

price-prediction-using-lstm

April 2, 2024

#importing libraries and modules

```
[23]: import math

import numpy as np
import pandas as pd
import pandas_datareader.data as web
import tensorflow as tf
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import Dense, LSTM
import matplotlib.pyplot as plt
import yfinance as yf
```

#importing Data set usign pd.DataReader()

```
[25]: ticker = yf.Ticker("BTC-USD")
df = ticker.history(period="max")
```

```
[48]: df.head()
```

```
[48]:
```

	Open	High	Low	Close \
Date				
2014-09-17 00:00:00+00:00	465.864014	468.174011	452.421997	457.334015
2014-09-18 00:00:00+00:00	456.859985	456.859985	413.104004	424.440002
2014-09-19 00:00:00+00:00	424.102997	427.834991	384.532013	394.795990
2014-09-20 00:00:00+00:00	394.673004	423.295990	389.882996	408.903992
2014-09-21 00:00:00+00:00	408.084991	412.425995	393.181000	398.821014

	Volume	Dividends	Stock Splits
Date			
2014-09-17 00:00:00+00:00	21056800	0.0	0.0
2014-09-18 00:00:00+00:00	34483200	0.0	0.0
2014-09-19 00:00:00+00:00	37919700	0.0	0.0
2014-09-20 00:00:00+00:00	36863600	0.0	0.0
2014-09-21 00:00:00+00:00	26580100	0.0	0.0

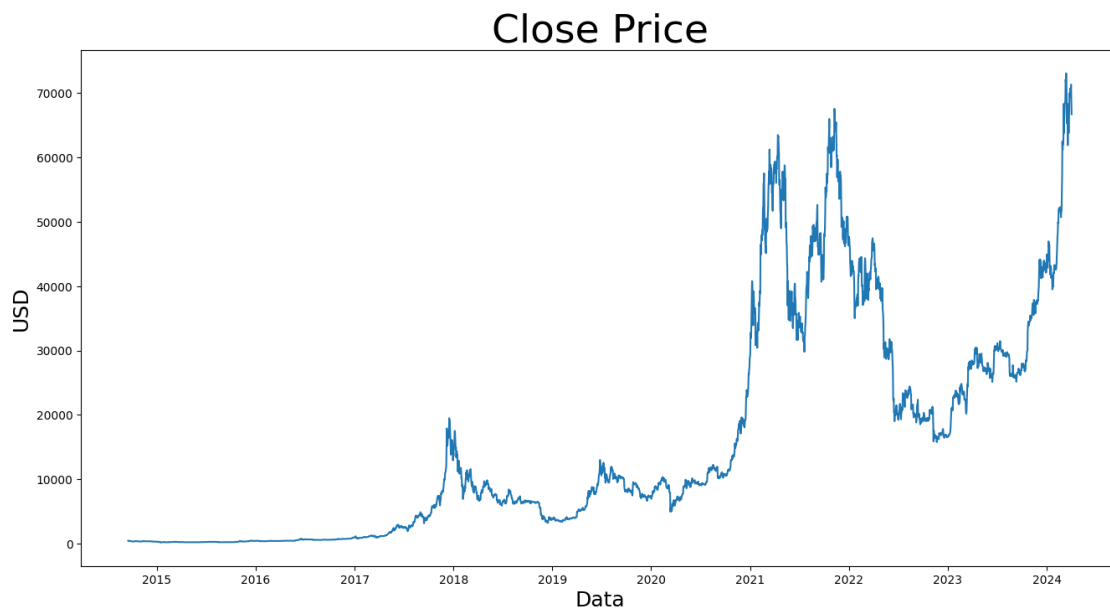
#checking shape of the data

```
[28]: df.shape
```

```
[28]: (3485, 7)
```

#let's plot our close price only

```
[32]: plt.figure(figsize=(16,8))
plt.title('Close Price', fontsize=34)
plt.plot(df['Close'])
plt.xlabel('Data', fontsize=18)
plt.ylabel('USD', fontsize=18)
plt.show()
```



#to work only with Close Price. let's use .filter method

```
[34]: data = df.filter(['Close'])
dataset = data.values
training_data_len = math.ceil(len(dataset) * .8)
training_data_len
```

```
[34]: 2788
```

