Bitcoin price prediction

Problem description

The problem presented in this notebook is the prediction of the price of Bitcoin. The dataset used in this notebook can be found online via: https://www.quandl.com/data/BCHARTS/KRAKENUSD-Bitcoin-Markets-krakenUSD .

Implementation

This notebook tries to solve the problem using a Reccurent Neural Network (RNNs), and, more specifically, Long Short Term Memory networks (LSTMs).

RNNs

RNNs make use of sequential information, its output being dependent on the previous computations. A way to think about them is that they have a "memory" which captures information about what has been calculated so far. The problem with RNNs is that the amount of past information it can hold is limited. In the case of Bitcoin prices, it would be useful to have a large amount of past prices. This is where LSTMs become useful.

LSTMs

LSTMs or Long Short Memory Networks are a special kind of RNN, capable of learning long-term dependencies. They are explicitly designed to avoid the long-term dependency problem that the RNNs have.

Imports

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn.preprocessing import MinMaxScaler
```

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LSTM, Dropout
```

Data fetching & statistics

In [2]:
```
dataframe = pd.read_csv(filepath_or_buffer = "BCHARTS-KRAKENUSD.csv")
dataframe = dataframe.iloc[::-1]

dataframe.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2689 entries, 2688 to 0
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Date               2689 non-null   object 
 1   Open               2689 non-null   float64
 2   High               2689 non-null   float64
 3   Low                2689 non-null   float64
 4   Close              2689 non-null   float64
 5   Volume (BTC)       2689 non-null   float64
 6   Volume (Currency)  2689 non-null   float64
 7   Weighted Price     2689 non-null   float64
dtypes: float64(7), object(1)
memory usage: 168.2+ KB
```

In [3]:
```
dataframe.describe()
```

Out[3]:

	Open	High	Low	Close	Volume (BTC)	Volume (Currency)	Weighted Price
count	2689.000000	2689.000000	2689.000000	2689.000000	2689.000000	2.689000e+03	2689.000000
mean	6763.144698	6976.471788	6517.329513	6772.348286	3780.178657	4.195755e+07	6755.894797
std	11086.022617	11451.426148	10634.910731	11091.484565	4374.233252	8.691776e+07	11068.481727
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000e+00	0.000000
25%	479.997990	500.000000	465.001430	475.006510	86.532707	2.753809e+04	477.180242
50%	3560.100000	3632.200000	3468.700000	3562.300000	2717.600653	1.356895e+07	3551.134905
75%	8712.800000	8933.700000	8421.000000	8716.500000	5630.447920	4.503784e+07	8665.858389

	Open	High	Low	Close	Volume (BTC)	Volume (Currency)	Weighted Price
max	63581.000000	64900.000000	62050.000000	63587.200000	45110.873425	1.237786e+09	63326.470550

In [4]:
```
dataframe.tail()
```

Out[4]:

	Date	Open	High	Low	Close	Volume (BTC)	Volume (Currency)	Weighted Price
4	2021-05-23	37474.8	38269.7	31078.7	34718.8	14832.738515	5.050181e+08	34047.528311
3	2021-05-24	34718.8	39989.9	34420.8	38833.8	11058.707601	4.155683e+08	37578.380688
2	2021-05-25	38843.0	39841.8	36500.0	38388.1	9236.125577	3.505080e+08	37949.674385
1	2021-05-26	38373.3	40893.6	37828.7	39283.9	9233.565257	3.624884e+08	39257.680017
0	2021-05-27	39290.0	40398.0	37230.0	38603.5	5757.923466	2.233911e+08	38797.164686

Data modification

What I am trying to predict is the Weighted Price column. To make it easier, I will extract the column into a separate DataFrame object and I will set its index column to the Date column which will be in datetime format.

