## **Stochastic Gradient Descent**

- 1. Loading Boston Dataset from Sklearn Library
- 2. Custom SGD Regressor implementation (PART-1)
- 2. Sklearn's SGD Regressor implementation (PART-2)
- 4. Comparing Both the implementation

NOTE :- In each implementation plot the graph for the predicted vs actual values in the dataset(part1, part 2)

In [126]:

```
#importing libraries
import warnings
warnings.filterwarnings("ignore")
from sklearn.datasets import load boston
from random import seed
from random import randrange
from csv import reader
from math import sqrt
from sklearn import preprocessing
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from prettytable import PrettyTable
from sklearn.linear_model import SGDRegressor
from sklearn import preprocessing
from sklearn.metrics import mean squared error
from sklearn.preprocessing import StandardScaler
from sklearn import linear_model
import seaborn as sns
from sklearn.model selection import train test split
from numpy import c
```

# 1. Loading Boston Dataset from Sklearn Library

```
In [127]:
```

```
dataset = load_boston()
X = pd.DataFrame(dataset.data)
y = dataset.target

print("="*100)
print("Dataset\n")
print(X[:4])
print(type(X))

print("="*100)
print("Actual price\n")
print(y[:4])
print(type(y))
```

\_\_\_\_\_\_

```
Dataset
```

```
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
```

## 2. Custom SGD Regressor implementation (PART-1)

In [130]:

```
#Fitting the train Dataset in the custom SGD Regressor model
# Modifying dataset for getting the random row according to batch size in each iteration in the cu
stom SGD model
X_tr = np.c_[np.ones((len(X_train),1)),X_train]
X train = X_tr
X_te = np.c_[np.ones((len(X_test),1)),X_test]
X \text{ test} = X \text{ te}
# initialising the values for fitting the model
max iter = 1000 #initialising no of iterations
learning rate=0.01 #initialising the learning
length = len(Y_train) # length of the data set
error = []
# Generating normally distributed values of the train dataset
weight = np.random.normal(0,1,X train.shape[1])
weight = np.c_[weight]
# MODEL
for k in range(max iter):
    for i in range(length):
       batch size = np.random.randint(0,length)
       X batch = X train[batch size,:].reshape(1,X train.shape[1])
       y_batch = Y_train[batch_size].reshape(1,1)
        prediction = np.dot(X batch, weight)
        weight = weight -(2/length)*learning rate*( X batch.T.dot((prediction - y batch)))
```

```
In [131]:
```

```
pred_custom = X_test.dot(weight)
pred_custom = pred_custom.ravel()
```

### In [132]:

```
#Weights from Custom SGD Model
# weight custom = []
```

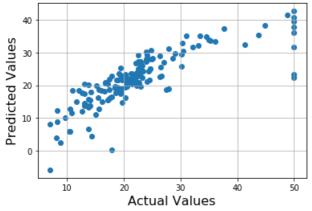
```
# for i in weight:
# weight_custom.append(i)
weight_custom = weight.ravel()
print(c_[weight_custom])
[[22.54034743]
```

[[22.54034743] [-1.22434741] [0.89977223] [-0.28205546] [0.19912563] [-1.34718894] [2.8248531] [-0.30299525] [-2.71286166] [2.44520023] [-1.81463673] [-2.04418207] [1.1216619] [-3.28606046]

## In [133]:

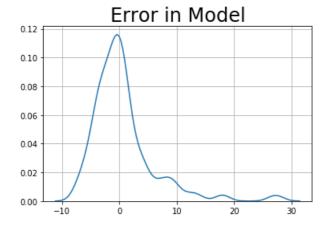
```
# Plotting graph for actual vs predicted price
plt.scatter(Y_test, pred_custom)
plt.xlabel("Actual Values", size=16)
plt.ylabel("Predicted Values", size=16)
plt.title("Actual Values vs Predicted Values", size=24)
plt.grid()
plt.show()
```

# Actual Values vs Predicted Values



### In [134]:

```
error = Y_test - pred_custom; #error = actual_price - predicted_price
sns.kdeplot(error)
plt.title("Error in Model", size=24)
plt.grid()
plt.show()
```



#### In [135]:

```
# Obtaining Mean Squared Error (MSE)
MSE_CUSTOM = mean_squared_error(Y_test, pred_custom)
print("Mean Squared Error (MSE) = ",MSE_CUSTOM)
```

Mean Squared Error (MSE) = 30.52018558400602

## 3. Sklearn's SGD Regressor implementation (PART-2)

```
In [136]:
```

```
model = linear_model.SGDRegressor(penalty='none', max_iter=1000, learning_rate='constant')
model.fit(X_train,Y_train)
pred_sklearn = model.predict(X_test)
```

#### In [137]:

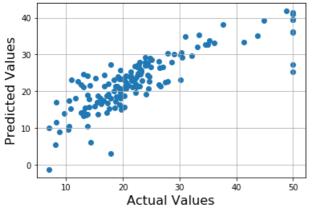
```
#Weights from Sklearn Model
weight_sklearn = model.coef_
print(c_[weight_sklearn])
```

[[11.66921283] [-0.71637651] [0.76089547] [0.13184507] [0.25055041] [-1.24878103] [3.11008312] [-0.22604507] [-3.02407402] [3.24388265] [-1.64174153] [-1.77595867] [1.49545237] [-3.20159722]]

## In [138]:

```
# Plotting graph for actual vs predicted price
plt.scatter(Y_test, pred_sklearn)
plt.xlabel("Actual Values", size=16)
plt.ylabel("Predicted Values", size=16)
plt.title("Actual Values vs Predicted Values", size=24)
plt.grid()
plt.show()
```

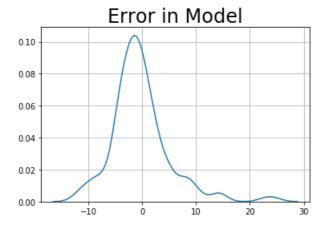
# Actual Values vs Predicted Values



#### In [139]:

```
error = Y_test - pred_sklearn; #error = actual_price - predicted_price
sns.kdeplot(error)
plt.title("Error in Model", size=24)
plt.grid()
```

```
plt.show()
```



## In [140]:

```
# Obtaining Mean Squared Error (MSE)
MSE_SKLEARN = mean_squared_error(Y_test, pred_sklearn)
print("Mean Squared Error (MSE) = ", MSE_SKLEARN)
```

Mean Squared Error (MSE) = 30.089575756454817

# 4. Comparing Both the implementation

#### In [141]:

```
# Creating the table using PrettyTable library
from prettytable import PrettyTable

# Initializing prettytable
preety_table = PrettyTable()

slno = [1,2,3,4,5,6,7,8,9,10,11,12,13,14]

# Adding columns
preety_table.add_column("SL NO.",slno)
preety_table.add_column("Weights of Manual SGD",weight_custom)
preety_table.add_column("Weights of Sklearn's SGD",weight_sklearn)

# Printing the Table
print(preety_table)
```

```
| SL NO. | Weights of Manual SGD | Weights of Sklearn's SGD |
  1
      | 22.540347429394803 | 11.669212830204986
      0.1991256302227841 | 0.25055040542801027
      | -1.3471889373772865 | -1.2487810324327755
      | 2.8248531020463727 |
                                3.110083115199914
      i
         -0.3029952450970284
                                -0.22604507263175322
                            -2.7128616606927336 |
  9
                               -3.0240740233393377
  10 |
          2.4452002261934
                                3.2438826506048106
  11 | -1.814636731115359 | -1.6417415250485121
  12 | -2.0441820664854395 | -1.7759586709623616
      | 1.1216618963717684 | 1.4954523650534282
| -3.2860604557159188 | -3.201597217478671
  13
```

#### In [142]:

```
# Creating the table using PrettyTable library
from prettytable import PrettyTable
```

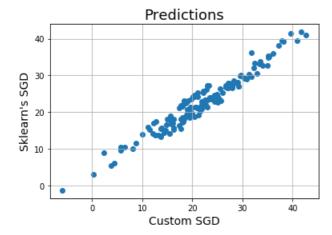
```
# Initializing prettytable
preety_table = PrettyTable()

preety_table.field_names = ["SGD Type", "Mean Squared Error"]
preety_table.add_row(["Custom SGD", MSE_CUSTOM])
preety_table.add_row(["Sklearn SGD", MSE_SKLEARN])

print(preety_table)
```

#### In [143]:

```
# Scatter Plot of the predictions of both manual SGD Regression and Sklearn's SGD Regression
plt.scatter(pred_custom, pred_sklearn)
plt.xlabel("Custom SGD",size=14)
plt.ylabel("Sklearn's SGD",size=14)
plt.title("Predictions",size=18)
plt.grid()
plt.show()
```



## Conclusion

- MSE of Custom SGD is slightly higher than the Sklearn SGD, therefore the custom model is performing well here
- Weights of both the models are approximately similar
- As we can see on the above prediction graph that the predicted value in sklearn and custom are giving approximately same value of predicted price

## \*\*\*END\*\*\*