

# **NYCU DL**

## **Lab1 - Backpropagation**

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# Outline

- Lab Objectives
- Scoring Criteria
- Time Schedule

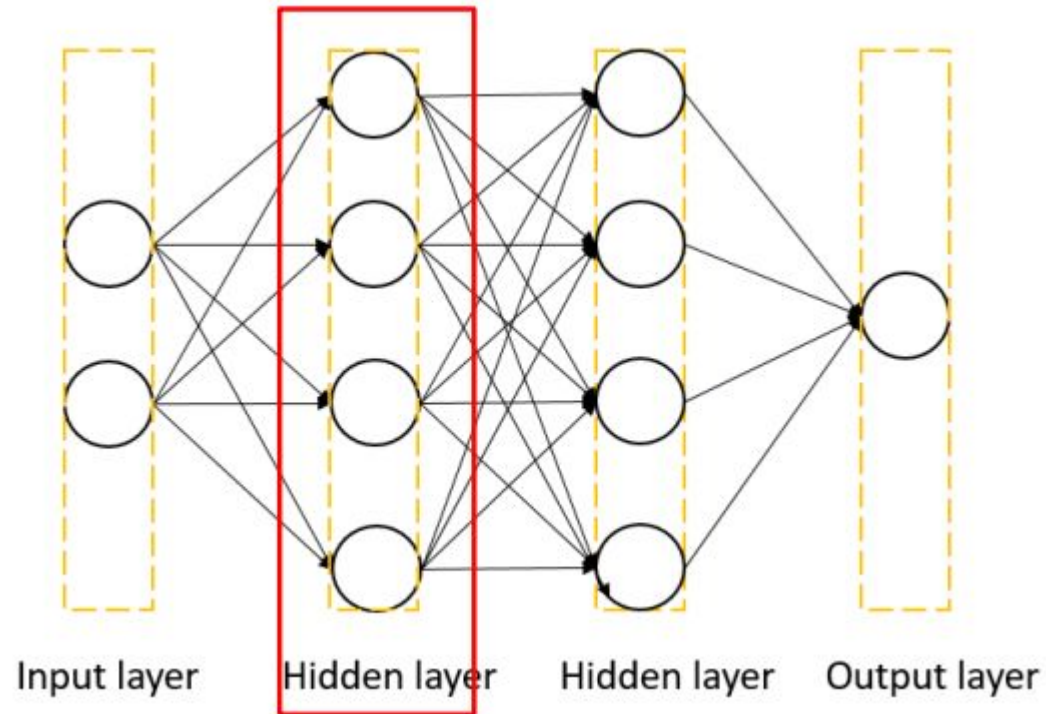
# Lab Objectives

- **Implement a Simple Neural Network:** Build a fully-connected NN with **two hidden** layers using **only Numpy**
- **Master Backpropagation:** Implement a backpropagation algorithm to calculate gradients and update model weights
- **Visualize Learning:** Plot the learning curve and show the prediction-vs-ground\_truth figure
- **Evaluation:** Calculate and print the accuracy of your trained model

