In [1]:
```python
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
data = pd.read_csv("Advertising.csv")
data.head()
```

Out[1]:

	Unnamed: 0	TV	radio	newspaper	sales
0	1	230.1	37.8	69.2	22.1
1	2	44.5	39.3	45.1	10.4
2	3	17.2	45.9	69.3	9.3
3	4	151.5	41.3	58.5	18.5
4	5	180.8	10.8	58.4	12.9

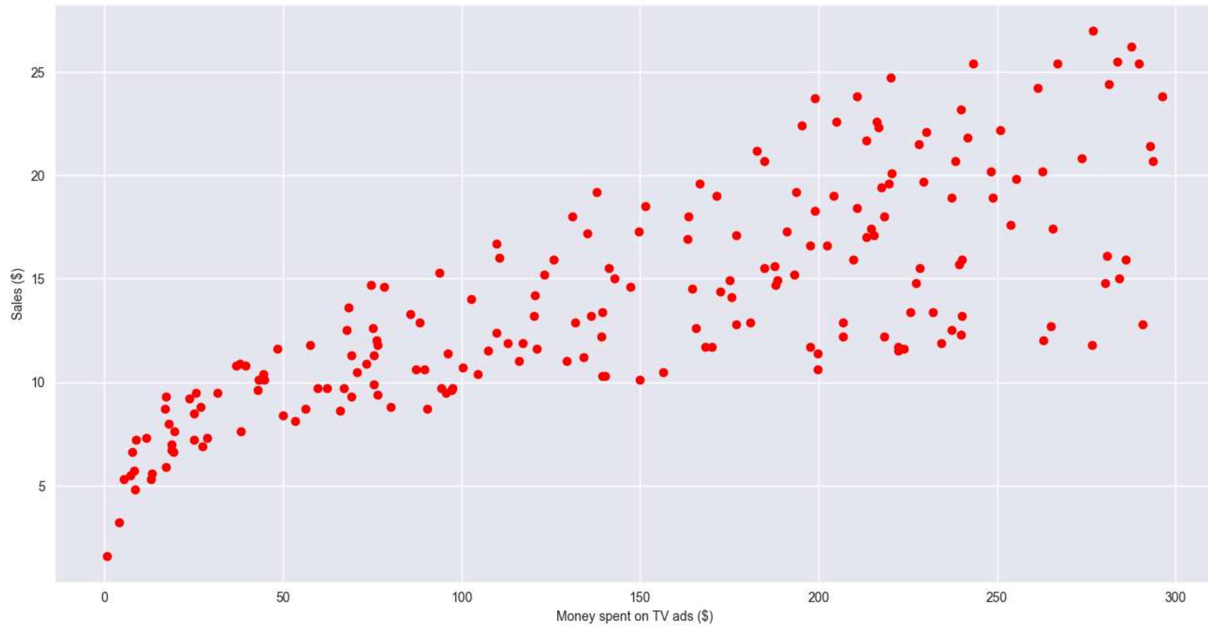
In [2]:
```python
data.drop(['Unnamed: 0'], axis=1)
```

Out[2]:

	TV	radio	newspaper	sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	9.3
3	151.5	41.3	58.5	18.5
4	180.8	10.8	58.4	12.9
...	...	...	...	...
195	38.2	3.7	13.8	7.6
196	94.2	4.9	8.1	9.7
197	177.0	9.3	6.4	12.8
198	283.6	42.0	66.2	25.5
199	232.1	8.6	8.7	13.4

