Boston Dataset-Linear Regression and Sctochastic Gradient Descent

In [1]:

```
%matplotlib inline
import warnings
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
import seaborn as sns
from sklearn import preprocessing
import pandas as pd
import numpy as np
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
```

Load Dataset

In [2]:

```
boston = load_boston()
```

In [3]:

```
type(boston)
```

Out[3]:

```
sklearn.utils.Bunch
```

In [4]:

```
print(boston.feature_names)
```

```
['CRIM' 'ZN' 'INDUS' 'CHAS' 'NOX' 'RM' 'AGE' 'DIS' 'RAD' 'TAX' 'PTRATIO'
 'B' 'LSTAT']
```

In [5]:

```
X = boston.data
Y = boston.target
```

In [6]:

```
print(boston.DESCR)
```

```
.. _boston_dataset:

Boston house prices dataset
---------------------------

**Data Set Characteristics:**

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive. Median Value (attribute 14) is
usually the target.
```

```
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 river; 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.
https://archive.ics.uci.edu/ml/machine-learning-databases/housing/


This dataset was taken from the StatLib library which is maintained at Carnegie 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 diagnostics
...', Wiley, 1980.   N.B. Various transformations are used in the table on
pages 244-261 of the latter.

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

.. topic:: References

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential Data and Sources of C
ollinearity', Wiley, 1980. 244-261.
   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning. In Proceedings on the T
enth International Conference of Machine Learning, 236-243, University of Massachusetts, Amherst.
Morgan Kaufmann.
```

In [7]:

```
print(type(X))
print(type(Y))
```

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

In [8]:

```
print(X.shape)
print(Y.shape)
```

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

Converting Numpy Array to DataFrame

In [9]:

```
boston_data=pd.DataFrame(X,columns=boston.feature_names)
```

In [10]:

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

In [11]:

```
print(boston_data.shape)
print(y.shape)
```

```
(506, 13)
(506, 1)
```

In [12]:

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

In [13]:

```
print(boston_data.shape)
```

```
(506, 14)
```

In [14]:

```
boston_data.describe()
```

Out[14]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTR
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.0
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	9.549407	408.237154	18.4
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259	168.537116	2.1
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.6
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000	279.000000	17.4
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000	330.000000	19.0
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000	666.000000	20.2
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.0

Mean and Standard Deviation of Output Column

In [15]:

```
mean_output=boston_data['Output'].mean()
```

In [16]:

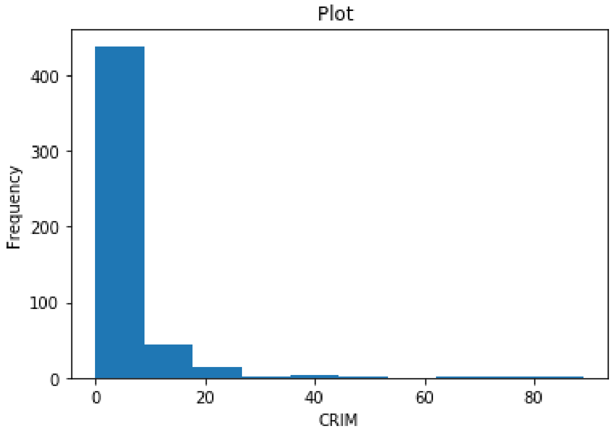
```
std_output=boston_data['Output'].std()
```

Analysis of Distribution of Features via Plots

CRIM Plots

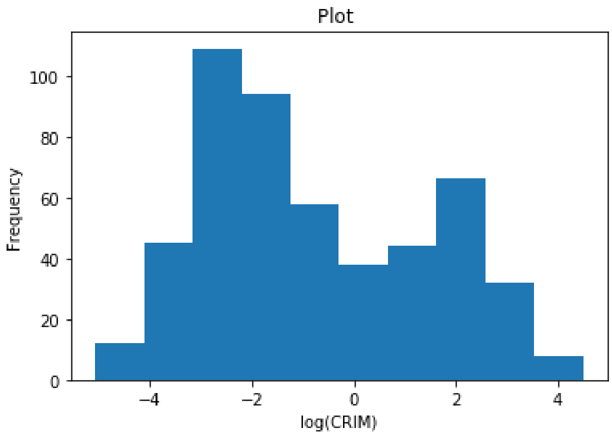
In [17]:

```
plt.hist(boston_data["CRIM"])
plt.title("Plot ")
plt.xlabel("CRIM")
plt.ylabel("Frequency")
plt.show()
```



In [18]:

```
plt.hist((np.log(boston_data["CRIM"])))
plt.title("Plot ")
plt.xlabel("log(CRIM)")
plt.ylabel("Frequency")
plt.show()
```

