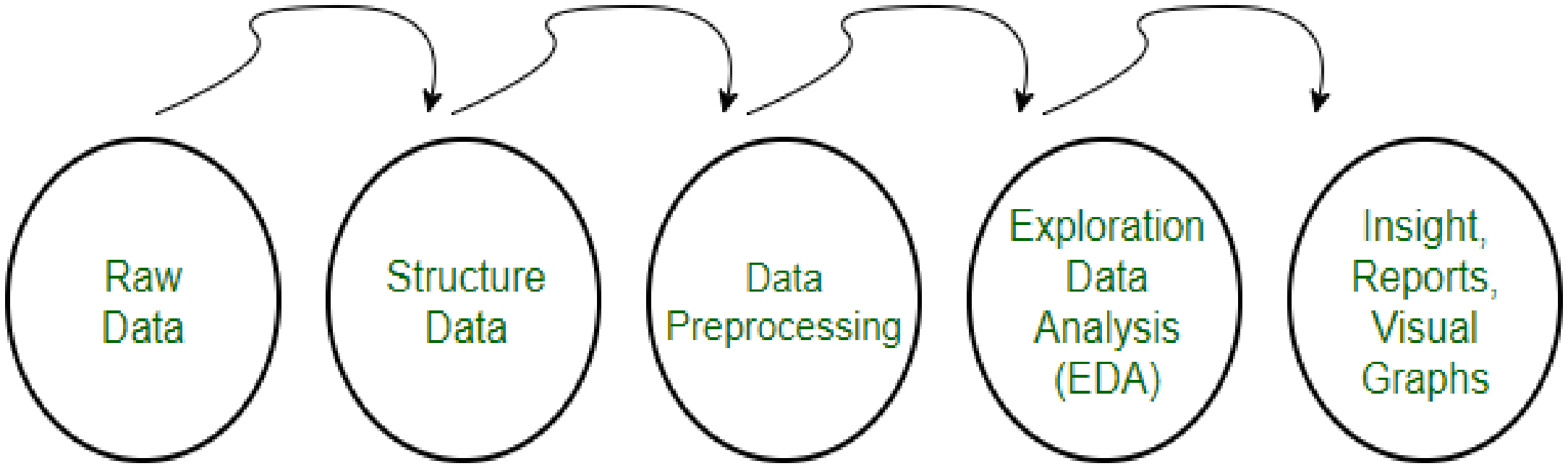
Stock price prediction

Definition:

- **Stock Price Prediction** is the task of forecasting future stock prices based on historical data and various market indicators. It involves using statistical models and machine learning algorithms to analyze financial data and make predictions about the future performance of a stock.

Data preprocessing

- Data Preprocessing is the process of making data suitable for use while training a machine learning model. The dataset initially provided for training might not be in a ready-to-use state, for e.g. it might not be formatted properly, or **may contain missing or null values**.


Raw Data
Structure Data
Data Preprocessing
Exploration Data Analysis (EDA)
Insight, Reports, Visual Graphs

Data Preprocessing methods using Python

- Importing the libraries
- Importing the Dataset
- Handling of Missing Data
- Handling of Categorical Data
- Splitting the dataset into training and testing datasets
- Feature Scaling

Data Preparation Process

Data Collection

- Articulating the problem
- Defining data required
- Gathering and combining data from different sources

→

Data Preprocessing

- Formatting
- Cleaning
- Sampling

→

Data Transformation

Feature engineering

- Scaling/normalizing
- Decomposition
- Aggregation

Step1: Importing the libraries

- In the beginning, we'll import three basic libraries which are very common in machine learning and will be used every time you train a model
- NumPy:- it is a library that allows us to work with arrays and as most machine learning models work on arrays NumPy makes it easier
- matplotlib:- this library helps in plotting graphs and charts, which are very useful while showing the result of your model
- Pandas:- pandas allows us to import our dataset and also creates a matrix of features containing the dependent and independent variable.

