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	0.06450800
LTCBTC	0.00310100
BNBBTC	0.00785900
NEOBTC	0.00076300
QTUMETH	0.00345100
...	...
SHIBAUD	0.00003579
RAREBTC	0.00003497
RAREBNB	0.00445300
RAREBUSD	2.08100000
RAREUSDT	2.08300000

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']))
```

59500.27

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	59500.27000000	0.22141000
1	59500.37000000	0.78100000
2	59501.59000000	0.17263000
3	59503.91000000	0.13253000
4	59503.92000000	0.30420000

In [13]:
```
"""
Pulling historical daily data
"""
```

Out[13]: '\nPulling historical daily data\n'

In [14]:
```
btc_daily_data = client.get_historical_klines('BTCUSDT', Client.KLINE_INTERVAL_1DAY, '1 Jan 2021')
```

In [15]:
```
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 [16]:
```
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 [17]:
```
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 [18]:
```
btc_ohlcv_daily = btc_daily_df.iloc[:,0:6]
btc_ohlcv_daily = btc_ohlcv_daily.set_index('Open Time')
btc_ohlcv_daily
```

Out[18]:

	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
...	...	...	...	...	...
2021-10-11	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	57777.00	54167.19	57367.00	55808.444920
2021-10-14	57370.83	58532.54	56818.05	57347.94	43053.336781
2021-10-15	57347.94	59998.00	56850.00	59500.27	22985.941731

288 rows × 5 columns

In [19]:
```
btc_ohlcv_daily.to_csv("Resources/daily_btc_ohclv_2021.csv")
```

In [20]:
```
"""
Pulling historical minute data
"""
```

Out[20]: '\nPulling historical minute data \n'

In [21]:
```
historical_minute = client.get_historical_klines('BTCUSDC', Client.KLINE_INTERVAL_1MINUTE, '5 day ago UTC')
```

In [22]:
```
hist_min = pd.DataFrame(historical_minute)
```

In [23]:
```
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 [24]:
```
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 [25]:
```
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 [26]:

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

Out[26]:

Open Time	Open	High	Low	Close	Volume
2021-10-10 06:09:00	55709.36	55724.57	55706.70	55724.57	0.56403
2021-10-10 06:10:00	55742.80	55759.57	55742.80	55752.76	0.32922
2021-10-10 06:11:00	55751.30	55770.67	55748.26	55766.65	0.15288
2021-10-10 06:12:00	55768.60	55770.50	55745.04	55751.96	0.18513
2021-10-10 06:13:00	55741.08	55763.42	55739.91	55757.96	0.47958
...	...	...	...	...	...
2021-10-15 06:04:00	59632.53	59635.60	59621.07	59621.97	0.61397
2021-10-15 06:05:00	59642.96	59645.22	59590.38	59610.30	0.50913
2021-10-15 06:06:00	59620.23	59620.23	59549.26	59549.26	1.92446
2021-10-15 06:07:00	59580.22	59580.22	59503.90	59530.12	1.64753
2021-10-15 06:08:00	59518.61	59543.79	59511.87	59514.58	0.41735

7200 rows × 5 columns

In [27]:

```
btc_ohlcv_minute.to_csv("Resources/minute_btc_ohclv_2021.csv")
```

In [28]:

```
"""
Next, we will be using the daily data for our Recurrent Neural Network. We are using Recurrent Neural Network for its use of time series and sequential data
RNN specializes in using information from prior inputs and uses it to influence current inputs and outputs, and the cycle repeats.
"""
```

Out[28]:

```
'\nNext, we will be using the daily data for our Recurrent Neural Network. We are using Recurrent Neural Network for its use of time series and sequential d
ata. \nRNN specializes in using information from prior inputs and uses it to influence current inputs and outputs, and the cycle repeats. \n'
```

In [29]:

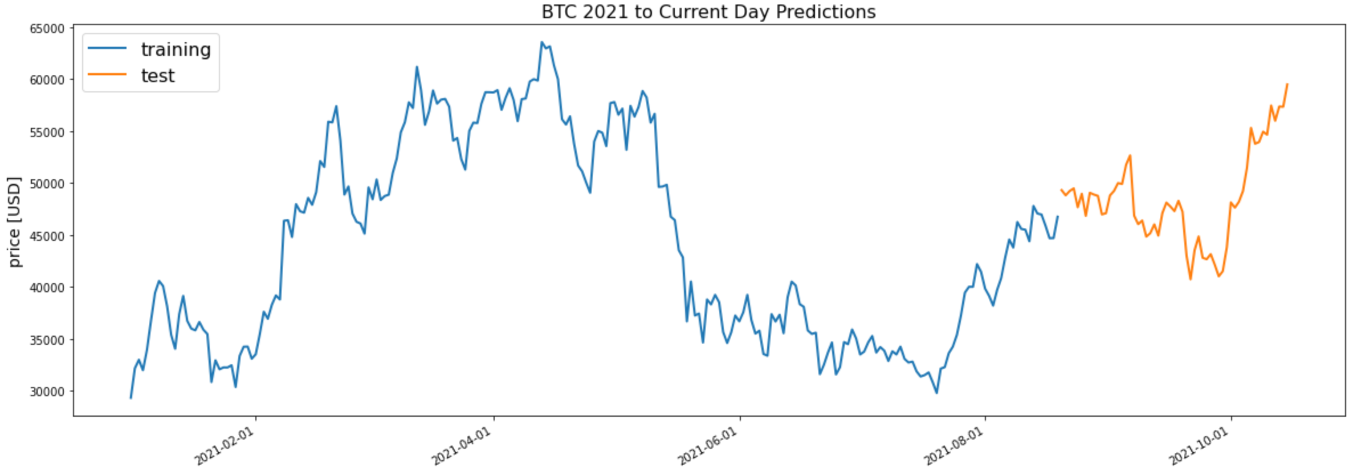
```
btc_df = pd.read_csv(Path("Resources/daily_btc_ohclv_2021.csv"),
                     index_col= "Open Time")
target_col = 'Close'
```

In [30]:

