co2-emissions-simple

October 7, 2023

1 Act 1. Regresion lineal Simple

CO2 Emission by Vehicles

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Contenidos

- **5.1** - Temas avanzados sobre análisis regresión
- **5.1.1** - Verificación de supuestos: QQ-plots & análisis de residuales
- **5.2** - Estadística para datos multivariados

1. ¿Cuáles son las caracteríaticas que más influyen en la emisión de CO2?

```
Considerando las pruebas realizadas en esta actividad, las
variables con más influencias en la emisión de Dioxido de Carbono
 (CO2) son:
  * Fuel Consumption Comb (mpg)
  * Fuel Consumption Comb (L/100 km)
  * Fuel Consumption City (L/100 km)

  Pues su correlación es mayor a 0.8
```

2. ¿Habrá alguna diferencia en la emisiones de CO2 cuando el consumo de combustible para la ciudad y carretera se consideran por separado?

```
Si, ya que el consumo de combustime en la ciudad tiene una mayor
correlación con el gasto total. Al combinarlos es más cercana la
predicción a las emisiones de Dioxido de Carbono (CO2) totales.
Esto se da ya que al suponer que las emisiones  Pues así al combiarlas
el consumo
```

##Llamado a librerías

[ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

[ ]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from scipy.stats import norm, uniform, skewnorm
```

##Importamos los datos a un DataFrame

[ ]:
```python
df = pd.read_csv('/content/drive/Shareddrives/Reto IA/Actividades/CO2_Emissions/
 ↪CO2 Emissions_Canada.csv')
df.head()
```

[ ]:
```
    Make       Model Vehicle Class  Engine Size(L)  Cylinders Transmission  \
0  ACURA         ILX       COMPACT             2.0          4          AS5
1  ACURA         ILX       COMPACT             2.4          4           M6
2  ACURA  ILX HYBRID       COMPACT             1.5          4          AV7
3  ACURA     MDX 4WD   SUV - SMALL             3.5          6          AS6
4  ACURA     RDX AWD   SUV - SMALL             3.5          6          AS6

  Fuel Type  Fuel Consumption City (L/100 km)  \
0         Z                               9.9
1         Z                              11.2
2         Z                               6.0
3         Z                              12.7
4         Z                              12.1

   Fuel Consumption Hwy (L/100 km)  Fuel Consumption Comb (L/100 km)  \
0                              6.7                               8.5
1                              7.7                               9.6
2                              5.8                               5.9
3                              9.1                              11.1
4                              8.7                              10.6

   Fuel Consumption Comb (mpg)  CO2 Emissions(g/km)
0                           33                  196
1                           29                  221
2                           48                  136
3                           25                  255
4                           27                  244
```

[ ]:
```python
df.isnull().sum()
```

[ ]:
```
Make                                0
Model                               0
Vehicle Class                       0
Engine Size(L)                      0
Cylinders                           0
Transmission                        0
Fuel Type                           0
Fuel Consumption City (L/100 km)    0
Fuel Consumption Hwy (L/100 km)     0
Fuel Consumption Comb (L/100 km)    0
Fuel Consumption Comb (mpg)         0
CO2 Emissions(g/km)                 0
dtype: int64
```

[ ]:
```
df.shape
```

[ ]:
```
(7385, 12)
```

[ ]:
```
df.columns
```

[ ]:
```
Index(['Make', 'Model', 'Vehicle Class', 'Engine Size(L)', 'Cylinders',
       'Transmission', 'Fuel Type', 'Fuel Consumption City (L/100 km)',
       'Fuel Consumption Hwy (L/100 km)', 'Fuel Consumption Comb (L/100 km)',
       'Fuel Consumption Comb (mpg)', 'CO2 Emissions(g/km)'],
      dtype='object')
```

[ ]:
```
df.describe()
```

[ ]:
```
       Engine Size(L)    Cylinders  Fuel Consumption City (L/100 km)  \
count     7385.000000  7385.000000                       7385.000000
mean         3.160068     5.615030                         12.556534
std          1.354170     1.828307                          3.500274
min          0.900000     3.000000                          4.200000
25%          2.000000     4.000000                         10.100000
50%          3.000000     6.000000                         12.100000
75%          3.700000     6.000000                         14.600000
max          8.400000    16.000000                         30.600000

       Fuel Consumption Hwy (L/100 km)  Fuel Consumption Comb (L/100 km)  \
count                      7385.000000                       7385.000000
mean                          9.041706                         10.975071
std                           2.224456                          2.892506
min                           4.000000                          4.100000
25%                           7.500000                          8.900000
50%                           8.700000                         10.600000
75%                          10.200000                         12.600000
max                          20.600000                         26.100000
```

```
       Fuel Consumption Comb (mpg)  CO2 Emissions(g/km)
count                  7385.000000          7385.000000
mean                     27.481652           250.584699
std                       7.231879            58.512679
min                      11.000000            96.000000
25%                      22.000000           208.000000
50%                      27.000000           246.000000
75%                      32.000000           288.000000
max                      69.000000           522.000000
```

##Funciones genereales

[ ]:
```
def plt_scatter(x, y, xl, yl):
  plt.subplot(1, 2, 1)
  plt.scatter(x, y)
  plt.xlabel(xl)
  plt.ylabel(yl)
  plt.grid()
```

[ ]:
```
def plt_scatter_w_line(x, y, b0, b1, xl, yl):
  x_line = np.linspace(min(x), max(x), 100)
  y_line = b0 + b1 * x_line
  plt.subplot(1, 2, 2)
  plt.scatter(x,y)
  plt.xlabel(xl)
  plt.ylabel(yl)
  plt.grid()

  plt.plot(x_line, y_line, color='red')
```

[ ]:
```
def Asimetric_Dist(r, title):
  plt.hist(r, density = True, bins = 'auto', histtype='stepfilled', alpha=0.2)
  plt.title(title)
  plt.grid()
  plt.show()
```

[ ]:
```
def OLS(x, y):
  x = sm.add_constant(x)
  model = sm.OLS(y, x)
  result = model.fit()
  print('Params:', result.params)
  print('R^2:', result.rsquared)
```

1.1 Engine Size(L)

[ ]:
```
x_ms = df['Engine Size(L)']
y = df['CO2 Emissions(g/km)']
```

[ ]:
```
X_ms = sm.add_constant(x_ms)
print(X_ms.shape)
print(X_ms)
```

```
(7385, 2)
      const  Engine Size(L)
0       1.0             2.0
1       1.0             2.4
2       1.0             1.5
3       1.0             3.5
4       1.0             3.5
…       …               …
7380    1.0             2.0
7381    1.0             2.0
7382    1.0             2.0
7383    1.0             2.0
7384    1.0             2.0

[7385 rows x 2 columns]
```

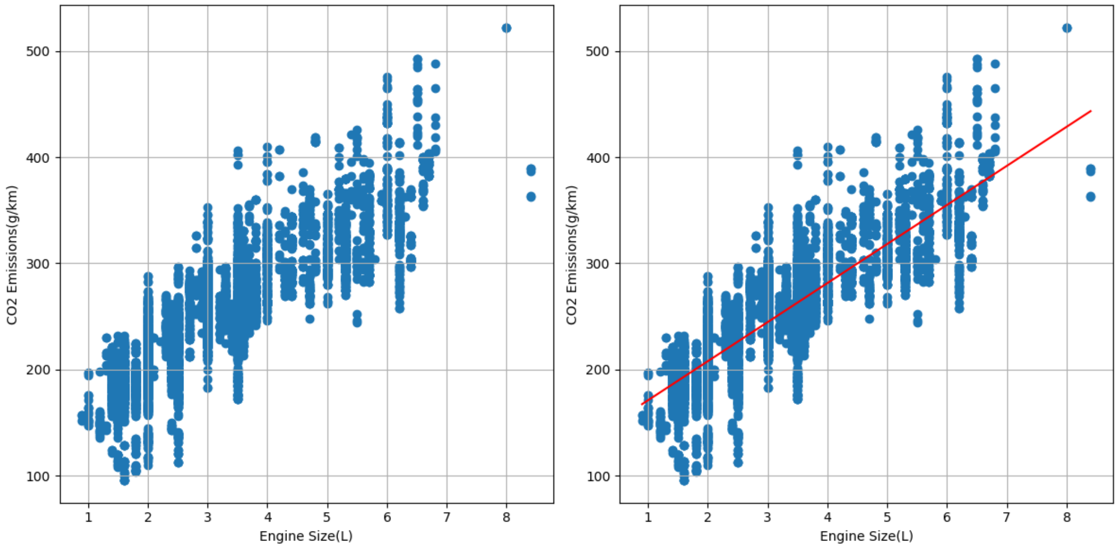
[ ]:
```
model = sm.OLS(y,X_ms)
result = model.fit()
result.params
```

[ ]:
```
const             134.365893
Engine Size(L)     36.777315
dtype: float64
```

[ ]:
```
print("\nR2: ", result.rsquared)
```

```

R2:  0.7244472046524082
```

[ ]:
```
plt.figure(figsize=(12, 6))
plt_scatter(x_ms, y, 'Engine Size(L)', 'CO2 Emissions(g/km)')
plt_scatter_w_line(x_ms, y, result.params[0], result.params[1], 'Engine␣
 ↪Size(L)', 'CO2 Emissions(g/km)')
plt.tight_layout()
plt.show()
```



1.2 Cylinders

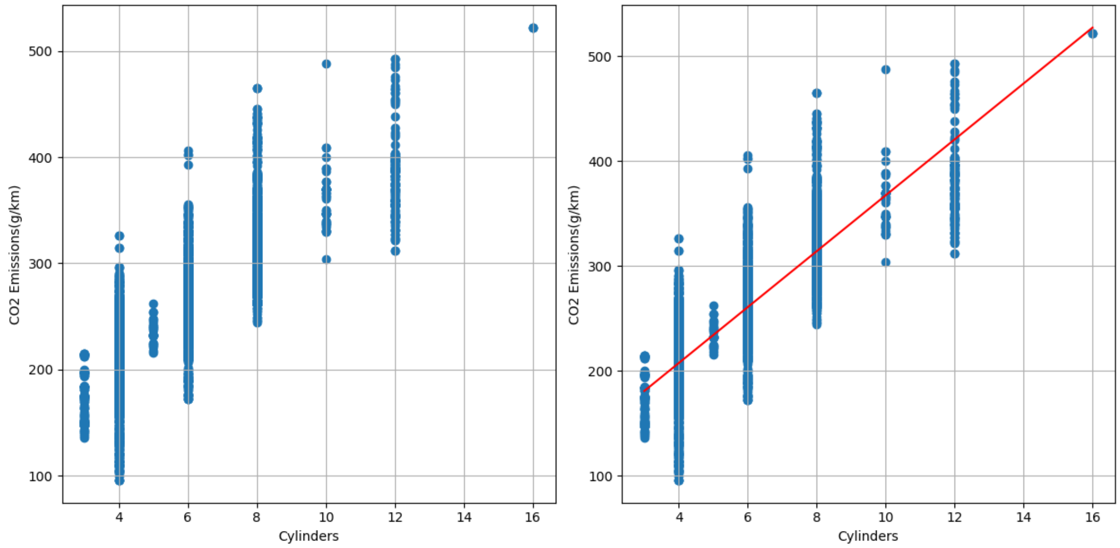
[ ]:
```
x_cyl = df['Cylinders']
X_cyl = sm.add_constant(x_cyl)
model = sm.OLS(y,X_cyl)
result = model.fit()
result.params
```

[ ]:
```
const        100.956915
Cylinders     26.647724
dtype: float64
```

[ ]:
```
print("\nR2: ", result.rsquared)
```

