

NYCU DL

Lab1 - Backpropagation

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Outline

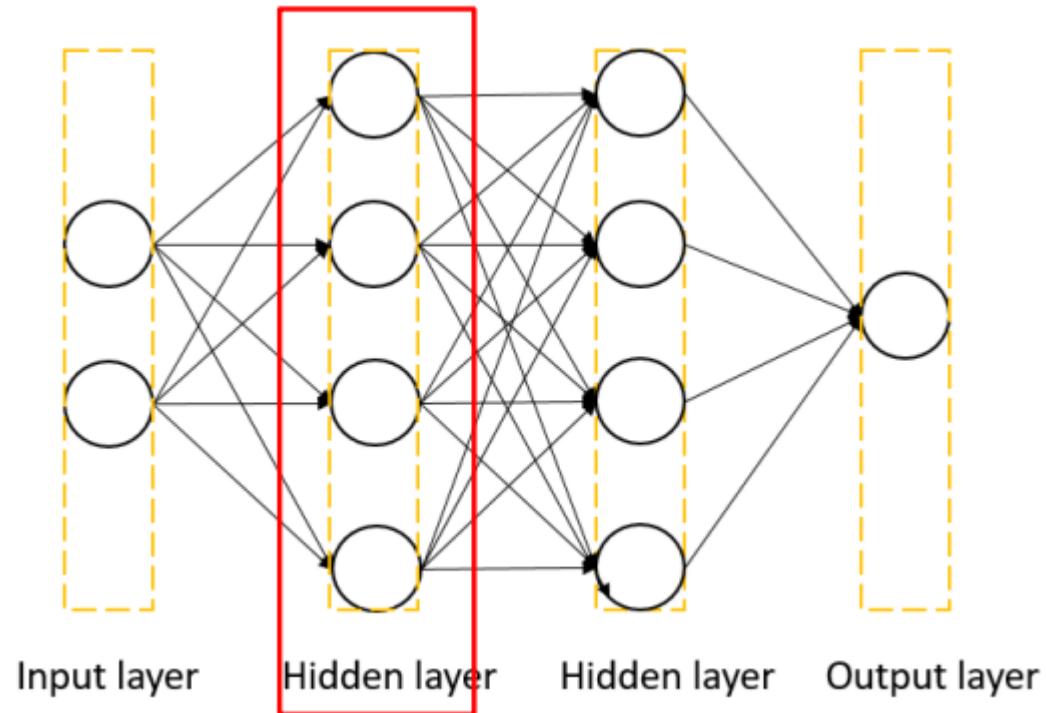
- Lab Description
- Scoring Criteria
- Time Schedule

Lab Description

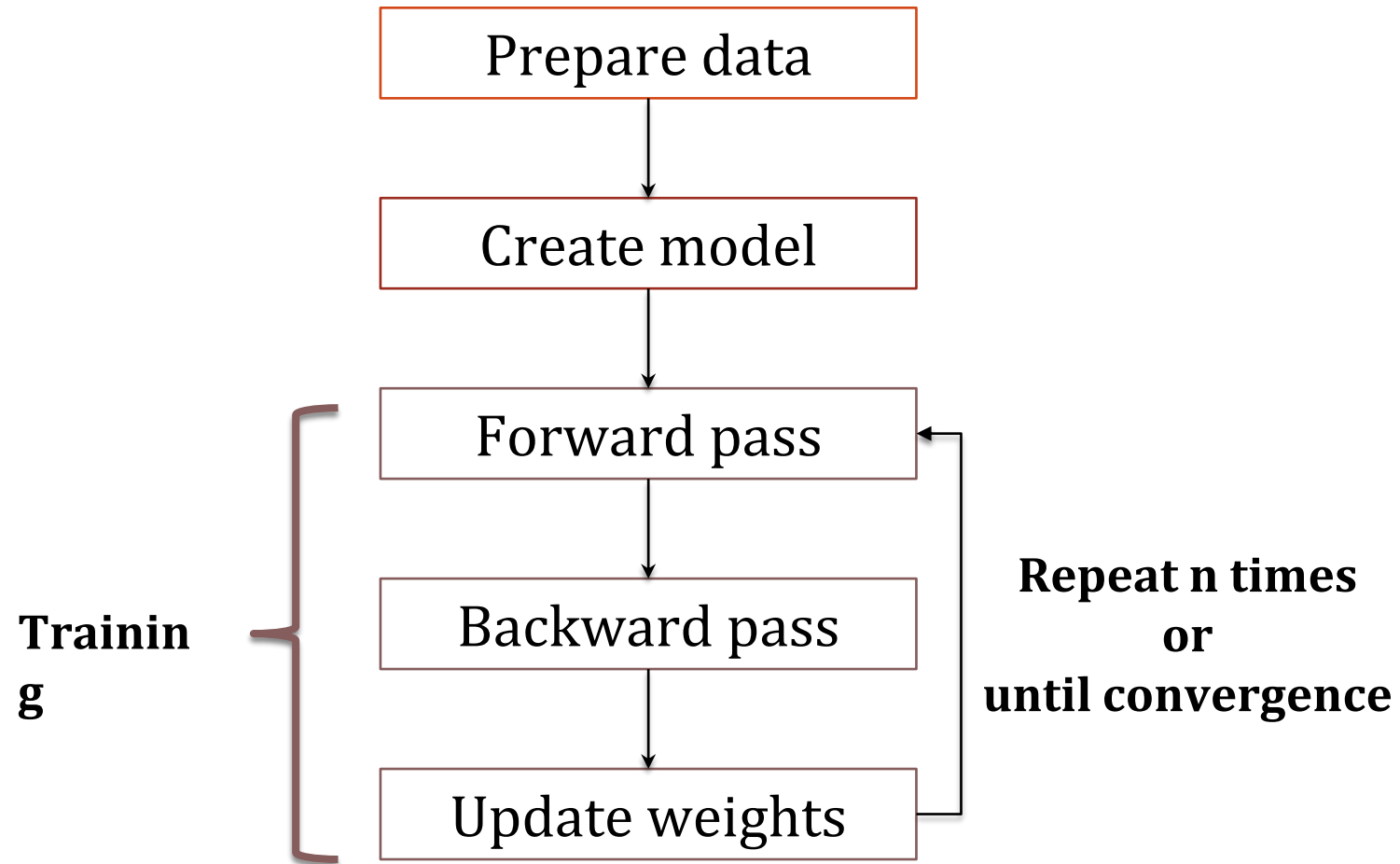
- Implement a simple neural network with two hidden layers
- Perform backpropagation to update model weights
- You can only use **Numpy** and other **python standard libraries**.
 - Pytorch, TensorFlow, ... frameworks are **NOT** allowed in this lab
- Visualization
 - Plot comparison figures showing the predictions and ground truth.
 - Plot your learning curve (loss vs. epoch).
 - Print the accuracy of your prediction.
 - You are allowed to use matplotlib

