

project

December 19, 2024

video link - <https://photos.app.goo.gl/8729ZBuzhP28cNDt9>

1 ELECTRIC VEHICLE DATA ANALYSIS PROJECT

In this project, We will analyze a dataset related to electric vehicles (EVs). The dataset contains various features such as electric range, energy consumption, price, and other relevant attributes. Our goal is to conduct a thorough analysis to uncover meaningful insights, tell a compelling story, conduct hypothesis testing.

Importing required libraries for the Project

```
[4]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
```

Uploading the data set of the EV vehicles and checking the available details using the .head() function to get the overview of the data

```
[6]: ev_df = pd.read_excel("FEV-data-Excel.xlsx ")
ev_df.head()
```

```
[6]:
```

	Car full name	Make	Model	\
0	Audi e-tron 55 quattro	Audi	e-tron 55 quattro	
1	Audi e-tron 50 quattro	Audi	e-tron 50 quattro	
2	Audi e-tron S quattro	Audi	e-tron S quattro	
3	Audi e-tron Sportback 50 quattro	Audi	e-tron Sportback 50 quattro	
4	Audi e-tron Sportback 55 quattro	Audi	e-tron Sportback 55 quattro	

	Minimal price (gross) [PLN]	Engine power [KM]	Maximum torque [Nm]	\
0	345700	360	664	
1	308400	313	540	
2	414900	503	973	
3	319700	313	540	
4	357000	360	664	

	Type of brakes	Drive type	Battery capacity [kWh]	Range (WLTP) [km]	\
0	disc (front + rear)	4WD	95.0	438	

1	disc (front + rear)	4WD	71.0	340
2	disc (front + rear)	4WD	95.0	364
3	disc (front + rear)	4WD	71.0	346
4	disc (front + rear)	4WD	95.0	447

	Permissable gross weight [kg]	Maximum load capacity [kg]	\
0	3130.0	640.0	
1	3040.0	670.0	
2	3130.0	565.0	
3	3040.0	640.0	
4	3130.0	670.0	

	Number of seats	Number of doors	Tire size [in]	Maximum speed [kph]	\
0	5	5	19	200	
1	5	5	19	190	
2	5	5	20	210	
3	5	5	19	190	
4	5	5	19	200	

	Boot capacity (VDA) [l]	Acceleration 0-100 kph [s]	\
0	660.0	5.7	
1	660.0	6.8	
2	660.0	4.5	
3	615.0	6.8	
4	615.0	5.7	

	Maximum DC charging power [kW]	mean - Energy consumption [kWh/100 km]
0	150	24.45
1	150	23.80
2	150	27.55
3	150	23.30
4	150	23.85

[5 rows x 25 columns]

1.1 Task 1 : Filtering EV Dataset Based on Conditions

First lets start by filtering the EVs for a customer who has a budget of 350,000 PLN and he wants a minimum Range of EV to be 400 KM.

```
[9]: """ Task 1 """
filter_data=ev_df[(ev_df["Minimal price (gross) [PLN]"] <= 350000) &
↳(ev_df["Range (WLTP) [km]"] >= 400)]
sorted_by_price = filter_data.sort_values(by=["Minimal price (gross)"]
↳["PLN"],ascending = False)
display(sorted_by_price)
```

	Car full name	Make \
0	Audi e-tron 55 quattro	Audi
22	Mercedes-Benz EQC	Mercedes-Benz
8	BMW iX3	BMW
41	Tesla Model 3 Performance	Tesla
40	Tesla Model 3 Long Range	Tesla
49	Volkswagen ID.4 1st	Volkswagen
39	Tesla Model 3 Standard Range Plus	Tesla
48	Volkswagen ID.3 Pro S	Volkswagen
15	Hyundai Kona electric 64kWh	Hyundai
18	Kia e-Niro 64kWh	Kia
20	Kia e-Soul 64kWh	Kia
47	Volkswagen ID.3 Pro Performance	Volkswagen

	Model	Minimal price (gross) [PLN] \
0	e-tron 55 quattro	345700
22	EQC	334700
8	iX3	282900
41	Model 3 Performance	260490
40	Model 3 Long Range	235490
49	ID.4 1st	202390
39	Model 3 Standard Range Plus	195490
48	ID.3 Pro S	179990
15	Kona electric 64kWh	178400
18	e-Niro 64kWh	167990
20	e-Soul 64kWh	160990
47	ID.3 Pro Performance	155890

	Engine power [KM]	Maximum torque [Nm]	Type of brakes \
0	360	664	disc (front + rear)
22	408	760	disc (front + rear)
8	286	400	disc (front + rear)
41	480	639	disc (front + rear)
40	372	510	disc (front + rear)
49	204	310	disc (front) + drum (rear)
39	285	450	disc (front + rear)
48	204	310	disc (front) + drum (rear)
15	204	395	disc (front + rear)
18	204	395	disc (front + rear)
20	204	395	disc (front + rear)
47	204	310	disc (front) + drum (rear)

	Drive type	Battery capacity [kWh]	Range (WLTP) [km]	... \
0	4WD	95.0	438	...
22	4WD	80.0	414	...
8	2WD (rear)	80.0	460	...
41	4WD	75.0	567	...
40	4WD	75.0	580	...

49	2WD (rear)	77.0	500 ...
39	2WD (rear)	54.0	430 ...
48	2WD (rear)	77.0	549 ...
15	2WD (front)	64.0	449 ...
18	2WD (front)	64.0	455 ...
20	2WD (front)	64.0	452 ...
47	2WD (rear)	58.0	425 ...

	Permissable gross weight [kg]	Maximum load capacity [kg]	\
0	3130.0	640.0	
22	2940.0	445.0	
8	2725.0	540.0	
41	NaN	NaN	
40	NaN	NaN	
49	2660.0	661.0	
39	NaN	NaN	
48	2280.0	412.0	
15	2170.0	485.0	
18	2230.0	493.0	
20	1682.0	498.0	
47	2270.0	540.0	

	Number of seats	Number of doors	Tire size [in]	Maximum speed [kph]	\
0	5	5	19	200	
22	5	5	19	180	
8	5	5	19	180	
41	5	5	20	261	
40	5	5	18	233	
49	5	5	20	160	
39	5	5	18	225	
48	5	5	19	160	
15	5	5	17	167	
18	5	5	17	167	
20	5	5	17	167	
47	5	5	18	160	

	Boot capacity (VDA) [l]	Acceleration 0-100 kph [s]	\
0	660.0	5.7	
22	500.0	5.1	
8	510.0	6.8	
41	425.0	3.3	
40	425.0	4.4	
49	543.0	8.5	
39	425.0	5.6	
48	385.0	7.9	
15	332.0	7.6	
18	451.0	7.8	
20	315.0	7.9	

47

385.0

7.3

	Maximum DC charging power [kW]	mean - Energy consumption [kWh/100 km]
0	150	24.45
22	110	21.85
8	150	18.80
41	150	NaN
40	150	NaN
49	125	18.00
39	150	NaN
48	125	15.90
15	100	15.40
18	100	15.90
20	100	15.70
47	100	15.40

[12 rows x 25 columns]

Now we try to group the above filtered data for the customer based on the Manufacturer.

```
[11]: """b) Group them by the manufacturer (Make)"""
group_by_make= filter_data.groupby("Make").agg(Cars_available=("Make", "count"))
b=group_by_make.sort_values(by=["Cars_available"],ascending=False)
b
```

```
[11]: Cars_available
Make
Tesla          3
Volkswagen     3
Kia            2
Audi           1
BMW            1
Hyundai        1
Mercedes-Benz  1
```

From above we can see above customer specification there are 3 Models available from Tesla 3 Models available from Volkswagen 2 models available fromm kia 1 model each from Audi,BMW,Hyundai,Mercedes-Benz

Moving now we will try compare the Average Battery Capacity for above customer Requiriments.

```
[14]: """c) Calculate the average battery capacity for each manufacturer. """
avg_capacity_by_make = filter_data.groupby("Make").
    ↪agg(Avg_battery_capacity=("Battery capacity [kWh]", "mean"))
a=avg_capacity_by_make.sort_values(by=["Avg_battery_capacity"],ascending=False)
a
```

```
[14]: Avg_battery_capacity
Make
```

Audi	95.000000
BMW	80.000000
Mercedes-Benz	80.000000
Volkswagen	70.666667
Tesla	68.000000
Hyundai	64.000000
Kia	64.000000

We can see that based on the above customer requirements the maximum battery capacity affordable is around 95 kWh from Audi and minimum of 64 Kwh from kia.

1.2 Task 2: Finding outliers in mean - Energy consumption [kWh/100 km] Column.

Checking for the NULL values in the mean - Energy consumption [kWh/100 km] Column

```
[18]: null_values = ev_df["mean - Energy consumption [kWh/100 km]"].isnull().sum()
null_values
```

```
[18]: 9
```

From above we can see there 9 Null values in our mean column which may effect the results which we are getting so we try to remove this null values and use that Dataet for accurate analysis of outliers

```
[20]: mean_energy = ev_df.dropna()
mean_energy_2 = mean_energy["mean - Energy consumption [kWh/100 km]"]
null_values_1 = mean_energy_2.isnull().sum()
null_values_1
```

```
[20]: 0
```

We can see Null Values Have been removed so we can proceed for our Outlier Detection.

```
[22]: mean_energy_2.describe()
```

```
[22]: count    42.000000
mean      18.610714
std        4.134293
min       13.100000
25%       15.600000
50%       16.875000
75%       22.937500
max       27.550000
Name: mean - Energy consumption [kWh/100 km], dtype: float64
```

1.2.1 Finding Outliers using IQR Method

The Interquartile Range (IQR) method is a popular technique for detecting outliers in a dataset.

Calculating q1,q3 and iqr values for outlier detection.

```
[24]: q1 = np.quantile(mean_energy_2,0.25)
      q3 = np.quantile(mean_energy_2,0.75)
      iqr=q3-q1
      print(f"The q1 quartile range is:{q1}\nThe q3 quartile range is:{q3}\nThe iqr_
            ↳for the follwing dataset is:{iqr}")
```

The q1 quartile range is:15.6

The q3 quartile range is:22.9375

The iqr for the follwing dataset is:7.3375

Creating Upper and Lower bonds for outlier detection using q1,q3 and iqr values .

```
[25]: upper_bound = q3+(1.5*iqr)
      lower_bound = q1-(1.5*iqr)
      print(f"The iqr of follwing dataset is {iqr},\nThe Upper bound of the_
            ↳dataset{upper_bound},\nThe Lower bound of the dataset{ lower_bound}")
```

The iqr of follwing dataset is 7.3375,

The Upper bound of the dataset33.94375,

The Lower bound of the dataset4.5937499999999998

Checking for outliers values in our mean energy Consumption.

```
[26]: outliers = mean_energy_2[(mean_energy_2 <= lower_bound) | (mean_energy_2>=_
            ↳upper_bound)]
      print(f'The following are the outliers in the boxplot:\n{outliers}')
```

The following are the outliers in the boxplot:

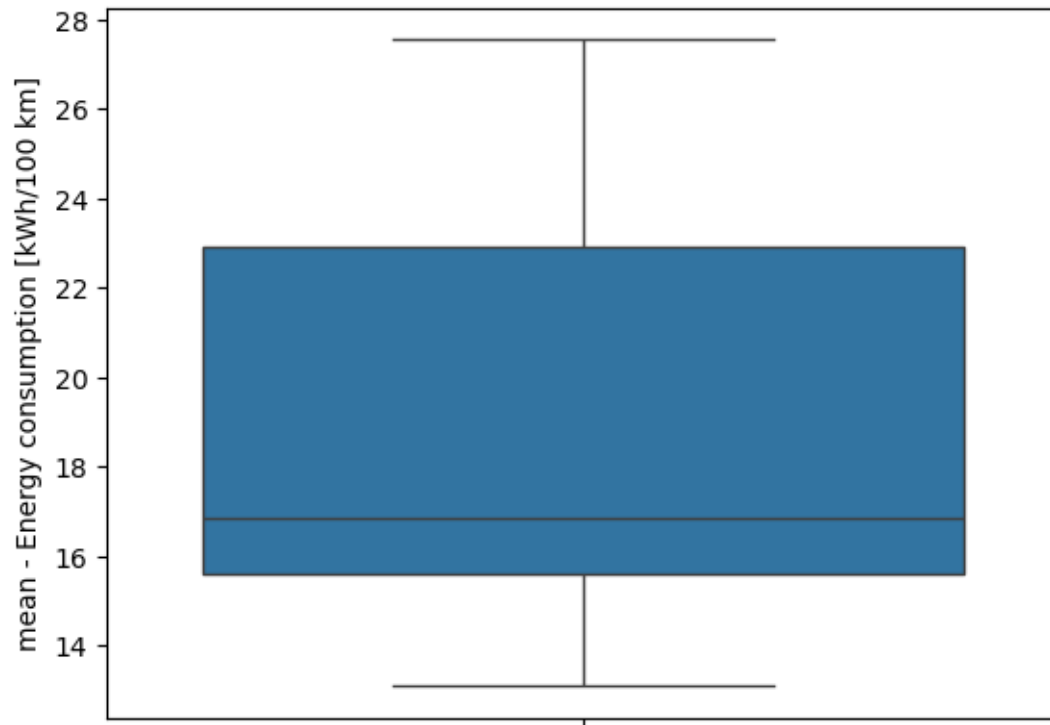
Series([], Name: mean - Energy consumption [kWh/100 km], dtype: float64)

From the above IQR results we can see that there are no significant Ouliers in our Mean Energy Consumption

1.2.2 Finding Outliers Using Boxplot Visualization

Finding the ouliers in the mean energy computation to double Check our results.For this Task we are choosing the Python in Built visualisation BOXPLOT which is extremely used to find ouliers in an dataset BOXPLOT creates the upper bond and lower bond and point out the data points which are outliers in the dataset

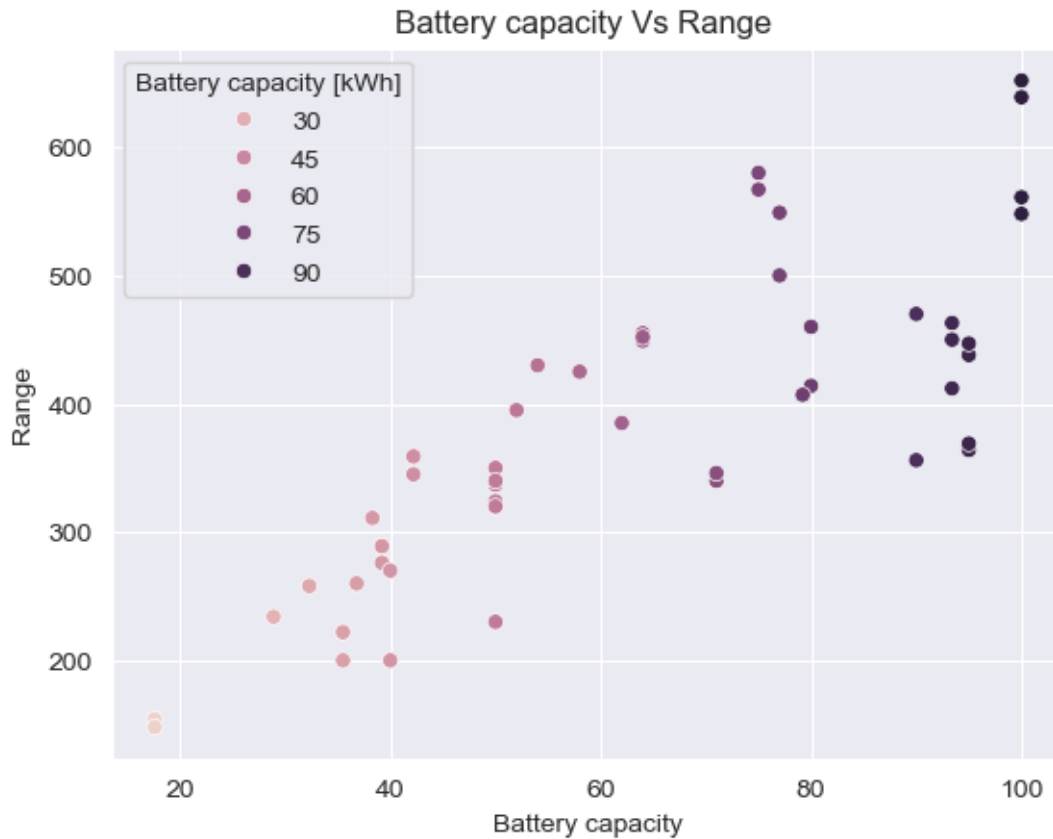
```
[30]: sns.boxplot(mean_energy_2)
      plt.show()
```



