In [1]:

```
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, mean_absolute_error
from sklearn.model_selection import train_test_split
```

In [2]:

```
# Citation
# https://www.kaggle.com/premvardhan/stocasticgradientdescent-implementation-lr-python
# https://www.kaggle.com/arpandas65/simple-sgd-implementation-of-linear-regression
```

In [3]:

```
boston = load_boston()

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
        - 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 [4]:

```
# Split train and test data
X = boston.data
Y = boston.target

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.33, random_state=5)
```

In [5]:

```
# Create Data Frame
boston_data = pd.DataFrame(boston.data, columns=boston.feature_names)

# show data
boston_data.head()
```

Out[5]:

	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	396.90	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

In [6]:

```
boston_data.shape
```

Out[6]:

```
(506, 13)
```

In [7]:

```
# Standrize data
scaler = preprocessing.StandardScaler()

scaler.fit(X_train)

X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
```

In [8]:

```
print(X_train.shape)
print(X_test.shape)
print(Y_train.shape)
print(Y_test.shape)
```

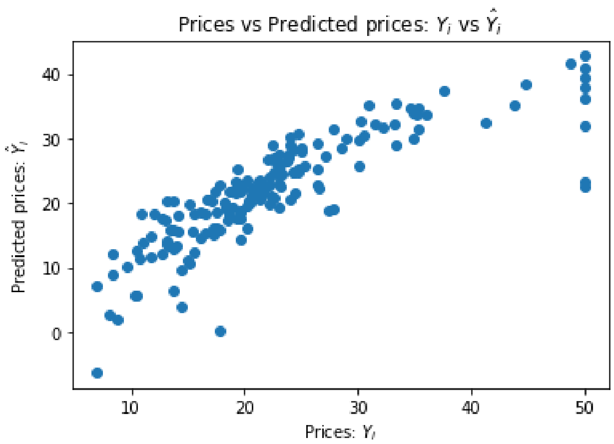
```
(339, 13)
(167, 13)
```

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

In [9]:

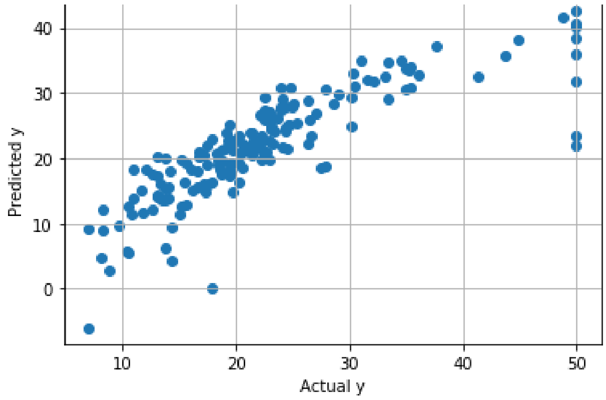
```
# Implement Linear Regression
# code source:https://medium.com/@haydar_ai/learning-data-science-day-9-linear-regression-on-bosto
n-housing-dataset-cd62a80775ef
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt

lm = LinearRegression()
lm.fit(X_train, Y_train)

Y_pred = lm.predict(X_test)

print('Coefficients: \n', lm.coef_)
# The mean squared error
print("Mean squared error: %.2f" % mean_squared_error(Y_test, Y_pred))
# Explained variance score: 1 is perfect prediction
# print("R^2 score: %.2f"  % lm.score(X_test, Y_test))
print('Variance score: %.2f' % r2_score(Y_test, Y_pred))

plt.scatter(Y_test, Y_pred)
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.show()
```

```
Coefficients: 
 [-1.31193031  0.86187745 -0.16719287  0.18957843 -1.48658584  2.79131565
 -0.32737703 -2.77204093  2.97567549 -2.2727549  -2.13375869  1.05842993
 -3.33495407]
Mean squared error: 28.53
Variance score: 0.70
```



In [10]:

```
# First implement SKLearn SGD
# SkLearn SGD classifier
clf_ = SGDRegressor()
clf_.fit(X_train, Y_train)

plt.scatter(Y_test,clf_.predict(X_test))
plt.grid()
plt.xlabel('Actual y')
plt.ylabel('Predicted y')
plt.title('scatter plot between actual y and predicted y')
plt.show()
print('Mean Squared Error :',mean_squared_error(Y_test, clf_.predict(X_test)))
print('Mean Absolute Error :',mean_absolute_error(Y_test, clf_.predict(X_test)))
```




```
Mean Squared Error : 28.545951396225185
Mean Absolute Error : 3.450685306695088
```

In [11]:

```
# SkLearn SGD classifier predicted weight matrix
sklearn_w=clf_.coef_
sklearn_w
```

Out[11]:

```
array([-1.19998397,  0.70823758, -0.47154859,  0.24990282, -1.25091027,
        2.89665502, -0.38369813, -2.64985472,  1.78730939, -1.05960085,
       -2.08913235,  1.03175028, -3.31171865])
```

In [12]:

```
# Implement Custom SGD
boston_data.describe()
```

Out[12]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTR
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.0
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	9.549407	408.237154	18.4
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259	168.537116	2.1
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.6
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000	279.000000	17.4
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000	330.000000	19.0
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000	666.000000	20.2
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.0

In [13]:

```
boston_data = ((boston_data - boston_data.mean())/boston_data.std())

boston_data.head()
```

Out[13]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	-0.419367	0.284548	-1.286636	-0.272329	-0.144075	0.413263	-0.119895	0.140075	-0.981871	-0.665949	-1.457558	0.440616	-1.074499
1	-0.416927	-0.487240	-0.592794	-0.272329	-0.739530	0.194082	0.366803	0.556609	-0.867024	-0.986353	-0.302794	0.440616	-0.491953
2	-0.416929	-0.487240	-0.592794	-0.272329	-0.739530	1.281446	-0.265549	0.556609	-0.867024	-0.986353	-0.302794	0.396035	-1.207532
3	-0.416338	-0.487240	-1.305586	-0.272329	-0.834458	1.015298	-0.809088	1.076671	-0.752178	-1.105022	0.112920	0.415751	-1.360171

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
4	-0.412074	-0.487240	-1.305586	-0.272329	-0.834458	1.227362	-0.510674	1.076671	-0.752178	-1.105022	0.112920	0.440616	-1.025487

In [14]:

```
boston_data["PRICE"] = boston.target

boston_data.head()
# X = boston_data
# Y = boston.target

# print(X.shape)
# print(Y.shape)

# X.head()
# Y.head()
```

Out[14]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	-0.419367	0.284548	-1.286636	-0.272329	-0.144075	0.413263	-0.119895	0.140075	-0.981871	-0.665949	-1.457558	0.440616	-1.074499
1	-0.416927	-0.487240	-0.592794	-0.272329	-0.739530	0.194082	0.366803	0.556609	-0.867024	-0.986353	-0.302794	0.440616	-0.491953
2	-0.416929	-0.487240	-0.592794	-0.272329	-0.739530	1.281446	-0.265549	0.556609	-0.867024	-0.986353	-0.302794	0.396035	-1.207532
3	-0.416338	-0.487240	-1.305586	-0.272329	-0.834458	1.015298	-0.809088	1.076671	-0.752178	-1.105022	0.112920	0.415751	-1.360171
4	-0.412074	-0.487240	-1.305586	-0.272329	-0.834458	1.227362	-0.510674	1.076671	-0.752178	-1.105022	0.112920	0.440616	-1.025487

In [15]:

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

print(X.shape)
print(Y.shape)

print(X.head())
print("*"*100)
print(Y.head())
```

```
(506, 13)
(506,)
       CRIM        ZN     INDUS      CHAS       NOX        RM       AGE  \
0 -0.419367  0.284548 -1.286636 -0.272329 -0.144075  0.413263 -0.119895
1 -0.416927 -0.487240 -0.592794 -0.272329 -0.739530  0.194082  0.366803
2 -0.416929 -0.487240 -0.592794 -0.272329 -0.739530  1.281446 -0.265549
3 -0.416338 -0.487240 -1.305586 -0.272329 -0.834458  1.015298 -0.809088
4 -0.412074 -0.487240 -1.305586 -0.272329 -0.834458  1.227362 -0.510674

        DIS       RAD       TAX   PTRATIO         B     LSTAT
0  0.140075 -0.981871 -0.665949 -1.457558  0.440616 -1.074499
1  0.556609 -0.867024 -0.986353 -0.302794  0.440616 -0.491953
2  0.556609 -0.867024 -0.986353 -0.302794  0.396035 -1.207532
3  1.076671 -0.752178 -1.105022  0.112920  0.415751 -1.360171
4  1.076671 -0.752178 -1.105022  0.112920  0.440616 -1.025487
****************************************************************************************************

0    24.0
1    21.6
2    34.7
3    33.4
4    36.2
Name: PRICE, dtype: float64
```

In [16]:

```
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size = 0.3)
```

```
print(x_train.shape, x_test.shape, y_train.shape, y_test.shape)
```

(354, 13) (152, 13) (354,) (152,)

In [17]:

```
x_train["PRICE"] = y_train
```

In [18]:

```
def cost_function(b, m, features, target):
    totalError = 0
    for i in range(0, len(features)):
        x = features
        y = target
        #error = (y-ypred)^2
        totalError += (y[:,i] - (np.dot(x[i] , m) + b)) ** 2
    return totalError / len(x)
```

In [19]:

```
def absolute_cost_function(b, m, features, target):
    totalError = 0
    for i in range(0, len(features)):
        x = features
        y = target
        #error = (y-ypred)
        totalError += (y[:,i] - (np.dot(x[i] , m) + b))
    return totalError / len(x)
```

In [20]:

```
# The total sum of squares (proportional to the variance of the data)i.e. ss_tot
# The sum of squares of residuals, also called the residual sum of squares i.e. ss_res
# the coefficient of determination i.e. r^2(r squared)
def r_sq_score(b, m, features, target):
    for i in range(0, len(features)):
        x = features
        y = target
        mean_y = np.mean(y)
        ss_tot = sum((y[:,i] - mean_y) ** 2)
        # sum((y-(mx+b)))^2
        ss_res = sum(((y[:,i]) - (np.dot(x[i], m) + b)) ** 2)
        r2 = 1 - (ss_res / ss_tot)
    return r2
```

In [21]:

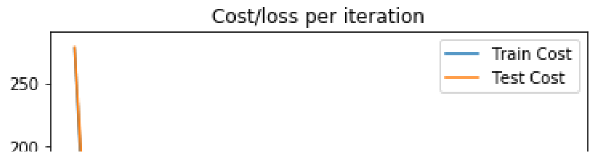
```
def gradient_decent(w0, b0, train_data, x_test, y_test, learning_rate):
    n_iter = 500
    partial_deriv_m = 0
    partial_deriv_b = 0
    cost_train = []
    cost_test = []
    for j in range(1, n_iter):

        # Train sample
        train_sample = train_data.sample(160)
        y = np.asmatrix(train_sample["PRICE"])
        x = np.asmatrix(train_sample.drop("PRICE", axis = 1))
        # Test sample
        #x_test["PRICE"] = [y_test]
        #test_data = x_test
        #test_sample = test_data.sample()
        #y_test = np.asmatrix(test_sample["PRICE"])
        #x_test = np.asmatrix(test_sample.drop("PRICE", axis = 1))

        for i in range(len(x)):
            partial_deriv_m += np.dot(-2*x[i].T , (y[:,i] - np.dot(x[i] , w0) + b0))
            partial_deriv_b += -2*(y[:,i] - (np.dot(x[i] , w0) + b0))
```

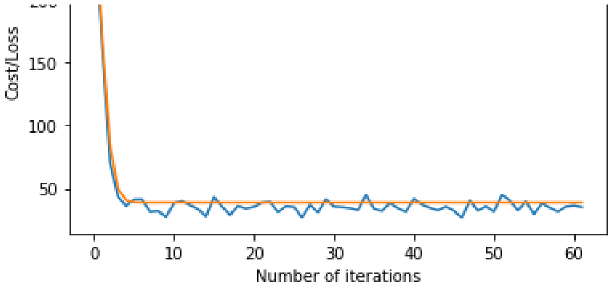
```
        w1 = w0 - learning_rate * partial_deriv_m
        b1 = b0 - learning_rate * partial_deriv_b

        if (w0==w1).all():
            #print("W0 are\n", w0)
            #print("\nW1 are\n", w1)
            #print("\n X are\n", x)
            #print("\n y are\n", y)
            break
        else:
            w0 = w1
            b0 = b1
            learning_rate = learning_rate/2


        error_train = cost_function(b0, w0, x, y)
        cost_train.append(error_train)
        error_test = cost_function(b0, w0, np.asmatrix(x_test), np.asmatrix(y_test))
        cost_test.append(error_test)

        #print("After {0} iteration error = {1}".format(j, error_train))
        #print("After {0} iteration error = {1}".format(j, error_test))

    return w0, b0, cost_train, cost_test
```

In [22]:

```
# Run our model
learning_rate = 0.001
w0_random = np.random.rand(13)
w0 = np.asmatrix(w0_random).T
b0 = np.random.rand()

optimal_w, optimal_b, cost_train, cost_test = gradient_decent(w0, b0, x_train, x_test, y_test, lear
ning_rate)
print("Coefficient: {} \n y_intercept: {}".format(optimal_w, optimal_b))

'''
error = cost_function(optimal_b, optimal_w, np.asmatrix(x_test), np.asmatrix(y_test))
print("Mean squared error:",error)
'''

plt.figure()
plt.plot(range(len(cost_train)), np.reshape(cost_train,[len(cost_train), 1]), label = "Train Cost")
plt.plot(range(len(cost_test)), np.reshape(cost_test, [len(cost_test), 1]), label = "Test Cost")
plt.title("Cost/loss per iteration")
plt.xlabel("Number of iterations")
plt.ylabel("Cost/Loss")
plt.legend()
plt.show()

#error = cost_function(optimal_b, optimal_w, np.asmatrix(x_test), np.asmatrix(y_test))
#print("Mean squared error: %.2f" % error)
```

```
Coefficient: [[-0.41144214]
 [-1.32743691]
 [-1.6211677 ]
 [ 1.4974427 ]
 [ 0.34429883]
 [ 4.27231502]
 [-0.16421896]
 [-1.517363  ]
 [ 1.05404979]
 [-0.82986638]
 [ 0.22719132]
 [-0.03506302]
 [-3.44585941]]
 y_intercept: [[21.27676176]]
```





Compare Custom SGD with Sklearn SGD

In [23]:

```
# Sklearn SGD
# The mean squared error
print("Mean squared error: %.2f" % mean_squared_error(Y_test, Y_pred))
# Explained variance score: 1 is perfect prediction
print("Variance score: %.2f" % r2_score(Y_test, Y_pred))
# The mean absolute error
print("Mean Absolute Error: %.2f" % mean_absolute_error(Y_test, Y_pred))
```

```
Mean squared error: 28.53
Variance score: 0.70
Mean Absolute Error: 3.46
```

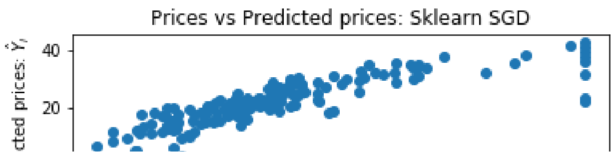
In [24]:

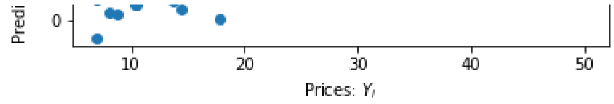
```
# Implemented SGD
# The mean squared error
error = cost_function(optimal_b, optimal_w, np.asmatrix(x_test), np.asmatrix(y_test))
print("Mean squared error: %.2f" % (error))
# Explained variance score : 1 is perfect prediction
r_squared = r_sq_score(optimal_b, optimal_w, np.asmatrix(x_test), np.asmatrix(y_test))
print("Variance score: %.2f" % r_squared)
absolute_error = absolute_cost_function(optimal_b, optimal_w, np.asmatrix(x_test),
np.asmatrix(y_test))
print("Mean Absolute Error: %.2f" % absolute_error)
```

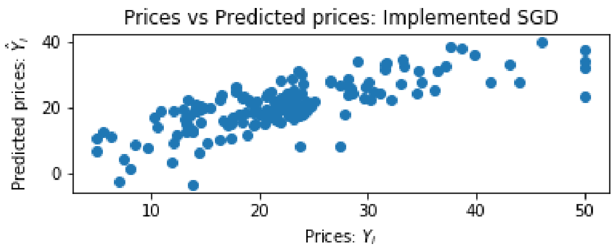
```
Mean squared error: 38.63
Variance score: 0.36
Mean Absolute Error: 1.77
```

In [25]:

```
# Scatter plot of test vs predicted
# sklearn SGD
plt.figure(1)
plt.subplot(211)
plt.scatter(Y_test, Y_pred)
plt.xlabel("Prices: $Y_i$")
plt.ylabel("Predicted prices: $\hat{Y}_i$")
plt.title("Prices vs Predicted prices: Sklearn SGD")
plt.show()

# Implemented SGD
plt.subplot(212)
plt.scatter([y_test], [(np.dot(np.asmatrix(x_test), optimal_w) + optimal_b)])
plt.xlabel("Prices: $Y_i$")
plt.ylabel("Predicted prices: $\hat{Y}_i$")
plt.title("Prices vs Predicted prices: Implemented SGD")
plt.show()
```

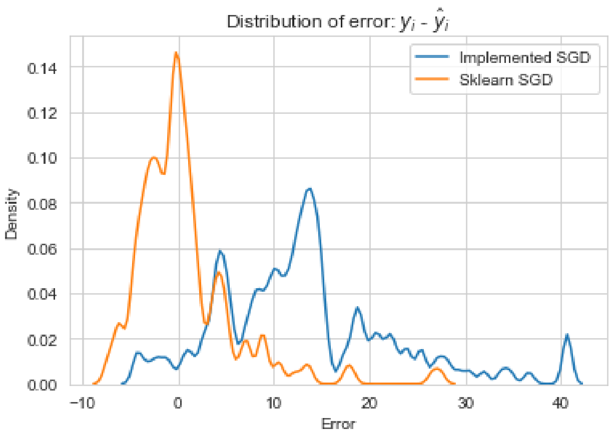






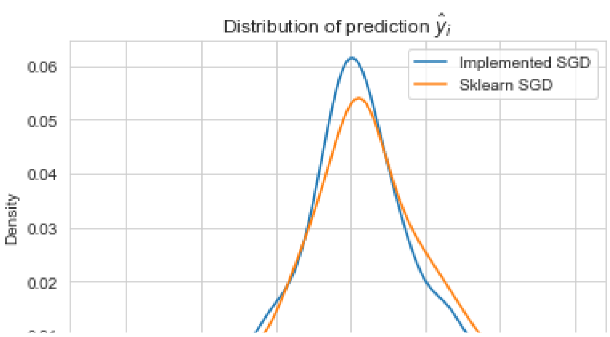
In [26]:

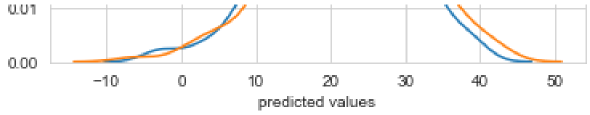
```
# Distribution of error
delta_y_im = np.asmatrix(y_test) - (np.dot(np.asmatrix(x_test), optimal_w) + optimal_b)
delta_y_sk = Y_test - Y_pred
import seaborn as sns;
import numpy as np;
sns.set_style('whitegrid')
sns.kdeplot(np.asarray(delta_y_im)[0], label = "Implemented SGD", bw = 0.5)
sns.kdeplot(np.array(delta_y_sk), label = "Sklearn SGD", bw = 0.5)
plt.title("Distribution of error: $y_i$ - $\hat{y}_i$")
plt.xlabel("Error")
plt.ylabel("Density")
plt.legend()
plt.show()
```



In [27]:

```
# Distribution of predicted value
sns.set_style('whitegrid')
sns.kdeplot(np.array(np.dot(np.asmatrix(x_test), optimal_w) + optimal_b).T[0], label = "Implemented
SGD")
sns.kdeplot(Y_pred, label = "Sklearn SGD")
plt.title("Distribution of prediction $\hat{y}_i$")
plt.xlabel("predicted values")
plt.ylabel("Density")
plt.show()
```





In [28]:

```python
from prettytable import PrettyTable
# MSE = mean squared error
# MAE =mean absolute error
x=PrettyTable()#np.asmatrix(x_test),
x.field_names=['Model','Weight Vector','MSE','MAE', 'Variance Score']
x.add_row(['sklearn',sklearn_w,mean_squared_error(Y_test,
clf_.predict(X_test)),mean_absolute_error(Y_test, clf_.predict(X_test)),r2_score(Y_test, Y_pred)])
x.add_row(['custom',optimal_w,error,absolute_error,r_squared])
print(x)
```

```
+---------+-------------------------------------------------------------------------+-------------
---+-------------------+--------------------+
|  Model  |                            Weight Vector                                |        MSE
|        MAE         |   Variance Score   |
+---------+-------------------------------------------------------------------------+-------------
---+-------------------+--------------------+
| sklearn | [-1.19998397  0.70823758 -0.47154859  0.24990282 -1.25091027  2.89665502 |
28.545951396225185 | 3.450685306695088 | 0.6956551656111603 |
|         |  -0.38369813 -2.64985472  1.78730939 -1.05960085 -2.08913235  1.03175028 |
|                   |                    |
|         |                             -3.31171865]                                |
|                   |                    |
|  custom |                            [[-0.41144214]                               |
[[38.62996824]]   |   [[1.77117924]]  |   [[0.3646231]]    |
|         |                             [-1.32743691]                               |
|                   |                    |
|         |                             [-1.6211677 ]                               |
|                   |                    |
|         |                             [ 1.4974427 ]                               |
|                   |                    |
|         |                             [ 0.34429883]                               |
|                   |                    |
|         |                             [ 4.27231502]                               |
|                   |                    |
|         |                             [-0.16421896]                               |
|                   |                    |
|         |                             [-1.517363  ]                               |
|                   |                    |
|         |                             [ 1.05404979]                               |
|                   |                    |
|         |                             [-0.82986638]                               |
|                   |                    |
|         |                             [ 0.22719132]                               |
|                   |                    |
|         |                             [-0.03506302]                               |
|                   |                    |
|         |                            [-3.44585941]]                               |
|                   |                    |
+---------+-------------------------------------------------------------------------+-------------
---+-------------------+--------------------+
```

In [29]:

```python
sklearn_pred=clf_.predict(x_test)
implemented_pred=(np.dot(np.asmatrix(x_test), optimal_w) + optimal_b)
x=PrettyTable()
x.field_names=['SKLearn SGD predicted value','Implemented SGD predicted value']
for itr in range(15):
    x.add_row([sklearn_pred[itr],implemented_pred[itr]])
print(x)
```

```
+-----------------------------+---------------------------------+
| SKLearn SGD predicted value | Implemented SGD predicted value |
+-----------------------------+---------------------------------+
|      11.010976872064473     |          [[9.34267897]]         |
|      28.13265575430431      |         [[21.81915391]]         |
|      32.610429206840855     |         [[27.97043084]]         |
```

```
|      32.610429206840855      |          [[27.97043084]]          |
|      19.47265691695546       |          [[22.43740506]]          |
|      26.99547481859689       |          [[20.51530473]]          |
|      18.17885314254281       |          [[15.23322088]]          |
|      6.450183867637406       |          [[10.74021524]]          |
|      25.429866825378358      |          [[23.82642385]]          |
|      21.60484164577307       |          [[19.48934147]]          |
|      24.084364627932437      |          [[21.50028139]]          |
|      6.151923708168887       |           [[7.03308681]]          |
|      27.77673286644099       |          [[21.02386188]]          |
|      10.057460526020344      |           [[7.98370263]]          |
|      15.644363660603457      |          [[16.73402384]]          |
|      23.502153086425825      |          [[21.90299932]]          |
+------------------------------+-----------------------------------+
```