#finally we Separated dataframe. Lets start the normalization of the data

```
[35]: scaler = MinMaxScaler(feature_range=(0,1))
scaled_data = scaler.fit_transform(dataset)
scaled_data
```

```
[35]: array([[0.00383005],
            [0.00337886],
            [0.00297225],
            ...,
            [0.95284032],
            [0.97599833],
            [0.91277148]])
```

#LSTM network needs to have the last output values of network layer for the input of the next layer of network. So we can't use train_test_split and randomize our train/test data

```
[36]: #Our model will predict the price by looking the last 60 days of price. this
      →will help our model to predict a better price and not just a random number
      →that would have less than %50 accuracy
```

```
# Creat the training dataset
train_data = scaled_data[0:training_data_len, :]
# Split the data into X_train and y_train data sets
X_train = []
y_train = []

for i in range(60, len(train_data)):
    X_train.append(train_data[i-60: i, 0])
    y_train.append(train_data[i, 0])

    if i <= 60:
        print(X_train)
        print(y_train)
        print()
```

```
[array([0.00383005, 0.00337886, 0.00297225, 0.00316576, 0.00302746,
        0.00307315, 0.00353455, 0.00336192, 0.00320238, 0.00310432,
        0.00303705, 0.00273063, 0.00270712, 0.00286455, 0.00281889,
        0.00270171, 0.00248828, 0.00206793, 0.00195331, 0.00208456,
        0.00216834, 0.00239814, 0.00256391, 0.0025164 , 0.00252651,
        0.0027494 , 0.00291214, 0.00305556, 0.00297193, 0.00280436,
        0.00282085, 0.00292624, 0.00290024, 0.00280832, 0.00285812,
        0.00281262, 0.00247326, 0.00247227, 0.00232038, 0.00242233,
        0.00239881, 0.0024623 , 0.00216017, 0.00229341, 0.00219762,
        0.00202517, 0.00202713, 0.00204993, 0.00209023, 0.00221359,
        0.00234807, 0.00225377, 0.00229592, 0.00253974, 0.00258995,
        0.00260052, 0.0033668 , 0.00332804, 0.0030137 , 0.00271626])])
[0.0028774137488077373]
```

```
[37]: len(X_train)
```

[37]: 2728

#so now x_train has 2728 array which any of them contains 60 days of price in them and y_train contains 2083 days of price which is the price of the last 60 days.

```
[38]: # Convert the X_train and y_train to numpy array
X_train, y_train = np.array(X_train), np.array(y_train)
```

```
[39]: X_train.shape
```

[39]: (2728, 60)

#LSTM needs the data to be inputted by 3 dimension

```
[40]: # Reshape the data because LSTM needs 3 dim
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1)) # we
    ↪ make it like pros. it wanna say "np.reshape(X_train, (2083, 60, 1))"
X_train.shape
```

[40]: (2728, 60, 1)

```
[41]: # Create the testing dataset
# Create a new array containing scaled values from index 2083
test_data = scaled_data[training_data_len - 60 : , :]

#Create the data sets X_test and y_test
X_test = []
y_test = dataset[training_data_len : , :]
for i in range(60, len(test_data)):
    X_test.append(test_data[i-60 : i, 0])
```

```
[42]: # Convert the data to a numpy array
X_test = np.array(X_test)
```

```
[43]: # Reshape the test data
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
```

#Creating the model

```
[44]: # Build LSTM model
tf.random.set_seed(42)

model_1 = Sequential()
model_1.add(LSTM(50, return_sequences=True, input_shape=(X_train.shape[1], 1)))
    ↪ # we made it like pros ;) , the simple form is "input_shape(60, 1)"
model_1.add(LSTM(50, return_sequences=False))
model_1.add(Dense(25))
model_1.add(Dense(1))
```

```
[45]: # Compile the model
model_1.compile(optimizer='adam', loss='mse')
```

#Here we make a variable call callback which has the job to stop training the model whenever the loss is no longer decreasing

```
[47]: # Train the model
callback = tf.keras.callbacks.EarlyStopping(monitor='loss', patience=2)
history = model_1.fit(X_train, y_train, batch_size=1, epochs=10)
```

```
Epoch 1/10
2728/2728 [=====] - 88s 32ms/step - loss: 5.3398e-04
Epoch 2/10
2728/2728 [=====] - 87s 32ms/step - loss: 3.5993e-04
Epoch 3/10
2728/2728 [=====] - 89s 33ms/step - loss: 3.2609e-04
Epoch 4/10
2728/2728 [=====] - 88s 32ms/step - loss: 3.0726e-04
Epoch 5/10
2728/2728 [=====] - 89s 33ms/step - loss: 2.7119e-04
Epoch 6/10
2728/2728 [=====] - 89s 32ms/step - loss: 2.9371e-04
Epoch 7/10
2728/2728 [=====] - 87s 32ms/step - loss: 2.8112e-04
Epoch 8/10
2728/2728 [=====] - 90s 33ms/step - loss: 2.7453e-04
Epoch 9/10
2728/2728 [=====] - 88s 32ms/step - loss: 2.8536e-04
Epoch 10/10
2728/2728 [=====] - 87s 32ms/step - loss: 2.6139e-04
```

```
[49]: # Get the model_1 predicted price values
predictions_1 = model_1.predict(X_test)
predictions_1 = scaler.inverse_transform(predictions_1)
print("Model_1 predicted price")
len(predictions_1)
```

```
22/22 [=====] - 2s 19ms/step
Model_1 predicted price
```

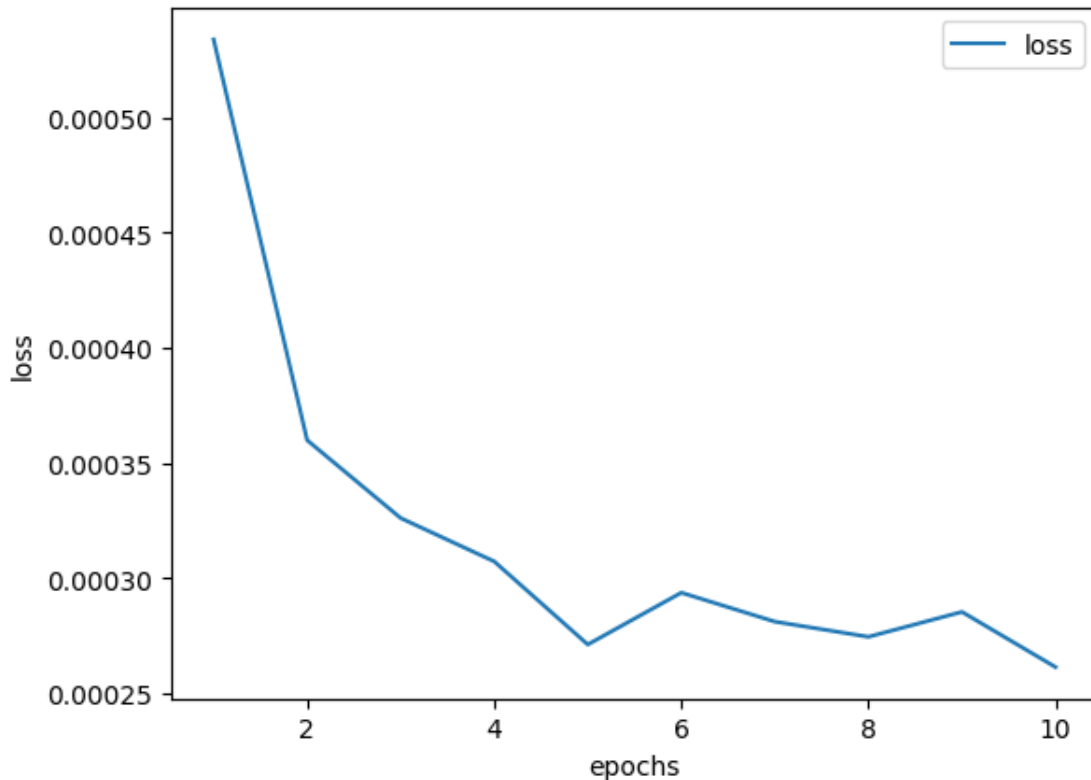
```
[49]: 697
```

```
[50]: # Get the root mean squared error (RMSE) for model_1
rmse = np.sqrt(np.mean(predictions_1 - y_test)**2)
rmse
```

```
[50]: 190.75124557254304
```

```
[51]: # Let's plot the history of model_1 and see what's going on
historyForPlot = pd.DataFrame(history.history)
historyForPlot.index += 1 # we plus 1 to the number of indexing so our epochs
    ↳ Plot picture will be counting from 1 not 0.
historyForPlot.plot()
plt.ylabel("loss")
plt.xlabel("epochs")
```

```
[51]: Text(0.5, 0, 'epochs')
```



```
[52]: # Train the model again with 7 epochs
# but first we need to create another model so we can compare them together

# building LSTM model_2
tf.random.set_seed(42)

model_2 = Sequential()
model_2.add(LSTM(50, return_sequences=True, input_shape=(X_train.shape[1], 1)))
    ↳ # we made it like pros ;) | the simple form is "input_shape(60, 1)"
model_2.add(LSTM(50, return_sequences=False))
model_2.add(Dense(25))
```

```

model_2.add(Dense(1))

# Compile model_2
model_2.compile(optimizer='Adam', loss='mse')

# Fit model_2
history_2 = model_2.fit(X_train, y_train, batch_size=1, epochs=6)

```

```

Epoch 1/6
2728/2728 [=====] - 94s 33ms/step - loss: 0.0016
Epoch 2/6
2728/2728 [=====] - 89s 33ms/step - loss: 6.9331e-04
Epoch 3/6
2728/2728 [=====] - 90s 33ms/step - loss: 4.7906e-04
Epoch 4/6
2728/2728 [=====] - 90s 33ms/step - loss: 3.8224e-04
Epoch 5/6
2728/2728 [=====] - 88s 32ms/step - loss: 3.2873e-04
Epoch 6/6
2728/2728 [=====] - 90s 33ms/step - loss: 3.3683e-04

```

```

[53]: # Get the model_2 predicted price values
predictions_2 = model_2.predict(X_test)
predictions_2 = scaler.inverse_transform(predictions_2)
len(predictions_2)

```

```

22/22 [=====] - 2s 24ms/step

```

[53]: 697

```

[54]: # Get the root mean squared error (RMSE) for model_2
rmse_2 = np.sqrt(np.mean(predictions_2 - y_test)**2)
rmse_2

```

[54]: 333.1571424968615

#let's see what did our models with predictions and compare our 2 models together:

```

[57]: # Plot the data
train = data[:training_data_len]

#data for model_1
valid_1 = data[training_data_len:]
valid_1['Predictions'] = predictions_1

# data for model_2
valid_2 = data[training_data_len:]
valid_2['Predictions'] = predictions_2

```

```

# Visualized the data
#model_1
plt.figure(figsize=(14, 10))
plt.subplot(2, 1, 1)
plt.title('Model_1 with 10 epochs')
plt.xlabel('Data', fontsize=18)
plt.ylabel('Close Price USD', fontsize=18)
plt.plot(train['Close'])
plt.plot(valid_1[['Close', 'Predictions']])

plt.legend(['Train', 'Valid', 'Predictions'], loc='upper left')

#model_2
plt.subplot(2, 1, 2)
plt.title('Model_2 with 6 epochs')
plt.xlabel('Data', fontsize=18)
plt.ylabel('Close Price USD', fontsize=18)
plt.plot(train['Close'])
plt.plot(valid_2[['Close', 'Predictions']])

plt.legend(['Train', 'Valid', 'Predictions'], loc='upper left')

plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=1,
                    wspace=0.4,
                    hspace=0.4)

plt.show()

```

<ipython-input-57-8f41bf5e5744>:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using `.loc[row_indexer,col_indexer] = value` instead

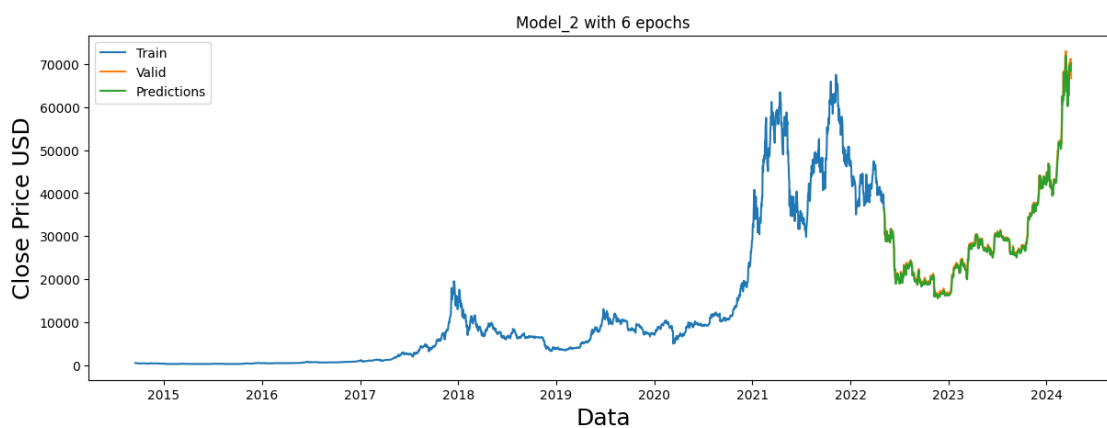
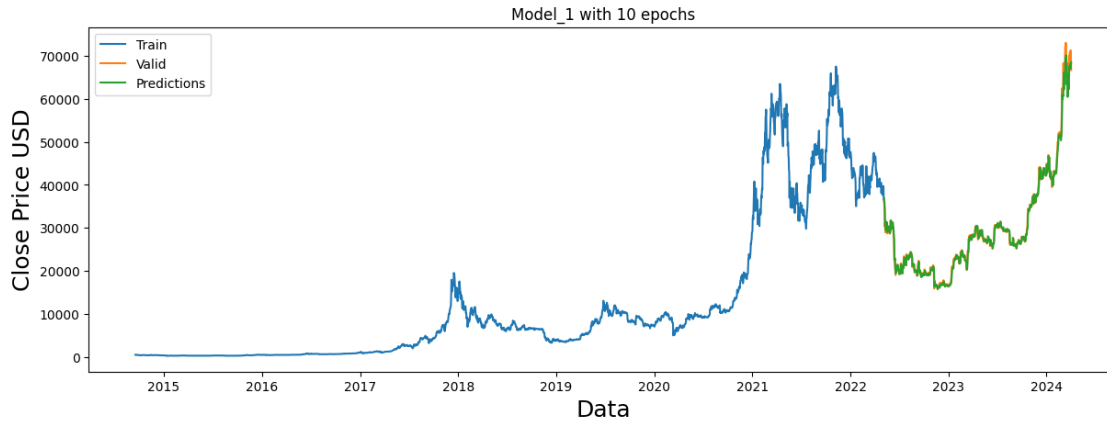
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
valid_1['Predictions'] = predictions_1
```

<ipython-input-57-8f41bf5e5744>:10: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using `.loc[row_indexer,col_indexer] = value` instead

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

```
valid_2['Predictions'] = predictions_2
```

#Both models model_1 & model_2 has a better predictions .It's time to predict a future day price which is not in train or test set. In other words we want to predict a price out of the dataframe which is the price of today

```
[58]: #Get the last 60 day closing price values and convert the datadrame to an array
last_60_days = data[-60:].values
# Scale the data to be values between 0 and 1
last_60_days_scaled = scaler.fit_transform(last_60_days)
# create an empty list
new_X_test = []
# Append the past 60 days
new_X_test.append(last_60_days_scaled)
# Convert the X_test data set to a numpy array
new_X_test = np.array(new_X_test)
# Reshape the data
new_X_test = np.reshape(new_X_test, (new_X_test.shape[0], new_X_test.shape[1], 1))
# Get the predicted scaled price
pred_price = model_1.predict(new_X_test)
```

```
# Undo the scaling
pred_price = scaler.inverse_transform(pred_price)
print(pred_price)
```

```
1/1 [=====] - 0s 30ms/step
[[66344.86]]
```

Market Summary > Bitcoin

66,676.50 USD

+ Follow

-3,005.30 (4.31%) ↓ today

2 Apr, 5:49 am UTC · [Disclaimer](#)

1D | 5D | 1M | 6M | YTD | 1Y | 5Y | Max



Here both models `model_1` and `model_2` predicted almost the current real time price of the Bitcoin