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```
In [1]:
           Data (Daily & Minute): Binance API-Will need Binance API keys to be able to pull the data.
           Binance API Documentation: https://binance-docs.github.io/apidocs/spot/en/#introduction
           '\nData (Daily & Minute): Binance API-Will need Binance API keys to be able to pull the data. \nBinance API Documentation: https://binance-docs.github.io/ap
 Out[1]:
          idocs/spot/en/#introduction\n\n'
 In [2]:
           \# J.Guanzon Comment-Imports needed to run this file
            from binance import Client, ThreadedWebsocketManager, ThreadedDepthCacheManager
           import pandas as pd
            import mplfinance as mpl
           {\color{red} \textbf{import}} \ {\color{blue} \textbf{mplfinance}} \ {\color{blue} \textbf{as}} \ {\color{blue} \textbf{mpf}}
           import os
            import json
            import requests
           from keras.models import Sequential
from keras.layers import Activation, Dense, Dropout, LSTM
            import matplotlib.pyplot as plt
           import numpy as np
from pathlib import Path
            import seaborn as sns
            from sklearn.metrics import mean_absolute_error
            %matplotlib inline
 In [3]:
           # Pull API keys from .env file
           api_key = os.environ.get("api_key")
api_secret = os.environ.get("api_secret")
 In [4]:
           client = Client(api_key, api_secret)
           # J.Guanzon Comment: Gather tickers for all
           tickers = client.get_all_tickers()
           ticker_df = pd.DataFrame(tickers)
 In [7]:
           ticker_df.set_index('symbol', inplace=True)
           ticker_df
 Out[7]:
              symbol
              ETHBTC 0.06134900
              LTCBTC 0.00306600
              BNBBTC 0.00715700
             NEOBTC 0.00077000
           QTUMETH 0.00360400
            SHIBAUD 0.00004148
            RAREBTC 0.00004936
            RAREBNB 0.00688200
           RAREBUSD 2.79300000
           RAREUSDT 2.79600000
          1695 rows × 1 columns
 In [8]: """
           Ability to save csv file of all tickers.
           Allows the user to see what types of cryptocurrencies are out there. For now, we will only focus on Bitcoin ^{\rm min}
           ' \nAbility to save csv file of all tickers.\nAllows the user to see what types of cryptocurrencies are out there.\nFor now, we will only focus on Bitcoin
 Out[8]:
           ticker_df.to_csv("Resources/binance_tickers.csv")
In [10]:
           display(float(ticker_df.loc['BTCUSDT']['price']))
           56699.98
           depth = client.get_order_book(symbol='BTCUSDT')
           depth_df = pd.DataFrame(depth['asks'])
depth_df.columns = ['Price', 'Volume']
            depth_df.head()
```

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```
Price
                             Volume
         0 56700.00000000 14.45333000
         1 56701.25000000 0.03819000
         2 56704.02000000 0.04689000
         3 56704.47000000 0.06963000
         4 56704.98000000 0.02000000
In [13]:
          # J.Guanzon Comment: Pulling historical daily data
          btc_daily_data = client.get_historical_klines('BTCUSDT', Client.KLINE_INTERVAL_1DAY, '1 Jan 2021')
          In [14]:
In [15]:
          btc_daily_df['Open Time'] = pd.to_datetime(btc_daily_df['Open Time']/1000, unit='s')
          btc_daily_df['Close Time'] = pd.to_datetime(btc_daily_df['Close Time']/1000, unit='s')
          numeric_columns = ['Open', 'High', 'Low', 'Close', 'Volume', 'Quote Asset Volume', 'TB Base Volume', 'TB Quote Volume']
btc_daily_df[numeric_columns] = btc_daily_df[numeric_columns].apply(pd.to_numeric, axis=1)
          btc_ohlcv_daily = btc_daily_df.iloc[:,0:6]
          btc_ohlcv_daily = btc_ohlcv_daily.set_index('Open Time')
          btc ohlcv daily
                      Open High Low Close
                                                           Volume
          Open Time
         2021-01-01 28923.63 29600.00 28624.57 29331.69 54182.925011
         2021-01-02 29331.70 33300.00 28946.53 32178.33 129993.873362
         2021-01-03 32176.45 34778.11 31962.99 33000.05 120957.566750
         2021-01-04 33000.05 33600.00 28130.00 31988.71 140899.885690
         2021-01-05 31989.75 34360.00 29900.00 33949.53 116049.997038
         2021-10-08 53785.22 56100.00 53617.61 53951.43 46160.257850
         2021-10-09 53955.67 55489.00 53661.67 54949.72 55177.080130
         2021-10-10 54949.72 56561.31 54080.00 54659.00 89237.836128
         2021-10-11 54659.01 57839.04 54415.06 57471.35 52933.165751
         2021-10-12 57471.35 57471.35 56588.00 56699.99 5579.448520
         285 rows × 5 columns
In [18]:
          btc_ohlcv_daily.to_csv("Resources/daily_btc_ohclv_2021.csv")
In [19]:
          # J.Guanzon Comment: Pulling historical minute data
          historical_minute = client.get_historical_klines('BTCUSDC', Client.KLINE_INTERVAL_1MINUTE, '5 day ago UTC')
In [20]:
          hist_min = pd.DataFrame(historical_minute)
In [21]:
          In [22]:
          hist_min['Open Time'] = pd.to_datetime(hist_min['Open Time']/1000, unit='s'
          hist_min['Close Time'] = pd.to_datetime(hist_min['Close Time']/1000, unit='s')
          numeric_columns = ['Open', 'High', 'Low', 'Close', 'Volume', 'Quote Asset Volume', 'TB Base Volume', 'TB Quote Volume']
hist_min[numeric_columns] = hist_min[numeric_columns].apply(pd.to_numeric, axis=1)
In [24]:
          btc_ohlcv_minute = hist_min.iloc[:,0:6]
          btc_ohlcv_minute = btc_ohlcv_minute.set_index('Open Time')
          btc ohlcv minute
Out[24]:
                             Open High Low Close Volume
                 Open Time
          2021-10-07 02:56:00 55070.95 55115.94 55047.85 55111.11 2.49405
          2021-10-07 02:57:00 55117.50 55118.17 55067.64 55067.64 1.78542
         2021-10-07 02:58:00 55082.99 55113.22 55070.03 55070.50 1.98333
         2021-10-07 02:59:00 55099.85 55126.99 55059.01 55113.87 2.68683
```

Close Volume

Open

High

```
Open Time
           2021-10-07 03:00:00 55113.87 55185.82 55102.77 55138.53 5.07494
           2021-10-12 02:51:00 56813.93 56815.13 56797.73 56815.13 0.26982
           2021-10-12 02:52:00 56802.72 56827.77 56799.73 56827.77 0.24521
           2021-10-12 02:53:00 56822.42 56822.42 56701.97 56743.31 1.74763
           2021-10-12 02:54:00 56751.64 56751.64 56714.40 56724.88 0.69013
           2021-10-12 02:55:00 56723.72 56723.72 56717.44 56717.44 0.04539
          7200 rows × 5 columns
            btc ohlcv minute.to csv("Resources/minute btc ohclv 2021.csv")
            Next, we will be using the daily data for our Recurrent Neural Network. We are using Recurrent Neural Network.
