In [ ]:

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
```

In [ ]:

```
path_to_dataset = '/content/drive/MyDrive/Colab Notebooks/project-ea/bitstampUSD_1-min_da
ta_2012-01-01_to_2021-03-31.csv'
bitcoin_dataset = pd.read_csv(path_to_dataset)
```

In [ ]:

```
#showing the data
bitcoin_dataset
```

Out[ ]:

	Timestamp	Open	High	Low	Close	Volume_(BTC)	Volume_(Currency)	Weighted_Price
0	1325317920	4.39	4.39	4.39	4.39	0.455581	2.000000	4.390000
1	1325317980	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	1325318040	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	1325318100	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	1325318160	NaN	NaN	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...
4857372	1617148560	58714.31	58714.31	58686.00	58686.00	1.384487	81259.372187	58692.753339
4857373	1617148620	58683.97	58693.43	58683.97	58685.81	7.294848	428158.146640	58693.226508
4857374	1617148680	58693.43	58723.84	58693.43	58723.84	1.705682	100117.070370	58696.198496
4857375	1617148740	58742.18	58770.38	58742.18	58760.59	0.720415	42332.958633	58761.866202
4857376	1617148800	58767.75	58778.18	58755.97	58778.18	2.712831	159417.751000	58764.349363

4857377 rows × 8 columns

In [ ]:

```
bitcoin_dataset.describe()
```

Out[ ]:

	Timestamp	Open	High	Low	Close	Volume_(BTC)	Volume_(Currency)	Weighted_F
count	4.857377e+06	3.613769e+06	3.613769e+06	3.613769e+06	3.613769e+06	3.613769e+06	3.613769e+06	3.613769e
mean	1.471301e+09	6.009024e+03	6.013357e+03	6.004488e+03	6.009014e+03	9.323249e+00	4.176284e+04	6.008935e
std	8.428019e+07	8.996247e+03	9.003521e+03	8.988778e+03	8.996360e+03	3.054989e+01	1.518248e+05	8.995992e
min	1.325318e+09	3.800000e+00	3.800000e+00	1.500000e+00	1.500000e+00	0.000000e+00	0.000000e+00	3.800000e
25%	1.398179e+09	4.438600e+02	4.440000e+02	4.435200e+02	4.438600e+02	4.097759e-01	4.521422e+02	4.438306e
50%	1.471428e+09	3.596970e+03	3.598190e+03	3.595620e+03	3.597000e+03	1.979811e+00	3.810124e+03	3.596804e
75%	1.544288e+09	8.627270e+03	8.632980e+03	8.621090e+03	8.627160e+03	7.278216e+00	2.569821e+04	8.627637e
max	1.617149e+09	6.176356e+04	6.178183e+04	6.167355e+04	6.178180e+04	5.853852e+03	1.390067e+07	6.171621e

In [ ]:

```
#checking for nulls
bitcoin_dataset.isnull().sum()
```

Out[ ]:

```
Timestamp                  0
Open                 1243608
High                 1243608
Low                  1243608
Close                1243608
Volume_(BTC)         1243608
Volume_(Currency)    1243608
Weighted_Price       1243608
dtype: int64
```

In [ ]:

```
#we need to know about how much percent of data is required for proper dataset
bitcoin_dataset.isnull().mean().round(4) * 100
```

Out[ ]:

```
Timestamp             0.0
Open                 25.6
High                 25.6
Low                  25.6
Close                25.6
Volume_(BTC)         25.6
Volume_(Currency)    25.6
Weighted_Price       25.6
dtype: float64
```

In [ ]:

```
#in each row we have like 28% null values. Even though it's lot of null data, it's still
invalid and so safe to delete!!!
bitcoin_dataset.dropna(inplace=True)
```

In [ ]:

```
#now we can inspect the null free dataser!!
bitcoin_dataset
```

Out[ ]:

	Timestamp	Open	High	Low	Close	Volume_(BTC)	Volume_(Currency)	Weighted_Price
0	1325317920	4.39	4.39	4.39	4.39	0.455581	2.000000	4.390000
478	1325346600	4.39	4.39	4.39	4.39	48.000000	210.720000	4.390000
547	1325350740	4.50	4.57	4.50	4.57	37.862297	171.380338	4.526411
548	1325350800	4.58	4.58	4.58	4.58	9.000000	41.220000	4.580000
1224	1325391360	4.58	4.58	4.58	4.58	1.502000	6.879160	4.580000
...	...	...	...	...	...	...	...	...
4857372	1617148560	58714.31	58714.31	58686.00	58686.00	1.384487	81259.372187	58692.753339
4857373	1617148620	58683.97	58693.43	58683.97	58685.81	7.294848	428158.146640	58693.226508
4857374	1617148680	58693.43	58723.84	58693.43	58723.84	1.705682	100117.070370	58696.198496
4857375	1617148740	58742.18	58770.38	58742.18	58760.59	0.720415	42332.958633	58761.866202
4857376	1617148800	58767.75	58778.18	58755.97	58778.18	2.712831	159417.751000	58764.349363

3613769 rows × 8 columns

In [ ]:

```
#for more visualization, we need to import seaborn and matplotlib
```

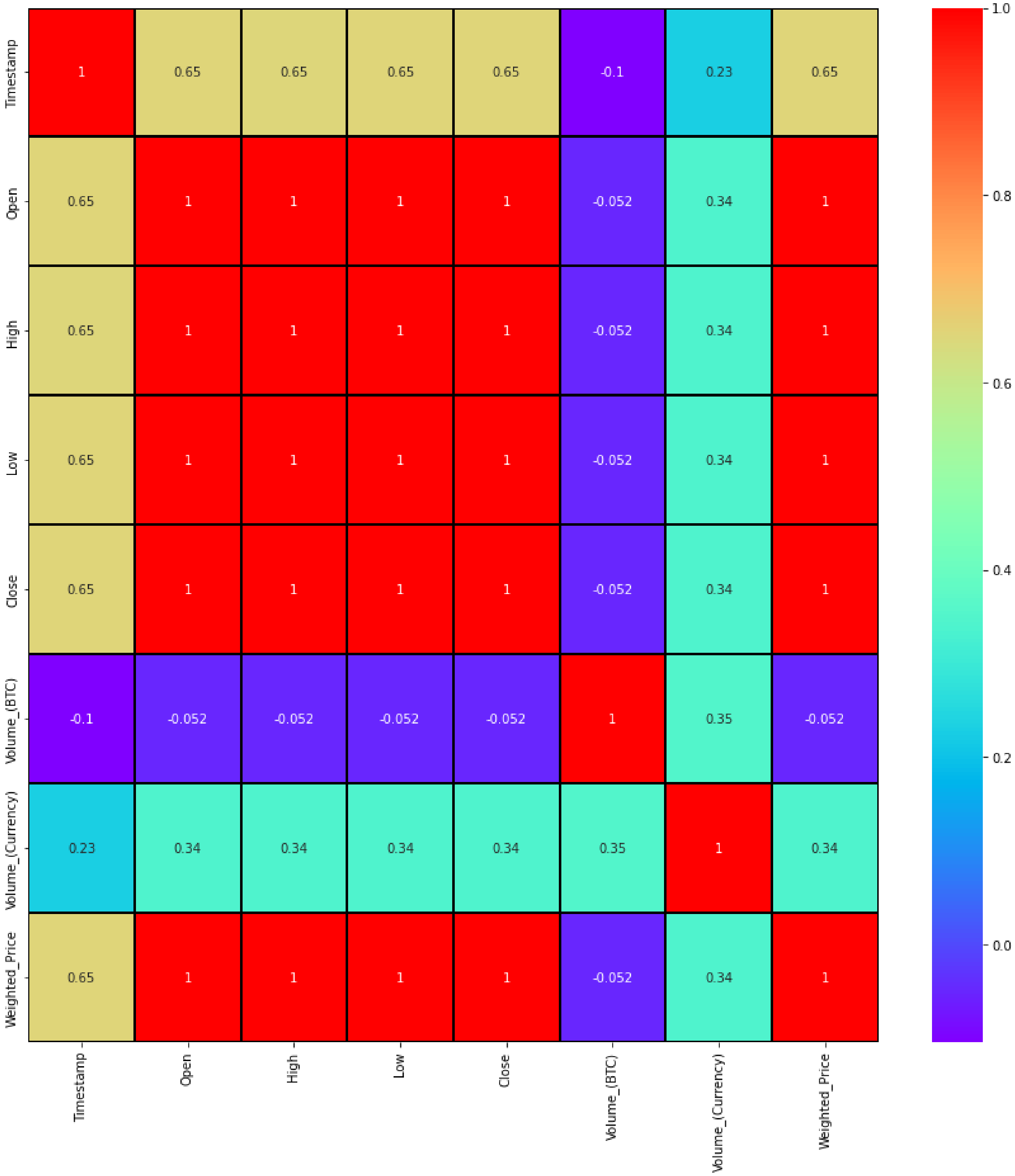
```
import seaborn as sbn
import matplotlib.pyplot as plt
```

In [ ]:

```
#correlation helps us to find out which of the fields are related to each other..
plt.figure(figsize=(15, 15))
sbn.heatmap(bitcoin_dataset.corr(), annot=True, cmap='rainbow', linewidths=1, linecolor='black')
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7862983fd0>
```



In [ ]:

```
#we should change the names of column just in case to avoid any feature errors
```

```
bitcoin_dataset.rename(columns={"Volume_(BTC)" : "Volume_BTC", "Volume_(Currency)" : "Volume_Currency"}, inplace=True)
```

In [ ]:

```
#similarly, we need to get the timestamp values to be human understandable
bitcoin_dataset['New_Dates'] = pd.to_datetime(bitcoin_dataset['Timestamp'], unit='s')

bitcoin_dataset
```

Out[ ]:

	Timestamp	Open	High	Low	Close	Volume_BTC	Volume_Currency	Weighted_Price	New_Dates
0	1325317920	4.39	4.39	4.39	4.39	0.455581	2.000000	4.390000	2011-12-31 07:52:00
478	1325346600	4.39	4.39	4.39	4.39	48.000000	210.720000	4.390000	2011-12-31 15:50:00
547	1325350740	4.50	4.57	4.50	4.57	37.862297	171.380338	4.526411	2011-12-31 16:59:00
548	1325350800	4.58	4.58	4.58	4.58	9.000000	41.220000	4.580000	2011-12-31 17:00:00
1224	1325391360	4.58	4.58	4.58	4.58	1.502000	6.879160	4.580000	2012-01-01 04:16:00
...	...	...	...	...	...	...	...	...	...
4857372	1617148560	58714.31	58714.31	58686.00	58686.00	1.384487	81259.372187	58692.753339	2021-03-30 23:56:00
4857373	1617148620	58683.97	58693.43	58683.97	58685.81	7.294848	428158.146640	58693.226508	2021-03-30 23:57:00
4857374	1617148680	58693.43	58723.84	58693.43	58723.84	1.705682	100117.070370	58696.198496	2021-03-30 23:58:00
4857375	1617148740	58742.18	58770.38	58742.18	58760.59	0.720415	42332.958633	58761.866202	2021-03-30 23:59:00
4857376	1617148800	58767.75	58778.18	58755.97	58778.18	2.712831	159417.751000	58764.349363	2021-03-31 00:00:00

3613769 rows × 9 columns

In [ ]:

```
required_features = ['Open', 'High', 'Low', 'Volume_BTC', 'Volume_Currency', 'Weighted_Price']
output_label = 'Close'
```

In [ ]:

