AUTOSCOUT24 CAR PRICE PREDICTION (EDA and ML)

Linear Regression Models (Linear-Ridge-Lasso-ElasticNet)

Duygu Jones | Data Scientist | July 2024
Follow me: duygujones.com | Linkedin | GitHub | Kaggle | Medium | Tableau

Table of Content

Introduction

- This project aims to predict car prices using the Auto Scout dataset from AutoScout24, containing features of 9 different car models.
- By performing Exploratory Data Analysis (EDA) and implementing machine learning models, the goal is to gain insights into the data and build effective regression models for car price prediction.
- Additionally, these models can support automotive industry stakeholders in understanding market trends, optimizing pricing strategies, and making data-driven decisions. Consumers can also benefit by making informed choices when selecting vehicles.
- Ultimately, the goal is to leverage data-driven insights to enhance the understanding of the automotive market, improve pricing accuracy, and support sustainable development in the automotive industry.

Objectives

1. **Understand the dataset and its features.**
2. **Clean and prepare the data for modeling.**
3. **Implement various regression algorithms to predict car prices.**
4. **Optimize model performance by tuning hyperparameters and focusing on important features.**
5. **Compare the performance of different regression algorithms.**

The dataset and results are used for educational purposes, demonstrating the application of advanced machine learning techniques on real-world data. We aim to build effective regression models to predict car prices and gain a deeper understanding of machine learning techniques.

About the Dataset

The **Auto Scout** data is sourced from the online car trading company AutoScout24 in 2019 and contains various features of 9 different car models. This project uses a pre-processed and organized dataset to explore and understand machine learning algorithms, particularly for car price prediction using regression techniques.

Dataset: AutoScout24 Car Sales Dataset

- **Content:** Data on various features of 9 different car models.
- **Number of Rows:** 15,915
- **Number of Columns:** 23

Inputs:

- **make_model:** The make and model of the car
- **body_type:** The type of the car (e.g., Sedan)
- **price:** The price of the car (in EUR)
- **vat:** VAT status
- **km:** The car's mileage
- **Type:** The condition of the car (e.g., used)
- **Fuel:** The type of fuel (e.g., Diesel, Petrol)
- **Gears:** Number of gears
- **Comfort_Convenience:** Comfort and convenience features
- **Entertainment_Media:** Entertainment and media features
- **Extras:** Extra features
- **Safety_Security:** Safety and security features
- **age:** The age of the car
- **Previous_Owners:** Number of previous owners
- **hp_kW:** Engine power (in kW)
- **Inspection_new:** New inspection status
- **Paint_Type:** Type of paint
- **Upholstery_type:** Type of upholstery
- **Gearing_Type:** Type of gearing (e.g., automatic)
- **Displacement_cc:** Engine displacement (in cc)
- **Weight_kg:** The weight of the car (in kg)
- **Drive_chain:** Type of drive (e.g., front-wheel drive)
- **cons_comb:** Combined fuel consumption (L/100 km)

1. EXPLORATORY DATA ANALYSIS (EDA)

Import the Libraries

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

import matplotlib.pyplot as plt
import seaborn as sns

import plotly.express as px
import scipy.stats as stats

plt.rcParams["figure.figsize"] = (10,6)
pd.set_option('display.max_columns', 500)
pd.set_option('display.max_rows', 500)
pd.options.display.float_format = '{:.3f}'.format

%matplotlib inline

from scipy import stats
from sklearn.preprocessing import PolynomialFeatures
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler, MinMaxScaler, RobustScaler
from sklearn.pipeline import Pipeline

from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge, RidgeCV
from sklearn.linear_model import Lasso, LassoCV
from sklearn.linear_model import ElasticNet, ElasticNetCV

from sklearn.model_selection import cross_val_score, cross_validate

from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error


from yellowbrick.regressor import ResidualsPlot, PredictionError

import warnings
warnings.filterwarnings("ignore")
```

Read the Dataset

In [100…
```
df0 = pd.read_csv('autoscout_car_sales.csv')
df = df0.copy()
```

In [3]:
```
df.head()
```

Out[3]:

	make_model	body_type	price	vat	km	Type	Fuel	Gears	Comfort_Convenience	Entertainment_Media	Extras	Safet
0	Audi A1	Sedans	15770	VAT deductible	56013.000	Used	Diesel	7.000	Air conditioning,Armrest,Automatic climate con...	Bluetooth,Hands-free equipment,On-board comput...	Alloy wheels,Catalytic Converter,Voice Control	A lo
1	Audi A1	Sedans	14500	Price negotiable	80000.000	Used	Benzine	7.000	Air conditioning,Automatic climate control,Hil...	Bluetooth,Hands-free equipment,On-board comput...	Alloy wheels,Sport seats,Sport suspension,Voic...	A l doo
2	Audi A1	Sedans	14640	VAT deductible	83450.000	Used	Diesel	7.000	Air conditioning,Cruise control,Electrical sid...	MP3,On-board computer	Alloy wheels,Voice Control	A lo
3	Audi A1	Sedans	14500	VAT deductible	73000.000	Used	Diesel	6.000	Air suspension,Armrest,Auxiliary heating,Elect...	Bluetooth,CD player,Hands-free equipment,MP3,O...	Alloy wheels,Sport seats,Voice Control	syst doo
4	Audi A1	Sedans	16790	VAT deductible	16200.000	Used	Diesel	7.000	Air conditioning,Armrest,Automatic climate con...	Bluetooth,CD player,Hands-free equipment,MP3,O...	Alloy wheels,Sport package,Sport suspension,Vo...	A lock, air

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15915 entries, 0 to 15914
Data columns (total 23 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   make_model           15915 non-null  object 
 1   body_type            15915 non-null  object 
 2   price                15915 non-null  int64  
 3   vat                  15915 non-null  object 
 4   km                   15915 non-null  float64
 5   Type                 15915 non-null  object 
 6   Fuel                 15915 non-null  object 
 7   Gears                15915 non-null  float64
 8   Comfort_Convenience  15915 non-null  object 
 9   Entertainment_Media  15915 non-null  object 
 10  Extras               15915 non-null  object 
 11  Safety_Security      15915 non-null  object 
 12  age                  15915 non-null  float64
 13  Previous_Owners      15915 non-null  float64
 14  hp_kW                15915 non-null  float64
 15  Inspection_new       15915 non-null  int64  
 16  Paint_Type           15915 non-null  object 
 17  Upholstery_type      15915 non-null  object 
 18  Gearing_Type         15915 non-null  object 
 19  Displacement_cc      15915 non-null  float64
 20  Weight_kg            15915 non-null  float64
 21  Drive_chain          15915 non-null  object 
 22  cons_comb            15915 non-null  float64
dtypes: float64(8), int64(2), object(13)
memory usage: 2.8+ MB
```

Rename the Columns

In [5]:
```
df.columns
```

Out[5]:
```
Index(['make_model', 'body_type', 'price', 'vat', 'km', 'Type', 'Fuel',
       'Gears', 'Comfort_Convenience', 'Entertainment_Media', 'Extras',
       'Safety_Security', 'age', 'Previous_Owners', 'hp_kW', 'Inspection_new',
       'Paint_Type', 'Upholstery_type', 'Gearing_Type', 'Displacement_cc',
       'Weight_kg', 'Drive_chain', 'cons_comb'],
      dtype='object')
```

In [5]:
```
df.rename(columns={
    'make_model': 'make_model',
    'body_type': 'body_type',
    'price': 'price',
    'vat': 'vat',
    'km': 'km',
    'Type': 'type',
    'Fuel': 'fuel_type',
    'Gears': 'gears_num',
    'Comfort_Convenience': 'comfort_convenience',
    'Entertainment_Media': 'entertainment_media',
    'Extras': 'extras',
    'Safety_Security': 'safety_security',
    'age': 'age',
    'Previous_Owners': 'previous_owners',
    'hp_kW': 'hp_kw',
    'Inspection_new': 'inspection_new',
    'Paint_Type': 'paint_type',
    'Upholstery_type': 'upholstery_type',
    'Gearing_Type': 'gearing_type',
    'Displacement_cc': 'displacement_cc',
    'Weight_kg': 'weight_kg',
    'Drive_chain': 'drive_chain',
    'cons_comb': 'fuel_cons_comb'
}, inplace=True)
```

In [7]:
```
df.columns
```

Out[7]:
```
Index(['make_model', 'body_type', 'price', 'vat', 'km', 'type', 'fuel_type',
       'gears_num', 'comfort_convenience', 'entertainment_media', 'extras',
       'safety_security', 'age', 'previous_owners', 'hp_kw', 'inspection_new',
       'paint_type', 'upholstery_type', 'gearing_type', 'displacement_cc',
       'weight_kg', 'drive_chain', 'fuel_cons_comb'],
      dtype='object')
```

Check Missing Values

In [8]:
```
# Check out the missing values

missing_count = df.isnull().sum()
value_count = df.isnull().count()
missing_percentage = round(missing_count / value_count * 100, 2)
missing_df = pd.DataFrame({"count": missing_count, "percentage": missing_percentage})
missing_df
```

Out[8]:

	count	percentage
make_model	0	0.000
body_type	0	0.000
price	0	0.000
vat	0	0.000
km	0	0.000
type	0	0.000
fuel_type	0	0.000
gears_num	0	0.000
comfort_convenience	0	0.000
entertainment_media	0	0.000
extras	0	0.000
safety_security	0	0.000
age	0	0.000
previous_owners	0	0.000
hp_kw	0	0.000
inspection_new	0	0.000
paint_type	0	0.000
upholstery_type	0	0.000
gearing_type	0	0.000
displacement_cc	0	0.000
weight_kg	0	0.000
drive_chain	0	0.000
fuel_cons_comb	0	0.000

Check Duplicated Values

In [9]:
```
# Let's observe first the unique values

def get_unique_values(df):

    output_data = []

    for col in df.columns:

        # If the number of unique values in the column is less than or equal to 5
        if df.loc[:, col].nunique() <= 10:
            # Get the unique values in the column
            unique_values = df.loc[:, col].unique()
            # Append the column name, number of unique values, unique values, and data type to the output data
            output_data.append([col, df.loc[:, col].nunique(), unique_values, df.loc[:, col].dtype])
        else:
            # Otherwise, append only the column name, number of unique values, and data type to the output data
            output_data.append([col, df.loc[:, col].nunique(),"-", df.loc[:, col].dtype])

    output_df = pd.DataFrame(output_data, columns=['Column Name', 'Number of Unique Values', ' Unique Values ', 'Data Type'])

    return output_df
```

In [10]:
```
get_unique_values(df)
```

Out[10]:

	Column Name	Number of Unique Values	Unique Values	Data Type
0	make_model	9	[Audi A1, Audi A2, Audi A3, Opel Astra, Opel C...	object
1	body_type	8	[Sedans, Station wagon, Compact, Coupe, Van, O...	object
2	price	2952	-	int64
3	vat	2	[VAT deductible, Price negotiable]	object
4	km	6691	-	float64
5	type	5	[Used, Employee's car, New, Demonstration, Pre...	object
6	fuel_type	4	[Diesel, Benzine, LPG/CNG, Electric]	object
7	gears_num	4	[7.0, 6.0, 5.0, 8.0]	float64
8	comfort_convenience	6196	-	object
9	entertainment_media	346	-	object
10	extras	659	-	object
11	safety_security	4442	-	object
12	age	4	[3.0, 2.0, 1.0, 0.0]	float64
13	previous_owners	5	[2.0, 1.0, 0.0, 3.0, 4.0]	float64
14	hp_kw	77	-	float64
15	inspection_new	2	[1, 0]	int64
16	paint_type	3	[Metallic, Uni/basic, Perl effect]	object
17	upholstery_type	2	[Cloth, Part/Full Leather]	object
18	gearing_type	3	[Automatic, Manual, Semi-automatic]	object
19	displacement_cc	68	-	float64
20	weight_kg	432	-	float64
21	drive_chain	3	[front, 4WD, rear]	object
22	fuel_cons_comb	62	-	float64

In [6]:
```
# Checks duplicates and drops them

def duplicate_values(df):
    print("Duplicate check...")
    num_duplicates = df.duplicated(subset=None, keep='first').sum()
    if num_duplicates > 0:
        print("There are", num_duplicates, "duplicated observations in the dataset.")
        df.drop_duplicates(keep='first', inplace=True)
        print(num_duplicates, "duplicates were dropped!")
        print("No more duplicate rows!")
    else:
        print("There are no duplicated observations in the dataset.")

duplicate_values(df)
```

```
Duplicate check...
There are 1673 duplicated observations in the dataset.
1673 duplicates were dropped!
No more duplicate rows!
```

In [12]:
```
df.duplicated().sum()
```

Out[12]: 0

- Understanding the context and data collection methods is crucial to determine the cause of duplicates.
- Whether to drop duplicates depends on the analysis purpose.
- For analyzing changes over time or variations, keeping duplicates might be more appropriate.
- However, since I will be using a linear model, I dropped these rows because duplicate rows contain similar values.

Basic Statistics

In [13]:
```
# Basic statistics summary of Numerical features

df.describe().T
```

Out[13]:

	count	mean	std	min	25%	50%	75%	max
price	14242.000	18100.969	7421.214	4950.000	12950.000	16950.000	21900.000	74600.000
km	14242.000	32582.110	36856.863	0.000	3898.000	21000.000	47000.000	317000.000
gears_num	14242.000	5.940	0.703	5.000	5.000	6.000	6.000	8.000
age	14242.000	1.415	1.110	0.000	0.000	1.000	2.000	3.000
previous_owners	14242.000	1.041	0.337	0.000	1.000	1.000	1.000	4.000
hp_kw	14242.000	88.713	26.548	40.000	66.000	85.000	103.000	294.000
inspection_new	14242.000	0.256	0.437	0.000	0.000	0.000	1.000	1.000
displacement_cc	14242.000	1432.890	277.507	890.000	1229.000	1461.000	1598.000	2967.000
weight_kg	14242.000	1342.399	201.247	840.000	1165.000	1320.000	1487.000	2471.000
fuel_cons_comb	14242.000	4.825	0.862	3.000	4.100	4.800	5.400	9.100

In [14]:
```
# Basic statistics summary of Object features

df.describe(include= 'object').T
```

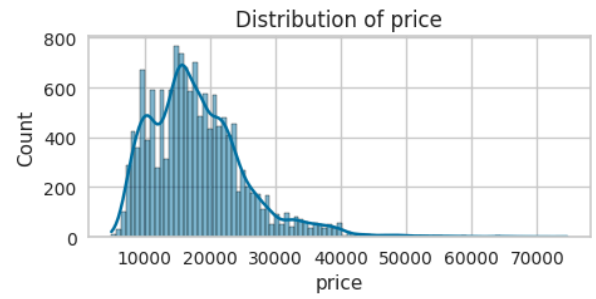
Out[14]:

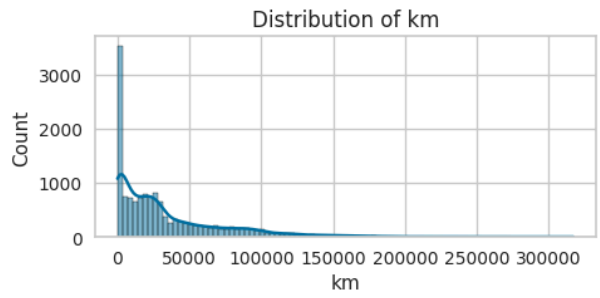
	count	unique	top	freq
make_model	14242	9	Audi A3	2758
body_type	14242	8	Sedans	7230
vat	14242	2	VAT deductible	13426
type	14242	5	Used	10172
fuel_type	14242	4	Benzine	7558
comfort_convenience	14242	6196	Air conditioning,Electrical side mirrors,Hill ...	312
entertainment_media	14242	346	Bluetooth,Hands-free equipment,On-board comput...	1562
extras	14242	659	Alloy wheels	5010
safety_security	14242	4442	ABS,Central door lock,Daytime running lights,D...	635
paint_type	14242	3	Metallic	13682
upholstery_type	14242	2	Cloth	10918
gearing_type	14242	3	Manual	7232
drive_chain	14242	3	front	14067

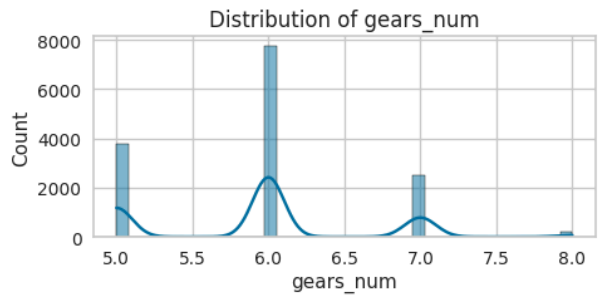
Numerical Features

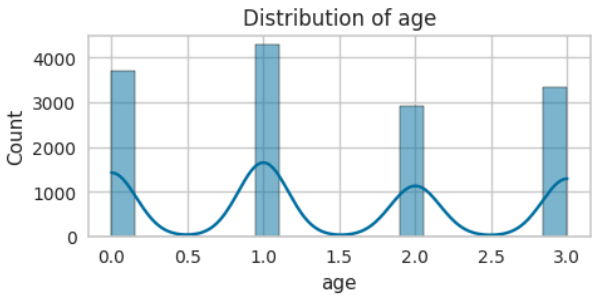
Distributions of Numerical Features

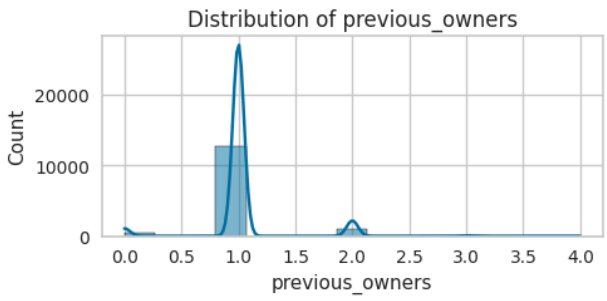
In [15]:
```
numerical_df = df.select_dtypes(include=['number'])

plt.figure(figsize=(15, 10))

num_vars = len(numerical_df.columns)

for i, var in enumerate(numerical_df.columns, 1):
    plt.subplot((num_vars // 3) + 1, 3, i)
    sns.histplot(data=df, x=var, kde=True)
    plt.title(f'Distribution of {var}')

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

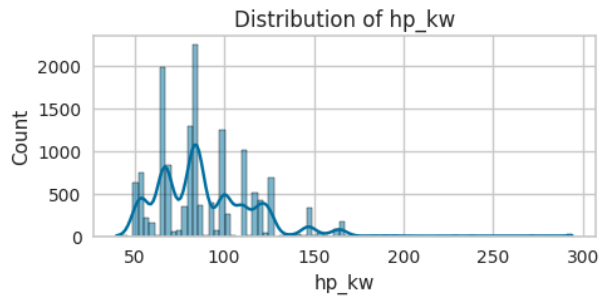


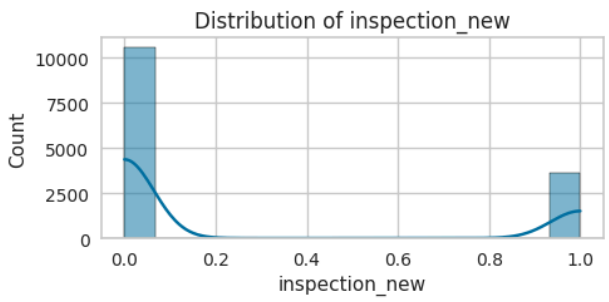


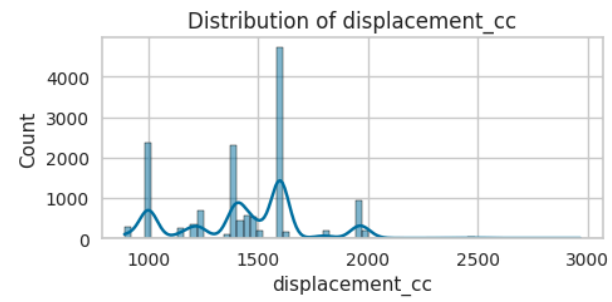


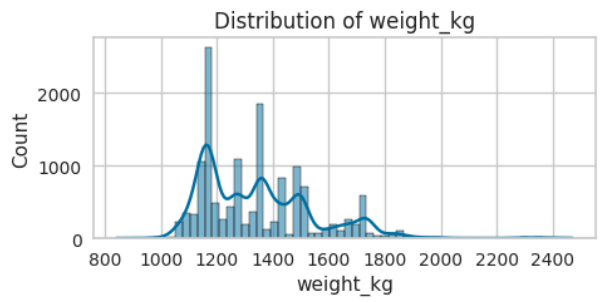


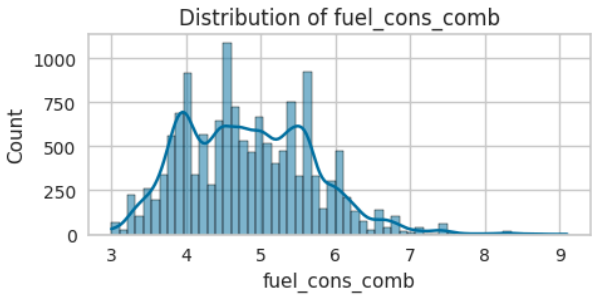












Distributions of the Numerical Features:

1. **Price:** Distribution is right-skewed, with most prices concentrated between 10,000 and 20,000 EUR. Some higher-end outliers, particularly above 40,000 EUR.
2. **Km (Mileage):** Distribution is right-skewed, with most vehicles having low mileage. Values above 150,000 km are less common.
3. **Gears Number:** Most vehicles have 5, 6, or 7 gears. Vehicles with 8 gears are rare.
4. **Age:** Peaks at 0, 1, 2, and 3 years, indicating these are common ages for vehicles. Vehicles are generally up to 3 years old.
5. **Previous Owners:** Most vehicles have had one or two previous owners. Vehicles with 3 or more previous owners are less common.
6. **Hp_kw (Engine Power in kW):** Distribution is right-skewed, with most vehicles between 50 and 150 kW. Vehicles above 200 kW are less frequent.
7. **Inspection_new (New Inspection):** Concentration at the extremes (values of 0 and 1). Mid-range values are rare.
8. **Displacement_cc (Engine Displacement in cc):** A peak at 1500 cc. Values above 2000 cc are less common.
9. **Weight_kg:** Most vehicles are between 1000 and 1500 kg. Vehicles above 2000 kg are rare.
10. **Fuel Consumption Combined:** Approximately normal distribution, with most values between 4 and 6 l/100 km. Values above 8 l/100 km are less frequent.

Overall:

- **Right-Skewed Distributions:** Many features like `price`, `km`, and `hp_kw` show right-skewed distributions. This skewness might affect the assumptions of linear models, which assume normally distributed residuals.
- **Peaks in Categorical Data:** Features such as `gears_num` and `age` have distinct peaks, indicating specific common values that could be significant predictors in the model.
- **Outliers:** While several features have some higher-end outliers, their impact on linear modeling needs careful assessment to ensure they do not disproportionately influence the model.
- **Data Transformation:** Consider data transformations (e.g., log transformation) to normalize the distributions of skewed features, improving the performance and accuracy of linear models.
- **Feature Scaling:** Ensure all features are appropriately scaled, especially those with wide ranges like `km` and `price`, to ensure effective model training.

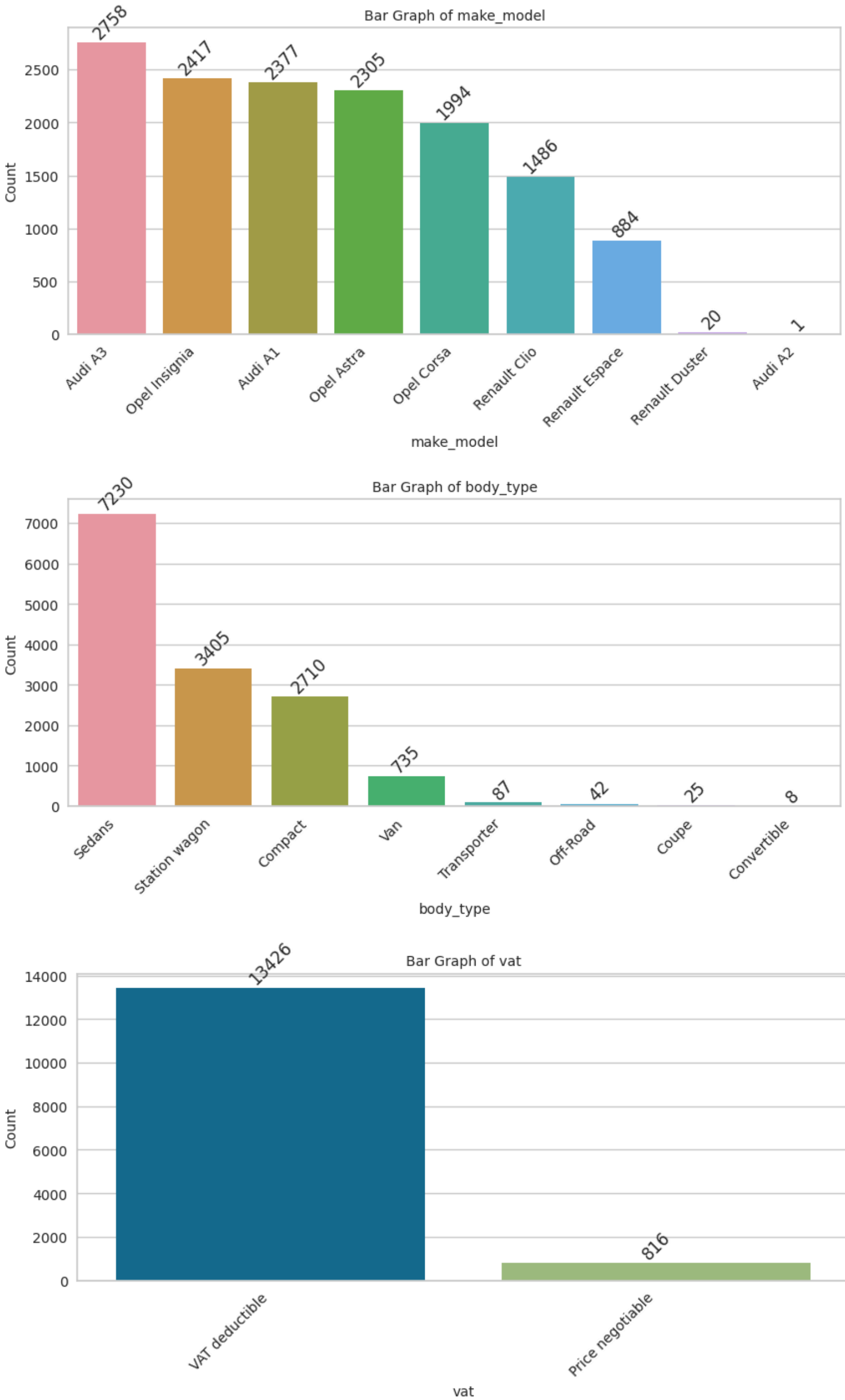
By addressing these considerations, linear modeling can be made more robust and accurate with this dataset.

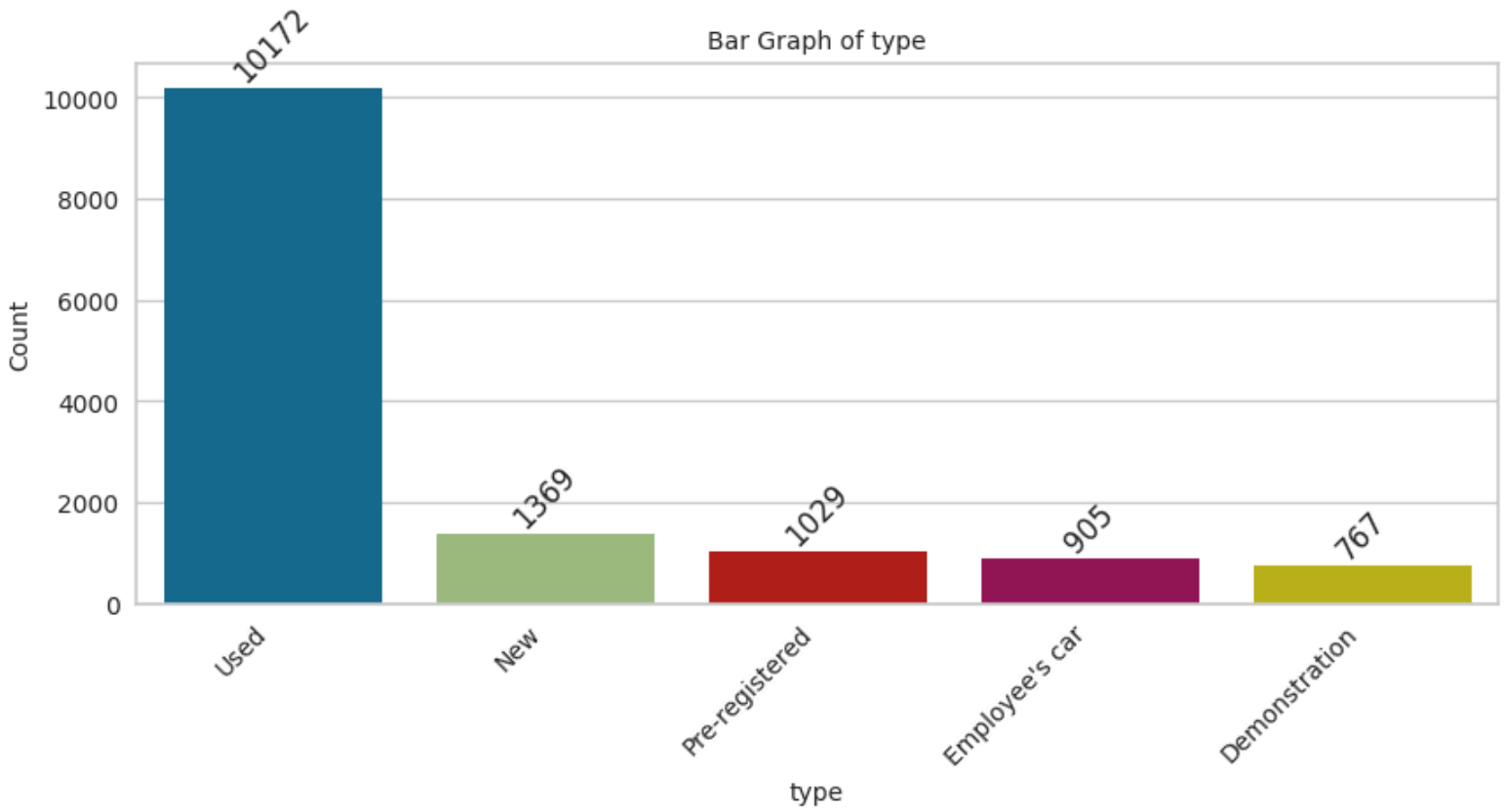
Categorical Features

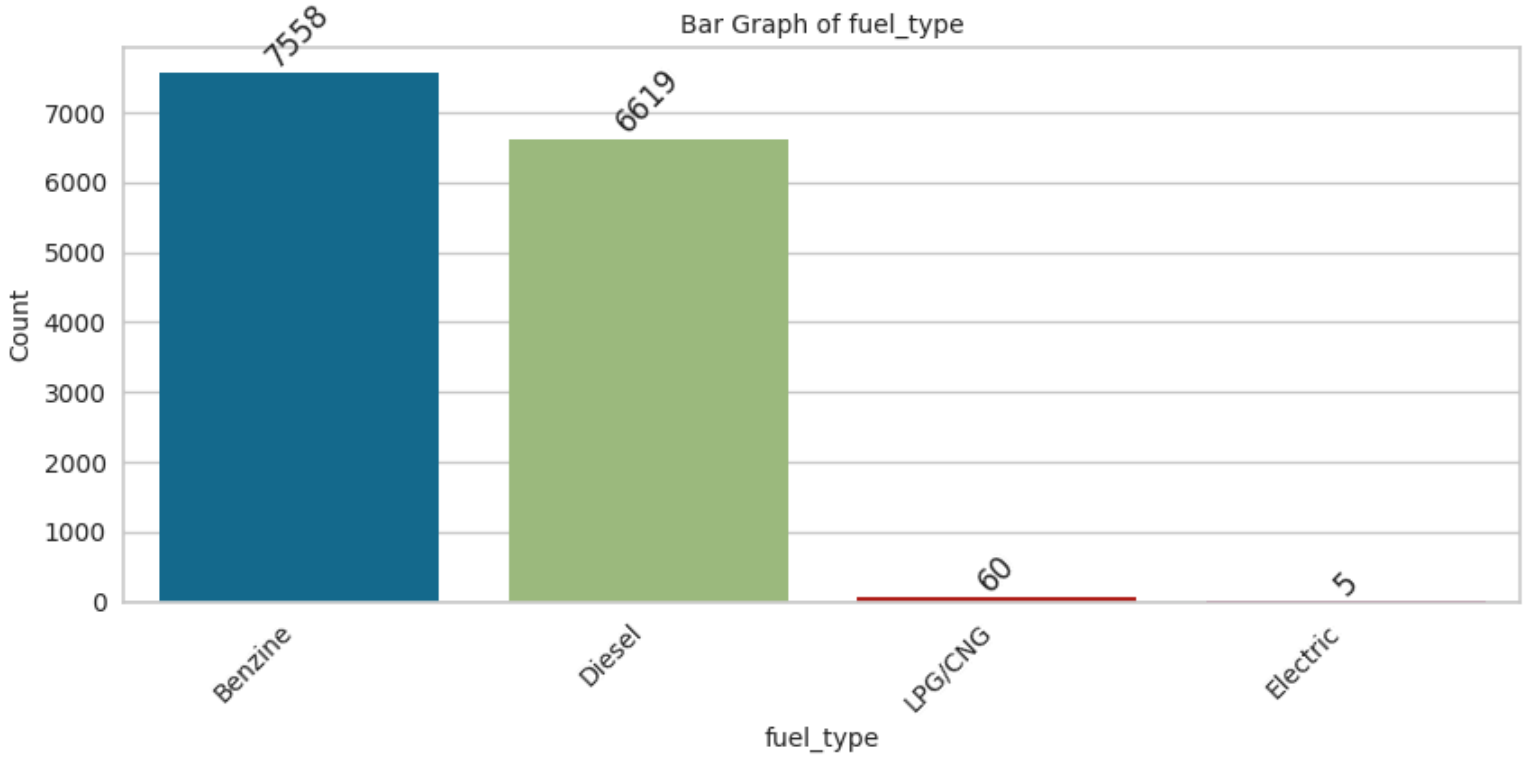
Distributions of Categorical Features

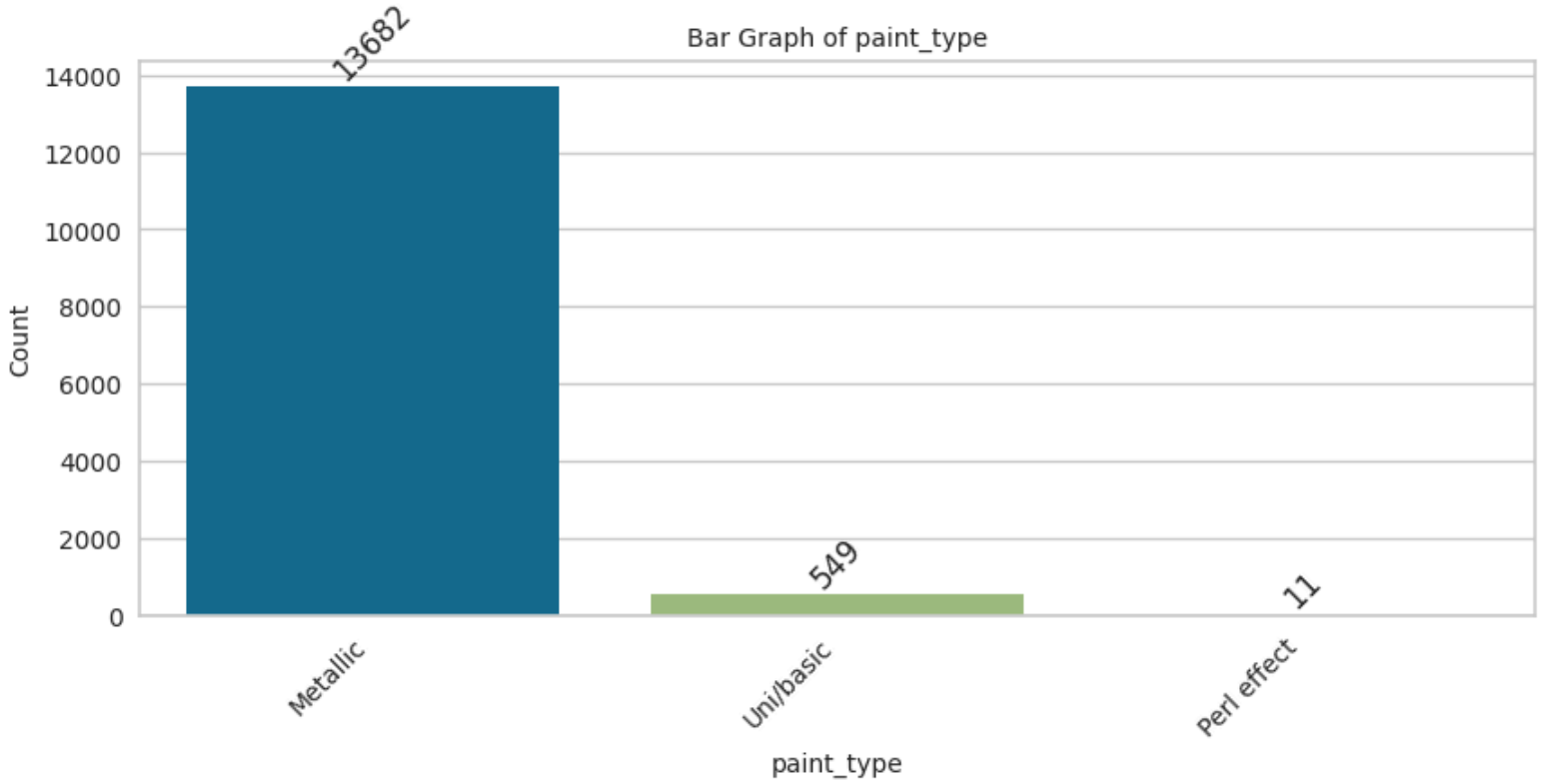
In [16]:
```
import plotly.graph_objects as go
import plotly.express as px

# Distribution of our categorical characteristics with bar graph


def plot_bar_graphs(df, columns):
    for column in columns:
        plt.figure(figsize=(10, 4))
        ax = sns.countplot(x=column,
                           data=df,
                           order=df[column].value_counts().index)
        ax.bar_label(ax.containers[0], rotation=45)
        plt.xlabel(column, fontsize=10)
        plt.ylabel('Count', fontsize=10)
```

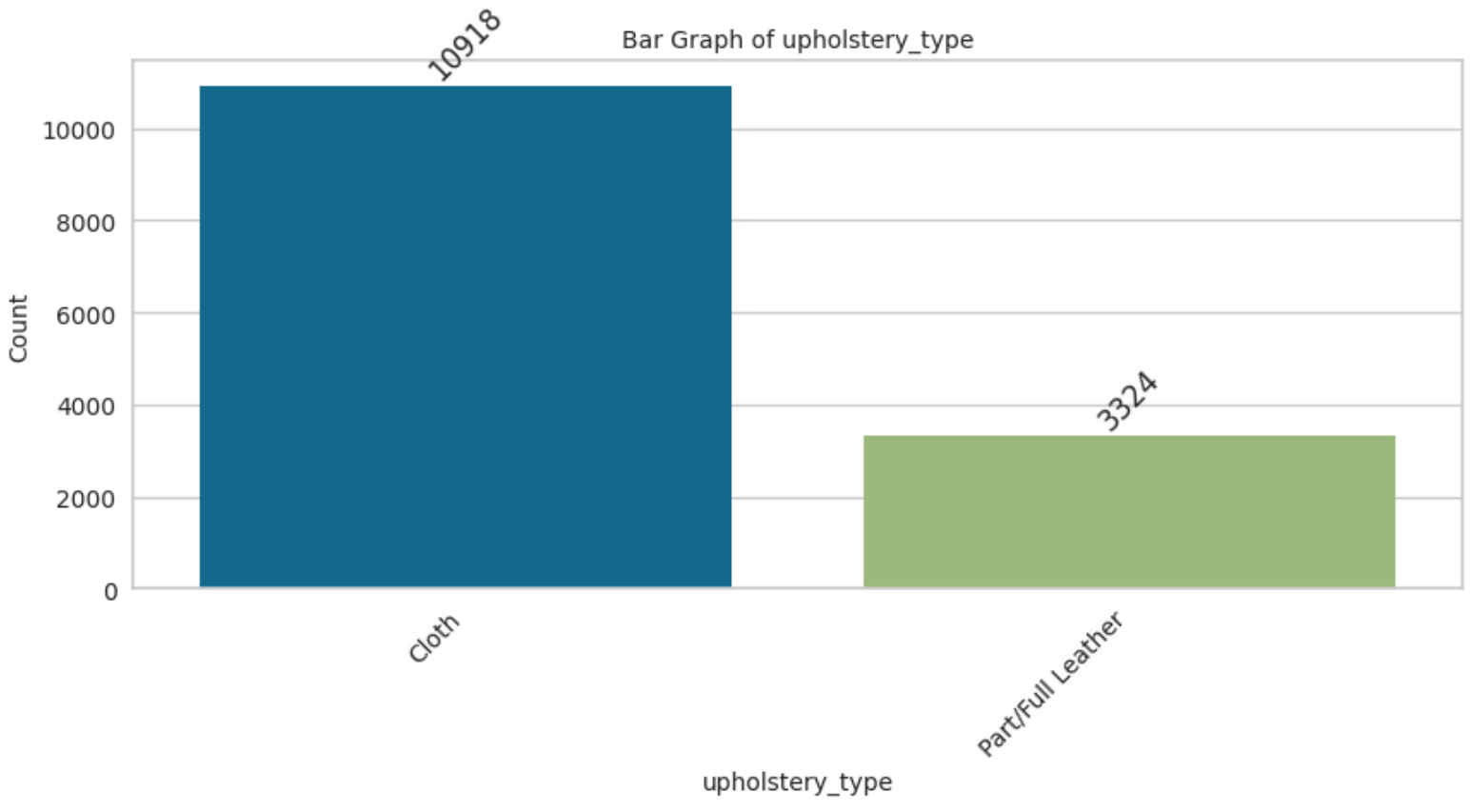
```
        plt.title(f'Bar Graph of {column}', fontsize=10)
        plt.xticks(rotation=45, ha='right', fontsize=10)
        plt.show()


cat_features = [
    'make_model', 'body_type', 'vat', 'type', 'fuel_type', 'paint_type',
    'upholstery_type', 'gearing_type', 'drive_chain'
]

plot_bar_graphs(df, cat_features)
```

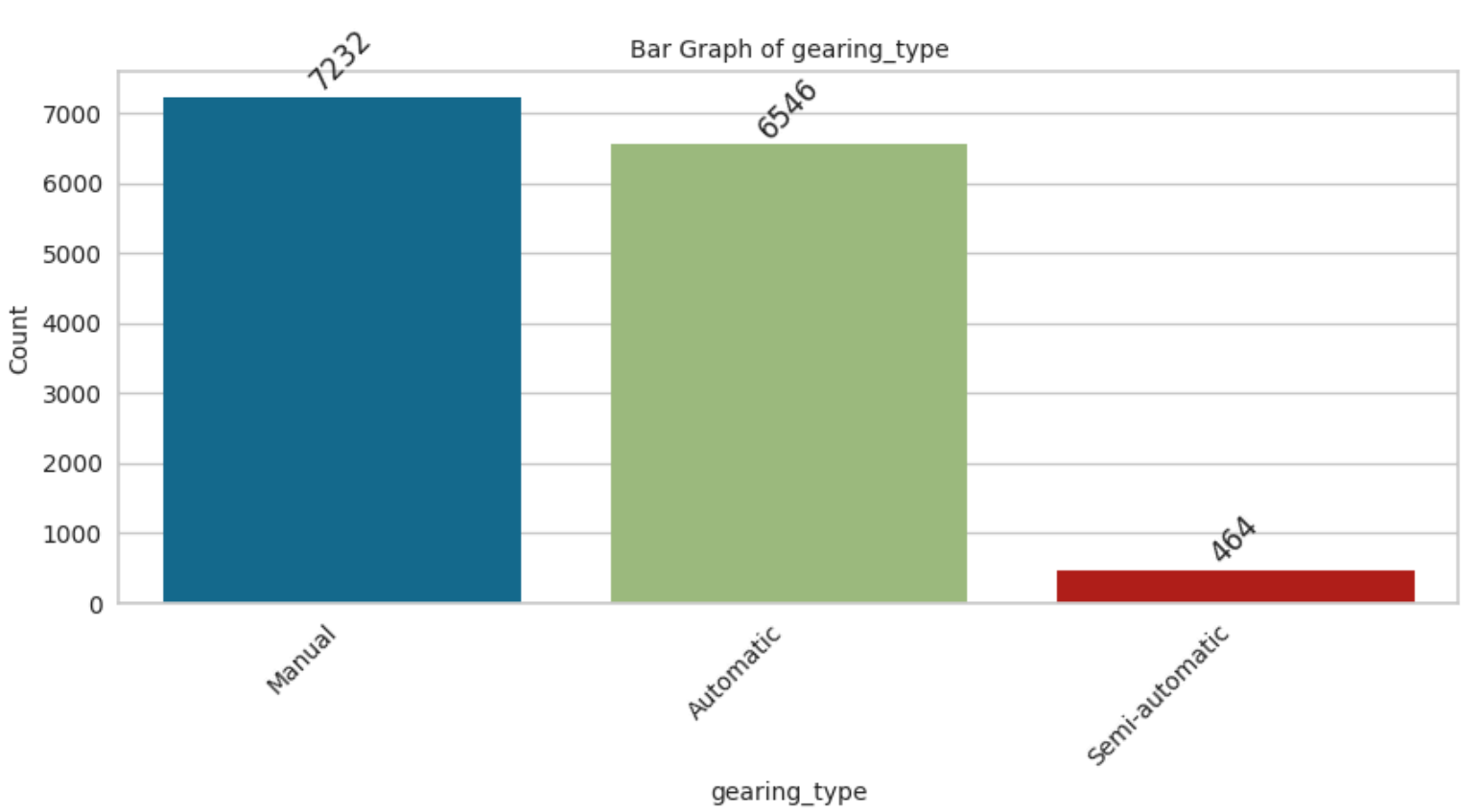


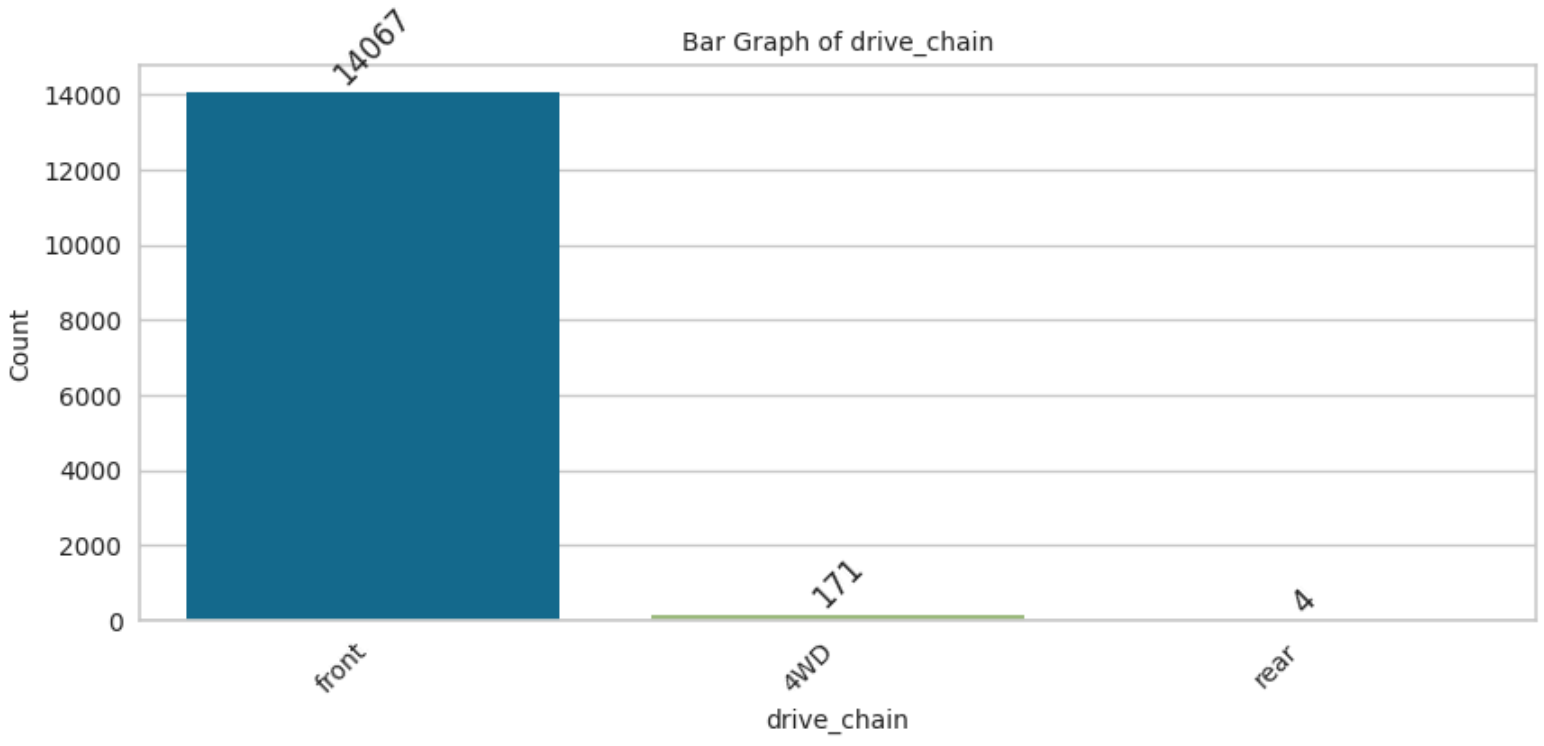

Bar Graph of type
Count
type
Used
New
Pre-registered
Employee's car
Demonstration
10172
1369
1029
905
767


Bar Graph of fuel_type
Count
fuel_type
Benzine
Diesel
LPG/CNG
Electric
7558
6619
60
5


Bar Graph of paint_type
Count
paint_type
Metallic
Uni/basic
Perl effect
13682
549
11

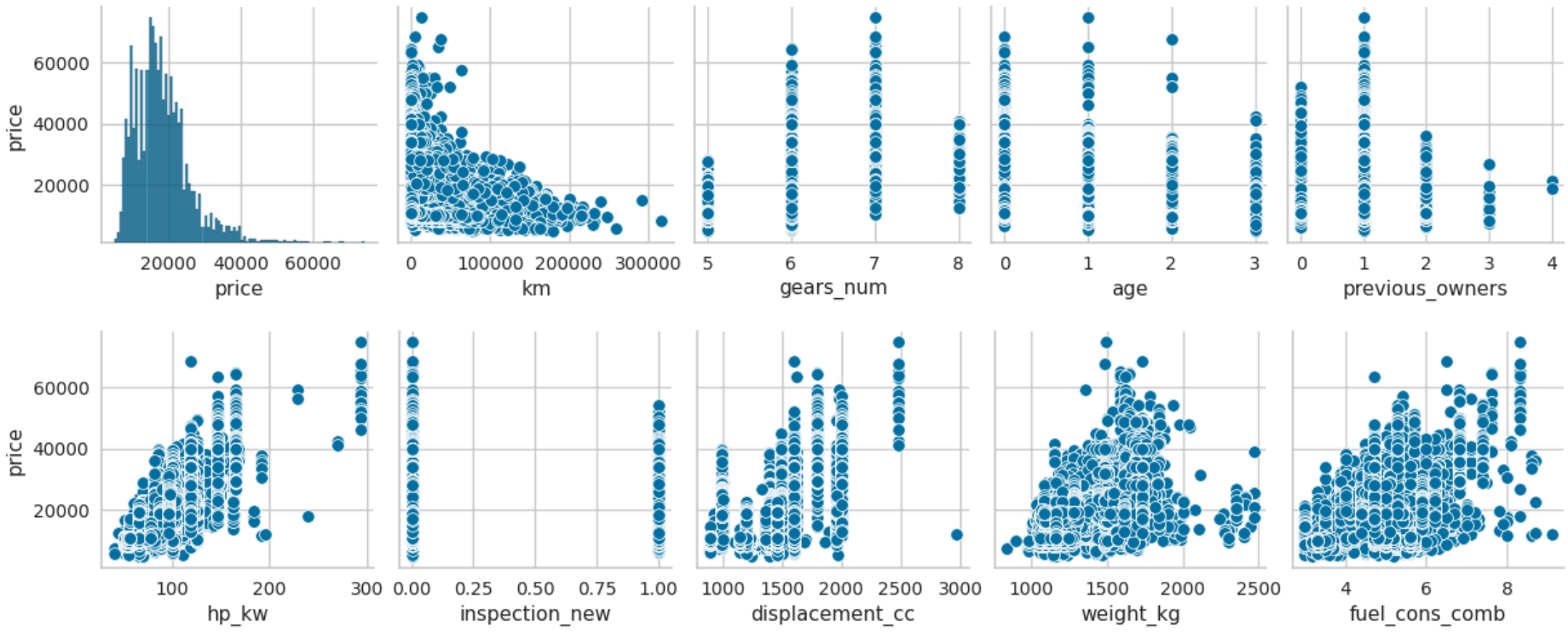






Correlations

In [20]:
```
# Target vs Numerical Features

numerical_df = df.select_dtypes(include=['number'])

for i in range(0, len(numerical_df.columns), 5):
    sns.pairplot(data=numerical_df,
                 x_vars=numerical_df.columns[i:i+5],
                 y_vars=['price'])
```



Label Encoding

In [101…

```
# Label the categorical features to see the correlation between categorical features and Target veraible.

from sklearn.preprocessing import LabelEncoder

# Copy the original dataframe to avoid modifying it directly
df_labeled = df.copy()

# List of categorical columns
categorical_columns = ['make_model', 'body_type', 'vat', 'type', 'fuel_type', 'comfort_convenience',
'entertainment_media', 'extras', 'safety_security', 'paint_type',
'upholstery_type', 'gearing_type', 'drive_chain']

# Apply Label Encoding to each categorical column
label_encoders = {}
for column in categorical_columns:
    le = LabelEncoder()
    df_labeled[column] = le.fit_transform(df_labeled[column])
    label_encoders[column] = le

# Display the first few rows of the labeled dataframe
print(df_labeled.head())
```

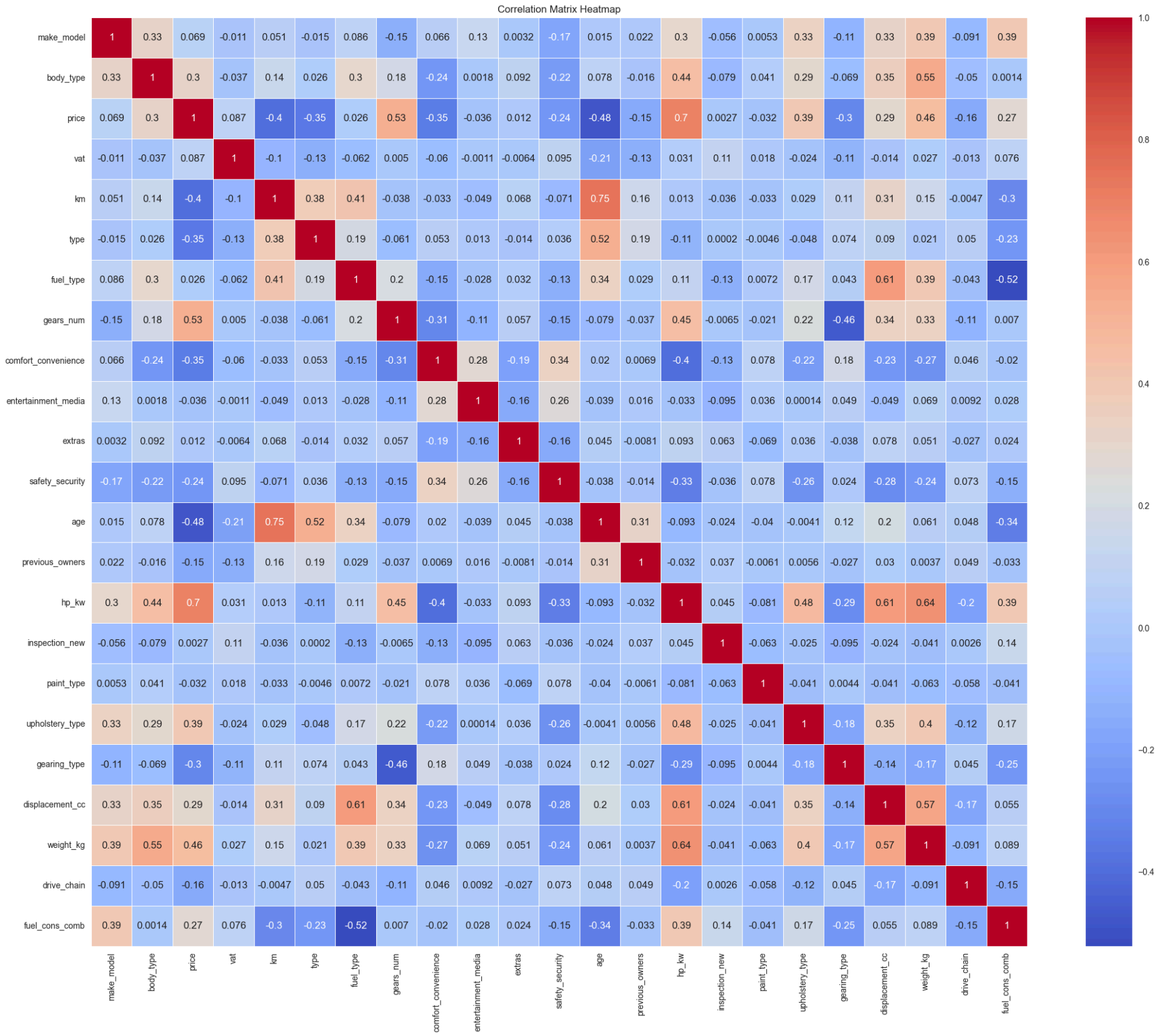
```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
File ~\anaconda3\Lib\site-packages\pandas\core\indexes\base.py:3805, in Index.get_loc(self, key)
   3804 try:
-> 3805     return self._engine.get_loc(casted_key)
   3806 except KeyError as err:

File index.pyx:167, in pandas._libs.index.IndexEngine.get_loc()

File index.pyx:196, in pandas._libs.index.IndexEngine.get_loc()

File pandas\\_libs\\hashtable_class_helper.pxi:7081, in pandas._libs.hashtable.PyObjectHashTable.get_item()

File pandas\\_libs\\hashtable_class_helper.pxi:7089, in pandas._libs.hashtable.PyObjectHashTable.get_item()

KeyError: 'type'

The above exception was the direct cause of the following exception:

KeyError                                  Traceback (most recent call last)
Cell In[101], line 17
     15 for column in categorical_columns:
     16     le = LabelEncoder()
---> 17     df_labeled[column] = le.fit_transform(df_labeled[column])
     18     label_encoders[column] = le
     20 # Display the first few rows of the labeled dataframe

File ~\anaconda3\Lib\site-packages\pandas\core\frame.py:4102, in DataFrame.__getitem__(self, key)
   4100 if self.columns.nlevels > 1:
   4101     return self._getitem_multilevel(key)
-> 4102 indexer = self.columns.get_loc(key)
   4103 if is_integer(indexer):
   4104     indexer = [indexer]

File ~\anaconda3\Lib\site-packages\pandas\core\indexes\base.py:3812, in Index.get_loc(self, key)
   3807     if isinstance(casted_key, slice) or (
   3808         isinstance(casted_key, abc.Iterable)
   3809         and any(isinstance(x, slice) for x in casted_key)
   3810     ):
   3811         raise InvalidIndexError(key)
-> 3812     raise KeyError(key) from err
   3813 except TypeError:
   3814     # If we have a listlike key, _check_indexing_error will raise
   3815     #  InvalidIndexError. Otherwise we fall through and re-raise
   3816     #  the TypeError.
   3817     self._check_indexing_error(key)

KeyError: 'type'
```

In [22]:
```
df_labeled.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 14241 entries, 0 to 15912
Data columns (total 23 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   make_model           14241 non-null  int64
 1   body_type            14241 non-null  int64
 2   price                14241 non-null  int64
 3   vat                  14241 non-null  int64
 4   km                   14241 non-null  float64
 5   type                 14241 non-null  int64
 6   fuel_type            14241 non-null  int64
 7   gears_num            14241 non-null  float64
 8   comfort_convenience  14241 non-null  int64
 9   entertainment_media  14241 non-null  int64
 10  extras               14241 non-null  int64
 11  safety_security      14241 non-null  int64
 12  age                  14241 non-null  float64
 13  previous_owners      14241 non-null  float64
 14  hp_kw                14241 non-null  float64
 15  inspection_new       14241 non-null  int64
 16  paint_type           14241 non-null  int64
 17  upholstery_type      14241 non-null  int64
 18  gearing_type         14241 non-null  int64
 19  displacement_cc      14241 non-null  float64
 20  weight_kg            14241 non-null  float64
 21  drive_chain          14241 non-null  int64
 22  fuel_cons_comb       14241 non-null  float64
dtypes: float64(8), int64(15)
memory usage: 2.6 MB
```

Heatmap

In [8]:
```
# Corr of all features used Labeled df

correlation_matrix = df_labeled.corr()

plt.figure(figsize=(25,20))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Matrix Heatmap')
plt.show()
```



In [9]:
```
# Check Multicolinarty between features

def color_custom(val):
    if val > 0.90 and val < 0.99:
        color = 'red'
    elif val >= 1:
        color = 'blue'
    else:
        color = 'black'
    return f'color: {color}'

df_labeled.corr().style.map(color_custom)
```

Out[9]:

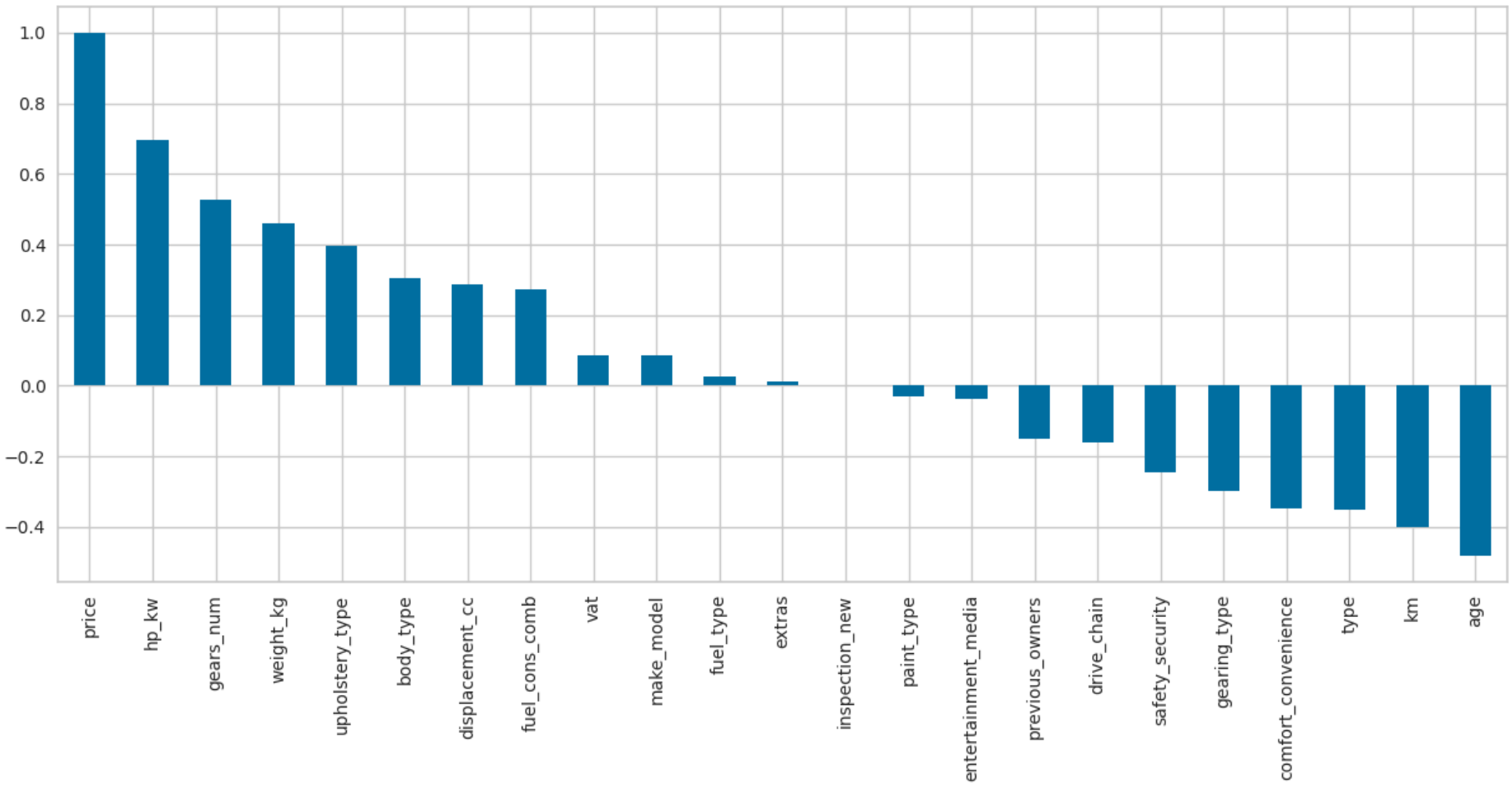
	make_model	body_type	price	vat	km	type	fuel_type	gears_num	comfort_convenience	entertainment_media
make_model	1.000000	0.327054	0.069439	-0.011138	0.051404	-0.015027	0.085748	-0.146270	0.065943	0.129709
body_type	0.327054	1.000000	0.304434	-0.036554	0.139391	0.026279	0.298733	0.182115	-0.236887	0.001831
price	0.069439	0.304434	1.000000	0.087051	-0.402373	-0.350389	0.025583	0.528101	-0.347764	-0.036164
vat	-0.011138	-0.036554	0.087051	1.000000	-0.104631	-0.127659	-0.062094	0.005016	-0.060231	-0.001129
km	0.051404	0.139391	-0.402373	-0.104631	1.000000	0.379356	0.413952	-0.038146	-0.033351	-0.049121
type	-0.015027	0.026279	-0.350389	-0.127659	0.379356	1.000000	0.193455	-0.060956	0.052919	0.013009
fuel_type	0.085748	0.298733	0.025583	-0.062094	0.413952	0.193455	1.000000	0.204353	-0.151186	-0.028285
gears_num	-0.146270	0.182115	0.528101	0.005016	-0.038146	-0.060956	0.204353	1.000000	-0.307914	-0.106910
comfort_convenience	0.065943	-0.236887	-0.347764	-0.060231	-0.033351	0.052919	-0.151186	-0.307914	1.000000	0.277904
entertainment_media	0.129709	0.001831	-0.036164	-0.001129	-0.049121	0.013009	-0.028285	-0.106910	0.277904	1.000000
extras	0.003234	0.091602	0.012074	-0.006407	0.068500	-0.014204	0.031707	0.057241	-0.194022	-0.157417
safety_security	-0.168685	-0.215044	-0.244648	0.095352	-0.071110	0.036312	-0.127852	-0.154906	0.344883	0.257983
age	0.014540	0.077671	-0.481426	-0.207585	0.748734	0.521802	0.338200	-0.079298	0.020332	-0.038928
previous_owners	0.022334	-0.015783	-0.148630	-0.134057	0.158776	0.190820	0.028637	-0.036680	0.006863	0.016184
hp_kw	0.300697	0.443754	0.697984	0.031094	0.013366	-0.114630	0.113218	0.451227	-0.402756	-0.033424
inspection_new	-0.055886	-0.079364	0.002714	0.111503	-0.036464	0.000203	-0.130849	-0.006485	-0.127837	-0.095123
paint_type	0.005281	0.041088	-0.031693	0.018431	-0.032642	-0.004602	0.007209	-0.021477	0.078492	0.036253
upholstery_type	0.333009	0.288684	0.394886	-0.023963	0.029223	-0.048139	0.174516	0.224129	-0.215277	0.000138
gearing_type	-0.109929	-0.068857	-0.299150	-0.114237	0.114087	0.074165	0.043201	-0.463721	0.179809	0.049091
displacement_cc	0.327960	0.353084	0.287056	-0.014385	0.305729	0.090366	0.612020	0.337763	-0.234556	-0.049247
weight_kg	0.387076	0.549287	0.460120	0.026726	0.152804	0.021155	0.387654	0.332270	-0.270643	0.068591
drive_chain	-0.091013	-0.050190	-0.160692	-0.012521	-0.004722	0.049896	-0.042669	-0.110661	0.045509	0.009168
fuel_cons_comb	0.387220	0.001373	0.273551	0.076376	-0.295297	-0.234526	-0.522230	0.006956	-0.019664	0.028278

In [25]:
```
# Corr between Target vs other Features

correlation_matrix = df_labeled.corr() # Labeled df

price_corr = correlation_matrix['price'].sort_values(ascending= False)
price_corr
```

Out[25]:
```
price                 1.000
hp_kw                 0.698
gears_num             0.528
weight_kg             0.460
upholstery_type       0.395
body_type             0.304
displacement_cc       0.287
fuel_cons_comb        0.274
vat                   0.087
make_model            0.085
fuel_type             0.025
extras                0.012
inspection_new        0.003
paint_type           -0.032
entertainment_media  -0.036
previous_owners      -0.149
drive_chain          -0.161
safety_security      -0.245
gearing_type         -0.299
comfort_convenience  -0.348
type                 -0.350
km                   -0.402
age                  -0.481
Name: price, dtype: float64
```

In [26]:
```
# Target vs other Features

price_corr.plot(kind='bar',figsize=(15,6))
```

Out[26]:
```
<Axes: >
```



NOTE:

1. **Strong Positive Correlations with Price:**
   - **Gears Number (`gears_num`):** Shows a strong positive correlation with `price` (0.53), indicating that cars with more gears tend to be more expensive.
   - **Engine Power (`hp_kW`):** Exhibits a moderate positive correlation with `price` (0.45), suggesting that higher-powered cars are generally more expensive.
   - **Engine Displacement (`displacement_cc`):** Has a moderate positive correlation with `price` (0.36), indicating that cars with larger engine displacements tend to be more expensive.
2. **Negative Correlations with Price:**
   - **Mileage (`km`):** Displays a negative correlation with `price` (-0.35), suggesting that cars with higher mileage tend to be cheaper.
   - **Age (`age`):** Exhibits a negative correlation with `price` (-0.21), indicating that older cars tend to be cheaper.
   - **Fuel Consumption (`fuel_cons_comb`):** Shows a moderate negative correlation with `price` (-0.30), indicating that cars with higher fuel consumption tend to be cheaper.
3. **Multicollinearity Considerations:**
   - **Gears Number (`gears_num`), Engine Power (`hp_kW`), and Engine Displacement (`displacement_cc`):** These features show strong correlations with each other and with `price`, suggesting potential multicollinearity.
   - **Mileage (`km`) and Age (`age`):** These features also show a strong correlation (0.76) with each other, indicating redundancy.

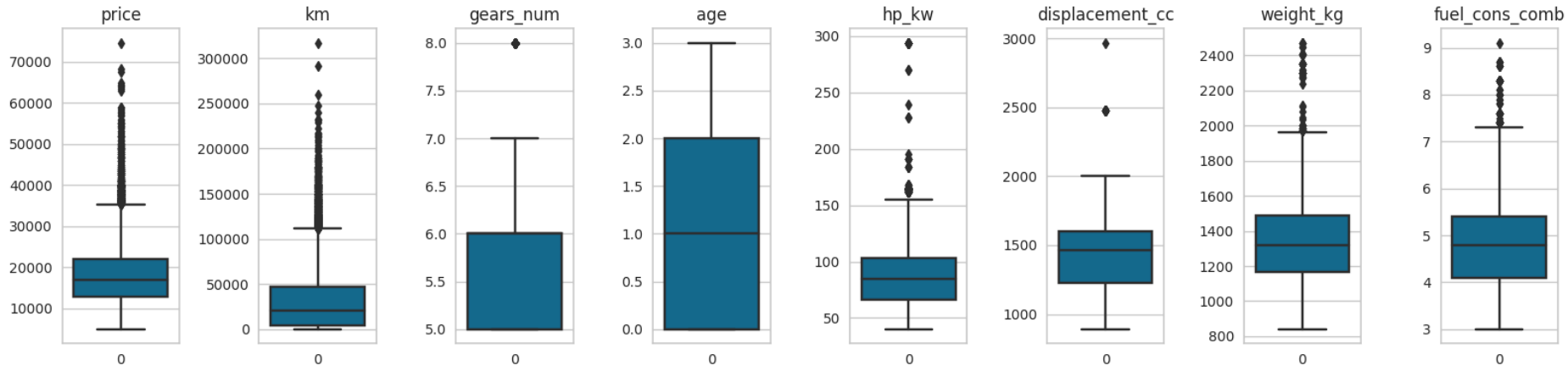
Managing multicollinearity among these highly correlated features is crucial to ensure model stability and performance. By addressing these correlations, we can build a more reliable and accurate price prediction model.

Outlier Analysis

Linear models are generally sensitive to outliers because they seek linear relationships between data points and employ MSE-like loss functions that amplify large errors. Some models, such as decision trees and robust regression, are more resilient to outliers and are less affected by such data. Therefore, when choosing a model, the characteristics of the dataset and the presence of outliers should be considered.

- However, we will not intervene with outliers at the moment, but we can take action later according to the model's forecasting performance.
- Let's observe the outliers for now.

In [27]:
```
# Checking Outliers

# Initialize the subplot counter
x = 0

#Numerical features;
numerical_columns = ['price', 'km','gears_num','age','hp_kw','displacement_cc','weight_kg','fuel_cons_comb']

# Create a figure with specified size
plt.figure(figsize=(16, 4))

# Loop through each numerical column and create a boxplot
for col in numerical_columns:
    x += 1
    plt.subplot(1, 8, x)
    sns.boxplot(data=df[col])
    plt.title(col)

# Show the plots
plt.tight_layout()  # Adjust subplots to fit in the figure area.
plt.show()
```



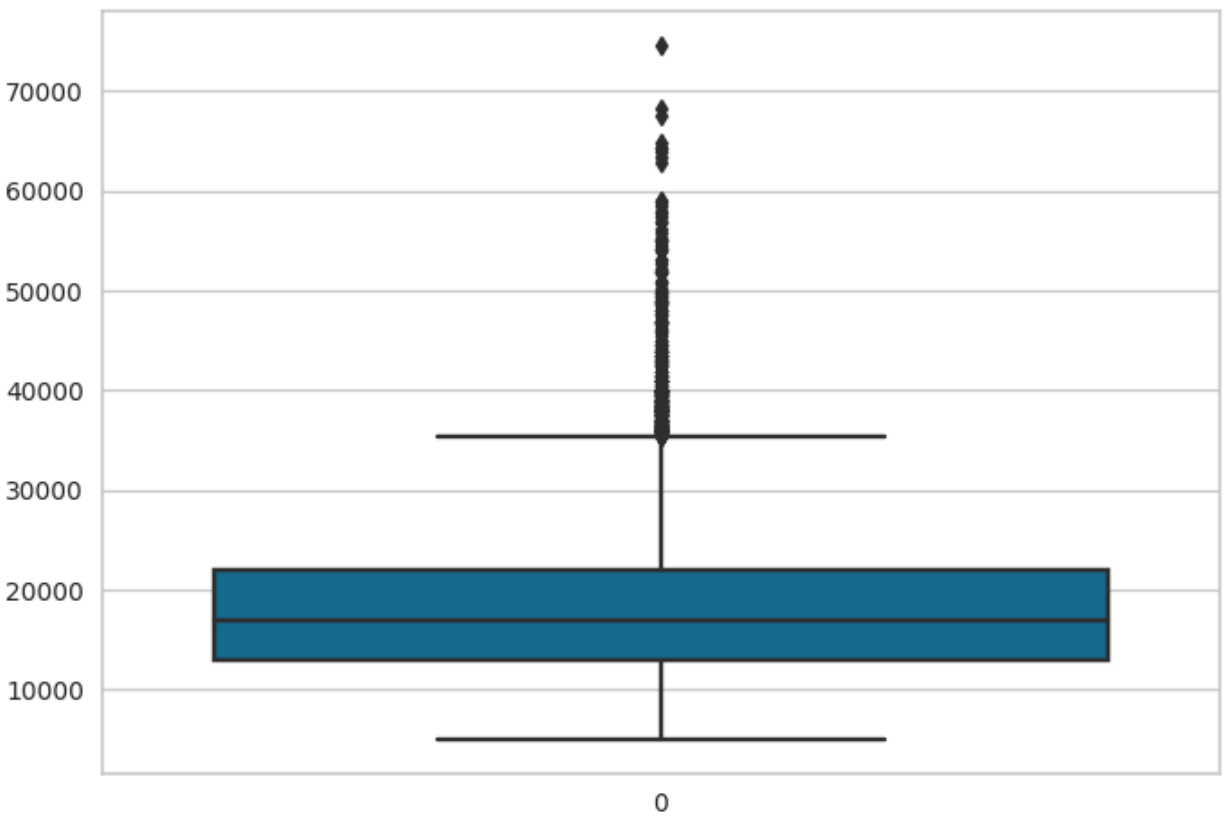
In [28]:
```
# Calculate skewness for numeric features

# A skewness value greater than 1 indicates positive skewness,
# a skewness value less than -1 indicates negative skewness,
# and a skewness value close to zero indicates a relatively symmetric distribution.

num_cols= df.select_dtypes('number').columns

skew_limit = 0.75               # define a limit above which we will log transform
skew_vals = df[num_cols].skew()


# Showing the skewed columns
skew_cols = (skew_vals
             .sort_values(ascending=False)
             .to_frame()
             .rename(columns={0:'Skew'})
             .query('abs(Skew) > {}'.format(skew_limit)))
skew_cols
```

Out[28]:

	Skew
km	1.651
hp_kw	1.330
price	1.269
inspection_new	1.116
previous_owners	1.103
weight_kg	1.069

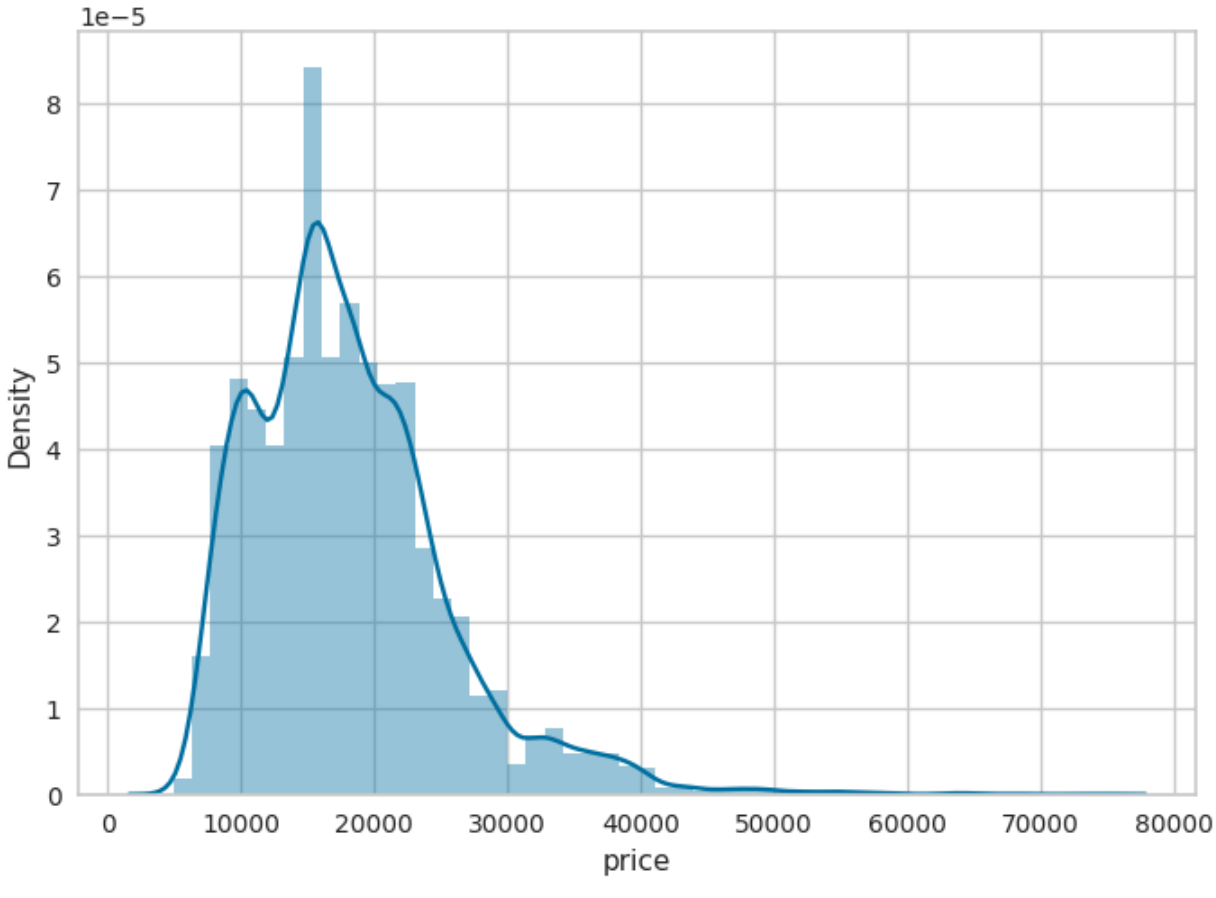
Target Variable

In [29]:
```
# Checking outliers for target variable 'price' with boxplot

sns.boxplot(df.price);
```



In [30]:
```
#Skewness of the target variable
print("Skewness: %f" % df['price'].skew())

# Distribution of target variable before log transformation
price_untransformed = sns.distplot(df['price'])
```

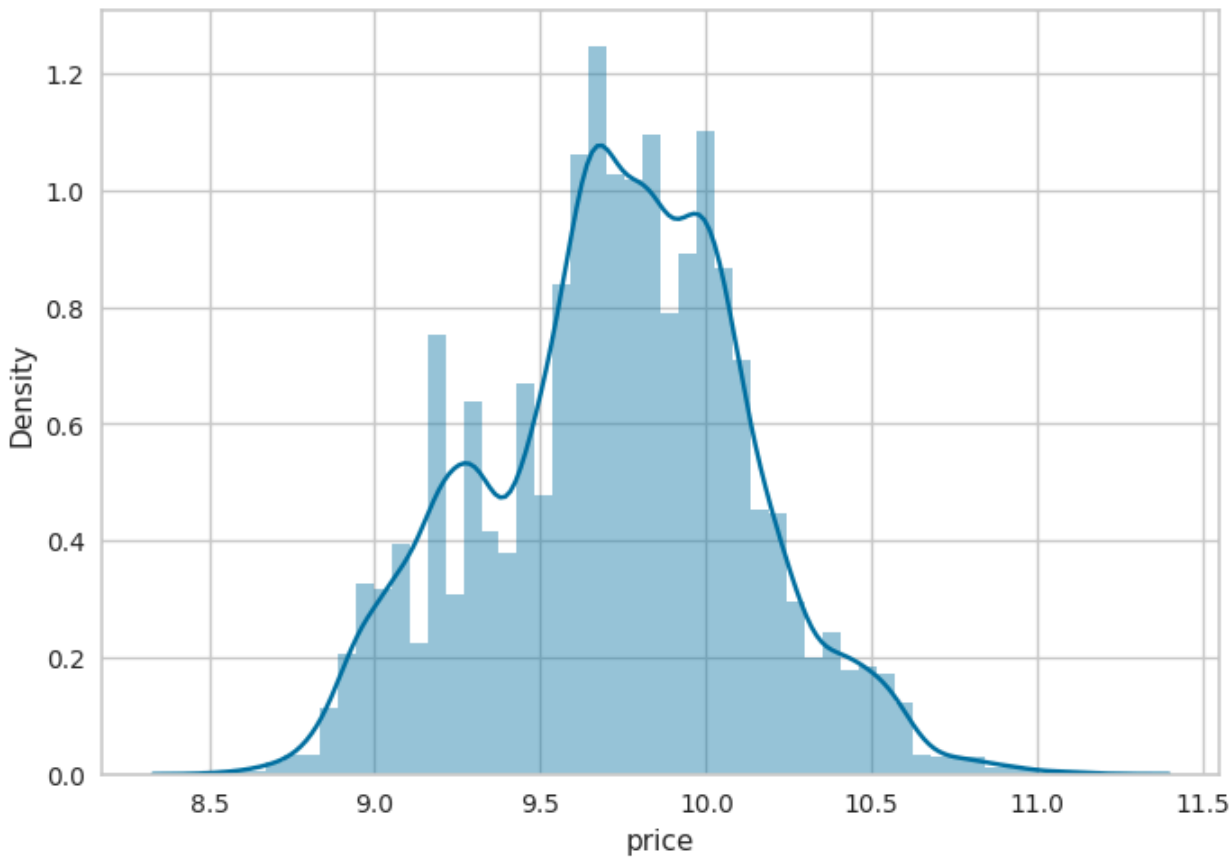
```
Skewness: 1.268788
```



- The range of skewness for a fairly symmetrical bell curve distribution is between -0.5 and 0.5;
- moderate skewness is -0.5 to -1.0 and 0.5 to 1.0;
- and highly skewed distribution is < -1.0 and > 1.0.

In our case, we have ~1.2, so it is considered skewed data. Now, we can try to transform our data, so it looks more normally distributed.

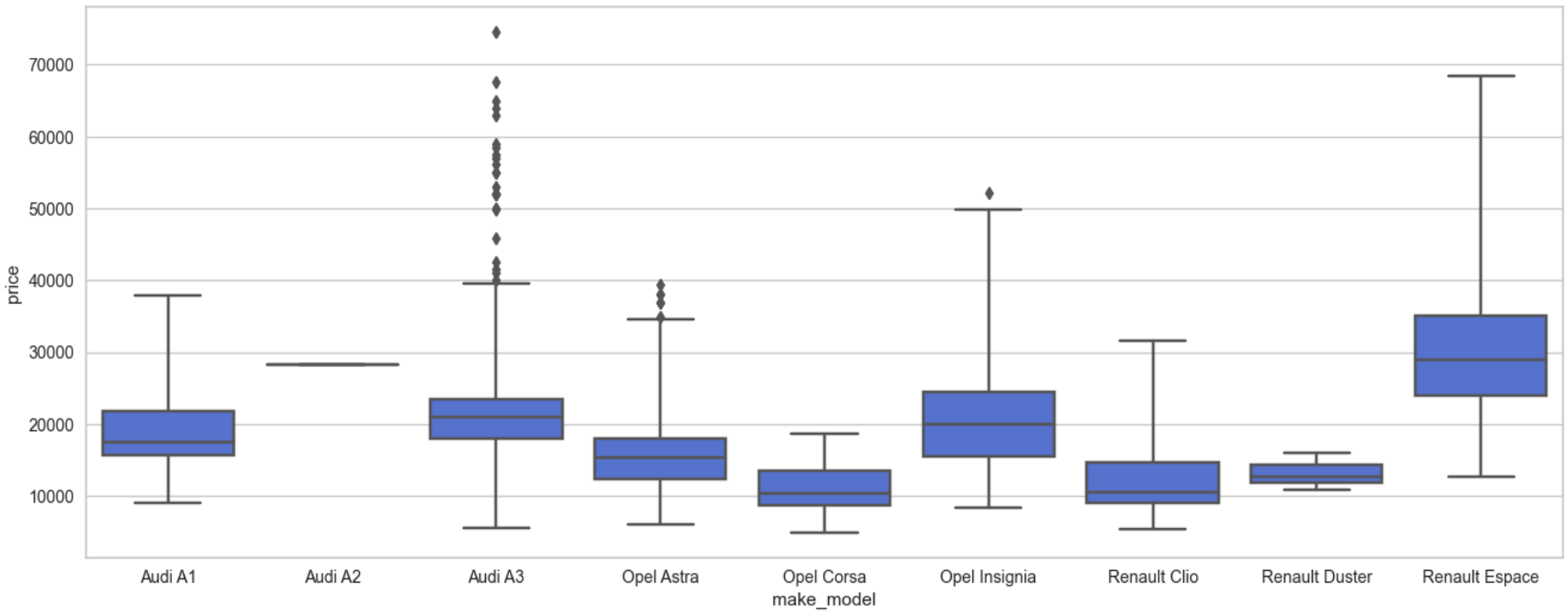
In [31]:
```
#After Log Transformation
price_transformed = sns.distplot(np.log(df['price']))
```



'Make_model' Feature

- *As we observed in the distributions of the `make_model` feature values above, Audi A2 has only one data point.
  - The fact that the Audi A2 has only one data point indicates that there is not enough data to represent this model.
  - it is insufficient for generalization and should be excluded from the analysis.
  - By removing Audi A2, we ensure the model's stability and accuracy.

In [10]:
```
# Make and Models

plt.figure(figsize=(16,6))
sns.boxplot(x="make_model", y="price", data=df, whis=3, color="royalblue")
plt.show()
```



In [11]:
```
# Outlier check for the make_model feature

total_outliers = []

for model in df.make_model.unique():

    car_prices = df[df["make_model"]== model]["price"]

    Q1 = car_prices.quantile(0.25)
    Q3 = car_prices.quantile(0.75)
    IQR = Q3-Q1
    lower_lim = Q1-1.5*IQR
    upper_lim = Q3+1.5*IQR

    count_of_outliers = (car_prices[(car_prices < lower_lim) | (car_prices > upper_lim)]).count()

    total_outliers.append(count_of_outliers)

    print(f" The count of outlier for {model:<15} : {count_of_outliers:<5}, \
          The rate of outliers : {(count_of_outliers/len(df[df['make_model']== model])).round(3)}")
print()
print("Total_outliers : ",sum(total_outliers), "The rate of total outliers :", (sum(total_outliers)/len(df)).round(3))
```

```
 The count of outlier for Audi A1         : 5    ,          The rate of outliers : 0.002
 The count of outlier for Audi A2         : 0    ,          The rate of outliers : 0.0
 The count of outlier for Audi A3         : 56   ,          The rate of outliers : 0.02
 The count of outlier for Opel Astra      : 127  ,          The rate of outliers : 0.055
 The count of outlier for Opel Corsa      : 0    ,          The rate of outliers : 0.0
 The count of outlier for Opel Insignia   : 109  ,          The rate of outliers : 0.045
 The count of outlier for Renault Clio    : 37   ,          The rate of outliers : 0.025
 The count of outlier for Renault Duster  : 0    ,          The rate of outliers : 0.0
 The count of outlier for Renault Espace  : 20   ,          The rate of outliers : 0.023

Total_outliers :  354 The rate of total outliers : 0.025
```

- Some models, like Opel Astra, Opel Insignia, and Renault Clio, have a high number of outliers, indicating significant price deviations.
- Models like Audi A1, Opel Corsa, and Renault Duster have more consistent price distributions with fewer outliers.
- The overall outlier rate is 2.6%, showing the dataset's sensitivity to outliers.
- These outliers should be considered in analysis and modeling.

Remove the AudiA2 model from the df

In [12]:
```
models = df.make_model.value_counts()
models
```

Out[12]:
```
make_model
Audi A3           2758
Opel Insignia     2417
Audi A1           2377
Opel Astra        2305
Opel Corsa        1994
Renault Clio      1486
Renault Espace     884
Renault Duster      20
Audi A2              1
Name: count, dtype: int64
```

In [13]:
```
# Dropping the only Audi A2 observation to increase model performance

df = df[df['make_model'] != 'Audi A2']
```

In [14]:
```
df[df.make_model=="Audi A2"]
```

Out[14]:

make_model	body_type	price	vat	km	type	fuel_type	gears_num	comfort_convenience	entertainment_media	extras	safety_security	age	previous_c

Feature Engineering

Get Dummies

Explanation:

Original Data: The `comfort_convenience`, `entertainment_media`, `extras`, and `safety_security` columns contain categorical values.

comfort_convenience	entertainment_media	extras	safety_security
Air Conditioning, Cruise Control	Bluetooth, CD Player	Alloy Wheels	ABS, Airbags

After Get Dummies:

- Each category has been converted into a separate column.
- For example, `Air Conditioning` and `Cruise Control` are represented as separate columns with the `cc_` prefix.
- Similarly, other categories are represented with their own prefixes, with the presence of a category indicated by 1 and its absence by 0.

cc_Air Conditioning	cc_Cruise Control	em_Bluetooth	em_CD Player	ex_Alloy Wheels	ss_ABS	ss_Airbags
1	1	1	1	1	1	1

This process allows machine learning models to interpret these categorical features as numerical data, thereby improving model performance.

In [30]:
```
# Select the categorical features that have more than one value to separate

selected_columns = df.loc[:, ['comfort_convenience', 'entertainment_media', 'extras', 'safety_security']]
selected_columns.head()
```

Out[30]:

	comfort_convenience	entertainment_media	extras	safety_security
0	Air conditioning,Armrest,Automatic climate con...	Bluetooth,Hands-free equipment,On-board comput...	Alloy wheels,Catalytic Converter,Voice Control	ABS,Central door lock,Daytime running lights,D...
1	Air conditioning,Automatic climate control,Hil...	Bluetooth,Hands-free equipment,On-board comput...	Alloy wheels,Sport seats,Sport suspension,Voic...	ABS,Central door lock,Central door lock with r...
2	Air conditioning,Cruise control,Electrical sid...	MP3,On-board computer	Alloy wheels,Voice Control	ABS,Central door lock,Daytime running lights,D...
3	Air suspension,Armrest,Auxiliary heating,Elect...	Bluetooth,CD player,Hands-free equipment,MP3,O...	Alloy wheels,Sport seats,Voice Control	ABS,Alarm system,Central door lock with remote...
4	Air conditioning,Armrest,Automatic climate con...	Bluetooth,CD player,Hands-free equipment,MP3,O...	Alloy wheels,Sport package,Sport suspension,Vo...	ABS,Central door lock,Driver-side airbag,Elect...

In [15]:
```
# Get Dummies and separe them

df = df.join(df["comfort_convenience"].str.get_dummies(sep = ",").add_prefix("cc_"))
df = df.join(df["entertainment_media"].str.get_dummies(sep = ",").add_prefix("em_"))
df = df.join(df["extras"].str.get_dummies(sep = ",").add_prefix("ex_"))
df = df.join(df["safety_security"].str.get_dummies(sep = ",").add_prefix("ss_"))
```

In [16]:
```
# Drop the original features we dont need anymore.

df.drop(["comfort_convenience","entertainment_media","extras","safety_security"], axis=1, inplace=True)
```

In [17]:
```
# One-Hot Encoding get_dummies for all df

df = pd.get_dummies(df, drop_first =True)
```

In [18]:
```
print(df.shape)

df.head(3)

#new features values are boolean dtype after get_dummies
```

```
(14241, 133)
```

Out[18]:

	price	km	gears_num	age	previous_owners	hp_kw	inspection_new	displacement_cc	weight_kg	fuel_cons_comb	cc_Air conditioning	cc_Air suspension
0	15770	56013.000	7.000	3.000	2.000	66.000	1	1422.000	1220.000	3.800	1	0
1	14500	80000.000	7.000	2.000	1.000	141.000	0	1798.000	1255.000	5.600	1	0
2	14640	83450.000	7.000	3.000	1.000	85.000	0	1598.000	1135.000	3.800	1	0

In [19]:
```
# Convert boolean columns(after get_dummy) to integers, changing True to 1 and False to 0.

bool_columns = df.columns[df.dtypes == 'bool']
df[bool_columns] = df[bool_columns].astype(int)
```

In [20]:
```
print(df.shape)
df.head(3)
```

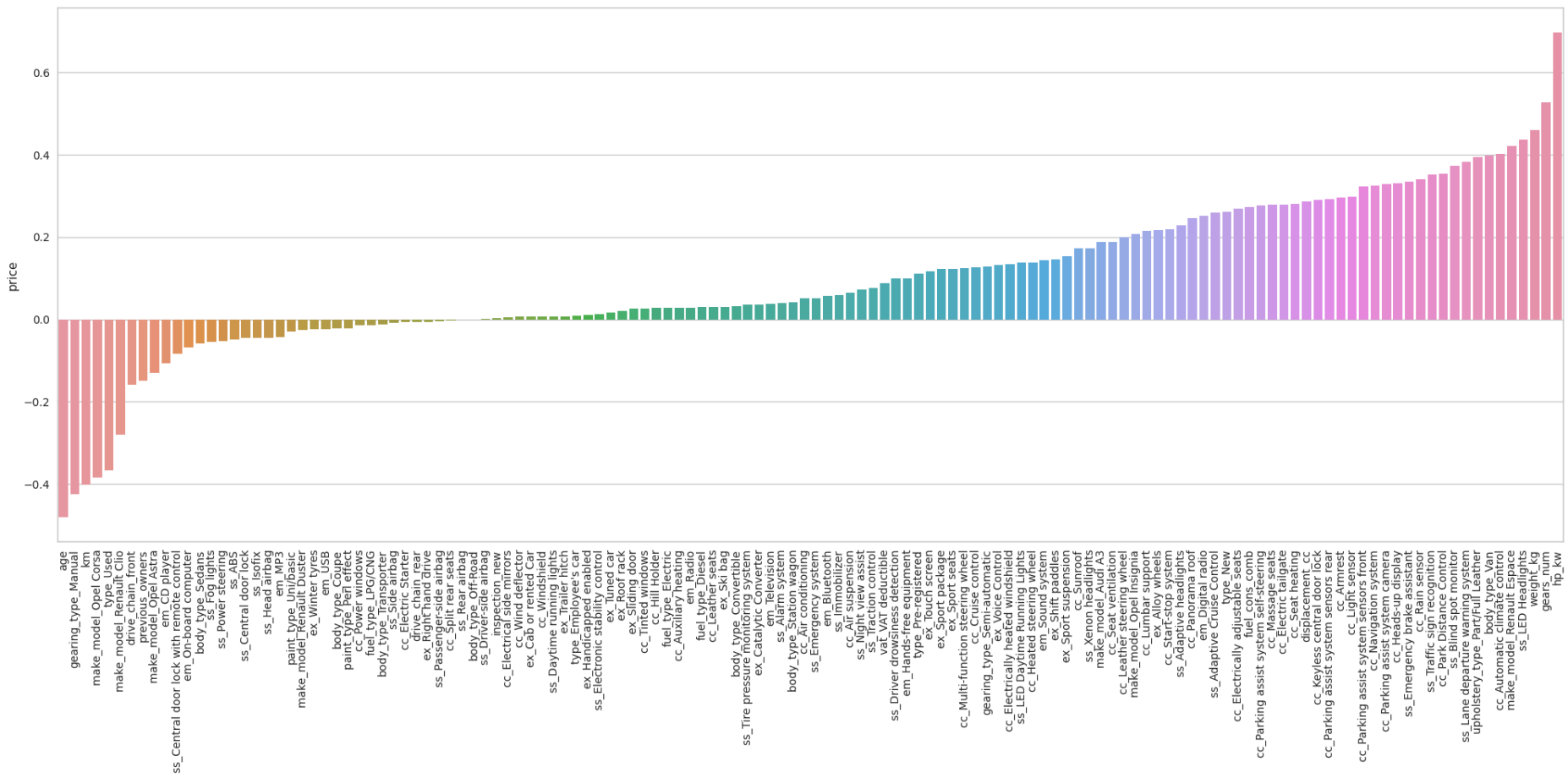
```
(14241, 133)
```

Out[20]:

	price	km	gears_num	age	previous_owners	hp_kw	inspection_new	displacement_cc	weight_kg	fuel_cons_comb	cc_Air conditioning	cc_Air suspension
0	15770	56013.000	7.000	3.000	2.000	66.000	1	1422.000	1220.000	3.800	1	0
1	14500	80000.000	7.000	2.000	1.000	141.000	0	1798.000	1255.000	5.600	1	0
2	14640	83450.000	7.000	3.000	1.000	85.000	0	1598.000	1135.000	3.800	1	0

In [ ]:
```
# Check the correlation between target and all features(Including new features after get dummy)
corr_by_price = df.corr()["price"].sort_values()[:-1]
corr_by_price
```

In [42]:
```
# Plot correlation between target and all features
plt.figure(figsize = (20,10))
sns.barplot(x = corr_by_price.index, y = corr_by_price)
plt.xticks(rotation=90)
plt.tight_layout();
```



MACHINE LEARNING MODELLING

Functions to use to evaluate the model's scores at the end.

--> Model Performance Evaluation Function: train_val()

- This function evaluates a model's performance on both the training and test datasets
- by calculating various metrics such as R^2, MAE, MSE, and RMSE.

In [21]:
```
def train_val(model, X_train, y_train, X_test, y_test, i):

    y_pred = model.predict(X_test)
    y_train_pred = model.predict(X_train)

    scores = {
    i+"_train": {
    "R2" : r2_score(y_train, y_train_pred),
    "mae" : mean_absolute_error(y_train, y_train_pred),
    "mse" : mean_squared_error(y_train, y_train_pred),
    "rmse" : np.sqrt(mean_squared_error(y_train, y_train_pred))},

    i+"_test": {
    "R2" : r2_score(y_test, y_pred),
    "mae" : mean_absolute_error(y_test, y_pred),
    "mse" : mean_squared_error(y_test, y_pred),
    "rmse" : np.sqrt(mean_squared_error(y_test, y_pred))}
              }

    return pd.DataFrame(scores)
```

--> Adjusted R^2 : adj_r2()

- R^2 Score: Indicates how much of the variance in the dependent variable is explained by the model.
- Adjusted R^2 Score: Adjusts the explanatory power of the model based on the number of independent variables, reducing the risk of overfitting.

In [22]:
```
def adj_r2(y_test, y_pred, df):
    r2 = r2_score(y_test, y_pred)
    n = df.shape[0]
    p = df.shape[1]-1
    adj_r2 = 1 - (1-r2)*(n-1)/(n-p-1)
    return adj_r2
```

Split the Data

In [23]:
```
# Split Target and Independent Features

X= df.drop(columns="price")
y= df.price
```

In [24]:
```
# Train-test Split

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

In [25]:
```
X.shape
```

Out[25]: (14241, 132)

Linear Regression

- Started with a simple, basic model without any special optimizations, manipulations,scaling or outlier handling on the dataset, which in machine learning and data science is referred to as a "vanilla model."
- By observing the performance of this initial model, we can compare it with more complex and optimized models in the end if we need.

Model

In [26]:
```
#Set and fit the model

linear_model = LinearRegression()

linear_model.fit(X_train, y_train)
```

Out[26]:
```
LinearRegression
LinearRegression()
```

Prediction

In [27]:
```
# Prediction
y_pred = linear_model.predict(X_test)

# Calculation of the metrics of the test data to compare models at the end.
lm_R2 = r2_score(y_test, y_pred)
lm_mae = mean_absolute_error(y_test, y_pred)
lm_rmse = np.sqrt(mean_squared_error(y_test, y_pred))

print(lm_R2)
print(lm_mae)
print(lm_rmse)
```

```
0.8839352080753037
1725.5088166161436
2501.8602245902453
```

Evaluating the Linear Model

In [28]:
```
# Check the coefficients to see how it affects top-10 feature importance

lm1_coef = pd.DataFrame(linear_model.coef_, index = X.columns, columns=["lm1_Coeff"]).sort_values("lm1_Coeff")
lm1_coef.head(10)
```

Out[28]:

	lm1_Coeff
make_model_Renault Duster	-10291.130
make_model_Renault Clio	-5255.546
make_model_Opel Corsa	-5086.767
drive_chain_rear	-3802.868
make_model_Opel Astra	-3786.396
type_Employee's car	-2982.985
type_Used	-2824.140
drive_chain_front	-2384.019
type_Pre-registered	-2191.709
age	-1588.903

In [29]:
```
# Performance metrics

lm_score = train_val(linear_model, X_train, y_train, X_test, y_test, 'linear')
lm_score

# The model shows a high R² score on the training data (0.89) and R² score on the test data (0.88),indicating potential overfitting.
# The difference between MAE and RMSE indicates outlier effect.
```

Out[29]:

	linear_train	linear_test
R2	0.890	0.884
mae	1718.455	1725.509
mse	6088991.592	6259304.583
rmse	2467.588	2501.860

In [30]:
```
# Normalized RMSE
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
print('rmse:', rmse)

#Average error rate;
print('avg_error', rmse/df.price.mean())
```

```
rmse: 2501.8602245902453
avg_error 0.13822233395909522
```

In [31]:
```
# Adjusted R²

adj_r2(y_test, y_pred, df)

# Additionally, the Adjusted R² score (0.882) for the test data confirms that while the model explains a large portion of the variance,
# the inclusion of more features may not significantly improve the model's performance.
```

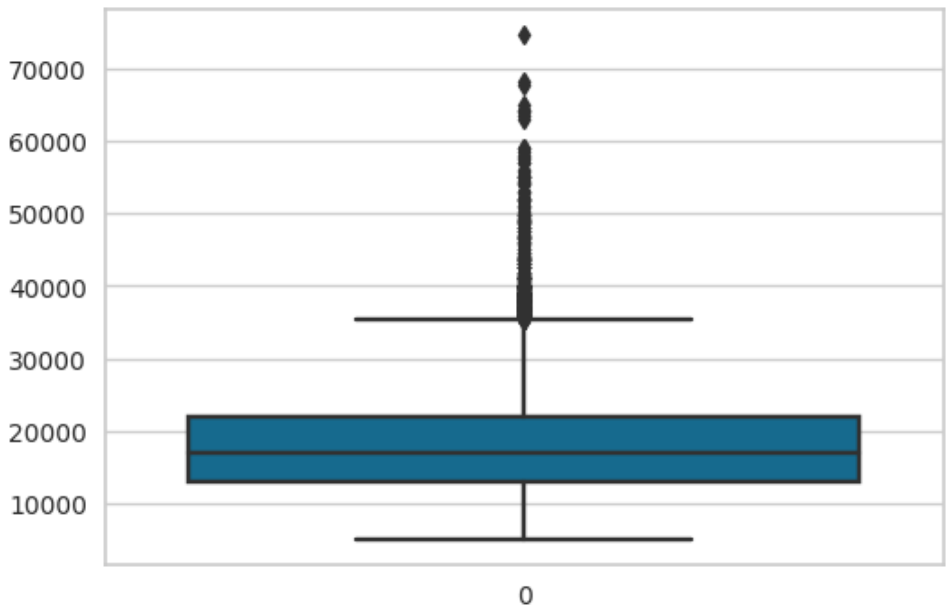
Out[31]: 0.8828492602064307

NOTE:

- Initial linear regression model was built using the provided dataset without any data manipulation.
- The model explains 88.2% of the variance in the target variable, indicating a strong fit but with some room for improvement.

Remove Outliers

In [141…
```
# Checking outliers for target variable 'price' with boxplot
plt.figure(figsize =(6,4))
sns.boxplot(df.price);
```

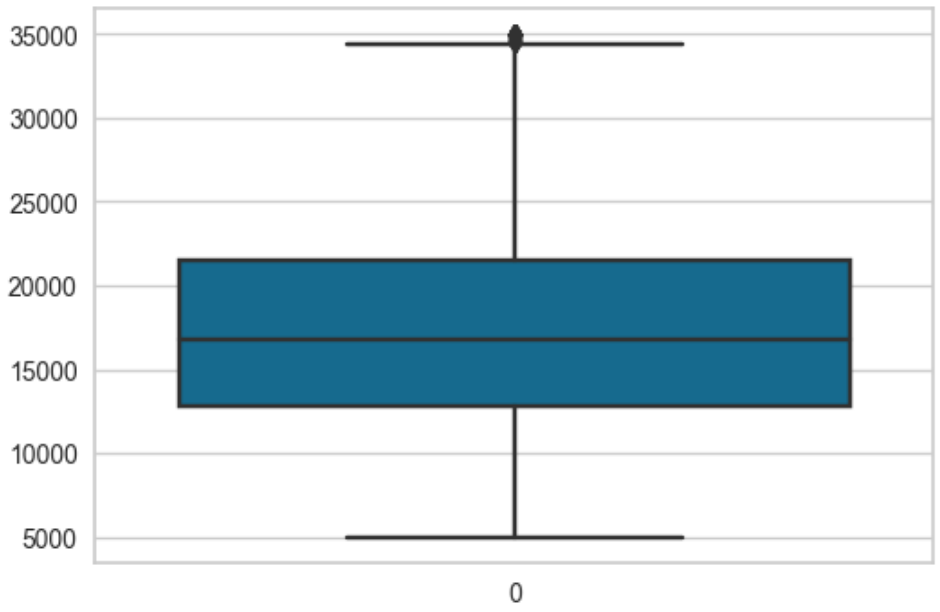


In [32]:
```
len(df[df.price > 35000])
```

Out[32]: 473

In [33]:
```
# Excluding rows where the price is greater than 35,000 using new df1

df1 = df[~(df.price > 35000)]
```

In [34]:
```
plt.figure(figsize = (6,4))
sns.boxplot(df1.price);
```



Linear Model Without Outliers

In [35]:
```
#Split the data for df1

X = df1.drop(columns = "price")
y = df1.price

#Split train-test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=101)
```

In [36]:
```
#Set and fit the model2

linear_model2 = LinearRegression()

linear_model2.fit(X_train, y_train)
```

Out[36]:
```
▾ LinearRegression

LinearRegression()
```

In [37]:
```
# Check the coefficients to see how it affects feature importance

lm2_coef = pd.DataFrame(linear_model2.coef_, index = X.columns, columns=["lm2_Coeff"]).sort_values("lm2_Coeff")
lm2_coef.head(10)
```

Out[37]:

	lm2_Coeff
make_model_Renault Duster	-9447.389
make_model_Renault Clio	-5424.873
make_model_Opel Corsa	-5245.299
make_model_Opel Astra	-3372.469
drive_chain_rear	-2859.199
type_Employee's car	-2090.024
type_Used	-1975.265
ex_Sliding door	-1618.279
gearing_type_Manual	-1581.537
age	-1445.872

In [38]:
```
# Prediction2

y_pred = linear_model2.predict(X_test)

# Calculation of the metrics of the test data to compare models at the end.
lm2_R2 = r2_score(y_test, y_pred)
lm2_mae = mean_absolute_error(y_test, y_pred)
lm2_rmse = np.sqrt(mean_squared_error(y_test, y_pred))

print(lm2_R2)
print(lm2_mae)
print(lm2_rmse)
```

```
0.8955794125789905
1415.3813117633913
1959.6494206641898
```

Evaluating the Model

In [40]:
```
# Performance Metrics

lm2_score = train_val(linear_model2, X_train, y_train, X_test, y_test, 'linear2_out')
lm2_score
```

Out[40]:

	linear2_out_train	linear2_out_test
R2	0.898	0.896
mae	1414.209	1415.381
mse	3792751.061	3840225.852
rmse	1947.499	1959.649

In [41]:
```
# Comparing the metric scores with Initial Linear Reg Model

results = pd.concat([lm_score, lm2_score], axis=1)
results
```

Out[41]:

	linear_train	linear_test	linear2_out_train	linear2_out_test
R2	0.890	0.884	0.898	0.896
mae	1718.455	1725.509	1414.209	1415.381
mse	6088991.592	6259304.583	3792751.061	3840225.852
rmse	2467.588	2501.860	1947.499	1959.649

In [42]:
```
# Normalized RMSE of linear model without outliers on target
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
print('rmse:', rmse)

#Average error rate;
print('avg_error', rmse/df1.price.mean())
```

```
rmse: 1959.6494206641898
avg_error 0.11316623260947056
```

- Before removing the outliers, our average prediction error was 13.81%.
- After excluding the outliers, it decreased to 11.31%.
- This represents an improvement of approximately 2.50% in our predictions.

Scale Data

- In this section, we will rebuild the models using data scaled with MinMaxScaler.
- Scaling the data helps to normalize the feature ranges, which can improve the performance and convergence speed of the models

In [43]:
```
#Split

X= df.drop(columns="price")
y= df.price
```

In [44]:
```
# Train-test split

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

In [45]:
```
#Scale -fit - transform

scaler = MinMaxScaler()

X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Regularization

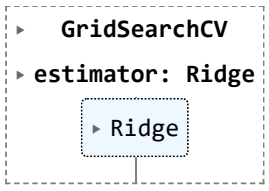
Ridge Regression

GridSearchCV for Ridge Model

In [46]:
```
from sklearn.model_selection import GridSearchCV

# Set the model
ridge = Ridge(random_state=42)



# Set the GridSearchCV and params
alpha_space = np.linspace(0.01, 100, 100)

param_grid = {"alpha":alpha_space}

ridge_model = GridSearchCV(estimator=ridge,
                           param_grid=param_grid,
                           scoring='neg_root_mean_squared_error',
                           cv=10,
                           n_jobs = -1)
```

In [47]:
```
# Fit the Model
ridge_model.fit(X_train_scaled,y_train)
```

Out[47]:



In [48]:
```
ridge_model.best_params_
```

Out[48]:
```
{'alpha': 1.02}
```

In [49]:
```
# We obtained the best parameters for the Ridge model with alpha=1.02 after performing GridSearchCV.

# Set the Ridge model again with best alpha value;
ridge_model_alpha = Ridge(alpha=1.02, random_state=42).fit(X_train_scaled, y_train)

# Check the coefficients to see how it affects feature importance
ridge_coef = pd.DataFrame(ridge_model_alpha.coef_, index = X.columns, columns=["ridge_Coef"]).sort_values("ridge_Coef")
ridge_coef.head(10)
```

Out[49]:

	ridge_Coef
km	-11817.904
make_model_Renault Duster	-9203.373
make_model_Renault Clio	-5251.673
make_model_Opel Corsa	-5205.966
age	-4820.489
make_model_Opel Astra	-3740.368
drive_chain_rear	-2987.850
type_Employee's car	-2968.042
type_Used	-2813.387
drive_chain_front	-2334.704

In [50]:
```
# Comparing the coefficients of the Ridge and initial linear regression models to assess feature importance

pd.concat([lm1_coef, ridge_coef], axis=1).head(10)
```

Out[50]:

	lm1_Coeff	ridge_Coef
make_model_Renault Duster	-10291.130	-9203.373
make_model_Renault Clio	-5255.546	-5251.673
make_model_Opel Corsa	-5086.767	-5205.966
drive_chain_rear	-3802.868	-2987.850
make_model_Opel Astra	-3786.396	-3740.368
type_Employee's car	-2982.985	-2968.042
type_Used	-2824.140	-2813.387
drive_chain_front	-2384.019	-2334.704
type_Pre-registered	-2191.709	-2169.132
age	-1588.903	-4820.489

- Prediction

In [51]:
```
# Prediction
y_pred = ridge_model.predict(X_test_scaled)

# Calculation of the metrics of the test data to compare models at the end.
ridge_R2 = r2_score(y_test, y_pred)
ridge_mae = mean_absolute_error(y_test, y_pred)
ridge_rmse = np.sqrt(mean_squared_error(y_test, y_pred))

print(ridge_R2)
print(ridge_mae)
print(ridge_rmse)
```

```
0.8841789579307733
1722.8854868936253
2499.231741944769
```

- Evaluating the Model

In [52]:
```
# Model evaluation metrics scores

ridge_scores = train_val(ridge_model, X_train_scaled, y_train, X_test_scaled, y_test, 'ridge')
ridge_scores
```

Out[52]:

	ridge_train	ridge_test
R2	0.890	0.884
mae	1716.690	1722.885
mse	6094440.410	6246159.300
rmse	2468.692	2499.232

In [53]:
```
# Comparing the metric scores of earlier Models vs Grid Ridge Model

result = pd.concat([results, ridge_scores], axis=1)
result
```

Out[53]:

	linear_train	linear_test	linear2_out_train	linear2_out_test	ridge_train	ridge_test
R2	0.890	0.884	0.898	0.896	0.890	0.884
mae	1718.455	1725.509	1414.209	1415.381	1716.690	1722.885
mse	6088991.592	6259304.583	3792751.061	3840225.852	6094440.410	6246159.300
rmse	2467.588	2501.860	1947.499	1959.649	2468.692	2499.232

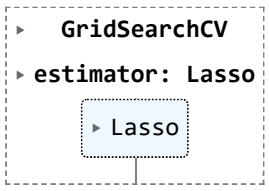
Lasso Regression

GridSearchCV for Lasso Model

In [54]:
```
# Set the model
lasso = Lasso(random_state=42)



# Set the GridSearchCV and params
alpha_space = np.linspace(0.01, 100, 100)

param_grid = {"alpha":alpha_space}

lasso_model = GridSearchCV(estimator=lasso,
                           param_grid=param_grid,
                           scoring='neg_root_mean_squared_error',
                           cv=10,
                           n_jobs = -1)
```

In [55]:
```
# Fit the Model
lasso_model.fit(X_train_scaled,y_train)
```

Out[55]:



In [167…
```
lasso_model.best_params_
```

Out[167…
```
{'alpha': 1.02}
```

In [56]:
```
# We obtained the best parameters for the Lasso model with alpha=1.02 after performing GridSearchCV.

# Set the Lasso model again with best alpha params;
lasso_model_alpha = Lasso(alpha=1.02, random_state=42).fit(X_train_scaled, y_train)

# Check the coefficients to see how it affects feature importance
lasso_coef = pd.DataFrame(lasso_model_alpha.coef_, index = X.columns, columns=["lasso_Coef"]).sort_values("lasso_Coef")
lasso_coef.head(10)
```

Out[56]:

	lasso_Coef
km	-11876.922
make_model_Renault Duster	-9094.844
make_model_Renault Clio	-5185.972
make_model_Opel Corsa	-5114.657
age	-4817.747
make_model_Opel Astra	-3749.536
type_Employee's car	-2890.334
type_Used	-2751.131
drive_chain_front	-2142.016
type_Pre-registered	-2080.564

In [57]:
```
pd.concat([ridge_coef, lasso_coef], axis=1).head(10)

# Comparing the coefficients of the Ridge and Lasso regression models,
# to understand how each regularization technique affects feature importance
```

Out[57]:

	ridge_Coef	lasso_Coef
km	-11817.904	-11876.922
make_model_Renault Duster	-9203.373	-9094.844
make_model_Renault Clio	-5251.673	-5185.972
make_model_Opel Corsa	-5205.966	-5114.657
age	-4820.489	-4817.747
make_model_Opel Astra	-3740.368	-3749.536
drive_chain_rear	-2987.850	-647.723
type_Employee's car	-2968.042	-2890.334
type_Used	-2813.387	-2751.131
drive_chain_front	-2334.704	-2142.016

- Prediction

In [58]:
```
# Prediction
y_pred = lasso_model.predict(X_test_scaled)

# Calculation of the metrics of the test data to compare models at the end.
lasso_R2 = r2_score(y_test, y_pred)
lasso_mae = mean_absolute_error(y_test, y_pred)
lasso_rmse = np.sqrt(mean_squared_error(y_test, y_pred))

print(lasso_R2)
print(lasso_mae)
print(lasso_rmse)
```

```
0.8845643139633643
1721.927898452896
2495.0705962639568
```

- Evaluating the Lasso Model

In [59]:
```
# Model evaluation metrics scores

lasso_scores = train_val(lasso_model, X_train_scaled, y_train, X_test_scaled, y_test, 'lasso')
lasso_scores
```

Out[59]:

	lasso_train	lasso_test
R2	0.890	0.885
mae	1719.602	1721.928
mse	6107178.086	6225377.280
rmse	2471.271	2495.071

In [60]:
```
# Comparing the metric scores of Grid Ridge and Grid Lasso models to evaluate their performance, and
# to assess how each regularization technique affects the model's predictive accuracy and error metrics.

result = pd.concat([result, lasso_scores], axis=1)
result
```

Out[60]:

	linear_train	linear_test	linear2_out_train	linear2_out_test	ridge_train	ridge_test	lasso_train	lasso_test
R2	0.890	0.884	0.898	0.896	0.890	0.884	0.890	0.885
mae	1718.455	1725.509	1414.209	1415.381	1716.690	1722.885	1719.602	1721.928
mse	6088991.592	6259304.583	3792751.061	3840225.852	6094440.410	6246159.300	6107178.086	6225377.280
rmse	2467.588	2501.860	1947.499	1959.649	2468.692	2499.232	2471.271	2495.071

- The comparison of metric scores indicates that both Grid Ridge and Grid Lasso models perform similarly,
- with Lasso slightly outperforming Ridge in test set R^2 and RMSE,
- suggesting marginally better generalization for the Lasso model.

Elastic-Net Regression

GridSearchCV for ElasticNet Model

In [61]:
```
# Set the model
elastic = ElasticNet(random_state=42)



# Set the GridSearchCV and params for ElasticNet (alpha and l1_ratio)
param_grid = {
    'alpha': [1.02, 2, 3, 4, 5, 7, 10, 11],
    'l1_ratio': [.5, .7, .9, .95, .99, 1]
}
```

```
elastic_model = GridSearchCV(estimator=elastic,
                             param_grid=param_grid,
                             scoring='neg_root_mean_squared_error',
                             cv=10,
                             n_jobs=-1)
```

alpha:

- This parameter controls the overall regularization strength.
- When alpha = 0, ElasticNet performs no regularization.

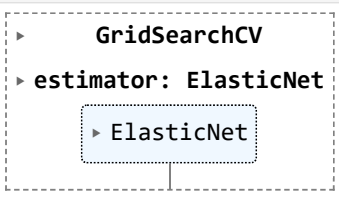
= As the alpha value increases, the strength of regularization increases, which can help the model become more resistant to overfitting.

l1_ratio:

- This parameter controls the mixture between L1 (Lasso) and L2 (Ridge) regularization.
- When l1_ratio = 1, it means this is entirely L1 (i.e., only Lasso).
- When l1_ratio = 0, it means this is entirely L2 (i.e., only Ridge).
- When 0 < l1_ratio < 1, you get a combination of both L1 and L2 regularizations.
- For example, if l1_ratio = 0.5, it means L1 and L2 regularizations are used equally.

In [62]:
```
# Fit the Model
elastic_model.fit(X_train_scaled,y_train)
```

Out[62]:



In [63]:
```
elastic_model.best_params_
```

Out[63]:
```
{'alpha': 1.02, 'l1_ratio': 1}
```

In [64]:
```
# Prediction
y_pred = elastic_model.predict(X_test_scaled)

# Calculation of the metrics of the test data to compare models at the end.
em_R2 = r2_score(y_test, y_pred)
em_mae = mean_absolute_error(y_test, y_pred)
em_rmse = np.sqrt(mean_squared_error(y_test, y_pred))

print(em_R2)
print(em_mae)
print(em_rmse)
```

```
0.8845643139633643
1721.927898452896
2495.0705962639568
```

In [65]:
```
# Model evaluation metrics scores

elastic_scores = train_val(elastic_model, X_train_scaled, y_train, X_test_scaled, y_test, 'elastic')
elastic_scores
```

Out[65]:

	elastic_train	elastic_test
R2	0.890	0.885
mae	1719.602	1721.928
mse	6107178.086	6225377.280
rmse	2471.271	2495.071

In [66]:
```
# Comparing the metric scores of models to evaluate their performance, and
# to assess how each regularization technique affects the model's predictive accuracy and error metrics.

result = pd.concat([result, elastic_scores], axis=1)
result
```

Out[66]:

	linear_train	linear_test	linear2_out_train	linear2_out_test	ridge_train	ridge_test	lasso_train	lasso_test	elastic_train	elastic_test
R2	0.890	0.884	0.898	0.896	0.890	0.884	0.890	0.885	0.890	0.885
mae	1718.455	1725.509	1414.209	1415.381	1716.690	1722.885	1719.602	1721.928	1719.602	1721.928
mse	6088991.592	6259304.583	3792751.061	3840225.852	6094440.410	6246159.300	6107178.086	6225377.280	6107178.086	6225377.280
rmse	2467.588	2501.860	1947.499	1959.649	2468.692	2499.232	2471.271	2495.071	2471.271	2495.071

Comparing all Models

- The linear2_out model, where outliers were excluded from the target feature, showed the best performance with the highest R^2 scores and the lowest MAE, MSE, and RMSE, But Considering Overfitting.
- Ridge, Lasso, and Elastic Net regressions with scale had similar performance, not significantly better than the second linear model.
- By combining the benefits of outlier removal and Lasso regularization, could achieve a more accurate and interpretable model.

--> Let's try to see the combined model: Lasso Model without Outliers

Lasso2 (alpha=1.02) Model without Outliers

In [67]:
```
# Excluding rows where the price is greater than 35,000 using df_final
print(len(df[df.price > 35000]))

df2 = df[~(df.price > 35000)]
```

```
473
```

In [68]:
```
#Split the data

X = df2.drop(columns = "price")
y = df2.price
```

In [69]:
```
# Split train-test

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=101)
```

In [70]:
```
#Scale -fit - transform - X

scaler = MinMaxScaler()

X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

- Model

In [71]:
```
# Set the model
lasso2 = Lasso(alpha=1.02, random_state=42)
```

In [72]:
```
# Fit the Model
lasso2.fit(X_train_scaled,y_train)
```

Out[72]:
```
Lasso(alpha=1.02, random_state=42)
```

- Prediction

In [73]:
```
# Prediction
y_pred = lasso2.predict(X_test_scaled)

# Calculation of the metrics of the test data to compare models at the end.
lasso2_R2 = r2_score(y_test, y_pred)
lasso2_mae = mean_absolute_error(y_test, y_pred)
lasso2_rmse = np.sqrt(mean_squared_error(y_test, y_pred))

print(lasso2_R2)
print(lasso2_mae)
print(lasso2_rmse)
```

```
0.8962714979555529
1408.9561317098285
1953.144480067058
```

- Evaluating the Lasso Model

In [74]:
```
# Model evaluation metrics scores

lasso2_scores = train_val(lasso2, X_train_scaled, y_train, X_test_scaled, y_test, 'lasso2')
lasso2_scores
```

Out[74]:

	lasso2_train	lasso2_test
R2	0.898	0.896
mae	1414.186	1408.956
mse	3806891.515	3814773.360
rmse	1951.126	1953.144

In [75]:
```
# Comparing the metric scores of Grid Ridge and Grid Lasso models to evaluate their performance, and
# to assess how each regularization technique affects the model's predictive accuracy and error metrics.

result = pd.concat([result, lasso2_scores], axis=1)
result
```

Out[75]:

	linear_train	linear_test	linear2_out_train	linear2_out_test	ridge_train	ridge_test	lasso_train	lasso_test	elastic_train	elastic_test	lasso2_tra
R2	0.890	0.884	0.898	0.896	0.890	0.884	0.890	0.885	0.890	0.885	0.8
mae	1718.455	1725.509	1414.209	1415.381	1716.690	1722.885	1719.602	1721.928	1719.602	1721.928	1414.1
mse	6088991.592	6259304.583	3792751.061	3840225.852	6094440.410	6246159.300	6107178.086	6225377.280	6107178.086	6225377.280	3806891.5
rmse	2467.588	2501.860	1947.499	1959.649	2468.692	2499.232	2471.271	2495.071	2471.271	2495.071	1951.1

Comparing Models:

- The Ridge model, while scaled, does not outperform the Linear2 and Final Lasso models, indicating that the additional complexity does not provide a significant benefit in this case.

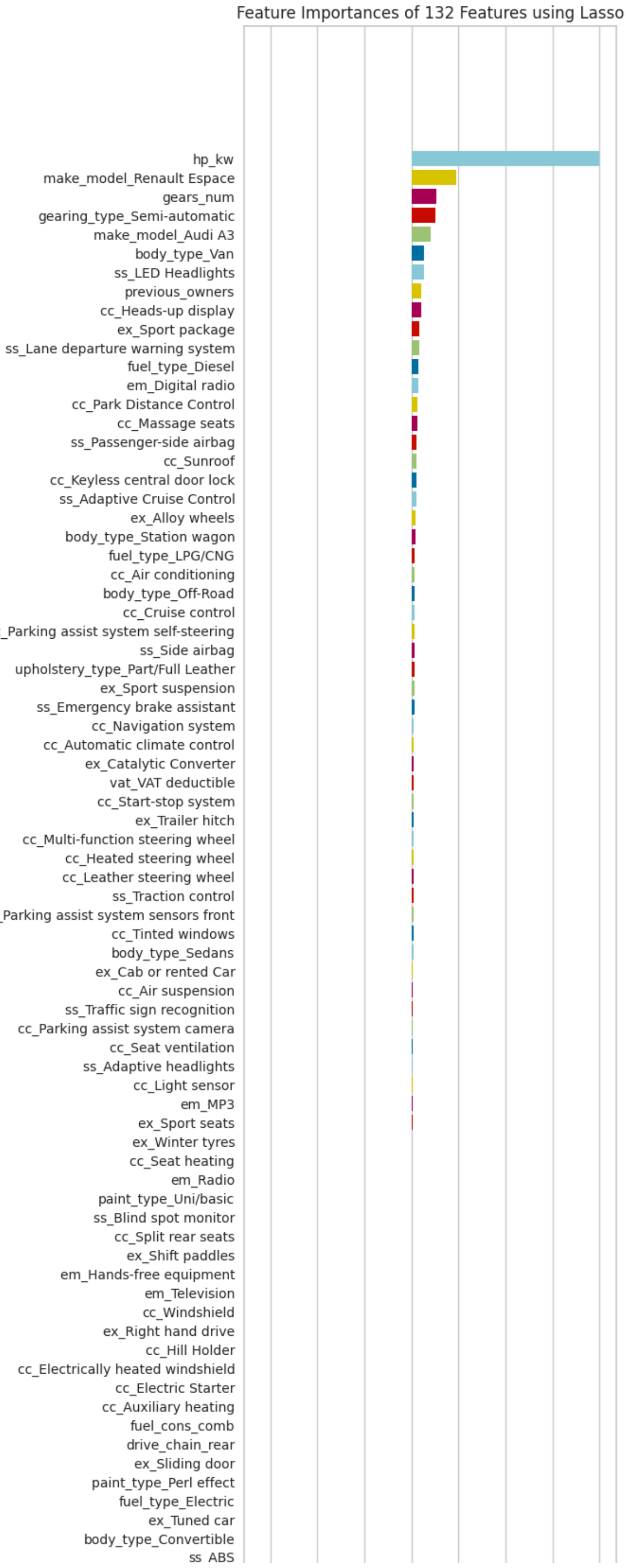
Recommendation for the Final Model:

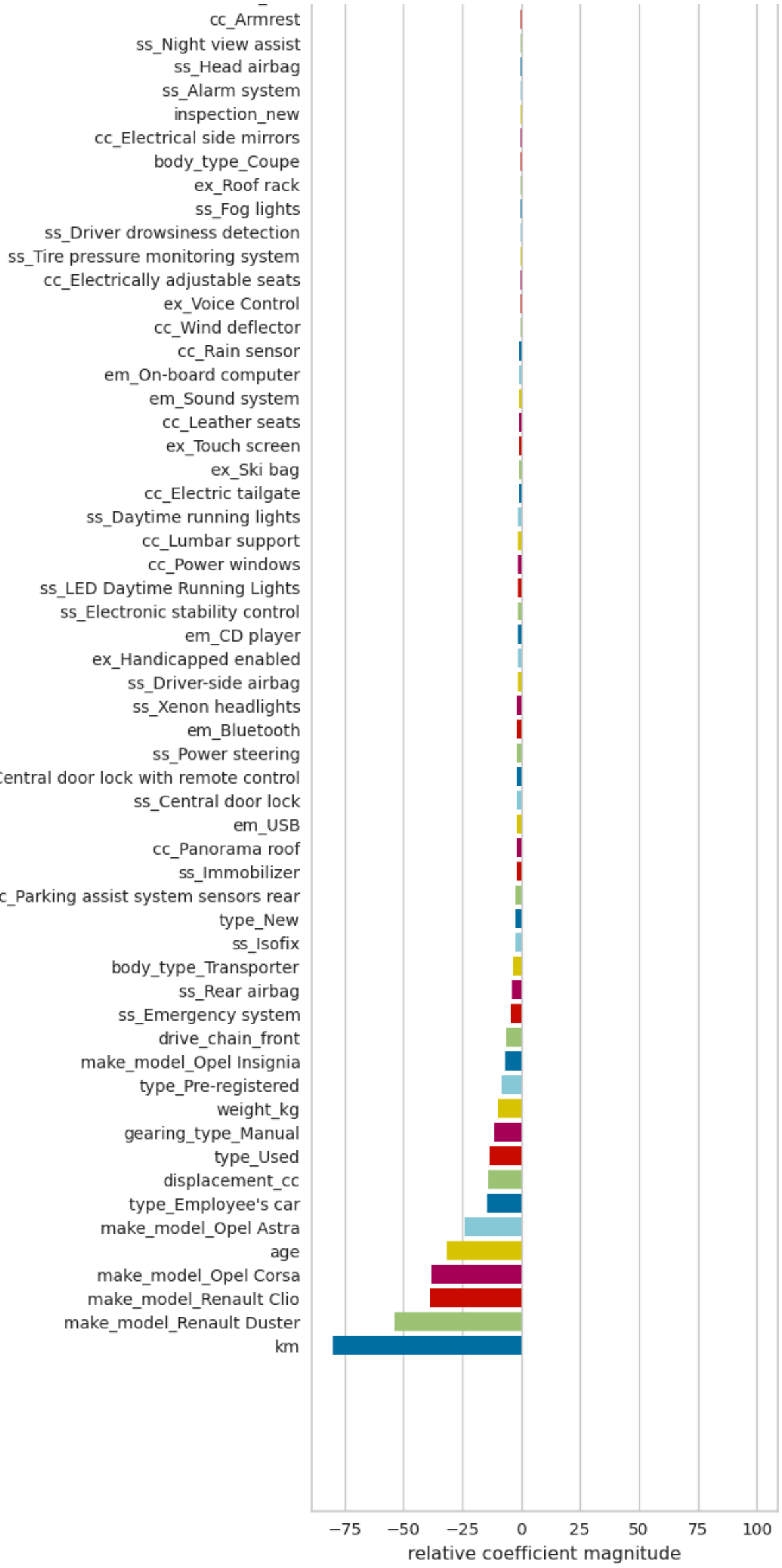
- The Lasso2 model is recommended as it combines the benefits of regularization through Lasso, data scaling, and outlier removal, leading to robust performance and minimal overfitting.

Feature Importance

In [103…

```
from yellowbrick.model_selection import FeatureImportances
from yellowbrick.features import RadViz

viz = FeatureImportances(Lasso(alpha=1.02), labels=X_train.columns) # Lasso Model is selected here
visualizer = RadViz(size=(720, 3000))
viz.fit(X_train_scaled, y_train)
viz.show()

# We will use Lasso for the Final model
```


Feature Importances of 132 Features using Lasso
hp_kw
make_model_Renault Espace
gears_num
gearing_type_Semi-automatic
make_model_Audi A3
body_type_Van
ss_LED Headlights
previous_owners
cc_Heads-up display
ex_Sport package
ss_Lane departure warning system
fuel_type_Diesel
em_Digital radio
cc_Park Distance Control
cc_Massage seats
ss_Passenger-side airbag
cc_Sunroof
cc_Keyless central door lock
ss_Adaptive Cruise Control
ex_Alloy wheels
body_type_Station wagon
fuel_type_LPG/CNG
cc_Air conditioning
body_type_Off-Road
cc_Cruise control
cc_Parking assist system self-steering
ss_Side airbag
upholstery_type_Part/Full Leather
ex_Sport suspension
ss_Emergency brake assistant
cc_Navigation system
cc_Automatic climate control
ex_Catalytic Converter
vat_VAT deductible
cc_Start-stop system
ex_Trailer hitch
cc_Multi-function steering wheel
cc_Heated steering wheel
cc_Leather steering wheel
ss_Traction control
cc_Parking assist system sensors front
cc_Tinted windows
body_type_Sedans
ex_Cab or rented Car
cc_Air suspension
ss_Traffic sign recognition
cc_Parking assist system camera
cc_Seat ventilation
ss_Adaptive headlights
cc_Light sensor
em_MP3
ex_Sport seats
ex_Winter tyres
cc_Seat heating
em_Radio
paint_type_Uni/basic
ss_Blind spot monitor
cc_Split rear seats
ex_Shift paddles
em_Hands-free equipment
em_Television
cc_Windshield
ex_Right hand drive
cc_Hill Holder
cc_Electrically heated windshield
cc_Electric Starter
cc_Auxiliary heating
fuel_cons_comb
drive_chain_rear
ex_Sliding door
paint_type_Perl effect
fuel_type_Electric
ex_Tuned car
body_type_Convertible
ss_ABS



Out[103… <Axes: title={'center': 'Feature Importances of 132 Features using Lasso'}, xlabel='relative coefficient magnitude'>

Lasso3 Model with Selected Features

In [76]:
```
# Create new df with the selected features

df_new = df0[["make_model", "hp_kW", "km", "age", "Gearing_Type", "price"]]

# Selecting the top 5 features with the most impact on prediction.
# You might wonder why the make_model feature was chosen. When examining the visualization above,
# it was observed that among the features with the most impact on prediction, the make_model feature includes unique categorical observations
```

In [189…
```
df_new.head()
```

Out[189...

	make_model	hp_kW	km	age	Gearing_Type	price
0	Audi A1	66.000	56013.000	3.000	Automatic	15770
1	Audi A1	141.000	80000.000	2.000	Automatic	14500
2	Audi A1	85.000	83450.000	3.000	Automatic	14640
3	Audi A1	66.000	73000.000	3.000	Automatic	14500
4	Audi A1	66.000	16200.000	3.000	Automatic	16790

In [77]:
```
df_new.make_model.value_counts()
```

Out[77]:
```
make_model
Audi A3           3097
Audi A1           2614
Opel Insignia     2598
Opel Astra        2525
Opel Corsa        2216
Renault Clio      1839
Renault Espace     991
Renault Duster      34
Audi A2              1
Name: count, dtype: int64
```

In [78]:
```
df_new = df_new[df_new['make_model'] != 'Audi A2']  # Excluding data has only 1 value
```

In [79]:
```
df_new = df_new[~(df_new.price > 35000)] # Excluding the Outliers from target feature
```

In [80]:
```
df_new = pd.get_dummies(df_new) # Get Dummies for the final dataset

print(len(df_new))
df_new.head(3)

# After get dummy, features have boolean dtype.
```

```
15419
```

Out[80]:

	hp_kW	km	age	price	make_model_Audi A1	make_model_Audi A3	make_model_Opel Astra	make_model_Opel Corsa	make_model_Opel Insignia	make_model_Renault Clio	m
0	66.000	56013.000	3.000	15770	True	False	False	False	False	False	
1	141.000	80000.000	2.000	14500	True	False	False	False	False	False	
2	85.000	83450.000	3.000	14640	True	False	False	False	False	False	

Split and Scale for df_new

In [81]:
```
X = df_new.drop(columns=["price"])
y = df_new.price
```

In [82]:
```
X_train, X_test, y_train, y_test = train_test_split(X,
                                                    y,
                                                    test_size=0.2,
                                                    random_state=42)
```

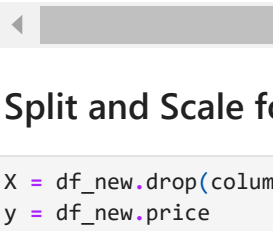
In [83]:
```
scaler = MinMaxScaler()
scaler.fit(X_train)

X_train_scaled = scaler.transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Model

In [84]:
```
lasso_model = Lasso(random_state=42)

param_grid = {'alpha': alpha_space}

lasso3 = GridSearchCV(estimator=lasso_model,
                      param_grid=param_grid,
                      scoring='neg_root_mean_squared_error',
                      cv=10,
                      n_jobs=-1)
```

In [85]:
```
lasso3.fit(X_train_scaled, y_train)
```

Out[85]:



In [86]:
```
lasso3.best_params_
```

Out[86]:
```
{'alpha': 0.01}
```

In [87]:
```
lasso3.best_score_ # best score of the test data
```

Out[87]: -2239.588352950935

In [88]:
```
#Prediction
y_pred = lasso3.predict(X_test_scaled)

lasso3_R2 = r2_score(y_test, y_pred)
lasso3_mae = mean_absolute_error(y_test, y_pred)
lasso3_rmse = np.sqrt(mean_squared_error(y_test, y_pred))
```

In [89]:
```
# Model evaluation metrics scores

lasso3_scores = train_val(lasso3, X_train_scaled, y_train, X_test_scaled, y_test, 'lasso3')
lasso3_scores
```

Out[89]:

	lasso3_train	lasso3_test
R2	0.867	0.877
mae	1611.742	1553.998
mse	5007030.903	4547724.302
rmse	2237.640	2132.539

In [90]:
```
result = pd.concat([result, lasso3_scores], axis=1)
result
```

Out[90]:

	linear_train	linear_test	linear2_out_train	linear2_out_test	ridge_train	ridge_test	lasso_train	lasso_test	elastic_train	elastic_test	lasso2_tra
R2	0.890	0.884	0.898	0.896	0.890	0.884	0.890	0.885	0.890	0.885	0.8
mae	1718.455	1725.509	1414.209	1415.381	1716.690	1722.885	1719.602	1721.928	1719.602	1721.928	1414.1
mse	6088991.592	6259304.583	3792751.061	3840225.852	6094440.410	6246159.300	6107178.086	6225377.280	6107178.086	6225377.280	3806891.5
rmse	2467.588	2501.860	1947.499	1959.649	2468.692	2499.232	2471.271	2495.071	2471.271	2495.071	1951.1

- The Lasso3 model, which included only the selected features `["make_model", "hp_kW", "km", "age", "Gearing_Type", "price"]`, demonstrated slightly lower performance with R^2 scores of 0.867 (train) and 0.877 (test), but it still maintained a reasonable prediction accuracy.

- Overall, the lasso2 model, where outlier excluded with Lasso regularization on the original df, provides the best balance of accuracy and robustness, indicating that removing outliers and focusing on relevant features significantly improves model performance.

Compare Models Performance

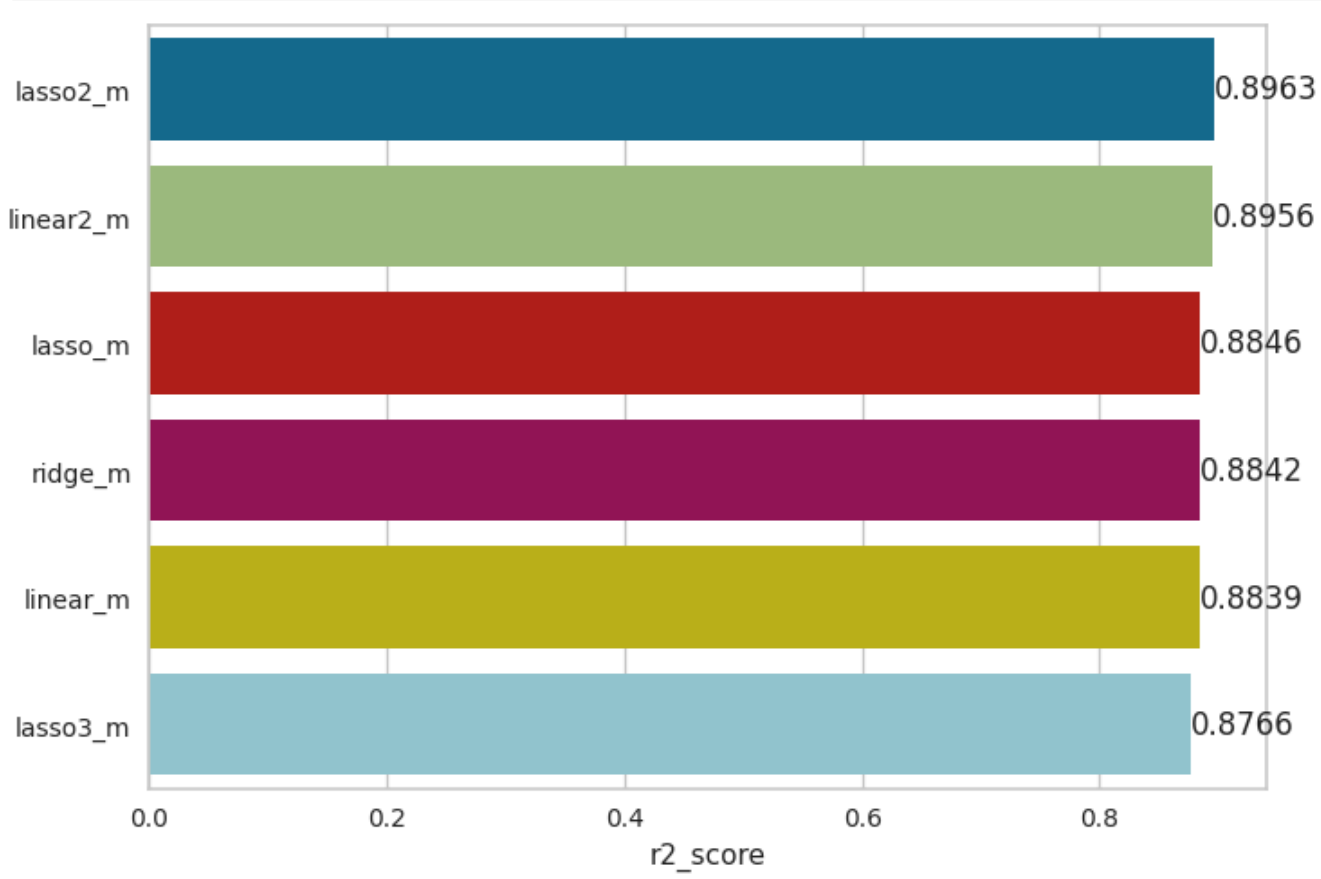
In [203…
```
scores = {
    "linear_m": {
        "r2_score": lm_R2,
        "mae": lm_mae,
        "rmse": lm_rmse
    },
    "linear2_m": {
        "r2_score": lm2_R2,
        "mae": lm2_mae,
        "rmse": lm2_rmse
    },
    "ridge_m": {
        "r2_score": ridge_R2,
        "mae": ridge_mae,
        "rmse": ridge_rmse
    },
    "lasso_m": {
        "r2_score": lasso_R2,
        "mae": lasso_mae,
        "rmse": lasso_rmse
    },
     "lasso2_m": {
        "r2_score": lasso2_R2,
        "mae": lasso2_mae,
        "rmse": lasso2_rmse
    },
    "lasso3_m": {
        "r2_score": lasso3_R2,
        "mae": lasso3_mae,
        "rmse": lasso3_rmse
    }
}
scores = pd.DataFrame(scores).T
scores
```

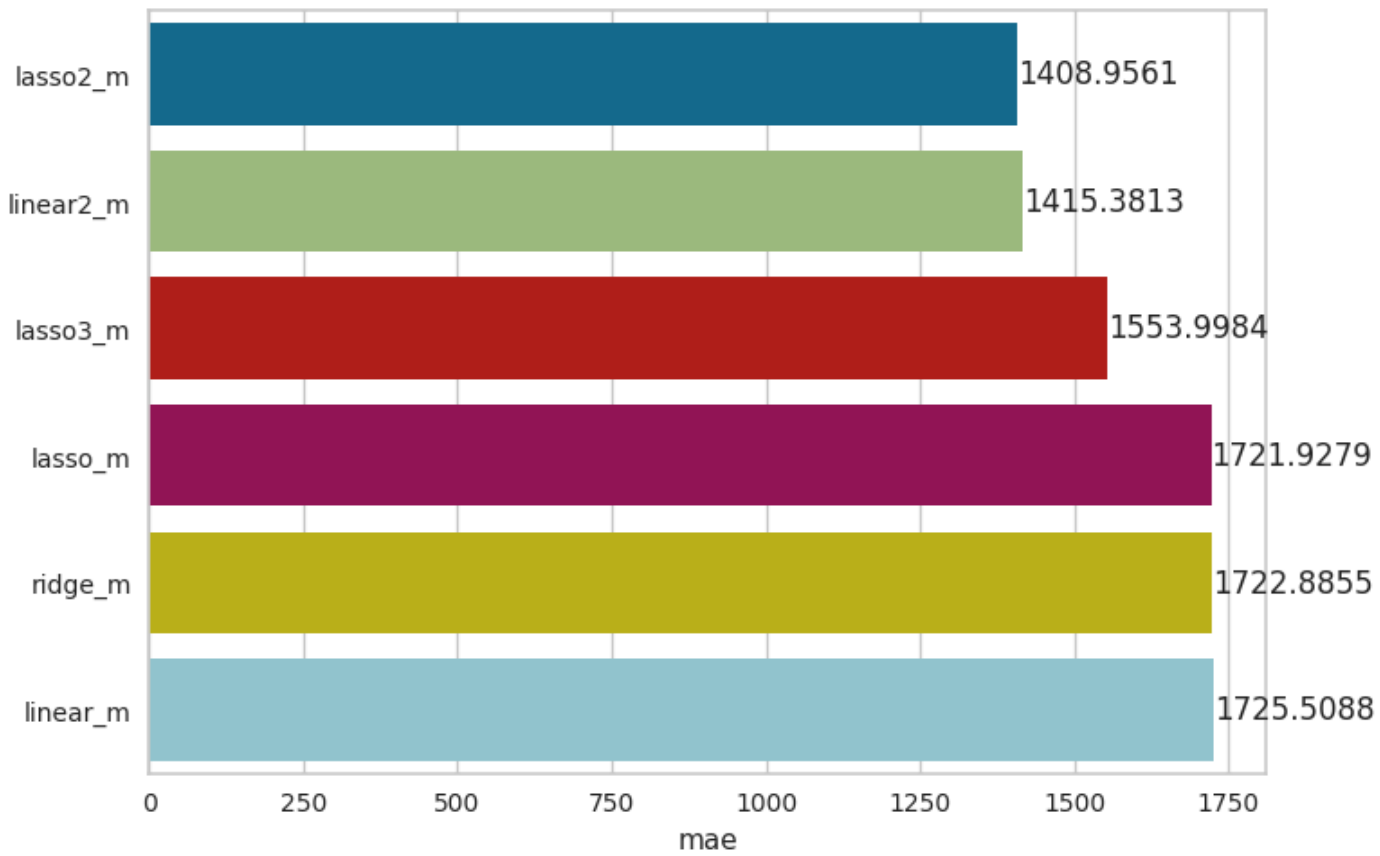
Out[203…

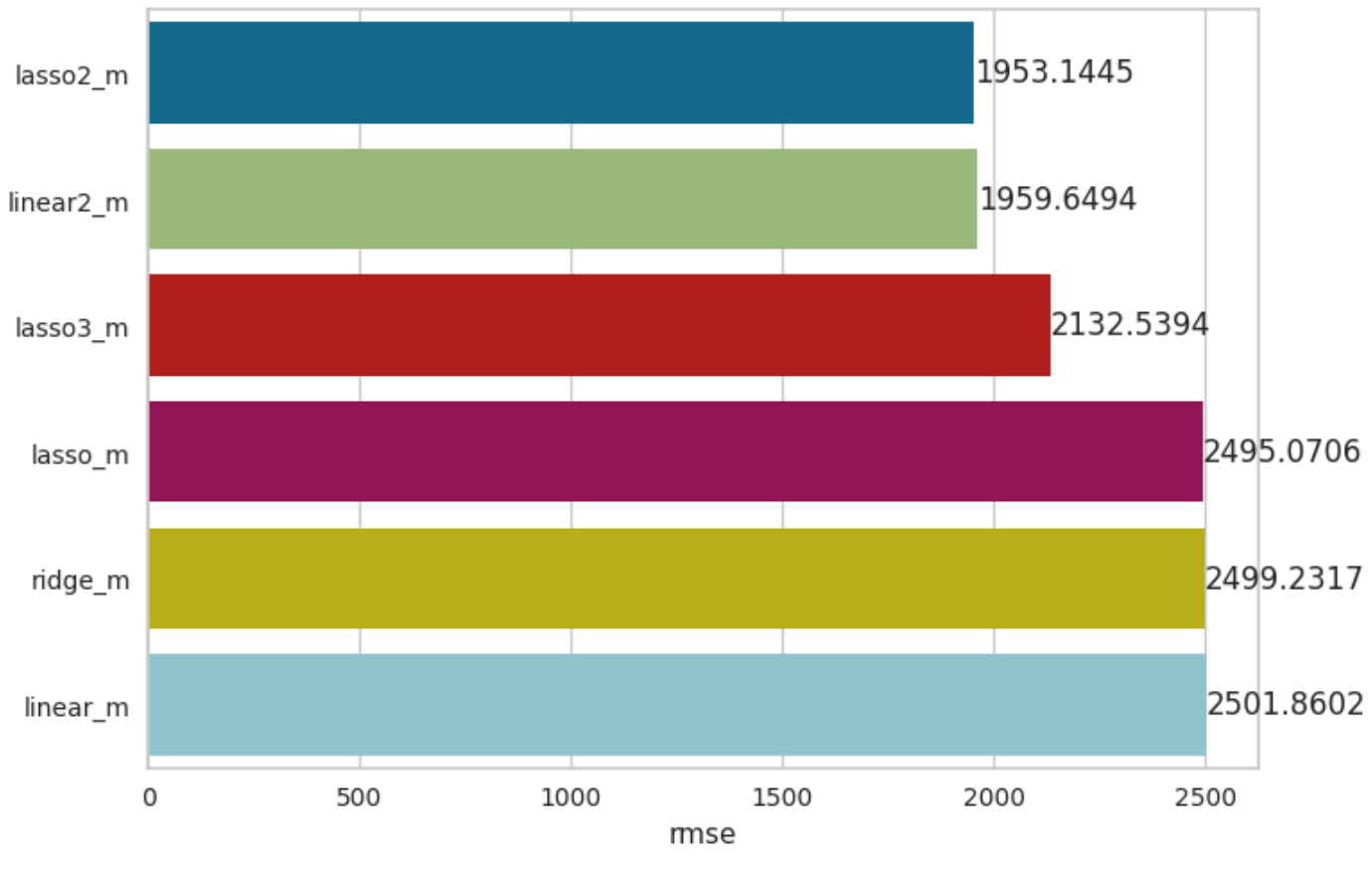
	r2_score	mae	rmse
linear_m	0.884	1725.509	2501.860
linear2_m	0.896	1415.381	1959.649
ridge_m	0.884	1722.885	2499.232
lasso_m	0.885	1721.928	2495.071
lasso2_m	0.896	1408.956	1953.144
lasso3_m	0.877	1553.998	2132.539

In [204…

```
#metrics = scores.columns

for i, j in enumerate(scores):
    plt.figure(i)
    if j == "r2_score":
        ascending = False
    else:
        ascending = True
    compare = scores.sort_values(by=j, ascending=ascending)
    ax = sns.barplot(x = compare[j] , y= compare.index)
    for p in ax.patches:
            width = p.get_width()                       # get bar length
            ax.text(width,                              # set the text at 1 unit right of the bar
                    p.get_y() + p.get_height() / 2,     # get Y coordinate + X coordinate / 2
                    '{:.4f}'.format(width),             # set variable to display, 2 decimals
                    ha = 'left',                        # horizontal alignment
                    va = 'center')
```







Conclusion:

- The lasso2_m model, which excludes outliers and applies Lasso regularization, consistently performs the best across all metrics (R^2, MAE, MSE), making it the most effective model.
- The final_m model, which includes feature selection, also shows good performance, particularly in MAE and MSE, but does not outperform lasso2_m.
- Regularization techniques like Lasso and Ridge improve model performance compared to the simple linear model, but removing outliers significantly enhances the results.
    - **Based on these metrics, the lasso2_m model is recommended for its superior accuracy and lower error rates.**

Final Model

- As selected, the Lasso2 model will be used for the final model where we removed the outliers and applied Lasso regularization alpha=0.01

Model

In [91]:
```
# Excluding rows where the price is greater than 35,000 using df_final
print(len(df[df.price > 35000]))

df2 = df[~(df.price > 35000)]
```

```
473
```

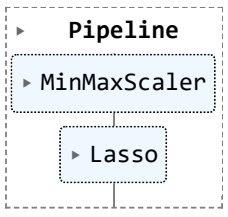
In [92]:
```
df2.shape
```

Out[92]:
```
(13768, 133)
```

In [93]:
```
#Split the data
X = df2.drop(columns = "price")
y = df2.price
```

In [94]:
```
# Set the model and scaler with pipline

operations = [('scaler', MinMaxScaler()),('lasso', Lasso(alpha=1.02))]
final_model = Pipeline(steps=operations)
final_model.fit(X,y)
```

Out[94]:



In [95]:
```
import pickle

# To export the model
pickle.dump(final_model, open('AutoScout24','wb'))
```

In [96]:
```
final_model = pickle.load(open('AutoScout24','rb'))
```

Predict New Observations

Creating new samples for prediction

In [97]:
```
# Get the columns of the original dataset
columns = df2.drop(columns=['price']).columns

# Generate random values (using normal distribution)
n_samples = 5
n_features = len(columns)
random_data = np.random.normal(loc=0, scale=1, size=(n_samples, n_features))

# Convert the new random data sample to a DataFrame
new_sample = pd.DataFrame(random_data, columns=columns)

print(new_sample.shape)
new_sample.head()
```

```
(5, 132)
```

Out[97]:

	km	gears_num	age	previous_owners	hp_kw	inspection_new	displacement_cc	weight_kg	fuel_cons_comb	cc_Air conditioning	cc_Air suspension	cc_Armrest
0	0.296	1.050	-1.339	-0.306	-0.132	1.263	-2.719	-0.722	-1.255	-0.375	-0.020	-0.828
1	0.197	1.646	-1.348	0.242	0.041	1.475	1.072	0.381	0.538	0.064	1.973	1.406
2	-0.651	-0.798	0.123	-1.315	0.029	-0.603	-1.799	-0.411	-1.713	1.751	-1.649	1.237
3	0.470	1.441	0.368	1.032	-0.175	0.694	-0.526	1.558	1.243	-0.327	-2.118	0.798
4	0.788	-0.072	1.740	-2.168	-0.597	2.094	1.436	-0.923	-0.838	0.012	0.157	1.753

In [98]:
```
# Scale the new sample data using the pre-fitted MinMaxScaler

new_sample_scaled = final_model.named_steps['scaler'].transform(new_sample)
```

In [99]:
```
# Prediction

y_pred = final_model.predict(new_sample_scaled)

y_pred_df = pd.DataFrame(y_pred, columns=['Predicted Prices'])
y_pred_df
```

Out[99]:

	Predicted Prices
0	10720.644
1	-1529.746
2	5049.185
3	19688.395
4	27830.784

Thank you...

Duygu Jones | Data Scientist | 2024

Follow me: duygujones.com | Linkedin | GitHub | Kaggle | Medium | Tableau