Assignment1 Report

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Part I: the perceptron

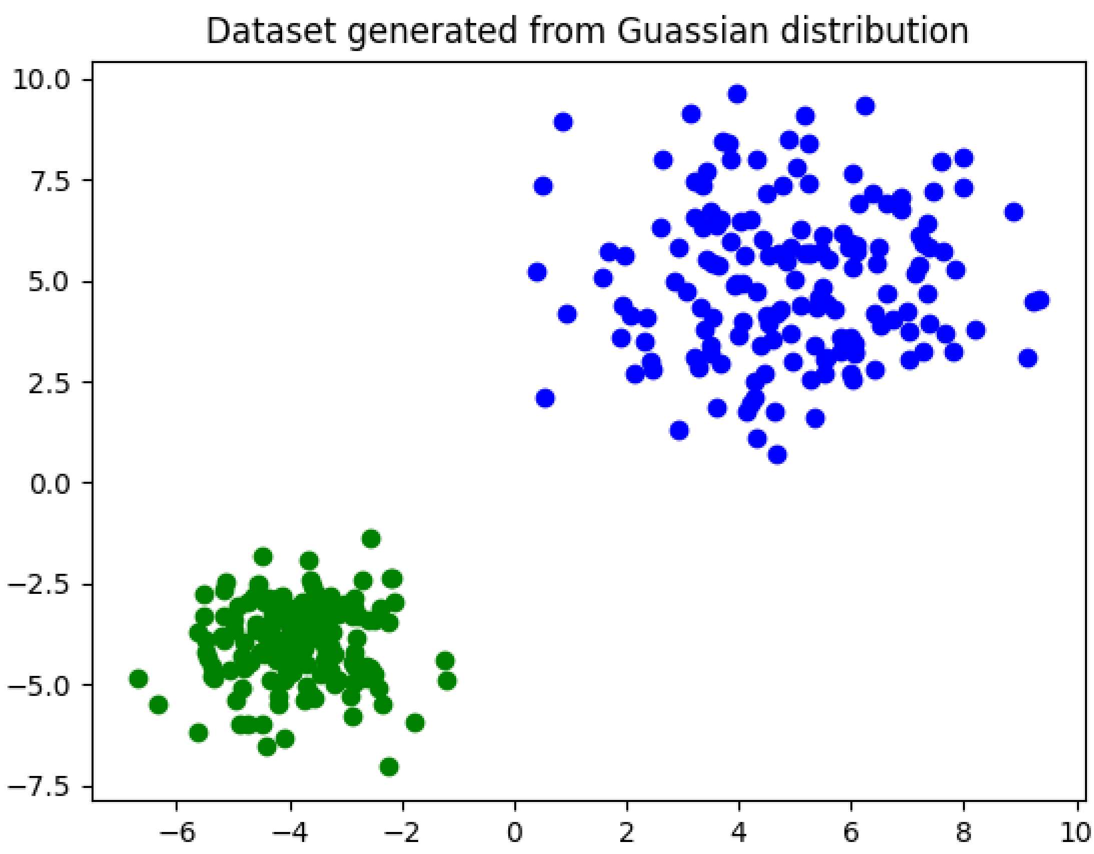
Instruction

run the main in part1/perceptron.py

Task1

We need to generate two Gaussian distributions and sample from each of them， which have different mean and covariance.

- let the user to input the desired mean and cov
- use np.random.multivariate_normal(mean, cov, 200) to generate the data
- use 320 points as training data and the rest 80 points as test data mean1=[5,5] cov1={[3,0],[0,3]} mean2=[-4,-4] cov2={[1,0],[0,1]}



Task2

- initiate perceptron (weights are zero and default n_inputs, max_epochs,learning_rate)
- shuffle the data at each epoch
- use current weight predict training input data.

- if the prediction is wrong, update weight (). Actually I find the pseudocode in perceptronslides.pdf is strange because there is no definition of bias.Howerver it still works.

Task3

Because of the data is produced by random,the accuracy changes each time,I do experiments for 10 times and get the acverage accuracy.

- label all the points from the first Gaussian distribution as 1 and all the points from the second Gussain distribution as -1.
- append together and each train epoch reshuffle the data.
- train the 320 training points and save the rest 80 for the test. For mean1=[5,5],cov1={[3,0],[0,3]},mean2=[-4,-4],cov2={[1,0],[0,1]} the accuracy is always 100%

Task 4

Use control variable method. Because of the data is sample by random,I do experiments for 10 times and get the acverage accuracy.

- cov is too high

Mean1	Cov1	Mean2	Cov2	Accuracy
[5,5]	{[3,0],[0,3]}	[-4,-4]	{[1,0],[0,1]}	100%
[5,5]	{[20,0],[0,20]}	[-4,-4]	{[10,0],[0,10]}	95%
[5,5]	{[50,0],[0,50]}	[-4,-4]	[{40,0],[0,40]}	78.75%
[5,5]	{[500,0],[0,500]}	[-4,-4]	{[400,0],[0,400]}	57.5%

As we can see,the higher the cov,the smaller the accuracy

- mean is too close

Mean1	Cov1	Mean2	Cov2	Accuracy
[10,10]	{[10,0],[0,10]}	[-8,-8]	{[8,0],[0,8]}	100%
[5,5]	{[10,0],[0,10]}	[-4,-4]	{[8,0],[0,8]}	97.5%
[2,2]	{[10,0],[0,10]}	[-3,-3]	{[8,0],[0,8]}	81.25%
[1,1]	{[10,0],[0,10]}	[-1,-1]	{[8,0],[0,8]}	63.75%

As we can see,the closer the means,the smaller the accuracy. All in all ,we can find that the accuracy is higher as two distributions have less overlap area.

Part II: the muti-layer perceptron

Instruction

run the main in part2/train_mlp_numpy.py,BGD.ipynb

Task1

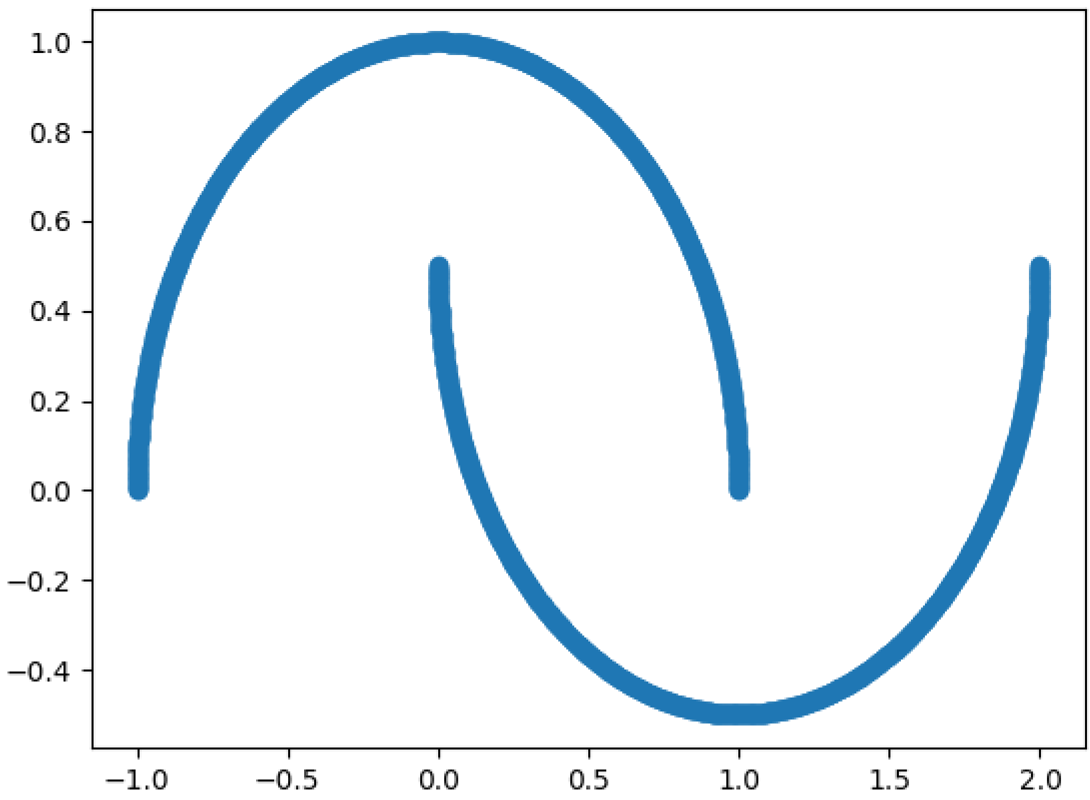
Based on the requirement of the assignment,I do some improvements.Relu and softmax is implemented as standard.

- Linear I record the weight,bias and the gradient of weight and bias in the class. I initialize bias with zeros, and the size is out_feature When I set std to 0.0001 as the comments say, the BGD does not work because loss and accuracy does not change .So I use std=1 to initiate the weight.I only record the summary of the gradient and I refresh the gradient after the update of weight each time. forward() return the dot production of weight and x plus the bias.It is just a linear transformation. I seperate origin backward() as backward() and update().Backward is used to update the gradients and update is use to update the weights and refresh the gradients.This can help me complete sgd() and bgd()elegantly and package the neural network perfect because I do not need to change weight in the train_mlp_numpy.py.
- CrossEntropy when I use -np.sum(y * np.log(x)) as forward the numpy warning so I use -np.sum(y * np.log(x+1e-7)).
- MLP I initiate a list of Linears representing and list of reLu for each layers. Forward() is to use the forward of all the layers' forward in **init** and add a SoftMax() on the outside. I seperate origin backward() as backward() and update() like what I do in linear.

Task2

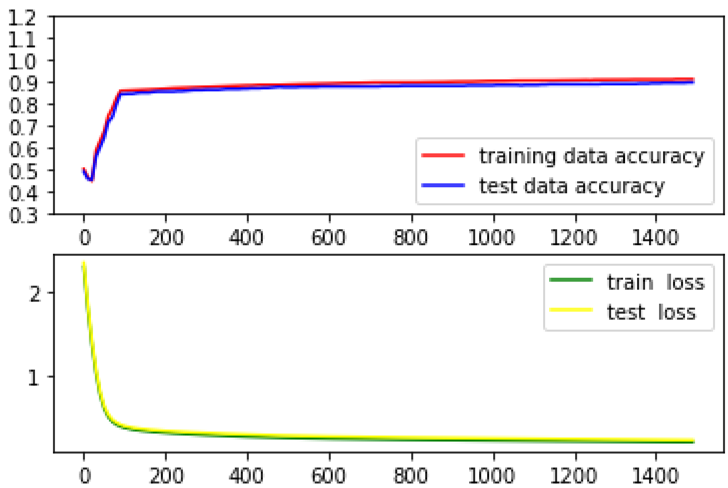
For each epoch
    For each data
        mlp.forward (data)
        mlp.backward()
        record dw and db
    Update w and b
    Test
        caculate loss and accuracy

- use datasets.make_moons(n_samples=2000, shuffle=True)to generate data.

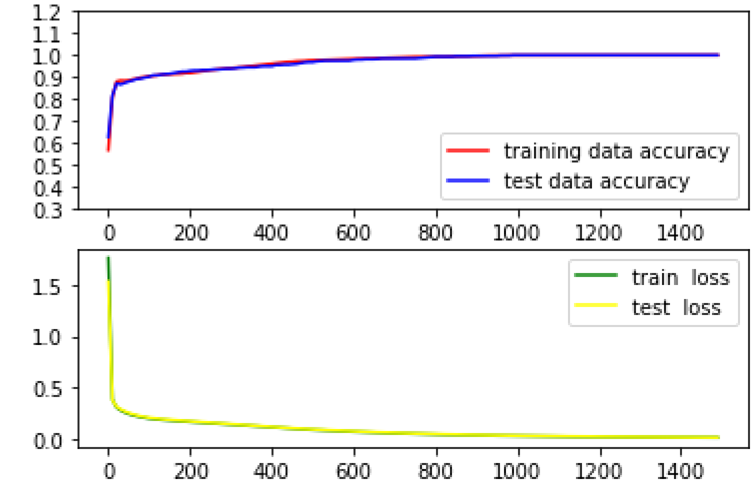


- split the dataset 70% and 30% by random.
- implement BGD in this part by using update() and backward() in Linear and MLP.

Task3



The default parameters are: learning rate = 1e-2, max steps = 1500, evaluation frequency = 10 epochs, hidden units = "20".Both train and test accuracy=90%.So we adjust the learning rate as 1e-1



Both train and test accuracy=100% and loss=0

Part III: Stochastic gradient descent

Instruction

run the main in part2/train_mlp_numpy.py,SGD.ipynb

Task1

implement the SGD(update the weight one by one) and reshuffle the train data each epoch by using update() and backward() of the mlp and linear. For each epoch

For each data

mlp.forward (data)

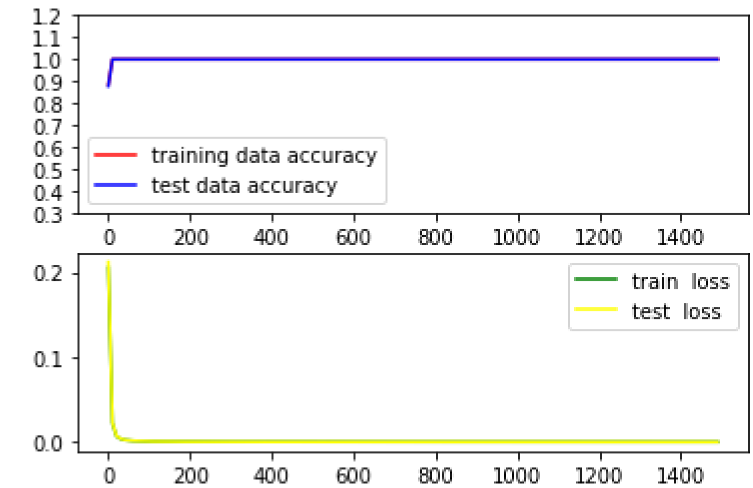
mlp.backward()

update w and b

test

caculate loss and accuracy

Task2



The SGD trains quicker than BGD under the default parameters.Both train and test accuracy=100% and loss=0

References

1. https://timvieira.github.io/blog/post/2014/02/11/exp-normalize-trick/
2. https://blog.csdn.net/JiaJunLee/article/details/79665062