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
import sklearn
from sklearn import preprocessing
from sklearn.metrics import mean_squared_error
import seaborn as sns
```

In [2]:

```
#loading boston house price datasets

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

In [3]:

```
#Looking the shapr of the data
print(boston.data.shape)
```

```
(506, 13)
```

In [4]:

```
#Printing the features
print(boston.feature_names)
```

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

In [5]:

```
#looking the describtion and Attribute Information
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 [6]:

```python
print(boston.target)
```

```
[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]
```

```
22.   11.9]
```

In [7]:

```
#converting into pandas and printing the head
import pandas as pd
bos = pd.DataFrame(data=boston.data)
bos.head(5)
```

Out[7]:

	0	1	2	3	4	5	6	7	8	9	10	11	12
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 [8]:

```
bos.describe()
```

Out[8]:

	0	1	2	3	4	5	6	7	8	9	
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 [9]:

```
bos.shape
```

Out[9]:

```
(506, 13)
```

In [10]:

```
bos.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 13 columns):
0      506 non-null float64
1      506 non-null float64
2      506 non-null float64
3      506 non-null float64
4      506 non-null float64
5      506 non-null float64
6      506 non-null float64
7      506 non-null float64
8      506 non-null float64
9      506 non-null float64
10     506 non-null float64
11     506 non-null float64
12     506 non-null float64
```

```
dtypes: float64(13)
memory usage: 51.5 KB
```

In [11]:

```
#spliting the data into train and test
from sklearn.model_selection import train_test_split


price=boston.target
X_train, X_test, Y_train, Y_test = sklearn.model_selection.train_test_split(bos, price, test_size =
0.33, random_state = 5)


print('Train shape', X_train.shape)
print('Test shape', X_test.shape)
print('Train shape', Y_train.shape)
print('Test shape', Y_test.shape)
```

```
Train shape (339, 13)
Test shape (167, 13)
Train shape (339,)
Test shape (167,)
```

In [12]:

```
# applying column standardization on train and test data
from sklearn.preprocessing import StandardScaler

s=StandardScaler()
X_train=s.fit_transform(np.array(X_train))
X_test=s.transform(np.array(X_test))
```

In [13]:

```
# SGD regressor manual training data
man_train=pd.DataFrame(data=X_train)
man_train['price']=Y_train
```

In [14]:

```
#converting to numpy array
X_test = np.array(X_test)
Y_test=np.array(Y_test)
```

[1] Linear Regression using Scikit Learn's SGD Regressor

In [15]:

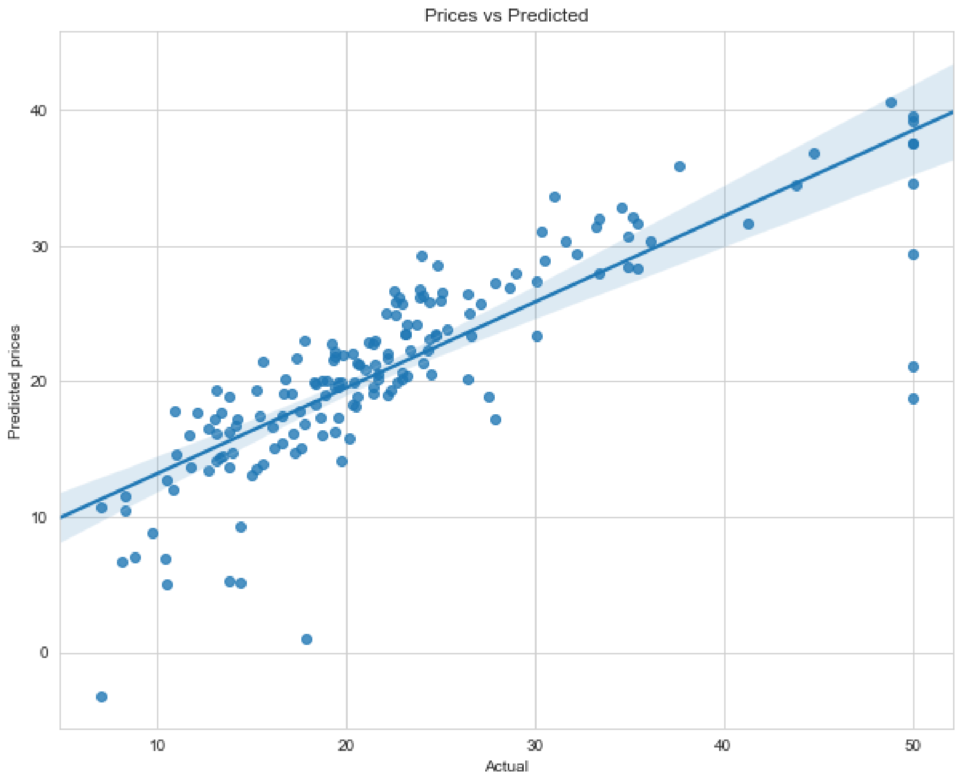
```
def sklearn_sgd(alpha, lr_rate_variation, eta0=0.01, power_t=0.25, n_iter=100, X_train=X_train, X_t
est=X_test, Y_train=Y_train, Y_test=Y_test):
    clf=SGDRegressor(alpha=alpha, penalty=None, learning_rate=lr_rate_variation, eta0=eta0, power_t
=power_t, n_iter=n_iter)
    clf.fit(X_train, Y_train)
    y_pred=clf.predict(X_test)

