In [1]:
```
import numpy as np
import pandas as pd
import sklearn
import seaborn as sns
from sklearn import linear_model
from sklearn import cross_validation
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import SGDRegressor
import matplotlib.pyplot as plt
import scipy.stats as stats
```

```
D:\Anaconda3\lib\site-packages\sklearn\cross_validation.py:41: DeprecationWar
ning: This module was deprecated in version 0.18 in favor of the model_select
ion module into which all the refactored classes and functions are moved. Als
o note that the interface of the new CV iterators are different from that of
this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

In [2]:
```
#Import the Boston Housing dataset and store in a variable
from sklearn.datasets import load_boston
boston = load_boston()
```

In [3]:
```
boston.keys()
```

Out[3]:
```
dict_keys(['data', 'target', 'feature_names', 'DESCR'])
```

In [4]:
```
boston.data.shape
```

Out[4]:
```
(506, 13)
```

In [5]:
```
boston.feature_names
```

Out[5]:
```
array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7')
```

In [6]:
```
boston.target
```

Out[6]:
```
array([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 [7]:
```
boston.DESCR
```

Out[7]:
```
"Boston House Prices dataset\n===========================\n\nNotes\n------\nD
ata Set Characteristics:  \n\n    :Number of Instances: 506 \n\n    :Number o
f Attributes: 13 numeric/categorical predictive\n    \n    :Median Value (att
ribute 14) is usually the target\n\n    :Attribute Information (in order):\n
- CRIM     per capita crime rate by town\n        - ZN       proportion of re
sidential land zoned for lots over 25,000 sq.ft.\n        - INDUS    proporti
on of non-retail business acres per town\n        - CHAS     Charles River du
mmy variable (= 1 if tract bounds river; 0 otherwise)\n        - NOX      nit
ric oxides concentration (parts per 10 million)\n        - RM       average n
umber of rooms per dwelling\n        - AGE      proportion of owner-occupied
units built prior to 1940\n        - DIS      weighted distances to five Bost
on employment centres\n        - RAD      index of accessibility to radial hi
ghways\n        - TAX      full-value property-tax rate per $10,000\n
- PTRATIO  pupil-teacher ratio by town\n        - B        1000(Bk - 0.63)^2
where Bk is the proportion of blacks by town\n        - LSTAT    % lower stat
us of the population\n        - MEDV     Median value of owner-occupied homes
in $1000's\n\n    :Missing Attribute Values: None\n\n    :Creator: Harrison,
D. and Rubinfeld, D.L.\n\nThis is a copy of UCI ML housing dataset.\nhttp://a
rchive.ics.uci.edu/ml/datasets/Housing\n\n\nThis dataset was taken from the S
tatLib library which is maintained at Carnegie Mellon University.\n\nThe Bost
on house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedonic\nprices and
the demand for clean air', J. Environ. Economics & Management,\nvol.5, 81-10
2, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnostics\n...', Wile
y, 1980.   N.B. Various transformations are used in the table on\npages 244-2
61 of the latter.\n\nThe Boston house-price data has been used in many machin
e learning papers that address regression\nproblems.   \n     \n**References*
*\n\n   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influen
tial Data and Sources of Collinearity', Wiley, 1980. 244-261.\n   - Quinlan,
R. (1993). Combining Instance-Based and Model-Based Learning. In Proceedings
on the Tenth International Conference of Machine Learning, 236-243, Universit
y of Massachusetts, Amherst. Morgan Kaufmann.\n   - many more! (see http://ar
chive.ics.uci.edu/ml/datasets/Housing)\n"
```

In [8]:
```
df = pd.DataFrame(boston.data, columns=boston.feature_names)
df['PRICE'] = boston.target
df.head()
```

Out[8]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B
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
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
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
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
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

In [9]:
```
df.describe()
```

Out[9]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	A
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000(
mean	3.593761	11.363636	11.136779	0.069170	0.554695	6.284634	68.5749(
std	8.596783	23.322453	6.860353	0.253994	0.115878	0.702617	28.1488(
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.90000(
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.0250(
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.5000(
75%	3.647423	12.500000	18.100000	0.000000	0.624000	6.623500	94.0750(
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000(

In [10]:
```
X = df.drop('PRICE', axis=1)
Y = df['PRICE']
```

In [11]:
```
from sklearn.preprocessing import StandardScaler
scalar = StandardScaler()
standarard_X = scalar.fit_transform(X)
```

SGDRegressor for linear regression using sklearn lib

In [12]:
```
clf = linear_model.SGDRegressor()
clf.fit(standarard_X, Y)
Y_Pred = clf.predict(standarard_X)
```

```
D:\Anaconda3\lib\site-packages\sklearn\linear_model\stochastic_gradient.py:12
8: FutureWarning: max_iter and tol parameters have been added in <class 'skle
arn.linear_model.stochastic_gradient.SGDRegressor'> in 0.19. If both are left
unset, they default to max_iter=5 and tol=None. If tol is not None, max_iter
defaults to max_iter=1000. From 0.21, default max_iter will be 1000, and defa
ult tol will be 1e-3.
  "and default tol will be 1e-3." % type(self), FutureWarning)
```

Finding Optimal weight and Intercept for sklearn SGD

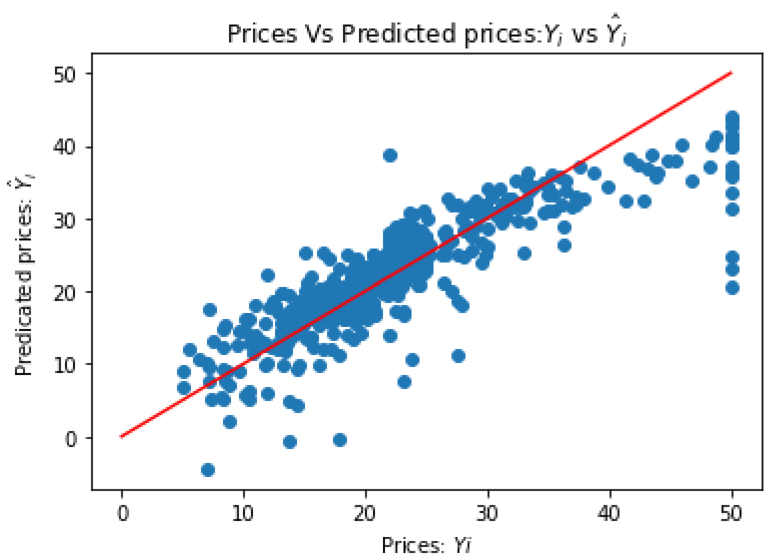
In [13]:
```
from numpy import c_
print(c_[clf.coef_])
clf.intercept_
```

```
[[-0.67749996]
 [ 0.64621265]
 [-0.39311328]
 [ 0.81576085]
 [-0.96565867]
 [ 3.18478262]
 [-0.12571484]
 [-2.03872396]
 [ 0.84166711]
 [-0.59078458]
 [-1.79203067]
 [ 0.92148609]
 [-3.41124639]]
```

Out[13]:
```
array([22.34568544])
```

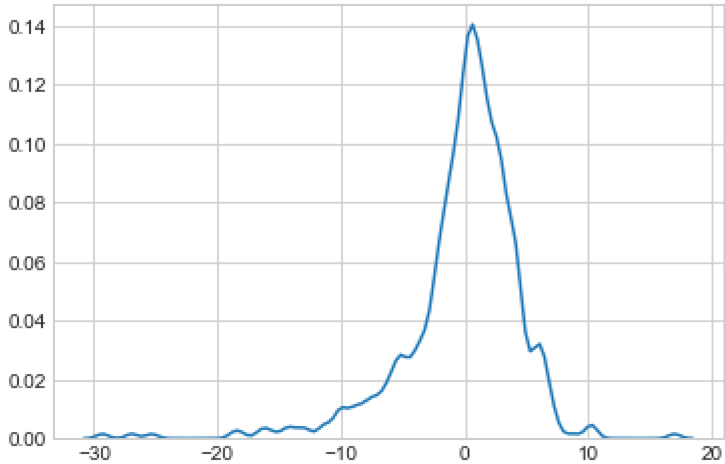
In [14]:
```
plt.scatter(Y, Y_Pred)
plt.xlabel('Prices: $Yi$')
plt.ylabel('Predicated prices: $\hat{Y}_i$')
plt.title('Prices Vs Predicted prices:$Y_i$ vs $\hat{Y}_i$')
plt.plot([0,50],[0,50], 'r-')
```

Out[14]:
```
[<matplotlib.lines.Line2D at 0x2e610e9ffd0>]
```



Plotting Delta Error for Actual Values and Predicted Values

In [15]:
```
delta_y = Y_Pred - Y
sns.set_style('whitegrid')
sns.kdeplot(np.array(delta_y), bw=0.5)
plt.show()
```



Observation

Delta: Blue plot indicates Difference between actual values and predicate values

In [16]:
```
from sklearn.metrics import mean_squared_error
test_MSE = mean_squared_error(Y, Y_Pred)
print("Mean Square Error - Test:", test_MSE)
```

```
Mean Square Error - Test: 22.83673830735814
```

SGD Regressor for linear regression from scratch

In [17]:
```
# SGDRegressor for linear regression from scratch which compututes optimal w a
nd MSE
def Stochastic_Gradient(X,y,weight,learning_rate=0.01,iterations=10):
    """Compute the optimal weight and intercept"""
    m = len(y) #  length of the data set

    for it in range(iterations): # iteration
        sum_error = 0

        for i in range(m):
            batch_size = np.random.randint(0,m)  # random batch size for every
iteration i.e k batch_size
            X_i = X[batch_size,:].reshape(1,X.shape[1])
            y_i = y[batch_size].reshape(1,1)
            prediction = np.dot(X_i,weight)

            #-------- error ---------
            error = prediction - y_i
            sum_error += error**2
            #--------- error ---------

            weight = weight -(2/m)*learning_rate*( X_i.T.dot((prediction - y_i
)))

        print('>epoch=%d, l_rate=%.3f, Error=%.3f' % (it, learning_rate, sum_e
rror/m))

    return weight

def Predict_Fun(X_b,weight):
    """Predict y using data x and weight"""
    y_pred = X_b.dot(weight)
    y_pred = y_pred.ravel()
    return y_pred
```

Implemeting self build SGDRegressor

In [18]:
```
learning_rate =0.2 #learning_rate
n_iter = 20 #no. of iterations

weight = np.random.randn(14,1) #picking the initial random weight and intercep
t

X_b = np.c_[np.ones((len(standarard_X),1)),standarard_X]

optimal_weight = Stochastic_Gradient(X_b,Y,weight,learning_rate,n_iter)
```

```
>epoch=0, l_rate=0.200, Error=395.556
>epoch=1, l_rate=0.200, Error=181.869
>epoch=2, l_rate=0.200, Error=98.556
>epoch=3, l_rate=0.200, Error=61.882
>epoch=4, l_rate=0.200, Error=45.647
>epoch=5, l_rate=0.200, Error=29.031
>epoch=6, l_rate=0.200, Error=28.277
>epoch=7, l_rate=0.200, Error=26.490
>epoch=8, l_rate=0.200, Error=24.004
>epoch=9, l_rate=0.200, Error=22.893
>epoch=10, l_rate=0.200, Error=24.267
>epoch=11, l_rate=0.200, Error=24.692
>epoch=12, l_rate=0.200, Error=23.318
>epoch=13, l_rate=0.200, Error=24.333
>epoch=14, l_rate=0.200, Error=23.878
>epoch=15, l_rate=0.200, Error=24.558
>epoch=16, l_rate=0.200, Error=19.472
>epoch=17, l_rate=0.200, Error=23.463
>epoch=18, l_rate=0.200, Error=24.424
>epoch=19, l_rate=0.200, Error=24.405
```

Optimal weights and intercept for self implemented SGDRegressor

In [19]:
```
print('Optimal Weights for self implemented SGD:\n')
print(optimal_weight[1:])

print('\nIntercept for self implemented SGD:  {:f}'.format(optimal_weight[0][0
]))
```

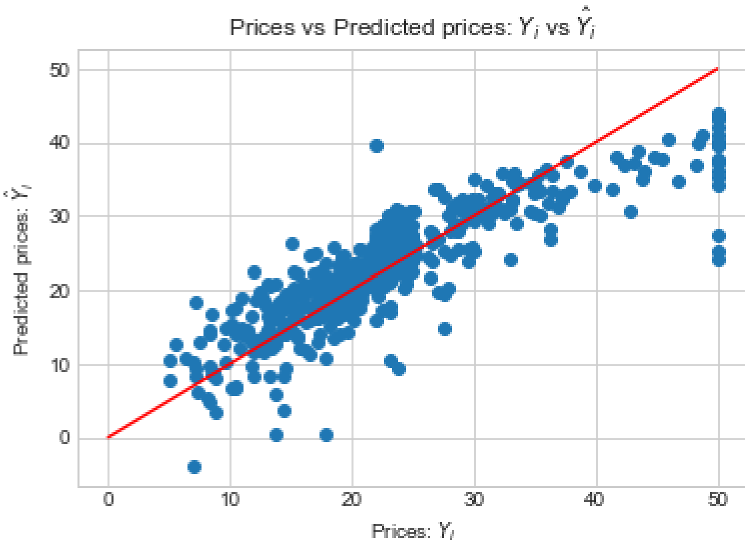
```
Optimal Weights for self implemented SGD:

[[-0.61880025]
 [ 0.72740428]
 [-0.25841607]
 [ 0.92167236]
 [-1.27624494]
 [ 2.74003105]
 [ 0.20673248]
 [-2.44157469]
 [ 1.41091106]
 [-0.61422894]
 [-1.93245967]
 [ 1.03213449]
 [-3.9985583 ]]

Intercept for self implemented SGD:  22.658095
```

Getting predicted Y using optimal weight for dataset X

In [20]:
```
Y_Predicted = Predict_Fun(X_b, optimal_weight)
```

Graph for predicted Y and actual Y (Self Implemented SGD)

In [21]:
```
plt.scatter(Y, Y_Predicted)
plt.xlabel("Prices: $Y_i$")
plt.ylabel("Predicted prices: $\hat{Y}_i$")
plt.title("Prices vs Predicted prices: $Y_i$ vs $\hat{Y}_i$")
plt.plot([0,50],[0,50], 'r-')
plt.show()
```



Plotting Error for Actual Y and Predicted Y

In [22]:
```
sns.set_style('whitegrid')
sns.kdeplot((Y_Predicted-Y))
plt.title("Error plot for self implemented SGD")
```

Out[22]: `Text(0.5,1,'Error plot for self implemented SGD')`

Mean_square_error for Self implemented SGD

In [23]:
```
## With reference of the link https://stackoverflow.com/questions/39064684/mea
n-squared-error-in-python

print("Mean Squared Error using the predicted Y and optimal weights :",np.mean
((Y-Y_Predicted)**2))
```

```
Mean Squared Error using the predicted Y and optimal weights : 22.58172913281
175
```

Comparing Sklearn SGD and Self Implemented SGD

In [24]:
```
sklearn_pred = Y_Pred
self_pred = Y_Predicted
sns.set_style('whitegrid')
sns.kdeplot((sklearn_pred-self_pred))
plt.title("Error plot for Sklearn SGD and Self Implemented SGD")
```

Out[24]:
```
Text(0.5,1,'Error plot for Sklearn SGD and Self Implemented SGD')
```

Optimal weight for Self implemented SGD and SKlearn SGD

In [25]:
```
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["SGD optimal Weight","Implemented SGD optimal Weight"]

x.add_row(["Sklearn",c_[clf.coef_]])
x.add_row(["Self",optimal_weight[1:]])

print(x)
```

```
+-------------------+-------------------------------+
| SGD optimal Weight | Implemented SGD optimal Weight |
+-------------------+-------------------------------+
|      Sklearn      |         [[-0.67749996]        |
|                   |          [ 0.64621265]        |
|                   |          [-0.39311328]        |
|                   |          [ 0.81576085]        |
|                   |          [-0.96565867]        |
|                   |          [ 3.18478262]        |
|                   |          [-0.12571484]        |
|                   |          [-2.03872396]        |
|                   |          [ 0.84166711]        |
|                   |          [-0.59078458]        |
|                   |          [-1.79203067]        |
|                   |          [ 0.92148609]        |
|                   |         [-3.41124639]]        |
|        Self       |         [[-0.61880025]        |
|                   |          [ 0.72740428]        |
|                   |          [-0.25841607]        |
|                   |          [ 0.92167236]        |
|                   |          [-1.27624494]        |
|                   |          [ 2.74003105]        |
|                   |          [ 0.20673248]        |
|                   |          [-2.44157469]        |
|                   |          [ 1.41091106]        |
|                   |          [-0.61422894]        |
|                   |          [-1.93245967]        |
|                   |          [ 1.03213449]        |
|                   |         [-3.9985583 ]]        |
+-------------------+-------------------------------+
```

Optimal Intercept for Self implemented SGD and SKlearn SGD

In [26]:
```
print("Sklearn SGD optimal intercept",clf.intercept_)
print("\nSelf implemented SGD optimal intercept",optimal_weight[0][0])
```

```
Sklearn SGD optimal intercept [22.34568544]

Self implemented SGD optimal intercept 22.658095494980408
```

Conclusion

In [27]:
```
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["SGD","MSE"]

x.add_row(["Sklearn",clf.intercept_])
x.add_row(["Self",optimal_weight[0][0]])

print(x)
```

```
+---------+--------------------+
|   SGD   |        MSE         |
+---------+--------------------+
| Sklearn |   [22.34568544]    |
|   Self  | 22.658095494980408 |
+---------+--------------------+
```

When comparing to scikit-learn linear regression and Self implemented linear regression using optimization algorithm(sgd) in python, we can see there are not much differences between both of them.