Assignment-6 Implement SGD for linear regression.

1. Loading the Boston price data set & generating train & test dataframes

In [1]:

```
import warnings
warnings.filterwarnings("ignore")
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 sklearn.linear_model import SGDRegressor
from sklearn.metrics import mean_squared_error
```

In [2]:

```
from sklearn.datasets import load_boston
boston = load_boston()
```

In [3]:

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

```
(506, 13)
['CRIM' 'ZN' 'INDUS' 'CHAS' 'NOX' 'RM' 'AGE' 'DIS' 'RAD' 'TAX' 'PTRATIO'
 'B' 'LSTAT']
[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 [4]:

```
import pandas as pd
bos = pd.DataFrame(boston.data)
print(bos.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
```

In [5]:

```
bos.columns.values
```

Out[5]:

```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12], dtype=int64)
```

In [6]:

```
bos['PRICE'] = boston.target
```

In [7]:

```
bos.columns.values
```

Out[7]:

```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 'PRICE'], dtype=object)
```

In [8]:

```
bos.head(10)
```

Out[8]:

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	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	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33
5	0.02985	0.0	2.18	0.0	0.458	6.430	58.7	6.0622	3.0	222.0	18.7	394.12	5.21
6	0.08829	12.5	7.87	0.0	0.524	6.012	66.6	5.5605	5.0	311.0	15.2	395.60	12.43
7	0.14455	12.5	7.87	0.0	0.524	6.172	96.1	5.9505	5.0	311.0	15.2	396.90	19.15
8	0.21124	12.5	7.87	0.0	0.524	5.631	100.0	6.0821	5.0	311.0	15.2	386.63	29.93
9	0.17004	12.5	7.87	0.0	0.524	6.004	85.9	6.5921	5.0	311.0	15.2	386.71	17.10

In [9]:

```
bos['PRICE'].describe()
```

Out[9]:

```
count    506.000000
mean      22.532806
std        9.197104
min        5.000000
25%       17.025000
50%       21.200000
75%       25.000000
max       50.000000
Name: PRICE, dtype: float64
```

In [10]:

```
X=bos.drop('PRICE', axis = 1)
Y = bos['PRICE']
```

1.1 Splitting the data

In [11]:

```
# splitting the data frame into train & test
import sklearn
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.33, random_stat
e = 5)
print(X_train.shape)
print(X_test.shape)
print(Y_train.shape)
print(Y_test.shape)
```

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

1.2 Standardizing the train & test data

In [23]:

```
#standardizing Xi's
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler
scaler1 = StandardScaler()
scaler1.fit(X_train)
X_train_std=scaler1.transform(X_train)
X_test_std=scaler1.transform(X_test)

print("After Standardization")
print(X_train_std.shape)
print(X_test_std.shape)
```

```
After Standardization
(339, 13)
(167, 13)
```

In [24]:

```
#standardizing Yi's
from sklearn.preprocessing import StandardScaler
scaler2 = StandardScaler()
scaler2.fit(Y_train.values.reshape(-1,1))
Y_train_std=scaler2.transform((Y_train).values.reshape(-1,1))
Y_test_std=scaler2.transform((Y_test).values.reshape(-1,1))

print("After Standardization")
print(Y_train_std.shape)
print(Y_test_std.shape)
```

```
After Standardization
(339, 1)
(167, 1)
```

1.2.1 Creating dataframes for train & test data using standardized values

1.2.1.1 To create train_data

In [25]:

```
#create df for X_train data
df1 = pd.DataFrame(X_train_std, columns=['CRIM','ZN', 'INDUS', 'CHAS', 'NOX', 'RM','AG
E', 'DIS', 'RAD', 'TAX', 'PTRATIO',
 'B', 'LSTAT'])
#df.head(5)
df1.head()
```

Out[25]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	D
0	0.911839	-0.502419	1.072305	-0.256978	1.633548	0.486034	0.962774	-0.8234
1	-0.411727	-0.502419	-1.129795	-0.256978	-0.552451	1.028078	0.668619	-0.1832
2	0.124583	-0.502419	1.072305	-0.256978	1.441946	-3.913414	0.725324	-1.0759
3	-0.406208	0.839388	-0.901940	-0.256978	-1.083710	0.097426	-0.515087	1.6005
4	0.021742	-0.502419	1.072305	-0.256978	1.398401	0.123238	0.743044	-0.6051

In [26]:

```
#create df for Y_train data
df2=pd.DataFrame(Y_train_std, columns=['PRICE'])
df2.head()
```

Out[26]:

	PRICE
0	-1.022679
1	0.118958
2	0.555465
3	-0.037738
4	-0.541401

In [27]:

```
#concatenate df1 & df2 to get train_data
train_data=pd.concat([df1,df2],axis=1)
train_data.head()
```

Out[27]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	D
0	0.911839	-0.502419	1.072305	-0.256978	1.633548	0.486034	0.962774	-0.8234
1	-0.411727	-0.502419	-1.129795	-0.256978	-0.552451	1.028078	0.668619	-0.1832
2	0.124583	-0.502419	1.072305	-0.256978	1.441946	-3.913414	0.725324	-1.0759
3	-0.406208	0.839388	-0.901940	-0.256978	-1.083710	0.097426	-0.515087	1.6005
4	0.021742	-0.502419	1.072305	-0.256978	1.398401	0.123238	0.743044	-0.6051

In [28]:

```
train_data.shape
```

Out[28]:

(339, 14)

In [29]:

```
train_data.shape[0]
```

Out[29]:

339

1.2.1.2 To create test_data

In [30]:

```
#create df for X_test data
df3 = pd.DataFrame(X_test_std, columns=['CRIM','ZN', 'INDUS', 'CHAS', 'NOX', 'RM','AGE'
, 'DIS', 'RAD', 'TAX', 'PTRATIO',
 'B', 'LSTAT'])
df3.head()
```

Out[30]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	D
0	-0.372923	-0.502419	-0.711561	-0.256978	-0.421814	2.509379	0.675707	-0.2849
1	-0.414165	3.075732	-0.898942	-0.256978	-1.231765	0.487468	-1.560575	0.65338
2	-0.412891	-0.502419	-1.129795	-0.256978	-0.552451	0.182031	-0.047275	-0.3458
3	0.905605	-0.502419	1.072305	-0.256978	1.006488	-1.984712	1.154151	-1.2926
4	-0.392026	0.392119	-0.597633	3.891382	-0.770180	2.008920	-0.554071	0.28308

In [31]:

```
#create df for Y_test data
df4=pd.DataFrame(Y_test_std, columns=['PRICE'])
df4.head()
```

Out[31]:

	PRICE
0	1.685909
1	0.600236
2	0.007032
3	-0.977908
4	1.417289

In [32]:

```
#concatenate df3 & df4 to get test_data
test_data=pd.concat([df3,df4],axis=1)
test_data.head()
```

Out[32]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	D
0	-0.372923	-0.502419	-0.711561	-0.256978	-0.421814	2.509379	0.675707	-0.2849
1	-0.414165	3.075732	-0.898942	-0.256978	-1.231765	0.487468	-1.560575	0.65338
2	-0.412891	-0.502419	-1.129795	-0.256978	-0.552451	0.182031	-0.047275	-0.3458
3	0.905605	-0.502419	1.072305	-0.256978	1.006488	-1.984712	1.154151	-1.2926
4	-0.392026	0.392119	-0.597633	3.891382	-0.770180	2.008920	-0.554071	0.28308

In [33]:

```
test_data.shape
```

Out[33]:

```
(167, 14)
```

2. Implementing own version of SGD

Reference: [https://machinelearningmastery.com/implement-linear-regression-stochastic-gradient-descent-scratch-python/ (https://machinelearningmastery.com/implement-linear-regression-stochastic-gradient-descent-scratch-python/)](https://machinelearningmastery.com/implement-linear-regression-stochastic-gradient-descent-scratch-python/)

2.1 To find best coefficients from Train data

In [34]:

```
# Make a prediction with coefficients
def predict(row, coefficients):
    yhat = coefficients[0]
    for i in range(len(row)-1):
        yhat += coefficients[i + 1] * row[i]
    return yhat
```

In [35]:

```
# Estimate linear regression coefficients for train data using stochastic gradient desc
ent

def coefficients_sgd(train, l_rate, n_epoch):
    MSE_list=[]
    coef = [0.0 for i in range(14)]
    for epoch in range(n_epoch):
        sum_error = 0
        for row in (train.values):
            yhat = predict(row, coef)
            error = yhat - row[-1]
            sum_error += error**2
            coef[0] = coef[0] - l_rate * error #corresponds to b0 or w0
            for i in range(len(row)-1):
                coef[i + 1] = coef[i + 1] - l_rate * error * row[i] #corresponds to bi
 or wi
        print('For epoch=%d:, lrate=%.8f error=%.3f' % (epoch,l_rate,((sum_error)/train
_data.shape[0])))
        l_rate=l_rate/2;
        MSE_list.append((sum_error)/(train_data.shape[0]))
    return coef, MSE_list

# Calculate coefficients
dataset = train_data
l_rate = 0.01
n_epoch = 100
coef, MSE_list = coefficients_sgd(dataset, l_rate, n_epoch)
print(coef)
```

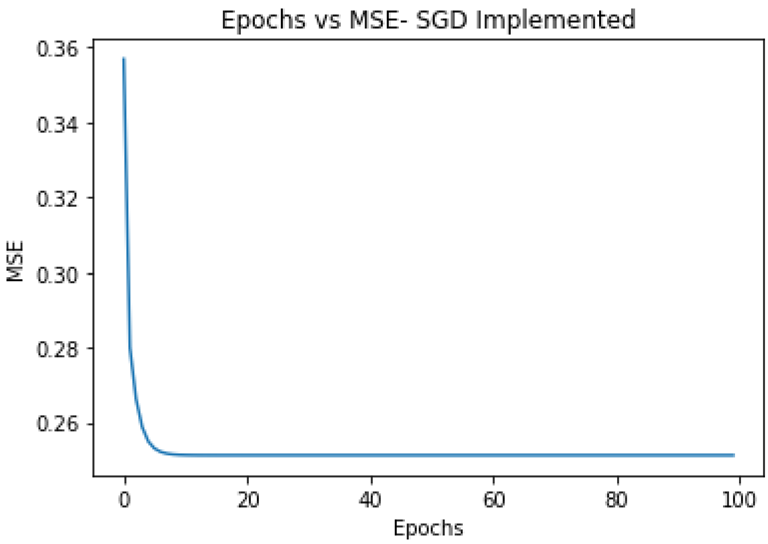
```
For epoch=0:, lrate=0.01000000 error=0.357
For epoch=1:, lrate=0.00500000 error=0.280
For epoch=2:, lrate=0.00250000 error=0.266
For epoch=3:, lrate=0.00125000 error=0.259
For epoch=4:, lrate=0.00062500 error=0.255
For epoch=5:, lrate=0.00031250 error=0.253
For epoch=6:, lrate=0.00015625 error=0.252
For epoch=7:, lrate=0.00007813 error=0.252
For epoch=8:, lrate=0.00003906 error=0.252
For epoch=9:, lrate=0.00001953 error=0.251
For epoch=10:, lrate=0.00000977 error=0.251
For epoch=11:, lrate=0.00000488 error=0.251
For epoch=12:, lrate=0.00000244 error=0.251
For epoch=13:, lrate=0.00000122 error=0.251
For epoch=14:, lrate=0.00000061 error=0.251
For epoch=15:, lrate=0.00000031 error=0.251
For epoch=16:, lrate=0.00000015 error=0.251
For epoch=17:, lrate=0.00000008 error=0.251
For epoch=18:, lrate=0.00000004 error=0.251
For epoch=19:, lrate=0.00000002 error=0.251
For epoch=20:, lrate=0.00000001 error=0.251
For epoch=21:, lrate=0.00000000 error=0.251
For epoch=22:, lrate=0.00000000 error=0.251
For epoch=23:, lrate=0.00000000 error=0.251
For epoch=24:, lrate=0.00000000 error=0.251
For epoch=25:, lrate=0.00000000 error=0.251
For epoch=26:, lrate=0.00000000 error=0.251
For epoch=27:, lrate=0.00000000 error=0.251
For epoch=28:, lrate=0.00000000 error=0.251
For epoch=29:, lrate=0.00000000 error=0.251
For epoch=30:, lrate=0.00000000 error=0.251
For epoch=31:, lrate=0.00000000 error=0.251
For epoch=32:, lrate=0.00000000 error=0.251
For epoch=33:, lrate=0.00000000 error=0.251
For epoch=34:, lrate=0.00000000 error=0.251
For epoch=35:, lrate=0.00000000 error=0.251
For epoch=36:, lrate=0.00000000 error=0.251
For epoch=37:, lrate=0.00000000 error=0.251
For epoch=38:, lrate=0.00000000 error=0.251
For epoch=39:, lrate=0.00000000 error=0.251
For epoch=40:, lrate=0.00000000 error=0.251
For epoch=41:, lrate=0.00000000 error=0.251
For epoch=42:, lrate=0.00000000 error=0.251
For epoch=43:, lrate=0.00000000 error=0.251
For epoch=44:, lrate=0.00000000 error=0.251
For epoch=45:, lrate=0.00000000 error=0.251
For epoch=46:, lrate=0.00000000 error=0.251
For epoch=47:, lrate=0.00000000 error=0.251
For epoch=48:, lrate=0.00000000 error=0.251
For epoch=49:, lrate=0.00000000 error=0.251
For epoch=50:, lrate=0.00000000 error=0.251
For epoch=51:, lrate=0.00000000 error=0.251
For epoch=52:, lrate=0.00000000 error=0.251
For epoch=53:, lrate=0.00000000 error=0.251
For epoch=54:, lrate=0.00000000 error=0.251
For epoch=55:, lrate=0.00000000 error=0.251
For epoch=56:, lrate=0.00000000 error=0.251
For epoch=57:, lrate=0.00000000 error=0.251
For epoch=58:, lrate=0.00000000 error=0.251
For epoch=59:, lrate=0.00000000 error=0.251
For epoch=60:, lrate=0.00000000 error=0.251
```

```
For epoch=61:, lrate=0.00000000 error=0.251
For epoch=62:, lrate=0.00000000 error=0.251
For epoch=63:, lrate=0.00000000 error=0.251
For epoch=64:, lrate=0.00000000 error=0.251
For epoch=65:, lrate=0.00000000 error=0.251
For epoch=66:, lrate=0.00000000 error=0.251
For epoch=67:, lrate=0.00000000 error=0.251
For epoch=68:, lrate=0.00000000 error=0.251
For epoch=69:, lrate=0.00000000 error=0.251
For epoch=70:, lrate=0.00000000 error=0.251
For epoch=71:, lrate=0.00000000 error=0.251
For epoch=72:, lrate=0.00000000 error=0.251
For epoch=73:, lrate=0.00000000 error=0.251
For epoch=74:, lrate=0.00000000 error=0.251
For epoch=75:, lrate=0.00000000 error=0.251
For epoch=76:, lrate=0.00000000 error=0.251
For epoch=77:, lrate=0.00000000 error=0.251
For epoch=78:, lrate=0.00000000 error=0.251
For epoch=79:, lrate=0.00000000 error=0.251
For epoch=80:, lrate=0.00000000 error=0.251
For epoch=81:, lrate=0.00000000 error=0.251
For epoch=82:, lrate=0.00000000 error=0.251
For epoch=83:, lrate=0.00000000 error=0.251
For epoch=84:, lrate=0.00000000 error=0.251
For epoch=85:, lrate=0.00000000 error=0.251
For epoch=86:, lrate=0.00000000 error=0.251
For epoch=87:, lrate=0.00000000 error=0.251
For epoch=88:, lrate=0.00000000 error=0.251
For epoch=89:, lrate=0.00000000 error=0.251
For epoch=90:, lrate=0.00000000 error=0.251
For epoch=91:, lrate=0.00000000 error=0.251
For epoch=92:, lrate=0.00000000 error=0.251
For epoch=93:, lrate=0.00000000 error=0.251
For epoch=94:, lrate=0.00000000 error=0.251
For epoch=95:, lrate=0.00000000 error=0.251
For epoch=96:, lrate=0.00000000 error=0.251
For epoch=97:, lrate=0.00000000 error=0.251
For epoch=98:, lrate=0.00000000 error=0.251
For epoch=99:, lrate=0.00000000 error=0.251
[0.009077332087515743, -0.13781089229710045, 0.06235467361715586, -0.06610
829067584187, 0.03282518890559946, -0.09966629740611256, 0.351165715732349
56, -0.05186144061840854, -0.24722673627286096, 0.14194842039861835, -0.07
707901958214271, -0.2278706710881424, 0.10383646506196041, -0.345892818811
7475]
```

2.2 Plotting Epochs vs Mean squared error(MSE)

In [36]:

```
#Plot of epochs vs Mean squared error

plt.plot(range(0,100), MSE_list)
plt.xlabel("Epochs")
plt.ylabel("MSE")
plt.title("Epochs vs MSE- SGD Implemented")
plt.show()
```



In [37]:

```
# To get the coefficients when there is not much of change in the error
dataset = train_data
l_rate = 0.01
n_epoch = 7
coef,MSE_list = coefficients_sgd(dataset, l_rate, n_epoch)
print(coef)
```

```
For epoch=0:, lrate=0.01000000 error=0.357
For epoch=1:, lrate=0.00500000 error=0.280
For epoch=2:, lrate=0.00250000 error=0.266
For epoch=3:, lrate=0.00125000 error=0.259
For epoch=4:, lrate=0.00062500 error=0.255
For epoch=5:, lrate=0.00031250 error=0.253
For epoch=6:, lrate=0.00015625 error=0.252
[0.009558946531683554, -0.13818718767629987, 0.06243946570609928, -0.06653
276256328082, 0.033085987060484955, -0.09943414546086045, 0.35178301798939
13, -0.05210974376059008, -0.24617355920767672, 0.14098947216684204, -0.07
69546176730711, -0.22803779179897943, 0.10347864673326172, -0.345793820987
20907]
```

In [38]:

```
coefficients_test=coef #assigning the best coefficients that are to be used for testing purpose
coefficients_test
```

Out[38]:

```
[0.009558946531683554,
 -0.13818718767629987,
 0.06243946570609928,
 -0.06653276256328082,
 0.033085987060484955,
 -0.09943414546086045,
 0.3517830179893913,
 -0.05210974376059008,
 -0.24617355920767672,
 0.14098947216684204,
 -0.0769546176730711,
 -0.22803779179897943,
 0.10347864673326172,
 -0.34579382098720907]
```

2.3 Applying the best coefficients on test data

In [110]:

```
def test_sgd(data, l_rate,coef):
    '''
    Function that returns the Mean squared error[MSE] and the list of predicted values
 for test data.

    '''
    best_coef=coef
    sum_error = 0
    pred=[];
    for row in (data.values):
        yhat = predict(row, best_coef)
        error = yhat - row[-1]
        sum_error += error**2
        MSE=sum_error/data.shape[0]
        pred.append(yhat)
    return MSE,pred
```

In [111]:

```
# Applying best learning rate & coefficients on test data

dataset = test_data
l_rate = 0.0002
MSE,pred = test_sgd(dataset, l_rate,coefficients_test)
print(f'The MSE for test data using custom implemented SGD is:{MSE}')
```

```
The MSE for test data using custom implemented SGD is:0.3678398415588903
```

2.4 Converting standardized outputs to original outputs using inverse_transform attribute

In [ ]:

```
sq_error= [i[0] for i in ((act_or-pred_or)**2)]
#print(sq_error)
MSE=sum(sq_error)/Y_test_std.shape[0]
print(f'The MSE for original test data using sklearn version of SGD is:{MSE}')
```

In [116]:

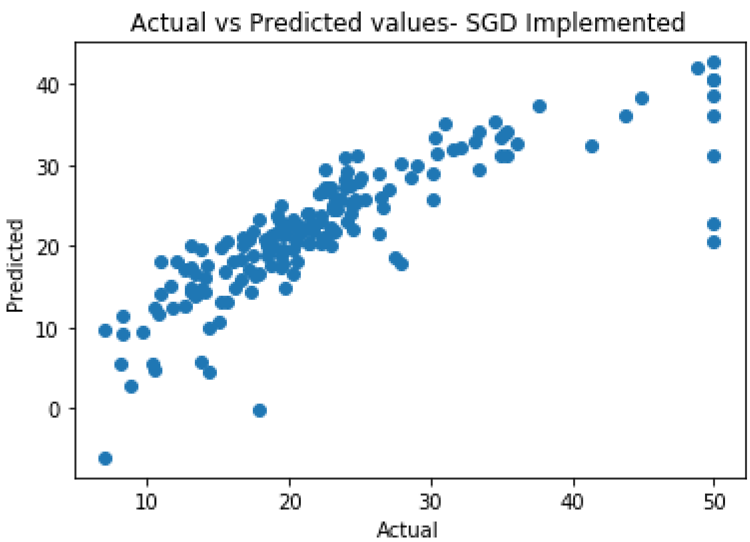
```
pred_or=scaler2.inverse_transform(pred)
pred_or=pred_or.reshape(-1,1)

act_or=scaler2.inverse_transform(Y_test_std)

sq_error= [i[0] for i in ((act_or-pred_or)**2)] #using list comprehension

MSE=sum(sq_error)/Y_test_std.shape[0]
print(f'The MSE for original test data using custom implemented SGD is:{MSE}')
```

```
The MSE for original test data using custom implemented SGD is:29.36322407
9377503
```

2.5 Plotting Actual vs Predicted values for test data

In [117]:

```
plt.scatter(act_or, pred_or)
plt.xlabel("Actual")
plt.ylabel("Predicted")
plt.title("Actual vs Predicted values- SGD Implemented")
plt.show()
```



3. Scikit learn version of SGD

3.1 Applying SGD

In [105]:

```
from sklearn.linear_model import SGDRegressor
from sklearn.metrics import mean_squared_error

reg = SGDRegressor(loss='squared_loss',max_iter=100, alpha=0.0001, tol=.0001,learning_r
ate='invscaling')

reg.fit (X_train_std, Y_train_std)

yhat=reg.predict(X_test_std)

MSE=mean_squared_error(Y_test_std,yhat)

print(f'The MSE for standardized test data using sklearn version of SGD is:{MSE}')
```

```
The MSE for standardized test data using sklearn version of SGD is:0.36072
161627698773
```

3.2 Converting standardized outputs to original outputs using inverse_transform attribute

In [106]:

```
yhat_=yhat.reshape(-1,1)
#print(yhat_.shape)
#print(Y_test_std.shape)
pred_or=scaler2.inverse_transform(yhat_)
#print(pred_or)
act_or=scaler2.inverse_transform(Y_test_std)
#print(act_or)
sq_error= [i[0] for i in ((act_or-pred_or)**2)]
#print(sq_error)
MSE=sum(sq_error)/Y_test_std.shape[0]
print(f'The MSE for original test data using sklearn version of SGD is:{MSE}')
```

```
The MSE for original test data using sklearn version of SGD is:28.79500383
680074
```

3.3 Co-efficients & intercept

In [107]:

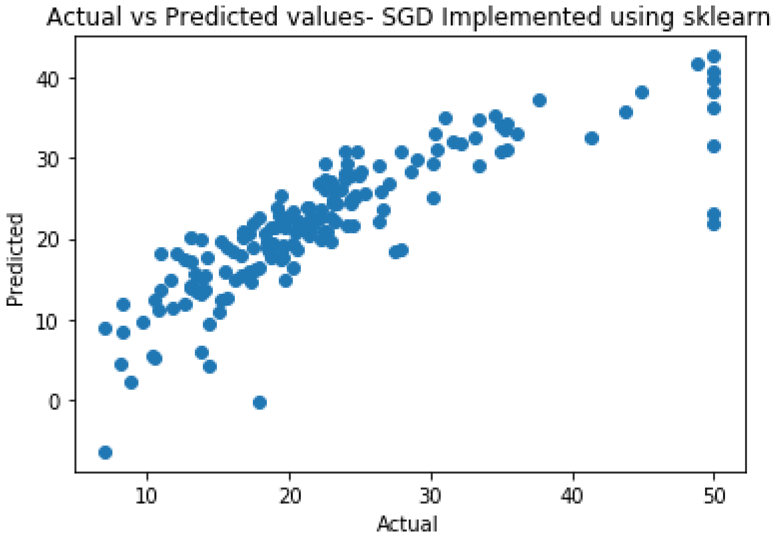
```
coefs=reg.coef_
print(coefs)
w0=reg.intercept_
print('Intercept=',w0)
```

```
[-0.13847363  0.08209953 -0.05357241  0.02511937 -0.1476366   0.32158284
 -0.04633332 -0.29991421  0.20889573 -0.12852264 -0.23329494  0.1176353
 -0.37131385]
Intercept= [6.66425325e-05]
```

3.4 Plotting Actual vs Predicted values

In [109]:

```
plt.scatter(act_or, pred_or)
plt.xlabel("Actual")
plt.ylabel("Predicted")
plt.title("Actual vs Predicted values- SGD Implemented using sklearn")
plt.show()
```



4. Summary

4.1 MSE summary

In [118]:

```
#Ref: http://zetcode.com/python/prettytable/
from prettytable import PrettyTable

x = PrettyTable()
x.field_names = ["Implementation type","MSE"]
x.add_row(["Manual", 29.4])
x.add_row(["Sklearn", 28.8])
print(x)
```

```
+---------------------+------+
| Implementation type | MSE  |
+---------------------+------+
|        Manual       | 29.4 |
|       Sklearn       | 28.8 |
+---------------------+------+
```

4.2 Co-efficients summary

In [119]:

```
# creating lists of co-effs for both the versions
man=[0.009558946531683554, -0.13818718767629987, 0.06243946570609928, -0.06653276256328
082, 0.033085987060484955, -0.09943414546086045, 0.3517830179893913, -0.052109743760590
08, -0.24617355920767672, 0.14098947216684204, -0.0769546176730711, -0.2280377917989794
3, 0.10347864673326172, -0.34579382098720907]
sk=[6.66425325e-05,-0.13847363,0.08209953,-0.05357241,0.02511937,-0.1476366,0.32158284,
-0.04633332,-0.29991421,0.20889573,-0.12852264,-0.23329494,0.1176353,-0.37131385]
```

In [120]:

```
# Creating a table in form of data frame
tab = pd.DataFrame(list(zip(man,sk)),index =['Intercept','CRIM','ZN', 'INDUS', 'CHAS',
'NOX', 'RM','AGE', 'DIS', 'RAD', 'TAX', 'PTRATIO',
 'B', 'LSTAT'],columns =['Manual','Sklearn'])
tab
```

Out[120]:

	Manual	Sklearn
Intercept	0.009559	0.000067
CRIM	-0.138187	-0.138474
ZN	0.062439	0.082100
INDUS	-0.066533	-0.053572
CHAS	0.033086	0.025119
NOX	-0.099434	-0.147637
RM	0.351783	0.321583
AGE	-0.052110	-0.046333
DIS	-0.246174	-0.299914
RAD	0.140989	0.208896
TAX	-0.076955	-0.128523
PTRATIO	-0.228038	-0.233295
B	0.103479	0.117635
LSTAT	-0.345794	-0.371314