Python [conda env:DataScience]

Model Development: Automovile v.11

UCI Machine Learning Repository: Automovile

- **Dataset with data for this instance:**
- Data folder: https://archive.ics.uci.edu/ml/machine-learning-databases/autos/imports-85.data
- Dataset description: https://archive.ics.uci.edu/ml/machine-learning-databases/autos/imports-85.names

Sources:

1. 1985 Imported Car and Truck Specifications, Ward's 1985 Automotive Yearbook.
2. Personal Automobile Manuals, Insurance Services Bureau, 160 Water Street, New York, NY 10038
3. Insurance Collision Report, Insurance Institute for Highway Safety, Watergate 600, Washington, DC 20037

Dataset Information:

This dataset consists of three types of entities: (a) a car's specification in terms of various characteristics, (b) its assigned insurance risk rating, (c) its normalized losses in use compared to other cars. The second rating corresponds to the degree to which the car is riskier than its price indicates. Cars are initially assigned a risk factor symbol associated with their price. Then, if it is riskier (or less), this symbol is adjusted by moving it up (or down) the scale. Actuaries call this process "symbolization." A value of +3 indicates that the car is risky, -3 that it is probably quite safe.

The third factor is the relative average loss payment per insured vehicle per year. This value is normalized to all cars within a particular size classification (small two-door, station wagon, sport/special, etc.) and represents the average loss per car per year.

Note: Several of the attributes in the database could be used as a "class" attribute.

Attribute Information:

Attribute: Attribute Range

1. symboling: -3, -2, -1, 0, 1, 2, 3.
2. normalized-losses: continuous from 65 to 256.
3. make:

alfa-romeo, audi, bmw, chevrolet, dodge, honda, isuzu, jaguar, mazda, mercedes-benz, mercury, mitsubishi, nissan, peugot, plymouth, porsche, renault, saab, subaru, toyota, volkswagen, volvo

4. fuel-type: diesel, gas.
5. aspiration: std, turbo.
6. num-of-doors: four, two.
7. body-style: hardtop, wagon, sedan, hatchback, convertible.
8. drive-wheels: 4wd, fwd, rwd.
9. engine-location: front, rear.
10. wheel-base: continuous from 86.6 120.9.
11. length: continuous from 141.1 to 208.1.
12. width: continuous from 60.3 to 72.3.
13. height: continuous from 47.8 to 59.8.
14. curb-weight: continuous from 1488 to 4066.
15. engine-type: dohc, dohcv, l, ohc, ohcf, ohcv, rotor.
16. num-of-cylinders: eight, five, four, six, three, twelve, two.
17. engine-size: continuous from 61 to 326.
18. fuel-system: 1bbl, 2bbl, 4bbl, idi, mfi, mpfi, spdi, spfi.
19. bore: continuous from 2.54 to 3.94.
20. stroke: continuous from 2.07 to 4.17.
21. compression-ratio: continuous from 7 to 23.
22. horsepower: continuous from 48 to 288.
23. peak-rpm: continuous from 4150 to 6600.
24. city-mpg: continuous from 13 to 49.
25. highway-mpg: continuous from 16 to 54.
26. price: continuous from 5118 to 45400.

- **Necessary packages and libraries:**

In [1]:
```
# Basic Library Imports
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
import datetime
import scipy.stats
import warnings
import re
import wget

# Jupyter Lab config
%matplotlib inline

# Data Preprocessing
from sklearn.preprocessing import StandardScaler

# Feature Selection and Dimensionality Reduction
from sklearn.feature_selection import RFE
from sklearn.decomposition import PCA
```

```python
from mpl_toolkits.mplot3d import Axes3D

# Models and Assessment Tools
from sklearn.model_selection import train_test_split, cross_val_score, Gr
from sklearn.linear_model import LinearRegression, Ridge
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegre
from sklearn.pipeline import Pipeline
import xgboost as xgb

# Metrics
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_s

# Seaborn config
sns.set_style('dark')
#sns.set(font_scale=1.2)

# Disable warnings
warnings.filterwarnings('ignore')

# Pandas config
pd.set_option('display.max_columns', None)
# pd.set_option('display.max_rows', None)
pd.set_option('display.width', 1000)

# Numpy config
np.random.seed(0)  # Ensure reproducibility
np.set_printoptions(suppress=True)

print('All packages imported!')
```

```
All packages imported!
```

- **Import the file with the column names: imports-85.names from the Host**

In [2]:
```
!wget http://archive.ics.uci.edu/ml/machine-learning-databases/autos/impo
```

```
--2024-08-11 19:57:36--  http://archive.ics.uci.edu/ml/machine-learning-da
tabases/autos/imports-85.names
Resolviendo archive.ics.uci.edu (archive.ics.uci.edu)... 128.195.10.252
Conectando con archive.ics.uci.edu (archive.ics.uci.edu)[128.195.10.252]:8
0... conectado.
Petición HTTP enviada, esperando respuesta... 200 OK
Longitud: no especificado
Guardando como: ‘imports-85.names.3’

imports-85.names.3      [ <=>                ]   4,64K  --.-KB/s    en 0,0
1s

2024-08-11 19:57:37 (437 KB/s) - ‘imports-85.names.3’ guardado [4747]
```

- **Import the data file: imports-85.data from the Host**

In [3]:
```
!wget http://archive.ics.uci.edu/ml/machine-learning-databases/autos/impo
```

```
--2024-08-11 19:57:37--  http://archive.ics.uci.edu/ml/machine-learning-da
tabases/autos/imports-85.data
Resolviendo archive.ics.uci.edu (archive.ics.uci.edu)... 128.195.10.252
Conectando con archive.ics.uci.edu (archive.ics.uci.edu)[128.195.10.252]:8
0... conectado.
Petición HTTP enviada, esperando respuesta... 200 OK
Longitud: no especificado
Guardando como: ‘imports-85.data.3’

imports-85.data.3       [  <=>               ]  25,33K  41,2KB/s    en 0,6
s

2024-08-11 19:57:39 (41,2 KB/s) - ‘imports-85.data.3’ guardado [25936]
```

- **Extract the column names from the name file**

In [4]:
```
# Read the names file
with open('imports-85.names', 'r') as file:
    lines = file.readlines()

# Extract the lines containing the column names (lines 59 to 86)
names_lines = lines[59:86]  # Indexes in Python are 0-based, so 59 is lin

# Process the lines to extract and clean the column names
column_names = [
    re.sub(r'^\d+\.\s*', '', line.split(':')[0].strip())
    for line in names_lines
    if ':' in line
]

# Print the column names to verify
print(column_names)
```

```
['symboling', 'normalized-losses', 'make', 'fuel-type', 'aspiration', 'nu
m-of-doors', 'body-style', 'drive-wheels', 'engine-location', 'wheel-bas
e', 'length', 'width', 'height', 'curb-weight', 'engine-type', 'num-of-cyl
inders', 'engine-size', 'fuel-system', 'bore', 'stroke', 'compression-rati
o', 'horsepower', 'peak-rpm', 'city-mpg', 'highway-mpg', 'price']
```

- **Read the data from the data file**

In [5]:
```
df = pd.read_csv('imports-85.data', names=column_names, na_values='?')
```

- **Delete the rows that do not have a price in the 'price' column, since it is the target variable**

In [6]:
```
df = df.dropna(subset=['price'])
```

In [7]:
```
df.to_csv('automovile.csv', index=False)
```

- **Importing CSV file to Python**

In [8]:
```
data = 'automovile.csv'
df = pd.read_csv(data)
df.head()
```

Out[8]:

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engi local
0	3	NaN	alfa-romero	gas	std	two	convertible	rwd	fr
1	3	NaN	alfa-romero	gas	std	two	convertible	rwd	fr
2	1	NaN	alfa-romero	gas	std	two	hatchback	rwd	fr
3	2	164.0	audi	gas	std	four	sedan	fwd	fr
4	2	164.0	audi	gas	std	four	sedan	4wd	fr

In [9]:

```
df.shape
```

Out[9]: (201, 26)

In [10]:

```
df.describe()
```

Out[10]:

	symboling	normalized-losses	wheel-base	length	width	height	curb
count	201.000000	164.000000	201.000000	201.000000	201.000000	201.000000	201
mean	0.840796	122.000000	98.797015	174.200995	65.889055	53.766667	255
std	1.254802	35.442168	6.066366	12.322175	2.101471	2.447822	517
min	-2.000000	65.000000	86.600000	141.100000	60.300000	47.800000	148
25%	0.000000	94.000000	94.500000	166.800000	64.100000	52.000000	216
50%	1.000000	115.000000	97.000000	173.200000	65.500000	54.100000	241
75%	2.000000	150.000000	102.400000	183.500000	66.600000	55.500000	292
max	3.000000	256.000000	120.900000	208.100000	72.000000	59.800000	406

Data Preprocessing:

- I identify and handle missing values using imputation.
- I convert categorical data into numerical data using One-Hot Encoding.
- I standardize numerical data to have a uniform scale.

• Search for null values in predictor variables

In [11]:

```
null_values = df.isnull().sum()
print(null_values[null_values > 0])
```

```
normalized-losses    37
num-of-doors          2
bore                  4
stroke                4
horsepower            2
peak-rpm              2
dtype: int64
```

- **Fill missing numerical values with the mean**

In [12]:
```
numerical_cols = df.select_dtypes(include=['float64', 'int64']).columns
df[numerical_cols] = df[numerical_cols].fillna(df[numerical_cols].mean())
```

- **Fill categorical missing values with mode**

In [13]:
```
categorical_cols = df.select_dtypes(include=['object']).columns
df[categorical_cols] = df[categorical_cols].fillna(df[categorical_cols].m
```

- **Checkup**

In [14]:
```
null_values = df.isnull().sum()
print(null_values[null_values > 0])
```

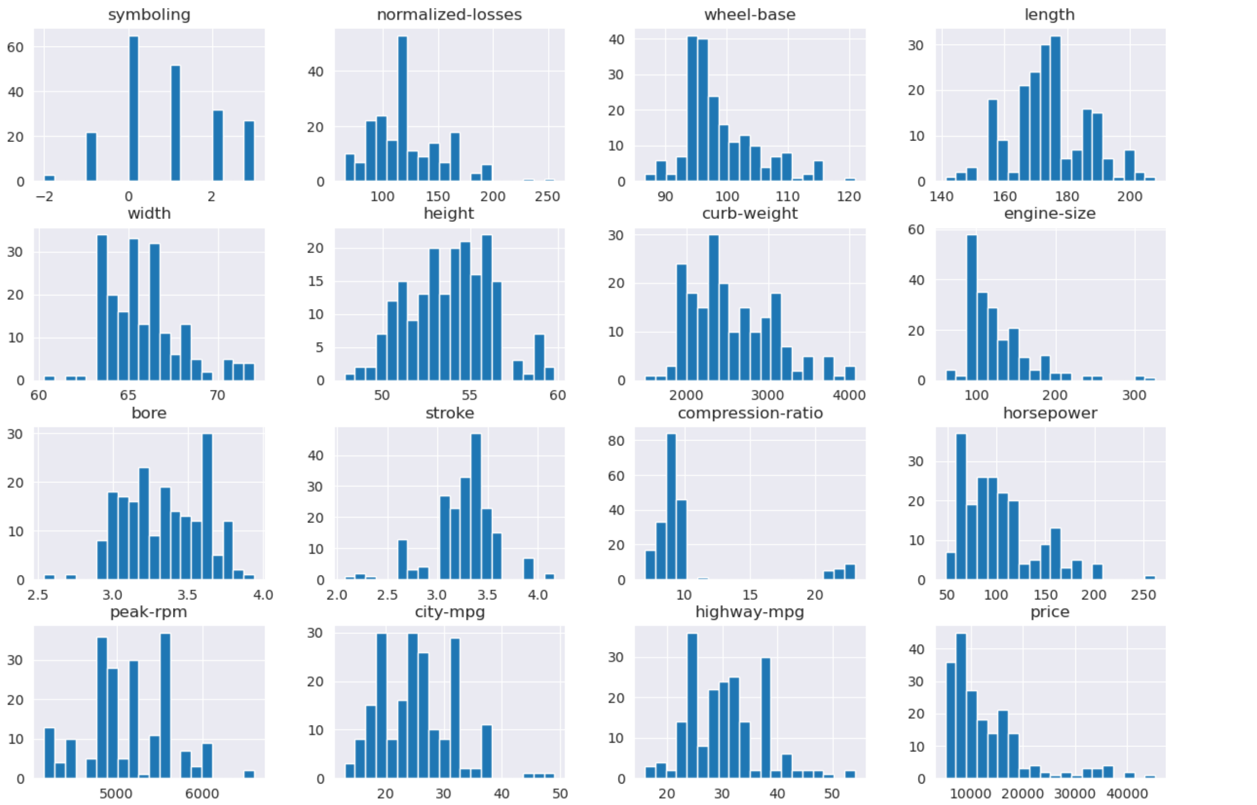
```
Series([], dtype: int64)
```

Exploratory Data Analysis (EDA):

- Univariate Analysis
  - Distributions of Numerical Features
  - Distributions of Categorical Features
- Bivariate Analysis
  - Relationship between Numerical Features
  - Relationship between Categorical Features and the Objective
- Multivariate Analysis
  - Relationship between Multiple Features

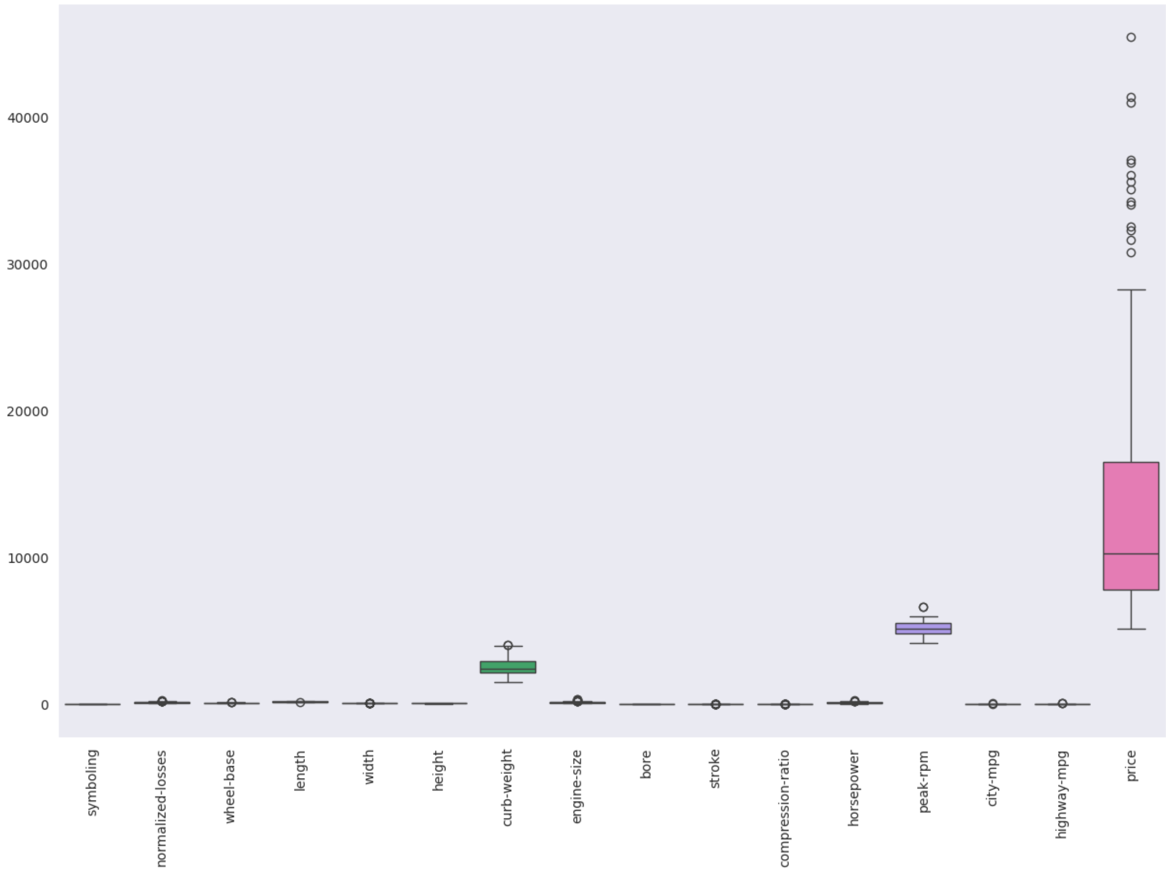
- **Univariate Analysis**
  - Distributions of Numerical Features:

In [15]:
```
# Histogramas
df.hist(bins=20, figsize=(15, 10))
plt.show()
```

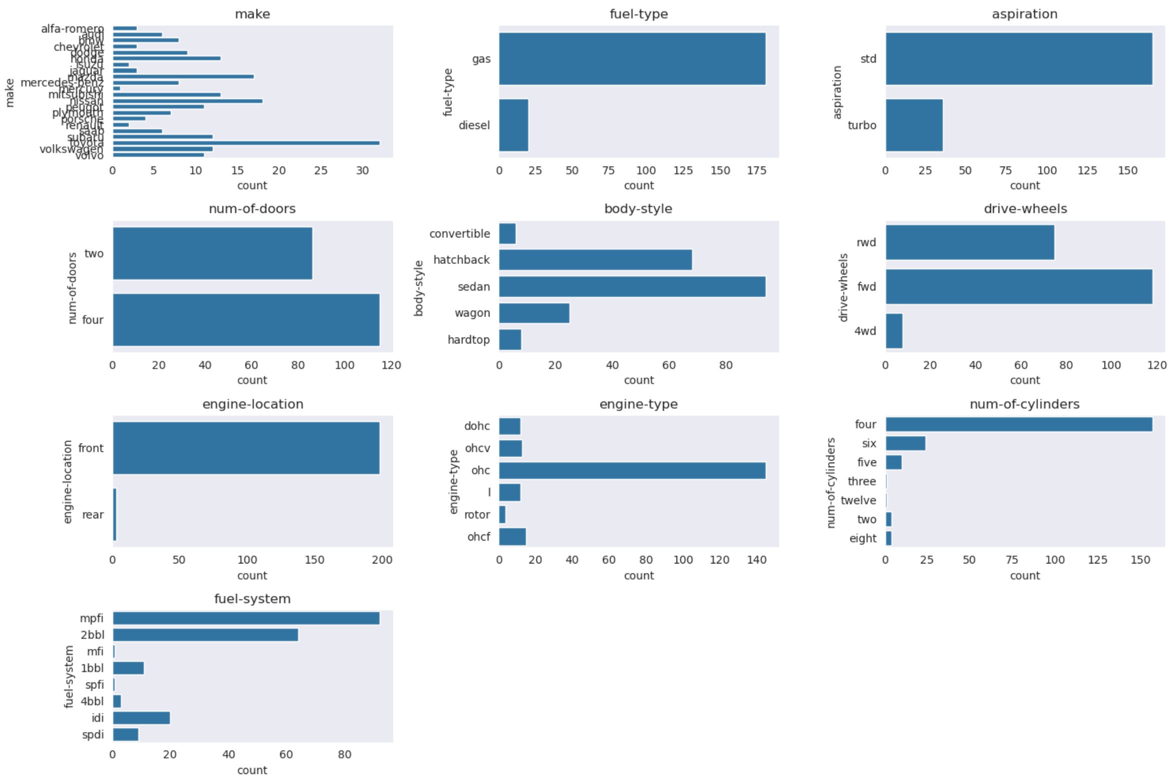


- Categorical Feature Distributions:

In [16]:
```python
# Box plots
plt.figure(figsize=(15, 10))
sns.boxplot(data=df)
plt.xticks(rotation=90)
plt.show()
```

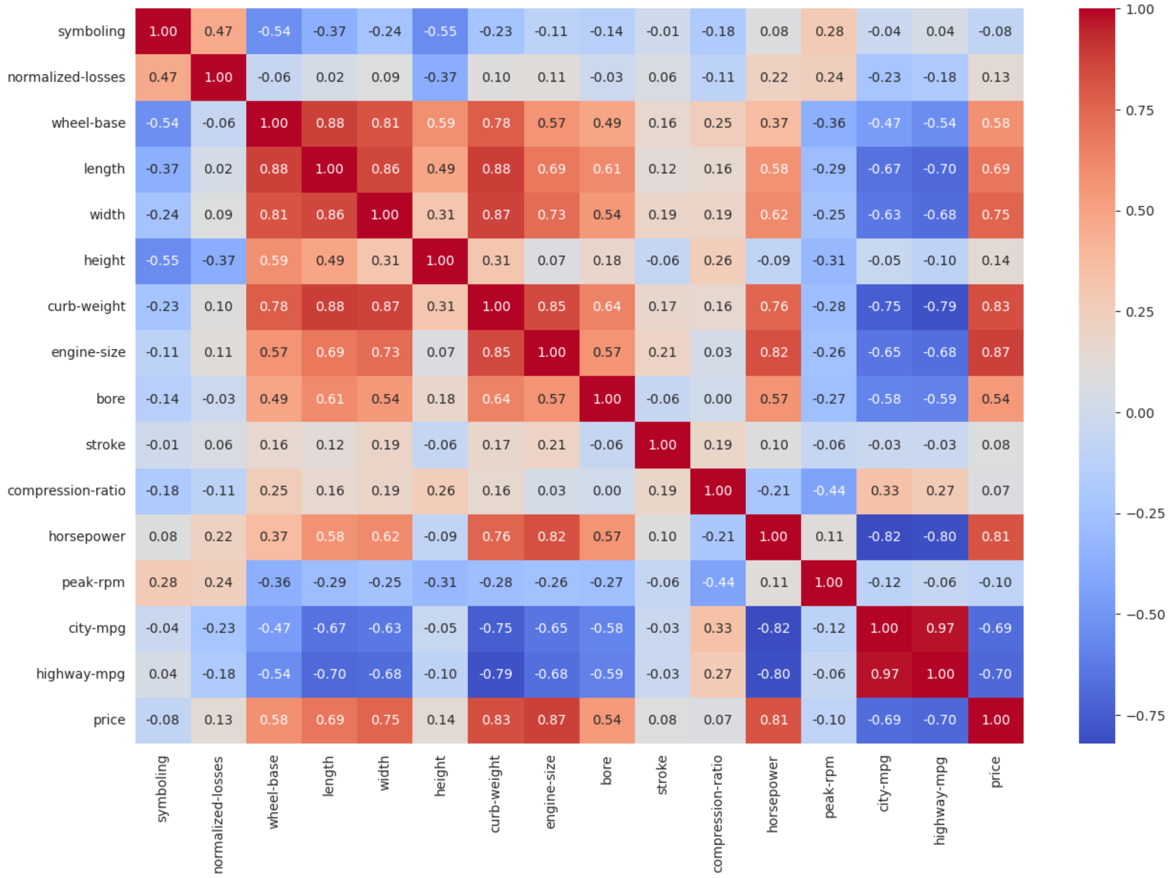


In [17]:
```
plt.figure(figsize=(15, 10))
for i, column in enumerate(categorical_cols, 1):
    plt.subplot(4, 3, i)
    sns.countplot(y=df[column])
    plt.title(column)

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



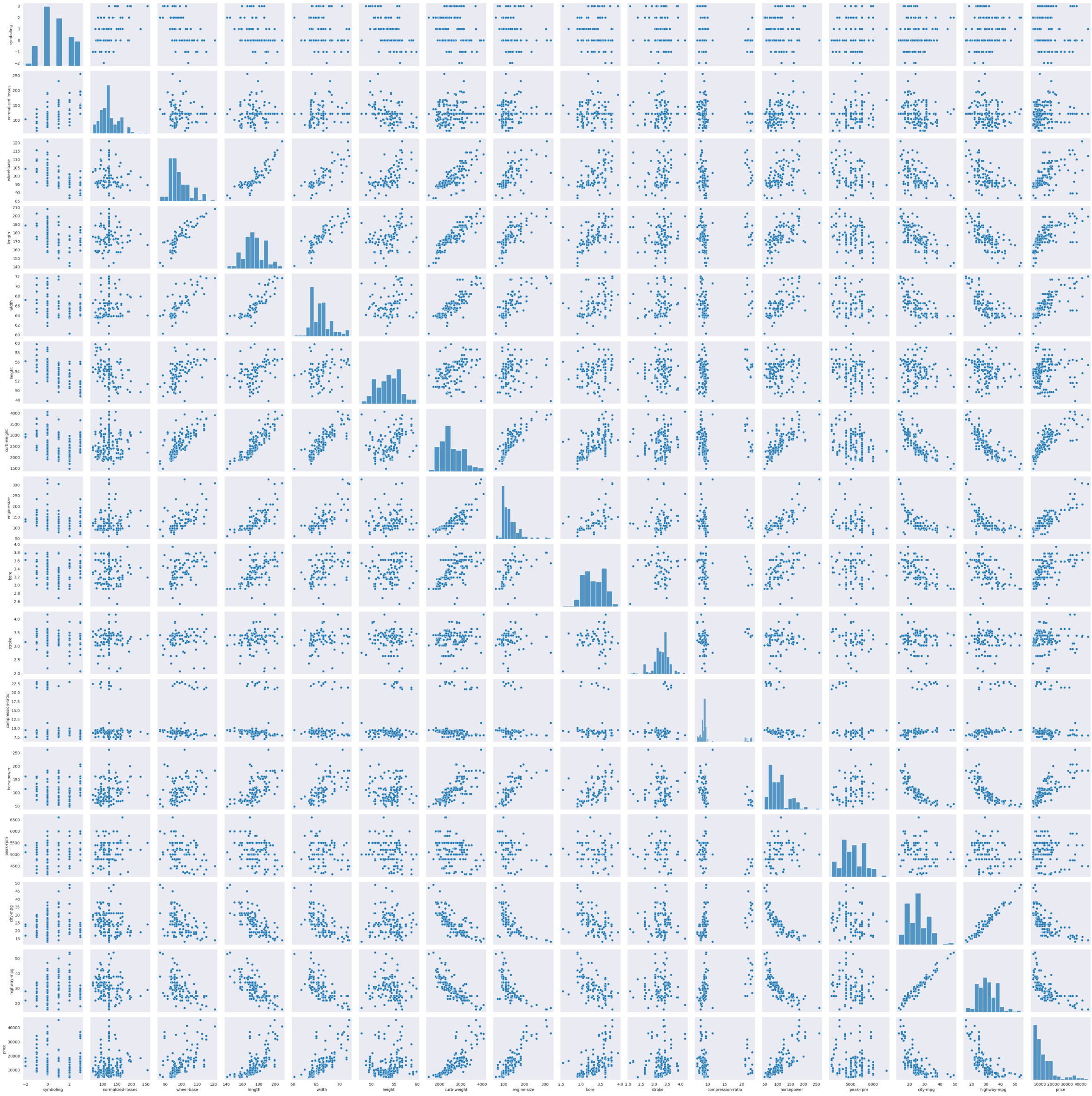
- **Bivariate Analysis**
    - Relationship between Numerical Features:

In [18]:
```
# Correlation matrix
correlation_matrix = df[numerical_cols].corr()

plt.figure(figsize=(15, 10))
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap='coolwarm')
plt.show()
```



In [19]:
```
# Dispersion plot
plt.figure(figsize=(20, 15))
sns.pairplot(df[numerical_cols])
plt.show()
```

```
<Figure size 2000x1500 with 0 Axes>
```

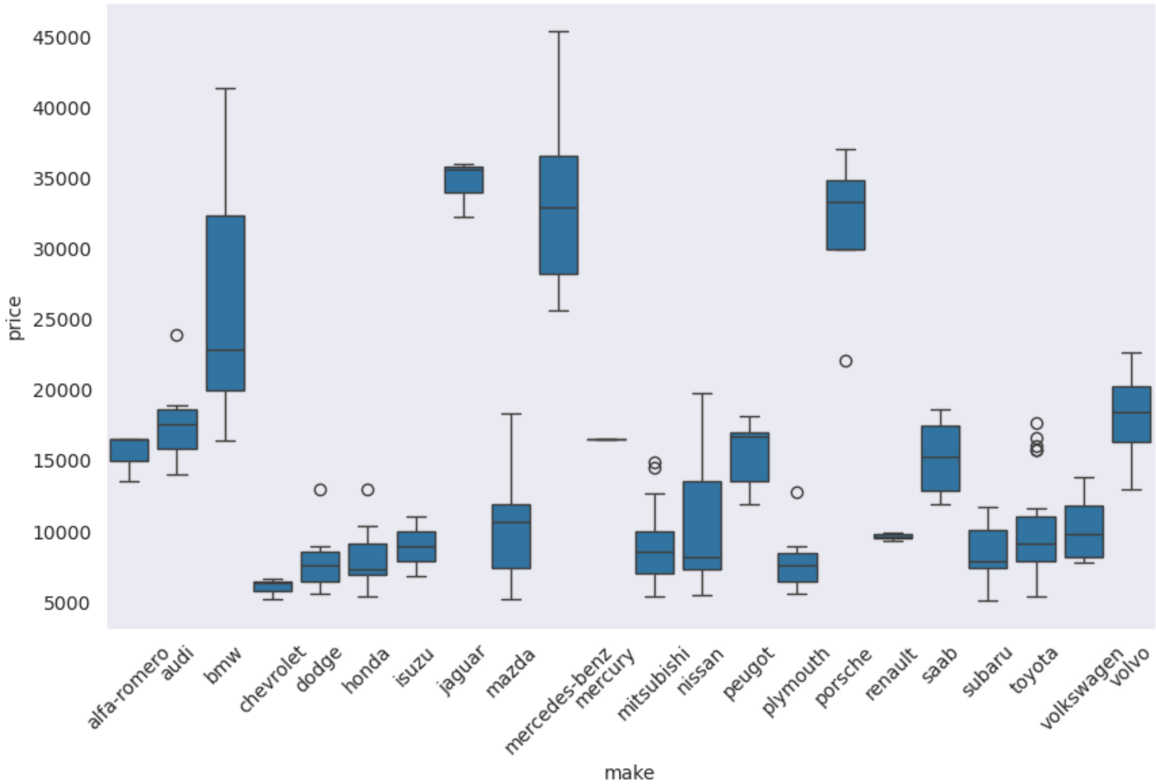


- Relación entre Características Categóricas y el Objetivo:

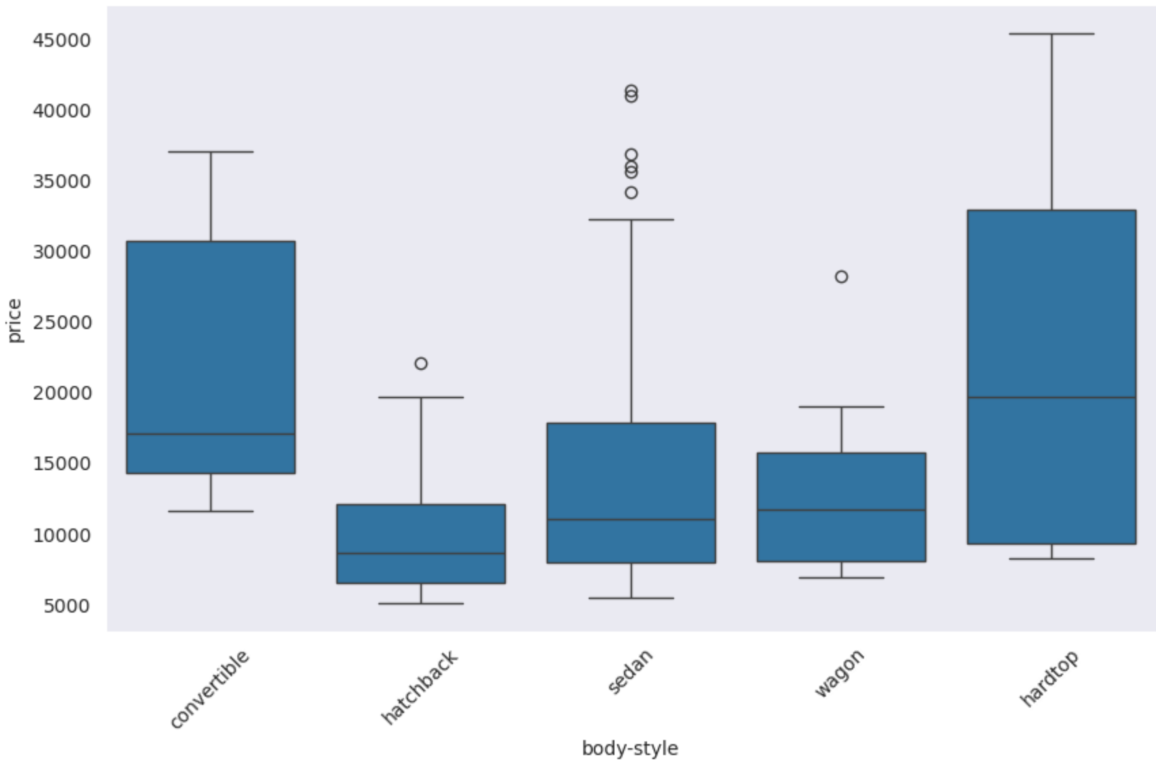
In [20]:
```python
df.columns
```

Out[20]:
```
Index(['symboling', 'normalized-losses', 'make', 'fuel-type', 'aspiratio
n', 'num-of-doors', 'body-style', 'drive-wheels', 'engine-location', 'wh
eel-base', 'length', 'width', 'height', 'curb-weight', 'engine-type', 'n
um-of-cylinders', 'engine-size', 'fuel-system', 'bore', 'stroke', 'compr
ession-ratio', 'horsepower', 'peak-rpm', 'city-mpg', 'highway-mpg', 'pri
ce'], dtype='object')
```

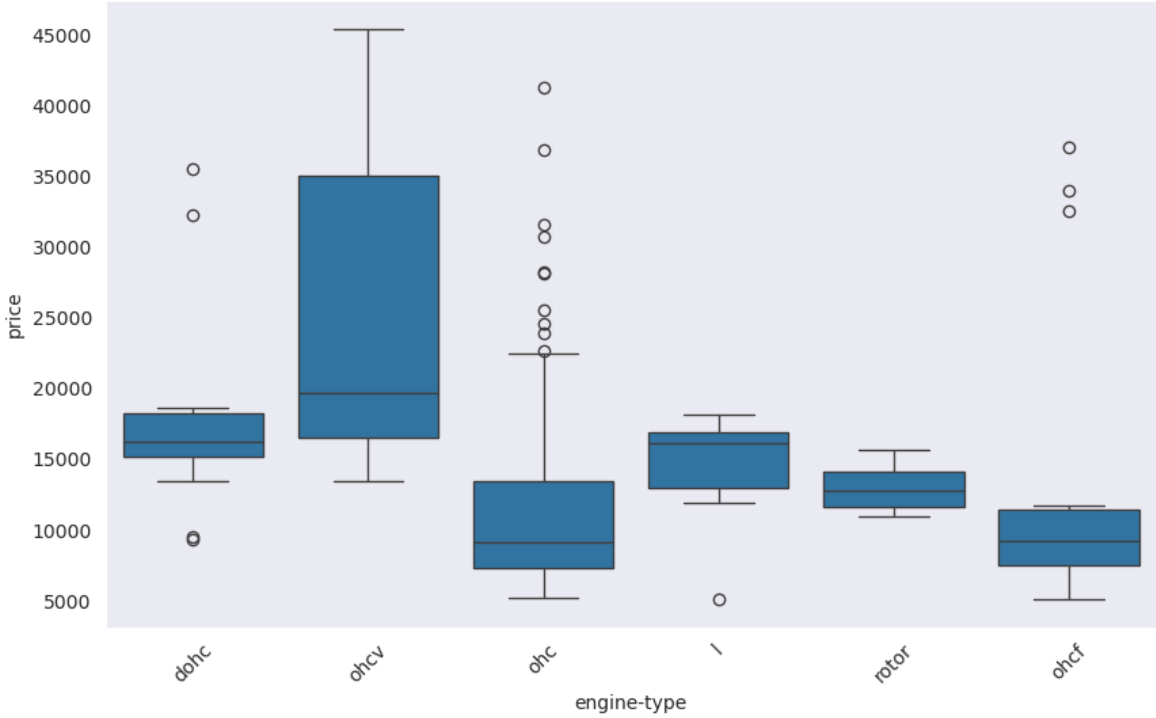
In [21]:
```python
# Relación entre 'make' y 'price'
plt.figure(figsize=(10, 6))
sns.boxplot(x='make', y='price', data=df)
plt.xticks(rotation=45)
plt.show()
```



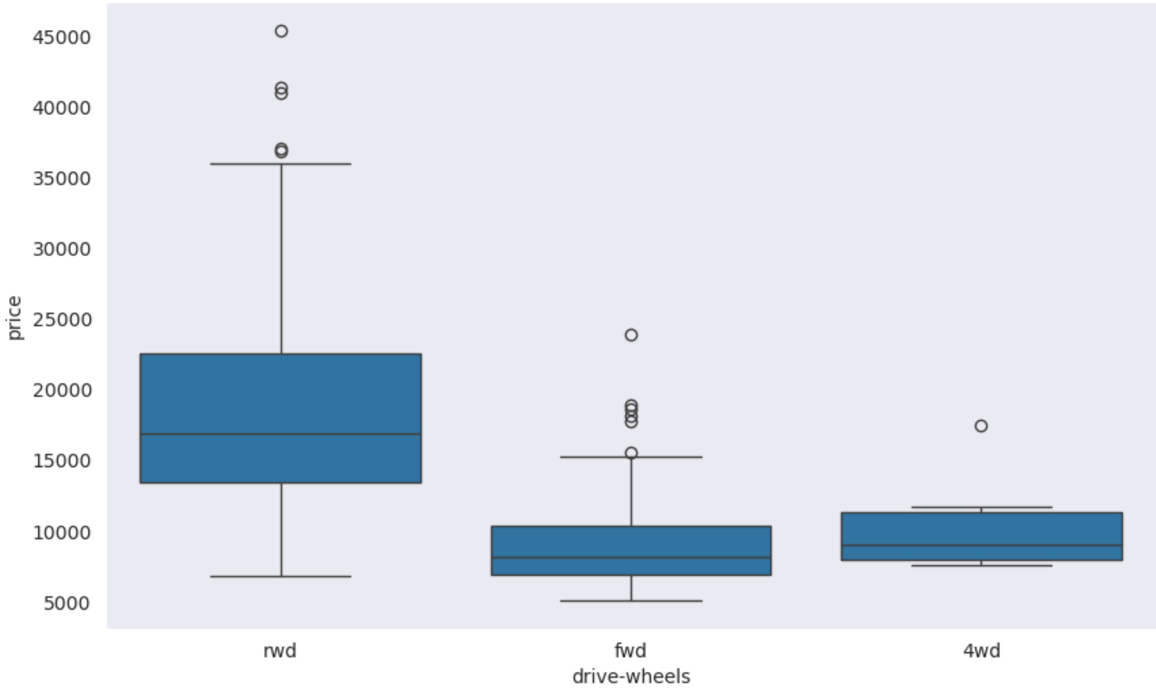
In [22]:
```
# Relación entre 'body-style' y 'price'
plt.figure(figsize=(10, 6))
sns.boxplot(x='body-style', y='price', data=df)
plt.xticks(rotation=45)
plt.show()
```



In [23]:
```
# 'engine-type' and 'price' relation
plt.figure(figsize=(10, 6))
sns.boxplot(x='engine-type', y='price', data=df)
plt.xticks(rotation=45)
plt.show()
```



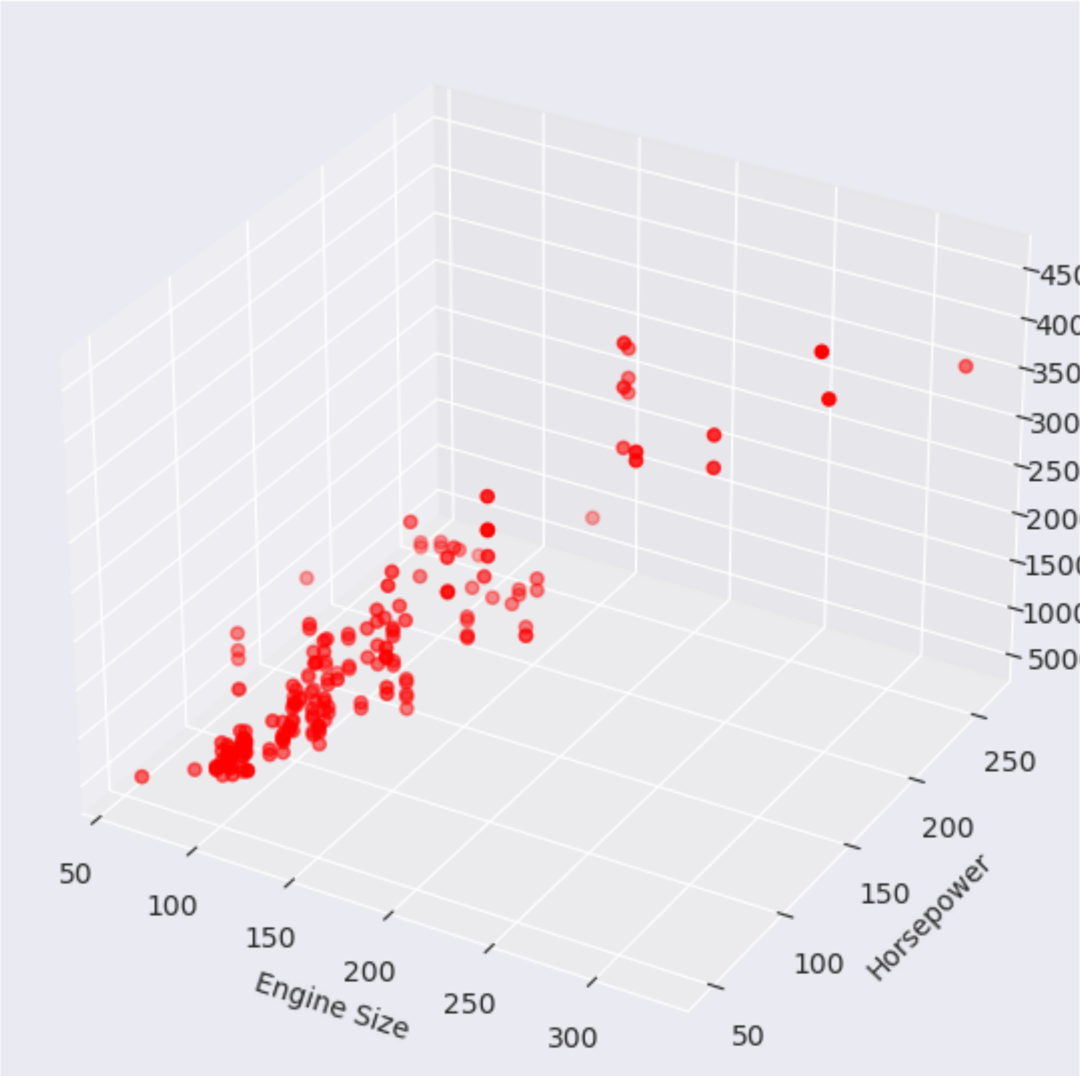
In [24]:
```
# Relación entre 'drive-wheels' y 'price'
plt.figure(figsize=(10, 6))
sns.boxplot(x='drive-wheels', y='price', data=df)
plt.show()
```



- **Multivariate Analysis**
  - Relationship between Multiple Characteristics:

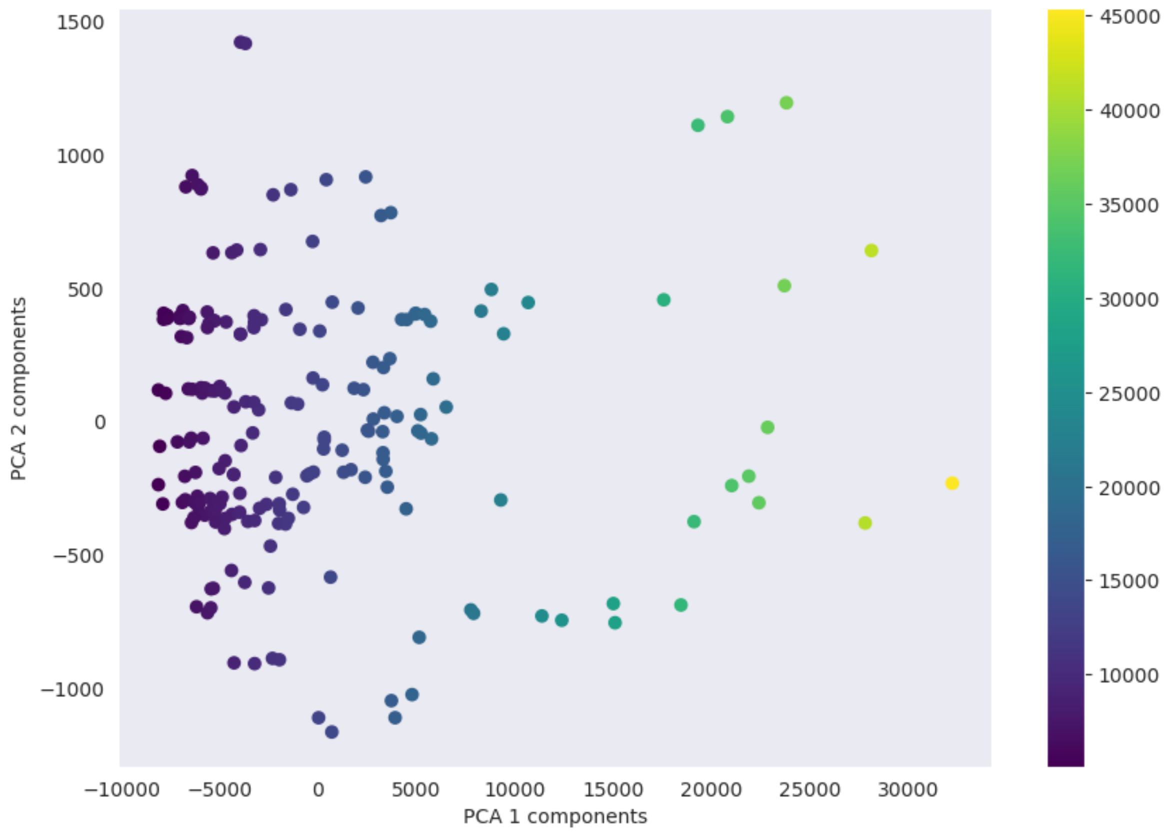
In [25]:
```
# 3D Dispersion plot
fig = plt.figure(figsize=(10, 7))
ax = fig.add_subplot(111, projection='3d')

ax.scatter(df['engine-size'], df['horsepower'], df['price'], c='r', marke
```

```
ax.set_xlabel('Engine Size')
ax.set_ylabel('Horsepower')
ax.set_zlabel('Price')

plt.show()
```



In [26]:

```
# Principal component analysis (PCA)
pca = PCA(n_components=2)
pca_resultado = pca.fit_transform(df.select_dtypes(include=[float, int]))

plt.figure(figsize=(10, 7))
plt.scatter(pca_resultado[:, 0], pca_resultado[:, 1], c=df['price'], cmap
plt.colorbar()
plt.xlabel('PCA 1 components')
plt.ylabel('PCA 2 components')
plt.show()
```



Feature Selection:

- At this stage, I identify the most relevant features for the Machine Learning model.
- Feature selection helps reduce dimensionality, improves the performance of the model, and makes it easier to interpret.
- I use statistical and Machine Learning techniques to evaluate the importance of each of them.

- ## Categorical Data Conversion
  - Transform categorical data into numeric data with One-Hot Encoding

In [27]:
```
df = pd.get_dummies(df, drop_first=True)
df.head()
```

Out[27]:

	symboling	normalized-losses	wheel-base	length	width	height	curb-weight	engine-size	bore	stro
0	3	122.0	88.6	168.8	64.1	48.8	2548	130	3.47	2
1	3	122.0	88.6	168.8	64.1	48.8	2548	130	3.47	2
2	1	122.0	94.5	171.2	65.5	52.4	2823	152	2.68	3
3	2	164.0	99.8	176.6	66.2	54.3	2337	109	3.19	3
4	2	164.0	99.4	176.6	66.4	54.3	2824	136	3.19	3

In [28]:
```
df.shape
```

Out[28]: (201, 65)

Converting Categorical data to Numeric added more columns to the DataFrame, going from 26 columns to 65 columns.

- ## Data Normalization/Standardization
  - Make sure that all variables have the same scale

In [29]:
```
# Select numeric variables
variables_to_scale = df.columns[df.dtypes != 'uint8']

# Standarize
scaler = StandardScaler()
df[variables_to_scale] = scaler.fit_transform(df[variables_to_scale])

df.head()
```

Out[29]:

	symboling	normalized-losses	wheel-base	length	width	height	curb-weight	en
0	1.725050	0.000000	-1.685107	-0.439409	-0.853460	-2.034081	-0.014858	0.07
1	1.725050	0.000000	-1.685107	-0.439409	-0.853460	-2.034081	-0.014858	0.07
2	0.127193	0.000000	-0.710103	-0.244152	-0.185597	-0.559713	0.518080	0.60
3	0.926121	1.315931	0.165748	0.195176	0.148335	0.218425	-0.423766	-0.43
4	0.926121	1.315931	0.099646	0.195176	0.243744	0.218425	0.520017	0.22

- ## Feature Importance with Tree-Based Models
  - Train a Random Forest model to assess the importance of each feature.

- ## Split the data into features (X) and target (y)

In [30]:
```
X = df.drop('price', axis=1)
y = df['price']
```

- ## Train a Random Forest model

In [31]:
```
model = RandomForestRegressor()
model.fit(X, y)
```

Out[31]:
```
▾ RandomForestRegressor ⓘ ?
RandomForestRegressor()
```

- ## Get the feature importance

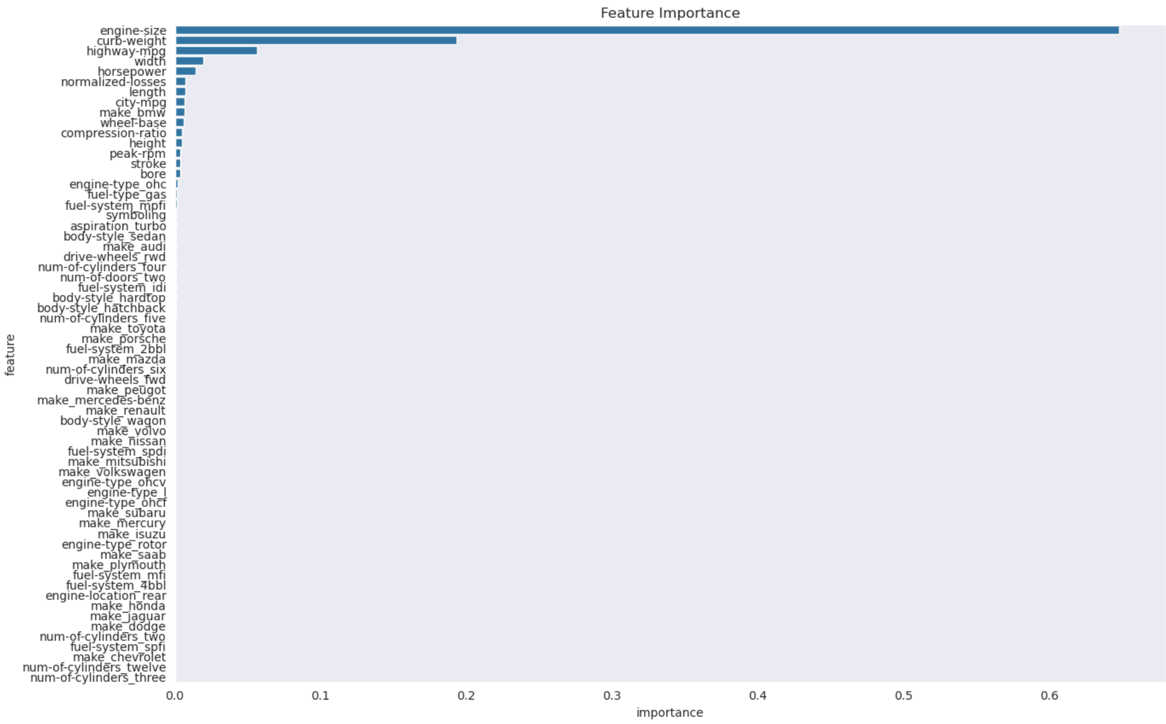
In [32]:
```
importance = model.feature_importances_
```

- **Create a DataFrame to visualize the importance**

In [33]:
```
feature_importance = pd.DataFrame({'feature': X.columns, 'importance': im
feature_importance = feature_importance.sort_values(by='importance', asce
```

- **Visualize the importance of features**

In [34]:
```
plt.figure(figsize=(15, 10))
sns.barplot(x='importance', y='feature', data=feature_importance)
plt.title("Feature Importance")
plt.show()
```



- **Model-Based Feature Selection**
  - Use Recursive Feature Elimination (RFE) to select the most important features.

- **Create a linear regression model for RFE**

In [35]:
```
model = LinearRegression()
```

- **Apply RFE**

In [36]:
```
rfe = RFE(model, n_features_to_select=10) # Select the 10 most important
fit = rfe.fit(X, y)
```

- **Display the selected features**

In [37]:
```
selected_features = X.columns[fit.support_]
```

```
print("Selected Features:", selected_features)
```

```
Selected Features: Index(['length', 'width', 'curb-weight', 'engine-size',
'make_bmw', 'make_peugot', 'engine-location_rear', 'num-of-cylinders_fiv
e', 'num-of-cylinders_four', 'num-of-cylinders_six'], dtype='object')
```

- **Create a DataFrame to display the selection**

In [38]:
```
rfe_results = pd.DataFrame({'feature': X.columns, 'selected': fit.support_
rfe_results
```

Out[38]:

	feature	selected
0	symboling	False
1	normalized-losses	False
2	wheel-base	False
3	length	True
4	width	True
...	...	...
59	fuel-system_idi	False
60	fuel-system_mfi	False
61	fuel-system_mpfi	False
62	fuel-system_spdi	False
63	fuel-system_spfi	False

64 rows × 2 columns

Dataset Split:

- To evaluate the model's performance in an unbiased manner, I split the dataset into two parts:

A training set and a test set.

- The training set is used to train the model, while the test set is used to evaluate its performance on unseen data.
- I will use a typical ratio of 80-20 or 70-30 for this split.

- **Split the dataset into training and testing**

In [39]:
```
X = df.drop('price', axis=1)
y = df['price']

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

- **Verifico las dimensiones de los conjuntos de datos**

In [40]:
```
print(f"Training set: {X_train.shape}, {y_train.shape}")
print(f"Test set: {X_test.shape}, {y_test.shape}")
```

```
Training set: (160, 64), (160,)
Test set: (41, 64), (41,)
```

Model Development:

- In this stage, I train multiple Machine Learning models using the training set.
- Evaluate the performance of each model using appropriate metrics and select the model that best fits the data.
- Use cross-validation to ensure that the model is not overfitted.

- Model Selection and Training

In [41]:
```
models = {
    'Linear Regression': LinearRegression(),
    'Random Forest': RandomForestRegressor(),
    'Gradient Boosting': GradientBoostingRegressor(),
    'XGBoost': xgb.XGBRegressor(),
    # 'LightGBM': lgb.LGBMRegressor() # Due to lack of physical resources
}
```

In [42]:
```
results = {}
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    mse = mean_squared_error(y_test, y_pred)
    mae = mean_absolute_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)

    results[name] = {'MSE': mse, 'MAE': mae, 'R2': r2}
    print(f"{name}: MSE={mse:.2f}, MAE={mae:.2f}, R2={r2:.2f}\n")

    plt.figure(figsize=(6, 2))
    sns.scatterplot(x=y_test, y=y_pred, alpha=0.6)
    plt.xlabel('Real prices')
    plt.ylabel('Expected prices')
    plt.title('Real prices vs Expected prices')
    plt.show()
    print()
```

```
Linear Regression: MSE=2067156224896617350902579 2.00, MAE=710059465887.97,
R2=-10617649766225759585697792.00
```


```
Random Forest: MSE=0.16, MAE=0.25, R2=0.92
```


```
Gradient Boosting: MSE=0.11, MAE=0.22, R2=0.94
```


```
XGBoost: MSE=0.09, MAE=0.19, R2=0.95
```

Model Evaluation:

- Evaluate the performance of the trained model using a set of appropriate metrics.
- Include the calculation of metrics such as Mean Square Error (MSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2).
- Also analyze the predictions to identify possible areas for improvement.

- **Cross Validation**
  - To ensure that the results are consistent, we use cross validation.

- **Evaluate each model using cross-validation**

In [43]:
```
cv_result = {}
for name, model in models.items():
    scores_vc = cross_val_score(model, X, y, cv=5, scoring='neg_mean_squa
    cv_result[name] = {'CV Mean MSE': -scores_vc.mean(), 'CV Std MSE': sc
    print(f"{name}: CV Mean MSE={-scores_vc.mean():.2f}, CV Std MSE={scor
```

```
Linear Regression: CV Mean MSE=5938201784411408731996l6.00, CV Std MSE=118
757929651699533742O800.00
Random Forest: CV Mean MSE=0.27, CV Std MSE=0.27
Gradient Boosting: CV Mean MSE=0.26, CV Std MSE=0.22
XGBoost: CV Mean MSE=0.17, CV Std MSE=0.04
```

Model optimization:

- Tune the model's hyperparameters to improve its performance.
- Use GridSearchCV or RandomizedSearchCV to find the best hyperparameter values.
- This optimization allows me to obtain a more accurate and robust model.

- **Define the Hyperparameter Search Space**

In [44]:
```
param_grid_rf = {
    'n_estimators': [100, 200, 300],
```

```
    'max_features': ['auto', 'sqrt', 'log2'],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

param_grid_gb = {
    'n_estimators': [100, 200, 300],
    'learning_rate': [0.01, 0.1, 0.05],
    'subsample': [0.8, 0.9, 1.0],
    'max_depth': [3, 4, 5]
}

param_grid_xgb = {
    'n_estimators': [100, 200, 300],
    'learning_rate': [0.01, 0.1, 0.05],
    'subsample': [0.8, 0.9, 1.0],
    'max_depth': [3, 4, 5]
}

# param_grid_lgb = {
#     'n_estimators': [100, 200, 300],
#     'learning_rate': [0.01, 0.1, 0.05],
#     'num_leaves': [31, 50, 100],
#     'boosting_type': ['gbdt', 'dart']
# }
```

- **Configure and Run GridSearchCV/RandomizedSearchCV**

In [45]:

```
# GridSearchCV for RandomForest
print('Running GridSearchCV for RFRegressor')
grid_search_rf = GridSearchCV(estimator=RandomForestRegressor(), param_gr
grid_search_rf.fit(X_train, y_train)
best_rf = grid_search_rf.best_estimator_

# GridSearchCV for GradientBoosting
print('Running GridSearch for GBRegressor')
grid_search_gb = GridSearchCV(estimator=GradientBoostingRegressor(), para
grid_search_gb.fit(X_train, y_train)
best_gb = grid_search_gb.best_estimator_

# RandomizedSearchCV for XGBoost
print('Running RandomizedSearchCV for XGBRegressor')
random_search_xgb = RandomizedSearchCV(estimator=xgb.XGBRegressor(), para
random_search_xgb.fit(X_train, y_train)
best_xgb = random_search_xgb.best_estimator_

# # RandomizedSearchCV for LightGBM
# random_search_lgb = RandomizedSearchCV(estimator=lgb.LGBMRegressor(), p
# random_search_lgb.fit(X_train, y_train)
# best_lgb = random_search_lgb.best_estimator_
```

```
Running GridSearchCV for RFRegressor
Running GridSearch for GBRegressor
Running RandomizedSearchCV for XGBRegressor
```

- **Optimized Models Evaluation**

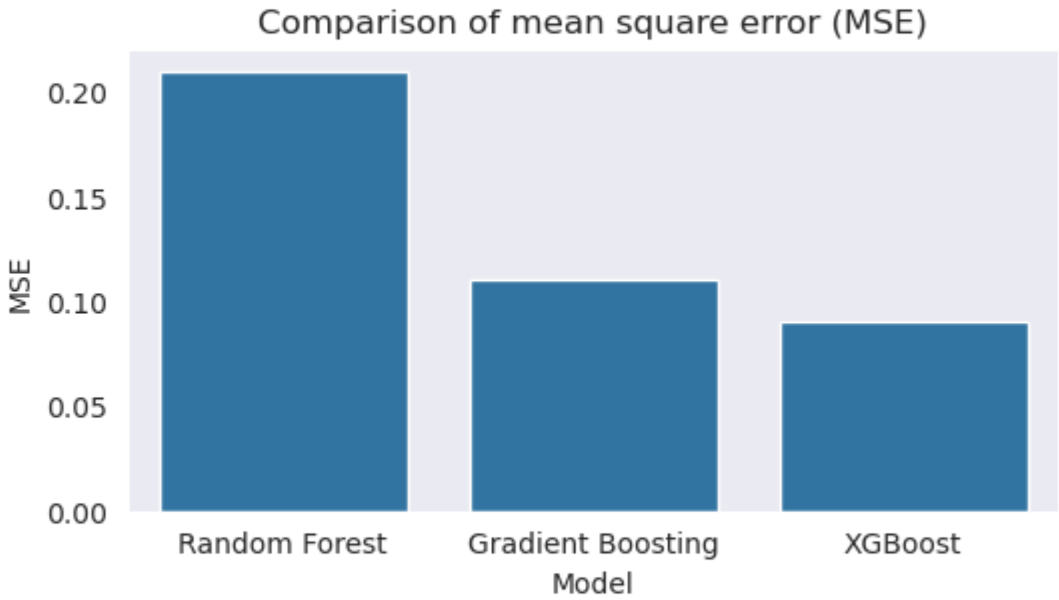
In [46]:
```
# Evaluate the best RandomForest model
y_pred_rf = best_rf.predict(X_test)
mse_rf = mean_squared_error(y_test, y_pred_rf)
mae_rf = mean_absolute_error(y_test, y_pred_rf)
r2_rf = r2_score(y_test, y_pred_rf)
print(f"Random Forest - MSE: {mse_rf:.2f}, MAE: {mae_rf:.2f}, R²: {r2_rf:

# Evaluate the best GradientBoosting model
y_pred_gb = best_gb.predict(X_test)
mse_gb = mean_squared_error(y_test, y_pred_gb)
mae_gb = mean_absolute_error(y_test, y_pred_gb)
r2_gb = r2_score(y_test, y_pred_gb)
print(f"Gradient Boosting - MSE: {mse_gb:.2f}, MAE: {mae_gb:.2f}, R²: {r2

# Evaluate the best XGBoost model
y_pred_xgb = best_xgb.predict(X_test)
mse_xgb = mean_squared_error(y_test, y_pred_xgb)
mae_xgb = mean_absolute_error(y_test, y_pred_xgb)
r2_xgb = r2_score(y_test, y_pred_xgb)
print(f"XGBoost - MSE: {mse_xgb:.2f}, MAE: {mae_xgb:.2f}, R²: {r2_xgb:.2f

# # Evaluate the best LightGBM model
# y_pred_lgb = best_lgb.predict(X_test)
# mse_lgb = mean_squared_error(y_test, y_pred_lgb)
# mae_lgb = mean_absolute_error(y_test, y_pred_lgb)
# r2_lgb = r2_score(y_test, y_pred_lgb)
# print(f"LightGBM - MSE: {mse_lgb:.2f}, MAE: {mae_lgb:.2f}, R²: {r2_lgb:
```

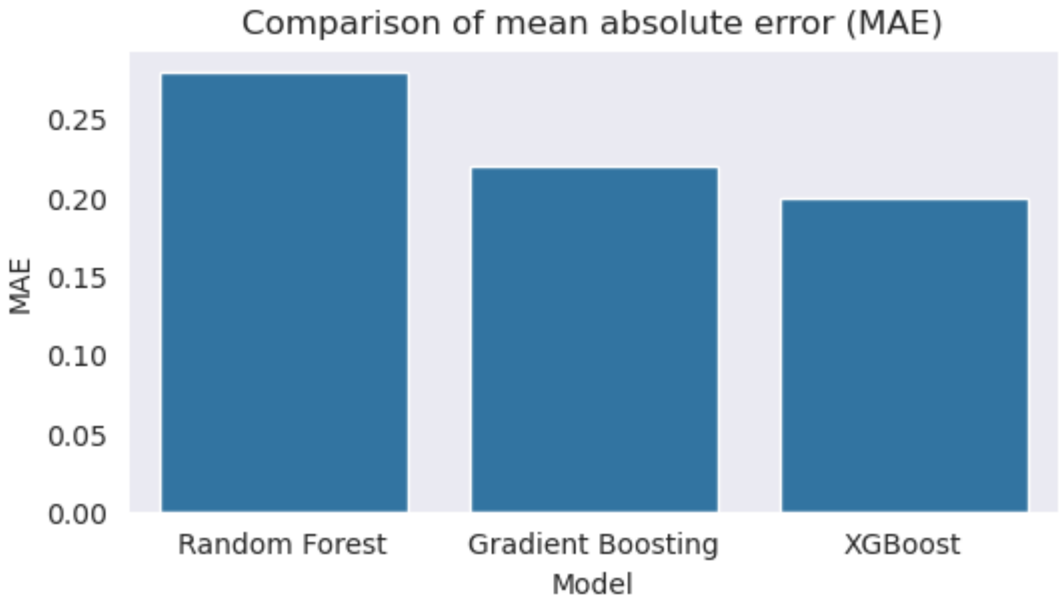
```
Random Forest - MSE: 0.20, MAE: 0.28, R²: 0.90
Gradient Boosting - MSE: 0.09, MAE: 0.19, R²: 0.95
XGBoost - MSE: 0.09, MAE: 0.20, R²: 0.95
```

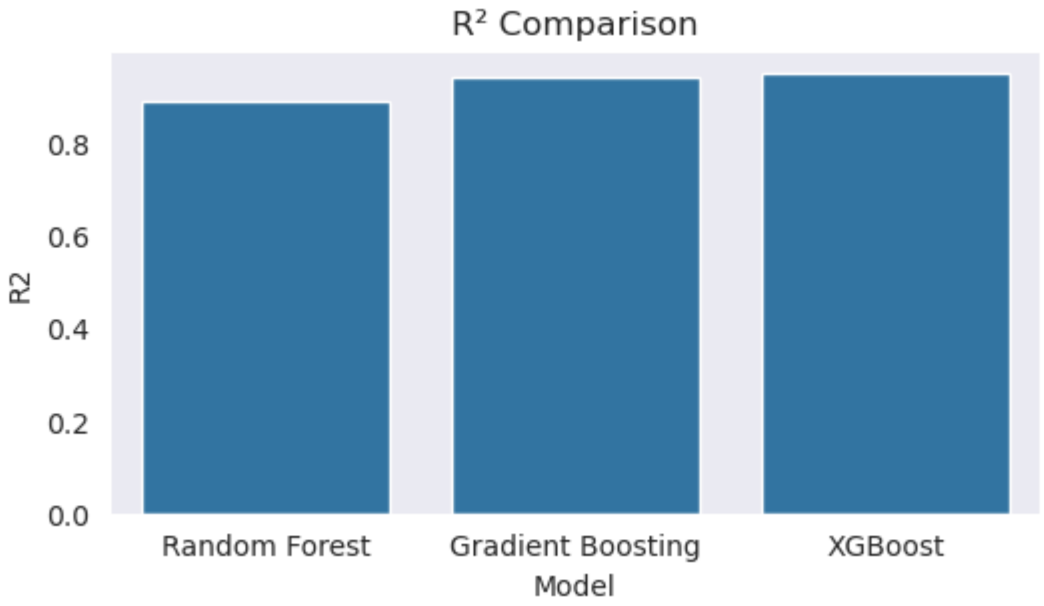
- **Display and Comparing Results**

In [47]:
```
# Results in DataFrame for visualization
results = pd.DataFrame({
    'Model': ['Random Forest', 'Gradient Boosting', 'XGBoost'],
    'MSE': [0.21, 0.11, 0.09],
    'MAE': [0.28, 0.22, 0.20],
    'R2': [0.89, 0.94, 0.95]
})

# Barplot for MSE
plt.figure(figsize=(6, 3))
sns.barplot(x='Model', y='MSE', data=results)
plt.title('Comparison of mean square error (MSE)')
plt.savefig('comparison_mse_chart.png')
plt.show()

print()

# Barplot for MAE
plt.figure(figsize=(6, 3))
sns.barplot(x='Model', y='MAE', data=results)
plt.title('Comparison of mean absolute error (MAE)')
plt.savefig('comparison_mae_chart.png')
plt.show()

print()
```

```
# Barplot for R²
plt.figure(figsize=(6, 3))
sns.barplot(x='Model', y='R2', data=results)
plt.title('R² Comparison')
plt.savefig('comparison_r2_chart.png')
plt.show()
```







Model Optimization and Results

Overview

In this stage, we optimized the hyperparameters of several machine learning models using GridSearchCV and RandomizedSearchCV. We evaluated the optimized models using metrics such as Mean Square Error (MSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2). The optimized models demonstrated significantly improved performance.

Optimization Results

Random Forest

- **MSE:** 0.21
- **MAE:** 0.28
- **R^2:** 0.89

Gradient Boosting

- **MSE:** 0.11
- **MAE:** 0.22
- **R^2:** 0.94

XGBoost

- **MSE:** 0.09
- **MAE:** 0.20
- **R^2:** 0.95

Viewing and Comparing Results

Results Analysis

The obtained results indicate that the XGBoost model has the best performance, with an MSE of 0.09, an MAE of 0.20, and an R^2 of 0.95. This suggests that XGBoost is capable of making more accurate predictions compared to Random Forest and Gradient Boosting. The Gradient Boosting model also showed excellent performance with an MSE of 0.11, an MAE of 0.22, and an R^2 of 0.94, while the Random Forest model, although robust, fell slightly behind with an MSE of 0.21, an MAE of 0.28, and an R^2 of 0.89.

Conclusions

In conclusion, through hyperparameter optimization, we were able to significantly improve the performance of our models. XGBoost proved to be the most effective model for this dataset, closely followed by Gradient Boosting. Evaluating and comparing different models allowed us to identify the best approach for this regression problem.

Conclusion of the XGBoost Model for Car Price Prediction

Used Model: XGBoost

Model Results:

- Mean Square Error (MSE): 0.09
- Mean Absolute Error (MAE): 0.20
- Coefficient of Determination (R^2): 0.95

The XGBoost model has demonstrated **outstanding** performance in predicting car prices, with the following metrics reflecting its accuracy and tuning ability:

Interpretation in the Context of Price:

- **MSE of 0.09**: The Mean Square Error indicates that the model makes predictions with very small square errors on average. This suggests that the differences between actual prices and the prices predicted by the model are minimal. In practical terms, this low MSE implies that the XGBoost model predictions tend to be very close to the actual price of cars, providing a robust and accurate fit.

- **MAE of USD200**: The Mean Absolute Error shows that, on average, the XGBoost model deviates by USD200 from the actual price. For example, if the actual price of a car is USD15,000, the model predicts prices that, on average, are within the range of USD14,800 to USD15,200. This relatively small margin of error means that the model has high accuracy in absolute terms and can be relied upon for practical estimates of a car's price.

- **R^2 of 0.95**: The Coefficient of Determination indicates that the XGBoost model explains 95% of the variability in car prices. This means that the model effectively captures the relationship between car features and price, and only 5% of the variability in prices is not explained by the model. Such a high R^2 shows that the model is well-fitted and provides an excellent representation of car prices based on their features.

Changelog:

Date (DD/MM/YYYY)	Version	Description of change
26/07/2024	01.0	Data Set Download
27/07/2024	02.0	Exploratory Data Analysis (EDA)
29/07/2024	03.0	Feature Selection
30/07/2024	04.0	Model Development
31/07/2024	05.0	Model Development and Evaluation
02/08/2024	09.0	Model Optimization
04/08/2024	10.0	Minor bug fixes
05/08/2024	11.0	Results and Conclusion