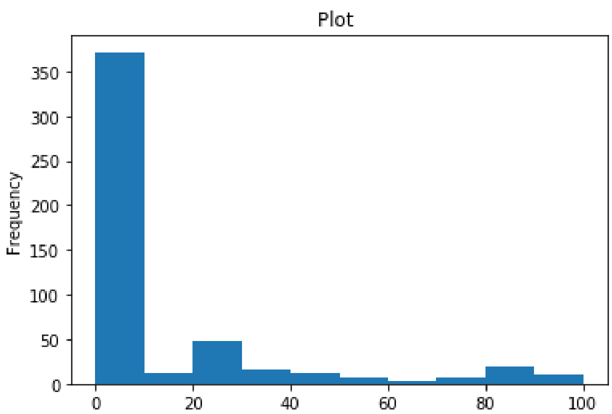


CRIM is an log normal distribution. So we apply log on it to get kind of Gaussian Distribution

ZN Plots

In [19]:

```
plt.hist(boston_data["ZN"])
plt.title("Plot ")
plt.xlabel("ZN")
plt.ylabel("Frequency")
plt.show()
```



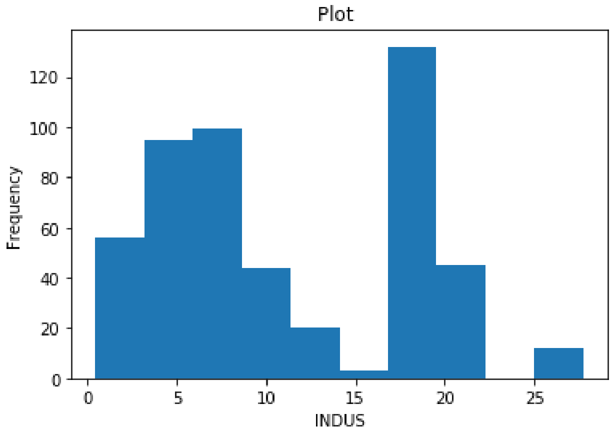
ZN

ZN plot looks like above one but any function is not giving any fruitful result.

INDUS Plots

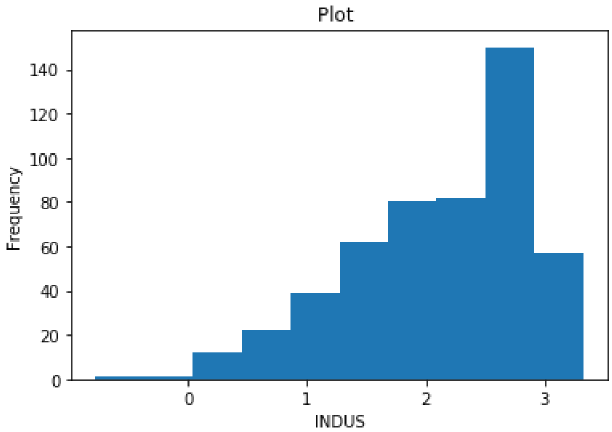
In [20]:

```
plt.hist(boston_data["INDUS"])
plt.title("Plot ")
plt.xlabel("INDUS")
plt.ylabel("Frequency")
plt.show()
```



In [21]:

```
plt.hist((np.log(boston_data["INDUS"])))
plt.title("Plot ")
plt.xlabel("INDUS")
plt.ylabel("Frequency")
plt.show()
```

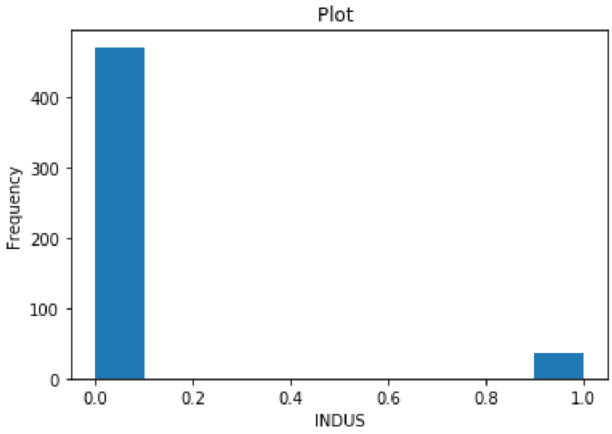


INDUS when applied with log gives a right skewed function. So transform is of no use.

CHAS Plots

In [22]:

```
plt.hist(boston_data["CHAS"])
plt.title("Plot ")
plt.xlabel("INDUS")
plt.ylabel("Frequency")
plt.show()
```

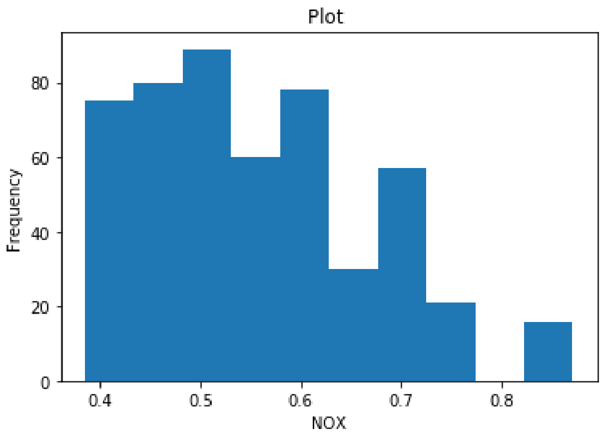


CHAS is a binary categorical feature which has very less 1.0 class features. So this feature may be ignored while creating prediciton model.

NOX Plots

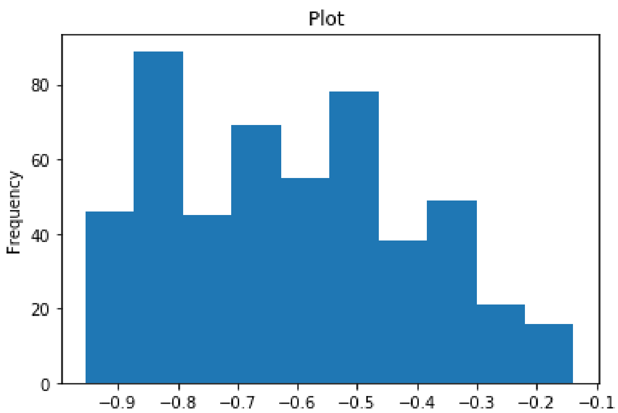
In [23]:

```
plt.hist(boston_data["NOX"])
plt.title("Plot ")
plt.xlabel("NOX")
plt.ylabel("Frequency")
plt.show()
```



In [24]:

```
plt.hist((np.log(boston_data["NOX"])))
plt.title("Plot ")
plt.xlabel("INDUS")
plt.ylabel("Frequency")
plt.show()
```



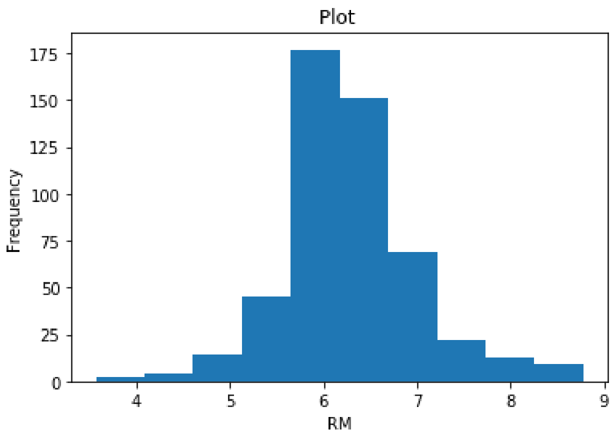
INDUS

NOX doesnt give any visually impressive plots when applied with log. So no need to apply log.

RM Plots

In [25]:

```
plt.hist(boston_data["RM"])
plt.title("Plot ")
plt.xlabel("RM")
plt.ylabel("Frequency")
plt.show()
```

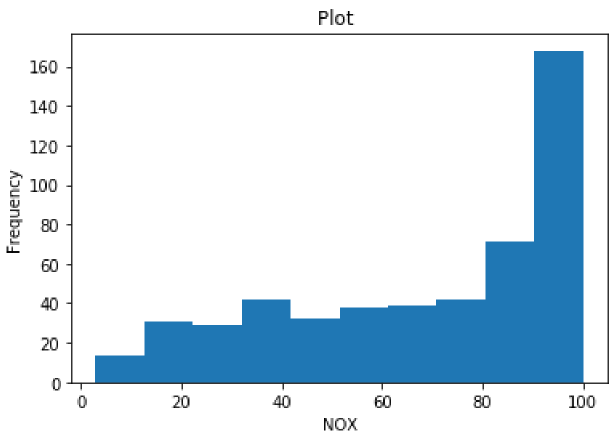


RM is already Gaussian Distributed.

AGE Plots

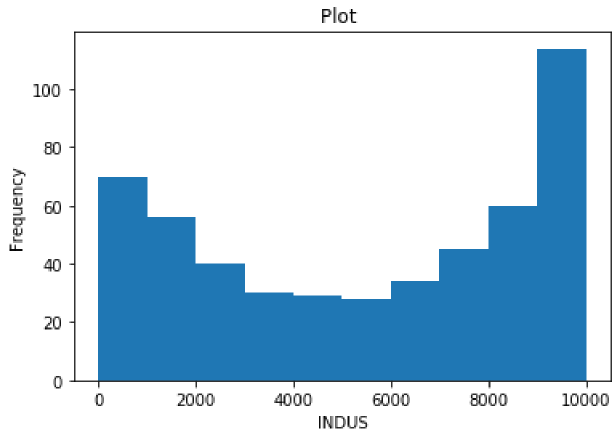
In [26]:

```
plt.hist(boston_data["AGE"])
plt.title("Plot ")
plt.xlabel("NOX")
plt.ylabel("Frequency")
plt.show()
```



In [27]:

```
plt.hist((np.square(boston_data["AGE"])))
plt.title("Plot ")
plt.xlabel("INDUS")
plt.ylabel("Frequency")
plt.show()
```

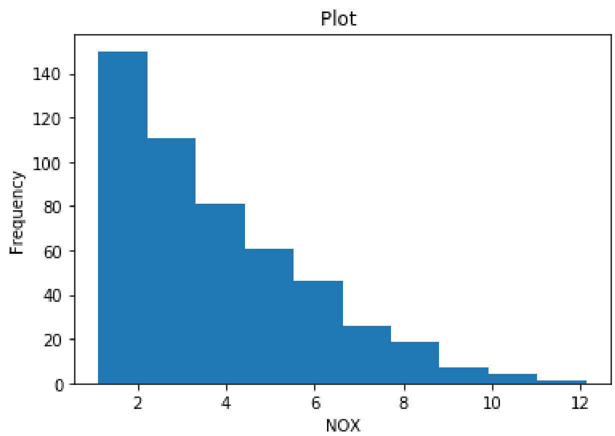


AGE is also a right skewed distribution. So its of no use to apply log on it. Better use square function on it.

DIS Plots

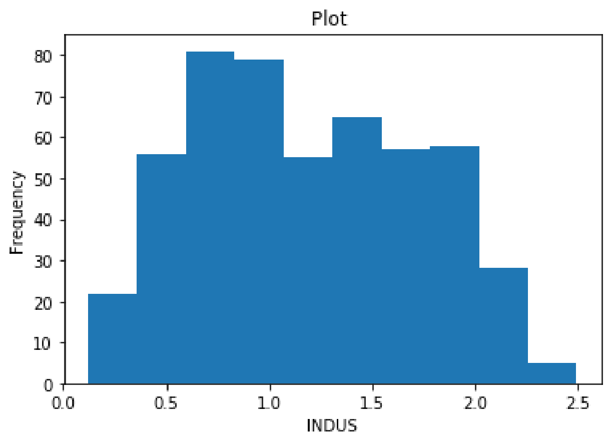
In [28]:

```
plt.hist(boston_data["DIS"])
plt.title("Plot ")
plt.xlabel("NOX")
plt.ylabel("Frequency")
plt.show()
```



In [29]:

```
plt.hist((np.log(boston_data["DIS"])))
plt.title("Plot ")
plt.xlabel("INDUS")
plt.ylabel("Frequency")
plt.show()
```

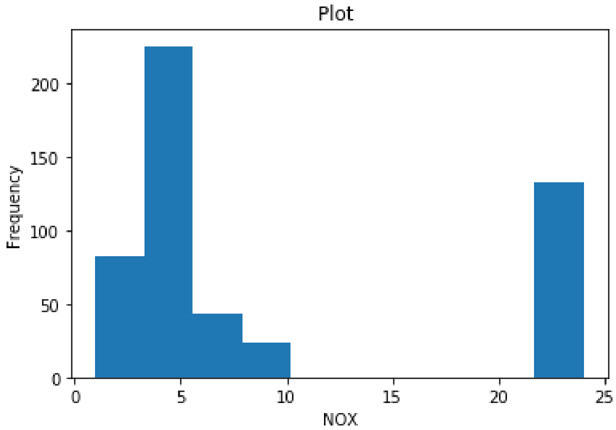


DIS is also log normal distribution. So we apply log on it to get kind of Gaussian Distribution.

RAD Plots

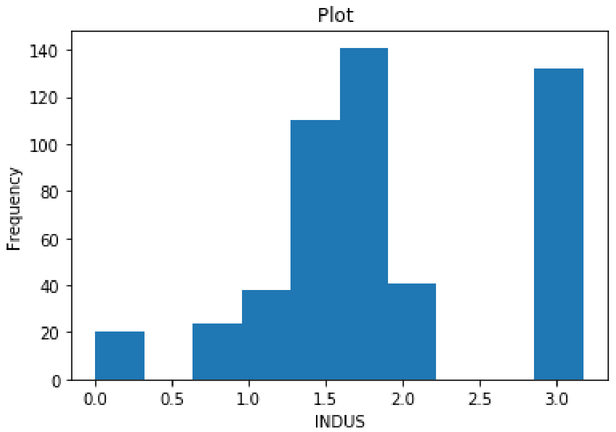
In [30]:

```
plt.hist(boston_data["RAD"])
plt.title("Plot ")
plt.xlabel("NOX")
plt.ylabel("Frequency")
plt.show()
```



In [31]:

```
plt.hist((np.log(boston_data["RAD"])))
plt.title("Plot ")
plt.xlabel("INDUS")
plt.ylabel("Frequency")
plt.show()
```



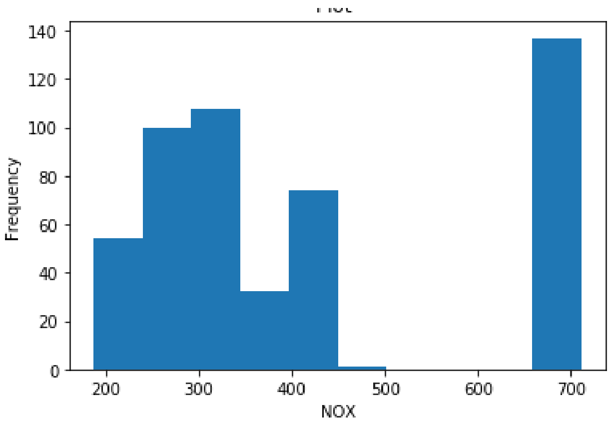
No use to apply any transform.

TAX Plots

In [32]:

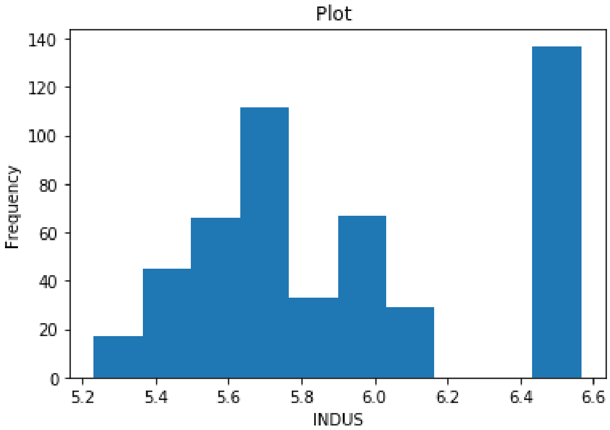
```
plt.hist(boston_data["TAX"])
plt.title("Plot ")
plt.xlabel("NOX")
plt.ylabel("Frequency")
plt.show()
```

Plot



In [33]:

```
plt.hist((np.log(boston_data["TAX"])))
plt.title("Plot ")
plt.xlabel("INDUS")
plt.ylabel("Frequency")
plt.show()
```

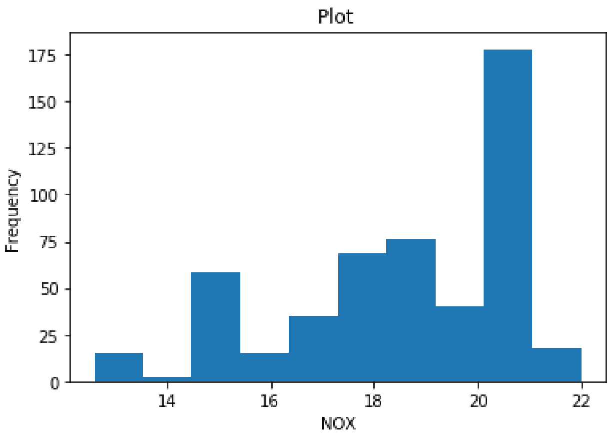


Here also, No use to apply any transform.

PTRATIO Plots

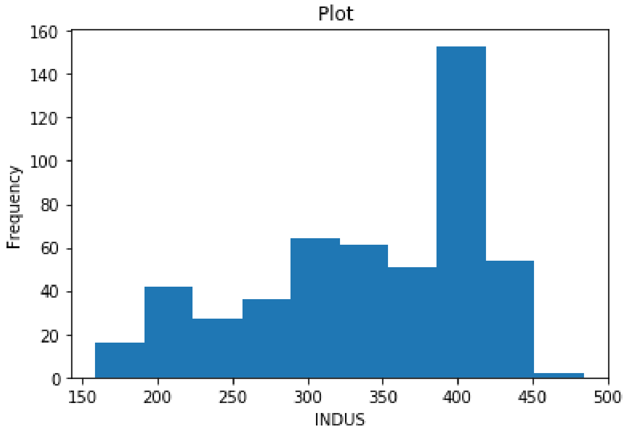
In [34]:

```
plt.hist(boston_data["PTRATIO"])
plt.title("Plot ")
plt.xlabel("NOX")
plt.ylabel("Frequency")
plt.show()
```



In [35]:

```
plt.hist((np.square(boston_data["PTRATIO"])))
plt.title("Plot ")
plt.xlabel("INDUS")
plt.ylabel("Frequency")
plt.show()
```

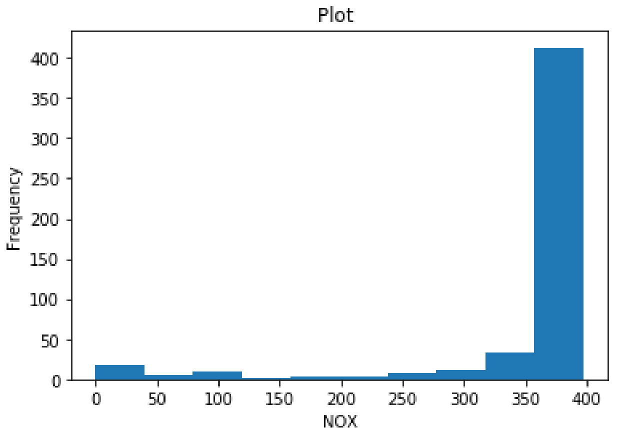


PTRATIO becomes somewhat more right skewed smoother distribution.

B Plots

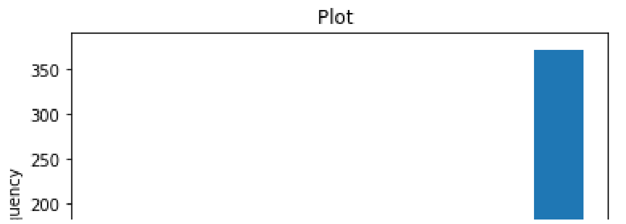
In [36]:

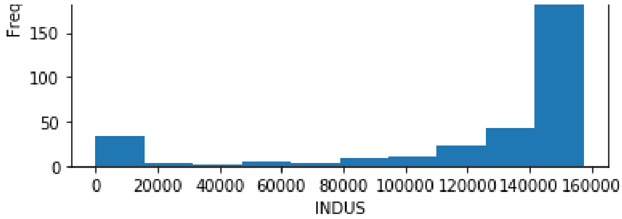
```
plt.hist(boston_data["B"])
plt.title("Plot ")
plt.xlabel("NOX")
plt.ylabel("Frequency")
plt.show()
```



In [37]:

```
plt.hist((np.square(boston_data["B"])))
plt.title("Plot ")
plt.xlabel("INDUS")
plt.ylabel("Frequency")
plt.show()
```



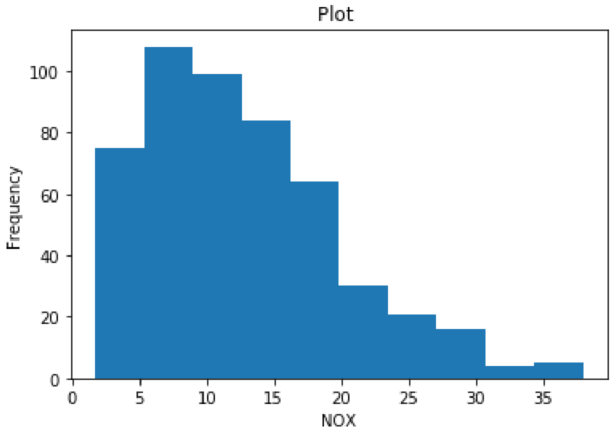


No such visible difference of any transform.

LSTAT Plots

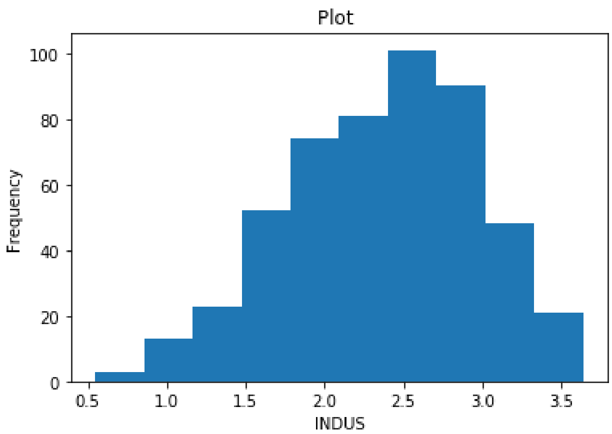
In [38]:

```
plt.hist(boston_data["LSTAT"])
plt.title("Plot ")
plt.xlabel("NOX")
plt.ylabel("Frequency")
plt.show()
```



In [39]:

```
plt.hist((np.log(boston_data["LSTAT"])))
plt.title("Plot ")
plt.xlabel("INDUS")
plt.ylabel("Frequency")
plt.show()
```



LSTAT becomes somewhat GAussian on applying log.

Tranforming Features

In [40]:

```
boston_data['CRIM']=np.log(boston_data['CRIM'])
```

In [41]:

```
boston_data['DIS']=np.log(boston_data['DIS'])
```

In [42]:

```
boston_data['AGE']=np.square(boston_data['AGE'])
```

In [43]:

```
boston_data['LSTAT']=np.log(boston_data['LSTAT'])
```

Feature Standardization

In [44]:

```
from sklearn.preprocessing import MinMaxScaler
```

In [45]:

```
Y = (boston_data["Output"])
```

In [46]:

```
X_data = boston_data.drop("Output",axis =1)
```

In [47]:

```
X_new=MinMaxScaler().fit_transform(X_data)
```

Linear Regression

Splitting data into Train and Test: Stratified Sampling

In [48]:

```
from sklearn.model_selection import train_test_split
X_train ,X_test ,y_train,y_test = train_test_split(X_new,Y,test_size = 0.3 ,random_state =100 )
print('Train - Predictors shape', X_train.shape)
print('Test - Predictors shape', X_test.shape)
print('Train - Target shape', y_train.shape)
print('Test - Target shape', y_test.shape)
```

```
Train - Predictors shape (354, 13)
Test - Predictors shape (152, 13)
Train - Target shape (354,)
Test - Target shape (152,)
```

Model Training

In [49]:

```
#initializing the linear regression model
from sklearn.linear_model import LinearRegression
lm = LinearRegression(fit_intercept = True ,normalize=False,n_jobs = -1)
lm.fit(X_train, y_train)
y_pred = lm.predict(X_test)
```

In [50]:

```
lr_coeff=lm.coef_
```

In [51]:

```
from prettytable import PrettyTable
#If you get a ModuleNotFoundError error , install prettytable using: pip3 install prettytable
x=PrettyTable()
x.field_names=["Weights"]
for i in lr_coeff:
    x.add_row([round(i,2)])
print(x)
```

```
+---------+
| Weights |
+---------+
|   2.94  |
|   0.5   |
|   -0.5  |
|   2.5   |
|  -7.48  |
|  14.38  |
|  -0.12  |
|  -12.63 |
|   4.3   |
|   -7.2  |
|  -7.32  |
|   3.93  |
|  -26.56 |
+---------+
```

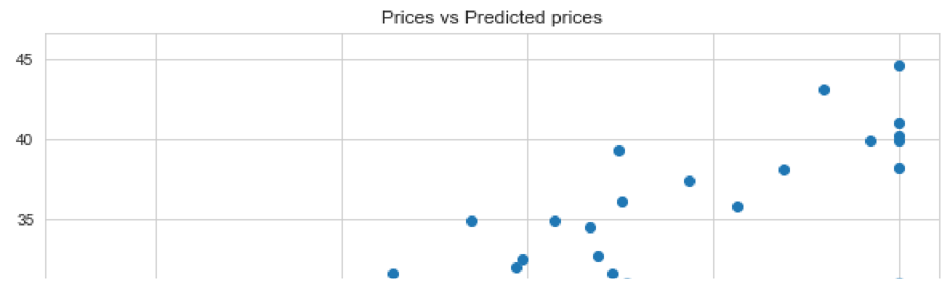
In [52]:

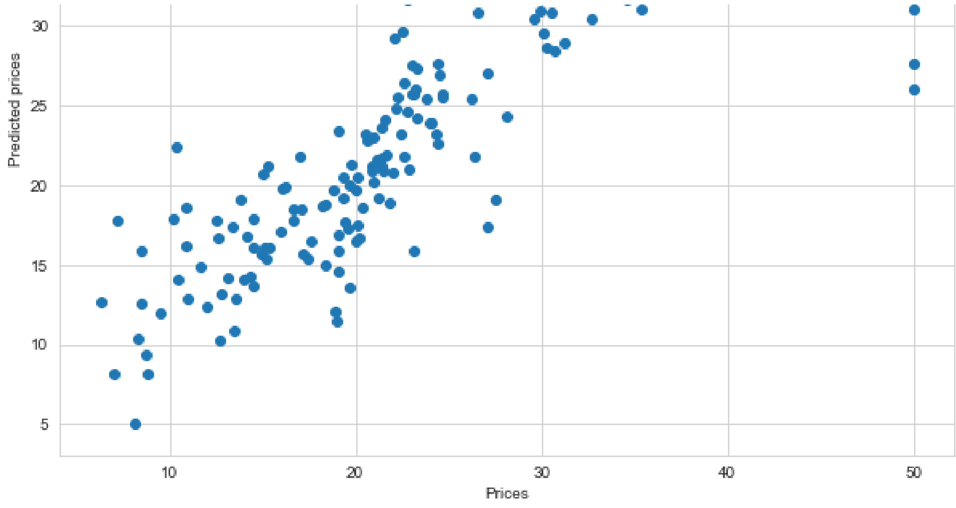
```
# Compute and print MSE and RMSE
from sklearn.metrics import mean_squared_error

mse = mean_squared_error(y_test,y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
R_squared= lm.score(X_test,y_test)
print("Mean squared error : ",mse)
print("Root Mean Squared Error: ",rmse)
print("Coefficient of Determination: ",R_squared)
```

```
Mean squared error :  25.50909295227186
Root Mean Squared Error:  5.050652725368461
Coefficient of Determination:  0.7481452815195181
```

In [53]:

```
#ploting
plt.figure(figsize=(10,8))
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()
```





Stochastic Gradient Descend : Manual

Splitting data into Train and Test: Stratified Sampling

In [54]:

```
std_data1 = MinMaxScaler().fit_transform(boston_data)
X_train ,X_test  = train_test_split(std_data1,test_size = 0.3 ,random_state =10000 )
```

Predict Function

In [55]:

```
# https://machinelearningmastery.com/implement-linear-regression-stochastic-gradient-descent-scrat
ch-python/
# Portion of codes taken from the above link.
```

In [56]:

```
def pred_price(row, coefficients):
    y_pred = coefficients[0]
    for i in range(len(row)-1):
        y_pred += coefficients[i + 1] * row[i]
    return y_pred
```

Calculating Coefficients/Weights via Manual Stochastic Gradient Descend

In [57]:

```
def coefficients_sgd(train, learning_rate, n_epoch):
    coef = [0.0 for i in range(len(train[0]))]
    for epoch in range(n_epoch):
        for row in train:
            y_pred = pred_price(row, coef)
            error = y_pred - row[-1]
            coef[0] = coef[0] - learning_rate * error
            for i in range(len(row)-1):
                coef[i + 1] = coef[i + 1] - learning_rate * error * row[i]

    return coef
```

Linear Regression via Stochastic Gradient Descend

In [58]:

```
def linear_regression_sgd(train, test, learning_rate, n_epoch):
    predictions = list()
    coef = coefficients_sgd(train, learning_rate, n_epoch)
    for row in test:
        y_pred = pred_price(row, coef)
        predictions.append(y_pred)
    return(predictions)
```

Coeficients/Weights

In [59]:

```
coef_sgd = coefficients_sgd(X_train,0.001,100)
```

In [60]:

```
from prettytable import PrettyTable
#If you get a ModuleNotFoundError error , install prettytable using: pip3 install prettytable
x=PrettyTable()
x.field_names=["Weights"]
for i in coef_sgd:
    x.add_row([round((i*mean_output*2)-std_output/2,2)])
print(x)
```

```
+---------+
| Weights |
+---------+
|   6.07  |
|  -2.49  |
|  -1.43  |
|   -5.5  |
|  -0.66  |
|  -5.39  |
|  12.59  |
|  -3.42  |
|   -3.8  |
|  -3.65  |
|  -6.81  |
|  -9.46  |
|   3.69  |
|  -18.43 |
+---------+
```

Weights of SGD Linear Regression differ from normal Linear Regression because while applying SGD we standardize output feature also which is not standardized in case of normal Linear Regression.

Prediction

In [61]:

```
y_pred_sgd = linear_regression_sgd(X_train,X_test,0.01,200)
```

Calculating Mean Square Error and Root Mean Square Error

In [62]:

```
y_test =[]
for i in range(len(X_test)):
    price = X_test[i][-1]
    y_test.append(price)
```

In [63]:

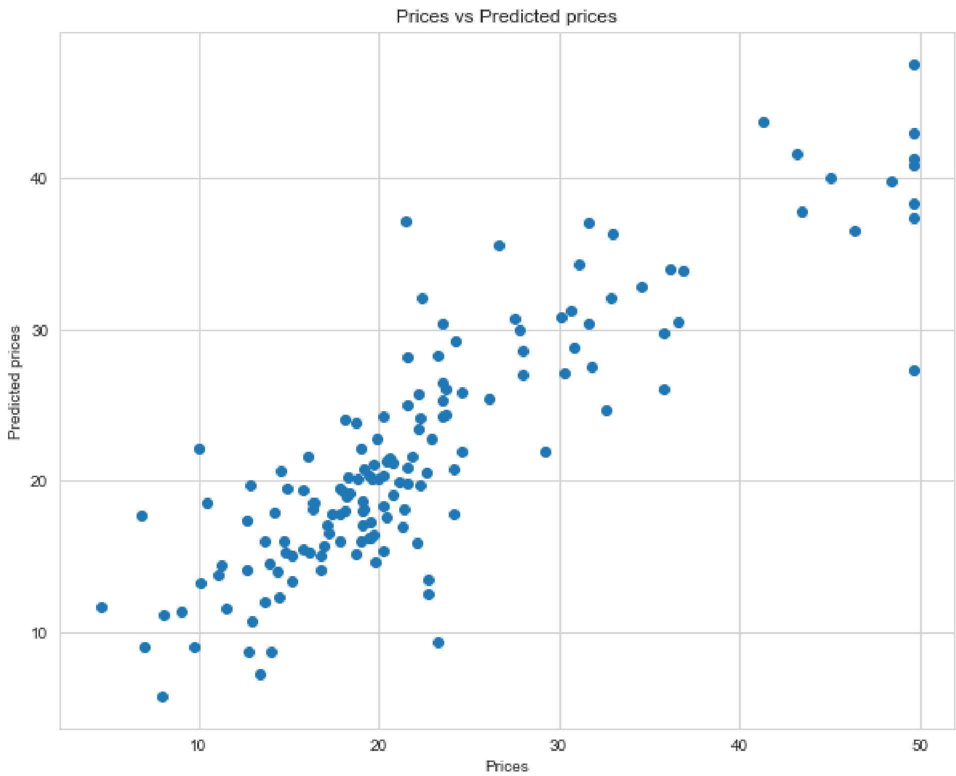
```
y_test_final = [((i * mean_output*2)+std_output/2) for i in y_test]
y_pred_final = [((i * mean_output*2)+std_output/2) for i in y_pred_sgd]
```

```
mse_sgd = mean_squared_error(y_test_final,y_pred_final)
rmse_sgd =mse_sgd**0.5
print("Mean squared error : {}".format(mse_sgd))
print("Root Mean Squared Error: {}".format(mse_sgd**0.5))
```

```
Mean squared error : 24.69289863223145
Root Mean Squared Error: 4.969194968224879
```

In [64]:

```
plt.figure(figsize=(10,8))
sns.set_style('whitegrid')
plt.scatter(y_test_final,y_pred_final)
plt.xlabel("Prices")
plt.ylabel("Predicted prices")
plt.title("Prices vs Predicted prices")
plt.grid(True)
plt.show()
```



Conclusion

In [65]:

```
from prettytable import PrettyTable
#If you get a ModuleNotFoundError error , install prettytable using: pip3 install prettytable
x=PrettyTable()
x.field_names=["Vectorizer","Model","AUC"]
x.add_row(["Linear Regression","MSE",round(mse,2)])
x.add_row(["Linear Regression","RMSE",round(rmse,2)])
x.add_row(["SGD Regression","MSE",round(mse_sgd,2)])
x.add_row(["SGD Regression","RMSE",round(rmse_sgd,2)])
print(x)
```

```
+-------------------+-------+-------+
|     Vectorizer    | Model |  AUC  |
+-------------------+-------+-------+
| Linear Regression |  MSE  | 25.51 |
| Linear Regression |  RMSE |  5.05 |
|   SGD Regression  |  MSE  | 24.69 |
|   SGD Regression  |  RMSE |  4.97 |
+-------------------+-------+-------+
```

In [ ]:

```
```