importing all the libraries required for the Linear Regression

Linear Regression :

In [2]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
```

Dataset

In [4]:

```
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 BostonHousing.csv to BostonHousing.csv
```

In [5]:

```
df = pd.read_csv("BostonHousing.csv")
```

In [6]:
```
df.head()
```

Out[6]:

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	b	lstat	medv
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	396.90	5.33	36.2

In [7]:
```
df.tail()
```

Out[7]:

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	b	lstat	medv
501	0.06263	0.0	11.93	0	0.573	6.593	69.1	2.4786	1	273	21.0	391.99	9.67	22.4
502	0.04527	0.0	11.93	0	0.573	6.120	76.7	2.2875	1	273	21.0	396.90	9.08	20.6
503	0.06076	0.0	11.93	0	0.573	6.976	91.0	2.1675	1	273	21.0	396.90	5.64	23.9
504	0.10959	0.0	11.93	0	0.573	6.794	89.3	2.3889	1	273	21.0	393.45	6.48	22.0
505	0.04741	0.0	11.93	0	0.573	6.030	80.8	2.5050	1	273	21.0	396.90	7.88	11.9

In [8]:
```
prices = df['medv']
features = df.drop('medv',axis = 1)
```

Calculation for Minumum, Maximum, Mean, Median, Standard deviation of prices :

In [10]:
```
# Calculation  of Minimum price
minimum_price = np.mean(prices)
# Calculation of Maximum price
maximum_price = np.max(prices)
# Calculation of Mean price
mean_price = np.mean(prices)
# Calculation of Median price
median_price = np.median(prices)
# Calculatoin of Standard deviation
std_price = np.std(prices)
# To show aboce calculated values

print("Minimum price: ${:,.2f}".format(minimum_price))
print("Maximum price: ${:,.2f}".format(maximum_price))
print("Mean price: ${:,.2f}".format(mean_price))
print("Median price ${:,.2f}".format(median_price))
print("Standard deviation of prices: ${:,.2f}".format(std_price))
```

```
Statistics for Boston housing dataset:

Minimum price: $22.53
Maximum price: $50.00
Mean price: $22.53
Median price $21.20
Standard deviation of prices: $9.19
```

Pre-Processing on the data; Missing Value / Data Type / correlation

In [12]:
```
df.isnull().sum()
```

Out[12]:
```
crim       0
zn         0
indus      0
chas       0
nox        0
rm         0
age        0
dis        0
rad        0
tax        0
ptratio    0
b          0
lstat      0
medv       0
dtype: int64
```

In [13]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   crim     506 non-null    float64
 1   zn       506 non-null    float64
 2   indus    506 non-null    float64
 3   chas     506 non-null    int64  
 4   nox      506 non-null    float64
 5   rm       506 non-null    float64
 6   age      506 non-null    float64
 7   dis      506 non-null    float64
 8   rad      506 non-null    int64  
 9   tax      506 non-null    int64  
 10  ptratio  506 non-null    float64
 11  b        506 non-null    float64
 12  lstat    506 non-null    float64
 13  medv     506 non-null    float64
dtypes: float64(11), int64(3)
memory usage: 55.5 KB
```

