# 06 Implement SGD

## April 11, 2019

```
In [318]: 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
In [319]: #loading boston house price datasets
          from sklearn.datasets import load_boston
          boston = load_boston()
In [320]: #Looking the shapr of the data
          print(boston.data.shape)
(506, 13)
In [321]: #Printing the features
          print(boston.feature_names)
['CRIM' 'ZN' 'INDUS' 'CHAS' 'NOX' 'RM' 'AGE' 'DIS' 'RAD' 'TAX' 'PTRATIO'
 'B' 'LSTAT']
In [322]: #looking the describtion and Attribute Information
          print(boston.DESCR)
```

## .. \_boston\_dataset:

## Boston house prices dataset

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\*\*Data Set Characteristics:\*\*

:Number of Instances: 506

:Number of Attributes: 13 numeric/categorical predictive. Median Value (attribute 14) is us

: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 highwaysTAX 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 Univers

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 regress problems.

.. topic:: References

- Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential Data and Sources
- Quinlan, R. (1993). Combining Instance-Based and Model-Based Learning. In Proceedings on the

## In [323]: 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
     14.4 13.4 15.6 11.8 13.8 15.6 14.6 17.8 15.4 21.5 19.6 15.3 19.4
     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.
              20.1 22.2 23.7 17.6 18.5 24.3 20.5 24.5 26.2 24.4 24.8
23.7 23.3 22.
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.
              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
11.9 27.9 17.2 27.5 15. 17.2 17.9 16.3 7.
                                             7.2 7.5 10.4 8.8
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]
```

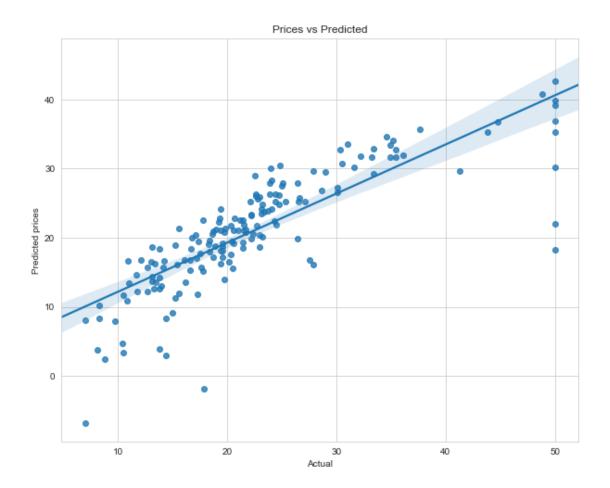
In [324]: #converting into pandas and printing the head import pandas as pd

bos = pd.DataFrame(data=boston.data)
bos.head(5)

```
Out [324]:
                   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
                                                                4.9671
                                                                         2.0
                                                                              242.0
                                                                                      17.8
                                                         61.1
          3
              0.03237
                         0.0
                              2.18
                                     0.0
                                          0.458
                                                  6.998
                                                          45.8
                                                                6.0622
                                                                         3.0
                                                                              222.0
                                                                                      18.7
              0.06905
                                                                         3.0
                         0.0
                              2.18
                                     0.0
                                          0.458
                                                  7.147
                                                          54.2
                                                                6.0622
                                                                              222.0
                                                                                      18.7
                  11
                         12
          0
              396.90
                      4.98
              396.90
          1
                      9.14
          2
              392.83
                      4.03
          3
              394.63
                      2.94
              396.90
                      5.33
In [325]: bos.describe()
Out [325]:
                           0
                                                     2
                                                                  3
                                                                                             5
                                        1
                                                                                4
          count
                  506.000000
                               506.000000
                                            506.000000
                                                          506.000000
                                                                       506.000000
                                                                                    506.000000
                    3.613524
                                11.363636
                                              11.136779
                                                            0.069170
                                                                         0.554695
                                                                                      6.284634
          mean
          std
                    8.601545
                                23.322453
                                               6.860353
                                                            0.253994
                                                                         0.115878
                                                                                      0.702617
                    0.006320
                                 0.000000
                                               0.460000
                                                            0.000000
                                                                         0.385000
                                                                                      3.561000
          min
          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%
                    3.677083
                                 12.500000
                                              18.100000
                                                            0.000000
                                                                         0.624000
                                                                                      6.623500
          max
                   88.976200
                               100.000000
                                              27.740000
                                                            1.000000
                                                                         0.871000
                                                                                      8.780000
                           6
                                        7
                                                     8
                                                                  9
                                                                                10
                                                                                             11
                  506.000000
                               506.000000
                                            506.000000
          count
                                                          506.000000
                                                                       506.000000
                                                                                    506.000000
                                  3.795043
                                                          408.237154
          mean
                   68.574901
                                               9.549407
                                                                        18.455534
                                                                                    356.674032
                   28.148861
                                 2.105710
                                               8.707259
                                                          168.537116
                                                                         2.164946
                                                                                     91.294864
          std
                                  1.129600
                    2.900000
                                               1.000000
                                                          187.000000
                                                                        12.600000
                                                                                      0.320000
          min
          25%
                   45.025000
                                               4.000000
                                                          279.000000
                                                                        17.400000
                                                                                    375.377500
                                  2.100175
          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
                           12
          count
                  506.000000
                   12.653063
          mean
          std
                    7.141062
          min
                    1.730000
          25%
                    6.950000
          50%
                   11.360000
          75%
                   16.955000
                   37.970000
          max
```

```
In [326]: bos.shape
Out[326]: (506, 13)
In [327]: bos.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 13 columns):
      506 non-null float64
1
      506 non-null float64
2
      506 non-null float64
     506 non-null float64
3
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
     506 non-null float64
9
10
     506 non-null float64
      506 non-null float64
11
     506 non-null float64
dtypes: float64(13)
memory usage: 51.5 KB
In [328]: #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, pri-
          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 [329]: # 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 [330]: # SGD regressor manual training data
          man_train=pd.DataFrame(data=X_train)
          man_train['price']=Y_train
In [331]: #converting to numpy array
          X_test = np.array(X_test)
          Y_test=np.array(Y_test)
In [332]: res=pd.DataFrame(columns=['sno', 'algo', 'alpha', 'lr_rate_variation', 'init_lr_rate
In [333]: def sklearn_sgd(alpha, lr_rate_variation, eta0=0.01, power_t=0.25, n_iter=100, X_tra
              clf=SGDRegressor(alpha=alpha, penalty=None, learning_rate=lr_rate_variation, eta
              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 [334]: # 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
```

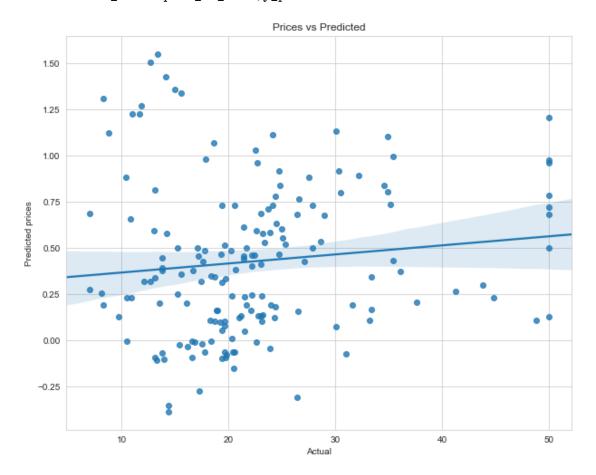


```
b_new=0
    t=1
    r=lr_rate
    while(t<=n_iter):</pre>
        w_old=w_new
        b_old=b_new
        w_=np.zeros(shape=(1,13))
        b = 0
        x_data=X.sample(10)
        x=np.array(x_data.drop('price',axis=1))
        y=np.array(x_data['price'])
        for i in range(10): # for getting 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
```



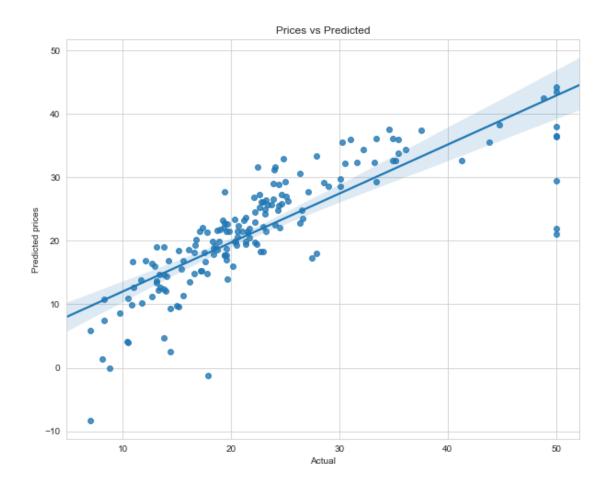
error= 581.1547866807905

```
In [338]: new=[2, 'manual sgd', 0.0001, 'constant', 0.01, 0.25, 1, manual_error]
    res.loc[1]=new
```

```
print('sgd weight---\n',w)
sgd weight---
[-1.15451538 0.62739545 -1.05270589 0.51272564 -0.00704808 3.28681963
-0.83093975 -1.65508507 0.83708974 -0.42540257 -1.59714823 0.79687425
-3.0168991 ]
********************************
sgd weight---
  \begin{bmatrix} [-0.02786544 & 0.09247879 & 0.07209797 & 0.09815829 & 0.00602633 & 0.03424121 \end{bmatrix} 
 -0.13781974 0.12929866 0.09491071 0.145088 -0.00473804 -0.25241295
 -0.10620876]]
In [340]: 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= [21.62476992]
Manual Intercept= [0.4058]
```

In [341]: w\_sgd, b\_sgd, error\_sgd=sklearn\_sgd(alpha=0.0001, lr\_rate\_variation='constant', eta0

In [339]: print('sgd weight---\n',w\_sgd)



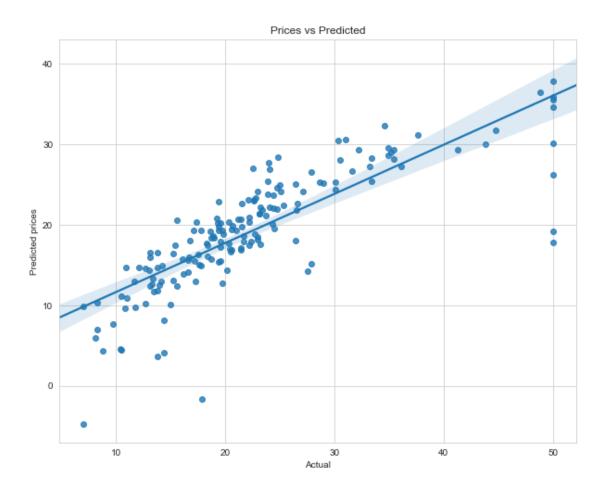
```
mean sqr error= 32.555806480087476
number of iterations = 100

---Slope---
[-1.42773685    1.33529848   -0.2202258    -0.16685147   -1.52507545    2.68300024
    -0.44231497    -2.69670534    2.90741932    -2.35707221    -2.45485885    1.01610677
    -3.56659361]

---Intercept---
[22.42432868]

In [342]: new=[3, 'SGDRegressor', 0.0001, 'constant', 0.01, 0.25, 100, error_sgd]
    res.loc[2]=new

In [343]: 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= 42.38091998722532

cnt=0

```
for i in range(13):
    if (percent[0][i]>30):
        cnt+=1

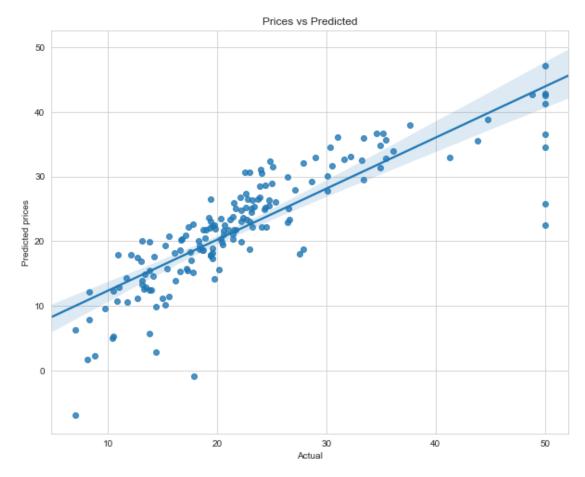
w_num.append(cnt)
print('number of points more than 30% in percent=',cnt)

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

number of points more than 30% in percent= 9
Sgd intercept= [22.42432868]
Manual Intercept= [19.638906]
```

In [346]: new=[4, 'manual sgd', 0.0001, 'constant', 0.01, 0.25, 100, manual\_error]
 res.loc[3]=new

In [347]: w\_sgd, b\_sgd, error\_sgd=sklearn\_sgd(alpha=0.0001, lr\_rate\_variation='constant', eta0=

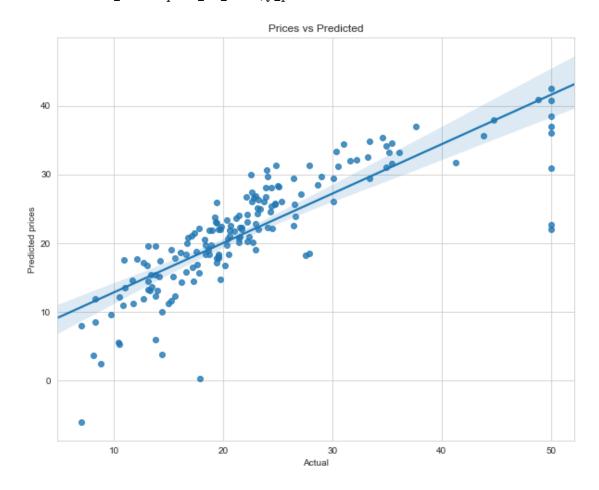


mean sqr error= 27.950880163842545 number of iterations = 1000

---Slope---

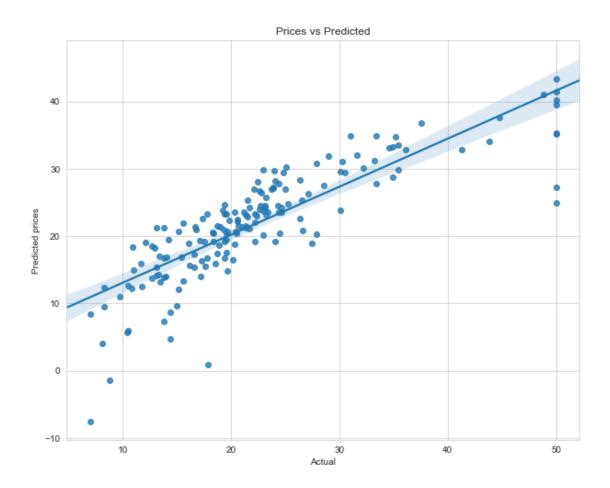
[-1.15487752 0.99163057 -0.21313446 0.84068331 -1.52606576 2.78784029 -0.18089243 -2.48709914 2.97349628 -2.23978358 -2.45049694 1.20003159 -3.512988 ]

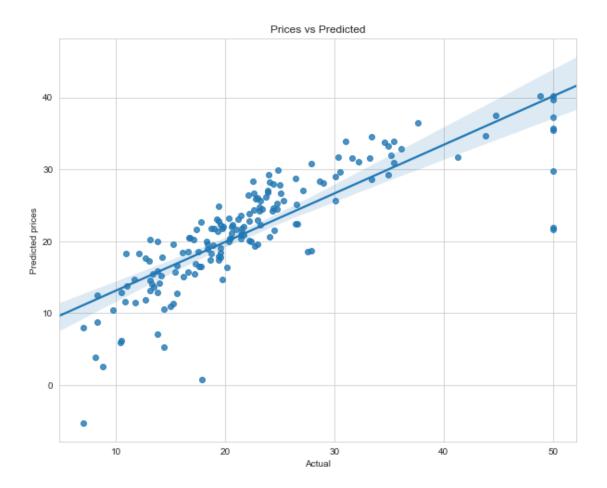
---Intercept--[22.87429928]



In [350]: print('sgd weight---\n',w\_sgd)

```
print('sgd weight---\n',w)
sgd weight---
[-1.15487752 0.99163057 -0.21313446 0.84068331 -1.52606576 2.78784029
-0.18089243 -2.48709914 2.97349628 -2.23978358 -2.45049694 1.20003159
-3.512988 ]
*********************************
sgd weight---
 \begin{bmatrix} [-1.21621368 & 0.73412432 & -0.55344236 & 0.17098119 & -1.54020225 & 2.6945703 \end{bmatrix} 
 -0.40897904 -2.52355861 2.1788653 -1.40340508 -2.06784118 1.00089669
 -3.33184554]]
In [351]: 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= [22.87429928]
Manual Intercept= [22.48522577]
In [352]: new=[6, 'manual sgd', 0.0001, 'constant', 0.01, 0.25, 1000, manual_error]
         res.loc[5]=new
In [353]: w_sgd, b_sgd, error_sgd=sklearn_sgd(alpha=0.0001, lr_rate_variation='constant', eta0
```





```
error= 30.108587396756242
```

```
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% 4
Sgd intercept= [22.61401268]
Manual Intercept= [22.29312088]
In [358]: res
Out [358]:
                                 alpha lr_rate_variation init_lr_rate power_t n_iter
            sno
                         algo
                               0.0001
                                                                   0.01
                                                                            0.25
          0
              1
                 SGDRegressor
                                                constant
                                                                                      1
          1
              2
                   manual sgd 0.0001
                                                                   0.01
                                                                            0.25
                                                                                      1
                                                constant
          2
              3
                                                                            0.25
                SGDRegressor 0.0001
                                                                   0.01
                                                                                    100
                                                constant
          3
              4
                                                                            0.25
                   manual sgd 0.0001
                                                                   0.01
                                                                                    100
                                                constant
          4
              5 SGDRegressor
                              0.0001
                                                constant
                                                                   0.01
                                                                            0.25
                                                                                   1000
          5
                   manual sgd
                               0.0001
                                                constant
                                                                   0.01
                                                                            0.25
                                                                                   1000
              7 SGDRegressor
                               0.0001
                                                constant
                                                                   0.01
                                                                            0.25 10000
                  error
          0
              32.689925
             581.154787
          1
              32.555806
          3
              42.380920
          4
              27.950880
          5
              29.461332
          6
              27.774537
```

### Observe: Elegent and fast and Increasing iterations reduces errors for manual sgd.