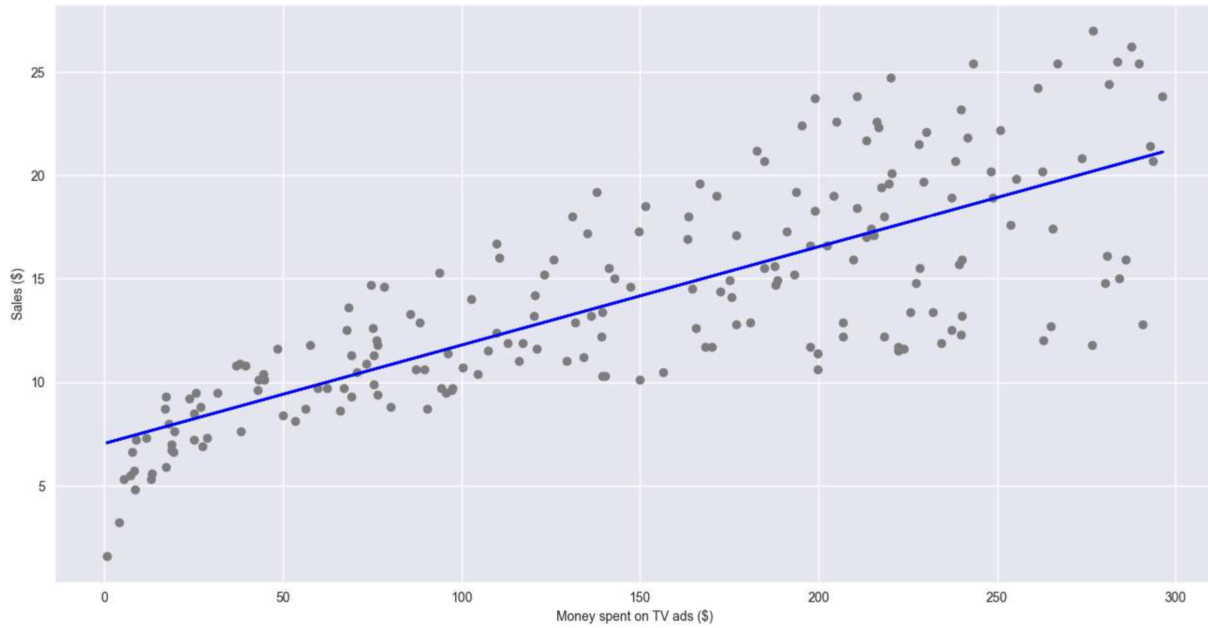
200 rows × 4 columns

In [3]:
```python
plt.figure(figsize=(16, 8))
plt.scatter(
 data['TV'],
 data['sales'],
 c='red'
)
plt.xlabel("Money spent on TV ads ($)")
plt.ylabel("Sales ($)")
plt.show()
```



In [4]:
```
X = data['TV'].values.reshape(-1, 1)
y = data['sales'].values.reshape(-1, 1)
reg = LinearRegression()
reg.fit(X, y)
print("The linear model is: Y = {:.5} +{:.5}X".format(reg.intercept_[0], reg.coef_[

"The linear model is: Y = 7.0326 + 0.047537X"
# Visualise the Best Fit Line
predictions = reg.predict(X)
plt.figure(figsize=(16, 8))
plt.scatter(
 data['TV'],
 data['sales'],
 c='grey'
)
plt.plot(
 data['TV'],
 predictions,
 c='blue',
 linewidth=2
)
plt.xlabel("Money spent on TV ads ($)")
plt.ylabel("Sales ($)")
plt.show()
```

```
The linear model is: Y = 7.0326 +0.047537X
```



Regressional Model Training

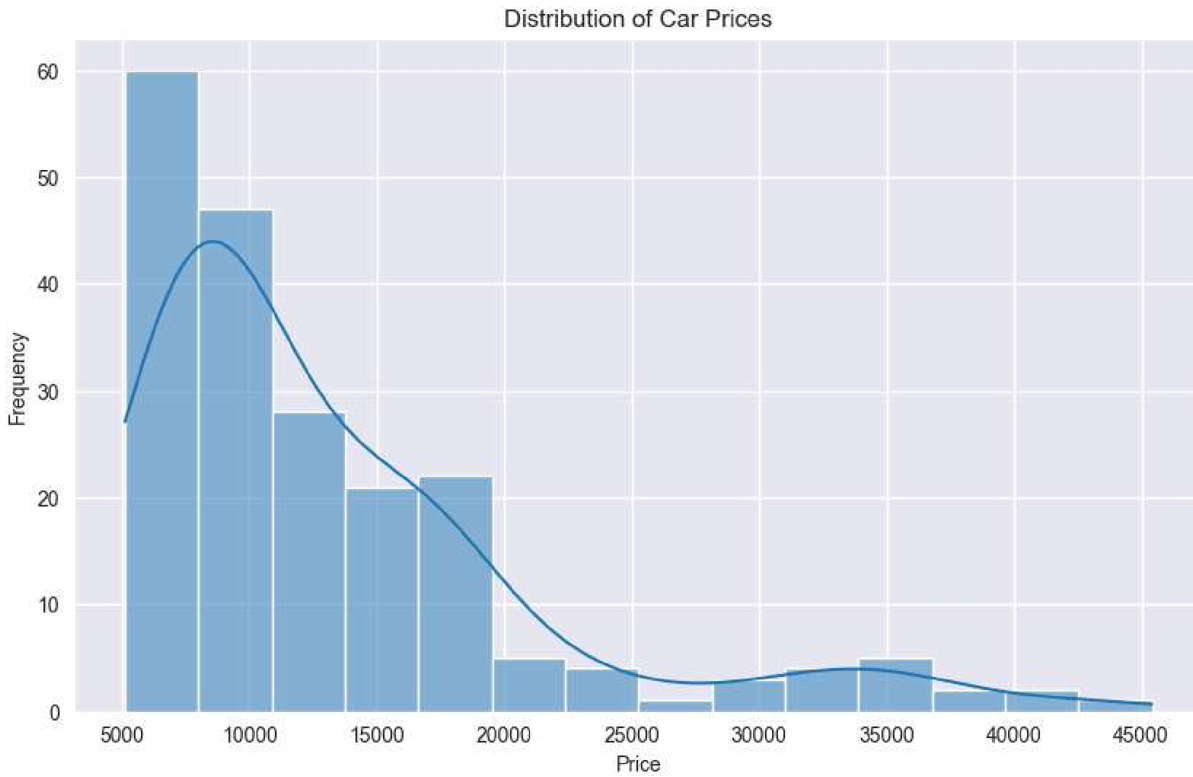
In [5]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.metrics import mean_squared_error, r2_score
import joblib
import matplotlib.pyplot as plt
import seaborn as sns
```

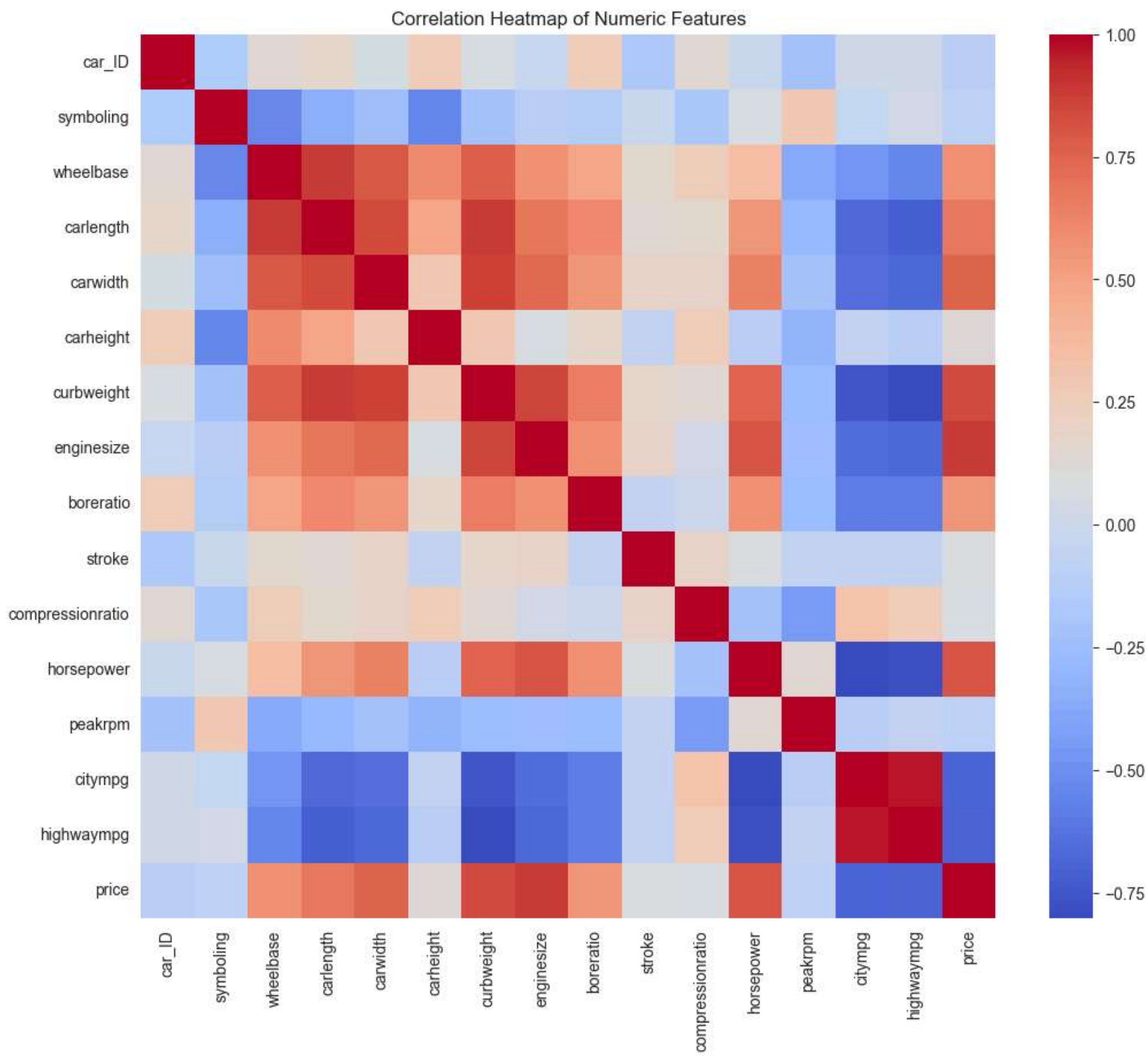
In [6]:
```
# Load the data
data = pd.read_csv("raw_data.csv")

# Data overview
print(data.info())
print("\nSample data:")
print(data.head())

# Visualize the distribution of the target variable (price)
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(10, 6))
sns.histplot(data['price'], kde=True)
plt.title('Distribution of Car Prices')
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.show()

# Correlation heatmap of numeric features
```

```
plt.figure(figsize=(12, 10))
numeric_data = data.select_dtypes(include=['int64', 'float64'])
sns.heatmap(numeric_data.corr(), annot=False, cmap='coolwarm')
plt.title('Correlation Heatmap of Numeric Features')
plt.show()

# Separate features and target
X = data.drop('price', axis=1)
y = data['price']

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

# Identify numeric and categorical columns
numeric_features = X.select_dtypes(include=['int64', 'float64']).columns
categorical_features = X.select_dtypes(include=['object']).columns
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   car_ID            205 non-null    int64  
 1   symboling         205 non-null    int64  
 2   CarName           205 non-null    object 
 3   fueltype          205 non-null    object 
 4   aspiration        205 non-null    object 
 5   doornumber        205 non-null    object 
 6   carbody           205 non-null    object 
 7   drivewheel        205 non-null    object 
 8   enginelocation    205 non-null    object 
 9   wheelbase         205 non-null    float64
 10  carlength         205 non-null    float64
 11  carwidth          205 non-null    float64
 12  carheight         205 non-null    float64
 13  curbweight        205 non-null    int64  
 14  enginetype        205 non-null    object 
 15  cylindernumber    205 non-null    object 
 16  enginesize        205 non-null    int64  
 17  fuelsystem        205 non-null    object 
 18  boreratio         205 non-null    float64
 19  stroke            205 non-null    float64
 20  compressionratio  205 non-null    float64
 21  horsepower        205 non-null    int64  
 22  peakrpm           205 non-null    int64  
 23  citympg           205 non-null    int64  
 24  highwaympg        205 non-null    int64  
 25  price             205 non-null    float64
dtypes: float64(8), int64(8), object(10)
memory usage: 41.8+ KB
None

Sample data:
   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  ...  enginesize  \
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   

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

[5 rows x 26 columns]
```



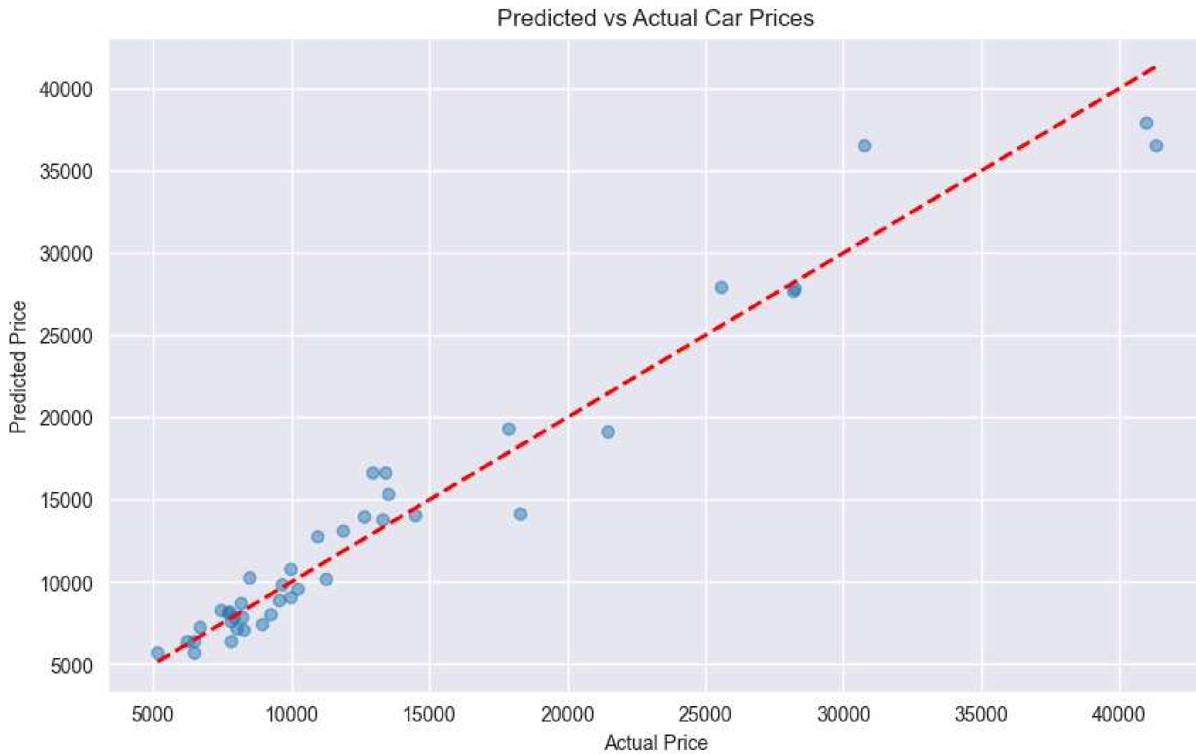


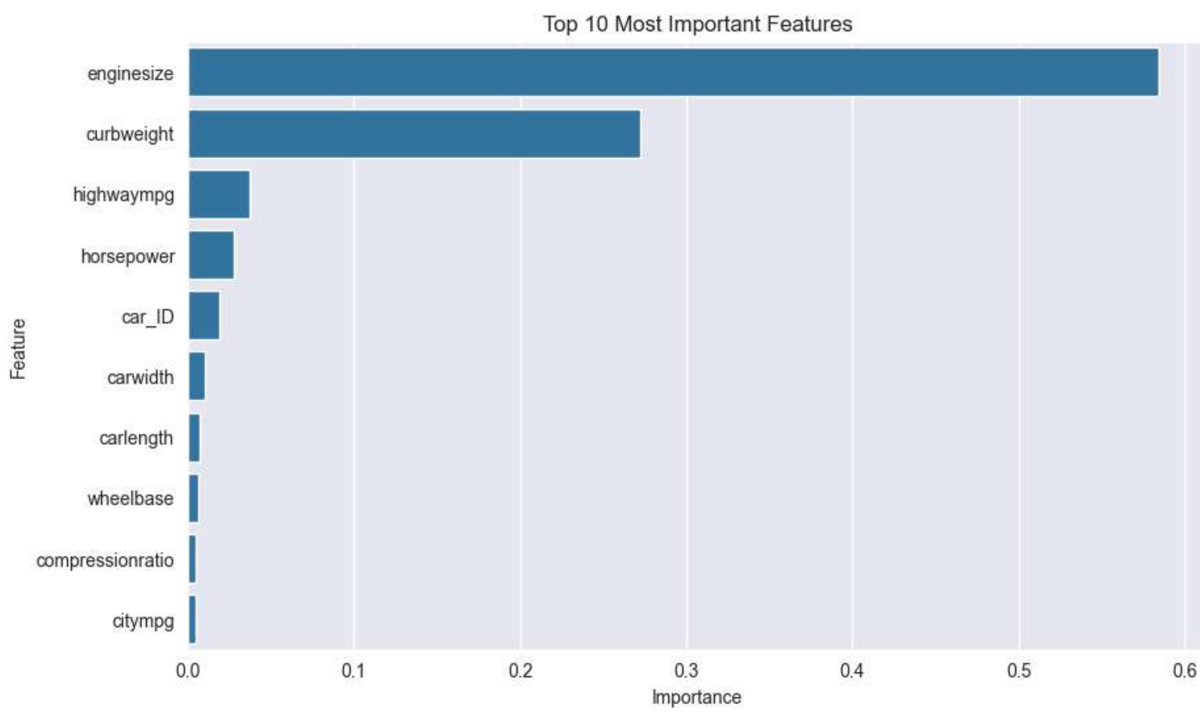
In [7]:
```python
# Create preprocessor
preprocessor = ColumnTransformer(
    transformers=[
        ('num', Pipeline([
            ('imputer', SimpleImputer(strategy='median')),
            ('scaler', StandardScaler())
        ]), numeric_features),
        ('cat', Pipeline([
            ('imputer', SimpleImputer(strategy='constant', fill_value='missing')),
            ('onehot', OneHotEncoder(handle_unknown='ignore'))
        ]), categorical_features)
    ])

