

```
In [1]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import pymysql
```

```
In [2]: # Load the dataset
file_path = "C:/Users/Komal Bhati/Desktop/New folder/used_cars.csv"
data = pd.read_csv(file_path)
```

```
In [4]: import pymysql

# Define your MySQL configuration
db_config = {
    'host': 'localhost',
    'user': 'root',
    'password': '1881arpit',
    'database': 'used_cars_db'
}

# Create mileage column
data['mileage'] = (data['city_mileage'] + data['highway_mileage']) / 2

# Establish MySQL Connection
try:
    connection = pymysql.connect(**db_config)
    cursor = connection.cursor()

    # Create database if not exists
    cursor.execute("CREATE DATABASE IF NOT EXISTS used_cars_db")
    cursor.execute("USE used_cars_db")

    # Create table
    create_table_query = """
    CREATE TABLE IF NOT EXISTS car_details (
        id INT AUTO_INCREMENT PRIMARY KEY,
        brand VARCHAR(50),
        model VARCHAR(50),
        year INT,
        price FLOAT,
        mileage FLOAT
    )"""
    cursor.execute(create_table_query)

    # Insert data
    for _, row in data.iterrows():
        insert_query = """
        INSERT INTO car_details (brand, model, year, price, mileage)
        VALUES (%s, %s, %s, %s, %s)
        """
        cursor.execute(insert_query, (row['brand'], row['model'], row['year'],
                                      row['price'], row['mileage']))

    connection.commit()
    print("Data inserted successfully")

except pymysql.MySQLError as e:
    print(f"Error: {e}")

finally:
```

```
if connection:  
    cursor.close()  
    connection.close()
```

Data inserted successfully

```
In [5]: # 1. Basic Information  
print('--- Dataset Info-')  
data.info()  
  
# 2. Checking for null values  
print('\n--- Missing Values ---')  
print(data.isnull().sum())
```

--- Dataset Info ---

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 52 entries, 0 to 51

Data columns (total 28 columns):

#	Column	Non-Null Count	Dtype
0	id	52 non-null	int64
1	brand	52 non-null	object
2	model	52 non-null	object
3	year	52 non-null	int64
4	miles	52 non-null	int64
5	city_mileage	52 non-null	int64
6	highway_mileage	52 non-null	int64
7	horsepower	52 non-null	int64
8	torque	52 non-null	int64
9	engine_capacity_litre	52 non-null	float64
10	fuel_capacity	52 non-null	float64
11	num_cylinder	52 non-null	int64
12	num_seat	52 non-null	int64
13	num_owners	52 non-null	int64
14	price	52 non-null	int64
15	link	52 non-null	object
16	condition	1 non-null	float64
17	type	52 non-null	object
18	doors	52 non-null	int64
19	wheel_drive	52 non-null	int64
20	engine_type	52 non-null	object
21	speed_levels	51 non-null	float64
22	front_headroom	52 non-null	float64
23	front_legroom	52 non-null	float64
24	rear_headroom	52 non-null	float64
25	rear_legroom	52 non-null	float64
26	service_records	52 non-null	int64
27	mileage	52 non-null	float64

dtypes: float64(9), int64(14), object(5)

memory usage: 11.5+ KB

--- Missing Values ---

id	0
brand	0
model	0
year	0
miles	0
city_mileage	0
highway_mileage	0
horsepower	0
torque	0
engine_capacity_litre	0
fuel_capacity	0
num_cylinder	0
num_seat	0
num_owners	0
price	0
link	0
condition	51
type	0
doors	0
wheel_drive	0
engine_type	0
speed_levels	1

```
front_headroom      0
front_legroom        0
rear_headroom        0
rear_legroom         0
service_records      0
mileage              0
dtype: int64
```

```
In [6]: # 3. Descriptive Statistics
print('\n--- Descriptive Statistics ---')
print(data.describe())

# 4. Unique values in each column
print('\n--- Unique Values in Each Column ---')
print(data.nunique())
```

## --- Descriptive Statistics ---

	id	year	miles	city_mileage	highway_mileage	\
count	52.000000	52.000000	52.000000	52.000000	52.000000	
mean	31.365385	2018.673077	33901.250000	29.038462	37.423077	
std	15.378912	1.396370	22700.646139	5.947356	4.136619	
min	3.000000	2014.000000	5000.000000	17.000000	24.000000	
25%	18.750000	2018.000000	16454.750000	26.500000	35.750000	
50%	31.500000	2019.000000	27448.500000	30.000000	38.000000	
75%	44.250000	2019.250000	42442.000000	30.000000	40.000000	
max	57.000000	2022.000000	97027.000000	55.000000	49.000000	

	horsepower	torque	engine_capacity_litre	fuel_capacity	\
count	52.000000	52.000000	52.000000	52.000000	
mean	176.865385	177.923077	1.832692	14.232692	
std	33.793507	47.256433	0.379743	2.603973	
min	143.000000	99.000000	1.400000	7.000000	
25%	152.000000	138.000000	1.500000	12.400000	
50%	159.500000	181.000000	2.000000	13.600000	
75%	192.000000	192.000000	2.000000	15.050000	
max	288.000000	294.000000	3.500000	19.000000	

	num_cylinder	...	condition	doors	wheel_drive	speed_levels	\
count	52.000000	...	1.0	52.0	52.000000	51.000000	
mean	4.038462	...	4.0	4.0	2.153846	6.313725	
std	0.277350	...	NaN	0.0	0.538138	0.761320	
min	4.000000	...	4.0	4.0	2.000000	6.000000	
25%	4.000000	...	4.0	4.0	2.000000	6.000000	
50%	4.000000	...	4.0	4.0	2.000000	6.000000	
75%	4.000000	...	4.0	4.0	2.000000	6.000000	
max	6.000000	...	4.0	4.0	4.000000	9.000000	

	front_headroom	front_legroom	rear_headroom	rear_legroom	\
count	52.000000	52.000000	52.000000	52.000000	
mean	38.680769	42.467308	37.238462	37.632692	
std	0.919087	1.045198	0.444202	1.604249	
min	37.500000	41.100000	35.800000	33.200000	
25%	37.725000	42.200000	37.075000	37.175000	
50%	38.500000	42.300000	37.200000	37.400000	
75%	39.300000	42.400000	37.500000	38.300000	
max	40.400000	45.500000	38.000000	40.400000	

	service_records	mileage
count	52.000000	52.000000
mean	7.326923	33.230769
std	4.714272	4.858247
min	1.000000	20.500000
25%	4.000000	30.875000
50%	6.000000	34.000000
75%	10.000000	35.000000
max	26.000000	52.000000

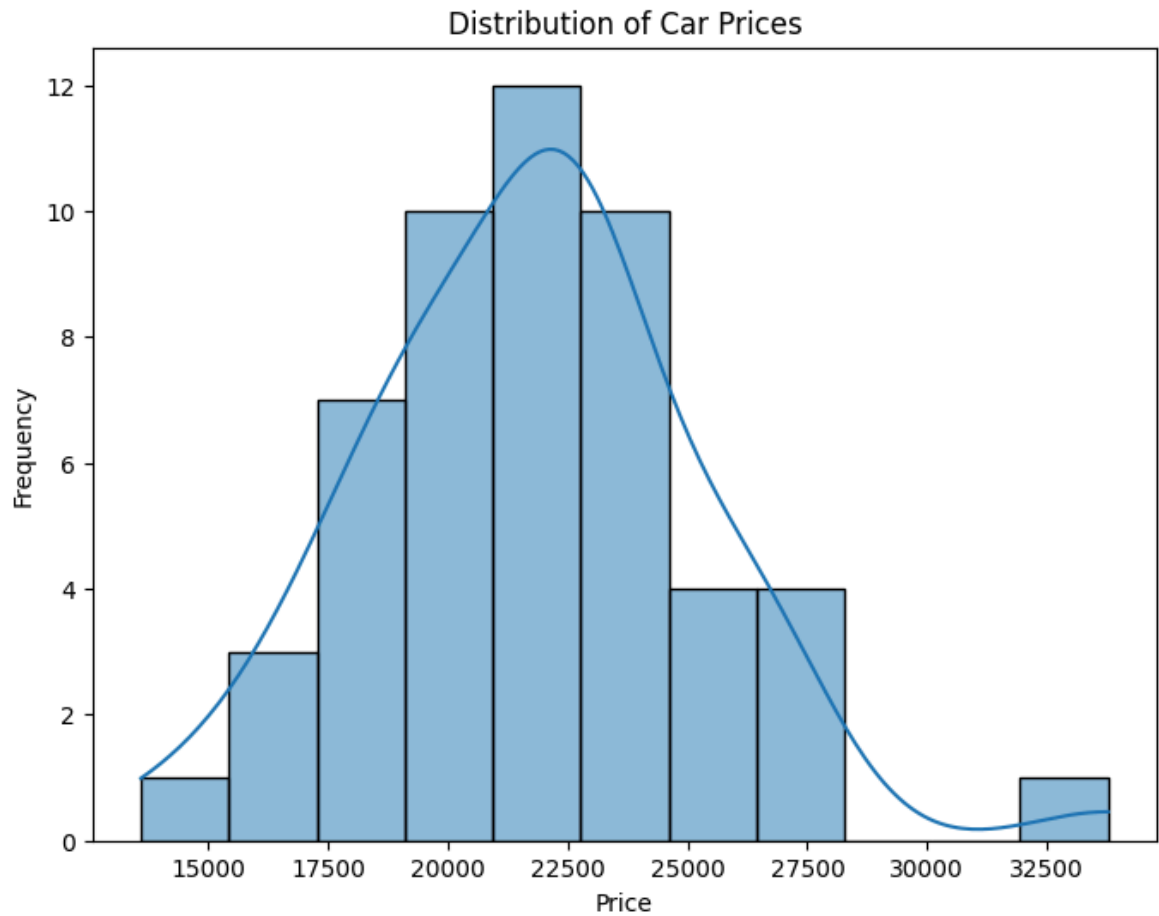
[8 rows x 23 columns]

## --- Unique Values in Each Column ---

id	52
brand	6
model	15
year	8
miles	50
city_mileage	15

```
highway_mileage      14
horsepower           20
torque               17
engine_capacity_litre 7
fuel_capacity        13
num_cylinder         2
num_seat             1
num_owners           3
price               47
link                51
condition            1
type                 1
doors                1
wheel_drive          2
engine_type           2
speed_levels         4
front_headroom       15
front_legroom        14
rear_headroom        11
rear_legroom         12
service_records      15
mileage              22
dtype: int64
```

```
In [7]: # 5. Distribution of target variable (if any)
        if 'price' in data.columns:
            plt.figure(figsize=(8, 6))
            sns.histplot(data['price'], kde=True)
            plt.title('Distribution of Car Prices')
            plt.xlabel('Price')
            plt.ylabel('Frequency')
            plt.show()
```



```
In [8]: import numpy as np

# Check for missing values
print("Missing values in each column:")
print(data.isnull().sum())

# Check for infinite values in numeric columns
numeric_data = data.select_dtypes(include=[np.number])
print("\nInfinite values in each numeric column:")
print(np.isinf(numeric_data).sum())
```

Missing values in each column:

id	0
brand	0
model	0
year	0
miles	0
city_mileage	0
highway_mileage	0
horsepower	0
torque	0
engine_capacity_litre	0
fuel_capacity	0
num_cylinder	0
num_seat	0
num_owners	0
price	0
link	0
condition	51
type	0
doors	0
wheel_drive	0
engine_type	0
speed_levels	1
front_headroom	0
front_legroom	0
rear_headroom	0
rear_legroom	0
service_records	0
mileage	0

dtype: int64

Infinite values in each numeric column:

id	0
year	0
miles	0
city_mileage	0
highway_mileage	0
horsepower	0
torque	0
engine_capacity_litre	0
fuel_capacity	0
num_cylinder	0
num_seat	0
num_owners	0
price	0
condition	0
doors	0
wheel_drive	0
speed_levels	0
front_headroom	0
front_legroom	0
rear_headroom	0
rear_legroom	0
service_records	0
mileage	0

dtype: int64

```
In [9]: data_clean = data.replace([np.inf, -np.inf], np.nan).dropna()
```



```
In [10]: # 6. Correlation Heatmap

corr_matrix = numeric_data.corr()
print(corr_matrix)

plt.figure(figsize=(12, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap of Numerical Features')
plt.show()
```

	id	year	miles	city_mileage	\
id	1.000000	0.314289	-0.140389	-0.274989	
year	0.314289	1.000000	-0.570330	-0.081093	
miles	-0.140389	-0.570330	1.000000	0.109841	
city_mileage	-0.274989	-0.081093	0.109841	1.000000	
highway_mileage	-0.213916	-0.165681	0.122973	0.852120	
horsepower	0.251407	0.251688	-0.072269	-0.493823	
torque	0.217796	0.322014	-0.207391	-0.519817	
engine_capacity_litre	0.033168	0.076018	-0.051521	-0.517143	
fuel_capacity	0.245833	0.274241	-0.130851	-0.754301	
num_cylinder	-0.049330	0.033104	0.026134	-0.286206	
num_seat	NaN	NaN	NaN	NaN	
num_owners	-0.476279	-0.431124	0.415837	0.107537	
price	-0.003663	0.581254	-0.500769	0.131767	
condition	NaN	NaN	NaN	NaN	
doors	NaN	NaN	NaN	NaN	
wheel_drive	-0.106434	0.276995	-0.033973	-0.295957	
speed_levels	0.187717	0.056380	-0.285384	-0.107265	
front_headroom	0.367012	0.305153	0.002602	-0.173121	
front_legroom	0.141772	0.051646	0.088820	-0.323113	
rear_headroom	0.371326	0.175567	0.025208	-0.650003	
rear_legroom	0.254622	0.334853	-0.045425	-0.169064	
service_records	-0.195053	-0.501725	0.412596	-0.129836	
mileage	-0.259388	-0.120172	0.119586	0.974863	

	highway_mileage	horsepower	torque	\
id	-0.213916	0.251407	0.217796	
year	-0.165681	0.251688	0.322014	
miles	0.122973	-0.072269	-0.207391	
city_mileage	0.852120	-0.493823	-0.519817	
highway_mileage	1.000000	-0.758562	-0.663951	
horsepower	-0.758562	1.000000	0.702836	
torque	-0.663951	0.702836	1.000000	
engine_capacity_litre	-0.649320	0.399601	0.122738	
fuel_capacity	-0.719426	0.438834	0.465158	
num_cylinder	-0.458816	0.464994	0.227627	
num_seat	NaN	NaN	NaN	
num_owners	0.018155	-0.082548	-0.011073	
price	-0.041956	0.301800	0.199764	
condition	NaN	NaN	NaN	
doors	NaN	NaN	NaN	
wheel_drive	-0.417376	0.344031	0.213281	
speed_levels	-0.037628	0.109859	0.298219	
front_headroom	-0.321700	0.146378	0.011929	
front_legroom	-0.441630	0.400069	0.227339	
rear_headroom	-0.688770	0.509124	0.351548	
rear_legroom	-0.138336	0.300567	0.255183	
service_records	0.031982	-0.132643	-0.030602	
mileage	0.947304	-0.625207	-0.600839	

	engine_capacity_litre	fuel_capacity	num_cylinder	\
id	0.033168	0.245833	-0.049330	
year	0.076018	0.274241	0.033104	
miles	-0.051521	-0.130851	0.026134	
city_mileage	-0.517143	-0.754301	-0.286206	
highway_mileage	-0.649320	-0.719426	-0.458816	
horsepower	0.399601	0.438834	0.464994	
torque	0.122738	0.465158	0.227627	
engine_capacity_litre	1.000000	0.475591	0.620809	
fuel_capacity	0.475591	1.000000	0.258862	

num_cylinder	0.620809	0.258862	1.000000
num_seat	NaN	NaN	NaN
num_owners	0.224878	-0.076055	0.375592
price	0.038197	0.027480	0.049216
condition	NaN	NaN	NaN
doors	NaN	NaN	NaN
wheel_drive	0.512227	0.329365	0.485071
speed_levels	-0.236593	-0.004260	-0.058857
front_headroom	0.420380	0.264980	0.049111
front_legroom	0.420684	0.417100	-0.076745
rear_headroom	0.402731	0.737816	0.178744
rear_legroom	-0.216792	0.343792	0.041187
service_records	-0.174761	0.095907	-0.189762
mileage	-0.592974	-0.767981	-0.370516

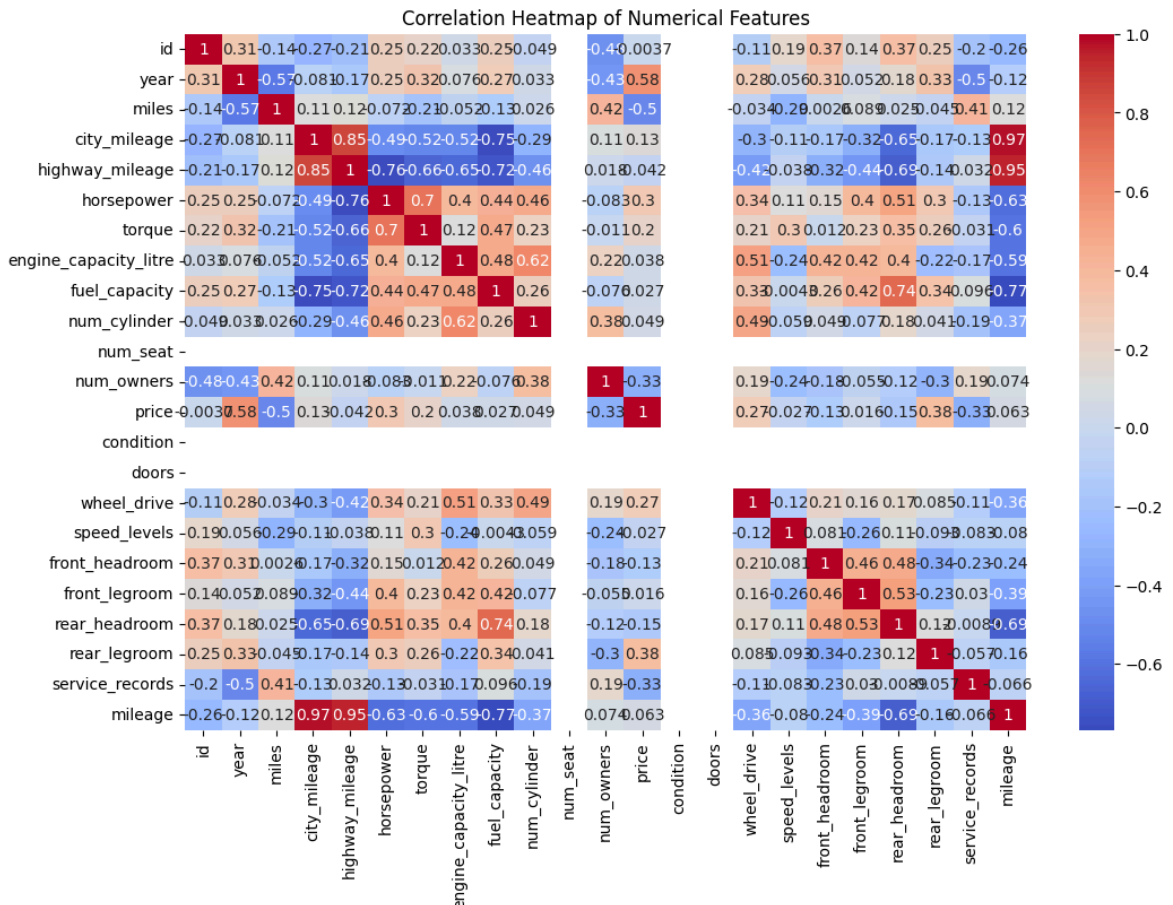
	...	condition	doors	wheel_drive	speed_levels	\
id	...	NaN	NaN	-0.106434	0.187717	
year	...	NaN	NaN	0.276995	0.056380	
miles	...	NaN	NaN	-0.033973	-0.285384	
city_mileage	...	NaN	NaN	-0.295957	-0.107265	
highway_mileage	...	NaN	NaN	-0.417376	-0.037628	
horsepower	...	NaN	NaN	0.344031	0.109859	
torque	...	NaN	NaN	0.213281	0.298219	
engine_capacity_litre	...	NaN	NaN	0.512227	-0.236593	
fuel_capacity	...	NaN	NaN	0.329365	-0.004260	
num_cylinder	...	NaN	NaN	0.485071	-0.058857	
num_seat	...	NaN	NaN	NaN	NaN	
num_owners	...	NaN	NaN	0.189074	-0.236658	
price	...	NaN	NaN	0.268273	-0.026826	
condition	...	NaN	NaN	NaN	NaN	
doors	...	NaN	NaN	NaN	NaN	
wheel_drive	...	NaN	NaN	1.000000	-0.121413	
speed_levels	...	NaN	NaN	-0.121413	1.000000	
front_headroom	...	NaN	NaN	0.212249	0.080521	
front_legroom	...	NaN	NaN	0.155533	-0.260503	
rear_headroom	...	NaN	NaN	0.171625	0.107920	
rear_legroom	...	NaN	NaN	0.084910	-0.092717	
service_records	...	NaN	NaN	-0.112962	-0.083293	
mileage	...	NaN	NaN	-0.358842	-0.079967	

	front_headroom	front_legroom	rear_headroom	\
id	0.367012	0.141772	0.371326	
year	0.305153	0.051646	0.175567	
miles	0.002602	0.088820	0.025208	
city_mileage	-0.173121	-0.323113	-0.650003	
highway_mileage	-0.321700	-0.441630	-0.688770	
horsepower	0.146378	0.400069	0.509124	
torque	0.011929	0.227339	0.351548	
engine_capacity_litre	0.420380	0.420684	0.402731	
fuel_capacity	0.264980	0.417100	0.737816	
num_cylinder	0.049111	-0.076745	0.178744	
num_seat	NaN	NaN	NaN	
num_owners	-0.176602	-0.054584	-0.119983	
price	-0.129595	0.015819	-0.145403	
condition	NaN	NaN	NaN	
doors	NaN	NaN	NaN	
wheel_drive	0.212249	0.155533	0.171625	
speed_levels	0.080521	-0.260503	0.107920	
front_headroom	1.000000	0.455325	0.477803	
front_legroom	0.455325	1.000000	0.526027	

rear_headroom	0.477803	0.526027	1.000000
rear_legroom	-0.338809	-0.229369	0.120095
service_records	-0.232937	0.029669	-0.008931
mileage	-0.242924	-0.385790	-0.691091

	rear_legroom	service_records	mileage
id	0.254622	-0.195053	-0.259388
year	0.334853	-0.501725	-0.120172
miles	-0.045425	0.412596	0.119586
city_mileage	-0.169064	-0.129836	0.974863
highway_mileage	-0.138336	0.031982	0.947304
horsepower	0.300567	-0.132643	-0.625207
torque	0.255183	-0.030602	-0.600839
engine_capacity_litre	-0.216792	-0.174761	-0.592974
fuel_capacity	0.343792	0.095907	-0.767981
num_cylinder	0.041187	-0.189762	-0.370516
num_seat	NaN	NaN	NaN
num_owners	-0.304058	0.187823	0.073551
price	0.377287	-0.327306	0.062791
condition	NaN	NaN	NaN
doors	NaN	NaN	NaN
wheel_drive	0.084910	-0.112962	-0.358842
speed_levels	-0.092717	-0.083293	-0.079967
front_headroom	-0.338809	-0.232937	-0.242924
front_legroom	-0.229369	0.029669	-0.385790
rear_headroom	0.120095	-0.008931	-0.691091
rear_legroom	1.000000	-0.057183	-0.162376
service_records	-0.057183	1.000000	-0.065856
mileage	-0.162376	-0.065856	1.000000

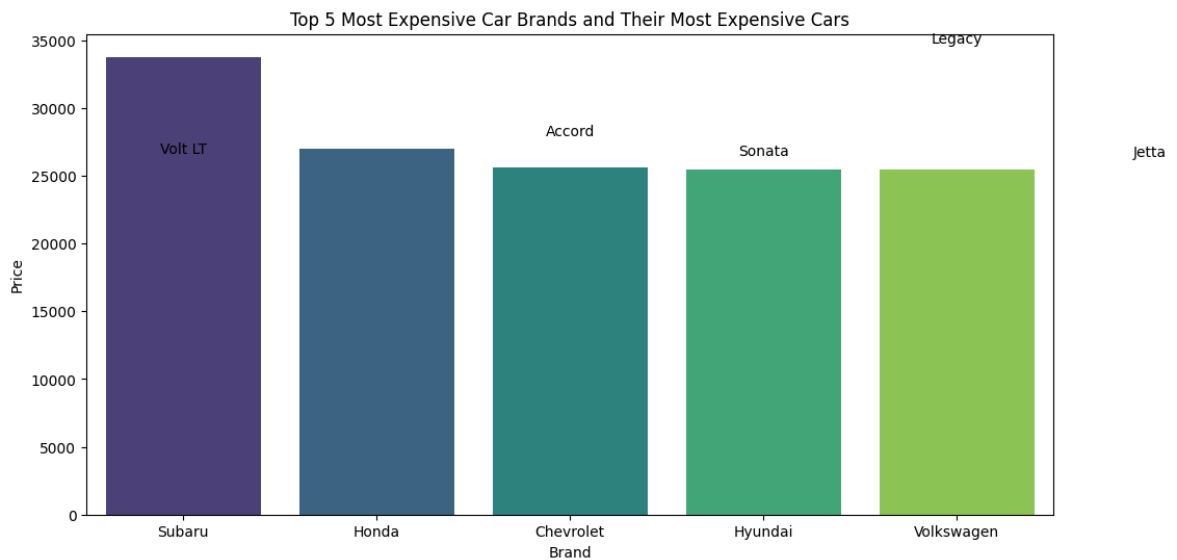
[23 rows x 23 columns]



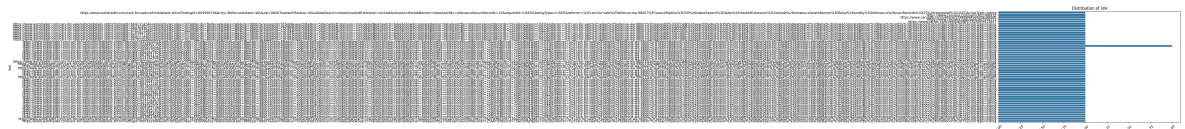
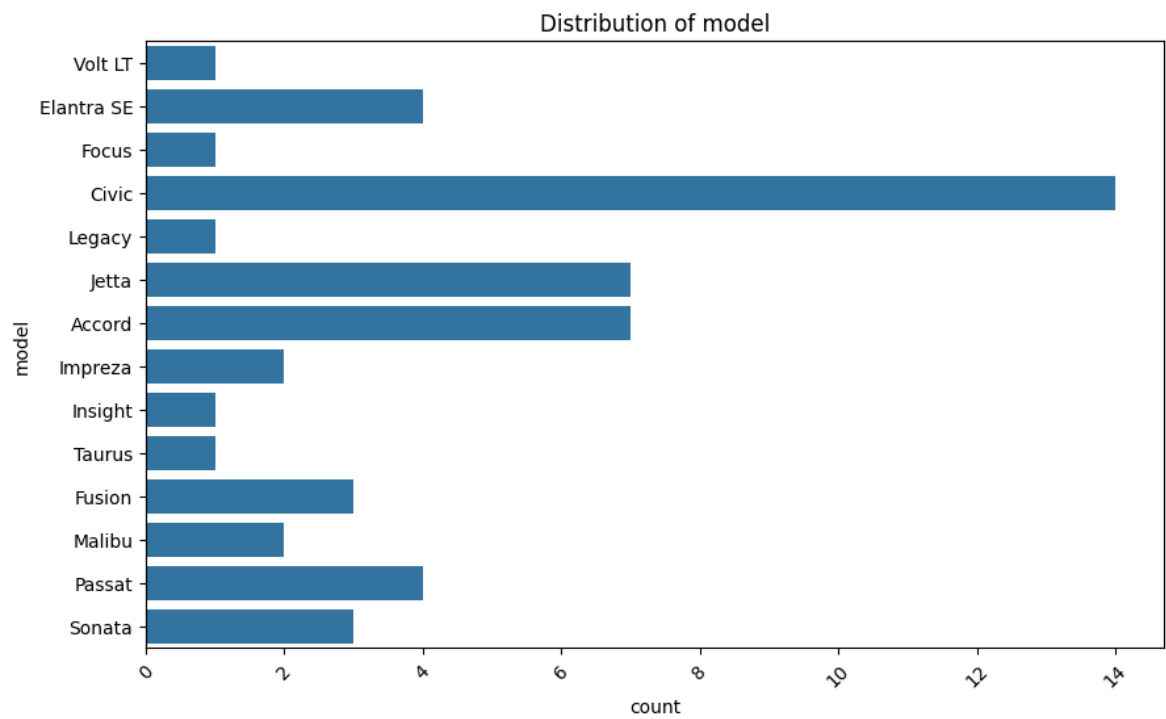
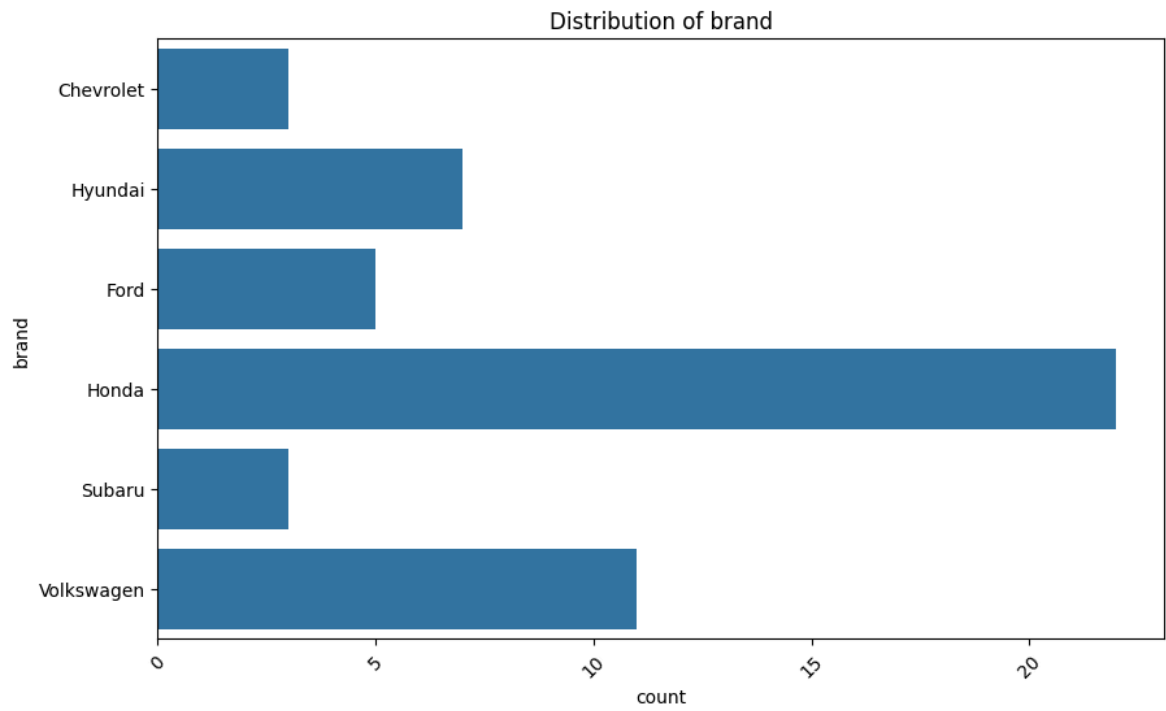
```
In [49]: # Plotting Top 5 Most Expensive Car Brands and Their Most Expensive Cars
plt.figure(figsize=(12, 6))
sns.barplot(x='brand', y='price', data=top_brands, palette='viridis', hue='brand')

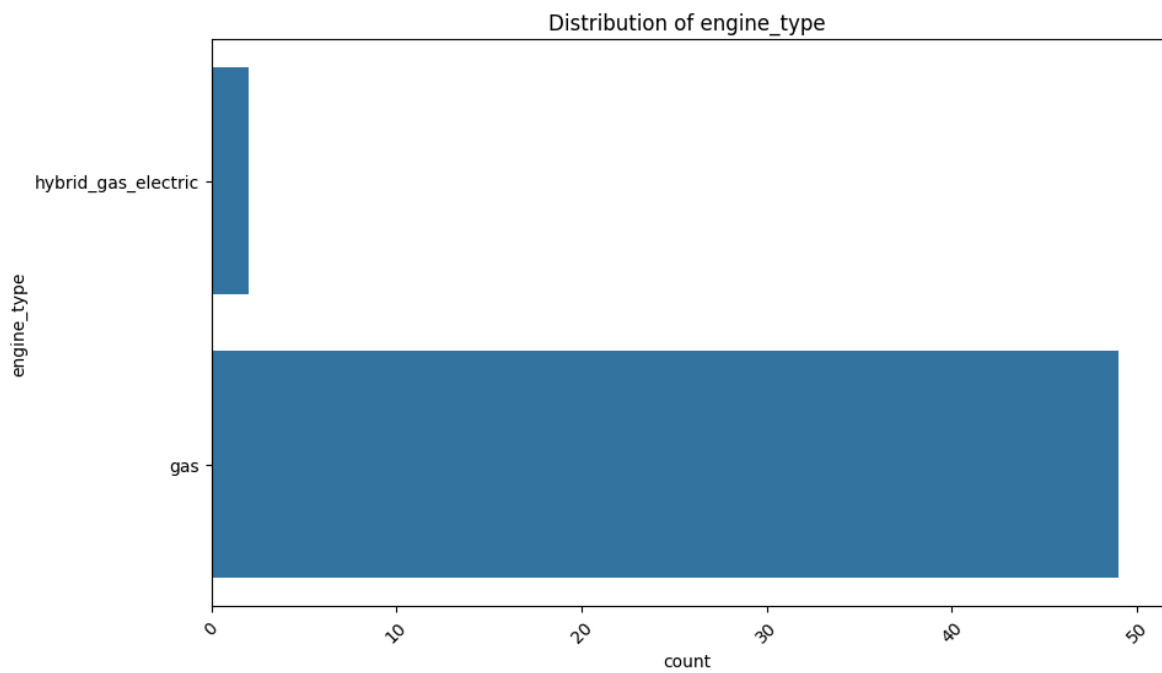
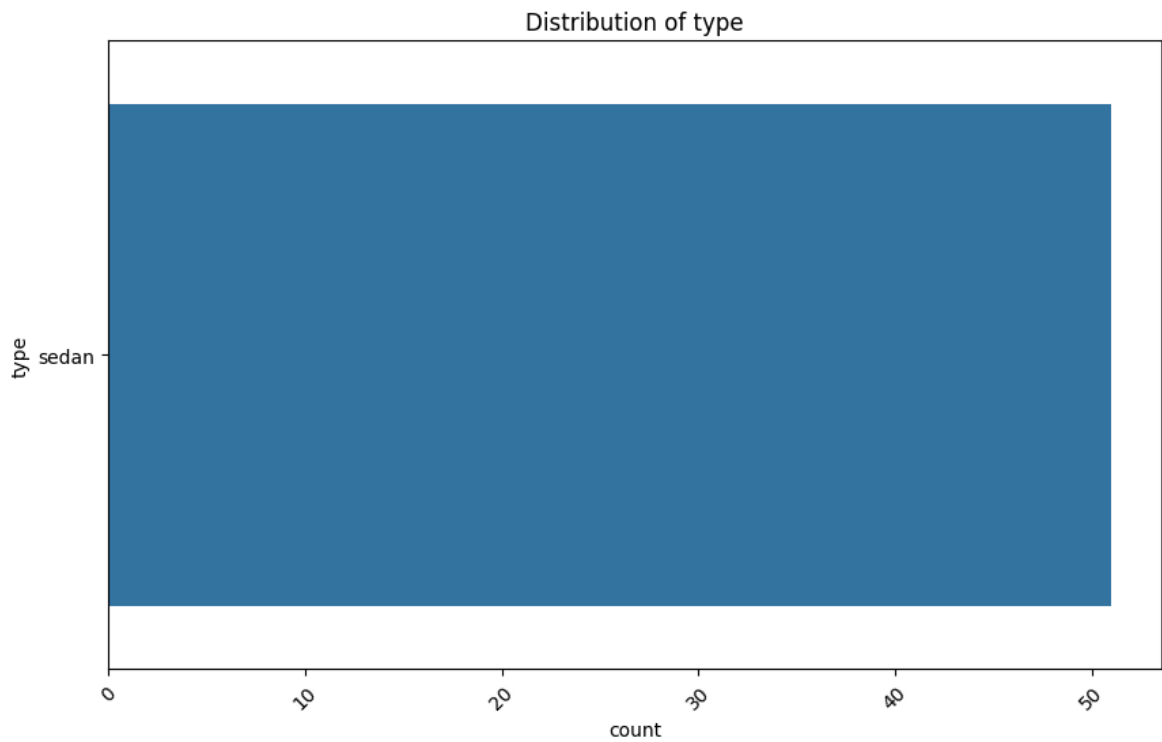
# Adding Labels for car models on top of bars
for index, row in top_brands.iterrows():
    plt.text(index, row['price'] + 1000, row['model'], color='black', ha='center')

plt.title('Top 5 Most Expensive Car Brands and Their Most Expensive Cars')
plt.xlabel('Brand')
plt.ylabel('Price')
plt.show()
```



```
In [45]: # 8. Plotting categorical variables
categorical_cols = data.select_dtypes(include=['object']).columns
for col in categorical_cols:
    plt.figure(figsize=(10, 6))
    sns.countplot(data[col])
    plt.title(f'Distribution of {col}')
    plt.xticks(rotation=45)
    plt.show()
```





```
In [26]: numeric_data = data.select_dtypes(include=['float64', 'int64'])
print(data.isnull().sum()) # Check for null values
print(np.isinf(numeric_data).sum()) # Check for infinite values
```

```

id          0
brand       0
model       0
year        0
miles       0
city_mileage 0
highway_mileage 0
horsepower  0
torque      0
engine_capacity_litre 0
fuel_capacity 0
num_cylinder 0
num_seat    0
num_owners  0
price       0
link        0
type        0
doors       0
wheel_drive 0
engine_type 0
speed_levels 0
front_headroom 0
front_legroom 0
rear_headroom 0
rear_legroom 0
service_records 0
mileage     0
dtype: int64
id          0
year        0
miles       0
city_mileage 0
highway_mileage 0
horsepower  0
torque      0
engine_capacity_litre 0
fuel_capacity 0
num_cylinder 0
num_seat    0
num_owners  0
price       0
doors       0
wheel_drive 0
speed_levels 0
front_headroom 0
front_legroom 0
rear_headroom 0
rear_legroom 0
service_records 0
mileage     0
dtype: int64

```

```

In [23]: print(data[data['condition'].isnull()])
          print(data[data['speed_levels'].isnull()])

          data.drop(columns=['condition'], inplace=True)
          data.dropna(subset=['speed_levels'], inplace=True)

```



	id	brand	model	year	miles	city_mileage	highway_mileage	\
0	3	Chevrolet	Volt LT	2019	27173	43	42	
1	6	Hyundai	Elantra SE	2017	76941	29	38	
2	7	Ford	Focus	2014	97027	27	37	
3	8	Honda	Civic	2016	95396	31	42	
5	11	Honda	Civic	2016	61459	31	41	
6	12	Subaru	Legacy	2022	6811	27	35	
7	13	Honda	Clarity	2018	29674	44	40	
8	14	Volkswagen	Jetta	2019	25044	30	40	
9	15	Volkswagen	Jetta	2017	26215	28	38	
10	16	Honda	Civic	2015	25939	29	37	
11	17	Honda	Civic	2019	32270	32	42	
12	18	Honda	Civic	2018	19950	31	40	
13	19	Honda	Accord	2020	19719	30	38	
14	20	Honda	Civic	2020	16076	32	42	
15	21	Subaru	Impreza	2019	28214	28	38	
16	22	Honda	Accord	2020	12395	30	38	
17	23	Honda	Civic	2019	33322	30	38	
18	24	Honda	Insight	2019	56233	55	49	
19	25	Volkswagen	Jetta	2019	24250	30	40	
20	26	Ford	Taurus	2019	38097	17	24	
21	27	Ford	Fusion	2020	35743	20	29	
22	28	Chevrolet	Malibu	2019	32946	29	36	
23	29	Volkswagen	Passat	2018	26905	25	36	
24	30	Volkswagen	Passat	2017	66329	23	34	
25	31	Volkswagen	Passat	2020	27457	23	34	
26	32	Honda	Accord	2020	12395	30	38	
27	33	Honda	Civic	2019	41799	30	38	
28	34	Hyundai	Sonata	2019	26910	25	33	
29	35	Honda	Civic	2018	16581	31	40	
30	36	Hyundai	Sonata	2019	9736	25	33	
31	37	Honda	Civic	2017	7743	31	40	
32	38	Subaru	Impreza	2019	44371	28	38	
33	39	Volkswagen	Jetta	2020	12944	25	32	
34	40	Volkswagen	Jetta	2019	5000	30	40	
35	41	Honda	Civic	2019	41799	30	38	
36	42	Chevrolet	Malibu	2018	13726	22	32	
37	43	Volkswagen	Jetta	2019	18898	30	40	
38	44	Honda	Accord	2018	51279	30	38	
39	45	Ford	Fusion	2020	36506	21	31	
40	46	Honda	Accord	2018	58126	30	38	
41	47	Honda	Civic	2019	27440	32	42	
42	48	Honda	Accord	2020	59090	30	38	
43	49	Honda	Civic	2019	47715	30	38	
44	50	Volkswagen	Passat	2020	9495	23	34	
45	51	Volkswagen	Jetta	2019	13721	30	40	
46	52	Honda	Civic	2018	72827	31	40	
47	53	Hyundai	Sonata	2019	33412	23	32	
48	54	Hyundai	Elantra SE	2020	13830	30	40	
49	55	Ford	Fusion	2019	23507	20	29	
50	56	Hyundai	Elantra SE	2020	11296	30	40	
51	57	Honda	Accord	2018	82729	30	38	

	horsepower	torque	engine_capacity_litre	...	doors	wheel_drive	\
0	149	294	1.5	...	4	2	
1	146	132	2.0	...	4	2	
2	159	146	2.0	...	4	2	
3	158	138	1.5	...	4	2	
5	158	138	2.0	...	4	2	
6	182	176	2.5	...	4	4	

7	212	99	1.5	...	4	2
8	147	184	1.4	...	4	2
9	150	184	1.4	...	4	2
10	143	129	1.8	...	4	2
11	174	162	1.5	...	4	2
12	158	138	2.0	...	4	2
13	192	192	1.5	...	4	2
14	174	162	1.5	...	4	2
15	152	145	2.0	...	4	2
16	192	192	1.5	...	4	2
17	158	138	2.0	...	4	2
18	151	99	1.5	...	4	2
19	147	184	1.4	...	4	2
20	288	254	3.5	...	4	4
21	245	275	2.0	...	4	4
22	160	184	1.5	...	4	2
23	174	184	2.0	...	4	2
24	170	184	1.8	...	4	2
25	174	206	2.0	...	4	2
26	192	192	1.5	...	4	2
27	158	138	2.0	...	4	2
28	185	178	2.4	...	4	2
29	158	138	2.0	...	4	2
30	185	178	2.4	...	4	2
31	158	138	2.0	...	4	2
32	152	145	2.0	...	4	4
33	228	258	2.0	...	4	2
34	147	184	1.4	...	4	2
35	158	138	2.0	...	4	2
36	250	260	2.0	...	4	2
37	158	184	1.4	...	4	2
38	192	192	1.5	...	4	2
39	245	275	2.0	...	4	2
40	192	192	1.5	...	4	2
41	174	162	1.5	...	4	2
42	192	192	1.5	...	4	2
43	158	138	2.0	...	4	2
44	174	206	2.0	...	4	2
45	147	184	1.4	...	4	2
46	158	138	2.0	...	4	2
47	245	260	2.0	...	4	2
48	147	132	2.0	...	4	2
49	245	275	2.0	...	4	2
50	147	132	2.0	...	4	2
51	192	192	1.5	...	4	2

	engine_type	speed_levels	front_headroom	front_legroom	\
0	hybrid_gas_electric	6.0	37.8	42.1	
1	gas	6.0	39.0	42.2	
2	gas	6.0	38.3	43.7	
3	gas	6.0	37.5	42.3	
5	gas	6.0	37.5	42.3	
6	gas	6.0	39.4	42.8	
7	hybrid_gas_electric	NaN	39.1	42.2	
8	gas	8.0	38.5	41.1	
9	gas	6.0	38.2	41.2	
10	gas	6.0	37.9	42.0	
11	gas	6.0	37.5	42.3	
12	gas	6.0	37.5	42.3	
13	gas	6.0	37.5	42.3	

14	gas	6.0	37.5	42.3
15	gas	6.0	39.8	43.1
16	gas	6.0	37.5	42.3
17	gas	6.0	39.3	42.3
18	hybrid_gas_electric	6.0	39.3	42.3
19	gas	8.0	38.5	41.1
20	gas	6.0	39.0	41.9
21	gas	6.0	39.2	44.3
22	gas	6.0	39.1	41.5
23	gas	6.0	38.3	42.4
24	gas	6.0	38.3	42.4
25	gas	6.0	38.3	42.4
26	gas	6.0	37.5	42.3
27	gas	6.0	39.3	42.3
28	gas	6.0	40.4	45.5
29	gas	6.0	37.5	42.3
30	gas	6.0	40.4	45.5
31	gas	6.0	37.5	42.3
32	gas	6.0	39.8	43.1
33	gas	7.0	38.5	41.1
34	gas	8.0	38.5	41.1
35	gas	6.0	39.3	42.3
36	gas	9.0	39.1	42.0
37	gas	8.0	38.5	41.1
38	gas	6.0	37.5	42.3
39	gas	6.0	39.2	44.3
40	gas	6.0	37.5	42.3
41	gas	6.0	37.5	42.3
42	gas	6.0	39.5	42.3
43	gas	6.0	39.3	42.3
44	gas	6.0	38.3	42.4
45	gas	8.0	38.5	41.1
46	gas	6.0	39.3	42.3
47	gas	8.0	40.4	45.5
48	gas	6.0	40.3	42.2
49	gas	6.0	39.2	44.3
50	gas	6.0	40.3	42.2
51	gas	6.0	39.5	42.3

	rear_headroom	rear_legroom	service_records	mileage
0	35.8	34.7	4	42.5
1	37.0	35.7	16	33.5
2	38.0	33.2	13	32.0
3	36.8	37.4	26	36.5
5	36.8	37.4	13	36.0
6	37.2	39.5	6	31.0
7	37.1	36.2	2	42.0
8	37.2	37.4	6	35.0
9	37.1	38.1	13	33.0
10	36.2	36.2	15	33.0
11	36.8	37.4	4	37.0
12	36.8	37.4	9	35.5
13	37.2	40.4	4	34.0
14	36.8	37.4	5	37.0
15	37.2	36.5	4	33.0
16	37.2	40.4	4	34.0
17	37.1	37.4	4	34.0
18	36.9	37.4	5	52.0
19	37.2	37.4	8	35.0
20	37.8	38.1	1	20.5

21	37.8	38.3	8	24.5
22	37.5	38.1	15	32.5
23	37.8	39.1	11	30.5
24	37.8	39.1	5	28.5
25	37.8	39.1	11	28.5
26	37.2	40.4	4	34.0
27	37.1	37.4	4	34.0
28	38.0	35.6	4	29.0
29	36.8	37.4	4	35.5
30	38.0	35.6	6	29.0
31	36.8	37.4	2	35.5
32	37.2	36.5	7	33.0
33	37.2	37.4	5	28.5
34	37.2	37.4	6	35.0
35	37.1	37.4	4	34.0
36	37.5	38.1	7	27.0
37	37.2	37.4	4	35.0
38	37.2	40.4	8	34.0
39	37.8	38.3	7	26.0
40	37.2	40.4	14	34.0
41	36.8	37.4	13	37.0
42	37.3	40.4	1	34.0
43	37.1	37.4	1	34.0
44	37.8	39.1	10	28.5
45	37.2	37.4	5	35.0
46	37.1	37.4	5	35.5
47	38.0	35.6	10	27.5
48	37.3	35.7	6	35.0
49	37.8	38.3	11	24.5
50	37.3	35.7	7	35.0
51	37.3	40.4	9	34.0

[51 rows x 28 columns]

	id	brand	model	year	miles	city_mileage	highway_mileage	horsepower	\
7	13	Honda	Clarity	2018	29674	44	40	212	

	torque	engine_capacity_litre	...	doors	wheel_drive	\
7	99	1.5	...	4	2	

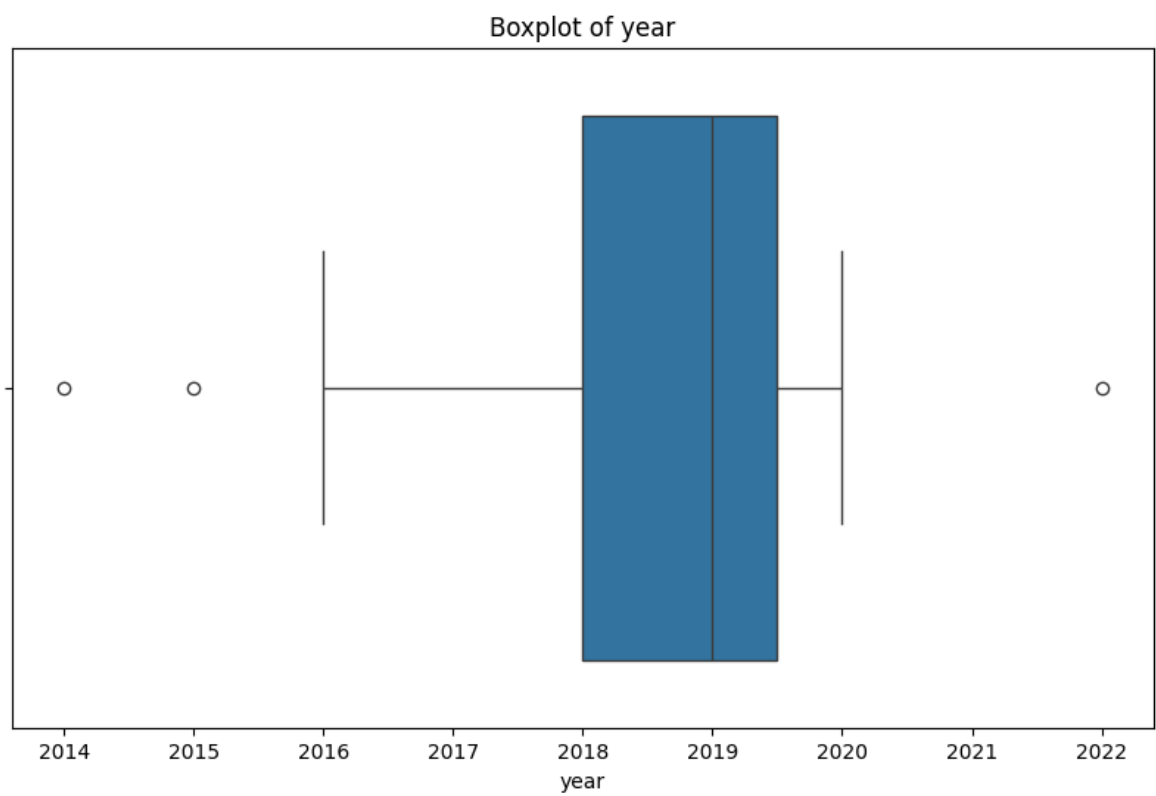
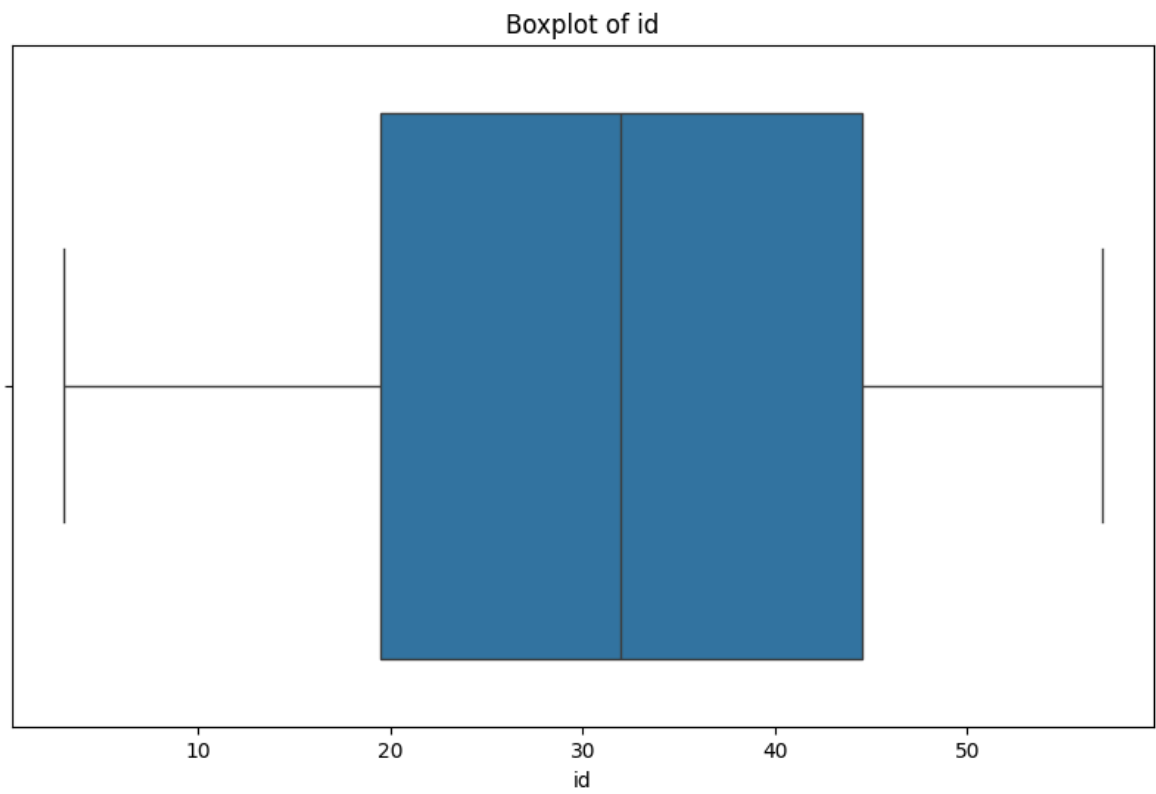
	engine_type	speed_levels	front_headroom	front_legroom	\
7	hybrid_gas_electric	NaN	39.1	42.2	

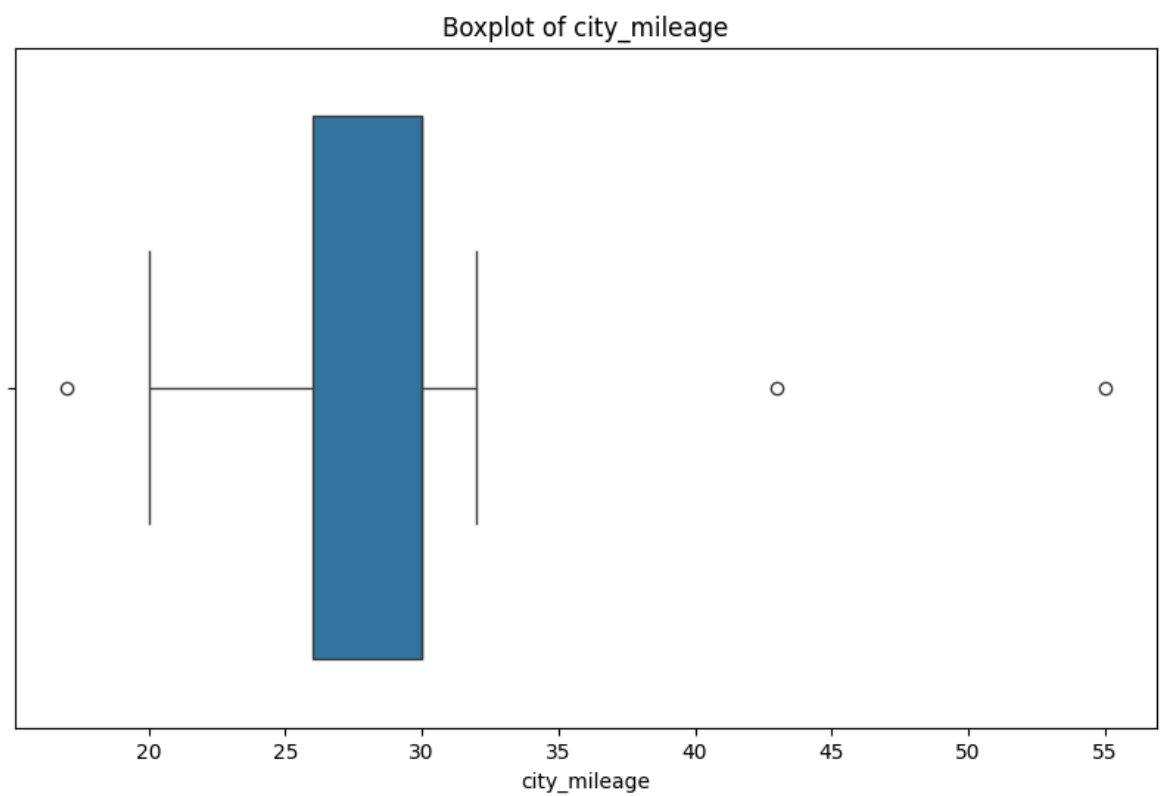
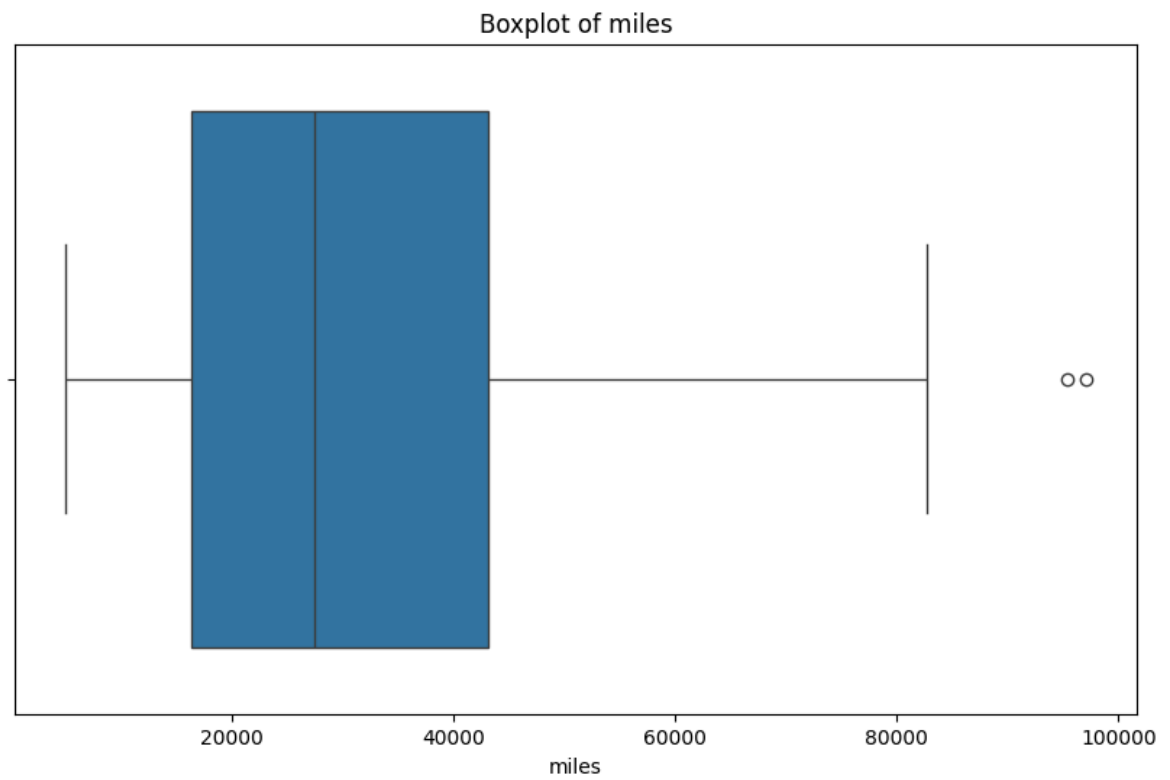
  

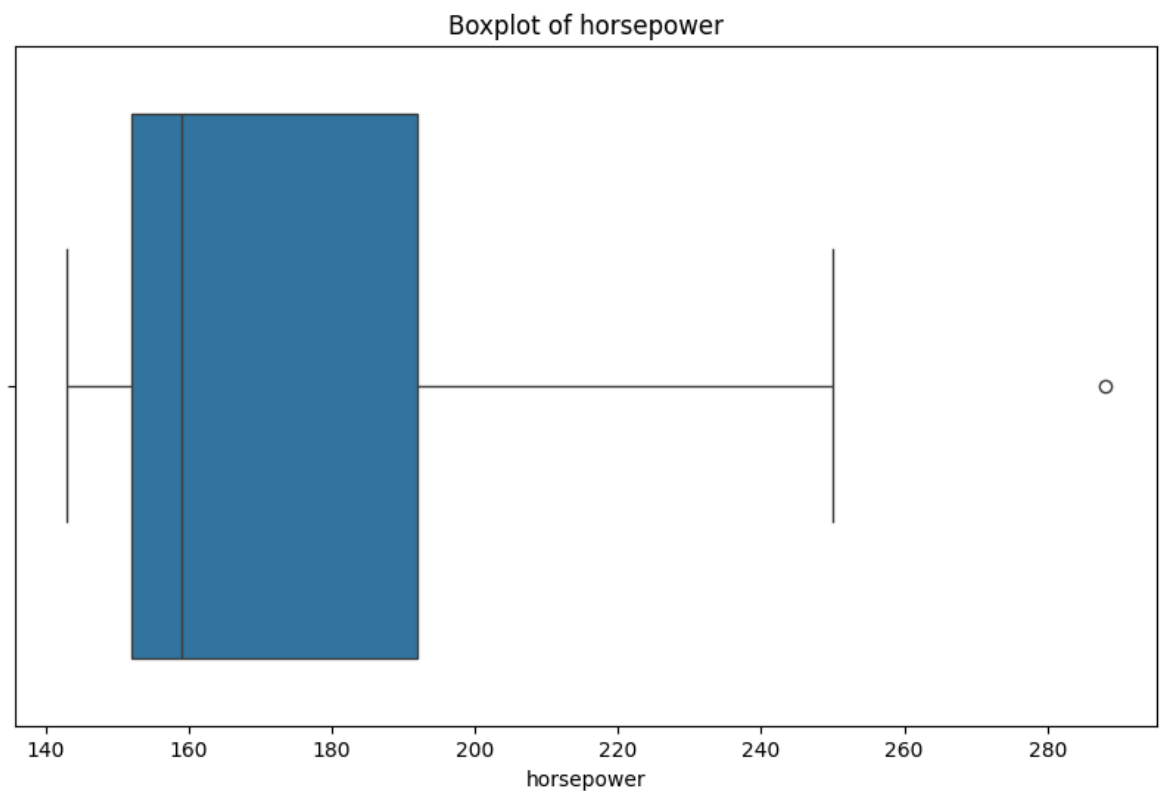
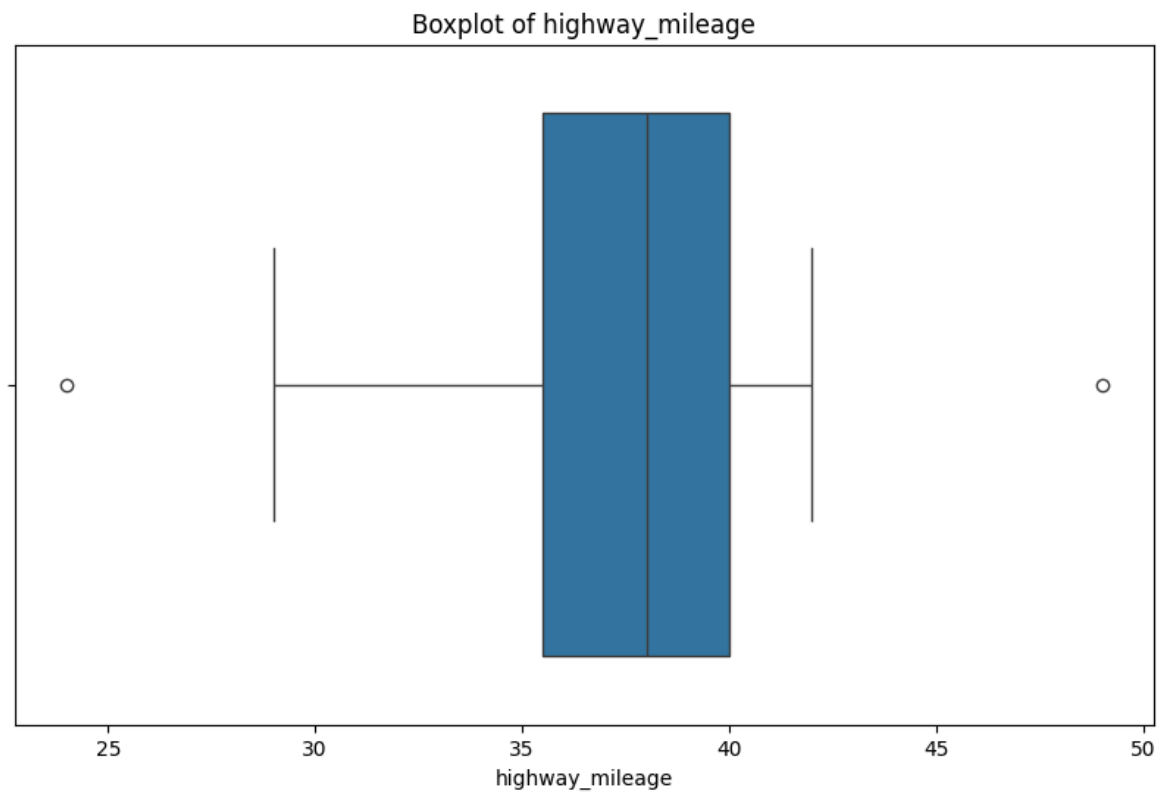
	rear_headroom	rear_legroom	service_records	mileage
7	37.1	36.2	2	42.0

[1 rows x 28 columns]

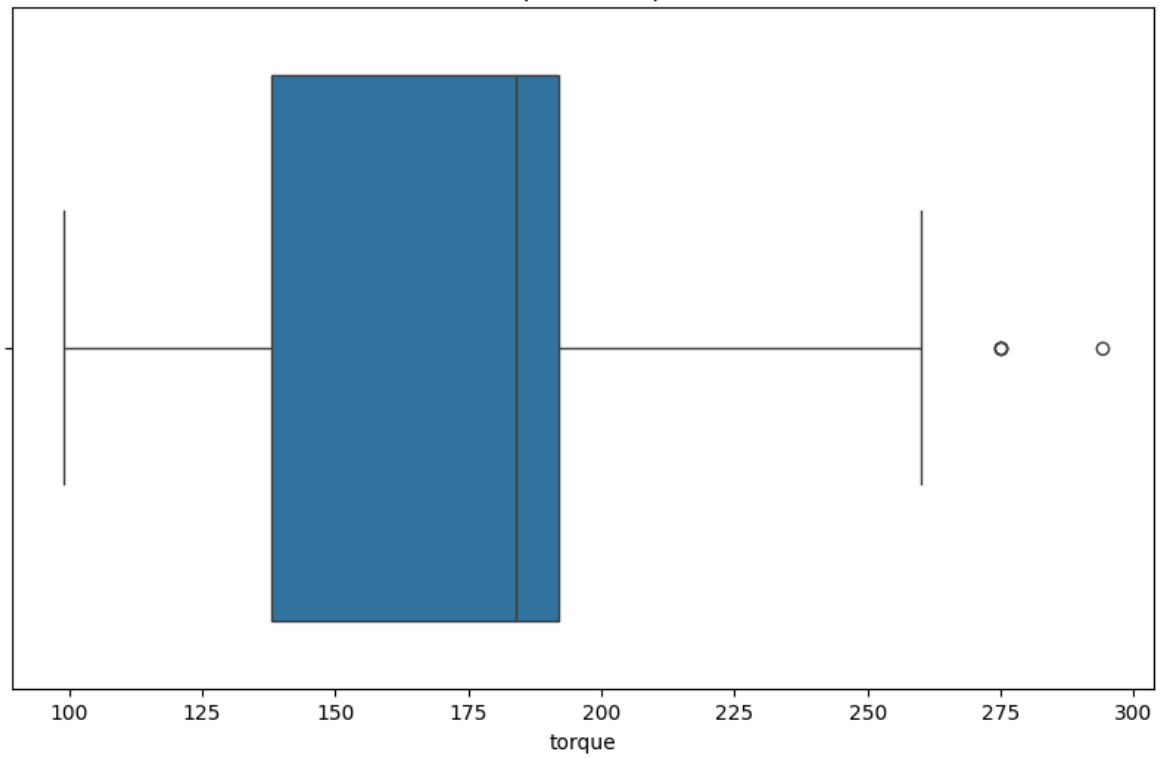
```
In [27]: # 10. Boxplots for outliers in numerical variables
numerical_cols = data.select_dtypes(include=['float64', 'int64']).columns
for col in numerical_cols:
    plt.figure(figsize=(10, 6))
    sns.boxplot(x=data[col])
    plt.title(f'Boxplot of {col}')
    plt.show()
```



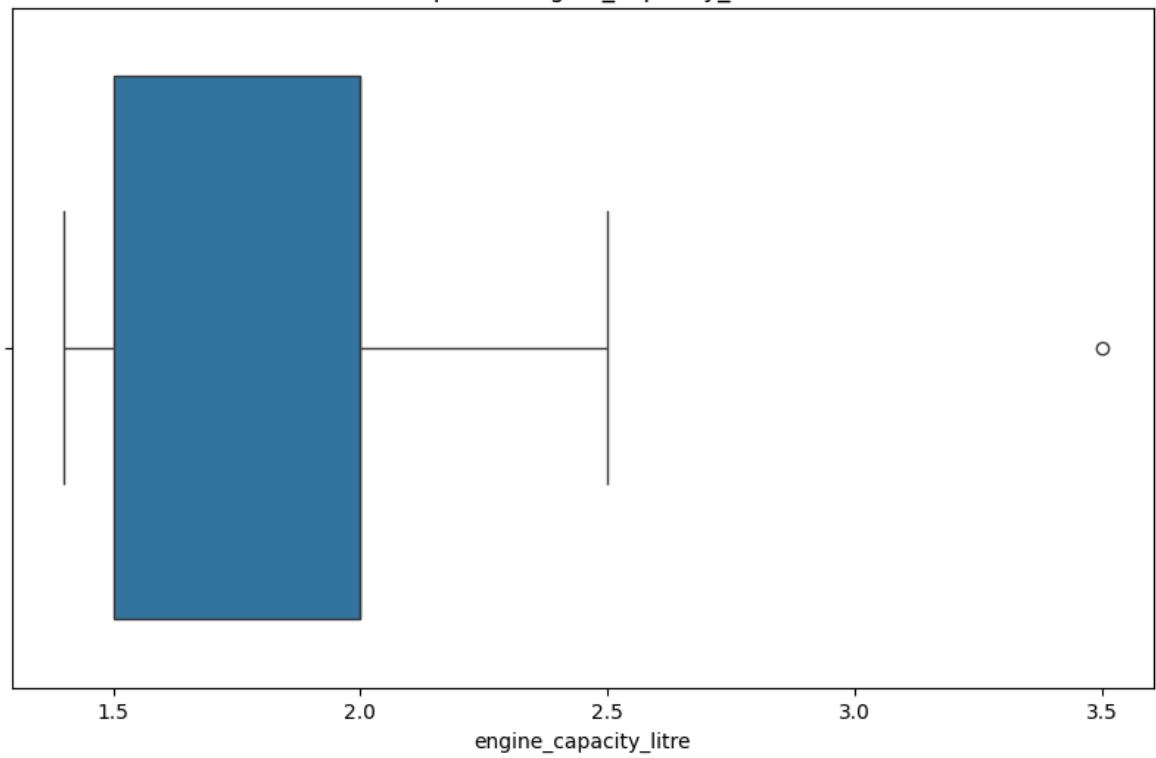




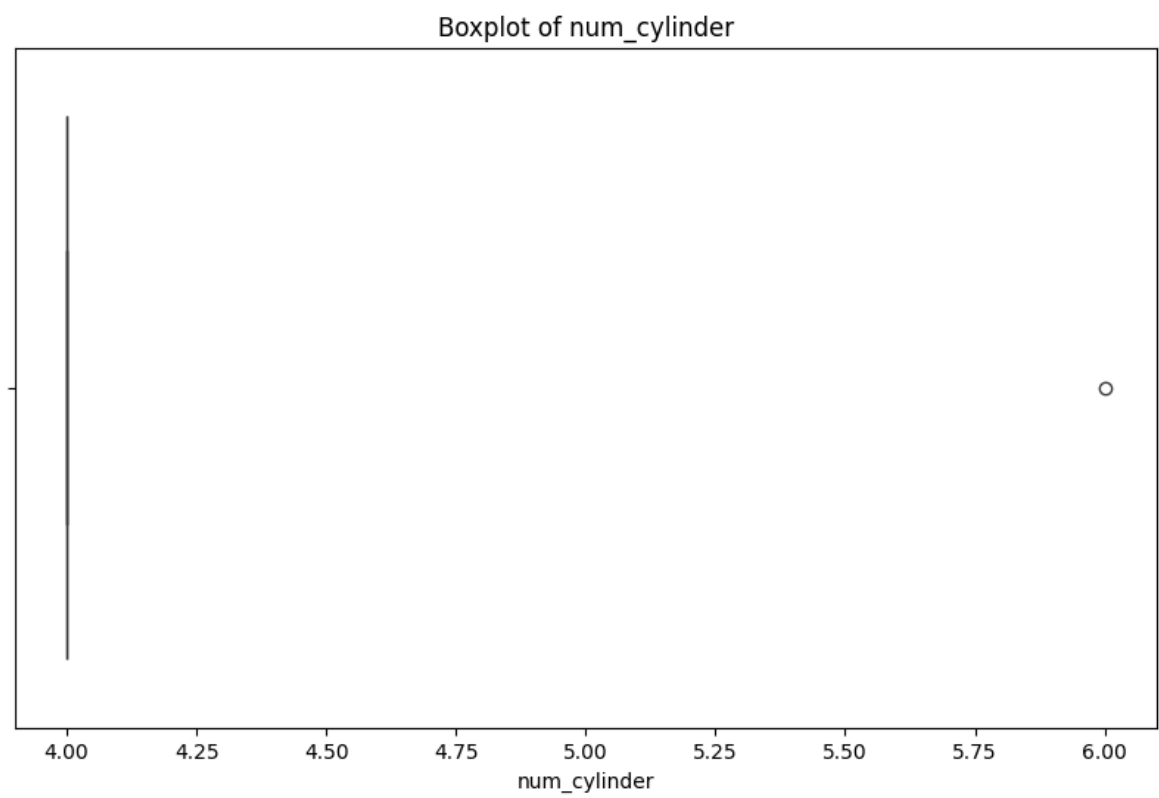
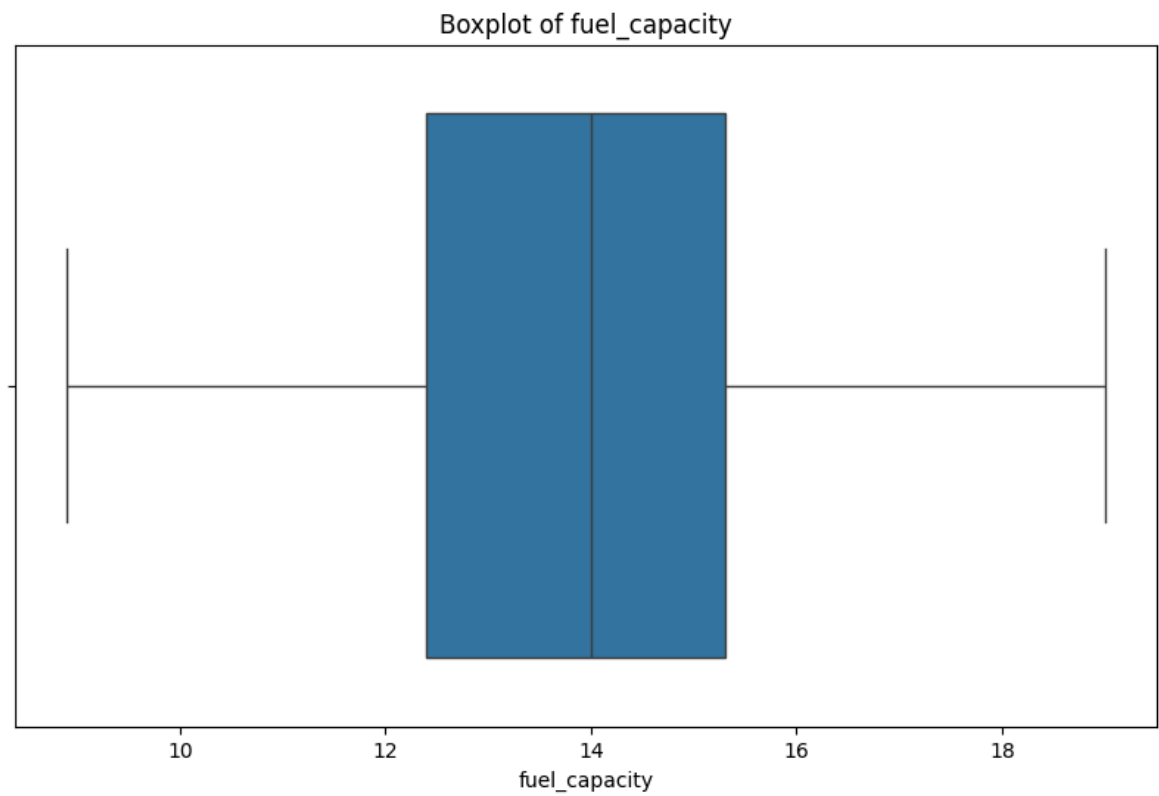
Boxplot of torque

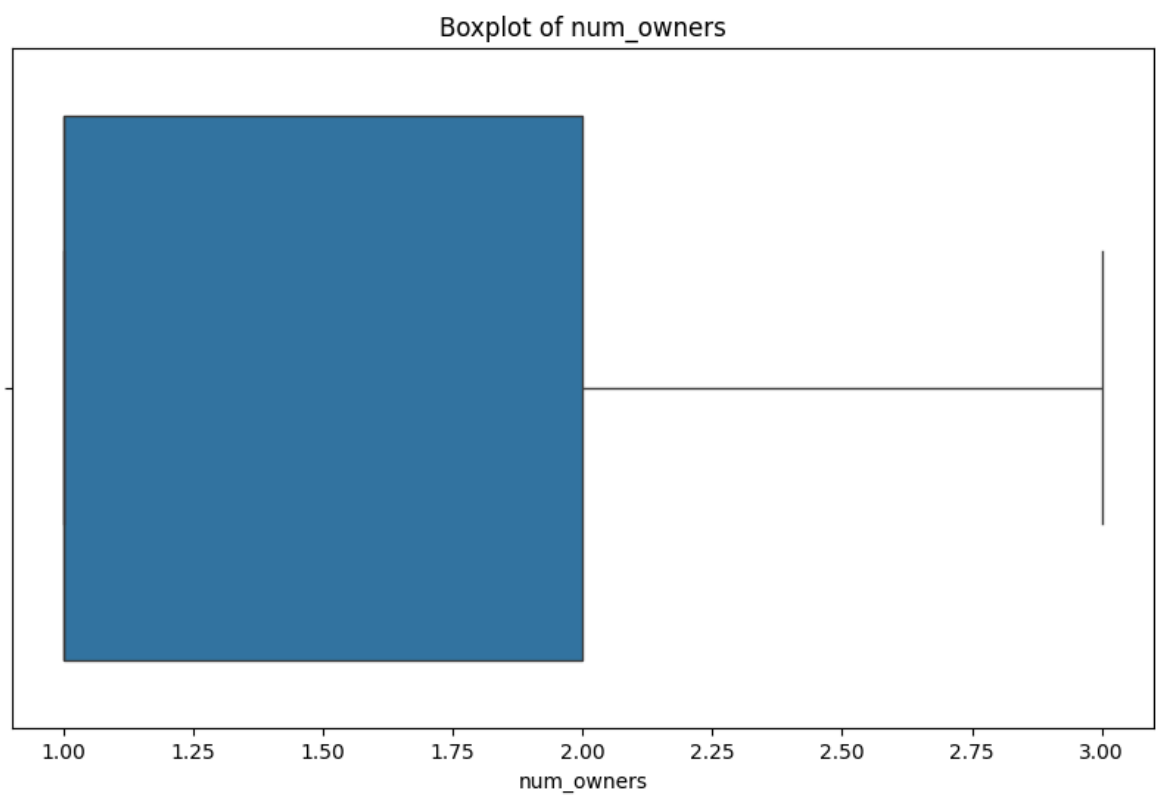
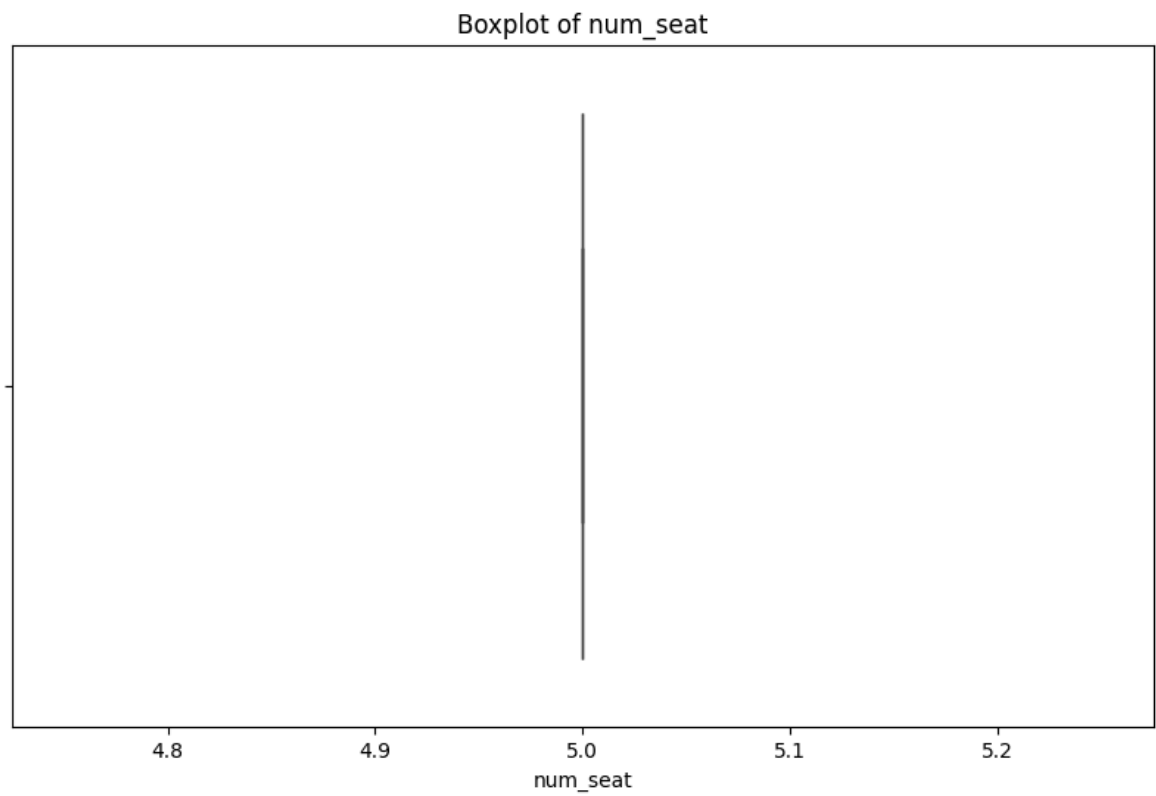


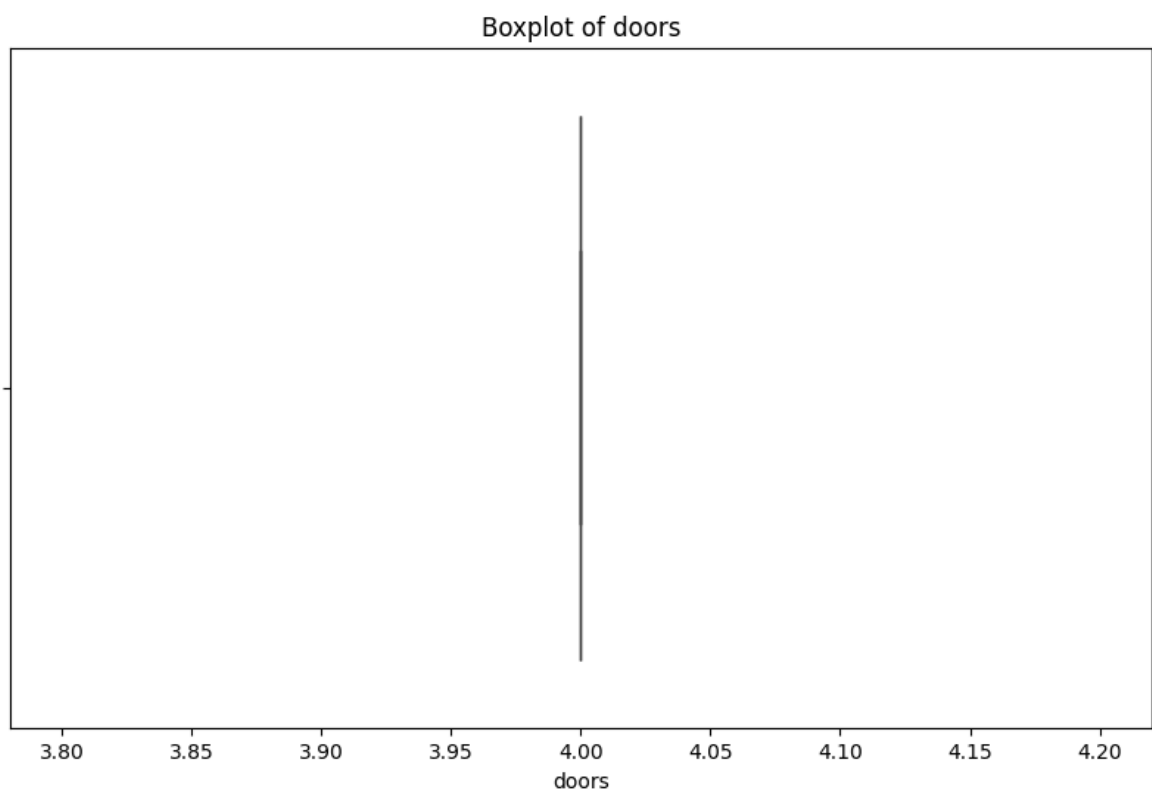
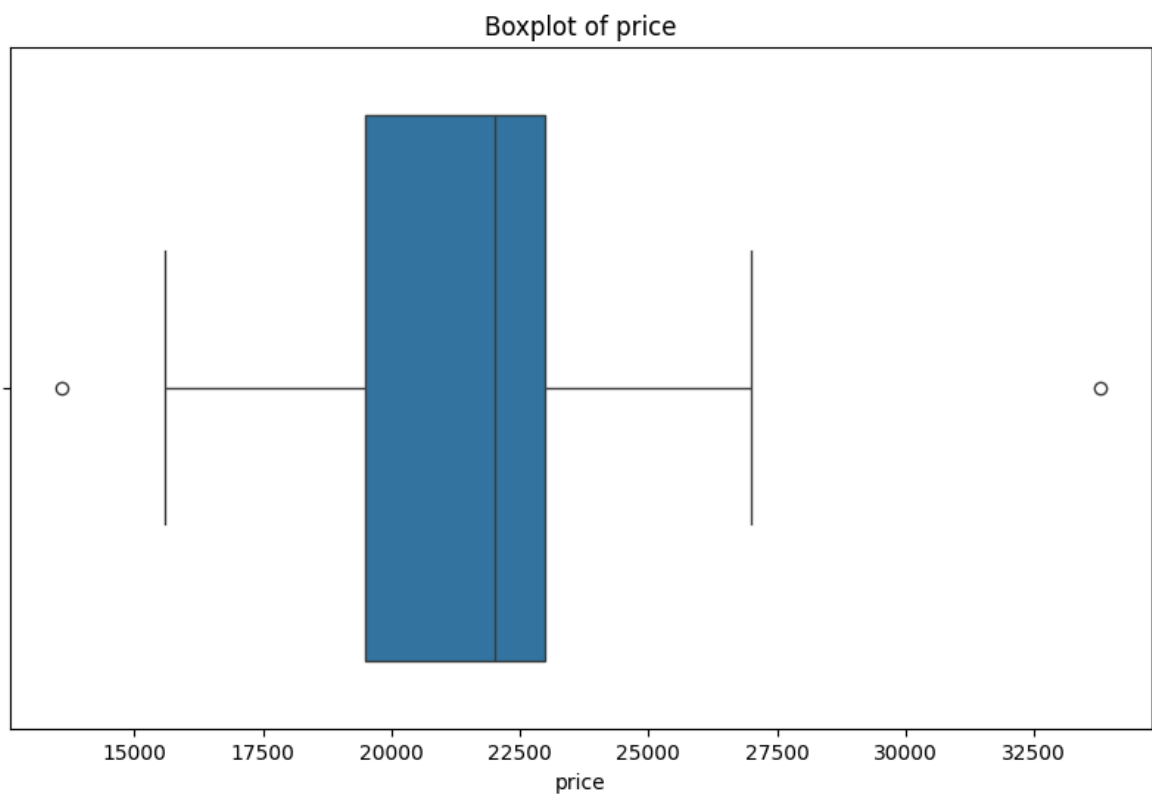
Boxplot of engine\_capacity\_litre

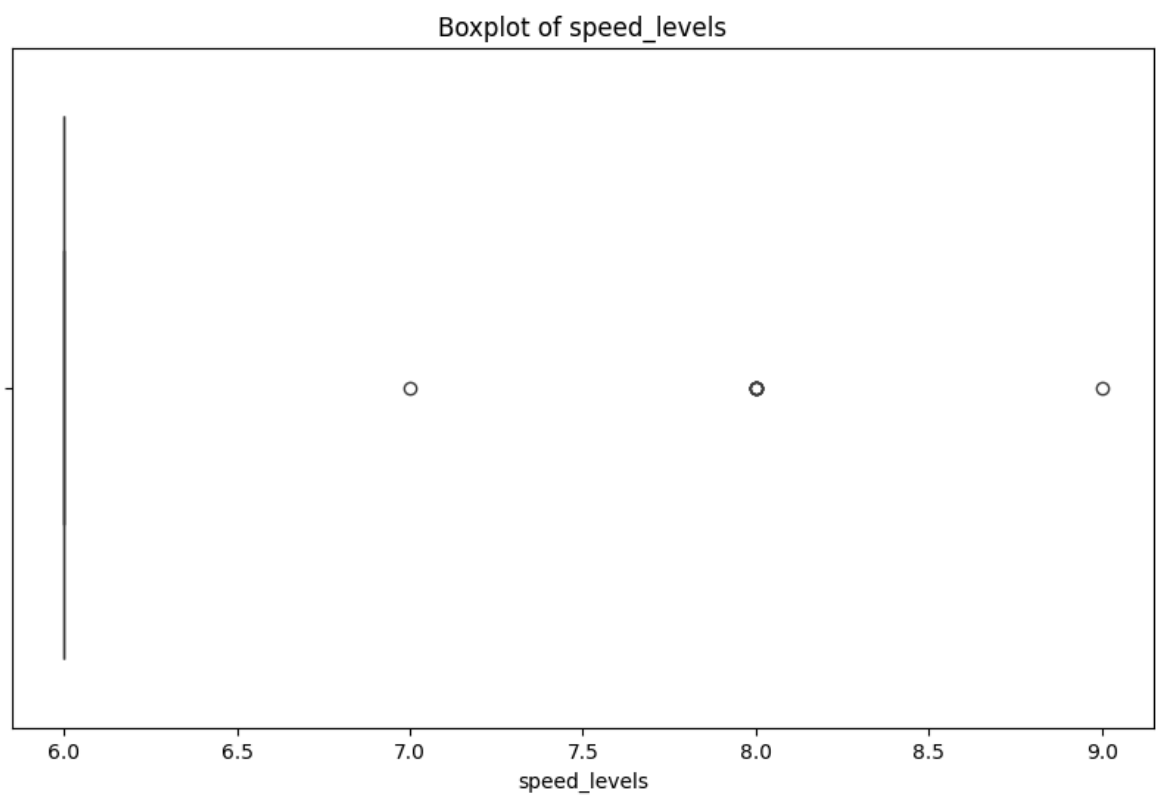
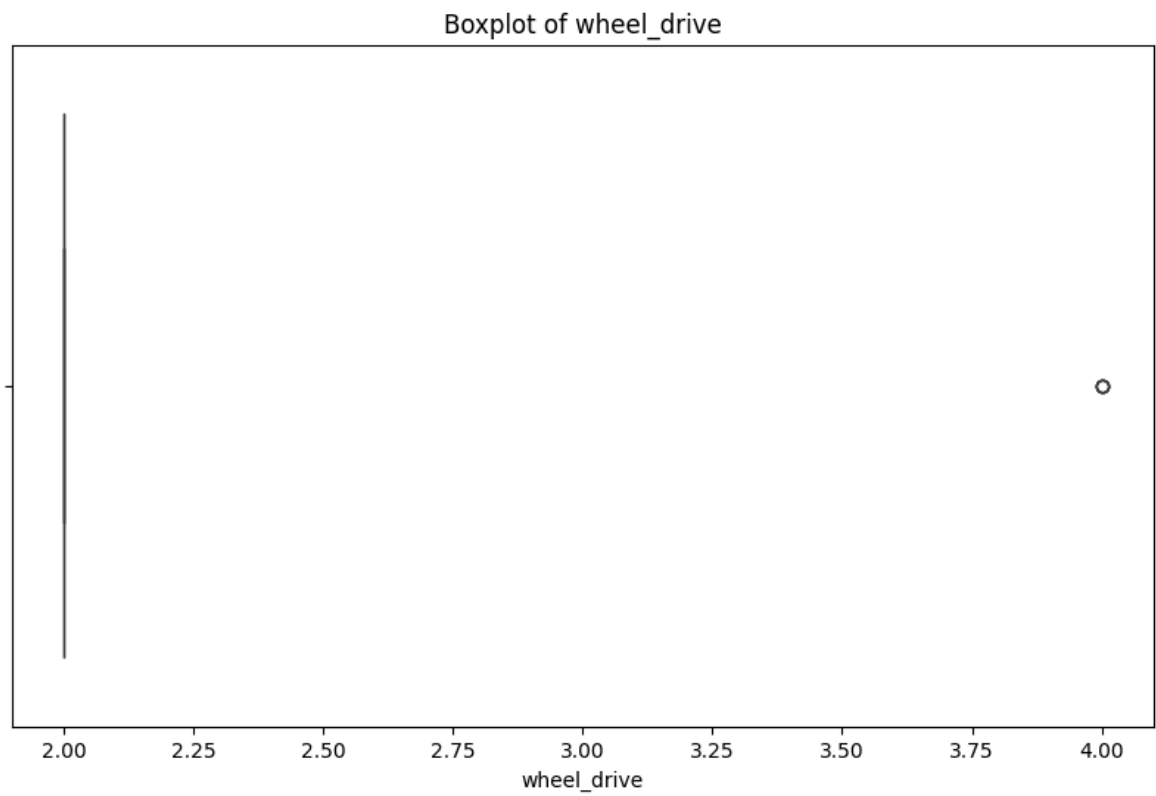


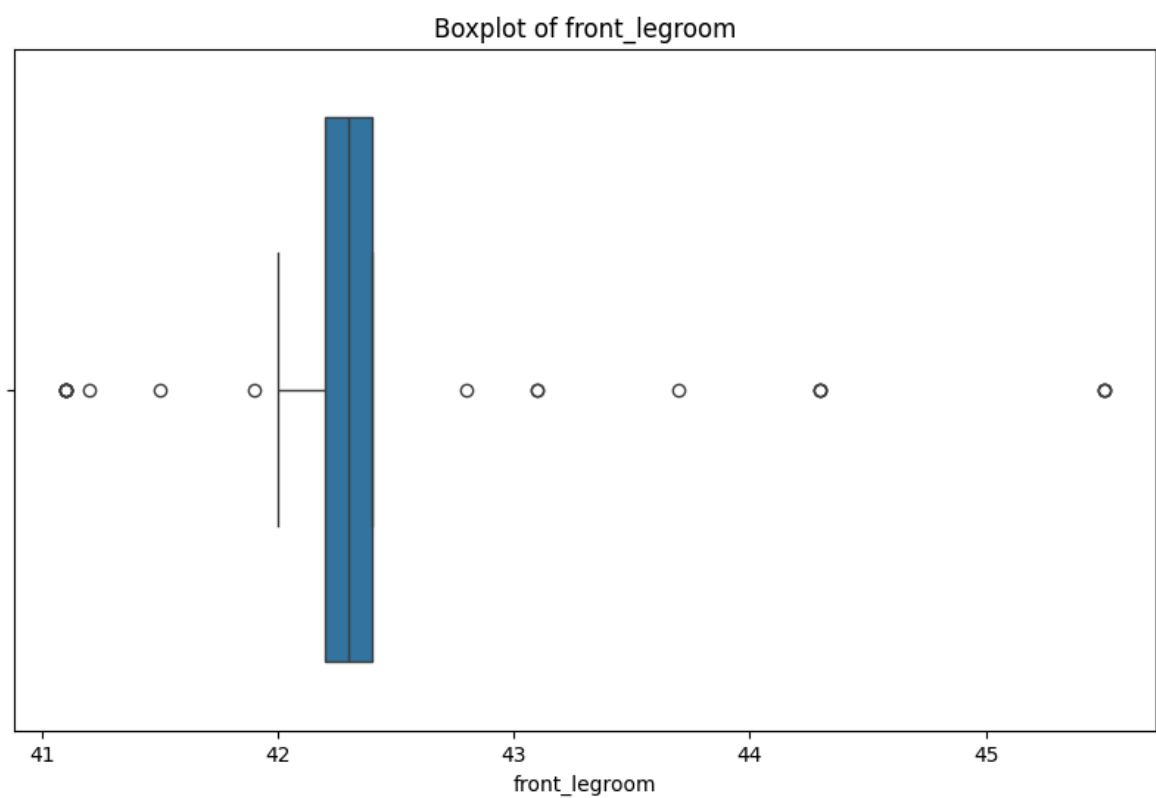
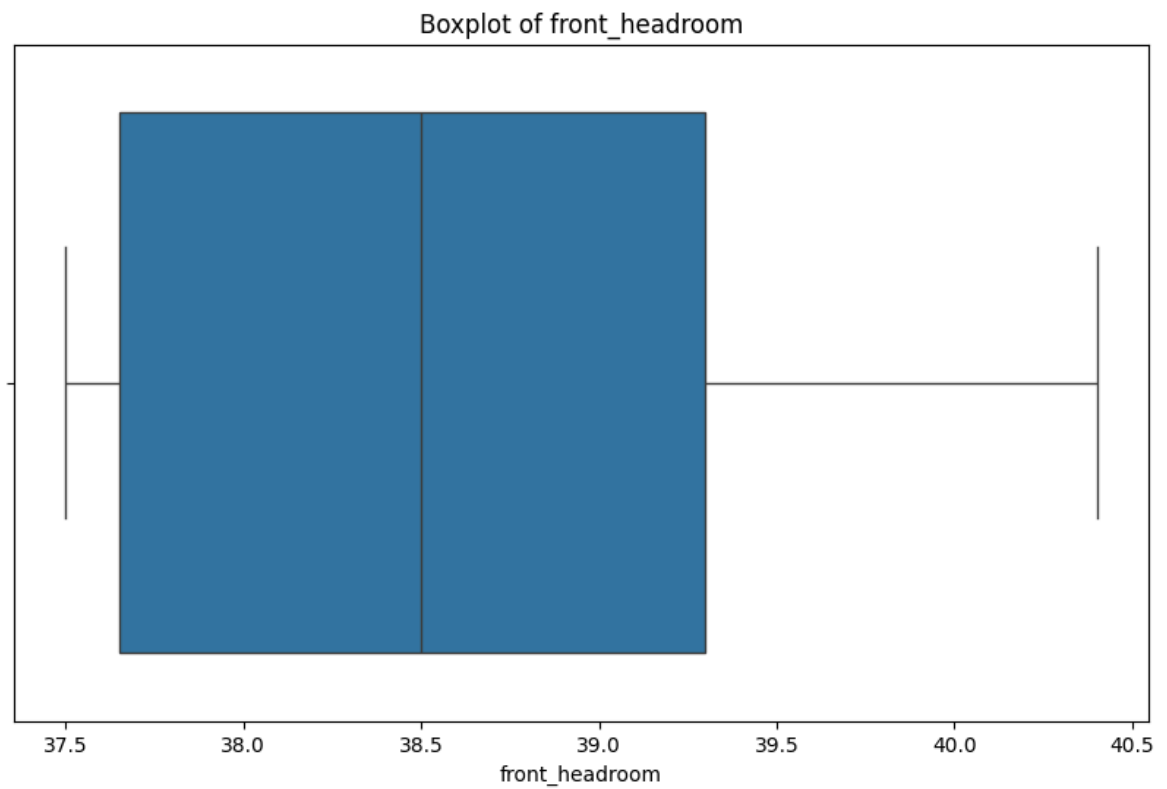


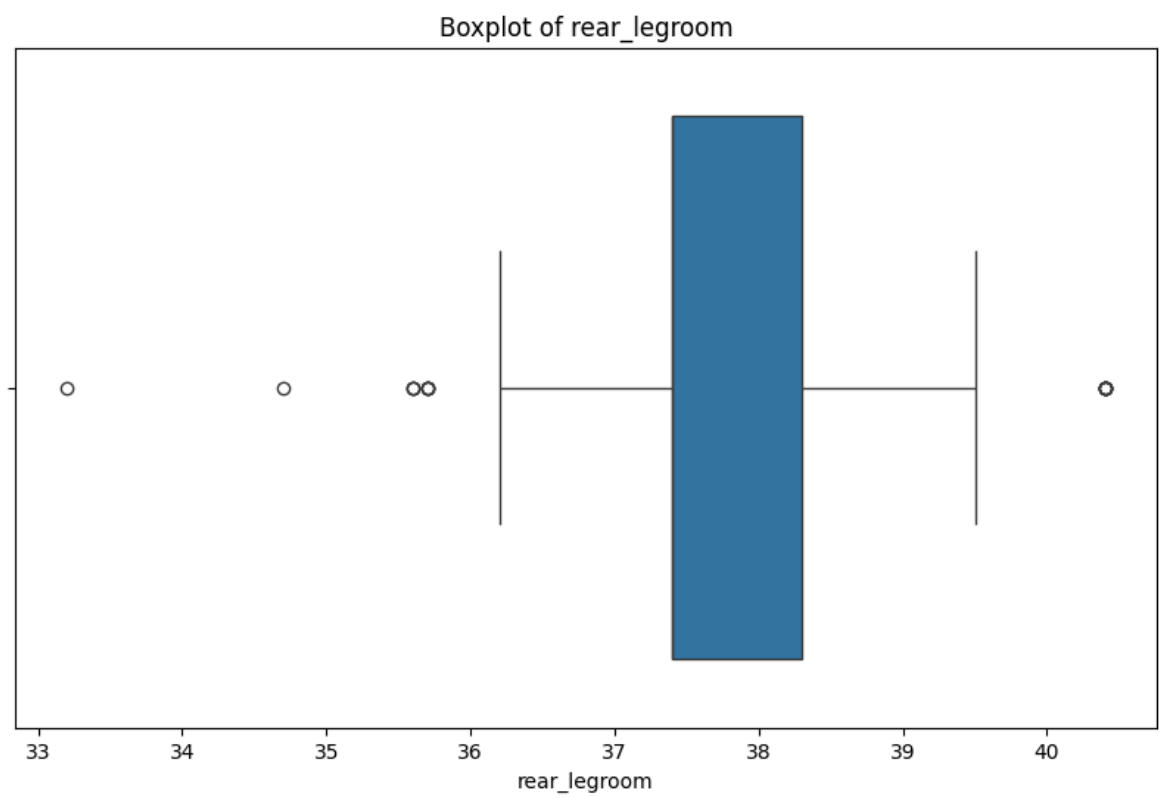
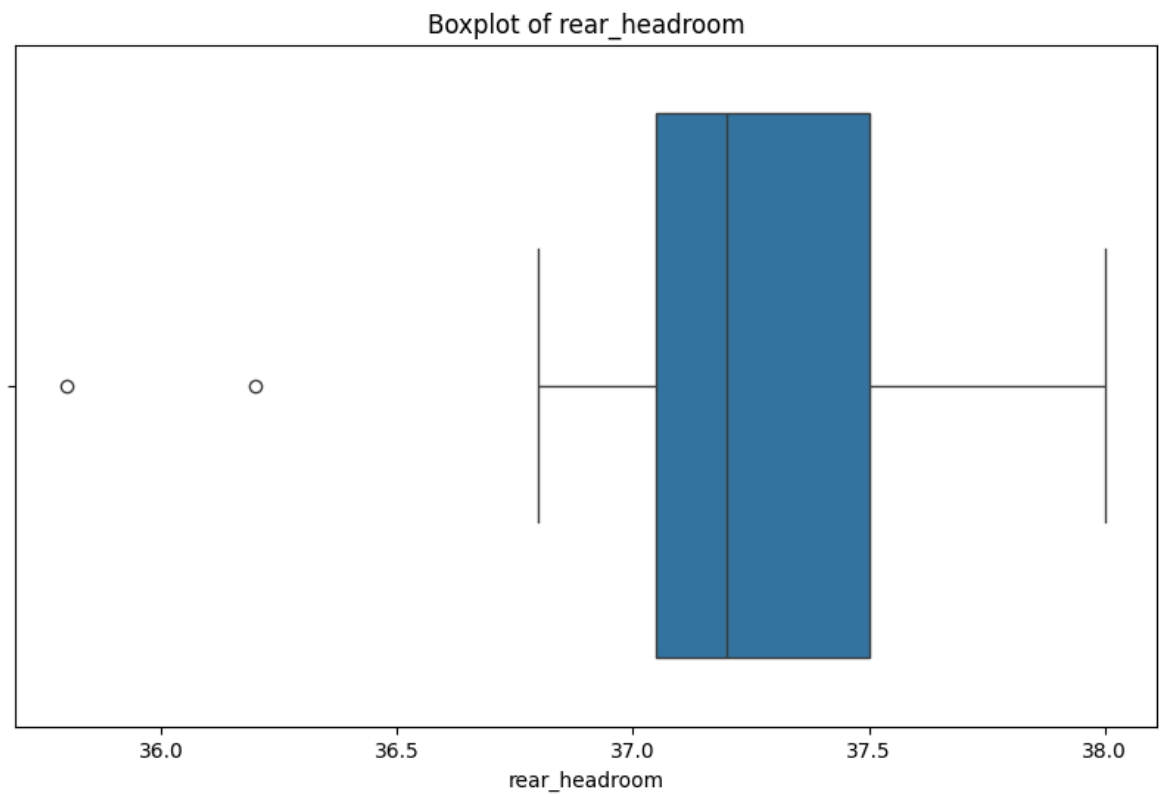


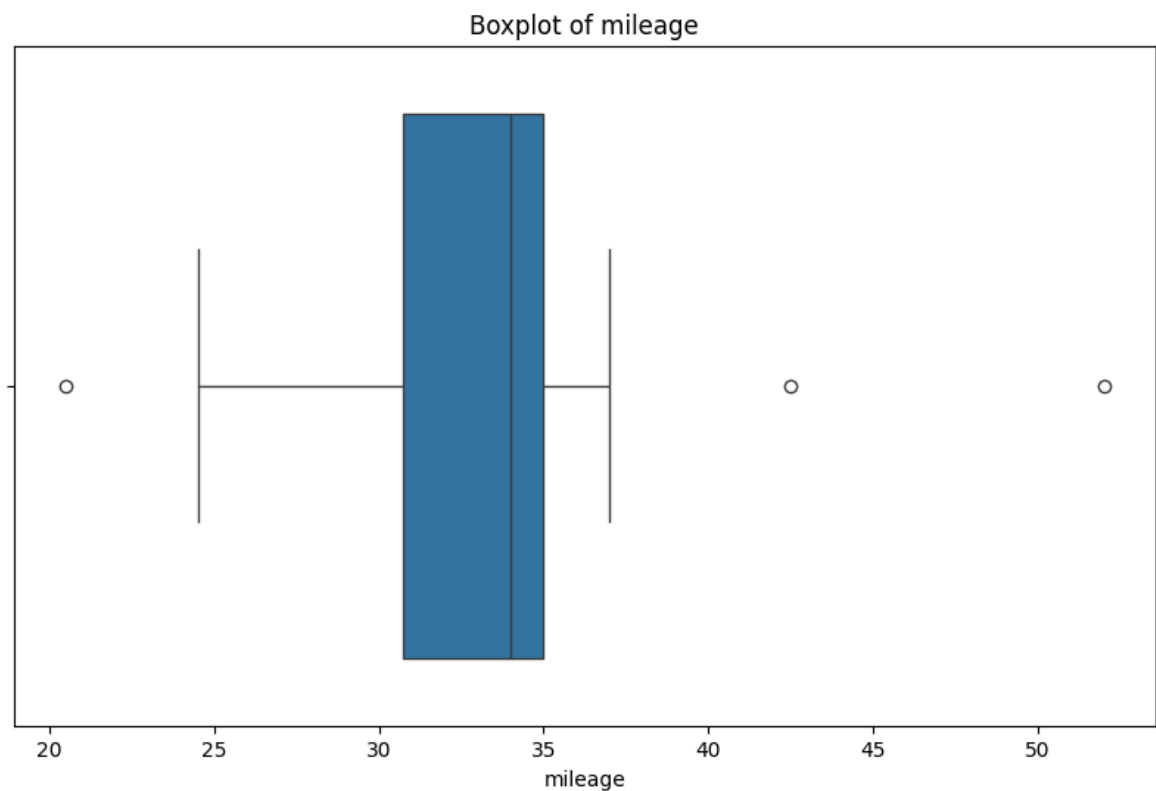
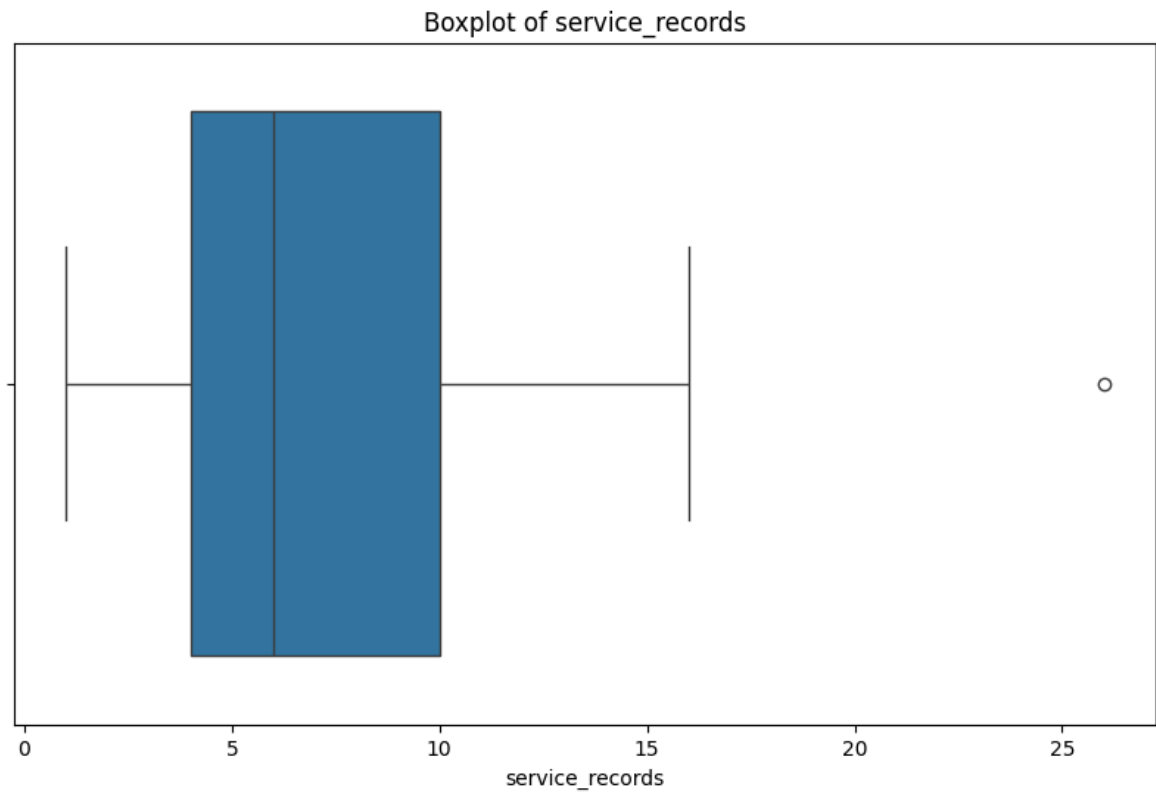












```
In [28]: # 11. Count of cars by brand (if brand column exists)
if 'brand' in data.columns:
    print('\n--- Count of Cars by Brand ---')
    print(data['brand'].value_counts())
    plt.figure(figsize=(12, 6))
    sns.countplot(y=data['brand'], order=data['brand'].value_counts().index)
    plt.title('Number of Cars by Brand')
    plt.show()
```

--- Count of Cars by Brand ---

brand

Honda 22

Volkswagen 11

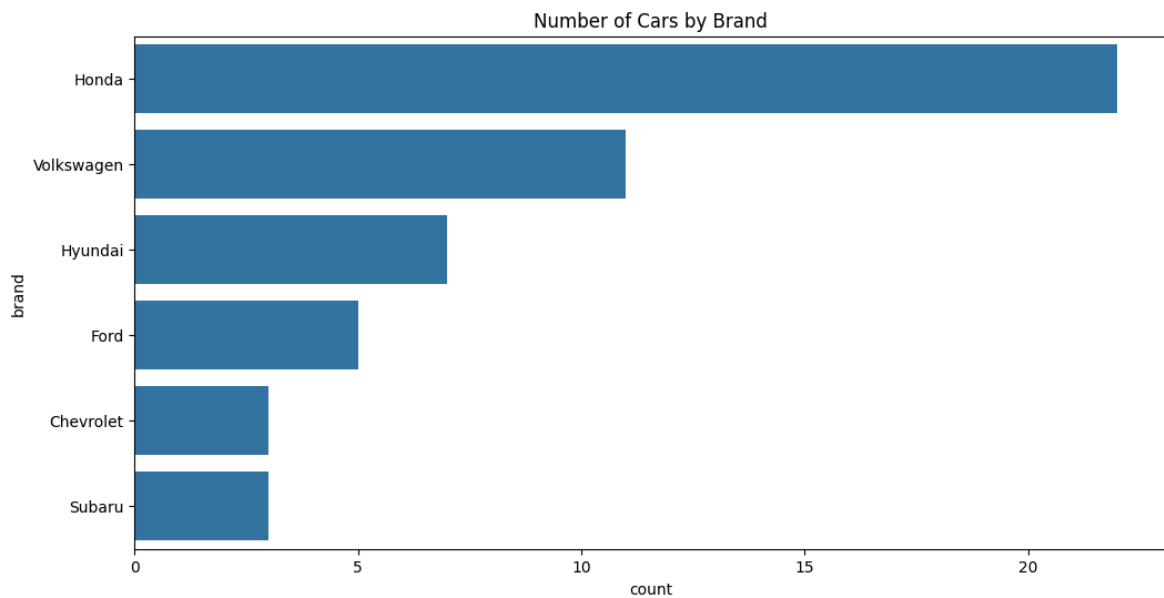
Hyundai 7

Ford 5

Chevrolet 3

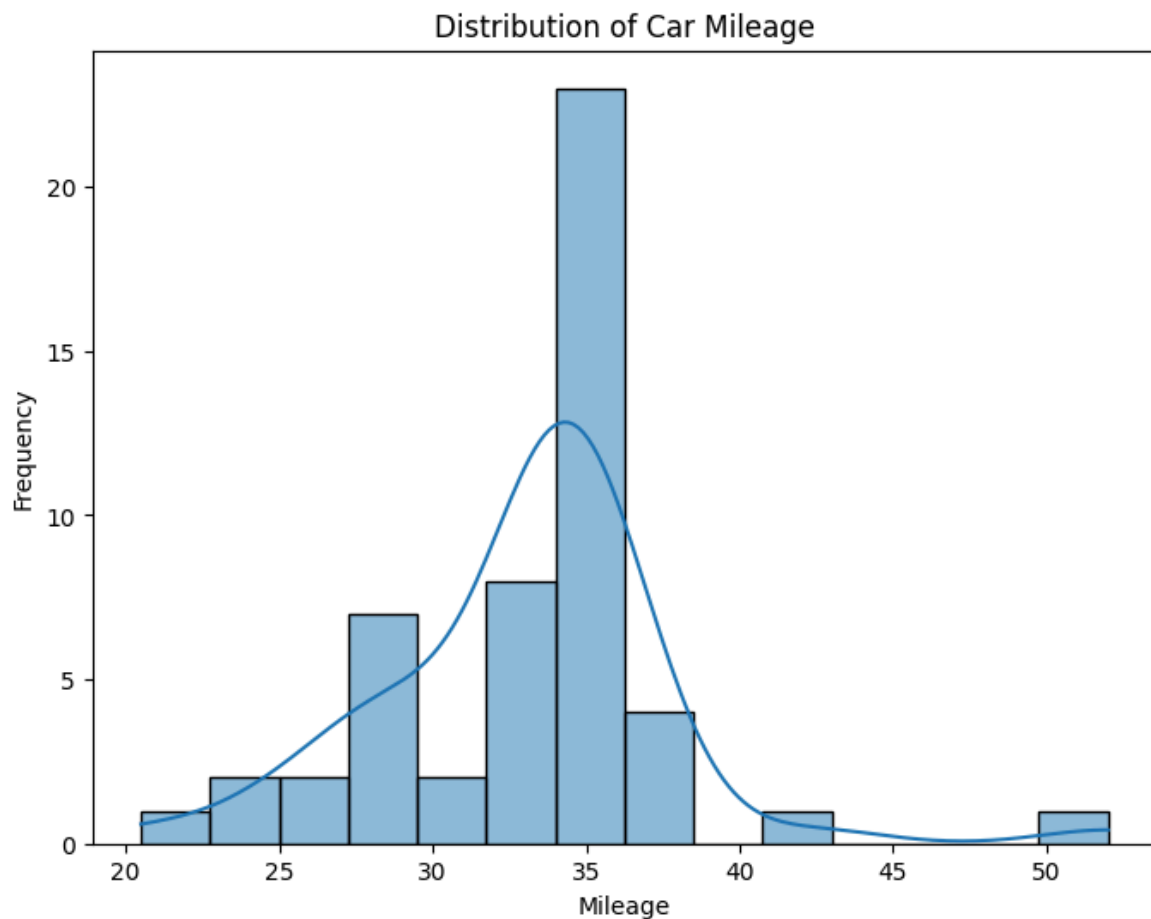
Subaru 3

Name: count, dtype: int64



```
In [29]: # 12. Mileage distribution
if 'mileage' in data.columns:
    plt.figure(figsize=(8, 6))
    sns.histplot(data['mileage'], kde=True)
    plt.title('Distribution of Car Mileage')
    plt.xlabel('Mileage')
    plt.ylabel('Frequency')
    plt.show()
```





```
In [31]: # 13. Transmission type count
if 'transmission' in data.columns:
    plt.figure(figsize=(6, 6))
    sns.countplot(data['transmission'])
    plt.title('Distribution of Transmission Types')
    plt.show()
```

```
# 14. Fuel type distribution
if 'fuelType' in data.columns:
    plt.figure(figsize=(6, 6))
    sns.countplot(data['fuelType'])
    plt.title('Distribution of Fuel Types')
    plt.show()
```

```
In [38]: # 15. Saving cleaned data (if needed)
data.to_csv('C:/Users/Komal Bhati/Desktop/data visualization proj/cleaned_used_c

print('My Full Data Analysis Completed')
```

My Full Data Analysis Completed

```
In [ ]:
```