

1. Introduction

這次作業為在不利用 Tensorflow、Pytorch 等函式庫的情況下實作具有 forward、back propagation 與 activation function 之 Neural Network。並使用 linear 與 XOR 之 data 對 Neural Network 進行訓練，觀測不同 learning rate、neural width 對整體的影響。

2. Experiment setups

a. Sigmoid functions

```
def sigmoid(x):  
    return 1.0 / (1.0 + np.exp(-x))  
  
def derivative_sigmoid(x):  
    return x * (1.0 - x)
```

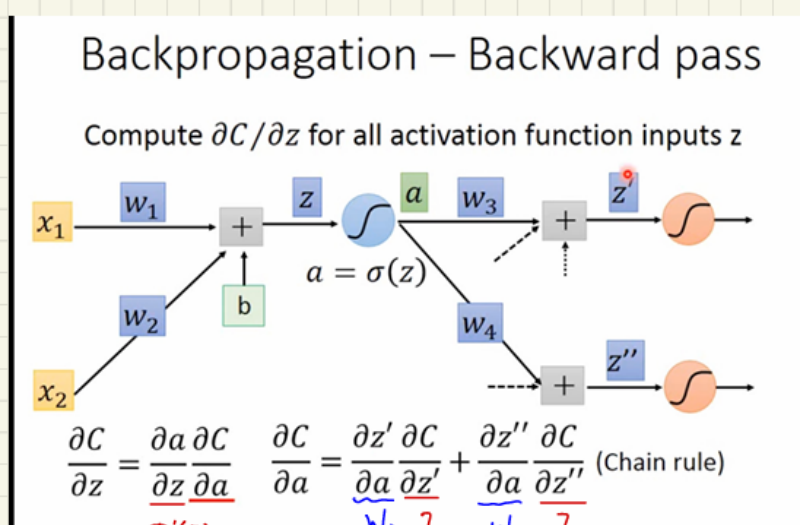
b. Neural networks

```
class Model:  
    def __init__(self, input_size = 2, hidden_size = 10, lr = 0.1):  
        self.layer1 = Layer(input_size, hidden_size)  
        self.layer2 = Layer(hidden_size, hidden_size)  
        self.output = Layer(hidden_size, output_size: 1)  
        self.lr = lr  
        self.loss = []  
        self.epoch = 0  
  
    def train(self, x, y, epoch):  
        self.epoch = epoch  
        for i in range(epoch):  
            output = self.output.forward(self.layer2.forward(self.layer1.forward(x)))  
            loss, grad = MSELoss(output, y)  
            self.layer1.backward(self.layer2.backward(self.output.backward(grad, self.lr), self.lr), self.lr)  
            self.loss.append(loss)  
            if i % 5000 == 0: #control how many cycle print loss  
                print(f"epoch {i} loss : {loss}")  
            self.prediction = output  
            plt.subplot( "args: 2, 1, 1)  
            plt.title( label: "Learning Curve", fontsize=18)  
            plt.xlabel("Epoch")  
            plt.ylabel("Loss")  
            plt.plot(self.loss)  
            return output  
  
    def show_result(self, x, y):  
        print(f"Accuracy : {sum((self.prediction > 0.5) == (y == 1)) / y.size}")  
        print("Prediction : ")  
        for i in range(y.size):  
            print(f"Iter{i + 1} | Ground truth: {y[i]} | prediction: {self.prediction[i]} |")  
        show_result(x, y, self.prediction > 0.5)  
  
plt.figure(figsize=(12, 12))
```

建立一個具有兩層 hidden layer 的神經網路，具有線性以及 activation function 的部分，Forward 以及 backward 的部分則是包含在 layer class 裡面。在 model 的最後面則是會輸出學習曲線。

c. Back propagation

① Compute backward pass: i.e. calculate $\frac{\partial C}{\partial z}$, $\frac{\partial C}{\partial z} = \frac{\partial C}{\partial a} \frac{\partial a}{\partial z} \sigma'(z)$



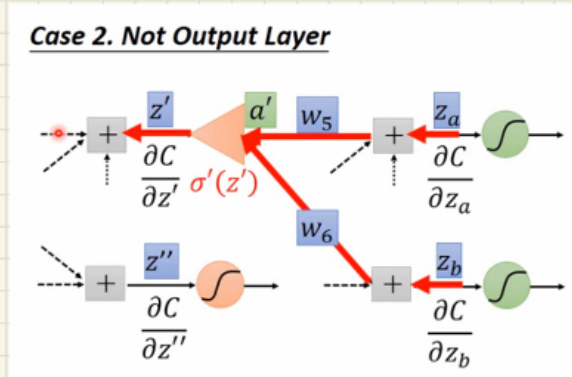
assume is known

$$\frac{\partial C}{\partial z} = \sigma'(z) \left[w_3 \frac{\partial C}{\partial z'} + w_4 \frac{\partial C}{\partial z''} \right]$$

① case 1: 已經是 output layer

$$\frac{\partial C}{\partial z'} = \frac{\partial C}{\partial y_1} \frac{\partial y_1}{\partial z'}, \quad \frac{\partial C}{\partial z''} = \frac{\partial C}{\partial y_2} \frac{\partial y_2}{\partial z''}$$

② Case 2: 非 output layer



⇒ 持續做到找到 output layer

由 op-amplifier 之圖知 $\frac{\partial C}{\partial z'} = \sigma'(z') \left[w_5 \frac{\partial C}{\partial z_a} + w_6 \frac{\partial C}{\partial z_b} \right]$

```
class Layer:
    def __init__(self, input_size, output_size):
        self.input_size = input_size
        self.output_size = output_size
        self.w = np.random.randn(input_size, output_size)

    def forward(self, x):
        self.x = x
        self.z = sigmoid(np.dot(x, self.w))
        return self.z

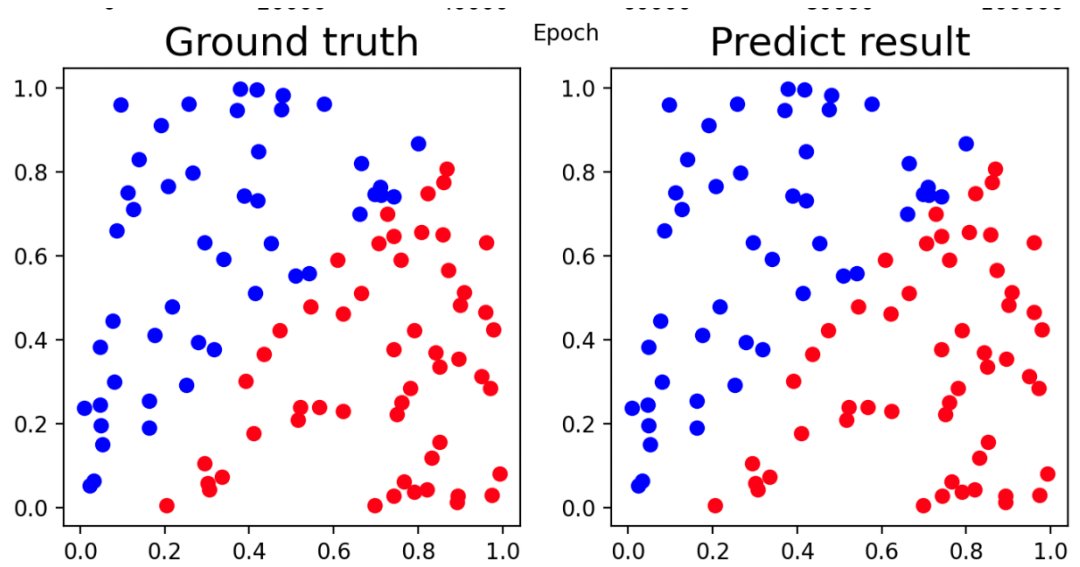
    def backward(self, pre_g, lr):
        self.w -= np.dot(self.x.T, (pre_g * derivative_sigmoid(self.z))) * lr
        return np.dot((pre_g * derivative_sigmoid(self.z)), self.w.T)
```

這邊定義了每一層 hidden layer 中 forward 與 backward 的計算過程。

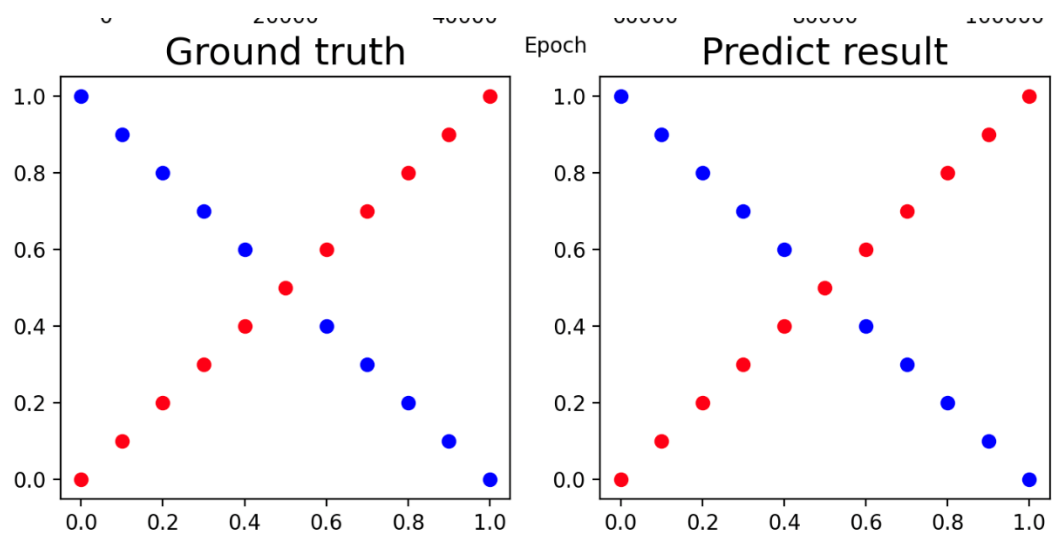
3. Result of your testing

a. Screenshot and comparison figure

Linear:



XOR:



b. Show the accuracy of your prediction

Learning rate = 0.1, hidden units = 10, using SGD to optimize

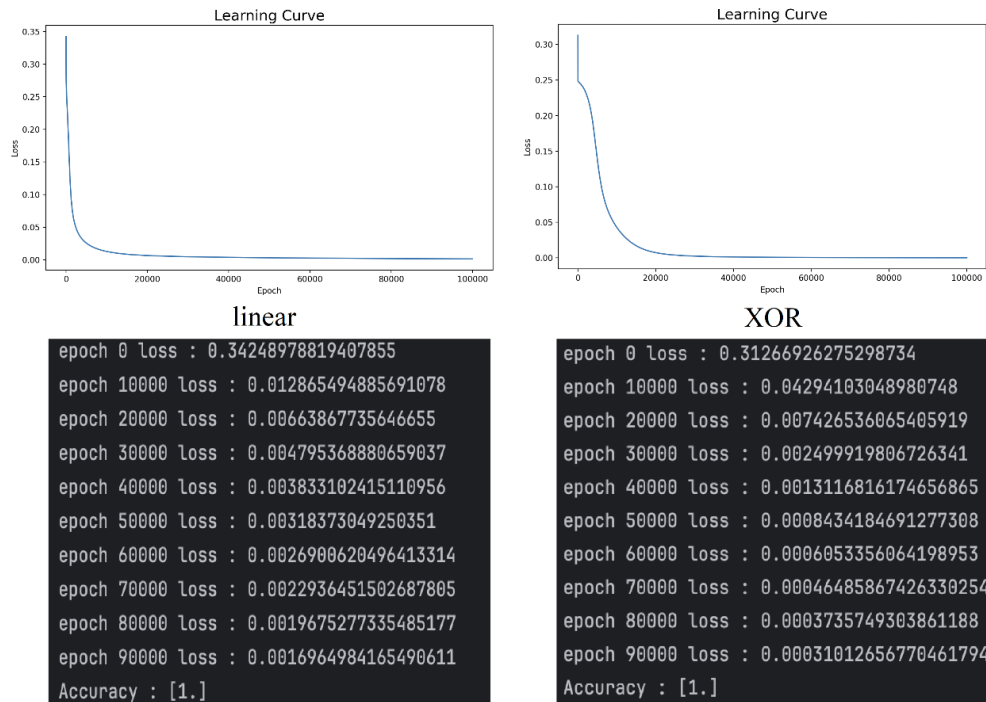
Linear:

Iter1		Ground truth: [0]		prediction: [1.08295064e-05]	
Iter2		Ground truth: [0]		prediction: [1.12183416e-05]	
Iter3		Ground truth: [1]		prediction: [0.99994474]	
Iter4		Ground truth: [0]		prediction: [7.21906516e-05]	
Iter5		Ground truth: [1]		prediction: [0.99624616]	
Iter6		Ground truth: [0]		prediction: [1.25404731e-05]	
Iter7		Ground truth: [1]		prediction: [0.99993656]	
Iter8		Ground truth: [0]		prediction: [3.79155452e-05]	
Iter9		Ground truth: [1]		prediction: [0.99990859]	
Iter10		Ground truth: [1]		prediction: [0.99994601]	
Iter11		Ground truth: [0]		prediction: [1.1098067e-05]	
Iter12		Ground truth: [1]		prediction: [0.99990169]	
Iter13		Ground truth: [1]		prediction: [0.99959192]	
Iter14		Ground truth: [0]		prediction: [4.34922614e-05]	
Iter15		Ground truth: [0]		prediction: [0.00010552]	
Iter16		Ground truth: [0]		prediction: [1.19640821e-05]	
Iter17		Ground truth: [0]		prediction: [1.03780129e-05]	
Iter18		Ground truth: [1]		prediction: [0.99984451]	
Iter19		Ground truth: [1]		prediction: [0.99947852]	

XOR:

Prediction :					
Iter1		Ground truth: [0]		prediction: [0.00042637]	
Iter2		Ground truth: [1]		prediction: [0.99253175]	
Iter3		Ground truth: [0]		prediction: [0.00142423]	
Iter4		Ground truth: [1]		prediction: [0.99693925]	
Iter5		Ground truth: [0]		prediction: [0.00516162]	
Iter6		Ground truth: [1]		prediction: [0.99862674]	
Iter7		Ground truth: [0]		prediction: [0.01433159]	
Iter8		Ground truth: [1]		prediction: [0.99875469]	
Iter9		Ground truth: [0]		prediction: [0.02460738]	
Iter10		Ground truth: [1]		prediction: [0.96697704]	
Iter11		Ground truth: [0]		prediction: [0.02643264]	
Iter12		Ground truth: [0]		prediction: [0.02015218]	
Iter13		Ground truth: [1]		prediction: [0.96413894]	
Iter14		Ground truth: [0]		prediction: [0.01253923]	
Iter15		Ground truth: [1]		prediction: [0.99965733]	
Iter16		Ground truth: [0]		prediction: [0.00714381]	
Iter17		Ground truth: [1]		prediction: [0.99993677]	
Iter18		Ground truth: [0]		prediction: [0.00403535]	
Iter19		Ground truth: [1]		prediction: [0.99996938]	
Iter20		Ground truth: [0]		prediction: [0.00236733]	
Iter21		Ground truth: [1]		prediction: [0.99997883]	

c. Learning curve(loss, epoch curva)

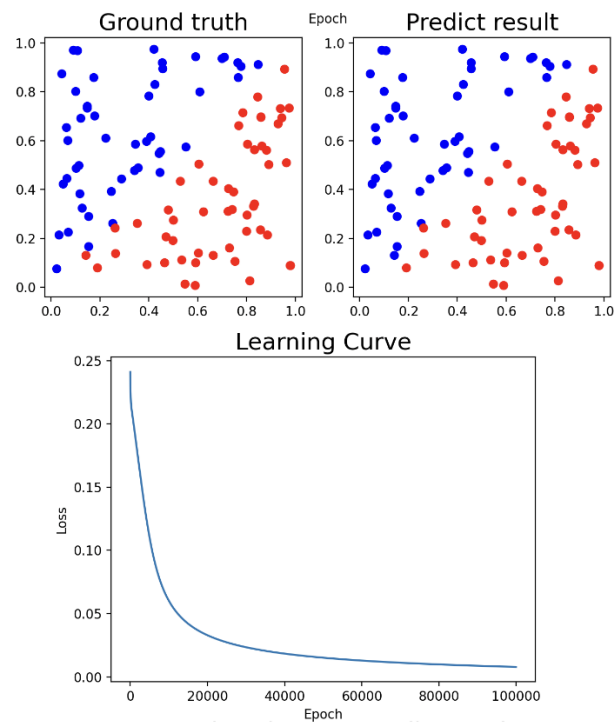


4. Discussion

a. Try different learning rates

Learning rate = 0.01, hidden units = 10, using SGD to optimize

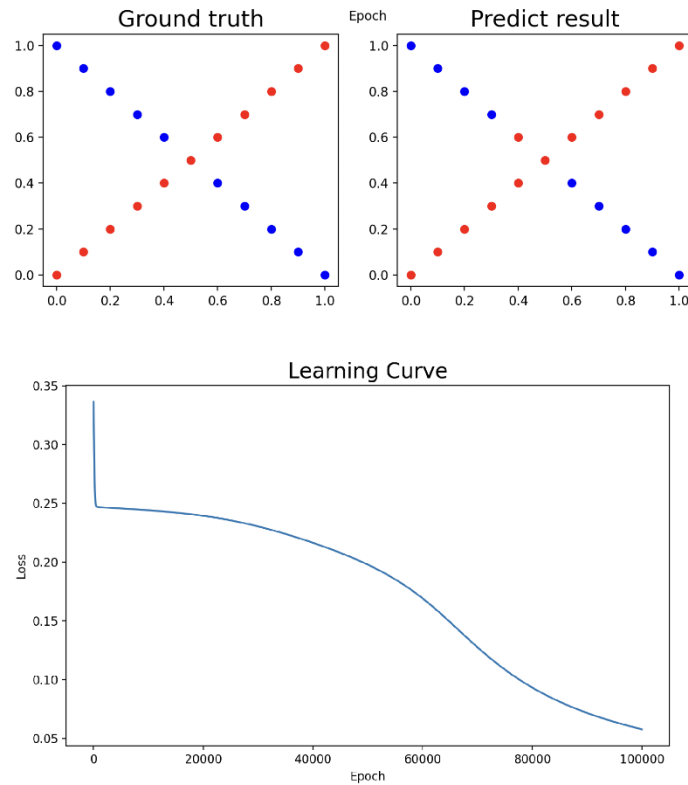
Linear:



當 learning rate 下降時，loss 下降速率也變慢，但在整體上

來說 accuracy 都可以保持在相當高的數值。

XOR:



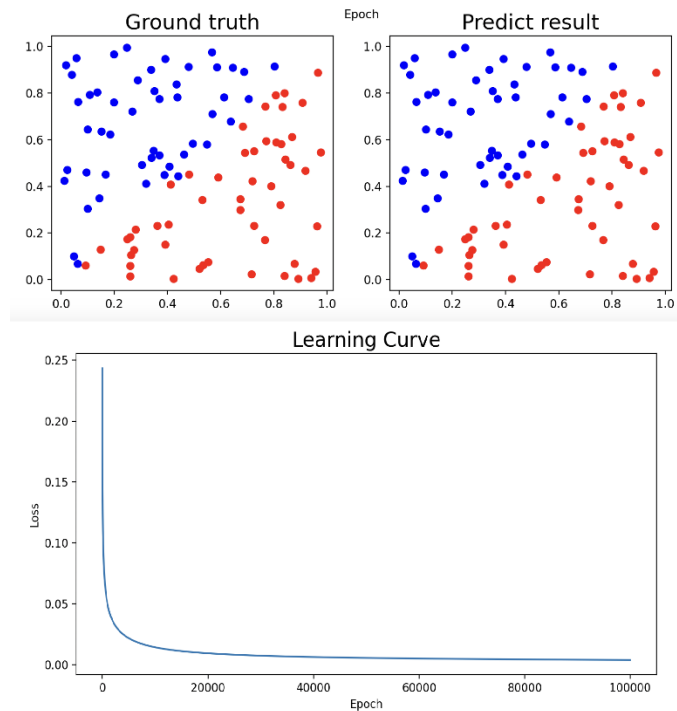
b. Try different numbers of hidden units

Linear with hidden units = 50, learning rate = 0.1:

在調整 linear 的 hidden units 時，並不會有太大的變化。可是

在調大時，與相同的 hidden units 的 XOR 相比，訓練時間會長

不少。



XOR with hidden units = 2, learning rate = 0.1:

XOR 在調低 hidden units 時會導致其 accuracy 變得相當差甚

至低於 0.9

```
epoch 0 loss : 0.2501862258875396
epoch 10000 loss : 0.24918486601504122
epoch 20000 loss : 0.2460436695161326
epoch 30000 loss : 0.19762502819911365
epoch 40000 loss : 0.18156912558033228
epoch 50000 loss : 0.17168559480099835
epoch 60000 loss : 0.1677714133011635
epoch 70000 loss : 0.1662090972711316
epoch 80000 loss : 0.16544432160211175
epoch 90000 loss : 0.16500884401828325
Accuracy : [0.76190476]
```