Share price estimation of TOP 5 GPU Companies

Project Hand-out, Faculty Development Program

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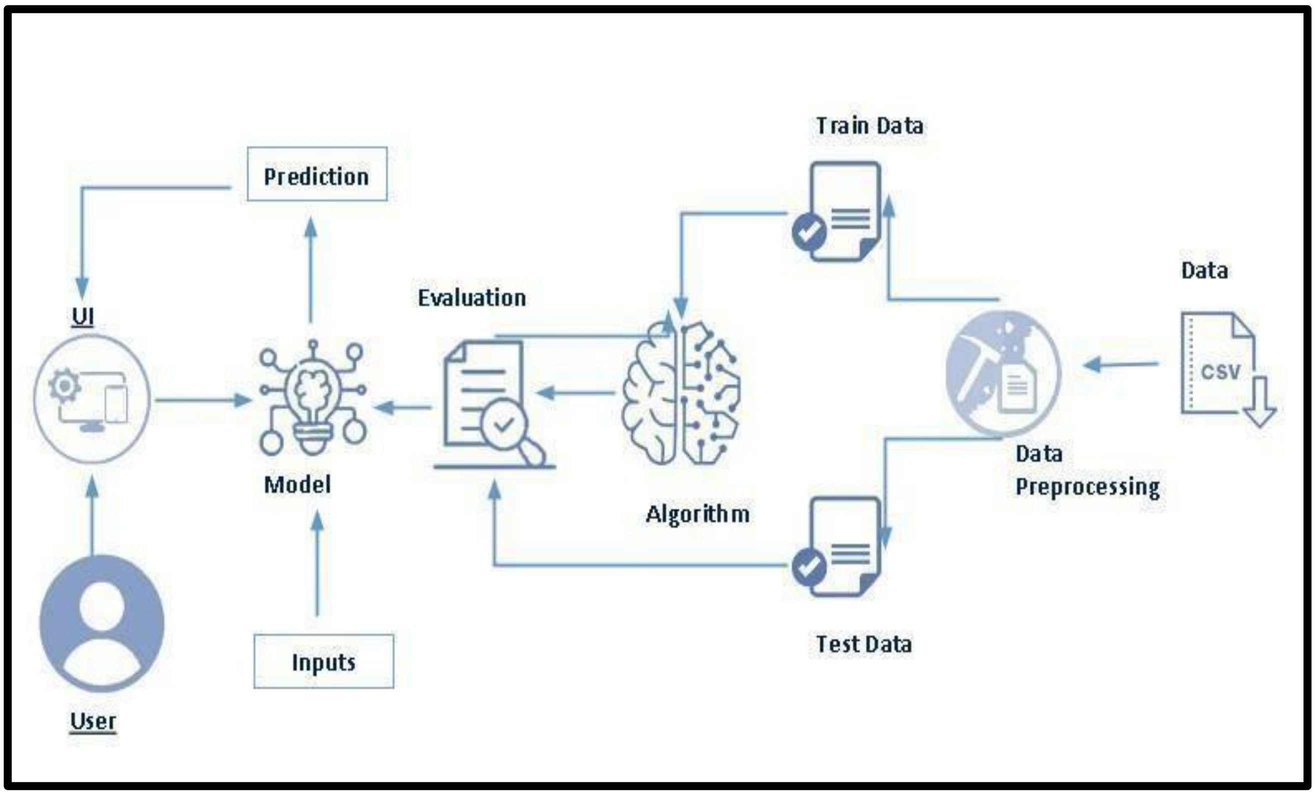
Share price estimation of TOP 5 GPU Companies

The objective of this project is to estimate the share prices of the top 5 GPU companies in the market using historical data and current market trends. The aim is to develop a predictive model that can forecast the future prices of these companies based on their historical performance and other relevant factors. The model should take into consideration various economic indicators, industry trends, company financials, and other relevant data to make accurate predictions. The analysis should be performed using statistical and machine learning/ Deep learning techniques and the results should be presented in a clear and concise manner. The final output of the project will be a report outlining the predicted share prices of the top 5 GPU companies in the market, along with an analysis of the factors that have contributed to their performance.

Technical Architecture:



Project Flow:

- User interacts with the UI to enter the input.
- Entered input is analysed by the model which is integrated.
- Once model analyses the input the prediction is showcased on the UI

To accomplish this, we have to complete all the activities listed below,

- Define Problem / Problem Understanding
  - Specify the business problem
  - Business requirements
  - Literature Survey
  - Social or Business Impact.
- Data Collection & Preparation
  - Collect the dataset
  - Data Preparation
- Exploratory Data Analysis
  - Descriptive statistical
  - Visual Analysis
- Model Building
  - Training the model in multiple algorithms
  - Testing the model
- Performance Testing & Hyperparameter Tuning
  - Testing model with multiple evaluation metrics
  - Comparing model accuracy before & after applying hyperparameter tuning
- Model Deployment
  - Save the best model
  - Integrate with Web Framework
- Project Demonstration & Documentation
  - Record explanation Video for project end to end solution
  - Project Documentation-Step by step project development procedure

Prior Knowledge:

To complete this project, you must require following software's , concepts and packages

- Anaconda navigator:
  - Refer to the link below to download anaconda navigator
  - Link : https://www.youtube.com/watch?v=5mDYijMfSzs
- Python packages:
  - open anaconda prompt as administrator
  - Type "pip install prophet" (make sure you are working on python 64 bit)
  - Type "pip install flask".
- Deep Learning Concepts
  - CNN: https://towardsdatascience.com/basics-of-the-classic-cnn-a3dce1225add
  - ARIMA: https://www.investopedia.com/terms/a/autoregressive-integrated-moving-average-arima.asp#:~:text=An%20autoregressive%20integrated%20moving%20average%2C%20or%20ARIMA%2C%20is%20a%20statistical,values%20based%20on%20past%20values.
  - LSTM: https://www.analyticsvidhya.com/blog/2021/03/introduction-to-long-short-term-memory-lstm/
  - SARIMA: https://machinelearningmastery.com/sarima-for-time-series-forecasting-in-python/
  - Facebook Prophet: https://www.geeksforgeeks.org/time-series-analysis-using-facebook-prophet/
  - Flask Basics : https://www.youtube.com/watch?v=lj4I_CvBnt0

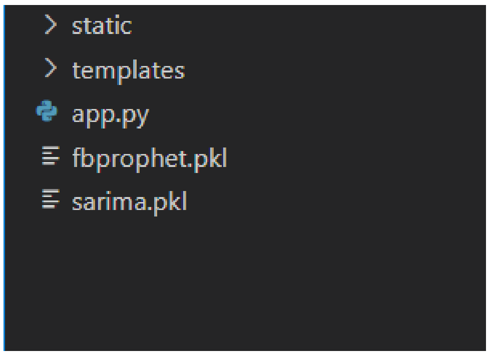
Project Objectives:

By the end of this project you will:

- know fundamental concepts and techniques of Convolutional Neural Network.
- gain a broad understanding of image data.
- Knowhow to pre-process/clean the data using different data preprocessing techniques.
- know how to build a web application using Flask framework.

Project Structure:

Create the Project folder which contains files as shown below



```
> static
> templates
app.py
fbprophet.pkl
sarima.pkl
```

- We are building a flask application which needs HTML pages stored in the templates folder and a python script app.py for scripting.
- Static folder and assets folder contain the CSS and JavaScript files along with images.
- **fbprophet.pkl, lstm.h5** and **sarima.pkl** are our saved models.
- Further we will use these models for flask integration.

Milestone 1: Define Problem / Problem Understanding

Activity 1: Specify the business problem

Refer Project Description

Activity 2: Business requirements

Here are some potential business requirements for Share price predictor:

a. Accurate forecasting: The predictor must be able to accurately forecast Share prices for a given time period in the future. The accuracy of the forecasting is crucial for investors, stock holders, and other stakeholders to make informed decisions on the production and marketing of rice.

b. Real-time data acquisition: The predictor must be able to acquire real-time data on stock information and other relevant factors that affect stock price prediction. The data acquisition must be seamless and efficient to ensure that the predictor is always up-to-date with the latest information.

c. User-friendly interface: The predictor must have a user-friendly interface that is easy to navigate and understand. The interface should present the results of the predictor in a clear and concise manner to enable farmers and other stakeholders to make informed decisions.

d. Report generation: Generate a report outlining the predicted share prices of the top 5 GPU companies in the market, along with an analysis of the factors that have contributed to their performance. The report should be presented in a clear and concise manner, with appropriate visualizations and insights to help stakeholders make informed decisions.

Activity 3: Literature Survey (Student Will Write)

A literature survey would involve researching and reviewing existing studies, articles, and other publications on the topic of project. The survey would aim to gather information on current systems, their strengths and weaknesses, and any gaps in knowledge that the project could address. The literature survey would also look at the methods and techniques used in previous projects, and any relevant data or findings that could inform the design and implementation of the current project.

Activity 4: Social or Business Impact.

The Share Price Estimation of Top 5 GPU Companies project can have both social and business impacts.

Social Impact:

The accurate prediction of share prices can help individual investors, particularly those who may not have extensive financial knowledge, make informed investment decisions, thereby enabling them to achieve their financial goals and potentially increase their wealth.

The project can also contribute to overall market stability by providing more accurate information to investors, helping them make informed decisions, and reducing market volatility and uncertainty.

Business Impact:

The project can be particularly useful for financial institutions, such as investment banks and hedge funds, who make investment decisions on behalf of their clients. Accurate prediction of share prices can help these institutions improve their investment strategies and potentially increase their returns.

Accurate share price predictions can also be useful for companies operating in the GPU industry, enabling them to anticipate changes in the market and adjust their strategies accordingly. This can help companies remain competitive and achieve their business goals.

Overall, the project can have a positive impact on the financial industry by improving the accuracy of share price predictions and increasing market efficiency.

Milestone 2: Data Collection & Preparation

DL depends heavily on data. It is the most crucial aspect that makes algorithm training possible. So, this section allows you to download the required dataset.

Activity 1: Collect the dataset.

There are many popular open sources for collecting the data. Eg: kaggle.com, UCI repository, etc.

In this project we have used .csv data. This data is downloaded from kaggle.com. Please refer to the link given below to download the dataset.

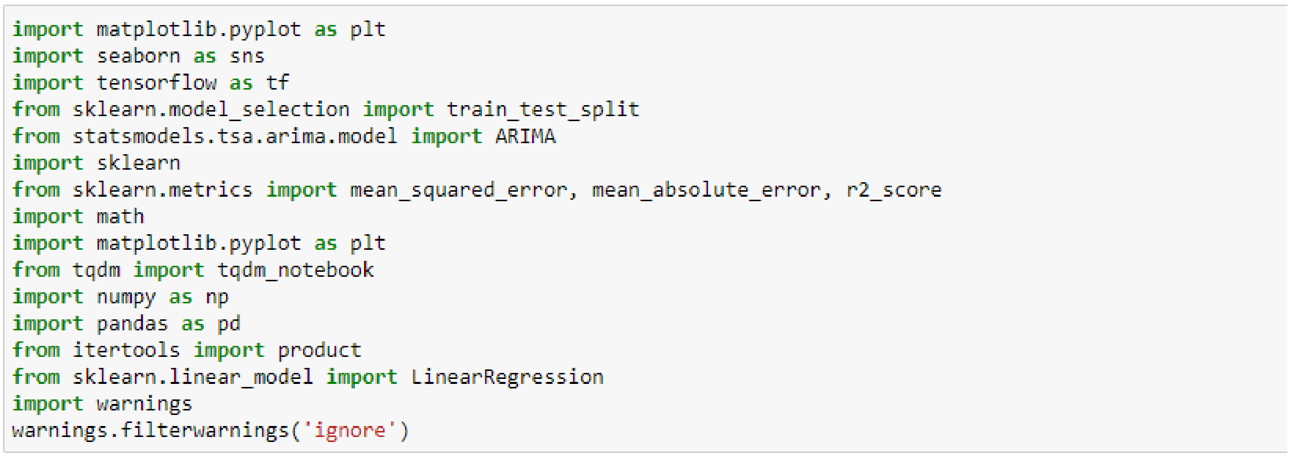
Link: https://www.kaggle.com/datasets/kapturovalexander/nvidia-amd-intel-asus-msi-share-prices

As the dataset is downloaded. Let us read and understand the data properly with the help of some visualisation techniques and some analysing techniques.

Note: There are a number of techniques for understanding the data. But here we have used some of it. In an additional way, you can use multiple techniques.

Activity 1.1: Importing the libraries

Import the necessary libraries as shown in the image.

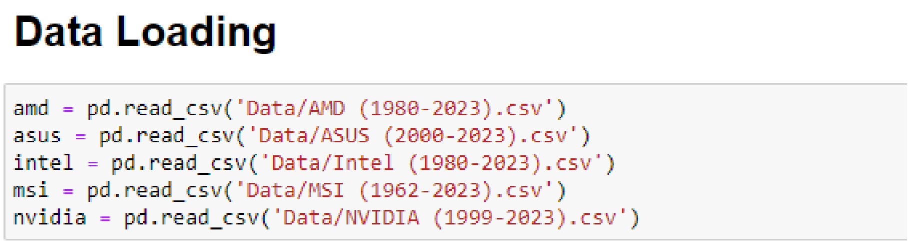


```
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf
from sklearn.model_selection import train_test_split
from statsmodels.tsa.arima.model import ARIMA
import sklearn
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
import math
import matplotlib.pyplot as plt
from tqdm import tqdm_notebook
import numpy as np
import pandas as pd
from itertools import product
from sklearn.linear_model import LinearRegression
import warnings
warnings.filterwarnings('ignore')
```

Activity 1.2: Read the Dataset

Our dataset format might be in .csv, excel files, .txt, .json, etc. We can read the dataset with the help of pandas.

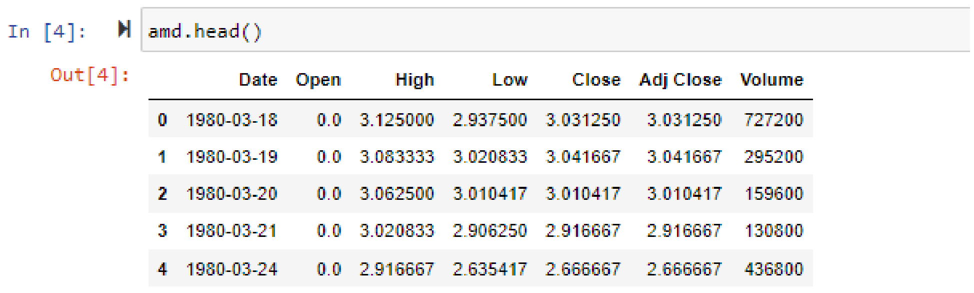
In pandas we have a function called read_csv() to read the dataset. As a parameter we have to give the directory of the csv file.



Data Loading

```
amd = pd.read_csv('Data/AMD (1980-2023).csv')
asus = pd.read_csv('Data/ASUS (2000-2023).csv')
intel = pd.read_csv('Data/Intel (1980-2023).csv')
msi = pd.read_csv('Data/MSI (1962-2023).csv')
nvidia = pd.read_csv('Data/NVIDIA (1999-2023).csv')
```

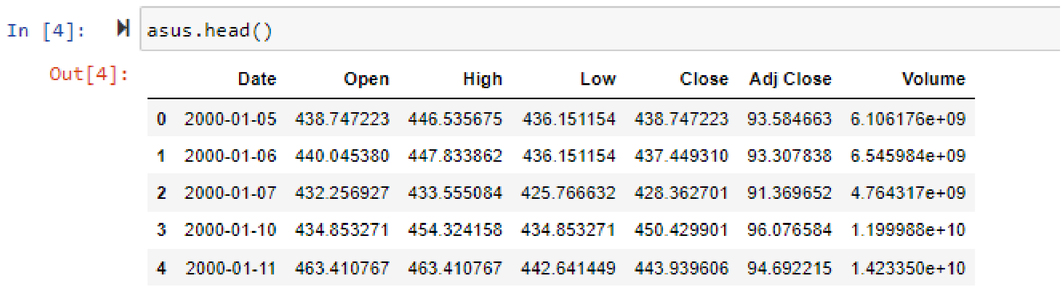
We can print the first 5 rows of the datasets using the **.head()** method as shown in below screenshots.



```
In [4]: amd.head()
```

Out[4]:

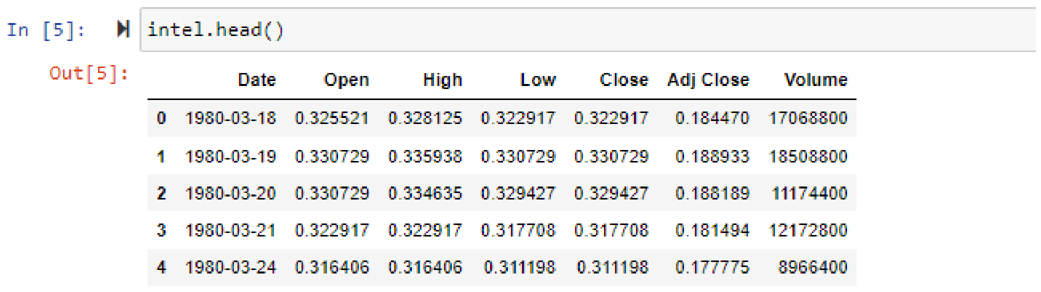
	Date	Open	High	Low	Close	Adj Close	Volume
0	1980-03-18	0.0	3.125000	2.937500	3.031250	3.031250	727200
1	1980-03-19	0.0	3.083333	3.020833	3.041667	3.041667	295200
2	1980-03-20	0.0	3.062500	3.010417	3.010417	3.010417	159600
3	1980-03-21	0.0	3.020833	2.906250	2.916667	2.916667	130800
4	1980-03-24	0.0	2.916667	2.635417	2.666667	2.666667	436800



```
In [4]: asus.head()
```

Out[4]:

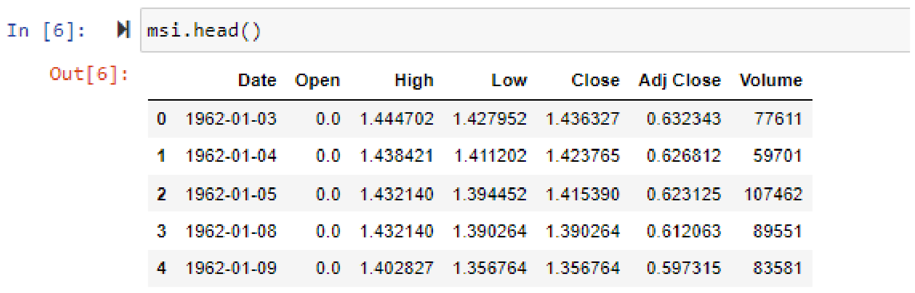
	Date	Open	High	Low	Close	Adj Close	Volume
0	2000-01-05	438.747223	446.535675	436.151154	438.747223	93.584663	6.106176e+09
1	2000-01-06	440.045380	447.833862	436.151154	437.449310	93.307838	6.545984e+09
2	2000-01-07	432.256927	433.555084	425.766632	428.362701	91.369652	4.764317e+09
3	2000-01-10	434.853271	454.324158	434.853271	450.429901	96.076584	1.199988e+10
4	2000-01-11	463.410767	463.410767	442.641449	443.939606	94.692215	1.423350e+10



```
In [5]: intel.head()
```

Out[5]:

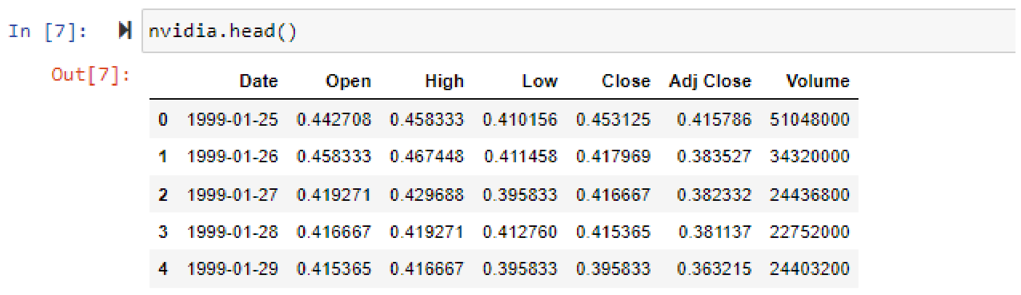
	Date	Open	High	Low	Close	Adj Close	Volume
0	1980-03-18	0.325521	0.328125	0.322917	0.322917	0.184470	17068800
1	1980-03-19	0.330729	0.335938	0.330729	0.330729	0.188933	18508800
2	1980-03-20	0.330729	0.334635	0.329427	0.329427	0.188189	11174400
3	1980-03-21	0.322917	0.322917	0.317708	0.317708	0.181494	12172800
4	1980-03-24	0.316406	0.316406	0.311198	0.311198	0.177775	8966400



```
In [6]: msi.head()
```

Out[6]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	1962-01-03	0.0	1.444702	1.427952	1.436327	0.632343	77611
1	1962-01-04	0.0	1.438421	1.411202	1.423765	0.626812	59701
2	1962-01-05	0.0	1.432140	1.394452	1.415390	0.623125	107462
3	1962-01-08	0.0	1.432140	1.390264	1.390264	0.612063	89551
4	1962-01-09	0.0	1.402827	1.356764	1.356764	0.597315	83581



```
In [7]:  nvidia.head()
Out[7]:
```

	Date	Open	High	Low	Close	Adj Close	Volume
0	1999-01-25	0.442708	0.458333	0.410156	0.453125	0.415786	51048000
1	1999-01-26	0.458333	0.467448	0.411458	0.417969	0.383527	34320000
2	1999-01-27	0.419271	0.429688	0.395833	0.416667	0.382332	24436800
3	1999-01-28	0.416667	0.419271	0.412760	0.415365	0.381137	22752000
4	1999-01-29	0.415365	0.416667	0.395833	0.395833	0.363215	24403200

Activity 2: Data Preparation

As we have understood how the data is, let's pre-process the collected data.

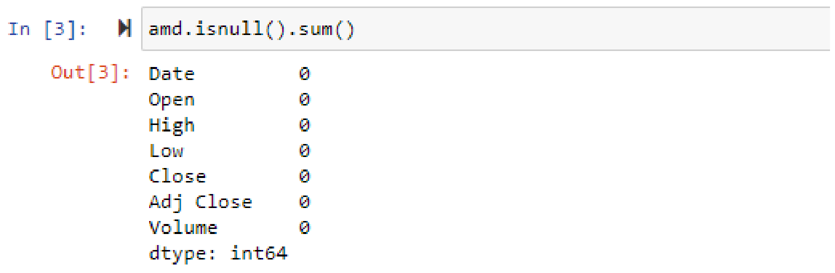
The download data set is not suitable for training the machine learning model as it might have so much randomness so we need to clean the dataset properly in order to fetch good results. This activity includes the following steps.

- Checking for missing values
- Data manipulation
- Resampling the data
- Merging and splitting data into test and train variables

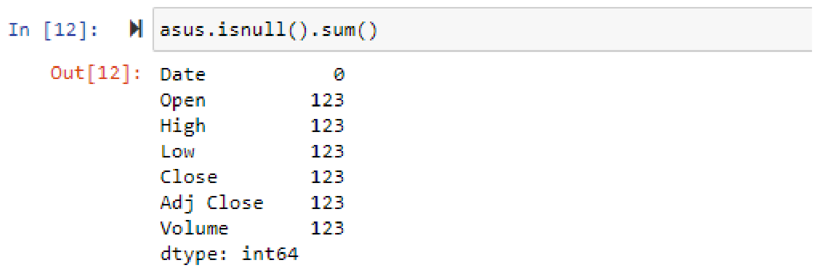
Note: These are the general steps of pre-processing the data before using it for training models. Depending on the condition of your dataset, you may or may not have to go through all these steps.

Activity 2.1: Checking for missing values

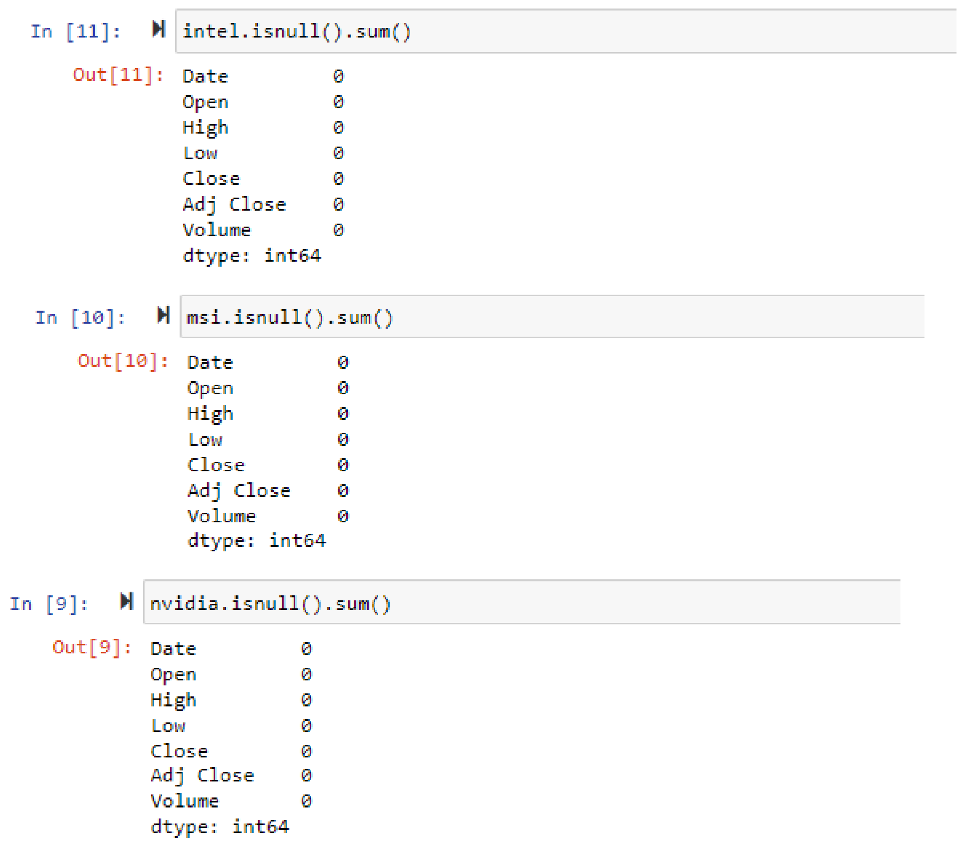
- For checking the null values, df.isnull() function is used. To sum those null values we use .sum() function. From the below image we found that there are no null values present in our dataset. So we can skip handling the missing values step.



```
In [3]:  amd.isnull().sum()

Out[3]:  Date         0
         Open         0
         High         0
         Low          0
         Close        0
         Adj Close    0
         Volume       0
         dtype: int64
```



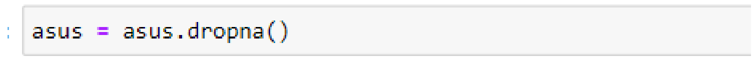
```
In [12]:  asus.isnull().sum()

Out[12]:  Date           0
          Open         123
          High         123
          Low          123
          Close        123
          Adj Close    123
          Volume       123
          dtype: int64
```



```
In [11]:  intel.isnull().sum()

Out[11]:  Date         0
          Open         0
          High         0
          Low          0
          Close        0
          Adj Close    0
          Volume       0
          dtype: int64

In [10]:  msi.isnull().sum()

Out[10]:  Date         0
          Open         0
          High         0
          Low          0
          Close        0
          Adj Close    0
          Volume       0
          dtype: int64

In [9]:  nvidia.isnull().sum()

Out[9]:  Date         0
         Open         0
         High         0
         Low          0
         Close        0
         Adj Close    0
         Volume       0
         dtype: int64
```

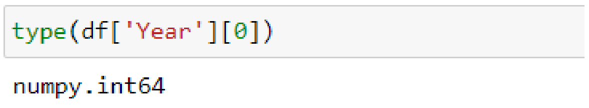
Activity 2.2: Data manipulation

Since we found null values in the dataset related to ASUS company we are going to drop the null values but we can also fill those null values using mean/median/mode of the respective volumns.



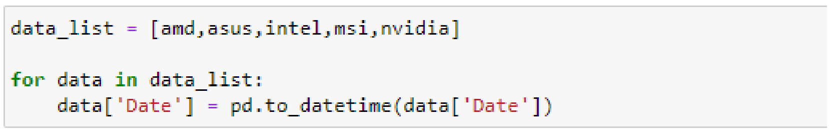
```
asus = asus.dropna()
```

To convert the date strings to time stamps we are going to perform below steps.
First let’s check the type of data of the column “**Year**” using the **type()** function.



```
type(df['Year'][0])

numpy.int64
```

We will convert the data of “**Year**” column using the pandas “**to_datetime**” function. We can change the ‘**Date’** columns of all the datasets using a for loop to reduce Lines of code..

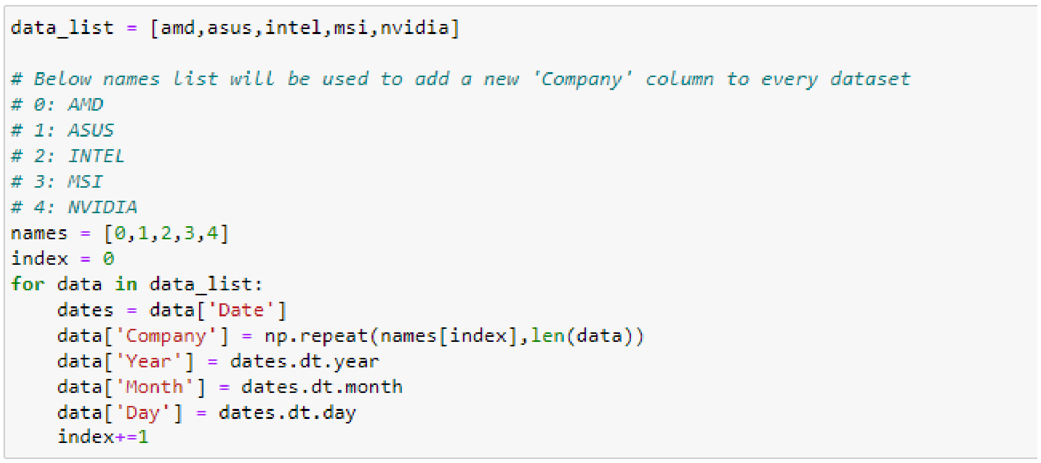


```
data_list = [amd,asus,intel,msi,nvidia]

for data in data_list:
    data['Date'] = pd.to_datetime(data['Date'])
```

Activity 2.3: Resampling the Data

Now we are going to add new columns to all the loaded datasets so that when we merge our data it will be easier to find which rows of data belong to which company and also so that our model will be able to differentiate the rows of data based on the value of the new column

named “Company”. The new column “Company” will be a categorical value ranging from 0 to 4 where each number denotes a company as shown below. We are going to process the datasets as mentioned above using a for loop.
We will also three new columns of data namely “Year”, “Day” and “Month” which are derived from the “Date” column. We will use these three columns for training not the “Date” columns but we use the “Date” column for analysis in later stages.

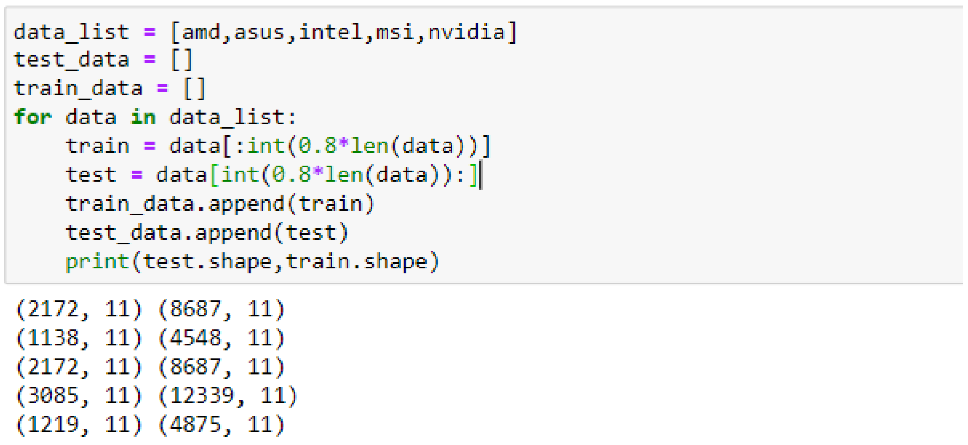


```
data_list = [amd,asus,intel,msi,nvidia]

# Below names list will be used to add a new 'Company' column to every dataset
# 0: AMD
# 1: ASUS
# 2: INTEL
# 3: MSI
# 4: NVIDIA
names = [0,1,2,3,4]
index = 0
for data in data_list:
    dates = data['Date']
    data['Company'] = np.repeat(names[index],len(data))
    data['Year'] = dates.dt.year
    data['Month'] = dates.dt.month
    data['Day'] = dates.dt.day
    index+=1
```

Activity 2.3: Merging and splitting data into test and train variables

Now we are going to merge our datasets, simultaneously we are also going to split the data to test and train variables using the below piece of code with a train to test ratio of 80 to 20.

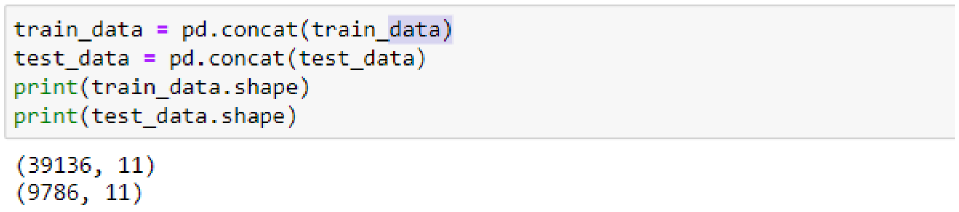
First we are going to take 2 lists of train and test in which we are going to append train and test splits of every dataset into these 2 lists. In the output each line represents the data of companies in order as stored in the data_list in below code.



```
data_list = [amd,asus,intel,msi,nvidia]
test_data = []
train_data = []
for data in data_list:
    train = data[:int(0.8*len(data))]
    test = data[int(0.8*len(data)):]
    train_data.append(train)
    test_data.append(test)
    print(test.shape,train.shape)
```

```
(2172, 11) (8687, 11)
(1138, 11) (4548, 11)
(2172, 11) (8687, 11)
(3085, 11) (12339, 11)
(1219, 11) (4875, 11)
```

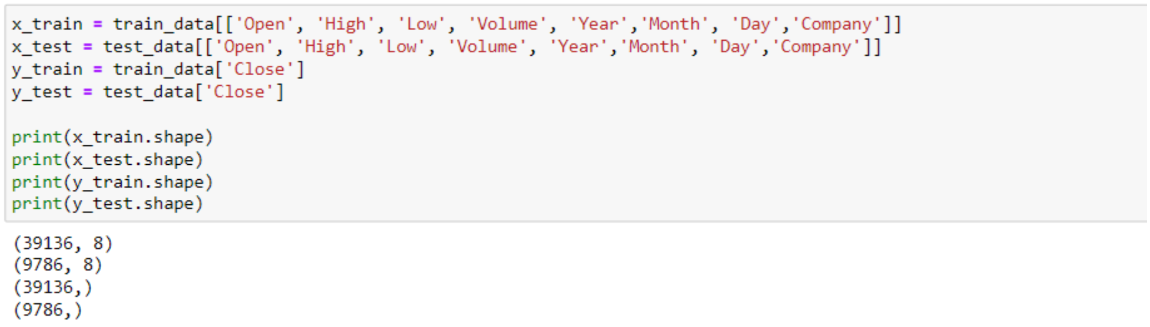
Next we are going to merge the data of each variable of train_data and test_data using the **pandas.concat()** function as shown below.



```
train_data = pd.concat(train_data)
test_data = pd.concat(test_data)
print(train_data.shape)
print(test_data.shape)
```

```
(39136, 11)
(9786, 11)
```

Finally we are going to split the train_data and test_data variables into x_train, y_train, x_test and y_test using the below piece of code.



```
x_train = train_data[['Open', 'High', 'Low', 'Volume', 'Year','Month', 'Day','Company']]
x_test = test_data[['Open', 'High', 'Low', 'Volume', 'Year','Month', 'Day','Company']]
y_train = train_data['Close']
y_test = test_data['Close']

print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(39136, 8)
(9786, 8)
(39136,)
(9786,)
```

Milestone 3: Exploratory Data Analysis

Activity 1: Descriptive statistical

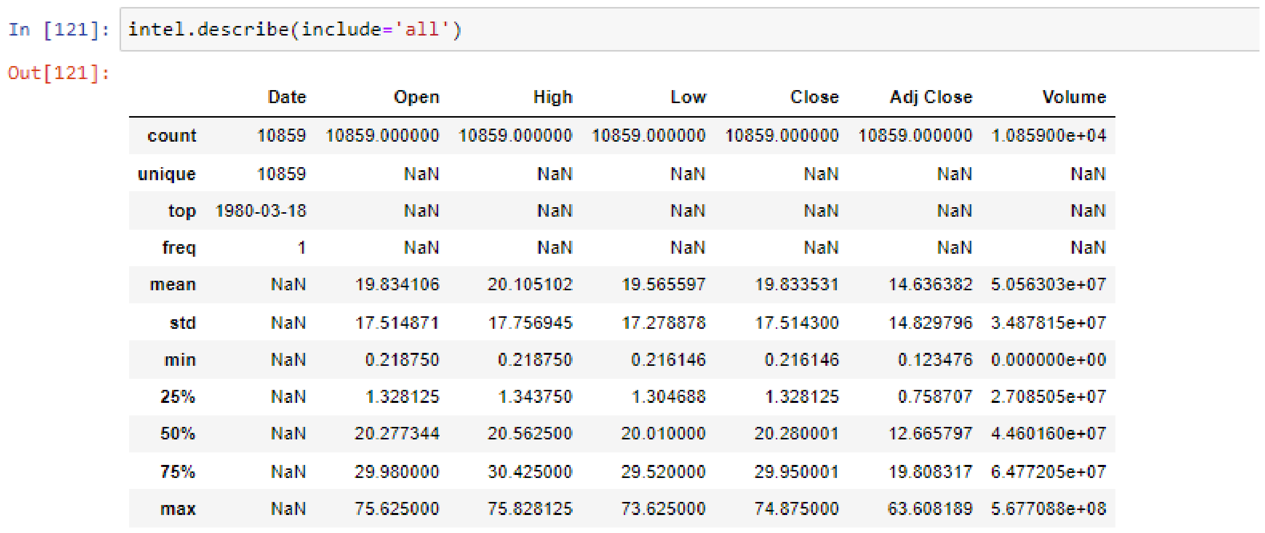
Descriptive analysis is to study the basic features of data with the statistical process. Here pandas has a worthy function called describe. With this describe function we can understand the unique, top and frequent values of categorical features. And we can find mean, std, min, max and percentile values of continuous features.

In [119]:
```
amd.describe(include='all')
```
Out[119]:

	Date	Open	High	Low	Close	Adj Close	Volume
count	10859	10859.000000	10859.000000	10859.000000	10859.000000	10859.000000	1.085900e+04
unique	10859	NaN	NaN	NaN	NaN	NaN	NaN
top	1980-03-18	NaN	NaN	NaN	NaN	NaN	NaN
freq	1	NaN	NaN	NaN	NaN	NaN	NaN
mean	NaN	16.350958	17.010710	16.280518	16.648080	16.648080	1.819320e+07
std	NaN	22.396174	22.668726	21.705814	22.196357	22.196357	2.794779e+07
min	NaN	0.000000	1.690000	1.610000	1.620000	1.620000	0.000000e+00
25%	NaN	4.937500	5.405000	5.120000	5.265000	5.265000	1.216500e+06
50%	NaN	9.810000	10.000000	9.562500	9.760000	9.760000	6.745600e+06
75%	NaN	16.000000	16.250000	15.687500	16.000000	16.000000	2.242935e+07
max	NaN	163.279999	164.460007	156.100006	161.910004	161.910004	3.250584e+08

In [120]:
```
asus.describe(include='all')
```
Out[120]:

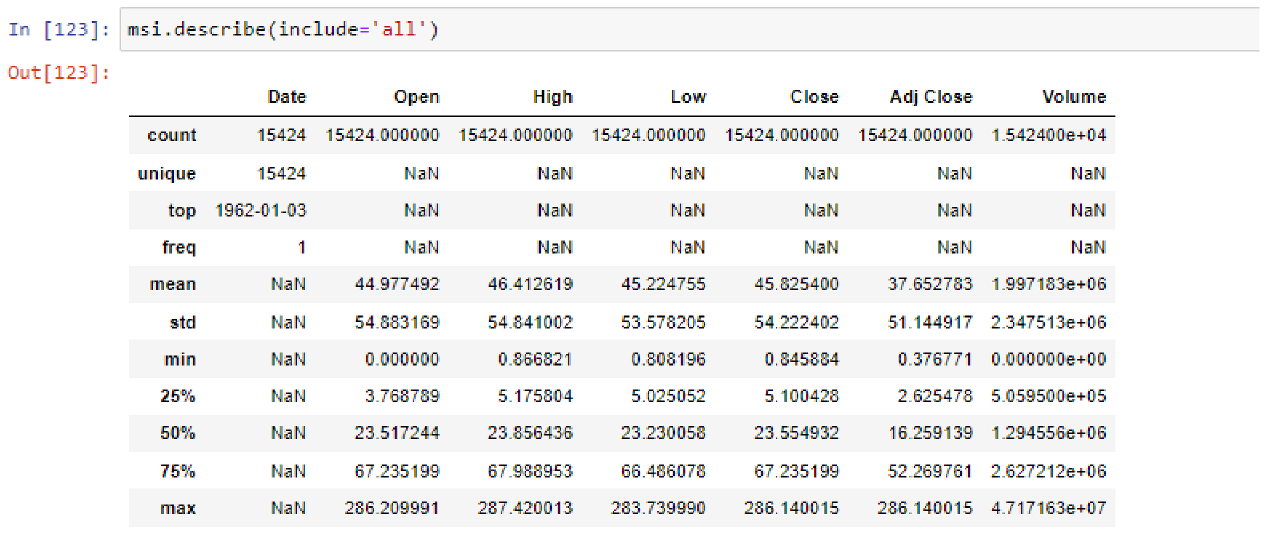
	Date	Open	High	Low	Close	Adj Close	Volume
count	5809	5686.000000	5686.000000	5686.000000	5686.000000	5686.000000	5.686000e+03
unique	5809	NaN	NaN	NaN	NaN	NaN	NaN
top	2000-01-05	NaN	NaN	NaN	NaN	NaN	NaN
freq	1	NaN	NaN	NaN	NaN	NaN	NaN
mean	NaN	290.387916	293.572143	286.947741	290.132960	133.244407	1.027367e+09
std	NaN	76.336647	77.122349	75.308642	75.978864	67.614911	2.186379e+09
min	NaN	127.106941	130.196335	127.106941	130.196335	30.318747	0.000000e+00
25%	NaN	234.106556	236.500000	231.500000	234.000000	79.519874	1.696933e+06
50%	NaN	277.500000	280.000000	275.000000	277.500000	125.252792	3.201000e+06
75%	NaN	331.005699	335.315742	327.000000	331.007599	170.654297	1.125660e+09
max	NaN	567.667419	575.104126	547.836243	565.188538	330.402832	2.833812e+10



```
In [121]: intel.describe(include='all')
```

Out[121]:

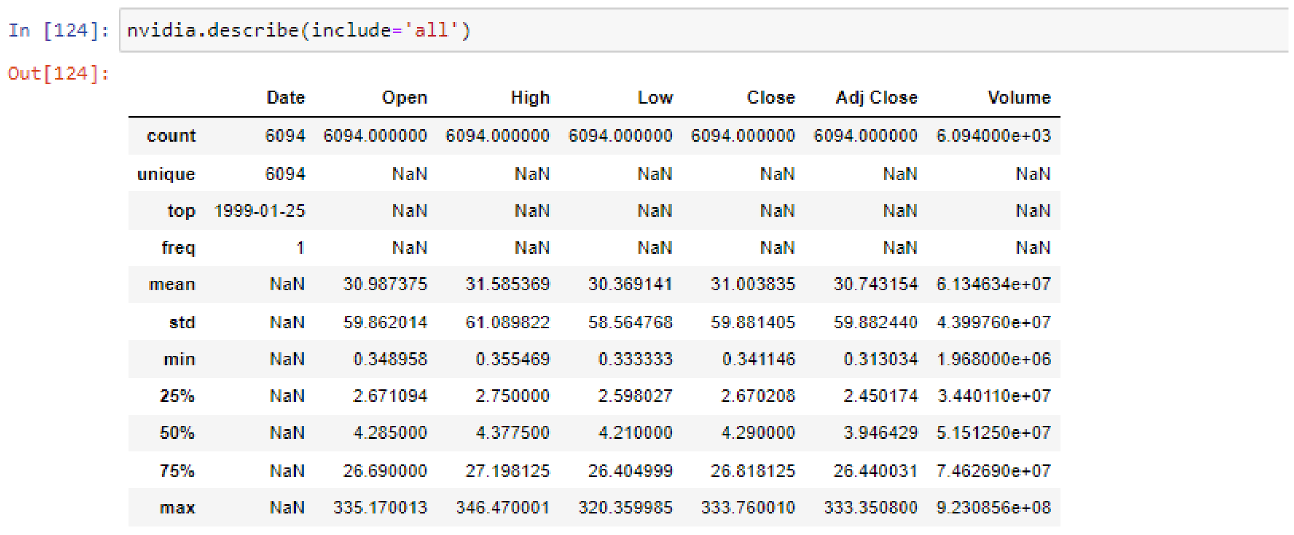
	Date	Open	High	Low	Close	Adj Close	Volume
count	10859	10859.000000	10859.000000	10859.000000	10859.000000	10859.000000	1.085900e+04
unique	10859	NaN	NaN	NaN	NaN	NaN	NaN
top	1980-03-18	NaN	NaN	NaN	NaN	NaN	NaN
freq	1	NaN	NaN	NaN	NaN	NaN	NaN
mean	NaN	19.834106	20.105102	19.565597	19.833531	14.636382	5.056303e+07
std	NaN	17.514871	17.756945	17.278878	17.514300	14.829796	3.487815e+07
min	NaN	0.218750	0.218750	0.216146	0.216146	0.123476	0.000000e+00
25%	NaN	1.328125	1.343750	1.304688	1.328125	0.758707	2.708505e+07
50%	NaN	20.277344	20.562500	20.010000	20.280001	12.665797	4.460160e+07
75%	NaN	29.980000	30.425000	29.520000	29.950001	19.808317	6.477205e+07
max	NaN	75.625000	75.828125	73.625000	74.875000	63.608189	5.677088e+08



```
In [123]: msi.describe(include='all')
```

Out[123]:

	Date	Open	High	Low	Close	Adj Close	Volume
count	15424	15424.000000	15424.000000	15424.000000	15424.000000	15424.000000	1.542400e+04
unique	15424	NaN	NaN	NaN	NaN	NaN	NaN
top	1962-01-03	NaN	NaN	NaN	NaN	NaN	NaN
freq	1	NaN	NaN	NaN	NaN	NaN	NaN
mean	NaN	44.977492	46.412619	45.224755	45.825400	37.652783	1.997183e+06
std	NaN	54.883169	54.841002	53.578205	54.222402	51.144917	2.347513e+06
min	NaN	0.000000	0.866821	0.808196	0.845884	0.376771	0.000000e+00
25%	NaN	3.768789	5.175804	5.025052	5.100428	2.625478	5.059500e+05
50%	NaN	23.517244	23.856436	23.230058	23.554932	16.259139	1.294556e+06
75%	NaN	67.235199	67.988953	66.486078	67.235199	52.269761	2.627212e+06
max	NaN	286.209991	287.420013	283.739990	286.140015	286.140015	4.717163e+07



```
In [124]: nvidia.describe(include='all')
```

Out[124]:

	Date	Open	High	Low	Close	Adj Close	Volume
count	6094	6094.000000	6094.000000	6094.000000	6094.000000	6094.000000	6.094000e+03
unique	6094	NaN	NaN	NaN	NaN	NaN	NaN
top	1999-01-25	NaN	NaN	NaN	NaN	NaN	NaN
freq	1	NaN	NaN	NaN	NaN	NaN	NaN
mean	NaN	30.987375	31.585369	30.369141	31.003835	30.743154	6.134634e+07
std	NaN	59.862014	61.089822	58.564768	59.881405	59.882440	4.399760e+07
min	NaN	0.348958	0.355469	0.333333	0.341146	0.313034	1.968000e+06
25%	NaN	2.671094	2.750000	2.598027	2.670208	2.450174	3.440110e+07
50%	NaN	4.285000	4.377500	4.210000	4.290000	3.946429	5.151250e+07
75%	NaN	26.690000	27.198125	26.404999	26.818125	26.440031	7.462690e+07
max	NaN	335.170013	346.470001	320.359985	333.760010	333.350800	9.230856e+08

Activity 2: Visual analysis

Visual analysis is the process of using visual representations, such as charts, plots, and graphs, to explore and understand data. It is a way to quickly identify patterns, trends, and outliers in the data, which can help to gain insights and make informed decisions.

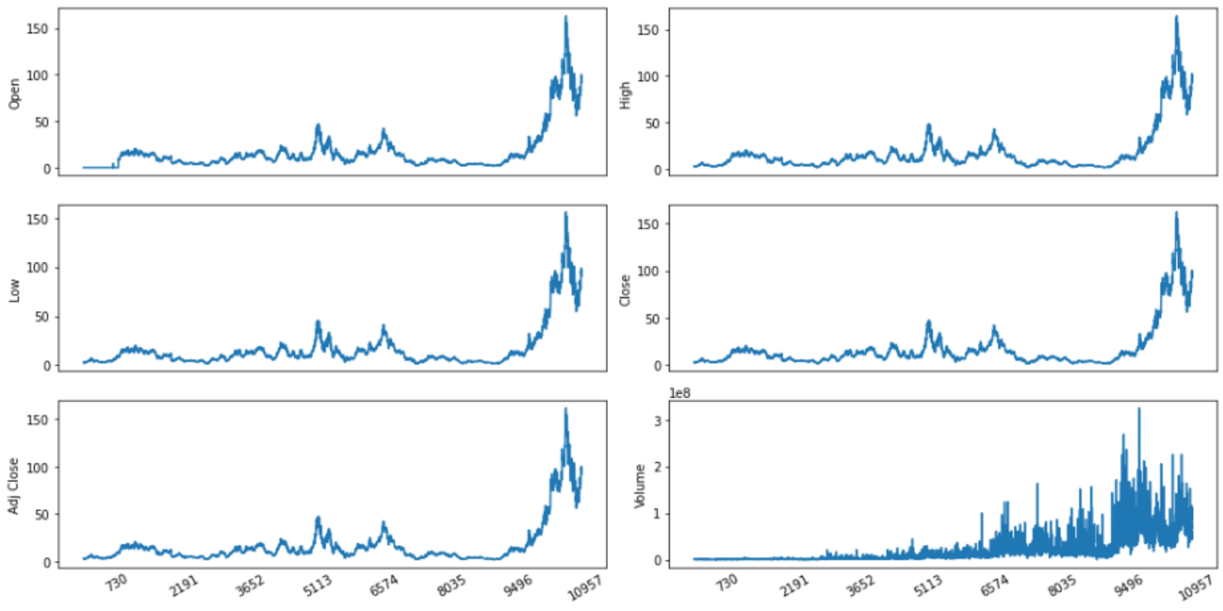
Activity 2.1: Univariate analysis

In simple words, univariate analysis is understanding the data with single feature. Here we don’t have much need to perform univariate analysis to understand the data as most of the columns provided are continuous.

Activity 2.2: Bivariate analysis

To find the relation between two features we use bivariate analysis.

```
In [126]: import matplotlib.dates as mdates
          # Plot line charts
          df_plot = amd.drop(columns=['Date'])

          ncols = 2
          nrows = int(round(df_plot.shape[1] / ncols, 0))

          fig, ax = plt.subplots(nrows=nrows, ncols=ncols, sharex=True, figsize=(14, 7))
          for i, ax in enumerate(fig.axes):
                  sns.lineplot(data = df_plot.iloc[:, i], ax=ax)
                  ax.tick_params(axis="x", rotation=30, labelsize=10, length=0)
                  ax.xaxis.set_major_locator(mdates.AutoDateLocator())
          fig.tight_layout()
          plt.show()
```



In the line plots visualised below following observations can be observed:

- There is sudden increase in the prices of stocks of AMD in the recent years and the price of the stock didn't retain for a long period but it soon fell to a lower price.
- The volume of the stocks being traded have increased tremendously in the recent years.

Similar to this, analysis on other companies can be done.

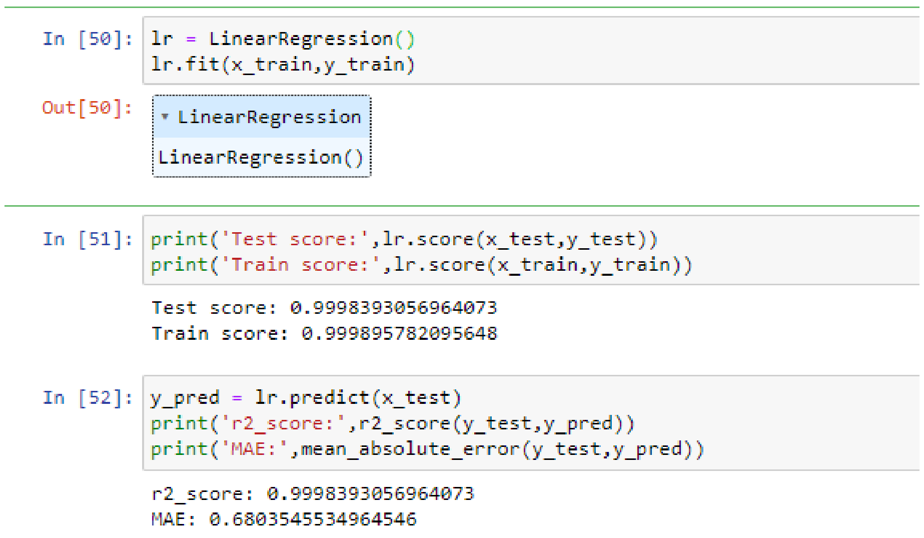
Milestone 4: Model Building

Now our data is cleaned and it's time to build the model. We can train our data on different algorithms. For this project we are applying seven classification algorithms. The best model is saved based on its performance.

Activity 1: Linear Regression model

Activity 1.1: Train the model

First we are going to initialise the LinearRegression() model and training data is passed to the model with.fit() function. Test data is forecasted/predicted with predict() function and saved in a new variable. For evaluating the model, train score, test score, r2_score and MAE scores are used.

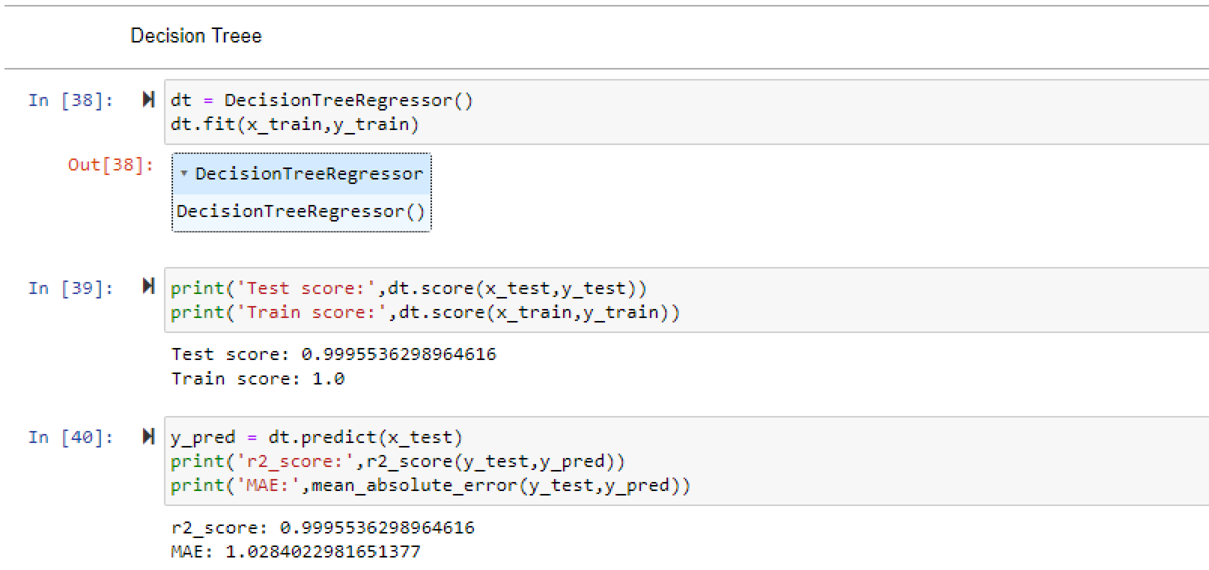


```
In [50]: lr = LinearRegression()
         lr.fit(x_train,y_train)

Out[50]: ▾ LinearRegression
         LinearRegression()

In [51]: print('Test score:',lr.score(x_test,y_test))
         print('Train score:',lr.score(x_train,y_train))

         Test score: 0.9998393056964073
         Train score: 0.999895782095648

In [52]: y_pred = lr.predict(x_test)
         print('r2_score:',r2_score(y_test,y_pred))
         print('MAE:',mean_absolute_error(y_test,y_pred))

         r2_score: 0.9998393056964073
         MAE: 0.6803545534964546
```

Activity 2: Decision Tree Regressor

Activity 2.1: Train the model

First we are going to initialise the DecisionTreeRegressor () model and training data is passed to the model with.fit() function. Test data is forecasted/predicted with predict() function and saved in a new variable. For evaluating the model, train score, test score, r2_score and MAE scores are used.



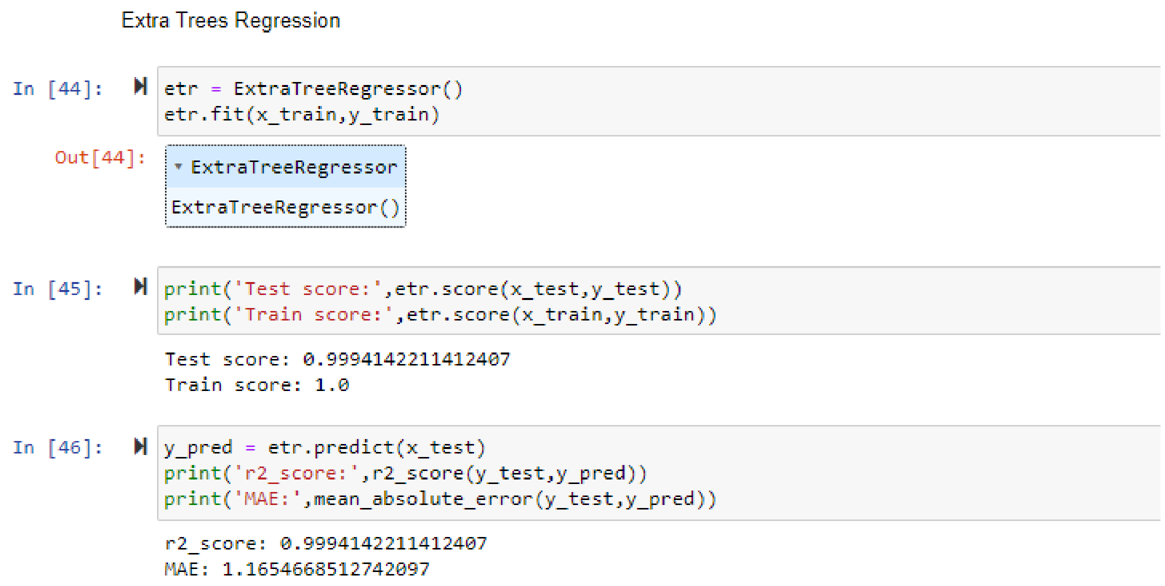
Decision Treee

```
In [38]:  dt = DecisionTreeRegressor()
          dt.fit(x_train,y_train)

Out[38]:  ▾ DecisionTreeRegressor
          DecisionTreeRegressor()

In [39]:  print('Test score:',dt.score(x_test,y_test))
          print('Train score:',dt.score(x_train,y_train))

          Test score: 0.9995536298964616
          Train score: 1.0

In [40]:  y_pred = dt.predict(x_test)
          print('r2_score:',r2_score(y_test,y_pred))
          print('MAE:',mean_absolute_error(y_test,y_pred))

          r2_score: 0.9995536298964616
          MAE: 1.0284022981651377
```

Activity 3: Extra Trees Regressor

Activity 3.1: Train the model

First we are going to initialise the ExtraTreeRegressor () model and training data is passed to the model with.fit() function. Test data is forecasted/predicted with predict() function and saved in a new variable. For evaluating the model, train score, test score, r2_score and MAE scores are used.



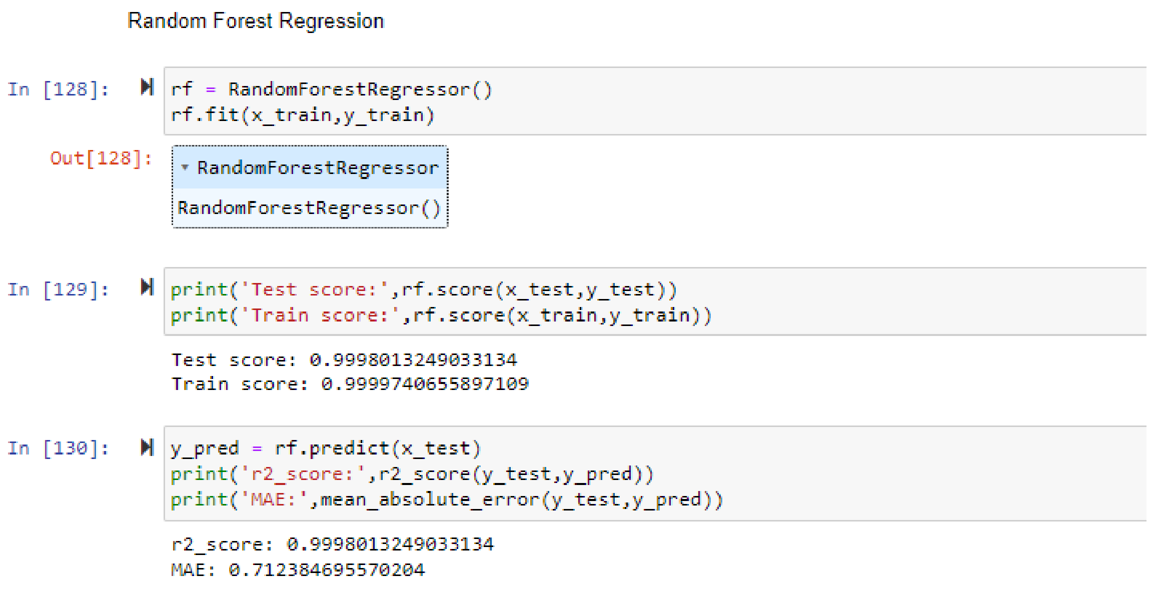
Extra Trees Regression

```
In [44]:  etr = ExtraTreeRegressor()
          etr.fit(x_train,y_train)

Out[44]:  ▾ ExtraTreeRegressor
          ExtraTreeRegressor()

In [45]:  print('Test score:',etr.score(x_test,y_test))
          print('Train score:',etr.score(x_train,y_train))

          Test score: 0.9994142211412407
          Train score: 1.0

In [46]:  y_pred = etr.predict(x_test)
          print('r2_score:',r2_score(y_test,y_pred))
          print('MAE:',mean_absolute_error(y_test,y_pred))

          r2_score: 0.9994142211412407
          MAE: 1.1654668512742097
```

Activity 3: Random Forest Regressor

Activity 3.1: Train the model

First we are going to initialise the RandomForestRegressor () model and training data is passed to the model with.fit() function. Test data is forecasted/predicted with predict() function and saved in a new variable. For evaluating the model, train score, test score, r2_score and MAE scores are used.


Random Forest Regression

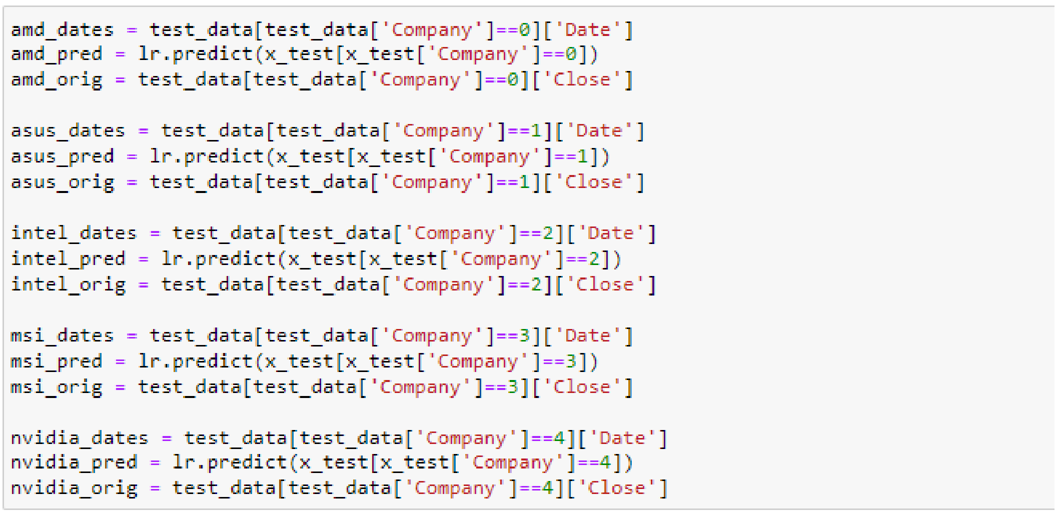
```
In [128]:  rf = RandomForestRegressor()
           rf.fit(x_train,y_train)

Out[128]:  ▾ RandomForestRegressor
           RandomForestRegressor()

In [129]:  print('Test score:',rf.score(x_test,y_test))
           print('Train score:',rf.score(x_train,y_train))

           Test score: 0.9998013249033134
           Train score: 0.9999740655897109

In [130]:  y_pred = rf.predict(x_test)
           print('r2_score:',r2_score(y_test,y_pred))
           print('MAE:',mean_absolute_error(y_test,y_pred))

           r2_score: 0.9998013249033134
           MAE: 0.712384695570204
```

Activity 4: Model comparison and evaluating best model

From the observed r2 scores and Mena absolute errors we can clearly see that the linear regression model has least Mean absolute error among others. So we are going to select Linear Regression model for final Flask application deployment.

To plot the predictions over the original values of all the companies we can use the following code.

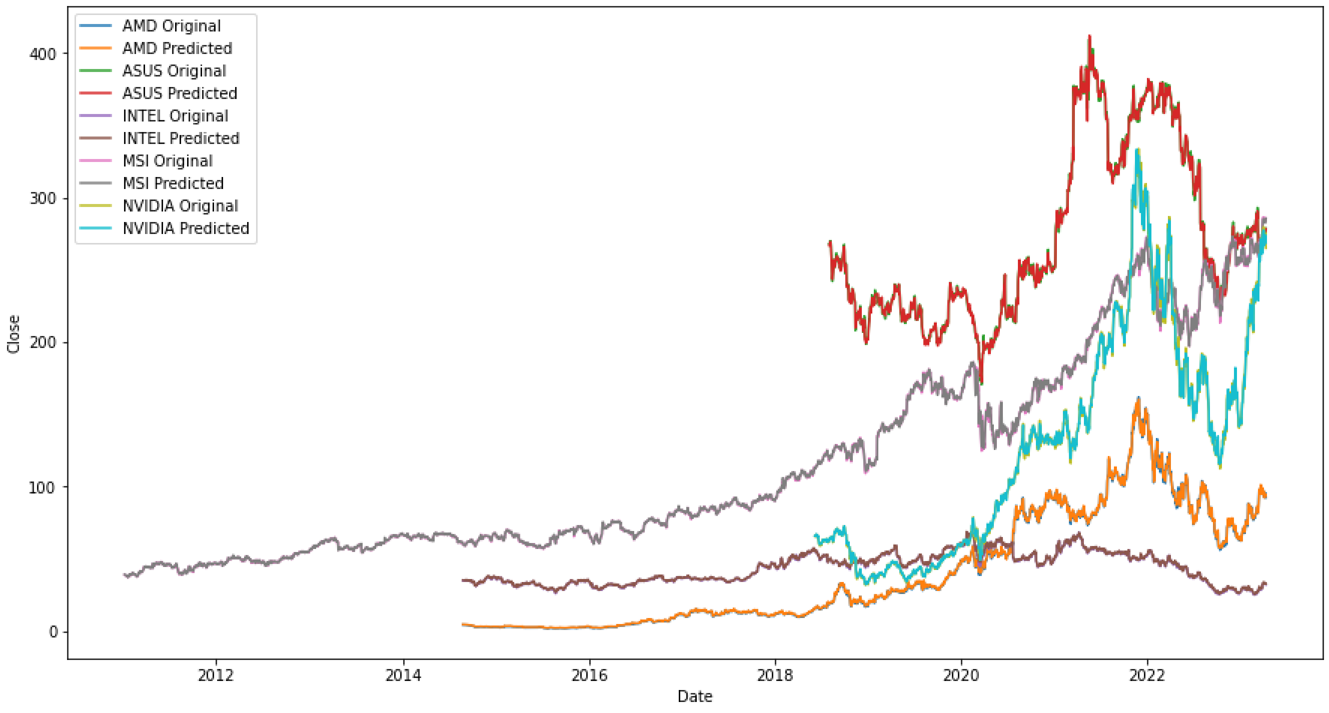
First, we are going to store the dates, original closing prices of stocks and predicted closing prices of stocks as shown below. We are going to access company specific rows of test_data and x_test variables using the "Company" column.



```
amd_dates = test_data[test_data['Company']==0]['Date']
amd_pred = lr.predict(x_test[x_test['Company']==0])
amd_orig = test_data[test_data['Company']==0]['Close']

asus_dates = test_data[test_data['Company']==1]['Date']
asus_pred = lr.predict(x_test[x_test['Company']==1])
asus_orig = test_data[test_data['Company']==1]['Close']

intel_dates = test_data[test_data['Company']==2]['Date']
intel_pred = lr.predict(x_test[x_test['Company']==2])
intel_orig = test_data[test_data['Company']==2]['Close']

msi_dates = test_data[test_data['Company']==3]['Date']
msi_pred = lr.predict(x_test[x_test['Company']==3])
msi_orig = test_data[test_data['Company']==3]['Close']

nvidia_dates = test_data[test_data['Company']==4]['Date']
nvidia_pred = lr.predict(x_test[x_test['Company']==4])
nvidia_orig = test_data[test_data['Company']==4]['Close']
```

Now using these columns we are going to plot the data as shown below.

```python
# Plot predictions and actual values
plt.figure(figsize=(15,8))


sns.lineplot(amd_dates,amd_orig)
sns.lineplot(amd_dates,amd_pred)

sns.lineplot(asus_dates,asus_orig)
sns.lineplot(asus_dates,asus_pred)

sns.lineplot(intel_dates,intel_orig)
sns.lineplot(intel_dates,intel_pred)

sns.lineplot(msi_dates,msi_orig)
sns.lineplot(msi_dates,msi_pred)

sns.lineplot(nvidia_dates,nvidia_orig)
sns.lineplot(nvidia_dates,nvidia_pred)

plt.legend(['AMD Original','AMD Predicted','ASUS Original','ASUS Predicted','INTEL Original',
            'INTEL Predicted','MSI Original','MSI Predicted','NVIDIA Original','NVIDIA Predicted'])
plt.show()
```



As we can see the lines plotted by the predicted and original data are almost perfectly overlapping.

You can save the model as pickle files using the following piece of code.

Saving Model

```python
import pickle as pkl
```

```python
pkl.dump(lr,open('lr.pkl','wb'))
```

Activity 2: Integrate with Web Framework

In this section, we will be building a web application that is integrated to the model we built. An UI is provided for the uses where he has to enter the values for predictions. The enter values are given to the saved model and prediction is showcased on the UI.

This section has the following tasks

- Building HTML Pages
- Building server-side script
- Run the web application

Activity 2.1: Building Html Pages:

For this project create two HTML files namely

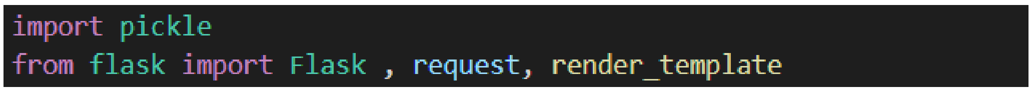
- index.html
- inner-page.html
- portfolio-details.html

and save them in the templates folder.

It is not necessary to follow the exact format as above so feel free to use whatever templates or format you like. Be creative!

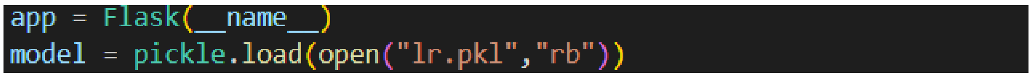
Activity 2.2: Build Python code:

Import the libraries



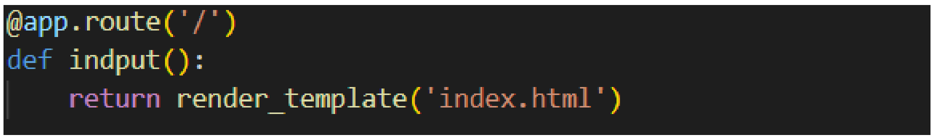
```python
import pickle
from flask import Flask , request, render_template
```

Load the saved model. Importing the flask module in the project is mandatory. An object of Flask class is our WSGI application. Flask constructor takes the name of the current module (__name__) as argument.



```python
app = Flask(__name__)
model = pickle.load(open("lr.pkl","rb"))
```

Render HTML page:

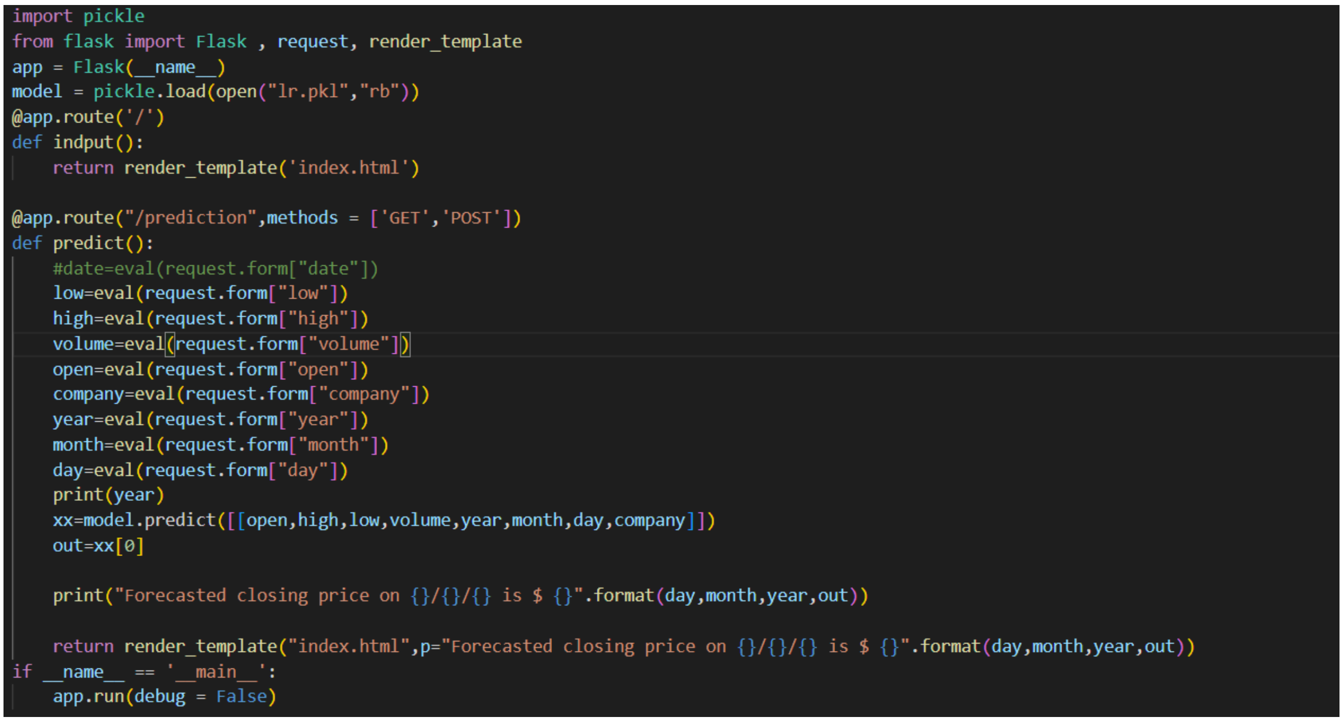


```python
@app.route('/')
def indput():
    return render_template('index.html')
```

Here we will be using a declared constructor to route to the HTML page which we have created earlier.

In the above example, '/' URL is bound with the index.html function. Hence, when the home page of the web server is opened in the browser, the html page will be rendered. Whenever you enter the values from the html page the values can be retrieved using POST Method.

Retrieves the value from UI:

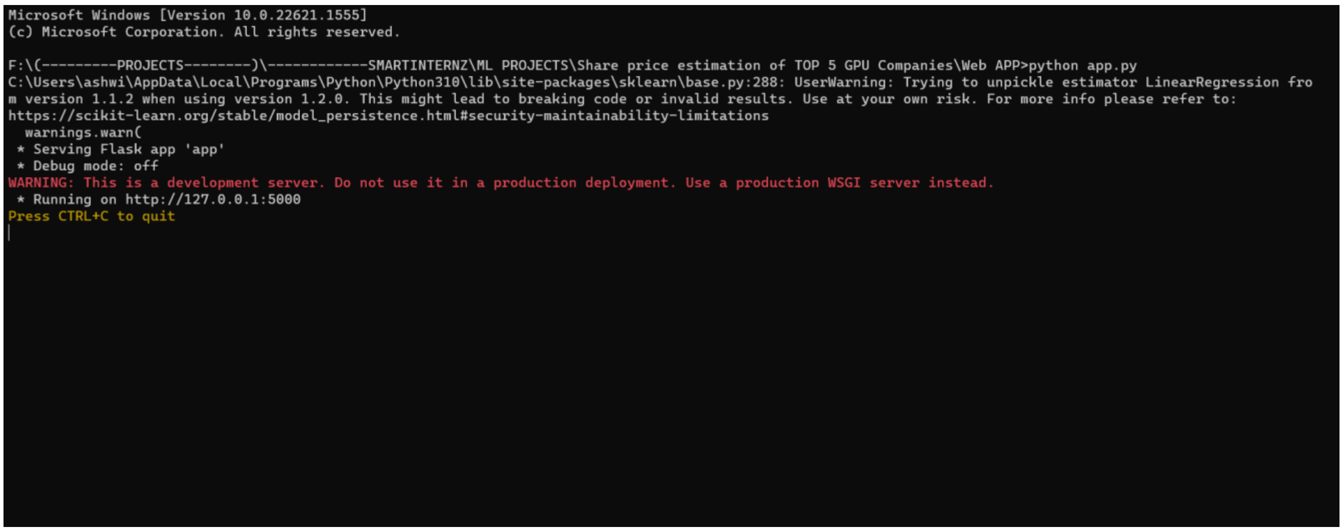


```python
import pickle
from flask import Flask , request, render_template
app = Flask(__name__)
model = pickle.load(open("lr.pkl","rb"))
@app.route('/')
def indput():
    return render_template('index.html')

@app.route("/prediction",methods = ['GET','POST'])
def predict():
    #date=eval(request.form["date"])
    low=eval(request.form["low"])
    high=eval(request.form["high"])
    volume=eval(request.form["volume"])
    open=eval(request.form["open"])
    company=eval(request.form["company"])
    year=eval(request.form["year"])
    month=eval(request.form["month"])
    day=eval(request.form["day"])
    print(year)
    xx=model.predict([[open,high,low,volume,year,month,day,company]])
    out=xx[0]

    print("Forecasted closing price on {}/{}/{} is $ {}".format(day,month,year,out))

    return render_template("index.html",p="Forecasted closing price on {}/{}/{} is $ {}".format(day,month,year,out))
if __name__ == '__main__':
    app.run(debug = False)
```

Here we are routing our app to predict() function. This function retrieves all the values from the HTML page using Post request. That is stored in an array. This array is passed to the model.predict() function. This function returns the prediction. And this prediction value will be rendered to the text that we have mentioned in the submit.html page earlier.

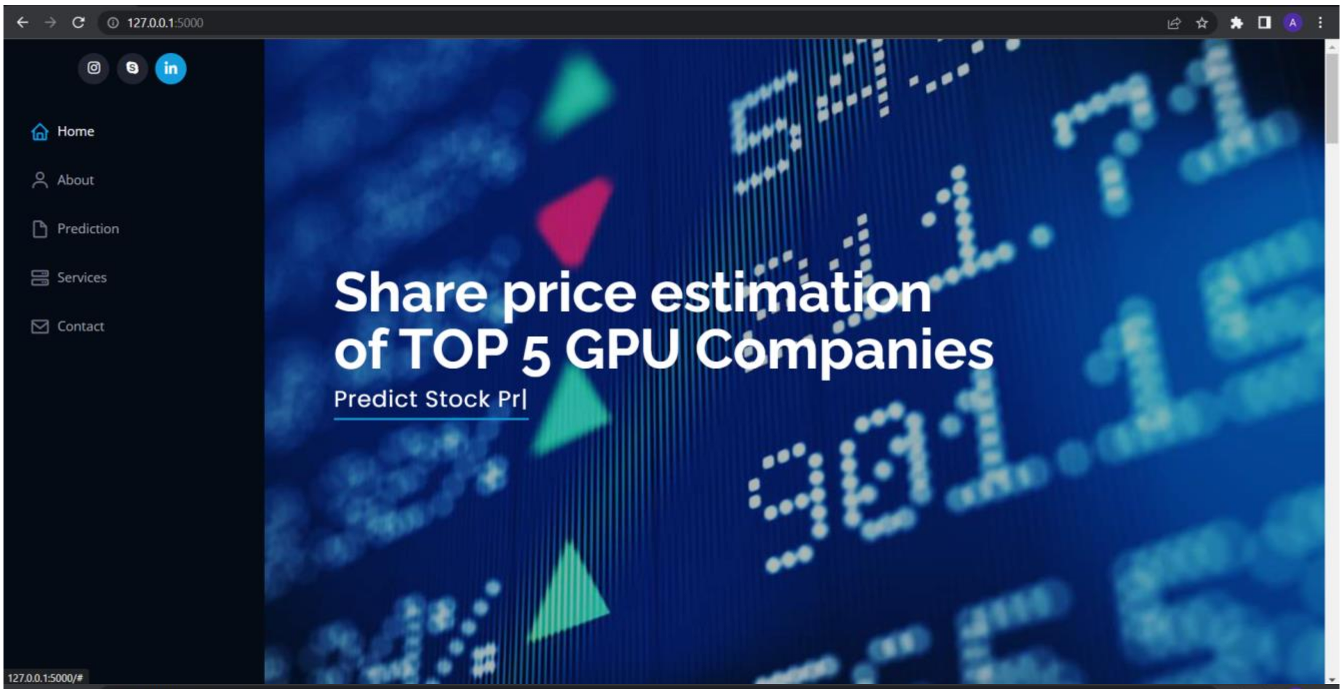
Activity 2.3: Run the web application

- Open anaconda prompt from the start menu
- Navigate to the folder where your python script is.
- Now type "python app.py" command
- Navigate to the localhost where you can view your web page.
- Click on the predict button from the top left corner, enter the inputs, click on the submit button, and see the result/prediction on the web.



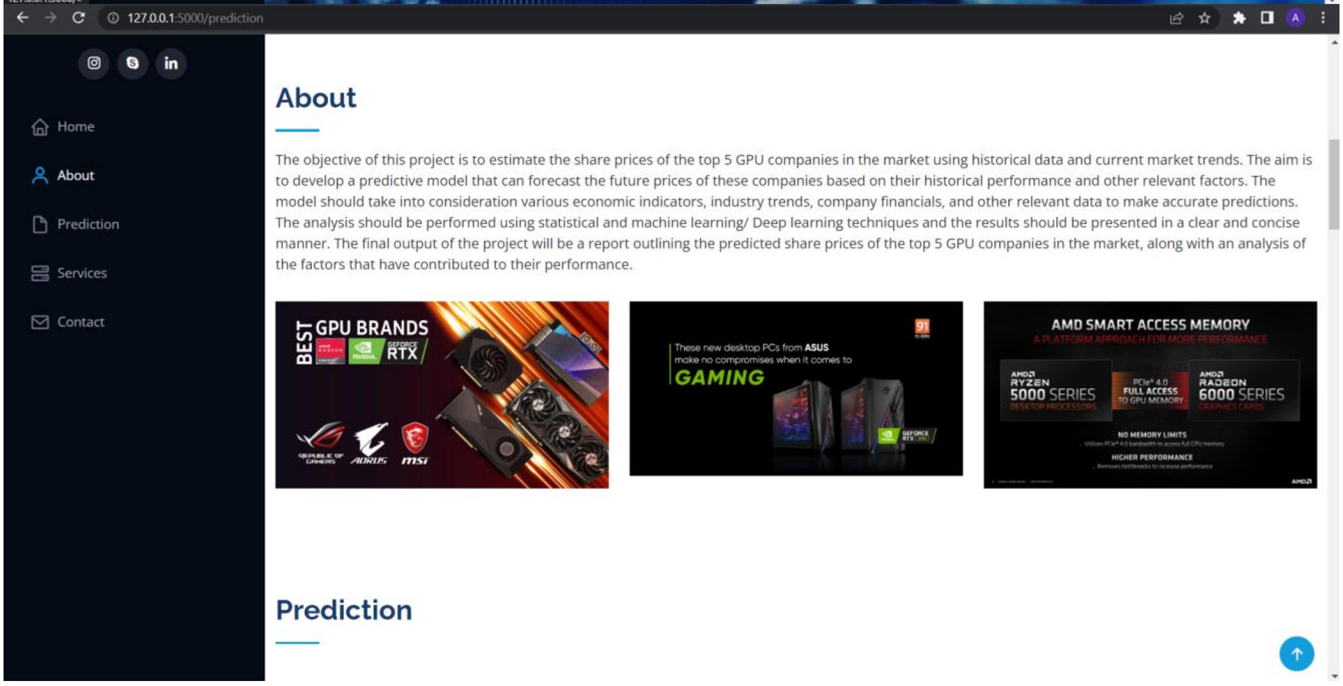
```
Microsoft Windows [Version 10.0.22621.1555]
(c) Microsoft Corporation. All rights reserved.

F:\(---------PROJECTS--------)\------------SMARTINTERNZ\ML PROJECTS\Share price estimation of TOP 5 GPU Companies\Web APP>python app.py
C:\Users\ashwi\AppData\Local\Programs\Python\Python310\lib\site-packages\sklearn\base.py:288: UserWarning: Trying to unpickle estimator LinearRegression fro
m version 1.1.2 when using version 1.2.0. This might lead to breaking code or invalid results. Use at your own risk. For more info please refer to:
https://scikit-learn.org/stable/model_persistence.html#security-maintainability-limitations
  warnings.warn(
 * Serving Flask app 'app'
 * Debug mode: off
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
 * Running on http://127.0.0.1:5000
Press CTRL+C to quit
```

Now, Go to the web browser and write the localhost URL (http://127.0.0.1:5000) to get the below result



Share price estimation of TOP 5 GPU Companies

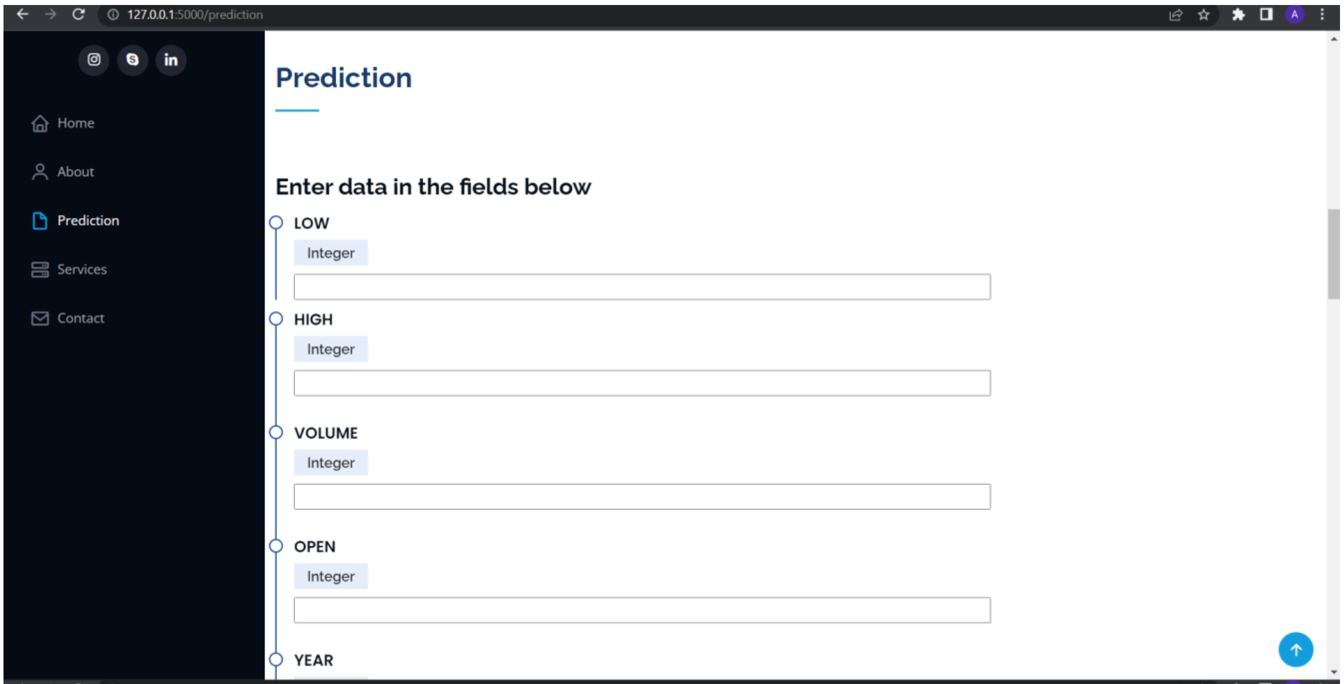
Predict Stock Pr|



About

The objective of this project is to estimate the share prices of the top 5 GPU companies in the market using historical data and current market trends. The aim is to develop a predictive model that can forecast the future prices of these companies based on their historical performance and other relevant factors. The model should take into consideration various economic indicators, industry trends, company financials, and other relevant data to make accurate predictions. The analysis should be performed using statistical and machine learning/ Deep learning techniques and the results should be presented in a clear and concise manner. The final output of the project will be a report outlining the predicted share prices of the top 5 GPU companies in the market, along with an analysis of the factors that have contributed to their performance.

Prediction



Prediction

Enter data in the fields below

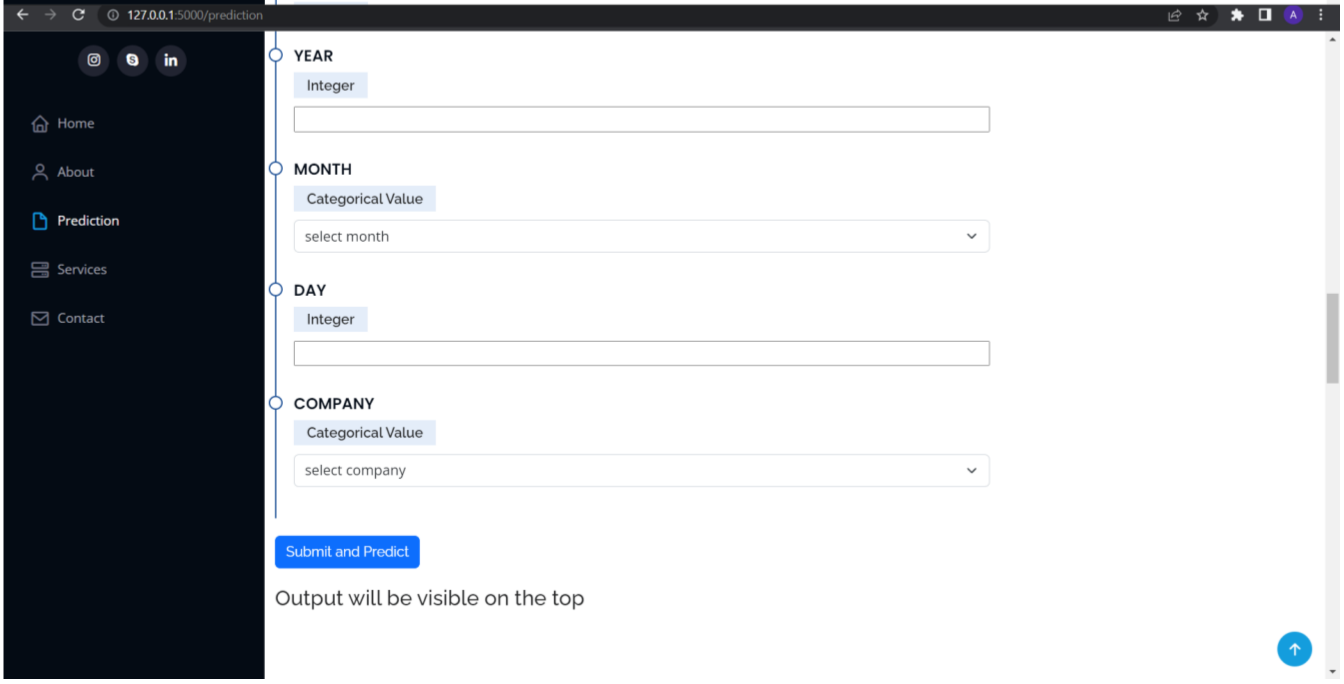
LOW
Integer

HIGH
Integer

VOLUME
Integer

OPEN
Integer

YEAR



YEAR
Integer

MONTH
Categorical Value
select month

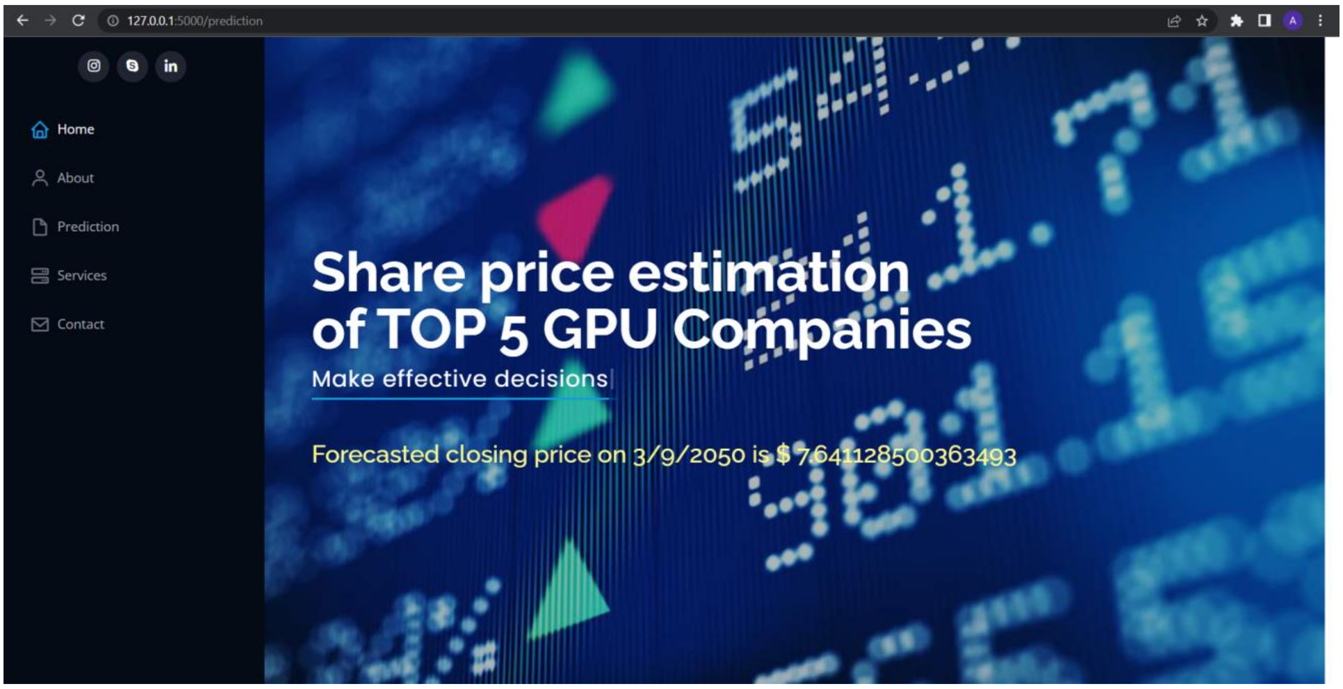
DAY
Integer

COMPANY
Categorical Value
select company

Submit and Predict

Output will be visible on the top

Upon entering the data in input fields and clicking on submit and predict we'll get the prediction as shown below.



Share price estimation of TOP 5 GPU Companies

Make effective decisions

Forecasted closing price on 3/9/2050 is $ 7.641128500363493

Milestone 7: Project Demonstration & Documentation

Below mentioned deliverables to be submitted along with other deliverables.

Activity 1: - Record explanation Video for project end to end solution.

Activity 2: - Project Documentation-Step by step project development procedure.

Create document as per the template provided.