Car Price Regression Project:

This project aims at preprocessing, cleaning, and applying feature engineering on a car price dataset and developing best machine learning model to predict the price of the care given the features.

1. Importing Necessary Libraries
2. Exploratory Data Analysis & Preprocessing
3. Feature Engineering (Dealing with outliers and scaling data)
4. Splitting Dataset
5. Developing The Model

Libraries

In [1]:
```
import pandas as pd #Pandas: Data manipulation library, used for working with dataframes
import numpy as np #Numpy: Numerical computing library, used for working with arrays
import matplotlib.pyplot as plt #Matplotlib: Visualization library, used for creating plots and charts
import seaborn as sns #Seaborn: Visualization library, used for creating plots and charts
from sklearn.preprocessing import LabelEncoder, OrdinalEncoder, RobustScaler #Scalers and encoders: Data preprocessi
from sklearn.model_selection import train_test_split #Train test split: Data splitting tool

# ********** Models **********
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from lightgbm import LGBMRegressor
# ********** Models **********

from sklearn.metrics import mean_squared_error, r2_score #Metrics: Model evaluation tools
import mlflow #MLflow: Experiment tracking tool
```

In [2]:
```
# Set the style of the plots
plt.style.use('seaborn-v0_8')
sns.set_palette("icefire")
```

EDA & Data Preprocessing

Exploring and viewing the dataset in order to get insights about cleaning and processing

In [3]:
```
df = pd.read_csv('car.csv') #Read the data from the CSV file
```

In [4]:
```
df.head() #Display the first few rows of the dataframe
```

Out[4]:

	Name	Location	Year	Kilometers_Driven	Fuel_Type	Transmission	Owner_Type	Mileage	Engine	Power	Seats	New
0	Maruti Wagon R LXI CNG	Mumbai	2010	72000	CNG	Manual	First	26.6 km/kg	998 CC	58.16 bhp	5.0	
1	Hyundai Creta 1.6 CRDi SX Option	Pune	2015	41000	Diesel	Manual	First	19.67 kmpl	1582 CC	126.2 bhp	5.0	
2	Honda Jazz V	Chennai	2011	46000	Petrol	Manual	First	18.2 kmpl	1199 CC	88.7 bhp	5.0	8.6
3	Maruti Ertiga VDI	Chennai	2012	87000	Diesel	Manual	First	20.77 kmpl	1248 CC	88.76 bhp	7.0	
4	Audi A4 New 2.0 TDI Multitronic	Coimbatore	2013	40670	Diesel	Automatic	Second	15.2 kmpl	1968 CC	140.8 bhp	5.0	

Insights Noticed:

1. We only need the brand name (first word) from the 'Name' column
2. In 'Mileage', 'Engine', and 'Power' the values are stored with their units meaning they're strings, but we need to clean it and get only the numerical value of the features
3. All Categorical data should be encoding according to their type (Nominal or Ordinal)

let's explore the data further..

In [5]:
```
df.isnull().sum() #Check for missing values in the dataframe
```

Out[5]:
```
Name                    0
Location                0
Year                    0
Kilometers_Driven       0
Fuel_Type               0
Transmission            0
Owner_Type              0
Mileage                 2
Engine                 36
Power                  36
Seats                  42
New_Price            5195
Price                   0
dtype: int64
```

New_Price has many missing values, it can't be beneficial for the problem at hand, would be wise to drop it

In [6]:
```
df.info() #Get a concise summary of the dataframe
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6019 entries, 0 to 6018
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Name               6019 non-null   object 
 1   Location           6019 non-null   object 
 2   Year               6019 non-null   int64  
 3   Kilometers_Driven  6019 non-null   int64  
 4   Fuel_Type          6019 non-null   object 
 5   Transmission       6019 non-null   object 
 6   Owner_Type         6019 non-null   object 
 7   Mileage            6017 non-null   object 
 8   Engine             5983 non-null   object 
 9   Power              5983 non-null   object 
 10  Seats              5977 non-null   float64
 11  New_Price          824 non-null    object 
 12  Price              6019 non-null   float64
dtypes: float64(2), int64(2), object(9)
memory usage: 611.4+ KB
```

Dropping duplicates, and 'New_Price' column filled with null values

In [7]:
```
df = df.drop_duplicates() #Drop duplicate rows from the dataframe
```

In [8]:
```
df.drop(['New_Price'], axis=1, inplace=True) #Drop the 'New_Price' column from the dataframe
```

Mileage

In [9]:
```
def clean_mileage(x): #Function to clean the 'Mileage' column
    try:
        return float(x.split(' ')[0]) #Split the string and return the first part as a float
    except:
        return np.nan #Return NaN if an error occurs
```

In [10]:
```
df['Mileage'] = df['Mileage'].apply(clean_mileage) #Apply the function to the 'Mileage' column
```

In [11]:
```
df['Mileage'].isnull().sum() #Check for missing values in the 'Mileage' column
```

Out[11]: 2

Engine

Same goes for Engine

In [12]:
```
df['Engine'].unique() #Get the unique values in the 'Engine' column
```

Out[12]:
```
array(['998 CC', '1582 CC', '1199 CC', '1248 CC', '1968 CC', '814 CC',
       '1461 CC', '2755 CC', '1598 CC', '1462 CC', '1497 CC', '2179 CC',
       '2477 CC', '1498 CC', '2143 CC', '1995 CC', '1984 CC', '1197 CC',
       '2494 CC', '1798 CC', '2696 CC', '2698 CC', '1061 CC', '1198 CC',
       '2987 CC', '796 CC', '624 CC', '1999 CC', '1991 CC', '2694 CC',
       '1120 CC', '2498 CC', '799 CC', '2393 CC', '1399 CC', '1796 CC',
       '2148 CC', '1396 CC', '1950 CC', '4806 CC', '1998 CC', '1086 CC',
       '1193 CC', '2982 CC', '1493 CC', '2967 CC', '2993 CC', '1196 CC',
       '1799 CC', '2497 CC', '2354 CC', '1373 CC', '2996 CC', '1591 CC',
       '2894 CC', '5461 CC', '1595 CC', '936 CC', '1997 CC', nan,
       '1896 CC', '1390 CC', '1364 CC', '2199 CC', '993 CC', '999 CC',
       '1405 CC', '2956 CC', '1794 CC', '995 CC', '2496 CC', '1599 CC',
       '2400 CC', '1495 CC', '2523 CC', '793 CC', '4134 CC', '1596 CC',
       '1395 CC', '2953 CC', '1586 CC', '2362 CC', '1496 CC', '1368 CC',
       '1298 CC', '1956 CC', '1299 CC', '3498 CC', '2835 CC', '1150 CC',
       '3198 CC', '1343 CC', '1499 CC', '1186 CC', '1590 CC', '2609 CC',
       '2499 CC', '2446 CC', '1978 CC', '2360 CC', '3436 CC', '2198 CC',
       '4367 CC', '2706 CC', '1422 CC', '2979 CC', '1969 CC', '1489 CC',
       '2489 CC', '1242 CC', '1388 CC', '1172 CC', '2495 CC', '1194 CC',
       '3200 CC', '1781 CC', '1341 CC', '2773 CC', '3597 CC', '1985 CC',
       '2147 CC', '1047 CC', '2999 CC', '2995 CC', '2997 CC', '1948 CC',
       '2359 CC', '4395 CC', '2349 CC', '2720 CC', '1468 CC', '3197 CC',
       '2487 CC', '1597 CC', '2771 CC', '72 CC', '4951 CC', '970 CC',
       '2925 CC', '2200 CC', '5000 CC', '2149 CC', '5998 CC', '2092 CC',
       '5204 CC', '2112 CC', '1797 CC'], dtype=object)
```

In [13]:
```
def clean_engine(x): #Function to clean the 'Engine' column
    try:
        return int(x.split(' ')[0]) #Split the string and return the first part as an integer
    except:
        return np.nan #Return NaN if an error occurs
```

In [14]:
```
df['Engine'] = df['Engine'].apply(clean_engine) #Apply the function to the 'Engine' column
```

In [15]:
```
df['Engine'].isnull().sum() #Check for missing values in the 'Engine' column
```

Out[15]:
```
36
```

Power

In [16]:
```
df['Power'].unique() #Get the unique values in the 'Power' column
```

Out[16]:
```
array(['58.16 bhp', '126.2 bhp', '88.7 bhp', '88.76 bhp', '140.8 bhp',
       '55.2 bhp', '63.1 bhp', '171.5 bhp', '103.6 bhp', '74 bhp',
       '103.25 bhp', '116.3 bhp', '187.7 bhp', '115 bhp', '175.56 bhp',
       '98.6 bhp', '83.8 bhp', '167.62 bhp', '190 bhp', '88.5 bhp',
       '177.01 bhp', '80 bhp', '67.1 bhp', '102 bhp', '108.45 bhp',
       '138.1 bhp', '184 bhp', '179.5 bhp', '103.5 bhp', '64 bhp',
       '82 bhp', '254.8 bhp', '73.9 bhp', '46.3 bhp', '37.5 bhp',
       '77 bhp', '82.9 bhp', '149.92 bhp', '138.03 bhp', '112.2 bhp',
       '163.7 bhp', '71 bhp', '105 bhp', '174.33 bhp', '75 bhp',
       '103.2 bhp', '53.3 bhp', '78.9 bhp', '147.6 bhp', '147.8 bhp',
       '68 bhp', '186 bhp', '170 bhp', '69 bhp', '140 bhp', '78 bhp',
       '194 bhp', '500 bhp', '108.5 bhp', '86.8 bhp', '187.74 bhp',
       'null bhp', '132 bhp', '86.7 bhp', '73.94 bhp', '117.3 bhp',
       '218 bhp', '168.5 bhp', '89.84 bhp', '110 bhp', '90 bhp',
       '82.85 bhp', '67 bhp', '241.4 bhp', '35 bhp', '270.9 bhp',
       '126.32 bhp', '73 bhp', '130 bhp', '100.6 bhp', '150 bhp',
       '75.94 bhp', '215 bhp', '107.3 bhp', '37.48 bhp', '120 bhp',
       '178 bhp', '152 bhp', '91.1 bhp', '85.80 bhp', '362.07 bhp',
       '121.3 bhp', '143 bhp', '81.80 bhp', '171 bhp', '76.8 bhp',
       '103.52 bhp', '444 bhp', '362.9 bhp', '67.06 bhp', '120.7 bhp',
       '258 bhp', '81.86 bhp', '112 bhp', '88.73 bhp', '57.6 bhp',
       '157.75 bhp', '102.5 bhp', '201.1 bhp', '83.1 bhp', '68.05 bhp',
       '88.50 bhp', nan, '106 bhp', '100 bhp', '81.83 bhp', '85 bhp',
       '64.1 bhp', '177.5 bhp', '246.7 bhp', '177.46 bhp', '65 bhp',
       '67.04 bhp', '189.08 bhp', '99 bhp', '53.5 bhp', '194.3 bhp',
       '70 bhp', '183 bhp', '254.79 bhp', '66.1 bhp', '76 bhp', '60 bhp',
       '123.24 bhp', '47.3 bhp', '118 bhp', '88.8 bhp', '177 bhp',
       '136 bhp', '201.15 bhp', '93.7 bhp', '177.6 bhp', '313 bhp',
       '245 bhp', '125 bhp', '141 bhp', '227 bhp', '62 bhp', '141.1 bhp',
       '83.14 bhp', '192 bhp', '67.05 bhp', '47 bhp', '235 bhp', '37 bhp',
       '87.2 bhp', '203 bhp', '204 bhp', '246.74 bhp', '122 bhp',
       '282 bhp', '181 bhp', '224 bhp', '94 bhp', '367 bhp', '98.79 bhp',
       '62.1 bhp', '174.3 bhp', '114 bhp', '335.2 bhp', '169 bhp',
       '191.34 bhp', '108.49 bhp', '138.02 bhp', '156 bhp', '187.4 bhp',
       '66 bhp', '103.3 bhp', '164.7 bhp', '79.4 bhp', '198.5 bhp',
       '154 bhp', '73.8 bhp', '181.43 bhp', '85.8 bhp', '207.8 bhp',
       '108.4 bhp', '88 bhp', '63 bhp', '82.5 bhp', '364.9 bhp',
       '107.2 bhp', '113.98 bhp', '126.3 bhp', '185 bhp', '237.4 bhp',
       '99.6 bhp', '66.7 bhp', '160 bhp', '306 bhp', '98.59 bhp',
       '92.7 bhp', '147.51 bhp', '197.2 bhp', '167.6 bhp', '165 bhp',
       '110.4 bhp', '73.97 bhp', '147.9 bhp', '116.6 bhp', '148 bhp',
       '34.2 bhp', '155 bhp', '197 bhp', '108.62 bhp', '118.3 bhp',
```

```
       '38.4 bhp', '241.38 bhp', '153.86 bhp', '163.5 bhp', '226.6 bhp',
       '84.8 bhp', '53.64 bhp', '158.2 bhp', '69.01 bhp', '181.03 bhp',
       '58.2 bhp', '104.68 bhp', '126.24 bhp', '73.75 bhp', '158 bhp',
       '130.2 bhp', '57.5 bhp', '97.7 bhp', '121.4 bhp', '98.96 bhp',
       '174.5 bhp', '308 bhp', '121.36 bhp', '138 bhp', '265 bhp',
       '84 bhp', '321 bhp', '91.72 bhp', '65.3 bhp', '88.2 bhp', '93 bhp',
       '35.5 bhp', '86.79 bhp', '157.7 bhp', '40.3 bhp', '91.7 bhp',
       '180 bhp', '114.4 bhp', '158.8 bhp', '157.8 bhp', '123.7 bhp',
       '56.3 bhp', '189 bhp', '104 bhp', '210 bhp', '270.88 bhp',
       '142 bhp', '255 bhp', '236 bhp', '167.7 bhp', '148.31 bhp',
       '80.46 bhp', '138.08 bhp', '250 bhp', '74.9 bhp', '91.2 bhp',
       '102.57 bhp', '97.6 bhp', '102.53 bhp', '240 bhp', '254 bhp',
       '112.4 bhp', '73.74 bhp', '108.495 bhp', '116.9 bhp', '101 bhp',
       '320 bhp', '70.02 bhp', '261.49 bhp', '105.5 bhp', '550 bhp',
       '168.7 bhp', '55.23 bhp', '94.68 bhp', '152.88 bhp', '163.2 bhp',
       '203.2 bhp', '241 bhp', '95 bhp', '200 bhp', '271.23 bhp',
       '63.12 bhp', '85.7 bhp', '308.43 bhp', '118.6 bhp', '199.3 bhp',
       '83.83 bhp', '55 bhp', '83 bhp', '300 bhp', '201 bhp', '262.6 bhp',
       '163 bhp', '58.33 bhp', '86.76 bhp', '76.9 bhp', '174.57 bhp',
       '301.73 bhp', '68.1 bhp', '162 bhp', '394.3 bhp', '80.9 bhp',
       '147.5 bhp', '272 bhp', '340 bhp', '120.33 bhp', '82.4 bhp',
       '231.1 bhp', '335.3 bhp', '333 bhp', '198.25 bhp', '224.34 bhp',
       '402 bhp', '261 bhp', '61 bhp', '144 bhp', '71.01 bhp',
       '271.72 bhp', '134 bhp', '135.1 bhp', '92 bhp', '64.08 bhp',
       '261.5 bhp', '123.37 bhp', '175.67 bhp', '53 bhp', '110.5 bhp',
       '178.4 bhp', '193.1 bhp', '41 bhp', '395 bhp', '48.21 bhp',
       '450 bhp', '421 bhp', '89.75 bhp', '387.3 bhp', '130.3 bhp',
       '281.61 bhp', '52.8 bhp', '139.01 bhp', '208 bhp', '503 bhp',
       '168 bhp', '98.82 bhp', '139.07 bhp', '83.11 bhp', '74.93 bhp',
       '382 bhp', '74.96 bhp', '552 bhp', '127 bhp', '560 bhp',
       '116.4 bhp', '161.6 bhp', '488.1 bhp', '103 bhp', '181.04 bhp'],
      dtype=object)
```

In [17]:
```
def clean_power(x): #Function to clean the 'Power' column by removing 'bhp' and converting to float
    try:
        return float(x.split(' ')[0]) #Split the string and return the first part as a float
    except:
        return np.nan
```

In [18]:
```
df['Power'] = df['Power'].apply(clean_power) #Apply the function to the 'Power' column
```

In [19]:
```
df['Power'].isnull().sum() #Check for missing values in the 'Power' column
```

Out[19]:
```
143
```

Names

In [20]:
```
df['Name'].unique() #Get the unique values in the 'Name' column
```

Out[20]:
```
array(['Maruti Wagon R LXI CNG', 'Hyundai Creta 1.6 CRDi SX Option',
       'Honda Jazz V', ..., 'Volkswagen Polo IPL II 1.2 Petrol Highline',
       'Tata Bolt Revotron XT', 'Mahindra Xylo D4 BSIV'], dtype=object)
```

In [21]:
```
def get_brand(x): #Function to extract the brand name from the 'Name' column
    return x.split(' ')[0] #Split the string and return the first part
```

In [22]:
```
df['Brand'] = df['Name'].apply(get_brand) #Apply the function to the 'Name' column
```

Data Transformation

In [23]:
```
df.info() #Get a concise summary of the dataframe
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6019 entries, 0 to 6018
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Name               6019 non-null   object 
 1   Location           6019 non-null   object 
 2   Year               6019 non-null   int64  
 3   Kilometers_Driven  6019 non-null   int64  
 4   Fuel_Type          6019 non-null   object 
 5   Transmission       6019 non-null   object 
 6   Owner_Type         6019 non-null   object 
 7   Mileage            6017 non-null   float64
 8   Engine             5983 non-null   float64
 9   Power              5876 non-null   float64
 10  Seats              5977 non-null   float64
 11  Price              6019 non-null   float64
 12  Brand              6019 non-null   object 
dtypes: float64(5), int64(2), object(6)
memory usage: 611.4+ KB
```

Encoding Data

In [24]:
```
Nominal_list = ['Name', 'Brand', 'Location', 'Fuel_Type', 'Transmission', 'Owner_Type'] #List of nominal columns
Ordinal_list = ['Owner_Type']    #List of ordinal columns
```

In [25]:
```
for column in Nominal_list: #Loop through the nominal columns
    le = LabelEncoder() #Create a label encoder
    df[column] = le.fit_transform(df[column]) #Fit and transform the column
```

In [26]:
```
for column in Ordinal_list: #Loop through the ordinal columns
    oe = OrdinalEncoder() #Create an ordinal encoder
    df[column] = oe.fit_transform(df[column].values.reshape(-1, 1)) #Fit and transform the column
```

In [27]:
```
df.info() #Get a concise summary of the dataframe
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6019 entries, 0 to 6018
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Name               6019 non-null   int32  
 1   Location           6019 non-null   int32  
 2   Year               6019 non-null   int64  
 3   Kilometers_Driven  6019 non-null   int64  
 4   Fuel_Type          6019 non-null   int32  
 5   Transmission       6019 non-null   int32  
 6   Owner_Type         6019 non-null   float64
 7   Mileage            6017 non-null   float64
 8   Engine             5983 non-null   float64
 9   Power              5876 non-null   float64
 10  Seats              5977 non-null   float64
 11  Price              6019 non-null   float64
 12  Brand              6019 non-null   int32  
dtypes: float64(6), int32(5), int64(2)
memory usage: 493.9 KB
```

In [28]:
```
df.isnull().sum() #Check for missing values in the dataframe
```

Out[28]:
```
Name                   0
Location               0
Year                   0
Kilometers_Driven      0
Fuel_Type              0
Transmission           0
Owner_Type             0
Mileage                2
Engine                36
Power                143
Seats                 42
Price                  0
Brand                  0
dtype: int64
```

In [29]:
```
df['Seats'].unique() #Get the unique values in the 'Seats' column
```

Out[29]:
```
array([ 5.,  7.,  8.,  4.,  6.,  2., nan, 10.,  9.,  0.])
```

In [30]:
```
df.head() #Display the first few rows of the dataframe
```

Out[30]:

	Name	Location	Year	Kilometers_Driven	Fuel_Type	Transmission	Owner_Type	Mileage	Engine	Power	Seats	Price	Bra
0	1200	9	2010	72000	0	1	0.0	26.60	998.0	58.16	5.0	1.75	
1	512	10	2015	41000	1	1	0.0	19.67	1582.0	126.20	5.0	12.50	
2	486	2	2011	46000	4	1	0.0	18.20	1199.0	88.70	5.0	4.50	
3	1059	2	2012	87000	1	1	0.0	20.77	1248.0	88.76	7.0	6.00	
4	23	3	2013	40670	1	0	2.0	15.20	1968.0	140.80	5.0	17.74	

Dropping Null Values

In [31]:
```
df.isnull().sum() #Check for missing values in the dataframe
```

Out[31]:
```
Name                   0
Location               0
Year                   0
Kilometers_Driven      0
Fuel_Type              0
Transmission           0
Owner_Type             0
Mileage                2
Engine                36
Power                143
Seats                 42
Price                  0
Brand                  0
dtype: int64
```

In [32]:
```
df.dropna(inplace=True) #Drop rows with missing values from the dataframe
```

In [33]:
```
df['Seats']
```

Out[33]:
```
0       5.0
1       5.0
2       5.0
3       7.0
4       5.0
       ...
6014    5.0
6015    5.0
6016    8.0
6017    5.0
6018    5.0
Name: Seats, Length: 5872, dtype: float64
```

In [34]:
```
# count values in the 'Seats' column
df['Seats'].value_counts()
```

Out[34]:
```
Seats
5.0     4919
7.0      672
8.0      133
4.0       99
6.0       29
2.0       13
10.0       4
9.0        3
Name: count, dtype: int64
```

Feature Engineering

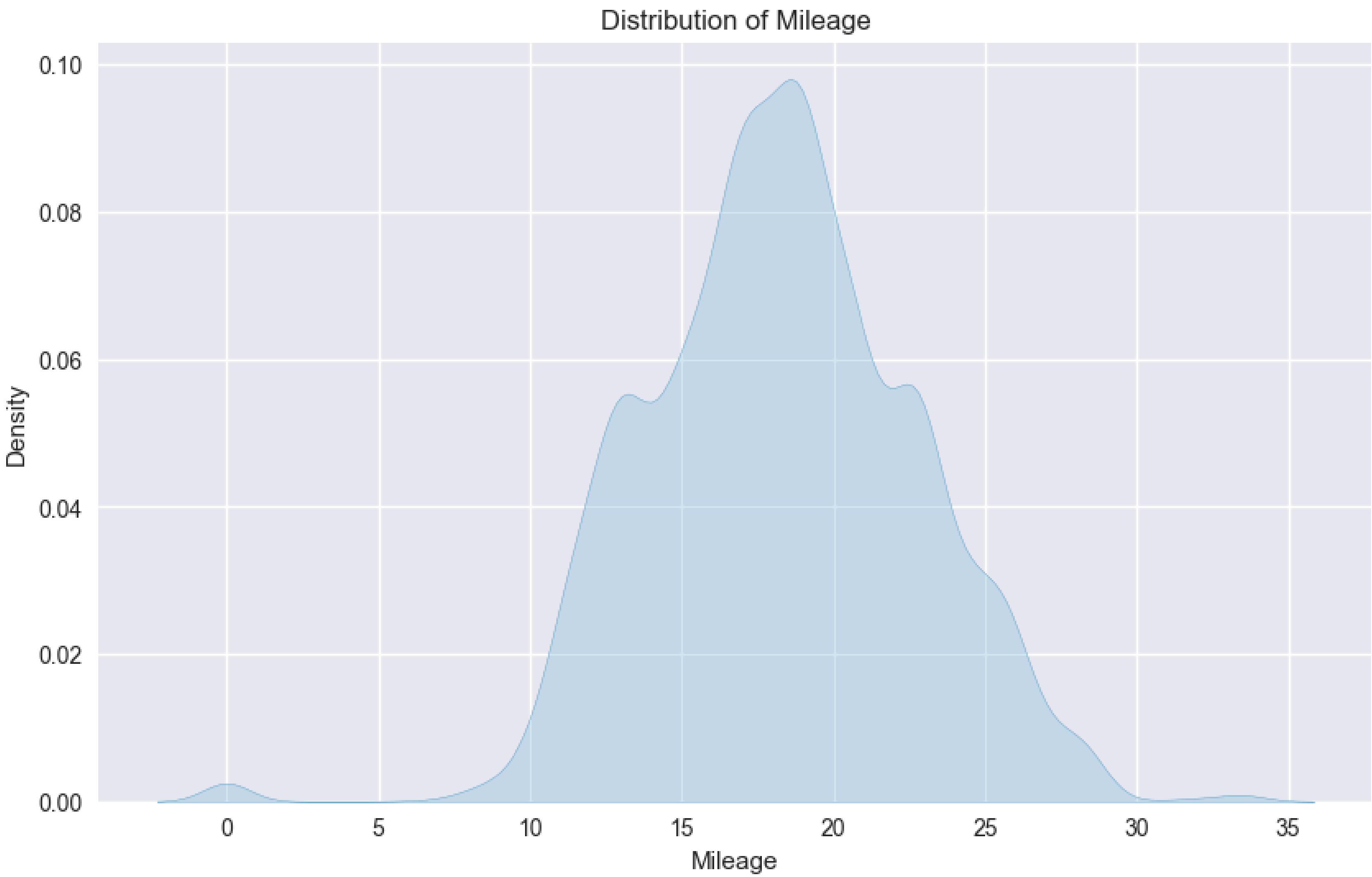
In [35]:
```
Numerical_list = ['Mileage', 'Engine', 'Power', 'Seats'] #List of numerical columns
```

The data is now cleaned, time for visualization and plotting to give insights about need Feature Engineering techniques

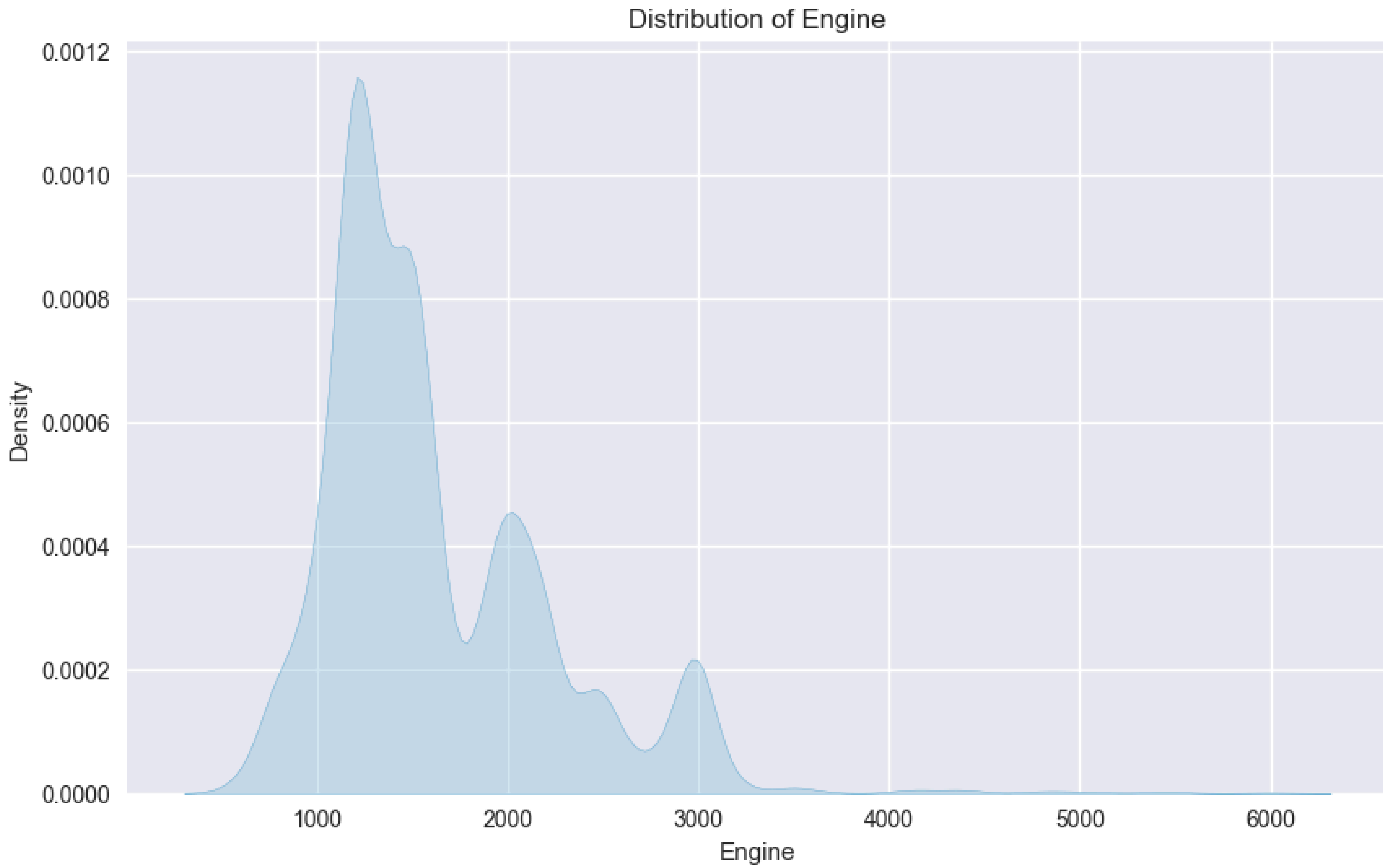
In [36]:
```
# Distribution of each numerical column after scaling
for column in Numerical_list:
    plt.figure(figsize=(10, 6)) # Set the figure size
    sns.kdeplot(data=df[column], fill=True) # Create a kernel density plot for each column
```

```
    plt.title(f'Distribution of {column}') # Set the title of the plot
    plt.show() # Display the plot
```

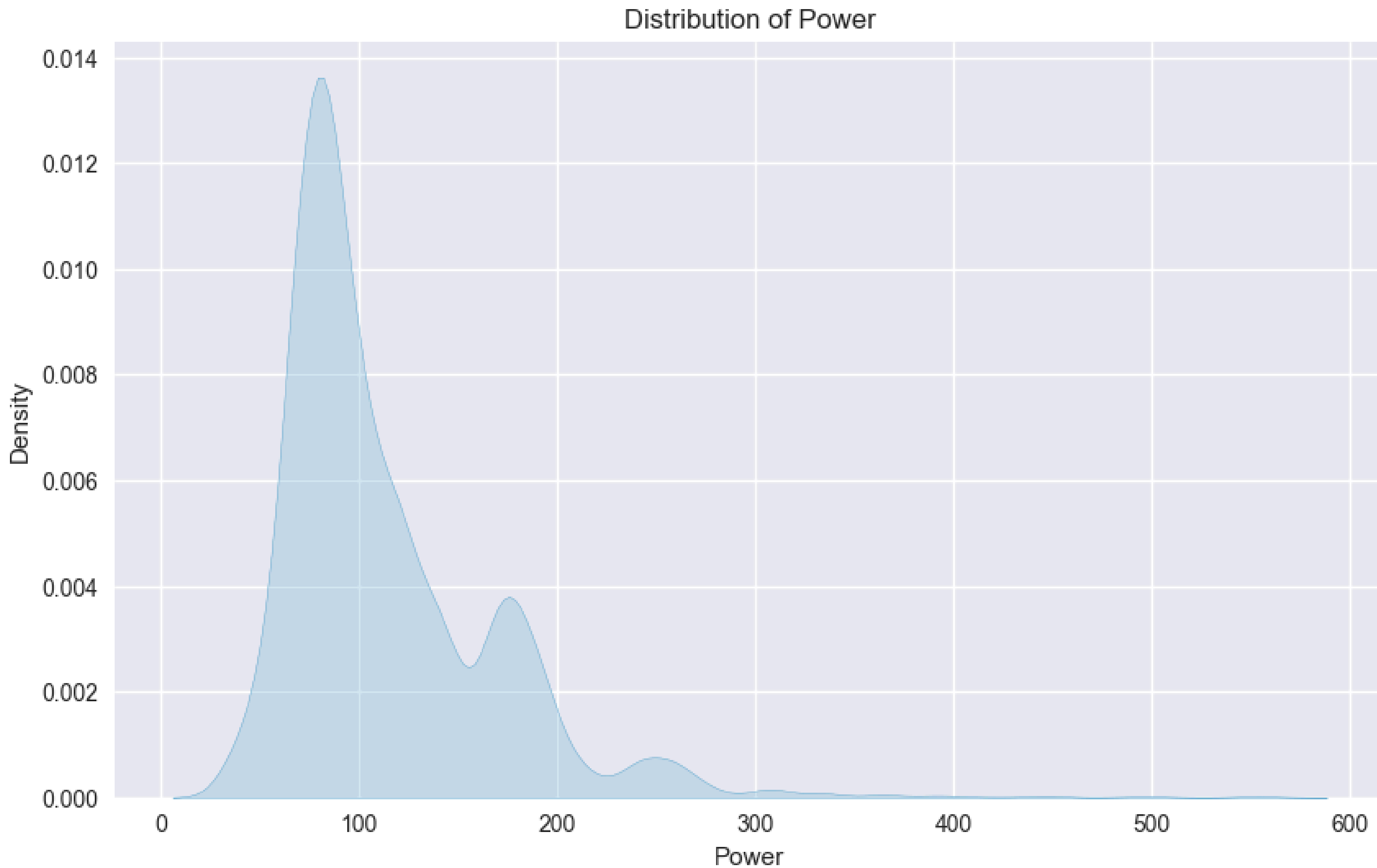
```
c:\Users\Ayman\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use
_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating i
nstead.
  with pd.option_context('mode.use_inf_as_na', True):
```



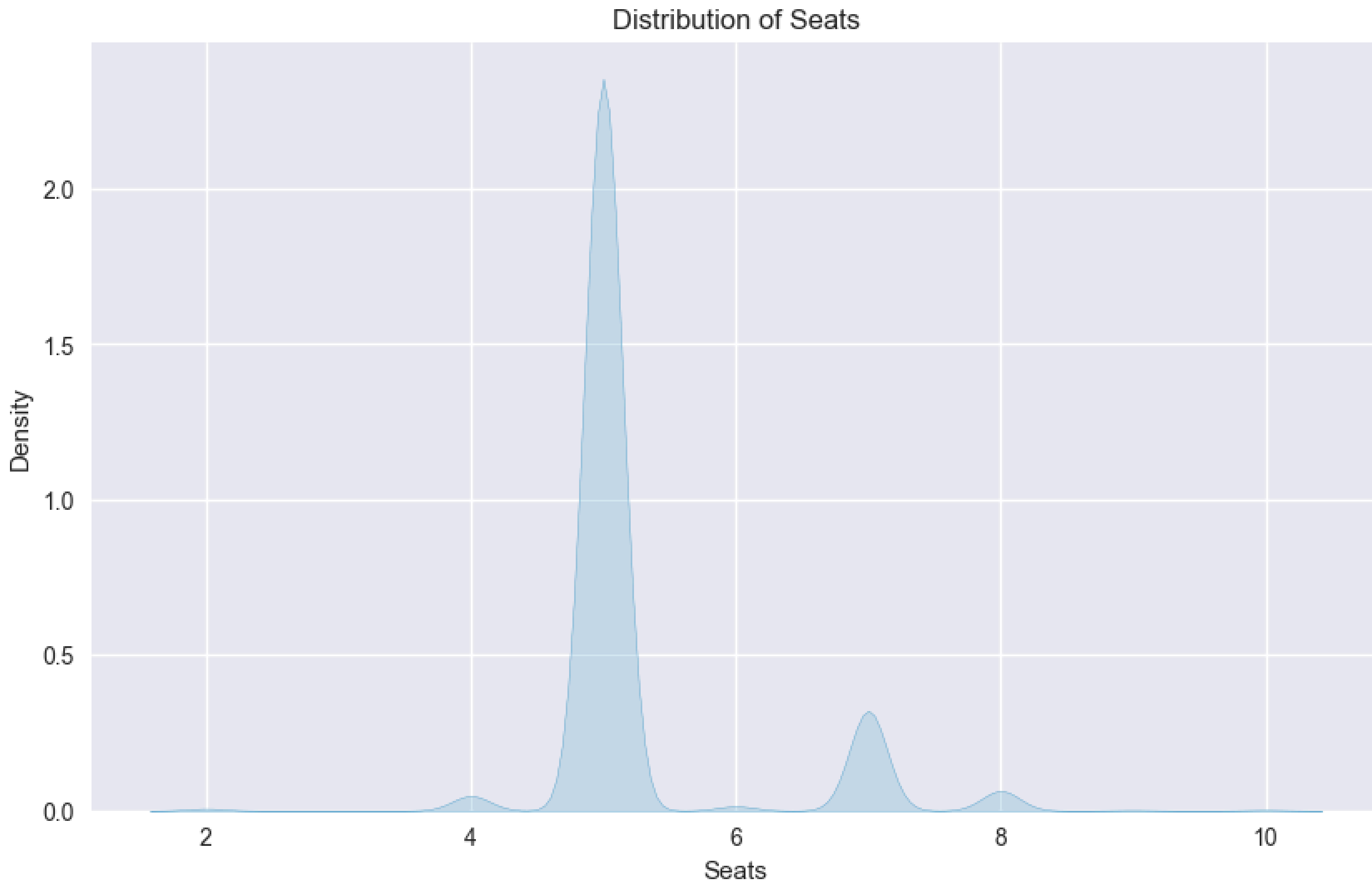
```
c:\Users\Ayman\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use
_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating i
nstead.
  with pd.option_context('mode.use_inf_as_na', True):
```




```
c:\Users\Ayman\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use
_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating i
nstead.
  with pd.option_context('mode.use_inf_as_na', True):
```

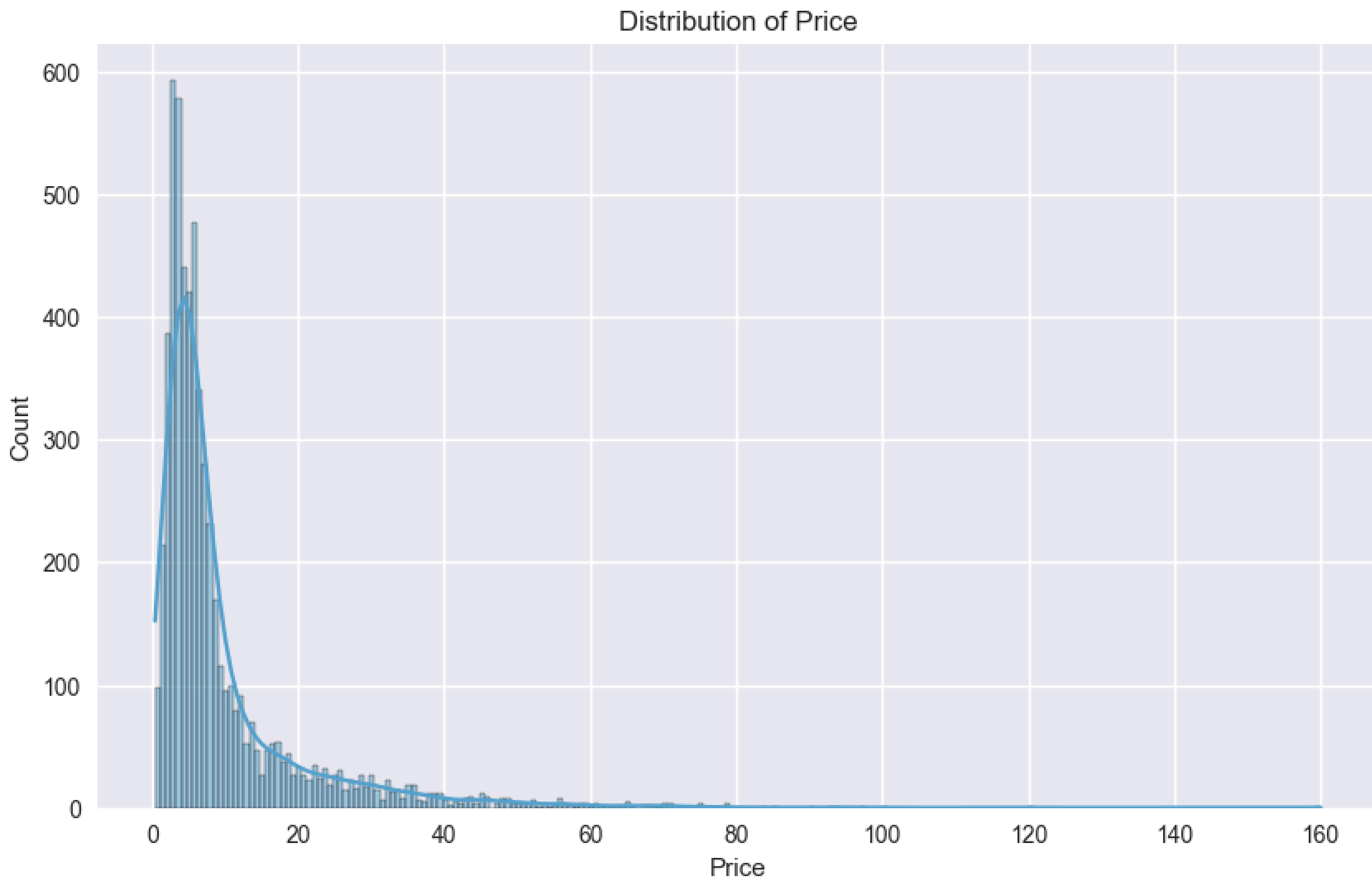



```
c:\Users\Ayman\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use
_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating i
nstead.
  with pd.option_context('mode.use_inf_as_na', True):
```



In [37]:
```
# plot the distribution of the target variable 'Price'
plt.figure(figsize=(10, 6)) #Set the figure size
sns.histplot(df['Price'], kde=True) #Create a histogram of the 'Price' column
plt.title('Distribution of Price') #Set the title of the plot
plt.show() #Display the plot
```

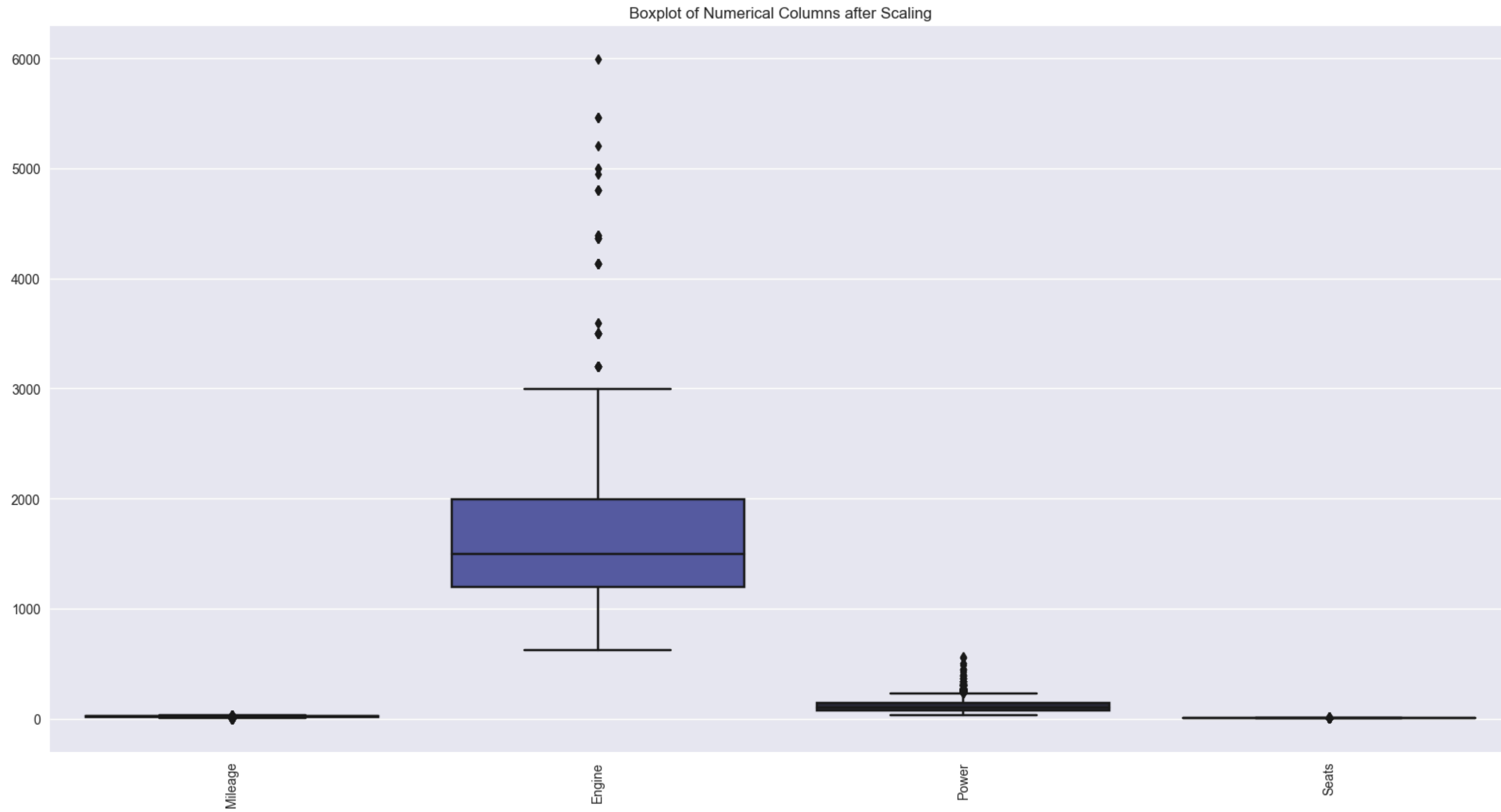
```
c:\Users\Ayman\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use
_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating i
nstead.
  with pd.option_context('mode.use_inf_as_na', True):
```



We should make box plot for the numerical values to check for outliers

```
In [38]: # boxplot for numerical columns after scaling
plt.figure(figsize=(20, 10)) #Set the figure size
```

```
sns.boxplot(data=df[Numerical_list]) #Create a boxplot of the numerical columns
plt.xticks(rotation=90) #Rotate the x-axis labels
plt.title('Boxplot of Numerical Columns after Scaling') #Set the title of the plot
plt.show() #Display the plot
```

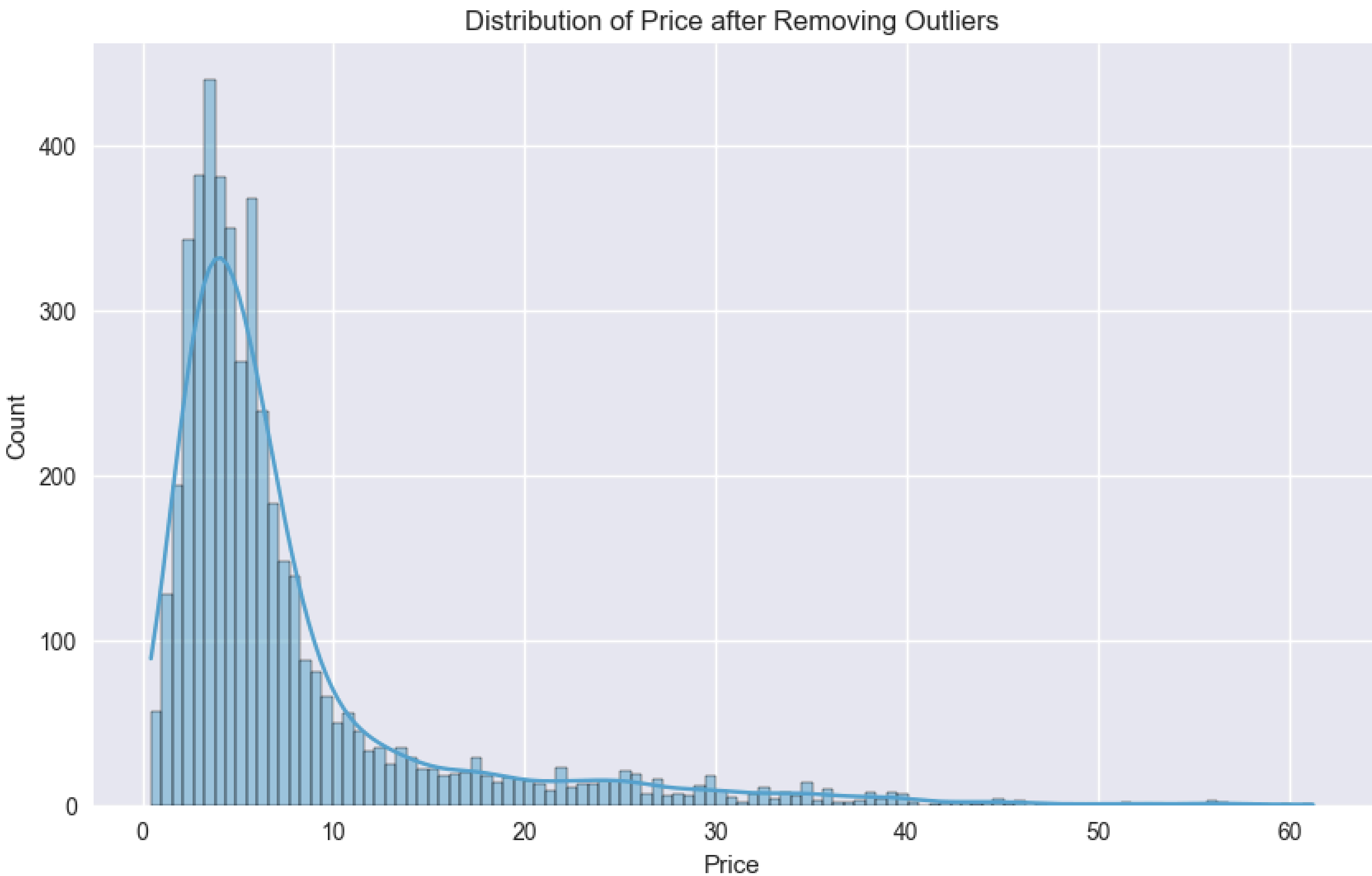


In [39]:
```
# Determine the outliers in the numerical columns and remove them
Q1 = df[Numerical_list].quantile(0.25) #Calculate the first quartile
Q3 = df[Numerical_list].quantile(0.75) #Calculate the third quartile
IQR = Q3 - Q1 #Calculate the interquartile range
outliers = df[~((df[Numerical_list] < (Q1 - 1.5 * IQR)) | (df[Numerical_list] > (Q3 + 1.5 * IQR))).any(axis=1)] #Dete
df = outliers #Update the dataframe with the rows that are not outliers
```

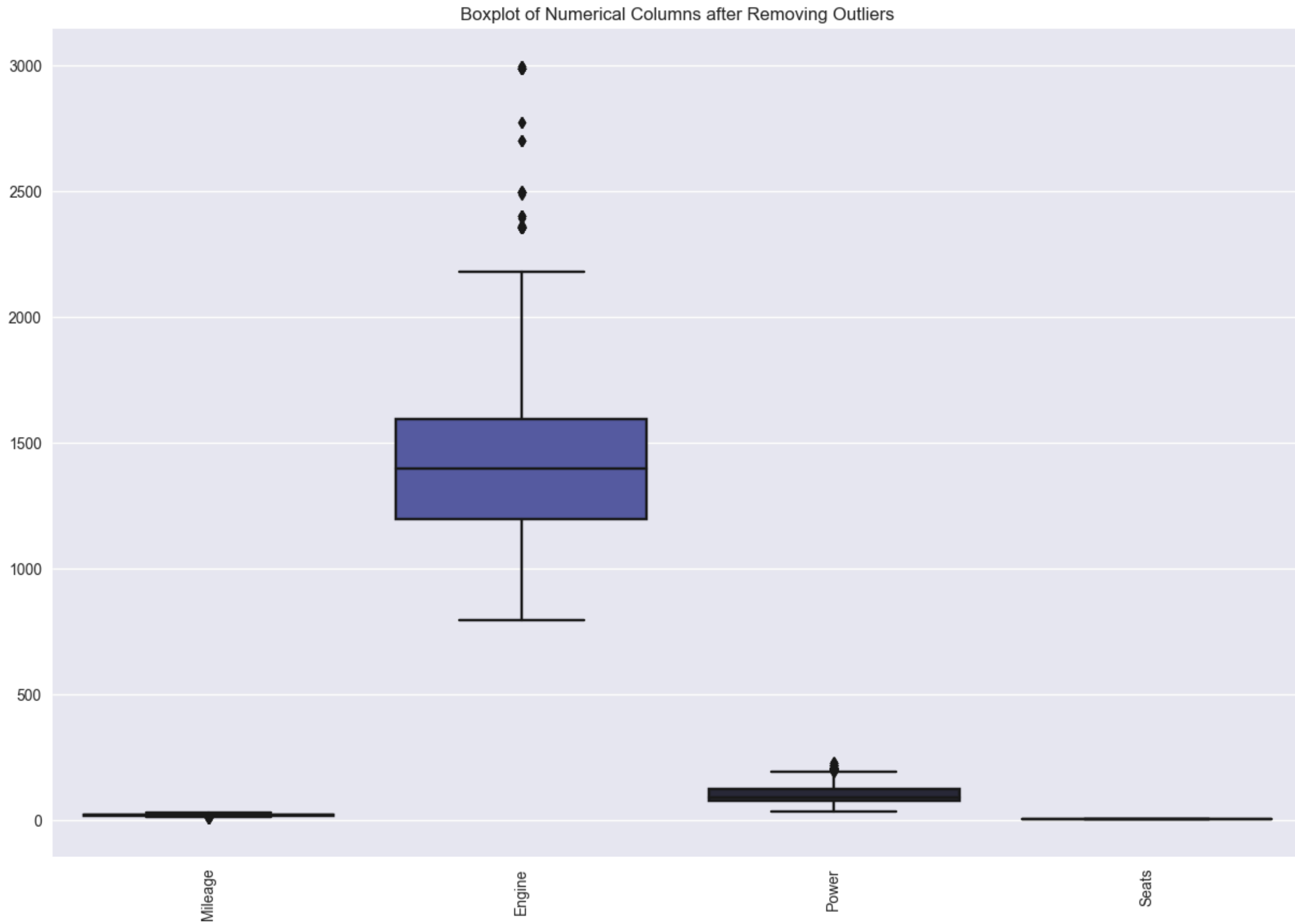
In [40]:
```
# plot the distribution of the target variable 'Price' after removing outliers
plt.figure(figsize=(10, 6)) #Set the figure size
```

```
sns.histplot(df['Price'], kde=True) #Create a histogram of the 'Price' column
plt.title('Distribution of Price after Removing Outliers') #Set the title of the plot
plt.show() #Display the plot
```

```
c:\Users\Ayman\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use
_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating i
nstead.
  with pd.option_context('mode.use_inf_as_na', True):
```



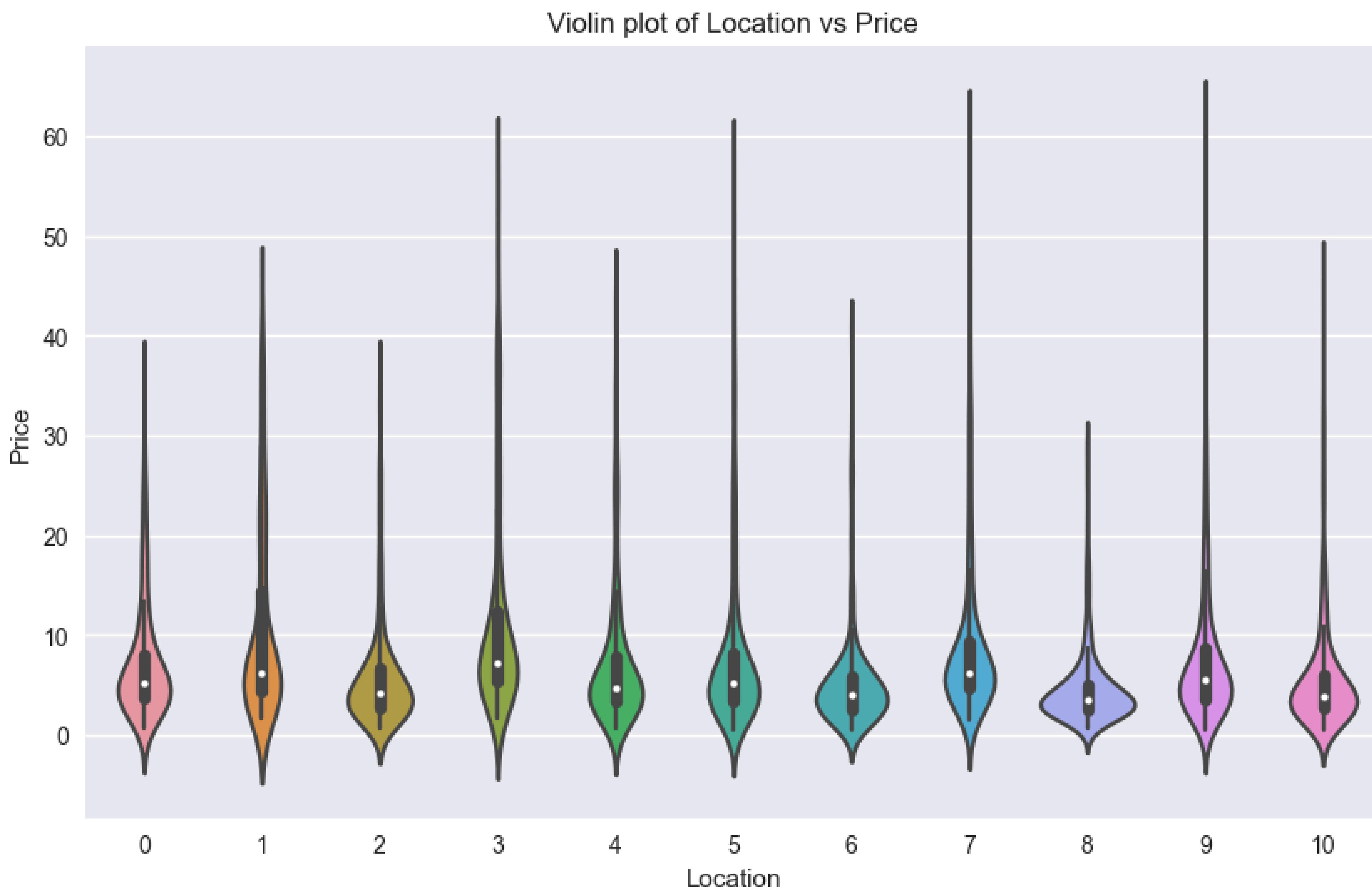
In [41]:
```
# plot boxplot for numerical columns after removing outliers
plt.figure(figsize=(15, 10)) #Set the figure size
sns.boxplot(data=df[Numerical_list]) #Create a boxplot of the numerical columns
plt.xticks(rotation=90) #Rotate the x-axis labels
plt.title('Boxplot of Numerical Columns after Removing Outliers') #Set the title of the plot
plt.show() #Display the plot
```

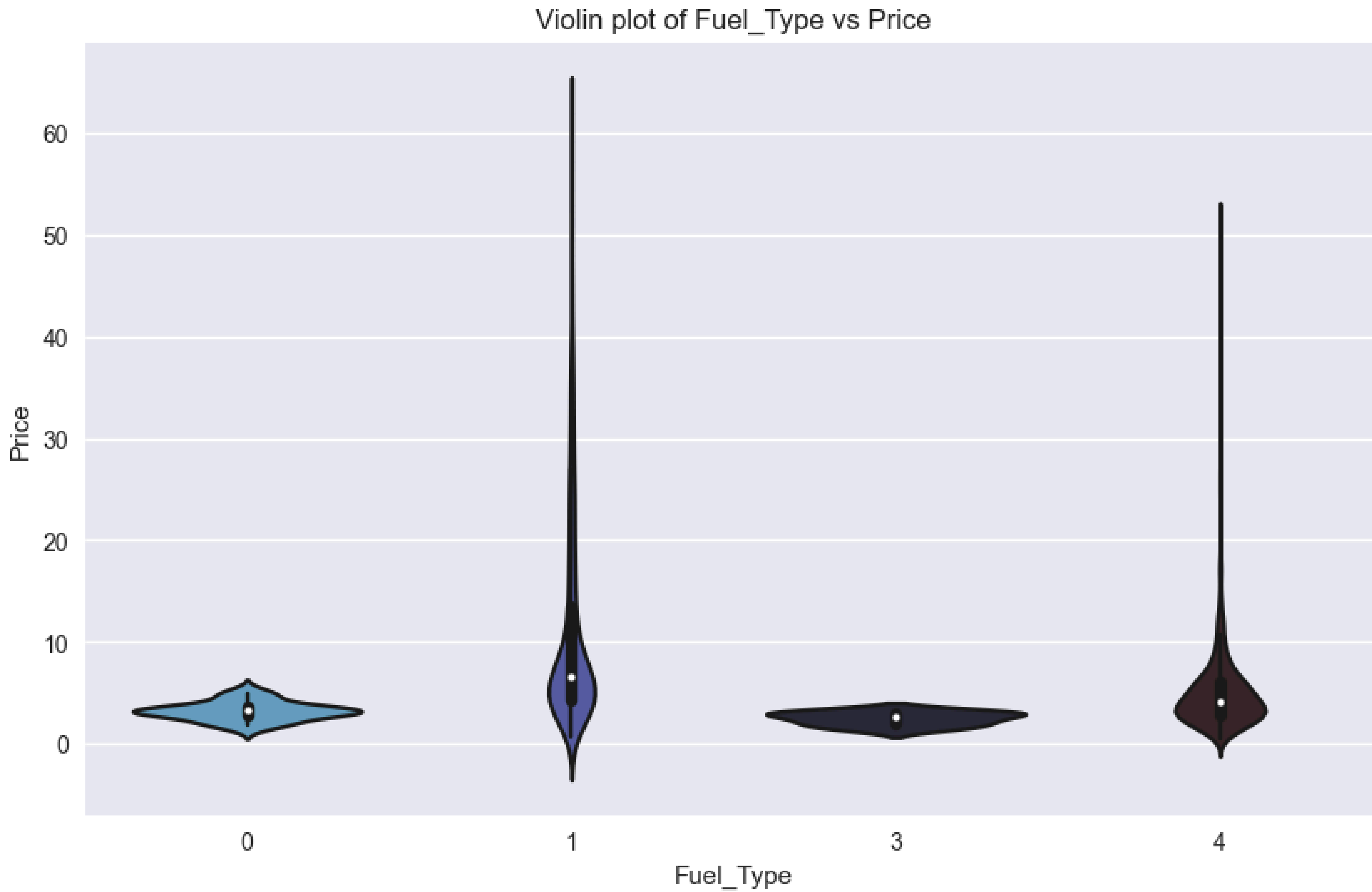


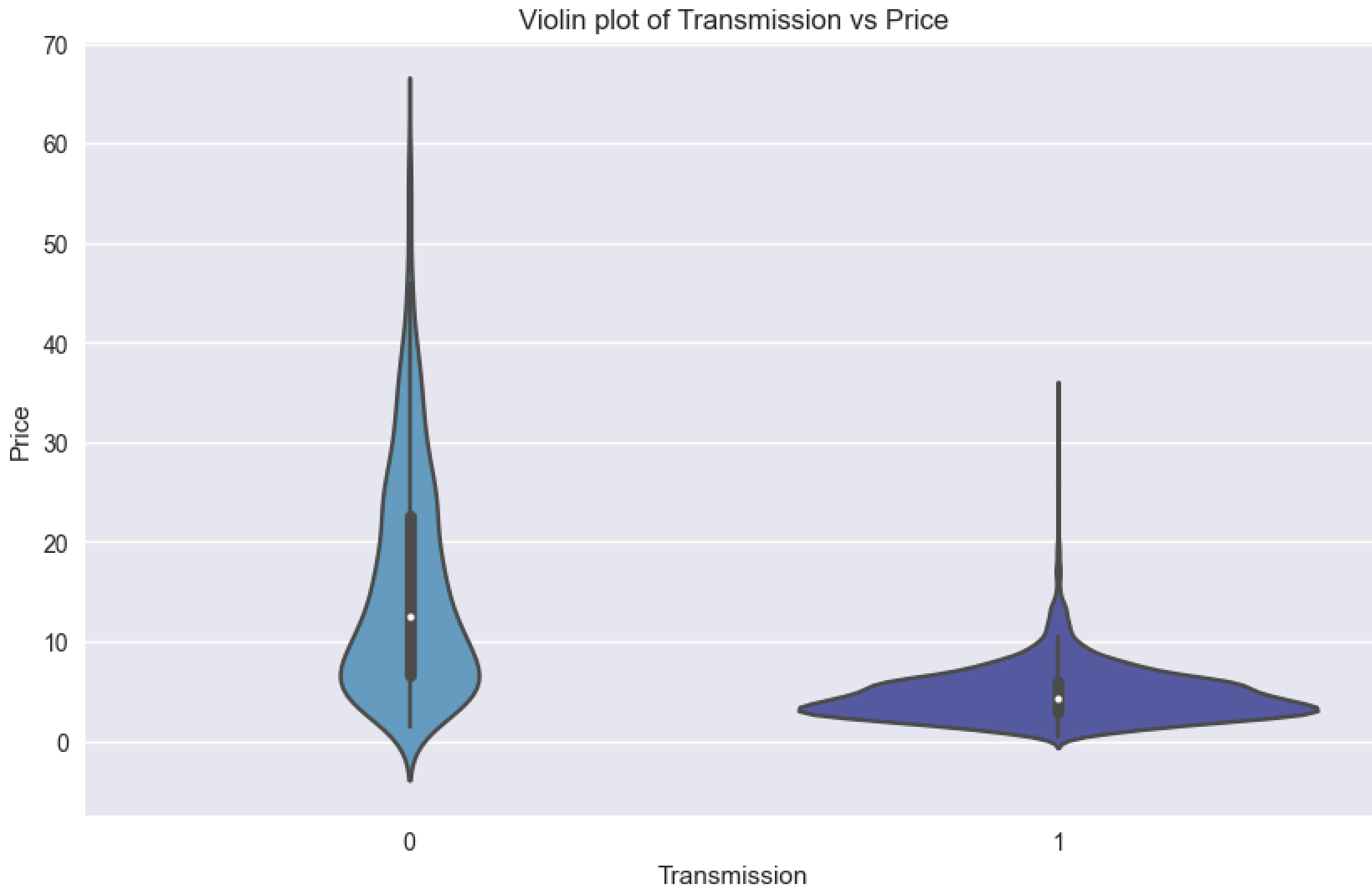
The features look noticeably better, some outliers still exist yet they may be valid points due to the inherent skewness in features and they're real values, time to scale the numerical features.

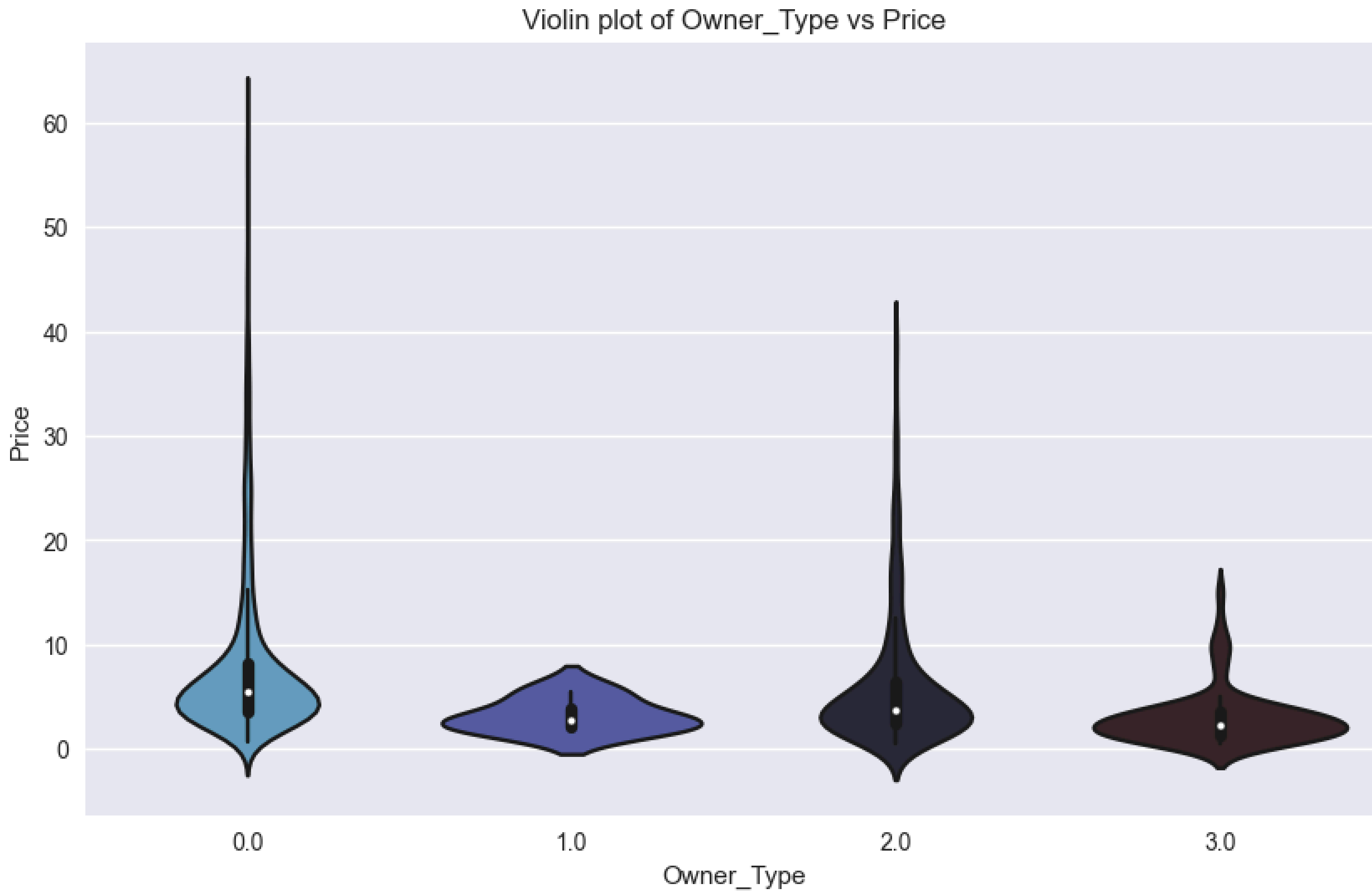
Violin Plots are a good way to understand the distribution and density of the features related to the price

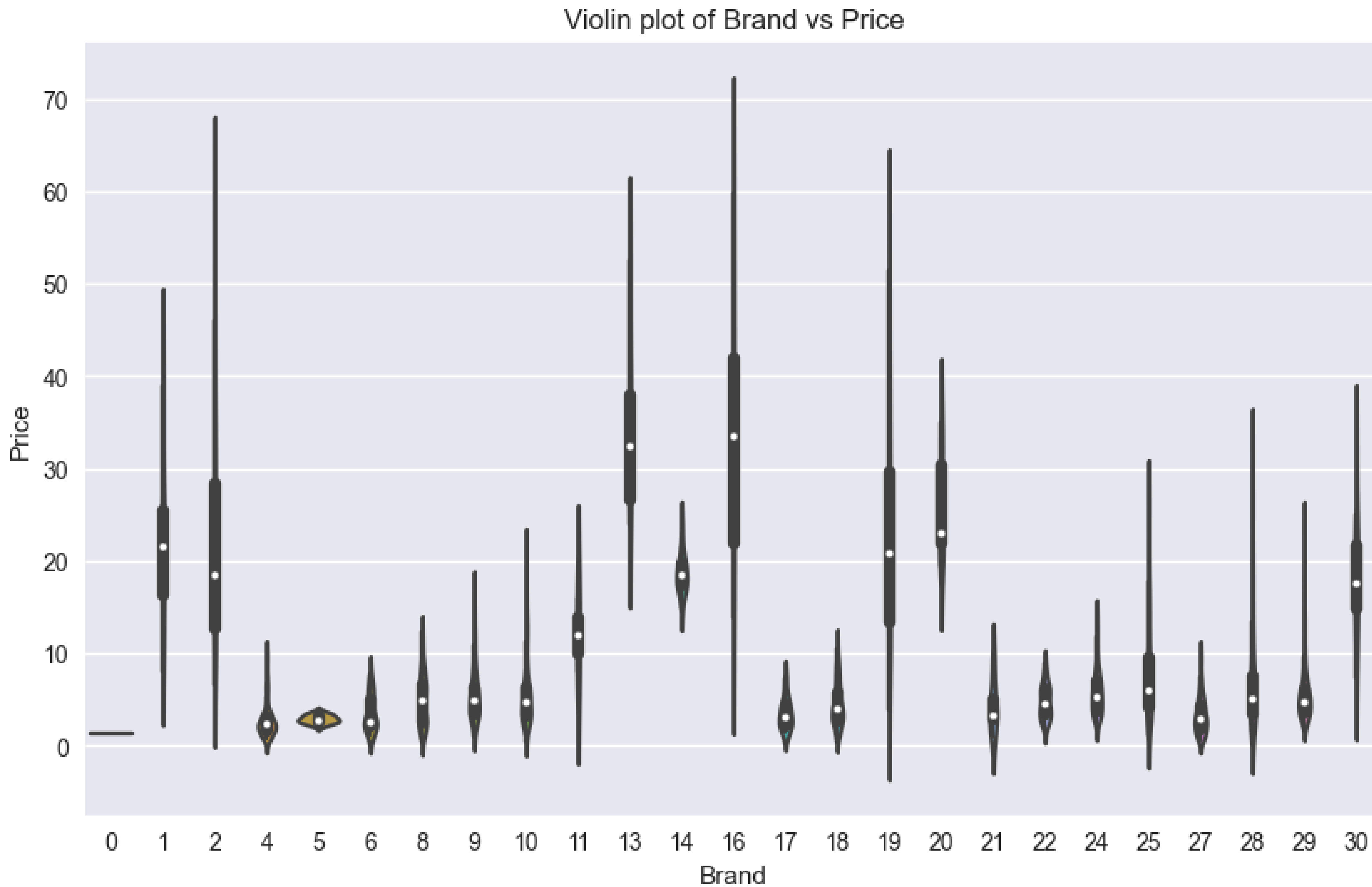
In [42]:
```
# violin plot for categorical columns
categorical_list = ['Location', 'Fuel_Type', 'Transmission', 'Owner_Type', 'Brand'] #List of categorical columns
for column in categorical_list: #Loop through the categorical columns
    plt.figure(figsize=(10, 6)) #Set the figure size
    sns.violinplot(x=column, y='Price', data=df) #Create a violin plot
    plt.title(f'Violin plot of {column} vs Price') #Set the title of the plot
    plt.show() #Display the plot
```




Violin plot of Fuel_Type vs Price
Price
60
50
40
30
20
10
0
0
1
3
4
Fuel_Type


Violin plot of Transmission vs Price
70
60
50
40
30
20
10
0
Price
0
1
Transmission


Violin plot of Owner_Type vs Price
Price
60
50
40
30
20
10
0
0.0
1.0
2.0
3.0
Owner_Type

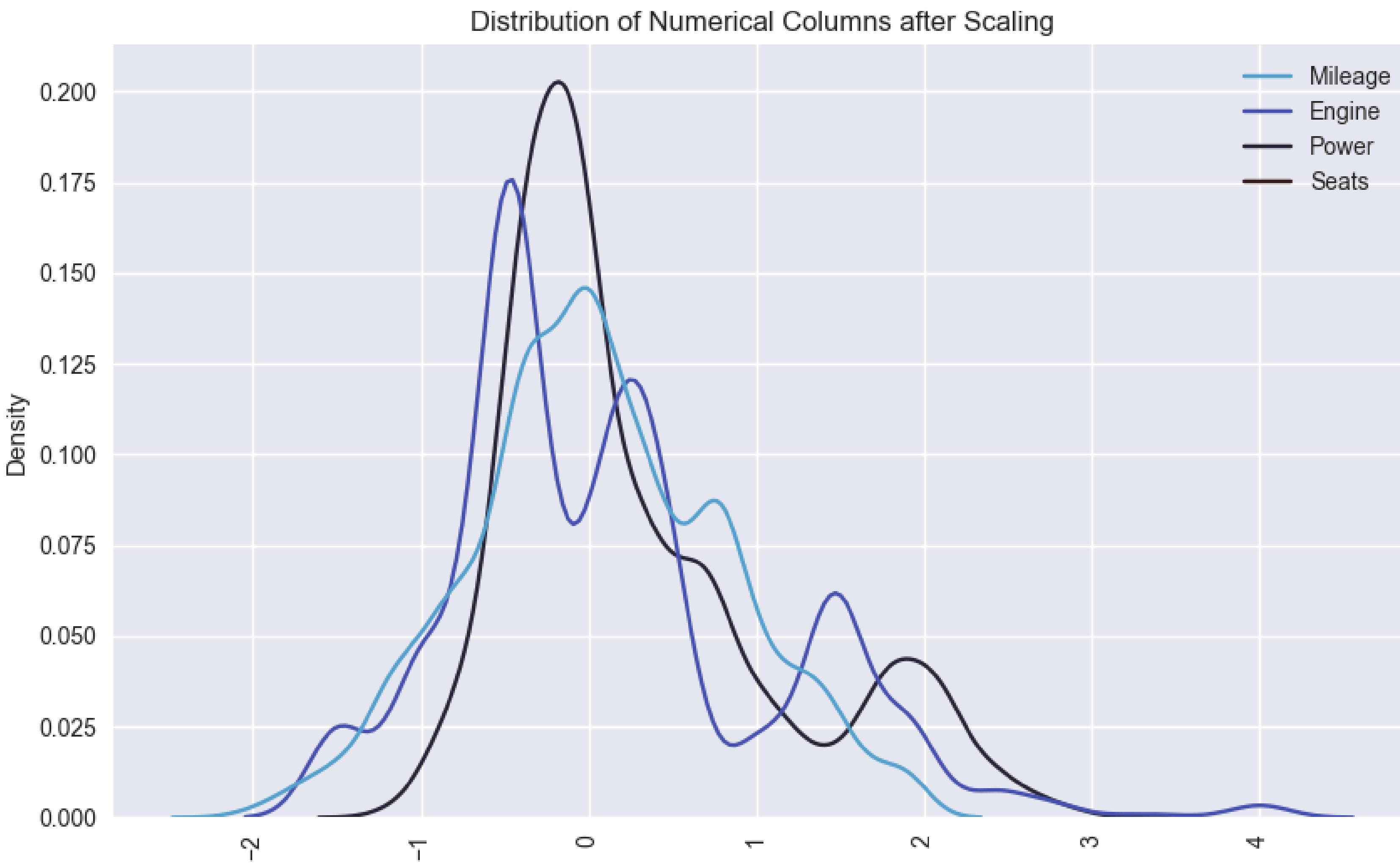


In [43]:
```
scaler = RobustScaler() #Create a robust scaler
for column in Numerical_list: #Loop through the numerical columns
    df[column] = scaler.fit_transform(df[column].values.reshape(-1, 1)) #Fit and transform the column
```

In [44]:
```
# Distribution of the numerical columns after scaling
plt.figure(figsize=(10, 6)) #Set the figure size
sns.kdeplot(data=df[Numerical_list]) #Create a kernel density plot
plt.xticks(rotation=90) #Rotate the x-axis labels
```

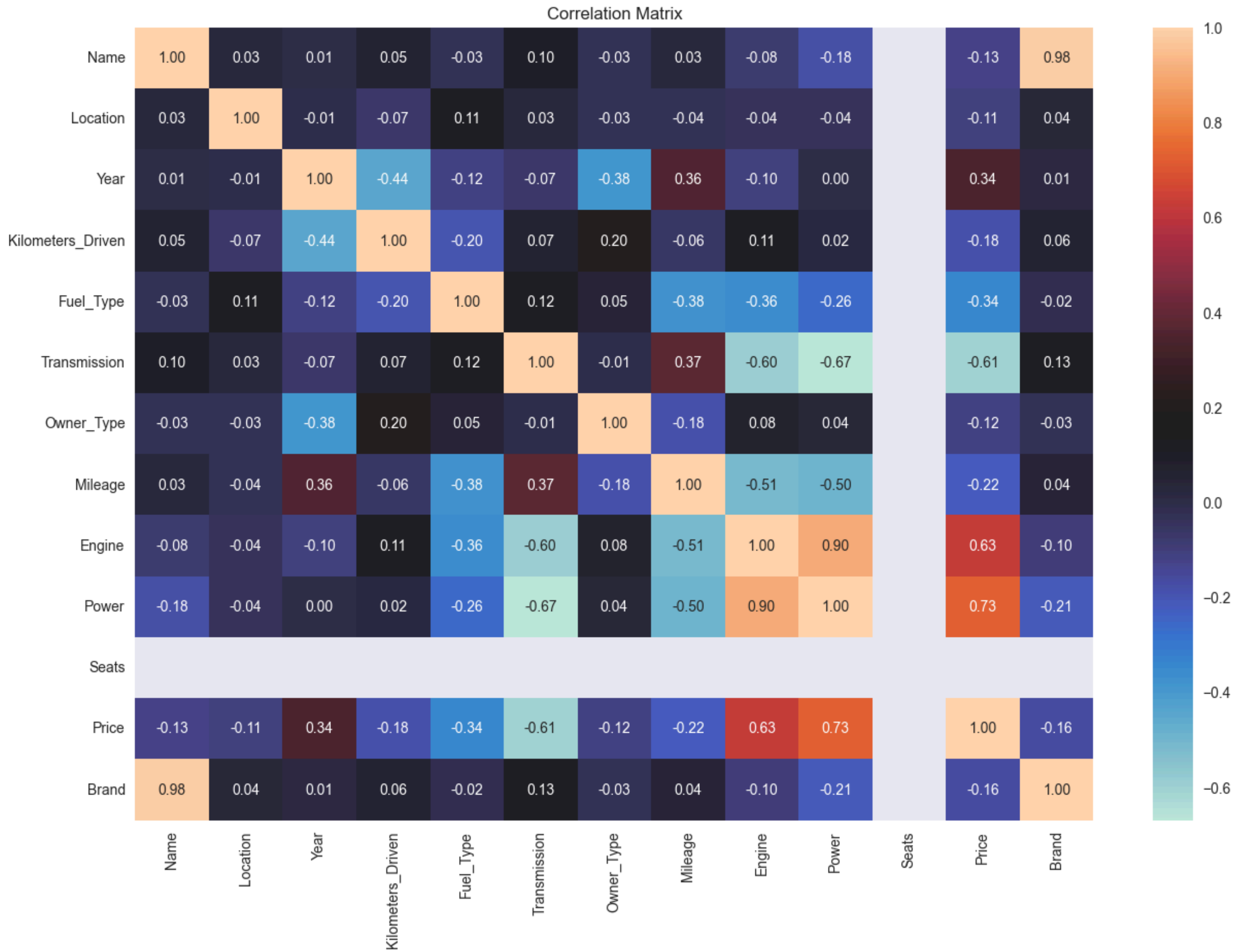
```
plt.title('Distribution of Numerical Columns after Scaling') #Set the title of the plot
plt.show() #Display the plot
```

```
c:\Users\Ayman\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use
_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating i
nstead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\Ayman\AppData\Local\Temp\ipykernel_21764\3502631429.py:3: UserWarning: Dataset has 0 variance; skipping dens
ity estimate. Pass `warn_singular=False` to disable this warning.
  sns.kdeplot(data=df[Numerical_list]) #Create a kernel density plot
```



Correlation Matrix: extracting the relations between the variable (including features and target) to know how strong they relate to each other linearly, a good way to apply feature selection with the important features only, and check for redundancy in features

In [45]:
```
# Correlation matrix
plt.figure(figsize=(15, 10)) #Set the figure size
sns.heatmap(df.corr(), annot=True, cmap='icefire', fmt='.2f') #Create a heatmap of the correlation matrix
plt.title('Correlation Matrix') #Set the title of the plot
plt.show() #Display the plot
```



Here we can see the correlation between our target "Price" and the features, we can also see the redundancy between 'Name' & 'Brand', we should get rid of one.

In [46]:
```
df.drop(['Name'], axis=1, inplace=True) #Drop the 'Name' column from the dataframe
```

Data Splitting

In [47]:
```
X = df.drop(['Price'], axis=1) #Get the features
y = df['Price'] #Get the target
```

In [48]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42) #Split the data into train
```

Modelling

1) Linear Regression

In [49]:
```
mlflow.set_tracking_uri("http://127.0.0.1:5000")

mlflow.set_experiment("linear_regression") #Set the experiment name
with mlflow.start_run():
    # Initialize and train the model
    lr = LinearRegression(n_jobs=-1)
    lr.fit(X_train, y_train)

    # Make predictions
    y_pred = lr.predict(X_test)

    # Calculate metrics
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)

    # Log parameters, metrics, and model
    mlflow.log_param("model_type", "LinearRegression")
    mlflow.log_metric("mse", mse)
    mlflow.log_metric("r2", r2)
    mlflow.sklearn.log_model(lr, "model")

    # Print metrics
    print(f'Mean Squared Error: {mse}')
    print(f'R2 Score: {r2}')
```

```
2024/09/23 03:02:48 WARNING mlflow.models.model: Model logged without a signature and input example. Please set `input_example` parameter when logging the model to auto infer the model signature.
2024/09/23 03:02:48 INFO mlflow.tracking._tracking_service.client: 🏃 View run bittersweet-calf-339 at: http://127.0.0.1:5000/#/experiments/631313091726538405/runs/ee4dc8baa88341f2a8dc2ad42b2c5489.
2024/09/23 03:02:48 INFO mlflow.tracking._tracking_service.client: 🧪 View experiment at: http://127.0.0.1:5000/#/experiments/631313091726538405.
Mean Squared Error: 19.34692264168782
R2 Score: 0.6989613769161241
```

2) Decision Tree Regressor

In [51]:
```python
# Define hyperparameters
dt_params = {
    'max_depth': 7,
    'random_state': 42,
    'criterion': 'squared_error',
    'splitter': 'best',
    'min_samples_split': 4,
    'min_samples_leaf': 3
}

mlflow.set_experiment("decision_tree") # Set the experiment name
with mlflow.start_run():
    # Initialize and train the model
    dt = DecisionTreeRegressor(**dt_params)
    dt.fit(X_train, y_train)

    # Make predictions
    y_pred = dt.predict(X_test)

    # Calculate metrics
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)

    # Log parameters, metrics, and model
    mlflow.log_param("model_type", "DecisionTree")
    mlflow.log_params(dt_params)
    mlflow.log_metric("mse", mse)
    mlflow.log_metric("r2", r2)
    mlflow.sklearn.log_model(dt, "model")
```

```
    # Print metrics
    print(f'Mean Squared Error: {mse}')
    print(f'R2 Score: {r2}')
```

```
2024/09/23 03:03:11 WARNING mlflow.models.model: Model logged without a signature and input example. Please set `input_example` parameter when logging the model to auto infer the model signature.
2024/09/23 03:03:11 INFO mlflow.tracking._tracking_service.client: 🏃 View run lyrical-bass-493 at: http://127.0.0.1:5000/#/experiments/446152044442393530/runs/80a01b8e75af46f49daf5f6687875df5.
2024/09/23 03:03:11 INFO mlflow.tracking._tracking_service.client: 🧪 View experiment at: http://127.0.0.1:5000/#/experiments/446152044442393530.
Mean Squared Error: 9.159022562798256
R2 Score: 0.8574853690086187
```

3) Random Forest Regressor

In [53]:
```
# Define hyperparameters
rf_params = {
    'n_estimators': 100,
    'max_depth': 10,
    'random_state': 42,
    'criterion': 'poisson',
    'min_samples_split': 2,
    'min_samples_leaf': 1
}

mlflow.set_experiment("random_forest") #Set the experiment name
with mlflow.start_run():
    # Initialize and train the model
    rf = RandomForestRegressor(**rf_params)
    rf.fit(X_train, y_train)

    # Make predictions
    y_pred = rf.predict(X_test)

    # Calculate metrics
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)

    # Log parameters, metrics, and model
    mlflow.log_param("model_type", "RandomForest")
    mlflow.log_params(rf_params)
    mlflow.log_metric("mse", mse)
```

```
    mlflow.log_metric("r2", r2)
    mlflow.sklearn.log_model(rf, "model")

    # Print metrics
    print(f'Mean Squared Error: {mse}')
    print(f'R2 Score: {r2}')
```

```
2024/09/23 03:03:38 WARNING mlflow.models.model: Model logged without a signature and input example. Please set `inpu
t_example` parameter when logging the model to auto infer the model signature.
2024/09/23 03:03:39 INFO mlflow.tracking._tracking_service.client: 🏃 View run carefree-fawn-805 at: http://127.0.0.
1:5000/#/experiments/667882316063888926/runs/78aebf225d7241218d11d727a0257f81.
2024/09/23 03:03:39 INFO mlflow.tracking._tracking_service.client: 🧪 View experiment at: http://127.0.0.1:5000/#/exp
eriments/667882316063888926.
Mean Squared Error: 6.127488634716787
R2 Score: 0.904656116338494
```

4) XGBoost Regressor

In [57]:

```
xgb_params = {
    'n_estimators': 100,
    'max_depth': 3,
    'learning_rate': 0.1,
    'random_state': 42,
    'objective': 'reg:squarederror',
    'booster': 'gbtree'
}

mlflow.set_experiment("xgboost") #Set the experiment name
with mlflow.start_run():
    # Initialize and train the model
    xgb = XGBRegressor(**xgb_params)
    xgb.fit(X_train, y_train)

    # Make predictions
    y_pred = xgb.predict(X_test)

    # Calculate metrics
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)

    # Log parameters, metrics, and model
    mlflow.log_param("model_type", "XGBoost")
```

```
    mlflow.log_params(xgb_params)
    mlflow.log_metric("mse", mse)
    mlflow.log_metric("r2", r2)
    mlflow.sklearn.log_model(xgb, "model")

    # Print metrics
    print(f'Mean Squared Error: {mse}')
    print(f'R2 Score: {r2}')
```

```
2024/09/23 03:04:23 WARNING mlflow.models.model: Model logged without a signature and input example. Please set `input_example` parameter when logging the model to auto infer the model signature.
2024/09/23 03:04:23 INFO mlflow.tracking._tracking_service.client: 🏃 View run gentle-fowl-492 at: http://127.0.0.1:5000/#/experiments/569611578839078095/runs/b271f70f7439423b8a5daecc3d8c2792.
2024/09/23 03:04:23 INFO mlflow.tracking._tracking_service.client: 🧪 View experiment at: http://127.0.0.1:5000/#/experiments/569611578839078095.
Mean Squared Error: 5.991319322403873
R2 Score: 0.9067749144049435
```

5) LightGBM Regressor

In [64]:

```
# Define hyperparameters
lgbm_params = {
    'n_estimators': 100,
    'max_depth': 10,
    'learning_rate': 0.1,
    'random_state': 42,
    'objective': 'regression',
    'boosting_type': 'gbdt',
    'num_leaves': 19
}

mlflow.set_experiment("lightgbm") #Set the experiment name
with mlflow.start_run():
    # Initialize and train the model
    lgbm = LGBMRegressor(**lgbm_params)
    lgbm.fit(X_train, y_train)

    # Make predictions
    y_pred = lgbm.predict(X_test)

    # Calculate metrics
    mse = mean_squared_error(y_test, y_pred)
```

```
    r2 = r2_score(y_test, y_pred)

    # Log parameters, metrics, and model
    mlflow.log_params(lgbm_params)
    mlflow.log_metric("mse", mse)
    mlflow.log_metric("r2", r2)
    mlflow.sklearn.log_model(lgbm, "model")

    # Print metrics
    print(f'Mean Squared Error: {mse}')
    print(f'R2 Score: {r2}')
```

```
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000188 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 820
[LightGBM] [Info] Number of data points in the train set: 3798, number of used features: 10
[LightGBM] [Info] Start training from score 7.679516
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
2024/09/23 03:07:44 WARNING mlflow.models.model: Model logged without a signature and input example. Please set `inpu
t_example` parameter when logging the model to auto infer the model signature.
2024/09/23 03:07:44 INFO mlflow.tracking._tracking_service.client: 🏃 View run puzzled-ram-135 at: http://127.0.0.1:5
000/#/experiments/897004280252505666/runs/e88d236fda954be79c6b0710fdf03995.
2024/09/23 03:07:44 INFO mlflow.tracking._tracking_service.client: 🧪 View experiment at: http://127.0.0.1:5000/#/exp
eriments/897004280252505666.
Mean Squared Error: 3.8554939310597427
R2 Score: 0.9400084134407223
```

Conclusion: after cleaning, processing, and applying feature engineering on our dataset, we were able to develop several models for car price prediction:

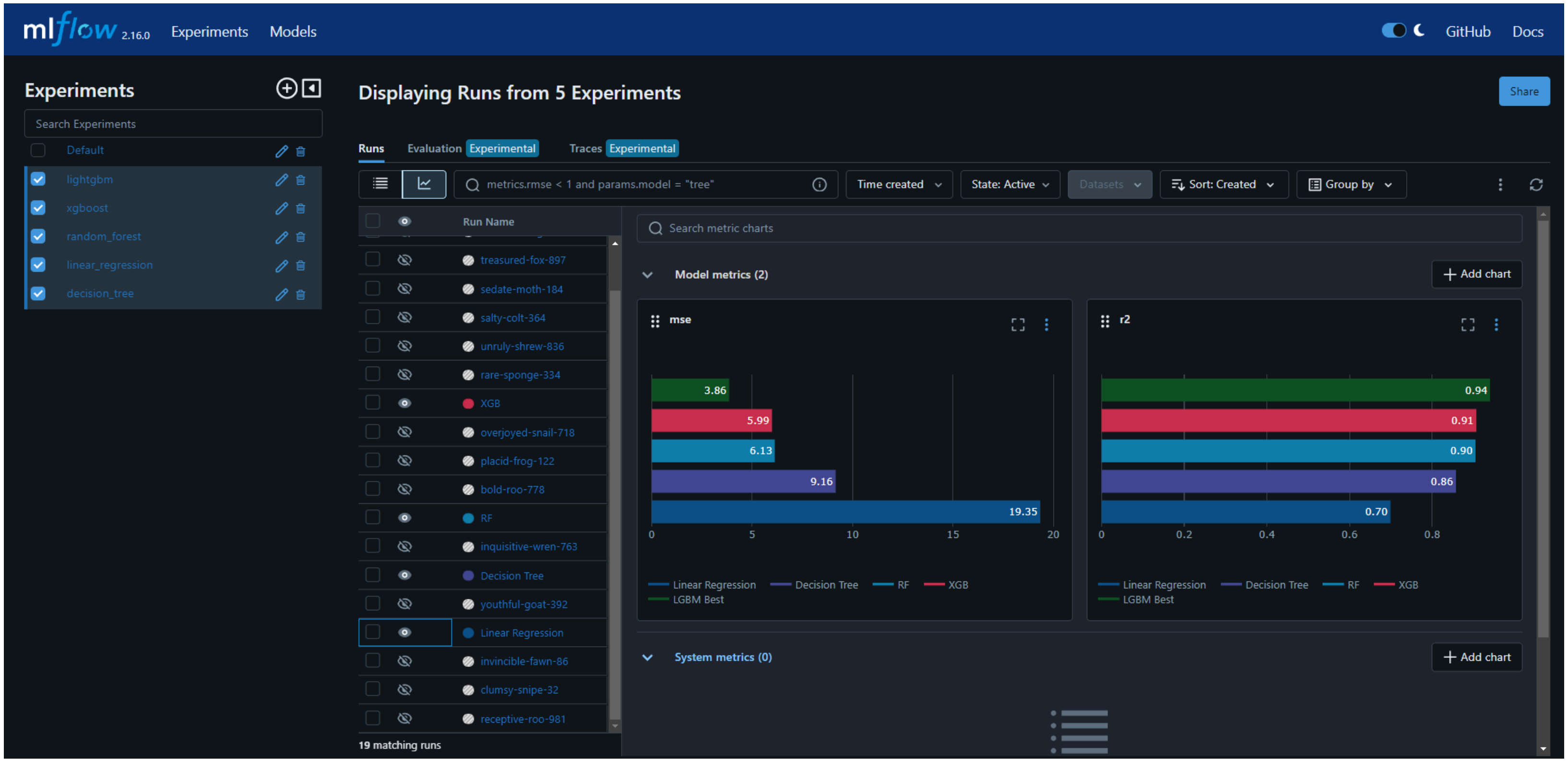
`1. Linear Regression (Mean Squared Error: 19.34692264168782, R2 Score: 0.6989613769161241)`

`2. Decision Tree (Mean Squared Error: 9.159022562798256, R2 Score: 0.8574853690086187)`

`3. Random Forest (Mean Squared Error: 6.127488634716787, R2 Score: 0.904656116338494)`

`4. XGBoost (Mean Squared Error: 5.991319322403873, R2 Score: 0.9067749144049435)`

`5. LightGBM (Mean Squared Error: 3.8554939310597427, R2 Score: 0.9400084134407223)`


mlflow 2.16.0
Experiments
Models
GitHub
Docs
Experiments
Search Experiments
Default
lightgbm
xgboost
random_forest
linear_regression
decision_tree
Displaying Runs from 5 Experiments
Share
Runs
Evaluation Experimental
Traces Experimental
metrics.rmse < 1 and params.model = "tree"
Time created
State: Active
Datasets
Sort: Created
Group by
Run Name
treasured-fox-897
sedate-moth-184
salty-colt-364
unruly-shrew-836
rare-sponge-334
XGB
overjoyed-snail-718
placid-frog-122
bold-roo-778
RF
inquisitive-wren-763
Decision Tree
youthful-goat-392
Linear Regression
invincible-fawn-86
clumsy-snipe-32
receptive-roo-981
19 matching runs
Search metric charts
Model metrics (2)
Add chart
mse
3.86
5.99
6.13
9.16
19.35
0
5
10
15
20
r2
0.94
0.91
0.90
0.86
0.70
0
0.2
0.4
0.6
0.8
Linear Regression
Decision Tree
RF
XGB
LGBM Best
System metrics (0)
Add chart