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 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	0.06135300
LTCBTC	0.00307100
BNBBTC	0.00716500
NEOBTC	0.00077000
QTUMETH	0.00360600
...	...
SHIBAUD	0.00004154
RAREBTC	0.00005001
RAREBNB	0.00701800
RAREBUSD	2.85700000
RAREUSDT	2.84900000

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']))
```

56798.2

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	56798.20000000	2.28350000
1	56798.92000000	0.39647000
2	56798.93000000	0.63719000
3	56800.00000000	9.19919000
4	56802.00000000	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]:

```
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					
2021-01-01	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	56798.20	5035.715240

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]:

```
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 02:47:00	55198.75	55198.75	55096.51	55106.42	0.90241
2021-10-07 02:48:00	55114.95	55114.95	55055.39	55072.11	1.22394
2021-10-07 02:49:00	55069.12	55072.24	54990.87	55004.59	2.76886
2021-10-07 02:50:00	55004.59	55007.38	54947.04	55007.38	2.46780

	Open	High	Low	Close	Volume
Open Time					
2021-10-07 02:51:00	55015.89	55028.06	54950.43	54990.18	3.26457
...	...	...	...	...	...
2021-10-12 02:42:00	57069.93	57104.77	57069.93	57101.57	0.53802
2021-10-12 02:43:00	57100.88	57100.88	57018.34	57018.34	3.87116
2021-10-12 02:44:00	57007.41	57007.41	56924.30	56929.00	0.96076
2021-10-12 02:45:00	56924.94	56936.35	56865.66	56873.73	0.83581
2021-10-12 02:46:00	56863.43	56863.43	56817.23	56841.58	0.72042

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'
```

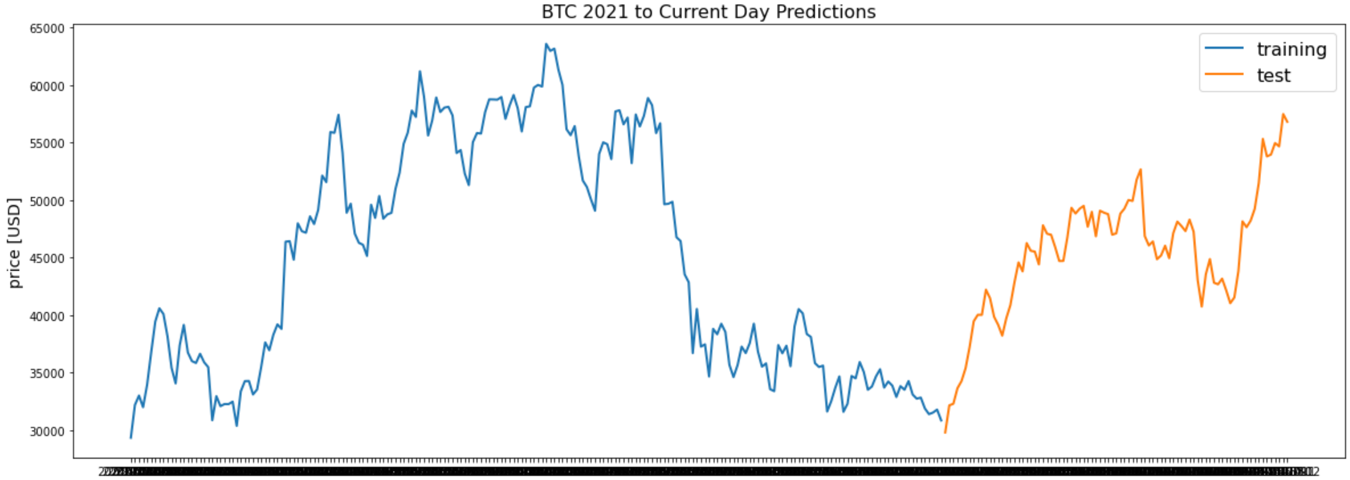
In [28]:
```
btc_df.head()
```

Out[28]:

	Open	High	Low	Close	Volume
Open Time					
2021-01-01	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 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')
```



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=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 [ ]:

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=400, 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
```

In [36]:
```
np.random.seed(45)
window_len = 5
test_size = 0.3
zero_base = True
lstm_neurons = 400
epochs = 50
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 1/50
7/7 [==============================] - 1s 16ms/step - loss: 0.0101
Epoch 2/50
7/7 [==============================] - 0s 15ms/step - loss: 0.0061
Epoch 3/50
7/7 [==============================] - 0s 16ms/step - loss: 0.0048
Epoch 4/50
7/7 [==============================] - 0s 15ms/step - loss: 0.0042
Epoch 5/50
7/7 [==============================] - 0s 14ms/step - loss: 0.0039
Epoch 6/50
7/7 [==============================] - 0s 14ms/step - loss: 0.0038
Epoch 7/50
7/7 [==============================] - 0s 15ms/step - loss: 0.0038
Epoch 8/50
7/7 [==============================] - 0s 15ms/step - loss: 0.0040
Epoch 9/50
7/7 [==============================] - 0s 15ms/step - loss: 0.0035
Epoch 10/50
7/7 [==============================] - 0s 16ms/step - loss: 0.0031
Epoch 11/50
7/7 [==============================] - 0s 17ms/step - loss: 0.0031
Epoch 12/50
7/7 [==============================] - 0s 20ms/step - loss: 0.0031
Epoch 13/50
7/7 [==============================] - 0s 14ms/step - loss: 0.0028
Epoch 14/50
7/7 [==============================] - 0s 14ms/step - loss: 0.0030
Epoch 15/50
7/7 [==============================] - 0s 15ms/step - loss: 0.0030
Epoch 16/50
7/7 [==============================] - 0s 15ms/step - loss: 0.0029
Epoch 17/50
7/7 [==============================] - 0s 15ms/step - loss: 0.0030
Epoch 18/50
7/7 [==============================] - 0s 15ms/step - loss: 0.0028
Epoch 19/50
7/7 [==============================] - 0s 16ms/step - loss: 0.0029
Epoch 20/50
7/7 [==============================] - 0s 17ms/step - loss: 0.0029
Epoch 21/50
7/7 [==============================] - 0s 18ms/step - loss: 0.0031
Epoch 22/50
7/7 [==============================] - 0s 17ms/step - loss: 0.0028
Epoch 23/50
7/7 [==============================] - 0s 15ms/step - loss: 0.0028
Epoch 24/50
7/7 [==============================] - 0s 16ms/step - loss: 0.0027
Epoch 25/50
7/7 [==============================] - 0s 16ms/step - loss: 0.0028
Epoch 26/50
7/7 [==============================] - 0s 16ms/step - loss: 0.0026
Epoch 27/50
7/7 [==============================] - 0s 15ms/step - loss: 0.0027
Epoch 28/50
7/7 [==============================] - 0s 15ms/step - loss: 0.0024
Epoch 29/50
7/7 [==============================] - 0s 14ms/step - loss: 0.0025
Epoch 30/50
7/7 [==============================] - 0s 17ms/step - loss: 0.0025
Epoch 31/50
7/7 [==============================] - 0s 15ms/step - loss: 0.0026
Epoch 32/50
7/7 [==============================] - 0s 15ms/step - loss: 0.0025
Epoch 33/50
7/7 [==============================] - 0s 17ms/step - loss: 0.0025
Epoch 34/50
7/7 [==============================] - 0s 17ms/step - loss: 0.0026
Epoch 35/50
7/7 [==============================] - 0s 17ms/step - loss: 0.0027
Epoch 36/50
7/7 [==============================] - 0s 16ms/step - loss: 0.0024
Epoch 37/50
7/7 [==============================] - 0s 17ms/step - loss: 0.0027
Epoch 38/50
7/7 [==============================] - 0s 16ms/step - loss: 0.0026
Epoch 39/50
7/7 [==============================] - 0s 16ms/step - loss: 0.0026
Epoch 40/50
```

```
7/7 [==============================] - 0s 16ms/step - loss: 0.0024
Epoch 41/50
7/7 [==============================] - 0s 16ms/step - loss: 0.0025
Epoch 42/50
7/7 [==============================] - 0s 16ms/step - loss: 0.0025
Epoch 43/50
7/7 [==============================] - 0s 17ms/step - loss: 0.0023
Epoch 44/50
7/7 [==============================] - 0s 16ms/step - loss: 0.0023
Epoch 45/50
7/7 [==============================] - 0s 16ms/step - loss: 0.0023
Epoch 46/50
7/7 [==============================] - 0s 15ms/step - loss: 0.0023
Epoch 47/50
7/7 [==============================] - 0s 15ms/step - loss: 0.0024
Epoch 48/50
7/7 [==============================] - 0s 14ms/step - loss: 0.0024
Epoch 49/50
7/7 [==============================] - 0s 15ms/step - loss: 0.0024
Epoch 50/50
7/7 [==============================] - 0s 16ms/step - loss: 0.0022
```

In [38]:

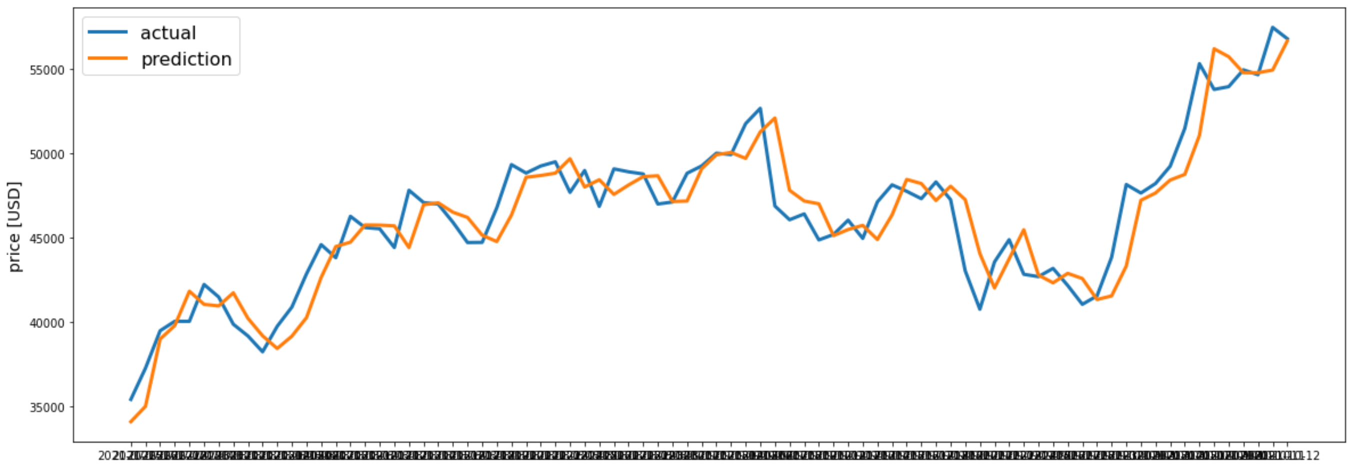
```
targets = test[target_col][window_len:]
preds = model.predict(X_test).squeeze()
mean_absolute_error(preds, y_test)
```

Out[38]:

```
0.030384629160716707
```

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 [ ]:

In [ ]:

In [ ]: