Assignment1

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1 Assignment 1

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1.1 Q.No 1

Write python programs to implement linear regression using Stochastic GD, Batch GD, and mini-batch GD. Capture time needed to train the predict the models and compare each approach (Use data.csv).

1.1.1 Importing the required Libaries

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn import metrics
```

1.1.2 Gettting the Data

Reading the CSV file into pandas dataframe

[2]:
```
df = pd.read_csv('data/data.csv',header=None)
df.head()
```

[2]:

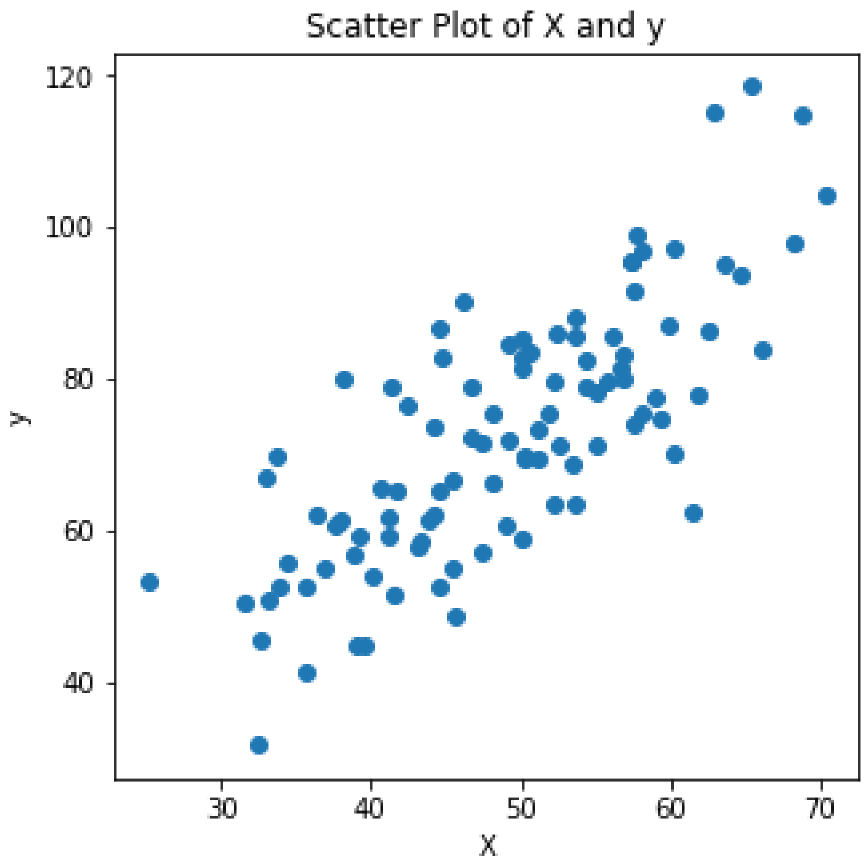
	0	1
0	32.502345	31.707006
1	53.426804	68.777596
2	61.530358	62.562382
3	47.475640	71.546632
4	59.813208	87.230925

Assigning first column as X(Independent Variable) and second column as y(Dependent Variable)

[3]:
```
X = df.iloc[:,0]
y = df.iloc[:,1]
```

1.1.3 Plotting the Data

[4]:
```
plt.figure(figsize=(5,5))
plt.scatter(X,y)
plt.title("Scatter Plot of X and y")
plt.xlabel('X')
plt.ylabel('y')
plt.show()
```



From the scatter plot we can see that the relationship between X and y is linear.

1.1.4 Batch Gradient Descent

In batch gradient descent we update the parameters(weights) once per epoch

Training the Model

[5]:
```
## %%timeit
w0 = 0
w1 = 0
lr = 0.0001
```

```
epochs = 1000
n=float(len(X))
for i in range(epochs):
    y_pred = w0+w1*X
    delw0 = (-2/n)*sum(y-y_pred)
    delw1 = (-2/n)*sum(X*(y-y_pred))
    w0=w0-lr*delw0
    w1=w1-lr*delw1
    if i%100==0:
        print(f"Iteration {i}\n w0 = {w0}\tw1 = {w1}")
```

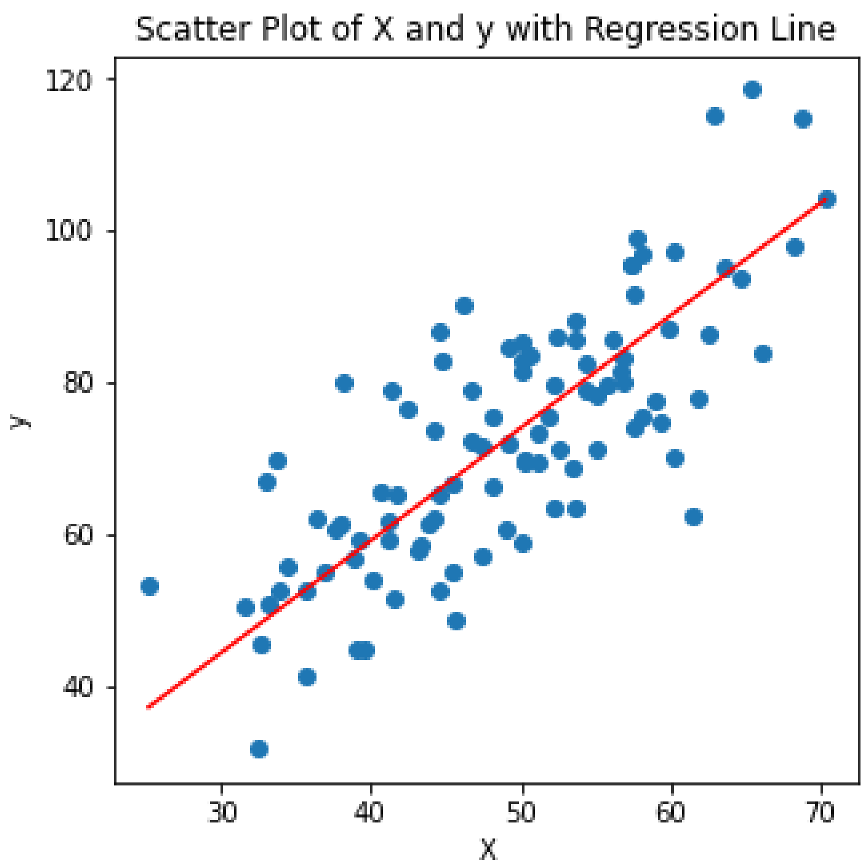
```
Iteration 0
 w0 = 0.014547010110737297      w1 = 0.7370702973591055
Iteration 100
 w0 = 0.03513502002912928       w1 = 1.4788015372774521
Iteration 200
 w0 = 0.04113767542736797       w1 = 1.4786835569145387
Iteration 300
 w0 = 0.047135801867800996      w1 = 1.4785656655669113
Iteration 400
 w0 = 0.05312940276749255       w1 = 1.4784478631674083
Iteration 500
 w0 = 0.059118481540928546      w1 = 1.478330149648919
Iteration 600
 w0 = 0.06510304160001894       w1 = 1.4782125249443832
Iteration 700
 w0 = 0.07108308635409932       w1 = 1.4780949889867918
Iteration 800
 w0 = 0.07705861920993279       w1 = 1.4779775417091856
Iteration 900
 w0 = 0.08302964357171239       w1 = 1.4778601830446565
```

Making the Predictions

[6]:
```
y_pred = w0+w1*X
```

Plotting the Result

[7]:
```
plt.figure(figsize=(5,5))
plt.scatter(X,y)
plt.plot([min(X),max(X)],[min(y_pred),max(y_pred)],color='red')
plt.title("Scatter Plot of X and y with Regression Line")
plt.xlabel('X')
plt.ylabel('y')
plt.show()
```



A function to perform model evaluation

[8]:
```
def model_evaluate(y,y_pred):
    mae = metrics.mean_absolute_error(y, y_pred)
    mse = metrics.mean_squared_error(y, y_pred)
    r2 = metrics.r2_score(y, y_pred)
    print("The model performance")
    print("--------------------------------------")
    print(f'MAE is {mae}')
    print(f'MSE is {mse}')
    print('R2 score is {}'.format(r2))
```

Model Evaluation

[9]:
```
model_evaluate(y,y_pred)
```

