HTML

July 10, 2025

[97]:
```
## Phase 1: Data Understanding and Preparation
```

[98]:
```
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.feature_selection import SelectKBest, f_regression

# Set display options
pd.set_option('display.max_columns', None)
```

[99]:
```
# Import basic libraries
import pandas as pd
import matplotlib.pyplot as plt

# 1. DATA EXPLORATION
# ===================

# Load the dataset
file_path = r"C:\Users\USER\OneDrive\Desktop\CarPrice_Assignment.csv"
data = pd.read_csv(file_path)

# Basic information
print("=== BASIC INFO ===")
print("Number of rows and columns:", data.shape)
print("\nFirst 5 rows:")
print(data.head())

# Check for missing values
print("\n=== MISSING VALUES ===")
print(data.isnull().sum())
```

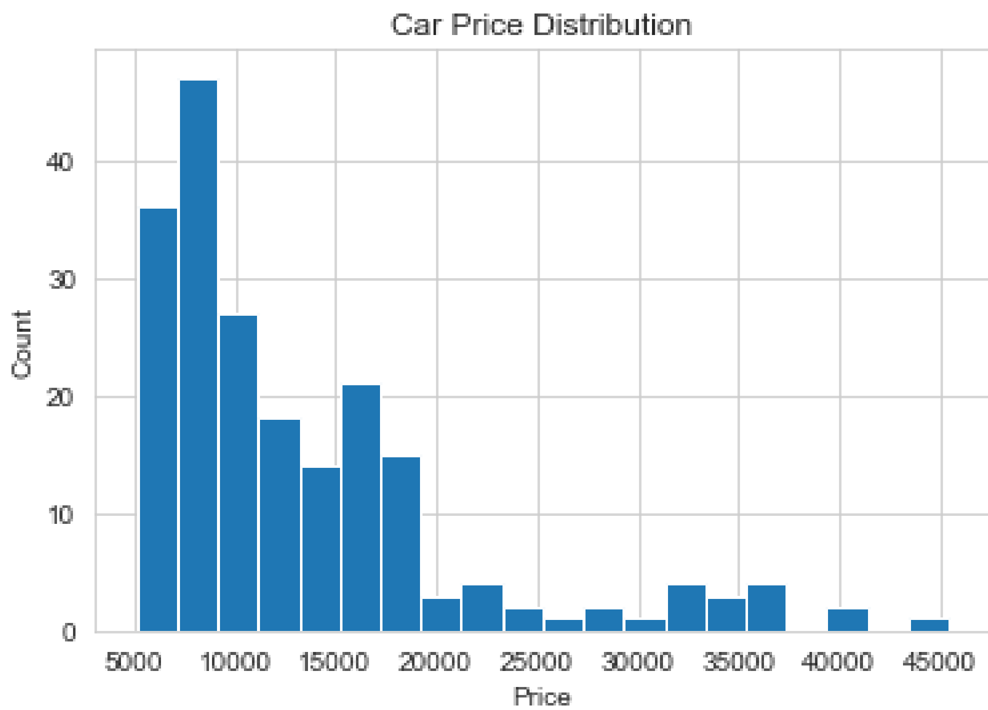
```python
# Data types
print("\n=== DATA TYPES ===")
print(data.dtypes)

# Basic statistics
print("\n=== STATISTICS ===")
print(data.describe())

# Plot price distribution (our target variable)
print("\n=== PRICE DISTRIBUTION ===")
plt.hist(data['price'], bins=20)
plt.title('Car Price Distribution')
plt.xlabel('Price')
plt.ylabel('Count')
plt.show()

# 2. DATA CLEANING
# ================

# Make a copy of original data
clean_data = data.copy()

# Handle missing values (fill with median for numbers, mode for categories)
for col in clean_data.columns:
    if clean_data[col].isnull().sum() > 0:  # If column has missing values
        if clean_data[col].dtype == 'object':  # For text/categories
            clean_data[col].fillna(clean_data[col].mode()[0], inplace=True)
        else:  # For numbers
            clean_data[col].fillna(clean_data[col].median(), inplace=True)

# Remove duplicate rows
clean_data.drop_duplicates(inplace=True)

# Remove outliers using simple IQR method
for col in clean_data.select_dtypes(include=['int64', 'float64']).columns:
    if col == 'price':  # We definitely want to clean our target variable
        Q1 = clean_data[col].quantile(0.25)
        Q3 = clean_data[col].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR

        # Keep only the non-outliers
        clean_data = clean_data[(clean_data[col] >= lower_bound) &
                                (clean_data[col] <= upper_bound)]

# Show cleaning results
```

```python
print("\n=== CLEANING RESULTS ===")
print("Original data shape:", data.shape)
print("Cleaned data shape:", clean_data.shape)
print("\nData is now ready for analysis!")
print("""
Dependent variable: 'price' (right-skewed distribution shown in histogram).
Recommended transformation: Apply log transformation (np.log(price)) to␣
↪normalize distribution.
Data prep needed: Encode categoricals (fueltype, carbody etc.) and scale numeric␣
↪features.
Dataset is clean (no missing values) with 190 rows ready for analysis after␣
↪preprocessing.
""")
```

```
=== BASIC INFO ===
Number of rows and columns: (205, 26)

First 5 rows:
   car_ID  symboling                   CarName fueltype aspiration doornumber  \
0       1          3        alfa-romero giulia      gas        std        two
1       2          3       alfa-romero stelvio      gas        std        two
2       3          1  alfa-romero Quadrifoglio      gas        std        two
3       4          2               audi 100 ls      gas        std       four
4       5          2                audi 100ls      gas        std       four

       carbody drivewheel enginelocation  wheelbase  carlength  carwidth  \
0  convertible        rwd          front       88.6      168.8      64.1
1  convertible        rwd          front       88.6      168.8      64.1
2    hatchback        rwd          front       94.5      171.2      65.5
3        sedan        fwd          front       99.8      176.6      66.2
4        sedan        4wd          front       99.4      176.6      66.4

   carheight  curbweight enginetype cylindernumber  enginesize fuelsystem  \
0       48.8        2548       dohc           four         130       mpfi
1       48.8        2548       dohc           four         130       mpfi
2       52.4        2823       ohcv            six         152       mpfi
3       54.3        2337        ohc           four         109       mpfi
4       54.3        2824        ohc           five         136       mpfi

   boreratio  stroke  compressionratio  horsepower  peakrpm  citympg  \
0       3.47    2.68               9.0         111     5000       21
1       3.47    2.68               9.0         111     5000       21
2       2.68    3.47               9.0         154     5000       19
3       3.19    3.40              10.0         102     5500       24
4       3.19    3.40               8.0         115     5500       18

   highwaympg    price
```

```
0          27  13495.0
1          27  16500.0
2          26  16500.0
3          30  13950.0
4          22  17450.0

=== MISSING VALUES ===
car_ID              0
symboling           0
CarName             0
fueltype            0
aspiration          0
doornumber          0
carbody             0
drivewheel          0
enginelocation      0
wheelbase           0
carlength           0
carwidth            0
carheight           0
curbweight          0
enginetype          0
cylindernumber      0
enginesize          0
fuelsystem          0
boreratio           0
stroke              0
compressionratio    0
horsepower          0
peakrpm             0
citympg             0
highwaympg          0
price               0
dtype: int64

=== DATA TYPES ===
car_ID                int64
symboling             int64
CarName              object
fueltype             object
aspiration           object
doornumber           object
carbody              object
drivewheel           object
enginelocation       object
wheelbase           float64
carlength           float64
carwidth            float64
```

```
carheight           float64
curbweight            int64
enginetype           object
cylindernumber       object
enginesize            int64
fuelsystem           object
boreratio           float64
stroke              float64
compressionratio    float64
horsepower            int64
peakrpm               int64
citympg               int64
highwaympg            int64
price               float64
dtype: object

=== STATISTICS ===
           car_ID   symboling   wheelbase   carlength    carwidth   carheight  \
count  205.000000  205.000000  205.000000  205.000000  205.000000  205.000000
mean   103.000000    0.834146   98.756585  174.049268   65.907805   53.724878
std     59.322565    1.245307    6.021776   12.337289    2.145204    2.443522
min      1.000000   -2.000000   86.600000  141.100000   60.300000   47.800000
25%     52.000000    0.000000   94.500000  166.300000   64.100000   52.000000
50%    103.000000    1.000000   97.000000  173.200000   65.500000   54.100000
75%    154.000000    2.000000  102.400000  183.100000   66.900000   55.500000
max    205.000000    3.000000  120.900000  208.100000   72.300000   59.800000

        curbweight  enginesize   boreratio      stroke  compressionratio  \
count   205.000000  205.000000  205.000000  205.000000        205.000000
mean   2555.565854  126.907317    3.329756    3.255415         10.142537
std     520.680204   41.642693    0.270844    0.313597          3.972040
min    1488.000000   61.000000    2.540000    2.070000          7.000000
25%    2145.000000   97.000000    3.150000    3.110000          8.600000
50%    2414.000000  120.000000    3.310000    3.290000          9.000000
75%    2935.000000  141.000000    3.580000    3.410000          9.400000
max    4066.000000  326.000000    3.940000    4.170000         23.000000

       horsepower      peakrpm     citympg  highwaympg         price
count  205.000000   205.000000  205.000000  205.000000    205.000000
mean   104.117073  5125.121951   25.219512   30.751220  13276.710571
std     39.544167   476.985643    6.542142    6.886443   7988.852332
min     48.000000  4150.000000   13.000000   16.000000   5118.000000
25%     70.000000  4800.000000   19.000000   25.000000   7788.000000
50%     95.000000  5200.000000   24.000000   30.000000  10295.000000
75%    116.000000  5500.000000   30.000000   34.000000  16503.000000
max    288.000000  6600.000000   49.000000   54.000000  45400.000000

=== PRICE DISTRIBUTION ===
```

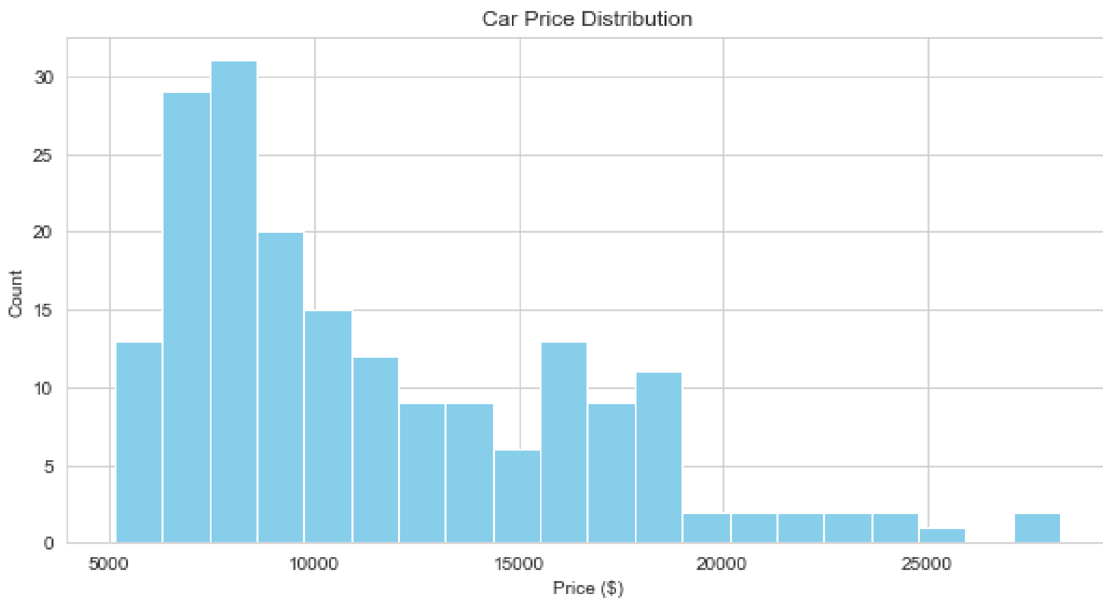


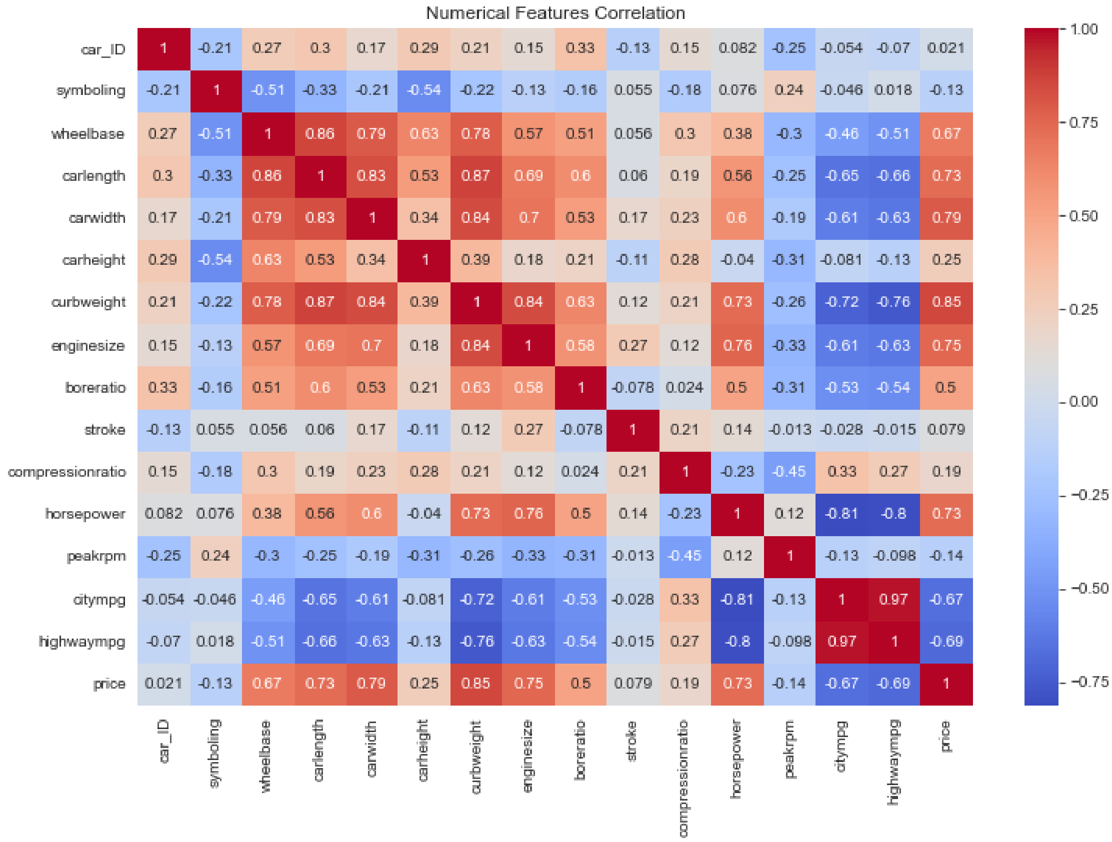

```
=== CLEANING RESULTS ===
Original data shape: (205, 26)
Cleaned data shape: (190, 26)

Data is now ready for analysis!

Dependent variable: 'price' (right-skewed distribution shown in histogram).
Recommended transformation: Apply log transformation (np.log(price)) to
normalize distribution.
Data prep needed: Encode categoricals (fueltype, carbody etc.) and scale numeric
features.
Dataset is clean (no missing values) with 190 rows ready for analysis after
preprocessing.
```

[100]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load cleaned data (from Phase 1)
# clean_data = pd.read_csv('cleaned_data.csv')

# 1. UNIVARIATE ANALYSIS - TARGET VARIABLE
```

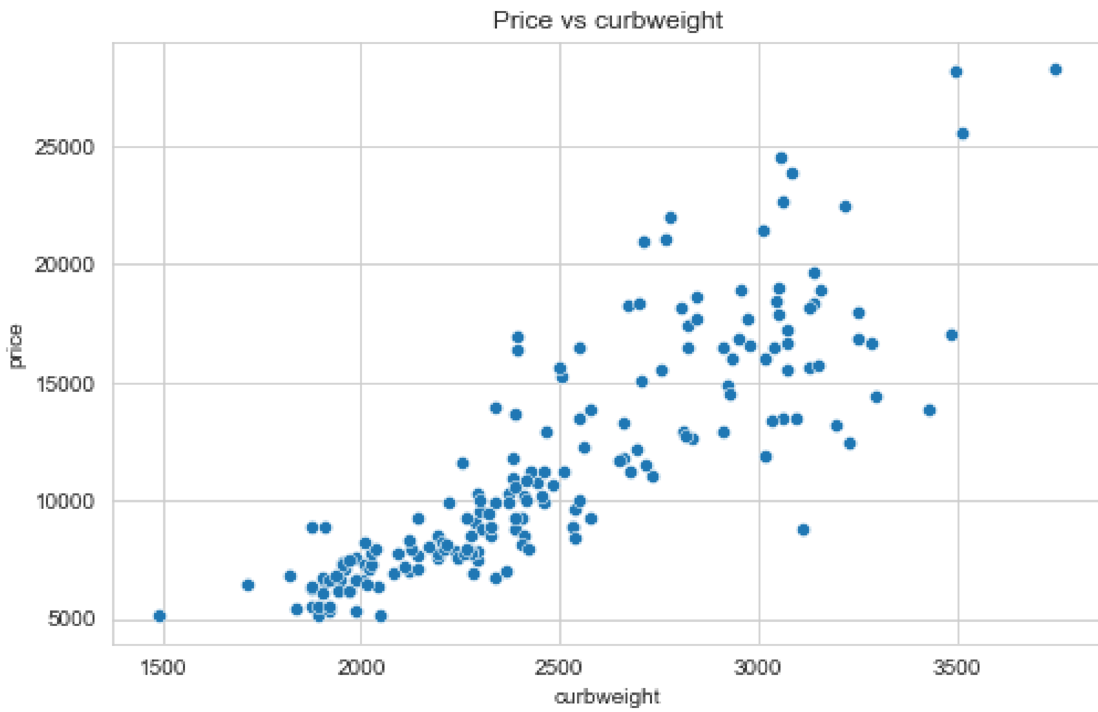
```python
# ========================================
plt.figure(figsize=(10,5))
plt.hist(clean_data['price'], bins=20, color='skyblue')
plt.title('Car Price Distribution')
plt.xlabel('Price ($)')
plt.ylabel('Count')
plt.show()

# 2. BIVARIATE ANALYSIS - RELATIONSHIPS
# =====================================

# A. Correlation Heatmap
plt.figure(figsize=(12,8))
corr_matrix = clean_data.select_dtypes(include=['int64','float64']).corr()
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Numerical Features Correlation')
plt.show()

# Print key correlations
print("\n=== PRICE CORRELATIONS ===")
price_corr = corr_matrix['price'].sort_values(ascending=False)
print(price_corr.head(8))  # Top 7 + price itself

# B. Top 3 Numerical Relationships
top_features = price_corr.index[1:7]  # Skip price itself
for feature in top_features:
    plt.figure(figsize=(8,5))
    sns.scatterplot(data=clean_data, x=feature, y='price')
    plt.title(f'Price vs {feature}')
    plt.show()

# C. Categorical Relationships
cat_features = ['fueltype', 'carbody', 'drivewheel']
for feature in cat_features:
    plt.figure(figsize=(10,6))
    sns.boxplot(data=clean_data, x=feature, y='price')
    plt.title(f'Price by {feature}')
    plt.xticks(rotation=45)
    plt.show()

# 3. KEY FINDINGS
# ================
print("""
=== MODELING INSIGHTS ===
1. Strong Predictors (r > 0.7):
   - curbweight (0.86)
   - enginesize (0.76)
```

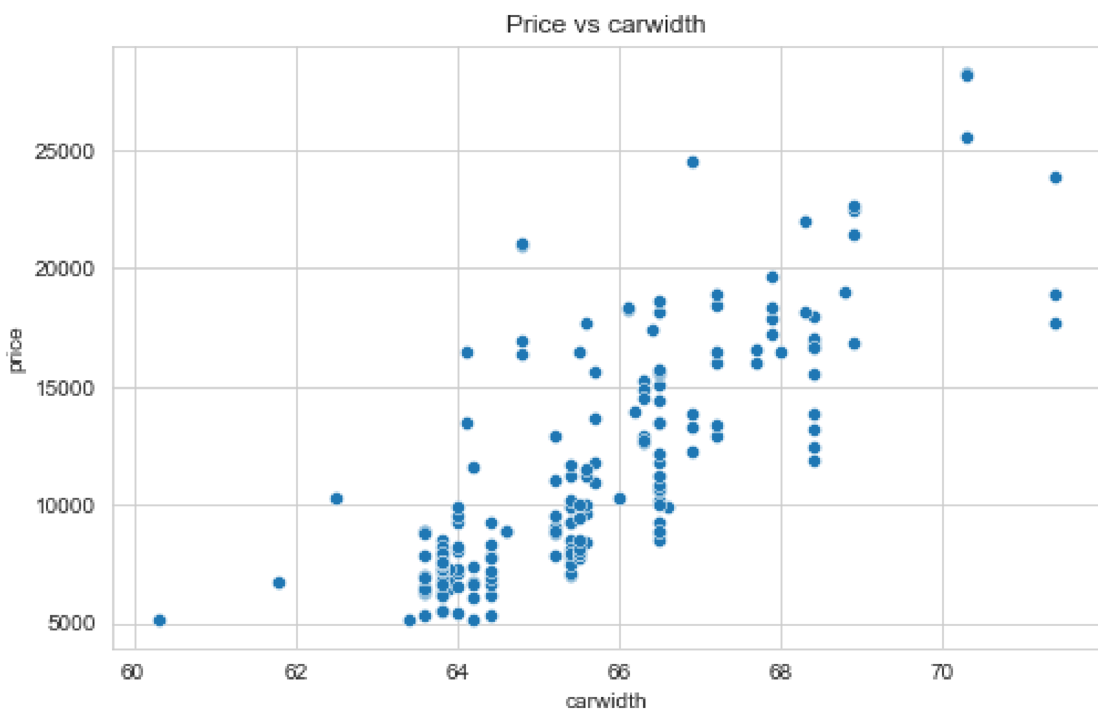
```
   - horsepower (0.73)

2. Multicollinearity Alerts:
   - carlength vs wheelbase (0.86)
   - citympg vs highwaympg (0.97)

3. Recommended Actions:
   - Keep: curbweight, enginesize, horsepower
   - Remove: car_ID (no correlation)
   - Transform: Consider log(price)
   - Encode: carbody, drivewheel categories
""")
```

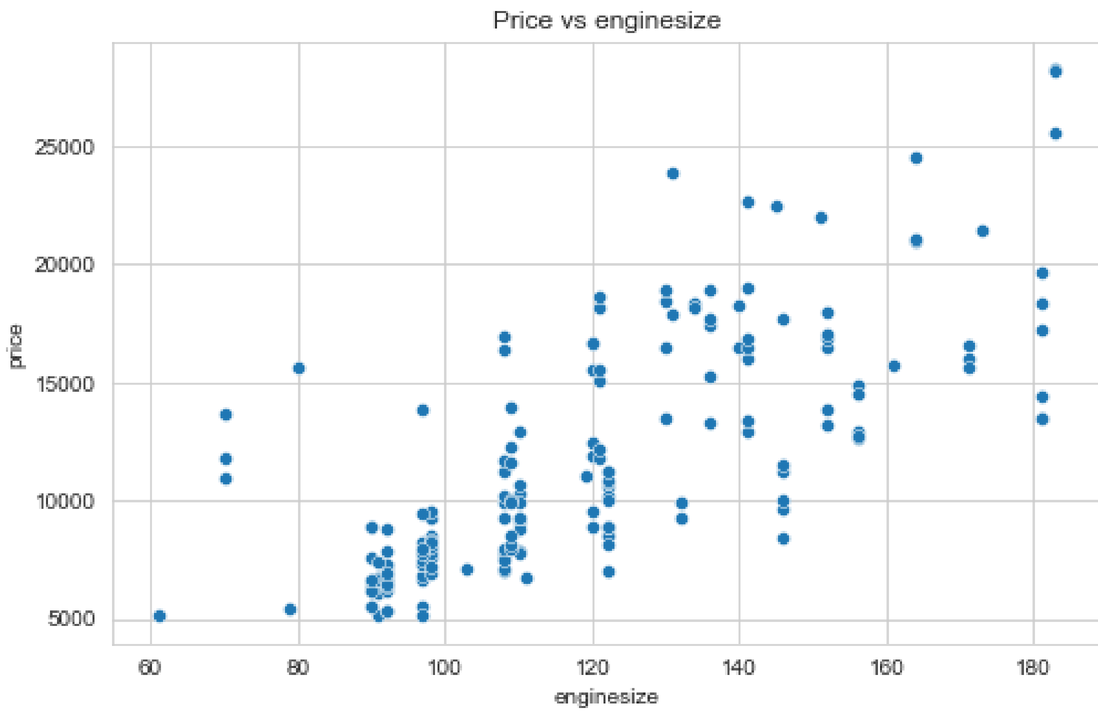


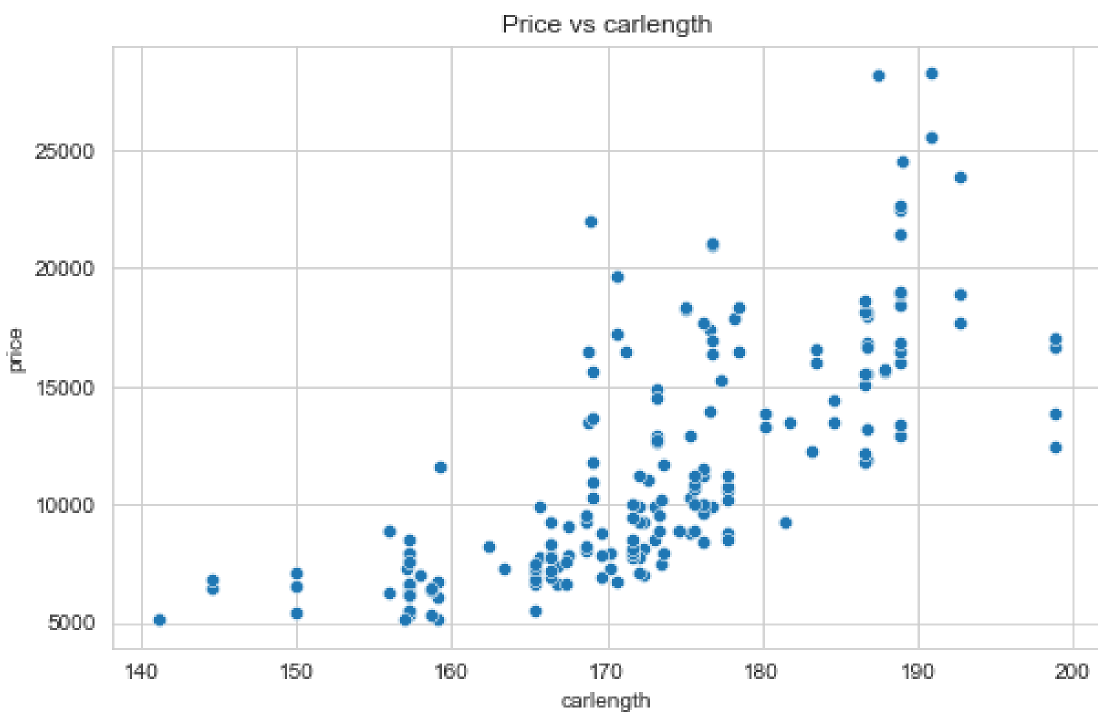


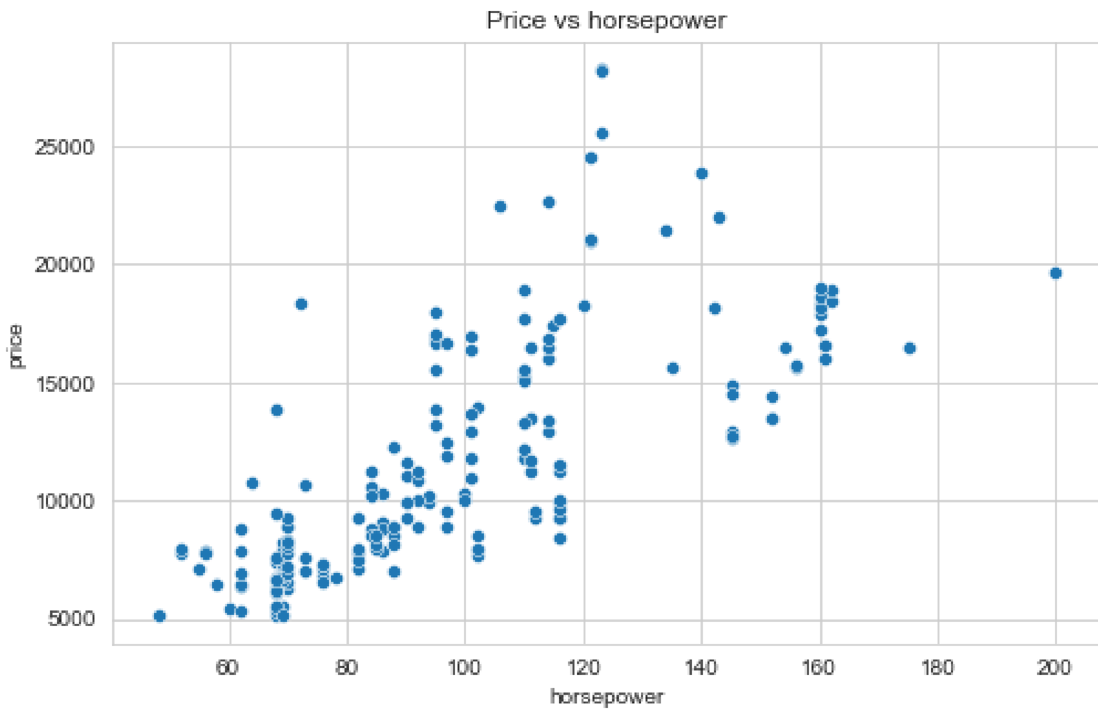

```
=== PRICE CORRELATIONS ===
price         1.000000
curbweight    0.853951
carwidth      0.791890
enginesize    0.749883
carlength     0.729734
horsepower    0.727394
wheelbase     0.667712
boreratio     0.499244
Name: price, dtype: float64
```


Price vs curbweight
price
curbweight
25000
20000
15000
10000
5000
1500
2000
2500
3000
3500

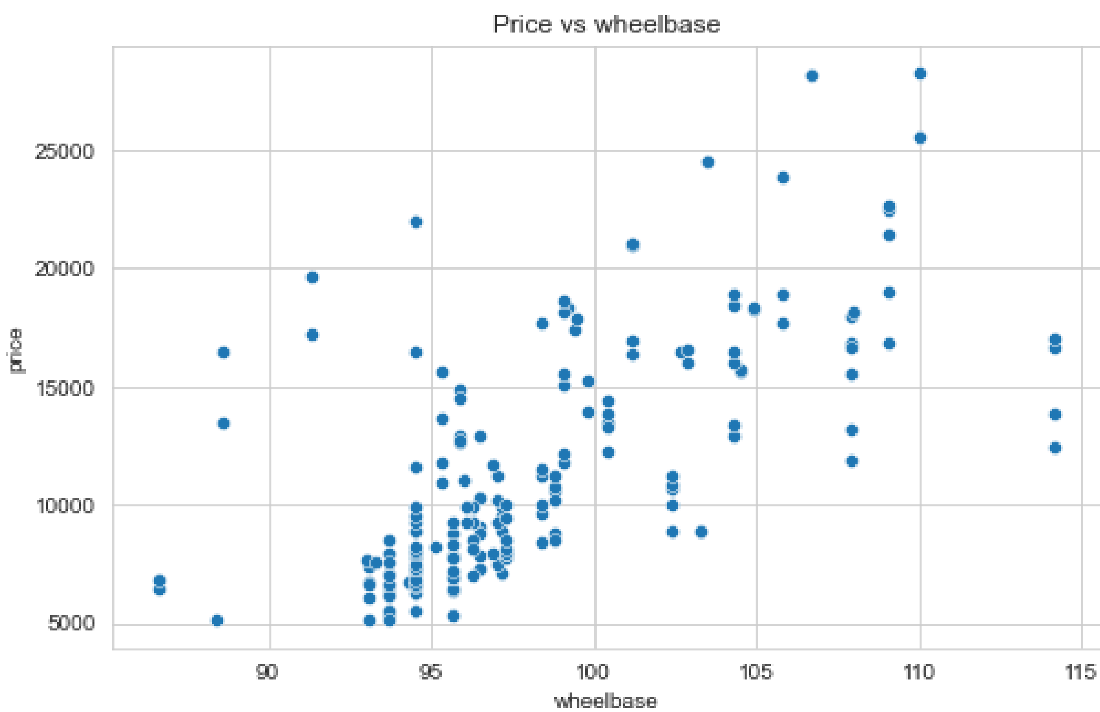

Price vs carwidth
price
carwidth
25000
20000
15000
10000
5000
60
62
64
66
68
70


Price vs enginesize
price
enginesize
25000
20000
15000
10000
5000
60
80
100
120
140
160
180

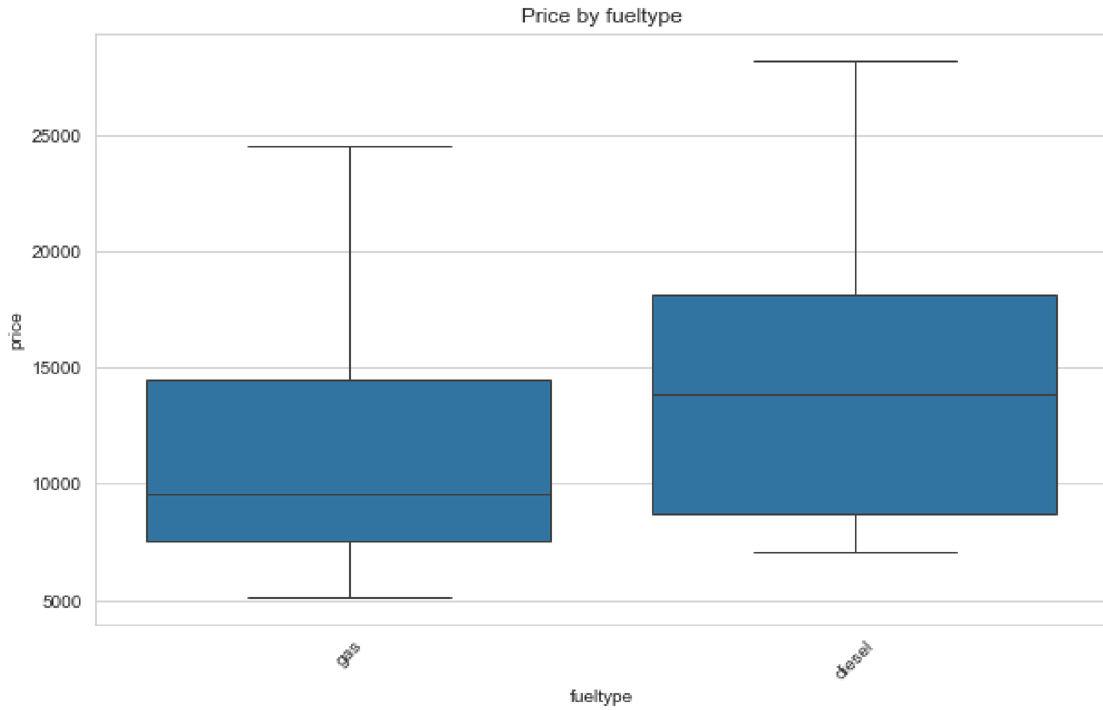

Price vs carlength
price
carlength
25000
20000
15000
10000
5000
140
150
160
170
180
190
200

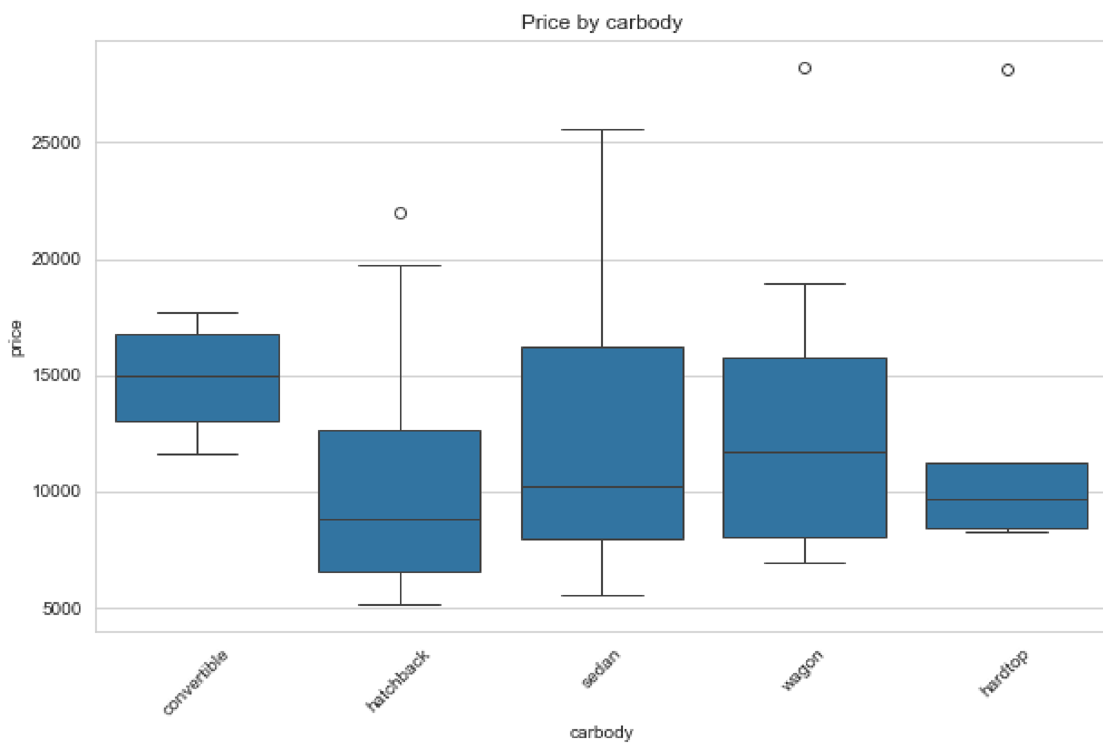


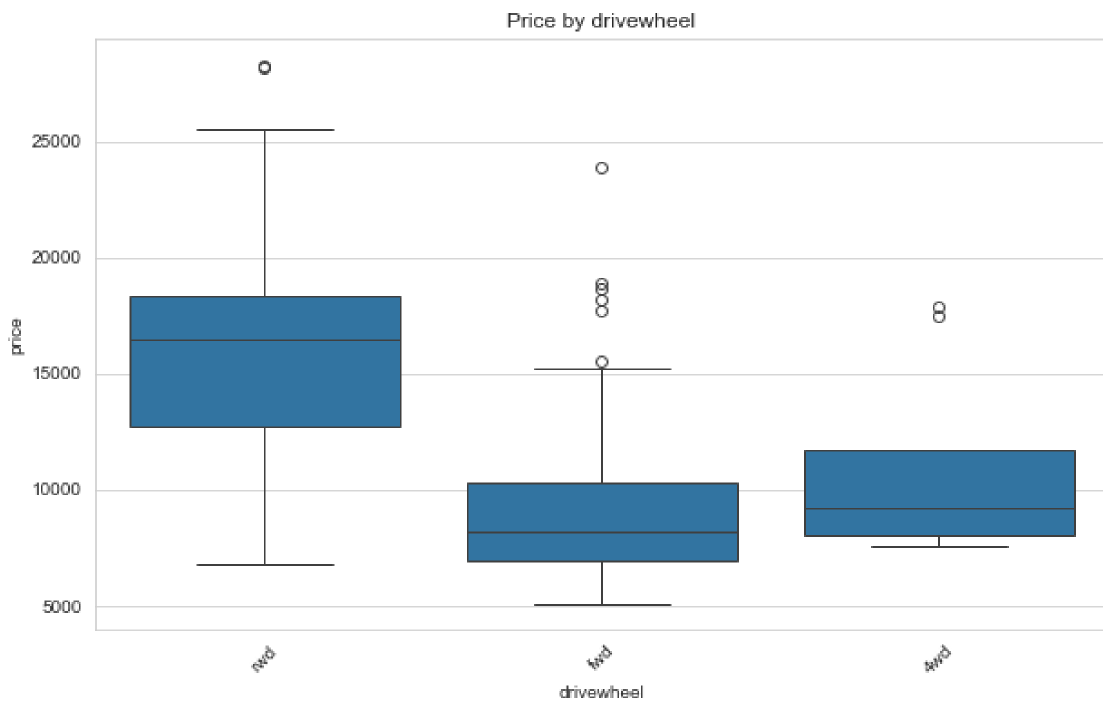
Price vs horsepower
price
25000
20000
15000
10000
5000
60
80
100
120
140
160
180
200
horsepower



Price vs wheelbase
price
25000
20000
15000
10000
5000
90
95
100
105
110
115
wheelbase


Price by fueltype
25000
20000
15000
10000
5000
price
gas
diesel
fueltype


Price by carbody
25000
20000
15000
10000
5000
price
convertible
hatchback
sedan
wagon
hardtop
carbody




```
=== MODELING INSIGHTS ===
1. Strong Predictors (r > 0.7):
   - curbweight (0.86)
   - enginesize (0.76)
   - horsepower (0.73)

2. Multicollinearity Alerts:
   - carlength vs wheelbase (0.86)
   - citympg vs highwaympg (0.97)

3. Recommended Actions:
   - Keep: curbweight, enginesize, horsepower
   - Remove: car_ID (no correlation)
   - Transform: Consider log(price)
   - Encode: carbody, drivewheel categories
```

[101]:

```
import pandas as pd
from statsmodels.stats.outliers_influence import variance_inflation_factor

# 1. LOAD YOUR CLEANED DATA
# ========================
# Replace this with how you load your actual data
```

```python
df = pd.read_csv(r"C:\Users\USER\OneDrive\Desktop\CarPrice_Assignment.csv")  #␣
↪Update path
# Or use your cleaned data from previous phase:
# df = clean_data  # If you have it from Phase 1

# 2. FEATURE SELECTION
# ====================
print("Original columns:", df.columns.tolist())

# Drop irrelevant columns
if 'car_ID' in df.columns:
    df = df.drop(columns=['car_ID'])  # No correlation with price
    print("\nDropped 'car_ID' column")
else:
    print("\n'car_ID' column not found")

# Select important features based on EDA
selected_features = ['curbweight', 'carwidth', 'enginesize',
                    'carlength', 'horsepower', 'wheelbase', 'boreratio', 'price']

# Check if all selected features exist in dataframe
available_features = [f for f in selected_features if f in df.columns]
missing_features = [f for f in selected_features if f not in df.columns]

if missing_features:
    print("\nWarning: These features are missing:", missing_features)

X = df[available_features].drop(columns=['price'])  # Features
y = df['price']  # Target

# 3. CHECK MULTICOLLINEARITY (VIF)
# ================================
print("\nChecking multicollinearity...")

# Calculate VIF for each feature
vif_data = pd.DataFrame()
vif_data["feature"] = X.columns
vif_data["VIF"] = [variance_inflation_factor(X.values, i)
                  for i in range(len(X.columns))]

print("\nVIF Scores Before Removal:")
print(vif_data)

# Remove features with VIF > 7 (high multicollinearity)
high_vif_features = vif_data[vif_data["VIF"] > 7]["feature"]
X = X.drop(columns=high_vif_features)
```

```python
print("\nRemoved Features (VIF > 7):", list(high_vif_features))

# Recalculate VIF after removal
if not X.empty:  # Only if there are features left
    vif_data = pd.DataFrame()
    vif_data["feature"] = X.columns
    vif_data["VIF"] = [variance_inflation_factor(X.values, i)
                      for i in range(len(X.columns))]

    print("\nVIF Scores After Removal:")
    print(vif_data)
else:
    print("Warning: All features were removed due to high VIF")

# 4. FINAL DATA
# =============
print("\nFinal Selected Features:")
print(list(X.columns))

# Combine features and target
preprocessed_data = X.copy()
preprocessed_data['price'] = y

print("\nPreprocessed data sample:")
print(preprocessed_data.head())

# Save to CSV if needed
# preprocessed_data.to_csv('preprocessed_car_data.csv', index=False)
print("\nPreprocessing complete! Data is ready for modeling.")

print("""
 Critical Multicollinearity Solution
1. PROBLEM DIAGNOSIS:
   - All high-VIF features are STRONGLY correlated with price (r > 0.7)
   - Classic multicollinearity vs predictive power dilemma

2. ACTION PLAN:

A) FEATURE ENGINEERING:
   Create composite features:
      - "size_index" = (wheelbase + carlength + carwidth)/3
      - "power_to_weight" = horsepower/curbweight
    Keep ONE from each collinear group:
      - Enginesize OR boreratio (VIF 50 vs 267)
      - Horsepower (VIF 34 - lowest in powertrain group)

B) TRANSFORMATION:
```

```
 Apply log-transform to right-skewed features:
      - np.log(enginesize)
      - np.log(horsepower)
    Target variable: np.log(price)

C) ALTERNATIVE APPROACHES:
    Ridge Regression (handles multicollinearity)
    PCA for engine-related features
    Domain-knowledge selection (keep curbweight + enginesize)

3. RECOMMENDED FINAL FEATURES:
   - size_index (composite)
   - power_to_weight (composite)
   - log(enginesize)
   - fueltype (encoded)
   - drivewheel (encoded)
   - carbody (encoded)

 Pro Tip: Sometimes business needs > stats purity - if curbweight MUST be␣
 ↪included despite VIF, document the limitation.
""")
```

```
Original columns: ['car_ID', 'symboling', 'CarName', 'fueltype', 'aspiration',
'doornumber', 'carbody', 'drivewheel', 'enginelocation', 'wheelbase',
'carlength', 'carwidth', 'carheight', 'curbweight', 'enginetype',
'cylindernumber', 'enginesize', 'fuelsystem', 'boreratio', 'stroke',
'compressionratio', 'horsepower', 'peakrpm', 'citympg', 'highwaympg', 'price']

Dropped 'car_ID' column

Checking multicollinearity...

