Vechile Price Prediction

Objective:

Build a system that can predict the prices for vehicles using data on Vehicle specifications, make, etc. Explore the data to understand the features and figure out an approach.

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1. Problem Statement

The task is to do EDA on dataset and build a model to predict Vechile Price based on the features provided. The challenge is to create a model that can accurately predict the outcome.

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2. Data Pre-Processing

2.1 Data Inspection and Summary Statistics

- **Load the Dataset:** Import the dataset and review its basic structure, including column names, data types, and a few initial records.
- **Generate Summary Statistics:** Calculate key statistics (mean, median, min, max, standard deviation, etc.) to understand the primary characteristics of each column.
- Changing column names and data types

2.2 Data Cleaning and Feature Engineering

- **Missing Values:** Check and handle missing values if present.
- **Duplicate Values:** Check duplicate values and handle if present.

2.3 Outlier Treatment

- **Outlier Detection:** Identify outliers in features box plots or Z-scores and apply treatment if necessary.

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3. Exploratory Data Analysis (EDA)

3.1 Univariate Analysis

- **Numerical Data:** Visualize distributions with histograms and box plots.
- **Categorical Data:** Use bar charts to observe the distribution of the outcome variable.

3.2 Bivariate Analysis

- Create scatter plots to observe relationships between numerical features.

- Use box plots to explore how numerical features differ based on the outcome variable.

3.3 Multivariate Analysis

- Generate a heatmap of the correlation matrix to identify potential relationships.

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4. Model Building

4.1 Encoding Categorical Variables:

- Convert the Categorical columns to binary format

4.2 Feature Engineering

- This step involves transforming raw data into meaningful features and outcome

4.3 Model Training

- Split the dataset into training and testing sets.
- Scalling the data
- Use a Linear Regression to train the model on the training data.
- Model Evaluation
- Visualize the result

5. Advanced Modeling:

- Experiment with more complex models like RandomForest and xgboost to improve predictions.

Import Required Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error,r2_score
from sklearn.model_selection import train_test_split

import warnings # to ignore warnings
warnings.filterwarnings('ignore')
```

Load the Dataset¶

```
data = pd.read_csv('C://Users//PC//Downloads//Projects-
20240722T093004Z-001//Projects//Vehicle Price
Prediction//dataset.csv')
```

```
data.head() # First  rows
```

```
                                        name  \
0      2024 Jeep Wagoneer Series II
1  2024 Jeep Grand Cherokee Laredo
2          2024 GMC Yukon XL Denali
3        2023 Dodge Durango Pursuit
4             2024 RAM 3500 Laramie

                                                     description   make
model  \
0  \n      \n        Heated Leather Seats, Nav Sy...   Jeep
Wagoneer
1  Al West is committed to offering every custome...   Jeep  Grand
Cherokee
2                                                NaN    GMC
Yukon XL
3  White Knuckle Clearcoat 2023 Dodge Durango Pur...  Dodge
Durango
4  \n      \n        2024 Ram 3500 Laramie Billet...    RAM
3500

   year    price                                              engine  \
0  2024  74600.0                           24V GDI DOHC Twin Turbo
1  2024  50170.0                                                 OHV
2  2024  96410.0  6.2L V-8 gasoline direct injection, variable v...
3  2023  46835.0                                       16V MPFI OHV
4  2024  81663.0                            24V DDI OHV Turbo Diesel

   cylinders      fuel  mileage       transmission       trim
body  \
0        6.0  Gasoline     10.0  8-Speed Automatic  Series II
SUV
1        6.0  Gasoline      1.0  8-Speed Automatic     Laredo
SUV
2        8.0  Gasoline      0.0          Automatic     Denali
SUV
3        8.0  Gasoline     32.0  8-Speed Automatic    Pursuit
SUV
4        6.0    Diesel     10.0  6-Speed Automatic    Laramie  Pickup
Truck
```

```
   doors           exterior_color    interior_color       drivetrain
0    4.0                    White      Global Black  Four-wheel Drive
1    4.0                 Metallic      Global Black  Four-wheel Drive
2    4.0             Summit White  Teak/Light Shale  Four-wheel Drive
3    4.0  White Knuckle Clearcoat             Black   All-wheel Drive
4    4.0                   Silver             Black  Four-wheel Drive
```

```
data.tail() # Last records
```

```
                                                 name  \
997   2024 Mercedes-Benz Sprinter 2500 Standard Roof
998           2024 Dodge Hornet Hornet R/T Plus Eawd
999                          2024 Jeep Wagoneer Base
1000           2024 Nissan Murano SV Intelligent AWD
1001                2024 Chevrolet Silverado 2500 WT

                                            description           make
\
997   2024 Mercedes-Benz Sprinter 2500 Cargo 144 WB ...  Mercedes-Benz
998   Dealer Comments +++ Price Ends 5/31/2024 +++ A...          Dodge
999   \n      \n        The ALL New Friendship CDJR ...           Jeep
1000  \n      \n        CVT with Xtronic, AWD.At Tod...         Nissan
1001  01u 2024 Chevrolet Silverado 2500HD Work Truck...      Chevrolet

               model  year    price  \
997    Sprinter 2500  2024  59037.0
998           Hornet  2024  49720.0
999         Wagoneer  2024  69085.0
1000          Murano  2024  43495.0
1001  Silverado 2500  2024  48995.0

                                                 engine  cylinders
fuel  \
997                           16V DDI DOHC Turbo Diesel        4.0
Diesel
998   4 gasoline direct injection, DOHC, Multiair va...        4.0
Gasoline
```

```
999                              24V GDI DOHC Twin Turbo       6.0
Gasoline
1000  6 DOHC, variable valve control, regular unlead...       6.0
Gasoline
1001  8 gasoline direct injection, variable valve co...       8.0
Gasoline

      mileage                         transmission
trim  \
997      10.0                   9-Speed Automatic         Standard
Roof
998       0.0  6-Spd Aisin F21-250 PHEV Auto Trans  Hornet R/T Plus
Eawd
999      20.0                   8-Speed Automatic
Base
1000      6.0                           Automatic    SV Intelligent
AWD
1001     31.0                           Automatic
WT

              body  doors       exterior_color interior_color  \
997      Cargo Van    3.0         Arctic White          Black
998            SUV    4.0        Acapulco Gold          Black
999            SUV    4.0        Diamond Black          Black
1000           SUV    4.0  Pearl White Tricoat       Graphite
1001  Pickup Truck    4.0     Wheatland Yellow      Jet Black

            drivetrain
997   Rear-wheel Drive
998    All-wheel Drive
999   Four-wheel Drive
1000   All-wheel Drive
1001  Rear-wheel Drive
```

2.Data Preprocessing¶

2.1 Data Inspection and Summary Statistics

```
data.shape # Rows and columns
```

```
(1002, 17)
```

```
data.ndim # Dimention of data
```

```
2
```

```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1002 entries, 0 to 1001
Data columns (total 17 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   name            1002 non-null   object 
 1   description     946 non-null    object 
 2   make            1002 non-null   object 
 3   model           1002 non-null   object 
 4   year            1002 non-null   int64  
 5   price           979 non-null    float64
 6   engine          1000 non-null   object 
 7   cylinders       897 non-null    float64
 8   fuel            995 non-null    object 
 9   mileage         968 non-null    float64
 10  transmission    1000 non-null   object 
 11  trim            1001 non-null   object 
 12  body            999 non-null    object 
 13  doors           995 non-null    float64
 14  exterior_color  997 non-null    object 
 15  interior_color  964 non-null    object 
 16  drivetrain      1002 non-null   object 
dtypes: float64(4), int64(1), object(12)
memory usage: 133.2+ KB
```

```python
data.describe() # Description of data
```

	year	price	cylinders	mileage	doors
count	1002.000000	979.000000	897.000000	968.000000	995.000000
mean	2023.916168	50202.985700	4.975474	69.033058	3.943719
std	0.298109	18700.392062	1.392526	507.435745	0.274409
min	2023.000000	0.000000	0.000000	0.000000	2.000000
25%	2024.000000	36600.000000	4.000000	4.000000	4.000000
50%	2024.000000	47165.000000	4.000000	8.000000	4.000000
75%	2024.000000	58919.500000	6.000000	13.000000	4.000000
max	2025.000000	195895.000000	8.000000	9711.000000	5.000000

Price , cylinder,mileage columns have min value 0 which is not feasible. These records will be handled during handling of outlers

```python
data.columns
```

```
Index(['name', 'description', 'make', 'model', 'year', 'price',
'engine',
       'cylinders', 'fuel', 'mileage', 'transmission', 'trim', 'body',
'doors',
       'exterior_color', 'interior_color', 'drivetrain'],
      dtype='object')
```

```python
# Checking unique values in each column

print("# unique values in name:", data['name'].nunique())
print("# unique values in description:",
data['description'].nunique())
print("# unique values in make:", data['make'].nunique())
print("# unique values in model:", data['model'].nunique())
print("# unique values in year:", data['year'].nunique())
print("# unique values in price:", data['price'].nunique())
print("# unique values in engine:", data['engine'].nunique())
print("# unique values in cylindersfuel:",
data['cylinders'].nunique())
print("# unique values in fuel:", data['fuel'].nunique())
print("# unique values in mileage:", data['mileage'].nunique())
print("# unique values in trim:", data['trim'].nunique())
print("# unique values in body:", data['body'].nunique())
print("# unique values in doors:", data['doors'].nunique())
print("# unique values in exterior_color:",
data['exterior_color'].nunique())
print("# unique values in interior_color:",
data['interior_color'].nunique())
print("# unique values in drivetraindrivetrain:",
data['drivetrain'].nunique())
```

```
# unique values in name: 358
# unique values in description: 761
# unique values in make: 28
# unique values in model: 153
# unique values in year: 3
# unique values in price: 859
# unique values in engine: 100
# unique values in cylindersfuel: 5
# unique values in fuel: 7
# unique values in mileage: 95
# unique values in trim: 197
# unique values in body: 8
# unique values in doors: 4
# unique values in exterior_color: 263
# unique values in interior_color: 91
# unique values in drivetraindrivetrain: 4
```

2.2 Data Cleaning¶

Duplicate Values

```
data.isnull().sum()
```

```
name                 0
description         56
make                 0
model                0
year                 0
price               23
engine               2
cylinders          105
fuel                 7
mileage             34
transmission         2
trim                 1
body                 3
doors                7
exterior_color       5
interior_color      38
drivetrain           0
dtype: int64
```

```
data = data.dropna() # Droppping null values
```

```
data.isnull().sum() # No Null values
```

```
name              0
description       0
make              0
model             0
year              0
price             0
engine            0
cylinders         0
fuel              0
mileage           0
transmission      0
trim              0
body              0
doors             0
exterior_color    0
interior_color    0
drivetrain        0
dtype: int64
```

Duplicate values

```
data.duplicated().sum()
```

```
16
```

```
data = data.drop_duplicates() # Dropping duplicates
```

```
data.duplicated().sum() # NO duplicate values
```

```
0
```

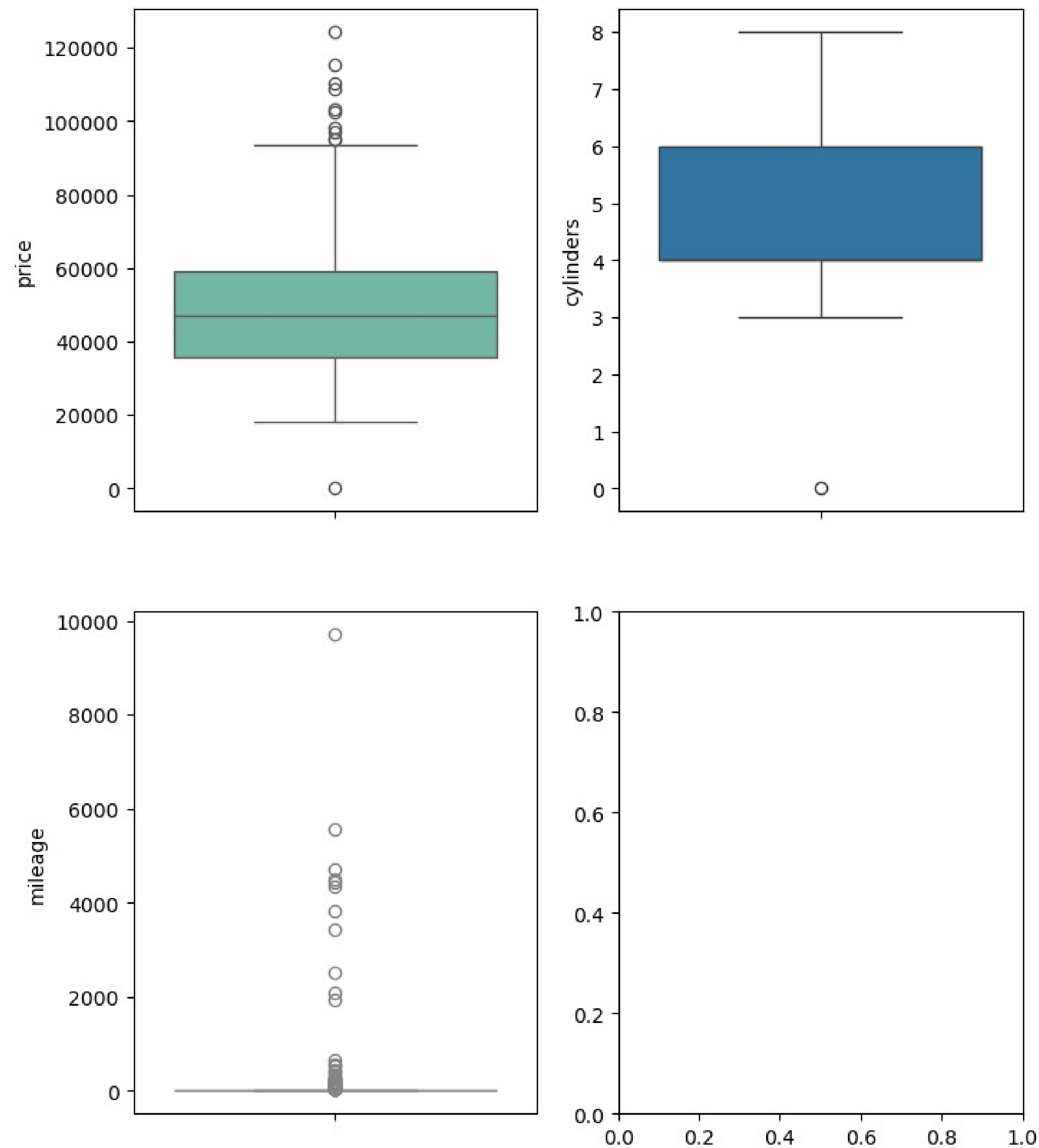
2.3 Outlier Treatment¶

```
data.dtypes
```

```
name                 object
description          object
make                 object
model                object
year                  int64
price               float64
engine               object
cylinders           float64
fuel                 object
mileage             float64
transmission         object
trim                 object
body                 object
doors               float64
exterior_color       object
interior_color       object
drivetrain           object
dtype: object
```

```
fig,axis = plt.subplots(2,2,figsize=(8,10))

sns.boxplot(ax = axis[0][0], data=data['price'],palette='Set2')
sns.boxplot(ax = axis[0][1], data=data['cylinders'])
sns.boxplot(ax = axis[1][0], data=data['mileage'],palette='coolwarm')
```

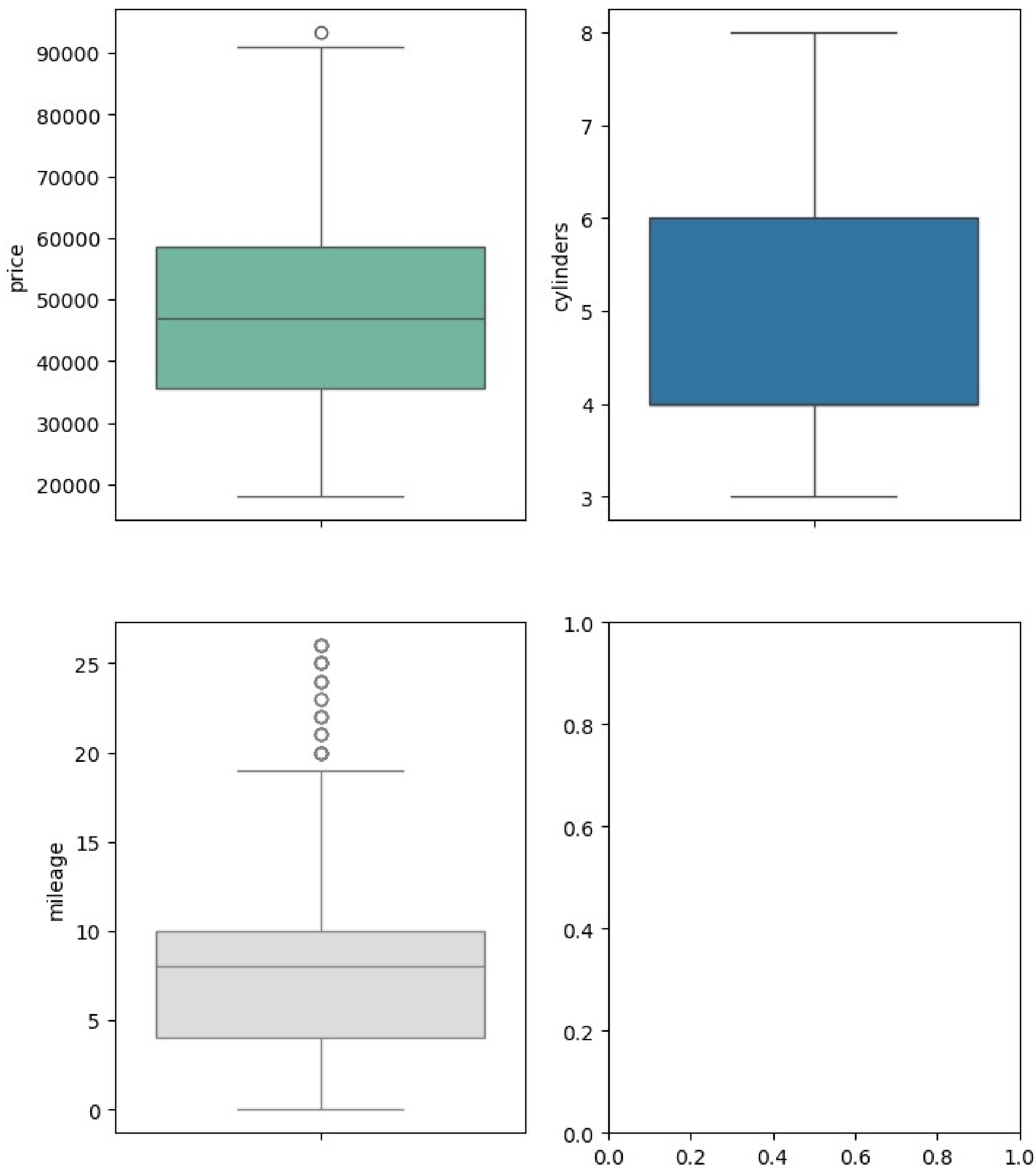
```
<Axes: ylabel='mileage'>
```




```
# Handling Outliers

def outlier(x):

    q1 = data[x].quantile(0.25)
    q3 = data[x].quantile(0.75)
    iqr = q3-q1
```

```
    lower = q1 - 1.5*iqr
    upper = q3 + 1.5*iqr
    median = np.median(data[x])
    for i in data[x]:
        if i <lower or i>upper:
            data[x]=data[x].replace({i:median})

outlier('price')
outlier('cylinders')
outlier('mileage')



fig,axis = plt.subplots(2,2,figsize=(8,10))

sns.boxplot(ax = axis[0][0], data=data['price'],palette='Set2')
sns.boxplot(ax = axis[0][1], data=data['cylinders'])
sns.boxplot(ax = axis[1][0], data=data['mileage'],palette='coolwarm')
```

```
<Axes: ylabel='mileage'>
```



price
90000
80000
70000
60000
50000
40000
30000
20000
cylinders
8
7
6
5
4
3
mileage
25
20
15
10
5
0
1.0
0.8
0.6
0.4
0.2
0.0
0.0 0.2 0.4 0.6 0.8 1.0

3. EDA

3.1 Univariate Analysis

Visualize individual variables to understand their distribution (e.g., histograms for numerical data, bar charts for categorical data).

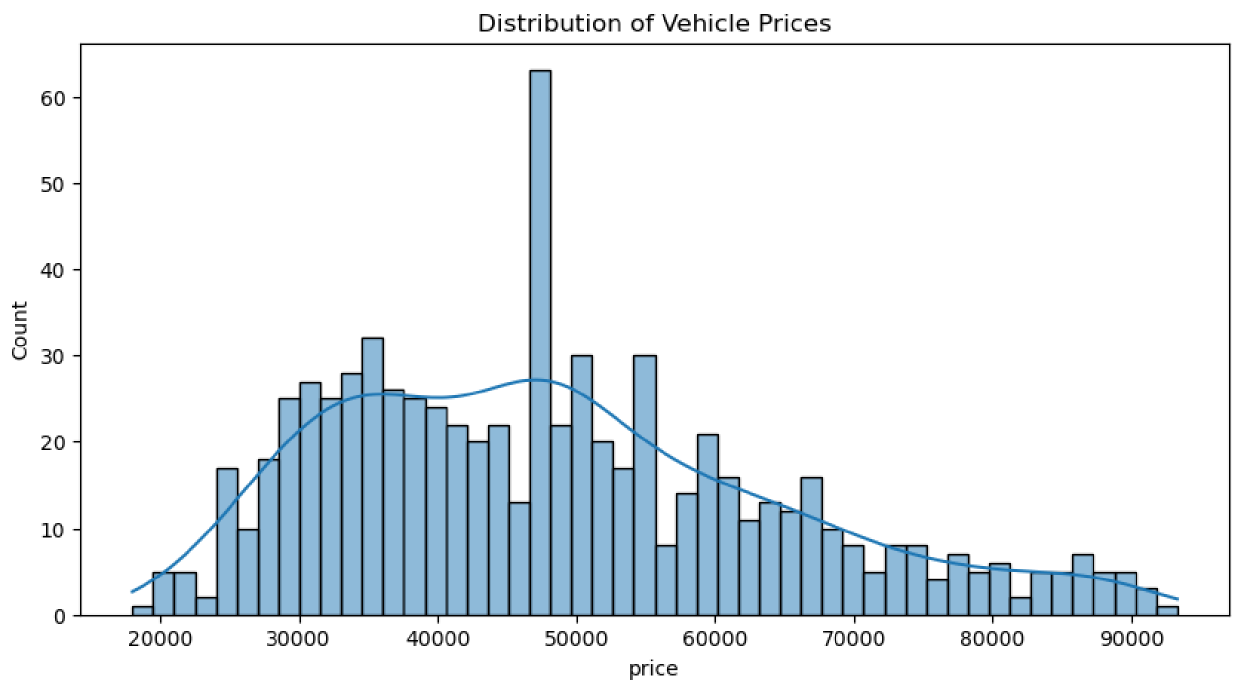
3.2 Bivariate and Multivariate Analysis

Explore relationships between variables by visualizing pairs of variables or groups of variables (e.g., scatter plots, heatmaps).

3.1 Univariate Analysis

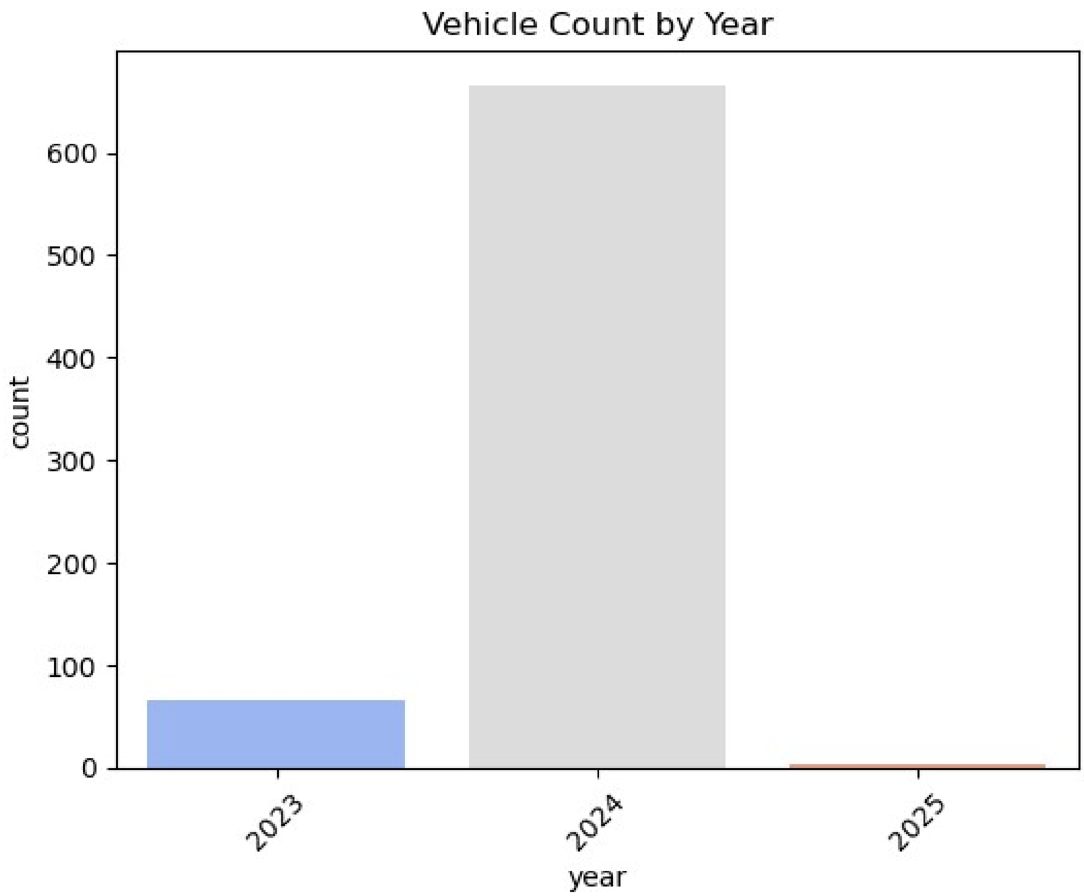
```
plt.figure(figsize=(10, 5))
sns.histplot(data['price'], bins=50, kde=True)
plt.title('Distribution of Vehicle Prices')
```

```
Text(0.5, 1.0, 'Distribution of Vehicle Prices')
```



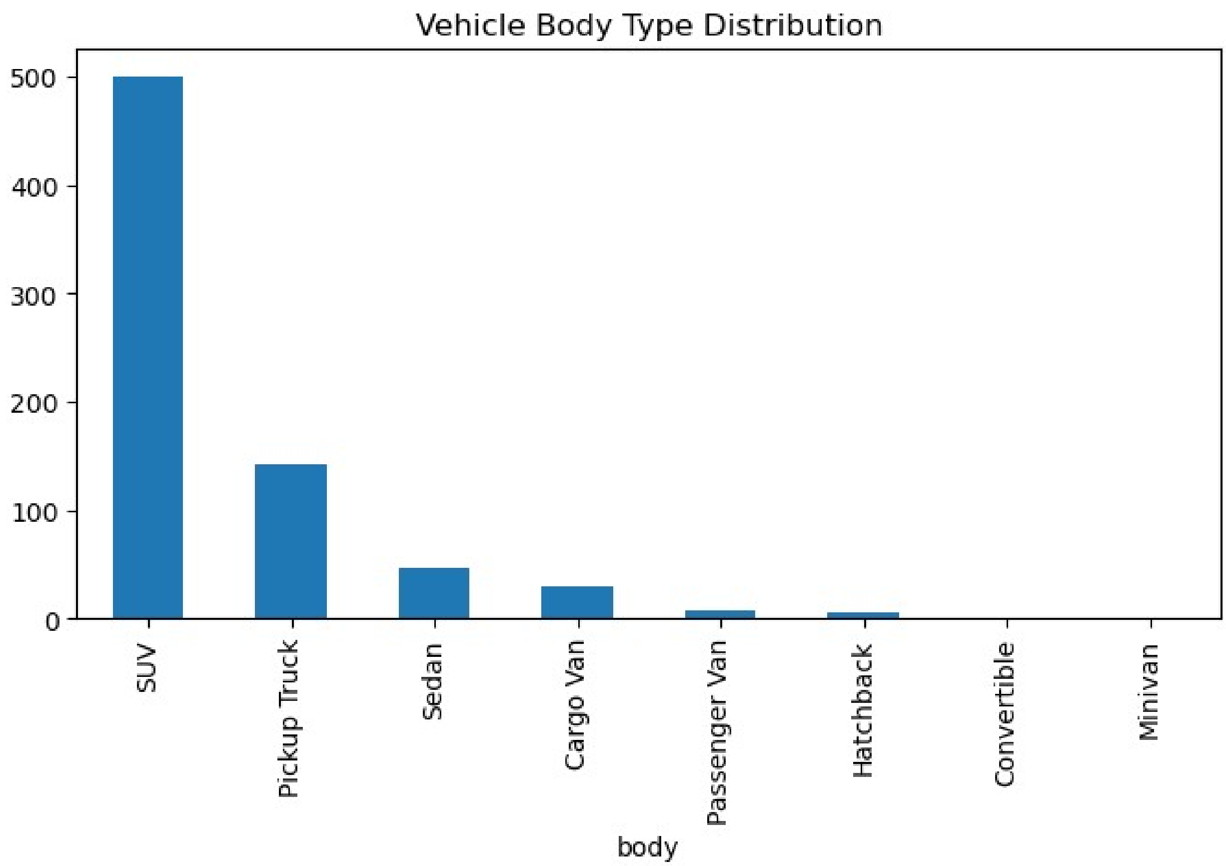
```python
sns.countplot(data=data, x='year',palette='coolwarm')
plt.xticks(rotation=45)
plt.title('Vehicle Count by Year')
```

```
Text(0.5, 1.0, 'Vehicle Count by Year')
```



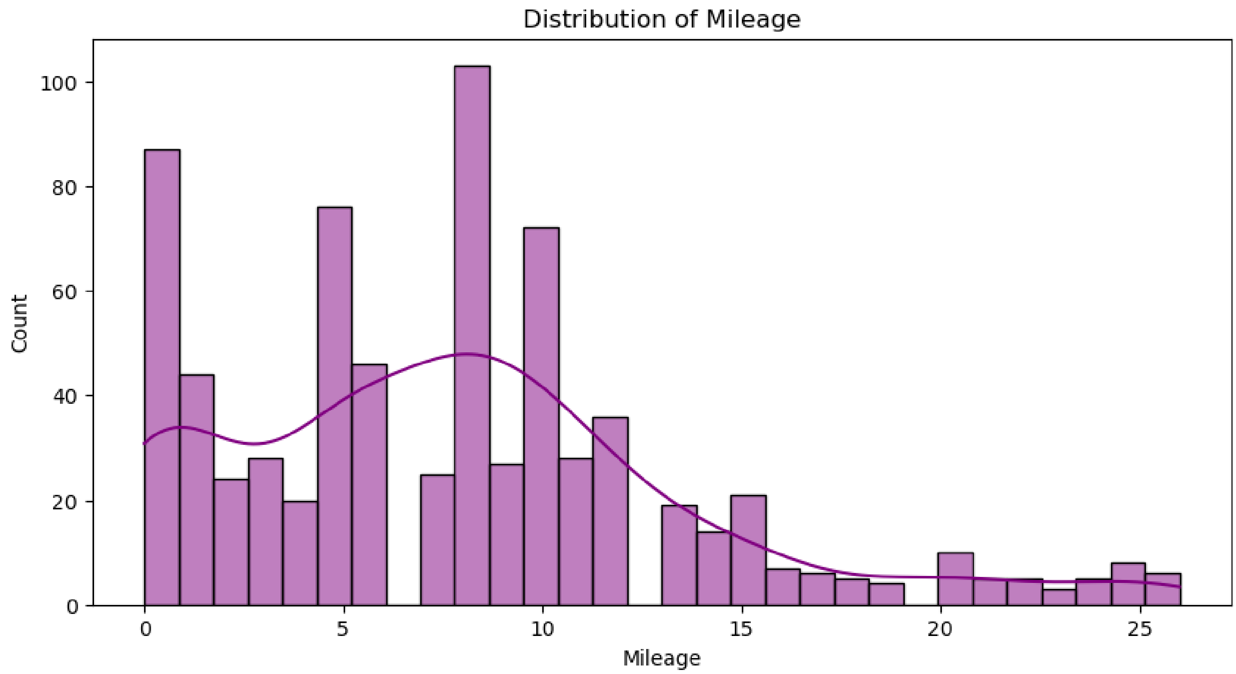

```python
data['body'].value_counts().plot(kind='bar', figsize=(8, 4))
plt.title('Vehicle Body Type Distribution')
```

```
Text(0.5, 1.0, 'Vehicle Body Type Distribution')
```

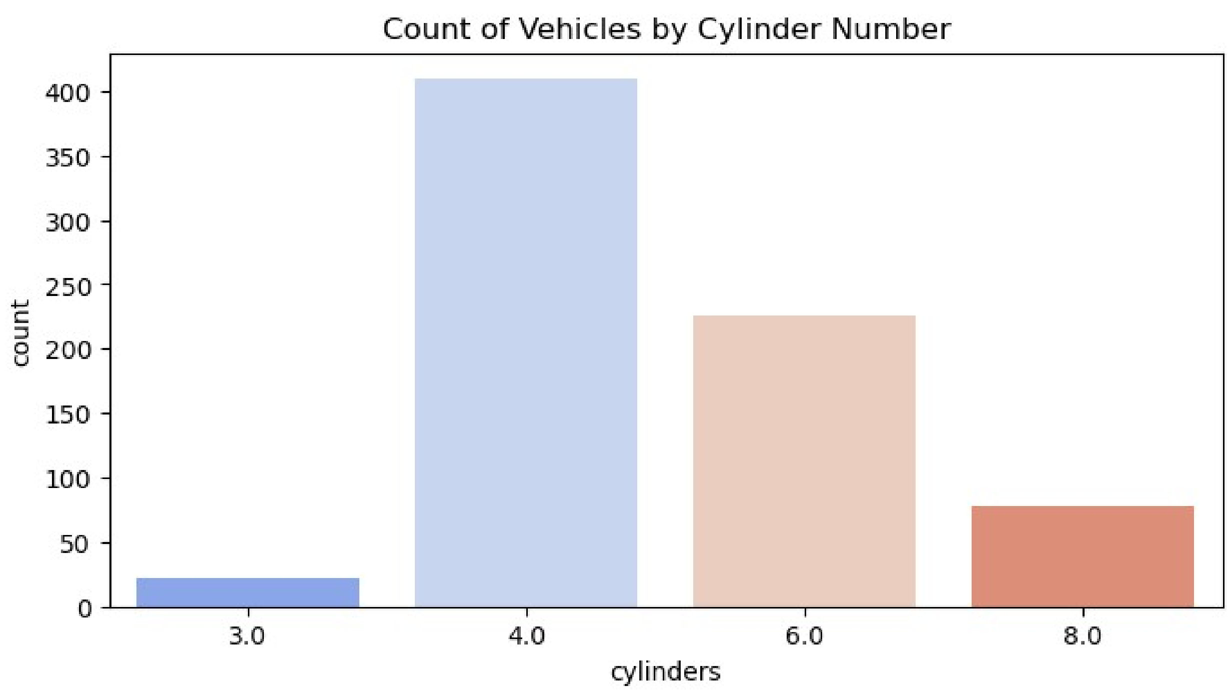



```
plt.figure(figsize=(10, 5))
sns.histplot(data['mileage'], bins=30, kde=True, color='purple')
plt.title('Distribution of Mileage')
plt.xlabel('Mileage')
```

```
Text(0.5, 0, 'Mileage')
```

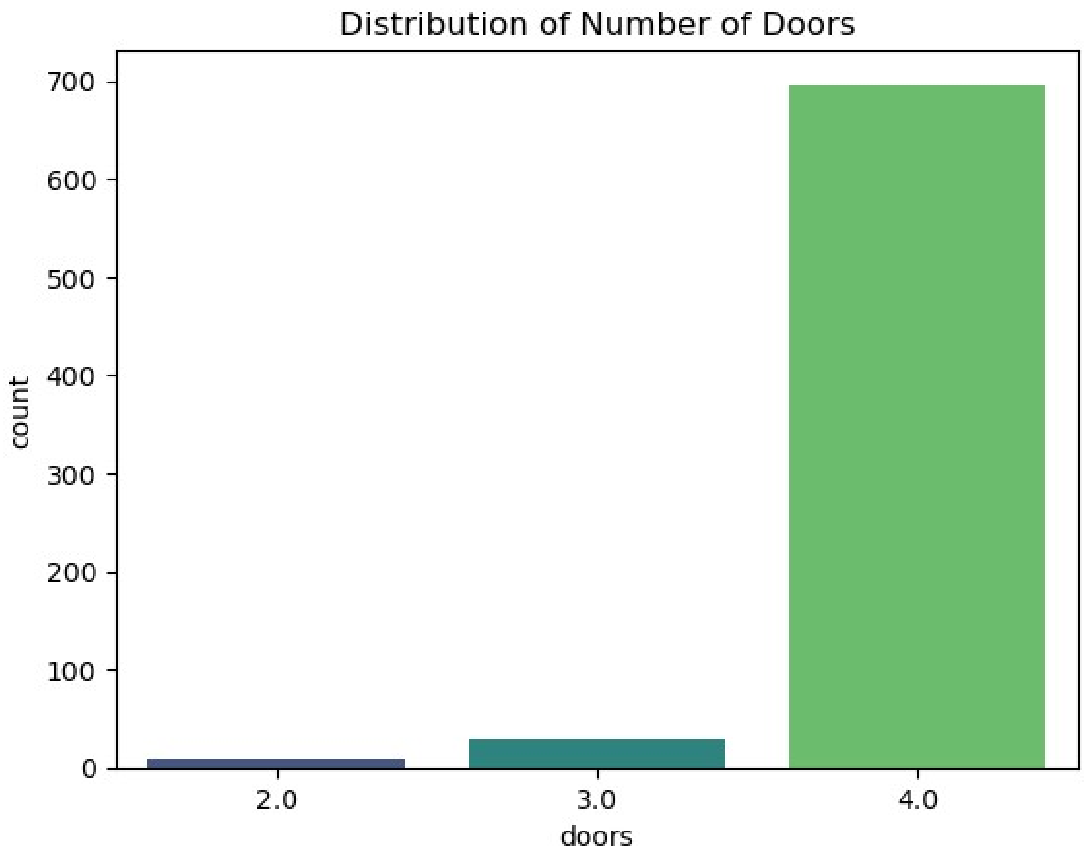



```
plt.figure(figsize=(8, 4))
sns.countplot(data=data, x='cylinders', palette='coolwarm')
plt.title('Count of Vehicles by Cylinder Number')

Text(0.5, 1.0, 'Count of Vehicles by Cylinder Number')
```



```
sns.countplot(data=data, x='doors', palette='viridis')
plt.title('Distribution of Number of Doors')
```

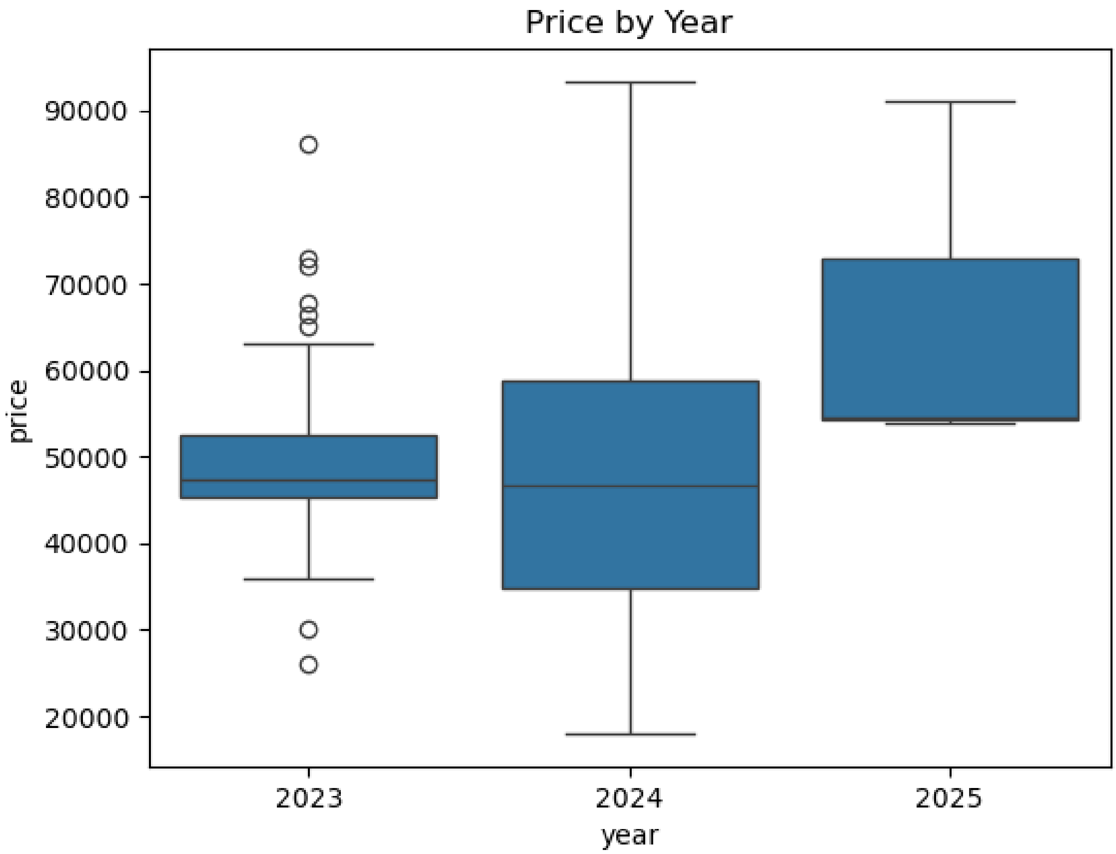
```
Text(0.5, 1.0, 'Distribution of Number of Doors')
```



3.2 Bivariate analysis

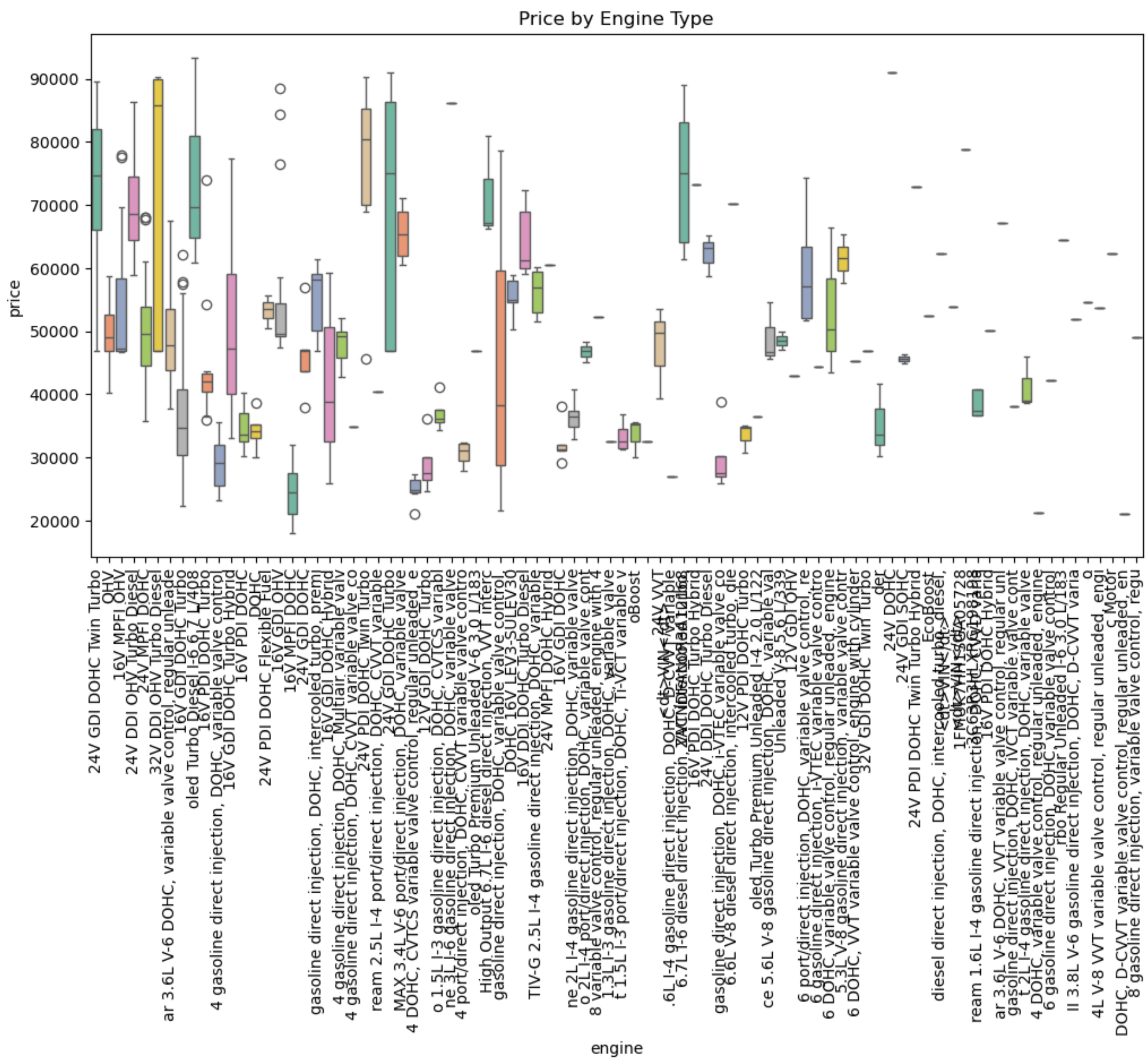
```
sns.boxplot(data=data, x='year', y='price')
plt.title('Price by Year')
```

```
Text(0.5, 1.0, 'Price by Year')
```



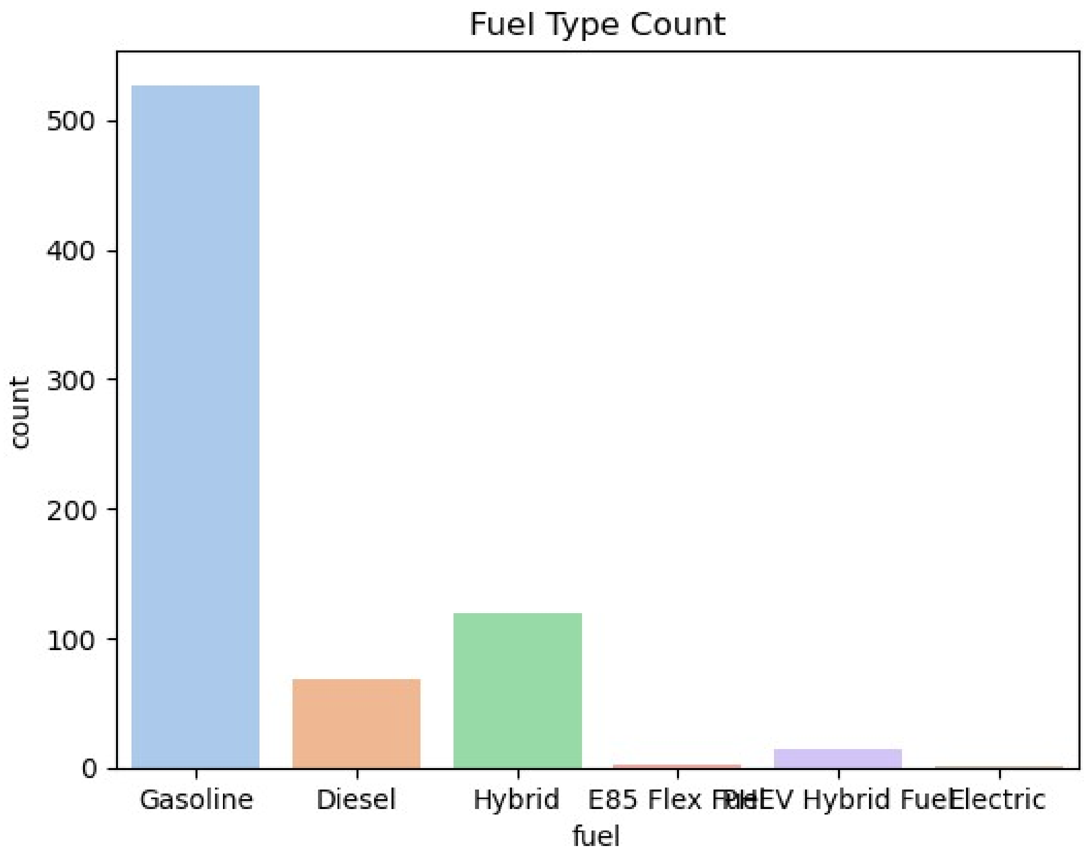

```
plt.figure(figsize=(12, 6))
sns.boxplot(data=data, x='engine', y='price',palette='Set2')
plt.xticks(rotation=90)
plt.title('Price by Engine Type')
```

```
Text(0.5, 1.0, 'Price by Engine Type')
```



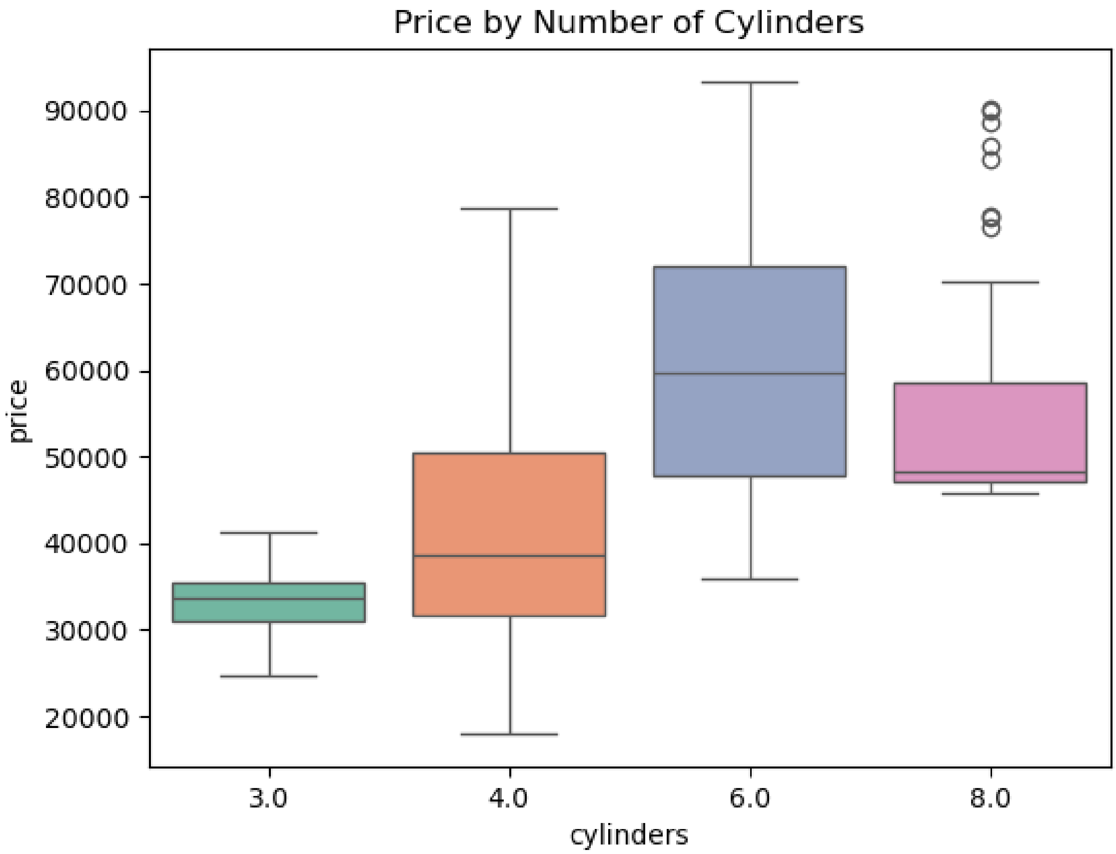

```
sns.countplot(data=data, x='fuel',palette='pastel')
plt.title('Fuel Type Count')
```

```
Text(0.5, 1.0, 'Fuel Type Count')
```



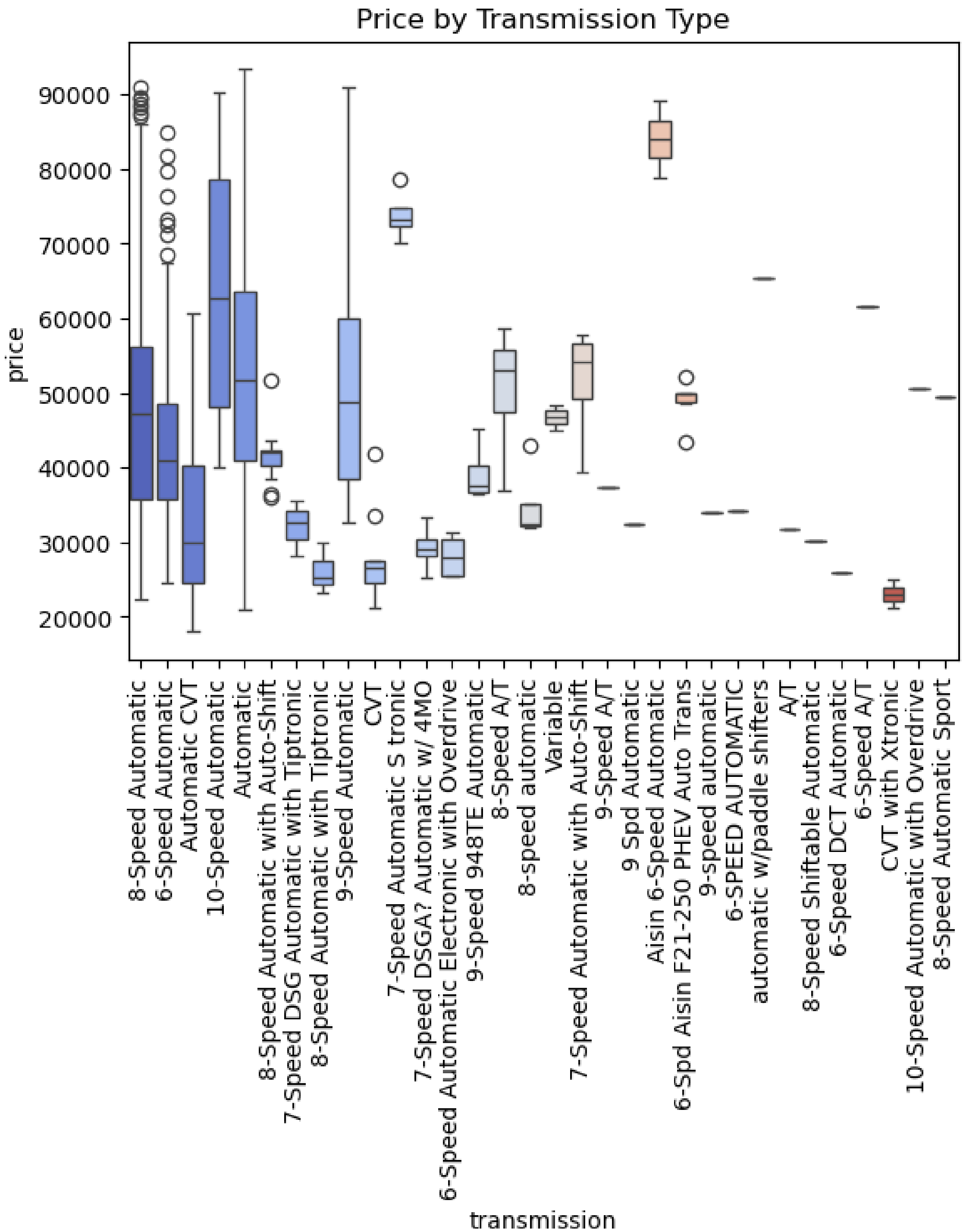

```python
sns.boxplot(data=data, x='cylinders', y='price', palette='Set2')
plt.title('Price by Number of Cylinders')
```

```
Text(0.5, 1.0, 'Price by Number of Cylinders')
```




```
sns.boxplot(data=data, x='transmission', y='price',palette='coolwarm')
plt.xticks(rotation=90)
plt.title('Price by Transmission Type')
```

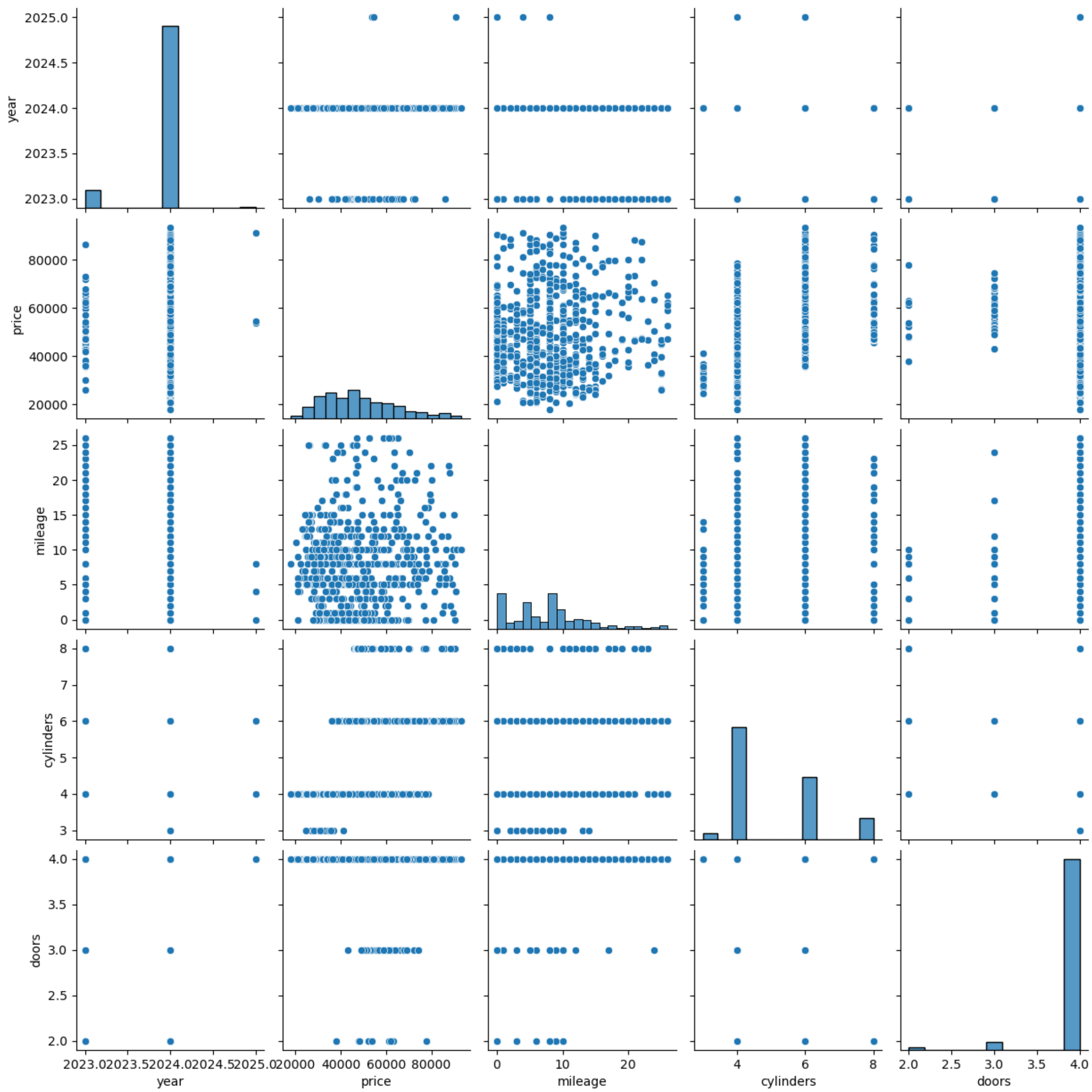
```
Text(0.5, 1.0, 'Price by Transmission Type')
```




```
num_features = ['year', 'price', 'mileage', 'cylinders', 'doors']

# Pairplot for correlations
```

```
sns.pairplot(data[num_features])
```

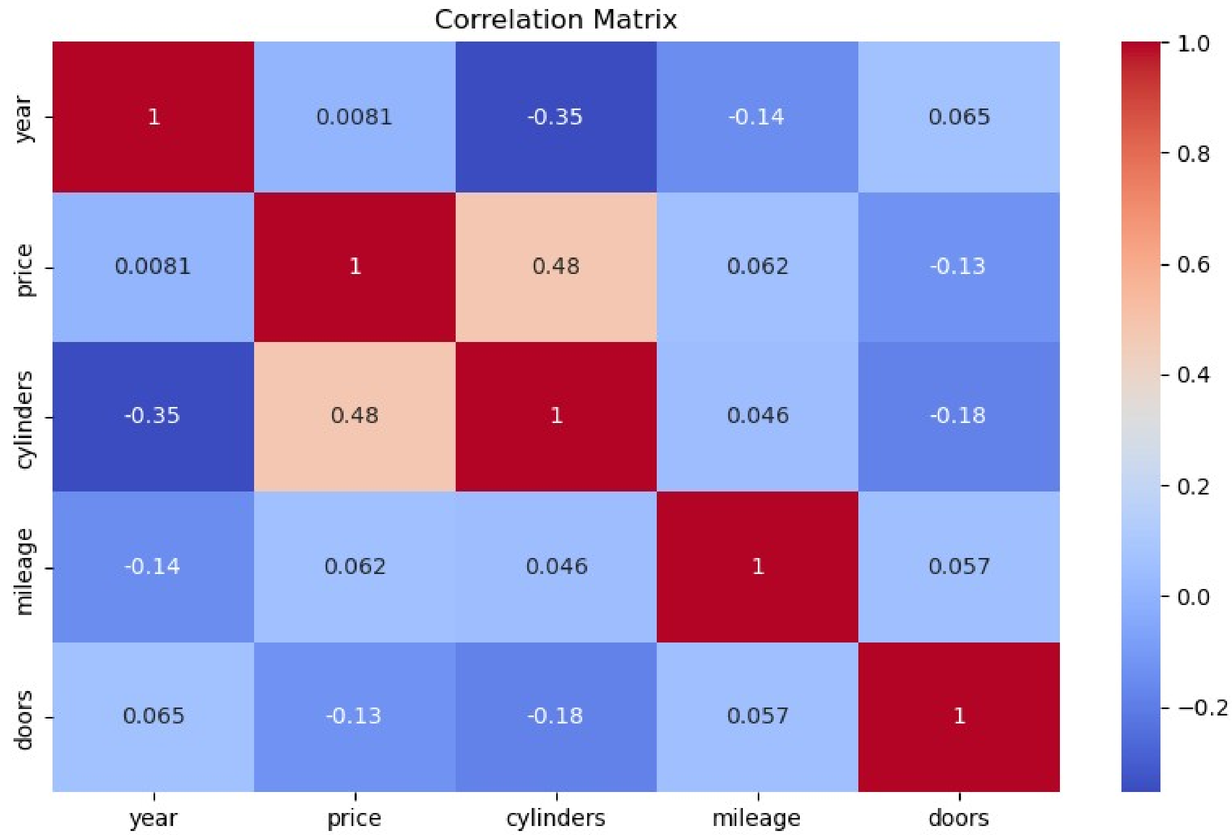
```
<seaborn.axisgrid.PairGrid at 0x1a0d01434a0>
```



3.3 Multivariant Analysis

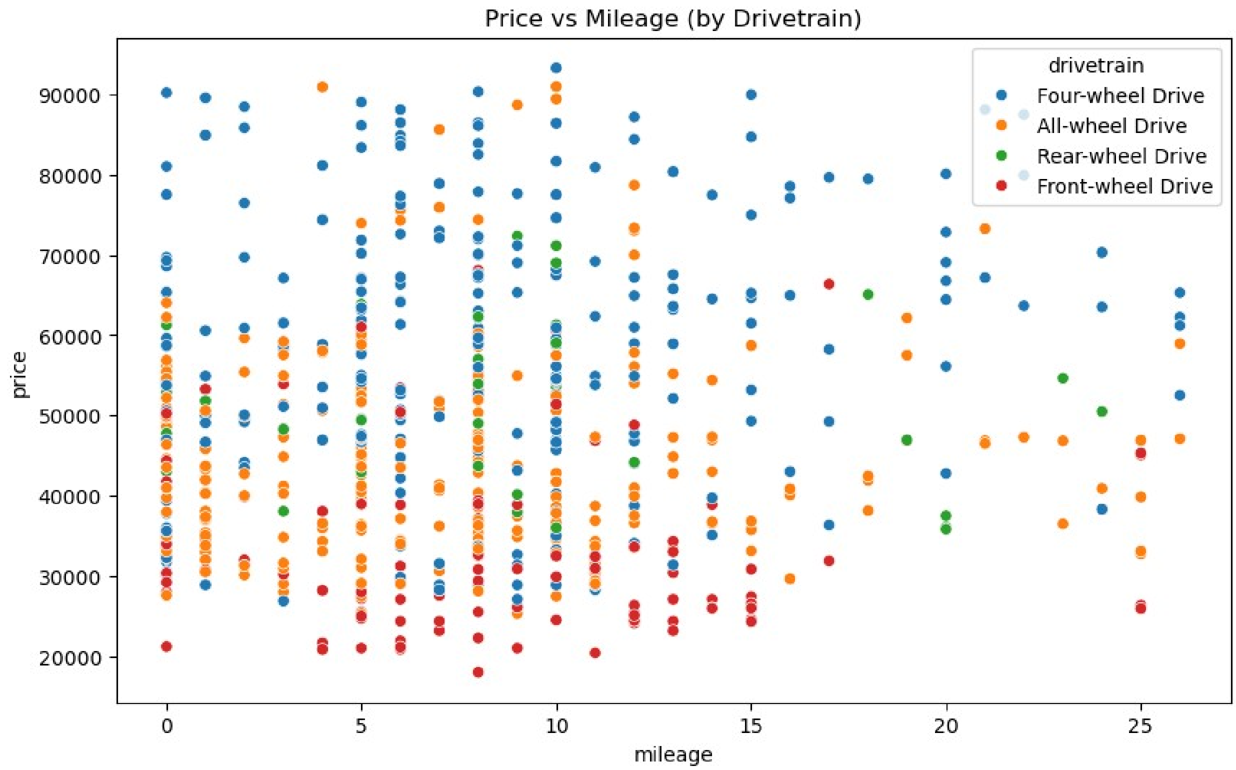
```
plt.figure(figsize=(10, 6))
sns.heatmap(data.corr(numeric_only=True), annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
```

```
Text(0.5, 1.0, 'Correlation Matrix')
```

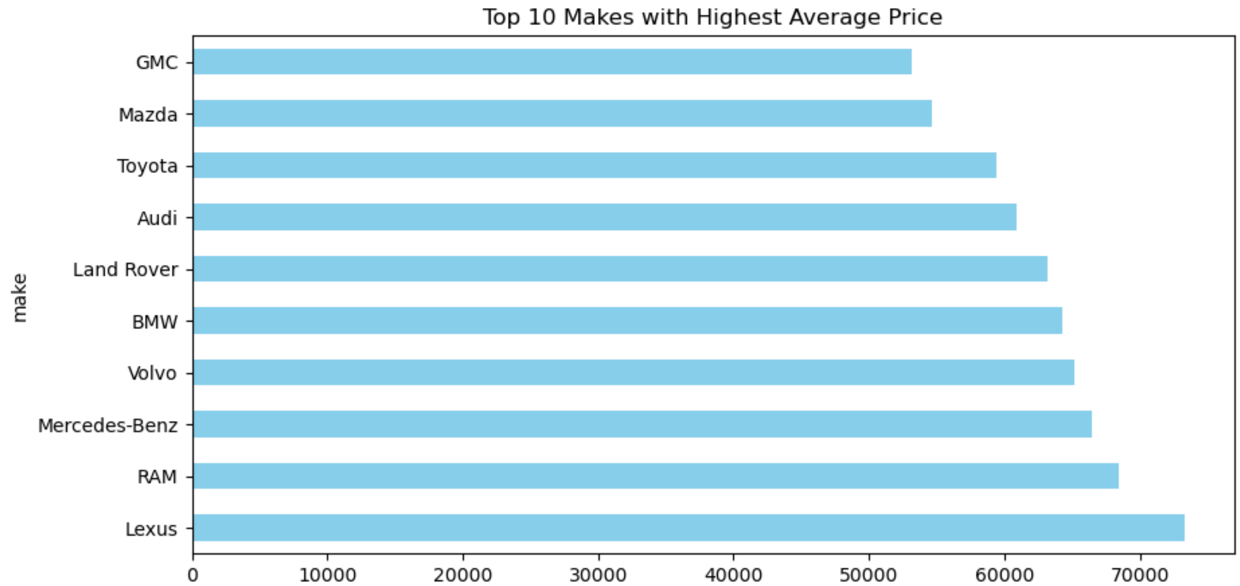



```
plt.figure(figsize=(10, 6))
sns.scatterplot(data=data, x='mileage', y='price', hue='drivetrain')
plt.title('Price vs Mileage (by Drivetrain)')
```

```
Text(0.5, 1.0, 'Price vs Mileage (by Drivetrain)')
```




```
avg_price_by_make = data.groupby('make')
['price'].mean().sort_values(ascending=False).head(10)
avg_price_by_make.plot(kind='barh', figsize=(10, 5), color='skyblue')
plt.title('Top 10 Makes with Highest Average Price')

Text(0.5, 1.0, 'Top 10 Makes with Highest Average Price')
```



Grouped rare categories in model, engine, and trim features into 'Other' to reduce cardinality and improve model generalization.

```
model_counts = data['model'].value_counts()
common_models = model_counts[model_counts > 5].index
data['model'] = data['model'].apply(lambda x: x if x in common_models
else 'Other')


engine_counts = data['engine'].value_counts()
common_engine = engine_counts[engine_counts > 5].index

# Replace engine models with 'Other'
data['engine'] = data['engine'].apply(lambda x: x if x in
common_engine else 'Other')


trim_counts = data['trim'].value_counts()
common_trim = trim_counts[trim_counts >3].index

# Replace rare Trim with 'Other'
data['trim'] = data['trim'].apply(lambda x: x if x in common_trim else
'Other')
```

4. Model Building

4.1 Encoding Categorical columns

```
data =
pd.get_dummies(data,columns=['make','fuel','body','doors','drivetrain'
,'model','engine','trim'],drop_first=True)
data.head()
```

```
                                    name  \
0     2024 Jeep Wagoneer Series II
1  2024 Jeep Grand Cherokee Laredo
3       2023 Dodge Durango Pursuit
4            2024 RAM 3500 Laramie
5      2024 Nissan Murano Platinum

                                         description  year    price  \
0  \n      \n        Heated Leather Seats, Nav Sy...  2024  74600.0
1  Al West is committed to offering every custome...  2024  50170.0
3  White Knuckle Clearcoat 2023 Dodge Durango Pur...  2023  46835.0
4  \n      \n        2024 Ram 3500 Laramie Billet...  2024  81663.0
5  \n      \n        Boasts 28 Highway MPG and 20...  2024  46000.0

   cylinders  mileage       transmission           exterior_color  \
0        6.0     10.0  8-Speed Automatic                    White
1        6.0      1.0  8-Speed Automatic                 Metallic
3        8.0      8.0  8-Speed Automatic  White Knuckle Clearcoat
4        6.0     10.0  6-Speed Automatic                   Silver
5        6.0      8.0      Automatic CVT                    White

  interior_color  make_BMW  ...  trim_Sahara  trim_Series II
trim_Series III  \
0   Global Black     False  ...        False            True
False
1   Global Black     False  ...        False           False
False
3          Black     False  ...        False           False
False
4          Black     False  ...        False           False
False
5           Gray     False  ...        False           False
False

   trim_Sport  trim_Sport S  trim_Tradesman  \
0       False         False           False
1       False         False           False
3       False         False           False
```

```
4       False         False            False
5       False         False            False

   trim_Tradesman Crew Cab 4x4 8&#39; Box  trim_Trailhawk  trim_XLT  \
0                                    False           False     False
1                                    False           False     False
3                                    False           False     False
4                                    False           False     False
5                                    False           False     False

   trim_xDrive40i
0           False
1           False
3           False
4           False
5           False

[5 rows x 164 columns]
```

4.2 Feature Engineering

```
X =
data.drop(columns=['name','description','price','exterior_color','inte
rior_color','transmission'])
y = data['price']
```

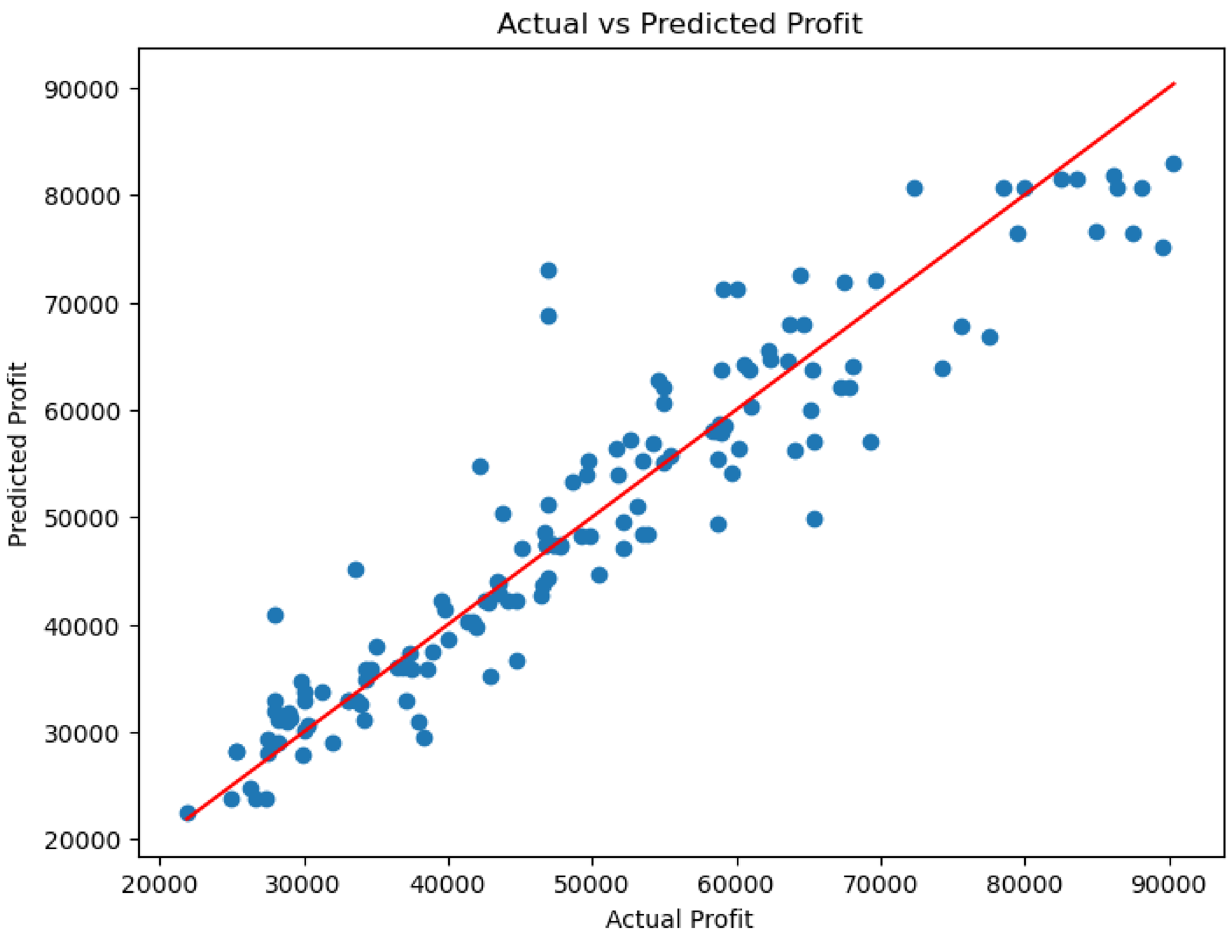
4.3 Model Training

```
# Split the data into training and testing

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

# Standarize the data

scaler = StandardScaler()
X_train_normalized = scaler.fit_transform(X_train)
X_test_normalized = scaler.transform(X_test)
```

```python
# Using Linear Regression to predict profit

model = LinearRegression()

# Training thw model
model.fit(X_train_normalized, y_train)

# Make Prediction
y_pred = model.predict(X_test_normalized)

mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

print(f"Root  Squared Error: {rmse}")
print(f"R-squared: {r2}")
```

```
Root  Squared Error: 5720.5809941552125
R-squared: 0.8814003113749823
```

```python
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred)
plt.plot([min(y_test), max(y_test)], [min(y_test),
max(y_test)], color='red')
plt.title('Actual vs Predicted Profit')
plt.xlabel('Actual Profit')
plt.ylabel('Predicted Profit')
plt.show()
```



5. Advance Model

```
# Random Forrest

from sklearn.ensemble import RandomForestRegressor
rf = RandomForestRegressor(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)
y_pred_log = rf.predict(X_test)



mse = mean_squared_error(y_test, y_pred_log)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred_log)

print(f"Root  Squared Error: {rmse}")
print(f"R-squared: {r2}")
```

```
Root  Squared Error: 5692.849758133807
R-squared: 0.8825473781654893
```

```python
# XGBoost

from xgboost import XGBRegressor
xgb = XGBRegressor(n_estimators=100, learning_rate=0.1,
random_state=42)
xgb.fit(X_train, y_train)
y_pred_xgb = xgb.predict(X_test)



mse = mean_squared_error(y_test, y_pred_xgb)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred_xgb)

print(f"Root  Squared Error: {rmse}")
print(f"R-squared: {r2}")
```

```
Root  Squared Error: 5839.966089939761
R-squared: 0.8763984486309568
```

Conclusion

To identify the best-performing algorithm for vehicle price prediction, we evaluated three models: Linear Regression, Random Forest, and XGBoost. Among

them, the Random Forest model delivered the most accurate results, achieving the lowest Root Mean Squared Error (RMSE) of 5692.85 and the highest R-

squared value of 0.8825. This indicates that the model captures approximately 88.25% of the variance in vehicle prices, making it the most reliable

choice. While Linear Regression and XGBoost also performed well, Random Forest showed a slightly better balance between prediction accuracy and variance explanation.