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	0.06222300
LTCBTC	0.00308300
BNBBTC	0.00815400
NEOBTC	0.00079000
QTUMETH	0.00380100
...	...
SHIBAUD	0.00004038
RAREBTC	0.00004351
RAREBNB	0.00530600
RAREBUSD	2.44900000
RAREUSDT	2.44700000

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']))
```

56318.22

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	56317.59000000	0.14099000
1	56318.78000000	0.00888000
2	56319.52000000	0.01759000
3	56319.53000000	0.05000000
4	56321.92000000	0.18494000

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
...	...	...	...	...	...
2021-10-09	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	56318.22	5130.710410

286 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					
2021-10-08 03:11:00	53798.92	53798.92	53735.50	53754.13	0.95261
2021-10-08 03:12:00	53768.45	53779.22	53734.02	53779.22	0.10660
2021-10-08 03:13:00	53778.00	53805.70	53764.95	53805.70	0.06100

	Open	High	Low	Close	Volume
Open Time					
2021-10-08 03:14:00	53832.02	53832.02	53793.41	53801.83	0.43310
2021-10-08 03:15:00	53815.62	53828.15	53759.55	53759.55	0.45406
...	...	...	...	...	...
2021-10-13 03:06:00	56352.92	56373.23	56352.92	56373.23	0.08229
2021-10-13 03:07:00	56341.96	56343.95	56341.96	56343.95	0.01169
2021-10-13 03:08:00	56332.86	56347.29	56299.10	56299.10	0.44776
2021-10-13 03:09:00	56314.20	56317.45	56314.20	56317.45	0.15415
2021-10-13 03:10:00	56321.97	56324.10	56319.09	56324.10	0.01488

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 [34]:

```
btc_df = pd.read_csv(Path("Resources/daily_btc_ohclv_2021.csv"),
                     index_col= "Open Time")
target_col = 'Close'
# btc_df=btc_ohlcv_daily.loc[:,['Close']]
```

In [35]:

```
btc_df=btc_df.drop(columns=['Open', 'High', 'Low', 'Volume'])
btc_df
```

Out[35]:

	Close
Open Time	
2021-01-01	29331.69
2021-01-02	32178.33
2021-01-03	33000.05
2021-01-04	31988.71
2021-01-05	33949.53
...	...
2021-10-09	54949.72
2021-10-10	54659.00
2021-10-11	57471.35
2021-10-12	55996.93
2021-10-13	56318.22

286 rows × 1 columns

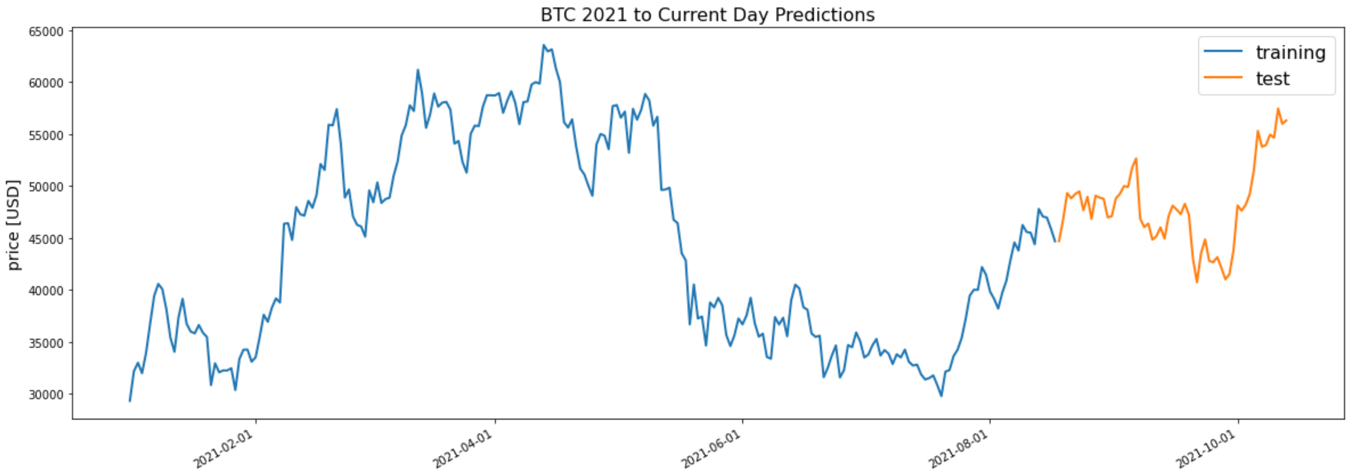
In [36]:

```
# 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 [37]:

```
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 [38]:
```
"""
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[38]:
```
'\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 [39]:
```
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 [40]:
```
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 [41]:
```
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 [42]:
```
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 [43]:

```
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 [44]:

```
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 [45]:

```
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: 0.0150
Epoch 2/20
7/7 [==============================] - 0s 4ms/step - loss: 0.0089
Epoch 3/20
7/7 [==============================] - 0s 4ms/step - loss: 0.0070
Epoch 4/20
7/7 [==============================] - 0s 5ms/step - loss: 0.0061
Epoch 5/20
7/7 [==============================] - 0s 4ms/step - loss: 0.0056
Epoch 6/20
7/7 [==============================] - 0s 4ms/step - loss: 0.0052
Epoch 7/20
7/7 [==============================] - 0s 4ms/step - loss: 0.0048
Epoch 8/20
7/7 [==============================] - 0s 4ms/step - loss: 0.0046
Epoch 9/20
7/7 [==============================] - 0s 4ms/step - loss: 0.0044
Epoch 10/20
7/7 [==============================] - 0s 4ms/step - loss: 0.0042
Epoch 11/20
7/7 [==============================] - 0s 4ms/step - loss: 0.0041
Epoch 12/20
7/7 [==============================] - 0s 4ms/step - loss: 0.0039
Epoch 13/20
7/7 [==============================] - 0s 4ms/step - loss: 0.0038
Epoch 14/20
7/7 [==============================] - 0s 4ms/step - loss: 0.0035
Epoch 15/20
7/7 [==============================] - 0s 4ms/step - loss: 0.0034
Epoch 16/20
7/7 [==============================] - 0s 5ms/step - loss: 0.0035
Epoch 17/20
7/7 [==============================] - 0s 4ms/step - loss: 0.0034
Epoch 18/20
7/7 [==============================] - 0s 4ms/step - loss: 0.0033
Epoch 19/20
7/7 [==============================] - 0s 4ms/step - loss: 0.0034
Epoch 20/20
7/7 [==============================] - 0s 4ms/step - loss: 0.0034
```

In [46]:

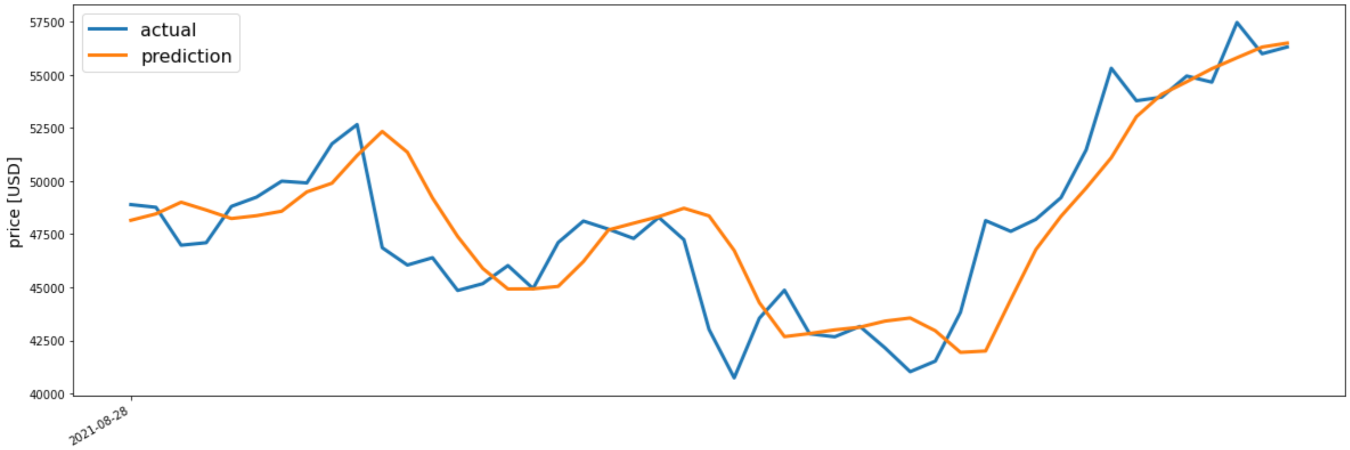
```
targets = test[target_col][window_len:]
preds = model.predict(X_test).squeeze()
mean_absolute_error(preds, y_test)
```

Out[46]:

```
0.03644739058996739
```

In [47]:

```
# 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)
```


actual
prediction
price [USD]
57500
55000
52500
50000
47500
45000
42500
40000
2021-08-28

```
In [ ]:
```

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In [ ]:
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In [ ]:
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In [ ]:
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