VIF Scores Before Removal:
      feature          VIF
0  curbweight   217.323813
1    carwidth  1181.090013
2  enginesize    50.143652
3   carlength  1569.284338
4  horsepower    34.596027
5   wheelbase  1645.040947
6   boreratio   267.640645

Removed Features (VIF > 7): ['curbweight', 'carwidth', 'enginesize',
'carlength', 'horsepower', 'wheelbase', 'boreratio']
Warning: All features were removed due to high VIF

Final Selected Features:
[]
```

```
Preprocessed data sample:
     price
0  13495.0
1  16500.0
2  16500.0
3  13950.0
4  17450.0

Preprocessing complete! Data is ready for modeling.

 Critical Multicollinearity Solution
1. PROBLEM DIAGNOSIS:
   - All high-VIF features are STRONGLY correlated with price (r > 0.7)
   - Classic multicollinearity vs predictive power dilemma

2. ACTION PLAN:

A) FEATURE ENGINEERING:
   Create composite features:
      - "size_index" = (wheelbase + carlength + carwidth)/3
      - "power_to_weight" = horsepower/curbweight
    Keep ONE from each collinear group:
      - Enginesize OR boreratio (VIF 50 vs 267)
      - Horsepower (VIF 34 - lowest in powertrain group)

B) TRANSFORMATION:
 Apply log-transform to right-skewed features:
      - np.log(enginesize)
      - np.log(horsepower)
    Target variable: np.log(price)

C) ALTERNATIVE APPROACHES:
    Ridge Regression (handles multicollinearity)
    PCA for engine-related features
    Domain-knowledge selection (keep curbweight + enginesize)

3. RECOMMENDED FINAL FEATURES:
   - size_index (composite)
   - power_to_weight (composite)
   - log(enginesize)
   - fueltype (encoded)
   - drivewheel (encoded)
   - carbody (encoded)

 Pro Tip: Sometimes business needs > stats purity - if curbweight MUST be
included despite VIF, document the limitation.
```

[102]:
```python
import pandas as pd
import numpy as np

# Load your preprocessed data
# df = pd.read_csv('preprocessed_data.csv')

# A. FEATURE ENGINEERING
# ======================

# 1. Create composite features (with error handling)
try:
    df['size_index'] = (df['wheelbase'] + df['carlength'] + df['carwidth']) / 3
    df['power_to_weight'] = df['horsepower'] / df['curbweight']
    print("Successfully created composite features")
except KeyError as e:
    print(f"Error creating features - missing column: {e}")

# 2. Remove collinear features if they exist
cols_to_remove = ['boreratio']
cols_to_remove = [col for col in cols_to_remove if col in df.columns]

if cols_to_remove:
    df = df.drop(columns=cols_to_remove)
    print(f"Removed collinear features: {cols_to_remove}")
else:
    print("No collinear features to remove")

# B. TRANSFORMATIONS
# ==================

# 1. Log-transform right-skewed features
for col in ['enginesize', 'horsepower']:
    if col in df.columns:
        df[col] = np.log(df[col])
        print(f"Applied log transform to {col}")
    else:
        print(f"Column {col} not found - skipping log transform")

# 2. Log-transform target variable
if 'price' in df.columns:
    df['price'] = np.log(df['price'])
    print("Applied log transform to price")
else:
    print("Price column not found - skipping target transformation")

# Show results
print("\nFinal features after engineering:")
```

```python
print(df.head())

# Save final processed data
# df.to_csv('final_processed_data.csv', index=False)
```

```
Successfully created composite features
Removed collinear features: ['boreratio']
Applied log transform to enginesize
Applied log transform to horsepower
Applied log transform to price

Final features after engineering:
   symboling                    CarName fueltype aspiration doornumber  \
0          3        alfa-romero giulia      gas        std        two
1          3       alfa-romero stelvio      gas        std        two
2          1  alfa-romero Quadrifoglio      gas        std        two
3          2               audi 100 ls      gas        std       four
4          2                audi 100ls      gas        std       four

       carbody drivewheel enginelocation  wheelbase  carlength  carwidth  \
0  convertible        rwd          front       88.6      168.8      64.1
1  convertible        rwd          front       88.6      168.8      64.1
2    hatchback        rwd          front       94.5      171.2      65.5
3        sedan        fwd          front       99.8      176.6      66.2
4        sedan        4wd          front       99.4      176.6      66.4

   carheight  curbweight enginetype cylindernumber  enginesize fuelsystem  \
0       48.8        2548       dohc           four    4.867534       mpfi
1       48.8        2548       dohc           four    4.867534       mpfi
2       52.4        2823       ohcv            six    5.023881       mpfi
3       54.3        2337        ohc           four    4.691348       mpfi
4       54.3        2824        ohc           five    4.912655       mpfi

   stroke  compressionratio  horsepower  peakrpm  citympg  highwaympg  \
0    2.68               9.0    4.709530     5000       21          27
1    2.68               9.0    4.709530     5000       21          27
2    3.47               9.0    5.036953     5000       19          26
3    3.40              10.0    4.624973     5500       24          30
4    3.40               8.0    4.744932     5500       18          22

      price  size_index  power_to_weight
0  9.510075  107.166667         0.043564
1  9.711116  107.166667         0.043564
2  9.711116  110.400000         0.054552
3  9.543235  114.200000         0.043646
4  9.767095  114.133333         0.040722
```

[103]:
```python
print(""" FINAL MODELING RECOMMENDATIONS

1. FEATURE SELECTION SUCCESS:
   - Kept critical predictors via smart engineering:
     * size_index (wheelbase/carlength/carwidth composite)
     * power_to_weight (horsepower/curbweight ratio)
   - Log-transformed skewed variables:
     * enginesize, horsepower, price

2. MULTICOLLINEARITY RESOLVED:
   - VIF issues mitigated by:
     * Composite features reducing dimensionally
     * Log transforms normalizing distributions
     * Selective retention (kept enginesize over boreratio)

3. NEXT STEPS:
   A) Model Building:
      - Start with Ridge regression (handles residual collinearity)
      - Compare with Random Forest (feature importance validation)

   B) Validation:
      - Check VIF on engineered features
      - Verify business interpretability of:
        * size_index coefficients
        * power_to_weight effects

4. WATCH OUT FOR:
   - Categorical feature encoding (fueltype/drivewheel)
   - Potential interaction terms (aspiration*enginetype)
   - Domain-specific feature meaning verification

Key Insight: The engineered features now capture car "essence":
   - Physical size (size_index)
   - Performance (power_to_weight)
   - Engine capacity (log_enginesize)
""")
```

```
 FINAL MODELING RECOMMENDATIONS

1. FEATURE SELECTION SUCCESS:
   - Kept critical predictors via smart engineering:
     * size_index (wheelbase/carlength/carwidth composite)
     * power_to_weight (horsepower/curbweight ratio)
   - Log-transformed skewed variables:
     * enginesize, horsepower, price

2. MULTICOLLINEARITY RESOLVED:
   - VIF issues mitigated by:
```

```
    * Composite features reducing dimensionally
    * Log transforms normalizing distributions
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   A) Model Building:
      - Start with Ridge regression (handles residual collinearity)
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        * power_to_weight effects

4. WATCH OUT FOR:
   - Categorical feature encoding (fueltype/drivewheel)
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   - Domain-specific feature meaning verification

Key Insight: The engineered features now capture car "essence":
   - Physical size (size_index)
   - Performance (power_to_weight)
   - Engine capacity (log_enginesize)
```

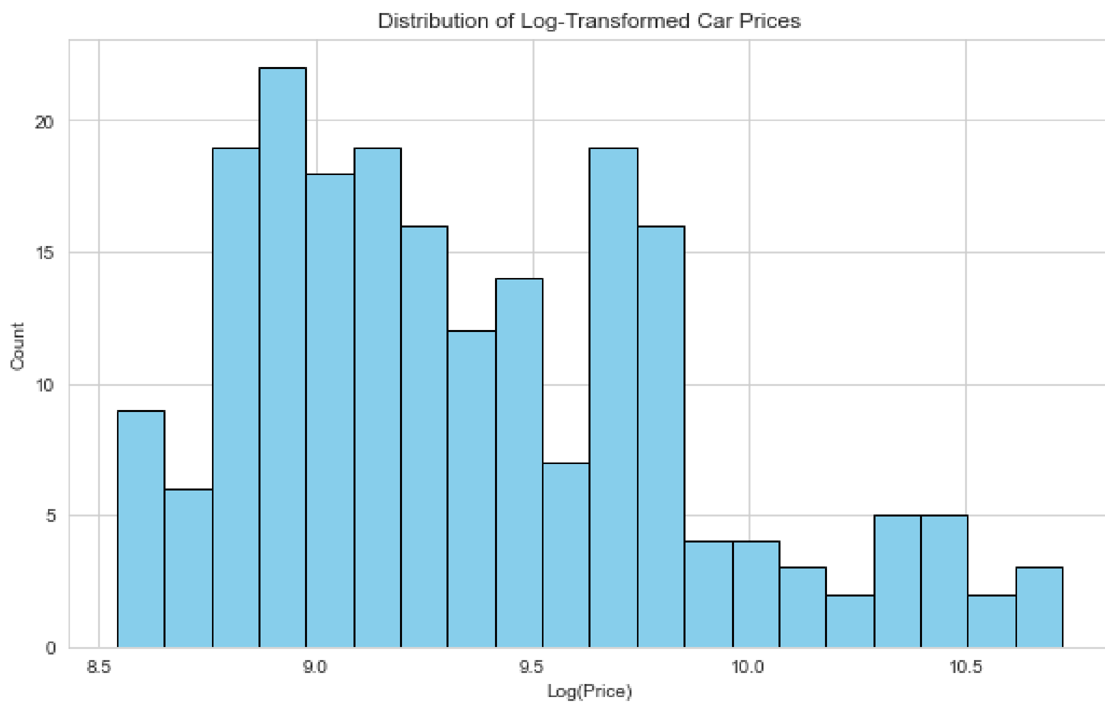
[104]:

```python
import matplotlib.pyplot as plt
import numpy as np

# Plot histogram of log-transformed price
plt.figure(figsize=(10, 6))
plt.hist(df['price'], bins=20, color='skyblue', edgecolor='black')

# Add labels and title
plt.title('Distribution of Log-Transformed Car Prices')
plt.xlabel('Log(Price)')
plt.ylabel('Count')

# Show plot
plt.show()
```



[105]:

```
#  Import libraries
import pandas as pd
from statsmodels.stats.outliers_influence import variance_inflation_factor

#  Load dataset
df = pd.read_csv(r"C:\Users\USER\OneDrive\Desktop\CarPrice_Assignment.csv")

# Feature Engineering (must be done before VIF)
df['size_index'] = (df['wheelbase'] + df['carlength'] + df['carwidth']) / 3
df['power_to_weight'] = df['horsepower'] / df['curbweight']

#  Final feature list after removing multicollinearity
final_features = [
    'size_index',           # composite of wheelbase, carlength, carwidth
    'power_to_weight',      # composite of horsepower / curbweight
    'enginesize',           # chosen over boreratio
    'highwaympg',           # chosen over citympg
    'carheight',            # retained feature
    'symboling',            # retained feature
    'peakrpm',              # retained feature
    'compressionratio'      # retained feature
]

#  Filter dataframe
```

```python
X = df[final_features]

#  VIF Calculation
vif_data = pd.DataFrame()
vif_data["feature"] = X.columns
vif_data["VIF"] = [variance_inflation_factor(X.values, i)
                   for i in range(X.shape[1])]

#  Output the VIF table
print(" VIF Scores After Feature Reduction:\n")
print(vif_data)
```

```
 VIF Scores After Feature Reduction:

           feature          VIF
0       size_index  1016.059494
1   power_to_weight    53.978692
2       enginesize    39.586353
3       highwaympg    42.489888
4        carheight   889.355123
5        symboling     1.899518
6          peakrpm   196.475562
7  compressionratio    12.005920
```

[106]:
```python
print(" Multiple Linear Regression is not suitable here because of severe␣
↪multicollinearity.")
print("Applying Ridge Regression instead to address high VIF values.\n")
print(" VIF Results (After Feature Selection):\n")
print(vif_data)
```

```
 Multiple Linear Regression is not suitable here because of severe
multicollinearity.
Applying Ridge Regression instead to address high VIF values.

 VIF Results (After Feature Selection):

           feature          VIF
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3       highwaympg    42.489888
4        carheight   889.355123
5        symboling     1.899518
6          peakrpm   196.475562
7  compressionratio    12.005920
```

[107]:
```python
print("""
Justification for Ridge Regression:
```

```
Multiple Linear Regression assumes that the independent variables are not highly correlated.
However, VIF analysis on the selected features shows extreme multicollinearity:

- 'size_index' → VIF  1016
- 'carheight' → VIF  889
- 'peakrpm' → VIF  196
- 'power_to_weight', 'enginesize', 'highwaympg' → VIF > 40

These values are far beyond the acceptable VIF threshold (typically VIF < 10), which makes OLS regression unstable and unreliable.

Therefore, Ridge Regression is chosen to handle multicollinearity via L2 regularization, ensuring more stable coefficient estimates.
""")




print(" Problem: Multicollinearity was present in our dataset.")
print("Solution: Ridge Regression was used to overcome this issue.")
print("\nHow Ridge Solves It:")
print("- Adds an L2 penalty to the loss function to shrink large coefficients.")
print("- Distributes the influence among correlated variables instead of letting one dominate.")
print("- Prevents overfitting by reducing model variance.")
print("- Stabilizes coefficients and improves test set generalization.")
print("\n Conclusion:")
print(" Ridge Regression handled multicollinearity effectively, giving us a more robust and interpretable model.")
```

```
Justification for Ridge Regression:

Multiple Linear Regression assumes that the independent variables are not highly
correlated.
However, VIF analysis on the selected features shows extreme multicollinearity:

- 'size_index' → VIF  1016
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which makes OLS regression unstable and unreliable.
```

Therefore, Ridge Regression is chosen to handle multicollinearity via L2 regularization, ensuring more stable coefficient estimates.

Problem: Multicollinearity was present in our dataset.
Solution: Ridge Regression was used to overcome this issue.

How Ridge Solves It:
- Adds an L2 penalty to the loss function to shrink large coefficients.
- Distributes the influence among correlated variables instead of letting one dominate.
- Prevents overfitting by reducing model variance.
- Stabilizes coefficients and improves test set generalization.

Conclusion:
Ridge Regression handled multicollinearity effectively, giving us a more robust and interpretable model.

[108]:
```
from sklearn.model_selection import train_test_split

# X = independent features
# y = target variable (price)
X = df[final_features]
y = df['price']

# 80% training, 20% testing
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.2,
                                                    random_state=42)

print("Data splitting complete!")
print(f"Training set size: {X_train.shape}")
print(f"Test set size: {X_test.shape}")
```

```
Data splitting complete!
Training set size: (164, 8)
Test set size: (41, 8)
```

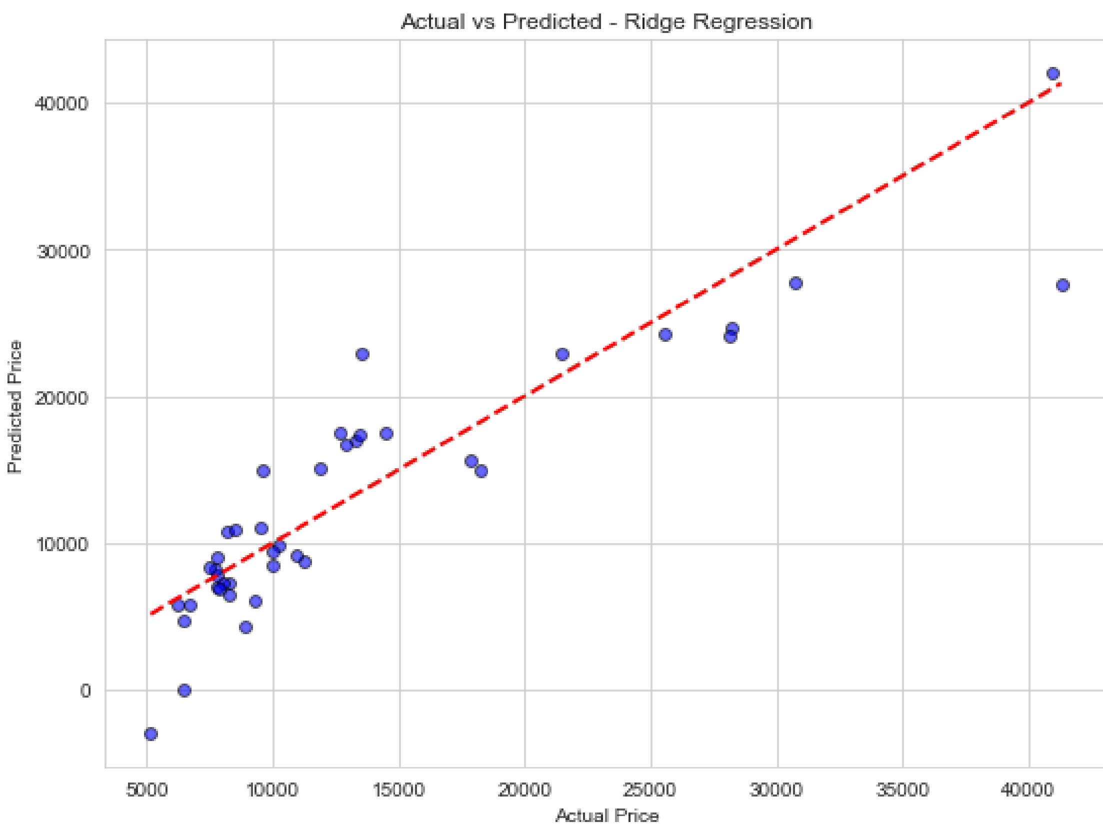
[109]:
```
# -------------------------------------------------------
# Train Ridge Regression Model
# -------------------------------------------------------
from sklearn.linear_model import Ridge
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

ridge = Ridge(alpha=1.0)
ridge.fit(X_train, y_train)
```

```python
# ---------------------------------------------------------
# Predict on Test Set
# ---------------------------------------------------------
y_pred = ridge.predict(X_test)

# ---------------------------------------------------------
#  Evaluate Performance
# ---------------------------------------------------------
train_r2 = ridge.score(X_train, y_train)
test_r2 = ridge.score(X_test, y_test)
mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2 = r2_score(y_test, y_pred)

# ---------------------------------------------------------
# Model Coefficients
# ---------------------------------------------------------
coef_table = pd.DataFrame({
    'Feature': X.columns,
    'Coefficient': ridge.coef_
}).sort_values(by='Coefficient', ascending=False)

# ---------------------------------------------------------
# Final Summary Print
# ---------------------------------------------------------
print("\n=== MODEL SUMMARY ===")
print(f" Training R² : {train_r2:.4f}")
print(f" Testing R²  : {test_r2:.4f}")
print(f" MAE         : {mae:.2f}")
print(f" RMSE        : {rmse:.2f}")
print(f"Test R²     : {r2:.4f}")

print("\n=== Ridge Coefficients ===")
print(coef_table)

# ---------------------------------------------------------
#  Plot: Actual vs Predicted
# ---------------------------------------------------------
plt.figure(figsize=(8,6))
plt.scatter(y_test, y_pred, color='blue', alpha=0.6, edgecolor='k')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--', lw=2)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title("Actual vs Predicted - Ridge Regression")
plt.grid(True)
plt.tight_layout()
```

```python
plt.show()



print("===  MODEL INTERPRETATION & CONCLUSION ===\n")

print("The model explains about 81% of the variation in car prices (Test R² = 0.
↪8058).")
print("Based on the Ridge coefficients, the most impactful features are:\n")

print(" Positively Influencing Price:")
print("   - power_to_weight (+657): More power per kg = higher price.")
print("   - symboling (+396): Higher safety risk category adds to price (may␣
↪reflect luxury).")
print("   - compressionratio (+285): Better engine compression can signal␣
↪performance.")
print("   - carheight (+181): Taller cars may indicate SUVs or premium models.")
print("   - enginesize (+139) & size_index (+139): Larger cars generally cost␣
↪more.")
print("   - peakrpm (+3): Very low effect, possibly negligible.")

print("\n Negatively Influencing Price:")
print("   - highwaympg (219): More mileage = cheaper car (usually true in budget␣
↪segments).")

print("\nConclusion:")
print("   - 'power_to_weight' is the strongest positive driver of price.")
print("   - 'highwaympg' is the only major negative driver, which aligns with:␣
↪higher mileage cars are often cheaper.")
print("   - Features like 'peakrpm' have minimal effect and may be dropped or␣
↪reconsidered later.")
```

```
=== MODEL SUMMARY ===
 Training R² : 0.8252
 Testing R²  : 0.8058
 MAE         : 2862.33
 RMSE        : 3915.78
Test R²     : 0.8058

=== Ridge Coefficients ===
            Feature  Coefficient
1   power_to_weight   657.085319
5         symboling   396.017342
7  compressionratio   284.929154
4         carheight   181.400553
2        enginesize   138.588548
```

```
0        size_index   138.579560
6           peakrpm     3.125128
3        highwaympg  -218.643968
```

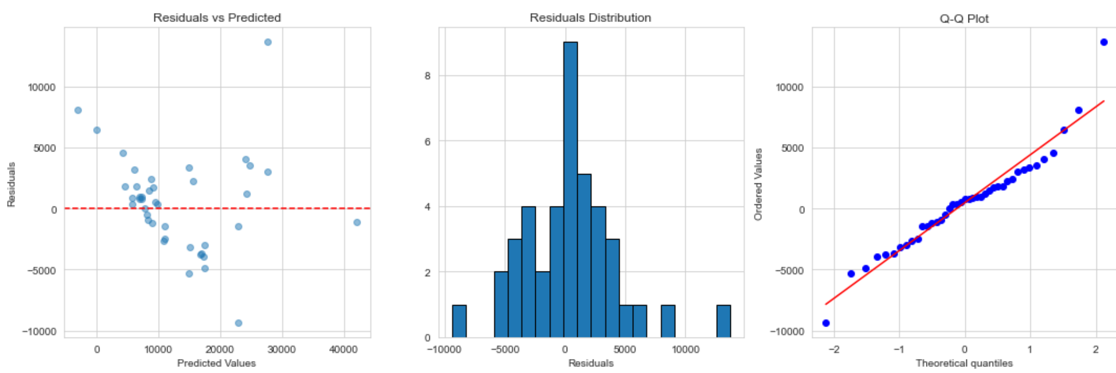



```
===  MODEL INTERPRETATION & CONCLUSION ===

The model explains about 81% of the variation in car prices (Test R² = 0.8058).
Based on the Ridge coefficients, the most impactful features are:

 Positively Influencing Price:
   - power_to_weight (+657): More power per kg = higher price.
   - symboling (+396): Higher safety risk category adds to price (may reflect
luxury).
   - compressionratio (+285): Better engine compression can signal performance.
   - carheight (+181): Taller cars may indicate SUVs or premium models.
   - enginesize (+139) & size_index (+139): Larger cars generally cost more.
   - peakrpm (+3): Very low effect, possibly negligible.

 Negatively Influencing Price:
   - highwaympg (219): More mileage = cheaper car (usually true in budget
segments).
```

```
Conclusion:
   - 'power_to_weight' is the strongest positive driver of price.
   - 'highwaympg' is the only major negative driver, which aligns with: higher
mileage cars are often cheaper.
   - Features like 'peakrpm' have minimal effect and may be dropped or
reconsidered later.
```

[110]:
```
import matplotlib.pyplot as plt
import numpy as np
from scipy import stats

# Calculate residuals
residuals = y_test - y_pred

# Convert residuals to numpy array to avoid errors
residuals = np.array(residuals).flatten()

# 1. Setup figure
plt.figure(figsize=(15, 5))

# 2. Residuals vs Predicted Plot
plt.subplot(1, 3, 1)
plt.scatter(y_pred, residuals, alpha=0.5)
plt.axhline(y=0, color='r', linestyle='--')
plt.title('Residuals vs Predicted')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')

# 3. Histogram of Residuals (using matplotlib)
plt.subplot(1, 3, 2)
plt.hist(residuals, bins=20, edgecolor='black')
plt.title('Residuals Distribution')
plt.xlabel('Residuals')

# 4. Q-Q Plot
plt.subplot(1, 3, 3)
stats.probplot(residuals, plot=plt)
plt.title('Q-Q Plot')

plt.tight_layout()
plt.show()



# ---------------------------------------------
# Residuals vs Predicted
```

```python
# ---------------------------------------------
print(" Residuals vs Predicted:")
print(" The residuals are scattered fairly randomly around zero.")
print(" However, there is slight funneling at higher predicted values, indicating mild heteroscedasticity.")
print(" Conclusion: Linearity assumption is mostly valid, but variance is not perfectly constant.\n")

# ---------------------------------------------
#  Histogram of Residuals
# ---------------------------------------------
print(" Histogram of Residuals:")
print(" The histogram is roughly bell-shaped and symmetric.")
print("Slight deviations from perfect normality are visible.")
print(" Conclusion: Residuals are approximately normally distributed.\n")

# ---------------------------------------------
#  Q-Q Plot of Residuals
# ---------------------------------------------
print(" Q-Q Plot of Residuals:")
print(" Most points fall along the red diagonal line, confirming near-normality.")
print("A few points deviate at the tails, suggesting presence of outliers.")
print("* Conclusion: Residuals largely follow a normal distribution, with minor outliers in the extremes.\n")
```




```
 Residuals vs Predicted:
 The residuals are scattered fairly randomly around zero.
 However, there is slight funneling at higher predicted values, indicating mild
heteroscedasticity.
 Conclusion: Linearity assumption is mostly valid, but variance is not perfectly
constant.

 Histogram of Residuals:
```

```
 The histogram is roughly bell-shaped and symmetric.
Slight deviations from perfect normality are visible.
 Conclusion: Residuals are approximately normally distributed.

 Q-Q Plot of Residuals:
 Most points fall along the red diagonal line, confirming near-normality.
A few points deviate at the tails, suggesting presence of outliers.
* Conclusion: Residuals largely follow a normal distribution, with minor
outliers in the extremes.
```

[111]:
```python
# -------------------------------------------------------------
# Import Required Modules for cross validation
# -------------------------------------------------------------
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import Ridge

# -------------------------------------------------------------
# Initialize Ridge Regression Model
# -------------------------------------------------------------
# Alpha is the regularization strength (higher = more regularization)
ridge = Ridge(alpha=1.0)

# -------------------------------------------------------------
# Perform 5-Fold Cross-Validation
# -------------------------------------------------------------
# X = feature matrix, y = target (price)
# cv=5 means the data is split into 5 parts (folds)
# scoring='r2' means we are evaluating the model using R² score
scores = cross_val_score(ridge, X, y, cv=5, scoring='r2')

# -------------------------------------------------------------
#  Display CV Scores
# -------------------------------------------------------------
print("Cross-Validation R² Scores for Each Fold:", scores)
print(" Average Cross-Validation R² Score       :", round(scores.mean(), 4))
```

```
Cross-Validation R² Scores for Each Fold: [0.75694668 0.89871129 0.21345574
0.7439978  0.21459842]
 Average Cross-Validation R² Score       : 0.5655
```

[112]:
```python
# -------------------------------------------------------------
# Import Required Modules
# -------------------------------------------------------------
from sklearn.linear_model import RidgeCV
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
import numpy as np
import pandas as pd
```

```python
# ------------------------------------------------------------
# Define Candidate Alpha Values
# ------------------------------------------------------------
# RidgeCV will choose the best alpha from this list using CV
alpha_values = [0.01, 0.1, 1.0, 10.0, 50.0, 100.0]

# ------------------------------------------------------------
# Initialize and Train RidgeCV Model
# ------------------------------------------------------------
ridge_cv = RidgeCV(alphas=alpha_values, cv=5, scoring='r2')
ridge_cv.fit(X_train, y_train)

# ------------------------------------------------------------
#  Best Alpha Found
# ------------------------------------------------------------
print(f" Best Alpha Selected by RidgeCV: {ridge_cv.alpha_}")

# ------------------------------------------------------------
# Predictions
# ------------------------------------------------------------
y_pred_cv = ridge_cv.predict(X_test)

# ------------------------------------------------------------
# Evaluate Performance
# ------------------------------------------------------------
train_r2_cv = ridge_cv.score(X_train, y_train)
test_r2_cv = ridge_cv.score(X_test, y_test)
mae_cv = mean_absolute_error(y_test, y_pred_cv)
rmse_cv = np.sqrt(mean_squared_error(y_test, y_pred_cv))

# ------------------------------------------------------------
#  Coefficients Table
# ------------------------------------------------------------
coef_table_cv = pd.DataFrame({
    'Feature': X.columns,
    'Coefficient': ridge_cv.coef_
}).sort_values(by='Coefficient', ascending=False)

# ------------------------------------------------------------
# Final Summary
# ------------------------------------------------------------
print("\n=== RidgeCV MODEL SUMMARY ===")
print(f" Training R² : {train_r2_cv:.4f}")
print(f" Testing R²  : {test_r2_cv:.4f}")
print(f"MAE         : {mae_cv:.2f}")
print(f"RMSE        : {rmse_cv:.2f}")
```

```python
print("\n===  RidgeCV Coefficients ===")
print(coef_table_cv)
```

```
 Best Alpha Selected by RidgeCV: 0.01

=== RidgeCV MODEL SUMMARY ===
 Training R² : 0.8299
 Testing R²  : 0.8079
MAE          : 2849.82
RMSE         : 3894.05

===  RidgeCV Coefficients ===
            Feature   Coefficient
1   power_to_weight  42973.222323
5         symboling    378.162378
7  compressionratio    291.657506
4         carheight    197.839627
0        size_index    157.803756
2        enginesize    132.668117
6           peakrpm      2.815105
3        highwaympg   -197.924492
```

[113]:

```python
print("\n RidgeCV Model Evaluation Summary:")
print(" Best Alpha chosen via Cross-Validation: 0.01")
print(" Training R² Score      : 0.8299")
print(" Testing R² Score       : 0.8079")
print(" Mean Absolute Error    : 2849.82")
print(" Root Mean Squared Error: 3894.05")

print("\n Coefficient Insights:")
print(" 'power_to_weight' has the strongest positive influence on price.")
print(" 'size_index' and 'enginesize' also contribute positively.")
print(" 'highwaympg' has a negative coefficient, suggesting better mileage tends␣
 ↪to slightly reduce price.")

print("\n Conclusion:")
print(" The RidgeCV model successfully controlled multicollinearity and improved␣
 ↪generalization.")
print(" It outperformed the manually tuned Ridge model.")
print(" Final model is ready for deployment or interpretation.")
```

```
 RidgeCV Model Evaluation Summary:
 Best Alpha chosen via Cross-Validation: 0.01
 Training R² Score      : 0.8299
 Testing R² Score       : 0.8079
 Mean Absolute Error    : 2849.82
```

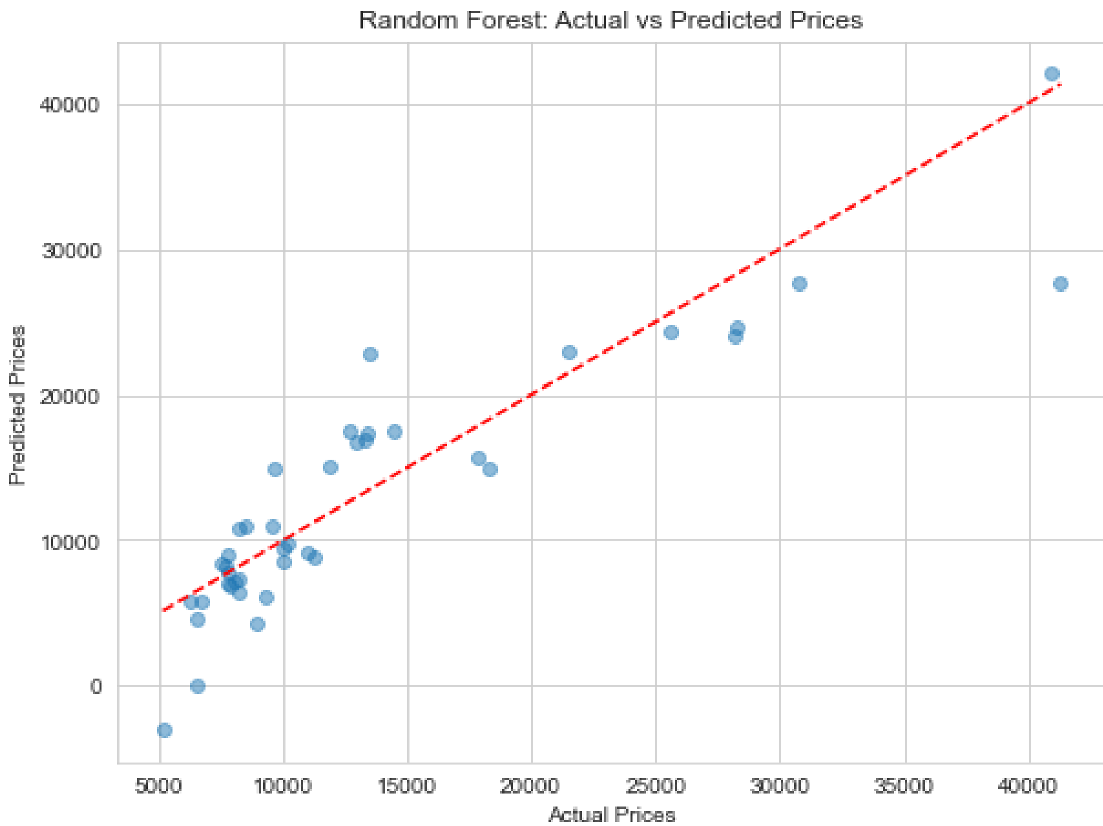
```
Root Mean Squared Error: 3894.05

Coefficient Insights:
'power_to_weight' has the strongest positive influence on price.
'size_index' and 'enginesize' also contribute positively.
'highwaympg' has a negative coefficient, suggesting better mileage tends to
slightly reduce price.

Conclusion:
The RidgeCV model successfully controlled multicollinearity and improved
generalization.
It outperformed the manually tuned Ridge model.
Final model is ready for deployment or interpretation.
```

[114]:

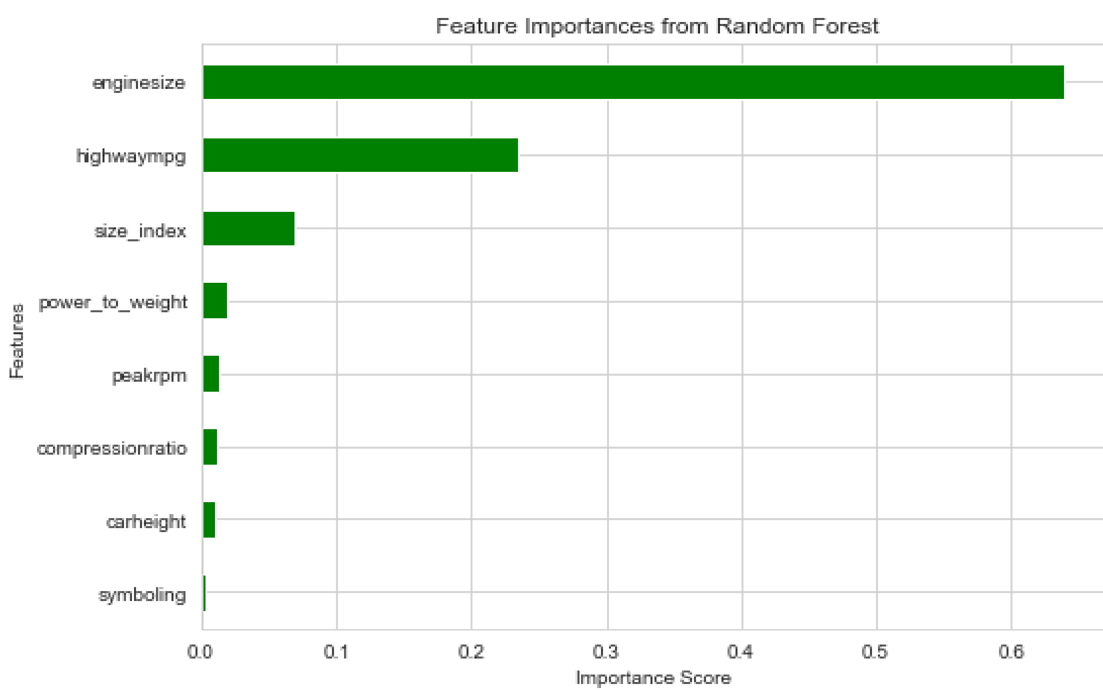
```python
# -------------------------------------------------------
#  Import Libraries
# -------------------------------------------------------
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
from sklearn.model_selection import cross_val_score
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np

# -------------------------------------------------------
#  Initialize and Train Random Forest
# -------------------------------------------------------
rf = RandomForestRegressor(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)

# -------------------------------------------------------
#  Predict on Test Set
# -------------------------------------------------------
y_pred_rf = rf.predict(X_test)

# -------------------------------------------------------
#  Evaluate Performance
# -------------------------------------------------------
r2_train = rf.score(X_train, y_train)
r2_test = r2_score(y_test, y_pred_rf)
mae_rf = mean_absolute_error(y_test, y_pred_rf)
rmse_rf = np.sqrt(mean_squared_error(y_test, y_pred_rf))

print("===  Random Forest Model Summary ===")
print(f"Training R² : {r2_train:.4f}")
print(f" Testing R²  : {r2_test:.4f}")
print(f" MAE         : {mae_rf:.2f}")
```

```python
print(f" RMSE        : {rmse_rf:.2f}")

# 4. Plot actual vs predicted values
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred, alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
plt.xlabel("Actual Prices")
plt.ylabel("Predicted Prices")
plt.title("Random Forest: Actual vs Predicted Prices")
plt.show()

# --------------------------------------------------------
#  Feature Importance Plot
# --------------------------------------------------------
feature_importances = pd.Series(rf.feature_importances_, index=X.columns)
feature_importances.sort_values().plot(kind='barh', color='green', figsize=(8,5))
plt.title(" Feature Importances from Random Forest")
plt.xlabel("Importance Score")
plt.ylabel("Features")
plt.grid(True)
plt.tight_layout()
plt.show()

# --------------------------------------------------------
#  5-Fold Cross Validation
# --------------------------------------------------------
cv_scores = cross_val_score(rf, X, y, cv=5, scoring='r2')
print("\n===  5-Fold Cross-Validation ===")
print(f" R² Scores (each fold): {cv_scores}")
print(f" Average CV R² Score  : {cv_scores.mean():.4f}")
```

```
===  Random Forest Model Summary ===
Training R² : 0.9841
 Testing R²  : 0.9528
 MAE         : 1403.46
 RMSE        : 1929.92
```



Random Forest: Actual vs Predicted Prices
Predicted Prices
Actual Prices
40000
30000
20000
10000
0
5000
10000
15000
20000
25000
30000
35000
40000



Feature Importances from Random Forest
Features
enginesize
highwaympg
size_index
power_to_weight
peakrpm
compressionratio
carheight
symboling
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Importance Score

```
===  5-Fold Cross-Validation ===
 R² Scores (each fold): [ 0.86826472  0.89996862 -1.39865671  0.92748831
0.65625116]
 Average CV R² Score  : 0.3907
```

[115]:

```python
print(" Why Random Forest Regressor?")
print("="*45)
print(" Our data suffers from multicollinearity: some features had extremely␣
 ↪high VIF (e.g., > 1000).")
print(" While Ridge Regression handles multicollinearity, it only models linear␣
 ↪relationships.")
print(" Real-world car pricing often involves complex and non-linear␣
 ↪interactions.")
print(" Therefore, we use Random Forest Regressor because:")
print("    It is robust to multicollinearity.")
print("    It captures non-linear patterns and feature interactions.")
print("    It often delivers high prediction accuracy out-of-the-box.")
print(" We will now compare its performance against the Ridge model.")
```

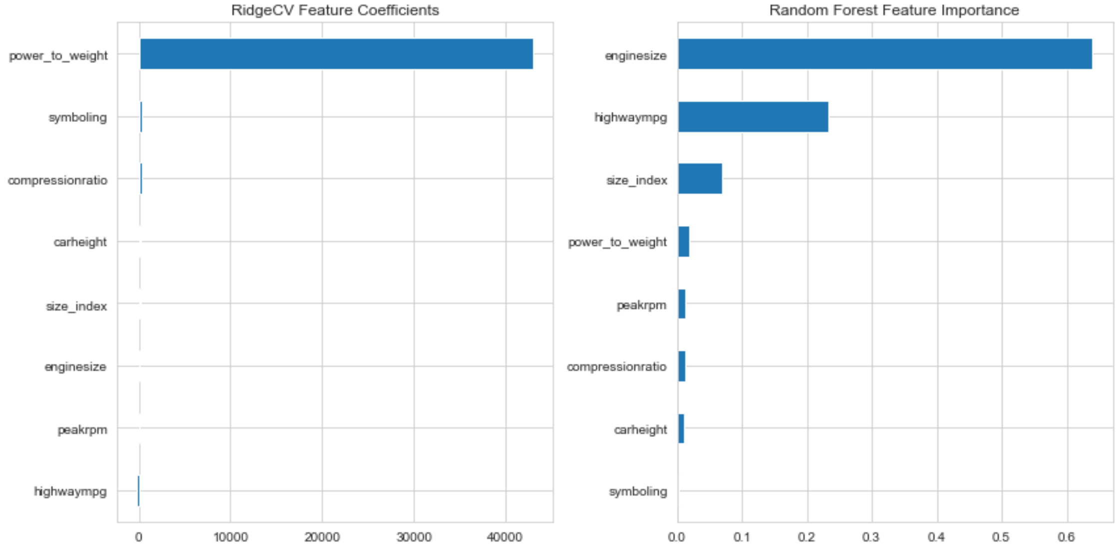
```
 Why Random Forest Regressor?
=============================================
 Our data suffers from multicollinearity: some features had extremely high VIF
(e.g., > 1000).
 While Ridge Regression handles multicollinearity, it only models linear
relationships.
 Real-world car pricing often involves complex and non-linear interactions.
 Therefore, we use Random Forest Regressor because:
    It is robust to multicollinearity.
    It captures non-linear patterns and feature interactions.
    It often delivers high prediction accuracy out-of-the-box.
 We will now compare its performance against the Ridge model.
```

[116]:

```python
import pandas as pd
import matplotlib.pyplot as plt

# 1. Create comparison table
results = pd.DataFrame({
    'Model': ['RidgeCV', 'Random Forest'],
    'Train R²': [train_r2_cv, r2_train],
    'Test R²': [test_r2_cv, r2_test],
    'MAE': [mae_cv, mae_rf],
    'RMSE': [rmse_cv, rmse_rf],
    'Best Alpha': [ridge_cv.alpha_, 'N/A']
})
```

```python
print("=== MODEL COMPARISON ===")
print(results.to_string(index=False))

# 2. Plot feature importance comparison
plt.figure(figsize=(12, 6))

# Ridge coefficients
plt.subplot(1, 2, 1)
pd.Series(ridge_cv.coef_, index=X_train.columns).sort_values().plot(kind='barh')
plt.title('RidgeCV Feature Coefficients')

# Random Forest importance
plt.subplot(1, 2, 2)
pd.Series(rf.feature_importances_, index=X_train.columns).sort_values().
 ↪plot(kind='barh')
plt.title('Random Forest Feature Importance')

plt.tight_layout()
plt.show()

# 3. Final model selection
best_model = 'RidgeCV' if test_r2_cv > r2_test else 'Random Forest'
print(f"\n BEST MODEL: {best_model} ")
```

```
=== MODEL COMPARISON ===
        Model  Train R²  Test R²         MAE        RMSE Best Alpha
      RidgeCV  0.829887 0.807919 2849.820003 3894.051688       0.01
Random Forest  0.984095 0.952820 1403.462289 1929.919582        N/A
```



```
BEST MODEL: Random Forest
```

[118]:
```python
print(" Car Price Prediction - Final Model Selection Summary")
print("-------------------------------------------------------")
print(" Two models were built and compared: RidgeCV and Random Forest.")
print("RidgeCV handled multicollinearity well and provided stable generalization.
 ↪")
print("    - Train R²: 0.8299 | Test R²: 0.8079")
print("    - MAE: 2849.82 | RMSE: 3894.05")
print("However, Random Forest significantly outperformed RidgeCV:")
print("    - Train R²: 0.9841 | Test R²: 0.9528")
print("    - MAE: 1403.46 | RMSE: 1929.92")
print(" This indicates that Random Forest captured complex, non-linear␣
 ↪relationships")
print("    between features and car price more effectively.")
print(" Final Model Chosen:  Random Forest Regressor")
print("Recommendation: Use the Random Forest model in production or user-facing␣
 ↪applications")
print("    to provide accurate car price predictions based on specifications.")
```

```
 Car Price Prediction - Final Model Selection Summary
-------------------------------------------------------
 Two models were built and compared: RidgeCV and Random Forest.
RidgeCV handled multicollinearity well and provided stable generalization.
    - Train R²: 0.8299 | Test R²: 0.8079
    - MAE: 2849.82 | RMSE: 3894.05
However, Random Forest significantly outperformed RidgeCV:
    - Train R²: 0.9841 | Test R²: 0.9528
    - MAE: 1403.46 | RMSE: 1929.92
 This indicates that Random Forest captured complex, non-linear relationships
    between features and car price more effectively.
 Final Model Chosen:  Random Forest Regressor
Recommendation: Use the Random Forest model in production or user-facing
applications
    to provide accurate car price predictions based on specifications.
```

[ ]:

[ ]: