

LovePythonProjectInternshal

January 21, 2025

Electric Vehicle Data Analysis Project

Project Overview

In this project, you 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. Your 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.

```
[1]: import numpy as np
import pandas as pd
```

```
[2]: df = pd.read_csv("FEV-data-Excel.xlsx - Auta elektryczne.csv")
```

Data Overview

Car full name: The full name or designation of the vehicle, often combining make, model, and variant. Make: The brand or manufacturer of the car. Model: The specific model or version of the car. Minimal price (gross) [PLN]: The minimum retail price of the car, in Polish złoty (PLN). Engine power [KM]: The car's engine power, measured in horsepower (KM in Polish). Maximum torque [Nm]: The peak torque the engine can produce, measured in Newton-meters (Nm). Type of brakes: The braking system used, such as disc or drum brakes. Drive type: The drivetrain configuration, like FWD (front-wheel drive), RWD (rear-wheel drive), or AWD (all-wheel drive). Battery capacity [kWh]: Total energy capacity of the car's battery, measured in kilowatt-hours (kWh). Range (WLTP) [km]: Estimated driving range on a full charge under WLTP standards, in kilometers. Wheelbase [cm]: The distance between the front and rear axles, in centimeters. Length [cm]: The overall length of the car, in centimeters. Width [cm]: The car's width, in centimeters. Height [cm]: The car's height, in centimeters. Minimal empty weight [kg]: The car's minimum weight when empty, measured in kilograms. Permissiblekg]: Maximum legally allowed weight, including passengers and cargo, in kilograms. Maximum load capacity [kg]: The maximum weight the car can carry, in kilograms. Number of seats: The number of passenger seats in the car. Number of doors: The number of doors on the car. Tire size [in]: The tire size, measured in inches. Maximum speed [kph]: The top speed of the car, in kilometers per hour. Boot capacity (VDA) [l]: Trunk or cargo space capacity, measured in liters according to VDA standards. Acceleration 0-100 kph [s]: Time taken to accelerate from 0 to 100 kilometers per hour, in seconds. Maximum DC charging power [kW]: The highest charging power supported when using a DC fast charger, in kilowatts (kW). Mean - Energy consumption [kWh/100 km]: Average energy consumption per 100 kilometers, in kilowatt-hours (kWh).

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

[4]:

	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

[5 rows x 25 columns]

The all about discription of dataset statics

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

```
[5]:
```

	Minimal price (gross) [PLN]	Engine power [KM]	Maximum torque [Nm]	\
count	53.000000	53.000000	53.000000	
mean	246158.509434	269.773585	460.037736	
std	149187.485190	181.298589	261.647000	
min	82050.000000	82.000000	160.000000	
25%	142900.000000	136.000000	260.000000	
50%	178400.000000	204.000000	362.000000	
75%	339480.000000	372.000000	640.000000	
max	794000.000000	772.000000	1140.000000	

	Battery capacity [kWh]	Range (WLTP) [km]	Wheelbase [cm]	Length [cm]	\
count	53.000000	53.000000	53.000000	53.000000	
mean	62.366038	376.905660	273.581132	442.509434	
std	24.170913	118.817938	22.740518	48.863280	
min	17.600000	148.000000	187.300000	269.500000	
25%	40.000000	289.000000	258.800000	411.800000	
50%	58.000000	364.000000	270.000000	447.000000	
75%	80.000000	450.000000	290.000000	490.100000	
max	100.000000	652.000000	327.500000	514.000000	

	Width [cm]	Height [cm]	Minimal empty weight [kg]	\
count	53.000000	53.000000	53.000000	
mean	186.241509	155.422642	1868.452830	
std	14.280641	11.275358	470.880867	
min	164.500000	137.800000	1035.000000	
25%	178.800000	148.100000	1530.000000	
50%	180.900000	155.600000	1685.000000	
75%	193.500000	161.500000	2370.000000	
max	255.800000	191.000000	2710.000000	

	Permissable gross weight [kg]	Maximum load capacity [kg]	\
count	45.000000	45.000000	
mean	2288.844444	520.466667	
std	557.796026	140.682848	
min	1310.000000	290.000000	
25%	1916.000000	440.000000	
50%	2119.000000	486.000000	
75%	2870.000000	575.000000	
max	3500.000000	1056.000000	

	Number of seats	Number of doors	Tire size [in]	Maximum speed [kph]	\
count	53.000000	53.000000	53.000000	53.000000	
mean	4.905660	4.849057	17.679245	178.169811	
std	0.838133	0.455573	1.868500	43.056196	
min	2.000000	3.000000	14.000000	123.000000	
25%	5.000000	5.000000	16.000000	150.000000	
50%	5.000000	5.000000	17.000000	160.000000	
75%	5.000000	5.000000	19.000000	200.000000	
max	8.000000	5.000000	21.000000	261.000000	

	Boot capacity (VDA) [l]	Acceleration 0-100 kph [s]	\
count	52.000000	50.00000	
mean	445.096154	7.36000	
std	180.178480	2.78663	
min	171.000000	2.50000	
25%	315.000000	4.87500	
50%	425.000000	7.70000	
75%	558.000000	9.37500	
max	870.000000	13.10000	

	Maximum DC charging power [kW]	mean - Energy consumption [kWh/100 km]
count	53.000000	44.000000
mean	113.509434	18.994318
std	57.166970	4.418253
min	22.000000	13.100000
25%	100.000000	15.600000
50%	100.000000	17.050000
75%	150.000000	23.500000
max	270.000000	28.200000

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

```
[6]: Car full name      0
      Make              0
      Model             0
      Minimal price (gross) [PLN] 0
      Engine power [KM]  0
      Maximum torque [Nm] 0
      Type of brakes     1
      Drive type         0
      Battery capacity [kWh] 0
      Range (WLTP) [km]  0
      Wheelbase [cm]     0
      Length [cm]        0
      Width [cm]         0
      Height [cm]        0
      Minimal empty weight [kg] 0
```

```

Permissable gross weight [kg]      8
Maximum load capacity [kg]         8
Number of seats                    0
Number of doors                    0
Tire size [in]                     0
Maximum speed [kph]                0
Boot capacity (VDA) [l]            1
Acceleration 0-100 kph [s]         3
Maximum DC charging power [kW]     0
mean - Energy consumption [kWh/100 km] 9
dtype: int64

```

here we see that column “types of break” having one null value and column permissible gross weight having and maximum load capacity having 8 null values.boot capacity having 1 null value, acceleration 0-100kph having 3 null value , mean-energy consumption having 9 null values Type of brakes are string type column Permissable gross weight [kg] is float type column. Maximum load capacity [kg] also a float type column Boot capacity (VDA) [l] also having int type column Acceleration 0-100 kph [s] is float type column mean - Energy consumption [kWh/100 km] is float type column

string type column replace null value using mode(which frequency is higher)

```

[7]: mode_value = df['Type of brakes'].mode()[0]
      print(mode_value)
      df['Type of brakes'].fillna(mode_value,inplace=True)

```

disc (front + rear)

For all type of float type column using Interpolate Missing Values which a prediction method

```

[8]: df['Permissable gross weight [kg]'].interpolate(method='linear', inplace=True)

[9]: df['Maximum load capacity [kg]'].interpolate(method='linear', inplace=True)

[10]: df['Boot capacity (VDA) [l]'].interpolate(method='linear', inplace=True)

[11]: df['Acceleration 0-100 kph [s]'].interpolate(method='linear', inplace=True)

[12]: df['mean - Energy consumption [kWh/100 km]'].interpolate(method='linear',
    ↪inplace=True)

[13]: df.head()

```

```

[13]:
          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	
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	Type of brakes	Drive type	Battery capacity [kWh]	Range (WLTP) [km]	\
0	disc (front + rear)	4WD	95.0	438	
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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]

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

```
[14]: Car full name      0
      Make              0
      Model             0
      Minimal price (gross) [PLN] 0
      Engine power [KM]  0
      Maximum torque [Nm] 0
      Type of brakes     0
      Drive type         0
      Battery capacity [kWh] 0
      Range (WLTP) [km]  0
      Wheelbase [cm]     0
      Length [cm]        0
      Width [cm]         0
      Height [cm]        0
      Minimal empty weight [kg] 0
      Permissible gross weight [kg] 0
      Maximum load capacity [kg] 0
      Number of seats    0
      Number of doors    0
      Tire size [in]     0
      Maximum speed [kph] 0
      Boot capacity (VDA) [l] 0
      Acceleration 0-100 kph [s] 0
      Maximum DC charging power [kW] 0
      mean - Energy consumption [kWh/100 km] 0
      dtype: int64
```

Here the dataset with null values

```
[ ]:
```

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.(2 Marks) b) Group them by the manufacturer (Make).(6 marks) c) Calculate the average battery capacity for each manufacturer.(8 Marks)

```
[15]: #filtered dataset
      filtered_df = df[(df['Minimal price (gross) [PLN]'] <= 350000) & (df['Range_
      ↳(WLTP) [km]'] >= 400)]
```

```
[16]: #making group using groupby() function
      grouped_by_make = filtered_df.groupby('Make')
```

```
[33]: avg_battery_capacity = grouped_by_make['Battery capacity [kWh]'].mean()
      avg_battery_capacity.reset_index(name='Average Battery Capacity [kWh]')
```

```
[33]:
```

	Make	Average 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

Task 2: You suspect some EVs have unusually high or low energy consumption.

<nFind the outliers in the mean - Energy consumption [kWh/100 km] column.(16 Marks)

to detect outlier mean-energy consumption we can use statical method such as interquartile range
step 1:

calculate the first and third quartile

step 2:

compute IQR $IQR = Q3 - Q1$

step 3:

Define Outliers as $[Q1 - 1.5IQR, Q3 + 1.5IQR]$

step 4:

identify outlier by conditions

```
[42]: # Step 1: Calculate Q1 and Q3
q1 = df['mean - Energy consumption [kWh/100 km]'].quantile(0.25)
q3 = df['mean - Energy consumption [kWh/100 km]'].quantile(0.75)
print(q1,q3)
```

```
15.5 21.85
```

```
[43]: # Step 2: Compute IQR
iqr = q3 - q1
print(iqr)
```

```
6.350000000000001
```

```
[45]: # Step 3: Define lower and upper bounds for outliers
lower_bound = q1 - 1.5 * iqr
upper_bound = q3 + 1.5 * iqr
print(lower_bound,upper_bound)
```

```
5.974999999999998 31.375000000000004
```

```
[49]: # Step 4: Identify outliers
outliers = df[
    (df['mean - Energy consumption [kWh/100 km]'] < lower_bound) |
```



```

(df['mean - Energy consumption [kWh/100 km]'] > upper_bound)
]

# Display the outliers
outliers

```

[49]: 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]]
Index: []

```

```
[0 rows x 25 columns]
```

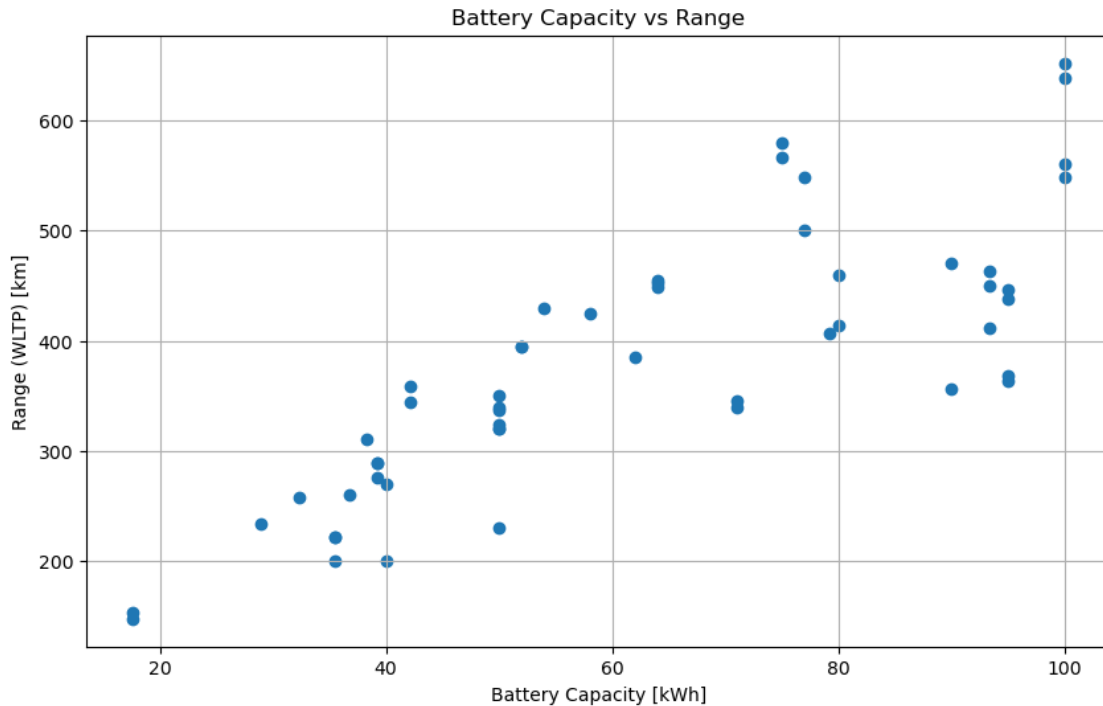
Task 3: Your manager wants to know if there's a strong relationship between battery capacity and range.

- Create a suitable plot to visualize.(8 Marks)
- Highlight any insights.(8 Marks)

```

[26]: import matplotlib.pyplot as plt
plt.figure(figsize=(10, 6))
plt.scatter(df['Battery capacity [kWh]'], df['Range (WLTP) [km]'])
plt.title('Battery Capacity vs Range')
plt.xlabel('Battery Capacity [kWh]')
plt.ylabel('Range (WLTP) [km]')
plt.grid(True)
plt.show()

```



Insights of datasets

Costumer prefer the brand and viechal which has higher Range(WLTP)[KM] AND having high Battery capacity with friendly budget

[]:

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 EVs matching their criteria. (8+8 Marks)

```
[52]: class EVRecommendation:
    def __init__(self, dataframe):
        self.dataframe = dataframe

    def recommend(self, budget, desired_range, battery_capacity):
        recommendations = self.dataframe[
            (self.dataframe['Minimal price (gross) [PLN]'] <= budget) &
            (self.dataframe['Range (WLTP) [km]'] >= desired_range) &
            (self.dataframe['Battery capacity [kWh]'] >= battery_capacity)
        ].nsmallest(3, 'Minimal price (gross) [PLN]')
        return recommendations

# Create an instance of the recommendation class
ev_recommender = EVRecommendation(df)
```

```
# Example usage
```

```
top_ev_recommendations = ev_recommender.recommend(350000, 400, 50)
```

```
top_ev_recommendations
```

```
[52]:
```

	Car full name	Make	Model	\
47	Volkswagen ID.3 Pro Performance	Volkswagen	ID.3 Pro Performance	
20	Kia e-Soul 64kWh	Kia	e-Soul 64kWh	
18	Kia e-Niro 64kWh	Kia	e-Niro 64kWh	

	Minimal price (gross) [PLN]	Engine power [KM]	Maximum torque [Nm]	\
47	155890	204	310	
20	160990	204	395	
18	167990	204	395	

	Type of brakes	Drive type	Battery capacity [kWh]	\
47	disc (front) + drum (rear)	2WD (rear)	58.0	
20	disc (front + rear)	2WD (front)	64.0	
18	disc (front + rear)	2WD (front)	64.0	

	Range (WLTP) [km]	...	Permissable gross weight [kg]	\
47	425	...	2270.0	
20	452	...	1682.0	
18	455	...	2230.0	

	Maximum load capacity [kg]	Number of seats	Number of doors	\
47	540.0	5	5	
20	498.0	5	5	
18	493.0	5	5	

	Tire size [in]	Maximum speed [kph]	Boot capacity (VDA) [l]	\
47	18	160	385.0	
20	17	167	315.0	
18	17	167	451.0	

	Acceleration 0-100 kph [s]	Maximum DC charging power [kW]	\
47	7.3	100	
20	7.9	100	
18	7.8	100	

	mean - Energy consumption [kWh/100 km]
47	15.4
20	15.7
18	15.9

```
[3 rows x 25 columns]
```

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. What insights can you draw from the test results? Recommendations and Conclusion: Provide actionable insights based on your analysis. (Conduct a two sample t-test using `ttest_ind` from `scipy.stats` module) (16 Marks)

Step 1:

Import the Library for hypothesis testing

```
[58]: from scipy.stats import ttest_ind
```

Step 2:

Filter the datasets on bases tesla and audi

```
[59]: tesla_audi_data = df[df['Make'].isin(['Tesla', 'Audi'])]
```

Step 3:

diffrenciate between manufactror as tesla and audi

```
[60]: tesla_power = tesla_audi_data[tesla_audi_data['Make'] == 'Tesla']['Engine power_
↳ [KM] ']
audi_power = tesla_audi_data[tesla_audi_data['Make'] == 'Audi']['Engine power_
↳ [KM] ']
```

Step 4:

conduct T-Test for

```
[61]: t_stat, p_value = ttest_ind(tesla_power, audi_power, equal_var=False)
t_stat, p_value
```

```
[61]: (1.7939951827297178, 0.10684105068839565)
```

insights

t-static is 1.793 p-value is 0.1106

P Value Insights

the p avlue is gretar than 0.05 this indicates that we fail to reject null hypothesis. there is no staticlly significant diffrance in the avrage engine power between audi and tesla viehal based on this dataset

T-static Value Insights

while the t-static is positive which tells us about that Tesla viehle may have a slightly higher avrage engine power than Audi the diffrance is not staticly significant

Task 6:

Project Video Explanation (20 Marks)

Video Explanation

[]: