```
# This Python 3 environment comes with many helpful analytics
libraries installed
# It is defined by the kaggle/python Docker image:
https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/"
directory
# For example, running this (by clicking run or pressing Shift+Enter)
will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/)
that gets preserved as output when you create a version using "Save &
Run All"
# You can also write temporary files to /kaggle/temp/, but they won't
be saved outside of the current session
```

```
/kaggle/input/electric-vehicle-specifications-dataset-2025/
electric_vehicles_spec_2025.csv.csv
```

imports

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.neighbors import KNeighborsRegressor
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.linear_model import LinearRegression
import xgboost as xgb
from tabulate import tabulate

import scipy.stats as stats
import warnings
warnings.filterwarnings('ignore')

import pandas as pd

df = pd.read_csv('/kaggle/input/electric-vehicle-specifications-
dataset-2025/electric_vehicles_spec_2025.csv.csv')
df.head()
```

```
    brand                 model  top_speed_kmh  battery_capacity_kWh  \
0  Abarth     500e Convertible            155                  37.8
1  Abarth       500e Hatchback            155                  37.8
2  Abarth  600e Scorpionissima            200                  50.8
3  Abarth         600e Turismo            200                  50.8
4  Aiways                   U5            150                  60.0

  battery_type  number_of_cells  torque_nm  efficiency_wh_per_km
range_km  \
0  Lithium-ion            192.0      235.0                   156
225
1  Lithium-ion            192.0      235.0                   149
225
2  Lithium-ion            102.0      345.0                   158
280
3  Lithium-ion            102.0      345.0                   158
280
4  Lithium-ion              NaN      310.0                   156
315

   acceleration_0_100_s  ...  towing_capacity_kg cargo_volume_l  seats
\
0                   7.0  ...                 0.0            185      4

1                   7.0  ...                 0.0            185      4

2                   5.9  ...                 0.0            360      5

3                   6.2  ...                 0.0            360      5

4                   7.5  ...                 NaN            496      5


  drivetrain       segment length_mm width_mm  height_mm
car_body_type  \
0        FWD   B - Compact      3673     1683       1518
Hatchback
1        FWD   B - Compact      3673     1683       1518
Hatchback
2        FWD  JB - Compact      4187     1779       1557
SUV
3        FWD  JB - Compact      4187     1779       1557
SUV
4        FWD   JC - Medium      4680     1865       1700
SUV

                                          source_url
0  https://ev-database.org/car/1904/Abarth-500e-C...
1  https://ev-database.org/car/1903/Abarth-500e-H...
2  https://ev-database.org/car/3057/Abarth-600e-S...
3  https://ev-database.org/car/3056/Abarth-600e-T...
```

```
4         https://ev-database.org/car/1678/Aiways-U5

[5 rows x 22 columns]
```

```
import pandas as pd

# Load the dataset
df = pd.read_csv('/kaggle/input/electric-vehicle-specifications-
dataset-2025/electric_vehicles_spec_2025.csv.csv')

# Basic Info
print("Shape:", df.shape)                    # Rows and columns
print("Columns:", df.columns.tolist())       # List of columns
df.info()                                    # Data types and non-null
counts
df.describe(include='all')                   # Summary statistics
(numeric & categorical)

# Display first & last rows
display(df.head())
display(df.tail())

# Check for missing values
print("\nMissing values per column:")
print(df.isnull().sum())

# Drop duplicate rows if any
df = df.drop_duplicates()

# Standardize column names (optional cleanup)
df.columns = df.columns.str.strip().str.lower().str.replace(' ',
'_').str.replace(r'[^\w]', '', regex=True)

# Check unique values per column (especially for categorical analysis)
for col in df.columns:
    print(f"\nUnique values in '{col}':", df[col].nunique())

# Correlation matrix for numeric columns
print("\nCorrelation matrix:")
print(df.corr(numeric_only=True))

# Value counts for categorical fields (if they exist)
categorical_cols = df.select_dtypes(include='object').columns
for col in categorical_cols:
    print(f"\nValue counts for '{col}':")
    print(df[col].value_counts().head())

# Example of filtering: EVs with top range
if 'range_km' in df.columns:
    top_range_vehicles = df.sort_values(by='range_km',
ascending=False).head(10)
```

```
    print("\nTop 10 electric vehicles by range:")
    display(top_range_vehicles)

# Save cleaned version (optional)
# df.to_csv("cleaned_ev_dataset.csv", index=False)
```

```
Shape: (478, 22)
Columns: ['brand', 'model', 'top_speed_kmh', 'battery_capacity_kWh',
'battery_type', 'number_of_cells', 'torque_nm',
'efficiency_wh_per_km', 'range_km', 'acceleration_0_100_s',
'fast_charging_power_kw_dc', 'fast_charge_port', 'towing_capacity_kg',
'cargo_volume_l', 'seats', 'drivetrain', 'segment', 'length_mm',
'width_mm', 'height_mm', 'car_body_type', 'source_url']
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 478 entries, 0 to 477
Data columns (total 22 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   brand                       478 non-null    object
 1   model                       477 non-null    object
 2   top_speed_kmh               478 non-null    int64
 3   battery_capacity_kWh        478 non-null    float64
 4   battery_type                478 non-null    object
 5   number_of_cells             276 non-null    float64
 6   torque_nm                   471 non-null    float64
 7   efficiency_wh_per_km        478 non-null    int64
 8   range_km                    478 non-null    int64
 9   acceleration_0_100_s        478 non-null    float64
 10  fast_charging_power_kw_dc   477 non-null    float64
 11  fast_charge_port            477 non-null    object
 12  towing_capacity_kg          452 non-null    float64
 13  cargo_volume_l              477 non-null    object
 14  seats                       478 non-null    int64
 15  drivetrain                  478 non-null    object
 16  segment                     478 non-null    object
 17  length_mm                   478 non-null    int64
 18  width_mm                    478 non-null    int64
 19  height_mm                   478 non-null    int64
 20  car_body_type               478 non-null    object
 21  source_url                  478 non-null    object
dtypes: float64(6), int64(7), object(9)
memory usage: 82.3+ KB
```

```
    brand                 model  top_speed_kmh  battery_capacity_kWh  \
0  Abarth     500e Convertible            155                  37.8
1  Abarth       500e Hatchback            155                  37.8
2  Abarth  600e Scorpionissima            200                  50.8
3  Abarth         600e Turismo            200                  50.8
4  Aiways                   U5            150                  60.0
```

```
  battery_type  number_of_cells  torque_nm  efficiency_wh_per_km
range_km  \
0  Lithium-ion            192.0      235.0                   156
225
1  Lithium-ion            192.0      235.0                   149
225
2  Lithium-ion            102.0      345.0                   158
280
3  Lithium-ion            102.0      345.0                   158
280
4  Lithium-ion              NaN      310.0                   156
315

   acceleration_0_100_s  ...  towing_capacity_kg cargo_volume_l  seats
\
0                   7.0  ...                 0.0            185      4

1                   7.0  ...                 0.0            185      4

2                   5.9  ...                 0.0            360      5

3                   6.2  ...                 0.0            360      5

4                   7.5  ...                 NaN            496      5


  drivetrain       segment length_mm width_mm  height_mm
car_body_type  \
0        FWD   B - Compact      3673     1683       1518
Hatchback
1        FWD   B - Compact      3673     1683       1518
Hatchback
2        FWD  JB - Compact      4187     1779       1557
SUV
3        FWD  JB - Compact      4187     1779       1557
SUV
4        FWD   JC - Medium      4680     1865       1700
SUV

                                          source_url
0  https://ev-database.org/car/1904/Abarth-500e-C...
1  https://ev-database.org/car/1903/Abarth-500e-H...
2  https://ev-database.org/car/3057/Abarth-600e-S...
3  https://ev-database.org/car/3056/Abarth-600e-T...
4         https://ev-database.org/car/1678/Aiways-U5

[5 rows x 22 columns]

       brand                   model  top_speed_kmh
battery_capacity_kWh  \
```

```
473    Zeekr           7X Premium RWD            210
71.0
474    Zeekr        X Core RWD (MY25)            190
49.0
475    Zeekr  X Long Range RWD (MY25)            190
65.0
476    Zeekr   X Privilege AWD (MY25)            190
65.0
477  firefly                      NaN            150
41.2

    battery_type  number_of_cells  torque_nm  efficiency_wh_per_km
range_km  \
473  Lithium-ion              NaN      440.0                   148
365
474  Lithium-ion              NaN      343.0                   148
265
475  Lithium-ion              NaN      343.0                   146
360
476  Lithium-ion              NaN      543.0                   153
350
477  Lithium-ion            112.0      200.0                   125
250

     acceleration_0_100_s  ...  towing_capacity_kg cargo_volume_l
seats  \
473                   6.0  ...              2000.0            539
5
474                   5.9  ...              1600.0            362
5
475                   5.6  ...              1600.0            362
5
476                   3.8  ...              1600.0            362
5
477                   8.1  ...                 0.0            404
5

    drivetrain       segment length_mm width_mm  height_mm
car_body_type  \
473        RWD    JD - Large      4787     1930       1650
SUV
474        RWD  JB - Compact      4432     1836       1566
SUV
475        RWD  JB - Compact      4432     1836       1566
SUV
476        AWD  JB - Compact      4432     1836       1566
SUV
477        RWD   B - Compact      4003     1885       1557
Hatchback
```

```
                                                source_url
473  https://ev-database.org/car/3081/Zeekr-7X-Prem...
474  https://ev-database.org/car/3197/Zeekr-X-Core-RWD
475  https://ev-database.org/car/3198/Zeekr-X-Long-...
476  https://ev-database.org/car/3199/Zeekr-X-Privi...
477   https://ev-database.org/car/3178/firefly-firefly

[5 rows x 22 columns]


Missing values per column:
brand                          0
model                          1
top_speed_kmh                  0
battery_capacity_kWh           0
battery_type                   0
number_of_cells              202
torque_nm                      7
efficiency_wh_per_km           0
range_km                       0
acceleration_0_100_s           0
fast_charging_power_kw_dc      1
fast_charge_port               1
towing_capacity_kg            26
cargo_volume_l                 1
seats                          0
drivetrain                     0
segment                        0
length_mm                      0
width_mm                       0
height_mm                      0
car_body_type                  0
source_url                     0
dtype: int64

Unique values in 'brand': 59

Unique values in 'model': 477

Unique values in 'top_speed_kmh': 38

Unique values in 'battery_capacity_kwh': 121

Unique values in 'battery_type': 1

Unique values in 'number_of_cells': 38

Unique values in 'torque_nm': 128

Unique values in 'efficiency_wh_per_km': 112
```

```
Unique values in 'range_km': 88

Unique values in 'acceleration_0_100_s': 97

Unique values in 'fast_charging_power_kw_dc': 71

Unique values in 'fast_charge_port': 2

Unique values in 'towing_capacity_kg': 26

Unique values in 'cargo_volume_l': 140

Unique values in 'seats': 7

Unique values in 'drivetrain': 3

Unique values in 'segment': 15

Unique values in 'length_mm': 172

Unique values in 'width_mm': 108

Unique values in 'height_mm': 162

Unique values in 'car_body_type': 8

Unique values in 'source_url': 478

Correlation matrix:
                           top_speed_kmh  battery_capacity_kwh  \
top_speed_kmh                   1.000000              0.708486
battery_capacity_kwh            0.708486              1.000000
number_of_cells                 0.361792              0.214515
torque_nm                       0.805513              0.756932
efficiency_wh_per_km            0.171242              0.383607
range_km                        0.732130              0.880433
acceleration_0_100_s           -0.823443             -0.643716
fast_charging_power_kw_dc       0.771810              0.728066
towing_capacity_kg              0.231041              0.451132
seats                          -0.315572              0.013413
length_mm                       0.443686              0.689293
width_mm                        0.535850              0.731496
height_mm                      -0.462712             -0.055999

                           number_of_cells  torque_nm
efficiency_wh_per_km  \
top_speed_kmh                     0.361792   0.805513
0.171242
battery_capacity_kwh              0.214515   0.756932
0.383607
number_of_cells                   1.000000   0.164120             -
```

```
0.077907
torque_nm                          0.164120   1.000000
0.370422
efficiency_wh_per_km              -0.077907   0.370422
1.000000
range_km                           0.311014   0.651651
0.022943
acceleration_0_100_s              -0.254122  -0.787623              -
0.066512
fast_charging_power_kw_dc          0.094389   0.656593
0.182031
towing_capacity_kg                 0.070286   0.352548
0.250221
seats                              0.030315  -0.162736
0.522634
length_mm                          0.181904   0.508932
0.644838
width_mm                           0.205763   0.572241
0.573535
height_mm                         -0.132658  -0.195872
0.512614

                            range_km  acceleration_0_100_s  \
top_speed_kmh               0.732130             -0.823443
battery_capacity_kwh        0.880433             -0.643716
number_of_cells             0.311014             -0.254122
torque_nm                   0.651651             -0.787623
efficiency_wh_per_km        0.022943             -0.066512
range_km                    1.000000             -0.712486
acceleration_0_100_s       -0.712486              1.000000
fast_charging_power_kw_dc   0.720932             -0.628553
towing_capacity_kg          0.333962             -0.286155
seats                      -0.248784              0.441376
length_mm                   0.496867             -0.254990
width_mm                    0.521392             -0.395869
height_mm                  -0.413798              0.494811

                            fast_charging_power_kw_dc
towing_capacity_kg  \
top_speed_kmh                                0.771810
0.231041
battery_capacity_kwh                         0.728066
0.451132
number_of_cells                              0.094389
0.070286
torque_nm                                    0.656593
0.352548
efficiency_wh_per_km                         0.182031
0.250221
```

```
range_km                                    0.720932
0.333962
acceleration_0_100_s                       -0.628553           -
0.286155
fast_charging_power_kw_dc                   1.000000
0.236353
towing_capacity_kg                          0.236353
1.000000
seats                                      -0.128115
0.151832
length_mm                                   0.474058
0.401418
width_mm                                    0.574412
0.468550
height_mm                                  -0.290376
0.300047

                             seats  length_mm  width_mm  height_mm
top_speed_kmh             -0.315572   0.443686  0.535850  -0.462712
battery_capacity_kwh       0.013413   0.689293  0.731496  -0.055999
number_of_cells            0.030315   0.181904  0.205763  -0.132658
torque_nm                 -0.162736   0.508932  0.572241  -0.195872
efficiency_wh_per_km       0.522634   0.644838  0.573535   0.512614
range_km                  -0.248784   0.496867  0.521392  -0.413798
acceleration_0_100_s       0.441376  -0.254990 -0.395869   0.494811
fast_charging_power_kw_dc -0.128115   0.474058  0.574412  -0.290376
towing_capacity_kg         0.151832   0.401418  0.468550   0.300047
seats                      1.000000   0.458281  0.305574   0.697256
length_mm                  0.458281   1.000000  0.849505   0.248637
width_mm                   0.305574   0.849505  1.000000   0.228964
height_mm                  0.697256   0.248637  0.228964   1.000000

Value counts for 'brand':
brand
Mercedes-Benz    42
Audi             28
Porsche          26
Volkswagen       23
Ford             22
Name: count, dtype: int64

Value counts for 'model':
model
500e Convertible              1
e-Traveller L2 50 kWh         1
4 Long Range Single Motor     1
4 Long Range Dual Motor       1
3 Long Range Single motor     1
Name: count, dtype: int64
```

```
Value counts for 'battery_type':
battery_type
Lithium-ion    478
Name: count, dtype: int64

Value counts for 'fast_charge_port':
fast_charge_port
CCS        476
CHAdeMO      1
Name: count, dtype: int64

Value counts for 'cargo_volume_l':
cargo_volume_l
520    17
490    10
519    10
407    10
405     9
Name: count, dtype: int64

Value counts for 'drivetrain':
drivetrain
AWD    191
FWD    156
RWD    131
Name: count, dtype: int64

Value counts for 'segment':
segment
JC - Medium          91
JD - Large           58
F - Luxury           51
N - Passenger Van    47
JB - Compact         44
Name: count, dtype: int64

Value counts for 'car_body_type':
car_body_type
SUV                    244
Sedan                   63
Hatchback               57
Small Passenger Van     47
Liftback Sedan          33
Name: count, dtype: int64

Value counts for 'source_url':
source_url
https://ev-database.org/car/1904/Abarth-500e-Convertible
1
https://ev-database.org/car/2256/Peugeot-e-Traveller-L2-50-kWh
```

```
1
https://ev-database.org/car/1841/Polestar-4-Long-Range-Single-Motor
1
https://ev-database.org/car/1842/Polestar-4-Long-Range-Dual-Motor
1
https://ev-database.org/car/2229/Polestar-3-Long-Range-Single-motor
1
Name: count, dtype: int64

Top 10 electric vehicles by range:

             brand                              model  top_speed_kmh  \
239  Mercedes-Benz                          EQS 450+            210
194          Lucid                 Air Grand Touring            270
238  Mercedes-Benz                    EQS 450 4MATIC            210
241  Mercedes-Benz                    EQS 580 4MATIC            210
240  Mercedes-Benz                    EQS 500 4MATIC            210
14            Audi  A6 Sportback e-tron performance            210
15            Audi      A6 Sportback e-tron quattro            210
242  Mercedes-Benz                EQS AMG 53 4MATIC+            250
196          Lucid                       Air Touring            250
11            Audi      A6 Avant e-tron performance            210

     battery_capacity_kwh battery_type  number_of_cells  torque_nm  \
239                 118.0  Lithium-ion              NaN      568.0
194                 112.0  Lithium-ion           6600.0     1200.0
238                 118.0  Lithium-ion              NaN      800.0
241                 118.0  Lithium-ion              NaN      858.0
240                 118.0  Lithium-ion              NaN      828.0
14                   94.9  Lithium-ion            180.0      565.0
15                   94.9  Lithium-ion            180.0      855.0
242                 118.0  Lithium-ion              NaN     1020.0
196                  92.0  Lithium-ion           5400.0        NaN
11                   94.9  Lithium-ion            180.0      565.0

     efficiency_wh_per_km  range_km  acceleration_0_100_s  ...  \
239                   173       685                   6.2  ...
194                   143       665                   3.0  ...
238                   180       655                   5.7  ...
241                   180       640                   4.4  ...
240                   180       640                   4.9  ...
14                    141       610                   5.4  ...
15                    147       590                   4.7  ...
242                   222       585                   3.4  ...
196                   142       580                   3.2  ...
11                    151       575                   5.4  ...

     towing_capacity_kg cargo_volume_l  seats drivetrain
segment  \
239               750.0            620      5        RWD      F -
```

```
Luxury
194                  0.0             456      5        AWD      F -
Luxury
238               1700.0             620      5        AWD      F -
Luxury
241               1700.0             620      5        AWD      F -
Luxury
240               1700.0             620      5        AWD      F -
Luxury
14                2100.0             502      5        RWD  JE -
Executive
15                2100.0             502      5        AWD  JE -
Executive
242               1700.0             620      5        AWD      F -
Luxury
196                  0.0             456      5        AWD      F -
Luxury
11                2100.0             502      5        RWD  JE -
Executive

    length_mm width_mm  height_mm   car_body_type  \
239      5223     1926       1518           Sedan
194      4975     1939       1410           Sedan
238      5223     1926       1518           Sedan
241      5223     1926       1518           Sedan
240      5223     1926       1518           Sedan
14       4928     1923       1455  Liftback Sedan
15       4928     1923       1455  Liftback Sedan
242      5223     1926       1518           Sedan
196      4975     1939       1410           Sedan
11       4928     1923       1455  Station/Estate

                                           source_url
239  https://ev-database.org/car/2193/Mercedes-Benz...
194  https://ev-database.org/car/1316/Lucid-Air-Gra...
238  https://ev-database.org/car/2194/Mercedes-Benz...
241  https://ev-database.org/car/2196/Mercedes-Benz...
240  https://ev-database.org/car/2195/Mercedes-Benz...
14   https://ev-database.org/car/2270/Audi-A6-Sport...
15   https://ev-database.org/car/3052/Audi-A6-Sport...
242  https://ev-database.org/car/2197/Mercedes-Benz...
196  https://ev-database.org/car/1317/Lucid-Air-Tou...
11   https://ev-database.org/car/2272/Audi-A6-Avant...

[10 rows x 22 columns]

df.shape

(478, 22)
```

```
df.columns
```

```
Index(['brand', 'model', 'top_speed_kmh', 'battery_capacity_kwh',
       'battery_type', 'number_of_cells', 'torque_nm',
'efficiency_wh_per_km',
       'range_km', 'acceleration_0_100_s',
'fast_charging_power_kw_dc',
       'fast_charge_port', 'towing_capacity_kg', 'cargo_volume_l',
'seats',
       'drivetrain', 'segment', 'length_mm', 'width_mm', 'height_mm',
       'car_body_type', 'source_url'],
      dtype='object')
```

```
categorical_cols = ['brand', 'model', 'battery_type',
'fast_charge_port',
                    'drivetrain', 'segment', 'car_body_type']

for col in categorical_cols:
    print(f"\n{col} value counts:")
    print(df[col].value_counts())
```

```
brand value counts:
brand
Mercedes-Benz    42
Audi             28
Porsche          26
Volkswagen       23
Ford             22
BMW              20
Peugeot          19
Volvo            18
BYD              17
Smart            17
Kia              16
Opel             14
Hyundai          14
Skoda            12
MG               12
NIO              12
Citroen          12
Renault          11
Tesla            11
Polestar          9
XPENG             9
Zeekr             9
Fiat              8
Mini              8
Toyota            7
Nissan            6
```

```
Lotus              6
GWM                6
Genesis            5
DS                 5
CUPRA              5
Abarth             4
Lucid              3
Hongqi             3
Maserati           3
Lexus              3
Alfa               2
Aiways             2
Alpine             2
Leapmotor          2
Jeep               2
Dacia              2
VinFast            2
Mazda              2
Skywell            2
Dongfeng           2
Elaris             1
Voyah              1
Cadillac           1
Maxus              1
Subaru             1
Honda              1
Rolls-Royce        1
Jaguar             1
KGM                1
Lancia             1
Omoda              1
Lynk&Co            1
firefly            1
Name: count, dtype: int64

model value counts:
model
500e Convertible              1
e-Traveller L2 50 kWh         1
4 Long Range Single Motor     1
4 Long Range Dual Motor       1
3 Long Range Single motor     1
                             ..
IONIQ 6 Long Range AWD        1
IONIQ 6 Long Range 2WD        1
IONIQ 5 N (MY24)              1
IONIQ 5 84 kWh RWD (MY24)     1
X Privilege AWD (MY25)        1
Name: count, Length: 477, dtype: int64
```

```
battery_type value counts:
battery_type
Lithium-ion    478
Name: count, dtype: int64

fast_charge_port value counts:
fast_charge_port
CCS        476
CHAdeMO      1
Name: count, dtype: int64

drivetrain value counts:
drivetrain
AWD    191
FWD    156
RWD    131
Name: count, dtype: int64

segment value counts:
segment
JC - Medium          91
JD - Large           58
F - Luxury           51
N - Passenger Van    47
JB - Compact         44
C - Medium           34
E - Executive        30
JF - Luxury          30
B - Compact          29
JE - Executive       28
D - Large            28
A - Mini              3
JA - Mini             2
G - Sports            2
I - Luxury            1
Name: count, dtype: int64

car_body_type value counts:
car_body_type
SUV                   244
Sedan                  63
Hatchback              57
Small Passenger Van    47
Liftback Sedan         33
Station/Estate         27
Cabriolet               5
Coupe                   2
Name: count, dtype: int64
```

```
numeric_cols = ['top_speed_kmh', 'battery_capacity_kwh',
'number_of_cells',
                'torque_nm', 'efficiency_wh_per_km', 'range_km',
                'acceleration_0_100_s', 'fast_charging_power_kw_dc',
                'towing_capacity_kg', 'cargo_volume_l', 'seats',
                'length_mm', 'width_mm', 'height_mm']

df[numeric_cols].describe().T  # Transposed for readability
```

	count	mean	std	min	25%	\
top_speed_kmh	478.0	185.487448	34.252773	125.0	160.0	
battery_capacity_kwh	478.0	74.043724	20.331058	21.3	60.0	
number_of_cells	276.0	485.293478	1210.819733	72.0	150.0	
torque_nm	471.0	498.012739	241.461128	113.0	305.0	
efficiency_wh_per_km	478.0	162.903766	34.317532	109.0	143.0	
range_km	478.0	393.179916	103.287335	135.0	320.0	
acceleration_0_100_s	478.0	6.882636	2.730696	2.2	4.8	
fast_charging_power_kw_dc	477.0	125.008386	58.205012	29.0	80.0	
towing_capacity_kg	452.0	1052.261062	737.851774	0.0	500.0	
seats	478.0	5.263598	1.003961	2.0	5.0	
length_mm	478.0	4678.506276	369.210573	3620.0	4440.0	
width_mm	478.0	1887.359833	73.656807	1610.0	1849.0	
height_mm	478.0	1601.125523	130.754851	1329.0	1514.0	

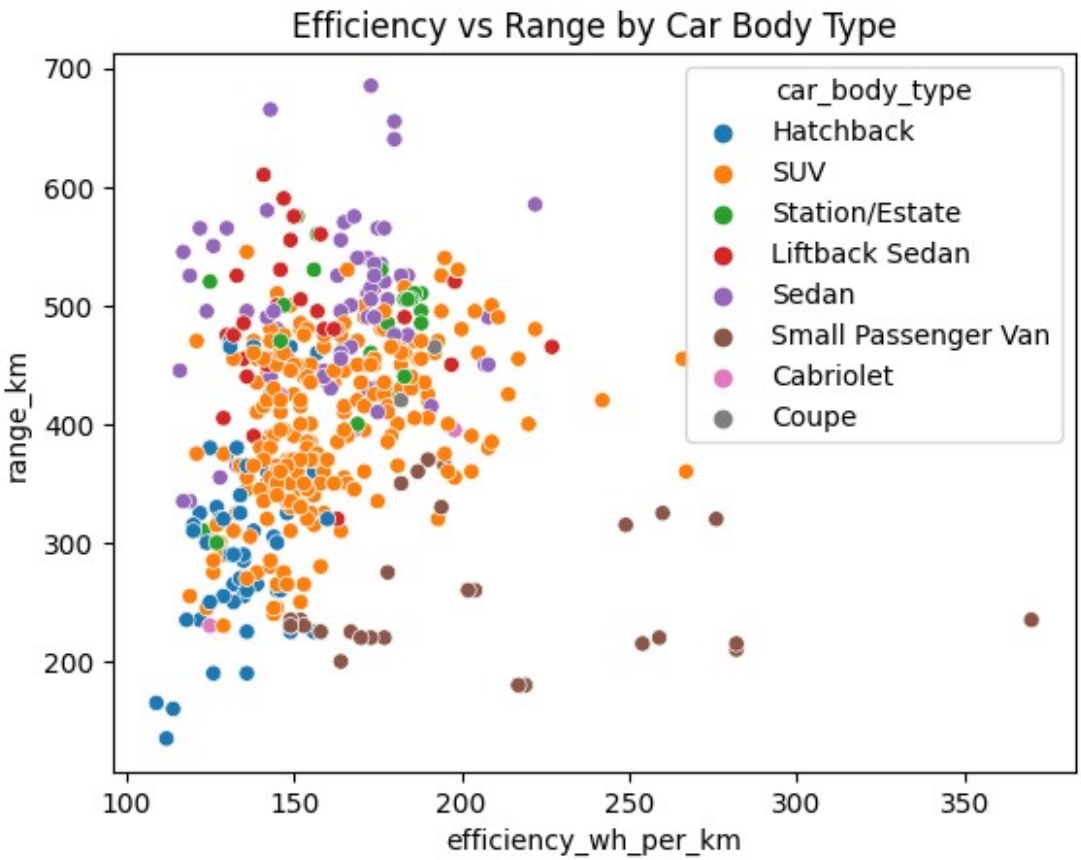
	50%	75%	max
top_speed_kmh	180.00	201.00	325.0
battery_capacity_kwh	76.15	90.60	118.0
number_of_cells	216.00	324.00	7920.0
torque_nm	430.00	679.00	1350.0
efficiency_wh_per_km	155.00	177.75	370.0
range_km	397.50	470.00	685.0
acceleration_0_100_s	6.60	8.20	19.1
fast_charging_power_kw_dc	113.00	150.00	281.0
towing_capacity_kg	1000.00	1600.00	2500.0
seats	5.00	5.00	9.0
length_mm	4720.00	4961.00	5908.0

```
width_mm                   1890.00  1939.00  2080.0
height_mm                  1596.00  1665.00  1986.0
```

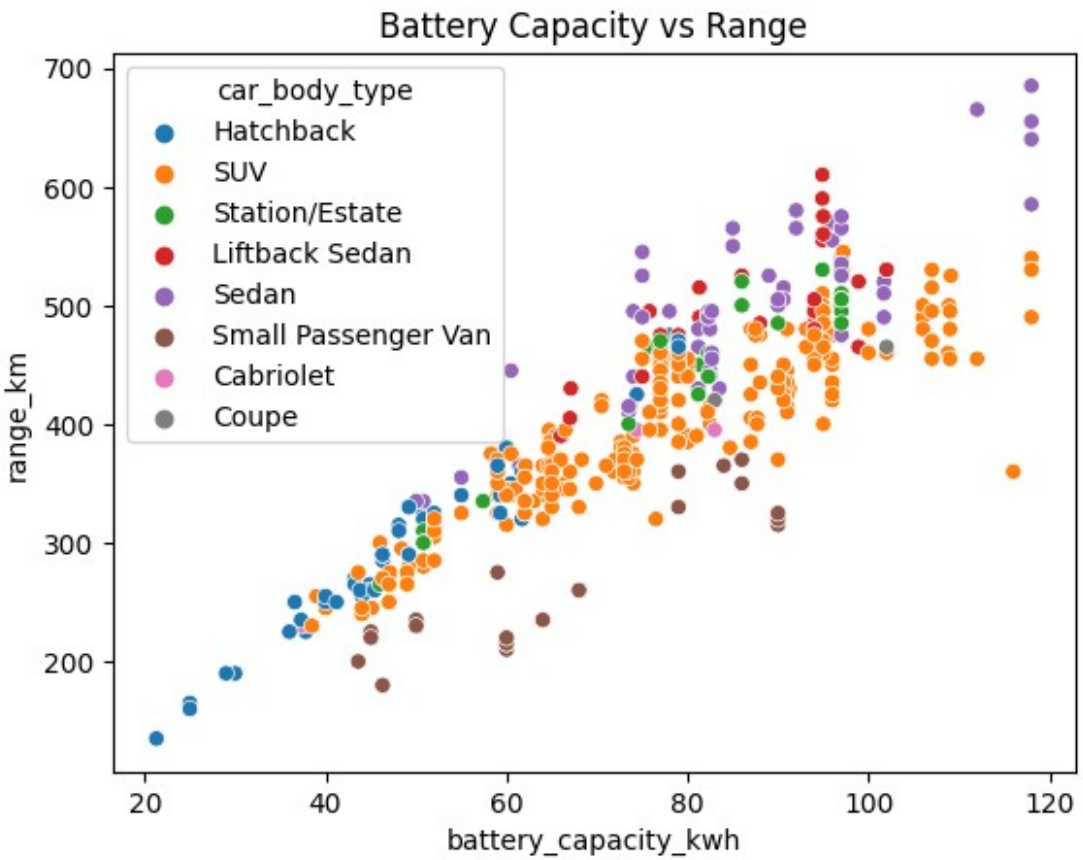
```
# Average range per brand
df.groupby('brand')['range_km'].mean().sort_values(ascending=False)

# Max acceleration by car segment
df.groupby('segment')['acceleration_0_100_s'].min().sort_values()
```

```
segment
F - Luxury             2.2
JF - Luxury            2.7
D - Large              3.2
G - Sports             3.2
JD - Large             3.3
JC - Medium            3.4
E - Executive          3.5
JE - Executive         3.5
JB - Compact           3.6
C - Medium             3.8
I - Luxury             4.5
B - Compact            5.9
N - Passenger Van      6.5
JA - Mini             10.6
A - Mini              12.7
Name: acceleration_0_100_s, dtype: float64
```

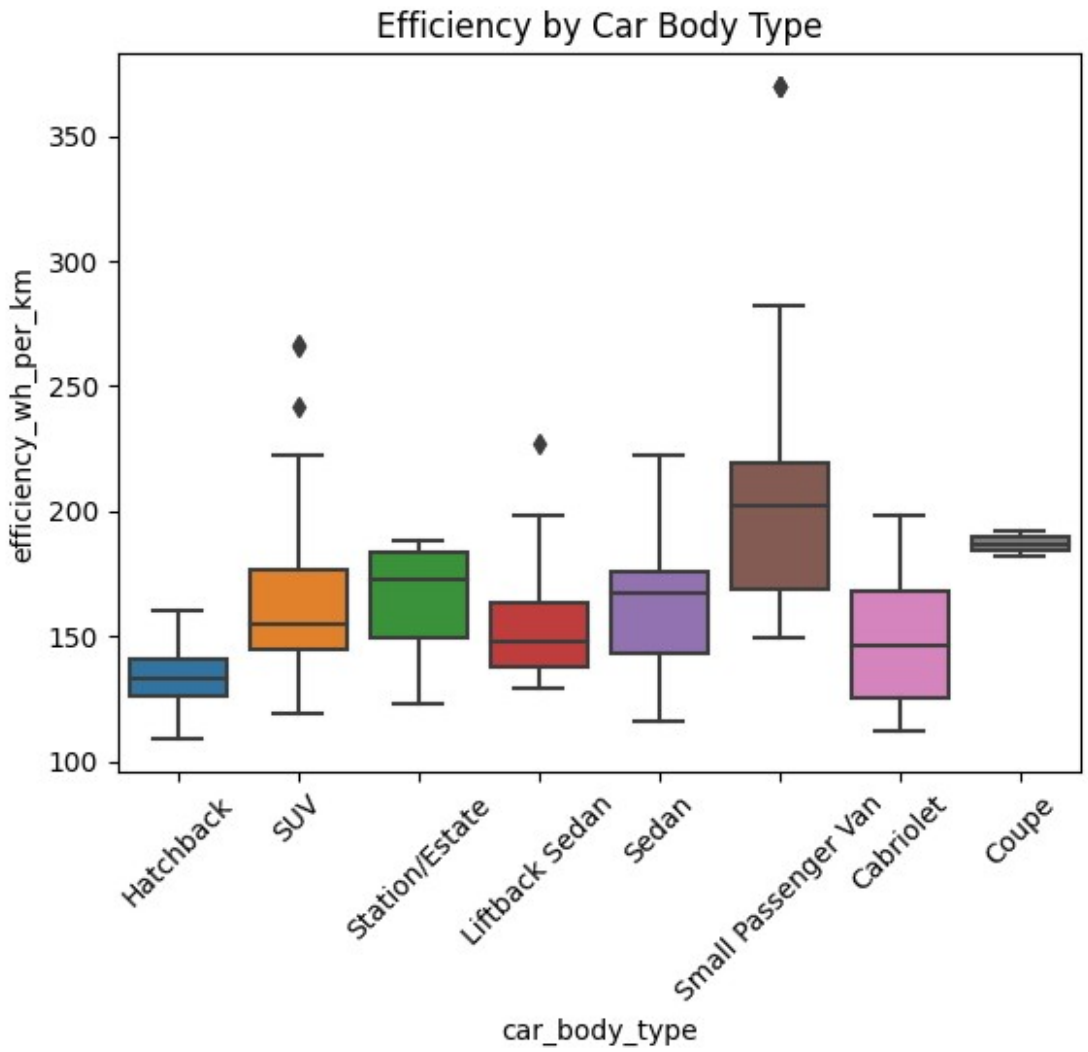
```
sns.scatterplot(data=df, x='efficiency_wh_per_km', y='range_km',
hue='car_body_type')
plt.title('Efficiency vs Range by Car Body Type')
plt.show()
```



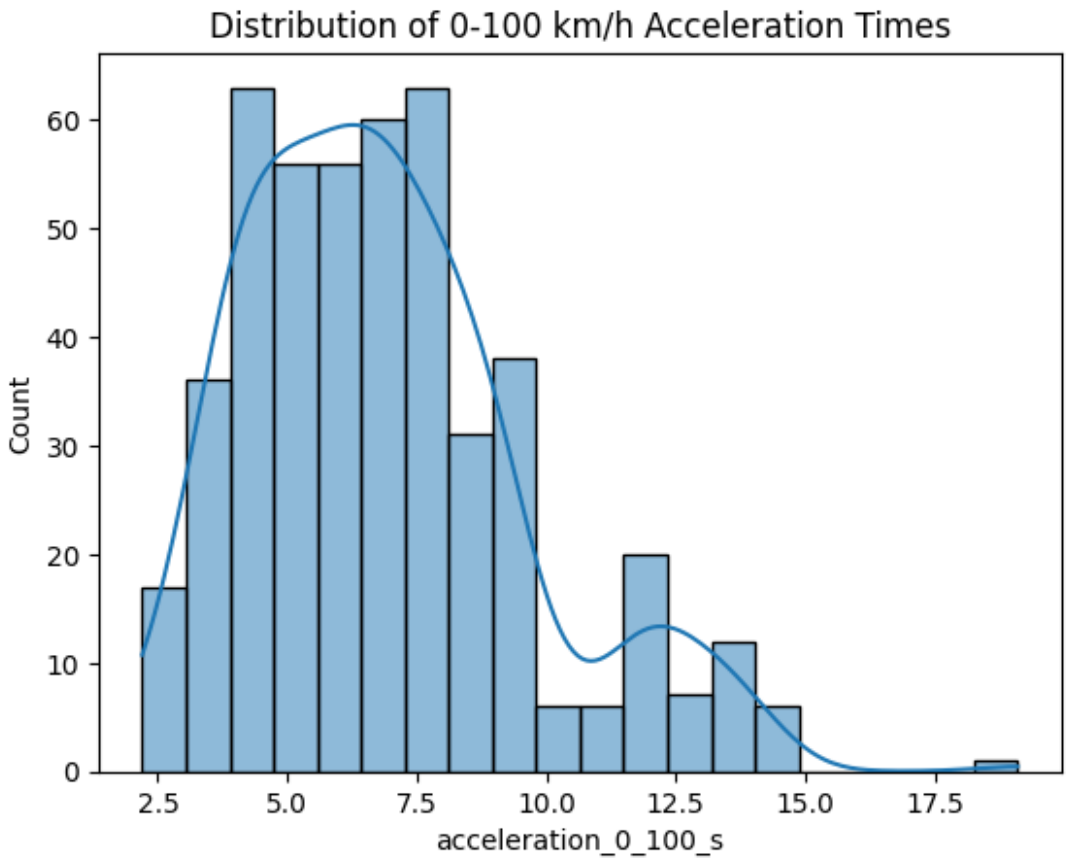

```
sns.scatterplot(data=df, x='battery_capacity_kwh', y='range_km',
hue='car_body_type')
plt.title('Battery Capacity vs Range')
plt.show()
```




```
sns.boxplot(data=df, x='car_body_type', y='efficiency_wh_per_km')
plt.xticks(rotation=45)
plt.title('Efficiency by Car Body Type')
plt.show()
```



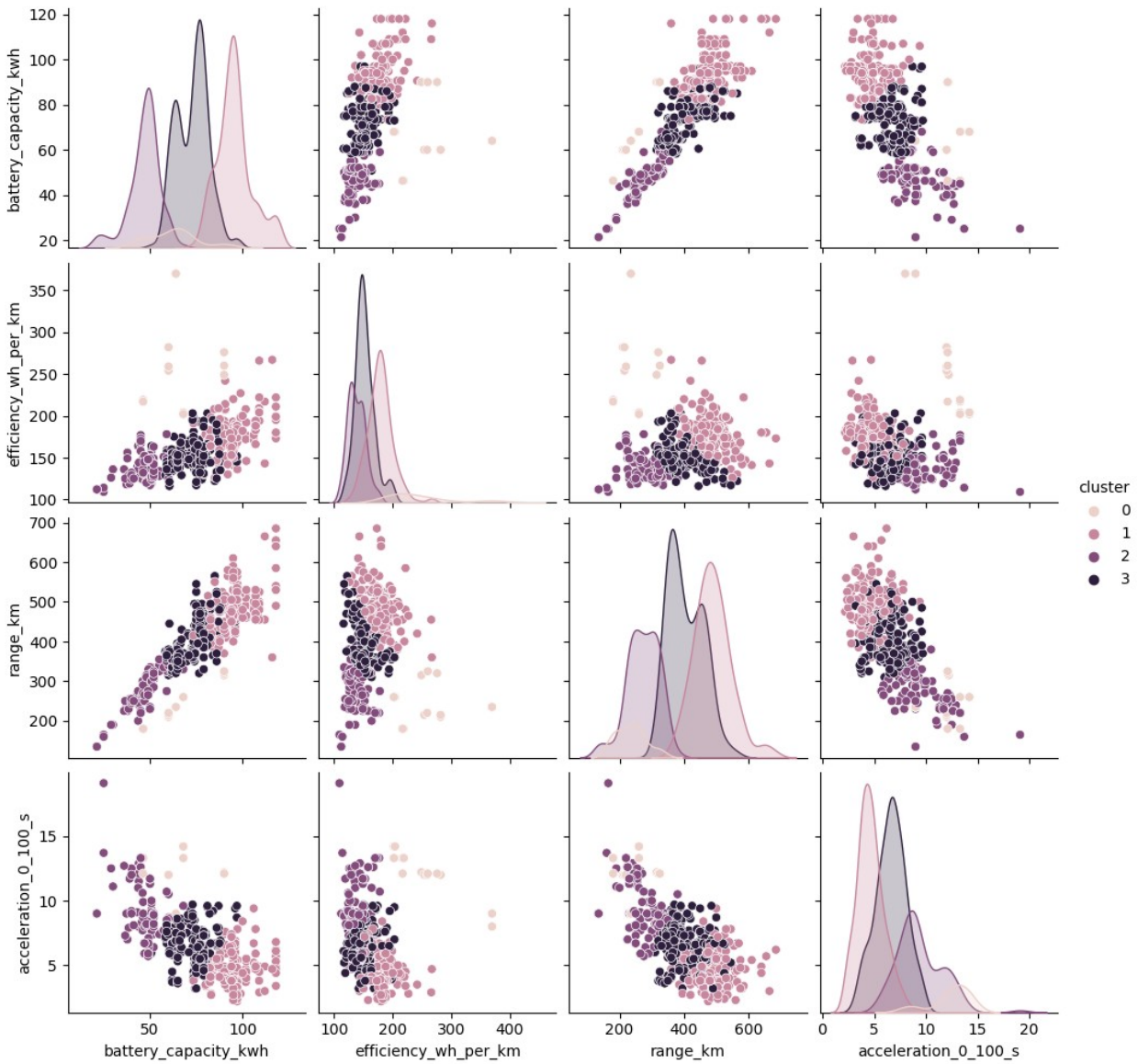

```
sns.histplot(df['acceleration_0_100_s'], bins=20, kde=True)
plt.title('Distribution of 0-100 km/h Acceleration Times')
plt.show()
```




```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error

# Επιλογή χαρακτηριστικών
features = ['battery_capacity_kwh', 'efficiency_wh_per_km',
'torque_nm',
            'acceleration_0_100_s', 'seats']
df_clean = df[features + ['range_km']].dropna()

X = df_clean[features]
y = df_clean['range_km']

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

model = RandomForestRegressor()
model.fit(X_train, y_train)

y_pred = model.predict(X_test)
print("MAE:", mean_absolute_error(y_test, y_pred))
```

```
MAE: 18.36068421052632
```

```
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

features = ['battery_capacity_kwh', 'efficiency_wh_per_km',
'range_km', 'acceleration_0_100_s']
df_cluster = df[features].dropna()

X_scaled = StandardScaler().fit_transform(df_cluster)

kmeans = KMeans(n_clusters=4, random_state=42)
df['cluster'] = kmeans.fit_predict(X_scaled)

sns.pairplot(df, vars=features, hue='cluster')
plt.show()
```



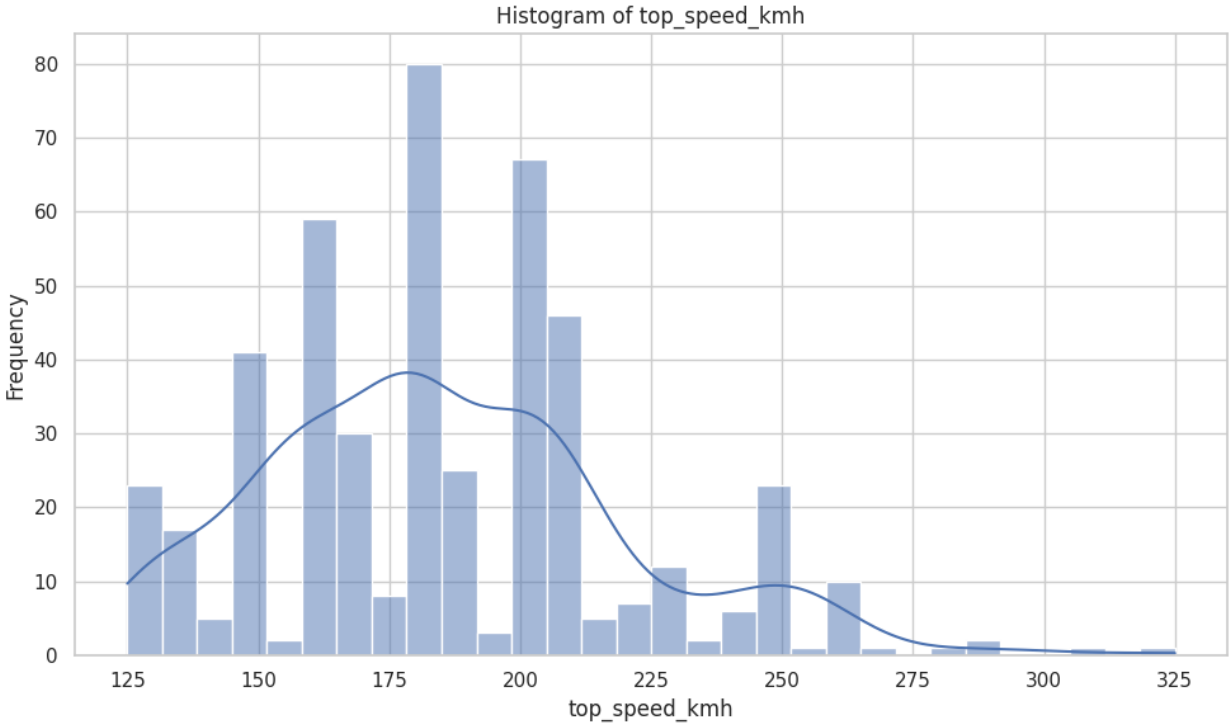
```python
# Προετοιμασία: μετατρέπουμε τις αριθμητικές στήλες σε float
columns_to_check = list(features_max.keys()) +
list(features_min.keys())

for col in columns_to_check:
    if col in df.columns:
        df[col] = pd.to_numeric(df[col], errors='coerce')  # μετατροπή
σε αριθμούς, αγνόηση λάθους

print("□ BEST ELECTRIC VEHICLES FOR 2025 FEATURES:\n")

# Μέγιστες τιμές = καλύτερες
for col, desc in features_max.items():
    if col in df.columns:
        best = df.loc[df[col].idxmax()]
        print(f"□ {desc}: {best['brand']} {best['model']} -
{best[col]}")

# Ελάχιστες τιμές = καλύτερες
for col, desc in features_min.items():
    if col in df.columns:
        best = df.loc[df[col].idxmin()]
        print(f"⚡ {desc}: {best['brand']} {best['model']} -
{best[col]}")
```

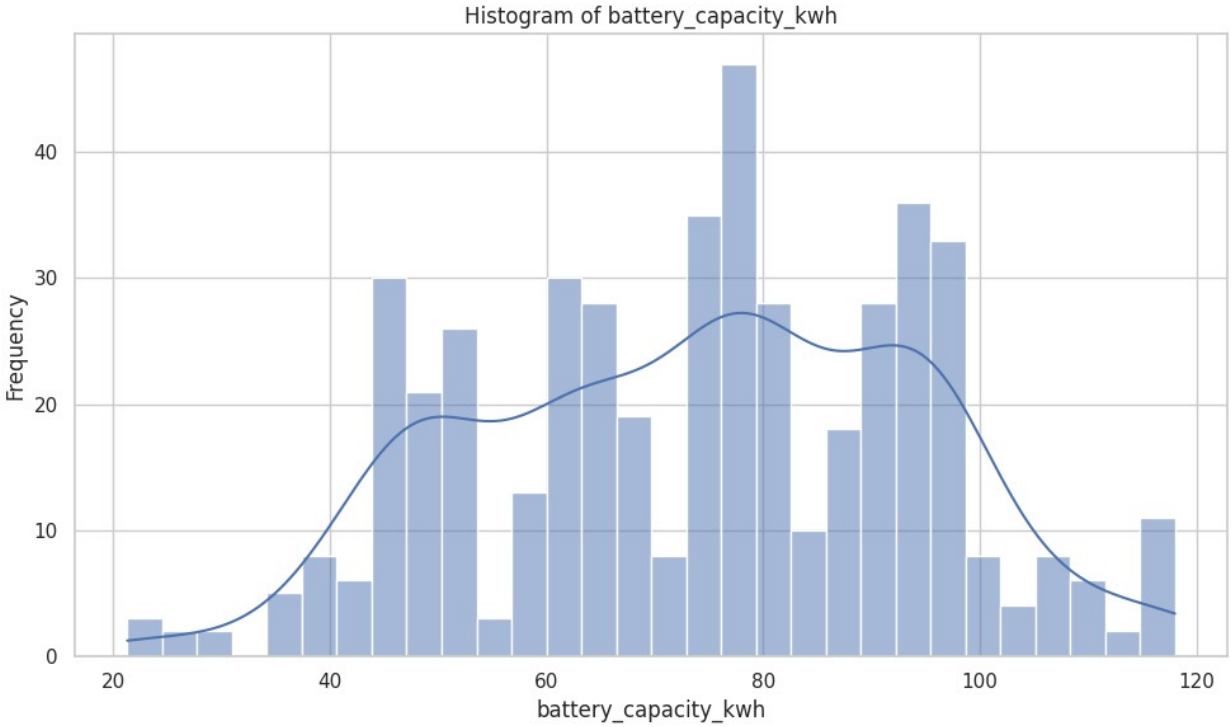
```
□ BEST ELECTRIC VEHICLES FOR 2025 FEATURES:

□ Top Speed (km/h): Maserati GranTurismo Folgore - 325
□ Battery Capacity (kWh): Mercedes-Benz EQS 450 4MATIC - 118.0
□ Torque (Nm): Maserati GranCabrio Folgore - 1350.0
□ Range (km): Mercedes-Benz EQS 450+ - 685
□ Fast Charging Power (kW): Audi e-tron GT RS - 281.0
□ Towing Capacity (kg): BMW iX M70 xDrive - 2500.0
□ Cargo Volume (L): Mercedes-Benz EQV 250 Extra-Long - 1410.0
□ Number of Seats: Citroen e-SpaceTourer M 50 kWh - 9
□ Longest EV: Ford e-Tourneo Custom L2 160 kW - 5908
□ Widest EV: Rolls-Royce Spectre - 2080
□ Tallest EV: Mercedes-Benz G 580 - 1986
⚡ Best Efficiency (Wh/km): Dacia Spring Electric 45 - 109
⚡ Fastest Acceleration (0-100 km/h): Porsche Taycan Turbo GT Weissach
- 2.2
```

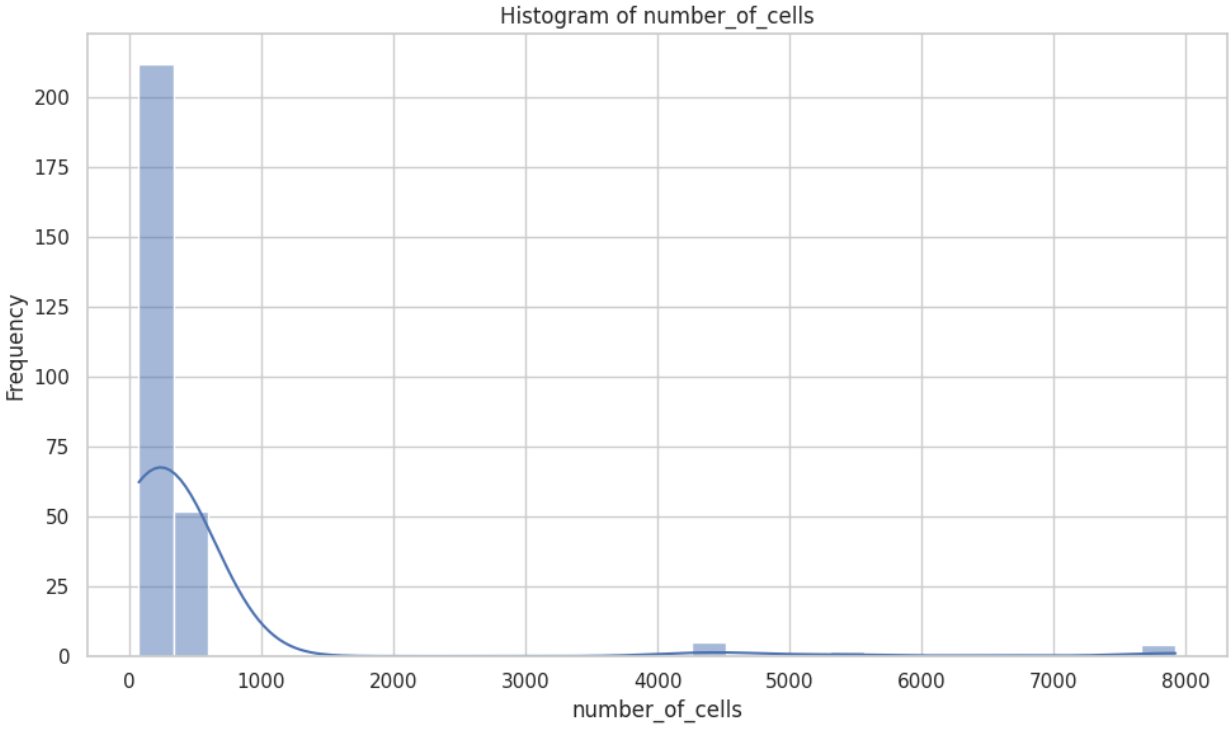
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Set style
sns.set(style="whitegrid")
plt.rcParams["figure.figsize"] = (10, 6)

# Μετατροπή όλων των αριθμητικών πεδίων σε float
```

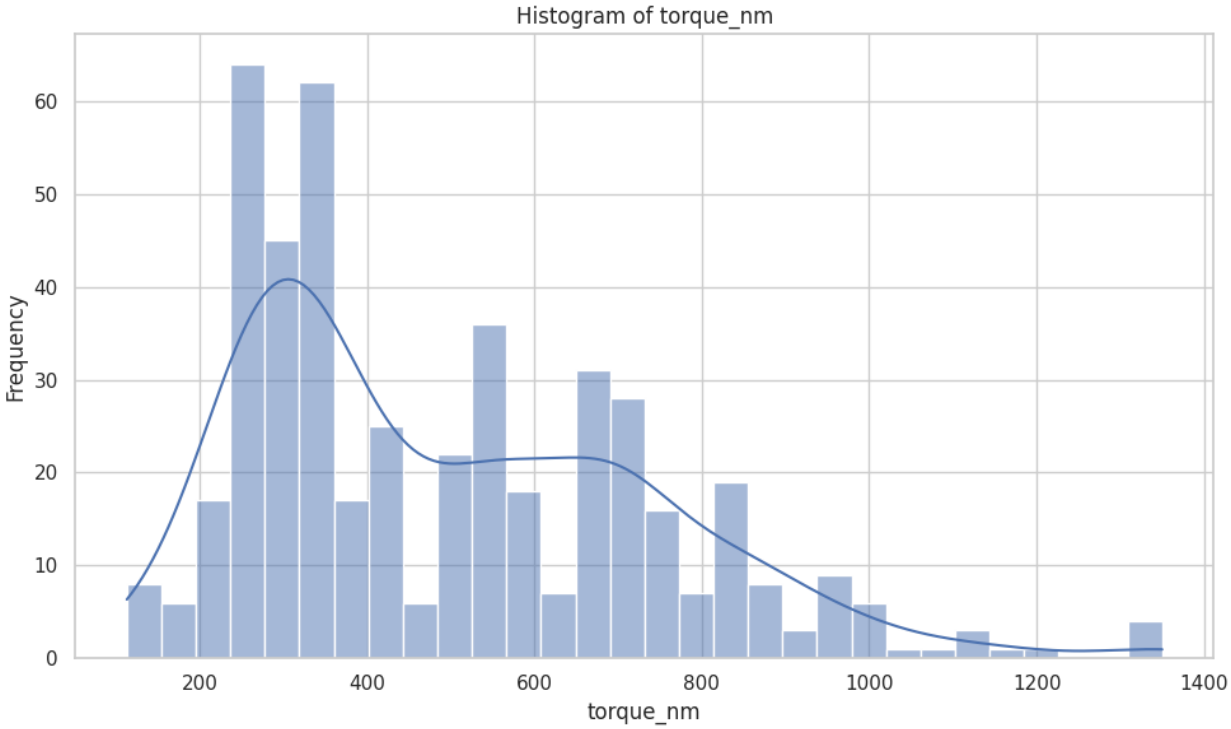
```
numeric_columns =
df.select_dtypes(include=['number']).columns.tolist()
for col in numeric_columns:
    df[col] = pd.to_numeric(df[col], errors='coerce')

# Κατηγορικές στήλες
categorical_columns =
df.select_dtypes(include='object').columns.tolist()

# ------------------------------
# □ HISTOGRAM για αριθμητικά
# ------------------------------
for col in numeric_columns:
    plt.figure()
    sns.histplot(df[col], bins=30, kde=True)
    plt.title(f"Histogram of {col}")
    plt.xlabel(col)
    plt.ylabel("Frequency")
    plt.tight_layout()
    plt.show()

# ------------------------------
# □ BOXPLOT για αριθμητικά
# ------------------------------
for col in numeric_columns:
    plt.figure()
    sns.boxplot(x=df[col])
    plt.title(f"Boxplot of {col}")
    plt.tight_layout()
    plt.show()

# ------------------------------
# □ BARPLOTS για κατηγορικές
# ------------------------------
for col in categorical_columns:
    plt.figure()
    top_vals = df[col].value_counts().head(10)
    sns.barplot(x=top_vals.values, y=top_vals.index)
    plt.title(f"Top 10 {col} values")
    plt.xlabel("Count")
    plt.ylabel(col)
    plt.tight_layout()
    plt.show()

# ------------------------------
# □ SCATTER PLOTS μεταξύ βασικών μεγεθών
# ------------------------------
scatter_pairs = [
    ("battery_capacity_kwh", "range_km"),
    ("efficiency_wh_per_km", "range_km"),
```

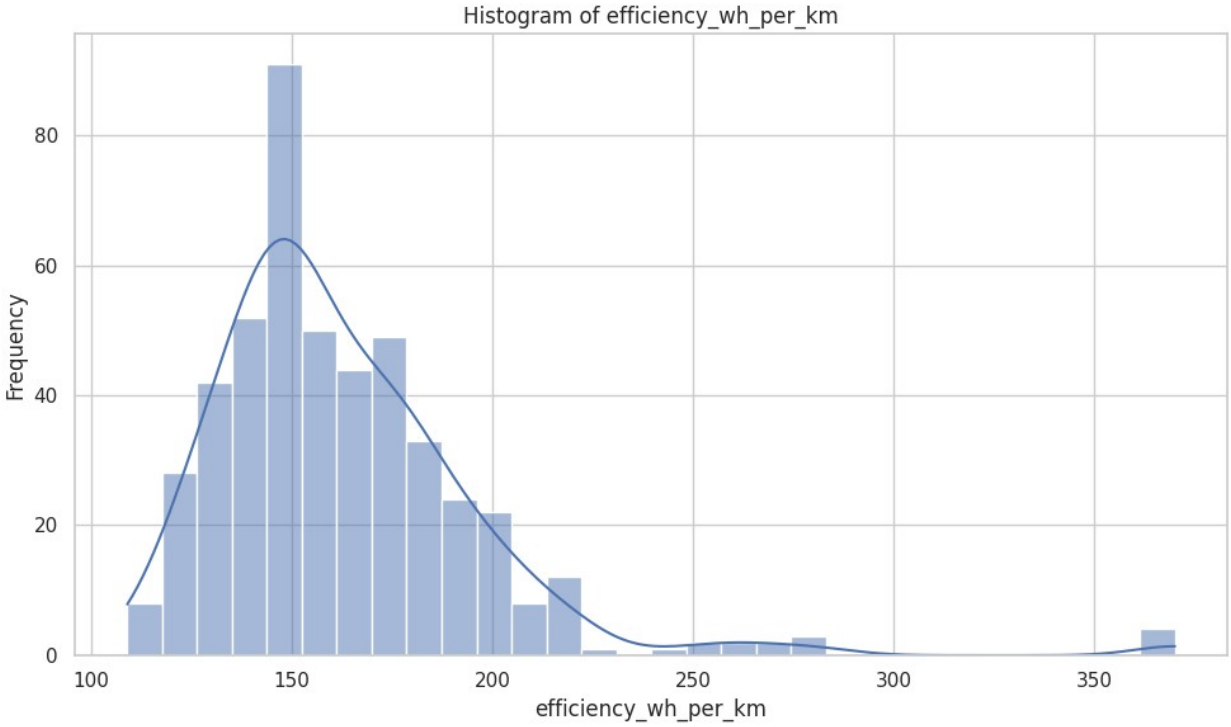
```
    ("acceleration_0_100_s", "top_speed_kmh"),
    ("torque_nm", "acceleration_0_100_s"),
    ("fast_charging_power_kw_dc", "range_km"),
]

for x, y in scatter_pairs:
    if x in df.columns and y in df.columns:
        plt.figure()
        sns.scatterplot(data=df, x=x, y=y, hue="car_body_type",
palette="tab10")
        plt.title(f"{y} vs {x}")
        plt.tight_layout()
        plt.show()
```

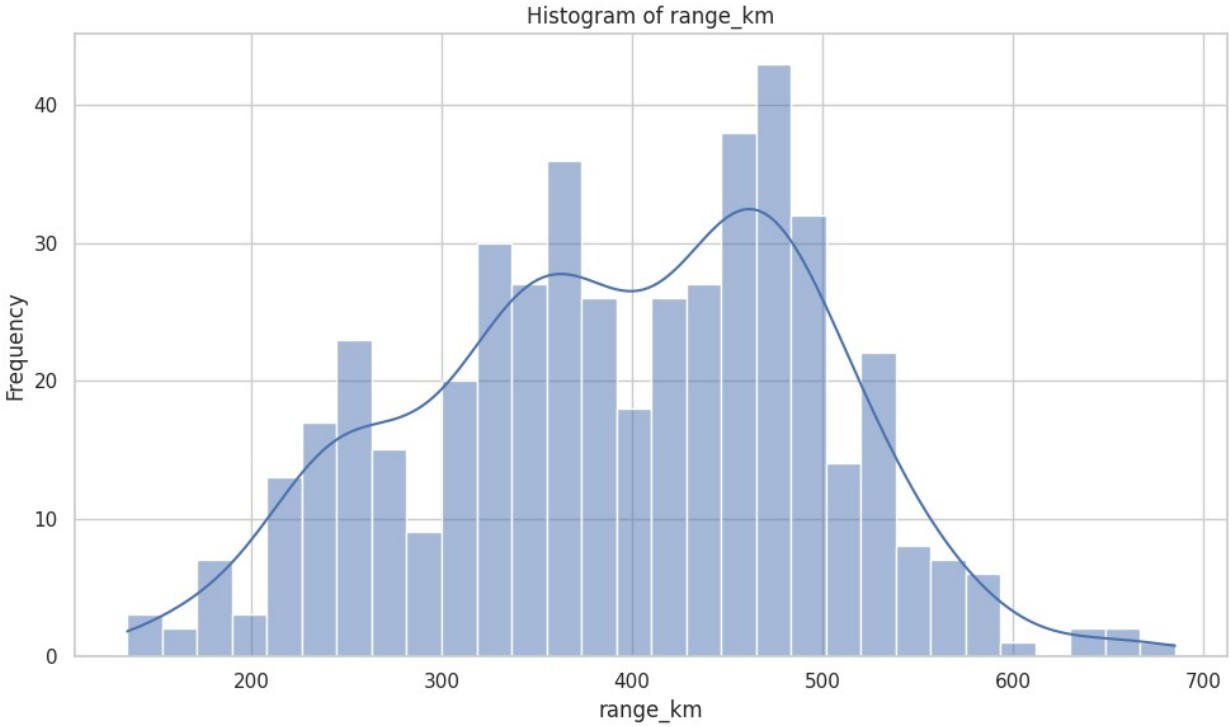


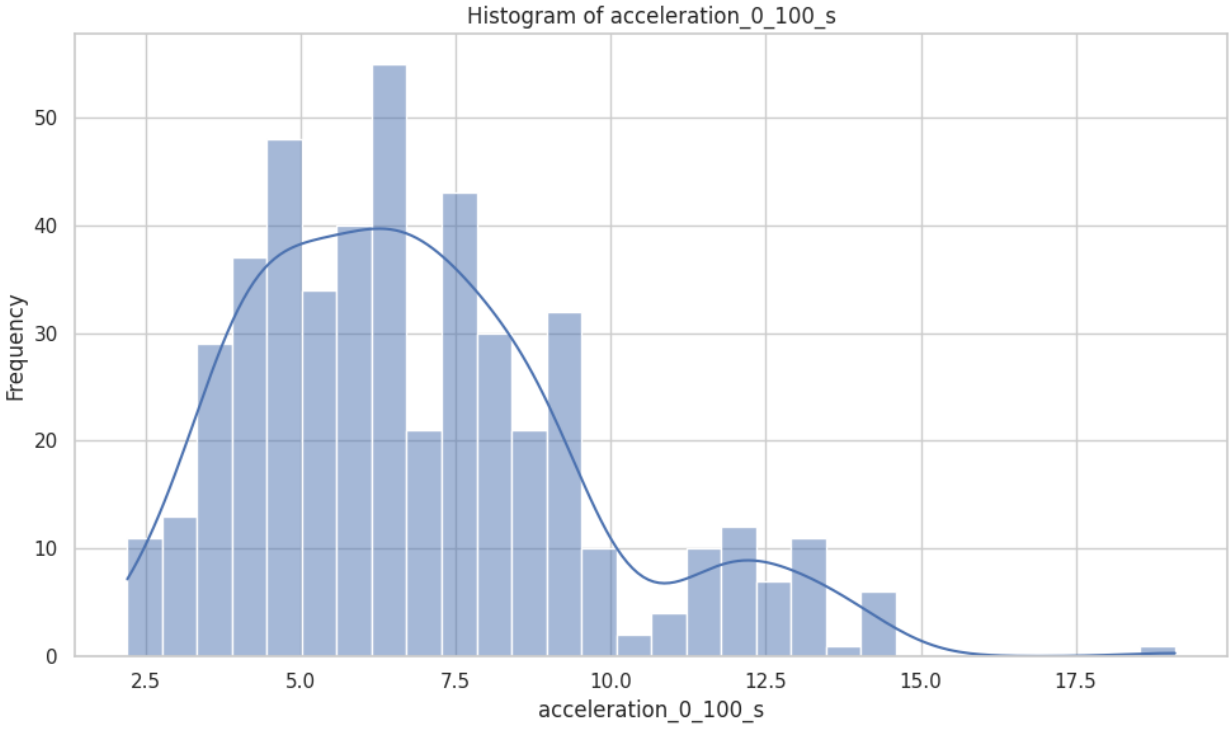

Histogram of battery_capacity_kwh
Frequency
0
10
20
30
40
20
40
60
80
100
120
battery_capacity_kwh

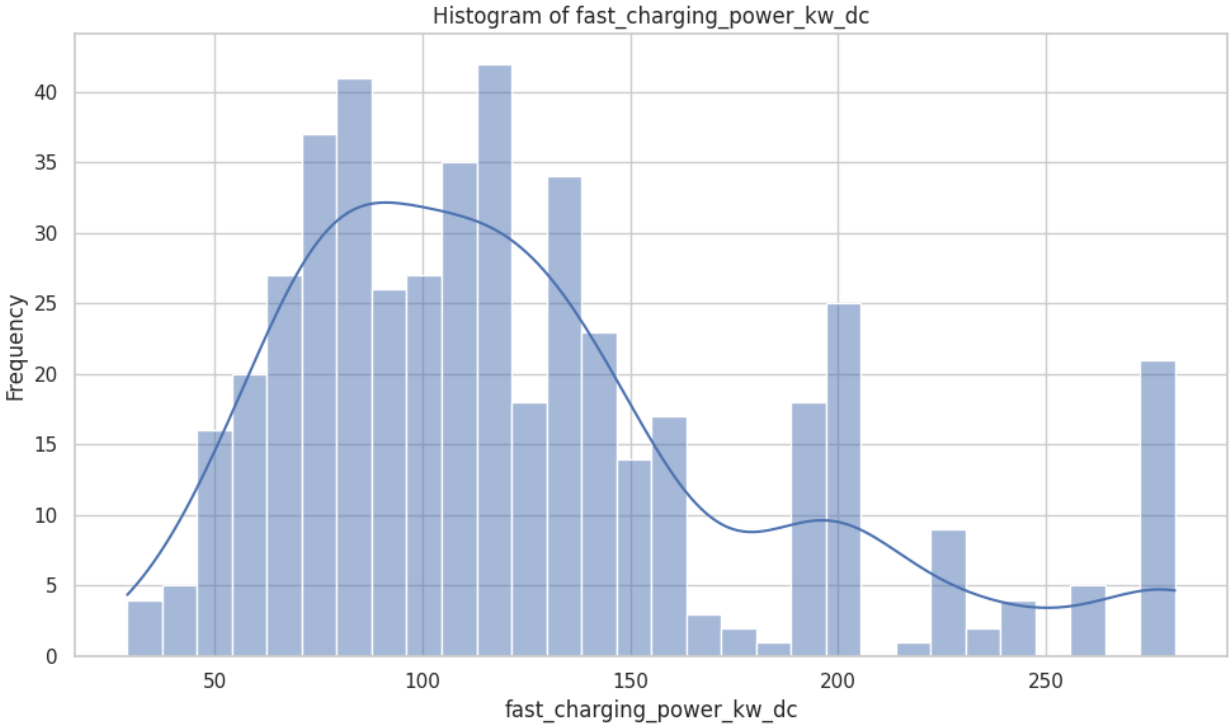

Histogram of number_of_cells
Frequency
0
25
50
75
100
125
150
175
200
0
1000
2000
3000
4000
5000
6000
7000
8000
number_of_cells

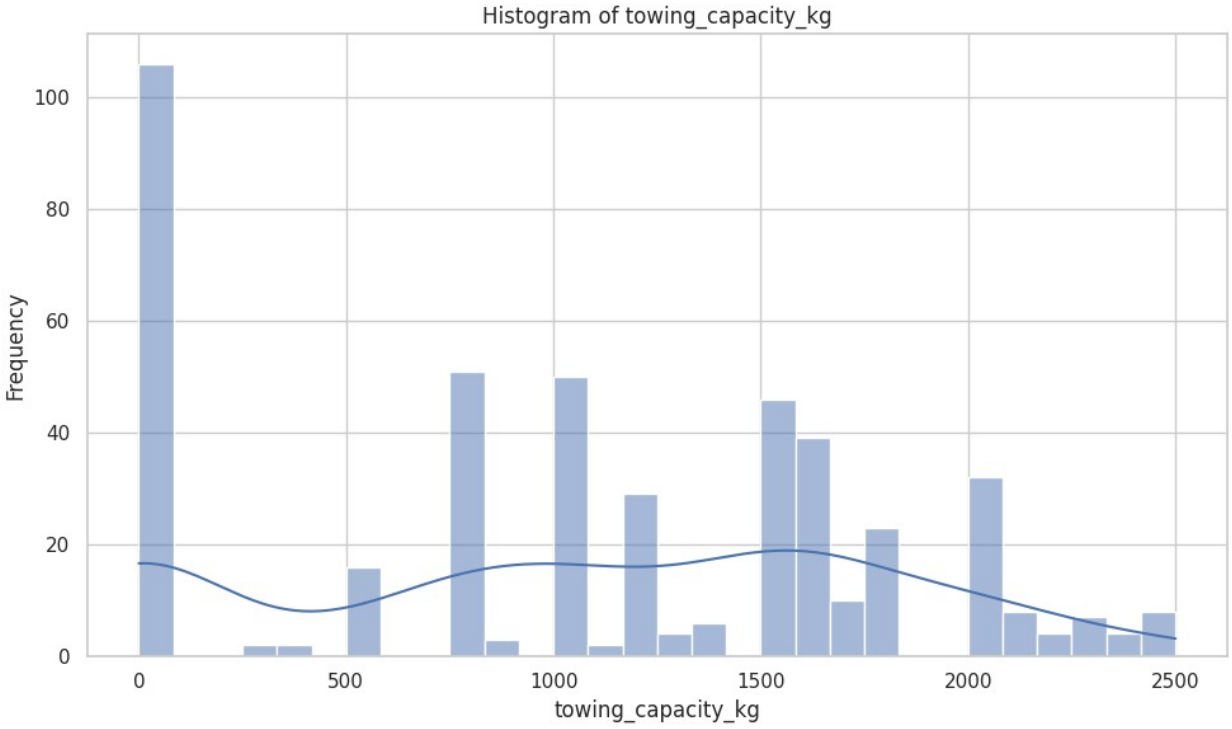

Histogram of torque_nm
Frequency
torque_nm
0
10
20
30
40
50
60
200
400
600
800
1000
1200
1400

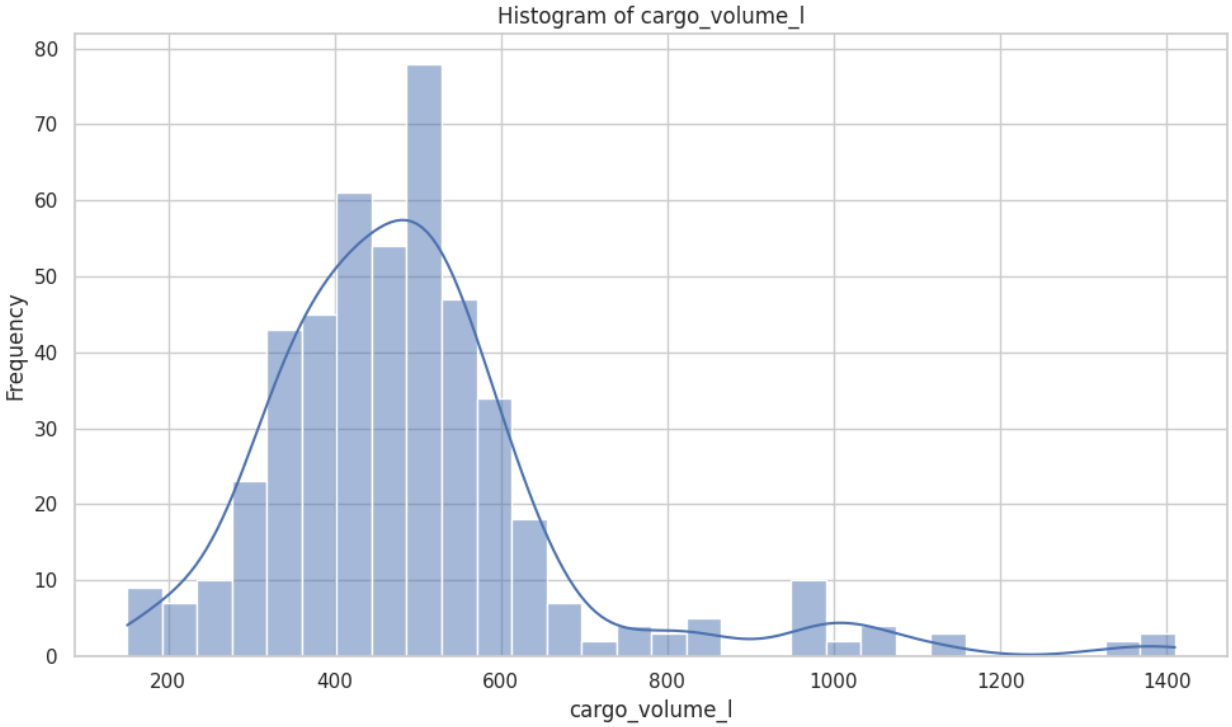

Histogram of efficiency_wh_per_km
Frequency
efficiency_wh_per_km
0
20
40
60
80
100
150
200
250
300
350

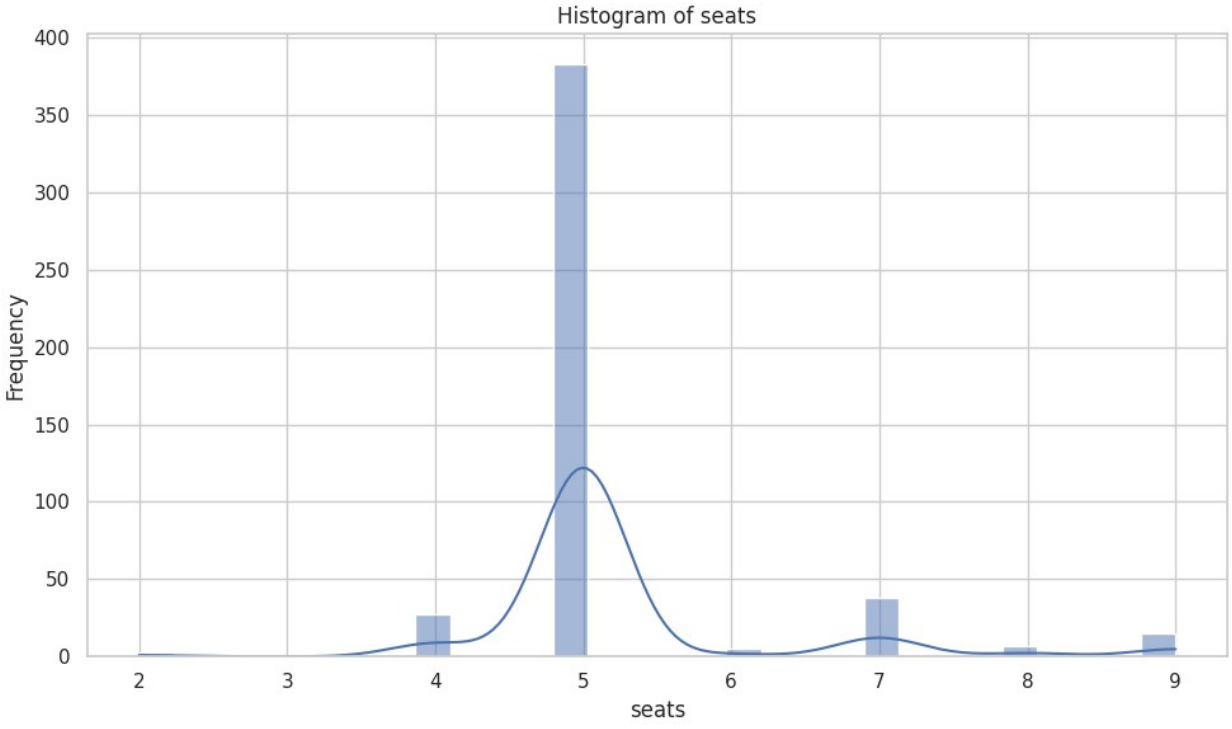

Histogram of range_km
Frequency
range_km
0
10
20
30
40
200
300
400
500
600
700

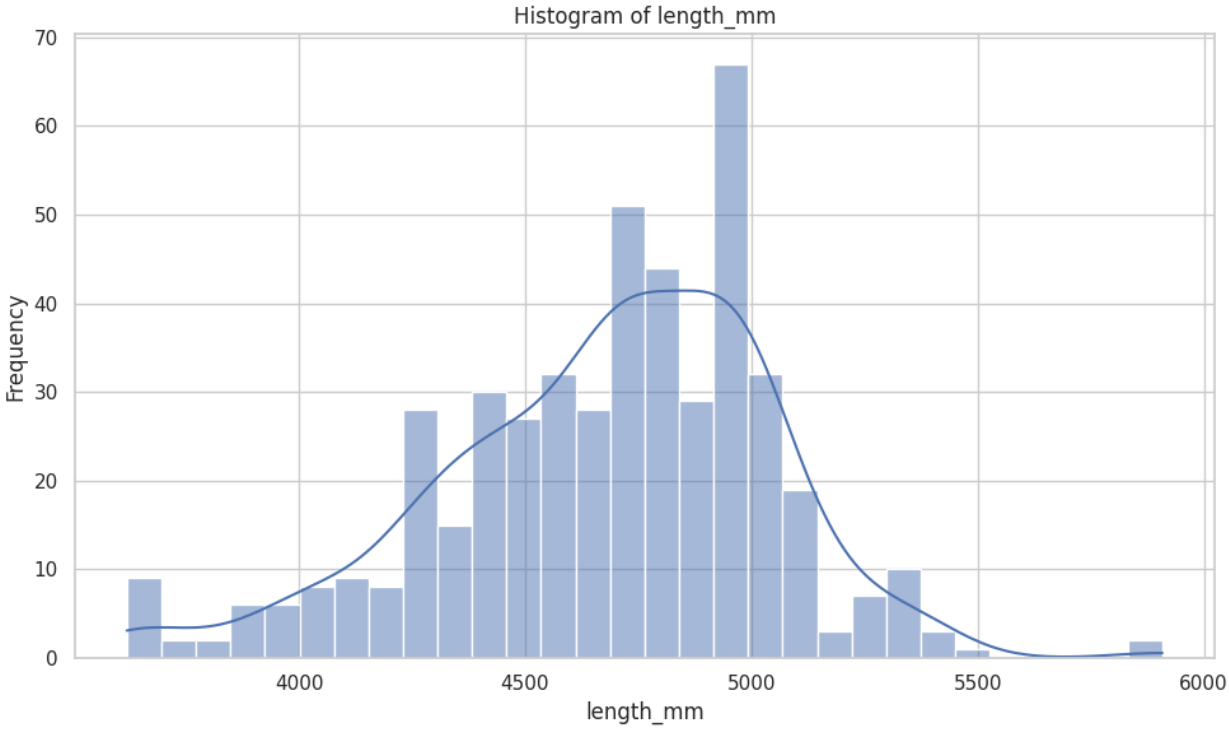

Histogram of acceleration_0_100_s
Frequency
acceleration_0_100_s
0
10
20
30
40
50
2.5
5.0
7.5
10.0
12.5
15.0
17.5

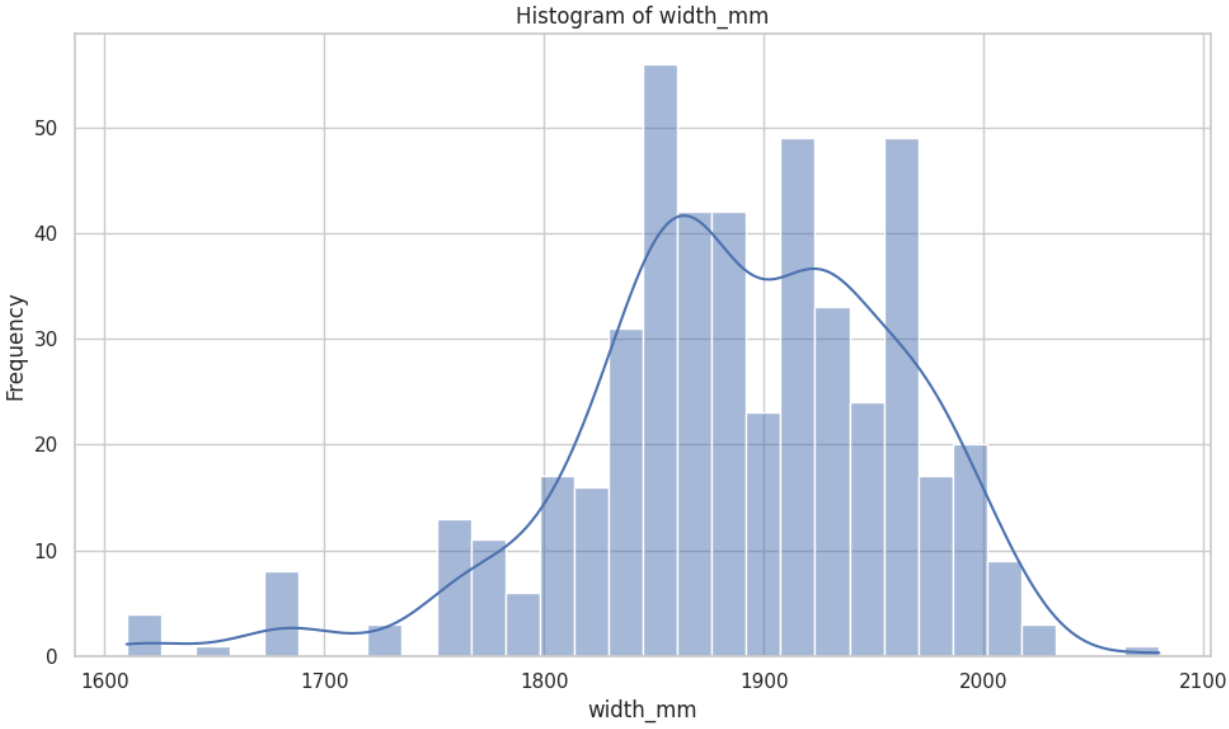

Histogram of fast_charging_power_kw_dc
Frequency
0
5
10
15
20
25
30
35
40
50
100
150
200
250
fast_charging_power_kw_dc

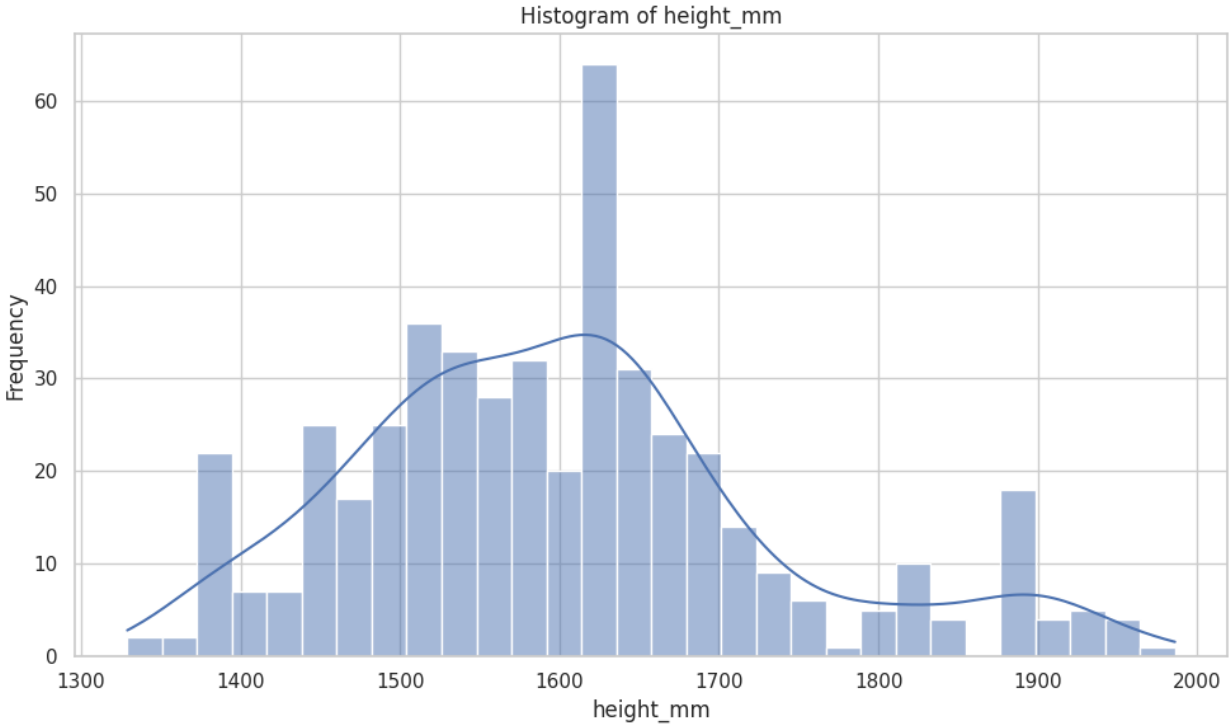

Histogram of towing_capacity_kg
Frequency
0
20
40
60
80
100
0
500
1000
1500
2000
2500
towing_capacity_kg

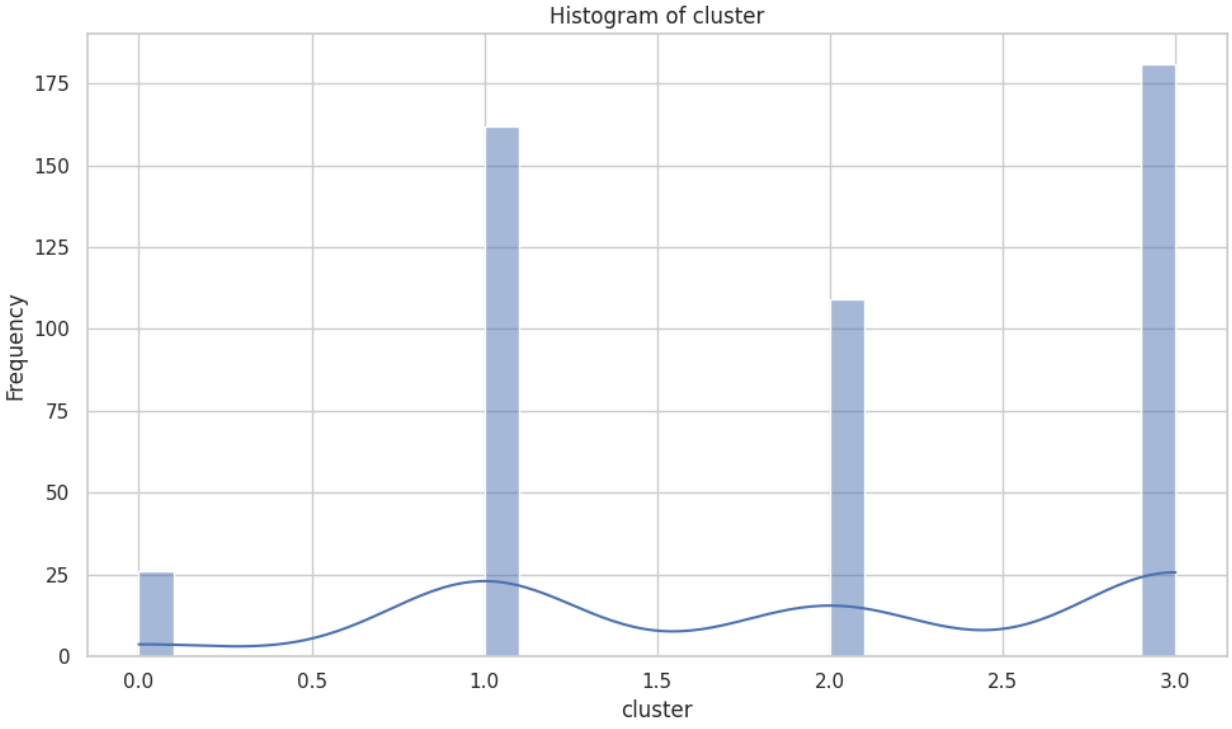

Histogram of cargo_volume_l
Frequency
cargo_volume_l
0
10
20
30
40
50
60
70
80
200
400
600
800
1000
1200
1400

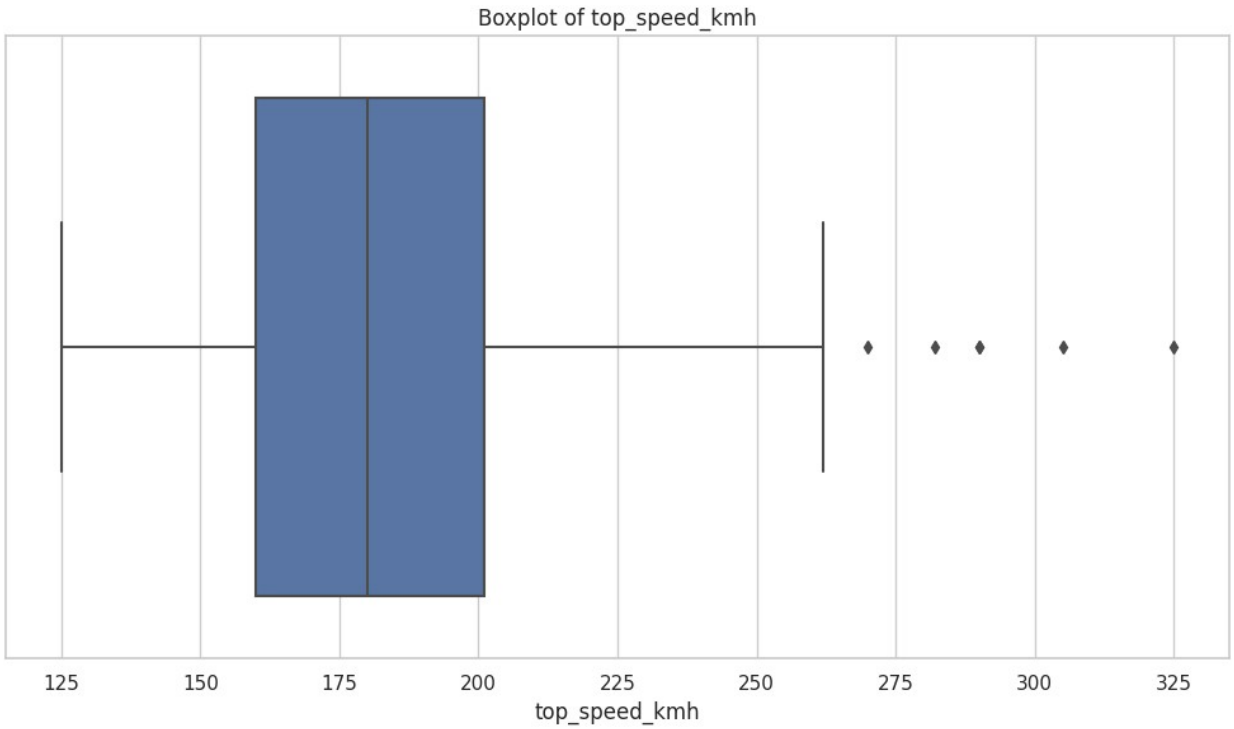

Histogram of seats
Frequency
seats
0
50
100
150
200
250
300
350
400
2
3
4
5
6
7
8
9

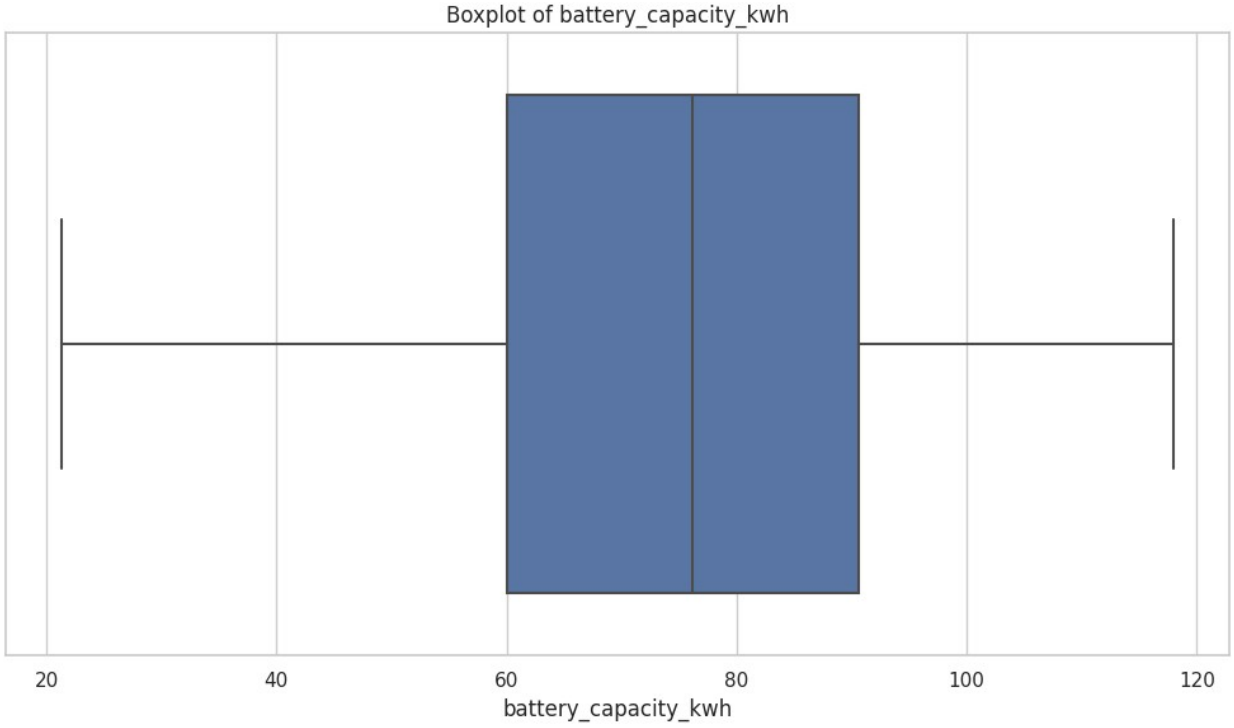

Histogram of length_mm
Frequency
length_mm
0
10
20
30
40
50
60
70
4000
4500
5000
5500
6000

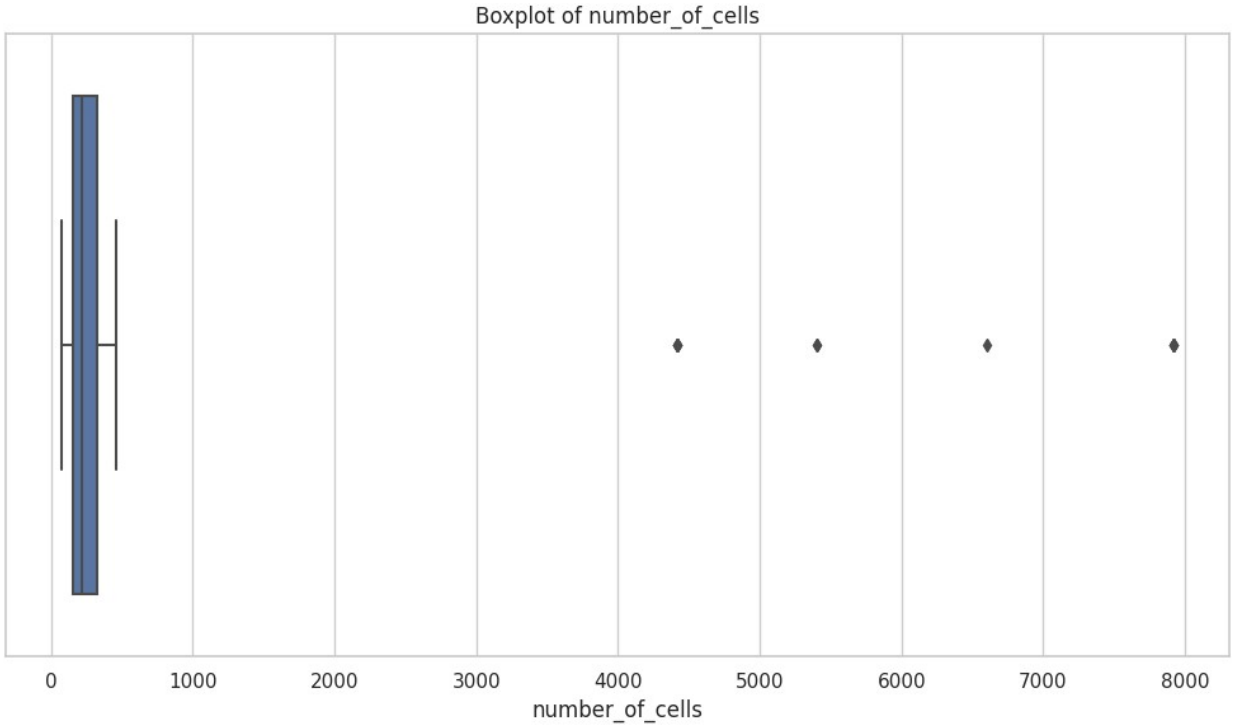

Histogram of width_mm
Frequency
width_mm
0
10
20
30
40
50
1600
1700
1800
1900
2000
2100

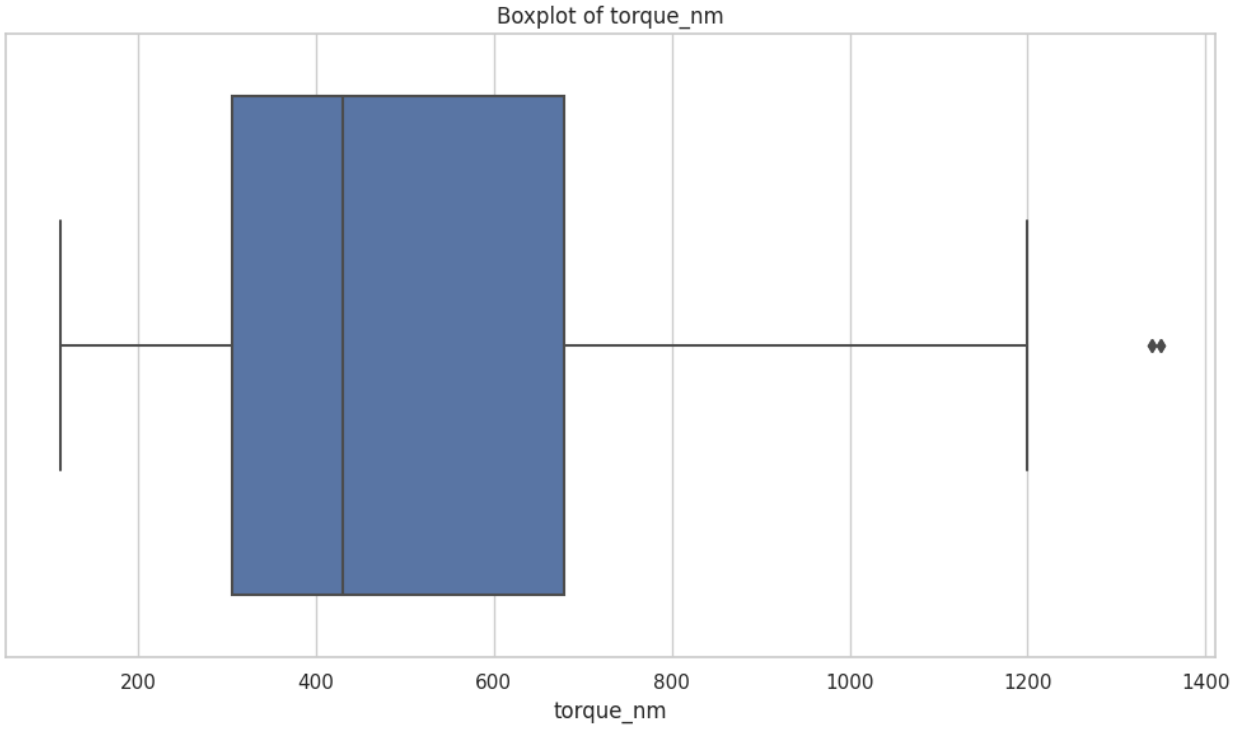

Histogram of height_mm
Frequency
height_mm
0
10
20
30
40
50
60
1300
1400
1500
1600
1700
1800
1900
2000

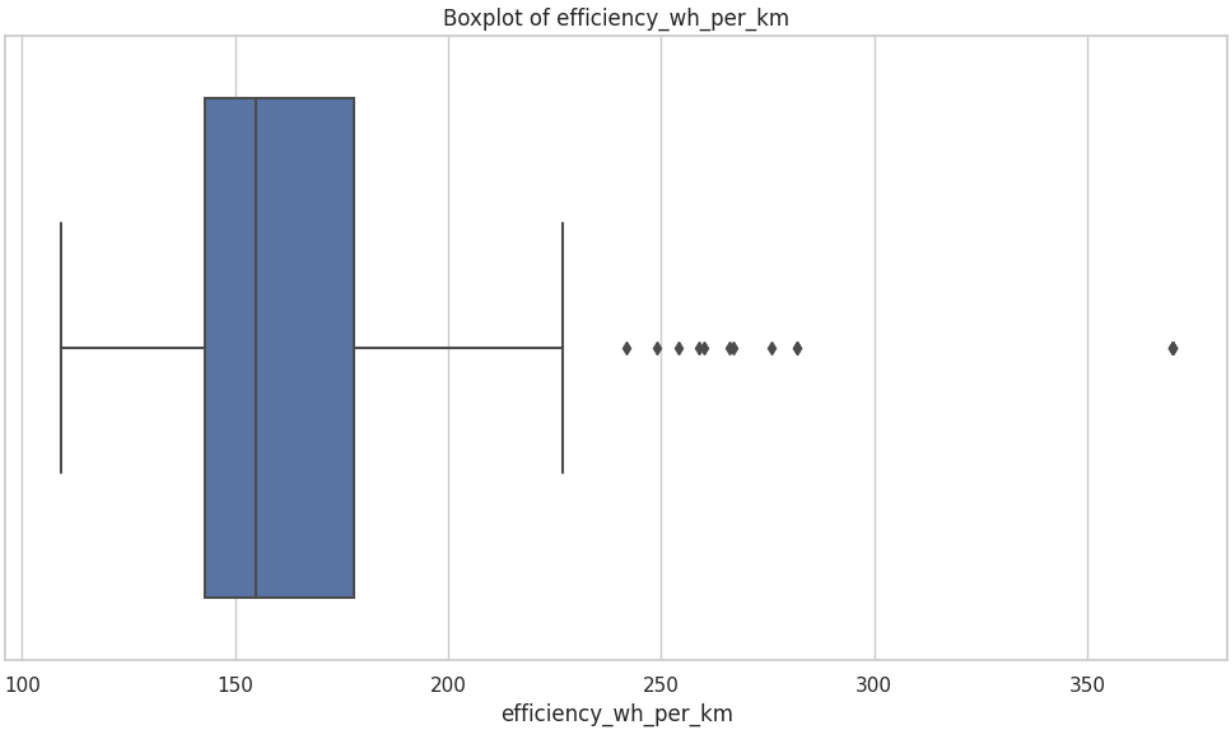

Histogram of cluster
Frequency
cluster
0
25
50
75
100
125
150
175
0.0
0.5
1.0
1.5
2.0
2.5
3.0

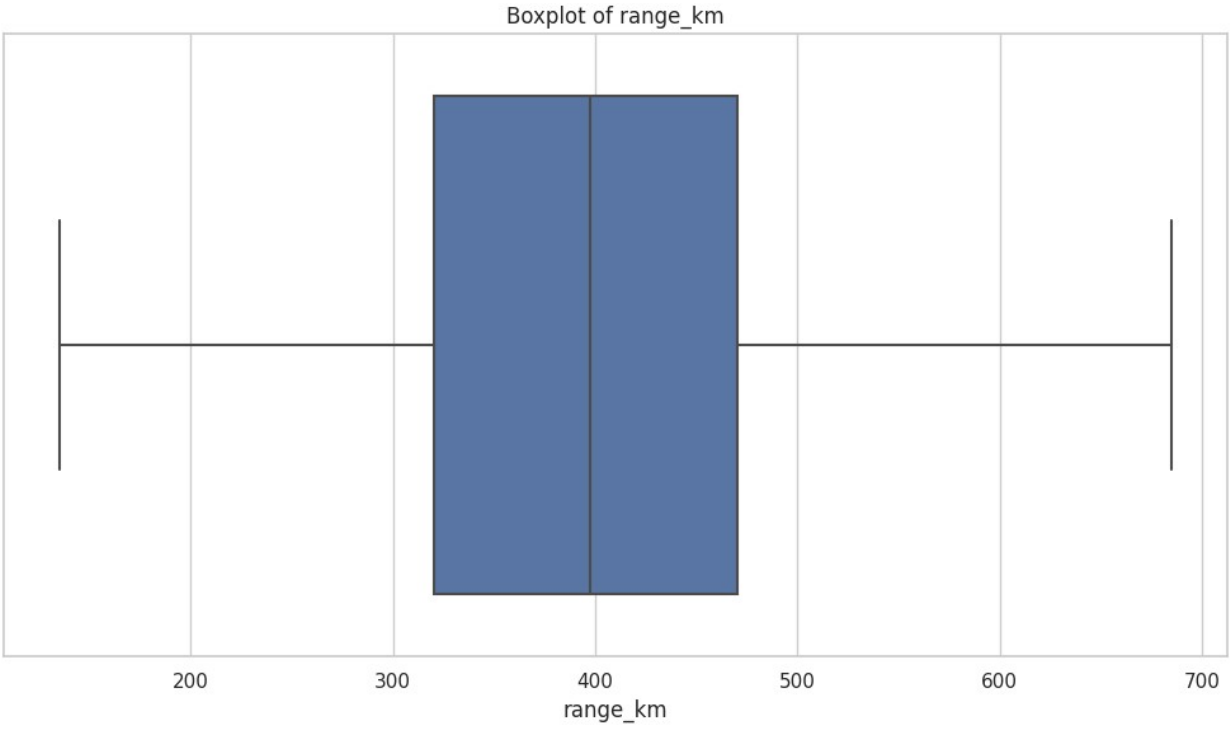

Boxplot of top_speed_kmh
125
150
175
200
225
250
275
300
325
top_speed_kmh

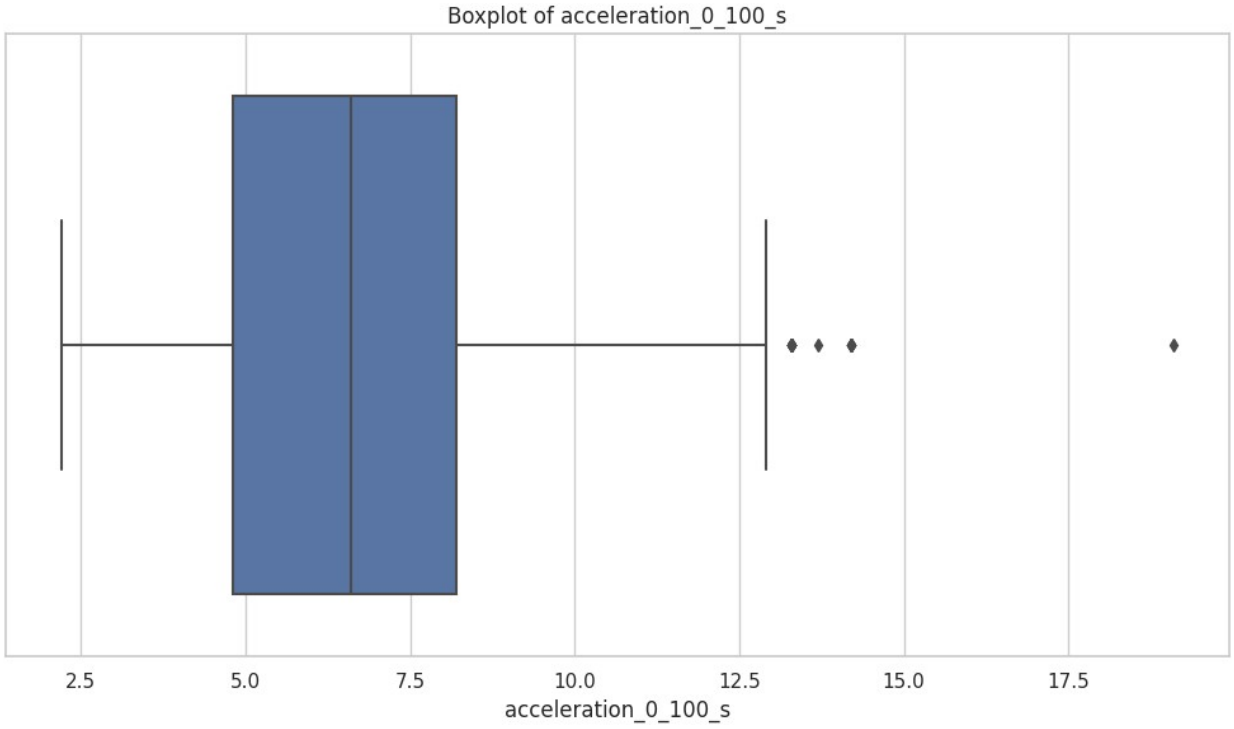

Boxplot of battery_capacity_kwh
20
40
60
80
100
120
battery_capacity_kwh

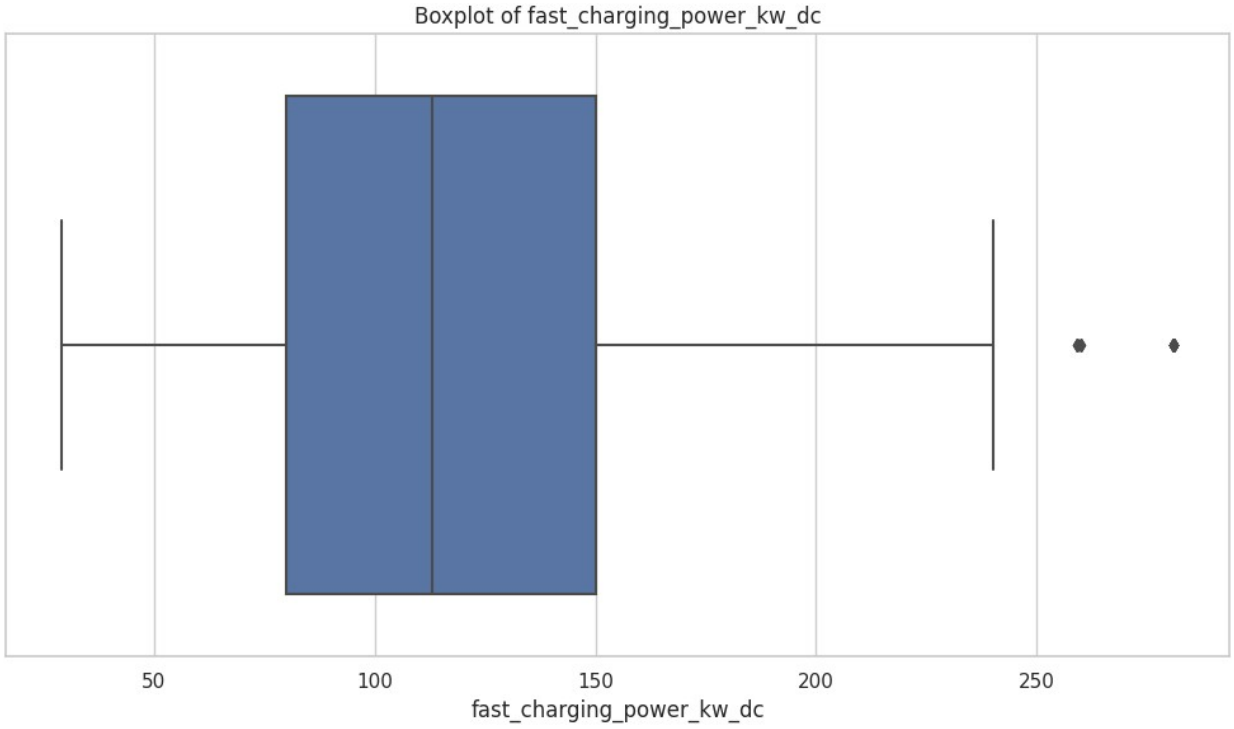

Boxplot of number_of_cells
0
1000
2000
3000
4000
5000
6000
7000
8000
number_of_cells

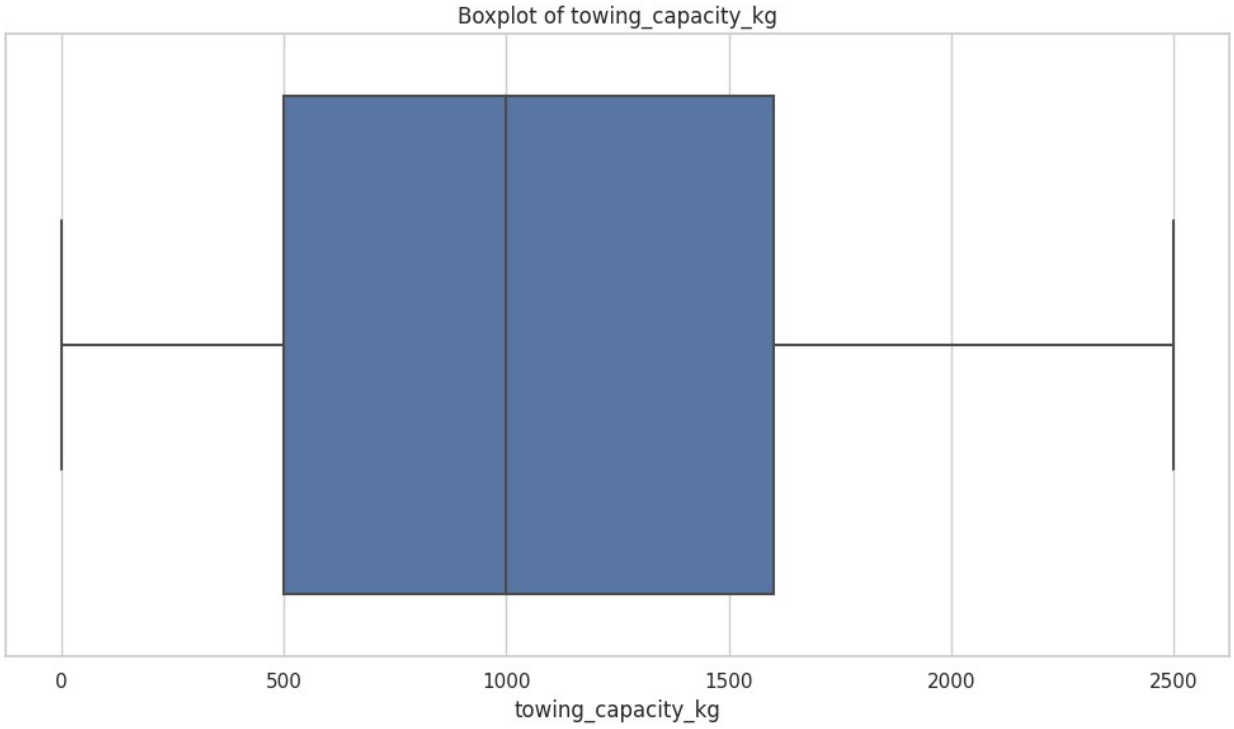

Boxplot of torque_nm
200
400
600
800
1000
1200
1400
torque_nm

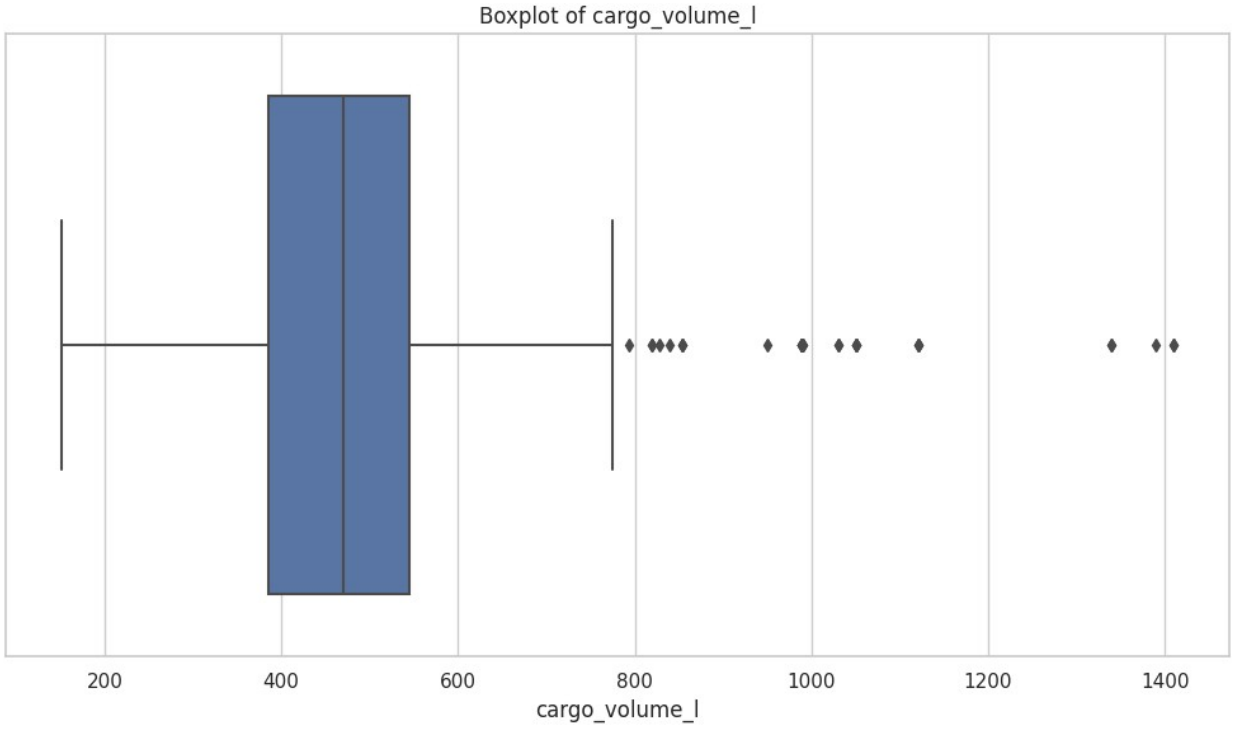

Boxplot of efficiency_wh_per_km
100
150
200
250
300
350
efficiency_wh_per_km

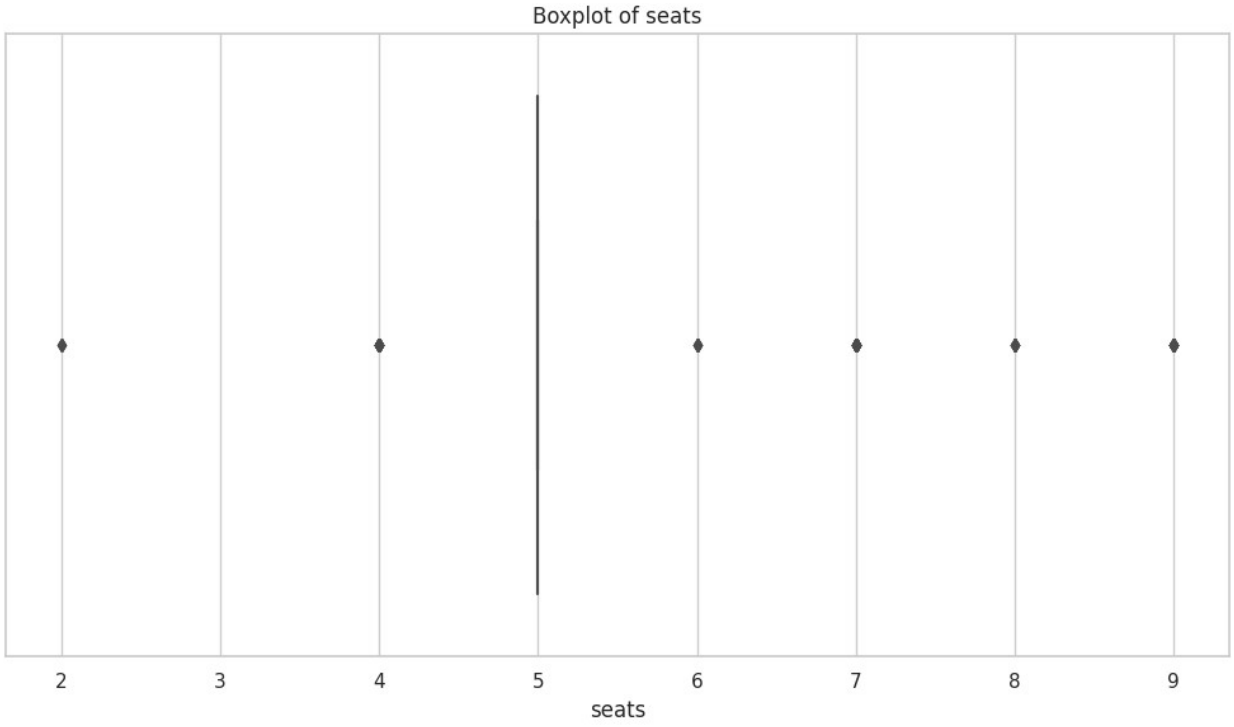

Boxplot of range_km
200
300
400
500
600
700
range_km

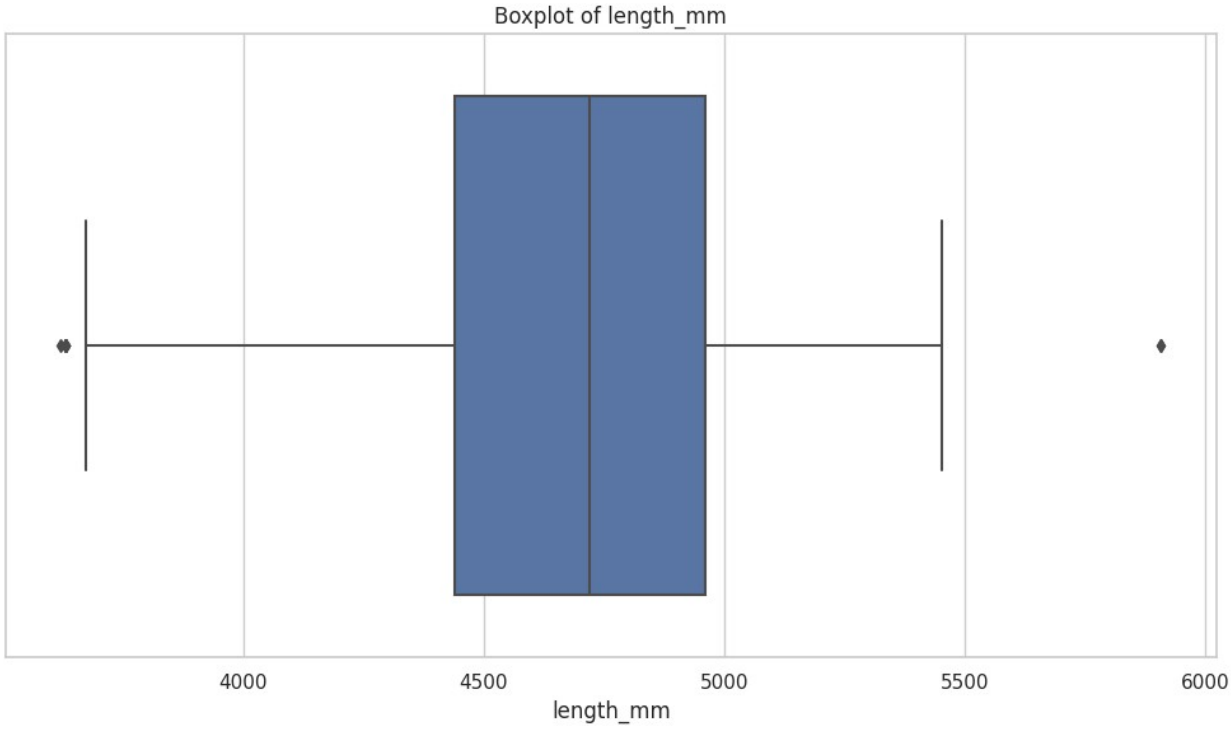

Boxplot of acceleration_0_100_s
2.5
5.0
7.5
10.0
12.5
15.0
17.5
acceleration_0_100_s

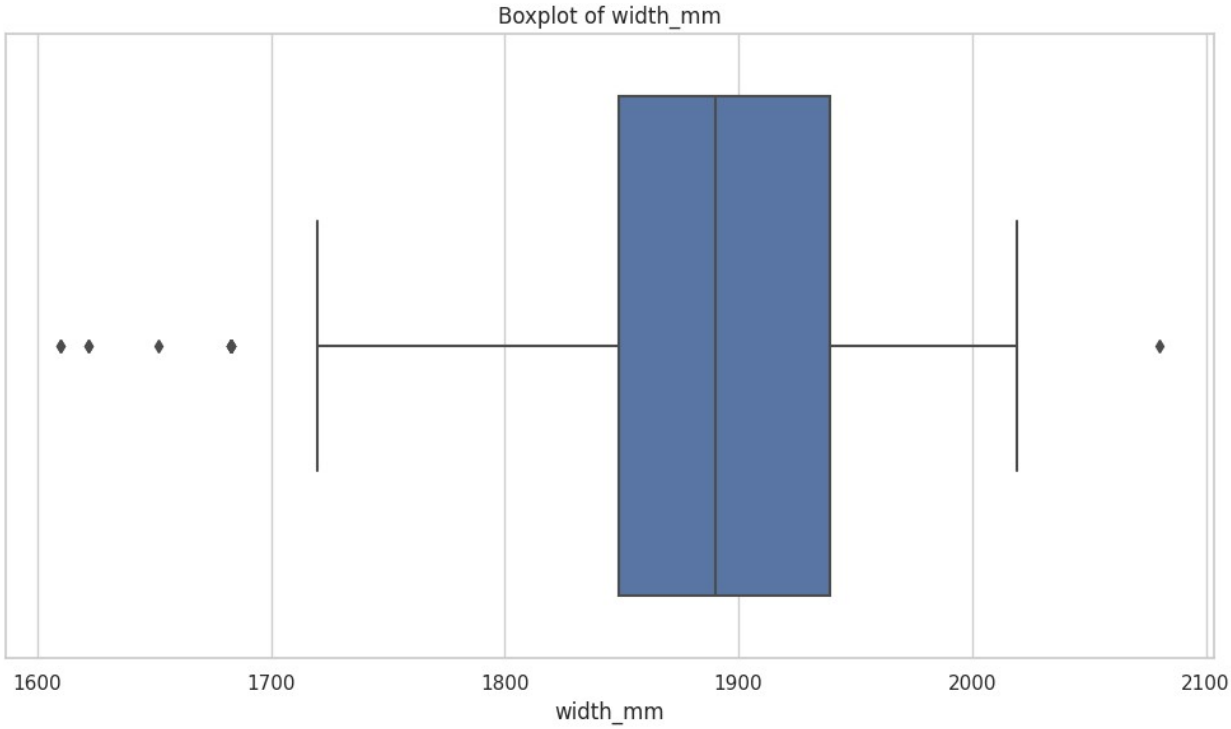

Boxplot of fast_charging_power_kw_dc
50
100
150
200
250
fast_charging_power_kw_dc

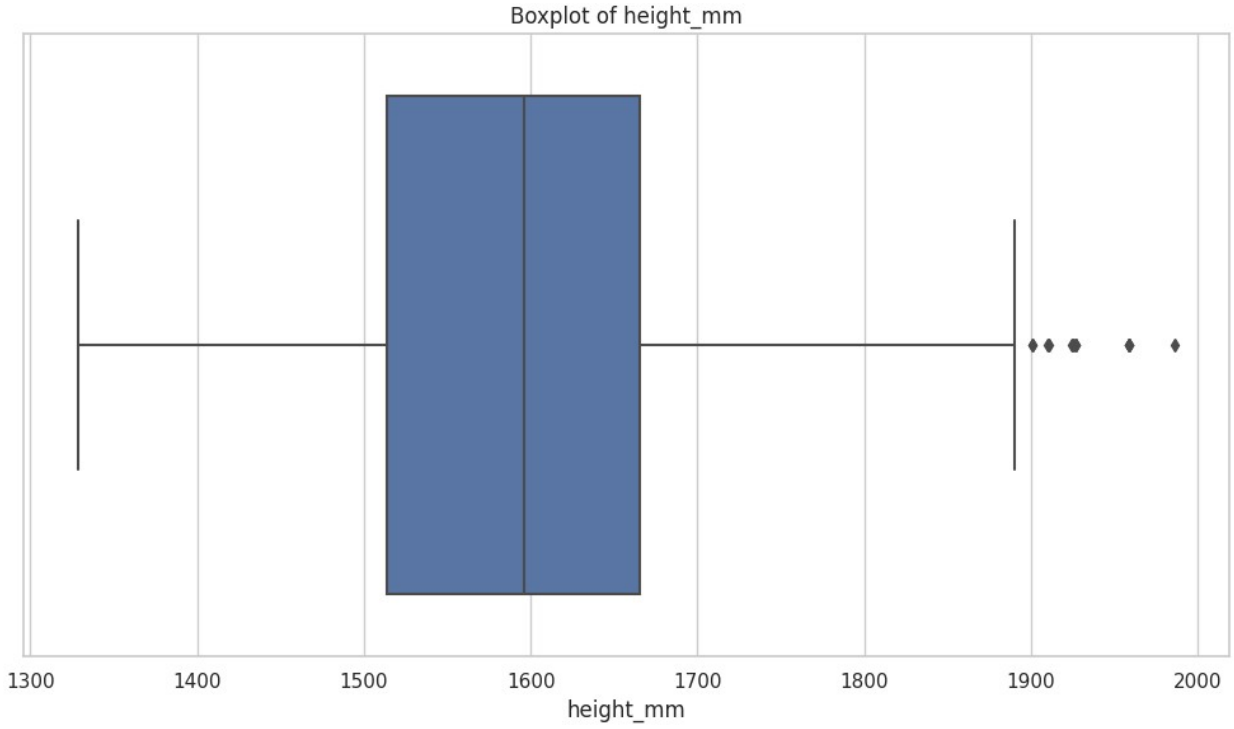

Boxplot of towing_capacity_kg
0
500
1000
1500
2000
2500
towing_capacity_kg

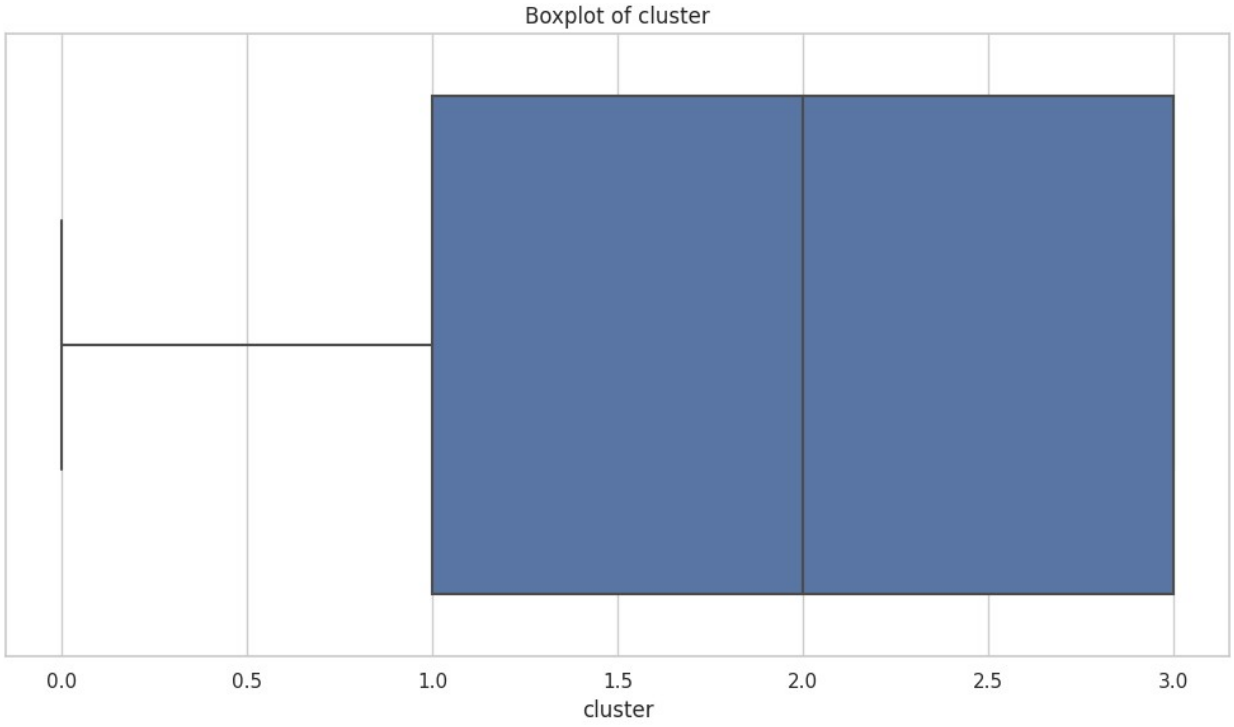

Boxplot of cargo_volume_l
200
400
600
800
1000
1200
1400
cargo_volume_l

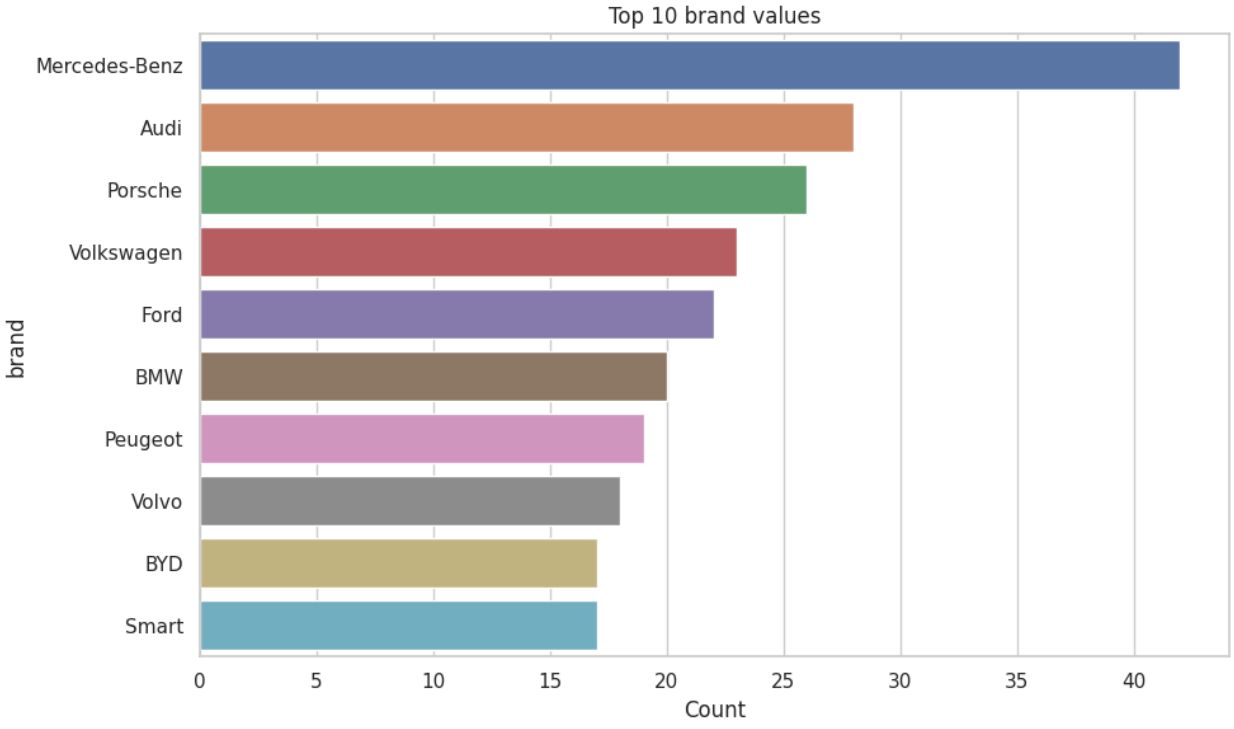

Boxplot of seats
2
3
4
5
6
7
8
9
seats

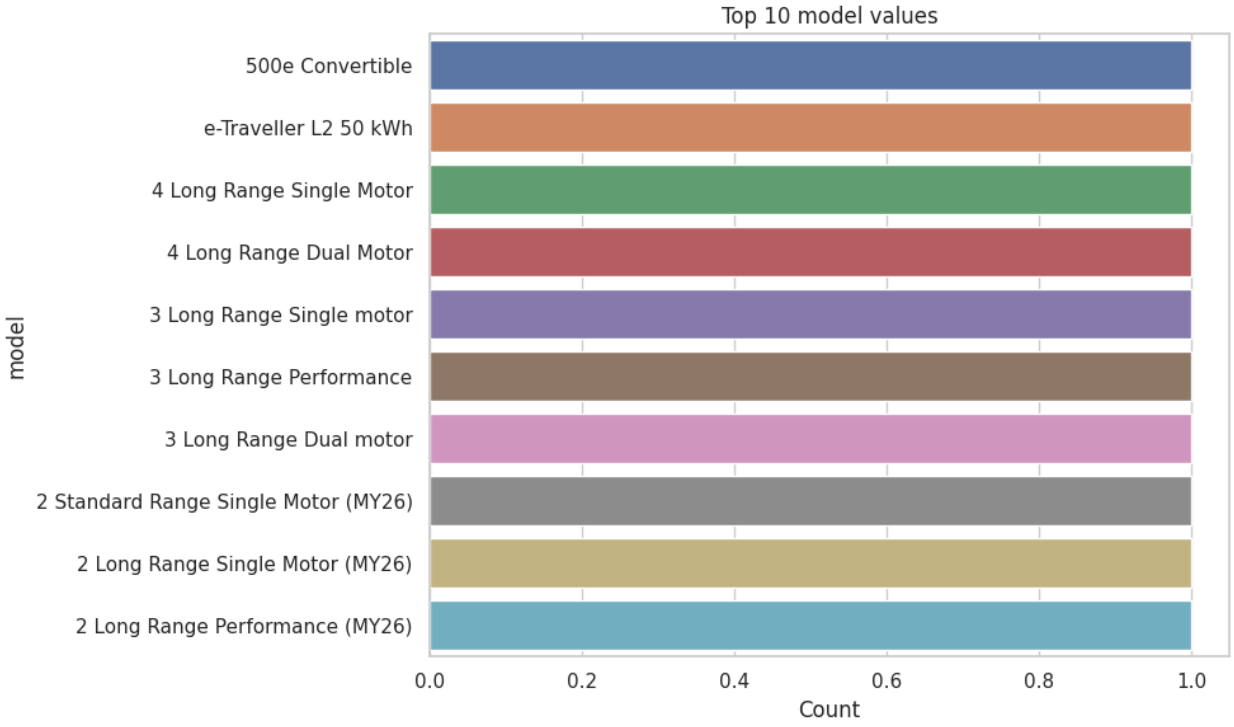

Boxplot of length_mm
4000
4500
5000
5500
6000
length_mm

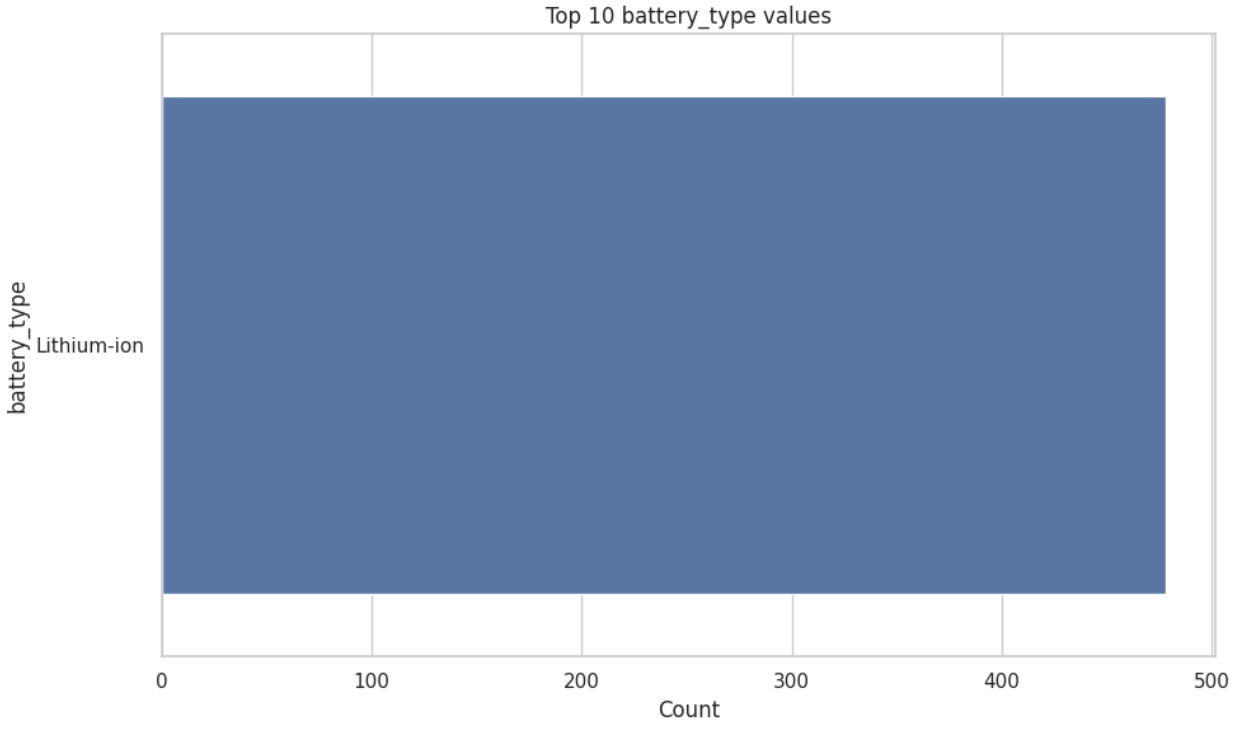

Boxplot of width_mm
1600
1700
1800
1900
2000
2100
width_mm

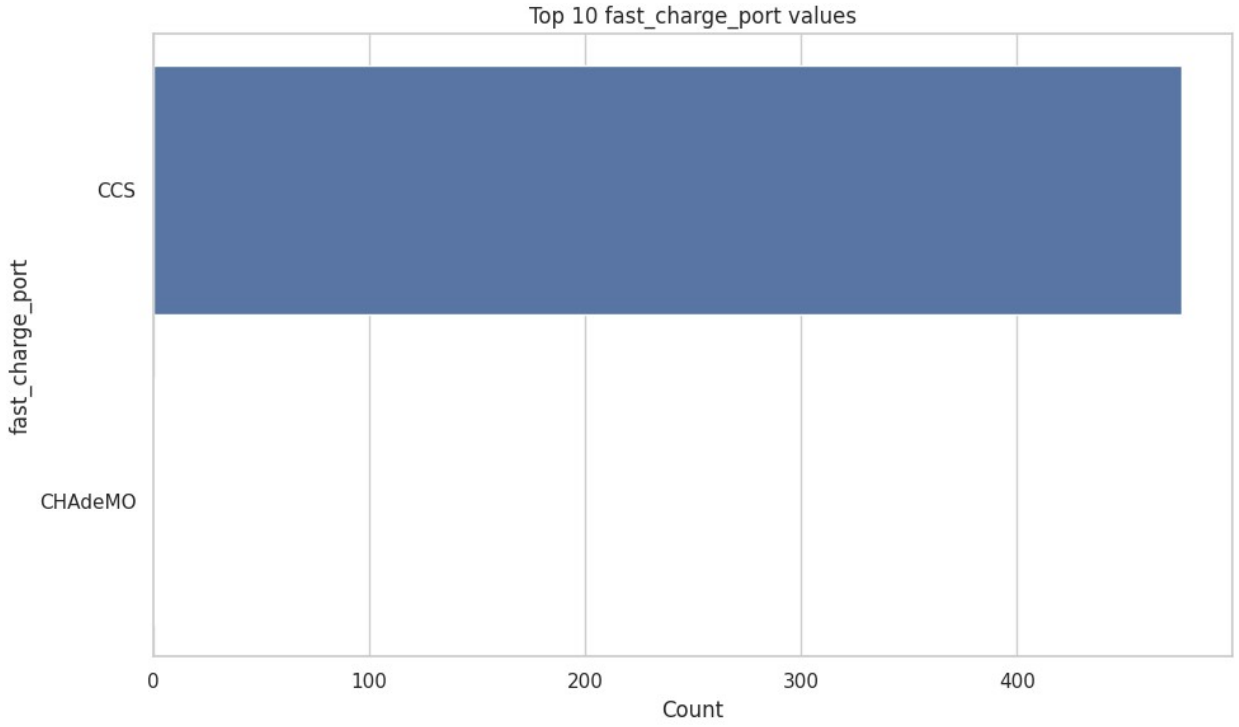

Boxplot of height_mm
1300
1400
1500
1600
1700
1800
1900
2000
height_mm

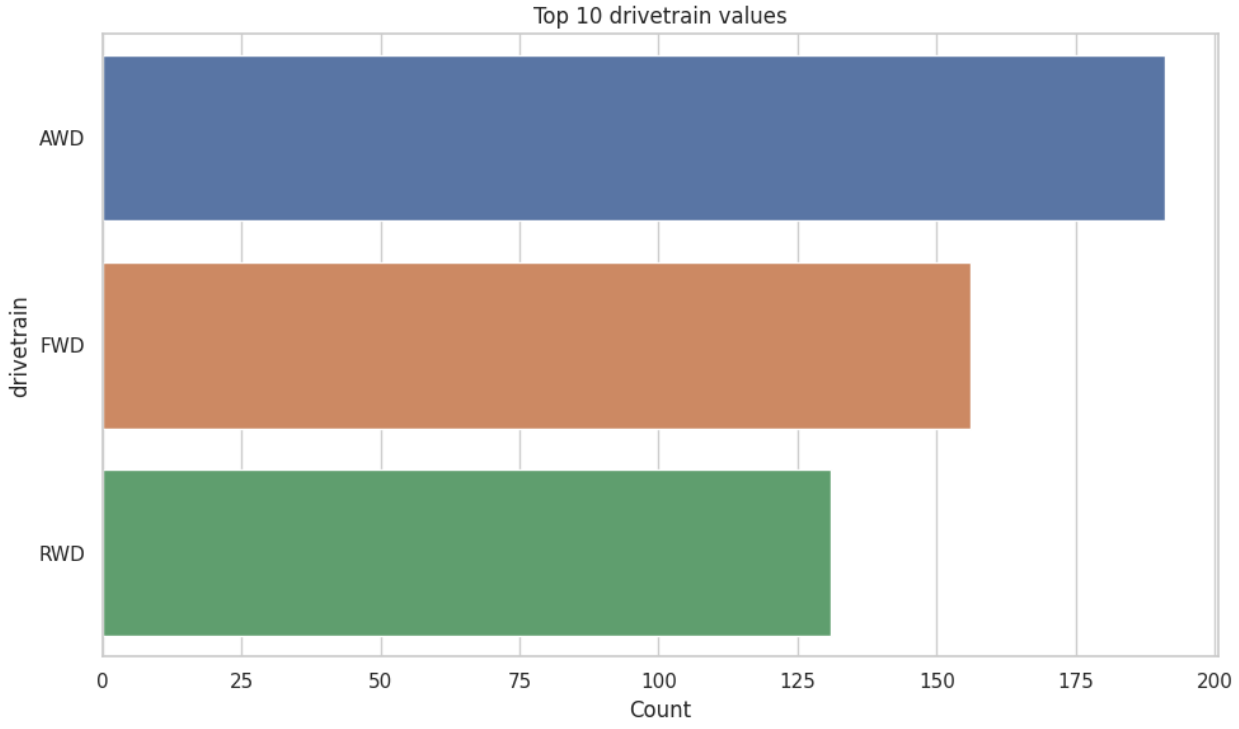

Boxplot of cluster
0.0
0.5
1.0
1.5
2.0
2.5
3.0
cluster

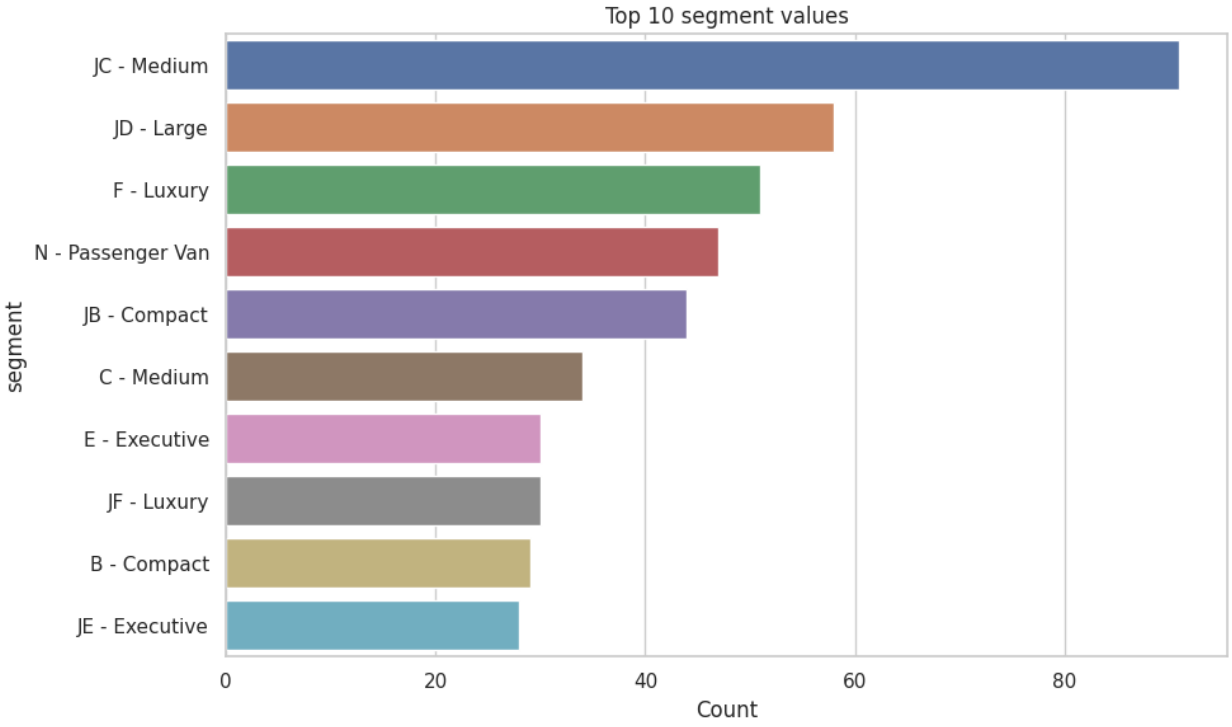

Top 10 brand values
Mercedes-Benz
Audi
Porsche
Volkswagen
Ford
BMW
Peugeot
Volvo
BYD
Smart
brand
0
5
10
15
20
25
30
35
40
Count

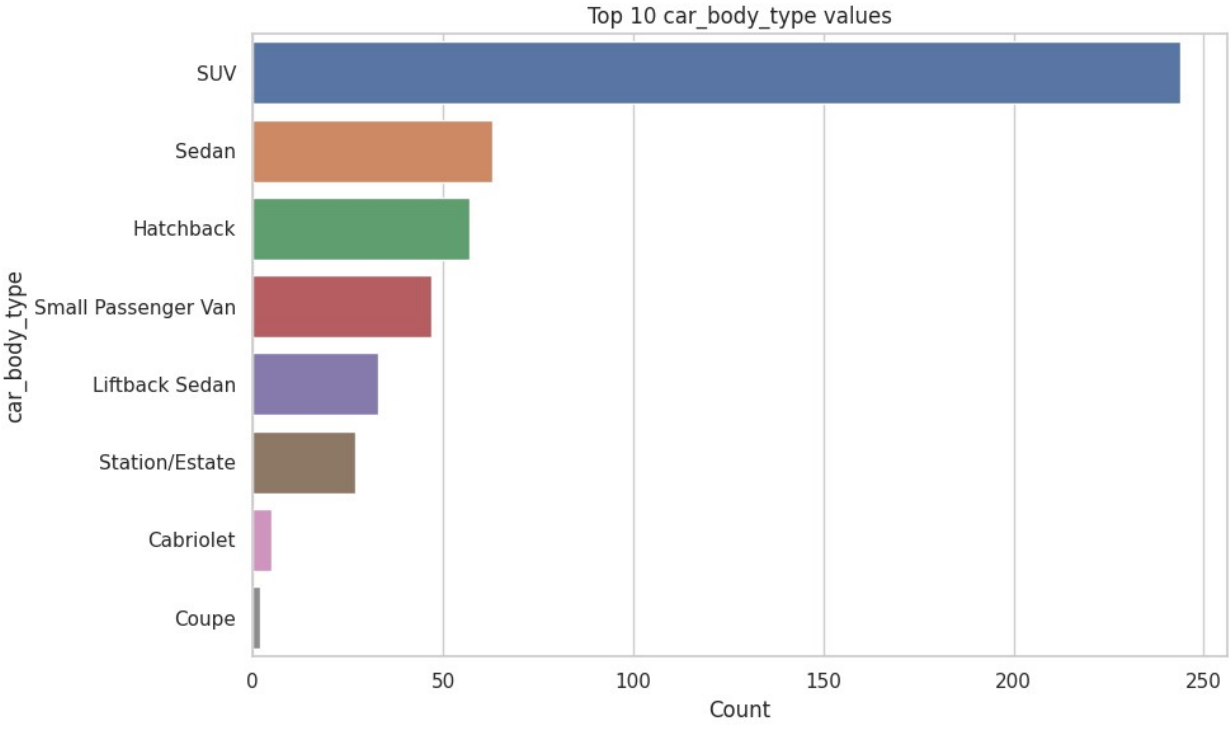

Top 10 model values
model
500e Convertible
e-Traveller L2 50 kWh
4 Long Range Single Motor
4 Long Range Dual Motor
3 Long Range Single motor
3 Long Range Performance
3 Long Range Dual motor
2 Standard Range Single Motor (MY26)
2 Long Range Single Motor (MY26)
2 Long Range Performance (MY26)
0.0
0.2
0.4
0.6
0.8
1.0
Count

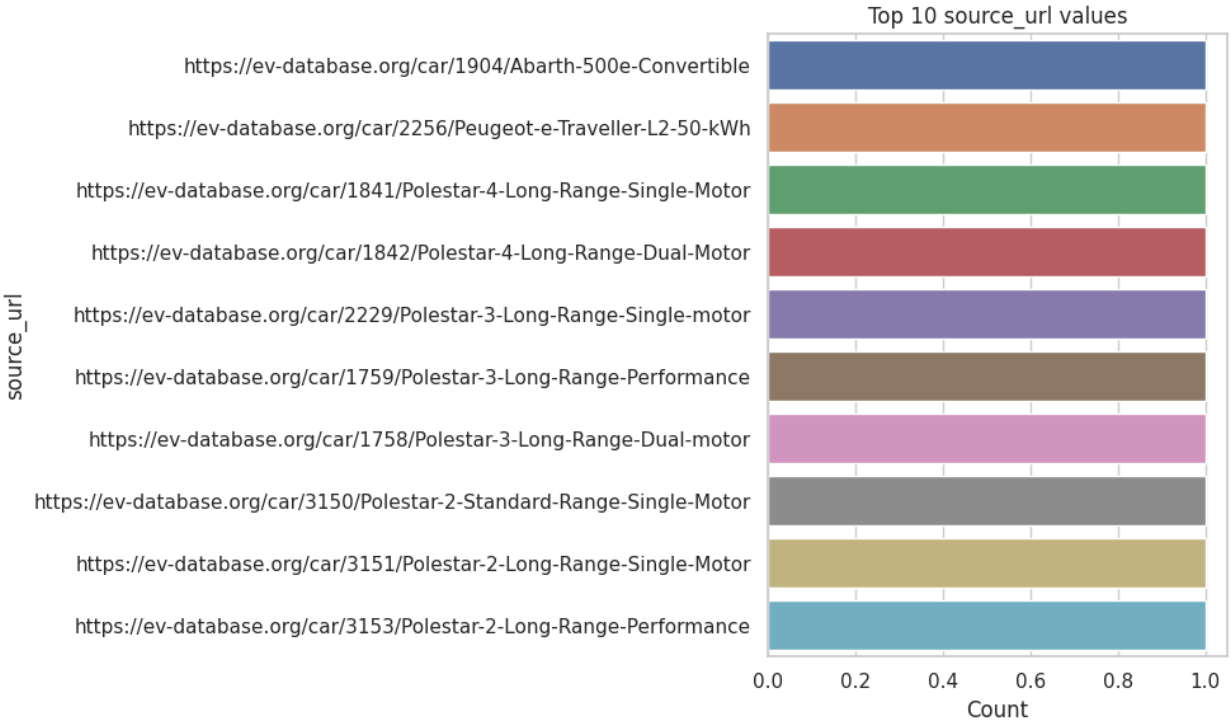

Top 10 battery_type values
battery_type
Lithium-ion
0
100
200
300
400
500
Count

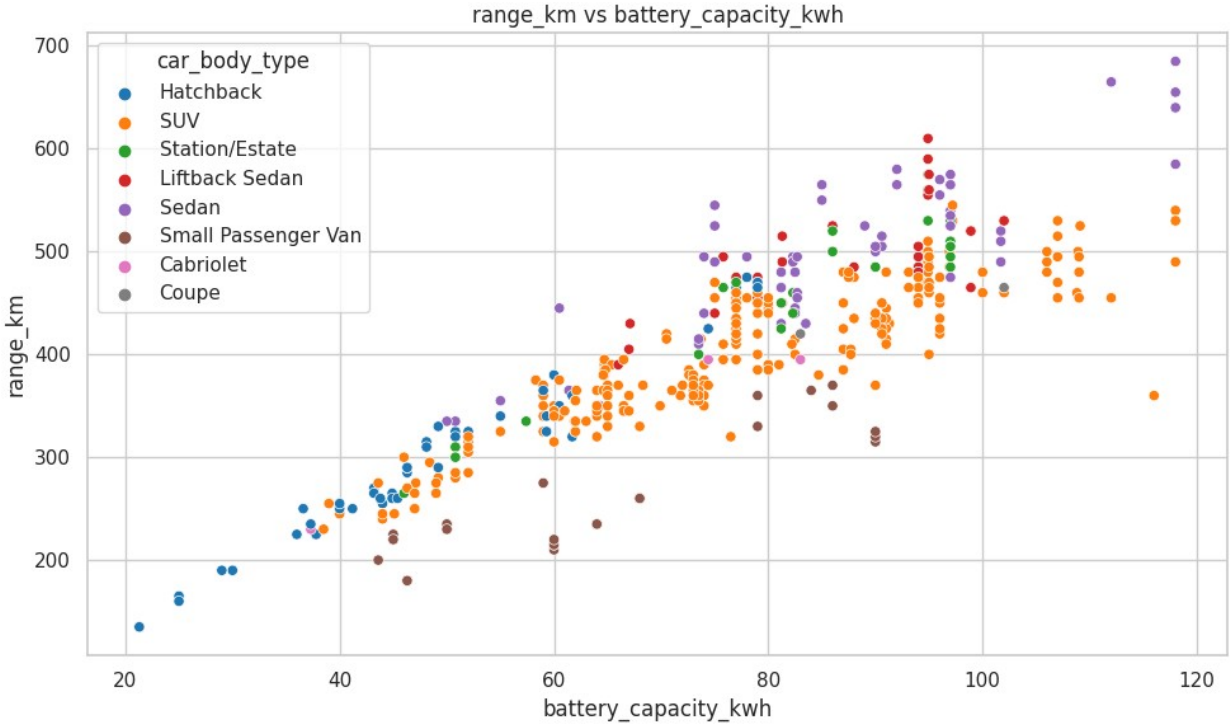

Top 10 fast_charge_port values
fast_charge_port
CCS
CHAdeMO
0
100
200
300
400
Count

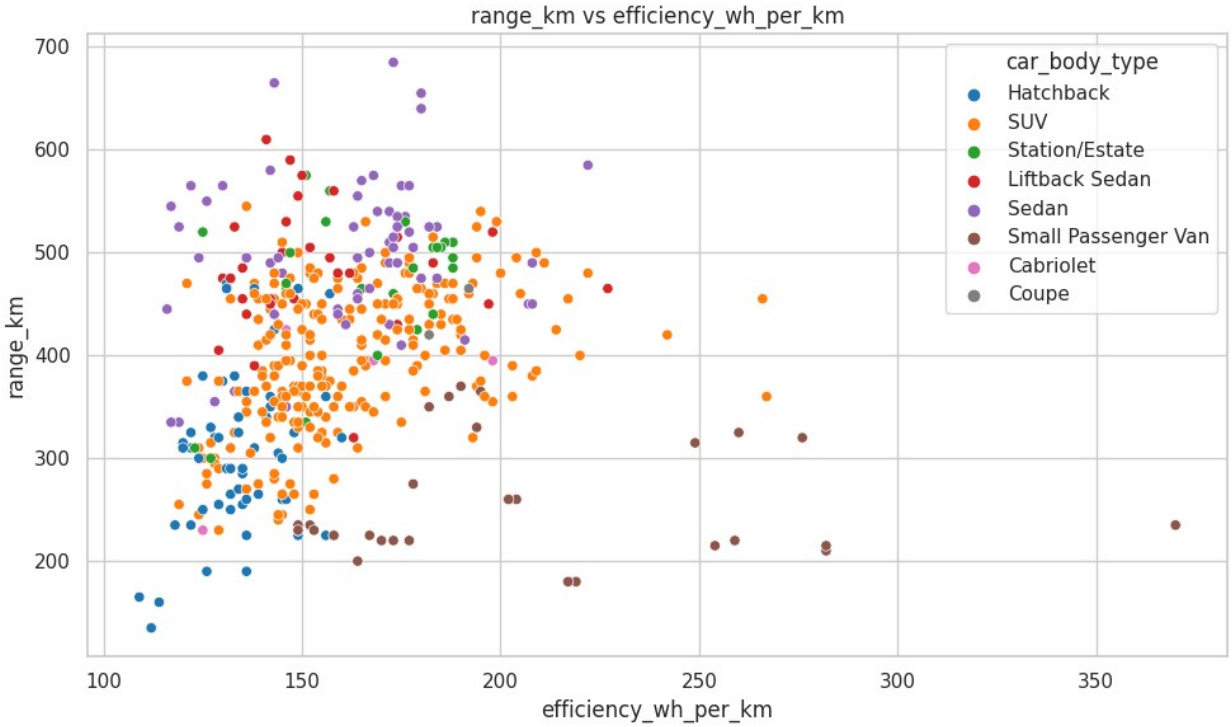

Top 10 drivetrain values
drivetrain
AWD
FWD
RWD
0
25
50
75
100
125
150
175
200
Count

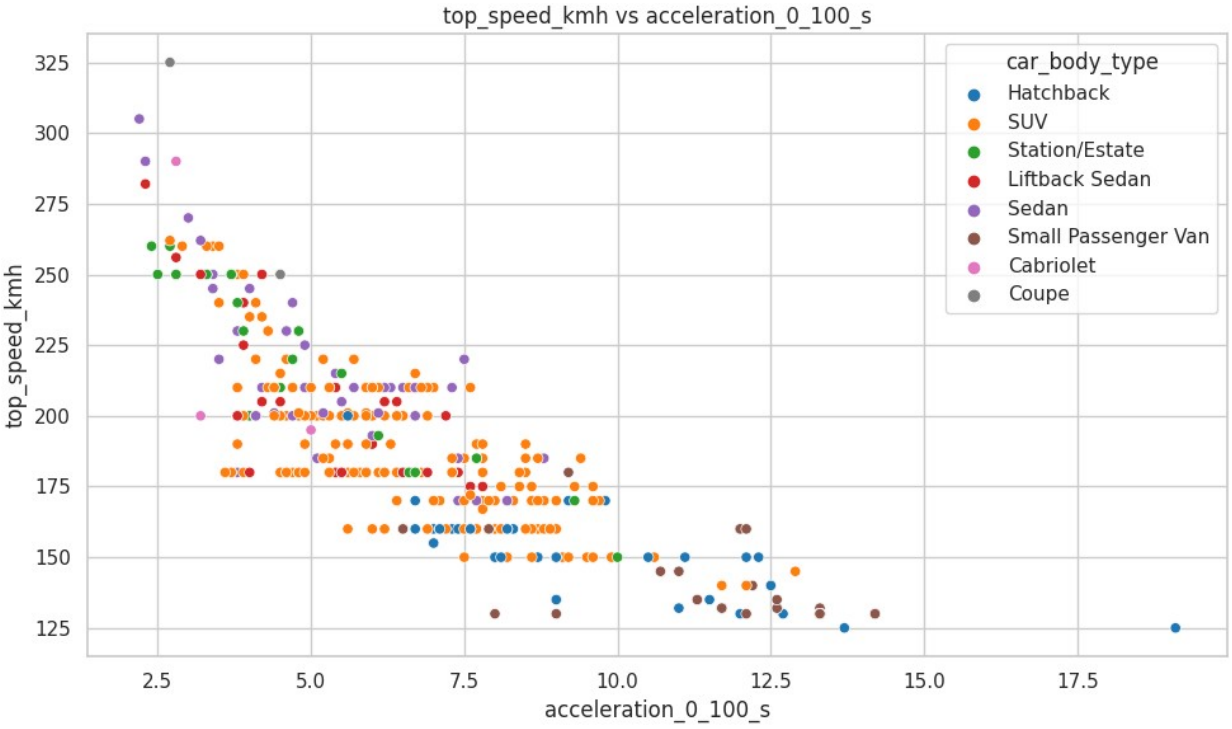

Top 10 segment values
JC - Medium
JD - Large
F - Luxury
N - Passenger Van
JB - Compact
C - Medium
E - Executive
JF - Luxury
B - Compact
JE - Executive
segment
0
20
40
60
80
Count

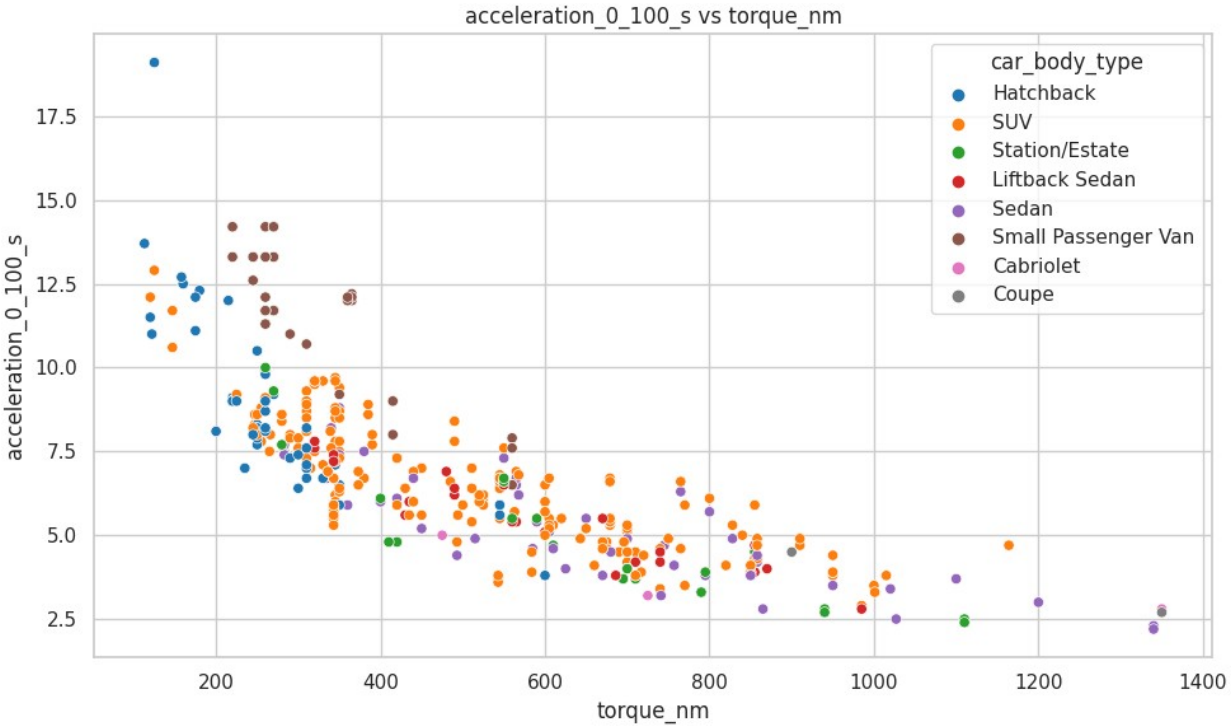

Top 10 car_body_type values
SUV
Sedan
Hatchback
Small Passenger Van
Liftback Sedan
Station/Estate
Cabriolet
Coupe
car_body_type
0
50
100
150
200
250
Count

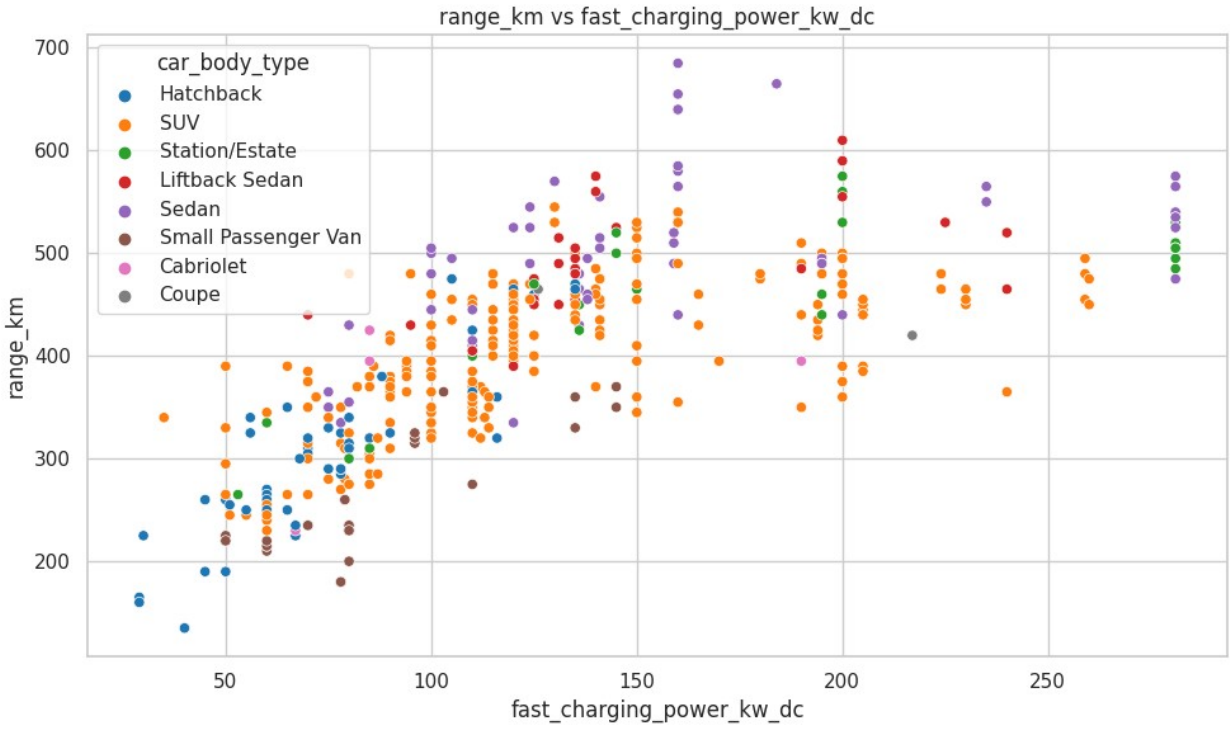

Top 10 source_url values
https://ev-database.org/car/1904/Abarth-500e-Convertible
https://ev-database.org/car/2256/Peugeot-e-Traveller-L2-50-kWh
https://ev-database.org/car/1841/Polestar-4-Long-Range-Single-Motor
https://ev-database.org/car/1842/Polestar-4-Long-Range-Dual-Motor
https://ev-database.org/car/2229/Polestar-3-Long-Range-Single-motor
https://ev-database.org/car/1759/Polestar-3-Long-Range-Performance
https://ev-database.org/car/1758/Polestar-3-Long-Range-Dual-motor
https://ev-database.org/car/3150/Polestar-2-Standard-Range-Single-Motor
https://ev-database.org/car/3151/Polestar-2-Long-Range-Single-Motor
https://ev-database.org/car/3153/Polestar-2-Long-Range-Performance
source_url
0.0
0.2
0.4
0.6
0.8
1.0
Count


range_km vs battery_capacity_kwh
car_body_type
Hatchback
SUV
Station/Estate
Liftback Sedan
Sedan
Small Passenger Van
Cabriolet
Coupe
range_km
700
600
500
400
300
200
20
40
60
80
100
120
battery_capacity_kwh


range_km vs efficiency_wh_per_km
range_km
efficiency_wh_per_km
car_body_type
Hatchback
SUV
Station/Estate
Liftback Sedan
Sedan
Small Passenger Van
Cabriolet
Coupe
700
600
500
400
300
200
100
150
200
250
300
350


top_speed_kmh vs acceleration_0_100_s
top_speed_kmh
acceleration_0_100_s
car_body_type
Hatchback
SUV
Station/Estate
Liftback Sedan
Sedan
Small Passenger Van
Cabriolet
Coupe
325
300
275
250
225
200
175
150
125
2.5
5.0
7.5
10.0
12.5
15.0
17.5





EV Recommendation System

```
import pandas as pd

# Υποθετική τιμή ανά kWh
```

```
kwh_price_eur = 0.25

# Ας καθαρίσουμε τα δεδομένα
df['range_km'] = pd.to_numeric(df['range_km'], errors='coerce')
df['cargo_volume_l'] = pd.to_numeric(df['cargo_volume_l'],
errors='coerce')
df['efficiency_wh_per_km'] = pd.to_numeric(df['efficiency_wh_per_km'],
errors='coerce')

# Αν έχεις στήλη 'price_eur' βάλε φίλτρο. Αλλιώς αφαίρεσέ το.
has_price = 'price_eur' in df.columns
if has_price:
    df['price_eur'] = pd.to_numeric(df['price_eur'], errors='coerce')

# Κριτήρια επιλογής
filtered = df[
    (df['range_km'] >= 400) &
    (df['cargo_volume_l'] >= 500)
]

if has_price:
    max_price = 60000  # βάλε όριο τιμής
    filtered = filtered[filtered['price_eur'] <= max_price]

# Υπολογισμός κόστους ανά 100km
filtered['cost_per_100km_eur'] = (filtered['efficiency_wh_per_km'] /
1000) * kwh_price_eur * 100

# Επιλογή βασικών πεδίων για προβολή
result = filtered[[
    'brand', 'model', 'range_km', 'cargo_volume_l',
'efficiency_wh_per_km',
    'fast_charging_power_kw_dc', 'drivetrain', 'seats'
]]

if has_price:
    result['price_eur'] = filtered['price_eur']

result['cost_per_100km_eur'] = filtered['cost_per_100km_eur'].round(2)

# Ταξινόμηση κατά αυτονομία ή κόστος
result = result.sort_values(by='range_km', ascending=False)

# Εμφάνιση top 10 EVs που ταιριάζουν
result.head(10)
```

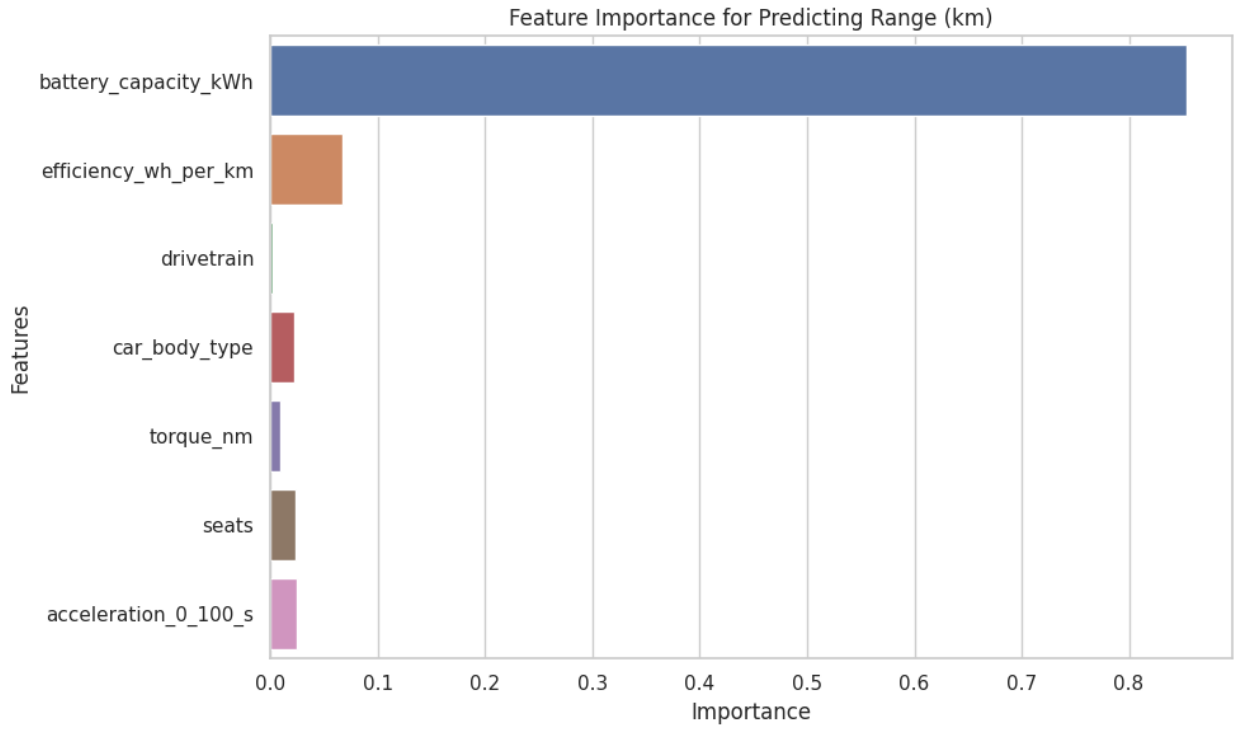
```
             brand                              model  range_km
cargo_volume_l  \
239  Mercedes-Benz                          EQS 450+       685
620.0
```

```
238  Mercedes-Benz                   EQS 450 4MATIC       655
620.0
240  Mercedes-Benz                   EQS 500 4MATIC       640
620.0
241  Mercedes-Benz                   EQS 580 4MATIC       640
620.0
14            Audi  A6 Sportback e-tron performance       610
502.0
15            Audi      A6 Sportback e-tron quattro       590
502.0
242  Mercedes-Benz               EQS AMG 53 4MATIC+       585
620.0
401          Tesla               Model S Dual Motor       575
709.0
11            Audi      A6 Avant e-tron performance       575
502.0
237  Mercedes-Benz                           EQS 350       570
620.0

     efficiency_wh_per_km  fast_charging_power_kw_dc drivetrain  seats
\
239                   173                      160.0        RWD      5

238                   180                      160.0        AWD      5

240                   180                      160.0        AWD      5

241                   180                      160.0        AWD      5

14                    141                      200.0        RWD      5

15                    147                      200.0        AWD      5

242                   222                      160.0        AWD      5

401                   150                      140.0        AWD      5

11                    151                      200.0        RWD      5

237                   165                      130.0        RWD      5


     cost_per_100km_eur
239                4.32
238                4.50
240                4.50
241                4.50
14                 3.52
15                 3.68
242                5.55
```

```
401                3.75
11                 3.78
237                4.12

print(df.columns)

Index(['brand', 'model', 'top_speed_kmh', 'battery_capacity_kWh',
       'battery_type', 'number_of_cells', 'torque_nm',
'efficiency_wh_per_km',
       'range_km', 'acceleration_0_100_s',
'fast_charging_power_kw_dc',
       'fast_charge_port', 'towing_capacity_kg', 'cargo_volume_l',
'seats',
       'drivetrain', 'segment', 'length_mm', 'width_mm', 'height_mm',
       'car_body_type', 'source_url'],
      dtype='object')

import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder

# Υποθετικός δρόμος για το dataset (αλλάξτε το με το σωστό path)
file_path = "/kaggle/input/electric-vehicle-specifications-dataset-
2025/electric_vehicles_spec_2025.csv.csv"
df = pd.read_csv(file_path)

# Καθαρισμός δεδομένων
df['battery_capacity_kWh'] = pd.to_numeric(df['battery_capacity_kWh'],
errors='coerce')
df['efficiency_wh_per_km'] = pd.to_numeric(df['efficiency_wh_per_km'],
errors='coerce')
df['torque_nm'] = pd.to_numeric(df['torque_nm'], errors='coerce')
df['seats'] = pd.to_numeric(df['seats'], errors='coerce')
df['acceleration_0_100_s'] = pd.to_numeric(df['acceleration_0_100_s'],
errors='coerce')

# Κατηγορηματικές στήλες
categorical_cols = ['drivetrain', 'car_body_type']

# Εφαρμογή LabelEncoder για κατηγορηματικές στήλες
encoder = LabelEncoder()
for col in categorical_cols:
    df[col] = encoder.fit_transform(df[col].astype(str))

# Αφαίρεση NaN τιμών
df = df.dropna(subset=['range_km', 'battery_capacity_kWh',
```

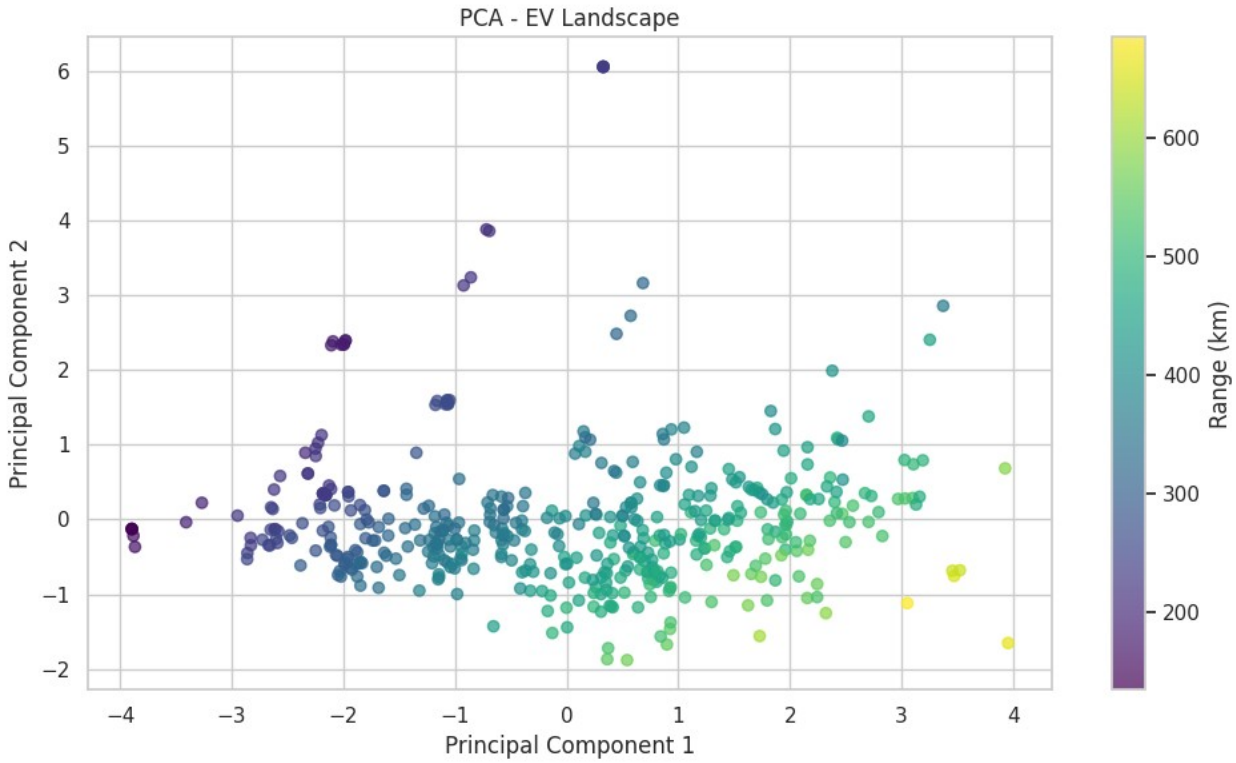
```
'efficiency_wh_per_km', 'torque_nm', 'seats', 'acceleration_0_100_s'])

# Χαρακτηριστικά (features) και στόχος (target)
X = df[['battery_capacity_kWh', 'efficiency_wh_per_km', 'drivetrain',
'car_body_type', 'torque_nm', 'seats', 'acceleration_0_100_s']]
y = df['range_km']

# Διάσπαση σε σύνολο εκπαίδευσης και δοκιμής
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Δημιουργία και εκπαίδευση του μοντέλου
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Πρόβλεψη και αξιολόγηση του μοντέλου
y_pred = model.predict(X_test)

# Υπολογισμός μετρικών
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f'Mean Squared Error: {mse}')
print(f'R^2 Score: {r2}')

# Διαγράμματα Feature Importance
feature_importance = model.feature_importances_
feature_names = X.columns

# Δημιουργία του γραφήματος
plt.figure(figsize=(10, 6))
sns.barplot(x=feature_importance, y=feature_names)
plt.title("Feature Importance for Predicting Range (km)")
plt.xlabel("Importance")
plt.ylabel("Features")
plt.tight_layout()
plt.show()
```

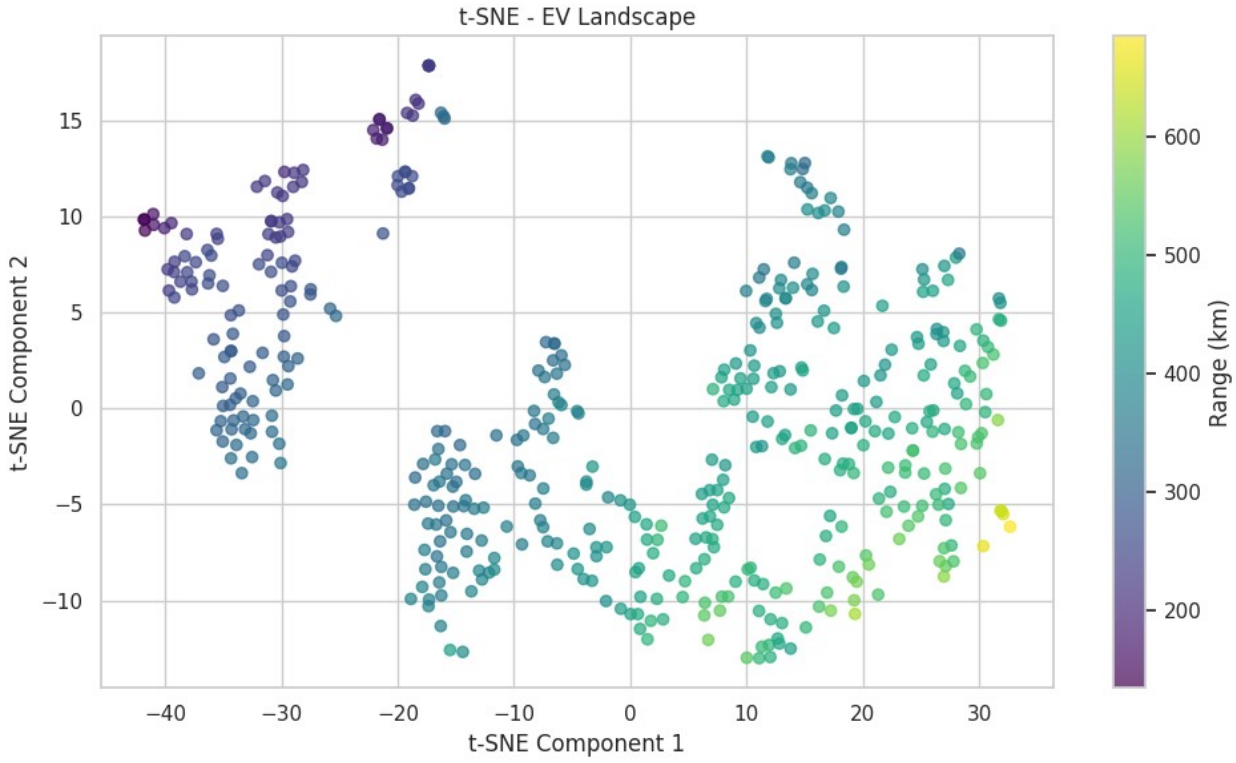
```
Mean Squared Error: 520.0928441154971
R^2 Score: 0.9428524025508827
```




```
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt
import seaborn as sns

# Επιλογή χαρακτηριστικών για την ανάλυση
features_for_pca = ['battery_capacity_kWh', 'torque_nm',
'efficiency_wh_per_km', 'range_km']

# Καθαρισμός των δεδομένων για την ανάλυση
df_pca = df[features_for_pca].dropna()

# Standardize τα δεδομένα για PCA ή t-SNE
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
df_pca_scaled = scaler.fit_transform(df_pca)

# PCA ανάλυση
pca = PCA(n_components=2)
pca_result = pca.fit_transform(df_pca_scaled)

# Εμφάνιση αποτελεσμάτων PCA
plt.figure(figsize=(10, 6))
plt.scatter(pca_result[:, 0], pca_result[:, 1], c=df['range_km'],
cmap='viridis', alpha=0.7)
plt.colorbar(label='Range (km)')
plt.title('PCA - EV Landscape')
```

```
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.tight_layout()
plt.show()

# ή

# Ανάλυση με t-SNE
tsne = TSNE(n_components=2, random_state=42)
tsne_result = tsne.fit_transform(df_pca_scaled)

# Εμφάνιση αποτελεσμάτων t-SNE
plt.figure(figsize=(10, 6))
plt.scatter(tsne_result[:, 0], tsne_result[:, 1], c=df['range_km'],
cmap='viridis', alpha=0.7)
plt.colorbar(label='Range (km)')
plt.title('t-SNE - EV Landscape')
plt.xlabel('t-SNE Component 1')
plt.ylabel('t-SNE Component 2')
plt.tight_layout()
plt.show()
```






```
print(df.columns)
```

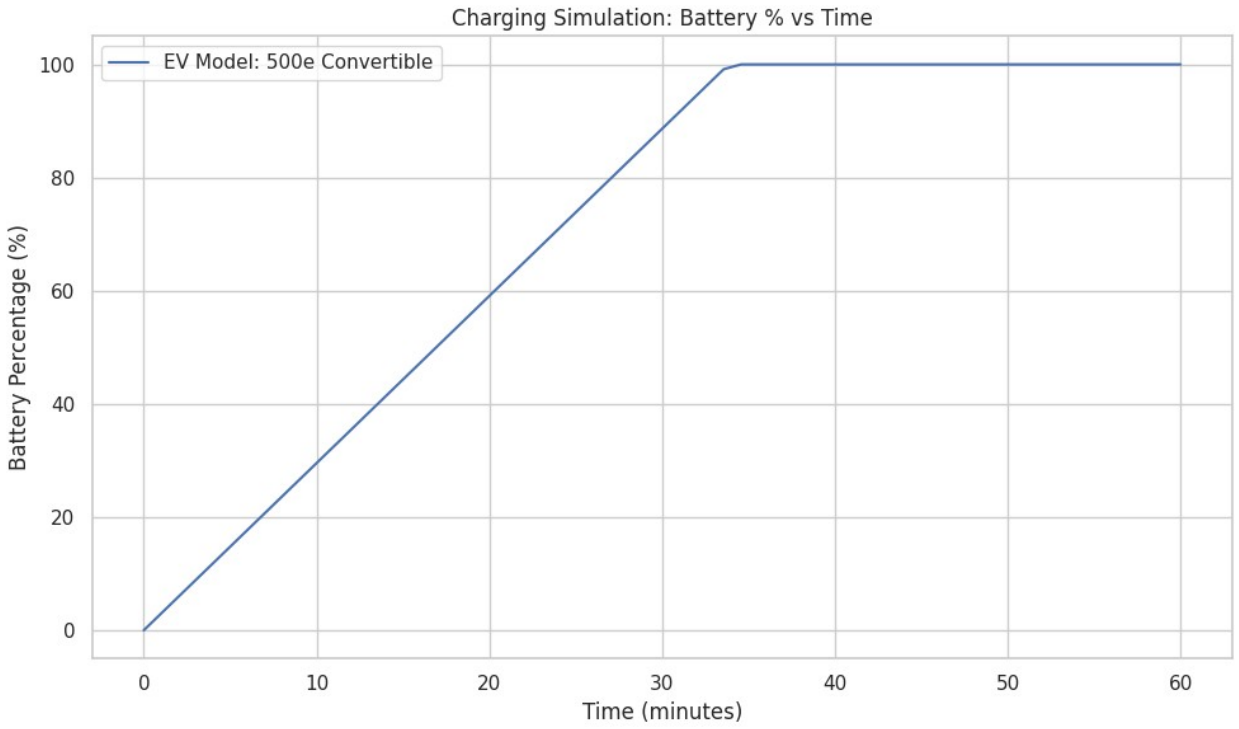
```
Index(['brand', 'model', 'top_speed_kmh', 'battery_capacity_kWh',
       'battery_type', 'number_of_cells', 'torque_nm',
'efficiency_wh_per_km',
       'range_km', 'acceleration_0_100_s',
'fast_charging_power_kw_dc',
       'fast_charge_port', 'towing_capacity_kg', 'cargo_volume_l',
'seats',
       'drivetrain', 'segment', 'length_mm', 'width_mm', 'height_mm',
       'car_body_type', 'source_url'],
      dtype='object')
```

```
print(df_charging_cleaned.head())  # Έλεγξε τα πρώτα δεδομένα για να
δεις τι περιέχουν
```

```
   battery_capacity_kWh  fast_charging_power_kw_dc
0                  37.8                       67.0
1                  37.8                       67.0
2                  50.8                       79.0
3                  50.8                       79.0
4                  60.0                       78.0
```

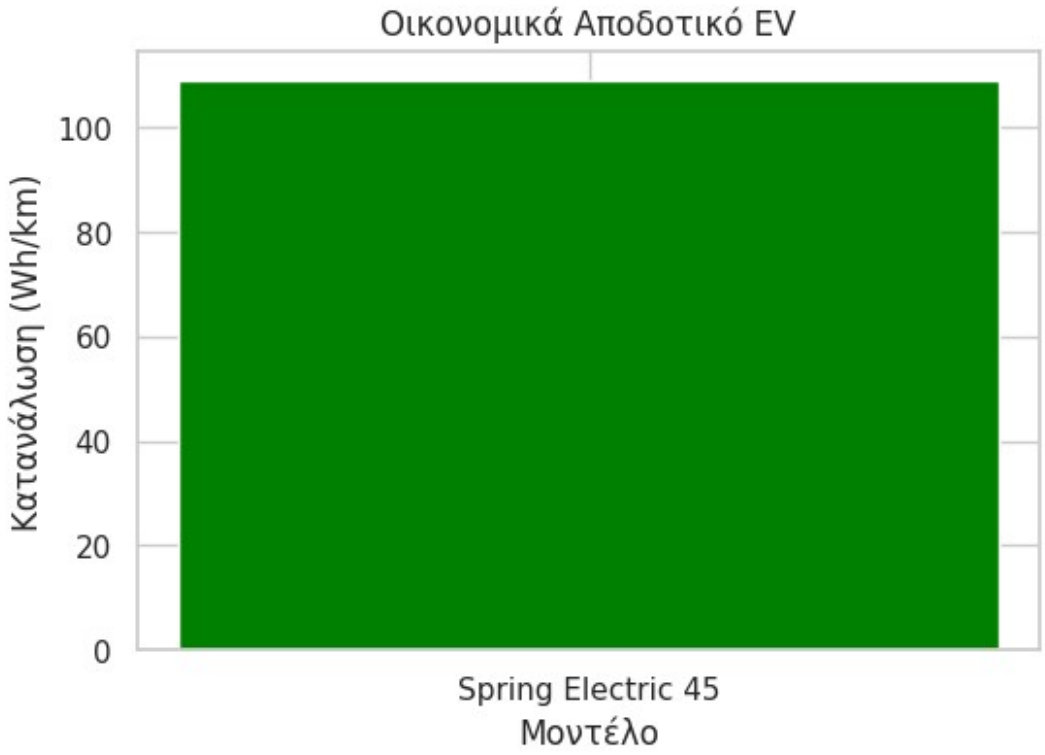
```
import numpy as np
import matplotlib.pyplot as plt

# Συνάρτηση υπολογισμού φόρτισης
```

```
def charging_simulation(row):
    # Βασικά δεδομένα
    battery_capacity = row["battery_capacity_kWh"]
    fast_charging_power = row["fast_charging_power_kw_dc"]

    # Υπολογισμός του χρόνου φόρτισης σε λεπτά και ποσοστό φόρτισης
    time = np.linspace(0, 60, 60)  # 60 λεπτά
    charging_percentage = (time / 60) * (fast_charging_power /
battery_capacity) * 100

    # Περιορίζουμε το ποσοστό φόρτισης στο 100%
    charging_percentage = np.clip(charging_percentage, 0, 100)

    return time, charging_percentage

# Επιλέγουμε το πρώτο όχημα ή δείγμα που δεν έχει NaN τιμές
df_charging_cleaned = df.dropna()

if not df_charging_cleaned.empty:
    row = df_charging_cleaned.iloc[0]  # Επιλέγουμε το πρώτο όχημα

    # Δημιουργία του γραφήματος φόρτισης
    time, charging_percentage = charging_simulation(row)

    # Δημιουργία του γραφήματος
    plt.figure(figsize=(10, 6))
    plt.plot(time, charging_percentage, label=f'EV Model:
{row["model"]}')
    plt.title("Charging Simulation: Battery % vs Time")
    plt.xlabel("Time (minutes)")
    plt.ylabel("Battery Percentage (%)")
    plt.grid(True)
    plt.legend()
    plt.tight_layout()
    plt.show()
else:
    print("Δεν βρέθηκαν δεδομένα χωρίς NaN τιμές.")
```

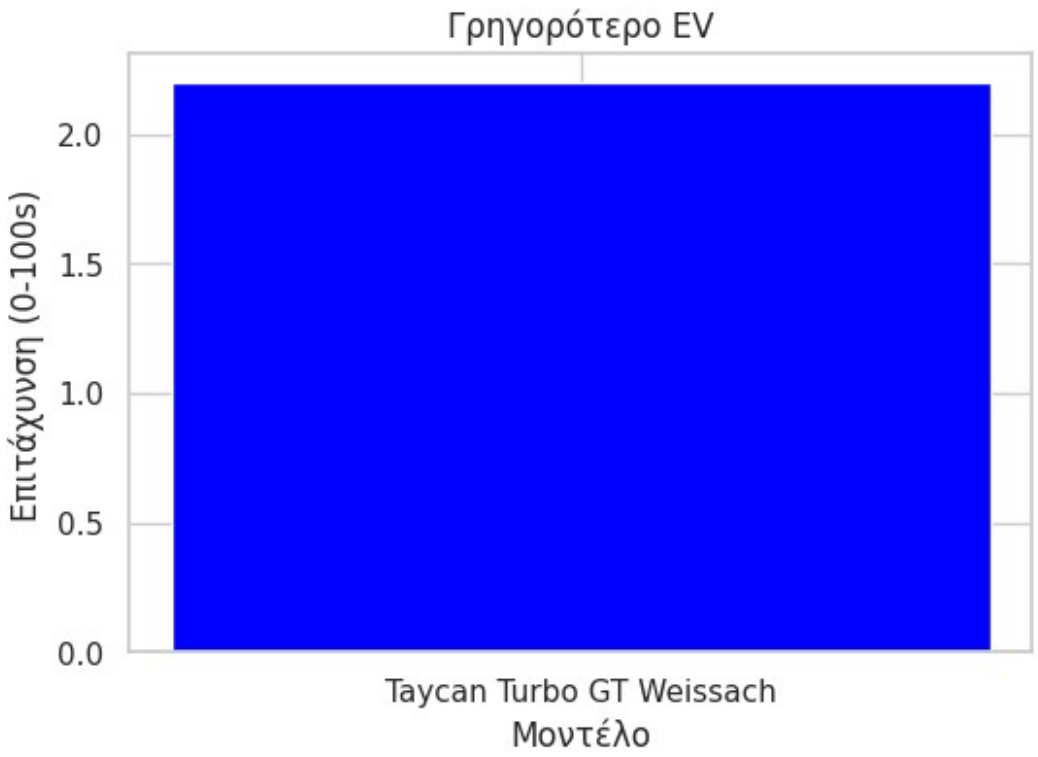



```
best_efficiency = df.loc[df['efficiency_wh_per_km'].idxmin()]

fastest = df.loc[df['acceleration_0_100_s'].idxmin()]

best_towing = df.loc[df['towing_capacity_kg'].idxmax()]

travel_ready = df.loc[(df['range_km'] >= 400) &
(df['fast_charging_power_kw_dc'] >= 100)]

urban_ev = df.loc[(df['length_mm'] < 4000) &
(df['efficiency_wh_per_km'] < 150)]

# 1. Οικονομικά αποδοτικό (χαμηλότερη efficiency_wh_per_km)
best_efficiency = df.loc[df['efficiency_wh_per_km'].idxmin()]

# 2. Γρηγορότερο (χαμηλότερη acceleration_0_100_s)
fastest = df.loc[df['acceleration_0_100_s'].idxmin()]

# 3. Ικανό για ρυμούλκηση (μεγαλύτερη towing_capacity_kg)
best_towing = df.loc[df['towing_capacity_kg'].idxmax()]

# 4. Κατάλληλο για ταξίδια (μεγαλύτερο range_km + υψηλή
fast_charging_power_kw_dc)
travel_ready = df.loc[(df['range_km'] >= 400) &
(df['fast_charging_power_kw_dc'] >= 100)]

# 5. Urban EV (μικρό μέγεθος + καλή κατανάλωση)
```

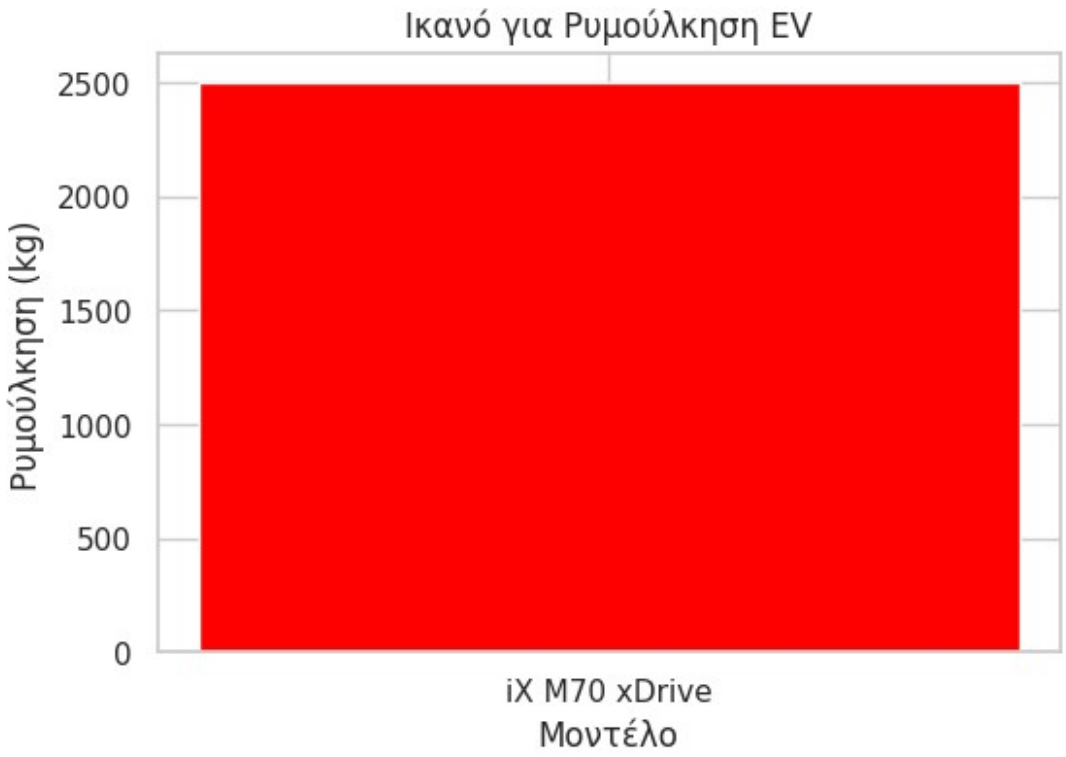
```
urban_ev = df.loc[(df['length_mm'] < 4000) &
(df['efficiency_wh_per_km'] < 150)]

import matplotlib.pyplot as plt

# Οικονομικά αποδοτικό
plt.figure(figsize=(6, 4))
plt.bar(best_efficiency['model'],
best_efficiency['efficiency_wh_per_km'], color='green')
plt.title("Οικονομικά Αποδοτικό EV")
plt.xlabel("Μοντέλο")
plt.ylabel("Κατανάλωση (Wh/km)")
plt.show()
```



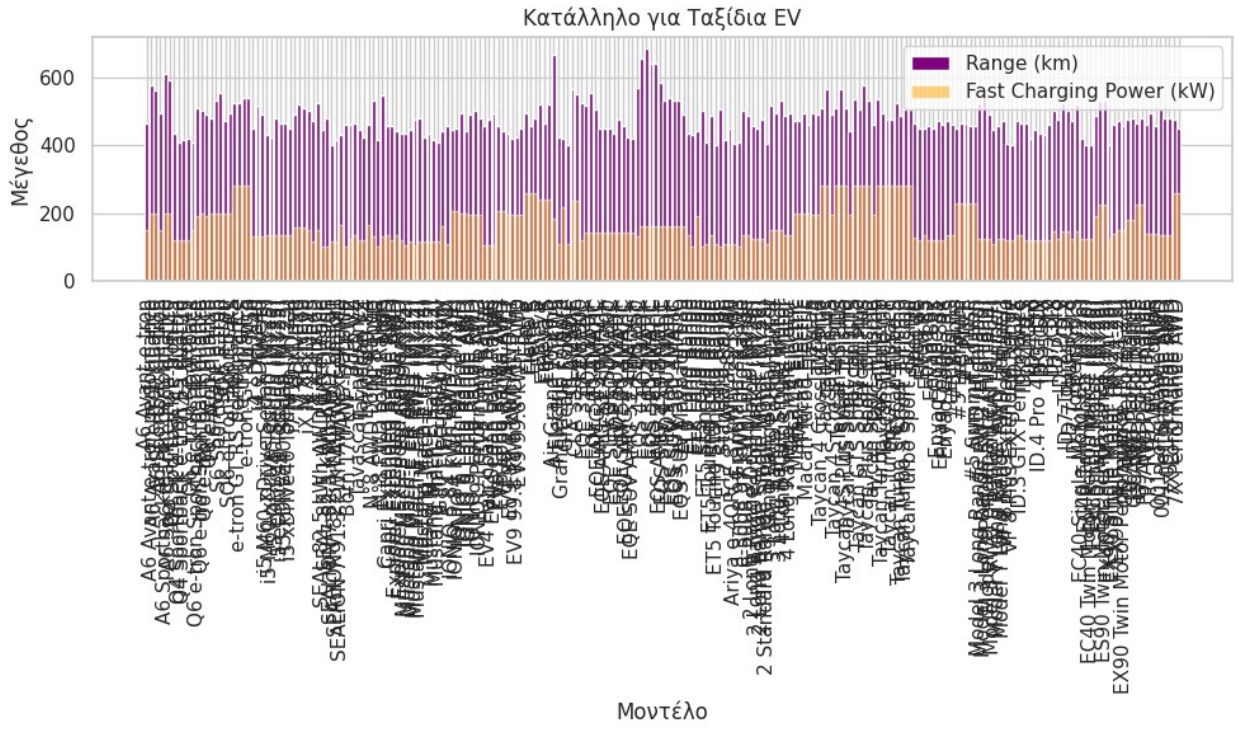

```
# Γρηγορότερο
plt.figure(figsize=(6, 4))
plt.bar(fastest['model'], fastest['acceleration_0_100_s'],
color='blue')
plt.title("Γρηγορότερο EV")
plt.xlabel("Μοντέλο")
plt.ylabel("Επιτάχυνση (0-100s)")
plt.show()
```



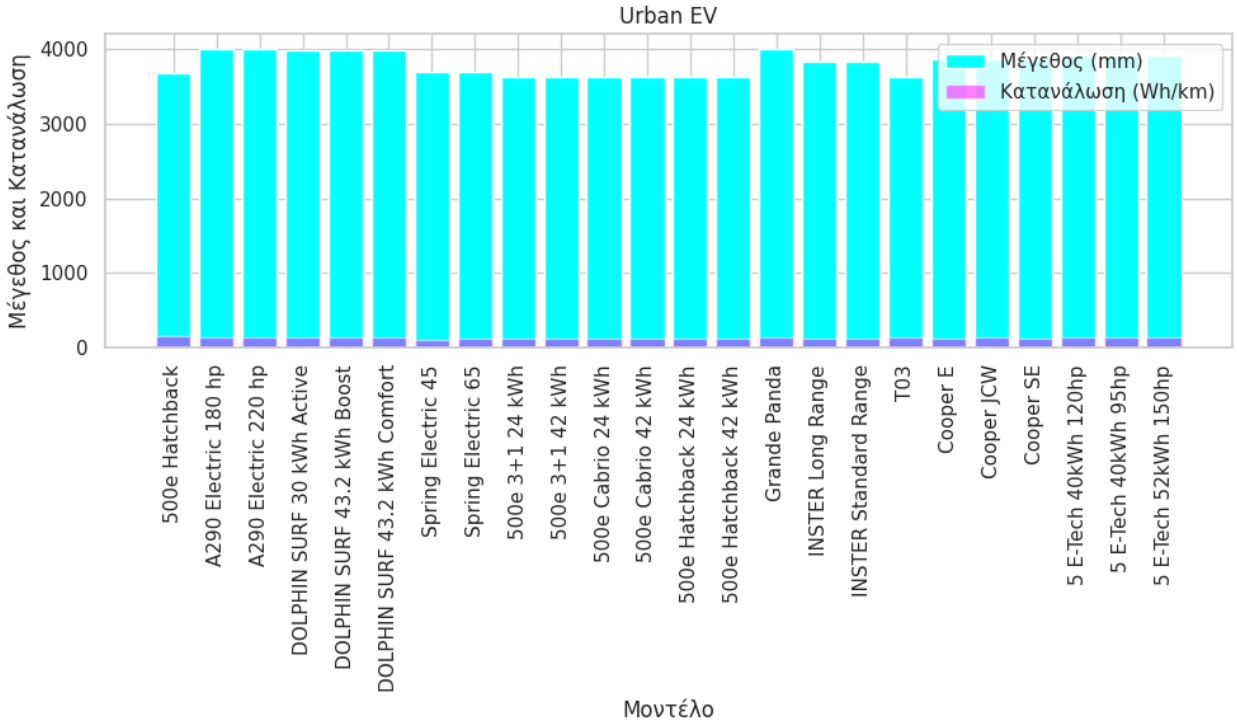

```
# Ικανό για ρυμούλκηση
plt.figure(figsize=(6, 4))
plt.bar(best_towing['model'], best_towing['towing_capacity_kg'],
color='red')
plt.title("Ικανό για Ρυμούλκηση EV")
plt.xlabel("Μοντέλο")
plt.ylabel("Ρυμούλκηση (kg)")
plt.show()
```




```
# Κατάλληλο για ταξίδια
travel_ready_models = travel_ready[['model', 'range_km',
'fast_charging_power_kw_dc']]

plt.figure(figsize=(10, 6))
plt.bar(travel_ready_models['model'], travel_ready_models['range_km'],
color='purple', label="Range (km)")
plt.bar(travel_ready_models['model'],
travel_ready_models['fast_charging_power_kw_dc'], color='orange',
alpha=0.5, label="Fast Charging Power (kW)")

plt.title("Κατάλληλο για Ταξίδια EV")
plt.xlabel("Μοντέλο")
plt.ylabel("Μέγεθος")
plt.xticks(rotation=90)
plt.legend()
plt.tight_layout()
plt.show()
```

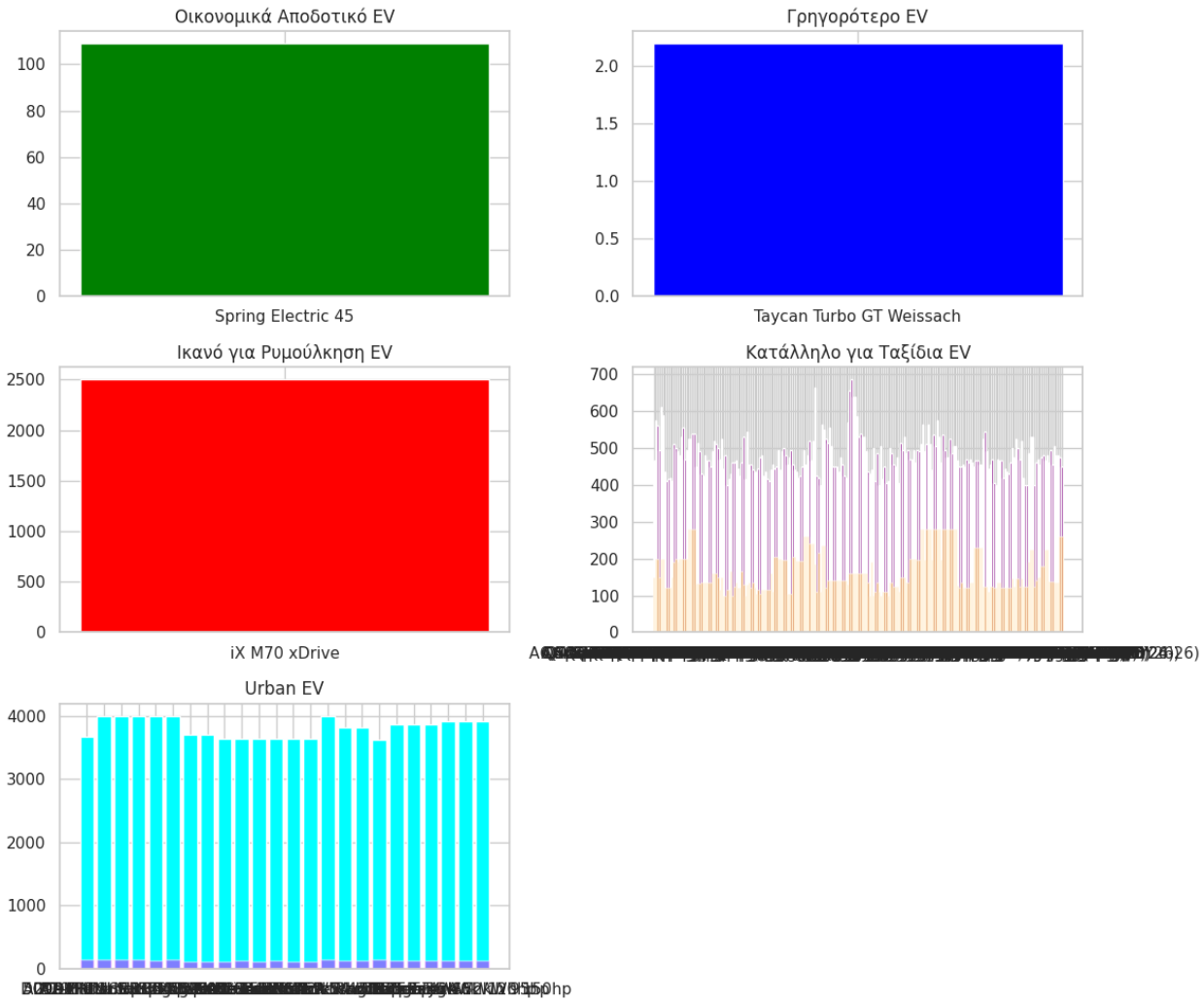



```
# Urban EV
urban_ev_models = urban_ev[['model', 'length_mm',
'efficiency_wh_per_km']]

plt.figure(figsize=(10, 6))
plt.bar(urban_ev_models['model'], urban_ev_models['length_mm'],
color='cyan', label="Μέγεθος (mm)")
plt.bar(urban_ev_models['model'],
urban_ev_models['efficiency_wh_per_km'], color='magenta', alpha=0.5,
label="Κατανάλωση (Wh/km)")

plt.title("Urban EV")
plt.xlabel("Μοντέλο")
plt.ylabel("Μέγεθος και Κατανάλωση")
plt.xticks(rotation=90)
plt.legend()
plt.tight_layout()
plt.show()
```



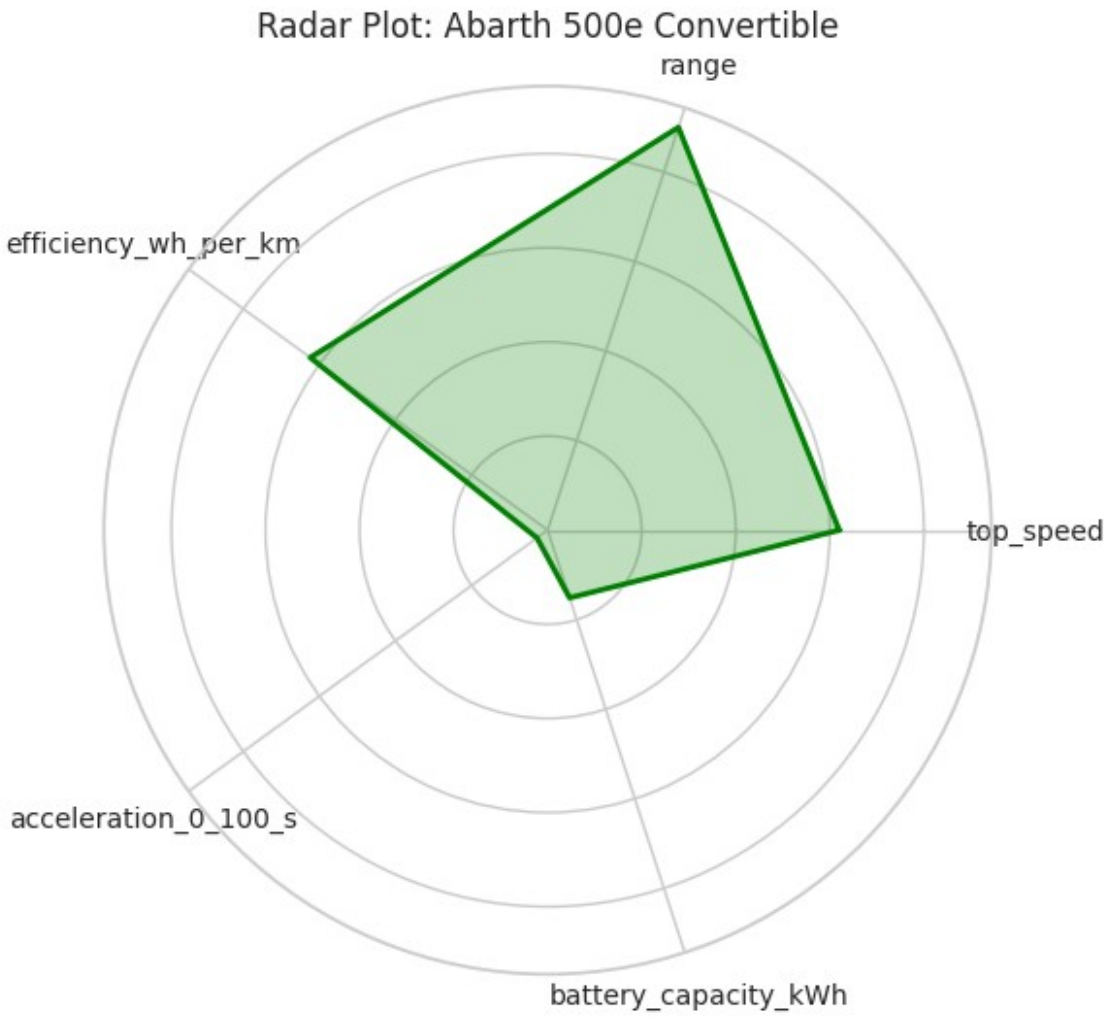

```
fig, axes = plt.subplots(3, 2, figsize=(12, 10))

# Οικονομικά αποδοτικό
axes[0, 0].bar(best_efficiency['model'],
best_efficiency['efficiency_wh_per_km'], color='green')
axes[0, 0].set_title("Οικονομικά Αποδοτικό EV")

# Γρηγορότερο
axes[0, 1].bar(fastest['model'], fastest['acceleration_0_100_s'],
color='blue')
axes[0, 1].set_title("Γρηγορότερο EV")

# Ικανό για ρυμούλκηση
axes[1, 0].bar(best_towing['model'],
best_towing['towing_capacity_kg'], color='red')
axes[1, 0].set_title("Ικανό για Ρυμούλκηση EV")

# Κατάλληλο για ταξίδια
axes[1, 1].bar(travel_ready_models['model'],
travel_ready_models['range_km'], color='purple', label="Range (km)")
axes[1, 1].bar(travel_ready_models['model'],
travel_ready_models['fast_charging_power_kw_dc'], color='orange',
alpha=0.5, label="Fast Charging Power (kW)")
axes[1, 1].set_title("Κατάλληλο για Ταξίδια EV")

# Urban EV
axes[2, 0].bar(urban_ev_models['model'], urban_ev_models['length_mm'],
```

```
color='cyan', label="Μέγεθος (mm)")
axes[2, 0].bar(urban_ev_models['model'],
urban_ev_models['efficiency_wh_per_km'], color='magenta', alpha=0.5,
label="Κατανάλωση (Wh/km)")
axes[2, 0].set_title("Urban EV")

# Κενό subplot για ευκολία
axes[2, 1].axis('off')

plt.tight_layout()
plt.show()
```

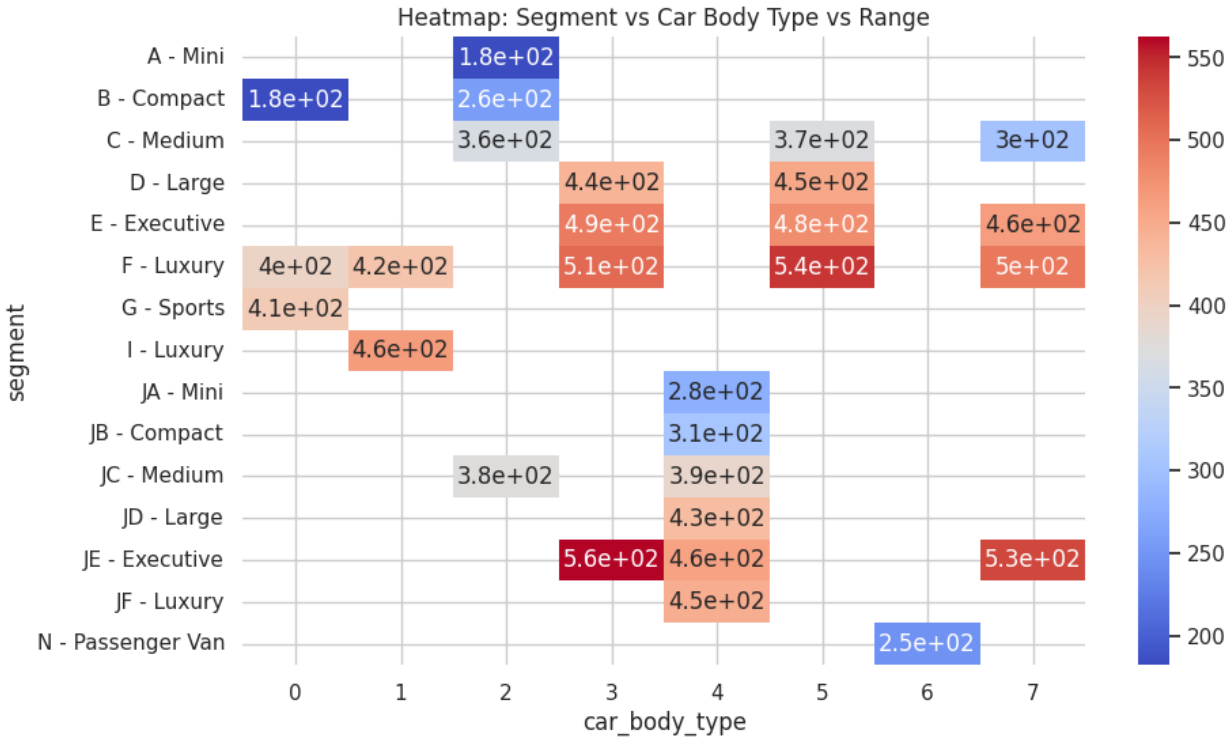



```
import matplotlib.pyplot as plt
import numpy as np

def radar_plot(row):
    categories = ['top_speed', 'range', 'efficiency_wh_per_km',
'acceleration_0_100_s', 'battery_capacity_kWh']
```

```
    values = [row['top_speed_kmh'], row['range_km'],
row['efficiency_wh_per_km'], row['acceleration_0_100_s'],
row['battery_capacity_kWh']]

    # Ορισμός του πλήρους κύκλου για το διάγραμμα
    num_vars = len(categories)
    angles = np.linspace(0, 2 * np.pi, num_vars,
endpoint=False).tolist()

    values += values[:1]
    angles += angles[:1]

    fig, ax = plt.subplots(figsize=(6, 6),
subplot_kw=dict(polar=True))
    ax.fill(angles, values, color='green', alpha=0.25)
    ax.plot(angles, values, color='green', linewidth=2)

    ax.set_yticklabels([])
    ax.set_xticks(angles[:-1])
    ax.set_xticklabels(categories, fontsize=10)

    plt.title(f'Radar Plot: {row["brand"]} {row["model"]}')
    plt.tight_layout()
    plt.show()

# Εφαρμογή για το πρώτο δείγμα
radar_plot(df.iloc[0])
```




```
import plotly.express as px

fig = px.scatter(df, x="top_speed_kmh", y="range_km", color="brand",
size="battery_capacity_kWh", hover_name="model")
fig.update_layout(title="EVs: Top Speed vs Range")
fig.show()

import seaborn as sns

# Δημιουργία heatmap για segment vs car_body_type vs range_km
pivot_table = df.pivot_table(values='range_km', index='segment',
columns='car_body_type', aggfunc='mean')
sns.heatmap(pivot_table, annot=True, cmap='coolwarm')
plt.title("Heatmap: Segment vs Car Body Type vs Range")
plt.show()
```


Heatmap: Segment vs Car Body Type vs Range
A - Mini
B - Compact
C - Medium
D - Large
E - Executive
F - Luxury
G - Sports
I - Luxury
JA - Mini
JB - Compact
JC - Medium
JD - Large
JE - Executive
JF - Luxury
N - Passenger Van
segment
0
1
2
3
4
5
6
7
car_body_type
1.8e+02
2.6e+02
3.6e+02
3.7e+02
3e+02
4.4e+02
4.5e+02
4.9e+02
4.8e+02
4.6e+02
4e+02
4.2e+02
5.1e+02
5.4e+02
5e+02
4.1e+02
4.6e+02
2.8e+02
3.1e+02
3.8e+02
3.9e+02
4.3e+02
5.6e+02
4.6e+02
5.3e+02
4.5e+02
2.5e+02
550
500
450
400
350
300
250
200