#Car Price Prediction Analysis

Cell 1: Import 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.preprocessing import OneHotEncoder, StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score
```

Cell 2: Load Dataset and Add Column Names

```
# Define column names based on the dataset description
column_names = [
    'symboling', 'normalized_losses', 'make', 'fuel_type',
'aspiration',
    'num_doors', 'body_style', 'drive_wheels', 'engine_location',
    'wheel_base', 'length', 'width', 'height', 'curb_weight',
    'engine_type', 'num_cylinders', 'engine_size', 'fuel_system',
    'bore', 'stroke', 'compression_ratio', 'horsepower', 'peak_rpm',
    'city_mpg', 'highway_mpg', 'price'
]

# Load the dataset
df = pd.read_csv('imports-85.data.txt', names=column_names,
na_values='?')

# Display the first few rows
print(df.head())

   symboling  normalized_losses         make fuel_type aspiration
num_doors  \
0          3                NaN  alfa-romero       gas        std
two
1          3                NaN  alfa-romero       gas        std
two
2          1                NaN  alfa-romero       gas        std
two
3          2              164.0         audi       gas        std
four
4          2              164.0         audi       gas        std
four

    body_style drive_wheels engine_location  wheel_base  ...
```

```
engine_size  \
0  convertible          rwd            front         88.6  ...
130
1  convertible          rwd            front         88.6  ...
130
2    hatchback          rwd            front         94.5  ...
152
3        sedan          fwd            front         99.8  ...
109
4        sedan          4wd            front         99.4  ...
136

   fuel_system  bore  stroke compression_ratio horsepower  peak_rpm
city_mpg  \
0         mpfi  3.47    2.68               9.0      111.0    5000.0
21
1         mpfi  3.47    2.68               9.0      111.0    5000.0
21
2         mpfi  2.68    3.47               9.0      154.0    5000.0
19
3         mpfi  3.19    3.40              10.0      102.0    5500.0
24
4         mpfi  3.19    3.40               8.0      115.0    5500.0
18

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

[5 rows x 26 columns]
```

Cell 3: Check for Missing Values

```
# Check for missing values
print(df.isnull().sum())

symboling             0
normalized_losses    41
make                  0
fuel_type             0
aspiration            0
num_doors             2
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_cylinders        0
engine_size          0
fuel_system          0
bore                 4
stroke               4
compression_ratio    0
horsepower           2
peak_rpm             2
city_mpg             0
highway_mpg          0
price                4
dtype: int64
```

Cell 4: Handle Missing Values

```
# Handle missing values
# 1. Fill 'normalized_losses' with the median value
df['normalized_losses'].fillna(df['normalized_losses'].median(),
inplace=True)

# 2. Fill 'num_doors' with the most common value
most_common_doors = df['num_doors'].mode()[0]
df['num_doors'].fillna(most_common_doors, inplace=True)

# 3. Fill 'bore', 'stroke', 'horsepower', 'peak_rpm' with median
values
df['bore'].fillna(df['bore'].median(), inplace=True)
df['stroke'].fillna(df['stroke'].median(), inplace=True)
df['horsepower'].fillna(df['horsepower'].median(), inplace=True)
df['peak_rpm'].fillna(df['peak_rpm'].median(), inplace=True)

# Verify missing values are handled
print("Missing values after cleaning:\n", df.isnull().sum())
```

```
Missing values after cleaning:
 symboling            0
normalized_losses    0
make                 0
fuel_type            0
aspiration           0
num_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_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                4
dtype: int64

<ipython-input-29-c98c639d4415>:3: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment
using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try
using 'df.method({col: value}, inplace=True)' or df[col] =
df[col].method(value) instead, to perform the operation inplace on the
original object.


  df['normalized_losses'].fillna(df['normalized_losses'].median(),
inplace=True)
<ipython-input-29-c98c639d4415>:7: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment
using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try
using 'df.method({col: value}, inplace=True)' or df[col] =
df[col].method(value) instead, to perform the operation inplace on the
original object.


  df['num_doors'].fillna(most_common_doors, inplace=True)
<ipython-input-29-c98c639d4415>:10: FutureWarning: A value is trying
to be set on a copy of a DataFrame or Series through chained
```

```
assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try
using 'df.method({col: value}, inplace=True)' or df[col] =
df[col].method(value) instead, to perform the operation inplace on the
original object.


  df['bore'].fillna(df['bore'].median(), inplace=True)
<ipython-input-29-c98c639d4415>:11: FutureWarning: A value is trying
to be set on a copy of a DataFrame or Series through chained
assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try
using 'df.method({col: value}, inplace=True)' or df[col] =
df[col].method(value) instead, to perform the operation inplace on the
original object.


  df['stroke'].fillna(df['stroke'].median(), inplace=True)
<ipython-input-29-c98c639d4415>:12: FutureWarning: A value is trying
to be set on a copy of a DataFrame or Series through chained
assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try
using 'df.method({col: value}, inplace=True)' or df[col] =
df[col].method(value) instead, to perform the operation inplace on the
original object.


  df['horsepower'].fillna(df['horsepower'].median(), inplace=True)
<ipython-input-29-c98c639d4415>:13: FutureWarning: A value is trying
to be set on a copy of a DataFrame or Series through chained
assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try
using 'df.method({col: value}, inplace=True)' or df[col] =
df[col].method(value) instead, to perform the operation inplace on the
```

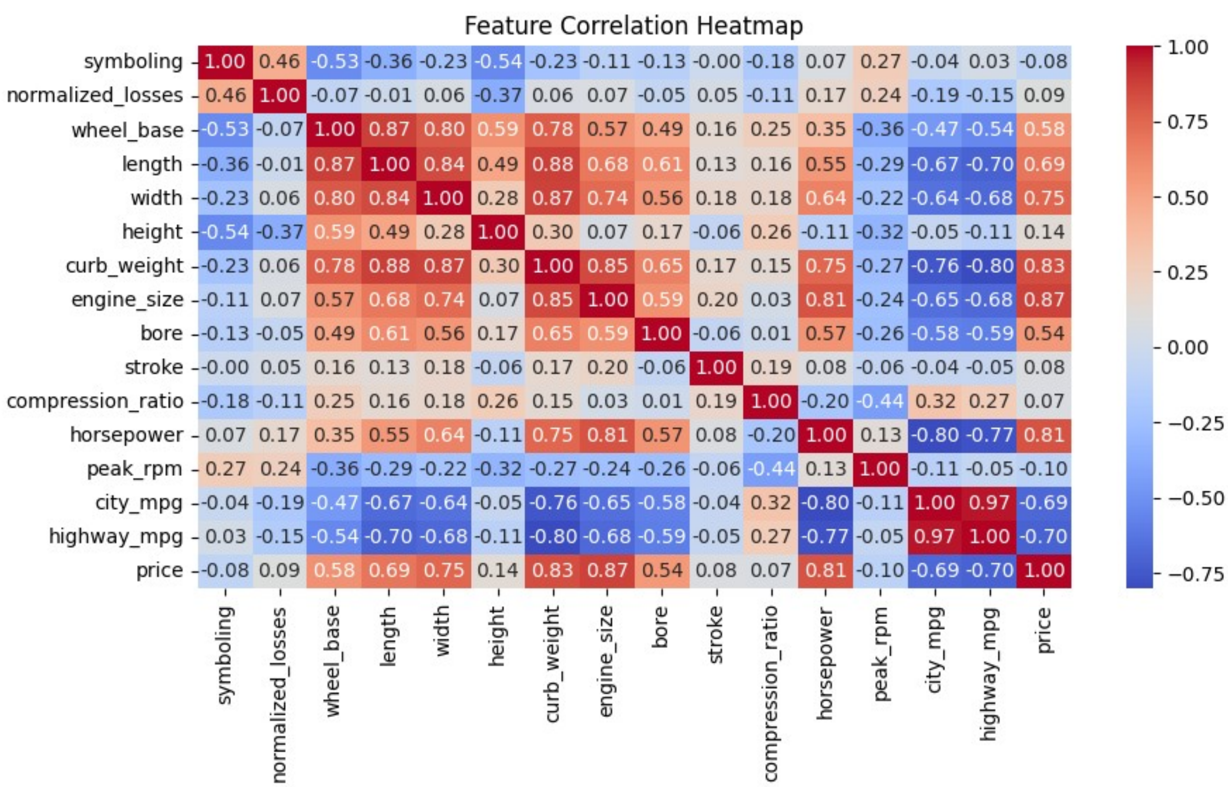
```
original object.


  df['peak_rpm'].fillna(df['peak_rpm'].median(), inplace=True)
```

Cell 5: Save the Cleaned Dataset

```
# Save the cleaned dataset
df.to_csv("cleaned_car_data.csv", index=False)
```

Cell 6: Feature Correlation Heatmap

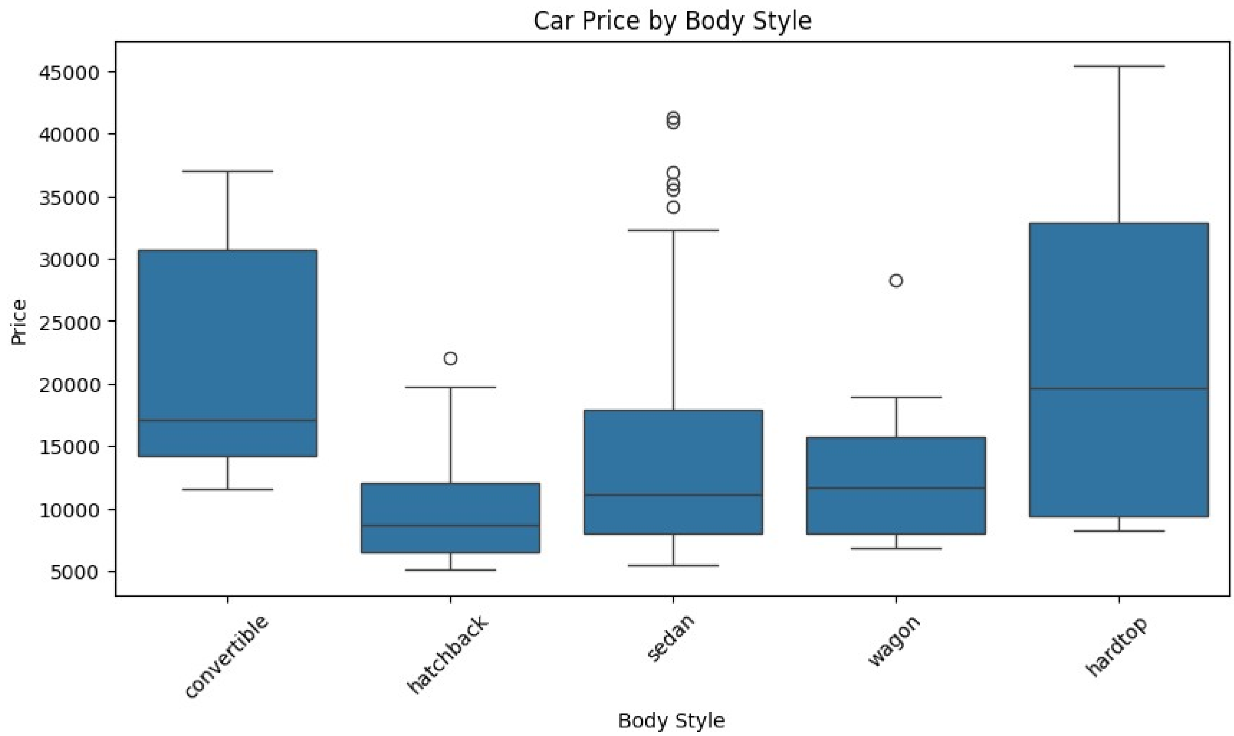
```
# Feature Correlation Heatmap With Numerical Variables
numeric_df = df.select_dtypes(include=['number'])
plt.figure(figsize=(10, 5))
sns.heatmap(numeric_df.corr(), annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Feature Correlation Heatmap')
plt.show()
```



Cell 7: Car Price by Body Style

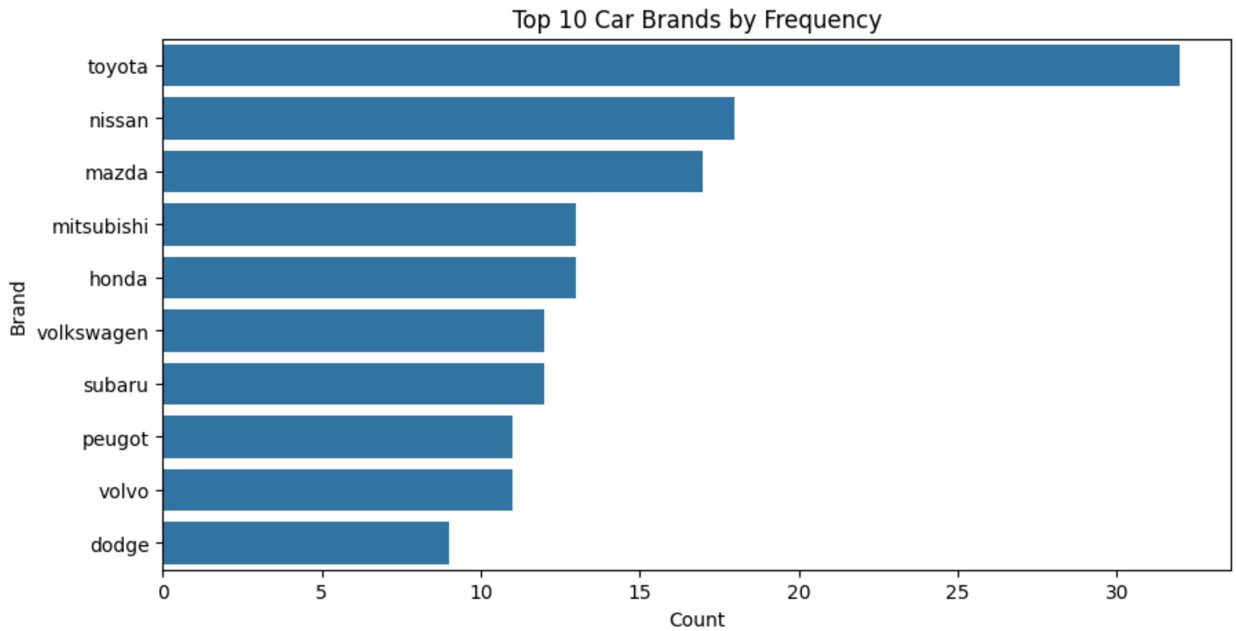
```
# Car Price by Body Style
plt.figure(figsize=(10, 5))
sns.boxplot(x=df['body_style'], y=df['price'])
plt.title('Car Price by Body Style')
```

```
plt.xlabel('Body Style')
plt.ylabel('Price')
plt.xticks(rotation=45)
plt.show()
```



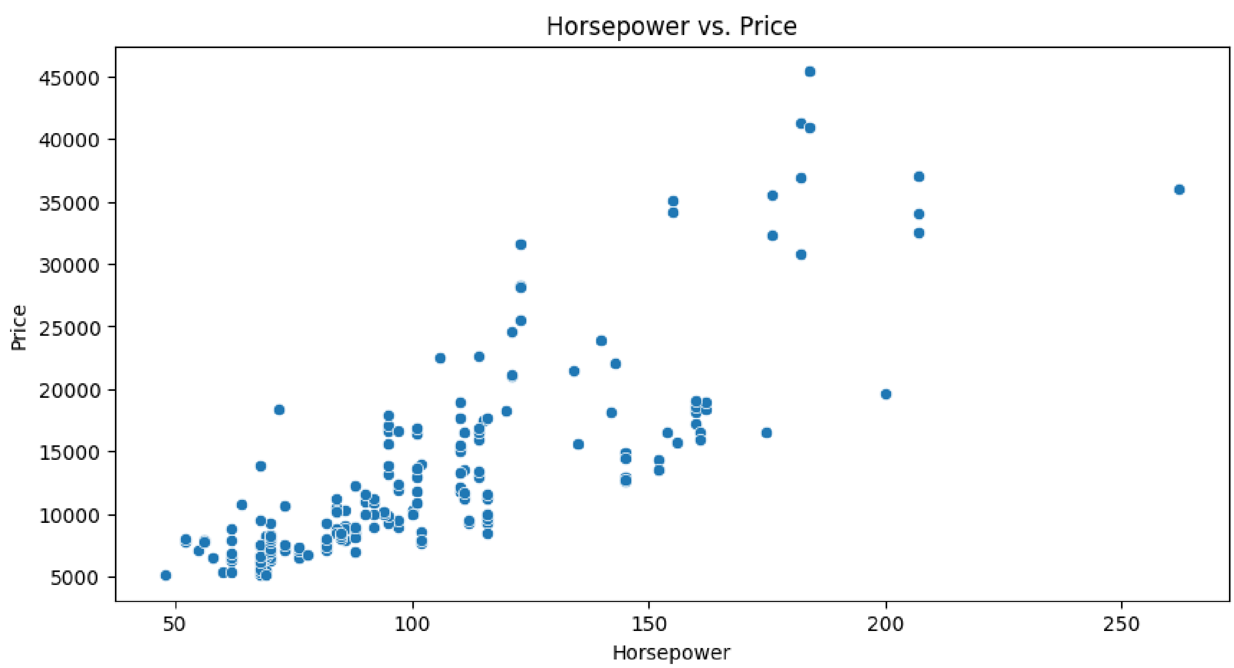
Cell 8: Top 10 Car Brands by Frequency

