```
#import library
from ast import increment_lineno
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
pd.set_option('display.max_columns', None)


from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor



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
```

```
car_dataset=pd.read_csv('CarPrice_Assignment.csv',encoding='latin-1')
print('car_dataset')
```

```
car_dataset
```

```
car_dataset.head()
```

	car_ID	symboling	CompanyName	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocat
0	1	3	alfa-romero	gas	std	two	convertible	rwd	fr
1	2	3	alfa-romero	gas	std	two	convertible	rwd	fr
2	3	1	alfa-romero	gas	std	two	hatchback	rwd	fr
3	4	2	audi	gas	std	four	sedan	fwd	fr
4	5	2	audi	gas	std	four	sedan	4wd	fr

```
car_dataset.tail()
```

	car_ID	symboling	CompanyName	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocat
200	201	-1	volvo	gas	std	four	sedan	rwd	fr
201	202	-1	volvo	gas	turbo	four	sedan	rwd	fr
202	203	-1	volvo	gas	std	four	sedan	rwd	fr
203	204	-1	volvo	diesel	turbo	four	sedan	rwd	fr
204	205	-1	volvo	gas	turbo	four	sedan	rwd	fr

```
car_dataset.shape
```

```
(205, 26)
```

```
car_dataset.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
```

```
car_dataset.describe()
```

	car_ID	symboling	wheelbase	carlength	carwidth	carheight	curbweight	enginesize	bo
count	205.000000	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	126.907317	
std	59.322565	1.245307	6.021776	12.337289	2.145204	2.443522	520.680204	41.642693	
min	1.000000	-2.000000	86.600000	141.100000	60.300000	47.800000	1488.000000	61.000000	
25%	52.000000	0.000000	94.500000	166.300000	64.100000	52.000000	2145.000000	97.000000	
50%	103.000000	1.000000	97.000000	173.200000	65.500000	54.100000	2414.000000	120.000000	
75%	154.000000	2.000000	102.400000	183.100000	66.900000	55.500000	2935.000000	141.000000	
max	205.000000	3.000000	120.900000	208.100000	72.300000	59.800000	4066.000000	326.000000	

```
car_dataset.isnull().sum()
```

```
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
```

```
car_dataset.head(5)
```

	car_ID	symboling	CompanyName	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocat
0	1	3	alfa-romero	gas	std	two	convertible	rwd	fr
1	2	3	alfa-romero	gas	std	two	convertible	rwd	fr
2	3	1	alfa-romero	gas	std	two	hatchback	rwd	fr
3	4	2	audi	gas	std	four	sedan	fwd	fr
4	5	2	audi	gas	std	four	sedan	4wd	fr

```
car_dataset.columns
```

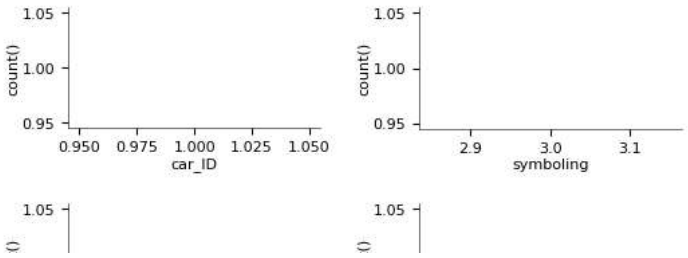
```
Index(['car_ID', 'symboling', 'CarName', 'fueltype', 'aspiration',
       'doornumber', 'carbody', 'drivewheel', 'enginelocation', 'wheelbase',
       'carlength', 'carwidth', 'carheight', 'curbweight', 'enginetype',
       'cylindernumber', 'enginesize', 'fuelsystem', 'boreratio', 'stroke',
   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

```
CompanyName = car_dataset['CarName'].apply(lambda x : x.split(' ')[0])
car_dataset.insert(3,"CompanyName",CompanyName)
car_dataset.drop(['CarName'],axis=1,inplace=True)
```

```
car_dataset.head(1)
```

	car_ID	symboling	CompanyName	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocat
0	1	3	alfa-romero	gas	std	two	convertible	rwd	fr

Time series




```
car_dataset.CompanyName.unique()
```

```
array(['alfa-romero', 'audi', 'bmw', 'chevrolet', 'dodge', 'honda',
       'isuzu', 'jaguar', 'maxda', 'mazda', 'buick', 'mercury',
       'mitsubishi', 'Nissan', 'nissan', 'peugeot', 'plymouth', 'porsche',
       'porcshce', 'renault', 'saab', 'subaru', 'toyota', 'toyouta',
       'vokswagen', 'volkswagen', 'vw', 'volvo'], dtype=object)
```

```
car_dataset.CompanyName = car_dataset.CompanyName.str.lower()
```

```
car_dataset.CompanyName.unique()
```

```
array(['alfa-romero', 'audi', 'bmw', 'chevrolet', 'dodge', 'honda',
       'isuzu', 'jaguar', 'maxda', 'mazda', 'buick', 'mercury',
       'mitsubishi', 'nissan', 'peugeot', 'plymouth', 'porsche',
       'porcshce', 'renault', 'saab', 'subaru', 'toyota', 'toyouta',
       'vokswagen', 'volkswagen', 'vw', 'volvo'], dtype=object)
```

```
def replace_name(a,b):
    car_dataset.CompanyName.replace(a,b,inplace=True)

replace_name('maxda','mazda')
replace_name('porcshce','porsche')
replace_name('toyouta','toyota')
replace_name('vokswagen','volkswagen')
replace_name('vw','volkswagen')
```

```
car_dataset.CompanyName.unique()
```

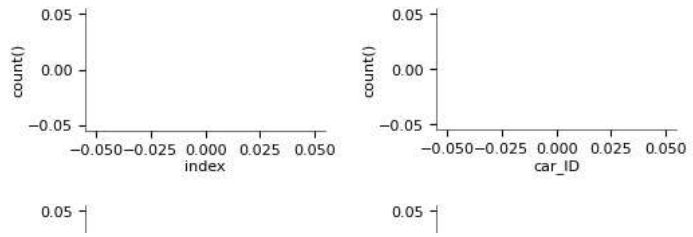
```
array(['alfa-romero', 'audi', 'bmw', 'chevrolet', 'dodge', 'honda',
       'isuzu', 'jaguar', 'mazda', 'buick', 'mercury', 'mitsubishi',
       'nissan', 'peugeot', 'plymouth', 'porsche', 'renault', 'saab',
       'subaru', 'toyota', 'volkswagen', 'volvo'], dtype=object)
```

```
car_dataset.loc[car_dataset.duplicated()]
```

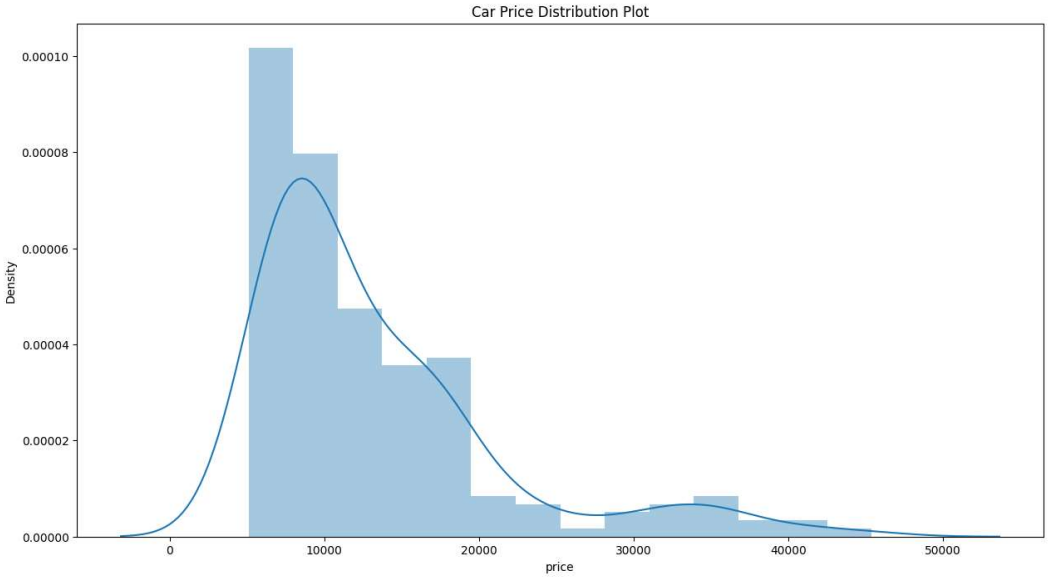
car_ID	symboling	CompanyName	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation

```
Warning: Total number of columns (26) exceeds max_columns (20) limiting to first (20) columns.
```

Time series




```
plt.figure(figsize=(15,8))
plt.title('Car Price Distribution Plot')
sns.distplot(car_dataset.price)
plt.show()
```

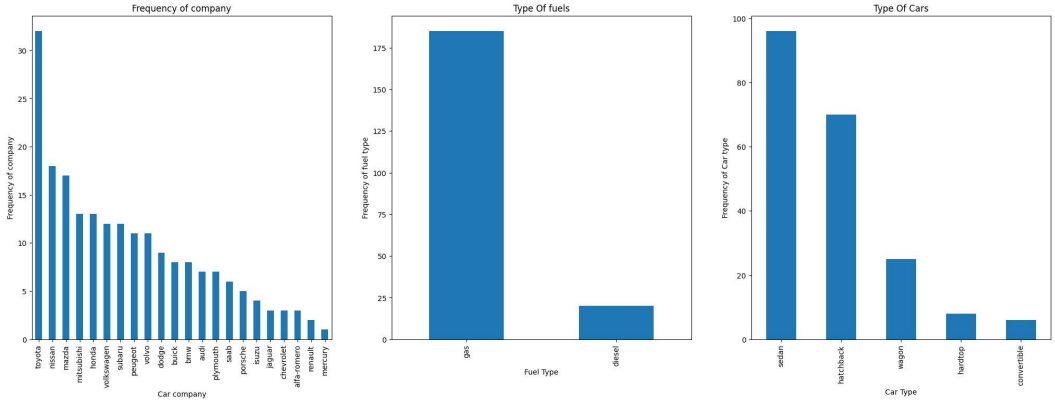



```
car_dataset.price.describe(percentiles = [0.25,0.50,0.75,0.85,0.90,1])
```

```
count      205.000000
mean     13276.710571
std       7988.852332
min       5118.000000
25%       7788.000000
```

```
50%      10295.000000
75%      16503.000000
85%      18500.000000
90%      22563.000000
100%     45400.000000
max      45400.000000
Name: price, dtype: float64
```

```
plt.figure(figsize=(25, 8))

plt.subplot(1,3,1)
plt1 = car_dataset.CompanyName.value_counts().plot(kind='bar')
plt.title('Frequency of company')
plt1.set(xlabel = 'Car company', ylabel='Frequency of company')

plt.subplot(1,3,2)
plt1 = car_dataset.fueltype.value_counts().plot(kind='bar')
plt.title('Type Of fuels')
plt1.set(xlabel = 'Fuel Type', ylabel='Frequency of fuel type')

plt.subplot(1,3,3)
plt1 = car_dataset.carbody.value_counts().plot(kind='bar')
plt.title('Type Of Cars')
plt1.set(xlabel = 'Car Type', ylabel='Frequency of Car type')

plt.show()
```

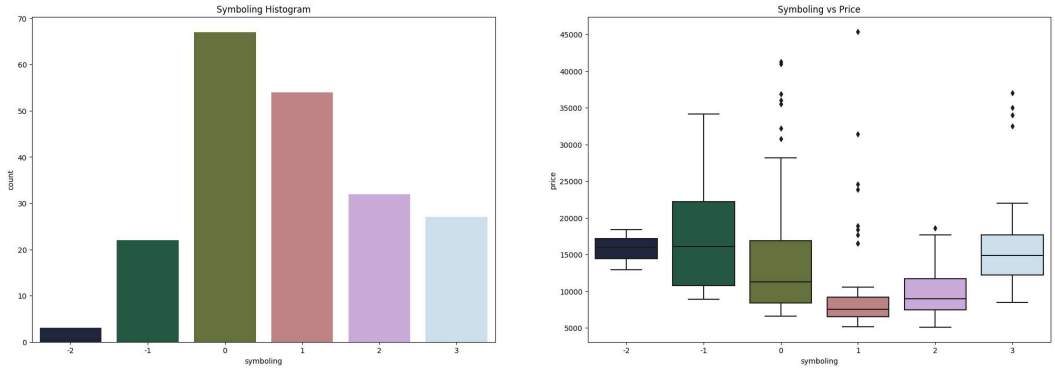



```
car_dataset.head()
```

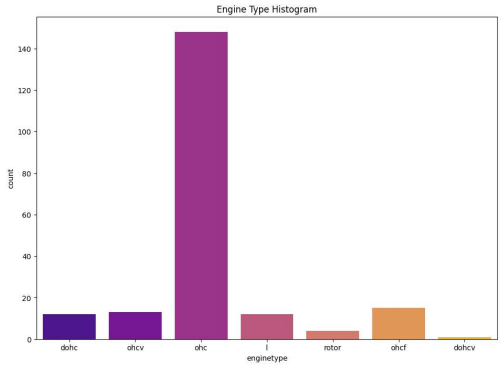
	car_ID	symboling	CompanyName	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocat
0	1	3	alfa-romero	gas	std	two	convertible	rwd	fr
1	2	3	alfa-romero	gas	std	two	convertible	rwd	fr
2	3	1	alfa-romero	gas	std	two	hatchback	rwd	fr
3	4	2	audi	gas	std	four	sedan	fwd	fr
4	5	2	audi	gas	std	four	sedan	4wd	fr

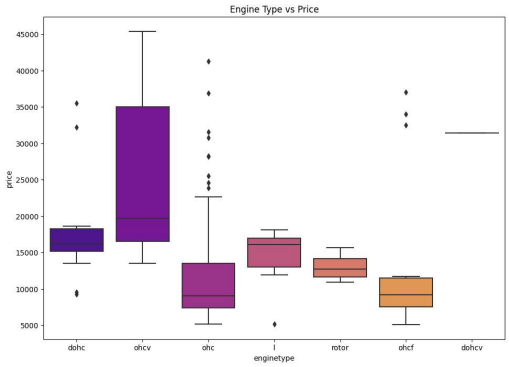
```
plt.figure(figsize=(25,8))

plt.subplot(1,2,1)
plt.title('Symboling Histogram')
```

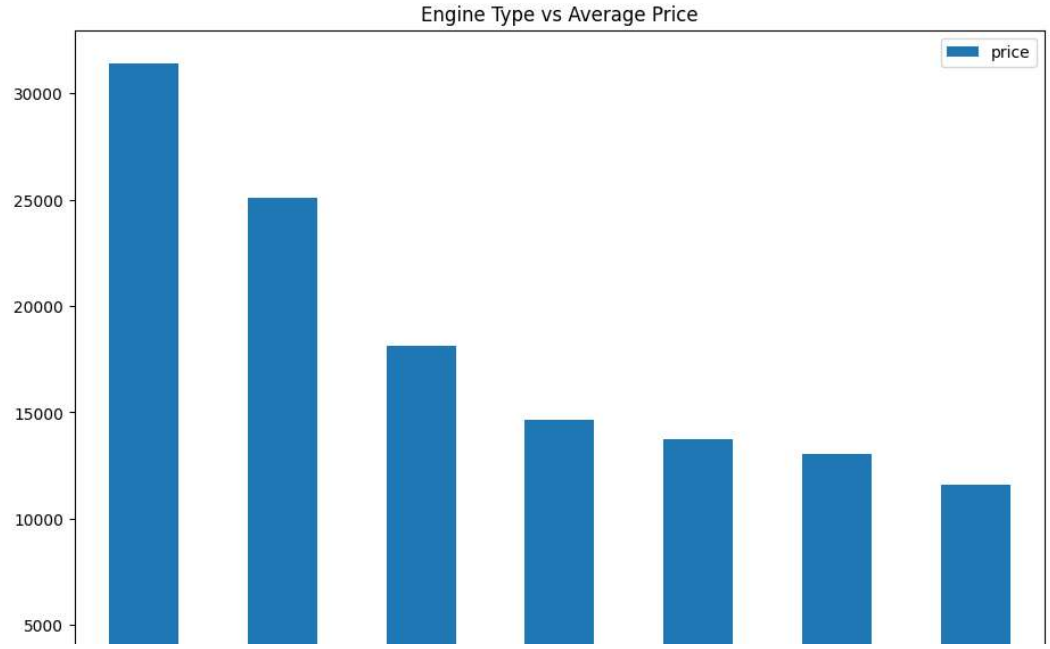
```
sns.countplot(car_dataset.symboling, x=car_dataset.symboling,palette=("cubehelix"))

plt.subplot(1,2,2)
plt.title('Symboling vs Price')
sns.boxplot(x=car_dataset.symboling, y=car_dataset.price, palette=("cubehelix"))

plt.show()
```



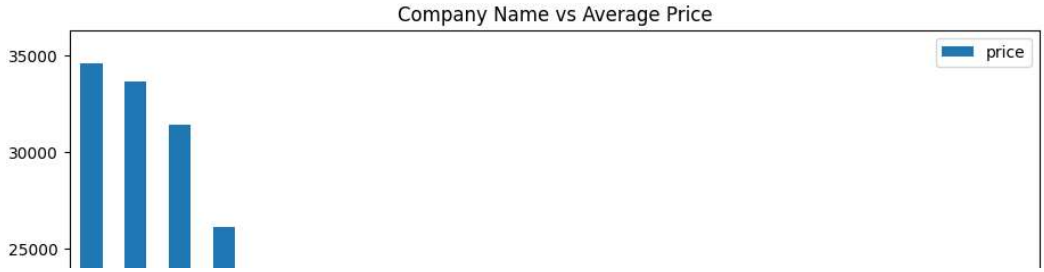

```
plt.figure(figsize=(25,8))

plt.subplot(1,2,1)
plt.title('Engine Type Histogram')
sns.countplot(car_dataset.enginetype, x=car_dataset.enginetype,palette=("plasma"))

plt.subplot(1,2,2)
plt.title('Engine Type vs Price')
sns.boxplot(x=car_dataset.enginetype, y=car_dataset.price, palette=("plasma"))

plt.show()