In [5]:
```
dataframe_price = pd.DataFrame(dataframe['Weighted Price'])
dataframe_price.index = pd.to_datetime(dataframe['Date'])
print(dataframe_price.index)
print()
print(dataframe_price)
```

```
DatetimeIndex(['2014-01-07', '2014-01-08', '2014-01-09', '2014-01-10',
               '2014-01-11', '2014-01-12', '2014-01-13', '2014-01-14',
               '2014-01-15', '2014-01-16',
               ...
               '2021-05-18', '2021-05-19', '2021-05-20', '2021-05-21',
               '2021-05-22', '2021-05-23', '2021-05-24', '2021-05-25',
               '2021-05-26', '2021-05-27'],
              dtype='datetime64[ns]', name='Date', length=2689, freq=None)

            Weighted Price
Date
2014-01-07      841.835522
2014-01-08      839.156269
```

```
2014-01-09      831.572913
2014-01-10      844.938794
2014-01-11      890.671709
...                    ...
2021-05-23    34047.528311
2021-05-24    37578.380688
2021-05-25    37949.674385
2021-05-26    39257.680017
2021-05-27    38797.164686

[2689 rows x 1 columns]
```

In [6]:

```
dataframe_price.describe()
```

Out[6]:

	Weighted Price
count	2689.000000
mean	6755.894797
std	11068.481727
min	0.000000
25%	477.180242
50%	3551.134905
75%	8665.858389
max	63326.470550

As it can be seen in the min row, there are some dates with 0 Weighted Price. To fix this, we will replace replace every 0 value with the previous non-zero value.

In [7]:

```
dataframe_price.replace(to_replace = 0, method = 'ffill', inplace = True)
dataframe_price.describe()
```

Out[7]:

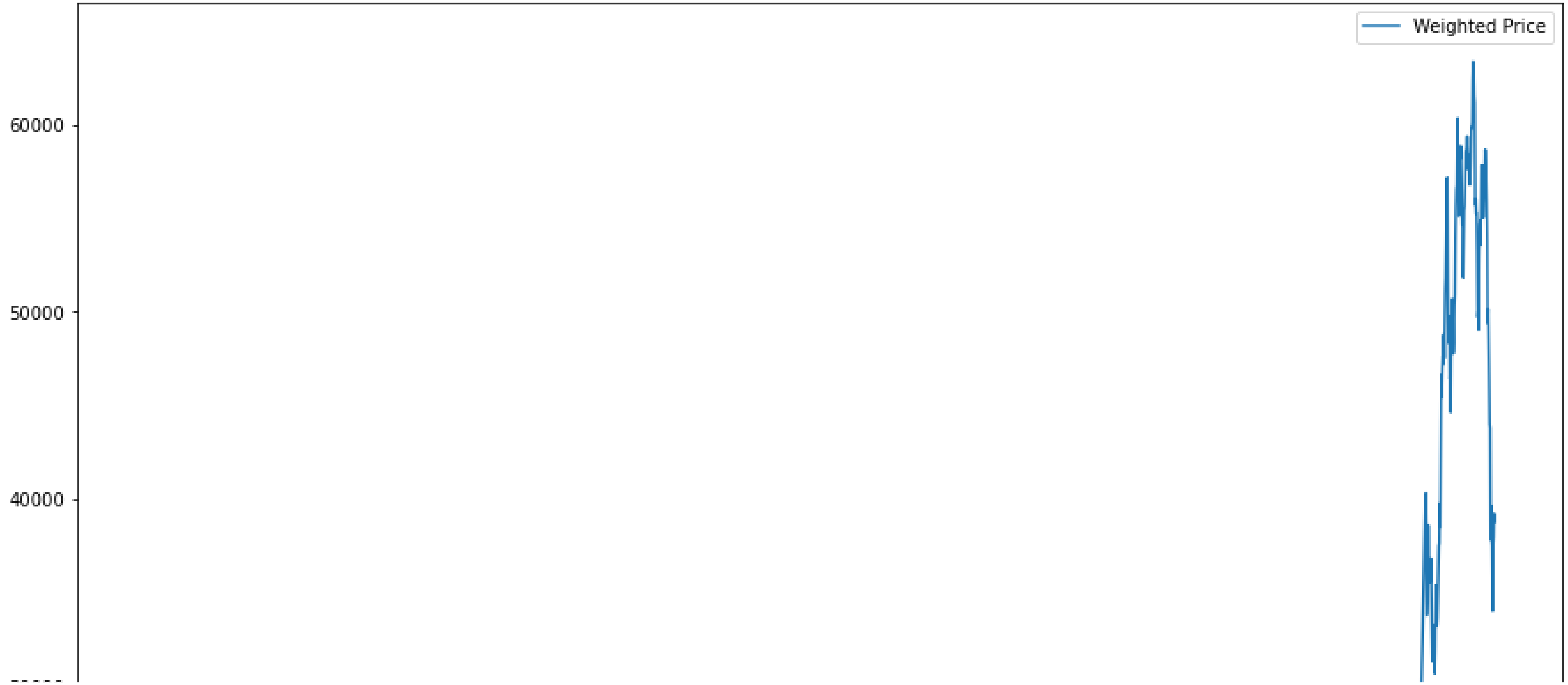
	Weighted Price
count	2689.000000
mean	6765.569675
std	11063.393706

