Background

You volunteer for a public policy advocacy organization in Canada, and your colleague asked you to help her draft recommendations for guidelines on CO2 emissions rules.

After researching emissions data for a wide range of Canadian vehicles, she would like you to investigate which vehicles produce lower emissions.

The data

- "Make" The company that manufactures the vehicle.
- "Model" The vehicle's model.
- · "Vehicle Class" Vehicle class by utility, capacity, and weight.
- "Engine Size(L)" The engine's displacement in liters.
- · "Cylinders" The number of cylinders.
- "Transmission" The transmission type: A = Automatic, AM = Automatic Manual, AS = Automatic with select shift, AV = Continuously variable, M = Manual, 3 10 = the number of gears.
- "Fuel Type" The fuel type: X = Regular gasoline, Z = Premium gasoline, D = Diesel, E = Ethanol (E85), N = natural gas.
- "Fuel Consumption Comb (L/100 km)" Combined city/highway (55%/45%) fuel consumption in liters per 100 km (L/100 km).
- "CO2 Emissions(g/km)" The tailpipe carbon dioxide emissions in grams per kilometer for combined city and highway driving.

The data comes from the Government of Canada's open data <u>website (https://open.canada.ca/en)</u>.- "Make" - The company that manufactures the vehicle.

💪 Challenge I

Help your colleague gain insights on the type of vehicles that have lower CO2 emissions. Include:

- 1. What is the median engine size in liters?
- 2. What is the average fuel consumption for regular gasoline (Fuel Type = X), premium gasoline (Z), ethanol (E), and diesel (D)?
- 3. What is the correlation between fuel consumption and CO2 emissions?
- 4. Which vehicle class has lower average CO2 emissions, 'SUV SMALL' or 'MID-SIZE'?
- 5. What are the average CO2 emissions for all vehicles? For vehicles with an engine size of 2.0 liters or smaller?
- 6. Any other insights you found during your analysis?

Collaborators

- · Imoh Essien
- · Favour Aghaegbe
- Grace Akindoyin

In [1]:

```
#Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Importing and Exploring the Data

In [2]:

```
co2 = pd.read_csv("C:\\Users\\essie\\Downloads\\co2_emissions_canada.csv")
co2.head(10)
```

Out[2]:

	Make	Model	Vehicle Class	Engine Size(L)	Cylinders	Transmission	Fuel Type	Fuel Consumption Comb (L/100 km)	Emissio
0	ACURA	ILX	COMPACT	2.0	4	AS5	Z	8.5	
1	ACURA	ILX	COMPACT	2.4	4	M6	Z	9.6	
2	ACURA	ILX HYBRID	COMPACT	1.5	4	AV7	Z	5.9	
3	ACURA	MDX 4WD	SUV - SMALL	3.5	6	AS6	Z	11.1	
4	ACURA	RDX AWD	SUV - SMALL	3.5	6	AS6	Z	10.6	
5	ACURA	RLX	MID-SIZE	3.5	6	AS6	Z	10.0	
6	ACURA	TL	MID-SIZE	3.5	6	AS6	Z	10.1	
7	ACURA	TL AWD	MID-SIZE	3.7	6	AS6	Z	11.1	
8	ACURA	TL AWD	MID-SIZE	3.7	6	M6	Z	11.6	
9	ACURA	TSX	COMPACT	2.4	4	AS5	Z	9.2	
4									>

In [3]:

co2.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7385 entries, 0 to 7384
Data columns (total 9 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 Comb (L/100 km)	7385 non-null	float64
8	CO2 Emissions(g/km)	7385 non-null	int64

dtypes: float64(2), int64(2), object(5)

memory usage: 519.4+ KB

In [4]:

co2.describe()

Out[4]:

	Engine Size(L)	Cylinders	Fuel Consumption Comb (L/100 km)	CO2 Emissions(g/km)
count	7385.000000	7385.000000	7385.000000	7385.000000
mean	3.160068	5.615030	10.975071	250.584699
std	1.354170	1.828307	2.892506	58.512679
min	0.900000	3.000000	4.100000	96.000000
25%	2.000000	4.000000	8.900000	208.000000
50%	3.000000	6.000000	10.600000	246.000000
75%	3.700000	6.000000	12.600000	288.000000
max	8.400000	16.000000	26.100000	522.000000

In [5]:

co2.shape

Out[5]:

(7385, 9)

In [6]:

```
co2['Fuel Type'].unique()
```

Out[6]:

array(['Z', 'D', 'X', 'E', 'N'], dtype=object)

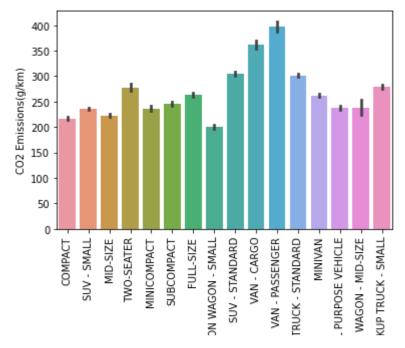
In [7]:

```
co2['Vehicle Class'].unique()
```

Out[7]:

In [12]:

```
#relationship between vehicle class and CO2 Emissions
s = sns.barplot(x='Vehicle Class', y= 'CO2 Emissions(g/km)', data=co2)
s.set_xticklabels(s.get_xticklabels(), rotation = 90);
```



The Following cars emit high levels of CO2

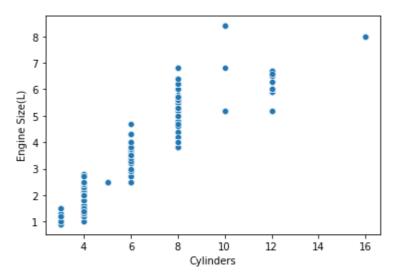
VAN(Passenger), followed by VAN(Cargo) and SUV-Standard.

In [13]:

```
#relationship between engine size and cylinders
sns.scatterplot(x='Cylinders', y= 'Engine Size(L)', data =co2)
```

Out[13]:

<AxesSubplot:xlabel='Cylinders', ylabel='Engine Size(L)'>



The larger the Cylinders, the Larger the size of the Engine.

Solutions to the Challenges

In [14]:

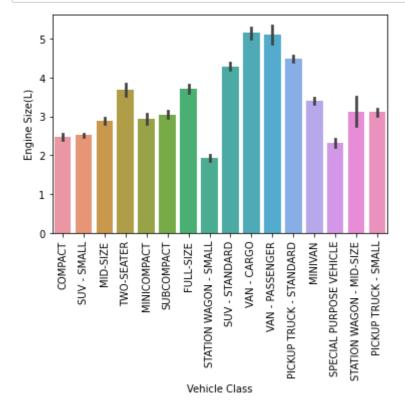
```
#What is the median size in liters
median_enginesize = co2['Engine Size(L)'].median()
print(f'The median Engine size is {median_enginesize}')
```

The median Engine size is 3.0

In [16]:

```
#what is the average fuel consumption for regular gasoline(Fuel Type = X), premium gasoline
#and Diesel(D)
#make a copy of the date
co2copy = co2.copy()
co2copy['median_engine'] = co2copy['Engine Size(L)'].median()
```

In [18]:



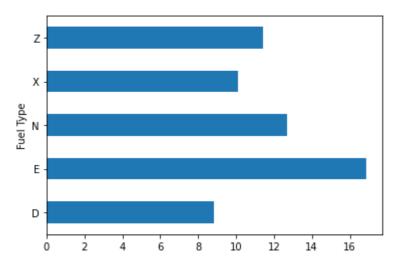
Station wagon had the smallest median engine size among the vehicle class group while Van passenger and van cargo had the largest median engine size

In [20]:

```
#what is the average fuel consumption for regular gasoline
cat_ave = co2copy['Ave Consumption']= co2.groupby(['Fuel Type'])['Fuel Consumption Comb (L/cat_ave.plot(kind='barh', fontsize=10)
```

Out[20]:

<AxesSubplot:ylabel='Fuel Type'>



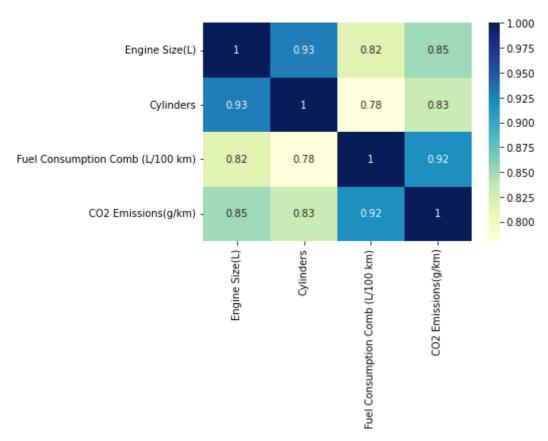
Type $\mathit{Markdown}$ and LaTeX: α^2

In [23]:

```
#what is the correlation between fuel consumption and CO2 emissions?
co2.corr()
sns.heatmap(co2.corr(), cmap= 'YlGnBu', annot=True)
```

Out[23]:

<AxesSubplot:>



The correlation between Fuel Consumption and Co2 Emissions of the various vehicles is a very high positive one (0.92)

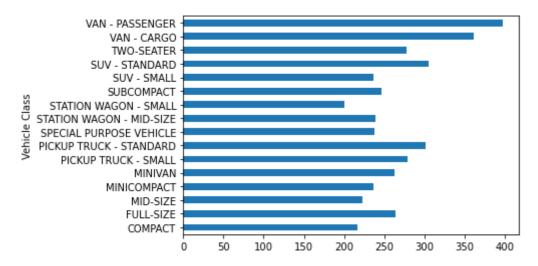
In [24]:

```
#Which vehicle class has lower average CO2 emissions, 'SUV - SMALL' or 'MID-SIZE'?

cat_avs = co2copy['Ave Consumption'] = co2copy.groupby(['Vehicle Class'])['CO2 Emissions(g/cat_avs.plot(kind='barh', fontsize =10)
```

Out[24]:

<AxesSubplot:ylabel='Vehicle Class'>



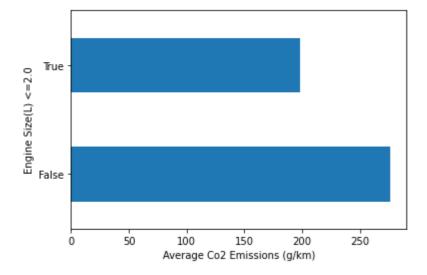
Cars in Mid-size vehicle class have lower average Co2 Emissions than Cars in SUV small Vehicle Class

In [26]:

```
#What are the average CO2 emissions for all vehicles? For vehicles with an engine size of 2
cat_avd = co2copy['Ave Consumption']= co2copy.groupby(co2copy['Engine Size(L)']<=2.0)['CO2
cat_avd.plot(kind='barh', fontsize =10)
plt.ylabel('Engine Size(L) <=2.0')
plt.xlabel('Average Co2 Emissions (g/km)')</pre>
```

Out[26]:

Text(0.5, 0, 'Average Co2 Emissions (g/km)')



In [27]:

cat_avd = co2copy['Ave Consumption']= co2copy.groupby(co2copy['Engine Size(L)']<=2.0)['CO2
cat_avd</pre>

Out[27]:

Engine Size(L)

False 276.605231 True 198.267835

Name: CO2 Emissions(g/km), dtype: float64

In []:

#insights found during my analysis is written in the conclusion.

In [1]:

#The client wants us to create a model that predicts the Co2 emissions of cars, we want to #This would help our customers choose cars that emit low co2 in order to protect the environ

In [2]:

```
#Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [3]:

co2 = pd.read_csv("C:\\Users\\essie\\Downloads\\co2_emissions_canada.csv")
co2.head(10)

Out[3]:

	Make	Model	Vehicle Class	Engine Size(L)	Cylinders	Transmission	Fuel Type	Fuel Consumption Comb (L/100 km)	Emissio
0	ACURA	ILX	COMPACT	2.0	4	AS5	Z	8.5	
1	ACURA	ILX	COMPACT	2.4	4	M6	Z	9.6	
2	ACURA	ILX HYBRID	COMPACT	1.5	4	AV7	Z	5.9	
3	ACURA	MDX 4WD	SUV - SMALL	3.5	6	AS6	Z	11.1	
4	ACURA	RDX AWD	SUV - SMALL	3.5	6	AS6	Z	10.6	
5	ACURA	RLX	MID-SIZE	3.5	6	AS6	Z	10.0	
6	ACURA	TL	MID-SIZE	3.5	6	AS6	Z	10.1	
7	ACURA	TL AWD	MID-SIZE	3.7	6	AS6	Z	11.1	
8	ACURA	TL AWD	MID-SIZE	3.7	6	M6	Z	11.6	
9	ACURA	TSX	COMPACT	2.4	4	AS5	Z	9.2	

```
In [12]:
y = co2['CO2 Emissions(g/km)']
У
Out[12]:
        196
0
        221
1
2
        136
3
        255
        244
7380
        219
7381
        232
7382
        240
7383
        232
7384
        248
Name: CO2 Emissions(g/km), Length: 7385, dtype: int64
In [13]:
co2['Fuel Type']
Out[13]:
0
        Z
        Z
1
2
        Z
3
        Ζ
4
        Ζ
7380
       Ζ
7381
        Ζ
7382
        Ζ
7383
        Ζ
7384
        Ζ
Name: Fuel Type, Length: 7385, dtype: object
In [21]:
#Selecting the features for our model
co2_feature = ['Engine Size(L)', 'Cylinders', 'Fuel Consumption Comb (L/100 km)']
```

```
In [22]:
```

```
X = co2[co2_feature]
X
```

Out[22]:

	Engine Size(L)	Cylinders	Fuel Consumption Comb (L/100 km)
0	2.0	4	8.5
1	2.4	4	9.6
2	1.5	4	5.9
3	3.5	6	11.1
4	3.5	6	10.6
7380	2.0	4	9.4
7381	2.0	4	9.9
7382	2.0	4	10.3
7383	2.0	4	9.9
7384	2.0	4	10.7

7385 rows × 3 columns

In [23]:

```
from sklearn.tree import DecisionTreeRegressor

#define the model
co2_model = DecisionTreeRegressor(random_state=20)
```

In [24]:

```
co2_model.fit(X,y)
```

Out[24]:

DecisionTreeRegressor(random_state=20)

In [25]:

```
print('making predictions for the first five data point')
print(co2_model.predict(X.head(5)))
print(X.head(5))
```

```
making predictions for the first five data point
                                         258.88888889 245.92307692]
[199.52380952 223.8
                            136.
   Engine Size(L) Cylinders Fuel Consumption Comb (L/100 km)
0
              2.0
                                                             8.5
                                                             9.6
              2.4
                            4
1
2
              1.5
                            4
                                                             5.9
3
              3.5
                            6
                                                            11.1
4
                                                            10.6
              3.5
                            6
```

```
In [26]:
```

y.head(5)

Out[26]:

0 196

1 221

2 136

3 255

4 244

Name: CO2 Emissions(g/km), dtype: int64

In [29]:

```
#dropping the non-features column
co2_drop = co2.drop(['Make', 'Model', 'Vehicle Class', 'Transmission', 'Fuel Type'], axis =
co2_drop
```

Out[29]:

	Engine Size(L)	Cylinders	Fuel Consumption Comb (L/100 km)	CO2 Emissions(g/km)
0	2.0	4	8.5	196
1	2.4	4	9.6	221
2	1.5	4	5.9	136
3	3.5	6	11.1	255
4	3.5	6	10.6	244
7380	2.0	4	9.4	219
7381	2.0	4	9.9	232
7382	2.0	4	10.3	240
7383	2.0	4	9.9	232
7384	2.0	4	10.7	248

7385 rows × 4 columns

In [30]:

```
#split data into target and feature

x= co2_drop[['Engine Size(L)', 'Cylinders', 'Fuel Consumption Comb (L/100 km)']]
y = co2_drop['CO2 Emissions(g/km)']
```

In [31]:

```
#split into test and train data
from sklearn.model_selection import train_test_split
```

In [32]:

```
#split into test and train data
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size= 0.3, random_state = 101
from sklearn.linear_model import LinearRegression
mod = LinearRegression()
```

```
In [45]:
#Predicting co2 Emissions with our chosen features
mod.predict([[3.5, 6, 10]])
C:\Users\essie\anaconda3\lib\site-packages\sklearn\base.py:450: UserWarning:
X does not have valid feature names, but LinearRegression was fitted with fe
ature names
  warnings.warn(
Out[45]:
array([241.68103043])
In [33]:
mod.fit(x_train, y_train)
Out[33]:
LinearRegression()
In [34]:
mod.coef
Out[34]:
array([ 4.88759591, 6.71692388, 13.47005044])
In [35]:
mod.intercept_
Out[35]:
49.57239708704685
```

In [36]:

from sklearn.metrics import r2_score

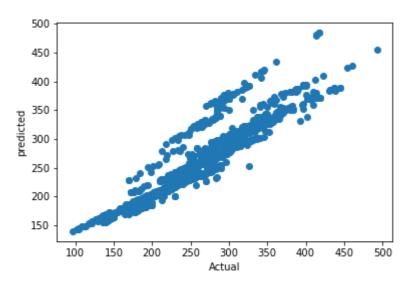
pred = mod.predict(x_test)

In [37]:

```
plt.scatter(y_test, pred)
plt.xlabel("Actual")
plt.ylabel("predicted")
```

Out[37]:

Text(0, 0.5, 'predicted')



In [39]:

```
from sklearn.metrics import r2_score
r2_score(y_test, pred)
```

Out[39]:

0.877962929205225

In [40]:

from sklearn.metrics import mean_absolute_error #measures distance without the square, bett
from sklearn.metrics import mean_squared_error
mean_absolute_error(y_test, pred)

Out[40]:

13.181639917747388

In [41]:

```
MSE= mean_squared_error(y_test, pred)
MSE
```

Out[41]:

412.1833096645876

```
In [42]:
```

```
#Root Mean Squared Error
import math
math.sqrt(MSE)
```

Out[42]:

20.30229813751605

```
In [43]:
```

```
from sklearn.metrics import mean_squared_log_error
MSLE = mean_squared_log_error(y_test, pred)
MSLE
math.sqrt(MSLE)
```

Out[43]:

0.07635093625850248

CONCLUSION

CO2 has been known to be dangerous at high amounts for more than a century. However, CO2 is a gas that occurs naturally in the air we breathe at a concentration of roughly 0.037% and is safe to breathe at these levels. but as the amount of CO2 in the air increases, it can be fatal. Burning carbon-containing fuels causes CO2 emissions to enter the earth's atmosphere. Ever since CO2 emissions became a hot-button issue in the early 1990s, federal and state governments have worked with engine and equipment manufacturers to limit the amount of harmful material entering the atmosphere. Hence the CO2 emissions rules.

From this data on CO2 Emissions from Canadian Vehicles, My team and I were able to explore the data and draft some insights and reccomendations on the guidlines of Co2 Emission rules.

Insights

- The correlation between fuel consumption and CO2 emissions of cars is very high, suggesting that the more fuel a car uses, the higher the level of CO2.
- Cars in the mid-size vehicle class have lower average CO2 emissions than cars in the SUV small vehicle class.
- Engines with 2.0 liters or less emit lower levels of CO2 of 198.23g/km when compared with engines with 2.0 liters or more.
- VAN for passengers and cargo alongside SUVs emit high levels of CO2.

Reccomendation

- Given that vehicles with engine liters of 2.0 or less and low fuel consumption generate relatively little CO2, automakers may aim to create vehicles with fewer engine liters and lower fuel consumption.
- I was able to develop a model to forecast the CO2 emissions of cars using some of the important characteristics in this data, such as the Engine Liter, Fuel consumption, and Cylinders.
- The model has an excellent r2 score of 0.877962929205225.

```
In [ ]:
```