In [1]:
```
# 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
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import SGDRegressor
from sklearn.metrics import mean_squared_error, r2_score
import seaborn as sns
```

In [2]:
```
#Loading boston house price data
boston = load_boston()
```

In [3]:
```
#Understanding Boston Dataset
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 Collinearity', Wiley, 1980. 244-
261.
   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning. In Proceedings on the Tenth International Conference o
f Machine Learning, 236-243, University of Massachusetts, Amherst. Morgan Kaufmann.
```

In [4]:
```
# Let's load it into pandas dataframe
data = pd.DataFrame(boston.data, columns = boston.feature_names)
data.head()
```

Out[4]:

	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 [5]:
```
data.shape
```

Out[5]: (506, 13)

In [6]:
```
data.columns
```

Out[6]:
```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX',
       'PTRATIO', 'B', 'LSTAT'],
      dtype='object')
```

In [7]:
```
# Printing Statistical summary
data.describe()
```

Out[7]:

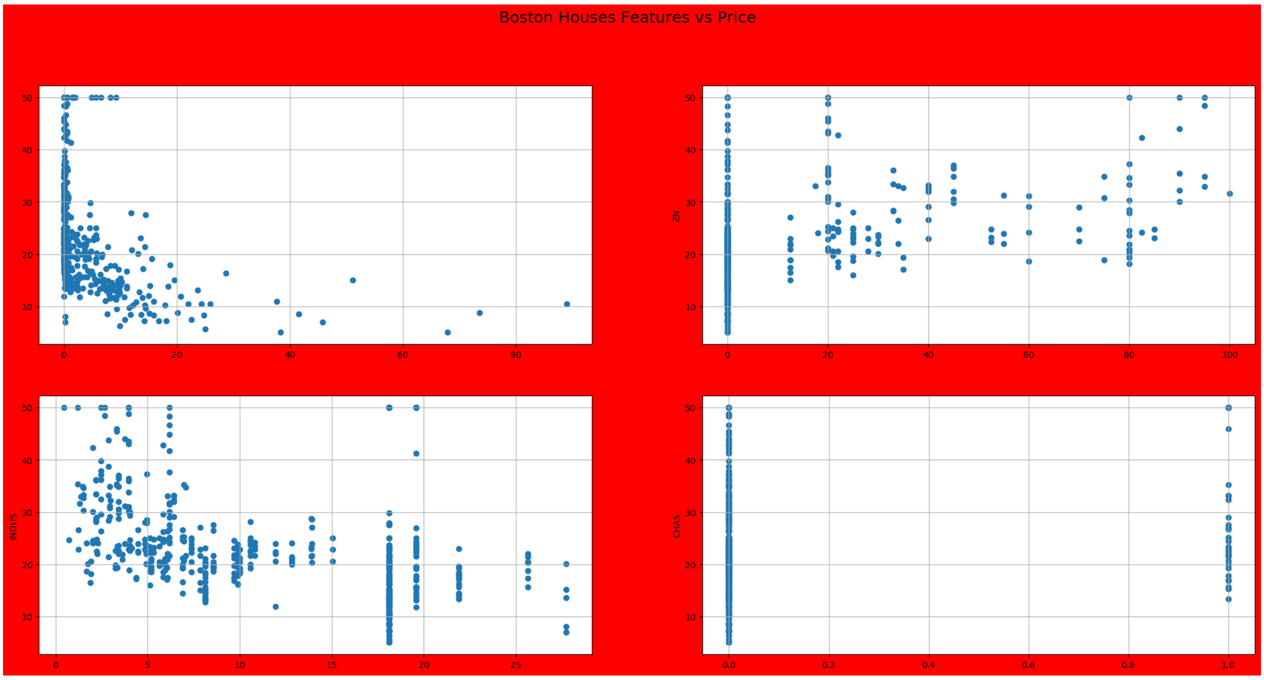
	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LS
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.00
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	9.549407	408.237154	18.455534	356.674032	12.65
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259	168.537116	2.164946	91.294864	7.14
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.600000	0.320000	1.73
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000	279.000000	17.400000	375.377500	6.95
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000	330.000000	19.050000	391.440000	11.36
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000	666.000000	20.200000	396.225000	16.95
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.000000	396.900000	37.97

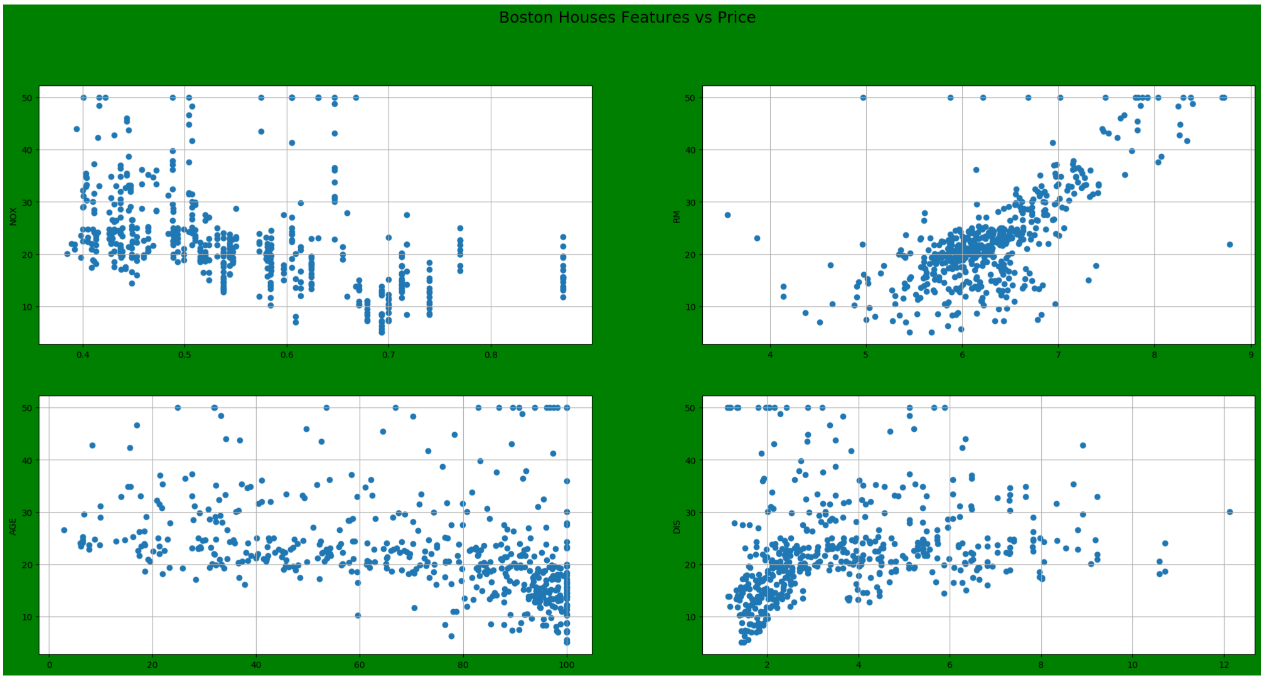
In [8]:
```
#Adding Target feature
data['price'] = boston.target
```

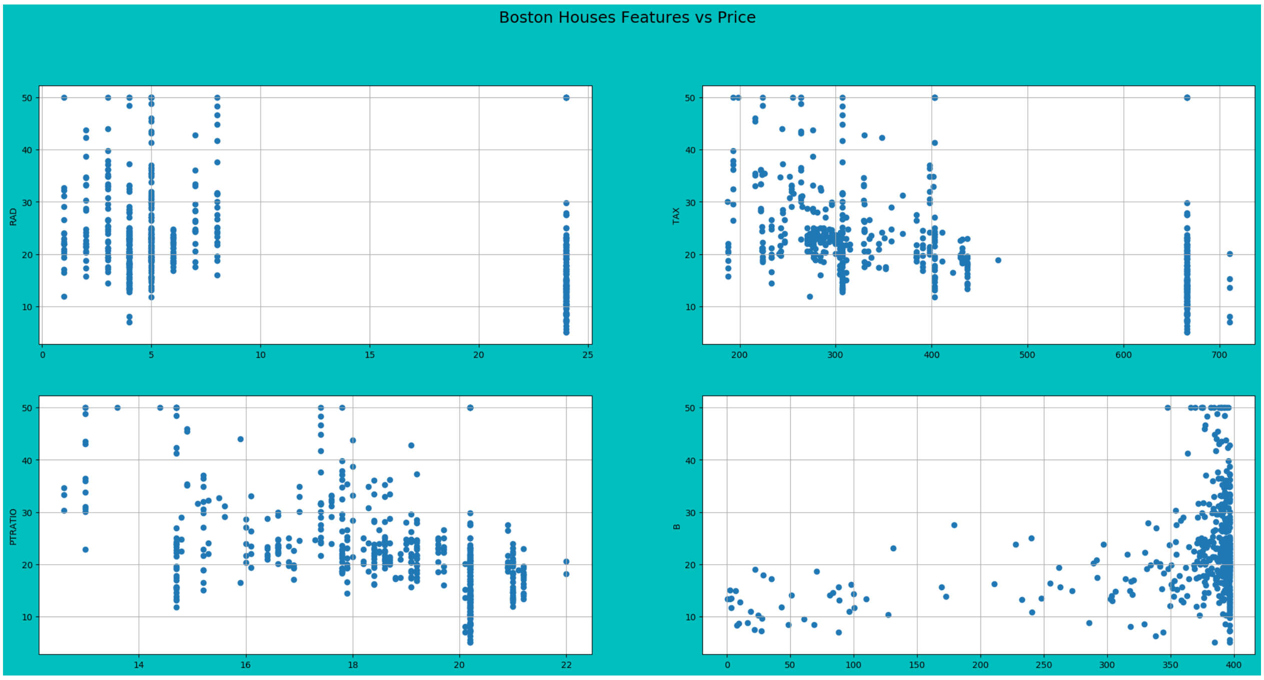
EDA:

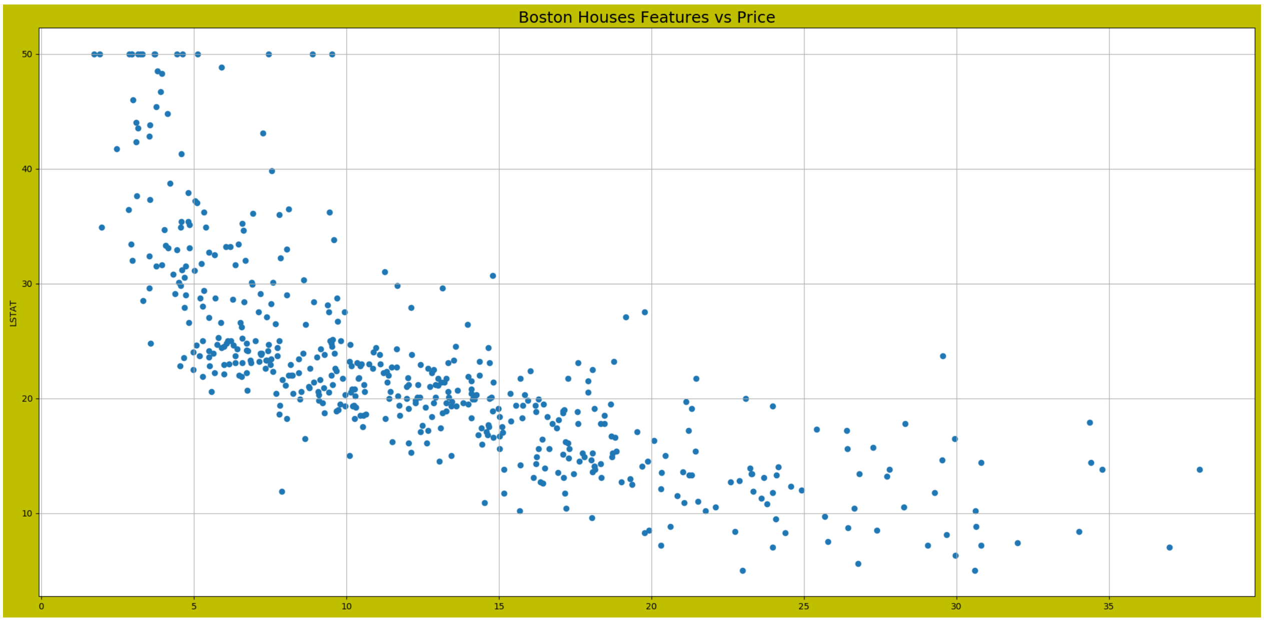
Boston house Features vs Price:

In [9]:
```
fig = plt.figure(num=None, figsize=(25, 12), dpi=100, facecolor='r', edgecolor='k')
fig.suptitle('Boston Houses Features vs Price', fontsize=18)
ax1 = fig.add_subplot(221)

ax1.scatter(data.CRIM, data.price)
plt.grid()
ax2 = fig.add_subplot(222)
plt.ylabel('CRIM')
ax2.scatter(data.ZN,data.price)
plt.ylabel('ZN')
plt.grid()
ax3 = fig.add_subplot(223)

ax3.scatter(data.INDUS,data.price)
plt.ylabel('INDUS')
plt.grid()
ax4 = fig.add_subplot(224)
ax4.scatter(data.CHAS,data.price)
plt.ylabel('CHAS')
plt.grid()
plt.show()
fig1 = plt.figure(num=None, figsize=(25, 12), dpi=100, facecolor='g', edgecolor='k')
fig1.suptitle('Boston Houses Features vs Price', fontsize=18)
ax5 = fig1.add_subplot(221)
ax5.scatter(data.NOX,data.price)
plt.ylabel('NOX')
plt.grid()
ax6 = fig1.add_subplot(222)
ax6.scatter(data.RM,data.price)
plt.ylabel('RM')
plt.grid()
ax7 = fig1.add_subplot(223)
ax7.scatter(data.AGE,data.price)
plt.ylabel('AGE')
plt.grid()
ax8 = fig1.add_subplot(224)
ax8.scatter(data.DIS,data.price)
plt.ylabel('DIS')
plt.grid()
plt.show()
fig2 = plt.figure(num=None, figsize=(25, 12), dpi=100, facecolor='c', edgecolor='k')
fig2.suptitle('Boston Houses Features vs Price', fontsize=18)
ax9 = fig2.add_subplot(221)
ax9.scatter(data.RAD,data.price)
plt.ylabel('RAD')
plt.grid()
ax10 = fig2.add_subplot(222)
ax10.scatter(data.TAX,data.price)
plt.ylabel('TAX')
plt.grid()
ax11 = fig2.add_subplot(223)
ax11.scatter(data.PTRATIO,data.price)
plt.ylabel('PTRATIO')
plt.grid()
ax12 = fig2.add_subplot(224)
ax12.scatter(data.B,data.price)
plt.ylabel('B')
plt.grid()
fig3 = plt.figure(num=None, figsize=(25, 12), dpi=100, facecolor='y', edgecolor='k')

plt.scatter(data.LSTAT,data.price)
plt.title('Boston Houses Features vs Price', fontsize=18)
plt.ylabel('LSTAT')
plt.grid()
plt.show()
```


Boston Houses Features vs Price
ZN
INDUS
CHAS


Boston Houses Features vs Price
NOX
RM
AGE
DIS


Boston Houses Features vs Price
RAD
TAX
PTRATIO
B



In [10]:
```
# Data preparation for model building

X = data[data.columns[~data.columns.isin(['price'])]]
y = data['price']
```

In [11]:
```
#Splitting data into training and testing set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 1)
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(404, 13)
(102, 13)
(404,)
(102,)
```

In [12]:
```
#Scaling data using StandardScaler

sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

Own SGD Implementation:

In [13]:
```
def sgd_predict(values, coordinates):
    res = 0
    for i in range(0, len(coordinates)-1):
        res += values[i] * coordinates[i]
    res += coordinates[len(coordinates)-1]
    return res
```

In [14]:
```
def sgd_optimize(x_train, coordinates, y_train,
                 learning_rate, n_ephochs):
    for i in range(n_ephochs):

        total_error = 0
        for j in range(len(x_train)):
            err = y_train.iloc[j] - sgd_predict(x_train[j], coordinates)
            total_error += abs(err)

            for k in range(len(coordinates)-1):
                coordinates[k] = coordinates[k] \
                                + (learning_rate * err * x_train[j][k])

            coordinates[len(coordinates)-1] = coordinates[len(coordinates)-1] \
                                            + (learning_rate * err)
        if i % 100 == 0:
            print('Epoch: ', i, 'Error: ', round(total_error,3))
    return coordinates
```

In [15]:
```
coordinates = np.random.rand(len(X_train[0])+1)
coordinates = sgd_optimize(X_train, coordinates, y_train, 0.0001, 101)
```

```
Epoch:  0 Error:  8867.977
Epoch:  100 Error:  1264.39
```

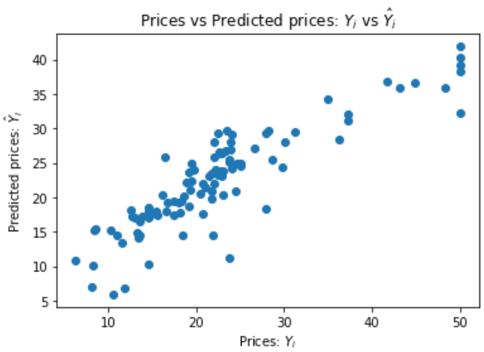
In [16]:
```
train_pred = []
for row in X_train:
    train_pred.append(sgd_predict(row, coordinates))

test_pred = []
for row in X_test:
    test_pred.append(sgd_predict(row, coordinates))
```

In [17]:
```
from sklearn.metrics import mean_squared_error

train_mse = mean_squared_error(y_train, train_pred)
test_mse = mean_squared_error(y_test, test_pred)
test_r2 =  r2_score(y_test, test_pred)
print('Mean Square error-Train: ', train_mse)
print('Mean Square error-Test: ', test_mse)
print('Variance score-Test: ', test_r2)
```

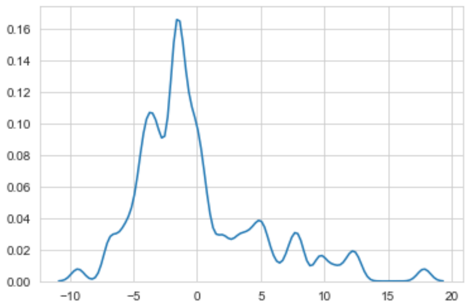
```
Mean Square error-Train:  23.31177728191987
Mean Square error-Test:  23.583925547508073
Variance score-Test:  0.7613624555395188
```

In [18]:
```
performance = []
performance.append(['Regressor', 'Training MSE', 'Testing MSE', 'Variance_Score'])
performance.append(['Own SGD', round(train_mse,2), round(test_mse,2), round(test_r2,2)])
```

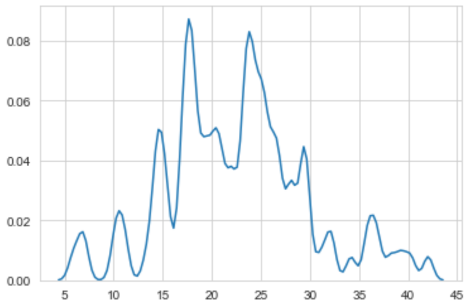
In [19]:
```
plt.scatter(y_test, test_pred)
plt.xlabel("Prices: $Y_i$")
plt.ylabel("Predicted prices: $\hat{Y}_i$")
plt.title("Prices vs Predicted prices: $Y_i$ vs $\hat{Y}_i$")
plt.show()
```



In [20]:
```
#Ploting error

delta_y = y_test - test_pred

import seaborn as sns;
sns.set_style('whitegrid')
sns.kdeplot(np.array(delta_y), bw=0.5)
plt.show()
```



In [21]:
```
sns.set_style('whitegrid')
sns.kdeplot(np.array(test_pred), bw=0.5)
plt.show()
```



Implementing Sklearn's SGD Calssifier:

In [22]:
```
from sklearn.linear_model import SGDRegressor

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:
 [-0.93544285  1.07614658 -0.24158305  0.63441235 -1.92056057  2.26921422
  0.03421202 -2.83022807  1.5995588  -0.85402936 -2.10212273  0.69495299
 -3.86464509]
Y_intercept [22.5156812]
```

In [23]:
```
train_mse1 = mean_squared_error(y_train, clf.predict(X_train))
test_mse1 = mean_squared_error(y_test, y_pred)
test_r2_1 = r2_score(y_test, y_pred)
print('Train Mean Square error: ', train_mse1)
print('Test Mean Square error: ', test_mse1)
print('Variance score-Test: ', test_r2_1)
```

```
Train Mean Square error:  22.056256949059023
Test Mean Square error:  23.357018429462357
Variance score-Test:  0.7636584497904315
```

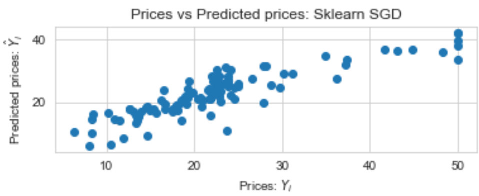
In [24]:
```
performance.append(['SGD Classifier', round(train_mse1,2), round(test_mse1,2), round(test_r2_1,2)])
```

Comparison between implemented SGD and sklearn SGD:

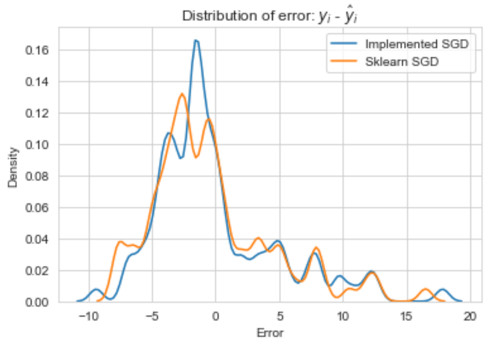
In [25]:
```
from prettytable import PrettyTable

table = PrettyTable()
table.field_names = ['Regressor', 'Training MSE', 'Testing MSE', 'Variance Score']
for i in range(1,3):
    table.add_row(performance[i])
print(table)
```

```
+----------------+--------------+-------------+----------------+
|   Regressor    | Training MSE | Testing MSE | Variance Score |
+----------------+--------------+-------------+----------------+
|    Own SGD     |    23.31     |    23.58    |      0.76      |
| SGD Classifier |    22.06     |    23.36    |      0.76      |
+----------------+--------------+-------------+----------------+
```

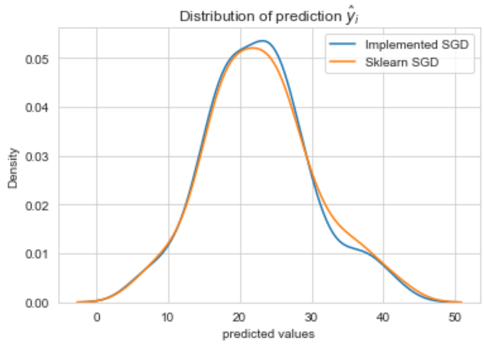
In [26]:
```
# Scatter plots of test set vs predicted set  for both Own SGD and Sklearn SGD

# Implemented SGD
plt.subplot(212)
plt.scatter(y_test, test_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()


# 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()
```



In [27]:
```
# Distribution of error

delta_y = y_test - test_pred
delta_y_sk = y_test - y_pred

sns.set_style('whitegrid')
sns.kdeplot(np.array(delta_y), 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 [28]:
```
# Distribution of predicted value

sns.set_style('whitegrid')
sns.kdeplot(test_pred, 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()
```



Observations

1. Coefficient of determination tells about the goodness of fit of a model and for implemented SGD, r-squared score is 0.77 which means regression prediction does not perfectly fit the data in this case. An r-squared error of 1 indicates that regression prediction perfect fit the data.
2. The mean squared error(MSE) for test set is 23.09 in case of own SGD compared to 23.43 in sklearn's SGD classifier which is similar for both cases i.e. there are much more difference b/w predicted and actual points. Hence average squared difference between the actual target value and predicted target value is high.
3. r-squared score for sklearn SGD is 0.76, means the fit explain 76% of the total variation in the data about the average.
4. Distribution of prediction graphs for both the SGDs are overlapping and sklearn SGD graph is smoother compared to own implemented SGD.

Conclusions

1. While comparing sklearn implemented SGD regressor and own implemented SGD regressor in python, we could not see much of a difference in terms of r-squared error.
2. Overall we can say that regression lines don't fit to the data perfectly in both the cases.