

# Configuration of Neural Networks

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- Regression
- Binary-Class Classification
- Multi-Class Classification
- Nominal Input

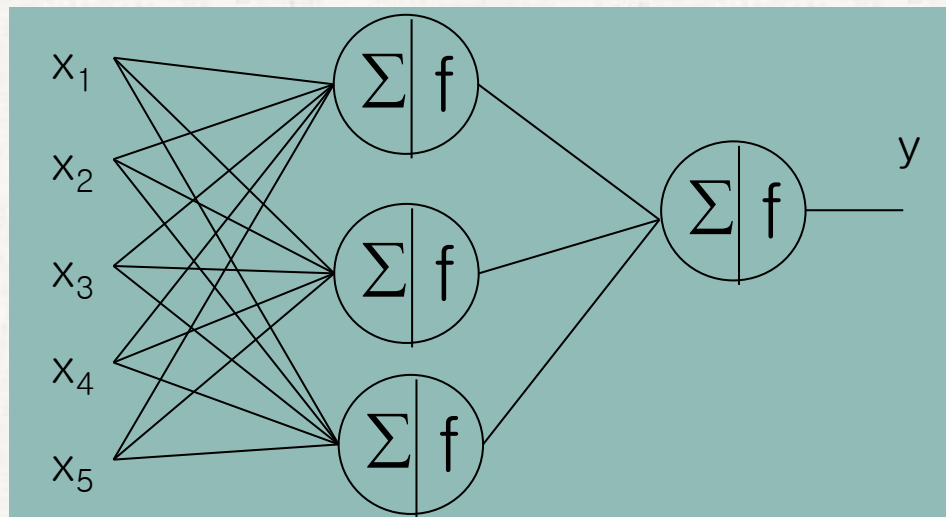
# Regression

## ● Regression: Stock Index Prediction

(2500, 2550, 2530, 2540, 2550)  $\rightarrow$  2600

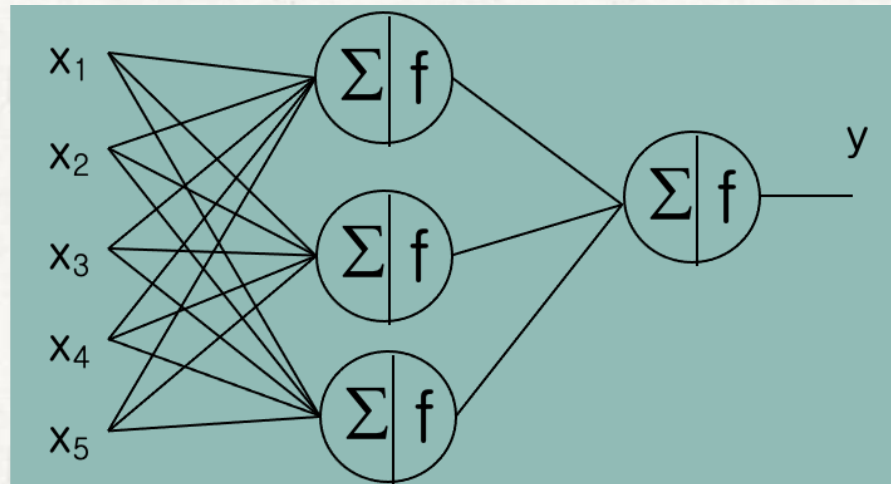
(2400, 2410, 2420, 2430, 2440)  $\rightarrow$  2450

(2470, 2460, 2450, 2470, 2480)  $\rightarrow$  2470



# Regression

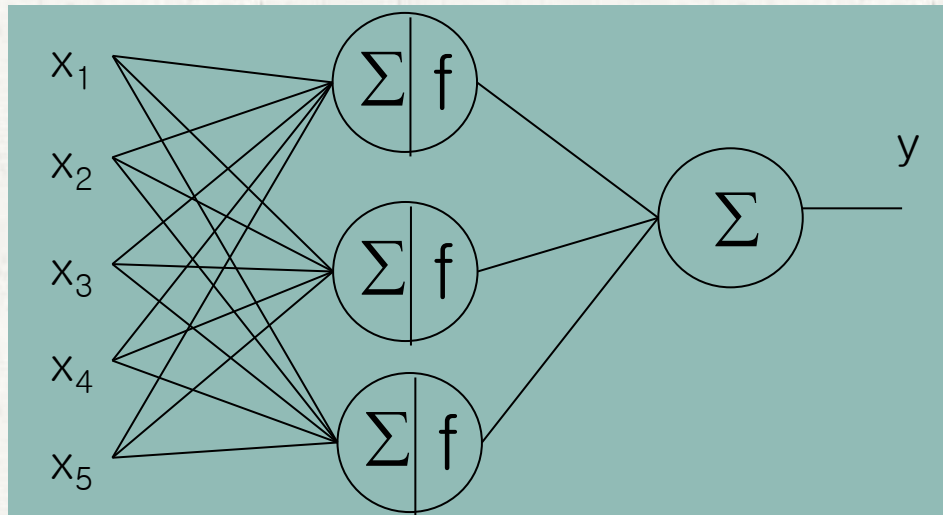
- Following Neural Network is OK for regression?



