

EV_Data_Analysis

July 20, 2025

```
[14]: # Load the electric vehicle dataset and required Python libraries
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```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import ttest_ind

df = pd.read_excel("FEV-data-Excel.xlsx")

print(df.head())
```

| | 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]

```
[15]: # Task 1: Filter EVs under 350,000 PLN with at least 400 km range,
# group the filtered EVs by manufacturer (Make), and calculate
# the average battery capacity per manufacturer.

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import ttest_ind

df = pd.read_excel("FEV-data-Excel.xlsx")

filtered_df = df[(df["Minimal price (gross) [PLN]"] <= 350000) & (df["Range_
↳(WLTP) [km]"] >= 400)]
print("Filtered EVs:\n", filtered_df[["Car full name", "Make", "Minimal price_
↳(gross) [PLN]", "Range (WLTP) [km]"]])

grouped_by_make = filtered_df.groupby("Make")
print("\nGrouped by Manufacturer:\n", grouped_by_make.size())

avg_battery_by_make = grouped_by_make["Battery capacity [kWh]"].mean().
↳reset_index()
```

```
print("\nAverage Battery Capacity per Make:\n", avg_battery_by_make)
```

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 |

| | Minimal price (gross) [PLN] | Range (WLTP) [km] |
|----|-----------------------------|-------------------|
| 0 | 345700 | 438 |
| 8 | 282900 | 460 |
| 15 | 178400 | 449 |
| 18 | 167990 | 455 |
| 20 | 160990 | 452 |
| 22 | 334700 | 414 |
| 39 | 195490 | 430 |
| 40 | 235490 | 580 |
| 41 | 260490 | 567 |
| 47 | 155890 | 425 |
| 48 | 179990 | 549 |
| 49 | 202390 | 500 |

Grouped by Manufacturer:

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

dtype: int64

Average Battery Capacity per Make:

| | Make | Battery capacity [kWh] |
|---|---------|------------------------|
| 0 | Audi | 95.000000 |
| 1 | BMW | 80.000000 |
| 2 | Hyundai | 64.000000 |
| 3 | Kia | 64.000000 |

| | | |
|---|---------------|-----------|
| 4 | Mercedes-Benz | 80.000000 |
| 5 | Tesla | 68.000000 |
| 6 | Volkswagen | 70.666667 |

```
[16]: # Task 2: Detect outlier vehicles based on their mean energy consumption
# using the Interquartile Range (IQR) method.
import pandas as pd

df = pd.read_excel("FEV-data-Excel.xlsx")

Q1 = df["mean - Energy consumption [kWh/100 km]"].quantile(0.25)
Q3 = df["mean - Energy consumption [kWh/100 km]"].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

outliers = df[(df["mean - Energy consumption [kWh/100 km]"] < lower_bound) |
               (df["mean - Energy consumption [kWh/100 km]"] > upper_bound)]

print("Outliers in Energy Consumption:\n", outliers[["Car full name", "mean - Energy consumption [kWh/100 km]"]])
```

