aapl prediction

June 4, 2023

```
[48]: import yfinance as yf
      import pandas as pd
      import numpy as np
      import matplotlib.pyplot as plt
      from sklearn.preprocessing import MinMaxScaler
      from tensorflow.keras.models import Sequential
      from tensorflow.keras.layers import Dense
      from tensorflow.keras.layers import LSTM
      from tensorflow.keras.layers import Dropout
      from sklearn.metrics import mean_squared_error, mean_absolute_error
 [2]: aapl=pd.read_csv("C:/Users/jakey/OneDrive/Documents/personal projects/
       ⇒predicting AAPL stock price\AAPL.csv",index_col='Date')
      aapl
      #10409 days
 [2]:
                                                                   Adj Close \
                        Open
                                    High
                                                           Close
                                                 Low
      Date
                                0.128906
                                                        0.128348
      1980-12-12
                    0.128348
                                            0.128348
                                                                    0.100323
      1980-12-15
                    0.122210
                                0.122210
                                            0.121652
                                                        0.121652
                                                                    0.095089
      1980-12-16
                    0.113281
                                0.113281
                                            0.112723
                                                        0.112723
                                                                    0.088110
      1980-12-17
                    0.115513
                                0.116071
                                            0.115513
                                                        0.115513
                                                                    0.090291
      1980-12-18
                                0.119420
                                            0.118862
                                                        0.118862
                                                                    0.092908
                    0.118862
      2022-03-18 160.509995
                                                      163.979996
                              164.479996
                                          159.759995
                                                                  163.979996
      2022-03-21 163.509995
                              166.350006
                                          163.009995
                                                      165.380005
                                                                  165.380005
      2022-03-22 165.509995
                              169.419998
                                          164.910004
                                                      168.820007
                                                                  168.820007
                              172.639999
      2022-03-23 167.990005
                                          167.649994 170.210007
                                                                  170.210007
      2022-03-24 171.059998
                              174.139999
                                          170.210007
                                                      174.070007
                                                                  174.070007
                     Volume
      Date
      1980-12-12
                  469033600
      1980-12-15
                  175884800
      1980-12-16 105728000
      1980-12-17
                   86441600
      1980-12-18
                   73449600
```

```
    2022-03-18
    123351200

    2022-03-21
    95811400

    2022-03-22
    81532000

    2022-03-23
    98062700

    2022-03-24
    90018700
```

[10409 rows x 6 columns]

[3]: aapl.describe()

[3]:		Open	High	Low	Close	Adj Close	\
	count	10409.000000	10409.000000	10409.000000	10409.000000	10409.000000	
	mean	13.959910	14.111936	13.809163	13.966757	13.350337	
	std	30.169244	30.514878	29.835055	30.191696	29.911132	
	min	0.049665	0.049665	0.049107	0.049107	0.038384	
	25%	0.281964	0.287946	0.274554	0.281250	0.234799	
	50%	0.468750	0.477679	0.459821	0.468750	0.386853	
	75%	14.217857	14.364286	14.043571	14.206071	12.188149	
	max	182.630005	182.940002	179.119995	182.009995	181.778397	

Volume

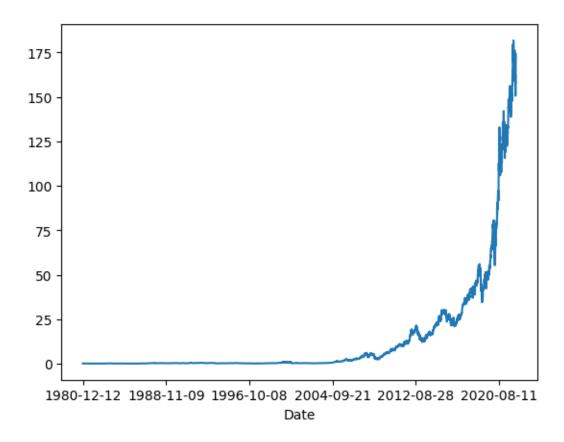
```
1.040900e+04
count
       3.321778e+08
mean
std
       3.393344e+08
       0.000000e+00
min
25%
       1.247604e+08
50%
       2.199680e+08
75%
       4.126108e+08
max
       7.421641e+09
```

[4]: #Check for any missing values values aapl.isnull().values.any()

[4]: False

[5]: aapl['Adj Close'].plot()

[5]: <Axes: xlabel='Date'>



```
[6]: #target variable=dependent variable
target=pd.DataFrame(aapl['Adj Close'])
#feature variables=independent variables
features=['Open','High','Low','Volume']
#Scaling data between 0 and 1 for precision and memory consumption
scaler=MinMaxScaler(feature_range=(0,1))
features_transform=scaler.fit_transform(aapl[features])
feature_transform=pd.
DataFrame(columns=features,data=features_transform,index=aapl.index)
feature_transform
```

[6]:		Open	High	Low	Volume
	Date				
	1980-12-12	0.000431	0.000433	0.000443	0.063198
	1980-12-15	0.000397	0.000397	0.000405	0.023699
	1980-12-16	0.000348	0.000348	0.000355	0.014246
	1980-12-17	0.000361	0.000363	0.000371	0.011647
	1980-12-18	0.000379	0.000381	0.000390	0.009897
	•••	•••	•••		
	2022-03-18	0.878848	0.899065	0.891886	0.016620
	2022-03-21	0.895279	0.909290	0.910036	0.012910

```
2022-03-23  0.919816  0.943682  0.935947  0.013213
    2022-03-24 0.936631 0.951884 0.950243 0.012129
    [10409 rows x 4 columns]
[51]: #Split Training and Test sets with 80/20
    test_ratio=.1
    training_ratio=1-test_ratio
    test_size=int(test_ratio*len(aapl))
    training_size=int(training_ratio*len(aapl))
    x_train,x_test=feature_transform[:
     →training_size],feature_transform[training_size:]
    y_train,y_test=target[:training_size],target[training_size:]
    train_x,test_x=np.array(x_train),np.array(x_test)
    \#n \times m \rightarrow n \text{ arrays containing 1 array with } m \text{ elements}
    x_train=train_x.reshape(x_train.shape[0],1,x_train.shape[1])
    x_test=test_x.reshape(x_test.shape[0],1,x_test.shape[1])
[52]: lstm=Sequential()
    lstm.add(LSTM(32,input_shape=(1,train_x.
    ⇔shape[1]),activation='relu',return_sequences=False))
    lstm.add(Dense(1))
    lstm.compile(loss='mean squared error',optimizer='adam')
    history=lstm.
     -fit(x train,y train,epochs=100,batch size=32,verbose=1,shuffle=False)
   Epoch 1/100
   293/293 [============== ] - 1s 716us/step - loss: 88.7918
   Epoch 2/100
   293/293 [============ ] - 0s 680us/step - loss: 76.9560
   Epoch 3/100
   Epoch 4/100
   Epoch 5/100
   Epoch 6/100
   Epoch 7/100
   Epoch 8/100
   Epoch 9/100
   Epoch 10/100
   293/293 [============= ] - 0s 719us/step - loss: 35.5283
   Epoch 11/100
```

2022-03-22 0.906233 0.926076 0.920646 0.010986

293/293 [======]	_	0s	740us/step	_	loss:	29.3769
Epoch 12/100			. 10 a2, 200p			
293/293 [=========]	_	0s	712us/step	_	loss:	23.1234
Epoch 13/100			-			
293/293 [====================================	_	0s	711us/step	_	loss:	17.2399
Epoch 14/100			_			
293/293 [====================================	-	0s	705us/step	_	loss:	12.1046
Epoch 15/100			_			
293/293 [====================================	-	0s	710us/step	-	loss:	7.9437
Epoch 16/100						
293/293 [=======]	-	0s	698us/step	-	loss:	4.8293
Epoch 17/100						
293/293 [========]	-	0s	701us/step	-	loss:	2.6983
Epoch 18/100						
293/293 [========]	-	0s	684us/step	-	loss:	1.3810
Epoch 19/100						
293/293 [=======]	-	0s	701us/step	-	loss:	0.6531
Epoch 20/100						
293/293 [====================================	-	0s	686us/step	-	loss:	0.2975
Epoch 21/100						
293/293 [====================================	-	0s	677us/step	-	loss:	0.1457
Epoch 22/100						
293/293 [====================================	-	0s	683us/step	-	loss:	0.0900
Epoch 23/100						
293/293 [====================================	-	0s	679us/step	-	loss:	0.0732
Epoch 24/100						
293/293 [====================================	-	0s	679us/step	-	loss:	0.0699
Epoch 25/100						
293/293 [====================================	-	0s	672us/step	-	loss:	0.0704
Epoch 26/100						
293/293 [====================================	-	0s	692us/step	-	loss:	0.0715
Epoch 27/100						
293/293 [====================================	-	0s	682us/step	-	loss:	0.0724
Epoch 28/100						
293/293 [====================================	-	0s	711us/step	_	loss:	0.0729
Epoch 29/100			_			
293/293 [====================================	-	0s	730us/step	_	loss:	0.0728
Epoch 30/100			_			
293/293 [====================================	-	0s	718us/step	-	loss:	0.0723
Epoch 31/100			_			
293/293 [====================================	-	0s	698us/step	-	loss:	0.0712
Epoch 32/100			_			
293/293 [====================================	-	0s	710us/step	_	loss:	0.0697
Epoch 33/100			_			
293/293 [====================================	-	0s	715us/step	_	loss:	0.0681
Epoch 34/100			-			
293/293 [====================================	-	0s	687us/step	_	loss:	0.0666
Epoch 35/100			-			

293/293 [====================================	0653
Epoch 36/100	
293/293 [====================================	0643
Epoch 37/100	
293/293 [====================================	0637
Epoch 38/100	
293/293 [====================================	0634
Epoch 39/100 293/293 [====================================	0622
Epoch 40/100	0633
293/293 [====================================	0634
Epoch 41/100	0004
293/293 [====================================	0637
Epoch 42/100	
293/293 [====================================	0640
Epoch 43/100	
293/293 [============] - Os 696us/step - loss: 0.	0643
Epoch 44/100	
293/293 [============] - Os 720us/step - loss: 0.	0647
Epoch 45/100	
293/293 [====================================	0652
Epoch 46/100	
293/293 [====================================	0656
Epoch 47/100	0001
293/293 [====================================	0661
Epoch 48/100 293/293 [====================================	0666
Epoch 49/100	0666
293/293 [====================================	0672
Epoch 50/100	0012
293/293 [====================================	0677
Epoch 51/100	
293/293 [====================================	0684
Epoch 52/100	
293/293 [===========] - Os 698us/step - loss: 0.	0690
Epoch 53/100	
293/293 [====================================	0696
Epoch 54/100	
293/293 [====================================	0702
Epoch 55/100	
293/293 [====================================	0708
Epoch 56/100	0711
293/293 [====================================	0714
Epoch 57/100 293/293 [====================================	071a
Epoch 58/100	0113
293/293 [====================================	0724
Epoch 59/100	— -
1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	

293/293 [========]	_	0s	692us/step	_	loss:	0.0729
Epoch 60/100			-			
293/293 [====================================	-	0s	682us/step	-	loss:	0.0734
Epoch 61/100			_			
293/293 [====================================	_	0s	722us/step	-	loss:	0.0739
Epoch 62/100			_			
293/293 [====================================	_	0s	708us/step	-	loss:	0.0743
Epoch 63/100			_			
293/293 [====================================	_	0s	695us/step	-	loss:	0.0746
Epoch 64/100						
293/293 [==========]	-	0s	698us/step	-	loss:	0.0750
Epoch 65/100			_			
293/293 [====================================	-	0s	685us/step	-	loss:	0.0753
Epoch 66/100			_			
293/293 [====================================	-	0s	712us/step	-	loss:	0.0755
Epoch 67/100						
293/293 [====================================	-	0s	679us/step	-	loss:	0.0758
Epoch 68/100						
293/293 [====================================	-	0s	698us/step	-	loss:	0.0760
Epoch 69/100			_			
293/293 [====================================	-	0s	685us/step	-	loss:	0.0762
Epoch 70/100						
293/293 [=========]	-	0s	684us/step	-	loss:	0.0763
Epoch 71/100						
293/293 [========]	-	0s	699us/step	-	loss:	0.0764
Epoch 72/100						
293/293 [========]	-	0s	689us/step	-	loss:	0.0766
Epoch 73/100						
293/293 [=======]	-	0s	700us/step	-	loss:	0.0767
Epoch 74/100						
293/293 [========]	-	0s	710us/step	-	loss:	0.0767
Epoch 75/100						
293/293 [=======]	-	0s	694us/step	-	loss:	0.0768
Epoch 76/100						
293/293 [========]	-	0s	714us/step	-	loss:	0.0768
Epoch 77/100						
293/293 [======]	-	0s	688us/step	-	loss:	0.0769
Epoch 78/100						
293/293 [======]	-	0s	700us/step	-	loss:	0.0769
Epoch 79/100						
293/293 []	-	0s	692us/step	-	loss:	0.0769
Epoch 80/100						
293/293 [======]	-	0s	704us/step	-	loss:	0.0769
Epoch 81/100						
293/293 [=======]	-	0s	709us/step	-	loss:	0.0768
Epoch 82/100						
293/293 [=======]	-	0s	681us/step	-	loss:	0.0768
Epoch 83/100						

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293/293 [============= ] - 0s 681us/step - loss: 0.0768
   Epoch 84/100
   Epoch 85/100
   Epoch 86/100
   293/293 [=========== ] - 0s 691us/step - loss: 0.0766
   Epoch 87/100
   293/293 [=========== ] - 0s 704us/step - loss: 0.0766
   Epoch 88/100
   Epoch 89/100
   Epoch 90/100
   293/293 [=========== ] - 0s 699us/step - loss: 0.0764
   Epoch 91/100
   293/293 [=========== ] - 0s 701us/step - loss: 0.0763
   Epoch 92/100
   293/293 [=========== ] - Os 685us/step - loss: 0.0763
   Epoch 93/100
   Epoch 94/100
   Epoch 95/100
   293/293 [============ ] - 0s 693us/step - loss: 0.0760
   Epoch 96/100
   293/293 [============= ] - 0s 713us/step - loss: 0.0760
   Epoch 97/100
   293/293 [============= ] - 0s 700us/step - loss: 0.0759
   Epoch 98/100
   293/293 [============= ] - 0s 715us/step - loss: 0.0758
   Epoch 99/100
   Epoch 100/100
   293/293 [=========== ] - Os 710us/step - loss: 0.0756
[55]: y_pred=lstm.predict(x_test)
   33/33 [========= ] - 0s 512us/step
[59]: y_test['Predicted']=y_pred
[60]: plt.figure(figsize=(50,10))
   plt.plot(y_train['Adj Close'],label='Training Data')
   plt.plot(y_test['Adj Close'],label='Test Data')
   plt.plot(y_test['Predicted'],label='Prediction')
   plt.legend()
   plt.show()
```

The Mean Squared Error: 76.6663812472651
The Mean Absolute Error: 6.302792272016746
The Root Mean Squared Error: 8.755934059097584