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1- Introduction

In this research we will discuss a sensitive matter that affects the climate each day, We use cars daily in our lives without thinking of the CO2 car's emissions that have a serious impact on the climate, Regardless of the development that we have reached today and the laws that try to limit this issue, The climate still suffer from this impact. In this research, we will try to help with dealing with this issue by providing an AI algorithm to classify all the cars in the Netherlands that are provided from the RDW database from 1 to 10 according to the CO2 emissions it emits and fuel consumption.

2- Data Requirments

First I will give you a general information about the RDW datasets, Then I will list all the columns names and explain them for each dataset, Lastly, I will provide a short description of the European cars categorize because we are going to use them .

overview about the dataset:

The Registered_vehicles data set contains 14.4 million rows and 67 columns.
The Registered_vehicles_fuel dataset has 13.7 million rows and 34 column.
The date of the last update was on October 12 2021 for both datasets.
The Datasets is in a CSV format

Note: I will only choose the columns that I will need because we have 2 data sets the datasets contain a total of 101 columns

Open Data RDW: Gekentekende_voertuigen (Registered_vehicles)columns names and explanation :

License Plate
The license plate of a vehicle consists of a combination of numbers and letters. This combination is stated on the registration certificate and the number plate. The license plate makes a vehicle unique and identifiable.

Vehicle type type of vehicle (personal or commercial)

Brand The brand of the vehicle

number of seats number of seats in the vehicle

Amount of cilinders The numbers of cilinders that exist in the car engin.The more cylders the more fuel consumption

Mass of empty vehicle

number of doors

European vehicle category European classification for vehicle category, based in UNECE standards

Technical max. vehicle mass

Open Data RDW:Gekentekende_voertuigen_brandstof(Registered_vehicles_fuel) columns names and explanation:

License Plate
The license plate of a vehicle consists of a combination of numbers and letters. This combination is stated on the registration certificate and the number plate. The license plate makes a vehicle unique and identifiable.

Fuel Sequence Number
Sequence number with which the emission data can be shown in the desired order for a specific fuel.

Fuel description specific fuel name

Out-of-town fuel consumption
The fuel consumption in l/100 km, during a standardized extra-urban journey, tested on a chassis dynamometer.

Fuel consumption combined
Fuel consumption in l/100 km, during a combination of standardized urban and extra-urban driving, tested on a chassis dynamometer.

City fuel consumption
The fuel consumption in l/100 km, during a standardized urban driving cycle, tested on a chassis dynamometer.

CO2 emissions combined
The weighted CO2 emissions in g/km of a plug-in hybrid vehicle, during a combination of an urban and an extra-urban trip, tested on a chassis dynamometer. The value is calculated based on the emissions generated by driving once with empty batteries and once with full batteries.

Weighted CO2 emissions
CO2 emissions measured on a vehicle measured on a chassis dynamometer, applicable to an externally rechargeable hybrid electric vehicle, weighted with an external charging combined according to the calculation in the directive.

overview over the European Commission and the United Nations classifieds vehicles as part of emission standards and other vehicle regulations

Because I will do my classification per Eu cars category I will explain how do they categorize them below per each category

CATEGORY: M

Category M – Motor vehicles having at least four wheels and for the carriage of passengers
Category Vehicle Description:

Category M – Motor vehicles having at least four wheels and for the carriage of passengers

Category	Vehicle Description
M_1	Vehicles designed and constructed for the carriage of passengers and comprising no more than eight seats in addition to the driver's seat, and having a maximum mass ("technically permissible maximum laden mass") not exceeding 3.5 tons
M_2	Vehicles designed and constructed for the carriage of passengers, comprising more than eight seats in addition to the driver's seat, and having a maximum mass ("technically permissible maximum laden mass") not exceeding 5 tons
M_3	Vehicles designed and constructed for the carriage of passengers, comprising more than eight seats in addition to the driver's seat, and having a maximum mass exceeding 5 tons

CATEGORY: N

Category N – Power-driven vehicles having at least four wheels and for the carriage of goods

Category Vehicle Description:

Category	Vehicle Description
N_1	Vehicles for the carriage of goods and having a maximum mass not exceeding 3.5 tonnes
N_2	Vehicles for the carriage of goods and having a maximum mass exceeding 3.5 tonnes but not exceeding 12 tonnes
N_3	Vehicles for the carriage of goods and having a maximum mass exceeding 12 tonnes

Vehicles Category N1—Weight Classes

Class	Reference Mass, RW	
	Euro 1-2	Euro 3+
I	RW ≤ 1250 kg	RW ≤ 1305 kg
II	1250 kg < RW ≤ 1700 kg	1305 kg < RW ≤ 1760 kg
III	1700 kg < RW	1760 kg < RW

CATEGORY: L
Motor vehicles with less than four wheels [but does include light four-wheelers]

image-2.png

CATEGORY: O
Trailers (including semi–trailers)

Category	Vehicle Description
O1	Trailers with a maximum mass not exceeding 0.75 tonnes
O2	Trailers with a maximum mass exceeding 0.75 tonnes, but not exceeding 3.5 tonnes
O3	Trailers with a maximum mass exceeding 3.5 tonnes, but not exceeding 10 tonnes
O4	Trailers with a maximum mass exceeding 10 tonnes

3- Data collection

We are using for our analysis two datasets, the first dataset name is Gekentekende_voertuigen (https://opendata.rdw.nl/Voertuigen/Open-Data-RDW-Gekentekende_voertuigen/m9d7-ebf2) (Registered_vehicles), and the second is Gekentekende_voertuigen_brandstof (https://opendata.rdw.nl/Voertuigen/Open-Data-RDW-Gekentekende_voertuigen_brandstof/8ys7-d773)(Registered_vehicles_fuel).
Those datasets are provided from RDW(Rijksdienst voor het Wegverkeer (https://opendata.rdw.nl/)) (Road Traffic Department).

The dataset is licensed under Creative Commons Zero. As part of Creative Commons Zero.

The RDW website has different formats for the datasets(Export as (CSV, Excel,etc..),API), I used CSV files.

Problems encountered and possible solutions:

- The dataset is too large which could take a long time to load from API unless you're going to filter/search API is faster, but since this research need all the dataset it's better to export it as a CSV file and just read it.
- The dataset does not separate the hybrid and electric car, It's just saved as electric this problem could be solved by checking the column of CO2 emission if the car is electric the row will be zero since the electric car doesn't emit CO2.

4- Load data

In [1]:
```
import numpy as np
import pandas as pd
import sklearn as sk
import matplotlib
import itertools
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
import statsmodels
import statsmodels.api as sm
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
from sklearn.cluster import MiniBatchKMeans, KMeans
import plotly.express as px
from sklearn.preprocessing import StandardScaler
```

In [2]:
```
#    from google.colab import drive
#    drive.mount('/content/drive/')
```

In [3]:
```
#  cd drive/MyDrive/Fontys/S4/Challenges/classify impacts of cars on climate
```

Loading Data

In [4]:
```
col_list = ["Kenteken", "Voertuigsoort","Merk",'Handelsbenaming',"Aantal zitplaatsen","Aantal cilinders","Massa ledig vo
            "Europese voertuigcategorie","Technische max. massa voertuig"]
Registered_vehicles=pd.read_csv('Open_Data_RDW__Gekentekende_voertuigen.csv',usecols=col_list)




col_list = ["Kenteken","Brandstof omschrijving","Brandstofverbruik buiten de stad","Brandstofverbruik gecombineerd",
            "Brandstofverbruik stad","CO2 uitstoot gecombineerd"]
Registered_vehicles_fuel=pd.read_csv('Open_Data_RDW__Gekentekende_voertuigen_brandstof.csv',usecols=col_list)
```

5- Data Understanding

First, I will print the shapes of our datasets and print the first 5 rows and check if we have duplicated rows, Then print the types of data to see what we are dealing with

In [5]:
```
print(' dataset shape: {}'.format(Registered_vehicles.shape))
Registered_vehicles.head()
```

```
 dataset shape: (14359160, 10)
```

Out[5]:

	Kenteken	Voertuigsoort	Merk	Handelsbenaming	Aantal zitplaatsen	Aantal cilinders	Massa ledig voertuig	Aantal deuren	Europese voertuigcategorie	Technische max. massa voertuig
0	GS589N	Personenauto	NISSAN	NISSAN ALMERA	5.0	4.0	1226.0	4.0	M1	1710.0
1	2TDZ45	Personenauto	SEAT	LEON	5.0	4.0	1160.0	5.0	M1	1730.0
2	56NNFB	Personenauto	FIAT	FIAT PUNTO	5.0	4.0	835.0	2.0	M1	1370.0
3	20SGRP	Personenauto	BMW	3ER REIHE	4.0	6.0	1550.0	2.0	M1	1995.0
4	89TZPK	Personenauto	MINI	MINI COOPER S	4.0	4.0	1215.0	2.0	M1	1640.0

In [6]:
```
Registered_vehicles.dtypes
```

Out[6]:
```
Kenteken                          object
Voertuigsoort                     object
Merk                              object
Handelsbenaming                   object
Aantal zitplaatsen               float64
Aantal cilinders                 float64
Massa ledig voertuig             float64
Aantal deuren                    float64
Europese voertuigcategorie        object
Technische max. massa voertuig   float64
dtype: object
```

In [7]:
```
Registered_vehicles.describe()
```

Out[7]:

	Aantal zitplaatsen	Aantal cilinders	Massa ledig voertuig	Aantal deuren	Technische max. massa voertuig
count	1.141328e+07	1.229534e+07	1.393472e+07	1.291778e+07	1.370538e+07
mean	4.348436e+00	3.592200e+00	1.265088e+03	2.705507e+00	2.388887e+03
std	1.776908e+00	1.247446e+00	1.585481e+03	1.871985e+00	5.105317e+03
min	1.000000e+00	0.000000e+00	1.000000e+00	0.000000e+00	0.000000e+00
25%	4.000000e+00	3.000000e+00	8.300000e+02	0.000000e+00	1.320000e+03
50%	5.000000e+00	4.000000e+00	1.090000e+03	4.000000e+00	1.675000e+03
75%	5.000000e+00	4.000000e+00	1.382000e+03	4.000000e+00	2.010000e+03
max	2.020000e+02	9.200000e+01	9.999900e+04	9.000000e+00	9.999900e+04

In [8]:
```
Registered_vehicles.duplicated(subset='Kenteken').sum()
```

Out[8]: 0

In [9]:
```
print(' dataset shape: {}'.format(Registered_vehicles_fuel.shape))
Registered_vehicles_fuel.head()
```

```
 dataset shape: (13650842, 6)
```

Out[9]:

	Kenteken	Brandstof omschrijving	Brandstofverbruik buiten de stad	Brandstofverbruik gecombineerd	Brandstofverbruik stad	CO2 uitstoot gecombineerd
0	VFZ09K	Diesel	7.4	7.3	7.1	191.0
1	25MLST	Benzine	NaN	NaN	NaN	NaN
2	H655LS	Benzine	4.8	6.3	9.1	150.0
3	VDN70V	Benzine	NaN	NaN	NaN	NaN
4	10MLSX	Benzine	NaN	NaN	NaN	NaN

In [10]:
```
Registered_vehicles_fuel.dtypes
```

Out[10]:
```
Kenteken                             object
Brandstof omschrijving               object
Brandstofverbruik buiten de stad    float64
Brandstofverbruik gecombineerd      float64
Brandstofverbruik stad              float64
CO2 uitstoot gecombineerd           float64
dtype: object
```

In [11]:
```
Registered_vehicles_fuel.describe()
```

Out[11]:

	Brandstofverbruik buiten de stad	Brandstofverbruik gecombineerd	Brandstofverbruik stad	CO2 uitstoot gecombineerd
count	8.689929e+06	8.822610e+06	8.690352e+06	9.058195e+06
mean	4.949092e+00	5.827283e+00	7.395133e+00	1.402199e+02
std	1.181519e+00	1.656149e+00	2.494889e+00	4.240628e+01
min	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00
25%	4.100000e+00	4.600000e+00	5.500000e+00	1.090000e+02
50%	4.800000e+00	5.600000e+00	7.000000e+00	1.340000e+02
75%	5.600000e+00	6.700000e+00	8.700000e+00	1.630000e+02
max	6.100000e+01	9.360000e+01	9.758000e+01	9.990000e+02

In [12]:
```
Registered_vehicles_fuel.duplicated(subset='Kenteken').sum()
```

Out[12]:
```
621923
```

I see here that the data format and types are good, but we have the column names in dutch which need to be renamed in English also I see that the data has some null values which need to be deleted or filled, And we have duplicated rows (licenses) in the second dataset(Registered_vehicles_fuel), We see also that some values in the data are in dutch, the main two columns that I will use to analyze and predict will be the CO2 emission combined and the fuel consumption, Eu car category, and fuel description

