Lab1: back-propagation

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I. Introduction:

利用兩層 hidden layer 的 Neural network 來訓練 input 為二維的資料(range from 0.0 to 1.0) 以及其所對應到的 label 為一維的 ground truth (0 or 1)。因為資料集較小,故 training set 同時也是 testing set。

II. Experiment setups

A. Activation functions

• Sigmoid function:

```
def sigmoid(self, x, derivative=False):
    if derivative:
        return (np.exp(-x))/((np.exp(-x)+1)**2)
    return 1/(1 + np.exp(-x))
```

Sigmoid function 是一種 activation function, 其輸出為 0至 1。

derivative 若設為 True 則是 sigmoid 微分後的函數。反之則為 sigmoid function。

• Relu funtion:

```
def relu(self, x, derivative=False):
   if derivative:
       return np.where(x < 0, 0, 1)
   return np.maximum(0, x)</pre>
```

Relu 也是一種 activation function,假定輸入為 x,則輸出為 max(0, x)。

比較麻煩的是其在0這個點無法進行微分(因為左右兩點的斜率不同)。

B. Neural network

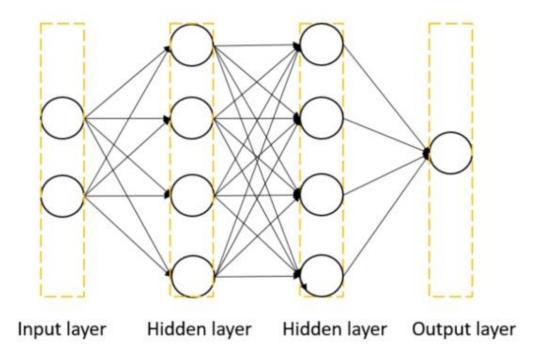


Figure 1. Two-layer neural network

• Layers:

- Input layer: 由於 input 是二維,所以兩個 neuron。
- Hidden layer: 要求至少兩層 hidden layers。我預設兩層(h1, h2)各 4 個 neuron。
- Output layer: 由於 label 是 0 或 1, 所以一個 neuron。

• Training process:

- 1. 先隨機初始化 parameters (此 lab 即 weights)
- 2. 透過 feed_forward 得出 output
- 3. 進行 back_propagation(將 Loss funtion 對各 weights 做微分,算出各 weights 之 gradient)
- 4. 透過 optimize 更新各 weights
- 5. 重複進行 Step 2 4

C. Back propagation:

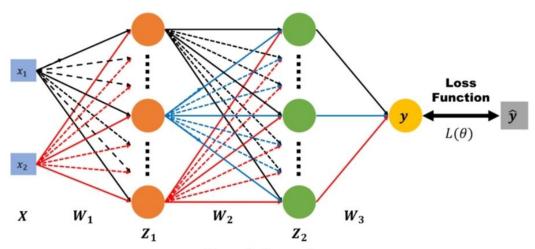


Figure 2. Forward pass

- In the figure 2, we use the following definitions for the notations:
 - 1. x_1, x_2 : nerual network inputs
 - 2. $X : [x_1, x_2]$
 - 3. y: nerual network outputs
 - 4. \hat{y} : ground truth
 - 5. $L(\theta)$: loss function
 - 6. W_1, W_2, W_3 : weight matrix of network layers

$$Z_1 = \sigma(XW_1)$$

$$Z_2 = \sigma(Z_1 W_2)$$

$$y = \sigma(Z_2W_3)$$

- 由 output 依序向前更新各 weights
- 更新方法為:

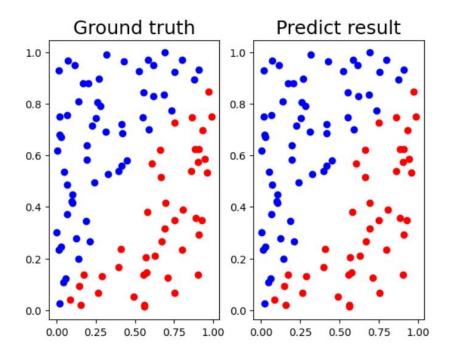
將對 Loss function 對各 weight 做偏微分,計算出各 weight 之 gradients 後, 算出 new_weight = old_weight - learning_rate * weight_gradient。如下圖所示 (依序更新 W3,W2,W1)

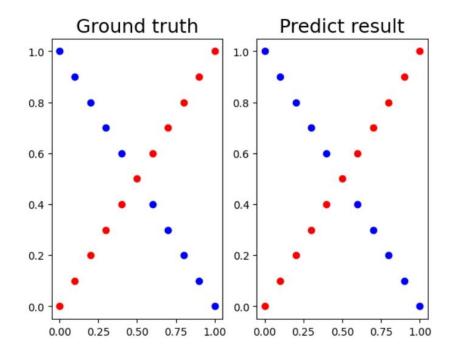
$$\frac{1}{(100,12)} \times \frac{1}{(2,4)} \times \frac{1}{(100,14)} \times \frac{1}{(1$$

III. Results of your testing

A. Screenshot and comparison figure

• Case 1: Linear





B. Show the accuracy of your prediction

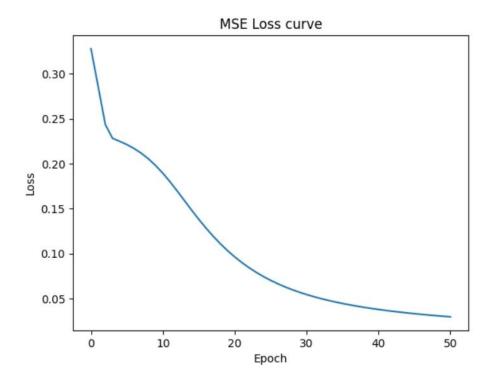
• Case 1: Linear

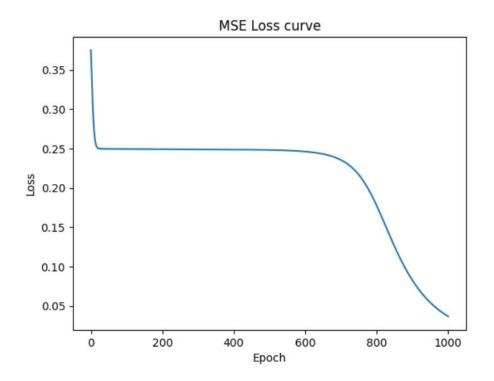
```
Epoch: 0 loss:0.327794 acc:58.00%
Epoch: 5 loss:0.221193 acc:58.00%
Epoch: 10 loss:0.189331 acc:77.00%
Epoch: 15 loss:0.138072 acc:92.00%
Epoch: 20 loss:0.096261 acc:96.00%
Epoch: 25 loss:0.070163 acc:99.00%
Epoch: 30 loss:0.054393 acc:99.00%
Epoch: 35 loss:0.044466 acc:99.00%
Epoch: 40 loss:0.037827 acc:100.00%
Epoch: 45 loss:0.033126 acc:100.00%
Epoch: 50 loss:0.029633 acc:100.00%
```

```
Epoch: 0 loss:0.374859 acc:47.62% Epoch: 100 loss:0.249373 acc:52.38% Epoch: 200 loss:0.249138 acc:52.38% Epoch: 300 loss:0.248945 acc:52.38% Epoch: 400 loss:0.248721 acc:52.38% Epoch: 500 loss:0.248721 acc:52.38% Epoch: 600 loss:0.248191 acc:52.38% Epoch: 600 loss:0.246140 acc:57.14% Epoch: 700 loss:0.235422 acc:71.43% Epoch: 800 loss:0.177223 acc:90.48% Epoch: 900 loss:0.082453 acc:95.24% Epoch:1000 loss:0.036723 acc:100.00%
```

C. Learning curve(loss, epoch curve)

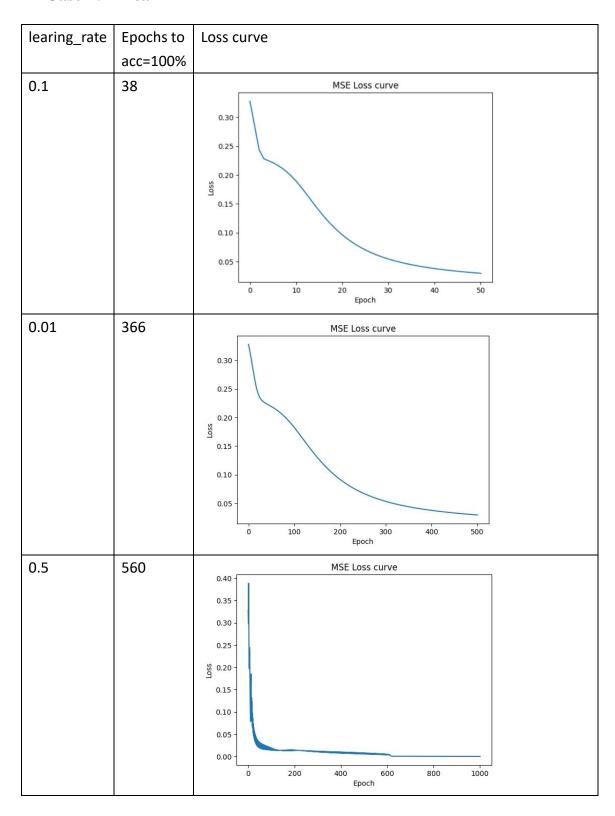
• Case 1: Linear

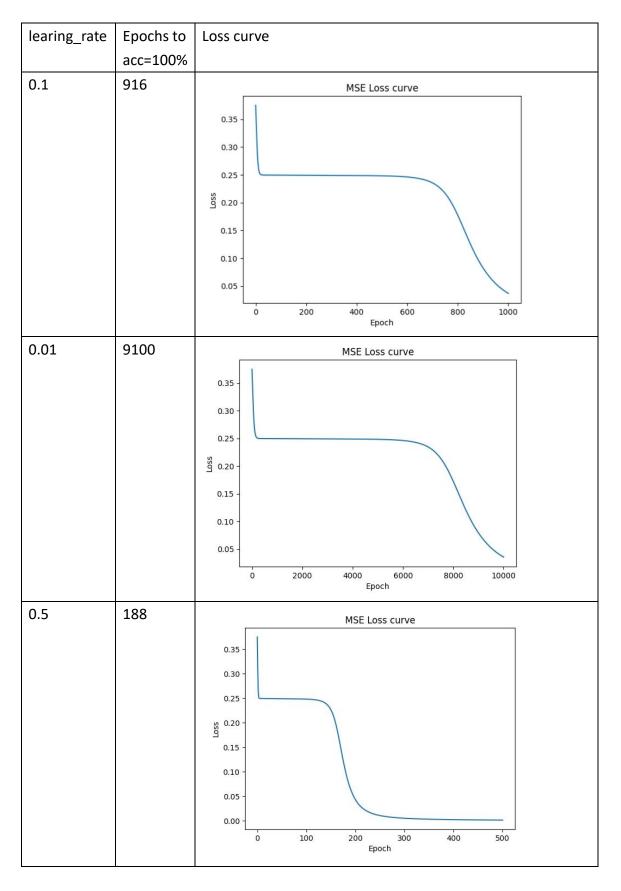




4. Discussion

A. Try different learning rates





B. Try different numbers of hidden units

Hidden layers	Epochs to	Loss curve
Induction	acc=100%	2033 641 76
[2, 4, 4, 1]	38	MSE Loss curve
[2, 4, 4, 1]	36	MSE LOSS CUIVE
		0.30 -
		0.25 -
		0.20
		0.20 -
		0.15
		0.10
		0.05 -
		0 10 20 30 40 50 Epoch
[2, 6, 6, 1]	33	MSE Loss curve
		0.25
		0.20 -
		3
		§ 0.15 -
		0.10 -
		0.05 -
		0 10 20 30 40 50 Epoch
[2, 10, 10, 1]	36	MSE Loss curve
[2, 10, 10, 1]	30	0.35 -
		0.30 -
		0.25 -
		V √ ∧
		§ 0.20 -
		0.15 -
		0.10 -
		0.05 -
		0 10 20 30 40 50
		Epoch

Hidden layers	Epochs to	Loss curve
	acc=100%	
[2, 4, 4, 1]	916	0.35 - 0.30 - 0.25 - 0.20 -
		0.15 - 0.10 - 0.05 - 0 200 400 600 800 1000 Epoch
[2, 6, 6, 1]	661	MSE Loss curve
		0.25 - 0.20 - 0.15 - 0.10 - 0.05 - 0.05 - 0.00 Epoch
[2, 10, 10, 1]	587	0.25 - 0.20 - 0.15 - 0.10 - 0.05 - 0.05 - 0.00 Epoch

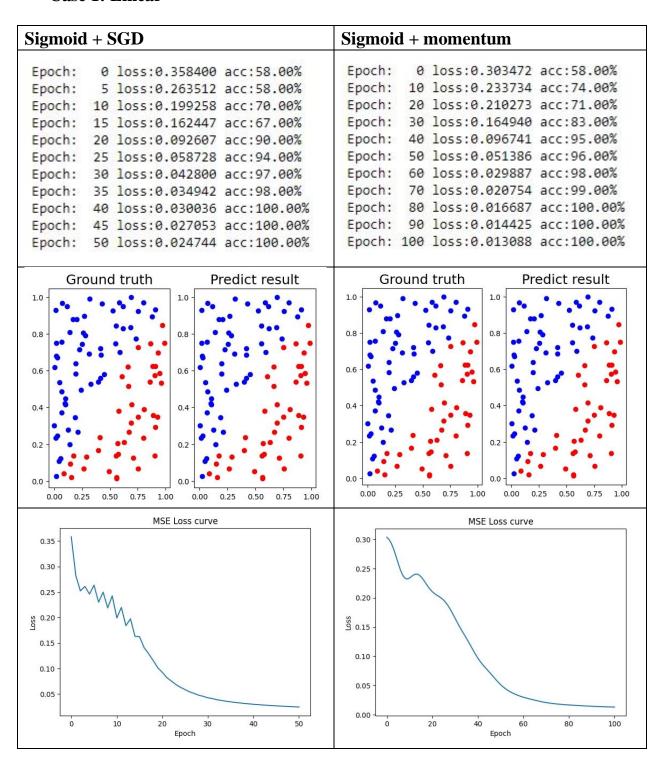
C. Try without activation functions

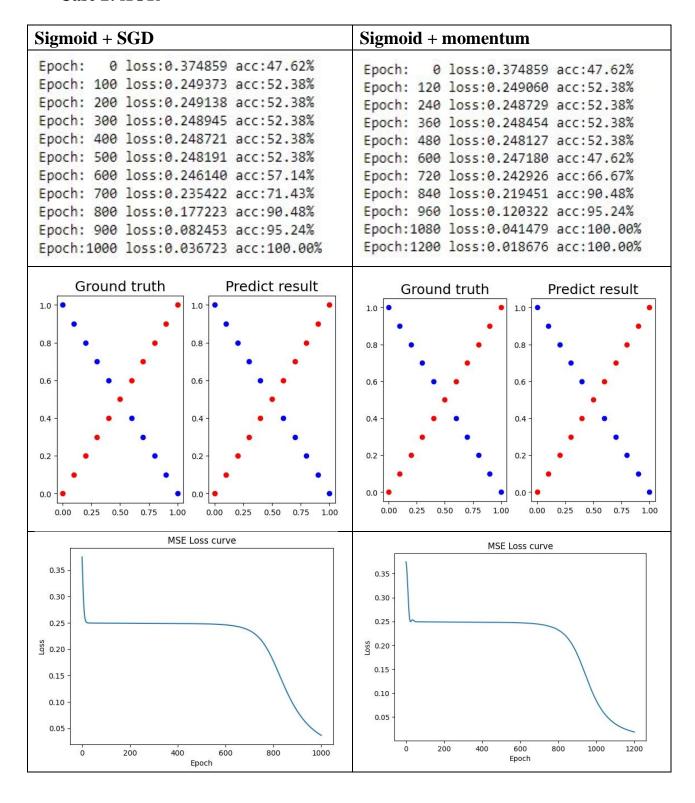
With sigmoid	Without sigmoid
Learning_rate = 0.1	Learning_rate = 0.0001
	(if use 0.1, cannot converge)
Epoch: 0 loss:0.327794 acc:58.00% Epoch: 5 loss:0.221193 acc:58.00% Epoch: 10 loss:0.189331 acc:77.00% Epoch: 15 loss:0.138072 acc:92.00% Epoch: 20 loss:0.096261 acc:96.00% Epoch: 25 loss:0.070163 acc:99.00% Epoch: 30 loss:0.054393 acc:99.00% Epoch: 35 loss:0.044466 acc:99.00% Epoch: 40 loss:0.037827 acc:100.00% Epoch: 45 loss:0.033126 acc:100.00% Epoch: 50 loss:0.029633 acc:100.00%	Epoch: 0 loss:132.981598 acc:1.00% Epoch: 50 loss:0.131182 acc:82.00% Epoch: 100 loss:0.125672 acc:84.00% Epoch: 150 loss:0.123602 acc:84.00% Epoch: 200 loss:0.122839 acc:86.00% Epoch: 250 loss:0.122562 acc:86.00% Epoch: 300 loss:0.122462 acc:87.00% Epoch: 350 loss:0.122463 acc:87.00% Epoch: 400 loss:0.122413 acc:87.00% Epoch: 450 loss:0.122409 acc:87.00% Epoch: 500 loss:0.122407 acc:87.00%
MSE Loss curve	MSE Loss curve
0.30 - 0.25 - 0.20 - 0.10 - 0.05 - 0 10 20 30 40 50	120 - 100 - 80 - 80 - 40 - 20 - 0 100 200 300 400 500 Epoch

With sigmoid	Without sigmoid
Learning_rate = 0.1	Learning_rate = 0.01
Epoch: 0 loss:0.374859 acc:47.62% Epoch: 100 loss:0.249373 acc:52.38% Epoch: 200 loss:0.249138 acc:52.38% Epoch: 300 loss:0.248945 acc:52.38%	(if use 0.1, cannot converge) Epoch: 0 loss:1.093362 acc:52.38% Epoch: 5 loss:0.528004 acc:52.38% Epoch: 10 loss:0.386753 acc:66.67% Epoch: 15 loss:0.288937 acc:33.33%
Epoch: 400 loss:0.248721 acc:52.38% Epoch: 500 loss:0.248191 acc:52.38% Epoch: 600 loss:0.246140 acc:57.14% Epoch: 700 loss:0.235422 acc:71.43% Epoch: 800 loss:0.177223 acc:90.48% Epoch: 900 loss:0.082453 acc:95.24% Epoch:1000 loss:0.036723 acc:100.00%	Epoch: 20 loss:0.288715 acc:33.33% Epoch: 25 loss:0.288714 acc:33.33% Epoch: 30 loss:0.288714 acc:33.33% Epoch: 35 loss:0.288714 acc:33.33% Epoch: 40 loss:0.288714 acc:33.33% Epoch: 45 loss:0.288714 acc:33.33% Epoch: 50 loss:0.288714 acc:33.33%
MSE Loss curve	MSE Loss curve
0.35 - 0.30 - 0.25 - 9 0.20 - 0.15 - 0.10 - 0.05 - 0 200 400 600 800 1000	14 - 12 - 10 - 50 8 - 6 - 4 - 2 - 0
0 200 400 600 800 1000 Epoch	0 10 20 30 40 50 Epoch

5. Extra

A. Implement different optimizers





B. Implement different activation functions

