CS4132 Data Analytics

Lab 8: Data Modelling

Submission Instructions

- Complete the following questions and upload your `.ipynb` file to Coursemology.
- Name the file in the following format: `Lab<num><YourName>.ipynb`
- Before submitting, please ensure you click on "Kernel" > "Restart and Run All" on your jupyter notebook.
- Finally, print a copy of your final solution to OneNote > Your Individual Student Notebook > Labs. Name the page `Lab <num>`.

Q1

We will use the used car dataset from the notes for this question.

In [132]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
import seaborn as sns
df = pd.read_csv("Lab8Q1.csv")
df.head()
```

Out[132]:

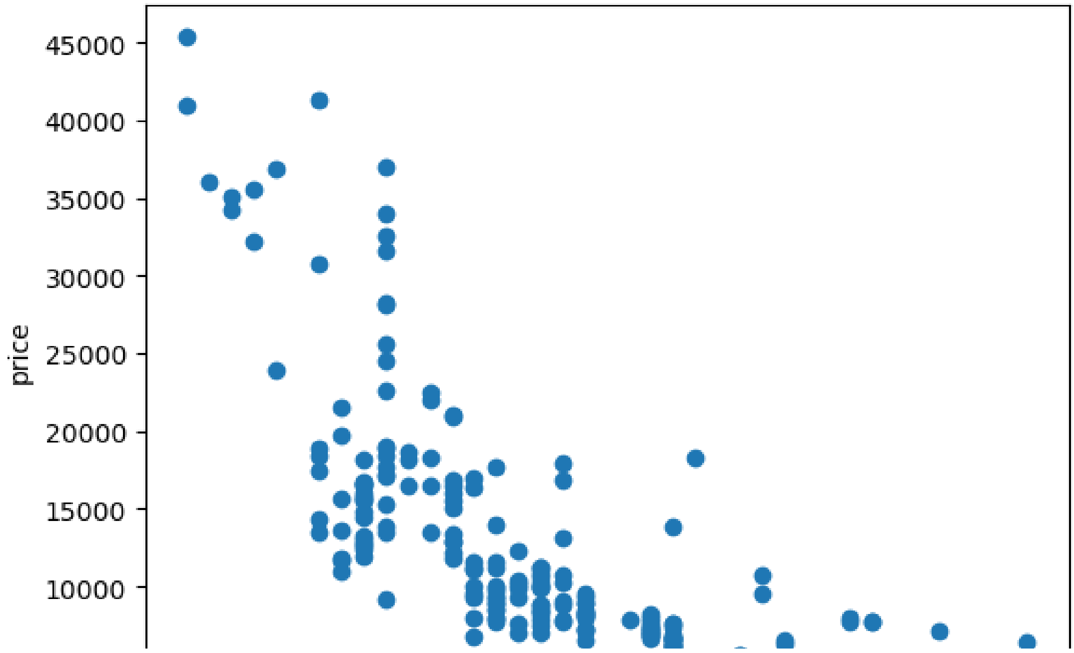
	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wh b
0	3	NaN	alfa-romero	gas	std	two	convertible	rwd	front	8
1	3	NaN	alfa-romero	gas	std	two	convertible	rwd	front	8
2	1	NaN	alfa-romero	gas	std	two	hatchback	rwd	front	9
3	2	164.0	audi	gas	std	four	sedan	fwd	front	9
4	2	164.0	audi	gas	std	four	sedan	4wd	front	9

5 rows × 26 columns

a) Draw a scatterplot to investigate the relationship between `highway-mpg` and the `price` of cars.

In [111]:

```
#your solution
plt.scatter(df['highway-mpg'], df.price)
plt.xlabel('highway-mpg')
plt.ylabel('price')
plt.show()
```



b) Develop a SLRM for the data in (a) using `scikitlearn`. Ensure you split the dataset into training and test data.

In [112]:

```
#your solution
lm = LinearRegression()
df2 = df[(~df.price.isna()) & (~df['highway-mpg'].isna())]
X_train, X_test, y_train, y_test = train_test_split(df2[['highway-mpg']], df2['price'],
lm.fit(X_train, y_train)
```

Out[112]:

```
LinearRegression()
```

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On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

Hence, print the equation of your model.

In [113]:

```
#your solution
print("Equation is " + str(lm.coef_[0].round(5)) + "x + " + str(lm.intercept_.round(3)))
```

```
Equation is -802.54205x + 37696.717
```

c) Now, make predictions using your test data. Display the predicted results.

In [114]:

```
#your solution
yhat = lm.predict(X_test)
yhat
```

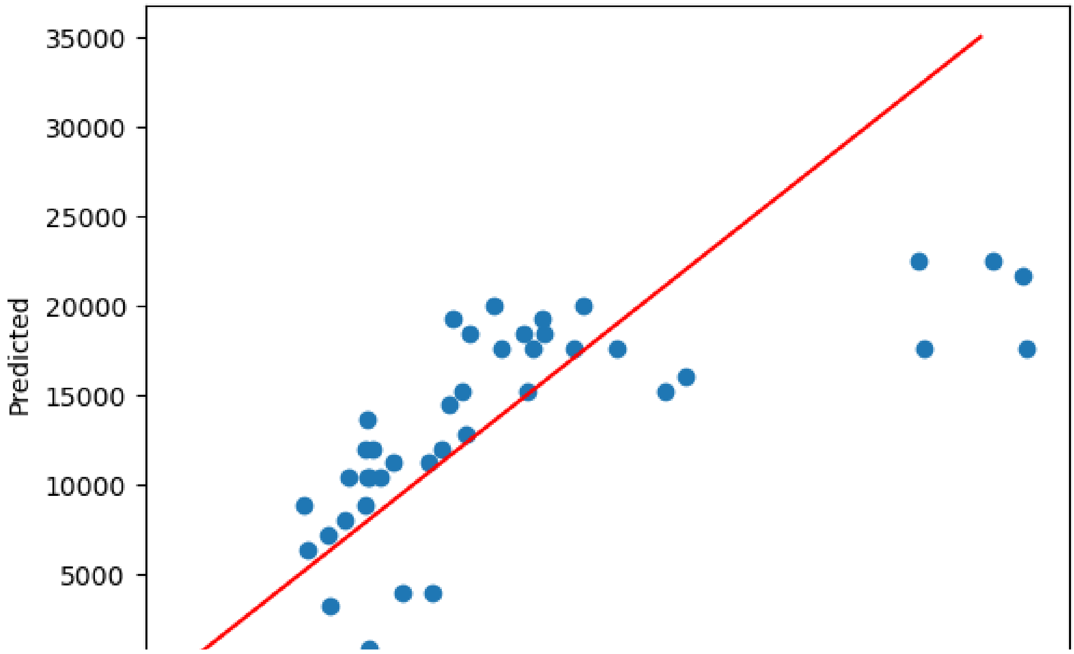
Out[114]:

```
array([ 3187.40889536, 11212.82939403, 17633.16579297, 20040.79194257,
       18435.70784284, 10410.28734417, 17633.16579297,  6397.57709483,
       15225.53964337,  8002.66119456, 12015.3714439 , 17633.16579297,
         779.78274576,  8805.20324443, 18435.70784284, 17633.16579297,
       10410.28734417, 15225.53964337, 11212.82939403,  7200.1191447 ,
        3989.95094523, 19238.2498927 , 22448.41809217, 10410.28734417,
        3989.95094523, 17633.16579297, 10410.28734417, 14422.9975935 ,
       16028.08169324, 22448.41809217, 21645.87604231, 19238.2498927 ,
       12015.3714439 , 17633.16579297, 13620.45554363, 12817.91349377,
       15225.53964337, 20040.79194257, 12015.3714439 , 18435.70784284,
        8805.20324443])
```

d) Evaluate your model by plotting a scatter plot of Actual vs Predicted.

In [115]:

```
#your solution
plt.scatter(y_test, yhat)
plt.plot([0, 35000], [0, 35000], color="red")
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.show()
```



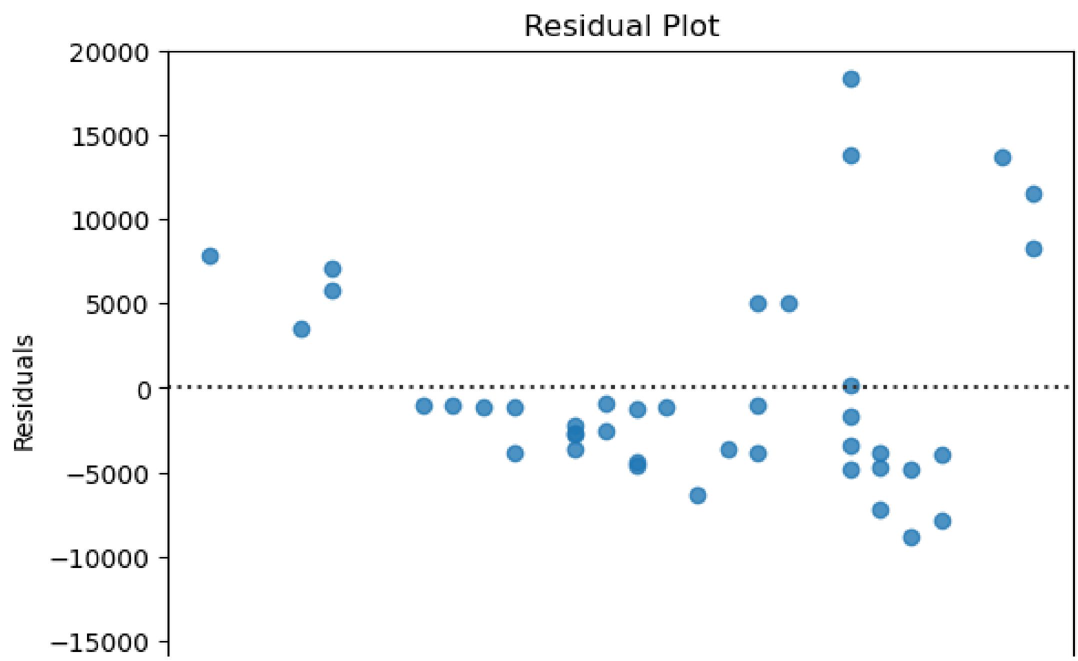
State your observations.

The points get further away from the line as the value increases. This means that the higher the value, the less accurate the predictions.

e) Evaluate your model by plotting a residual plot.

In [139]:

```
#your solution
residual = (y_test - yhat).to_frame()
sns.residplot(x = yhat, y = residual)
plt.xlabel('')
plt.ylabel('Residuals')
plt.title('Residual Plot')
plt.ylim((-20000, 20000))
plt.show()
```



State your observations/conclusion.

A linear regression model is not suitable since the points are not randomly and evenly spread, instead crowding around 0 and the positive extremities.

Q2

We will use the data Lab8Q2.csv for this question. This dataset contains model-specific fuel consumption ratings and estimated carbon dioxide emissions for new light-duty vehicles for retail sale in Canada.

- **MODELYEAR** e.g. 2014
- **MAKE** e.g. Acura
- **MODEL** e.g. ILX
- **VEHICLE CLASS** e.g. SUV
- **ENGINE SIZE** e.g. 4.7
- **CYLINDERS** e.g 6
- **TRANSMISSION** e.g. A6
- **FUEL CONSUMPTION in CITY(L/100 km)** e.g. 9.9
- **FUEL CONSUMPTION in HWY (L/100 km)** e.g. 8.9
- **FUEL CONSUMPTION COMB (L/100 km)** e.g. 9.2
- **CO2 EMISSIONS (g/km)** e.g. 182 --> low --> 0

In [155]:

```
df = pd.read_csv("Lab8Q2.csv")
df.head()
```

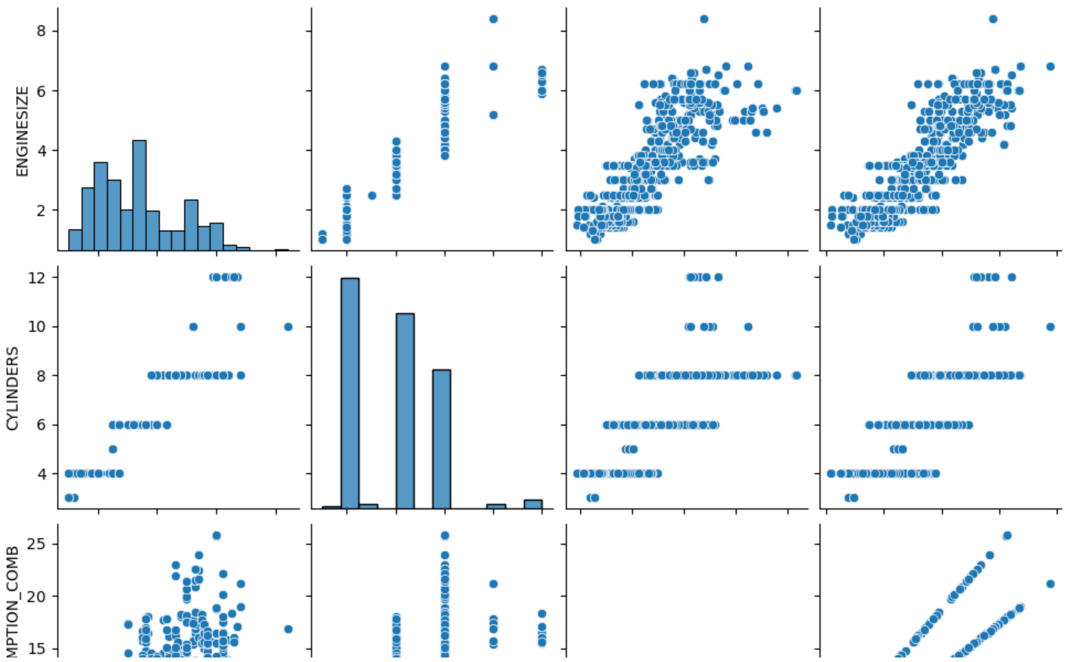
Out[155]:

	MODELYEAR	MAKE	MODEL	VEHICLECLASS	ENGINESIZE	CYLINDERS	TRANSMISSIO
0	2014	ACURA	ILX	COMPACT	2.0	4	AS
1	2014	ACURA	ILX	COMPACT	2.4	4	M
2	2014	ACURA	ILX HYBRID	COMPACT	1.5	4	AV
3	2014	ACURA	MDX 4WD	SUV - SMALL	3.5	6	AS
4	2014	ACURA	RDX AWD	SUV - SMALL	3.5	6	AS

a) Perform relevant EDA for the following features: `'ENGINESIZE','CYLINDERS','FUELCONSUMPTION_COMB','CO2EMISSIONS'`

In [156]:

```
#your solution
df.dropna(subset=["ENGINESIZE"], axis=0, inplace= True)
dfsub = df[['ENGINESIZE','CYLINDERS','FUELCONSUMPTION_COMB','CO2EMISSIONS']]
sns.pairplot(dfsub)
plt.show()
```



b) Based on the observations from (a), select ONE suitable feature and develop a SLRM to predict the CO2 emissions. Ensure you split the dataset into training and test data.

In [157]:

```
#your solution
lm = LinearRegression()
df2 = df[(~df.ENGINESIZE.isna()) & (~df.CO2EMISSIONS.isna())]
X_train, X_test, y_train, y_test = train_test_split(df2[['ENGINESIZE']], df2['CO2EMISSIO
lm.fit(X_train, y_train)
```

Out[157]:

```
LinearRegression()
```

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On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

Hence, print the equation of your model.

In [158]:

```
#your solution
print("Equation is " + str(lm.coef_[0].round(5)) + "x + " + str(lm.intercept_.round(3)))
```

```
Equation is 39.24838x + 126.189
```

c) Now, make predictions using your test data. Display the predicted results.

In [159]:

```
#your solution
yhat = lm.predict(X_test)
yhat
```

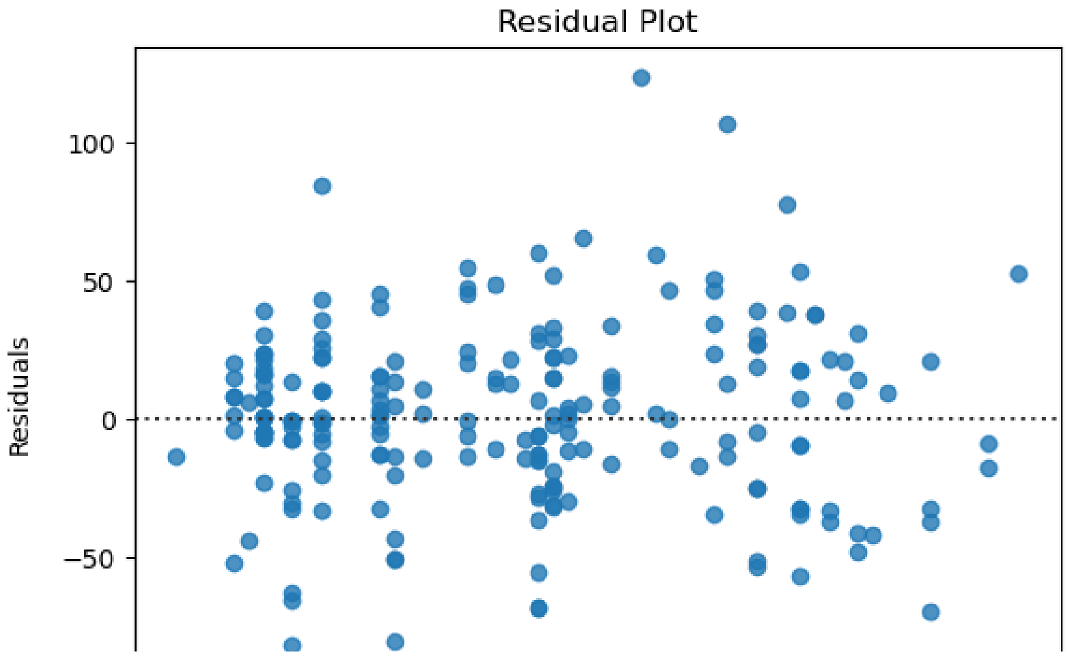
Out[159]:

```
array([342.05531526, 220.3853239 , 220.3853239 , 232.15983919,
       224.31016233, 298.88209252, 220.3853239 , 267.48338507,
       220.3853239 , 322.43112311, 267.48338507, 393.07821487,
       243.93435448, 298.88209252, 181.13693958, 283.1827388 ,
       314.58144625, 188.98661645, 263.55854664, 385.22853801,
       196.83629331, 263.55854664, 263.55854664, 204.68597017,
       224.31016233, 243.93435448, 275.33306193, 334.2056384 ,
       342.05531526, 204.68597017, 345.9801537 , 224.31016233,
       263.55854664, 243.93435448, 196.83629331, 188.98661645,
       349.90499213, 220.3853239 , 232.15983919, 267.48338507,
       196.83629331, 196.83629331, 220.3853239 , 204.68597017,
       342.05531526, 204.68597017, 220.3853239 , 188.98661645,
       334.2056384 , 357.75466899, 310.65660781, 271.4082235 ,
       267.48338507, 196.83629331, 220.3853239 , 188.98661645,
       306.73176938, 196.83629331, 251.78403135, 204.68597017,
       188.98661645, 224.31016233, 204.68597017, 334.2056384 ,
       267.48338507, 314.58144625, 322.43112311, 267.48338507,
       188.98661645, 181.13693958, 353.82983056, 263.55854664,
```

d) Evaluate your model by plotting a residual plot.

In [160]:

```
#your solution
residual = (y_test - yhat).to_frame()
sns.residplot(x = yhat, y = residual)
plt.xlabel('')
plt.ylabel('Residuals')
plt.title('Residual Plot')
plt.show()
```



State your observations/conclusion.

The points are randomly and evenly scattered about the line y = 0. This means the linear regression model is appropriate to use in this case and the relationship between enginesize and co2emissions is linear.

e) Calculate the MSE.

In [161]:

```
#your solution
from sklearn.metrics import mean_squared_error
mean_squared_error(y_test, yhat)
```

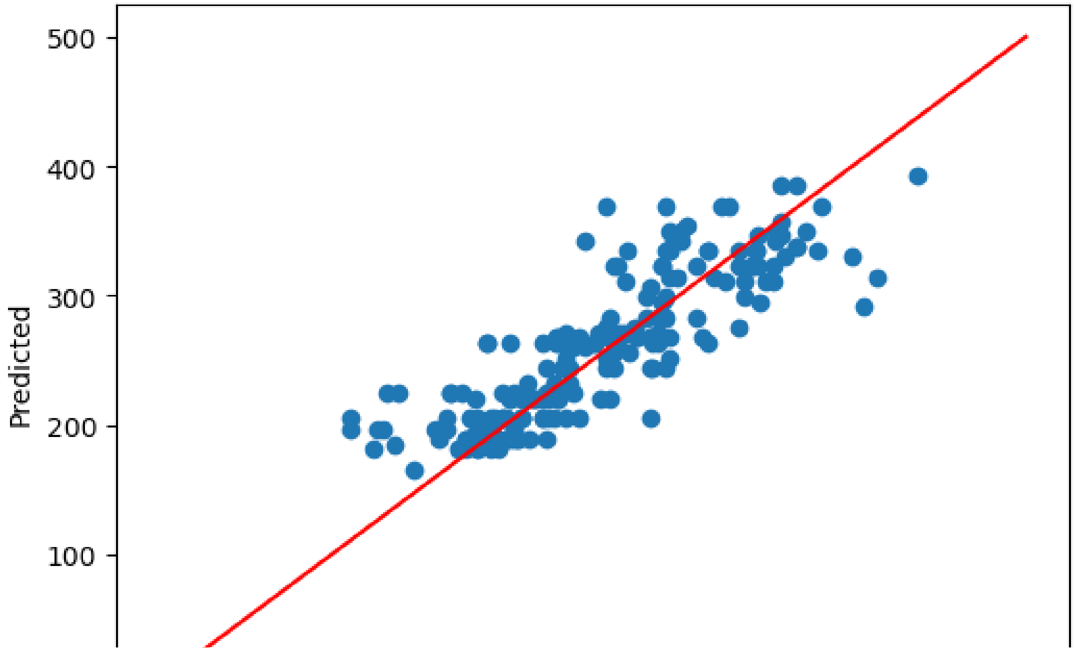
Out[161]:

```
1181.528809303555
```

f) Evaluate your model by plotting a scatter plot of Actual vs Predicted.

In [162]:

```
#your solution
plt.scatter(y_test, yhat)
plt.plot([0, 500], [0, 500], color="red")
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.show()
```



What insights can you draw from the scatterplot?

All points are relatively close and clustered around the line y = x. This means that the linear regression model is a good prediction of the actual values.

Q3

In reality, there are multiple variables that predict the Co2emission. When more than one independent variable is present, the process is called multiple linear regression. For example, predicting co2emission using FUELCONSUMPTION_COMB, EngineSize and Cylinders of cars. The good thing here is that Multiple linear regression is the extension of simple linear regression model.

a) Develop a MLRM using the 3 attributes stated above.

In [173]:

```
#your solution
df3 = df.dropna(subset=['ENGINESIZE','CYLINDERS','FUELCONSUMPTION_COMB','CO2EMISSIONS'],
features = df3[['ENGINESIZE','CYLINDERS','FUELCONSUMPTION_COMB']]
mlm = LinearRegression()
X_train2, X_test2, y_train2, y_test2 = train_test_split(features, df['CO2EMISSIONS'], te
mlm.fit(X_train2, y_train2)
```

Out[173]:

```
LinearRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

Print the equation for the MLRM.

In [178]:

```
#your solution
'Equation is ' + str(mlm.coef_[0].round(3)) + ' * ENGINESIZE + ' + str(mlm.coef_[1].roun
```

Out[178]:

```
'Equation is 11.99 * ENGINESIZE + 7.545 * CYLINDERS + 8.987 * FUELCONSUMPT
ION_COMB + 69.05221'
```

b) Now, make predictions using your test data. Display the predicted results.

In [179]:

```
#your solution
yhat2 = mlm.predict(X_test2)
yhat2
```

Out[179]:

```
array([334.65227307, 209.78816154, 217.87642537, 229.37322867,
       194.81062694, 296.29986196, 210.68685752, 265.32765366,
       207.09207359, 319.67034797, 279.70678935, 381.69354216,
       224.88194401, 291.80638206, 185.21648722, 278.922146  ,
       348.72672119, 205.58839296, 254.24300481, 378.91867664,
       195.40463534, 229.97821332, 251.54691687, 217.57393304,
       180.43149124, 260.82978325, 266.82694379, 358.3164704 ,
       291.51486598, 166.34826212, 336.74996211, 222.67020235,
       284.79866816, 242.85586363, 195.40463534, 194.80404119,
       312.7854677 , 214.28164144, 224.16949248, 250.04982198,
       192.7085474 , 192.7085474 , 207.09207359, 187.91696567,
       311.28617756, 200.4987094 , 229.55947312, 188.51316932,
       386.17604581, 370.52572523, 317.87076076, 320.44840557,
       270.71982954, 171.13984386, 217.87642537, 188.51316932,
       295.10306416, 182.82289161, 253.34211358, 204.99218931,
       199.29752109, 209.18976263, 211.28306117, 358.3164704 ,
       259.93547777, 303.79192214, 327.7586118 , 286.8963572 ,
       199.29752109, 164.54647966, 317.57924468, 229.97821332,
```

c) Calculate the MSE.

In [180]:

```
#your solution
mean_squared_error(y_test2, yhat2)
```

Out[180]:

```
589.2351940837909
```

d) Calculate R-squared

In [182]:

```
#your solution
mlm.score(X_train2, y_train2)
```

Out[182]:

```
0.8639958377437472
```

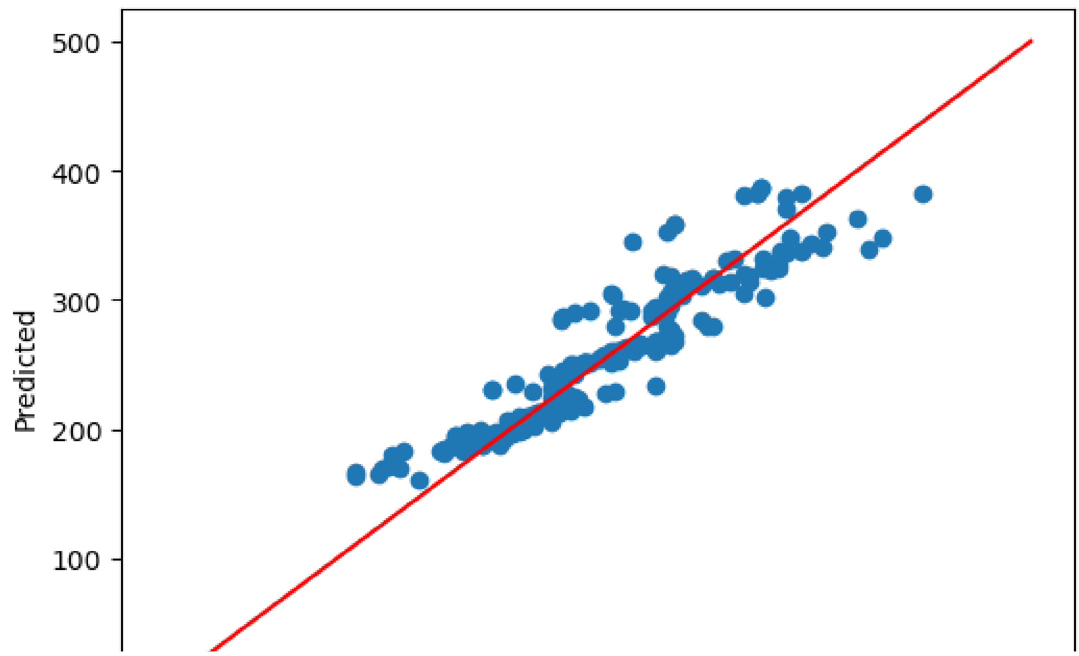
What can you conclude based on the R-squared value?

86.4% of variance of co2emissions can be attributed to the 3 factors.

e) Evaluate the model by plotting a scatterplot of Actual vs Predicted.

In [185]:

```
#your solution
plt.scatter(y_test2, yhat2)
plt.plot([0, 500], [0, 500], color="red")
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.show()
```



What insights can you draw from the scatterplot?

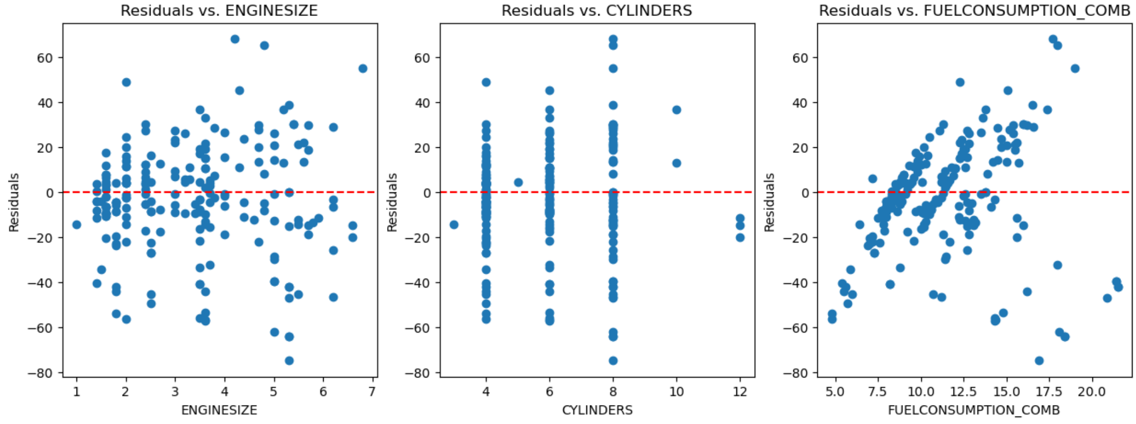
All points are relatively close and clustered around the line y = x. This means that the linear regression model is a good prediction of the actual values.

f) Draw a residual plot for each independent variable.

In [187]:

```
#your solution
fig, axs = plt.subplots(1, 3, figsize=(15, 5))
residuals = y_test2 - yhat2
for i, ax in enumerate(axs):
    ax.scatter(X_test2.iloc[:, i], residuals)
    ax.axhline(y=0, color='r', linestyle='--')
    ax.set_xlabel(X_test2.columns[i])
    ax.set_ylabel('Residuals')
    ax.set_title(f'Residuals vs. {X_test2.columns[i]}')

plt.show()
```



What insights and conclusion can you draw from the residual plots?

ENGINESIZE: The points are randomly and evenly scattered about y = 0. This means there is a linear relationship between engine size and co2 emissions.

CYLINDERS: The points are randomly and evenly scattered about y = 0. This means there is a linear relationship between cylinders and co2 emissions.

FUELCONSUMPTION_COMB: The points are in a fan shape. This means there is no linear relationship between fuel consumption and co2 emissions.