Multiple Linear Regression

Importing the libraries

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

Importing the dataset

In [17]:
```
dataset = pd.read_csv(r"C:\Users\Admin\Downloads\automobile_emissions.csv")
```

EDA Steps

In [18]:
```
dataset.head()
```

Out[18]:

	Engine Size (L)	Horsepower	Fuel Type	CO2 Emissions (g/km)
0	3.0	102	Electric	0
1	1.3	274	Diesel	214
2	2.0	284	Diesel	341
3	1.8	129	Electric	0
4	3.3	274	Diesel	543

In [19]:
```
dataset.columns
```

Out[19]:
```
Index(['Engine Size (L)', 'Horsepower', 'Fuel Type', 'CO2 Emissions (g/k
m)'], dtype='object')
```

In [20]:
```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 4 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Engine Size (L)       100 non-null    float64
 1   Horsepower            100 non-null    int64  
 2   Fuel Type             100 non-null    object 
 3   CO2 Emissions (g/km)  100 non-null    int64  
dtypes: float64(1), int64(2), object(1)
memory usage: 3.3+ KB
```

In [21]:
```
dataset.describe()
```

Out[21]:

	Engine Size (L)	Horsepower	CO2 Emissions (g/km)
count	100.000000	100.000000	100.000000
mean	2.544000	234.590000	296.100000
std	0.827595	75.717857	238.195171
min	1.200000	100.000000	0.000000
25%	1.800000	167.000000	0.000000
50%	2.550000	238.000000	290.000000
75%	3.200000	295.250000	414.500000
max	4.000000	350.000000	906.000000

Preprocessing Steps

1. Preparing Data as input and output

In [22]:

```
X = dataset.iloc[:,:-1].values
y = dataset.iloc[:,-1].values
```

In [23]:

```
print(X)
```

```
[[3.0 102 'Electric']
 [1.3 274 'Diesel']
 [2.0 284 'Diesel']
 [1.8 129 'Electric']
 [3.3 274 'Diesel']
 [3.1 326 'Petrol']
 [3.7 237 'Petrol']
 [1.4 292 'Petrol']
 [2.4 168 'Petrol']
 [1.3 296 'Diesel']
 [1.8 264 'Petrol']
 [2.6 187 'Electric']
 [1.3 128 'Electric']
 [1.8 175 'Petrol']
 [3.0 211 'Electric']
 [2.7 140 'Petrol']
 [1.8 216 'Petrol']
 [2.8 100 'Petrol']
 [3.5 344 'Electric']
 [1.2 284 'Electric']
 [3.5 324 'Petrol']
 [3.2 284 'Petrol']
 [2.2 167 'Petrol']
 [1.6 348 'Petrol']
 [3.9 228 'Diesel']
 [2.1 295 'Petrol']
 [1.5 145 'Electric']
 [1.5 229 'Petrol']
 [3.6 333 'Diesel']
 [2.9 127 'Electric']
 [3.5 322 'Diesel']
 [3.2 260 'Petrol']
 [2.7 176 'Electric']
 [3.9 315 'Petrol']
 [2.3 263 'Electric']
 [2.7 229 'Electric']
 [3.5 255 'Electric']
 [2.9 150 'Diesel']
 [3.6 139 'Petrol']
 [2.8 195 'Diesel']
 [3.2 295 'Diesel']
 [1.3 141 'Petrol']
 [1.8 238 'Petrol']
 [2.0 344 'Petrol']
 [1.4 299 'Electric']
 [1.9 336 'Diesel']
 [1.5 235 'Diesel']
 [2.0 335 'Diesel']
 [3.0 100 'Diesel']
 [2.2 253 'Diesel']
 [2.2 182 'Electric']
 [1.8 225 'Petrol']
 [1.9 104 'Electric']
 [3.8 128 'Electric']
 [3.0 337 'Electric']
 [2.9 192 'Petrol']
```

```
[1.7 324 'Petrol']
[3.2 312 'Diesel']
[1.7 306 'Electric']
[2.3 178 'Diesel']
[4.0 161 'Petrol']
[3.0 114 'Petrol']
[2.8 161 'Petrol']
[3.1 324 'Petrol']
[3.6 245 'Electric']
[3.4 342 'Diesel']
[1.8 120 'Petrol']
[1.3 121 'Diesel']
[2.1 287 'Petrol']
[1.9 224 'Diesel']
[1.8 308 'Diesel']
[3.8 117 'Petrol']
[3.7 350 'Petrol']
[2.1 294 'Diesel']
[3.0 236 'Electric']
[2.3 296 'Petrol']
[3.8 132 'Petrol']
[2.5 132 'Electric']
[1.9 268 'Electric']
[1.9 221 'Petrol']
[2.8 342 'Petrol']
[1.9 240 'Petrol']
[2.8 142 'Petrol']
[3.7 167 'Diesel']
[2.3 235 'Diesel']
[1.8 323 'Diesel']
[4.0 255 'Petrol']
[2.6 208 'Diesel']
[1.5 346 'Petrol']
[1.3 154 'Petrol']
[1.5 337 'Diesel']
[3.0 238 'Petrol']
[3.4 293 'Diesel']
[2.4 286 'Diesel']
[1.4 276 'Diesel']
[2.3 151 'Diesel']
[4.0 282 'Diesel']
[2.7 179 'Electric']
[3.9 202 'Electric']
[3.6 271 'Electric']]
```

2. Encoding categorical data

In [24]:
```
dataset['Fuel Type'].value_counts()
```

Out[24]:
```
Fuel Type
Petrol      42
Diesel      32
Electric    26
Name: count, dtype: int64
```

In [25]:
```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(), [2])], rem
X = np.array(ct.fit_transform(X))
```

In [26]:
```
print(X)
```

```
[[0.0 1.0 0.0 3.0 102]
 [1.0 0.0 0.0 1.3 274]
 [1.0 0.0 0.0 2.0 284]
 [0.0 1.0 0.0 1.8 129]
 [1.0 0.0 0.0 3.3 274]
 [0.0 0.0 1.0 3.1 326]
 [0.0 0.0 1.0 3.7 237]
 [0.0 0.0 1.0 1.4 292]
 [0.0 0.0 1.0 2.4 168]
 [1.0 0.0 0.0 1.3 296]
 [0.0 0.0 1.0 1.8 264]
 [0.0 1.0 0.0 2.6 187]
 [0.0 1.0 0.0 1.3 128]
 [0.0 0.0 1.0 1.8 175]
 [0.0 1.0 0.0 3.0 211]
 [0.0 0.0 1.0 2.7 140]
 [0.0 0.0 1.0 1.8 216]
 [0.0 0.0 1.0 2.8 100]
 [0.0 1.0 0.0 3.5 344]
 [0.0 1.0 0.0 1.2 284]
 [0.0 0.0 1.0 3.5 324]
 [0.0 0.0 1.0 3.2 284]
 [0.0 0.0 1.0 2.2 167]
 [0.0 0.0 1.0 1.6 348]
 [1.0 0.0 0.0 3.9 228]
 [0.0 0.0 1.0 2.1 295]
 [0.0 1.0 0.0 1.5 145]
 [0.0 0.0 1.0 1.5 229]
 [1.0 0.0 0.0 3.6 333]
 [0.0 1.0 0.0 2.9 127]
 [1.0 0.0 0.0 3.5 322]
 [0.0 0.0 1.0 3.2 260]
 [0.0 1.0 0.0 2.7 176]
 [0.0 0.0 1.0 3.9 315]
 [0.0 1.0 0.0 2.3 263]
 [0.0 1.0 0.0 2.7 229]
 [0.0 1.0 0.0 3.5 255]
 [1.0 0.0 0.0 2.9 150]
 [0.0 0.0 1.0 3.6 139]
 [1.0 0.0 0.0 2.8 195]
 [1.0 0.0 0.0 3.2 295]
 [0.0 0.0 1.0 1.3 141]
 [0.0 0.0 1.0 1.8 238]
 [0.0 0.0 1.0 2.0 344]
 [0.0 1.0 0.0 1.4 299]
 [1.0 0.0 0.0 1.9 336]
 [1.0 0.0 0.0 1.5 235]
 [1.0 0.0 0.0 2.0 335]
 [1.0 0.0 0.0 3.0 100]
 [1.0 0.0 0.0 2.2 253]
 [0.0 1.0 0.0 2.2 182]
 [0.0 0.0 1.0 1.8 225]
 [0.0 1.0 0.0 1.9 104]
 [0.0 1.0 0.0 3.8 128]
 [0.0 1.0 0.0 3.0 337]
 [0.0 0.0 1.0 2.9 192]
```

```
[0.0 0.0 1.0 1.7 324]
[1.0 0.0 0.0 3.2 312]
[0.0 1.0 0.0 1.7 306]
[1.0 0.0 0.0 2.3 178]
[0.0 0.0 1.0 4.0 161]
[0.0 0.0 1.0 3.0 114]
[0.0 0.0 1.0 2.8 161]
[0.0 0.0 1.0 3.1 324]
[0.0 1.0 0.0 3.6 245]
[1.0 0.0 0.0 3.4 342]
[0.0 0.0 1.0 1.8 120]
[1.0 0.0 0.0 1.3 121]
[0.0 0.0 1.0 2.1 287]
[1.0 0.0 0.0 1.9 224]
[1.0 0.0 0.0 1.8 308]
[0.0 0.0 1.0 3.8 117]
[0.0 0.0 1.0 3.7 350]
[1.0 0.0 0.0 2.1 294]
[0.0 1.0 0.0 3.0 236]
[0.0 0.0 1.0 2.3 296]
[0.0 0.0 1.0 3.8 132]
[0.0 1.0 0.0 2.5 132]
[0.0 1.0 0.0 1.9 268]
[0.0 0.0 1.0 1.9 221]
[0.0 0.0 1.0 2.8 342]
[0.0 0.0 1.0 1.9 240]
[0.0 0.0 1.0 2.8 142]
[1.0 0.0 0.0 3.7 167]
[1.0 0.0 0.0 2.3 235]
[1.0 0.0 0.0 1.8 323]
[0.0 0.0 1.0 4.0 255]
[1.0 0.0 0.0 2.6 208]
[0.0 0.0 1.0 1.5 346]
[0.0 0.0 1.0 1.3 154]
[1.0 0.0 0.0 1.5 337]
[0.0 0.0 1.0 3.0 238]
[1.0 0.0 0.0 3.4 293]
[1.0 0.0 0.0 2.4 286]
[1.0 0.0 0.0 1.4 276]
[1.0 0.0 0.0 2.3 151]
[1.0 0.0 0.0 4.0 282]
[0.0 1.0 0.0 2.7 179]
[0.0 1.0 0.0 3.9 202]
[0.0 1.0 0.0 3.6 271]]
```

3. Splitting the dataset into the Training set and Test set

In [27]:
```
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)
```

In [28]:
```
X_train.shape
```

Out[28]:
```
(80, 5)
```

Training the Multiple Linear Regression model on the Training set

In [29]:
```
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train,y_train)
```

Out[29]:
```
▾ LinearRegression
LinearRegression()
```

In [30]:
```
# check th attribute of our model
print("Coefficient of our model", regressor.coef_)
print("intercept  of our model", regressor.intercept_)
```

```
Coefficient of our model [  91.14906599 -237.07050803  145.92144204  110.713
87938    1.26180237]
intercept  of our model -313.09430164575804
```

In [31]:
```
# score of our model
print("Training Accuracy of our model", regressor.score(X_train, y_train))
print("Testing Accuracy of our model", regressor.score(X_test, y_test))
```

```
Training Accuracy of our model 0.8578769278374371
Testing Accuracy of our model 0.8588591953057938
```

Predicting the Test set results

In [32]:
```
y_pred = regressor.predict(X_test)
print(y_test)
print(y_pred)
```

```
[  0 714 341 390 477 412 272 370   0 208   0 598   0 220 286 676 257 534
 860 282]
[-201.13264672  597.44226268  357.83439667  396.16344595  460.96256498
  404.64355316  304.66143556  381.52380832  207.20422771  223.22884504
   32.05863553  524.19004914   -1.64540325  252.92753832  356.27286406
  571.85370585  287.1186711   497.52983466  662.07901705  310.52324934]
```

Getting the final linear regression equation with the values of the coefficients

variance score: 1 means perfect prediction

In [36]:
```
print('Variance score: {}'.format(regressor.score(X_test, y_test)))
```

```
Variance score: 0.8588591953057938
```

In above example, we determine accuracy score using Explained Variance Score.

We define: **explained_variance_score = 1 - Var{y - y'}/Var{y}**

where

- y' is the estimated target output,
- y the corresponding (correct) target output
- Var is Variance, the square of the standard deviation.

***The best possible score is 1.0, lower values are worse.**

plot for residual error

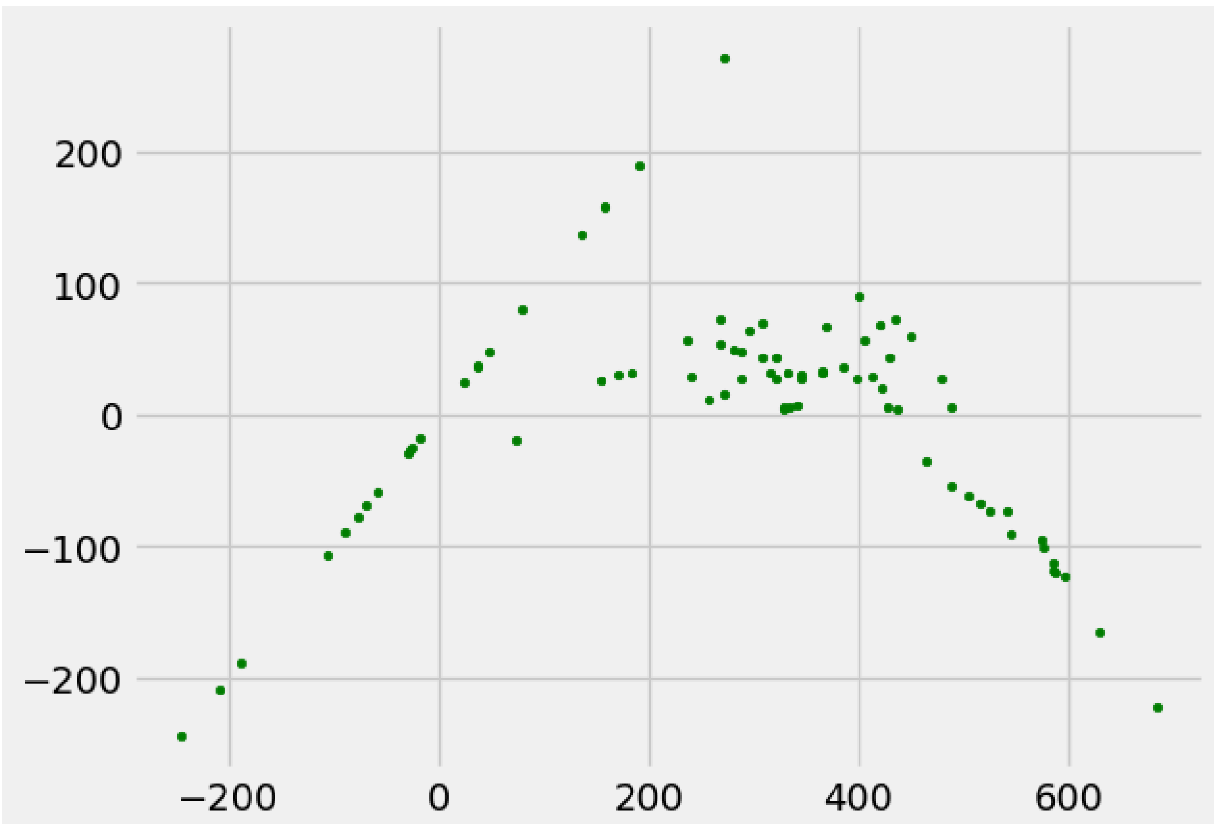
setting plot style

In [37]:
```
plt.style.use('fivethirtyeight')
```

plotting residual errors in training data

In [38]:
```
plt.scatter(regressor.predict(X_train),
            regressor.predict(X_train) - y_train,
            color = "green", s = 10, label = 'Train data')
```

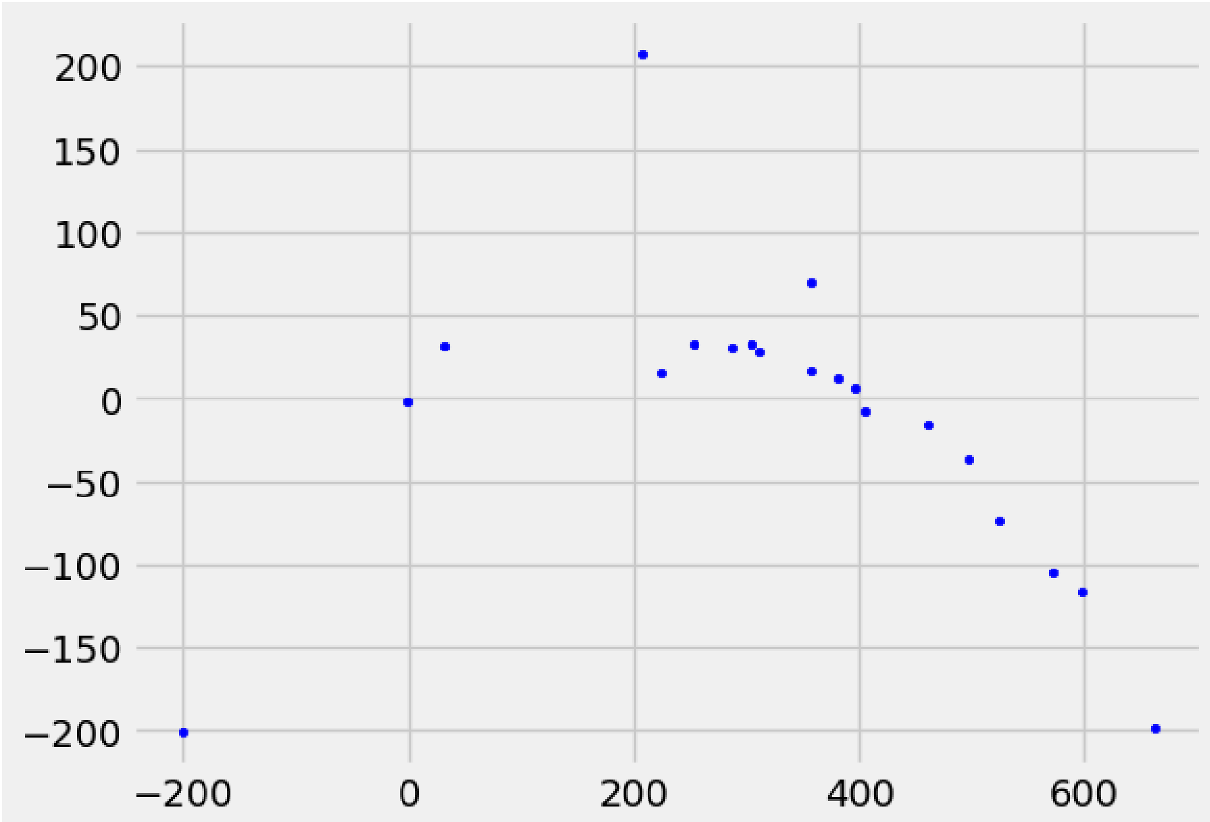
Out[38]: <matplotlib.collections.PathCollection at 0x187fcd17680>



plotting residual errors in test data

In [39]:
```
plt.scatter(regressor.predict(X_test),
            regressor.predict(X_test) - y_test,
            color = "blue", s = 10, label = 'Test data')
```

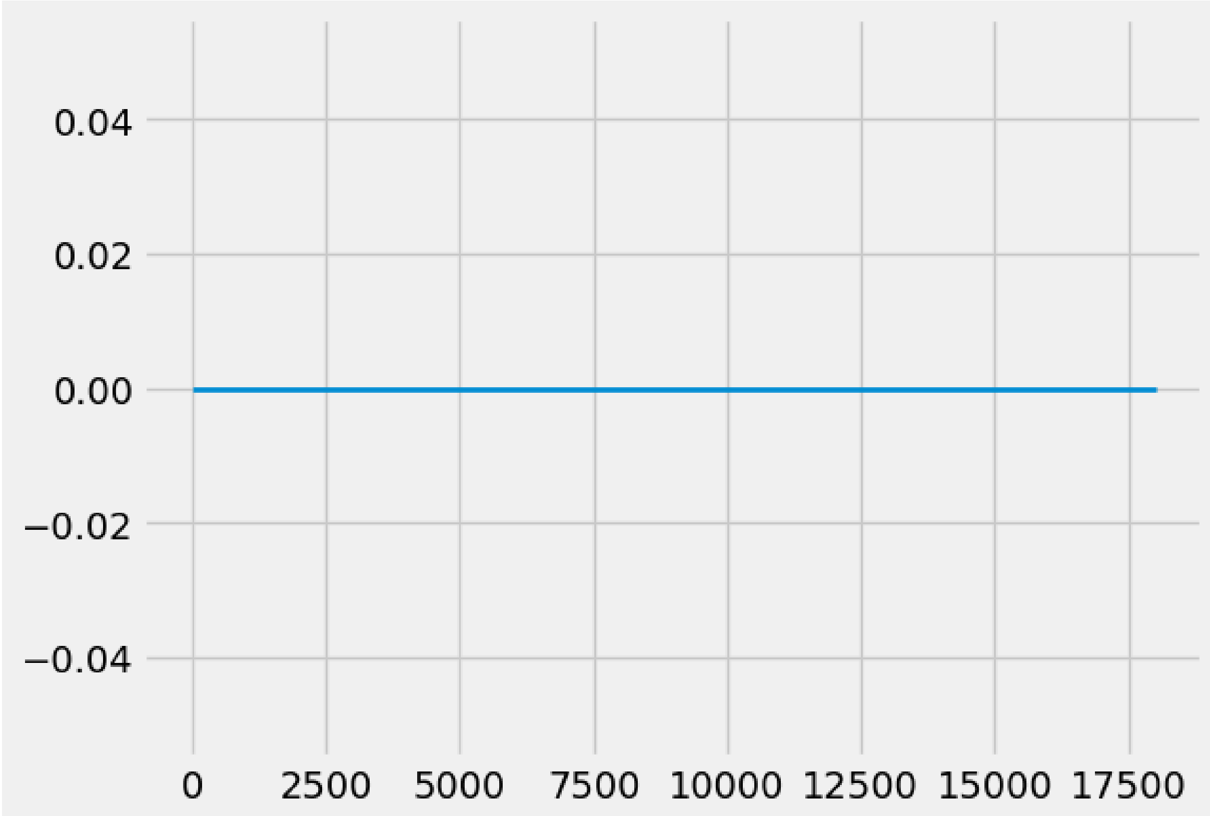
Out[39]: <matplotlib.collections.PathCollection at 0x187fcda6f30>



plotting line for zero residual error

In [40]:
```
plt.hlines(y = 0, xmin = 0, xmax = 18000, linewidth = 2)
```

Out[40]: <matplotlib.collections.LineCollection at 0x187fd1b4380>

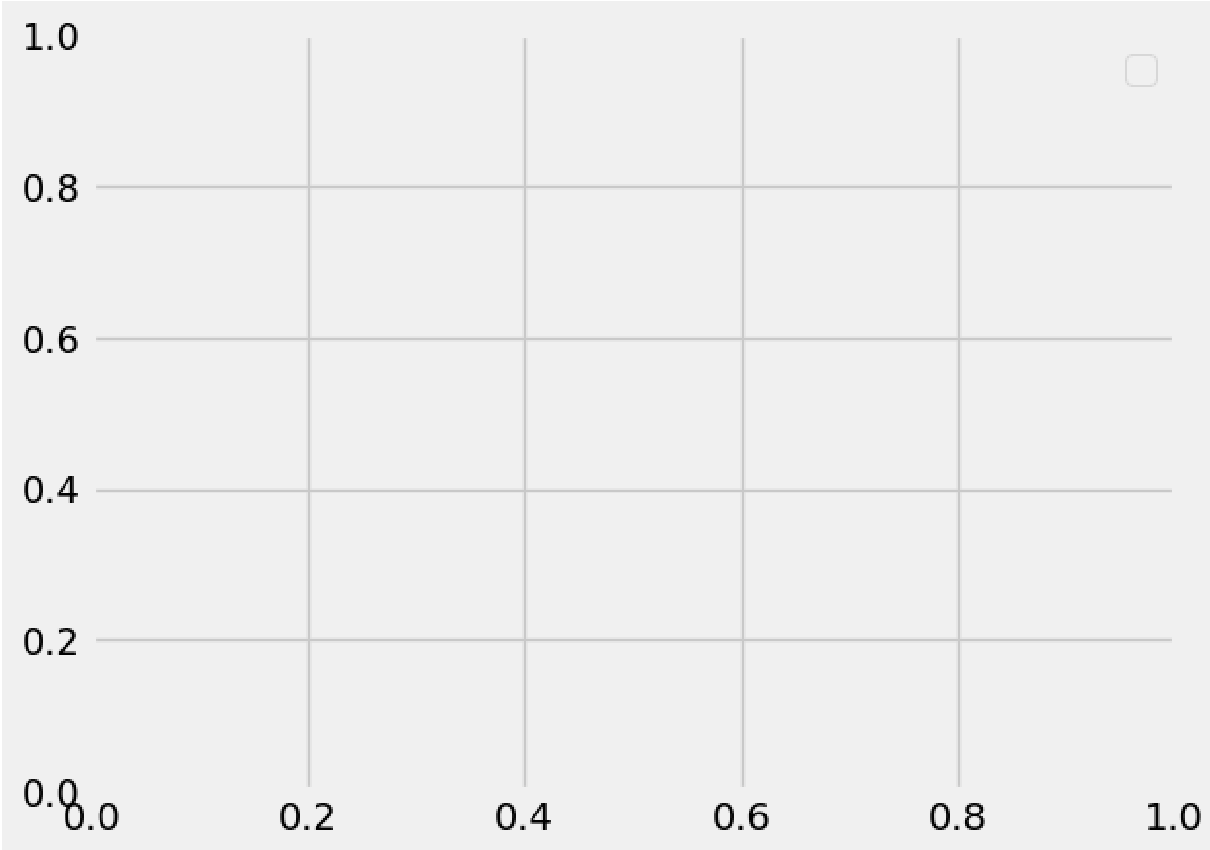


plotting legend

In [46]:
```
plt.legend(loc = 'upper right')
```

```
C:\Users\Admin\AppData\Local\Temp\ipykernel_12040\3738487734.py:1: UserWarni
ng: No artists with labels found to put in legend.  Note that artists whose
label start with an underscore are ignored when legend() is called with no a
rgument.
  plt.legend(loc = 'upper right')
```

Out[46]:
```
<matplotlib.legend.Legend at 0x187ff8959a0>
```



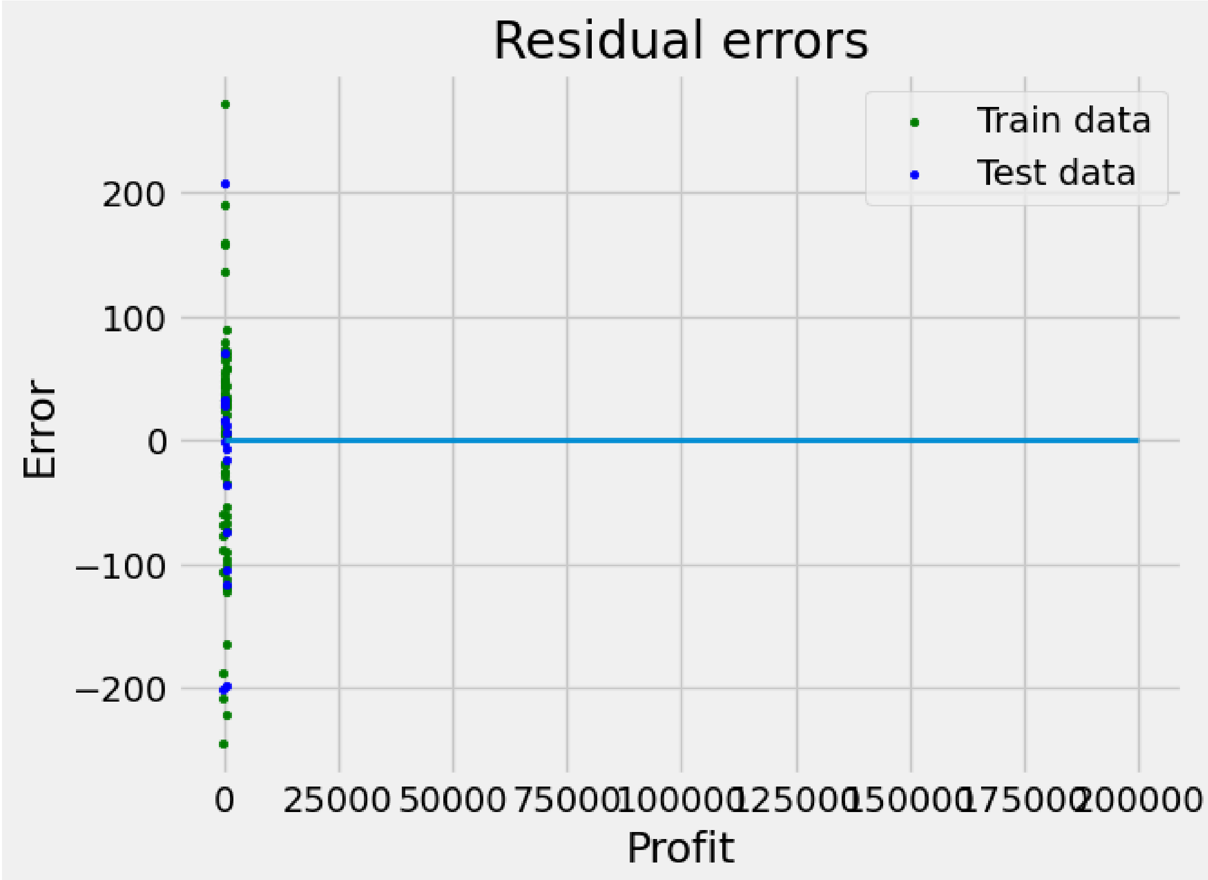
plot title

In [42]:
```
plt.title("Residual errors")
```

Out[42]:
```
Text(0.5, 1.0, 'Residual errors')
```

function to show plot

In [43]:
```
plt.style.use('fivethirtyeight')
plt.scatter(regressor.predict(X_train), regressor.predict(X_train) - y_trair
plt.scatter(regressor.predict(X_test), regressor.predict(X_test) - y_test,cc
plt.hlines(y = 0, xmin = 0, xmax = 200000, linewidth = 2)
plt.legend(loc = 'upper right')
plt.title("Residual errors")
plt.xlabel("Profit")
plt.ylabel("Error")
plt.show()
```



EVALUATING A MODEL USING R2 METRIC

Find the R^2

In [45]:
```
from sklearn.metrics import r2_score
print(r2_score(y_test,y_pred))
```

```
0.8588591953057938
```