MTK DLP
Lab1 - Backpropagation

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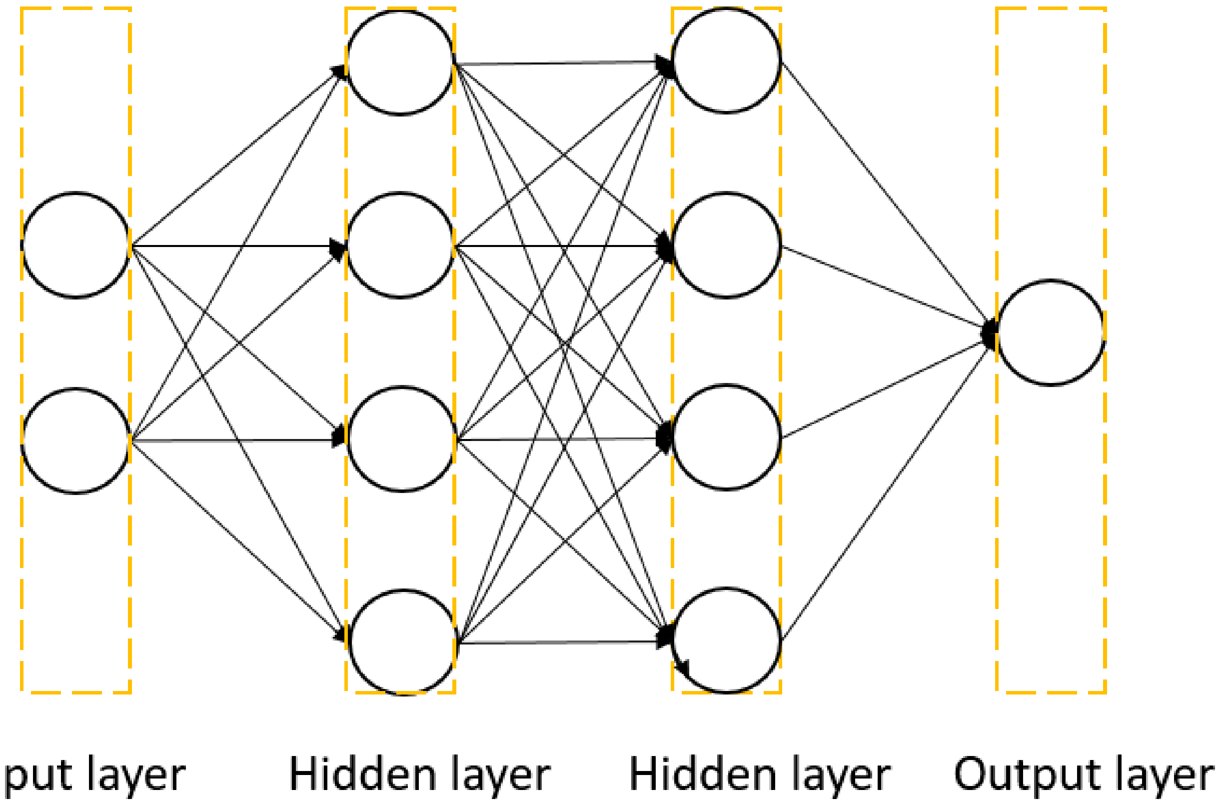
Aug 19, 2020

Outline

- Lab Objective
- Important Date
- Lab Description
- Scoring Criteria

Lab Objective

- In this lab, you will need to understand and implement a simple neural network with forward and backward pass using two hidden layers



Important Date

- Report Submission Deadline: 9/2 (Wed) 11:59 a.m

- Demo date: 9/2 (Wed)

- Zip all files in one file
  - Report (.pdf)
  - Source code

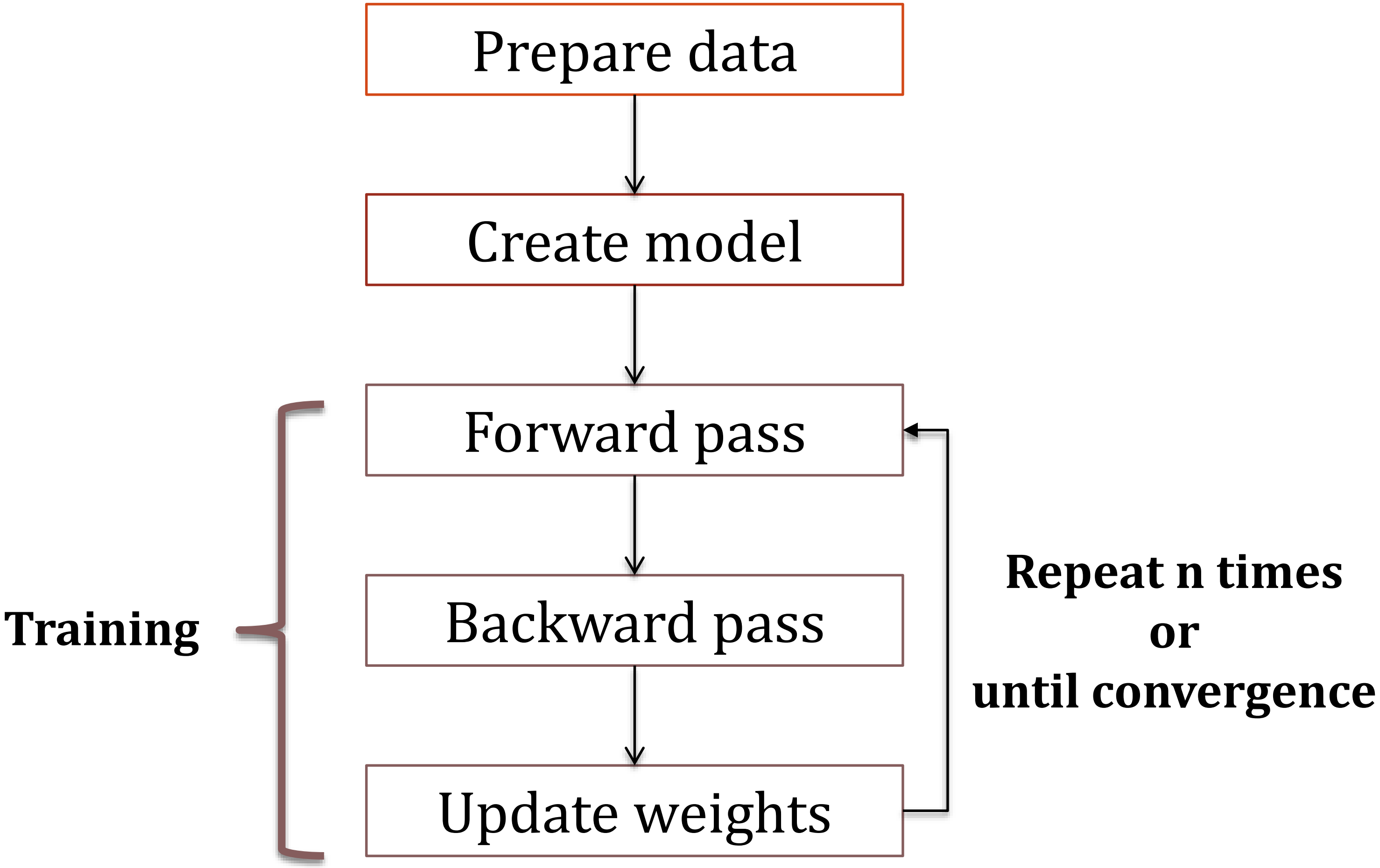
- name it like「DLP_LAB1_yourID_name.zip」
  - ex: 「DLP_LAB1_0756172_鍾嘉峻.zip」

- Email to
  - Zivzhong.cs07g@nctu.edu.tw

Lab Description

- Implement a simple neural network with two hidden layers
- You can only use Numpy and other python standard libraries.
- Plot your comparison figure showing the predictions and ground truth.
- Plot your learning curve (loss, epoch).
- Print the accuracy of your prediction.

Lab Description – Flowchart



Lab Implementation Steps

- Data prepare
- Create a model
- Train
- Test
- Plot result

Lab Implementation Steps

- Data prepare
- Create a model
- Train
- Test
  - We don't need to do this this time
- Plot result

Lab Implementation Steps

- Data prepare
- Create a model
- Train
- ~~Test~~
  - ~~We don't need to do this this time~~
- Plot result

Just show the loss of training set we create!!

Lab Implementatio

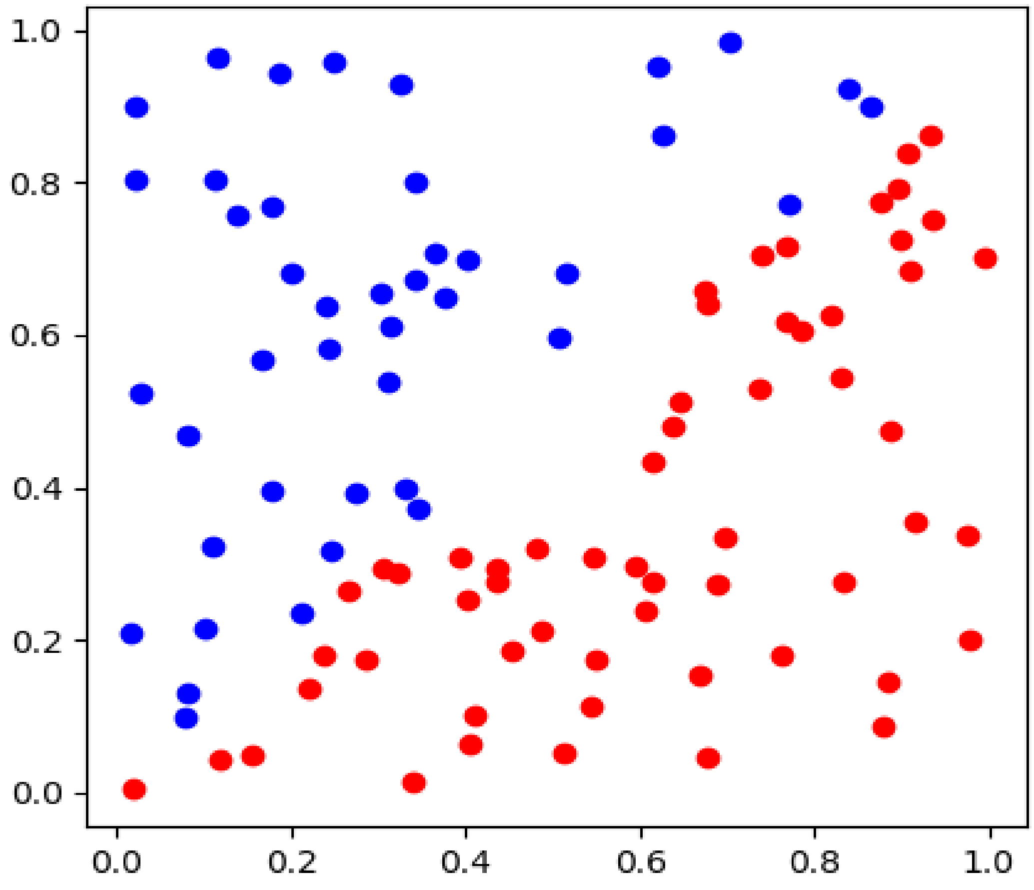
- Data prepare
- Create a model
- Train
- Plot result

```python
import numpy as np


def generate_linear(n=100):

def generate_XOR_easy():

def show_result(x, y, y_pred):

def derivative(f, *args):

def sigmoid(x, derivative=False):

def mse(y_pred, y_data, derivative=False):

class NN:

nn = NN(dim=[2, 3, 3, 1])
lr, epoch, done = 0.8, 0, False

X, Y = generate_XOR_easy()
#X, Y = generate_linear()
while not done:
    loss = []
    for x, y in zip(X, Y):
        x, y = x.reshape(1, -1), y.reshape(1, -1)
        y_pred = nn.predict(x)
        nn.backprop(y)
        nn.update(lr)
        loss += [mse(y_pred, y)]
        epoch += 1
        if epoch % 5000 == 0:
            print('epoch', epoch, 'loss:', loss[-1])
    done = all(np.array(loss) < 0.04)

Y_pred = [int(nn.predict(x.reshape(1, -1)) >= 0.5) for x in X]
show_result(X, Y, Y_pred)
```

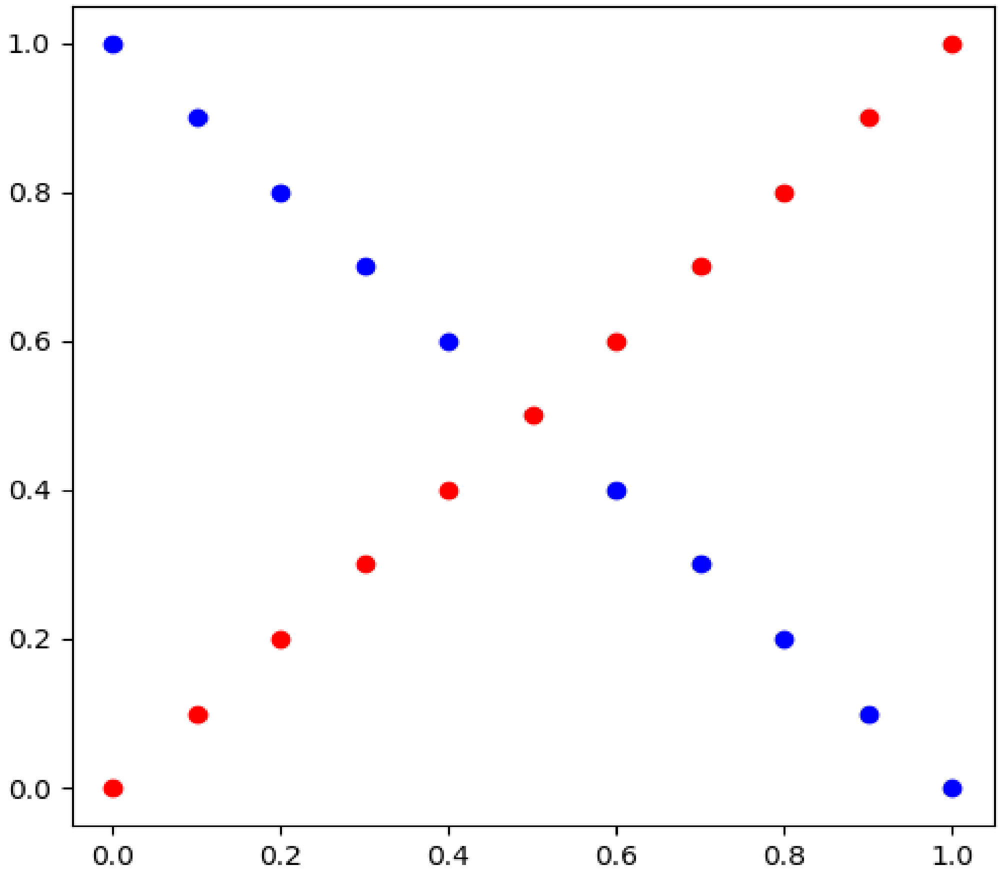
Lab Implementation Steps

- Data prepare
  - Use the functions TA prepare
- Create a model
- Train
- Plot result

Lab Description - Data



generate_linear()



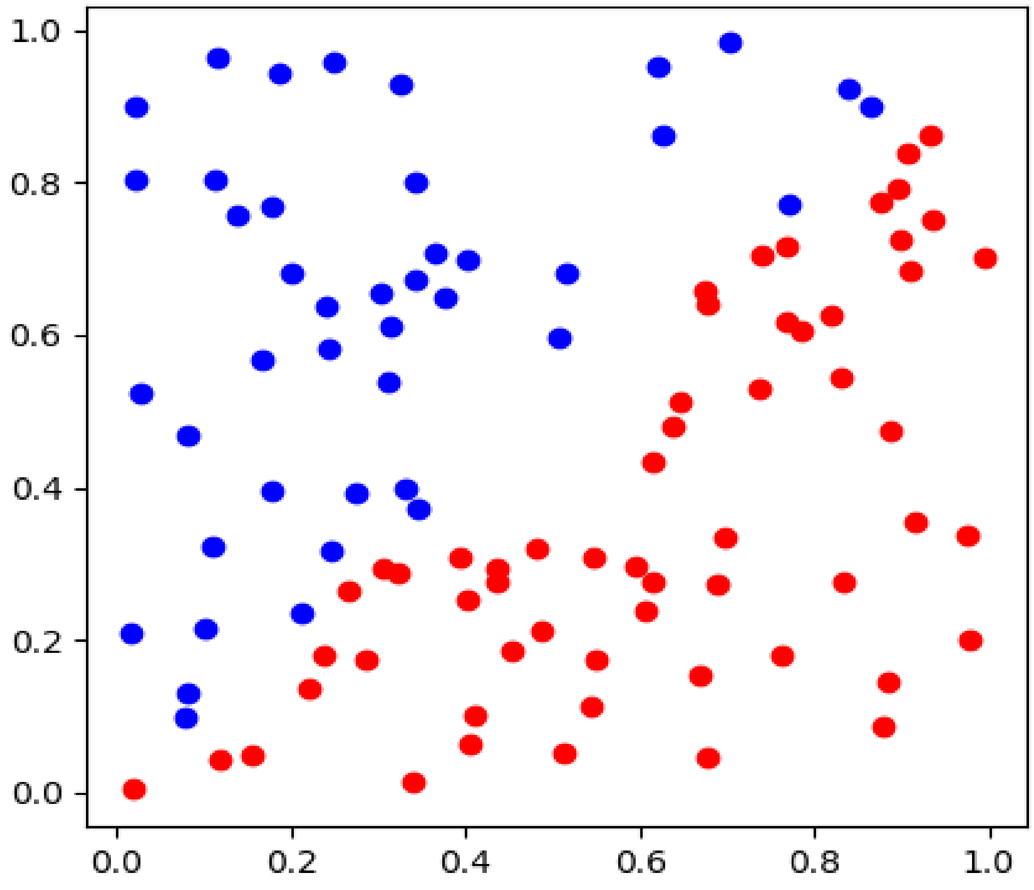
generate_XOR_easy()

Lab Description - Data

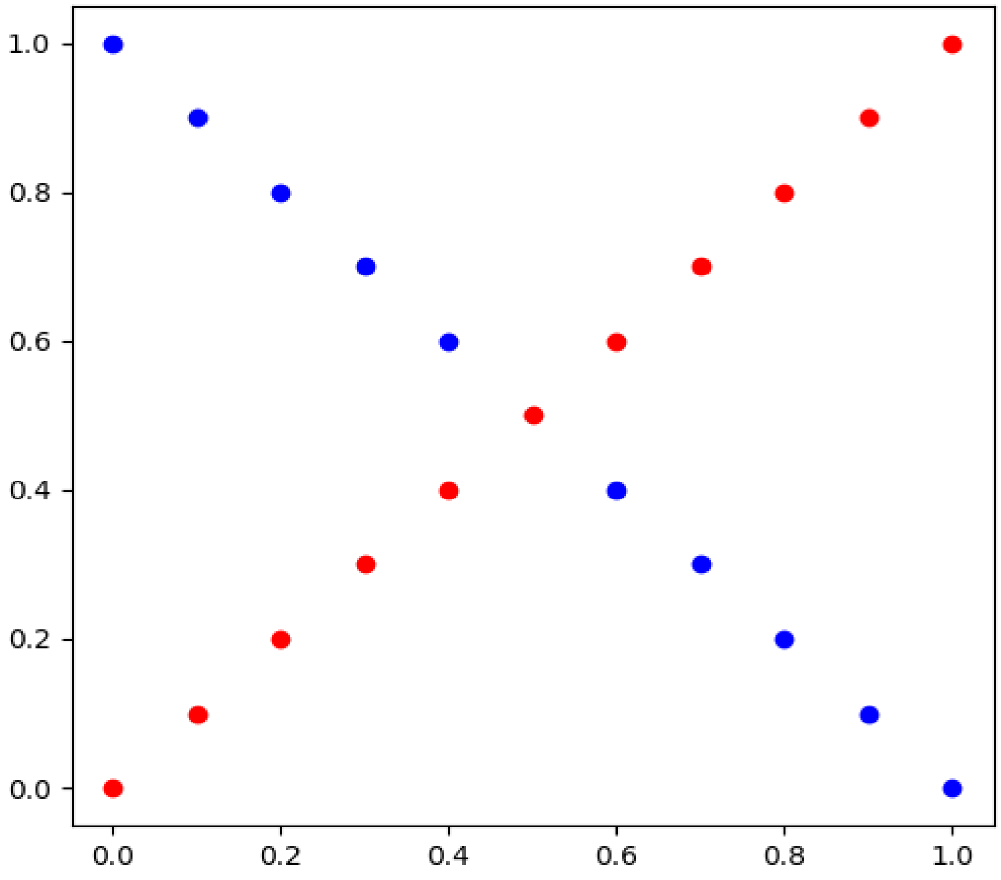
- generate_linear()

```python
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)
```

Lab Description - Data



generate_linear()



generate_XOR_easy()

Lab Description - Data

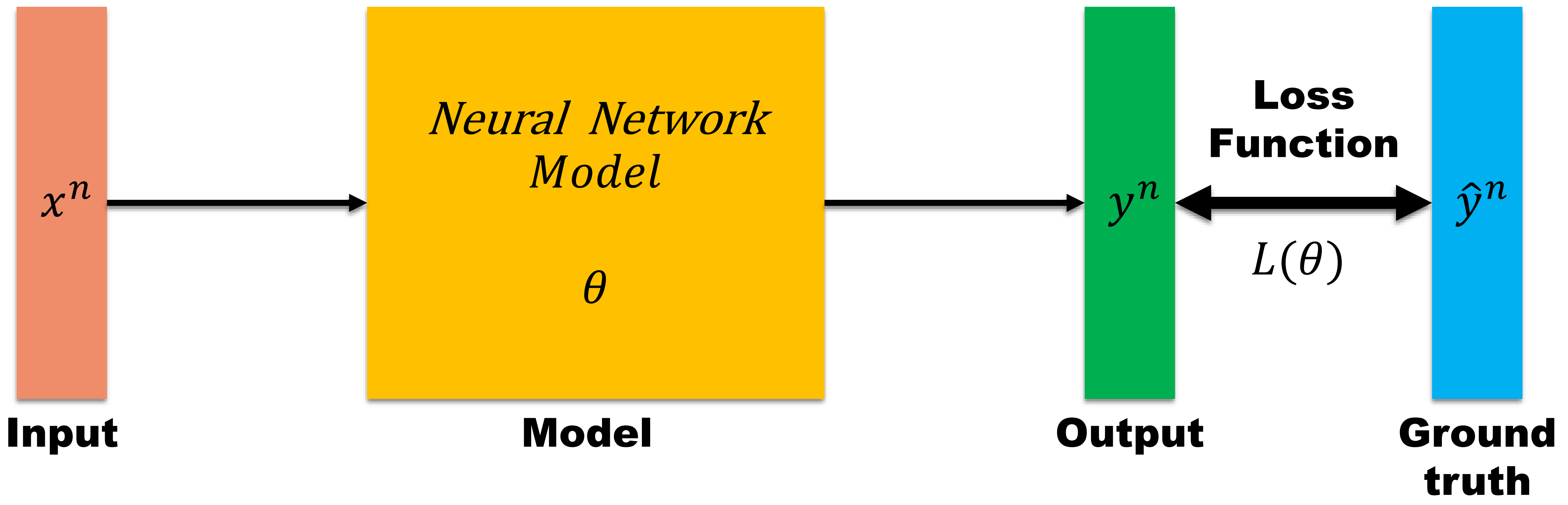
- generate_XOR_easy()

```python
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 Implementation Steps

- Data prepare
- Create a model
  - You can only use numpy or other standard python library
- Train
- Plot result

Lab Description



$$\theta = \{w_1, w_2, w_3, w_4, \cdots\}$$

$$\boldsymbol{\nabla L(\theta)} = \begin{bmatrix} \partial L(\theta)/\partial w_1 \\ \partial L(\theta)/\partial w_2 \\ \partial L(\theta)/\partial w_3 \\ \vdots \\ \vdots \end{bmatrix}$$

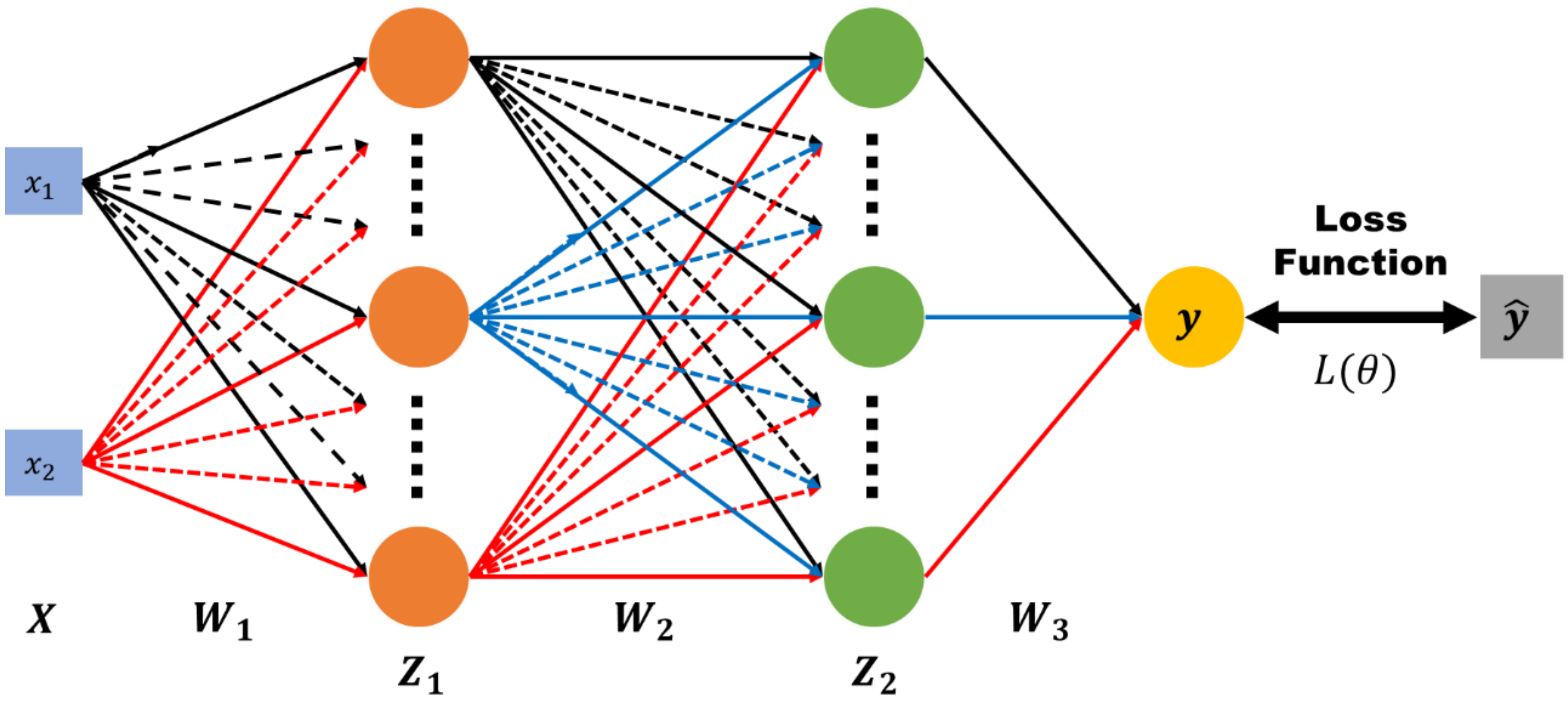
Compute $\nabla L(\theta^0)$ $\quad \theta^1 = \theta^0 - \rho \nabla L(\theta^0)$

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

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

ρ : Learning rate

Lab Description – Architecture



X : $[x_1, x_2]$ y : *outputs* $\hat{y}$: *ground truth*

W_1, W_2, W_3 : *weight matrix of network layers*

Lab Description – Architecture

- Define 4 layers
  - One input layer
  - Two hidden layers
  - One output layer

- Define 3 groups of weights
  - Between any two adjacent layers

Lab Description – Create a Model

```python
class NN:
    """Dense Layer"""

    def __init__(self, dim, activation=sigmoid, loss=mse):

    def predict(self, X):

    def backprop(self, y_data):

    def update(self, lr):
```

```python
nn = NN(dim=[2, 3, 3, 1])
```

Lab Description – Create a Model

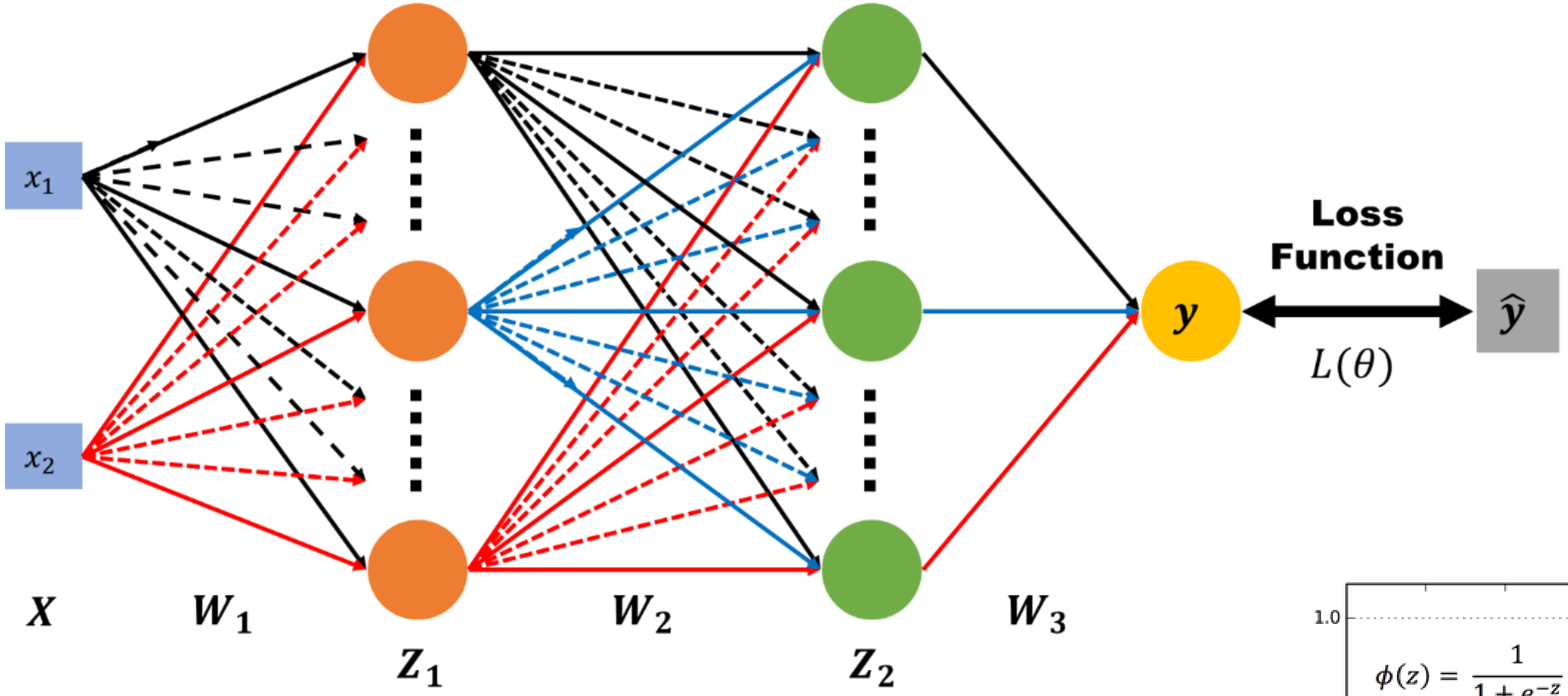
```
    def __init__(self, dim, activation=sigmoid, loss=mse):
        def init_weights(d):

        self.layers = [None] * len(dim)
        self.weights = [init_weights(d) for d in zip(dim[:-1], dim[1:])]
        self.act = activation
        self.loss = loss
```

```
nn = NN(dim=[2, 3, 3, 1])
```

Lab Implementation Steps

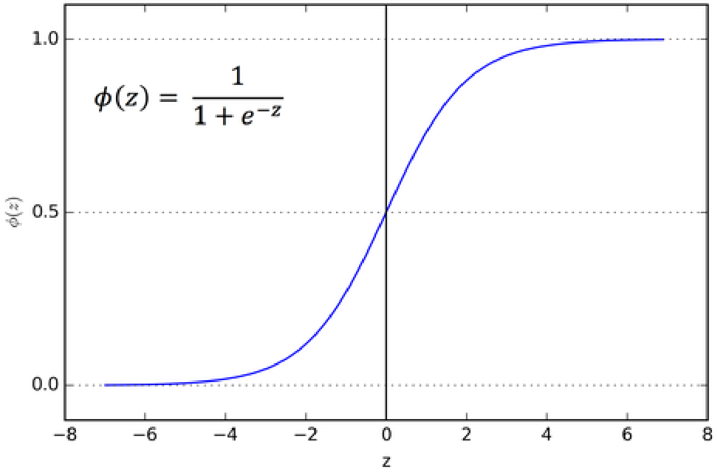
- Data prepare
- Create a model
- Train
  - Loss
  - Forward
  - Backward
- Plot result

Lab Description – Forward



$$Z_1 = \sigma(XW_1) \qquad Z_2 = \sigma(Z_1W_2) \qquad y = \sigma(Z_2W_3)$$

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



Lab Description – Training Part

```python
class NN:
    """Dense Layer"""

    def __init__(self, dim, activation=sigmoid, loss=mse):

    def predict(self, X):

    def backprop(self, y_data):

    def update(self, lr):
```

Lab Description – Loss

- MSE Loss

```
def mse(y_pred, y_data, derivative=False):
```

Lab Description – Forward(Predict)

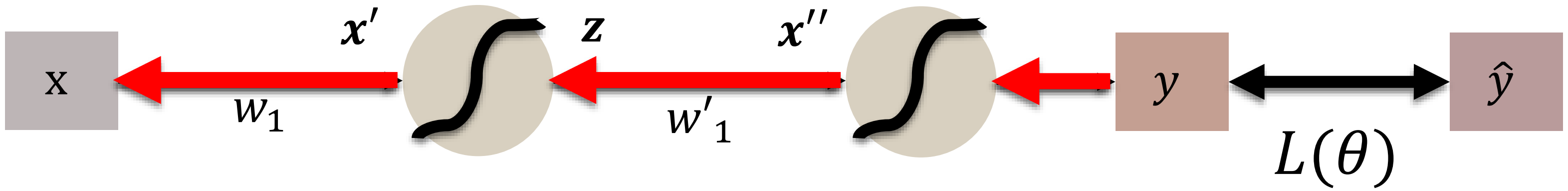
- Forward(Predict)
  - Z = X
  - for i, W in enumerate(self.weights):
  - Z = self.act(Z @ W)
  - Remember move to next layer
    - (e.g self.layers[next_layer] = np.array(Z))

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

$$\sigma'(y) = \sigma(y)(1 - \sigma(y))$$

- Ref Link:
  - https://medium.com/pyradise/%E4%BD%BF%E7%94%A8-python-%E4%BE%86%E8%AA%8D%E8%AD%98%E7%9F%A9%E9%99%A3-915376207187

Lab Description – Backward



$\boldsymbol{x' = xw_1}$ $\quad$ $\boldsymbol{z = \sigma(x')}$ $\quad$ $\boldsymbol{x'' = zw'_1}$ $\quad$ $\boldsymbol{y = \sigma(x'')}$

Chain rule

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

$$\mathbf{x} \xrightarrow{\mathbf{g}()} \boldsymbol{y} \xrightarrow{\boldsymbol{h}()} \boldsymbol{z} \qquad \frac{d\boldsymbol{z}}{d\boldsymbol{x}} = \frac{d\boldsymbol{z}}{\cancel{d\boldsymbol{y}}}\frac{\cancel{d\boldsymbol{y}}}{d\boldsymbol{x}}$$

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

Lab Description – Gradient descent

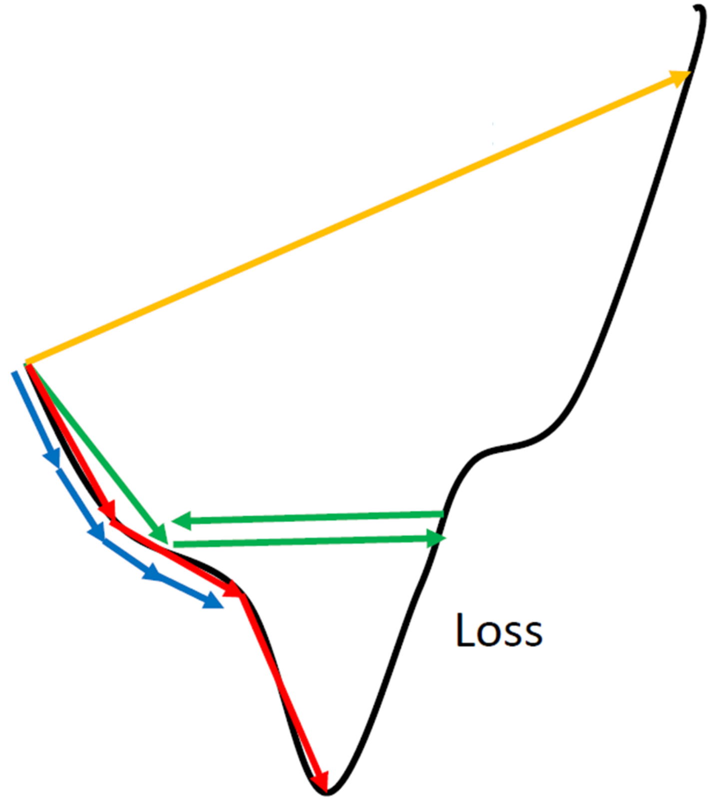
Network Parameters $\theta = \{w_1, w_2, w_3, w_4, \cdots\}$

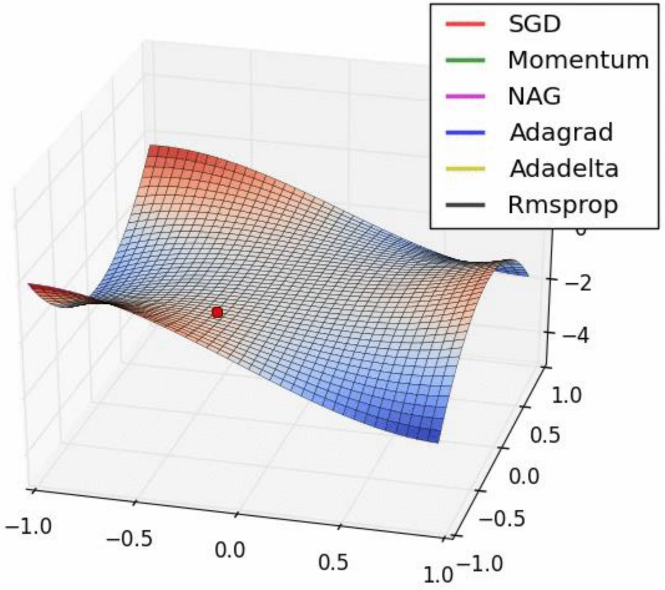
$$\theta^1 = \theta^0 - \rho \nabla L(\theta^0)$$

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

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

ρ : Learning rate





http://www.denizyuret.com/2015/03/alec-radfords-animations-for.html

Lab Description – Backward & Update

- Backward the gradient & update

```
class NN:
    """Dense Layer"""

    def __init__(self, dim, activation=sigmoid, loss=mse):

    def predict(self, X):

    def backprop(self, y_data):

    def update(self, lr):
```

Lab Description – Backward & Update

- Backward the gradient & update
  - Gradient

```
# dw = dL / dW
dw = np.kron(Z.T, dz)
dW.append(np.array(dw))
# dz = dL / dZ * s(Z)
dz = np.multiply(dz @ W.T, derivative(self.act, Z))
dZ.append(np.array(dz))
```

  - Update

```
self.weights[i] -= lr * dw
```

Lab Implementation Steps

- Data prepare
- Create a model
- Train
- Plot result
  - Screenshot of loss
  - Plot the prediction & ground truth

Lab Description - Prediction

- In the training, you need to print loss

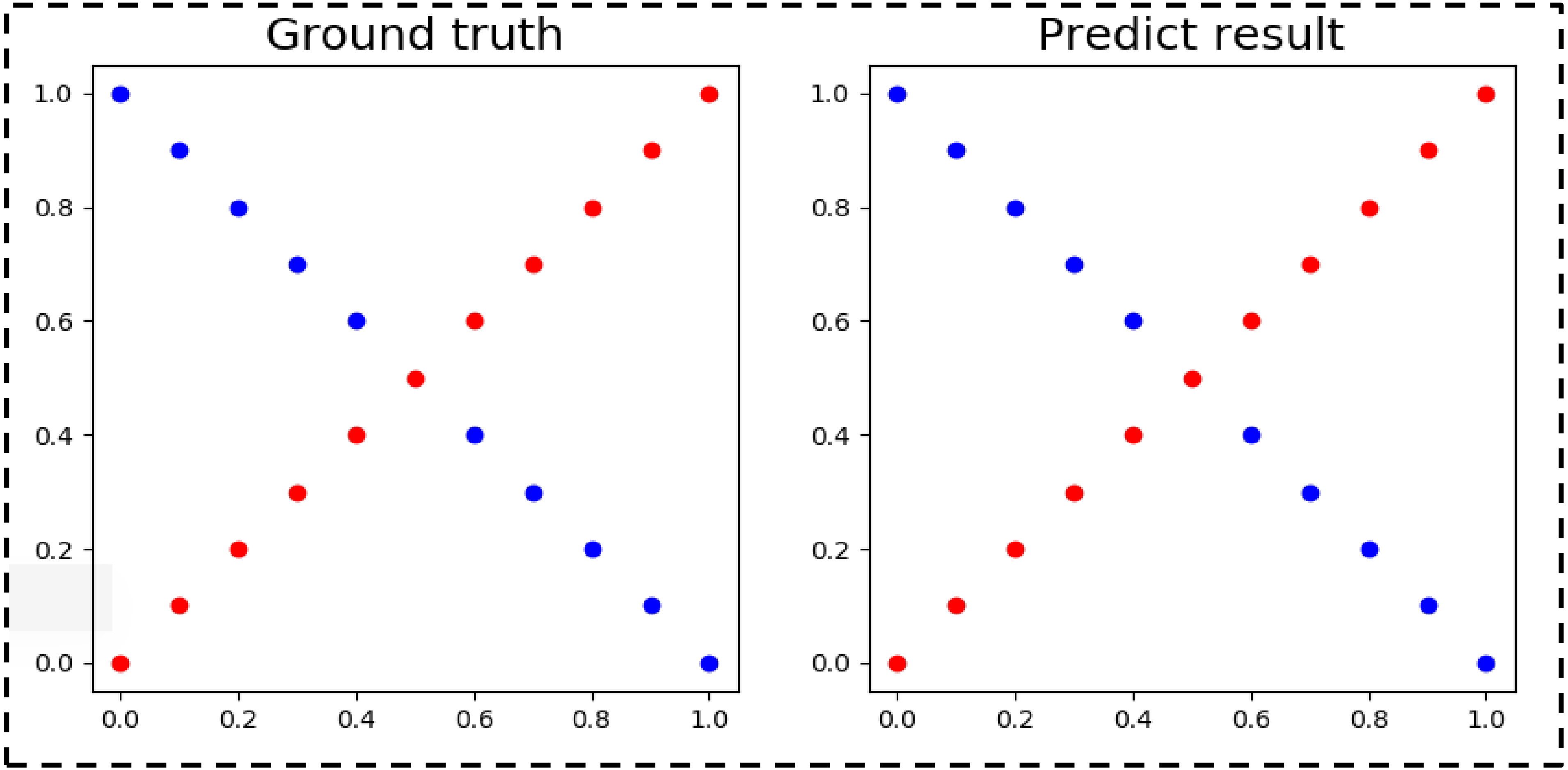
```
epoch 10000 loss : 0.16234523253277644
epoch 15000 loss : 0.2524336634177614
epoch 20000 loss : 0.1590783047540092
epoch 25000 loss : 0.22099447030234853
epoch 30000 loss : 0.3292173477217561
epoch 35000 loss : 0.40406233282426085
epoch 40000 loss : 0.43052897480298924
epoch 45000 loss : 0.4207525735586605
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
```

- In the testing, you need to show your predictions, also the accuracy

```
[[0.01025062]
 [0.99730607]
 [0.02141321]
 [0.99722154]
 [0.03578171]
 [0.99701922]
 [0.04397049]
 [0.99574117]
 [0.04162245]
 [0.92902792]
 [0.03348791]
 [0.02511045]
 [0.94093942]
 [0.01870069]
 [0.99622948]
 [0.01431959]
 [0.99434455]
 [0.01143039]
 [0.98992477]
 [0.00952752]
 [0.98385905]]
```

Lab Description - Prediction

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



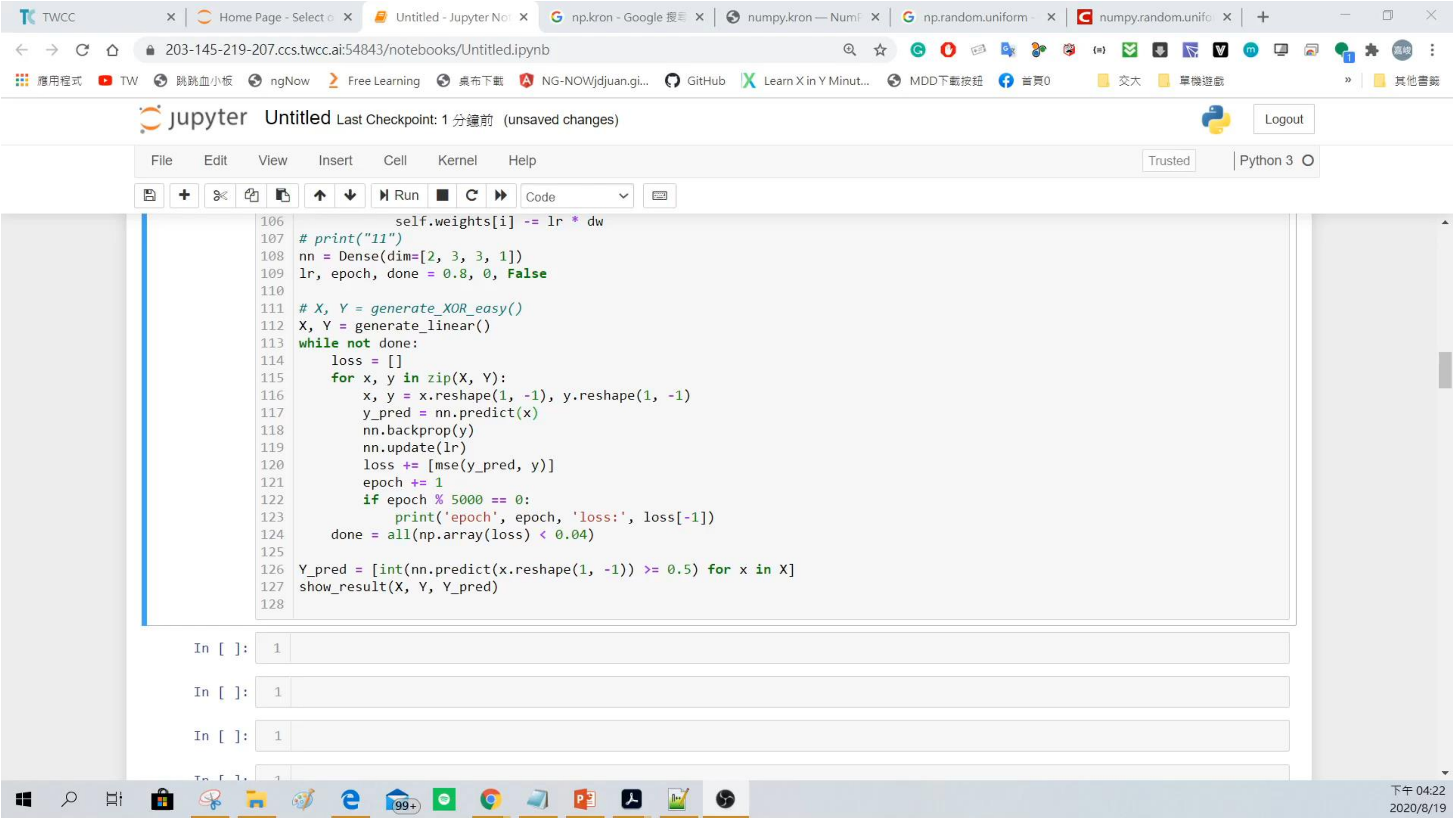
Lab Description - Prediction

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

```
def show_result(x, y, pred_y):
    import matplotlib.pyplot as plt
    plt.subplot(1,2,1)
    plt.title('Ground truth', fontsize=18)
    for i in range(x.shape[0]):
        if y[i] == 0:
            plt.plot(x[i][0], x[i][1], 'ro')
        else:
            plt.plot(x[i][0], x[i][1], 'bo')

    plt.subplot(1,2,2)
    plt.title('Predict result', fontsize=18)
    for i in range(x.shape[0]):
        if pred_y[i] == 0:
            plt.plot(x[i][0], x[i][1], 'ro')
        else:
            plt.plot(x[i][0], x[i][1], 'bo')

    plt.show()
```

Demo

- Video Link: https://youtu.be/OdwA9SaMh4E



jupyter Untitled Last Checkpoint: 1 分鐘前 (unsaved changes)

```python
            self.weights[i] -= lr * dw
# print("11")
nn = Dense(dim=[2, 3, 3, 1])
lr, epoch, done = 0.8, 0, False

# X, Y = generate_XOR_easy()
X, Y = generate_linear()
while not done:
    loss = []
    for x, y in zip(X, Y):
        x, y = x.reshape(1, -1), y.reshape(1, -1)
        y_pred = nn.predict(x)
        nn.backprop(y)
        nn.update(lr)
        loss += [mse(y_pred, y)]
        epoch += 1
        if epoch % 5000 == 0:
            print('epoch', epoch, 'loss:', loss[-1])
    done = all(np.array(loss) < 0.04)

Y_pred = [int(nn.predict(x.reshape(1, -1)) >= 0.5) for x in X]
show_result(X, Y, Y_pred)
```

In [ ]:

In [ ]:

In [ ]:

Scoring Criteria

- Report (40%)
- Demo(60%)
  - Experimental results (40%)
  - Questions (20%)
- Late report or demo
  - Score *0.8

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*

Backup Slide

- In python, you may observe some weird things
  - 0.1+0.2 != 0.3 (because IEEE 754
    - 0.2+0.1 != 0.3
    - 0.1+0.2 == 0.2+0.1

Backup Slide

- In python, you may observe some weird things
  - 0.1+0.2 != 0.3 (because IEEE 754
    - 0.2+0.1 != 0.3
    - 0.1+0.2 == 0.2+0.1
  - 0.1+0.2+0.1+0.2 != 0.6
    - 0.2+0.1+0.2+0.1 == 0.6
    - 0.1+0.2+0.1+0.2 != 0.2+0.1+0.2+0.1

```
(base) pc3433@pc3433-B360-HD3:~$ python
Python 3.7.4 (default, Aug 13 2019, 20:35:49)
[GCC 7.3.0] :: Anaconda, Inc. on linux
Type "help", "copyright", "credits" or "license" for more information.
>>> 0.1 + 0.2
0.30000000000000004
>>> 0.2 +0.1
0.30000000000000004
>>> 0.1 + 0.2 == 0.2 + 0.1
True
>>> 0.1 + 0.2 + 0.1 + 0.2
0.6000000000000001
>>> 0.2 + 0.1 + 0.2 + 0.1
0.6
>>> a = 0.1 + 0.2 + 0.1 + 0.2
>>> b = 0.2 + 0.1 + 0.2 + 0.1
>>> a == b
False
>>>
```

Backup Slide

- In python, you may observe some weird things
  - 0.1+0.2 != 0.3 (because IEEE 754
    - 0.2+0.1 != 0.3
    - 0.1+0.2 == 0.2+0.1
  - 0.1+0.2+0.1+0.2 != 0.6
    - 0.2+0.1+0.2+0.1 == 0.6
    - 0.1+0.2+0.1+0.2 != 0.2+0.1+0.2+0.1
- Check WTFPython
  - https://github.com/satwikkansal/wtfpython