- Maybe NO!! Why?
- The activation functions produces a value between  $[0,1]$

# Regression

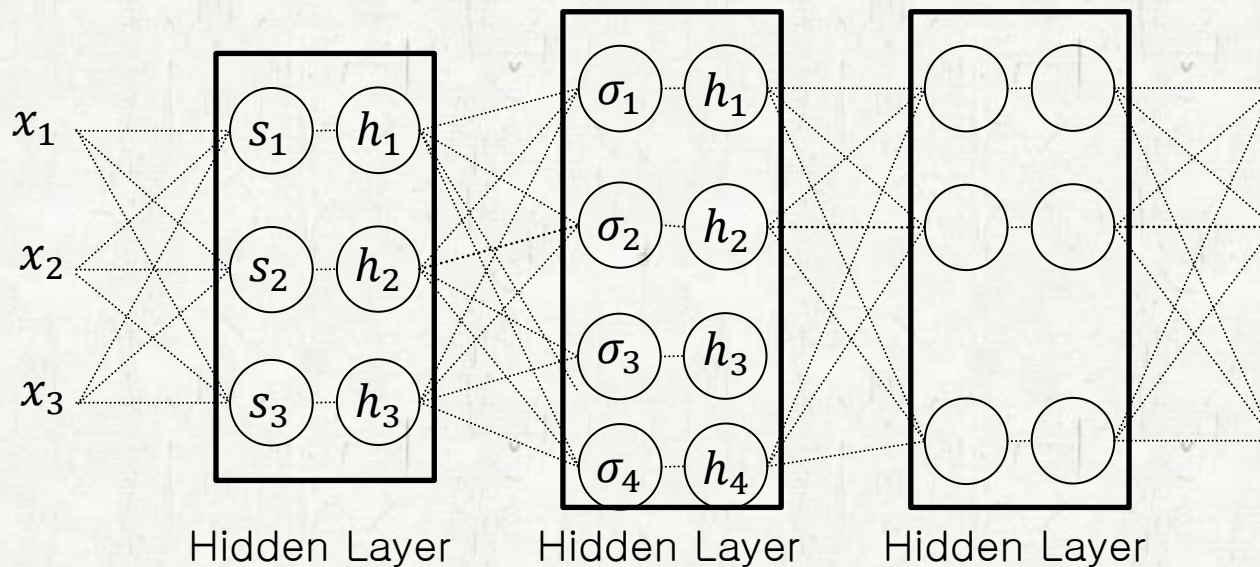
- Solution
  - Use a linear output node





# Regression

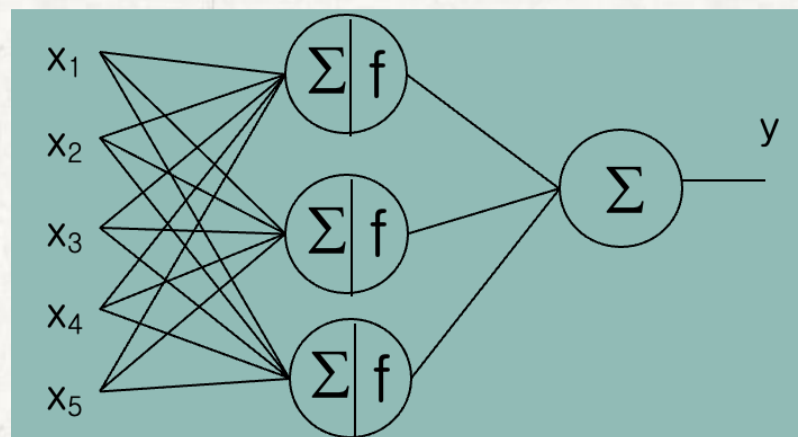
- What layers do



# Regression

## Summary

### ① Linear Activation Function at output node

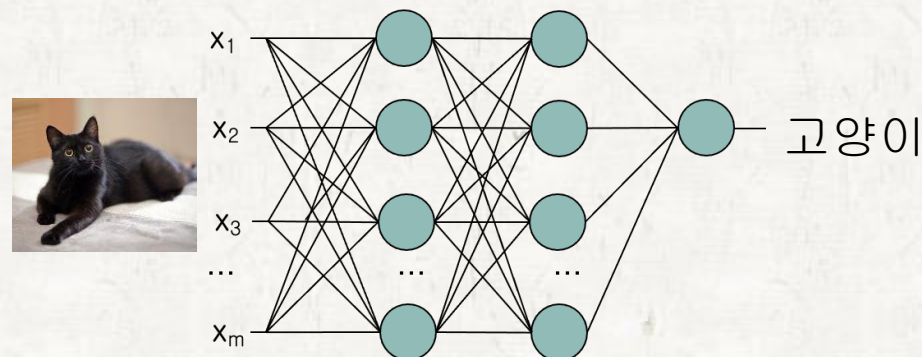
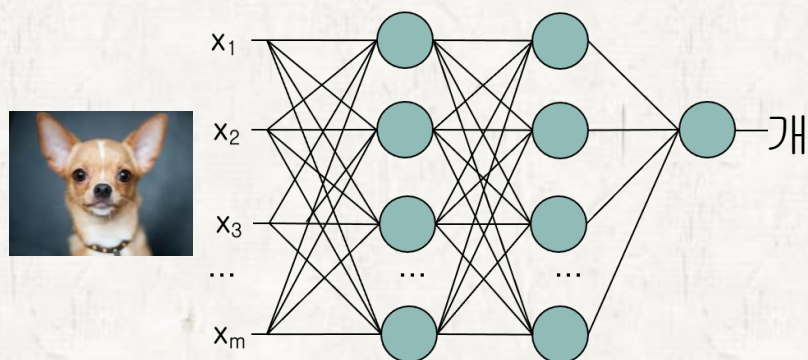
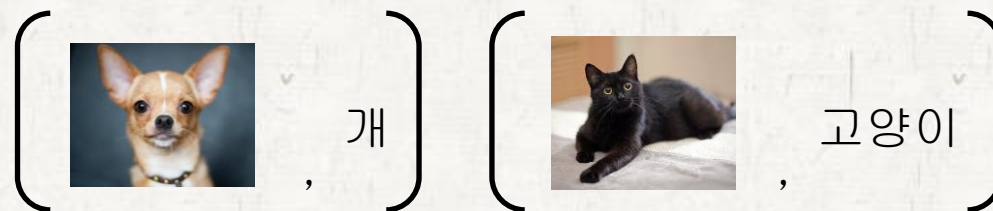


