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In [1]: 1 # This program predicts stock price using four machine Learning regression models
2 # 1) Creates a .csv file with historical data of the stock
3 # 2) Calculates and plots stock's Rolling Mean/Moving Average, stock Return
4 # 3) Performs/plots Linear Regression, predicts stock price, calculates rmse,
5 # 4) Performs/plots Ridge Regression, predicts stock price, calculates rmse,
6 # 5) Performs/plots Lasso Regression, predicts stock price, calculates rmse,
7 # 6) Performs/plots KNN Regression, predicts stock price, calculates rmse, v
8
9 # Import yfinance with alias of yf
10 import yfinance as yf
11 # Import numpy as np for large, multi-dimensional arrays, matrices and mathematical operations
12 import numpy as np
13 # Import pandas as pd for data manipulation, analysis, data structures and data I/O
14 import pandas as pd
15 # import external pandas_datareader library with alias of pdr
16 import pandas_datareader as pdr
17 # import matplotlib library with alias of mplt. Pyplot module provides simple interface for plotting
18 import matplotlib.pyplot as plt
19 from matplotlib import style
20 %matplotlib inline
21 # import datetime internal datetime python module which supplies classes for manipulating dates and times
22 import datetime
23 # import math module for mathematical operations can be performed with ease
24 import math
25 from math import sqrt
26 import warnings
27 warnings.filterwarnings('ignore')
28 # sklearn.metrics has a mean_squared_error function. The RMSE is just the square root of the mean_squared_error
29 from sklearn.metrics import mean_squared_error
30 # R^2 (coefficient of determination) regression score function. Best possible value is 1.0 and worst is 0.0.
31 from sklearn.metrics import r2_score
32 # split the dataset into the training and the testing datasets; train_test_split
33 from sklearn.model_selection import train_test_split
34 # LinearRegression(fit_intercept=True, normalize=False, copy_X=True, n_jobs=None)
35 from sklearn.linear_model import LinearRegression
36 # supervised learning through Ridge regression. In ridge regression, the coefficients are penalized by a constant value
37 from sklearn.linear_model import Ridge
38 # supervised learning through Lasso regression. Lasso performs both variable selection and regularization
39 from sklearn.linear_model import Lasso
40 # KNN algorithm uses 'feature similarity' to predict values of any new data
41 from sklearn.neighbors import KNeighborsRegressor
42
43 ### define the stock, start date and end date for downloading stock data from yahoo
44 start = datetime.datetime(2017,1,1)
45 end = datetime.datetime(2019,9,12)
46
47 # Choose the stock ticker symbol
48 myStock = 'AAPL'
49
50 ### Extract stock historical data from Yahoo into dataframe
51 df_Stock = pdr.DataReader(myStock, 'yahoo', start, end)
52 # Create .csv file with stock historical data
53 df_Stock.to_csv(myStock + '.csv')
54 print ('1- Downloaded ' + myStock + ' stock historical data from ' + start.strftime('%Y-%m-%d') + ' to ' + end.strftime('%Y-%m-%d'))
55 # Display the last 5 records of the stock dataframe
56 print ('\033[1m \033[4mStock Prices from Yahoo Finance \033[0m' + "\n")

