In [111]:

```
import warnings
warnings.filterwarnings("ignore")
# import necessary libraries
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 prettytable import PrettyTable
from sklearn import preprocessing
from sklearn.metrics import mean_squared_error,mean_absolute_error
from numpy import random
```

In [112]:

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

In [113]:

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

```
(506, 13)
```

In [114]:

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

```
(506,)
```

In [115]:

```
print(boston.feature_names)
```

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

In [116]:

```
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 [117]:

```
boston_data=pd.DataFrame(boston.data,columns=load_boston().feature_names)
```

In [118]:

```
boston_data.head(5)
```

Out[118]:

	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 [119]:

```
df = boston.data
```

In [120]:

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
standardized_data = sc.fit_transform(df)
```

In [121]:

```
new_features = np.ones(boston.data.shape[0])
```

```
new_features = np.ones(boston.data.shape[0])
features = np.vstack((new_features,standardized_data.T)).T
```

In [122]:

```
target_price = boston.target
```

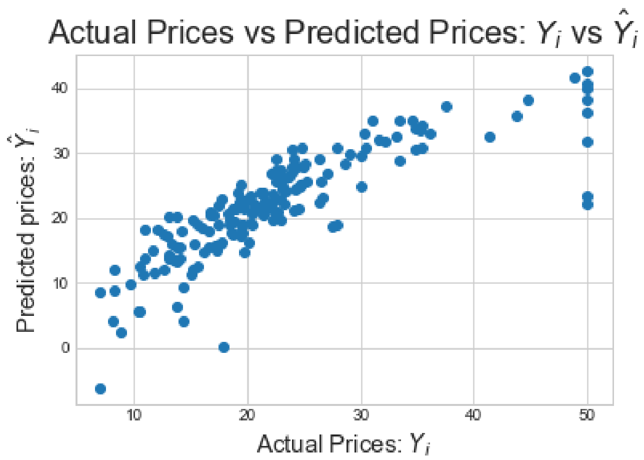
In [123]:

```
#train_test_split
from sklearn.model_selection import train_test_split
X_train,x_test,y_train,y_test = train_test_split(features,target_price,test_size = 0.33,random_stat
e = 5)
```

sklearn_sgd_implementation

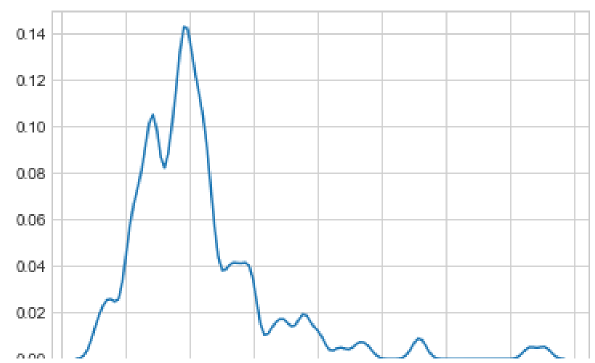
In [124]:

```
from sklearn.linear_model import SGDRegressor
sgd = SGDRegressor(penalty='none', max_iter=1000, learning_rate='constant' , eta0=0.001  )
sgd.fit(X_train, y_train)

sklearn_sgd_predictions = sgd.predict(x_test)

# Weights of Sklearn's SGD
sklearn_sgd_weights = sgd.coef_

plt.scatter(y_test, sklearn_sgd_predictions)
plt.xlabel("Actual Prices: $Y_i$",size=15)
plt.ylabel("Predicted prices: $\hat{Y}_i$",size=15)
plt.title("Actual Prices vs Predicted Prices: $Y_i$ vs $\hat{Y}_i$",size=20)
plt.show()
```



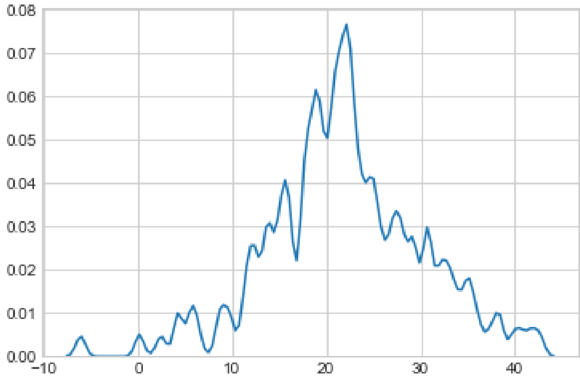
In [125]:

```
fy = y_test - sklearn_sgd_predictions;
sns.set_style('whitegrid')
sns.kdeplot(np.array(fy), bw=0.5)
plt.show()
```



In [126]:

```
sns.set_style('whitegrid')
sns.kdeplot(np.array(sklearn_sgd_predictions), bw=0.5)
plt.show()
```



In [127]:

```
# Calculating accuracy of SGD using sklearn
from sklearn.metrics import mean_absolute_error,mean_squared_error

# calculate Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE)
print(mean_absolute_error(y_test,sklearn_sgd_predictions))
print(mean_squared_error(y_test, sklearn_sgd_predictions))
print(np.sqrt(mean_squared_error(y_test,sklearn_sgd_predictions)))
```

```
3.459556761699631
28.476769979474394
5.33636299172708
```

manual_sgd_implementation

In [128]:

```
#https://media.geeksforgeeks.org/wp-content/uploads/gradiant_descent.jpg
```

In [129]:

```
#https://www.geeksforgeeks.org/gradient-descent-in-linear-regression/

# Stochastic Gradient Descent Algorithm :

# Let 'K' be the number of random rows selected out of the dataset
# Initialize the weight vector
#Let r = learning_rate and m = number of training_examples
# Let r =1
# repeat until convergence {
#    weight[j] = weight[j] - (r/m)*((Σfrom i=1 to K)of(((weight.T * feature_data[i]) -
target_price[i])* feature_data[i,j])
#    r /= 2
#}

# Final hypothesis for linear regression
# predicted_prices = (final_weights.T)*(test_data_matrix)
```

In [130]:

```
#initializing weights vectors

w = np.random.normal(0,1,features.shape[1])
w
```

Out[130]:

```
array([-0.04178054,  0.21295249,  0.364612  , -1.46012581, -0.83815318,
       -0.35844214, -0.42165175,  0.08965714, -0.1998211 , -0.09961203,
        0.62951439, -0.099141  ,  1.79061801,  0.31543617])
```

In [131]:

```
#creating a temporary weight vector to storing the intermidiate computed weight values

temp_v = np.zeros(features.shape[1])
```

In [132]:

```
#initializing the learning rate
rate = 0.001
n_train = X_train.shape[0]
```

In [133]:

```
#batch size for gradient_descent

batch_size = 20
from numpy import random
random_i = random.choice(n_train,n_train,replace=False)
x_shuffled = X_train[random_i,:]
y_shuffled = y_train[random_i]
mini_batches = [(x_shuffled[i:i+batch_size,:], y_shuffled[i:i+batch_size]) for i in range(0, n_trai
n, batch_size)]
```

In [134]:

```
iterations = 1000 # iteration for training data
```

In [135]:

```
#stockastic_gradient_descent
while(iterations > 0 ):
    for batch in mini_batches:
        x_batch = batch[0]
        y_batch = batch[1]
        for j in range(0,features.shape[1]):
            temp_sum = 0
            for i in range(0,x_batch.shape[0]):
                temp_sum += (( (np.sum( sc.inverse_transform(w[1:14] * x_batch[i,1:])) + w[0]*x_batc
h[i,0]) - y_batch[i]) * x_batch[i,j])
            temp_v[j] = w[j] - ((rate/x_batch.shape[0])*temp_sum)
        w = temp_v
    iterations -= 1

# Weights of manual sgd
manual_sgd_weights = w
```

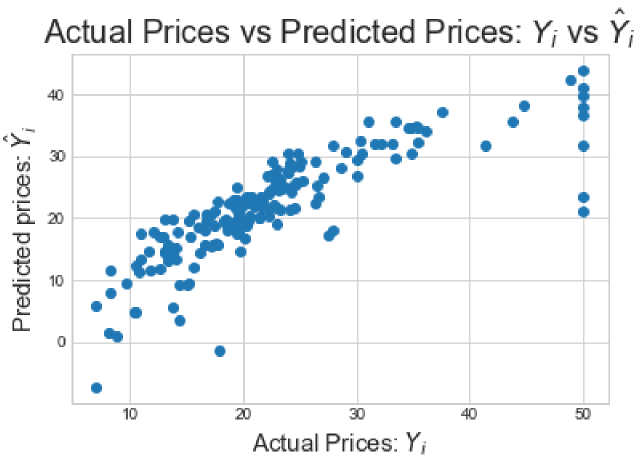
In [136]:

```
# Now predicting the house prices on x_test data
manual_sgd_predictions = np.zeros(x_test.shape[0])
for i in range(0,x_test.shape[0]):
    manual_sgd_predictions[i] = np.sum(sc.inverse_transform(w[1:14]*x_test[i,1:])) + w[0]*x_test[i,0
]
```

In [137]:

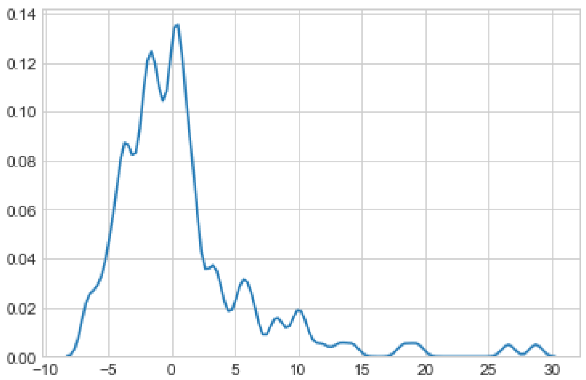
```
#scatter_plot for actual_price vs predicted_price

import matplotlib.pyplot as plt
%matplotlib inline

plt.scatter(y_test, manual_sgd_predictions)
plt.xlabel("Actual Prices: $Y_i$",size=15)
```

```python
plt.ylabel("Predicted prices: $\hat{Y}_i$",size=15)
plt.title("Actual Prices vs Predicted Prices: $Y_i$ vs $\hat{Y}_i$",size=20)
plt.show()
```



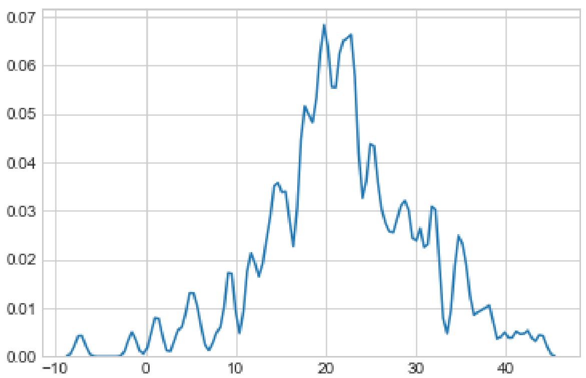
In [138]:

```python
fy = y_test - manual_sgd_predictions;
import seaborn as sns;
import numpy as np;
sns.set_style('whitegrid')
sns.kdeplot(np.array(fy), bw=0.5)
plt.show()
```



In [139]:

```python
sns.set_style('whitegrid')
sns.kdeplot(np.array(manual_sgd_predictions), bw=0.5)
plt.show()
```



In [140]:

```python
from sklearn.metrics import mean_absolute_error,mean_squared_error

# calculate Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE)
print(mean_absolute_error(y_test, manual_sgd_predictions))
print(mean_squared_error(y_test, manual_sgd_predictions))
```

```
print(np.sqrt(mean_squared_error(y_test,manual_sgd_predictions)))
```

```
3.5174970474311973
29.83399657408489
5.462050583259449
```

Results comparison of manual_sgd and sklean_sgd

In [141]:

```
from prettytable import PrettyTable

numbering = [1,2,3,4,5,6,7,8,9,10,11,12,13,14]
# Initializing prettytable
table = PrettyTable()

# Adding columns
table.add_column("S.no.",numbering)
table.add_column("Weights of Sklearn's SGD",sklearn_sgd_weights)
table.add_column("Weights of Manual SGD",manual_sgd_weights)
print(table)
```

```
+--------+--------------------------+------------------------+
| S.no.  | Weights of Sklearn's SGD | Weights of Manual SGD  |
+--------+--------------------------+------------------------+
|   1    |    11.171987537549956    |   -888.6595983829926   |
|   2    |    -1.279700072646803    |  -0.16011812289540817  |
|   3    |    0.7894394794215622    |  0.04114444689661235   |
|   4    |   -0.42368089087640315   |  -0.06764978034840359  |
|   5    |   0.24184463443991208    |   1.6253128376897086   |
|   6    |    -1.370485009260177    |   -4.191761693921897   |
|   7    |    2.875644594386829     |   4.155374713308406    |
|   8    |   -0.3721401278535712    | -0.021804811020539785  |
|   9    |   -2.8631224110918523    |  -1.2281401833727539   |
|   10   |    2.1335087837165996    |   0.3094725189579569   |
|   11   |   -1.3893128036801325    | -0.015198288531831536  |
|   12   |   -2.1239405739498816    |  -0.8878123611969337   |
|   13   |    1.089839656001719     |  0.012528838090981752  |
|   14   |   -3.3438699237425573    |  -0.4702138752001458   |
+--------+--------------------------+------------------------+
```