```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remour
```

```
%cd /content/drive/MyDrive/SBUX.US_D1.csv
```

```
[Errno 20] Not a directory: '/content/drive/MyDrive/SBUX.US_D1.csv'
/content
```

```
!ls
```

```
DataForML.pkl  drive  Final_XGB_Model.pkl  sample_data
```

```
# Supressing the warning messages
import warnings
warnings.filterwarnings('ignore')
```

1. Reading The dataset

```
# Reading the dataset
import pandas as pd
import numpy as np
StarbucksData=pd.read_csv('/content/drive/MyDrive/SBUX.US_D1.csv', encoding='latin')
print('Shape before deleting duplicate values:', StarbucksData.shape)

# Removing duplicate rows
StarbucksData=StarbucksData.drop_duplicates()
print('Shape After deleting duplicate values:', StarbucksData.shape)

# Start observing the Quantitative/Categorical/Qualitative variables
StarbucksData.head(10)
```

```
Shape before deleting duplicate values: (6639, 6)
Shape After deleting duplicate values: (6639, 6)
```

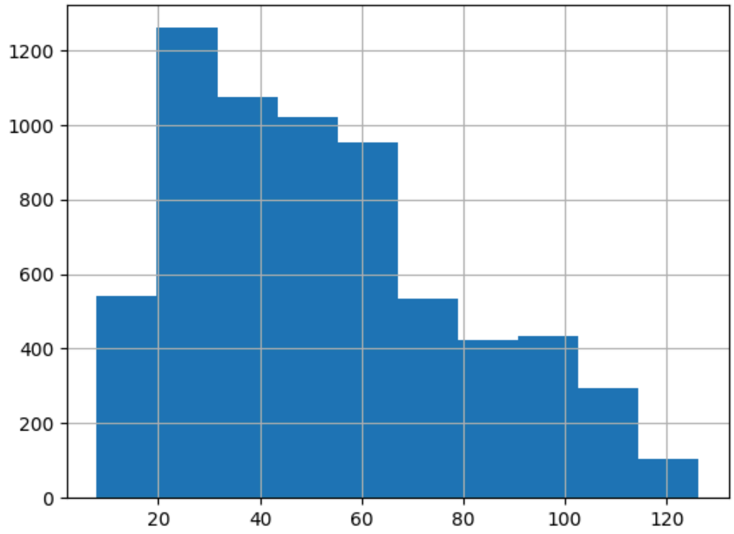
	datetime	open	high	low	close	volume
0	1998-01-02	38.38	38.63	37.31	37.50	594000
1	1998-01-05	37.63	37.78	36.75	37.13	644000
2	1998-01-06	37.13	37.38	35.56	35.63	1183300
3	1998-01-07	35.50	36.44	34.25	34.69	2039005
4	1998-01-08	34.56	36.01	34.00	35.76	1638105
5	1998-01-09	35.75	36.01	34.37	35.13	713703
6	1998-01-12	34.50	35.37	34.25	35.19	855603
7	1998-01-13	35.38	35.63	35.00	35.56	460200
8	1998-01-14	35.63	35.63	35.07	35.19	336200
9	1998-01-15	35.13	35.26	33.75	34.00	742700

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

3. Targeted Variable Distribution

```
%matplotlib inline
StarbucksData['high'].hist()
```

<Axes: >




```
StarbucksData.head()
```

	open	high	low	close	volume
0	38.38	38.63	37.31	37.50	594000
1	37.63	37.78	36.75	37.13	644000
2	37.13	37.38	35.56	35.63	1183300
3	35.50	36.44	34.25	34.69	2039005
4	34.56	36.01	34.00	35.76	1638105

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

```
StarbucksData.tail()
```

	open	high	low	close	volume
6634	90.95	91.53	90.60	91.07	5115057
6635	91.06	91.09	91.05	91.05	4882
6636	91.26	92.96	91.17	92.07	3796900
6637	92.00	92.72	91.21	92.42	6207319
6638	92.55	92.87	90.87	91.59	4772185

Removing Unwanted columns

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# List of columns to remove
columns_to_remove = ['datetime']

for col in columns_to_remove:
    if col in StarbucksData.columns:
        StarbucksData = StarbucksData.drop(columns=col)
        print(f"Removed column: {col}")
    else:
        print(f"Column not found: {col}")

# To see the DataFrame after attempting to drop the columns
print(StarbucksData.head())
```

```
Column not found: datetime
    open   high    low  close   volume
0  38.38  38.63  37.31  37.50   594000
1  37.63  37.78  36.75  37.13   644000
2  37.13  37.38  35.56  35.63  1183300
3  35.50  36.44  34.25  34.69  2039005
```

```
4  34.56  36.01  34.00  35.76  1638105
```

```
StarbucksData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6639 entries, 0 to 6638
Data columns (total 5 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   open    6639 non-null   float64
 1   high    6639 non-null   float64
 2   low     6639 non-null   float64
 3   close   6639 non-null   float64
 4   volume  6639 non-null   int64
dtypes: float64(4), int64(1)
memory usage: 259.5 KB
```

2. Problem statement definition

```
StarbucksData.describe(include='all')
```

	open	high	low	close	volume
count	6639.000000	6639.000000	6639.000000	6639.000000	6.639000e+03
mean	52.025905	52.605072	51.438399	52.034272	5.793768e+06
std	27.161870	27.312972	26.994025	27.155434	4.658699e+06
min	7.520000	7.900000	7.060000	7.200000	3.000000e+02
25%	29.735000	30.130000	29.290000	29.665000	2.875130e+06
50%	49.340000	50.000000	48.660000	49.400000	4.693841e+06
75%	71.500000	72.215000	70.680000	71.390000	7.301760e+06
max	126.080000	126.320000	124.810000	126.060000	7.234445e+07

```
StarbucksData.nunique()
```

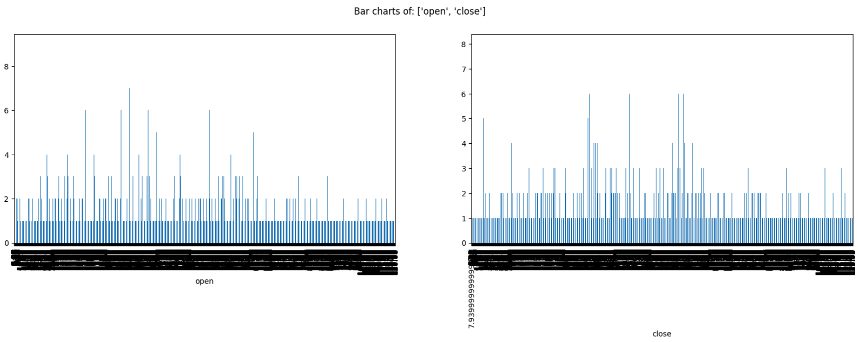
	0
open	4356
high	4370
low	4301
close	4417
volume	6623

dtype: int64

4. Visualising the distribution of Target

```
def PlotBarCharts(inpData, colsToPlot):
    %matplotlib inline

    import matplotlib.pyplot as plt

    # Generating multiple subplots
    fig, subPlot=plt.subplots(nrows=1, ncols=len(colsToPlot), figsize=(20,5))
    fig.suptitle('Bar charts of: '+ str(colsToPlot))

    for colName, plotNumber in zip(colsToPlot, range(len(colsToPlot))):
        inpData.groupby(colName).size().plot(kind='bar',ax=subPlot[plotNumber])
```

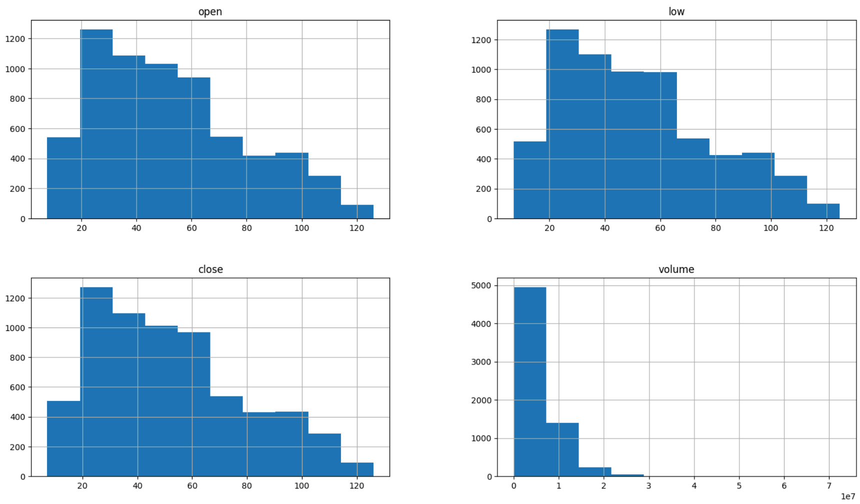
```
PlotBarCharts(inpData=StarbucksData, colsToPlot=['open','close'])
```



5. Data exploration at basic level

```
StarbucksData.hist(['open', 'low', 'close', 'volume'], figsize=(18,10))
```

```
array([[<Axes: title={'center': 'open'}>,
        <Axes: title={'center': 'low'}>],
       [<Axes: title={'center': 'close'}>,
        <Axes: title={'center': 'volume'}>]], dtype=object)
```




```
StarbucksData['volume'][StarbucksData['volume']<60].sort_values(ascending=False)
```

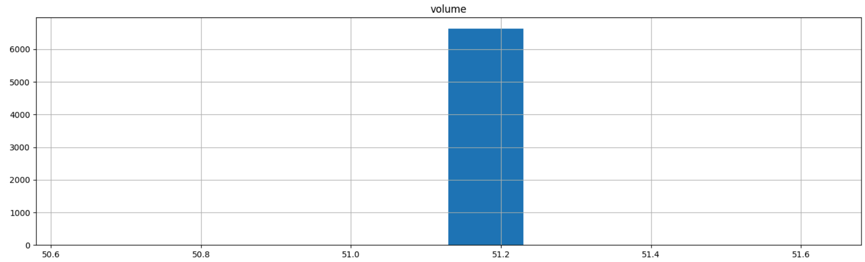
volume

dtype: int64

