Implementation Of SGD On Boston Dataset

In [1]:
```
import warnings
from scipy import stats
warnings.filterwarnings("ignore")
from sklearn.datasets import load_boston
from random import seed
from random import randrange
from csv import reader
from math import sqrt
from sklearn import preprocessing
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from prettytable import PrettyTable
from sklearn.linear_model import SGDRegressor
from sklearn import preprocessing
from sklearn.metrics import mean_squared_error
```

In [2]:
```
boston=load_boston()
```

In [3]:
```
print(boston.DESCR)
```

```
Boston House Prices dataset
===========================

Notes
------
Data Set Characteristics:

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive

    :Median Value (attribute 14) is usually the target

    :Attribute Information (in order):
        - CRIM     per capita crime rate by town
        - ZN       proportion of residential land zoned for lots over 25,
000 sq.ft.
        - INDUS    proportion of non-retail business acres per town
        - CHAS     Charles River dummy variable (= 1 if tract bounds rive
r; 0 otherwise)
        - NOX      nitric oxides concentration (parts per 10 million)
        - RM       average number of rooms per dwelling
        - AGE      proportion of owner-occupied units built prior to 1940
        - DIS      weighted distances to five Boston employment centres
        - RAD      index of accessibility to radial highways
        - TAX      full-value property-tax rate per $10,000
        - PTRATIO  pupil-teacher ratio by town
        - B        1000(Bk - 0.63)^2 where Bk is the proportion of blacks
by town
        - LSTAT    % lower status of the population
        - MEDV     Median value of owner-occupied homes in $1000's
```

```
    :Missing Attribute Values: None

    :Creator: Harrison, D. and Rubinfeld, D.L.

This is a copy of UCI ML housing dataset.
http://archive.ics.uci.edu/ml/datasets/Housing


This dataset was taken from the StatLib library which is maintained at Ca
rnegie Mellon University.

The Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedonic
prices and the demand for clean air', J. Environ. Economics & Management,
vol.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnos
tics
...', Wiley, 1980.   N.B. Various transformations are used in the table o
n
pages 244-261 of the latter.

The Boston house-price data has been used in many machine learning papers
that address regression
problems.

**References**

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influent
ial Data and Sources of Collinearity', Wiley, 1980. 244-261.
   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learnin
g. In Proceedings on the Tenth International Conference of Machine Learni
ng, 236-243, University of Massachusetts, Amherst. Morgan Kaufmann.
   - many more! (see http://archive.ics.uci.edu/ml/datasets/Housing)
```

In [4]:
```
X = load_boston().data
Y = load_boston().target
```

In [5]:
```
print(X.shape)
print(Y.shape)
```

```
(506, 13)
(506,)
```

In [6]:
```
print(type(X))
print(type(Y))
```

```
<class 'numpy.ndarray'>
<class 'numpy.ndarray'>
```

In [7]:
```
boston.feature_names
```

Out[7]:
```
array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7')
```

CREATING A DATAFRAME :

In [8]:
```
boston_load=pd.DataFrame(X,columns=boston.feature_names)
```

In [9]:
```
y=pd.DataFrame(Y,columns=['Output'])
```

In [10]:
```
boston_data=pd.concat([boston_load,y], axis=1, sort=False)
```

In [11]:
```
print(boston_data.shape)
```

```
(506, 14)
```

In [12]:
```
boston_data.describe()
```

Out[12]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.593761	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901
std	8.596783	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000
75%	3.647423	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000

In [13]:
```
boston_data.head(5)
```

Out[13]:

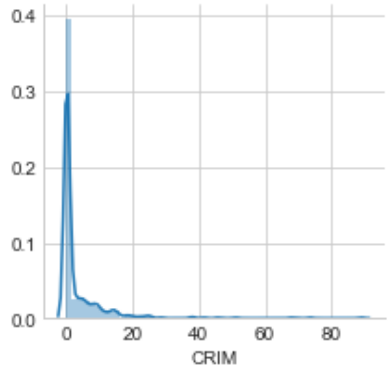
	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LS
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.9
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.1
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.0
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.9
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.3

Analysis Of Various Features

CRIM

In [14]:
```
sns.set_style("whitegrid")
sns.FacetGrid(boston_data).map(sns.distplot,"CRIM").add_legend();
plt.title('PLOTTING PDFS OF CRIM')
plt.show();
```

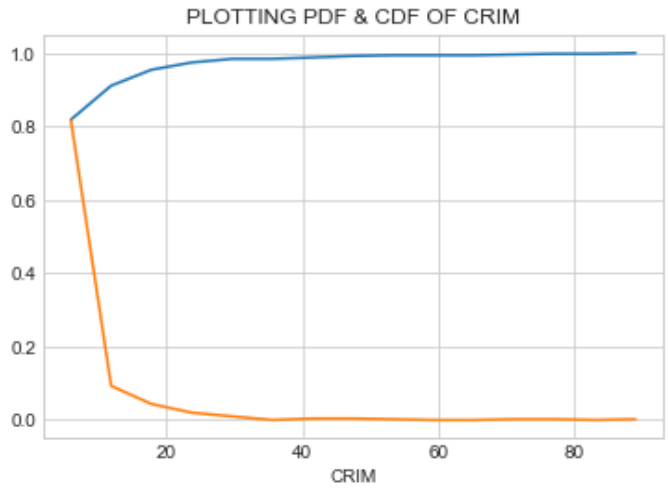
```
F:\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:6462: UserWarnin
g: The 'normed' kwarg is deprecated, and has been replaced by the 'densit
y' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



We observe that the distribution is almost like a Power Law Distribution. So we need to apply boxcox transform to convert it into gaussian distribution

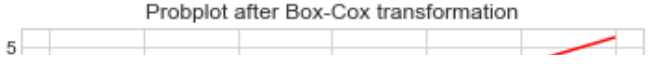
In [15]:
```
counts,binedges=np.histogram(boston_data['CRIM'],bins=15,density=True)
pdf=counts/(sum(counts))
print(pdf);
print(binedges)
cdf=np.cumsum(pdf)
plt.plot(binedges[1:],cdf)
plt.plot(binedges[1:],pdf)
plt.title('PLOTTING PDF & CDF OF CRIM')
plt.xlabel('CRIM')
plt.show();
```

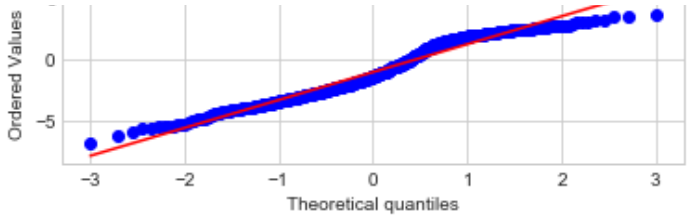
```
[0.81818182 0.09288538 0.04347826 0.01976285 0.00988142 0.
 0.00395257 0.00395257 0.00197628 0.         0.         0.00197628
 0.00197628 0.         0.00197628]
[6.32000000e-03 5.93764533e+00 1.18689707e+01 1.78002960e+01
 2.37316213e+01 2.96629467e+01 3.55942720e+01 4.15255973e+01
 4.74569227e+01 5.33882480e+01 5.93195733e+01 6.52508987e+01
 7.11822240e+01 7.71135493e+01 8.30448747e+01 8.89762000e+01]
```



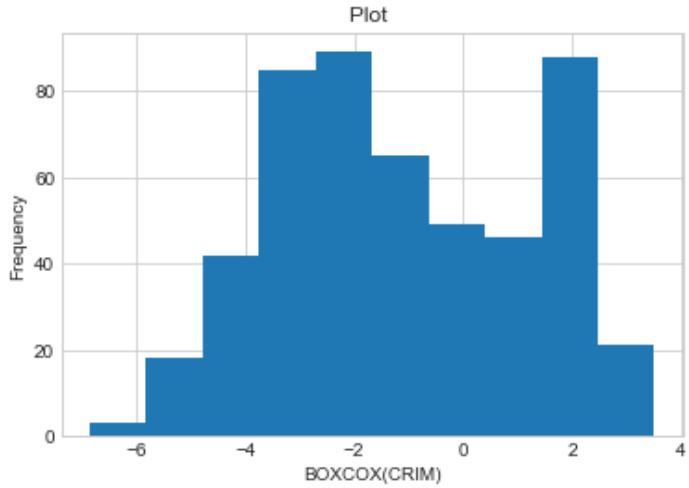
In [16]:
```
fig = plt.figure()
ax2 = fig.add_subplot(212)
crim,_ = stats.boxcox(boston_data["CRIM"])
prob = stats.probplot(crim, dist=stats.norm, plot=ax2)
ax2.set_title('Probplot after Box-Cox transformation')
```

Out[16]:
```
Text(0.5,1,'Probplot after Box-Cox transformation')
```





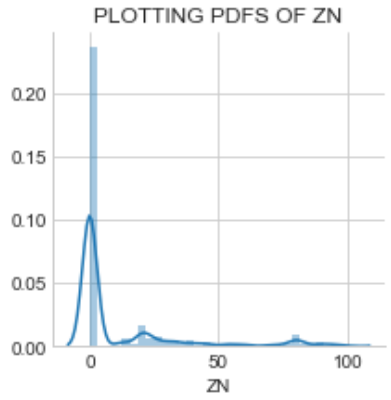
In [17]:
```
plt.hist(crim)
plt.title("Plot ")
plt.xlabel("BOXCOX(CRIM)")
plt.ylabel("Frequency")
plt.show()
```



ZN :

In [18]:
```
sns.set_style("whitegrid")
sns.FacetGrid(boston_data).map(sns.distplot,"ZN").add_legend();
plt.title('PLOTTING PDFS OF ZN')
plt.show();
```

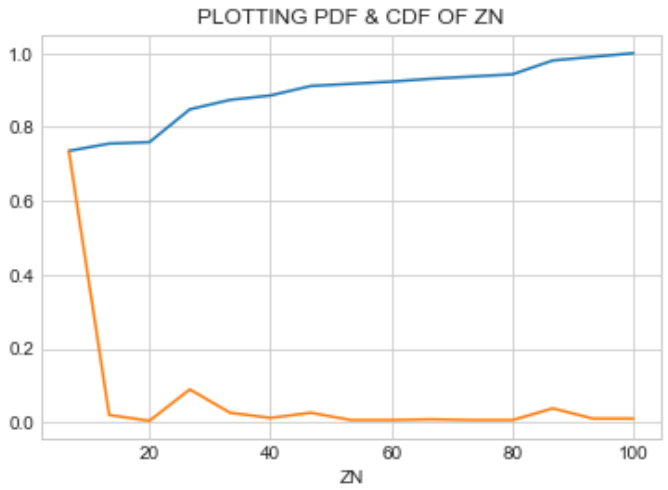
```
F:\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:6462: UserWarnin
g: The 'normed' kwarg is deprecated, and has been replaced by the 'densit
y' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



In [19]:
```
counts,binedges=np.histogram(boston_data['ZN'],bins=15,density=True)
pdf=counts/(sum(counts))
print(pdf);
print(binedges)
```

```
cdf=np.cumsum(pdf)
plt.plot(binedges[1:],cdf)
plt.plot(binedges[1:],pdf)
plt.title('PLOTTING PDF & CDF OF ZN')
plt.xlabel('ZN')
plt.show();
```

```
[0.73517787 0.01976285 0.00395257 0.08893281 0.0256917  0.01185771
 0.0256917  0.00592885 0.00592885 0.00790514 0.00592885 0.00592885
 0.03754941 0.00988142 0.00988142]
[  0.           6.66666667  13.33333333  20.          26.66666667
  33.33333333  40.          46.66666667  53.33333333  60.
  66.66666667  73.33333333  80.          86.66666667  93.33333333
 100.        ]
```

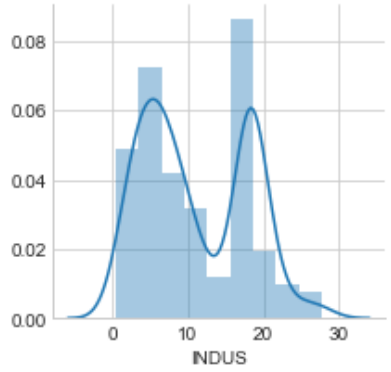


Here Data Is negative so box-cox transformation is having error here. So not getting any proper distribution

INDUS

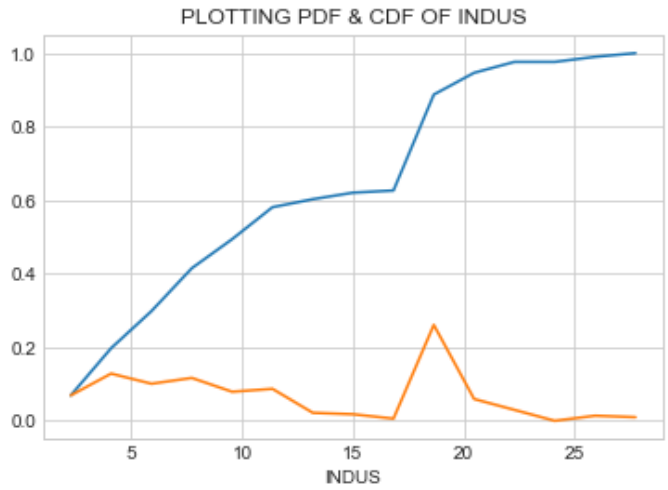
In [20]:
```
sns.set_style("whitegrid")
sns.FacetGrid(boston_data).map(sns.distplot,"INDUS").add_legend();
plt.title('PLOTTING PDFS OF INDUS')
plt.show();
```

```
F:\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:6462: UserWarnin
g: The 'normed' kwarg is deprecated, and has been replaced by the 'densit
y' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



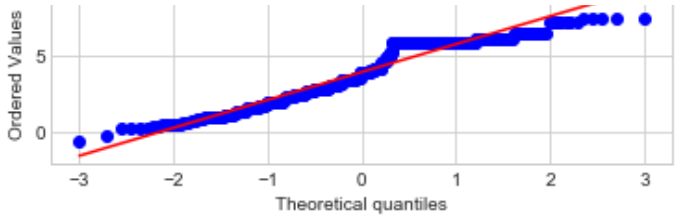
In [21]:
```
counts,binedges=np.histogram(boston_data['INDUS'],bins=15,density=True)
pdf=counts/(sum(counts))
print(pdf);
print(binedges)
cdf=np.cumsum(pdf)
plt.plot(binedges[1:],cdf)
plt.plot(binedges[1:],pdf)
plt.title('PLOTTING PDF & CDF OF INDUS')
plt.xlabel('INDUS')
plt.show();
```

```
[0.06916996 0.1284585  0.10079051 0.11660079 0.07905138 0.08695652
 0.02173913 0.01778656 0.00592885 0.26086957 0.05928854 0.02964427
 0.         0.01383399 0.00988142]
[ 0.46        2.27866667  4.09733333  5.916       7.73466667  9.55333333
 11.372      13.19066667 15.00933333 16.828      18.64666667 20.46533333
 22.284      24.10266667 25.92133333 27.74      ]
```

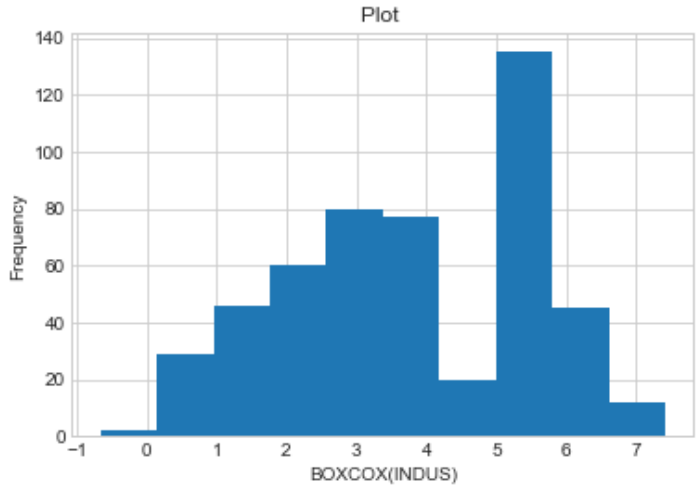


In [22]:
```
fig = plt.figure()
ax2 = fig.add_subplot(212)
indus,_ = stats.boxcox(boston_data["INDUS"])
prob = stats.probplot(indus, dist=stats.norm, plot=ax2)
ax2.set_title('Probplot after Box-Cox transformation')
```

Out[22]: Text(0.5,1,'Probplot after Box-Cox transformation')



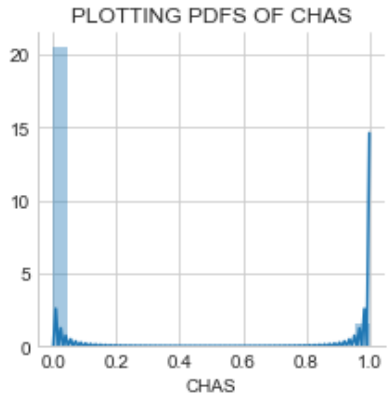
In [23]:
```
plt.hist(indus)
plt.title("Plot ")
plt.xlabel("BOXCOX(INDUS)")
plt.ylabel("Frequency")
plt.show()
```



CHAS

In [24]:
```
sns.set_style("whitegrid")
sns.FacetGrid(boston_data).map(sns.distplot,"CHAS").add_legend();
plt.title('PLOTTING PDFS OF CHAS')
plt.show();
```

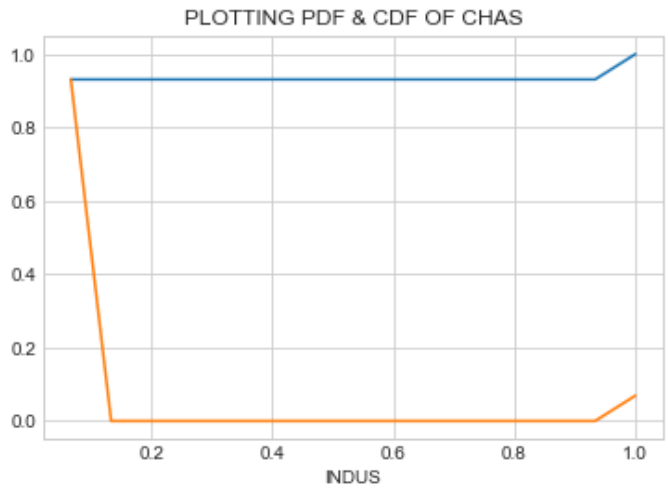
```
F:\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:6462: UserWarnin
g: The 'normed' kwarg is deprecated, and has been replaced by the 'densit
y' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



In [25]:
```
counts,binedges=np.histogram(boston_data['CHAS'],bins=15,density=True)
pdf=counts/(sum(counts))
print(pdf);
print(binedges)
```

```
cdf=np.cumsum(pdf)
plt.plot(binedges[1:],cdf)
plt.plot(binedges[1:],pdf)
plt.title('PLOTTING PDF & CDF OF CHAS')
plt.xlabel('INDUS')
plt.show();
```

```
[0.93083004 0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.06916996]
[0.         0.06666667 0.13333333 0.2        0.26666667 0.33333333
 0.4        0.46666667 0.53333333 0.6        0.66666667 0.73333333
 0.8        0.86666667 0.93333333 1.        ]
```

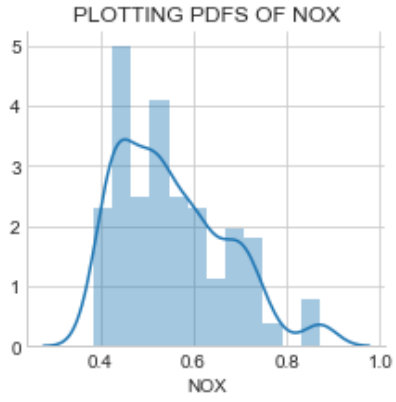


CHAS is a binary categorical feature which has very less 1.0 class features.

NOX

In [26]:
```
sns.set_style("whitegrid")
sns.FacetGrid(boston_data).map(sns.distplot,"NOX").add_legend();
plt.title('PLOTTING PDFS OF NOX')
plt.show();
```

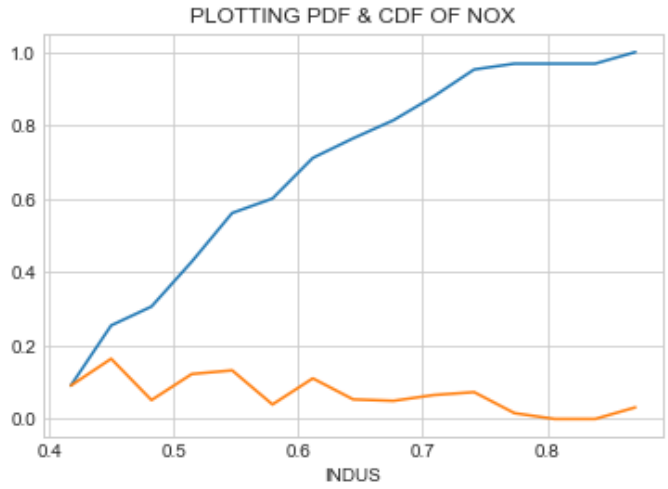
```
F:\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:6462: UserWarnin
g: The 'normed' kwarg is deprecated, and has been replaced by the 'densit
y' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



In [27]:
```
counts,binedges=np.histogram(boston_data['NOX'],bins=15,density=True)
```

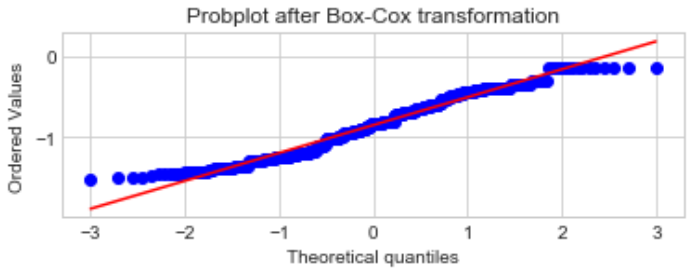
```
pdf=counts/(sum(counts))
print(pdf);
print(binedges)
cdf=np.cumsum(pdf)
plt.plot(binedges[1:],cdf)
plt.plot(binedges[1:],pdf)
plt.title('PLOTTING PDF & CDF OF NOX')
plt.xlabel('INDUS')
plt.show();
```

```
[0.09090909 0.16403162 0.0513834  0.12252964 0.13241107 0.03952569
 0.11067194 0.05335968 0.04940711 0.06521739 0.07312253 0.01581028
 0.         0.         0.03162055]
[0.385  0.4174 0.4498 0.4822 0.5146 0.547  0.5794 0.6118 0.6442 0.6766
 0.709  0.7414 0.7738 0.8062 0.8386 0.871 ]
```

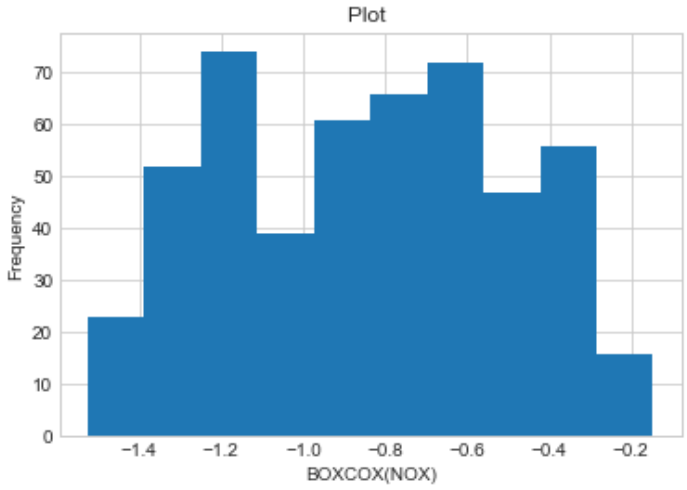


In [28]:
```
fig = plt.figure()
ax2 = fig.add_subplot(212)
nox,_ = stats.boxcox(boston_data["NOX"])
prob = stats.probplot(nox, dist=stats.norm, plot=ax2)
ax2.set_title('Probplot after Box-Cox transformation')
```

Out[28]:
```
Text(0.5,1,'Probplot after Box-Cox transformation')
```



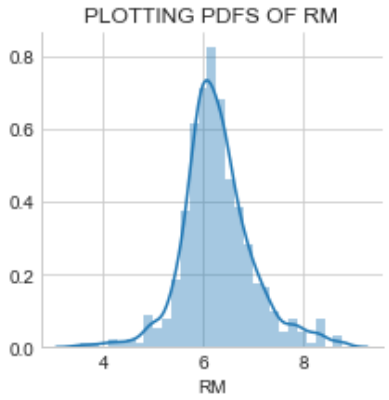
In [29]:
```
plt.hist(nox)
plt.title("Plot ")
plt.xlabel("BOXCOX(NOX)")
plt.ylabel("Frequency")
plt.show()
```



RM

In [30]:
```
sns.set_style("whitegrid")
sns.FacetGrid(boston_data).map(sns.distplot,"RM").add_legend();
plt.title('PLOTTING PDFS OF RM')
plt.show();
```

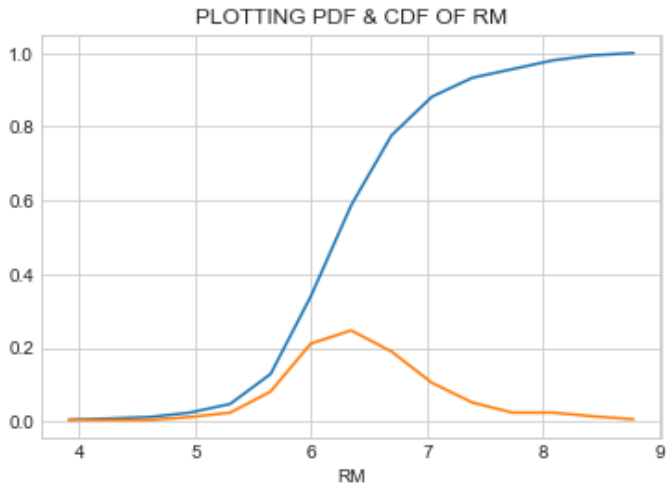
```
F:\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:6462: UserWarnin
g: The 'normed' kwarg is deprecated, and has been replaced by the 'densit
y' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



In [31]:
```
counts,binedges=np.histogram(boston_data['RM'],bins=15,density=True)
pdf=counts/(sum(counts))
print(pdf);
print(binedges)
cdf=np.cumsum(pdf)
plt.plot(binedges[1:],cdf)
plt.plot(binedges[1:],pdf)
plt.title('PLOTTING PDF & CDF OF RM')
plt.xlabel('RM')
plt.show();
```

```
[0.00395257 0.00395257 0.00395257 0.01185771 0.02371542 0.08102767
 0.21146245 0.24703557 0.18972332 0.10474308 0.0513834  0.02371542
 0.02371542 0.01383399 0.00592885]
[3.561      3.90893333 4.25686667 4.6048     4.95273333 5.30066667


 5.6486     5.99653333 6.34446667 6.6924     7.04033333 7.38826667
```

```
7.7362      8.08413333 8.43206667 8.78       ]
```

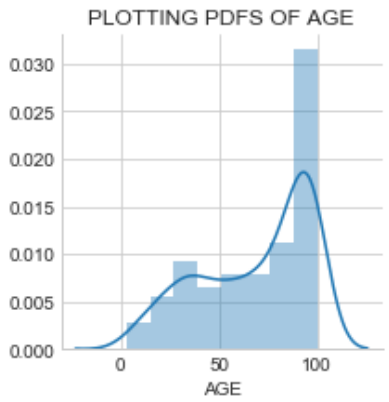


THIS DISTRIBUTION SEEMS TO BE ALMOST GAUSSIAN DISTRIBUTION

AGE

In [32]:
```
sns.set_style("whitegrid")
sns.FacetGrid(boston_data).map(sns.distplot,"AGE").add_legend();
plt.title('PLOTTING PDFS OF AGE')
plt.show();
```

```
F:\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:6462: UserWarnin
g: The 'normed' kwarg is deprecated, and has been replaced by the 'densit
y' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



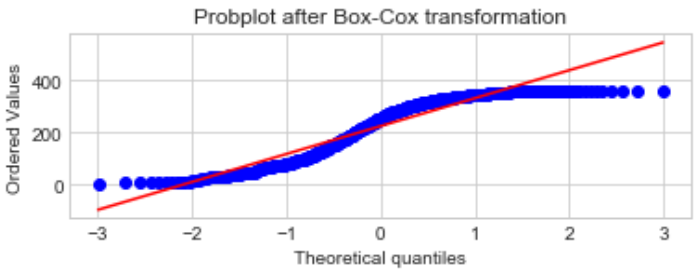
In [33]:
```
counts,binedges=np.histogram(boston_data['AGE'],bins=15,density=True)
pdf=counts/(sum(counts))
print(pdf);
print(binedges)
cdf=np.cumsum(pdf)
plt.plot(binedges[1:],cdf)
plt.plot(binedges[1:],pdf)
plt.title('PLOTTING PDF & CDF OF AGE')
plt.xlabel('AGE')
plt.show();
```

```
[0.02173913 0.01778656 0.04940711 0.02371542 0.06719368 0.04940711
 0.04940711 0.04940711 0.03952569 0.04743083 0.05533597 0.05731225
```

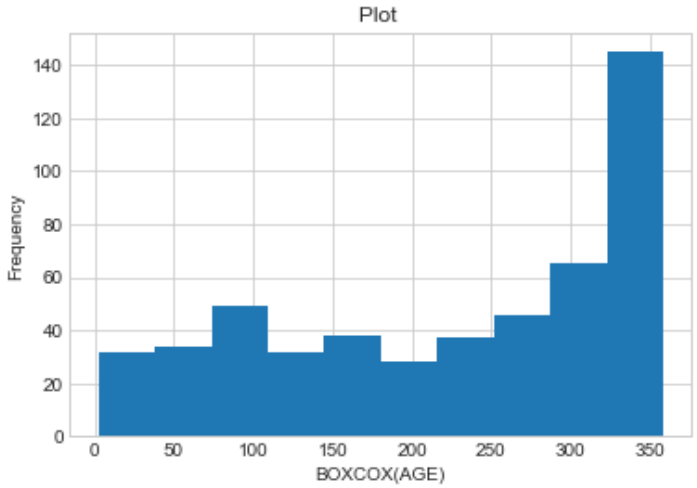
```
 0.08300395 0.12450593 0.26482213]
[  2.9          9.37333333  15.84666667  22.32        28.79333333
  35.26666667  41.74        48.21333333  54.68666667  61.16
  67.63333333  74.10666667  80.58        87.05333333  93.52666667
 100.        ]
```

In [34]:
```
fig = plt.figure()
ax2 = fig.add_subplot(212)
age,_ = stats.boxcox(boston_data["AGE"])
prob = stats.probplot(age, dist=stats.norm, plot=ax2)
ax2.set_title('Probplot after Box-Cox transformation')
```

Out[34]:
```
Text(0.5,1,'Probplot after Box-Cox transformation')
```



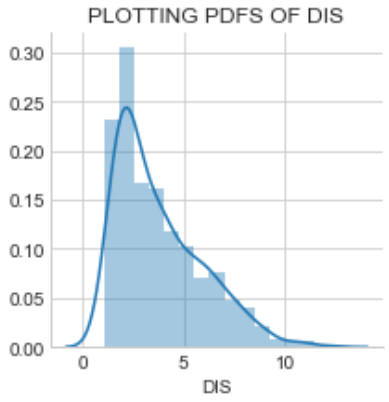
In [35]:
```
plt.hist(age)
plt.title("Plot ")
plt.xlabel("BOXCOX(AGE)")
plt.ylabel("Frequency")
plt.show()
```



DIS

In [36]:
```
sns.set_style("whitegrid")
sns.FacetGrid(boston_data).map(sns.distplot,"DIS").add_legend();
plt.title('PLOTTING PDFS OF DIS')
plt.show();
```

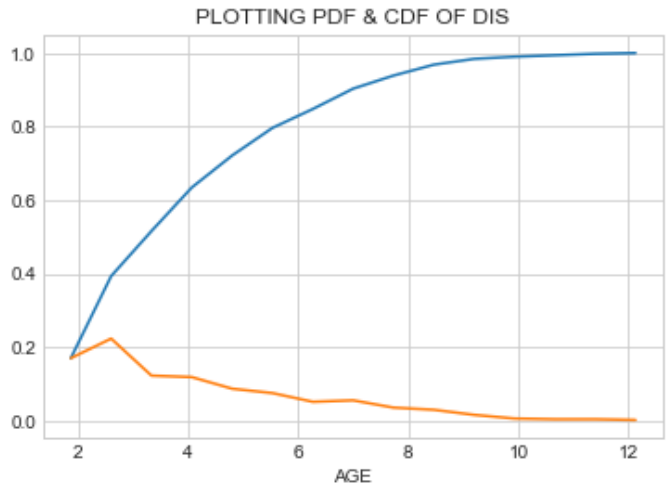
```
F:\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:6462: UserWarnin
g: The 'normed' kwarg is deprecated, and has been replaced by the 'densit
y' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



In [37]:
```
counts,binedges=np.histogram(boston_data['DIS'],bins=15,density=True)
pdf=counts/(sum(counts))
print(pdf);
print(binedges)
cdf=np.cumsum(pdf)
plt.plot(binedges[1:],cdf)
plt.plot(binedges[1:],pdf)
plt.title('PLOTTING PDF & CDF OF DIS')
plt.xlabel('AGE')
plt.show();
```

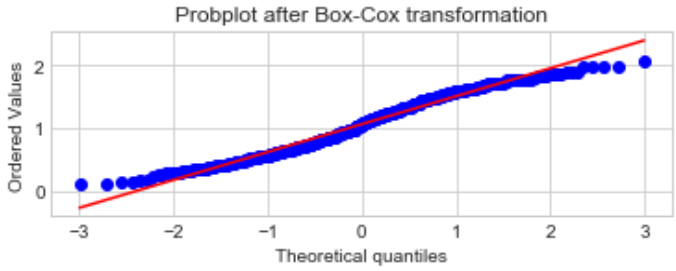
```
[0.16996047 0.22332016 0.12252964 0.11857708 0.08695652 0.07509881
 0.0513834  0.05533597 0.03557312 0.02964427 0.01581028 0.00592885
 0.00395257 0.00395257 0.00197628]
[ 1.1296      1.86272667  2.59585333  3.32898     4.06210667  4.79523333


  5.52836     6.26148667  6.99461333  7.72774     8.46086667  9.19399333
```

```
 9.92712    10.66024667 11.39337333 12.1265    ]
```

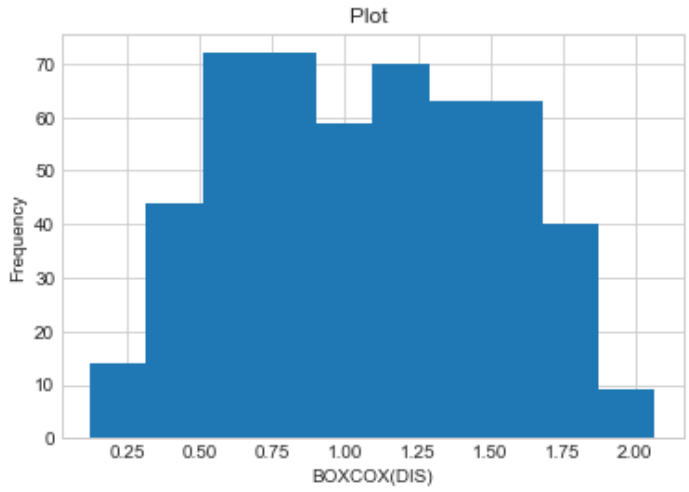


In [38]:
```
fig = plt.figure()
ax2 = fig.add_subplot(212)
dis,_ = stats.boxcox(boston_data["DIS"])
prob = stats.probplot(dis, dist=stats.norm, plot=ax2)
ax2.set_title('Probplot after Box-Cox transformation')
```

Out[38]:
```
Text(0.5,1,'Probplot after Box-Cox transformation')
```



In [39]:
```
plt.hist(dis)
plt.title("Plot ")
plt.xlabel("BOXCOX(DIS)")
plt.ylabel("Frequency")
plt.show()
```

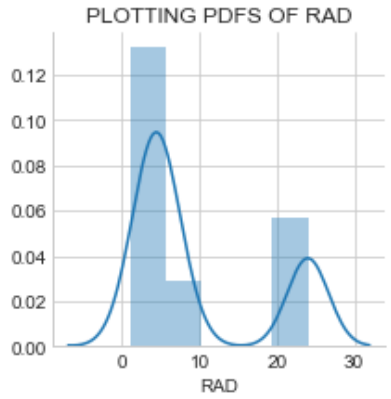


WE APPLY BOX COX TRANSFORM HERE AND SEE ALMOST GETTING LIKE A GAUSSIAN PATTERN

RAD

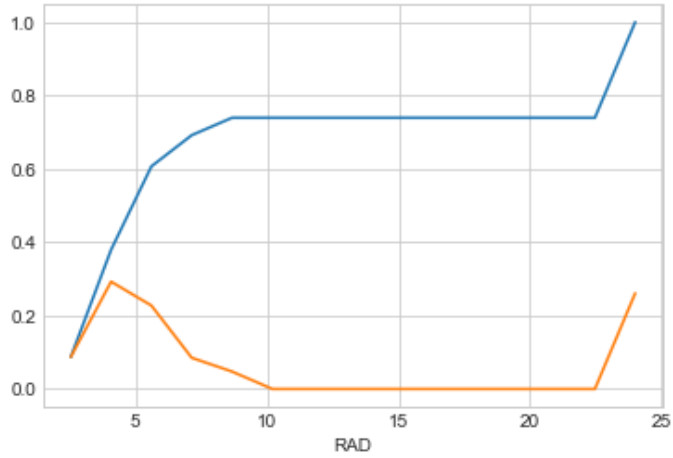
In [40]:
```
sns.set_style("whitegrid")
sns.FacetGrid(boston_data).map(sns.distplot,"RAD").add_legend();
plt.title('PLOTTING PDFS OF RAD')
plt.show();
```

```
F:\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:6462: UserWarnin
g: The 'normed' kwarg is deprecated, and has been replaced by the 'densit
y' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



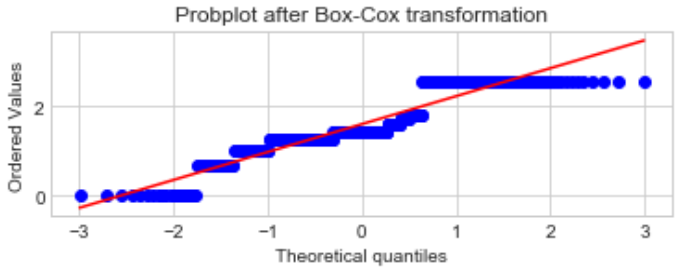
In [41]:
```
counts,binedges=np.histogram(boston_data['RAD'],bins=15,density=True)
pdf=counts/(sum(counts))
print(pdf);
print(binedges)
cdf=np.cumsum(pdf)
plt.plot(binedges[1:],cdf)
plt.plot(binedges[1:],pdf)
plt.title('PLOTTING PDF & CDF OF RAD')
plt.xlabel('RAD')
plt.show();
```

```
[0.08695652 0.29249012 0.22727273 0.08498024 0.04743083 0.
 0.         0.         0.         0.         0.
 0.         0.         0.26086957]
[ 1.          2.53333333  4.06666667  5.6         7.13333333  8.66666667
 10.2        11.73333333 13.26666667 14.8        16.33333333 17.86666667
 19.4        20.93333333 22.46666667 24.        ]
```

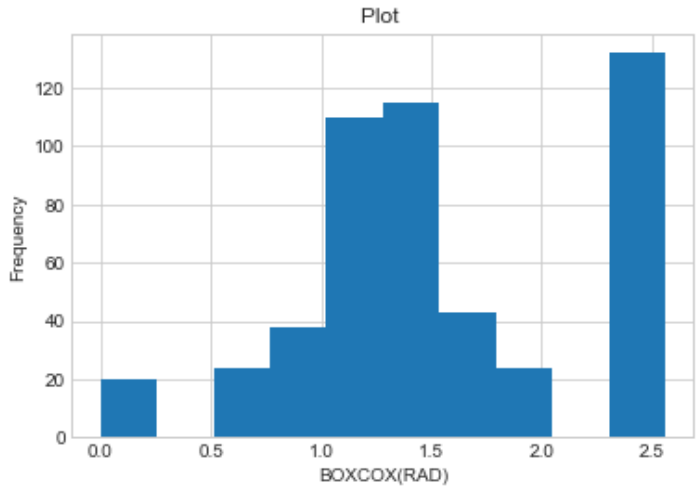


In [42]:
```
prob = stats.probplot(rad, dist=stats.norm, plot=ax2)
ax2.set_title('Probplot after Box-Cox transformation')
```

Out[42]: Text(0.5,1,'Probplot after Box-Cox transformation')



In [43]:
```
plt.hist(rad)
plt.title("Plot ")
plt.xlabel("BOXCOX(RAD)")
plt.ylabel("Frequency")
plt.show()
```



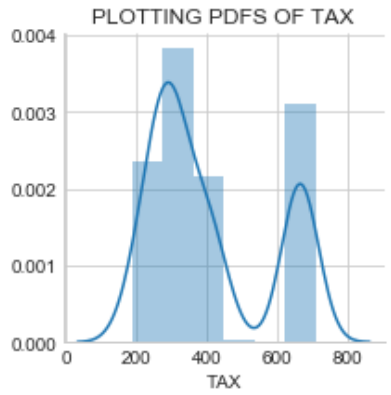
NOT SO USEFUL IN APPLYING BOX-COX TRANSFORM

TAX

In [44]:
```
sns.set_style("whitegrid")
sns.FacetGrid(boston_data).map(sns.distplot,"TAX").add_legend();
```

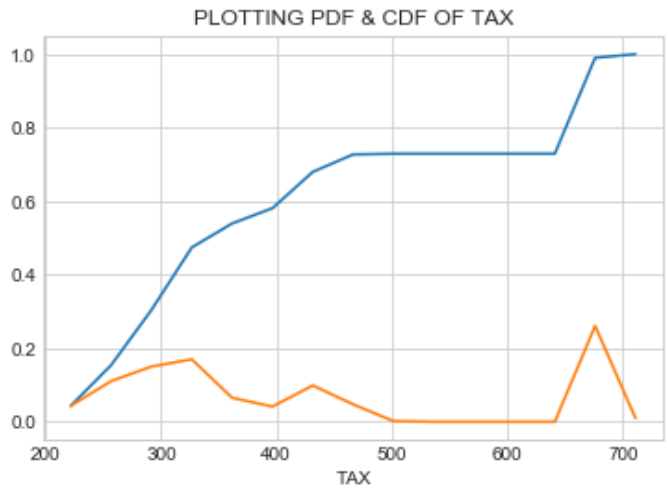
```
plt.title('PLOTTING PDFS OF TAX')
plt.show();
```

```
F:\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:6462: UserWarnin
g: The 'normed' kwarg is deprecated, and has been replaced by the 'densit
y' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



In [45]:
```
counts,binedges=np.histogram(boston_data['TAX'],bins=15,density=True)
pdf=counts/(sum(counts))
print(pdf);
print(binedges)
cdf=np.cumsum(pdf)
plt.plot(binedges[1:],cdf)
plt.plot(binedges[1:],pdf)
plt.title('PLOTTING PDF & CDF OF TAX')
plt.xlabel('TAX')
plt.show();
```

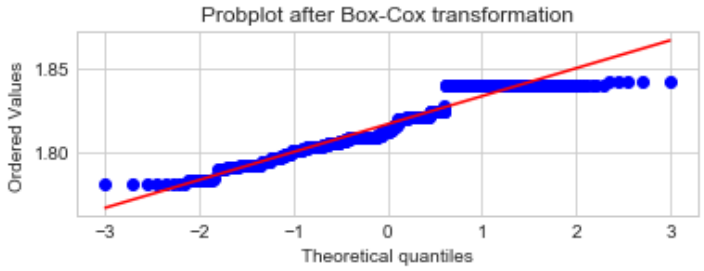
```
[0.04347826 0.11067194 0.15019763 0.16996047 0.06521739 0.04150198
 0.09881423 0.04743083 0.00197628 0.         0.         0.
 0.         0.26086957 0.00988142]
[187.         221.93333333 256.86666667 291.8        326.73333333
 361.66666667 396.6        431.53333333 466.46666667 501.4
 536.33333333 571.26666667 606.2        641.13333333 676.06666667
 711.        ]
```



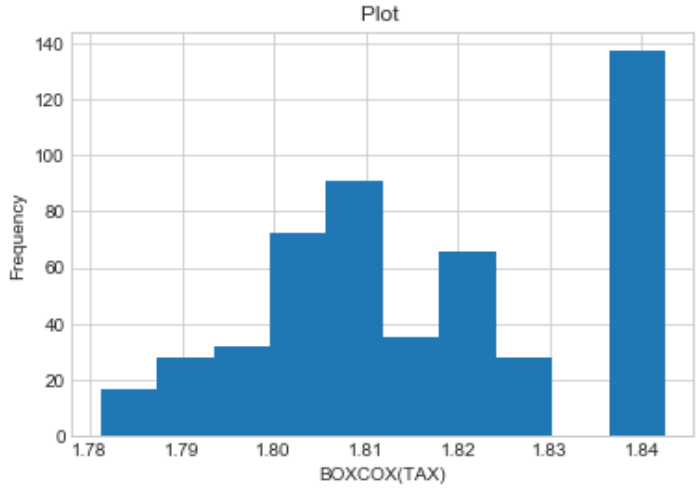
In [46]:
```
fig = plt.figure()
ax2 = fig.add_subplot(212)
tax,_ = stats.boxcox(boston_data["TAX"])
```

```
prob = stats.probplot(tax, dist=stats.norm, plot=ax2)
ax2.set_title('Probplot after Box-Cox transformation')
```

Out[46]: Text(0.5,1,'Probplot after Box-Cox transformation')



In [47]:
```
plt.hist(tax)
plt.title("Plot ")
plt.xlabel("BOXCOX(TAX)")
plt.ylabel("Frequency")
plt.show()
```

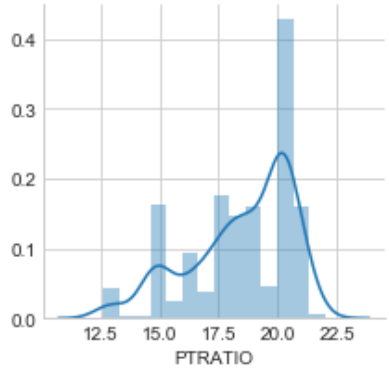


NOT SO USEFUL IN APPLYING BOX COX TRANSFORM

PTRATIO

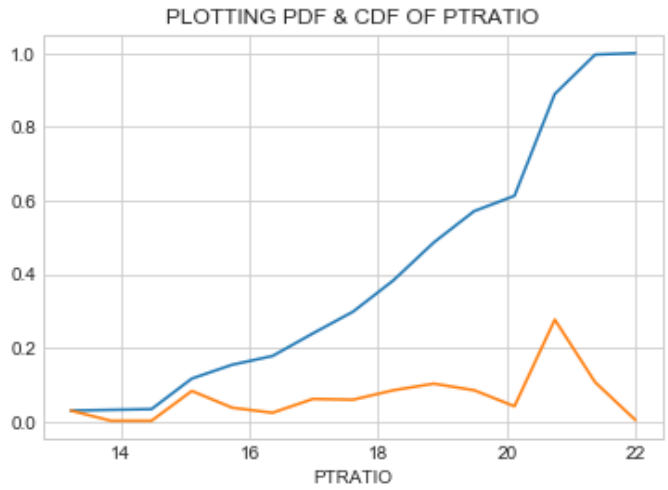
In [48]:
```
sns.set_style("whitegrid")
sns.FacetGrid(boston_data).map(sns.distplot,"PTRATIO").add_legend();
plt.title('PLOTTING PDFS OF PTRATIO')
plt.show();
```

```
F:\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:6462: UserWarnin
g: The 'normed' kwarg is deprecated, and has been replaced by the 'densit
y' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



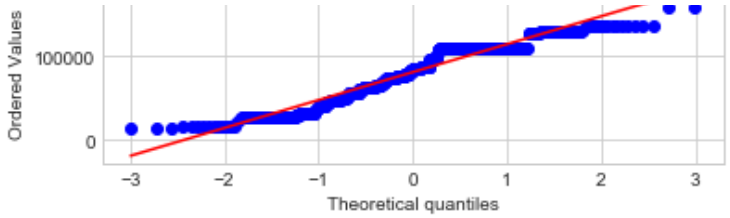
In [49]:
```
counts,binedges=np.histogram(boston_data['PTRATIO'],bins=15,density=True)
pdf=counts/(sum(counts))
print(pdf);
print(binedges)
cdf=np.cumsum(pdf)
plt.plot(binedges[1:],cdf)
plt.plot(binedges[1:],pdf)
plt.title('PLOTTING PDF & CDF OF PTRATIO')
plt.xlabel('PTRATIO')
plt.show();
```

```
[0.02964427 0.00197628 0.00197628 0.08300395 0.03754941 0.02371542
 0.06126482 0.05928854 0.08498024 0.1027668  0.08498024 0.04150198
 0.27667984 0.10671937 0.00395257]
[12.6        13.22666667 13.85333333 14.48       15.10666667 15.73333333
 16.36       16.98666667 17.61333333 18.24       18.86666667 19.49333333
 20.12       20.74666667 21.37333333 22.        ]
```

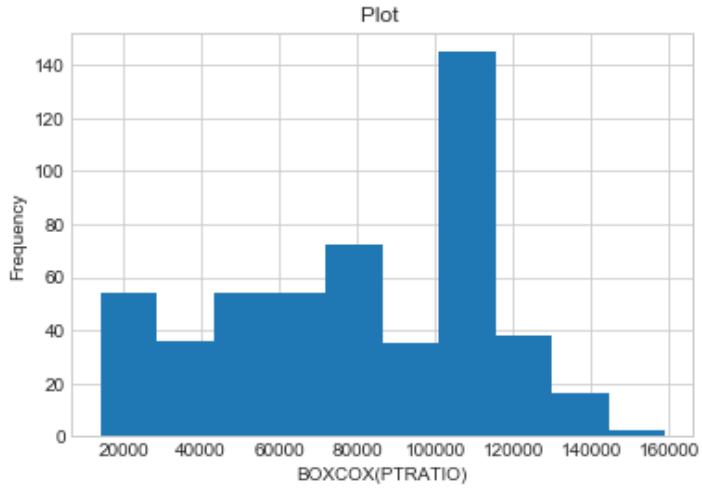


In [50]:
```
fig = plt.figure()
ax2 = fig.add_subplot(212)
ptratio,_ = stats.boxcox(boston_data["PTRATIO"])
prob = stats.probplot(ptratio, dist=stats.norm, plot=ax2)
ax2.set_title('Probplot after Box-Cox transformation')
```

Out[50]: Text(0.5,1,'Probplot after Box-Cox transformation')



In [51]:
```
plt.hist(ptratio)
plt.title("Plot ")
plt.xlabel("BOXCOX(PTRATIO)")
plt.ylabel("Frequency")
plt.show()
```

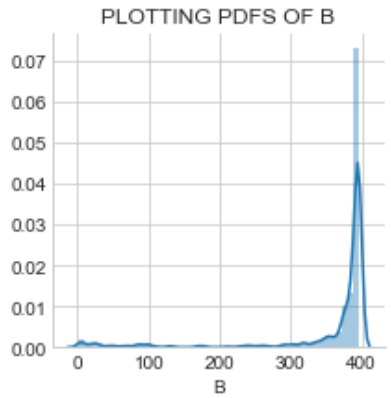


NOT MUCH USEFUL WE CAN CLEARLY SEE RIGHT SKEWED DISTRIBUTION

B

In [52]:
```
sns.set_style("whitegrid")
sns.FacetGrid(boston_data).map(sns.distplot,"B").add_legend();
plt.title('PLOTTING PDFS OF B')
plt.show();
```

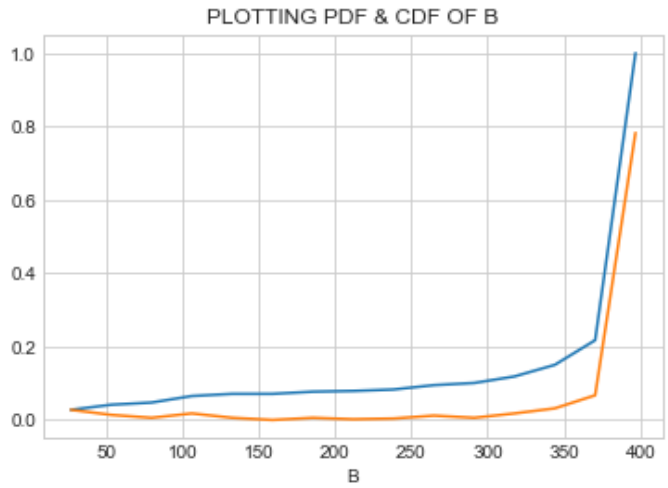
```
F:\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:6462: UserWarnin
g: The 'normed' kwarg is deprecated, and has been replaced by the 'densit
y' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



In [53]:
```
counts,binedges=np.histogram(boston_data['B'],bins=15,density=True)
```

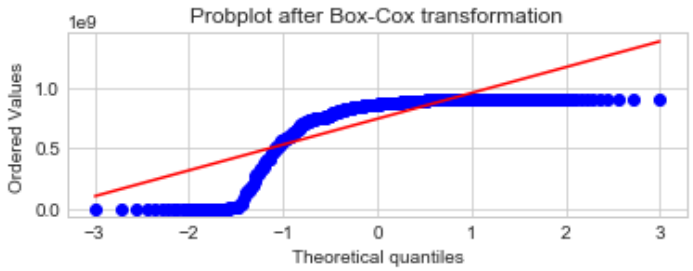
```
pdf=counts/(sum(counts))
print(pdf);
print(binedges)
cdf=np.cumsum(pdf)
plt.plot(binedges[1:],cdf)
plt.plot(binedges[1:],pdf)
plt.title('PLOTTING PDF & CDF OF B')
plt.xlabel('B')
plt.show();
```

```
[0.02766798 0.01383399 0.00592885 0.01778656 0.00592885 0.
 0.00592885 0.00197628 0.00395257 0.01185771 0.00592885 0.01778656
 0.03162055 0.06719368 0.7826087 ]
[3.20000000e-01 2.67586667e+01 5.31973333e+01 7.96360000e+01
 1.06074667e+02 1.32513333e+02 1.58952000e+02 1.85390667e+02
 2.11829333e+02 2.38268000e+02 2.64706667e+02 2.91145333e+02
 3.17584000e+02 3.44022667e+02 3.70461333e+02 3.96900000e+02]
```

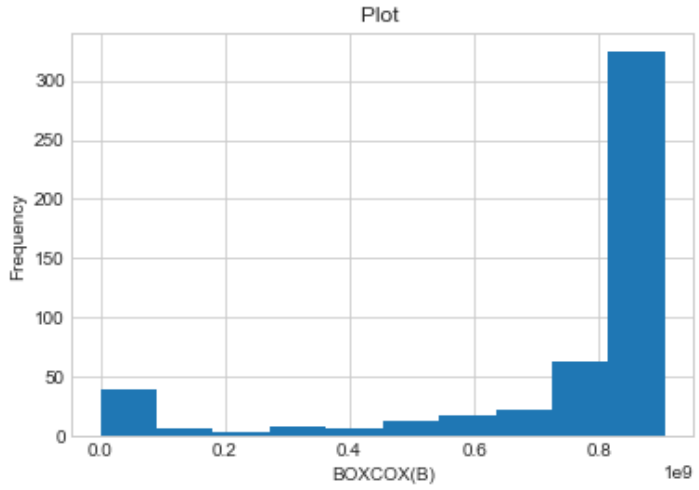


In [54]:
```
fig = plt.figure()
ax2 = fig.add_subplot(212)
b,_ = stats.boxcox(boston_data["B"])
prob = stats.probplot(b, dist=stats.norm, plot=ax2)
ax2.set_title('Probplot after Box-Cox transformation')
```

Out[54]: Text(0.5,1,'Probplot after Box-Cox transformation')



In [55]:
```
plt.hist(b)
plt.title("Plot ")
plt.xlabel("BOXCOX(B)")
plt.ylabel("Frequency")
plt.show()
```

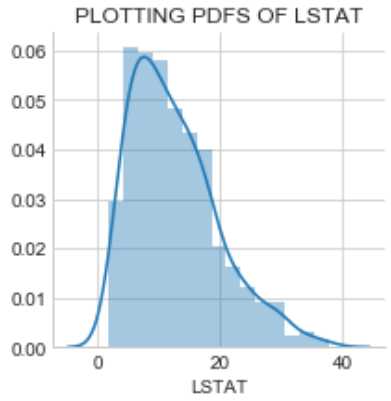


RIGHT SKEWED DISTRIBUTION. SO NOT MUCH USEFUL PERFORMING BOX COX TRANSFORM

LSTAT

In [56]:
```
sns.set_style("whitegrid")
sns.FacetGrid(boston_data).map(sns.distplot,"LSTAT").add_legend();
plt.title('PLOTTING PDFS OF LSTAT')
plt.show();
```

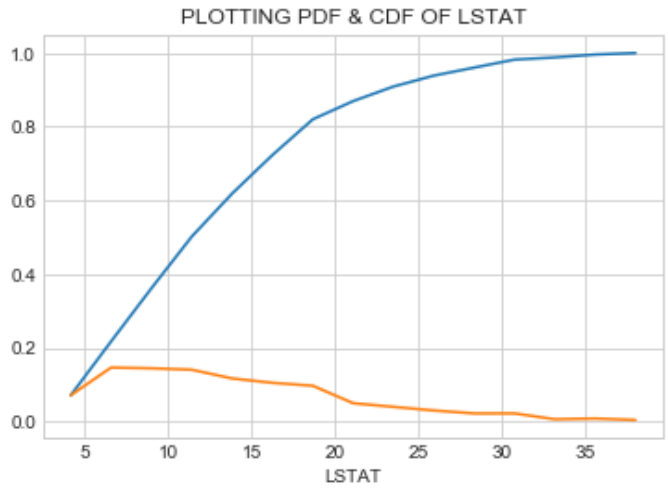
```
F:\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:6462: UserWarnin
g: The 'normed' kwarg is deprecated, and has been replaced by the 'densit
y' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



In [57]:
```
counts,binedges=np.histogram(boston_data['LSTAT'],bins=15,density=True)
pdf=counts/(sum(counts))
print(pdf);
print(binedges)
cdf=np.cumsum(pdf)
plt.plot(binedges[1:],cdf)
plt.plot(binedges[1:],pdf)
plt.title('PLOTTING PDF & CDF OF LSTAT')
plt.xlabel('LSTAT')
plt.show();
```

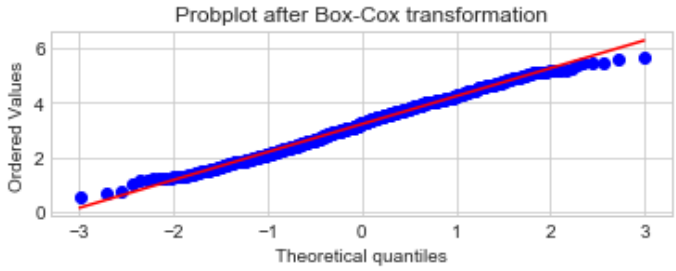
```
[0.07114625 0.14624506 0.14426877 0.14031621 0.11660079 0.10474308
 0.09683794 0.04940711 0.03952569 0.02964427 0.02173913 0.02173913
 0.00592885 0.00790514 0.00395257]
[ 1.73   4.146  6.562  8.978 11.394 13.81  16.226 18.642 21.058 23.474
```

```
25.89  28.306 30.722 33.138 35.554 37.97 ]
```

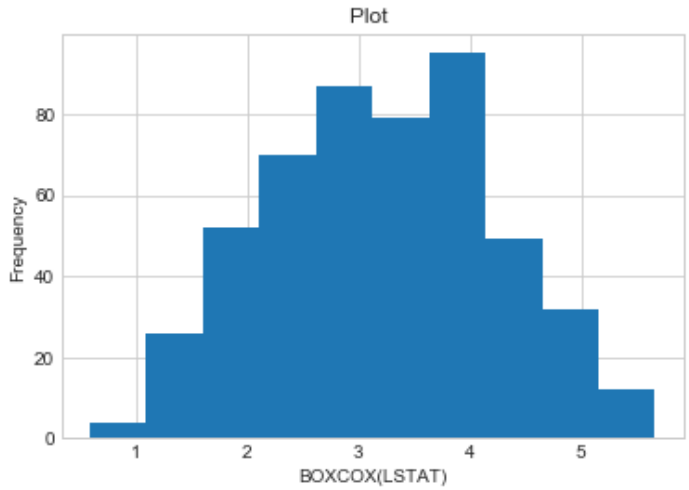


In [58]:
```
fig = plt.figure()
ax2 = fig.add_subplot(212)
lstat,_ = stats.boxcox(boston_data["LSTAT"])
prob = stats.probplot(lstat, dist=stats.norm, plot=ax2)
ax2.set_title('Probplot after Box-Cox transformation')
```

Out[58]:
```
Text(0.5,1,'Probplot after Box-Cox transformation')
```



In [59]:
```
plt.hist(lstat)
plt.title("Plot ")
plt.xlabel("BOXCOX(LSTAT)")
plt.ylabel("Frequency")
plt.show()
```



THE DISTRIBUTION ALMOST SEEMS LIKE A GAUSSIAN DISTRIBUTION

TRANSFORMING THE REQUIRED FEATURES : LSTAT,DIS,CRIM :

In [60]:
```
boston_data['CRIM']=crim
```

In [61]:
```
boston_data['DIS']=dis
```

In [62]:
```
boston_data['LSTAT']=lstat
```

In [63]:
```
boston_data.head()
```

Out[63]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B
0	-6.857264	18.0	2.31	0.0	0.538	6.575	65.2	1.264870	1.0	296.0	15.3	396.90
1	-4.453811	0.0	7.07	0.0	0.469	6.421	78.9	1.418585	2.0	242.0	17.8	396.90
2	-4.454917	0.0	7.07	0.0	0.469	7.185	61.1	1.418585	2.0	242.0	17.8	392.83
3	-4.199825	0.0	2.18	0.0	0.458	6.998	45.8	1.571460	3.0	222.0	18.7	394.63
4	-3.125902	0.0	2.18	0.0	0.458	7.147	54.2	1.571460	3.0	222.0	18.7	396.90

STANDARD SCALING OF THE FEATURES :

In [64]:
```
X=boston_data.drop("Output",axis =1)
Y=boston_data["Output"]
```

In [65]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size = 0.21,random
_state=100)
X_train,X_cv,Y_train,Y_cv = train_test_split(X_train,Y_train,test_size=0.25,
random_state=100)
print('Train - Predictors shape', X_train.shape)
print('CV - Predictors shape', X_cv.shape)
print('Test - Predictors shape', X_test.shape)
print('Train - Target shape', Y_train.shape)
print('CV - Target shape', Y_cv.shape)
print('Test - Target shape', Y_test.shape)
```

```
Train - Predictors shape (299, 13)
CV - Predictors shape (100, 13)
Test - Predictors shape (107, 13)
Train - Target shape (299,)
CV - Target shape (100,)
Test - Target shape (107,)
```

In [66]:
```
from sklearn.preprocessing import StandardScaler
crim = StandardScaler()
crim.fit(X_train['CRIM'].values.reshape(-1,1))
crim_train = crim.transform(X_train['CRIM'].values.reshape(-1,1))
crim_cv = crim.transform(X_cv['CRIM'].values.reshape(-1,1))
crim_test = crim.transform(X_test['CRIM'].values.reshape(-1,1))
print(crim_train.shape, Y_train.shape)
print(crim_cv.shape, Y_cv.shape)
print(crim_test.shape, Y_test.shape)
```

```
zn = StandardScaler()
zn.fit(X_train['ZN'].values.reshape(-1,1))
zn_train = zn.transform(X_train['ZN'].values.reshape(-1,1))
zn_cv = zn.transform(X_cv['ZN'].values.reshape(-1,1))
zn_test = zn.transform(X_test['ZN'].values.reshape(-1,1))
print(zn_train.shape, Y_train.shape)
print(zn_cv.shape, Y_cv.shape)
print(zn_test.shape, Y_test.shape)

indus = StandardScaler()
indus.fit(X_train['INDUS'].values.reshape(-1,1))
indus_train = indus.transform(X_train['INDUS'].values.reshape(-1,1))
indus_cv = indus.transform(X_cv['INDUS'].values.reshape(-1,1))
indus_test = indus.transform(X_test['INDUS'].values.reshape(-1,1))
print(indus_train.shape, Y_train.shape)
print(indus_cv.shape, Y_cv.shape)
print(indus_test.shape, Y_test.shape)

nox = StandardScaler()
nox.fit(X_train['NOX'].values.reshape(-1,1))
nox_train = nox.transform(X_train['NOX'].values.reshape(-1,1))
nox_cv = nox.transform(X_cv['NOX'].values.reshape(-1,1))
nox_test = nox.transform(X_test['NOX'].values.reshape(-1,1))
print(nox_train.shape, Y_train.shape)
print(nox_cv.shape, Y_cv.shape)
print(nox_test.shape, Y_test.shape)

rm = StandardScaler()
rm.fit(X_train['RM'].values.reshape(-1,1))
rm_train = rm.transform(X_train['RM'].values.reshape(-1,1))
rm_cv = rm.transform(X_cv['RM'].values.reshape(-1,1))
rm_test = rm.transform(X_test['RM'].values.reshape(-1,1))
print(rm_train.shape, Y_train.shape)
print(rm_cv.shape, Y_cv.shape)
print(rm_test.shape, Y_test.shape)

age = StandardScaler()
age.fit(X_train['AGE'].values.reshape(-1,1))
age_train = age.transform(X_train['AGE'].values.reshape(-1,1))
age_cv = age.transform(X_cv['AGE'].values.reshape(-1,1))
age_test = age.transform(X_test['AGE'].values.reshape(-1,1))
print(age_train.shape, Y_train.shape)
print(age_cv.shape, Y_cv.shape)
print(age_test.shape, Y_test.shape)

dis = StandardScaler()
dis.fit(X_train['DIS'].values.reshape(-1,1))
dis_train = dis.transform(X_train['DIS'].values.reshape(-1,1))
dis_cv = dis.transform(X_cv['DIS'].values.reshape(-1,1))
dis_test = dis.transform(X_test['DIS'].values.reshape(-1,1))
print(dis_train.shape, Y_train.shape)
print(dis_cv.shape, Y_cv.shape)
print(dis_test.shape, Y_test.shape)

rad = StandardScaler()
rad.fit(X_train['RAD'].values.reshape(-1,1))
rad_train = rad.transform(X_train['RAD'].values.reshape(-1,1))
rad_cv = rad.transform(X_cv['RAD'].values.reshape(-1,1))
rad_test = rad.transform(X_test['RAD'].values.reshape(-1,1))
print(rad_train.shape, Y_train.shape)
print(rad_cv.shape, Y_cv.shape)
print(rad_test.shape, Y_test.shape)
```

```
tax = StandardScaler()
tax.fit(X_train['TAX'].values.reshape(-1,1))
tax_train = tax.transform(X_train['TAX'].values.reshape(-1,1))
tax_cv = tax.transform(X_cv['TAX'].values.reshape(-1,1))
tax_test = tax.transform(X_test['TAX'].values.reshape(-1,1))
print(tax_train.shape, Y_train.shape)
print(tax_cv.shape, Y_cv.shape)
print(tax_test.shape, Y_test.shape)

ptratio = StandardScaler()
ptratio.fit(X_train['PTRATIO'].values.reshape(-1,1))
ptratio_train = ptratio.transform(X_train['PTRATIO'].values.reshape(-1,1))
ptratio_cv = ptratio.transform(X_cv['PTRATIO'].values.reshape(-1,1))
ptratio_test = ptratio.transform(X_test['PTRATIO'].values.reshape(-1,1))
print(ptratio_train.shape, Y_train.shape)
print(ptratio_cv.shape, Y_cv.shape)
print(ptratio_test.shape, Y_test.shape)

b = StandardScaler()
b.fit(X_train['B'].values.reshape(-1,1))
b_train = b.transform(X_train['B'].values.reshape(-1,1))
b_cv = b.transform(X_cv['B'].values.reshape(-1,1))
b_test = b.transform(X_test['B'].values.reshape(-1,1))
print(b_train.shape, Y_train.shape)
print(b_cv.shape, Y_cv.shape)
print(b_test.shape, Y_test.shape)

lstat = StandardScaler()
lstat.fit(X_train['LSTAT'].values.reshape(-1,1))
lstat_train = lstat.transform(X_train['LSTAT'].values.reshape(-1,1))
lstat_cv = lstat.transform(X_cv['LSTAT'].values.reshape(-1,1))
lstat_test = lstat.transform(X_test['LSTAT'].values.reshape(-1,1))
print(lstat_train.shape, Y_train.shape)
print(lstat_cv.shape, Y_cv.shape)
print(lstat_test.shape, Y_test.shape)
```

```
(299, 1) (299,)
(100, 1) (100,)
(107, 1) (107,)
(299, 1) (299,)
(100, 1) (100,)
(107, 1) (107,)
(299, 1) (299,)
(100, 1) (100,)
(107, 1) (107,)
(299, 1) (299,)
(100, 1) (100,)
(107, 1) (107,)
(299, 1) (299,)
(100, 1) (100,)
(107, 1) (107,)
(299, 1) (299,)
(100, 1) (100,)
(107, 1) (107,)
(299, 1) (299,)
(100, 1) (100,)
(107, 1) (107,)
(299, 1) (299,)
(100, 1) (100,)
(107, 1) (107,)
(299, 1) (299,)
(100, 1) (100,)
```

```
(107, 1) (107,)
(299, 1) (299,)
(100, 1) (100,)
(107, 1) (107,)
(299, 1) (299,)
(100, 1) (100,)
(107, 1) (107,)
(299, 1) (299,)
(100, 1) (100,)
(107, 1) (107,)
```

In [67]:
```
import scipy
crim_train = scipy.sparse.coo_matrix(crim_train)
crim_cv = scipy.sparse.coo_matrix(crim_cv)
crim_test = scipy.sparse.coo_matrix(crim_test)
zn_train = scipy.sparse.coo_matrix(zn_train)
zn_cv = scipy.sparse.coo_matrix(zn_cv)
zn_test = scipy.sparse.coo_matrix(zn_test)
indus_train = scipy.sparse.coo_matrix(indus_train)
indus_cv = scipy.sparse.coo_matrix(indus_cv)
indus_test = scipy.sparse.coo_matrix(indus_test)
nox_train = scipy.sparse.coo_matrix(nox_train)
nox_cv = scipy.sparse.coo_matrix(nox_cv)
nox_test = scipy.sparse.coo_matrix(nox_test)
rm_train = scipy.sparse.coo_matrix(rm_train)
rm_cv = scipy.sparse.coo_matrix(rm_cv)
rm_test = scipy.sparse.coo_matrix(rm_test)
age_train = scipy.sparse.coo_matrix(age_train)
age_cv = scipy.sparse.coo_matrix(age_cv)
age_test = scipy.sparse.coo_matrix(age_test)
dis_train = scipy.sparse.coo_matrix(dis_train)
dis_cv = scipy.sparse.coo_matrix(dis_cv)
dis_test = scipy.sparse.coo_matrix(dis_test)
rad_train = scipy.sparse.coo_matrix(rad_train)
rad_cv = scipy.sparse.coo_matrix(rad_cv)
rad_test = scipy.sparse.coo_matrix(rad_test)
tax_train = scipy.sparse.coo_matrix(tax_train)
tax_cv = scipy.sparse.coo_matrix(tax_cv)
tax_test = scipy.sparse.coo_matrix(tax_test)
ptratio_train = scipy.sparse.coo_matrix(ptratio_train)
ptratio_cv = scipy.sparse.coo_matrix(ptratio_cv)
ptratio_test = scipy.sparse.coo_matrix(ptratio_test)
b_train = scipy.sparse.coo_matrix(b_train)
b_cv = scipy.sparse.coo_matrix(b_cv)
b_test = scipy.sparse.coo_matrix(b_test)
lstat_train = scipy.sparse.coo_matrix(lstat_train)
lstat_cv = scipy.sparse.coo_matrix(lstat_cv)
lstat_test = scipy.sparse.coo_matrix(lstat_test)
```

In [68]:
```
from scipy.sparse import hstack
X_tr = hstack([crim_train,zn_train,indus_train,nox_train,rm_train,age_train,
dis_train,rad_train,tax_train,ptratio_train,b_train,lstat_train])
X_cv = hstack([crim_cv,zn_cv,indus_cv,nox_cv,rm_cv,age_cv,dis_cv,rad_cv,tax_
cv,ptratio_cv,b_cv,lstat_cv])
X_te = hstack([crim_test,zn_test,indus_test,nox_test,rm_test,age_test,dis_te
st,rad_test,tax_test,ptratio_test,b_test,lstat_test])
X_tr = X_tr.todense()
X_cv = X_cv.todense()
X_te = X_te.todense()
print("Final Data matrix")
```

```
print(X_tr.shape, Y_train.shape)
print(X_cv.shape, Y_cv.shape)
print(X_te.shape, Y_test.shape)
```

```
Final Data matrix
(299, 12) (299,)
(100, 12) (100,)
(107, 12) (107,)
```

LINEAR REGRESSION

In [69]:
```
from sklearn.linear_model import LinearRegression
linear = LinearRegression(fit_intercept = True ,normalize=False,n_jobs = -1)
linear.fit(X_tr, Y_train)
Y_pred = linear.predict(X_te)
```

In [70]:
```
linear_coeff=linear.coef_
```

In [71]:
```
from prettytable import PrettyTable
x=PrettyTable()
x.field_names=["Weights"]
for i in linear_coeff:
    x.add_row([round(i,2)])
print(x)
```

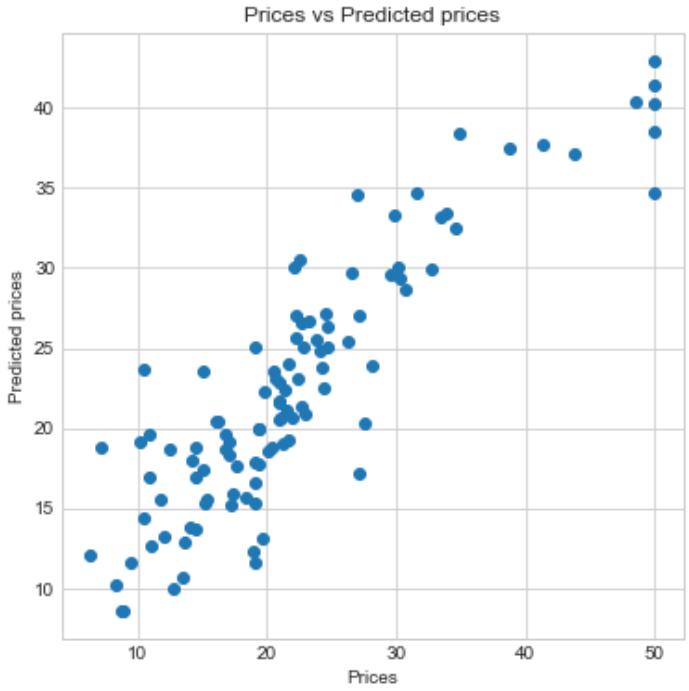
```
+---------+
| Weights |
+---------+
|   1.05  |
|   0.49  |
|  -0.01  |
|  -2.39  |
|   1.5   |
|   0.56  |
|  -3.22  |
|   1.76  |
|  -2.16  |
|   -1.7  |
|   0.96  |
|  -5.61  |
+---------+
```

In [72]:
```
from sklearn.metrics import mean_squared_error
mse = mean_squared_error(Y_test,Y_pred)
rmse = np.sqrt(mean_squared_error(Y_test, Y_pred))
R_squared= linear.score(X_te,Y_test)
print("Mean squared error : ",mse)
print("Root Mean Squared Error: ",rmse)
print("Coefficient of Determination: ",R_squared)
```

```
Mean squared error :  21.410761337697338
Root Mean Squared Error:  4.627176389300211
Coefficient of Determination:  0.7794783877320747
```

In [73]:
```
#ploting
plt.figure(figsize=(6,6))
sns.set_style('whitegrid')
plt.scatter(Y_test,Y_pred)
plt.xlabel("Prices")
```

```
plt.ylabel("Predicted prices")
plt.title("Prices vs Predicted prices")
plt.grid(True)
plt.show()
```



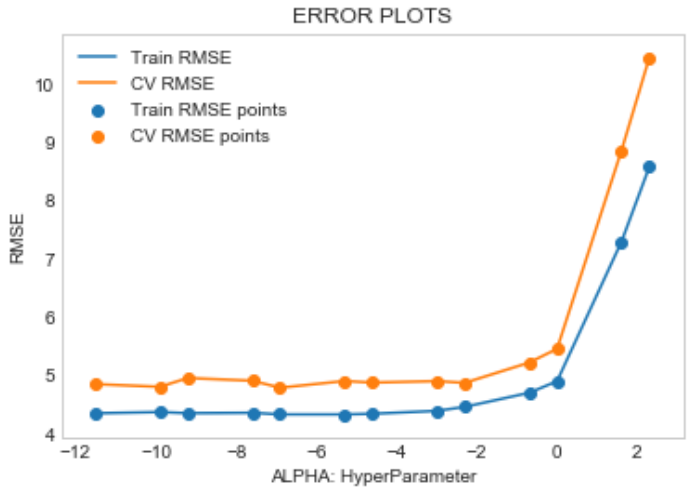
USING SCHOTASTIC GRADIENT DESCENT :

In [74]:
```
import tqdm
from sklearn.linear_model import SGDRegressor
train_rmse = []
cv_rmse = []
alphas = [0.00001, 0.00005, 0.0001, 0.0005, 0.001, 0.005, 0.01, 0.05, 0.1,
0.5, 1, 5, 10]
```

In [75]:
```
for i in alphas:
    sgd = SGDRegressor(loss='squared_loss',penalty='l1',alpha=i)
    sgd.fit(X_tr, Y_train)
    Y_predtrain = sgd.predict(X_tr)
    Y_predcv = sgd.predict(X_cv)
    rmsetrain = np.sqrt(mean_squared_error(Y_train, Y_predtrain))
    train_rmse.append(rmsetrain)
    rmsecv = np.sqrt(mean_squared_error(Y_cv, Y_predcv))
    cv_rmse.append(rmsecv)
```

In [76]:
```
import numpy
plt.plot(numpy.log(alphas), train_rmse, label='Train RMSE')
plt.plot(numpy.log(alphas), cv_rmse, label='CV RMSE')

plt.scatter(numpy.log(alphas), train_rmse, label='Train RMSE points')
plt.scatter(numpy.log(alphas), cv_rmse, label='CV RMSE points')

plt.legend()
plt.xlabel("ALPHA: HyperParameter")
plt.ylabel("RMSE")
plt.title("ERROR PLOTS")
```

```
plt.grid()
plt.show()
```



In [77]:
```
sgd = SGDRegressor(loss='squared_loss',penalty='l1',alpha=0.0001)
sgd.fit(X_tr, Y_train)
Y_pred= sgd.predict(X_te)
sgd_coeff=sgd.coef_
```

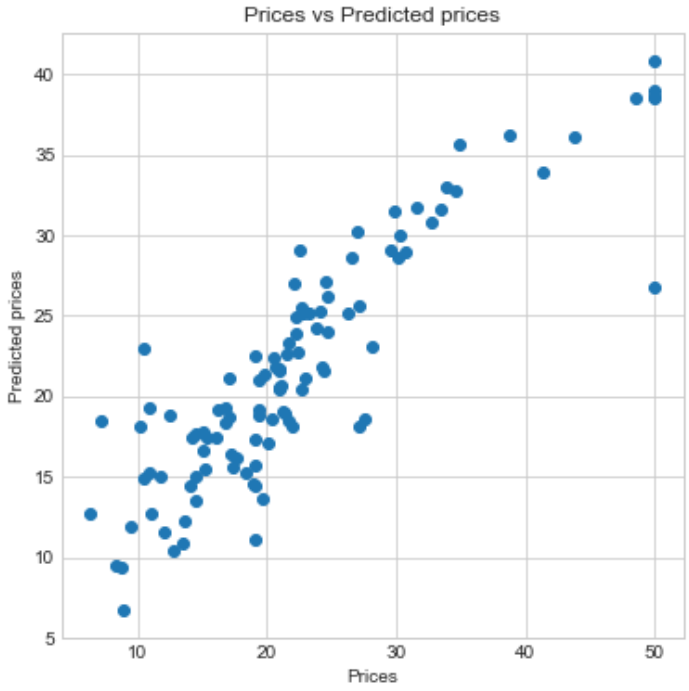
In [78]:
```
from prettytable import PrettyTable
x=PrettyTable()
x.field_names=["Weights"]
for i in sgd_coeff:
    x.add_row([round(i,2)])
print(x)
```

```
+---------+
| Weights |
+---------+
|   0.4   |
|   0.3   |
|   -0.6  |
|  -0.62  |
|   2.41  |
|  -0.03  |
|  -2.04  |
|   0.57  |
|  -0.62  |
|  -1.58  |
|   1.12  |
|  -4.12  |
+---------+
```

In [79]:
```
from sklearn.metrics import mean_squared_error
mse = mean_squared_error(Y_test,Y_pred)
rmse = np.sqrt(mean_squared_error(Y_test, Y_pred))
R_squared= sgd.score(X_te,Y_test)
print("Mean squared error : ",mse)
print("Root Mean Squared Error: ",rmse)
print("Coefficient of Determination: ",R_squared)
```

```
Mean squared error :  23.176867753650995
Root Mean Squared Error:  4.814235947027419
Coefficient of Determination:  0.7612882529610562
```

In [80]:
```
#ploting
plt.figure(figsize=(6,6))
sns.set_style('whitegrid')
plt.scatter(Y_test,Y_pred)
plt.xlabel("Prices")
plt.ylabel("Predicted prices")
plt.title("Prices vs Predicted prices")
plt.grid(True)
plt.show()
```



MANUAL SGD :

In [81]:
```
W,B,iteration,lr_rate,k=np.zeros(shape=(1,12)),0,750,0.01,299 #intialise W and B to zero
while iteration>=0:
    w,b,temp_vectors,temp_intercept=W,B,np.zeros(shape=(1,12)),0
    x=np.array(X_tr)
    y=np.array(Y_train)
    for i in range(k):
        temp_vectors+=(-2)*x[i]*(y[i]-(np.dot(w,x[i])+b))#partial differentiation wrt w dl/dw=1/k(-2x)*(y-wTx-b)
        temp_intercept+=(-2)*(y[i]-(np.dot(w,x[i])+b))#partial differentiation wrt b dl/db=1/k(-2)*(y-wTx-b)
    W=(w-lr_rate*(temp_vectors)/k)
    B=(b-lr_rate*(temp_intercept)/k)
    iteration-=1

print(W)
print(B)
```

```
[[ 1.01749806  0.41132651 -0.27180488 -2.11330295  1.59508463  0.48735389
  -3.0880859   1.22786145 -1.55280306 -1.65623543  0.98137146 -5.5160784
]]
[22.26220163]
```

In [82]:
```
W.shape
```

Out[82]: (1, 12)

In [83]:
```
X_te.T.shape
```

Out[83]: (12, 107)

In [84]:
```
#prediction on x_test
#https://www.geeksforgeeks.org/numpy-asscalar-in-python/
y_predic_lr=[]
for i in range(len(X_te)):
    val=(np.dot(W,X_te[i].T))+B   #val= wTx+b
    y_predic_lr.append(np.asscalar(val))
```

In [85]:
```
#Scatter plot of actual price vs predicted price

plt.scatter(Y_test,y_predic_lr)
plt.xlabel('Actual price')
plt.ylabel('Predictd price')
plt.title('Actual price vs Predicted price')
plt.show()
```

In [86]:
```
MSE_lr=mean_squared_error(Y_test,y_predic_lr)
print('mean squared error =',MSE_lr)
```

```
mean squared error = 21.369335685761953
```

In [87]:
```
from prettytable import PrettyTable
x = PrettyTable()
W=np.ravel(W)
x.field_names=['Weight vector manual']
W
```

Out[87]:
```
array([ 1.01749806,  0.41132651, -0.27180488, -2.11330295,  1.59508463,
        0.48735389, -3.0880859 ,  1.22786145, -1.55280306, -1.65623543,
        0.98137146, -5.5160784 ])
```

In [88]:
```
for i in range(len(W)):
    x.add_row([W[i]])
print(x)
```

```
+----------------------+
| Weight vector manual |
+----------------------+
|  1.0174980637590862  |
```

```
| 0.41132650855750125  |
| -0.2718048821473227  |
|  -2.113302946192935  |
|  1.595084634910593   |
|  0.4873538891187208  |
| -3.0880858981816974  |
|  1.2278614528949607  |
| -1.5528030594175883  |
| -1.6562354295573578  |
|  0.9813714589503894  |
|  -5.516078397158724  |
+----------------------+
```

CONCLUSION :

In [89]:
```
from prettytable import PrettyTable
#If you get a ModuleNotFoundError error , install prettytable using: pip3 in
stall prettytable
x=PrettyTable()
x.field_names=["Model","Metric","Value"]
x.add_row(["Linear Regression","MSE",21.410761337697338])
x.add_row(["Linear Regression","RMSE",4.627176389300211])
x.add_row(["SGD Regression(SKLEARN)","MSE",22.580122026939538])
x.add_row(["SGD Regression(SKLEARN)","RMSE",4.751854588151824])
x.add_row(["SGD Regression(MANUAL)","MSE",21.369335685761953])
print(x)
```

```
+--------------------------+--------+--------------------+
|          Model           | Metric |       Value        |
+--------------------------+--------+--------------------+
|    Linear Regression     |  MSE   | 21.410761337697338 |
|    Linear Regression     |  RMSE  | 4.627176389300211  |
| SGD Regression(SKLEARN)  |  MSE   | 22.580122026939538 |
| SGD Regression(SKLEARN)  |  RMSE  | 4.751854588151824  |
|  SGD Regression(MANUAL)  |  MSE   | 21.369335685761953 |
+--------------------------+--------+--------------------+
```