

# **Artificial Neural Networks**

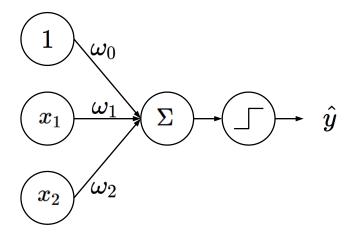
Industrial AI Lab.
Prof. Seungchul Lee
Yunseob Hwang, Illjeok Kim



## **Artificial Neural Networks from MLP**

#### **Artificial Neural Networks: Perceptron**

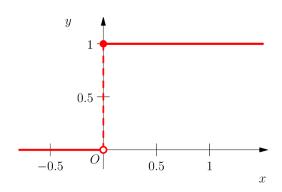
- Perceptron for  $h(\theta)$  or  $h(\omega)$ 
  - Neurons compute the weighted sum of their inputs
  - A neuron is activated or fired when the sum a is positive



- A step function is not differentiable
- One neuron is often not enough
  - One hyperplane

$$a=\omega_0+\omega_1x_1+\omega_2x_2$$

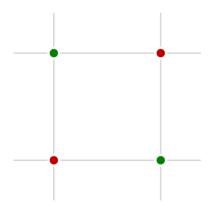
$$\hat{y} = g(a) = egin{cases} 1 & a > 0 \ 0 & ext{otherwise} \end{cases}$$

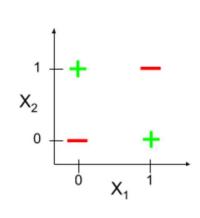


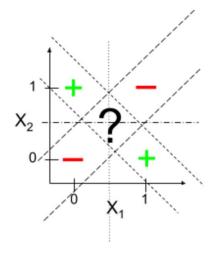
#### **XOR Problem**

- Minsky-Papert Controversy on XOR
  - Not linearly separable
  - Limitation of perceptron

$x_1$	$x_2$	$x_1$ <b>XOR</b> $x_2$
0	0	0
0	1	1
1	0	1
1	1	0



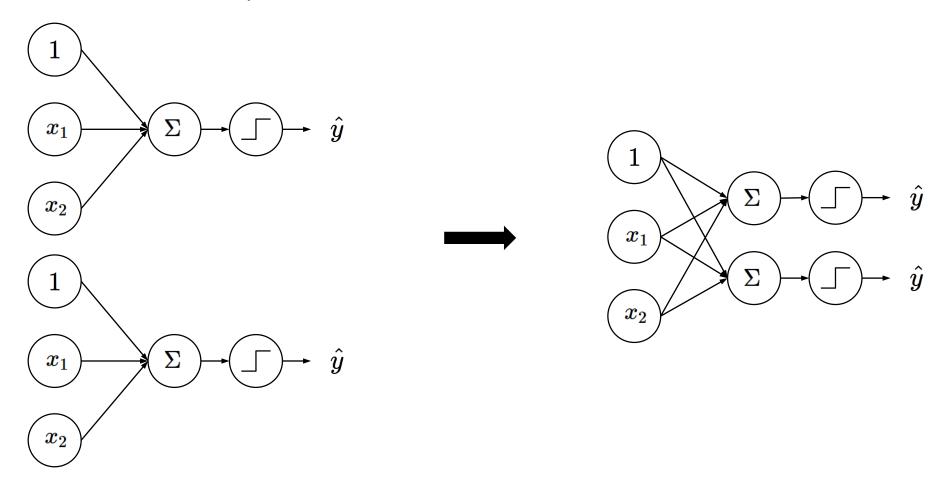




• Single neuron = one linear classification boundary

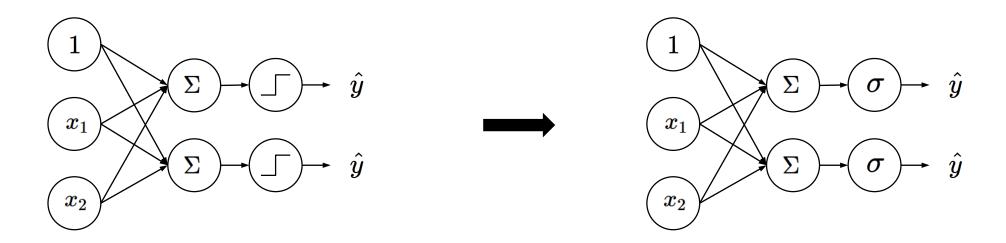
#### **Artificial Neural Networks: MLP**

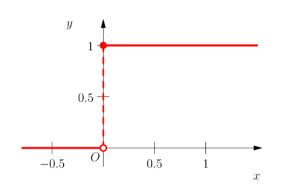
- Multi-layer Perceptron (MLP) = Artificial Neural Networks (ANN)
  - Multi neurons = multiple linear classification boundaries

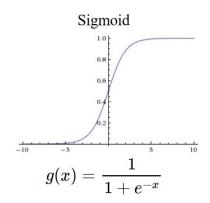


#### **Artificial Neural Networks: Activation Function**

• Differentiable nonlinear activation function

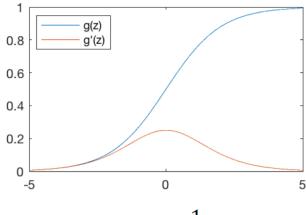






#### **Common Activation Functions**

#### Sigmoid Function

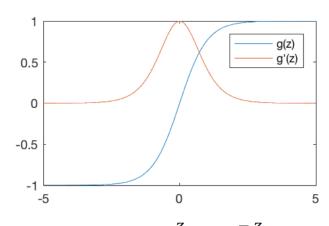


$$g(z) = \frac{1}{1 + e^{-z}}$$

$$g'(z) = g(z)(1 - g(z))$$



#### Hyperbolic Tangent



$$g(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}}$$

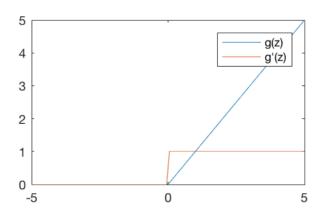
$$g'(z) = 1 - g(z)^2$$



#### Discuss later



#### Rectified Linear Unit (ReLU)



$$g(z) = \max(0, z)$$

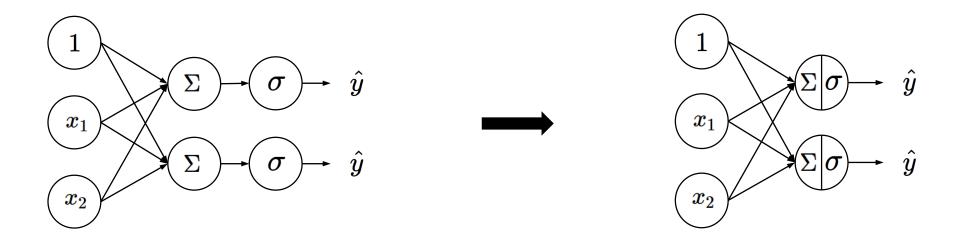
$$g'(z) = \begin{cases} 1, & z > 0 \\ 0, & \text{otherwise} \end{cases}$$





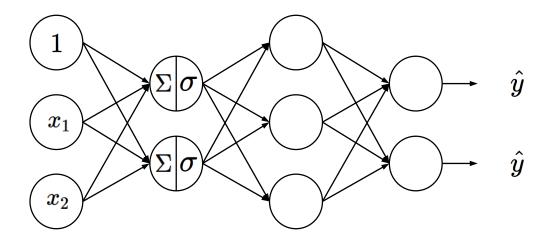
#### **Artificial Neural Networks**

• In a compact representation



#### **Artificial Neural Networks**

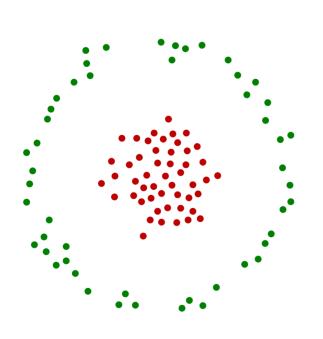
- A single layer is not enough to be able to represent complex relationship between input and output
  - ⇒ perceptron with many layers and units



- Multi-layer perceptron
  - Features of features
  - Mapping of mappings

# **ANN** as Kernel Learning

### **Nonlinear Classification**



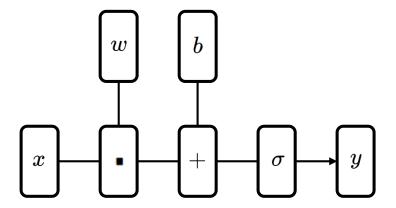
SVM with a polynomial Kernel visualization

> Created by: Udi Aharoni

#### **Neuron**

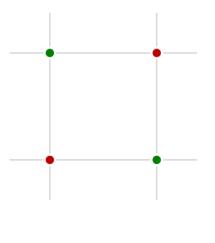
• We can represent this "neuron" as follows:

$$f(x) = \sigma(w \cdot x + b)$$



# **XOR Problem**

- The main weakness of linear predictors is their lack of capacity.
- For classification, the populations have to be linearly separable.

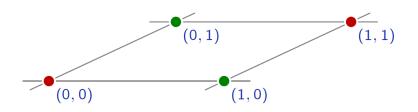


"xor"



# **Nonlinear Mapping**

• The XOR example can be solved by pre-processing the data to make the two populations linearly separable.

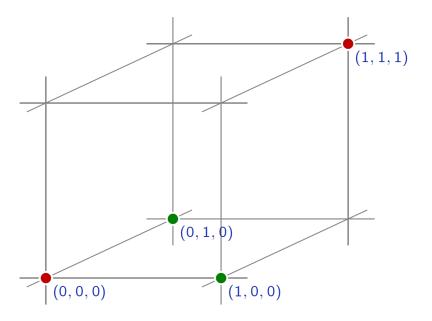




## **Nonlinear Mapping**

• The XOR example can be solved by pre-processing the data to make the two populations linearly separable.

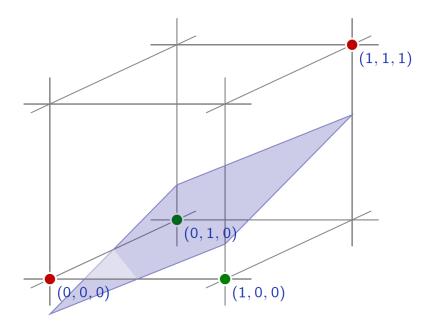
$$\phi:(x_u,x_v) o (x_u,x_v,x_ux_v)$$



## **Nonlinear Mapping**

• The XOR example can be solved by pre-processing the data to make the two populations linearly separable.

$$\phi:(x_u,x_v) o (x_u,x_v,x_ux_v)$$



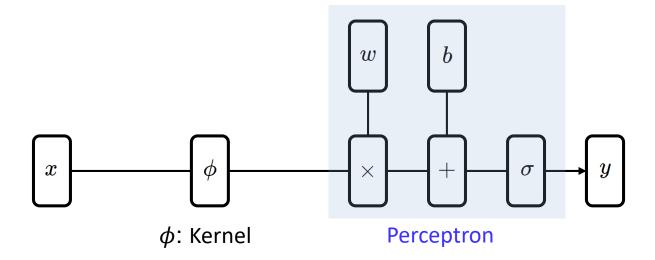
#### Kernel

- Often we want to capture nonlinear patterns in the data
  - nonlinear regression: input and output relationship may not be linear
  - nonlinear classification: classes may not be separable by a linear boundary
- Linear models (e.g. linear regression, linear SVM) are not just rich enough
  - by mapping data to higher dimensions where it exhibits linear patterns
  - apply the linear model in the new input feature space
  - mapping = changing the feature representation
- Kernels: make linear model work in nonlinear settings

### **Kernel + Neuron**

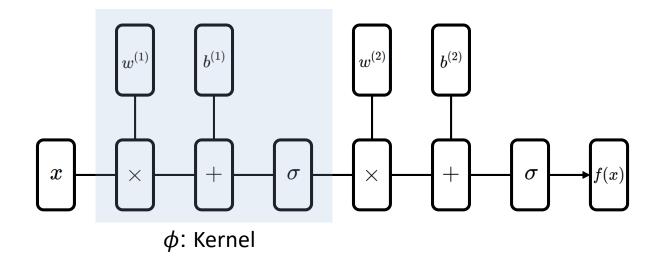
• Nonlinear mapping + neuron

$$\phi:(x_u,x_v) o (x_u,x_v,x_ux_v)$$



#### **Neuron + Neuron**

Nonlinear mapping can be represented by another neurons

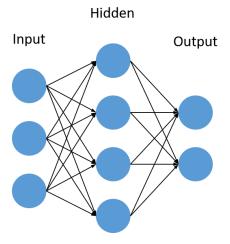


- Nonlinear Kernel
  - Nonlinear activation functions

#### **Summary**

- Universal function approximator
- Universal function classifier

Parameterized

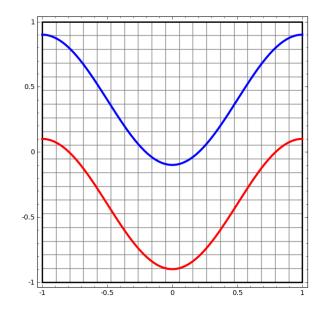


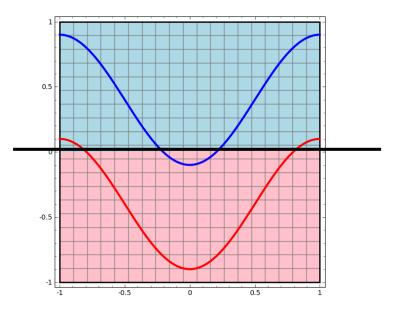
$$\hat{y} = f_{\omega_1, \cdots, \omega_k}(x) \hspace{1cm} \longrightarrow \hspace{1cm} \mathcal{y}$$

# **Looking at Hidden Layers**

### **Example: Linear Classifier**

• Perceptron tries to separate the two classes of data by dividing them with a line

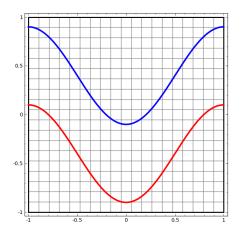


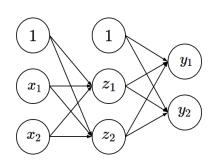


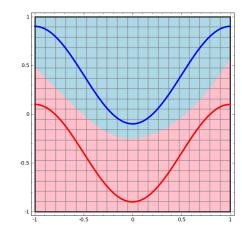


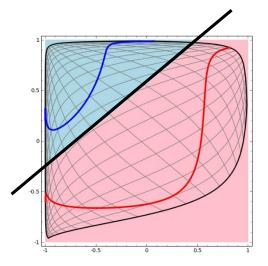
### **Example: Neural Networks**

• The hidden layer learns a representation so that the data gets linearly separable

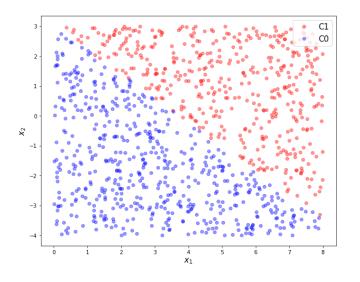




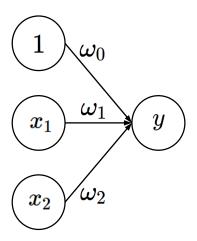


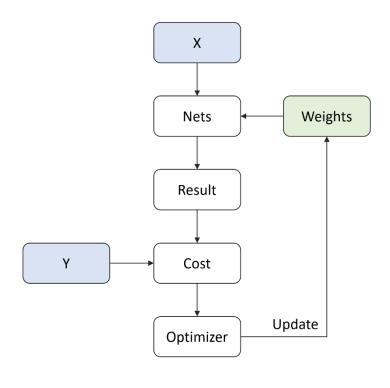


# **Logistic Regression in a Form of Neural Network**



$$y=\sigma\left(\omega_{0}+\omega_{1}x_{1}+\omega_{2}x_{2}
ight)$$







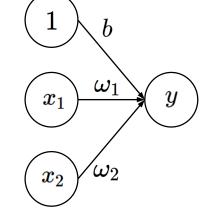
### **Logistic Regression in a Form of Neural Network**

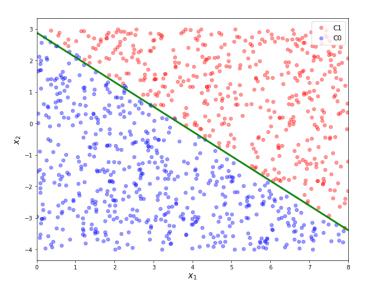
Neural network convention

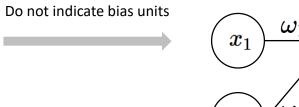
$$y = \sigma \left(\omega_0 + \omega_1 x_1 + \omega_2 x_2\right)$$

$$\begin{array}{cccc} & \omega_0 & & & \\ & \omega_1 & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & \\ & & & \\ & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & &$$

$$y=\sigma\left(b+\omega_{1}x_{1}+\omega_{2}x_{2}
ight)$$





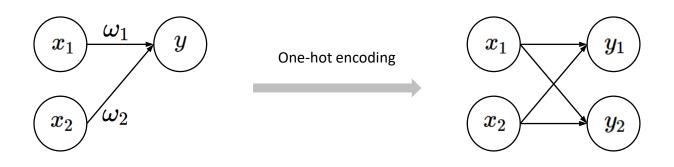


n\_input = 2 n\_output = 1

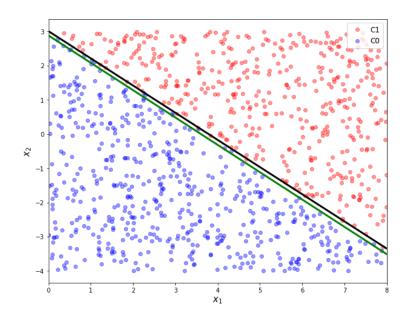
#### **Logistic Regression in a Form of Neural Network**

- One-hot encoding
  - One-hot encoding is a conventional practice for a multi-class classification

$$y^{(i)} \in \{1,0\} \quad \implies \quad y^{(i)} \in \{[0,1],[1,0]\}$$

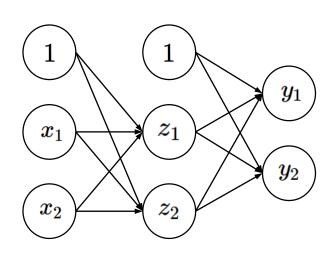


n\_input = 2 n\_output = 2

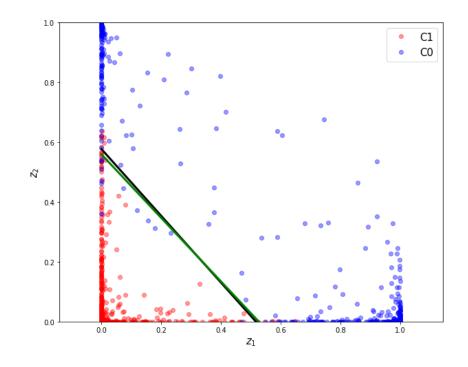


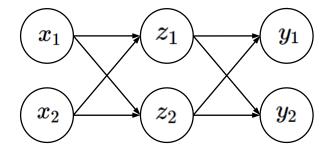
# **Multi Layers**

• z space



Do not include bias units

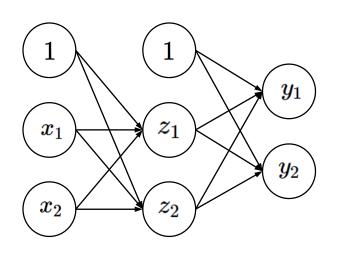




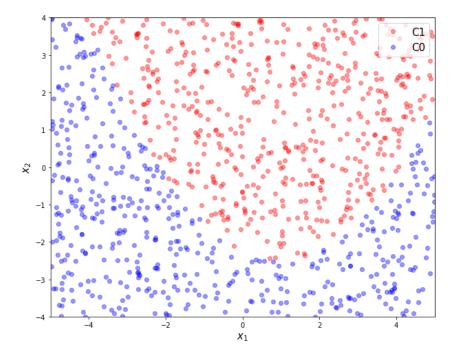
n\_input = 2
n\_hidden = 2
n\_output = 2

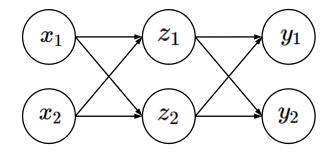
## **Nonlinearly Distributed Data**

- Example to understand network's behavior
  - Include a hidden layer



Do not include bias units

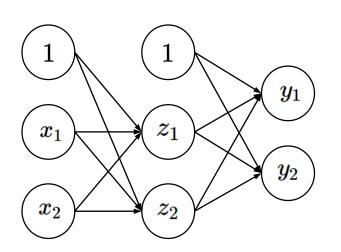




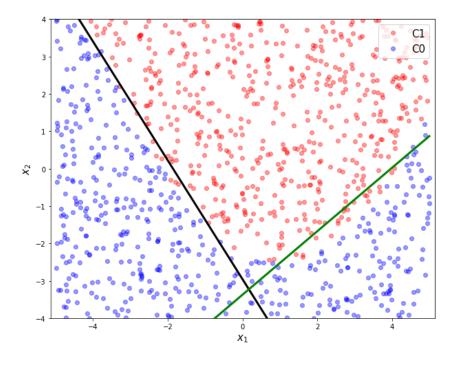
n\_input = 2
n\_hidden = 2
n\_output = 2

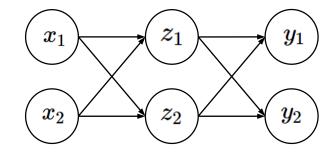
# **Multi Layers**

• x space



Do not include bias units

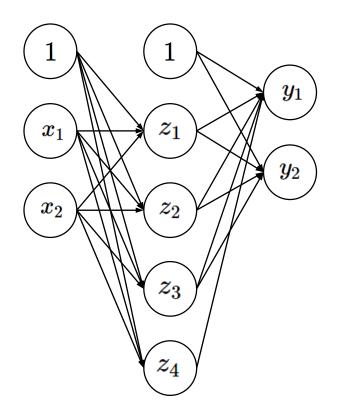




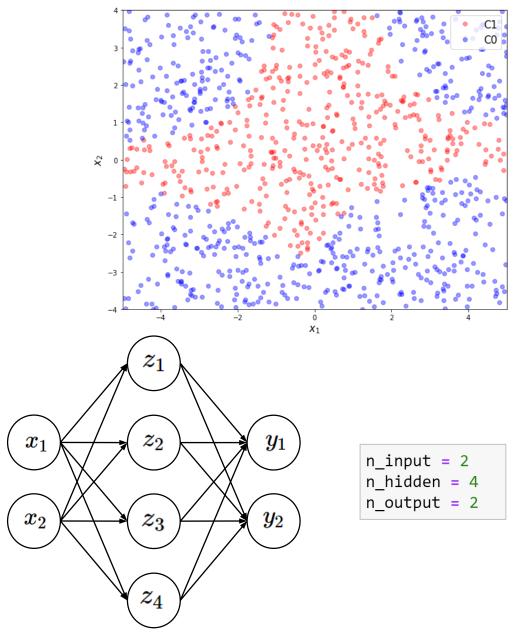
n\_input = 2
n\_hidden = 2
n\_output = 2

## **Nonlinearly Distributed Data**

• More neurons in hidden layer

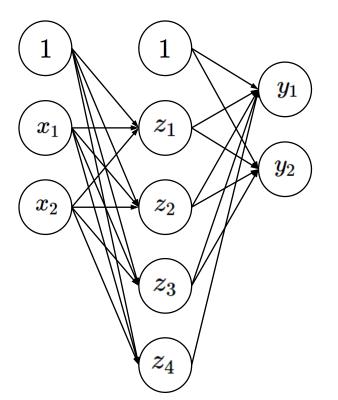


Do not include bias units



# **Multi Layers**

• Multiple linear classification boundaries



Do not include bias units