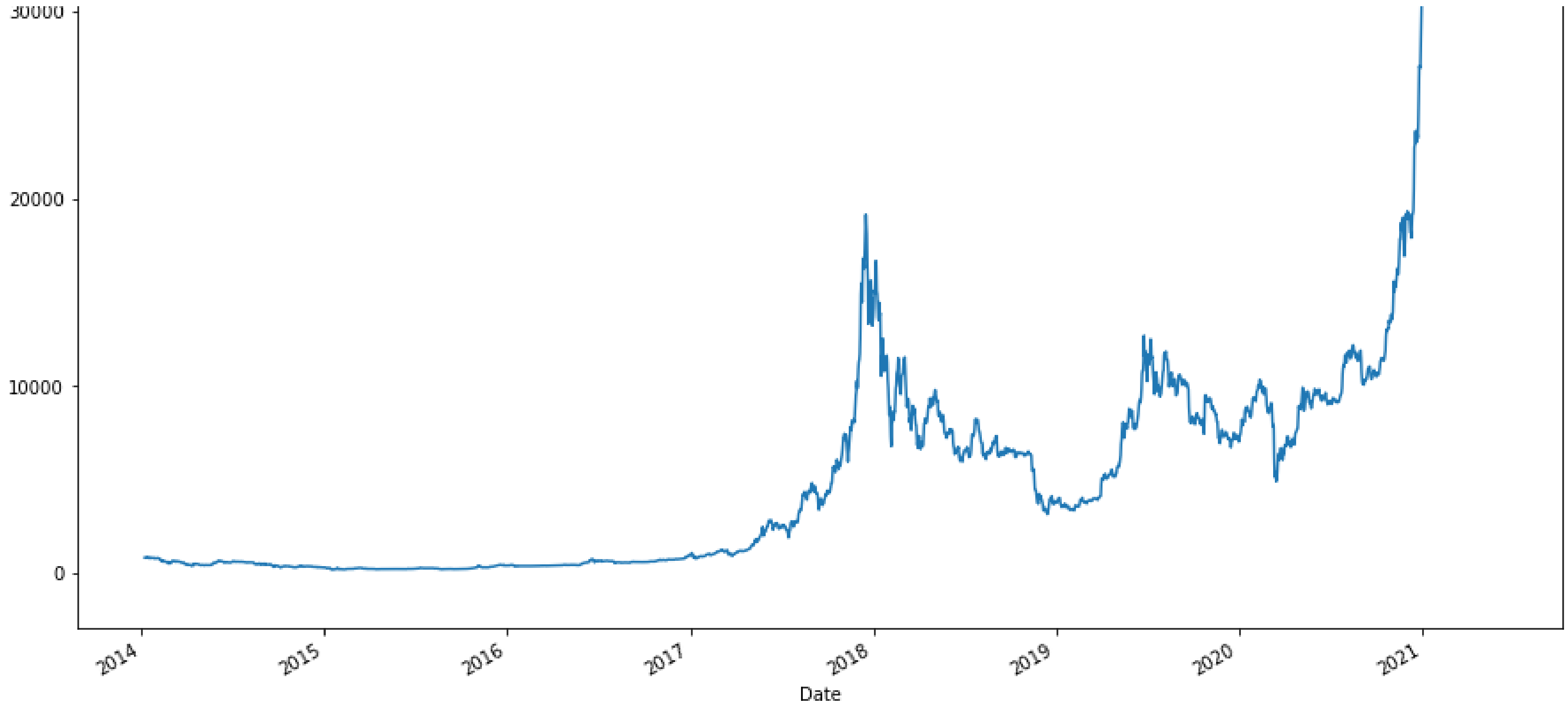
	Weighted Price
min	199.628389
25%	488.077565
50%	3551.464453
75%	8665.858389
max	63326.470550

Data visualization

In [8]:
```
dataframe_price.plot(figsize = (15, 15))
```

Out[8]: <AxesSubplot:xlabel='Date'>





Data splitting

In [9]:
```
test_size = 150

df_train = dataframe_price[: len(dataframe_price) - test_size]
trainset = df_train.values

df_test = dataframe_price[len(dataframe_price) - test_size :]
testset = df_test.values
pred_input = testset

trainset
```

Out[9]:
```
array([[  841.8355223 ],
       [  839.15626937],
```

```
       [  831.57291257],
       ...,
       [22738.61136594],
       [22855.91137875],
       [23557.57947433]])
```

Data scaling

In [10]:
```
scaler = MinMaxScaler()

trainset = scaler.fit_transform(trainset)
pred_input = scaler.transform(pred_input)

print(trainset)

X_train = trainset[0 : len(trainset) - 1]
y_train = trainset[1 : len(trainset)]
```

```
[[0.02749416]
 [0.02737945]
 [0.02705479]
 ...
 [0.96493836]
 [0.9699602 ]
 [1.        ]]
```

Reshape for keras

In [15]:
```
X_train = np.reshape(X_train, (len(X_train), 1, 1))
pred_input = np.reshape(pred_input, (len(pred_input), 1, 1))
```

Model fitting

In [12]:
```
model = Sequential()

model.add(LSTM(units = 4, activation = 'sigmoid', input_shape = (None, 1)))
#model.add(Dropout(0.2))
model.add(Dense(units = 1))
model.compile(optimizer = 'adam', loss = 'mean_squared_error')
```

```python
model.fit(X_train, y_train, batch_size = 5, epochs = 100)
```

```
Epoch 1/100
508/508 [==============================] - 1s 1ms/step - loss: 0.0317
Epoch 2/100
508/508 [==============================] - 1s 1ms/step - loss: 0.0200
Epoch 3/100
508/508 [==============================] - 1s 1ms/step - loss: 0.0109
Epoch 4/100
508/508 [==============================] - 1s 1ms/step - loss: 0.0043
Epoch 5/100
508/508 [==============================] - 1s 1ms/step - loss: 0.0011
Epoch 6/100
508/508 [==============================] - 1s 1ms/step - loss: 2.5946e-04
Epoch 7/100
508/508 [==============================] - 1s 1ms/step - loss: 1.5393e-04
Epoch 8/100
508/508 [==============================] - 1s 1ms/step - loss: 1.4691e-04
Epoch 9/100
508/508 [==============================] - 1s 1ms/step - loss: 1.4588e-04
Epoch 10/100
508/508 [==============================] - 1s 1ms/step - loss: 1.4439e-04
Epoch 11/100
508/508 [==============================] - 1s 1ms/step - loss: 1.4378e-04
Epoch 12/100
508/508 [==============================] - 1s 1ms/step - loss: 1.4098e-04
Epoch 13/100
508/508 [==============================] - 1s 1ms/step - loss: 1.4133e-04
Epoch 14/100
508/508 [==============================] - 1s 1ms/step - loss: 1.3713e-04
Epoch 15/100
508/508 [==============================] - 1s 1ms/step - loss: 1.3305e-04
Epoch 16/100
508/508 [==============================] - 1s 1ms/step - loss: 1.3327e-04
Epoch 17/100
508/508 [==============================] - 1s 1ms/step - loss: 1.3118e-04
Epoch 18/100
508/508 [==============================] - 1s 1ms/step - loss: 1.3020e-04
Epoch 19/100
508/508 [==============================] - 1s 1ms/step - loss: 1.2749e-04
Epoch 20/100
508/508 [==============================] - 1s 1ms/step - loss: 1.2629e-04
Epoch 21/100
508/508 [==============================] - 1s 1ms/step - loss: 1.2532e-04
```

```
Epoch 22/100
508/508 [==============================] - 1s 1ms/step - loss: 1.2484e-04
Epoch 23/100
508/508 [==============================] - 1s 1ms/step - loss: 1.2354e-04
Epoch 24/100
508/508 [==============================] - 1s 1ms/step - loss: 1.2184e-04
Epoch 25/100
508/508 [==============================] - 1s 2ms/step - loss: 1.2151e-04
Epoch 26/100
508/508 [==============================] - 1s 2ms/step - loss: 1.2172e-04
Epoch 27/100
508/508 [==============================] - 1s 1ms/step - loss: 1.2036e-04
Epoch 28/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1951e-04
Epoch 29/100
508/508 [==============================] - 1s 1ms/step - loss: 1.2056e-04
Epoch 30/100
508/508 [==============================] - 1s 2ms/step - loss: 1.1800e-04
Epoch 31/100
508/508 [==============================] - 1s 1ms/step - loss: 1.2011e-04
Epoch 32/100
508/508 [==============================] - 1s 2ms/step - loss: 1.1790e-04
Epoch 33/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1790e-04
Epoch 34/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1584e-04
Epoch 35/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1881e-04
Epoch 36/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1585e-04
Epoch 37/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1562e-04
Epoch 38/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1455e-04
Epoch 39/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1449e-04
Epoch 40/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1605e-04
Epoch 41/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1420e-04
Epoch 42/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1613e-04
Epoch 43/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1517e-04