In [14]:
```
cor = df.corr()
```

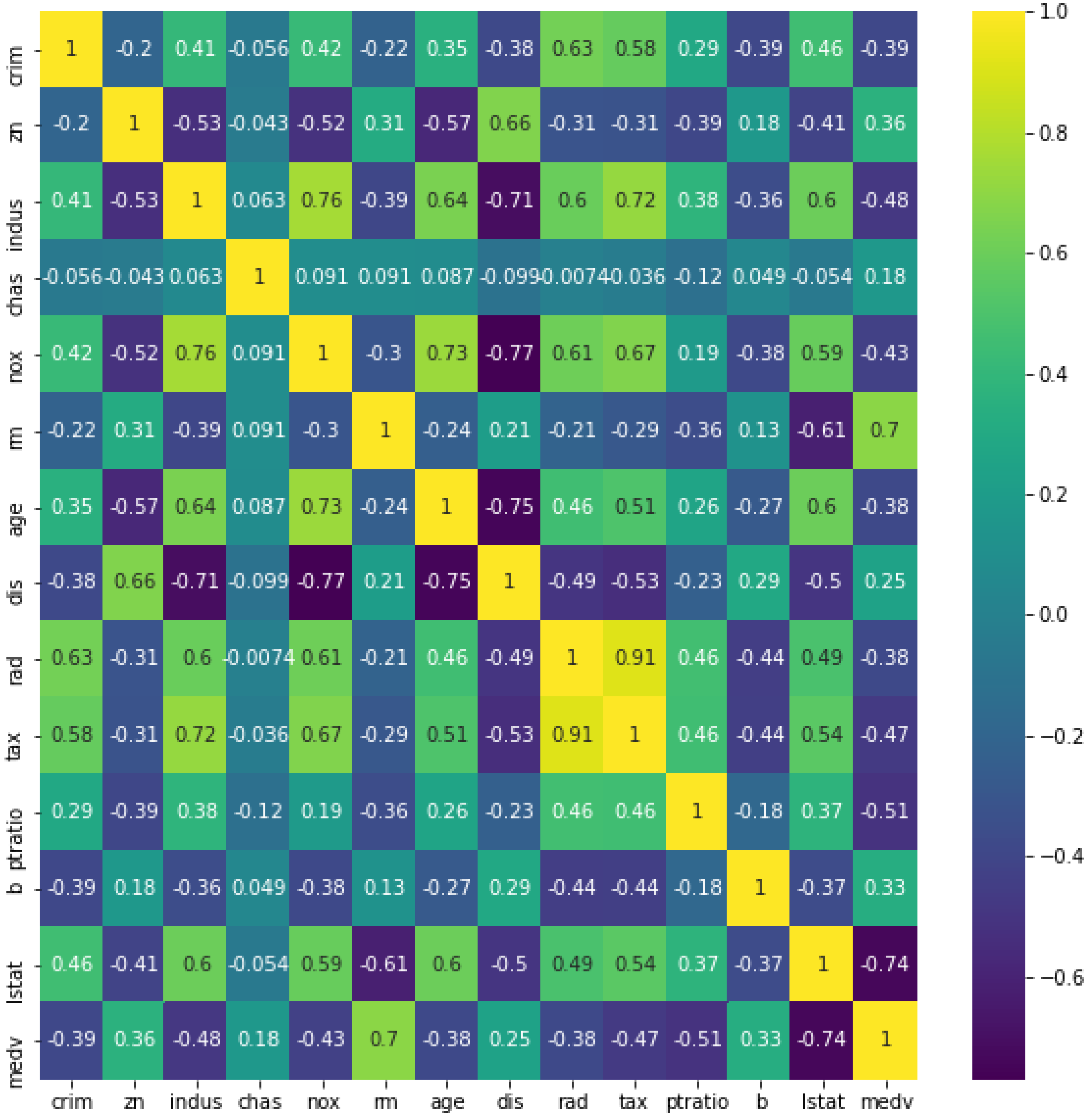
In [15]:
```
cor
```

Out[15]:

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	b	lstat
crim	1.000000	-0.200469	0.406583	-0.055892	0.420972	-0.219247	0.352734	-0.379670	0.625505	0.582764	0.289946	-0.385064	0.455621
zn	-0.200469	1.000000	-0.533828	-0.042697	-0.516604	0.311991	-0.569537	0.664408	-0.311948	-0.314563	-0.391679	0.175520	-0.412995
indus	0.406583	-0.533828	1.000000	0.062938	0.763651	-0.391676	0.644779	-0.708027	0.595129	0.720760	0.383248	-0.356977	0.603800
chas	-0.055892	-0.042697	0.062938	1.000000	0.091203	0.091251	0.086518	-0.099176	-0.007368	-0.035587	-0.121515	0.048788	-0.053929
nox	0.420972	-0.516604	0.763651	0.091203	1.000000	-0.302188	0.731470	-0.769230	0.611441	0.668023	0.188933	-0.380051	0.590879
rm	-0.219247	0.311991	-0.391676	0.091251	-0.302188	1.000000	-0.240265	0.205246	-0.209847	-0.292048	-0.355501	0.128069	-0.613808
age	0.352734	-0.569537	0.644779	0.086518	0.731470	-0.240265	1.000000	-0.747881	0.456022	0.506456	0.261515	-0.273534	0.602339
dis	-0.379670	0.664408	-0.708027	-0.099176	-0.769230	0.205246	-0.747881	1.000000	-0.494588	-0.534432	-0.232471	0.291512	-0.496996
rad	0.625505	-0.311948	0.595129	-0.007368	0.611441	-0.209847	0.456022	-0.494588	1.000000	0.910228	0.464741	-0.444413	0.488676
tax	0.582764	-0.314563	0.720760	-0.035587	0.668023	-0.292048	0.506456	-0.534432	0.910228	1.000000	0.460853	-0.441808	0.543993
ptratio	0.289946	-0.391679	0.383248	-0.121515	0.188933	-0.355501	0.261515	-0.232471	0.464741	0.460853	1.000000	-0.177383	0.374044
b	-0.385064	0.175520	-0.356977	0.048788	-0.380051	0.128069	-0.273534	0.291512	-0.444413	-0.441808	-0.177383	1.000000	-0.366087
lstat	0.455621	-0.412995	0.603800	-0.053929	0.590879	-0.613808	0.602339	-0.496996	0.488676	0.543993	0.374044	-0.366087	1.000000
medv	-0.388305	0.360445	-0.483725	0.175260	-0.427321	0.695360	-0.376955	0.249929	-0.381626	-0.468536	-0.507787	0.333461	-0.737663

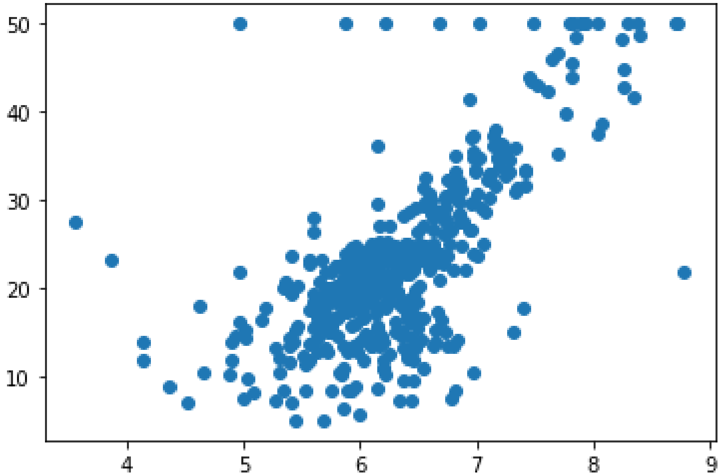
Correlation Visualiazation using heatmap

In [18]:
```
plt.figure(figsize=(10,10))
sns.heatmap(df.corr(),annot=True,cmap="viridis")
plt.show()
```



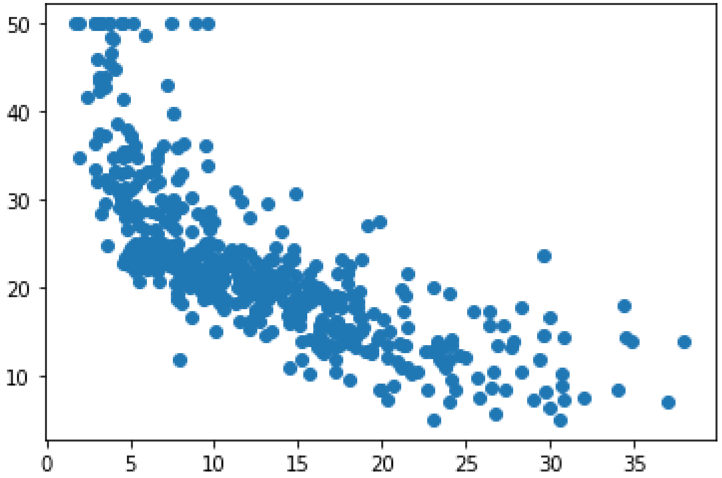
Scatter Plot for rm and medv :

In [19]:
```
plt.figure()
plt.scatter(df["rm"],df["medv"])
plt.show()
```



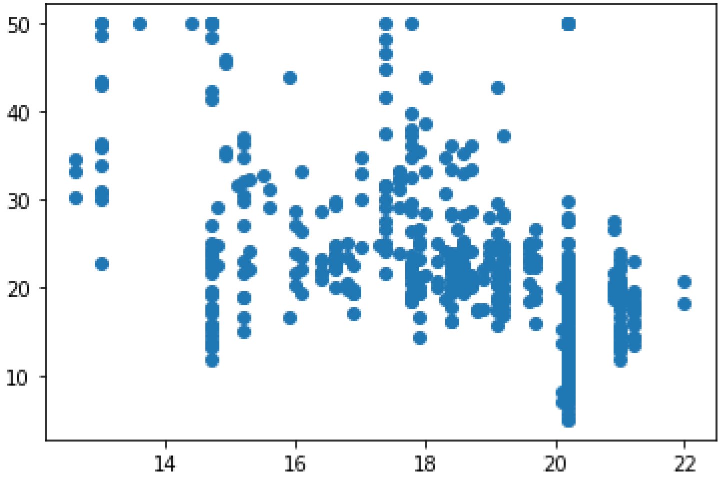
Scatter Plot for lstat and medv :

In [22]:
```
plt.figure()
plt.scatter(df["lstat"],df["medv"])
plt.show()
```



Scatter Plot for ptratio and medv :

In [23]:
```
plt.figure()
plt.scatter(df["ptratio"],df["medv"])
plt.show()
```



Seprating the target and features :

In [30]:
```
X = df[["rm"]]
y = df["medv"]
```

Seprate training and testing data :

In [31]:
```
from sklearn.model_selection import train_test_split
```

In [32]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3, random_state=1)
```

In [33]:
```
model = LinearRegression()
```

ols : oridinary least Square theta1 = sum(x-xbar)(y-ybar)/(x-xbar)2 theta0 = y - theta1x

In [34]:
```
model.fit(X_train,y_train)
```

Out[34]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [35]:
```
model.intercept_
```

Out[35]:
```
-30.571032410898336
```

In [36]:
```
model.coef_
```

Out[36]:
```
array([8.46109164])
```

In [38]:
```
y_pred = model.predict(X_test)
```

Model Evaluation : Mean Squared Error & Root of mse & R2 Score

In [39]:
```
from sklearn.metrics import mean_squared_error, r2_score
```

In [40]:
```
mse  = mean_squared_error(y_test,y_pred)
```

In [41]:
```
mse
```

Out[41]:
```
36.517214730838624
```

In [44]:
```
rmse = np.sqrt(mse)
```

In [45]:
```
rmse
```

Out[45]:
```
6.042947520112898
```

In [42]:
```
r2 = r2_score(y_test,y_pred)
```

In [43]:
```
r2
```

Out[43]:
```
0.6015774471545622
```

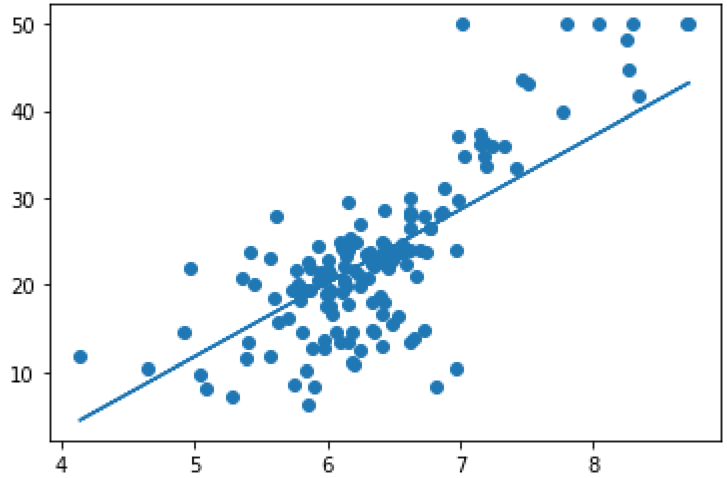
Output values of mse / rmse and r2 :

In [46]:
```
print("mse: {}, rmse: {}, r2: {}".format(mse,rmse,r2))
```

```
mse: 36.517214730838624, rmse: 6.042947520112898, r2: 0.6015774471545622
```

Plotting the model :

In [47]:
```
plt.figure()
plt.scatter(X_test,y_test)
plt.plot(X_test,y_pred)
plt.show()
```



Now , for ltest and medv column :

In [51]:
```
X = df[["lstat"]]
y = df["medv"]
```

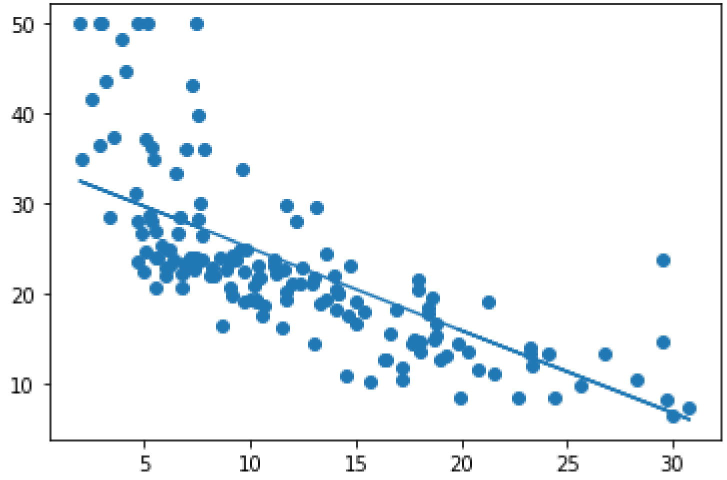
In [52]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3, random_state=1)
```

In [49]:
```
model = LinearRegression()
model.fit(X_train,y_train)
print(model.intercept_)
print(model.coef_)
y_pred = model.predict(X_test)
mse = mean_squared_error(y_test,y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test,y_pred)
print("mse: {}, rmse: {}, r2: {}".format(mse,rmse,r2))
```

```
34.22183685037717
[-0.9166916]
mse: 42.62024347153971, rmse: 6.528418144661057, r2: 0.5349901044757204
```

Plotting the Model :

In [50]:
```
plt.figure()
plt.scatter(X_test,y_test)
plt.plot(X_test,y_pred)
plt.show()
```



Now , for ptratio and medv column :

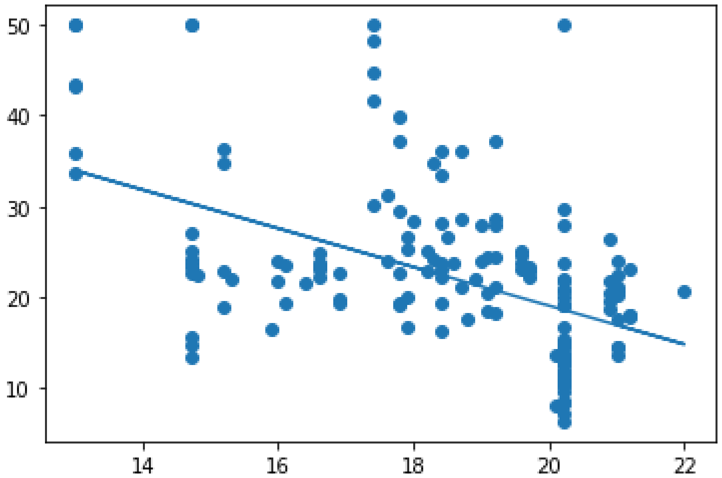
In [53]:
```
X = df[["ptratio"]]
y = df["medv"]
```

In [54]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3, random_state=1)
```

In [55]:
```
model = LinearRegression()
model.fit(X_train,y_train)
print(model.intercept_)
print(model.coef_)
y_pred = model.predict(X_test)
mse = mean_squared_error(y_test,y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test,y_pred)
print("mse: {}, rmse: {}, r2: {}".format(mse,rmse,r2))
```

```
61.728347935790936
[-2.13474825]
mse: 68.41481947991122, rmse: 8.27132513445767, r2: 0.2535573364354444
```

In [56]:
```
plt.figure()
plt.scatter(X_test,y_test)
plt.plot(X_test,y_pred)
plt.show()
```



Multiple Linear Regression :

In [57]:
```
X = df[["rm","lstat","ptratio"]]
y = df["medv"]
```

In [58]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3, random_state=1)
```

In [59]:
```
model = LinearRegression()
model.fit(X_train,y_train)
print(model.intercept_)
print(model.coef_)
y_pred = model.predict(X_test)
mse = mean_squared_error(y_test,y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test,y_pred)
print("mse: {}, rmse: {}, r2: {}".format(mse,rmse,r2))
```

```
25.373484464182265
[ 3.52839125 -0.60681801 -0.93396631]
mse: 25.40090941218404, rmse: 5.039931488838319, r2: 0.7228623473287099
```

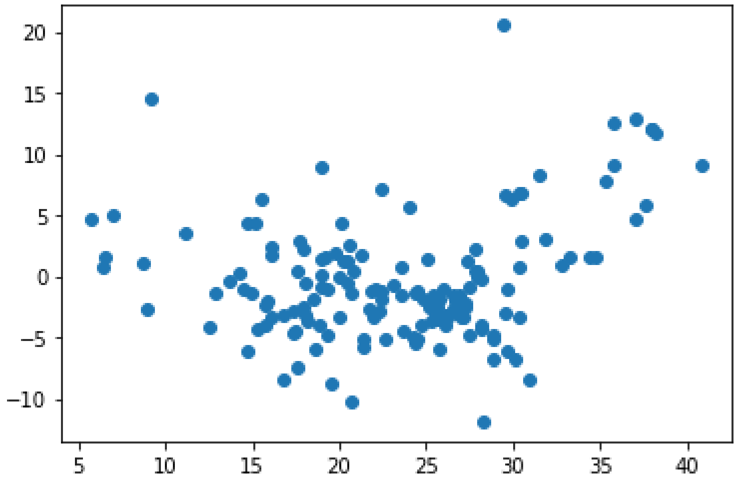
In [64]:
```
# # multi-dimentional plotting trick : y_pred and residual (assumption : linearity)
residual = y_test - y_pred
```

In [61]:
```
residual
```

Out[61]:
```
307    0.414884
343   -4.304832
47    -1.923508
67    -1.546179
362    1.556877
         ...
467    4.349062
95     0.497657
122    2.812779
260    0.972460
23     0.292812
Name: medv, Length: 152, dtype: float64
```

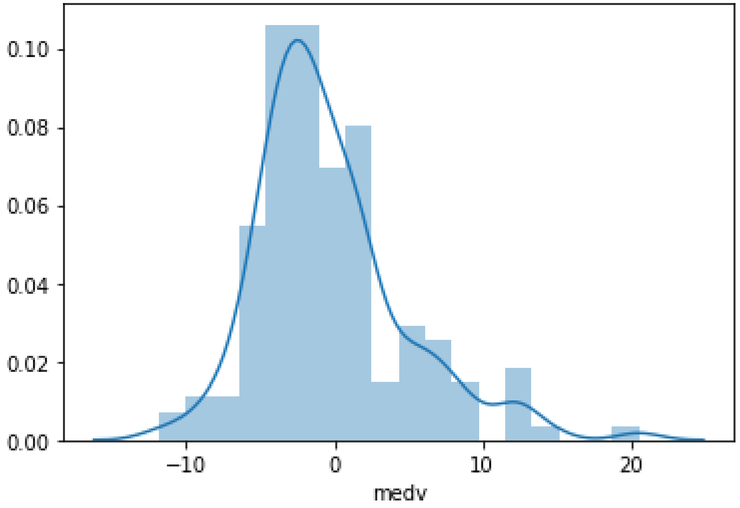
Scatter plot of y_pred & residual :

In [62]:
```
plt.figure()
plt.scatter(y_pred,residual)
plt.show()
```



Residual Histogram : (assumption : normal distribution)

In [63]:
```
plt.figure()
sns.distplot(residual)
plt.show()
```



Polynomial Regression :

In [70]:
```
from sklearn.preprocessing import PolynomialFeatures
```

In [71]:
```
poly = PolynomialFeatures(2)
```

In [72]:
```
X = df[["rm","lstat"]]
y = df["medv"]
```

In [73]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3, random_state=1)
```

In [74]:
```
X_train_poly = poly.fit_transform(X_train)
X_test_poly = poly.transform(X_test)
```

In [75]:
```
model = LinearRegression()
```

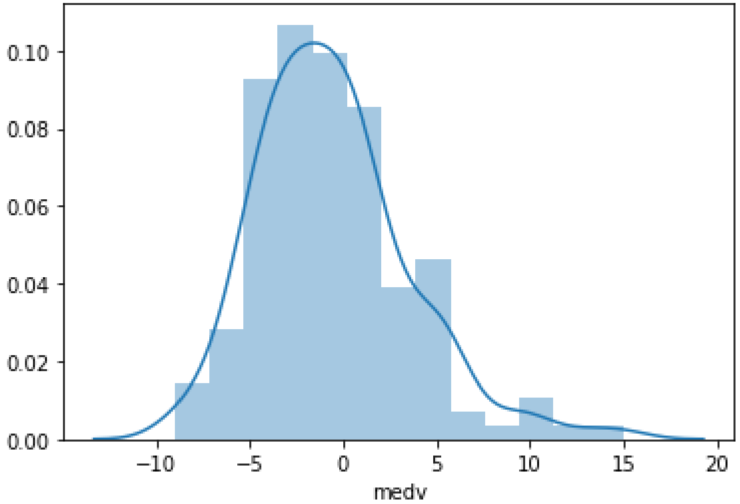
In [76]:
```
model.fit(X_train_poly, y_train)
y_pred = model.predict(X_test_poly)
```

In [77]:
```
mse = mean_squared_error(y_test,y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test,y_pred)

print("mse: {}, rmse: {}, r2: {}".format(mse,rmse,r2))
residual = y_test - y_pred
```

```
mse: 16.91540677390628, rmse: 4.112834396606102, r2: 0.8154437681254126
```

In [78]:
```
plt.figure()
sns.distplot(residual)
plt.show()
```



In [ ]: