Importing the Libraries

```
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
from sklearn.linear_model import LinearRegression
from sklearn import metrics
```

Data Collection & Analysis

Data Collection

```
# Loading the data from csv file to pandas dataset
insurance = pd.read_csv('/content/insurance.csv')

insurance
```

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92400
1	18	male	33.770	1	no	southeast	1725.55230
2	28	male	33.000	3	no	southeast	4449.46200
3	33	male	22.705	0	no	northwest	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520
...	...	...	...	...	...	...	...
1333	50	male	30.970	3	no	northwest	10600.54830
1334	18	female	31.920	0	no	northeast	2205.98080
1335	18	female	36.850	0	no	southeast	1629.83350
1336	21	female	25.800	0	no	southwest	2007.94500
1337	61	female	29.070	0	yes	northwest	29141.36030

1338 rows × 7 columns

```
#Number of rows and columns
insurance.shape
```

```
(1338, 7)
```

```
# Getting some informations about the dataset
insurance.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       1338 non-null   int64
 1   sex       1338 non-null   object
 2   bmi       1338 non-null   float64
 3   children  1338 non-null   int64
```

```
 4   smoker    1338 non-null   object
 5   region    1338 non-null   object
 6   charges   1338 non-null   float64
dtypes: float64(2), int64(2), object(3)
memory usage: 73.3+ KB
```

There are total 7 columns in this dataset. Column 'charges' is the target (dependent) variable and rest of the columns are the features (independent varible).

There are 3 categorical features which contains non numeric values.

- sex
- smoker
- region

```
# Checking for missing values
insurance.isnull()
```

	age	sex	bmi	children	smoker	region	charges
0	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...
1333	False	False	False	False	False	False	False
1334	False	False	False	False	False	False	False
1335	False	False	False	False	False	False	False
1336	False	False	False	False	False	False	False
1337	False	False	False	False	False	False	False

1338 rows × 7 columns

```
insurance.isnull().sum()
```

```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

So there are no null values.

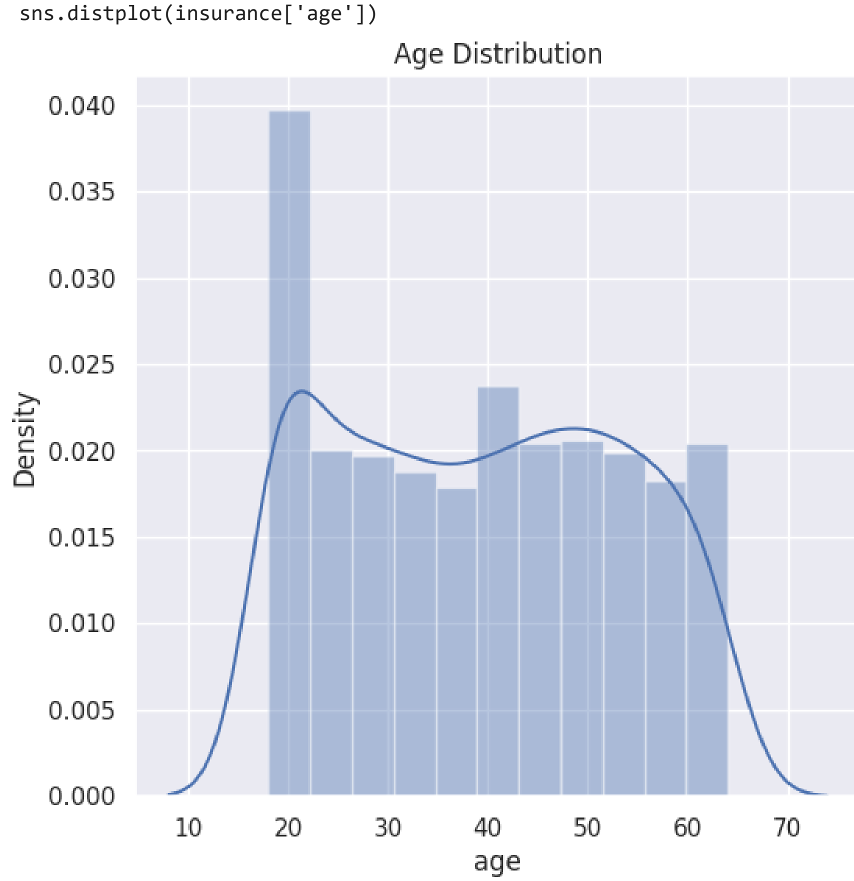
Data Analysis

```
# Statistical Measurment of the dataset
insurance.describe()
```

	age	bmi	children	charges
count	1338.000000	1338.000000	1338.000000	1338.000000
mean	39.207025	30.663397	1.094918	13270.422265
std	14.049960	6.098187	1.205493	12110.011237
min	18.000000	15.960000	0.000000	1121.873900
25%	27.000000	26.296250	0.000000	4740.287150
50%	39.000000	30.400000	1.000000	9382.033000
75%	51.000000	34.693750	2.000000	16639.912515

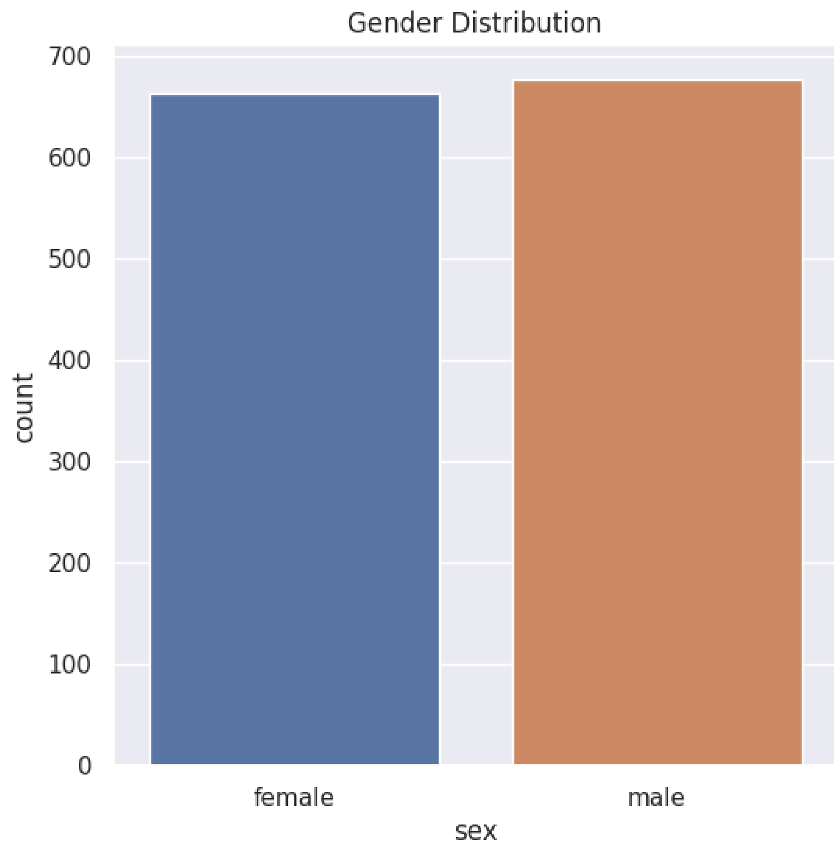
```
# Distribution of the age values

sns.set()
plt.figure(figsize = (6,6))
sns.distplot(insurance['age'])
plt.title('Age Distribution')
plt.show()
```

```
<ipython-input-43-cb7a2ce222a7>:5: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(insurance['age'])
```



From the distribution plot, it is clearly visible that there is most number of people within the age range of around 20-23.

```
# Distribution of the gender

plt.figure(figsize = (6,6))
sns.countplot(x = 'sex', data = insurance)
plt.title('Gender Distribution')
plt.show()
```



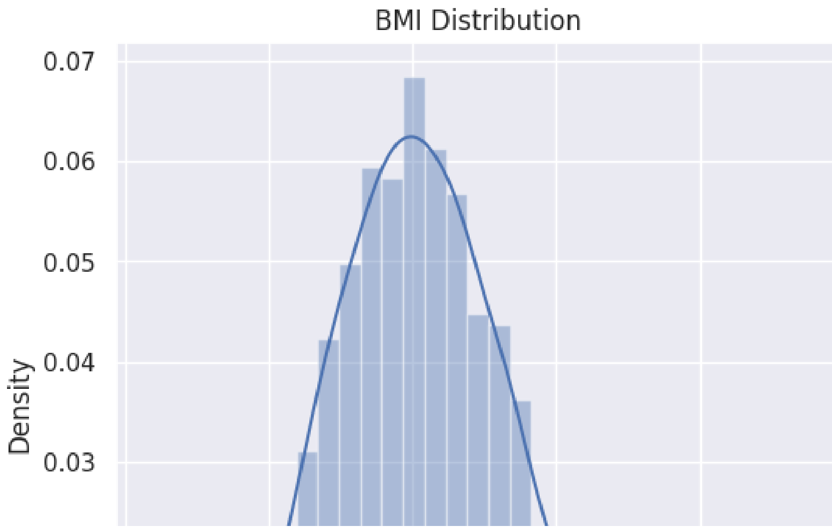

```
insurance['sex'].value_counts()
```

```
male      676
female    662
Name: sex, dtype: int64
```

There are 14 more male than female in this dataset. But it can be considered almost equal.

```
# Distribution of the bmi values

plt.figure(figsize = (6,6))
sns.distplot(insurance['bmi'])
plt.title('BMI Distribution')
plt.show()
```

```
<ipython-input-46-4a89a522ce65>:4: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(insurance['bmi'])
```



It is observed that most number of people have BMI 28-32 as the distribution is Normal distribution. This means maximum people is overweight in this dataset.

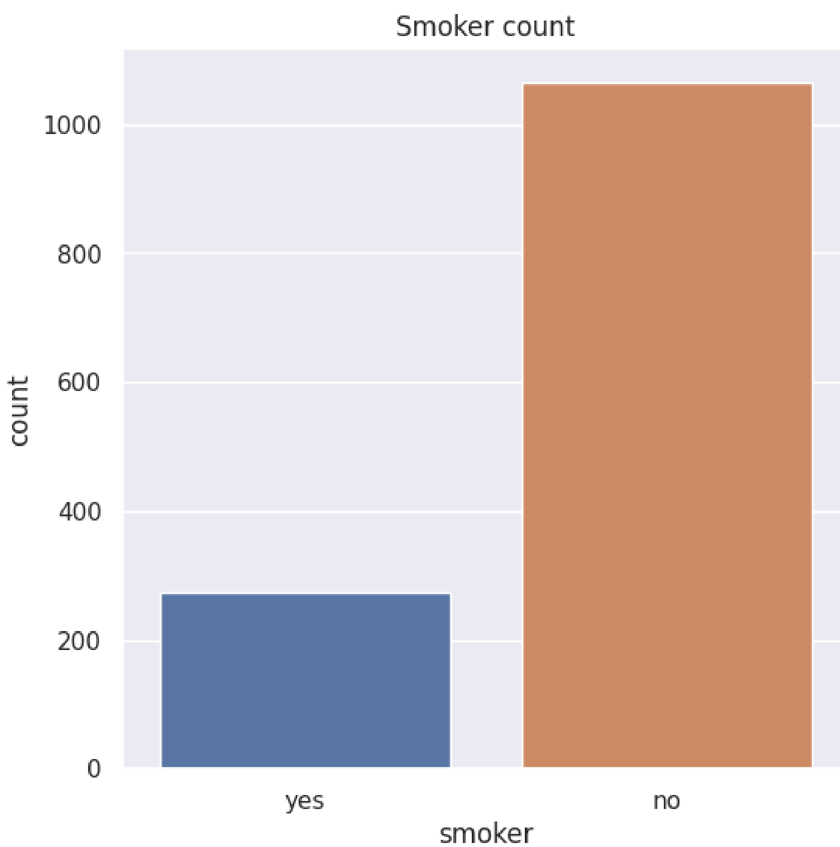
```
# Count of children

plt.figure(figsize = (6,6))
sns.countplot(x = "children", data = insurance)
plt.title('Children count')
plt.show()
```


```
insurance['children'].value_counts()
```

```
0    574
1    324
2    240
3    157
4     25
5     18
Name: children, dtype: int64
```

From the plot, it is observed that a large number of people doesn't have any children. It is a 600 people which is almost all the people. Almost half of the people have one children.

```
# Count of smoker

plt.figure(figsize = (6,6))
sns.countplot(x = "smoker", data = insurance)
plt.title('Smoker count')
plt.show()
```

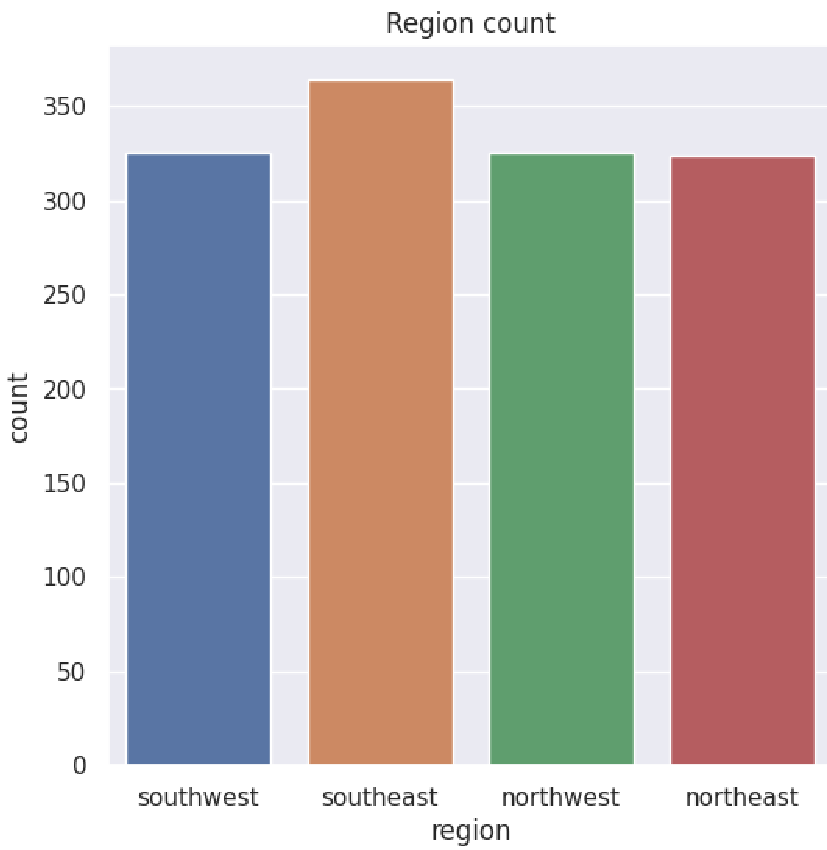



```
insurance['smoker'].value_counts()
```

```
no     1064
yes     274
Name: smoker, dtype: int64
```

Therefore, maximum people in this dataset are non smoker.

```
# Region column

plt.figure(figsize = (6,6))
sns.countplot(x = "region", data = insurance)
plt.title('Region count')
plt.show()
```



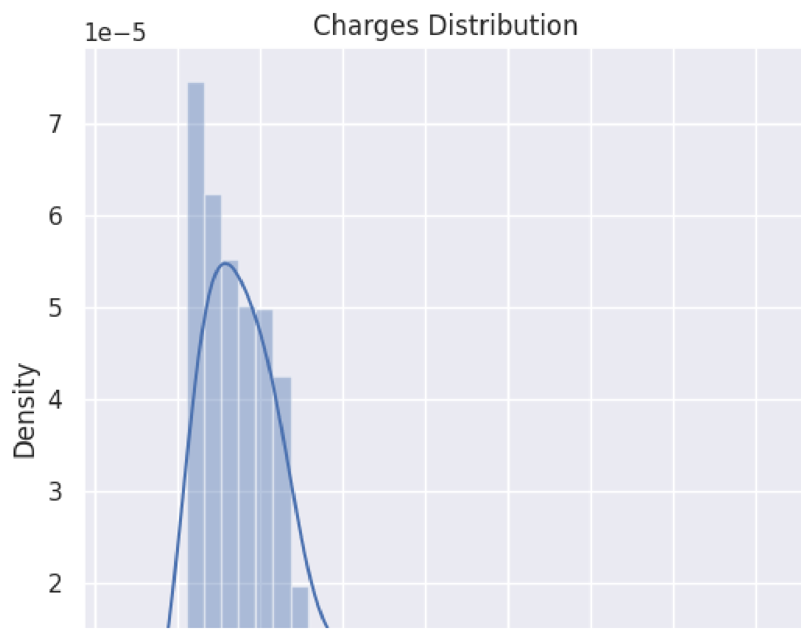

```
insurance['region'].value_counts()
```

```
southeast    364
southwest    325
northwest    325
northeast    324
Name: region, dtype: int64
```

Almost same number of people comes from southwest, northwest and northeast region. Slightly more people comes from southeast region. But the differences are almost neglegible.

```
# Distribution of the charges

plt.figure(figsize = (6,6))
sns.distplot(insurance['charges'])
plt.title('Charges Distribution')
plt.show()
```

```
<ipython-input-53-02ad18772756>:4: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(insurance['charges'])
```



From the distribution we can see maximum amount of people are charged in 10,000- 17,000 dollar. Charges over 25,000 dollar are very little.

Data Preprocessing

Label Encoding

We can not feed categorical/ text data to our machine learning model. Computer just understand numerical values. So we have to convert the categorical values to mumerical values. This is called label encoding

```
#encoding 'sex' column
insurance.replace({'sex' : {'male':0, 'female':1}}, inplace = True)

#encoding 'smoker' column
insurance.replace({'smoker' : {'yes':0, 'no':1}}, inplace = True)

#encoding 'region' column
insurance.replace({'region' : {'southeast':0, 'southwest':1, 'northeast':2, 'northwest':3}}, inplace = True)
```

```
insurance
```

	age	sex	bmi	children	smoker	region	charges
0	19	1	27.900	0	0	1	16884.92400
1	18	0	33.770	1	1	0	1725.55230
2	28	0	33.000	3	1	0	4449.46200
3	33	0	22.705	0	1	3	21984.47061
4	32	0	28.880	0	1	3	3866.85520
...	...	...	...	...	...	...	...
1333	50	0	30.970	3	1	3	10600.54830
1334	18	1	31.920	0	1	2	2205.98080
1335	18	1	36.850	0	1	0	1629.83350

Spliting the features (independent variable) and target (dependent variable)

```
x = insurance.drop(columns = 'charges', axis = 1)
y = insurance['charges']
```

```
x
```

	age	sex	bmi	children	smoker	region
0	19	1	27.900	0	0	1
1	18	0	33.770	1	1	0
2	28	0	33.000	3	1	0
3	33	0	22.705	0	1	3
4	32	0	28.880	0	1	3
...	...	...	...	...	...	...
1333	50	0	30.970	3	1	3
1334	18	1	31.920	0	1	2
1335	18	1	36.850	0	1	0
1336	21	1	25.800	0	1	1
1337	61	1	29.070	0	0	3

1338 rows × 6 columns

```
y
```

```
0       16884.92400
1        1725.55230
2        4449.46200
3       21984.47061
4        3866.85520
           ...
1333    10600.54830
1334     2205.98080
1335     1629.83350
1336     2007.94500
1337    29141.36030
Name: charges, Length: 1338, dtype: float64
```

Spliting the dataset into Training data and Test data

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2, random_state = 2)
```

```
x_train
```

	age	sex	bmi	children	smoker	region
882	21	1	22.135	0	1	2
505	37	0	30.875	3	1	3
798	58	1	33.100	0	1	1
792	22	1	23.180	0	1	2
201	48	1	32.230	1	1	0
...	...	...	...	...	...	...
466	60	1	28.700	1	1	1
299	48	1	28.880	1	1	3
493	61	0	43.400	0	1	1
527	51	1	25.800	1	1	1
1192	58	1	32.395	1	1	2

1070 rows × 6 columns

```
x_test
```

	age	sex	bmi	children	smoker	region
17	23	0	23.845	0	1	2
1091	55	1	29.830	0	1	2
273	50	0	27.455	1	1	2
270	18	0	29.370	1	1	0
874	44	0	21.850	3	1	2
...	...	...	...	...	...	...
232	19	1	17.800	0	1	1
323	57	0	40.945	0	1	2
1337	61	1	29.070	0	0	3
1066	48	0	37.290	2	1	0
966	51	0	24.795	2	0	3

268 rows × 6 columns

```
y_train
```

```
882      2585.85065
505      6796.86325
798     11848.14100
792      2731.91220
201      8871.15170
           ...
466     13224.69300
299      9249.49520
493     12574.04900
527      9861.02500
1192    13019.16105
Name: charges, Length: 1070, dtype: float64
```

```
y_test
```

```
17       2395.17155
1091    11286.53870
273      9617.66245
270      1719.43630
874      8891.13950
            ...
232      1727.78500
323     11566.30055
1337    29141.36030
1066     8978.18510
966     23967.38305
Name: charges, Length: 268, dtype: float64
```

```
print(x.shape, x_train.shape, x_test.shape)
```

```
(1338, 6) (1070, 6) (268, 6)
```

Model Training

Linear Regression

```
# Loading the linear regression model

regressor = LinearRegression()
```

```
# Seeing the coefficients

regressor.coef_
```

```
array([   251.40512196,     26.11715966,    330.64637157,    580.27438296,
       -23928.10171061,    212.22242728])
```

```
# Seeing the intercept

regressor.intercept_
```

```
11357.668742540951
```

```
# Training the model

regressor.fit(x_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

Model Evaluation

Prediction on training data

```
training_data_prediction = regressor.predict(x_train)
```

```
# R squared value

r2_train = metrics.r2_score(y_train, training_data_prediction)
print('R Squared value: ', r2_train)
```

```
R Squared value:  0.751505643411174
```

Prediction on test data

```
test_data_prediction = regressor.predict(x_test)
```

```
test_data_prediction
```

```
array([ 1520.59242161, 11570.5920178 , 10082.43849883,  2246.21754312,
        7881.28362035, 11081.50227956,  3538.24791808,   698.03224036,
       12223.4851558 ,  9611.93217623, 11657.51046259,  4891.0539656 ,
       29947.50192274,  -370.8384887 , 12401.36048618, 13243.21522903,
        3814.42216541,  7883.39384825, 29431.34485576,  2362.83672121,
       12505.50452609,  2256.75277238, 34468.01948464, 31742.4859866 ,
       30306.19118561,  9027.76110059,  1923.87420399, 15247.09503907,
        6542.61302531,  2104.79910554,  9484.36642532,  5794.91649267,
        4425.26853454,  5015.3811241 ,  9579.4545934 ,  4601.74838962,
       29875.58083252,  6797.04084444, 27239.25811383, 13999.0938259 ,
         313.55184653, 28415.75044713,  7886.54751277,  1478.09056648,
       10273.28966107,  8003.09003405, 11612.15283896,  8175.95966058,
       10753.45200738, 13802.18082647,  5740.90172027,  -737.13333209,
       26346.21771217, 37192.66032995,  7364.09646118, 17845.51752284,
        1412.63748094, 11042.48090545,  2159.33597148, 34066.1609094 ,
       11646.83178834,   874.98548929,  4020.66706965, 35913.0386546 ,
       -1034.71506651, 13963.49470486, 14840.86595147,  3395.11689253,
       12935.74119039, 11199.38639761, 11579.90265947, 16132.93772732,
       10183.88439249,  9888.34374983, 15157.35586536, 12377.94812939,
        4387.77863628,  3680.0942183 ,  5347.06219182, 13291.0174177 ,
        9158.24253865, 11935.82529104,  9522.10094863, 27668.10801212,
       12639.34008179,  3989.82506218, 38550.3600665 , 11191.86138788,
        8088.76475698, 11068.02157864, 10956.54972199, 15139.01708371,
       11077.7652618 , 13045.02707757,  5283.33522041, 25958.0327765 ,
        4962.43983078, 10543.57361001,  2709.95649343, 29007.79585973,
        6350.41196404,  3478.11303549,  2661.5079005 , 15990.91366368,
        7905.79980945, 10304.73937225,  9962.86575973,  5066.24762376,
       14869.35897203, 33752.1676117 ,  3761.88660755, 11521.18346955,
       24631.42819661, 14803.95189475,  1734.60861523, 10401.39588933,
        9202.60416666,  6288.03801508, 11838.14846799, 28871.88920869,
        6579.83915531,  7172.5493248 , 15845.7059381 , 16235.1462466 ,
        8251.21825771, 26323.60251235, 35303.7543364 , 11847.13682432,
        8073.11495528,  9326.25448529,  8467.39129356,  2933.9917805 ,
        3322.8695607 ,  4683.92759642,  8307.29448212,  8002.16943038,
        7053.31134868, 28990.07000293, 35181.28277884,  4167.15930146,
       27886.14685479,  4144.07006286,  6628.26922773, 13311.51217138,
        8025.49599525, 36451.54381063, 11784.84114664, 11347.89349827,
        8294.89578165,   524.38645586,  6503.27709943,  7165.34947975,
        4638.1194905 , 11666.09138657, 11630.93778466, 15478.52566732,
        5856.27738941, 27679.01778802,  1979.26736391, 11476.47168147,
       16974.37864533, 13934.2661456 ,  9520.8147517 ,  2269.28578271,
        4396.04458266,  8922.70311363, 19309.54145116, 28276.8594048 ,
       12676.31036501,  2965.72503913, 32305.95532934, 13107.14725741,
       32778.03744536, 34349.43983065, 11161.90211021,  7576.16565725,
        2633.64298278,  2362.83672121, 11656.06768299,  7884.51285855,
        2926.10661155,  1166.95403524, 31658.17342743,  7134.58660758,
        5557.65095352, 27325.26552208,  6609.80947788,  2654.92453849,
        7915.90908586, 35382.85588438,  7986.35556548,  4319.94677933,
        9477.98125702, 26872.46549002,  5713.52005266, 40198.16671135,
       37499.39947482, 12998.97434383, 26841.49272812, 11921.07008303,
       37470.06851291,  7403.67284293,  4214.20198795,  1961.81400965,
       14048.97433527, 14018.66010565,  2180.00417375, 35697.72795561,
       12791.22900693,  8748.61933066,  1132.66189998, 30647.68798314,
        3495.69714418,  3469.35222538, 12600.42201939, 15082.03691758,
       29668.01412306,   -90.72967482,  3183.27545559,  8454.89054624,
```

```
       39754.78580876,  7972.36417173, 35120.73194872, 27504.76077554,
       13731.00485102, 28889.95796905, 16499.4845035 ,  7606.95831393,
```

```
# R squared value

r2_test = metrics.r2_score(y_test, test_data_prediction)
print('R Squared value: ', r2_test)
```

```
R Squared value:  0.7447273869684076
```

So this model shows a good accuracy with a R squared value of 0.74 and there is also no issue of overfitting as prediction on train data and test data almost showed equal efficiency.

Comparing the given charges values (y_train) and predicted charges value (test_data_prediction) corresponding to test data values (y_test)

```
print(np.concatenate((test_data_prediction.reshape(len(test_data_prediction) , 1),
                      y_test.values.reshape(len(test_data_prediction),1)) , 1))
```

```
[[ 1520.59242161  2395.17155   ]
 [11570.5920178  11286.5387    ]
 [10082.43849883  9617.66245   ]
 [ 2246.21754312  1719.4363    ]
 [ 7881.28362035  8891.1395    ]
 [11081.50227956  5662.225     ]
 [ 3538.24791808 12609.88702   ]
 [  698.03224036  2196.4732    ]
 [12223.4851558  14254.6082    ]
 [ 9611.93217623  7209.4918    ]
 [11657.51046259 12222.8983    ]
 [ 4891.0539656   2219.4451    ]
 [29947.50192274 19444.2658    ]
 [ -370.8384887   1121.8739    ]
 [12401.36048618 26392.26029   ]
 [13243.21522903 12925.886     ]
 [ 3814.42216541  3645.0894    ]
 [ 7883.39384825  5327.40025   ]
 [29431.34485576 18972.495     ]
 [ 2362.83672121  2203.47185   ]
 [12505.50452609 11840.77505   ]
 [ 2256.75277238  2597.779     ]
 [34468.01948464 40182.246     ]
 [31742.4859866  22331.5668    ]
 [30306.19118561 37484.4493    ]
 [ 9027.76110059 10577.087     ]
 [ 1923.87420399  3206.49135   ]
 [15247.09503907  8944.1151    ]
 [ 6542.61302531  3577.999     ]
 [ 2104.79910554  3176.8159    ]
 [ 9484.36642532  5397.6167    ]
 [ 5794.91649267  3956.07145   ]
 [ 4425.26853454  4931.647     ]
 [ 5015.3811241   4239.89265   ]
 [ 9579.4545934  14478.33015   ]
 [ 4601.74838962  1631.6683    ]
 [29875.58083252 38792.6856    ]
 [ 6797.04084444 20420.60465   ]
 [27239.25811383 35147.52848   ]
 [13999.0938259  27000.98473   ]
 [  313.55184653  2117.33885   ]
 [28415.75044713 34472.841     ]
 [ 7886.54751277  7419.4779    ]
 [ 1478.09056648  2007.945     ]
 [10273.28966107  6781.3542    ]
 [ 8003.09003405  5375.038     ]
 [11612.15283896 10264.4421    ]
 [ 8175.95966058  3471.4096    ]
```

```
 [10753.45200738  4266.1658    ]
 [13802.18082647 20630.28351   ]
 [ 5740.90172027  4915.05985   ]
 [ -737.13333209  1242.816     ]
 [26346.21771217 17748.5062    ]
 [37192.66032995 43921.1837    ]
 [ 7364.09646118  6496.886     ]
 [17845.51752284 11538.421     ]
 [ 1412.63748094  1969.614     ]
 [11042.48090545  7160.3303    ]
```

```
#Model Accuracy

print('Model Accuracy: ',regressor.score(x_test, y_test)*100 , ' %')
```

```
Model Accuracy:  74.47273869684075  %
```

✓ 0s completed at 11:02 PM