6- Data Preparation

First, I will rename the dataset columns into English

In [13]:
```
#col_list = ["License_plate", "Vehicle_type","Brand","number_of_seats","Amount_of_cilinders","Mass_of_empty_vehicle","nur
#"European_vehicle_category","Technical_max_vehicle_mass"]
Registered_vehicles.columns=["License_plate","Vehicle_type","Brand",'Trade name',"number_of_seats","Amount_of_cilinders"



#col_list = ["License_plate", "Fuel_sequence_number","Fuel_description","Out_of_town_fuel_consumption","Fuel_consumption_
#           "City_fuel_consumption","CO2_emissions_combined","Weighted_CO2_emissions","Class_hybrid_electric_vehicle"]

Registered_vehicles_fuel.columns=["License_plate", "Fuel_description","Out_of_town_fuel_consumption","Fuel_consumption_c
```

Now before I join the tables I will check if we have null values in the license plate because I'm going to join on it

In [14]:
```
Registered_vehicles.isnull().sum()
```

Out[14]:
```
License_plate                   0
Vehicle_type                    0
Brand                         532
Trade name                 235305
number_of_seats           2945885
Amount_of_cilinders       2063821
Mass_of_empty_vehicle      424441
number_of_doors           1441381
European_vehicle_category    2536
Technical_max_vehicle_mass  653784
dtype: int64
```

In [15]:
```
Registered_vehicles_fuel.isnull().sum()
```

Out[15]:
```
License_plate                      0
Fuel_description                   0
Out_of_town_fuel_consumption    4960913
Fuel_consumption_combined       4828232
City_fuel_consumption           4960490
CO2_emissions_combined          4592647
dtype: int64
```

Since I will use the Fuel_consumption_combined and CO2_emissions_combined because it is the main aspect to classify the cars I will delete all the rows that it's null so that we don't classify a car as the eco-environment because the values are null, I will also delete the European_vehicle_category null values because we will classify cars per category

In [16]:
```
Registered_vehicles = Registered_vehicles[Registered_vehicles['European_vehicle_category'].notna()]

Registered_vehicles_fuel = Registered_vehicles_fuel[Registered_vehicles_fuel['Fuel_consumption_combined'].notna()]
Registered_vehicles_fuel = Registered_vehicles_fuel[Registered_vehicles_fuel['CO2_emissions_combined'].notna()]
```

Now I will delete the duplicated value in the second dataset(Registered_vehicles_fuel)

In [17]:
```
Registered_vehicles_fuel['License_plate'].drop_duplicates(keep='last',inplace=True)
```

Now I will join the two tables, to have all the information needed in one table, We will use the license plate column to merge on.

In [18]:
```
df=pd.merge(Registered_vehicles,Registered_vehicles_fuel,on='License_plate')
```

In [19]:
```
import gc
del Registered_vehicles
del Registered_vehicles_fuel
gc.collect()
```

Out[19]:
```
120
```

In [20]:
```
df.head()
```

Out[20]:

	License_plate	Vehicle_type	Brand	Trade name	number_of_seats	Amount_of_cilinders	Mass_of_empty_vehicle	number_of_doors	European_vehic
0	GS589N	Personenauto	NISSAN	NISSAN ALMERA	5.0	4.0	1226.0	4.0	
1	2TDZ45	Personenauto	SEAT	LEON	5.0	4.0	1160.0	5.0	
2	56NNFB	Personenauto	FIAT	FIAT PUNTO	5.0	4.0	835.0	2.0	
3	20SGRP	Personenauto	BMW	3ER REIHE	4.0	6.0	1550.0	2.0	
4	89TZPK	Personenauto	MINI	MINI COOPER S	4.0	4.0	1215.0	2.0	

Now we will check how many null values do we have in the combined dataset and what should we delete and what can we fill

In [21]:
```
df.isnull().sum()
```

Out[21]:
```
License_plate                     0
Vehicle_type                      0
Brand                             0
Trade name                      639
number_of_seats                1953
Amount_of_cilinders             351
Mass_of_empty_vehicle             0
number_of_doors               63169
European_vehicle_category         0
Technical_max_vehicle_mass      818
Fuel_description                  0
Out_of_town_fuel_consumption 130650
Fuel_consumption_combined         0
City_fuel_consumption        130389
CO2_emissions_combined            0
dtype: int64
```

We still have some null values but we will not use them for our study it's just an extra information. I will mkae sure that the data is right byl searching my car license in the dataset to see if the info is correct

In [22]:
```
print(' dataset shape: {}'.format(df.shape))
df.loc[df['License_plate'] == '85TJRG']
```

```
 dataset shape: (8808932, 15)
```

Out[22]:

	License_plate	Vehicle_type	Brand	Trade name	number_of_seats	Amount_of_cilinders	Mass_of_empty_vehicle	number_of_doors	Europea
445645	85TJRG	Personenauto	CHEVROLET	MATIZ	5.0	3.0	750.0	4.0	

Okay everything seems right, Now I want to group by fuel description to see what types of fuels do we have

In [23]:
```
df['Fuel_description'].value_counts()
```

Out[23]:
```
Benzine          7132832
Diesel           1592486
LPG                68246
CNG                11816
Alcohol             3515
Elektriciteit         24
LNG                   10
Waterstof              3
Name: Fuel_description, dtype: int64
```

We see that the majority of cars run on Benzine

In [24]:
```
# I will check here the electric cars to see if we need to classify them
df.loc[df['Fuel_description'] == 'Elektriciteit']
```

Out[24]:

	License_plate	Vehicle_type	Brand	Trade name	number_of_seats	Amount_of_cilinders	Mass_of_empty_vehicle	number_of_doors	Euro
317780	HB221B	Personenauto	MERCEDES-BENZ	S 400 HYBRID	5.0	6.0	1855.0	4.0	
967773	86KPJ3	Personenauto	MERCEDES-BENZ	S 400 HYBRID	5.0	6.0	1855.0	4.0	
1002758	NZ882V	Personenauto	TOYOTA	TOYOTA AURIS	5.0	4.0	1285.0	4.0	
1378135	44LHZ9	Personenauto	MERCEDES-BENZ	S 400 HYBRID	5.0	6.0	1920.0	4.0	
1704333	4ZKX98	Personenauto	LEXUS	LEXUS RX450H	5.0	6.0	2085.0	4.0	
1886671	HX170J	Personenauto	MERCEDES-BENZ	S 400 HYBRID	5.0	6.0	1855.0	4.0	
1954491	RF273V	Personenauto	TOYOTA	TOYOTA PRIUS	5.0	4.0	1400.0	4.0	
2007902	51ZDJ3	Personenauto	TOYOTA	TOYOTA PRIUS	5.0	4.0	1340.0	4.0	
2322672	33JKP8	Personenauto	MERCEDES-BENZ	S 400 HYBRID	5.0	6.0	1920.0	4.0	
3180894	JP808X	Personenauto	TOYOTA	TOYOTA YARIS HYBRID	5.0	4.0	1060.0	4.0	
3549388	JP327T	Personenauto	TOYOTA	TOYOTA YARIS HYBRID	5.0	4.0	1060.0	4.0	
3859857	25ZTL6	Personenauto	TOYOTA	TOYOTA PRIUS PLUS	7.0	4.0	1470.0	4.0	
3998842	JP144Z	Personenauto	TOYOTA	TOYOTA YARIS HYBRID	5.0	4.0	1060.0	4.0	

	License_plate	Vehicle_type	Brand	Trade name	number_of_seats	Amount_of_cilinders	Mass_of_empty_vehicle	number_of_doors	Euro
4339329	26NFB8	Personenauto	MERCEDES-BENZ	S 400 HYBRID	5.0	6.0	1855.0	4.0	
4375363	6TZP78	Personenauto	MERCEDES-BENZ	S 400 HYBRID	5.0	6.0	1855.0	4.0	
4894011	1ZLV09	Personenauto	MERCEDES-BENZ	S 400 HYBRID	5.0	6.0	1855.0	4.0	
5066223	ZJ143R	Personenauto	TOYOTA	CAMRY HYBRID	5.0	4.0	1600.0	4.0	
5278070	24JVV3	Personenauto	MERCEDES-BENZ	S 400 HYBRID	5.0	6.0	1855.0	4.0	
5407837	8SGF50	Personenauto	LEXUS	LEXUS RX450H	5.0	6.0	2085.0	4.0	
6900071	9XRG93	Personenauto	MERCEDES-BENZ	S 400 HYBRID	5.0	6.0	1855.0	4.0	
6907372	5KBN07	Personenauto	AUDI	AUDI Q5 HYBRID	5.0	4.0	1885.0	4.0	
7623119	HJ145G	Personenauto	TOYOTA	TOYOTA PRIUS PLUS	7.0	4.0	1475.0	4.0	
7906896	XT856Z	Personenauto	TOYOTA	TOYOTA RAV4	5.0	4.0	1600.0	4.0	
8143319	KH738L	Personenauto	MERCEDES-BENZ	S 400 HYBRID	5.0	6.0	1920.0	4.0	

We can see that all the electric car is not only electric but hybrid so we need to keep the hybrid and delete the electic because it's not relevant to our study since it has 0 CO2 emissions and we need to find fuel cars that use the minimal CO2, So I will delete them,but of course that you noticed that we already delete all columns that doesnt have CO2 emission and electric cars is from them,but since I said that my research will help people with buying cheap fuel cars that have low emission unfortunately hybrid cars can not be listed because the minimum price of hybrid cars start 20000 Euro so I will exclude them from my research

In [25]:
```
df = df[df.Fuel_description != "Elektriciteit"]
```

In [26]:
```
df.dtypes
```

Out[26]:
```
License_plate                     object
Vehicle_type                      object
Brand                             object
Trade name                        object
number_of_seats                  float64
Amount_of_cilinders              float64
Mass_of_empty_vehicle            float64
number_of_doors                  float64
European_vehicle_category         object
Technical_max_vehicle_mass       float64
Fuel_description                  object
Out_of_town_fuel_consumption     float64
Fuel_consumption_combined        float64
City_fuel_consumption            float64
CO2_emissions_combined           float64
dtype: object
```

In [27]:
```
df['CO2_emissions_combined']=df['CO2_emissions_combined'].astype('int')
```

In [28]:
```
df.describe()
```

Out[28]:

	number_of_seats	Amount_of_cilinders	Mass_of_empty_vehicle	number_of_doors	Technical_max_vehicle_mass	Out_of_town_fuel_consumption
count	8.806955e+06	8.808557e+06	8.808908e+06	8.745739e+06	8.808090e+06	8.678266e+06
mean	4.709003e+00	3.822197e+00	1.208043e+03	3.491754e+00	1.796578e+03	4.947297e+00
std	8.895015e-01	7.255544e-01	3.470386e+02	1.373422e+00	4.774387e+02	1.177525e+00
min	1.000000e+00	0.000000e+00	5.500000e+01	0.000000e+00	0.000000e+00	0.000000e+00
25%	4.000000e+00	3.000000e+00	9.600000e+02	4.000000e+00	1.495000e+03	4.100000e+00
50%	5.000000e+00	4.000000e+00	1.170000e+03	4.000000e+00	1.740000e+03	4.800000e+00
75%	5.000000e+00	4.000000e+00	1.371000e+03	4.000000e+00	1.975000e+03	5.600000e+00
max	1.090000e+02	1.700000e+01	7.336000e+03	7.000000e+00	1.138500e+04	6.100000e+01

I noticed here that there is cars with fuel consumption combined equal to 0 which is strange since we already deleted all electric cars so I will investigate more below

In [29]:
```
df[df['Fuel_consumption_combined'] == df['Fuel_consumption_combined'].min()]
```

Out[29]:

	License_plate	Vehicle_type	Brand	Trade name	number_of_seats	Amount_of_cilinders	Mass_of_empty_vehicle	number_of_doo
35312	3VPF62	Bedrijfsauto	TOYOTA	TUNDRA 4X2	5.0	8.0	2559.0	Na
51806	VN742X	Bedrijfsauto	DODGE	RAM 1500	5.0	8.0	2504.0	Na
246212	3KNL24	Personenauto	AUDI	AUDI A2	4.0	4.0	870.0	4
328368	VN392X	Bedrijfsauto	FORD	F 150	5.0	8.0	2453.0	Na
744512	VN278P	Bedrijfsauto	DODGE	DODGE RAM 1500 SLT	5.0	6.0	2371.0	Na
...	...	...	...	...	...	...	...	
8545757	VL881N	Bedrijfsauto	CADILLAC	ESCALADE	2.0	8.0	2664.0	Na
8617827	VL936J	Bedrijfsauto	DODGE	DODGE RAM 1500	5.0	8.0	2723.0	Na

So we have cars that doesn't have a fuel consumption combined, previously when we deleted the null values I did not make sure that we could have null values but saved as 0, so I will delete them now

In [30]:
```
df= df[df['Fuel_consumption_combined'] != 0]
```

The data have a lot of duplicate and null values, I deleted all the values that will be used by the algorithm to analyze and predict,I merged the data by the license plate, And now the data is clean and ready for analyzing and predicting

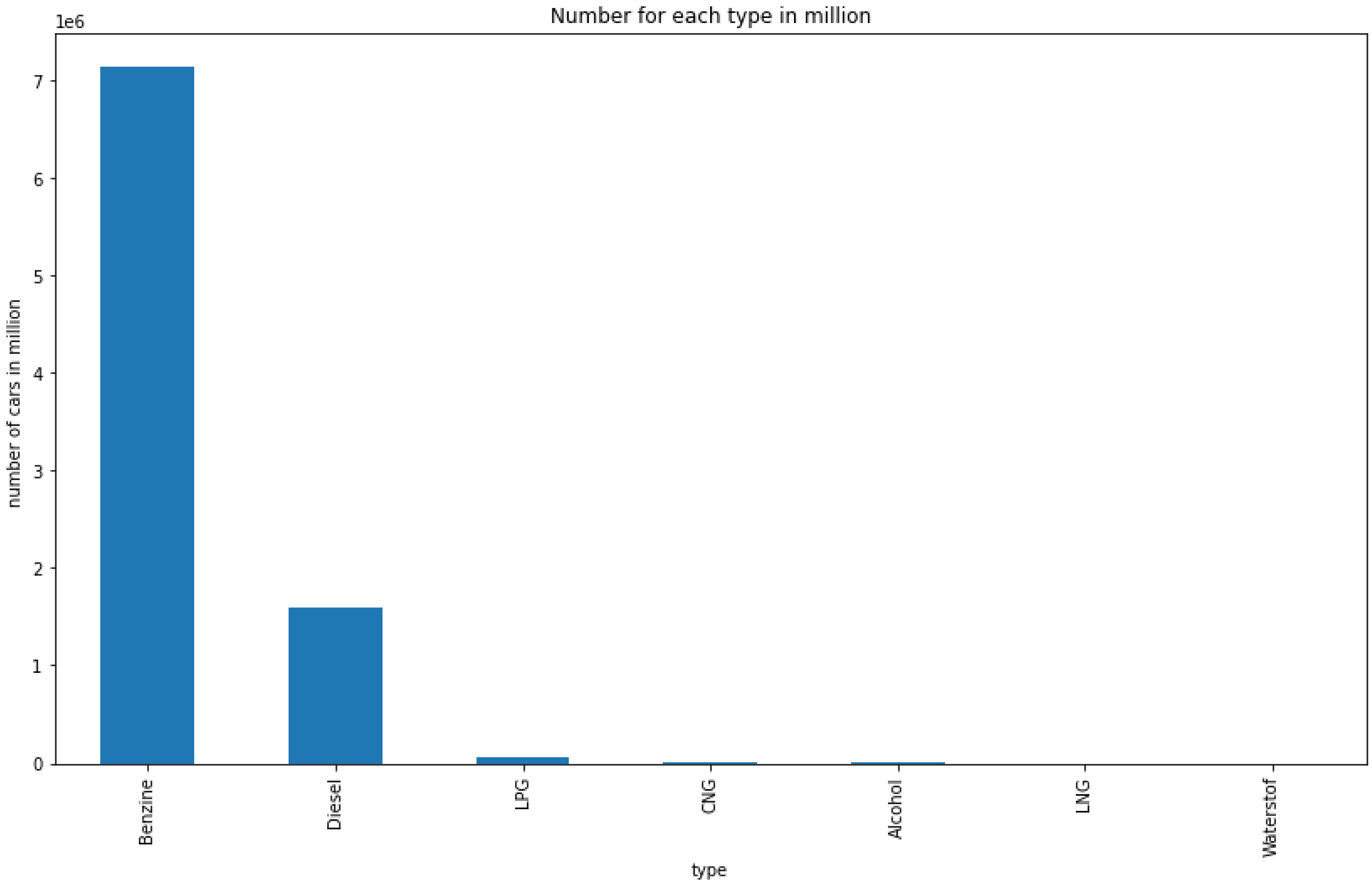
7-Analysing and visualising data

I will check here how many cars do we have per fuel type

In [31]:
```
df['Fuel_description'].value_counts()
```

Out[31]:
```
Benzine      7132827
Diesel       1592486
LPG            68185
CNG            11816
Alcohol         3515
LNG               10
Waterstof          3
Name: Fuel_description, dtype: int64
```

In [32]:
```
ax=df['Fuel_description'].value_counts().plot(kind='bar',title="Number for each type in million", figsize=(14,8),xlabel=
```



I will check here how many Eu cars categories do we have in the dataset

In [33]:
```
df.groupby('European_vehicle_category').count()
```

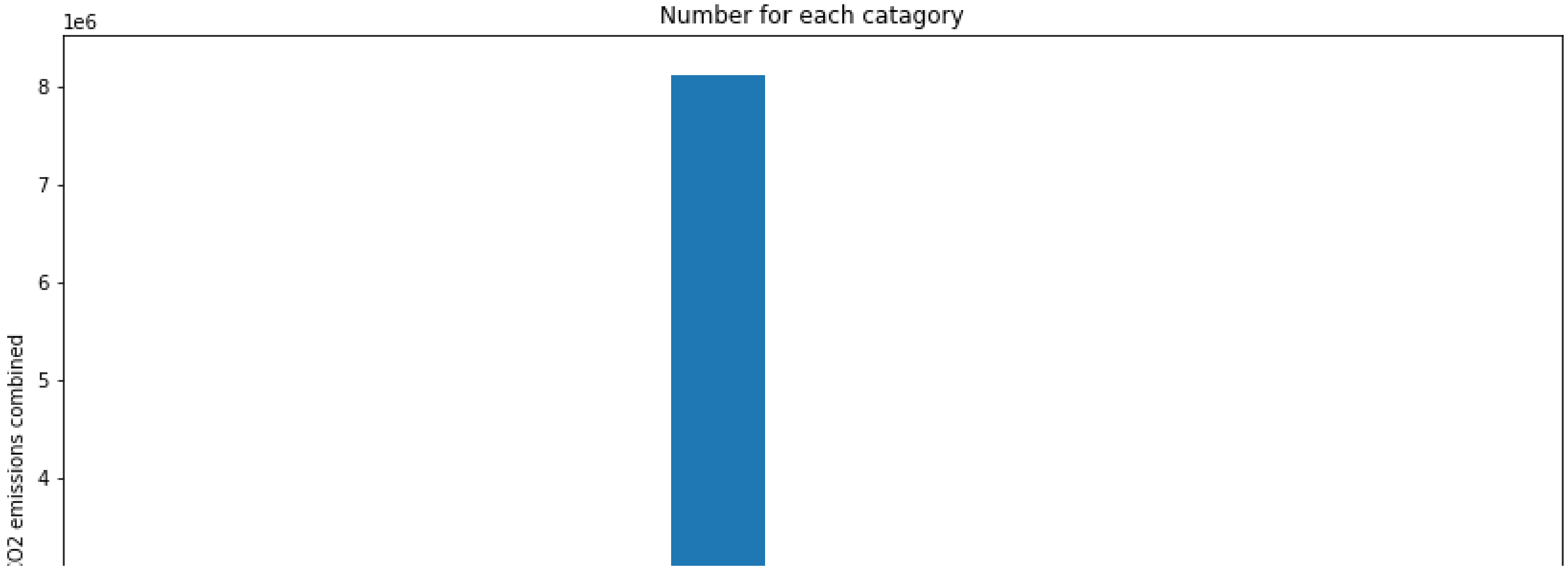
Out[33]:

	License_plate	Vehicle_type	Brand	Trade name	number_of_seats	Amount_of_cilinders	Mass_of_empty_vehicle	number_of
European_vehicle_category								
L1	51352	51352	51352	51164	51352	51352	51352	
L3	615	615	615	615	615	615	615	
L5	364	364	364	364	364	364	364	
M1	8117903	8117903	8117903	8117711	8115953	8117603	8117903	8
M2	29	29	29	29	29	29	29	
M3	4	4	4	4	4	4	4	
N1	635134	635134	635134	634875	635133	635083	635134	
N2	3441	3441	3441	3441	3439	3441	3441	

In [34]:

```
ax = df.groupby('European_vehicle_category')['CO2_emissions_combined'].count().plot.bar(title="Number for each catagory"
ax.set_xlabel('catagory')
ax.set_ylabel('CO2 emissions combined')
```

Out[34]: Text(0, 0.5, 'CO2 emissions combined')



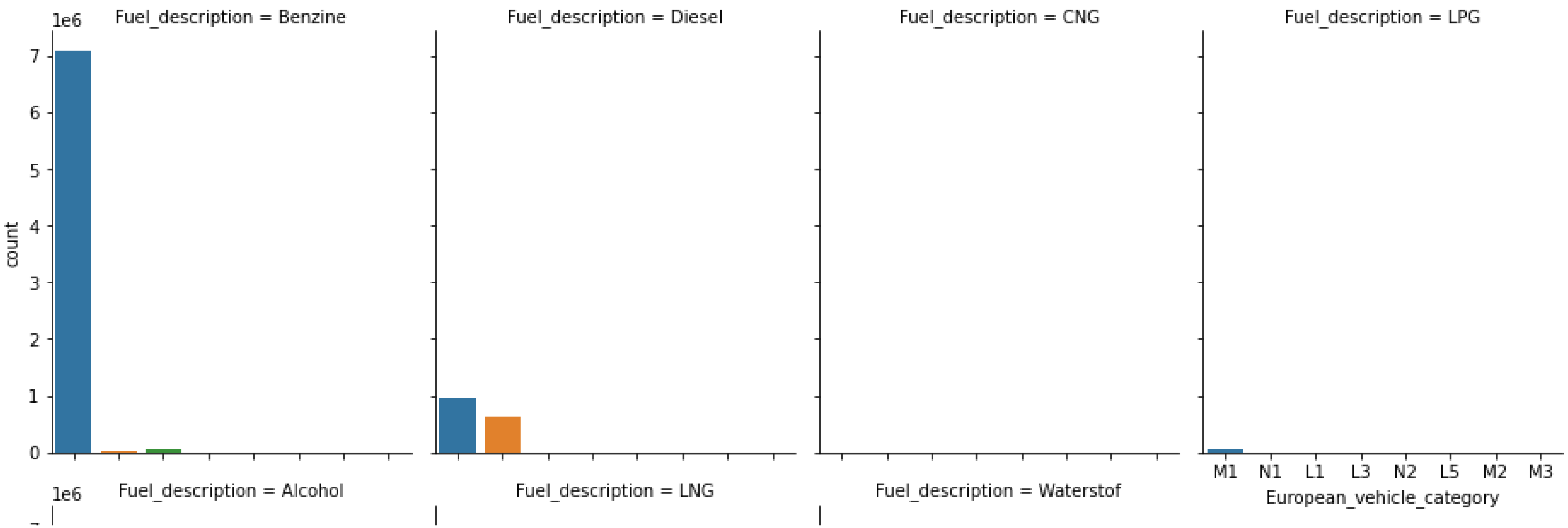
I will check here how many Eu cars categories per fuel type do we have in the dataset

In [35]:
```
df.groupby(['Fuel_description', 'European_vehicle_category']).size()
```

Out[35]:
```
Fuel_description  European_vehicle_category
Alcohol           M1                              3512
                  N1                                 3
Benzine           L1                             51352
                  L3                               615
                  L5                               364
                  M1                           7070648
                  N1                              9844
                  N2                                 4
CNG               M1                              8824
                  N1                              2971
                  N2                                21
Diesel            M1                            967258
                  M2                                29
                  M3                                 4
                  N1                            621782
                  N2                              3413
LNG               M1                                 9
                  N1                                 1
LPG               M1                             67649
                  N1                               533
                  N2                                 3
Waterstof         M1                                 3
dtype: int64
```

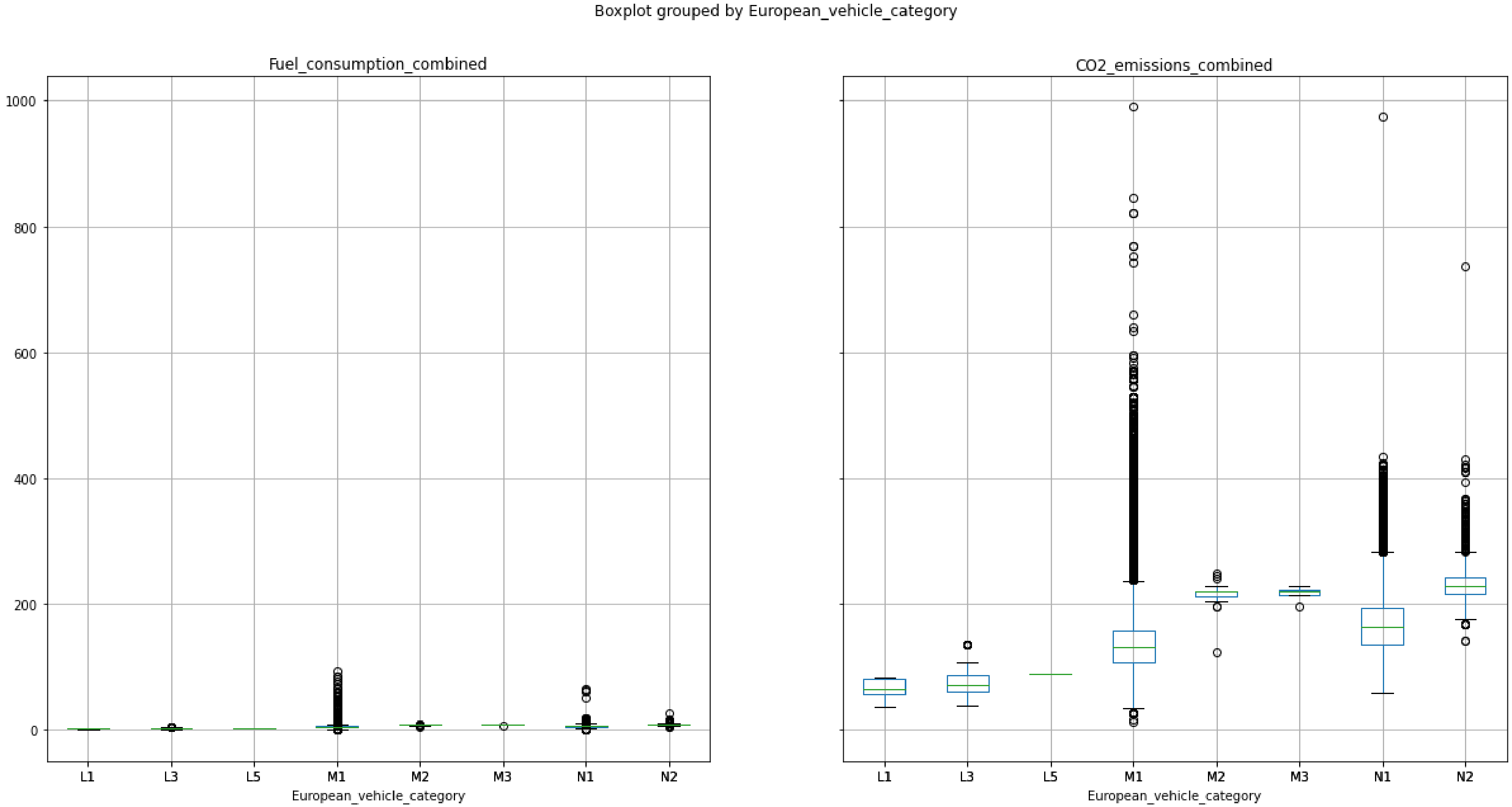
In [36]:
```
sns.catplot(data=df,kind='count',x='European_vehicle_category',col='Fuel_description',col_wrap=4, height=4, aspect=.8)
```

Out[36]: <seaborn.axisgrid.FacetGrid at 0x2033c75fd00>



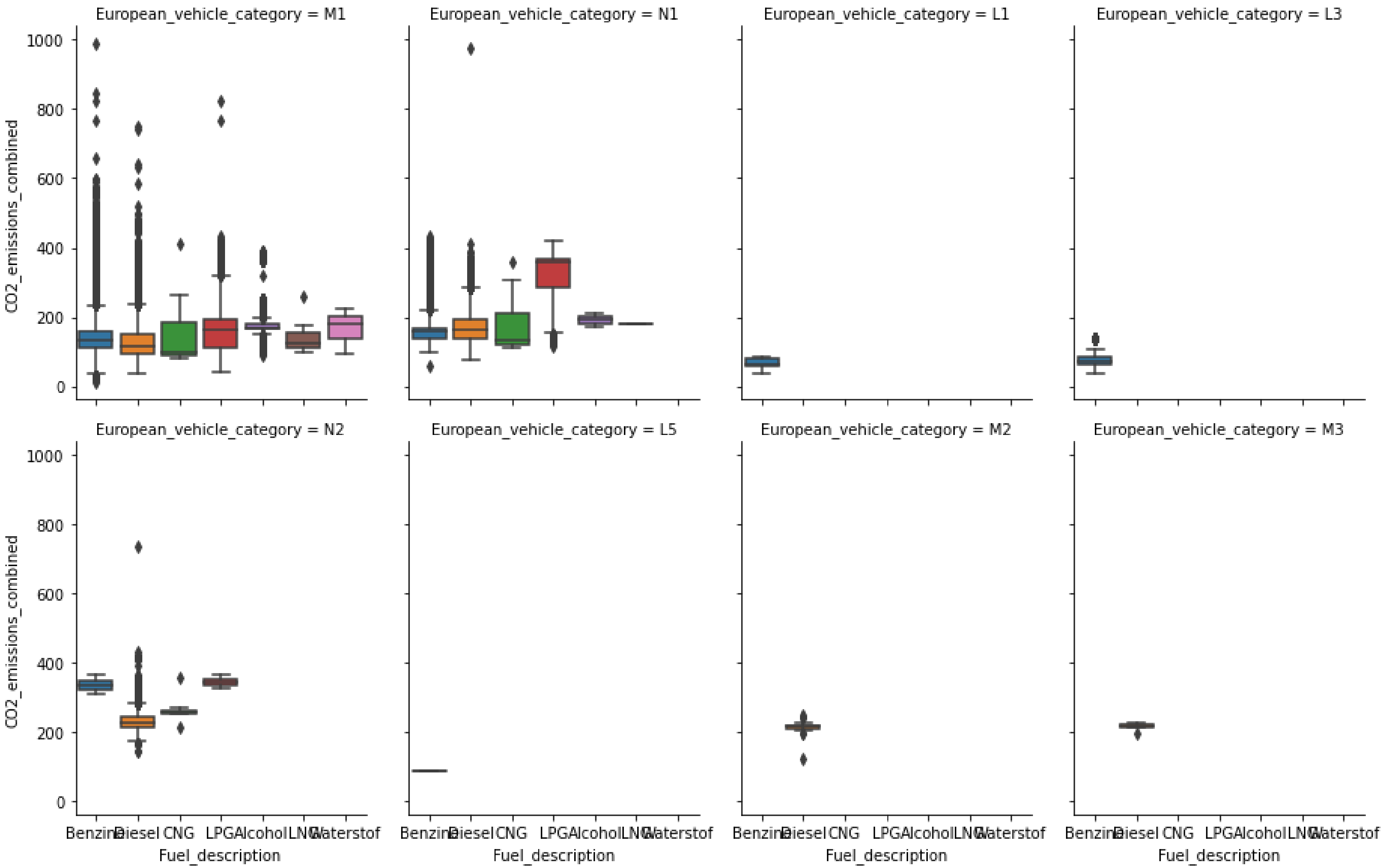
Now I will create a box plot to see if we can classify cars by the CO2 emission or by fuel consumption and to see what can we understand from the patterns and to see the outliers

In [37]:
```
df_features = tuple(df.columns[[12,14]].values)
df.boxplot(column=df_features, by='European_vehicle_category', figsize=(20,10), layout=(1,2));
```

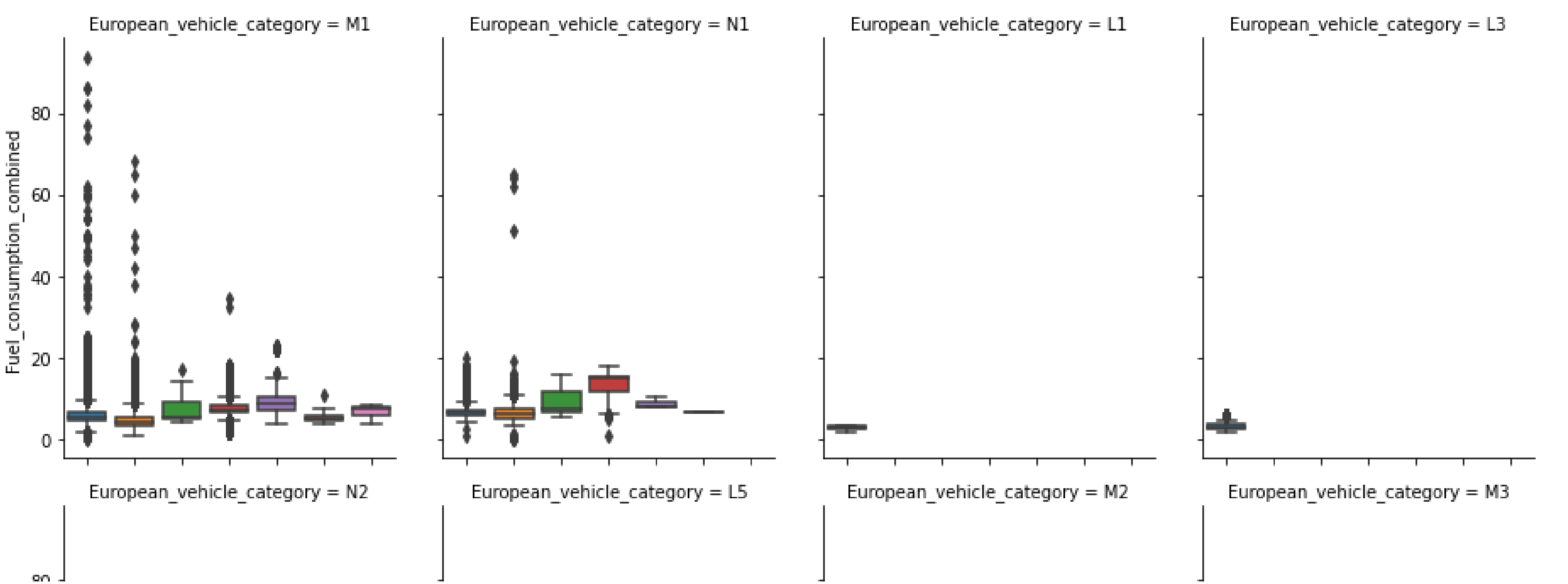


I will create another two boxplots one for the CO_2 emission and the other for fuel consumption and plot them per Eu category to see if could see clear relations between them

In [38]:
```
g = sns.catplot(x='Fuel_description', y="CO2_emissions_combined",col_wrap=4, col="European_vehicle_category", data=df, k
```



In [39]:
```
g = sns.catplot(x='Fuel_description', y="Fuel_consumption_combined",col_wrap=4, col="European_vehicle_category", data=df
```



we can conclude from those diagrams that there is a lot of inconsistency (outliers) and that we see that a lot of cars have huge fuel consumption and co2 emission on the other hand we can see from now that we do have average cars that could be used and classified as eco-friendly cars instead of non-eco-friendly cars

8. Data Munging

8.1. Transform the Data

In [40]:
```
df['fuel_number'] = df['Fuel_description'].map( {'Benzine': 1, 'LPG': 2, 'Diesel': 3,'LNG':4,'Waterstof':5,'CNG':6,'Alco
df['eu_ctagory_number'] = df['European_vehicle_category'].map( {'L1': 1, 'L3': 2, 'L5': 3,'M1':4,'M2':5,'M3':6,'N1':7,'N
```

8.2. Hot Encoding

Hot Encoding, We have a categorical feature attribute: Fuel_description, European_vehicle_category that we need to change to numbers and split each category in a separate column so we don't get a biased result