           '\nNext, we will be using the daily data for our Recurrent Neural Network. We are using Recurrent Neural Network.\n\n'
Out[26]:
In [27]:
            btc_df = pd.read_csv(Path("Resources/daily_btc_ohclv_2021.csv"),
                                     index_col= "Open Time")
            target_col = 'Close'
In [28]:
            btc df.head()
Out[28]:
                          Open High
                                             Low Close
                                                                      Volume
           Open Time
           2021-01-01 28923.63 29600.00 28624.57 29331.69 54182.925011
           2021-01-02 29331.70 33300.00 28946.53 32178.33 129993.873362
           2021-01-03 32176.45 34778.11 31962.99 33000.05 120957.566750
           2021-01-04 33000.05 33600.00 28130.00 31988.71 140899.885690
           2021-01-05 31989.75 34360.00 29900.00 33949.53 116049.997038
           # J.Guanzon Comment: Using an 80/20 split for our training data and testing data. Testing 2 other testing sizes to see if there are any differences in accura
            def train_test_split(btc_df, test_size=0.2):
              split_row = len(btc_df) - int(test_size * len(btc_df))
train_data = btc_df.iloc[:split_row]
              test_data = btc_df.iloc[split_row:]
              return train_data, test_data
            train, test = train_test_split(btc_df, test_size=0.2)
            # def train_test_split(btc_df, test_size=0.3):
# split_row = len(btc_df) - int(test_size * len(btc_df))
# train_data = btc_df.iloc[:split_row]
               test_data = btc_df.iloc[split_row:]
return train_data, test_data
            # train, test = train_test_split(btc_df, test_size=0.3)
            # def train_test_split(btc_df, test_size=0.1):
# split_row = len(btc_df) - int(test_size * len(btc_df))
# train_data = btc_df.iloc[:split_row]
                 test_data = btc_df.iloc[split_row:]
                return train_data, test_data
            # train, test = train_test_split(btc_df, test_size=0.1)
In [30]:
            def line_plot(line1, line2, label1=None, label2=None, title='', lw=2):
                fig, ax = plt.subplots(1, figsize=(20, 7))
ax.plot(line1, label=label1, linewidth=lw)
ax.plot(line2, label=label2, linewidth=lw)
                 ax.set_ylabel('price [USD]', fontsize=14)
                ax.set_title(title, fontsize=16)
ax.legend(loc='best', fontsize=16)
            line_plot(train[target_col], test[target_col], 'training', 'test', title='BTC 2021 to Current Day Predictions')
```

65000

```
training
                                                                                                                                                                                     test
              60000
              55000
              50000
              45000
              40000
              35000
              30000
            Next, we have to prep the data for RNN by normalizing the numeric columns in the dataset to a common scale, without distorting differences in the range of v
           '\nNext, we have to prep the data for RNN by normalizing the numeric columns in the dataset to a common scale, without distorting differences in the range o
           f values.\n'
           def normalise_zero_base(df):
    return df / df.iloc[0] - 1
            def normalise_min_max(df):
                return (df - df.min()) / (data.max() - df.min())
           def extract_window_data(btc_df, window_len=5, zero_base=True):
                window data = []
                 for idx in range(len(btc_df) - window_len):
                     tmp = btc_df[idx: (idx + window_len)].copy()
                     if zero_base:
                         tmp = normalise zero base(tmp)
                     window_data.append(tmp.values)
                return np.array(window_data)
In [34]:
           def prepare_data(btc_df, target_col, window_len=10, zero_base=True, test_size=0.2):
                 train_data, test_data = train_test_split(btc_df, test_size=test_size)
                X_train = extract_window_data(train_data, window_len, zero_base)
X_test = extract_window_data(test_data, window_len, zero_base)
y_train = train_data[target_col][window_len:].values
                 y_test = test_data[target_col][window_len:].values
                if zero base:
                     y_train = y_train / train_data[target_col][:-window_len].values - 1
                     y_test = y_test / test_data[target_col][:-window_len].values - 1
                return train_data, test_data, X_train, X_test, y_train, y_test
            # def prepare_data(btc_df, target_col, window_len=10, zero_base=True, test_size=0.3):
                   train_data, test_data = train_test_split(btc_df, test_size=test_size)
X_train = extract_window_data(train_data, window_len, zero_base)
                   X_test = extract_window_data(test_data, window_len, zero_base)
                   y_train = train_data[target_col][window_len:].values
                   y test = test_data[target_col][window_len:].values
                   if zero_base:
                       y_train = y_train / train_data[target_col][:-window_len].values - 1
                       y_test = y_test / test_data[target_col][:-window_len].values - 1
                   return train_data, test_data, X_train, X_test, y_train, y_test
            # def prepare_data(btc_df, target_col, window_len=10, zero_base=True, test_size=0.1):
                   train_data, test_data = train_test_split(btc_df, test_size=test_size)
X_train = extract_window_data(train_data, window_len, zero_base)
                   X_test = extract_window_data(test_data, window_len, zero_base)
                   y_train = train_data[target_col][window_len:].values
y_test = test_data[target_col][window_len:].values
                       y_train = y_train / train_data[target_col][:-window_len].values - 1
y_test = y_test / test_data[target_col][:-window_len].values - 1
                   return train_data, test_data, X_train, X_test, y_train, y_test
In [35]:
           def build_lstm_model(input_data, output_size, neurons=100, activ_func='linear', dropout=0.2, loss='mse', optimizer='adam'):
                model = Sequential()
                model.add(LSTM(neurons, input_shape=(input_data.shape[1], input_data.shape[2])))
                 model.add(Dropout(dropout))
                 model.add(Dense(units=output_size))
                model.add(Activation(activ func))
                model.compile(loss=loss, optimizer=optimizer)
                 return model
           np.random.seed(42)
```

BTC 2021 to Current Day Predictions

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```
window len = 5
                  test\_size = 0.2
                   zero_base = True
                  lstm_neurons = 100
                   epochs = 20
                   batch_size = 32
                  loss = 'mse'
dropout = 0.2
                  optimizer = 'adam'
In [37]:
                  train, test, X_train, X_test, y_train, y_test = prepare_data(
    btc_df, target_col, window_len=window_len, zero_base=zero_base, test_size=test_size)
                   model = build_lstm_model(
                         X_train, output_size=1, neurons=lstm_neurons, dropout=dropout, loss=loss,
                          optimizer=optimizer)
                   history = model.fit(
                         X_train, y_train, epochs=epochs, batch_size=batch_size, verbose=1, shuffle=True)
                 Epoch 1/20
                 7/7 [======== ] - 1s 4ms/step - loss: 0.0101
                 Epoch 2/20
                                                       ========] - 0s 3ms/step - loss: 0.0069
                 Epoch 3/20
                  7/7 [======
                                                 ========= | - 0s 4ms/step - loss: 0.0057
                 Epoch 4/20
                  7/7 [===
                                                                                     - 0s 4ms/step - loss: 0.0049
                 Epoch 5/20
                  7/7 [=====
                                                                                     - 0s 3ms/step - loss: 0.0045
                  Epoch 6/20
                 7/7 [=====
                                                                                     - 0s 4ms/step - loss: 0.0041
                 Epoch 7/20
                  7/7 [=====
                                        ======== | - Os 3ms/step - loss: 0.0041
                  Epoch 8/20
                 7/7 [=====
                                                                                     - 0s 3ms/step - loss: 0.0039
                 Epoch 9/20
                  7/7 [==
                                                                                      - 0s 4ms/step - loss: 0.0038
                  Epoch 10/20
                 7/7 [=====
                                                                                     - 0s 3ms/step - loss: 0.0038
                 Epoch 11/20
                  7/7 [=====
                                                 Epoch 12/20
                  7/7 [========================] - 0s 5ms/step - loss: 0.0035
                 Epoch 13/20
                                                                                      - 0s 3ms/step - loss: 0.0035
                 Epoch 14/20
                  7/7 [=====
                                                                                     - 0s 3ms/step - loss: 0.0034
                  Epoch 15/20
                 7/7 [===
                                                                                     - 0s 3ms/step - loss: 0.0032
                 Epoch 16/20
                  7/7 [======
                                                   ======== ] - 0s 3ms/step - loss: 0.0032
                  Epoch 17/20
                  7/7 [=====
                                                        ========] - 0s 4ms/step - loss: 0.0032
                 Epoch 18/20
                 7/7 [=====
                                                                                      - 0s 3ms/step - loss: 0.0030
                  Epoch 19/20
                 7/7 [=====
                                                            ======= ] - 0s 6ms/step - loss: 0.0031
                 Epoch 20/20
                 7/7 [=====
                                                            ========] - 0s 5ms/step - loss: 0.0030
In [38]:
                  targets = test[target_col][window_len:]
                  preds = model.predict(X_test).squeeze()
                  mean_absolute_error(preds, y_test)
                 0.03376383137740681
Out[38]:
In [39]:
                  # Plotting predictions against the actual.
                  preds = test[target_col].values[:-window_len] * (preds + 1)
                   preds = pd.Series(index=targets.index, data=preds)
                  line_plot(targets, preds, 'actual', 'prediction', lw=3)
                      57500
                                             actual
                                              prediction
                      55000
                      52500
                price [USD]
                      45000
                      42500
                      40000
                                     202 ражимильный принципературы и принципе
```