Stock Price Prediction Using the TensorFlow

Importing the basic libraries to load the data

```
import numpy as np
import pandas as pd
```

```
GOOG_DATA = pd.read_csv("/content/Google.csv")
```

Exploratory Data Analysis

Exploratory data analysis (EDA) is **a statistical approach for summarizing the main characteristics of data sets**. It involves using statistical graphics and other data visualization methods to describe the data. The goal of EDA is to explore, investigate, and learn, rather than confirm statistical hypotheses.Exploratory Data Analysis (EDA) is **an analysis approach that identifies general patterns in the data**. These patterns include outliers and features of the data that might be unexpected. EDA is an important first step in any data analysis.

- Data collection
- Finding all variables and understanding them
- Cleaning the dataset
- Visualizing and analyzing results

For better understanding click on the below link

> Exploratory Data Analysis (YouTube)

```
type(GOOG_DATA)
```

```
pandas.core.frame.DataFrame
def __init__(data=None, index: Axes | None=None, columns: Axes | None=None, dtype: Dtype |
None=None, copy: bool | None=None) -> None

/usr/local/lib/python3.10/dist-packages/pandas/core/frame.py
Two-dimensional, size-mutable, potentially heterogeneous tabular data.

Data structure also contains labeled axes (rows and columns).
Arithmetic operations align on both row and column labels. Can be
thought of as a dict-like container for Series objects. The primary
```

```
GOOG_DATA.head()
```

	Date	Open	High	Low	Close	Adj Close	Volume
0	19-08-2004	2.490664	2.591785	2.390042	2.499133	2.499133	897427216
1	20-08-2004	2.515820	2.716817	2.503118	2.697639	2.697639	458857488
2	23-08-2004	2.758411	2.826406	2.716070	2.724787	2.724787	366857939
3	24-08-2004	2.770615	2.779581	2.579581	2.611960	2.611960	306396159
4	25-08-2004	2.614201	2.689918	2.587302	2.640104	2.640104	184645512

Next steps: Generate code with GOOG_DATA | View recommended plots | New interactive sheet

Data prepration for the EDA

```
from datetime import datetime
```

```
GOOG_DATA['Date'] = pd.to_datetime(GOOG_DATA['Date']) #, format='%Y-%m-%d'
```

```
<ipython-input-6-5a0b443f2350>:1: UserWarning: Parsing dates in %d-%m-%Y format when dayfirst=False (the default) was specified. Pass `d
  GOOG_DATA['Date'] = pd.to_datetime(GOOG_DATA['Date']) #, format='%Y-%m-%d'
```

```
GOOG_DATA['Date'] = pd.to_datetime(GOOG_DATA['Date'], format='%Y-%m-%d')
GOOG_DATA.set_index(['Date'],drop=False,inplace=True)
```

```
GOOG_DATA.head()
```

Date	Date	Open	High	Low	Close	Adj Close	Volume
2004-08-19	2004-08-19	2.490664	2.591785	2.390042	2.499133	2.499133	897427216
2004-08-20	2004-08-20	2.515820	2.716817	2.503118	2.697639	2.697639	458857488
2004-08-23	2004-08-23	2.758411	2.826406	2.716070	2.724787	2.724787	366857939
2004-08-24	2004-08-24	2.770615	2.779581	2.579581	2.611960	2.611960	306396159
2004-08-25	2004-08-25	2.614201	2.689918	2.587302	2.640104	2.640104	184645512

```
GOOG_DATA.tail()
```

Date	Date	Open	High	Low	Close	Adj Close	Volume
2009-06-26	2009-06-26	10.303380	10.665772	10.289184	10.593294	10.593294	130756276
2009-06-29	2009-06-29	10.610230	10.655062	10.516581	10.563904	10.563904	87097243
2009-06-30	2009-06-30	10.560417	10.640367	10.416457	10.500392	10.500392	104144903
2009-07-01	2009-07-01	10.565398	10.620193	10.414713	10.435635	10.435635	92778458
2009-07-02	2009-07-02	10.346469	10.346469	10.132272	10.174115	10.174115	101081463

```
GOOG_DATA.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1227 entries, 2004-08-19 to 2009-07-02
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       1227 non-null   datetime64[ns]
 1   Open       1227 non-null   float64
 2   High       1227 non-null   float64
 3   Low        1227 non-null   float64
 4   Close      1227 non-null   float64
 5   Adj Close  1227 non-null   float64
 6   Volume     1227 non-null   int64
dtypes: datetime64[ns](1), float64(5), int64(1)
memory usage: 76.7 KB
```

Data Visualization using Plotly, Matplotlib

A candlestick chart is **a financial chart that shows the price movements of a security, derivative, or currency over a given time period**. Each candlestick represents four pieces of information for that day: the open and close in the thick body, and high and low in the "candle wick". Candlestick charts are similar to bar charts.

```
import matplotlib.pyplot as plt
%matplotlib inline
import plotly.graph_objects as go
```

```
df = GOOG_DATA
Figure = go.Figure(data=[go.Candlestick(x=df['Date'],
                                        open = df['Open'],
                                        high = df['High'],
                                        low = df['Low'],
                                        close = df['Close'])])
Figure.update_layout(
    autosize=False,
    width = 1400,
    height = 550,
    title = 'Candle Stick Chart of GOOGLE',
    template='plotly'
```

```
)

Figure.update_xaxes(title='Date')
Figure.update_yaxes(title='Price')
Figure.show()
```

```
/usr/local/lib/python3.10/dist-packages/_plotly_utils/basevalidators.py:105: FutureWarning: The behavior of DatetimeProperties.to_pydate
  v = v.dt.to_pydatetime()
```

Break Down version of the above Graph Dated[2004-08-19] to [2009-08-19] i.e 5 years

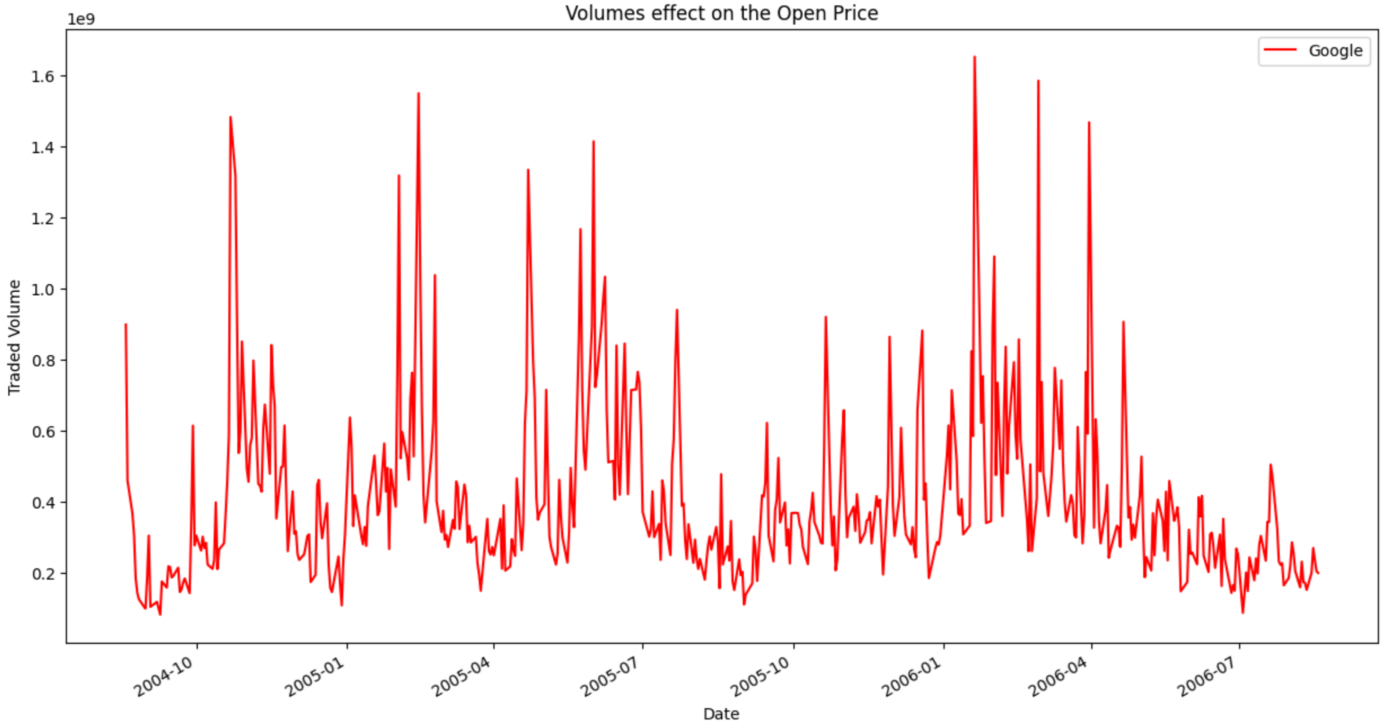
```
GOOG = GOOG_DATA.loc['2004-08-19':'2006-08-19'] #5 years gap


df = GOOG
Figure = go.Figure(data=[go.Candlestick(x=df['Date'],
                                        open = df['Open'],
                                        high = df['High'],
                                        low = df['Low'],
                                        close = df['Close'])])
Figure.update_layout(
    autosize=False,
    width = 1400,
    height = 550,
    title = 'Candle Stick Chart of GOOGLE',
    template='plotly'
)

Figure.update_xaxes(title='Date')
Figure.update_yaxes(title='Price')
Figure.show()
```

```
/usr/local/lib/python3.10/dist-packages/_plotly_utils/basevalidators.py:105: FutureWarning:

The behavior of DatetimeProperties.to_pydatetime is deprecated, in a future version this will return a Series containing python datetime
```

Effect of the spikes in the volume on the Opening Price of the Stock

```
GOOG['Volume'].plot(label='Google',figsize=(15,8),color='r')
plt.legend()
plt.title('Volumes effect on the Open Price')
plt.xlabel('Date')
plt.ylabel('Traded Volume')
```

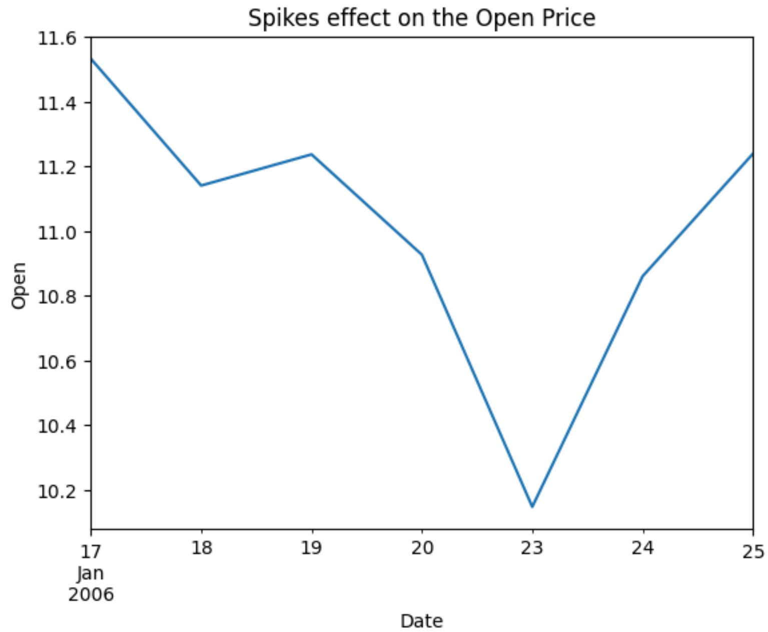
```
Text(0, 0.5, 'Traded Volume')
```




```
GOOG.iloc[[GOOG['Volume'].argmax()]]
```

	Date	Open	High	Low	Close	Adj Close	Volume
Date							
2006-01-20	2006-01-20	10.926545	10.95967	9.831649	9.949208	9.949208	1650832619

```
GOOG.loc['2006-01-15':'2006-01-25']['Open'].plot(kind='line')
plt.xlabel('Date')
plt.ylabel('Open')
plt.title('Spikes effect on the Open Price')
plt.show()
```



Finding when the stock was the most valuable in the given time period (5 years)

What is the relationship between open interest and volume?

Volume refers to the number of trades completed each day and is an important measure of strength and interest in a particular trade. Open interest reflects the number of contracts held by traders in active positions, ready to be traded.

```
GOOG['Total Traded'] = GOOG['Open'] * GOOG['Volume']
```

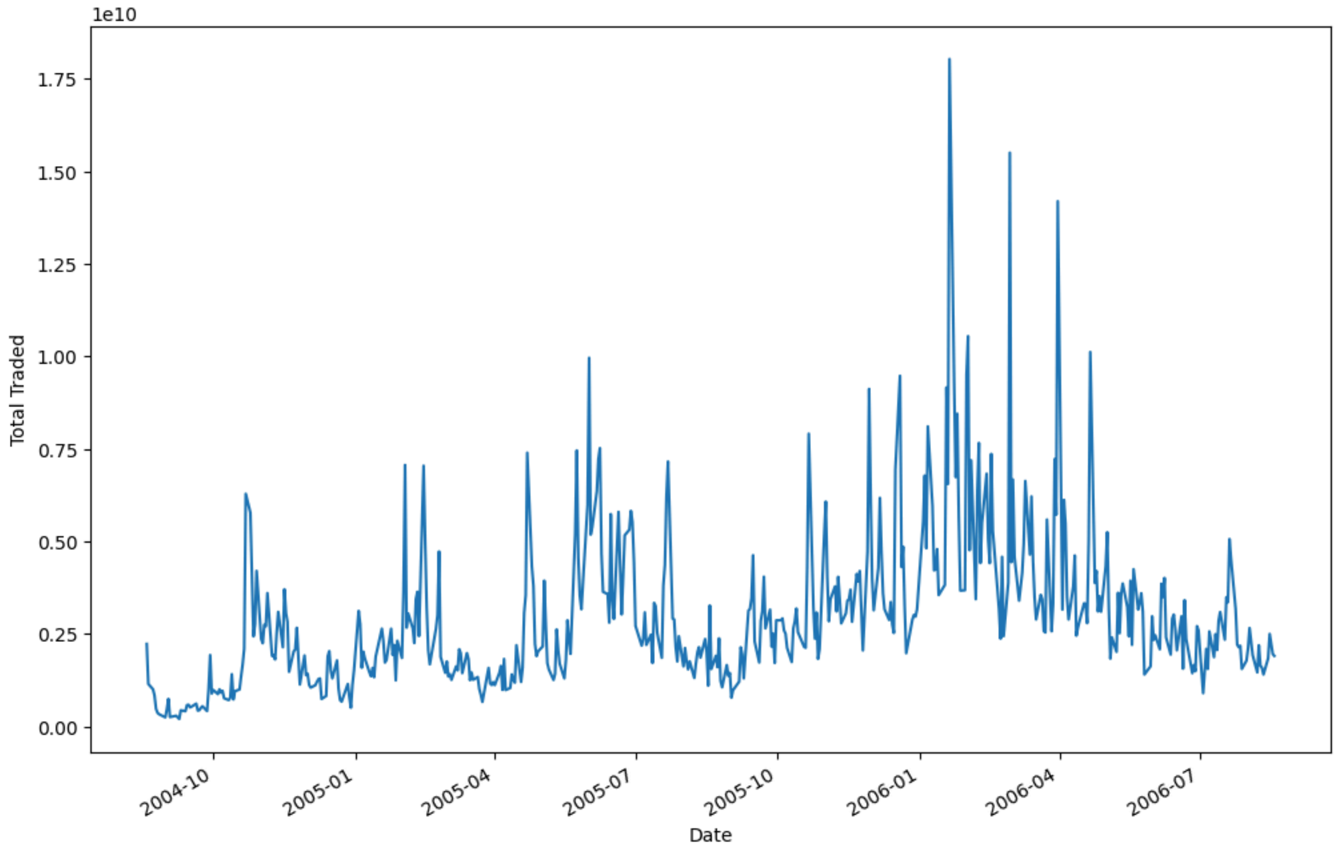
```
<ipython-input-18-1ead9fe29ea5>:1: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cc
```

```
GOOG.head()
```

Date	Date	Open	High	Low	Close	Adj Close	Volume	Total Traded
2004-08-19	2004-08-19	2.490664	2.591785	2.390042	2.499133	2.499133	897427216	2.235190e+09
2004-08-20	2004-08-20	2.515820	2.716817	2.503118	2.697639	2.697639	458857488	1.154403e+09
2004-08-23	2004-08-23	2.758411	2.826406	2.716070	2.724787	2.724787	366857939	1.011945e+09
2004-08-24	2004-08-24	2.770615	2.779581	2.579581	2.611960	2.611960	306396159	8.489058e+08
2004-08-25	2004-08-25	2.614201	2.689918	2.587302	2.640104	2.640104	184645512	4.827005e+08

```
GOOG['Total Traded'].plot(label='Google',figsize=(12,8));
plt.xlabel('Date')
plt.ylabel('Total Traded')
```

```
Text(0, 0.5, 'Total Traded')
```




```
GOOG.iloc[[GOOG['Total Traded'].argmax()]]
```

	Date	Open	High	Low	Close	Adj Close	Volume	Total Traded
Date								
2006-01-20	2006-01-20	10.926545	10.95967	9.831649	9.949208	9.949208	1650832619	1.803790e+10

Calculating the Daily Return

Daily return, in the context of stock prices, refers to the percentage change in a stock's price from one day's closing price to the previous day's closing price. It's a metric used to gauge the stock's performance over a short-term period (one day).

```
GOOG['Returns'] = (GOOG['Close']/GOOG['Close'].shift(1))-1
```

```
<ipython-input-22-f032ee0783ec>:1: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cc
```

```
GOOG.head()
```

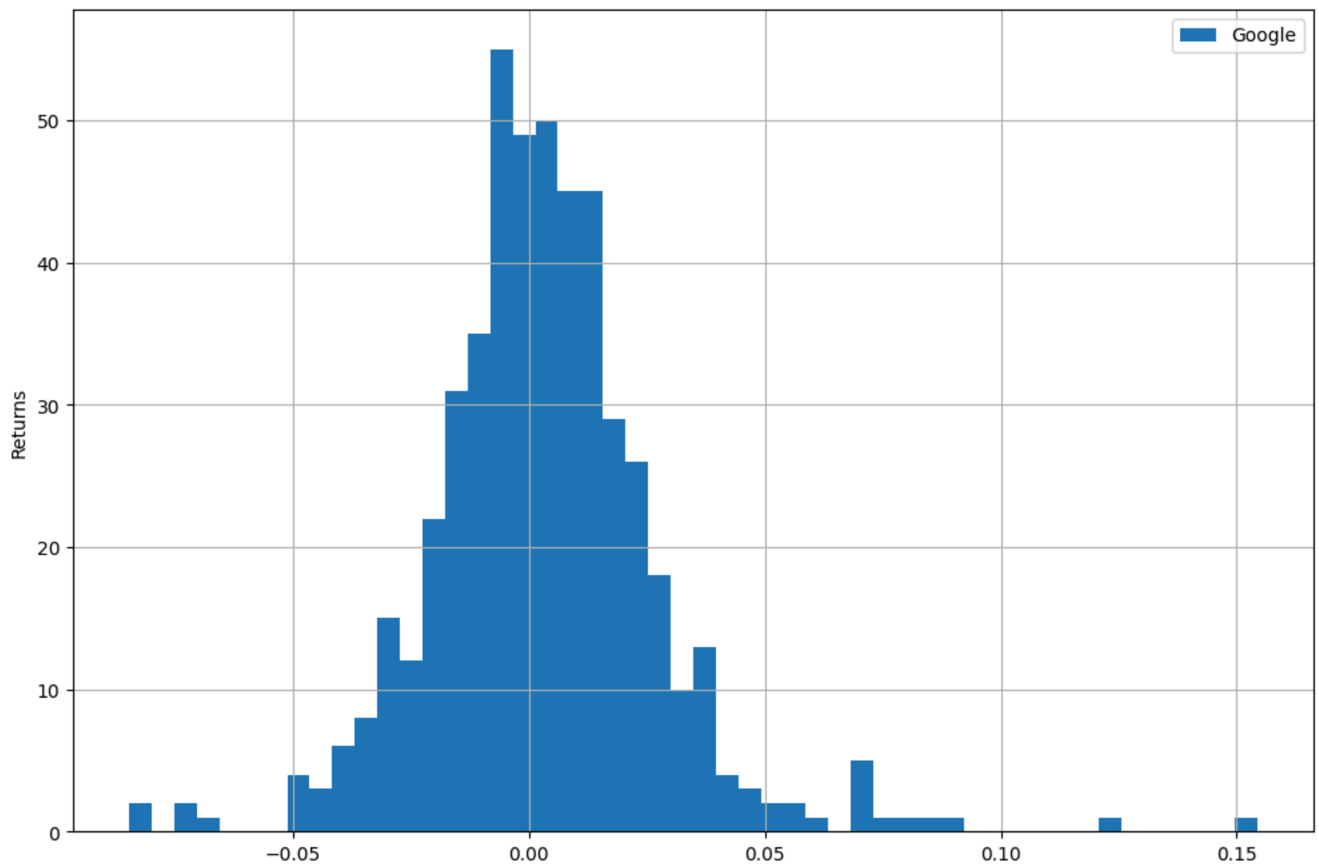
	Date	Open	High	Low	Close	Adj Close	Volume	Total Traded	Returns
Date									
2004-08-19	2004-08-19	2.490664	2.591785	2.390042	2.499133	2.499133	897427216	2.235190e+09	NaN
2004-08-20	2004-08-20	2.515820	2.716817	2.503118	2.697639	2.697639	458857488	1.154403e+09	0.079430
2004-08-23	2004-08-23	2.758411	2.826406	2.716070	2.724787	2.724787	366857939	1.011945e+09	0.010064
2004-08-24	2004-08-24	2.770615	2.779581	2.579581	2.611960	2.611960	306396159	8.489058e+08	-0.041408
2004-08-25	2004-08-25	2.614201	2.689918	2.587302	2.640104	2.640104	184645512	4.827005e+08	0.010775

```
GOOG.tail()
```

