in in fr	<pre>port pandas as pd port numpy as np port matplotlib.pyplot as plt port seaborn as sns com scipy.stats import ttest_ind Load the dataset is pd read csy(r"electric csy")</pre>							
	name (gross) [KM] [Nm] brakes type [kWh] [km] weight [kg] capa	num load Number acity of seats [kg]		size	Maximum speed [kph]	capacity	Acceleration 0-100 kph [s]	cha
0	quattro Audi e- tron 50 quattro e-tron 50 quattro disc tron 50 quattro Audi e- tron 50 quattro disc rear) Audi e- tron 50 quattro disc rear)	40.0 5 70.0 5		19	200	660.0	5.7 6.8	
3	tron S Audi e-tron S 414900 503 973 (front + 4WD 95.0 364 3130.0 56 quattro Audi e-tron e-tron disc	65.0 5 40.0 5		19	190	615.0	6.8	
	Audi e- tron e-tron disc Sportback Audi Sportback 357000 360 664 (front + 4WD 95.0 447 3130.0 66 55 55 quattro quattro ws × 25 columns	70.0 5	5	19	200	615.0	5.7	
fi	Filter EVs based on budget and range ltered_evs = df[(df['Minimal price (gross) [PLN]'] <= 350000) & (df['Range (WLTP) [km]'] cint(filtered_evs) Car full name Audi e-tron 55 quattro BMW iX3 BMW	>= 400)]						
15 18 20 22 39 40 41 47	Hyundai Kona electric 64kWh Hyundai Kia e-Niro 64kWh Kia Kia e-Soul 64kWh Kia Mercedes-Benz EQC Mercedes-Benz Tesla Model 3 Standard Range Plus Tesla Tesla Model 3 Long Range Tesla Tesla Model 3 Performance Tesla Volkswagen ID.3 Pro Performance Volkswagen							
47 48 49 0 8 15 18	Volkswagen ID.3 Pro Performance Volkswagen Volkswagen ID.4 1st Volkswagen Model Minimal price (gross) [PLN] \ e-tron 55 quattro iX3 282900 Kona electric 64kWh e-Niro 64kWh 178400 e-Niro 64kWh 167990							
20 22 39 40 41 47 48 49	e-Soul 64kWh 160990 EQC 334700							
0 8 15 18 20 22	Engine power [KM] Maximum torque [Nm] Type of brakes \							
39 40 41 47 48 49	285							
0 8 15 18 20 22 39 40	AWD 95.0 438 2WD (rear) 80.0 460 2WD (front) 64.0 449 2WD (front) 64.0 455 2WD (front) 64.0 452 4WD 80.0 414 2WD (rear) 54.0 430 4WD 75.0 580							
41 47 48 49	AWD 75.0 567 2WD (rear) 58.0 425 2WD (rear) 77.0 549 2WD (rear) 77.0 500 Permissable gross weight [kg] Maximum load capacity [kg] \							
15 18 20 22 39 40 41 47	2170.0 485.0 2230.0 493.0 1682.0 498.0 2940.0 445.0 NAN NAN NAN NAN NAN NAN 2270.0 540.0							
47 48 49 0 8 15 18	Number of seats Number of doors Tire size [in] Maximum speed [kph] Number of seats Seats							
20 22 39 40 41 47 48 49	5 5 17 167 5 5 19 180 5 5 18 225 5 5 18 233 5 5 20 261 5 5 18 160 5 5 19 160 5 5 20 160							
0 8 15 18 20	Boot capacity (VDA) [1] Acceleration 0-100 kph [s] \ 660.0 5.7 510.0 6.8 332.0 7.6 451.0 7.8 315.0 7.9							
22 39 40 41 47 48 49	500.0 5.1 425.0 5.6 425.0 4.4 425.0 3.3 385.0 7.3 385.0 7.9 543.0 8.5							
0 8 15 18 20 22 39	Maximum DC charging power [kW] mean - Energy consumption [kWh/100 km] 150 24.45 150 18.80 100 15.40 100 15.70 110 21.85 150 NaN							
	150 NaN 150 NaN 150 15.40 125 15.90 125 18.00							
gr pr Mal Aud BMI Hyv	Ri 1 V 1 undai 1							
Kia Men Tes Vol dty	a 2 ccedes-Benz 1							
pr Mal Aud BMV	rint(avg_battery_capacity) se di 95.000000							
Kia Men Tes Vol Nar	64.000000 ccedes-Benz 80.000000 classia 68.000000 classwagen 70.666667 ne: Battery capacity [kWh], dtype: float64 Calculate the IQR to detect outliers							
q2 iq # lc up	= df["mean - Energy consumption [kWh/100 km]"].quantile(0.25) = df["mean - Energy consumption [kWh/100 km]"].quantile(0.75) = q2 - q1 Define lower and upper bounds for outliers wer_bound = q1 - 1.5 * iqr pper_bound = q2 + 1.5 * iqr							
] #	Filter out the outliers ttliers = df[(df["mean - Energy consumption [kWh/100 km]"] < lower_bound) (df["mean - Energy consumption [kWh/100 km]"] > upper_bound) Check if the DataFrame is empty and display appropriate message outliers.empty:							
e]	<pre>print("No outliers detected in the 'mean - Energy consumption [kWh/100 km]' column.") se: print("Outliers in mean Energy Consumption [kWh/100 km]:") print(outliers[["Make", "Model", "mean - Energy consumption [kWh/100 km]"]]) Display bounds for reference Fint(f"\nLower Bound: {lower_bound:.2f}, Upper Bound: {upper_bound:.2f}")</pre>							
Lov	outliers detected in the 'mean - Energy consumption [kWh/100 km]' column. Wer Bound: 3.75, Upper Bound: 35.35 Task 3: Visualize relationship between battery capacity and range t scatter(df['Battery capacity [kWh]'] df['Bange (WLTP) [km]'])							
pl pl	t.scatter(df['Battery capacity [kWh]'], df['Range (WLTP) [km]']) t.xlabel('Battery Capacity (kWh)') t.ylabel('Range (WLTP) [km]') t.title('Battery Capacity vs. Range') t.show() Battery Capacity vs. Range							
Range (WLTP) [km]	500 -							
	200 40 60 80 100 Battery Capacity (kWh)							
	<pre>the above graph clearly shows that when the battery capacity increases the range also inc ass EVRecommendation: definit(self, df): self.df = df</pre>	creases						
ez	<pre>def recommend(self, budget, desired_range, battery_capacity): recommendations = self.df[(self.df['Minimal price (gross) [PLN]'] <= budget) &</pre>							
to pr	Car full name Make Model \ Volkswagen ID.3 Pro Performance Volkswagen ID.3 Pro Performance Kia e-Soul 64kWh Kia e-Niro 64kWh Kia e-Niro 64kWh							
47 20 18 47 20	Minimal price (gross) [PLN] Engine power [KM] Maximum torque [Nm] \							
20 18 47 20 18	disc (front + rear) 2WD (front) 64.0 Range (WLTP) [km] Permissable gross weight [kg] \ 425 2270.0 452 1682.0 455 2230.0							
47 20 18 47 20 18	Maximum load capacity [kg] Number of seats Number of doors \							
18 47 20 18	17 167 451.0 Acceleration 0-100 kph [s] Maximum DC charging power [kW] \ 7.3 100 7.9 100 7.8 100 mean - Energy consumption [kWh/100 km]							
47 20 18	15.4 15.7 15.9 rows x 25 columns] Filter data for Tesla and Audi esla = df[df['Make'] == 'Tesla']['Engine power [KM]']							
	esla = df[df['Make'] == 'Tesla']['Engine power [KM]'] di = df[df['Make'] == 'Audi']['Engine power [KM]'] Perform t-test							
# te au # t_	<pre>stat, p_value = ttest_ind(tesla, audi) int(f"T-statistic: {t_stat}, P-value: {p_value}") Insights</pre>							