BITCOIN PRICE PREDICTION

In [1]:

```
#import library
from IPython.display import Image
#load image from local storage
Image(filename = r'F:\IBM_prjkt\bitcoin.jpg',width=1000,height=300)
```

Out[1]:

- **IMPORTING LIBRARIES**

In [2]:

```
import pandas as pd
import numpy as np
#for visualization
import matplotlib.pyplot as plt
import seaborn as sns
#for data preprocessing and processing
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.metrics import mean_squared_error

#for modelling of data
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.tree import DecisionTreeRegressor
import datetime as dt
from sklearn.preprocessing import MinMaxScaler
from sklearn import metrics
from sklearn.metrics import r2_score
```

- **Loading the datasets**

In [3]:

```
data_1 = pd.read_csv(r'F:\IBM_prjkt\bitstampUSD_1-min_data_2012-01-01_to_2019-08-12.csv')
data_2 = pd.read_csv(r'F:\IBM_prjkt\coinbaseUSD_1-min_data_2014-12-01_to_2019-01-09.csv')
```

In [4]:

```
data_1.head()
```

Out[4]:

	Timestamp	Open	High	Low	Close	Volume_(BTC)	Volume_(Currency)	Weighted_Price
0	1325317920	4.39	4.39	4.39	4.39	0.455581	2.0	4.39
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

In [5]:

```
data_2.head()
```

Out[5]:

	Timestamp	Open	High	Low	Close	Volume_(BTC)	Volume_(Currency)	Weighted_Price
0	1417411980	300.0	300.0	300.0	300.0	0.01	3.0	300.0
1	1417412040	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	1417412100	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	1417412160	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	1417412220	NaN	NaN	NaN	NaN	NaN	NaN	NaN

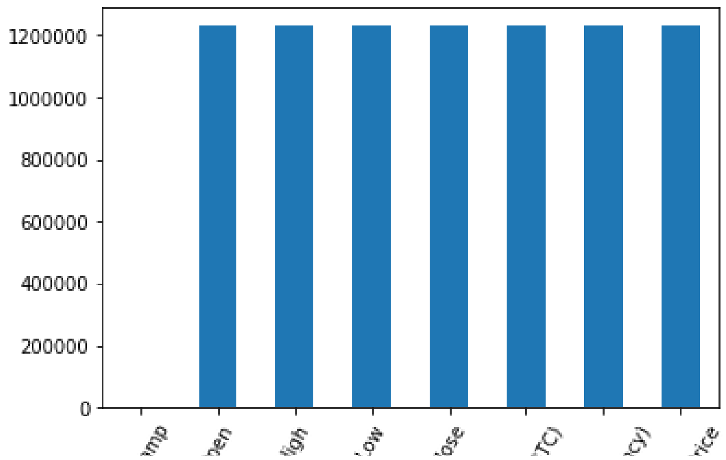
- **Check if any NaN values are present**

In [6]:

```
missing_val = data_1.isnull().sum()     #Too many null values
missing_val.to_frame()
missing_val.sort_values(missing_val[0],inplace=True)
```

In [7]:

```
missing_val.plot.bar( rot=60)
plt.show()
```



In [8]:

```
data_2.isnull().sum()     #Too many null values
```

Out[8]:

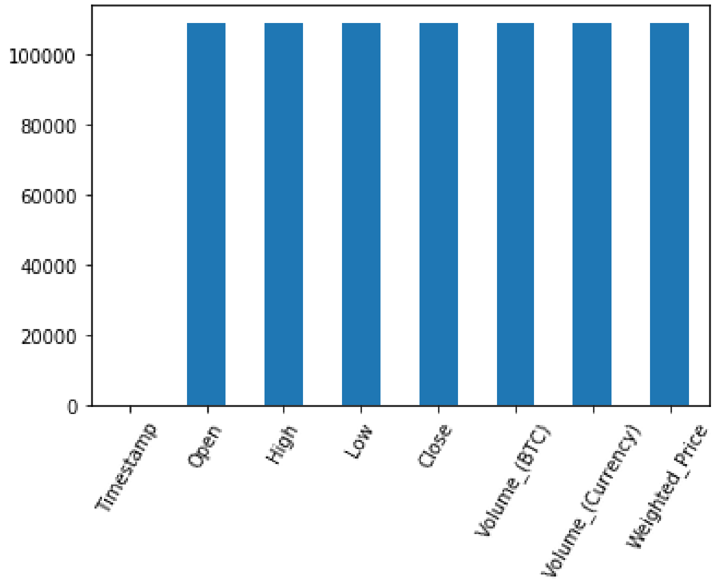
```
Timestamp                 0
Open                 109069
High                 109069
Low                  109069
Close                109069
Volume_(BTC)         109069
Volume_(Currency)    109069
Weighted_Price       109069
dtype: int64
```

In [9]:

```
missing_val = data_2.isnull().sum()     #Too many null values
missing_val.to_frame()
missing_val.sort_values(missing_val[0],inplace=True)
```

In [10]:

```
missing_val.plot.bar( rot=60)
plt.show()
```



- **Shape of the datasets**

In [11]:

```
print('The number of rows in dataset_1 are {} and columns are {}'.format(data_1.shape[0],
data_1.shape[1]))
print('The number of rows in dataset_2 are {} and columns are {}'.format(data_2.shape[0],
data_2.shape[1]))
```

```
The number of rows in dataset_1 are 3997697 and columns are 8
The number of rows in dataset_2 are 2099760 and columns are 8
```

Checking Datatypes

In [12]:

```
data_1.dtypes
```

Out[12]:

```
Timestamp              int64
Open                 float64
High                 float64
Low                  float64
Close                float64
Volume_(BTC)         float64
Volume_(Currency)    float64
Weighted_Price       float64
dtype: object
```

In [13]:

```
data_2.dtypes
```

Out[13]:

```
Timestamp              int64
Open                 float64
High                 float64
Low                  float64
Close                float64
Volume_(BTC)         float64
Volume_(Currency)    float64
Weighted_Price       float64
dtype: object
```

- **Info about datasets**

In [14]:

```
data_1.describe()
```

Out[14]:

	Timestamp	Open	High	Low	Close	Volume_(BTC)	Volume_(Currency)	Weighted_F
count	3.997697e+06	2.765819e+06	2.765819e+06	2.765819e+06	2.765819e+06	2.765819e+06	2.765819e+06	2.765819e
mean	1.445483e+09	3.059659e+03	3.062027e+03	3.057022e+03	3.059638e+03	1.042232e+01	2.686812e+04	3.059499e
std	6.940318e+07	3.741168e+03	3.744835e+03	3.736985e+03	3.741134e+03	3.375010e+01	9.620425e+04	3.740910e
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%	1.385283e+09	3.742700e+02	3.745200e+02	3.740000e+02	3.742500e+02	4.530000e-01	2.865515e+02	3.742434e
50%	1.445637e+09	7.794500e+02	7.799100e+02	7.790100e+02	7.794900e+02	2.100451e+00	2.209966e+03	7.794137e
75%	1.505603e+09	5.635745e+03	5.639500e+03	5.631100e+03	5.635355e+03	8.179424e+00	1.554689e+04	5.635118e
max	1.565568e+09	1.966576e+04	1.966600e+04	1.964996e+04	1.966575e+04	5.853852e+03	7.569437e+06	1.966330e

In [15]:

```
data_1.describe()
```

Out[15]:

	Timestamp	Open	High	Low	Close	Volume_(BTC)	Volume_(Currency)	Weighted_F
count	3.997697e+06	2.765819e+06	2.765819e+06	2.765819e+06	2.765819e+06	2.765819e+06	2.765819e+06	2.765819e
mean	1.445483e+09	3.059659e+03	3.062027e+03	3.057022e+03	3.059638e+03	1.042232e+01	2.686812e+04	3.059499e
std	6.940318e+07	3.741168e+03	3.744835e+03	3.736985e+03	3.741134e+03	3.375010e+01	9.620425e+04	3.740910e
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%	1.385283e+09	3.742700e+02	3.745200e+02	3.740000e+02	3.742500e+02	4.530000e-01	2.865515e+02	3.742434e
50%	1.445637e+09	7.794500e+02	7.799100e+02	7.790100e+02	7.794900e+02	2.100451e+00	2.209966e+03	7.794137e

	Timestamp	Open	High	Low	Close	Volume_(BTC)	Volume_(Currency)	Weighted_P
75%	1.505603e+09	5.635745e+03	5.639500e+03	5.631100e+03	5.635355e+03	8.179424e+00	1.554689e+04	5.635118e
max	1.565568e+09	1.966576e+04	1.966600e+04	1.964996e+04	1.966575e+04	5.853852e+03	7.569437e+06	1.966330e

Converting the datatype of Timestamp column into DateTime

In [16]:

```
data_1['Timestamp'] = pd.to_datetime(data_1['Timestamp'],unit="s")
data_2['Timestamp'] = pd.to_datetime(data_2['Timestamp'],unit="s")
```

In [17]:

```
data_1['Timestamp'].head()
```

Out[17]:

```
0   2011-12-31 07:52:00
1   2011-12-31 07:53:00
2   2011-12-31 07:54:00
3   2011-12-31 07:55:00
4   2011-12-31 07:56:00
Name: Timestamp, dtype: datetime64[ns]
```

In [18]:

```
data_2['Timestamp'].head()
```

Out[18]:

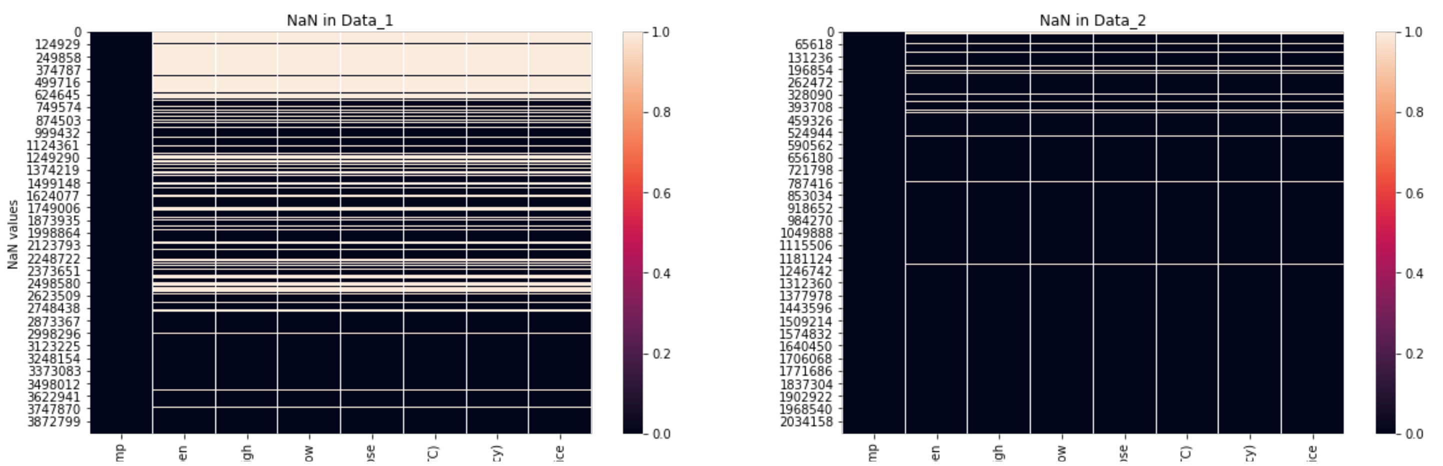
```
0   2014-12-01 05:33:00
1   2014-12-01 05:34:00
2   2014-12-01 05:35:00
3   2014-12-01 05:36:00
4   2014-12-01 05:37:00
Name: Timestamp, dtype: datetime64[ns]
```

Data Preprocessing

Treating NaN's first

In [19]:

```
plt.figure(figsize=(20,6))
plt.subplot(121)
bar = sns.heatmap(data_1.isnull())    #NaN presence plot using heatmap
bar.set_title('NaN in Data_1')
bar.set_xlabel('Columns')
bar.set_ylabel('NaN values')
plt.subplot(122)
bar = sns.heatmap(data_2.isnull())    #NaN presence plot using heatmap
bar.set_title('NaN in Data_2')
plt.show()
```



- **Filling the NaN using Mean**

In [20]:

```
data_1['Open'].fillna(np.mean(data_1['Open']),inplace=True)
data_2['Open'].fillna(np.mean(data_1['Open']),inplace=True)
data_1['High'].fillna(np.mean(data_1['High']),inplace=True)
data_2['High'].fillna(np.mean(data_1['High']),inplace=True)
data_1['Low'].fillna(np.mean(data_1['Low']),inplace=True)
data_2['Low'].fillna(np.mean(data_1['Low']),inplace=True)
data_1['Close'].fillna(np.mean(data_1['Close']),inplace=True)
data_2['Close'].fillna(np.mean(data_1['Close']),inplace=True)
data_1['Volume_(BTC)'].fillna(np.mean(data_1['Volume_(BTC)']),inplace=True)
data_2['Volume_(BTC)'].fillna(np.mean(data_1['Volume_(BTC)']),inplace=True)
data_1['Volume_(Currency)'].fillna(np.mean(data_1['Volume_(Currency)']),inplace=True)
data_2['Volume_(Currency)'].fillna(np.mean(data_1['Volume_(Currency)']),inplace=True)
data_1['Weighted_Price'].fillna(np.mean(data_1['Weighted_Price']),inplace=True)
data_2['Weighted_Price'].fillna(np.mean(data_1['Weighted_Price']),inplace=True)
```

In [21]:

```
data_1.isnull().sum().to_frame()
```

Out[21]:

	0
Timestamp	0
Open	0
High	0
Low	0
Close	0
Volume_(BTC)	0
Volume_(Currency)	0
Weighted_Price	0

In [22]:

```
data_2.isnull().sum().to_frame()
```

Out[22]:

	0
Timestamp	0
Open	0
High	0
Low	0
Close	0
Volume_(BTC)	0
Volume_(Currency)	0
Weighted_Price	0

Resampling the datatime : Instead of using all the datetime values we are taking the average over a month

In [23]:

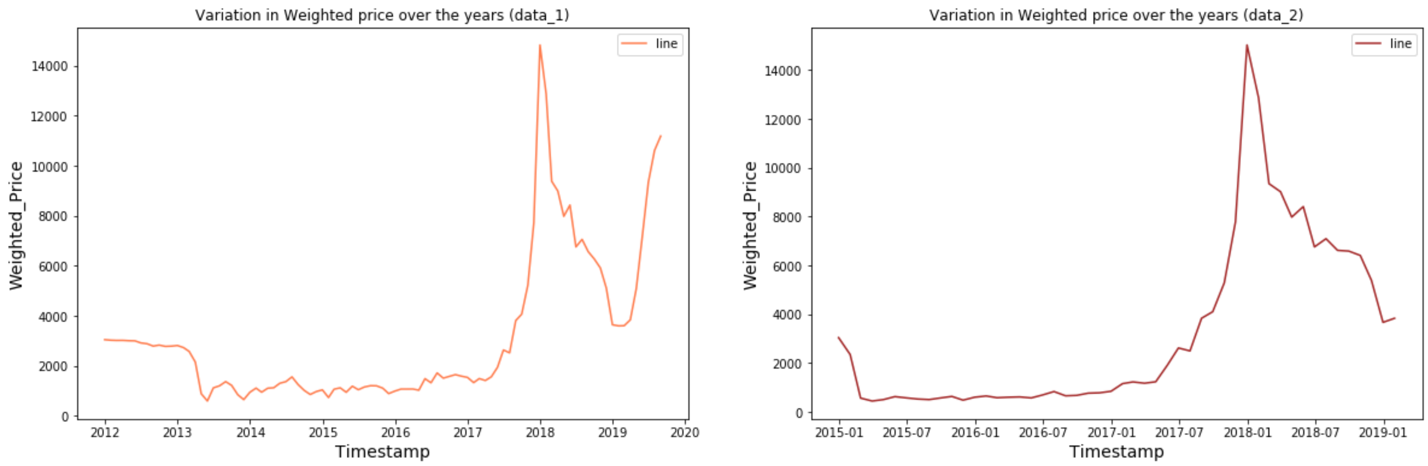
```
dataframe1=data_1
dataframe2=data_2
dataframe1.index = dataframe1.Timestamp
dataframe2.index = dataframe2.Timestamp
dataframe1 = dataframe1.resample('m').mean()
dataframe2 = dataframe2.resample('m').mean()
print('The number of rows in dataset_1 are {} and columns are {}'.format(dataframe1.shape
[0],data_1.shape[1]))
print('The number of rows in dataset_2 are {} and columns are {}'.format(dataframe2.shape
[0],data_2.shape[1]))
```

```
The number of rows in dataset_1 are 93 and columns are 8
The number of rows in dataset_2 are 50 and columns are 8
```

Data Exploration

In [24]:

```
plt.figure(figsize=(20,6))
plt.subplot(121)
sns.lineplot(x=dataframe1.index,y=dataframe1.Weighted_Price, color="coral", label="line"
)
plt.title('Variation in Weighted price over the years (data_1)')
plt.xlabel('Timestamp',fontsize=14)
plt.ylabel('Weighted_Price',fontsize=14)
plt.subplot(122)
sns.lineplot(x=dataframe2.index,y=dataframe2.Weighted_Price, color="brown", label="line"
)
plt.xlabel('Timestamp',fontsize=14)
plt.ylabel('Weighted_Price',fontsize=14)
plt.title('Variation in Weighted price over the years (data_2)')
plt.show()
```

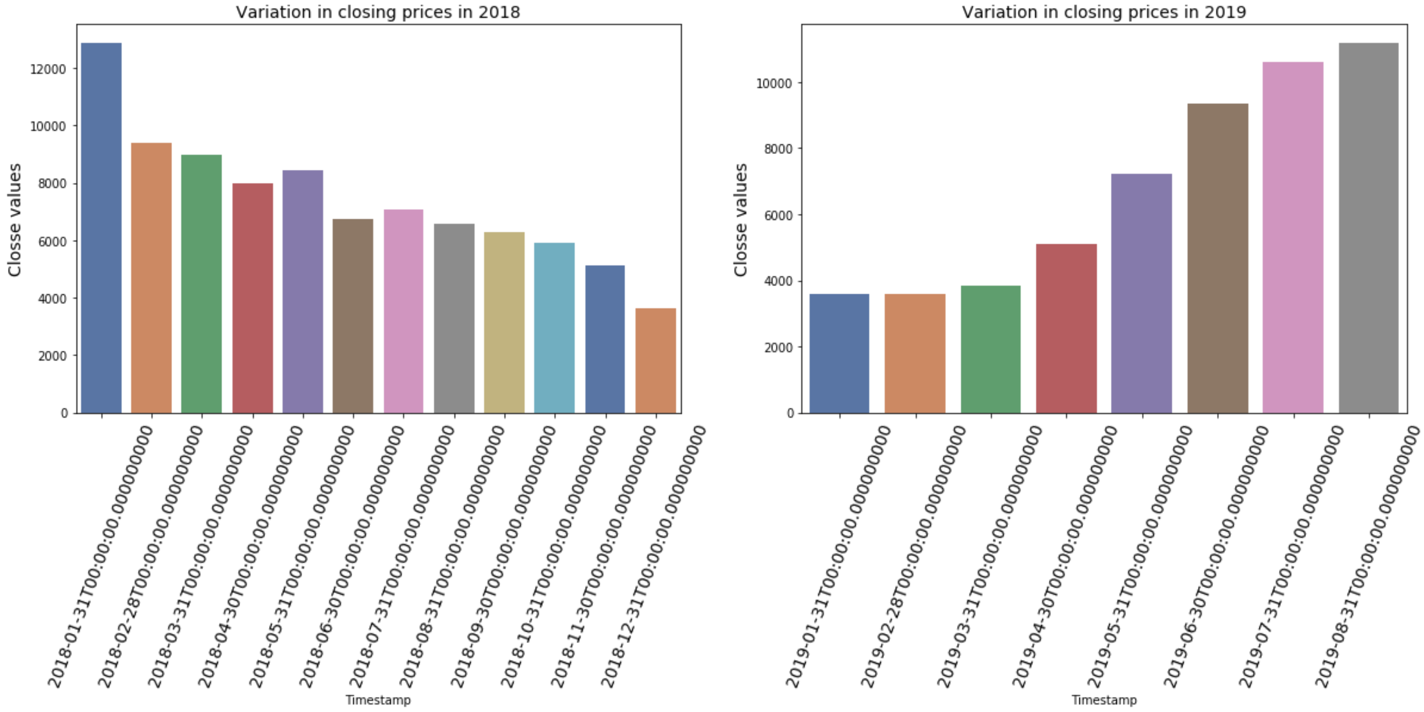


As we can see there are significant changes between 2018 and 2019 we will have a look at the closing vales of the corresponding years

In [25]:

```
plt.figure(figsize=(20,6))
data2018 = dataframe1['2018']
data2019 = dataframe1['2019']
plt.subplot(121)
bar = sns.barplot(x=data2018.index,y=data2018.Close,palette = 'deep')
plt.ylabel('Closse values',fontsize=14)
plt.title('Variation in closing prices in 2018',fontsize=14)
bar.set_xticklabels(bar.get_xticklabels(), fontsize=14, rotation=70)
plt.subplot(122)
bar = sns.barplot(x=data2019.index,y=data2019.Close,palette = 'deep')
plt.ylabel('Closse values',fontsize=14)
plt.title('Variation in closing prices in 2019',fontsize=14)
bar.set_xticklabels(bar.get_xticklabels(), fontsize=14, rotation=70)
```

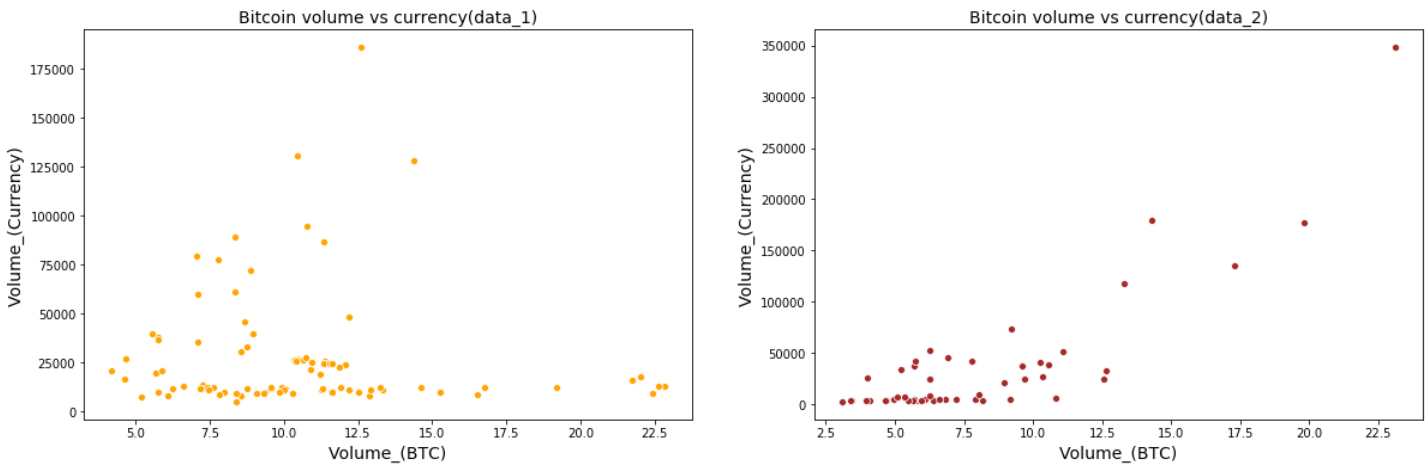
```
plt.show()
```



Now we will look at the attributes Volume *(BTC) and Volume*(Currency) and how they are related. We will use scatter plot for this.

In [26]:

```
plt.figure(figsize=(20,6))
plt.subplot(121)
sns.scatterplot(x='Volume_(BTC)',y='Volume_(Currency)',data = dataframe1 ,color='orange')
plt.title('Bitcoin volume vs currency(data_1)',fontsize=14)
plt.xlabel('Volume_(BTC)',fontsize=14)
plt.ylabel('Volume_(Currency)',fontsize=14)
plt.subplot(122)
sns.scatterplot(x='Volume_(BTC)',y='Volume_(Currency)',data = dataframe2 ,color='brown')
plt.title('Bitcoin volume vs currency(data_2)',fontsize=14)
plt.xlabel('Volume_(BTC)',fontsize=14)
plt.ylabel('Volume_(Currency)',fontsize=14)
plt.show()
```



In [27]:

```
dataframe1['Volume_(BTC)'].corr(dataframe1['Volume_(Currency)'])  #as we can see there is no much relation between them
```

Out[27]:

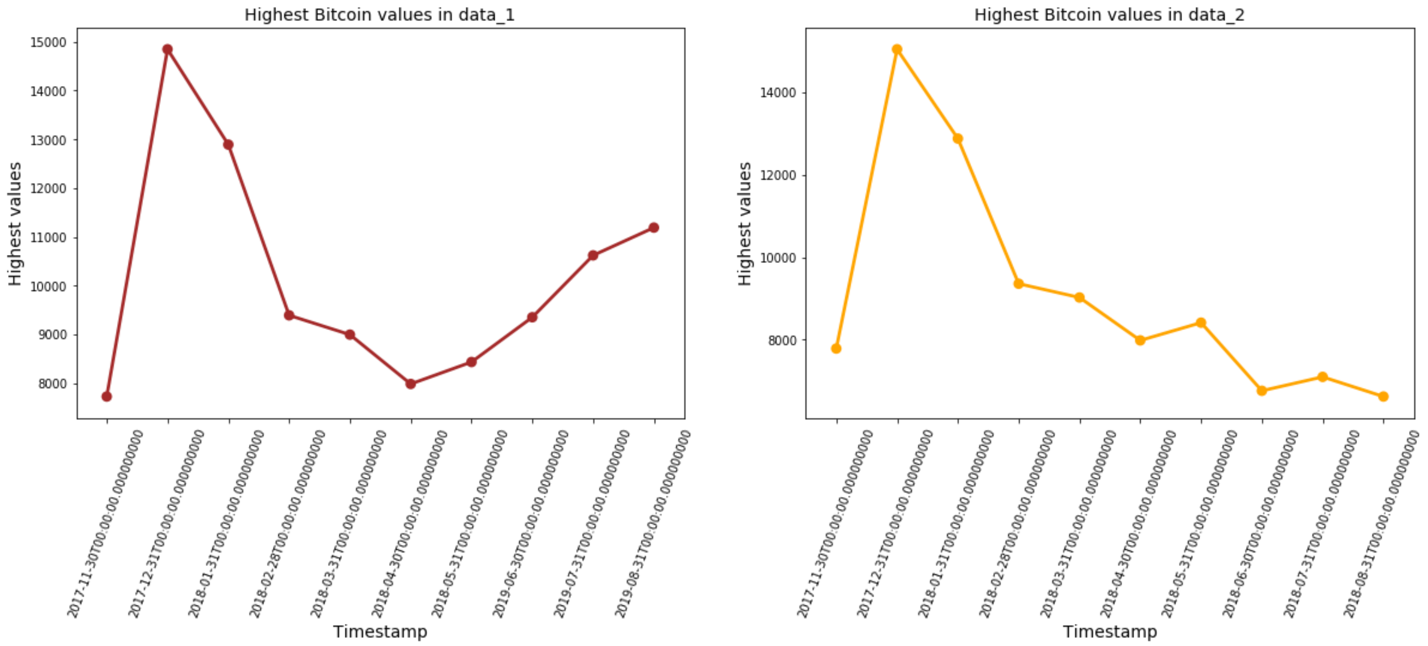
```
-0.045749917010774944
```

In [28]:

```python
high_df1 = dataframe1.sort_values(by=['High'],ascending =False).head(10)
high_df2 = dataframe2.sort_values(by=['High'],ascending =False).head(10)

plt.figure(figsize=(20,6))
plt.subplot(121)
bar = sns.pointplot(x=high_df1.index,y=high_df1['High'],color='brown')
bar.set_xticklabels(bar.get_xticklabels(),rotation = 70)
bar.set_title('Highest Bitcoin values in data_1',fontsize=14)
bar.set_xlabel('Timestamp',fontsize=14)    #can use matplotlib func or seaborn while label
ling the plots
bar.set_ylabel('Highest values',fontsize=14)

plt.subplot(122)
bar = sns.pointplot(x=high_df2.index,y=high_df2['High'],color='orange')
bar.set_xticklabels(bar.get_xticklabels(),rotation = 70)
bar.set_title('Highest Bitcoin values in data_2',fontsize=14)
bar.set_xlabel('Timestamp',fontsize=14)    #can use matplotlib func or seaborn while label
ling the plots
bar.set_ylabel('Highest values',fontsize=14)
plt.show()
```

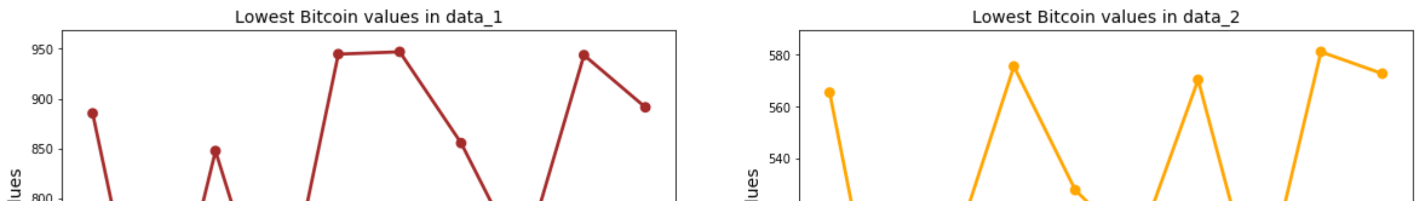


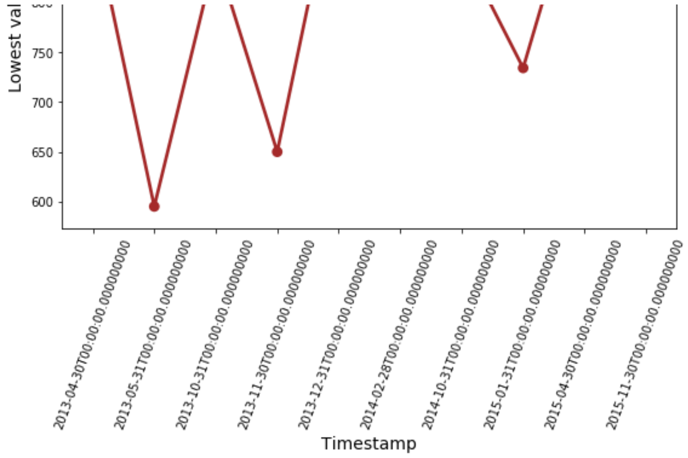
In [29]:

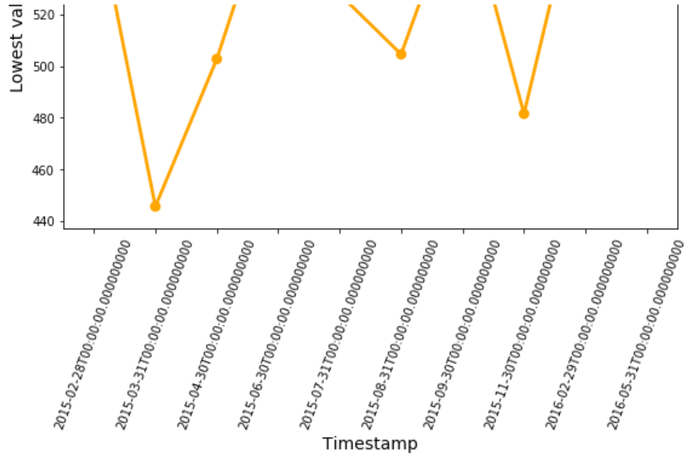
```python
low_df1 = dataframe1.sort_values(by=['Low'],ascending =True).head(10)
low_df2 = dataframe2.sort_values(by=['Low'],ascending =True).head(10)

plt.figure(figsize=(20,6))
plt.subplot(121)
bar = sns.pointplot(x=low_df1.index,y=low_df1['Low'],color='brown')
bar.set_xticklabels(bar.get_xticklabels(),rotation = 70)
bar.set_title('Lowest Bitcoin values in data_1',fontsize=14)
bar.set_xlabel('Timestamp',fontsize=14)    #can use matplotlib func or seaborn while label
ling the plots
bar.set_ylabel('Lowest values',fontsize=14)

plt.subplot(122)
bar = sns.pointplot(x=low_df2.index,y=low_df2['Low'],color='orange')
bar.set_xticklabels(bar.get_xticklabels(),rotation = 70)
bar.set_title('Lowest Bitcoin values in data_2',fontsize=14)
bar.set_xlabel('Timestamp',fontsize=14)    #can use matplotlib func or seaborn while label
ling the plots
bar.set_ylabel('Lowest values',fontsize=14)
plt.show()
```







In [30]:

```
low_df1
```

Out[30]:

Timestamp	Open	High	Low	Close	Volume_(BTC)	Volume_(Currency)	Weighted_Price
2013-05-31	595.540093	595.985019	594.991351	595.485126	8.394732	5130.413328	595.480136
2013-11-30	650.960689	651.829047	649.908069	650.892962	22.847183	12708.130418	650.847858
2015-01-31	734.904346	735.545550	734.205633	734.902035	22.428407	9515.159038	734.865889
2013-10-31	848.303774	848.946374	847.589318	848.295275	16.527848	8618.776222	848.258885
2014-10-31	856.199559	856.872644	855.462466	856.193813	15.290324	9649.265426	856.154953
2013-04-30	886.129584	886.911555	885.241365	886.112685	12.873303	8147.476408	886.073221
2015-11-30	892.117427	892.853430	891.297788	892.106554	22.630831	12854.031742	892.065309
2015-04-30	944.315089	944.968796	943.591291	944.308324	8.549585	8135.641395	944.270112
2013-12-31	946.336284	947.977986	944.592386	946.322056	22.030653	17936.437702	946.204577
2014-02-28	947.918598	948.924389	946.869142	947.945274	21.742440	15871.602989	947.871318

In [31]:

```
low_df2
```

Out[31]:

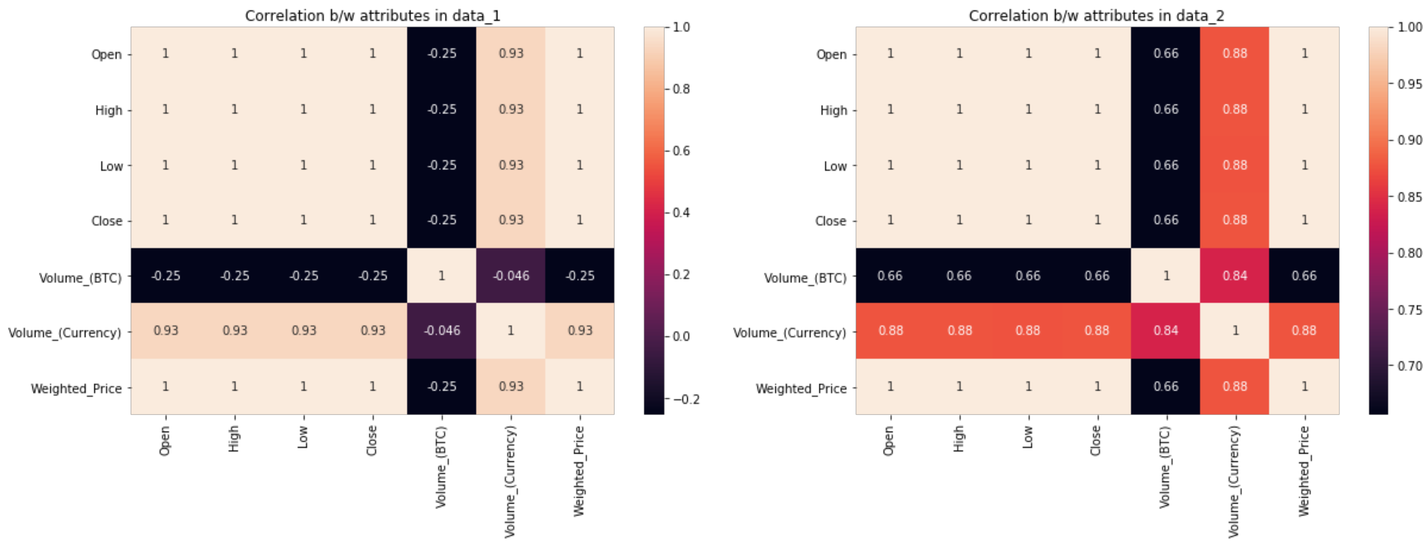
Timestamp	Open	High	Low	Close	Volume_(BTC)	Volume_(Currency)	Weighted_Price
2015-03-31	445.969924	446.241305	445.684931	445.980249	8.188753	3725.861710	445.966384
2015-11-30	481.857342	482.127375	481.533107	481.842495	9.182913	4490.045355	481.825793
2015-04-30	503.042899	503.334015	502.728595	503.046190	6.386673	3812.222331	503.032524
2015-08-31	504.862600	505.133449	504.569840	504.861968	5.956152	3643.602651	504.851095
2015-07-31	528.116538	528.389859	527.821109	528.117717	5.764401	3757.892567	528.105204
2015-02-28	565.849208	566.259147	565.423618	565.856275	7.889051	4727.078095	565.845248
2015-09-30	570.678425	570.988728	570.338361	570.676803	5.675641	4236.772250	570.661269
2016-05-31	572.934922	573.132819	572.714726	572.941484	4.645056	3100.855145	572.925403
2015-06-30	575.844856	576.168404	575.491124	575.843838	5.702604	4283.028054	575.828358
2016-02-29	581.370759	581.590429	581.117058	581.366213	5.644032	3795.341206	581.351103

Finding correlation between different attributes.

In [32]:

```
plt.figure(figsize=(20,6))
plt.subplot(121)
sns.heatmap(dataframe1.corr(),annot=True)
plt.title('Correlation b/w attributes in data_1')
#plt.xlabel('Attributes',fontsize=14)
#plt.ylabel('Attributes',fontsize=14)
plt.subplot(122)
plt.subplot(122)
sns.heatmap(dataframe2.corr(),annot=True)
plt.title('Correlation b/w attributes in data_2')
#plt.xlabel('Attributes',fontsize=14)
#plt.ylabel('Attributes',fontsize=14)
plt.show()
```

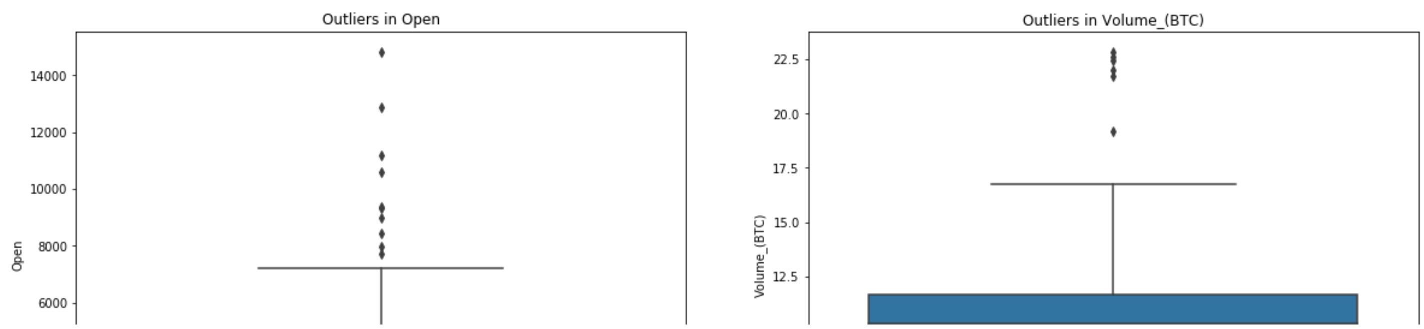
```
C:\Users\Venkatesh M\anaconda3\lib\site-packages\ipykernel_launcher.py:8: MatplotlibDeprecationWarning: Adding an axes using the same arguments as a previous axes currently reuses the earlier instance.  In a future version, a new instance will always be created and returned.  Meanwhile, this warning can be suppressed, and the future behavior ensured, by passing a unique label to each axes instance.
```

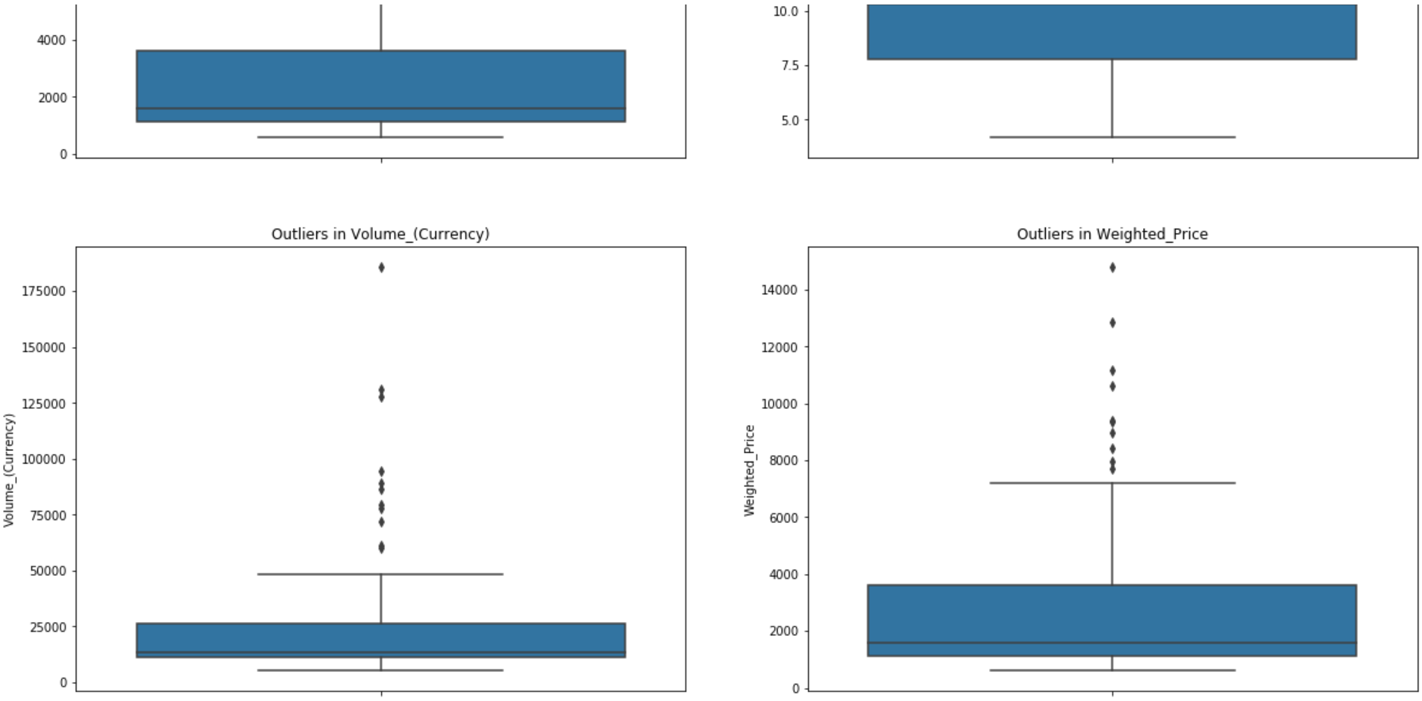


Now we look at the outliers in each attribute. We don't know whether these outliers will have a positive or negative effect so after finding the accuracy if it's less then we deal with outliers.

In [33]:

```
plt.figure(figsize=(20,15))
plt.subplot(221)
sns.boxplot(dataframe1['Open'],orient='v')
plt.title('Outliers in Open')
plt.subplot(222)
sns.boxplot(dataframe1['Volume_(BTC)'],orient='v')
plt.title('Outliers in Volume_(BTC)')
plt.subplot(223)
sns.boxplot(dataframe1['Volume_(Currency)'],orient='v')
plt.title('Outliers in Volume_(Currency)')
plt.subplot(224)
sns.boxplot(dataframe1['Weighted_Price'],orient='v')
plt.title('Outliers in Weighted_Price')
plt.show()
```





Data Processing

In [34]:

```
data = data_1
data['Timestamp']=data['Timestamp'].map(dt.datetime.toordinal)
x=data['Timestamp'].values
pd.DataFrame(x).head()
```

Out[34]:

	0
0	734502
1	734502
2	734502
3	734502
4	734502

In [35]:

```
x=x.reshape(-1,1) #changing into column form [x_values_count,1]
y=data['Weighted_Price']
pd.DataFrame(x).head()
```

Out[35]:

	0
0	734502
1	734502
2	734502
3	734502
4	734502

- **Taking Timestamp as individual variable and doing the prediction**

In [36]:

```
#Standardizing the data
```

```
#Standardising the data
scaler=MinMaxScaler()
x=scaler.fit_transform(x)
```

In [37]:

```
#splitting the data into training set and testing set
xtrain,xtest,ytrain,ytest = train_test_split(x,y,test_size=0.3,random_state=10)
scaler=MinMaxScaler()
```

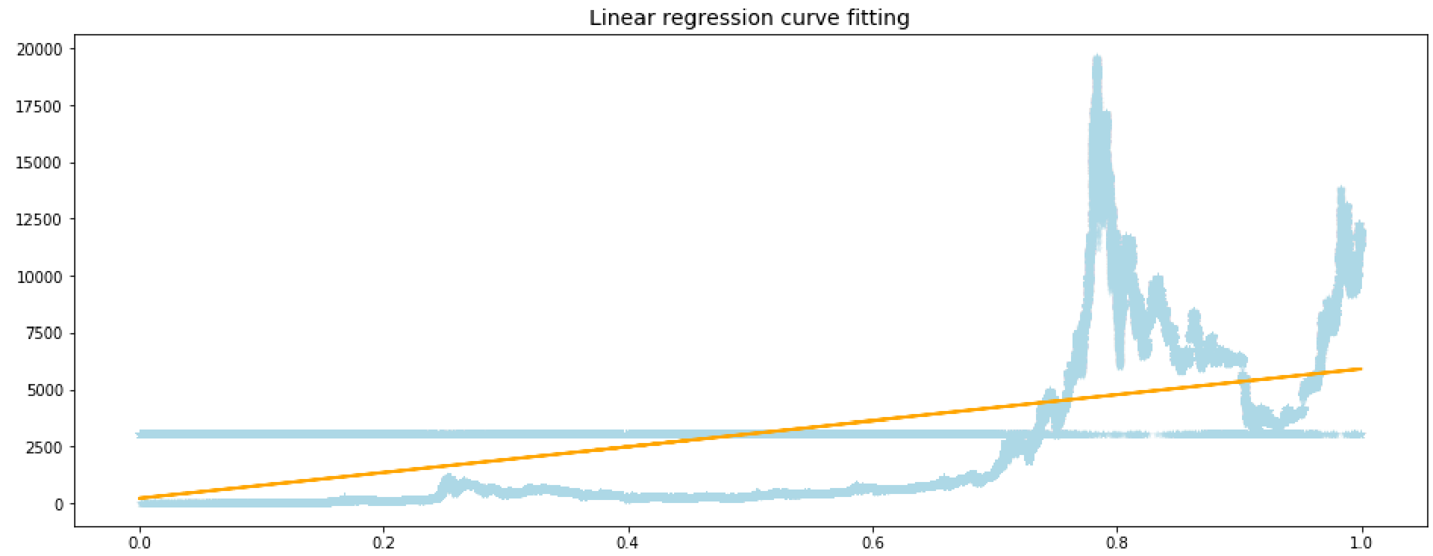
In [38]:

```
#linear regression
linear_reg = LinearRegression()
linear_reg.fit(xtrain,ytrain)
y_pred = linear_reg.predict(xtest)
linear_accuracy = linear_reg.score(xtest,ytest)
print('r squared value is ',linear_accuracy)
```

```
r squared value is  0.2788524008010894
```

In [39]:

```
plt.figure(figsize=(16,6))
plt.scatter(xtest,ytest,marker='*',linewidth=0,color='lightblue',alpha=0.3)
plt.plot(xtest,y_pred,color='orange',linewidth=2)
plt.title('Linear regression curve fitting',fontsize=14)
plt.show()
```



In [40]:

```
df = pd.DataFrame({'Actual': ytest, 'Predicted': y_pred})
df.head(10)
```

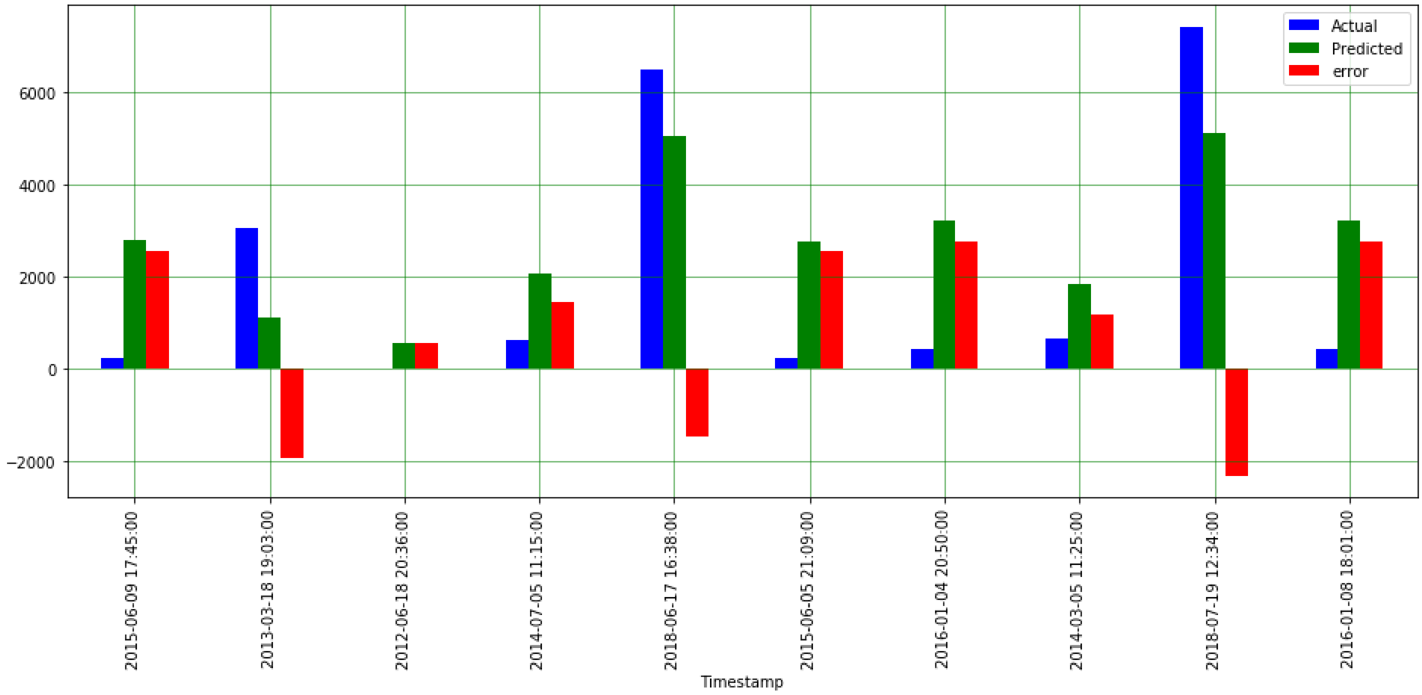
Out[40]:

	Actual	Predicted
Timestamp		
2015-06-09 17:45:00	230.338734	2784.856144
2013-03-18 19:03:00	3059.499288	1119.899698
2012-06-18 20:36:00	6.100000	560.818382
2014-07-05 11:15:00	630.860000	2090.612312
2018-06-17 16:38:00	6509.227500	5045.756410
2015-06-05 21:09:00	224.821167	2776.664476
2016-01-04 20:50:00	434.140000	3212.870778
2014-03-05 11:25:00	666.182404	1840.766449

2018-07-19 12:34:00	7417.948119	5111.289751
	Actual	**Predicted**
2016-01-08 18:01:00	448.000000	3221.062445
Timestamp		

In [41]:

```
df['error'] = (df.Predicted - df.Actual)
result_sam = df.head(10)
result_sam.plot(kind='bar',figsize=(16,6),color={'blue','green','red'})
plt.grid(which='major',linestyle='-',linewidth='0.5',color='green')
plt.grid(which='minor',linestyle=':',linewidth='0.5',color='black')
plt.show()
```



In [42]:

```
#polynomial regression
from sklearn.preprocessing import PolynomialFeatures
ploy_reg = PolynomialFeatures(degree=2)
x_poly=ploy_reg.fit_transform(x)
lin_reg = LinearRegression()
lin_reg.fit(x_poly,y)
poly_ac = lin_reg.score(x_poly,y)
print('r squared value is :',poly_ac)
```

```
r squared value is : 0.49712704912554634
```

In [43]:

```
#Decission tree
tree_reg = DecisionTreeRegressor(random_state=0)
tree_reg.fit(xtrain,ytrain)
y_pred = tree_reg.predict(xtest)
tree_ac=tree_reg.score(xtest,ytest)
print('r squared value is :',tree_ac)
```

```
r squared value is : 0.91400384899948
```

In [44]:

```
#comparision of models
Models=['Linear regression','Polynomial regression','Decision tree']
score = [linear_accuracy,poly_ac,tree_ac]
accuracy=[]
for i in score:
    accuracy.append(round(i*100))
accuracy
```

Out[44]:

```
[28.0, 50.0, 91.0]
```

In [45]:

```
Accuracy_of_models = pd.DataFrame({'Model':Models,'Accuracy':accuracy}).sort_values(by='
Accuracy',ascending = False)
Accuracy_of_models
```

Out[45]:

	Model	Accuracy
2	**Decision tree**	**91.0**
1	**Polynomial regression**	**50.0**
0	**Linear regression**	**28.0**

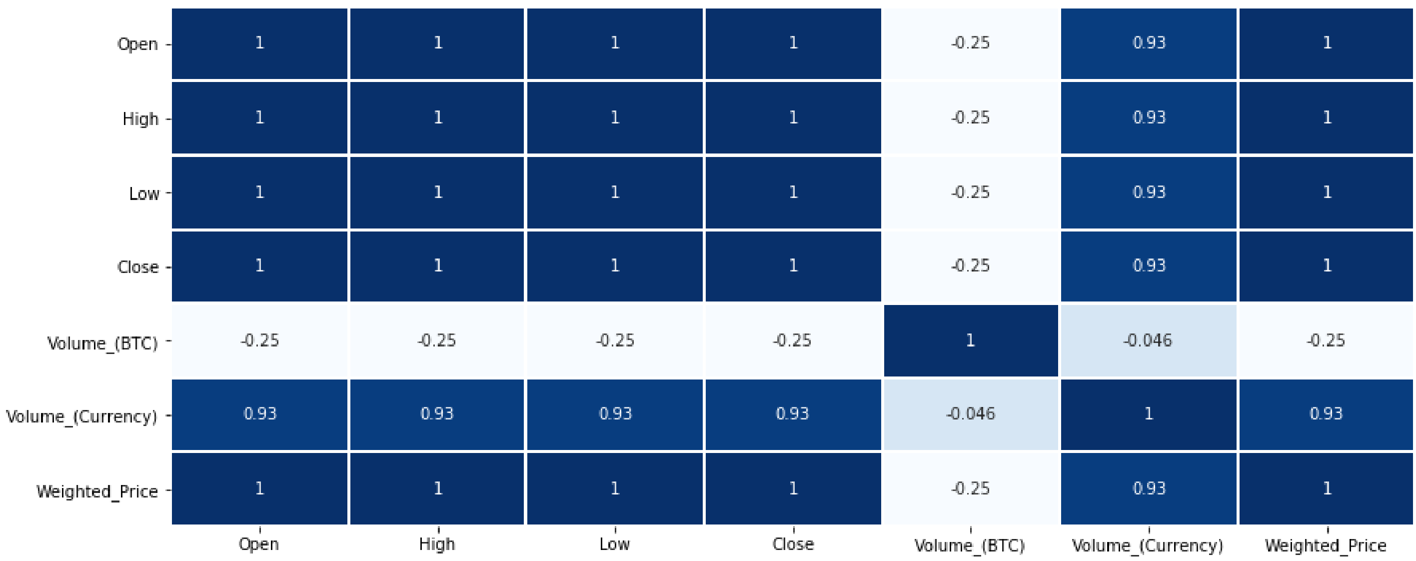
As we can see the accuracy levels are low. So, using the attributes Open, Low, High, Close and Volume_(Currency) to predict the Weighted_Price as their correlation values are higher

In [46]:

```
plt.figure(figsize=(14,6))
sns.heatmap(data=dataframe1.corr(),cbar=False,annot=True,linewidth=1,cmap='Blues')
```

Out[46]:

<matplotlib.axes._subplots.AxesSubplot at 0x19085f32548>



In [47]:

```
x=dataframe1[['Open','High','Low','Close','Volume_(Currency)']]
pd.DataFrame(x).head()
y=dataframe1['Weighted_Price']
pd.DataFrame(x).head()
```

Out[47]:

Timestamp	**Open**	**High**	**Low**	**Close**	**Volume_(Currency)**
2011-12-31	3047.034727	3049.392910	3044.408085	3047.013352	26757.534105
2012-01-31	3025.391793	3027.733153	3022.783806	3025.370506	26566.858391
2012-02-29	3017.456296	3019.791494	3014.855154	3017.435034	26497.465486
2012-03-31	3019.081055	3021.417511	3016.478512	3019.059783	26512.218919
2012-04-30	3005.920033	3008.246293	3003.328868	3005.898874	26397.343962

In [48]:

```
#splitting the data into training set and testing set
xtrain,xtest,ytrain,ytest = train_test_split(x,y,test_size=0.3,random_state=10)
```

In [49]:

```
#linear regression
linear_reg = LinearRegression()
linear_reg.fit(xtrain,ytrain)
y_pred = linear_reg.predict(xtest)
linear_accuracy_high_corr = linear_reg.score(xtest,ytest)
print('r squared value is ',linear_accuracy_high_corr)
```

```
r squared value is  0.9999999991613893
```

In [50]:

```
df = pd.DataFrame({'Actual': ytest, 'Predicted': y_pred})
df.head(10)
```

Out[50]:

	Actual	**Predicted**
Timestamp		
2014-10-31	856.154953	856.150741
2019-06-30	9342.968139	9342.757709
2012-03-31	3018.922959	3018.920409
2014-11-30	972.497645	972.494219
2013-07-31	1203.505948	1203.501759
2017-06-30	2635.124906	2635.178708
2017-03-31	1415.386659	1415.363735
2015-05-31	1187.788475	1187.789097
2015-08-31	1208.690856	1208.688836
2017-11-30	7716.694698	7716.942776

- **As we can see that both the predicted and original values almost same. The accuracy is also excellent.**

In [51]:

```
#polynomial regression
from sklearn.preprocessing import PolynomialFeatures
ploy_reg = PolynomialFeatures(degree=2)
x_poly=ploy_reg.fit_transform(x)
lin_reg = LinearRegression()
lin_reg.fit(x_poly,y)
poly_ac_high_corr = lin_reg.score(x_poly,y)
print('r squared value is :',poly_ac_high_corr)
```

```
r squared value is : 0.9999999999874449
```

In [52]:

```
#Decission tree
tree_reg = DecisionTreeRegressor(random_state=0)
tree_reg.fit(xtrain,ytrain)
y_pred = tree_reg.predict(xtest)
tree_ac_high_corr=tree_reg.score(xtest,ytest)
print('r squared value is :',tree_ac_high_corr)
```

```
r squared value is : 0.9982756355966461
```

In [53]:

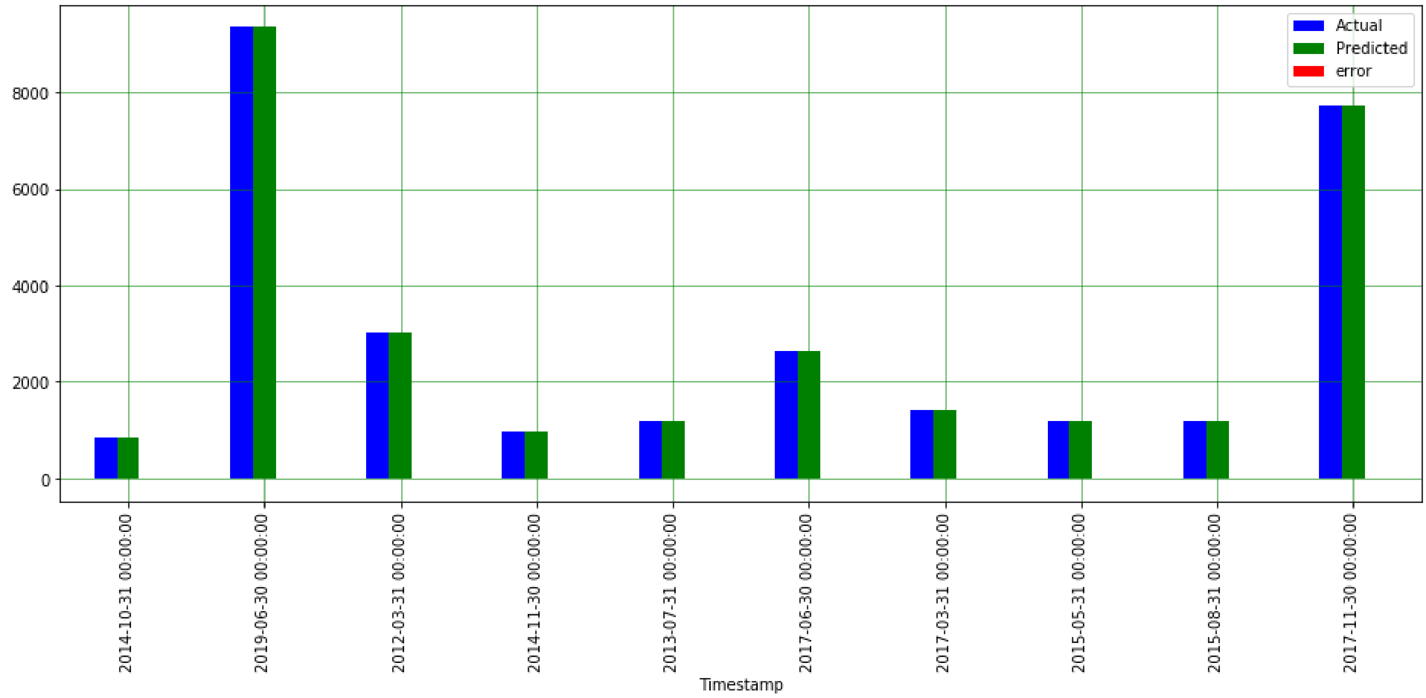
```
#comparision of models
Models=['Linear regression','Polynomial regression','Decision tree']
score = [linear_accuracy_high_corr,poly_ac_high_corr,tree_ac_high_corr]
accuracy=[]
for i in score:
    accuracy.append(round(i*100))
accuracy
```

Out[53]:

```
[100.0, 100.0, 100.0]
```

In [54]:

```
df['error'] = (df.Predicted - df.Actual)
result_sam = df.head(10)
result_sam.plot(kind='bar',figsize=(16,6),color={'blue','green','red'})
#.set_xticklabels(bar.get_xticklabels(), fontsize=14, rotation=70)
plt.grid(which='major',linestyle='-',linewidth='0.5',color='green')
plt.grid(which='minor',linestyle=':',linewidth='0.5',color='black')
plt.show()
```



In [55]:

```
Accuracy_of_models = pd.DataFrame({'Model':Models,'Accuracy':accuracy}).sort_values(by='
Accuracy',ascending = False) #changing into dataframe.
Accuracy_of_models
```

Out[55]:

	Model	Accuracy
0	Linear regression	100.0
1	Polynomial regression	100.0
2	Decision tree	100.0

- **R2 shows how well terms (data points) fit a curve or line**

In [56]:

```
r2_score(ytest,y_pred)
```

Out[56]:

```
0.998275635596646
```

We can see that the prediction models are very accurate and predicts the weighted_price with minute or no error.

THE END

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In [ ]:

```

```