In [1]:

```
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:

```
# importing advertising data set

adv = pd.read_csv('advertising.csv')
```

In [3]:

```
adv.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 4 columns):
TV           200 non-null float64
Radio        200 non-null float64
Newspaper    200 non-null float64
Sales        200 non-null float64
dtypes: float64(4)
memory usage: 6.4 KB
```

In [4]:

```
adv.head()
```

Out[4]:

	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	12.0
3	151.5	41.3	58.5	16.5
4	180.8	10.8	58.4	17.9

In [5]:

```
adv.isnull().sum()
```

Out[5]:

```
TV           0
Radio        0
Newspaper    0
Sales        0
dtype: int64
```

In [6]:

```
adv.describe()
```

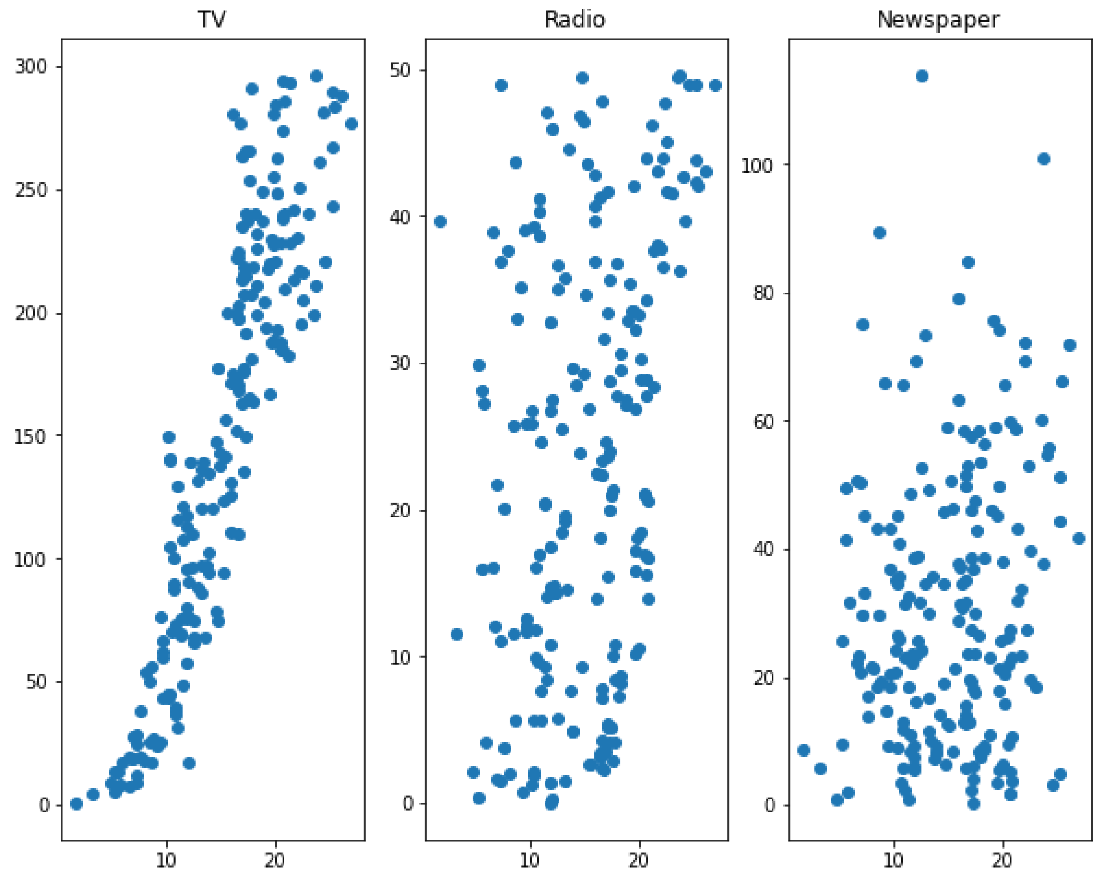
Out[6]:

	TV	Radio	Newspaper	Sales
count	200.000000	200.000000	200.000000	200.000000
mean	147.042500	23.264000	30.554000	15.130500

	TV	Radio	Newspaper	Sales
std	85.854236	14.846809	21.778621	5.283892
min	0.700000	0.000000	0.300000	1.600000
25%	74.375000	9.975000	12.750000	11.000000
50%	149.750000	22.900000	25.750000	16.000000
75%	218.825000	36.525000	45.100000	19.050000
max	296.400000	49.600000	114.000000	27.000000

In [7]:

