

Task 1: Filter EVs by Criteria and Analyze

a) Filter EVs by Budget and Range:

```
import pandas as pd
df = pd.read_excel(r"C:\Users\ABC\Downloads\FEV-data-excel.xlsx")
filtered_evs = df[(df['Minimal price (gross) [PLN]'] <= 350000) &
(df['Range (WLTP) [km]'] >= 400)]
print(filtered_evs)
```

	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	160990
22	EQC	334700
39	Model 3 Standard Range Plus	195490
40	Model 3 Long Range	235490
41	Model 3 Performance	260490
47	ID.3 Pro Performance	155890
48	ID.3 Pro S	179990
49	ID.4 1st	202390

	Engine power [KM]	Maximum torque [Nm]	Type of brakes
0	360	664	disc (front + rear)
8	286	400	disc (front + rear)
15	204	395	disc (front + rear)
18	204	395	disc (front + rear)

20	204	395	disc (front + rear)
22	408	760	disc (front + rear)
39	285	450	disc (front + rear)
40	372	510	disc (front + rear)
41	480	639	disc (front + rear)
47	204	310	disc (front) + drum (rear)
48	204	310	disc (front) + drum (rear)
49	204	310	disc (front) + drum (rear)

	Drive type	Battery capacity [kWh]	Range (WLTP) [km]	...	\
0	4WD	95.0	438	...	
8	2WD (rear)	80.0	460	...	
15	2WD (front)	64.0	449	...	
18	2WD (front)	64.0	455	...	
20	2WD (front)	64.0	452	...	
22	4WD	80.0	414	...	
39	2WD (rear)	54.0	430	...	
40	4WD	75.0	580	...	
41	4WD	75.0	567	...	
47	2WD (rear)	58.0	425	...	
48	2WD (rear)	77.0	549	...	
49	2WD (rear)	77.0	500	...	

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

	Number of seats	Number of doors	Tire size [in]	Maximum speed [kph]	\
0	5	5	19		
200					
8	5	5	19		

180			
15	5	5	17
167			
18	5	5	17
167			
20	5	5	17
167			
22	5	5	19
180			
39	5	5	18
225			
40	5	5	18
233			
41	5	5	20
261			
47	5	5	18
160			
48	5	5	19
160			
49	5	5	20
160			

	Boot capacity (VDA) [l]	Acceleration 0-100 kph [s]	\
0	660.0	5.7	
8	510.0	6.8	
15	332.0	7.6	
18	451.0	7.8	
20	315.0	7.9	
22	500.0	5.1	
39	425.0	5.6	
40	425.0	4.4	
41	425.0	3.3	
47	385.0	7.3	
48	385.0	7.9	
49	543.0	8.5	

	Maximum DC charging power [kW]	mean - Energy consumption [kWh/100 km]
0	150	
24.45		
8	150	
18.80		
15	100	
15.40		
18	100	
15.90		
20	100	
15.70		
22	110	

21.85	
39	150
NaN	
40	150
NaN	
41	150
NaN	
47	100
15.40	
48	125
15.90	
49	125
18.00	

[12 rows x 25 columns]

b) Group by Manufacturer (Make):

```
grouped_evs = filtered_evs.groupby('Make')
print(grouped_evs.size())
```

Make	
Audi	1
BMW	1
Hyundai	1
Kia	2
Mercedes-Benz	1
Tesla	3
Volkswagen	3

dtype: int64

c) Calculate Average Battery Capacity:

```
avg_battery = grouped_evs['Battery capacity [kWh]'].mean()
print(avg_battery)
```

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

Name: Battery capacity [kWh], dtype: float64

Task 2: Find Outliers in Energy Consumption

```
from scipy.stats import zscore

df['Z-score'] = zscore(df['mean - Energy consumption [kWh/100 km]'])

# Filter out rows with Z-scores greater than 3 or less than -3
# (typical threshold for outliers)
outliers = df[(df['Z-score'] > 3) | (df['Z-score'] < -3)]

print(outliers)
```

Empty DataFrame
Columns: [Car full name, Make, Model, Minimal price (gross) [PLN], Engine power [KM], Maximum torque [Nm], Type of brakes, Drive type, Battery capacity [kWh], Range (WLTP) [km], Wheelbase [cm], Length [cm], Width [cm], Height [cm], Minimal empty weight [kg], Permissible gross weight [kg], Maximum load capacity [kg], Number of seats, Number of doors, Tire size [in], Maximum speed [kph], Boot capacity (VDA) [l], Acceleration 0-100 kph [s], Maximum DC charging power [kW], mean - Energy consumption [kWh/100 km], Z-score]
Index: []

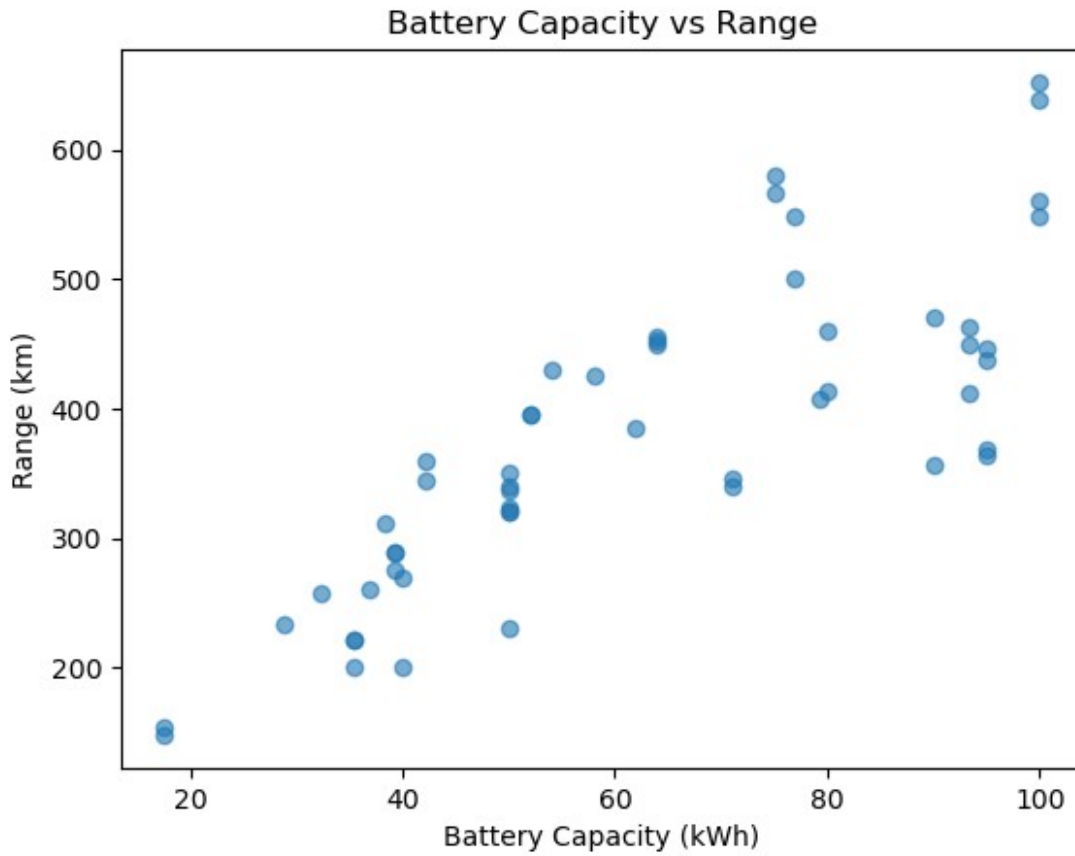
[0 rows x 26 columns]

Task 3: Relationship Between Battery Capacity and Range

a) Create a Visualization:

```
import matplotlib.pyplot as plt

# Scatter plot
plt.scatter(df['Battery capacity [kWh]'], df['Range (WLTP) [km]'],
            alpha=0.6)
plt.xlabel('Battery Capacity (kWh)')
plt.ylabel('Range (km)')
plt.title('Battery Capacity vs Range')
plt.show()
```



(b): Highlight Insights from Scatter Plot and Correlation Coefficient

```
correlation = df['Battery capacity [kWh]'].corr(df['Range (WLTP) [km]'])  
print("Correlation Coefficient:", correlation)
```

Correlation Coefficient: 0.8104385771936845

Based on the scatter plot provided (Battery Capacity vs Range) and the correlation coefficient (0.8104385771936845), here are the observations and insights:

Key Insights: Strong Positive Correlation:

The correlation coefficient of 0.81 indicates a strong positive relationship between battery capacity and range. This means that electric vehicles with higher battery capacities tend to achieve longer ranges, which aligns with expectations—larger batteries store more energy, enabling greater distances.

Efficient EVs and Trends:

The majority of points on the scatter plot follow an upward trend, confirming that most EVs adhere to this correlation. However, some vehicles exhibit exceptional efficiency or inefficiency:

Highly Efficient EVs: Vehicles with lower battery capacities but longer ranges suggest optimized energy consumption.

Inefficient EVs: Vehicles with higher battery capacities but shorter ranges might indicate heavier weight or less efficient energy usage.

Outliers:

There could be a few outliers visible in the plot:

Outliers with High Battery Capacity but Low Range: These might represent vehicles designed for performance rather than distance.

Outliers with Low Battery Capacity but High Range: These showcase advanced technology or lightweight designs.

General Observation:

The data supports the hypothesis that battery capacity is a significant determinant of range. However, external factors like aerodynamics, vehicle weight, and powertrain efficiency also play crucial roles.

Task 4: Build an EV Recommendation Class

```
class EVRecommender:
    def __init__(self, data):
        self.data = data

    def recommend(self, budget, desired_range, min_battery_capacity):
        recommendations = self.data[(self.data['Minimal price (gross)
[PLN]'] <= budget) &
                                     (self.data['Range (WLTP) [km]']
                                     >= desired_range) &
                                     (self.data['Battery capacity
[kWh]'] >= min_battery_capacity)]
        return recommendations.nlargest(3, 'Range (WLTP) [km]') #
Return top 3 EVs by range
```

```
recommender = EVRecommender(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] ... Maximum load capacity [kg] Number of
seats \
40      580 ... NaN
5
41      567 ... NaN
5
48      549 ... 412.0
5

Number of doors  Tire size [in]  Maximum speed [kph] \
40      5      18      233
41      5      20      261
48      5      19      160

Boot capacity (VDA) [l]  Acceleration 0-100 kph [s] \
40      425.0      4.4
41      425.0      3.3
48      385.0      7.9

Maximum DC charging power [kW] mean - Energy consumption [kWh/100
km] \
40      150
NaN
41      150
NaN
48      125
15.9

Z-score
40      NaN
41      NaN
48      NaN

[3 rows x 26 columns]

```

Task 5 : Hypothesis testing

```

from scipy.stats import ttest_ind

tesla_power = df[df['Make'] == 'Tesla']['Engine power [KM]']

```



```
audi_power = df[df['Make'] == 'Audi']['Engine power [KM]']  
  
t_stat, p_value = ttest_ind(tesla_power, audi_power, equal_var=False)  
print(f'T-Statistic: {t_stat}, P-Value: {p_value}')
```

if p_value < 0.05:
 print('There is a significant difference in average engine power
between Tesla and Audi.')

else:
 print('No significant difference in average engine power between
Tesla and Audi.')

T-Statistic: 1.7939951827297178, P-Value: 0.10684105068839565
No significant difference in average engine power between Tesla and
Audi.

Video Link

[Watch the Project Video](#)

https://drive.google.com/file/d/1loZcDgKfCFg5c0pMcvUJ1pbxnb5JdKMN/view?usp=drive_link