LinearRegression_on_bostan_house_price_using_SGD_reopen

October 3, 2018

1 Boston House price prediction using LinearRegression

```
In [1090]: # Importing necessary libraries

           import pandas as pd
           import numpy as np
           from sklearn.datasets import load_boston
           from sklearn.model_selection import train_test_split
           import matplotlib.pyplot as plt
           boston = load_boston()
```

```
In [1091]: print(boston.data.shape)
```

```
(506, 13)
```

```
In [1092]: print(boston.feature_names)
```

```
['CRIM' 'ZN' 'INDUS' 'CHAS' 'NOX' 'RM' 'AGE' 'DIS' 'RAD' 'TAX' 'PTRATIO'
 'B' 'LSTAT']
```

```
In [1093]: print(boston.target.shape)
```

```
(506,)
```

```
In [1094]: print(boston.DESCR)
```

```
Boston House Prices dataset
===========================

Notes
------
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.
http://archive.ics.uci.edu/ml/datasets/Housing


This dataset was taken from the StatLib library which is maintained at Carnegie Mellon Universi

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 regressi
problems.

**References**

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential Data and Sources
   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning. In Proceedings on t
   - many more! (see http://archive.ics.uci.edu/ml/datasets/Housing)
```

```
In [1095]: # Loading data into pandas dataframe
           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 [1096]: bos['PRICE'] = boston.target

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

```
In [1097]: # Split data into train and test
           X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.33, random_s
           print(X_train.shape)
           print(X_test.shape)
           print(Y_train.shape)
           print(Y_test.shape)
```

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

```
In [1098]: # Standardization

           from sklearn.preprocessing import StandardScaler
           std = StandardScaler()
           X_train = std.fit_transform(X_train)
           X_test = std.fit_transform(X_test)
```

```
In [1099]: from sklearn.linear_model import SGDRegressor
           from sklearn.metrics import mean_squared_error, r2_score
           clf = SGDRegressor()
           clf.fit(X_train, Y_train)
           Y_pred = clf.predict(X_test)
```

```
print("Coefficients: \n", clf.coef_)
print("Y_intercept", clf.intercept_)
```

```
Coefficients:
 [-0.87665426  0.37375936 -0.50588548  0.28410849 -0.40718428  3.13195112
 -0.38808112 -1.72845725  0.61670451 -0.5408917  -1.9444916   0.94032915
 -3.13142456]
Y_intercept [ 21.88507084]
```

2 Stochastic Gradient Decent(SGD) for Linear Regression

In [246]:
```
# Imported necessary libraries
from sklearn.datasets import load_boston
from sklearn.model_selection import train_test_split
import pandas as pd
import numpy as np
```

In [247]:
```
# Data loaded
bostan = load_boston()
```

In [248]:
```
# Data shape
bostan.data.shape
```

Out[248]:
```
(506, 13)
```

In [249]:
```
# Feature name
bostan.feature_names
```

Out[249]:
```
array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'],
      dtype='<U7')
```

In [250]:
```
# This is y value i.e. target
bostan.target.shape
```

Out[250]:
```
(506,)
```

In [251]:
```
# Convert it into pandas dataframe
data = pd.DataFrame(bostan.data, columns = bostan.feature_names)
data.head()
```

Out[251]:
```
      CRIM    ZN  INDUS  CHAS    NOX     RM   AGE     DIS  RAD    TAX  \
0  0.00632  18.0   2.31   0.0  0.538  6.575  65.2  4.0900  1.0  296.0
1  0.02731   0.0   7.07   0.0  0.469  6.421  78.9  4.9671  2.0  242.0
2  0.02729   0.0   7.07   0.0  0.469  7.185  61.1  4.9671  2.0  242.0
3  0.03237   0.0   2.18   0.0  0.458  6.998  45.8  6.0622  3.0  222.0
4  0.06905   0.0   2.18   0.0  0.458  7.147  54.2  6.0622  3.0  222.0
```

```
   PTRATIO       B  LSTAT
0     15.3  396.90   4.98
1     17.8  396.90   9.14
2     17.8  392.83   4.03
3     18.7  394.63   2.94
4     18.7  396.90   5.33
```

In [252]:
```python
# Statistical summary
data.describe()
```

Out[252]:
```
             CRIM          ZN       INDUS        CHAS         NOX          RM  \
count  506.000000  506.000000  506.000000  506.000000  506.000000  506.000000
mean     3.593761   11.363636   11.136779    0.069170    0.554695    6.284634
std      8.596783   23.322453    6.860353    0.253994    0.115878    0.702617
min      0.006320    0.000000    0.460000    0.000000    0.385000    3.561000
25%      0.082045    0.000000    5.190000    0.000000    0.449000    5.885500
50%      0.256510    0.000000    9.690000    0.000000    0.538000    6.208500
75%      3.647423   12.500000   18.100000    0.000000    0.624000    6.623500
max     88.976200  100.000000   27.740000    1.000000    0.871000    8.780000

              AGE         DIS         RAD         TAX     PTRATIO           B  \
count  506.000000  506.000000  506.000000  506.000000  506.000000  506.000000
mean    68.574901    3.795043    9.549407  408.237154   18.455534  356.674032
std     28.148861    2.105710    8.707259  168.537116    2.164946   91.294864
min      2.900000    1.129600    1.000000  187.000000   12.600000    0.320000
25%     45.025000    2.100175    4.000000  279.000000   17.400000  375.377500
50%     77.500000    3.207450    5.000000  330.000000   19.050000  391.440000
75%     94.075000    5.188425   24.000000  666.000000   20.200000  396.225000
max    100.000000   12.126500   24.000000  711.000000   22.000000  396.900000

            LSTAT
count  506.000000
mean    12.653063
std      7.141062
min      1.730000
25%      6.950000
50%     11.360000
75%     16.955000
max     37.970000
```

In [253]:
```python
#standardize for fast convergence to minima
data = (data - data.mean())/data.std()
data.head()
```

Out[253]:
```
       CRIM        ZN     INDUS      CHAS       NOX        RM       AGE  \
0 -0.417300  0.284548 -1.286636 -0.272329 -0.144075  0.413263 -0.119895
1 -0.414859 -0.487240 -0.592794 -0.272329 -0.739530  0.194082  0.366803
2 -0.414861 -0.487240 -0.592794 -0.272329 -0.739530  1.281446 -0.265549
```

```
3 -0.414270 -0.487240 -1.305586 -0.272329 -0.834458  1.015298 -0.809088
4 -0.410003 -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
```

In [256]:
```python
# MEDV(median value is usually target), change it to price
data["PRICE"] = bostan.target
data.head()
```

Out[256]:
```
       CRIM        ZN     INDUS      CHAS       NOX        RM       AGE  \
0 -0.417300  0.284548 -1.286636 -0.272329 -0.144075  0.413263 -0.119895
1 -0.414859 -0.487240 -0.592794 -0.272329 -0.739530  0.194082  0.366803
2 -0.414861 -0.487240 -0.592794 -0.272329 -0.739530  1.281446 -0.265549
3 -0.414270 -0.487240 -1.305586 -0.272329 -0.834458  1.015298 -0.809088
4 -0.410003 -0.487240 -1.305586 -0.272329 -0.834458  1.227362 -0.510674

        DIS       RAD       TAX   PTRATIO         B     LSTAT  PRICE
0  0.140075 -0.981871 -0.665949 -1.457558  0.440616 -1.074499   24.0
1  0.556609 -0.867024 -0.986353 -0.302794  0.440616 -0.491953   21.6
2  0.556609 -0.867024 -0.986353 -0.302794  0.396035 -1.207532   34.7
3  1.076671 -0.752178 -1.105022  0.112920  0.415751 -1.360171   33.4
4  1.076671 -0.752178 -1.105022  0.112920  0.440616 -1.025487   36.2
```

In [257]:
```python
# Target and features
Y = data["PRICE"]
X = data.drop("PRICE", axis = 1)
```

In [258]:
```python
from sklearn.model_selection import train_test_split
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 [262]:
```python
x_train["PRICE"] = y_train
#x_test["PRICE"] = y_test
```

```
C:\Users\premvardhan\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: SettingWithCopyWarni
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.htm
  """Entry point for launching an IPython kernel.
```

In [264]:
```
def cost_function(b, m, features, target):
    totalError = 0
    for i in range(0, len(features)):
        x = features
        y = target
        totalError += (y[:,i] - (np.dot(x[i] , m) + b)) ** 2
    return totalError / len(x)
```

In [265]:
```
# 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_r
# 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)
        ss_res = sum(((y[:,i]) - (np.dot(x[i], m) + b)) ** 2)
        r2 = 1 - (ss_res / ss_tot)
    return r2
```

In [770]:
```
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))
        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
```

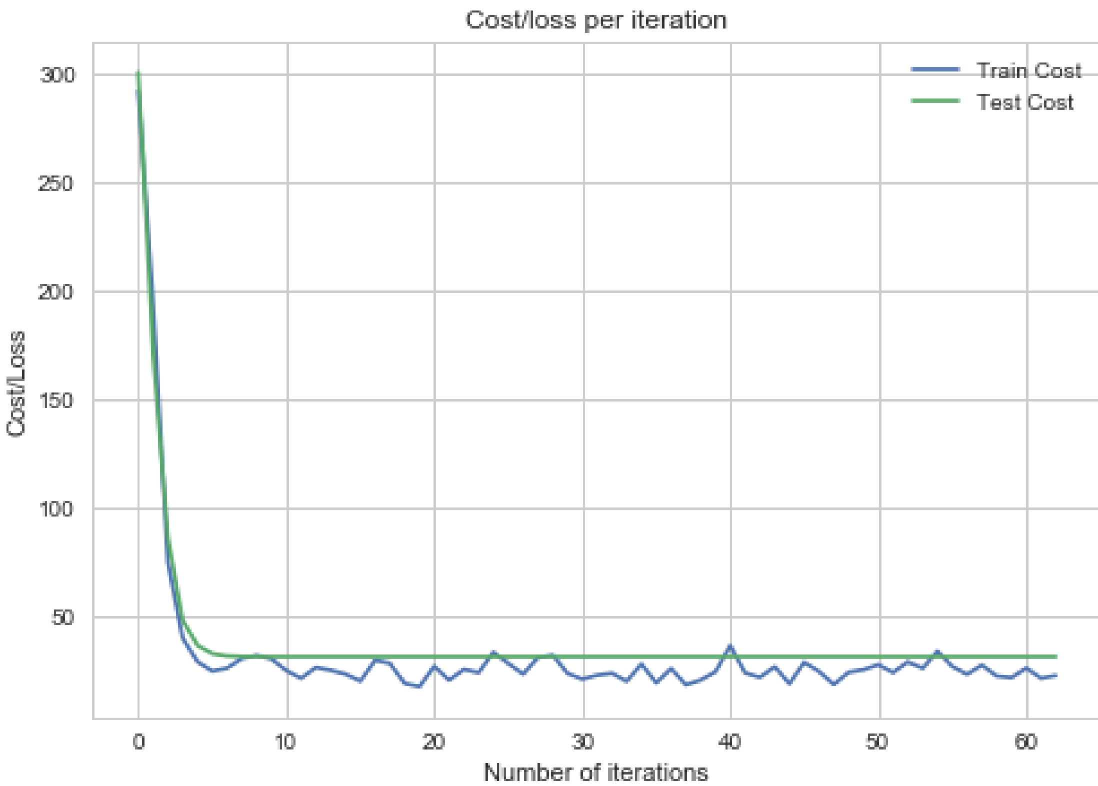
In [1085]:

```
# 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_tes
print("Coefficient: {} \n y_intercept: {}".format(optimal_w, optimal_b))

# Plot train and test error in each iteration
plt.figure()
plt.plot(range(len(cost_train)), np.reshape(cost_train,[len(cost_train), 1]), label
plt.plot(range(len(cost_test)), np.reshape(cost_test, [len(cost_test), 1]), label =
plt.title("Cost/loss per iteration")
plt.xlabel("Number of iterations")
plt.ylabel("Cost/Loss")
plt.legend()
plt.show()
```

```
Coefficient: [[-0.88458053]
 [-0.0295242 ]
 [-0.51389881]
 [ 1.54572575]
 [-1.04071224]
 [ 4.49241384]
 [ 0.43792264]
 [-1.23405424]
 [ 0.3800213 ]
 [ 0.03293416]
 [-1.57925241]
 [ 0.30357244]
 [-2.65148873]]
 y_intercept: [[ 21.56359801]]
```



3 Comparison between sklearn SGD and implemented SGD in python

In [1100]:
```
# 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))
```

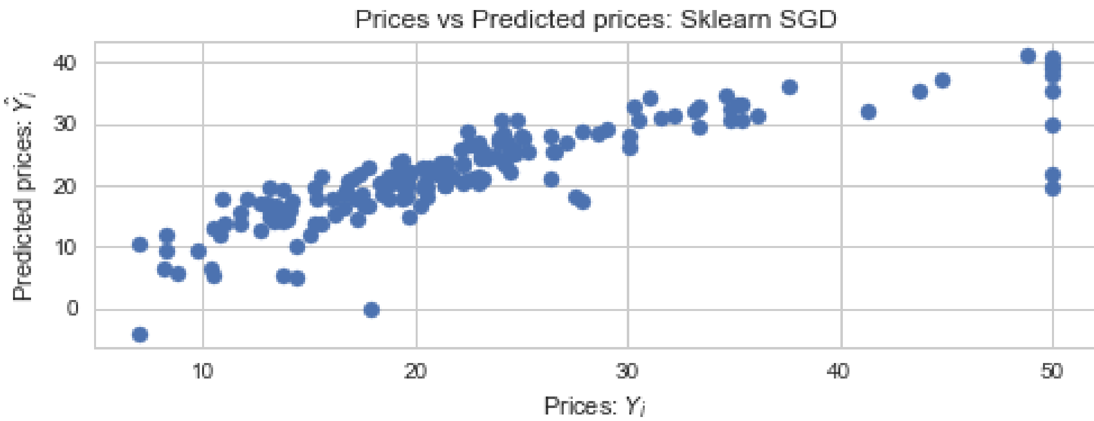
```
Mean squared error: 30.35
Variance score: 0.68
```

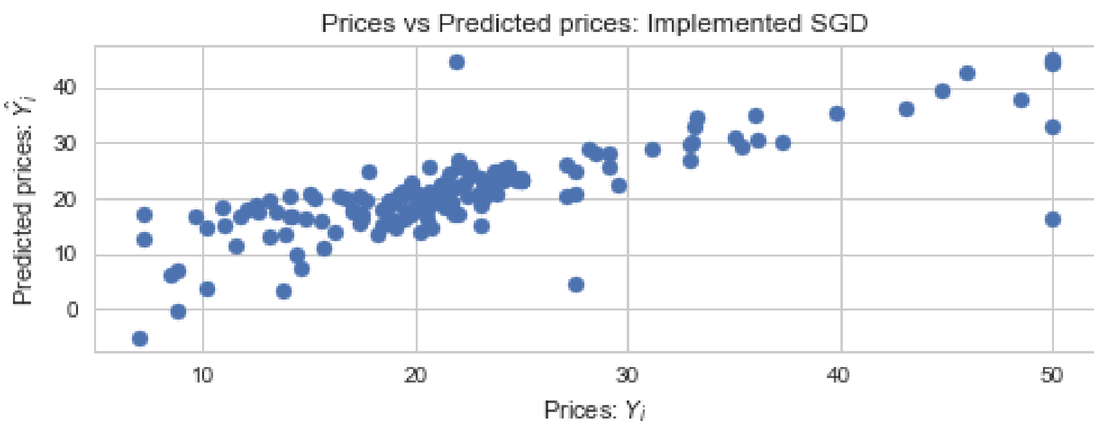
In [1101]:
```
# Implemented SGD
# The mean squared error
error = cost_function(optimal_b, optimal_w, np.asmatrix(x_test), np.asmatrix(y_test
print("Mean squared error: %.2f" % (error))
# Explained variance score : 1 is perfect prediction
r_squared = r_sq_score(optimal_b, optimal_w, np.asmatrix(x_test), np.asmatrix(y_tes
print("Variance score: %.2f" % r_squared)
```

```
Mean squared error: 31.74
Variance score: 0.86
```

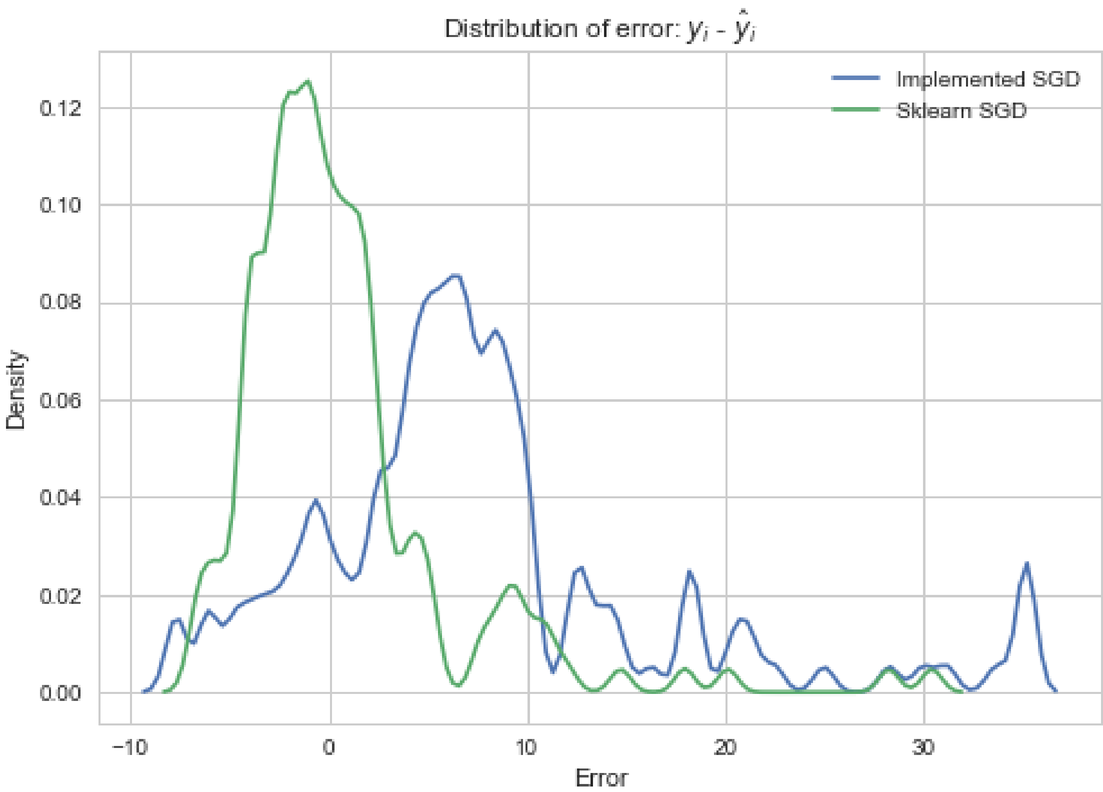
In [1102]:
```
# Scatter plot of test vs predicted
# sklearn SGD
plt.figure(1)
plt.subplot(211)
plt.scatter(Y_test, Y_pred)
plt.xlabel("Prices: $Y_i$")
plt.ylabel("Predicted prices: $\hat{Y}_i$")
plt.title("Prices vs Predicted prices: Sklearn SGD")
plt.show()

# 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()
```

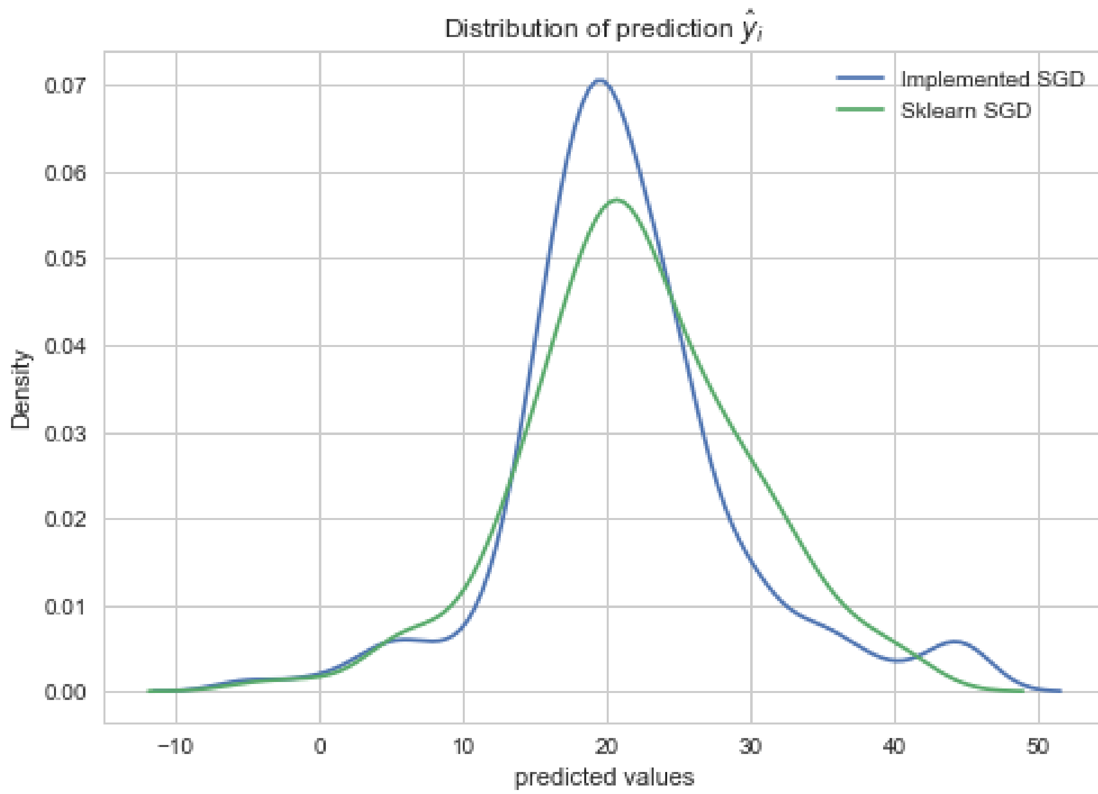




In [1103]:
```
# Distribution of error
delta_y_im = np.asmatrix(y_test) - (np.dot(np.asmatrix(x_test), optimal_w) + optimal
delta_y_sk = Y_test - Y_pred
import seaborn as sns;
import numpy as np;
sns.set_style('whitegrid')
sns.kdeplot(np.asarray(delta_y_im)[0], label = "Implemented SGD", bw = 0.5)
sns.kdeplot(np.array(delta_y_sk), 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 [1104]:
```
# 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
sns.kdeplot(Y_pred, label = "Sklearn SGD")
plt.title("Distribution of prediction $\hat{y}_i$")
plt.xlabel("predicted values")
plt.ylabel("Density")
plt.show()
```



observations * MSE is 30.35 means the total loss/error(squared difference of true/actual target value and predicted target value)i.e. we make while prediction. 0.0 is perfect i.e. no loss. * coefficient of determination tells about the goodness of fit of a model and here, r^2 is 0.68 which means regression prediction does not perfectly fit the data. An r^2 of 1 indicates that regression prediction perfect fit the data. * The mean squared error(mse) is quite high in implemented SGD means there are much more difference b/w predicted and actual points. i.e. average squared difference between the actual target value and predicted target value is high. lower value is better. * r-squared score is 0.86, means the fit explain 86% of the total variation in the data about the average. * After looking at the error graph we can say +ve side of the graph, error is more in implemented SGD whereas in sklearn SGD error is balanced or more error is at zero. i.e. * By looking at the distribution of predicted value graph, It is clear that prediction of implemented SGD and sklearn SGD both are ovelapping(not perfectly) but the density of sklearn SGD is ~58% whereas implemented SGD is ~72% means the implemented SGD is predicting high value but in actual it is not.

Conclusions

- While comparing scikit-learn implemented linear regression and explicitly implemented linear regression using optimization algorithm(sgd) in python we see there are not much differences between both of them but sklearn SGD performs well over implemented SGD.
- Overall we can say the regression line not fits data perfectly but it is okay. But our goal is to find the line/plane that best fits our data means minimize the error i.e. mse should be close to 0.
- None of the above model are perfect but okay.