df = pd.DataFrame(car_dataset.groupby(['enginetype'])['price'].mean().sort_values(ascending = False))
df.plot.bar(figsize=(11,8))
plt.title('Engine Type vs Average Price')
plt.show()
```



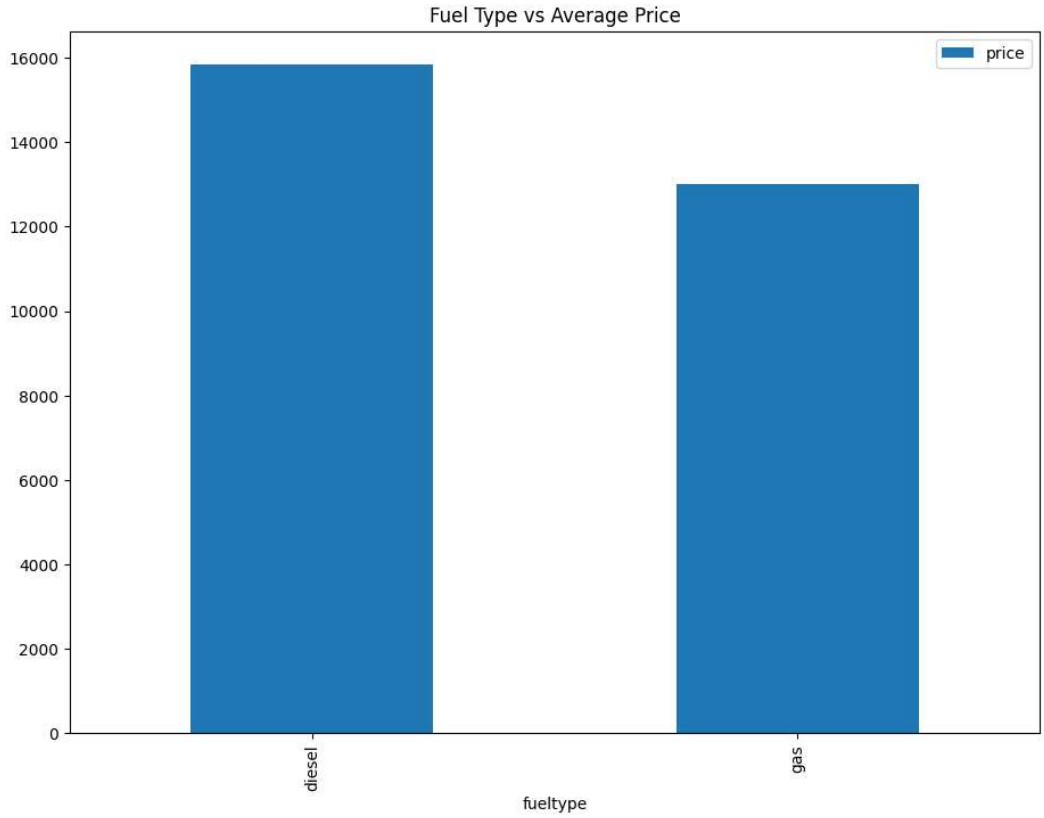




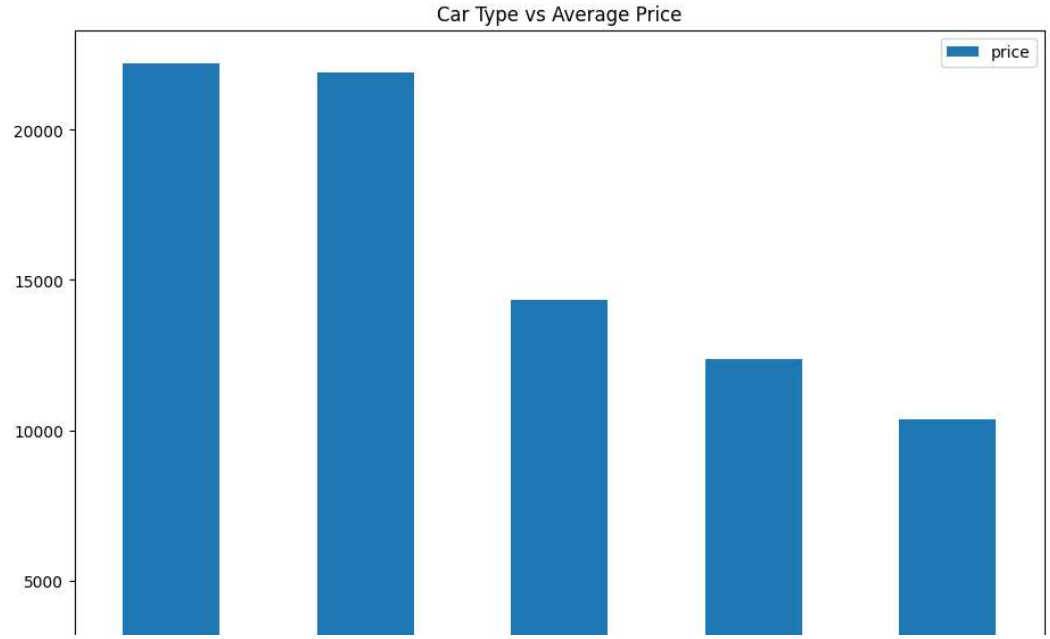

```
df = pd.DataFrame(car_dataset.groupby(['CompanyName'])['price'].mean().sort_values(ascending = False))
df.plot.bar(figsize=(11,8))
plt.title('Company Name vs Average Price')
plt.show()
```



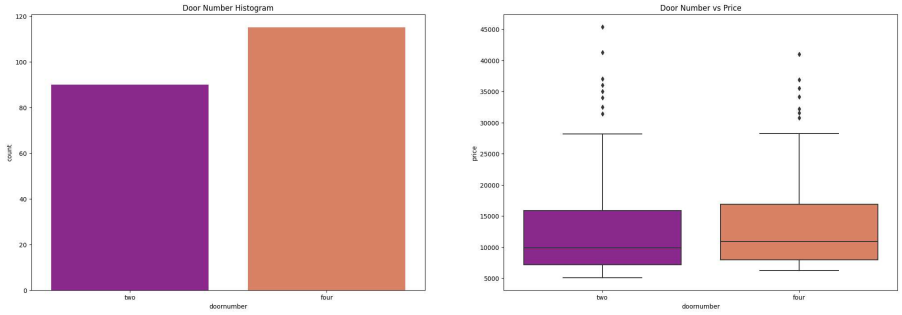

```
df = pd.DataFrame(car_dataset.groupby(['fueltype'])['price'].mean().sort_values(ascending = False))
df.plot.bar(figsize=(11,8))
plt.title('Fuel Type vs Average Price')
plt.show()
```



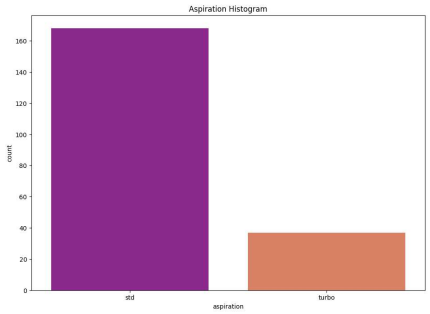

```
df = pd.DataFrame(car_dataset.groupby(['carbody'])['price'].mean().sort_values(ascending = False))
df.plot.bar(figsize=(11,8))
plt.title('Car Type vs Average Price')
plt.show()
```

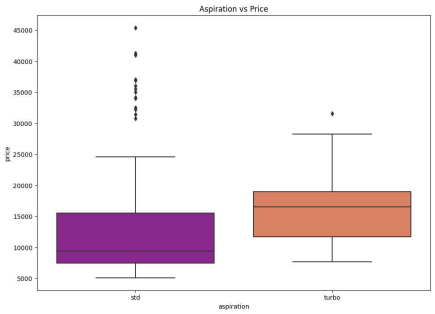



```
plt.figure(figsize=(25,8))

plt.subplot(1,2,1)
plt.title('Door Number Histogram')
sns.countplot(x=car_dataset.doornumber, palette=("plasma"))

plt.subplot(1,2,2)
plt.title('Door Number vs Price')
sns.boxplot(x=car_dataset.doornumber, y=car_dataset.price, palette=("plasma"))

plt.show()
```




```
plt.figure(figsize=(25,8))

plt.subplot(1,2,1)
plt.title('Aspiration Histogram')
sns.countplot(x=car_dataset.aspiration, palette=("plasma"))

plt.subplot(1,2,2)
plt.title('Aspiration vs Price')
sns.boxplot(x=car_dataset.aspiration, y=car_dataset.price, palette=("plasma"))

plt.show()
```






```
np.corrcoef(car_dataset['carlength'], car_dataset['carwidth'])[0, 1]
```

```
0.841118268481846
```

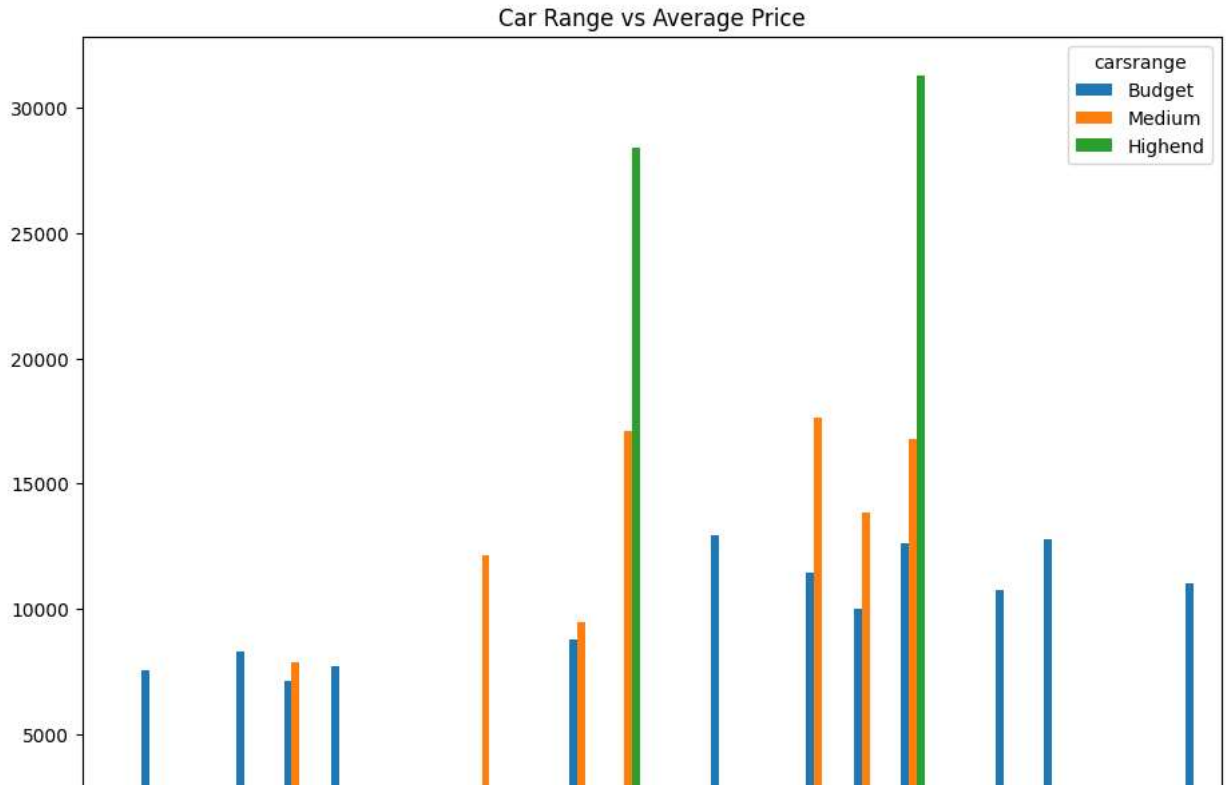
```
#fueleconomy
car_dataset['fueleconomy'] = (0.55 * car_dataset['citympg']) + (0.45 * car_dataset['highwaympg'])
```

```
#Binning the Car Companies based on avg prices of each Company.
car_dataset['price'] = car_dataset['price'].astype('int')
temp = car_dataset.copy()
table = temp.groupby(['CompanyName'])['price'].mean()
temp = temp.merge(table.reset_index(), how='left',on='CompanyName')
bins = [0,10000,20000,40000]
cars_bin=['Budget','Medium','Highend']
car_dataset['carsrange'] = pd.cut(temp['price_y'],bins,right=False,labels=cars_bin)
```

```
car_dataset.head()
```

	car_ID	symboling	CompanyName	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	wheelbase	carlength	carwidt
0	1	3	alfa-romero	gas	std	two	convertible	rwd	front	88.6	168.8	64.
1	2	3	alfa-romero	gas	std	two	convertible	rwd	front	88.6	168.8	64.
2	3	1	alfa-romero	gas	std	two	hatchback	rwd	front	94.5	171.2	65.
3	4	2	audi	gas	std	four	sedan	fwd	front	99.8	176.6	66.
4	5	2	audi	gas	std	four	sedan	4wd	front	99.4	176.6	66.

```
df = pd.DataFrame(car_dataset.groupby(['fuelsystem','drivewheel','carsrange'])['price'].mean().unstack(fill_value=0))
df.plot.bar(figsize=(11,8))
plt.title('Car Range vs Average Price')

plt.show()
```




```
cars_lr = car_dataset[['price', 'fueltype', 'aspiration','carbody', 'drivewheel','wheelbase',
                'curbweight', 'enginetype', 'cylindernumber', 'enginesize', 'boreratio','horsepower',
                  'fueleconomy', 'carlength','carwidth', 'carsrange']]
cars_lr.head()
```

	price	fueltype	aspiration	carbody	drivewheel	wheelbase	curbweight	enginetype	cylindernumber	enginesize	boreratio	horsepow
0	13495	gas	std	convertible	rwd	88.6	2548	dohc	four	130	3.47	
1	16500	gas	std	convertible	rwd	88.6	2548	dohc	four	130	3.47	
2	16500	gas	std	hatchback	rwd	94.5	2823	ohcv	six	152	2.68	1
3	13950	gas	std	sedan	fwd	99.8	2337	ohc	four	109	3.19	1
4	17450	gas	std	sedan	4wd	99.4	2824	ohc	five	136	3.19	1

```
# Defining the map function
def dummies(x,df):
    temp = pd.get_dummies(df[x], drop_first = True)
    df = pd.concat([df, temp], axis = 1)
    df.drop([x], axis = 1, inplace = True)
    return df


# Applying the function to the cars_lr

cars_lr = dummies('fueltype',cars_lr)
cars_lr = dummies('aspiration',cars_lr)
cars_lr = dummies('carbody',cars_lr)
cars_lr = dummies('drivewheel',cars_lr)
cars_lr = dummies('enginetype',cars_lr)
cars_lr = dummies('cylindernumber',cars_lr)
cars_lr = dummies('carsrange',cars_lr)


cars_lr.head()
```

	price	wheelbase	curbweight	enginesize	boreratio	horsepower	fueleconomy	carlength	carwidth	gas	turbo	hardtop	hatchback	sed
0	13495	88.6	2548	130	3.47	111	23.70	168.8	64.1	1	0	0	0	
1	16500	88.6	2548	130	3.47	111	23.70	168.8	64.1	1	0	0	0	

```
cars_lr.shape
```

```
(205, 31)
```

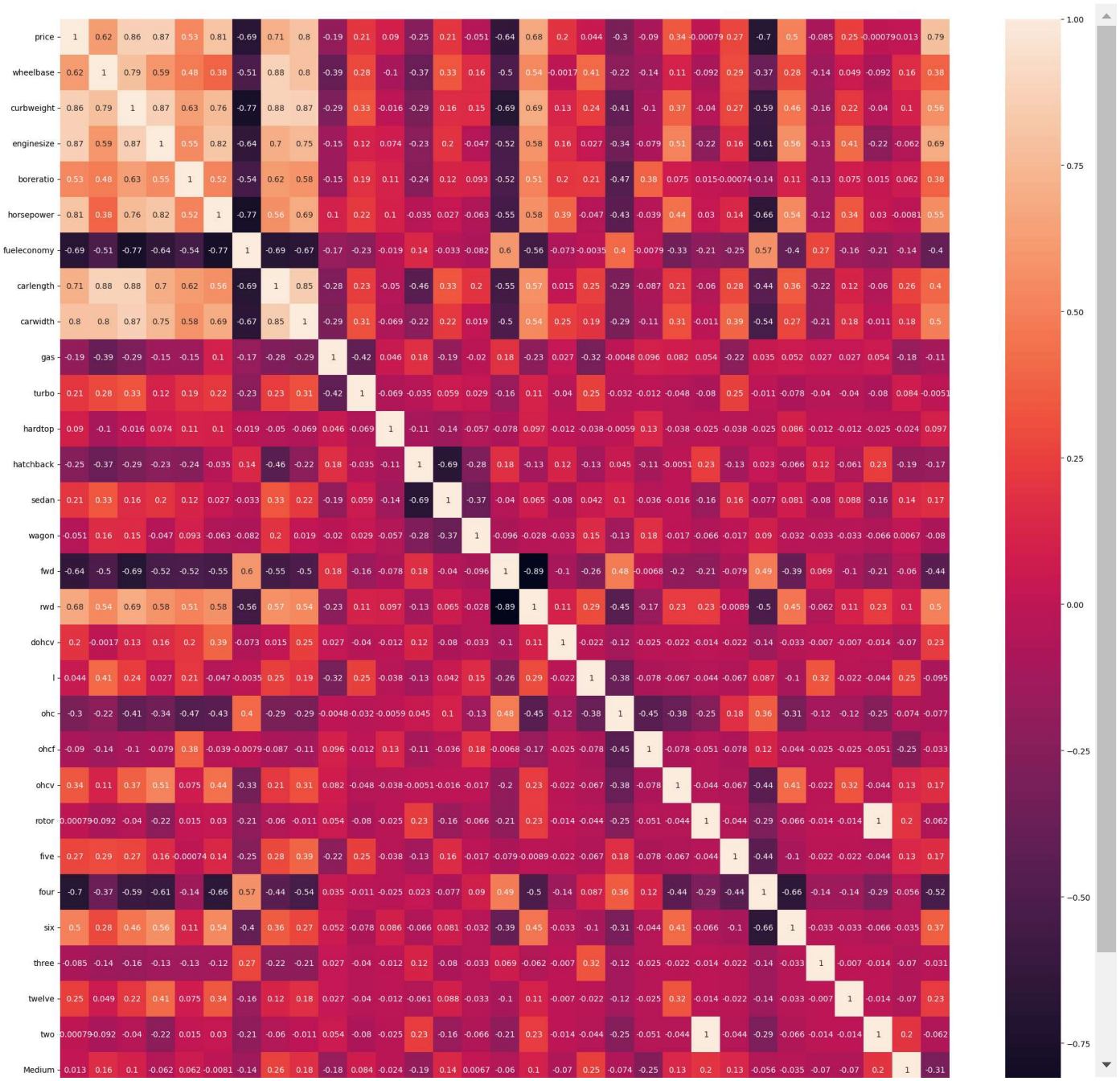
```
#Train-Test
from sklearn.model_selection import train_test_split

np.random.seed(0)
df_train, df_test = train_test_split(cars_lr, train_size = 0.7, test_size = 0.3, random_state = 100)


from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
num_vars = ['wheelbase', 'curbweight', 'enginesize', 'boreratio', 'horsepower','fueleconomy','carlength','carwidth','price']
df_train[num_vars] = scaler.fit_transform(df_train[num_vars])


df_train.head()
```

	price	wheelbase	curbweight	enginesize	boreratio	horsepower	fueleconomy	carlength	carwidt
122	0.068818	0.244828	0.272692	0.139623	0.230159	0.083333	0.530864	0.426016	0.29166
125	0.466890	0.272414	0.500388	0.339623	1.000000	0.395833	0.213992	0.452033	0.66666
166	0.122110	0.272414	0.314973	0.139623	0.444444	0.266667	0.344307	0.448780	0.30833
1	0.314446	0.068966	0.411171	0.260377	0.626984	0.262500	0.244170	0.450407	0.31666
199	0.382131	0.610345	0.647401	0.260377	0.746032	0.475000	0.122085	0.775610	0.57500

```
df_train.describe()
```

	price	wheelbase	curbweight	enginesize	boreratio	horsepower	fueleconomy	carlength	carwidth	gas	turbo
count	143.000000	143.000000	143.000000	143.000000	143.000000	143.000000	143.000000	143.000000	143.000000	143.000000	143.000000
mean	0.219309	0.411141	0.407878	0.241351	0.497946	0.227302	0.358265	0.525476	0.461655	0.909091	0.181818
std	0.215682	0.205581	0.211269	0.154619	0.207140	0.165511	0.185980	0.204848	0.184517	0.288490	0.387050
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.067298	0.272414	0.245539	0.135849	0.305556	0.091667	0.198903	0.399187	0.304167	1.000000	0.000000
50%	0.140343	0.341379	0.355702	0.184906	0.500000	0.191667	0.344307	0.502439	0.425000	1.000000	0.000000
75%	0.313479	0.503448	0.559542	0.301887	0.682540	0.283333	0.512346	0.669919	0.550000	1.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

```
plt.figure(figsize = (25, 25))
sns.heatmap(df_train.corr(), annot = True)
plt.show()
```




```
#Model Building
#Dividing data into X and y variables
y_train = df_train.pop('price')
X_train = df_train


lm = LinearRegression()
lm.fit(X_train,y_train)
rfe = RFE(lm)
```

```
rfe = rfe.fit(X_train, y_train)
```

```
list(zip(X_train.columns,rfe.support_,rfe.ranking_))
```

```
[('wheelbase', True, 1),
 ('curbweight', True, 1),
 ('enginesize', False, 8),
 ('boreratio', False, 5),
 ('horsepower', True, 1),
 ('fueleconomy', True, 1),
 ('carlength', False, 6),
 ('carwidth', True, 1),
 ('gas', False, 12),
 ('turbo', False, 13),
 ('hardtop', True, 1),
 ('hatchback', True, 1),
 ('sedan', True, 1),
 ('wagon', True, 1),
 ('fwd', False, 11),
 ('rwd', False, 10),
 ('dohcv', True, 1),
 ('l', False, 14),
 ('ohc', False, 2),
 ('ohcf', False, 3),
 ('ohcv', False, 4),
 ('rotor', False, 16),
 ('five', True, 1),
 ('four', True, 1),
 ('six', True, 1),
 ('three', False, 9),
 ('twelve', True, 1),
 ('two', False, 15),
 ('Medium', False, 7),
 ('Highend', True, 1)]
```

```
X_train.columns[rfe.support_]
```

```
Index(['wheelbase', 'curbweight', 'horsepower', 'fueleconomy', 'carwidth',
       'hardtop', 'hatchback', 'sedan', 'wagon', 'dohcv', 'five', 'four',
       'six', 'twelve', 'Highend'],
      dtype='object')
```

```
X_train_rfe = X_train[X_train.columns[rfe.support_]]
```

```
X_train_rfe.head()
```

	wheelbase	curbweight	horsepower	fueleconomy	carwidth	hardtop	hatchback	sedan	wagon	dohcv	five	four	six	twelve	Highend
122	0.244828	0.272692	0.083333	0.530864	0.291667	0	0	1	0	0	0	1	0	0	0
125	0.272414	0.500388	0.395833	0.213992	0.666667	0	1	0	0	0	0	1	0	0	1
166	0.272414	0.314973	0.266667	0.344307	0.308333	0	1	0	0	0	0	1	0	0	0
1	0.068966	0.411171	0.262500	0.244170	0.316667	0	0	0	0	0	0	1	0	0	0
199	0.610345	0.647401	0.475000	0.122085	0.575000	0	0	0	1	0	0	1	0	0	0

```
def build_model(X,y):
    X = sm.add_constant(X)
    lm = sm.OLS(y,X).fit()
    print(lm.summary())
    return X
```

```
def checkVIF(X):
    vif = pd.DataFrame()
    vif['Features'] = X.columns
    vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
    vif['VIF'] = round(vif['VIF'], 2)
    vif = vif.sort_values(by = "VIF", ascending = False)
    return(vif)
```

```
X_train_new = build_model(X_train_rfe,y_train)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.936
Model:                            OLS   Adj. R-squared:                  0.929
Method:                 Least Squares   F-statistic:                     124.4
Date:                Fri, 11 Aug 2023   Prob (F-statistic):           3.16e-68
Time:                        14:00:32   Log-Likelihood:                 213.80
No. Observations:                 143   AIC:                            -395.6
Df Residuals:                     127   BIC:                            -348.2
Df Model:                          15
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0108      0.050      0.214      0.831      -0.089       0.110
wheelbase      0.0814      0.063      1.298      0.197      -0.043       0.205
curbweight     0.2017      0.081      2.482      0.014       0.041       0.362
horsepower     0.4801      0.098      4.923      0.000       0.287       0.673
fueleconomy    0.1300      0.054      2.418      0.017       0.024       0.236
carwidth       0.2140      0.074      2.903      0.004       0.068       0.360
hardtop       -0.0611      0.048     -1.278      0.204      -0.156       0.034
hatchback     -0.1379      0.035     -3.977      0.000      -0.206      -0.069
sedan         -0.1119      0.036     -3.133      0.002      -0.183      -0.041
wagon         -0.1350      0.036     -3.708      0.000      -0.207      -0.063
dohcv         -0.2880      0.086     -3.360      0.001      -0.458      -0.118
five          -0.0416      0.031     -1.346      0.181      -0.103       0.020
four          -0.0802      0.025     -3.249      0.001      -0.129      -0.031
six           -0.0425      0.030     -1.400      0.164      -0.103       0.018
twelve        -0.1348      0.075     -1.790      0.076      -0.284       0.014
Highend        0.2416      0.020     12.095      0.000       0.202       0.281
==============================================================================
Omnibus:                       54.936   Durbin-Watson:                   2.013
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              231.186
Skew:                           1.331   Prob(JB):                     6.29e-51
Kurtosis:                       8.632   Cond. No.                         46.8
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

```
X_train_new = X_train_new.drop(["fueleconomy"], axis = 1)
```

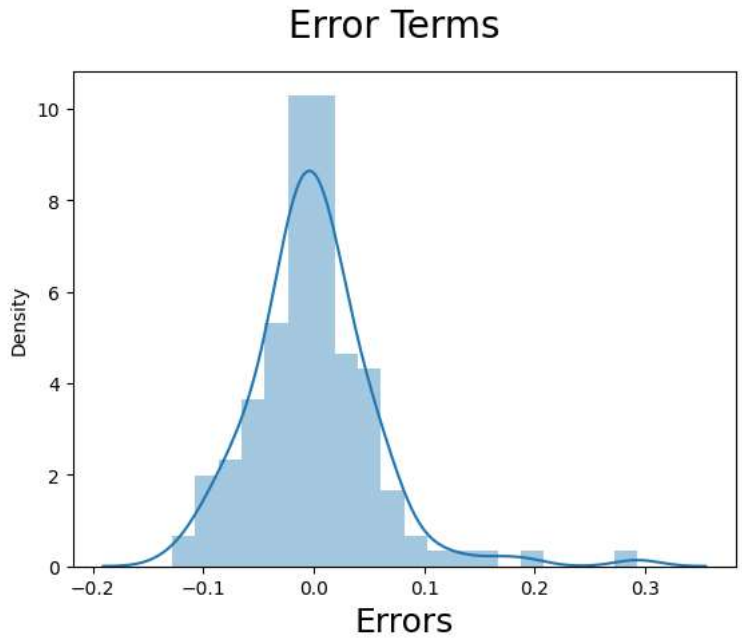
```
X_train_new = build_model(X_train_new,y_train)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.933
Model:                            OLS   Adj. R-squared:                  0.926
Method:                 Least Squares   F-statistic:                     128.0
Date:                Fri, 11 Aug 2023   Prob (F-statistic):           4.67e-68
Time:                        14:00:53   Log-Likelihood:                 210.58
No. Observations:                 143   AIC:                            -391.2
Df Residuals:                     128   BIC:                            -346.7
Df Model:                          14
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0739      0.044      1.690      0.093      -0.013       0.160
wheelbase      0.0594      0.063      0.940      0.349      -0.066       0.184
curbweight     0.1875      0.083      2.271      0.025       0.024       0.351
horsepower     0.3425      0.081      4.246      0.000       0.183       0.502
carwidth       0.2264      0.075      3.023      0.003       0.078       0.375
hardtop       -0.0430      0.048     -0.895      0.373      -0.138       0.052
hatchback     -0.1256      0.035     -3.596      0.000      -0.195      -0.056
sedan         -0.1001      0.036     -2.778      0.006      -0.171      -0.029
wagon         -0.1288      0.037     -3.482      0.001      -0.202      -0.056
dohcv         -0.2002      0.079     -2.532      0.013      -0.357      -0.044
five          -0.0378      0.031     -1.203      0.231      -0.100       0.024
four          -0.0694      0.025     -2.807      0.006      -0.118      -0.020
six           -0.0216      0.030     -0.729      0.467      -0.080       0.037
twelve        -0.0793      0.073     -1.085      0.280      -0.224       0.065
Highend        0.2484      0.020     12.327      0.000       0.209       0.288
==============================================================================
Omnibus:                       53.309   Durbin-Watson:                   2.045
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              212.461
Skew:                           1.307   Prob(JB):                     7.32e-47
Kurtosis:                       8.369   Cond. No.                         39.7
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

```
lm = sm.OLS(y_train,X_train_new).fit()
y_train_price = lm.predict(X_train_new)
```

```
fig = plt.figure()
sns.distplot((y_train - y_train_price), bins = 20)
fig.suptitle('Error Terms', fontsize = 20)
plt.xlabel('Errors', fontsize = 18)
```

```
Text(0.5, 0, 'Errors')
```




```
print(lm.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.933
Model:                            OLS   Adj. R-squared:                  0.926
Method:                 Least Squares   F-statistic:                     128.0
Date:                Fri, 11 Aug 2023   Prob (F-statistic):          4.67e-68
Time:                        14:01:22   Log-Likelihood:                 210.58
No. Observations:                 143   AIC:                            -391.2
Df Residuals:                     128   BIC:                            -346.7
Df Model:                          14
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0739      0.044      1.690      0.093      -0.013       0.160
wheelbase      0.0594      0.063      0.940      0.349      -0.066       0.184
curbweight     0.1875      0.083      2.271      0.025       0.024       0.351
horsepower     0.3425      0.081      4.246      0.000       0.183       0.502
carwidth       0.2264      0.075      3.023      0.003       0.078       0.375
hardtop       -0.0430      0.048     -0.895      0.373      -0.138       0.052
hatchback     -0.1256      0.035     -3.596      0.000      -0.195      -0.056
sedan         -0.1001      0.036     -2.778      0.006      -0.171      -0.029
wagon         -0.1288      0.037     -3.482      0.001      -0.202      -0.056
dohcv         -0.2002      0.079     -2.532      0.013      -0.357      -0.044
five          -0.0378      0.031     -1.203      0.231      -0.100       0.024
four          -0.0694      0.025     -2.807      0.006      -0.118      -0.020
six           -0.0216      0.030     -0.729      0.467      -0.080       0.037
twelve        -0.0793      0.073     -1.085      0.280      -0.224       0.065
Highend        0.2484      0.020     12.327      0.000       0.209       0.288
==============================================================================
Omnibus:                       53.309   Durbin-Watson:                   2.045
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              212.461
Skew:                           1.307   Prob(JB):                     7.32e-47
Kurtosis:                       8.369   Cond. No.                         39.7
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```