```
plt.figure(figsize=(10,8))
plt.subplot(1,3,1)
plt.title('TV')
plt.scatter(adv['Sales'],adv['TV'])
plt.subplot(1,3,2)
plt.title('Radio')
plt.scatter(adv['Sales'],adv['Radio'])
plt.subplot(1,3,3)
plt.title('Newspaper')
plt.scatter(adv['Sales'],adv['Newspaper'])
plt.show()
```



In [8]:

```
adv.corr()
```

Out[8]:

	TV	Radio	Newspaper	Sales
TV	1.000000	0.054809	0.056648	0.901208
Radio	0.054809	1.000000	0.354104	0.349631
Newspaper	0.056648	0.354104	1.000000	0.157960
Sales	0.901208	0.349631	0.157960	1.000000

In [9]:

```
#Lets built simple linear regression with TV and Sales
```

```
#Lets built simple linear regression with TV and Sales

X = adv['TV']
y = adv['Sales']
```

In [10]:

```
#test train split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size = 0.7, test_size =
0.3, random_state = 100)
```

In [11]:

```
X_train.head()
```

Out[11]:

```
74     213.4
3      151.5
185    205.0
26     142.9
90     134.3
Name: TV, dtype: float64
```

In [12]:

```
X_test.head()
```

Out[12]:

```
126      7.8
104    238.2
99     135.2
92     217.7
111    241.7
Name: TV, dtype: float64
```

In [13]:

```
#Performing the linear regression using statsmodel
import statsmodels.api as sm
```

In [14]:

```
#Statsmodel fits the line passing through the origin hence we add constant for the interc
ept

X_train_sm = sm.add_constant(X_train)
```

In [15]:

```
lr = sm.OLS(y_train,X_train_sm).fit()
```

In [16]:

```
lr.params
```

Out[16]:

```
const    6.948683
TV       0.054546
dtype: float64
```

In [ ]:

```
Sales = 0.05*TV + 6.95
```

In [17]:

```
lr.summary()
```

Out[17]:

Out[17]:

OLS Regression Results

Dep. Variable:	Sales	**R-squared:**	0.816
Model:	OLS	**Adj. R-squared:**	0.814
Method:	Least Squares	**F-statistic:**	611.2
Date:	Mon, 13 Apr 2020	**Prob (F-statistic):**	1.52e-52
Time:	11:33:19	**Log-Likelihood:**	-321.12
No. Observations:	140	**AIC:**	646.2
Df Residuals:	138	**BIC:**	652.1
Df Model:	1		
Covariance Type:	nonrobust		

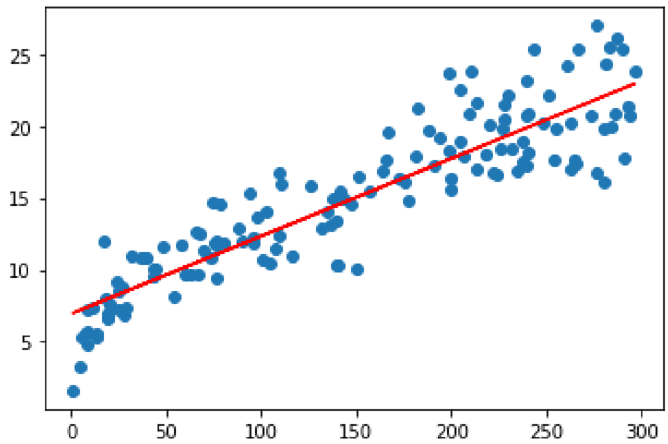
	coef	std err	t	P>|t|	[0.025	0.975]
const	6.9487	0.385	18.068	0.000	6.188	7.709
TV	0.0545	0.002	24.722	0.000	0.050	0.059

Omnibus:	0.027	**Durbin-Watson:**	2.196
Prob(Omnibus):	0.987	**Jarque-Bera (JB):**	0.150
Skew:	-0.006	**Prob(JB):**	0.928
Kurtosis:	2.840	**Cond. No.**	328.

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

In [18]:

```
#plotting the scatter graph
plt.scatter(X_train,y_train)
plt.plot(X_train, 6.948 + 0.054*X_train, 'r')
plt.show()
```



In [19]:

```
#calculating the residues
y_train_pred = lr.predict(X_train_sm)
res = (y_train - y_train_pred)
```

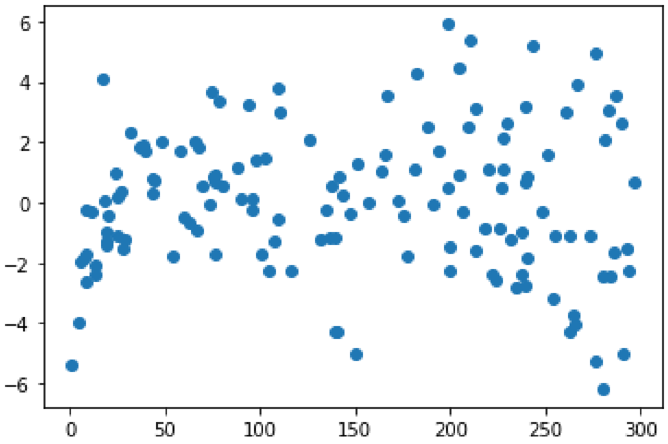
In [20]:

```
#scatter plot
plt.scatter(X_train,res)
```

Out[20]:

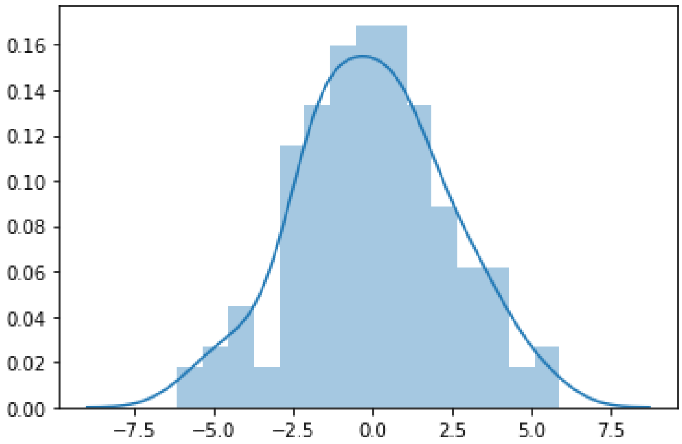
```
<matplotlib.collections.PathCollection at 0x141ac5081c8>
```

<matplotlib.collections.PathCollection at 0x141cc5081c8>



In [21]:

```
#error term distribution
sns.distplot(res,bins=15)
plt.show()
```



In [22]:

```
#Predicting it on the test data
X_test_sm = sm.add_constant(X_test)

# Predict the y values corresponding to X_test_sm
y_pred = lr.predict(X_test_sm)
```

In [23]:

```
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
```

In [24]:

```
#checking the accuracy
np.sqrt(mean_squared_error(y_test, y_pred)) #rmse root mean square error
```

Out[24]:

```
2.019296008966233
```

In [25]:

```
r2_score(y_test,y_pred)
```

Out[25]:

```
0.7921031601245658
```

Is it better to scale the variables..

Yes, it would be better so that all variables will be in the same scale.

There are two kinds of scaling

Standard scaling --> mean is 0 and std.dev is 1 min-max scaling --> all the values will be b/w 0 and 1

In [26]:

```
from sklearn.preprocessing import StandardScaler, MinMaxScaler
```

In [27]:

```
scaler = MinMaxScaler()
```

In [28]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size = 0.7, test_size =
0.3, random_state = 100)
```

In [29]:

```
X_train.head()
X_train.shape
type(X_train)
```

Out[29]:

```
pandas.core.series.Series
```

In [30]:

```
X_train_scaled = np.array(X_train)
```

In [31]:

```
X_train_scaled1 = X_train_scaled.reshape(-1,1)
```

In [32]:

```
X_train_scaled2 = pd.DataFrame(X_train_scaled1)
```

In [33]:

```
y_train_scaled=np.array(y_train)
y_train_scaled1 = y_train_scaled.reshape(-1,1)
y_train_scaled2 = pd.DataFrame(y_train_scaled1)
```

In [34]:

```
X_train_scaled3 = scaler.fit_transform(X_train_scaled2)
y_train_scaled3 = scaler.fit_transform(y_train_scaled2)
```

In [35]:

```
# Let's fit the regression line following exactly the same steps as done before
X_train_scaled4 = sm.add_constant(X_train_scaled3)

lr_scaled = sm.OLS(y_train_scaled3,X_train_scaled4).fit()
```

In [36]:

```
lr_scaled.params
```

Out[36]:

```
array([0.21208131, 0.63500705])
```

In [37]:

```
lr_scaled.summary()
```

Out[37]:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.816
Model:	OLS	**Adj. R-squared:**	0.814
Method:	Least Squares	**F-statistic:**	611.2
Date:	Mon, 13 Apr 2020	**Prob (F-statistic):**	1.52e-52
Time:	11:33:22	**Log-Likelihood:**	131.74
No. Observations:	140	**AIC:**	-259.5
Df Residuals:	138	**BIC:**	-253.6
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.2121	0.015	14.055	0.000	0.182	0.242
x1	0.6350	0.026	24.722	0.000	0.584	0.686

Omnibus:	0.027	**Durbin-Watson:**	2.196
Prob(Omnibus):	0.987	**Jarque-Bera (JB):**	0.150
Skew:	-0.006	**Prob(JB):**	0.928
Kurtosis:	2.840	**Cond. No.**	4.05

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