

```
In [30]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import ttest_ind
```

```
In [31]: df = pd.read_excel("FEV-data-Excel.xlsx")
```

```
In [32]: df
```

Out[32]:

	Car full name	Make	Model	Minimal price (gross) [PLN]	Engine power [KM]	Maximum torque [Nm]	Type of brakes	Drive type	Bat capacity [kWh]
0	Audi e-tron 55 quattro	Audi	e-tron 55 quattro	345700	360	664	disc (front + rear)	4WD	95
1	Audi e-tron 50 quattro	Audi	e-tron 50 quattro	308400	313	540	disc (front + rear)	4WD	75
2	Audi e-tron S quattro	Audi	e-tron S quattro	414900	503	973	disc (front + rear)	4WD	95
3	Audi e-tron Sportback 50 quattro	Audi	e-tron Sportback 50 quattro	319700	313	540	disc (front + rear)	4WD	75

```
In [33]: #task1
def filter_evs(budget, min_range):
    filtered_df = df[(df['Minimal price (gross) [PLN]'] <= budget) & (df['Rang
    return filtered_df

filtered_evs = filter_evs(350000, 400)
print(filtered_evs)
# Group by manufacturer and calculate average battery capacity
grouped_evs = filtered_evs.groupby("Make")
avg_battery_capacity = grouped_evs["Battery capacity [kWh]"].mean()
print(avg_battery_capacity)
```

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

	Model	Minimal price (gross) [PLN] \
0	e-tron 55 quattro	345700
8	iX3	282900
15	Kona electric 64kWh	178400
18	e-Niro 64kWh	167990
20	e-Soul 64kWh	160000

Explanation:

- Filters EVs below 350,000 PLN and range  $\geq 400$  km.
- Groups the filtered EVs by manufacturer.
- Computes average battery capacity per manufacturer.

```
In [34]: # Task 2: Find outliers in energy consumption
def find_outliers(column):
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = df[(df[column] < lower_bound) | (df[column] > upper_bound)]
    return outliers

outlier_evs = find_outliers("mean - Energy consumption [kWh/100 km]")
print(outlier_evs[["Car full name", "mean - Energy consumption [kWh/100 km]"]])
```

Empty DataFrame

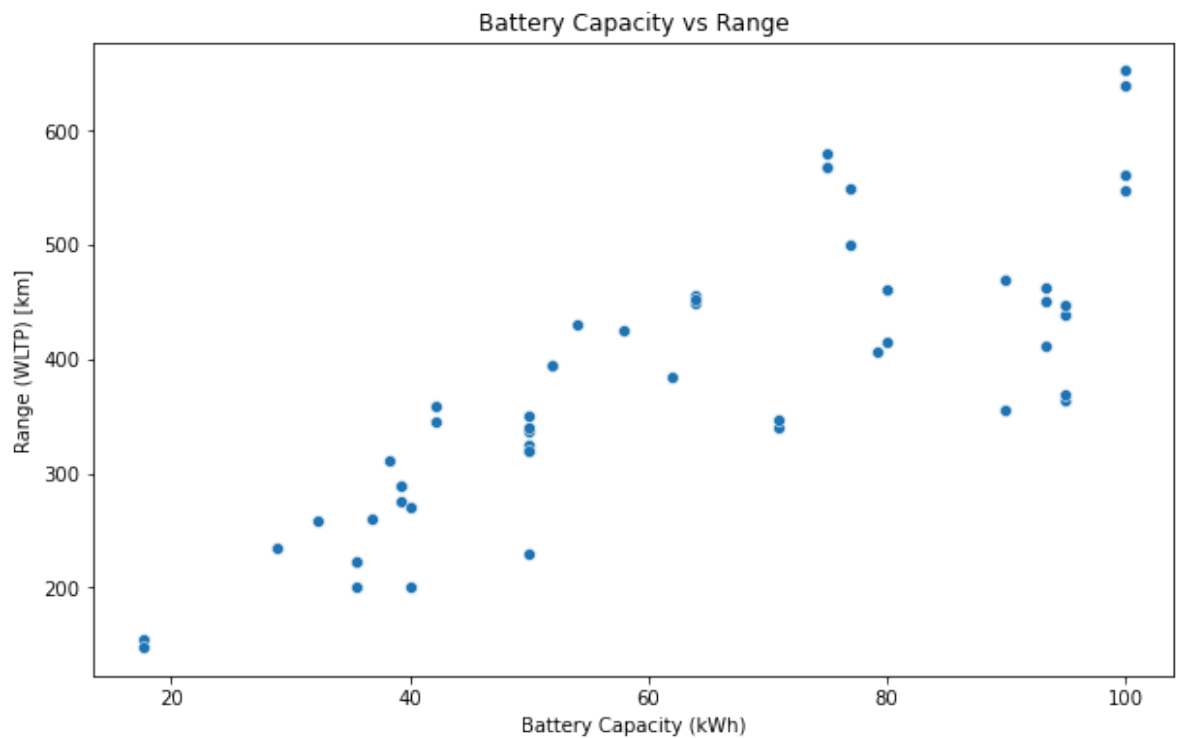
Columns: [Car full name, mean - Energy consumption [kWh/100 km]]

Index: []

Explanation:

- Uses Z-score method to detect outliers (values beyond  $\pm 2.5$  standard deviations).
- Helps identify highly inefficient or energy-efficient EVs.

```
In [35]: #task3
plt.figure(figsize=(10, 6))
sns.scatterplot(x=df['Battery capacity [kWh]'], y=df['Range (WLTP) [km]'])
plt.xlabel("Battery Capacity (kWh)")
plt.ylabel("Range (WLTP) [km]")
plt.title("Battery Capacity vs Range")
plt.show()
```



Explanation:

- Plots battery capacity vs. range using a scatter plot.
- Helps visualize if higher battery capacity = longer range.

```
In [36]: #task4
class EVRecommendation:
    def __init__(self, df):
        self.df = df

    def recommend(self, budget, min_range, min_battery):
        recommended = self.df[(self.df['Minimal price (gross) [PLN]'] <= budget &
                                (self.df['Range (WLTP) [km]'] >= min_range) &
                                (self.df['Battery capacity [kWh]'] >= min_battery)]
        return recommended.nlargest(3, 'Range (WLTP) [km]')

recommender = EVRecommendation(df)
print(recommender.recommend(350000, 400, 50))
```

	Car full name	Make	Model	\
40	Tesla Model 3 Long Range	Tesla	Model 3 Long Range	
41	Tesla Model 3 Performance	Tesla	Model 3 Performance	
48	Volkswagen ID.3 Pro S	Volkswagen	ID.3 Pro S	

	Minimal price (gross) [PLN]	Engine power [KM]	Maximum torque [Nm]	\
40	235490	372	510	
41	260490	480	639	
48	179990	204	310	

	Type of brakes	Drive type	Battery capacity [kWh]	\
40	disc (front + rear)	4WD	75.0	
41	disc (front + rear)	4WD	75.0	
48	disc (front) + drum (rear)	2WD (rear)	77.0	

	Range (WLTP) [km]	...	Permissible gross weight [kg]	\
40	580	...	NaN	
41	567	...	NaN	
48	549	...	2280.0	

	Maximum load capacity [kg]	Number of seats	Number of doors	\
40	NaN	5	5	
41	NaN	5	5	
48	412.0	5	5	

	Tire size [in]	Maximum speed [kph]	Boot capacity (VDA) [l]	\
40	18	233	425.0	
41	20	261	425.0	
48	19	160	385.0	

	Acceleration 0-100 kph [s]	Maximum DC charging power [kW]	\
40	4.4	150	
41	3.3	150	
48	7.9	125	

	mean - Energy consumption [kWh/100 km]
40	NaN
41	NaN
48	15.9

[3 rows x 25 columns]

Explanation:

- Filters EVs based on user input.
- Sorts by range and selects the top 3.

```
In [37]: #task5
tesla_power = df[df["Make"] == "Tesla"]["Engine power [KM]"].dropna()
audi_power = df[df["Make"] == "Audi"]["Engine power [KM]"].dropna()

stat, p_value = ttest_ind(tesla_power, audi_power, equal_var=False)
print(f"T-statistic: {stat}, P-value: {p_value}")
if p_value < 0.05:
    print("Significant difference in engine power between Tesla and Audi.")
else:
    print("No significant difference in engine power between Tesla and Audi.")
```

T-statistic: 1.7939951827297183, P-value: 0.10684105068839563  
No significant difference in engine power between Tesla and Audi.

Explanation:

- Uses Independent T-test to compare Tesla & Audi engine power.
- P-value < 0.05 → Significant difference.
- P-value > 0.05 → No significant difference.

GOOGLE DRIVE LINK :  
[https://drive.google.com/file/d/1VKt4CgS7j\\_f3hnkKxC2C02dQzyvX8j74/view?usp=sharing](https://drive.google.com/file/d/1VKt4CgS7j_f3hnkKxC2C02dQzyvX8j74/view?usp=sharing)