

```
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
"""

Out[1]: '\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/apidocs/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
import mplfinance as 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 matplotlib.dates as mdates
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)

In [5]: # J.Guanzon Comment: Gather tickers for all
tickers = client.get_all_tickers()

In [6]: ticker_df = pd.DataFrame(tickers)

In [7]: ticker_df.set_index('symbol', inplace=True)
ticker_df

Out[7]:
           price
symbol
ETHBTC  0.06236100
LTCBTC  0.00309000
BNBBTC  0.00820900
NEOBTC  0.00079200
QTUMETH 0.00380100
...         ...
SHIBAUD 0.00004011
RAREBTC 0.00004376
RAREBNB 0.00533000
RAREBUSD 2.46800000
RAREUSDT 2.46800000

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
"""

Out[8]: '\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\n'

In [9]: ticker_df.to_csv("Resources/binance_tickers.csv")

In [10]: display(float(ticker_df.loc['BTCUSDT']['price']))

56406.6

In [11]: depth = client.get_order_book(symbol='BTCUSDT')

In [12]: depth_df = pd.DataFrame(depth['asks'])
depth_df.columns = ['Price', 'Volume']
depth_df.head()
```

Out[12]:

	Price	Volume
0	56408.01000000	0.00036000
1	56410.03000000	0.00887000
2	56411.32000000	0.00118000
3	56413.38000000	0.08864000
4	56413.53000000	0.17876000

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]:

```
btc_daily_df = pd.DataFrame(btc_daily_data)
btc_daily_df.columns = ['Open Time', 'Open', 'High', 'Low', 'Close', 'Volume', 'Close Time', 'Quote Asset Volume',
                        'Number of Trades', 'TB Base Volume', 'TB Quote Volume', 'Ignore']
```

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')
```

In [16]:

```
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)
```

In [17]:

```
btc_ohlcw_daily = btc_daily_df.iloc[:,0:6]
btc_ohlcw_daily = btc_ohlcw_daily.set_index('Open Time')
btc_ohlcw_daily
```

Out[17]:

	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
...	...	...	...	...	...
2021-10-09	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	57680.00	53879.00	55996.93	53471.285500
2021-10-13	55996.91	56599.99	55825.90	56406.65	4823.003770

286 rows × 5 columns

In [18]:

```
btc_ohlcw_daily.to_csv("Resources/daily_btc_ohlcw_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]:

```
hist_min.columns = ['Open Time', 'Open', 'High', 'Low', 'Close', 'Volume', 'Close Time', 'Quote Asset Volume',
                    'Number of Trades', 'TB Base Volume', 'TB Quote Volume', 'Ignore']
```

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')
```

In [23]:

```
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_ohlcw_minute = hist_min.iloc[:,0:6]
btc_ohlcw_minute = btc_ohlcw_minute.set_index('Open Time')
btc_ohlcw_minute
```

Out[24]:

	Open	High	Low	Close	Volume
Open Time					
2021-10-08 02:58:00	53885.64	53905.89	53842.65	53842.65	0.95274
2021-10-08 02:59:00	53850.75	53877.20	53846.88	53863.59	0.16733
2021-10-08 03:00:00	53851.93	53882.65	53851.93	53882.39	0.10060

	Open	High	Low	Close	Volume
Open Time					
2021-10-08 03:01:00	53927.69	53927.69	53892.56	53894.27	0.11298
2021-10-08 03:02:00	53882.65	53882.65	53853.37	53853.37	0.25666
...	...	...	...	...	...
2021-10-13 02:53:00	56323.28	56335.42	56323.27	56328.07	0.26958
2021-10-13 02:54:00	56330.36	56351.55	56324.53	56335.49	0.42222
2021-10-13 02:55:00	56340.34	56370.46	56335.43	56365.10	0.31977
2021-10-13 02:56:00	56367.08	56389.71	56364.71	56382.66	1.86522
2021-10-13 02:57:00	56378.26	56409.65	56361.85	56409.65	0.27224

7200 rows x 5 columns

```
In [25]: btc_ohlcv_minute.to_csv("Resources/minute_btc_ohlcv_2021.csv")
```

```
In [26]: """
Next, we will be using the daily data for our Recurrent Neural Network. We are using Recurrent Neural Network.
"""

Out[26]: '\nNext, we will be using the daily data for our Recurrent Neural Network. We are using Recurrent Neural Network.\n\n'
```

```
In [27]: btc_df = pd.read_csv(Path("Resources/daily_btc_ohlcv_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

```
In [29]: # 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 differnces in accuracy

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

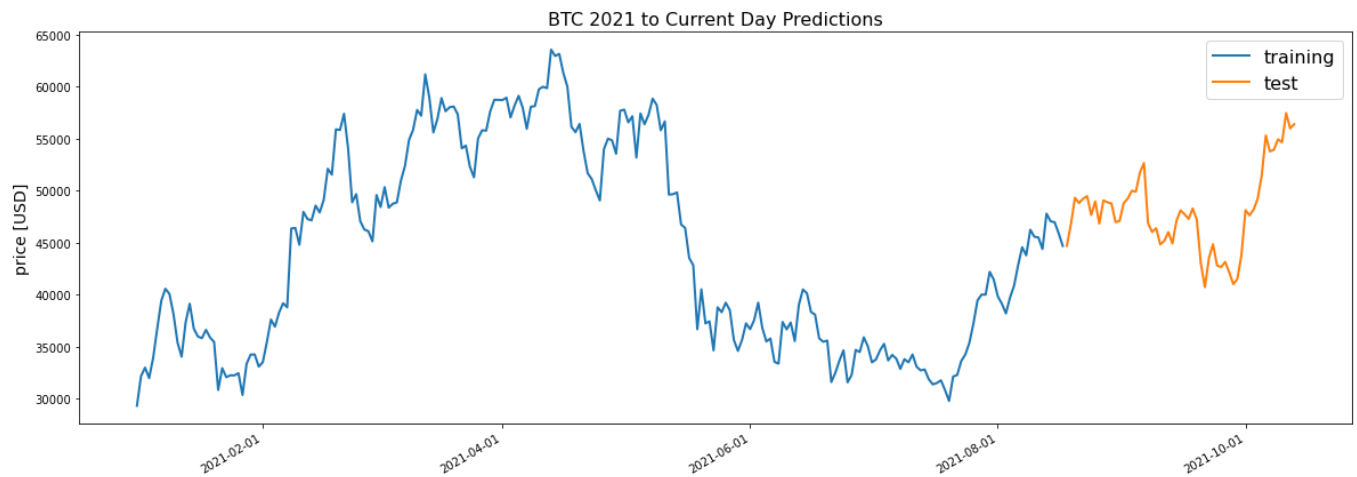
# train, test = train_test_split(btc_df, test_size=0.3)

# 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)
fmt_bimonthly = mdates.MonthLocator(interval=2)
ax.xaxis.set_major_locator(fmt_bimonthly)
ax.set_title(title, fontsize=16)
fig.autofmt_xdate()
ax.legend(loc='best', fontsize=16)

line_plot(train[target_col], test[target_col], 'training', 'test', title='BTC 2021 to Current Day Predictions')
```



```
In [31]: """
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
"""
```

```
Out[31]: '\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'
```

```
In [32]: def normalise_zero_base(df):
return df / df.iloc[0] - 1

def normalise_min_max(df):
return (df - df.min()) / (data.max() - df.min())
```

```
In [33]: def extract_window_data(btc_df, window_len=10, 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]: X_train= btc_df[:"2021-06-01"]
X_test = btc_df["2021-06-01":]
y_train = btc_df.loc[:"2021-06-01",target_col]
y_test = btc_df.loc["2021-06-01":,target_col]
```

```
In [35]: 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
# 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
```

```
In [36]: def build_lstm_model(input_data, output_size, neurons=100, activ_func='linear', dropout=0.2, loss='mse', optimizer='adam'):
model = Sequential()
stm= LSTM(neurons, input_shape=(input_data.shape[1], input_data.shape[2]))
model.add(stm)
model.add(Dropout(dropout))
model.add(Dense(units=output_size))
```

```

model.add(Activation(activ_func))
model.compile(loss=loss, optimizer=optimizer)
return model

```

```

In [37]: np.random.seed(50)
window_len = 10
test_size = 0.2
zero_base = True
lstm_neurons = 100
epochs = 20
batch_size = 32
loss = 'mse'
dropout = 0.2
optimizer = 'adam'

```

```

In [38]: 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 6ms/step - loss: 0.0177
Epoch 2/20
7/7 [=====] - 0s 4ms/step - loss: 0.0090
Epoch 3/20
7/7 [=====] - 0s 4ms/step - loss: 0.0078
Epoch 4/20
7/7 [=====] - 0s 4ms/step - loss: 0.0066
Epoch 5/20
7/7 [=====] - 0s 4ms/step - loss: 0.0055
Epoch 6/20
7/7 [=====] - 0s 4ms/step - loss: 0.0054
Epoch 7/20
7/7 [=====] - 0s 5ms/step - loss: 0.0050
Epoch 8/20
7/7 [=====] - 0s 5ms/step - loss: 0.0047
Epoch 9/20
7/7 [=====] - 0s 4ms/step - loss: 0.0050
Epoch 10/20
7/7 [=====] - 0s 4ms/step - loss: 0.0046
Epoch 11/20
7/7 [=====] - 0s 4ms/step - loss: 0.0038
Epoch 12/20
7/7 [=====] - 0s 4ms/step - loss: 0.0042
Epoch 13/20
7/7 [=====] - 0s 4ms/step - loss: 0.0040
Epoch 14/20
7/7 [=====] - 0s 4ms/step - loss: 0.0041
Epoch 15/20
7/7 [=====] - 0s 4ms/step - loss: 0.0038
Epoch 16/20
7/7 [=====] - 0s 4ms/step - loss: 0.0036
Epoch 17/20
7/7 [=====] - 0s 4ms/step - loss: 0.0034
Epoch 18/20
7/7 [=====] - 0s 4ms/step - loss: 0.0035
Epoch 19/20
7/7 [=====] - 0s 4ms/step - loss: 0.0032
Epoch 20/20
7/7 [=====] - 0s 4ms/step - loss: 0.0035

```

```

In [39]: targets = test[target_col][window_len:]
preds = model.predict(X_test).squeeze()
mean_absolute_error(preds, y_test)

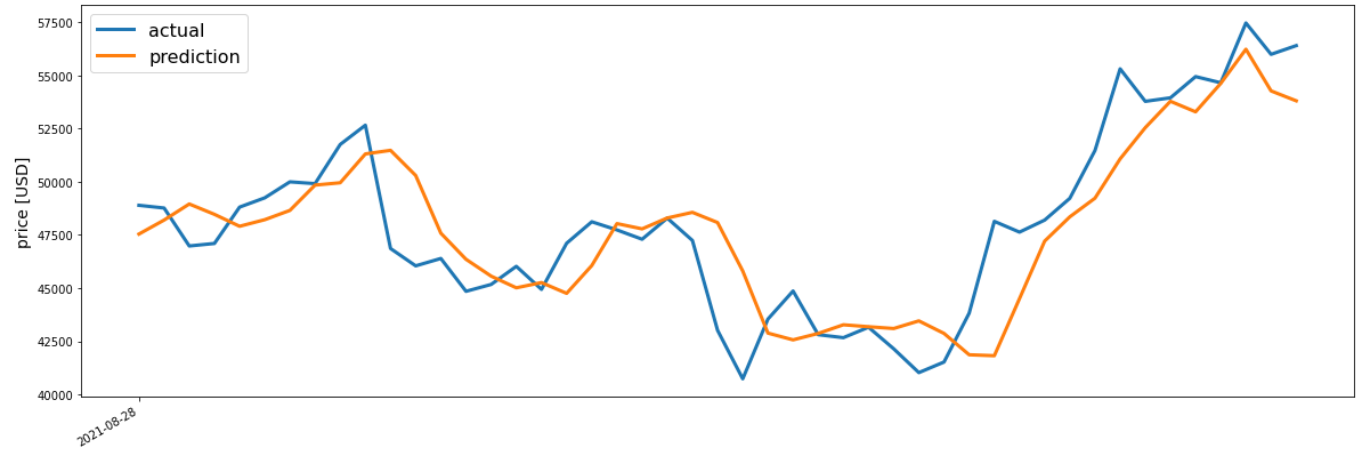
```

Out[39]: 0.0363802390395882

```

In [40]: # 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)

```



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In [ ]:
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