    plt.figure(figsize=(10,8))
    sns.set_style('whitegrid')
    sns.regplot(Y_test,y_pred)
    plt.xlabel("Actual")
    plt.ylabel("Predicted prices")
    plt.title("Prices vs Predicted")
    plt.grid(True)
    plt.show()


    sgd_error=mean_squared_error(Y_test,y_pred)
    print('mean sqr error=', sgd_error)
    print('number of iterations =', n_iter)
```

```
    print("\n ---Slope--- \n",clf.coef_)
    print("\n---Intercept--- \n",clf.intercept_)
    return clf.coef_, clf.intercept_, sgd_error
```

In [16]:

```
# SGDRegressor, n_iter=1, lr_rate=0.01, lr_rate_variation='constant'
w_sgd, b_sgd, error_sgd=sklearn_sgd(alpha=0.0001, lr_rate_variation='constant', eta0=0.01, n_iter=1
)
```

```
C:\Anaconda3\lib\site-packages\sklearn\linear_model\stochastic_gradient.py:152:
DeprecationWarning: n_iter parameter is deprecated in 0.19 and will be removed in 0.21. Use
max_iter and tol instead.
  DeprecationWarning)
```




```
mean sqr error= 31.557058355086674
number of iterations = 1

 ---Slope---
 [-0.78491875  0.30335981 -0.36274146  0.17836393 -0.53338592  3.29719428
 -0.2271675  -1.94241771  0.52889753 -0.48295875 -1.83749686  0.56247034
 -2.84998778]

---Intercept---
 [21.54474007]
```

In [17]:

```
MSE_skl_1=error_sgd
```

[2] Linear Regression using Manual SGD Regressor

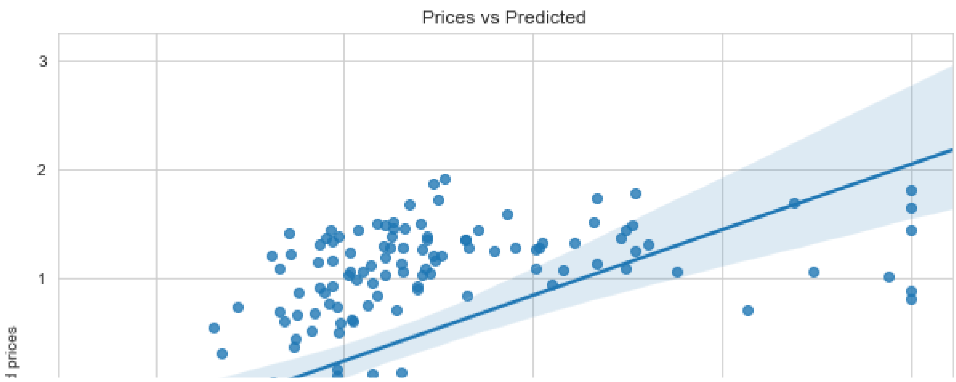
In [18]:

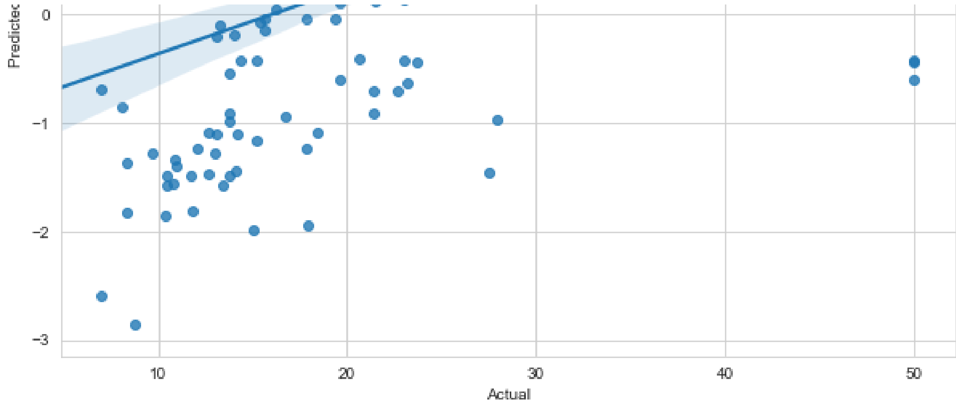
```
# Manual sgd, n_iter=1, lr_rate=0.01, lr_rate_variation='constant'

def manual_fixed(X, lr_rate_variation, alpha=0.0001, lr_rate=0.01, power_t=0.25, n_iter=100):
    w_new=np.zeros(shape=(1,13))
    b_new=0
    t=1
    r=lr_rate
```

```
    while(t<=n_iter):
        w_old=w_new
        b_old=b_new
        w_=np.zeros(shape=(1,13))
        b_=0
        x_data=X.sample(10)
        x=np.array(x_data.drop('price',axis=1))
        y=np.array(x_data['price'])


        for i in range(10):  # for getting the derivatives using sgd with k=10
            y_curr=np.dot(w_old,x[i])+b_old
            w_+=x[i] * (y[i] - y_curr)
            b_+=(y[i]-y_curr)


        w_*=(-2/x.shape[0])
        b_*=(-2/x.shape[0])

        #updating the parameters
        w_new=(w_old-r*w_)
        b_new=(b_old-r*b_)


        if(lr_rate_variation=='invscaling'):
            r = lr_rate / pow(t, power_t)
        t+=1

    return w_new, b_new


def pred(x,w, b):
    y_pred=[]
    for i in range(len(x)):
        y=np.asscalar(np.dot(w,x[i])+b)
        y_pred.append(y)
    return np.array(y_pred)


def plot_(X_test,y_pred):
    plt.figure(figsize=(10,8))
    sns.set_style('whitegrid')
    sns.regplot(Y_test,y_pred)
    plt.xlabel("Actual")
    plt.ylabel("Predicted prices")
    plt.title("Prices vs Predicted")
    plt.grid(True)
    plt.show()


    manual_error=mean_squared_error(Y_test,y_pred)
    print('error=',manual_error)

    return manual_error
```

In [19]:

```
w, b=manual_fixed(X=man_train, lr_rate_variation='constant' , n_iter=1)
y_pred=pred(X_test, w=w, b=b)
manual_error=plot_(X_test,y_pred)
```






```
error= 573.583682975236
```

In [20]:

```
MSE_manual_1=manual_error
```

In [21]:

```
print('sgd weight---\n',w_sgd)
print('**********************************************************************************')
print('sgd weight---\n',w)
```

```
sgd weight---
 [-0.78491875  0.30335981 -0.36274146  0.17836393 -0.53338592  3.29719428
 -0.2271675  -1.94241771  0.52889753 -0.48295875 -1.83749686  0.56247034
 -2.84998778]
**********************************************************************************
sgd weight---
 [[-0.16221574 -0.1522003  -0.11762953  0.03939841 -0.16748392 -0.06336656
  -0.1677686  -0.0187847  -0.23270744 -0.2931616  -0.12109165  0.10522269
  -0.20425752]]
```

In [22]:

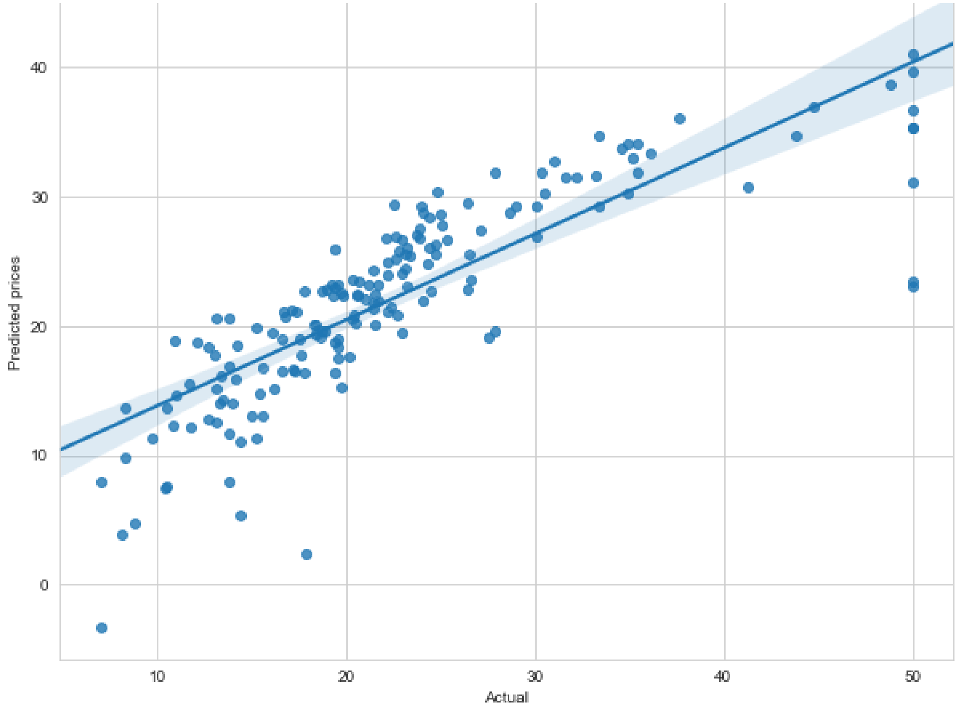
```
b_diff=[]
w_num=[]

percent=abs((w_sgd-w)/w)*100
cnt=0
for i in range(13):
    if (percent[0][i]>30):
        cnt+=1
w_num.append(cnt)
print('Number of points more than 30% =',cnt)
print('Sgd Intercept=',b_sgd)
print('Manual Intercept=',b)
b_diff.append(abs(b_sgd-b))
```

```
Number of points more than 30% = 13
Sgd Intercept= [21.54474007]
Manual Intercept= [0.4698]
```

In [23]:

```
w_sgd, b_sgd, error_sgd=sklearn_sgd(alpha=0.0001, lr_rate_variation='constant', eta0=0.01, n_iter=1
00)
```

```
C:\Anaconda3\lib\site-packages\sklearn\linear_model\stochastic_gradient.py:152:
DeprecationWarning: n_iter parameter is deprecated in 0.19 and will be removed in 0.21. Use
max_iter and tol instead.
  DeprecationWarning)
```



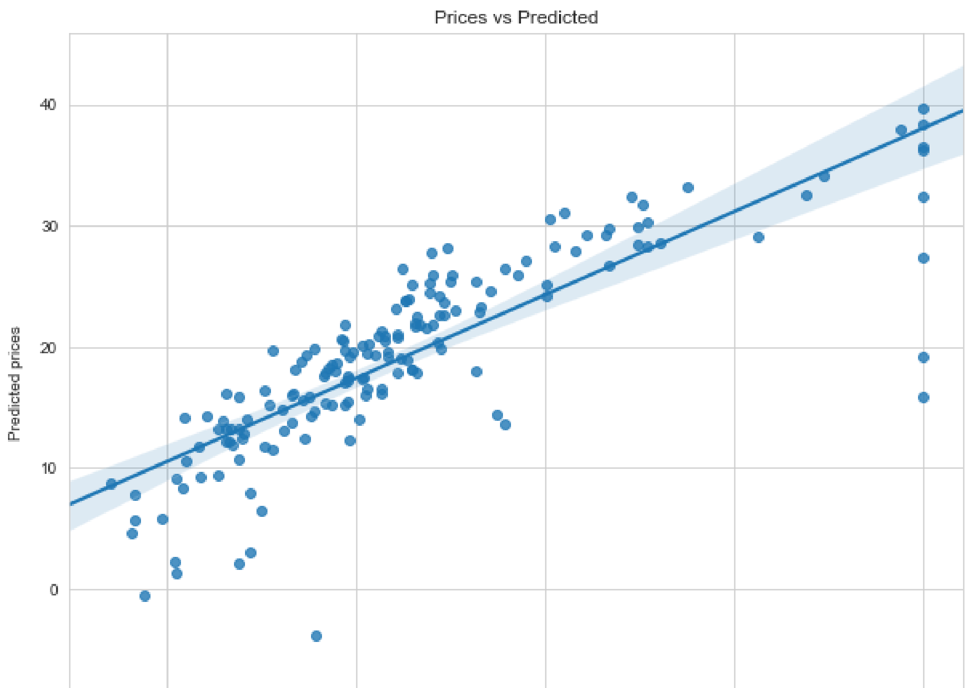

```
mean sqr error= 29.077178124810295
number of iterations = 100

 ---Slope---
 [-1.04243285  0.76979356 -0.06847369  0.10970933 -1.6821843   2.44558355
 -0.57077074 -2.38177343  3.03289927 -2.27258205 -1.66648347  1.05691597
 -3.13483739]

---Intercept---
 [22.84406673]
```

In [24]:

```
MSE_skl_100= error_sgd
```

In [25]:

```
w, b = manual_fixed(X=man_train, lr_rate_variation='constant' , n_iter=100)
y_pred=pred(X_test, w=w, b=b)
manual_error=plot_(X_test,y_pred)
```




```
error= 42.35256087525845
```

In [26]:

```
print('sgd weight---\n',w_sgd)
print('*********************************************************************************')
print('sgd weight---\n',w)
```

```
sgd weight---
 [-1.04243285  0.76979356 -0.06847369  0.10970933 -1.6821843   2.44558355
 -0.57077074 -2.38177343  3.03289927 -2.27258205 -1.66648347  1.05691597
 -3.13483739]
*********************************************************************************
sgd weight---
 [[-1.18621926  0.43569393 -0.28419657  0.51399279 -0.40941625  3.14992029
  -0.43755354 -1.38170762  0.21993616 -0.37262852 -1.84838797  0.87918284
  -2.8721713 ]]
```

In [27]:

```
percent=abs((w_sgd-w)/w)*100
cnt=0
for i in range(13):
    if (percent[0][i]>30):
        cnt+=1
w_num.append(cnt)
print('number of points more than 30% in percent=',cnt)

print('Sgd intercept=',b_sgd)
print('Manual Intercept=',b)
b_diff.append(abs(b_sgd-b))
```