```
# Top 10 Car Brands by Frequency
plt.figure(figsize=(10, 5))
sns.countplot(y=df['make'],
order=df['make'].value_counts().index[:10])
plt.title('Top 10 Car Brands by Frequency')
plt.xlabel('Count')
plt.ylabel('Brand')
plt.show()
```



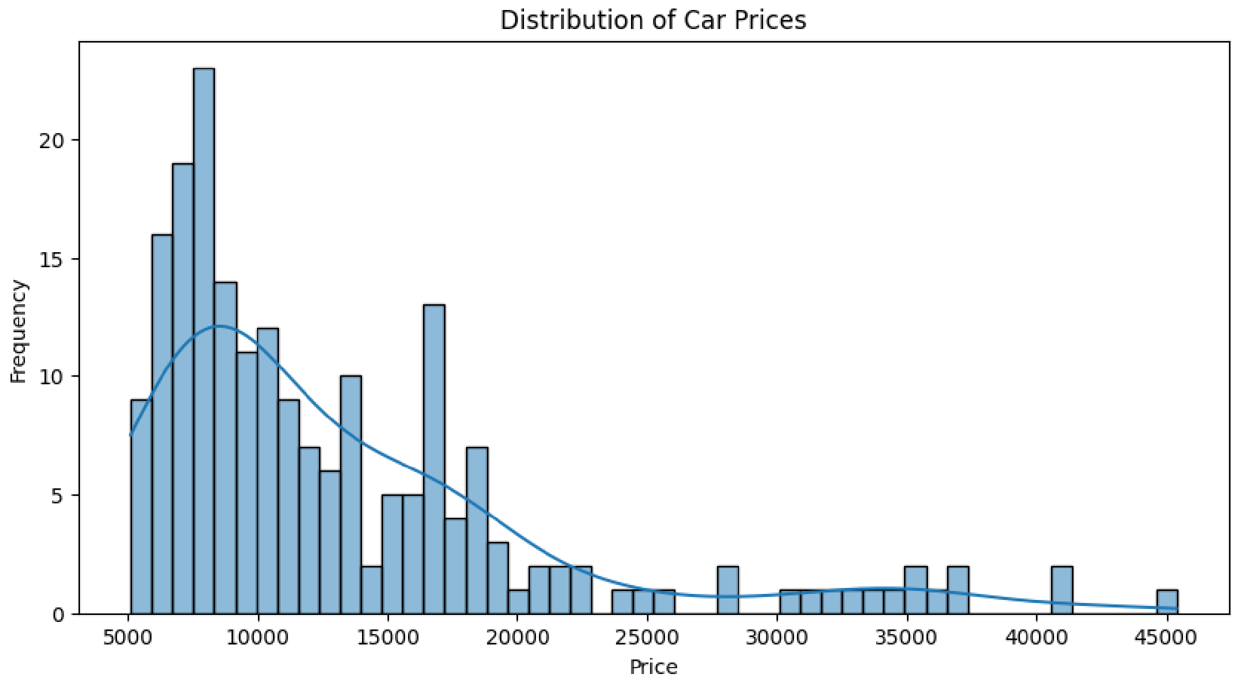
Cell 9: Horsepower vs. Price

```
# Horsepower vs. Price
plt.figure(figsize=(10, 5))
sns.scatterplot(x=df['horsepower'], y=df['price'])
plt.title('Horsepower vs. Price')
plt.xlabel('Horsepower')
plt.ylabel('Price')
plt.show()
```



Cell 10: Distribution of Car Prices

```
# Distribution of Car Prices
plt.figure(figsize=(10, 5))
sns.histplot(df['price'], bins=50, kde=True)
plt.title('Distribution of Car Prices')
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.show()
```



Cell 11: Feature Engineering

```
# Feature Engineering
df['mpg_ratio'] = df['highway_mpg'] / df['city_mpg']
```

Cell 12: Selecting Relevant Features & Target

```
# Selecting Relevant Features & Target
features = [
    'wheel_base', 'length', 'width', 'height', 'curb_weight',
    'engine_size', 'bore', 'stroke', 'compression_ratio',
    'horsepower', 'peak_rpm', 'city_mpg', 'highway_mpg',
    'mpg_ratio', 'make', 'fuel_type', 'aspiration', 'num_doors',
    'body_style', 'drive_wheels'
]
X = df[features]
y = df['price']
```

```python
# Drop rows where the target variable (price) is NaN
X = X[~y.isna()]
y = y[~y.isna()]
```

Cell 13: One-Hot Encoding for Categorical Variables

```python
# One-Hot Encoding for Categorical Variables
X = pd.get_dummies(X, columns=['make', 'fuel_type', 'aspiration',
'num_doors', 'body_style', 'drive_wheels'], drop_first=True)
```

Cell 14: Train-Test Split

```python
# Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
```

Cell 15: Standardizing Numerical Features

```python
# Standardizing Numerical Features
scaler = StandardScaler()
numeric_features = [
    'wheel_base', 'length', 'width', 'height', 'curb_weight',
    'engine_size', 'bore', 'stroke', 'compression_ratio',
    'horsepower', 'peak_rpm', 'city_mpg', 'highway_mpg', 'mpg_ratio'
]
X_train[numeric_features] =
scaler.fit_transform(X_train[numeric_features])
X_test[numeric_features] = scaler.transform(X_test[numeric_features])
```

Cell 16: Model Training

```python
# Model Training
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)
```

```
RandomForestRegressor(random_state=42)
```

Cell 17: Model Evaluation

```python
# Model Evaluation
y_pred = model.predict(X_test)
print("Model Performance:")
print(f"MAE: {mean_absolute_error(y_test, y_pred)}")
print(f"MSE: {mean_squared_error(y_test, y_pred)}")
print(f"R2 Score: {r2_score(y_test, y_pred)}\n")
```

```
Model Performance:
MAE: 1700.162699186992
```

```
MSE: 7312771.0328956945
R2 Score: 0.9402291466408084
```

Cell 18: Function to Predict Car Price

```python
# Function to Predict Car Price
def predict_car_price(input_data):
    input_df = pd.DataFrame([input_data])
    input_df = pd.get_dummies(input_df, columns=['make', 'fuel_type', 
'aspiration', 'num_doors', 'body_style', 'drive_wheels'], 
drop_first=True)

    # Ensure all columns are present
    missing_cols = set(X_train.columns) - set(input_df.columns)
    for col in missing_cols:
        input_df[col] = 0  # Add missing columns with default value 0

    input_df = input_df[X_train.columns]  # Ensure correct order
    input_df[numeric_features] = 
scaler.transform(input_df[numeric_features])  # Scale numerical values

    return model.predict(input_df)[0]
```

Cell 19: Prediction

```python
# Prediction
new_car = {
    'wheel_base': 88.6, 'length': 168.8, 'width': 64.1, 'height': 
48.8,
    'curb_weight': 2548, 'engine_size': 130, 'bore': 3.47, 'stroke': 
2.68,
    'compression_ratio': 9.0, 'horsepower': 111, 'peak_rpm': 5000,
    'city_mpg': 21, 'highway_mpg': 27, 'mpg_ratio': 27 / 21,
    'make': 'alfa-romero', 'fuel_type': 'gas', 'aspiration': 'std',
    'num_doors': 'two', 'body_style': 'convertible', 'drive_wheels': 
'rwd'
}

predicted_price = predict_car_price(new_car)
print(f"Predicted Car Price: ${predicted_price:,.2f}")

Predicted Car Price: $14,127.91
```