Assignment 6: Implement SGD for linear regression

To implement stochastic gradient descent to optimize a linear regression algorithm on Boston House Prices dataset which is already exists in sklearn as a sklearn.linear_model.SGDRegressor.here,SGD algorithm is defined manually and then comapring the both results.Linear regression is technique to predict on real values.

stochastic gradient descent technique , evaluates and updates the coefficients every iteration to minimize the error of a model on training data.

Objective:

To Implement stochastic gradient descent on Bostan House Prices dataset for linear Regression

1)Implement SGD and deploy on Bostan House Prices dataset.

2)Comapare the Results with sklearn.linear_model.SGDRegressor

In [21]:

```
from sklearn.datasets import load_boston # to load  datasets from sklearn
import matplotlib.pyplot as plt
from sklearn.cross_validation import cross_val_score

import sklearn.cross_validation
from sklearn.cross_validation import KFold
import numpy as np
import seaborn as sns

from collections import Counter
from sklearn.metrics import accuracy_score
from sklearn import cross_validation
from sklearn.preprocessing import StandardScaler
import pandas as pd
import math

import pytablewriter
```

In [22]:

```
boston=load_boston()
#shape of Boston datasets
print(boston.data.shape)
```

```
(506, 13)
```

In [23]:

```
#to understand datasets
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 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.
http://archive.ics.uci.edu/ml/datasets/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.

**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.
   - many more! (see http://archive.ics.uci.edu/ml/datasets/Housing)
```

In [24]:

```
col=boston.feature_names
print(col)
```

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

In [25]:

```
#real price values of boston house datasets
#Output is real valued number
print(boston.target[:10])
```

```
[24.  21.6 34.7 33.4 36.2 28.7 22.9 27.1 16.5 18.9]
```

In [32]:

```
# Boston datasets
bostan = pd.DataFrame(boston.data)
print(bostan.head())
# Boston dataset with columns names
bostan_col =pd.DataFrame(boston.data,columns=col)
print(bostan_col.head())
```

```
        0     1     2    3      4      5     6       7    8      9    10  \
0  0.00632  18.0  2.31  0.0  0.538  6.575  65.2  4.0900  1.0  296.0  15.3
```

```
1  0.02731   0.0  7.07  0.0  0.469  6.421  78.9  4.9671  2.0  242.0  17.8
2  0.02729   0.0  7.07  0.0  0.469  7.185  61.1  4.9671  2.0  242.0  17.8
3  0.03237   0.0  2.18  0.0  0.458  6.998  45.8  6.0622  3.0  222.0  18.7
4  0.06905   0.0  2.18  0.0  0.458  7.147  54.2  6.0622  3.0  222.0  18.7

       11    12
0  396.90  4.98
1  396.90  9.14
2  392.83  4.03
3  394.63  2.94
4  396.90  5.33
      CRIM    ZN  INDUS  CHAS    NOX     RM   AGE     DIS  RAD    TAX  \
0  0.00632  18.0   2.31   0.0  0.538  6.575  65.2  4.0900  1.0  296.0
1  0.02731   0.0   7.07   0.0  0.469  6.421  78.9  4.9671  2.0  242.0
2  0.02729   0.0   7.07   0.0  0.469  7.185  61.1  4.9671  2.0  242.0
3  0.03237   0.0   2.18   0.0  0.458  6.998  45.8  6.0622  3.0  222.0
4  0.06905   0.0   2.18   0.0  0.458  7.147  54.2  6.0622  3.0  222.0

   PTRATIO       B  LSTAT
0     15.3  396.90   4.98
1     17.8  396.90   9.14
2     17.8  392.83   4.03
3     18.7  394.63   2.94
4     18.7  396.90   5.33
```

In [56]:

```
bostan['PRICE'] = boston.target
print(bostan.head())
```

```
         0     1     2    3      4      5     6       7    8      9    10  \
0  0.00632  18.0  2.31  0.0  0.538  6.575  65.2  4.0900  1.0  296.0  15.3
1  0.02731   0.0  7.07  0.0  0.469  6.421  78.9  4.9671  2.0  242.0  17.8
2  0.02729   0.0  7.07  0.0  0.469  7.185  61.1  4.9671  2.0  242.0  17.8
3  0.03237   0.0  2.18  0.0  0.458  6.998  45.8  6.0622  3.0  222.0  18.7
4  0.06905   0.0  2.18  0.0  0.458  7.147  54.2  6.0622  3.0  222.0  18.7

       11    12  PRICE
0  396.90  4.98   24.0
1  396.90  9.14   21.6
2  392.83  4.03   34.7
3  394.63  2.94   33.4
4  396.90  5.33   36.2
```

Summary Statistics

In [58]:

```
print(bostan_col.describe())
```

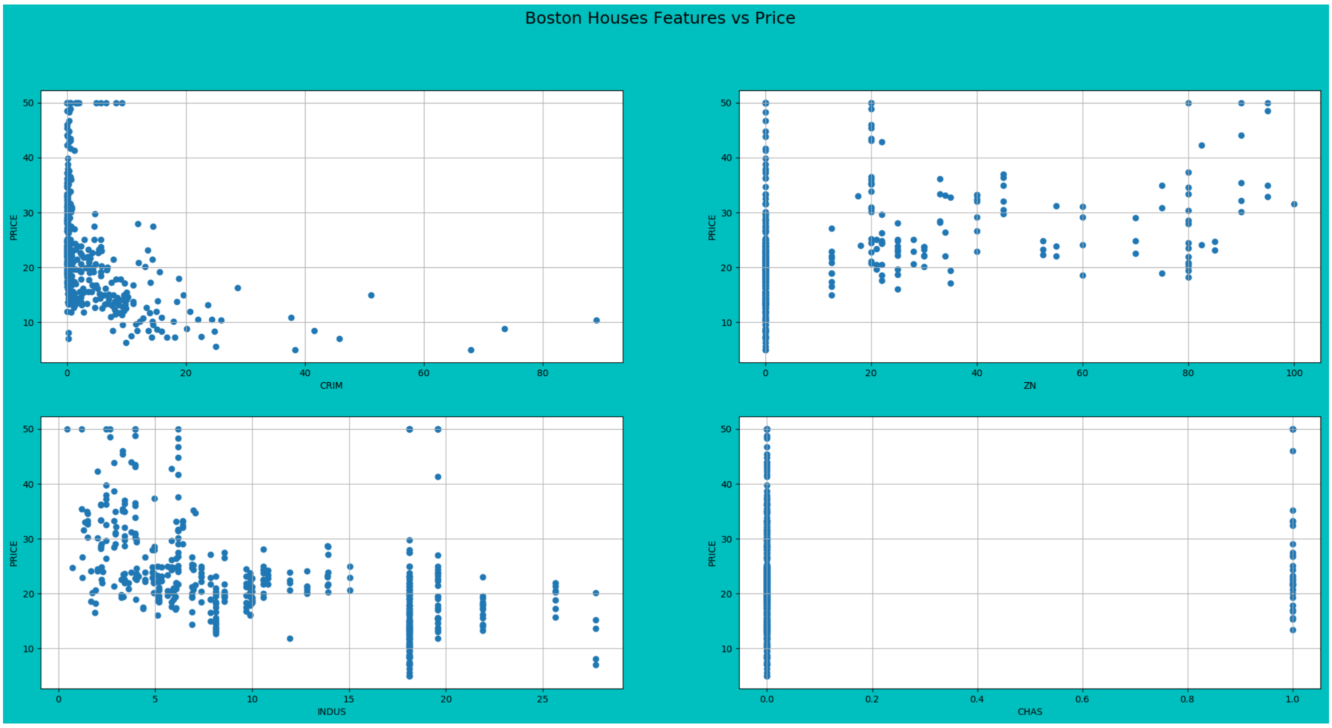
```
             CRIM          ZN       INDUS        CHAS         NOX          RM  \
count  506.000000  506.000000  506.000000  506.000000  506.000000  506.000000
mean     3.593761   11.363636   11.136779    0.069170    0.554695    6.284634
std      8.596783   23.322453    6.860353    0.253994    0.115878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

              AGE         DIS         RAD         TAX     PTRATIO           B  \
count  506.000000  506.000000  506.000000  506.000000  506.000000  506.000000
mean    68.574901    3.795043    9.549407  408.237154   18.455534  356.674032
std     28.148861    2.105710    8.707259  168.537116    2.164946   91.294864
min      2.900000    1.129600    1.000000  187.000000   12.600000    0.320000
25%     45.025000    2.100175    4.000000  279.000000   17.400000  375.377500
50%     77.500000    3.207450    5.000000  330.000000   19.050000  391.440000
75%     94.075000    5.188425   24.000000  666.000000   20.200000  396.225000
max    100.000000   12.126500   24.000000  711.000000   22.000000  396.900000

            LSTAT
count  506.000000
```

```
mean     12.653063
std       7.141062
min       1.730000
25%       6.950000
50%      11.360000
75%      16.955000
max      37.970000
```

Boston Houses Features vs Price

In [59]:

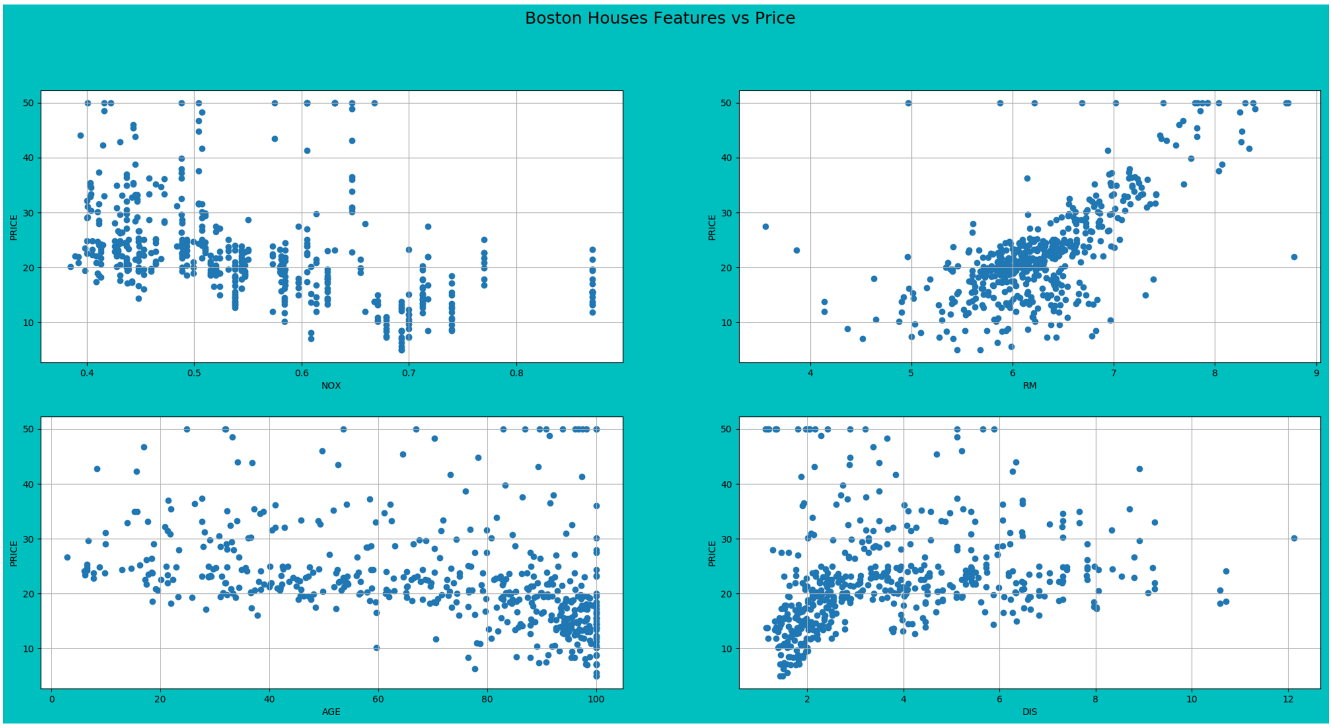
```
fig1 = plt.figure(num=None, figsize=(25, 12), dpi=100, facecolor='c', edgecolor='k')
fig1.suptitle('Boston Houses Features vs Price', fontsize=18)
ax1 = fig1.add_subplot(221)
ax1.scatter(bostan_col.CRIM,boston.target)
plt.xlabel('CRIM')
plt.ylabel('PRICE')
plt.grid()
ax2 = fig1.add_subplot(222)
ax2.scatter(bostan_col.ZN,boston.target)
plt.xlabel('ZN')
plt.ylabel('PRICE')
plt.grid()
ax3 = fig1.add_subplot(223)
ax3.scatter(bostan_col.INDUS,boston.target)
plt.xlabel('INDUS')
plt.ylabel('PRICE')
plt.grid()
ax4 = fig1.add_subplot(224)
ax4.scatter(bostan_col.CHAS,boston.target)
plt.xlabel('CHAS')
plt.ylabel('PRICE')
plt.grid()
plt.show()
```



In [60]:

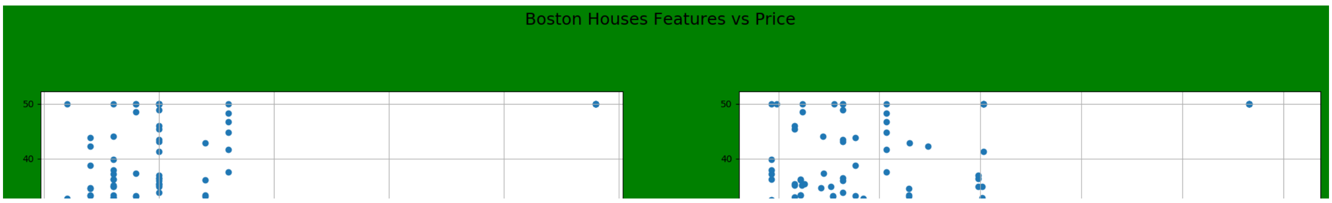
```
fig1 = plt.figure(num=None, figsize=(25, 12), dpi=100, facecolor='c', edgecolor='k')
fig1.suptitle('Boston Houses Features vs Price', fontsize=18)
ax5 = fig1.add_subplot(221)
ax5.scatter(bostan_col.NOX,boston.target)
plt.xlabel('NOX')
plt.ylabel('PRICE')
plt.grid()
ax6 = fig1.add_subplot(222)
ax6.scatter(bostan_col.RM,boston.target)
```

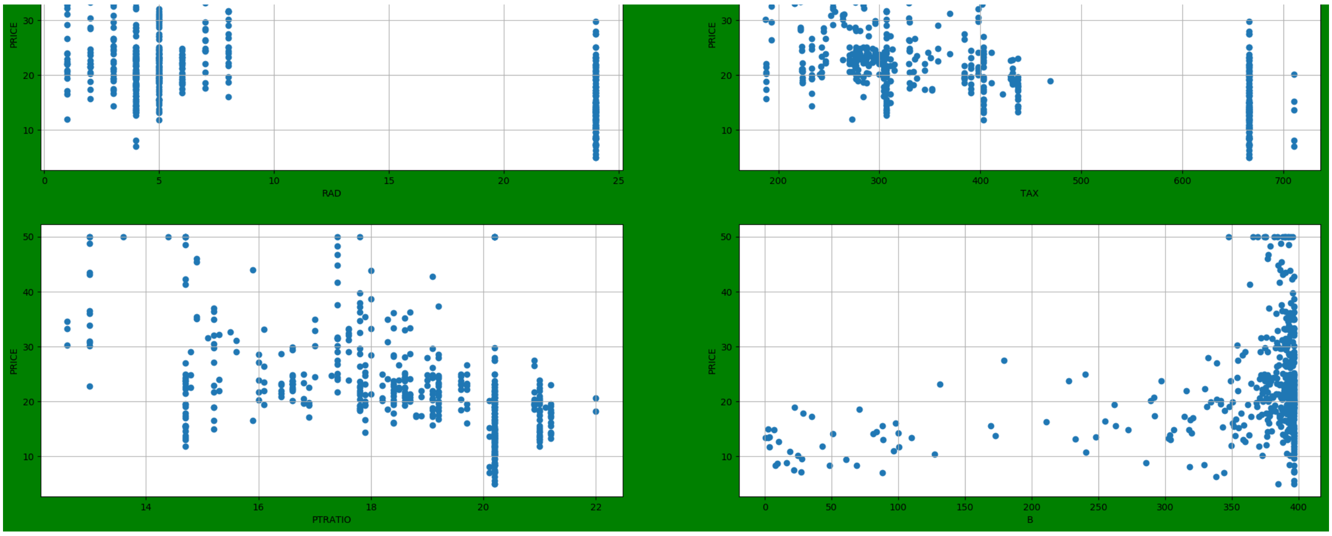
```
plt.xlabel('RM')
plt.ylabel('PRICE')
plt.grid()
ax7 = fig1.add_subplot(223)
ax7.scatter(bostan_col.AGE,boston.target)
plt.xlabel('AGE')
plt.ylabel('PRICE')
plt.grid()
ax8 = fig1.add_subplot(224)
ax8.scatter(bostan_col.DIS,boston.target)
plt.xlabel('DIS')
plt.ylabel('PRICE')
plt.grid()
plt.show()
```



In [61]:

```
fig2 = plt.figure(num=None, figsize=(25, 12), dpi=100, facecolor='g', edgecolor='k')
fig2.suptitle('Boston Houses Features vs Price', fontsize=18)
ax9 = fig2.add_subplot(221)
ax9.scatter(bostan_col.RAD,boston.target)
plt.xlabel('RAD')
plt.ylabel('PRICE')
plt.grid()
ax10 = fig2.add_subplot(222)
ax10.scatter(bostan_col.TAX,boston.target)
plt.xlabel('TAX')
plt.ylabel('PRICE')
plt.grid()
ax11 = fig2.add_subplot(223)
ax11.scatter(bostan_col.PTRATIO,boston.target)
plt.xlabel('PTRATIO')
plt.ylabel('PRICE')
plt.grid()
ax12 = fig2.add_subplot(224)
ax12.scatter(bostan_col.B,boston.target)
plt.xlabel('B')
plt.ylabel('PRICE')
plt.grid()
fig3 = plt.figure(num=None, figsize=(25, 12), dpi=100, facecolor='y', edgecolor='k')
```

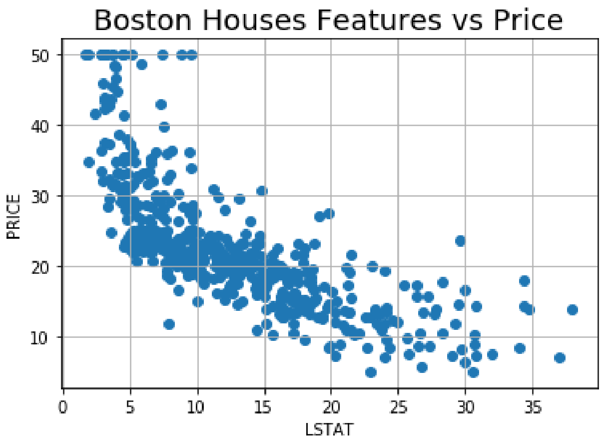





```
<matplotlib.figure.Figure at 0x1873ae1ae48>
```

In [62]:

```
plt.scatter(bostan_col.LSTAT,boston.target)
plt.title('Boston Houses Features vs Price', fontsize=18)
plt.xlabel('LSTAT')
plt.ylabel('PRICE')
plt.grid()
plt.show()
```



In [63]:

```
bostan['PRICE'] = boston.target
# Boston datasets with 13 feautures  label as X
X = bostan.drop('PRICE', axis = 1)
#Boston dataset's price for 13 features lanel as Y
Y = bostan['PRICE']

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

```
         0     1     2    3      4      5     6       7    8      9    10  \
0  0.00632  18.0  2.31  0.0  0.538  6.575  65.2  4.0900  1.0  296.0  15.3
1  0.02731   0.0  7.07  0.0  0.469  6.421  78.9  4.9671  2.0  242.0  17.8
2  0.02729   0.0  7.07  0.0  0.469  7.185  61.1  4.9671  2.0  242.0  17.8
3  0.03237   0.0  2.18  0.0  0.458  6.998  45.8  6.0622  3.0  222.0  18.7
4  0.06905   0.0  2.18  0.0  0.458  7.147  54.2  6.0622  3.0  222.0  18.7

       11    12
0  396.90  4.98
1  396.90  9.14
2  392.83  4.03
3  394.63  2.94
4  396.90  5.33
(506,)
```

Training and testing datasets splitting with cross_validation

In [64]:

```
from sklearn import preprocessing
min_max_scaler=preprocessing.MinMaxScaler()
X_df=pd.DataFrame(min_max_scaler.fit_transform(pd.DataFrame(X)))
Y_df=Y
```

In [65]:

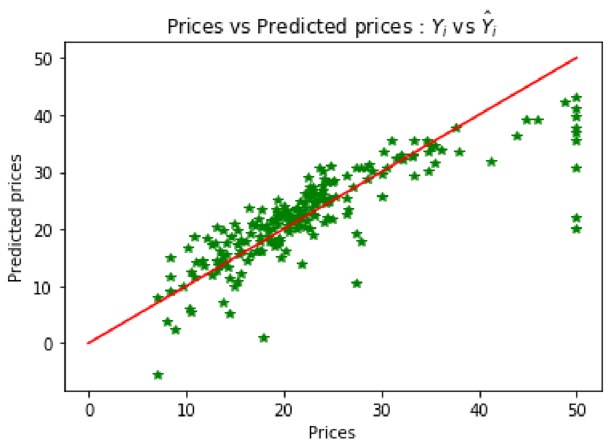
```
# Training and testing datasets splitting with cross_validation
# Training and testing splitting data with 70% and 30%
# randomserach cross_validation is used
X_train, X_test, Y_train, Y_test = sklearn.cross_validation.train_test_split(X_df,
                                                                              Y_df,
                                                                              test_size = 0.40,
                                                                              random_state = 5)
print(X_train.shape)
print(X_test.shape)
print(Y_train.shape)
print(Y_test.shape)
print(type(X_train))
```

```
(303, 13)
(203, 13)
(303,)
(203,)
<class 'pandas.core.frame.DataFrame'>
```

In [66]:

```
# code source:https://medium.com/@haydar_ai/learning-data-science-day-9-linear-regression-on-bosto
n-housing-dataset-cd62a80775ef
from sklearn.linear_model import LinearRegression
lm = LinearRegression()
lm.fit(X_train, Y_train)
Y_pred = lm.predict(X_test)
error=abs(Y_test-Y_pred)
total_error = np.dot(error,error)
# Compute RMSE
rmse_lr= np.sqrt(total_error/len(error))
print('RMSE=',rmse_lr)
#plt.show()
plt.plot(Y_test, Y_pred,'g*')
plt.plot([0,50],[0,50], 'r-')
plt.title("Prices vs Predicted prices : $Y_i$ vs $\hat{Y}_i$")
plt.xlabel('Prices')
plt.ylabel('Predicted prices')
plt.show()
```

```
RMSE= 5.389698975977017
```



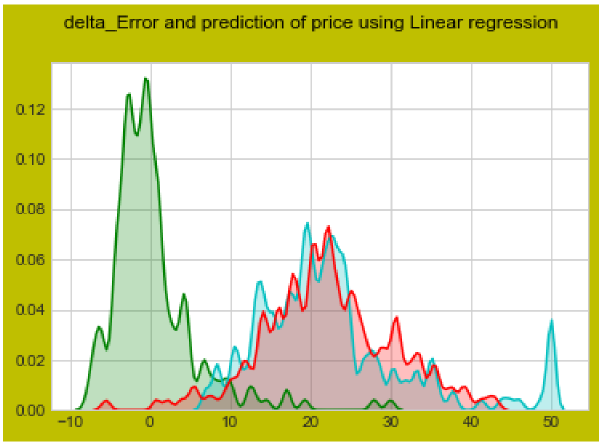
Delta_Error and Prediction of price using Linear regression

In [67]:

```
delta_y = Y_test - Y_pred
import seaborn as sns
fig3 = plt.figure( facecolor='y', edgecolor='k')
fig3.suptitle('delta_Error and prediction of price using Linear regression', fontsize=12)

sns.set_style('whitegrid')
sns.kdeplot(np.array(delta_y),shade=True, color="g", bw=0.5)
sns.kdeplot(np.array(Y_test),shade=True, color="c", bw=0.5)
sns.kdeplot(np.array(Y_pred),shade=True, color="r", bw=0.5)
```

Out[67]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1873adb6e80>
```



1)Red region is predicted price for bostan house datsets

2)Blue Region is for y_test

3)Green Region is difference between actual one and Predicted one.

sklearn.linear_model.SGDRegressor

alpha is as learning rate

n_iter is as batch size

In [72]:

```
models_performence1 = {
    'Model':[],
    'Batch_Size':[],
    'RMSE': [],
    'MSE':[],
    'Iteration':[],
    'Optimal learning Rate':[],


}
columns = ["Model","Batch_Size","RMSE","MSE", "Iteration", "Optimal learning Rate"]
pd.DataFrame(models_performence1, columns=columns)
```

Out[72]:

	Model	Batch_Size	RMSE	MSE	Iteration	Optimal learning Rate

In [73]:

```
def square(list):
```

```
        return [(i ** 2) for i in list]
```

In [78]:

```
from sklearn import linear_model
import warnings
warnings.filterwarnings("ignore")
#Here, alpha is as learning rate

def sgdreg_function(x,initial_batch_size):
    #initial_batch_size=100
    batch=[]

    for l in range(x):
        batch_size_value= initial_batch_size + initial_batch_size * l
        batch.append(batch_size_value)
        z=0
        scale_max=np.max(Y_test[0:batch_size_value])

        Learning_rate=1 # initial learning rate=1
        score=[]
        LR=[] # storing value for learning rate
        Total_score=[]
        epoch1=[]
        global delta_error
        delta_error=[]
        Y_Test=[]
        global Y_hat_Predicted
        Y_hat_Predicted=[]
        test_cost=[]
        train_cost=[]
        n_iter=100
        for k in range(1,batch_size_value+1):
            # Appending learning rate
            LR.append(Learning_rate)

            # SGDRegressor
            sgdreg = linear_model.SGDRegressor(penalty='none',
                                               alpha=Learning_rate
                                               , n_iter=100)


            yii=Y_train[0:batch_size_value]
            xii=X_train[0:batch_size_value]
            xtt=X_test[0:batch_size_value]
            ytt=Y_test[0:batch_size_value]
            Y_Test.append(ytt)

            clf=sgdreg.fit(xii,yii)
            Traing_score=clf.score(xii,yii)
            train_cost.append(Traing_score)
            training_error=1-Traing_score

            # p predicting on x_test

            y_hat = sgdreg.predict(xtt)
            #testing_score=clf.score()
            clf1=sgdreg.fit(xtt,ytt)
            Testing_score=clf1.score(xtt,ytt)
            test_cost.append(Testing_score)
            Testing_error=1-Testing_score
            Y_hat_Predicted.append(y_hat)
            # error = Y_test - y_prediction
            err = abs(ytt - y_hat)
            delta_error.append(err)

            score.append(Testing_score)
            # print(rmse)

            # Iteration
            iteration_no=sgdreg.n_iter_
            epoch1.append(iteration_no)
            #print('Epoch=',iteration_no)
            #print('Learning_rate',Learning_rate)

            Learning_rate=Learning_rate/2
```

```
            z+=1
        print("Training Error=",training_error)
        print("Testing_error",Testing_error)

        models_performence1['Model'].append('sklearn.linear_model.SGDRegressor')
        # graph  (Y_test) Prices Vs   (Y_prediction) Predicted prices
        fig4 = plt.figure( facecolor='c', edgecolor='k')
        fig4.suptitle('(Y_test) Prices Vs   (Y_prediction) Predicted prices: $Y_i$ vs $\hat{Y}_i$ wi
th batch size='+str(batch[l]), fontsize=12)
        plt.plot(Y_Test,Y_hat_Predicted,'g*')
        plt.plot([0,batch_size_value],[0,batch_size_value], 'r-')

        plt.xlabel('Y_test')
        plt.ylabel('Y_predicted')
        plt.show()


        # Plot delta_Error and prediction of price
        fig3 = plt.figure( facecolor='y', edgecolor='k')
        fig3.suptitle('delta_Error and prediction of price with batch size='+str(batch[l]), fontsiz
e=12)
        sns.set_style('darkgrid')
        Y_sklearn=np.array(sum(delta_error)/len(delta_error))
        sns.distplot(Y_sklearn,kde_kws={"color": "g", "lw": 3, "label": "Delta_error_sklearn"} )
        sns.kdeplot(np.array(y_hat),shade=True, color="r", bw=0.5)
        plt.show()

        # Plot epoch Vs   RMSE
        fig = plt.figure( facecolor='y', edgecolor='k')
        fig.suptitle('epoch Vs  RMSE with batch size='+str(batch[l]), fontsize=12)
        ax1 = fig.add_subplot(111)
        plt.plot(epoch1,score,'m*',linestyle='dashed')
        plt.grid()
        plt.xlabel('epoch')
        plt.ylabel('RMSE with batch size=')


        models_performence1['Iteration'].append(sum(epoch1)/len(epoch1))

        # plot Iterations Vs Train Cost & Test cost
        fig4 = plt.figure( facecolor='c', edgecolor='k')
        fig4.suptitle('Iterations Vs Train Cost & Test cost with batch size='+str(batch[l]), fontsi
ze=12)
        plt.plot(epoch1,train_cost,'m*',linestyle='dashed', label='Train cost')
        plt.plot(epoch1,test_cost,'r*', linestyle='dashed',label='Test cost')
        plt.legend(loc='lower left')
        plt.grid()
        plt.xlabel('Iterations ')
        plt.ylabel('Performance Cost  ')
        plt.show()

        # Plot Learning rate Vs   RMSE
        fig2 = plt.figure( facecolor='y', edgecolor='k')
        fig2.suptitle('Learning rate Vs  RMSE with batch size='+str(batch[l]), fontsize=12)
        ax2 = fig2.add_subplot(111)
        #ax2.set_title("Learning rate Vs  RMSE")
        plt.plot(LR,score,'m*',linestyle='dashed')
        plt.grid()
        plt.xlabel('Learning rate')
        plt.ylabel('RMSE')
        plt.show()


        global best_Learning_rate
        best_Learning_rate=LR[score.index(min(score))]
        models_performence1['Optimal learning Rate'].append(best_Learning_rate)
        print('\nThe best value of best_Learning_rate is %d.' % (best_Learning_rate),7)
        MSEscore=scale_max*sum(score)/len(score)
        score_value=np.sqrt(MSEscore)
        print('Batch Size',batch[l])

        models_performence1['Batch_Size'].append(batch[l])
        print("RMSE with batch size="+str(batch[l]),score_value)
        models_performence1['RMSE'].append(score_value)
        print("MSE with batch size="+str(batch[l]),MSEscore)
        models_performence1['MSE'].append(MSEscore)
```

sgdreg_function is function for stochastic gradient descen for linear regression using linear_model.SGDRegressor in sklearn.

In this function different batch size (50,100,150,200) is applied on linear_model.SGDRegressor to get best learning rate,epoch value,error rate.

here,delta_Error and prediction of price with batch size graph is shown.

RMSE vs epoch graph is shown

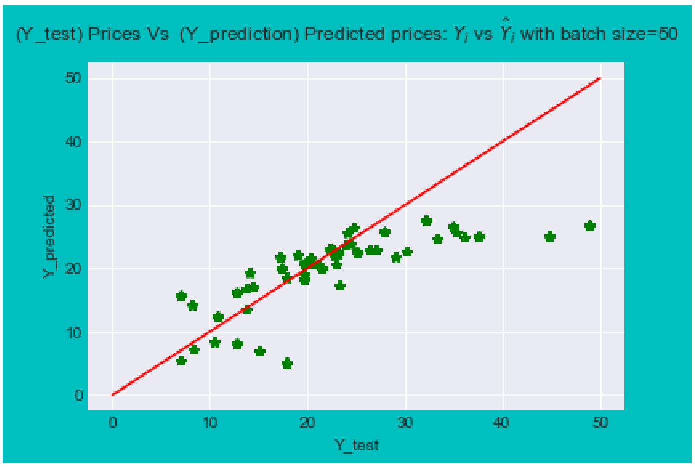
Also,RMSE vs learning rate graph is shown for different batch value.

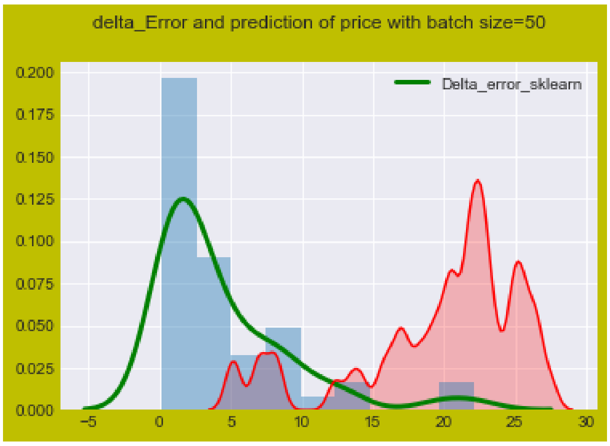
linear_model.SGDRegressor in sklearn for different batch size

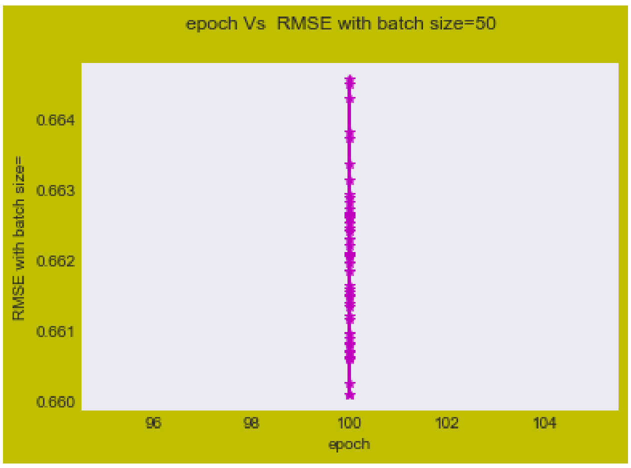
In [81]:

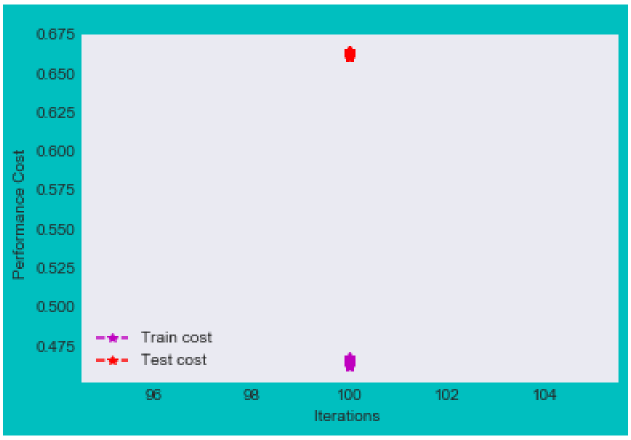
```
sgdreg_function(4,50)
```

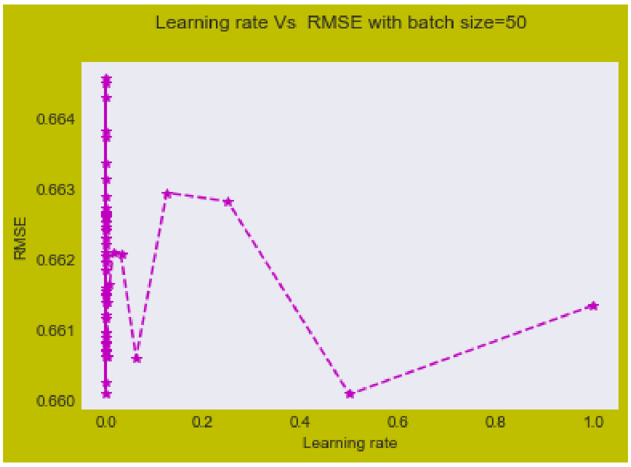
```
Training Error= 0.5361775424871296
Testing_error 0.3356944155260637
```



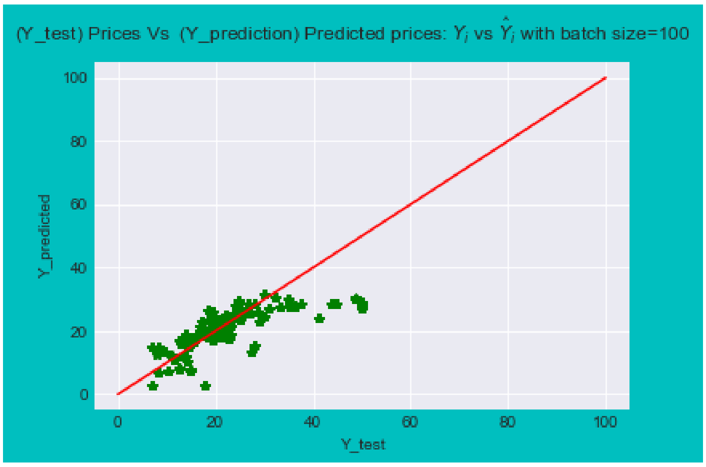


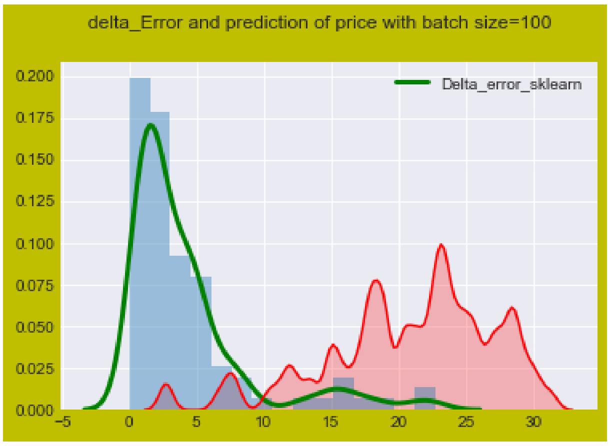


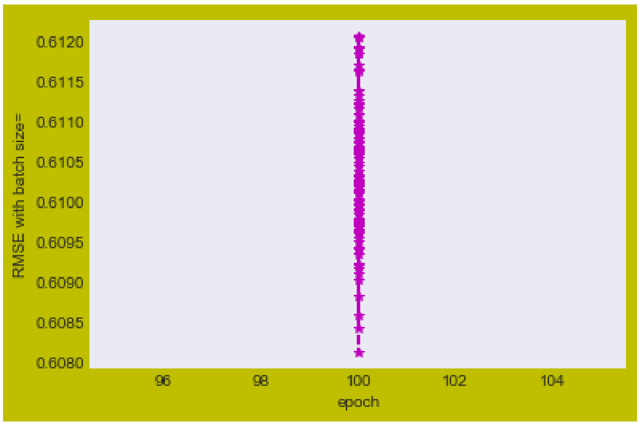


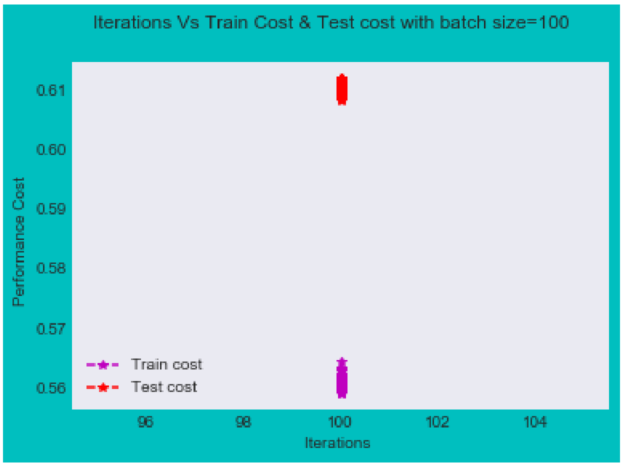


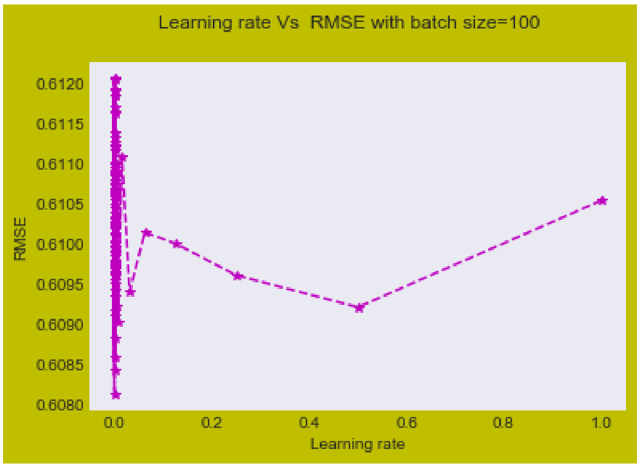

```
The best value of best_Learning_rate is 0. 7
Batch Size 50
RMSE with batch size=50 5.683823302310756
MSE with batch size=50 32.305847331890746
Training Error= 0.44010334334877754
Testing_error 0.3886684777964968
```



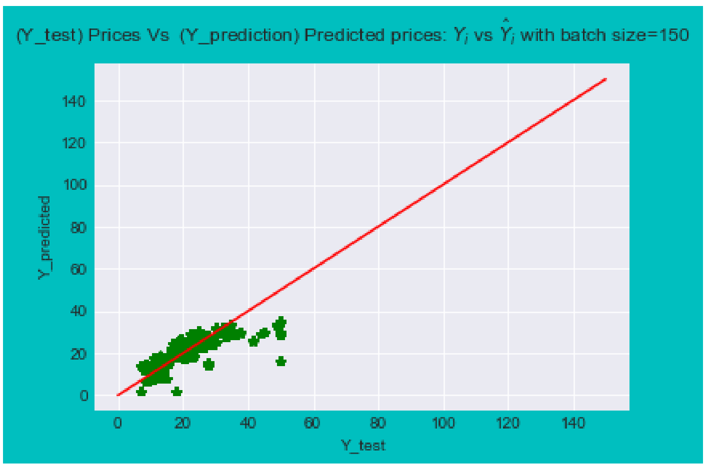


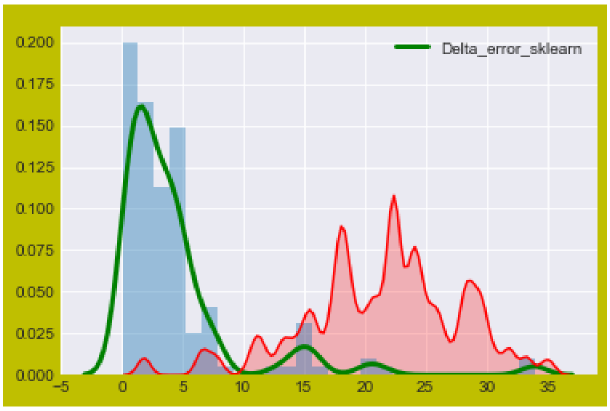


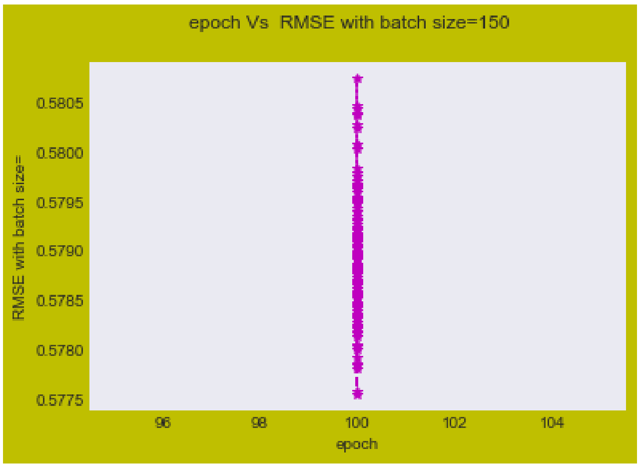


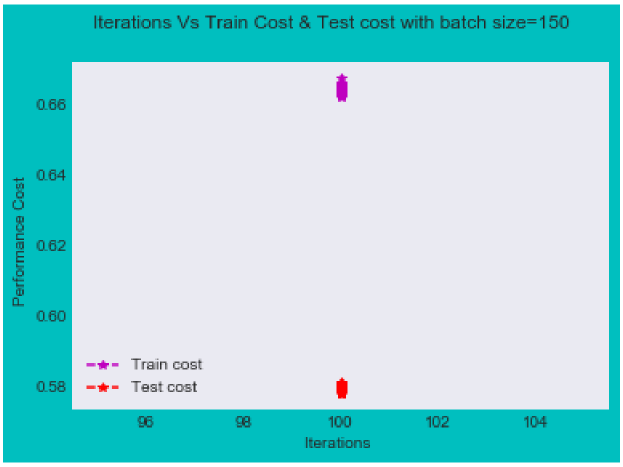


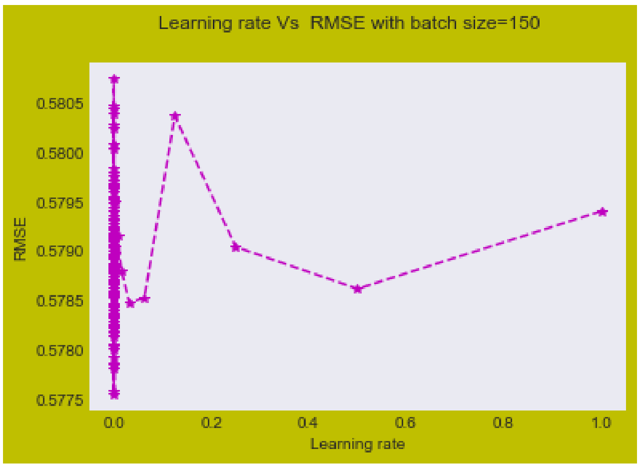

```
The best value of best_Learning_rate is 0. 7
Batch Size 100
RMSE with batch size=100 5.524136269870145
MSE with batch size=100 30.51608152809484
Training Error= 0.33590409774933305
Testing_error 0.42121952426204157
```



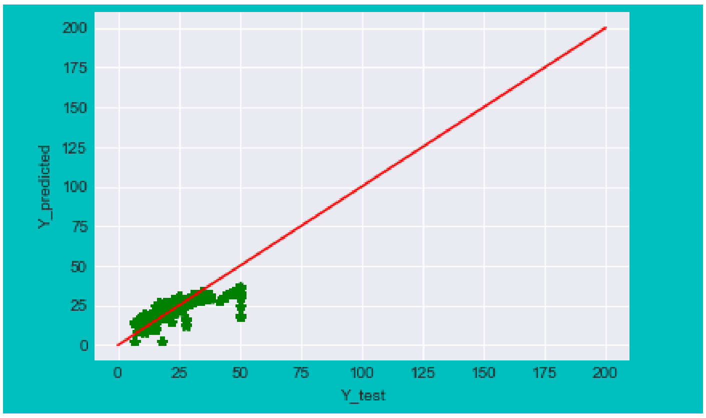


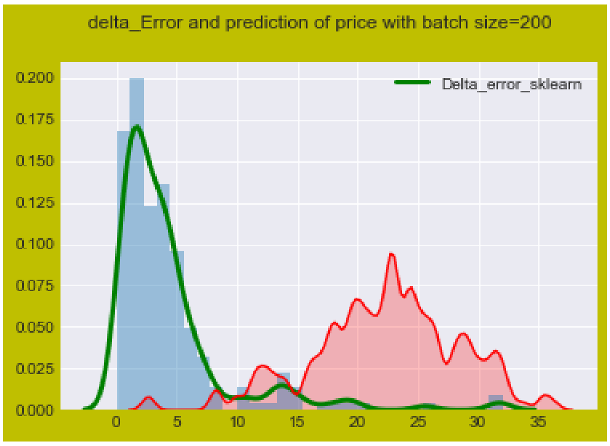


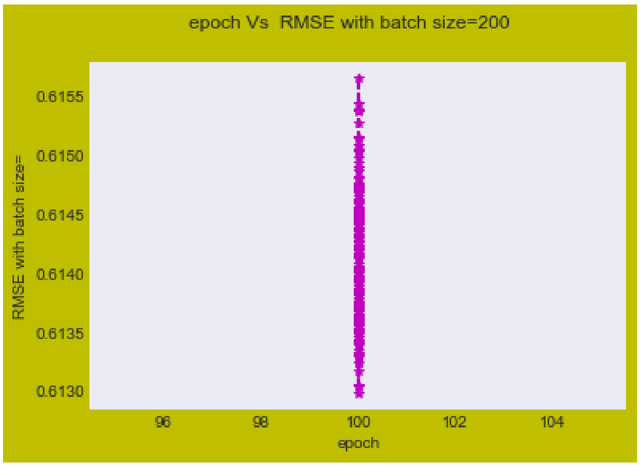


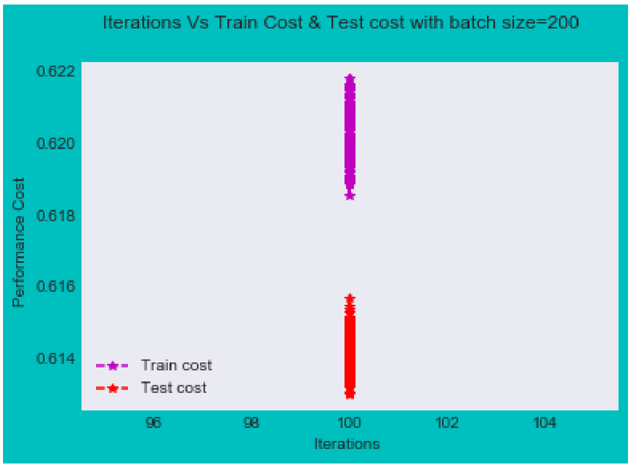


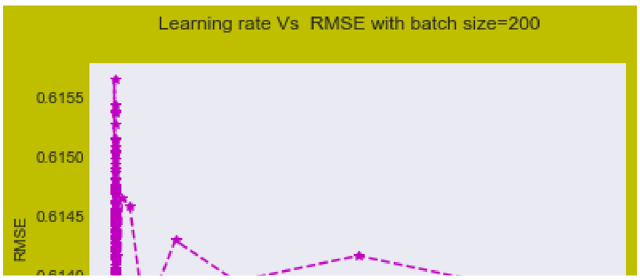

```
The best value of best_Learning_rate is 0. 7
Batch Size 150
RMSE with batch size=150 5.380203184707596
MSE with batch size=150 28.946586308737757
Training Error= 0.38099998334028884
Testing_error 0.3862137377202932
```

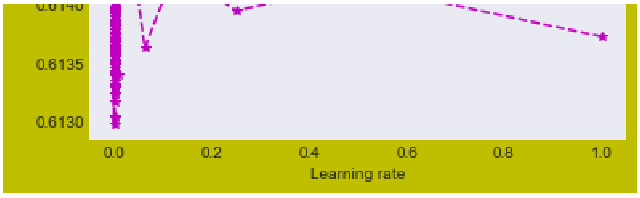

Y_predicted
Y_test
0
25
50
75
100
125
150
175
200


delta_Error and prediction of price with batch size=200
Delta_error_sklearn
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
0
5
10
15
20
25
30
35


epoch Vs RMSE with batch size=200
RMSE with batch size=
epoch
0.6155
0.6150
0.6145
0.6140
0.6135
0.6130
96
98
100
102
104


Iterations Vs Train Cost & Test cost with batch size=200
Performance Cost
Iterations
Train cost
Test cost
0.622
0.620
0.618
0.616
0.614
96
98
100
102
104


Learning rate Vs RMSE with batch size=200
RMSE
0.6155
0.6150
0.6145




```
The best value of best_Learning_rate is 0. 7
Batch Size 200
RMSE with batch size=200 5.5412656277668955
MSE with batch size=200 30.705624757470847
```

In [82]:

```
columns = ["Model","Batch_Size","RMSE","MSE", "Iteration", "Optimal learning Rate"]
pd.DataFrame(models_performence1, columns=columns)
```

Out[82]:

	Model	Batch_Size	RMSE	MSE	Iteration	Optimal learning Rate
0	sklearn.linear_model.SGDRegressor	50	5.681750	32.282286	100.0	4.882812e-04
1	sklearn.linear_model.SGDRegressor	100	5.523540	30.509489	100.0	5.551115e-17
2	sklearn.linear_model.SGDRegressor	150	5.380124	28.945734	100.0	1.121039e-44
3	sklearn.linear_model.SGDRegressor	200	5.541237	30.705304	100.0	2.067952e-25
4	sklearn.linear_model.SGDRegressor	50	5.681529	32.279775	100.0	3.051758e-05
5	sklearn.linear_model.SGDRegressor	100	5.523835	30.512755	100.0	4.768372e-07
6	sklearn.linear_model.SGDRegressor	150	5.380063	28.945074	100.0	7.812500e-03
7	sklearn.linear_model.SGDRegressor	200	5.541342	30.706470	100.0	2.117582e-22
8	sklearn.linear_model.SGDRegressor	50	5.683320	32.300131	100.0	2.500000e-01
9	sklearn.linear_model.SGDRegressor	100	5.524091	30.515580	100.0	2.273737e-13
10	sklearn.linear_model.SGDRegressor	150	5.380450	28.949246	100.0	1.387779e-17
11	sklearn.linear_model.SGDRegressor	200	5.541424	30.707380	100.0	1.336382e-51
12	sklearn.linear_model.SGDRegressor	50	5.683823	32.305847	100.0	5.000000e-01
13	sklearn.linear_model.SGDRegressor	100	5.524136	30.516082	100.0	3.388132e-21
14	sklearn.linear_model.SGDRegressor	150	5.380203	28.946586	100.0	4.882812e-04
15	sklearn.linear_model.SGDRegressor	200	5.541266	30.705625	100.0	1.593092e-58

Observation:

In sklearn SGDRegressor,It is observed that as batch size increases optimal learning rate decreses.

RMSE value is around 5 and MSE value is around 30

RMSE value for batch size 50 is high comparatively with others batch size.

For Batch size=200, RMSE & learning Rate is lowest.

Standardization training and testing data accourding to batch size

Manual SGD function

L(w,b)=min w,b{sum(square{yi-wTxi-b})}

Derivative of Lw w.r.t w ==>

Lw= sum({-2*xi}{yi-wT.xi-b})

Derivative of Lb w.r.t b==>

lb=sum(-2*{yi-wTxi-b})

In [83]:

```
models_performence1 = {
    'Model':[],
    'Batch_Size':[],
    'RMSE': [],
    'MSE':[],
    'Iteration':[],
    'Optimal learning Rate':[],


}
columns = ["Model","Batch_Size","RMSE","MSE", "Iteration", "Optimal learning Rate"]
pd.DataFrame(models_performence1, columns=columns)
```

Out[83]:

	Model	Batch_Size	RMSE	MSE	Iteration	Optimal learning Rate

In [84]:

```
def denorm(scale,list):
    return [(scale*i) for i in list]

# scale
scale=np.max(Y_test)
print(scale)
```

```
50.0
```

In [88]:

```
##https://github.com/priyagunjate/Implement-SGD-for-linear-
regression/blob/master/Assignment6_working%20on.ipynb
# SGD function
#L(w,b)=min w,b{sum(square{yi-wTxi-b})}
def SGD(batch_size):
    X_batch_size =X_train[:batch_size]
    price_batch_size =Y_train[:batch_size]
    X_test_batch=X_test[:batch_size]
    ytt_batch_size= Y_test[:batch_size]




    N = len(X_batch_size)

    xi_1=[]
    yprice=[]
    xtt=[]
    ytt=[]
    ytt1=[]
    for j in range(N):
        # standardization of datasets
        scaler = StandardScaler()
        scaler.fit(X_batch_size)
        X_scaled_batch_size = scaler.transform(X_batch_size)
        X_scaled_batch_size=preprocessing.normalize(X_scaled_batch_size)
        xi_1.append(X_scaled_batch_size)

        X_test_batch_size=scaler.transform(X_test_batch)
        X_test_batch_size=preprocessing.normalize(X_test_batch_size)
```

```
    xtt.append(X_test_batch_size)
    Y_scaled_batch_size=np.asmatrix(price_batch_size)
    #Y_scaled_batch_size=preprocessing.normalize(Y_scaled_batch_size)
    yprice.append(Y_scaled_batch_size)
    Ytt_scaled_batch_size1=np.asmatrix(Y_test[:batch_size])
    Ytt_scaled_batch_size=preprocessing.normalize(Ytt_scaled_batch_size1)
    ytt1.append(Ytt_scaled_batch_size1)
    ytt.append(Ytt_scaled_batch_size)

xi=xi_1
price=yprice

Lw = 0
Lb = 0
learning_rate = 1
iteration = 1
w0_random = np.random.rand(13)
w0 = np.asmatrix(w0_random).T
b = np.random.rand()
b0 = np.random.rand()
global learning_rate1
learning_rate1=[]
global epoch
epoch=[]
global rmse1
rmse1=[]
global y_hat_manual_SGD
y_hat_manual_SGD=[]
global delta_Error
delta_Error=[]


while True:
    learning_rate1.append(learning_rate)
    epoch.append(iteration)

    for i in range(N):
        wj=w0
        bj=b0
        #derivative of Lw w.r.t w
        #Lw= sum({-2*xi}{yi-wT.xi-b})
        #print(price[i] .shape)
        Lw = (1/N)*np.dot((-2*xi[i].T ), (price[i] - np.dot( xi[i],wj) - bj))
        #derivative of Lb w.r.t b
        #lb=sum(-2*{yi-wTxi-b})
        Lb = (-2/N)*(price[i] - np.dot( xi[i],wj ) - bj)
        #print('yi',Lw.shape)
        y_new=(1/N)*(xtt[i].dot(Lw))+Lb
        #print(y_new[i])
        y_pred=np.absolute(np.array(y_new[i]))
        y_hat_manual_SGD.append( y_pred)

        delta_error = np.absolute(np.array(ytt[i] ) - np.array(y_new[i]))
        delta_Error.append(delta_error.mean())
        #delta_error=price[i]  - y_new[i]

        error=np.sum(np.dot(delta_error ,delta_error.T))

    rmse1.append(error)

    w0_new = Lw * learning_rate
    b0_new = Lb * learning_rate
    wj = w0 - w0_new
    bj = b0 - b0_new
    iteration += 1
    if (w0==wj).all():
        break
    else:
        w0 = wj
        b0 = bj
        learning_rate = learning_rate/2

print('For batch size'+str(batch_size))


RMSE=(scale*np.asarray(rmse1))
```

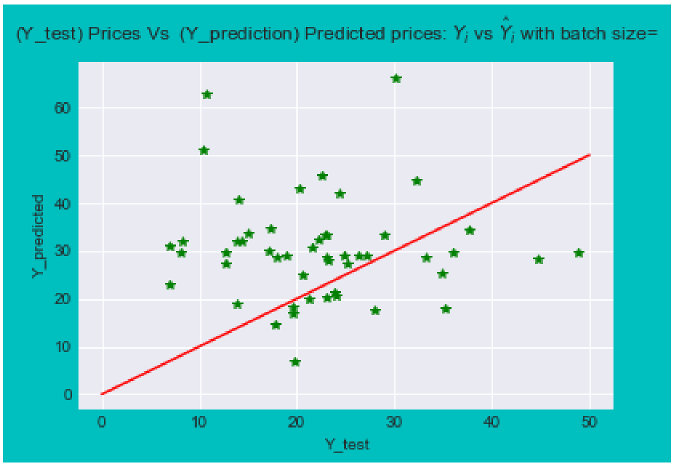
```
    # Y_test function
    vvv=denorm(1,ytt1)
    cv=vvv[0]
    # Y_hat_test function after normationzation
    cvv=denorm(scale,y_hat_manual_SGD[batch_size])
    #print(sum(delta_error)/len(delta_error))
    fig4 = plt.figure( facecolor='c', edgecolor='k')
    fig4.suptitle('(Y_test) Prices Vs  (Y_prediction) Predicted prices: $Y_i$ vs $\hat{Y}_i$ with 
batch size=', fontsize=12)
    plt.plot(cv,cvv,'g*')
    plt.plot([0,batch_size],[0,batch_size], 'r-')

    plt.xlabel('Y_test')
    plt.ylabel('Y_predicted')
    plt.show()

     # Plot delta_Error and prediction of price
    fig3 = plt.figure( facecolor='y', edgecolor='k')
    fig3.suptitle('delta_Error  with batch size='+str(batch_size), fontsize=12)
    sns.set_style('darkgrid')
    sns.distplot(np.array(delta_Error),kde_kws={"color": "r", "lw": 3, "label": 
"Delta_error_manual"} )
    #sns.kdeplot(np.array(ghy),shade=True, color="r", bw=0.5)
    plt.show()

    #For plotting epoch vs RMSE
    models_performence1['Model'].append('SGD Manual Function')
    models_performence1['Batch_Size'].append(batch_size)
    fig = plt.figure( facecolor='c', edgecolor='k')
    fig.suptitle('epoch Vs RMSE with batch size='+str(batch_size), fontsize=12)
    ax1 = fig.add_subplot(111)
    plt.plot(epoch,RMSE,'r*',linestyle='dashed')
    plt.xlabel('epoch')
    plt.ylabel('RMSE with batch size='+str(batch_size))
    plt.plot(epoch,RMSE,'y',linestyle='dashed')
    plt.show()

    #Best learning rate
    global best_Learning_rate1
    best_Learning_rate1=learning_rate1[rmse1.index(min(rmse1))]
    print('\nThe best value of best_Learning_rate is %d.' % (best_Learning_rate1))
    models_performence1['Optimal learning Rate'].append(best_Learning_rate1)
    fig1 = plt.figure( facecolor='y', edgecolor='k')
    fig1.suptitle('Learning rate Vs RMSE with batch size='+str(batch_size), fontsize=12)
    ax1 = fig1.add_subplot(111)
    plt.plot(learning_rate1,rmse1,'m*')
    plt.xlabel('Learning rate')
    plt.ylabel('RMSE')


    global RMSE_value
    MSE_value = sum(rmse1)/len(rmse1)
    print("MSE_value=",MSE_value  )
    models_performence1['MSE'].append(MSE_value)
    RMSE_value =np.sqrt(MSE_value)
    models_performence1['RMSE'].append(RMSE_value)


    models_performence1['Iteration'].append(iteration)

    print("RMSE = ",RMSE_value)
    print('For batch size'+str(batch_size))


    print('iteration =',iteration)

    print('Total number of learning_rate=',len(learning_rate1))
    plt.plot(learning_rate1,rmse1,'y',linestyle='dashed')
    plt.show()
```

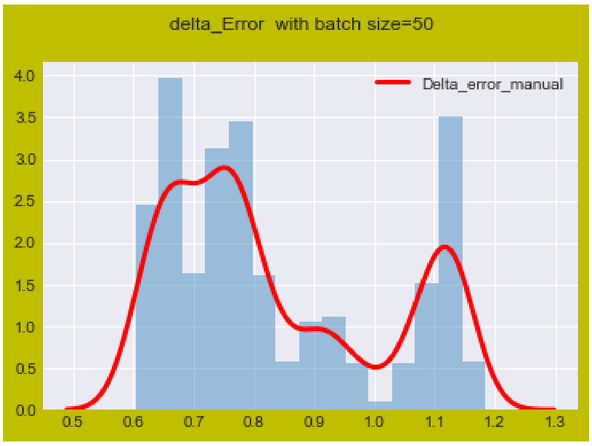
In [86]:

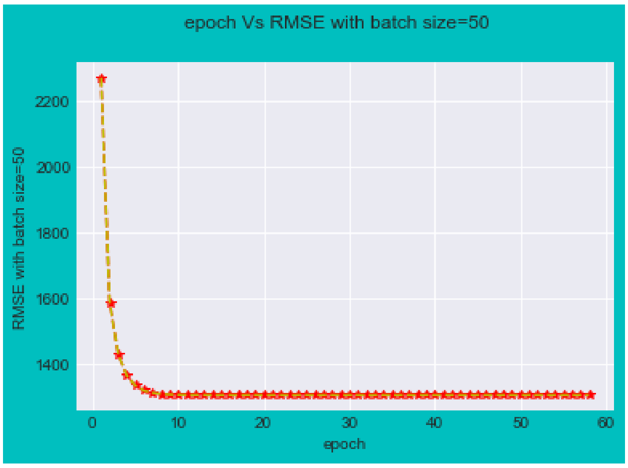
```
initial_batch_size=50

for l in range(4):
    batch_size_value= initial_batch_size + initial_batch_size * l
```

```
    print(batch_size_value)
    SGD(batch_size_value)
```

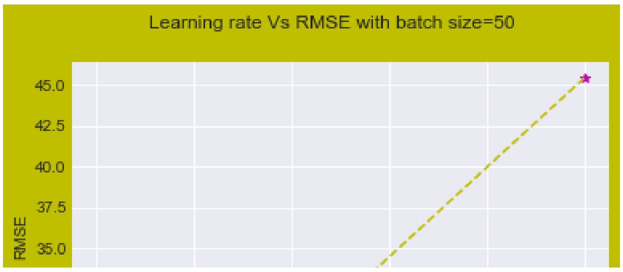
```
50
For batch size50
```

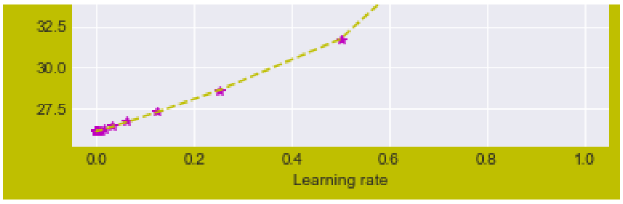




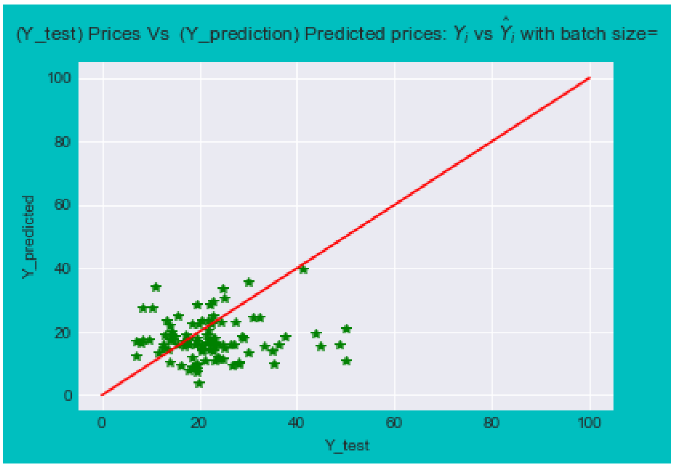


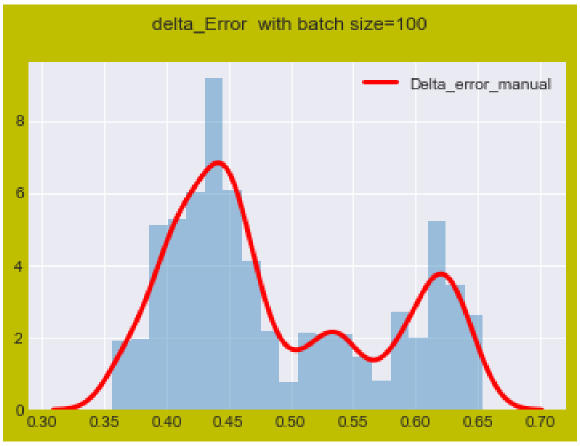

```
The best value of best_Learning_rate is 0.
MSE_value= 26.605770571510888
RMSE =  5.158078185866407
For batch size50
iteration = 59
Total number of learning_rate= 58
```

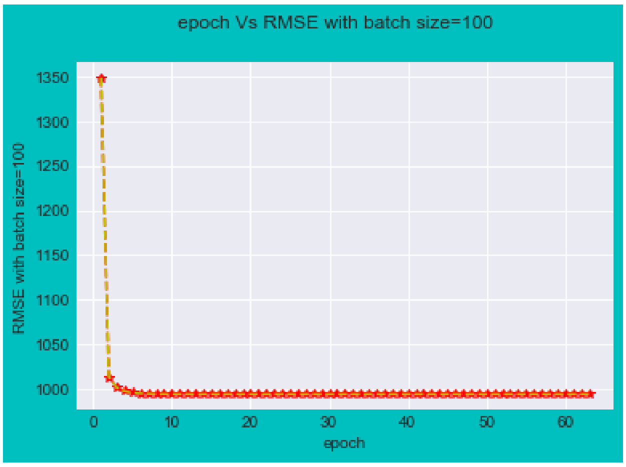




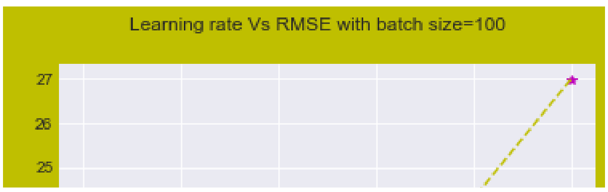
100
For batch size100

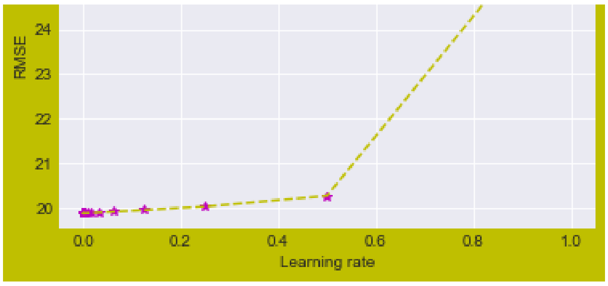




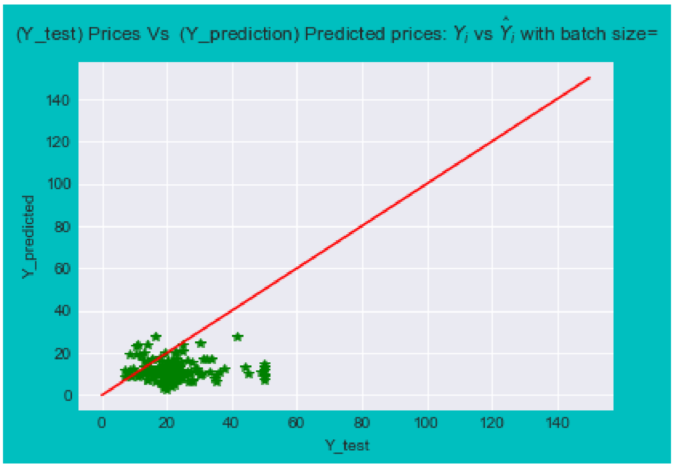


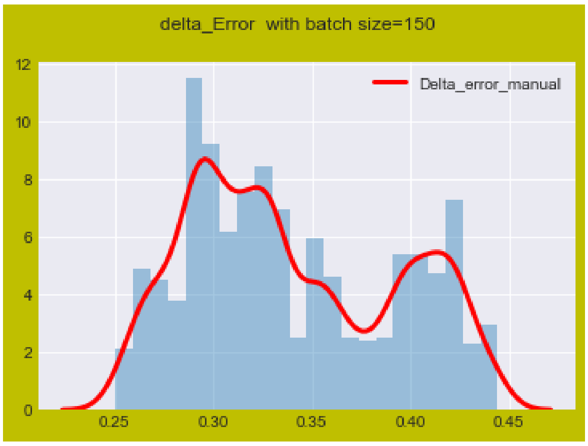
The best value of best_Learning_rate is 0.
MSE_value= 19.99683446578691
RMSE = 4.471782023509969
For batch size100
iteration = 64
Total number of learning_rate= 63

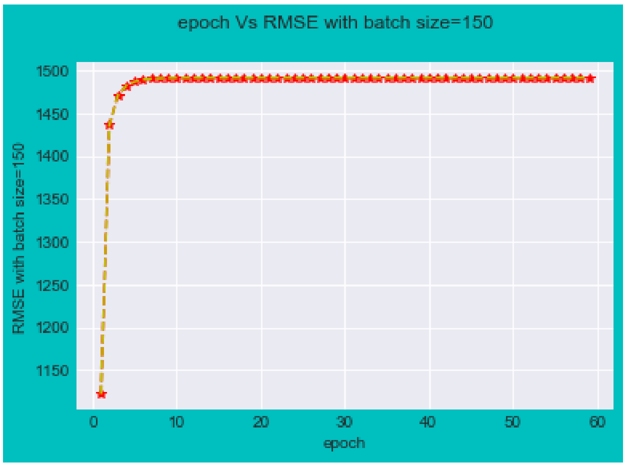




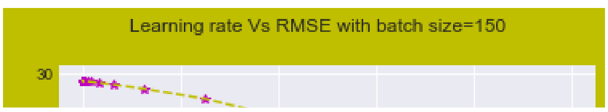
150
For batch size150

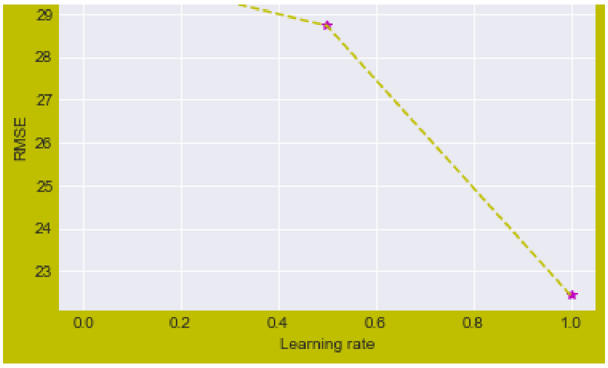




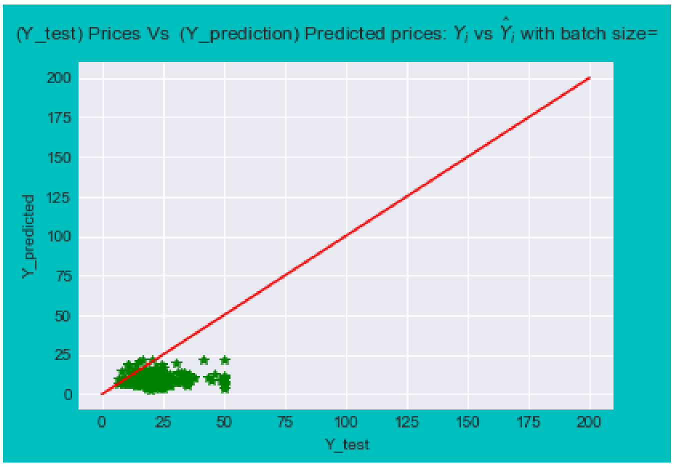


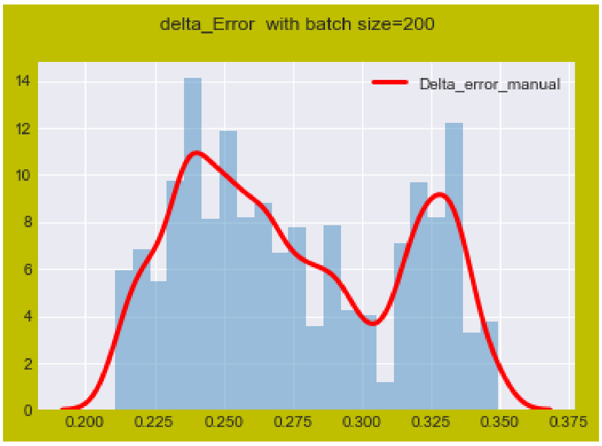
The best value of best_Learning_rate is 1.
MSE_value= 29.67533256082048
RMSE = 5.44750700420114
For batch size150
iteration = 60
Total number of learning_rate= 59

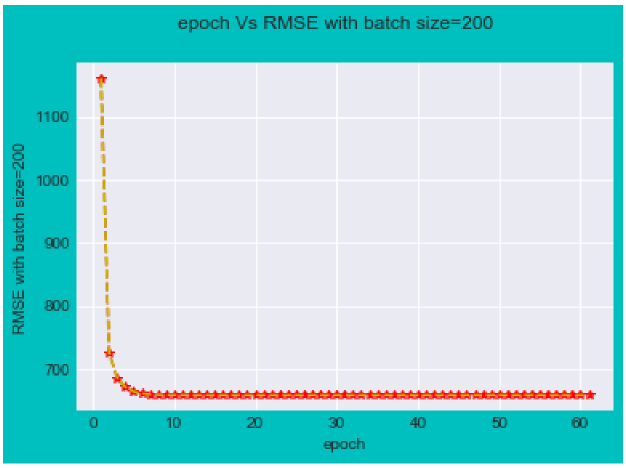




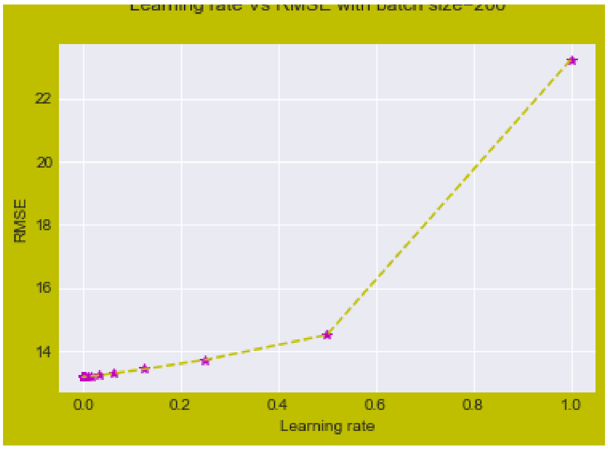

```
200
For batch size200
```








```
The best value of best_Learning_rate is 0.
MSE_value= 13.381442002196659
RMSE =  3.658065335966084
For batch size200
iteration = 62
Total number of learning_rate= 61
```



In [87]:

```
columns = ["Model","Batch_Size","RMSE","MSE", "Iteration", "Optimal learning Rate"]
pd.DataFrame(models_performence1, columns=columns)
```

Out[87]:

	Model	Batch_Size	RMSE	MSE	Iteration	Optimal learning Rate
0	SGD Manual Function	50	5.158078	26.605771	59	4.440892e-16
1	SGD Manual Function	100	4.471782	19.996834	64	1.776357e-15
2	SGD Manual Function	150	5.447507	29.675333	60	1.000000e+00
3	SGD Manual Function	200	3.658065	13.381442	62	4.440892e-16

SGD_Manual Vs SGD_sklearn

In [89]:

```
models_performence1 = {
    'Model':[],
    'Batch_Size':[],
    'RMSE': [],
    'MSE':[],
    'Iteration':[],
    'Optimal learning Rate':[],


}
columns = ["Model","Batch_Size","RMSE","MSE", "Iteration", "Optimal learning Rate"]
pd.DataFrame(models_performence1, columns=columns)
```

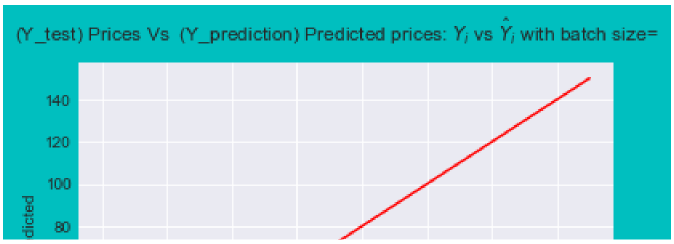
Out[89]:

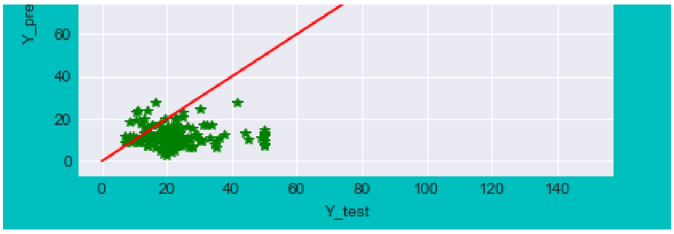
	Model	Batch_Size	RMSE	MSE	Iteration	Optimal learning Rate

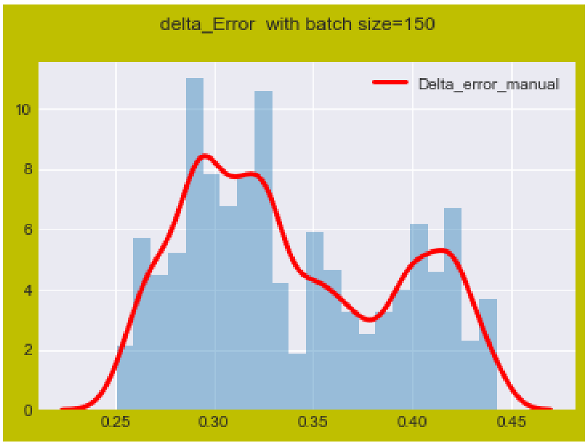
In [90]:

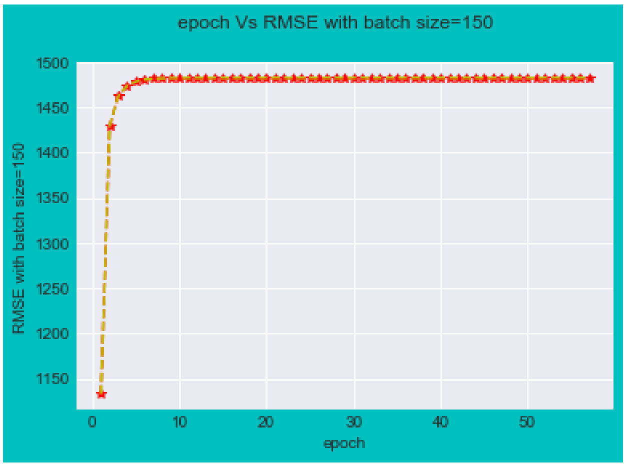
```
SGD(150)
```

```
For batch size150
```

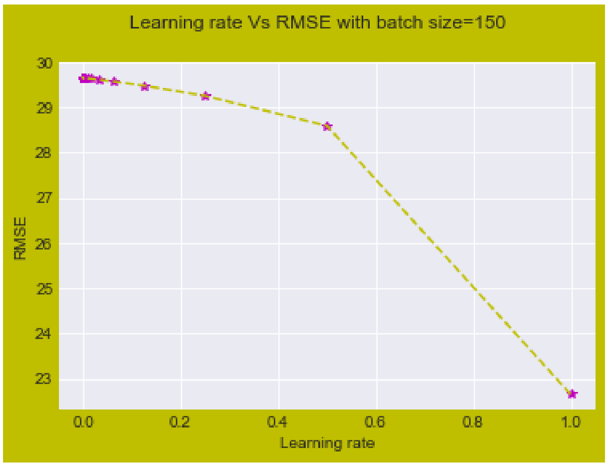








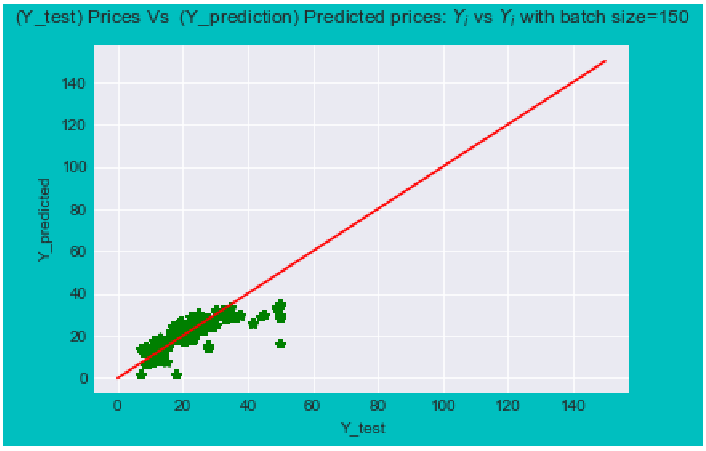

```
The best value of best_Learning_rate is 1.
MSE_value= 29.49822327030651
RMSE =  5.431226681911418
For batch size150
iteration = 58
Total number of learning_rate= 57
```

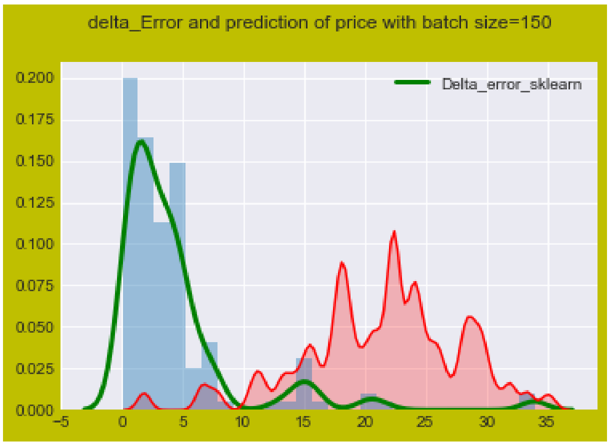


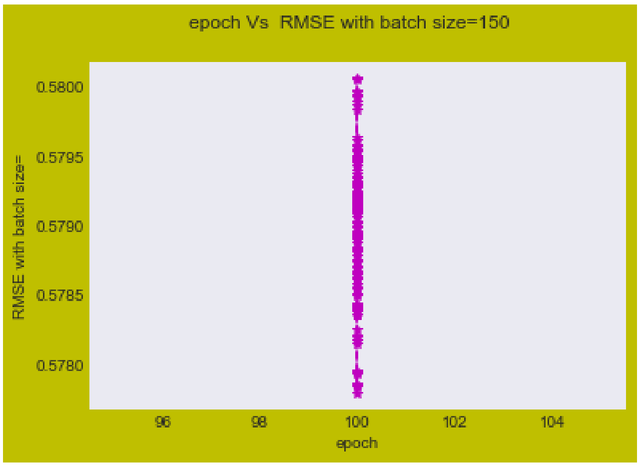
In [91]:

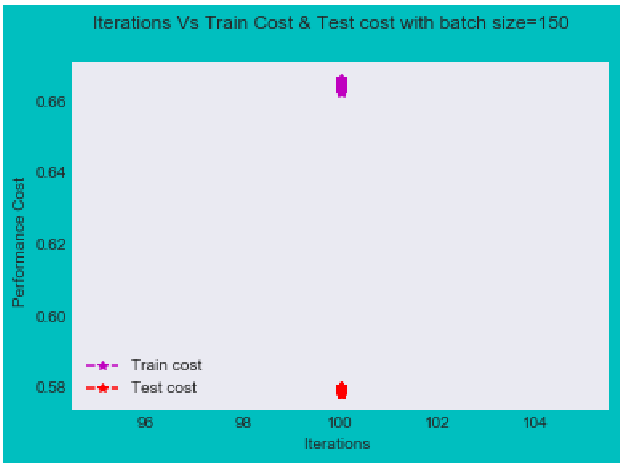
```
sgdreg_function(1,150)
```

```
Training Error= 0.33493265571208486
Testing_error 0.420935006557569
```

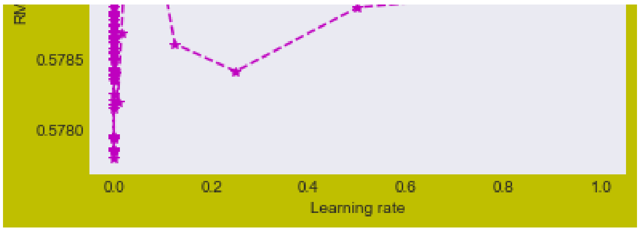

(Y_test) Prices Vs (Y_prediction) Predicted prices: Y_i vs $\hat{Y}_i$ with batch size=150
Y_predicted
Y_test


delta_Error and prediction of price with batch size=150
Delta_error_sklearn


epoch Vs RMSE with batch size=150
RMSE with batch size=
epoch


Iterations Vs Train Cost & Test cost with batch size=150
Performance Cost
Train cost
Test cost
Iterations


Learning rate Vs RMSE with batch size=150




```
The best value of best_Learning_rate is 0. 7
Batch Size 150
RMSE with batch size=150 5.380435668792099
MSE with batch size=150 28.949087986010284
```

Y_predicted using manual SGD Vs Y_predicted using Sklearn SGD

Y_predicted using manual SGD == y_hat_manual_SGD

Error(y-y_hat) for manual SGD == delta_Error

Y_predicted using Sklearn SGD == Y_hat_Predicted

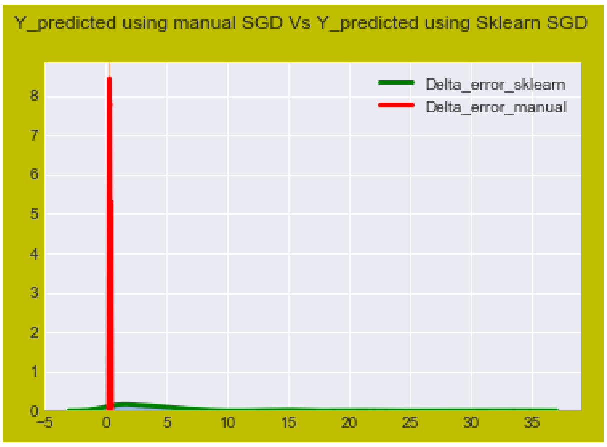
Error(y-y_hat) for SKlearn SGD == delta_error

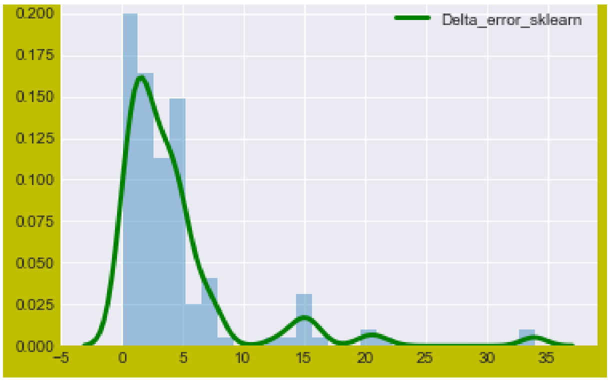
In [92]:

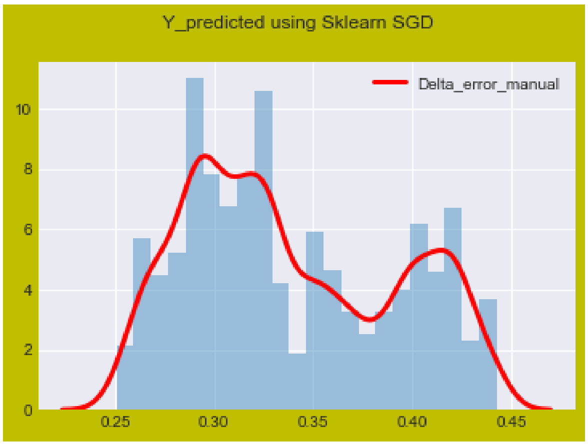
```
def y_hat_cal(delta_error_sklearn,delta_Error_manual):
    fig41 = plt.figure( facecolor='y', edgecolor='k')
    fig41.suptitle('Y_predicted using manual SGD Vs Y_predicted using Sklearn SGD ', fontsize=12)

    sns.set_style('darkgrid')
    Y_sklearn=np.array(sum(delta_error_sklearn)/len(delta_error_sklearn))

    Y_manual=np.array(delta_Error_manual)
    #print(Y_manual[0])
    sns.distplot(Y_sklearn,kde_kws={"color": "g", "lw": 3, "label": "Delta_error_sklearn"} )
    sns.distplot(Y_manual,kde_kws={"color": "r", "lw": 3, "label": "Delta_error_manual"} )
    fig51 = plt.figure( facecolor='y', edgecolor='k')
    fig51.suptitle('Y_predicted using manual SGD ', fontsize=12)
    sns.distplot(Y_sklearn,kde_kws={"color": "g", "lw": 3, "label": "Delta_error_sklearn"} )

    fig41 = plt.figure( facecolor='y', edgecolor='k')
    fig41.suptitle(' Y_predicted using Sklearn SGD ', fontsize=12)
    sns.distplot(Y_manual,kde_kws={"color": "r", "lw": 3, "label": "Delta_error_manual"} )
```

In [93]:

```
y_hat_cal(delta_error,delta_Error)
```





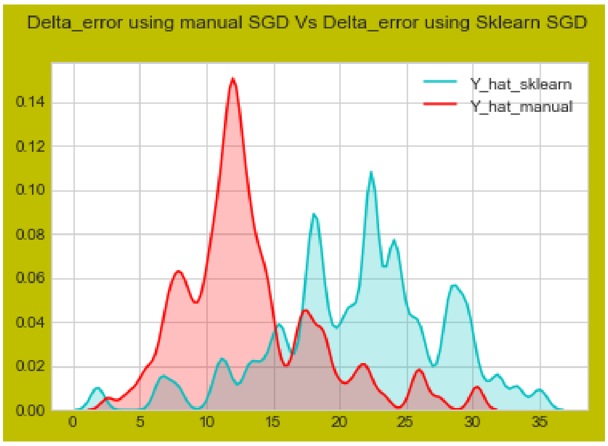


In [94]:

```
def y_skl_maual(y_hat_sklearn,y_hat_maunal):
    fig41 = plt.figure( facecolor='y', edgecolor='k')
    fig41.suptitle('Delta_error using manual SGD Vs Delta_error using Sklearn SGD ', fontsize=12)

    sns.set_style('whitegrid')
    Y_sklearn=np.array(sum(y_hat_sklearn)/len(y_hat_sklearn))

    Y_manual=np.array(scale*sum(y_hat_maunal)/len(y_hat_maunal))
    #print(Y_manual[0])

    sns.kdeplot(Y_sklearn,shade=True, color="c", bw=0.5,label='Y_hat_sklearn')
    sns.kdeplot(Y_manual[0],shade=True, color="r", bw=0.5,label='Y_hat_manual')
```

In [95]:

```
y_skl_maual(Y_hat_Predicted,y_hat_manual_SGD)
```



In [96]:

```
columns = ["Model","Batch_Size","RMSE","MSE", "Iteration", "Optimal learning Rate"]
pd.DataFrame(models_performence1, columns=columns)
```

Out[96]:

	Model	Batch_Size	RMSE	MSE	Iteration	Optimal learning Rate
0	SGD Manual Function	150	5.431227	29.498223	58.0	1.000000e+00
1	sklearn.linear_model.SGDRegressor	150	5.380436	28.949088	100.0	2.524355e-29

Observation:

In stochastic gradient descent Manual model(a user designed model),RMSE(root mean squared error) is varied as compared to sklearn designed stochastic gradient descent model for varied number of batch_size.

Graphs between learning rate vs RMSE & Epoch Vs RMSE are plotted.

From the graph , stochastic gradient descent model performance can be observed

Comparision of SGD_sklearn and SGD_manual with batch_size=150 :-

- Distributions Plots for errors(y - y_hat) and It is overlapping as shown in graph "y_hat_cal(delta_error,delta_Error)".Seperate distribuation plots for both of implementations are plotted below it.
- "Delta_error using manual SGD Vs Delta_error using Sklearn SGD" graph is plotted .Varience(spread) of Blue graph(SGD sklearn) is high as comapared to spread of Red graph (manual SGD) .
- RMSE Vs epoch for manual SGD graph looks like almost "L" shape.So, Model doesn't leads to overfitting. In case od SGD sklearn , it is straight vertical line at epoch.
- RMSE value and MSE value for batch_size 150 is almost similar as seen in above table
- Optimal learning rate is low for SGD sklearn and 1 which high in this case is for SGD manual.