scale (Independent features)



**Feature scaling**

**Normalization**

**Standardization**

$$X_{new} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

$$\mathrm{X}' = \frac{\mathrm{X} - \mathrm{Mean}}{\mathrm{Standard\ deviation}}$$

Mean = 0
Std dev = 1

MinMaxScaler
0-1

StandardScaler
-3 to 3

# MinMax Scaler

$$Age_{scaled} = \frac{age - \min(age)}{\max(age) - \min(age)} = \frac{age - 25}{45 - 25} = \frac{age - 25}{20}$$

$$Income_{scaled} = \frac{income - \min(income)}{\max(income) - \min(income)} = \frac{income - 50000}{150000 - 50000} = \frac{income - 50000}{100000}$$

| Age | Income | Purchase |
|---|---|---|
| 25 | 50,000 | 1,000 |
| 30 | 60,000 | 2,000 |
| 35 | 70,000 | 3,000 |
| 40 | 125,000 | 4,000 |
| 45 | 150,000 | 5,000 |

$$\xrightarrow[\text{MinMaxScaler}]{}$$

| Age | Income | Purchase |
|---|---|---|
| 0 | 0 | 1,000 |
| 0.25 | 0.1 | 2,000 |
| 0.50 | 0.2 | 3,000 |
| 0.75 | 0.75 | 4,000 |
| 1 | 1 | 5,000 |

# Standard Scaler - Z scores

$$Z_{age} = \frac{age - mean(age)}{stdev(age)} = \frac{age - 35}{7.9057}$$

$$Z_{income} = \frac{income - mean(income)}{stdev(income)} = \frac{income - 91000}{43931.7653}$$

Converts all data in
Mean = 0
Stdev = 1

| Age | Income | Purchase |
|---|---|---|
| 25 | 50,000 | 1,000 |
| 30 | 60,000 | 2,000 |
| 35 | 70,000 | 3,000 |
| 40 | 125,000 | 4,000 |
| 45 | 150,000 | 5,000 |

→
StandardScaler

| Age | Income | Purchase |
|---|---|---|
| -1.2649 | -0.9333 | 1,000 |
| -0.6325 | -0.7056 | 2,000 |
| 0.0000 | -0.4780 | 3,000 |
| 0.6325 | 0.7739 | 4,000 |
| 1.2649 | 1.3430 | 5,000 |

# Thank You

PING ME ON SKYPE FOR ANY QUERIES