BLENDED_LEARNING

Implementation-of-Linear-Regression-for-Predicting-Car-Prices

AIM:

To write a program to predict car prices using a linear regression model and test the assumptions for linear regression.

Equipments Required:

1. Hardware – PCs
2. Anaconda – Python 3.7 Installation / Jupyter notebook

Algorithm

1.Import Libraries: Bring in essential libraries such as pandas, numpy, matplotlib, and sklearn.

2.Load Dataset: Import the dataset containing car prices along with relevant features.

3.Data Preprocessing: Manage missing data and select key features for the model, if required.

4.Split Data: Divide the dataset into training and testing subsets.

5.Train Model: Build a linear regression model and train it using the training data.

6.Make Predictions: Apply the model to predict outcomes for the test set.

7.Evaluate Model: Measure the model's performance using metrics like R^2 score, Mean Absolute Error (MAE), etc.

8.Check Assumptions: Plot residuals to verify assumptions like homoscedasticity, normality, and linearity.

9.Output Results: Present the predictions and evaluation metrics.

Program:

```
/*
 Program to implement linear regression model for predicting car prices and test assum
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*/
```
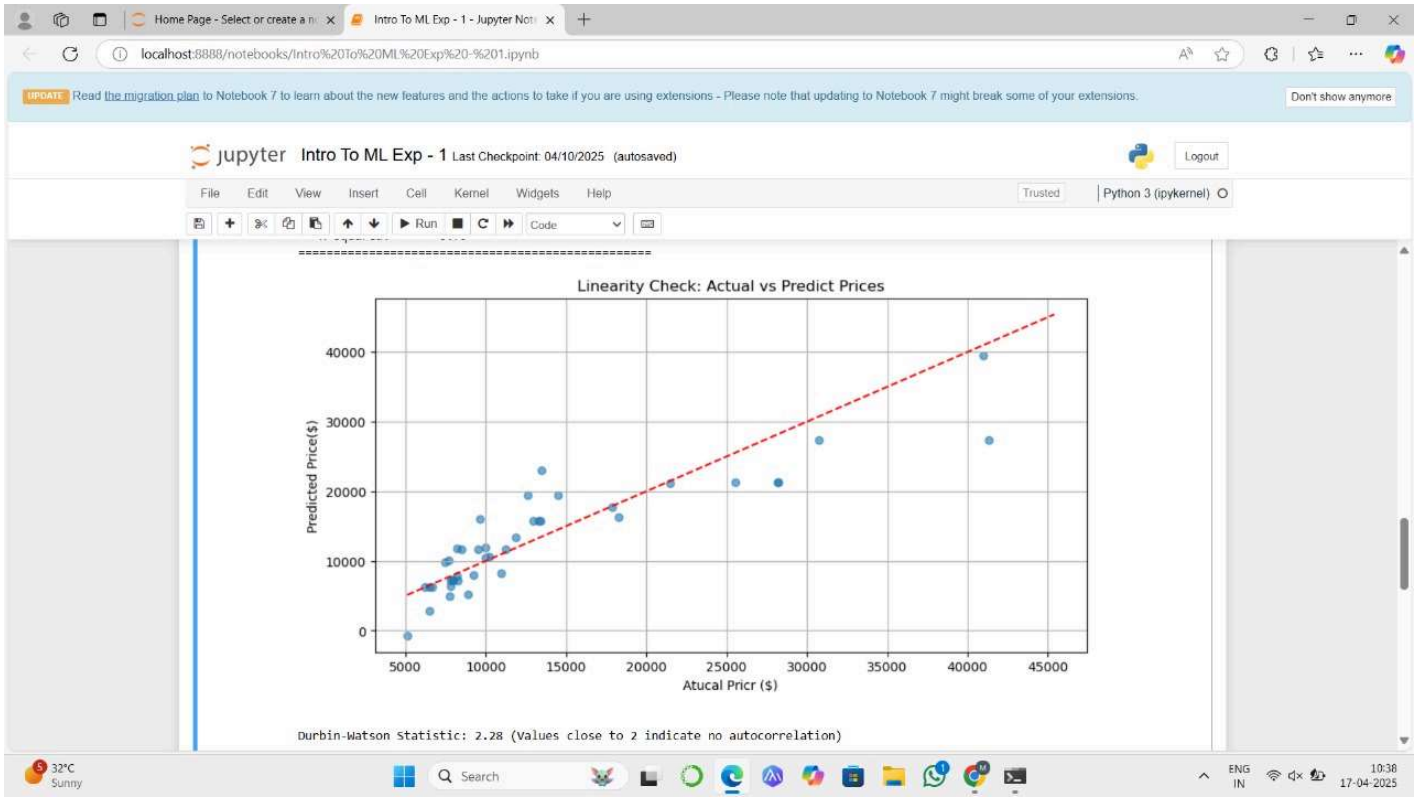

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
#Load the dataset
df=pd.read_csv('CarPrice_Assignment.csv')
#Select features and target
X = df[['enginesize', 'horsepower', 'citympg', 'highwaympg']] # Numerical features onl
y = df['price']
# Split data
X_train, X_test, y_train, y_test =train_test_split(X, y, test_size=0.2, random_state=4
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
#Train model
model = LinearRegression()
model.fit(X_train_scaled, y_train)
#Predictions
y_pred = model.predict(X_test_scaled)
#Model coefficients and metrics
print("="*50)
print("MODEL COEFFICIENTS:")
for feature, coef in zip(X.columns, model.coef_):
    print(f"{feature:>12}: {coef:>10.2f}")
print(f"{'Intercept':>12}: {model.intercept_:>10.2f}")
print("\nMODEL PERFORMANCE:")
print(f"{'MSE':>12}: {mean_squared_error(y_test, y_pred):>10.2f}")
print(f"{'RMSE':>12}: {np.sqrt(mean_squared_error(y_test, y_pred)):>10.2f}")
print(f"{'R-squared':>12}: {r2_score(y_test, y_pred): >10.2f}")
print("="*50)
plt.figure(figsize=(10,5))
plt.scatter(y_test,y_pred,alpha=0.6)
plt.plot([y.min(),y.max()],[y.min(),y.max()],'r--')
plt.title("Linearity Check: Actual vs Predict Prices")
plt.xlabel("Atucal Pricr ($)")
plt.ylabel("Predicted Price($)")
plt.grid(True)
plt.show()

# 2. Independence (Durbin-Watson)
residuals = y_test - y_pred
dw_test = sm.stats.durbin_watson(residuals)
print(f"\nDurbin-Watson Statistic: {dw_test:.2f} (Values close to 2 indicate no autoco

# 3. Homoscedasticity
plt.figure(figsize=(10, 5))
sns.residplot(x=y_pred, y=residuals, lowess=True, line_kws={'color': 'red'})
plt.title("Homoscedasticity Check: Residuals vs Predicted")
```

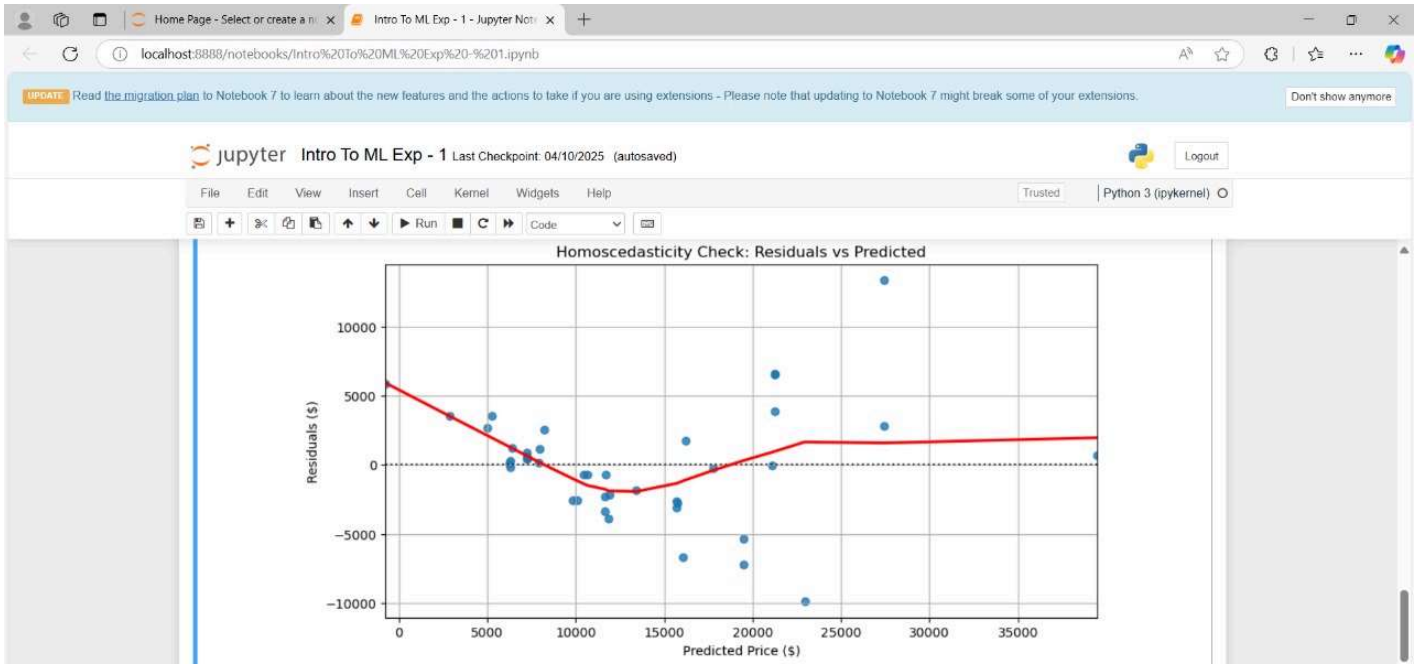
```
plt.xlabel("Predicted Price ($)")
plt.ylabel("Residuals ($)")
plt.grid(True)
plt.show()

#4
fig, (ax1,ax2)=plt.subplots(1,2,figsize=(12,5))
sns.histplot(residuals,kde=True,ax=ax1)
ax1.set_title("Residuals Distribution")
sm.qqplot(residuals,line='45',fit=True,ax=ax2)
ax2.set_title("Q-Q Plot")
plt.tight_layout()
plt.show()
```

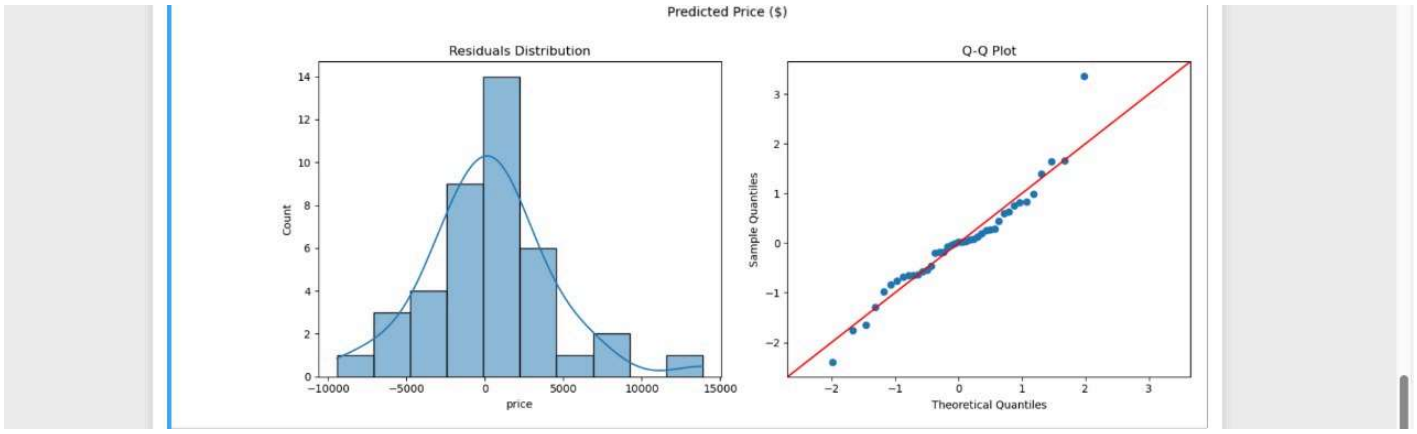
Output:


simple linear regression model for predicting the marks scored

```
==================================================
MODEL COEFFICIENTS:
  enginesize:    4523.40
  horsepower:    1694.22
     citympg:    -392.57
  highwaympg:    -816.36
   Intercept:   13223.41

MODEL PERFORMANCE:
         MSE: 16471505.90
        RMSE:    4058.51
   R-squared:       0.79
==================================================
```


Linearity Check: Actual vs Predict Prices
Predicted Price($)
Atucal Pricr ($)
Durbin-Watson Statistic: 2.28 (Values close to 2 indicate no autocorrelation)


Homoscedasticity Check: Residuals vs Predicted
Residuals ($)
Predicted Price ($)


Predicted Price ($)
Residuals Distribution
Count
price
Q-Q Plot
Sample Quantiles
Theoretical Quantiles

Result:

Thus, the program to implement a linear regression model for predicting car prices is written and verified using Python programming, along with the testing of key assumptions for linear regression.