Zomato Restaurants Data

Zomato API Analysis is one of the most useful analysis for foodies who want to taste the best cuisines of every part of the world which lies in their budget. Data has been collected from the Zomato API in the form of .json files(raw data).The target of the zomato restaurant dataset is Aggregate Rating.We need to predict the aggregate rating based on different features.

[Zomato Restaurant Data (https://www.kaggle.com/shrutimehta/zomato-restaurants-data)](https://www.kaggle.com/shrutimehta/zomato-restaurants-data)

Importing the libraries

In [9]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
%matplotlib inline
```

Data Preprocessing

Loading the dataset

In [10]:
```
df = pd.read_csv("zomato.csv",encoding='ISO-8859-1')
```

In [11]:
```
df.head()
```

Out[11]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longituc
0	6317637	Le Petit Souffle	162	Makati City	Third Floor, Century City Mall, Kalayaan Avenu...	Century City Mall, Poblacion, Makati City	Century City Mall, Poblacion, Makati City, Mak...	121.02753
1	6304287	Izakaya Kikufuji	162	Makati City	Little Tokyo, 2277 Chino Roces Avenue, Legaspi...	Little Tokyo, Legaspi Village, Makati City	Little Tokyo, Legaspi Village, Makati City, Ma...	121.01410
2	6300002	Heat - Edsa Shangri-La	162	Mandaluyong City	Edsa Shangri-La, 1 Garden Way, Ortigas, Mandal...	Edsa Shangri-La, Ortigas, Mandaluyong City	Edsa Shangri-La, Ortigas, Mandaluyong City, Ma...	121.05683
3	6318506	Ooma	162	Mandaluyong City	Third Floor, Mega Fashion Hall, SM Megamall, O...	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City, Mandal...	121.05647
4	6314302	Sambo Kojin	162	Mandaluyong City	Third Floor, Mega Atrium, SM Megamall, Ortigas...	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City, Mandal...	121.05750

5 rows × 21 columns

Keys of the zomato restaurant

In [12]:
```
df.keys()
```

Out[12]:
```
Index(['Restaurant ID', 'Restaurant Name', 'Country Code', 'City', 'Address',
       'Locality', 'Locality Verbose', 'Longitude', 'Latitude', 'Cuisines',
       'Average Cost for two', 'Currency', 'Has Table booking',
       'Has Online delivery', 'Is delivering now', 'Switch to order menu',
       'Price range', 'Aggregate rating', 'Rating color', 'Rating text',
       'Votes'],
      dtype='object')
```

Feature Engineering

Multilabel Binarizer

Converting the multivalues in the data to the matrix format

In [101]:
```
from sklearn.preprocessing import MultiLabelBinarizer
```

In [15]:
```
mlb = MultiLabelBinarizer()
```

In [16]:
```
 new_cuisine=pd.DataFrame(mlb.fit_transform(df['Cuisines'].astype(str)))
```

In [17]:
```
new_cuisine.head()
```

Out[17]:

	0	1	2	3	4	5	6	7	8	9	...	42	43	44	45	46	47	48	49	50	51
0	1	1	0	0	0	0	1	0	1	0	...	1	1	1	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	...	0	1	0	0	0	0	0	0	0	0
2	1	1	0	1	0	0	0	0	1	0	...	0	1	0	0	0	0	0	0	0	0
3	1	1	0	0	0	0	0	0	0	0	...	0	1	0	1	0	0	0	0	0	0
4	1	1	0	0	0	0	0	0	0	0	...	1	1	0	0	0	0	0	0	0	0

5 rows × 52 columns

In [18]:
```
 restaurant_name=pd.DataFrame(mlb.fit_transform(df['Restaurant Name'].astype(st
```

In [19]:
```
new_city=pd.DataFrame(mlb.fit_transform(df['City'].astype(str)))
```

In [20]:
```
new_address=pd.DataFrame(mlb.fit_transform(df['Address'].astype(str)))
```

In [21]:
```
new_locality=pd.DataFrame(mlb.fit_transform(df['Locality'].astype(str)))
```

In [22]:
```
locality_verbose=pd.DataFrame(mlb.fit_transform(df['Locality Verbose'].astype(s
```

In [23]:
```
df['new cost'] = 0
```

Coverting all various currencies into dollar

In [24]:
```
d = {'Botswana Pula(P)':0.095, 'Brazilian Real(R$)':0.266,'Dollar($)':1,'Emirat
    'Indian Rupees(Rs.)':0.014,'Indonesian Rupiah(IDR)':0.00007,'NewZealand($)'
    'Qatari Rial(QR)':0.274,'Rand(R)':0.072,'Sri Lankan Rupee(LKR)':0.0055,'Tur

df['new cost'] = df['Average Cost for two'] * df['Currency'].map(d)
```

In [25]:
```
df['cuisine'] = 0
```

Principle Component Analysis

PCA is used to reduce larger dimension columns into specified columns without losing the contents

In [26]:
```
from sklearn.decomposition import PCA
```

In [27]:
```
pca=PCA()
```

Here I am converting the cuisine,restaurant,city,address,locality,locality_verbose into single column

In [28]:
```
cuisine = pca.fit_transform(new_cuisine)
pca = PCA(n_components=1)
cuisine = pca.fit_transform(cuisine)
df['cuisine']=cuisine
```

In [29]:
```
df['cuisine'].head()
```

Out[29]:
```
0    0.705835
1    1.787682
2    0.014785
3    0.610066
4    0.877396
Name: cuisine, dtype: float64
```

In [30]:
```
restaurant = pca.fit_transform(restaurant_name)
pca = PCA(n_components=1)
restaurant = pca.fit_transform(restaurant)
df['restaurant']=restaurant
```

In [31]:
```
city = pca.fit_transform(new_city)
pca = PCA(n_components=1)
city = pca.fit_transform(city)
df['city']=city
```

In [32]:
```
address = pca.fit_transform(new_address)
pca = PCA(n_components=1)
address = pca.fit_transform(address)
df['address']=address
```

In [33]:
```
locality = pca.fit_transform(new_locality)
pca = PCA(n_components=1)
locality = pca.fit_transform(locality)
df['locality']=locality
```

In [34]:
```
locality_verbose = pca.fit_transform(locality_verbose)
pca = PCA(n_components=1)
locality_verbose = pca.fit_transform(locality_verbose)
df['locality_verbose']=locality_verbose
```

In [35]:
```
cuisine.shape
```

Out[35]:
```
(9551, 1)
```

Label Encoder

Converting the single categorical values in the dataset into numerical values

In [36]:
```
from sklearn.preprocessing import LabelEncoder
labelencoder = LabelEncoder()
```

Here i am converting Has table booking, Has online delivery, Is delivering now, Rating text, City, Rating Color, Switch to order menu to equivalent integer values

In [37]:
```
df['Has Table booking'] = labelencoder.fit_transform(df['Has Table booking'])
```

In [38]:
```
df['Has Online delivery'] = labelencoder.fit_transform(df['Has Online delivery'
```

In [39]:
```
df['Is delivering now'] = labelencoder.fit_transform(df['Is delivering now'])
```

In [40]:
```
df['Rating text']= labelencoder.fit_transform(df['Rating text'])
```

In [41]:
```
df['Rating text'].head()
```

Out[41]:
```
0    1
1    1
2    5
3    1
4    1
Name: Rating text, dtype: int32
```

In [42]:
```
df['City'] = labelencoder.fit_transform(df['City'])
```

In [43]:
```
df['Rating color'] = labelencoder.fit_transform(df['Rating color'])
```

In [44]:
```
df['Switch to order menu'] = labelencoder.fit_transform(df['Switch to order mer
```

Renaming the column names

In [45]:
```

df.rename(columns = {"Aggregate rating":"Aggregate_rating",
                    "Price range":"Price_range",
                    "Rating color":"Rating_color",
                      "Restaurant ID":"Restaurant_id",
                      "new cost":"new_cost",
                        "Rating text":"Rating_text"},
                                 inplace = True)
```

Dropping the few attributes which is already exits in the dataset

In [46]:
```
zomato=df.drop(['Restaurant Name','Cuisines','City','Address','Locality','Local
       'Average Cost for two', 'Currency'],axis=1)
```

Updated Dataset

Converting all categorical values into numerical values

In [47]:
```
zomato.head()
```

Out[47]:

	Restaurant_id	Country Code	Longitude	Latitude	Has Table booking	Has Online delivery	Is delivering now	Switch to order menu	Price_rar
0	6317637	162	121.027535	14.565443	1	0	0	0	
1	6304287	162	121.014101	14.553708	1	0	0	0	
2	6300002	162	121.056831	14.581404	1	0	0	0	
3	6318506	162	121.056475	14.585318	0	0	0	0	
4	6314302	162	121.057508	14.584450	1	0	0	0	

In [48]:
```
zomato.shape
```

Out[48]: (9551, 20)

Counting the each value for the particular feature

In [49]:
```
zomato['Has Online delivery'].value_counts()
```

Out[49]:
```
0    7100
1    2451
Name: Has Online delivery, dtype: int64
```

In [50]:
```

zomato['Has Table booking'].value_counts()
```

Out[50]:
```
0    8393
1    1158
Name: Has Table booking, dtype: int64
```

In [51]:
```
df['Is delivering now'].value_counts()
```

Out[51]:
```
0    9517
1      34
Name: Is delivering now, dtype: int64
```

In [52]:
```
zomato['Switch to order menu'].value_counts()
```

Out[52]:
```
0    9551
Name: Switch to order menu, dtype: int64
```

In [53]:
```
zomato['Price_range'].value_counts()
```

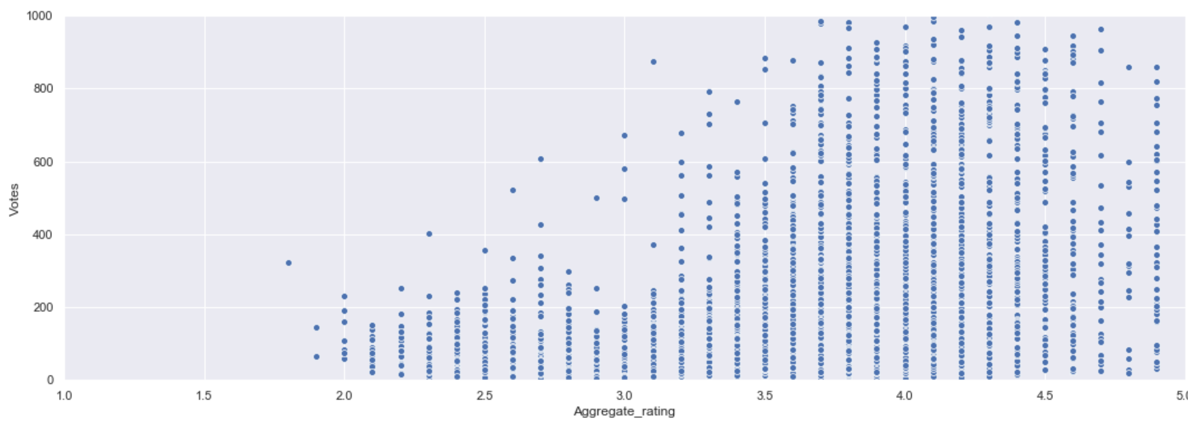
Out[53]:
```
1    4444
2    3113
3    1408
4     586
Name: Price_range, dtype: int64
```

Data Visualization

Plotting the graph for Votes with respect to Aggregate rating using seaborn

In [54]:
```
sns.set(rc={'figure.figsize':(18,6)})
sns.scatterplot(data=zomato,x='Aggregate_rating',y='Votes')
plt.ylim(0,1000)
plt.xlim(1,5)
```

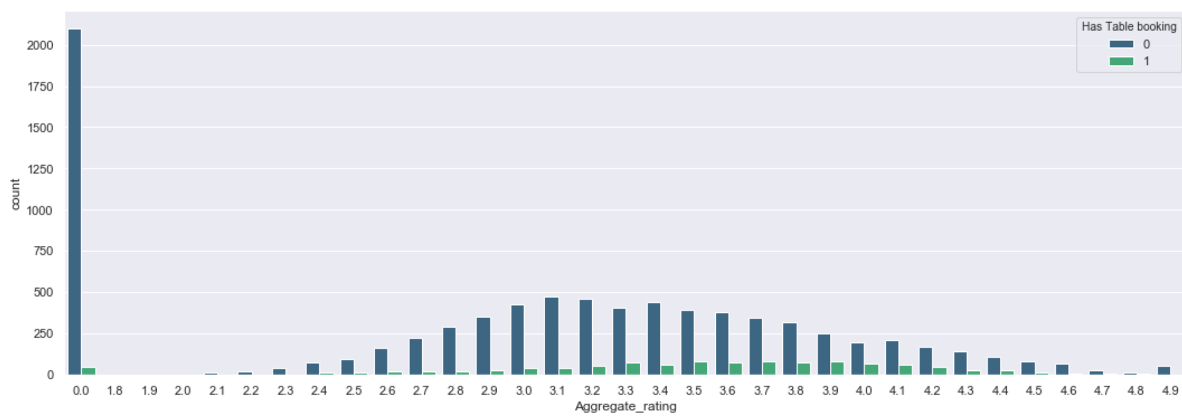
Out[54]: (1, 5)



Plotting the graph of Aggregate rating using seaborn

In [55]:
```
sns.set(rc={'figure.figsize':(18,6)})
sns.countplot(data=zomato,x='Aggregate_rating',hue='Has Table booking',palette=
```

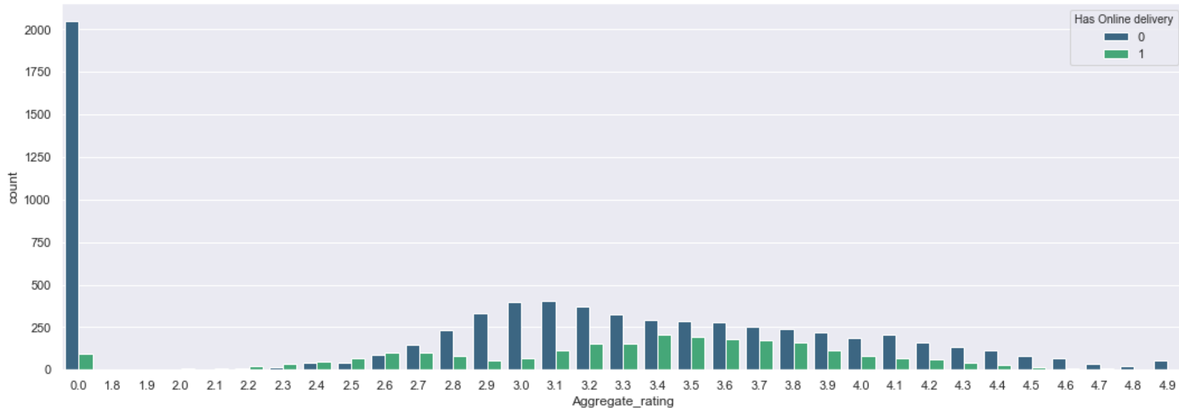
Out[55]: <matplotlib.axes._subplots.AxesSubplot at 0x200643f52b0>



Plotting the graph for Has Online Delivery with respect to Aggregate rating using seaborn

In [56]:
```
sns.set(rc={'figure.figsize':(18,6)})
sns.countplot(data=zomato,x='Aggregate_rating',hue='Has Online delivery',palett
```

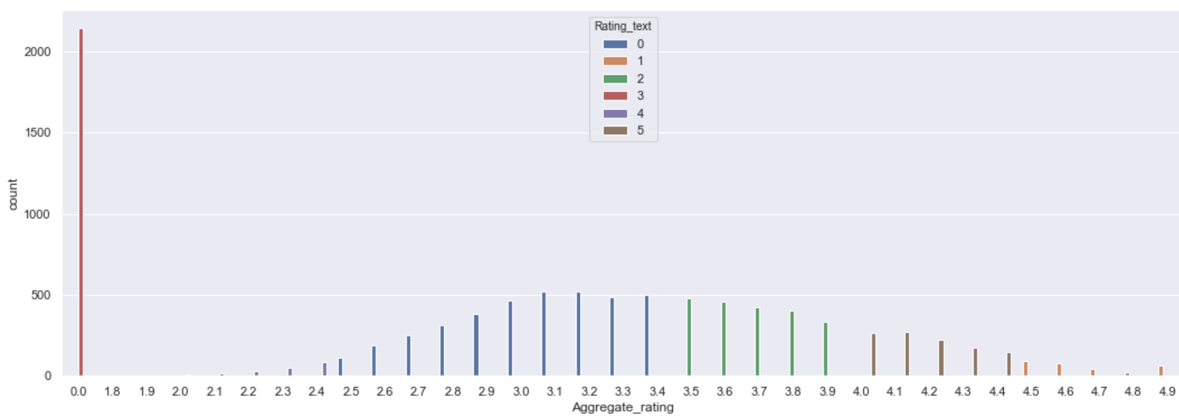
Out[56]: <matplotlib.axes._subplots.AxesSubplot at 0x200653eeb00>



Plotting the graph for Rating text with respect to Aggregate rating using seaborn

In [57]:
```
sns.set(rc={'figure.figsize':(18,6)})
sns.countplot(data=zomato,x='Aggregate_rating',hue='Rating_text')
```

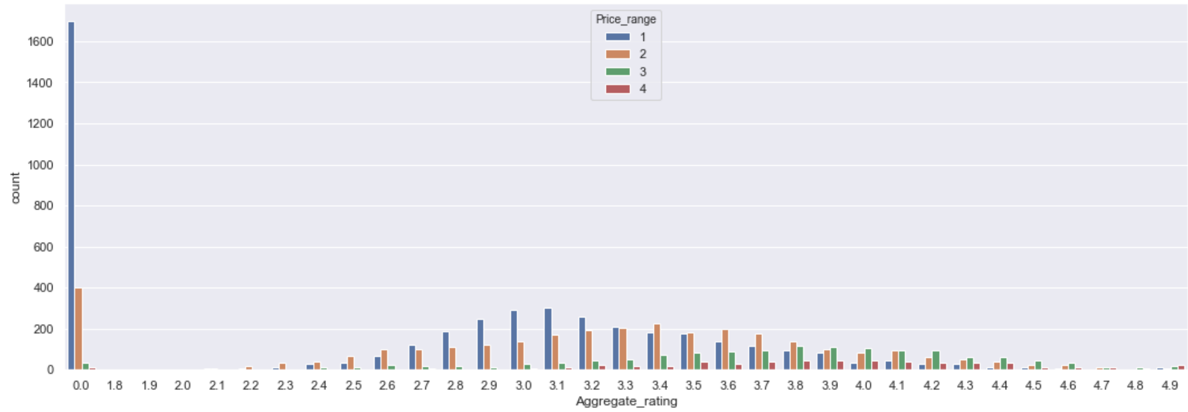
Out[57]: <matplotlib.axes._subplots.AxesSubplot at 0x200654e74e0>



Plotting the graph for Price range with respect to Aggregate rating using seaborn

In [58]:
```
sns.set(rc={'figure.figsize':(18,6)})
sns.countplot(data=zomato,x='Aggregate_rating',hue='Price_range')
```

Out[58]: <matplotlib.axes._subplots.AxesSubplot at 0x20065c143c8>

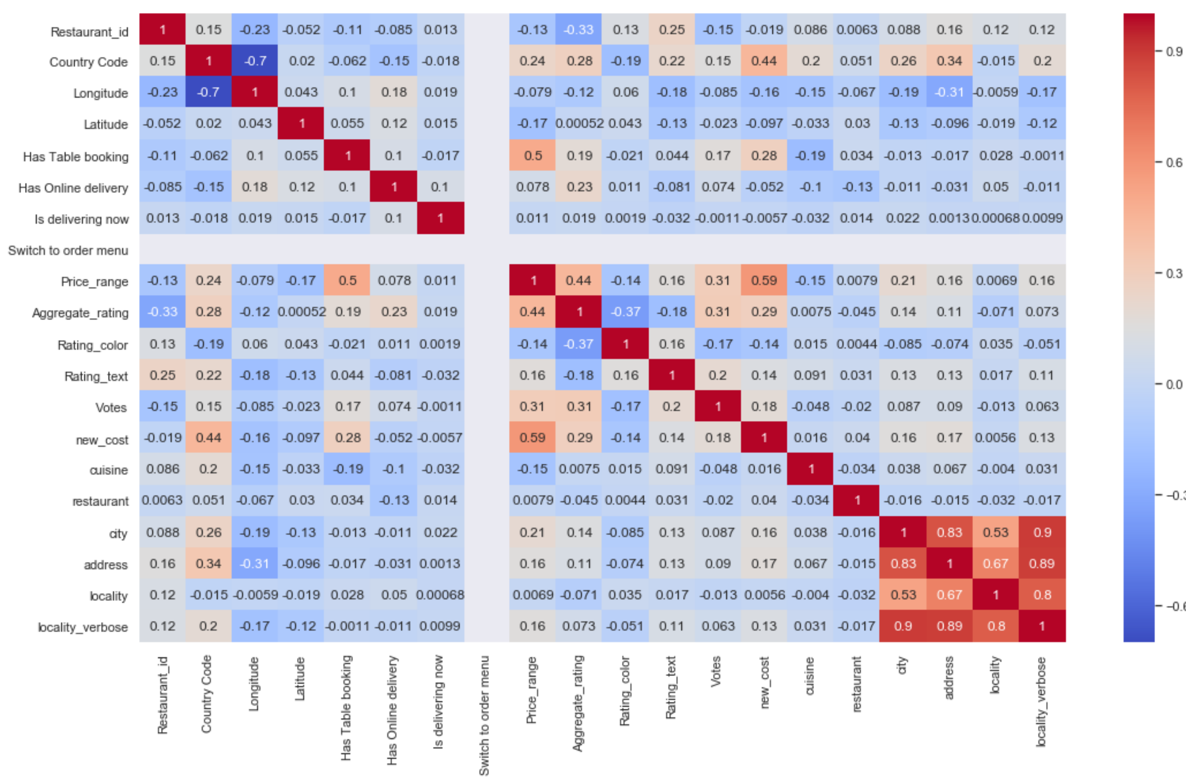


Feature Selection

Seaborn graph

In [59]:
```
sns.set(rc={'figure.figsize':(18,10)})
sns.heatmap(data=zomato.corr(),cmap='coolwarm',annot=True)
```

Out[59]: <matplotlib.axes._subplots.AxesSubplot at 0x20064413978>



Performing the pearson's correlation for choosing the best feature which is highly related to the target values [Aggregate rating]

In [61]:
```
corr=zomato.corr('pearson')
abs(corr['Aggregate_rating']).sort_values(ascending=False)
```

Out[61]:
```
Aggregate_rating        1.000000
Price_range             0.437944
Rating_color            0.367054
Restaurant_id           0.326212
Votes                   0.313691
new_cost                0.289929
Country Code            0.282189
Has Online delivery     0.225699
Has Table booking       0.189998
Rating_text             0.182662
city                    0.144101
Longitude               0.116818
address                 0.113871
locality_verbose        0.073368
locality                0.070685
restaurant              0.045395
Is delivering now       0.019180
cuisine                 0.007479
Latitude                0.000516
Switch to order menu         NaN
Name: Aggregate_rating, dtype: float64
```

In [63]:
```
zomato.head()
```

Out[63]:

	Restaurant_id	Country Code	Longitude	Latitude	Has Table booking	Has Online delivery	Is delivering now	Switch to order menu	Price_rar
0	6317637	162	121.027535	14.565443	1	0	0	0	
1	6304287	162	121.014101	14.553708	1	0	0	0	
2	6300002	162	121.056831	14.581404	1	0	0	0	
3	6318506	162	121.056475	14.585318	0	0	0	0	
4	6314302	162	121.057508	14.584450	1	0	0	0	

In [64]:
```
zomato.shape
```

Out[64]:
```
(9551, 20)
```

Get dummies is used to add the features of seperate column values in the dataset

In [82]:
```
zomato = pd.get_dummies(zomato, columns=['Price_range','Rating_text','Has Table
```

Linear Regression using sklearn

In [84]:
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
```

Separing the features and the target with seperate dataframes

In [85]:
```
X = np.array(zomato.drop(['Aggregate_rating'], axis=1))
Y = np.array(zomato['Aggregate_rating'])
```

Splitting the dataset

We are splitting the dataset for training and testing the datapoints in the ratio 3:2.So that we can train our model and test the datapoints on the same model.

In [86]:
```
from sklearn.model_selection import train_test_split
```

In [87]:
```
X_train,X_test,Y_train,Y_test=train_test_split(X,Y,test_size=0.3)
```

Importing Linear Regression Sklearn model

In [88]:
```
from sklearn.linear_model import LinearRegression
```

In [89]:
```
regressor = LinearRegression()
```

Fitting the Linear model for trained dataset

In [90]:
```
regressor.fit(X_train,Y_train)
```

Out[90]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

Predicting the Linear Model for test datapoints

In [91]:
```
Y_pred=regressor.predict(X_test)
```

In [92]:
```
for i in zip(Y_pred,Y_test):
    print(i)
```

```
(4.109607296052049, 4.1)
(3.1067477397126133, 3.1)
(3.051044686470563, 3.4)
(3.0370688561141987, 3.0)
(-0.006647638430577807, 0.0)
(3.072361742369823, 3.2)
(-0.0444221880029545, 0.0)
(3.029173167113939, 3.3)
(3.0727690985626452, 3.4)
(4.139812293019679, 4.0)
(3.007752882527799, 2.6)
(3.0296198491642947, 3.1)
(3.690670833434327, 3.8)
(3.7626656761653994, 3.7)
(4.293355856503346, 4.1)
(3.091292099539448, 3.1)
(3.056253410017008, 3.0)
(0.03955793826148213, 0.0)
(3.650532777151067, 3.9)
```

In [93]:
```
from sklearn.metrics import mean_squared_error, r2_score
```

Mean Squared Error

In [94]:
```
mean_squared_error(Y_test,Y_pred)
```

Out[94]:
```
0.03191557892722236
```

Root mean squared error

In [95]:
```
np.sqrt(mean_squared_error(Y_test,Y_pred))
```

Out[95]:
```
0.17864931829487166
```

Computing the r2_score for Linear Regression

In [96]:
```
r2_score(Y_test,Y_pred)
```

Out[96]:
```
0.9861738024247685
```

In [100]:

```
from sklearn import metrics

print('Mean Absolute Error:', metrics.mean_absolute_error(Y_test, Y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(Y_test, Y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(Y_test, Y_
```

```
Mean Absolute Error: 0.13028919538947403
Mean Squared Error: 0.03191557892722236
Root Mean Squared Error: 0.17864931829487166
```

In [ ]:

In [ ]: