Assignment 6

Implementing the SGD on Linear Regression for Boston House Price Dataset.

Objective:
To implement custom SGD on boston house price dataset and compare the results of custom SGD with the SKlearn SGD dataset results.

In [0]:

```
# Importing the required librarie
import warnings
warnings.filterwarnings("ignore")
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_boston                    #Used to load the Boston dataset
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import SGDRegressor
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
from prettytable import PrettyTable
import seaborn as sns

```

Understanding the Dataset

In [0]:

```python
Boston_DS=pd.DataFrame(load_boston().data,columns=load_boston().feature_names)
print("-"*120)
print(f'Shape of the Boston dataset: {(Boston_DS.shape)}')
print("-"*120)
print(f'No of features present in the Boston dataset: {(load_boston().feature_names)}')
print("-"*120)
Boston_DS.head(2)
```

```
------------------------------------------------------------------------------------------------------------------------
Shape of the Boston dataset: (506, 13)
------------------------------------------------------------------------------------------------------------------------
No of features present in the Boston dataset: ['CRIM' 'ZN' 'INDUS' 'CHAS' 'NOX' 'RM' 'AGE' 'DIS' 'RAD' 'TAX' 'PTRATIO'
 'B' 'LSTAT']
------------------------------------------------------------------------------------------------------------------------
```

Out[726]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.9	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.9	9.14

Segregating the target from the features

In [0]:

```python
Boston_DS['Price'] = load_boston().target
X_SKLN = Boston_DS.drop('Price', axis = 1)
Y_SKLN = Boston_DS['Price']
```

Splitting the data into Train and Test

In [0]:

```
X_SKLN_Train,X_SKLN_Test,Y_SKLN_Train,Y_SKLN_Test = train_test_split(X_SKLN,Y_SKLN,test_size =0.33,random_state=42)
print(X_SKLN_Train.shape)
print(X_SKLN_Test.shape)
print(Y_SKLN_Train.shape)
print(Y_SKLN_Test.shape)
X_SKLN_Train.mean()
```

```
(339, 13)
(167, 13)
(339,)
(167,)
```

Out[728]:

```
CRIM         3.351324
ZN          11.716814
INDUS       11.261858
CHAS         0.076696
NOX          0.557498
RM           6.327324
AGE         68.940118
DIS          3.762468
RAD          9.483776
TAX        409.132743
PTRATIO     18.261652
B          358.431475
LSTAT       12.497611
dtype: float64
```

Standardizating the Data

In [0]:

```
std = StandardScaler()
X_SKLN_Train = std.fit_transform(X_SKLN_Train)
X_SKLN_Test = std.transform(X_SKLN_Test)
SKLN_SGD_RG = SGDRegressor()
SKLN_SGD_RG.fit(X_SKLN_Train, Y_SKLN_Train)
Y_SKLN_PRD = SKLN_SGD_RG.predict(X_SKLN_Test)
SkLearn_w=SKLN_SGD_RG.coef_
print(f"Sklearn's SGD regressor Coefficients:{(SKLN_SGD_RG.coef_)}")
print(f"Sklearn's SGD regressor Y Intercept:{(SKLN_SGD_RG.intercept_)}")
```

```
Sklearn's SGD regressor Coefficients:[-0.89378768  0.71539225  0.14751301  0.89272288 -1.67100139  2.85790581
 -0.41028437 -2.85475367  1.32968721 -0.67137791 -2.01879448  1.04490366
 -3.92669325]
Sklearn's SGD regressor Y Intercept:[22.97865716]
```

Implementing the own SGD Regressor for Linear Regression

In [0]:

```
OWN_Boston_DS = load_boston()
OWN_Boston_DS.data.shape
OWN_Boston_DS.feature_names
OWN_Boston_DS.target.shape
OWN_Boston_DS_data = pd.DataFrame(OWN_Boston_DS.data, columns = OWN_Boston_DS.feature_names)
print(OWN_Boston_DS_data.head())
```

```
      CRIM    ZN  INDUS  CHAS    NOX  ...  RAD    TAX  PTRATIO       B  LSTAT
0  0.00632  18.0   2.31   0.0  0.538  ...  1.0  296.0     15.3  396.90   4.98
1  0.02731   0.0   7.07   0.0  0.469  ...  2.0  242.0     17.8  396.90   9.14
2  0.02729   0.0   7.07   0.0  0.469  ...  2.0  242.0     17.8  392.83   4.03
3  0.03237   0.0   2.18   0.0  0.458  ...  3.0  222.0     18.7  394.63   2.94
4  0.06905   0.0   2.18   0.0  0.458  ...  3.0  222.0     18.7  396.90   5.33

[5 rows x 13 columns]
```

Normalizing the data

In [0]:

```
mean= OWN_Boston_DS_data.mean()
std= OWN_Boston_DS_data.std()
OWN_Boston_DS_data = (OWN_Boston_DS_data - mean)/std
print(OWN_Boston_DS_data.head())
```

```
       CRIM        ZN     INDUS  ...   PTRATIO         B     LSTAT
0 -0.419367  0.284548 -1.286636  ... -1.457558  0.440616 -1.074499
1 -0.416927 -0.487240 -0.592794  ... -0.302794  0.440616 -0.491953
2 -0.416929 -0.487240 -0.592794  ... -0.302794  0.396035 -1.207532
3 -0.416338 -0.487240 -1.305586  ...  0.112920  0.415751 -1.360171
4 -0.412074 -0.487240 -1.305586  ...  0.112920  0.440616 -1.025487

[5 rows x 13 columns]
```

In [0]:

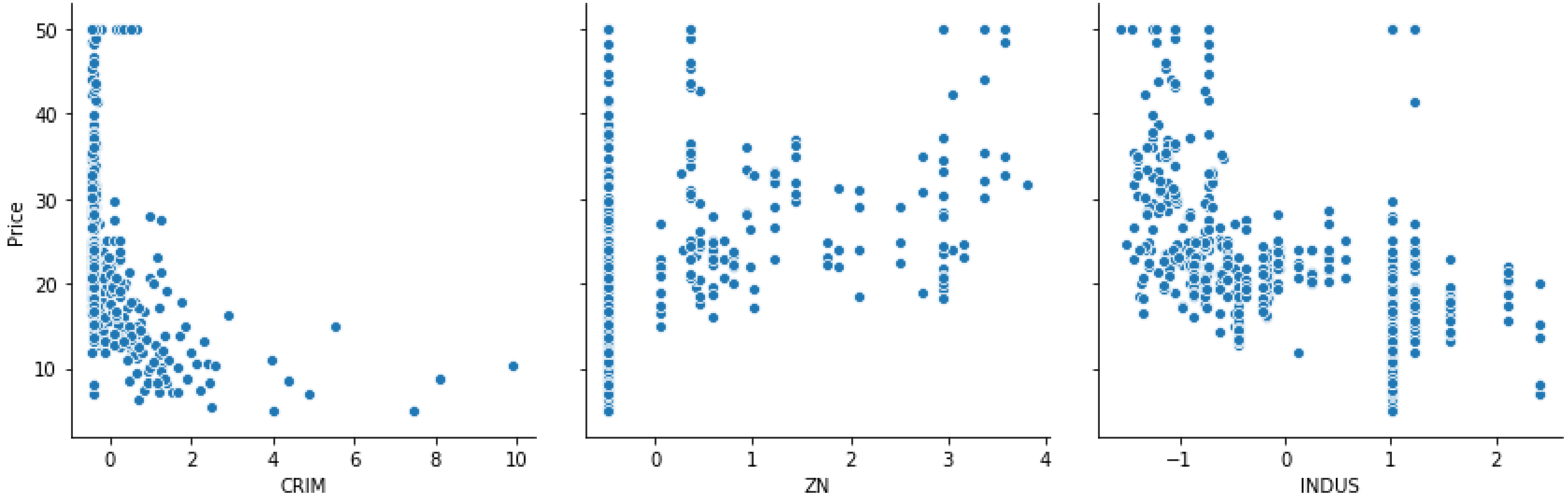
```
OWN_Boston_DS_data["Price"] = OWN_Boston_DS.target
OWN_Boston_DS_data.head()
OWN_Boston_Y = OWN_Boston_DS_data["Price"]
OWN_Boston_X = OWN_Boston_DS_data.drop("Price", axis = 1)
OWN_Train_X,OWN_Test_X,OWN_Train_Y,OWN_Test_Y=train_test_split(OWN_Boston_X,OWN_Boston_Y,test_size=0.33,random_state=42)
print(OWN_Train_X.shape,OWN_Train_Y.shape,OWN_Test_X.shape,OWN_Test_Y.shape)
OWN_Train_X["Price"] = OWN_Train_Y
x_sh=OWN_Train_X.shape[1]-1
```

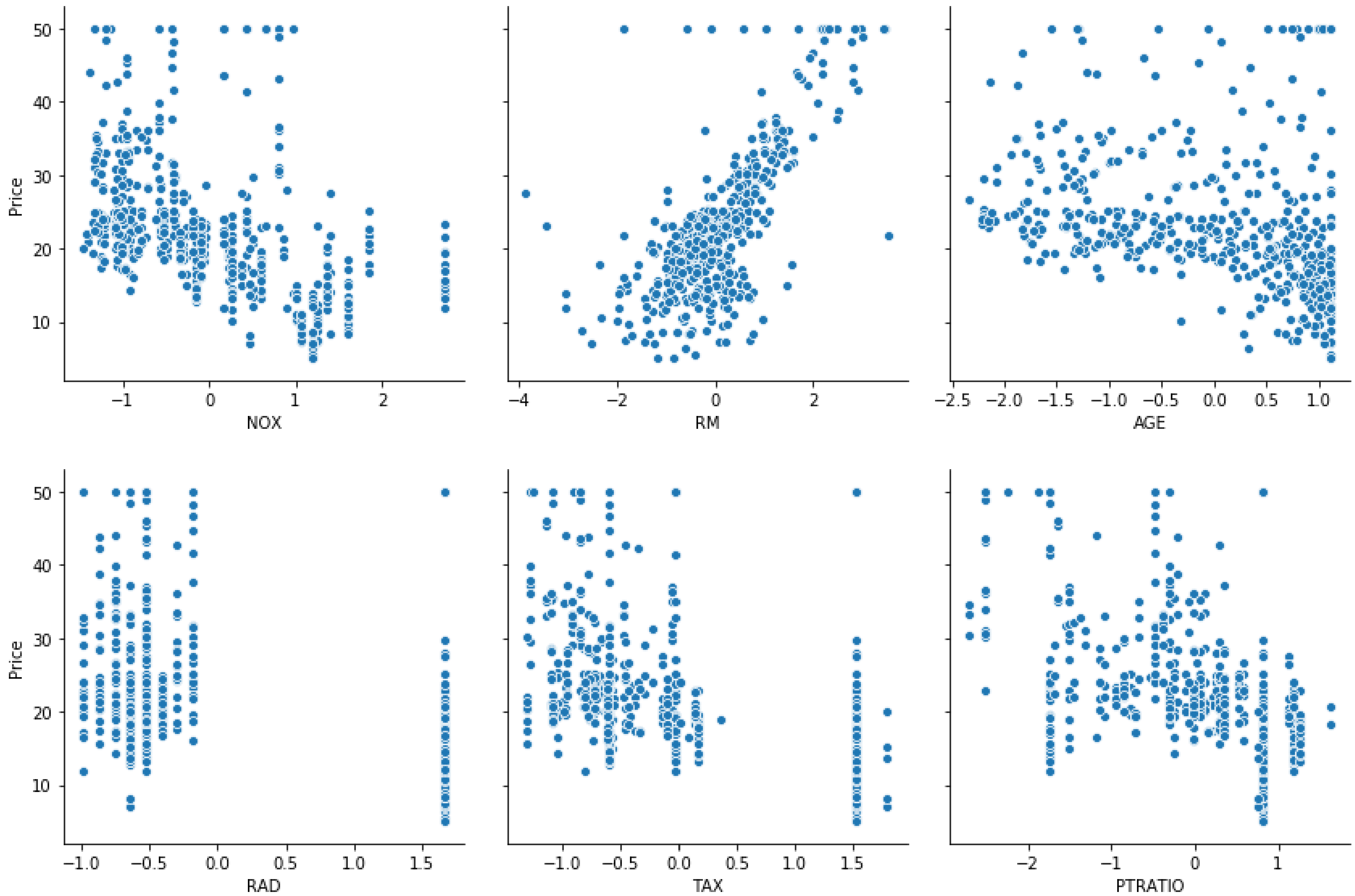
```
(339, 13) (339,) (167, 13) (167,)
```

Comparing the price with the each features in the data

In [0]:

```python
#https://stackoverflow.com/questions/31966494/compare-1-independent-vs-many-dependent-variables-using-seaborn-pairplot-in-an-h
plt.close();
Plot1 = sns.pairplot(data=OWN_Boston_DS_data,height=4,
                 y_vars=['Price'],
                 x_vars=['CRIM', 'ZN', 'INDUS'])
Plot2 = sns.pairplot(data=OWN_Boston_DS_data,height=4,
                 y_vars=['Price'],
                 x_vars=['NOX', 'RM', 'AGE'])
Plot3 = sns.pairplot(data=OWN_Boston_DS_data,height=4,
                 y_vars=['Price'],
                 x_vars=['RAD', 'TAX', 'PTRATIO'])
Plot4 = sns.pairplot(data=OWN_Boston_DS_data,height=4,
                 y_vars=['Price'],
                 x_vars=['CHAS', 'DIS', 'B', 'LSTAT'])
```





Price
NOX
RM
AGE
Price
RAD
TAX
PTRATIO

OBSERVATION:

1.The prices increase as the value of RM increases linearly.Also we can see few outliers

2.The prices tend to decrease with an increase in LSTAT.

3.CRIM rate seems to be high at the place of price ranges from 10 to 30.

In [0]:
```
print(OWN_Boston_DS_data.head(5))
```

```
       CRIM        ZN     INDUS      CHAS  ...   PTRATIO         B     LSTAT  Price
0 -0.419367  0.284548 -1.286636 -0.272329  ... -1.457558  0.440616 -1.074499   24.0
1 -0.416927 -0.487240 -0.592794 -0.272329  ... -0.302794  0.440616 -0.491953   21.6
2 -0.416929 -0.487240 -0.592794 -0.272329  ... -0.302794  0.396035 -1.207532   34.7
3 -0.416338 -0.487240 -1.305586 -0.272329  ...  0.112920  0.415751 -1.360171   33.4
4 -0.412074 -0.487240 -1.305586 -0.272329  ...  0.112920  0.440616 -1.025487   36.2

[5 rows x 14 columns]
```

In [0]:
```
#https://www.geeksforgeeks.org/ml-r-squared-in-regression-analysis/
def Loss_Function(intr_DS,weig_DS,X_DS,Y_DS):
    loss = 0
    for i in range(0, len(X_DS)):
        Exp1=Y_DS[:,i] - (np.dot(X_DS[i] , weig_DS) + intr_DS)
        loss += (Exp1) ** 2
    return loss/len(X_DS)

```

OBSERVATION:

The loss funcation is calculated based on the below formula

$$\sum_{i=1}^{K}[y[i] - x[i].\, w^{T} + b]$$

Where W= Weight and b=Intercept

In [0]:

```
# https://stackoverflow.com/questions/50328545/stochastic-gradient-descent-for-linear-regression-on-partial-derivatives

def Own_regressor(weig, intr, Full_DS, X1, Y1, LR):

    """Implementation of own SGD Gradient Descent for Linear regression"""

    Weig_deriv=0
    Intr_deriv=0
    Iterations=1000
    loss_Train=[]
    loss_Test=[]
    j=0
    while j < 1000:
        Full_DS_Batch=Full_DS.sample(100)
        x = np.asmatrix(Full_DS_Batch.drop("Price", axis = 1))
        y = np.asmatrix(Full_DS_Batch["Price"])
        for i in range(len(x)):
            tmp=y[:,i]-np.dot(x[i],weig)+intr
            Weig_deriv+=np.dot(-2*x[i].T,tmp)
            Intr_deriv+=(-2*tmp)
        weig_update=weig-(LR*Weig_deriv)
        b_update=intr-(LR*Intr_deriv)
        if (weig==weig_update).all():
            break
        else:
            weig=weig_update
            intr=b_update
            LR=LR/2
        # Evaluating the loss in the custom built SGD regressor of train data
        loss_TR=Loss_Function(intr,weig,x,y)
        loss_Train.append(loss_TR)
        # Evaluating the loss in the custom built SGD regressor of test data
        loss_TS=Loss_Function(intr,weig,np.asmatrix(X1),np.asmatrix(Y1))
        loss_Test.append(loss_TS)
        j=j+1
    return weig,intr,loss_Train,loss_Test
```

OBSERVATION:

1.At initial, keeping the Weight and Intercept values as zero

2.Setting up the iteration value

3.Settingup the batch of datasize

4.Calculating the

$$\frac{\partial \mathbf{L}}{\partial \mathbf{w}} \, and \, \frac{\partial \mathbf{L}}{\partial \mathbf{b}}$$

Where W= Weight and b=Intercept

$$\frac{\partial \mathbf{L}}{\partial \mathbf{w}} = \sum_{i=1}^{K}[(-2.xi)(yi - (xi.w^T) + b)]$$

$$\frac{\partial \mathbf{L}}{\partial \mathbf{b}} = \sum_{i=1}^{K}[(-2)(yi - (xi.w^T) + b)]$$

5.At each iteration learning rate is reduced by half.

6.And the loop was keep executing till the weight get saturated.

7.At some point weight gets saturated. Finding that point and taking its previous value.

In [0]:

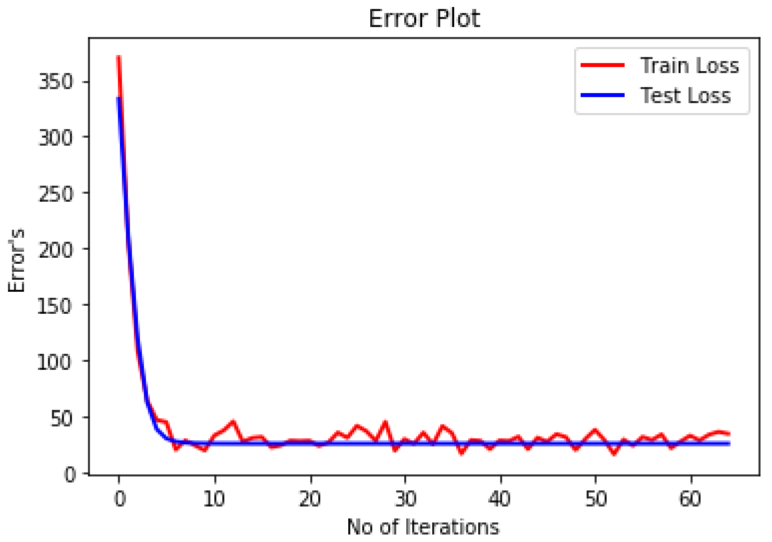
```
#https://matplotlib.org/3.1.1/tutorials/introductory/pyplot.html
lr = 0.001
# Choosing random values for w and b
intercept = np.random.rand()
wgt = np.random.rand(x_sh)
bias = np.asmatrix(wgt).T   #Transpose of weight matrix
weig_, intr_, loss_Train_, loss_Test_ = Own_regressor(bias, intercept, OWN_Train_X, OWN_Test_X, OWN_Test_Y, lr)
print(f"SGD Coefficient: {(weig_)}")
print(f"Y_Intercept: {(intr_)}")

print(f"Train Loss = {(loss_Train_)}")
print(f"Test Loss= {(loss_Test_)} ")

OWN_Prediction=(np.dot(np.asmatrix(OWN_Test_X), weig_) + intr_)
OWN_Prediction_List=np.array(OWN_Prediction).T[0]
# Error Plot
plt.close();
plt.figure()
plt.plot(range(len(loss_Train_)), np.reshape(loss_Train_,[len(loss_Train_), 1]), label = "Train Loss",c='red', ls='-',lw=2)
plt.plot(range(len(loss_Test_)), np.reshape(loss_Test_, [len(loss_Test_), 1]), label = "Test Loss",c='blue', ls='-',lw=2)
plt.title("Error Plot")
plt.xlabel("No of Iterations")
plt.ylabel("Error's")
plt.legend()
plt.show()
```

```
SGD Coefficient: [[ 2.58298431e-01]
 [ 3.39221477e-01]
 [-7.37036275e-01]
 [ 1.06994685e+00]
 [-4.42579777e-02]
 [ 4.87969387e+00]
 [ 8.78820383e-01]
 [-7.40355353e-01]
 [ 4.58860351e-01]
 [-7.82629557e-04]
 [-2.52489286e+00]
 [ 9.83409962e-01]
 [-3.01768581e+00]]
Y_Intercept: [[22.35480459]]
Train Loss = [matrix([[370.20906386]]), matrix([[206.28317897]]), matrix([[107.22916446]]), matrix([[63.09551347]]), matrix([[4
6.62212318]]), matrix([[44.68280846]]), matrix([[19.99057045]]), matrix([[28.32658378]]), matrix([[23.63833973]]), matrix([[19.
31282885]]), matrix([[32.69288678]]), matrix([[37.32332292]]), matrix([[45.33978117]]), matrix([[27.19064905]]), matrix([[30.54
485685]]), matrix([[31.40479638]]), matrix([[22.16166989]]), matrix([[23.80463751]]), matrix([[28.07904338]]), matrix([[27.6488
0512]]), matrix([[28.02435142]]), matrix([[23.37228194]]), matrix([[26.39519442]]), matrix([[35.32755431]]), matrix([[30.714889
46]]), matrix([[41.37173085]]), matrix([[36.56274588]]), matrix([[27.86868173]]), matrix([[44.96784203]]), matrix([[19.1549883
```

```
2]]), matrix([[29.51981789]]), matrix([[25.23836093]]), matrix([[35.3341809]]), matrix([[24.72771804]]), matrix([[41.1465723
3]]), matrix([[34.8920409]]), matrix([[16.4503138]]), matrix([[28.57268481]]), matrix([[27.93365648]]), matrix([[20.4252530
7]]), matrix([[28.24650822]]), matrix([[27.7299853]]), matrix([[31.66732353]]), matrix([[20.44955594]]), matrix([[30.7528899
7]]), matrix([[27.12810323]]), matrix([[33.87632713]]), matrix([[31.23352924]]), matrix([[19.84307825]]), matrix([[29.7415559
3]]), matrix([[37.83352244]]), matrix([[28.52807276]]), matrix([[15.90941553]]), matrix([[29.13836987]]), matrix([[23.5719250
6]]), matrix([[31.43396008]]), matrix([[28.64001372]]), matrix([[33.70799357]]), matrix([[21.36893175]]), matrix([[27.3358663
8]]), matrix([[32.57981728]]), matrix([[28.34200241]]), matrix([[33.47536797]]), matrix([[35.994549]]), matrix([[34.2852009
1]])]
Test Loss= [matrix([[333.35646627]]), matrix([[210.55681943]]), matrix([[118.4269877]]), matrix([[61.78602196]]), matrix([[38.3
4514617]]), matrix([[30.0605345]]), matrix([[27.24552424]]), matrix([[26.21840312]]), matrix([[25.83149185]]), matrix([[25.6502
2477]]), matrix([[25.56572522]]), matrix([[25.52442028]]), matrix([[25.50339129]]), matrix([[25.49155178]]), matrix([[25.484802
67]]), matrix([[25.48101331]]), matrix([[25.478937]]), matrix([[25.47783064]]), matrix([[25.47722448]]), matrix([[25.4768957
3]]), matrix([[25.47672248]]), matrix([[25.47663493]]), matrix([[25.4765898]]), matrix([[25.47656576]]), matrix([[25.4765535
6]]), matrix([[25.47654727]]), matrix([[25.47654391]]), matrix([[25.4765422]]), matrix([[25.47654132]]), matrix([[25.4765408
5]]), matrix([[25.47654061]]), matrix([[25.47654049]]), matrix([[25.47654042]]), matrix([[25.47654039]]), matrix([[25.4765403
7]]), matrix([[25.47654036]]), matrix([[25.47654036]]), matrix([[25.47654036]]), matrix([[25.47654035]]), matrix([[25.4765403
5]]), matrix([[25.47654035]]), matrix([[25.47654035]]), matrix([[25.47654035]]), matrix([[25.47654035]]), matrix([[25.4765403
5]]), matrix([[25.47654035]]), matrix([[25.47654035]]), matrix([[25.47654035]]), matrix([[25.47654035]]), matrix([[25.4765403
5]]), matrix([[25.47654035]]), matrix([[25.47654035]]), matrix([[25.47654035]]), matrix([[25.47654035]]), matrix([[25.4765403
5]]), matrix([[25.47654035]]), matrix([[25.47654035]]), matrix([[25.47654035]]), matrix([[25.47654035]]), matrix([[25.4765403
5]]), matrix([[25.47654035]]), matrix([[25.47654035]]), matrix([[25.47654035]]), matrix([[25.47654035]]), matrix([[25.4765403
5]])]
```



OBSERVATION:

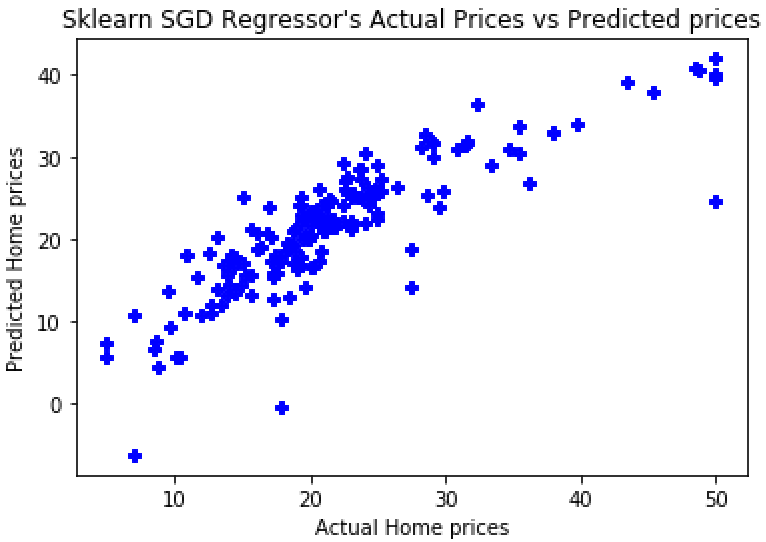
When learning rate is set to 0.1 and 0.01the model perform very bad

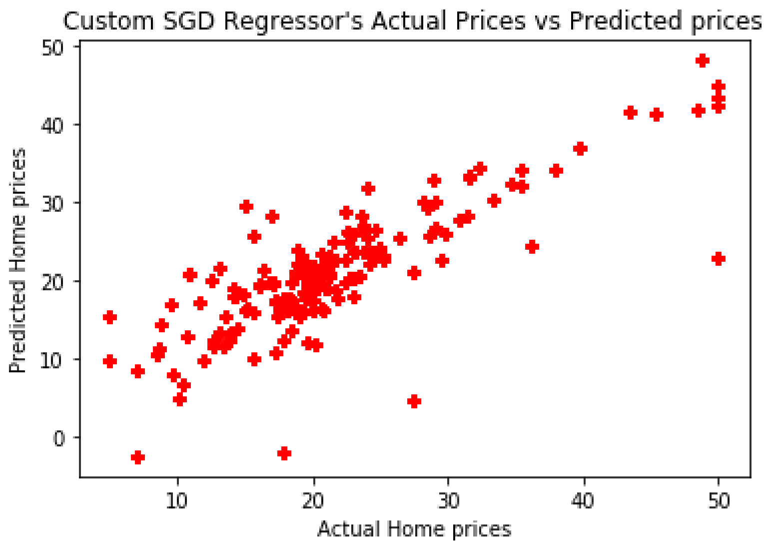
Comparing the sklearn's SGD Regressor and Own implementation of SGDreg using the scatter plot

In [0]:

```
#https://matplotlib.org/3.1.1/api/_as_gen/matplotlib.markers.MarkerStyle.html#matplotlib.markers.MarkerStyle
#https://matplotlib.org/3.1.1/api/_as_gen/matplotlib.pyplot.scatter.html
# Applying skLearn SGD Regressor.
plt.close();
plt.figure(1)
plt.subplot(111)
plt.scatter(Y_SKLN_Test, Y_SKLN_PRD,marker='P',c='blue')
plt.xlabel("Actual Home prices")
plt.ylabel("Predicted Home prices")
plt.title("Sklearn SGD Regressor's Actual Prices vs Predicted prices")
plt.show()

# Applying own SGD Regressor
plt.close();
plt.figure(2)
plt.subplot(111)
plt.scatter([OWN_Test_Y], [(np.dot(np.asmatrix(OWN_Test_X), weig_) + intr_)],marker='P',c='red')
plt.xlabel("Actual Home prices")
plt.ylabel("Predicted Home prices")
plt.title("Custom SGD Regressor's Actual Prices vs Predicted prices")
plt.show()
```





In [0]:

```
# Sklearn SGD Regression
print(f"MSE of Sk learn's prediction:{(mean_squared_error(Y_SKLN_Test, Y_SKLN_PRD))}")
print(f"r2_score of Sk learn's prediction:{(r2_score(Y_SKLN_Test, Y_SKLN_PRD))}")
```

```
MSE of Sk learn's prediction:21.228706973845743
r2_score of Sk learn's prediction:0.7194883008348725
```

In [0]:

```
# https://stackoverflow.com/questions/40901445/function-to-calculate-r2-r-squared-in-r
#import math
OWN_loss = Loss_Function(intr_, weig_, np.asmatrix(OWN_Test_X), np.asmatrix(OWN_Test_Y))
print(f"MSE of own SGD_reg :{(float(OWN_loss))}")

X1=np.asmatrix(OWN_Test_X)
Y1=np.asmatrix(OWN_Test_Y)
for i in range(0, len(X1)):
    Avg_Y = np.mean(Y1)
    Exp2=(Y1[:,i] - Avg_Y)
    Exp3=(Y1[:,i] - (np.dot(X1[i], weig_) + intr_))
    Sum_of_squares = sum((Exp2)**2)
    Residual_sum = sum((Exp3)**2)
    R_Square = 1-(Residual_sum/Sum_of_squares)

print(f"r2_score of own SGDreg :{(float(R_Square))}")
```

```
MSE of own SGD_reg :25.476540352979335
r2_score of own SGDreg :0.9992409296653334
```

OBSERVATION:

Calculating the r sqaure from the below formula

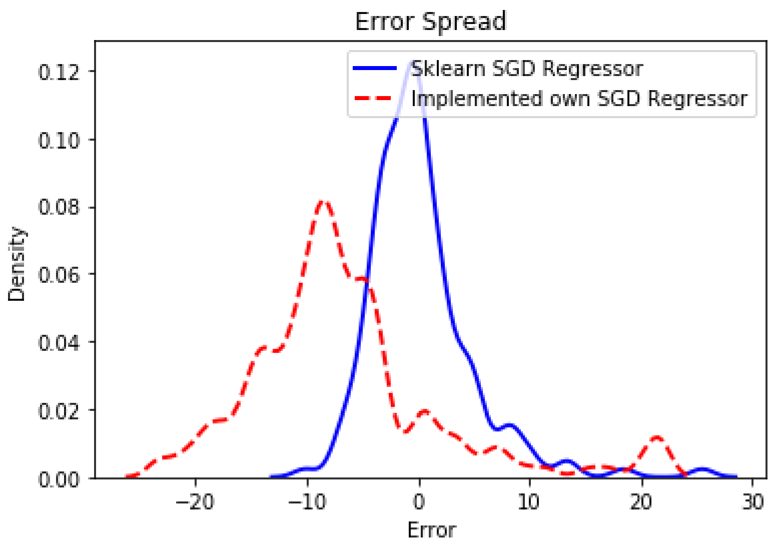
Where

$$r^2 = 1 - \frac{Residual\ Sum\ of\ squares}{Sum\ of\ squares}$$

In [0]:

```
# Error distribution
OWN_Loss_Y = np.asmatrix(OWN_Test_Y) - (OWN_Prediction)
SKLN_Loss_Y = Y_SKLN_Test - Y_SKLN_PRD

sns.kdeplot(np.array(SKLN_Loss_Y), label = "Sklearn SGD Regressor", bw =1,c='blue', ls='-',lw=2)
sns.kdeplot(np.asarray(OWN_Loss_Y)[0], label = "Implemented own SGD Regressor", bw =1,c='red', ls='--',lw=2)
plt.title("Error Spread")
plt.xlabel("Error")
plt.ylabel("Density")
plt.legend()
plt.show()
```

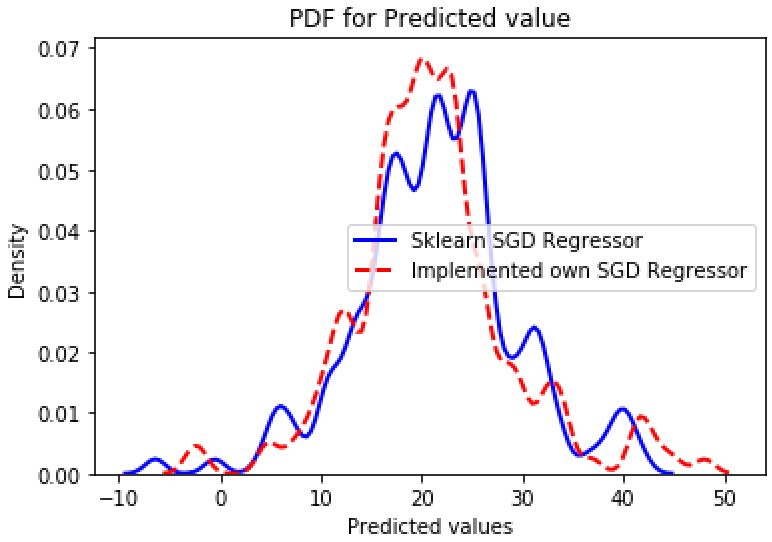


OBSERVATION:

From above plot SKLearn SGD is working better than custom implementation regressor. Because the over all distribution of SKlearn with respectiv error is low.

In [0]:

```
# Predicted value distribution
sns.kdeplot(Y_SKLN_PRD, label = "Sklearn SGD Regressor", bw =1,c='blue', ls='-',lw=2)
sns.kdeplot(OWN_Prediction_List, label = "Implemented own SGD Regressor", bw =1,c='red', ls='--',lw=2)
plt.title("PDF for Predicted value")
plt.xlabel("Predicted values")
plt.ylabel("Density")
plt.show()
```



OBSERVATION:
From above plot you can see the most of the predicted values are overlap.

Comparison with Pretty Table

In [0]:
```
PT = PrettyTable()
PT.field_names=['S.No','Custom SGD Regressor','SkLearn SGD Regressor']
for i in range(x_sh):
    PT.add_row([i+1,float(weig_[i]),SkLearn_w[i]])
print(PT)
```

S.No	Custom SGD Regressor	SkLearn SGD Regressor
1	0.2582984312172637	-0.8937876809095562
2	0.3392214765870696	0.7153922469815946
3	-0.7370362747081937	0.14751301403165415
4	1.0699468487113792	0.8927228844675043
5	-0.044257977677794621	-1.6710013907984682
6	4.8796938688994365	2.8579058082668083
7	0.87882038297057	-0.4102843692600765
8	-0.7403553528758017	-2.854753671182647
9	0.45886035113737783	1.3296872106166655
10	-0.0007826295570831534	-0.6713779089268122
11	-2.5248928602744205	-2.0187944797150936
12	0.983409961680586	1.044903661065243
13	-3.0176858146709526	-3.9266932523379334

SUMMARY:
Overall when we compare the custom implemeneted SGD regressor with the SKlearn SGD regressor they are working little similar.
But still we can see the Sklearn SGD regressor model is performing good when we consider the MSE and r square values.
Hence i conclude the Sklearn SGD regressor model have better performance when ccompare to the custom SGD regressor.

REFERENCE:

To create a mathematical equations in the Jupyter Notebook
https://www.math.ubc.ca/~pwalls/math-python/jupyter/latex/ (https://www.math.ubc.ca/~pwalls/math-python/jupyter/latex/)
https://jupyter-notebook.readthedocs.io/en/stable/examples/Notebook/Working%20With%20Markdown%20Cells.html (https://jupyter-notebook.readthedocs.io/en/stable/examples/Notebook/Working%20With%20Markdown%20Cells.html)
https://jupyter-notebook.readthedocs.io/en/stable/examples/Notebook/Typesetting%20Equations.html (https://jupyter-notebook.readthedocs.io/en/stable/examples/Notebook/Typesetting%20Equations.html)