```
bitcoin_dataset
```

Out[ ]:

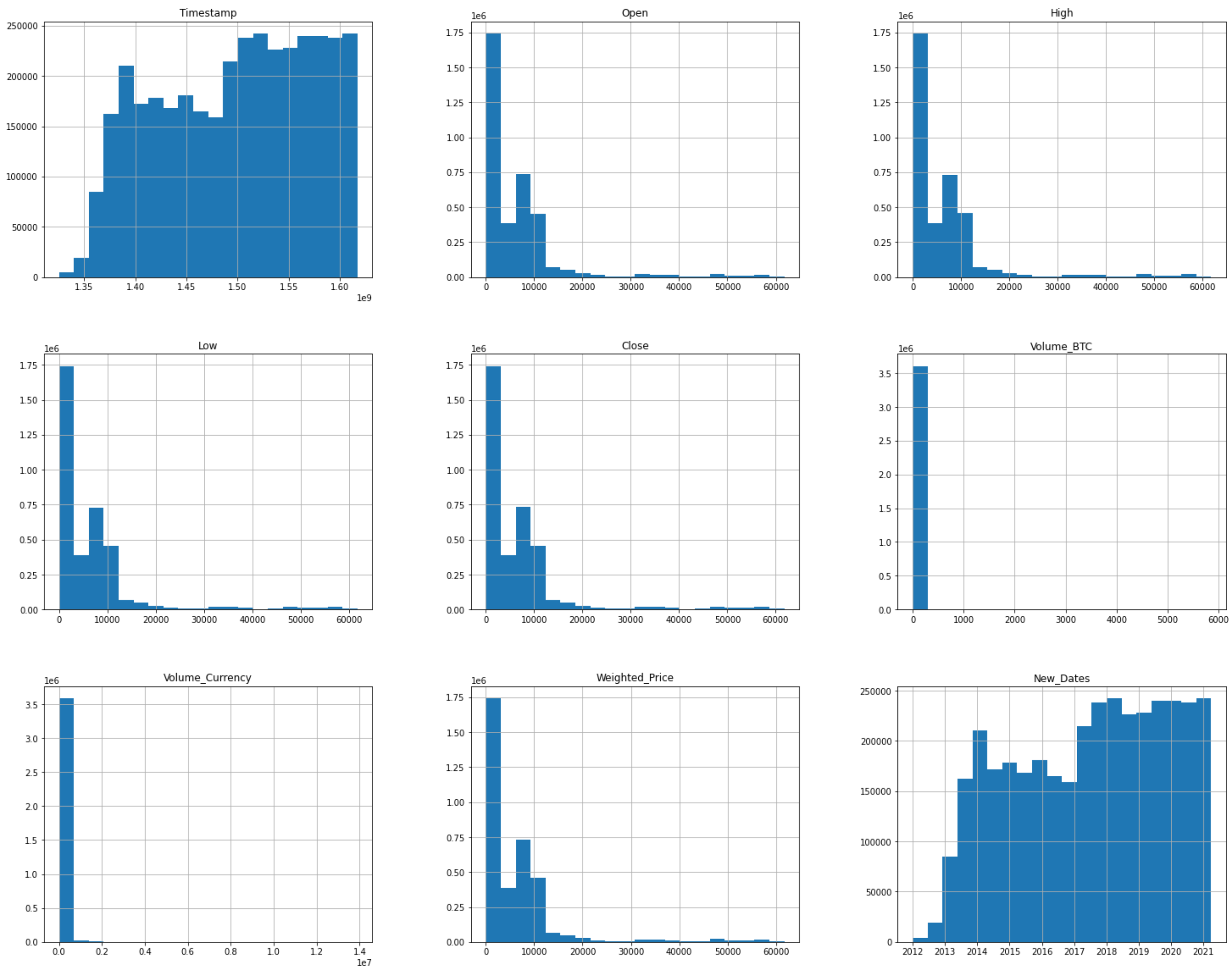
	Timestamp	Open	High	Low	Close	Volume_BTC	Volume_Currency	Weighted_Price	New_Dates
0	1325317920	4.39	4.39	4.39	4.39	0.455581	2.000000	4.390000	2011-12-31 07:52:00
478	1325346600	4.39	4.39	4.39	4.39	48.000000	210.720000	4.390000	2011-12-31 15:50:00
547	1325350740	4.50	4.57	4.50	4.57	37.862297	171.380338	4.526411	2011-12-31 16:59:00
548	1325350800	4.58	4.58	4.58	4.58	9.000000	41.220000	4.580000	2011-12-31 17:00:00
1224	1325391360	4.58	4.58	4.58	4.58	1.502000	6.879160	4.580000	2012-01-01 04:16:00
...	...	...	...	...	...	...	...	...	...

	Timestamp	Open	High	Low	Close	Volume_BTC	Volume_Currency	Weighted_Price	New_Dates
4857372	1617148560	58714.31	58714.31	58686.00	58686.00	1.384487	81259.372187	58692.753339	2021-03-30 23:56:00
4857373	1617148620	58683.97	58693.43	58683.97	58685.81	7.294848	428158.146640	58693.226508	2021-03-30 23:57:00
4857374	1617148680	58693.43	58723.84	58693.43	58723.84	1.705682	100117.070370	58696.198496	2021-03-30 23:58:00
4857375	1617148740	58742.18	58770.38	58742.18	58760.59	0.720415	42332.958633	58761.866202	2021-03-30 23:59:00
4857376	1617148800	58767.75	58778.18	58755.97	58778.18	2.712831	159417.751000	58764.349363	2021-03-31 00:00:00

3613769 rows × 9 columns

In [ ]:

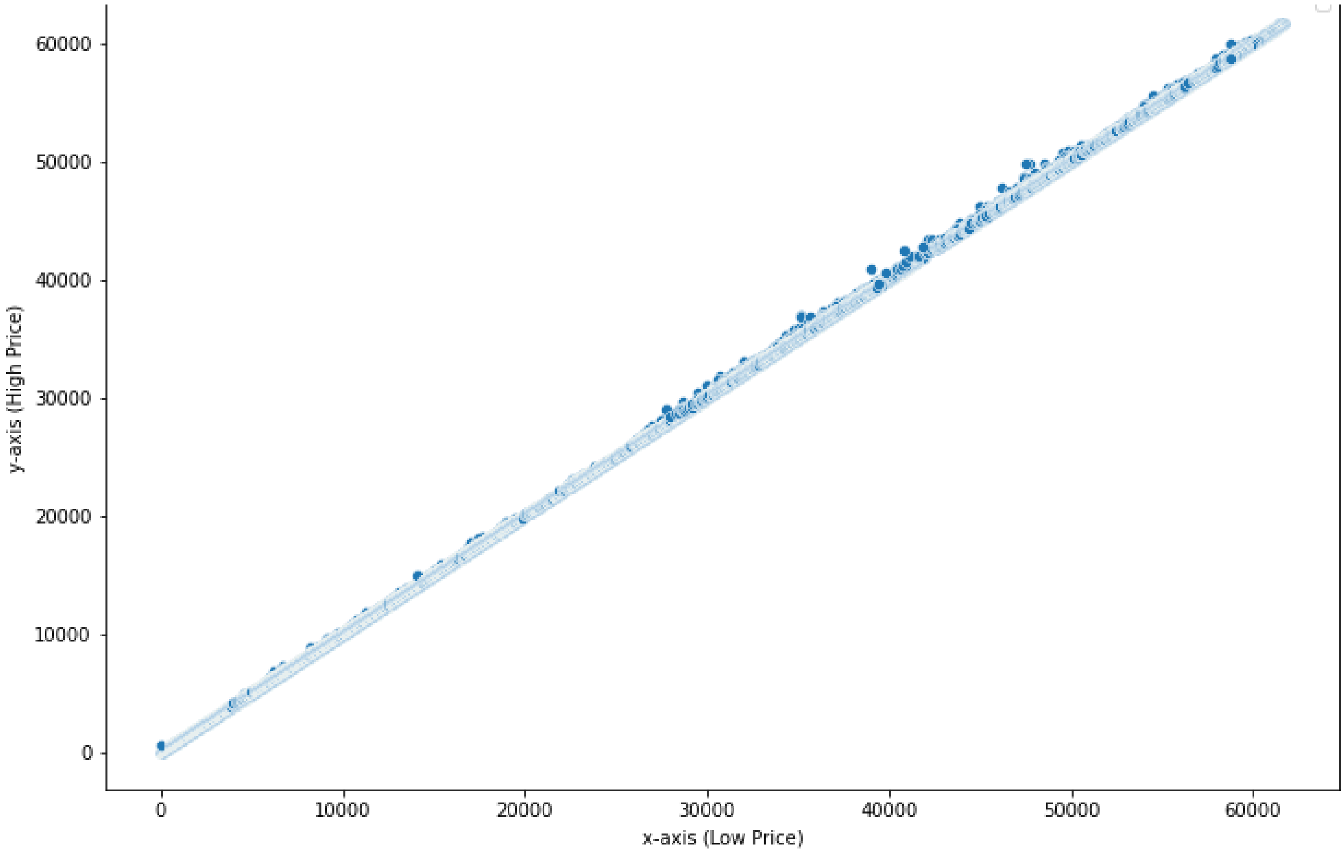
```
bitcoin_dataset.hist(bins=20, legend=False, figsize=(25, 20))
plt.show()
```



In [ ]:

```
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(12,8))
sns.scatterplot(x='Low', y='High', data=bitcoin_dataset)
plt.xlabel("x-axis (Low Price)")
plt.ylabel("y-axis (High Price)")
plt.legend()
plt.show()
```

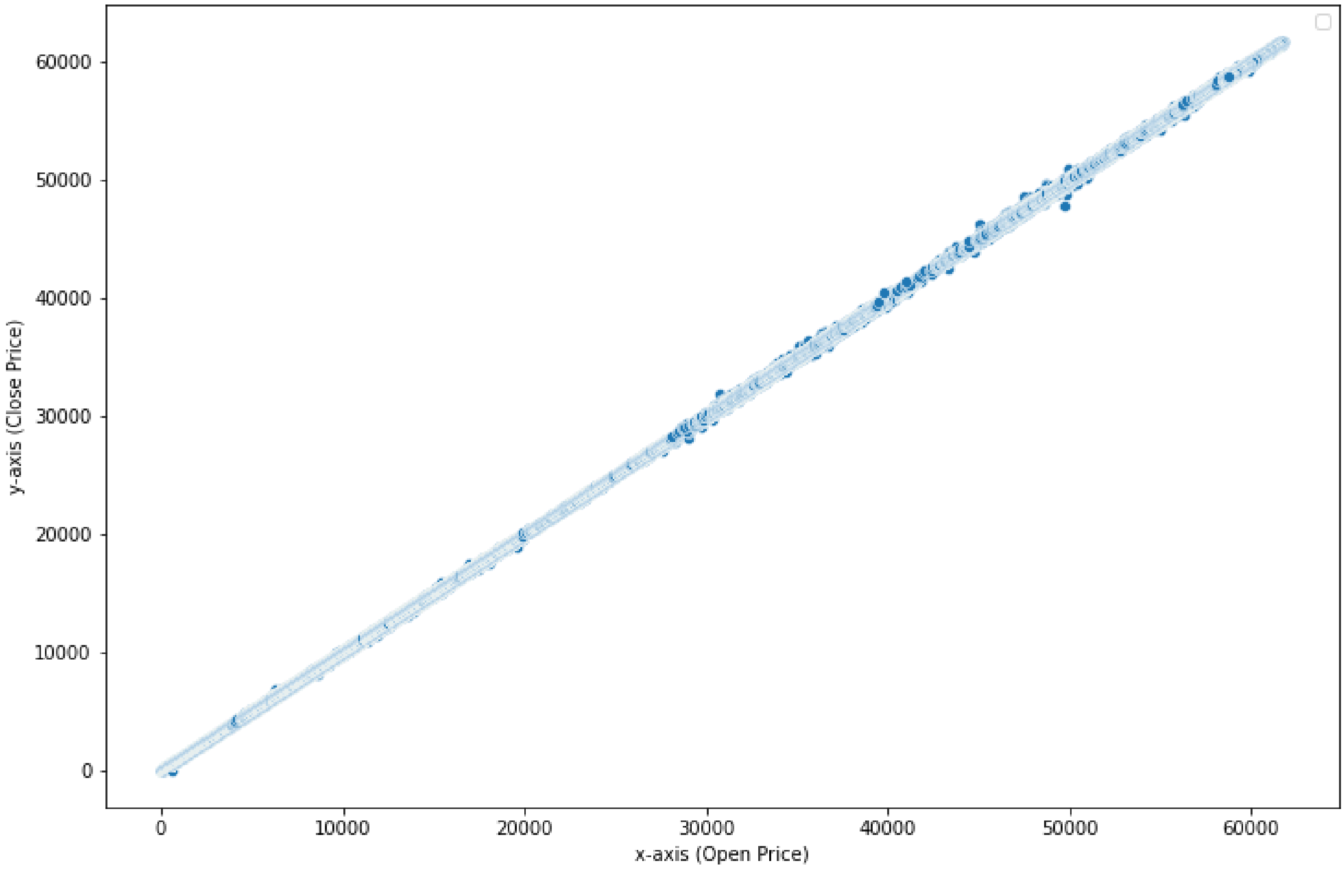
```
WARNING:matplotlib.legend:No handles with labels found to put in legend.
```



In [ ]:

```
plt.figure(figsize=(12,8))
sns.scatterplot(x='Open', y='Close', data=bitcoin_dataset)
plt.xlabel("x-axis (Open Price)")
plt.ylabel("y-axis (Close Price)")
plt.legend()
plt.show()
```

```
WARNING:matplotlib.legend:No handles with labels found to put in legend.
```



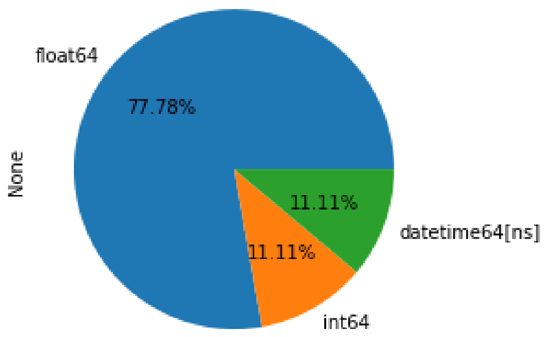
In [ ]:

```
bitcoin_dataset.dtypes.value_counts().plot.pie(autopct=('%0.2f%%'))
```

```
bitcoin_dataset.dtypes.value_counts().plot.pie(autopct='%0.2f%%')
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f784c781ee0>
```



In [ ]:

```
all_cols = bitcoin_dataset.select_dtypes(include=('float','int')).columns
float_data = bitcoin_dataset.select_dtypes(include=('float')).columns
float_data
```

Out[ ]:

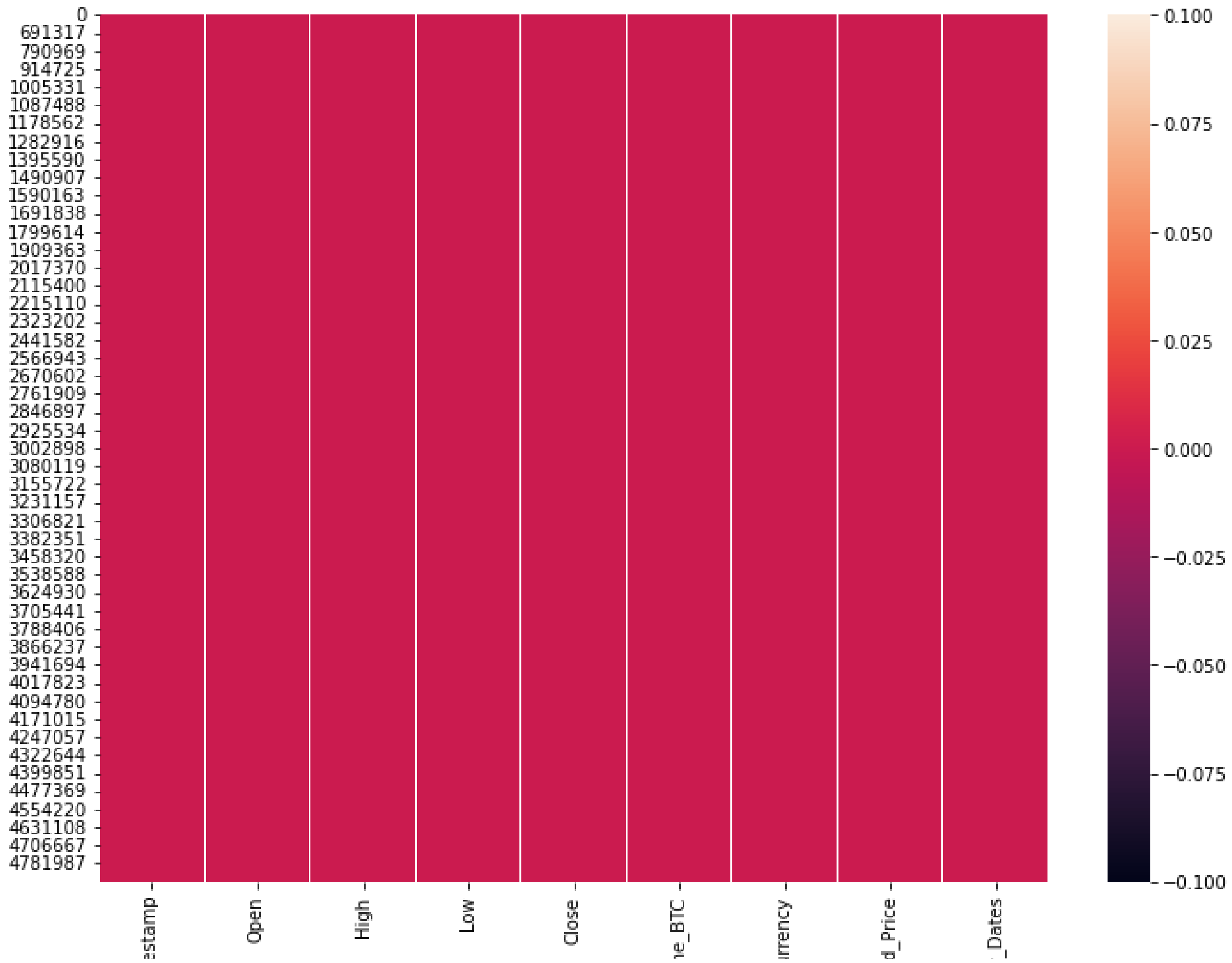
```
Index(['Open', 'High', 'Low', 'Close', 'Volume_BTC', 'Volume_Currency',
       'Weighted_Price'],
      dtype='object')
```

In [ ]:

```
plt.figure(figsize=(12,9))
sns.heatmap(bitcoin_dataset.isnull())
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f784d366e80>
```

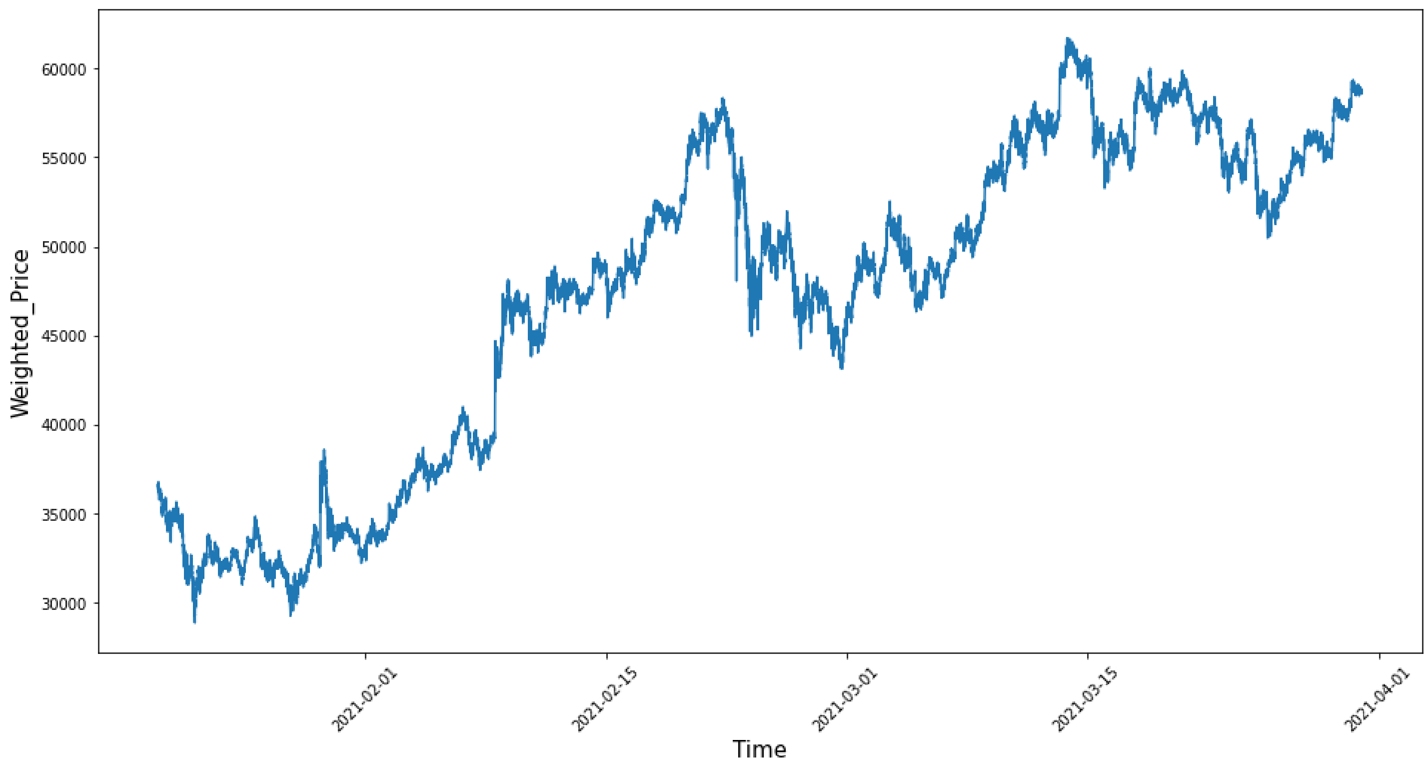


In [ ]:

```
def plotfig(data):
    plt.figure(figsize = (16,8))
    plt.plot(data["Weighted_Price"])
    plt.xlabel('Time',fontsize=15)
    plt.ylabel('Weighted_Price',fontsize=15)
    plt.xticks(rotation=45)
    plt.show()
```

In [ ]:

```
bitcoin_dataset["Timestamp"] = pd.to_datetime(bitcoin_dataset["Timestamp"], infer_dateti
me_format=True, unit="s")
data = bitcoin_dataset.set_index("Timestamp")

# Considering data of last 70 days only
freq = 60
c = int(60/freq)
days = 70

data = data.tail(days*24*60)
plotfig(data)
print(data.shape)

#taking interval of 10 minutes

data = data[::freq]
data.dropna(axis=0,inplace=True)

data = data["Weighted_Price"]

data = data.values.reshape(-1,1)
print("No. of days: ",data.shape[0]/(24*c))
```




```
(100800, 8)
No. of days:  70.0
```

```
/usr/local/lib/python3.8/dist-packages/pandas/util/_decorators.py:311: SettingWithCopyWar
ning:
A value is trying to be set on a copy of a slice from a DataFrame
```

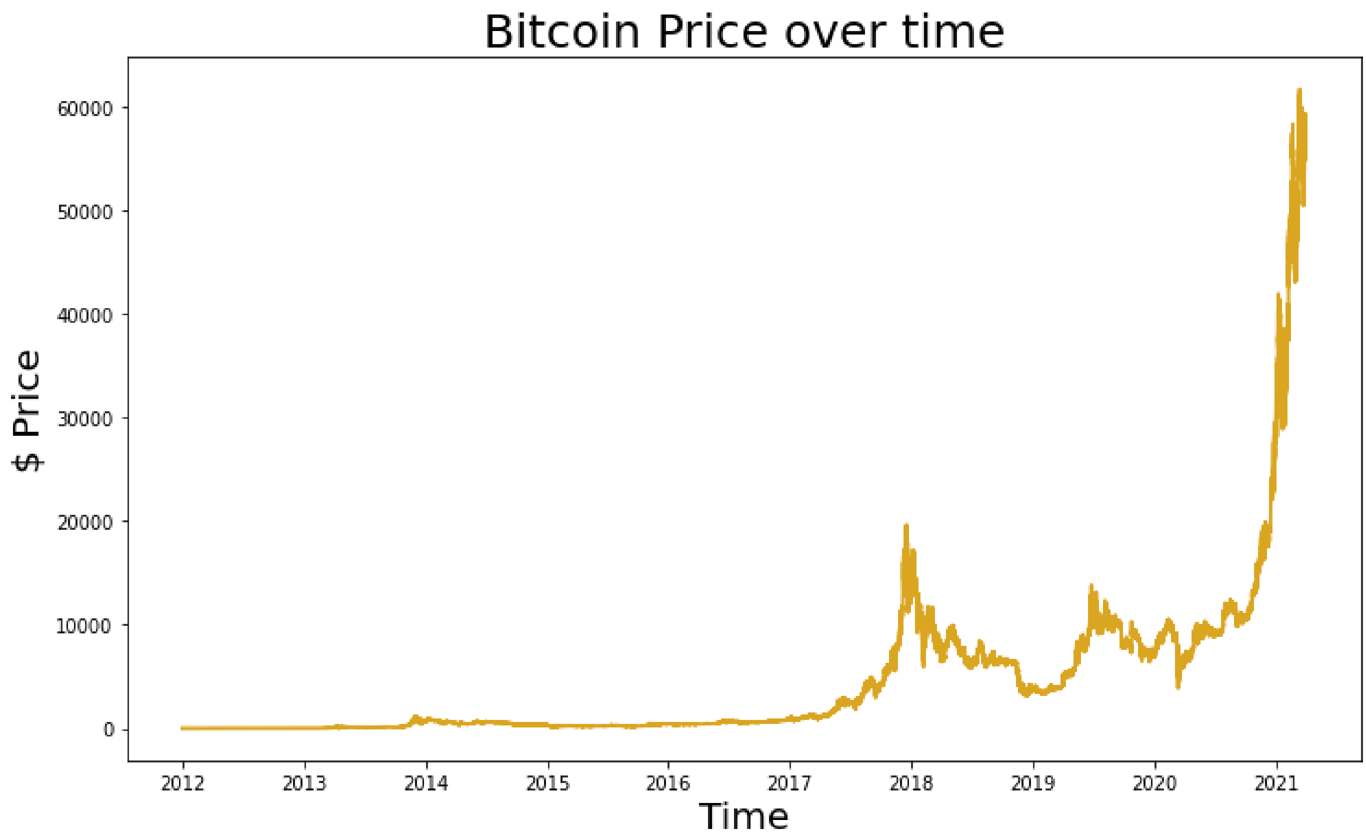
```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  return func(*args, **kwargs)
```

In [ ]:

```
plt.figure(figsize = (12, 7))
plt.plot(bitcoin_dataset["Timestamp"], bitcoin_dataset["Weighted_Price"], color='goldenro
d', lw=2)
plt.title("Bitcoin Price over time", size=25)
plt.xlabel("Time", size=20)
plt.ylabel("$ Price", size=20)
```

Out[ ]:

```
Text(0, 0.5, '$ Price')
```

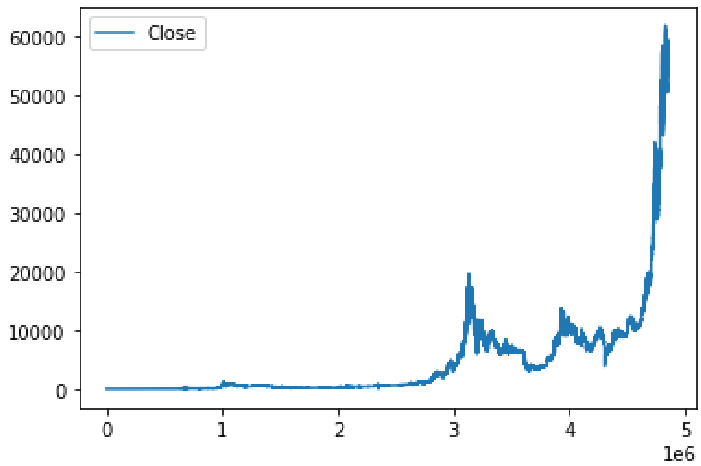


In [ ]:

```
#Plot the close price in time
Close = pd.DataFrame(bitcoin_dataset.Close)
Close.index = bitcoin_dataset.index
Close.plot()
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f784dc986a0>
```



In [ ]:

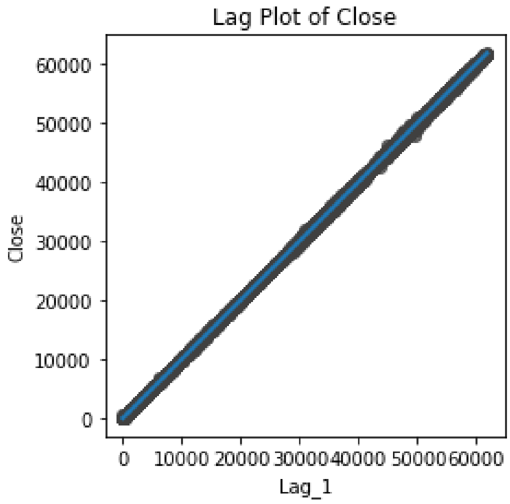
```
#Create a new column with the previous close price
Close['Lag_1'] = Close['Close'].shift(1)
Close = Close.reindex(columns=['Close', 'Lag_1'])
```

In [ ]:

```
#Plot the previous and the current price
fig, ax = plt.subplots()
ax = sns.regplot(x='Lag_1', y='Close', data=Close, ci=None, scatter_kws=dict(color='0.25
'))
ax.set_aspect('equal')
ax.set_title('Lag Plot of Close')
```

Out[ ]:

```
Text(0.5, 1.0, 'Lag Plot of Close')
```

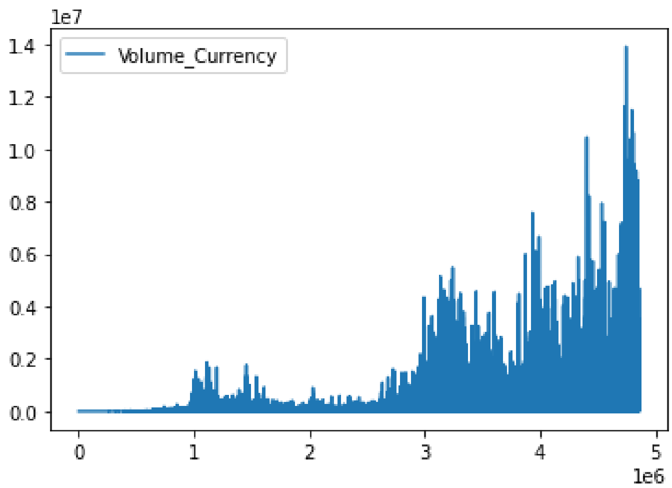


In [ ]:

```
Volume_Curency = pd.DataFrame(bitcoin_dataset['Volume_Currency'])
Volume_Curency.index = bitcoin_dataset.index
Volume_Curency.plot()
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f784d7575e0>
```



In [ ]:

```
Volume_Curency['Lag_1'] = Volume_Curency['Volume_Currency'].shift(1)
Volume_Curency = Volume_Curency.reindex(columns=['Volume_Currency', 'Lag_1'])
```

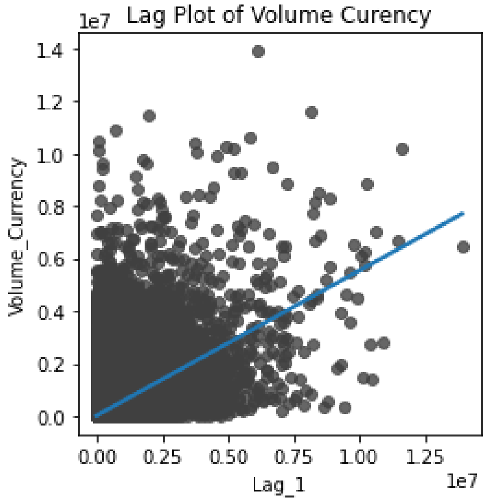
In [ ]:

```
fig, ax = plt.subplots()
```

```
ax = sns.regplot(x='Lag_1', y='Volume_Currency', data=Volume_Curency, ci=None, scatter_k
ws=dict(color='0.25'))
ax.set_aspect('equal')
ax.set_title('Lag Plot of Volume Curency')
```

Out[ ]:

```
Text(0.5, 1.0, 'Lag Plot of Volume Curency')
```

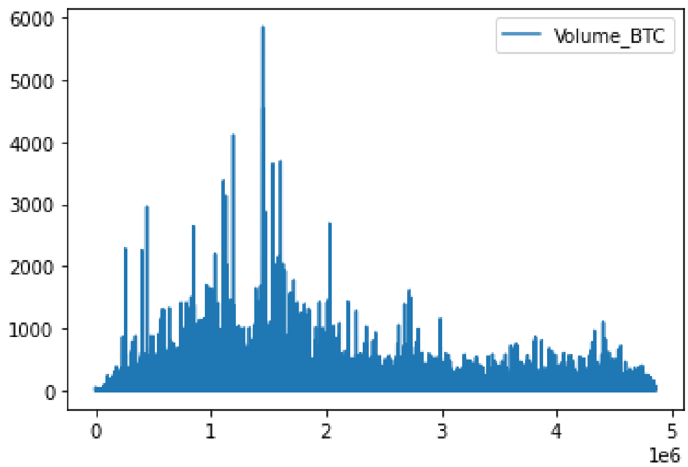


In [ ]:

```
Volume = pd.DataFrame(bitcoin_dataset['Volume_BTC'])
Volume.index = bitcoin_dataset.index
Volume.plot()
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f782f871460>
```



In [ ]:

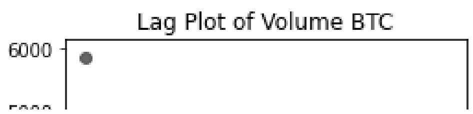
```
Volume['Lag_1'] = Volume['Volume_BTC'].shift(1)
Volume = Volume.reindex(columns=['Volume_BTC', 'Lag_1'])
```

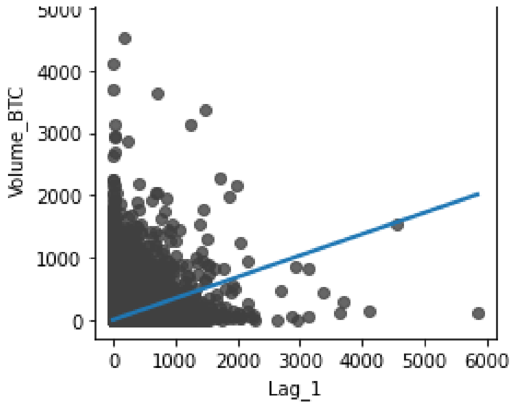
In [ ]:

```
fig, ax = plt.subplots()
ax = sns.regplot(x='Lag_1', y='Volume_BTC', data=Volume, ci=None, scatter_kws=dict(color
='0.25'))
ax.set_aspect('equal')
ax.set_title('Lag Plot of Volume BTC')
```

Out[ ]:

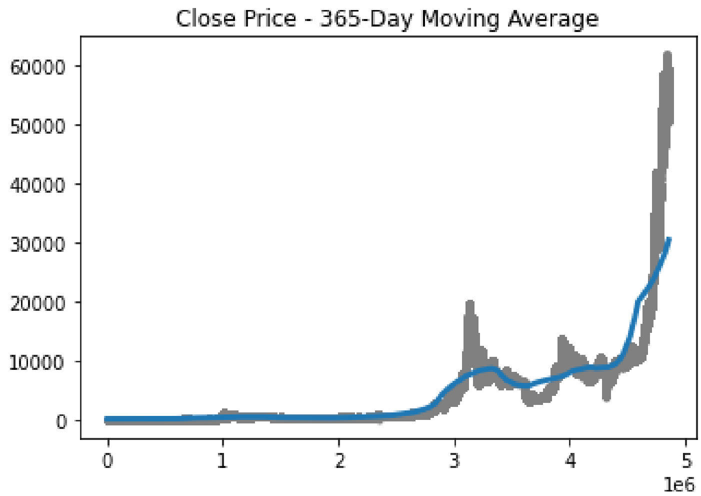
```
Text(0.5, 1.0, 'Lag Plot of Volume BTC')
```





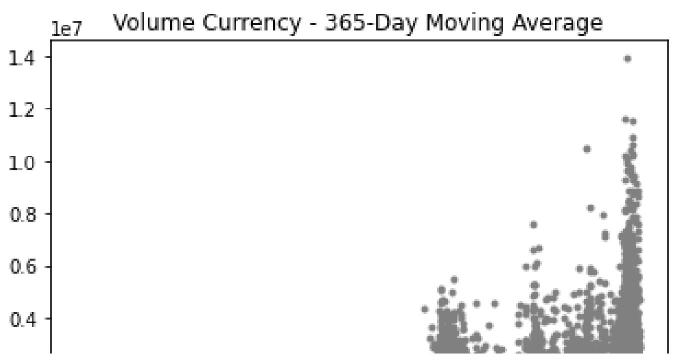
In [ ]:

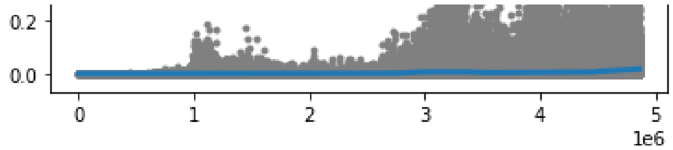
```
moving_average = Close['Close'].rolling(
    window=60*24*365,                             # 365-day window
    center=True,                                  # puts the average at the center of the window
    min_periods=int((60*24*365) / 2),            # choose about half the window size
).mean()                                        # compute the mean (could also do median, std, min
, max, ...)

ax = Close['Close'].plot(style=".", color="0.5")
moving_average.plot(
    ax=ax, linewidth=3, title="Close Price - 365-Day Moving Average", legend=False,
);
```



In [ ]:

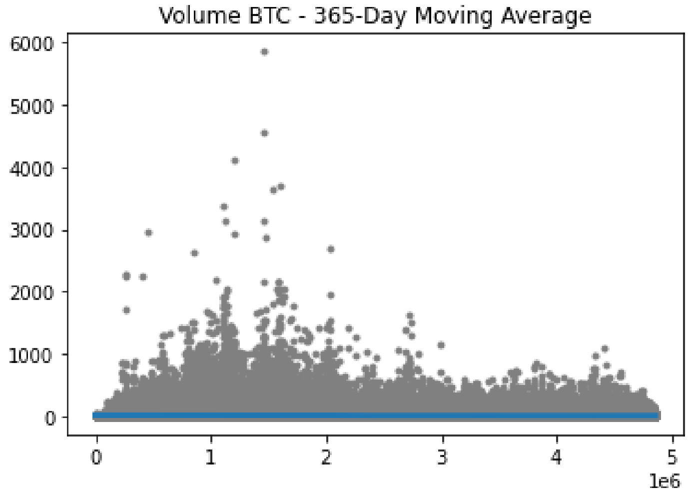
```
moving_average = Volume_Curency['Volume_Currency'].rolling(
    window=60*24*365,                                     # 365-day window
    center=True,                                          # puts the average at the center of the w
indow
    min_periods=int((60*24*365) / 2),                    # choose about half the window size
).mean()                                                # compute the mean (could also do median, s
td, min, max, ...)

ax = Volume_Curency['Volume_Currency'].plot(style=".", color="0.5")
moving_average.plot(
    ax=ax, linewidth=3, title="Volume Currency - 365-Day Moving Average", legend=False,
);
```





In [ ]:

```
moving_average = Volume['Volume_BTC'].rolling(
    window=60*24*365,                         # 365-day window
    center=True,                             # puts the average at the center of the wind
ow
    min_periods=int((60*24*365) / 2),       # choose about half the window size
).mean()                                    # compute the mean (could also do median, std,
min, max, ...)

ax = Volume['Volume_BTC'].plot(style=".", color="0.5")
moving_average.plot(
    ax=ax, linewidth=3, title="Volume BTC - 365-Day Moving Average", legend=False,
);
```



In [ ]:

```
#Helper fuctions
def plot_multistep(y, every=1, ax=None, palette_kwargs=None):
    palette_kwargs_ = dict(palette='husl', n_colors=16, desat=None)
    if palette_kwargs is not None:
        palette_kwargs_.update(palette_kwargs)
    palette = sns.color_palette(**palette_kwargs_)
    if ax is None:
        fig, ax = plt.subplots()
    ax.set_prop_cycle(plt.cycler('color', palette))
    for date, preds in y[::every].iterrows():
        preds.index = pd.period_range(start=date, periods=len(preds))
        preds.plot(ax=ax)
    return ax

def make_lags(ts, lags, lead_time=1):
    return pd.concat(
        {
            f'y_lag_{i}': ts.shift(i)
            for i in range(lead_time, lags + lead_time)
        },
        axis=1)

def make_multistep_target(ts, steps):
    return pd.concat(
        {f'y_step_{i + 1}': ts.shift(-i)
         for i in range(steps)},
        axis=1)
```

In [ ]:

```
Close = Close.drop('Lag_1', axis = 1)
```

```
Volume_Curency = Volume_Curency.drop('Lag_1', axis = 1)
Volume = Volume.drop('Lag_1', axis = 1)
```

In [ ]:

```
y = Close.Close.copy()
X = make_lags(y, lags=10).fillna(0.0)

# Five step forecast
y = make_multistep_target(y, steps=5).dropna()
y, X = y.align(X, join='inner', axis=0)

# Create splits
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, shuffle=False)

model = LinearRegression()
model.fit(X_train, y_train)

y_fit = pd.DataFrame(model.predict(X_train), index=X_train.index, columns=y.columns)
y_pred = pd.DataFrame(model.predict(X_test), index=X_test.index, columns=y.columns)

train_rmse = mean_squared_error(y_train, y_fit, squared=False)
test_rmse = mean_squared_error(y_test, y_pred, squared=False)
print((f"Train RMSE Linear Regression: {train_rmse:.2f}\n" f"Test RMSE Linear Regression
: {test_rmse:.2f}"))
```

```
Train RMSE Linear Regression: 13.51
Test RMSE Linear Regression: 47.23
```

In [ ]:

```
y_test
```

Out[ ]:

	y_step_1	y_step_2	y_step_3	y_step_4	y_step_5
3941685	11906.57	11921.54	11907.46	11916.60	11916.57
3941686	11921.54	11907.46	11916.60	11916.57	11923.89
3941687	11907.46	11916.60	11916.57	11923.89	11921.42
3941688	11916.60	11916.57	11923.89	11921.42	11932.26
3941689	11916.57	11923.89	11921.42	11932.26	11924.30
...	...	...	...	...	...
4857367	58699.90	58698.50	58739.95	58714.31	58686.00
4857369	58698.50	58739.95	58714.31	58686.00	58685.81
4857370	58739.95	58714.31	58686.00	58685.81	58723.84
4857371	58714.31	58686.00	58685.81	58723.84	58760.59
4857372	58686.00	58685.81	58723.84	58760.59	58778.18

903442 rows × 5 columns

In [ ]:

```
y = Volume_Curency['Volume_Currency'].copy()
X = make_lags(y, lags=10).fillna(0.0)

# Five step forecast
y = make_multistep_target(y, steps=5).dropna()
y, X = y.align(X, join='inner', axis=0)

# Create splits
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, shuffle=False)

model = LinearRegression()
model.fit(X_train, y_train)
```

```
y_fit = pd.DataFrame(model.predict(X_train), index=X_train.index, columns=y.columns)
y_pred = pd.DataFrame(model.predict(X_test), index=X_test.index, columns=y.columns)

train_rmse = mean_squared_error(y_train, y_fit, squared=False)
test_rmse = mean_squared_error(y_test, y_pred, squared=False)
print((f"Train RMSE: {train_rmse:.2f}\n" f"Test RMSE: {test_rmse:.2f}"))
```

```
Train RMSE: 77926.03
Test RMSE: 211690.65
```

In [ ]:

```
y = Volume['Volume_BTC'].copy()
X = make_lags(y, lags=10).fillna(0.0)

# Five step forecast
y = make_multistep_target(y, steps=5).dropna()
y, X = y.align(X, join='inner', axis=0)

# Create splits
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, shuffle=False)

model = LinearRegression()
model.fit(X_train, y_train)

y_fit = pd.DataFrame(model.predict(X_train), index=X_train.index, columns=y.columns)
y_pred = pd.DataFrame(model.predict(X_test), index=X_test.index, columns=y.columns)

train_rmse = mean_squared_error(y_train, y_fit, squared=False)
test_rmse = mean_squared_error(y_test, y_pred, squared=False)
print((f"Train RMSE: {train_rmse:.2f}\n" f"Test RMSE: {test_rmse:.2f}"))
```

```
Train RMSE: 32.03
Test RMSE: 14.49
```

In [ ]:

```
from sklearn.linear_model import ElasticNet
y = Volume['Volume_BTC'].copy()
X = make_lags(y, lags=10).fillna(0.0)

# Five step forecast
y = make_multistep_target(y, steps=5).dropna()
y, X = y.align(X, join='inner', axis=0)

# Create splits
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, shuffle=False)

model = ElasticNet()
model.fit(X_train, y_train)

y_fit = pd.DataFrame(model.predict(X_train), index=X_train.index, columns=y.columns)
y_pred = pd.DataFrame(model.predict(X_test), index=X_test.index, columns=y.columns)

train_rmse = mean_squared_error(y_train, y_fit, squared=False)
test_rmse = mean_squared_error(y_test, y_pred, squared=False)
print((f"Train RMSE DecisionTreeRegressor: {train_rmse:.2f}\n" f"Test RMSE DecisionTreeRe
gressor: {test_rmse:.2f}"))
```

```
Train RMSE DecisionTreeRegressor: 32.03
Test RMSE DecisionTreeRegressor: 14.49
```

In [ ]:

```
#scaling

scaler_train = MinMaxScaler(feature_range=(0, 1))
data = scaler_train.fit_transform(data)
```

In [ ]:

```
# Train-test split

train_split_time = 30*24*c
test_split_time = 50*24*c

train_data = data[:train_split_time]
valid_data = data[train_split_time:test_split_time]
test_data = data[test_split_time:]

window_size = 30
batch_size = 32
shuffle_buffer_size = 1000
```

In [ ]:

```
data.shape
```

Out[ ]:

```
(1680, 1)
```

In [ ]:

```
Total = ['Open', 'High', 'Low', 'Close','Volume_BTC', 'Volume_Currency', 'Weighted_Price
']
btc_new_x = ['Open', 'High', 'Low', 'Volume_BTC', 'Volume_Currency', 'Weighted_Price']
btc_new_y = ['Close']
```

In [ ]:

```
X_train, X_test, y_train, y_test = train_test_split( bitcoin_dataset[btc_new_x], bitcoin
_dataset[btc_new_x], test_size = 0.3)
```

In [ ]:

```
regression_model = LinearRegression()
regression_model = LinearRegression()
regression_model.fit(X_train, y_train)
```

Out[ ]:

```
LinearRegression()
```

In [ ]:

```
#our model is ready!! Time to test accuracy!!!
regression_model.score(X_test, y_test)
```

Out[ ]:

```
1.0
```

In [ ]:

```
# We got 99% accuracy on our test data also..that means our model is quite good
#now we can test for actual predictions!!

#we will take some data from test set and try to predict that

#we will take row number 55 from our original dataset, i.e from one before splitting
sample_data = bitcoin_dataset.iloc[55]
sample_data
```

Out[ ]:

```
Timestamp          2012-01-06 18:42:00
Open                               6.4
High                               6.4
Low                                6.4
Close                              6.4
Volume_BTC                    9.110853
Volume_Currency              58.309457
Weighted_Price                     6.4
```

```
New_Dates          2012-01-06 18:42:00
Name: 9290, dtype: object
```

from above, it's clear that original price was 6.4 and out model predicted it as 6.4 which is pretty much equal

In [ ]:

```
#to make predictions of future values we will need to shift data by 30 days!!
future_set = bitcoin_dataset.shift(periods=30).tail(30)
```

In [ ]:

```
#similarly we can use r2_score to see our accuracy
predictions = regression_model.predict(X_test)
print('Accuracy of model : ', r2_score(predictions, y_test))
```

```
Accuracy of model :  1.0
```