From the above Boxplot Visualizationsn we can see that there are no significant Ouliers in our Mean Energy Consumption

1.3 Task 3: Checking For Relationship between Baterry Capacity and Range

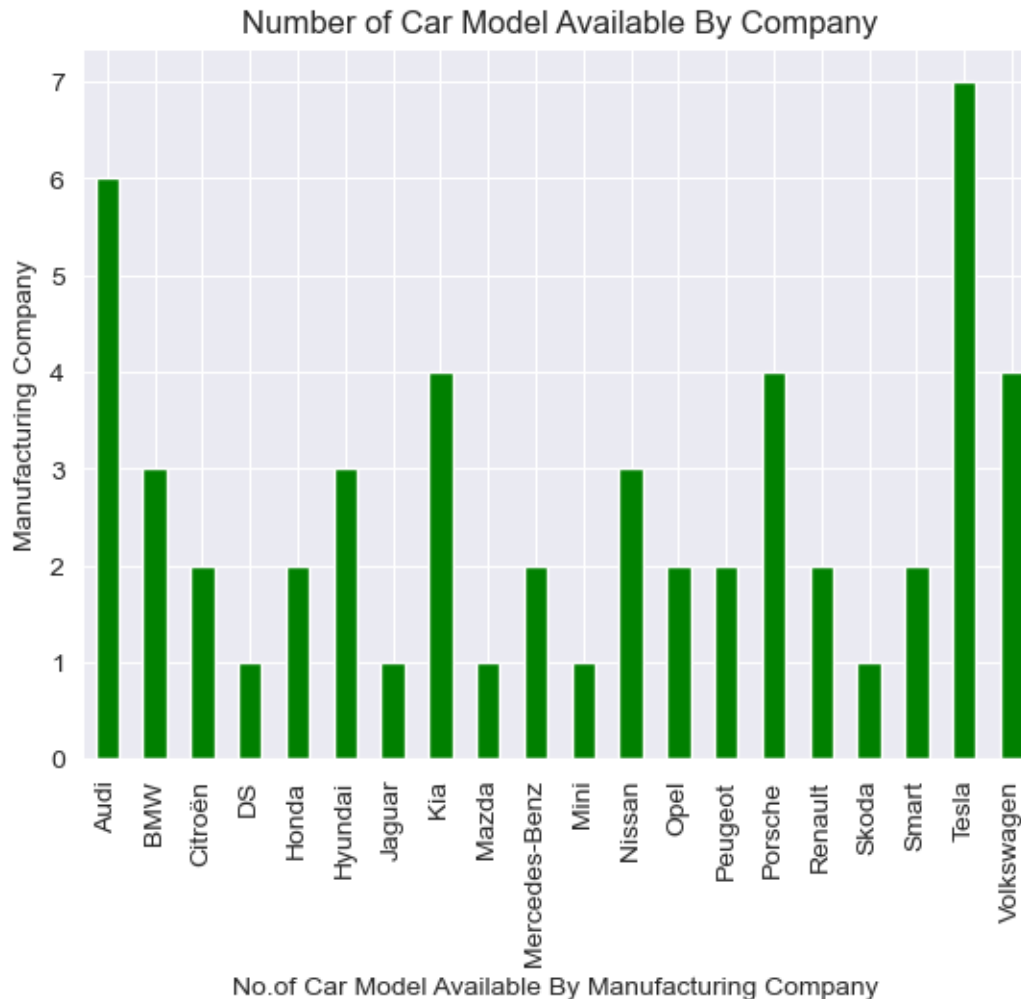
```
[33]: """ a) Create a suitable plot to visualize."""
sns.set_style("darkgrid")
sns.scatterplot(x="Battery capacity [kWh]",y="Range (WLTP) [km]",data =_
    ↪ev_df,hue="Battery capacity [kWh]")
plt.title("Battery capacity Vs Range ")
plt.xlabel("Battery capacity")
plt.ylabel(" Range ")
plt.show()
```

From the above visual we can see that there is a linear relationship between the Battery Capacity of the EV and Range Of the EV which means the EV models with Higher Battery Capacity are providing the higher Ranges and EV models with lower Battery Capacity are Providing Lower Ranges

1.3.1 Models Manufactured by Each Company

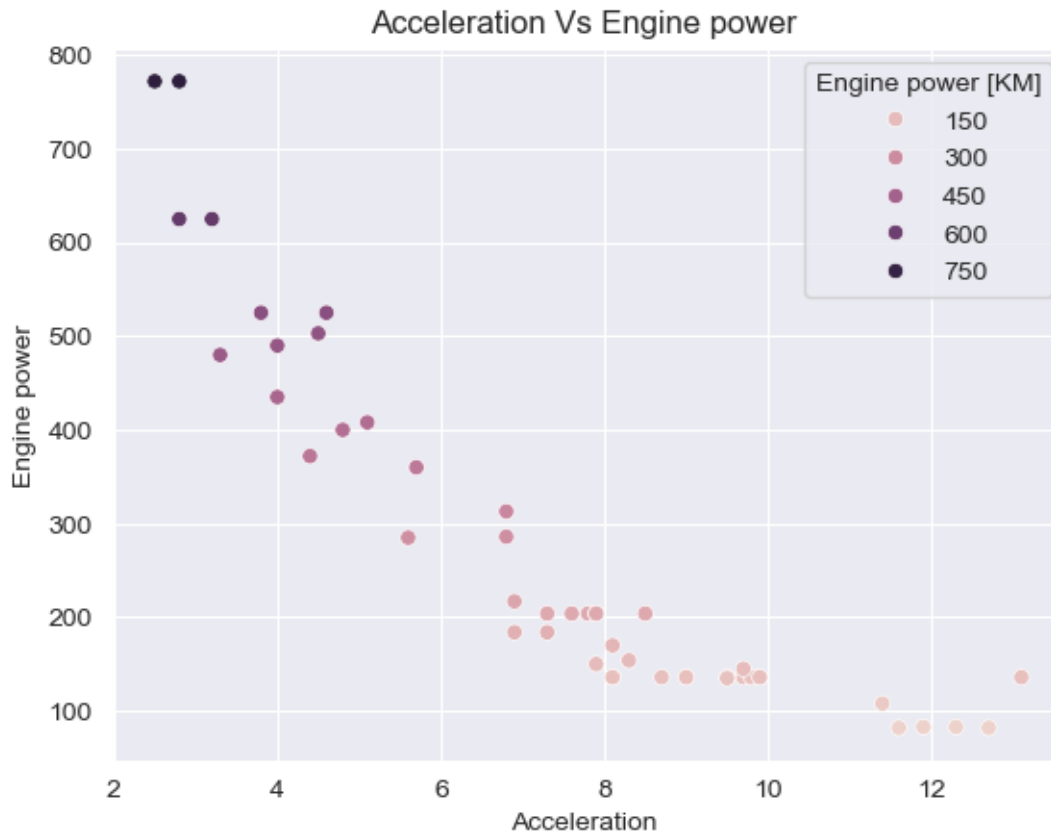
```
[36]: """ b) Highlight any insights."""
Cars_by_company=ev_df.groupby("Make")["Make"].count()
Cars_by_company
Cars_by_company.plot(kind="bar",color="Green")
plt.title("Number of Car Model Available By Company")
plt.xlabel("No.of Car Model Available By Manufacturing Company ")
plt.ylabel("Manufacturing Company")
plt.show()
```



From the above visual we can see the most number of models from a single company are 7 Models from Tesla 6 Models from Audi 4 Models from 3 Companies -Kia,Porsche,Volkswagen 3 models from 3 MCompanies - BMW,Hyundai,Nissan 2 models from 6 Companies - Citroen,Honda,Opel,Peugeot,Renault,Smart 1 Models from 5 Companies - Skoda,jaguar,Ds,Mini and Mazda

1.3.2 Relationship Between Acceleration and Engine Power

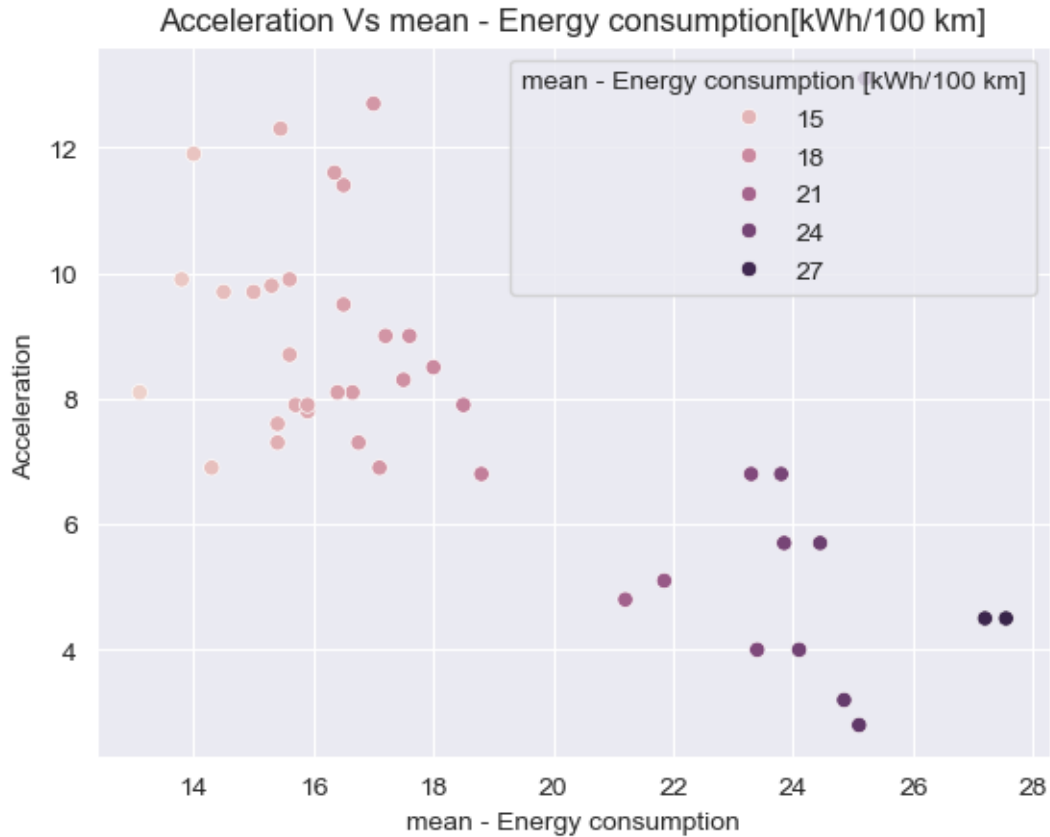
```
[39]: sns.set_style("darkgrid")
sns.scatterplot(x="Acceleration 0-100 kph [s]",y="Engine power [KM]",data =_
    ↪ev_df,hue="Engine power [KM]")
plt.title("Acceleration Vs Engine power ")
plt.xlabel("Acceleration ")
plt.ylabel("Engine power")
plt.show()
```



Now we are trying to see the relationship between the Acceleration and Engine power we can see the the model with the higher engine power are taking less time to accelerate means having Higher acceleration rate we can see the the model with the lower engine power are taking more time to accelerate means having Lower acceleration rate

1.3.3 Relationship Between Acceleration and Mean Energy Consumption[kWh/100 km]

```
[42]: sns.set_style("darkgrid")
sns.scatterplot(y="Acceleration 0-100 kph [s]",x="mean - Energy consumption_
↪[kWh/100 km]",data = ev_df,hue="mean - Energy consumption [kWh/100 km]")
plt.title("Acceleration Vs mean - Energy consumption[kWh/100 km]")
plt.ylabel("Acceleration ")
plt.xlabel("mean - Energy consumption")
plt.show()
```



Now we are trying to see the relationship between the Acceleration and Mean Energy Consumption we can see the the model having Higher acceleration rate means taking less time to reach 0-100kph are consuming more Energy per 100 km we can see the the model having Lower acceleration rate means taking less time to reach 0-100kph are consuming less Energy per 100 km

1.4 Task 4: Build an EV Recommendation Class

For this Task we assigned to make EV Recommendation Class Where the user inputs his specific Budget Allocation, Desired Range, Battery capacity he requires. Then we will Return him the top 3 EV's based on His desired Inputs:

```
[46]: """ Task 4 """

class ev_recommendation:
    def __init__(self,budget,range_km,battery_capacity):
        self.budget = budget
        self.range_km = range_km
        self.battery_capacity = battery_capacity
        print(f"Your budget Allocation : {self.budget}\nYour Desired Range: {self.range_km}\nBattery Capacity Required: {self.battery_capacity}")
```

```

if self.budget==0:
    print("Enter Valid Budget")
elif self.range_km == 0:
    print("Enter Valid Range")
elif self.battery_capacity == 0:
    print("Enter Valid Battery Capacity")
else:
    print("The Top Three EV with in given parameters")
    ev_with_in_range=ev_df[(ev_df["Range (WLTP) [km]"< self.range_km)&
    ↪ (ev_df["Battery capacity [kWh]"< self.battery_capacity) &
    ↪ (ev_df["Minimal price (gross) [PLN]"<=self.budget)]
    top_3_range =ev_with_in_range.nlargest(3,["Range (WLTP) [km]"])
    display("Top 3 Based On Your Desired Range:",top_3_range)
    top_3_battery=ev_with_in_range.nlargest(3,["Minimal price (gross)
    ↪ [PLN]"])
    display("Top 3 Based On Your Desired Budget:",top_3_battery)
    top_3_budget=ev_with_in_range.nlargest(3,["Battery capacity [kWh]"])
    display("Top 3 Based On Your Battery Capacity Required:
    ↪ ",top_3_budget)

```

1.4.1 User Based Inputs will we given Here

```

[48]: #first input in budget second input is range third input is Battery Capacity
ev_recommendation(400000,500,80)

```

Your budget Allocation : 400000

Your Desired Range: 500

Battery Capacity Required: 80

The Top Three EV with in given parameters

'Top 3 Based On Your Desired Range:'

	Car full name	Make	Model \
18	Kia e-Niro 64kWh	Kia	e-Niro 64kWh
20	Kia e-Soul 64kWh	Kia	e-Soul 64kWh
15	Hyundai Kona electric 64kWh	Hyundai	Kona electric 64kWh

	Minimal price (gross) [PLN]	Engine power [KM]	Maximum torque [Nm] \
18	167990	204	395
20	160990	204	395
15	178400	204	395

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

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

18	455	...	2230.0
20	452	...	1682.0
15	449	...	2170.0

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

	Tire size [in]	Maximum speed [kph]	Boot capacity (VDA) [l] \
18	17	167	451.0
20	17	167	315.0
15	17	167	332.0

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

	mean - Energy consumption [kWh/100 km]
18	15.9
20	15.7
15	15.4

[3 rows x 25 columns]

'Top 3 Based On Your Desired Budget:'

	Car full name	Make	Model \
3	Audi e-tron Sportback 50 quattro	Audi	e-tron Sportback 50 quattro
1	Audi e-tron 50 quattro	Audi	e-tron 50 quattro
50	Citroën ë-Spacetourer (M)	Citroën	ë-Spacetourer (M)

	Minimal price (gross) [PLN]	Engine power [KM]	Maximum torque [Nm] \
3	319700	313	540
1	308400	313	540
50	215400	136	260

	Type of brakes	Drive type	Battery capacity [kWh] \
3	disc (front + rear)	4WD	71.0
1	disc (front + rear)	4WD	71.0
50	disc (front + rear)	2WD (front)	50.0

	Range (WLTP) [km] ...	Permissable gross weight [kg] \
3	346 ...	3040.0
1	340 ...	3040.0
50	230 ...	2810.0

	Maximum load capacity [kg]	Number of seats	Number of doors \
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3	640.0	5	5
1	670.0	5	5
50	1056.0	8	5

	Tire size [in]	Maximum speed [kph]	Boot capacity (VDA) [l]	\
3	19	190	615.0	
1	19	190	660.0	
50	16	130	603.0	

	Acceleration 0-100 kph [s]	Maximum DC charging power [kW]	\
3	6.8	150	
1	6.8	150	
50	13.1	100	

	mean - Energy consumption [kWh/100 km]
3	23.3
1	23.8
50	25.2

[3 rows x 25 columns]

'Top 3 Based On Your Battery Capacity Required:'

	Car full name	Make	Model	\
1	Audi e-tron 50 quattro	Audi	e-tron 50 quattro	
3	Audi e-tron Sportback 50 quattro	Audi	e-tron Sportback 50 quattro	
15	Hyundai Kona electric 64kWh	Hyundai	Kona electric 64kWh	

	Minimal price (gross) [PLN]	Engine power [KM]	Maximum torque [Nm]	\
1	308400	313	540	
3	319700	313	540	
15	178400	204	395	

	Type of brakes	Drive type	Battery capacity [kWh]	\
1	disc (front + rear)	4WD	71.0	
3	disc (front + rear)	4WD	71.0	
15	disc (front + rear)	2WD (front)	64.0	

	Range (WLTP) [km]	...	Permissable gross weight [kg]	\
1	340	...	3040.0	
3	346	...	3040.0	
15	449	...	2170.0	

	Maximum load capacity [kg]	Number of seats	Number of doors	\
1	670.0	5	5	
3	640.0	5	5	
15	485.0	5	5	

	Tire size [in]	Maximum speed [kph]	Boot capacity (VDA) [l]	\
--	----------------	---------------------	-------------------------	---

1	19	190	660.0
3	19	190	615.0
15	17	167	332.0

	Acceleration 0-100 kph [s]	Maximum DC charging power [kW]	\
1	6.8	150	
3	6.8	150	
15	7.6	100	

	mean - Energy consumption [kWh/100 km]
1	23.8
3	23.3
15	15.4

[3 rows x 25 columns]

[48]: <__main__.ev_recommendation at 0x22d698efb90>

1.5 Task 5: Inferential Statistics

We are assigned to test whether there is significant difference between the average Engine power [KM] of vehicles manufactured by two leading manufacturers i.e. Tesla and Audi. For testing we are going to use hypothesis testing first let's start with our Null Hypothesis (H0) = There is no significant Relationship between the mean engine power of two manufacturers Tesla and Audi. Alternate Hypothesis (H1) = There is a significant relationship between the mean engine power of two manufacturers Tesla and Audi. Let's start with preparing our Two sample datasets consisting of engine power of Tesla and Audi

1.5.1 Preparation our Two sample datasets consisting of engine power of Tesla and Audi

Filtering the two datasets of Tesla and Audi from EV dataset.

[53]: *"""Task 5: """*

```
tesla = ev_df[ev_df["Make"] == "Tesla"]
display(tesla.head(4))

audi = ev_df[ev_df["Make"] == "Audi"]
display(audi.head(4))
```

	Car full name	Make	Model	\
39	Tesla Model 3 Standard Range Plus	Tesla	Model 3 Standard Range Plus	
40	Tesla Model 3 Long Range	Tesla	Model 3 Long Range	
41	Tesla Model 3 Performance	Tesla	Model 3 Performance	
42	Tesla Model S Long Range Plus	Tesla	Model S Long Range Plus	

	Minimal price (gross) [PLN]	Engine power [KM]	Maximum torque [Nm]	\
39	195490	285	450	

40	235490	372	510
41	260490	480	639
42	368990	525	755

	Type of brakes	Drive type	Battery capacity [kWh]	\
39	disc (front + rear)	2WD (rear)	54.0	
40	disc (front + rear)	4WD	75.0	
41	disc (front + rear)	4WD	75.0	
42	disc (front + rear)	4WD	100.0	

	Range (WLTP) [km]	...	Permissable gross weight [kg]	\
39	430	...	NaN	
40	580	...	NaN	
41	567	...	NaN	
42	652	...	NaN	

	Maximum load capacity [kg]	Number of seats	Number of doors	\
39	NaN	5	5	
40	NaN	5	5	
41	NaN	5	5	
42	NaN	5	5	

	Tire size [in]	Maximum speed [kph]	Boot capacity (VDA) [l]	\
39	18	225	425.0	
40	18	233	425.0	
41	20	261	425.0	
42	19	250	745.0	

	Acceleration 0-100 kph [s]	Maximum DC charging power [kW]	\
39	5.6	150	
40	4.4	150	
41	3.3	150	
42	3.8	150	

	mean - Energy consumption [kWh/100 km]
39	NaN
40	NaN
41	NaN
42	NaN

[4 rows x 25 columns]

	Car full name	Make	Model	\
0	Audi e-tron 55 quattro	Audi	e-tron 55 quattro	
1	Audi e-tron 50 quattro	Audi	e-tron 50 quattro	
2	Audi e-tron S quattro	Audi	e-tron S quattro	
3	Audi e-tron Sportback 50 quattro	Audi	e-tron Sportback 50 quattro	

	Minimal price (gross) [PLN]	Engine power [KM]	Maximum torque [Nm]	\
0	345700	360	664	
1	308400	313	540	
2	414900	503	973	
3	319700	313	540	

	Type of brakes	Drive type	Battery capacity [kWh]	Range (WLTP) [km]	\
0	disc (front + rear)	4WD	95.0	438	
1	disc (front + rear)	4WD	71.0	340	
2	disc (front + rear)	4WD	95.0	364	
3	disc (front + rear)	4WD	71.0	346	

	... Permissable gross weight [kg]	Maximum load capacity [kg]	\
0	...	3130.0	640.0
1	...	3040.0	670.0
2	...	3130.0	565.0
3	...	3040.0	640.0

	Number of seats	Number of doors	Tire size [in]	Maximum speed [kph]	\
0	5	5	19	200	
1	5	5	19	190	
2	5	5	20	210	
3	5	5	19	190	

	Boot capacity (VDA) [l]	Acceleration 0-100 kph [s]	\
0	660.0	5.7	
1	660.0	6.8	
2	660.0	4.5	
3	615.0	6.8	

	Maximum DC charging power [kW]	mean - Energy consumption [kWh/100 km]
0	150	24.45
1	150	23.80
2	150	27.55
3	150	23.30

[4 rows x 25 columns]

1.5.2 Creating and Checking The Two Sample Datasets for any error and null values

In this phase we try to create the sample datasets For Hypothesis Testing for Engine Power

```
[56]: tesla_engine=tesla[["Engine power [KM]"]]
display(tesla_engine)
audi_engine = audi[["Engine power [KM]"]]
display(audi_engine)
```

	Engine power [KM]
39	285
40	372
41	480
42	525
43	772
44	525
45	772

	Engine power [KM]
0	360
1	313
2	503
3	313
4	360
5	503

We can see there are no null values and error so we can proceed with this data for Hypothesis testing. The two sample datasets are small and independent datasets so we can go ahead with the Two Sample T Test

1.5.3 Checking the Variances Of the Sample Datasets

To Conduct Two sample T test First of all we have check the variance of the Two Sample datasets

```
[60]: tesla_var = np.var(tesla["Engine power [KM]"])
audi_var = np.var(audi["Engine power [KM]"])
print("The Variance of Tesla Dataset:",tesla_var,"\n\nThe Variance of Audi_
Dataset:",audi_var)
```

The Variance of Tesla Dataset: 29229.14285714286

The Variance of Audi Dataset: 6528.666666666667

We can see their difference between ratio of the two datasets is Greater than 4:1

1.5.4 Performing Two Sample T Test

Now with the Sample datasets ready and variances is known we conduct the Two Sample T test

```
[64]: statistic,p_value=stats.
ttest_ind(tesla_engine,audi_engine,equal_var=False)#variance not in ratio of
4:1
print("The Two Sample T test Results:")
print(f"T Statistic:{statistic}")
print(f"P-Value:{p_value}")
```

The Two Sample T test Results:

T Statistic: [1.79399518]

P-Value: [0.10684105]

1.5.5 Interpreting the T- Test Results

Based on the P value of 0.10684105 from the Two Sample T-Tet we can verifying the Hyothesis we made. we are Taking Significance level(alpha) =0.05(confidence level of 95%)

```
[67]: alpha = 0.05
      if p_value < 0.05:
          print("We Reject The Null Hypothesis.There is a signigicant Difference_
          ↳between both Tesla and Audi Mean Energy Power")
      else:
          print("We Fail to Reject the NULL Hypotheses Means\nWe do not have_
          ↳sufficient evidence to say that the mean Engine Power between the two data_
          ↳groups Tesla and Audi is different.")
```

We Fail to Reject the NULL Hypotheses Means

We do not have sufficient evidence to say that the mean Engine Power between the two data groups Tesla and Audi is different.

Here, since the p-value (0.10684105) is greater than $\alpha = 0.05$ so we cannot reject the null hypothesis of the test. We do not have sufficient evidence to say that the mean Engine Power between the two data groups Tesla and Audi is different.

```
[ ]:
```

```
[ ]:
```