Lecture 4.
Neural Network Basics

Review

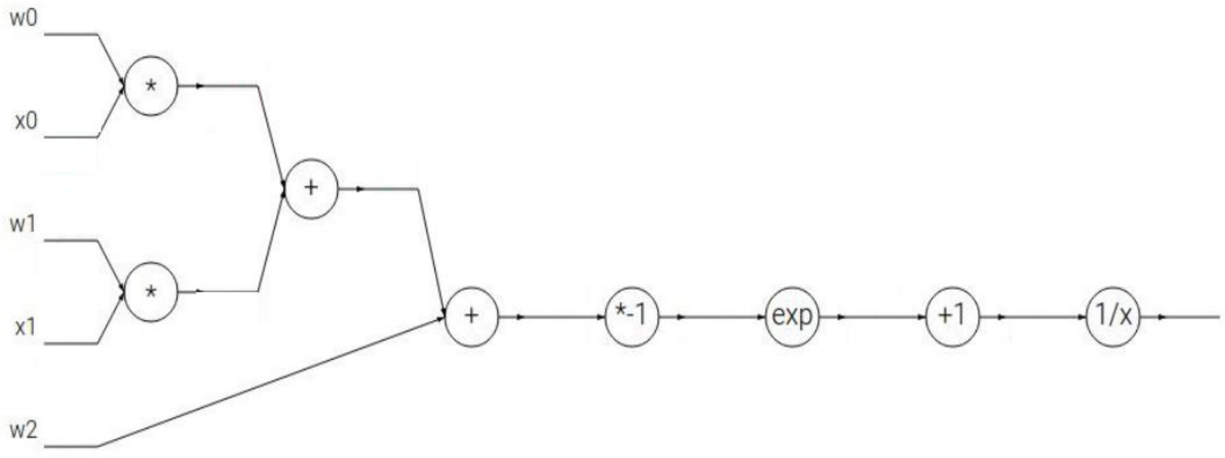
1. **Optimization**
    - SGD vs. ~~Random Search~~
    - Analytic Gradient vs. ~~Numeric Gradient~~
2. **Backpropagation**
    - Chain Rule
    - Computational Graph
        - scalar
        - vector
        - matrix
    - Implementation

Review

learning rate

$$\omega_{new} = \omega_{old} - lr \cdot \frac{\partial L}{\partial \omega}\Big|_{\omega=\omega_{old}} \qquad b_{new} = b_{old} - lr \cdot \frac{\partial L}{\partial b}\Big|_{b=b_{old}}.$$

$$f(\omega, x) = \frac{1}{1+e^{-(\omega_0 x_0 + \omega_1 x_1 + \omega_2)}}$$



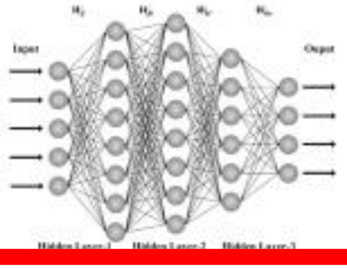
Review

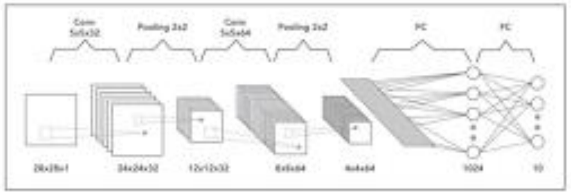
Optimization : Calculating Gradient

IDEA 2. Analytic

지금은 simple linear classifier만 다루고 있지만,

앞으로 다룰 model은





then, how should we derive the gradient?

Multilayer Perceptron

Linear Classifier 단독으로는

풀 수 없는 문제들 존재...

여러 개를 중첩시켜 보자!

Today's Contents

1. **Limitation of Linear Classifier**
2. **Perceptron**
3. **MLP(Multilayer Perceptron)**
4. **Limitations of MLP**

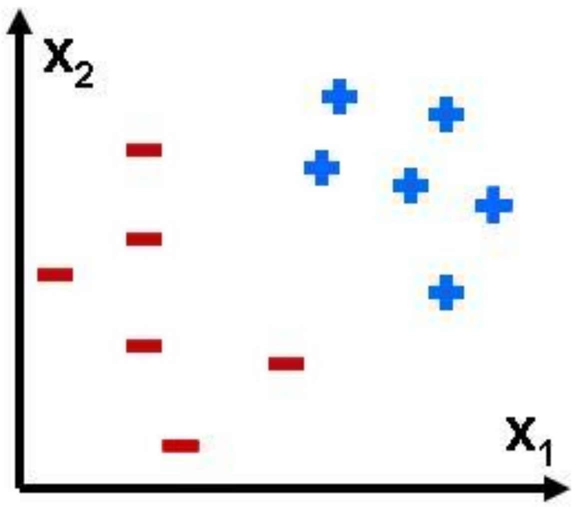
Limitation of Linear Classifier

What's wrong with our "Linear" Classifier?

What about Nonlinear Classification Problems?

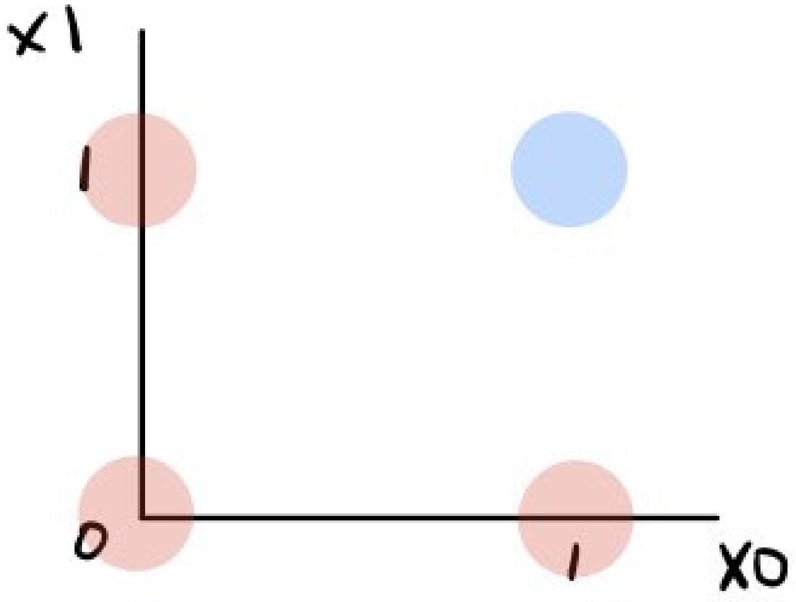
Limitation of Linear Classifier

Binary Classification : AND / OR / XOR Gate with Linear Classifier



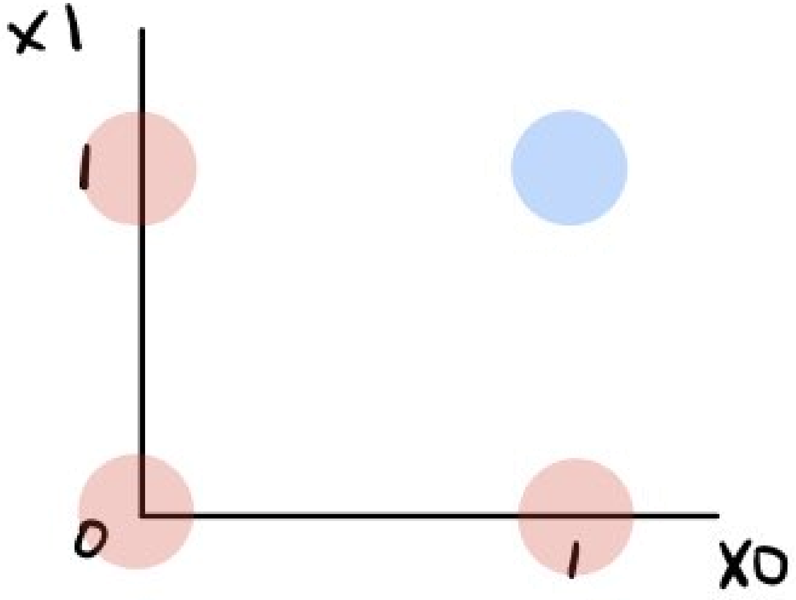
Define h(x) = 1 if x > 0, 0 otherwise

Linear Classification : AND Gate

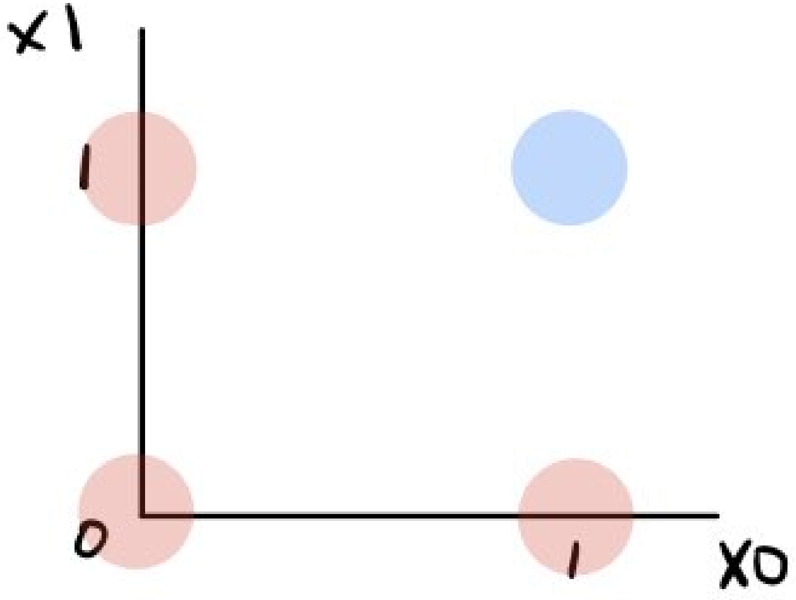


x0	x1	ANS
1	1	T
1	0	F
0	1	F
0	0	F

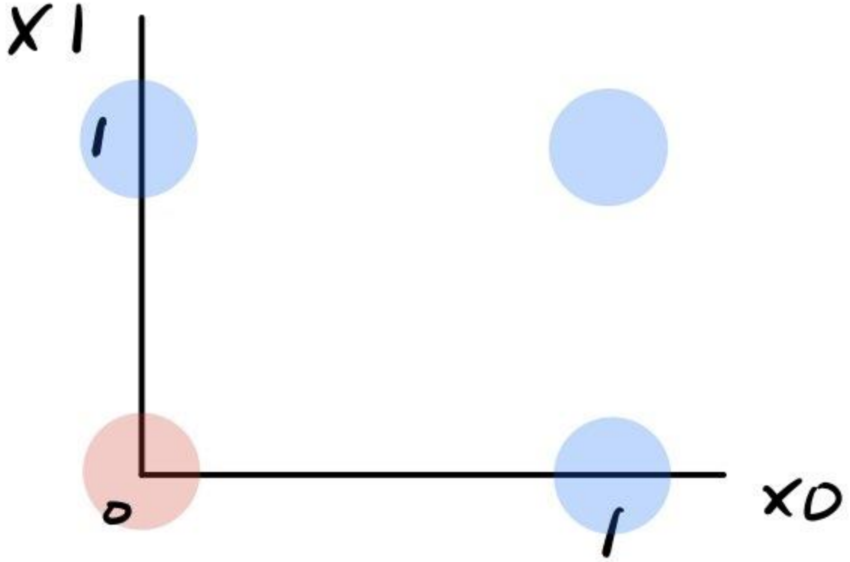
Linear Classification : AND Gate



Linear Classification : AND Gate

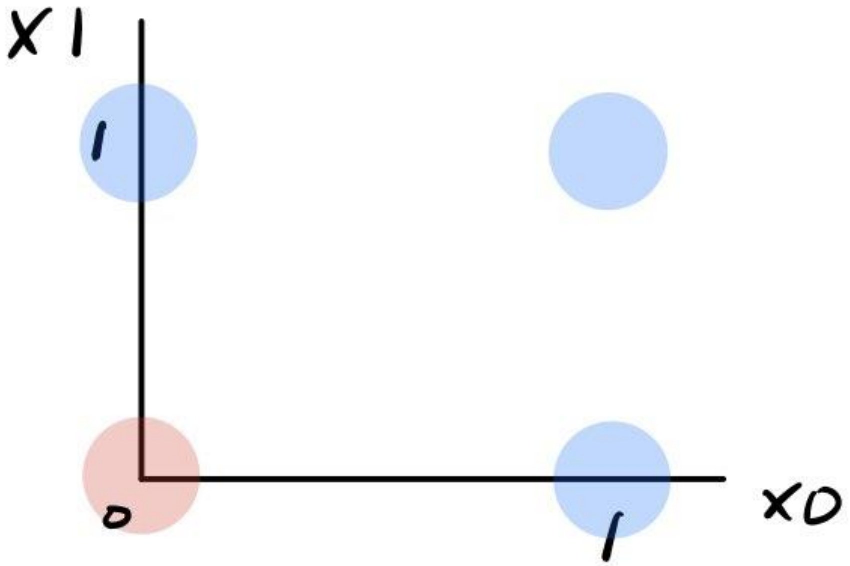


Linear Classification : OR Gate

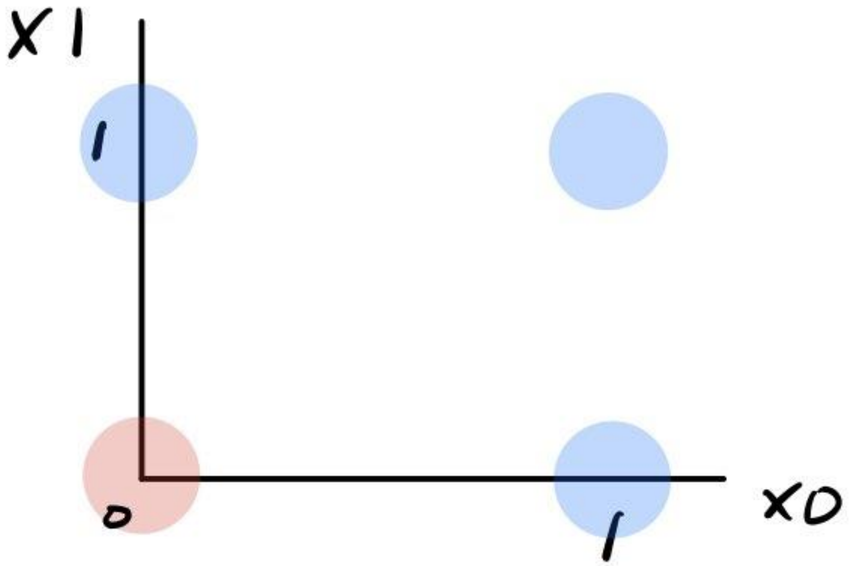


x0	x1	ANS
1	1	T
1	0	T
0	1	T
0	0	F

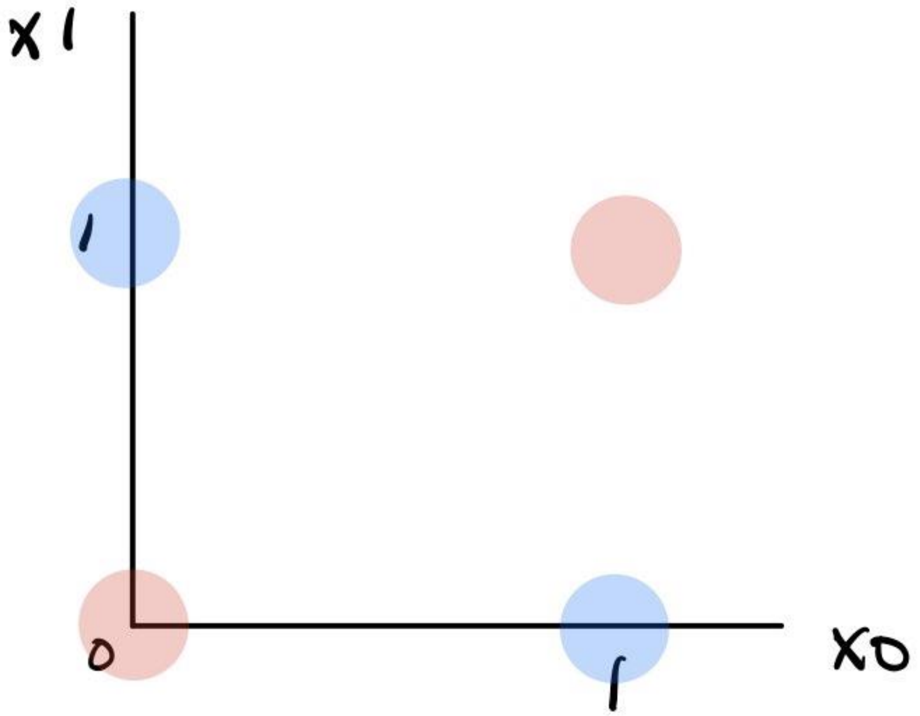
Linear Classification : OR Gate



Linear Classification : OR Gate

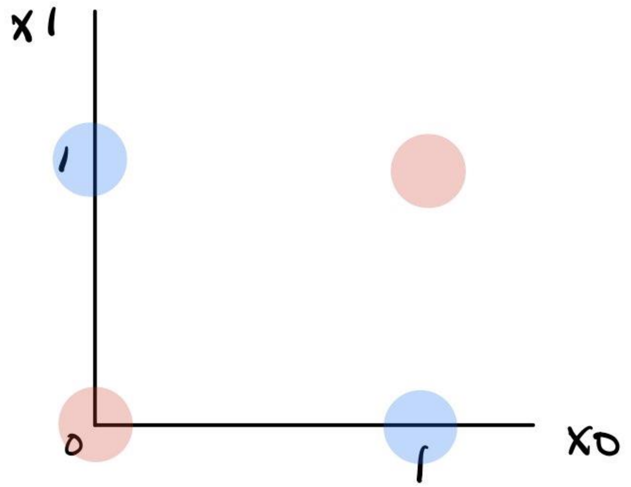


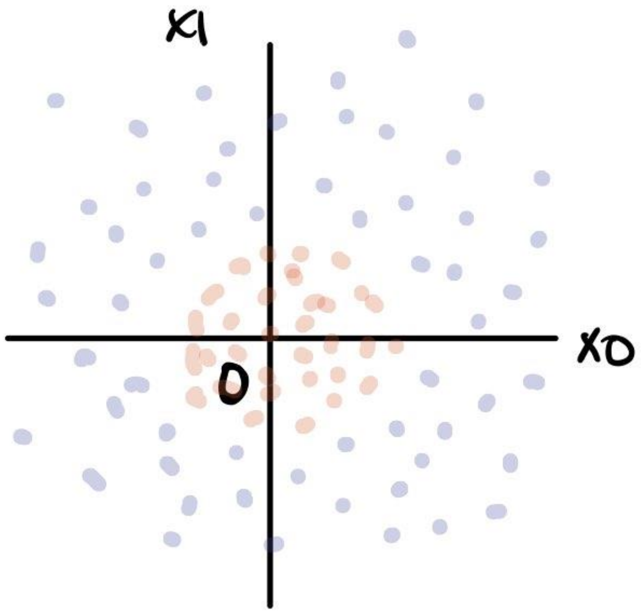
Linear Classification : XOR Gate



x0	x1	ANS
1	1	F
1	0	T
0	1	T
0	0	F

Limitation of Linear Classifier : Overcoming





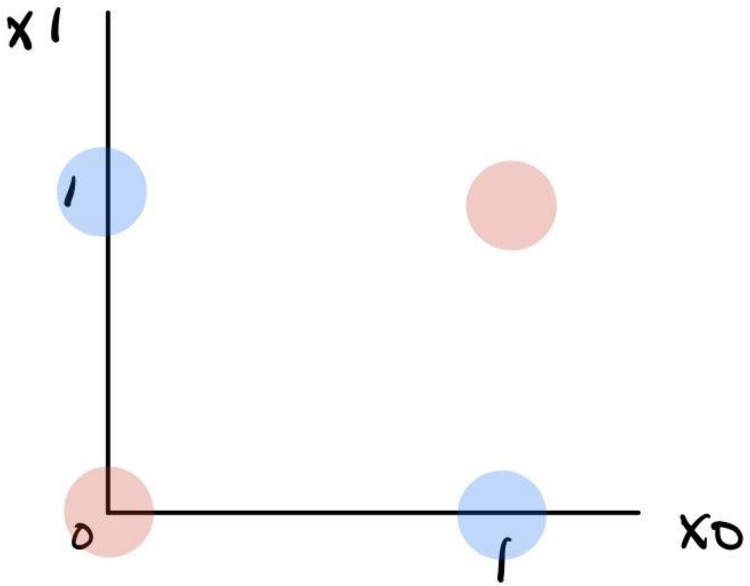
Linear Classifier 단독으로는 풀지 못하는 classification 문제 존재...!

then, how should we classify them?

Limitation of Linear Classifier : Overcoming

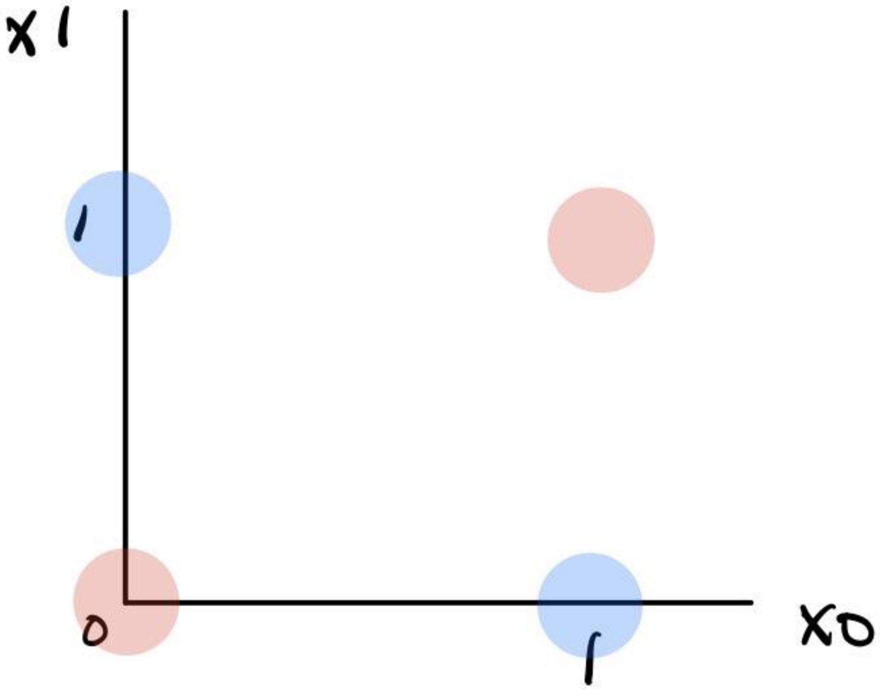
IDEA. Mapping the Data into Other Dimension

Map the Feature into other dimension, so that it becomes Linearly Separable



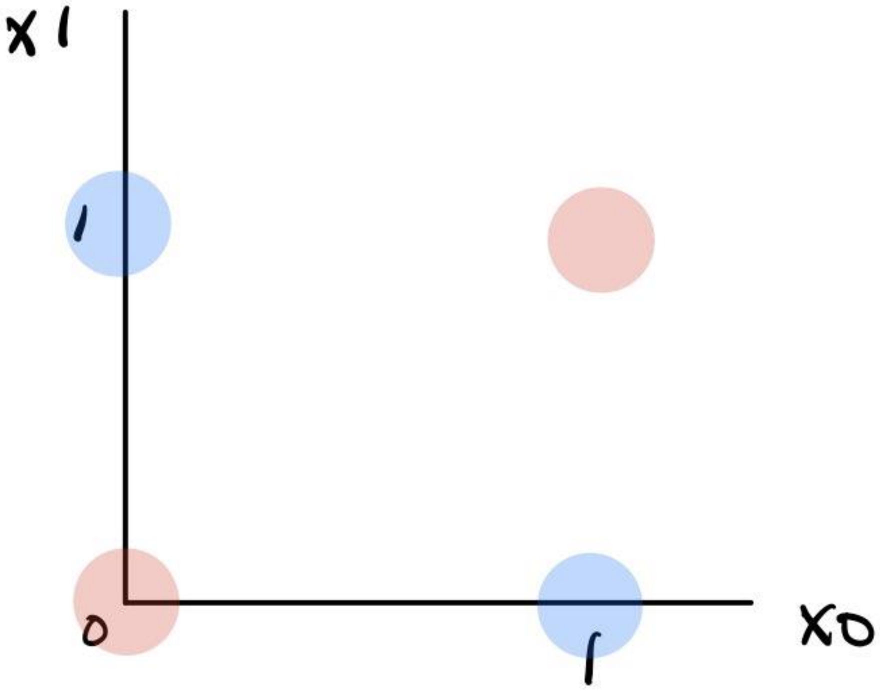
Limitation of Linear Classifier : Overcoming

IDEA. Mapping the Data into Other Dimension



Limitation of Linear Classifier : Overcoming

IDEA. Mapping the Data into Other Dimension



Limitation of Linear Classifier : Overcoming

IDEA. Mapping the Data into Other Dimension

$$f = h(W_2 h(W_1 x + b_1) + b_2)$$

Linear Classifier로 다른 차원에 Map된 Input을,

또다른 Linear Classifier로 Classify!

This model is called the **Multilayer Perceptron**, or **Artificial Neural Network**.

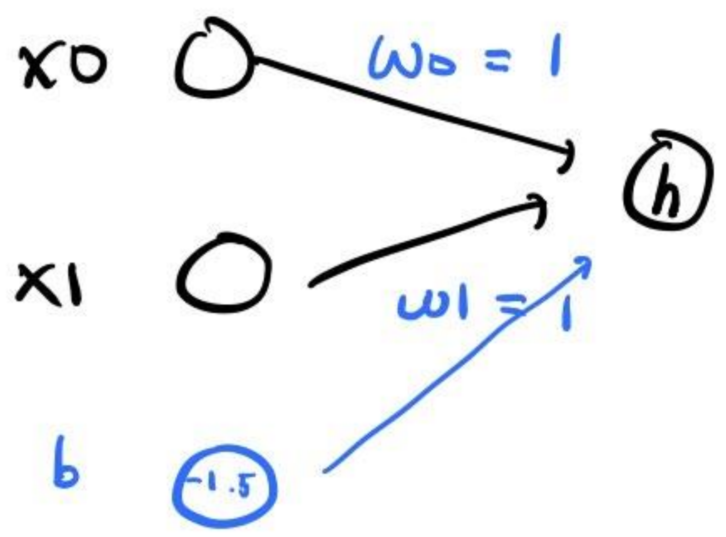
Limitation of Linear Classifier : Overcoming

What is a **"Perceptron"**...?

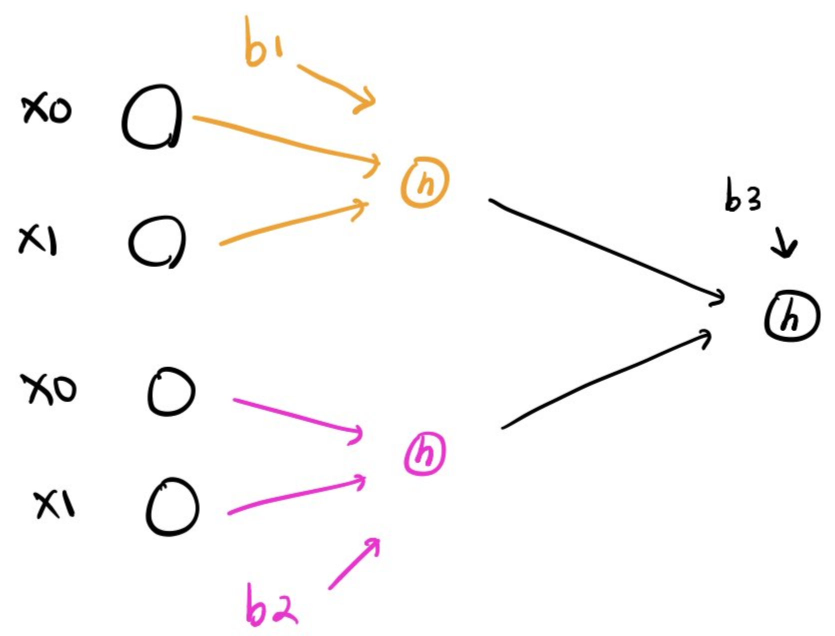
What does **"Neural"** mean...?

Perceptron : A Linear Classifier

AND Gate

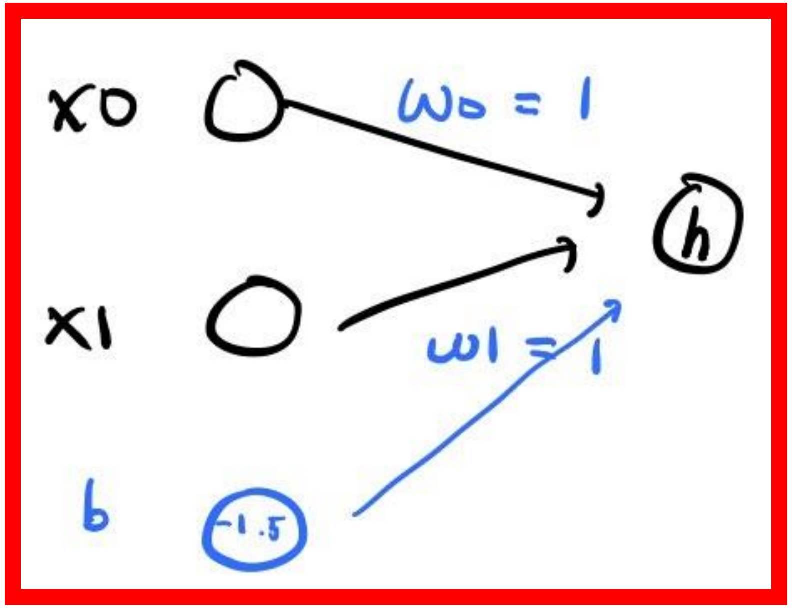


XOR Gate

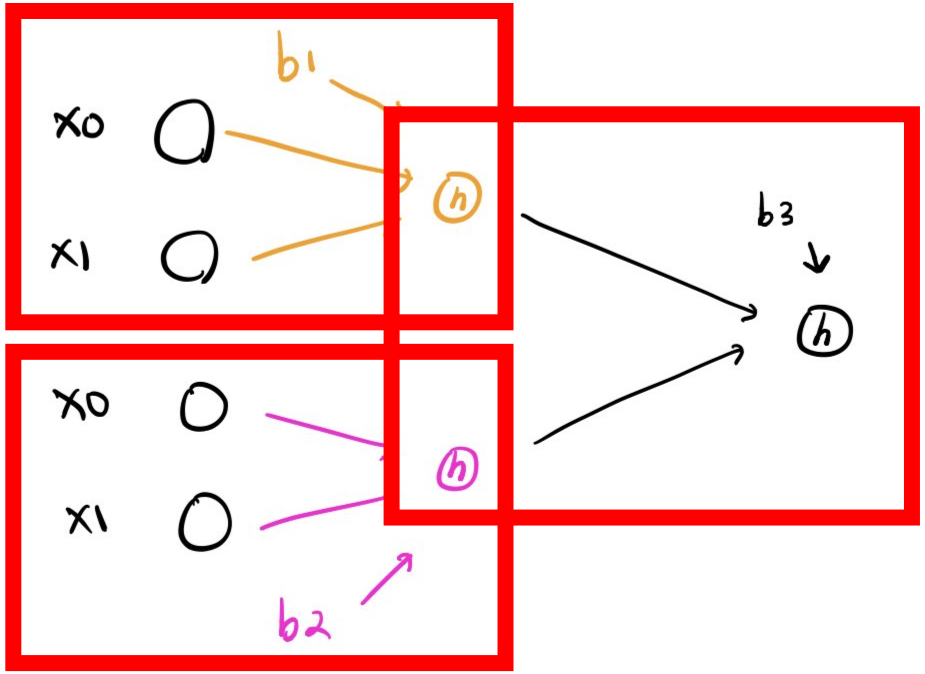


Perceptron : A Linear Classifier

AND Gate



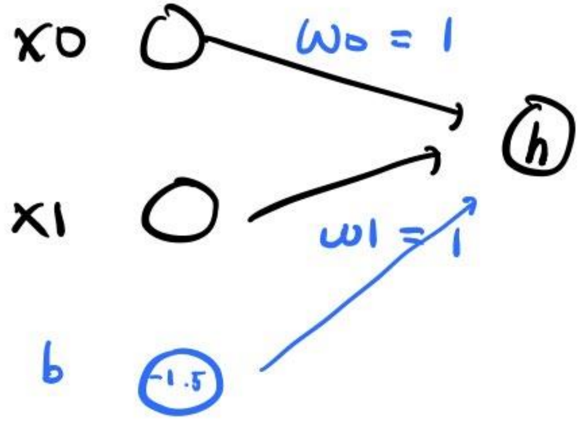
XOR Gate



Perceptron : A Linear Classifier

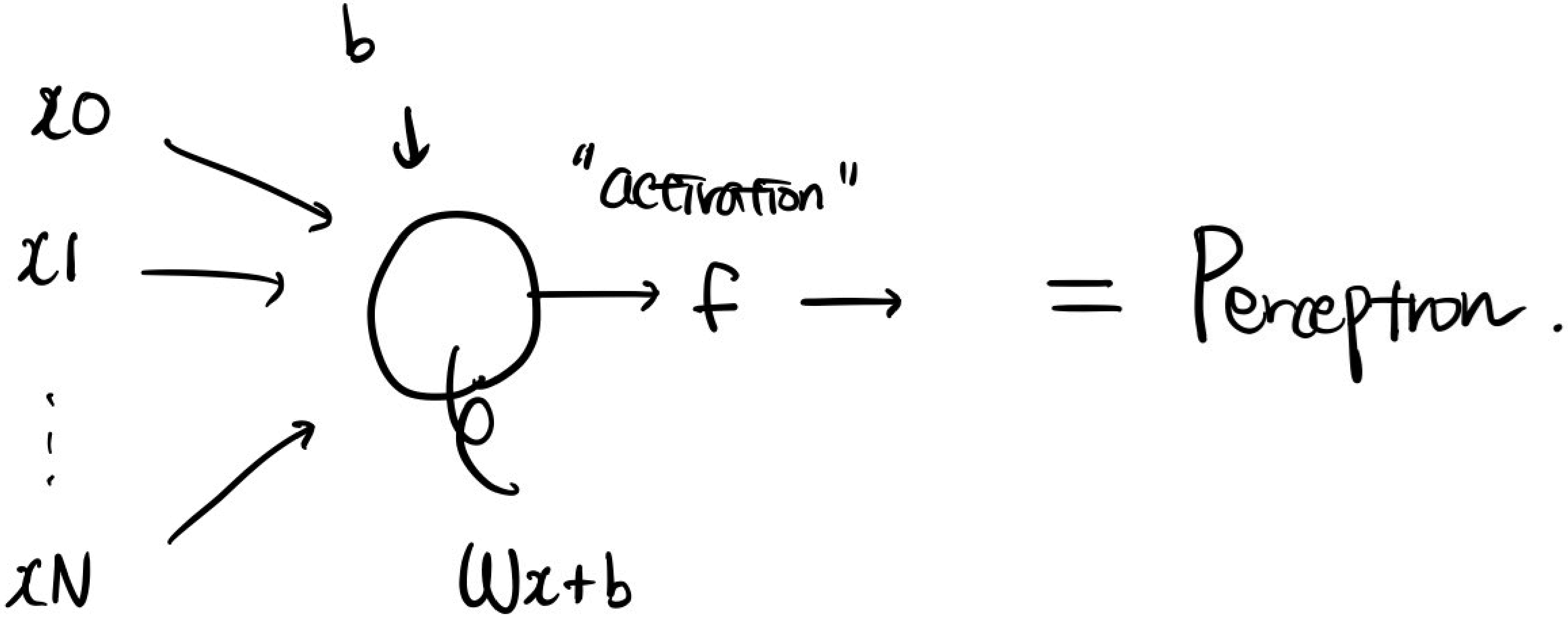
Each represents a Decision Hyperplane, where

1. Input들에 가중치를 곱한 값들을 받아서,
2. 그들의 Linear Combination을 취한 뒤,
3. 특정 함수를 통과시켜 다음 Node의 Input으로 보냄



Perceptron : A Linear Classifier

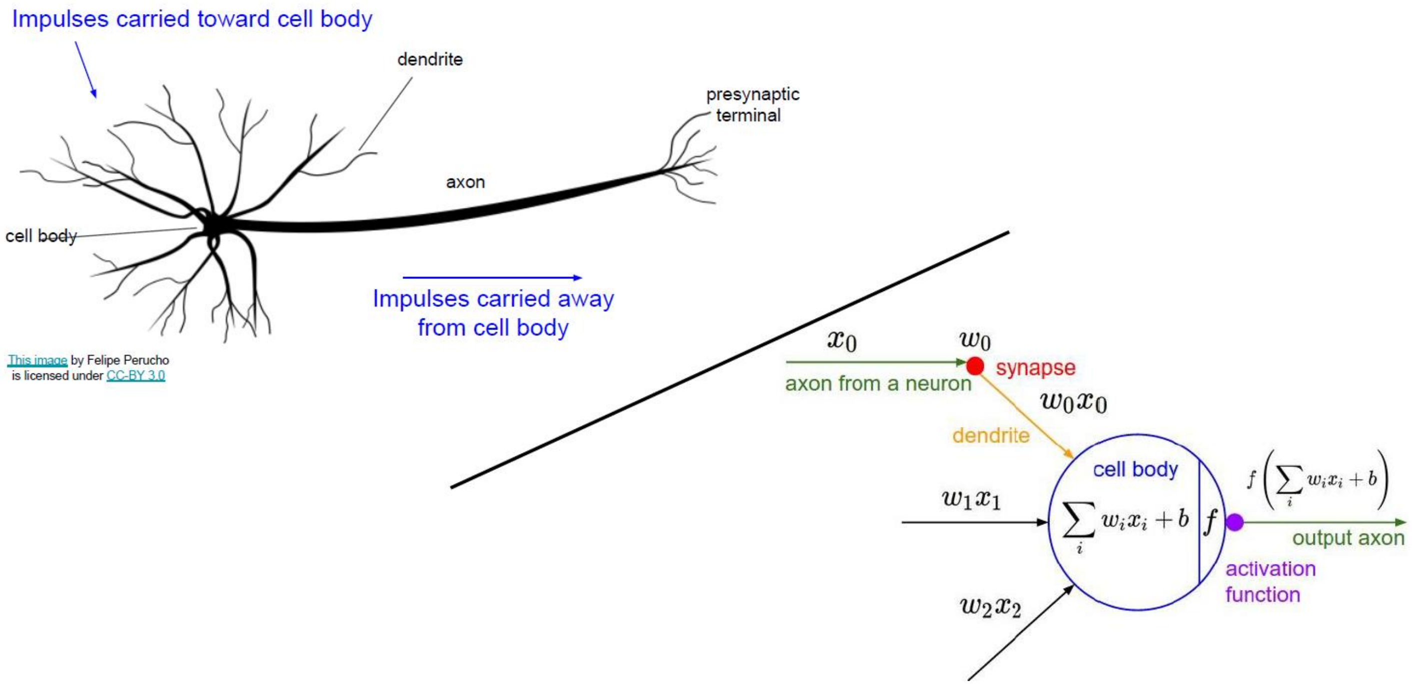
We will call this a **Perceptron**



Perceptron : Analogy to Neurons

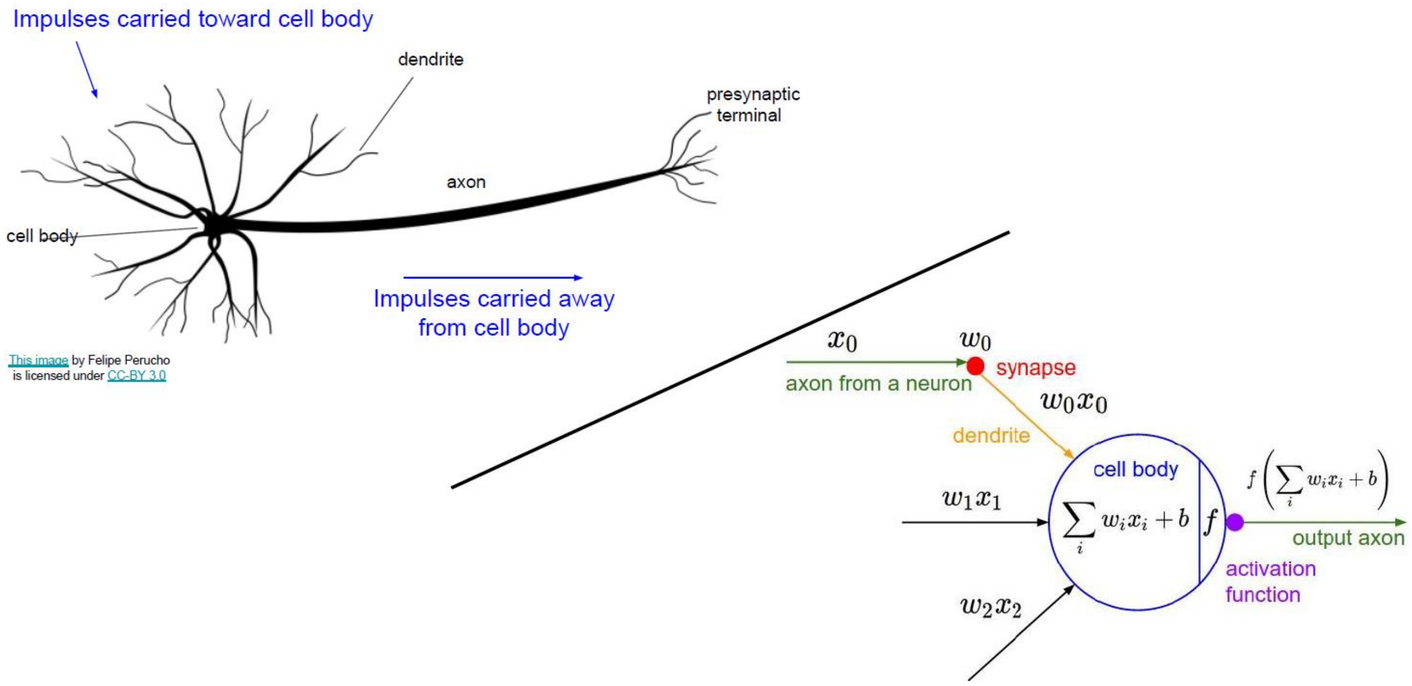
Perceptron Model은 신경계의 **Neuron**을 모방한 것

1. Dendrite로 신호 수신
2. Cell Body에서 신호 합침
3. 신호의 강도 조절하여,
   Axon을 통해 신호 출력



Perceptron : Analogy to Neurons

Perceptron Model은 신경계의 **Neuron**을 모방한 것



1. Input들에 가중치 곱한 값들 받아
2. 그들의 Linear Combination 취한 뒤,
3. 특정 함수를 통과시켜 출력

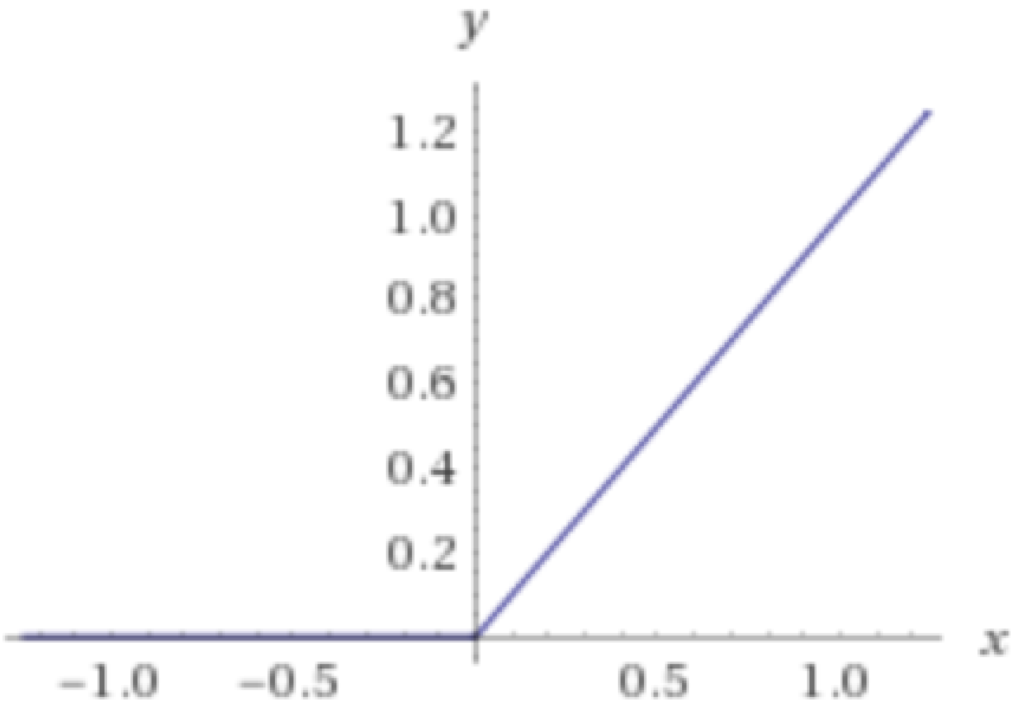
Perceptron : Activation Function

Perceptron = Linear Classifier + Activation Function

Activation Function을 통해, 출력 신호의 강도 조절

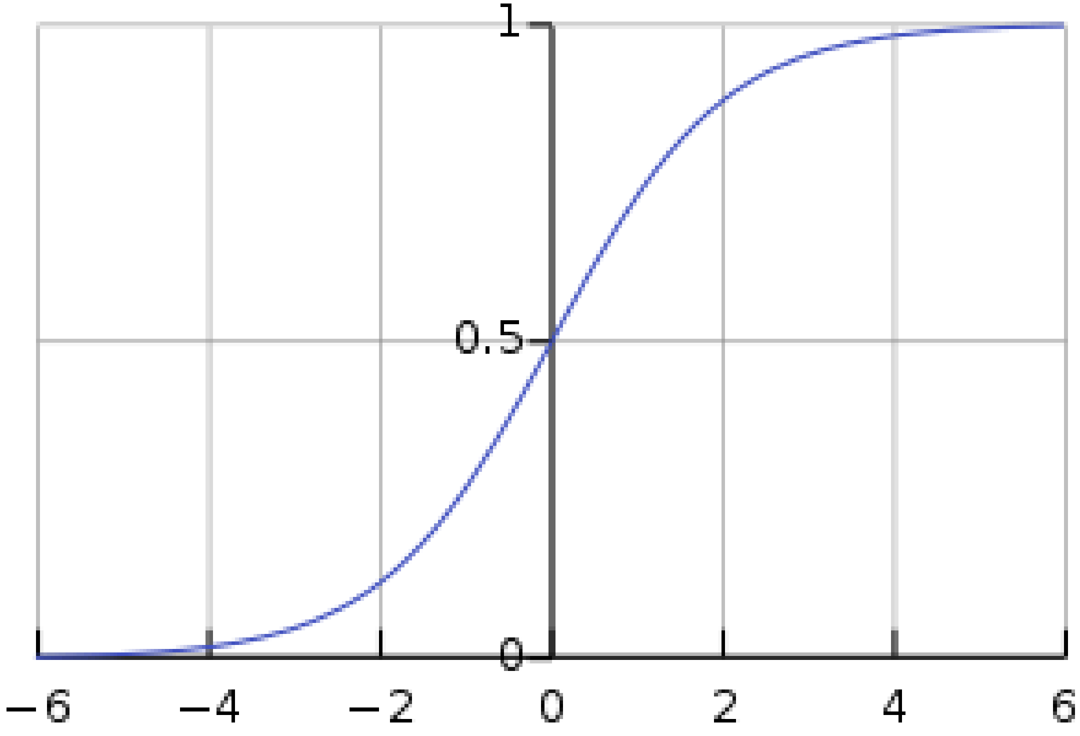
Perceptron : Activation Function

1. RELU



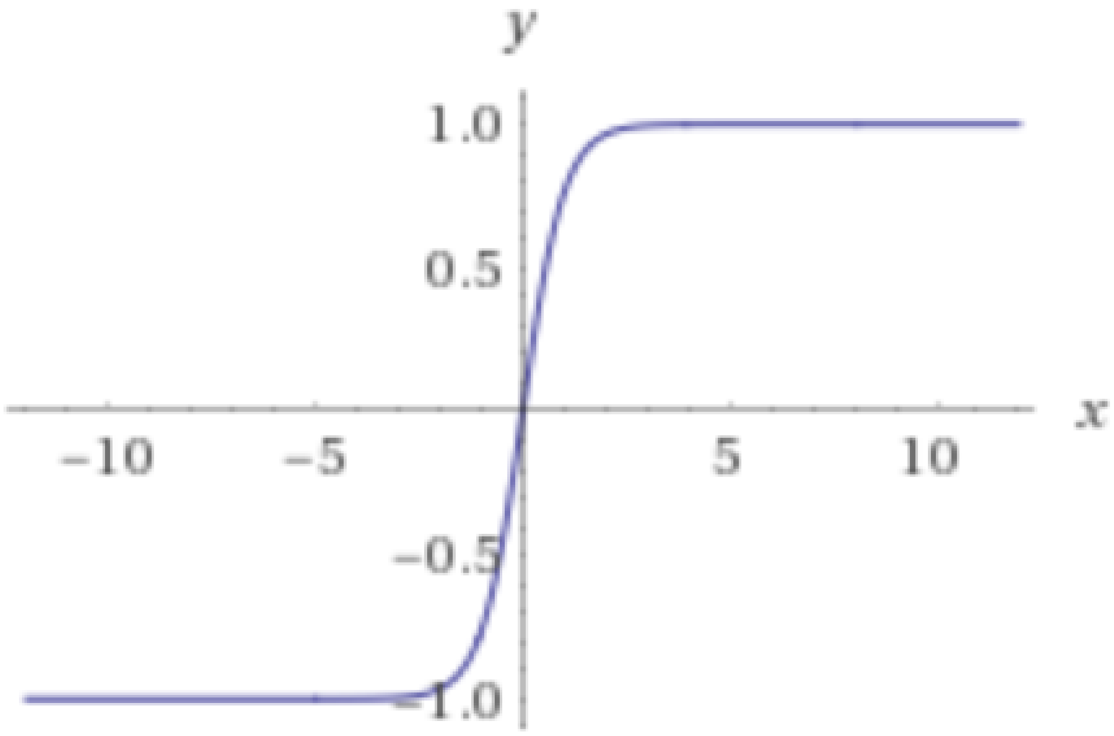
Perceptron : Activation Function

2. Sigmoid



Perceptron : Activation Function

3. Tanh

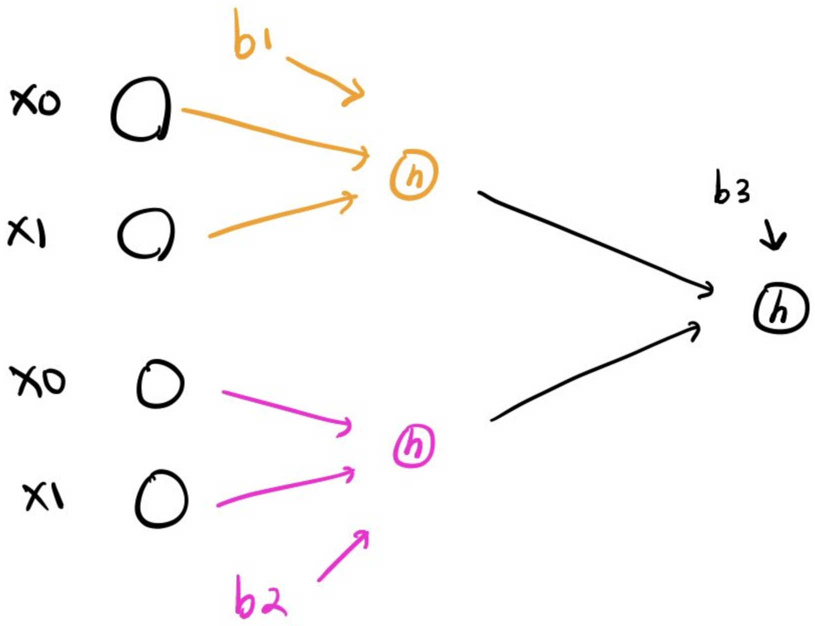


Perceptron : Activation Function

They are also … **Hyperparameters**!!!

Perceptron : Activation Function

But, what if there is no Activation Function…?



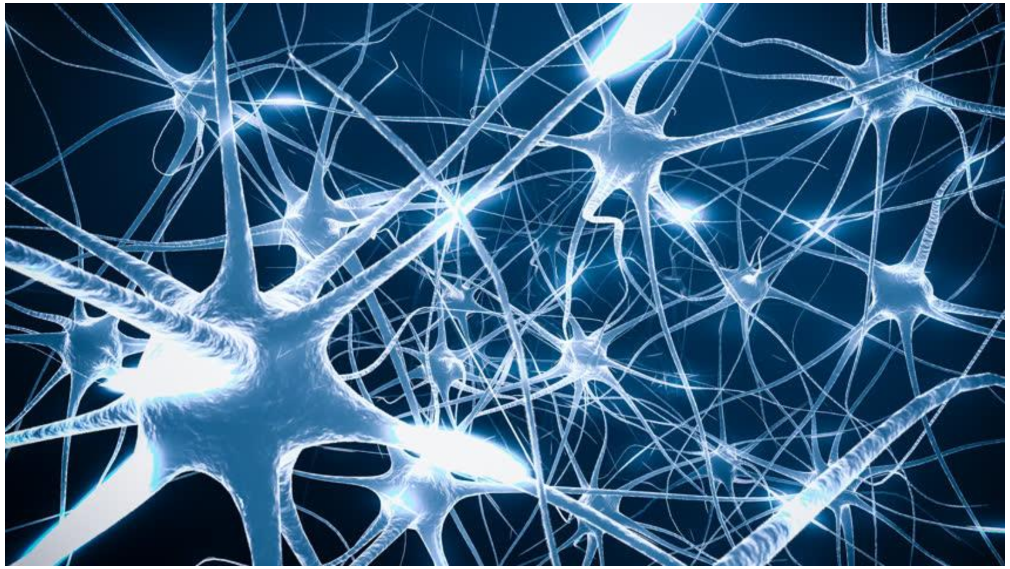
Perceptron : Activation Function

Activation Function gives the capacity for Linear Classifiers to,

handle Nonlinear Classification Problems

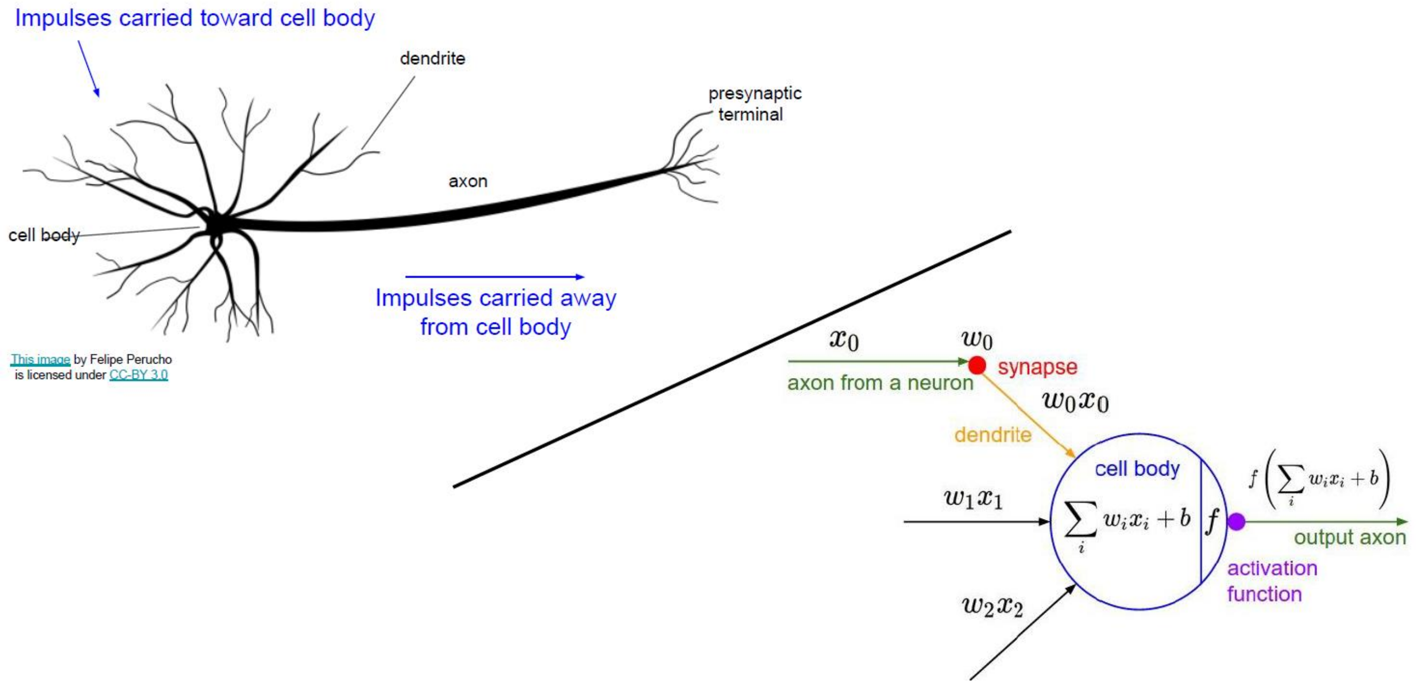
MLP : Idea

Human Neural Network



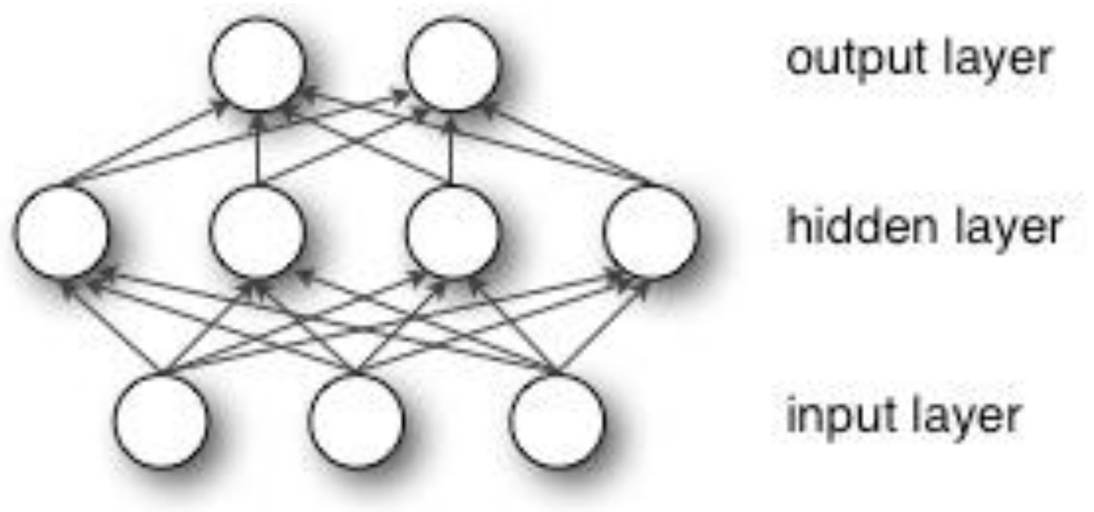
MLP : Idea

Neuron and Perceptron

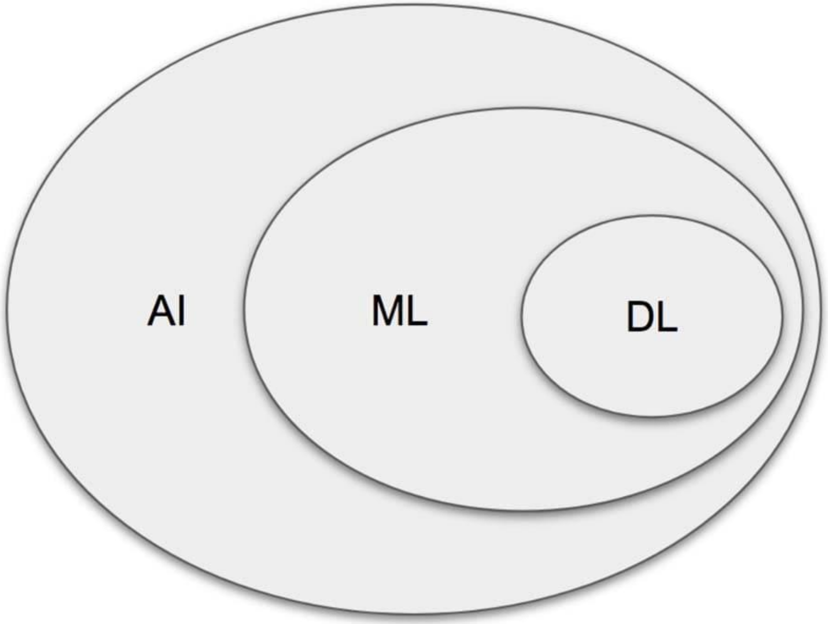


MLP : Idea

Multilayer Perceptron / Artificial Neural Network



MLP : Intro to DL

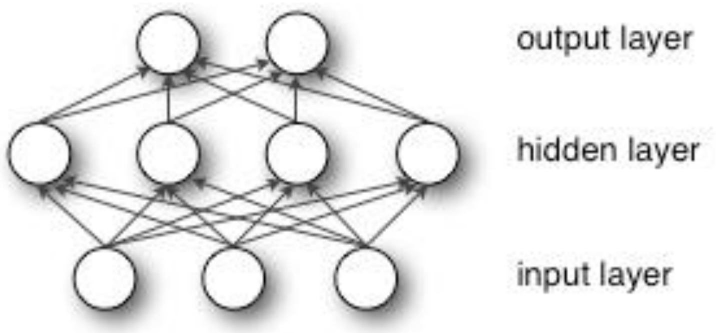


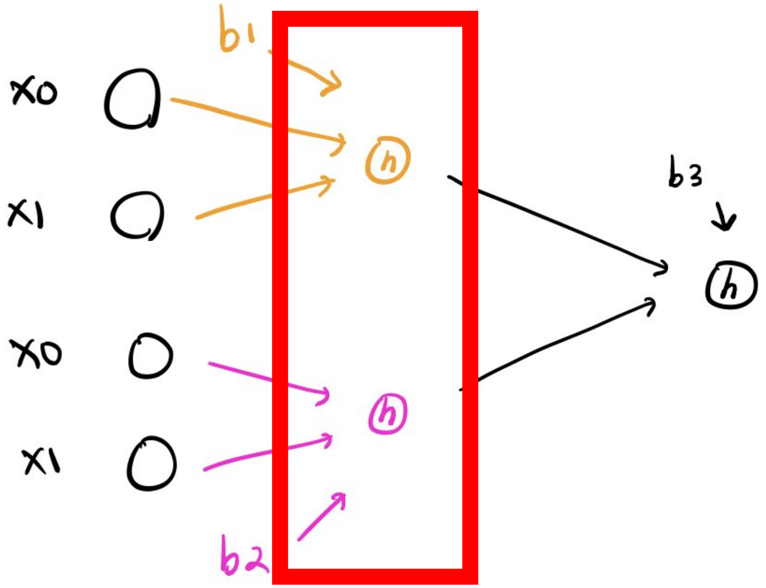
복잡한 Dataset 처리

via ANNs

MLP : Hidden Layer

Multilayer Perceptron / Artificial Neural Network

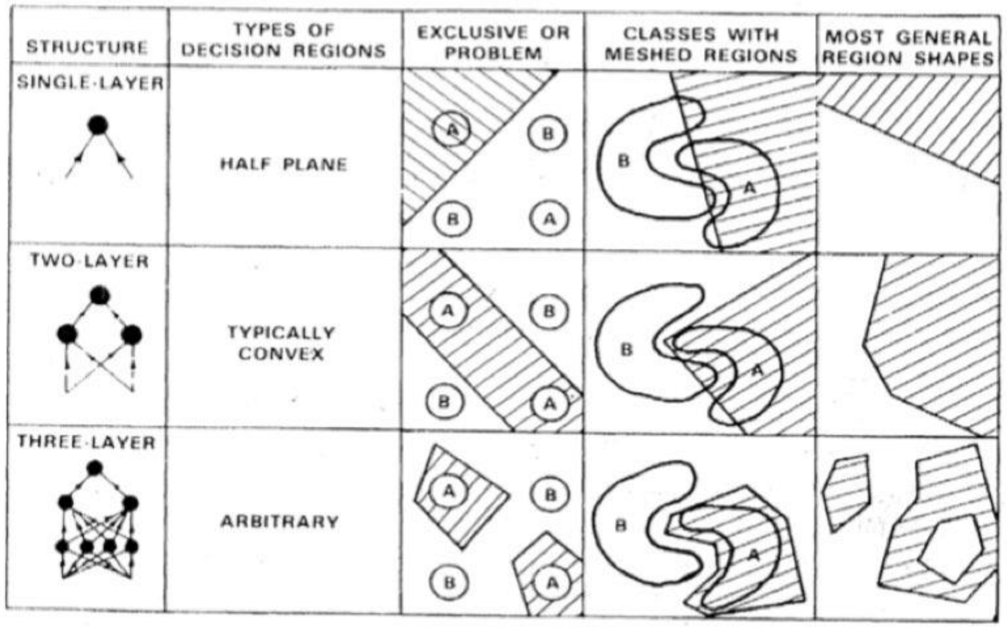




MLP : Hidden Layer

What does a Hidden Layer do?

Map the Input Feature into other dimension, so that it becomes Linearly Separable



MLP : Idea

However, can we guarantee that

the MLP will eventually give the correct classification?

MLP : The Universal Approximation Theorem

1개의 hidden layer를 가진 MLP를 이용해 어떠한 함수도 근사할 수 있다.

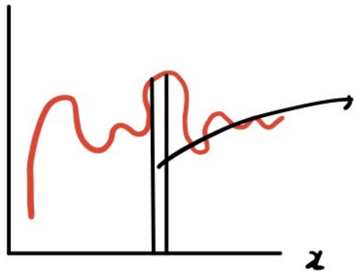
** when Activation Function is nonlinear

** when Hyperparameters are appropriately chosen

MLP : The Universal Approximation Theorem

Idea of Proof (Optional)

NN은 아주 복잡한 함수를 근사하는 것.



이 작은 조각들을 근사.

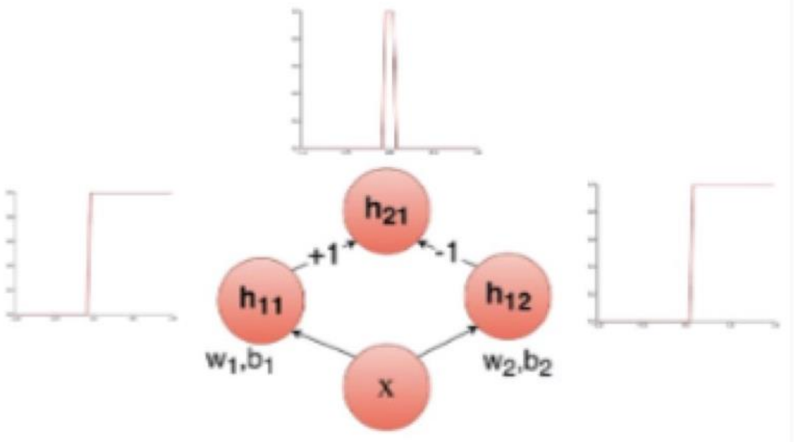
How..?

sigmoid 2개로, tower를 build 가능.

↓

weight로 sigmoid 위치 조절, (into hidden layer)

두 sigmoid 빼서 tower 형성, (out of hidden layer)



For more detail, https://hackernoon.com/illustrative-proof-of-universal-approximation-theorem-5845c02822f6

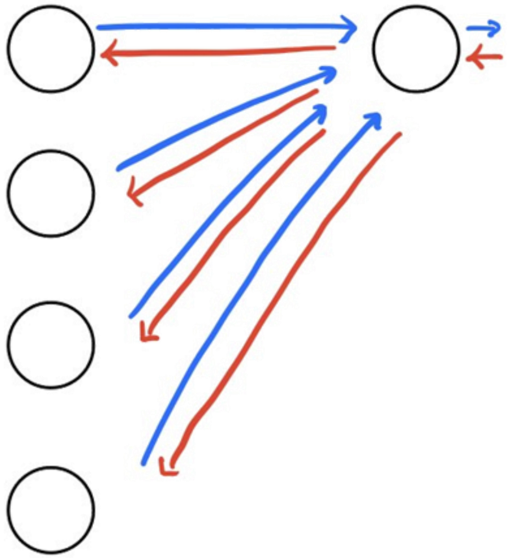
MLP : Looking Back at Backpropagation

MLP를 통해, 복잡한 Classification Function을 근사하고 있다.

Thus, we should utilize **Backpropagation** to compute the gradient

MLP : Looking Back at Backpropagation

with Backpropagation,



→ : feed forward

perceptron에서의 계산 결과가 다음 perceptron의 input으로 들어감.

← : backpropagation

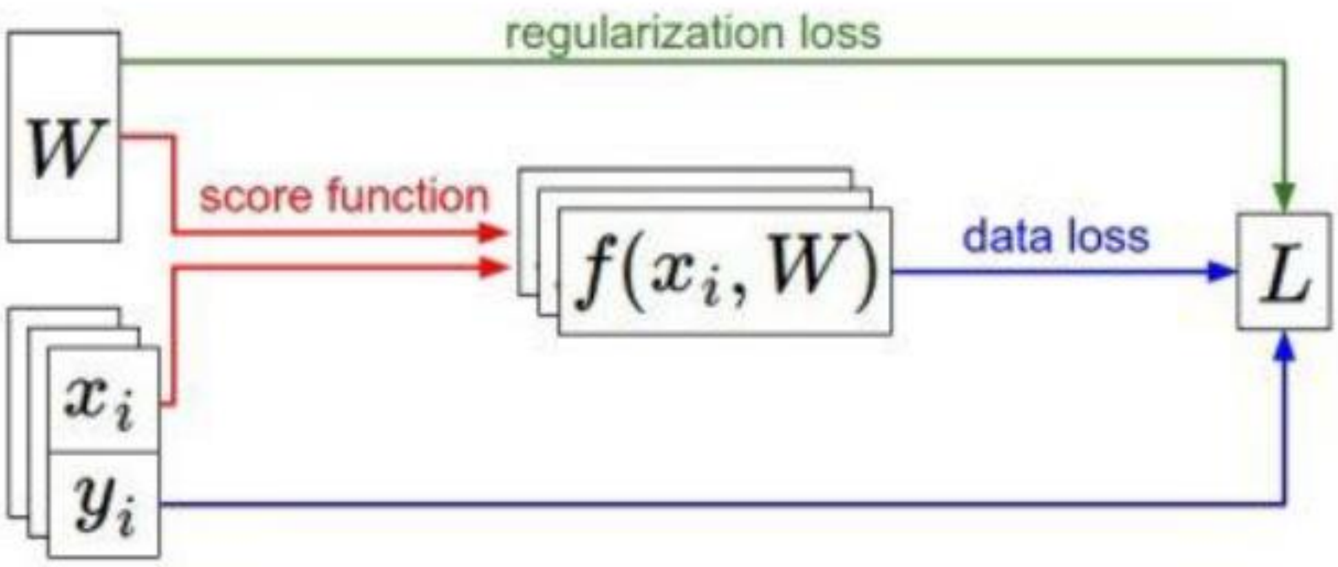
앞 perceptron에서의 gradient가 전 perceptron의 upstream gradient로 들어감.

chain rule에 의해,

(upstream gradient) x (local gradient)

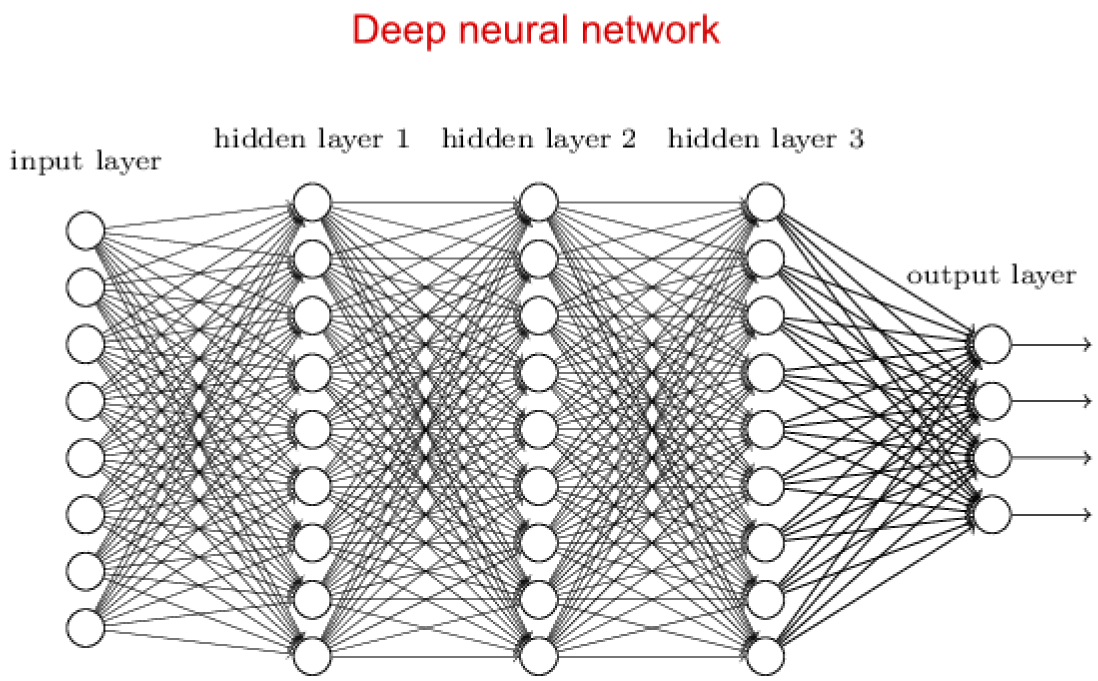
MLP : Looking Back at Backpropagation

지난 Lecture까지는,

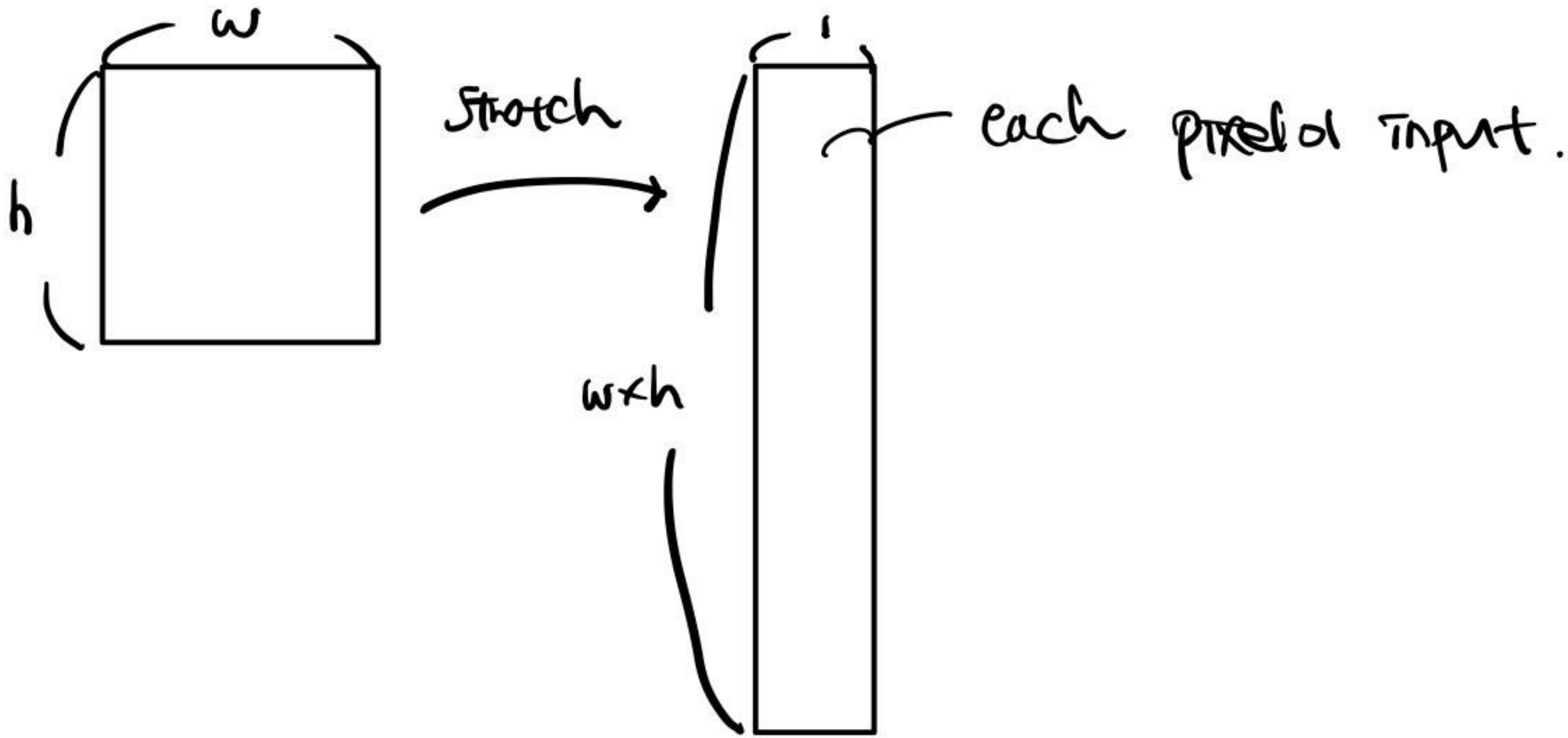


MLP : Looking Back at Backpropagation

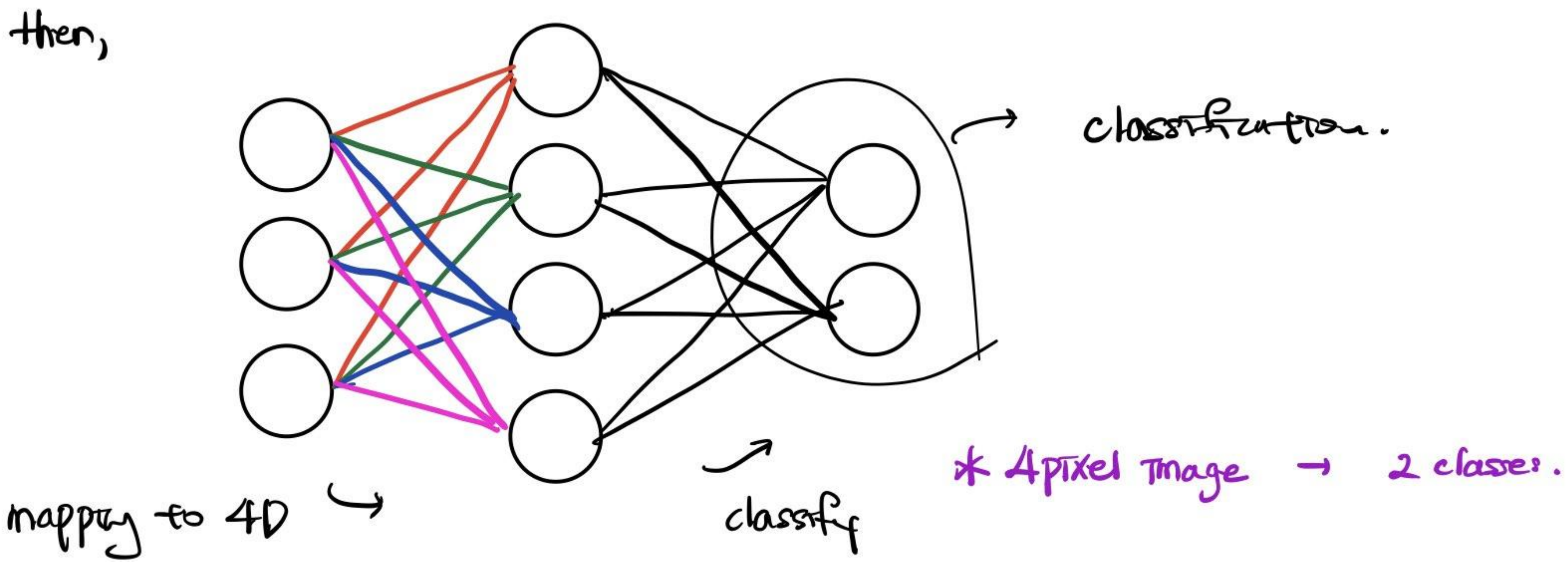
but now,



MLP : Implementation on Image Classification

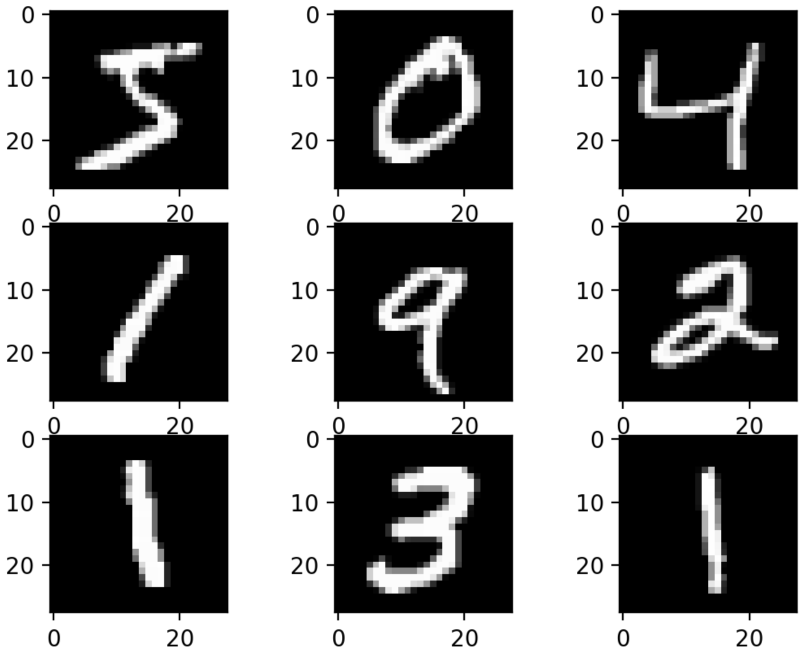


MLP : Implementation on Image Classification



MLP : Implementation on Image Classification

MNIST Dataset



MLP : Implementation on Image Classification

TensorFlow

Keras

Limitations of MLP

MLP + Backpropagation 이론이 나온 것은, 1980s

However, 2010s부터 본격적으로 쓰이기 시작

Why so?

Limitations of MLP

1. Needs a lot of Labeled Data
2. Vanishing Gradient
3. Overfitting
4. Gets stuck in the Local Minima / Saddle Point

Review

1. Limitation of Linear Classifier

- XOR Gate

2. Perceptron

- Perceptron = Linear Classifier
- Analogy to Neurons
- Building Block of the Neural Network

3. MLP

- MLP and the Neural Network
- The Universal Approximation Theorem
- Where Backpropagation becomes Important

4. Limitations of MLP

Preview on Next Lecture(s)

Limitations of MLP

1. Needs a lot of Labeled Data
2. Vanishing Gradient
3. Overfitting
4. Gets stuck in the Local Minima

How to overcome these limitations

: Dropout, Adam, Ensemble, Batch Normalization…

From 2010s, NNs became widely used

: **CNN for Image Classification**