Epoch 44/100
```

```
508/508 [==============================] - 1s 2ms/step - loss: 1.1452e-04
Epoch 45/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1535e-04
Epoch 46/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1445e-04
Epoch 47/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1577e-04
Epoch 48/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1299e-04
Epoch 49/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1457e-04
Epoch 50/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1430e-04
Epoch 51/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1476e-04
Epoch 52/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1512e-04
Epoch 53/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1549e-04
Epoch 54/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1228e-04
Epoch 55/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1598e-04
Epoch 56/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1382e-04
Epoch 57/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1561e-04
Epoch 58/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1534e-04
Epoch 59/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1407e-04
Epoch 60/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1594e-04
Epoch 61/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1483e-04
Epoch 62/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1466e-04
Epoch 63/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1568e-04
Epoch 64/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1476e-04
Epoch 65/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1432e-04
Epoch 66/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1110e-04
```

```
Epoch 67/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1342e-04
Epoch 68/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1346e-04
Epoch 69/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1578e-04
Epoch 70/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1471e-04
Epoch 71/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1276e-04
Epoch 72/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1343e-04
Epoch 73/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1424e-04
Epoch 74/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1665e-04
Epoch 75/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1270e-04
Epoch 76/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1151e-04
Epoch 77/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1274e-04
Epoch 78/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1507e-04
Epoch 79/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1479e-04
Epoch 80/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1471e-04
Epoch 81/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1440e-04
Epoch 82/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1325e-04
Epoch 83/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1392e-04
Epoch 84/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1283e-04
Epoch 85/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1216e-04
Epoch 86/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1332e-04
Epoch 87/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1346e-04
Epoch 88/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1564e-04
Epoch 89/100
```

```
508/508 [==============================] - 1s 1ms/step - loss: 1.1323e-04
Epoch 90/100
508/508 [==============================] - 1s 2ms/step - loss: 1.1269e-04
Epoch 91/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1296e-04
Epoch 92/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1388e-04
Epoch 93/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1377e-04
Epoch 94/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1380e-04
Epoch 95/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1363e-04
Epoch 96/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1203e-04
Epoch 97/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1449e-04
Epoch 98/100
508/508 [==============================] - 1s 2ms/step - loss: 1.1441e-04
Epoch 99/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1460e-04
Epoch 100/100
508/508 [==============================] - 1s 1ms/step - loss: 1.1499e-04
```

Out[12]:
```
<tensorflow.python.keras.callbacks.History at 0x29ffeac0bb0>
```

Prediction

In [13]:
```python
predicted_price = model.predict(pred_input)
predicted_price = scaler.inverse_transform(predicted_price)
```

In [14]:
```python
plt.figure(figsize=(25,15), dpi=50, facecolor='w', edgecolor='k')
plt.plot(testset, color = 'red', label = 'Real Price')
plt.plot(predicted_price, color = 'blue', label = 'Predicted Price')
plt.title('Bitcoin Price Prediction', fontsize=20)
plt.xlabel('Days', fontsize=20)
plt.ylabel('Price (USD)', fontsize=20)
plt.legend(loc=2, prop={'size': 25})
plt.show()
```

Bitcoin Price Prediction
Real Price
Predicted Price
Price (USD)
60000
50000
40000
30000
0
20
40
60
80
100
120
140
Days