# Create a pipeline
model = Pipeline([
    ('preprocessor', preprocessor),
    ('regressor', RandomForestRegressor(n_estimators=200, max_depth=20, min_samples
])
```

In [8]:
```python
# Fit the model
model.fit(X_train, y_train)
```

```python
# Make predictions
y_pred_train = model.predict(X_train)
y_pred_test = model.predict(X_test)

# Print results
print('Train RMSE:', np.sqrt(mean_squared_error(y_train, y_pred_train)))
print('Test RMSE:', np.sqrt(mean_squared_error(y_test, y_pred_test)))
print('Train R2 Score:', r2_score(y_train, y_pred_train))
print('Test R2 Score:', r2_score(y_test, y_pred_test))

# Visualize predicted vs actual prices
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_test, alpha=0.5)
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('Predicted vs Actual Car Prices')
plt.show()

# Visualize feature importance
feature_importance = model.named_steps['regressor'].feature_importances_
feature_names = (model.named_steps['preprocessor']
                 .named_transformers_['num'].get_feature_names_out().tolist() +
                 model.named_steps['preprocessor']
                 .named_transformers_['cat'].get_feature_names_out().tolist())

feature_importance_df = pd.DataFrame({'feature': feature_names, 'importance': featu
feature_importance_df = feature_importance_df.sort_values('importance', ascending=F

plt.figure(figsize=(10, 6))
sns.barplot(x='importance', y='feature', data=feature_importance_df)
plt.title('Top 10 Most Important Features')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.show()
```

```
Train RMSE: 1178.9016630648398
Test RMSE: 1895.8606076632911
Train R2 Score: 0.9766958496133668
Test R2 Score: 0.9544704284930133
```





In [9]:

```python
# Save the model
joblib.dump(model, 'car_price_model.joblib')

print("Model saved as 'car_price_predictor.joblib'")
```

```
Model saved as 'car_price_predictor.joblib'
```

In [10]:

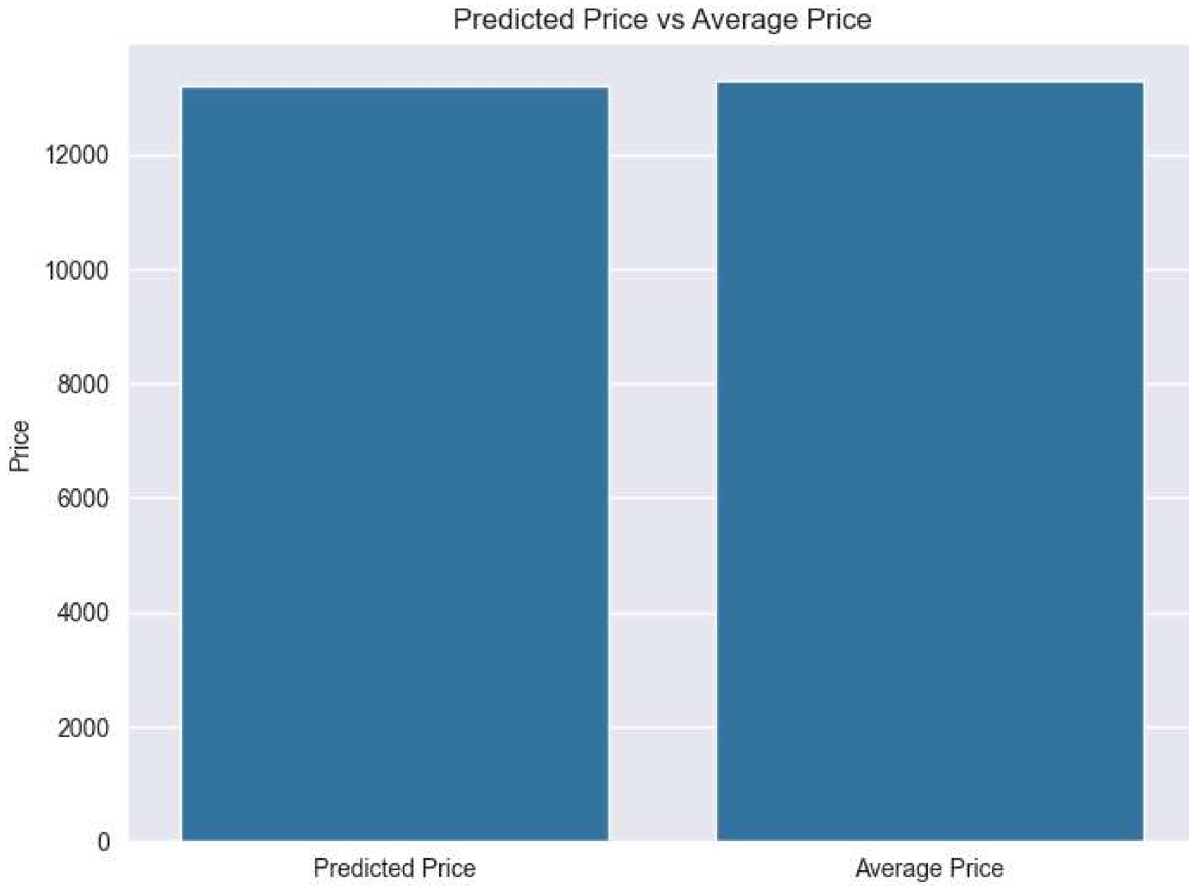
```python
# Function to make predictions
def predict_price(features):
    # Load the model
    loaded_model = joblib.load('car_price_model.joblib')
```

```python
    # Make prediction
    prediction = loaded_model.predict(features)

    return prediction[0]
```

In [11]:

```python
# Example usage
example_features = pd.DataFrame({
    'symboling': [3],
    'CarName': ['mazda rx-7 gs'],
    'fueltype': ['gas'],
    'aspiration': ['std'],
    'doornumber': ['four'],
    'carbody': ['sedan'],
    'drivewheel': ['fwd'],
    'enginelocation': ['front'],
    'wheelbase': [102.4],
    'carlength': [175.6],
    'carwidth': [66.5],
    'carheight': [54.9],
    'curbweight': [2414],
    'enginetype': ['ohc'],
    'cylindernumber': ['four'],
    'enginesize': [122],
    'fuelsystem': ['mpfi'],
    'boreratio': [3.31],
    'stroke': [3.54],
    'compressionratio': [8.7],
    'horsepower': [92],
    'peakrpm': [4200],
    'citympg': [27],
    'highwaympg': [32],
    'car_ID': [1]
}, index=[0])

predicted_price = predict_price(example_features)
print(f"Predicted price: ${predicted_price:.2f}")

# Visualize the prediction
plt.figure(figsize=(8, 6))
sns.barplot(x=['Predicted Price', 'Average Price'],
            y=[predicted_price, data['price'].mean()])
plt.title('Predicted Price vs Average Price')
plt.ylabel('Price')
plt.show()
```

```
Predicted price: $13195.92
```


Predicted Price vs Average Price
Price
0
2000
4000
6000
8000
10000
12000
Predicted Price
Average Price