```
StarbucksData['volume'][StarbucksData['volume']>60] =51.13
```

```
StarbucksData.hist(['volume'], figsize=(18,5))
```

```
array([[<Axes: title={'center': 'volume'}>]], dtype=object)
```



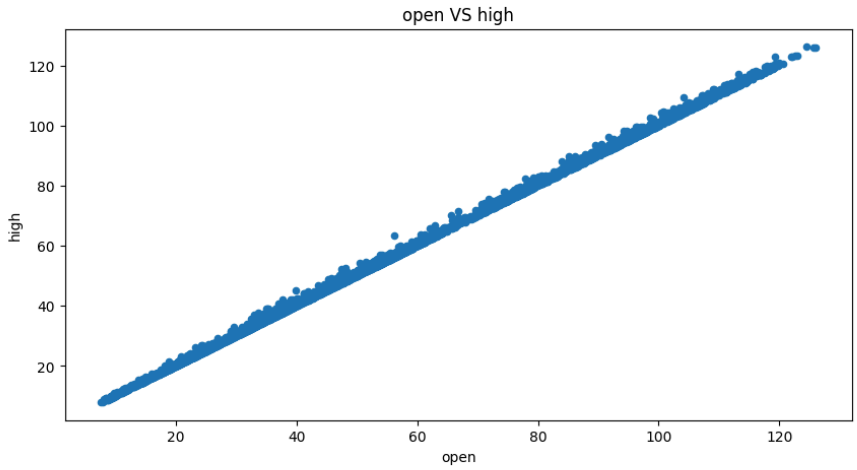
9. Removal of outliers and missing values

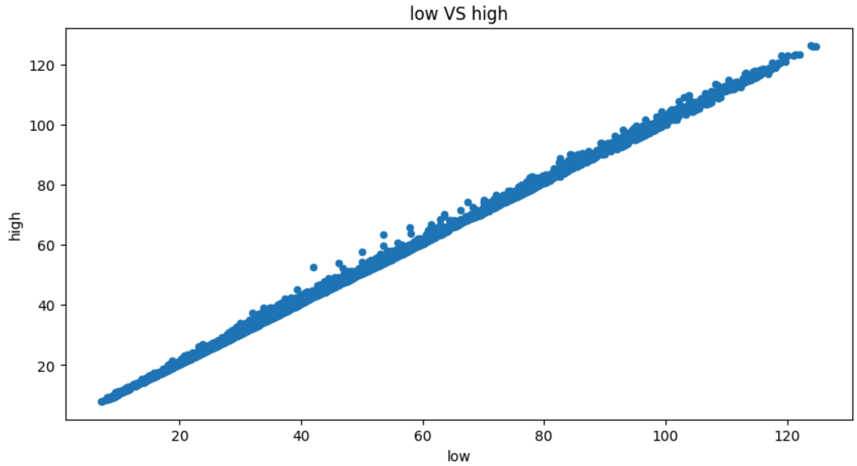
```
StarbucksData.isnull().sum()
```

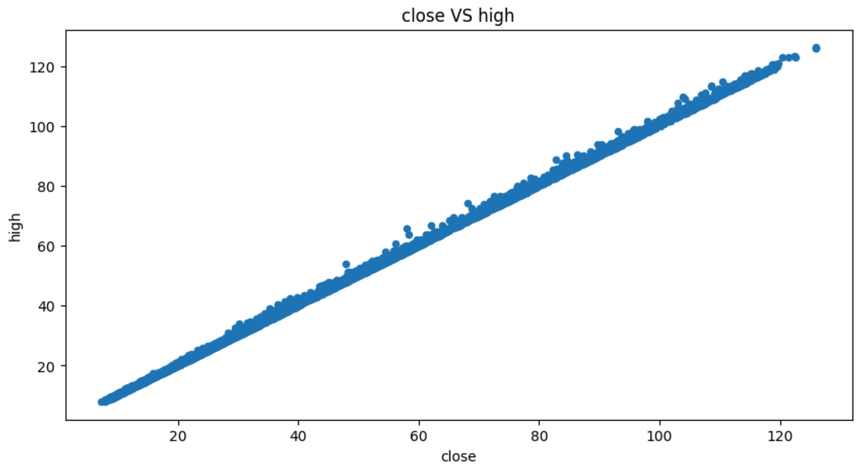
	0
open	0
high	0
low	0
close	0
volume	0

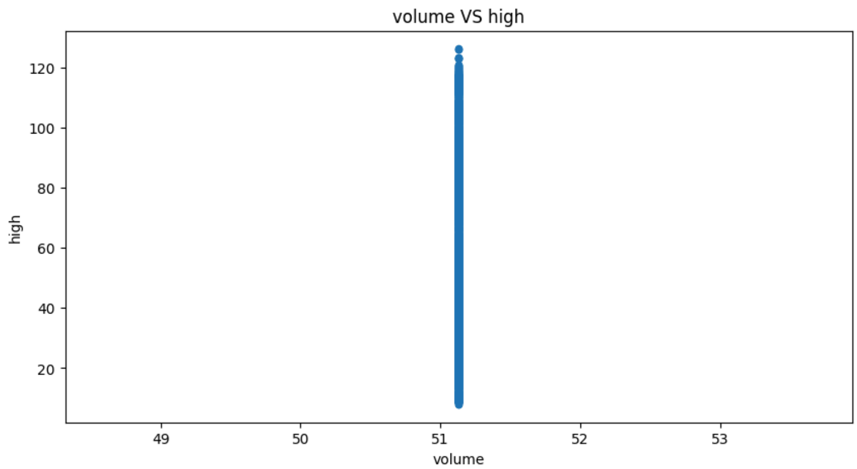
dtype: int64

```
ContinuousCols=['open', 'low', 'close', 'volume']

# Plotting scatter chart for each predictor vs the target variable
for predictor in ContinuousCols:
    StarbucksData.plot.scatter(x=predictor, y='high', figsize=(10,5), title=predictor+" VS "+ 'high')
```


open VS high
high
open
20
40
60
80
100
120


low VS high
high
low
20
40
60
80
100
120


close VS high
high
close
20
40
60
80
100
120


volume VS high
high
volume
20
40
60
80
100
120
49
50
51
52
53

8. Feature Selection based on data distribution

```
# Calculating correlation matrix
ContinuousCols=['high', 'open', 'low', 'close', 'volume']  # Removed 'datetime'

# Creating the correlation matrix
CorrelationData=StarbucksData[ContinuousCols].corr()
CorrelationData
```

	high	open	low	close	volume
high	1.000000	0.999763	0.999640	0.999770	NaN
open	0.999763	1.000000	0.999742	0.999524	NaN
low	0.999640	0.999742	1.000000	0.999762	NaN
close	0.999770	0.999524	0.999762	1.000000	NaN
volume	NaN	NaN	NaN	NaN	NaN

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

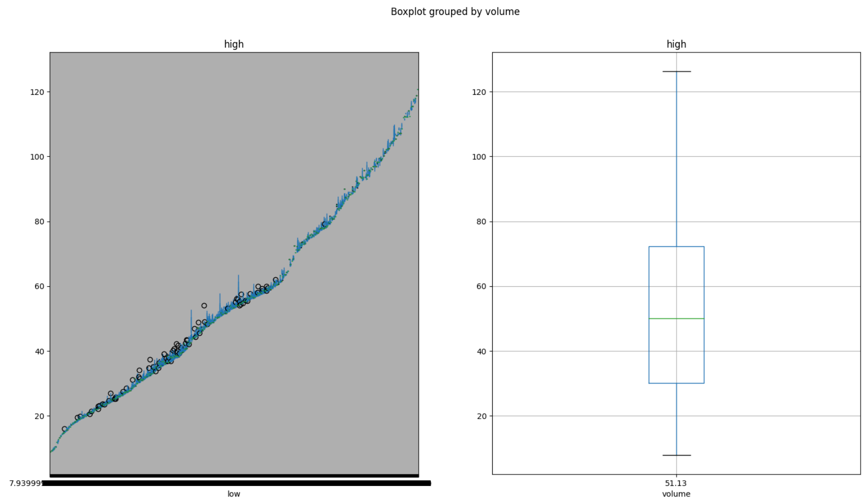
```
CorrelationData['high'][abs(CorrelationData['high']) > 0.5 ]
```

	high
high	1.000000
open	0.999763
low	0.999640
close	0.999770

dtype: float64

10. Visual and Statistic Correlation analysis for selection of best features

```
CategoricalColsList=['low', 'volume']

import matplotlib.pyplot as plt
fig, PlotCanvas=plt.subplots(nrows=1, ncols=len(CategoricalColsList), figsize=(18,10))

# Creating box plots for each continuous predictor against the Target Variable "high"
for PredictorCol , i in zip(CategoricalColsList, range(len(CategoricalColsList))):
    StarbucksData.boxplot(column='high', by=PredictorCol, figsize=(5,5), vert=True, ax=PlotCanvas[i])
```




```
def FunctionAnova(inpData, TargetVariable, CategoricalPredictorList):
    from scipy.stats import f_oneway

    # Creating an empty list of final selected predictors
    SelectedPredictors=[]

    print('##### ANOVA Results ##### \n')
    for predictor in CategoricalPredictorList:
        CategoryGroupLists=inpData.groupby(predictor)[TargetVariable].apply(list)
        AnovaResults = f_oneway(*CategoryGroupLists)

        # If the ANOVA P-Value is <0.05, that means we reject H0
        if (AnovaResults[1] < 0.05):
            print(predictor, 'is correlated with', TargetVariable, '| P-Value:', AnovaResults[1])
            SelectedPredictors.append(predictor)
        else:
            print(predictor, 'is NOT correlated with', TargetVariable, '| P-Value:', AnovaResults[1])

    return(SelectedPredictors)

CategoricalPredictorList=['open', 'close']
FunctionAnova(inpData=StarbucksData,
              TargetVariable='high',
              CategoricalPredictorList=CategoricalPredictorList)
```

```
##### ANOVA Results #####

open is correlated with high | P-Value: 0.0
close is correlated with high | P-Value: 0.0
['open', 'close']
```

```
SelectedColumns=['open', 'high', 'low', 'close', 'volume']  # Removed 'datetime'

# final columns
DataForML=StarbucksData[SelectedColumns]
DataForML.head()
```

	open	high	low	close	volume
0	38.38	38.63	37.31	37.50	51.13
1	37.63	37.78	36.75	37.13	51.13
2	37.13	37.38	35.56	35.63	51.13
3	35.50	36.44	34.25	34.69	51.13
4	34.56	36.01	34.00	35.76	51.13

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

11. Data Conversion to numeric values for machine learning predictive analysis

```
DataForML.to_pickle('DataForML.pkl')
```

```
# Treating all the nominal variables at once using dummy variables
DataForML_Numeric=pd.get_dummies(DataForML)

# putting Target Variable to the data
DataForML_Numeric['high']=StarbucksData['high']

# sample rows
DataForML_Numeric.head()
```

	open	high	low	close	volume
0	38.38	38.63	37.31	37.50	51.13
1	37.63	37.78	36.75	37.13	51.13
2	37.13	37.38	35.56	35.63	51.13
3	35.50	36.44	34.25	34.69	51.13
4	34.56	36.01	34.00	35.76	51.13

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

```
DataForML_Numeric.columns
```

```
Index(['open', 'high', 'low', 'close', 'volume'], dtype='object')
```

```
TargetVariable='high'
Predictors=['open', 'low', 'close', 'volume']  # Removed 'datetime'

X=DataForML_Numeric[Predictors].values
y=DataForML_Numeric[TargetVariable].values

# Split the data into training and testing set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=428)


#Standardization of the data
from sklearn.preprocessing import StandardScaler, MinMaxScaler

PredictorScaler=MinMaxScaler()

PredictorScalerFit=PredictorScaler.fit(X)

X=PredictorScalerFit.transform(X)

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)


# Sanity check for the sampled data
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(4647, 4)
(4647,)
(1992, 4)
```

```
(1992,)
```

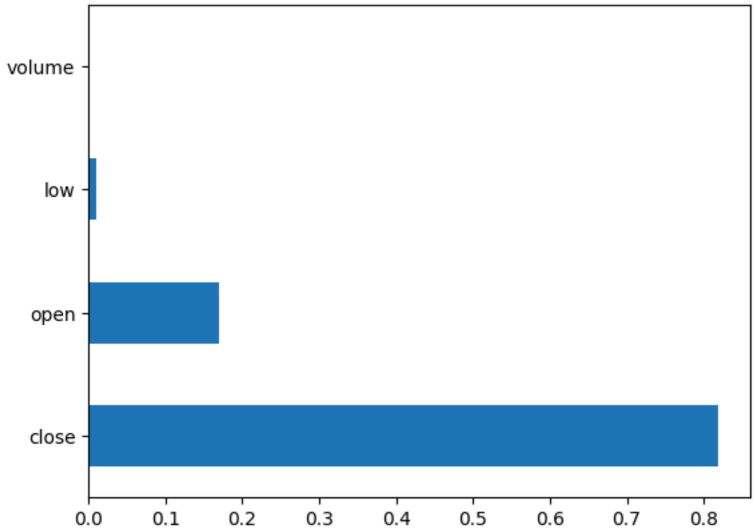
13. Investigating multiple Regression algorithms

```
#Multiple Linear Regression
from sklearn.linear_model import LinearRegression
RegModel = LinearRegression()

# Printing all the parameters of Linear regression
print(RegModel)

# Creating the model on
LREG=RegModel.fit(X_train,y_train)
prediction=LREG.predict(X_test)

from sklearn import metrics
# Measuring fit in Training data
print('R2 Value:',metrics.r2_score(y_train, LREG.predict(X_train)))

print('\n##### Model Validation and Accuracy Calculations ##########')

# Printing some sample values of prediction
TestingDataResults=pd.DataFrame(data=X_test, columns=Predictors)
TestingDataResults[TargetVariable]=y_test
TestingDataResults[('Predicted'+TargetVariable)]=np.round(prediction)

# Printing sample prediction values
print(TestingDataResults.head())

# Calculating the error for each row
TestingDataResults['APE']=100 * ((abs(
  TestingDataResults['high']-TestingDataResults['Predictedhigh']))/TestingDataResults['high'])

MAPE=np.mean(TestingDataResults['APE'])
MedianMAPE=np.median(TestingDataResults['APE'])

Accuracy =100 - MAPE
MedianAccuracy=100- MedianMAPE
print('Mean Accuracy on test data:', Accuracy) # Can be negative sometimes due to outlier
print('Median Accuracy on test data:', MedianAccuracy)

# Defining a custom function to calculate accuracy
# Make sure there are no zeros in the Target variable if you are using MAPE
def Accuracy_Score(orig,pred):
    MAPE = np.mean(100 * (np.abs(orig-pred)/orig))
    #print('#'*70,'Accuracy:', 100-MAPE)
    return(100-MAPE)

# Custom Scoring MAPE calculation
from sklearn.metrics import make_scorer
custom_Scoring=make_scorer(Accuracy_Score, greater_is_better=True)

# Importing cross validation function from sklearn
from sklearn.model_selection import cross_val_score

# Running 10-Fold Cross validation on a given algorithm
# Passing full data X and y because the K-fold will split the data and automatically choose train/test
Accuracy_Values=cross_val_score(RegModel, X , y, cv=10, scoring=custom_Scoring)
print('\nAccuracy values for 10-fold Cross Validation:\n',Accuracy_Values)
print('\nFinal Average Accuracy of the model:', round(Accuracy_Values.mean(),2))
```

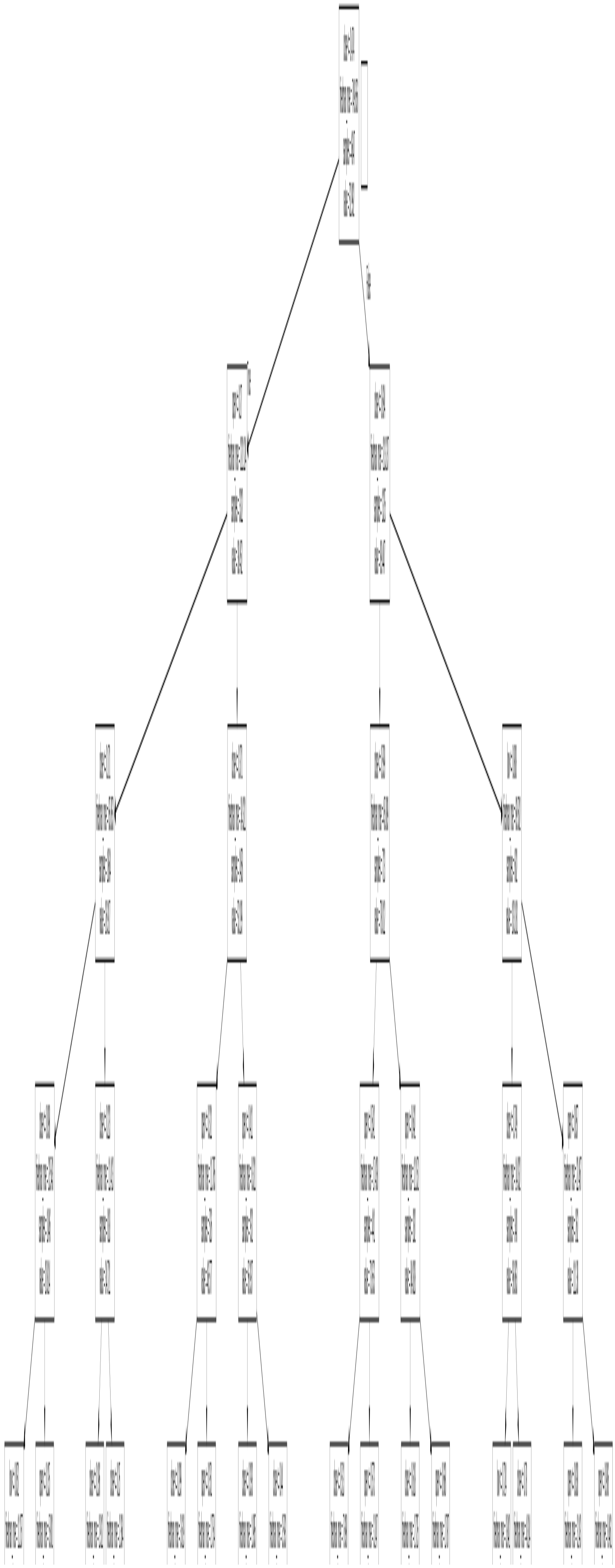
```
LinearRegression()
R2 Value: 0.9998302780695274

##### Model Validation and Accuracy Calculations ##########
       open       low     close  volume    high  Predictedhigh
0  0.334683  0.337410  0.335100     0.0   47.54           48.0
1  0.502530  0.509469  0.512788     0.0   68.21           68.0
2  0.119686  0.122887  0.122665     0.0   21.85           22.0
3  0.249663  0.252144  0.254417     0.0   37.65           38.0
4  0.875843  0.870998  0.871025     0.0  111.69          112.0
Mean Accuracy on test data: 99.10775768180177
Median Accuracy on test data: 99.32885906040269

Accuracy values for 10-fold Cross Validation:
 [98.97014598 99.24794514 99.5535399  99.45022545 99.24955049 99.59638437
 99.65028454 99.64707299 99.57719054 99.57230884]

Final Average Accuracy of the model: 99.45
```

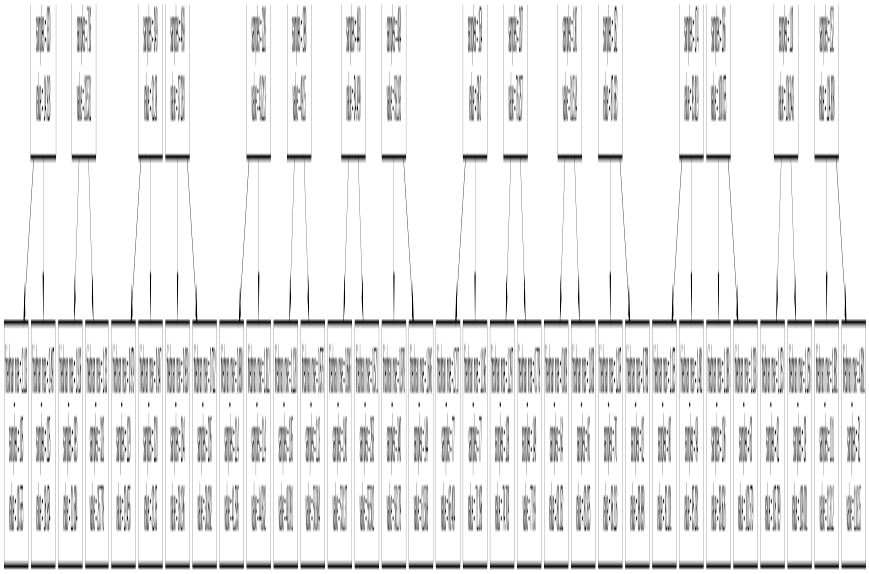
```
# Decision Trees (Multiple if-else statements!)
from sklearn.tree import DecisionTreeRegressor
RegModel = DecisionTreeRegressor(max_depth=5,criterion='friedman_mse')

# Printing all the parameters of Decision Tree
print(RegModel)

# Creating the model on Training Data
DT=RegModel.fit(X_train,y_train)
prediction=DT.predict(X_test)

from sklearn import metrics
# Measuring Goodness of fit in Training data
print('R2 Value:',metrics.r2_score(y_train, DT.predict(X_train)))

# Plotting the feature importance for Top 10 most important columns
%matplotlib inline
feature_importances = pd.Series(DT.feature_importances_, index=Predictors)
feature_importances.nlargest(10).plot(kind='barh')

print('\n##### Model Validation and Accuracy Calculations ##########')

# Printing some sample values of prediction
TestingDataResults=pd.DataFrame(data=X_test, columns=Predictors)
TestingDataResults[TargetVariable]=y_test
TestingDataResults[('Predicted'+TargetVariable)]=np.round(prediction)

# Printing sample prediction values
print(TestingDataResults.head())

# Calculating the error for each row
TestingDataResults['APE']=100 * ((abs(
  TestingDataResults['high']-TestingDataResults['Predictedhigh']))/TestingDataResults['high'])

MAPE=np.mean(TestingDataResults['APE'])
MedianMAPE=np.median(TestingDataResults['APE'])

Accuracy =100 - MAPE
MedianAccuracy=100- MedianMAPE
print('Mean Accuracy on test data:', Accuracy) # Can be negative sometimes due to outlier
print('Median Accuracy on test data:', MedianAccuracy)

# Defining a custom function to calculate accuracy
# Make sure there are no zeros in the Target variable if you are using MAPE
def Accuracy_Score(orig,pred):
    MAPE = np.mean(100 * (np.abs(orig-pred)/orig))
    #print('#'*70,'Accuracy:', 100-MAPE)
    return(100-MAPE)

# Custom Scoring MAPE calculation
from sklearn.metrics import make_scorer
custom_Scoring=make_scorer(Accuracy_Score, greater_is_better=True)

# Importing cross validation function from sklearn
from sklearn.model_selection import cross_val_score

# Passing full data X and y because the K-fold will split the data and automatically choose train/test
Accuracy_Values=cross_val_score(RegModel, X , y, cv=10, scoring=custom_Scoring)
print('\nAccuracy values for 10-fold Cross Validation:\n',Accuracy_Values)
print('\nFinal Average Accuracy of the model:', round(Accuracy_Values.mean(),2))
```

```
DecisionTreeRegressor(criterion='friedman_mse', max_depth=5)
R2 Value: 0.9983077844357447

##### Model Validation and Accuracy Calculations ##########
       open       low     close  volume    high  Predictedhigh
0  0.334683  0.337410  0.335100     0.0   47.54           48.0
1  0.502530  0.509469  0.512788     0.0   68.21           66.0
2  0.119686  0.122887  0.122665     0.0   21.85           22.0
3  0.249663  0.252144  0.254417     0.0   37.65           39.0
4  0.875843  0.870998  0.871025     0.0  111.69          113.0
Mean Accuracy on test data: 97.07822162752849
Median Accuracy on test data: 98.22595704948645

Accuracy values for 10-fold Cross Validation:
 [97.11249377 95.20326796 97.77182835 95.28085053 80.12682526 98.23486658
 98.60751822 98.02095888 98.23145466 98.14946372]

Final Average Accuracy of the model: 95.67
```



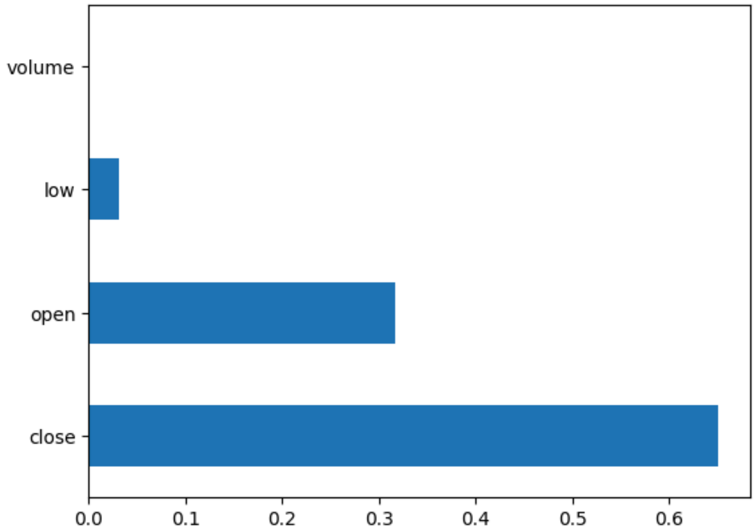

```
# Load libraries
from IPython.display import Image
from sklearn import tree
import pydotplus

# Create DOT data
dot_data = tree.export_graphviz(RegModel, out_file=None,
                                feature_names=Predictors) # Remove class_names for regression


#print(dot_data)

# Draw graph
graph = pydotplus.graph_from_dot_data(dot_data)

# Show graph
Image(graph.create_png(), width=2000,height=2000)
# Double-click on the graph to zoom in
```



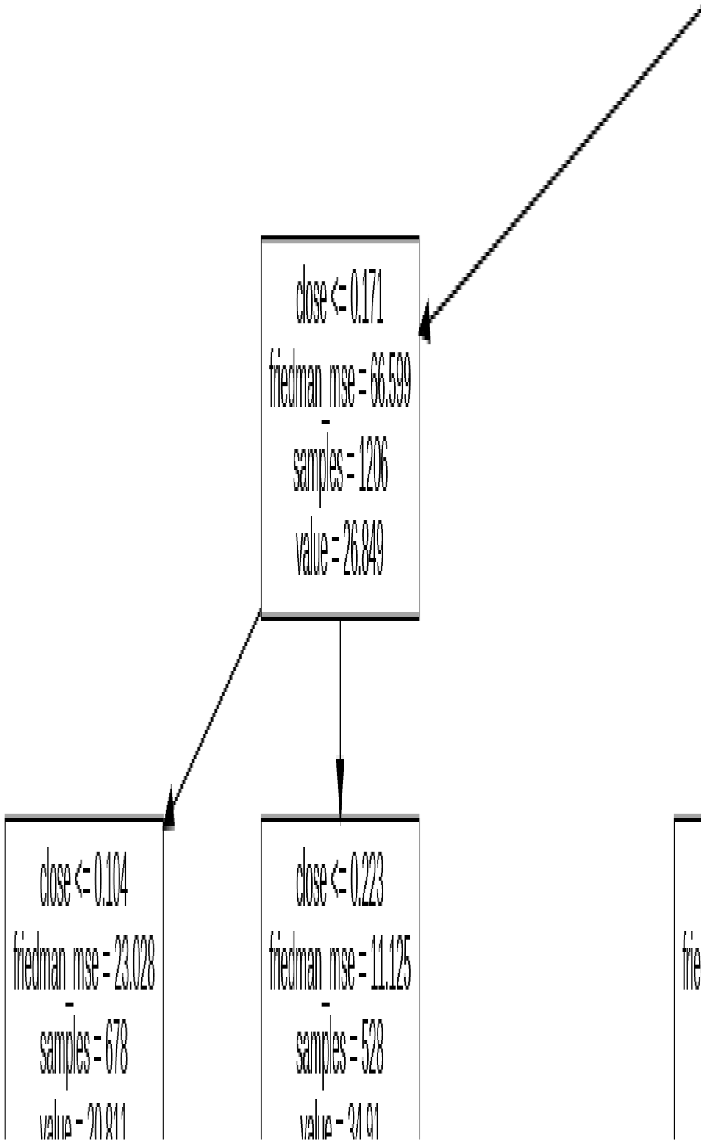


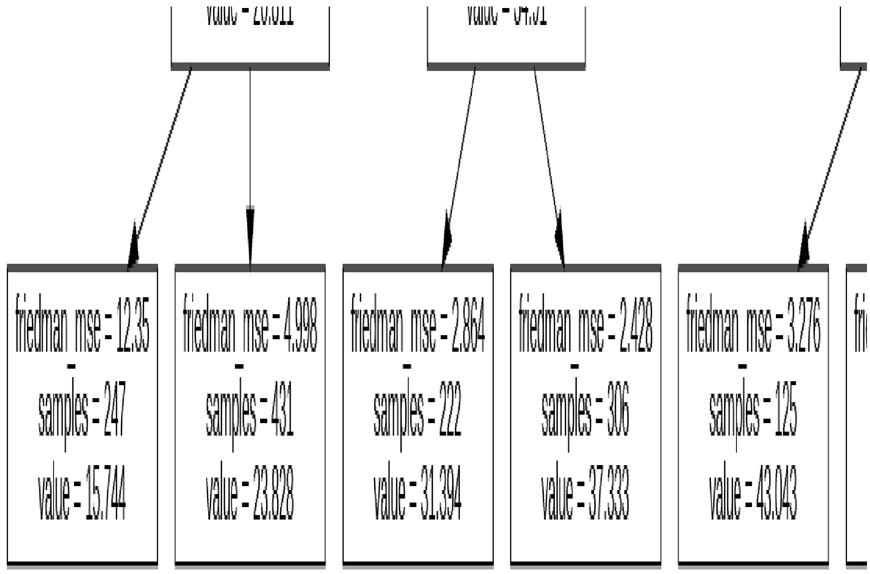
```
# Random Forest (Bagging of multiple Decision Trees)
from sklearn.ensemble import RandomForestRegressor
RegModel = RandomForestRegressor(max_depth=4, n_estimators=400,criterion='friedman_mse')

# Printing all the parameters of Random Forest
print(RegModel)

# Creating the model on Training Data
RF=RegModel.fit(X_train,y_train)
prediction=RF.predict(X_test)

from sklearn import metrics
# Measuring Goodness of fit in Training data
print('R2 Value:',metrics.r2_score(y_train, RF.predict(X_train)))

# Plotting the feature importance for Top 10 most important columns
%matplotlib inline
feature_importances = pd.Series(RF.feature_importances_, index=Predictors)
feature_importances.nlargest(10).plot(kind='barh')

print('\n##### Model Validation and Accuracy Calculations ##########')

# Printing some sample values of prediction
TestingDataResults=pd.DataFrame(data=X_test, columns=Predictors)
TestingDataResults[TargetVariable]=y_test
TestingDataResults[('Predicted'+TargetVariable)]=np.round(prediction)

# Printing sample prediction values
print(TestingDataResults.head())

# Calculating the error for each row
TestingDataResults['APE']=100 * ((abs(
  TestingDataResults['high']-TestingDataResults['Predictedhigh']))/TestingDataResults['high'])

MAPE=np.mean(TestingDataResults['APE'])
MedianMAPE=np.median(TestingDataResults['APE'])

Accuracy =100 - MAPE
MedianAccuracy=100- MedianMAPE
print('Mean Accuracy on test data:', Accuracy) # Can be negative sometimes due to outlier
print('Median Accuracy on test data:', MedianAccuracy)


# Defining a custom function to calculate accuracy
# Make sure there are no zeros in the Target variable if you are using MAPE
def Accuracy_Score(orig,pred):
    MAPE = np.mean(100 * (np.abs(orig-pred)/orig))
    #print('#'*70,'Accuracy:', 100-MAPE)
    return(100-MAPE)

# Custom Scoring MAPE calculation
from sklearn.metrics import make_scorer
custom_Scoring=make_scorer(Accuracy_Score, greater_is_better=True)

# Importing cross validation function from sklearn
from sklearn.model_selection import cross_val_score

# Passing full data X and y because the K-fold will split the data and automatically choose train/test
Accuracy_Values=cross_val_score(RegModel, X , y, cv=10, scoring=custom_Scoring)
print('\nAccuracy values for 10-fold Cross Validation:\n',Accuracy_Values)
print('\nFinal Average Accuracy of the model:', round(Accuracy_Values.mean(),2))
```

```
RandomForestRegressor(criterion='friedman_mse', max_depth=4, n_estimators=400
R2 Value: 0.996258641309678

##### Model Validation and Accuracy Calculations ##########
       open       low     close  volume    high  Predictedhigh
0  0.334683  0.337410  0.335100     0.0   47.54           49.0
1  0.502530  0.509469  0.512788     0.0   68.21           68.0
2  0.119686  0.122887  0.122665     0.0   21.85           23.0
3  0.249663  0.252144  0.254417     0.0   37.65           37.0
4  0.875843  0.870998  0.871025     0.0  111.69          115.0
Mean Accuracy on test data: 95.675328748515
Median Accuracy on test data: 97.7336327490655

Accuracy values for 10-fold Cross Validation:
 [96.2520956  92.31335095 96.67624995 93.02809603 73.77033573 97.85475085
 97.84415209 97.54290656 97.73315978 97.26907368]

Final Average Accuracy of the model: 94.03
```



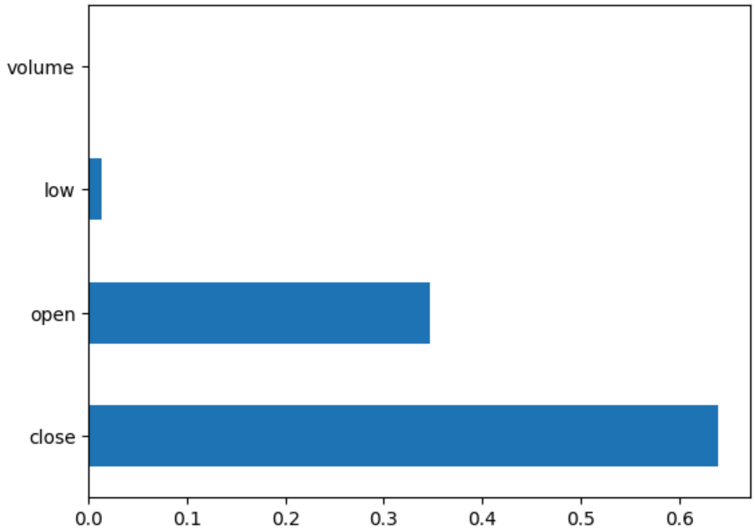

```
from IPython.display import Image
from sklearn import tree
import pydotplus

# Create DOT data for the 6th Decision Tree in Random Forest
# Removing the class_names argument
dot_data = tree.export_graphviz(RegModel.estimators_[5] , out_file=None, feature_names=Predictors)
# Draw graph
graph = pydotplus.graph_from_dot_data(dot_data)

# Show graph
Image(graph.create_png(), width=2000,height=2000)
# Double-click on the graph to zoom in
```


close <= 0.171
friedman_mse = 66.599
samples = 1206
value = 26.849
close <= 0.104
friedman_mse = 23.028
samples = 678
close <= 0.223
friedman_mse = 11.125
samples = 528


friedman_mse = 12.35
samples = 247
value = 15.744
friedman_mse = 4.998
samples = 431
value = 23.828
friedman_mse = 2.864
samples = 222
value = 31.394
friedman_mse = 2.428
samples = 306
value = 37.333
friedman_mse = 3.276
samples = 125
value = 43.043

```
# Adaboost (Boosting of multiple Decision Trees)
from sklearn.ensemble import AdaBoostRegressor
from sklearn.tree import DecisionTreeRegressor

# Choosing Decision Tree with 6 level as the weak learner
DTR=DecisionTreeRegressor(max_depth=3)
RegModel = AdaBoostRegressor(n_estimators=100, base_estimator=DTR ,learning_rate=0.04)

# Printing all the parameters of Adaboost
print(RegModel)

# Creating the model on Training Data
AB=RegModel.fit(X_train,y_train)
prediction=AB.predict(X_test)

from sklearn import metrics
# Measuring Goodness of fit in Training data
print('R2 Value:',metrics.r2_score(y_train, AB.predict(X_train)))

# Plotting the feature importance for Top 10 most important columns
%matplotlib inline
feature_importances = pd.Series(AB.feature_importances_, index=Predictors)
feature_importances.nlargest(10).plot(kind='barh')

###########################################################################
print('\n##### Model Validation and Accuracy Calculations ##########')

# Printing some sample values of prediction
TestingDataResults=pd.DataFrame(data=X_test, columns=Predictors)
TestingDataResults[TargetVariable]=y_test
TestingDataResults[('Predicted'+TargetVariable)]=np.round(prediction)

# Printing sample prediction values
print(TestingDataResults.head())

# Calculating the error for each row
TestingDataResults['APE']=100 * ((abs(
  TestingDataResults['high']-TestingDataResults['Predictedhigh']))/TestingDataResults['high'])

MAPE=np.mean(TestingDataResults['APE'])
MedianMAPE=np.median(TestingDataResults['APE'])

Accuracy =100 - MAPE
MedianAccuracy=100- MedianMAPE
print('Mean Accuracy on test data:', Accuracy) # Can be negative sometimes due to outlier
print('Median Accuracy on test data:', MedianAccuracy)


# Defining a custom function to calculate accuracy
# Make sure there are no zeros in the Target variable if you are using MAPE
def Accuracy_Score(orig,pred):
    MAPE = np.mean(100 * (np.abs(orig-pred)/orig))
    #print('#'*70,'Accuracy:', 100-MAPE)
    return(100-MAPE)

# Custom Scoring MAPE calculation
from sklearn.metrics import make_scorer
custom_Scoring=make_scorer(Accuracy_Score, greater_is_better=True)

# Importing cross validation function from sklearn
from sklearn.model_selection import cross_val_score

# Running 10-Fold Cross validation on a given algorithm
# Passing full data X and y because the K-fold will split the data and automatically choose train/test
Accuracy_Values=cross_val_score(RegModel, X , y, cv=10, scoring=custom_Scoring)
print('\nAccuracy values for 10-fold Cross Validation:\n',Accuracy_Values)
print('\nFinal Average Accuracy of the model:', round(Accuracy_Values.mean(),2))
```

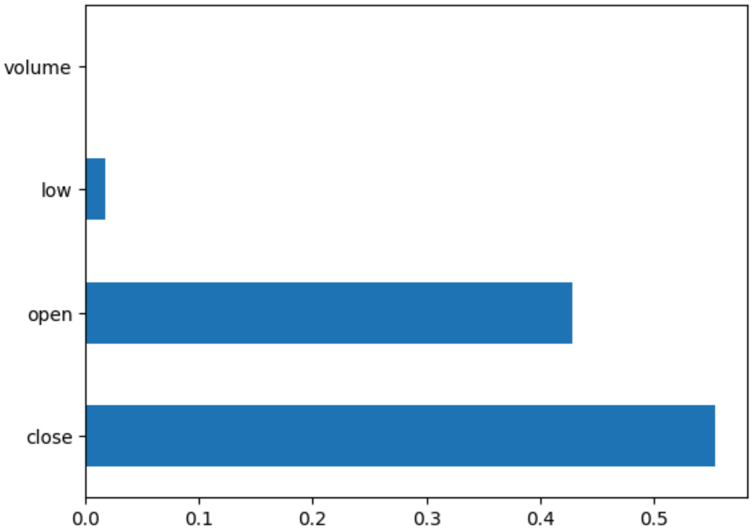
```
AdaBoostRegressor(base_estimator=DecisionTreeRegressor(max_depth=3),
                  learning_rate=0.04, n_estimators=100)
R2 Value: 0.9874194246823305

##### Model Validation and Accuracy Calculations ##########
       open       low     close  volume    high  Predictedhigh
0  0.334683  0.337410  0.335100     0.0   47.54           46.0
1  0.502530  0.509469  0.512788     0.0   68.21           71.0
2  0.119686  0.122887  0.122665     0.0   21.85           20.0
3  0.249663  0.252144  0.254417     0.0   37.65           35.0
4  0.875843  0.870998  0.871025     0.0  111.69          112.0
Mean Accuracy on test data: 92.66827528649962
Median Accuracy on test data: 95.39398369434332

Accuracy values for 10-fold Cross Validation:
 [91.76600783 89.07292865 94.2555468  94.12720287 60.16465789 94.60177776
 95.92341731 94.32449787 96.60050225 97.55173965]

Final Average Accuracy of the model: 90.84
```



XGBoost Regressor

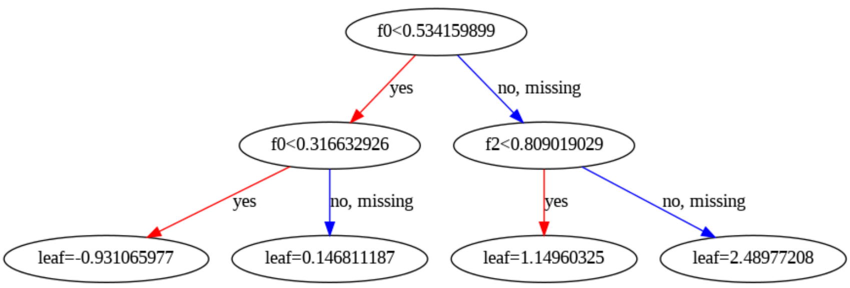
```
# Xtreme Gradient Boosting (XGBoost)
from xgboost import XGBRegressor
RegModel=XGBRegressor(max_depth=2,
                      learning_rate=0.1,
                      n_estimators=1000,
                      objective='reg:linear',
                      booster='gbtree')

# Printing all the parameters of XGBoost
print(RegModel)

# Creating the model on Training Data
XGB=RegModel.fit(X_train,y_train)
prediction=XGB.predict(X_test)

from sklearn import metrics
# Measuring Goodness of fit in Training data
print('R2 Value:',metrics.r2_score(y_train, XGB.predict(X_train)))

# Plotting the feature importance for Top 10 most important columns
%matplotlib inline
feature_importances = pd.Series(XGB.feature_importances_, index=Predictors)
feature_importances.nlargest(10).plot(kind='barh')
###########################################################################
print('\n##### Model Validation and Accuracy Calculations ##########')

# Printing some sample values of prediction
TestingDataResults=pd.DataFrame(data=X_test, columns=Predictors)
TestingDataResults[TargetVariable]=y_test
TestingDataResults[('Predicted'+TargetVariable)]=np.round(prediction)

# Printing sample prediction values
print(TestingDataResults.head())

# Calculating the error for each row
TestingDataResults['APE']=100 * ((abs(
  TestingDataResults['high']-TestingDataResults['Predictedhigh']))/TestingDataResults['high'])


MAPE=np.mean(TestingDataResults['APE'])
MedianMAPE=np.median(TestingDataResults['APE'])

Accuracy =100 - MAPE
MedianAccuracy=100- MedianMAPE
print('Mean Accuracy on test data:', Accuracy) # Can be negative sometimes due to outlier
print('Median Accuracy on test data:', MedianAccuracy)


# Defining a custom function to calculate accuracy
# Make sure there are no zeros in the Target variable if you are using MAPE
def Accuracy_Score(orig,pred):
    MAPE = np.mean(100 * (np.abs(orig-pred)/orig))
    #print('#'*70,'Accuracy:', 100-MAPE)
    return(100-MAPE)

# Custom Scoring MAPE calculation
from sklearn.metrics import make_scorer
custom_Scoring=make_scorer(Accuracy_Score, greater_is_better=True)

# Importing cross validation function from sklearn
from sklearn.model_selection import cross_val_score

# Running 10-Fold Cross validation on a given algorithm
# Passing full data X and y because the K-fold will split the data and automatically choose train/test
Accuracy_Values=cross_val_score(RegModel, X , y, cv=10, scoring=custom_Scoring)
print('\nAccuracy values for 10-fold Cross Validation:\n',Accuracy_Values)
print('\nFinal Average Accuracy of the model:', round(Accuracy_Values.mean(),2))
```

```
XGBRegressor(base_score=None, booster='gbtree', callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.1, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=2, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimators=1000, n_jobs=None,
             num_parallel_tree=None, objective='reg:linear', ...)
R2 Value: 0.9997998976798858

##### Model Validation and Accuracy Calculations ##########
       open       low     close  volume    high  Predictedhigh
0  0.334683  0.337410  0.335100     0.0   47.54           48.0
1  0.502530  0.509469  0.512788     0.0   68.21           69.0
2  0.119686  0.122887  0.122665     0.0   21.85           22.0
3  0.249663  0.252144  0.254417     0.0   37.65           38.0
4  0.875843  0.870998  0.871025     0.0  111.69          112.0
Mean Accuracy on test data: 98.96280690999289
Median Accuracy on test data: 99.2652058103633

Accuracy values for 10-fold Cross Validation:
 [98.60613862 98.92574274 99.32153111 99.08876165 89.44445044 99.38595723
 99.50926339 99.46141599 99.19441203 99.22176472]

Final Average Accuracy of the model: 98.22
```




```
#Plotting a single Decision tree out of XGBoost
from xgboost import plot_tree
import matplotlib.pyplot as plt
fig, ax = plt.subplots(figsize=(20, 8))
plot_tree(XGB, num_trees=10, ax=ax)
```

```
<Axes: >
```



12. Training/Testing Sampling and K- fold cross validation

```
#kNN
# K-Nearest Neighbor(KNN)
from sklearn.neighbors import KNeighborsRegressor
RegModel = KNeighborsRegressor(n_neighbors=3)

# Printing all the parameters of KNN
print(RegModel)

# Creating the model on Training Data
KNN=RegModel.fit(X_train,y_train)
prediction=KNN.predict(X_test)

from sklearn import metrics
# Measuring Goodness of fit in Training data
print('R2 Value:',metrics.r2_score(y_train, KNN.predict(X_train)))

# Plotting the feature importance for Top 10 most important columns
# The variable importance chart is not available for KNN

###########################################################################
print('\n##### Model Validation and Accuracy Calculations ##########')

# Printing some sample values of prediction
TestingDataResults=pd.DataFrame(data=X_test, columns=Predictors)
TestingDataResults[TargetVariable]=y_test
TestingDataResults[('Predicted'+TargetVariable)]=np.round(prediction)

# Printing sample prediction values
print(TestingDataResults.head())

# Calculating the error for each row
TestingDataResults['APE']=100 * ((abs(
  TestingDataResults['high']-TestingDataResults['Predictedhigh']))/TestingDataResults['high'])

MAPE=np.mean(TestingDataResults['APE'])
MedianMAPE=np.median(TestingDataResults['APE'])

Accuracy =100 - MAPE
MedianAccuracy=100- MedianMAPE
print('Mean Accuracy on test data:', Accuracy) # Can be negative sometimes due to outlier
print('Median Accuracy on test data:', MedianAccuracy)

# Defining a custom function to calculate accuracy
# Make sure there are no zeros in the Target variable if you are using MAPE
def Accuracy_Score(orig,pred):
    MAPE = np.mean(100 * (np.abs(orig-pred)/orig))
    #print('#'*70,'Accuracy:', 100-MAPE)
    return(100-MAPE)

# Custom Scoring MAPE calculation
from sklearn.metrics import make_scorer
custom_Scoring=make_scorer(Accuracy_Score, greater_is_better=True)

# Importing cross validation function from sklearn
from sklearn.model_selection import cross_val_score

# Running 10-Fold Cross validation on a given algorithm
# Passing full data X and y because the K-fold will split the data and automatically choose train/test
Accuracy_Values=cross_val_score(RegModel, X , y, cv=10, scoring=custom_Scoring)
print('\nAccuracy values for 10-fold Cross Validation:\n',Accuracy_Values)
print('\nFinal Average Accuracy of the model:', round(Accuracy_Values.mean(),2))
```

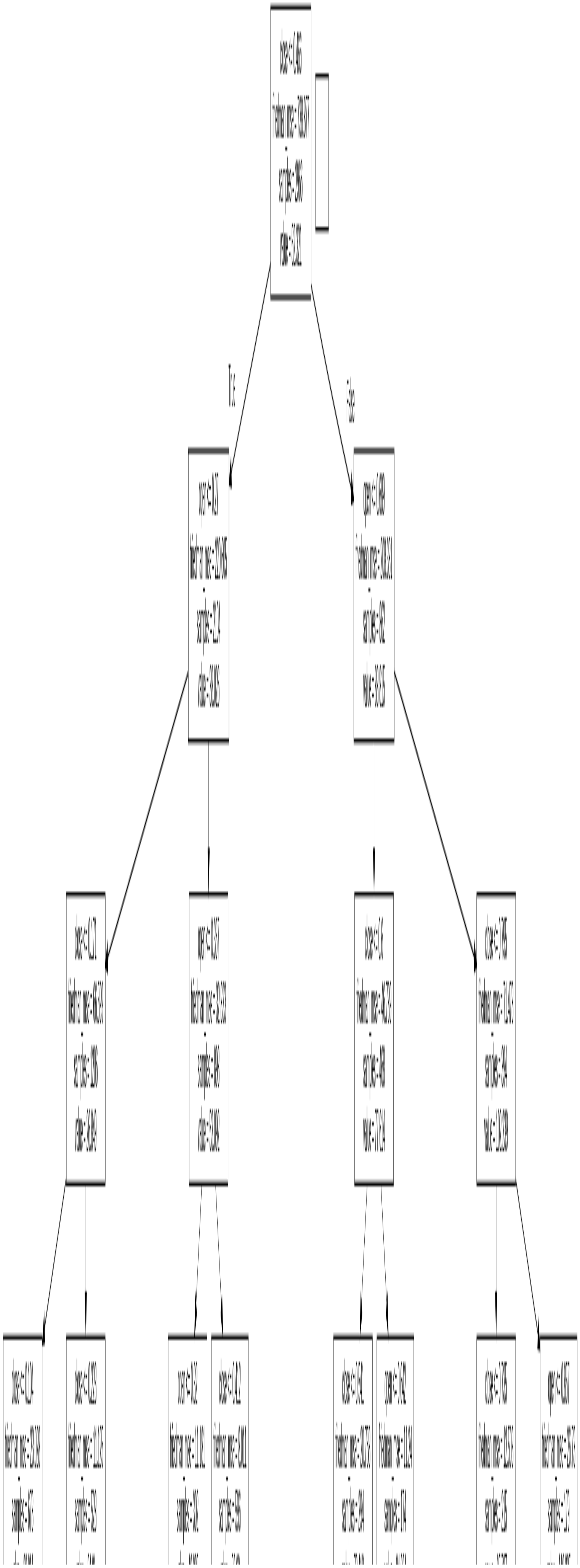
```
KNeighborsRegressor(n_neighbors=3)
R2 Value: 0.9998997766543954

##### Model Validation and Accuracy Calculations ##########
       open       low     close  volume    high  Predictedhigh
0  0.334683  0.337410  0.335100     0.0   47.54           47.0
1  0.502530  0.509469  0.512788     0.0   68.21           68.0
2  0.119686  0.122887  0.122665     0.0   21.85           22.0
3  0.249663  0.252144  0.254417     0.0   37.65           38.0
4  0.875843  0.870998  0.871025     0.0  111.69          112.0
Mean Accuracy on test data: 99.0950033696335
Median Accuracy on test data: 99.33113976415768

Accuracy values for 10-fold Cross Validation:
 [98.8361444  99.24144402 99.48532681 99.30671441 91.17665692 99.53015031
 99.62043971 99.62963944 99.38185102 99.4795387 ]

Final Average Accuracy of the model: 98.57
```

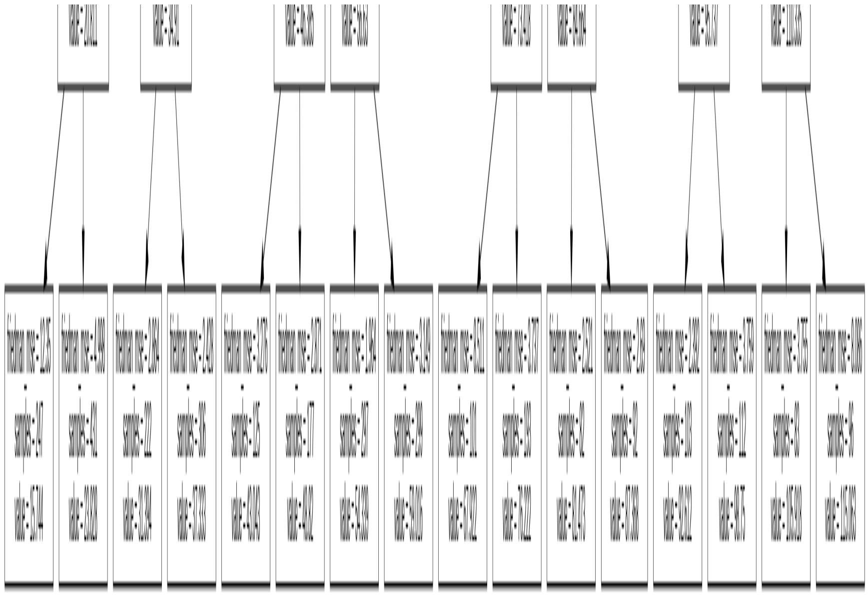
```
# Support Vector Machines(SVM)
from sklearn import svm
RegModel = svm.SVR(C=50, kernel='rbf', gamma=0.01)

# Printing all the parameters
print(RegModel)

# Creating the model on Training Data
SVM=RegModel.fit(X_train,y_train)
prediction=SVM.predict(X_test)

from sklearn import metrics
# Measuring Goodness of fit in Training data
print('R2 Value:',metrics.r2_score(y_train, SVM.predict(X_train)))

# Plotting the feature importance for Top 10 most important columns
# The built in attribute SVM.coef_ works only for linear kernel
%matplotlib inline
#feature_importances = pd.Series(SVM.coef_[0], index=Predictors)
#feature_importances.nlargest(10).plot(kind='barh')

###########################################################################
print('\n##### Model Validation and Accuracy Calculations ##########')

# Printing some sample values of prediction
TestingDataResults=pd.DataFrame(data=X_test, columns=Predictors)
TestingDataResults[TargetVariable]=y_test
TestingDataResults[('Predicted'+TargetVariable)]=np.round(prediction)

# Printing sample prediction values
print(TestingDataResults.head())

# Calculating the error for each row
TestingDataResults['APE']=100 * ((abs(
  TestingDataResults['high']-TestingDataResults['Predicted'+ TargetVariable]))/TestingDataResults['high']) # Added the Targ

MAPE=np.mean(TestingDataResults['APE'])
MedianMAPE=np.median(TestingDataResults['APE'])

Accuracy =100 - MAPE
MedianAccuracy=100- MedianMAPE
print('Mean Accuracy on test data:', Accuracy) # Can be negative sometimes due to outlier
print('Median Accuracy on test data:', MedianAccuracy)

# Defining a custom function to calculate accuracy
# Make sure there are no zeros in the Target variable if you are using MAPE
def Accuracy_Score(orig,pred):
    MAPE = np.mean(100 * (np.abs(orig-pred)/orig))
    #print('#'*70,'Accuracy:', 100-MAPE)
    return(100-MAPE)

# Custom Scoring MAPE calculation
from sklearn.metrics import make_scorer
custom_Scoring=make_scorer(Accuracy_Score, greater_is_better=True)

# Importing cross validation function from sklearn
from sklearn.model_selection import cross_val_score

# Running 10-Fold Cross validation on a given algorithm
# Passing full data X and y because the K-fold will split the data and automatically choose train/test
Accuracy_Values=cross_val_score(RegModel, X , y, cv=10, scoring=custom_Scoring)
print('\nAccuracy values for 10-fold Cross Validation:\n',Accuracy_Values)
print('\nFinal Average Accuracy of the model:', round(Accuracy_Values.mean(),2))
```

```
SVR(C=50, gamma=0.01)
R2 Value: 0.9996608084282836

##### Model Validation and Accuracy Calculations ##########
       open       low     close  volume    high  Predictedhigh
0  0.334683  0.337410  0.335100     0.0   47.54           48.0
1  0.502530  0.509469  0.512788     0.0   68.21           68.0
2  0.119686  0.122887  0.122665     0.0   21.85           22.0
3  0.249663  0.252144  0.254417     0.0   37.65           38.0
4  0.875843  0.870998  0.871025     0.0  111.69          112.0
Mean Accuracy on test data: 98.98048053844327
Median Accuracy on test data: 99.2679050568941

Accuracy values for 10-fold Cross Validation:
 [98.31689232 99.09031641 99.55386758 99.37347612 98.90716127 99.5076312
 99.57891793 99.50554101 99.45227024 99.43884569]

Final Average Accuracy of the model: 99.27
```

```
# Plotting a single Decision Tree from Random Forest
# Load libraries
from IPython.display import Image
from sklearn import tree
import pydotplus

# Create DOT data for the 6th Decision Tree in Random Forest
print("Visualizing individual trees is not supported for Support Vector Regression models.")

# Draw graph
graph = pydotplus.graph_from_dot_data(dot_data)

# Show graph
Image(graph.create_png(), width=2000,height=2000)
# Double click on the graph to zoom in
```

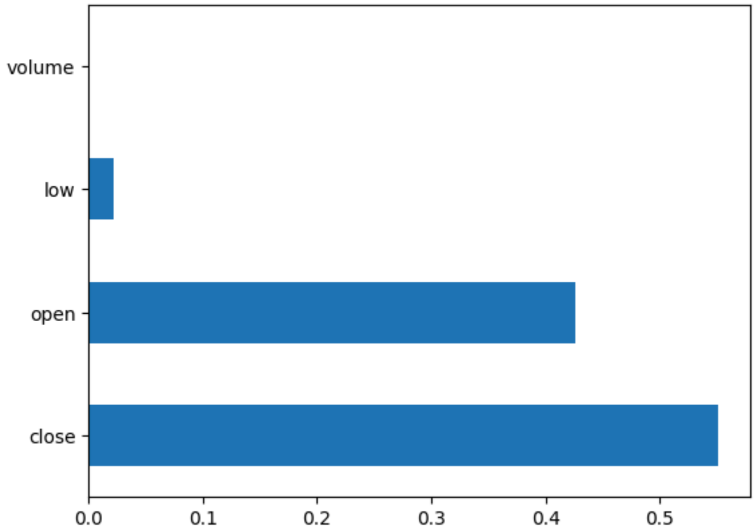
Visualizing individual trees is not supported for Support Vector Regression m





```
# Adaboost (Boosting of multiple Decision Trees)
from sklearn.ensemble import AdaBoostRegressor
from sklearn.tree import DecisionTreeRegressor

# Choosing Decision Tree with 6 level as the weak learner
DTR=DecisionTreeRegressor(max_depth=3)
RegModel = AdaBoostRegressor(n_estimators=100, base_estimator=DTR ,learning_rate=0.04)

# Printing all the parameters of Adaboost
print(RegModel)

# Creating the model on Training Data
AB=RegModel.fit(X_train,y_train)
prediction=AB.predict(X_test)

from sklearn import metrics
# Measuring Goodness of fit in Training data
print('R2 Value:',metrics.r2_score(y_train, AB.predict(X_train)))

# Plotting the feature importance for Top 10 most important columns
%matplotlib inline
feature_importances = pd.Series(AB.feature_importances_, index=Predictors)
feature_importances.nlargest(10).plot(kind='barh')

###########################################################################
print('\n##### Model Validation and Accuracy Calculations ##########')

# Printing some sample values of prediction
TestingDataResults=pd.DataFrame(data=X_test, columns=Predictors)
TestingDataResults[TargetVariable]=y_test
TestingDataResults[('Predicted'+TargetVariable)]=np.round(prediction)

# Printing sample prediction values
print(TestingDataResults.head())

# Calculating the error for each row
TestingDataResults['APE']=100 * ((abs(
  TestingDataResults['high']-TestingDataResults['Predictedhigh']))/TestingDataResults['high'])

MAPE=np.mean(TestingDataResults['APE'])
MedianMAPE=np.median(TestingDataResults['APE'])

Accuracy =100 - MAPE
MedianAccuracy=100- MedianMAPE
print('Mean Accuracy on test data:', Accuracy) # Can be negative sometimes due to outlier
print('Median Accuracy on test data:', MedianAccuracy)


# Defining a custom function to calculate accuracy
# Make sure there are no zeros in the Target variable if you are using MAPE
def Accuracy_Score(orig,pred):
    MAPE = np.mean(100 * (np.abs(orig-pred)/orig))
    #print('#'*70,'Accuracy:', 100-MAPE)
    return(100-MAPE)

# Custom Scoring MAPE calculation
from sklearn.metrics import make_scorer
custom_Scoring=make_scorer(Accuracy_Score, greater_is_better=True)

# Importing cross validation function from sklearn
from sklearn.model_selection import cross_val_score

# Running 10-Fold Cross validation on a given algorithm
# Passing full data X and y because the K-fold will split the data and automatically choose train/test
Accuracy_Values=cross_val_score(RegModel, X , y, cv=10, scoring=custom_Scoring)
print('\nAccuracy values for 10-fold Cross Validation:\n',Accuracy_Values)
print('\nFinal Average Accuracy of the model:', round(Accuracy_Values.mean(),2))
```

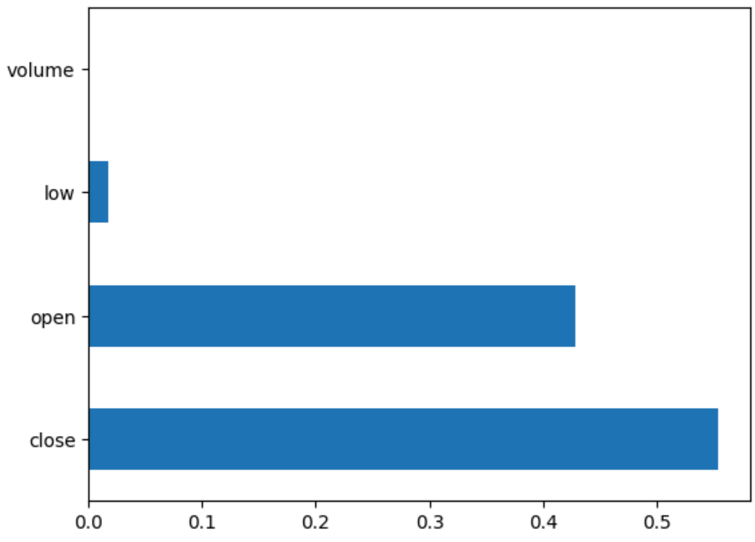
```
AdaBoostRegressor(base_estimator=DecisionTreeRegressor(max_depth=3),
                  learning_rate=0.04, n_estimators=100)
R2 Value: 0.987605442319262

##### Model Validation and Accuracy Calculations ##########
       open       low     close  volume    high  Predictedhigh
0  0.334683  0.337410  0.335100     0.0   47.54           46.0
1  0.502530  0.509469  0.512788     0.0   68.21           71.0
2  0.119686  0.122887  0.122665     0.0   21.85           20.0
3  0.249663  0.252144  0.254417     0.0   37.65           35.0
4  0.875843  0.870998  0.871025     0.0  111.69          112.0
Mean Accuracy on test data: 93.01571284455025
Median Accuracy on test data: 95.38306865989696

Accuracy values for 10-fold Cross Validation:
 [91.66285458 89.43540147 94.34355801 94.24665785 60.26502079 94.56559998
 96.29470434 94.3389756  96.67187198 97.52740301]

Final Average Accuracy of the model: 90.94
```




```
# Xtreme Gradient Boosting (XGBoost)
from xgboost import XGBRegressor
RegModel=XGBRegressor(max_depth=2,
                      learning_rate=0.1,
                      n_estimators=1000,
                      objective='reg:linear',
                      booster='gbtree')

# Printing all the parameters of XGBoost
print(RegModel)

# Creating the model on Training Data
XGB=RegModel.fit(X_train,y_train)
prediction=XGB.predict(X_test)

from sklearn import metrics

print('R2 Value:',metrics.r2_score(y_train, XGB.predict(X_train)))

# Plotting the feature importance for Top 10 most important columns
%matplotlib inline
feature_importances = pd.Series(XGB.feature_importances_, index=Predictors)
feature_importances.nlargest(10).plot(kind='barh')

print('\n##### Model Validation and Accuracy Calculations ##########')

# Printing some sample values of prediction
TestingDataResults=pd.DataFrame(data=X_test, columns=Predictors)
TestingDataResults[TargetVariable]=y_test
TestingDataResults[('Predicted'+TargetVariable)]=np.round(prediction)

# Printing sample prediction values
print(TestingDataResults.head())

# Calculating the error for each row
TestingDataResults['APE']=100 * ((abs(
  TestingDataResults['high']-TestingDataResults['Predictedhigh']))/TestingDataResults['high'])


MAPE=np.mean(TestingDataResults['APE'])
MedianMAPE=np.median(TestingDataResults['APE'])
```

```
Accuracy =100 - MAPE
MedianAccuracy=100- MedianMAPE
print('Mean Accuracy on test data:', Accuracy) # Can be negative sometimes due to outlier
print('Median Accuracy on test data:', MedianAccuracy)


# Defining a custom function to calculate accuracy
# Make sure there are no zeros in the Target variable if you are using MAPE
def Accuracy_Score(orig,pred):
    MAPE = np.mean(100 * (np.abs(orig-pred)/orig))
    #print('#'*70,'Accuracy:', 100-MAPE)
    return(100-MAPE)

# Custom Scoring MAPE calculation
from sklearn.metrics import make_scorer
custom_Scoring=make_scorer(Accuracy_Score, greater_is_better=True)

# Importing cross validation function from sklearn
from sklearn.model_selection import cross_val_score

# Running 10-Fold Cross validation on a given algorithm
# Passing full data X and y because the K-fold will split the data and automatically choose train/test
Accuracy_Values=cross_val_score(RegModel, X , y, cv=10, scoring=custom_Scoring)
print('\nAccuracy values for 10-fold Cross Validation:\n',Accuracy_Values)
print('\nFinal Average Accuracy of the model:', round(Accuracy_Values.mean(),2))
```

```
XGBRegressor(base_score=None, booster='gbtree', callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.1, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=2, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimators=1000, n_jobs=None,
             num_parallel_tree=None, objective='reg:linear', ...)
R2 Value: 0.9997998976798858

##### Model Validation and Accuracy Calculations ##########
       open       low     close  volume    high  Predictedhigh
0  0.334683  0.337410  0.335100     0.0   47.54           48.0
1  0.502530  0.509469  0.512788     0.0   68.21           69.0
2  0.119686  0.122887  0.122665     0.0   21.85           22.0
3  0.249663  0.252144  0.254417     0.0   37.65           38.0
4  0.875843  0.870998  0.871025     0.0  111.69          112.0
Mean Accuracy on test data: 98.96280690999289
Median Accuracy on test data: 99.2652058103633

Accuracy values for 10-fold Cross Validation:
 [98.60613862 98.92574274 99.32153111 99.08876165 89.44445044 99.38595723
 99.50926339 99.46141599 99.19441203 99.22176472]

Final Average Accuracy of the model: 98.22
```



Decision Tree out of XGBoost

```
#Plotting a single Decision tree out of XGBoost
from xgboost import plot_tree
import matplotlib.pyplot as plt
fig, ax = plt.subplots(figsize=(20, 8))
plot_tree(XGB, num_trees=10, ax=ax)
```

```
<Axes: >
```