```
from google.colab import files
uploaded = files.upload()
```

Choose files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.
Saving CarPrice_Assignment.csv to CarPrice_Assignment.csv

```
import pandas as pd

df = pd.read_csv('CarPrice_Assignment.csv')
df.head()
```

	car_ID	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	wheelbase	...	en
0	1	3	alfa-romero giulia	gas	std	two	convertible	rwd	front	88.6	...	
1	2	3	alfa-romero stelvio	gas	std	two	convertible	rwd	front	88.6	...	
2	3	1	alfa-romero Quadrifoglio	gas	std	two	hatchback	rwd	front	94.5	...	
3	4	2	audi 100 ls	gas	std	four	sedan	fwd	front	99.8	...	
4	5	2	audi 100ls	gas	std	four	sedan	4wd	front	99.4	...	

5 rows × 26 columns


```
df = pd.read_csv('CarPrice_Assignment.csv')
df.head()
```

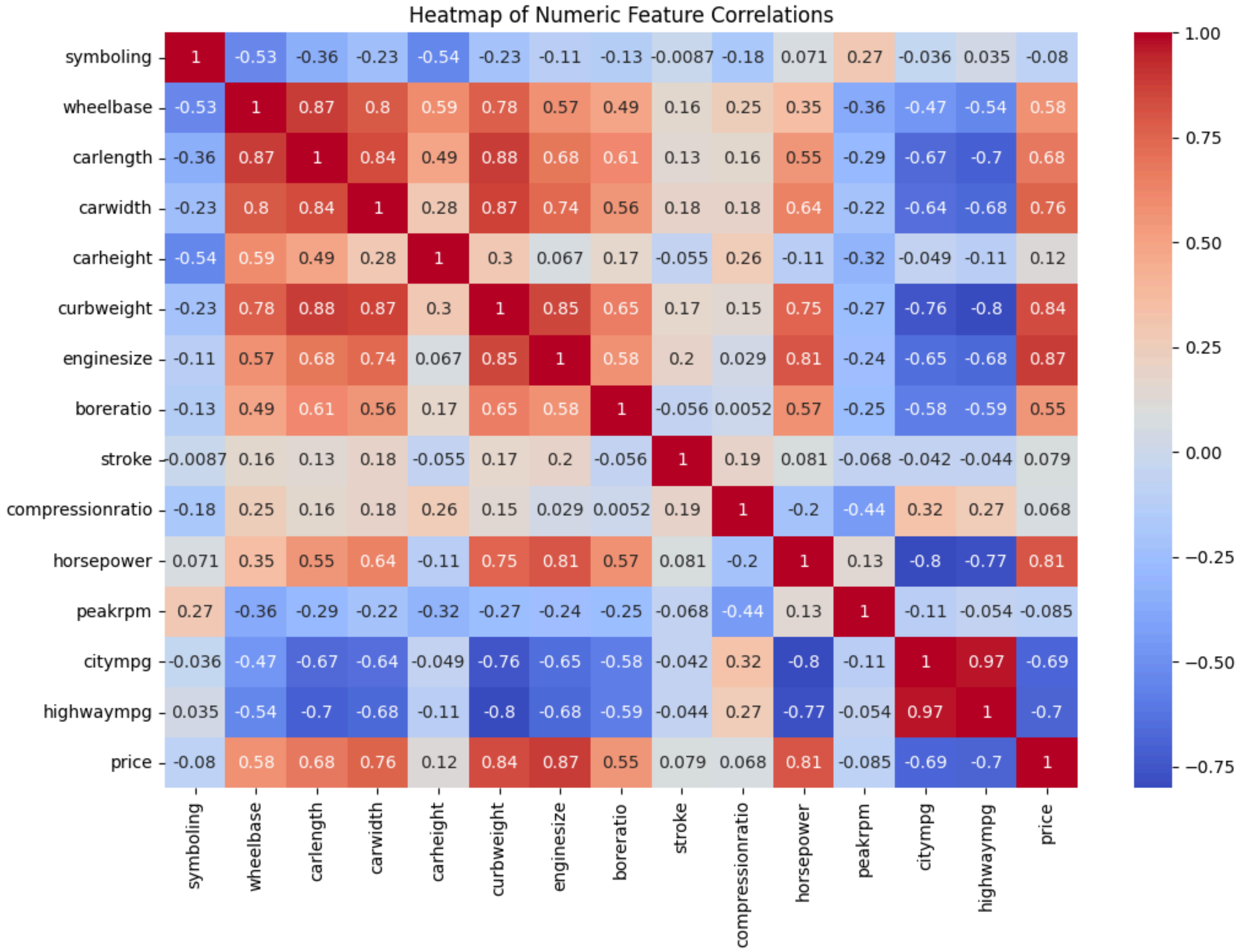
	car_ID	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	wheelbase	...	en
0	1	3	alfa-romero giulia	gas	std	two	convertible	rwd	front	88.6	...	
1	2	3	alfa-romero stelvio	gas	std	two	convertible	rwd	front	88.6	...	
2	3	1	alfa-romero Quadrifoglio	gas	std	two	hatchback	rwd	front	94.5	...	
3	4	2	audi 100 ls	gas	std	four	sedan	fwd	front	99.8	...	
4	5	2	audi 100ls	gas	std	four	sedan	4wd	front	99.4	...	

5 rows × 26 columns


```
#Data Cleaning
df.drop(['car_ID'], axis=1, inplace=True)

df['CarCompany'] = df['CarName'].apply(lambda x: x.split(' ')[0].lower())

df.drop(['CarName'], axis=1, inplace=True)

df['CarCompany'] = df['CarCompany'].replace({
    'vw': 'volkswagen',
    'vokswagen': 'volkswagen',
    'porcshce': 'porsche',
    'toyouta': 'toyota',
    'maxda': 'mazda',
    'Nissan': 'nissan'
})

df[['CarCompany']].drop_duplicates().sort_values(by='CarCompany')
```

	CarCompany
0	alfa-romero
3	audi
10	bmw
67	buick
18	chevrolet
21	dodge
30	honda
43	isuzu
47	jaguar
50	mazda
75	mercury
76	mitsubishi
89	nissan
107	peugeot
118	plymouth
125	porsche
130	renault
132	saab
138	subaru
150	toyota
182	volkswagen
194	volvo

```
import matplotlib.pyplot as plt
import seaborn as sns

numeric_df = df.select_dtypes(include=['number'])

plt.figure(figsize=(12, 8))
sns.heatmap(numeric_df.corr(), annot=True, cmap='coolwarm')
plt.title("Heatmap of Numeric Feature Correlations")
plt.show()
```




```
df.drop(['carlength', 'carwidth', 'curbweight', 'highwaympg'], axis=1, inplace=True)

df.columns
```

```
Index(['symboling', 'fueltype', 'aspiration', 'doornumber', 'carbody',
       'drivewheel', 'enginelocation', 'wheelbase', 'carheight', 'enginetype',
       'cylindernumber', 'enginesize', 'fuelsystem', 'boreratio', 'stroke',
       'compressionratio', 'horsepower', 'peakrpm', 'citympg', 'price',
       'CarCompany'],
      dtype='object')
```

```
df = pd.get_dummies(df, drop_first=True)

df.head()
```

	symboling	wheelbase	carheight	enginesize	boreratio	stroke	compressionratio	horsepower	peakrpm	citympg	...	Car
0	3	88.6	48.8	130	3.47	2.68	9.0	111	5000	21	...	
1	3	88.6	48.8	130	3.47	2.68	9.0	111	5000	21	...	
2	1	94.5	52.4	152	2.68	3.47	9.0	154	5000	19	...	
3	2	99.8	54.3	109	3.19	3.40	10.0	102	5500	24	...	
4	2	99.4	54.3	136	3.19	3.40	8.0	115	5500	18	...	

5 rows × 61 columns

```
from sklearn.model_selection import train_test_split

X = df.drop('price', axis=1)
y = df['price']

X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, random_state=100)

X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((143, 60), (62, 60), (143,), (62,))
```

```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

X_train_scaled = pd.DataFrame(scaler.fit_transform(X_train), columns=X_train.columns)
X_test_scaled = pd.DataFrame(scaler.transform(X_test), columns=X_test.columns)

X_train_scaled.head()
```

	symboling	wheelbase	carheight	enginesize	boreratio	stroke	compressionratio	horsepower	peakrpm	citympg	...	Ca
0	0.6	0.244828	0.265487	0.139623	0.230159	0.525253	0.15000	0.083333	0.551020	0.500000	...	
1	1.0	0.272414	0.212389	0.339623	1.000000	0.464646	0.15625	0.395833	0.551020	0.166667	...	
2	0.6	0.272414	0.424779	0.139623	0.444444	0.449495	0.15000	0.266667	1.000000	0.361111	...	
3	1.0	0.068966	0.088496	0.260377	0.626984	0.247475	0.12500	0.262500	0.346939	0.222222	...	
4	0.2	0.610345	0.858407	0.260377	0.746032	0.484848	0.03125	0.475000	0.387755	0.111111	...	

5 rows × 60 columns

```
from sklearn.linear_model import LinearRegression
from sklearn.feature_selection import RFE

lm = LinearRegression()

rfe = RFE(estimator=lm, n_features_to_select=15)
rfe = rfe.fit(X_train_scaled, y_train)

selected_cols = X_train_scaled.columns[rfe.support_]
selected_cols
```

```
Index(['wheelbase', 'enginesize', 'boreratio', 'stroke', 'enginelocation_rear',
       'enginetype_rotor', 'cylindernumber_five', 'cylindernumber_four',
       'cylindernumber_three', 'cylindernumber_twelve', 'cylindernumber_two',
       'CarCompany_bmw', 'CarCompany_peugeot', 'CarCompany_porsche',
       'CarCompany_saab'],
      dtype='object')
```

```
X_train_rfe = X_train_scaled[selected_cols]
```

```
y_train = y_train.reset_index(drop=True)
```

```
import statsmodels.api as sm

X_train_sm = sm.add_constant(X_train_rfe)

model = sm.OLS(y_train, X_train_sm).fit()

print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.920
Model:                            OLS   Adj. R-squared:                  0.911
Method:                 Least Squares   F-statistic:                     105.2
Date:                Sat, 21 Jun 2025   Prob (F-statistic):           4.83e-63
Time:                        09:25:23   Log-Likelihood:                -1303.4
No. Observations:                 143   AIC:                             2637.
Df Residuals:                     128   BIC:                             2681.
Df Model:                          14
Covariance Type:            nonrobust
=========================================================================================
                            coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
const                 -2681.9757   1522.550     -1.762      0.081   -5694.601     330.649
wheelbase              9345.5364   1728.433      5.407      0.000    5925.536    1.28e+04
enginesize             6.605e+04   5717.693     11.552      0.000    5.47e+04    7.74e+04
boreratio             -1.224e+04   2243.488     -5.457      0.000   -1.67e+04   -7804.384
stroke                -1.063e+04   1935.359     -5.494      0.000   -1.45e+04   -6803.369
enginelocation_rear    6332.9278   2917.617      2.171      0.032     559.924    1.21e+04
enginetype_rotor       1.103e+04   1354.568      8.145      0.000    8353.331    1.37e+04
cylindernumber_five    8604.9276   1291.905      6.661      0.000    6048.672    1.12e+04
cylindernumber_four    8165.8463   1618.410      5.046      0.000    4963.545    1.14e+04
cylindernumber_three      1.4e+04   3068.240      4.562      0.000    7927.684    2.01e+04
cylindernumber_twelve -2.092e+04   3955.073     -5.288      0.000   -2.87e+04   -1.31e+04
cylindernumber_two     1.103e+04   1354.568      8.145      0.000    8353.331    1.37e+04
```

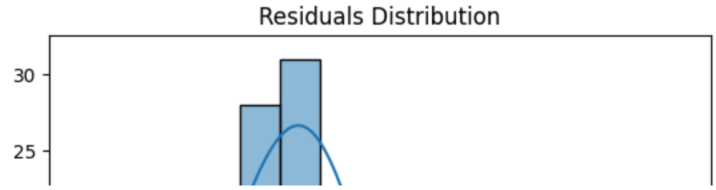
```
CarCompany_bmw         8500.8200    1091.750      7.786      0.000    6340.606    1.07e+04
CarCompany_peugeot    -2178.9655    1119.054     -1.947      0.054   -4393.206      35.275
CarCompany_porsche      1.04e+04    1843.467      5.644      0.000    6756.984    1.41e+04
CarCompany_saab        3941.6876    1391.261      2.833      0.005    1188.840    6694.535
==============================================================================
Omnibus:                       20.586   Durbin-Watson:                   1.912
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               29.137
Skew:                           0.780   Prob(JB):                     4.71e-07
Kurtosis:                       4.567   Cond. No.                     1.64e+17
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.25e-32. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

```
X_train_rfe = X_train_rfe.drop('CarCompany_peugeot', axis=1)
```

```
X_train_sm = sm.add_constant(X_train_rfe)
model = sm.OLS(y_train, X_train_sm).fit()
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.918
Model:                            OLS   Adj. R-squared:                  0.909
Method:                 Least Squares   F-statistic:                     110.6
Date:                Sat, 21 Jun 2025   Prob (F-statistic):           2.87e-63
Time:                        09:27:14   Log-Likelihood:                -1305.5
No. Observations:                 143   AIC:                             2639.
Df Residuals:                     129   BIC:                             2681.
Df Model:                          13
Covariance Type:            nonrobust
=======================================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------
const               -1807.3445   1470.437     -1.229      0.221   -4716.641    1101.952
wheelbase            7423.9684   1434.279      5.176      0.000    4586.212    1.03e+04
enginesize           6.581e+04   5777.814     11.389      0.000    5.44e+04    7.72e+04
boreratio           -1.202e+04   2264.580     -5.306      0.000   -1.65e+04   -7536.458
stroke              -1.025e+04   1946.119     -5.267      0.000   -1.41e+04   -6400.546
enginelocation_rear  5662.5883   2928.413      1.934      0.055    -131.349    1.15e+04
enginetype_rotor     1.073e+04   1359.969      7.889      0.000    8037.985    1.34e+04
cylindernumber_five  8680.7402   1305.215      6.651      0.000    6098.340    1.13e+04
cylindernumber_four  7561.7451   1605.488      4.710      0.000    4385.248    1.07e+04
cylindernumber_three  1.304e+04  3061.069      4.260      0.000    6983.628    1.91e+04
cylindernumber_twelve -2.079e+04 3997.090     -5.201      0.000   -2.87e+04   -1.29e+04
cylindernumber_two   1.073e+04   1359.969      7.889      0.000    8037.985    1.34e+04
CarCompany_bmw       8612.3999   1101.978      7.815      0.000    6432.110    1.08e+04
CarCompany_porsche   1.019e+04   1859.922      5.478      0.000    6508.483    1.39e+04
CarCompany_saab      4230.7827   1398.202      3.026      0.003    1464.405    6997.161
==============================================================================
Omnibus:                       22.726   Durbin-Watson:                   1.913
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               35.142
Skew:                           0.808   Prob(JB):                     2.34e-08
Kurtosis:                       4.813   Cond. No.                     1.39e+17
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.75e-32. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

```
y_train_pred = model.predict(X_train_sm)

residuals = y_train - y_train_pred

import seaborn as sns
import matplotlib.pyplot as plt

sns.histplot(residuals, kde=True)
plt.title("Residuals Distribution")
plt.xlabel("Error")
plt.ylabel("Frequency")
plt.show()
```


Residuals Distribution
30
25