	Date	Open	High	Low	Close	Adj Close	Volume	Total Traded	Returns
Date									
2006-08-14	2006-08-14	9.252818	9.343229	9.182332	9.201261	9.201261	199476896	1.845723e+09	0.002524
2006-08-15	2006-08-15	9.317825	9.506119	9.280215	9.488684	9.488684	268932260	2.505864e+09	0.031237
2006-08-16	2006-08-16	9.551200	9.674986	9.517327	9.656804	9.656804	235005569	2.244585e+09	0.017718
2006-08-17	2006-08-17	9.623678	9.713591	9.562159	9.608983	9.608983	203969673	1.962938e+09	-0.004952
2006-08-18	2006-08-18	9.621686	9.641113	9.483205	9.548211	9.548211	198830482	1.913084e+09	-0.006324

```
GOOG['Returns'].hist(bins=50,label='Google',alpha=1,figsize=(12,8))
plt.legend()
plt.ylabel('Returns')
```

```
Text(0, 0.5, 'Returns')
```



How much does one get in return for investing one dollar in the stock on any specified date.

```
GOOG['C_Return'] = (1+GOOG['Returns']).cumprod()
```

```
<ipython-input-26-0ba7f265f59e>:1: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cc
```

```
GOOG['C_Return']
```

Date	C_Return
2004-08-19	NaN
2004-08-20	1.079430
2004-08-23	1.090293
2004-08-24	1.045146
2004-08-25	1.056408
...	...
2006-08-14	3.681781
2006-08-15	3.796790
2006-08-16	3.864062
2006-08-17	3.844927
2006-08-18	3.820609

505 rows × 1 columns

dtype: float64

```
GOOG['C_Return'].tail(1)
```

Date	C_Return
2006-08-18	3.820609

dtype: float64

Data Preprocessing

Data preprocessing in Machine Learning refers to **the technique of preparing (cleaning and organizing) the raw data to make it suitable for a building and training Machine Learning models.**

```
GOOG_DATA.describe()
```

	Date	Open	High	Low	Close	Adj Close	Volume
count	1227	1227.000000	1227.000000	1227.000000	1227.000000	1227.000000	1.227000e+03
mean	2007-01-25 02:16:08.215158784	9.886899	10.016610	9.743528	9.878143	9.878143	3.009997e+08
min	2004-08-19 00:00:00	2.470490	2.534002	2.390042	2.490913	2.490913	6.538015e+07
25%	2005-11-03 12:00:00	7.603251	7.751321	7.487311	7.622678	7.622678	1.742989e+08
50%	2007-01-26 00:00:00	10.099644	10.207490	9.981088	10.063280	10.063280	2.503790e+08
75%	2008-04-15 12:00:00	12.020569	12.151329	11.906621	12.012474	12.012474	3.543593e+08
max	2009-07-02 00:00:00	18.459061	18.611240	18.057318	18.475498	18.475498	1.650833e+09
std	NaN	3.351993	3.376509	3.309505	3.341707	3.341707	1.968202e+08

```
GOOG_DATA.isnull().sum()
```

	0
Date	0
Open	0
High	0
Low	0
Close	0
Adj Close	0
Volume	0

dtype: int64

```
GOOG_DATA.shape
```

```
(1227, 7)
```

Feature Engineering

Feature Engineering is **the process of creating new features or transforming existing features to improve the performance of a machine-learning model**. It involves selecting relevant information from raw data and transforming it into a format that can be easily understood by a model. *The goal is to improve model accuracy by providing more meaningful and relevant information.*

```
Close = GOOG_DATA['Close'].values.reshape(-1, 1)
Volume = GOOG_DATA['Volume'].values.reshape(-1, 1)
High = GOOG_DATA['High'].values.reshape(-1, 1)
Low =  GOOG_DATA['Low'].values.reshape(-1, 1)
```

```
DataFramE = np.concatenate((Close, Volume, High, Low), axis=1)
```

```
type(DataFramE)
```

```
numpy.ndarray
```

Data Scaling

This means that you're **transforming your data so that it fits within a specific scale, like 0-100 or 0-1**. You want to scale data when you're using methods based on measures of how far apart data points are, like support vector machines (SVM) or k-nearest neighbors (KNN).

In this case LSTM and the scale required is 0-1

```
from sklearn.preprocessing import MinMaxScaler
```

```
# Scaling data
scalers = []
for i in range(DataFramE.shape[1]):
    scaler = MinMaxScaler(feature_range=(0, 1))
    scaled_feature = scaler.fit_transform(DataFramE[:, i].reshape(-1, 1))
    scalers.append(scaler)
    DataFramE[:, i] = scaled_feature.flatten()
```

Spliting the Data Set

Data splitting is commonly used in machine learning **to split data into a train, test, or validation set**. This approach allows us to find the model hyper-parameter and also estimate the generalization performance.

```
# Split data into train and test sets
training_size = int(len(DataFramE) * 0.7)
train_data, test_data = DataFramE[:training_size], DataFramE[training_size:]
```

```
def prepare_data(data, n_steps):
    X, Y = [], []
    for i in range(len(data)):
        end_ix = i + n_steps
        if end_ix > len(data)-1:
            break
        seq_x, seq_y = data[i:end_ix, :], data[end_ix, 0]
        X.append(seq_x)
        Y.append(seq_y)
    return np.array(X), np.array(Y)


n_steps = 60
X_train, Y_train = prepare_data(train_data, n_steps)
X_test, Y_test = prepare_data(test_data, n_steps)
```

Model Definig, Compiling and Training

Model compilation is **an activity performed after writing the statements in a model and before training starts**. It checks for format errors, and defines the loss function, the optimizer or learning rate, and the metrics. A compiled model is needed for training but not necessary for predicting.

What is Model Training?

Model training is the phase in the **data science development lifecycle where practitioners try to fit the best combination of weights and bias to a machine learning algorithm to minimize a loss function over the prediction range**.

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LSTM, Dropout
import time


# Define LSTM model
model = Sequential()
model.add(LSTM(50, return_sequences=True, input_shape=(X_train.shape[1], X_train.shape[2])))
model.add(Dropout(0.2))
model.add(LSTM(50, return_sequences=True))
model.add(Dropout(0.2))
model.add(LSTM(50))
model.add(Dense(1))
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204: UserWarning:

Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the
```

```
# Compile model
model.compile(optimizer='adam', loss='mean_squared_error')


Start = time.time()
history = model.fit(X_train, Y_train, validation_data=(X_test, Y_test), epochs=10, batch_size=64, verbose=1)
End = time.time()
```

```
Epoch 1/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 8s 156ms/step - loss: 0.1433 - val_loss: 0.0102
Epoch 2/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 2s 109ms/step - loss: 0.0135 - val_loss: 0.0131
Epoch 3/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 1s 110ms/step - loss: 0.0054 - val_loss: 0.0036
Epoch 4/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 108ms/step - loss: 0.0023 - val_loss: 0.0029
Epoch 5/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 113ms/step - loss: 0.0023 - val_loss: 0.0030
Epoch 6/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 2s 183ms/step - loss: 0.0023 - val_loss: 0.0029
Epoch 7/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 2s 158ms/step - loss: 0.0020 - val_loss: 0.0027
Epoch 8/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 1s 111ms/step - loss: 0.0019 - val_loss: 0.0030
Epoch 9/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 116ms/step - loss: 0.0019 - val_loss: 0.0038
Epoch 10/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 2s 108ms/step - loss: 0.0022 - val_loss: 0.0035
```

```
model.summary()
```

```
Model: "sequential"
```

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 60, 50)	11,000
dropout (Dropout)	(None, 60, 50)	0
lstm_1 (LSTM)	(None, 60, 50)	20,200
dropout_1 (Dropout)	(None, 60, 50)	0
lstm_2 (LSTM)	(None, 50)	20,200
dense (Dense)	(None, 1)	51

```
Total params: 154,355 (602.95 KB)
Trainable params: 51,451 (200.98 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 102,904 (401.97 KB)
```

```
#calculating the training time
print(f"Training time: {End-Start}s")
```

```
Training time: 28.503700494766235s
```

```
# Make predictions
train_predict = model.predict(X_train)
test_predict = model.predict(X_test)
```

```
25/25 ━━━━━━━━━━━━━━━━━━━━ 1s 38ms/step
10/10 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step
```

```
# Inverse transform predictions
train_predict = scalers[0].inverse_transform(train_predict)
test_predict = scalers[0].inverse_transform(test_predict)
```

```
# Inverse transform Y_train and Y_test
Y_train_inv = scalers[0].inverse_transform(Y_train.reshape(-1, 1))
Y_test_inv = scalers[0].inverse_transform(Y_test.reshape(-1, 1))
```

Root Mean Square Error

The Root Mean Squared Error (RMSE) is **one of the two main performance indicators for a regression model**. It measures the average difference between values predicted by a model and the actual values. It provides an estimation of how well the model is able to predict the target value (accuracy).

```
from sklearn.metrics import mean_squared_error
```

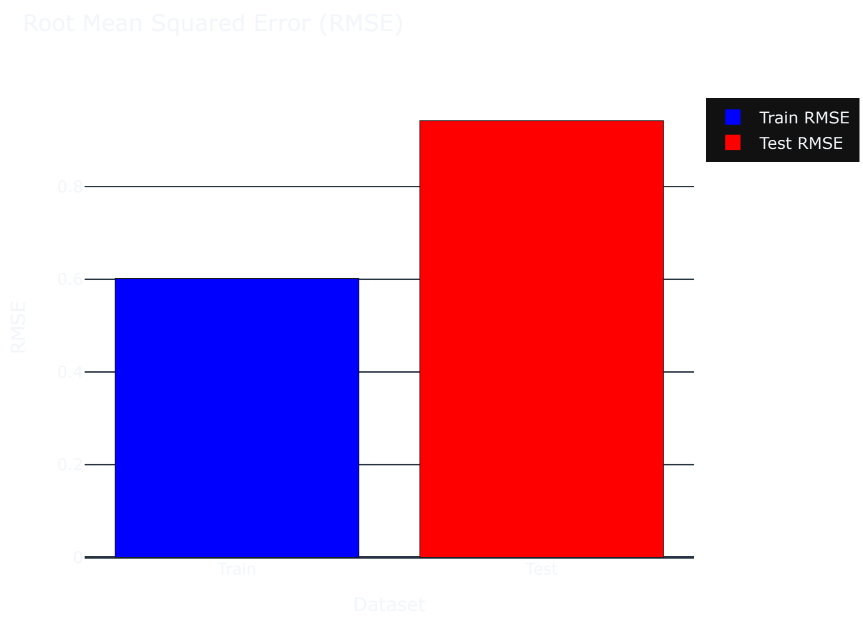
```
# Calculate RMSE
rmse_train = np.sqrt(mean_squared_error(Y_train_inv, train_predict))
rmse_test = np.sqrt(mean_squared_error(Y_test_inv, test_predict))
```

```
print("Train RMSE:", rmse_train)
print("Test RMSE:", rmse_test)
```

```
Train RMSE: 0.6015830163773137
Test RMSE: 0.9419442511620838
```

```
# Create a Plotly figure
fig_rmse = go.Figure()

# Add traces for train RMSE and test RMSE
fig_rmse.add_trace(go.Bar(x=['Train'], y=[rmse_train], name='Train RMSE', marker_color='blue'))
fig_rmse.add_trace(go.Bar(x=['Test'], y=[rmse_test], name='Test RMSE', marker_color='red'))

# Update layout
fig_rmse.update_layout(title='Root Mean Squared Error (RMSE)',
                       xaxis_title='Dataset',
```

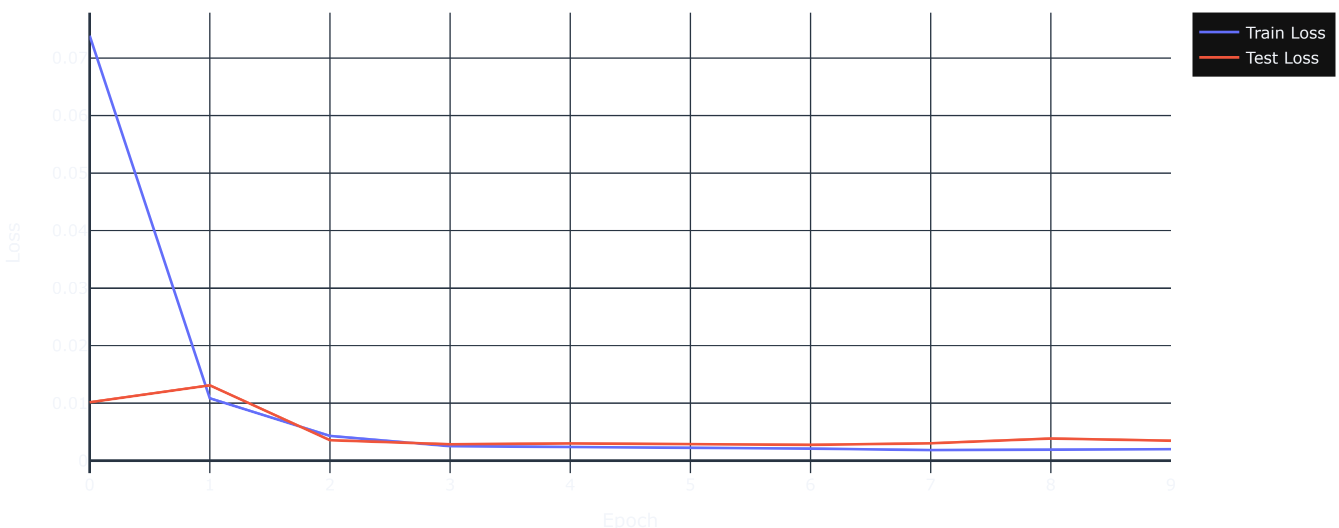
```
                       yaxis_title='RMSE',
                       template='plotly_dark')

# Show the figure
fig_rmse.show()
```



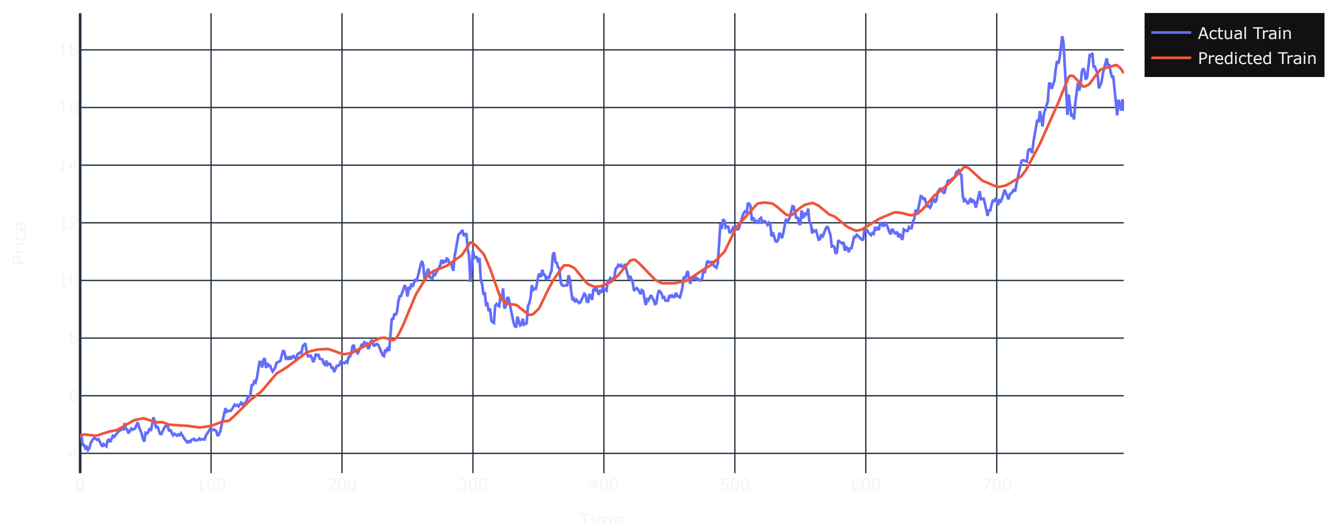
Visulatization of the values using the Plotly liberary

```
import plotly.graph_objects as go

# Plot loss history
fig_loss = go.Figure()
fig_loss.add_trace(go.Scatter(x=np.arange(len(history.history['loss'])), y=history.history['loss'], mode='lines', name='Train Loss'))
fig_loss.add_trace(go.Scatter(x=np.arange(len(history.history['val_loss'])), y=history.history['val_loss'], mode='lines', name='Test Loss'))
fig_loss.update_layout(title='Training and Test Loss',
                       xaxis_title='Epoch',
                       yaxis_title='Loss',
                       template='plotly_dark')
fig_loss.show()

# Plot actual vs predicted for train data
fig_train = go.Figure()
fig_train.add_trace(go.Scatter(x=np.arange(len(Y_train_inv)), y=Y_train_inv[:, 0], mode='lines', name='Actual Train'))
fig_train.add_trace(go.Scatter(x=np.arange(len(train_predict)), y=train_predict[:, 0], mode='lines', name='Predicted Train'))
fig_train.update_layout(title='Actual vs Predicted Stock Prices for Train Data',
                        xaxis_title='Time',
                        yaxis_title='Price',
                        template='plotly_dark')
fig_train.show()

# Plot actual vs predicted for test data
fig_test = go.Figure()
fig_test.add_trace(go.Scatter(x=np.arange(len(Y_test_inv)), y=Y_test_inv[:, 0], mode='lines', name='Actual Test'))
fig_test.add_trace(go.Scatter(x=np.arange(len(train_predict), len(train_predict) + len(test_predict)), y=test_predict[:, 0], mode='lines', r
fig_test.update_layout(title='Actual vs Predicted Stock Prices for Test Data',
                       xaxis_title='Time',
                       yaxis_title='Price',
                       template='plotly_dark')
fig_test.show()
```

Training and Test Loss



Actual vs Predicted Stock Prices for Train Data



Actual vs Predicted Stock Prices for Test Data