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File Edit View Insert Cell Kernel Widgets Help

Trusted | Python 3 (ipykernel)

In [7]:
```
data['day']=data['Date'].apply(lambda x:x.split('-')[0])
data['month']=data['Date'].apply(lambda x:x.split('-')[1])
data['year']=data['Date'].apply(lambda x:x.split('-')[2])
data
```

Out[7]:

	Date	Open	High	Low	Close	Adj Close	Volume	day	month	year
0	1986-03-13	0.088542	0.101563	0.088542	0.097222	0.062549	1031788800	1986	03	13
1	1986-03-14	0.097222	0.102431	0.097222	0.100694	0.064783	308160000	1986	03	14
2	1986-03-17	0.100694	0.103299	0.100694	0.102431	0.065899	133171200	1986	03	17
3	1986-03-18	0.102431	0.103299	0.098958	0.099826	0.064224	67766400	1986	03	18
4	1986-03-19	0.099826	0.100694	0.097222	0.098090	0.063107	47894400	1986	03	19
...	...	...	...	...	...	...	...	...	...	...
8520	2019-12-31	156.770004	157.770004	156.449997	157.699997	157.699997	18369400	2019	12	31
8521	2020-01-02	158.779999	160.729996	158.330002	160.619995	160.619995	22622100	2020	01	02
8522	2020-01-03	158.320007	159.949997	158.059998	158.619995	158.619995	21116200	2020	01	03
8523	2020-01-06	157.080002	159.100006	156.509995	159.029999	159.029999	20813700	2020	01	06
8524	2020-01-07	159.320007	159.669998	157.330002	157.580002	157.580002	18017762	2020	01	07

8525 rows × 10 columns

Step2: Importing the dataset

- There are two types of variables:
- Independent variable
- Dependent variable
- The **independent variable** is the columns that we are going to use to predict the **dependent variable**, or in other words, the independent variable **affects** the dependent variable

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Trusted | Python 3 (ipykernel)

In [4]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
stock_price_df=pd.read_csv('C:/Users/Dhinesh PC/Downloads/MSFT.csv')
stock_price_df.shape
```

Out[4]:
```
(8525, 7)
```

In [5]:
```
stock_price_df.columns
```

Out[5]:
```
Index(['Date', 'Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume'], dtype='object')
```

In [6]:
```
stock_price_df.head(8000)
```

Out[6]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	1986-03-13	0.088542	0.101563	0.088542	0.097222	0.062549	1031788800
1	1986-03-14	0.097222	0.102431	0.097222	0.100694	0.064783	308160000
2	1986-03-17	0.100694	0.103299	0.100694	0.102431	0.065899	133171200
3	1986-03-18	0.102431	0.103299	0.098958	0.099826	0.064224	67766400
4	1986-03-19	0.099826	0.100694	0.097222	0.098090	0.063107	47894400
...	...	...	...	...	...	...	...
7995	2017-11-28	84.070000	85.059998	84.019997	84.879997	82.219917	21926000

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Trusted | Python 3 (ipykernel)

In [5]:
```
stock_price_df.columns
```

Out[5]:
```
Index(['Date', 'Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume'], dtype='object')
```

In [6]:
```
stock_price_df.head(8000)
```

Out[6]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	1986-03-13	0.088542	0.101563	0.088542	0.097222	0.062549	1031788800
1	1986-03-14	0.097222	0.102431	0.097222	0.100694	0.064783	308160000
2	1986-03-17	0.100694	0.103299	0.100694	0.102431	0.065899	133171200
3	1986-03-18	0.102431	0.103299	0.098958	0.099826	0.064224	67766400
4	1986-03-19	0.099826	0.100694	0.097222	0.098090	0.063107	47894400
...	...	...	...	...	...	...	...
7995	2017-11-28	84.070000	85.059998	84.019997	84.879997	82.219917	21926000
7996	2017-11-29	84.709999	84.919998	83.180000	83.339996	80.728165	27381100
7997	2017-11-30	83.510002	84.519997	83.339996	84.169998	81.532158	33054600
7998	2017-12-01	83.599998	84.809998	83.220001	84.260002	81.619354	29532100
7999	2017-12-04	84.419998	84.430000	80.699997	81.080002	78.539001	39094900

8000 rows × 7 columns

In [ ]:

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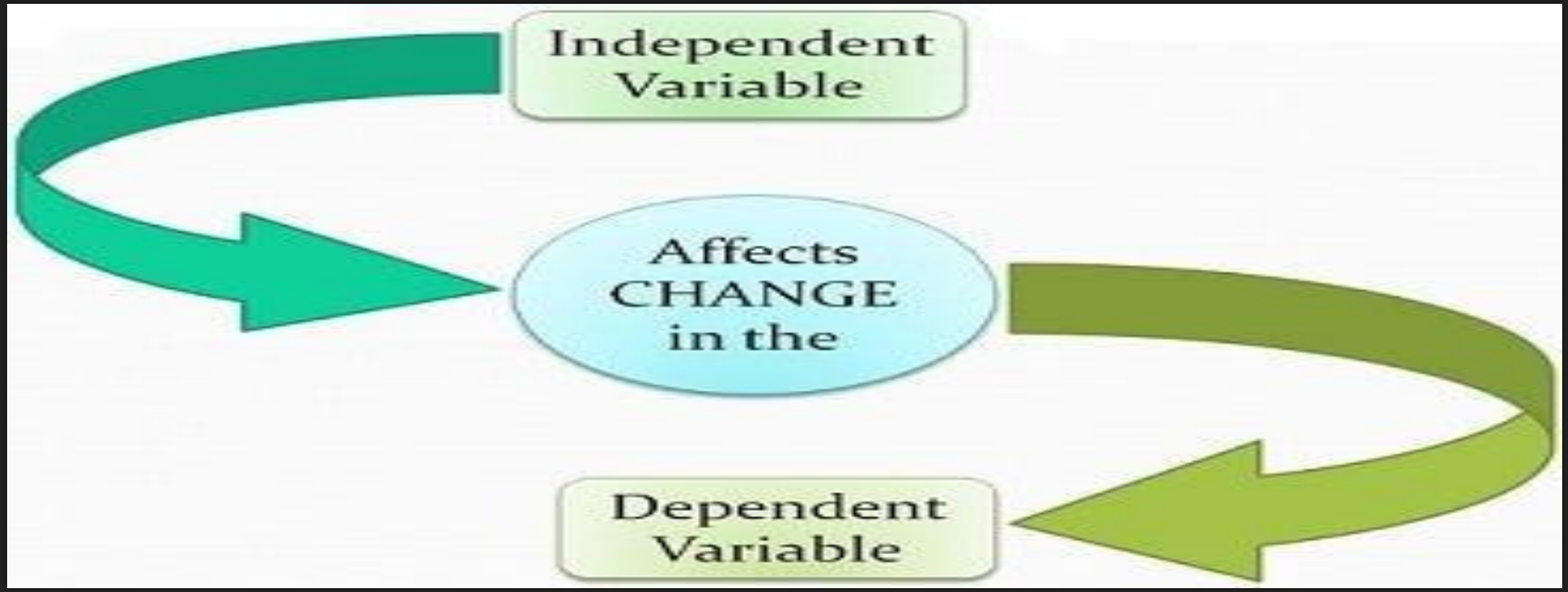
Independent Variable
Affects CHANGE in the
Dependent Variable

Step3: Handling the missing data

- To handle missing values, one of them is to ignore them and delete the entire entry/row, this is commonly done in datasets containing a very large number of entries, where the missing values only constitute 0.1% of the total data. Thus they affect the model negligibly and can be removed.

- The dataset is very small and we cannot just ignore those rows. So we use another method, in which we take the mean of the entire column containing the the missing values with that mean.

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```
25%    3.667960e+07
50%    5.370240e+07
75%    7.412350e+07
max    1.031789e+09
```