In [41]:
```
df['Benzine'] = df['Fuel_description'].map( {'Benzine': 1, 'LPG': 0, 'Diesel': 0,'LNG':0,'Waterstof':0,'CNG':0,'Alcohol'
df['LPG'] = df['Fuel_description'].map( {'Benzine': 0, 'LPG': 1, 'Diesel': 0,'LNG':0,'Waterstof':0,'CNG':0,'Alcohol':0}
df['Diesel'] = df['Fuel_description'].map( {'Benzine': 0, 'LPG': 0, 'Diesel': 1,'LNG':0,'Waterstof':0,'CNG':0,'Alcohol':
df['LNG'] = df['Fuel_description'].map( {'Benzine': 0, 'LPG': 0, 'Diesel': 0,'LNG':1,'Waterstof':0,'CNG':0,'Alcohol':0}
df['Waterstof'] = df['Fuel_description'].map( {'Benzine': 0, 'LPG': 0, 'Diesel': 0,'LNG':0,'Waterstof':1,'CNG':0,'Alcoho
df['CNG'] = df['Fuel_description'].map( {'Benzine': 0, 'LPG': 0, 'Diesel': 0,'LNG':0,'Waterstof':0,'CNG':1,'Alcohol':0}
df['Alcohol'] = df['Fuel_description'].map( {'Benzine': 0, 'LPG': 0, 'Diesel': 0,'LNG':0,'Waterstof':0,'CNG':0,'Alcohol'


df['L1'] = df['European_vehicle_category'].map( {'L1': 1, 'L3': 0, 'L5': 0,'M1':0,'M2':0,'M3':0,'N1':0,'N2':0} ).astype(
df['L3'] = df['European_vehicle_category'].map( {'L1': 0, 'L3': 1, 'L5': 0,'M1':0,'M2':0,'M3':0,'N1':0,'N2':0} ).astype(
df['L5'] = df['European_vehicle_category'].map( {'L1': 0, 'L3': 0, 'L5': 1,'M1':0,'M2':0,'M3':0,'N1':0,'N2':0} ).astype(
df['M1'] = df['European_vehicle_category'].map( {'L1': 0, 'L3': 0, 'L5': 0,'M1':1,'M2':0,'M3':0,'N1':0,'N2':0} ).astype(
df['M2'] = df['European_vehicle_category'].map( {'L1': 0, 'L3': 0, 'L5': 0,'M1':0,'M2':1,'M3':0,'N1':0,'N2':0} ).astype(
df['M3'] = df['European_vehicle_category'].map( {'L1': 0, 'L3': 0, 'L5': 0,'M1':0,'M2':0,'M3':1,'N1':0,'N2':0} ).astype(
df['N1'] = df['European_vehicle_category'].map( {'L1': 0, 'L3': 0, 'L5': 0,'M1':0,'M2':0,'M3':0,'N1':1,'N2':0} ).astype(
df['N2'] = df['European_vehicle_category'].map( {'L1': 0, 'L3': 0, 'L5': 0,'M1':0,'M2':0,'M3':0,'N1':0,'N2':1} ).astype(
```

8.3. Check missing Values

In [42]:
```
df.isna().sum()
```

Out[42]:
```
License_plate                       0
Vehicle_type                        0
Brand                               0
Trade name                        639
number_of_seats                  1953
Amount_of_cilinders               351
Mass_of_empty_vehicle               0
number_of_doors                 63119
European_vehicle_category           0
Technical_max_vehicle_mass        818
Fuel_description                    0
Out_of_town_fuel_consumption   130579
Fuel_consumption_combined           0
City_fuel_consumption          130318
CO2_emissions_combined              0
fuel_number                         0
eu_ctagory_number                   0
Benzine                             0
LPG                                 0
Diesel                              0
LNG                                 0
Waterstof                           0
CNG                                 0
Alcohol                             0
L1                                  0
L3                                  0
L5                                  0
M1                                  0
M2                                  0
M3                                  0
N1                                  0
N2                                  0
dtype: int64
```

The columns the we are going to use them hav 0 cull values

9- Selecting the features

I will use Fuel_consumption_combined, CO2_emissions_combined, Fuel_consumption_combined and CO2_emissions_combined to determine the cars echo-friendly number(from 1 to 10)

In [43]:
```
df.shape
```

Out[43]:
```
(8808842, 32)
```

In [44]:
```
# here I will try to make the classification with using hot encoding
x_df=df[['Benzine','LPG','Diesel','LNG','Waterstof','CNG','Alcohol','L1','L3','L5','M1','M2','M3','N1','N2','Fuel_consum

# here I will try to make the classification without using hot encoding
x_df_without_hot_encoding=df[['fuel_number','eu_ctagory_number','Fuel_consumption_combined','CO2_emissions_combined']]

# here I will try to make the classification after normalization
scaler = StandardScaler()
scaled_features = scaler.fit_transform(x_df)
```

In [45]:
```
x_df.head()
```

Out[45]:

	Benzine	LPG	Diesel	LNG	Waterstof	CNG	Alcohol	L1	L3	L5	M1	M2	M3	N1	N2	Fuel_consumption_combined	CO2_emissions_combinec
0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	6.7	16(
1	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	3.2	8!
2	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	5.7	13(
3	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	9.8	23(
4	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	8.8	21'

In [46]:
```
scaled_features
```

Out[46]:
```
array([[ 0.48473916, -0.08832271, -0.46976303, ..., -0.01976823,
         0.53041184,  0.51206336],
       [-2.06296517, -0.08832271,  2.12873286, ..., -0.01976823,
        -1.59180818, -1.3301047 ],
       [ 0.48473916, -0.08832271, -0.46976303, ..., -0.01976823,
        -0.07593674, -0.07743042],
       ...,
       [ 0.48473916, -0.08832271, -0.46976303, ..., -0.01976823,
         1.13676041,  1.1998061 ],
       [-2.06296517, -0.08832271,  2.12873286, ..., -0.01976823,
         0.10596783,  0.43837663],
       [ 0.48473916, -0.08832271, -0.46976303, ..., -0.01976823,
        -0.86418989, -0.88798437]])
```

10-Training Machine learning algorithm and predicting

I will first start MiniBatchKMeans and check the result then I will scale the data and perform the same algorithms to see the difference,I will also try the algorithm without hot encoding

Showing the Maximum and minimum of fuel consumption and CO2 to help us later to compare the result

In [47]:
```
print('fuel consumption min:',df['Fuel_consumption_combined'].min(),'fuel consumption max:',df['Fuel_consumption_combine
print(' Co2 min:',df['CO2_emissions_combined'].min(),'Co2 max:',df['CO2_emissions_combined'].max())
```

```
fuel consumption min: 0.2 fuel consumption max: 93.6
 Co2 min: 12 Co2 max: 990
```

The effect of the initial cluster centroids

In [48]:
```
# for n in range (20):
#     mbk = MiniBatchKMeans(n_clusters=10, random_state=n)
#     mbk.fit(x_df)
#     print('Random state = ',n,'\tNr iterations',mbk.n_iter_,'\tSum of squared distances ',mbk.inertia_)
```

So I will choose the minimum inertia: Random state = 12 Nr iterations 17 Sum of squared distances 380626823.54407,

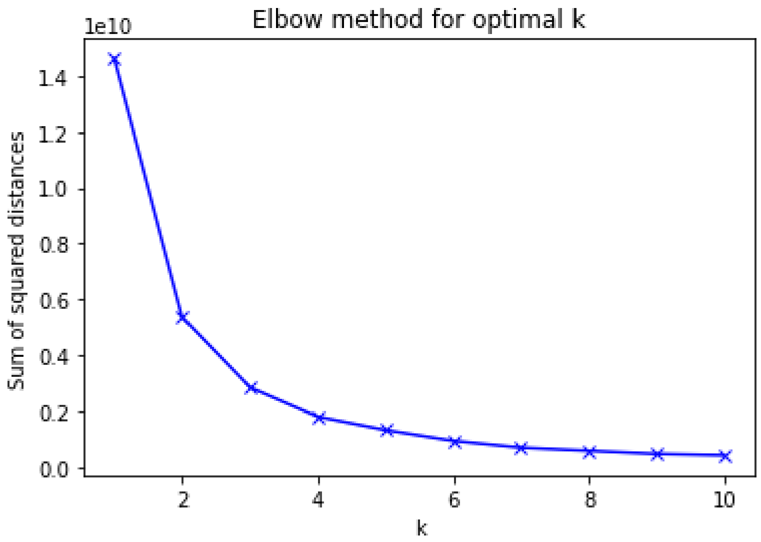
I will comment this code since I already execute it and got my result because it takes tremendous time.

The Elbow method

In [49]:
```
Sum_of_squared_distances = []
K = range(1,11)
for k in K:
    mbk = MiniBatchKMeans(n_clusters=k, random_state=1,batch_size=3072)
    mbk.fit(x_df)
    Sum_of_squared_distances.append(mbk.inertia_)
    print('Nr clusters',k,'\tSum of squared distances ',mbk.inertia_)
```

```
Nr clusters 1   Sum of squared distances  14629065515.052933
Nr clusters 2   Sum of squared distances  5354163319.034832
Nr clusters 3   Sum of squared distances  2841173333.3897324
Nr clusters 4   Sum of squared distances  1791384786.2536974
Nr clusters 5   Sum of squared distances  1314824811.2003906
Nr clusters 6   Sum of squared distances  930311557.2815778
Nr clusters 7   Sum of squared distances  688648478.7868526
Nr clusters 8   Sum of squared distances  575726638.3087895
Nr clusters 9   Sum of squared distances  465382719.79970336
Nr clusters 10  Sum of squared distances  416202356.5038332
```

In [50]:
```
plt.plot(K, Sum_of_squared_distances, 'bx-')
plt.xlabel('k')
plt.ylabel('Sum of squared distances')
plt.title('Elbow method for optimal k')
plt.show()
```



as we see in the elbow method the best clusters is between 3 and 4 but my research objectives are to classify them from 1 to 10 for several reasons one of them is to have a variety of choices and to classify cars in a more detailed way ,So I will choose 10 clusters because it has the least sum of squared distance

MiniBatchKMeans algorithm

The MiniBatchKMeans is a variant of the KMeans algorithm which uses mini-batches to reduce the computation time, while still attempting to optimise the same objective function.

In [51]:
```
mbk  = MiniBatchKMeans(n_clusters=10,random_state=12,batch_size=3072)
```

In [52]:
```
mbk  = mbk.fit(x_df)
```

In [53]:
```
cluster_centers = mbk.cluster_centers_
print(cluster_centers)
```

```
[[8.37612892e-01 1.07136533e-02 1.51319285e-01 0.00000000e+00
  0.00000000e+00 3.54170356e-04 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 9.73968479e-01 0.00000000e+00
  0.00000000e+00 2.60315212e-02 0.00000000e+00 4.53056490e+00
  1.05966619e+02]
 [6.13787701e-01 1.60595378e-02 3.65452409e-01 0.00000000e+00
  0.00000000e+00 4.30865648e-03 3.91696044e-04 0.00000000e+00
  0.00000000e+00 0.00000000e+00 7.35213474e-01 0.00000000e+00
  0.00000000e+00 2.60086173e-01 4.70035253e-03 8.53216608e+00
  2.10370153e+02]
 [8.73558801e-01 2.56213169e-03 1.23238534e-01 0.00000000e+00
  0.00000000e+00 3.84319754e-04 2.56213169e-04 0.00000000e+00
  0.00000000e+00 0.00000000e+00 9.44273636e-01 0.00000000e+00
  0.00000000e+00 5.57263643e-02 0.00000000e+00 5.86869459e+00
  1.39374327e+02]
 [7.17656012e-01 1.52207002e-02 2.60273973e-01 0.00000000e+00
  0.00000000e+00 3.80517504e-03 3.04414003e-03 0.00000000e+00
  0.00000000e+00 0.00000000e+00 8.34094368e-01 0.00000000e+00
  0.00000000e+00 1.57534247e-01 8.37138508e-03 9.96511416e+00
  2.43712329e+02]
 [8.13391197e-01 1.09526762e-02 1.72143005e-01 0.00000000e+00
  0.00000000e+00 2.06654267e-04 3.30646828e-03 0.00000000e+00
  0.00000000e+00 0.00000000e+00 8.92333127e-01 0.00000000e+00
  0.00000000e+00 1.07666873e-01 0.00000000e+00 7.08310395e+00
  1.70636495e+02]
 [7.33244637e-01 1.16414435e-03 2.61599867e-01 0.00000000e+00
  0.00000000e+00 3.99135207e-03 0.00000000e+00 5.03908199e-02
  4.98919009e-04 0.00000000e+00 9.48943955e-01 0.00000000e+00
  0.00000000e+00 1.66306336e-04 0.00000000e+00 3.72091302e+00
  8.81137535e+01]
 [8.26558266e-01 3.52303523e-02 1.38211382e-01 0.00000000e+00
  0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 9.37669377e-01 0.00000000e+00
  0.00000000e+00 5.69105691e-02 5.42005420e-03 1.28628455e+01
  3.12276423e+02]
 [8.24197211e-01 5.51410963e-03 1.67693805e-01 0.00000000e+00
  0.00000000e+00 1.62179695e-03 9.73078171e-04 0.00000000e+00
  0.00000000e+00 0.00000000e+00 9.15342199e-01 0.00000000e+00
```

```
  0.00000000e+00 8.46578008e-02 0.00000000e+00 6.44660396e+00
  1.54871878e+02]
 [8.53529121e-01 1.97433366e-03 1.42892399e-01 0.00000000e+00
  0.00000000e+00 1.60414610e-03 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 9.39042448e-01 0.00000000e+00
  0.00000000e+00 6.09575518e-02 0.00000000e+00 5.20541214e+00
  1.22611303e+02]
 [7.47742963e-01 1.32766861e-02 2.38980351e-01 0.00000000e+00
  0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
  0.00000000e+00 0.00000000e+00 8.50770048e-01 0.00000000e+00
  0.00000000e+00 1.48433351e-01 7.96601168e-04 7.72380510e+00
  1.88135422e+02]]
```

In [54]:

```
print(np.unique(mbk.labels_))
```

```
[0 1 2 3 4 5 6 7 8 9]
```

Maximum number of iterations for a single run

In [55]:

```
print(mbk.n_iter_)
```

```
14
```

Inertia: Intuitively, inertia tells how far away the points within a cluster are. Therefore, a small of inertia is aimed for. The range of inertia’s value starts from zero and goes up.

In [56]:

```
print(mbk.inertia_)
```

```
407780586.9390222
```

In [57]:
```
df['Cluster'] = mbk.labels_.astype(int)
df.head(10)
```

3	20SGRP	Personenauto	BMW	3ER REIHE	4.0	6.0	1550.0	2.0
4	89TZPK	Personenauto	MINI	MINI COOPER S	4.0	4.0	1215.0	2.0
5	NJ731T	Personenauto	OPEL	ASTRA SPORTS TOURER+	5.0	4.0	1212.0	5.0
6	22STV1	Personenauto	PEUGEOT	3008	5.0	4.0	1434.0	4.0
7	VN677N	Bedrijfsauto	VOLKSWAGEN	CADDY	2.0	4.0	1404.0	0.0
8	L216BV	Personenauto	VOLKSWAGEN	T-ROC	5.0	4.0	1247.0	5.0
9	75LVGH	Personenauto	BMW	7ER REIHE	5.0	6.0	1875.0	4.0

10 rows × 33 columns

Exploring the result with 1 to see the CO2 and fuel consumption values if it makes sense

In [58]:
```
df[['European_vehicle_category','Fuel_consumption_combined','CO2_emissions_combined','Cluster']].loc[(df['Cluster']==1) &
```

Out[58]:

	European_vehicle_category	Fuel_consumption_combined	CO2_emissions_combined	Cluster
4	M1	8.8	211	1
13	M1	8.6	202	1
51	M1	8.6	205	1
103	M1	9.2	220	1
138	M1	9.0	226	1
...	...	...	...	...
8808620	M1	8.8	211	1
8808655	M1	9.1	218	1
8808681	M1	9.3	223	1
8808734	M1	9.4	225	1
8808742	M1	8.5	203	1

239597 rows × 4 columns

In [59]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 5) )]
print('  min:',df2['CO2_emissions_combined'].min(),'max:',df2['CO2_emissions_combined'].max())
```

```
  min: 12 max: 97
```

In [60]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 6) )]

print('  min:',df2['CO2_emissions_combined'].min(),' max:',df2['CO2_emissions_combined'].max())
```

```
  min: 278  max: 990
```

In [61]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 7) )]
print('  min:',df2['CO2_emissions_combined'].min(),' max:',df2['CO2_emissions_combined'].max())
```

```
  min: 148  max: 162
```

In [62]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 8) )]
print('  min:',df2['CO2_emissions_combined'].min(),' max:',df2['CO2_emissions_combined'].max())
```

```
  min: 113  max: 131
```

In [63]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 9) )]
print('  min:',df2['CO2_emissions_combined'].min(),' max:',df2['CO2_emissions_combined'].max())
```

```
  min: 179  max: 199
```

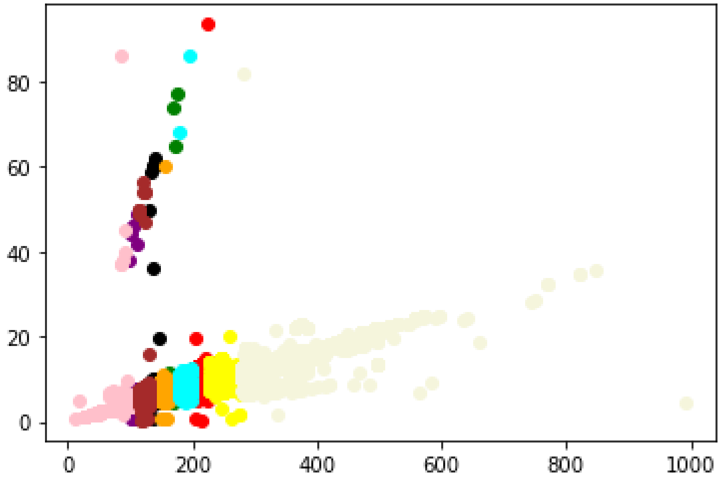
In [64]:
```
#Plot the clusters obtained using k means
# fig = plt.figure()
# ax = fig.add_subplot(111)
# scatter = ax.scatter(df['CO2_emissions_combined'],df['Fuel_consumption_combined'],
#                       c=df['Cluster'])
# ax.set_title('MiniBatchKMeans Clustering')
# ax.set_xlabel('CO2_emissions_combined')
# ax.set_ylabel('Fuel_consumption_combined')
# plt.colorbar(scatter)
```

First, I used this code to plot the clusters but It takes a very long time to execute so I replaced it with the below code which is much faster and has the same result

In [65]:
```
#filter rows of original data
filtered_label0 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 0) )]
filtered_label1 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 1) )]
filtered_label2 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 2) )]
filtered_label3 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 3) )]
filtered_label4 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 4) )]
filtered_label5 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 5) )]
filtered_label6 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 6) )]
filtered_label7 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 7) )]
filtered_label8 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 8) )]
filtered_label9 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 9) )]



#Plotting the results
plt.scatter(filtered_label0['CO2_emissions_combined'] ,filtered_label0['Fuel_consumption_combined'] ,color = 'purple')
plt.scatter(filtered_label1['CO2_emissions_combined'] ,filtered_label1['Fuel_consumption_combined'],color = 'red')
plt.scatter(filtered_label2['CO2_emissions_combined'],filtered_label2['Fuel_consumption_combined'],color = 'black')
plt.scatter(filtered_label3['CO2_emissions_combined'] ,filtered_label3['Fuel_consumption_combined'],color = 'yellow')
plt.scatter(filtered_label4['CO2_emissions_combined'] ,filtered_label4['Fuel_consumption_combined'],color = 'green')
plt.scatter(filtered_label5['CO2_emissions_combined'] ,filtered_label5['Fuel_consumption_combined'],color = 'pink' )
plt.scatter(filtered_label6['CO2_emissions_combined'] ,filtered_label6['Fuel_consumption_combined'] ,color = 'beige')
plt.scatter(filtered_label7['CO2_emissions_combined'] ,filtered_label7['Fuel_consumption_combined'] ,color = 'orange')
plt.scatter(filtered_label8['CO2_emissions_combined'] ,filtered_label8['Fuel_consumption_combined'] ,color = 'brown')
plt.scatter(filtered_label9['CO2_emissions_combined'] ,filtered_label9['Fuel_consumption_combined'],color = 'cyan' )
plt.show()
```



If we manually compare the result of the first five rows from the category M1 we can see that cars with high CO2 and fuel consumption has a wrong result depending on other cars from the same category M1 ,but when we show the minimum and maximum co2 emission we notice that the data is classified but it's not organized like cluster 1 should have the data of cluster 3 so it's not sorted by cluster number.
Note: we have to compare manually because we don't have the data we are generating

Conclusion
After doing more research about this issue I discovered that This behavior is normal, as the ordering of cluster labels is dependent on the initialization. Cluster 0 from the first run could be labeled cluster 1 in the second run and vice versa. This doesn’t affect clustering evaluation metrics.

But know the problem is how to make it organise it from the smaller to the bigger in clustering

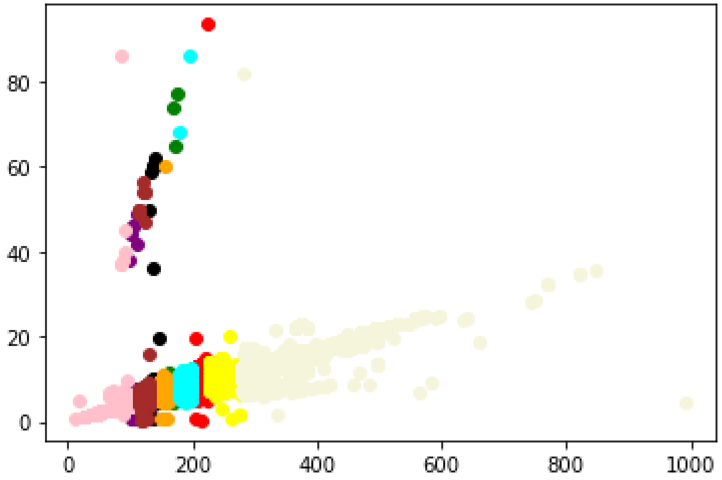
after further investigation and researching I couldn't find a way to make Kmeans sort the clusters from small to big so I will hot encoding it

In [66]:
```
df['soorted_cluster'] = df['Cluster'].map( {0: 1, 9: 2, 4:3 ,6:4,2:5,1:6,7:7,3:8,8:9,5:10} ).astype(int)
```

In [67]:
```
#filter rows of original data
filtered_label0 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 0) )]
filtered_label1 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 1) )]
filtered_label2 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 2) )]
filtered_label3 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 3) )]
filtered_label4 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 4) )]
filtered_label5 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 5) )]
filtered_label6 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 6) )]
filtered_label7 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 7) )]
filtered_label8 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 8) )]
filtered_label9 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 9) )]



#Plotting the results
plt.scatter(filtered_label0['CO2_emissions_combined'] ,filtered_label0['Fuel_consumption_combined'] ,color = 'purple')
plt.scatter(filtered_label1['CO2_emissions_combined'] ,filtered_label1['Fuel_consumption_combined'],color = 'red')
plt.scatter(filtered_label2['CO2_emissions_combined'],filtered_label2['Fuel_consumption_combined'],color = 'black')
plt.scatter(filtered_label3['CO2_emissions_combined'] ,filtered_label3['Fuel_consumption_combined'],color = 'yellow')
plt.scatter(filtered_label4['CO2_emissions_combined'] ,filtered_label4['Fuel_consumption_combined'],color = 'green')
plt.scatter(filtered_label5['CO2_emissions_combined'] ,filtered_label5['Fuel_consumption_combined'],color = 'pink' )
plt.scatter(filtered_label6['CO2_emissions_combined'] ,filtered_label6['Fuel_consumption_combined'] ,color = 'beige')
plt.scatter(filtered_label7['CO2_emissions_combined'] ,filtered_label7['Fuel_consumption_combined'] ,color = 'orange')
plt.scatter(filtered_label8['CO2_emissions_combined'] ,filtered_label8['Fuel_consumption_combined'] ,color = 'brown')
plt.scatter(filtered_label9['CO2_emissions_combined'] ,filtered_label9['Fuel_consumption_combined'],color = 'cyan' )
plt.show()
```



MiniBatchKMeans algorithm with scalling

We still have a wrong result, I will try now first to scle the data than do the same algorithms

In [68]:
```
mbk   = MiniBatchKMeans(n_clusters=10,random_state=12,batch_size=3072)
```

In [69]:
```
mbk   = mbk.fit(scaled_features)
```

In [70]:
```
print(np.unique(mbk.labels_))
```

```
[0 1 2 3 4 5 6 7 8 9]
```

In [71]:
```
print(mbk.n_iter_)
```

```
11
```

In [72]:
```
df['Cluster'] = mbk.labels_.astype(int)
df.head(10)
```

3	20SGRP	Personenauto	BMW	3ER REIHE	4.0	6.0	1550.0	2.0
4	89TZPK	Personenauto	MINI	MINI COOPER S	4.0	4.0	1215.0	2.0
5	NJ731T	Personenauto	OPEL	ASTRA SPORTS TOURER+	5.0	4.0	1212.0	5.0
6	22STV1	Personenauto	PEUGEOT	3008	5.0	4.0	1434.0	4.0
7	VN677N	Bedrijfsauto	VOLKSWAGEN	CADDY	2.0	4.0	1404.0	0.0
8	L216BV	Personenauto	VOLKSWAGEN	T-ROC	5.0	4.0	1247.0	5.0
9	75LVGH	Personenauto	BMW	7ER REIHE	5.0	6.0	1875.0	4.0

10 rows × 34 columns

In [73]:
```
df[['European_vehicle_category','Fuel_consumption_combined','CO2_emissions_combined','Cluster']].loc[(df['Cluster']==1) &
```

Out[73]:

	European_vehicle_category	Fuel_consumption_combined	CO2_emissions_combined	Cluster
3	M1	9.8	236	1
4	M1	8.8	211	1
13	M1	8.6	202	1
21	M1	8.1	193	1
23	M1	8.0	190	1
...	...	...	...	...
8808901	M1	8.4	199	1
8808906	M1	8.3	198	1
8808907	M1	8.2	196	1
8808919	M1	7.5	176	1
8808929	M1	7.7	188	1

1093746 rows × 4 columns

In [74]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 5) )]
print('  min:',df2['CO2_emissions_combined'].min(),'max:',df2['CO2_emissions_combined'].max())
```

```
  min: 39 max: 337
```

In [75]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 6) )]

print('  min:',df2['CO2_emissions_combined'].min(),' max:',df2['CO2_emissions_combined'].max())
```

```
  min: 79  max: 410
```

In [76]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 7) )]
print('  min:',df2['CO2_emissions_combined'].min(),' max:',df2['CO2_emissions_combined'].max())
```

```
min: 42  max: 822
```

In [77]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 8) )]
print('  min:',df2['CO2_emissions_combined'].min(),' max:',df2['CO2_emissions_combined'].max())
```

```
min: 88  max: 388
```

In [78]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 9) )]
print('  min:',df2['CO2_emissions_combined'].min(),' max:',df2['CO2_emissions_combined'].max())
```

```
min: 94  max: 275
```

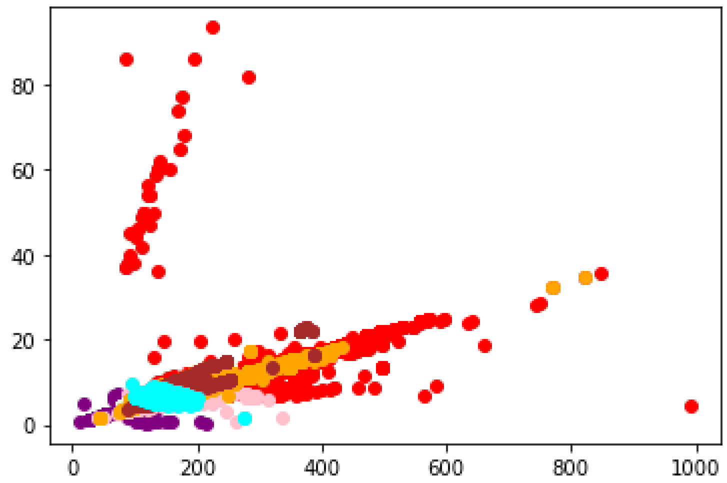
In [79]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 4) )]
print('  min:',df2['CO2_emissions_combined'].min(),' max:',df2['CO2_emissions_combined'].max())
```

```
min: nan  max: nan
```

In [80]:
```
#filter rows of original data
filtered_label0 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 0) )]
filtered_label1 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 1) )]
filtered_label2 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 2) )]
filtered_label3 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 3) )]
filtered_label4 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 4) )]
filtered_label5 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 5) )]
filtered_label6 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 6) )]
filtered_label7 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 7) )]
filtered_label8 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 8) )]
filtered_label9 = df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 9) )]



#Plotting the results
plt.scatter(filtered_label0['CO2_emissions_combined'] ,filtered_label0['Fuel_consumption_combined'] ,color = 'purple')
plt.scatter(filtered_label1['CO2_emissions_combined'] ,filtered_label1['Fuel_consumption_combined'],color = 'red')
plt.scatter(filtered_label2['CO2_emissions_combined'],filtered_label2['Fuel_consumption_combined'],color = 'black')
plt.scatter(filtered_label3['CO2_emissions_combined'] ,filtered_label3['Fuel_consumption_combined'],color = 'yellow')
plt.scatter(filtered_label4['CO2_emissions_combined'] ,filtered_label4['Fuel_consumption_combined'],color = 'green')
plt.scatter(filtered_label5['CO2_emissions_combined'] ,filtered_label5['Fuel_consumption_combined'],color = 'pink' )
plt.scatter(filtered_label6['CO2_emissions_combined'] ,filtered_label6['Fuel_consumption_combined'] ,color = 'beige')
plt.scatter(filtered_label7['CO2_emissions_combined'] ,filtered_label7['Fuel_consumption_combined'] ,color = 'orange')
plt.scatter(filtered_label8['CO2_emissions_combined'] ,filtered_label8['Fuel_consumption_combined'] ,color = 'brown')
plt.scatter(filtered_label9['CO2_emissions_combined'] ,filtered_label9['Fuel_consumption_combined'],color = 'cyan' )
plt.show()
```



As we see in the above plot and results something is wrong, My best estimation is that scaling a categorical data is not a good option

MiniBatchKMeans without hot encoding

In [81]:
```
#df=df.drop(['Benzine','LPG','Diesel','LNG','Waterstof','CNG','Alcohol','L1','L3','L5','M1','M2','M3','N1','N2'], axis=1,
```

In [82]:
```
mbk  = MiniBatchKMeans(n_clusters=10,random_state=12,batch_size=3072)
mbk.fit(x_df_without_hot_encoding)
```

Out[82]:
```
MiniBatchKMeans(batch_size=3072, n_clusters=10, random_state=12)
```

In [83]:
```
print(np.unique(mbk.labels_))
```

```
[0 1 2 3 4 5 6 7 8 9]
```

Maximum number of iterations for a single run

In [84]:
```
print(mbk.n_iter_)
```

```
29
```

Sum of squared distances

In [85]:
```
print(mbk.inertia_)
```

```
392139289.2835744
```

In [86]:
```
mbk.labels_
```

Out[86]:
```
array([2, 4, 6, ..., 7, 2, 8])
```

In [87]:
```
df['Cluster'] = mbk.labels_
df[['European_vehicle_category','Fuel_consumption_combined','CO2_emissions_combined','Cluster']].head(10)
```

Out[87]:

	European_vehicle_category	Fuel_consumption_combined	CO2_emissions_combined	Cluster
0	M1	6.7	160	2
1	M1	3.2	85	4
2	M1	5.7	136	6
3	M1	9.8	236	1
4	M1	8.8	211	1
5	M1	4.9	114	0
6	M1	7.1	167	3
7	N1	5.6	147	2
8	M1	5.3	120	0
9	M1	8.5	227	1

In [88]:
```
#df=df.drop(['Benzine','LPG','Diesel','LNG','Waterstof','CNG','Alcohol','L1','L3','L5','M1','M2','M3','N1','N2'], axis=1,
```

Exploring the result with 1 to see the CO2 and fuel consumption values if it makes sense

In [89]:
```
df[['European_vehicle_category','Fuel_consumption_combined','CO2_emissions_combined','Cluster']].loc[(df['Cluster']==1)
```

	European_vehicle_category	Fuel_consumption_combined	CO2_emissions_combined	Cluster
3	M1	9.8	236	1
4	M1	8.8	211	1
103	M1	9.2	220	1
138	M1	9.0	226	1
150	M1	9.2	220	1
...	...	...	...	...
8808620	M1	8.8	211	1
8808655	M1	9.1	218	1
8808681	M1	9.3	223	1
8808734	M1	9.4	225	1
8808777	M1	10.1	242	1

225277 rows × 4 columns

In [90]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 0) )]
print(' Co2 min:',df2['CO2_emissions_combined'].min(),' CO2 max:',df2['CO2_emissions_combined'].max())
print(' Fuel consumption min:',df2['Fuel_consumption_combined'].min(),' Fuel consumption max:',df2['Fuel_consumption_com
```

```
 Co2 min: 108  CO2 max: 125
 Fuel consumption min: 0.3  Fuel consumption max: 56.3
```

In [91]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 1) )]
print(' Co2 min:',df2['CO2_emissions_combined'].min(),' CO2 max:',df2['CO2_emissions_combined'].max())
print(' Fuel consumption min:',df2['Fuel_consumption_combined'].min(),' Fuel consumption max:',df2['Fuel_consumption_com
```

```
 Co2 min: 210  CO2 max: 245
 Fuel consumption min: 0.3  Fuel consumption max: 93.6
```

In [92]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 2) )]
print(' Co2 min:',df2['CO2_emissions_combined'].min(),' CO2 max:',df2['CO2_emissions_combined'].max())
print(' Fuel consumption min:',df2['Fuel_consumption_combined'].min(),' Fuel consumption max:',df2['Fuel_consumption_com
```

```
 Co2 min: 144  CO2 max: 162
 Fuel consumption min: 0.7  Fuel consumption max: 60.0
```

In [93]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 3) )]
print(' Co2 min:',df2['CO2_emissions_combined'].min(),' CO2 max:',df2['CO2_emissions_combined'].max())
print(' Fuel consumption min:',df2['Fuel_consumption_combined'].min(),' Fuel consumption max:',df2['Fuel_consumption_com
```

```
 Co2 min: 163  CO2 max: 183
 Fuel consumption min: 4.6  Fuel consumption max: 77.0
```

In [94]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 4) )]
print(' Co2 min:',df2['CO2_emissions_combined'].min(),' CO2 max:',df2['CO2_emissions_combined'].max())
print(' Fuel consumption min:',df2['Fuel_consumption_combined'].min(),' Fuel consumption max:',df2['Fuel_consumption_com
```

```
 Co2 min: 12  CO2 max: 92
 Fuel consumption min: 0.6  Fuel consumption max: 86.0
```

In [95]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 5) )]
print(' Co2 min:',df2['CO2_emissions_combined'].min(),' CO2 max:',df2['CO2_emissions_combined'].max())
print(' Fuel consumption min:',df2['Fuel_consumption_combined'].min(),' Fuel consumption max:',df2['Fuel_consumption_com
```

```
 Co2 min: 306  CO2 max: 990
 Fuel consumption min: 1.71  Fuel consumption max: 35.55
```

In [96]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 6) )]
print(' Co2 min:',df2['CO2_emissions_combined'].min(),' CO2 max:',df2['CO2_emissions_combined'].max())
print(' Fuel consumption min:',df2['Fuel_consumption_combined'].min(),' Fuel consumption max:',df2['Fuel_consumption_com
```

```
 Co2 min: 124  CO2 max: 143
 Fuel consumption min: 0.5  Fuel consumption max: 62.0
```

In [97]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 7) )]
print(' Co2 min:',df2['CO2_emissions_combined'].min(),' CO2 max:',df2['CO2_emissions_combined'].max())
print(' Fuel consumption min:',df2['Fuel_consumption_combined'].min(),' Fuel consumption max:',df2['Fuel_consumption_com
```

```
 Co2 min: 184  CO2 max: 209
 Fuel consumption min: 0.9  Fuel consumption max: 86.0
```

In [98]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 8) )]
print(' Co2 min:',df2['CO2_emissions_combined'].min(),' CO2 max:',df2['CO2_emissions_combined'].max())
print(' Fuel consumption min:',df2['Fuel_consumption_combined'].min(),' Fuel consumption max:',df2['Fuel_consumption_com
```

```
 Co2 min: 92  CO2 max: 107
 Fuel consumption min: 0.5  Fuel consumption max: 46.0
```

In [99]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['Cluster'] == 9) )]
print(' Co2 min:',df2['CO2_emissions_combined'].min(),' CO2 max:',df2['CO2_emissions_combined'].max())
print(' Fuel consumption min:',df2['Fuel_consumption_combined'].min(),' Fuel consumption max:',df2['Fuel_consumption_com
```

```
 Co2 min: 246  CO2 max: 305
 Fuel consumption min: 0.88  Fuel consumption max: 82.0
```

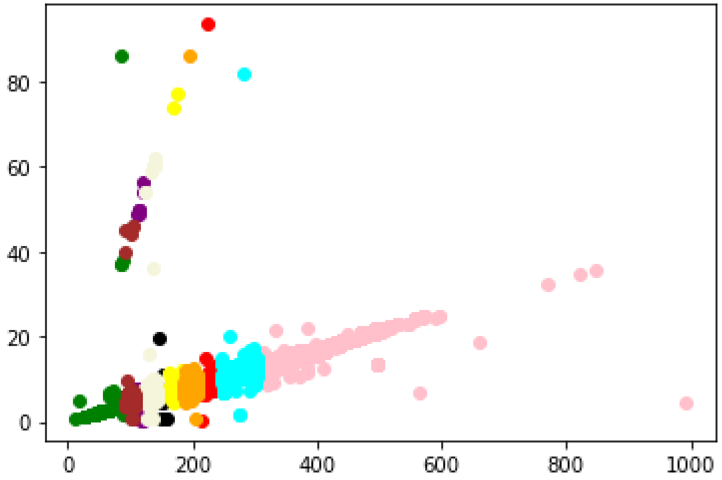
View only the cars with M1 catagory and Benzin to see the difference since the algorithm take fuel type into consideration

In [100]:
```
#filter rows of original data
filtered_label0 = df.loc[(df['Cluster']==0) & (df['Benzine']== 1) & (df['European_vehicle_category']== 'M1')]
filtered_label1 = df.loc[(df['Cluster']==1) & (df['Benzine']== 1) & (df['European_vehicle_category']== 'M1')]
filtered_label2 = df.loc[(df['Cluster']==2) & (df['Benzine']== 1) & (df['European_vehicle_category']== 'M1')]
filtered_label3 = df.loc[(df['Cluster']==3) & (df['Benzine']== 1) & (df['European_vehicle_category']== 'M1')]
filtered_label4 = df.loc[(df['Cluster']==4) & (df['Benzine']== 1) & (df['European_vehicle_category']== 'M1')]
filtered_label5 = df.loc[(df['Cluster']==5) & (df['Benzine']== 1) & (df['European_vehicle_category']== 'M1')]
filtered_label6 = df.loc[(df['Cluster']==6) & (df['Benzine']== 1) & (df['European_vehicle_category']== 'M1')]
filtered_label7 = df.loc[(df['Cluster']==7) & (df['Benzine']== 1) & (df['European_vehicle_category']== 'M1')]
filtered_label8 = df.loc[(df['Cluster']==8) & (df['Benzine']== 1) & (df['European_vehicle_category']== 'M1')]
filtered_label9 = df.loc[(df['Cluster']==9) & (df['Benzine']== 1) & (df['European_vehicle_category']== 'M1')]



#Plotting the results
plt.scatter(filtered_label0['CO2_emissions_combined'] ,filtered_label0['Fuel_consumption_combined'] ,color = 'purple')
plt.scatter(filtered_label1['CO2_emissions_combined'] ,filtered_label1['Fuel_consumption_combined'],color = 'red')
plt.scatter(filtered_label2['CO2_emissions_combined'],filtered_label2['Fuel_consumption_combined'],color = 'black')
plt.scatter(filtered_label3['CO2_emissions_combined'] ,filtered_label3['Fuel_consumption_combined'],color = 'yellow')
plt.scatter(filtered_label4['CO2_emissions_combined'] ,filtered_label4['Fuel_consumption_combined'],color = 'green')
plt.scatter(filtered_label5['CO2_emissions_combined'] ,filtered_label5['Fuel_consumption_combined'],color = 'pink' )
plt.scatter(filtered_label6['CO2_emissions_combined'] ,filtered_label6['Fuel_consumption_combined'] ,color = 'beige')
plt.scatter(filtered_label7['CO2_emissions_combined'] ,filtered_label7['Fuel_consumption_combined'] ,color = 'orange')
plt.scatter(filtered_label8['CO2_emissions_combined'] ,filtered_label8['Fuel_consumption_combined'] ,color = 'brown')
plt.scatter(filtered_label9['CO2_emissions_combined'] ,filtered_label9['Fuel_consumption_combined'],color = 'cyan' )

plt.show()
```



After further investigation and researching I couldn't find a way to make Kmeans sort the clusters from small to big so I will hot encoding it

```
In [101]: df['soorted_cluster'] = df['Cluster'].map( {4:1, 8:2, 0:3 , 6:4 , 2:5 , 3:6 , 7:7 , 1:8 , 9:9 , 5:10} ).astype(int)
```

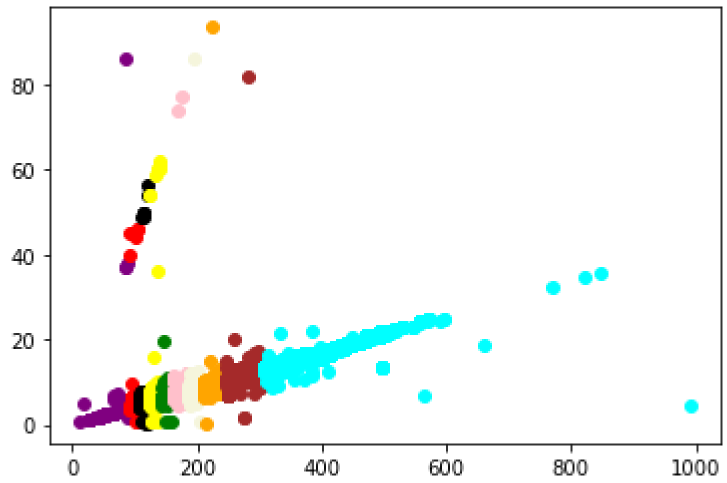
View only the cars with M1 catagory and Benzin to see the difference since the algorithm take fuel type into consideration

In [102]:
```
#filter rows of original data
filtered_label0 = df.loc[(df['soorted_cluster']==1) & (df['Benzine']== 1) & (df['European_vehicle_category']== 'M1')]
filtered_label1 = df.loc[(df['soorted_cluster']==2) & (df['Benzine']== 1) & (df['European_vehicle_category']== 'M1')]
filtered_label2 = df.loc[(df['soorted_cluster']==3) & (df['Benzine']== 1) & (df['European_vehicle_category']== 'M1')]
filtered_label3 = df.loc[(df['soorted_cluster']==4) & (df['Benzine']== 1) & (df['European_vehicle_category']== 'M1')]
filtered_label4 = df.loc[(df['soorted_cluster']==5) & (df['Benzine']== 1) & (df['European_vehicle_category']== 'M1')]
filtered_label5 = df.loc[(df['soorted_cluster']==6) & (df['Benzine']== 1) & (df['European_vehicle_category']== 'M1')]
filtered_label6 = df.loc[(df['soorted_cluster']==7) & (df['Benzine']== 1) & (df['European_vehicle_category']== 'M1')]
filtered_label7 = df.loc[(df['soorted_cluster']==8) & (df['Benzine']== 1) & (df['European_vehicle_category']== 'M1')]
filtered_label8 = df.loc[(df['soorted_cluster']==9) & (df['Benzine']== 1) & (df['European_vehicle_category']== 'M1')]
filtered_label9 = df.loc[(df['soorted_cluster']==10) & (df['Benzine']== 1) & (df['European_vehicle_category']== 'M1')]



#Plotting the results
plt.scatter(filtered_label0['CO2_emissions_combined'] ,filtered_label0['Fuel_consumption_combined'] ,color = 'purple')
plt.scatter(filtered_label1['CO2_emissions_combined'] ,filtered_label1['Fuel_consumption_combined'],color = 'red')
plt.scatter(filtered_label2['CO2_emissions_combined'],filtered_label2['Fuel_consumption_combined'],color = 'black')
plt.scatter(filtered_label3['CO2_emissions_combined'] ,filtered_label3['Fuel_consumption_combined'],color = 'yellow')
plt.scatter(filtered_label4['CO2_emissions_combined'] ,filtered_label4['Fuel_consumption_combined'],color = 'green')
plt.scatter(filtered_label5['CO2_emissions_combined'] ,filtered_label5['Fuel_consumption_combined'],color = 'pink' )
plt.scatter(filtered_label6['CO2_emissions_combined'] ,filtered_label6['Fuel_consumption_combined'] ,color = 'beige')
plt.scatter(filtered_label7['CO2_emissions_combined'] ,filtered_label7['Fuel_consumption_combined'] ,color = 'orange')
plt.scatter(filtered_label8['CO2_emissions_combined'] ,filtered_label8['Fuel_consumption_combined'] ,color = 'brown')
plt.scatter(filtered_label9['CO2_emissions_combined'] ,filtered_label9['Fuel_consumption_combined'],color = 'cyan' )

plt.show()
```



In [103]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['soorted_cluster'] == 1) )]
print(' Co2 min:',df2['CO2_emissions_combined'].min(),' CO2 max:',df2['CO2_emissions_combined'].max())
print(' Fuel consumption min:',df2['Fuel_consumption_combined'].min(),' Fuel consumption max:',df2['Fuel_consumption_coml
```

```
 Co2 min: 12  CO2 max: 92
 Fuel consumption min: 0.6  Fuel consumption max: 86.0
```

In [104]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['soorted_cluster'] == 2) )]
print(' Co2 min:',df2['CO2_emissions_combined'].min(),' CO2 max:',df2['CO2_emissions_combined'].max())
print(' Fuel consumption min:',df2['Fuel_consumption_combined'].min(),' Fuel consumption max:',df2['Fuel_consumption_coml
```

```
 Co2 min: 92  CO2 max: 107
 Fuel consumption min: 0.5  Fuel consumption max: 46.0
```

In [105]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['soorted_cluster'] == 3) )]
print(' Co2 min:',df2['CO2_emissions_combined'].min(),' CO2 max:',df2['CO2_emissions_combined'].max())
print(' Fuel consumption min:',df2['Fuel_consumption_combined'].min(),' Fuel consumption max:',df2['Fuel_consumption_coml
```

```
 Co2 min: 108  CO2 max: 125
 Fuel consumption min: 0.3  Fuel consumption max: 56.3
```

In [106]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['soorted_cluster'] == 4) )]
print(' Co2 min:',df2['CO2_emissions_combined'].min(),' CO2 max:',df2['CO2_emissions_combined'].max())
print(' Fuel consumption min:',df2['Fuel_consumption_combined'].min(),' Fuel consumption max:',df2['Fuel_consumption_com
```

```
 Co2 min: 124  CO2 max: 143
 Fuel consumption min: 0.5  Fuel consumption max: 62.0
```

In [107]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['soorted_cluster'] == 5) )]
print(' Co2 min:',df2['CO2_emissions_combined'].min(),' CO2 max:',df2['CO2_emissions_combined'].max())
print(' Fuel consumption min:',df2['Fuel_consumption_combined'].min(),' Fuel consumption max:',df2['Fuel_consumption_com
```

```
 Co2 min: 144  CO2 max: 162
 Fuel consumption min: 0.7  Fuel consumption max: 60.0
```

In [108]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['soorted_cluster'] == 6) )]
print(' Co2 min:',df2['CO2_emissions_combined'].min(),' CO2 max:',df2['CO2_emissions_combined'].max())
print(' Fuel consumption min:',df2['Fuel_consumption_combined'].min(),' Fuel consumption max:',df2['Fuel_consumption_com
```

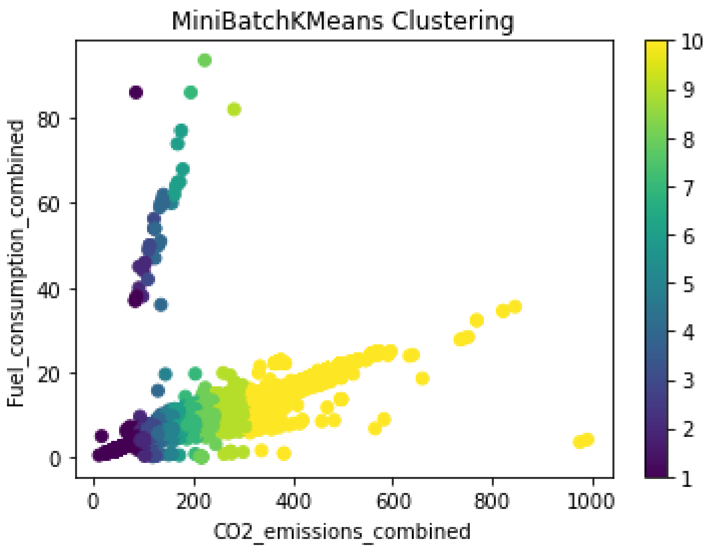
```
 Co2 min: 163  CO2 max: 183
 Fuel consumption min: 4.6  Fuel consumption max: 77.0
```

In [109]:
```
df2=df[((df['European_vehicle_category'] == 'M1') & (df['soorted_cluster'] == 7) )]
print(' Co2 min:',df2['CO2_emissions_combined'].min(),' CO2 max:',df2['CO2_emissions_combined'].max())
print(' Fuel consumption min:',df2['Fuel_consumption_combined'].min(),' Fuel consumption max:',df2['Fuel_consumption_com
```

```
 Co2 min: 184  CO2 max: 209
 Fuel consumption min: 0.9  Fuel consumption max: 86.0
```

In [110]:
```
#Plot the clusters obtained using k means
fig = plt.figure()
ax = fig.add_subplot(111)
scatter = ax.scatter(df['CO2_emissions_combined'],df['Fuel_consumption_combined'],
                     c=df['soorted_cluster'])
ax.set_title('MiniBatchKMeans Clustering')
ax.set_xlabel('CO2_emissions_combined')
ax.set_ylabel('Fuel_consumption_combined')
plt.colorbar(scatter)
```

Out[110]: <matplotlib.colorbar.Colorbar at 0x2048cf39bb0>



Conclusion

The research was successfully completed and I got the result I wanted, By using the Kmeans algorithm which is useful for unsupervised ML for the unlabeled datasets, As we see in this research I achieved my goal to classify all the cars in the RDW dataset is a really efficient way, I learned a lot of useful information about data provisioning ,ML in specific Kmeans and MiniBatchKMeans algorithms and domain understanding different methods and techniques.