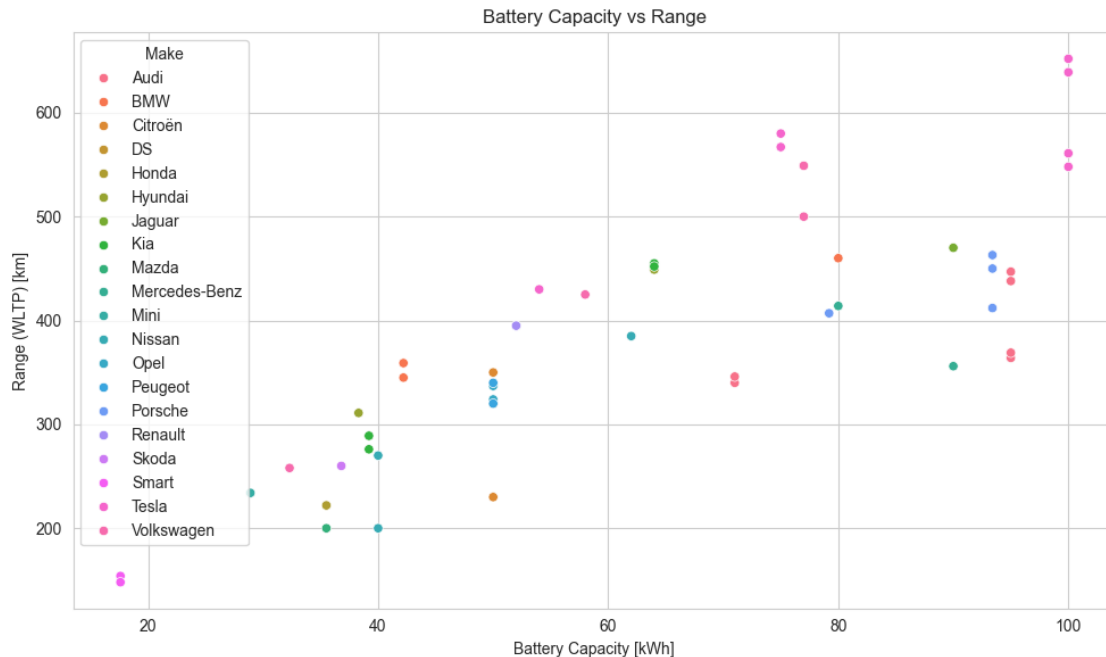
```
Outliers in Energy Consumption:
Empty DataFrame
Columns: [Car full name, mean - Energy consumption [kWh/100 km]]
Index: []
```

```
[17]: # Task 3: Visualize the relationship between battery capacity and vehicle range
# using a scatter plot with manufacturer-based coloring.

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

df = pd.read_excel("FEV-data-Excel.xlsx")

plt.figure(figsize=(10, 6))
sns.scatterplot(data=df, x="Battery capacity [kWh]", y="Range (WLTP) [km]",
               hue="Make")
plt.title("Battery Capacity vs Range")
plt.xlabel("Battery Capacity [kWh]")
plt.ylabel("Range (WLTP) [km]")
plt.grid(True)
plt.tight_layout()
plt.show()
```



```
[18]: # Task 4: Build a recommendation system class that filters the top 3 EVs
# based on user's budget, minimum range, and battery capacity.

import pandas as pd

df = pd.read_excel("FEV-data-Excel.xlsx")

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

    def recommend(self, budget, min_range, min_battery):
        filtered = self.data[
            (self.data["Minimal price (gross) [PLN]"] <= budget) &
            (self.data["Range (WLTP) [km]"] >= min_range) &
            (self.data["Battery capacity [kWh]"] >= min_battery)
        ]
        top = filtered.sort_values(by="Range (WLTP) [km]", ascending=False).
        ↪head(3)
        return top[["Car full name", "Make", "Minimal price (gross) [PLN]",
        ↪"Range (WLTP) [km]", "Battery capacity [kWh]"]]

recommender = EVRecommender(df)
top3 = recommender.recommend(budget=330000, min_range=350, min_battery=60)
print("Top 3 Recommended EVs:\n", top3)
```

Top 3 Recommended EVs:

| | Car full name | Make | Minimal price (gross) [PLN] | \ |
|----|---------------------------|------------|-----------------------------|---|
| 40 | Tesla Model 3 Long Range | Tesla | 235490 | |
| 41 | Tesla Model 3 Performance | Tesla | 260490 | |
| 48 | Volkswagen ID.3 Pro S | Volkswagen | 179990 | |

| | Range (WLTP) [km] | Battery capacity [kWh] |
|----|-------------------|------------------------|
| 40 | 580 | 75.0 |
| 41 | 567 | 75.0 |
| 48 | 549 | 77.0 |

```
[19]: # Task 5: Perform a two-sample t-test to determine whether the average  
# engine power of Tesla and Audi vehicles differ significantly.
```

```
import pandas as pd  
from scipy.stats import ttest_ind  
  
df = pd.read_excel("FEV-data-Excel.xlsx")  
  
tesla = df[df["Make"].str.lower() == "tesla"]["Engine power [KM]"]  
audi = df[df["Make"].str.lower() == "audi"]["Engine power [KM]"]  
  
t_stat, p_value = ttest_ind(tesla, audi, equal_var=False)  
  
print("Tesla Engine Power:\n", tesla.describe())  
print("\nAudi Engine Power:\n", audi.describe())  
print("\nT-statistic:", t_stat)  
print("P-value:", p_value)
```

Tesla Engine Power:

| | |
|-------|------------|
| count | 7.000000 |
| mean | 533.000000 |
| std | 184.663658 |
| min | 285.000000 |
| 25% | 426.000000 |
| 50% | 525.000000 |
| 75% | 648.500000 |
| max | 772.000000 |

Name: Engine power [KM], dtype: float64

Audi Engine Power:

| | |
|-------|------------|
| count | 6.000000 |
| mean | 392.000000 |
| std | 88.512146 |
| min | 313.000000 |
| 25% | 324.750000 |
| 50% | 360.000000 |
| 75% | 467.250000 |

max 503.000000
Name: Engine power [KM], dtype: float64

T-statistic: 1.7939951827297178
P-value: 0.10684105068839565

Google Drive Link to Project Video Explanation - https://drive.google.com/drive/folders/14Ch77-29g_9UH9fMBHQ7kSa7JzV-h1ob?usp=sharing

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