In [25]:
```
data.isnull().sum()
```

Out[25]:
```
Date          0
Open          0
High          0
Low           0
Close         0
Adj Close     0
Volume        0
year          0
month         0
day           0
dtype: int64
```

In [ ]:

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In [26]:
```
data.isnull()
```

Out[26]:

	Date	Open	High	Low	Close	Adj Close	Volume	year	month	day
0	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...
8520	False	False	False	False	False	False	False	False	False	False
8521	False	False	False	False	False	False	False	False	False	False
8522	False	False	False	False	False	False	False	False	False	False
8523	False	False	False	False	False	False	False	False	False	False
8524	False	False	False	False	False	False	False	False	False	False

8525 rows × 10 columns

In [ ]:

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Trusted | Python 3 (ipykernel)

8525 rows × 10 columns

In [31]:
```
data.notnull()
```

Out[31]:

	Date	Open	High	Low	Close	Adj Close	Volume	year	month	day
0	True	True	True	True	True	True	True	True	True	True
1	True	True	True	True	True	True	True	True	True	True
2	True	True	True	True	True	True	True	True	True	True
3	True	True	True	True	True	True	True	True	True	True
4	True	True	True	True	True	True	True	True	True	True
...	...	...	...	...	...	...	...	...	...	...
8520	True	True	True	True	True	True	True	True	True	True
8521	True	True	True	True	True	True	True	True	True	True
8522	True	True	True	True	True	True	True	True	True	True
8523	True	True	True	True	True	True	True	True	True	True
8524	True	True	True	True	True	True	True	True	True	True

8525 rows × 10 columns

In [ ]:

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Step4: Encoding categorical variable

- we have two categorical columns, the *country* column, and the *purchased* column.
- **<u>OneHot Encoding</u>**
- In the *country* column, we have three different categories: France, Germany, Spain. We can simply label France as 0, Germany as 1, and Spain as 2 but doing this might lead our machine learning model to interpret that there is some correlation between these numbers and the outcome.

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Trusted | Python 3 (ipykernel)

In [33]:
```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
ct=ColumnTransformer(transformers=[('encoder',OneHotEncoder(),[0])],remainder='passthrough')
data=pd.DataFrame(ct.fit_transform(data))
data
```

Out[33]:

	0
0	(0, 0)\t1.0\n (0, 8525)\t0.088542\n (0, 85...
1	(0, 1)\t1.0\n (0, 8525)\t0.097222\n (0, 85...
2	(0, 2)\t1.0\n (0, 8525)\t0.100694\n (0, 85...
3	(0, 3)\t1.0\n (0, 8525)\t0.102431\n (0, 85...
4	(0, 4)\t1.0\n (0, 8525)\t0.099826\n (0, 85...
...	...
8520	(0, 8520)\t1.0\n (0, 8525)\t156.770004\n (...
8521	(0, 8521)\t1.0\n (0, 8525)\t158.779999\n (...
8522	(0, 8522)\t1.0\n (0, 8525)\t158.320007\n (...
8523	(0, 8523)\t1.0\n (0, 8525)\t157.080002\n (...
8524	(0, 8524)\t1.0\n (0, 8525)\t159.320007\n (...

8525 rows × 1 columns

In [ ]:

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In [33]:
```python
import pandas as pd
from sklearn.preprocessing import LabelEncoder, OneHotEncoder

# Sample data
data =pd.read_csv('C:/Users/Dhinesh PC/Documents/MSFT.csv')
data
# Label Encoding (for ordinal data)
label_encoder = LabelEncoder()
data['Category_LabelEncoded'] = label_encoder.fit_transform(data['Adj Close'])

# One-Hot Encoding (for nominal data)
one_hot_encoder = OneHotEncoder(sparse=False)
encoded_categories = one_hot_encoder.fit_transform(data[['Adj Close']])
encoded_categories_df = pd.DataFrame(encoded_categories, columns=one_hot_encoder.get_feature_names(['Adj Close']))

print(data)
print(encoded_categories_df)
```

```
          Volume  Category_LabelEncoded
0     1031788800                      8
1      308160000                     13
2      133171200                     15
3       67766400                     11
4       47894400                      9
...          ...                    ...
8520    18369400                   6422
8521    22622100                   6427
8522    21116200                   6423
8523    20813700                   6426
```

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Trusted | Python 3 (ipykernel)

In [33]:
```python
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# Sample data
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data
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# One-Hot Encoding (for nominal data)
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encoded_categories = one_hot_encoder.fit_transform(data[['Adj Close']])
encoded_categories_df = pd.DataFrame(encoded_categories, columns=one_hot_encoder.get_feature_names(['Adj Close']))

print(data)
print(encoded_categories_df)
```

```
      Adj Close_0.061711  Adj Close_0.06199  Adj Close_0.062549  \
0                    0.0                0.0                 1.0
1                    0.0                0.0                 0.0
2                    0.0                0.0                 0.0
3                    0.0                0.0                 0.0
4                    0.0                0.0                 0.0
...                  ...                ...                 ...
8520                 0.0                0.0                 0.0
8521                 0.0                0.0                 0.0
8522                 0.0                0.0                 0.0
8523                 0.0                0.0                 0.0
8524                 0.0                0.0                 0.0
```

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- **Label Encoding**
- In the last column, i.e. the purchased column, the data is in binary form meaning that there are only two outcomes either Yes or No. Therefore here we need to perform Label Encoding.

Step5: Normalizing the dataset

- Feature scaling is bringing all of the features on the dataset to the same scale, this is necessary while training a machine learning model because in some cases the **dominant features become so dominant that the other ordinary features are not even considered by the model.**

Step6: Splitting the dataset

- Before we begin training our model there is one final step to go, which is splitting of the testing and training dataset. In machine learning, a **larger part** of the dataset is used to train the model, and a small part is used to test the trained model for finding out the accuracy and the efficiency of the model.
- Now before we begin splitting the dataset we need to separate the dependent and independent variables

- The last (*purchased*) column is the dependent variable and the rest are independent variables, so we'll store the dependent variable in 'y' and the independent variables in 'X'.
- Another important part we need to remember is that while training the model accepts data as arrays so it is necessary that **we convert the data to arrays**. We do that while separating the dependent and independent variables by adding ***.values*** while storing data in 'X' and 'y'.

Transformation variable:

- “Transformation variable" is not a standard concept in Python. It's possible that you're referring to a variable used in transformations or operations on data.
- In Python, a variable is a name that refers to a value. You can use variables to store and manipulate data. Transformation variables, in this context, could be any variable you use to hold intermediate or final results during a transformation

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In [7]:
```
data['day']=data['Date'].apply(lambda x:x.split('-')[0])
data['month']=data['Date'].apply(lambda x:x.split('-')[1])
data['year']=data['Date'].apply(lambda x:x.split('-')[2])
data
```

Out[7]:

	Date	Open	High	Low	Close	Adj Close	Volume	day	month	year
0	1986-03-13	0.088542	0.101563	0.088542	0.097222	0.062549	1031788800	1986	03	13
1	1986-03-14	0.097222	0.102431	0.097222	0.100694	0.064783	308160000	1986	03	14
2	1986-03-17	0.100694	0.103299	0.100694	0.102431	0.065899	133171200	1986	03	17
3	1986-03-18	0.102431	0.103299	0.098958	0.099826	0.064224	67766400	1986	03	18
4	1986-03-19	0.099826	0.100694	0.097222	0.098090	0.063107	47894400	1986	03	19
...	...	...	...	...	...	...	...	...	...	...
8520	2019-12-31	156.770004	157.770004	156.449997	157.699997	157.699997	18369400	2019	12	31
8521	2020-01-02	158.779999	160.729996	158.330002	160.619995	160.619995	22622100	2020	01	02
8522	2020-01-03	158.320007	159.949997	158.059998	158.619995	158.619995	21116200	2020	01	03
8523	2020-01-06	157.080002	159.100006	156.509995	159.029999	159.029999	20813700	2020	01	06
8524	2020-01-07	159.320007	159.669998	157.330002	157.580002	157.580002	18017762	2020	01	07

8525 rows × 10 columns

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In [39]:
```
import numpy as np
data['Log_Transformed'] = np.log(data['Volume'])
data['Sqrt_Transformed'] = np.sqrt(data['Volume'])
from scipy import stats
data['BoxCox_Transformed'], _ = stats.boxcox(data['Volume'])
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
data['Standardized'] = scaler.fit_transform(data[['Volume']])
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
data['Normalized'] = scaler.fit_transform(data[['Volume']])
print(data)
```

```
            Date        Open        High         Low       Close   Adj Close  \
0     1986-03-13    0.088542    0.101563    0.088542    0.097222    0.062549
1     1986-03-14    0.097222    0.102431    0.097222    0.100694    0.064783
2     1986-03-17    0.100694    0.103299    0.100694    0.102431    0.065899
3     1986-03-18    0.102431    0.103299    0.098958    0.099826    0.064224
4     1986-03-19    0.099826    0.100694    0.097222    0.098090    0.063107
...          ...         ...         ...         ...         ...         ...
8520  2019-12-31  156.770004  157.770004  156.449997  157.699997  157.699997
8521  2020-01-02  158.779999  160.729996  158.330002  160.619995  160.619995
8522  2020-01-03  158.320007  159.949997  158.059998  158.619995  158.619995
8523  2020-01-06  157.080002  159.100006  156.509995  159.029999  159.029999
8524  2020-01-07  159.320007  159.669998  157.330002  157.580002  157.580002

          Volume  Category_LabelEncoded  Log_Transformed  Sqrt_Transformed  \
0     1031788800                      8        20.754560      32121.469456
1      308160000                     13        19.546130      17554.486606
2      133171200                     15        18.707146      11539.982669
```

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Notebook saved Trusted Python 3 (ipykernel)

In [39]:
```
import numpy as np
data['Log_Transformed'] = np.log(data['Volume'])
data['Sqrt_Transformed'] = np.sqrt(data['Volume'])
from scipy import stats
data['BoxCox_Transformed'], _ = stats.boxcox(data['Volume'])
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
data['Standardized'] = scaler.fit_transform(data[['Volume']])
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
data['Normalized'] = scaler.fit_transform(data[['Volume']])
print(data)
```

```
            Date        Open        High         Low       Close   Adj Close  \
0     1986-03-13    0.088542    0.101563    0.088542    0.097222    0.062549
1     1986-03-14    0.097222    0.102431    0.097222    0.100694    0.064783
2     1986-03-17    0.100694    0.103299    0.100694    0.102431    0.065899
3     1986-03-18    0.102431    0.103299    0.098958    0.099826    0.064224
4     1986-03-19    0.099826    0.100694    0.097222    0.098090    0.063107
...          ...         ...         ...         ...         ...         ...
8520  2019-12-31  156.770004  157.770004  156.449997  157.699997  157.699997
8521  2020-01-02  158.779999  160.729996  158.330002  160.619995  160.619995
8522  2020-01-03  158.320007  159.949997  158.059998  158.619995  158.619995
8523  2020-01-06  157.080002  159.100006  156.509995  159.029999  159.029999
8524  2020-01-07  159.320007  159.669998  157.330002  157.580002  157.580002

          Volume  Category_LabelEncoded  Log_Transformed  Sqrt_Transformed  \
0     1031788800                      8        20.754560      32121.469456
1      308160000                     13        19.546130      17554.486606
2      133171200                     15        18.707146      11539.982669
```

