Electric Vehicle Data Analysis Project

August 16, 2025

1 *****Electric Vehicle Data Analysis*****

2 Import library

[2]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

3 Import dataset

[3]:
```
df = pd.read_csv("Auta .csv")
```

3.0.1 Top Five data show

[4]:
```
df.head()
```

[4]:

	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]
0	Audi e-tron 55 quattro	Audi	e-tron 55 quattro	345700	360	664	disc (front + rear)	4WD	95.0	438
1	Audi e-tron 50 quattro	Audi	e-tron 50 quattro	308400	313	540	disc (front + rear)	4WD	71.0	340
2	Audi e-tron S quattro	Audi	e-tron S quattro	414900	503	973	disc (front + rear)	4WD	95.0	364
3	Audi e-tron Sportback 50 quattro	Audi	e-tron Sportback 50 quattro	319700	313	540	disc (front + rear)	4WD	71.0	346
4	Audi e-tron Sportback 55 quattro	Audi	e-tron Sportback 55 quattro	357000	360	664				

```
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]
```

3.0.2 Change Column Name

[5]:
```python
# Column renaming mapping
col_map = {
    "Car full name": "car_full_name",
    "Make": "make",
    "Model": "model",
    "Minimal price (gross) [PLN]": "price_pln",
    "Engine power [KM]": "engine_power_km",
    "Maximum torque [Nm]": "max_torque_nm",
    "Type of brakes": "brake_type",
    "Drive type": "drive_type",
    "Battery capacity [kWh]": "battery_kwh",
    "Range (WLTP) [km]": "range_km",
    "Wheelbase [cm]": "wheelbase_cm",
```

```
    "Length [cm]": "length_cm",
    "Width [cm]": "width_cm",
    "Height [cm]": "height_cm",
    "Minimal empty weight [kg]": "empty_weight_kg",
    "Permissable gross weight [kg]": "gross_weight_kg",
    "Maximum load capacity [kg]": "max_load_kg",
    "Number of seats": "seats",
    "Number of doors": "doors",
    "Tire size [in]": "tire_in",
    "Maximum speed [kph]": "max_speed_kph",
    "Boot capacity (VDA) [l]": "boot_l",
    "Acceleration 0-100 kph [s]": "accel_0_100_s",
    "Maximum DC charging power [kW]": "dc_power_kw",
    "mean - Energy consumption [kWh/100 km]": "energy_kwh_per_100km"
}

# Apply renaming
df = df.rename(columns=col_map)
```

[6]:
```
df.head(1)
```

[6]:
```
             car_full_name  make              model  price_pln  \
0  Audi e-tron 55 quattro  Audi  e-tron 55 quattro     345700

   engine_power_km  max_torque_nm           brake_type drive_type  \
0              360            664  disc (front + rear)        4WD

   battery_kwh  range_km  …  gross_weight_kg  max_load_kg  seats  doors  \
0         95.0       438  …           3130.0        640.0      5      5

   tire_in  max_speed_kph  boot_l  accel_0_100_s  dc_power_kw  \
0       19            200   660.0            5.7          150

   energy_kwh_per_100km
0                 24.45

[1 rows x 25 columns]
```

3.0.3 Check null value

[7]:
```
df.isnull().sum()
```

[7]:
```
car_full_name          0
make                   0
model                  0
price_pln              0
engine_power_km        0
```

```
max_torque_nm           0
brake_type              1
drive_type              0
battery_kwh             0
range_km                0
wheelbase_cm            0
length_cm               0
width_cm                0
height_cm               0
empty_weight_kg         0
gross_weight_kg         8
max_load_kg             8
seats                   0
doors                   0
tire_in                 0
max_speed_kph           0
boot_l                  1
accel_0_100_s           3
dc_power_kw             0
energy_kwh_per_100km    9
dtype: int64
```

[8]:
```
# 1. Fill brake_type missing with mode
df["brake_type"] = df["brake_type"].fillna(df["brake_type"].mode()[0])

# 2. Fill gross_weight_kg missing with median
df["gross_weight_kg"] = df["gross_weight_kg"].fillna(df["gross_weight_kg"].
 ↪median())

# 3. Fill max_load_kg by calculation where possible, else median
mask = df["max_load_kg"].isna() & df["gross_weight_kg"].notna() &␣
 ↪df["empty_weight_kg"].notna()
df.loc[mask, "max_load_kg"] = df.loc[mask, "gross_weight_kg"] - df.loc[mask,␣
 ↪"empty_weight_kg"]
df["max_load_kg"] = df["max_load_kg"].fillna(df["max_load_kg"].median())

# 4. Fill boot_l with median
df["boot_l"] = df["boot_l"].fillna(df["boot_l"].median())

# 5. Fill accel_0_100_s with median per make
df["accel_0_100_s"] = df.groupby("make")["accel_0_100_s"].transform(lambda x: x.
 ↪fillna(x.median()))

# 6. Fill energy_kwh_per_100km by calculation if possible, else median
mask = df["energy_kwh_per_100km"].isna() & df["battery_kwh"].notna() &␣
 ↪df["range_km"].notna()
```

```
df.loc[mask, "energy_kwh_per_100km"] = (df.loc[mask, "battery_kwh"] / df.
  ↪loc[mask, "range_km"]) * 100
df["energy_kwh_per_100km"] = df["energy_kwh_per_100km"].
  ↪fillna(df["energy_kwh_per_100km"].median())
```

[9]:
```
df.isnull().sum()
```

[9]:
```
car_full_name          0
make                   0
model                  0
price_pln              0
engine_power_km        0
max_torque_nm          0
brake_type             0
drive_type             0
battery_kwh            0
range_km               0
wheelbase_cm           0
length_cm              0
width_cm               0
height_cm              0
empty_weight_kg        0
gross_weight_kg        0
max_load_kg            0
seats                  0
doors                  0
tire_in                0
max_speed_kph          0
boot_l                 0
accel_0_100_s          0
dc_power_kw            0
energy_kwh_per_100km   0
dtype: int64
```

3.0.4 Find Information

[10]:
```
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   price_pln             53 non-null     int64
 4   engine_power_km       53 non-null     int64
```

```
 5   max_torque_nm         53 non-null     int64
 6   brake_type            53 non-null     object
 7   drive_type            53 non-null     object
 8   battery_kwh           53 non-null     float64
 9   range_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  empty_weight_kg       53 non-null     int64
 15  gross_weight_kg       53 non-null     float64
 16  max_load_kg           53 non-null     float64
 17  seats                 53 non-null     int64
 18  doors                 53 non-null     int64
 19  tire_in               53 non-null     int64
 20  max_speed_kph         53 non-null     int64
 21  boot_l                53 non-null     float64
 22  accel_0_100_s         53 non-null     float64
 23  dc_power_kw           53 non-null     int64
 24  energy_kwh_per_100km  53 non-null     float64
dtypes: float64(10), int64(10), object(5)
memory usage: 10.5+ KB
```

3.0.5 Describe

[11]:
```
df.describe()
```

[11]:

	price_pln	engine_power_km	max_torque_nm	battery_kwh	range_km
count	53.000000	53.000000	53.000000	53.000000	53.000000
mean	246158.509434	269.773585	460.037736	62.366038	376.905660
std	149187.485190	181.298589	261.647000	24.170913	118.817938
min	82050.000000	82.000000	160.000000	17.600000	148.000000
25%	142900.000000	136.000000	260.000000	40.000000	289.000000
50%	178400.000000	204.000000	362.000000	58.000000	364.000000
75%	339480.000000	372.000000	640.000000	80.000000	450.000000
max	794000.000000	772.000000	1140.000000	100.000000	652.000000

	wheelbase_cm	length_cm	width_cm	height_cm	empty_weight_kg
count	53.000000	53.000000	53.000000	53.000000	53.000000
mean	273.581132	442.509434	186.241509	155.422642	1868.452830
std	22.740518	48.863280	14.280641	11.275358	470.880867
min	187.300000	269.500000	164.500000	137.800000	1035.000000
25%	258.800000	411.800000	178.800000	148.100000	1530.000000
50%	270.000000	447.000000	180.900000	155.600000	1685.000000
75%	290.000000	490.100000	193.500000	161.500000	2370.000000
max	327.500000	514.000000	255.800000	191.000000	2710.000000

	gross_weight_kg	max_load_kg	seats	doors	tire_in

```
count        53.000000    53.000000  53.000000  53.000000  53.000000
mean       2263.207547   446.773585   4.905660   4.849057  17.679245
std         516.756614   264.158944   0.838133   0.455573   1.868500
min        1310.000000  -405.000000   2.000000   3.000000  14.000000
25%        1970.000000   417.000000   5.000000   5.000000  16.000000
50%        2119.000000   485.000000   5.000000   5.000000  17.000000
75%        2725.000000   565.000000   5.000000   5.000000  19.000000
max        3500.000000  1056.000000   8.000000   5.000000  21.000000

       max_speed_kph      boot_l  accel_0_100_s  dc_power_kw  \
count      53.000000   53.000000      53.000000    53.000000
mean      178.169811  444.716981       7.332075   113.509434
std        43.056196  178.458935       2.724940    57.166970
min       123.000000  171.000000       2.500000    22.000000
25%       150.000000  315.000000       5.100000   100.000000
50%       160.000000  425.000000       7.600000   100.000000
75%       200.000000  543.000000       9.000000   150.000000
max       261.000000  870.000000      13.100000   270.000000

       energy_kwh_per_100km
count             53.000000
mean              18.329014
std                4.357560
min               12.558140
25%               15.400000
50%               16.650000
75%               21.850000
max               28.200000
```

3.0.6 Find Duplicate

[12]:
```
df.duplicated().any()
```

[12]:
```
False
```

3.0.7 Last Five row

[13]:
```
df.tail()
```

[13]:
```
                car_full_name           make              model  price_pln  \
48      Volkswagen ID.3 Pro S     Volkswagen         ID.3 Pro S     179990
49        Volkswagen ID.4 1st     Volkswagen           ID.4 1st     202390
50  Citroën ë-Spacetourer (M)        Citroën  ë-Spacetourer (M)     215400
51   Mercedes-Benz EQV (long)  Mercedes-Benz         EQV (long)     339480
52      Nissan e-NV200 evalia         Nissan     e-NV200 evalia     164328

    engine_power_km  max_torque_nm                 brake_type   drive_type  \
```

```
48              204            310  disc (front) + drum (rear)   2WD (rear)
49              204            310  disc (front) + drum (rear)   2WD (rear)
50              136            260        disc (front + rear)  2WD (front)
51              204            362        disc (front + rear)  2WD (front)
52              109            254        disc (front + rear)  2WD (front)

    battery_kwh  range_km  …  gross_weight_kg  max_load_kg  seats  doors  \
48         77.0       549  …           2280.0        412.0      5      5
49         77.0       500  …           2660.0        661.0      5      5
50         50.0       230  …           2810.0       1056.0      8      5
51         90.0       356  …           3500.0        865.0      6      5
52         40.0       200  …           2250.0        658.0      5      5

    tire_in  max_speed_kph  boot_l  accel_0_100_s  dc_power_kw  \
48       19            160   385.0            7.9          125
49       20            160   543.0            8.5          125
50       16            130   603.0           13.1          100
51       17            160   425.0            5.1          110
52       15            123   870.0            7.4           50

    energy_kwh_per_100km
48                  15.9
49                  18.0
50                  25.2
51                  28.2
52                  25.9

[5 rows x 25 columns]
```

3.0.8 Cleaning Process

[14]:
```
import unidecode
# 1. Fix encoding issues in text columns
for col in ["car_full_name", "make", "model"]:
    df[col] = (
        df[col]
        .astype(str)  # ensure text
        .str.strip()  # remove spaces
        .apply(lambda x: x.encode('latin1', errors='ignore').decode('utf-8',␣
 ↪errors='ignore'))
        .apply(unidecode.unidecode)  # remove accents if needed
    )
```

[15]:
```
# Clean Drive Type
df["drive_type"] = df["drive_type"].str.strip().str.upper()  # Remove spaces,␣
 ↪make uppercase
```

```
# Clean Brake Type
df["brake_type"] = df["brake_type"].str.strip().str.lower()  # Remove spaces,␣
 ↪make lowercase
df["brake_type"] = df["brake_type"].replace({
    "disc (front + rear)": "disc_all",
    "disc (front) + drum (rear)": "disc_drum"
})
```

[16]:
```
df.head(3)
```

[16]:

	car_full_name	make	model	price_pln	\
0	Audi e-tron 55 quattro	Audi	e-tron 55 quattro	345700	
1	Audi e-tron 50 quattro	Audi	e-tron 50 quattro	308400	
2	Audi e-tron S quattro	Audi	e-tron S quattro	414900	

	engine_power_km	max_torque_nm	brake_type	drive_type	battery_kwh	\
0	360	664	disc_all	4WD	95.0	
1	313	540	disc_all	4WD	71.0	
2	503	973	disc_all	4WD	95.0	

	range_km	…	gross_weight_kg	max_load_kg	seats	doors	tire_in	\
0	438	…	3130.0	640.0	5	5	19	
1	340	…	3040.0	670.0	5	5	19	
2	364	…	3130.0	565.0	5	5	20	

	max_speed_kph	boot_l	accel_0_100_s	dc_power_kw	energy_kwh_per_100km
0	200	660.0	5.7	150	24.45
1	190	660.0	6.8	150	23.80
2	210	660.0	4.5	150	27.55