### ② MSE Loss Function

$$E = \sum_{n=1}^N (t_n - y_n)^2$$

# Binary-Class Classification

- Binary-Class Classification:
  - Choosing one from two classes

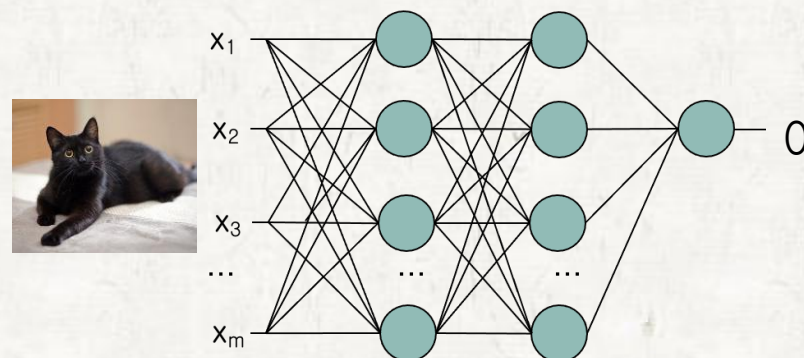
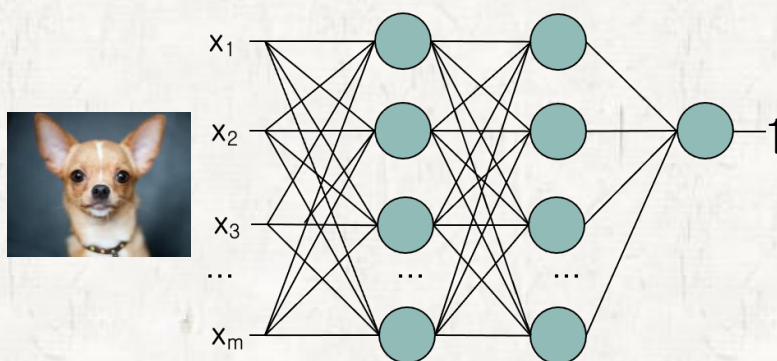




# Binary-Class Classification

- Binary-Class Classification:
  - Choosing one from two classes

$$\left( \begin{array}{c} \text{Chihuahua Image} \\ 1 \end{array} \right) \quad \left( \begin{array}{c} \text{Black Cat Image} \\ 0 \end{array} \right)$$



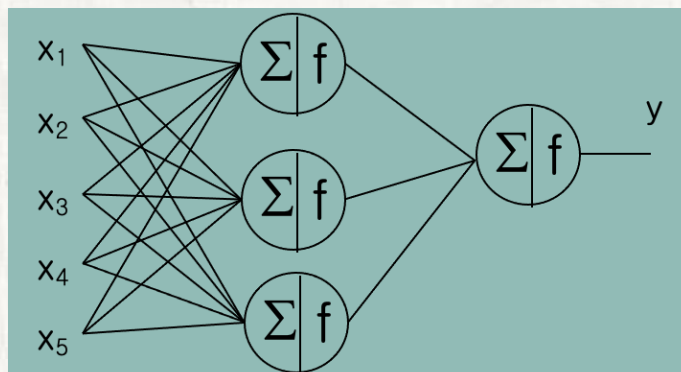
# Binary-Class Classification

- Categorical Value  $\rightarrow$  1 or 0 로 변환

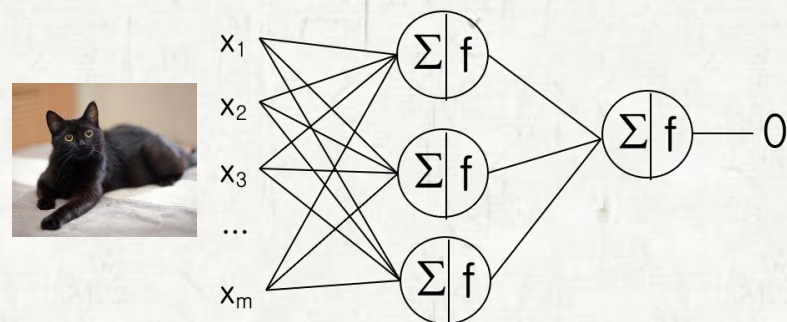
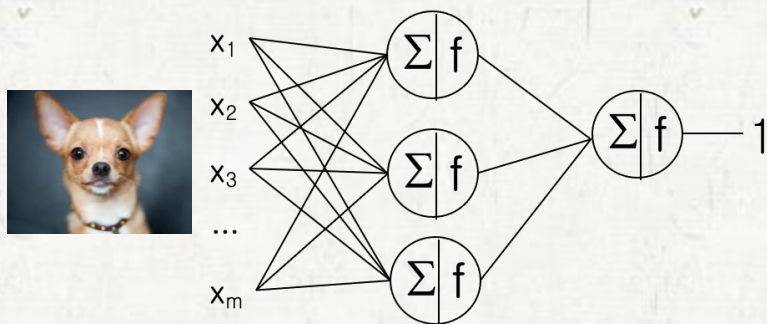


# Binary-Class Classification

- Activation Function of output nodes

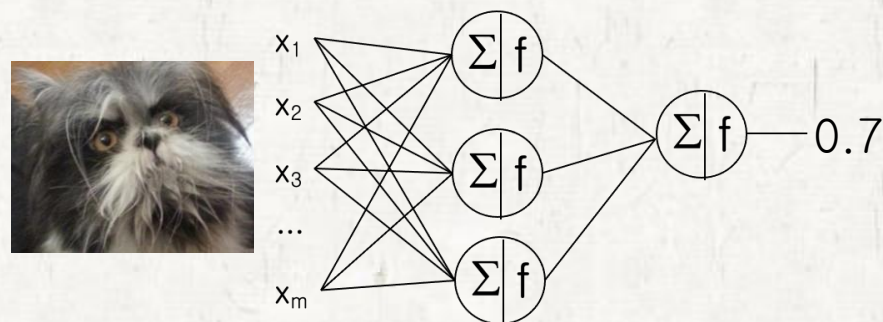
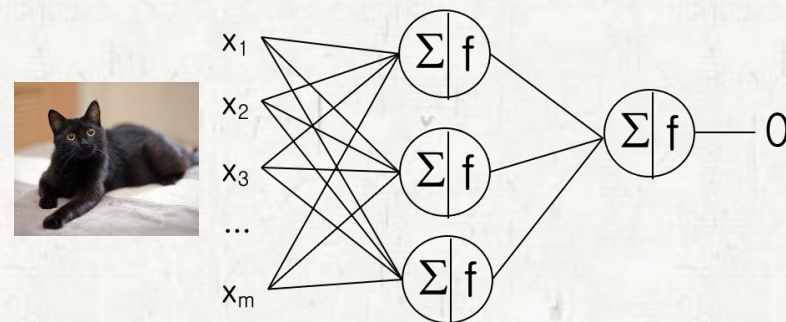
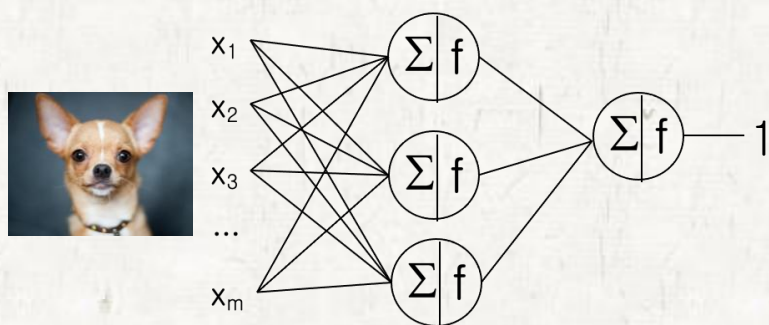


- Sigmoid is OK, but it means probability



# Binary-Class Classification

## ● Activation Function of output nodes

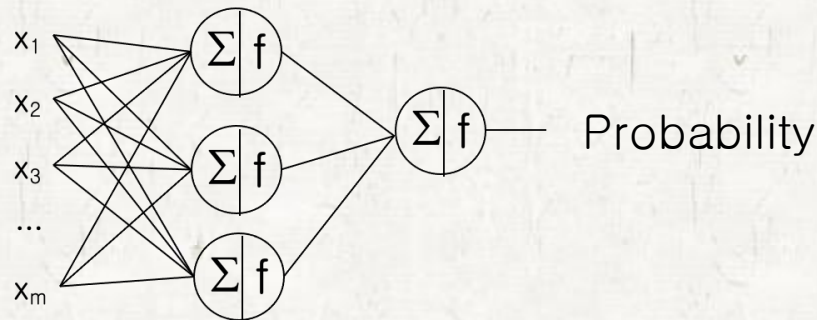


The output is **regarded** as “**Probability** of Dog”



# Binary-Class Classification

- Loss Function
  - The output means probability



- Cross Entropy

$$E = - \sum_{n=1}^N (t_n \log(y_n) + (1 - t_n) \log(1 - y_n))$$

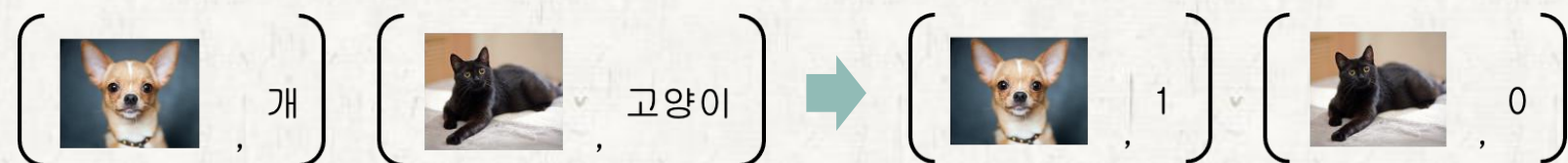
where  $t_n \in \{0,1\}$  and  $y_n \in [0,1]$



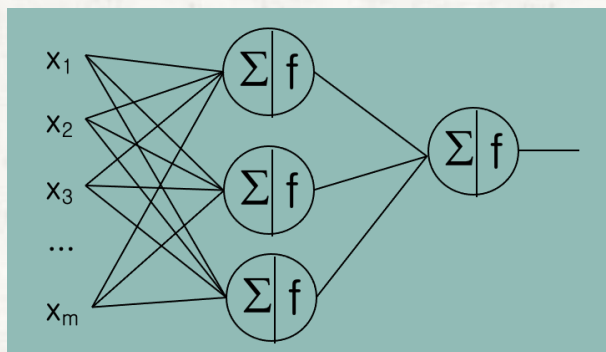
# Binary-Class Classification

## Summary

### ① Preprocessing



### ② Sigmoid at output node



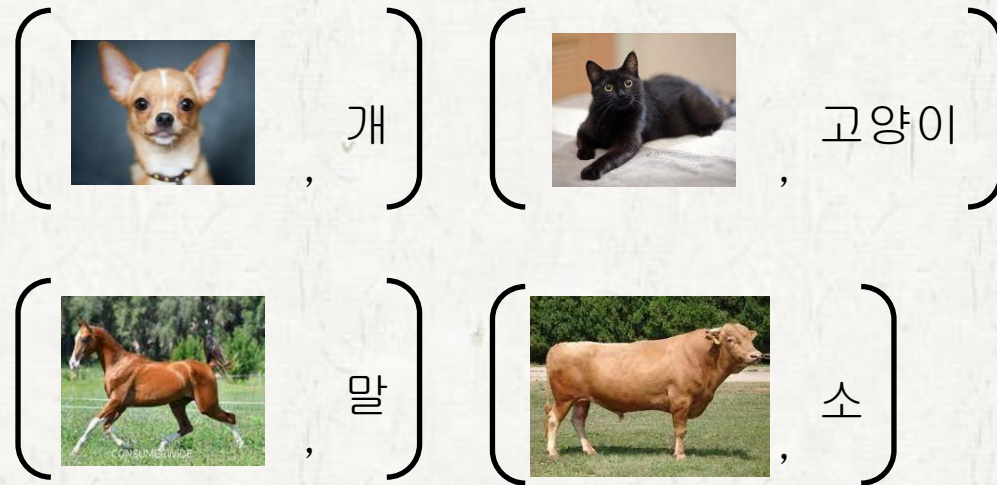
### ③ Cross Entropy

$$E = - \sum_{n=1}^N (t_n \log(y_n) + (1 - t_n) \log(1 - y_n))$$

where  $t_n \in \{0,1\}$  and  $y_n \in [0,1]$

# Multi-Class Classification

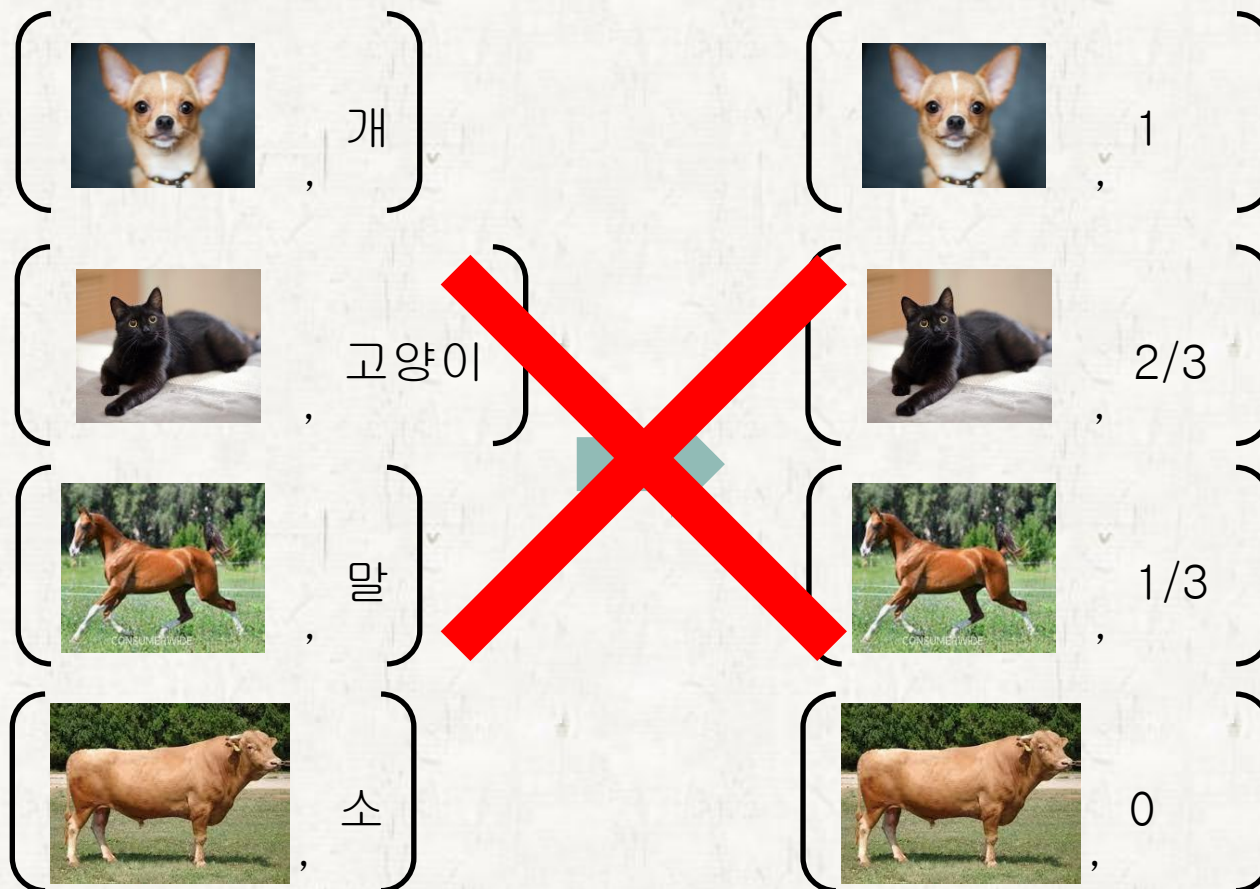
- We have 4 classes



- How to Conver Categorical Values

# Multi-Class Classification

## Categorical Value Conversion



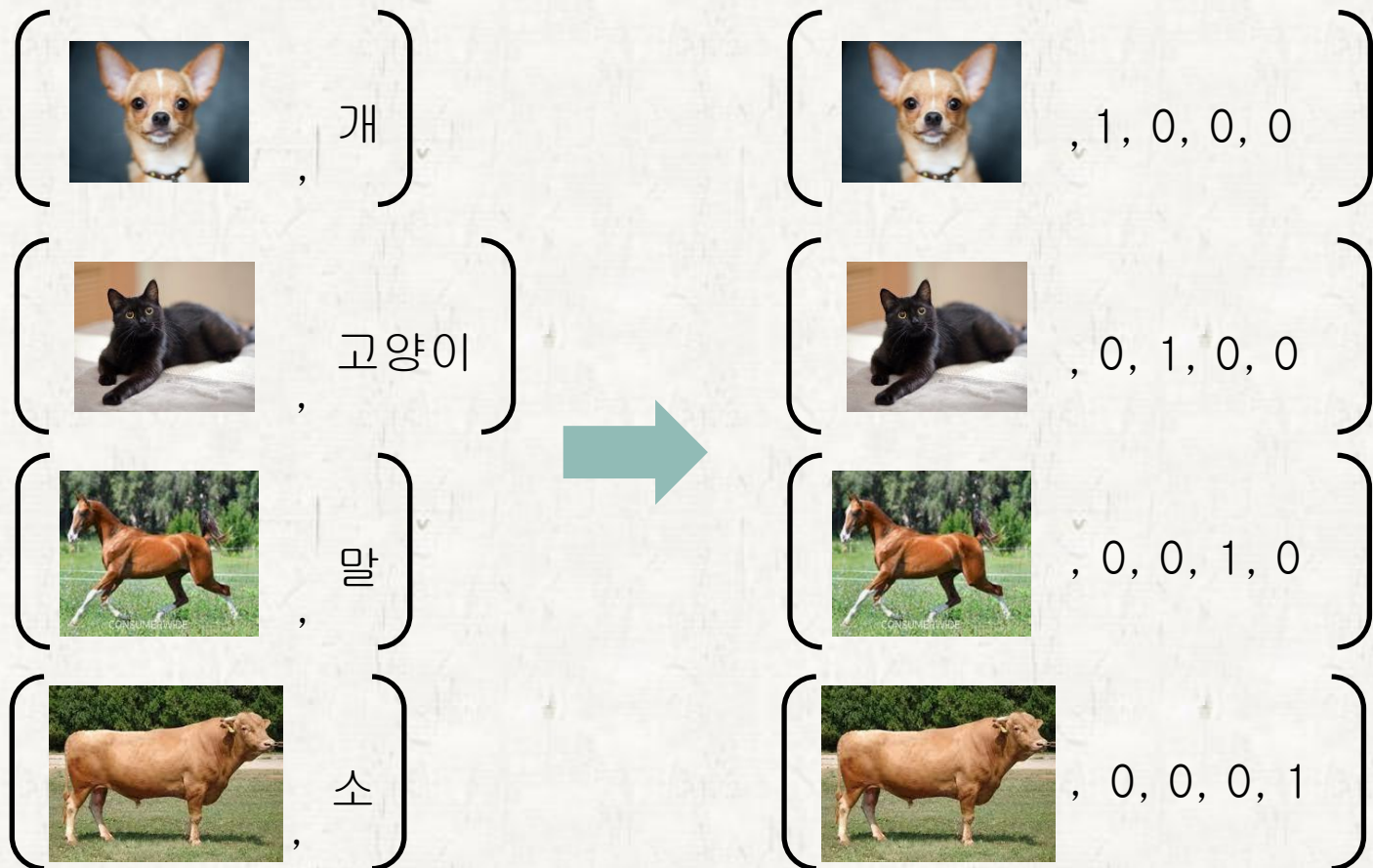
# Multi-Class Classification

- Not Good... why?

개	→	1.0
고양이	→	2/3
말	→	1/3
소	→	0.0

# Multi-Class Classification

## • Categorical Value Conversion: One-hot-encoding

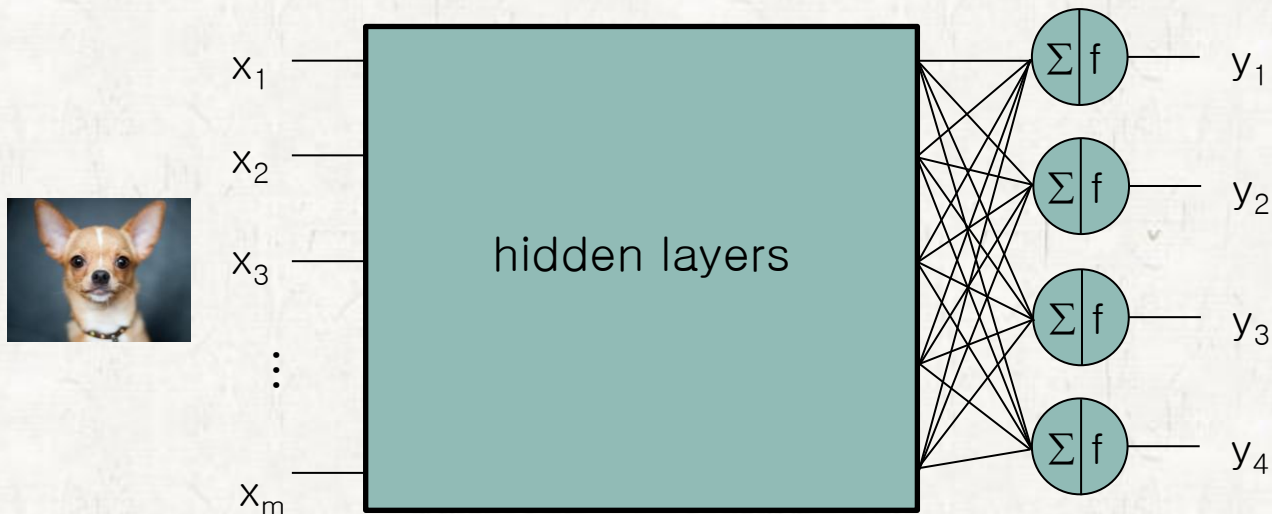




# Multi-Class Classification

## Structure of Neural Network

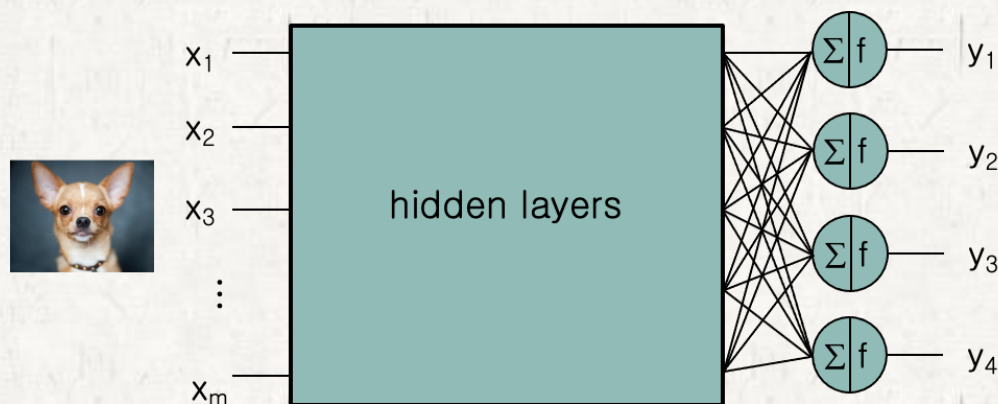
$$\left( \begin{array}{c} \text{Chihuahua} \\ , 1, 0, 0, 0 \end{array} \right) \left( \begin{array}{c} \text{Black Cat} \\ , 0, 1, 0, 0 \end{array} \right) \left( \begin{array}{c} \text{Brown Horse} \\ , 0, 0, 1, 0 \end{array} \right) \left( \begin{array}{c} \text{Brown Cow} \\ , 0, 0, 0, 1 \end{array} \right)$$



# Multi-Class Classification

- Activation Function of Output nodes

$f = \text{Softmax}$



- Loss Function: Cross Entropy

$$E = \sum_{n=1}^{Data} \sum_{k=1}^{Class} -t_{nk} \log(y_{nk})$$

# Multi-Class Classification

③ Choose the softmax instead of max

$$(y_1, y_2, y_3) = \text{softmax}(x_1, x_2, x_3)$$

$$y_k = \frac{e^{x_k}}{\sum_{i=1}^n e^{x_i}}$$

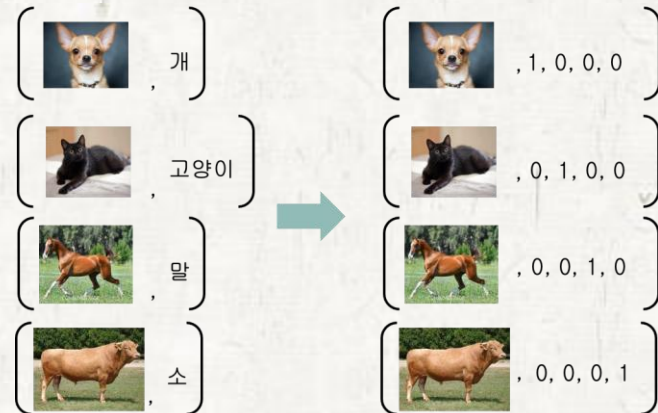
$y_1$	$y_2$	$y_3$
0.301	0.332	0.367
0.090	0.245	0.665
0.042	0.114	0.844
0.017	0.047	0.936
0.000	0.000	1.000
0.000	0.000	1.000

$x_1$	$x_2$	$x_3$
1	1.1	1.2
1	2	3
1	2	4
1	2	5
1	2	10
1	2	20

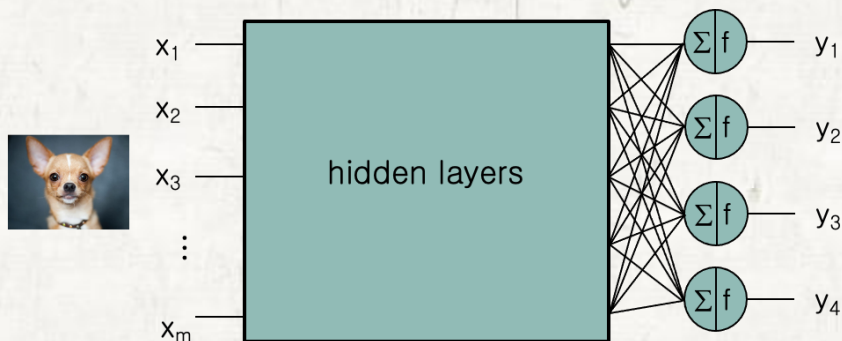
# Multi-Class Classification

## Summary

### ① One-hot-encoding



### ② Use softmax



### ③ Use cross entropy

$$E = \sum_{n=1}^{Data} \sum_{k=1}^{Class} -t_{nk} \log(y_{nk})$$

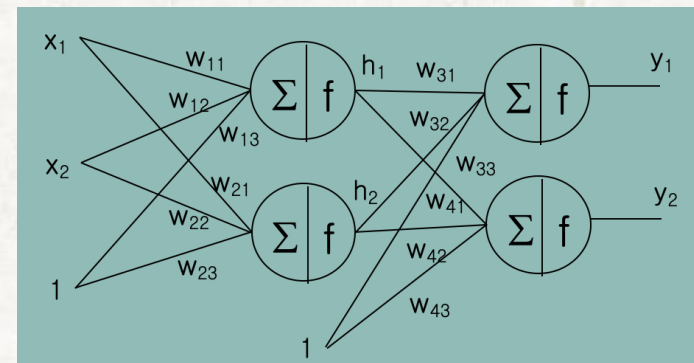
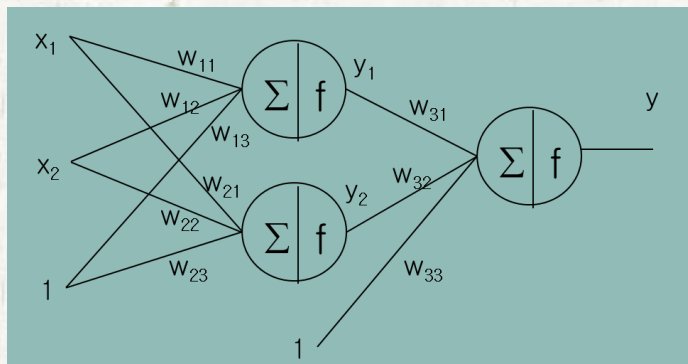
# Multi-Class Classification

## ● Cross Entropy for Multi-Class

$(x_{11}, x_{12}, Red)$   
 $(x_{21}, x_{22}, Red)$   
 $(x_{31}, x_{32}, Black)$   
 $(x_{41}, x_{42}, Red)$   
 $(x_{51}, x_{52}, Black)$

$(x_{11}, x_{12}, 1)$   
 $(x_{21}, x_{22}, 1)$   
 $(x_{31}, x_{32}, 0)$   
 $(x_{41}, x_{42}, 1)$   
 $(x_{51}, x_{52}, 0)$

$(x_{11}, x_{12}, 1, 0)$   
 $(x_{21}, x_{22}, 1, 0)$   
 $(x_{31}, x_{32}, 0, 1)$   
 $(x_{41}, x_{42}, 1, 0)$   
 $(x_{51}, x_{52}, 0, 1)$



$$-(t_n \log(y_n) + (1 - t_n) \log(1 - y_n)) \quad -(t_{n1} \log(y_{n1}) + t_{n2} \log(y_{n2})) = - \sum_{k=1}^{Class} t_{nk} \log(y_{nk})$$



# Nominal Inputs

- What if you have categorical inputs

- Two inputs and one output

$$x_1 \in R$$

$$x_2 \in \{Red, Yellow, Blue\}$$

$$y \in \{0,1\}$$

- Create a new input variable for each categorical value

$$x_2 = \begin{cases} 1 & \text{if original } x_2 \text{ is Yellow} \\ 0 & \text{Otherwise} \end{cases}$$

$$x_3 = \begin{cases} 1 & \text{if original } x_2 \text{ is Red} \\ 0 & \text{Otherwise} \end{cases}$$

$$x_4 = \begin{cases} 1 & \text{if original } x_2 \text{ is Blue} \\ 0 & \text{Otherwise} \end{cases}$$

(0.1, Red, 0)

(0.2, Blue, 1)

(0.3, Yellow, 0)

(0.4, Red, 1)



(0.1, 1, 0, 0, 0)

(0.2, 0, 0, 1, 1)

(0.3, 0, 1, 0, 0)

(0.4, 1, 0, 0, 1)

# Summary

Problem	Activation Function		Loss function
	Hidden Layer	Output Layer	
Regression	ReLU	Linear	MSE
2-class Classification	ReLU	Sigmoid	CE
Multi-class Classification	ReLU	Softmax	CE