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/ap
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
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	0.06132900
LTCBTC	0.00305700
BNBBTC	0.00716900
NEOBTC	0.00076400
QTUMETH	0.00358300
...	...
SHIBAUD	0.00004137
RAREBTC	0.00004778
RAREBNB	0.00667600
RAREBUSD	2.71200000
RAREUSDT	2.70900000

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']))
```

```
56599.0
```

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	56599.01000000	0.22169000
1	56600.00000000	0.37972000
2	56604.67000000	0.20750000
3	56607.32000000	0.08832000
4	56608.31000000	0.01000000

In [13]:

```
# J.Guanzon Comment: Pulling historical daily data
btc_daily_data = client.get_historical_klines('BTCUSDT', Client.KLINE_INTERVAL_1DAY, '1 Jun 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_ohlcv_daily = btc_daily_df.iloc[:,0:6]
btc_ohlcv_daily = btc_ohlcv_daily.set_index('Open Time')
btc_ohlcv_daily
```

Out[17]:

	Open	High	Low	Close	Volume
Open Time					
2021-06-01	37253.82	37894.81	35666.00	36693.09	81234.663770
2021-06-02	36694.85	38225.00	35920.00	37568.68	67587.372495
2021-06-03	37568.68	39476.00	37170.00	39246.79	75889.106011
2021-06-04	39246.78	39289.07	35555.15	36829.00	91317.799245
2021-06-05	36829.15	37925.00	34800.00	35513.20	70459.621490
...	...	...	...	...	...
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	56400.00	56599.00	7189.281650

134 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]:

```
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_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 03:32:00	54899.08	54925.31	54898.89	54908.92	0.30462
2021-10-07 03:33:00	54913.83	54919.84	54891.49	54919.34	0.62240
2021-10-07 03:34:00	54893.31	54904.69	54886.12	54897.27	0.07774

	Open	High	Low	Close	Volume
Open Time					
2021-10-07 03:35:00	54908.60	54909.43	54873.30	54882.68	0.25142
2021-10-07 03:36:00	54886.18	54927.84	54886.18	54927.84	0.02461
...	...	...	...	...	...
2021-10-12 03:27:00	56721.68	56765.35	56709.71	56765.35	0.38781
2021-10-12 03:28:00	56765.35	56765.35	56683.24	56683.24	0.52568
2021-10-12 03:29:00	56679.89	56685.50	56666.30	56672.84	0.28205
2021-10-12 03:30:00	56673.95	56689.97	56630.80	56630.80	2.07063
2021-10-12 03:31:00	56611.96	56639.36	56611.96	56632.46	0.03097

7200 rows × 5 columns

In [25]:

```
btc_ohlcv_minute.to_csv("Resources/minute_btc_ohclv_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_ohclv_2021.csv"),
                     index_col= "Open Time")
target_col = 'Close'
```

In [28]:

```
btc_df.head()
```

Out[28]:

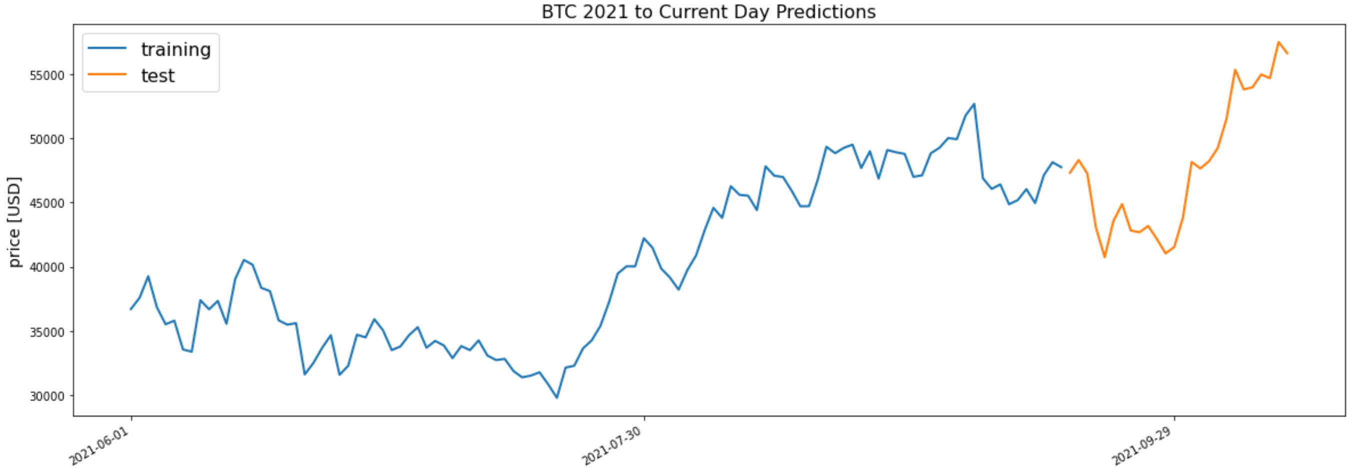
	Open	High	Low	Close	Volume
Open Time					
2021-06-01	37253.82	37894.81	35666.00	36693.09	81234.663770
2021-06-02	36694.85	38225.00	35920.00	37568.68	67587.372495
2021-06-03	37568.68	39476.00	37170.00	39246.79	75889.106011
2021-06-04	39246.78	39289.07	35555.15	36829.00	91317.799245
2021-06-05	36829.15	37925.00	34800.00	35513.20	70459.621490

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 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)
    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]:

```
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 [35]:

```
def build_lstm_model(input_data, output_size, neurons=150, 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 [36]:

```
np.random.seed(42)
```

```
window_len = 10
test_size = 0.2
zero_base = True
lstm_neurons = 150
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
4/4 [==============================] - 1s 6ms/step - loss: 0.0132
Epoch 2/20
4/4 [==============================] - 0s 6ms/step - loss: 0.0102
Epoch 3/20
4/4 [==============================] - 0s 6ms/step - loss: 0.0061
Epoch 4/20
4/4 [==============================] - 0s 5ms/step - loss: 0.0066
Epoch 5/20
4/4 [==============================] - 0s 6ms/step - loss: 0.0052
Epoch 6/20
4/4 [==============================] - 0s 5ms/step - loss: 0.0047
Epoch 7/20
4/4 [==============================] - 0s 5ms/step - loss: 0.0042
Epoch 8/20
4/4 [==============================] - 0s 5ms/step - loss: 0.0038
Epoch 9/20
4/4 [==============================] - 0s 5ms/step - loss: 0.0044
Epoch 10/20
4/4 [==============================] - 0s 6ms/step - loss: 0.0040
Epoch 11/20
4/4 [==============================] - 0s 6ms/step - loss: 0.0035
Epoch 12/20
4/4 [==============================] - 0s 6ms/step - loss: 0.0033
Epoch 13/20
4/4 [==============================] - 0s 5ms/step - loss: 0.0032
Epoch 14/20
4/4 [==============================] - 0s 5ms/step - loss: 0.0030
Epoch 15/20
4/4 [==============================] - 0s 5ms/step - loss: 0.0028
Epoch 16/20
4/4 [==============================] - 0s 5ms/step - loss: 0.0027
Epoch 17/20
4/4 [==============================] - 0s 5ms/step - loss: 0.0031
Epoch 18/20
4/4 [==============================] - 0s 5ms/step - loss: 0.0028
Epoch 19/20
4/4 [==============================] - 0s 5ms/step - loss: 0.0025
Epoch 20/20
4/4 [==============================] - 0s 6ms/step - loss: 0.0031
```

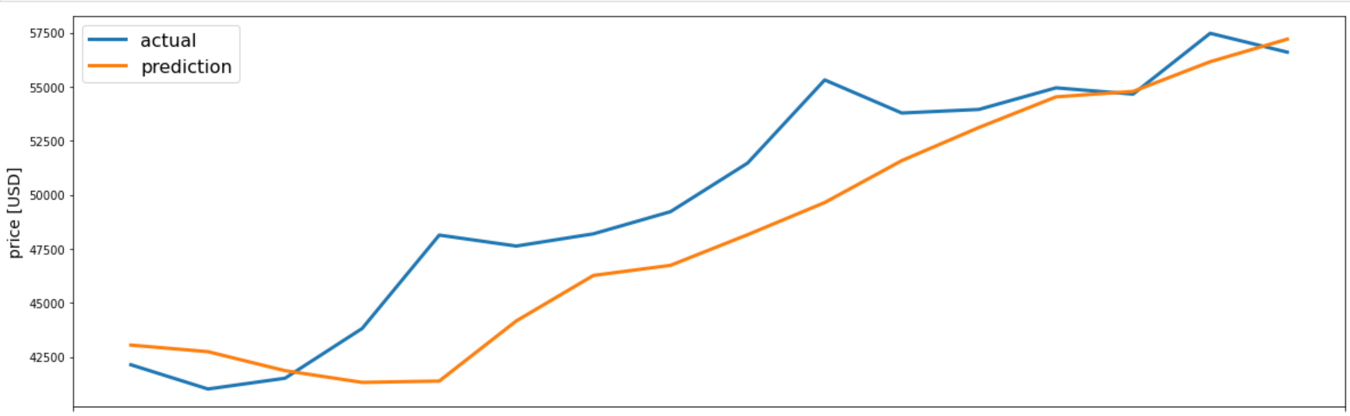
In [38]:

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

Out[38]: 0.050030655543981326

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)
```



In [ ]:

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