Assignment 6: Implement SGD for linear regression

Linear regression is technique to predict on real values. stochastic gradient descent technique will evaluate and update the coefficients for every iteration to reduce the error of a model on training data. Goal: In this assignment our Objective is to Implement stochastic gradient descent on Bostan House Prices dataset for linear Regression. steps: Implement SGD and deploy on Bostan House Prices dataset. Comapare the Results with sklearn.linear_model.SGDRegressor

In [40]:

```
from sklearn.datasets import load_boston # to load  datasets from sklearn
import matplotlib.pyplot as plt
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
import numpy as np
import seaborn as sns
from collections import Counter
from sklearn.metrics import accuracy_score
from sklearn import model_selection
from sklearn.preprocessing import StandardScaler
import pandas as pd
import math
import sklearn
import pytablewriter
```

In [7]:

```
boston=load_boston()
```

In [8]:

```
print(boston.data.shape)
```

```
(506, 13)
```

In [9]:

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

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

In [10]:

```
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.

    :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
```

```
        - 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 [11]:

```python
print(boston.target)
```

```
[24.  21.6 34.7 33.4 36.2 28.7 22.9 27.1 16.5 18.9 15.  18.9 21.7 20.4
 18.2 19.9 23.1 17.5 20.2 18.2 13.6 19.6 15.2 14.5 15.6 13.9 16.6 14.8
 18.4 21.  12.7 14.5 13.2 13.1 13.5 18.9 20.  21.  24.7 30.8 34.9 26.6
 25.3 24.7 21.2 19.3 20.  16.6 14.4 19.4 19.7 20.5 25.  23.4 18.9 35.4
 24.7 31.6 23.3 19.6 18.7 16.  22.2 25.  33.  23.5 19.4 22.  17.4 20.9
 24.2 21.7 22.8 23.4 24.1 21.4 20.  20.8 21.2 20.3 28.  23.9 24.8 22.9
 23.9 26.6 22.5 22.2 23.6 28.7 22.6 22.  22.9 25.  20.6 28.4 21.4 38.7
 43.8 33.2 27.5 26.5 18.6 19.3 20.1 19.5 19.5 20.4 19.8 19.4 21.7 22.8
 18.8 18.7 18.5 18.3 21.2 19.2 20.4 19.3 22.  20.3 20.5 17.3 18.8 21.4
 15.7 16.2 18.  14.3 19.2 19.6 23.  18.4 15.6 18.1 17.4 17.1 13.3 17.8
 14.  14.4 13.4 15.6 11.8 13.8 15.6 14.6 17.8 15.4 21.5 19.6 15.3 19.4
 17.  15.6 13.1 41.3 24.3 23.3 27.  50.  50.  50.  22.7 25.  50.  23.8
 23.8 22.3 17.4 19.1 23.1 23.6 22.6 29.4 23.2 24.6 29.9 37.2 39.8 36.2
 37.9 32.5 26.4 29.6 50.  32.  29.8 34.9 37.  30.5 36.4 31.1 29.1 50.
 33.3 30.3 34.6 34.9 32.9 24.1 42.3 48.5 50.  22.6 24.4 22.5 24.4 20.
 21.7 19.3 22.4 28.1 23.7 25.  23.3 28.7 21.5 23.  26.7 21.7 27.5 30.1
 44.8 50.  37.6 31.6 46.7 31.5 24.3 31.7 41.7 48.3 29.  24.  25.1 31.5
 23.7 23.3 22.  20.1 22.2 23.7 17.6 18.5 24.3 20.5 24.5 26.2 24.4 24.8
 29.6 42.8 21.9 20.9 44.  50.  36.  30.1 33.8 43.1 48.8 31.  36.5 22.8
 30.7 50.  43.5 20.7 21.1 25.2 24.4 35.2 32.4 32.  33.2 33.1 29.1 35.1
 45.4 35.4 46.  50.  32.2 22.  20.1 23.2 22.3 24.8 28.5 37.3 27.9 23.9
 21.7 28.6 27.1 20.3 22.5 29.  24.8 22.  26.4 33.1 36.1 28.4 33.4 28.2
 22.8 20.3 16.1 22.1 19.4 21.6 23.8 16.2 17.8 19.8 23.1 21.  23.8 23.1
 20.4 18.5 25.  24.6 23.  22.2 19.3 22.6 19.8 17.1 19.4 22.2 20.7 21.1
 19.5 18.5 20.6 19.  18.7 32.7 16.5 23.9 31.2 17.5 17.2 23.1 24.5 26.6
 22.9 24.1 18.6 30.1 18.2 20.6 17.8 21.7 22.7 22.6 25.  19.9 20.8 16.8
 21.9 27.5 21.9 23.1 50.  50.  50.  50.  50.  13.8 13.8 15.  13.9 13.3
 13.1 10.2 10.4 10.9 11.3 12.3  8.8  7.2 10.5  7.4 10.2 11.5 15.1 23.2
  9.7 13.8 12.7 13.1 12.5  8.5  5.   6.3  5.6  7.2 12.1  8.3  8.5  5.
 11.9 27.9 17.2 27.5 15.  17.2 17.9 16.3  7.   7.2  7.5 10.4  8.8  8.4
 16.7 14.2 20.8 13.4 11.7  8.3 10.2 10.9 11.   9.5 14.5 14.1 16.1 14.3
 11.7 13.4  9.6  8.7  8.4 12.8 10.5 17.1 18.4 15.4 10.8 11.8 14.9 12.6
 14.1 13.  13.4 15.2 16.1 17.8 14.9 14.1 12.7 13.5 14.9 20.  16.4 17.7
 19.5 20.2 21.4 19.9 19.  19.1 19.1 20.1 19.9 19.6 23.2 29.8 13.8 13.3
 16.7 12.  14.6 21.4 23.  23.7 25.  21.8 20.6 21.2 19.1 20.6 15.2  7.
  8.1 13.6 20.1 21.8 24.5 23.1 19.7 18.3 21.2 17.5 16.8 22.4 20.6 23.9
 22.  11.9]
```

In [12]:

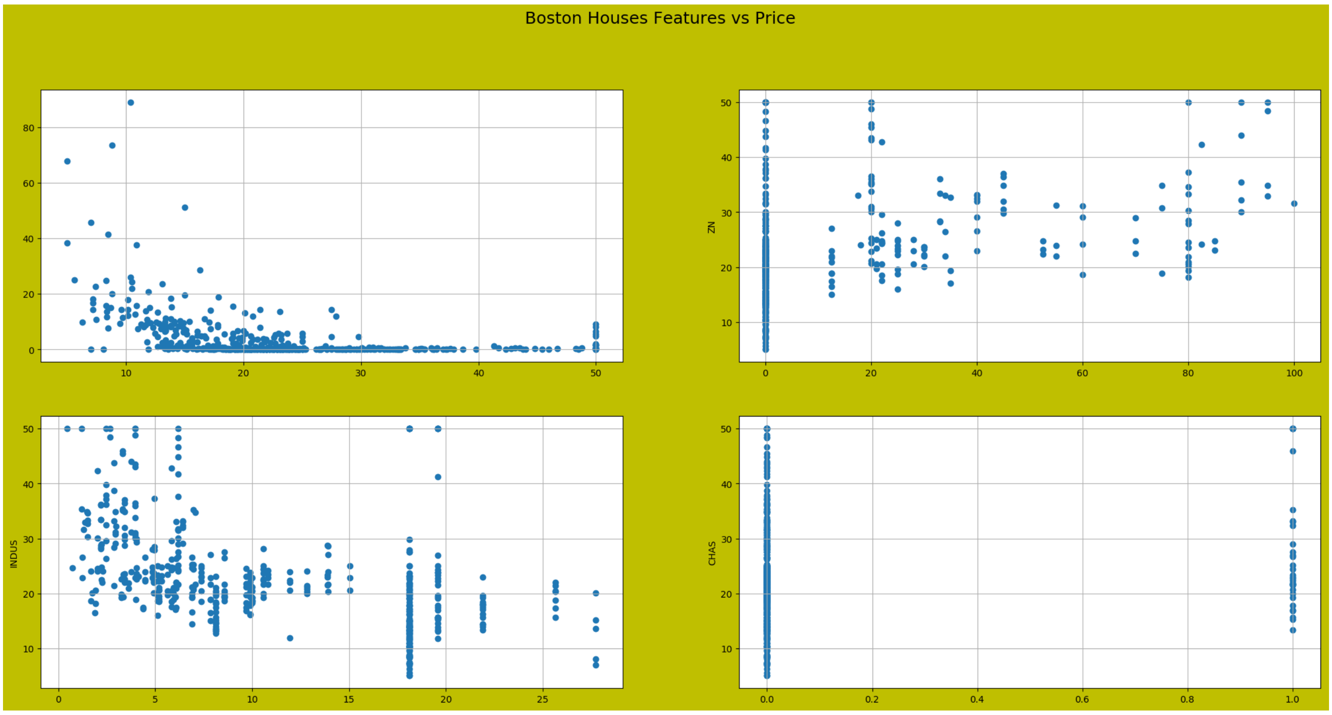
```
# Boston datasets
bostan = pd.DataFrame(boston.data)
print(bostan.head())
# Boston dataset with columns names
bostan_col =pd.DataFrame(boston.data,columns=boston.feature_names)
print(bostan_col.head())
```

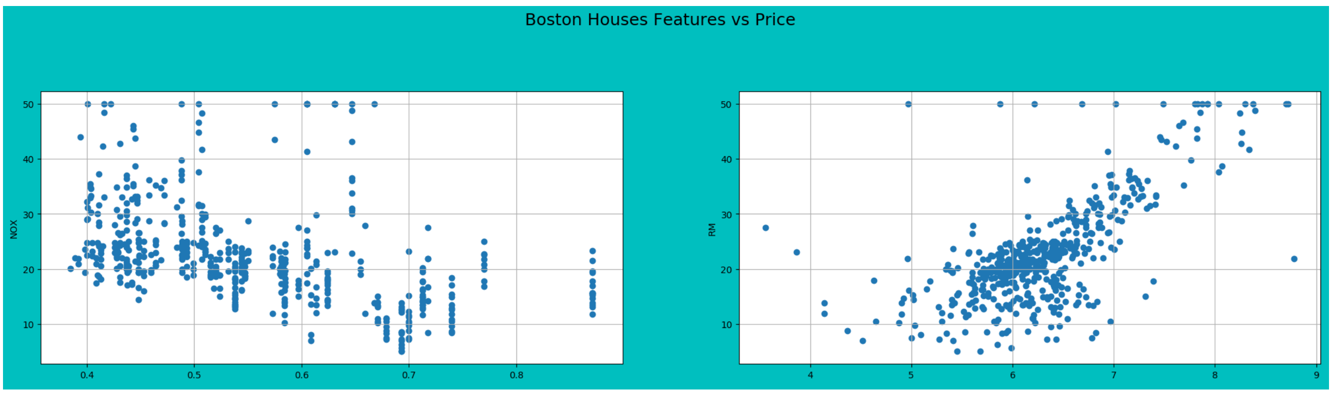
```
        0     1     2    3      4      5     6       7    8      9    10  \
0  0.00632  18.0  2.31  0.0  0.538  6.575  65.2  4.0900  1.0  296.0  15.3
1  0.02731   0.0  7.07  0.0  0.469  6.421  78.9  4.9671  2.0  242.0  17.8
2  0.02729   0.0  7.07  0.0  0.469  7.185  61.1  4.9671  2.0  242.0  17.8
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
```

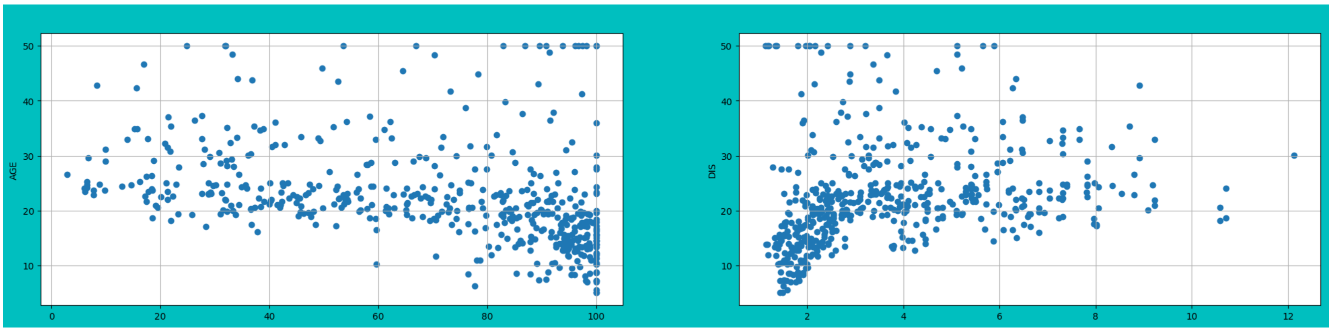
In [13]:

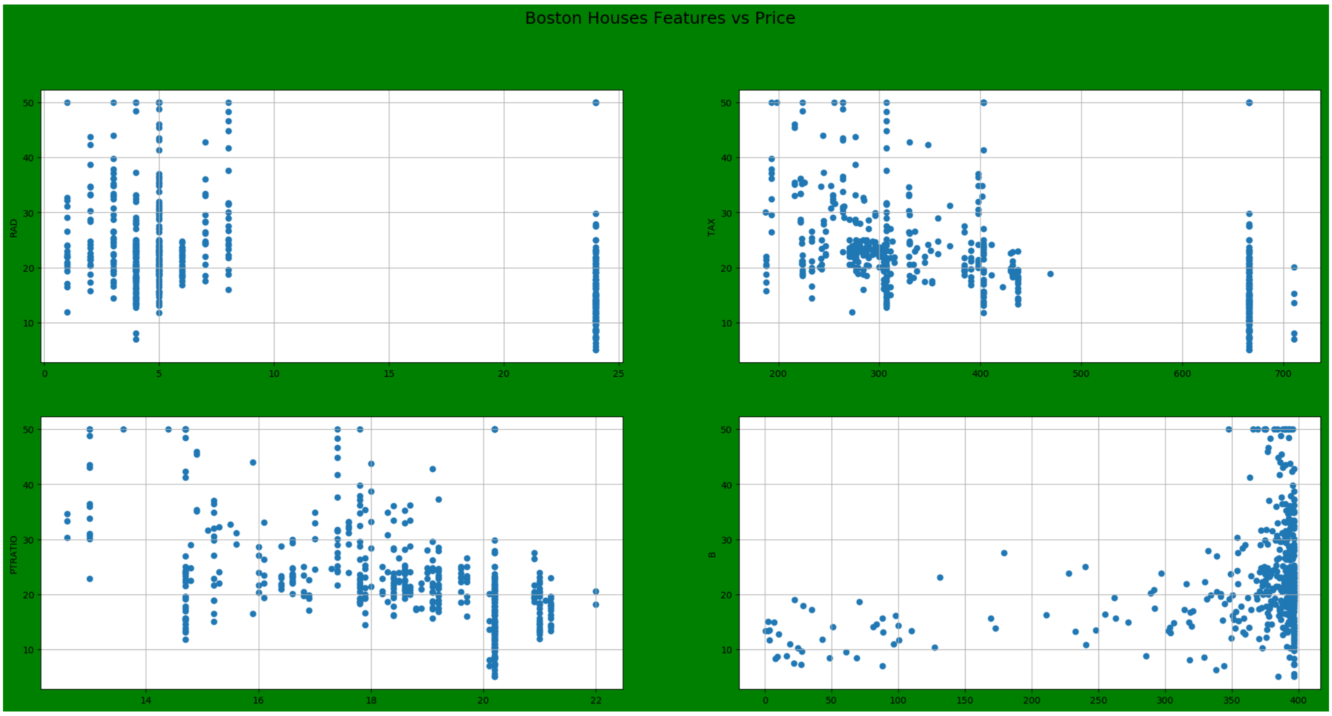
```
#Boston Houses Features vs Price


#ax.title.set_text('Boston Houses Features vs Price')
fig = plt.figure(num=None, figsize=(25, 12), dpi=100, facecolor='y', edgecolor='k')
fig.suptitle('Boston Houses Features vs Price', fontsize=18)
ax1 = fig.add_subplot(221)

ax1.scatter(boston.target,bostan_col.CRIM)
plt.grid()
ax2 = fig.add_subplot(222)
plt.ylabel('CRIM')
ax2.scatter(bostan_col.ZN,boston.target)
plt.ylabel('ZN')
plt.grid()
ax3 = fig.add_subplot(223)

ax3.scatter(bostan_col.INDUS,boston.target)
plt.ylabel('INDUS')
plt.grid()
ax4 = fig.add_subplot(224)
ax4.scatter(bostan_col.CHAS,boston.target)
plt.ylabel('CHAS')
plt.grid()
plt.show()
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.ylabel('NOX')
plt.grid()
ax6 = fig1.add_subplot(222)
ax6.scatter(bostan_col.RM,boston.target)
plt.ylabel('RM')
plt.grid()
```

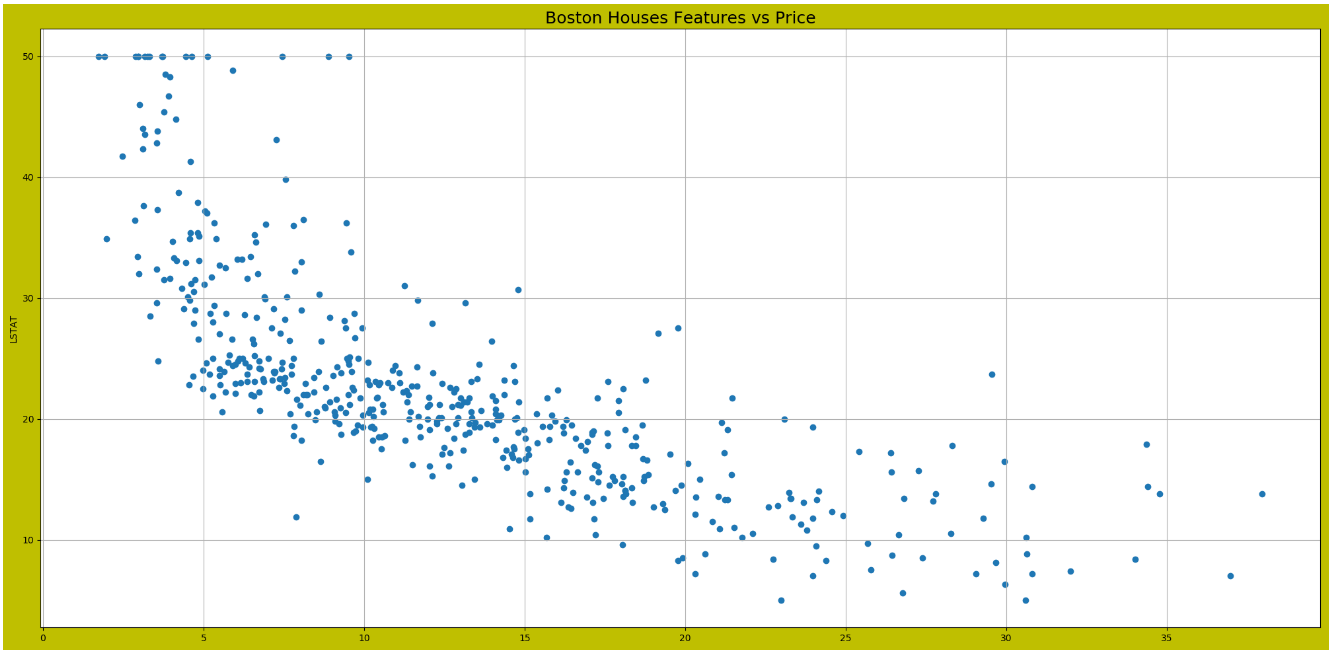
```
ax7 = fig1.add_subplot(223)
ax7.scatter(bostan_col.AGE,boston.target)
plt.ylabel('AGE')
plt.grid()
ax8 = fig1.add_subplot(224)
ax8.scatter(bostan_col.DIS,boston.target)
plt.ylabel('DIS')
plt.grid()
plt.show()
fig2 = plt.figure(num=None, figsize=(25, 12), dpi=100, facecolor='g', edgecolor='k')
fig2.suptitle('Boston Houses Features vs Price', fontsize=18)
ax9 = fig2.add_subplot(221)
ax9.scatter(bostan_col.RAD,boston.target)
plt.ylabel('RAD')
plt.grid()
ax10 = fig2.add_subplot(222)
ax10.scatter(bostan_col.TAX,boston.target)
plt.ylabel('TAX')
plt.grid()
ax11 = fig2.add_subplot(223)
ax11.scatter(bostan_col.PTRATIO,boston.target)
plt.ylabel('PTRATIO')
plt.grid()
ax12 = fig2.add_subplot(224)
ax12.scatter(bostan_col.B,boston.target)
plt.ylabel('B')
plt.grid()
fig3 = plt.figure(num=None, figsize=(25, 12), dpi=100, facecolor='y', edgecolor='k')

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











In [14]:

```
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,)
```

In [15]:

```
#Training and testing datasets splitting with cross_validation


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 [19]:

```
# 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.model_selection.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))
```

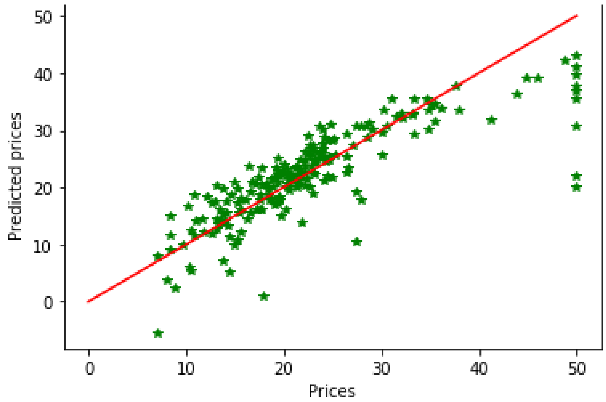
```
(303, 13)
(203, 13)
(303,)
(203,)
<class 'pandas.core.frame.DataFrame'>
```

In [20]:

```
#linear Regression on Bostan House Dataset


#code source:https://medium.com/@haydar_ai/learning-data-science-day-9-linear
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= 5.38813125502015
```

Prices vs Predicted prices : Y_i vs $\hat{Y}_i$



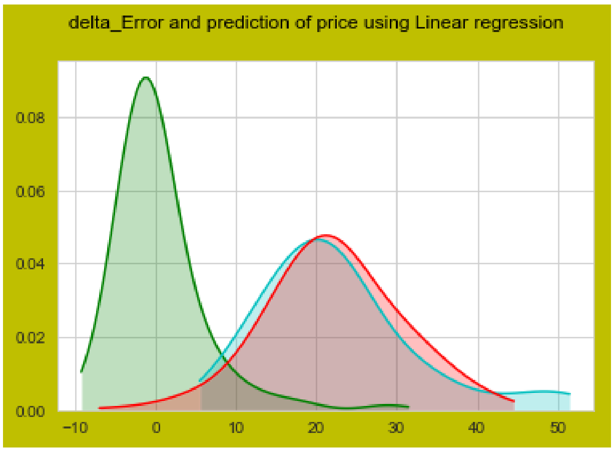
Delta_Error and Prediction of price using Linear regression

In [21]:

```
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')
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[21]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1848b09a828>
```



• Red region is predicted price for bostan house datsets • Blue Region is for y_test • 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 [22]:

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

Out[22]:

Model	Batch_Size	RMSE	MSE	Iteration	Optimal learning Rate

In [23]:

```python
def square(list):
    return [(i ** 2) for i in list]
```

In [24]:

```python
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)
```

```
models_performence['MSE'].append(MSEscore)
```

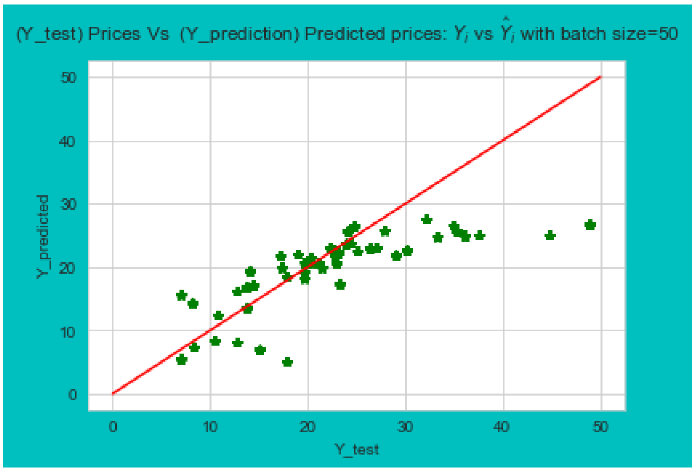
• sgdreg_function is function for stochastic gradient descen for linear regression using linear_ model.SGDRegressor in sklearn. • In this function different batch size (50,100,150,200) is applied on linear_ model.SGDRegressor to get best learning rate,epoch value,error rate. • here,delta_Error and prediction 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.

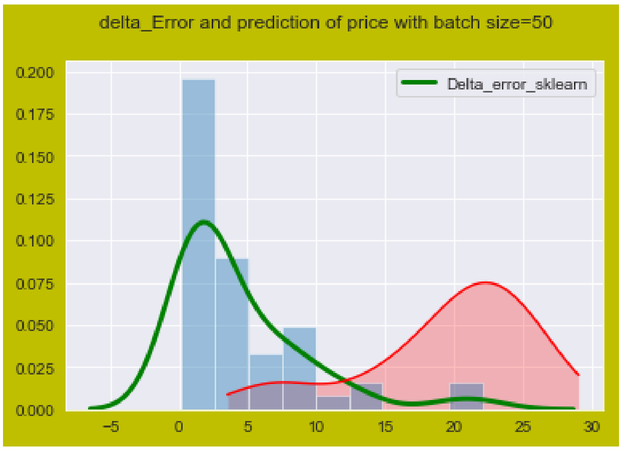
linear_model.SGDRegressor in sklearn for different batch size

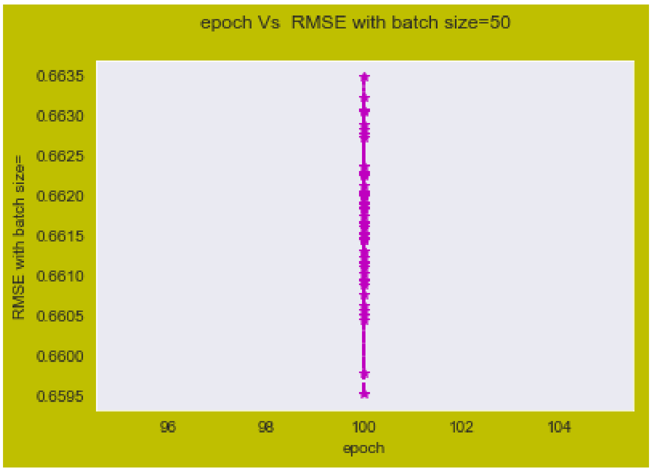
In [25]:

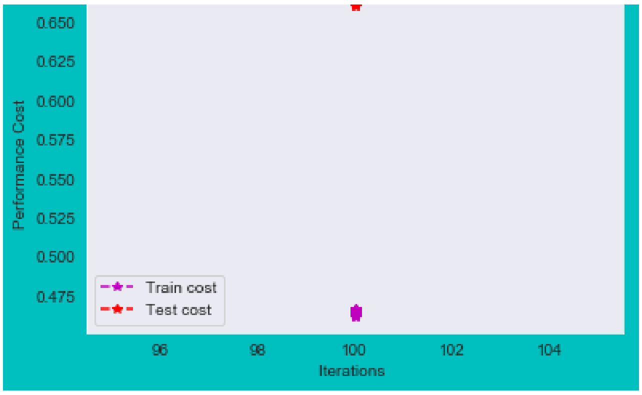
```
sgdreg_function(4,50)
```

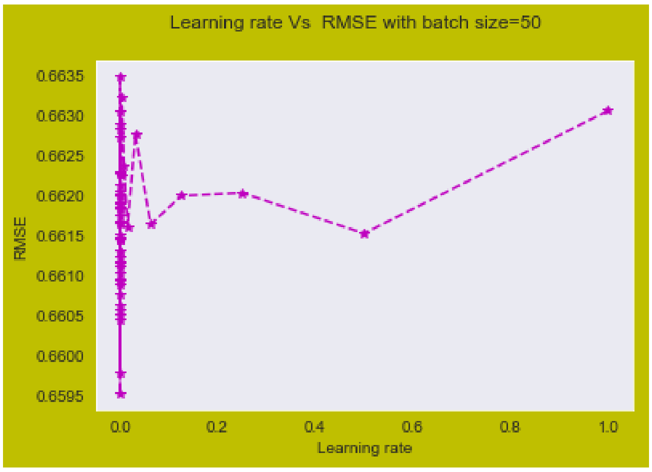
```
Training Error= 0.5354782847881729
Testing_error 0.33800042197410185
```



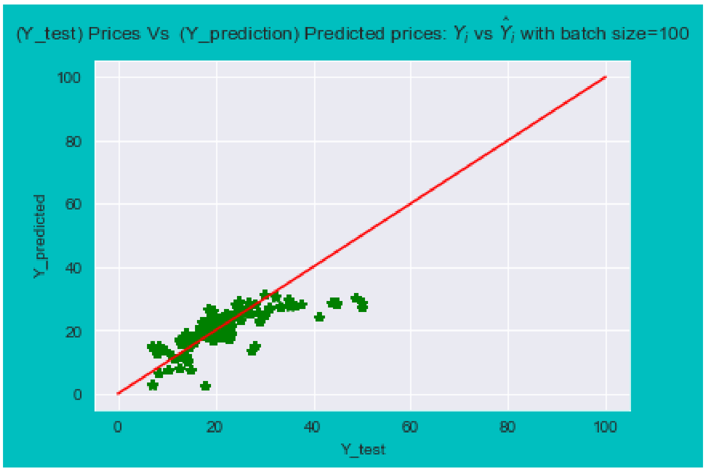


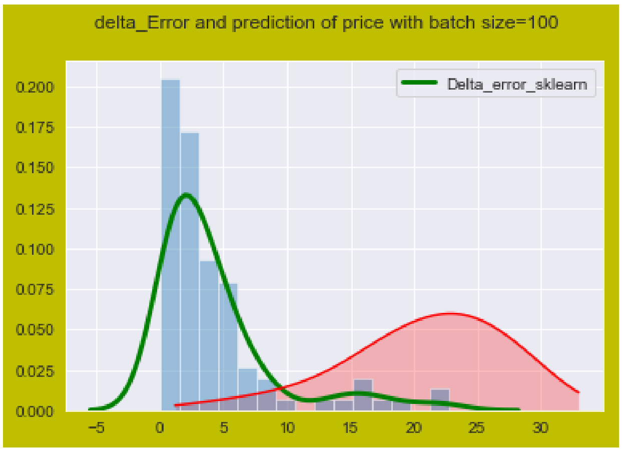


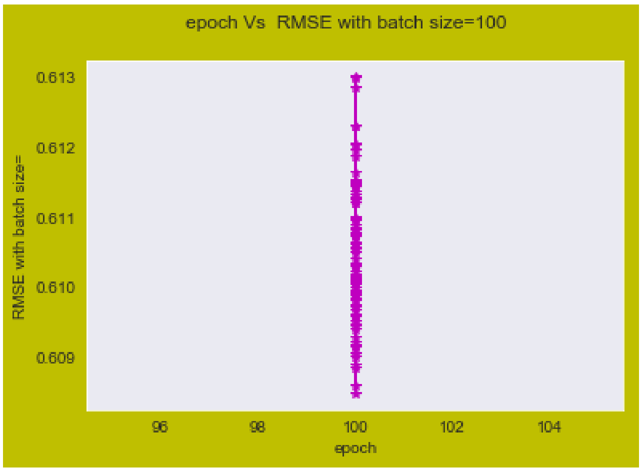


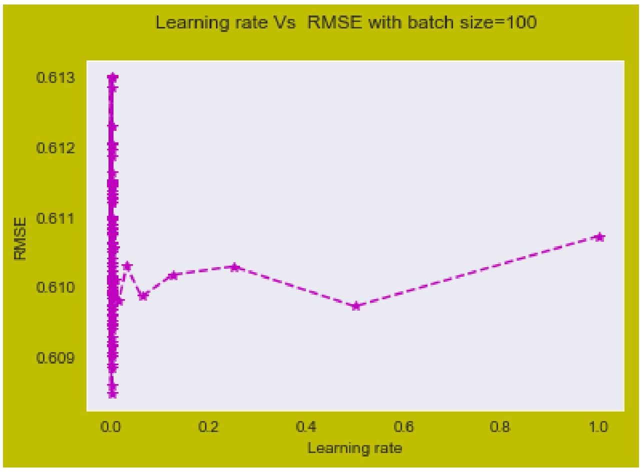



```
The best value of best_Learning_rate is 0. 7
Batch Size 50
RMSE with batch size=50 5.682338862804557
MSE with batch size=50 32.28897495173899
Training Error= 0.4408312897204105
Testing_error 0.3911212507535229
```

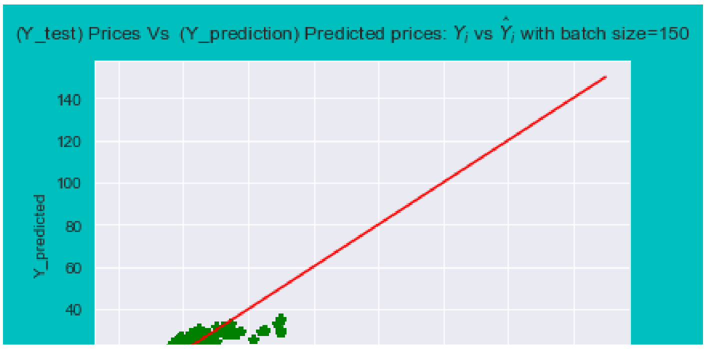


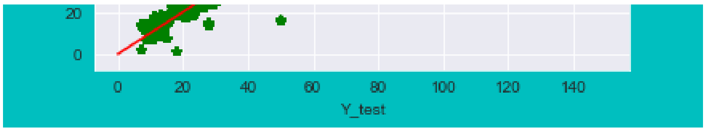




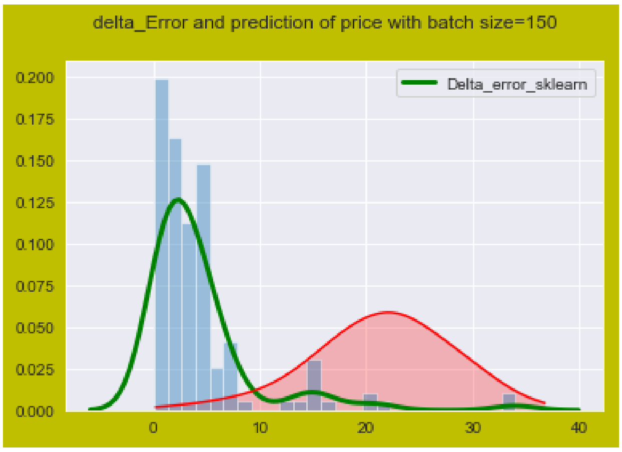



```
The best value of best_Learning_rate is 0. 7
Batch Size 100
RMSE with batch size=100 5.524602742667597
MSE with batch size=100 30.521235464290342
Training Error= 0.3366746305380679
Testing_error 0.4210652461732962
```

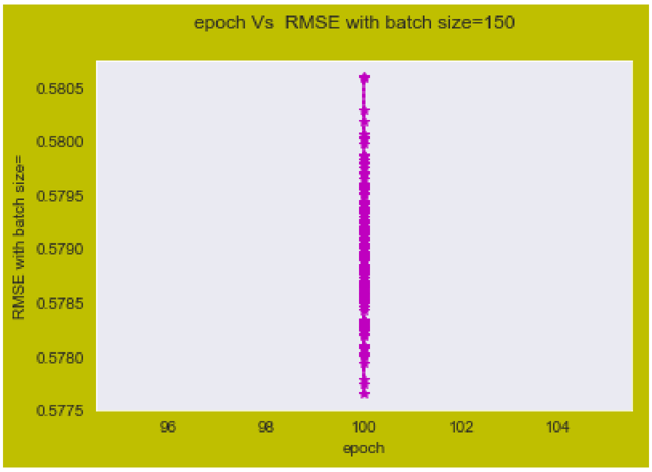




20
0
0
20
40
60
80
100
120
140
Y_test

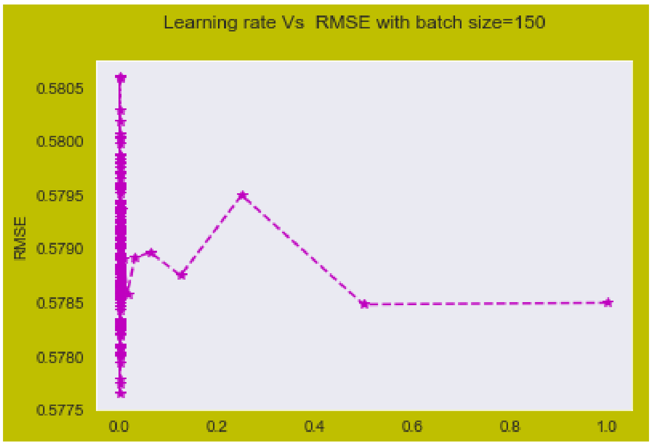


delta_Error and prediction of price with batch size=150
Delta_error_sklearn
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
0
10
20
30
40



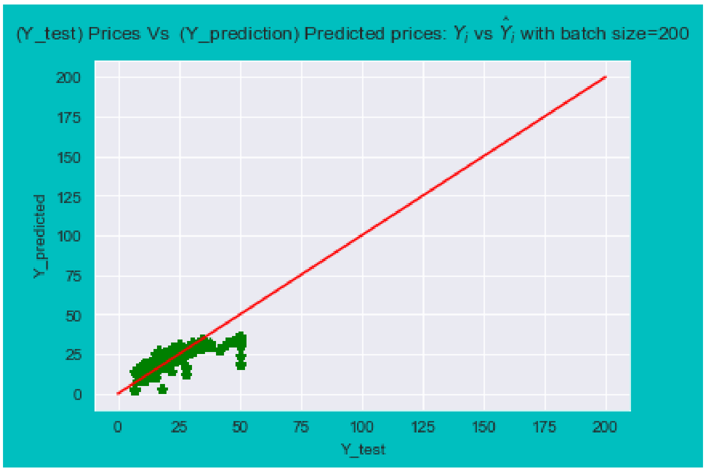
epoch Vs RMSE with batch size=150
RMSE with batch size=
0.5805
0.5800
0.5795
0.5790
0.5785
0.5780
0.5775
96
98
100
102
104
epoch

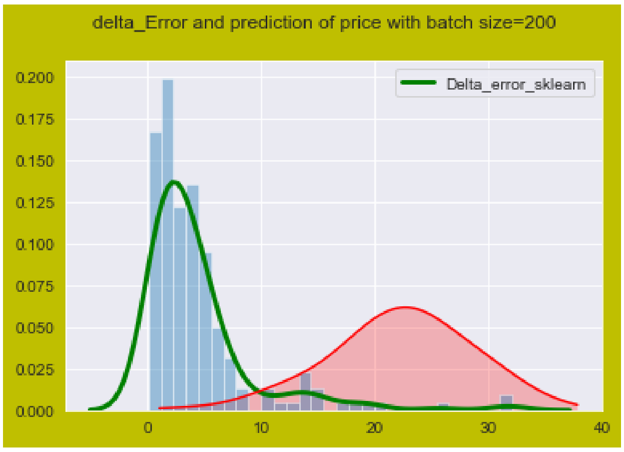
Iterations Vs Train Cost & Test cost with batch size=150
Performance Cost
0.66
0.64
0.62
0.60
0.58
Train cost
Test cost
96
98
100
102
104
Iterations

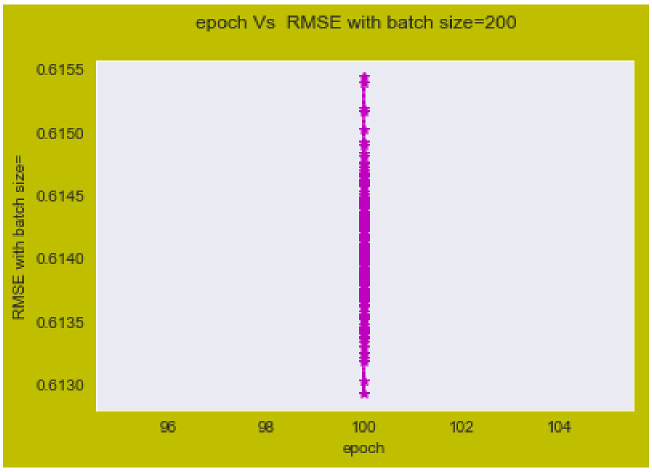


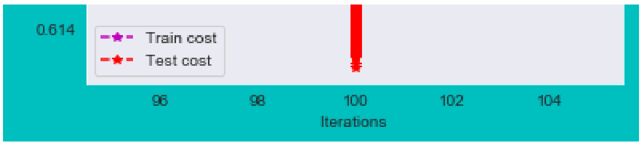
Learning rate Vs RMSE with batch size=150
RMSE
0.5805
0.5800
0.5795
0.5790
0.5785
0.5780
0.5775
0.0
0.2
0.4
0.6
0.8
1.0

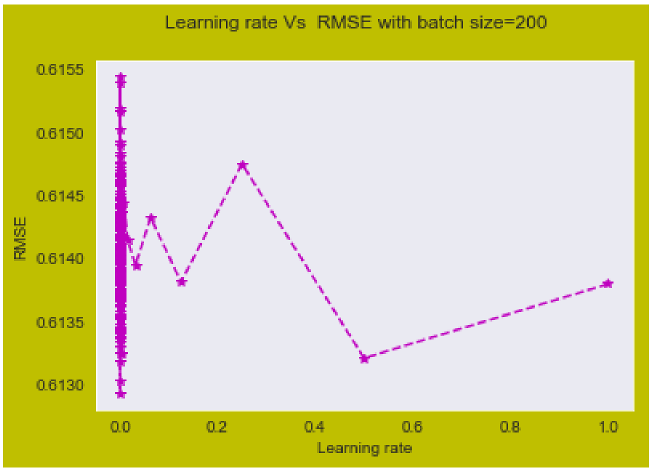

```
The best value of best_Learning_rate is 0. 7
Batch Size 150
RMSE with batch size=150 5.380419330394379
MSE with batch size=150 28.948912170881503
Training Error= 0.3792389668901831
Testing_error 0.3855008250352814
```












```
The best value of best_Learning_rate is 0. 7
Batch Size 200
RMSE with batch size=200 5.5410809637587795
MSE with batch size=200 30.703578246929922
```

In [26]:

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

Out[26]:

	Model	Batch_Size	RMSE	MSE	Iteration	Optimal learning Rate
0	sklearn.linear_model.SGDRegressor	50	5.682339	32.288975	100.0	4.547474e-13
1	sklearn.linear_model.SGDRegressor	100	5.524603	30.521235	100.0	2.441406e-04
2	sklearn.linear_model.SGDRegressor	150	5.380419	28.948912	100.0	1.323489e-23
3	sklearn.linear_model.SGDRegressor	200	5.541081	30.703578	100.0	4.135903e-25

observations: • 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 100 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 [27]:

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

Out[27]:

Model	Batch_Size	RMSE	MSE	Iteration	Optimal learning Rate

In [28]:

```
def denorm(scale,list):
    return [(scale*i) for i in list]
# scale
scale=np.max(Y_test)
print(scale)
```

```
50.0
```

In [29]:

```
# 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 [ ]:

```
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=[]
```

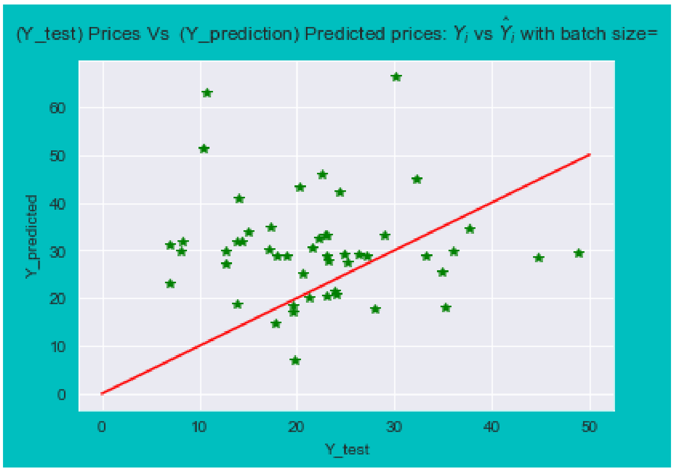
```
    global epoch
    epoch=[]
    global rmse1
    rmse1=[]
    global y_hat_manual_SGD
    y_hat_manual_SGD=[]
    global delta_Error
    delta_Error=[]
    while True:
        learning_rate1.append(learning_rate)
        epoch.append(iteration)
        for i in range(N):
            wj=w0
            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)) #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_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=sns.set_style('darkgrid')
    sns.distplot(np.array(delta_Error),kde_kws={"color": "r", "lw": 3, "label":
#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=ax1 = fig.add_subplot(1
11)
    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))]
```

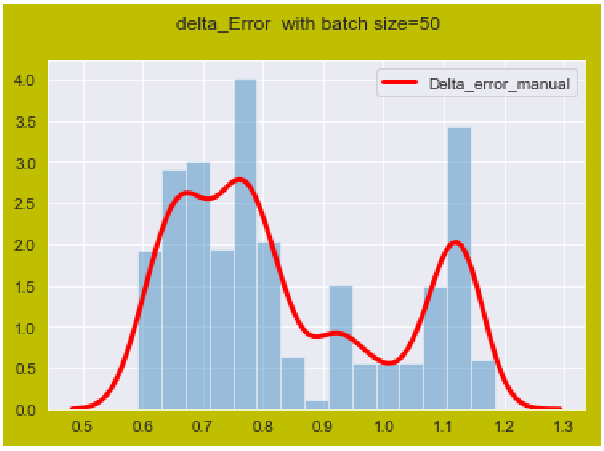
```
    print('\nThe best value of best_Learning_rate is %d.' % (best_Learning_rate))
```

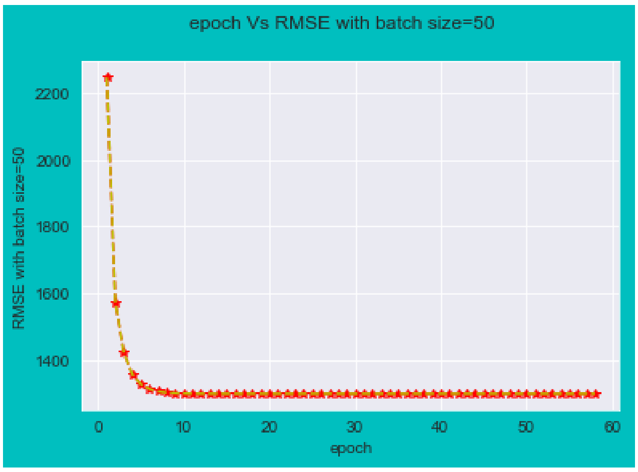
In [30]:

```
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
```

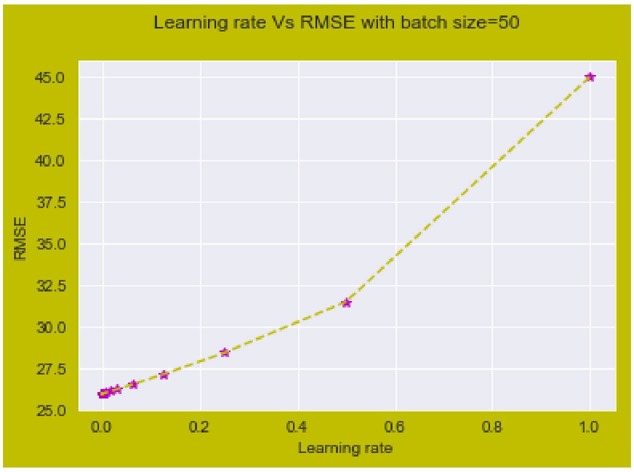




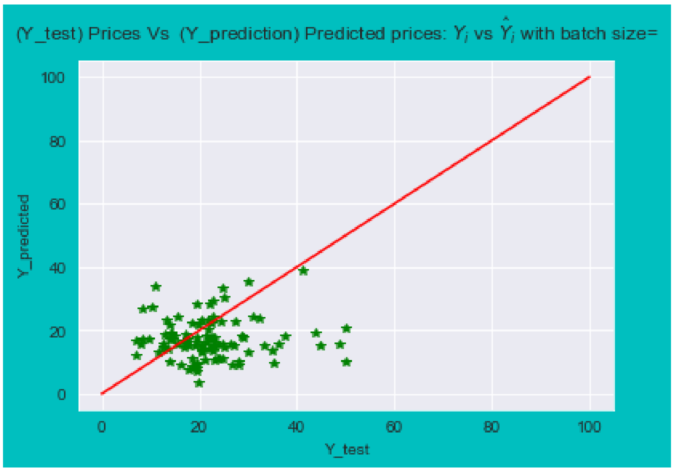


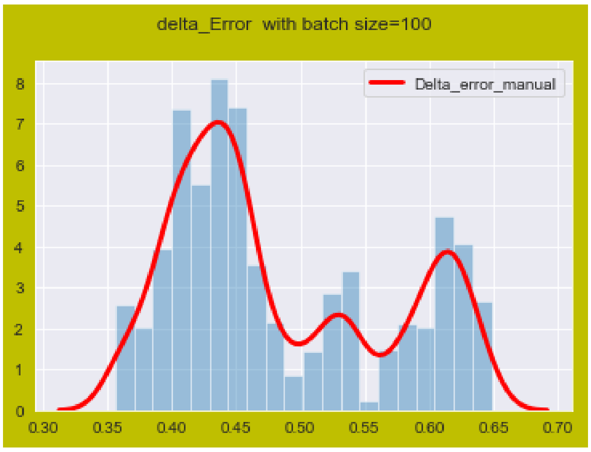

```
The best value of best_Learning_rate is 0.
MSE_value= 26.455867357378217
RMSE =  5.143526743138235
For batch size50
iteration = 59
```

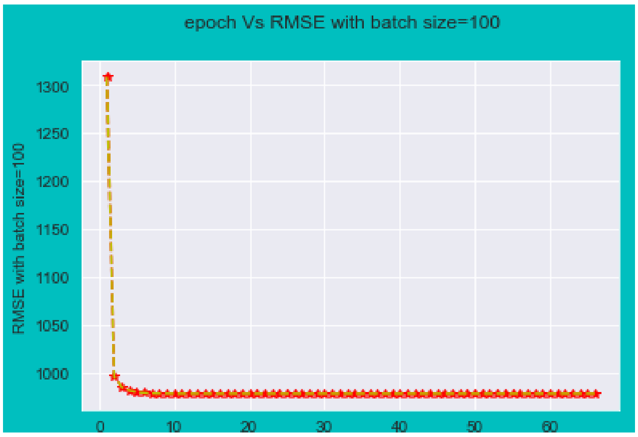
```
Total number of learning_rate= 58
```



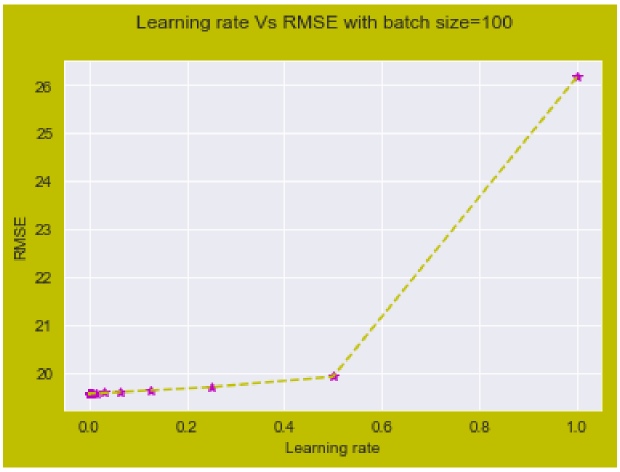

```
100
For batch size100
```



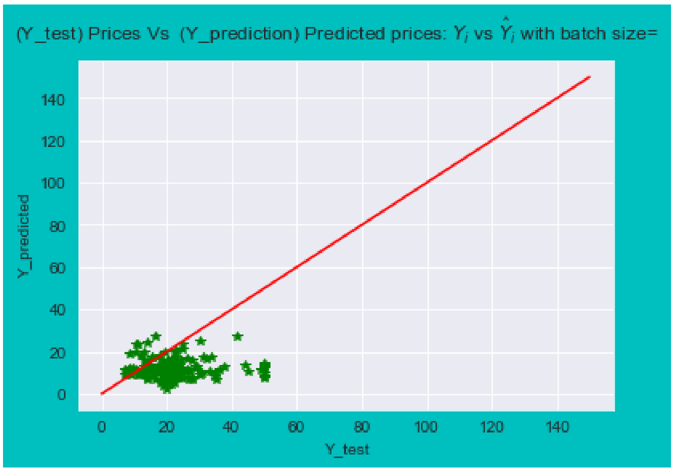


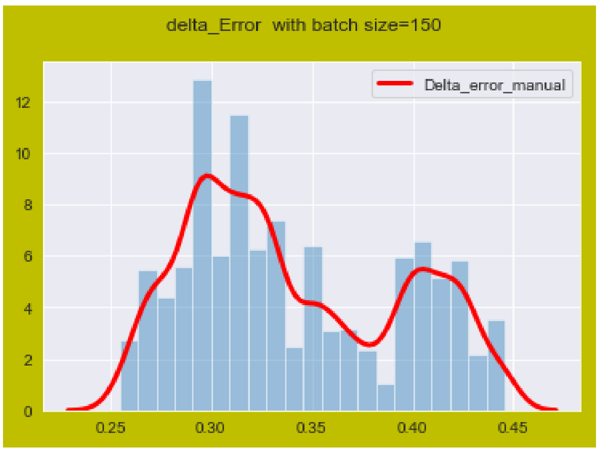


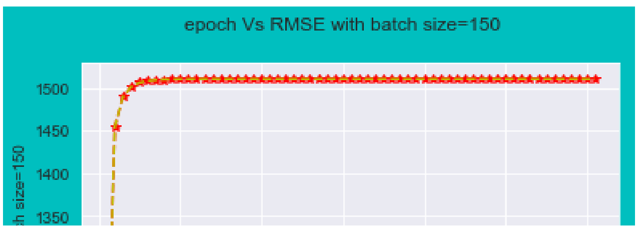

```
The best value of best_Learning_rate is 0.
MSE_value= 19.669658760643173
RMSE =  4.4350489017194805
For batch size100
iteration = 67
Total number of learning_rate= 66
```

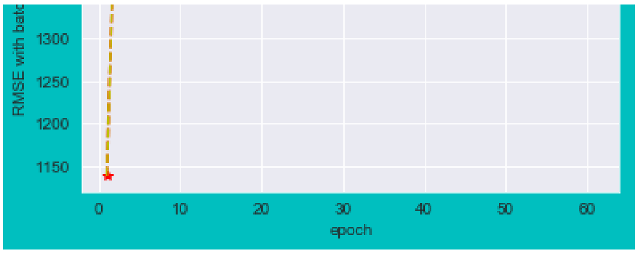



```
150
For batch size150
```

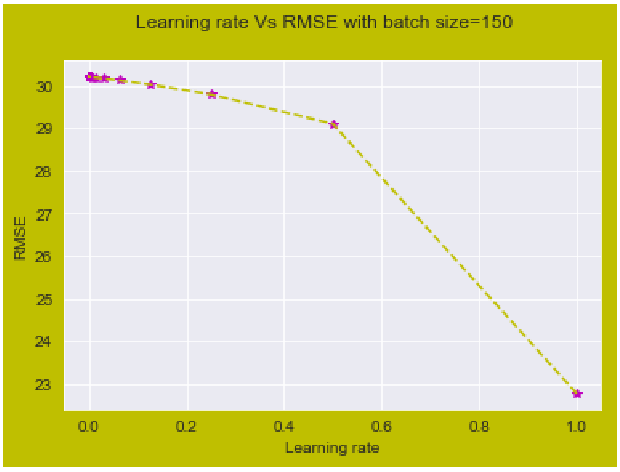




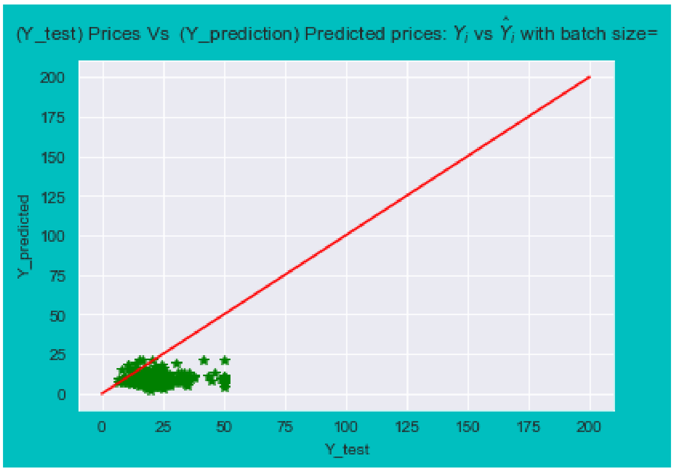


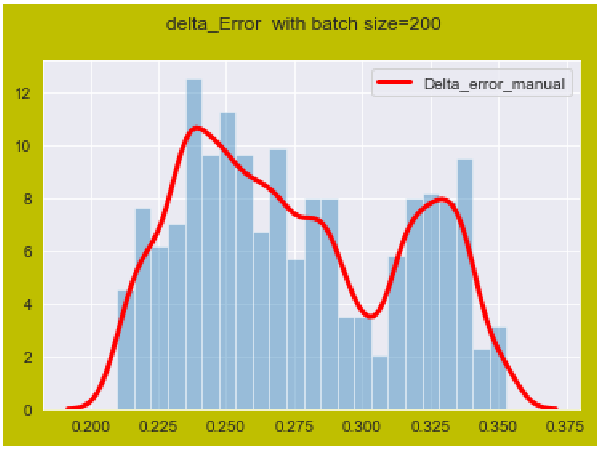


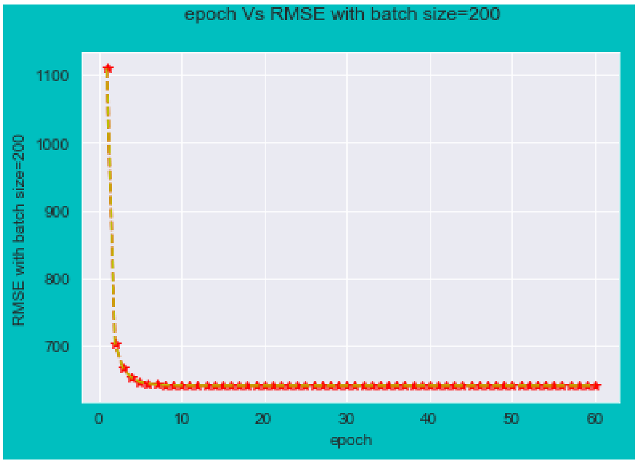

```
The best value of best_Learning_rate is 1.
MSE_value= 30.052165135524493
RMSE =  5.4819855103351465
For batch size150
iteration = 62
Total number of learning_rate= 61
```



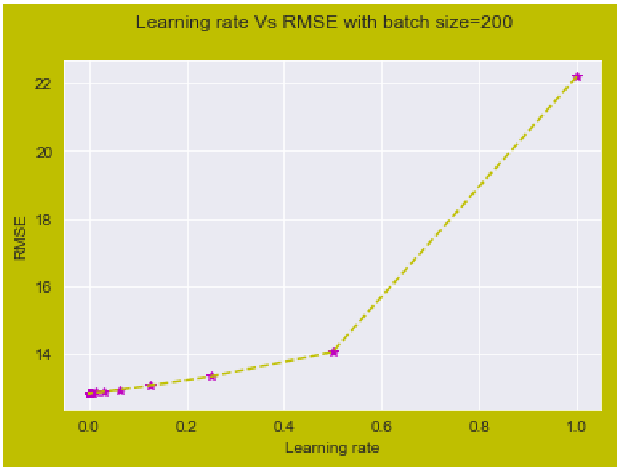

```
200
For batch size200
```








```
The best value of best_Learning_rate is 0.
MSE_value= 13.011328285991997
RMSE =  3.607121883994495
For batch size200
iteration = 61
Total number of learning_rate= 60
```



In [31]:

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

Out[31]:

	Model	Batch_Size	RMSE	MSE	Iteration	Optimal learning Rate
0	SGD Manual Function	50	5.143527	26.455867	59	2.220446e-16
1	SGD Manual Function	100	4.435049	19.669659	67	8.881784e-16
2	SGD Manual Function	150	5.481986	30.052165	62	1.000000e+00
3	SGD Manual Function	200	3.607122	13.011328	61	2.220446e-16

SGD_Manual Vs SGD_sklearn

In [32]:

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

Out[32]:

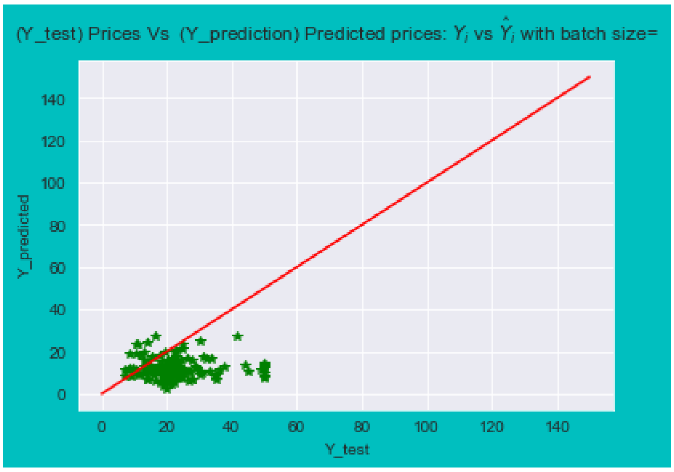
Model	Batch_Size	RMSE	MSE	Iteration	Optimal learning Rate

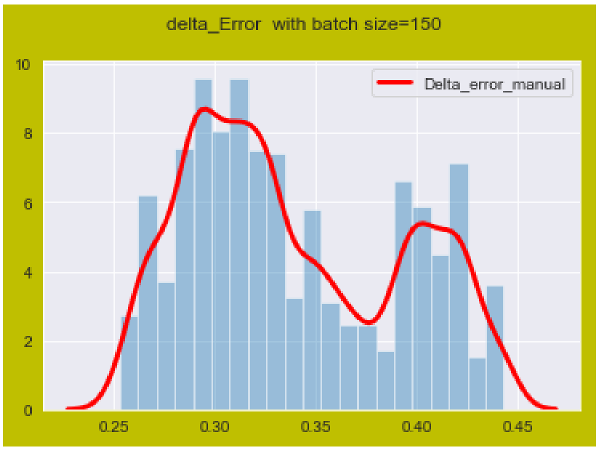
for batch size 150

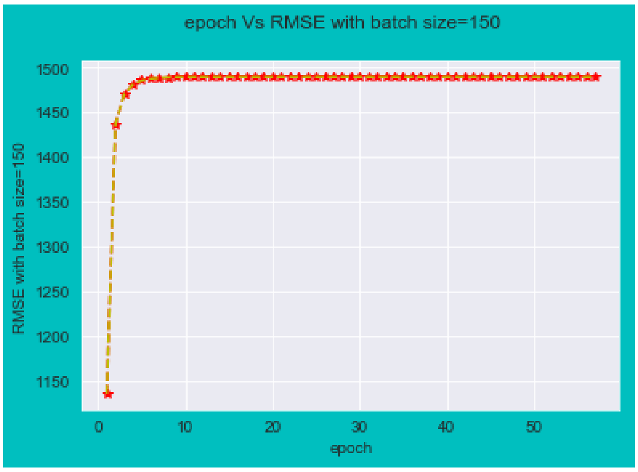
In [33]:

```
SGD(150)
```

```
For batch size150
```

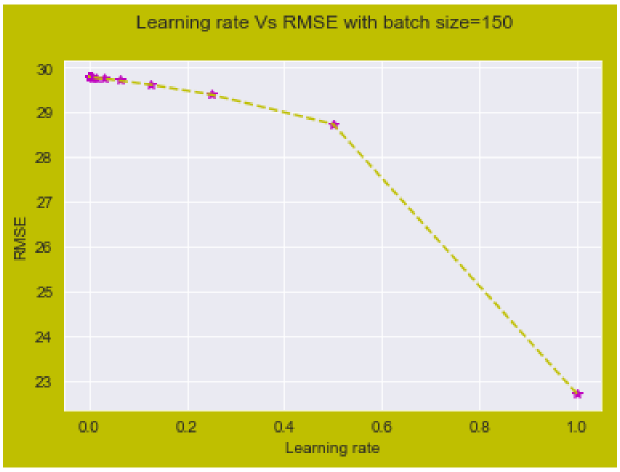







```
The best value of best_Learning_rate is 1.
MSE_value= 29.637043260961814
RMSE =  5.443991482447581
For batch size150
iteration = 58
```

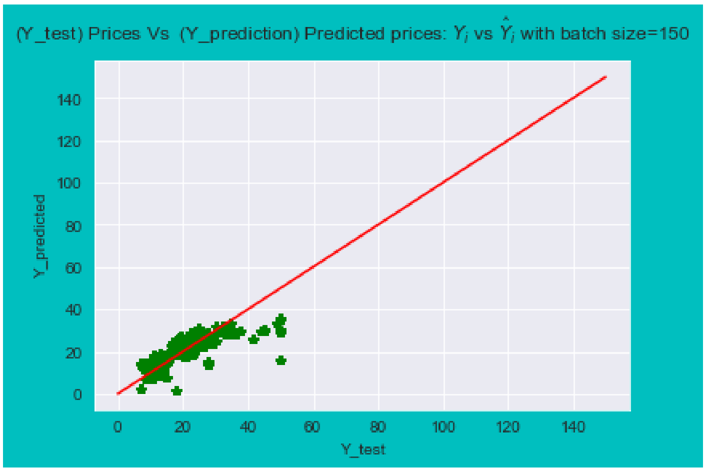
```
Total number of learning_rate= 57
```

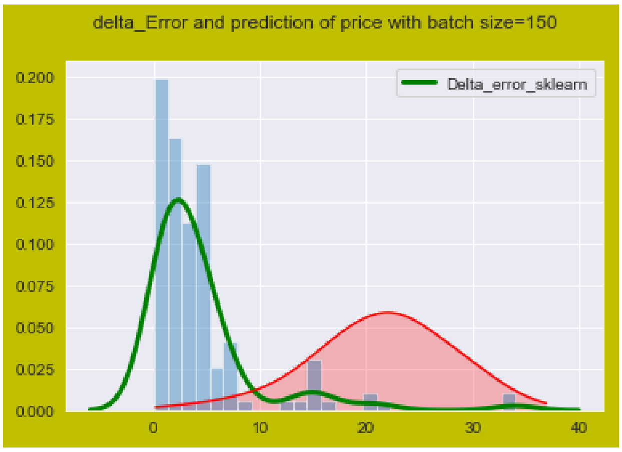


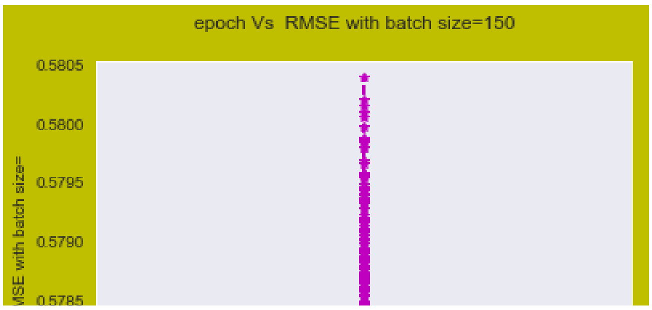
In [34]:

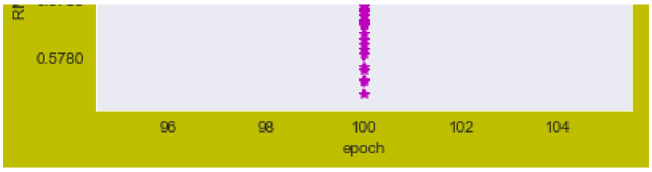
```
sgdreg_function(1,150)
```

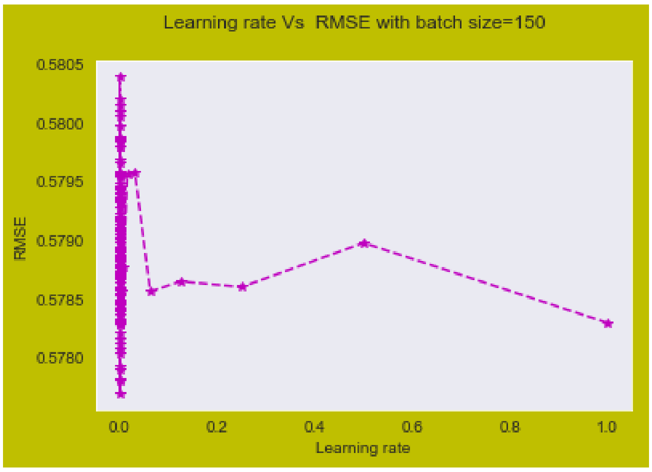
```
Training Error= 0.33563472830624475
Testing_error 0.42192424660967787
```












```
The best value of best_Learning_rate is 0. 7
Batch Size 150
RMSE with batch size=150 5.380197606600564
MSE with batch size=150 28.946526286070437
```

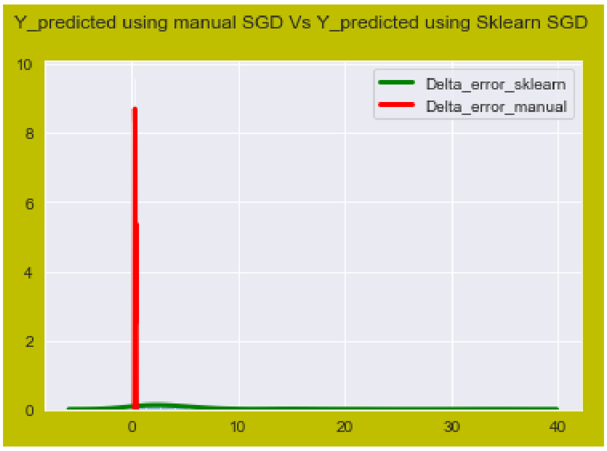
Y_predicted using manual SGD Vs Y_predicted using Sklearn SGD Y_predicted using manual SGD == y_hat_manual_SGD Error(y-y_hat) for manual SGD == delta_Error Y_predicted using Sklearn SGD == Y_hat_Predicted Error(y-y_hat) for SKlearn SGD == delta_error

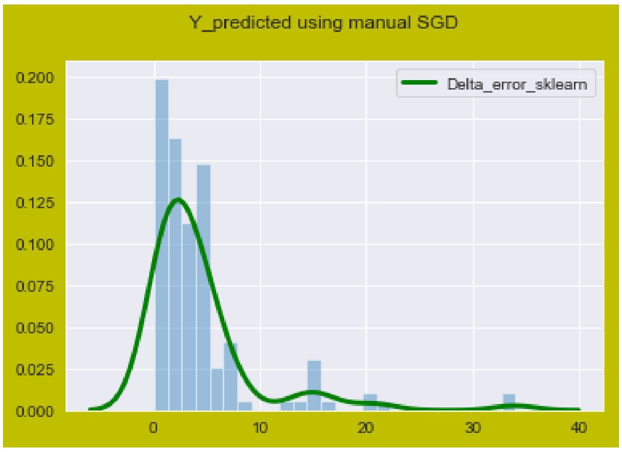
In [35]:

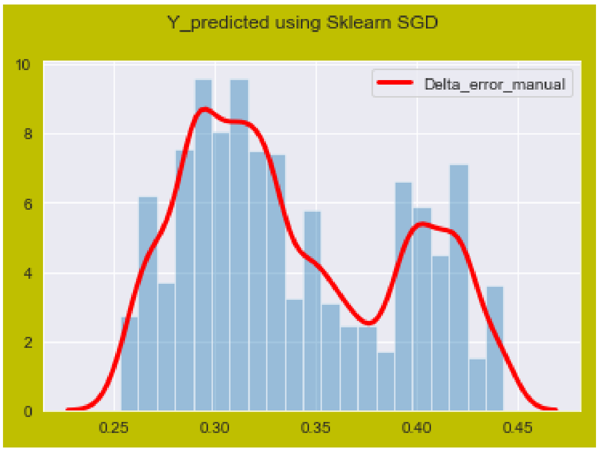
```
def y_hat_cal(delta_error_sklearn,delta_Error_manual):
    fig41 = plt.figure( facecolor='y', edgecolor='k')
    fig41.suptitle('Y_predicted using manual SGD Vs Y_predicted using Sklearn SGD ', fontsize=12)

    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 [36]:

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





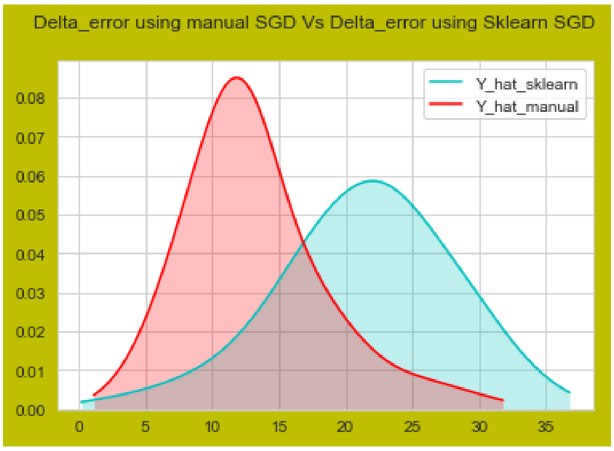


In [37]:

```
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 [38]:

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



In [39]:

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

Out[39]:

	Model	Batch_Size	RMSE	MSE	Iteration	Optimal learning Rate
0	SGD Manual Function	150	5.443991	29.637043	58.0	1.000000e+00
1	sklearn.linear_model.SGDRegressor	150	5.380198	28.946526	100.0	1.972152e-31

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.