```
R2:  0.6932953649936133
```

[ ]:
```
plt.figure(figsize=(12, 6))
plt_scatter(x_cyl, y, 'Cylinders', 'CO2 Emissions(g/km)')
plt_scatter_w_line(x_cyl, y, result.params[0], result.params[1], 'Cylinders',␣
  ↪'CO2 Emissions(g/km)')
plt.tight_layout()
plt.show()
```

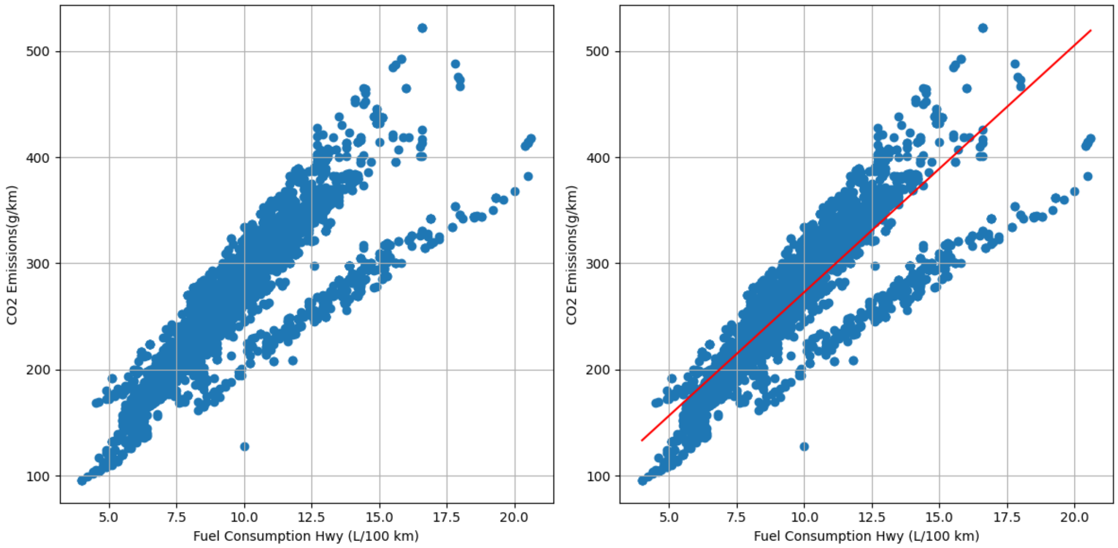


1.3 Fuel Consumption Hwy (L/100 km)

```
[ ]: x_fch = df['Fuel Consumption Hwy (L/100 km)']
X_fch = sm.add_constant(x_fch)
model = sm.OLS(y,X_fch)
result = model.fit()
print(result.params)
print("\nR2: ", result.rsquared)
```

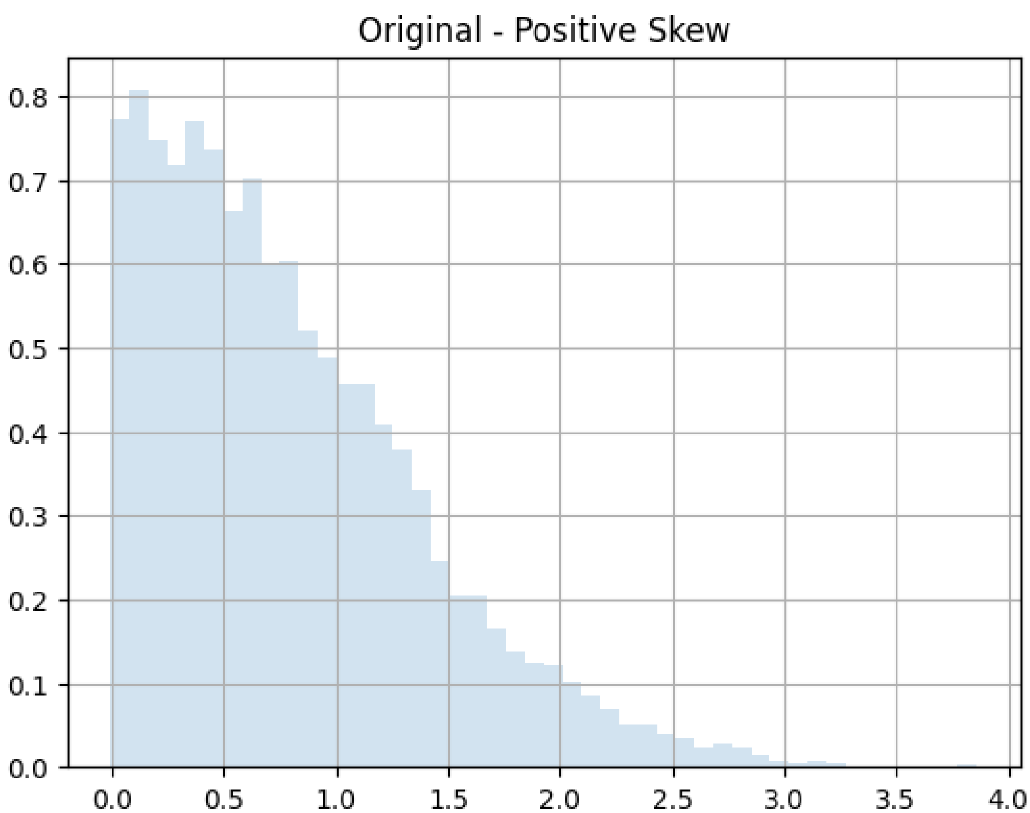
```
const                              40.448581
Fuel Consumption Hwy (L/100 km)    23.240759
dtype: float64

R2:  0.7806357669286315
```

```
[ ]: plt.figure(figsize=(12, 6))
plt_scatter(x_fch, y, 'Fuel Consumption Hwy (L/100 km)', 'CO2 Emissions(g/km)')
plt_scatter_w_line(x_fch, y, result.params[0], result.params[1], 'Fuel␣
↪Consumption Hwy (L/100 km)', 'CO2 Emissions(g/km)')
plt.tight_layout()
plt.show()
```

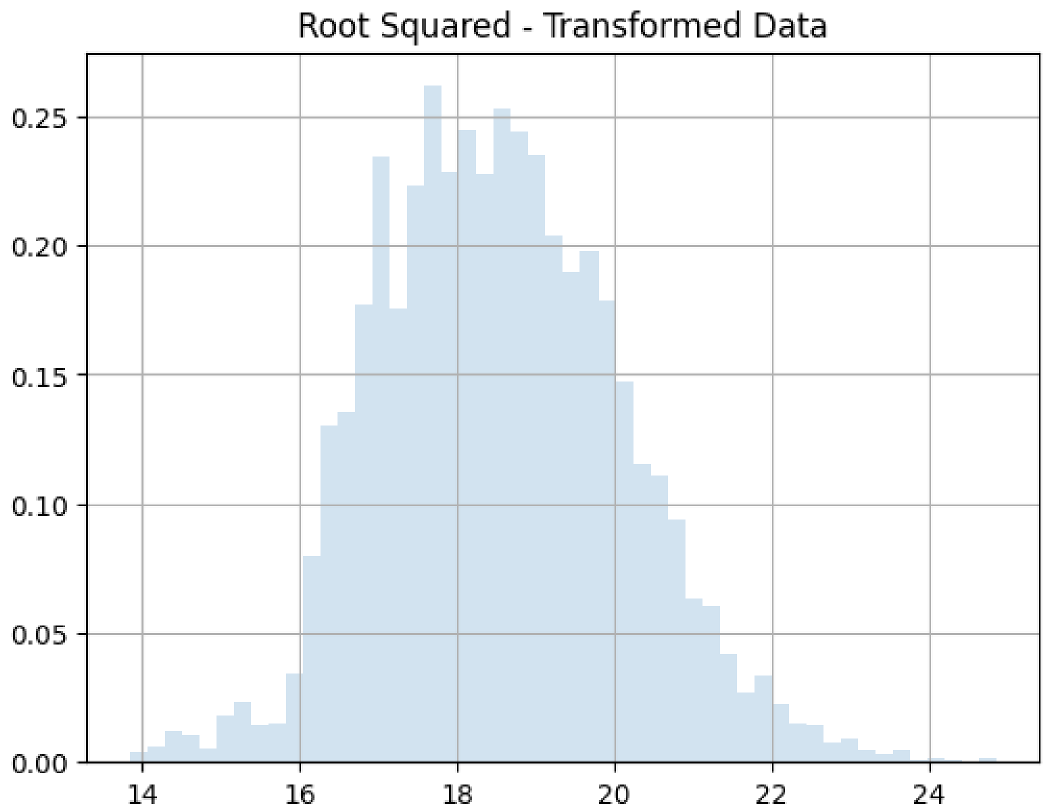


##Análisis de distribuciones

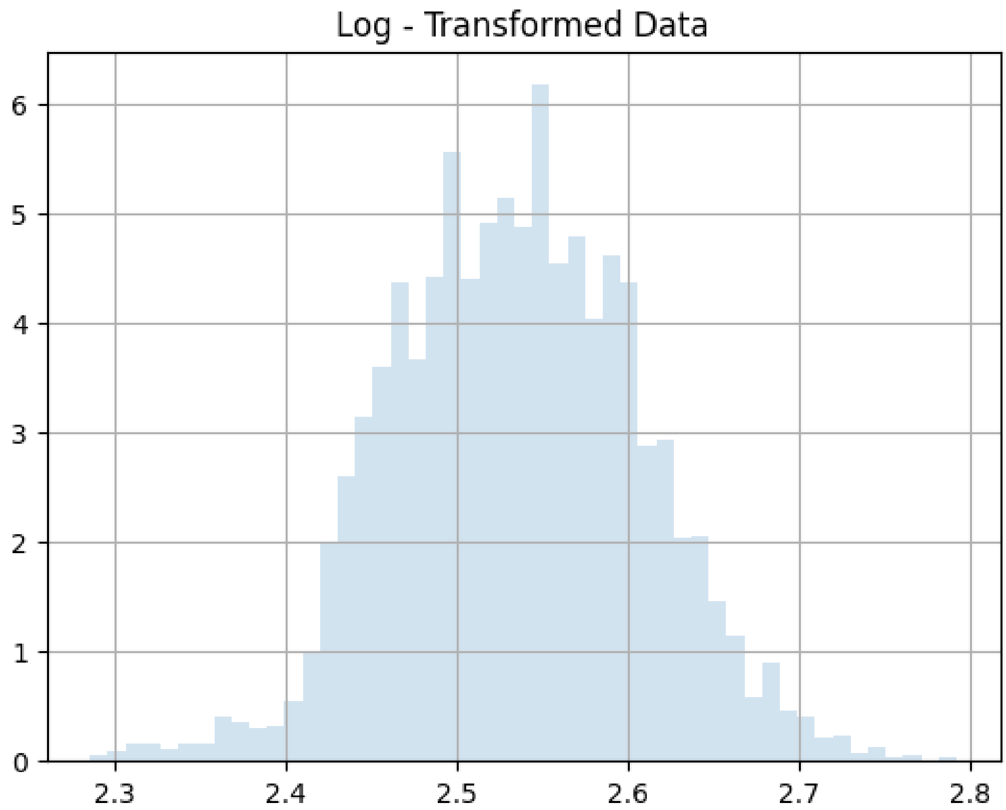
[ ]:
```python
y_skew = skewnorm.rvs(y)
Asimetric_Dist(y_skew, 'Original - Positive Skew')
```



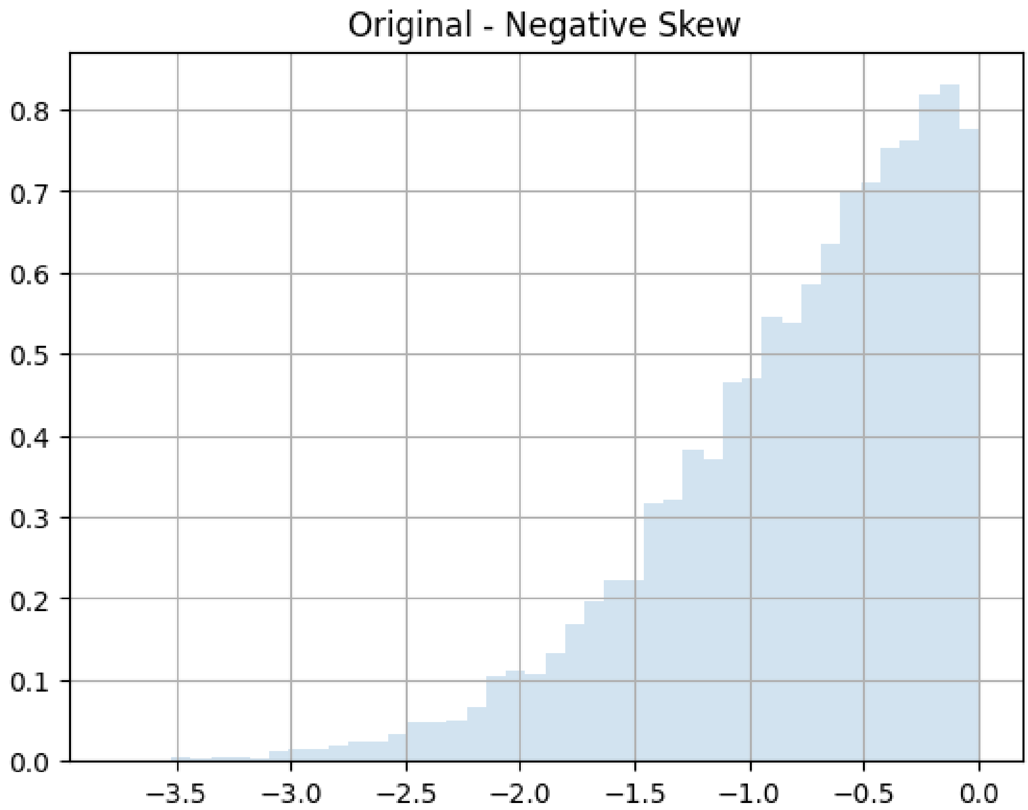
[ ]:
```
y_root = np.sqrt(y + abs(min(y)))
Asimetric_Dist(y_root, 'Root Squared - Transformed Data')
```



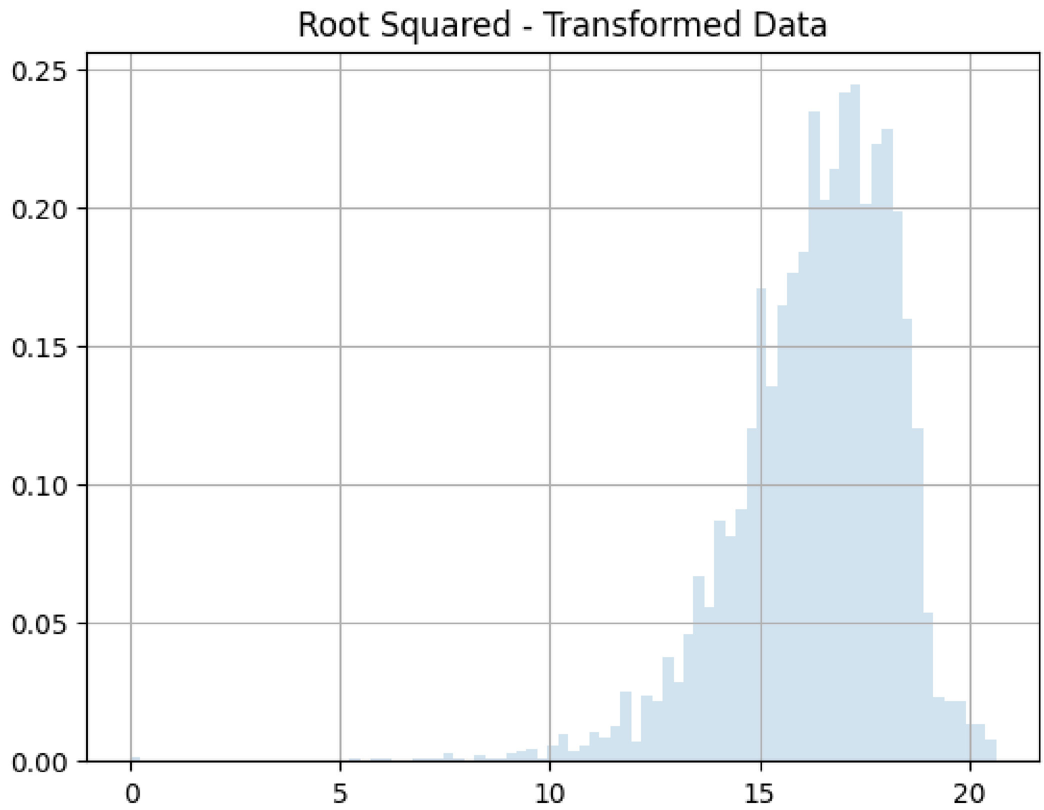
[ ]:
```
y_log = np.log10(1 + y + abs(min(y)))
Asimetric_Dist(y_log, 'Log - Transformed Data')
```



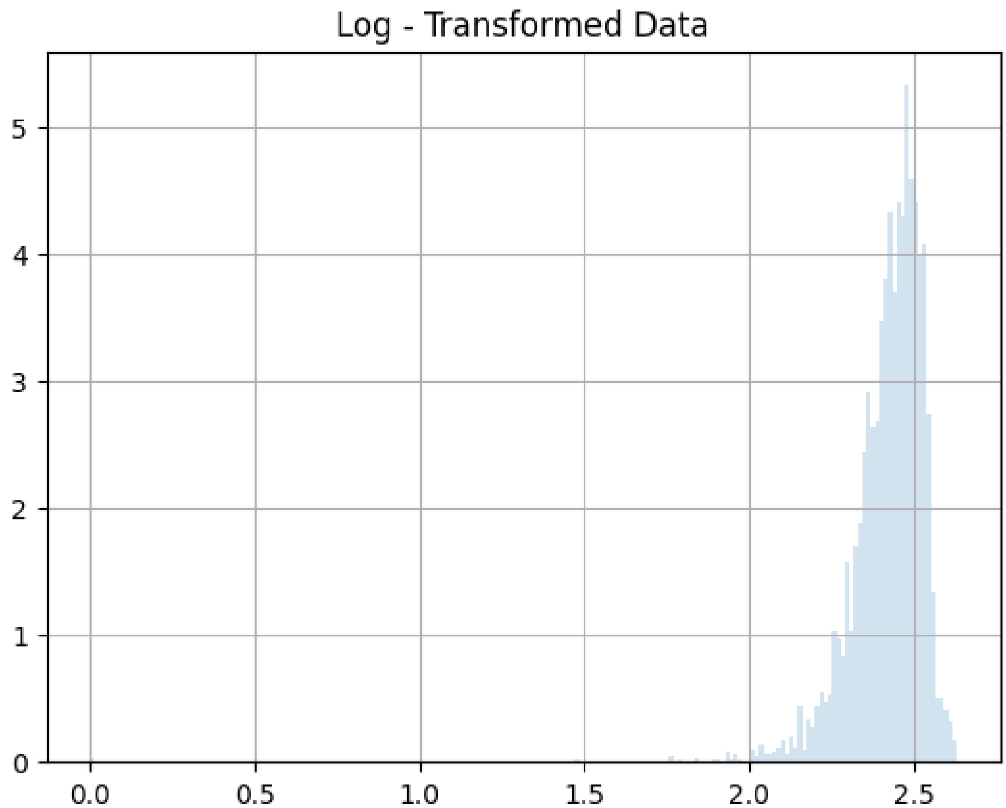

```
[ ]: y_skew_neg = -skewnorm.rvs(y)
     Asimetric_Dist(y_skew_neg, 'Original - Negative Skew')
```



[ ]:
```
y_pos = y + abs(min(y))
y_root_neg = np.sqrt(max(y_pos) - y_pos)
Asimetric_Dist(y_root_neg, 'Root Squared - Transformed Data')
```




```
[ ]: y_positive = y + abs(min(y))
     y_log_neg = np.log10(1 + max(y_positive) - y_positive)
     Asimetric_Dist(y_log_neg, 'Log - Transformed Data')
```



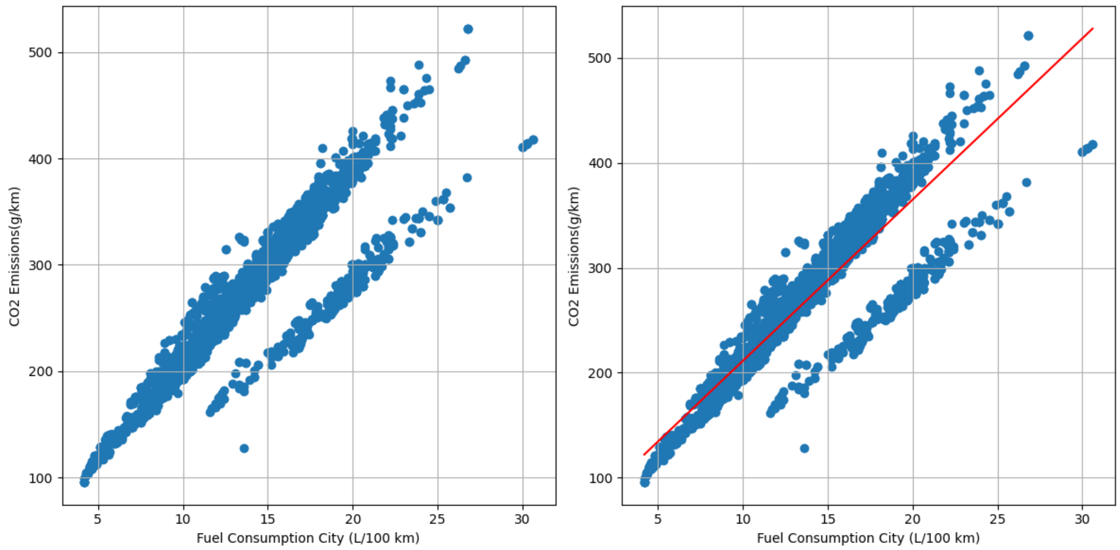
1.4 Fuel Consumption City (L/100 km)

[ ]:
```
x_fcct = df['Fuel Consumption City (L/100 km)']
X_fcct = sm.add_constant(x_fcct)
model = sm.OLS(y,X_fcct)
result = model.fit()
print(result.params)
print("\nR2: ", result.rsquared)
```

```
const                               57.559903
Fuel Consumption City (L/100 km)    15.372459
dtype: float64

R2:  0.8456503198972763
```

[ ]:
```
plt.figure(figsize=(12, 6))
plt_scatter(x_fcct, y, 'Fuel Consumption City (L/100 km)', 'CO2 Emissions(g/
↪km)')
plt_scatter_w_line(x_fcct, y, result.params[0], result.params[1], 'Fuel␣
↪Consumption City (L/100 km)', 'CO2 Emissions(g/km)')
```

```
plt.tight_layout()
plt.show()
```

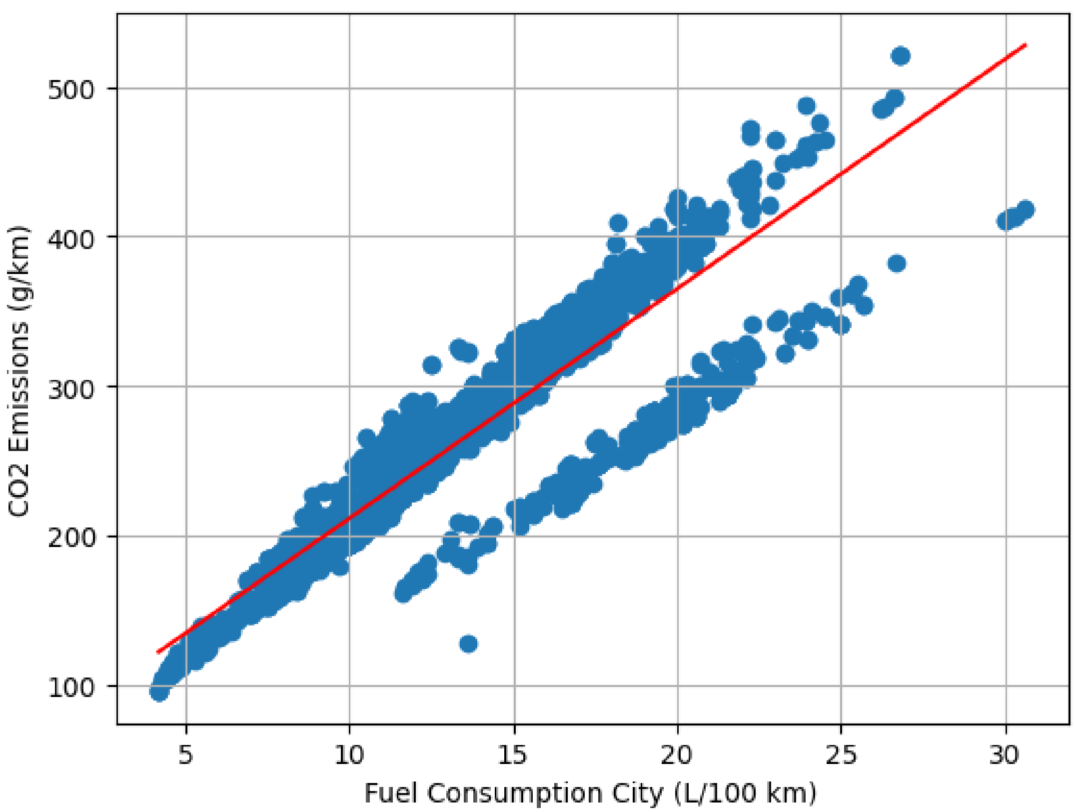



```
[ ]: print(result.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      CO2 Emissions(g/km)   R-squared:                       0.846
Model:                              OLS   Adj. R-squared:                  0.846
Method:                   Least Squares   F-statistic:                 4.045e+04
Date:                  Sat, 07 Oct 2023   Prob (F-statistic):               0.00
Time:                          02:13:24   Log-Likelihood:                -33630.
No. Observations:                  7385   AIC:                         6.726e+04
Df Residuals:                      7383   BIC:                         6.728e+04
Df Model:                             1
Covariance Type:              nonrobust
================================================================================
====================
                                       coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------------------
--------------------
const                               57.5599      0.996     57.772      0.000
55.607      59.513
Fuel Consumption City (L/100 km)    15.3725      0.076    201.122      0.000
15.223      15.522
==============================================================================
Omnibus:                     3089.403   Durbin-Watson:                   1.913
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            16424.392
```

```
Skew:                          -1.963   Prob(JB):                         0.00
Kurtosis:                       9.161   Cond. No.                         48.8
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

[ ]:
```
x_line = np.linspace(min(x_fcct), max(x_fcct), 100)
y_line = result.params[0] + result.params[1] * x_line
plt.scatter(x_fcct,y)
plt.xlabel('Fuel Consumption City (L/100 km)')
plt.ylabel('CO2 Emissions (g/km)')
plt.grid()

plt.plot(x_line, y_line, color='red')

plt.show()
```

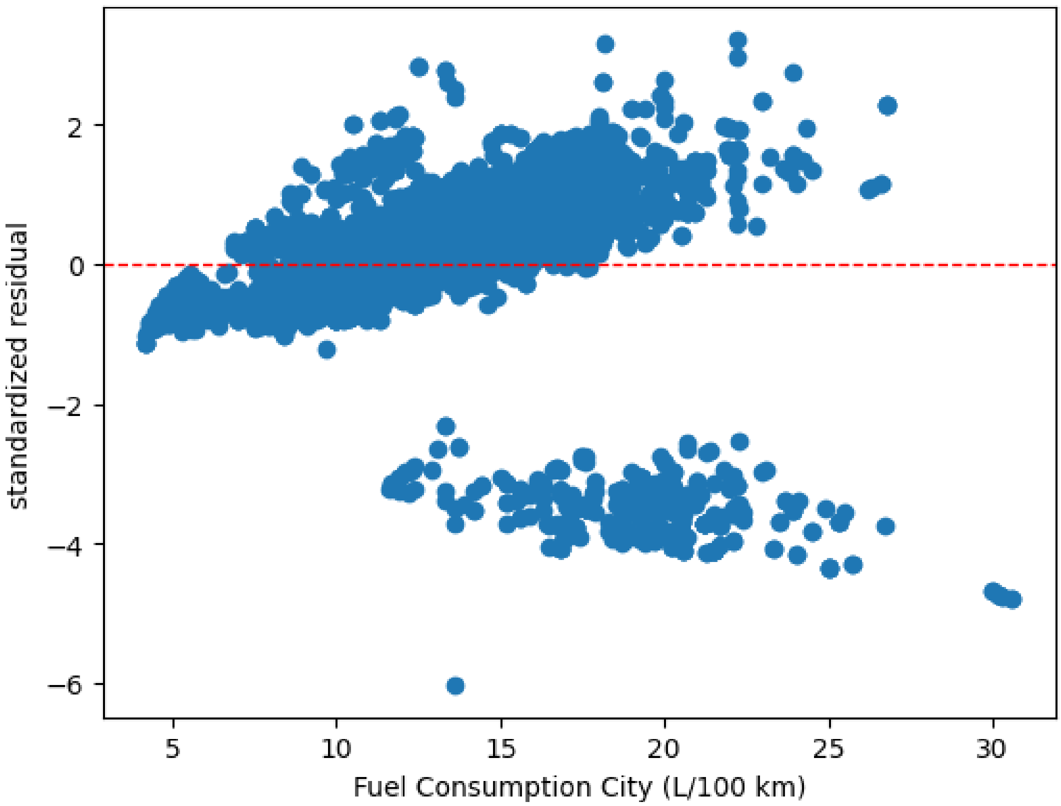


[ ]:
```
influence = result.get_influence()
std_residual = influence.resid_studentized_internal
```

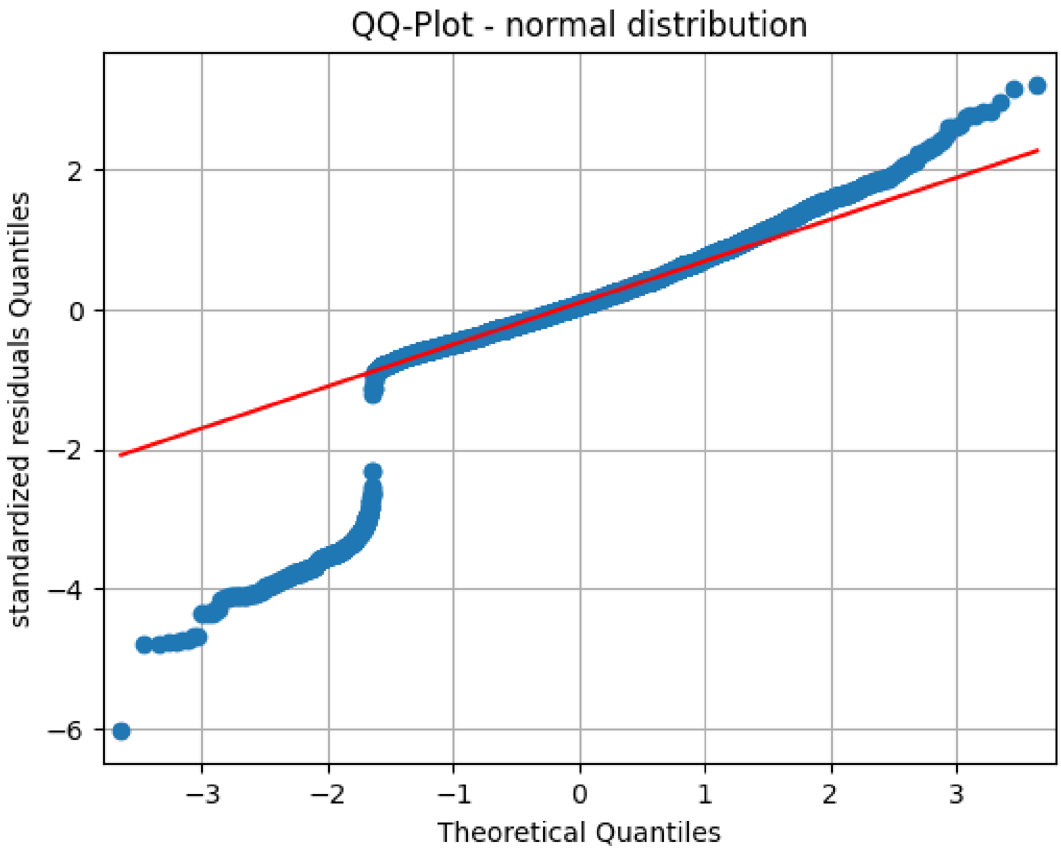
```python
print(std_residual)
```

```
[-0.5980394  -0.37982853 -0.60022109 …  0.11233374  0.09868503
  0.12598264]
```

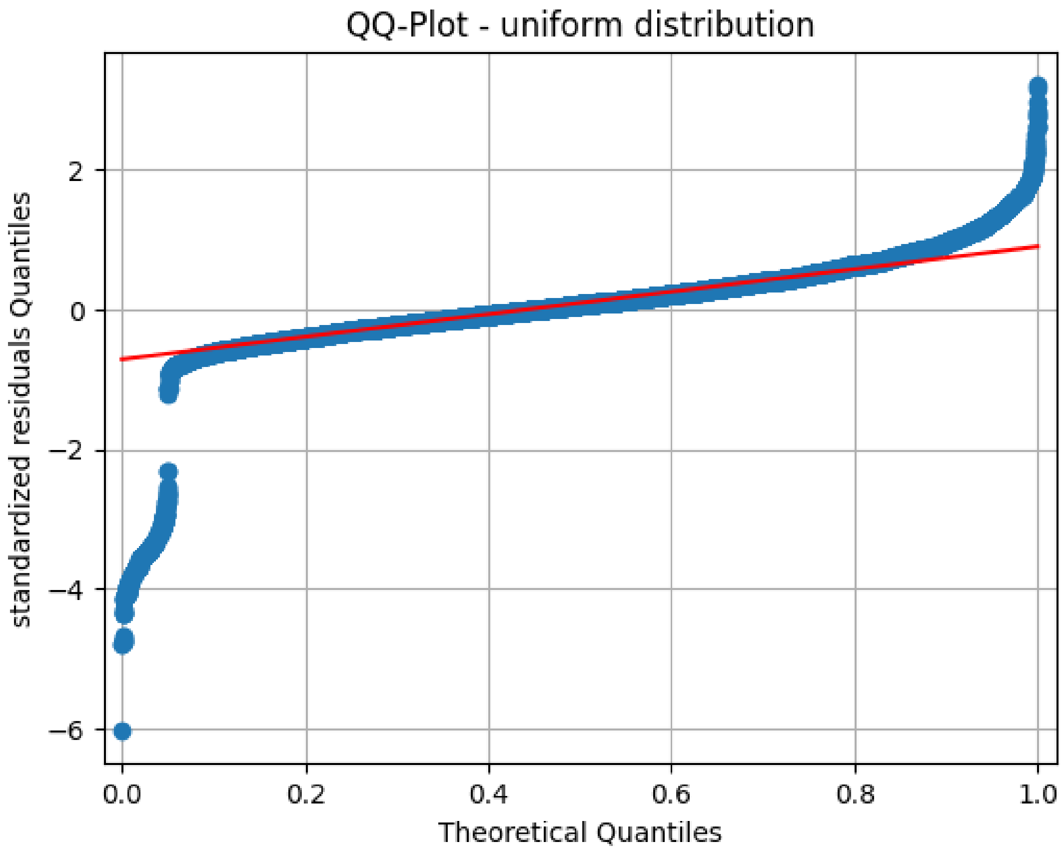
[ ]:
```python
plt.scatter(x_fcct, std_residual)
plt.xlabel('Fuel Consumption City (L/100 km)')
plt.ylabel('standardized residual')
plt.axhline(y=0, color='red', linestyle='--', linewidth=1)
plt.show()
```



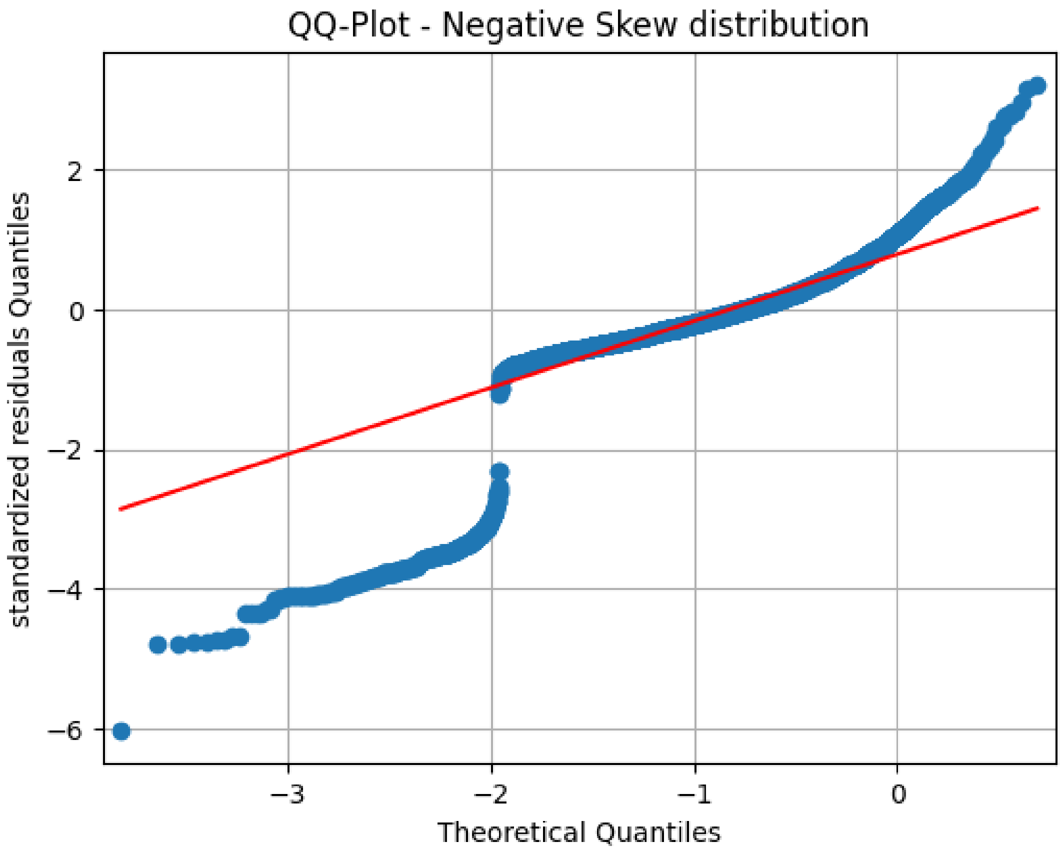
[ ]:
```python
fig = sm.qqplot(std_residual, dist=norm, line="q")
plt.ylabel("standardized residuals Quantiles")
plt.title("QQ-Plot - normal distribution")
plt.grid()
```



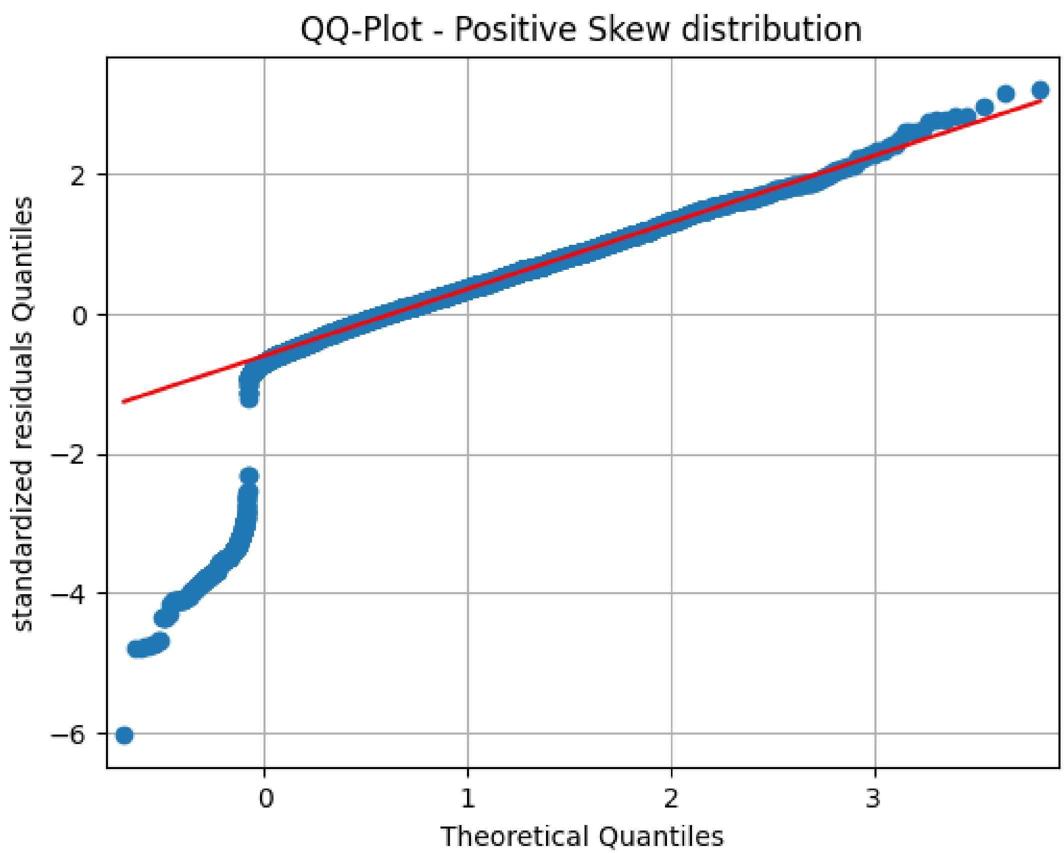
[ ]:
```
fig = sm.qqplot(std_residual, dist=uniform, line="q")
plt.ylabel("standardized residuals Quantiles")
plt.title("QQ-Plot - uniform distribution")
plt.grid()
```



[ ]:
```
fig = sm.qqplot(std_residual, skewnorm(-4), line="q")
plt.ylabel("standardized residuals Quantiles")
plt.title("QQ-Plot - Negative Skew distribution")
plt.grid()
```



[ ]:
```
fig = sm.qqplot(std_residual, skewnorm(4), line="q")
plt.ylabel("standardized residuals Quantiles")
plt.title("QQ-Plot - Positive Skew distribution")
plt.grid()
```



[ ]:
```
OLS(x_fcct, y_root)
```

```
Params: const                                  13.419645
Fuel Consumption City (L/100 km)      0.408706
dtype: float64
R^2: 0.844322646434444
```

[ ]:
```
OLS(x_fcct, y_log)
```

```
Params: const                                  2.296990
Fuel Consumption City (L/100 km)     0.018955
dtype: float64
R^2: 0.836968070475829
```

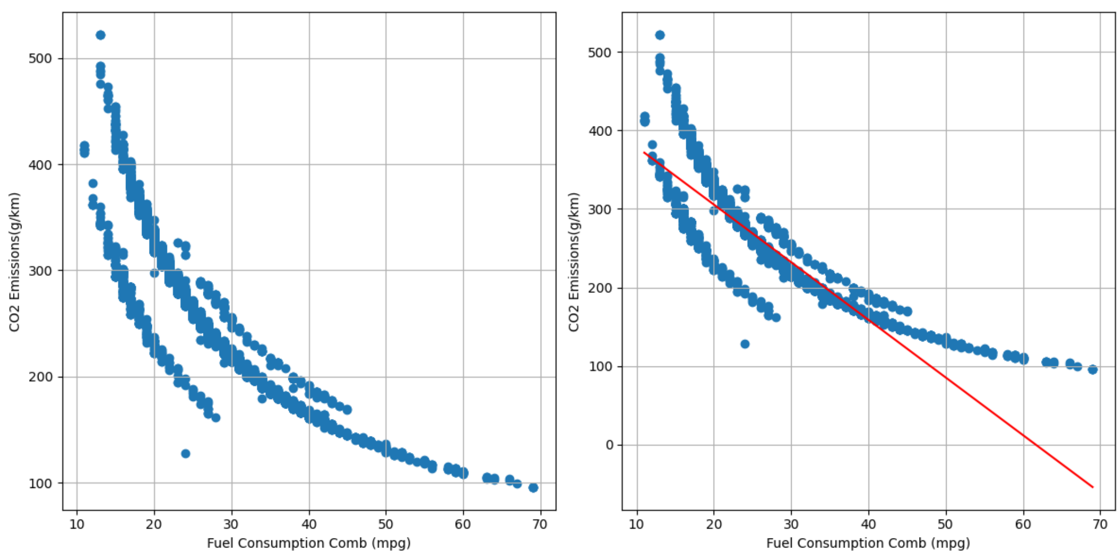
1.5 Fuel Consumption Comb (mpg)

[ ]:
```
x_fcc = df['Fuel Consumption Comb (mpg)']
X_fcc = sm.add_constant(x_fcc)
model = sm.OLS(y,X_fcc)
result = model.fit()
```

```
print(result.params)
print("\nR2: ", result.rsquared)
```

```
const                             452.353036
Fuel Consumption Comb (mpg)        -7.341929
dtype: float64

R2:  0.8234224657110062
```

[ ]:
```
plt.figure(figsize=(12, 6))
plt_scatter(x_fcc, y, 'Fuel Consumption Comb (mpg)', 'CO2 Emissions(g/km)')
plt_scatter_w_line(x_fcc, y, result.params[0], result.params[1], 'Fuel␣
 ↪Consumption Comb (mpg)', 'CO2 Emissions(g/km)')
plt.tight_layout()
plt.show()
```



[ ]:
```
print(result.summary())
```

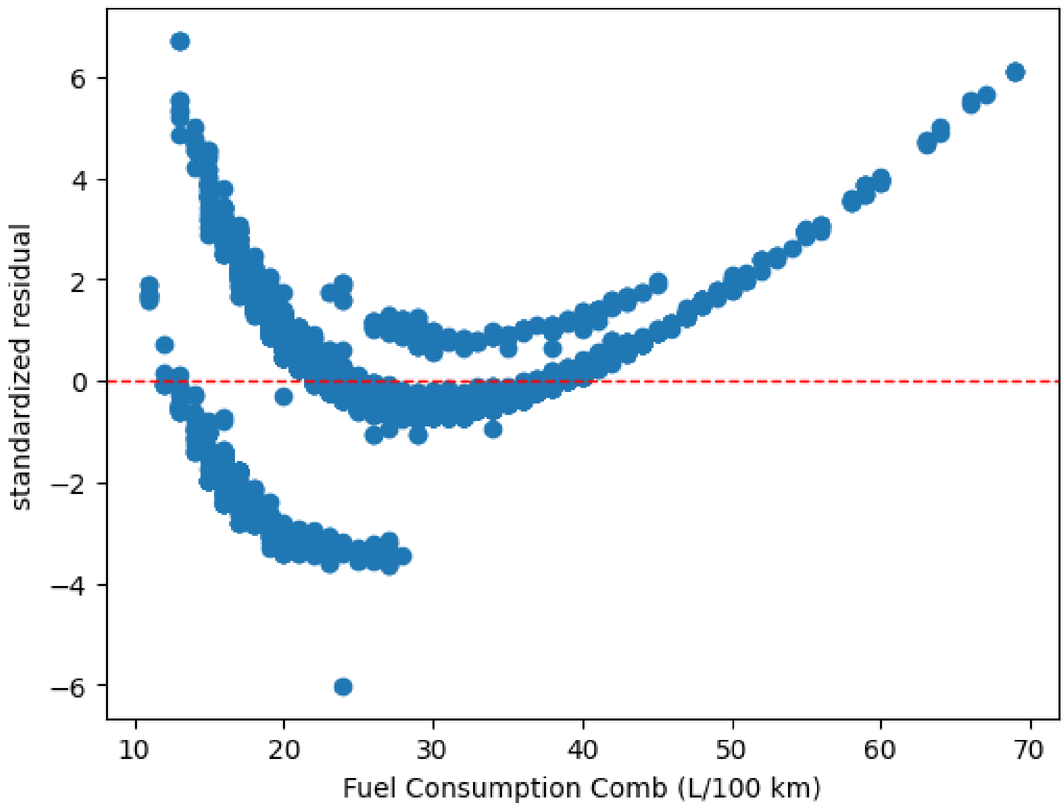
```
                            OLS Regression Results
==============================================================================
Dep. Variable:     CO2 Emissions(g/km)   R-squared:                       0.823
Model:                             OLS   Adj. R-squared:                  0.823
Method:                  Least Squares   F-statistic:                 3.443e+04
Date:                 Sat, 07 Oct 2023   Prob (F-statistic):               0.00
Time:                         02:13:29   Log-Likelihood:                -34127.
No. Observations:                 7385   AIC:                         6.826e+04
Df Residuals:                     7383   BIC:                         6.827e+04
Df Model:                            1
Covariance Type:             nonrobust
```

```
================================================================================
===============
                                  coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------------------
---------------
const                         452.3530      1.124    402.297      0.000
450.149     454.557
Fuel Consumption Comb (mpg)    -7.3419      0.040   -185.550      0.000
-7.419      -7.264
==============================================================================
Omnibus:                     1935.010   Durbin-Watson:                   1.326
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            13170.162
Skew:                           1.080   Prob(JB):                         0.00
Kurtosis:                       9.176   Cond. No.                         112.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

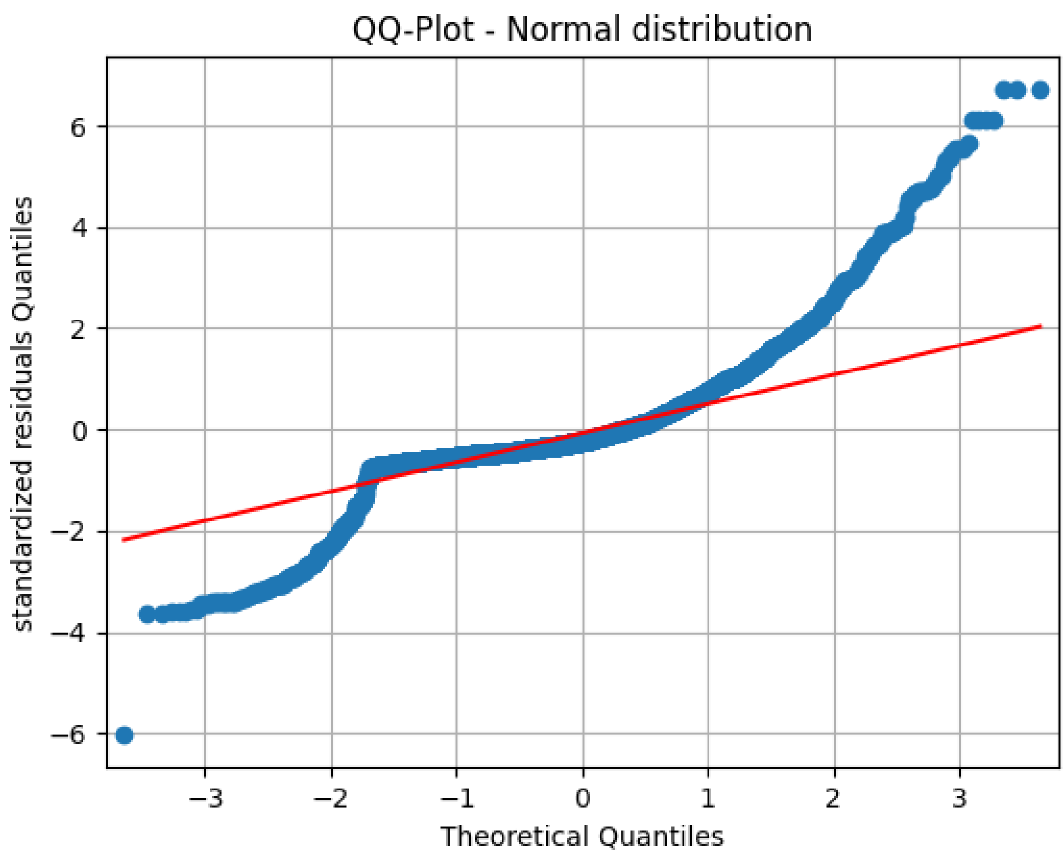
[ ]:
```python
influence = result.get_influence()
std_residual = influence.resid_studentized_internal
print(std_residual)
```

```
[-0.57223492 -0.74985292  1.46736968 … -0.57431008 -0.30247323
 -0.54754722]
```

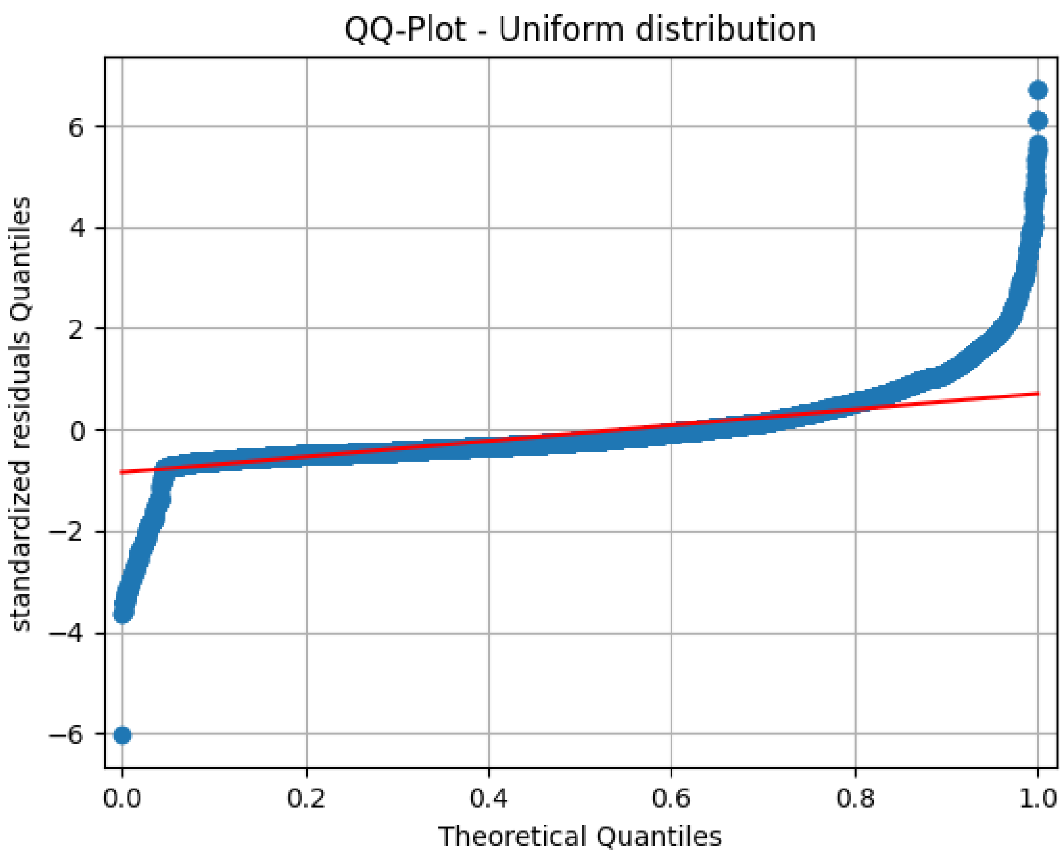
[ ]:
```python
plt.scatter(x_fcc, std_residual)
plt.xlabel('Fuel Consumption Comb (L/100 km)')
plt.ylabel('standardized residual')
plt.axhline(y=0, color='red', linestyle='--', linewidth=1)
plt.show()
```



[ ]:
```
fig = sm.qqplot(std_residual, dist=norm, line="q")
plt.ylabel("standardized residuals Quantiles")
plt.title("QQ-Plot - Normal distribution")
plt.grid()
```

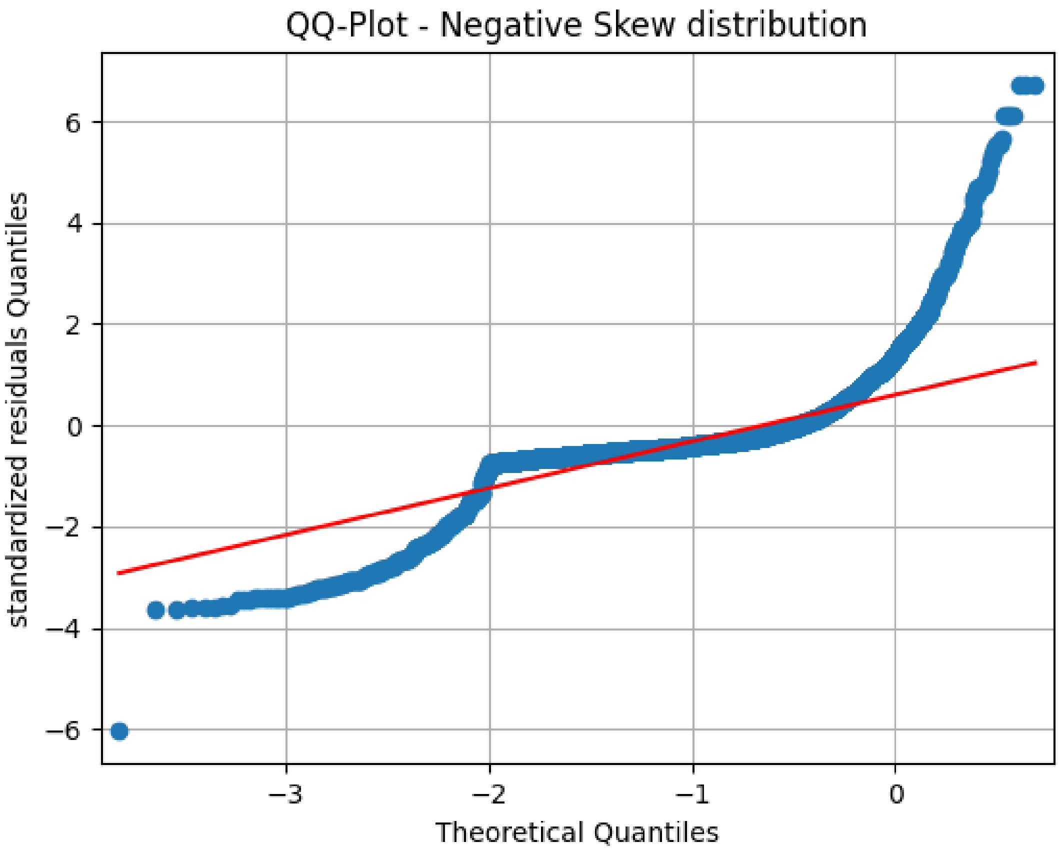


[ ]:
```
fig = sm.qqplot(std_residual, dist=uniform, line="q")
plt.ylabel("standardized residuals Quantiles")
plt.title("QQ-Plot - Uniform distribution")
plt.grid()
```

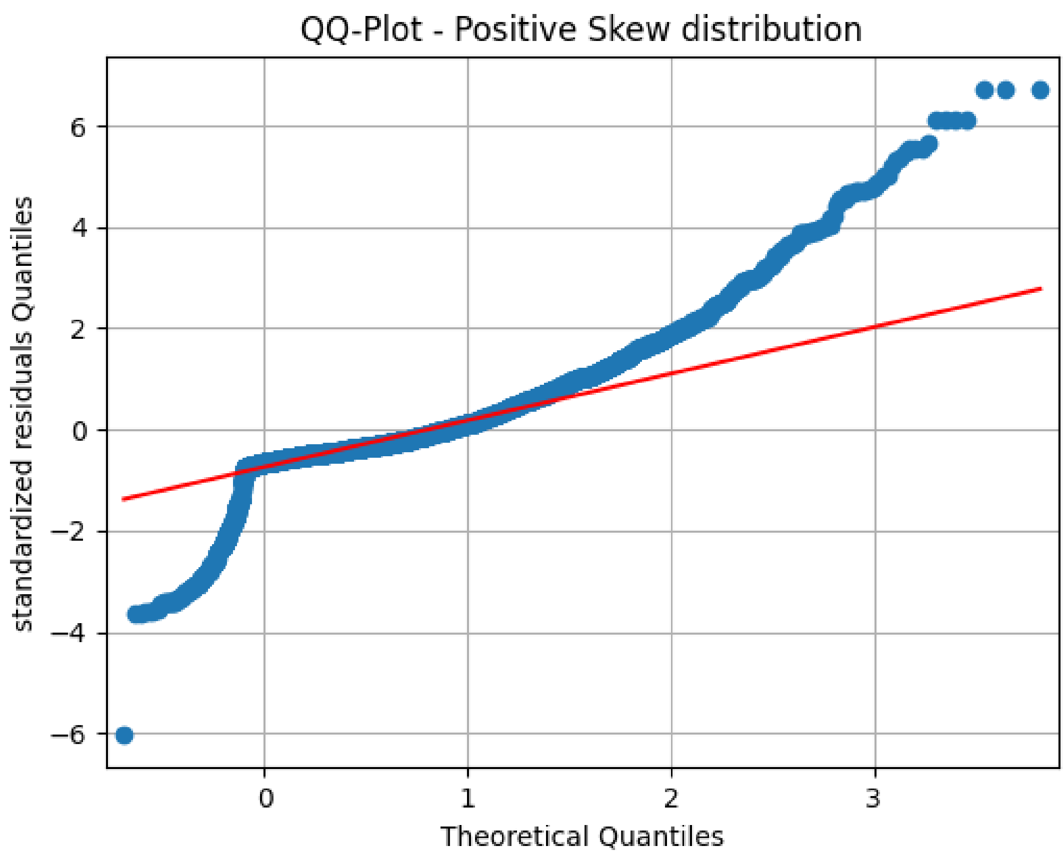


[ ]:

```
fig = sm.qqplot(std_residual, skewnorm(-4), line="q")
plt.ylabel("standardized residuals Quantiles")
plt.title("QQ-Plot - Negative Skew distribution")
plt.grid()
```



[ ]:
```python
fig = sm.qqplot(std_residual, skewnorm(4), line="q")
plt.ylabel("standardized residuals Quantiles")
plt.title("QQ-Plot - Positive Skew distribution")
plt.grid()
```



[ ]:
```
OLS(x_fcc, y_root)
```

```
Params: const                             24.024339
Fuel Consumption Comb (mpg)    -0.199142
dtype: float64
R^2: 0.8556794221893714
```

[ ]:
```
OLS(x_fcc, y_log)
```

```
Params: const                             2.793990
Fuel Consumption Comb (mpg)   -0.009424
dtype: float64
R^2: 0.8831148871092463
```

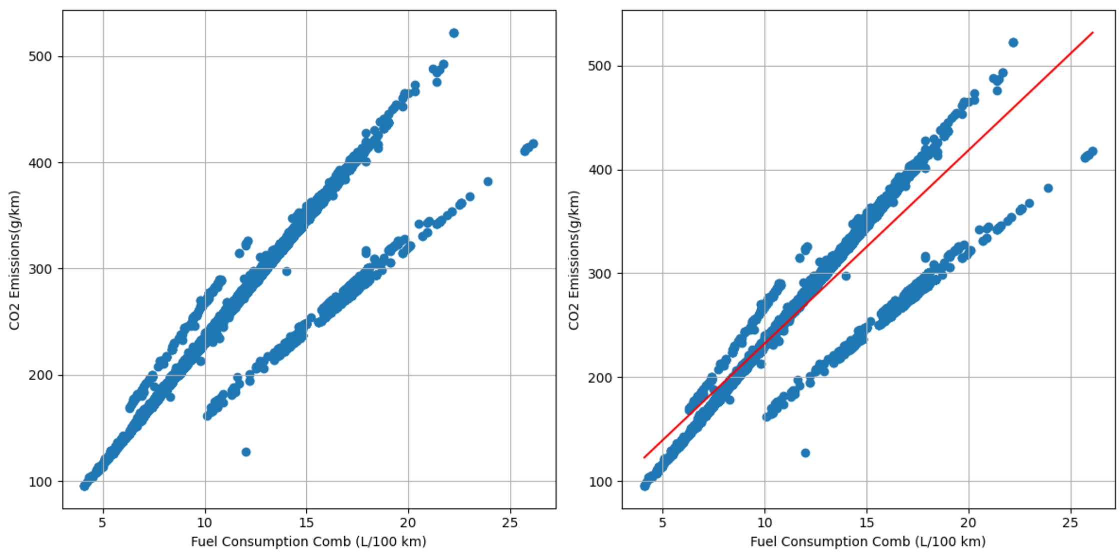
1.6 Fuel Consumption Comb (L/100 km)

[ ]:
```
x_fccl = df['Fuel Consumption Comb (L/100 km)']
X_fccl = sm.add_constant(x_fccl)
model = sm.OLS(y,X_fccl)
result = model.fit()
```

```
print(result.params)
print("\nR2: ", result.rsquared)
```

```
const                                46.763152
Fuel Consumption Comb (L/100 km)     18.571319
dtype: float64

R2:  0.8428186895623988
```

[ ]:
```
plt.figure(figsize=(12, 6))
plt_scatter(x_fccl, y, 'Fuel Consumption Comb (L/100 km)', 'CO2 Emissions(g/
↪km)')
plt_scatter_w_line(x_fccl, y, result.params[0], result.params[1], 'Fuel␣
↪Consumption Comb (L/100 km)', 'CO2 Emissions(g/km)')
plt.tight_layout()
plt.show()
```



[ ]:
```
print(result.summary())
```

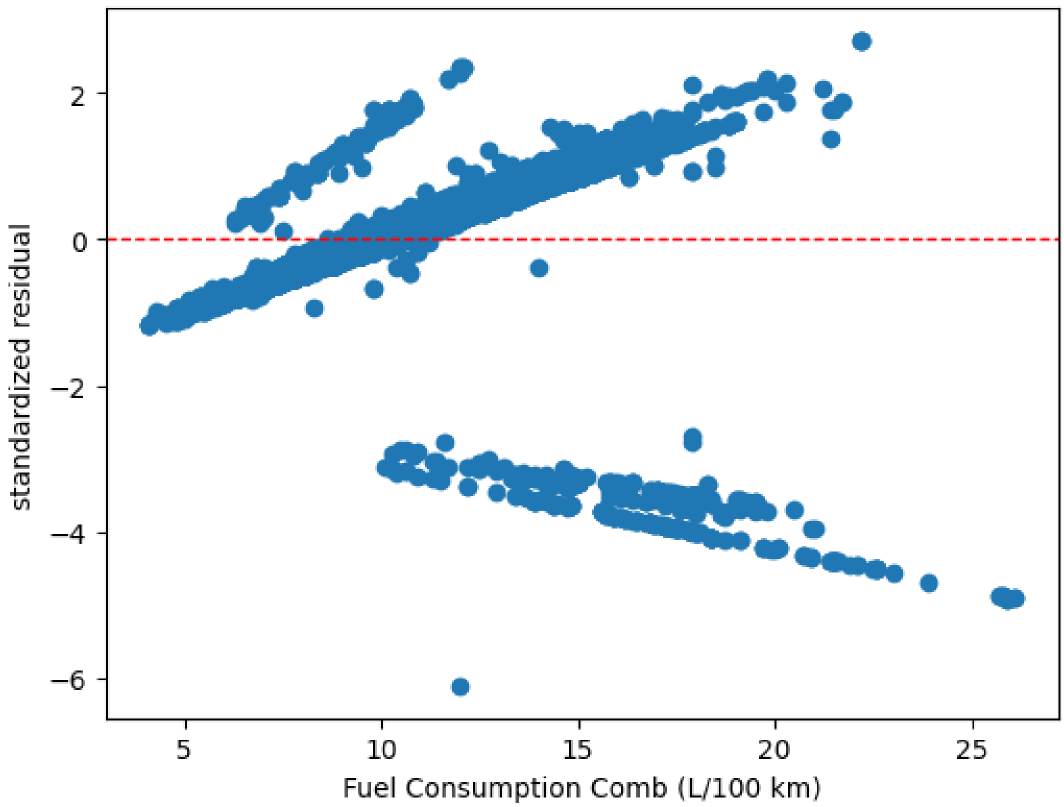
```
                            OLS Regression Results
==============================================================================
Dep. Variable:     CO2 Emissions(g/km)   R-squared:                       0.843
Model:                             OLS   Adj. R-squared:                  0.843
Method:                  Least Squares   F-statistic:                 3.959e+04
Date:                 Sat, 07 Oct 2023   Prob (F-statistic):               0.00
Time:                         02:13:27   Log-Likelihood:                -33697.
No. Observations:                 7385   AIC:                         6.740e+04
Df Residuals:                     7383   BIC:                         6.741e+04
Df Model:                            1
```

```
Covariance Type:            nonrobust
================================================================================
====================
                                        coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------------------
--------------------
const                                46.7632      1.059     44.142      0.000
44.686      48.840
Fuel Consumption Comb (L/100 km)    18.5713      0.093    198.968      0.000
18.388      18.754
==============================================================================
Omnibus:                     3592.018   Durbin-Watson:                   1.986
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            22309.895
Skew:                          -2.290   Prob(JB):                         0.00
Kurtosis:                      10.178   Cond. No.                         44.9
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

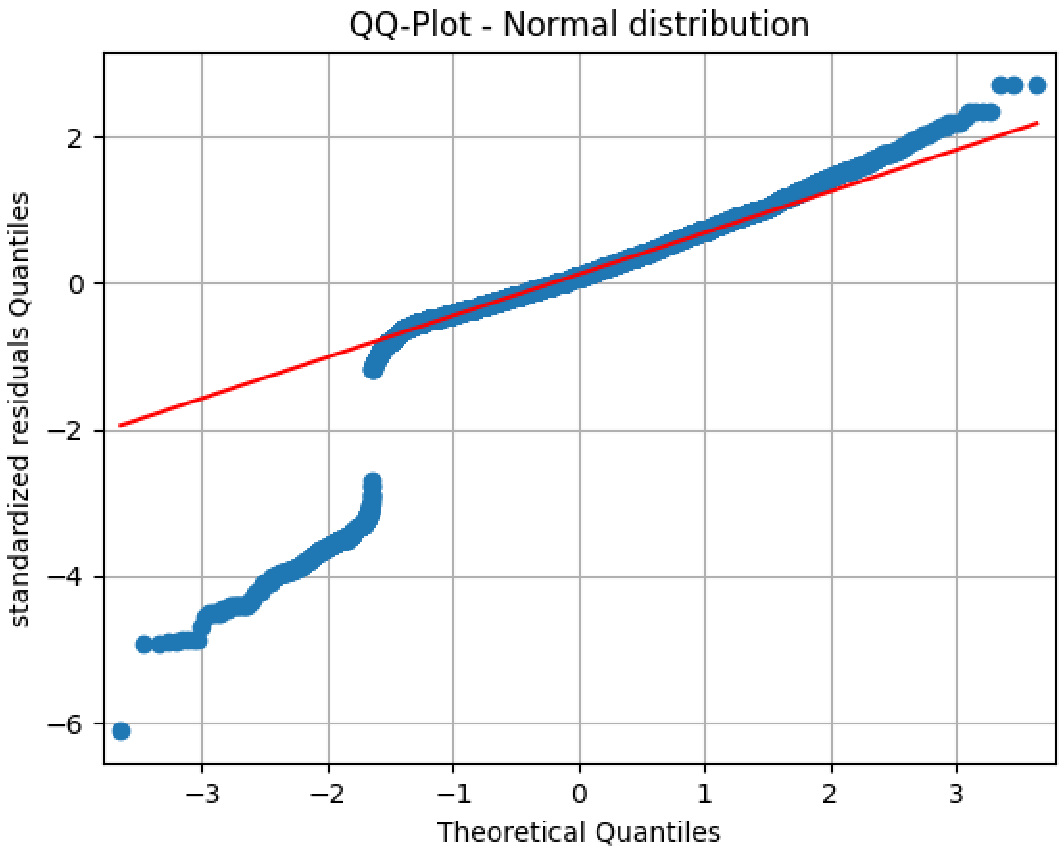
[ ]:
```
influence = result.get_influence()
std_residual = influence.resid_studentized_internal
print(std_residual)
```

```
[-0.37157485 -0.17449253 -0.87672126 …  0.0841568   0.05952249
  0.10879112]
```

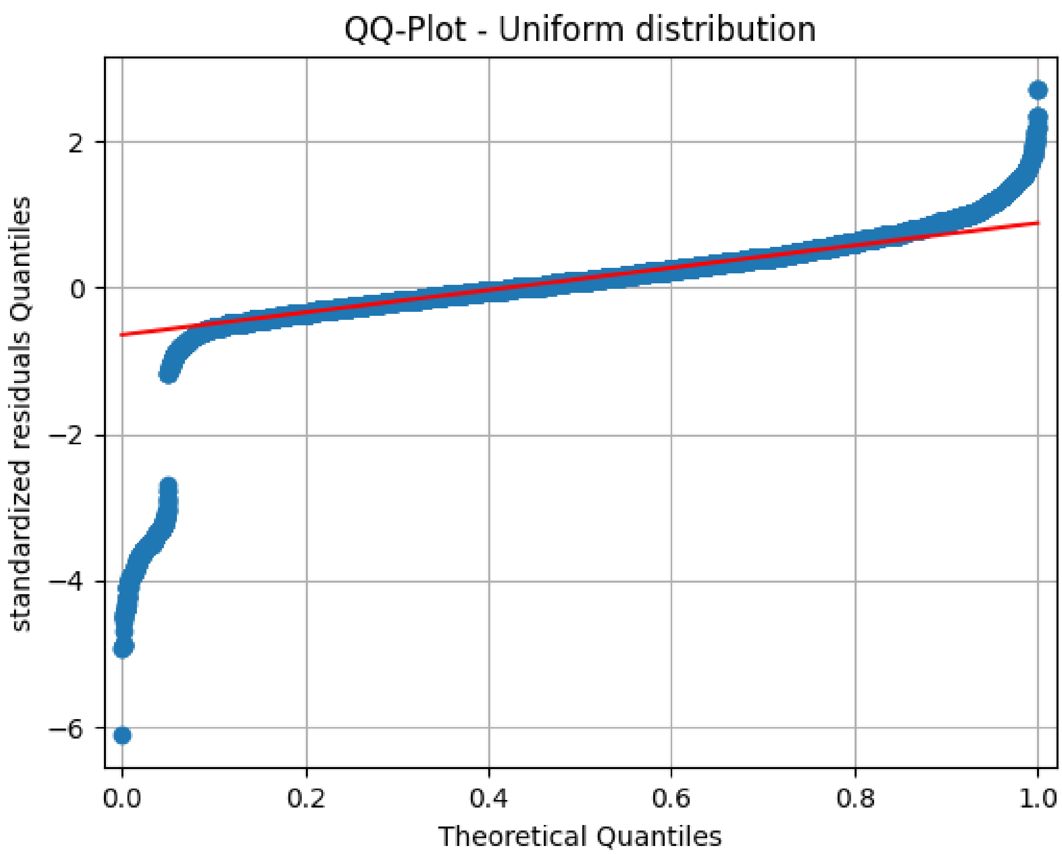
[ ]:
```
plt.scatter(df['Fuel Consumption Comb (L/100 km)'], std_residual)
plt.xlabel('Fuel Consumption Comb (L/100 km)')
plt.ylabel('standardized residual')
plt.axhline(y=0, color='red', linestyle='--', linewidth=1)
plt.show()
```



[ ]:
```
fig = sm.qqplot(std_residual, dist=norm, line="q")
plt.ylabel("standardized residuals Quantiles")
plt.title("QQ-Plot - Normal distribution")
plt.grid()
```

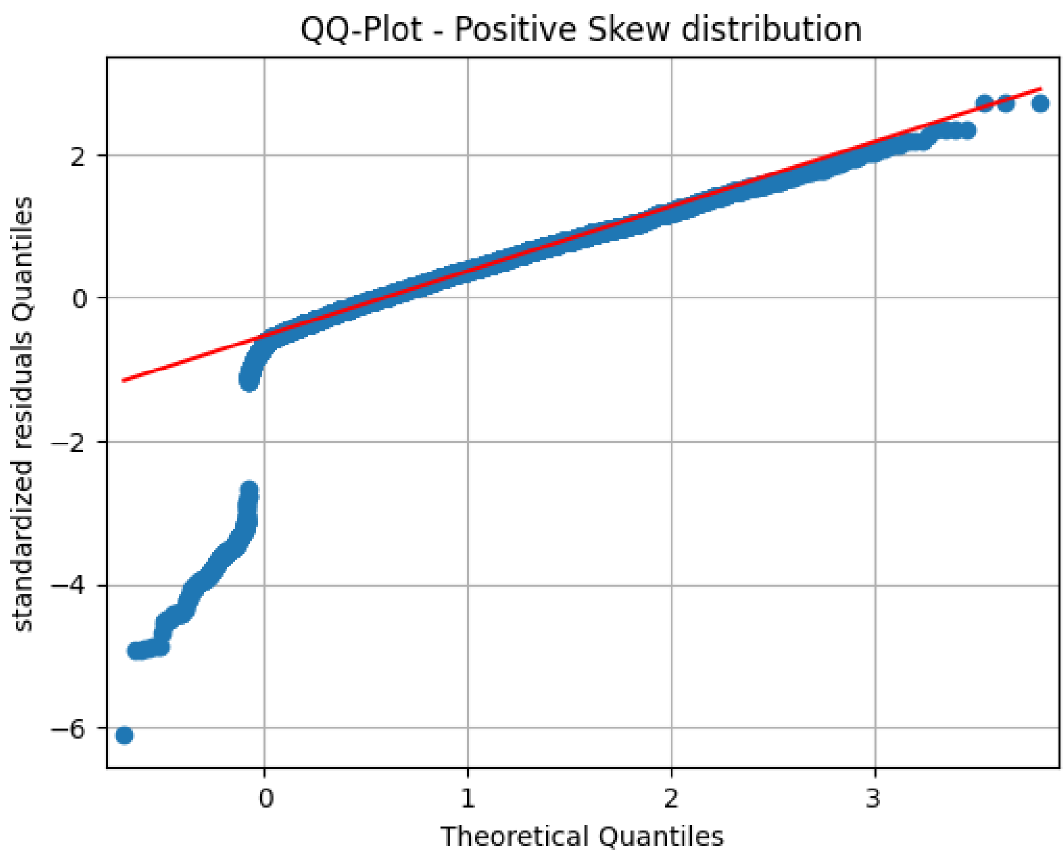


[ ]:
```
fig = sm.qqplot(std_residual, dist=uniform, line="q")
plt.ylabel("standardized residuals Quantiles")
plt.title("QQ-Plot - Uniform distribution")
plt.grid()
```




```
[ ]: fig = sm.qqplot(std_residual, skewnorm(-4), line="q")
     plt.ylabel("standardized residuals Quantiles")
     plt.title("QQ-Plot - Negative Skew distribution")
     plt.grid()
```


```
[ ]: fig = sm.qqplot(std_residual, skewnorm(4), line="q")
     plt.ylabel("standardized residuals Quantiles")
     plt.title("QQ-Plot - Positive Skew distribution")
     plt.grid()
```



[ ]:
```
OLS(x_fccl, y_root)
```

```
Params: const                              13.134986
Fuel Consumption Comb (L/100 km)     0.493536
dtype: float64
R^2: 0.8407523790886398
```

[ ]:
```
OLS(x_fccl, y_log)
```

```
Params: const                              2.283923
Fuel Consumption Comb (L/100 km)    0.022877
dtype: float64
R^2: 0.8325284987248827
```