```
                           **Internshala Python Electric Vehicle Data Analysis Project**
```

Video link - https://drive.google.com/file/d/1JyMfzHkq9-EVK8TOtmpPmsQVdpk51VwK/view?usp=sharing

```python
#importing data using pandas
import pandas as pd

EV_df = pd.read_excel(r'C:\Users\LENOVO\Downloads\FEV-data-Excel.xlsx')
EV_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53 entries, 0 to 52
Data columns (total 25 columns):
 #   Column                                  Non-Null Count  Dtype
---  ------                                  --------------  -----
 0   Car full name                           53 non-null     object
 1   Make                                    53 non-null     object
 2   Model                                   53 non-null     object
 3   Minimal price (gross) [PLN]             53 non-null     int64
 4   Engine power [KM]                       53 non-null     int64
 5   Maximum torque [Nm]                     53 non-null     int64
 6   Type of brakes                          52 non-null     object
 7   Drive type                              53 non-null     object
 8   Battery capacity [kWh]                  53 non-null     float64
 9   Range (WLTP) [km]                       53 non-null     int64
 10  Wheelbase [cm]                          53 non-null     float64
 11  Length [cm]                             53 non-null     float64
 12  Width [cm]                              53 non-null     float64
 13  Height [cm]                             53 non-null     float64
 14  Minimal empty weight [kg]               53 non-null     int64
 15  Permissable gross weight [kg]           45 non-null     float64
 16  Maximum load capacity [kg]              45 non-null     float64
 17  Number of seats                         53 non-null     int64
 18  Number of doors                         53 non-null     int64
 19  Tire size [in]                          53 non-null     int64
 20  Maximum speed [kph]                     53 non-null     int64
 21  Boot capacity (VDA) [l]                 52 non-null     float64
 22  Acceleration 0-100 kph [s]              50 non-null     float64
 23  Maximum DC charging power [kW]          53 non-null     int64
```

```
 24  mean - Energy consumption [kWh/100 km]  44 non-null     float64
dtypes: float64(10), int64(10), object(5)
memory usage: 10.5+ KB
```

```
#before moving onto the task and analysis, lets check the data to see
if there are any nulls or not

EV_df.isnull().sum()
```

```
Car full name                             0
Make                                      0
Model                                     0
Minimal price (gross) [PLN]               0
Engine power [KM]                         0
Maximum torque [Nm]                       0
Type of brakes                            1
Drive type                                0
Battery capacity [kWh]                    0
Range (WLTP) [km]                         0
Wheelbase [cm]                            0
Length [cm]                               0
Width [cm]                                0
Height [cm]                               0
Minimal empty weight [kg]                 0
Permissable gross weight [kg]             8
Maximum load capacity [kg]                8
Number of seats                           0
Number of doors                           0
Tire size [in]                            0
Maximum speed [kph]                       0
Boot capacity (VDA) [l]                   1
Acceleration 0-100 kph [s]                3
Maximum DC charging power [kW]            0
mean - Energy consumption [kWh/100 km]    9
dtype: int64
```

```
# as I can see Type of brakes has null, lets find out

EV_df[EV_df['Type of brakes'].isnull()]
```

```
               Car full name           Make       Model  \
51  Mercedes-Benz EQV (long)  Mercedes-Benz  EQV (long)

    Minimal price (gross) [PLN]  Engine power [KM]  Maximum torque
[Nm]  \
51                       339480                204
362

   Type of brakes   Drive type  Battery capacity [kWh]  Range (WLTP)
[km]  \
51            NaN  2WD (front)                    90.0
```

```
356

    ...  Permissable gross weight [kg]  Maximum load capacity [kg]  \
51  ...                         3500.0                       865.0

    Number of seats  Number of doors  Tire size [in]  Maximum speed
[kph]  \
51                6                5              17
160

    Boot capacity (VDA) [l]  Acceleration 0-100 kph [s]  \
51                      NaN                         NaN

    Maximum DC charging power [kW]  mean - Energy consumption [kWh/100
km]
51                             110
28.2

[1 rows x 25 columns]
```

I could have used EV_df[EV_df['Type of brakes'].fillna(EV_df[EV_df['Type of brakes'].mode()[0], inplace=True), to fill the missing value with the most occuring value in that column however I am keep it as it is, as it's a categorical column and there is just one NaN, so it is not critical.

```
print(EV_df.shape)

(53, 25)

# Lets drop duplicates if any

EV_df = EV_df.drop_duplicates()
EV_df = EV_df.reset_index(drop=True) # it will arrange the row index
correctly after dropping duplivcatws rows
len(EV_df)

53
```

No duplicates rows above

```
EV_df.describe()

       Minimal price (gross) [PLN]  Engine power [KM]  Maximum torque
[Nm]  \
count                    53.000000          53.000000
53.000000
mean                 246158.509434         269.773585
460.037736
std                  149187.485190         181.298589
261.647000
```

```
min                   82050.000000         82.000000
160.000000
25%                  142900.000000        136.000000
260.000000
50%                  178400.000000        204.000000
362.000000
75%                  339480.000000        372.000000
640.000000
max                  794000.000000        772.000000
1140.000000

       Battery capacity [kWh]  Range (WLTP) [km]  Wheelbase [cm]
Length [cm]  \
count                53.000000          53.000000       53.000000
53.000000
mean                 62.366038         376.905660      273.581132
442.509434
std                  24.170913         118.817938       22.740518
48.863280
min                  17.600000         148.000000      187.300000
269.500000
25%                  40.000000         289.000000      258.800000
411.800000
50%                  58.000000         364.000000      270.000000
447.000000
75%                  80.000000         450.000000      290.000000
490.100000
max                 100.000000         652.000000      327.500000
514.000000

       Width [cm]  Height [cm]  Minimal empty weight [kg]  \
count   53.000000    53.000000                  53.000000
mean   186.241509   155.422642                1868.452830
std     14.280641    11.275358                 470.880867
min    164.500000   137.800000                1035.000000
25%    178.800000   148.100000                1530.000000
50%    180.900000   155.600000                1685.000000
75%    193.500000   161.500000                2370.000000
max    255.800000   191.000000                2710.000000

       Permissable gross weight [kg]  Maximum load capacity [kg]  \
count                      45.000000                   45.000000
mean                     2288.844444                  520.466667
std                       557.796026                  140.682848
min                      1310.000000                  290.000000
25%                      1916.000000                  440.000000
50%                      2119.000000                  486.000000
75%                      2870.000000                  575.000000
max                      3500.000000                 1056.000000
```

```
       Number of seats  Number of doors  Tire size [in]  Maximum speed
[kph]  \
count        53.000000        53.000000       53.000000
53.000000
mean          4.905660         4.849057       17.679245
178.169811
std           0.838133         0.455573        1.868500
43.056196
min           2.000000         3.000000       14.000000
123.000000
25%           5.000000         5.000000       16.000000
150.000000
50%           5.000000         5.000000       17.000000
160.000000
75%           5.000000         5.000000       19.000000
200.000000
max           8.000000         5.000000       21.000000
261.000000

       Boot capacity (VDA) [l]  Acceleration 0-100 kph [s]  \
count                52.000000                    50.00000
mean                445.096154                     7.36000
std                 180.178480                     2.78663
min                 171.000000                     2.50000
25%                 315.000000                     4.87500
50%                 425.000000                     7.70000
75%                 558.000000                     9.37500
max                 870.000000                    13.10000

       Maximum DC charging power [kW]  mean - Energy consumption
[kWh/100 km]
count                       53.000000
44.000000
mean                       113.509434
18.994318
std                         57.166970
4.418253
min                         22.000000
13.100000
25%                        100.000000
15.600000
50%                        100.000000
17.050000
75%                        150.000000
23.500000
max                        270.000000
28.200000
```

Task 1: A customer has a budget of 350,000 PLN and wants an EV with a minimum range of 400 km. a) Your task is to filter out EVs that meet these criteria.(2 Marks) b) Group them by the manufacturer (Make).(6 marks) c) Calculate the average battery capacity for each manufacturer. (8 Marks)

```
# Task 1 (a)

''' I had ensured using .info() function to see the dtypes were
correct or not however for better safety as
is a large data I will use pd.numeric pandas function to esnure if
there are any commas, the
value gets converted into numeric'''

for i in ['Minimal price (gross) [PLN]', 'Range (WLTP) [km]']:
    EV_df[i] = pd.to_numeric(EV_df[i], errors='coerce') #coerce is a
way of handling errors, like if there are any commas, the value will
turn NaN
    # instead of causing errors

Customer_Car_requirement = EV_df[(EV_df['Minimal price (gross) [PLN]']
<= 350000) & (EV_df['Range (WLTP) [km]'] >= 400)]
Customer_Car_requirement.head()
```

```
                  Car full name     Make                Model  \
0        Audi e-tron 55 quattro     Audi    e-tron 55 quattro
8                       BMW iX3      BMW                  iX3
15  Hyundai Kona electric 64kWh  Hyundai  Kona electric 64kWh
18             Kia e-Niro 64kWh      Kia         e-Niro 64kWh
20             Kia e-Soul 64kWh      Kia         e-Soul 64kWh

    Minimal price (gross) [PLN]  Engine power [KM]  Maximum torque
[Nm]  \
0                        345700                360
664
8                        282900                286
400
15                       178400                204
395
18                       167990                204
395
20                       160990                204
395

          Type of brakes   Drive type  Battery capacity [kWh]  \
0   disc (front + rear)          4WD                    95.0
8   disc (front + rear)   2WD (rear)                    80.0
15  disc (front + rear)  2WD (front)                    64.0
18  disc (front + rear)  2WD (front)                    64.0
20  disc (front + rear)  2WD (front)                    64.0

    Range (WLTP) [km]  ...  Permissable gross weight [kg]  \
```

```
0                  438  ...                          3130.0
8                  460  ...                          2725.0
15                 449  ...                          2170.0
18                 455  ...                          2230.0
20                 452  ...                          1682.0

    Maximum load capacity [kg]  Number of seats  Number of doors  \
0                        640.0                5                5
8                        540.0                5                5
15                       485.0                5                5
18                       493.0                5                5
20                       498.0                5                5

    Tire size [in]  Maximum speed [kph]  Boot capacity (VDA) [l]  \
0               19                  200                    660.0
8               19                  180                    510.0
15              17                  167                    332.0
18              17                  167                    451.0
20              17                  167                    315.0

    Acceleration 0-100 kph [s]  Maximum DC charging power [kW]  \
0                          5.7                             150
8                          6.8                             150
15                         7.6                             100
18                         7.8                             100
20                         7.9                             100

    mean - Energy consumption [kWh/100 km]
0                                    24.45
8                                    18.80
15                                   15.40
18                                   15.90
20                                   15.70

[5 rows x 25 columns]
```

I first converted the Minimal price (gross) [PLN] and Range (WLTP) [km] columns to numeric to avoid any dtype errors and then filtered the data according to the customer's needs.

```
# Task 1 (b) b) Group them by the manufacturer (Make).


grouped_by_make =
Customer_Car_requirement.groupby('Make').size().sort_values(ascending=
False)
print(grouped_by_make)

Make
Volkswagen       3
Tesla            3
```

```
Kia                 2
Hyundai             1
BMW                 1
Audi                1
Mercedes-Benz       1
dtype: int64
```

I grouped the filtered data to check which brand offer more EV's to meet the needs of the customer. I can check Volkswagen and Tesla offering the highest number of Ev's followed by Kia.

```
# Task 1 (c) Calculate the average battery capacity for each
manufacturer.

Average_capacity = Customer_Car_requirement.groupby('Make')['Battery
capacity [kWh]'].mean().round(2).sort_values(ascending=False)
print(Average_capacity)

Make
Audi                95.00
BMW                 80.00
Mercedes-Benz       80.00
Volkswagen          70.67
Tesla               68.00
Hyundai             64.00
Kia                 64.00
Name: Battery capacity [kWh], dtype: float64
```

For the above task I grouped the filtered data by Make and did average aggregation, I used .round(2) to get only 2 decimals after the mean. So here I can check Audi has the most battery capacity followed by BMW and Mercedes. We can suggest the customer to buy Audi.

Task 2: You suspect some EVs have unusually high or low energy consumption. Find the outliers in the mean - Energy consumption [kWh/100 km] column.(16 Marks)

```
EV_df['mean - Energy consumption [kWh/100 km]']

0     24.45
1     23.80
2     27.55
3     23.30
4     23.85
5     27.20
6     13.10
7     14.30
8     18.80
9       NaN
10    15.60
11    17.20
12    17.50
```

```
13    13.80
14    15.00
15    15.40
16    21.20
17    15.30
18    15.90
19    15.60
20    15.70
21    14.50
22    21.85
23    16.75
24    18.50
25    17.10
26    16.65
27    17.60
28    16.40
29      NaN
30    23.40
31    24.10
32    24.85
33    25.10
34    16.50
35    16.50
36    15.45
37    16.35
38    17.00
39      NaN
40      NaN
41      NaN
42      NaN
43      NaN
44      NaN
45      NaN
46    14.00
47    15.40
48    15.90
49    18.00
50    25.20
51    28.20
52    25.90
Name: mean - Energy consumption [kWh/100 km], dtype: float64
```

```
# Lets first remove the null values

r = 'mean - Energy consumption [kWh/100 km]'

Cleaned_Energy = EV_df[r].dropna()

Cleaned_Energy.isnull().sum()
```

```
np.int64(0)
```

```
# Now I will find Q1 and Q3. Q2 is the median

Q1 = Cleaned_Energy.quantile(0.25)
Q3 = Cleaned_Energy.quantile(0.75)

# Finding IQR

IQR = Q3 - Q1

# Finding boundries of outliers

Lower_bound = Q1 - 1.5*IQR
Upper_bound = Q3 + 1.5*IQR

# Finding Outliers omn the full dataset

Outliers = EV_df[(EV_df[r] < Lower_bound) | (EV_df[r] > Upper_bound)]
[['Car full name', 'Make', 'Model', r]]
print(Outliers)
```

```
Empty DataFrame
Columns: [Car full name, Make, Model, mean - Energy consumption
[kWh/100 km]]
Index: []
```

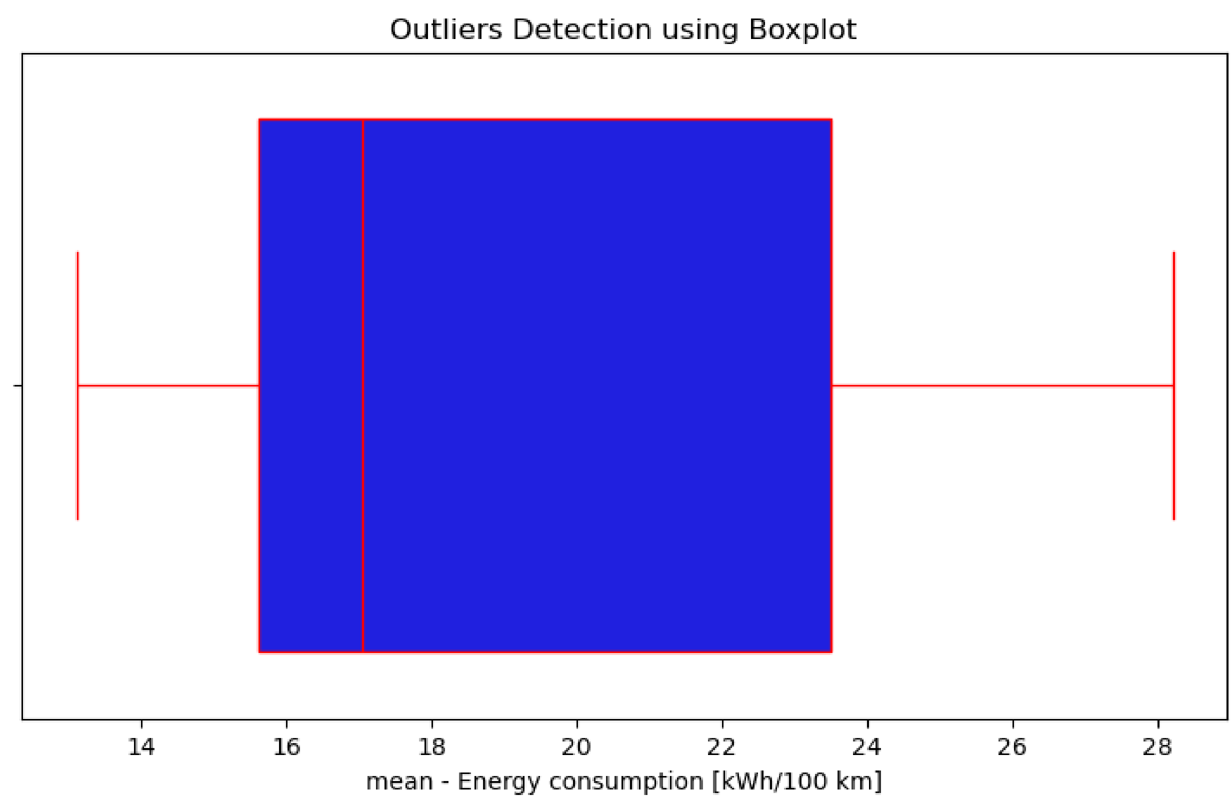
Using 1.5 I could not find outliers, changing values to 1.3

```
Lower_bound2 = Q1 - 1.3*IQR
Upper_bound2 = Q3 + 1.3*IQR

Outliers2 = EV_df[(EV_df[r] < Lower_bound2) | (EV_df[r] >
Upper_bound2)][['Car full name', 'Make', 'Model', r]]
print(Outliers2)
```

```
Empty DataFrame
Columns: [Car full name, Make, Model, mean - Energy consumption
[kWh/100 km]]
Index: []
```

```
# Using 1.3 I could not find anything, using 1.1

Lower_bound3 = Q1 - 1.1*IQR
Upper_bound3 = Q3 + 1.1*IQR

Outliers3 = EV_df[(EV_df[r] < Lower_bound3) | (EV_df[r] >
Upper_bound3)][['Car full name', 'Make', 'Model', r]]
print(Outliers3)
```

```
Empty DataFrame
Columns: [Car full name, Make, Model, mean - Energy consumption
[kWh/100 km]]
Index: []

## Using Box plot

import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(7,5))
plt.figure(figsize=(9,5))
sns.boxplot(x=EV_df['mean - Energy consumption [kWh/100 km]'], y=None,
color='blue', saturation=0.75, linecolor='red')
plt.title('Outliers Detection using Boxplot')
plt.show()

<Figure size 700x500 with 0 Axes>
```



For Task 2 I used the IQR method, I had taken the standard 1.5 IQR rule, then a stricter 1.3 IQR and 1.1 IQR however no ouliers detected. Then for confirmation I used boxplot, then also I could not find any extreme values hence 'mean - Energy consumption [kWh/100 km]' column has no outliers.

```python
''' Task 3: Your manager wants to know if there's a strong
relationship between battery
capacity and range.'''

# As I have checked both battery capacity and range are numerical
columns, for this t test paired sample will be the best

EV_df[['Battery capacity [kWh]', 'Range (WLTP) [km]']].isnull().sum()
```

```
Battery capacity [kWh]    0
Range (WLTP) [km]         0
dtype: int64
```

```python
# Step 1 - Null Hypothesis - No relation
# Alternative Hypothesis - There is a relation

from scipy.stats import ttest_rel

t_stat, p_value = ttest_rel(EV_df['Battery capacity [kWh]'],
EV_df['Range (WLTP) [km]'])

print(f't_stat is {t_stat} and p_value is {p_value}')
```

```
t_stat is -22.845347089287355 and p_value is 8.868036810160167e-29
```

From the above test, we got p_value of 8.868036810160167e-29 which is far less than 0.05, so we reject the null hypothesis. We can say there is a strong relation between battery capacity and range columns. So it means when the battery capacity increases, the range also increases.

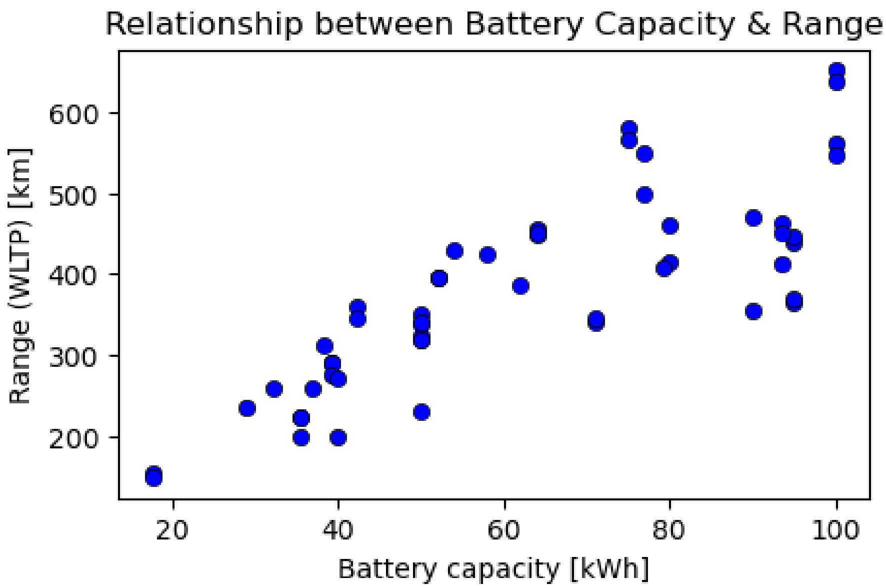
```python
# Now I use use correlation to confirm the result

import numpy as np

relation = np.corrcoef(EV_df['Battery capacity [kWh]'],  EV_df['Range
(WLTP) [km]'])
print(relation)
```

```
[[1.         0.81043858]
 [0.81043858 1.        ]]
```

From the numpy correlation test I found out the relation is 0.81, which is very strong. We can now confirm that there is a strong relation between battery capacity and range columns.

```python
# Using a scatter plot to show relation as there are two numerical
columns

import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(5,3))
```

```
sns.scatterplot(x=EV_df['Battery capacity [kWh]'], y=EV_df['Range
(WLTP) [km]'], color='blue', edgecolor='black')
plt.title('Relationship between Battery Capacity & Range')
plt.show()
```



We can see as battery capacity increasing, range is also increasing. Thus there is a postive relation between them.

Task 4: Build an EV recommendation class. The class should allow users to input their budget, desired range, and battery capacity. The class should then return the top three EVs matching their criteria.

```
class EV_recommendation: #class
    def __init__(self, customerbudget, customerrange,
customercapacity):
        self.budget = customerbudget
        self.range = customerrange
        self.capacity = customercapacity

    # creating function to call top 3
    def top3(self, EV_df):
        needs = EV_df[(EV_df['Minimal price (gross) [PLN]'] <=
self.budget) & (EV_df['Range (WLTP) [km]'] >= self.range)
        & (EV_df['Battery capacity [kWh]'] >= self.capacity)]
        return needs[['Car full name', 'Make', 'Model', 'Minimal price
(gross) [PLN]', 'Range (WLTP) [km]',
                      'Battery capacity
[kWh]']].sort_values(by=['Minimal price (gross) [PLN]', 'Range (WLTP)
[km]',
                                                         'Battery capacity
```

```
[kWh]'], ascending=[True, False, False]).head(3)


# creating 2 objects
customer1 = EV_recommendation(350000, 400, 50)
customer2 = EV_recommendation(459999, 500, 70)

customer1.top3(EV_df) #calling the function

                      Car full name        Make                 Model
\
47  Volkswagen ID.3 Pro Performance  Volkswagen  ID.3 Pro Performance

20                    Kia e-Soul 64kWh         Kia          e-Soul 64kWh

18                    Kia e-Niro 64kWh         Kia          e-Niro 64kWh


    Minimal price (gross) [PLN]  Range (WLTP) [km]  Battery capacity
[kWh]
47                       155890                425
58.0
20                       160990                452
64.0
18                       167990                455
64.0

customer2.top3(EV_df)

               Car full name        Make                 Model  \
48     Volkswagen ID.3 Pro S  Volkswagen           ID.3 Pro S
49       Volkswagen ID.4 1st  Volkswagen             ID.4 1st
40  Tesla Model 3 Long Range       Tesla  Model 3 Long Range

    Minimal price (gross) [PLN]  Range (WLTP) [km]  Battery capacity
[kWh]
48                       179990                549
77.0
49                       202390                500
77.0
40                       235490                580
75.0

## This is just an addition just to check my knowledge. Adding a child
class, so that customer can choose a brand if he/she wants


class EV_recommendation:
    def __init__(self, customerbudget, customerrange,
customercapacity):
        self.__budget = customerbudget #private encapsulation, cannot
```

```
be used in sub class
        self.range = customerrange
        self.capacity = customercapacity

    # getter method to use budget inside sub class
    @property # its an in built python decorator, I used it so that i
dont have to use () after budget
    def get_budget(self):
        return self.__budget

# adding child class
class premiumEV_recommendation(EV_recommendation):
    def __init__(self, customerbudget, customerrange,
customercapacity, customerbrand=None):
        super().__init__(customerbudget, customerrange,
customercapacity)
        self.brand = customerbrand


    # creating function to call top 3
    def top3(self, EV_df):
        needs = EV_df[(EV_df['Minimal price (gross) [PLN]'] <=
self.get_budget) & (EV_df['Range (WLTP) [km]'] >= self.range)
        & (EV_df['Battery capacity [kWh]'] >= self.capacity)]

        # this will run only if customer passed a brand. Thats why I
used customerbrand=None.
        if self.brand:
            check = needs['Make'].str.lower() == self.brand.lower()
            needs = needs[check]
            if not check.any(): # if true then run the below codes.
Means if brand not with us then.
                brand = EV_df['Make'].unique()
                return f'That brand is not available with us. Brand
available with us are {brand}'


        # This will always run even if the customer doesnt choose a
brand
        return needs[['Car full name', 'Make', 'Model', 'Minimal price
(gross) [PLN]', 'Range (WLTP) [km]',
                      'Battery capacity
[kWh]']].sort_values(by=['Minimal price (gross) [PLN]', 'Range (WLTP)
[km]',
                                                  'Battery capacity
[kWh]'], ascending=[True, False, False]).head(3)
```

```
# creating objects. Object 1 with brand
customer1 = premiumEV_recommendation(350000, 400, 50, 'audi')
customer1.top3(EV_df)
```

```
            Car full name  Make                Model  \
0  Audi e-tron 55 quattro  Audi  e-tron 55 quattro

   Minimal price (gross) [PLN]  Range (WLTP) [km]  Battery capacity
[kWh]
0                       345700                438
95.0
```

```
#object 2. Without brand
customer2 = premiumEV_recommendation(459999, 500, 70)
customer2.top3(EV_df)
```

```
               Car full name        Make                Model  \
48     Volkswagen ID.3 Pro S  Volkswagen           ID.3 Pro S
49       Volkswagen ID.4 1st  Volkswagen             ID.4 1st
40  Tesla Model 3 Long Range       Tesla  Model 3 Long Range

    Minimal price (gross) [PLN]  Range (WLTP) [km]  Battery capacity
[kWh]
48                       179990                549
77.0
49                       202390                500
77.0
40                       235490                580
75.0
```

```
# wrong brand passed Object 3

customer3 = premiumEV_recommendation(459999, 500, 70, 'ratnajit')
customer3.top3(EV_df)
```

```
"That brand is not available with us. Brand available with us are
['Audi' 'BMW' 'Citroën' 'DS' 'Honda' 'Hyundai' 'Jaguar' 'Kia' 'Mazda'\
n 'Mercedes-Benz' 'Mini' 'Nissan' 'Opel' 'Peugeot' 'Porsche'
'Renault'\n 'Skoda' 'Smart' 'Tesla' 'Volkswagen']"
```

So in the above task, I used the concept of Encapsulation, used single inheritance concept of OOP.

Task 5: Inferential Statistics – Hypothesis Testing: Test whether there is a significant difference in the average Engine power [KM] of vehicles manufactured by two leading manufacturers i.e. Tesla and Audi. What insights can you draw from the test results? Recommendations and Conclusion: Provide actionable insights based on your analysis. (Conduct a two sample t-test using ttest_ind from scipy.stats module)

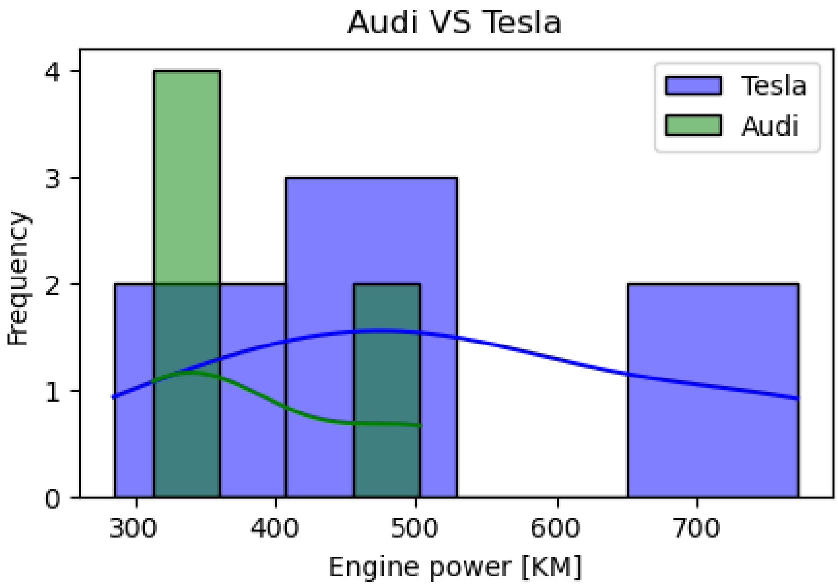
```python
# So in this task I will be using t-test two sample because I have to compare two groups.
# More than two groups use Annova

EV_df[['Make', 'Engine power [KM]']].isnull().sum()
```

```
Make                 0
Engine power [KM]    0
dtype: int64
```

```python
Tesla = EV_df[EV_df['Make'] == 'Tesla']['Engine power [KM]']
Audi = EV_df[EV_df['Make'] == 'Audi']['Engine power [KM]']

# Null Hypothesis = No differenvce
# Alternative Hypothesis = There is a differenvce

from scipy.stats import ttest_ind

t_stat, p_value = ttest_ind(Tesla, Audi, equal_var=False) #equal_var=False means variance of both variable are not same

print(f't_stat is {t_stat} and p_value is {p_value}')
```

```
t_stat is 1.7939951827297178 and p_value is 0.10684105068839565
```

```python
## Visulisation

plt.figure(figsize=(5,3))
sns.histplot(Tesla, color='blue', edgecolor='black', label='Tesla', kde=True)
sns.histplot(Audi, color='green', edgecolor='black', label='Audi', kde=True)
plt.legend()
plt.title('Audi VS Tesla')
plt.ylabel('Frequency')
plt.show()
```



Result of Task 5: My p_value is 0.10 which is above 0.05, so it failed to reject null hypothesis, hence there is no significant difference. It signifies both brand are delivering same performance in terms of Engine power. My recommendation will be that brands like Audi, Tesla they can focus more on automation, range, energy efficiency and provide more affordable cars to customer so that ther sale can increase.

Thank you