machine-learning-assignment-01

April 22, 2025

1 Predicting Car Prices: A Machine Learning Journey

The goal of this project is to analyze the dataset, preprocess the data, apply machine learning models, and evaluate their performance in predicting car prices.

2 Mounting Google Drive in Google Colab

[ ]:
```
from google.colab import drive
drive.mount("/content/drive")
```

```
Mounted at /content/drive
```

3 Importing Necessary Libraries for Machine Learning and Data Analysis

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
```

3.1 *Section 1: Data Exploration (EDA)*

3.2 1.1 Loading the Data

[ ]:
```
df = pd.read_csv("/content/drive/MyDrive/cars_price.csv")
```

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

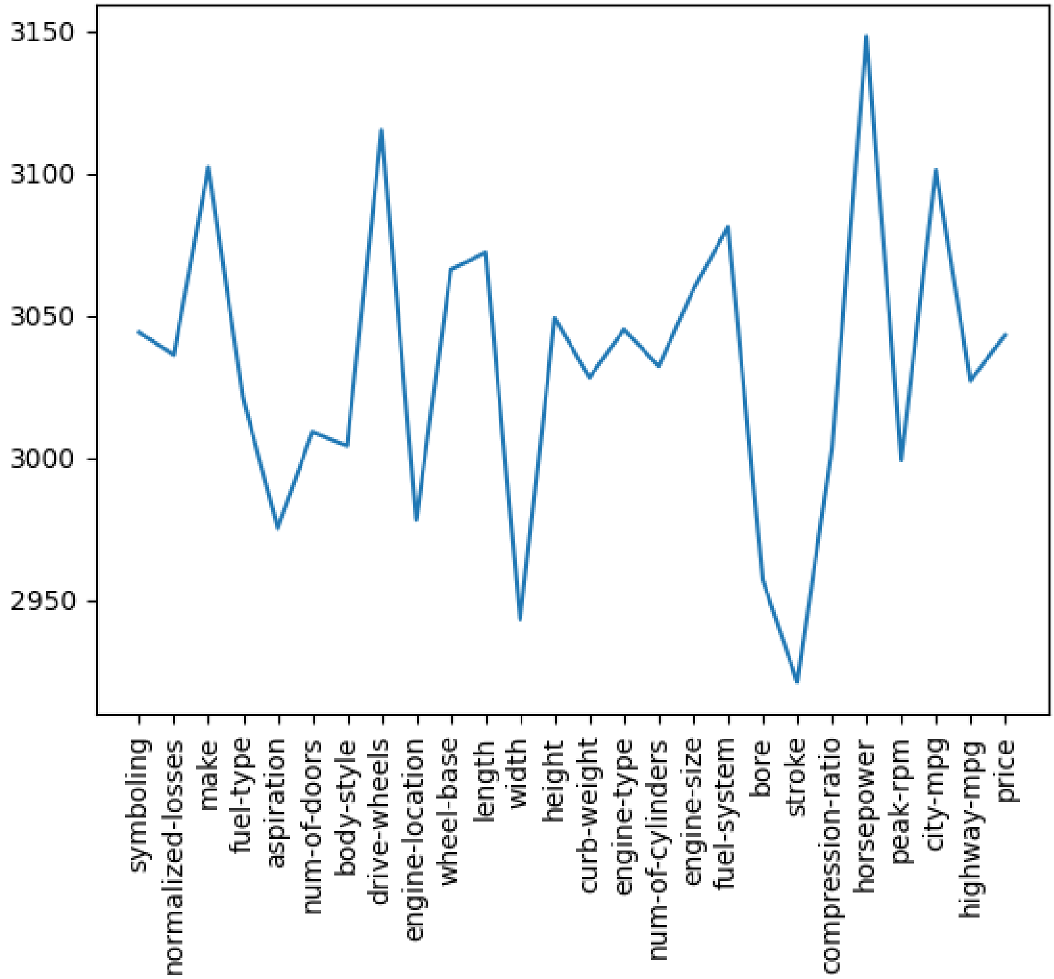
[ ]:
```
   symboling normalized-losses         make fuel-type aspiration num-of-doors  \
0        3.0               NaN  alfa-romero       gas        std          two
1        3.0                 ?  alfa-romero       gas        std          two
2        1.0                 ?  alfa-romero       gas        std          two
3        2.0               164         audi       gas        std         four
4        2.0               164         audi       gas        std          NaN

    body-style drive-wheels engine-location  wheel-base  …  engine-size  \
0  convertible          rwd           front        88.6  …          NaN
1  convertible          rwd           front        88.6  …        130.0
2    hatchback          rwd             NaN        94.5  …        152.0
3        sedan          fwd           front        99.8  …        109.0
4        sedan          4wd           front        99.4  …        136.0

   fuel-system  bore  stroke compression-ratio horsepower  peak-rpm city-mpg  \
0         mpfi  3.47    2.68               9.0        111       NaN     21.0
1         mpfi  3.47    2.68               9.0        111       NaN     21.0
2         mpfi   NaN    3.47               9.0        154       NaN     19.0
3         mpfi  3.19     NaN              10.0        102      5500     24.0
4         mpfi   NaN     3.4               8.0        115      5500     18.0

  highway-mpg  price
0        27.0  13495
1        27.0  16500
2        26.0  16500
3        30.0  13950
4        22.0  17450

[5 rows x 26 columns]
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30330 entries, 0 to 30329
Data columns (total 26 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   symboling          27286 non-null  float64
 1   normalized-losses  27294 non-null  object
 2   make               27228 non-null  object
 3   fuel-type          27309 non-null  object
 4   aspiration         27355 non-null  object
 5   num-of-doors       27321 non-null  object
 6   body-style         27326 non-null  object
 7   drive-wheels       27215 non-null  object
```

```
 8   engine-location    27352 non-null  object
 9   wheel-base         27264 non-null  float64
 10  length             27258 non-null  float64
 11  width              27387 non-null  float64
 12  height             27281 non-null  float64
 13  curb-weight        27302 non-null  float64
 14  engine-type        27285 non-null  object
 15  num-of-cylinders   27298 non-null  object
 16  engine-size        27271 non-null  float64
 17  fuel-system        27249 non-null  object
 18  bore               27373 non-null  object
 19  stroke             27409 non-null  object
 20  compression-ratio  27327 non-null  float64
 21  horsepower         27182 non-null  object
 22  peak-rpm           27331 non-null  object
 23  city-mpg           27229 non-null  float64
 24  highway-mpg        27303 non-null  float64
 25  price              27287 non-null  object
dtypes: float64(10), object(16)
memory usage: 6.0+ MB
```

[ ]:
```
x = df.isnull().sum()
plt.plot(x)
plt.xticks(rotation=90)
plt.show()
```



3.3 1.2 Statistical Summary and Distributions

[ ]:
```
df.describe()
```

[ ]:
```
          symboling    wheel-base        length         width        height  \
count  27286.000000  27264.000000  27258.000000  27387.000000  27281.000000
mean       0.839075     98.807875    174.158302     65.918114     53.732059
std        1.239600      6.037800     12.366150      2.143679      2.438541
min       -2.000000     86.600000    141.100000     60.300000     47.800000
25%        0.000000     94.500000    166.300000     64.100000     52.000000
50%        1.000000     97.000000    173.200000     65.500000     54.100000
75%        2.000000    102.400000    183.500000     66.900000     55.500000
max        3.000000    120.900000    208.100000     72.300000     59.800000

        curb-weight   engine-size  compression-ratio      city-mpg  \
count  27302.000000  27271.000000       27327.000000  27229.000000
```

```
mean    2560.265988   127.322834          10.128243     25.158507
std      522.483478    41.863332           3.943566      6.517297
min     1488.000000    61.000000           7.000000     13.000000
25%     2145.000000    97.000000           8.500000     19.000000
50%     2414.000000   120.000000           9.000000     24.000000
75%     2954.000000   146.000000           9.400000     30.000000
max     4066.000000   326.000000          23.000000     49.000000

        highway-mpg
count  27303.000000
mean      30.709885
std        6.862626
min       16.000000
25%       25.000000
50%       30.000000
75%       34.000000
max       54.000000
```

[ ]:
```
print(df['curb-weight'].skew())
```

```
0.6634854302785074
```

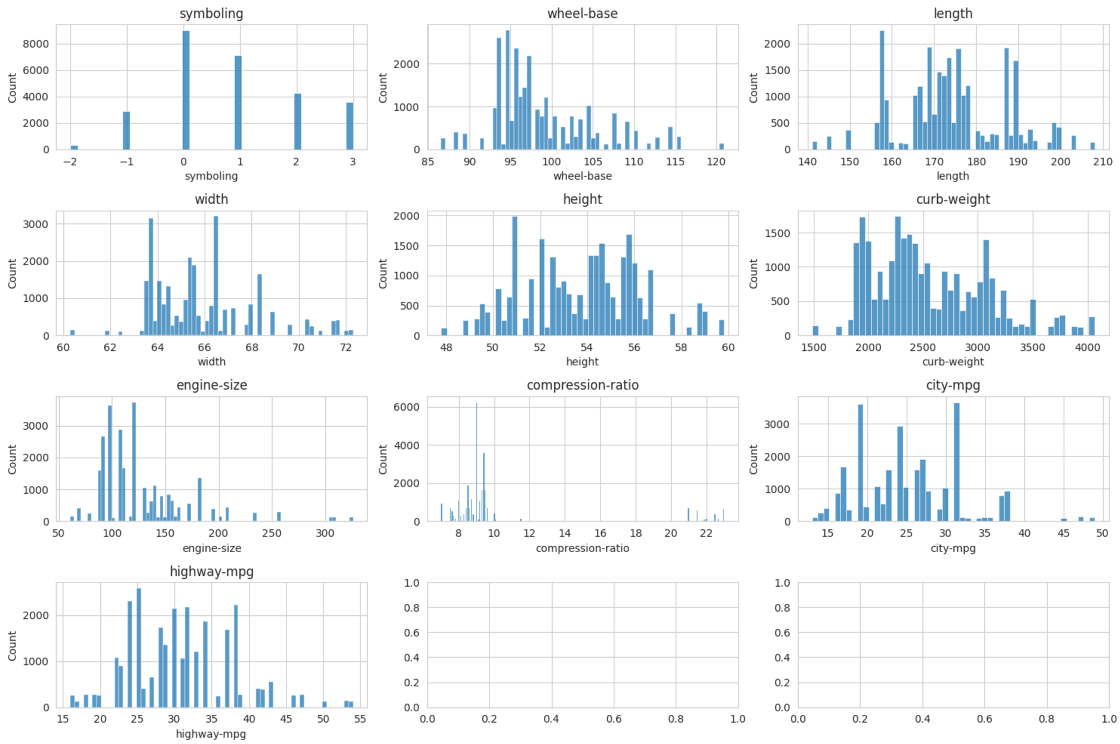
[ ]:
```
df_num = df.select_dtypes(include=['int64', 'float64'])
print(df_num.shape)
```

```
(30330, 10)
```

[ ]:
```
df_cat = df.select_dtypes(include=['object'])
print(df_cat.shape)
```

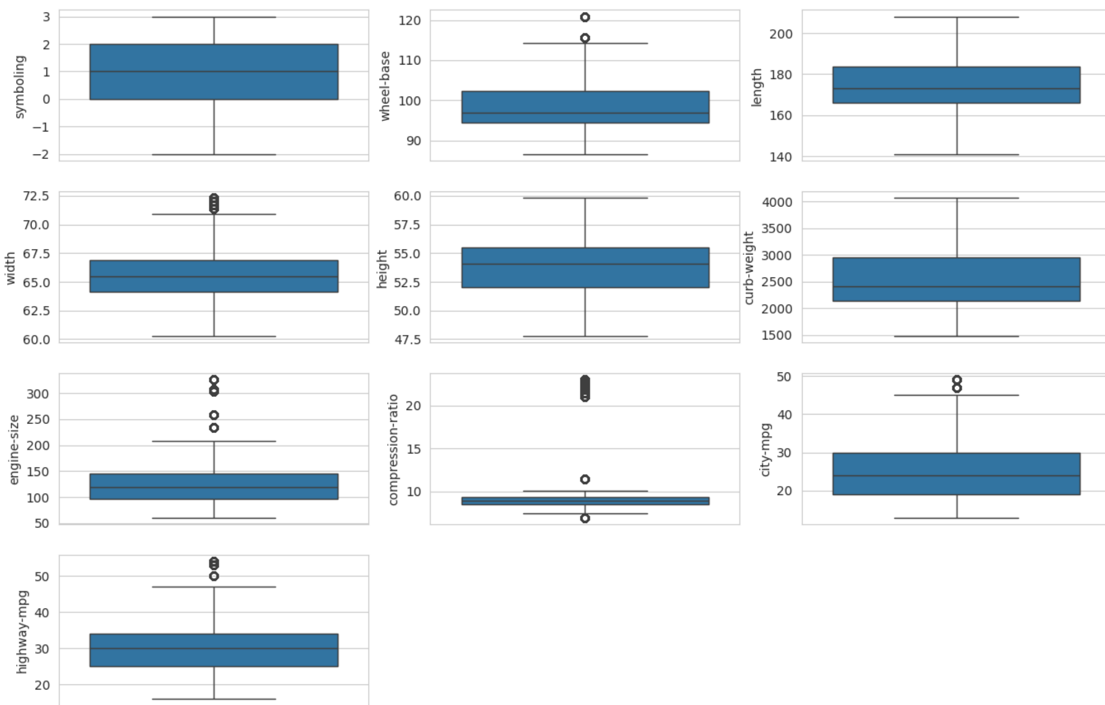
```
(30330, 16)
```

[ ]:
```
sns.set_style("whitegrid")
fig, axes = plt.subplots(nrows=4, ncols=3, figsize=(15, 10))
axes = axes.flatten()

for i, column in enumerate(df_num.columns):
    sns.histplot(df_num[column], ax=axes[i])
    axes[i].set_title(column)
plt.tight_layout()
plt.show()
```



[ ]:

```
figure = plt.figure(figsize=(15, 10))
for i, column in enumerate(df_num.columns):
  plt.subplot(4, 3, i+1)
  sns.boxplot(df_num[column])
plt.show()
```



[ ]:
```
print(df_num.skew())
```

```
symboling            0.222439
wheel-base           1.036002
length               0.142167
width                0.886104
height               0.066674
curb-weight          0.663485
engine-size          1.895392
compression-ratio    2.600568
city-mpg             0.670895
highway-mpg          0.552298
dtype: float64
```

The skewness of more than 1 requires transformation for regression modelling.

[ ]:
```
df_reg = pd.DataFrame(df)
df_reg['wheel-base'] = np.log1p(df_reg['wheel-base'])
df_reg['engine-size'] = np.log1p(df_reg['engine-size'])
df_reg['compression-ratio'] = np.log1p(df_reg['compression-ratio'])
df_reg_num = df_reg.select_dtypes(include=['int64', 'float64'])
print(df_reg_num.skew())
```

```
symboling            0.222439
wheel-base           0.874010
```

```
length               0.142167
width                0.886104
height               0.066674
curb-weight          0.663485
engine-size          0.836621
compression-ratio    2.368462
city-mpg             0.670895
highway-mpg          0.552298
dtype: float64
```

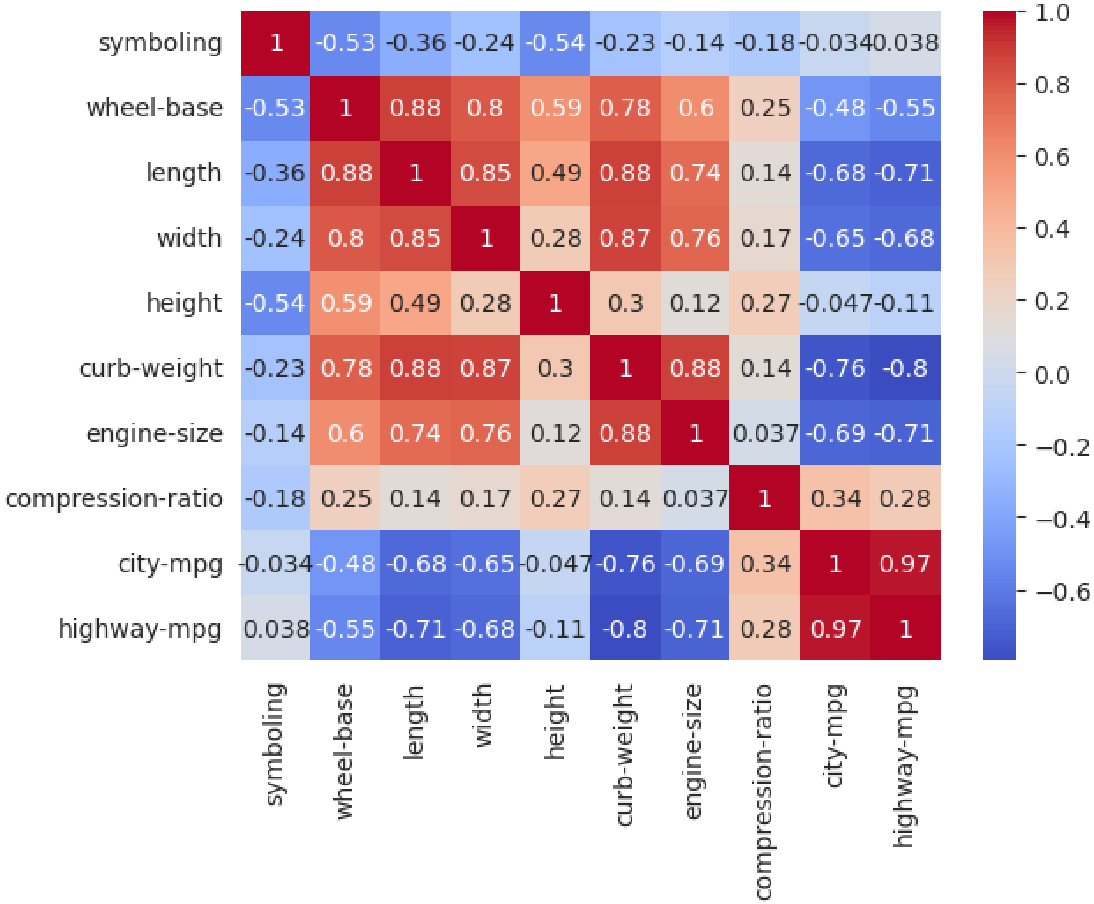
[ ]:
```python
from sklearn.preprocessing import PowerTransformer

pt = PowerTransformer(method='yeo-johnson')
df_reg['compression-ratio'] = pt.fit_transform(df_reg[['compression-ratio']])
```

[ ]:
```python
print(df_reg['compression-ratio'].skew())
```

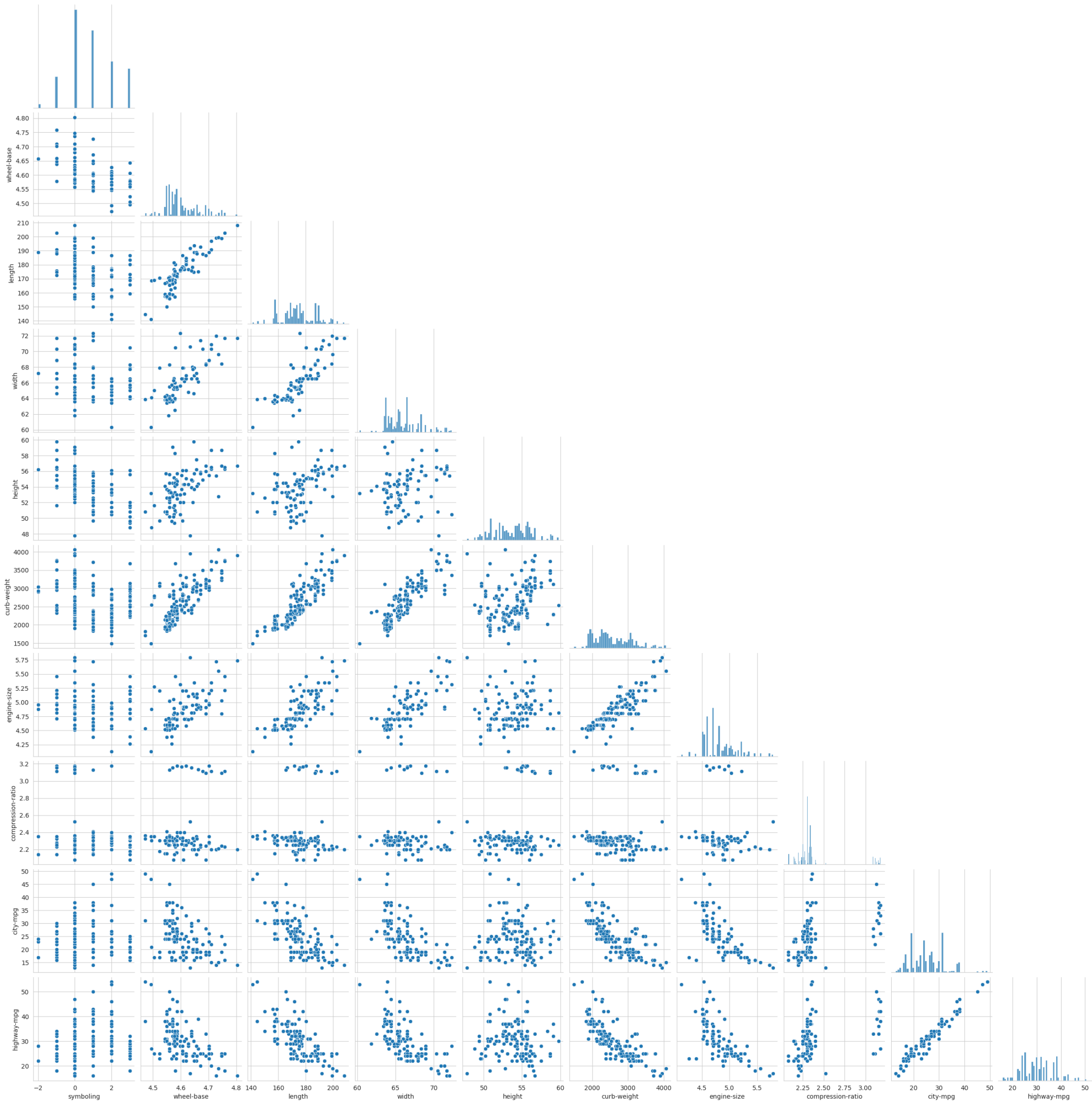
```
-0.039631763577591336
```

3.4 1.3 Relationships Between Features

[ ]:
```python
df_reg_corr = df_reg_num.corr()
sns.heatmap(df_reg_corr, annot=True, cmap='coolwarm')
plt.show()
```



[ ]:
```
sns.pairplot(df_reg_num,corner=True)
plt.show()
```



The correlation matrix and the pairplots show that the correlated features have a somewhat linear relationship and regression will work.

[ ]:
```
df_reg.columns
```

[ ]:
```
Index(['symboling', 'normalized-losses', 'make', 'fuel-type', 'aspiration',
       'num-of-doors', 'body-style', 'drive-wheels', 'engine-location',
       'wheel-base', 'length', 'width', 'height', 'curb-weight', 'engine-type',
       'num-of-cylinders', 'engine-size', 'fuel-system', 'bore', 'stroke',
       'compression-ratio', 'horsepower', 'peak-rpm', 'city-mpg',
       'highway-mpg', 'price'],
      dtype='object')
```

[ ]:
```
df_reg['price'] = pd.to_numeric(df_reg['price'], errors='coerce')
```

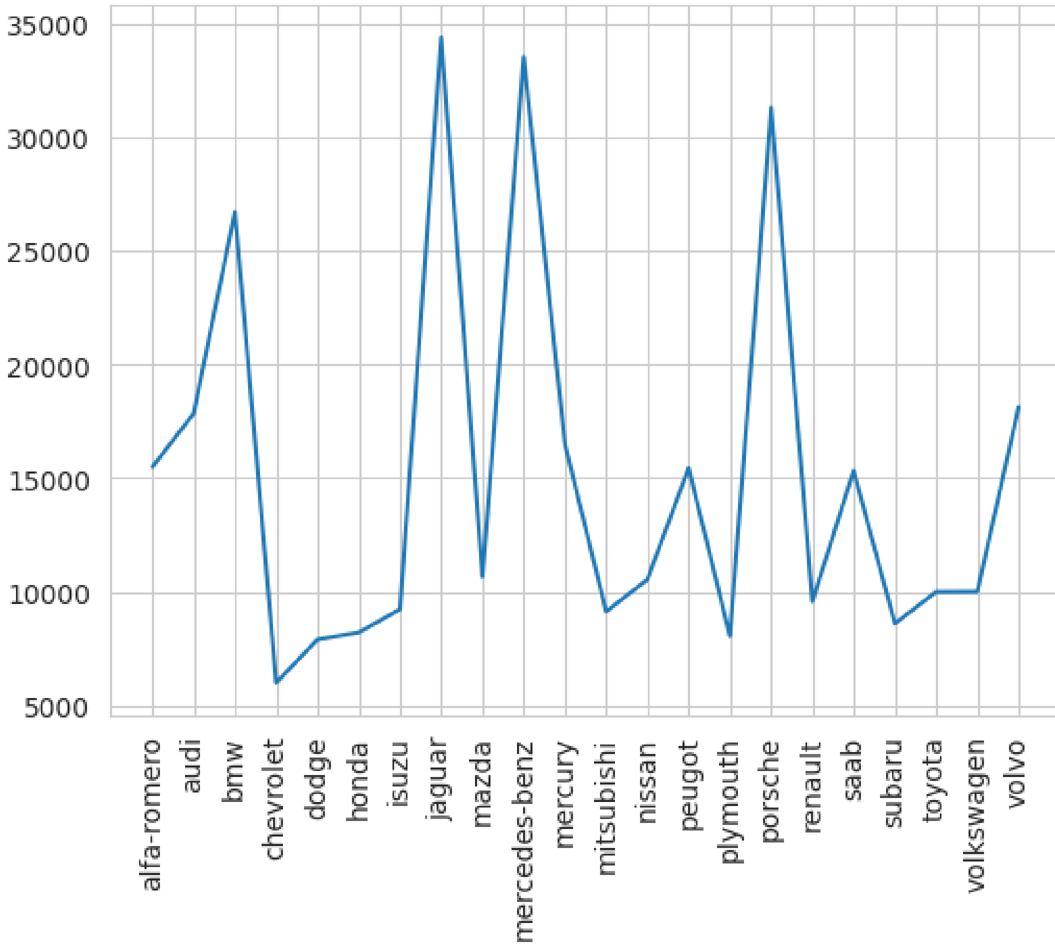
[ ]:
```
pd.pivot_table(df_reg, index='fuel-type', values='price').
 ↪sort_values(by='price', ascending=False)
```

[ ]:
```
                   price
fuel-type
diesel     16106.236786
gas        12923.557840
```

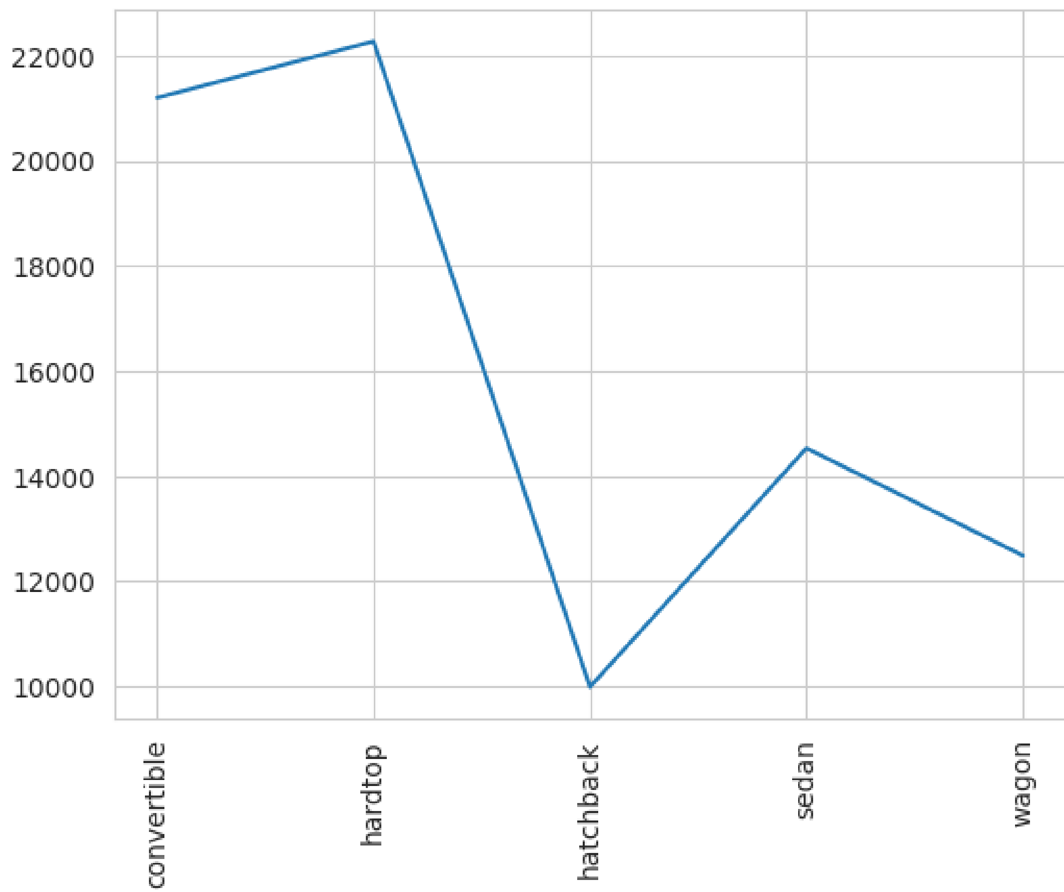
[ ]:
```
df_reg.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30330 entries, 0 to 30329
Data columns (total 26 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   symboling          27286 non-null  float64
 1   normalized-losses  27294 non-null  object
 2   make               27228 non-null  object
 3   fuel-type          27309 non-null  object
 4   aspiration         27355 non-null  object
 5   num-of-doors       27321 non-null  object
 6   body-style         27326 non-null  object
 7   drive-wheels       27215 non-null  object
 8   engine-location    27352 non-null  object
 9   wheel-base         27264 non-null  float64
 10  length             27258 non-null  float64
 11  width              27387 non-null  float64
 12  height             27281 non-null  float64
 13  curb-weight        27302 non-null  float64
 14  engine-type        27285 non-null  object
 15  num-of-cylinders   27298 non-null  object
 16  engine-size        27271 non-null  float64
 17  fuel-system        27249 non-null  object
 18  bore               27373 non-null  object
 19  stroke             27409 non-null  object
 20  compression-ratio  27327 non-null  float64
 21  horsepower         27182 non-null  object
 22  peak-rpm           27331 non-null  object
 23  city-mpg           27229 non-null  float64
 24  highway-mpg        27303 non-null  float64
 25  price              26724 non-null  float64
dtypes: float64(11), object(15)
memory usage: 6.0+ MB
```

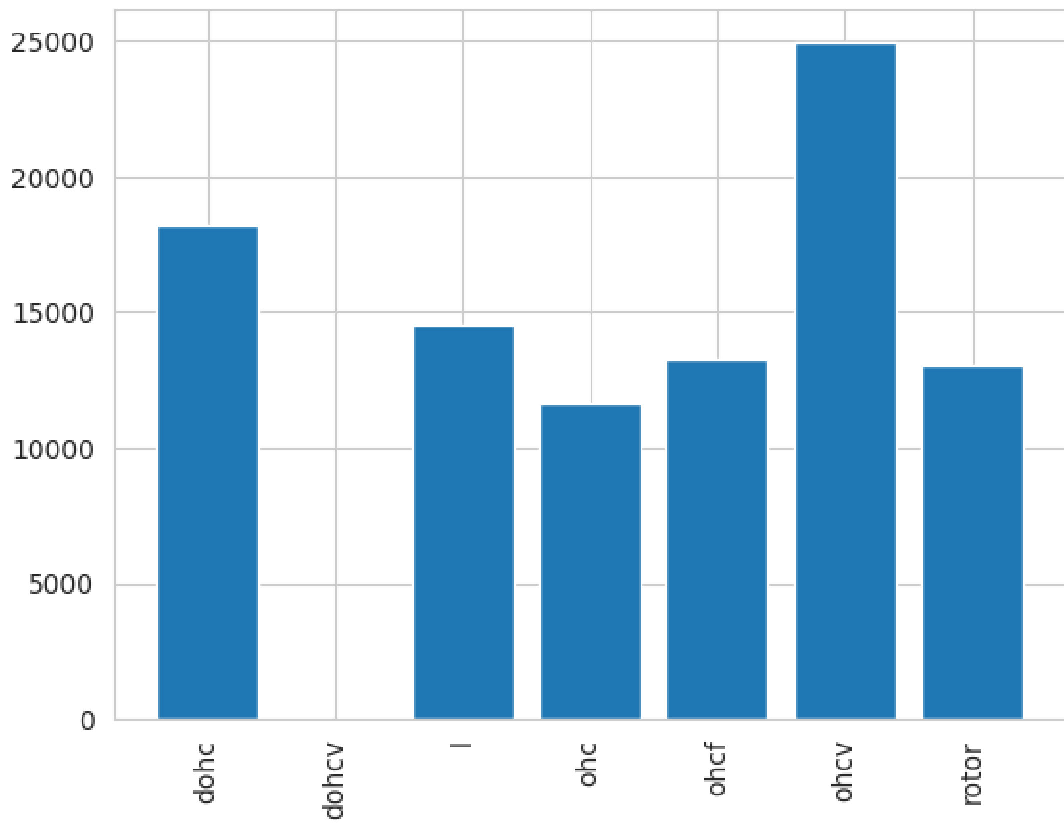
[ ]:
```python
plt.plot(df_reg.groupby('make')['price'].mean())
plt.xticks(rotation=90)
plt.show()
```



[ ]:
```python
plt.plot(df_reg.groupby('body-style')['price'].mean())
plt.xticks(rotation=90)
plt.show()
```




```
[ ]: plt.bar(df_reg.groupby('engine-type')['price'].mean().index, df_reg.
       ↪groupby('engine-type')['price'].mean().values)
     plt.xticks(rotation=90)
     plt.show()
```



4 *Section 2: Data Preprocessing*

5 Section 2: Data Preprocessing

[ ]:
```
(df_reg.isnull().sum()/df_reg.shape[0]*100).sort_values(ascending=False)
```

[ ]:
```
price                11.889219
horsepower           10.379163
drive-wheels         10.270359
make                 10.227498
city-mpg             10.224200
fuel-system          10.158259
length               10.128586
wheel-base           10.108803
engine-size          10.085724
height               10.052753
engine-type          10.039565
symboling            10.036268
normalized-losses    10.009891
```

```
num-of-cylinders      9.996703
curb-weight           9.983515
highway-mpg           9.980218
fuel-type             9.960435
num-of-doors          9.920870
body-style            9.904385
compression-ratio     9.901088
peak-rpm              9.887900
engine-location       9.818661
aspiration            9.808770
bore                  9.749423
width                 9.703264
stroke                9.630729
dtype: float64
```

[ ]:
```
df_reg.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30330 entries, 0 to 30329
Data columns (total 26 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
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 1   normalized-losses  27294 non-null  object
 2   make               27228 non-null  object
 3   fuel-type          27309 non-null  object
 4   aspiration         27355 non-null  object
 5   num-of-doors       27321 non-null  object
 6   body-style         27326 non-null  object
 7   drive-wheels       27215 non-null  object
 8   engine-location    27352 non-null  object
 9   wheel-base         27264 non-null  float64
 10  length             27258 non-null  float64
 11  width              27387 non-null  float64
 12  height             27281 non-null  float64
 13  curb-weight        27302 non-null  float64
 14  engine-type        27285 non-null  object
 15  num-of-cylinders   27298 non-null  object
 16  engine-size        27271 non-null  float64
 17  fuel-system        27249 non-null  object
 18  bore               27373 non-null  object
 19  stroke             27409 non-null  object
 20  compression-ratio  27327 non-null  float64
 21  horsepower         27182 non-null  object
 22  peak-rpm           27331 non-null  object
 23  city-mpg           27229 non-null  float64
 24  highway-mpg        27303 non-null  float64
```

```
 25  price              26724 non-null  float64
dtypes: float64(11), object(15)
memory usage: 6.0+ MB
```

[ ]:
```
num_cols = df_reg.select_dtypes(include=['number']).columns
cat_cols = df_reg.select_dtypes(include=['object']).columns
num_imputer = SimpleImputer(strategy='median')
df_reg[num_cols] = num_imputer.fit_transform(df_reg[num_cols])
cat_imputer = SimpleImputer(strategy='most_frequent')
df_reg[cat_cols] = cat_imputer.fit_transform(df_reg[cat_cols])
print(df_reg.isnull().sum())
```

```
symboling            0
normalized-losses    0
make                 0
fuel-type            0
aspiration           0
num-of-doors         0
body-style           0
drive-wheels         0
engine-location      0
wheel-base           0
length               0
width                0
height               0
curb-weight          0
engine-type          0
num-of-cylinders     0
engine-size          0
fuel-system          0
bore                 0
stroke               0
compression-ratio    0
horsepower           0
peak-rpm             0
city-mpg             0
highway-mpg          0
price                0
dtype: int64
```

5.1 2.2 Encoding Categorical Features

[ ]:
```
for col in df_reg.select_dtypes(include=['object']).columns:
    print(f"Column: {col}")
    print(df_reg[col].unique(), "\n")
```

```
Column: normalized-losses
['?' '164' '158' '192' '188' '121' '98' '81' '118' '148' '110' '145' '137'
```

```
 '101' '78' '106' '85' '107' '104' '113' '150' '129' '115' '93' '161'
 '153' '125' '128' '103' '122' '108' '194' '231' '119' '154' '74' '186'
 '83' '102' '89' '87' '77' '91' '168' '134' '65' '197' '90' '94' '256'
 '95' '142']

Column: make
['alfa-romero' 'audi' 'toyota' 'bmw' 'chevrolet' 'dodge' 'honda' 'isuzu'
 'jaguar' 'mazda' 'mercedes-benz' 'mercury' 'mitsubishi' 'nissan' 'peugot'
 'plymouth' 'porsche' 'renault' 'saab' 'subaru' 'volkswagen' 'volvo']

Column: fuel-type
['gas' 'diesel']

Column: aspiration
['std' 'turbo']

Column: num-of-doors
['two' 'four' '?']

Column: body-style
['convertible' 'hatchback' 'sedan' 'wagon' 'hardtop']

Column: drive-wheels
['rwd' 'fwd' '4wd']

Column: engine-location
['front' 'rear']

Column: engine-type
['dohc' 'ohc' 'ohcv' 'l' 'rotor' 'ohcf' 'dohcv']

Column: num-of-cylinders
['four' 'six' 'five' 'three' 'two' 'eight' 'twelve']

Column: fuel-system
['mpfi' '2bbl' 'mfi' '1bbl' 'spfi' '4bbl' 'idi' 'spdi']

Column: bore
['3.47' '3.62' '3.19' '3.13' '3.5' '3.31' '2.91' '3.03' '2.97' '3.34'
 '3.6' '2.92' '3.15' '3.63' '3.54' '3.08' '?' '3.39' '3.76' '3.43' '3.58'
 '3.46' '3.8' '3.78' '3.17' '3.35' '3.59' '2.99' '3.33' '3.7' '3.61'
 '3.94' '3.74' '2.54' '3.05' '3.27' '3.24' '3.01' '2.68']

Column: stroke
['2.68' '3.47' '3.4' '2.8' '3.19' '3.39' '3.03' '3.11' '3.23' '3.46' '3.9'
 '3.41' '3.07' '3.58' '4.17' '2.76' '3.15' '?' '3.16' '3.64' '3.1' '3.35'
 '3.12' '3.86' '3.29' '3.27' '3.52' '2.19' '3.21' '2.9' '2.07' '2.36'
 '2.64' '3.08' '3.5' '3.54' '2.87']
```

```
Column: horsepower
['111' '154' '102' '115' '110' '68' '140' '160' '101' '121' '182' '48'
 '70' '88' '145' '76' '60' '86' '100' '78' '90' '176' '262' '135' '84'
 '64' '120' '72' '123' '155' '184' '175' '116' '55' '69' '97' '152' '200'
 '95' '143' '207' '288' '?' '73' '82' '94' '62' '56' '112' '92' '161'
 '156' '85' '52' '114' '162' '134' '106' '142' '58']

Column: peak-rpm
['5500' '5800' '4250' '5400' '5100' '5000' '4800' '6000' '4750' '4650'
 '4200' '4350' '4500' '5200' '4150' '5600' '5900' '5750' '?' '5250' '4400'
 '6600' '5300' '4900']
```

[ ]:
```python
df_reg.replace("?", np.nan, inplace=True)
```

[ ]:
```python
num_cols = ['bore', 'stroke', 'horsepower','peak-rpm','normalized-losses']  #␣
↪Replace with actual column names

for col in num_cols:
    df_reg[col] = pd.to_numeric(df_reg[col])
```

[ ]:
```python
df_reg[num_cols] = df_reg[num_cols].fillna(df_reg[num_cols].median())
```

[ ]:
```python
df_reg['num-of-doors'] = df_reg['num-of-doors'].fillna(df_reg['num-of-doors'].
↪mode()[0])
```

[ ]:
```python
for col in df_reg.select_dtypes(include=['object']).columns:
    print(f"Column: {col}")
    print(df_reg[col].unique(), "\n")
```

```
Column: make
['alfa-romero' 'audi' 'toyota' 'bmw' 'chevrolet' 'dodge' 'honda' 'isuzu'
 'jaguar' 'mazda' 'mercedes-benz' 'mercury' 'mitsubishi' 'nissan' 'peugot'
 'plymouth' 'porsche' 'renault' 'saab' 'subaru' 'volkswagen' 'volvo']

Column: fuel-type
['gas' 'diesel']

Column: aspiration
['std' 'turbo']

Column: num-of-doors
['two' 'four']

Column: body-style
['convertible' 'hatchback' 'sedan' 'wagon' 'hardtop']
```

```
Column: drive-wheels
['rwd' 'fwd' '4wd']

Column: engine-location
['front' 'rear']

Column: engine-type
['dohc' 'ohc' 'ohcv' 'l' 'rotor' 'ohcf' 'dohcv']

Column: num-of-cylinders
['four' 'six' 'five' 'three' 'two' 'eight' 'twelve']

Column: fuel-system
['mpfi' '2bbl' 'mfi' '1bbl' 'spfi' '4bbl' 'idi' 'spdi']
```

[ ]:
```
ordinal_cols = ['num-of-doors', 'num-of-cylinders']
nominal_cols = ['make','fuel-type', 'aspiration', 'body-style', 'drive-wheels',␣
↪'engine-location', 'engine-type', 'fuel-system']
for col in ordinal_cols:
    df_reg[col] = LabelEncoder().fit_transform(df_reg[col])
df_reg = pd.get_dummies(df_reg, columns=nominal_cols)
print(df_reg.head())
```

```
   symboling  normalized-losses  num-of-doors  wheel-base  length  width  \
0        3.0              115.0             1    4.495355   168.8   64.1
1        3.0              115.0             1    4.495355   168.8   64.1
2        1.0              115.0             1    4.559126   171.2   65.5
3        2.0              164.0             0    4.613138   176.6   66.2
4        2.0              164.0             0    4.609162   173.2   65.5

   height  curb-weight  num-of-cylinders  engine-size  …  engine-type_ohcv  \
0    54.1       2548.0                 2     4.795791  …             False
1    48.8       2548.0                 2     4.875197  …             False
2    52.4       2823.0                 3     5.030438  …              True
3    54.3       2337.0                 2     4.700480  …             False
4    54.3       2824.0                 1     4.919981  …             False

   engine-type_rotor  fuel-system_1bbl  fuel-system_2bbl  fuel-system_4bbl  \
0              False             False             False             False
1              False             False             False             False
2              False             False             False             False
3              False             False             False             False
4              False             False             False             False

   fuel-system_idi  fuel-system_mfi  fuel-system_mpfi  fuel-system_spdi  \
0            False            False              True             False
1            False            False              True             False
```

```
2            False            False              True             False
3            False            False              True             False
4            False            False              True             False

   fuel-system_spfi
0             False
1             False
2             False
3             False
4             False

[5 rows x 69 columns]
```

5.2 2.3 Feature Scaling

```
[ ]: num_col = df_reg.select_dtypes(include=['int64', 'float64']).columns
     scaler = StandardScaler()
     df_reg[num_col] = scaler.fit_transform(df_reg[num_col])
```

```
[ ]: correlation_matrix = df_reg.corr(numeric_only=True)
     price_corr = correlation_matrix['price'].sort_values(ascending=False)
```

```
[ ]: print(price_corr)
```

```
price                 1.000000
engine-size           0.738598
curb-weight           0.729870
width                 0.641442
horsepower            0.637149
                        …
engine-type_ohc      -0.275124
fuel-system_2bbl     -0.432490
drive-wheels_fwd     -0.502909
city-mpg             -0.595241
highway-mpg          -0.615324
Name: price, Length: 69, dtype: float64
```

```
[ ]: selected_features = price_corr[(price_corr.abs() > 0.3)].index.tolist()
     print(selected_features)
```

```
['price', 'engine-size', 'curb-weight', 'width', 'horsepower', 'length', 'drive-
wheels_rwd', 'wheel-base', 'make_mercedes-benz', 'bore', 'fuel-system_mpfi',
'engine-type_ohcv', 'make_bmw', 'make_jaguar', 'fuel-system_2bbl', 'drive-
wheels_fwd', 'city-mpg', 'highway-mpg']
```

5.3 2.4 Splitting Data for Model Training

[ ]:
```
df_cleaned = df_reg[selected_features]
X=df_cleaned.drop('price',axis=1)
y=df_cleaned['price']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

5.4 *Section 3: Model Building*

5.5 3.1 Applying Regression Models

[ ]:
```
lr = LinearRegression()
lr.fit(X_train, y_train)
y_pred = lr.predict(X_test)
mse_lr = mean_squared_error(y_test, y_pred)
r2_lr = r2_score(y_test, y_pred)
print("Mean Squared Error:", mse_lr)
print("R-squared:", r2_lr)
```

```
Mean Squared Error: 0.28636826965646905
R-squared: 0.7108872757303984
```

[ ]:
```
dt = DecisionTreeRegressor()
dt.fit(X_train, y_train)
y_pred = dt.predict(X_test)
mse_dt = mean_squared_error(y_test, y_pred)
r2_dt = r2_score(y_test, y_pred)
print("Mean Squared Error:", mse_dt)
print("R-squared:", r2_dt)
```

```
Mean Squared Error: 0.16699872205055608
R-squared: 0.8314008198621401
```

[ ]:
```
rf = RandomForestRegressor()
rf.fit(X_train, y_train)
y_pred = rf.predict(X_test)
mse_rf = mean_squared_error(y_test, y_pred)
r2_rf = r2_score(y_test, y_pred)
print("Mean Squared Error:", mse_rf)
print("R-squared:", r2_rf)
```

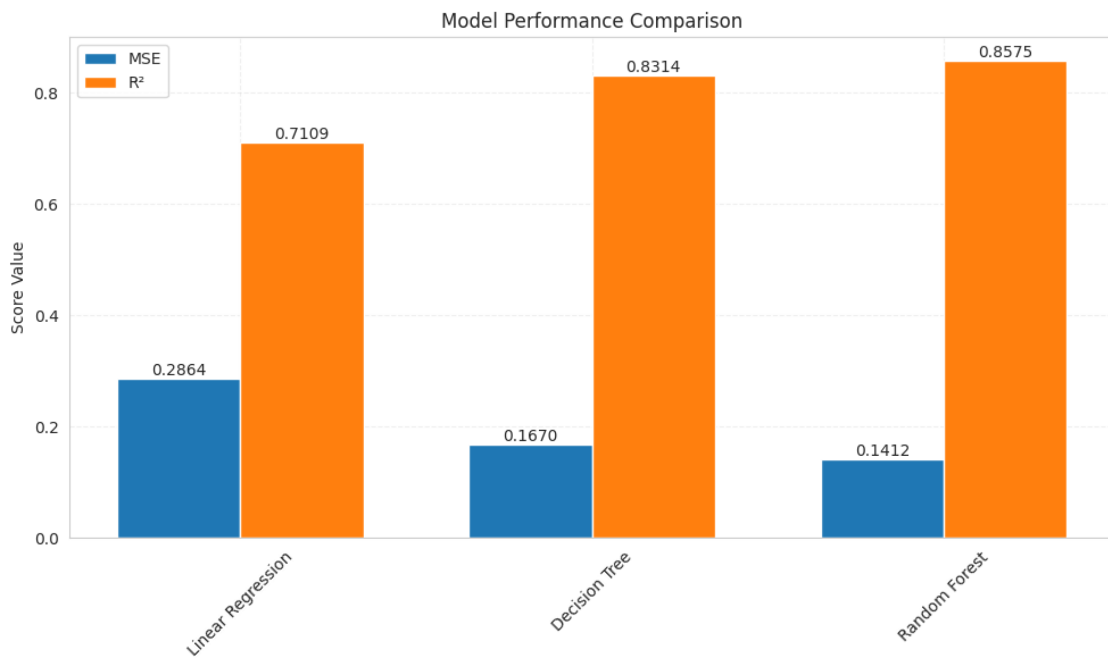
```
Mean Squared Error: 0.1408889534364651
R-squared: 0.8577608154828988
```

5.6 3.2 Evaluating Model Performances

[ ]:
```
table = pd.DataFrame({
    'Model': ['Linear Regression', 'Decision Tree', 'Random Forest'],
    'MSE': [mse_lr, mse_dt, mse_rf],
    'R-squared': [r2_lr, r2_dt, r2_rf]
})
print(table)
```

```
               Model       MSE  R-squared
0  Linear Regression  0.286368   0.710887
1      Decision Tree  0.166999   0.831401
2      Random Forest  0.141184   0.857463
```

[ ]:
```
plt.figure(figsize=(10, 6))
width = 0.35
x = np.arange(len(table['Model']))
mse_bars = plt.bar(x - width/2, table['MSE'], width, label='MSE',␣
 ↪color='#1f77b4')
r2_bars = plt.bar(x + width/2, table['R-squared'], width, label='R²',␣
 ↪color='#ff7f0e')
plt.title('Model Performance Comparison')
plt.ylabel('Score Value')
plt.xticks(x, table['Model'], rotation=45)
plt.grid(True, linestyle='--', alpha=0.3)
for bars in [mse_bars, r2_bars]:
    for bar in bars:
        height = bar.get_height()
        plt.text(bar.get_x() + bar.get_width()/2., height,
                f'{height:.2f}' if bar.get_label() == 'MSE' else f'{height:.
 ↪4f}',
                ha='center', va='bottom')
plt.legend()
plt.tight_layout()
plt.show()
```



6 *Section 4: Reporting & Insights*

6.1 Section 4: Reporting & Insights

6.1.1 4.1 Summary of Findings

---

31. Key Insights Gained from EDA on Car Prices

- **Strong Associations with Technical Attributes**:
  Exploratory Data Analysis revealed that engine-related specifications like **`engine-size`**, **`horsepower`**, and **`curb-weight`** had the most significant positive correlation with car prices. Larger engines and heavier vehicles typically indicate premium performance or luxury status.

- **Brand Influence**:
  Luxury brands such as **BMW**, **Mercedes-Benz**, and **Jaguar** consistently showed higher price points, underscoring the strong role of brand reputation in market valuation. In contrast, economy brands like **Chevrolet** and **Honda** tended to be more budget-friendly.

- **Fuel Efficiency Trade-off**:
  Features like **`city-mpg`** and **`highway-mpg`** demonstrated a negative correlation with price, implying that fuel-efficient cars are generally priced lower, whereas high-performance,

fuel-consuming vehicles command a premium.

- **Body Style Preferences**:
  Sportier body types such as **convertibles** and **hardtops** were typically priced above sedans and hatchbacks, indicating market preference for aesthetics and luxury.

- **Missing and Noisy Data**:
  Columns like **`normalized-losses`** contained numerous missing values (e.g., '?'), requiring careful imputation and cleaning to ensure modeling accuracy.

---

32. Most Influential Features in Price Prediction

- **Top Predictors**:
  1. **Engine Size** – The strongest indicator of price.

  2. **Horsepower** – Higher horsepower models were notably more expensive.

  3. **Curb Weight** – Often correlates with vehicle class (luxury/performance).

  4. **Brand (Make)** – Cars from high-end brands clearly fetched higher prices.

  5. **Aspiration Type** – Turbocharged vehicles had a noticeable impact on pricing.

- **Less Significant Factors**:
  Features like **`num-of-doors`** and **`fuel-type`** showed weak correlation with price, suggesting they contribute minimally to price variation.

---

33. Key Challenges During Preprocessing and Modeling

- **Data Inconsistencies**:
  Numerous missing values (especially in `normalized-losses`, `bore`, `stroke`) and inconsistent formats (`?`, NaN) complicated the cleaning process. We employed **median imputation** for numerical features and **mode** for categorical ones.

- **Categorical Encoding**:
  Transforming non-numeric features such as `make`, `body-style`, and `drive-wheels` required thoughtful encoding strategies (e.g., **one-hot** and **label encoding**) to prepare the data for machine learning algorithms.

- **Feature Scaling**:
  Normalizing continuous features like `engine-size` and `horsepower` was crucial, especially for models like **Linear Regression**, to ensure consistent influence across features.

- **Model-Specific Challenges**:
  - **Overfitting**: Tree-based models, particularly **Decision Trees**, initially overfitted the

training data. Hyperparameter tuning like `max_depth` helped generalize performance.

  – **Interpretability**: While **Linear Regression** offered clear coefficient-based insights, models like **Random Forest** required feature importance plots to interpret behavior.

---

34. Steps for Handling a Larger Dataset with More Features If provided with a more complex dataset, the following steps would enhance modeling efficiency and performance:

1. **Advanced Feature Engineering**:
   - Develop interaction terms (e.g., `engine-size × horsepower`) or polynomial features to capture non-linear relationships.

   - Derive new features like **vehicle age**, if manufacturing year is available.
2. **Dimensionality Reduction Techniques**:
   - Apply **Principal Component Analysis (PCA)** or **t-SNE** to manage high-dimensional data and reduce redundancy or noise.
3. **Model Optimization & Hyperparameter Tuning**:
   - Utilize **GridSearchCV**, **RandomizedSearch**, or **Bayesian Optimization** for fine-tuning.

   - Experiment with advanced models such as **XGBoost**, **LightGBM**, or **deep neural networks** for enhanced predictive performance.
4. **Feature Selection for Scalability**:
   - Use techniques like **Recursive Feature Elimination (RFE)** or **SHAP values** to identify the most impactful features and improve model explainability.
5. **Data Augmentation**:
   - Consider generating synthetic samples for underrepresented categories (e.g., luxury or rare brands) to balance the dataset.
6. **End-to-End Pipeline Automation**:
   - Build robust, scalable pipelines using tools like **`ColumnTransformer`**, **`Pipeline`**, and version control to ensure reproducibility and modularity.
