In this project, I 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.

MY goal is to conduct a thorough analysis to uncover meaningful insights, tell a

compelling story, conduct hypothesis testing and provide actionable recommendations based on the data.

Imported all the libraries and handled the missing values.

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

# Loaded the EV dataset from the Excel file into a DataFrame for
analysis
carinfo = pd.read_excel("FEV-data-Excel.xlsx")

# Some columns have missing values which are filled with median and
mode respectively.

# Selected numerical columns where missing values will be filled using
the median
median_cols = [
    "Permissable gross weight [kg]",
    "Maximum load capacity [kg]",
    "Boot capacity (VDA) [l]",
```

```
    "Acceleration 0-100 kph [s]",
    "mean - Energy consumption [kWh/100 km]"
]

# Filled numerical missing values with median
carinfo[median_cols] =
carinfo[median_cols].fillna(carinfo[median_cols].median())

# Filled categorical missing value with mode
carinfo["Type of brakes"] = carinfo["Type of
brakes"].fillna(carinfo["Type of brakes"].mode()[0])


carinfo.info() #NOw the data is ready for analysis
```

```
<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   Minimal price (gross) [PLN]           53 non-null     int64
 4   Engine power [KM]                     53 non-null     int64
 5   Maximum torque [Nm]                   53 non-null     int64
 6   Type of brakes                        53 non-null     object
 7   Drive type                            53 non-null     object
 8   Battery capacity [kWh]                53 non-null     float64
 9   Range (WLTP) [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  Minimal empty weight [kg]             53 non-null     int64
 15  Permissable gross weight [kg]         53 non-null     float64
 16  Maximum load capacity [kg]            53 non-null     float64
 17  Number of seats                       53 non-null     int64
 18  Number of doors                       53 non-null     int64
 19  Tire size [in]                        53 non-null     int64
 20  Maximum speed [kph]                   53 non-null     int64
 21  Boot capacity (VDA) [l]               53 non-null     float64
 22  Acceleration 0-100 kph [s]            53 non-null     float64
 23  Maximum DC charging power [kW]        53 non-null     int64
 24  mean - Energy consumption [kWh/100 km]  53 non-null     float64
dtypes: float64(10), int64(10), object(5)
memory usage: 10.5+ KB
```

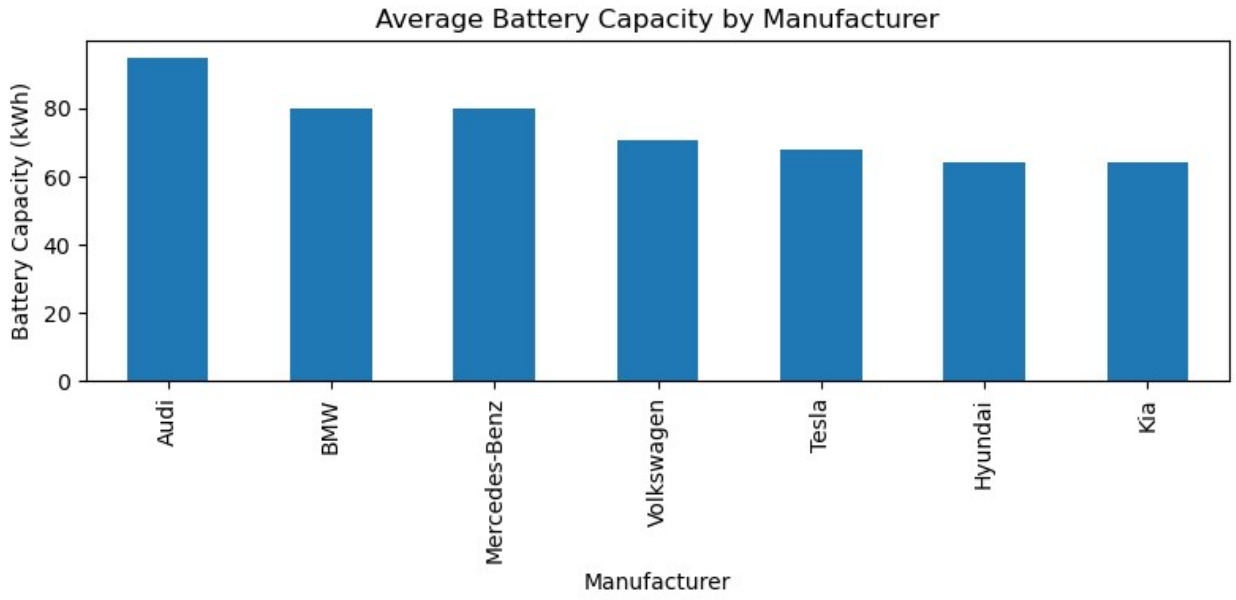
Task 1:

A customer has a budget of 350,000 PLN and wants an EV with a minimum range of 400 km.

```
#filtered out EVs that meet these criteria
filtered_data = carinfo[(carinfo["Minimal price (gross) [PLN]"] <=
350000) & (carinfo["Range (WLTP) [km]"] >= 400)]

#Calculated the average battery capacity  and Grouped them by the
manufacturer
avg_battery_cap_by_make = filtered_data.groupby("Make")["Battery
capacity [kWh]"].mean().sort_values(ascending=False)

#Visualized the average battery capacity for each manufacturer
avg_battery_cap_by_make.plot(kind='bar', figsize=(8,4), title='Average
Battery Capacity by Manufacturer')
plt.ylabel('Battery Capacity (kWh)')
plt.xlabel('Manufacturer')
plt.tight_layout()
plt.show()
```



My Analysis

Audi tops the chart, signaling long-range luxury and premium engineering.

BMW and Mercedes-Benz stay close, delivering solid performance in the high-end EV space.

Tesla, Hyundai, and Kia show leaner battery profiles—likely optimizing for efficiency, affordability, or smart design.

Task 2:

Suspected some EVs have unusually high or low energy consumption.

```
# Solution for this is to find
# the outliers in the mean- Energy consumption [kWh/100 km] column.

#calculated z score to measure how far each value is from the mean in
terms of standard deviation
zscore = np.abs(stats.zscore(carinfo["mean - Energy consumption
[kWh/100 km]"]))

# took threshold as 2 to filter out outliers
outliers = carinfo[zscore > 2]

#print the output with the specific columns
print("Energy Consumption Outliers:")
outliers[["Make", "Model", "mean - Energy consumption [kWh/100 km]"]]
```

```
Energy Consumption Outliers:

             Make                         Model  \
2            Audi            e-tron S quattro
5            Audi  e-tron Sportback S quattro
51  Mercedes-Benz                  EQV (long)

    mean - Energy consumption [kWh/100 km]
2                                    27.55
```

```
5                                       27.20
51                                      28.20
```

My analysis

1.Audi e-tron S & Sportback S has High energy use which reflects performance.

2.Mercedes-Benz EQV (long) , its elevated consumption aligns with its van format—built for space and utility.

Task 3:

My manager wants to know if there's a strong relationship between battery capacity and range.

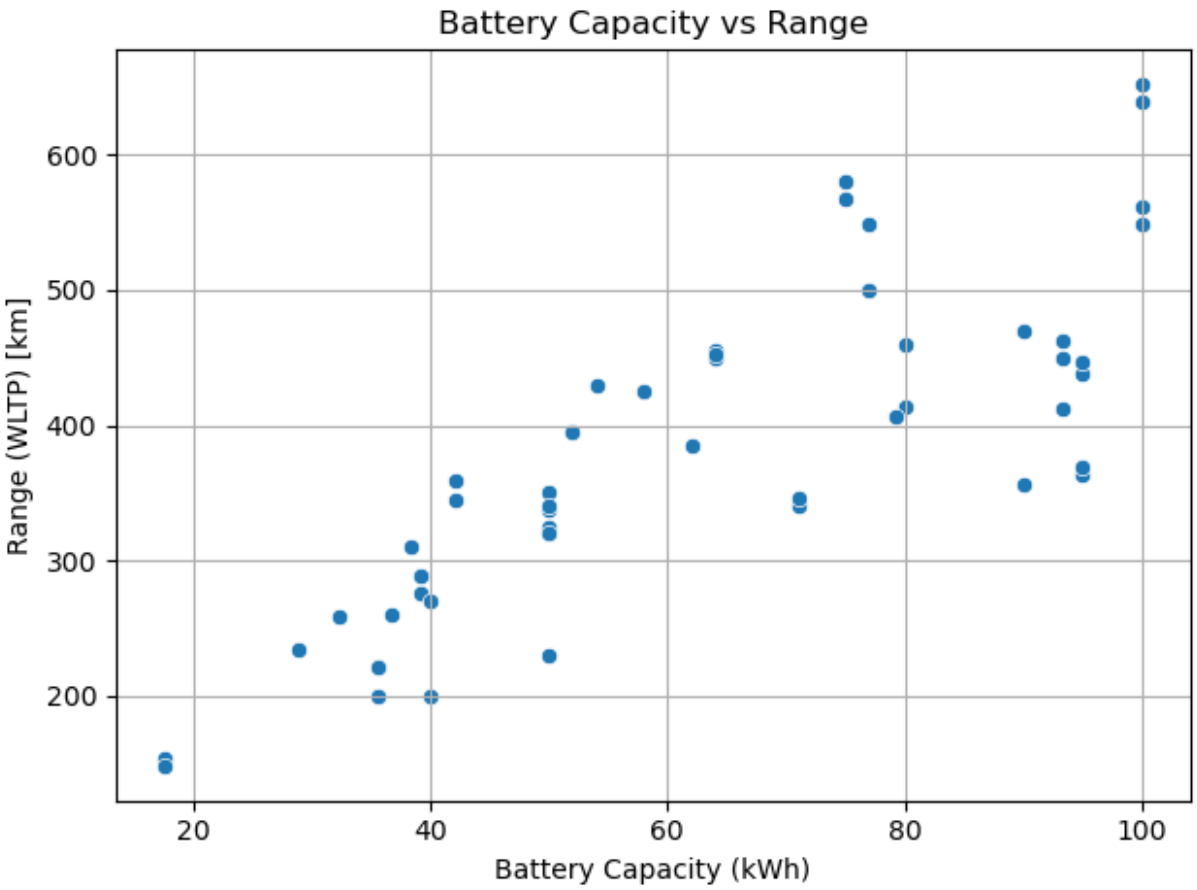
```
from scipy.stats import pearsonr

# Used correlation and p value to find relationship b/w range and
capacity
corr, p_value = pearsonr(carinfo["Battery capacity [kWh]"],
carinfo["Range (WLTP) [km]"])
print(f"Pearson correlation coefficient: {corr:.2f}")
print(f"P-value: {p_value:.4f}")

#Created a scatter plot to visualize.
x = carinfo["Battery capacity [kWh]"]
y = carinfo["Range (WLTP) [km]"]

sns.scatterplot(x=x, y=y)
plt.title("Battery Capacity vs Range")
plt.xlabel("Battery Capacity (kWh)")
plt.ylabel("Range (WLTP) [km]")
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
Pearson correlation coefficient: 0.81
P-value: 0.0000
```



Insights

Strong Correlation confirms positive relationship—larger batteries generally deliver longer range.

Some EVs achieve high range with smaller batteries, indicating smart energy optimization.

Premium models cluster in the high-capacity, high-range zone; others focus on efficiency over size.

Task 4: ### Build an EV recommendation class.

```
#This class should allow users to input their budget, desired range,
and battery capacity.
#It should return the top three EVs matching their criteria.
class EVRecommender:
    def __init__(self, data):
        self.data = data.copy()

    def recommend(self):
        try:
            #To take user input
            budget = int(input("Enter your budget (in PLN): "))
            min_range = int(input("Enter your desired minimum range
(in km): "))
            min_capacity = float(input("Enter your minimum battery
capacity (in kWh): "))

            # To filter based on criteria
            filtered = self.data[
                (self.data["Minimal price (gross) [PLN]"] <= budget) &
                (self.data["Range (WLTP) [km]"] >= min_range) &
                (self.data["Battery capacity [kWh]"] >= min_capacity)
            ].copy()

            # This will sort and return top 3
            top_ev = filtered.sort_values(by="Range (WLTP) [km]",
ascending=False).head(3)

            print("\nTop 3 EVs matching your criteria:\n")
            print(top_ev[[
                "Car full name",
                "Minimal price (gross) [PLN]"
            ]])

        except ValueError:
            print("Invalid input. Please enter numeric values only.")


recommender = EVRecommender(filtered_data)
recommender.recommend()
```

```
Enter your budget (in PLN):  180000
Enter your desired minimum range (in km):  250
Enter your minimum battery capacity (in kWh):  45


Top 3 EVs matching your criteria:

            Car full name  Minimal price (gross) [PLN]
48  Volkswagen ID.3 Pro S                       179990
18       Kia e-Niro 64kWh                       167990
20       Kia e-Soul 64kWh                       160990
```

TASK 5:

Inferential Statistics– Hypothesis Testing:

```
# Imported t-test function from scipy.stats
from scipy.stats import ttest_ind

# Assigned variables to extract engine power values for Tesla and
Audi.
tesla_power = carinfo[carinfo["Make"] == "Tesla"]["Engine power [KM]"]
audi_power = carinfo[carinfo["Make"] == "Audi"]["Engine power [KM]"]

# Two-sample t-test to compare the average engine power between Tesla
and Audi
t_stat, p_value = ttest_ind(tesla_power, audi_power, equal_var=False)

# Display the test statistic and p-value for interpretation
print(f"T-statistic: {t_stat:.2f}")
print(f"P-value: {p_value:.4f}")
print("Since the p-value is 0.1068 (> 0.05)")
print("There is no statistically significant difference in avg engine
power between Tesla and Audi EVs at the 95% confidence level.")
```

```
T-statistic: 1.79
P-value: 0.1068
Since the p-value is 0.1068 (> 0.05)
There is no statistically significant difference in avg engine power
between Tesla and Audi EVs at the 95% confidence level.
```

Insights:

Despite Tesla's reputation for performance, Audi's EVs appear comparable in engine power.

This could suggest that Audi is competitive in the high-performance EV segment, which may surprise some stakeholders.

It also implies that engine power alone may not be a differentiator between these brands — other factors like acceleration, torque, or battery efficiency might be more telling.

Recommendations & Conclusion

Marketing teams should highlight Audi's parity in engine power to challenge Tesla's dominance narrative.

Product teams might explore differentiating features beyond raw power — such as charging speed, driving experience, or tech integration.

Consider extending the analysis to include acceleration, torque, or energy efficiency for a more holistic performance comparison.

TASK 6:

video explaintion : https://drive.google.com/file/d/1Lm3kShY-wIV62Gn-5iUbnKuIxnD1CBZP/view?usp=drive_link

```
print("╔═══════════════════════════════════════════════════════════════════════════════╗")
print("          THANK YOU ,Your feedback WILL BE helpful.")
print("╚═══════════════════════════════════════════════════════════════════════════════╝")
```

```
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          THANK YOU ,Your feedback WILL BE helpful.
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```