Lab Description

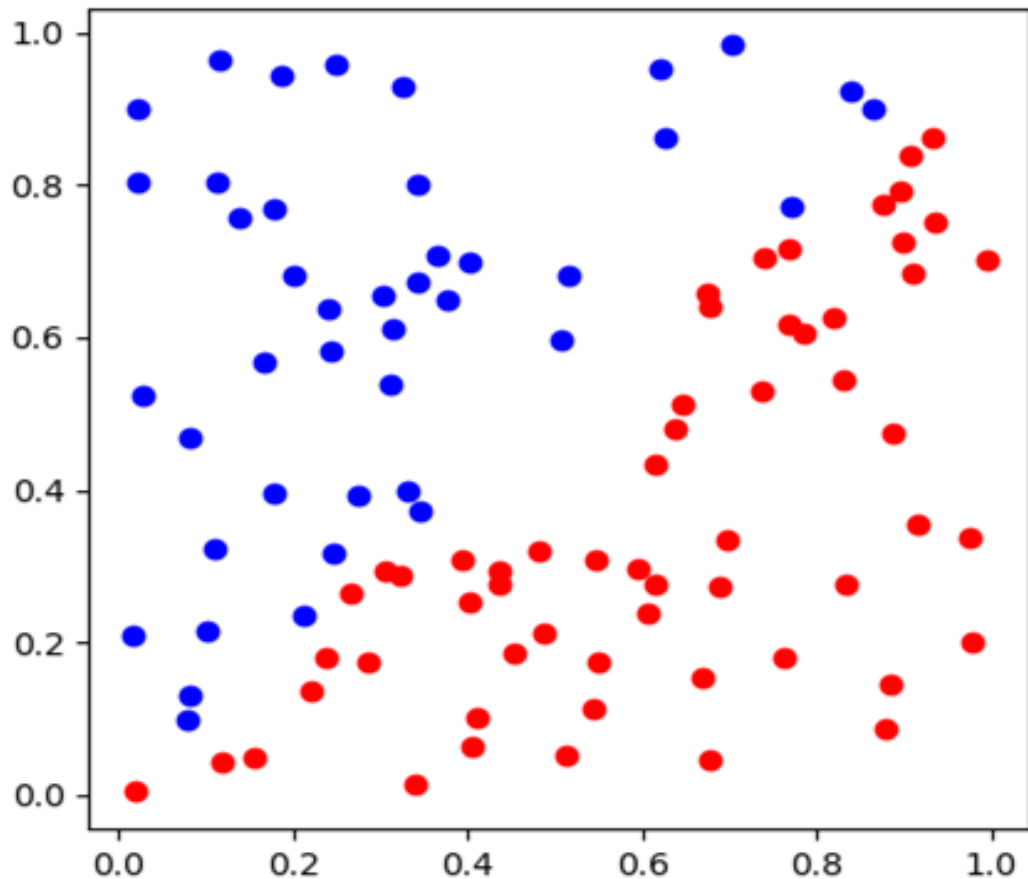
- Each layer should contain
 - At least one transformation (e.g., Linear, CNN, ...)
 - One activation function (e.g., sigmoid, tanh, relu, ...)



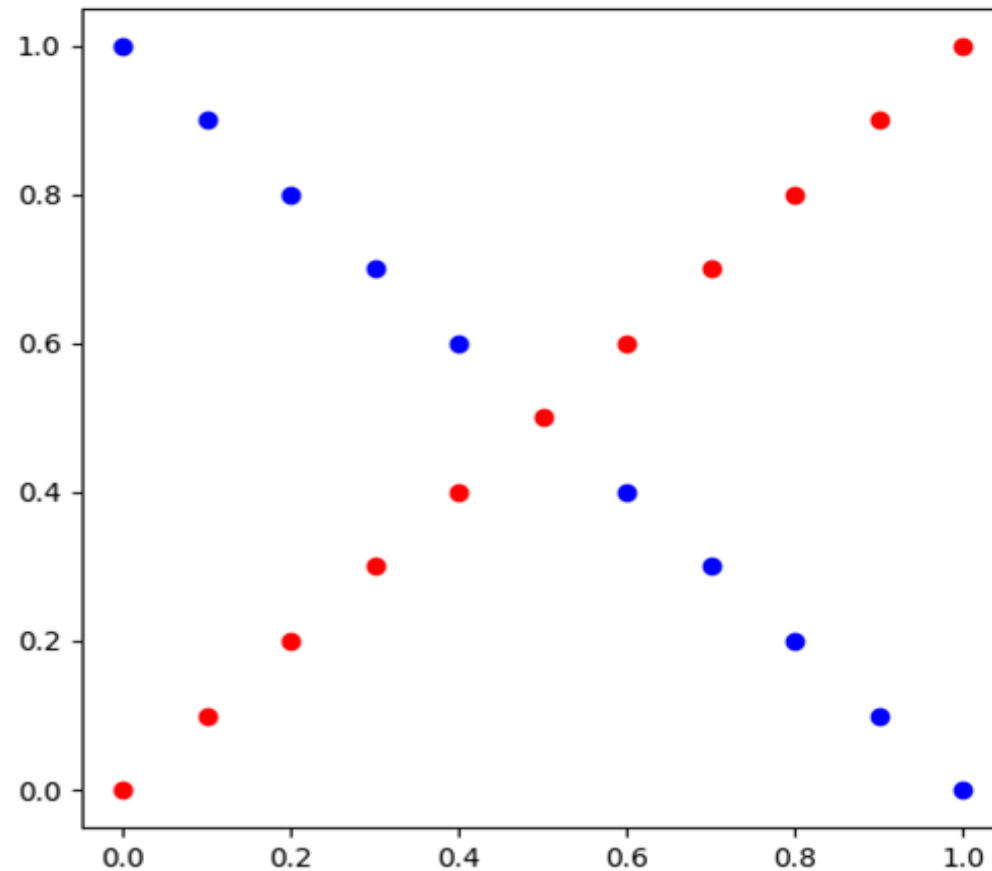
Lab Description – Flowchart



Lab Description - Data



generate_linear()



generate_XOR_easy()

Data Generation

- Do **NOT** overwrite these functions
- Training and Testing with the same data

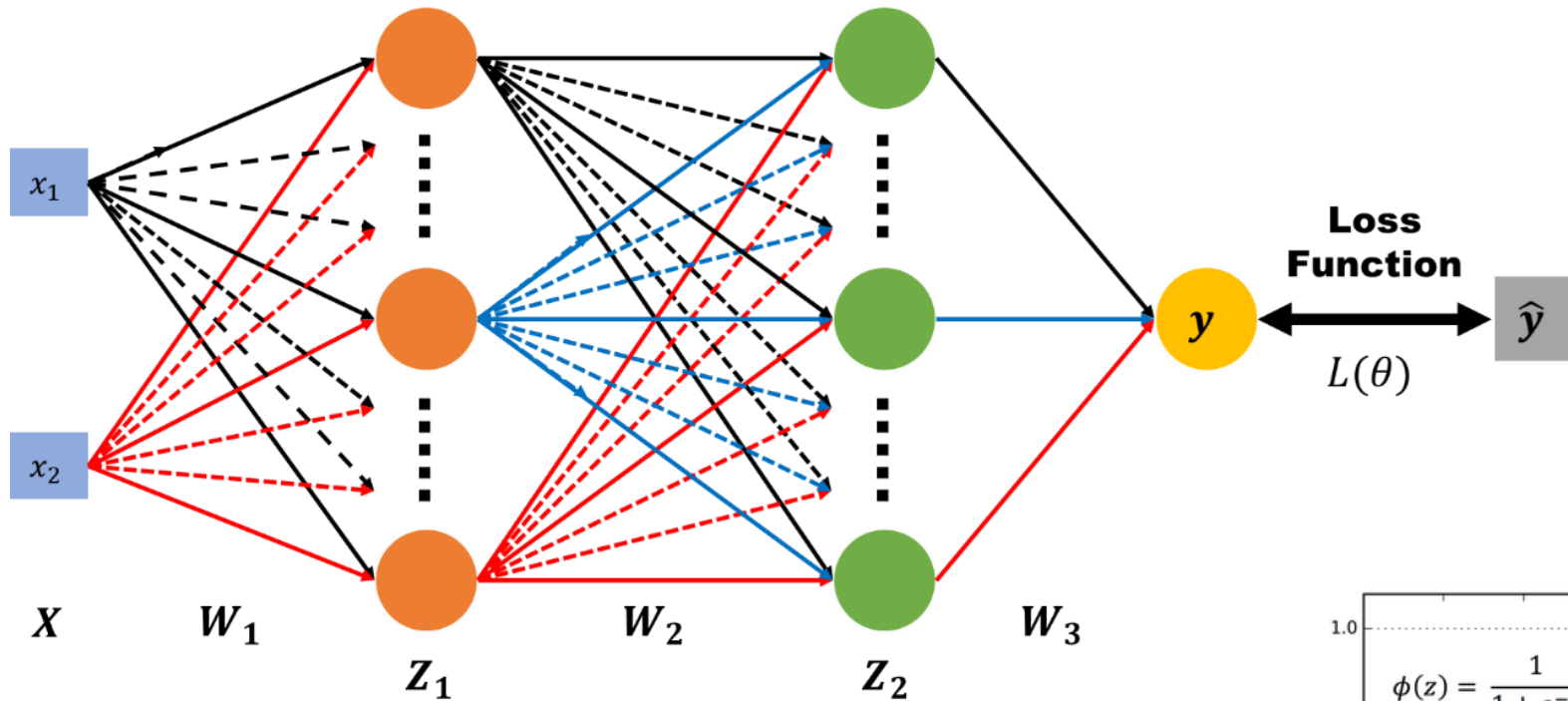
Function usage

```
[x, y = generate_linear(n=100)]  
[x, y = generate_XOR_easy()]
```

```
def generate_linear(n=100):  
    import numpy as np  
    pts = np.random.uniform(0, 1, (n, 2))  
    inputs = []  
    labels = []  
    for pt in pts:  
        inputs.append([pt[0], pt[1]])  
        distance = (pt[0]-pt[1])/1.414  
        if pt[0] > pt[1]:  
            labels.append(0)  
        else:  
            labels.append(1)  
    return np.array(inputs), np.array(labels).reshape(n, 1)
```

```
def generate_XOR_easy():  
    import numpy as np  
    inputs = []  
    labels = []  
  
    for i in range(11):  
        inputs.append([0.1*i, 0.1*i])  
        labels.append(0)  
  
        if 0.1*i == 0.5:  
            continue  
  
        inputs.append([0.1*i, 1-0.1*i])  
        labels.append(1)  
  
    return np.array(inputs), np.array(labels).reshape(21, 1)
```

Lab Description – Forward

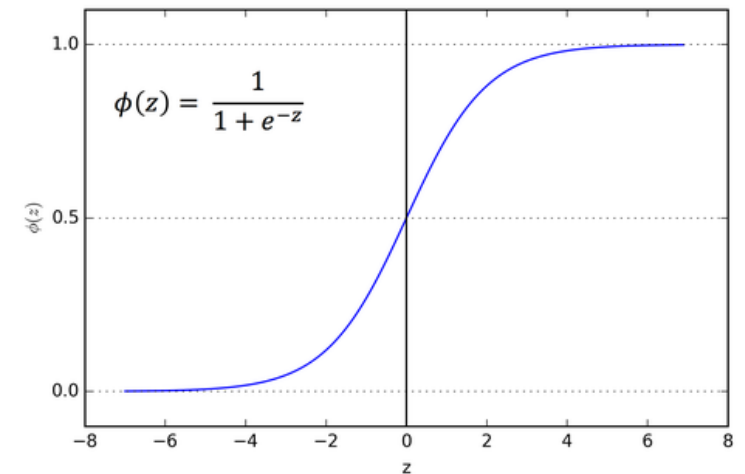


$$Z_1 = \sigma(XW_1)$$

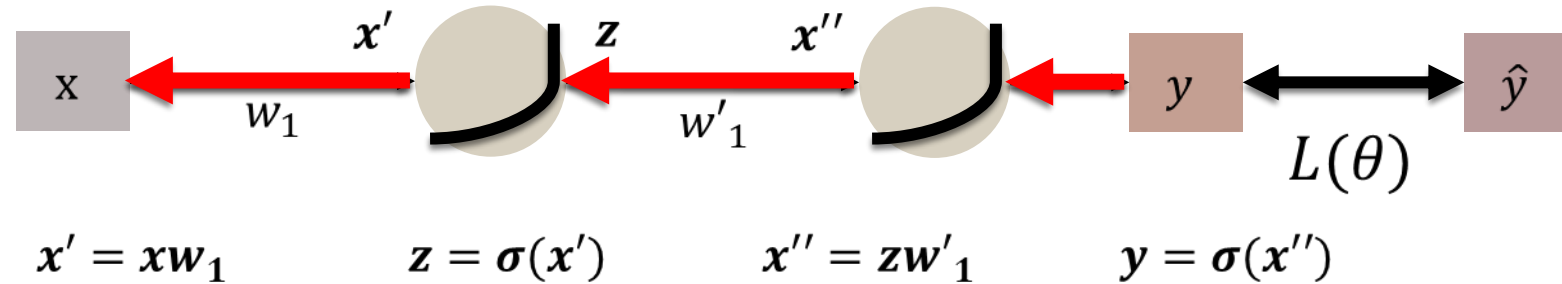
$$Z_2 = \sigma(Z_1W_2)$$

$$y = \sigma(Z_2W_3)$$

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$



Lab Description – Backward



Chain rule

$$y = g(x) \quad z = h(y)$$

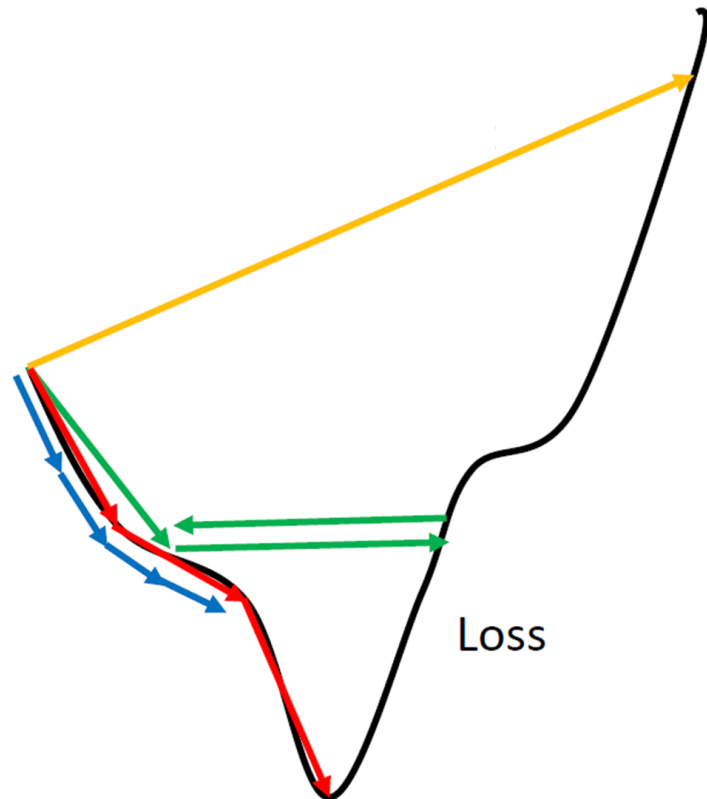
$$\mathbf{x} \xrightarrow{g()} \mathbf{y} \xrightarrow{h()} \mathbf{z}$$

$$\frac{dz}{dx} = \frac{dz}{dy} \frac{dy}{dx}$$

$$\begin{aligned} \frac{\partial L(\theta)}{\partial w_1} &= \frac{\partial y}{\partial w_1} \frac{\partial L(\theta)}{\partial y} \\ &= \frac{\partial y}{\partial x''} \frac{\partial L(\theta)}{\partial y} \frac{\partial x''}{\partial w_1} \\ &= \frac{\partial y}{\partial z} \frac{\partial L(\theta)}{\partial y} \frac{\partial x''}{\partial z} \frac{\partial z}{\partial w_1} \\ &= \frac{\partial y}{\partial x'} \frac{\partial L(\theta)}{\partial y} \frac{\partial x''}{\partial z} \frac{\partial z}{\partial x'} \frac{\partial x'}{\partial w_1} \end{aligned}$$

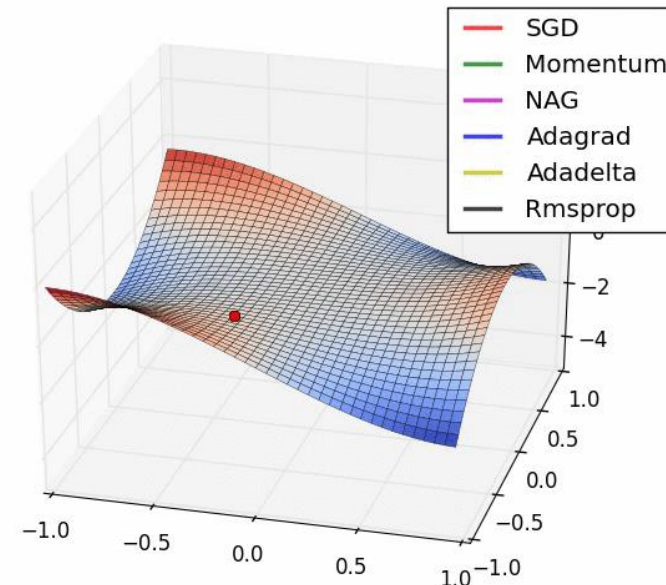
Lab Description – Gradient descent

Network Parameters $\theta = \{w_1, w_2, w_3, w_4, \dots\}$



$$\begin{aligned}\theta^1 &= \theta^0 - \rho \nabla L(\theta^0) \\ \theta^2 &= \theta^1 - \rho \nabla L(\theta^1) \\ \theta^3 &= \theta^2 - \rho \nabla L(\theta^2)\end{aligned}$$

ρ : Learning rate



Lab Description - Prediction

- During training, print the loss

```
epoch 10000 loss : 0.16234523253277644
epoch 15000 loss : 0.2524336634177614
epoch 20000 loss : 0.1590783047540092
epoch 25000 loss : 0.22099447030234853
epoch 30000 loss : 0.3292173477217561
epoch 35000 loss : 0.40406233282426085
epoch 40000 loss : 0.43052897480298924
epoch 45000 loss : 0.4207525735586605
epoch 50000 loss : 0.3934759509342479
epoch 55000 loss : 0.3615008372106921
epoch 60000 loss : 0.33077879872648525
epoch 65000 loss : 0.30333537090819584
epoch 70000 loss : 0.2794858089741792
epoch 75000 loss : 0.25892812312991587
epoch 80000 loss : 0.24119780823897027
epoch 85000 loss : 0.22583656353511342
epoch 90000 loss : 0.21244497028971704
epoch 95000 loss : 0.2006912468389013
```

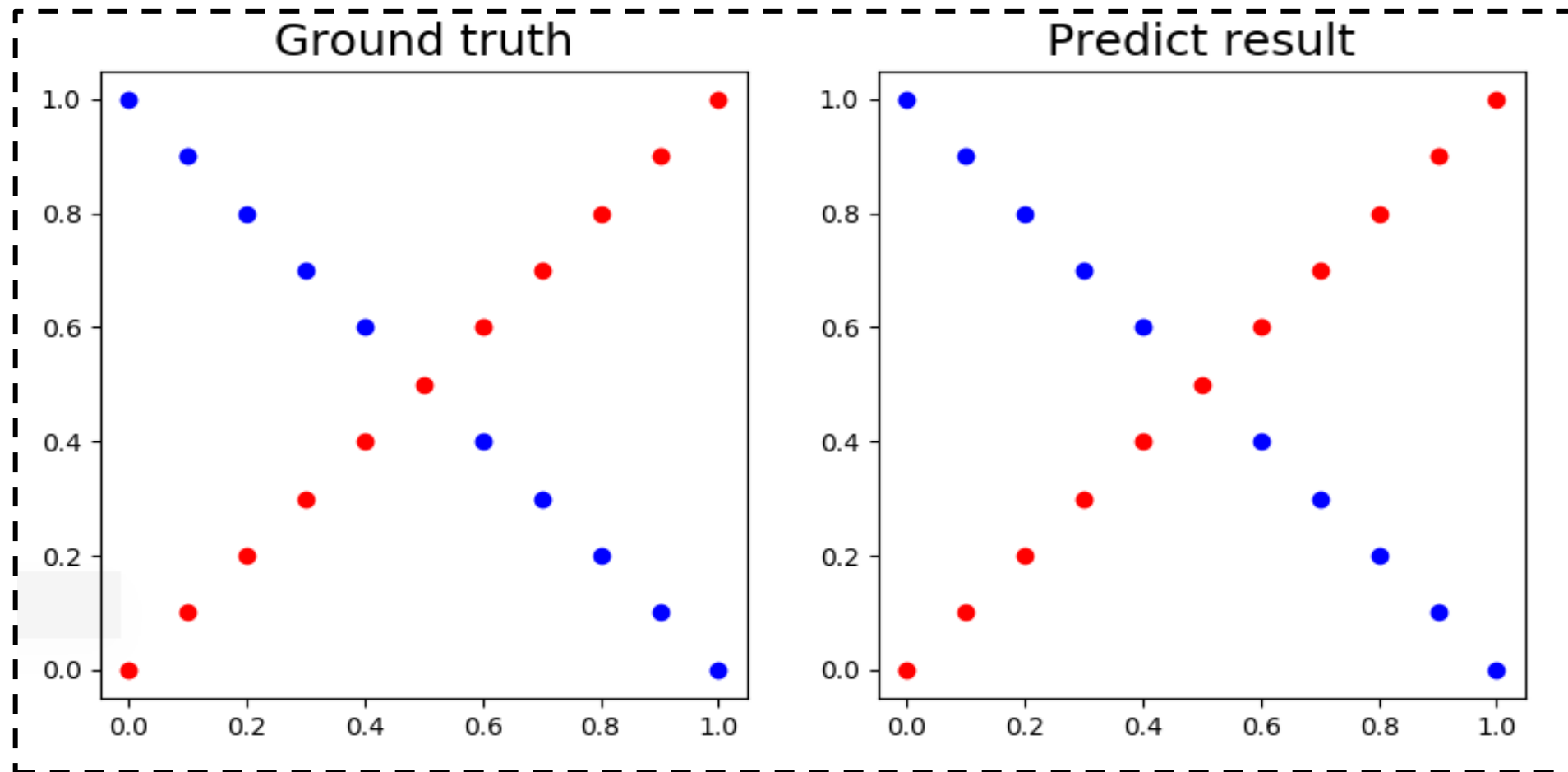
- During testing, show the predictions and the accuracy

Iter91	Ground truth: 1.0	prediction: 0.99943
Iter92	Ground truth: 1.0	prediction: 0.99987
Iter93	Ground truth: 1.0	prediction: 0.99719
Iter94	Ground truth: 1.0	prediction: 0.99991
Iter95	Ground truth: 0.0	prediction: 0.00013
Iter96	Ground truth: 1.0	prediction: 0.77035
Iter97	Ground truth: 1.0	prediction: 0.98981
Iter98	Ground truth: 1.0	prediction: 0.99337
Iter99	Ground truth: 0.0	prediction: 0.20275

loss=0.03844 accuracy=100.00%

Lab Description - Prediction

- Visualize the predictions and ground truth at the end of the training process



Scoring Criteria

- Achieve 90% accuracy in testing to get 40% experimental results score

Report Spec:

1. Introduction (5%)
2. Implementation Details (15%):
 - A. Sigmoid function
 - B. Neural network architecture
 - C. Back-propagation
3. Experimental Results (45%)
 - A. Screenshot and comparison figure
 - B. Show the accuracy of your prediction (40%) (achieve 90% accuracy)
 - C. Learning curve (loss-epoch curve)
 - D. Anything you want to present
4. Discussion (15%)
 - A. Try different learning rates
 - B. Try different numbers of hidden units
 - C. Try without activation functions
 - D. Anything you want to share
5. Questions (20%)
 - A. What is the purpose of activation functions? (6%)
 - B. What might happen if the learning rate is too large or too small? (7%)
 - C. What is the purpose of weights and biases in a neural network? (7%)
6. Extra (10%)
 - A. Implement different optimizers. (2%)
 - B. Implement different activation functions. (3%)
 - C. Implement convolutional layers. (5%)

Important Date

- Report Submission Deadline: **3/11 (Tue.) 23:59**
- Zip all files in one file
 - Report (report.pdf)
 - Source code
- Name it like 「DL_LAB1_yourstudentID_name.zip」
 - E.g., 「DL_LAB1_313551157_陳敬中.zip」
- If there are any format errors in your files, you will receive a **5-point** penalty

Reference

1. <http://www.denizyuret.com/2015/03/alec-radfords-animations-for.html>
2. http://speech.ee.ntu.edu.tw/~tlkagk/courses_ML17_2.html