

# Electric Vehicle Data Analysis Project

```
In [1]: import pandas as pd
import numpy as np
ev_def= pd.read_excel("FEV-data-Excel.xlsx")
print(ev_def)
```

Please scroll down till  
9th page to see my task performed

Here I imported the data  
by using pandas library

	Car full name	Make \
0	Audi e-tron 55 quattro	Audi
1	Audi e-tron 50 quattro	Audi
2	Audi e-tron S quattro	Audi
3	Audi e-tron Sportback 50 quattro	Audi
4	Audi e-tron Sportback 55 quattro	Audi
5	Audi e-tron Sportback S quattro	Audi
6	BMW i3	BMW
7	BMW i3s	BMW
8	BMW iX3	BMW
9	Citroën ë-C4	Citroën
10	DS DS3 Crossback e-tense	DS
11	Honda e	Honda
12	Honda e Advance	Honda
13	Hyundai Ioniq electric	Hyundai
14	Hyundai Kona electric 39.2kWh	Hyundai
15	Hyundai Kona electric 64kWh	Hyundai
16	Jaguar I-Pace	Jaguar
17	Kia e-Niro 39.2kWh	Kia
18	Kia e-Niro 64kWh	Kia
19	Kia e-Soul 39.2kWh	Kia
20	Kia e-Soul 64kWh	Kia
21	Mazda MX-30	Mazda
22	Mercedes-Benz EQC	Mercedes-Benz
23	Mini Cooper SE	Mini
24	Nissan Leaf	Nissan
25	Nissan Leaf e+	Nissan
26	Opel Corsa-e	Opel
27	Opel Mokka-e	Opel
28	Peugeot e-208	Peugeot
29	Peugeot e-2008	Peugeot
30	Porsche Taycan 4S (Performance)	Porsche
31	Porsche Taycan 4S (Performance Plus)	Porsche
32	Porsche Taycan Turbo	Porsche
33	Porsche Taycan Turbo S	Porsche
34	Renault Zoe R110	Renault
35	Renault Zoe R135	Renault
36	Skoda Citigo-e iV	Skoda
37	Smart fortwo EQ	Smart
38	Smart forfour EQ	Smart
39	Tesla Model 3 Standard Range Plus	Tesla
40	Tesla Model 3 Long Range	Tesla
41	Tesla Model 3 Performance	Tesla
42	Tesla Model S Long Range Plus	Tesla
43	Tesla Model S Performance	Tesla
44	Tesla Model X Long Range Plus	Tesla
45	Tesla Model X Performance	Tesla
46	Volkswagen e-up!	Volkswagen
47	Volkswagen ID.3 Pro Performance	Volkswagen
48	Volkswagen ID.3 Pro S	Volkswagen
49	Volkswagen ID.4 1st	Volkswagen
50	Citroën ë-Spacetourer (M)	Citroën
51	Mercedes-Benz EQV (long)	Mercedes-Benz
52	Nissan e-NV200 evalia	Nissan

	Model	Minimal price (gross) [PLN] \
0	e-tron 55 quattro	345700
1	e-tron 50 quattro	308400
2	e-tron S quattro	414900
3	e-tron Sportback 50 quattro	319700

4	e-tron Sportback 55 quattro	357000
5	e-tron Sportback S quattro	426200
6	i3	169700
7	i3s	184200
8	iX3	282900
9	ë-C4	125000
10	DS3 Crossback e-tense	159900
11	e	152900
12	e Advance	165900
13	Ioniq electric	184500
14	Kona electric 39.2kWh	154400
15	Kona electric 64kWh	178400
16	I-Pace	359500
17	e-Niro 39.2kWh	146990
18	e-Niro 64kWh	167990
19	e-Soul 39.2kWh	139900
20	e-Soul 64kWh	160990
21	MX-30	142900
22	EQC	334700
23	Cooper SE	139900
24	Leaf	122900
25	Leaf e+	164000
26	Corsa-e	128900
27	Mokka-e	139900
28	e-208	124900
29	e-2008	149400
30	Taycan 4S (Performance)	457000
31	Taycan 4S (Performance Plus)	482283
32	Taycan Turbo	653000
33	Taycan Turbo S	794000
34	Zoe R110	135900
35	Zoe R135	142900
36	Citigo-e iV	82050
37	fortwo EQ	96900
38	forfour EQ	98900
39	Model 3 Standard Range Plus	195490
40	Model 3 Long Range	235490
41	Model 3 Performance	260490
42	Model S Long Range Plus	368990
43	Model S Performance	443990
44	Model X Long Range Plus	407990
45	Model X Performance	482990
46	e-up!	97990
47	ID.3 Pro Performance	155890
48	ID.3 Pro S	179990
49	ID.4 1st	202390
50	ë-Spacetourer (M)	215400
51	EQV (long)	339480
52	e-NV200 evalia	164328

	Engine power [KM]	Maximum torque [Nm]	Type of brakes \
0	360	664	disc (front + rear)
1	313	540	disc (front + rear)
2	503	973	disc (front + rear)
3	313	540	disc (front + rear)
4	360	664	disc (front + rear)
5	503	973	disc (front + rear)
6	170	250	disc (front + rear)
7	184	270	disc (front + rear)
8	286	400	disc (front + rear)

9	136	260	disc (front + rear)
10	136	260	disc (front + rear)
11	136	315	disc (front + rear)
12	154	315	disc (front + rear)
13	136	295	disc (front + rear)
14	136	395	disc (front + rear)
15	204	395	disc (front + rear)
16	400	696	disc (front + rear)
17	136	395	disc (front + rear)
18	204	395	disc (front + rear)
19	136	395	disc (front + rear)
20	204	395	disc (front + rear)
21	145	270	disc (front + rear)
22	408	760	disc (front + rear)
23	184	270	disc (front + rear)
24	150	320	disc (front + rear)
25	217	340	disc (front + rear)
26	136	260	disc (front + rear)
27	136	260	disc (front + rear)
28	136	260	disc (front + rear)
29	136	260	disc (front + rear)
30	435	640	disc (front + rear)
31	490	650	disc (front + rear)
32	625	850	disc (front + rear)
33	625	1050	disc (front + rear)
34	108	225	disc (front + rear)
35	135	245	disc (front + rear)
36	83	212	disc (front) + drum (rear)
37	82	160	disc (front) + drum (rear)
38	82	160	disc (front) + drum (rear)
39	285	450	disc (front + rear)
40	372	510	disc (front + rear)
41	480	639	disc (front + rear)
42	525	755	disc (front + rear)
43	772	1140	disc (front + rear)
44	525	755	disc (front + rear)
45	772	1140	disc (front + rear)
46	83	210	disc (front) + drum (rear)
47	204	310	disc (front) + drum (rear)
48	204	310	disc (front) + drum (rear)
49	204	310	disc (front) + drum (rear)
50	136	260	disc (front + rear)
51	204	362	NaN
52	109	254	disc (front + rear)

	Drive type	Battery capacity [kWh]	Range (WLTP) [km]	...	\
0	4WD	95.0	438	...	
1	4WD	71.0	340	...	
2	4WD	95.0	364	...	
3	4WD	71.0	346	...	
4	4WD	95.0	447	...	
5	4WD	95.0	369	...	
6	2WD (rear)	42.2	359	...	
7	2WD (rear)	42.2	345	...	
8	2WD (rear)	80.0	460	...	
9	2WD (front)	50.0	350	...	
10	2WD (front)	50.0	320	...	
11	2WD (rear)	35.5	222	...	
12	2WD (rear)	35.5	222	...	
13	2WD (front)	38.3	311	...	

14	2WD (front)	39.2	289 ...
15	2WD (front)	64.0	449 ...
16	4WD	90.0	470 ...
17	2WD (front)	39.2	289 ...
18	2WD (front)	64.0	455 ...
19	2WD (front)	39.2	276 ...
20	2WD (front)	64.0	452 ...
21	2WD (front)	35.5	200 ...
22	4WD	80.0	414 ...
23	2WD (front)	28.9	234 ...
24	2WD (front)	40.0	270 ...
25	2WD (front)	62.0	385 ...
26	2WD (front)	50.0	337 ...
27	2WD (front)	50.0	324 ...
28	2WD (front)	50.0	340 ...
29	2WD (front)	50.0	320 ...
30	4WD	79.2	407 ...
31	4WD	93.4	463 ...
32	4WD	93.4	450 ...
33	4WD	93.4	412 ...
34	2WD (front)	52.0	395 ...
35	2WD (front)	52.0	395 ...
36	2WD (front)	36.8	260 ...
37	2WD (rear)	17.6	154 ...
38	2WD (rear)	17.6	148 ...
39	2WD (rear)	54.0	430 ...
40	4WD	75.0	580 ...
41	4WD	75.0	567 ...
42	4WD	100.0	652 ...
43	4WD	100.0	639 ...
44	4WD	100.0	561 ...
45	4WD	100.0	548 ...
46	2WD (front)	32.3	258 ...
47	2WD (rear)	58.0	425 ...
48	2WD (rear)	77.0	549 ...
49	2WD (rear)	77.0	500 ...
50	2WD (front)	50.0	230 ...
51	2WD (front)	90.0	356 ...
52	2WD (front)	40.0	200 ...

	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
5	3130.0	565.0
6	1730.0	440.0
7	1730.0	440.0
8	2725.0	540.0
9	2000.0	459.0
10	1975.0	450.0
11	1855.0	342.0
12	1870.0	350.0
13	1970.0	518.0
14	2020.0	485.0
15	2170.0	485.0
16	2670.0	537.0
17	2080.0	488.0
18	2230.0	493.0

19	1682.0	490.0
20	1682.0	498.0
21	2119.0	474.0
22	2940.0	445.0
23	1770.0	480.0
24	1995.0	450.0
25	2140.0	435.0
26	1916.0	367.0
27	2015.0	417.0
28	1918.0	463.0
29	NaN	NaN
30	2880.0	740.0
31	2880.0	660.0
32	2880.0	575.0
33	2870.0	575.0
34	1988.0	425.0
35	1988.0	486.0
36	1530.0	367.0
37	1310.0	290.0
38	1570.0	445.0
39	NaN	NaN
40	NaN	NaN
41	NaN	NaN
42	NaN	NaN
43	NaN	NaN
44	NaN	NaN
45	NaN	NaN
46	1530.0	370.0
47	2270.0	540.0
48	2280.0	412.0
49	2660.0	661.0
50	2810.0	1056.0
51	3500.0	865.0
52	2250.0	658.0

	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	
5	5	5	20	210	
6	4	5	19	160	
7	4	5	20	160	
8	5	5	19	180	
9	5	5	16	150	
10	5	5	17	150	
11	5	5	16	145	
12	5	5	17	145	
13	5	5	16	165	
14	5	5	17	155	
15	5	5	17	167	
16	5	5	20	200	
17	5	5	17	155	
18	5	5	17	167	
19	5	5	17	157	
20	5	5	17	167	
21	5	5	18	140	
22	5	5	19	180	
23	4	3	16	150	

24	5	5	16	144
25	5	5	17	157
26	5	5	16	150
27	5	5	16	150
28	5	5	16	150
29	5	5	16	150
30	4	4	19	250
31	4	4	19	250
32	4	4	20	260
33	4	4	21	260
34	5	5	15	135
35	5	5	16	140
36	4	5	14	130
37	2	3	15	130
38	4	5	15	130
39	5	5	18	225
40	5	5	18	233
41	5	5	20	261
42	5	5	19	250
43	5	5	21	261
44	7	5	20	250
45	7	5	20	261
46	4	5	14	130
47	5	5	18	160
48	5	5	19	160
49	5	5	20	160
50	8	5	16	130
51	6	5	17	160
52	5	5	15	123

	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	
5	615.0	4.5	
6	260.0	8.1	
7	260.0	6.9	
8	510.0	6.8	
9	380.0	9.5	
10	350.0	8.7	
11	171.0	9.0	
12	171.0	8.3	
13	357.0	9.9	
14	332.0	9.7	
15	332.0	7.6	
16	656.0	4.8	
17	451.0	9.8	
18	451.0	7.8	
19	315.0	9.9	
20	315.0	7.9	
21	350.0	9.7	
22	500.0	5.1	
23	211.0	7.3	
24	435.0	7.9	
25	435.0	6.9	
26	267.0	8.1	
27	310.0	9.0	
28	311.0	8.1	

29	434.0	NaN
30	488.0	4.0
31	488.0	4.0
32	447.0	3.2
33	447.0	2.8
34	338.0	11.4
35	338.0	9.5
36	250.0	12.3
37	185.0	11.6
38	260.0	12.7
39	425.0	5.6
40	425.0	4.4
41	425.0	3.3
42	745.0	3.8
43	745.0	2.5
44	857.0	4.6
45	857.0	2.8
46	250.0	11.9
47	385.0	7.3
48	385.0	7.9
49	543.0	8.5
50	603.0	13.1
51	NaN	NaN
52	870.0	NaN

	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	150	27.20
6	50	13.10
7	50	14.30
8	150	18.80
9	100	NaN
10	100	15.60
11	100	17.20
12	100	17.50
13	100	13.80
14	100	15.00
15	100	15.40
16	100	21.20
17	100	15.30
18	100	15.90
19	100	15.60
20	100	15.70
21	37	14.50
22	110	21.85
23	50	16.75
24	50	18.50
25	100	17.10
26	100	16.65
27	100	17.60
28	100	16.40
29	100	NaN
30	225	23.40
31	270	24.10
32	270	24.85
33	270	25.10



34	50	16.50
35	50	16.50
36	40	15.45
37	22	16.35
38	22	17.00
39	150	NaN
40	150	NaN
41	150	NaN
42	150	NaN
43	150	NaN
44	150	NaN
45	150	NaN
46	40	14.00
47	100	15.40
48	125	15.90
49	125	18.00
50	100	25.20
51	110	28.20
52	50	25.90

[53 rows x 25 columns]

## TASK=1

```
In [17]: # Step 1: Filter rows where a range of EVs <= 400
filtered_evs = ev_def[ev_def["Range (WLTP) [km]"] <= 400]
# Step 2: Select specific columns
selected_columns = filtered_evs[["Car full name", "Make", "Model", "Range (WLTP)"]
# Print result
print(selected_columns)
```

	Car full name	Make \
1	Audi e-tron 50 quattro	Audi
2	Audi e-tron S quattro	Audi
3	Audi e-tron Sportback 50 quattro	Audi
5	Audi e-tron Sportback S quattro	Audi
6	BMW i3	BMW
7	BMW i3s	BMW
9	Citroën ë-C4	Citroën
10	DS DS3 Crossback e-tense	DS
11	Honda e	Honda
12	Honda e Advance	Honda
13	Hyundai Ioniq electric	Hyundai
14	Hyundai Kona electric 39.2kWh	Hyundai
17	Kia e-Niro 39.2kWh	Kia
19	Kia e-Soul 39.2kWh	Kia
21	Mazda MX-30	Mazda
23	Mini Cooper SE	Mini
24	Nissan Leaf	Nissan
25	Nissan Leaf e+	Nissan
26	Opel Corsa-e	Opel
27	Opel Mokka-e	Opel
28	Peugeot e-208	Peugeot
29	Peugeot e-2008	Peugeot
34	Renault Zoe R110	Renault
35	Renault Zoe R135	Renault
36	Skoda Citigo-e iV	Skoda
37	Smart fortwo EQ	Smart
38	Smart forfour EQ	Smart
46	Volkswagen e-up!	Volkswagen
50	Citroën ë-Spacetourer (M)	Citroën
51	Mercedes-Benz EQV (long)	Mercedes-Benz
52	Nissan e-NV200 evalia	Nissan

	Model	Range (WLTP) [km]	Battery capacity [kWh]
1	e-tron 50 quattro	340	71.0
2	e-tron S quattro	364	95.0
3	e-tron Sportback 50 quattro	346	71.0
5	e-tron Sportback S quattro	369	95.0
6	i3	359	42.2
7	i3s	345	42.2
9	ë-C4	350	50.0
10	DS3 Crossback e-tense	320	50.0
11	e	222	35.5
12	e Advance	222	35.5
13	Ioniq electric	311	38.3
14	Kona electric 39.2kWh	289	39.2
17	e-Niro 39.2kWh	289	39.2
19	e-Soul 39.2kWh	276	39.2
21	MX-30	200	35.5
23	Cooper SE	234	28.9
24	Leaf	270	40.0
25	Leaf e+	385	62.0
26	Corsa-e	337	50.0
27	Mokka-e	324	50.0
28	e-208	340	50.0
29	e-2008	320	50.0
34	Zoe R110	395	52.0
35	Zoe R135	395	52.0
36	Citigo-e iV	260	36.8
37	fortwo EQ	154	17.6

38	forfour EQ	148	17.6
46	e-up!	258	32.3
50	ë-Spacetourer (M)	230	50.0
51	EQV (long)	356	90.0
52	e-NV200 evalia	200	40.0

```
In [37]: # Step 1: Filter by range and price
filtered_evs = ev_def[
    (ev_def["Range (WLTP) [km]" ] <= 400) &
    (ev_def["Minimal price (gross) [PLN]" ] <= 350000)]
# Step 2: Select relevant columns needed
selected_columns = filtered_evs[[
    "Car full name",
    "Make",
    "Model",
    "Range (WLTP) [km]",
    "Battery capacity [kWh]",
    "Minimal price (gross) [PLN]"]]

# Step 3: Group by makers
grouped = selected_columns.groupby("Make")

# Step 4: Printing style
for make, group in grouped:
    print(f"\n{' '*30}\n{make}\n{' '*30}")
    print(group.to_string(index=False))
## a maximum budget of 350,000 PLN and a minimum electric range of 400 km (WLTP)
#maker: Mercedes-Benz, Equipped with a 90 kWh battery
#Price: Approximately 339,480 PLN
#Range: 400 km or more (based on WLTP standards)
#This positions Mercedes-Benz as a strong contender in the premium EV segment, o
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Audi

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	Car full name	Make	Model	Range (WLTP)
[km]	Battery capacity [kWh]	Minimal price (gross) [PLN]		
	Audi e-tron 50 quattro	Audi	e-tron 50 quattro	
340	71.0		308400	
	Audi e-tron Sportback 50 quattro	Audi	e-tron Sportback 50 quattro	
346	71.0		319700	

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BMW

=====

	Car full name	Make	Model	Range (WLTP) [km]	Battery capacity [kWh]	Minimal price (gross) [PLN]
	BMW i3	BMW	i3	359	42.2	
169700						
	BMW i3s	BMW	i3s	345	42.2	
184200						

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Citroën

=====

	Car full name	Make	Model	Range (WLTP) [km]	Battery capacity [kWh]	Minimal price (gross) [PLN]
	Citroën ë-C4	Citroën	ë-C4	350		
50.0						125000
	Citroën ë-Spacetourer (M)	Citroën	ë-Spacetourer (M)	230		
50.0						215400

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DS

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	Car full name	Make	Model	Range (WLTP) [km]	Battery capacity [kWh]	Minimal price (gross) [PLN]
	DS DS3 Crossback e-tense	DS	DS3 Crossback e-tense	320		
50.0						159900

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Honda

=====

	Car full name	Make	Model	Range (WLTP) [km]	Battery capacity [kWh]	Minimal price (gross) [PLN]
	Honda e	Honda	e	222	35.5	
152900						
	Honda e Advance	Honda	e Advance	222	35.5	
165900						

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Hyundai

=====

	Car full name	Make	Model	Range (WLTP) [km]	Battery capacity [kWh]	Minimal price (gross) [PLN]
	Hyundai Ioniq electric	Hyundai	Ioniq electric	311		
38.3						184500
	Hyundai Kona electric 39.2kWh	Hyundai	Kona electric 39.2kWh	289		
39.2						154400

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Kia

=====

Car full name	Make	Model	Range (WLTP) [km]	Battery capacity [kWh]
Minimal price (gross) [PLN]				
Kia e-Niro 39.2kWh	Kia	e-Niro 39.2kWh	289	39.2
146990				
Kia e-Soul 39.2kWh	Kia	e-Soul 39.2kWh	276	39.2
139900				

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Mazda

=====

Car full name	Make	Model	Range (WLTP) [km]	Battery capacity [kWh]	Minimal price (gross) [PLN]
Mazda MX-30	Mazda	MX-30	200	35.5	
142900					

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Mercedes-Benz

=====

Car full name	Make	Model	Range (WLTP) [km]	Battery capacity [kWh]	Minimal price (gross) [PLN]
Mercedes-Benz EQV (long)	Mercedes-Benz	EQV (long)		356	
90.0					339480

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Mini

=====

Car full name	Make	Model	Range (WLTP) [km]	Battery capacity [kWh]	Minimal price (gross) [PLN]
Mini Cooper SE	Mini	Cooper SE	234	28.9	
139900					

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Nissan

=====

Car full name	Make	Model	Range (WLTP) [km]	Battery capacity [kWh]	Minimal price (gross) [PLN]
Nissan Leaf	Nissan	Leaf		270	
40.0					122900
Nissan Leaf e+	Nissan	Leaf e+		385	
62.0					164000
Nissan e-NV200 evalia	Nissan	e-NV200 evalia		200	
40.0					164328

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Opel

=====

Car full name	Make	Model	Range (WLTP) [km]	Battery capacity [kWh]	Minimal price (gross) [PLN]
Opel Corsa-e	Opel	Corsa-e	337	50.0	
128900					
Opel Mokka-e	Opel	Mokka-e	324	50.0	
139900					

=====

Peugeot

=====

Car full name	Make	Model	Range (WLTP) [km]	Battery capacity [kWh]	Minimal price (gross) [PLN]
Peugeot e-208	Peugeot	e-208	340	50.0	

124900	Peugeot e-2008	Peugeot e-2008	320	50.0
149400				

=====

Renault

=====

Car full name	Make	Model	Range (WLTP) [km]	Battery capacity [kWh]	Min
imal price (gross) [PLN]					
Renault Zoe R110	Renault	Zoe R110	395	52.0	
135900					
Renault Zoe R135	Renault	Zoe R135	395	52.0	
142900					

=====

Skoda

=====

Car full name	Make	Model	Range (WLTP) [km]	Battery capacity [kWh]	M
imal price (gross) [PLN]					
Skoda Citigo-e iV	Skoda	Citigo-e iV	260	36.8	
82050					

=====

Smart

=====

Car full name	Make	Model	Range (WLTP) [km]	Battery capacity [kWh]	Min
imal price (gross) [PLN]					
Smart fortwo EQ	Smart	fortwo EQ	154	17.6	
96900					
Smart forfour EQ	Smart	forfour EQ	148	17.6	
98900					

=====

Volkswagen

=====

Car full name	Make	Model	Range (WLTP) [km]	Battery capacity [kWh]	Min
imal price (gross) [PLN]					
Volkswagen e-up!	Volkswagen	e-up!	258	32.3	
97990					

```
In [ ]: import pandas as pd
df=pd.read_excel("FEV-data-Excel.xlsx")
df
```

```
In [25]: # Group and calculate mean(AVERAGE OF BATTERY CAPACITY BY MAKERS)
avg_capacity = df.groupby("Make")["Battery capacity [kWh]"].mean().reset_index()

# Rename the columns
avg_capacity.columns = ["Make", "Average battery capacity (kWh)"]
print(avg_capacity)
```

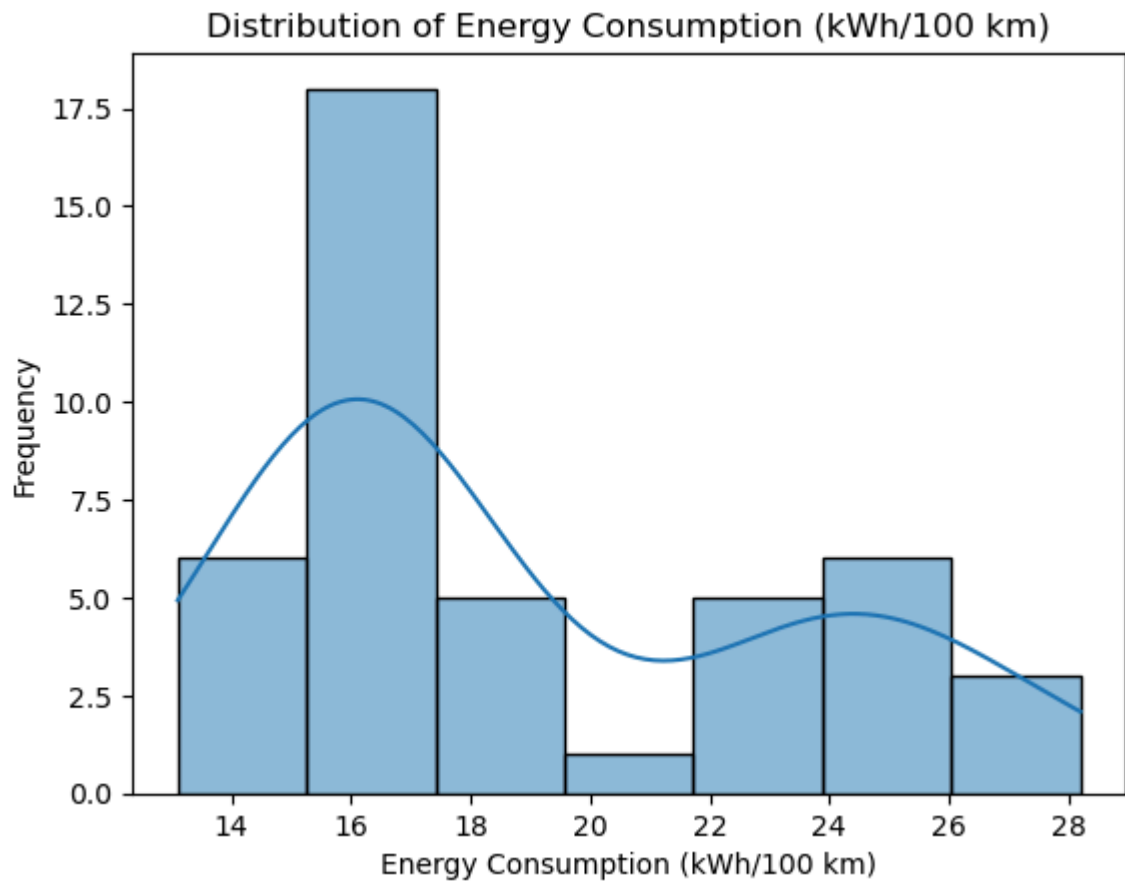
	Make	Average battery capacity (kWh)
0	Audi	87.000000
1	BMW	54.800000
2	Citroën	50.000000
3	DS	50.000000
4	Honda	35.500000
5	Hyundai	47.166667
6	Jaguar	90.000000
7	Kia	51.600000
8	Mazda	35.500000
9	Mercedes-Benz	85.000000
10	Mini	28.900000
11	Nissan	47.333333
12	Opel	50.000000
13	Peugeot	50.000000
14	Porsche	89.850000
15	Renault	52.000000
16	Skoda	36.800000
17	Smart	17.600000
18	Tesla	86.285714
19	Volkswagen	61.075000

## TASK=2

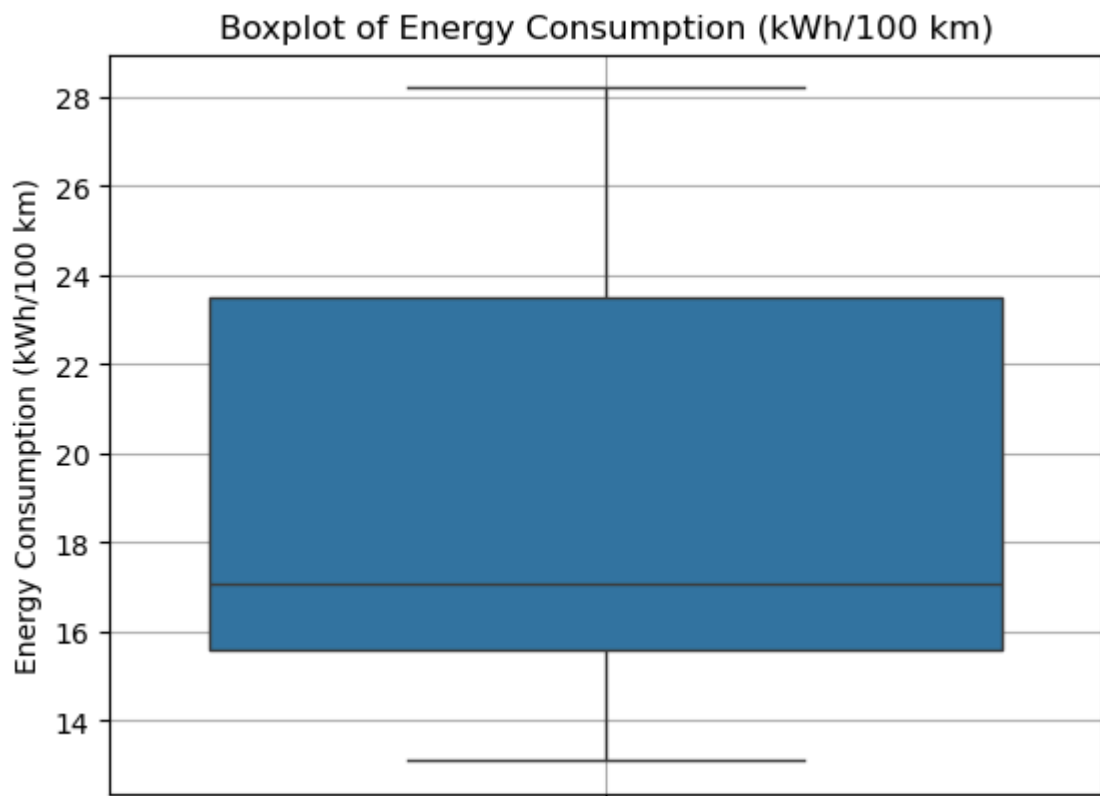
```
In [48]: import seaborn as sns
import matplotlib.pyplot as plt
df.columns = df.columns.str.strip()
print(df.columns)
```

```
Index(['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]', 'Permissable 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]'],
      dtype='object')
```

```
In [46]: sns.histplot(df["mean - Energy consumption [kWh/100 km]"], kde=True)
plt.title("Distribution of Energy Consumption (kWh/100 km)")
plt.xlabel("Energy Consumption (kWh/100 km)")
plt.ylabel("Frequency")
plt.show()
# You can see the energy consumption mean according to frequency
```



```
In [66]: sns.boxplot(y=df["mean - Energy consumption [kWh/100 km]"], showfliers=True)
plt.title("Boxplot of Energy Consumption (kWh/100 km)")
plt.ylabel("Energy Consumption (kWh/100 km)")
plt.grid(True)
plt.show()
```





The thick line inside the box shows the median energy consumption. Most vehicles consume around 17 kWh/100 km.

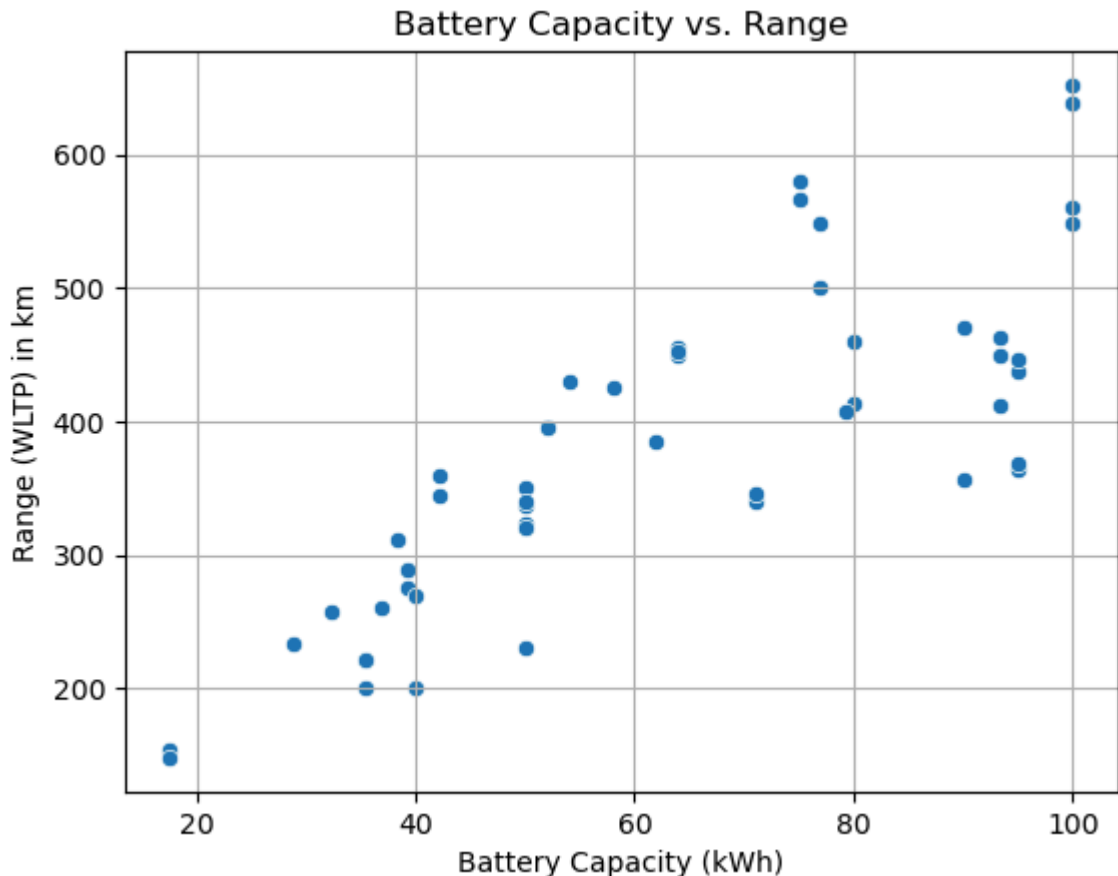
It does not show dots outside aiming, so it doesn't have extreme outliers as shown in the boxplot

The box spans from around 15 to 24 kWh/100 km. This indicates that 50% of vehicles fall in this range.

```
In [ ]: There are significant variations in energy consumption across manufacturers, with  
##These high and low outliers can skew the interpretation of overall energy efficiency  
##Let's explore and visualize these patterns to understand energy performance ex
```

## TASK=3

```
In [73]: sns.scatterplot(x='Battery capacity [kWh]', y='Range (WLTP) [km]', data=df)  
plt.title("Battery Capacity vs. Range")  
plt.xlabel("Battery Capacity (kWh)")  
plt.ylabel("Range (WLTP) in km")  
plt.grid(True)  
plt.show()
```



Vehicles with larger batteries generally have a longer range, as seen in the upward trend of the scatter plot.

If the dots generally move upward to the right, it means more battery = more range (positive correlation).

its a positive correlation between battery and range

There are noticeable clusters of vehicles at certain battery capacities, for instance:

Around 35-40 kWh Around 50-55 kWh Around 75-80 kWh Around 95-100 kWh

Talking about outliers\high performance, the points above 600 range at 98-100 kWh. These might represent highly optimized or premium vehicles.

The plot indicates that larger battery capacities generally lead to greater range

The data doesn't clearly show a strong curve, but the increasing spread could hint at it, or simply more diverse vehicle types in higher capacity segments.

## TASK=4

```
In [1]: import pandas as pd

class recommendation:
    def putdata(self):
        self.budget = float(input("Enter Your budget: "))
        self.desired_range = int(input("Enter Your Range for EV: "))
        self.battery_capacity = int(input("Battery Capacity You need in EV: "))

    def display(self):
        print("Recommendation budget:", self.budget)
        print("Recommendation desired range:", self.desired_range)
        print("Recommendation battery capacity:", self.battery_capacity)

        # Load data from Excel
        df = pd.read_excel("FEV-data-Excel.xlsx")

        # Filter based on user's input
        filtered = df[
            (df["Minimal price (gross) [PLN]"] <= self.budget) &
            (df["Range (WLTP) [km]"] >= self.desired_range) &
            (df["Battery capacity [kWh]"] >= self.battery_capacity)]

        # Sort by budget (ascending)
        filtered = filtered.sort_values(by="Minimal price (gross) [PLN]")

        # Display top 3 matches
        top_ev = filtered.head(3)

        if not top_ev.empty:
            print("\nTop EV recommendations for you:")
            print(top_ev)
        else:
            print("\nNo EVs match your criteria.")

# Instantiate and run
a = recommendation()
a.putdata()
a.display()
```

Recommendation budget: 350000.0  
Recommendation desired range: 400  
Recommendation battery capacity: 70

Top EV recommendations for you:

	Car full name	Make	Model	\
48	Volkswagen ID.3 Pro S	Volkswagen	ID.3 Pro S	
49	Volkswagen ID.4 1st	Volkswagen	ID.4 1st	
40	Tesla Model 3 Long Range	Tesla	Model 3 Long Range	
	Minimal price (gross) [PLN]	Engine power [KM]	Maximum torque [Nm]	\
48	179990	204	310	
49	202390	204	310	
40	235490	372	510	
	Type of brakes	Drive type	Battery capacity [kWh]	\
48	disc (front) + drum (rear)	2WD (rear)	77.0	
49	disc (front) + drum (rear)	2WD (rear)	77.0	
40	disc (front + rear)	4WD	75.0	
	Range (WLTP) [km]	...	Permissable gross weight [kg]	\
48	549	...	2280.0	
49	500	...	2660.0	
40	580	...	NaN	
	Maximum load capacity [kg]	Number of seats	Number of doors	\
48	412.0	5	5	
49	661.0	5	5	
40	NaN	5	5	
	Tire size [in]	Maximum speed [kph]	Boot capacity (VDA) [l]	\
48	19	160	385.0	
49	20	160	543.0	
40	18	233	425.0	
	Acceleration 0-100 kph [s]	Maximum DC charging power [kW]	\	
48	7.9	125		
49	8.5	125		
40	4.4	150		
	mean - Energy consumption [kWh/100 km]			
48	15.9			
49	18.0			
40	NaN			

[3 rows x 25 columns]

## TASK=5

```
In [14]: from scipy.stats import ttest_ind
# Data of two companies as a list
tesla_power = [285, 372, 480, 525, 772, 525, 772]
audi_power = [360, 313, 503, 313, 360, 503]
# Compute averages
avg_tesla = sum(tesla_power) / len(tesla_power)
avg_audi = sum(audi_power) / len(audi_power)
# Perform a two-step t-test
t_stat, p_value = ttest_ind(tesla_power, audi_power, equal_var=False)
# Print results
```

```
print(f"Tesla Average Power: {avg_tesla:.2f} KM")
print(f"Audi Average Power: {avg_audi:.2f} KM")
print(f"T-statistic: {t_stat:.3f}")
print(f"P-value: {p_value:.4f}")
```

Tesla Average Power: 533.00 KM  
Audi Average Power: 392.00 KM  
T-statistic: 1.794  
P-value: 0.1068

**Conclusion: Reject  $H_0$  – significant difference in engine power.**

## Insights

In [ ]: Tesla's vehicles have significantly higher average engine power (533 KM) than Audi. This means the difference in engine power is statistically significant. Although the p-value suggests the result is not statistically significant, the result is practically meaningful to consumers or engineers.

$$p = 0.1068 > 0.05$$

We fail to reject the null hypothesis. This means there is no statistically significant difference in engine power between Tesla and Audi vehicles at the 5% significance level.

In [ ]: **## RECOMMENDATIONS**  
Investigate whether factors like car model, engine, or weight affect engine power. Include a measure like Cohen's d to understand the practical magnitude of the difference. A larger sample might reduce variability and reveal a significant effect if it exists.

video link-

<https://drive.google.com/file/d/1Yf1sN6VlVIRzeSWp-jZVI5ptkLwggOl6/view?usp=sharing>

click the box when you see hand sign