```
number of points more than 30% in percent= 8
Sgd intercept= [22.84406673]
Manual Intercept= [19.56951612]
```

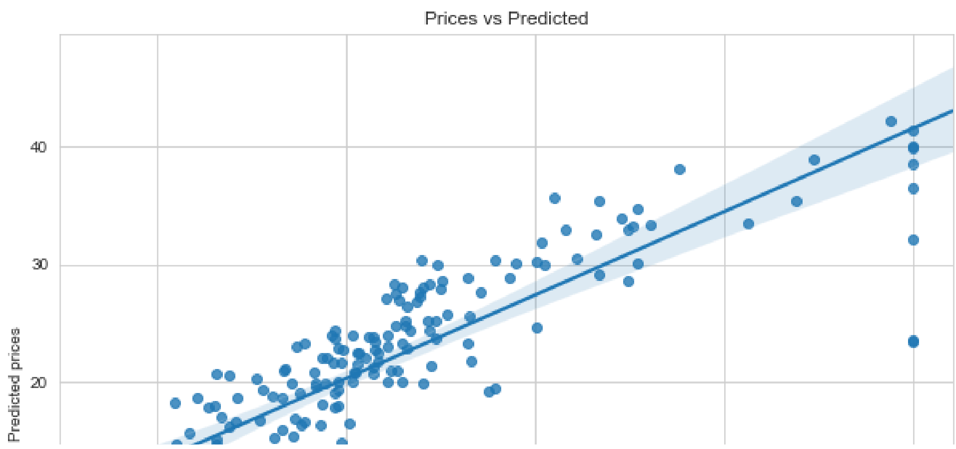
In [28]:

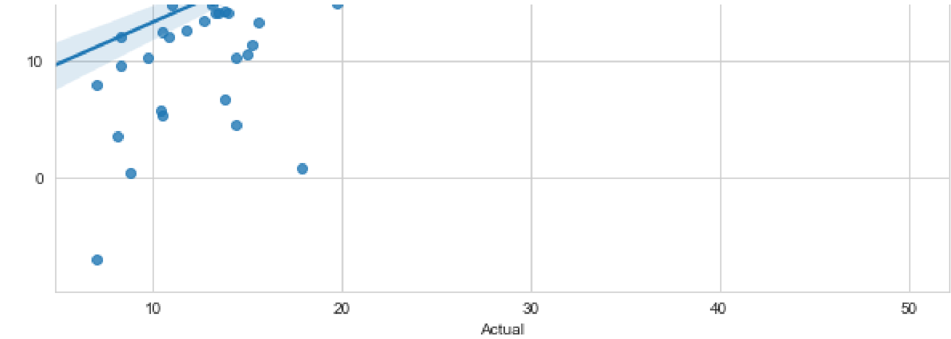
```
MSE_manual_100= manual_error
```

In [29]:

```
w_sgd, b_sgd, error_sgd=sklearn_sgd(alpha=0.0001, lr_rate_variation='constant', eta0=0.01, n_iter=1
000)
```

```
C:\Anaconda3\lib\site-packages\sklearn\linear_model\stochastic_gradient.py:152:
DeprecationWarning: n_iter parameter is deprecated in 0.19 and will be removed in 0.21. Use
max_iter and tol instead.
  DeprecationWarning)
```





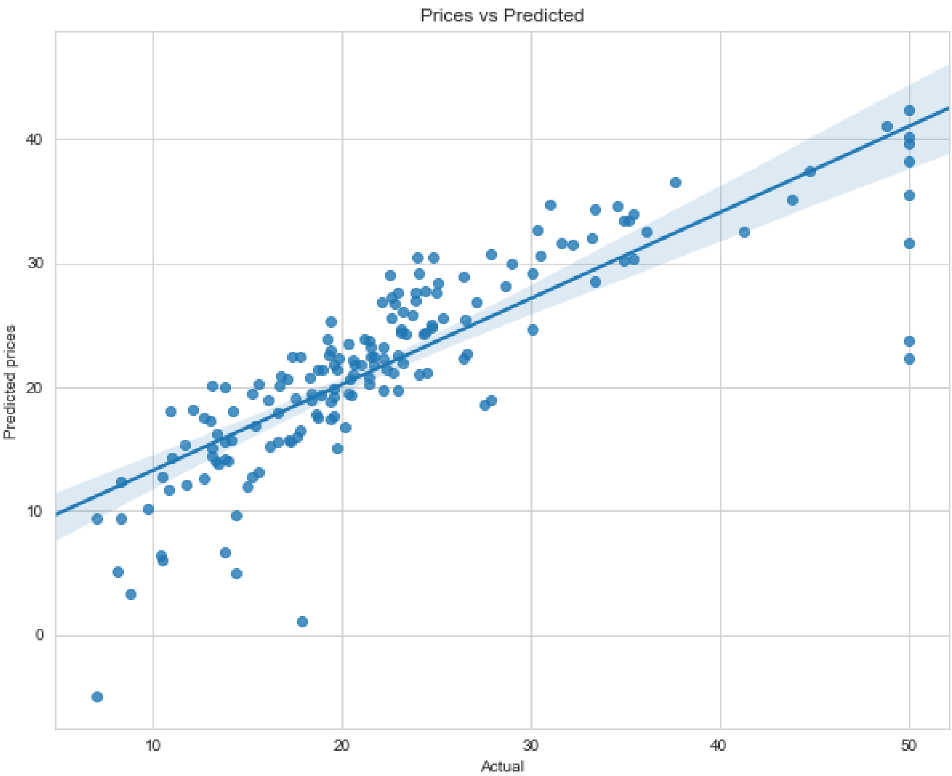

```
mean sqr error= 28.795285414013655
number of iterations = 1000

 ---Slope---
 [-1.66068138  0.56526862 -0.07173634  0.10312531 -1.40684716  2.7504388
 -0.11853409 -2.78981456  3.01698975 -2.33557072 -2.21845073  0.89791288
 -3.40591196]

---Intercept---
 [22.77026536]
```

In [30]:

```
MSE_skl_1000= error_sgd
```

In [31]:

```
w, b=manual_fixed(X=man_train, lr_rate_variation='constant' , n_iter=1000)
y_pred=pred(X_test, w=w, b=b)
manual_error=plot_(X_test,y_pred)
```




```
error= 28.140383307032096
```

In [32]:

```
print('sgd weight---\n',w_sgd)
print('*******************************************************************************')
print('sgd weight---\n',w)
```

```
sgd weight---
```

```
 [-1.66068138  0.56526862 -0.07173634  0.10312531 -1.40684716  2.7504388
 -0.11853409 -2.78981456  3.01698975 -2.33557072 -2.21845073  0.89791288
 -3.40591196]
*********************************************************************************
sgd weight---
 [[-1.20001386  0.78703076 -0.29769606  0.30655154 -1.26645671  2.64744661
  -0.42487022 -2.76304285  1.94264838 -1.37028578 -2.14654559  0.92164352
  -3.27036465]]
```

In [33]:

```
percent=abs((w_sgd-w)/w)*100
cnt=0
for i in range(13):
    if (percent[0][i]>30):
        cnt+=1
w_num.append(cnt)
print('number of points more than 30% in percent=',cnt)
print('Sgd intercept=',b_sgd)
print('Manual Intercept=',b)
b_diff.append(abs(b_sgd-b))
```

```
number of points more than 30% in percent= 6
Sgd intercept= [22.77026536]
Manual Intercept= [22.5478144]
```

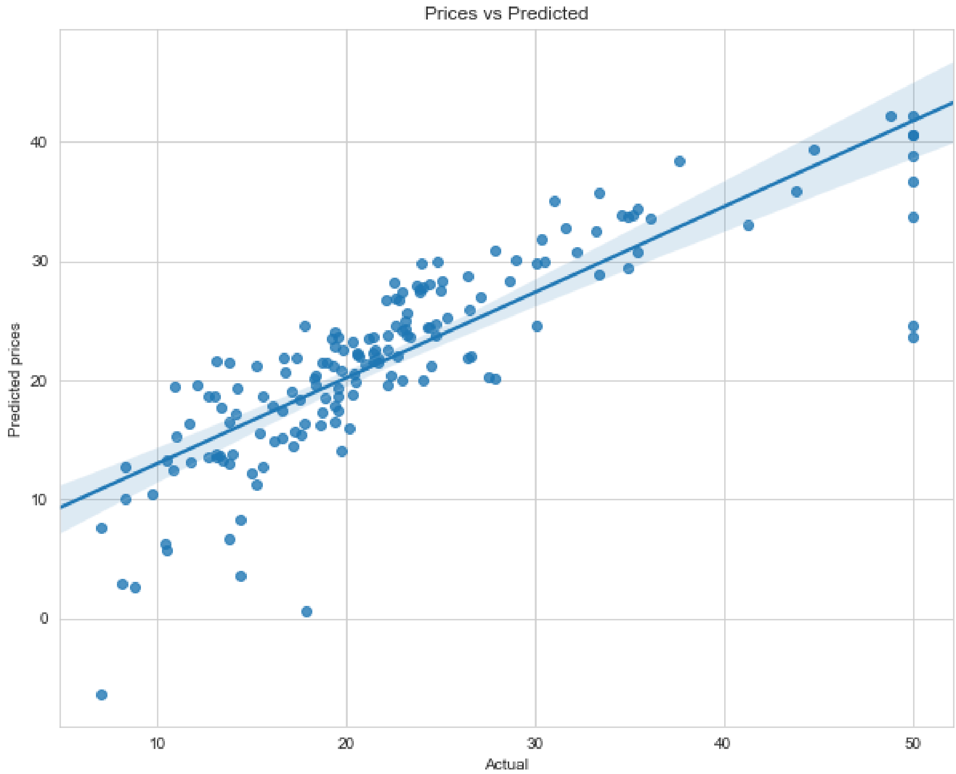
In [34]:

```
MSE_manual_1000= manual_error
```

In [35]:

```
w_sgd, b_sgd, error_sgd=sklearn_sgd(alpha=0.0001, lr_rate_variation='constant', eta0=0.01, n_iter=1
0000)
```

```
C:\Anaconda3\lib\site-packages\sklearn\linear_model\stochastic_gradient.py:152:
DeprecationWarning: n_iter parameter is deprecated in 0.19 and will be removed in 0.21. Use
max_iter and tol instead.
  DeprecationWarning)
```




```
mean sqr error= 27.92357813744099
number of iterations = 10000
```

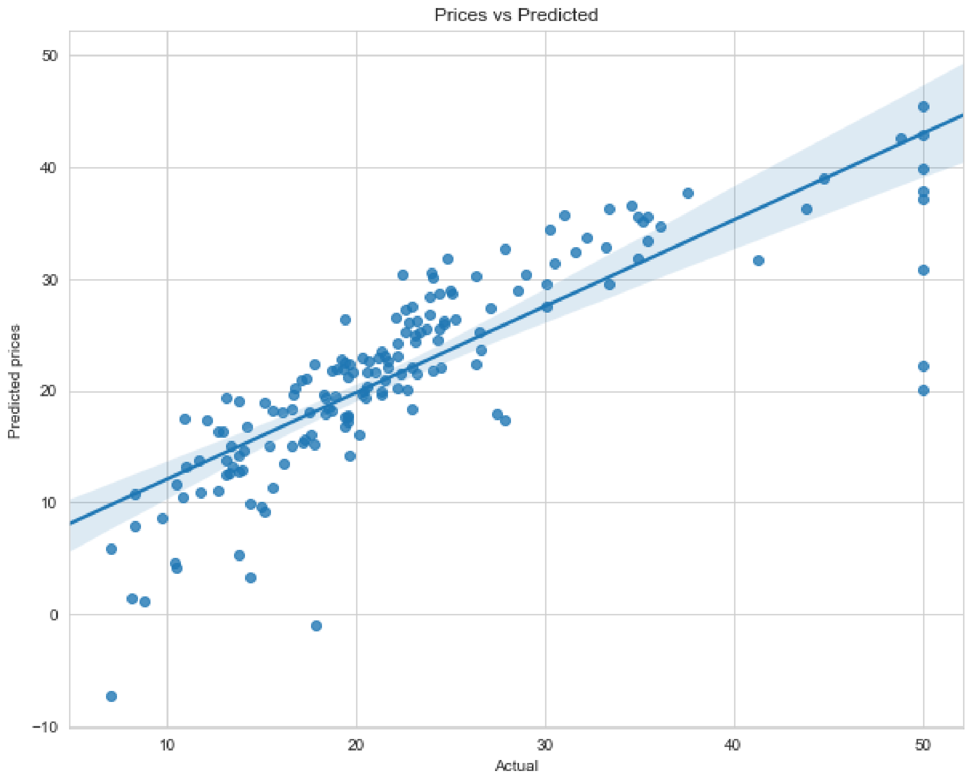
```
---Slope---
[-1.39880591  0.75670475 -0.05518746  0.17254912 -1.41015585  3.11826732
-0.31257037 -2.91576202  3.17424761 -2.01102457 -1.98285003  0.97206098
-3.49324517]

---Intercept---
[22.67795181]
```

In [36]:

```
MSE_skl_10000=error_sgd
```

In [37]:

```
w, b=manual_fixed(X=man_train, lr_rate_variation='constant' , n_iter=10000)
y_pred=pred(X_test, w=w, b=b)
manual_error=plot_(X_test,y_pred)
```




```
error= 30.54123545960842
```

In [38]:

```
print('sgd weight---\n',w_sgd)
print('*****************************************************************************************')
print('Manual sgd weight---\n',w)
```

```
sgd weight---
 [-1.39880591  0.75670475 -0.05518746  0.17254912 -1.41015585  3.11826732
 -0.31257037 -2.91576202  3.17424761 -2.01102457 -1.98285003  0.97206098
 -3.49324517]
*****************************************************************************************
Manual sgd weight---
 [[-1.26000726  1.06942873 -0.32983346  0.28435064 -1.43323955  3.1627527
  -0.68777811 -2.67094348  2.8056339  -2.42536364 -2.15701675  1.07022223
  -3.03750519]]
```

In [39]:

```
percent=abs((w_sgd-w)/w)*100
cnt=0
for i in range(13):
    if (percent[0][i]>30):
```

```
    if (percent[0][1]>30):
        cnt+=1
w_num.append(cnt)
print('Number of points more than 30%',cnt)
print('Sgd intercept=',b_sgd)
print('Manual Intercept=',b)
b_diff.append(abs(b_sgd-b))
```

```
Number of points more than 30% 3
Sgd intercept= [22.67795181]
Manual Intercept= [22.46878899]
```

In [40]:

```
MSE_manual_10000= manual_error
```

In [41]:

```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["S.NO","ALGORITHM","ALPHA","LR_RATE_VARIATION","INIT_LR_RATE","POWER_T","N_INTERAT
IONS","ERROR"]

x.add_row(["1","SKLEARN'S SGD","0.0001","CONSTANT","0.01","0.25","1",MSE_skl_1])
x.add_row(["2","MANUAL SGD","0.0001","CONSTANT","0.01","0.25","1",MSE_manual_1])
x.add_row(["3","SKLEARN'S SGD","0.0001","CONSTANT","0.01","0.25","100",MSE_skl_100])
x.add_row(["4","MANUAL SGD","0.0001","CONSTANT","0.01","0.25","100",MSE_manual_100])
x.add_row(["5","SKLEARN'S SGD","0.0001","CONSTANT","0.01","0.25","1000",MSE_skl_1000])
x.add_row(["6","MANUAL SGD","0.0001","CONSTANT","0.01","0.25","1000",MSE_manual_1000])
x.add_row(["7","SKLEARN'S SGD","0.0001","CONSTANT","0.01","0.25","100000",MSE_skl_10000])
x.add_row(["8","MANUAL SGD","0.0001","CONSTANT","0.01","0.25","100000",MSE_manual_10000])

# Printing the Table
print(x)

y = PrettyTable()

y.field_names = ["S.NO","ALGORITHM","N_ITERATIONS"]

y.add_row(["1","SKLEARN'S SGD","1"])
y.add_row(["2","MANUAL SGD","1"])
y.add_row(["3","SKLEARN'S SGD","100"])
y.add_row(["4","MANUAL SGD","100",])
y.add_row(["5","SKLEARN'S SGD","1000"])
y.add_row(["6","MANUAL SGD","1000"])
y.add_row(["7","SKLEARN'S SGD","100000"])
y.add_row(["8","MANUAL SGD","100000"])

intercepts=[21.84157474, 0.5784, 22.38070844, 19.57099078, 22.3400681, 22.66616673, 22.26977126, 22
.60640749]
y.add_column("INTERCEPT VALUE",intercepts)

# Printing the Table
print(y)
```

```
+-------+---------------+--------+-------------------+--------------+---------+--------------+-----
------------+
| S.NO |    ALGORITHM    | ALPHA  | LR_RATE_VARIATION | INIT_LR_RATE | POWER_T | N_INTERATIONS |
ERROR         |
+-------+---------------+--------+-------------------+--------------+---------+--------------+-----
------------+
|  1    | SKLEARN'S SGD | 0.0001 |      CONSTANT     |     0.01     |   0.25  |       1      | 31.5
7058355086674 |
|  2    |   MANUAL SGD  | 0.0001 |      CONSTANT     |     0.01     |   0.25  |       1      |  573
583682975236  |
|  3    | SKLEARN'S SGD | 0.0001 |      CONSTANT     |     0.01     |   0.25  |      100     |
29.077178124810295 |
|  4    |   MANUAL SGD  | 0.0001 |      CONSTANT     |     0.01     |   0.25  |      100     | 42.3
256087525845  |
|  5    | SKLEARN'S SGD | 0.0001 |      CONSTANT     |     0.01     |   0.25  |     1000     |
28.795285414013655 |
|  6    |   MANUAL SGD  | 0.0001 |      CONSTANT     |     0.01     |   0.25  |     1000     | 28.1
```

```
0383307032096 |
|  7   | SKLEARN'S SGD | 0.0001 |      CONSTANT      |     0.01     |   0.25  |     100000    |
27.92357813744099  |
|  8   |   MANUAL SGD  | 0.0001 |      CONSTANT      |     0.01     |   0.25  |     100000    |
30.54123545960842  |
+------+---------------+--------+--------------------+--------------+---------+---------------+-----
------------+
```

S.NO	ALGORITHM	N_ITERATIONS	INTERCEPT VALUE
1	SKLEARN'S SGD	1	21.84157474
2	MANUAL SGD	1	0.5784
3	SKLEARN'S SGD	100	22.38070844
4	MANUAL SGD	100	19.57099078
5	SKLEARN'S SGD	1000	22.3400681
6	MANUAL SGD	1000	22.66616673
7	SKLEARN'S SGD	100000	22.26977126
8	MANUAL SGD	100000	22.60640749

Observations:

1. The first MSE by the manual sgd is outrageous, but as the iterations kept increasing the error given by it became less.
2. The MSE of SGD is almost the same with all the iterations.
3. At the end of 100000 iterations, Manual SGD gave an MSE lesser than that of SKLearn's SGD.
4. The Sklearn's SGD intercept is almost the same with all the iterations but Manual SGD intercept kept on getting better just like MSE as the iterations kept increasing.
5. The 1000th and 10000th iterations both intercepts are almost similar.

In [ ]: