import required libraries

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error,r2_score
import re

import warnings
warnings.filterwarnings('ignore')
```

importing the Data

In [2]:
```
car_price = pd.read_csv("CarPrice_Assignment.csv")
```

In [3]:
```
car_price.head()
```

Out[3]:

	car_ID	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	engi
0	1	3	alfa-romero giulia	gas	std	two	convertible	rwd	
1	2	3	alfa-romero stelvio	gas	std	two	convertible	rwd	
2	3	1	alfa-romero Quadrifoglio	gas	std	two	hatchback	rwd	
3	4	2	audi 100 ls	gas	std	four	sedan	fwd	
4	5	2	audi 100ls	gas	std	four	sedan	4wd	

5 rows × 26 columns

Data preprocessing

In [4]:
```
car_price.describe()
```

Out[4]:

	car_ID	symboling	wheelbase	carlength	carwidth	carheight	curbweight	en
count	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	20
mean	103.000000	0.834146	98.756585	174.049268	65.907805	53.724878	2555.565854	12
std	59.322565	1.245307	6.021776	12.337289	2.145204	2.443522	520.680204	4
min	1.000000	-2.000000	86.600000	141.100000	60.300000	47.800000	1488.000000	6
25%	52.000000	0.000000	94.500000	166.300000	64.100000	52.000000	2145.000000	9
50%	103.000000	1.000000	97.000000	173.200000	65.500000	54.100000	2414.000000	12
75%	154.000000	2.000000	102.400000	183.100000	66.900000	55.500000	2935.000000	14
max	205.000000	3.000000	120.900000	208.100000	72.300000	59.800000	4066.000000	32

In [5]:
```
car_price.isnull().sum()
```

Out[5]:
```
car_ID              0
symboling           0
CarName             0
fueltype            0
aspiration          0
doornumber          0
carbody             0
drivewheel          0
enginelocation      0
wheelbase           0
carlength           0
carwidth            0
carheight           0
curbweight          0
enginetype          0
cylindernumber      0
enginesize          0
fuelsystem          0
boreratio           0
stroke              0
compressionratio    0
horsepower          0
peakrpm             0
citympg             0
highwaympg          0
price               0
dtype: int64
```

In [6]:
```
car_price.duplicated().sum()
```

Out[6]:
```
0
```

In [7]:
```
car_price.info()
```

```
<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
```

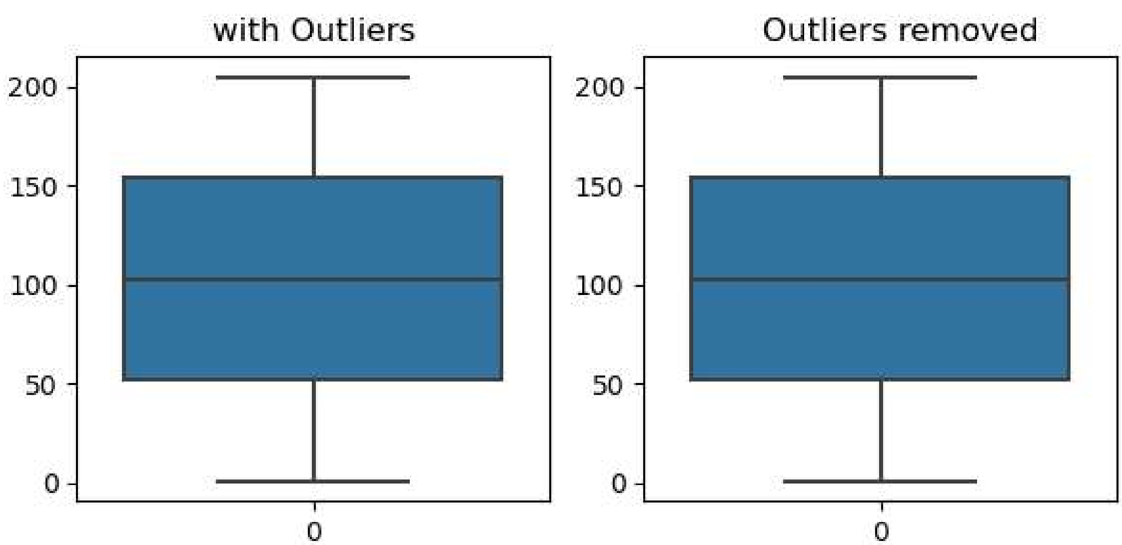
In [8]:
```
numerical_columns =car_price.select_dtypes(include=['number']).columns
numerical_columns
```

Out[8]:
```
Index(['car_ID', 'symboling', 'wheelbase', 'carlength', 'carwidth',
       'carheight', 'curbweight', 'enginesize', 'boreratio', 'stroke',
       'compressionratio', 'horsepower', 'peakrpm', 'citympg', 'highwaympg',
       'price'],
      dtype='object')
```

Handling Outliers

In [9]:
```
for i in numerical_columns:
    print(i)
    fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(7, 3))
    sns.boxplot(data=car_price[i], ax=axes[0])
    axes[0].set_title('with Outliers')

