sgd_imp_final

September 7, 2018

1 Objective- Implement SGD to Linear Regression

1.1 About the dataset-

1.2 Boston House Prices dataset

1.3 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 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.

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 of Machine Learning, 236-243, University of Massachusetts, Amherst. Morgan Kaufmann.
- many more! (see http://archive.ics.uci.edu/ml/datasets/Housing)

In [76]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [77]:
```
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.cross_validation import train_test_split
```

In [78]:
```
# loading boston datasets
from sklearn.datasets import load_boston
import pandas as pd
boston=load_boston()
```

In [79]:
```
# spliting the data into train and test

pd_boston=pd.DataFrame(data=boston.data)
price=boston.target
train_data, test_data, train_y, test_y=train_test_split(pd_boston, price, test_size=0.3
```

In [80]:
```
# applying column standardization on train and test data

s=StandardScaler()
train_data=s.fit_transform(np.array(train_data))
test_data=s.transform(np.array(test_data))
```

In [81]:
```
#preparing training data for manual sgd regressor
manual_train=pd.DataFrame(data=train_data)
manual_train['price']=train_y
```

In [82]:
```
manual_train.head(3)
```

Out[82]:
```
          0         1         2         3         4         5         6  \
0  0.911839 -0.502419  1.072305 -0.256978  1.633548  0.486034  0.962774
1 -0.411727 -0.502419 -1.129795 -0.256978 -0.552451  1.028078  0.668619
2  0.124583 -0.502419  1.072305 -0.256978  1.441946 -3.913414  0.725324
```

```
           7         8         9        10        11        12  price
0 -0.823477  1.655334  1.552100  0.808078 -2.842959  1.523203   13.4
1 -0.183274 -0.871371 -0.802704 -0.304174  0.427436 -0.995240   23.6
2 -1.075955  1.655334  1.552100  0.808078 -0.053353 -0.765646   27.5
```

In [83]:
```
# converting to numpy array, which will be available for both SGDRegressor of sklearn a
test_data=np.array(test_data)
test_y=np.array(test_y)
```

In [84]:
```
results=pd.DataFrame(columns=['sno', 'algo', 'alpha', 'lr_rate_variation', 'init_lr_rat
```

2 Experiment-1 ----SGDRegressor vs manual sgd

- fixing initial learning rate to 0.01, and making it constant and changing number of iteration

In [85]:
```
b_diff=[]
w_num=[]
```

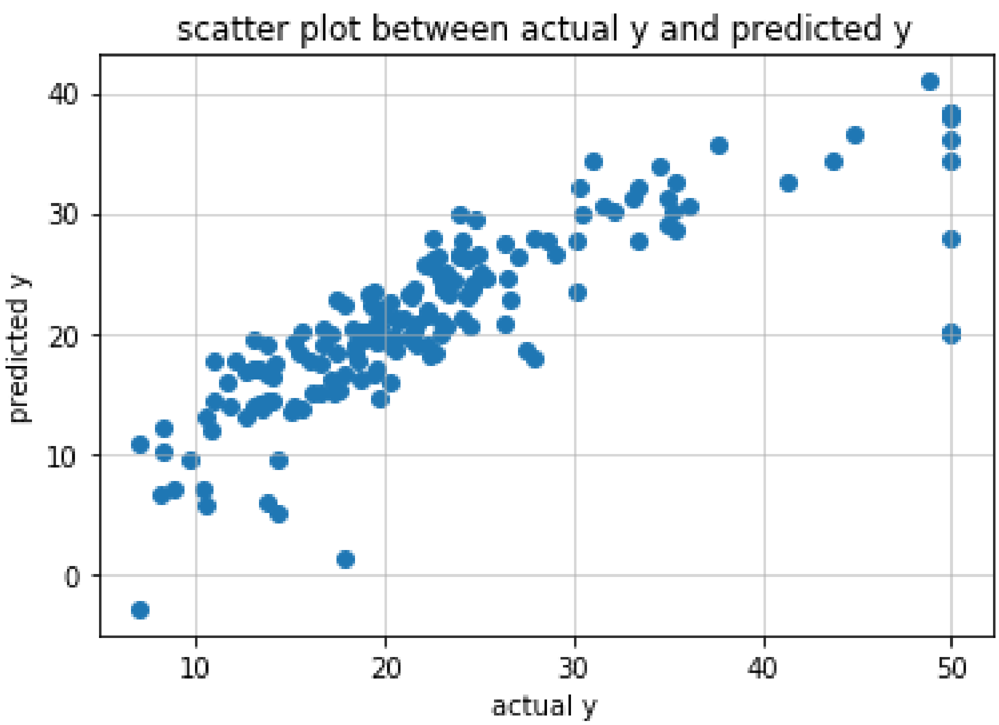
In [86]:
```
import seaborn as sns
import numpy as np
from sklearn.linear_model import SGDRegressor
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
%matplotlib inline
```

In [87]:
```
#the functioning of this function is to use sklearn SGDRegressor and predict the price
#this function takes alpha, learning rate variation , initial learning rate(eta0), numb
#this function returns weight, intercept and mean squared error
def sklearn_sgd(alpha, lr_rate_variation, eta0=0.01, power_t=0.25, n_iter=100, train_da
    clf=SGDRegressor(alpha=alpha, penalty=None, learning_rate=lr_rate_variation, eta0=e
    clf.fit(train_data, train_y)
    y_pred=clf.predict(test_data)

    #scatter plot
    plt.scatter(test_y,y_pred)
    plt.title('scatter plot between actual y and predicted y')
    plt.xlabel('actual y')
    plt.ylabel('predicted y')
    plt.grid(b=True, linewidth=0.5)
    plt.show()
    print('**********************************************************')

    #kdeplot


    sgd_error=mean_squared_error(test_y,y_pred)
    print('mean sq error=', sgd_error)
```

```
print('number of iteration=', n_iter)

return clf.coef_, clf.intercept_, sgd_error
```

2.0.1 1.1 SGDRegressor, n_iter=1, lr_rate=0.01, lr_rate_variation='constant'

```
In [88]: w_sgd, b_sgd, error_sgd=sklearn_sgd(alpha=0.0001, lr_rate_variation='constant', eta0=0.
```




```
*************************************************************
mean sq error= 32.4694319228102
number of iteration= 1
```

```
In [89]: new=[1, 'SGDRegressor', 0.0001, 'constant', 0.01, 0.25, 1, error_sgd]
         results.loc[0]=new
```

2.0.2 1.2 manual sgd, n_iter=1, lr_rate=0.01, lr_rate_variation='constant'

```
In [90]: # this function is a simple implementation of sgd to linear regression, here we didn't
         # we need to provide the pandas data with price, initial learning rate , and learning r
         # here we have implemented constant learning rate and invscaling learning rate
         # checking the significant difference in loss i.e stopping condition might take lots of
         # this function returns weight (w) and bias (b)
```

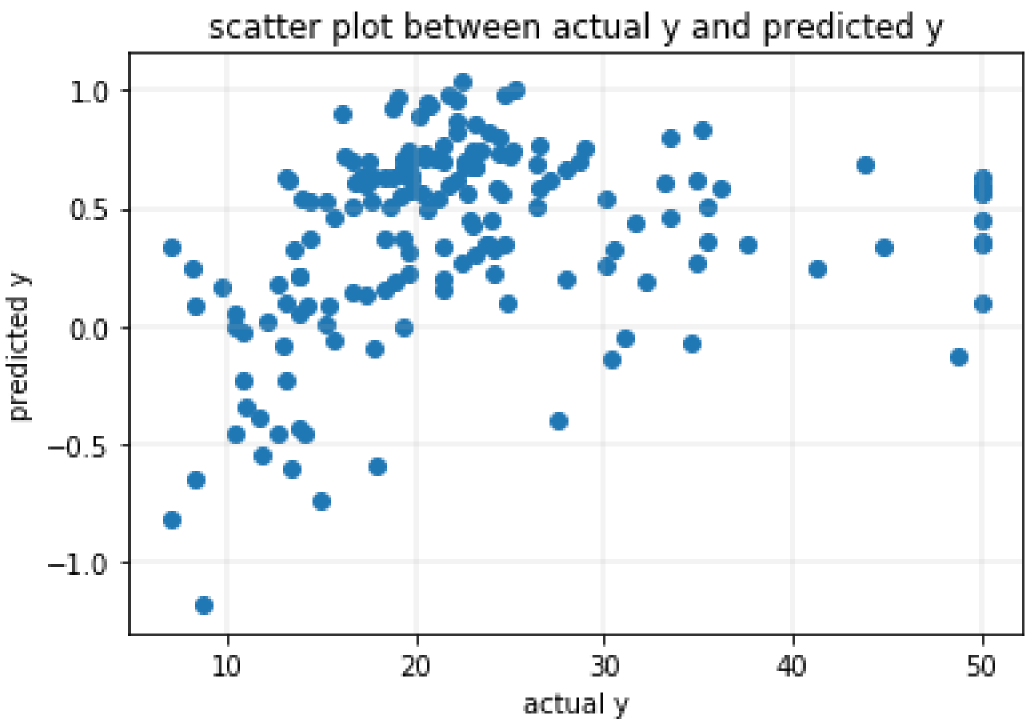
```
# here we have taken sgd with batch size=10
def manual_fit(X, lr_rate_variation, alpha=0.0001, lr_rate=0.01, power_t=0.25, n_iter=1
    w_new=np.zeros(shape=(1,13))
    b_new=0
    t=1
    r=lr_rate

    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_(test_data,y_pred):
```

```
    #scatter plot
    plt.scatter(test_y,y_pred)
    plt.grid(b=True, linewidth=0.3)
    plt.title('scatter plot between actual y and predicted y')
    plt.xlabel('actual y')
    plt.ylabel('predicted y')
    plt.show()
    print('**************************************************************')



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

    return manual_error
```

```
In [91]: w, b=manual_fit(X=manual_train, lr_rate_variation='constant' , n_iter=1)
```

```
In [92]: y_pred=pred(test_data, w=w, b=b)
```

```
In [93]: manual_error=plot_(test_data,y_pred)
```




```
**************************************************************
error= 581.624165381566
```

```
In [94]: new=[2, 'manual sgd', 0.0001, 'constant', 0.01, 0.25, 1, manual_error]
         results.loc[1]=new

In [95]: print('sklearn sgd weight---\n',w_sgd)
         print('******************************************************************************
         print('manual sgd weight---\n',w)
```

```
sklearn sgd weight---
 [-0.77008046  0.42065046 -0.25558241 -0.24505272 -0.66806225  2.91767122
 -0.36144425 -2.17215701  0.76521321 -0.58565128 -2.26093013  0.66030604
 -3.02096064]
*********************************************************************************
manual sgd weight---
 [[-0.08355681 -0.08929878  0.03343449  0.06242365 -0.03662863 -0.1098788
  -0.11197472 -0.04678205 -0.06058561 -0.11706459  0.14065918  0.15133454
  -0.11639935]]
```

```
In [96]: 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)
```

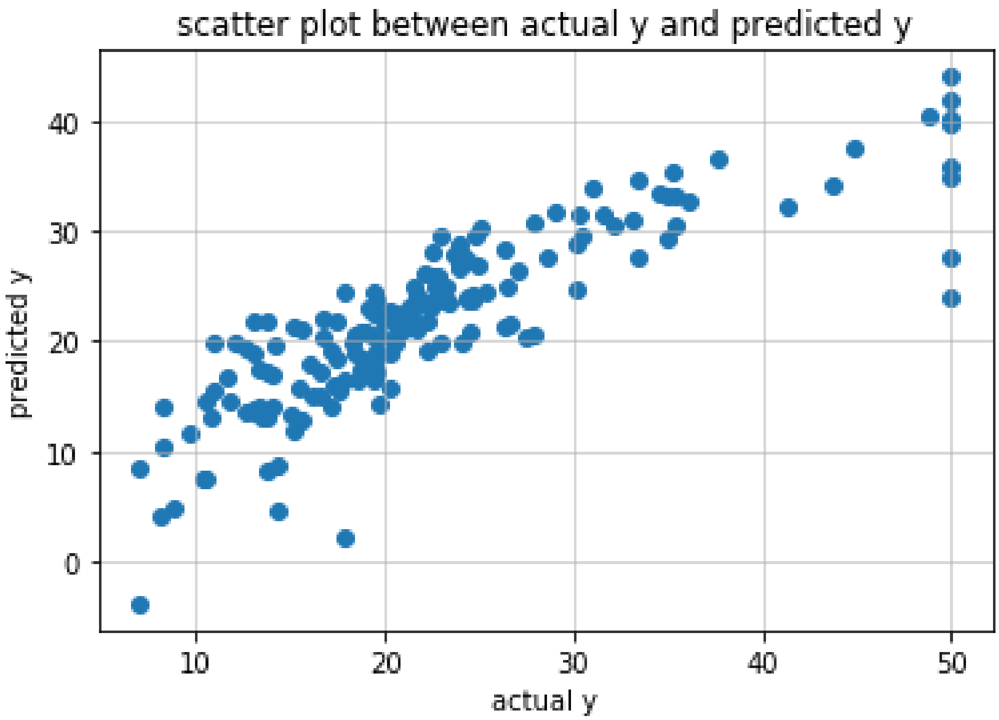
```
number of points more than 30% in percent= 13
```

```
In [97]: print('sklearn sgd intercept=',b_sgd)
         print('manual sgd intercept=',b)
         b_diff.append(abs(b_sgd-b))
```

```
sklearn sgd intercept= [21.75070444]
manual sgd intercept= [0.4254]
```

2.0.3 1.3 SGDRegressor, n_iter=100, lr_rate=0.01, lr_rate_variation='constant'

```
In [98]: w_sgd, b_sgd, error_sgd=sklearn_sgd(alpha=0.0001, lr_rate_variation='constant', eta0=0.
```

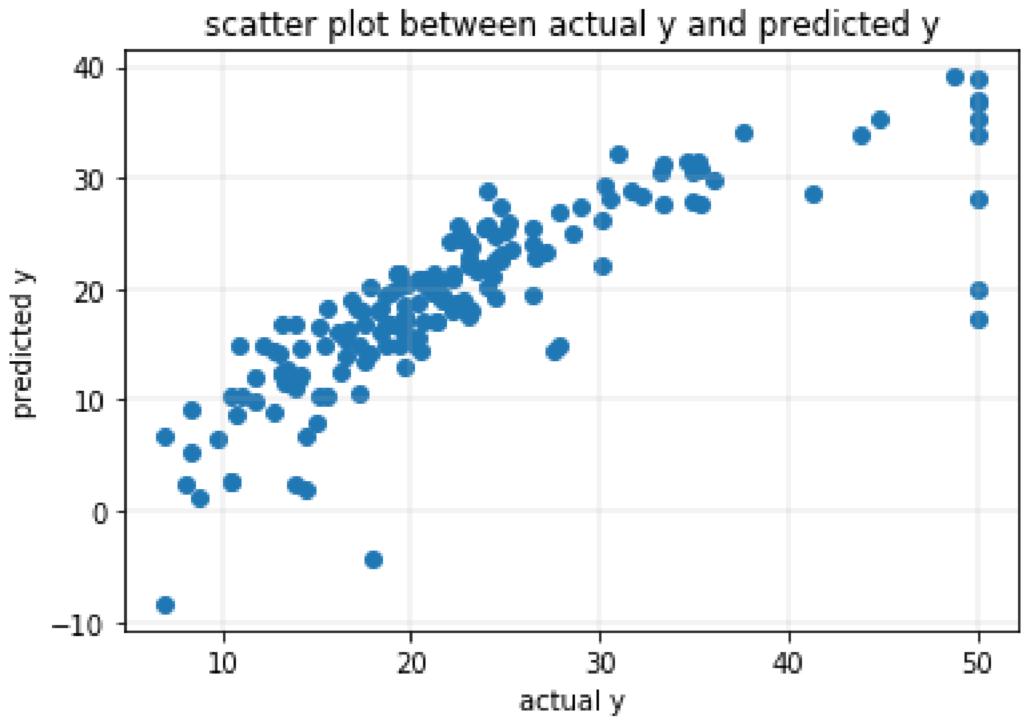



```
*************************************************************
mean sq error= 26.421014310724512
number of iteration= 100
```

```
In [99]: new=[3, 'SGDRegressor', 0.0001, 'constant', 0.01, 0.25, 100, error_sgd]
         results.loc[2]=new
```

2.0.4 1.4 manual sgd, n_iter=100, lr_rate=0.01, lr_rate_variation='constant'

```
In [100]: w, b=manual_fit(X=manual_train, lr_rate_variation='constant' , n_iter=100)
          y_pred=pred(test_data, w=w, b=b)
          manual_error=plot_(test_data,y_pred)
```




```
****************************************************************
error= 40.9308974983889
```

```
In [101]: print('sklearn sgd weight---\n',w_sgd)
          print('*******************************************************************************
          print('manual sgd weight---\n',w)
```

```
sklearn sgd weight---
 [-1.1371407   0.99874755  0.14161615  0.82448679 -1.40394899  2.80182323
 -0.33442715 -2.83317463  3.18843639 -1.92079597 -1.94073416  1.06314335
 -3.28030336]
**********************************************************************************
manual sgd weight---
 [[-0.89886694  0.29481971 -1.19493164  0.37709722 -0.18391089  3.02874083
  -0.64268846 -2.17634777  0.49062769 -0.45743251 -1.63743473  1.11168167
  -3.19637659]]
```

```
In [102]: 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)
```

```
number of points more than 30% in percent= 8
```

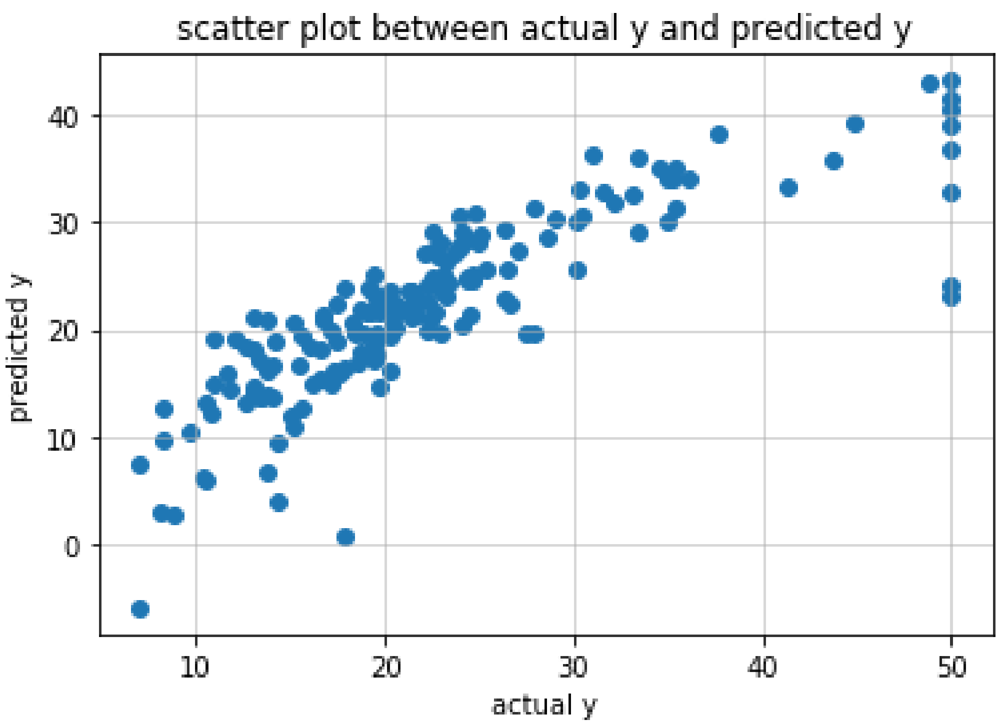
```
In [103]: print('sklearn sgd intercept=',b_sgd)
          print('manual sgd intercept=',b)
          b_diff.append(abs(b_sgd-b))
```

```
sklearn sgd intercept= [22.63004335]
manual sgd intercept= [19.81853613]
```

```
In [104]: new=[4, 'manual sgd', 0.0001, 'constant', 0.01, 0.25, 100, manual_error]
          results.loc[3]=new
```

2.0.5 1.5 SGDRegressor, n_iter=1000, lr_rate=0.01, lr_rate_variation='constant'

```
In [105]: w_sgd, b_sgd, error_sgd=sklearn_sgd(alpha=0.0001, lr_rate_variation='constant', eta0=0
```

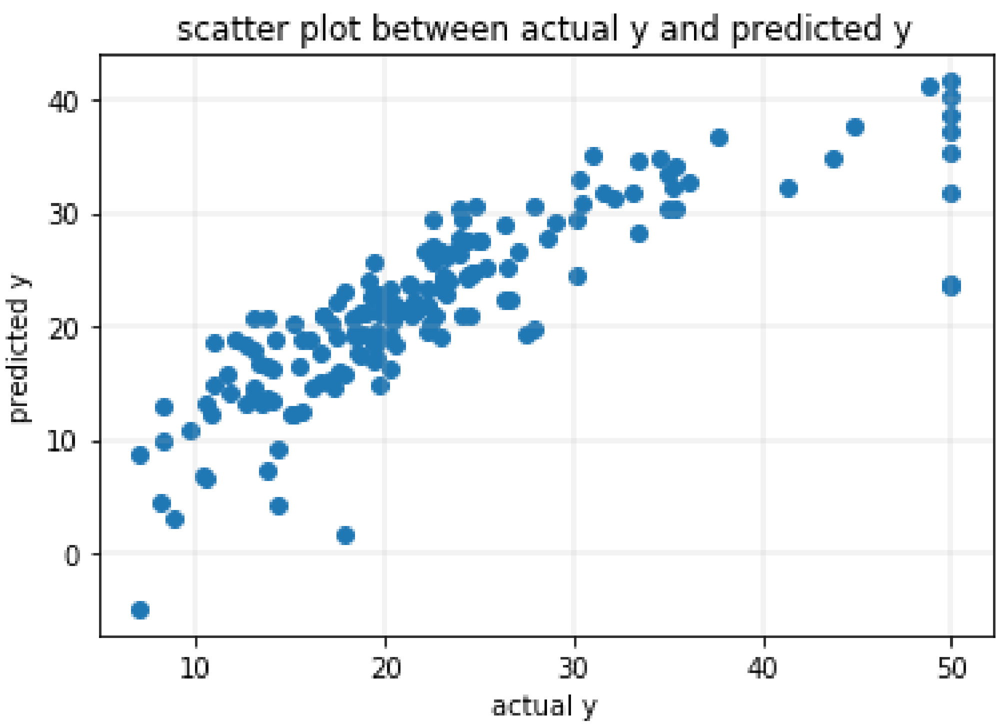



```
************************************************************
mean sq error= 27.937633160007227
number of iteration= 1000
```

```
In [106]: new=[5, 'SGDRegressor', 0.0001, 'constant', 0.01, 0.25, 1000, error_sgd]
          results.loc[4]=new
```

2.0.6 1.6 manual sgd, n_iter=1000, lr_rate=0.01, lr_rate_variation='constant'

```
In [107]: w, b=manual_fit(X=manual_train, lr_rate_variation='constant' , n_iter=1000)
          y_pred=pred(test_data, w=w, b=b)
          manual_error=plot_(test_data,y_pred)
```




```
************************************************************
error= 28.715571769031584
```

```
In [108]: print('sklearn sgd weight---\n',w_sgd)
          print('****************************************************************************
          print('manual sgd weight---\n',w)
```

```
sklearn sgd weight---
 [-1.34537691  0.8897758  -0.1886713   0.183283   -1.3000193   2.9597542
 -0.22311329 -2.87684979  3.04540382 -2.22196887 -2.19830817  0.99274593
 -3.39516832]
******************************************************************************
manual sgd weight---
 [[-1.32145342  0.84111238 -0.50082887  0.09970994 -1.36476836  2.56922172
```

```
  -0.37830626 -2.87731518  2.46793651 -1.22291347 -2.26022257  0.9423407
  -3.35226073]]
```

```
In [109]: 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)
```

```
number of points more than 30% in percent= 4
```

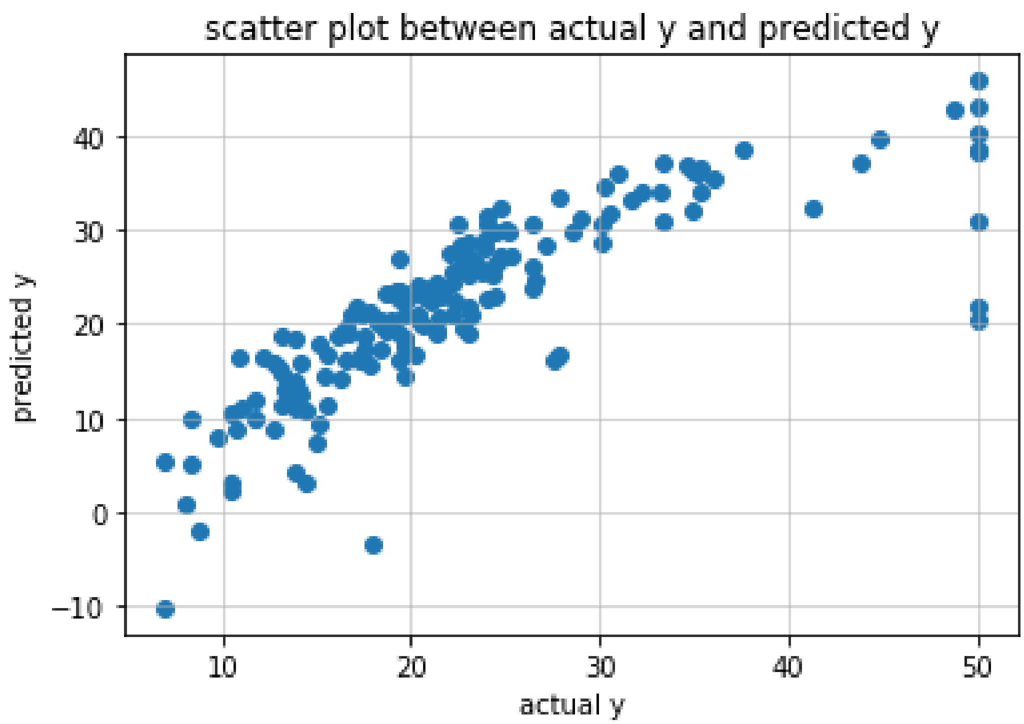
```
In [110]: print('sklearn sgd intercept=',b_sgd)
          print('manual sgd intercept=',b)
          b_diff.append(abs(b_sgd-b))
```

```
sklearn sgd intercept= [22.88083494]
manual sgd intercept= [22.53417493]
```

```
In [111]: new=[6, 'manual sgd', 0.0001, 'constant', 0.01, 0.25, 1000, manual_error]
          results.loc[5]=new
```

2.0.7 1.7 SGDRegressor, n_iter=10000, lr_rate=0.01, lr_rate_variation='constant'

```
In [112]: w_sgd, b_sgd, error_sgd=sklearn_sgd(alpha=0.0001, lr_rate_variation='constant', eta0=0
```

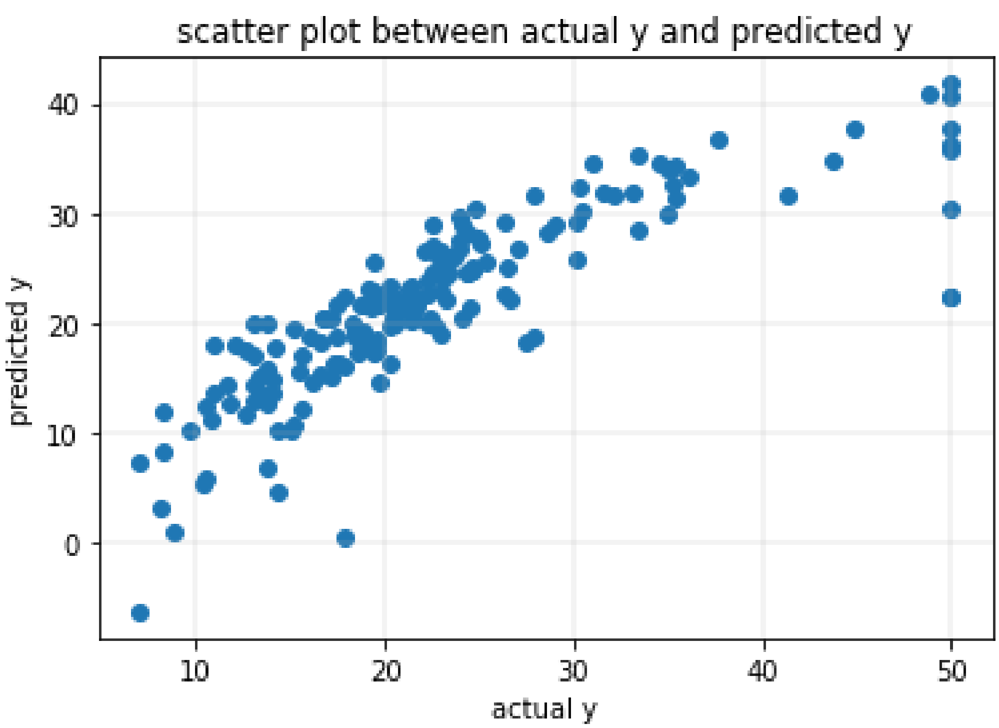


```
***********************************************************
mean sq error= 33.450943163385986
number of iteration= 10000
```

```
In [113]: new=[7, 'SGDRegressor', 0.0001, 'constant', 0.01, 0.25, 10000, error_sgd]
          results.loc[6]=new
```

2.0.8 1.8 manual sgd, n_iter=10000, lr_rate=0.01, lr_rate_variation='constant'

```
In [114]: w, b=manual_fit(X=manual_train, lr_rate_variation='constant' , n_iter=10000)
          y_pred=pred(test_data, w=w, b=b)
          manual_error=plot_(test_data,y_pred)
```




```
**************************************************************
error= 29.756766863714148
```

```
In [115]: print('sklearn sgd weight---\n',w_sgd)
          print('*******************************************************************************
          print('manual sgd weight---\n',w)
```

```
sklearn sgd weight---
 [-1.36094479  0.89764471 -0.39733237  0.31477308 -1.65340069  2.96797705
 -0.39234886 -2.54215416  2.5585151  -2.67070389 -2.05238445  1.42629492
 -3.37907957]
********************************************************************************
manual sgd weight---
 [[-1.37796125  0.96283919 -0.15591904  0.02522011 -1.55036088  2.65693101
  -0.37272644 -2.8043049   2.90950702 -2.28167746 -2.04179418  1.13504042
  -3.15273839]]
```

In [116]:
```python
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)
```

```
number of points more than 30% in percent= 2
```

In [117]:
```python
print('sklearn sgd intercept=',b_sgd)
print('manual sgd intercept=',b)
b_diff.append(abs(b_sgd-b))
```

```
sklearn sgd intercept= [22.68195516]
manual sgd intercept= [22.33865171]
```

In [118]:
```python
new=[8, 'manual sgd', 0.0001, 'constant', 0.01, 0.25, 10000, manual_error]
results.loc[7]=new
```

In [119]:
```python
import tabulate
table1 = [['n_iter', 'no. of points>30% in w', 'difference in intercept'],
          [1,w_num[0], b_diff[0]],
          [100, w_num[1], b_diff[1]],
          [1000, w_num[2], b_diff[2]],
          [10000, w_num[3], b_diff[3]]]
```

In [120]:
```python
print(tabulate.tabulate(table1, tablefmt='fancy_grid'))
```

n_iter	no. of points>30% in w	difference in intercept
1	13	[21.32530444]
100	8	[2.81150721]

```
1000     4                        [0.34666002]

10000    2                        [0.34330345]
```

```
In [121]: results
```

```
Out[121]:   sno          algo   alpha lr_rate_variation  init_lr_rate  power_t n_iter  \
          0   1  SGDRegressor  0.0001          constant          0.01     0.25      1
          1   2    manual sgd  0.0001          constant          0.01     0.25      1
          2   3  SGDRegressor  0.0001          constant          0.01     0.25    100
          3   4    manual sgd  0.0001          constant          0.01     0.25    100
          4   5  SGDRegressor  0.0001          constant          0.01     0.25   1000
          5   6    manual sgd  0.0001          constant          0.01     0.25   1000
          6   7  SGDRegressor  0.0001          constant          0.01     0.25  10000
          7   8    manual sgd  0.0001          constant          0.01     0.25  10000

                  error
          0   32.469432
          1  581.624165
          2   26.421014
          3   40.930897
          4   27.937633
          5   28.715572
          6   33.450943
          7   29.756767
```

2.1 Observation-

- we have fixed learning rate and lr_rate_variation, and only changing n_iter
- as we can see , by increasing manual sgd n_iter , error reducing.
- with increase in iteration the number of element manual sgd weight and SGDRegressor weight is going to be more similar
- with increasing the iteration number the intercept value also coming closer

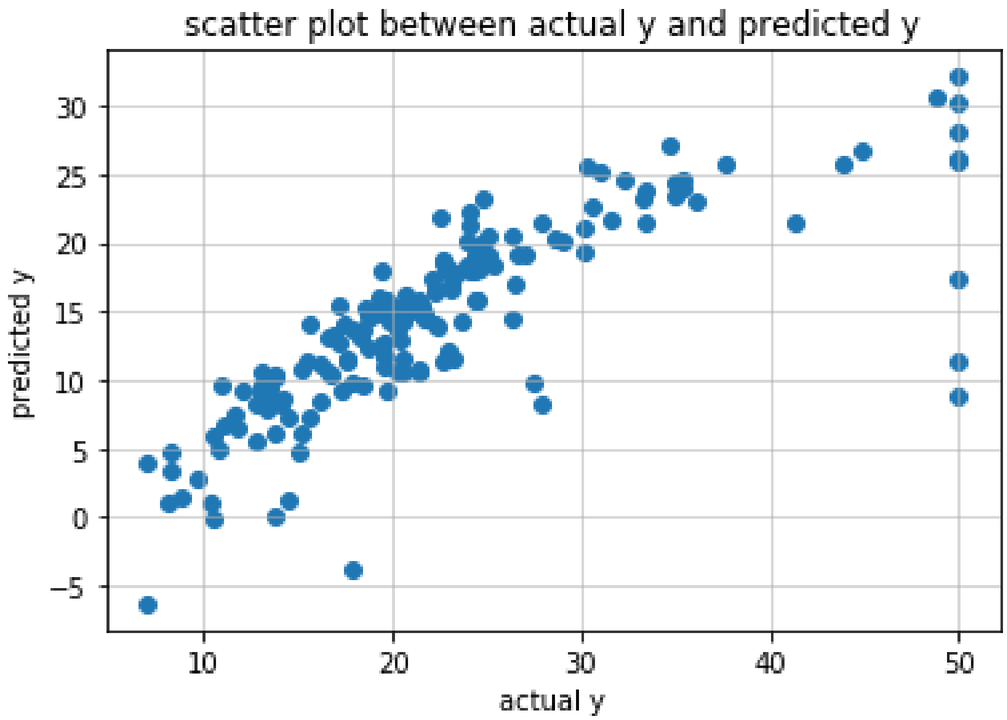
3 Experiment 2-- using 'optimal' learning rate

- using optimal learning rate variation and changing the n_iter

```
In [122]: b1_diff=[]
          w1_num=[]
```

3.0.1 2.1 SGDRegressor, n_iter=1, lr_rate=0.01, lr_rate_variation='invscaling'

```
In [123]: w_sgd, b_sgd, error_sgd=sklearn_sgd(alpha=0.0001, lr_rate_variation='invscaling', eta0
```

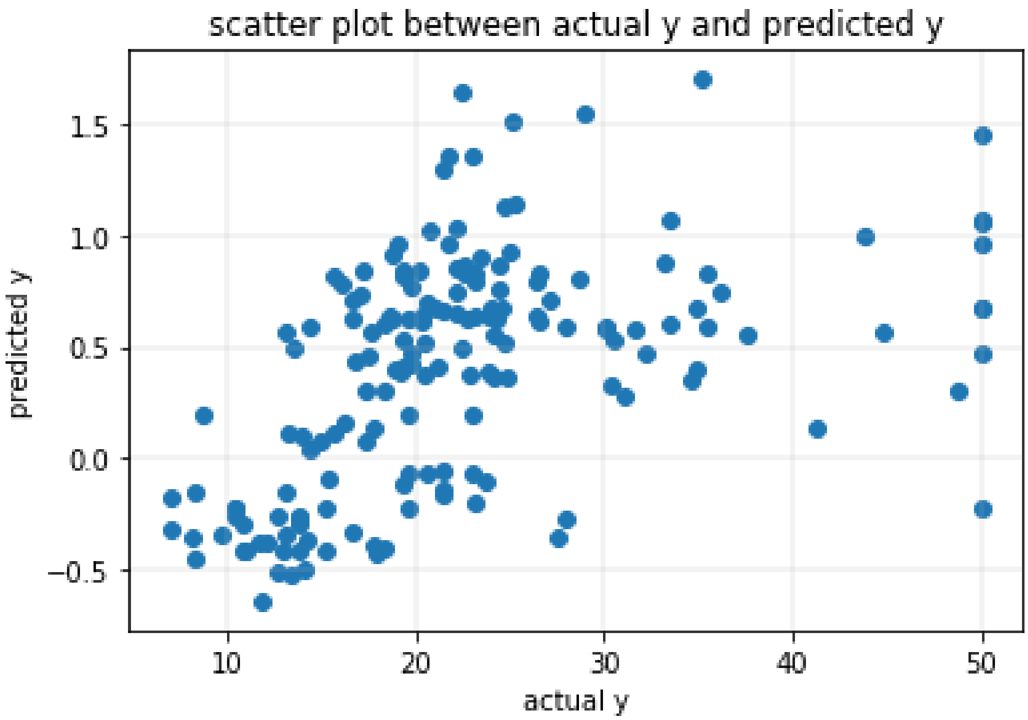



```
************************************************************
mean sq error= 101.58053374738331
number of iteration= 1
```

In [124]:
```
new=[9, 'SGDRegressor', 0.0001, 'invscaling', 0.01, 0.25, 1, error_sgd]
results.loc[8]=new
```

3.0.2 2.2 manual sgd, n_iter=1, lr_rate=0.01, lr_rate_variation='invscaling'

In [125]:
```
w, b=manual_fit(X=manual_train, lr_rate_variation='invscaling' , n_iter=1)
y_pred=pred(test_data, w=w, b=b)
manual_error=plot_(test_data,y_pred)
```




```
**************************************************************
error= 578.8764857796865
```

```
In [126]: new=[10, 'manual sgd', 0.0001, 'invscaling', 0.01, 0.25, 1, manual_error]
          results.loc[9]=new
```

```
In [127]: print('sklearn sgd weight---\n',w_sgd)
          print('********************************************************************************
          print('manual sgd weight---\n',w)
```

```
sklearn sgd weight---
 [-0.46854321  0.4724331  -0.6496289   0.16486177 -0.21711983  2.65847285
 -0.49965287 -0.83211868 -0.06008395 -0.85214502 -1.6239637   0.62380042
 -1.84834241]
*********************************************************************************
manual sgd weight---
 [[ 0.09207488 -0.14637757 -0.09939261  0.22252834 -0.06329277 -0.01724493
  -0.12158593  0.0213669  -0.13893235 -0.18303903  0.05256919  0.03641551
  -0.05460941]]
```

```
In [128]: percent=abs((w_sgd-w)/w)*100
          cnt=0
```

```
for i in range(13):
    if (percent[0][i]>30):
        cnt+=1
w1_num.append(cnt)
print('number of points more than 30% in percent=',cnt)
```

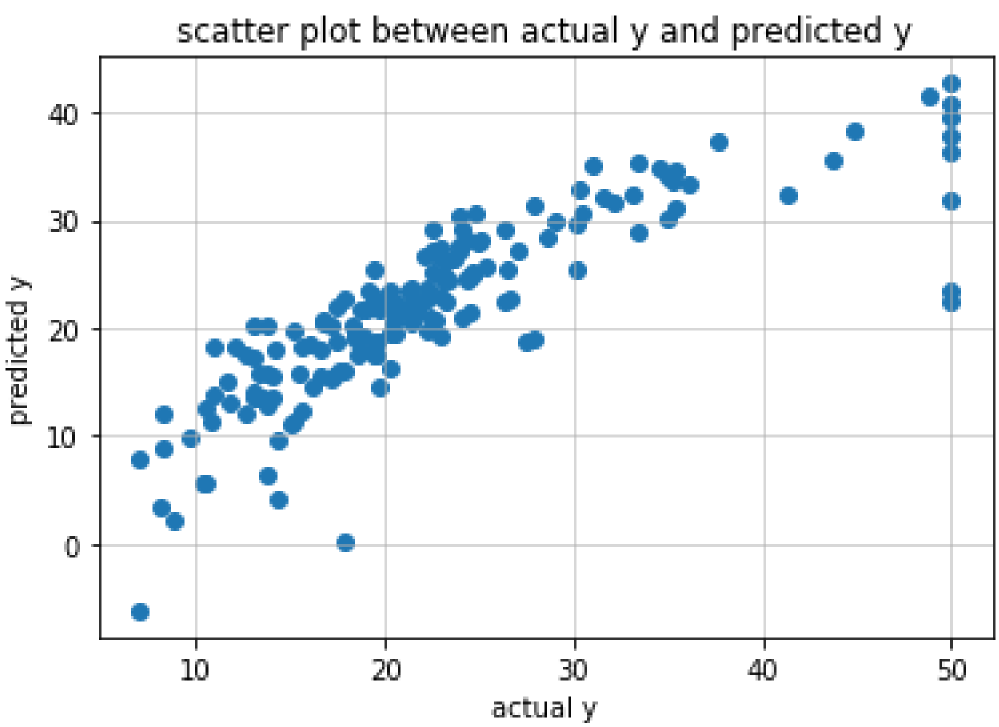
```
number of points more than 30% in percent= 12
```

```
In [129]: print('sklearn sgd intercept=',b_sgd)
          print('manual sgd intercept=',b)
          b1_diff.append(abs(b_sgd-b))
```

```
sklearn sgd intercept= [14.80617437]
manual sgd intercept= [0.4158]
```

3.0.3 2.3 SGDRegressor, n_iter=100, lr_rate=0.01, lr_rate_variation='invscaling'

```
In [130]: w_sgd, b_sgd, error_sgd=sklearn_sgd(alpha=0.0001, lr_rate_variation='invscaling', eta0
```

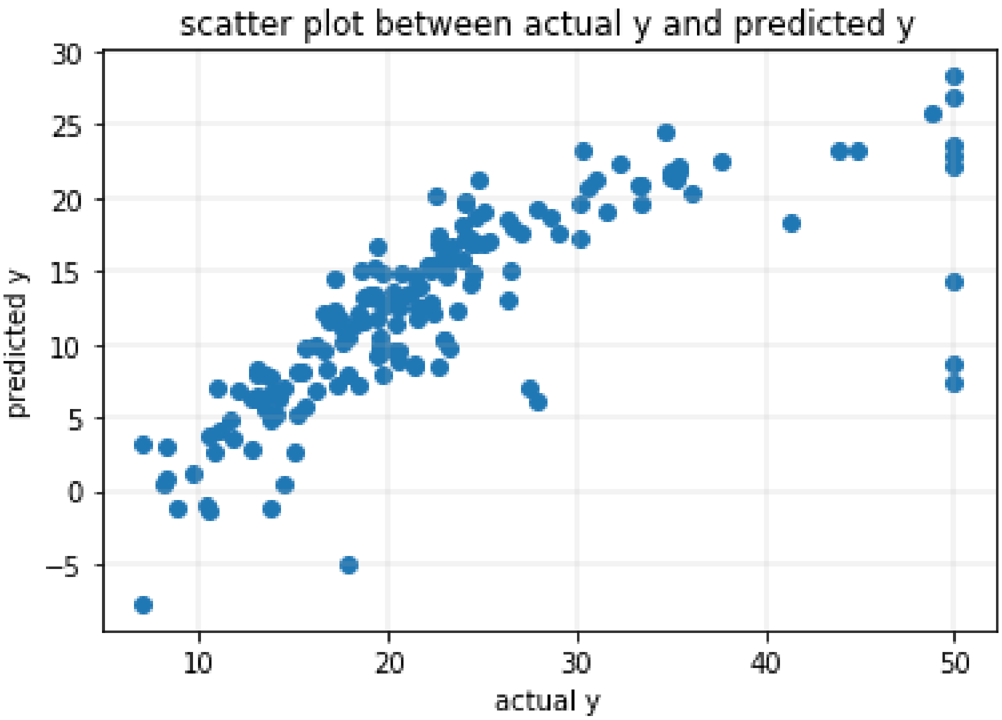



```
**********************************************************
mean sq error= 28.520739561292004
number of iteration= 100
```

```
In [131]: new=[11, 'SGDRegressor', 0.0001, 'invscaling', 0.01, 0.25, 100, error_sgd]
          results.loc[10]=new
```

3.0.4 2.4 manual sgd, n_iter=100, lr_rate=0.01, lr_rate_variation='invscaling'

```
In [132]: w, b=manual_fit(X=manual_train, lr_rate_variation='invscaling' , n_iter=100)
          y_pred=pred(test_data, w=w, b=b)
          manual_error=plot_(test_data,y_pred)
```




```
**************************************************************
error= 141.29104924426753
```

```
In [133]: new=[12, 'manual sgd', 0.0001, 'invscaling', 0.01, 0.25, 100, manual_error]
          results.loc[11]=new

In [134]: print('sklearn sgd weight---\n',w_sgd)
          print('*****************************************************************************
          print('manual sgd weight---\n',w)
```

```
sklearn sgd weight---
 [-1.28894266  0.83378893 -0.27388982  0.19259325 -1.48220185  2.818715
 -0.35469951 -2.78418868  2.62774407 -1.87686818 -2.1187219   1.05589147
 -3.32980906]
```

```
********************************************************************************
manual sgd weight---
 [[-0.47336964  0.27569868 -0.66478012  0.07329669 -0.70365531  2.17159412
  -0.45335688 -0.49509334 -0.27766142 -0.54942043 -1.43280873  0.72796356
  -1.77741166]]
```

```
In [135]: percent=abs((w_sgd-w)/w)*100
          cnt=0
          for i in range(13):
              if (percent[0][i]>30):
                  cnt+=1
          w1_num.append(cnt)
          print('number of points more than 30% in percent=',cnt)
```

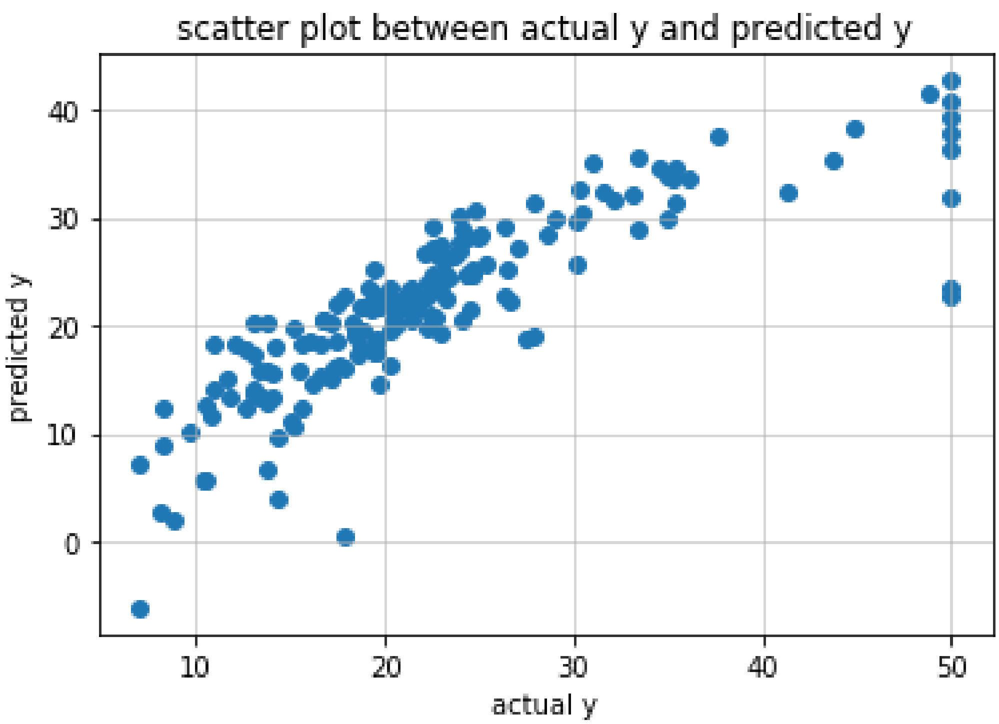
```
number of points more than 30% in percent= 11
```

```
In [136]: print('sklearn sgd intercept=',b_sgd)
          print('manual sgd intercept=',b)
          b1_diff.append(abs(b_sgd-b))
```

```
sklearn sgd intercept= [22.54763312]
manual sgd intercept= [12.82409838]
```

3.0.5 2.5 SGDRegressor, n_iter=1000, lr_rate=0.01, lr_rate_variation='invscaling'

```
In [137]: w_sgd, b_sgd, error_sgd=sklearn_sgd(alpha=0.0001, lr_rate_variation='invscaling', eta0
```

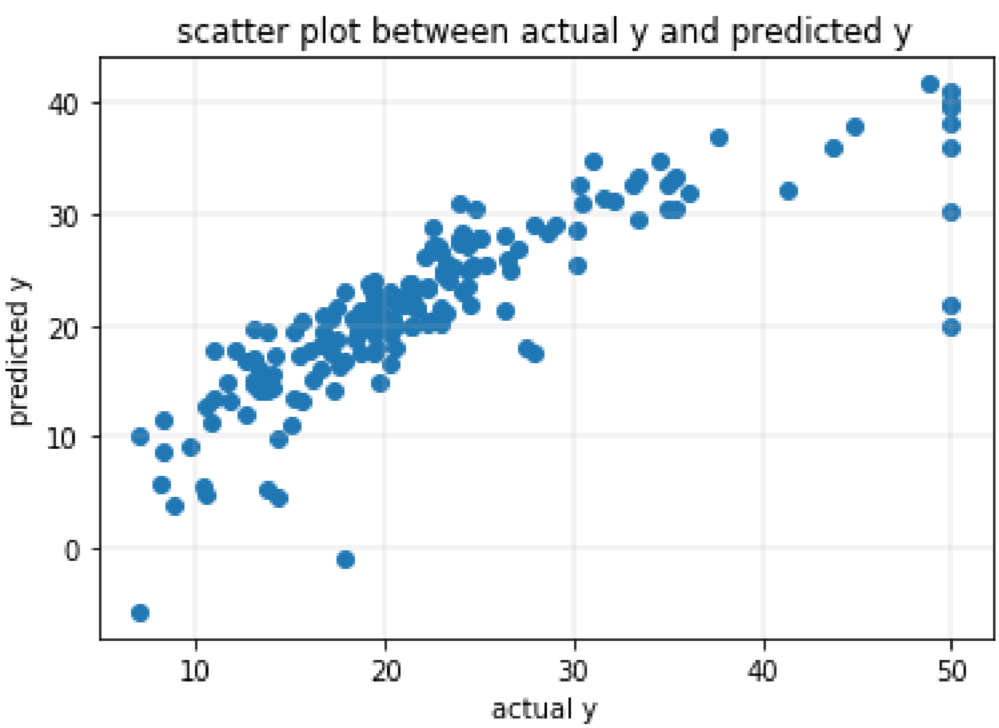


```
***********************************************************
mean sq error= 28.486745880890606
number of iteration= 1000
```

```
In [138]: new=[13, 'SGDRegressor', 0.0001, 'invscaling', 0.01, 0.25, 1000, error_sgd]
          results.loc[12]=new
```

3.0.6 2.6 manual sgd, n_iter=1000, lr_rate=0.01, lr_rate_variation='invscaling'

```
In [139]: w, b=manual_fit(X=manual_train, lr_rate_variation='invscaling' , n_iter=1000)
          y_pred=pred(test_data, w=w, b=b)
          manual_error=plot_(test_data,y_pred)
```




```
**************************************************************
error= 30.341260603855936
```

```
In [140]: new=[14, 'manual sgd', 0.0001, 'invscaling', 0.01, 0.25, 1000, manual_error]
          results.loc[13]=new
```

```
In [141]: print('sklearn sgd weight---\n',w_sgd)
          print('*********************************************************************************
          print('manual sgd weight---\n',w)
```

```
sklearn sgd weight---
 [-1.30942253  0.8574275  -0.16241595  0.18699791 -1.48256772  2.77786572
 -0.31772189 -2.77676449  2.98086019 -2.26890425 -2.13146151  1.05516787
 -3.32856774]
********************************************************************************
manual sgd weight---
 [[-1.00402039  0.34507519 -0.63875838  0.18570054 -0.60304093  3.14183048
  -0.37921798 -1.9099759   0.75611146 -0.47484811 -1.93973178  0.97591047
  -3.12890969]]
```

```
In [142]: percent=abs((w_sgd-w)/w)*100
          cnt=0
          for i in range(13):
              if (percent[0][i]>30):
                  cnt+=1
          w1_num.append(cnt)
          print('number of points more than 30% in percent=',cnt)
```

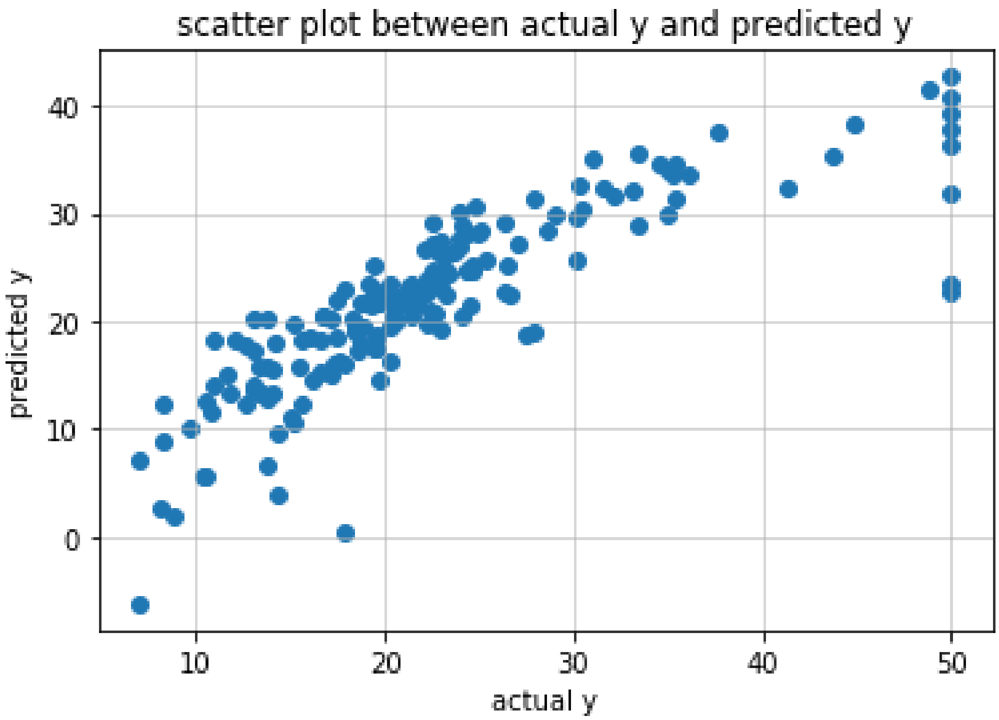
```
number of points more than 30% in percent= 7
```

```
In [143]: print('sklearn sgd intercept=',b_sgd)
          print('manual sgd intercept=',b)
          b1_diff.append(abs(b_sgd-b))
```

```
sklearn sgd intercept= [22.53830622]
manual sgd intercept= [22.34256084]
```

3.0.7 2.7 SGDRegressor, n_iter=10000, lr_rate=0.01, lr_rate_variation='invscaling'

```
In [144]: w_sgd, b_sgd, error_sgd=sklearn_sgd(alpha=0.0001, lr_rate_variation='invscaling', eta0
```

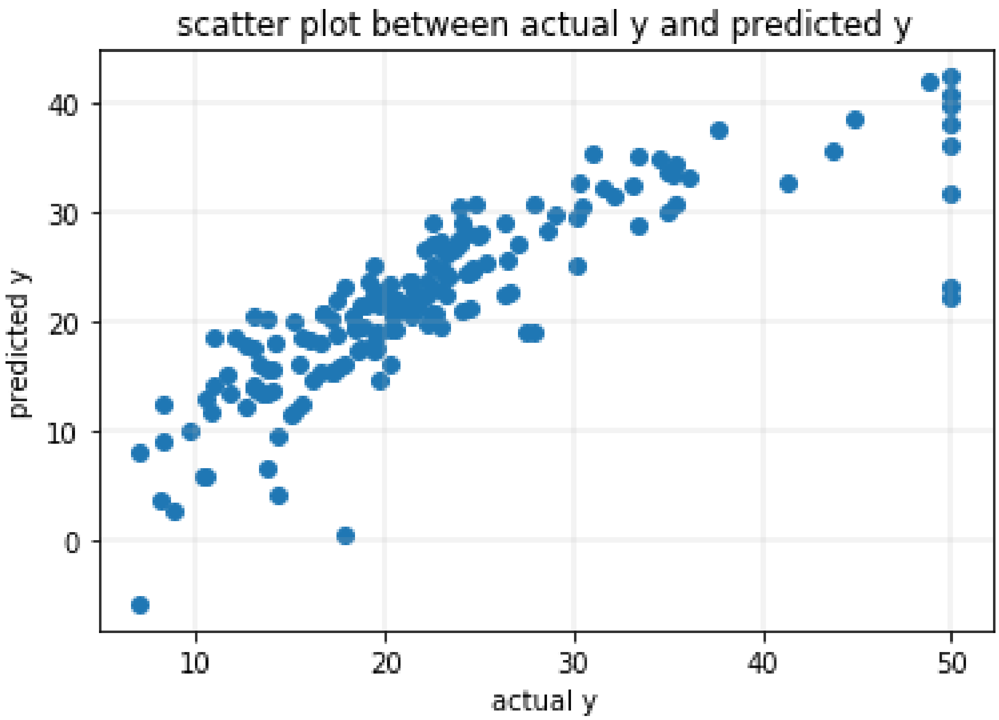



```
*************************************************************
mean sq error= 28.49430793794667
number of iteration= 10000
```

```
In [145]: new=[15, 'SGDRegressor', 0.0001, 'invscaling', 0.01, 0.25, 10000, error_sgd]
          results.loc[14]=new
```

3.0.8 2.8 manual sgd, n_iter=10000, lr_rate=0.01, lr_rate_variation='invscaling'

```
In [146]: w, b=manual_fit(X=manual_train, lr_rate_variation='invscaling' , n_iter=10000)
          y_pred=pred(test_data, w=w, b=b)
          manual_error=plot_(test_data,y_pred)
```




```
******************************************************************
error= 28.406428232673615
```

```
In [147]: new=[16, 'manual sgd', 0.0001, 'invscaling', 0.01, 0.25, 10000, manual_error]
          results.loc[15]=new
```

```
In [148]: print('sklearn sgd weight---\n',w_sgd)
          print('********************************************************************************
          print('manual sgd weight---\n',w)
```

```
sklearn sgd weight---
 [-1.31056959  0.85903795 -0.16178747  0.18803679 -1.48263168  2.78621625
 -0.32223626 -2.77652255  2.98167093 -2.26832894 -2.12989636  1.05575739
 -3.33035346]
*********************************************************************************
manual sgd weight---
 [[-1.2288143   0.77118322 -0.31242219  0.16356881 -1.39009861  2.8989614
  -0.30770978 -2.74835738  2.45079942 -1.65732448 -2.16402752  1.05292411
  -3.26737259]]
```

```
In [149]: percent=abs((w_sgd-w)/w)*100
          cnt=0
```

```
for i in range(13):
    if (percent[0][i]>30):
        cnt+=1
w1_num.append(cnt)
print('number of points more than 30% in percent=',cnt)
```

```
number of points more than 30% in percent= 2
```

```
In [150]: print('sklearn sgd intercept=',b_sgd)
          print('manual sgd intercept=',b)
          b1_diff.append(abs(b_sgd-b))
```

```
sklearn sgd intercept= [22.53724582]
manual sgd intercept= [22.56382067]
```

```
In [151]: results[8:]
```

```
Out[151]:    sno          algo   alpha lr_rate_variation  init_lr_rate  power_t n_iter  \
          8    9  SGDRegressor  0.0001        invscaling          0.01     0.25      1
          9   10    manual sgd  0.0001        invscaling          0.01     0.25      1
          10  11  SGDRegressor  0.0001        invscaling          0.01     0.25    100
          11  12    manual sgd  0.0001        invscaling          0.01     0.25    100
          12  13  SGDRegressor  0.0001        invscaling          0.01     0.25   1000
          13  14    manual sgd  0.0001        invscaling          0.01     0.25   1000
          14  15  SGDRegressor  0.0001        invscaling          0.01     0.25  10000
          15  16    manual sgd  0.0001        invscaling          0.01     0.25  10000

                   error
          8   101.580534
          9   578.876486
          10   28.520740
          11  141.291049
          12   28.486746
          13   30.341261
          14   28.494308
          15   28.406428
```

```
In [152]: import tabulate
          table2 = [['n_iter', 'no. of points>30% in w', 'difference in intercept'],
                    [1,w1_num[0], b1_diff[0]],
                    [100, w1_num[1], b1_diff[1]],
                    [1000, w1_num[2], b1_diff[2]],
                    [10000, w1_num[3], b1_diff[3]]]
          print(tabulate.tabulate(table2, tablefmt='fancy_grid'))
```

```
 n_iter   no. of points>30% in w   difference in intercept
```

1	12	[14.39037437]
100	11	[9.72353475]
1000	7	[0.19574538]
10000	2	[0.02657485]

3.0.9 Observation-

- by increasing iteration number, weights of SGDRegressor and manual sgd becomes more similar
- with increasing in n_iter, the difference in intercepts of SGDRegressor and manual sgd becomes lesser

3.1 Conclusion-

- we have taken boston house price dataset
- we prepared the data for training and testing
- we used column standardization
- we have SGDRegressor and manual sgd regressor implemented here
- we didn't use any regularization term
- we have taken 'constant' and 'invscaling' learning rate variation in SGDRegressor and the same in manual sgd regressor
- in both 'constant' and 'invscaling' implementation we have seen that with higher number of iteration , manual sgd seems similar to SGDRegressor
- in manual sgd regressor , error reduces with increasing in iteration number