In [2]:

```
# This program predicts stock price using four machine learning regression m
# 1) Creates a .csv file with historical data of the stock
# 2) Calculates and plots stock's Rolling Mean/Moving Average, stock Return
# 3) Performs/plots Linear Regression, predicts stock price, calculates rmse
# 4) Performs/plots Ridge Regression, predicts stock price, calculates rmse,
# 5) Performs/plots Lasso Regression, predicts stock price, calculates rmse,
# 6) Performs/plots KNN Regression, predicts stock price, calculates rmse, v

# Import yfinance with alias of yf
import yfinance as yf
# Import numpy as np for large, multi-dimensional arrays, matrices and mathe
import numpy as np
# Import pandas as pd for data manipulation, analysis, data structures and d
import pandas as pd
# import external pandas_datareader library with alias of pdr
import pandas_datareader as pdr
# import matplot library with alias of mplt. Pyplot module provides simple f
import matplotlib.pyplot as mplt
from matplotlib import style
%matplotlib inline
# import datetime internal datetime python module which supplies classes for
import datetime
# import math module for mathematical operations can be performed with ease
import math
from math import sqrt
import warnings
warnings.filterwarnings('ignore')
# sklearn.metrics has a mean_squared_error function. The RMSE is just the sq
from sklearn.metrics import mean_squared_error
# R^2 (coefficient of determination) regression score function. Best possibl
from sklearn.metrics import r2_score
# split the dataset into the training and the testing datasets; train_test_s
from sklearn.model_selection import train_test_split
# LinearRegression(fit_intercept=True, normalize=False, copy_X=True, n_jobs=
from sklearn.linear_model import LinearRegression
#  supervised learning through Ridge regression. In ridge regression, the co
from sklearn.linear_model import Ridge
#  supervised learning through Lasso regression. Lasso performs both variabl
from sklearn.linear_model import Lasso
# KNN alogrithm uses ‘feature similarity’ to predict values of any new data
from sklearn.neighbors import KNeighborsRegressor

### define the stock, start date and end date for downloading stock data fro
start = datetime.datetime(2017,1,1)
end = datetime.datetime(2019,9,12)

# Choose the stock ticker symbol
myStock = 'AAPL'

### Extract stock historical data from Yahoo into dataframe
df_Stock = pdr.DataReader(myStock, 'yahoo', start, end)
# Create .csv file with stock historical data
df_Stock.to_csv(myStock + '.csv')
print ('1- Downloaded ' + myStock + ' stock historical data from ' + start.s
# Display the last 5 records of the stock dataframe
print ('\033[1m \033[4mStock Prices from Yahoo Finance \033[0m' + "\n")
```

```
with pd.option_context('expand_frame_repr', False):
    print(df_Stock.tail())
print("\n")

### Plot stock's adjusted close price and moving average
print ('2- Note: ' + myStock + ' Moving Average steadily rises over the winc
# Plot stock's adjusted close price
df_Stock["Adj Close"].plot(title=df_Stock.columns[5], label = myStock, color
# Calculate the Rolling Mean (Moving Average) of the stock to determine the
df_Stock_close_pr = df_Stock['Close']
df_Stock_MovingAv = df_Stock_close_pr.rolling(window=50).mean()
# Display the last 5 stock moving average records
with pd.option_context('expand_frame_repr', False):
    print('\033[1m \033[4mStock Rolling Mean/Moving Average(50 Day)\033[0m'
    print(df_Stock_MovingAv.tail().to_string(header=None))
# Plot Stock's Rolling Mean Moving Averge
df_Stock_MovingAv.plot(title=df_Stock.columns[5], label = myStock + ' Moving
mplt.show()

### Calculate stock's return rate
df_Stock_ret_rate = (df_Stock['Adj Close'] / df_Stock['Adj Close'].shift(1))
# Display stock's last 5 return rate records
df_Stock_ret_rate.tail().T
# Plot stock return rate
print('\033[1m \033[4m3- Stock Return Rate \033[0m')
df_Stock_ret_rate.plot(title=df_Stock.columns[-1], label=myStock+' Return Ra
mplt.show()

### Feature Engineering
df_Stock_Pr_Regr = df_Stock.loc[:,['Adj Close','Volume']]
df_Stock_Pr_Regr['HL_PCT'] = ((df_Stock['High']-df_Stock['Low'])/df_Stock['C
df_Stock_Pr_Regr['PCT_change'] = ((df_Stock['Close']-df_Stock['Open'])/df_St
# Display the last 5 records of the dataframe
print('\033[1m \033[4m4-Display Stock Adj Close, Volume, Price(High-Low) % C
with pd.option_context('expand_frame_repr', False):
    print(df_Stock_Pr_Regr.tail())
print("\n")

print('\033[1m \033[4m5- Regression Data Details\033[0m' '\n')
# Split 80% data to train and 20% data to test the model
Total_Data_Ind = df_Stock.shape[0]
print('Total data size is ' + str(Total_Data_Ind))
train_size = 0.8
#Keep 80% data for training
Train_Data_Ind = int(train_size * Total_Data_Ind)
print('Training data size is ' + str(Train_Data_Ind))
#Keep 20% data for testing
Test_Data_Ind = Total_Data_Ind - Train_Data_Ind
print('Test data size is ' + str(Test_Data_Ind))
Train_test_split_time = df_Stock.index[Train_Data_Ind]
print('Train Test Split Time is = ' + str(Train_test_split_time) + '\n')

# Create X and y train data sets to train the model
X_daterange = df_Stock.iloc[:,:-1].to_numpy()
y_closepx = df_Stock.iloc[:,-1].to_numpy()

# Split into 80% train data and 20 % test data
```

```
X_daterange_train, X_daterange_test, y_closepx_train, y_closepx_test = trai

##################### Linear Regression ####################################

print ('\x1b[43m \033[1m \033[4m6- Starting Linear Regression \033[0m \x1b[

# Create Linear Regression Estimator/Model Object for training, testing/pre
LinReg_Model = LinearRegression(n_jobs= -1)

# Train the Liner Regression model using training set
LinReg_Model.fit(X_daterange_train, y_closepx_train)

# Test to predict with this model using training data
Training_Predications = LinReg_Model.predict(X_daterange_train).reshape(-1,

# Test to predict with this model using test data
Test_Predictions = LinReg_Model.predict(X_daterange_test).reshape(-1,1)

# Combine the training and testing predictions; Joining the two arrays along
All_Predictions = np.concatenate((Training_Predications, Test_Predictions),

# transform the prediction data to dataframe and plot the prediction results
df_lin_reg = pd.DataFrame(All_Predictions, columns=[myStock+' Linear Regr '
df_lin_reg[df_Stock.columns[-1]] = y_closepx
# plot the results of linear regression
df_lin_reg.plot(title=df_Stock.columns[-1], label=myStock+'_Linear Regressi
# Add the train and test split timing line
mplt.axvline(pd.Timestamp(Train_test_split_time),color='r', linestyle='--')
print('\033[1m \033[4m6A- Plot Linear Regression \033[0m' '\n')
mplt.show()

# calculate the coefficients
print('\033[1m \033[4m6B- Linear Regression Coefficients \033[0m' '\n')
print('  Coeficiencts: ', list(LinReg_Model.coef_))
print('\n')

# calculate root mean squared error
Training_rmse = sqrt(mean_squared_error(y_closepx_train.reshape(-1,1), Trai
Test_rmse = sqrt(mean_squared_error(y_closepx_test.reshape(-1,1), Test_Pred
print('\033[1m \033[4m6C- Linear Regression Root Mean Square Error \033[0m'
print('     Linear Regression Training RMSE = ' + str(Training_rmse))
print('     Linear Regression Testing RMSE = ' + str(Test_rmse))
print('\n')

# calculate the variance which is squared deviation of a variable from its 
#A low value for variance indicates that the data are clustered together an
# whereas a high value would indicate that the data in the given set are mu
print('\033[1m \033[4m6D-  Linear Regression Variance \033[0m' '\n')
print('  Variance: ', r2_score(y_closepx_test, Test_Predictions))
print('\n')

### Use the score method to evaluate the trained model
# The score method finds the mean accuracy of self.predict(X) with y of the
Confidence_Score = LinReg_Model.score(X_daterange_test, y_closepx_test)
print('\033[1m \033[4m6E-  Linear Regression Confidence \033[0m' '\n')
print(' The linear regression confidence is ' + str(Confidence_Score) + '\n
```

```
##################### Ridge Regression ######################################
# Ridge Regression is a technique for analyzing multiple regression data tha
# By adding a degree of bias to the regression estimates, ridge regression r
# Create Ridge Estimator/Model Object for training, testing/prediction

print ('\x1b[43m \033[1m \033[4m7- Starting Ridge Regression \033[0m \x1b[0m

RidgeReg_Model = Ridge(alpha=.5,normalize=True)
RidgeReg_Model.fit(X_daterange_train, y_closepx_train)

# Test to predict with this model using training data
Ridge_Training_Predications = RidgeReg_Model.predict(X_daterange_train).resh

# Test to predict with this model using test data
Ridge_Test_Predictions = RidgeReg_Model.predict(X_daterange_test).reshape(-1

# Combine the training and testing predictions; Joining the two arrays along
Ridge_All_Predictions = np.concatenate((Ridge_Training_Predications, Ridge_T

# transform the prediction data to dataframe and plot the prediction results
df_Ridge_reg = pd.DataFrame(Ridge_All_Predictions, columns=[myStock+' Ridge
df_Ridge_reg[df_Stock.columns[-1]] = y_closepx
# plot the results of Ridge regression
df_Ridge_reg.plot(label=myStock+'_Ridge Regression', figsize=(14,7), title=c
Train_test_split_time = df_Stock.index[Train_Data_Ind]
# Add the train and test split timing line
mplt.axvline(pd.Timestamp(Train_test_split_time),color='r', linestyle='--')
print('\033[1m \033[4m7A- Plot Ridge Regression \033[0m' '\n')
mplt.show()

# calculate the coefficients
print('\033[1m \033[4m7B- Ridge Regression Coefficients \033[0m' '\n')
print('  Coeficiencts: ', list(RidgeReg_Model.coef_))
print('\n')

# calculate root mean squared error
Ridge_Training_rmse = sqrt(mean_squared_error(y_closepx_train.reshape(-1,1),
Ridge_Test_rmse = sqrt(mean_squared_error(y_closepx_test.reshape(-1,1), Ridg
print('\033[1m \033[4m7C- Ridge Root Mean Square Error \033[0m' '\n')
print('     Ridge Regression Training RMSE = ' + str(Ridge_Training_rmse))
print('     Ridge Regression Testing RMSE = ' + str(Ridge_Test_rmse))
print('\n')

# calculate the variance which is squared deviation of a variable from its m
#A low value for variance indicates that the data are clustered together and
# whereas a high value would indicate that the data in the given set are muc
print('\033[1m \033[4m7D-  Ridge Regression Variance \033[0m' '\n')
print('  Ridge Variance: ', r2_score(y_closepx_test, Ridge_Test_Predictions)
print('\n')

### Use the score method to evaluate the trained model
# The score method finds the mean accuracy of self.predict(X) with y of the
Ridge_Confidence_Score = RidgeReg_Model.score(X_daterange_test, y_closepx_te
print('\033[1m \033[4m7E-  Ridge Regression Confidence \033[0m'  '\n')
print(' The Ridge regression confidence is ' + str(Ridge_Confidence_Score) +

##################### Lasso Regression ######################################
```

```
# Lasso uses shrinkage. Shrinkage is where data values are shrunk towards a
# When alpha is 0 , Lasso produces same coefficients as linear regression. W
# Create Ridge Estimator/Model Object for training, testing/prediction

print ('\x1b[43m \033[1m \033[4m8- Starting Lasso Regression \033[0m \x1b[0m

LassoReg_Model = Lasso(alpha=.1,normalize=True)
LassoReg_Model.fit(X_daterange_train, y_closepx_train)

# Test to predict with this Lasso model using training data
Lasso_Training_Predications = LassoReg_Model.predict(X_daterange_train).resh

# Test to predict with this Lasso model using test data
Lasso_Test_Predictions = LassoReg_Model.predict(X_daterange_test).reshape(-1

# Combine the training and testing predictions; Joining the two arrays along
Lasso_All_Predictions = np.concatenate((Lasso_Training_Predications, Lasso_T

# transform the prediction data to dataframe and plot the prediction results
df_Lasso_reg = pd.DataFrame(Lasso_All_Predictions, columns=[myStock+' Lasso
df_Lasso_reg[df_Stock.columns[-1]] = y_closepx
# plot the results of Ridge regression
df_Lasso_reg.plot(label=myStock+'_Lasso Regression', figsize=(14,7), title=c
Train_test_split_time = df_Stock.index[Train_Data_Ind]
# Add the train and test split timing line
mplt.axvline(pd.Timestamp(Train_test_split_time),color='r', linestyle='--')
print('\033[1m \033[4m8A- Plot Lasso Regression \033[0m' '\n')
mplt.show()

# calculate the coefficients
print('\033[1m \033[4m8B- Lasso Regression Coefficients \033[0m' '\n')
print('  Coeficiencts: ', list(LassoReg_Model.coef_))
print('\n')

# calculate root mean squared error
Lasso_Training_rmse = sqrt(mean_squared_error(y_closepx_train.reshape(-1,1),
Lasso_Test_rmse = sqrt(mean_squared_error(y_closepx_test.reshape(-1,1), Lass
print('\033[1m \033[4m8C- Lasso Root Mean Square Error \033[0m' '\n')
print('     Lasso Regression Training RMSE = ' + str(Lasso_Training_rmse))
print('     Lasso Regression Testing RMSE = ' + str(Lasso_Test_rmse))
print('\n')

# calculate the variance which is squared deviation of a variable from its m
#A low value for variance indicates that the data are clustered together and
# whereas a high value would indicate that the data in the given set are muc
print('\033[1m \033[4m8D-  Lasso Regression Variance \033[0m' '\n')
print('  Lasso Variance: ', r2_score(y_closepx_test, Lasso_Test_Predictions)
print('\n')

### Use the score method to evaluate the trained model
# The score method finds the mean accuracy of self.predict(X) with y of the
Lasso_Confidence_Score = LassoReg_Model.score(X_daterange_test, y_closepx_te
print('\033[1m \033[4m8E-  Lasso Regression Confidence \033[0m'  '\n')
print(' The Lasso regression confidence is ' + str(Lasso_Confidence_Score) +

##################### KNN - K Nearest Neighbor Regression ##################
# K nearest neighbors is a simple algorithm that stores all available cases
```

```
# Create KNN Estimator/Model Object for training, testing/prediction

print ('\x1b[43m \033[1m \033[4m9- Starting KNN Regression \033[0m \x1b[0m'

KNNReg_Model = KNeighborsRegressor(n_neighbors=5)
KNNReg_Model.fit(X_daterange_train, y_closepx_train)

# Test to predict with this KNN model using training data
KNN_Training_Predications = KNNReg_Model.predict(X_daterange_train).reshape(

# Test to predict with this KNN model using test data
KNN_Test_Predictions = KNNReg_Model.predict(X_daterange_test).reshape(-1,1)

# Combine the training and testing predictions; Joining the two arrays along
KNN_All_Predictions = np.concatenate((KNN_Training_Predications, Lasso_Test_

# transform the prediction data to dataframe and plot the prediction results
df_KNN_reg = pd.DataFrame(KNN_All_Predictions, columns=[myStock+' KNN Regr '
df_KNN_reg[df_Stock.columns[-1]] = y_closepx
# plot the results of Ridge regression
df_KNN_reg.plot(label=myStock+'_KNN Regression', figsize=(14,7), title=df_St
Train_test_split_time = df_Stock.index[Train_Data_Ind]
# Add the train and test split timing line
mplt.axvline(pd.Timestamp(Train_test_split_time),color='r', linestyle='--')
print('\033[1m \033[4m9A- Plot KNN Regression \033[0m' '\n')
mplt.show()

# calculate the coefficients
print('\033[1m \033[4m9B- KNN Regression Coefficients \033[0m' '\n')
#print('  Coeficiencts: ', KNNReg_Model.coef_)
print('   KNN classifier does not expose .coef_ or "feature impoertances_" a
print('\n')

# calculate root mean squared error
KNN_Training_rmse = sqrt(mean_squared_error(y_closepx_train.reshape(-1,1), K
KNN_Test_rmse = sqrt(mean_squared_error(y_closepx_test.reshape(-1,1), KNN_Te
print('\033[1m \033[4m9C- KNN Root Mean Square Error \033[0m' '\n')
print('     KNN Regression Training RMSE = ' + str(KNN_Training_rmse))
print('     KNN Regression Testing RMSE = ' + str(KNN_Test_rmse))
print('\n')

# calculate the variance which is squared deviation of a variable from its m
#A low value for variance indicates that the data are clustered together and
# whereas a high value would indicate that the data in the given set are muc
print('\033[1m \033[4m9D-  KNN Regression Variance \033[0m' '\n')
print('  KNN Variance: ', r2_score(y_closepx_test, KNN_Test_Predictions))
print('\n')

### Use the score method to evaluate the trained model
# The score method finds the mean accuracy of self.predict(X) with y of the
KNN_Confidence_Score = KNNReg_Model.score(X_daterange_test, y_closepx_test)
print('\033[1m \033[4m9E-  KNN Regression Confidence \033[0m'  '\n')
print(' The KNN regression confidence is ' + str(KNN_Confidence_Score) + '\r
```

```
1- Downloaded AAPL stock historical data from 01/01/17 and stored to 09/12/19
stored to AAPL.csv file
```

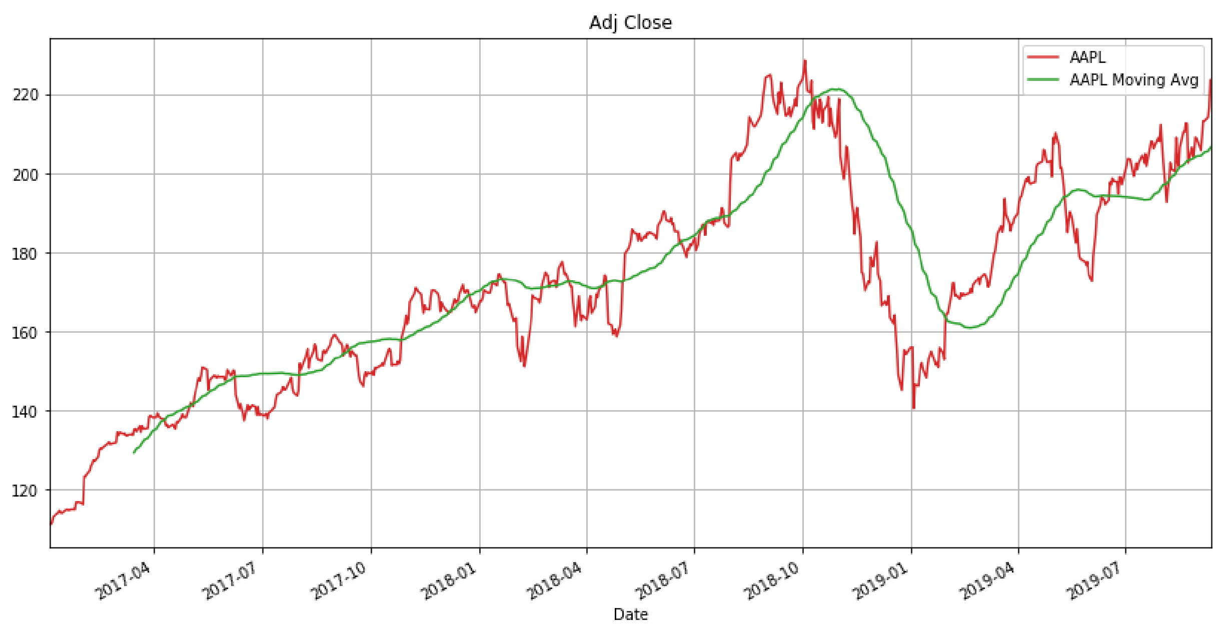
Stock Prices from Yahoo Finance

```
                  High         Low        Open       Close      Volume    Adj
 Close
Date
2019-09-06  214.419998  212.509995  214.050003  213.259995  19362300.0  213.2
59995
2019-09-09  216.440002  211.070007  214.839996  214.169998  27309400.0  214.1
69998
2019-09-10  216.779999  211.710007  213.860001  216.699997  31777900.0  216.6
99997
2019-09-11  223.710007  217.729996  218.070007  223.589996  44289600.0  223.5
89996
2019-09-12  226.419998  222.860001  224.800003  223.089996  32226700.0  223.0
89996
```

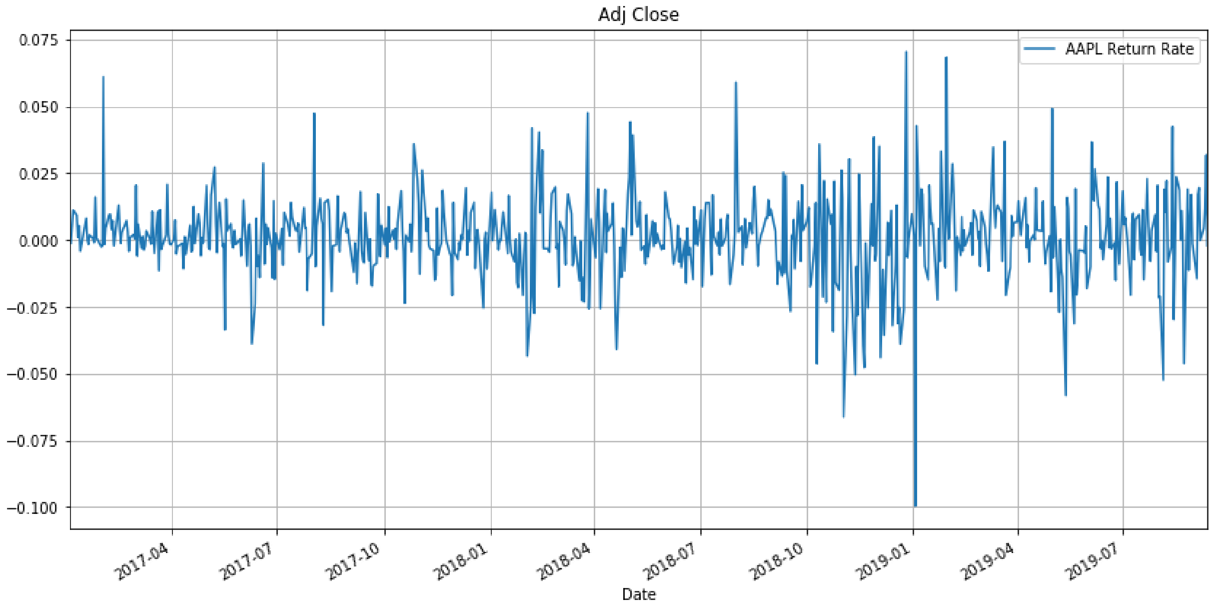
2- Note: AAPL Moving Average steadily rises over the window and does not foll
ow the jagged line of stocks price chart.

Stock Rolling Mean/Moving Average(50 Day)

```
2019-09-06    205.2584
2019-09-09    205.5470
2019-09-10    205.9226
2019-09-11    206.3634
2019-09-12    206.7706
```



3- Stock Return Rate



4-Display Stock Adj Close, Volume, Price(High-Low) % Change, Price(Open-Close) % Change

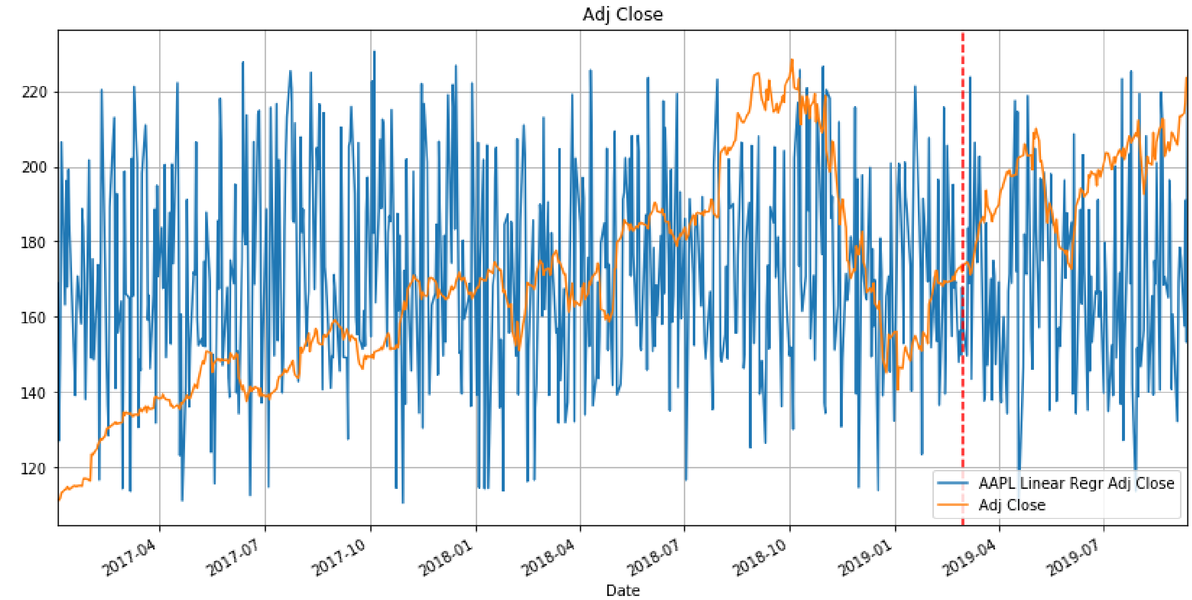
```
              Adj Close      Volume    HL_PCT  PCT_change
Date
2019-09-06  213.259995  19362300.0  0.895622   -0.369077
2019-09-09  214.169998  27309400.0  2.507352   -0.311859
2019-09-10  216.699997  31777900.0  2.339636    1.327970
2019-09-11  223.589996  44289600.0  2.674543    2.531292
2019-09-12  223.089996  32226700.0  1.595767   -0.760679
```

5- Regression Data Details

```
Total data size is 678
Training data size is 542
Test data size is 136
Train Test Split Time is = 2019-03-01 00:00:00
```

6- Starting Linear Regression

6A- Plot Linear Regression



6B- Linear Regression Coefficients

```
 Coeficiencts:  [0.23184183304399927, -0.1600277975748949, -0.0192132465164468
92, 0.9790344230602899, -1.1786819686943062e-08]
```

6C- Linear Regression Root Mean Square Error

```
    Linear Regression Training RMSE = 1.2658994143896096
    Linear Regression Testing RMSE = 1.3074252809265676
```

6D- Linear Regression Variance

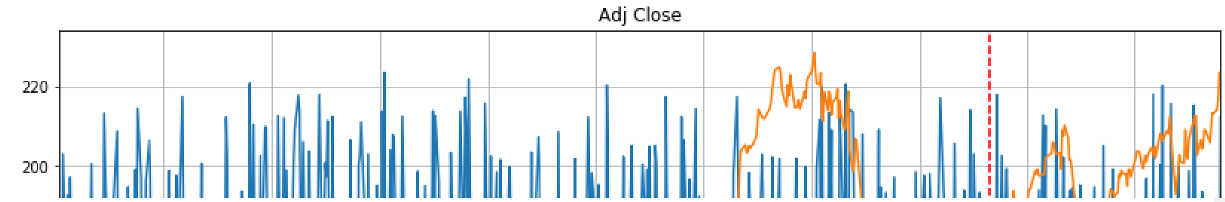
```
 Variance:  0.9973777860562006
```

6E- Linear Regression Confidence

```
The linear regression confidence is 0.9973777860562006
```

7- Starting Ridge Regression

7A- Plot Ridge Regression



7B- Ridge Regression Coefficients

```
 Coeficiencts:  [0.22697363525972097, 0.23332711607726236, 0.227512389182273
43, 0.23356822345700018, -1.6811634158736148e-09]
```

7C- Ridge Root Mean Square Error

```
    Ridge Regression Training RMSE = 3.4435495433147483
    Ridge Regression Testing RMSE = 3.390191221984911
```

7D- Ridge Regression Variance

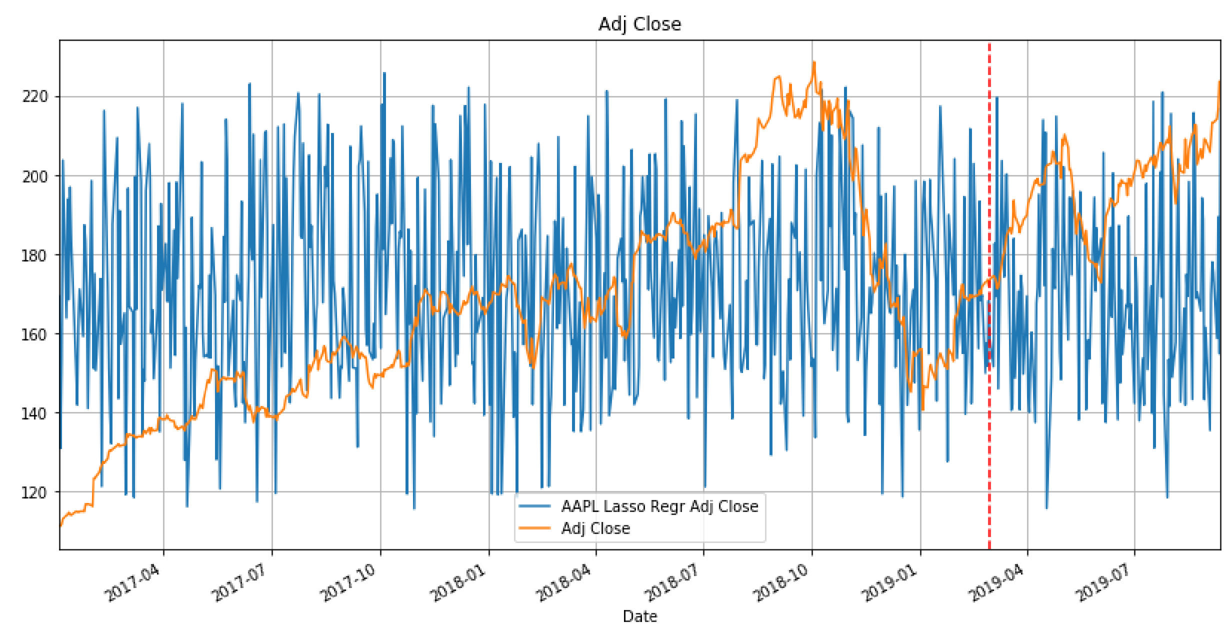
```
 Ridge Variance:  0.982368764118754
```

7E- Ridge Regression Confidence

```
The Ridge regression confidence is 0.982368764118754
```

8- Starting Lasso Regression

8A- Plot Lasso Regression



8B- Lasso Regression Coefficients

```
 Coeficiencts:  [0.08960611925402737, 0.0, 0.0, 0.8577694575702028, 0.0]
```

8C- Lasso Root Mean Square Error

```
Lasso Regression Training RMSE = 2.6564740441005776
Lasso Regression Testing RMSE = 2.642447814668225
```

8D- Lasso Regression Variance

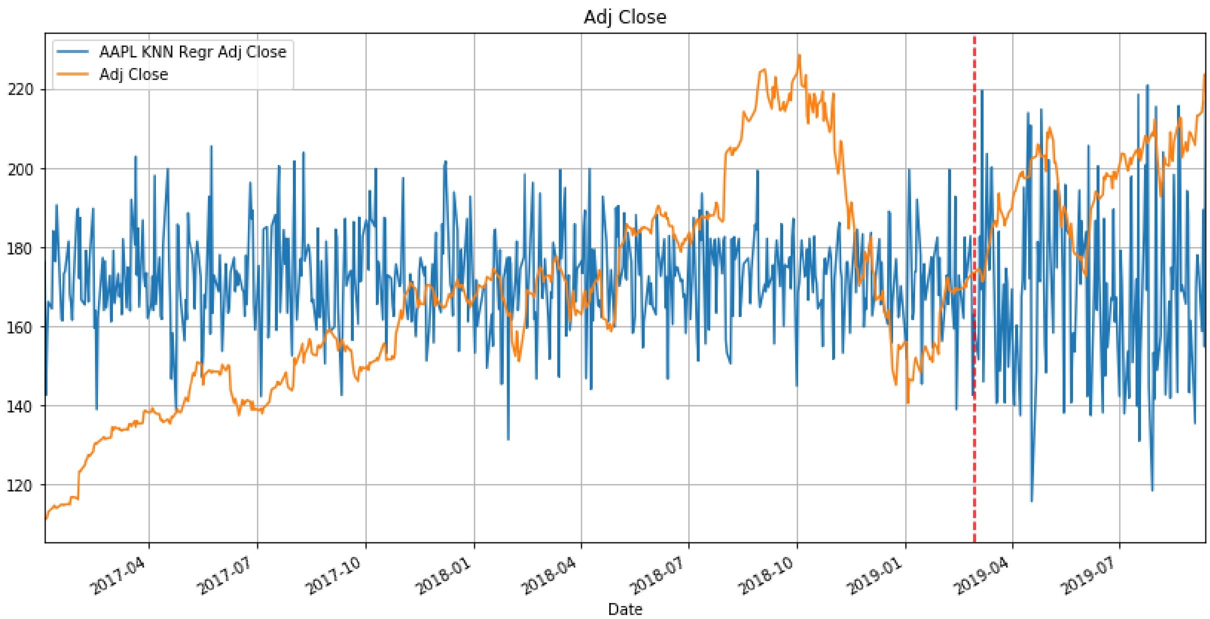
```
Lasso Variance:  0.989288576163058
```

8E- Lasso Regression Confidence

```
The Lasso regression confidence is 0.989288576163058
```

9- Starting KNN Regression

9A- Plot KNN Regression



9B- KNN Regression Coefficients

```
KNN classifier does not expose .coef_ or "feature impoertances_" attributes
```

9C- KNN Root Mean Square Error

```
KNN Regression Training RMSE = 24.11837396893226
KNN Regression Testing RMSE = 29.17366500844846
```

9D- KNN Regression Variance

```
KNN Variance:  -0.3056186623348609
```

9E- KNN Regression Confidence

```
The KNN regression confidence is -0.3056186623348609
```

In [ ]:

```
1
```