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```
            Volume  Category_LabelEncoded  Log_Transformed  Sqrt_Transformed  \
0     1031788800                      8        20.754560      32121.469456
1      308160000                     13        19.546130      17554.486606
2      133171200                     15        18.707146      11539.982669
3       67766400                     11        18.031577       8232.034985
4       47894400                      9        17.684509       6920.578011
...          ...                    ...              ...               ...
8520    18369400                   6422        16.726197       4285.953803
8521    22622100                   6427        16.934438       4756.269547
8522    21116200                   6423        16.865551       4595.236664
8523    20813700                   6426        16.851122       4562.203415
8524    18017762                   6420        16.706869       4244.733443

      BoxCox_Transformed  Standardized  Normalized
0             157.341204     24.963577    1.000000
1             129.177315      6.366058    0.297096
2             112.525895      1.868783    0.127119
3             100.616460      0.187856    0.063588
4              94.969637     -0.322861    0.044285
...                  ...           ...         ...
8520           80.877527     -1.081664    0.015605
8521           83.762953     -0.972368    0.019736
8522           82.798038     -1.011071    0.018273
8523           82.597238     -1.018845    0.017980
8524           80.614441     -1.090702    0.015264

[8525 rows x 13 columns]
```

In [ ]:

Outliers detection and treatment

- Detecting and treating outliers in Python typically involves using statistical methods and data visualization techniques to identify data points that significantly deviate from the rest of the dataset. Once identified, you can choose to handle outliers in various ways, such as removing them, transforming them, or imputing them

localhost:8889/notebooks/IBM.ipynb#

jupyter IBM Last Checkpoint: 11 minutes ago (unsaved changes)

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In [41]:
```
import pandas as pd

data=pd.read_csv('C:/Users/Dhinesh PC/Documents/MSFT.csv')
Q1 = data['High'].quantile(0.25)
Q3 = data['Low'].quantile(0.75)
IQR = Q3 - Q1

lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

outliers = data[(data['High'] < lower_bound) | (data['Low'] > upper_bound)]
print(outliers)
```

```
            Date        Open        High         Low       Close   Adj Close  \
7974  2017-10-27   84.370003   86.199997   83.610001   83.809998   80.777763
7975  2017-10-30   83.699997   84.330002   83.110001   83.889999   80.854881
7976  2017-10-31   84.360001   84.360001   83.110001   83.180000   80.170578
7977  2017-11-01   83.680000   83.760002   82.879997   83.180000   80.170578
7978  2017-11-02   83.349998   84.459999   83.120003   84.050003   81.009094
...          ...         ...         ...         ...         ...         ...
8520  2019-12-31  156.770004  157.770004  156.449997  157.699997  157.699997
8521  2020-01-02  158.779999  160.729996  158.330002  160.619995  160.619995
8522  2020-01-03  158.320007  159.949997  158.059998  158.619995  158.619995
8523  2020-01-06  157.080002  159.100006  156.509995  159.029999  159.029999
8524  2020-01-07  159.320007  159.669998  157.330002  157.580002  157.580002

        Volume
7974  71066700
```

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jupyter IBM Last Checkpoint: 11 minutes ago (autosaved)

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Trusted | Python 3 (ipykernel)

```
8521  2020-01-02  158.779999  160.729996  158.330002  160.619995  160.619995
8522  2020-01-03  158.320007  159.949997  158.059998  158.619995  158.619995
8523  2020-01-06  157.080002  159.100006  156.509995  159.029999  159.029999
8524  2020-01-07  159.320007  159.669998  157.330002  157.580002  157.580002

        Volume
7974  71066700
7975  31756700
7976  27086600
7977  22307400
7978  23992900
...        ...
8520  18369400
8521  22622100
8522  21116200
8523  20813700
8524  18017762

[551 rows x 7 columns]
```

In [ ]:

Conclusion

- Evaluate the model's performance on the testing data using appropriate metrics (e.g., accuracy, mean squared error, etc.). This step helps you understand how well your model is likely to perform on new, unseen data