co2_emissions

October 25, 2025

[221]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import PolynomialFeatures
import warnings
warnings.filterwarnings('ignore')
```

[222]:
```
co2_emissions = pd.read_csv('CO2_Emissions.csv')
co2_emissions.head()
```

[222]:
```
    Make       Model Vehicle Class    Engine Size(L)  Cylinders Transmission  \
0  ACURA         ILX       COMPACT 2.000000000000000          4          AS5
1  ACURA         ILX       COMPACT 2.400000000000000          4           M6
2  ACURA  ILX HYBRID       COMPACT 1.500000000000000          4          AV7
3  ACURA     MDX 4WD   SUV - SMALL 3.500000000000000          6          AS6
4  ACURA     RDX AWD   SUV - SMALL 3.500000000000000          6          AS6

  Fuel Type  Fuel Consumption City (L/100 km)  \
0         Z                 9.900000000000000
1         Z                11.199999999999999
2         Z                 6.000000000000000
3         Z                12.699999999999999
4         Z                12.100000000000000

   Fuel Consumption Hwy (L/100 km)  Fuel Consumption Comb (L/100 km)  \
0                6.700000000000000                 8.500000000000000
1                7.700000000000000                 9.600000000000000
2                5.800000000000000                 5.900000000000000
3                9.100000000000000                11.100000000000000
4                8.699999999999999                10.600000000000000

   Fuel Consumption Comb (mpg)  CO2 Emissions(g/km)
```

```
0                            33                   196
1                            29                   221
2                            48                   136
3                            25                   255
4                            27                   244
```

[223]:
```python
co2_emissions.shape
```

[223]:
```
(7385, 12)
```

[224]:
```python
co2_emissions.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7385 entries, 0 to 7384
Data columns (total 12 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   Make                              7385 non-null   object
 1   Model                             7385 non-null   object
 2   Vehicle Class                     7385 non-null   object
 3   Engine Size(L)                    7385 non-null   float64
 4   Cylinders                         7385 non-null   int64
 5   Transmission                      7385 non-null   object
 6   Fuel Type                         7385 non-null   object
 7   Fuel Consumption City (L/100 km)  7385 non-null   float64
 8   Fuel Consumption Hwy (L/100 km)   7385 non-null   float64
 9   Fuel Consumption Comb (L/100 km)  7385 non-null   float64
 10  Fuel Consumption Comb (mpg)       7385 non-null   int64
 11  CO2 Emissions(g/km)               7385 non-null   int64
dtypes: float64(4), int64(3), object(5)
memory usage: 692.5+ KB
```

[225]:
```python
co2_emissions.isna().sum()
```

[225]:
```
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
```

- All the columns are in correct data type

- There are no null values in the dataset

[226]:
```
co2_emissions.duplicated().sum()
```

[226]:
```
1103
```

- There are 1103 duplicated rows, we need to drop duplicate rows

[227]:
```
co2_emissions = co2_emissions.drop_duplicates(keep="first")
co2_emissions.shape
```

[227]:
```
(6282, 12)
```

[228]:
```
for c in co2_emissions.select_dtypes(include=['object']):
    print(c,co2_emissions[c].nunique())
```

```
Make 42
Model 2053
Vehicle Class 16
Transmission 27
Fuel Type 5
```

[229]:
```
co2_emissions.describe()
```

[229]:
```
            Engine Size(L)            Cylinders  \
count 6282.000000000000000 6282.000000000000000
mean     3.161811524992040    5.618911174785100
std      1.365201322627847    1.846250491573830
min      0.900000000000000    3.000000000000000
25%      2.000000000000000    4.000000000000000
50%      3.000000000000000    6.000000000000000
75%      3.700000000000000    6.000000000000000
max      8.400000000000000   16.000000000000000

       Fuel Consumption City (L/100 km)  Fuel Consumption Hwy (L/100 km)  \
count              6282.000000000000000             6282.000000000000000
mean                 12.610219675262654                9.070582617000953
std                   3.553066308659997                2.278884321464437
min                   4.200000000000000                4.000000000000000
25%                  10.100000000000000                7.500000000000000
50%                  12.100000000000000                8.699999999999999
75%                  14.699999999999999               10.300000000000001
max                  30.600000000000001               20.600000000000001

       Fuel Consumption Comb (L/100 km)  Fuel Consumption Comb (mpg)  \
count              6282.000000000000000         6282.000000000000000
mean                 11.017876472460999           27.411015600127350
std                   2.946875663766868            7.245317652179628
min                   4.100000000000000           11.000000000000000
```

```
25%                    8.900000000000000          22.000000000000000
50%                   10.600000000000000          27.000000000000000
75%                   12.699999999999999          32.000000000000000
max                   26.100000000000001          69.000000000000000

       CO2 Emissions(g/km)
count 6282.000000000000000
mean   251.157752308182097
std     59.290426441732635
min     96.000000000000000
25%    208.000000000000000
50%    246.000000000000000
75%    289.000000000000000
max    522.000000000000000
```

- All numeric columns doesn't have values <= 0, there are no null values too

[230]:
```python
co2_emissions['Make'].value_counts()
```

[230]:
```
Make
FORD             577
CHEVROLET        515
BMW              501
MERCEDES-BENZ    365
PORSCHE          296
GMC              289
TOYOTA           276
AUDI             263
NISSAN           213
MINI             200
JEEP             200
KIA              192
VOLKSWAGEN       187
HYUNDAI          184
DODGE            180
HONDA            164
CADILLAC         141
LEXUS            129
MAZDA            127
SUBARU           119
JAGUAR           118
VOLVO            118
BUICK             92
INFINITI          87
LINCOLN           81
LAND ROVER        76
MITSUBISHI        73
RAM               72
```

```
CHRYSLER          64
FIAT              56
MASERATI          52
ACURA             51
ROLLS-ROYCE       48
ASTON MARTIN      39
LAMBORGHINI       37
BENTLEY           35
SCION             21
ALFA ROMEO        19
GENESIS           14
SMART              7
SRT                2
BUGATTI            2
Name: count, dtype: int64
```

- All car names are in correct format without any spelling mistake or redundancy

[231]:
```python
co2_emissions['Vehicle Class'].value_counts()
```

[231]:
```
Vehicle Class
SUV - SMALL                 1006
MID-SIZE                     983
COMPACT                      903
SUV - STANDARD               613
SUBCOMPACT                   533
FULL-SIZE                    508
PICKUP TRUCK - STANDARD      475
TWO-SEATER                   381
MINICOMPACT                  274
STATION WAGON - SMALL        214
PICKUP TRUCK - SMALL         133
VAN - PASSENGER               66
SPECIAL PURPOSE VEHICLE       65
MINIVAN                       61
STATION WAGON - MID-SIZE      45
VAN - CARGO                   22
Name: count, dtype: int64
```

[232]:
```python
co2_emissions['Transmission'].value_counts()
```

[232]:
```
Transmission
AS6     1139
AS8     1056
M6       773
A6       684
AM7      383
A8       378
```

```
AS7      283
A9       263
AV       241
M5       168
AS10     151
AM6      107
AV7       92
AV6       89
A5        78
M7        78
AS9       65
A4        61
AM8       45
A7        44
AV8       34
A10       28
AS5       26
AV10       9
AM5        4
AS4        2
AM9        1
Name: count, dtype: int64
```

[233]:
```
co2_emissions['Fuel Type'].value_counts()
```

[233]:
```
Fuel Type
X    3039
Z    2765
E     330
D     147
N       1
Name: count, dtype: int64
```

- Replaced codes X, Z, D, E, N with their names for better readability

[234]:
```
co2_emissions.head()
```

[234]:
```
    Make       Model  Vehicle Class    Engine Size(L)  Cylinders Transmission  \
0  ACURA         ILX        COMPACT 2.000000000000000          4          AS5
1  ACURA         ILX        COMPACT 2.400000000000000          4           M6
2  ACURA  ILX HYBRID        COMPACT 1.500000000000000          4          AV7
3  ACURA     MDX 4WD    SUV - SMALL 3.500000000000000          6          AS6
4  ACURA     RDX AWD    SUV - SMALL 3.500000000000000          6          AS6

  Fuel Type  Fuel Consumption City (L/100 km)  \
0         Z                 9.900000000000000
1         Z                11.199999999999999
2         Z                 6.000000000000000
```

```
3         Z                12.699999999999999
4         Z                12.100000000000000

   Fuel Consumption Hwy (L/100 km)  Fuel Consumption Comb (L/100 km)  \
0                6.700000000000000                 8.500000000000000
1                7.700000000000000                 9.600000000000000
2                5.800000000000000                 5.900000000000000
3                9.100000000000000                11.100000000000000
4                8.699999999999999                10.600000000000000

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

[235]:
```python
co2_emissions.Model.nunique()
```

[235]: 2053

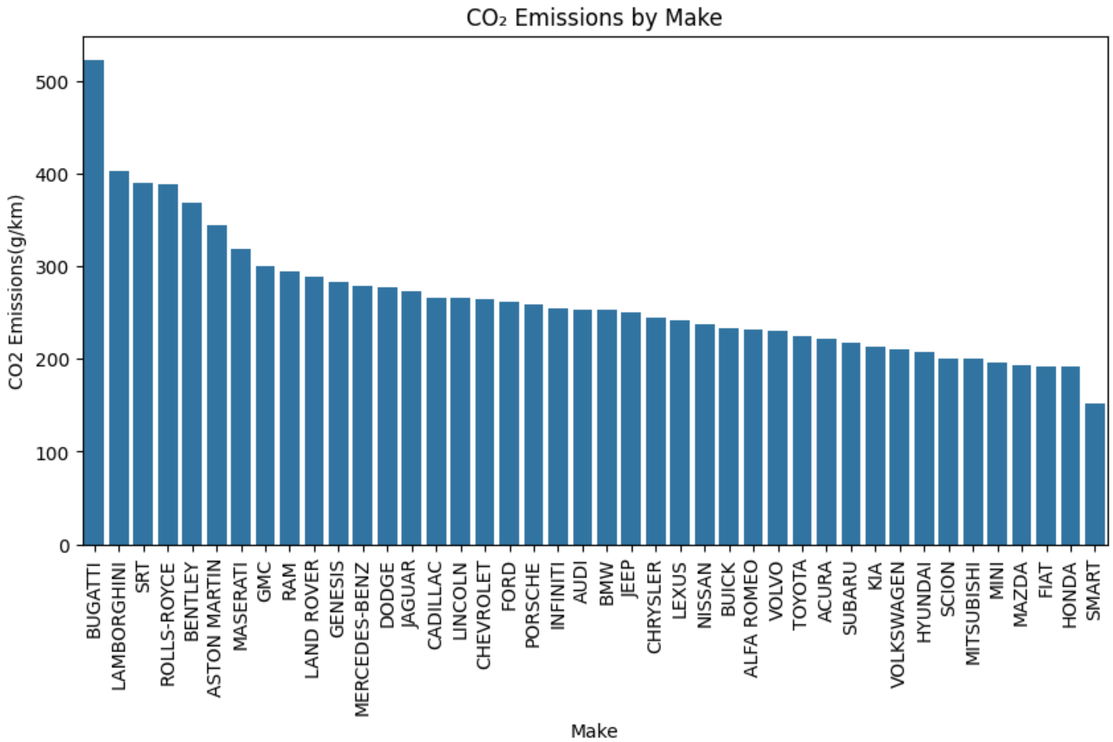
0.0.1 2. Examine the dataset for any inconsistencies, missing entries, or data quality issues. Consider what preprocessing steps may be necessary to make the dataset ready for meaningful analysis.

- The Model column (2053 unique values) is highly redundant with Vehicle Class, as most models belong to a single class, so the vehicle class already captures the majority of the structural and functional information relevant to CO emissions. Keeping it would greatly increase dimensionality without adding significant predictive value. Dropping it simplifies the pipeline, reduces overfitting risk, and retains essential information through other features.
- One hot encoding should be done for Make, Vehicle Class, Fuel Type, Transmission
- Replace code present in fuel type column with Actual fuel type name for interpretability
- Standardise the numerical columns Engine size, Cylinders, Fuel Consumption city, Fuel Consumption Hwy, Fuel Consumption Comb, Fuel Consumption Comb mpg, CO2 emissions

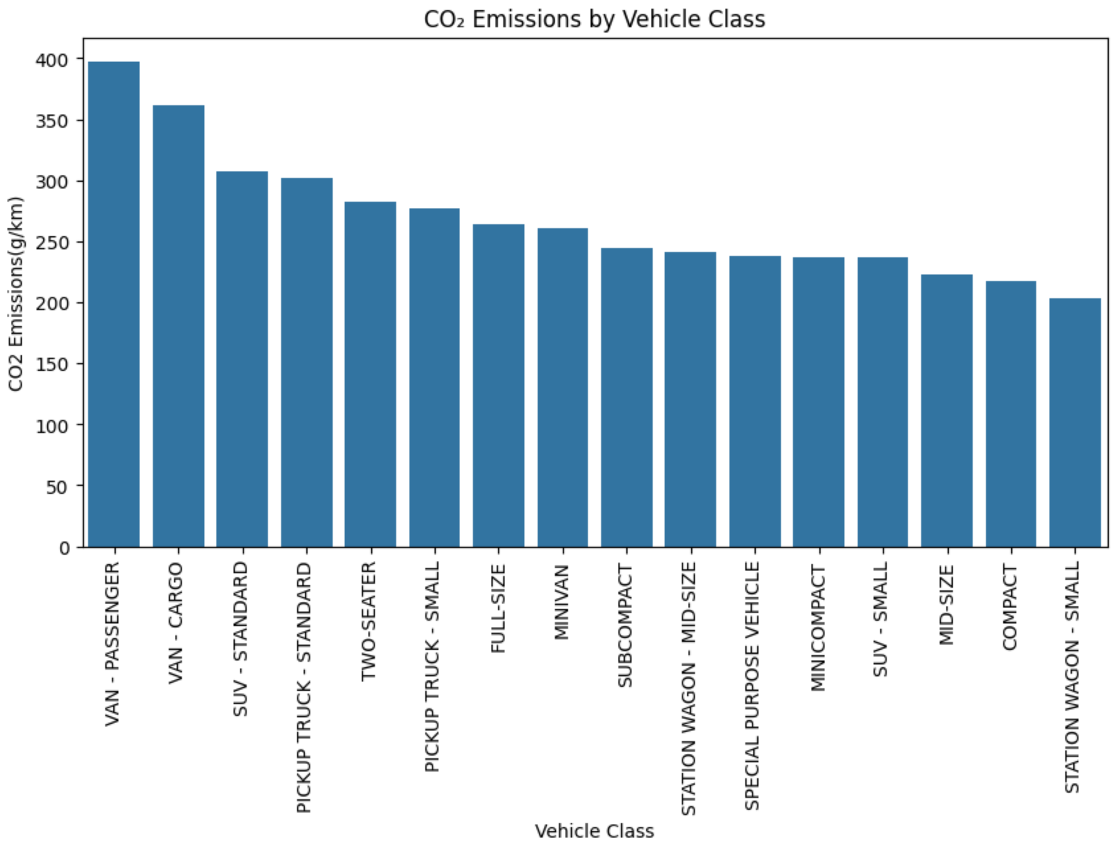
0.0.2 3. Study the relationships between various vehicle features and CO emissions. Which attributes appear to have stronger influence on emission levels? Use suitable methods to support your reasoning.

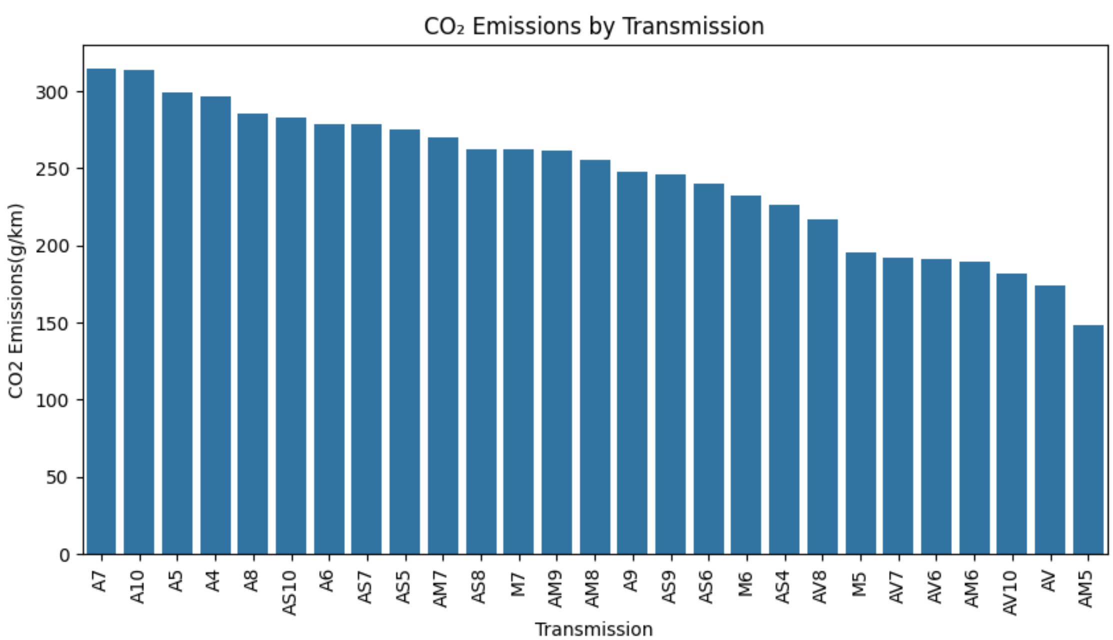
[236]:
```python
categorical_features = ['Make','Vehicle Class', 'Transmission', 'Fuel Type']

for col in categorical_features:
    col_avg_co2_emissions = co2_emissions.groupby(col)['CO2 Emissions(g/km)'].
↪mean().reset_index().sort_values(by='CO2 Emissions(g/km)',ascending=False)
    plt.figure(figsize=(10, 5))
    sns.barplot(x=col, y='CO2 Emissions(g/km)', data=col_avg_co2_emissions)
    plt.xticks(rotation=90)
    plt.title(f'CO  Emissions by {col}')
```

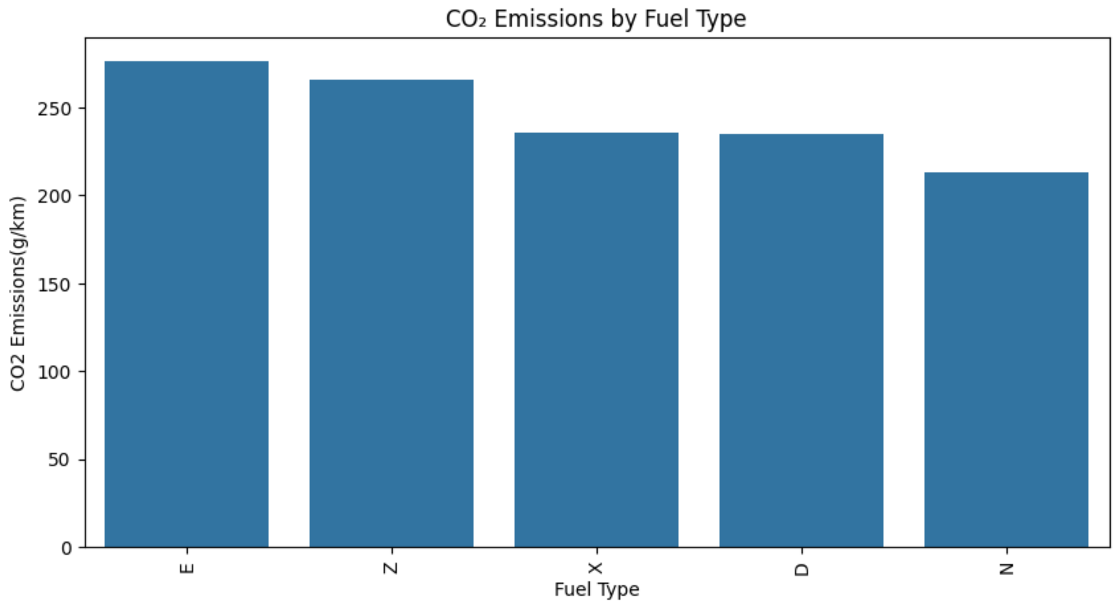
```
plt.show()
```



CO₂ Emissions by Make
CO2 Emissions(g/km)
0
100
200
300
400
500
BUGATTI
LAMBORGHINI
SRT
ROLLS-ROYCE
BENTLEY
ASTON MARTIN
MASERATI
GMC
RAM
LAND ROVER
GENESIS
MERCEDES-BENZ
DODGE
JAGUAR
CADILLAC
LINCOLN
CHEVROLET
FORD
PORSCHE
INFINITI
AUDI
BMW
JEEP
CHRYSLER
LEXUS
NISSAN
BUICK
ALFA ROMEO
VOLVO
TOYOTA
ACURA
SUBARU
KIA
VOLKSWAGEN
HYUNDAI
SCION
MITSUBISHI
MINI
MAZDA
FIAT
HONDA
SMART
Make


CO₂ Emissions by Vehicle Class
CO2 Emissions(g/km)
0
50
100
150
200
250
300
350
400
VAN - PASSENGER
VAN - CARGO
SUV - STANDARD
PICKUP TRUCK - STANDARD
TWO-SEATER
PICKUP TRUCK - SMALL
FULL-SIZE
MINIVAN
SUBCOMPACT
STATION WAGON - MID-SIZE
SPECIAL PURPOSE VEHICLE
MINICOMPACT
SUV - SMALL
MID-SIZE
COMPACT
STATION WAGON - SMALL
Vehicle Class


CO₂ Emissions by Transmission
CO2 Emissions(g/km)
0
50
100
150
200
250
300
A7
A10
A5
A4
A8
AS10
A6
AS7
AS5
AM7
AS8
M7
AM9
AM8
A9
AS9
AS6
M6
AS4
AV8
M5
AV7
AV6
AM6
AV10
AV
AM5
Transmission



- **Make** - High-performance and luxury brands (Bugatti, Lamborghini, Bentley, Rolls-Royce) show substantially higher CO emissions due to large, high-power engines. In contrast, efficiency-focused manufacturers (Honda, Hyundai, Mazda) produce lower-emission vehicles.
- **Vehicle Class** - One of the strongest categorical influences — larger and heavier vehicles such as SUVs, Vans, and Pickup Trucks emit significantly more CO , whereas compact and subcompact cars are much more fuel-efficient.
- **Transmission** - Vehicles with traditional automatic transmissions (A4–A7) tend to emit more CO , while modern systems like automated manuals (AM5) and CVTs (AV, AV10) show reduced emissions, reflecting efficiency improvements through technology.
- **Fuel Type** - Regular Gasoline (X) And Diesel vehicles exhibit the lowest average CO2 emissions, reflecting higher efficiency. In contrast, Ethanol and Premium Gasoline vehicles tend to emit more CO on average. While the single Natural Gas entry is insufficient for analysis.

[237]:
```
car_numeric = co2_emissions.select_dtypes(include=['float64','int64'])
corr_matrix = car_numeric.corr()
plt.figure(figsize=(16,8))
sns.heatmap(corr_matrix, cmap="YlGnBu", annot=True)
plt.show()
```

- The heatmap reveals that fuel consumption variables show the strongest influence on CO emission levels, with correlation coefficients around 0.9–0.92. Specifically, Fuel Consumption Comb (L/100 km) is the most representative predictor of CO emissions, as it captures both city and highway efficiency. Engine Size (L) and Cylinders also exhibit strong positive correlations (~0.83–0.85), indicating that larger and multi-cylinder engines produce higher CO emissions. Conversely, Fuel Consumption Comb (mpg) has a strong negative correlation (−0.91), reaffirming the inverse relationship between fuel efficiency and emissions.
- Overall, fuel consumption efficiency is the primary driver of CO emissions, supported by strong linear correlations with numeric features. Among categorical factors, Vehicle Class and Fuel Type exert the strongest influence, followed by Transmission and Make.

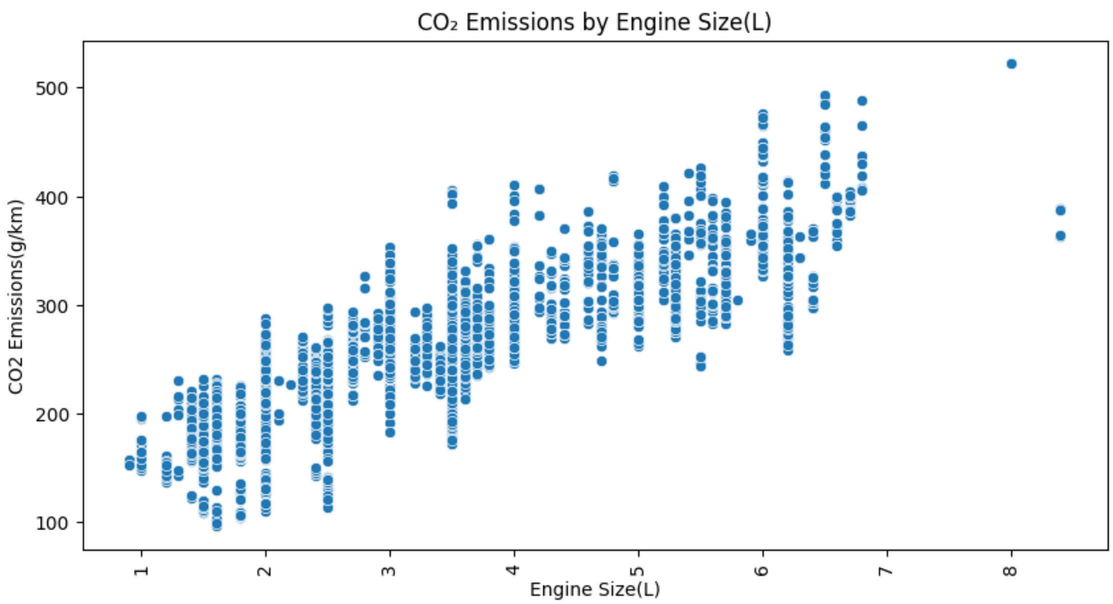
[238]:
```
co2_emissions.Transmission.nunique()
```

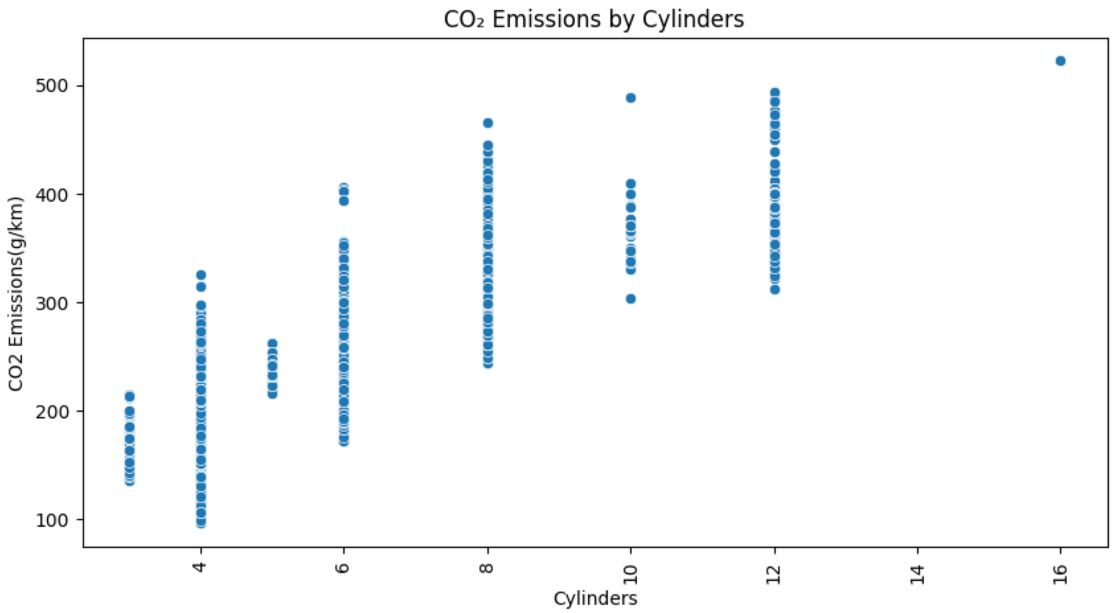
[238]: 27

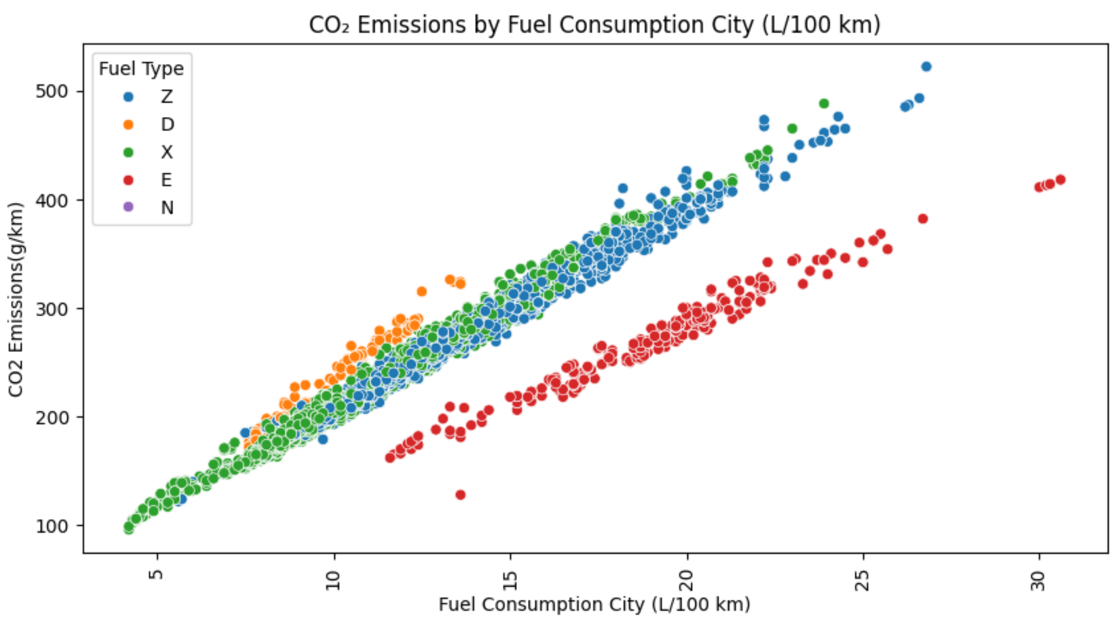
0.0.3 4. Create visual summaries that reveal how emission levels change with respect to different numerical variables in the dataset. Focus on uncovering patterns or trends that might not be immediately visible.

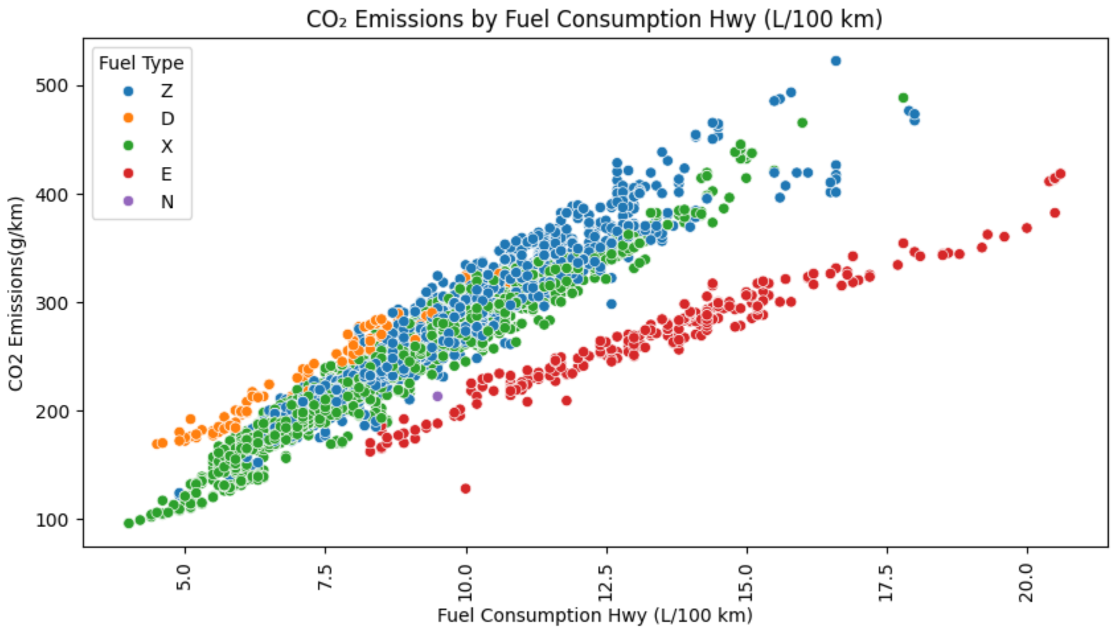
[239]:
```
numeric_columns = ['Engine Size(L)', 'Cylinders',
        'Fuel Consumption City (L/100 km)',
        'Fuel Consumption Hwy (L/100 km)', 'Fuel Consumption Comb (L/100 km)',
        'Fuel Consumption Comb (mpg)']
for col in numeric_columns:
```

```
    plt.figure(figsize=(10, 5))
    if col in ['Fuel Consumption City (L/100 km)',
       'Fuel Consumption Hwy (L/100 km)', 'Fuel Consumption Comb (L/100 km)',
       'Fuel Consumption Comb (mpg)']:
       sns.scatterplot(x=col, y='CO2 Emissions(g/km)',␣
↪data=co2_emissions,hue='Fuel Type')
    else:
       sns.scatterplot(x=col, y='CO2 Emissions(g/km)', data=co2_emissions)
    plt.xticks(rotation=90)
    plt.title(f'CO  Emissions by {col}')
    plt.show()
```

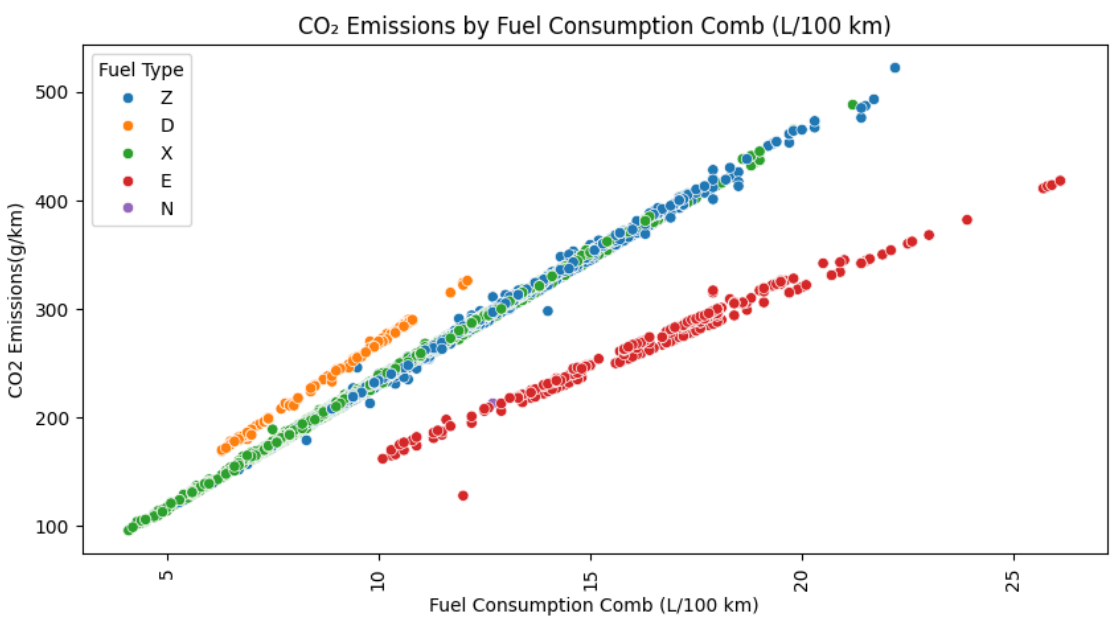



CO₂ Emissions by Cylinders
CO2 Emissions(g/km)
100
200
300
400
500
4
6
8
10
12
14
16
Cylinders

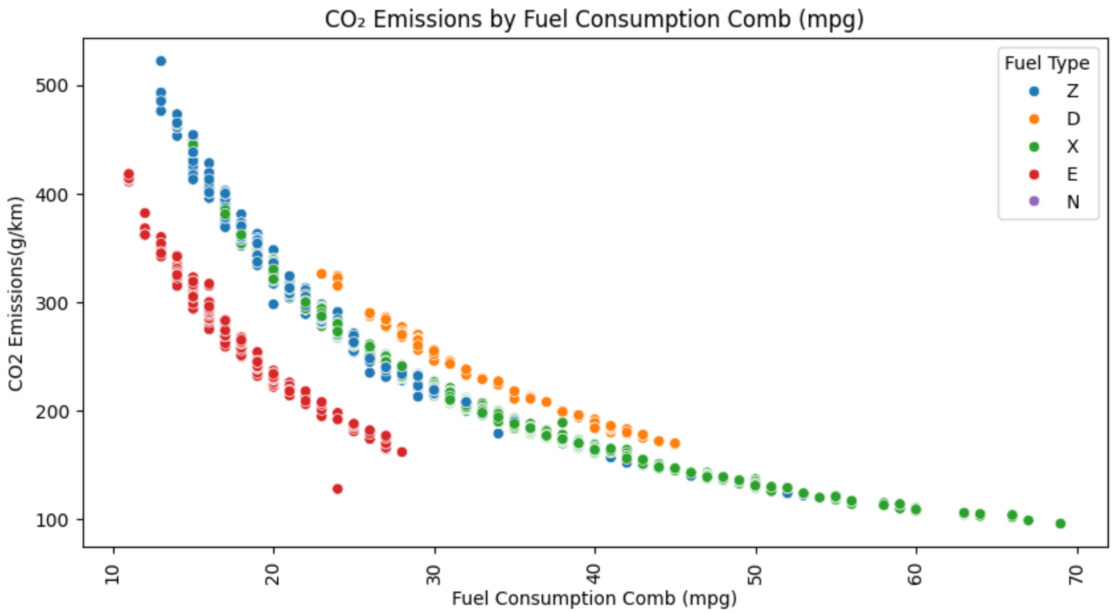

CO₂ Emissions by Fuel Consumption City (L/100 km)
Fuel Type
Z
D
X
E
N
CO2 Emissions(g/km)
100
200
300
400
500
5
10
15
20
25
30
Fuel Consumption City (L/100 km)



CO₂ Emissions by Fuel Consumption Hwy (L/100 km)
Fuel Type
Z
D
X
E
N
CO2 Emissions(g/km)
100
200
300
400
500
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Fuel Consumption Hwy (L/100 km)



CO₂ Emissions by Fuel Consumption Comb (L/100 km)
Fuel Type
Z
D
X
E
N
CO2 Emissions(g/km)
100
200
300
400
500
5
10
15
20
25
Fuel Consumption Comb (L/100 km)

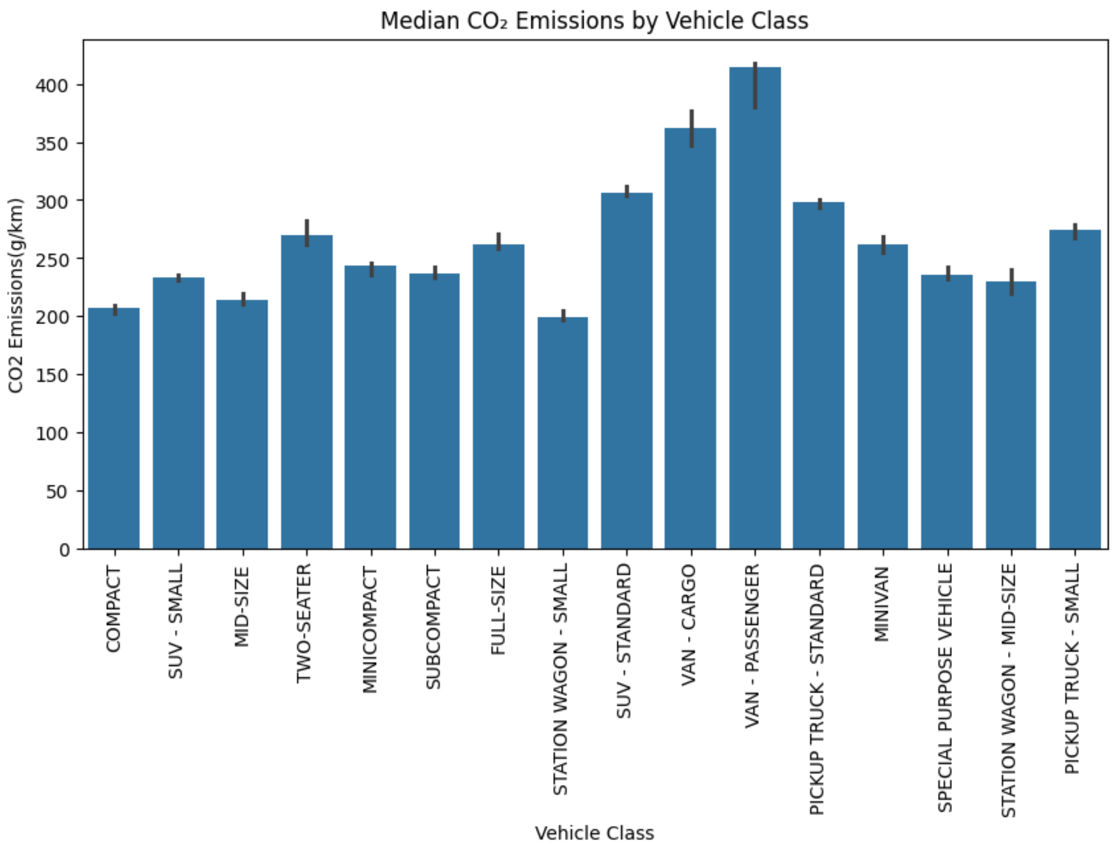


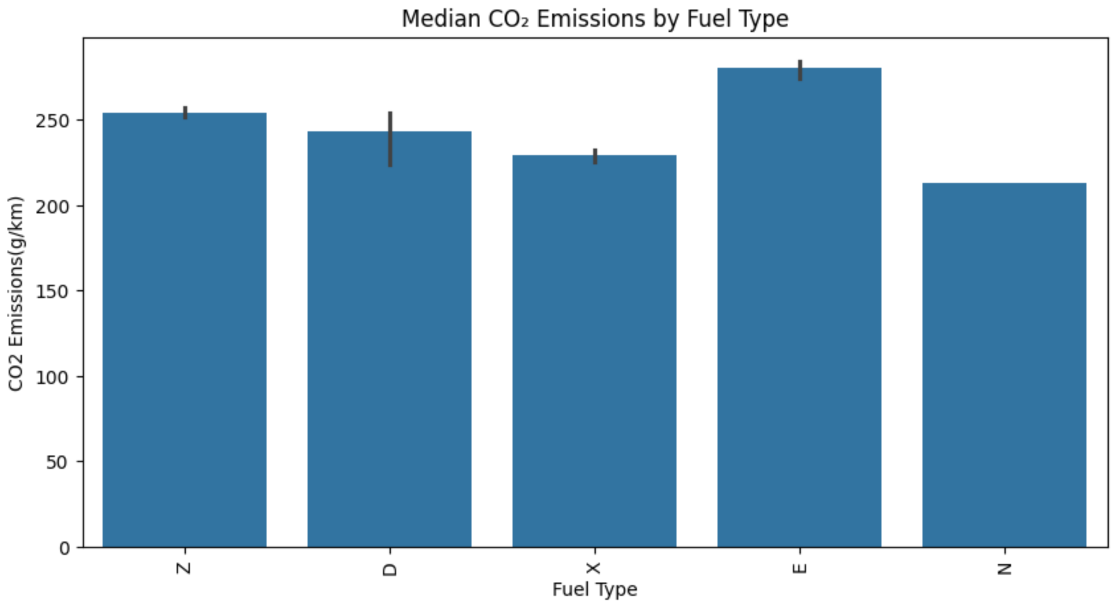
- **Engine Size(L)** - CO emissions increase significantly with engine size. Vehicles with larger engines are less fuel-efficient and emit higher CO per kilometer due to higher fuel combustion rates.
- **Cylinders** - CO emissions rise with the number of cylinders. Engines with more cylinders are designed for higher performance, but at the cost of efficiency, leading to greater CO emissions.
- **Fuel Consumption City, Hwy, Comb (L/100km)** - CO emissions are directly proportional to a vehicle's fuel consumption across all driving modes, with the combined fuel consumption (L/100 km) showing the strongest and most consistent correlation. This linear relationship demonstrates that fuel efficiency is the primary determinant of CO emissions, and improving it—especially in city driving—can substantially reduce a vehicle's environmental footprint. We can see seperate linear lines in the scatterplot because each fuel type can have different CO2 emission per L
- **Fuel Consumption Comb (mpg)** - The relationship between fuel consumption (mpg) and CO emissions is strongly nonlinear, violating the linearity assumption of linear regression. This occurs because mpg is inversely proportional to fuel consumption (L/100 km). If mpg were to be retained, a polynomial transformation would be required. Check VIF and drop high VIF columns and then If MPG is still present then we can use polynomial transformation.

0.0.4 5. Compare emission levels across different vehicle types or fuel categories. Identify any clear distinctions or surprising findings that emerge.

[240]:
```
categorical_features = ['Vehicle Class','Fuel Type']

for col in categorical_features:
    plt.figure(figsize=(10, 5))
```

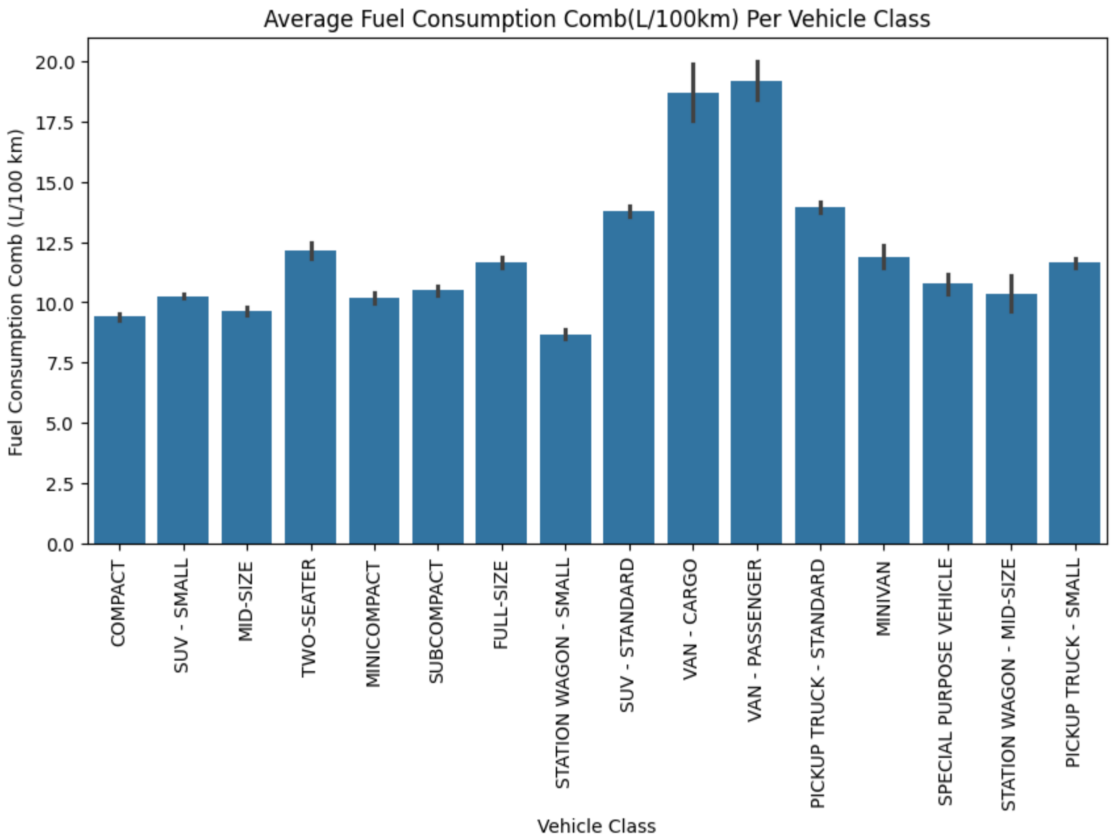
```
    sns.barplot(x=col, y='CO2 Emissions(g/km)',␣
↪data=co2_emissions,estimator='median')
    plt.xticks(rotation=90)
    plt.title(f'Median CO  Emissions by {col}')
    plt.show()
```





- Fuel Type significantly influences CO emissions, with Ethanol and Premium fuels tending toward higher emissions, while Regular Gasoline and Diesel offer relatively cleaner performance.
- Vehicle Class strongly determines emission levels — larger, heavier vehicles (SUVs, Vans, Trucks) emit significantly more CO , while compact and mid-size vehicles remain more fuel-efficient and environmentally friendly.
- Across all analyses, Vehicle Class and Fuel Type emerge as strong categorical determinants of CO emissions. Larger, performance-oriented vehicles and high-performance fuels are consistently associated with higher emission levels, while compact cars using regular or diesel fuels are the most environmentally efficient.

[241]:
```
plt.figure(figsize=(10, 5))
sns.barplot(data=co2_emissions,x='Vehicle Class',y= 'Fuel Consumption Comb (L/100 km)',estimator='mean')
plt.xticks(rotation = 90)
plt.title('Average Fuel Consumption Comb(L/100km) Per Vehicle Class')
plt.show()
```

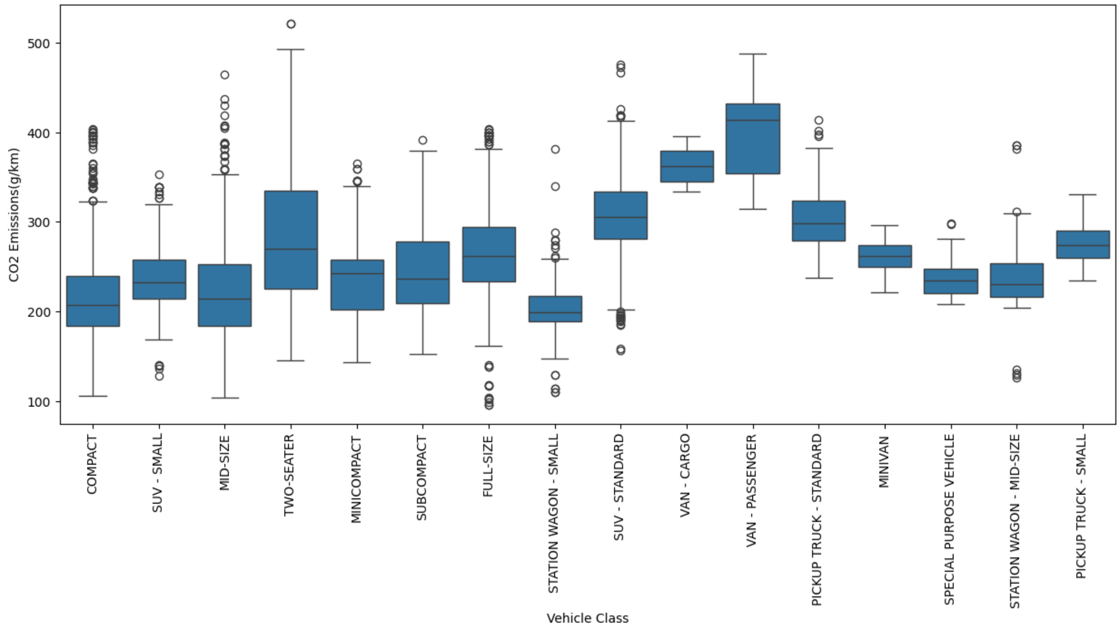


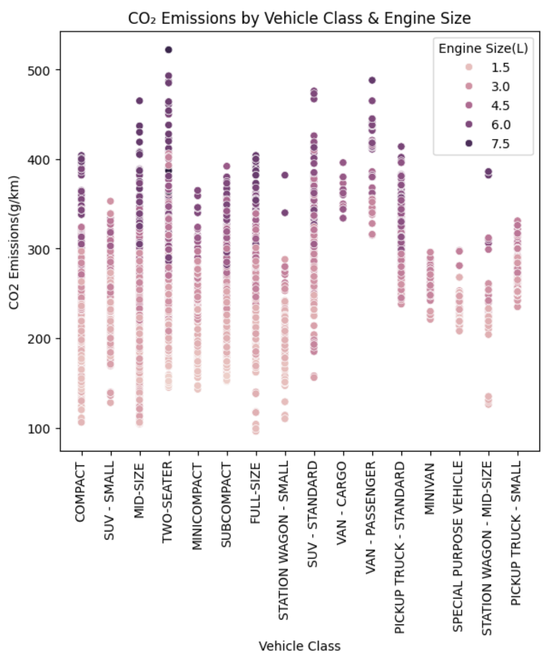
- Larger the vehicle more the fuel consumption comb (L/100km), larger the fuel consumption more CO2 emission.

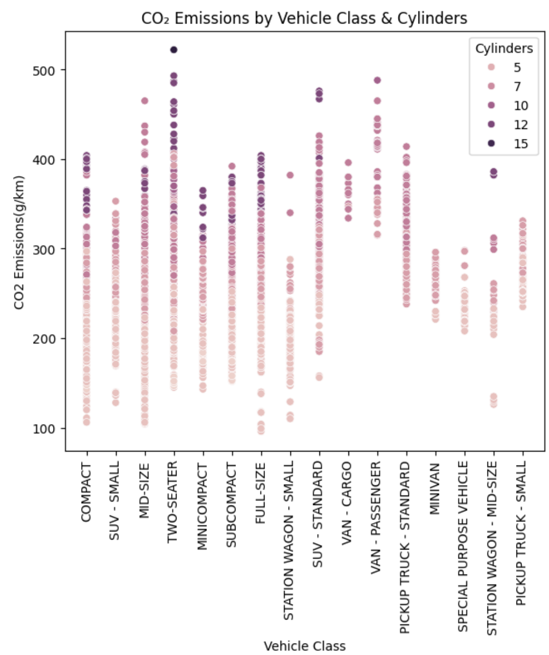
0.0.5 6. Observe if there are any vehicles that produce unusually high or low emissions compared to others with similar characteristics. Reflect on what could explain such deviations.

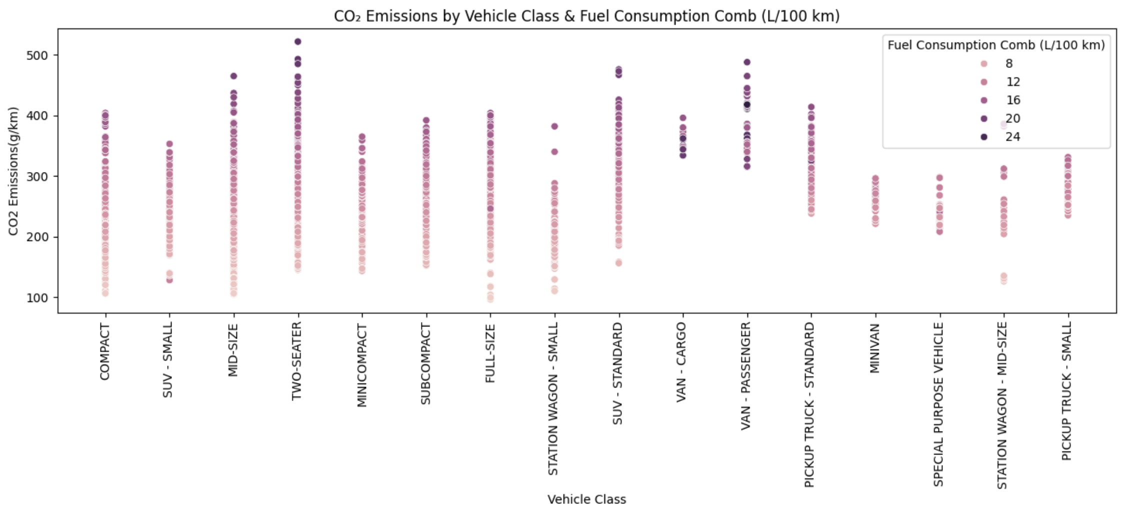
[242]:
```
# First row: CO  Emissions by Vehicle Class (no hue)
plt.figure(figsize=(15, 6))
sns.boxplot(
    x='Vehicle Class',
    y='CO2 Emissions(g/km)',
    data=co2_emissions,
)
plt.xticks(rotation=90)
plt.show()

# Second row: CO  Emissions by Vehicle Class & Engine Size
fig2, axes2 = plt.subplots(1, 2, figsize=(15, 6))
sns.scatterplot(
    x='Vehicle Class',
```

```
    y='CO2 Emissions(g/km)',
    hue='Engine Size(L)',
    data=co2_emissions,
    ax=axes2[0]
)
axes2[0].set_title('CO  Emissions by Vehicle Class & Engine Size')
axes2[0].tick_params(axis='x', rotation=90)

# Second row: CO  Emissions by Vehicle Class & Cylinders
sns.scatterplot(
    x='Vehicle Class',
    y='CO2 Emissions(g/km)',
    hue='Cylinders',
    data=co2_emissions,
    ax=axes2[1]
)
axes2[1].set_title('CO  Emissions by Vehicle Class & Cylinders')
axes2[1].tick_params(axis='x', rotation=90)

# Third row: CO  Emissions by Vehicle Class & Fuel Consumption Comb (L/100 km)
fig3, ax3 = plt.subplots(1, 1, figsize=(13, 6))
sns.scatterplot(
    x='Vehicle Class',
    y='CO2 Emissions(g/km)',
    hue='Fuel Consumption Comb (L/100 km)',
    data=co2_emissions,
    ax=ax3
)
ax3.set_title('CO  Emissions by Vehicle Class & Fuel Consumption Comb (L/100␣
 ↪km)')
ax3.tick_params(axis='x', rotation=90)
plt.tight_layout()
plt.show()
```


CO2 Emissions(g/km)
Vehicle Class
COMPACT
SUV - SMALL
MID-SIZE
TWO-SEATER
MINICOMPACT
SUBCOMPACT
FULL-SIZE
STATION WAGON - SMALL
SUV - STANDARD
VAN - CARGO
VAN - PASSENGER
PICKUP TRUCK - STANDARD
MINIVAN
SPECIAL PURPOSE VEHICLE
STATION WAGON - MID-SIZE
PICKUP TRUCK - SMALL

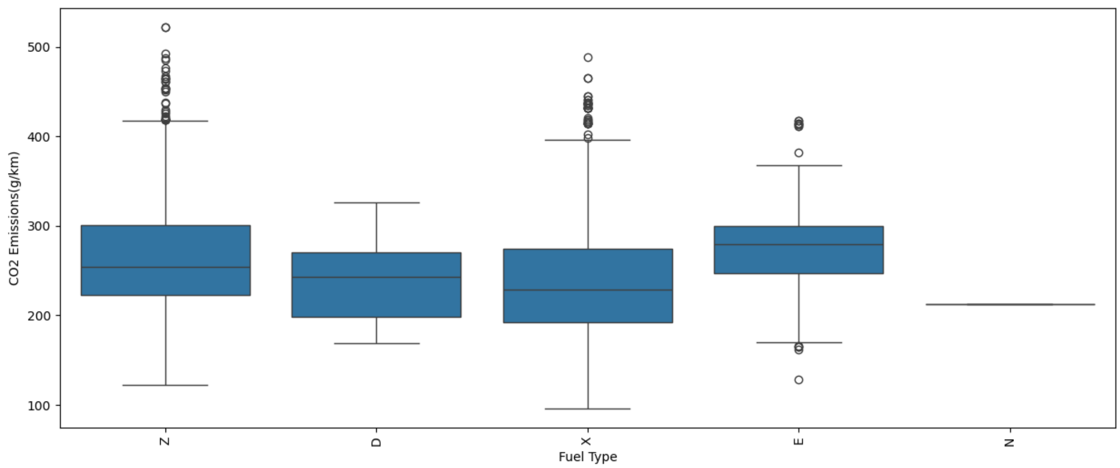

CO₂ Emissions by Vehicle Class & Engine Size
Engine Size(L)
1.5
3.0
4.5
6.0
7.5
CO2 Emissions(g/km)
Vehicle Class

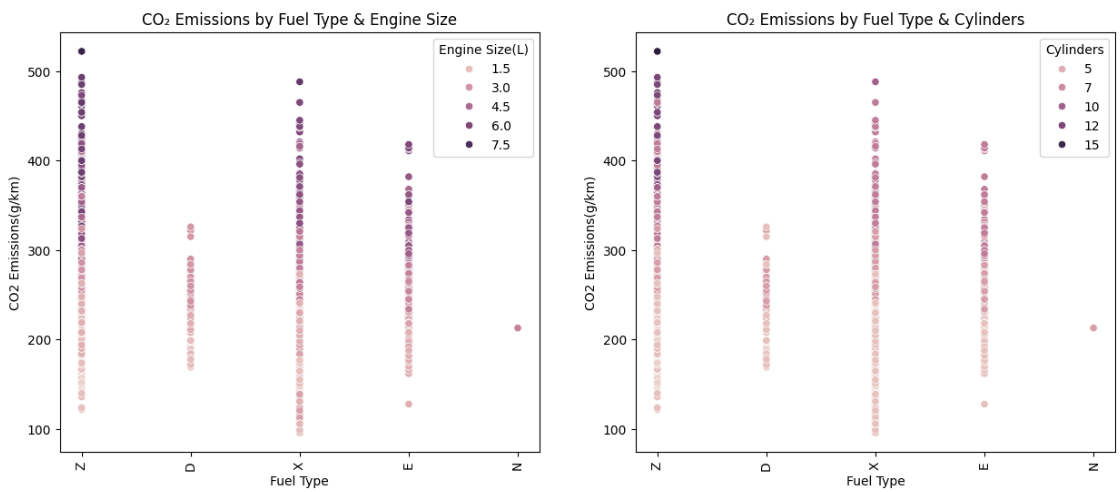

CO₂ Emissions by Vehicle Class & Cylinders
Cylinders
5
7
10
12
15
CO2 Emissions(g/km)
Vehicle Class

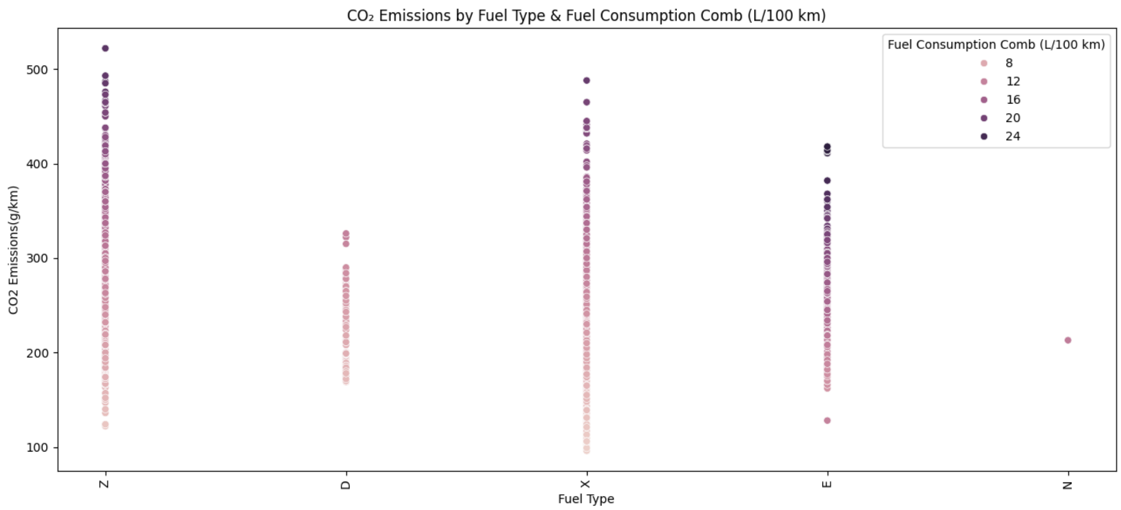


[243]:
```python
plt.figure(figsize=(15, 6))
sns.boxplot(
    x='Fuel Type',
    y='CO2 Emissions(g/km)',
    data=co2_emissions,
)
plt.xticks(rotation=90)
plt.show()

# Second row: CO  Emissions by Fuel Type & Engine Size
fig2, axes2 = plt.subplots(1, 2, figsize=(15, 6))
sns.scatterplot(
    x='Fuel Type',
    y='CO2 Emissions(g/km)',
    hue='Engine Size(L)',
    data=co2_emissions,
    ax=axes2[0]
)
axes2[0].set_title('CO  Emissions by Fuel Type & Engine Size')
axes2[0].tick_params(axis='x', rotation=90)

# Second row: CO  Emissions by Fuel Type & Cylinders
sns.scatterplot(
    x='Fuel Type',
    y='CO2 Emissions(g/km)',
    hue='Cylinders',
    data=co2_emissions,
    ax=axes2[1]
)
```

```python
axes2[1].set_title('CO  Emissions by Fuel Type & Cylinders')
axes2[1].tick_params(axis='x', rotation=90)

# Third row: CO  Emissions by Fuel Type & Fuel Consumption Comb (L/100 km)
fig3, ax3 = plt.subplots(1, 1, figsize=(13, 6))
sns.scatterplot(
    x='Fuel Type',
    y='CO2 Emissions(g/km)',
    hue='Fuel Consumption Comb (L/100 km)',
    data=co2_emissions,
    ax=ax3
)
ax3.set_title('CO  Emissions by Fuel Type & Fuel Consumption Comb (L/100 km)')
ax3.tick_params(axis='x', rotation=90)
plt.tight_layout()
plt.show()
```







- **High-Emission Outliers**
- Vehicles that emit significantly higher CO levels within the same class or fuel type are primarily associated with:
  - Larger engine sizes and higher cylinder counts (as confirmed by the scatter plots).
  - Performance-oriented or luxury models such as sports cars, SUVs, and full-size vehicles. These vehicles are often tuned for higher power output and acceleration, resulting in greater fuel consumption per kilometer which indeed leads to higher CO2 Emissions.
  - For example: Compact, Two-Seater, SUV–Standard categories show multiple high-emission outliers with darker points (indicating large engine sizes or 8–12 cylinders).
  - Such deviations are expected, as larger engines require more fuel combustion to deliver higher performance, directly increasing CO output.
- **Low-Emission Outliers**
  - Conversely, vehicles with unusually low emissions within their class or fuel type are often: Equipped with smaller or turbocharged engines and less cylinders, achieving better fuel efficiency.
  - Represented by lighter-colored points in the scatterplots, generally below 200 g/km.

0.0.6 7. Prepare the dataset for model building by ensuring that numerical and categorical features are appropriately represented. Consider any transformations or encodings that may improve interpretability.

1. Preprocessing - one hot encoding, standardization, replace fuel type codes, drop models, VIF to eliminate multicollinearity

- Replace fuel type code with fuel type name for readability and interpretability

[244]:
```python
def clean_fuel_type(fuel):
    if fuel == 'X':
        return 'Regular gasoline'
    elif fuel == 'Z':
        return 'Premium gasoline'
    elif fuel == 'D':
        return 'Diesel'
    elif fuel == 'E':
        return 'Ethanol'
    elif fuel == 'N':
        return 'Natural gas'
    else:
        return 'Others'

co2_emissions['Fuel Type'] = co2_emissions['Fuel Type'].apply(clean_fuel_type)
co2_emissions['Fuel Type'].head()
```

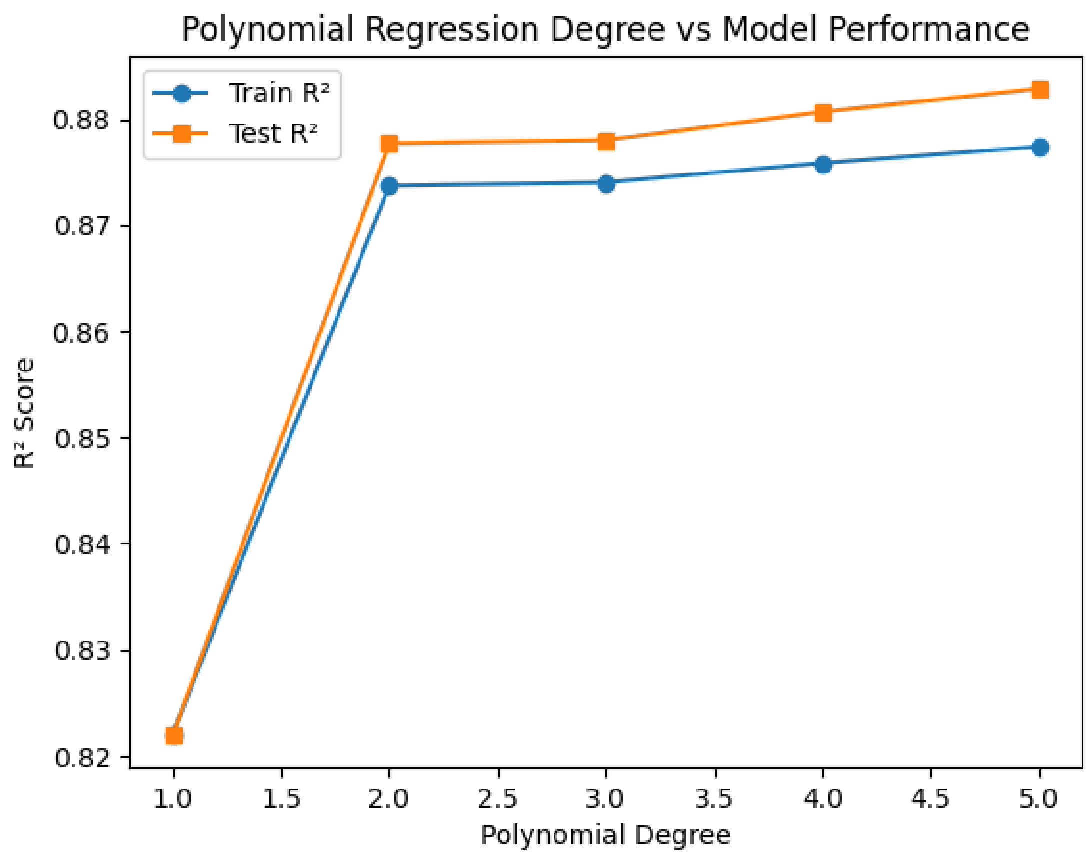
[244]:
```
0    Premium gasoline
1    Premium gasoline
2    Premium gasoline
3    Premium gasoline
4    Premium gasoline
Name: Fuel Type, dtype: object
```

- Since The relation between Fuel Consumption Comb (mpg) and CO2 Emissions was not linear we need to try different polynomial degrees

[245]:
```python
from sklearn.metrics import r2_score

# Independent & dependent variables
X = co2_emissions[['Fuel Consumption Comb (mpg)']]
y = co2_emissions['CO2 Emissions(g/km)']

# Split into training and testing (80-20)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=100)

# Range of polynomial degrees to test
degrees = [1, 2, 3, 4, 5]

# Store R2 scores
train_r2 = []
test_r2 = []

for d in degrees:
    # Generate polynomial features
    poly = PolynomialFeatures(degree=d, include_bias=False)
    X_train_poly = poly.fit_transform(X_train)
```

```
    X_test_poly = poly.transform(X_test)

    # Fit linear regression
    model = LinearRegression()
    model.fit(X_train_poly, y_train)

    # Predict
    y_train_pred = model.predict(X_train_poly)
    y_test_pred = model.predict(X_test_poly)

    # R2 scores
    train_r2.append(r2_score(y_train, y_train_pred))
    test_r2.append(r2_score(y_test, y_test_pred))

# Display results
r2_df = pd.DataFrame({'Degree': degrees, 'Train_R2': train_r2, 'Test_R2':
 ↪test_r2})
print(r2_df)

# Visualization
plt.plot(degrees, train_r2, marker='o', label='Train R²')
plt.plot(degrees, test_r2, marker='s', label='Test R²')
plt.xlabel("Polynomial Degree")
plt.ylabel("R² Score")
plt.title("Polynomial Regression Degree vs Model Performance")
plt.legend()
plt.show()
```

```
   Degree          Train_R2           Test_R2
0       1  0.822043357322460  0.821996784972211
1       2  0.873700404908932  0.877680843993483
2       3  0.874019531410553  0.877977836053358
3       4  0.875823807325157  0.880657264598321
4       5  0.877378358947925  0.882825197138175
```



- We can conclude that 2 is the best degree as the model R2 for both test and training score got stagnant after 2
- Adding Polynomials for fuel consumption comb (mpg) of degree 2

[246]:
```
# Identify the column to apply polynomial transformation
mpg_col = 'Fuel Consumption Comb (mpg)'

# Create a polynomial transformer (degree=2, no bias term)
poly = PolynomialFeatures(degree=2, include_bias=False)

# Fit-transform only the mpg column
mpg_poly = poly.fit_transform(co2_emissions[[mpg_col]])

# Create a DataFrame with the new polynomial features
mpg_poly_df = pd.DataFrame(mpg_poly, columns=['Fuel Consumption Comb (mpg)',␣
↪'Fuel Consumption Comb (mpg)^2'])

# Drop the original Fuel Consumption Comb (mpg) column from X
co2_emissions.drop(columns=[mpg_col],inplace=True)
```

```python
# Concatenate the new polynomial features with the rest of X
co2_emissions = pd.concat([co2_emissions.reset_index(drop=True), mpg_poly_df],
 ↪axis=1)

co2_emissions.head()
```

[246]:
```
    Make       Model Vehicle Class    Engine Size(L)  Cylinders Transmission  \
0  ACURA         ILX       COMPACT 2.000000000000000          4          AS5
1  ACURA         ILX       COMPACT 2.400000000000000          4           M6
2  ACURA  ILX HYBRID       COMPACT 1.500000000000000          4          AV7
3  ACURA     MDX 4WD   SUV - SMALL 3.500000000000000          6          AS6
4  ACURA     RDX AWD   SUV - SMALL 3.500000000000000          6          AS6

         Fuel Type  Fuel Consumption City (L/100 km)  \
0 Premium gasoline                 9.900000000000000
1 Premium gasoline                11.199999999999999
2 Premium gasoline                 6.000000000000000
3 Premium gasoline                12.699999999999999
4 Premium gasoline                12.100000000000000

  Fuel Consumption Hwy (L/100 km)  Fuel Consumption Comb (L/100 km)  \
0               6.700000000000000                 8.500000000000000
1               7.700000000000000                 9.600000000000000
2               5.800000000000000                 5.900000000000000
3               9.100000000000000                11.100000000000000
4               8.699999999999999                10.600000000000000

  CO2 Emissions(g/km)  Fuel Consumption Comb (mpg)  \
0                 196            33.000000000000000
1                 221            29.000000000000000
2                 136            48.000000000000000
3                 255            25.000000000000000
4                 244            27.000000000000000

  Fuel Consumption Comb (mpg)^2
0          1089.000000000000000
1           841.000000000000000
2          2304.000000000000000
3           625.000000000000000
4           729.000000000000000
```

- One hot encoding - Categorical Columns

[247]:
```python
co2_emissions = pd.get_dummies(data=co2_emissions ,columns=['Make','Vehicle␣
 ↪Class','Transmission','Fuel Type'],drop_first=True)
co2_emissions.head()
```

[247]:
```
         Model     Engine Size(L)  Cylinders  Fuel Consumption City (L/100 km)  \
0          ILX 2.000000000000000          4                 9.900000000000000
1          ILX 2.400000000000000          4                11.199999999999999
2   ILX HYBRID 1.500000000000000          4                 6.000000000000000
3      MDX 4WD 3.500000000000000          6                12.699999999999999
4      RDX AWD 3.500000000000000          6                12.100000000000000

   Fuel Consumption Hwy (L/100 km)  Fuel Consumption Comb (L/100 km)  \
0                6.700000000000000                 8.500000000000000
1                7.700000000000000                 9.600000000000000
2                5.800000000000000                 5.900000000000000
3                9.100000000000000                11.100000000000000
4                8.699999999999999                10.600000000000000

   CO2 Emissions(g/km)  Fuel Consumption Comb (mpg)  \
0                  196            33.000000000000000
1                  221            29.000000000000000
2                  136            48.000000000000000
3                  255            25.000000000000000
4                  244            27.000000000000000

   Fuel Consumption Comb (mpg)^2  Make_ALFA ROMEO  …  Transmission_AV6  \
0           1089.000000000000000            False  …             False
1            841.000000000000000            False  …             False
2           2304.000000000000000            False  …             False
3            625.000000000000000            False  …             False
4            729.000000000000000            False  …             False

   Transmission_AV7  Transmission_AV8  Transmission_M5  Transmission_M6  \
0             False             False            False            False
1             False             False            False             True
2              True             False            False            False
3             False             False            False            False
4             False             False            False            False

   Transmission_M7  Fuel Type_Ethanol  Fuel Type_Natural gas  \
0            False              False                  False
1            False              False                  False
2            False              False                  False
3            False              False                  False
4            False              False                  False

   Fuel Type_Premium gasoline  Fuel Type_Regular gasoline
0                        True                       False
1                        True                       False
2                        True                       False
3                        True                       False
```

```
4                        True                          False

[5 rows x 95 columns]
```

- Standardizing Numerical Columns

[248]:
```python
numeric_columns = co2_emissions.select_dtypes(include=['float64','int64']).
 ↪columns
scaler = StandardScaler()
co2_emissions[numeric_columns] = scaler.
 ↪fit_transform(co2_emissions[numeric_columns])
co2_emissions.head()
```

[248]:
```
        Model      Engine Size(L)           Cylinders  \
0         ILX -0.851086201165638 -0.876934116321554
1         ILX -0.558065798851599 -0.876934116321554
2  ILX HYBRID -1.217361704058187 -0.876934116321554
3     MDX 4WD  0.247740307512010  0.206428738886313
4     RDX AWD  0.247740307512010  0.206428738886313

   Fuel Consumption City (L/100 km)  Fuel Consumption Hwy (L/100 km)  \
0                -0.762844027857400               -1.040321045594652
1                -0.396933749341504               -0.601474899447351
2                -1.860574863405091               -1.435282577127224
3                 0.025270418176838                0.012909705158871
4                -0.143611248830499               -0.162628753300050

   Fuel Consumption Comb (L/100 km)  CO2 Emissions(g/km)  \
0                -0.854490378199558   -0.930371837167502
1                -0.481183972464408   -0.508685039648429
2                -1.736850973573548   -1.942420151213277
3                 0.027870217174433    0.064809004977510
4                -0.141814512705181   -0.120733185930882

   Fuel Consumption Comb (mpg)  Fuel Consumption Comb (mpg)^2  \
0            0.771454001395296               0.625147730747012
1            0.219329360351120               0.081445597869503
2            2.841921405310952               3.288849712384810
3           -0.332795280693055              -0.392101421088328
4           -0.056732960170967              -0.164097300849373

   Make_ALFA ROMEO  …  Transmission_AV6  Transmission_AV7  Transmission_AV8  \
0            False  …             False             False             False
1            False  …             False             False             False
2            False  …             False              True             False
3            False  …             False             False             False
4            False  …             False             False             False
```

```
   Transmission_M5  Transmission_M6  Transmission_M7  Fuel Type_Ethanol  \
0            False            False            False              False
1            False             True            False              False
2            False            False            False              False
3            False            False            False              False
4            False            False            False              False

   Fuel Type_Natural gas  Fuel Type_Premium gasoline  \
0                  False                        True
1                  False                        True
2                  False                        True
3                  False                        True
4                  False                        True

   Fuel Type_Regular gasoline
0                       False
1                       False
2                       False
3                       False
4                       False

[5 rows x 95 columns]
```

0.0.7 8. Develop a simple, interpretable model to estimate CO emissions using relevant features from the dataset. Summarize how the model captures the relationship between vehicle characteristics and emissions.

[249]:
```
X = co2_emissions.drop(['Model','CO2 Emissions(g/km)'],axis=1)
Y = co2_emissions['CO2 Emissions(g/km)']
```

- Train Test Split

[250]:
```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size = 0.3,␣
↪random_state=42)
```

[251]:
```
X_train.shape,X_test.shape
```

[251]:
```
((4397, 93), (1885, 93))
```

- Model Building

[252]:
```
model = LinearRegression()
model.fit(X_train,y_train)
```

[252]:
```
LinearRegression()
```

[253]:
```python
training_r2_score = model.score(X_train,y_train)
test_r2_score = model.score(X_test,y_test)
print('Training Score: ',training_r2_score)
print('Test Score: ',test_r2_score)
```

```
Training Score:  0.9945418626454711
Test Score:  0.9920123356135196
```

[254]:
```python
# Create a DataFrame mapping features to coefficients
coef_df = pd.DataFrame({
    'Feature': X_train.columns,
    'Coefficient': model.coef_
})
# Sort by absolute coefficient value (for importance)
coef_df['Abs(Coefficient)'] = coef_df['Coefficient'].abs()
coef_df = coef_df.sort_values(by='Abs(Coefficient)', ascending=False)

coef_df.head(10)
```

[254]:

	Feature	Coefficient	Abs(Coefficient)
89	Fuel Type_Ethanol	-2.337639011265126	2.337639011265126
5	Fuel Consumption Comb (mpg)	-0.673786932465421	0.673786932465421
12	Make_BUGATTI	0.619902430773368	0.619902430773368
92	Fuel Type_Regular gasoline	-0.536822574859961	0.536822574859961
91	Fuel Type_Premium gasoline	-0.528239949814299	0.528239949814299
2	Fuel Consumption City (L/100 km)	0.431928211069775	0.431928211069775
6	Fuel Consumption Comb (mpg)^2	0.376523545029431	0.376523545029431
3	Fuel Consumption Hwy (L/100 km)	0.243216360188621	0.243216360188621
28	Make_LAMBORGHINI	0.186514727848738	0.186514727848738
40	Make_ROLLS-ROYCE	0.173315186945613	0.173315186945613

- Since Multicollinearity affects the interpretability of each feature, checking for multicollinearity and eliminating columns which are having VIF >= 10

[255]:
```python
def calculate_VIF_Eliminate_Highest(X,vif_thres=10):
    dropped_columns = []
    numerical_columns = X.select_dtypes(include=['float64','int64'])
    while True:
        vif_data = pd.DataFrame()
        vif_data['Feature'] = numerical_columns.columns
        vif_data['VIF'] = [variance_inflation_factor(numerical_columns.values,␣
↪i) for i in range(numerical_columns.shape[1])]
        vif_data = vif_data.sort_values(by='VIF',ascending=False)
        if vif_data.iloc[0]['VIF'] < vif_thres:
            break
        dropped_columns.append(vif_data.iloc[0]['Feature'])
        numerical_columns = numerical_columns.drop(vif_data.
↪iloc[0]['Feature'],axis=1)
```

```
    return vif_data,dropped_columns
```

[256]:
```
vif_data,dropped_columns = calculate_VIF_Eliminate_Highest(X,vif_thres=10)
print(vif_data)
print("Dropped Columns: ",dropped_columns)
```

```
                        Feature               VIF
0                Engine Size(L) 8.608893466994010
1                     Cylinders 7.297603678657305
2  Fuel Consumption Hwy (L/100 km) 3.715207324343383
3    Fuel Consumption Comb (mpg)^2 2.784248068570130
Dropped Columns:  ['Fuel Consumption Comb (L/100 km)', 'Fuel Consumption Comb
(mpg)', 'Fuel Consumption City (L/100 km)']
```

[257]:
```
X.drop(dropped_columns,axis=1,inplace=True)
X.head()
```

[257]:
```
      Engine Size(L)          Cylinders  Fuel Consumption Hwy (L/100 km)  \
0 -0.851086201165638 -0.876934116321554               -1.040321045594652
1 -0.558065798851599 -0.876934116321554               -0.601474899447351
2 -1.217361704058187 -0.876934116321554               -1.435282577127224
3  0.247740307512010  0.206428738886313                0.012909705158871
4  0.247740307512010  0.206428738886313               -0.162628753300050

   Fuel Consumption Comb (mpg)^2  Make_ALFA ROMEO  Make_ASTON MARTIN  \
0              0.625147730747012            False              False
1              0.081445597869503            False              False
2              3.288849712384810            False              False
3             -0.392101421088328            False              False
4             -0.164097300849373            False              False

   Make_AUDI  Make_BENTLEY  Make_BMW  Make_BUGATTI  …  Transmission_AV6  \
0      False         False     False         False  …             False
1      False         False     False         False  …             False
2      False         False     False         False  …             False
3      False         False     False         False  …             False
4      False         False     False         False  …             False

   Transmission_AV7  Transmission_AV8  Transmission_M5  Transmission_M6  \
0             False             False            False            False
1             False             False            False             True
2              True             False            False            False
3             False             False            False            False
4             False             False            False            False

   Transmission_M7  Fuel Type_Ethanol  Fuel Type_Natural gas  \
0            False              False                  False
1            False              False                  False
```

```
2            False              False                  False
3            False              False                  False
4            False              False                  False

   Fuel Type_Premium gasoline  Fuel Type_Regular gasoline
0                        True                       False
1                        True                       False
2                        True                       False
3                        True                       False
4                        True                       False

[5 rows x 90 columns]
```

[258]:
```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size = 0.3,␣
↪random_state=42)
```

[259]:
```
model = LinearRegression()
model.fit(X_train,y_train)
```

[259]:
```
LinearRegression()
```

[260]:
```
# Create a DataFrame mapping features to coefficients
coef_df = pd.DataFrame({
    'Feature': X_train.columns,
    'Coefficient': model.coef_
})
# Sort by absolute coefficient value (for importance)
coef_df['Abs(Coefficient)'] = coef_df['Coefficient'].abs()
coef_df = coef_df.sort_values(by='Abs(Coefficient)', ascending=False)

coef_df.drop('Abs(Coefficient)',axis=1).head(15)
```

[260]:

	Feature	Coefficient
86	Fuel Type_Ethanol	-2.082365708910304
9	Make_BUGATTI	0.920075631809748
2	Fuel Consumption Hwy (L/100 km)	0.764473100591735
7	Make_BENTLEY	0.560668665986090
89	Fuel Type_Regular gasoline	-0.521298519392789
70	Transmission_AM9	-0.498100745308378
88	Fuel Type_Premium gasoline	-0.482561164603903
25	Make_LAMBORGHINI	0.447871679517322
29	Make_MASERATI	0.360964557630786
37	Make_ROLLS-ROYCE	0.341971215167913
36	Make_RAM	0.317891969392012
13	Make_CHRYSLER	0.286818994739778
80	Transmission_AV6	-0.243755425254524
60	Transmission_A4	-0.225137937705669

```
50  Vehicle Class_PICKUP TRUCK - STANDARD -0.220369831727024
```

- Engine Size And Cylinders

[261]:
```
coef_df.loc[coef_df['Feature'].str.
 ↪contains('Engine|Cylinder',case=False),['Feature','Coefficient']]
```

[261]:
```
           Feature       Coefficient
0  Engine Size(L) 0.140747912080098
1       Cylinders 0.067078820268113
```

- Positive coefficients confirm what my EDA showed — vehicles with bigger engines and more cylinders emit higher CO due to greater fuel consumption.

- Fuel Efficiency Variables

[262]:
```
coef_df.loc[coef_df['Feature'].str.contains('Fuel␣
 ↪Consumption',case=False),['Feature','Coefficient']]
```

[262]:
```
                              Feature        Coefficient
2  Fuel Consumption Hwy (L/100 km)  0.764473100591735
3    Fuel Consumption Comb (mpg)^2 -0.174770284835356
```

- The model confirms the inverse relationship between mpg and CO emissions that you observed earlier — more efficient vehicles emit less.
- The model also shows a strong positive relationship with highway fuel consumption (Fuel Consumption Hwy), which is consistent with the earlier EDA - More the fuel consumption more CO2 Emission

- Transmission Types

[263]:
```
coef_df.loc[coef_df['Feature'].str.
 ↪contains('Transmission',case=False),['Feature','Coefficient']]
```

[263]:
```
              Feature        Coefficient
70   Transmission_AM9 -0.498100745308378
80   Transmission_AV6 -0.243755425254524
60    Transmission_A4 -0.225137937705669
82   Transmission_AV8 -0.211317960046422
85    Transmission_M7  0.104168471617004
81   Transmission_AV7 -0.103002651308544
72   Transmission_AS4 -0.091532009846699
79  Transmission_AV10 -0.072983531548007
63    Transmission_A7  0.063632490670686
65    Transmission_A9  0.057894793334282
73   Transmission_AS5 -0.057346469177560
78    Transmission_AV -0.055668667304004
62    Transmission_A6  0.049005447067034
69   Transmission_AM8 -0.048095880864106
61    Transmission_A5  0.043741761274199
```

84	Transmission_M6	0.042823596352729
83	Transmission_M5	-0.034559688344615
77	Transmission_AS9	0.031499403811634
74	Transmission_AS6	0.029565005596423
75	Transmission_AS7	-0.025973945570864
66	Transmission_AM5	0.025340877365645
71	Transmission_AS10	0.018509442288124
68	Transmission_AM7	0.016827755807440
76	Transmission_AS8	0.014763971457655
67	Transmission_AM6	0.012927190629377
64	Transmission_A8	-0.004162502790012

- AM9 (−0.50) and CVT variants (AV6–AV10) show strong negative coefficients, implying these advanced systems lower emissions by maintaining optimal engine load and improving fuel efficiency.
- Older automatics (A4) also have mildly negative coefficients, likely due to pairing with smaller engines.
- Manual transmissions (M6, M7) and mid-range automatics (A5–A7) exhibit small positive coefficients, suggesting slightly higher CO output caused by less efficient or driver-dependent gear control.
- Most sequential (AS series) transmissions have near-zero coefficients, indicating neutral or minimal impact on emissions.

Conclusion: - Advanced transmissions — particularly AM9 and CVT types — are associated with lower CO emissions, confirming that newer gear systems enhance efficiency, while manual and mid-tier automatics contribute to slightly higher emissions.

- Fuel Type

[264]:
```
pd.options.display.float_format = '{:.15f}'.format
```

[265]:
```
coef_df.loc[coef_df['Feature'].str.contains('Fuel Type',case=False),['Feature','Coefficient']]
```

[265]:

	Feature	Coefficient
86	Fuel Type_Ethanol	-2.082365708910304
89	Fuel Type_Regular gasoline	-0.521298519392789
88	Fuel Type_Premium gasoline	-0.482561164603903
87	Fuel Type_Natural gas	0.000000000000003

- Ethanol vehicles emit less CO than Diesel vehicles when comparing cars of similar size and specifications.
- Regular gasoline emits slightly less CO than Diesel, reflecting cleaner combustion.
- Premium gasoline is marginally cleaner than Diesel, though differences are small after adjustment.
- The model identifies Diesel as the highest baseline emitter
- Ethanol's large negative coefficient (−2.08) doesn't mean ethanol cars are always cleaner in raw terms — it means for equivalent engines and vehicle characteristics, ethanol emits less

CO chemically than diesel.

For my information - Diesel acts as the baseline category for the Fuel Type variable. During one-hot encoding with drop_first=True, Diesel is dropped, and its effect becomes part of the model intercept ( ).

Therefore, when a vehicle is Diesel-powered, all dummy variables for other fuel types (Ethanol, Regular Gasoline, Premium Gasoline) take the value 0, and the Diesel contribution — already captured in the intercept — is applied.

For non-diesel vehicles, the corresponding fuel type coefficient is added to the intercept, representing how much their CO emission differs from Diesel after controlling for other factors.

- Vehicle Make and Class

[266]:
```
coef_df.loc[coef_df['Feature'].str.contains('Vehicle␣
↪Class',case=False),['Feature','Coefficient']]
```

[266]:
```
                                Feature       Coefficient
50   Vehicle Class_PICKUP TRUCK - STANDARD -0.220369831727024
58              Vehicle Class_VAN - CARGO -0.154323421203571
51   Vehicle Class_SPECIAL PURPOSE VEHICLE -0.135837805719790
47              Vehicle Class_MINICOMPACT -0.113483417671739
55              Vehicle Class_SUV - SMALL -0.088509457021266
49      Vehicle Class_PICKUP TRUCK - SMALL -0.078499597473158
56           Vehicle Class_SUV - STANDARD -0.076718823660523
59          Vehicle Class_VAN - PASSENGER  0.054986184342748
52  Vehicle Class_STATION WAGON - MID-SIZE -0.048946377617446
48                  Vehicle Class_MINIVAN -0.042899102303832
53     Vehicle Class_STATION WAGON - SMALL -0.038818274422467
45                Vehicle Class_FULL-SIZE  0.035897876060074
54               Vehicle Class_SUBCOMPACT -0.016753040803347
46                 Vehicle Class_MID-SIZE  0.005765651825376
57               Vehicle Class_TWO-SEATER  0.001952351249518
```

- Most negative coefficients suggest that many vehicle types emit less CO than the baseline (likely "Compact Car").
- Larger or performance-oriented classes (Full-Size, Passenger Van, Two-Seater) show positive coefficients, meaning higher adjusted emissions than Compact Car.

[267]:
```
coef_df.loc[coef_df['Feature'].str.
↪contains('Make',case=False),['Feature','Coefficient']].head(10)
```

[267]:
```
             Feature       Coefficient
9       Make_BUGATTI 0.920075631809748
7       Make_BENTLEY 0.560668665986090
25  Make_LAMBORGHINI 0.447871679517322
29     Make_MASERATI 0.360964557630786
37  Make_ROLLS-ROYCE 0.341971215167913
36          Make_RAM 0.317891969392012
```

```
13     Make_CHRYSLER 0.286818994739778
14        Make_DODGE 0.219614971166793
33   Make_MITSUBISHI 0.215091071600893
16         Make_FORD 0.212504274514240
```

- Luxury and performance manufacturers (Bugatti, Bentley, Lamborghini, Maserati, Rolls-Royce) show strong positive coefficients, meaning they emit more CO compared to the baseline manufacturer.
- Utility and truck-oriented brands (RAM, Ford, Chrysler) also have positive coefficients, aligning with their heavier and higher-capacity vehicles.

0.0.8 9. Assess how well the model performs in estimating emissions. Reflect on the meaning of the performance metrics and what they indicate about model reliability.

[268]:
```
y_test_pred = model.predict(X_test)
y_train_pred = model.predict(X_train)
test_r2_score = r2_score(y_test,y_test_pred)
train_r2_score = r2_score(y_train,y_train_pred)
print("Training R2 Score: ",train_r2_score)
print("Test R2 Score: ",test_r2_score)
```

```
Training R2 Score:  0.9819943591591352
Test R2 Score:  0.9788418854997403
```

- **Model Evaluation**
  - The R^2 score of 0.97 indicates that the model fits the data extremely well, with very little unexplained variance.
  - The small drop from 0.99 → 0.97 after removing multicollinear variables shows that the model became more stable and interpretable without losing much predictive strength.

0.0.9 10. Based on the analysis and model findings, summarize which factors most strongly influence CO emissions and suggest how such insights could support emission reduction efforts.

[269]:
```
coef_df[['Feature','Coefficient']].head(15)
```

[269]:

	Feature	Coefficient
86	Fuel Type_Ethanol	-2.082365708910304
9	Make_BUGATTI	0.920075631809748
2	Fuel Consumption Hwy (L/100 km)	0.764473100591735
7	Make_BENTLEY	0.560668665986090
89	Fuel Type_Regular gasoline	-0.521298519392789
70	Transmission_AM9	-0.498100745308378
88	Fuel Type_Premium gasoline	-0.482561164603903
25	Make_LAMBORGHINI	0.447871679517322
29	Make_MASERATI	0.360964557630786

```
37                      Make_ROLLS-ROYCE  0.341971215167913
36                              Make_RAM  0.317891969392012
13                         Make_CHRYSLER  0.286818994739778
80                      Transmission_AV6 -0.243755425254524
60                       Transmission_A4 -0.225137937705669
50  Vehicle Class_PICKUP TRUCK - STANDARD -0.220369831727024
```

0.1 Key Factors Influencing CO Emissions and Insights for Emission Reduction

0.1.1 1. Major Influencing Factors

Based on the regression model coefficients and overall analysis, the following factors most strongly influence vehicle CO emissions:

Factor	Effect on CO Emissions	Interpretation / Insight
Engine Size (L)	↑ Positive	Larger engines consume more fuel, directly increasing CO output.
Cylinders	↑ Positive	More cylinders mean more combustion per cycle, resulting in higher emissions.
Fuel Consumption (Hwy, L/100 km)	↑ Strong Positive	Higher fuel usage on highways correlates with higher emissions.
Fuel Efficiency ($(\text{mpg})^2$)	↓ Strong Negative	Better mileage strongly reduces emissions, capturing the non-linear relationship between efficiency and CO .
Transmission Type (CVT, AM9)	↓ Negative	Advanced gear systems improve fuel efficiency and reduce emissions.
Fuel Type (Relative to Diesel)	↓ Strong Negative	Diesel is the baseline and highest emitter; Ethanol and Gasoline fuels produce less CO .
Make (Manufacturer)	↑ Strong Positive for luxury/performance brands	High-performance and heavy luxury vehicles (e.g., Bugatti, Bentley, Lamborghini) emit significantly more CO .

0.1.2 2. Key Insights for Emission Reduction

1. **Engine Downsizing:**
   Encouraging smaller, turbocharged engines can maintain power while lowering fuel consumption and CO emissions.

2. **Promote Advanced Transmission Systems:**
   CVT and automated multi-speed transmissions (e.g., AM9) improve efficiency by keeping engines at optimal RPM ranges.

3. **Fuel Optimization:**
   Transitioning away from diesel toward ethanol and gasoline blends reduces carbon intensity per unit of energy used.
4. **Vehicle Weight and Design Efficiency:**
   Reducing vehicle mass and improving aerodynamics lowers energy demand and emissions.
5. **Encourage Cleaner Manufacturing Mix:**
   Manufacturers focusing on heavy, performance-oriented vehicles should balance portfolios with lighter, fuel-efficient models.
6. **Policy Implications:**
   Governments can incentivize hybrid, electric, or ethanol-based vehicles and impose stricter CO norms on large-engine vehicles.

0.1.3 Summary

- The model confirms that **engine-related characteristics (engine size, cylinders, fuel consumption)** are the dominant drivers of CO emissions.

- Meanwhile, **fuel type, transmission technology, and vehicle design** play critical roles in reducing emissions.

- These insights can guide **automakers**, **engineers**, and **policy-makers** toward strategies focused on **efficiency optimization, cleaner fuels, and smarter transmission systems** to effectively reduce vehicular CO emissions.

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