    def outliers(col):
        q1 = car_price[col].quantile(0.25)
        q3 = car_price[col].quantile(0.75)
        iqr = q3-q1
        pos_outlier = q3 + 1.5 * iqr
        neg_outlier = q1 - 1.5 * iqr
        car_price[col] = np.where(car_price[col] > pos_outlier,pos_outlier
                                  np.where(car_price[col] < neg_outlier
                                         car_price[col]) )

    outliers(i)

# Boxplot without outliers
    sns.boxplot(data=car_price[i], ax=axes[1], sym='')
    axes[1].set_title('    Outliers removed')

    plt.show()
```

car_ID



In [10]:
```
def unique_value(col):
    print(col)
    print('***************')
    print(car_price[col].unique())
    print('')

for i in list(car_price.select_dtypes(exclude=['float','int']).columns)[0
    unique_value(i)
```

```
CarName
***************
['alfa-romero giulia' 'alfa-romero stelvio' 'alfa-romero Quadrifoglio'
 'audi 100 ls' 'audi 100ls' 'audi fox' 'audi 5000' 'audi 4000'
 'audi 5000s (diesel)' 'bmw 320i' 'bmw x1' 'bmw x3' 'bmw z4' 'bmw x4'
 'bmw x5' 'chevrolet impala' 'chevrolet monte carlo' 'chevrolet vega 2300'
 'dodge rampage' 'dodge challenger se' 'dodge d200' 'dodge monaco (sw)'
 'dodge colt hardtop' 'dodge colt (sw)' 'dodge coronet custom'
 'dodge dart custom' 'dodge coronet custom (sw)' 'honda civic'
 'honda civic cvcc' 'honda accord cvcc' 'honda accord lx'
 'honda civic 1500 gl' 'honda accord' 'honda civic 1300' 'honda prelude'
 'honda civic (auto)' 'isuzu MU-X' 'isuzu D-Max ' 'isuzu D-Max V-Cross'
 'jaguar xj' 'jaguar xf' 'jaguar xk' 'maxda rx3' 'maxda glc deluxe'
 'mazda rx2 coupe' 'mazda rx-4' 'mazda glc deluxe' 'mazda 626' 'mazda glc'
 'mazda rx-7 gs' 'mazda glc 4' 'mazda glc custom l' 'mazda glc custom'
 'buick electra 225 custom' 'buick century luxus (sw)' 'buick century'
 'buick skyhawk' 'buick opel isuzu deluxe' 'buick skylark'
 'buick century special' 'buick regal sport coupe (turbo)'
 'mercury cougar' 'mitsubishi mirage' 'mitsubishi lancer'
```

In [11]:
```
car_list=car_price['CarName'].unique()
car_brands = [car.split(' ')[0] for car in car_list]
print(car_brands)
```

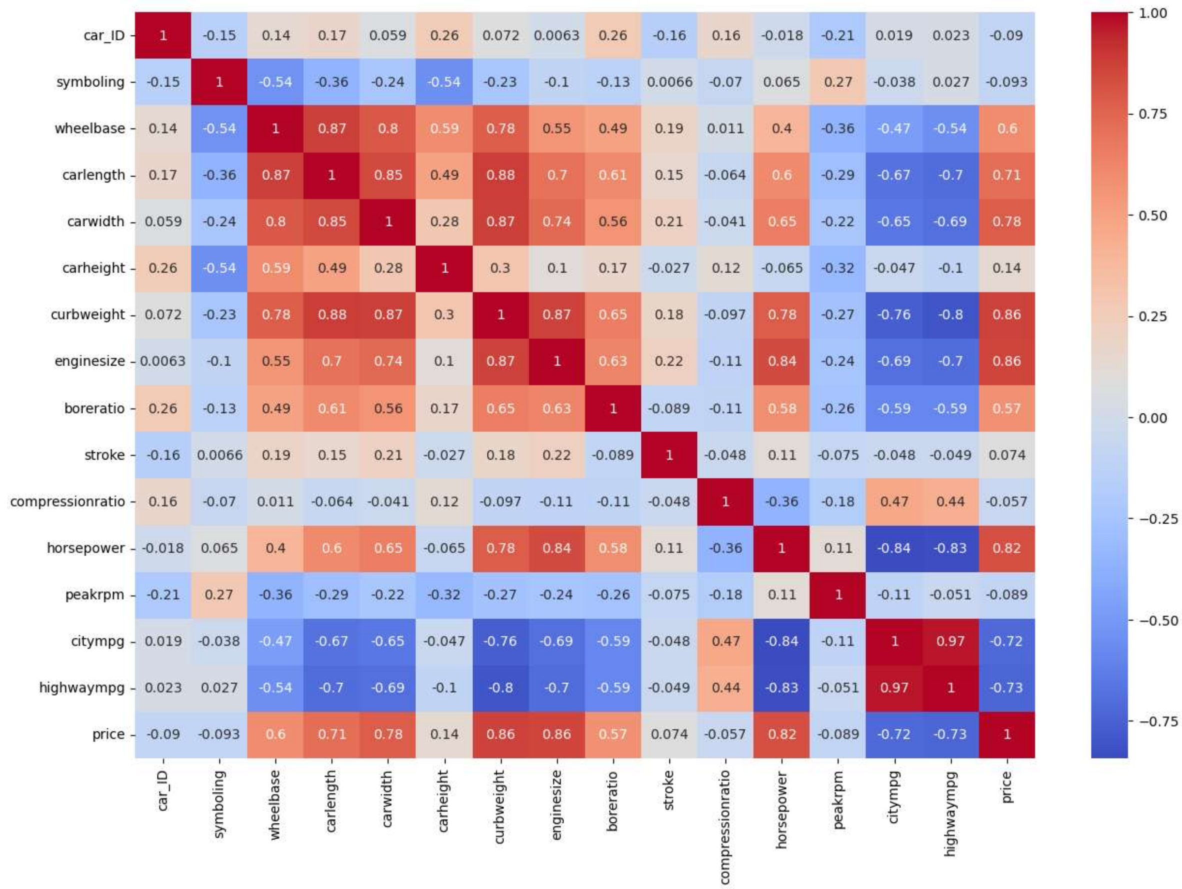
```
['alfa-romero', 'alfa-romero', 'alfa-romero', 'audi', 'audi', 'audi', 'audi',
'audi', 'audi', 'bmw', 'bmw', 'bmw', 'bmw', 'bmw', 'bmw', 'chevrolet', 'chevr
olet', 'chevrolet', 'dodge', 'dodge', 'dodge', 'dodge', 'dodge', 'dodge', 'do
dge', 'dodge', 'dodge', 'honda', 'honda', 'honda', 'honda', 'honda', 'honda',
'honda', 'honda', 'honda', 'isuzu', 'isuzu', 'isuzu', 'jaguar', 'jaguar', 'ja
guar', 'maxda', 'maxda', 'mazda', 'mazda', 'mazda', 'mazda', 'mazda', 'mazd
a', 'mazda', 'mazda', 'mazda', 'buick', 'buick', 'buick', 'buick', 'buick',
'buick', 'buick', 'buick', 'mercury', 'mitsubishi', 'mitsubishi', 'mitsubish
i', 'mitsubishi', 'mitsubishi', 'mitsubishi', 'mitsubishi', 'Nissan', 'nissa
n', 'nissan', 'nissan', 'nissan', 'nissan', 'nissan', 'nissan', 'nissan', 'ni
ssan', 'nissan', 'nissan', 'nissan', 'nissan', 'nissan', 'peugeot', 'peugeo
t', 'peugeot', 'peugeot', 'peugeot', 'plymouth', 'plymouth', 'plymouth', 'ply
mouth', 'plymouth', 'plymouth', 'porsche', 'porcshce', 'porsche', 'porsche',
'renault', 'renault', 'saab', 'saab', 'saab', 'subaru', 'subaru', 'subaru',
'subaru', 'subaru', 'subaru', 'subaru', 'subaru', 'toyota', 'toyota', 'toyot
a', 'toyota', 'toyota', 'toyota', 'toyota', 'toyota', 'toyota', 'toyota', 'to
yota', 'toyota', 'toyota', 'toyota', 'toyota', 'toyota', 'toyouta', 'vokswage
n', 'volkswagen', 'volkswagen', 'volkswagen', 'volkswagen', 'volkswagen', 'vo
lkswagen', 'vw', 'vw', 'volkswagen', 'volkswagen', 'volvo', 'volvo', 'volvo',
'volvo', 'volvo', 'volvo', 'volvo']
```

In [12]:
```
unique_values = list(set(car_brands))
print(unique_values)
```

```
['chevrolet', 'maxda', 'subaru', 'renault', 'bmw', 'porsche', 'alfa-romero',
'mitsubishi', 'porcshce', 'mazda', 'mercury', 'volvo', 'vokswagen', 'toyota',
'plymouth', 'vw', 'Nissan', 'saab', 'peugeot', 'audi', 'dodge', 'jaguar', 'ho
nda', 'buick', 'nissan', 'isuzu', 'volkswagen', 'toyouta']
```

Finding Correlation

In [13]:
```
plt.figure(figsize=(15,10))
corr = car_price[numerical_columns].corr()
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.show()
```



Encoding

In [14]:
```
categorical_columns = car_price.select_dtypes(include=object).columns.toli
label_encoder = LabelEncoder()
for column in categorical_columns:
    car_price[column] = label_encoder.fit_transform(car_price[column])

scaler = StandardScaler()
car_price[numerical_columns] = scaler.fit_transform(car_price[numerical_co
```

Train and Test Split

In [15]:
```
X = car_price.drop(['price', 'CarName'], axis=1)
y = car_price['price']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, r

```

In [16]:
```
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.25,

print(x_train.shape, x_test.shape, y_train.shape, y_test.shape)
```

```
(153, 24) (52, 24) (153,) (52,)
```

Building Linear Regression Model

In [17]:
```
from sklearn.linear_model import LinearRegression
lm = LinearRegression()
lm.fit(x_train, y_train)
```

Out[17]:
```
LinearRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [18]:
```
lm.score(x_train, y_train)
```

Out[18]:
```
0.9147112666490638
```

In [19]:
```
y_pred = lm.predict(x_test)
```

In [20]:
```
mse = mean_squared_error(y_test, y_pred)
r2_square = r2_score(y_test,y_pred)
print(f" R-squared: {r2_square}")
print(f'Mean Squared Error: {mse}')
```

```
 R-squared: 0.811205112500399
Mean Squared Error: 0.16747257388287745
```

ols method

In [21]:
```
from statsmodels.regression.linear_model import OLS
import statsmodels.regression.linear_model as smf
```

In [22]:
```
reg_model = smf.OLS(endog = y_train, exog=x_train).fit()
```

In [23]:
```
reg_model.summary()
```

Out[23]:

OLS Regression Results

Dep. Variable:	price	**R-squared (uncentered):**	0.914
Model:	OLS	**Adj. R-squared (uncentered):**	0.898
Method:	Least Squares	**F-statistic:**	56.95
Date:	Wed, 06 Dec 2023	**Prob (F-statistic):**	4.50e-57
Time:	20:03:38	**Log-Likelihood:**	-31.397
No. Observations:	153	**AIC:**	110.8
Df Residuals:	129	**BIC:**	183.5
Df Model:	24		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
car_ID	-0.1350	0.031	-4.386	0.000	-0.196	-0.074
symboling	0.0441	0.044	0.999	0.320	-0.043	0.131
fueltype	-0.0662	0.148	-0.447	0.656	-0.360	0.227
aspiration	-0.0134	0.110	-0.122	0.903	-0.232	0.205
doornumber	-0.1423	0.091	-1.557	0.122	-0.323	0.039
carbody	-0.0815	0.046	-1.756	0.081	-0.173	0.010
drivewheel	0.2819	0.074	3.808	0.000	0.135	0.428
enginelocation	1.2725	0.264	4.813	0.000	0.749	1.796
wheelbase	0.0456	0.088	0.518	0.605	-0.128	0.220
carlength	-0.0704	0.093	-0.761	0.448	-0.254	0.113
carwidth	0.2353	0.069	3.426	0.001	0.099	0.371
carheight	0.0533	0.044	1.214	0.227	-0.034	0.140
curbweight	0.3391	0.109	3.119	0.002	0.124	0.554
enginetype	0.0381	0.029	1.292	0.199	-0.020	0.096
cylindernumber	-0.0879	0.049	-1.785	0.077	-0.185	0.010
enginesize	0.0836	0.102	0.818	0.415	-0.119	0.286
fuelsystem	0.0028	0.020	0.141	0.888	-0.037	0.043
boreratio	-0.1719	0.047	-3.639	0.000	-0.265	-0.078
stroke	-0.1009	0.034	-2.927	0.004	-0.169	-0.033
compressionratio	0.1147	0.050	2.286	0.024	0.015	0.214
horsepower	0.3647	0.103	3.552	0.001	0.162	0.568
peakrpm	-0.0082	0.046	-0.176	0.860	-0.100	0.084
citympg	-0.2022	0.144	-1.404	0.163	-0.487	0.083
highwaympg	0.1700	0.139	1.220	0.225	-0.106	0.446

Omnibus:	3.059	**Durbin-Watson:**	1.874

Prob(Omnibus):	0.217	**Jarque-Bera (JB):**	3.016
Skew:	-0.130	**Prob(JB):**	0.221
Kurtosis:	3.637	**Cond. No.**	63.4

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Lasso regularization

In [24]:

```
from sklearn.linear_model import Lasso
lasso = Lasso(alpha=0.1)
lasso.fit(x_train, y_train)
print("Lasso Model :", (lasso.coef_))
```

```
Lasso Model : [-0.01122002  0.          -0.          -0.          -0.          -
0.
  0.          0.          0.          0.          0.16191883  0.
  0.21368857  0.          0.          0.23508076  0.          0.
 -0.00465022  0.02108939  0.27699019  0.         -0.          -0.        ]
```

In [25]:

```
y_pred_train_lasso = lasso.predict(x_train)
y_pred_test_lasso = lasso.predict(x_test)
```

In [26]:

```
print("Training Accuracy :", r2_score(y_train, y_pred_train_lasso))
print()
print("Test Accuracy :", r2_score(y_test, y_pred_test_lasso))
```

```
Training Accuracy : 0.8122353228881479

Test Accuracy : 0.8438095695530451
```

In [27]:

```
# Part 2 : Ridge Regression (L2- Regularization)
# closure to zero but not exact zero
# penalty - 0.3
from sklearn.linear_model import Ridge
ridge = Ridge(alpha=0.3)
ridge.fit(x_train, y_train)
print("Ridge Model :", (ridge.coef_))
```

```
Ridge Model : [-0.12681145  0.04700021 -0.28260993 -0.09038291 -0.17851067 -
0.1119754
  0.23937355  1.02613235  0.0528645  -0.06500153  0.21985275  0.04654629
  0.30633901  0.02839857 -0.0935127   0.08797257 -0.0094005  -0.1605917
 -0.11053408  0.09377869  0.40934991  0.00859067 -0.1934089   0.13577635]
```

In [28]:
```
y_pred_train_ridge = ridge.predict(x_train)
y_pred_test_ridge = ridge.predict(x_test)
```

In [29]:
```
print("Training Accuracy :", r2_score(y_train, y_pred_train_ridge))
print()
print("Test Accuracy :", r2_score(y_test, y_pred_test_ridge))
```

```
Training Accuracy : 0.9142724965562357

Test Accuracy : 0.8135911900533563
```

Elastic net

In [30]:
```
from sklearn.linear_model import ElasticNet
elastic = ElasticNet(alpha=0.3, l1_ratio=0.1)
elastic.fit(x_train, y_train)
```

Out[30]:
```
ElasticNet(alpha=0.3, l1_ratio=0.1)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [31]:
```
y_pred_train_elastic = elastic.predict(x_train)
y_pred_test_elastic = elastic.predict(x_test)
```

In [32]:
```
print("Training Accuracy :", r2_score(y_train, y_pred_train_elastic))
print()
print("Test Accuracy :", r2_score(y_test, y_pred_test_elastic))
```

```
Training Accuracy : 0.8495242350383081

Test Accuracy : 0.8560946047809289
```

In [33]:
```
from sklearn.model_selection import train_test_split
sc = StandardScaler()
sc_x = sc.fit_transform(X)
x_train, x_test, y_train, y_test = train_test_split(sc_x, y, test_size=0.2

print(x_train.shape, x_test.shape, y_train.shape, y_test.shape)
```

```
(153, 24) (52, 24) (153,) (52,)
```

performance matrix

In [39]:
```
from sklearn import metrics
print("MAE :", metrics.mean_absolute_error(y_test, y_pred))
print("MAPE :", metrics.mean_absolute_error(y_test, y_pred)/100)
print("MSE :", metrics.mean_squared_error(y_test, y_pred))
print("RMSE :", np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
MAE : 0.31268349981908583
MAPE : 0.0031268349981908583
MSE : 0.16747257388287745
RMSE : 0.4092341308870479
```

Gradient Descent

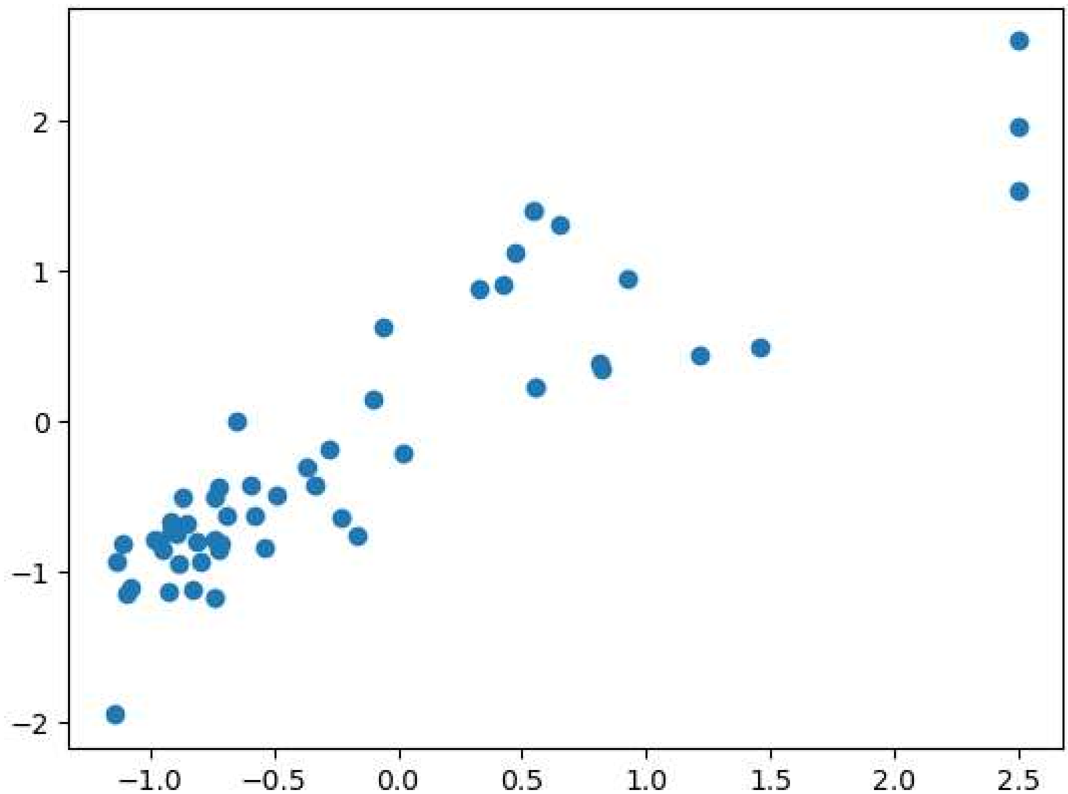
In [34]:
```
from sklearn.linear_model import SGDRegressor
gd_model = SGDRegressor()
gd_model.fit(x_train, y_train)
y_pred_gd_train = gd_model.predict(x_train)

y_pred_gd_test = gd_model.predict(x_test)

print("GD Trainging Accuracy :", r2_score(y_train, y_pred_gd_train))

print()

print("GD Test Accuracy :", r2_score(y_test, y_pred_gd_test))
```

```
GD Trainging Accuracy : 0.9053520122518992

GD Test Accuracy : 0.8514768054862887
```

test for autocorrelation

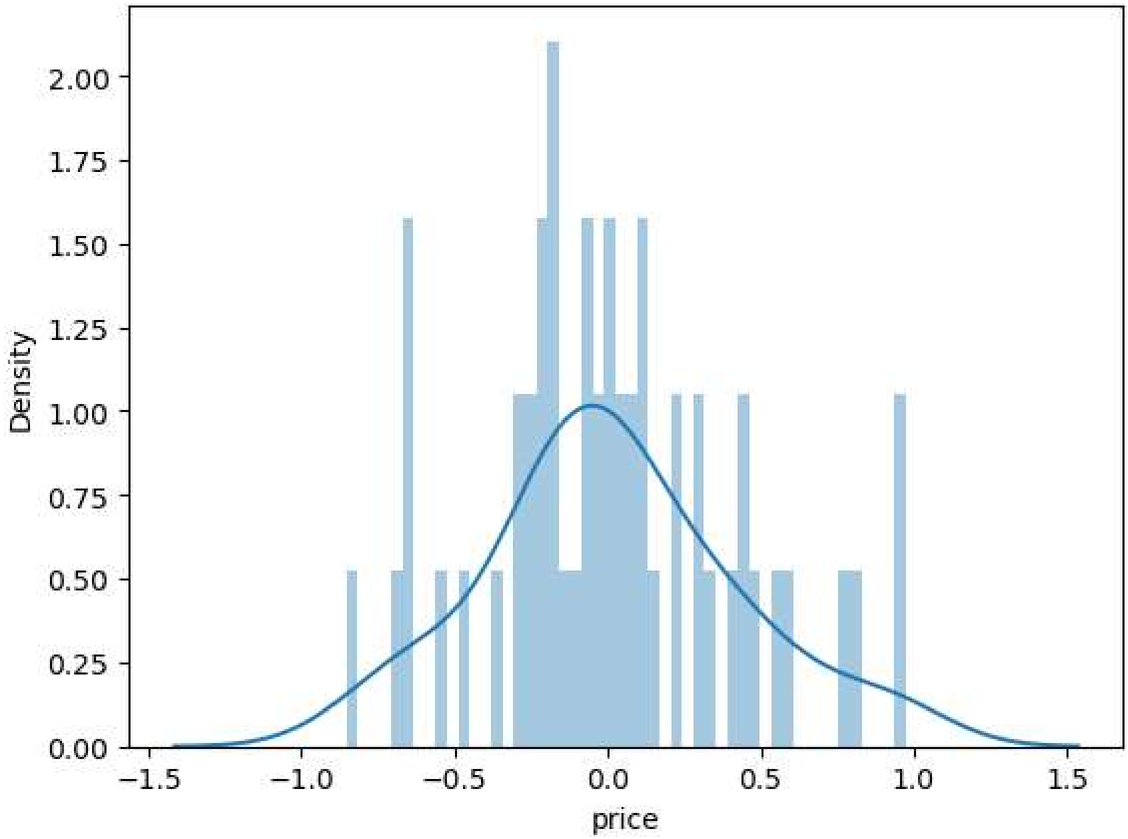
In [36]:
```
plt.scatter(y_test, y_pred)
```

Out[36]: <matplotlib.collections.PathCollection at 0x19819760df0>



In [37]:

```
sns.distplot((y_test - y_pred), bins=50)
plt.show()
```



In [ ]:

```

```