Linear Regression

In [54]:
```
import pandas as pd
```

In [55]:
```
path_to_file = './student_scores.csv'
df = pd.read_csv(path_to_file)
```

In [56]:
```
df.head()
```

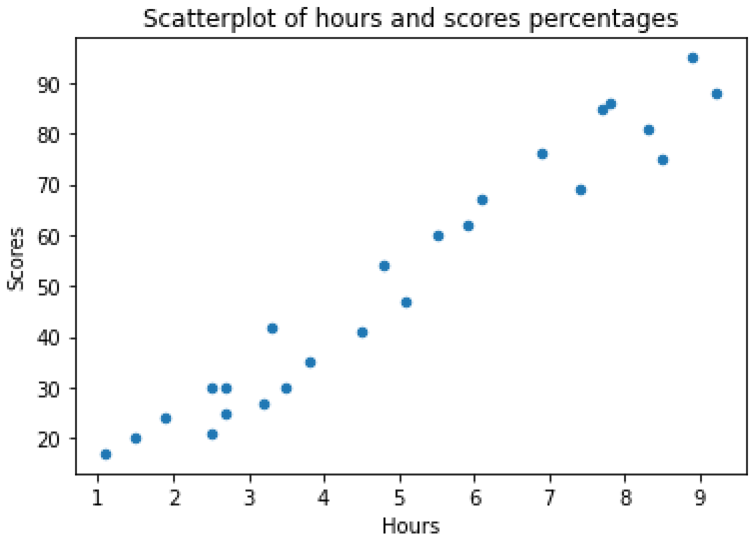
Out[56]:

	Hours	Scores
0	2.5	21
1	5.1	47
2	3.2	27
3	8.5	75
4	3.5	30

In [57]:
```
df.shape
```

Out[57]:
```
(25, 2)
```

In [58]:
```
df.plot.scatter(x='Hours', y='Scores', title='Scatterplot of hours and scores perce
```



In [59]:
```
print(df.corr())
```

```
           Hours    Scores
Hours   1.000000  0.976191
Scores  0.976191  1.000000
```

In [60]:
```
print(df.describe())
```

```
          Hours     Scores
count  25.000000  25.000000
mean    5.012000  51.480000
std     2.525094  25.286887
min     1.100000  17.000000
25%     2.700000  30.000000
50%     4.800000  47.000000
75%     7.400000  75.000000
max     9.200000  95.000000
```

In [61]:
```
Y = df['Scores'].values.reshape(-1, 1)
X = df['Hours'].values.reshape(-1, 1)
```

In [62]:
```
X
```

Out[62]:
```
array([[2.5],
       [5.1],
       [3.2],
       [8.5],
       [3.5],
       [1.5],
       [9.2],
       [5.5],
       [8.3],
       [2.7],
       [7.7],
       [5.9],
       [4.5],
       [3.3],
       [1.1],
       [8.9],
       [2.5],
       [1.9],
       [6.1],
       [7.4],
       [2.7],
       [4.8],
       [3.8],
       [6.9],
       [7.8]])
```

In [63]:
```
Y
```

```
Out[63]: array([[21],
                [47],
                [27],
                [75],
                [30],
                [20],
                [88],
                [60],
                [81],
                [25],
                [85],
                [62],
                [41],
                [42],
                [17],
                [95],
                [30],
                [24],
                [67],
                [69],
                [30],
                [54],
                [35],
                [76],
                [86]], dtype=int64)
```

In [64]:
```
from sklearn.model_selection import train_test_split
```

In [65]:
```
SEED = 85
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.2, random_s
```

In [66]:
```
print(X_train)
print(Y_train)
```

```
[[2.5]
 [4.8]
 [6.9]
 [2.7]
 [9.2]
 [5.5]
 [5.9]
 [8.5]
 [1.1]
 [2.7]
 [8.3]
 [5.1]
 [8.9]
 [1.5]
 [3.8]
 [7.4]
 [3.5]
 [3.3]
 [2.5]
 [7.7]]
[[30]
 [54]
 [76]
 [25]
 [88]
 [60]
 [62]
 [75]
 [17]
 [30]
 [81]
 [47]
 [95]
 [20]
 [35]
 [69]
 [30]
 [42]
 [21]
 [85]]
```

In [67]:
```
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
```

In [68]:
```
regressor.fit(X_train, Y_train)
```

Out[68]:
```
LinearRegression()
```

In [69]:
```
print(regressor.intercept_)
```

```
[3.55813277]
```

In [70]:
```
print(regressor.coef_)
```

```
[[9.53671262]]
```

In [71]:
```
def calc(slope, intercept, hours):
    return slope*hours+intercept

score = calc(regressor.coef_, regressor.intercept_, 9.5)
print(score)
```

```
[[94.15690265]]
```

In [72]:
```
score = regressor.predict([[9.5]])
print(score)
```

```
[[94.15690265]]
```

In [73]:
```
Y_pred = regressor.predict(X_test)
```

In [74]:
```
df_preds = pd.DataFrame({'Actual': Y_test.squeeze(), 'Predicted':Y_pred.squeeze()})
print(df_preds)
```

```
   Actual  Predicted
0      27  34.075613
1      86  77.944491
2      41  46.473340
3      24  21.677887
4      67  61.732080
```

In [75]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np
```

In [76]:
```
mae = mean_absolute_error(Y_test, Y_pred)
mse = mean_squared_error(Y_test, Y_pred)
rmse = np.sqrt(mse)
```

In [77]:
```
print(f'Mean absolute error: {mae:.2f}')
print(f'Mean squared error: {mse:.2f}')
print(f'Root mean squared error: {rmse:.2f}')
```