```
# 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 [31]:

```
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 [32]:
```
"""
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[32]: '\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 of values.\n'

In [33]:
```
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 [34]:
```
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 [35]:
```
# J.Guanzon Comment: We want to use the data from Jan-Jun 2021 and use the rest of the data to train and predict the rest of the data.
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 [36]:
```
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 [37]:
```
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 [38]:

```
np.random.seed(50)
window_len = 5
test_size = 0.2
zero_base = True
lstm_neurons = 100
epochs = 100
batch_size = 32
loss = 'mse'
dropout = 0.2
optimizer = 'adam'
```

In [39]:

```
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 1/100
8/8 [==============================] - 4s 10ms/step - loss: 0.0095
Epoch 2/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0065
Epoch 3/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0052
Epoch 4/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0045
Epoch 5/100
8/8 [==============================] - 0s 8ms/step - loss: 0.0042
Epoch 6/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0042
Epoch 7/100
8/8 [==============================] - 0s 10ms/step - loss: 0.0040
Epoch 8/100
8/8 [==============================] - 0s 8ms/step - loss: 0.0037
Epoch 9/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0039
Epoch 10/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0035
Epoch 11/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0033
Epoch 12/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0034
Epoch 13/100
8/8 [==============================] - 0s 10ms/step - loss: 0.0032
Epoch 14/100
8/8 [==============================] - 0s 8ms/step - loss: 0.0030
Epoch 15/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0033
Epoch 16/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0029
Epoch 17/100
8/8 [==============================] - 0s 8ms/step - loss: 0.0030
Epoch 18/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0030
Epoch 19/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0031
Epoch 20/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0031
Epoch 21/100
8/8 [==============================] - 0s 8ms/step - loss: 0.0028
Epoch 22/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0028
Epoch 23/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0028
Epoch 24/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0027
Epoch 25/100
8/8 [==============================] - 0s 8ms/step - loss: 0.0028
Epoch 26/100
8/8 [==============================] - 0s 8ms/step - loss: 0.0027
Epoch 27/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0027
Epoch 28/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0025
Epoch 29/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0026
Epoch 30/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0027
Epoch 31/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0026
Epoch 32/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0026
Epoch 33/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0029
Epoch 34/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0027
Epoch 35/100
8/8 [==============================] - 0s 7ms/step - loss: 0.0026
Epoch 36/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0026
Epoch 37/100
8/8 [==============================] - 0s 10ms/step - loss: 0.0025
Epoch 38/100
```

```
8/8 [==============================] - 0s 9ms/step - loss: 0.0025
Epoch 39/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0026
Epoch 40/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0026
Epoch 41/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0026
Epoch 42/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0024
Epoch 43/100
8/8 [==============================] - 0s 7ms/step - loss: 0.0026
Epoch 44/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0026
Epoch 45/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0026
Epoch 46/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0024
Epoch 47/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0026
Epoch 48/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0024
Epoch 49/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0024
Epoch 50/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0024
Epoch 51/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0022
Epoch 52/100
8/8 [==============================] - 0s 10ms/step - loss: 0.0024
Epoch 53/100
8/8 [==============================] - 0s 10ms/step - loss: 0.0026
Epoch 54/100
8/8 [==============================] - 0s 10ms/step - loss: 0.0025
Epoch 55/100
8/8 [==============================] - 0s 10ms/step - loss: 0.0023
Epoch 56/100
8/8 [==============================] - 0s 10ms/step - loss: 0.0024
Epoch 57/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0023
Epoch 58/100
8/8 [==============================] - 0s 8ms/step - loss: 0.0024
Epoch 59/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0023
Epoch 60/100
8/8 [==============================] - 0s 8ms/step - loss: 0.0024
Epoch 61/100
8/8 [==============================] - 0s 8ms/step - loss: 0.0024
Epoch 62/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0024
Epoch 63/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0023
Epoch 64/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0023
Epoch 65/100
8/8 [==============================] - 0s 8ms/step - loss: 0.0022
Epoch 66/100
8/8 [==============================] - 0s 8ms/step - loss: 0.0024
Epoch 67/100
8/8 [==============================] - 0s 8ms/step - loss: 0.0024
Epoch 68/100
8/8 [==============================] - 0s 8ms/step - loss: 0.0024
Epoch 69/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0023
Epoch 70/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0023
Epoch 71/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0022
Epoch 72/100
8/8 [==============================] - 0s 8ms/step - loss: 0.0024
Epoch 73/100
8/8 [==============================] - 0s 10ms/step - loss: 0.0024
Epoch 74/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0023
Epoch 75/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0025
Epoch 76/100
8/8 [==============================] - 0s 10ms/step - loss: 0.0023
Epoch 77/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0023
Epoch 78/100
8/8 [==============================] - 0s 10ms/step - loss: 0.0025
Epoch 79/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0026
Epoch 80/100
8/8 [==============================] - 0s 10ms/step - loss: 0.0022
Epoch 81/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0024
Epoch 82/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0021
Epoch 83/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0021
Epoch 84/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0021
Epoch 85/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0023
Epoch 86/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0025
Epoch 87/100
8/8 [==============================] - 0s 8ms/step - loss: 0.0024
Epoch 88/100
8/8 [==============================] - 0s 8ms/step - loss: 0.0022
Epoch 89/100
```

```
8/8 [==============================] - 0s 9ms/step - loss: 0.0022
Epoch 90/100
8/8 [==============================] - 0s 8ms/step - loss: 0.0021
Epoch 91/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0022
Epoch 92/100
8/8 [==============================] - 0s 7ms/step - loss: 0.0025
Epoch 93/100
8/8 [==============================] - 0s 8ms/step - loss: 0.0026
Epoch 94/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0024
Epoch 95/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0023
Epoch 96/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0022
Epoch 97/100
8/8 [==============================] - 0s 8ms/step - loss: 0.0022
Epoch 98/100
8/8 [==============================] - 0s 8ms/step - loss: 0.0020
Epoch 99/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0021
Epoch 100/100
8/8 [==============================] - 0s 9ms/step - loss: 0.0023
```

In [40]:

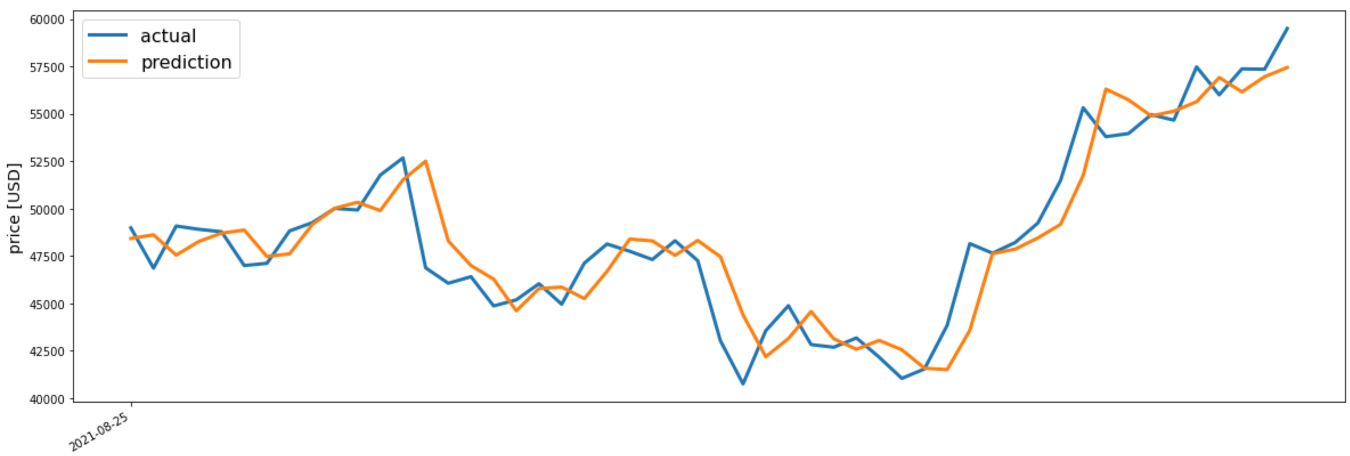
```
targets = test[target_col][window_len:]
preds = model.predict(X_test).squeeze()
mean_absolute_error(preds, y_test)
```

Out[40]:

```
0.028931695470333287
```

In [41]:

```
# 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 [ ]: