Multiple Linear Regression

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2 First we will load the file to the variable filepath and supress any kind of warnings that pop up

[1]:
```
# Supress Warnings

import warnings
warnings.filterwarnings('ignore')

import numpy as np
import pandas as pd
# Loading File
filepath ='/home/ex5/21MIS1174/MultipleReg.csv'
```

3 Using pandas library it enables us to read the csv file and store as a dataframe

[2]:
```
data=pd.read_csv(filepath)
```

4 Displaying first 5 records of the dataframe

[3]:
```
data.head()
```

[3]:
```
   symboling  normalized-losses  wheel-base      length      width     height  \
0          5                164   99.800003  176.600006  66.199997  54.299999
1          5                164   99.400002  176.600006  66.400002  54.299999
2          4                158  105.800003  192.699997  71.400002  55.700001
3          4                158  105.800003  192.699997  71.400002  55.900002
4          5                192  101.199997  176.800003  64.800003  54.299999

   curb-weight  engine-size  bore  stroke  compression-ratio  horsepower  \
0         2337          109  3.19     3.4               10.0         102
1         2824          136  3.19     3.4                8.0         115
```

```
2         2844           136   3.19      3.4                   8.5         110
3         3086           131   3.13      3.4                   8.3         140
4         2395           108   3.50      2.8                   8.8         101

   peak-rpm  city-mpg  highway-mpg  target
0      5500        24           30   13950
1      5500        18           22   17450
2      5500        19           25   17710
3      5500        17           20   23875
4      5800        23           29   16430
```

5 To check whether there are any null or empty values in the dataset, since none we proceed further without disturbing the dataset

[4]:
```python
data.isnull().sum()
```

[4]:
```
symboling            0
normalized-losses    0
wheel-base           0
length               0
width                0
height               0
curb-weight          0
engine-size          0
bore                 0
stroke               0
compression-ratio    0
horsepower           0
peak-rpm             0
city-mpg             0
highway-mpg          0
target               0
dtype: int64
```

6 To verify the datatypes of the dataset, as only numerical values shall be used

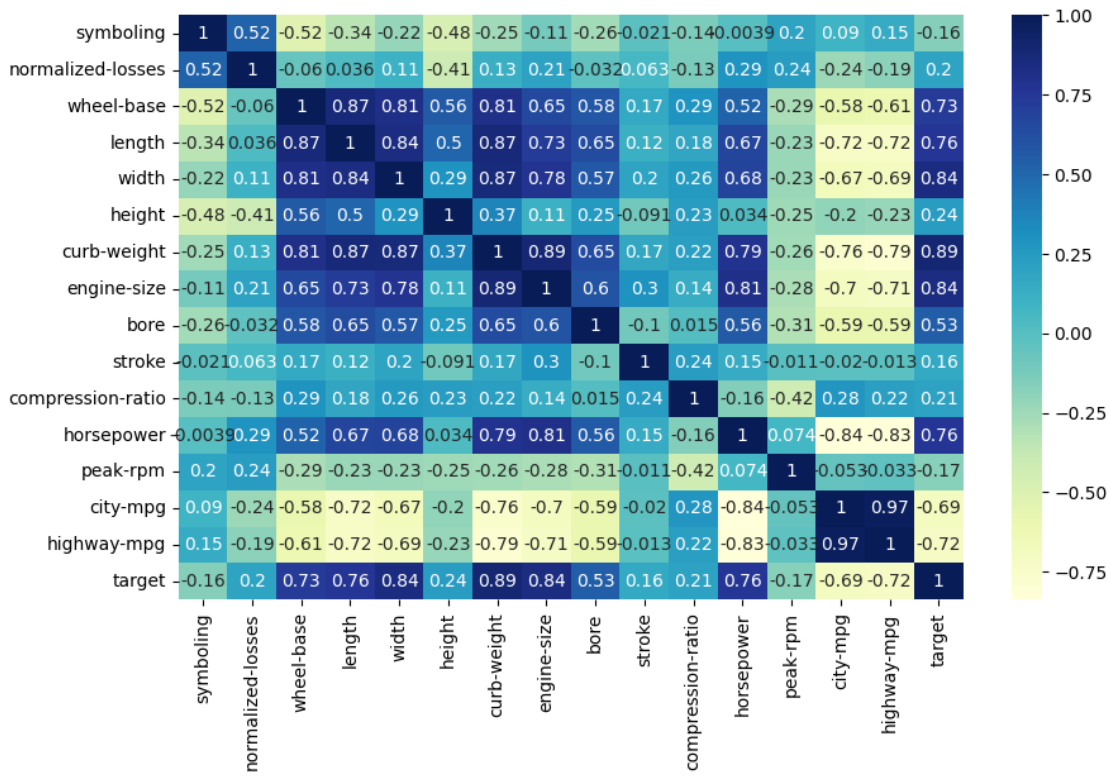
[5]:
```python
data.dtypes
```

[5]:
```
symboling              int64
normalized-losses      int64
wheel-base           float64
length               float64
```

```
width                  float64
height                 float64
curb-weight              int64
engine-size              int64
bore                   float64
stroke                 float64
compression-ratio      float64
horsepower               int64
peak-rpm                 int64
city-mpg                 int64
highway-mpg              int64
target                   int64
dtype: object
```

7 It is advisable to first find the correlation between features and target.. Higher the correlation coefficient better the Multiple Linear Regression analysis

[6]:
```python
# Data Visualisation
import matplotlib.pyplot as plt
import seaborn as sns

# sns.heatmap(x_selected.corr(), cmap="YlGnBu", annot=True)
plt.figure(figsize=(10, 6))
sns.heatmap(data.corr(), cmap="YlGnBu", annot=True)
plt.show()
```



8 As per the dataset 8 features are not deemed to be set as features as they have less correlation values with target variable… So it is better to drop them from the dataframe

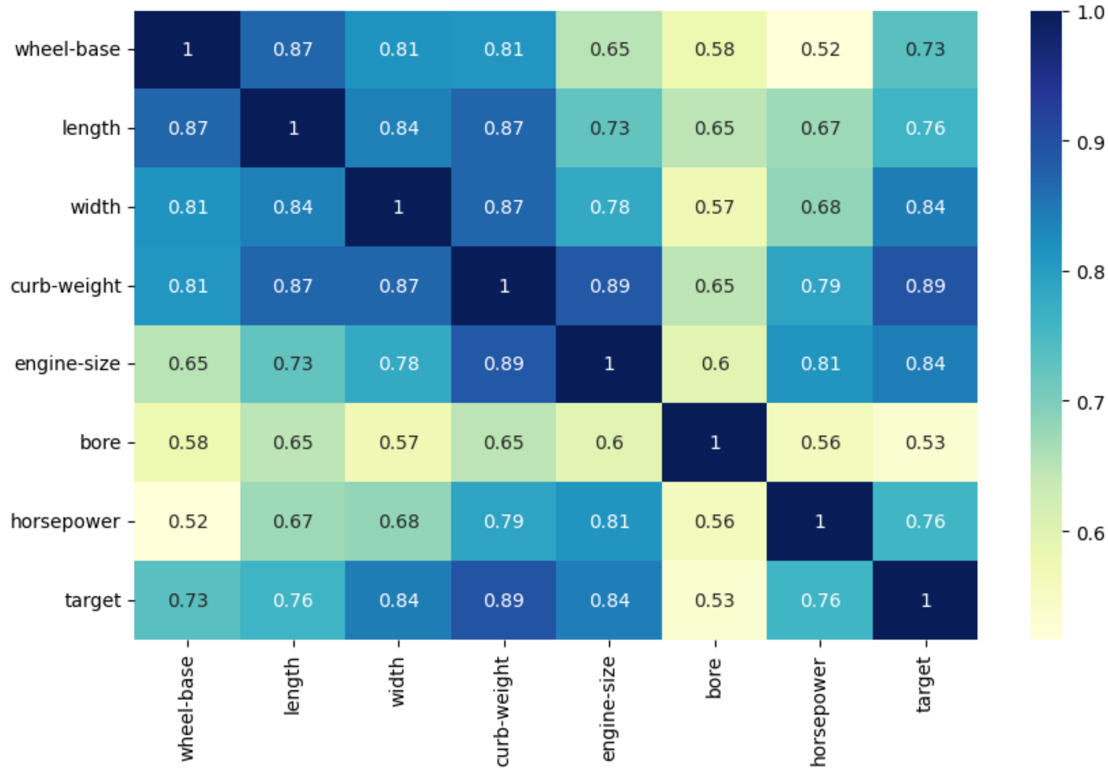
[7]:
```python
# Drop additional columns
columns_to_drop = ['symboling', 'normalized-losses', 'height', 'stroke',␣
 ↪'compression-ratio', 'peak-rpm', 'city-mpg', 'highway-mpg']
x_selected = data.drop(columns=columns_to_drop, axis=1)
x_selected
```

[7]:
```
      wheel-base      length      width  curb-weight  engine-size  bore  \
0      99.800003  176.600006  66.199997         2337          109  3.19
1      99.400002  176.600006  66.400002         2824          136  3.19
2     105.800003  192.699997  71.400002         2844          136  3.19
3     105.800003  192.699997  71.400002         3086          131  3.13
4     101.199997  176.800003  64.800003         2395          108  3.50
..           …           …          …           …          …    …
154   109.099998  188.800003  68.900002         2952          141  3.78
155   109.099998  188.800003  68.800003         3049          141  3.78
156   109.099998  188.800003  68.900002         3012          173  3.58
```

```
157  109.099998  188.800003  68.900002         3217           145   3.01
158  109.099998  188.800003  68.900002         3062           141   3.78

     horsepower  target
0           102   13950
1           115   17450
2           110   17710
3           140   23875
4           101   16430
..          …      …
154         114   16845
155         160   19045
156         134   21485
157         106   22470
158         114   22625

[159 rows x 8 columns]
```

[8]:

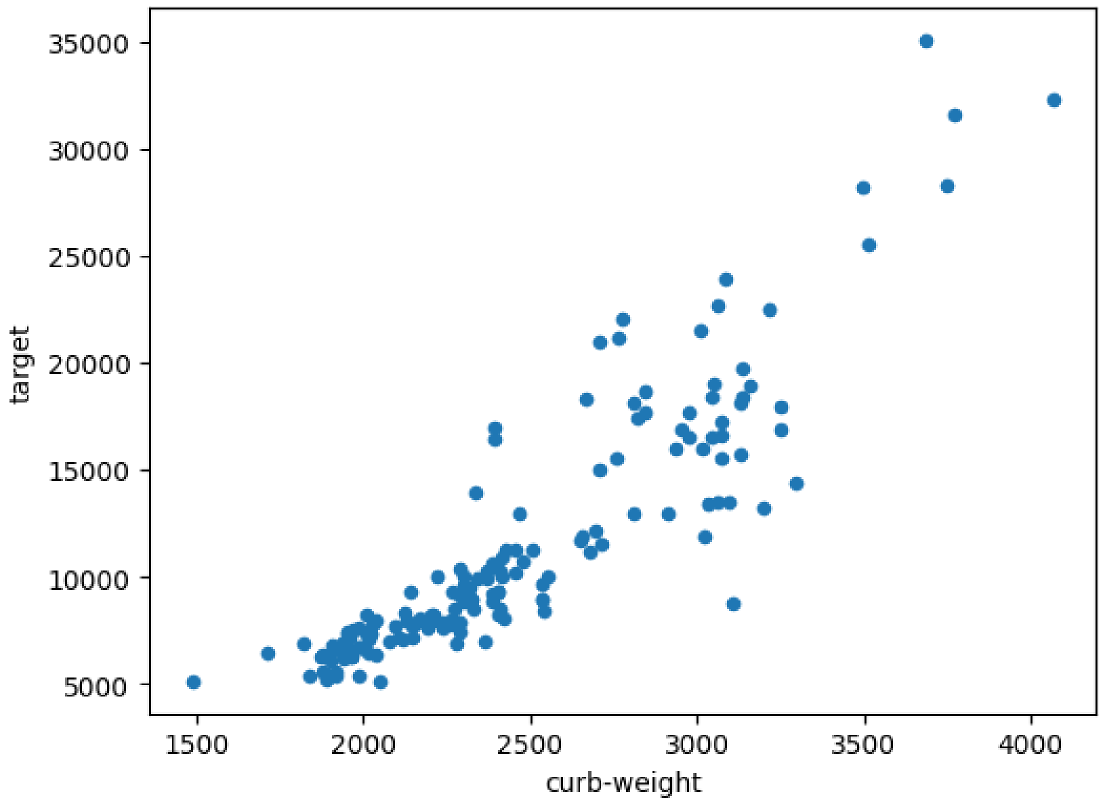
```
# Data Visualisation
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(10, 6))
sns.heatmap(x_selected.corr(), cmap="YlGnBu", annot=True)
plt.show()
```



9 Using the scatter plot between highest feature correlation curb-weight and target varible to check whether Multiple Linear Regression is feasible.. curb-weight and target have a correlation of 89 %

[9]:
```
# Visualise the relationship between the features and the response using␣
 ↪scatterplots
x_selected.plot(x='curb-weight',y='target',kind='scatter')
```

[9]:
```
<Axes: xlabel='curb-weight', ylabel='target'>
```



10 Here 'x' represents the independent variable (feature) and 'y' represents the dependent variable (target)

[10]:
```
x = x_selected.iloc[:, 0:-1].values
y = x_selected.iloc[:, -1].values
```

11 Since only one feature is being used so the size has to be increased by one more dimension using 'reshape'

[11]:
```
x.shape
```

[11]: (159, 7)

[12]:
```
y.shape
```

[12]: (159,)

12 Here we start splitting the dataset into training and testing using sklearn library and we split in that ratio of 80:20 where 80 represents training set and 20 testing/validating set

[13]:
```
# Splitting the dataset into training and test set.
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test= train_test_split(x, y, test_size = 0.2,␣
↪random_state = 0)
```

13 To check the dimensions of each training and testing set

[14]:
```
print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
```

```
(127, 7)
(127,)
(32, 7)
(32,)
```

14 Importing LinearRegression from 'sklearn' library and using the object to train the model on training set

[15]:
```
# import LinearRegression from sklearn
from sklearn.linear_model import LinearRegression

# Representing LinearRegression as lr(Creating LinearRegression Object)
lr = LinearRegression()

# Fit the model using lr.fit() now impose Multiple Linear Regression
lr.fit(x_train, y_train)
```

[15]:
```
LinearRegression()
```

15 One of the most important in Multiple Linear Regression model is the equation of line, i.e., y = mx + c, where m is the slope of the line and c is intercept on the y - axis

[16]:
```
# Print the intercept and coefficients
print(lr.intercept_)
print(lr.coef_)
```

```
-64839.22113786733
[  154.88809286   -55.05492444   886.17284651     5.12840424
    32.2589798  -2018.86434749    26.02111432]
```

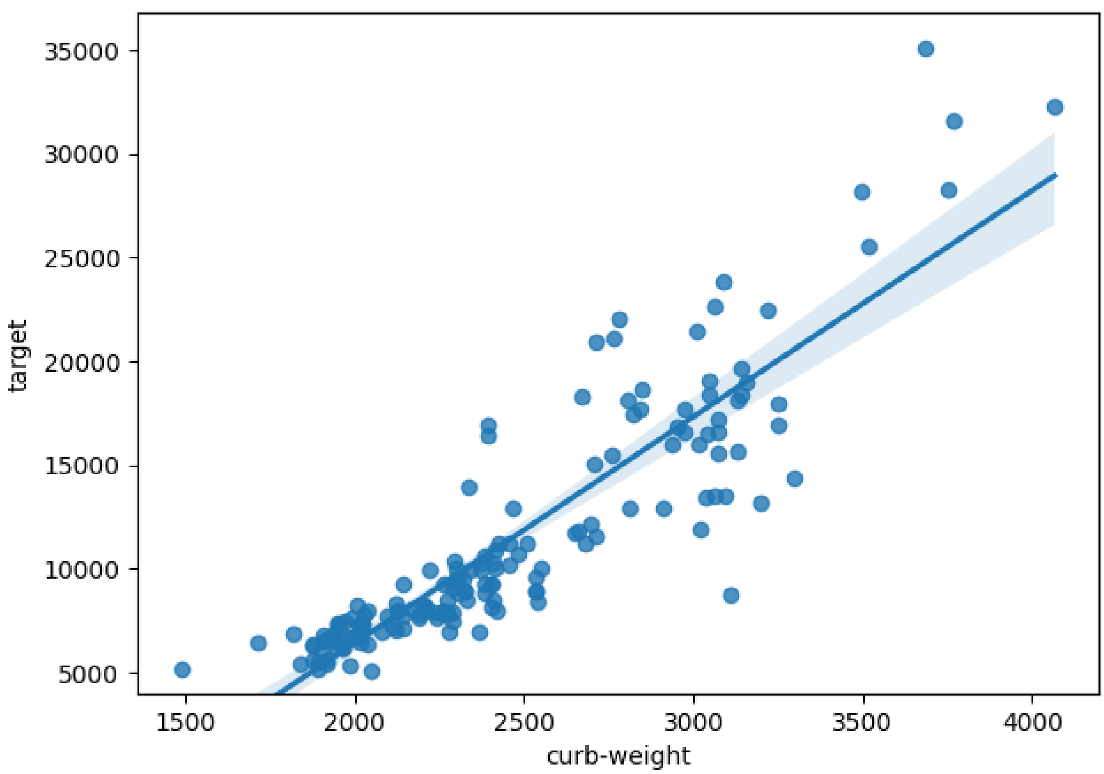
16 The equation of line hence is :-

17 y = 154.8881 * wheel-base - 55.0549 * length + 886.1728 * width + 5.1284 * curb-weight + 32.2589 * engine-size - 2018.8643 * bore + 26.0211 * horsepower - 64839.2211

18 where y is TARGET and x are FEATURES (training set)

19 Using the scatter plot we plot the points of one of the feature v target

[17]:
```
plt.figure(figsize = (7,5))

# Plotting the scatter plot of curb-weight v target
sns.regplot(x='curb-weight',y='target',data=x_selected)
plt.ylim(4000,)

# Display the plot
plt.show()
```



20 Predict the set of values on x_test and x_train and store in corresponding variables

[18]:
```
y_pred_test = lr.predict(x_test)
y_pred_train = lr.predict(x_train)
```

21 To verify the accuracy of the model we use Mean Squared Error and R² value which gives the goodness of fit, i.e., how close values are to the line and how much deviation of predicted from actual

[19]:
```
# The model accuracy of test data
from sklearn.metrics import mean_squared_error, r2_score
mse = mean_squared_error(y_test, y_pred_test)
r_squared = r2_score(y_test, y_pred_test)
print('Mean Squared Error : ', mse)
print('R² Value : ', r_squared)
```

```
Mean Squared Error :  6448622.182815665
R² Value :  0.8296223604246543
```

[20]:
```
print('Train Score: ', lr.score(x_train, y_train))
print('Test Score: ', lr.score(x_test, y_test))
```

```
Train Score:  0.8393176380989857
Test Score:  0.8296223604246543
```

[21]:
```
y_test.shape
```

[21]: (32,)

[22]:
```
y_pred_test.shape
```

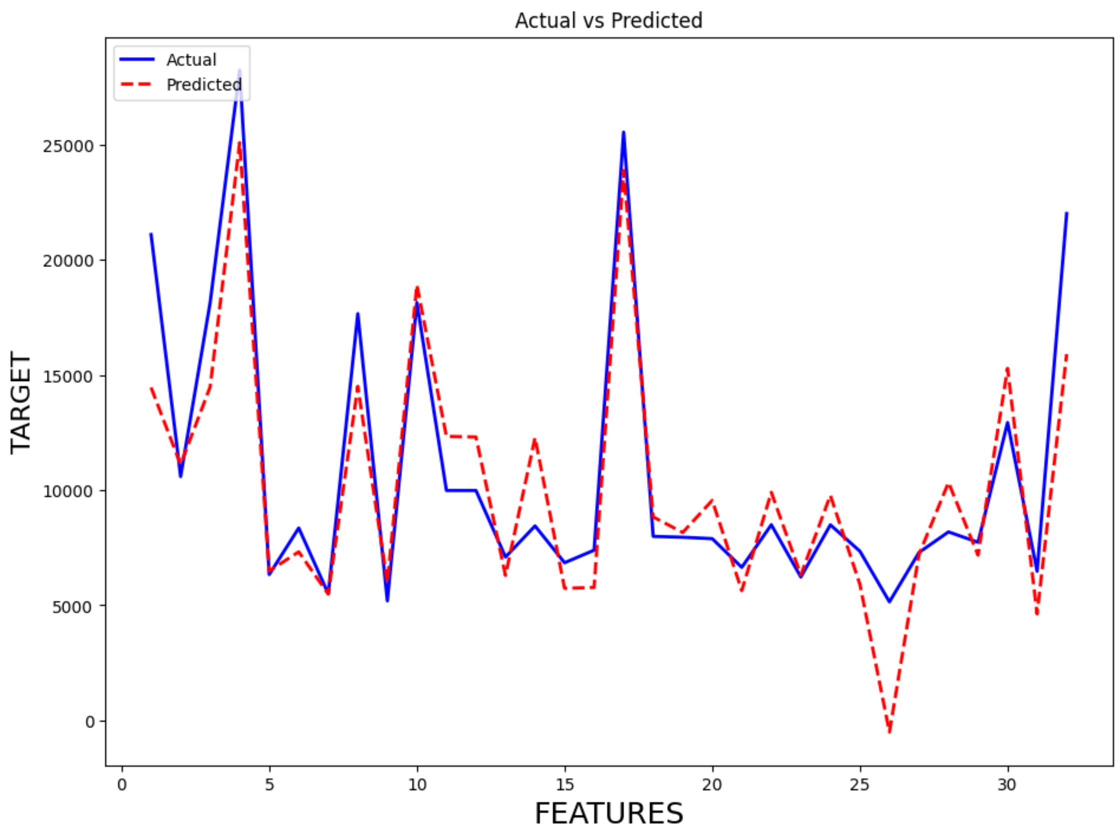
[22]: (32,)

22 **Mean Squared Error is 6448622.1828**

23 **R^2 value is 82.962 % (values are approx 83 % near to the line)**

24 **Based on mean squared value and R^2 value we already know that values are a bit distorted, with the help of graph we plot Actual vs Predicted to understand how the values vary**

[23]:
```
# Assuming you have already defined y_test and y_pred_test
c = [i for i in range(1, len(y_test)+1, 1)]  # generating index
fig = plt.figure(figsize=(11, 8))
plt.plot(c, y_test, color="blue", linewidth=2, linestyle="-", label='Actual')
plt.plot(c, y_pred_test, color="red", linewidth=2, linestyle="--",␣
 ↪label='Predicted')
plt.title('Actual vs Predicted')                              # Plot heading
plt.xlabel('FEATURES', fontsize=18)                   # X-label
plt.ylabel('TARGET', fontsize=16)                    # Y-label
plt.legend(loc='upper left')
plt.show()
```



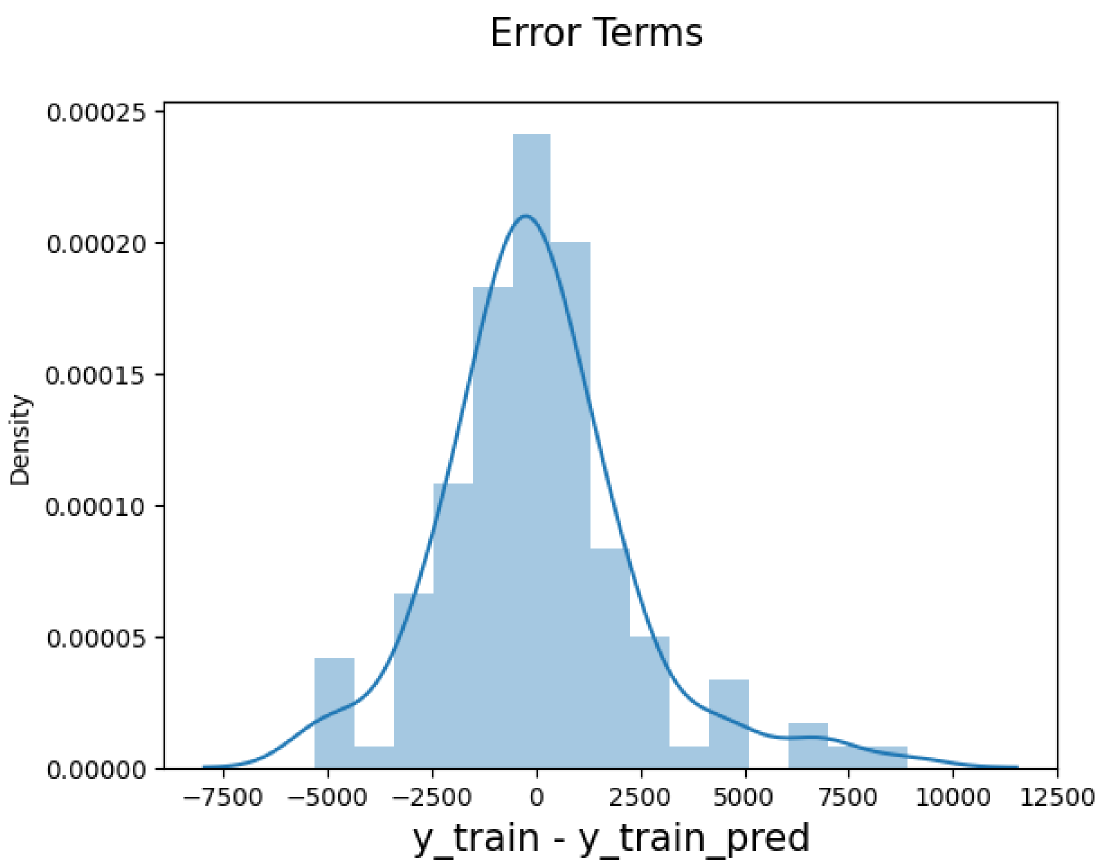
25 We plot whatever values differ as we already know Actual vs Predicted don't match with good accuracy

[24]:
```
# Error terms
c = [i for i in range(1,len(y_test)+1,1)]
fig = plt.figure()
plt.plot(c,y_test-y_pred_test, color="green", linewidth=2, linestyle="--")
plt.title('Error Terms')
plt.xlabel('No of Customers', fontsize=18)              # X-label
plt.ylabel('ytest-ypred', fontsize=16)                  # Y-label
```

[24]:
```
Text(0, 0.5, 'ytest-ypred')
```

26 We need to check if the error terms are also normally distributed (which is infact, one of the major assumptions of linear regression), the residuals are following the normally distributed with a mean 0.

[25]:
```
res = (y_train - y_pred_train)

fig = plt.figure()
sns.distplot(res, bins = 15)
fig.suptitle('Error Terms', fontsize = 15)                  # Plot heading
plt.xlabel('y_train - y_train_pred', fontsize = 15)         # X-label
plt.show()
```



27 Final Interpretation

The dataset contains 160 rows and 16 columns is used for Linear Regression model. The dataset is not used as a whole and only specific features are interlinked to the target values. Since no empty or null values are present in the dataset, and Correlation between one of the feature and target is 89 %. Based on 80:20 validating split, R^2 value is 82.962 % and Mean Squared Error is 6448622.1828.

From the line y = mx + c, we get the value of slope, i.e., m and value of intercept on y-axis, i.e., c. The model has quite a few uncertainities but still it is decent to predict the values.