```
Mean absolute error: 5.64
Mean squared error: 35.61
Root mean squared error: 5.97
```

In [78]:
```
#Train Error
regressor.score(X_train, Y_train)
```

Out[78]:
```
0.9555415361003867
```

In [79]:
```
#Test Error
regressor.score(X_test, Y_test)
```

Out[79]:
```
0.9378729367585895
```

Here we can see that training accuaracy is 94.91% and test accuracy is 96.78%.

Multiple Linear Regression

In [420…
```
import pandas as pd
```

In [421…
```
path_to_file = './petrol_consumption.csv'
df = pd.read_csv(path_to_file)
```

In [422…
```
df.head()
```

Out[422]:

	Petrol_tax	Average_income	Paved_Highways	Population_Driver_licence(%)	Petrol_Consumptior
0	9.0	3571	1976	0.525	541
1	9.0	4092	1250	0.572	524
2	9.0	3865	1586	0.580	561
3	7.5	4870	2351	0.529	414
4	8.0	4399	431	0.544	410

In [423…
```
df.shape
```

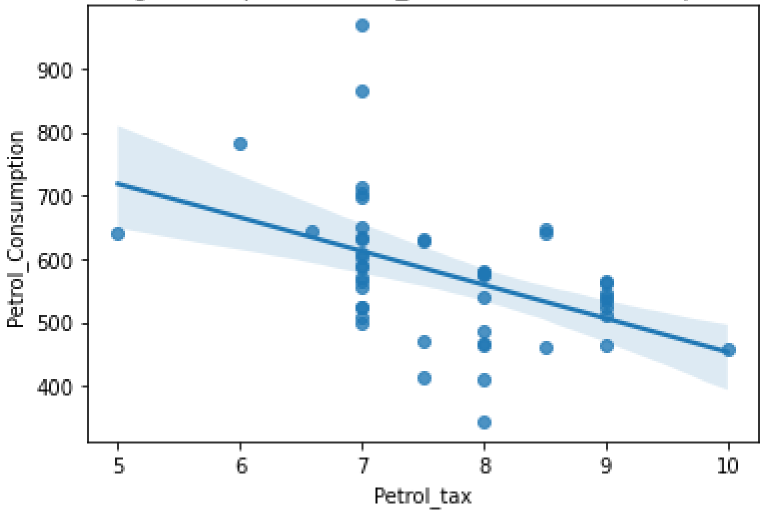
Out[423]:
```
(48, 5)
```

In [424…
```
#descriptive statistics of this data

print(df.describe().round(2).T)
```

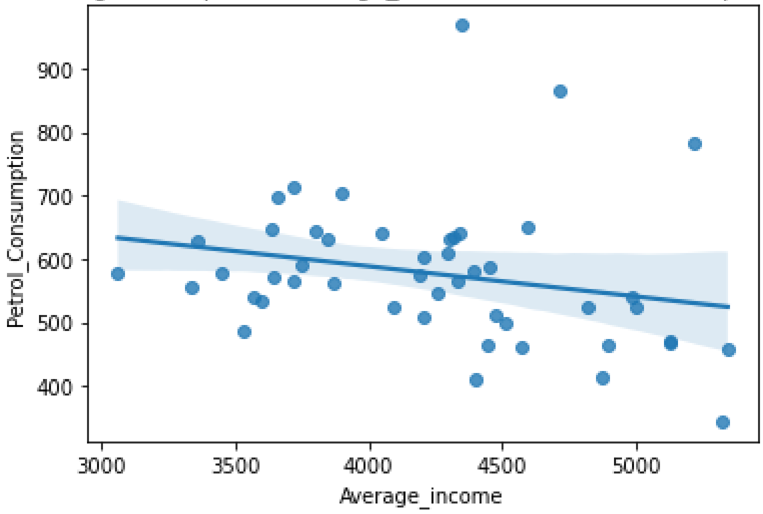
```
                              count     mean      std      min      25%  \
Petrol_tax                     48.0     7.67     0.95     5.00     7.00
Average_income                 48.0  4241.83   573.62  3063.00  3739.00
Paved_Highways                 48.0  5565.42  3491.51   431.00  3110.25
Population_Driver_licence(%)   48.0     0.57     0.06     0.45     0.53
Petrol_Consumption             48.0   576.77   111.89   344.00   509.50

                                  50%      75%       max
Petrol_tax                       7.50     8.12     10.00
Average_income                4298.00  4578.75   5342.00
Paved_Highways                4735.50  7156.00  17782.00
Population_Driver_licence(%)     0.56     0.60      0.72
Petrol_Consumption             568.50   632.75    968.00
```

In [425…
```
import seaborn as sns # Convention alias for Seaborn
import matplotlib.pyplot as plt

variables = ['Petrol_tax', 'Average_income', 'Paved_Highways','Population_Driver_li

for var in variables:
    plt.figure() # Creating a rectangle (figure) for each plot
    # Regression Plot also by default includes
    # best-fitting regression line
    # which can be turned off via `fit_reg=False`
    sns.regplot(x=var, y='Petrol_Consumption', data=df).set(title=f'Regression plot
```

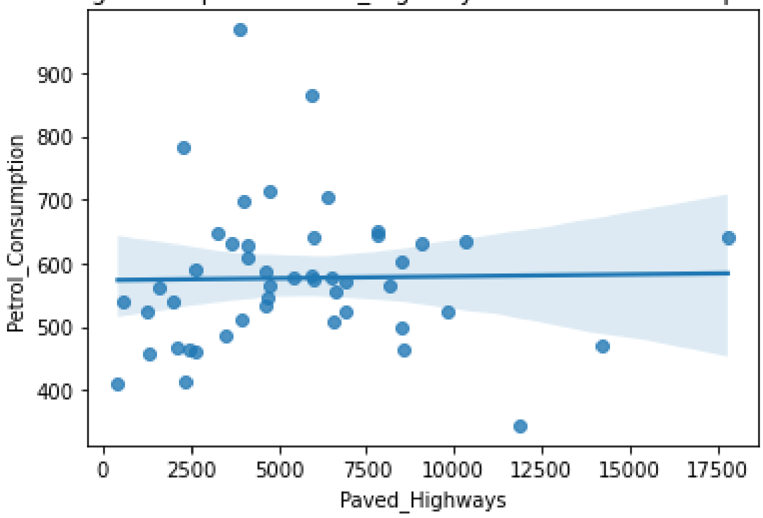
Regression plot of Petrol_tax and Petrol Consumption

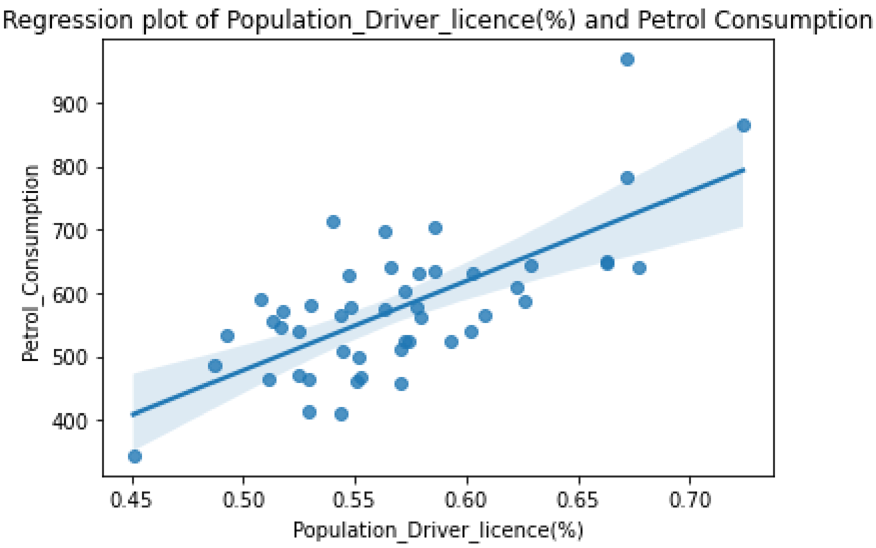


Regression plot of Average_income and Petrol Consumption

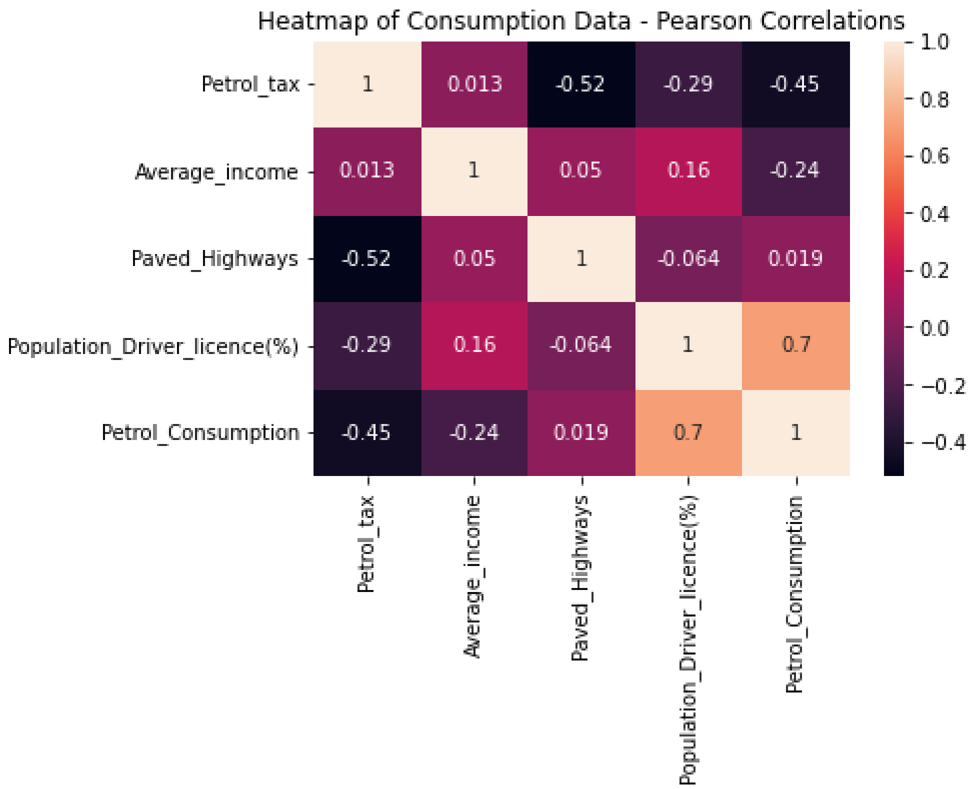


Regression plot of Paved_Highways and Petrol Consumption





In [426…
```
correlations = df.corr()
# annot=True displays the correlation values
sns.heatmap(correlations, annot=True).set(title='Heatmap of Consumption Data - Pear
```



In [427…
```
#Dataset for the model

y = df['Petrol_Consumption']
X = df[['Average_income', 'Paved_Highways',
       'Population_Driver_licence(%)', 'Petrol_tax']]
```

In [428…
```
#Splitting train and testing data

from sklearn.model_selection import train_test_split
SEED = 42
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.2,
                                                    random_state=SEED)
```

In [429…
```
#Fit data to the model
```

```python
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

Out[429]: LinearRegression()

In [430…
```python
regressor.intercept_
```

Out[430]: 361.4508790666836

In [431…
```python
print(regressor.coef_)
print(X.columns)
```

```
[-5.65355145e-02 -4.38217137e-03  1.34686930e+03 -3.69937459e+01]
Index(['Average_income', 'Paved_Highways', 'Population_Driver_licence(%)',
       'Petrol_tax'],
      dtype='object')
```

In [432…
```python
#Better representaions of coef

feature_names = X.columns
model_coefficients = regressor.coef_

coefficients_df = pd.DataFrame(data = model_coefficients,
                              index = feature_names,
                              columns = ['Coefficient value'])

print(coefficients_df)
```

```
                              Coefficient value
Average_income                        -0.056536
Paved_Highways                        -0.004382
Population_Driver_licence(%)        1346.869298
Petrol_tax                           -36.993746
```

In [433…
```python
#Model predections

y_pred = regressor.predict(X_test)
results = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
print(results)
```

```
    Actual   Predicted
27     631  606.692665
40     587  673.779442
26     577  584.991490
43     591  563.536910
24     460  519.058672
37     704  643.461003
12     525  572.897614
19     640  687.077036
4      410  547.609366
25     566  530.037630
```

In [434…
```python
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np

mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)

print(f'Mean absolute error: {mae:.2f}')
```

```
print(f'Mean squared error: {mse:.2f}')
print(f'Root mean squared error: {rmse:.2f}')
```

```
Mean absolute error: 53.47
Mean squared error: 4083.26
Root mean squared error: 63.90
```

In [435…
```
actual_minus_predicted = sum((y_test - y_pred)**2)
actual_minus_actual_mean = sum((y_test - y_test.mean())**2)
r2 = 1 - actual_minus_predicted/actual_minus_actual_mean
print('R²:', r2)
```

```
R²: 0.3913664001430537
```

In [436…
```
#Train Error
regressor.score(X_train, y_train)
```

Out[436]:
```
0.7068781342155135
```

In [437…
```
#Test Error
regressor.score(X_test, y_test)
```

Out[437]:
```
0.3913664001430538
```

For all variable can get 70.68% train accuary and 39.13% testing accuracy. Which shows that model is overfitted

Removing Average_income variable

In [438…
```
#Dataset for the model

y = df['Petrol_Consumption']
X = df[['Paved_Highways',
       'Population_Driver_licence(%)', 'Petrol_tax']]
```

In [439…
```
#Splitting train and testing data

SEED = 42
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.2,
                                                    random_state=SEED)
```

In [440…
```
#Fit data to the model

regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

Out[440]:
```
LinearRegression()
```

In [441…
```
regressor.intercept_
```

Out[441]:
```
278.9451691960404
```

In [442…
```
#Better representaions of coef

feature_names = X.columns
model_coefficients = regressor.coef_
```

```
coefficients_df = pd.DataFrame(data = model_coefficients,
                               index = feature_names,
                               columns = ['Coefficient value'])

print(coefficients_df)
```

```
                              Coefficient value
Paved_Highways                        -0.006526
Population_Driver_licence(%)        1202.432552
Petrol_tax                           -45.428979
```

In [443…
```
#Model predections

y_pred = regressor.predict(X_test)
results = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
print(results)
```

```
    Actual   Predicted
27     631  575.307626
40     587  683.392740
26     577  539.214550
43     591  554.739657
24     460  538.248584
37     704  623.901704
12     525  605.916050
19     640  667.626706
4      410  566.824103
25     566  493.237071
```

In [444…
```
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)

print(f'Mean absolute error: {mae:.2f}')
print(f'Mean squared error: {mse:.2f}')
print(f'Root mean squared error: {rmse:.2f}')
```

```
Mean absolute error: 72.26
Mean squared error: 6487.32
Root mean squared error: 80.54
```

In [445…
```
#Train Error
regressor.score(X_train, y_train)
```

Out[445]:
```
0.6286735791896659
```

In [446…
```
#Test Error
regressor.score(X_test, y_test)
```

Out[446]:
```
0.03302608023047027
```

By removing Average_income we can get 62.86% train accuarcy and 3.30% testing accuracy.

Removing Paved_Highways variable

In [447…
```
#Dataset for the model
```

```
y = df['Petrol_Consumption']
X = df[['Average_income',
       'Population_Driver_licence(%)', 'Petrol_tax']]
```

In [448…

```
#Splitting train and testing data

SEED = 42
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.2,
                                                    random_state=SEED)
```

In [449…

```
#Fit data to the model

regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

Out[449]:

```
LinearRegression()
```

In [450…

```
regressor.intercept_
```

Out[450]:

```
205.39240676596557
```

In [451…

```
#Better representaions of coef

feature_names = X.columns
model_coefficients = regressor.coef_

coefficients_df = pd.DataFrame(data = model_coefficients,
                              index = feature_names,
                              columns = ['Coefficient value'])

print(coefficients_df)
```

```
                              Coefficient value
Average_income                        -0.060255
Population_Driver_licence(%)        1454.069438
Petrol_tax                           -25.782603
```

In [452…

```
#Model predections

y_pred = regressor.predict(X_test)
results = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
print(results)
```

```
    Actual   Predicted
27     631  622.189623
40     587  667.088621
26     577  588.203528
43     591  537.927716
24     460  511.827675
37     704  642.186422
12     525  569.303291
19     640  709.079762
4      410  525.085058
25     566  540.155122
```

In [453…

```
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)

print(f'Mean absolute error: {mae:.2f}')
```

```
print(f'Mean squared error: {mse:.2f}')
print(f'Root mean squared error: {rmse:.2f}')
```

```
Mean absolute error: 52.11
Mean squared error: 3658.83
Root mean squared error: 60.49
```

In [454…
```
#Train Error
regressor.score(X_train, y_train)
```

Out[454]:
```
0.6963601784723381
```

In [455…
```
#Test Error
regressor.score(X_test, y_test)
```

Out[455]:
```
0.4546289176654955
```

By removing Paved_Highways we can get 69.36% train accuary and 45.46% testing accuracy. Which is overfitted model

Removing Petrol_tax variable

In [456…
```
#Dataset for the model

y = df['Petrol_Consumption']
X = df[['Average_income', 'Paved_Highways',
       'Population_Driver_licence(%)']]
```

In [457…
```
#Splitting train and testing data

SEED = 42
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.2,
                                                    random_state=SEED)
```

In [458…
```
#Fit data to the model

regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

Out[458]:
```
LinearRegression()
```

In [459…
```
regressor.intercept_
```

Out[459]:
```
-81.76841445582784
```

In [460…
```
#Better representaions of coef

feature_names = X.columns
model_coefficients = regressor.coef_

coefficients_df = pd.DataFrame(data = model_coefficients,
                              index = feature_names,
                              columns = ['Coefficient value'])
```

```
print(coefficients_df)
```

```
                              Coefficient value
Average_income                        -0.064640
Paved_Highways                         0.001826
Population_Driver_licence(%)        1626.613019
```

In [461…

```
#Model predections

y_pred = regressor.predict(X_test)
results = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
print(results)
```

```
    Actual   Predicted
27     631  627.979613
40     587  657.377300
26     577  596.594374
43     591  507.240521
24     460  523.612579
37     704  631.182638
12     525  553.189309
19     640  749.819293
4      410  519.542887
25     566  571.248652
```

In [462…

```
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)

print(f'Mean absolute error: {mae:.2f}')
print(f'Mean squared error: {mse:.2f}')
print(f'Root mean squared error: {rmse:.2f}')
```

```
Mean absolute error: 56.60
Mean squared error: 4659.27
Root mean squared error: 68.26
```

In [463…

```
#Train Error
regressor.score(X_train, y_train)
```

Out[463]: 0.6577092822857908

In [464…

```
#Test Error
regressor.score(X_test, y_test)
```

Out[464]: 0.3055078869820692

By removing Paved_Highways we can get 65.77% train accuarcy and 30.55% testing accuracy.

Removing Population_Driver_licence(%) variable

In [465…

```
#Dataset for the model

y = df['Petrol_Consumption']
X = df[['Average_income', 'Paved_Highways', 'Petrol_tax']]
```

In [466…
```
#Splitting train and testing data

SEED = 42
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.2,
                                                    random_state=SEED)
```

In [467…
```
#Fit data to the model

regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

Out[467]:
```
LinearRegression()
```

In [468…
```
regressor.intercept_
```

Out[468]:
```
1449.3580680851278
```

In [469…
```
#Better representaions of coef

feature_names = X.columns
model_coefficients = regressor.coef_

coefficients_df = pd.DataFrame(data = model_coefficients,
                              index = feature_names,
                              columns = ['Coefficient value'])

print(coefficients_df)
```

```
                Coefficient value
Average_income          -0.032935
Paved_Highways          -0.014477
Petrol_tax             -84.566887
```

In [470…
```
#Model predections

y_pred = regressor.predict(X_test)
results = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
print(results)
```

```
    Actual   Predicted
27     631  557.260421
40     587  643.703456
26     577  581.101195
43     591  696.249549
24     460  541.980679
37     704  636.605754
12     525  598.415804
19     640  500.561524
4      410  621.704238
25     566  496.996932
```

In [471…
```
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)

print(f'Mean absolute error: {mae:.2f}')
print(f'Mean squared error: {mse:.2f}')
print(f'Root mean squared error: {rmse:.2f}')
```

```
Mean absolute error: 88.27
Mean squared error: 10542.30
Root mean squared error: 102.68
```

In [472…

```
#Train Error
regressor.score(X_train, y_train)
```

Out[472]:

```
0.40244725995268826
```

In [473…

```
#Test Error
regressor.score(X_test, y_test)
```

Out[473]:

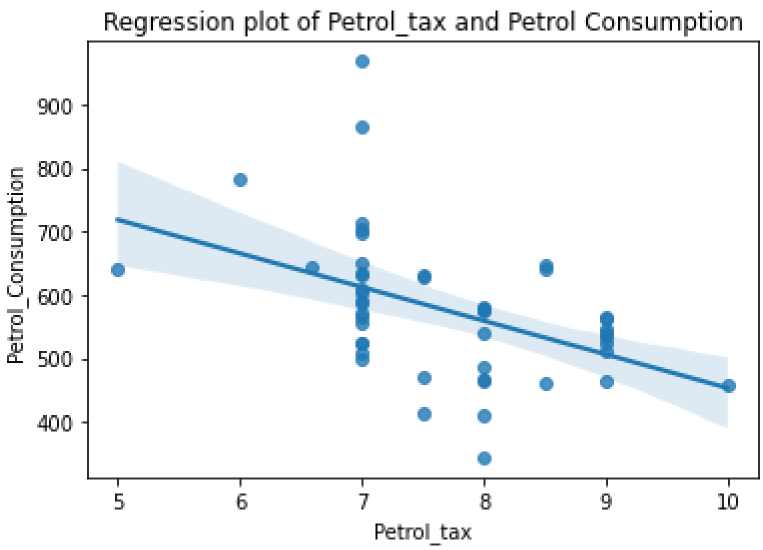
```
-0.5713923970639303
```

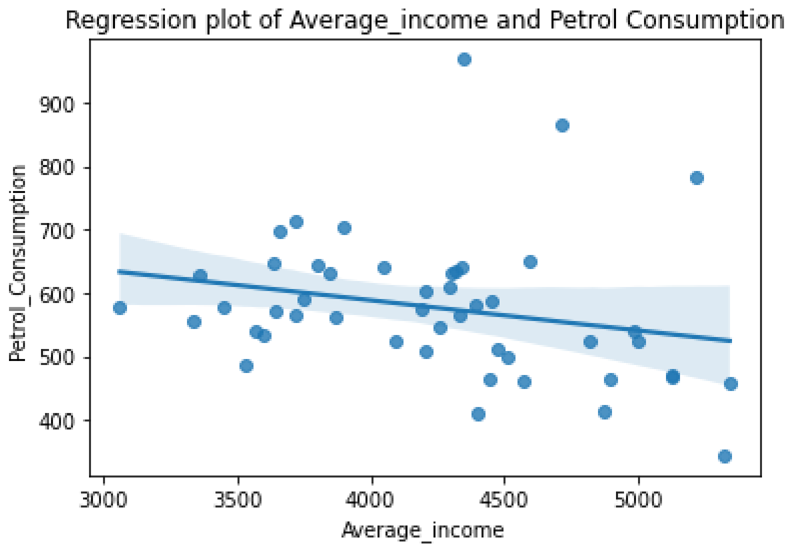
By removing Population_Driver_licence(%) we can get 40.24% train accuarcy and -57.13% testing accuracy.

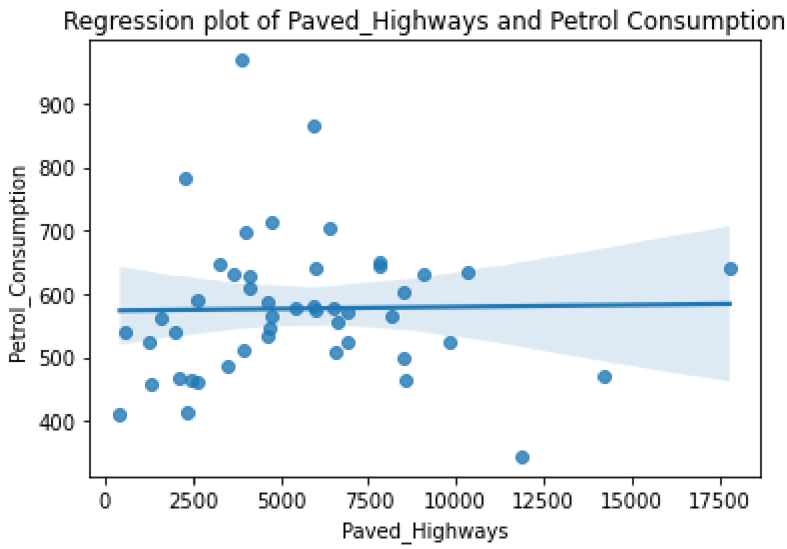
Removing Outliers

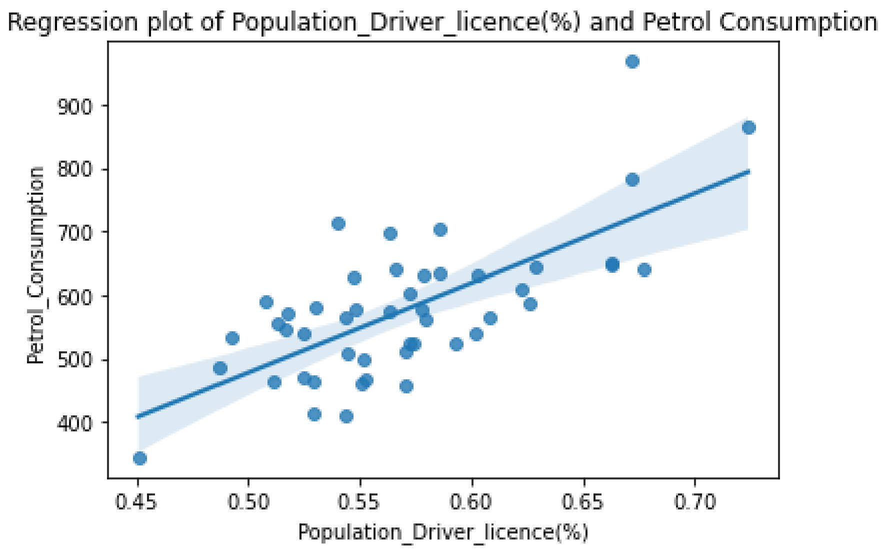
In [474…

```
variables = ['Petrol_tax', 'Average_income', 'Paved_Highways','Population_Driver_li

for var in variables:
    plt.figure()
    sns.regplot(x=var, y='Petrol_Consumption', data=df).set(title=f'Regression plot
```









In [475…
```
df.shape
```

Out[475]: (48, 5)

In [476…
```
#Removing outliers data in Petrol_tax variable

print(df[(df['Petrol_tax'] > 9.50)])
print(df[(df['Petrol_tax'] < 6.50)])
```

```
df = df[~(df['Petrol_tax'] > 9.50)]
df = df[~(df['Petrol_tax'] < 6.50)]
```

```
   Petrol_tax  Average_income  Paved_Highways  Population_Driver_licence(%)  \
5        10.0            5342            1333                         0.571

   Petrol_Consumption
5                 457
    Petrol_tax  Average_income  Paved_Highways  Population_Driver_licence(%)  \
36         5.0            4045           17782                         0.566
44         6.0            5215            2302                         0.672

    Petrol_Consumption
36                 640
44                 782
```

In [477…

```
df.shape
```

Out[477]: (45, 5)

In [478…

```
#Removing outliers data in Average_income variable

print(df[(df['Average_income'] < 3200)])
print(df[(df['Average_income'] > 5250)])

df = df[~(df['Average_income'] < 3200)]
df = df[~(df['Average_income'] > 5250)]
```

```
    Petrol_tax  Average_income  Paved_Highways  Population_Driver_licence(%)  \
32         8.0            3063            6524                         0.578

    Petrol_Consumption
32                 577
   Petrol_tax  Average_income  Paved_Highways  Population_Driver_licence(%)  \
6         8.0            5319           11868                         0.451

   Petrol_Consumption
6                 344
```

In [479…

```
df.shape
```

Out[479]: (43, 5)

In [480…

```
#Removing outliers data in Average_income variable

print(df[(df['Paved_Highways'] > 10000)])

df = df[~(df['Paved_Highways'] > 10000)]
```

```
    Petrol_tax  Average_income  Paved_Highways  Population_Driver_licence(%)  \
11         7.5            5126           14186                         0.525
15         7.0            4318           10340                         0.586

    Petrol_Consumption
11                 471
15                 635
```

In [481…

```
df.shape
```

Out[481]: (41, 5)

In [482…
```
#Removing outliers data in Average_income variable

print(df[(df['Population_Driver_licence(%)'] < 0.46)])
print(df[(df['Population_Driver_licence(%)'] > 0.68)])


df = df[~(df['Population_Driver_licence(%)'] < 0.46)]
df = df[~(df['Population_Driver_licence(%)'] > 0.68)]
```

```
Empty DataFrame
Columns: [Petrol_tax, Average_income, Paved_Highways, Population_Driver_licence
(%), Petrol_Consumption]
Index: []
    Petrol_tax  Average_income  Paved_Highways  Population_Driver_licence(%)  \
18         7.0            4716            5915                         0.724

    Petrol_Consumption
18                 865
```

In [483…
```
df.shape
```

Out[483]:
```
(40, 5)
```

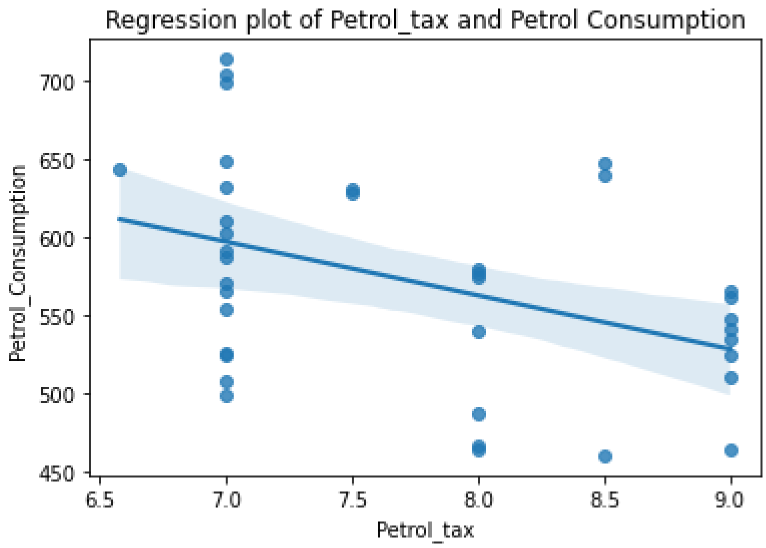
In [484…
```
#Removing outliers data in Petrol_Consumption variable

print(df[(df['Petrol_Consumption'] < 420)])
print(df[(df['Petrol_Consumption'] > 850)])


df = df[~(df['Petrol_Consumption'] < 420)]
df = df[~(df['Petrol_Consumption'] > 850)]
```

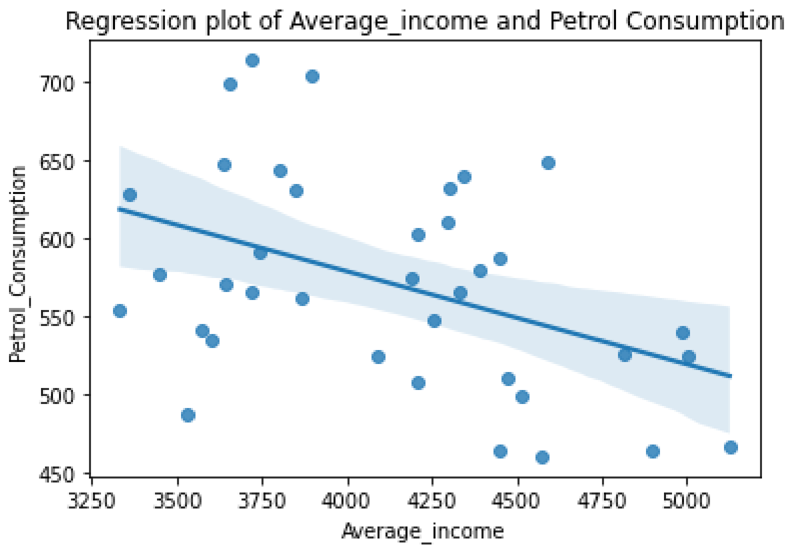
```
   Petrol_tax  Average_income  Paved_Highways  Population_Driver_licence(%)  \
3         7.5            4870            2351                         0.529
4         8.0            4399             431                         0.544

   Petrol_Consumption
3                 414
4                 410
    Petrol_tax  Average_income  Paved_Highways  Population_Driver_licence(%)  \
39         7.0            4345            3905                         0.672

    Petrol_Consumption
39                 968
```

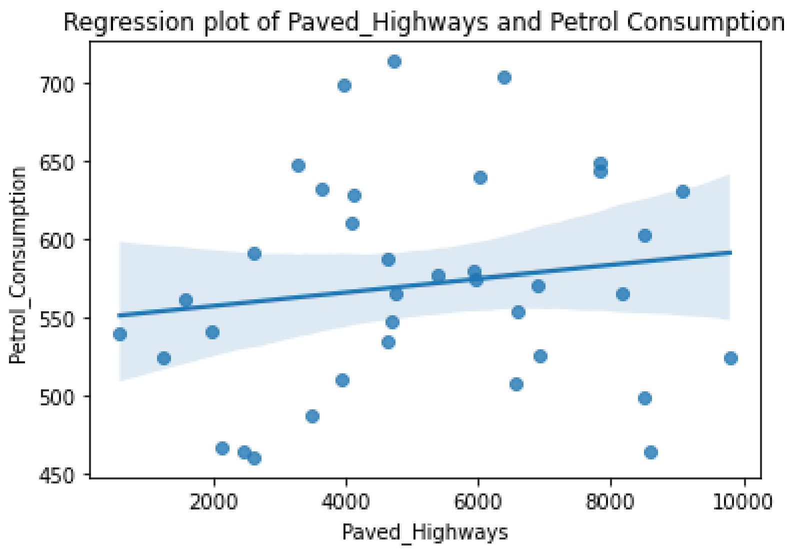
In [485…
```
df.shape
```

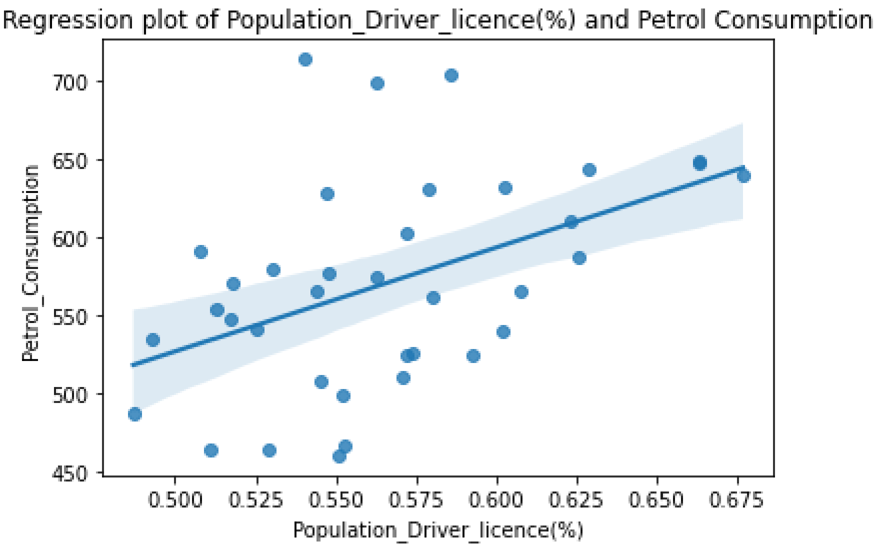
Out[485]:
```
(37, 5)
```

In [486…
```
variables = ['Petrol_tax', 'Average_income', 'Paved_Highways','Population_Driver_li

for var in variables:
    plt.figure()
    sns.regplot(x=var, y='Petrol_Consumption', data=df).set(title=f'Regression plot
```


Regression plot of Petrol_tax and Petrol Consumption
Petrol_Consumption
Petrol_tax
700
650
600
550
500
450
6.5
7.0
7.5
8.0
8.5
9.0


Regression plot of Average_income and Petrol Consumption
Petrol_Consumption
Average_income
700
650
600
550
500
450
3250
3500
3750
4000
4250
4500
4750
5000


Regression plot of Paved_Highways and Petrol Consumption
Petrol_Consumption
Paved_Highways
700
650
600
550
500
450
2000
4000
6000
8000
10000



In [487…

```
#Dataset for the model

y = df['Petrol_Consumption']
X = df[['Average_income', 'Paved_Highways',
       'Population_Driver_licence(%)', 'Petrol_tax']]
```

In [488…

```
SEED = 42
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.2,
                                                    random_state=SEED)
```

In [489…

```
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

Out[489]: LinearRegression()

In [490…

```
regressor.intercept_
```

Out[490]: 726.6734241137171

In [491…

```
#Better representaions of coef

feature_names = X.columns
model_coefficients = regressor.coef_

coefficients_df = pd.DataFrame(data = model_coefficients,
                              index = feature_names,
                              columns = ['Coefficient value'])

print(coefficients_df)
```

```
                              Coefficient value
Average_income                        -0.088267
Paved_Highways                        -0.004327
Population_Driver_licence(%)         799.624794
Petrol_tax                           -28.135246
```

In [492…

```
#Model predections

y_pred = regressor.predict(X_test)
results = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
print(results)
```

```
    Actual   Predicted
24     460  513.052137
20     649  620.569642
8      464  494.956518
38     648  682.658274
46     610  631.031145
33     628  638.910071
10     580  512.114196
34     487  564.480166
```

In [493…

```
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)

print(f'Mean absolute error: {mae:.2f}')
print(f'Mean squared error: {mse:.2f}')
print(f'Root mean squared error: {rmse:.2f}')
```

```
Mean absolute error: 40.55
Mean squared error: 2119.41
Root mean squared error: 46.04
```

In [494…

```
#Train Error
regressor.score(X_train, y_train)
```

Out[494]:

```
0.6402956657405138
```

In [495…

```
#Test Error
regressor.score(X_test, y_test)
```

Out[495]:

```
0.6428166780884602
```

By removing outliers we can get 64.02% train accuarcy and 64.28% testing accuracy.