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57 with pd.option_context('expand_frame_repr', False):
58     print(df_Stock.tail())
59 print("\n")
60
61 ### Plot stock's adjusted close price and moving average
62 print ('2- Note: ' + myStock + ' Moving Average steadily rises over the window')
63 # Plot stock's adjusted close price
64 df_Stock["Adj Close"].plot(title=df_Stock.columns[5], label = myStock, color='red')
65 # Calculate the Rolling Mean (Moving Average) of the stock to determine the trend
66 df_Stock_close_pr = df_Stock['Close']
67 df_Stock_MovingAv = df_Stock_close_pr.rolling(window=50).mean()
68 # Display the last 5 stock moving average records
69 with pd.option_context('expand_frame_repr', False):
70     print('\033[1m \033[4mStock Rolling Mean/Moving Average(50 Day)\033[0m')
71     print(df_Stock_MovingAv.tail().to_string(header=None))
72 # Plot Stock's Rolling Mean Moving Average
73 df_Stock_MovingAv.plot(title=df_Stock.columns[5], label = myStock + ' Moving Average', color='blue')
74 plt.show()
75
76 ### Calculate stock's return rate
77 df_Stock_ret_rate = (df_Stock['Adj Close'] / df_Stock['Adj Close'].shift(1)) - 1
78 # Display stock's last 5 return rate records
79 df_Stock_ret_rate.tail().T
80 # Plot stock return rate
81 print('\033[1m \033[4m3- Stock Return Rate \033[0m')
82 df_Stock_ret_rate.plot(title=df_Stock.columns[-1], label=myStock+' Return Rate', color='green')
83 plt.show()
84
85 ### Feature Engineering
86 df_Stock_Pr_Regr = df_Stock.loc[:,['Adj Close','Volume']]
87 df_Stock_Pr_Regr['HL_PCT'] = ((df_Stock['High']-df_Stock['Low'])/df_Stock['Adj Close']) * 100
88 df_Stock_Pr_Regr['PCT_change'] = ((df_Stock['Close']-df_Stock['Open'])/df_Stock['Open']) * 100
89 # Display the last 5 records of the dataframe
90 print('\033[1m \033[4m4-Display Stock Adj Close, Volume, Price(High-Low) % Change \033[0m')
91 with pd.option_context('expand_frame_repr', False):
92     print(df_Stock_Pr_Regr.tail())
93 print("\n")
94
95 print('\033[1m \033[4m5- Regression Data Details\033[0m' '\n')
96 # Split 80% data to train and 20% data to test the model
97 Total_Data_Ind = df_Stock.shape[0]
98 print('Total data size is ' + str(Total_Data_Ind))
99 train_size = 0.8
100 #Keep 80% data for training
101 Train_Data_Ind = int(train_size * Total_Data_Ind)
102 print('Training data size is ' + str(Train_Data_Ind))
103 #Keep 20% data for testing
104 Test_Data_Ind = Total_Data_Ind - Train_Data_Ind
105 print('Test data size is ' + str(Test_Data_Ind))
106 Train_test_split_time = df_Stock.index[Train_Data_Ind]
107 print('Train Test Split Time is = ' + str(Train_test_split_time) + '\n')
108
109 # Create X and y train data sets to train the model
110 X_daterange = df_Stock.iloc[:, :-1].to_numpy()
111 y_closepx = df_Stock.iloc[:, -1].to_numpy()
112
113 # Split into 80% train data and 20 % test data

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114 X_daterange_train, X_daterange_test, y_closepx_train, y_closepx_test = train
115
116 ##### Linear Regression #####
117
118 print ('\x1b[43m \033[1m \033[4m6- Starting Linear Regression \033[0m \x1b[0
119
120 # Create Linear Regression Estimator/Model Object for training, testing/pred
121 LinReg_Model = LinearRegression(n_jobs=-1)
122
123 # Train the Liner Regression model using training set
124 LinReg_Model.fit(X_daterange_train, y_closepx_train)
125
126 # Test to predict with this model using training data
127 Training_Predications = LinReg_Model.predict(X_daterange_train).reshape(-1,1)
128
129 # Test to predict with this model using test data
130 Test_Predictions = LinReg_Model.predict(X_daterange_test).reshape(-1,1)
131
132 # Combine the training and testing predictions; Joining the two arrays along
133 All_Predictions = np.concatenate((Training_Predications, Test_Predictions),
134
135 # transform the prediction data to dataframe and plot the prediction results
136 df_lin_reg = pd.DataFrame(All_Predictions, columns=[myStock+' Linear Regr '])
137 df_lin_reg[df_Stock.columns[-1]] = y_closepx
138 # plot the results of linear regression
139 df_lin_reg.plot(title=df_Stock.columns[-1], label=myStock+'_Linear Regressio
140 # Add the train and test split timing line
141 mplt.axvline(pd.Timestamp(Train_test_split_time),color='r', linestyle='--')
142 print('\033[1m \033[4m6A- Plot Linear Regression \033[0m' '\n')
143 mplt.show()
144
145 # calculate the coefficients
146 print('\033[1m \033[4m6B- Linear Regression Coefficients \033[0m' '\n')
147 print(' Coeficiencts: ', list(LinReg_Model.coef_))
148 print('\n')
149
150 # calculate root mean squared error
151 Training_rmse = sqrt(mean_squared_error(y_closepx_train.reshape(-1,1), Train
152 Test_rmse = sqrt(mean_squared_error(y_closepx_test.reshape(-1,1), Test_Pred
153 print('\033[1m \033[4m6C- Linear Regression Root Mean Square Error \033[0m'
154 print(' Linear Regression Training RMSE = ' + str(Training_rmse))
155 print(' Linear Regression Testing RMSE = ' + str(Test_rmse))
156 print('\n')
157
158 # calculate the variance which is squared deviation of a variable from its m
159 #A low value for variance indicates that the data are clustered together and
160 # whereas a high value would indicate that the data in the given set are muc
161 print('\033[1m \033[4m6D- Linear Regression Variance \033[0m' '\n')
162 print(' Variance: ', r2_score(y_closepx_test, Test_Predictions))
163 print('\n')
164
165 ### Use the score method to evaluate the trained model
166 # The score method finds the mean accuracy of self.predict(X) with y of the
167 Confidence_Score = LinReg_Model.score(X_daterange_test, y_closepx_test)
168 print('\033[1m \033[4m6E- Linear Regression Confidence \033[0m' '\n')
169 print(' The linear regression confidence is ' + str(Confidence_Score) + '\n'
170

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171 ##### Ridge Regression #####
172 # Ridge Regression is a technique for analyzing multiple regression data tha
173 # By adding a degree of bias to the regression estimates, ridge regression r
174 # Create Ridge Estimator/Model Object for training, testing/prediction
175
176 print ('\x1b[43m \033[1m \033[4m7- Starting Ridge Regression \033[0m \x1b[0m
177
178 RidgeReg_Model = Ridge(alpha=.5,normalize=True)
179 RidgeReg_Model.fit(X_daterange_train, y_closepx_train)
180
181 # Test to predict with this model using training data
182 Ridge_Training_Predications = RidgeReg_Model.predict(X_daterange_train).resh
183
184 # Test to predict with this model using test data
185 Ridge_Test_Predictions = RidgeReg_Model.predict(X_daterange_test).reshape(-1
186
187 # Combine the training and testing predictions; Joining the two arrays along
188 Ridge_All_Predictions = np.concatenate((Ridge_Training_Predications, Ridge_T
189
190 # transform the prediction data to dataframe and plot the prediction results
191 df_Ridge_reg = pd.DataFrame(Ridge_All_Predictions, columns=[myStock+' Ridge
192 df_Ridge_reg[df_Stock.columns[-1]] = y_closepx
193 # plot the results of Ridge regression
194 df_Ridge_reg.plot(label=myStock+'_Ridge Regression', figsize=(14,7), title=c
195 Train_test_split_time = df_Stock.index[Train_Data_Ind]
196 # Add the train and test split timing line
197 mplt.axvline(pd.Timestamp(Train_test_split_time),color='r', linestyle='--')
198 print('\033[1m \033[4m7A- Plot Ridge Regression \033[0m' '\n')
199 mplt.show()
200
201 # calculate the coefficients
202 print('\033[1m \033[4m7B- Ridge Regression Coefficients \033[0m' '\n')
203 print(' Coeficiencts: ', list(RidgeReg_Model.coef_))
204 print('\n')
205
206 # calculate root mean squared error
207 Ridge_Training_rmse = sqrt(mean_squared_error(y_closepx_train.reshape(-1,1),
208 Ridge_Test_rmse = sqrt(mean_squared_error(y_closepx_test.reshape(-1,1), Ridg
209 print('\033[1m \033[4m7C- Ridge Root Mean Square Error \033[0m' '\n')
210 print(' Ridge Regression Training RMSE = ' + str(Ridge_Training_rmse))
211 print(' Ridge Regression Testing RMSE = ' + str(Ridge_Test_rmse))
212 print('\n')
213
214 # calculate the variance which is squared deviation of a variable from its m
215 #A low value for variance indicates that the data are clustered together and
216 # whereas a high value would indicate that the data in the given set are muc
217 print('\033[1m \033[4m7D- Ridge Regression Variance \033[0m' '\n')
218 print(' Ridge Variance: ', r2_score(y_closepx_test, Ridge_Test_Predictions)
219 print('\n')
220
221 ### Use the score method to evaluate the trained model
222 # The score method finds the mean accuracy of self.predict(X) with y of the
223 Ridge_Confidence_Score = RidgeReg_Model.score(X_daterange_test, y_closepx_te
224 print('\033[1m \033[4m7E- Ridge Regression Confidence \033[0m' '\n')
225 print(' The Ridge regression confidence is ' + str(Ridge_Confidence_Score) +
226
227 ##### Lasso Regression #####

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228 # Lasso uses shrinkage. Shrinkage is where data values are shrunk towards a
229 # When alpha is 0 , Lasso produces same coefficients as linear regression.
230 # Create Ridge Estimator/Model Object for training, testing/prediction
231
232 print ('\x1b[43m \033[1m \033[4m8- Starting Lasso Regression \033[0m \x1b[0m')
233
234 LassoReg_Model = Lasso(alpha=.1,normalize=True)
235 LassoReg_Model.fit(X_daterange_train, y_closepx_train)
236
237 # Test to predict with this Lasso model using training data
238 Lasso_Training_Predications = LassoReg_Model.predict(X_daterange_train).reshape(-1)
239
240 # Test to predict with this Lasso model using test data
241 Lasso_Test_Predictions = LassoReg_Model.predict(X_daterange_test).reshape(-1)
242
243 # Combine the training and testing predictions; Joining the two arrays along
244 Lasso_All_Predictions = np.concatenate((Lasso_Training_Predications, Lasso_Test_Predictions))
245
246 # transform the prediction data to dataframe and plot the prediction results
247 df_Lasso_reg = pd.DataFrame(Lasso_All_Predictions, columns=[myStock+' Lasso'])
248 df_Lasso_reg[df_Stock.columns[-1]] = y_closepx
249 # plot the results of Ridge regression
250 df_Lasso_reg.plot(label=myStock+' _Lasso Regression', figsize=(14,7), title=myStock+' Lasso Regression')
251 Train_test_split_time = df_Stock.index[Train_Data_Ind]
252 # Add the train and test split timing line
253 plt.axvline(pd.Timestamp(Train_test_split_time),color='r', linestyle='--')
254 print('\033[1m \033[4m8A- Plot Lasso Regression \033[0m' '\n')
255 plt.show()
256
257 # calculate the coefficients
258 print('\033[1m \033[4m8B- Lasso Regression Coefficients \033[0m' '\n')
259 print(' Coeficients: ', list(LassoReg_Model.coef_))
260 print('\n')
261
262 # calculate root mean squared error
263 Lasso_Training_rmse = sqrt(mean_squared_error(y_closepx_train.reshape(-1,1), Lasso_Training_Predications))
264 Lasso_Test_rmse = sqrt(mean_squared_error(y_closepx_test.reshape(-1,1), Lasso_Test_Predictions))
265 print('\033[1m \033[4m8C- Lasso Root Mean Square Error \033[0m' '\n')
266 print(' Lasso Regression Training RMSE = ' + str(Lasso_Training_rmse))
267 print(' Lasso Regression Testing RMSE = ' + str(Lasso_Test_rmse))
268 print('\n')
269
270 # calculate the variance which is squared deviation of a variable from its mean
271 # A low value for variance indicates that the data are clustered together and
272 # whereas a high value would indicate that the data in the given set are much more spread out
273 print('\033[1m \033[4m8D- Lasso Regression Variance \033[0m' '\n')
274 print(' Lasso Variance: ', r2_score(y_closepx_test, Lasso_Test_Predictions))
275 print('\n')
276
277 ### Use the score method to evaluate the trained model
278 # The score method finds the mean accuracy of self.predict(X) with y of the
279 Lasso_Confidence_Score = LassoReg_Model.score(X_daterange_test, y_closepx_test)
280 print('\033[1m \033[4m8E- Lasso Regression Confidence \033[0m' '\n')
281 print(' The Lasso regression confidence is ' + str(Lasso_Confidence_Score) + '\n')
282
283 ##### KNN - K Nearest Neighbor Regression #####
284 # K nearest neighbors is a simple algorithm that stores all available cases

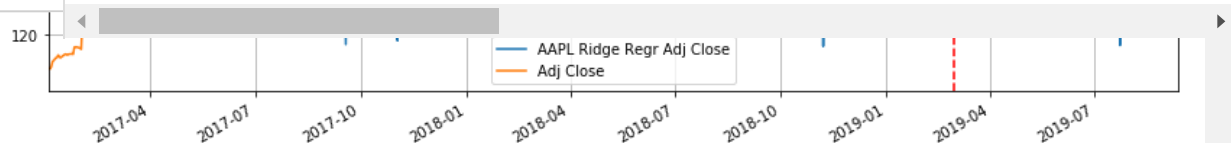
```



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285 # Create KNN Estimator/Model Object for training, testing/prediction
286
287 print ('\x1b[43m \033[1m \033[4m9- Starting KNN Regression \033[0m \x1b[0m'
288
289 KNNReg_Model = KNeighborsRegressor(n_neighbors=5)
290 KNNReg_Model.fit(X_daterange_train, y_closepx_train)
291
292 # Test to predict with this KNN model using training data
293 KNN_Training_Predications = KNNReg_Model.predict(X_daterange_train).reshape(
294
295 # Test to predict with this KNN model using test data
296 KNN_Test_Predictions = KNNReg_Model.predict(X_daterange_test).reshape(-1,1)
297
298 # Combine the training and testing predictions; Joining the two arrays along
299 KNN_All_Predictions = np.concatenate((KNN_Training_Predications, Lasso_Test_
300
301 # transform the prediction data to dataframe and plot the prediction results
302 df_KNN_reg = pd.DataFrame(KNN_All_Predictions, columns=[myStock+' KNN Regr '
303 df_KNN_reg[df_Stock.columns[-1]] = y_closepx
304 # plot the results of Ridge regression
305 df_KNN_reg.plot(label=myStock+'_KNN Regression', figsize=(14,7), title=df_St
306 Train_test_split_time = df_Stock.index[Train_Data_Ind]
307 # Add the train and test split timing line
308 plt.axvline(pd.Timestamp(Train_test_split_time),color='r', linestyle='--')
309 print('\033[1m \033[4m9A- Plot KNN Regression \033[0m' '\n')
310 plt.show()
311
312 # calculate the coefficients
313 print('\033[1m \033[4m9B- KNN Regression Coefficients \033[0m' '\n')
314 #print(' Coeficiencts: ', KNNReg_Model.coef_)
315 print(' KNN classifier does not expose .coef_ or "feature impoertances_" a
316 print('\n')
317
318 # calculate root mean squared error
319 KNN_Training_rmse = sqrt(mean_squared_error(y_closepx_train.reshape(-1,1), K
320 KNN_Test_rmse = sqrt(mean_squared_error(y_closepx_test.reshape(-1,1), KNN_Te
321 print('\033[1m \033[4m9C- KNN Root Mean Square Error \033[0m' '\n')
322 print(' KNN Regression Training RMSE = ' + str(KNN_Training_rmse))
323 print(' KNN Regression Testing RMSE = ' + str(KNN_Test_rmse))
324 print('\n')
325
326 # calculate the variance which is squared deviation of a variable from its m
327 #A low value for variance indicates that the data are clustered together and
328 # whereas a high value would indicate that the data in the given set are muc
329 print('\033[1m \033[4m9D- KNN Regression Variance \033[0m' '\n')
330 print(' KNN Variance: ', r2_score(y_closepx_test, KNN_Test_Predictions))
331 print('\n')
332
333 ### Use the score method to evaluate the trained model
334 # The score method finds the mean accuracy of self.predict(X) with y of the
335 KNN_Confidence_Score = KNNReg_Model.score(X_daterange_test, y_closepx_test)
336 print('\033[1m \033[4m9E- KNN Regression Confidence \033[0m' '\n')
337 print(' The KNN regression confidence is ' + str(KNN_Confidence_Score) + '\n

```



7B- Ridge Regression Coefficients

Coefficients: [0.22711130079399186, 0.23305398592477777, 0.22726519086366118, 0.23427660564532615, 1.037471050896199e-09]

7C- Ridge Root Mean Square Error

Ridge Regression Training RMSE = 3.3533378052243212

Ridge Regression Testing RMSE = 3.6930781224734592

7D- Ridge Regression Variance

variance inflation factor (VIF) = 1.0000000000000002