

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from scipy import stats
df = pd.read_excel('FEV-data-Excel.xlsx')
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 (WLTP) [km]	Drive type	Battery capacity [kWh]	Range
\				
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]
```

```
#Task1(a)
```

```
filtered_df = df[(df['Minimal price (gross) [PLN]'] <= 350000) &  
(df['Range (WLTP) [km]'] >= 400)]
```

```
filtered_df
```

```
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	Minimal price (gross) [PLN]	\
0	e-tron 55 quattro	345700	
8	iX3	282900	
15	Kona electric 64kWh	178400	
18	e-Niro 64kWh	167990	
20	e-Soul 64kWh	160990	
22	EQC	334700	
39	Model 3 Standard Range Plus	195490	
40	Model 3 Long Range	235490	
41	Model 3 Performance	260490	
47	ID.3 Pro Performance	155890	
48	ID.3 Pro S	179990	
49	ID.4 1st	202390	

	Engine power [KM]	Maximum torque [Nm]	Type of brakes
\			
0	360	664	disc (front + rear)
8	286	400	disc (front + rear)
15	204	395	disc (front + rear)
18	204	395	disc (front + rear)
20	204	395	disc (front + rear)
22	408	760	disc (front + rear)
39	285	450	disc (front + rear)
40	372	510	disc (front + rear)
41	480	639	disc (front + rear)
47	204	310	disc (front) + drum (rear)
48	204	310	disc (front) + drum (rear)
49	204	310	disc (front) + drum (rear)

	Drive type	Battery capacity [kWh]	Range (WLTP) [km]	...	\
0	4WD	95.0	438	...	
8	2WD (rear)	80.0	460	...	
15	2WD (front)	64.0	449	...	

18	2WD (front)	64.0	455	...
20	2WD (front)	64.0	452	...
22	4WD	80.0	414	...
39	2WD (rear)	54.0	430	...
40	4WD	75.0	580	...
41	4WD	75.0	567	...
47	2WD (rear)	58.0	425	...
48	2WD (rear)	77.0	549	...
49	2WD (rear)	77.0	500	...

	Permissable gross weight [kg]	Maximum load capacity [kg]	\
0	3130.0	640.0	
8	2725.0	540.0	
15	2170.0	485.0	
18	2230.0	493.0	
20	1682.0	498.0	
22	2940.0	445.0	
39	NaN	NaN	
40	NaN	NaN	
41	NaN	NaN	
47	2270.0	540.0	
48	2280.0	412.0	
49	2660.0	661.0	

	Number of seats	Number of doors	Tire size [in]	Maximum speed [kph]	\
0	5	5	19		
200					
8	5	5	19		
180					
15	5	5	17		
167					
18	5	5	17		
167					
20	5	5	17		
167					
22	5	5	19		
180					
39	5	5	18		
225					
40	5	5	18		
233					
41	5	5	20		
261					
47	5	5	18		
160					
48	5	5	19		
160					
49	5	5	20		

160

	Boot capacity (VDA) [l]	Acceleration 0-100 kph [s]	\
0	660.0	5.7	
8	510.0	6.8	
15	332.0	7.6	
18	451.0	7.8	
20	315.0	7.9	
22	500.0	5.1	
39	425.0	5.6	
40	425.0	4.4	
41	425.0	3.3	
47	385.0	7.3	
48	385.0	7.9	
49	543.0	8.5	

	Maximum DC charging power [kW]	mean - Energy consumption [kWh/100 km]
0	150	
24.45		
8	150	
18.80		
15	100	
15.40		
18	100	
15.90		
20	100	
15.70		
22	110	
21.85		
39	150	
NaN		
40	150	
NaN		
41	150	
NaN		
47	100	
15.40		
48	125	
15.90		
49	125	
18.00		

[12 rows x 25 columns]

#Task 1(b)

```
grouped_by_make = filtered_df.groupby('Make')
grouped_by_make
```

```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x000001EA1241DD60>
```

```
#Task 1(c)
```

```
avg_battery_capacity = grouped_by_make['Battery capacity [kWh]'].mean()
```

```
avg_battery_capacity
```

```
Make
```

```
Audi          95.000000
```

```
BMW           80.000000
```

```
Hyundai       64.000000
```

```
Kia           64.000000
```

```
Mercedes-Benz 80.000000
```

```
Tesla         68.000000
```

```
Volkswagen    70.666667
```

```
Name: Battery capacity [kWh], dtype: float64
```

```
import pandas as pd
```

```
import numpy as np
```

```
import matplotlib.pyplot as plt
```

```
from scipy import stats
```

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

```
column_name = 'Mean - Energy consumption [kWh/100 km]'
```

```
if 'mean - Energy consumption [kWh/100 km]' in df.columns:
```

```
    column_name = 'mean - Energy consumption [kWh/100 km]'
```

```
iqr_outliers = df[
```

```
    (df[column_name] < (df[column_name].quantile(0.25) -
```

```
1.5*(df[column_name].quantile(0.75)-df[column_name].quantile(0.25))))
```

```
|
```

```
    (df[column_name] > (df[column_name].quantile(0.75) +
```

```
1.5*(df[column_name].quantile(0.75)-df[column_name].quantile(0.25))))
```

```
].dropna(subset=[column_name])
```

```
clean_df = df.dropna(subset=[column_name]).copy()
```

```
z_scores = np.abs(stats.zscore(clean_df[column_name]))
```

```
z_outliers = clean_df[z_scores > 3]
```

```
plt.figure(figsize=(12, 6))
```

```
plt.boxplot(clean_df[column_name], vert=False)
```

```
plt.title("Energy Consumption Distribution (Clean Data)", pad=20)
```

```
plt.xlabel("kWh/100 km")
```

```
plt.yticks([])
```

```
plt.grid(True)
```

```
for i, x in enumerate(z_outliers[column_name]):
```

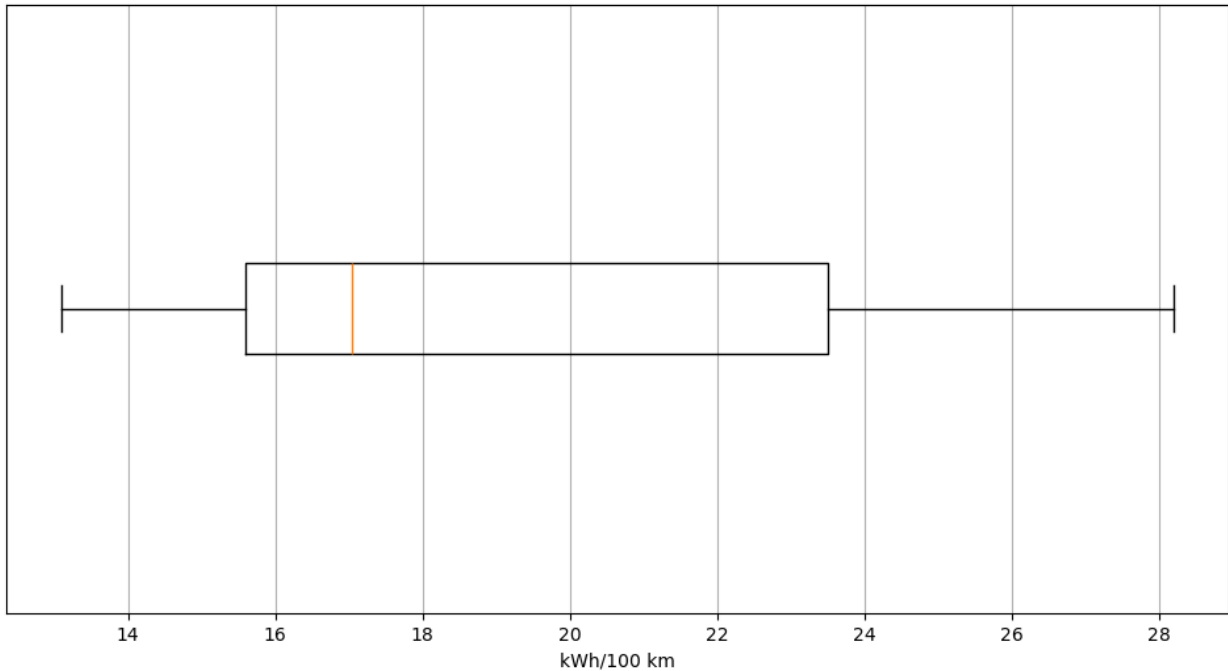
```
    plt.plot(x, 1, 'ro', alpha=0.5)
```

```
    plt.text(x, 1.1, f"{x:.1f}", ha='center')
```

```
plt.show()
```

```
final_outliers = pd.concat([iqr_outliers,
z_outliers]).drop_duplicates()
print(f"Total outliers found: {len(final_outliers)}")
```

Energy Consumption Distribution (Clean Data)

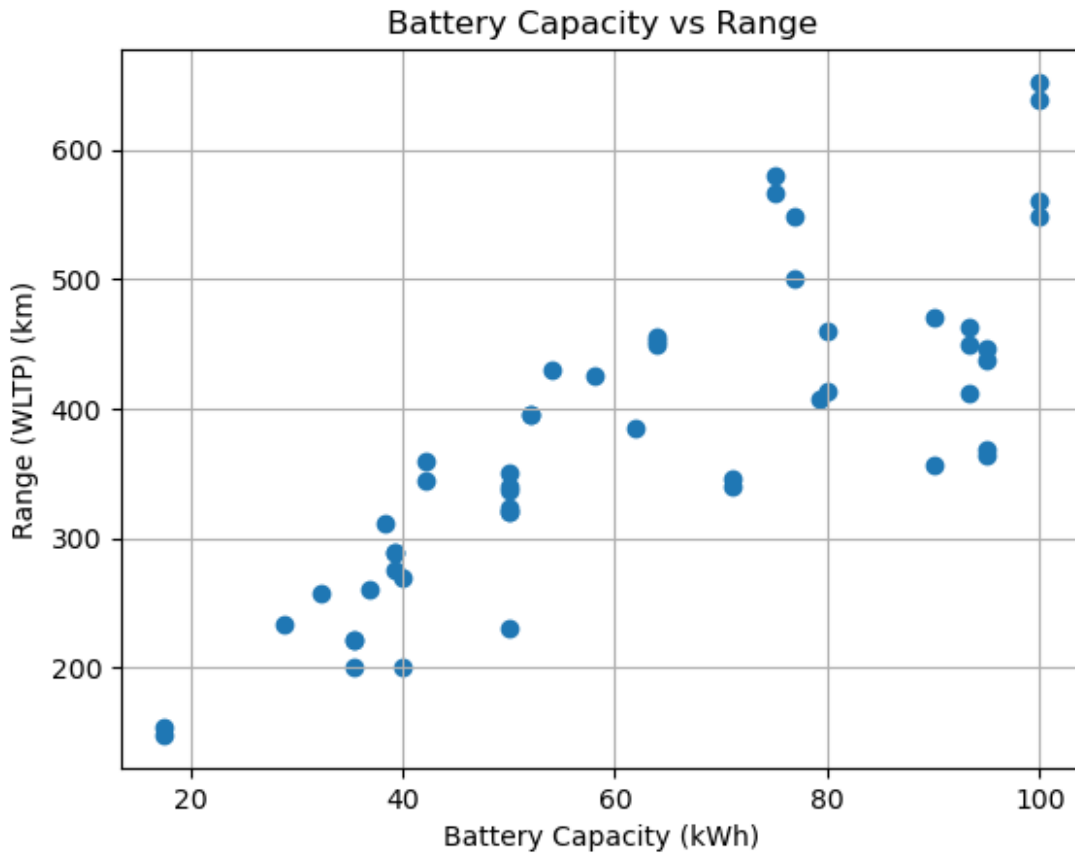


Total outliers found: 0

#Task 3

```
import matplotlib.pyplot as plt
```

```
plt.scatter(df['Battery capacity [kWh]'], df['Range (WLTP) [km]'])
plt.xlabel('Battery Capacity (kWh)')
plt.ylabel('Range (WLTP) (km)')
plt.title('Battery Capacity vs Range')
plt.grid(True)
plt.show()
```



```
"""
```

Task 3 Insights :

This is being clear from the chart that the battery capacity is directly correlated by the Range of the EV but after 80 KWh Capacity the range is more or less stagnant in under 500 Kilometers.

```
"""
```

#Task 4

```
class EVRecommendation:
```

```
    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)]
```

```
        return filtered.sort_values('Minimal price (gross)
                                     [PLN]').head(3)
```



```
recommender = EVRecommendation(df)
recommender.recommend(300000, 350, 50)
```

	Car full name	Make	Model	Minimal price (gross)
[PLN] \				
9	Citroën ë-C4	Citroën	ë-C4	125000
34	Renault Zoe R110	Renault	Zoe R110	135900
35	Renault Zoe R135	Renault	Zoe R135	142900

	Engine power [KM]	Maximum torque [Nm]	Type of brakes
Drive type \			
9	136	260	disc (front + rear) 2WD
(front)			
34	108	225	disc (front + rear) 2WD
(front)			
35	135	245	disc (front + rear) 2WD
(front)			

	Battery capacity [kWh]	Range (WLTP) [km]	...	\
9	50.0	350	...	
34	52.0	395	...	
35	52.0	395	...	

	Permissable gross weight [kg]	Maximum load capacity [kg]	\
9	2000.0	459.0	
34	1988.0	425.0	
35	1988.0	486.0	

	Number of seats	Number of doors	Tire size [in]	Maximum speed
[kph] \				
9	5	5	16	
150				
34	5	5	15	
135				
35	5	5	16	
140				

	Boot capacity (VDA) [l]	Acceleration 0-100 kph [s]	\
9	380.0	9.5	
34	338.0	11.4	
35	338.0	9.5	

	Maximum DC charging power [kW]	mean - Energy consumption [kWh/100 km]
9	100	
NaN		
34	50	

```
16.5
35
16.5
```

	50
--	----

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

```
#Task 5
```

```
from scipy.stats import ttest_ind
```

```
tesla = df[df['Make'] == 'Tesla']['Engine power [KM]']
```

```
audi = df[df['Make'] == 'Audi']['Engine power [KM]']
```

```
t_stat, p_value = ttest_ind(tesla, audi, equal_var=False)
```

```
print('t-statistic:', t_stat)
```

```
print('p-value:', p_value)
```

```
t-statistic: 1.7939951827297178
```

```
p-value: 0.10684105068839565
```

```
"""
```

```
KEY INSIGHTS :
```

```
Based on a two-sample t-test ( $p = 0.1068 > 0.05$ ), there is no significant difference in engine power between Tesla and Audi vehicles in the dataset.
```

```
Although Tesla may appear to have slightly higher engine power on average, the difference is not statistically significant.
```

```
"""
```