```
The model performance
--------------------------------------
MAE is 8.422711763776555
MSE is 112.6148101161347
```

```
R2 score is 0.5900746017527791
```

The value of R2 is 0.59 which means the model was able to explain 59% variance in dependent variable caused by independent variable

1.1.5 Stochastic Gradient Descent

In Stochastic Gradient Descent, we update the weights for each data point

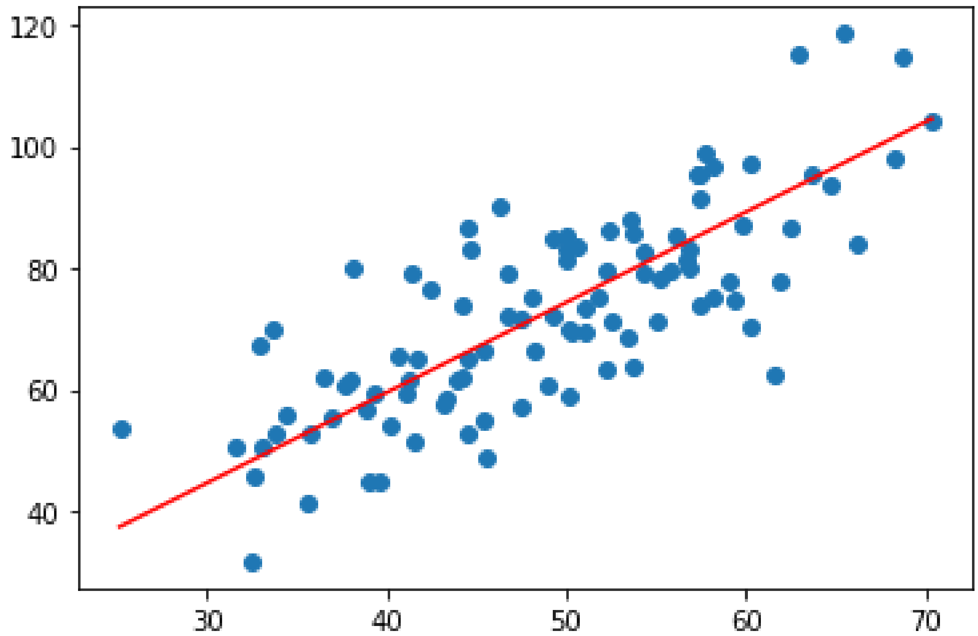
[10]:
```
##%%timeit
w0 = 0
w1 = 0
lr = 0.0001
epochs = 1000
n=float(len(X))
for i in range(epochs):
    for j in range(len(X)):
        y_pred = w0+w1*X[j]
        delw0 = (-2/n)*(y[j]-y_pred)
        delw1 = (-2/n)*(X[j]*(y[j]-y_pred))
        w0=w0-lr*delw0
        w1=w1-lr*delw1
    if i%100==0:
        print(f"Iteration {i}\n w0 = {w0}\tw1 = {w1}")
```

```
Iteration 0
 w0 = 0.011535171934851532      w1 = 0.584587889442503
Iteration 100
 w0 = 0.03523614521353354       w1 = 1.4860346596605525
Iteration 200
 w0 = 0.041235436305053094      w1 = 1.4859166759703657
Iteration 300
 w0 = 0.04723019163675254       w1 = 1.4857987814816669
Iteration 400
 w0 = 0.05322041463788957       w1 = 1.485680976127012
Iteration 500
 w0 = 0.05920610873512941       w1 = 1.4855632598390125
Iteration 600
 w0 = 0.06518727735254774       w1 = 1.48544563255033
Iteration 700
 w0 = 0.07116392391162962       w1 = 1.4853280941936795
Iteration 800
 w0 = 0.0771360518312743        w1 = 1.4852106447018176
Iteration 900
 w0 = 0.08310366452779498       w1 = 1.4850932840075641
```

[11]:
```
y_pred = w0+w1*X
```

[12]:

```
plt.scatter(X,y)
plt.plot([min(X),max(X)],[min(y_pred),max(y_pred)],color='red')
plt.show()
```



[13]:

```
model_evaluate(y,y_pred)
```

```
The model performance
--------------------------------------
MAE is 8.453062495891446
MSE is 112.74522422785401
R2 score is 0.5895998857129575
```

1.1.6 Mini Batch Gradient Descent

In Mini Batch Gradient descent we create small batches and update weights for each batch

[14]:

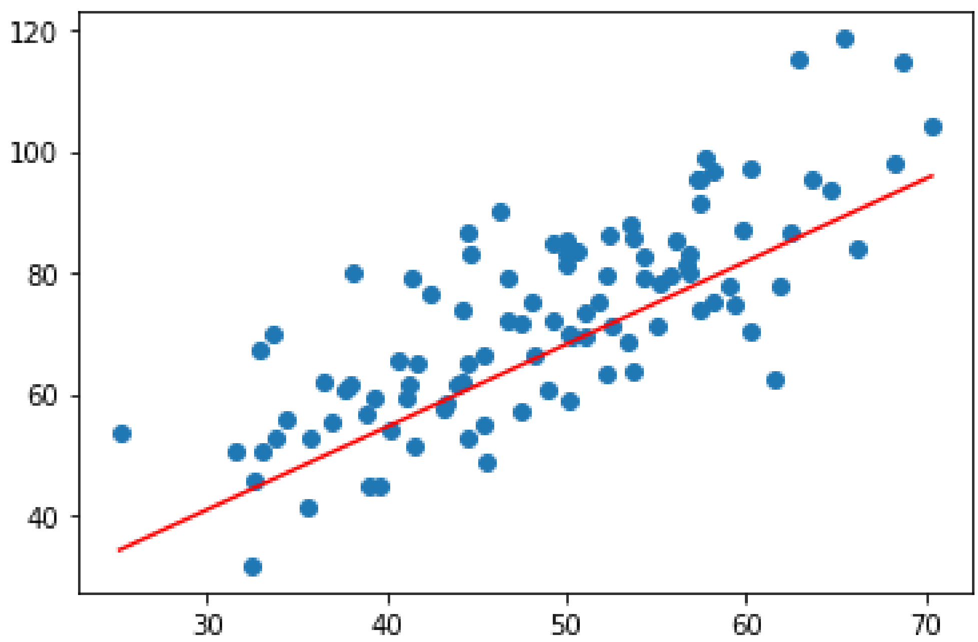
```
## %%timeit
w0 = 0
w1 = 0
lr = 0.0001
epochs = 1000
batch_size=10
start=0
end=batch_size
n=float(len(X))
for i in range(epochs):
```

```
    X_batch = X[start:end]
    y_batch = y[start:end]
    y_pred = w0+w1*X_batch
    delw0 = (-2/n)*sum(y_batch-y_pred)
    delw1 = (-2/n)*sum(X_batch*(y_batch-y_pred))
    w0=w0-lr*delw0
    w1=w1-lr*delw1
    if i%100==0:
        print(f"Iteration {i}\n w0 = {w0}\tw1 = {w1}")
```

```
Iteration 0
 w0 = 0.0013709632886396014      w1 = 0.07067196410837259
Iteration 100
 w0 = 0.026467223749741465       w1 = 1.3567149469196205
Iteration 200
 w0 = 0.026769888160102662       w1 = 1.362977176826608
Iteration 300
 w0 = 0.026951745926235903       w1 = 1.3630041923927687
Iteration 400
 w0 = 0.027133005244266 7        w1 = 1.3630008295879839
Iteration 500
 w0 = 0.027314251780591662       w1 = 1.3629973189679998
Iteration 600
 w0 = 0.027495488389173314       w1 = 1.3629938078189732
Iteration 700
 w0 = 0.027676715084456016       w1 = 1.3629902968584853
Iteration 800
 w0 = 0.02785793186704974        w1 = 1.3629867860900216
Iteration 900
 w0 = 0.028039138737497037       w1 = 1.362983275513589
```

[15]:
```
y_pred = w0+w1*X
```

[16]:
```
plt.scatter(X,y)
plt.plot([min(X),max(X)],[min(y_pred),max(y_pred)],color='red')
plt.show()
```



[17]:
```
model_evaluate(y,y_pred)
```

```
The model performance
--------------------------------------
MAE is 9.675271274449019
MSE is 146.1437280915331
R2 score is 0.46802711048862267
```

1.1.7 Conclusion:

Based on the R2 value we can say that the model trained using batch gradient descent is the best.

The run time obtained from using `%%timeit` magic function in jupyter notebook is given below 1. **Batch GD**: 842 ms ± 51.2 ms per loop (mean ± std. dev. of 7 runs, 1 loop each) 2. **Stocastic GD**: 913 ms ± 49.9 ms per loop (mean ± std. dev. of 7 runs, 1 loop each) 3. **Mini Batch GD**: 52.2 s ± 154 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

1.2 Q.NO 2

Write python programs to predict diabetes using logistic regression. Implement the algorithm using library and without using library. Find accuracy, precision, recall, and F1-score and compare both strategies (Use diabetes.csv). Assume train/test split is 70:30.

[18]:
```
db_df = pd.read_csv('data/Diabetes.csv')
```

[19]:
```
db_df.head()
```

[19]:

```
   Pragnency  Glucose  Blod Pressure  Skin Thikness  Insulin   BMI    DFP  \
0          1       85             66             29        0  26.6  0.351
1          8      183             64              0        0  23.3  0.672
2          1       89             66             23       94  28.1  0.167
3          0      137             40             35      168  43.1  2.288
4          5      116             74              0        0  25.6  0.201

   Age  Diabetes
0   31         0
1   32         1
2   21         0
3   33         1
4   30         0
```

[22]:

```python
db_df.describe()
```

[22]:

```
        Pragnency     Glucose  Blod Pressure  Skin Thikness     Insulin  \
count  767.000000  767.000000     767.000000     767.000000  767.000000
mean     3.842243  120.859192      69.101695      20.517601   79.903520
std      3.370877   31.978468      19.368155      15.954059  115.283105
min      0.000000    0.000000       0.000000       0.000000    0.000000
25%      1.000000   99.000000      62.000000       0.000000    0.000000
50%      3.000000  117.000000      72.000000      23.000000   32.000000
75%      6.000000  140.000000      80.000000      32.000000  127.500000
max     17.000000  199.000000     122.000000      99.000000  846.000000

              BMI         DFP         Age    Diabetes
count  767.000000  767.000000  767.000000  767.000000
mean    31.990482    0.471674   33.219035    0.348110
std      7.889091    0.331497   11.752296    0.476682
min      0.000000    0.078000   21.000000    0.000000
25%     27.300000    0.243500   24.000000    0.000000
50%     32.000000    0.371000   29.000000    0.000000
75%     36.600000    0.625000   41.000000    1.000000
max     67.100000    2.420000   81.000000    1.000000
```

[36]:

```python
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report,plot_confusion_matrix
```

[51]:

```python
X=db_df.drop(columns=['Diabetes']).values
y=db_df['Diabetes'].values
```

[60]:

```python
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.
 ↪3,random_state=0)
```

1.2.1 Logistic Regression Using Scikit-Learn Library

[61]:
```
sk_lgr = LogisticRegression()
```

[62]:
```
sk_lgr.fit(X_train,y_train)
```

```
/home/xenon/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:763: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[62]:
```
LogisticRegression()
```

[63]:
```
y_pred = sk_lgr.predict(X_test)
```

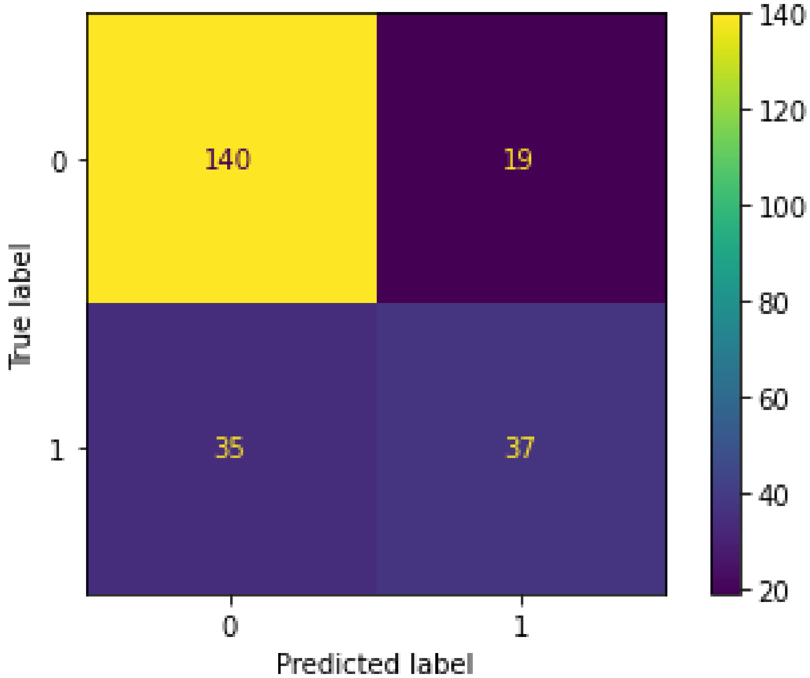
[64]:
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.80      0.88      0.84       159
           1       0.66      0.51      0.58        72

    accuracy                           0.77       231
   macro avg       0.73      0.70      0.71       231
weighted avg       0.76      0.77      0.76       231
```

[65]:
```
plot_confusion_matrix(sk_lgr,X_test,y_test)
plt.show()
```



1.2.2 Logistic Regression From Scratch

[66]:
```
# Define the sigmoid function
def sigmoid(input):
    output = 1 / (1 + np.exp(-input))
    return output
```

[76]:
```
# Initializing weights and bias to zeros.
m,n=X_train.shape
w = np.zeros((n,1))
b = 0
# Reshaping y so that the dot product is possible
y_train = y_train.reshape(m,1)
epochs = 10000
lr = 0.0001
for epoch in range(epochs):
    y_hat = sigmoid(np.dot(X_train, w) + b)
    dw = (1/m)*np.dot(X_train.T, (y_hat - y_train))
    db = (1/m)*np.sum((y_hat - y_train))
    # Updating the weights
    w -= lr*dw
    b -= lr*db
```

[77]:
```
preds = sigmoid(np.dot(X_test, w) + b)
```

[78]:
```
pred_class = [1 if i > 0.5 else 0 for i in preds]
```

[79]:
```
print(classification_report(y_test,pred_class))
```

```
              precision    recall  f1-score   support

           0       0.76      0.86      0.81       159
           1       0.57      0.40      0.47        72

    accuracy                           0.72       231
   macro avg       0.66      0.63      0.64       231
weighted avg       0.70      0.72      0.70       231
```

1.2.3 Conclusion

The accuracy of Scikit Learn is 77% and model implemented from scratch is 72%.