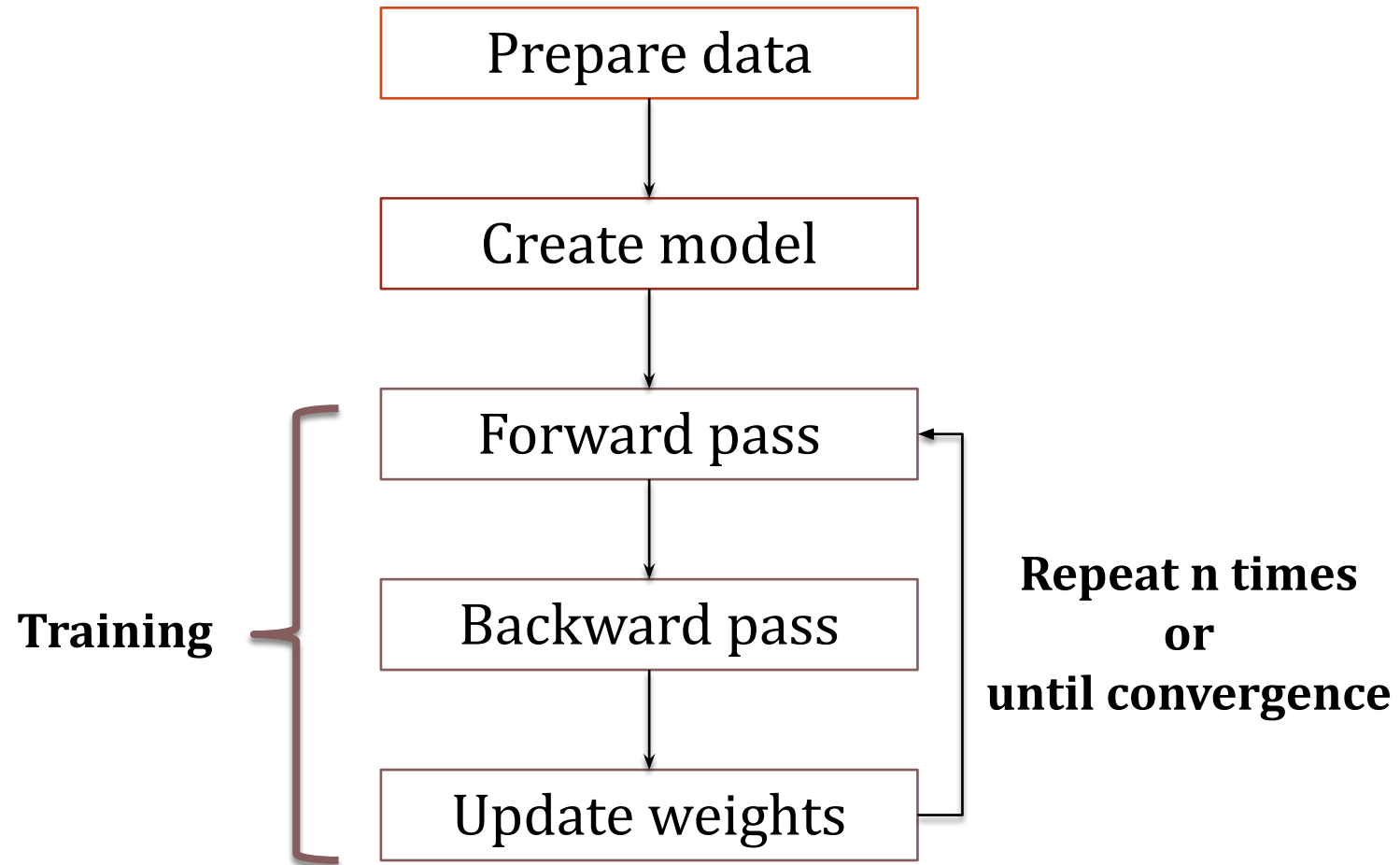
NOTE: You are NOT allowed to use DL frameworks like PyTorch or TensorFlow

# Lab Description

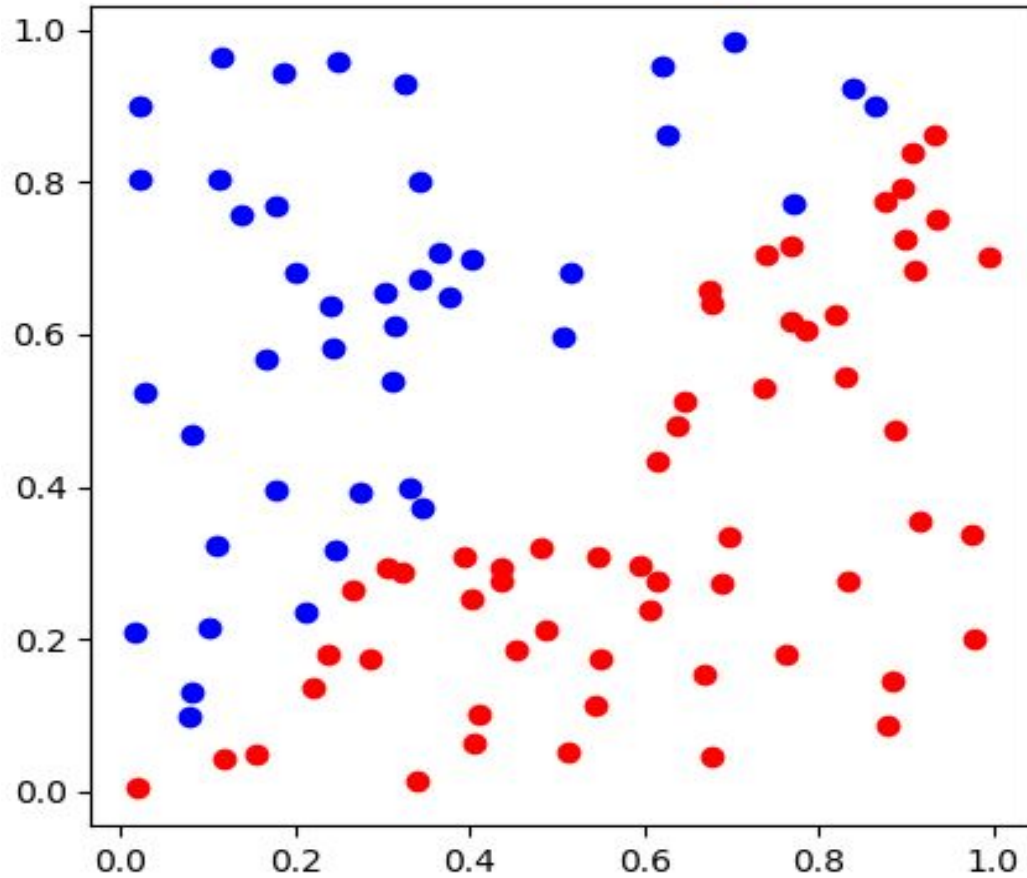
- Each layer should contain
  - One transformation (e.g., Linear, CNN, ...)
  - One activation function (e.g., sigmoid, tanh, relu, ...)



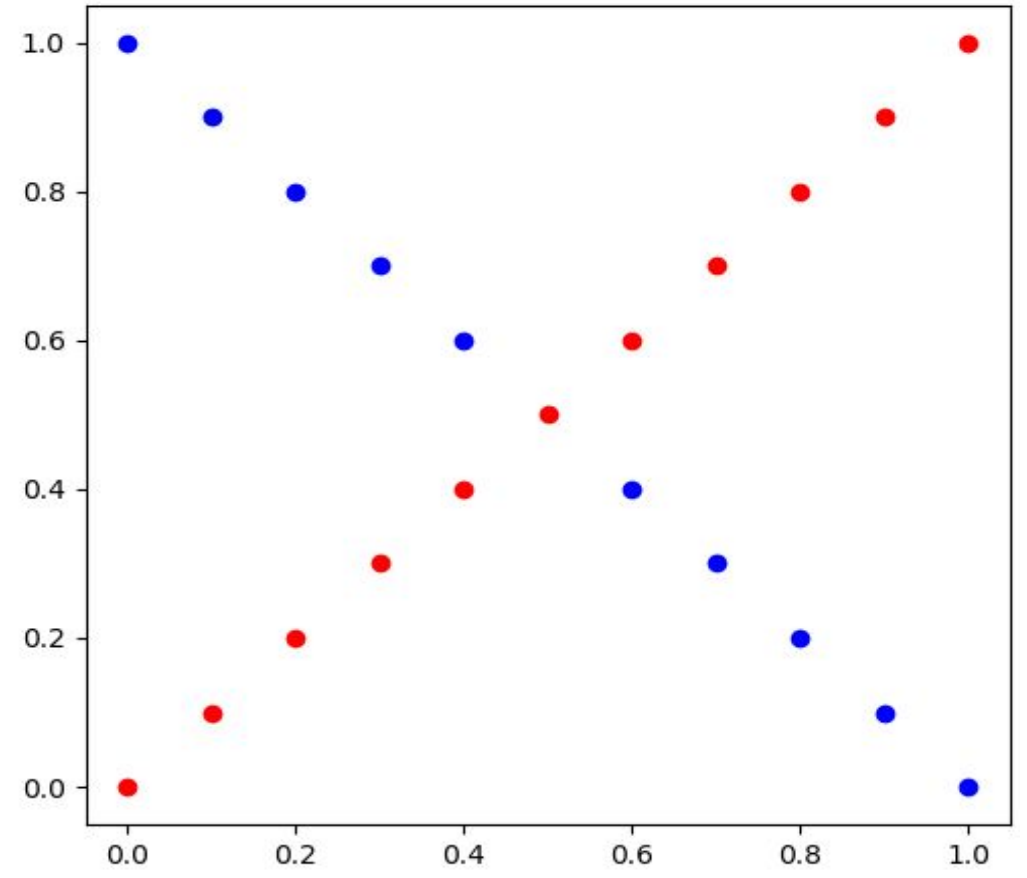
# Lab Description – Flowchart



# Lab Description - Data



generate\_linear()



generate\_XOR\_easy()

# Data Generation

- Do **NOT** overwrite these functions
- Training and Testing with the same data
- For the linear dataset, train and test with n=100

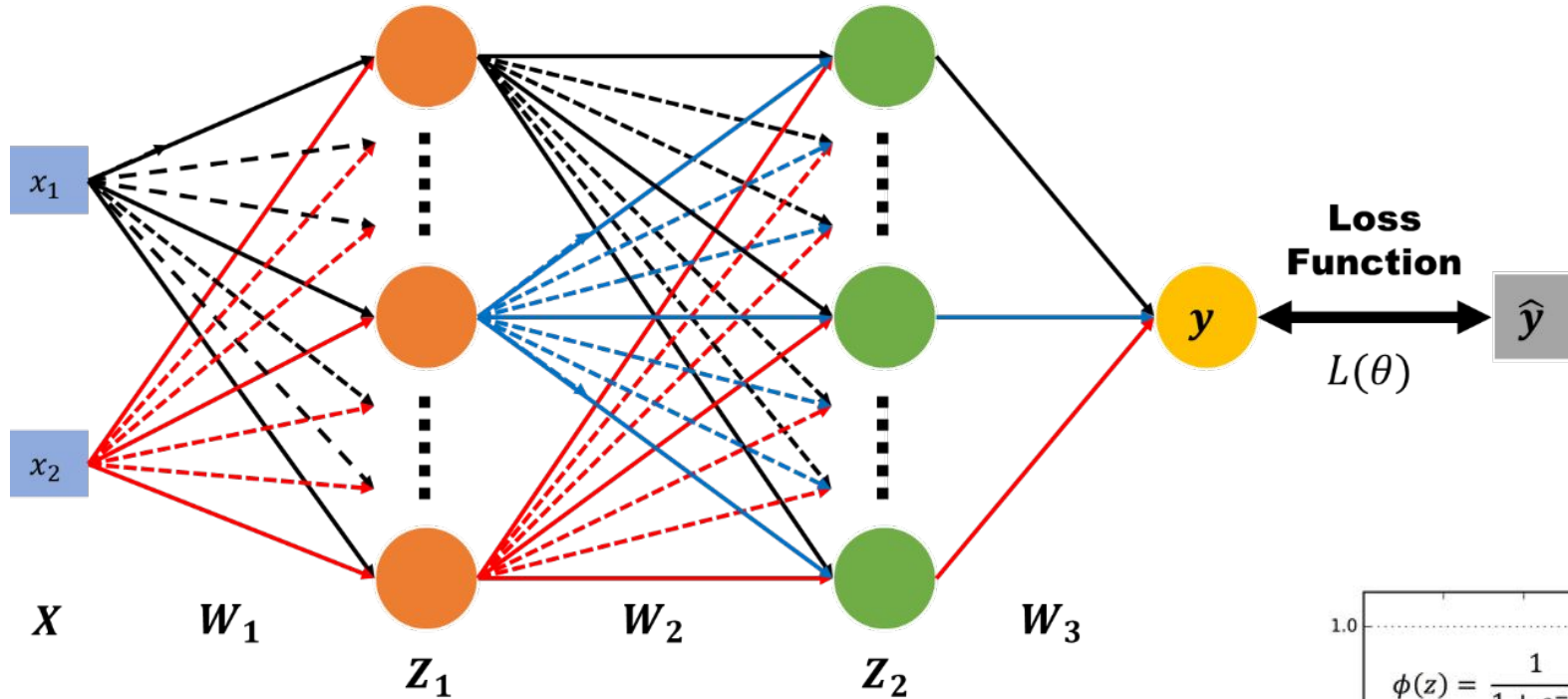
## Function usage

```
[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

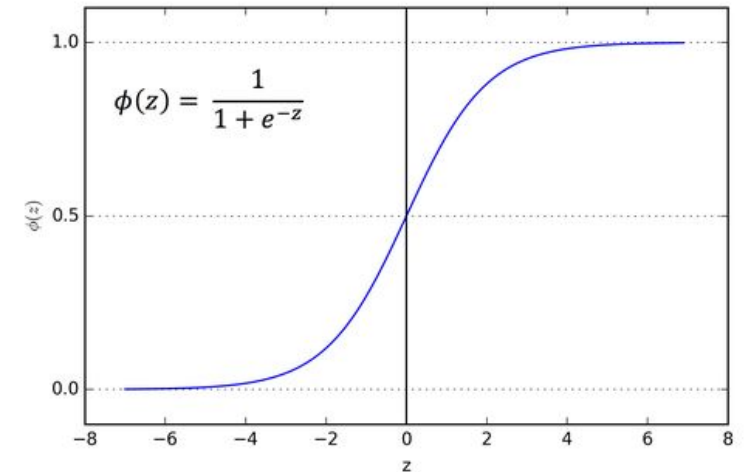


$$Z_1 = \sigma(XW_1)$$

$$Z_2 = \sigma(Z_1W_2)$$

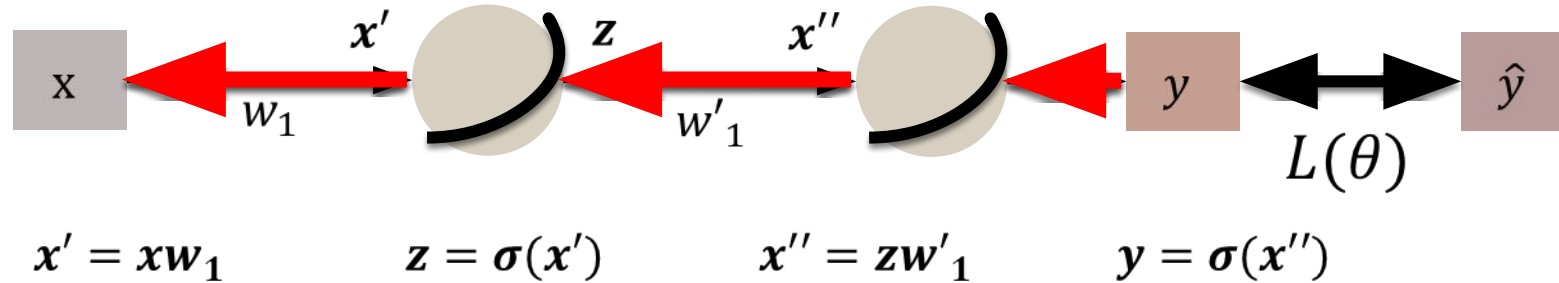
$$y = \sigma(Z_2W_3)$$

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





# Lab Description – Backward



## Chain rule

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

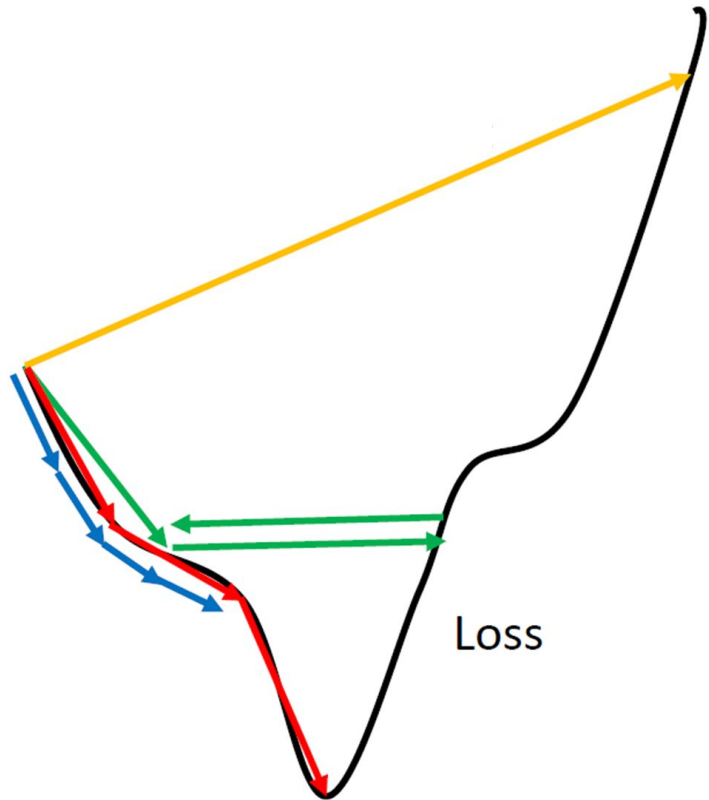
$$\mathbf{x} \xrightarrow{g()} \mathbf{y} \xrightarrow{h()} \mathbf{z}$$

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

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

# Lab Description – Gradient descent

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

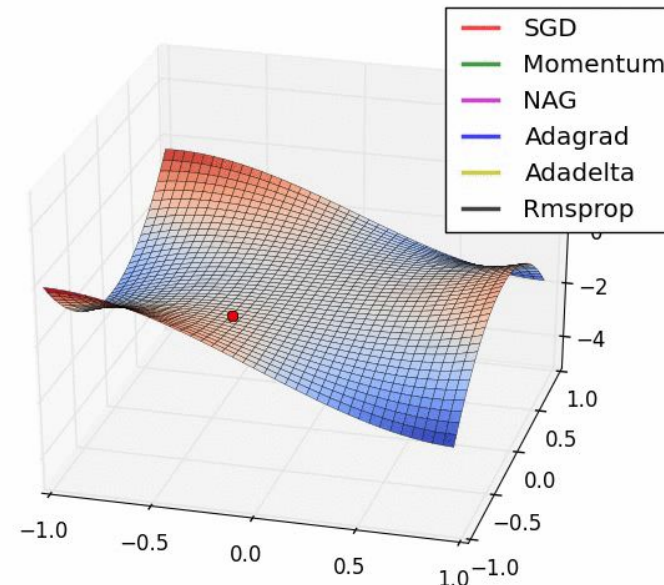


$$\theta^1 = \theta^0 - \rho \nabla L(\theta^0)$$

$$\theta^2 = \theta^1 - \rho \nabla L(\theta^1)$$

$$\theta^3 = \theta^2 - \rho \nabla L(\theta^2)$$

$\rho$  : 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
```

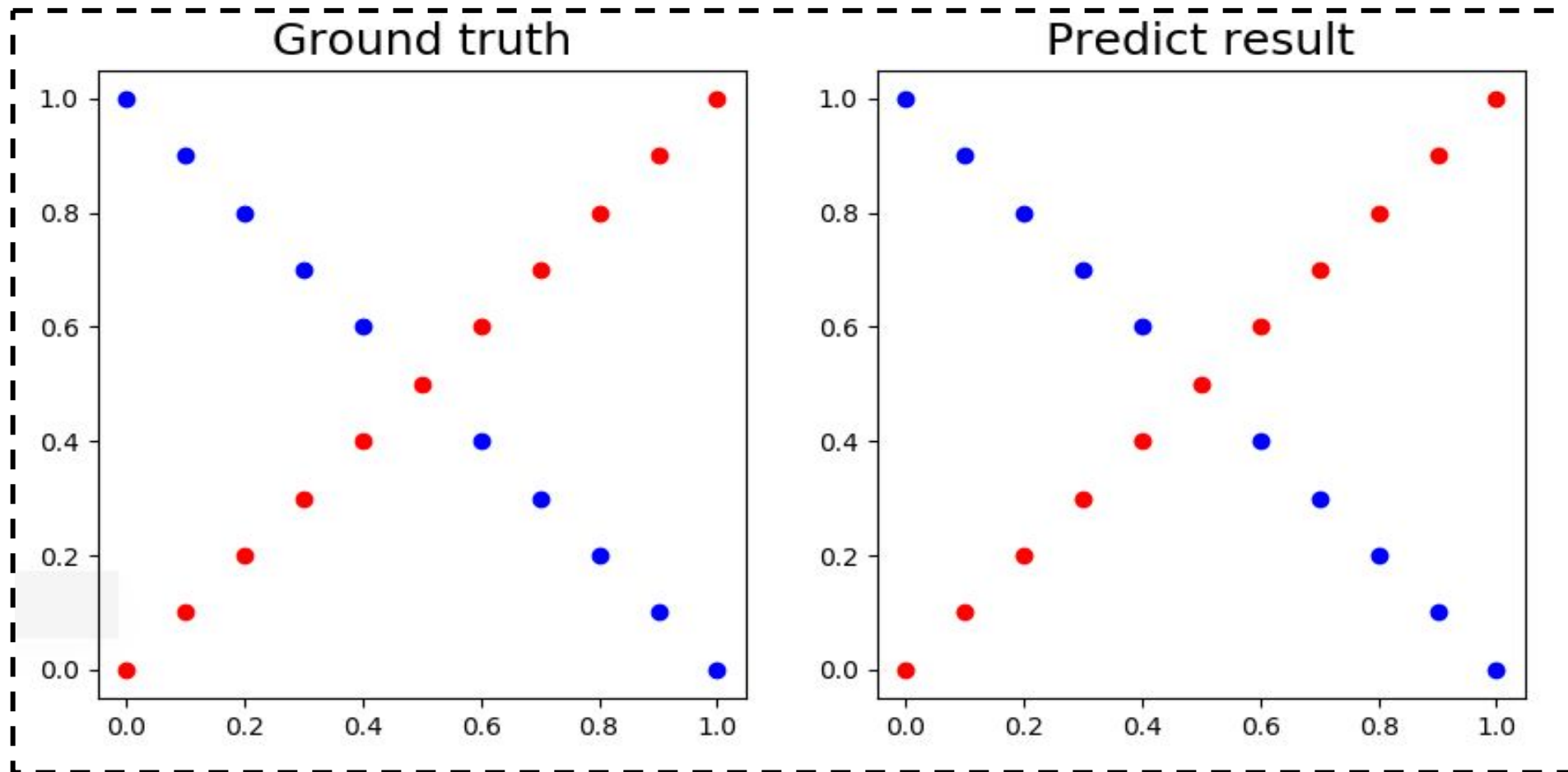
- During testing, show the predictions and the accuracy

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

- Write clearly your what, why, and how.
- Visualize your results
- Strictly follow the spec

- **Report Spec:**

1. Introduction (5%)
2. Implementation Details (25%):
  - A. Network Architecture
  - B. Activation Functions
  - C. Backpropagation
  - D. Extra Implementation
3. Experimental Results (40%)
  - A. Screenshot and comparison figure (5%)
  - B. Show the accuracy of your prediction (30% \* accuracy)
  - C. Learning curve (loss-epoch curve) (5%)
  - D. Anything you want to present
4. Discussions (21%)
  - A. Try different learning rates
  - B. Try different numbers of hidden units
  - C. Try without activation functions
  - D. Extra Implementation Discussions
5. Questions (9%)
  - A. What are the purposes of activation functions? (3%)
  - B. What if the learning rate is too large or too small? (3%)
  - C. What are the purposes of weights and biases in a neural network? (3%)
6. Bonus (10%)
  - A. Optimizers. (5%)
  - B. Activation functions. (5%)

# Important Date

- Report Submission Deadline: 7/10 (Thu.) 23:59
- Zip all files in one file
  - Report (report.pdf)
  - Source code
- Do NOT submit model weights and figures
- 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, or if you do not follow the requirements, you will receive a **10-point** penalty each