[3 rows x 25 columns]

[17]:
```
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   price_pln             53 non-null     int64
 4   engine_power_km       53 non-null     int64
 5   max_torque_nm         53 non-null     int64
 6   brake_type            53 non-null     object
 7   drive_type            53 non-null     object
 8   battery_kwh           53 non-null     float64
```

```
 9   range_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  empty_weight_kg       53 non-null     int64
 15  gross_weight_kg       53 non-null     float64
 16  max_load_kg           53 non-null     float64
 17  seats                 53 non-null     int64
 18  doors                 53 non-null     int64
 19  tire_in               53 non-null     int64
 20  max_speed_kph         53 non-null     int64
 21  boot_l                53 non-null     float64
 22  accel_0_100_s         53 non-null     float64
 23  dc_power_kw           53 non-null     int64
 24  energy_kwh_per_100km  53 non-null     float64
dtypes: float64(10), int64(10), object(5)
memory usage: 10.5+ KB
```

3.0.9 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.

[18]:
```
# Filter EVs
filtered_df = df[
    (df["price_pln"] <= 350000) &
    (df["range_km"] >= 400)
]

# Show only key columns
print(filtered_df[["car_full_name", "make", "model", "price_pln", "range_km",␣
 ↪"battery_kwh"]])
```

```
                       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  price_pln  range_km  battery_kwh
```

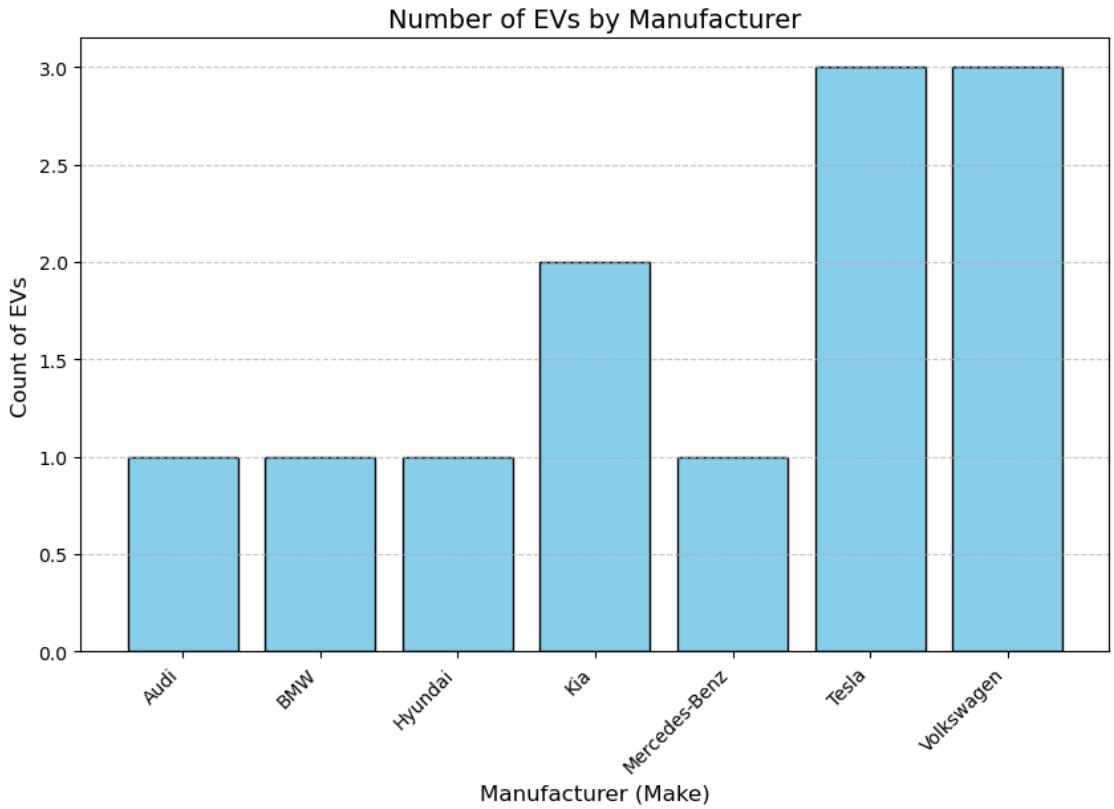
```
0              e-tron 55 quattro     345700       438         95.0
8                           iX3      282900       460         80.0
15          Kona electric 64kWh      178400       449         64.0
18                e-Niro 64kWh      167990       455         64.0
20                e-Soul 64kWh      160990       452         64.0
22                         EQC      334700       414         80.0
39  Model 3 Standard Range Plus      195490       430         54.0
40           Model 3 Long Range      235490       580         75.0
41          Model 3 Performance      260490       567         75.0
47         ID.3 Pro Performance      155890       425         58.0
48                  ID.3 Pro S      179990       549         77.0
49                    ID.4 1st      202390       500         77.0
```

3.0.10 b) Group them by the manufacturer (Make).

[19]:
```
grouped_by_make = filtered_df.groupby("make").size().reset_index(name="count")
print(grouped_by_make)
```

```
           make  count
0          Audi      1
1           BMW      1
2       Hyundai      1
3           Kia      2
4  Mercedes-Benz      1
5         Tesla      3
6    Volkswagen      3
```

[20]:
```
# Bar plot of EV count per manufacturer
plt.figure(figsize=(10, 6))
plt.bar(grouped_by_make["make"], grouped_by_make["count"], color="skyblue",␣
 ↪edgecolor="black")

plt.title("Number of EVs by Manufacturer", fontsize=14)
plt.xlabel("Manufacturer (Make)", fontsize=12)
plt.ylabel("Count of EVs", fontsize=12)
plt.xticks(rotation=45, ha="right")
plt.grid(axis="y", linestyle="--", alpha=0.7)

plt.show()
```



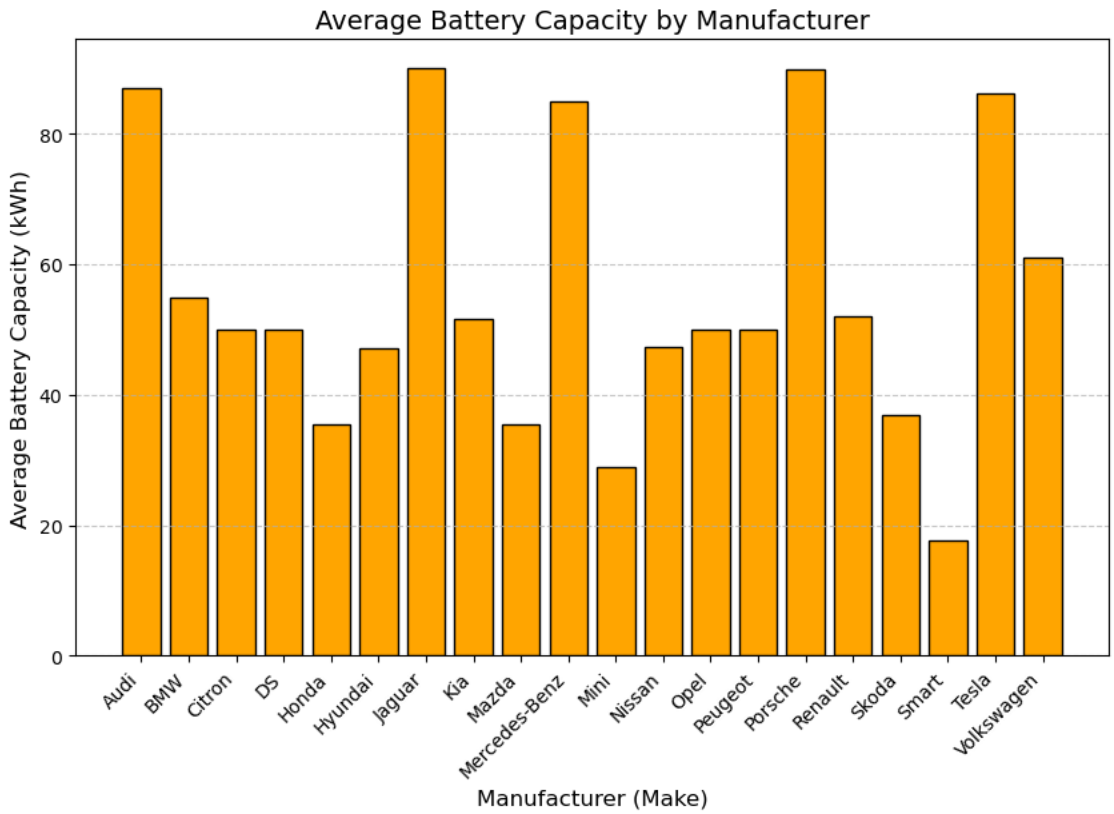
3.0.11 c) Calculate the average battery capacity for each manufacturer.

[21]:
```
# Calculate average battery capacity by manufacturer
avg_battery_capacity = df.groupby("make")["battery_kwh"].mean().reset_index()

# Rename column for clarity
avg_battery_capacity.columns = ["make", "avg_battery_kwh"]

print(avg_battery_capacity)
```

```
            make  avg_battery_kwh
0           Audi        87.000000
1            BMW        54.800000
2          Citron        50.000000
3             DS        50.000000
4          Honda        35.500000
5        Hyundai        47.166667
6         Jaguar        90.000000
7            Kia        51.600000
8          Mazda        35.500000
9   Mercedes-Benz        85.000000
10          Mini        28.900000
```

```
11          Nissan        47.333333
12            Opel        50.000000
13         Peugeot        50.000000
14         Porsche        89.850000
15         Renault        52.000000
16           Skoda        36.800000
17           Smart        17.600000
18           Tesla        86.285714
19      Volkswagen        61.075000
```

[22]:
```python
# Plot average battery capacity by manufacturer
plt.figure(figsize=(10, 6))
plt.bar(avg_battery_capacity["make"], avg_battery_capacity["avg_battery_kwh"],
        color="orange", edgecolor="black")

plt.title("Average Battery Capacity by Manufacturer", fontsize=14)
plt.xlabel("Manufacturer (Make)", fontsize=12)
plt.ylabel("Average Battery Capacity (kWh)", fontsize=12)
plt.xticks(rotation=45, ha="right")
plt.grid(axis="y", linestyle="--", alpha=0.7)

plt.show()
```

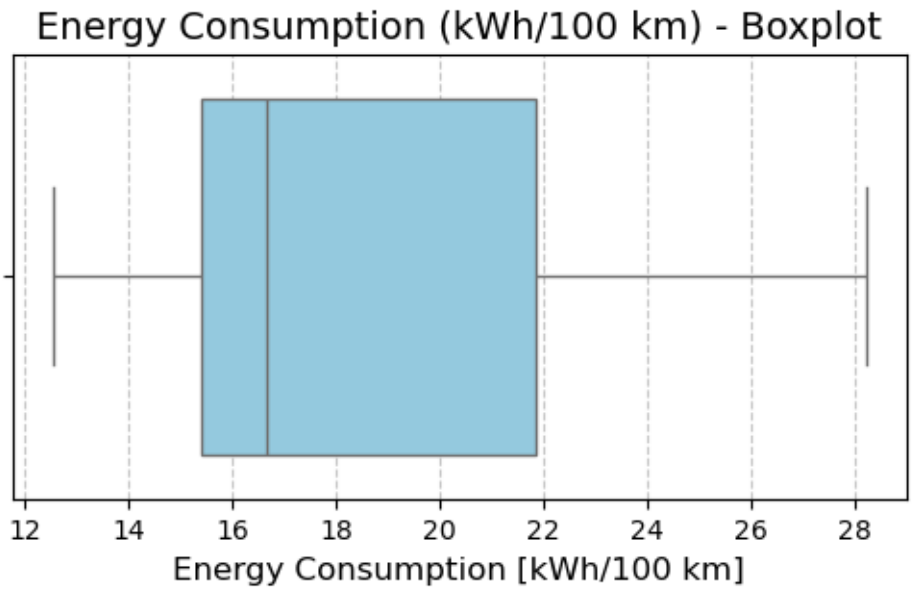


3.0.12 Task 2: You suspect some EVs have unusually high or low energy consumption. Find the outliers in the mean - Energy consumption [kWh/100 km] column

[23]:
```
# Calculate Q1 and Q3
Q1 = df["energy_kwh_per_100km"].quantile(0.25)
Q3 = df["energy_kwh_per_100km"].quantile(0.75)
IQR = Q3 - Q1

# Define lower and upper bounds
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Filter outliers
outliers = df[(df["energy_kwh_per_100km"] < lower_bound) |␣
 ↪(df["energy_kwh_per_100km"] > upper_bound)]

print("Outliers in energy consumption:")
print(outliers[["car_full_name", "make", "energy_kwh_per_100km"]])
if outliers.empty:
    print("No outliers detected in energy consumption using IQR method.")
```

```
Outliers in energy consumption:
Empty DataFrame
Columns: [car_full_name, make, energy_kwh_per_100km]
Index: []
No outliers detected in energy consumption using IQR method.
```

[24]:
```
plt.figure(figsize=(6, 3))
sns.boxplot(x=df["energy_kwh_per_100km"], color="skyblue")

plt.title("Energy Consumption (kWh/100 km) - Boxplot", fontsize=14)
plt.xlabel("Energy Consumption [kWh/100 km]", fontsize=12)
plt.grid(axis="x", linestyle="--", alpha=0.7)

plt.show()
```



3.0.13 Show the all columns

[25]:
```
df.columns
```

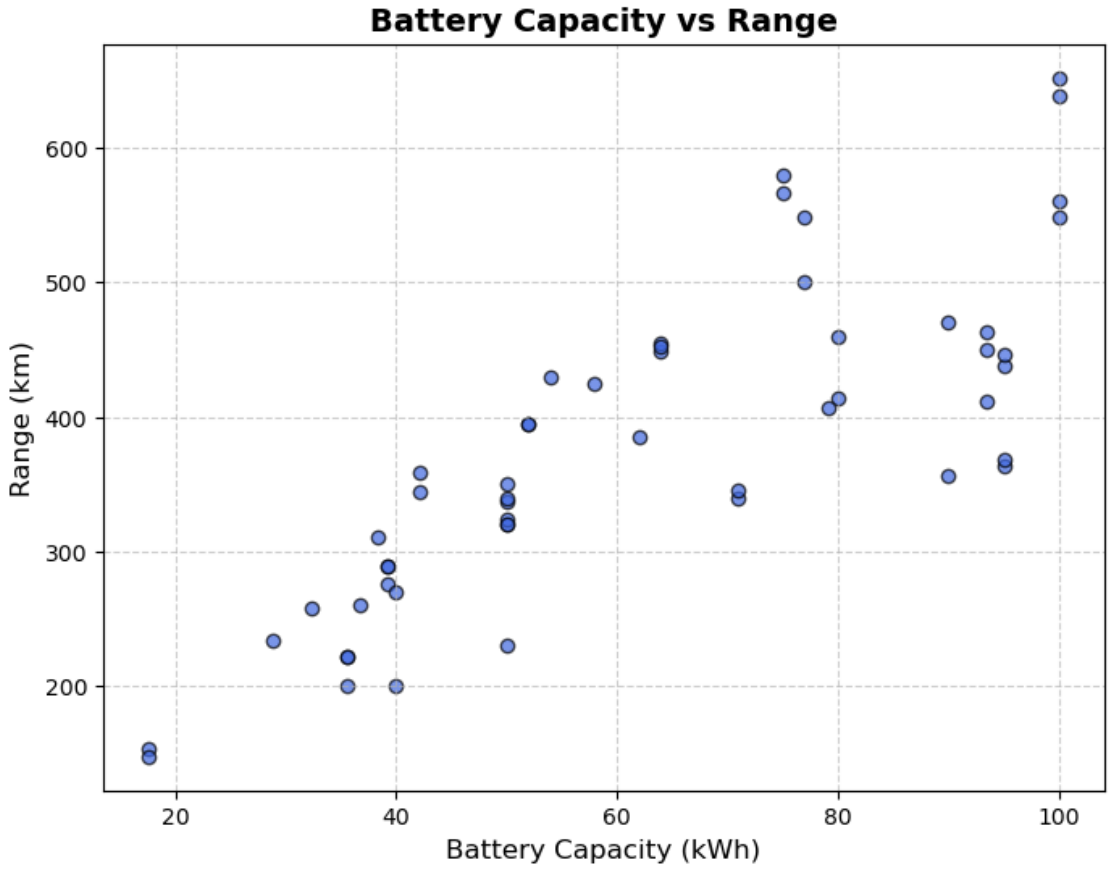
[25]:
```
Index(['car_full_name', 'make', 'model', 'price_pln', 'engine_power_km',
       'max_torque_nm', 'brake_type', 'drive_type', 'battery_kwh', 'range_km',
       'wheelbase_cm', 'length_cm', 'width_cm', 'height_cm', 'empty_weight_kg',
       'gross_weight_kg', 'max_load_kg', 'seats', 'doors', 'tire_in',
       'max_speed_kph', 'boot_l', 'accel_0_100_s', 'dc_power_kw',
       'energy_kwh_per_100km'],
      dtype='object')
```

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

a) Create a suitable plot to visualize.

[26]:
```
# Scatter plot for Battery Capacity vs Range
plt.figure(figsize=(8, 6))
plt.scatter(df["battery_kwh"], df["range_km"],
            color="royalblue", alpha=0.7, edgecolor="black")

# Titles and labels
plt.title("Battery Capacity vs Range", fontsize=14, fontweight="bold")
plt.xlabel("Battery Capacity (kWh)", fontsize=12)
plt.ylabel("Range (km)", fontsize=12)

# Grid for better readability
```

```
plt.grid(True, linestyle="--", alpha=0.6)

plt.show()
```



3.0.15 b) Highlight any insights.

Insights Positive correlation – Cars with higher battery capacity generally have a higher range, indicating that battery size is a strong driver of range. Diminishing returns – The relationship isn't perfectly linear; after around 80–100 kWh, increases in capacity yield smaller gains in range, possibly due to vehicle weight and efficiency limits.

Outliers – Some EVs achieve high range with a relatively smaller battery (likely due to better aerodynamics and energy efficiency). Others have large batteries but lower-than-expected range (possibly heavy SUVs or performance-oriented EVs). Manufacturer effect – Certain brands consistently position above the trend line, meaning they are more efficient at converting battery capacity into range.

3.0.16 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 EVsmatching their criteria

[27]:
```
class EVRecommender:
    def __init__(self, df):
        self.df = df

    def recommend(self):
        # Show min-max values from dataset
        print(f"\nPrice range in dataset: {self.df['price_pln'].min()} - {self.
 ↪df['price_pln'].max()} PLN")
        print(f"Range (km) in dataset: {self.df['range_km'].min()} - {self.
 ↪df['range_km'].max()} km")
        print(f"Battery capacity in dataset: {self.df['battery_kwh'].min()} -␣
 ↪{self.df['battery_kwh'].max()} kWh\n")

        # Get user inputs
        budget = float(input("Enter your budget (PLN): "))
        min_range = float(input("Enter minimum desired range (km): "))
        min_battery = float(input("Enter minimum battery capacity (kWh): "))

        # Filter dataset based on criteria
        filtered = self.df[
            (self.df["price_pln"] <= budget) &
            (self.df["range_km"] >= min_range) &
            (self.df["battery_kwh"] >= min_battery)
        ]

        # Sort by range (highest first) and price (lowest first)
        filtered = filtered.sort_values(by=["range_km", "price_pln"],␣
 ↪ascending=[False, True])

        # Show results
        if filtered.empty:
            print("\nNo matching EVs found for your criteria.")
        else:
            print("\nTop 3 matching EVs:")
            print(filtered[["car_full_name", "make", "price_pln", "range_km",␣
 ↪"battery_kwh"]].head(3))


# Example usage:
#recommender = EVRecommender(df)
# recommender.recommend()
```

3.0.17 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.

[28]:
```
from scipy.stats import ttest_ind
import pandas as pd

# Load dataset
df = pd.read_csv("my_file.csv")

# Filter data for Tesla and Audi
tesla_power = df[df["make"] == "Tesla"]["engine_power_km"]
audi_power = df[df["make"] == "Audi"]["engine_power_km"]

# Perform Welch's t-test (does not assume equal variance)
t_stat, p_value = ttest_ind(tesla_power, audi_power, equal_var=False)

print("T-statistic:", round(t_stat, 3))
print("P-value:", round(p_value, 5))

# Interpretation
alpha = 0.05
if p_value < alpha:
    print("\n Conclusion: There IS a statistically significant difference in␣
 ↪average engine power between Tesla and Audi.")
else:
    print("\n Conclusion: There is NO statistically significant difference in␣
 ↪average engine power between Tesla and Audi.")
```

```
T-statistic: 1.794
P-value: 0.10684

 Conclusion: There is NO statistically significant difference in average engine
power between Tesla and Audi.
```

3.0.18 What insights can you draw from the test results?

3.0.19 Recommendations and Conclusion: Provide actionable insights based on your analysis.

Insight We compared the engine power of Tesla and Audi electric vehicles (EVs) using a t-test to see if one brand has consistently stronger engines. The T-statistic is 1.794, and the P-value is 0.10684. Since the P-value is greater than 0.05, the difference in engine power between Tesla and Audi is likely due to chance rather than a real difference.

Conclusion There is no statistically significant difference in average engine power between Tesla and Audi EVs. This means that, on average, both brands perform similarly in terms of engine power.

Recommendation Since there's no clear winner in engine power, customers should consider other

factors when choosing between Tesla and Audi EVs, such as price, driving range, charging speed, features, and brand preference, rather than focusing solely on engine power.

[30]:
```
df.to_csv("Final.csv", index= False)
```

[ ]:
```

```