

(딥러닝 기초, 실습 강의)

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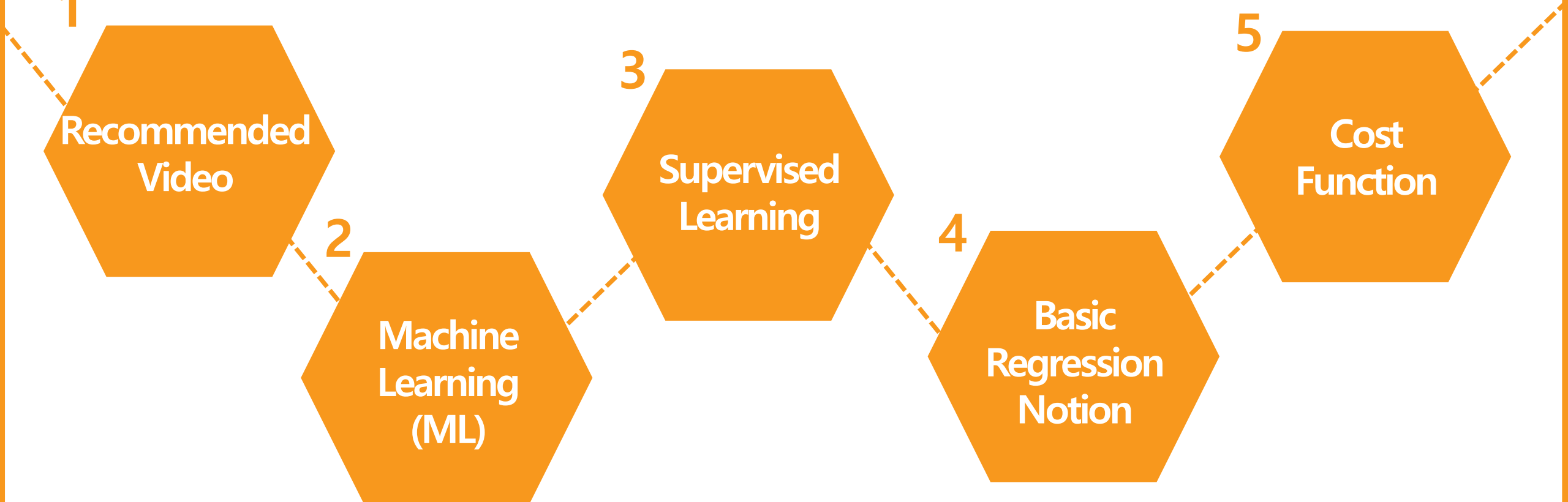
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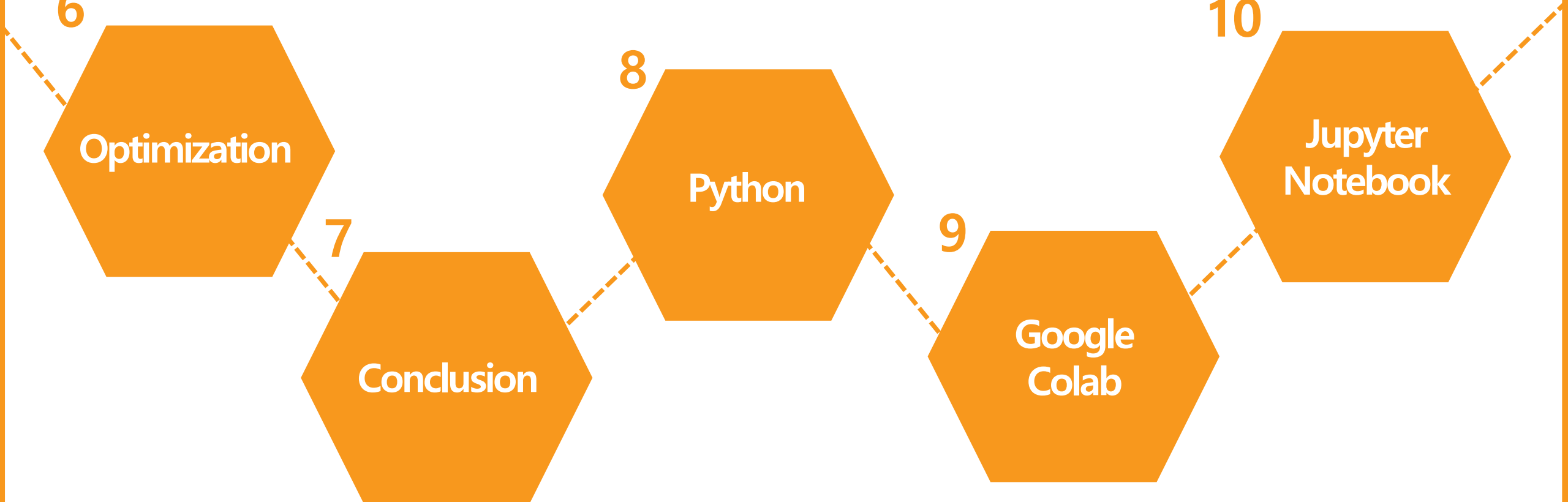
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Recommended Video, Lecture

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선형대수

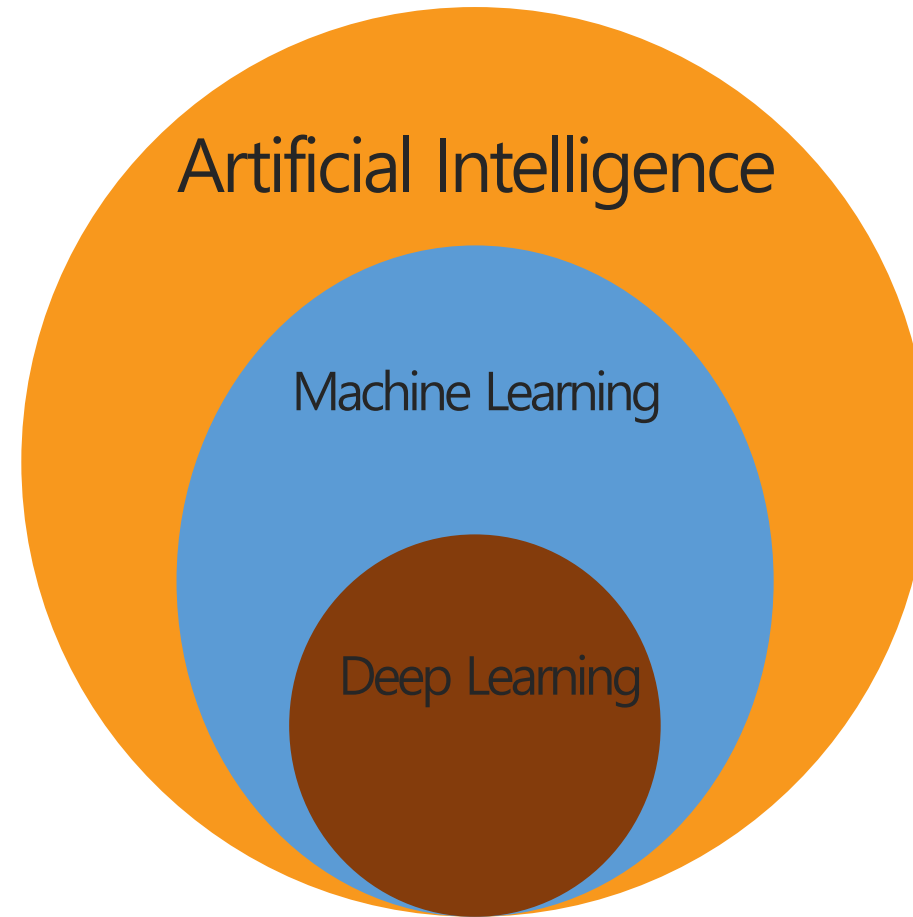
신호 및 시스템 1,2

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....

필수는 아닙니다.

Machine Learning



Machine Learning

Classification	Clustering
Regression	Dimensionality Reduction

강화학습이 제외되어 있습니다.

Supervised Learning

Classification

Regression

Basic Regression Notion

$$X=Y$$

$$X=Y$$

Sample X

[1,1]

[2,2]

[3,3]

[4,4]

$$X=Y$$

If) $X=5$, $Y=?$

가지고 있는 Data로 회귀모형을 만들어
새로운 데이터를 예측한다.

HOW TO MAKE

어떻게 만들 것인가?

Hypothesis

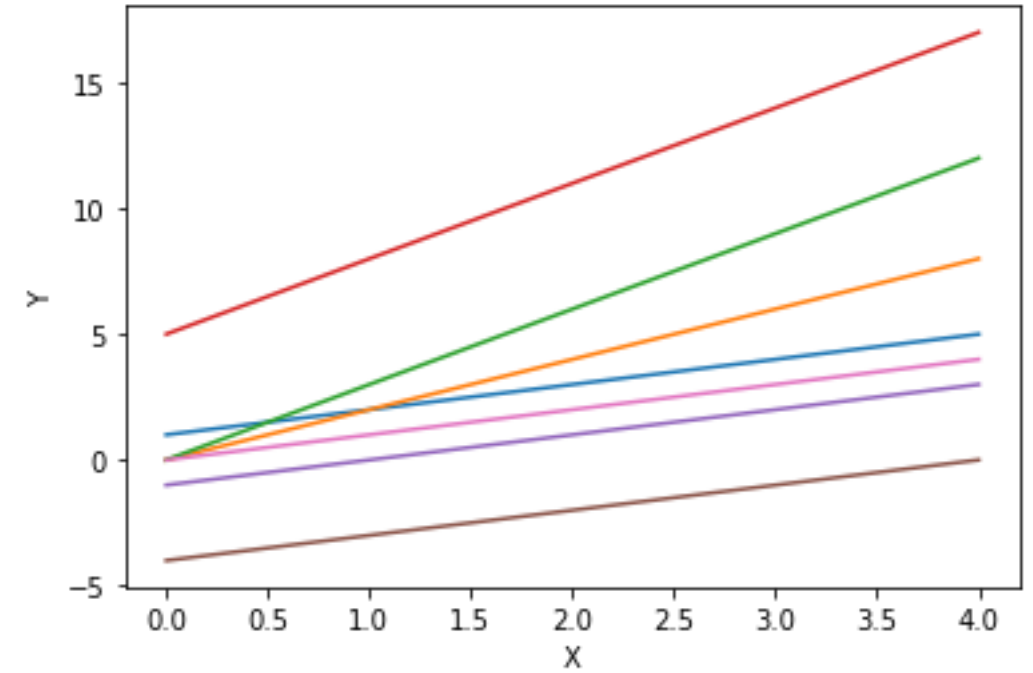


Hypothesis 란?

쉽게 생각하면 가설 $WX+B=Y$ 안에
모든 (W,B) 를 생각하여 풀이하는 방식이다.

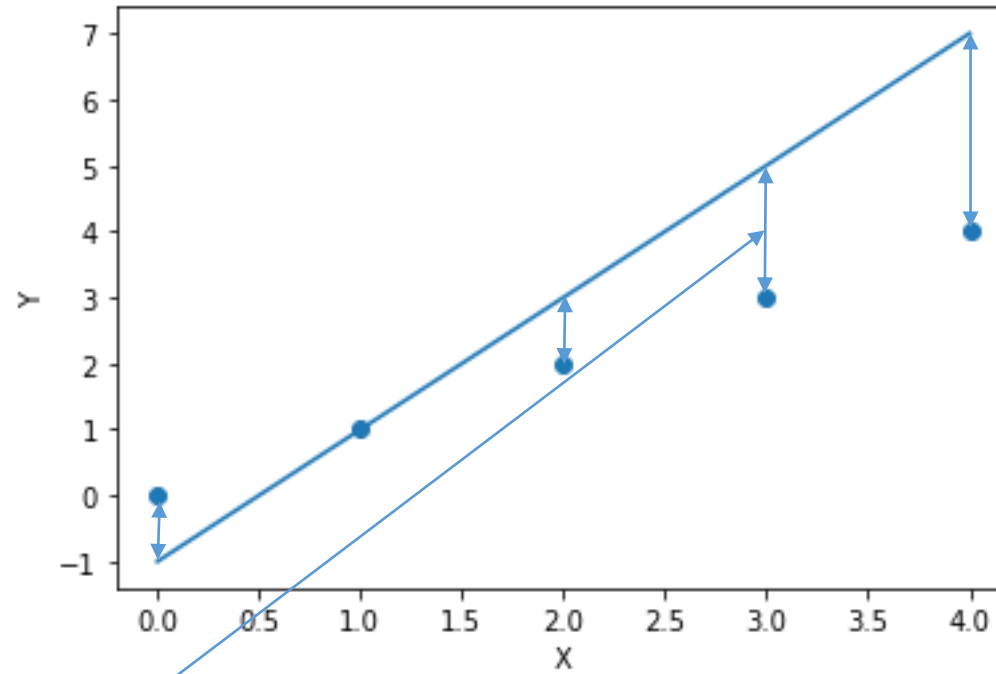
Hypothesis

X	Y
1	1
2	2
3	3
4	4



$H(x)=?$

Hypothesis



$H(x) - y$

Cost function

What is?

Cost Function

X	Y
0	0
1	1
2	2
3	3
4	4

Cost Function



MSE, Cross Entropy

Cost Function은 간단히 2가지를 고려 가능하다.

$Y \Rightarrow$ Continuous, Discrete

Cost Function



MSE(Mean Square Error)

Y => Continuous

Ex)
$$\frac{(H(x^{(1)}) - y^{(1)})^2 + (H(x^{(2)}) - y^{(2)})^2 + (H(x^{(3)}) - y^{(3)})^2}{3}$$

$$\text{cost} = \frac{1}{m} \sum_{i=1}^m (H(x^{(i)}) - y^{(i)})^2$$

Minimize cost(W, b)

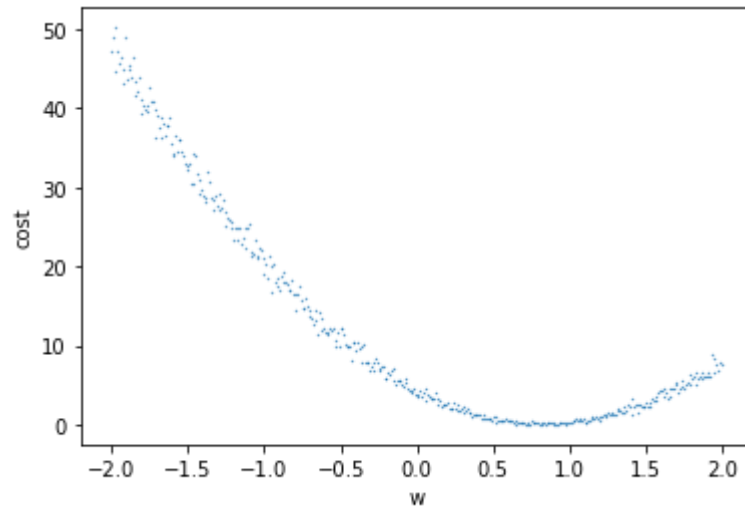
W, b -> Minimize

How to Minimize

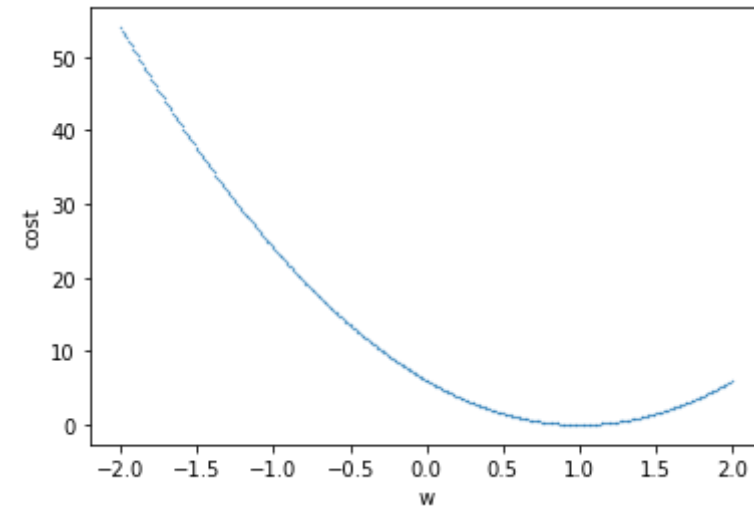
Cost Function

Gradient Descent

$$\text{cost} = \frac{1}{m} \sum_{i=1}^m (H(x^{(i)}) - y^{(i)})^2$$

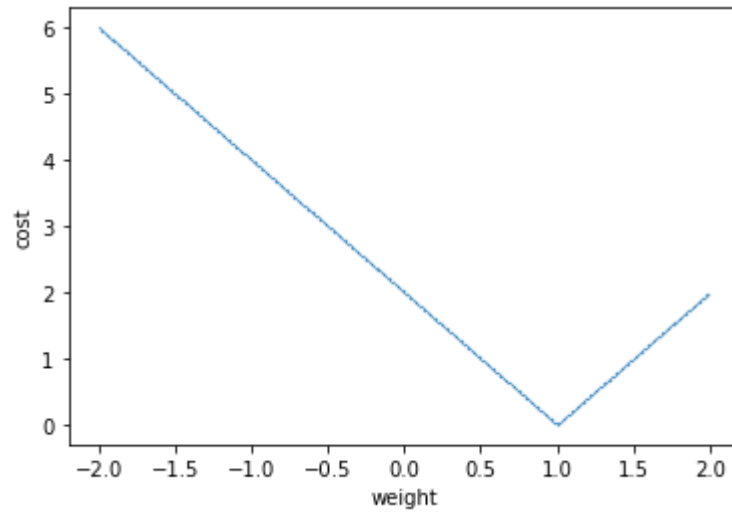


Bias Existence O

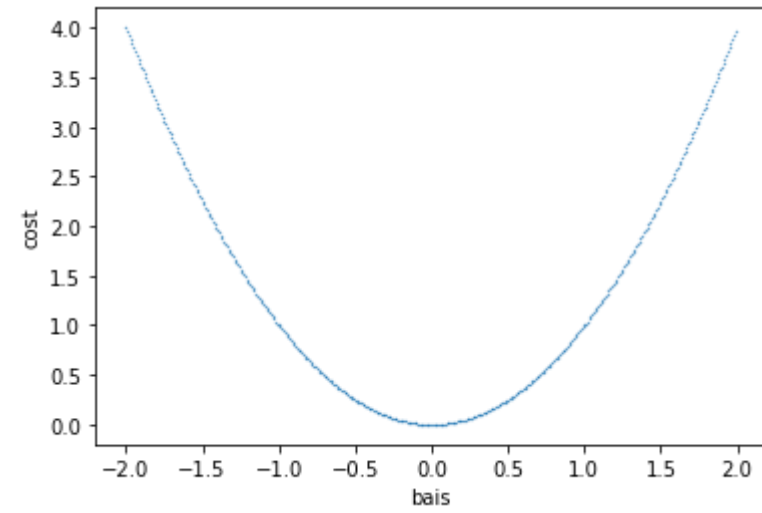


Bias Existence X

Gradient Descent

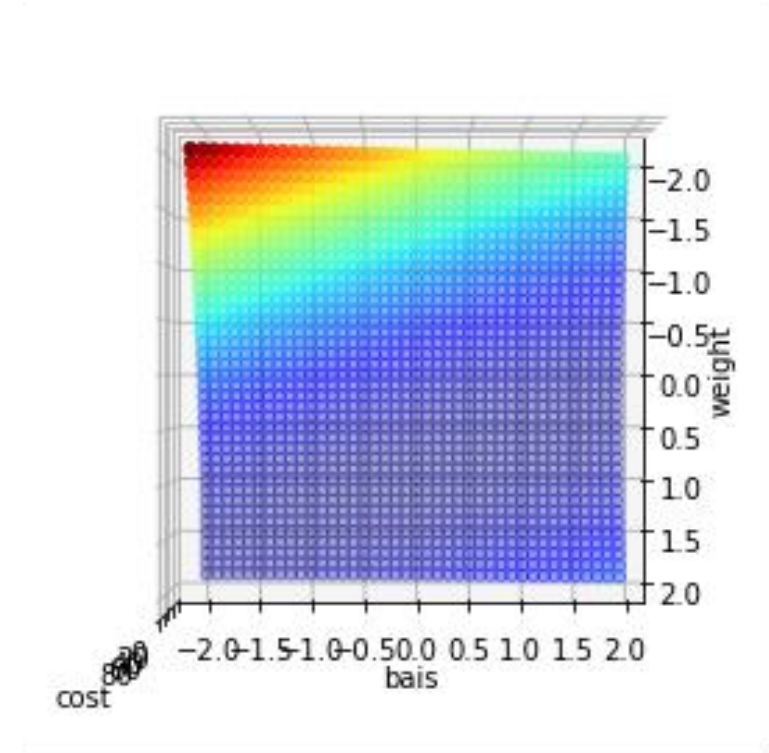
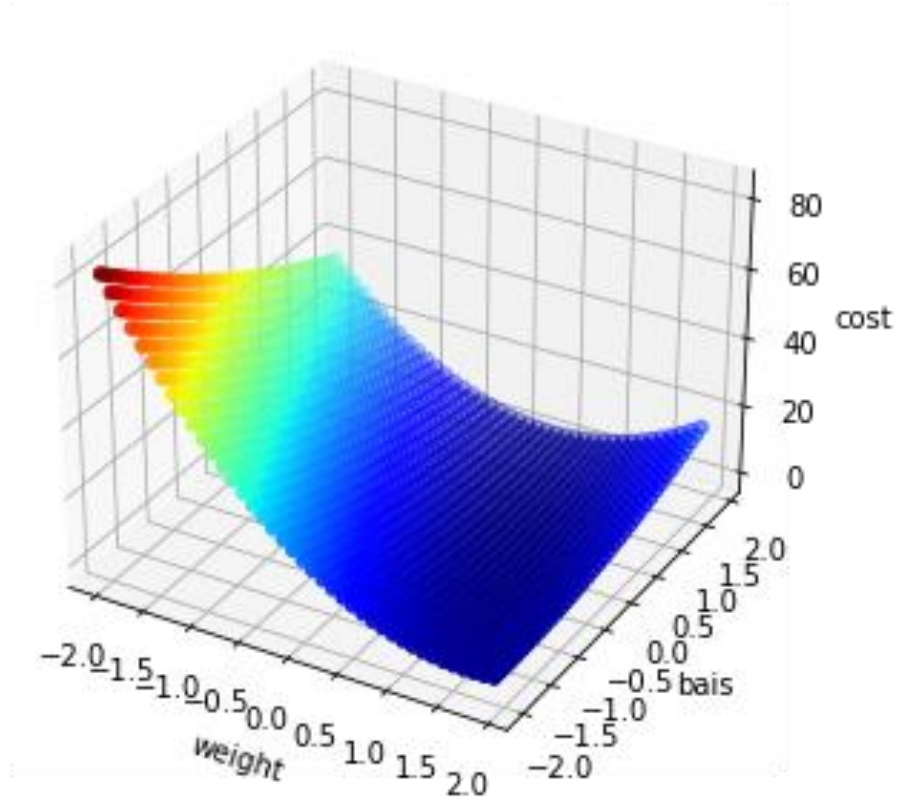


absolute

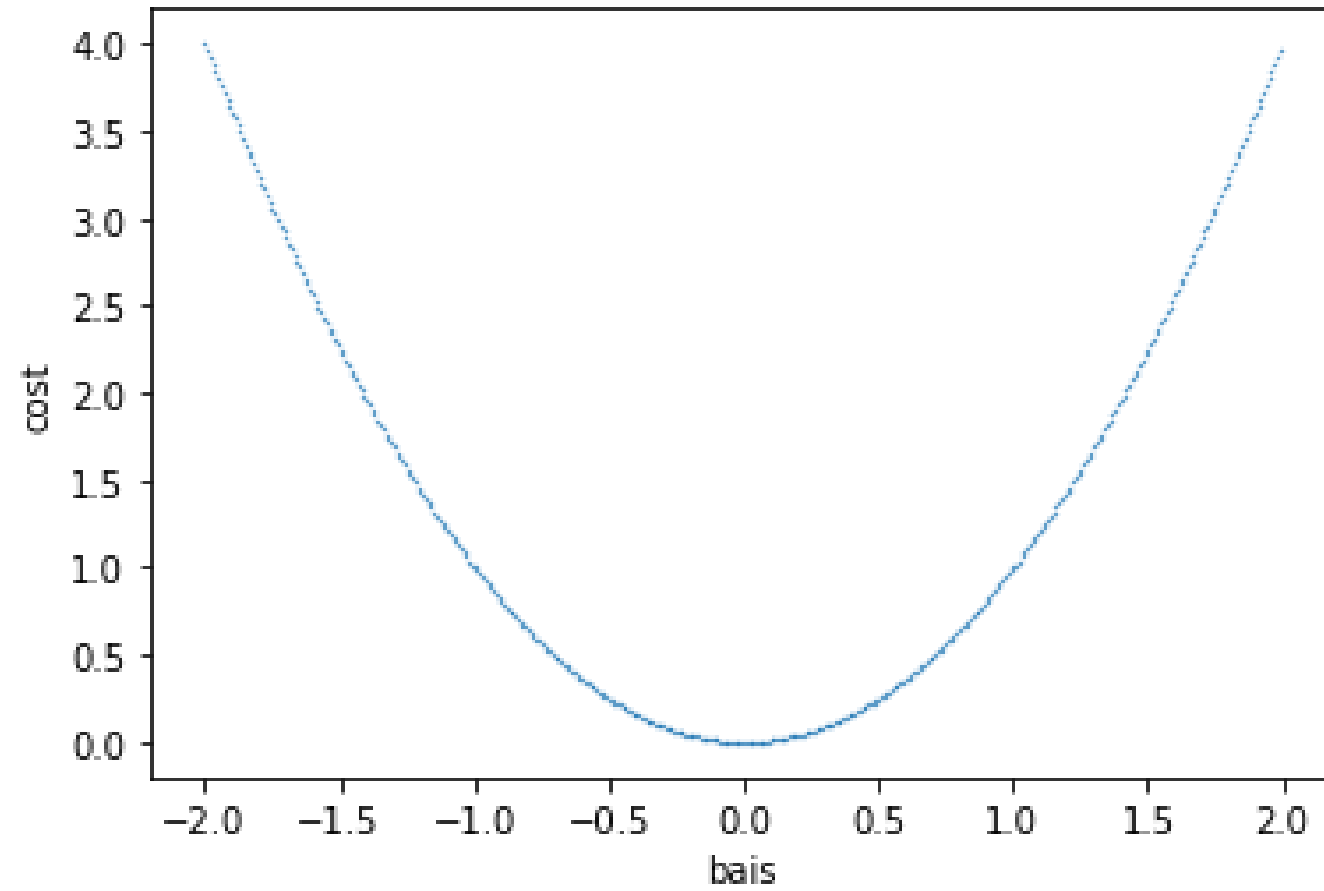


MSE

Gradient Descent



Gradient Descent



Gradient Descent

Consider only Weight for understand

$$cost(W) = \frac{1}{m} \sum_{i=1}^m (Wx^i - y^i)^2$$

$$W := W - \alpha \frac{\partial}{\partial W} cost(W)$$

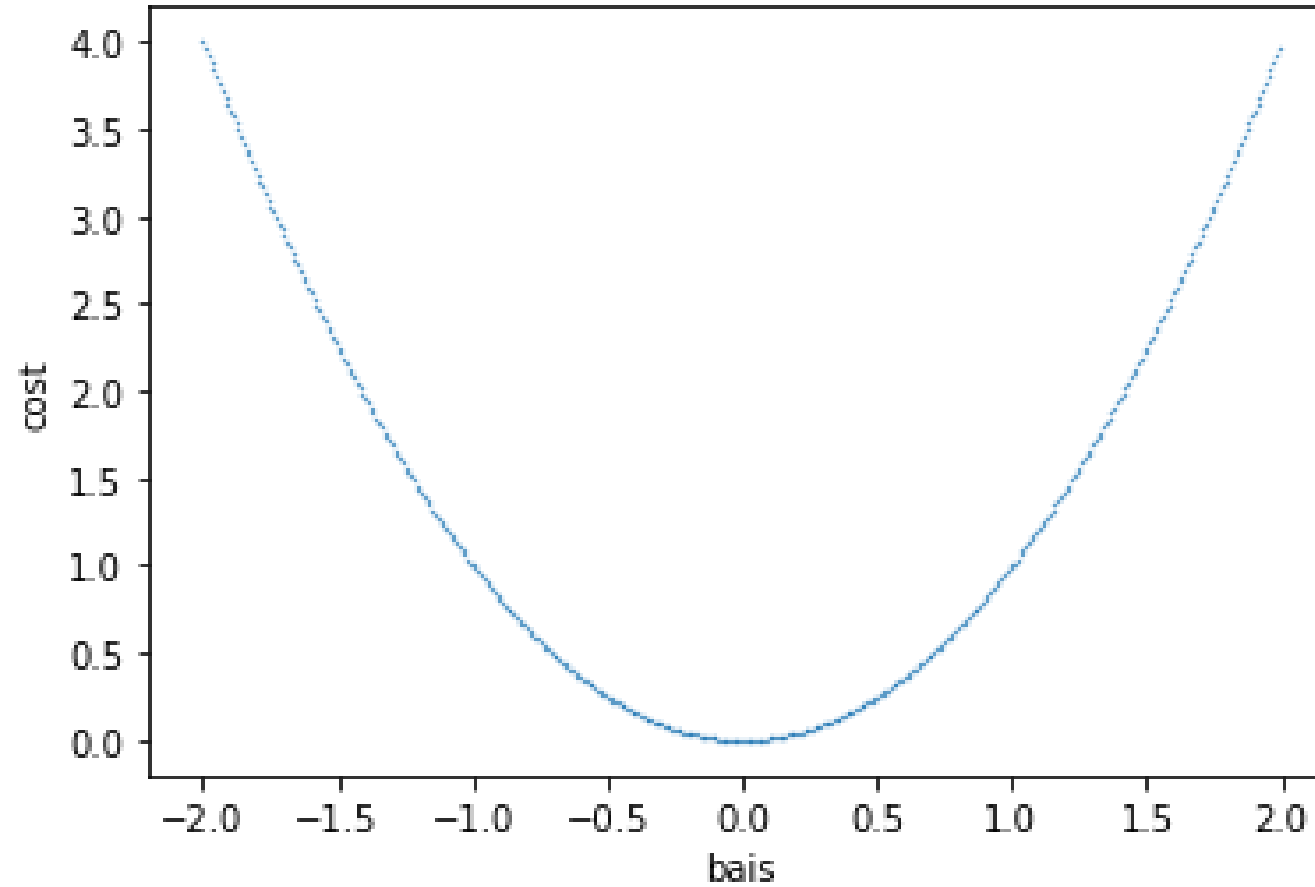
Gradient Descent

Gradient Descent

Consider only Weight for understand

$$W := W - \alpha \frac{1}{m} \sum_{i=1}^m (Wx^i - y^i)x^i \quad \alpha : \textit{Learning Rate}$$

Why use Learning Rate



Problem

Local Minimum, Global Minimum

Multi-Variable

	f1	f2	f3	f4	f5	Y
X1	1	3	1	4	2	0
X2	2	4	3	5	6	1.3
X3	1	3	1	2	3	1.2
X4	2	3	2	1	2	2.3
X5	2	4	3	3	1	3.4

Multi-Variable

	f1	f2	f3	f4	f5	Y
X1	1	3	1	4	2	0
X2	2	4	3	5	6	1.3
X3	1	3	1	2	3	1.2
X4	2	3	2	1	2	2.3
X5	2	4	3	3	1	3.4

$$H(x) = Wx + b$$

$$H(f_1, f_2, f_3, f_4, f_5) = w_1 f_1 + \dots + w_5 f_5 + b$$

$$cost(W, b) = \frac{1}{m} \sum_{i=1}^m (H(f_1^i, f_2^i, \dots, f_5^i) - y^i)^2$$

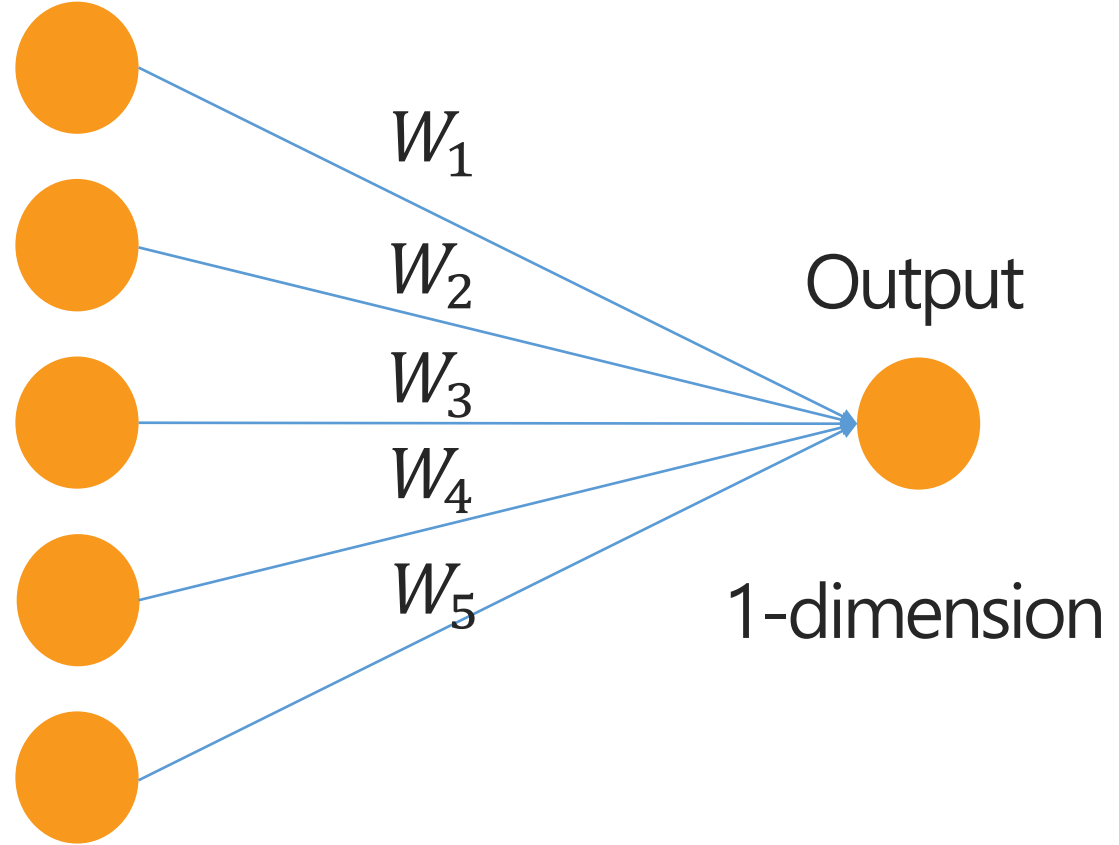
Matrix

$$w_1 f_1 + \dots + w_5 f_5 + b$$

$$\begin{bmatrix} f_1^1 & \dots & f_5^1 \\ f_1^2 & \dots & f_5^2 \end{bmatrix} * \begin{bmatrix} w_1 \\ \vdots \\ w_5 \end{bmatrix} + \begin{bmatrix} b_1 \\ \vdots \\ b_5 \end{bmatrix} = \text{output}$$

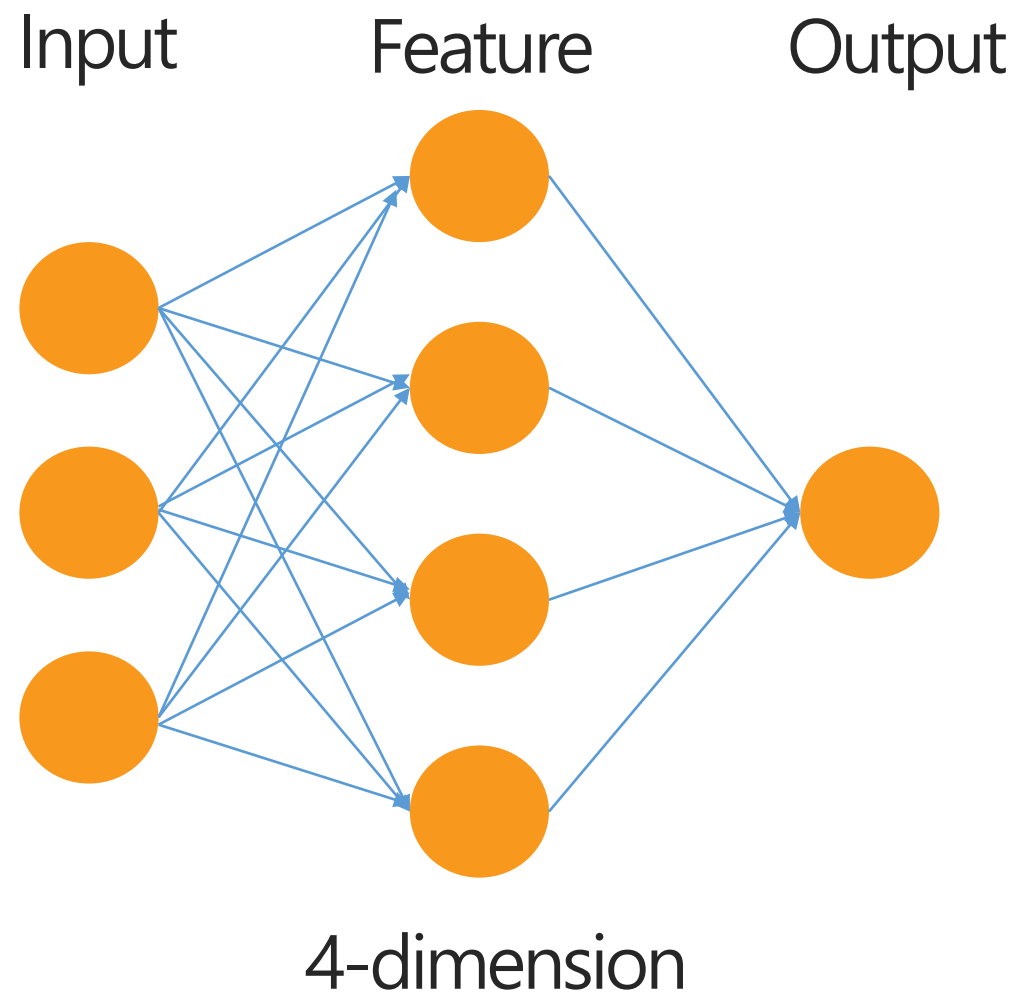
$$H(X) = XW + B$$

Feature



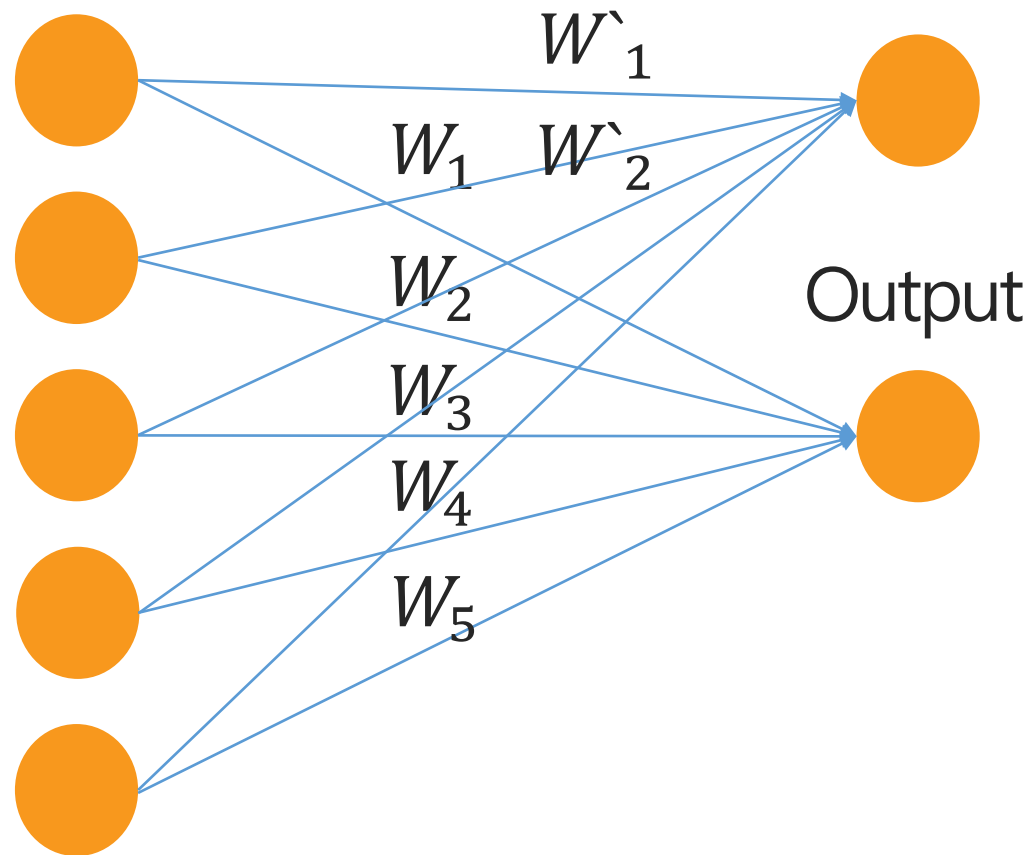
How to Increase Dimension

Basic Model



Matrix_Problem

Feature



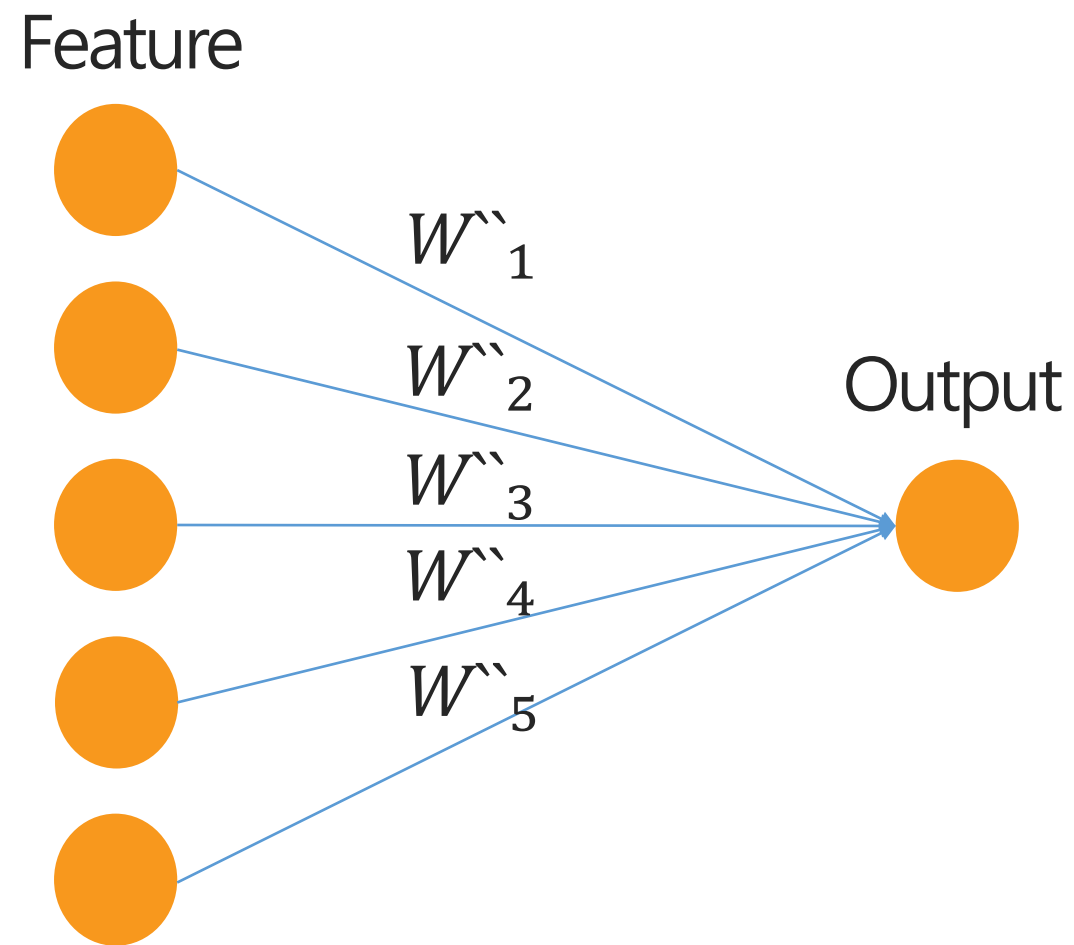
Matrix_Problem

$$\begin{bmatrix} f_1^1 & \dots & f_5^1 \\ f_1^2 & \dots & f_5^2 \end{bmatrix} * \begin{bmatrix} w_1 \\ \vdots \\ w_5 \end{bmatrix} + \begin{bmatrix} b_1 \\ \vdots \\ b_5 \end{bmatrix} = output$$

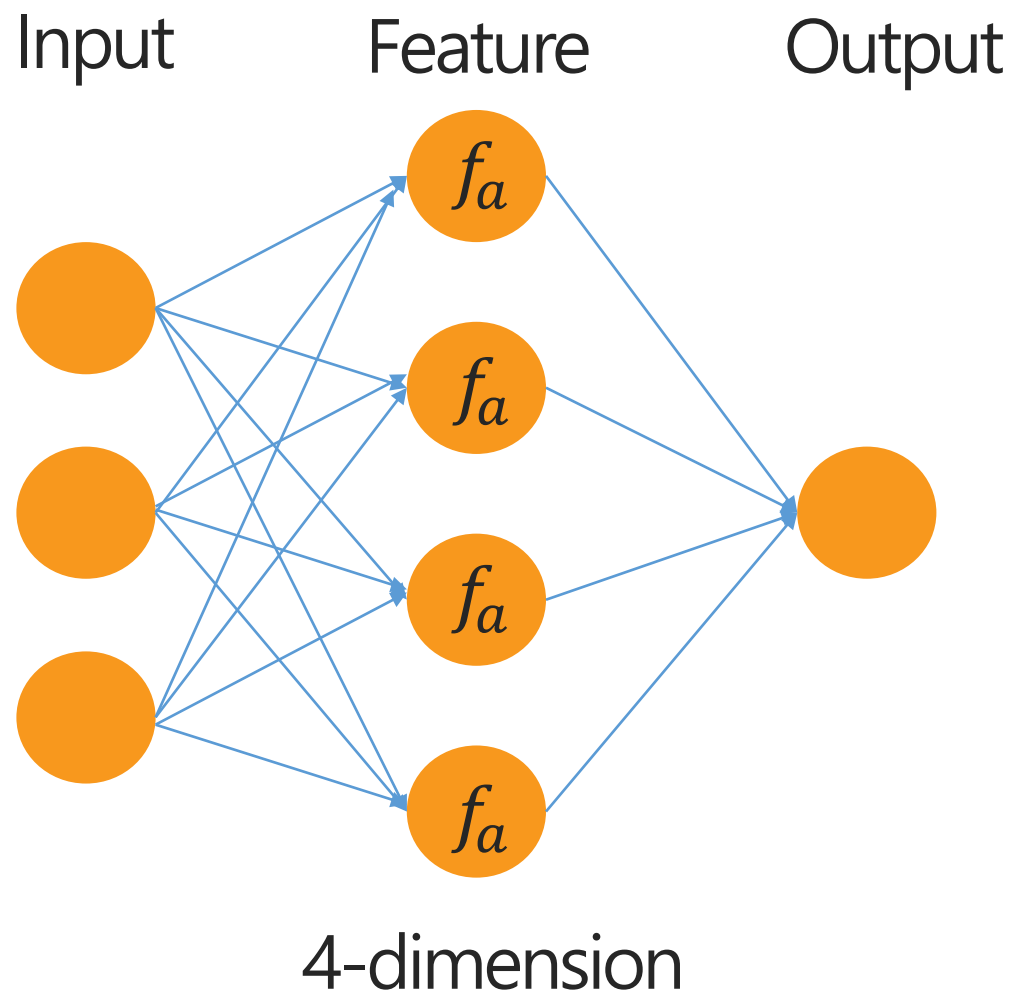
$$\begin{bmatrix} w_1 \\ \vdots \\ w_5 \end{bmatrix} + \begin{bmatrix} w'_1 \\ \vdots \\ w'_5 \end{bmatrix} = \begin{bmatrix} w''_1 \\ \vdots \\ w''_5 \end{bmatrix}$$

$$\begin{bmatrix} f_1^1 & \dots & f_5^1 \\ f_1^2 & \dots & f_5^2 \end{bmatrix} * \begin{bmatrix} w'_1 \\ \vdots \\ w'_5 \end{bmatrix} + \begin{bmatrix} b'_1 \\ \vdots \\ b'_5 \end{bmatrix} = output$$

Matrix_Problem



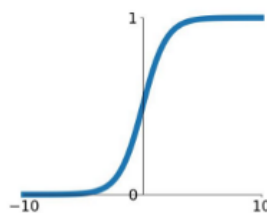
Matrix_Problem



Activation Functions

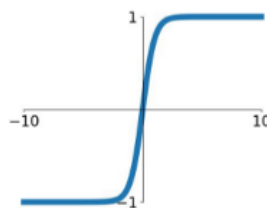
Sigmoid

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



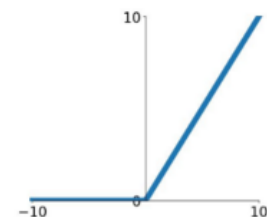
tanh

$$\tanh(x)$$



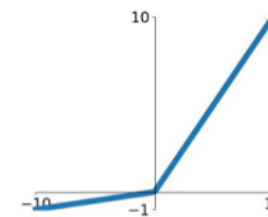
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

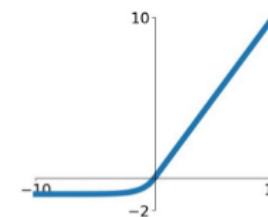


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



추후에 자세히 다룰 예정

Final Out_Range

	f1	f2	f3	f4	f5	Y
X1	1	3	1	4	2	0
X2	2	4	3	5	6	1.3
X3	1	3	1	2	3	1.2
X4	2	3	2	1	2	2.3
X5	2	4	3	3	1	3.4

Output => Continue

Ex) 0~3.4

Final Out_Range



Cat=0

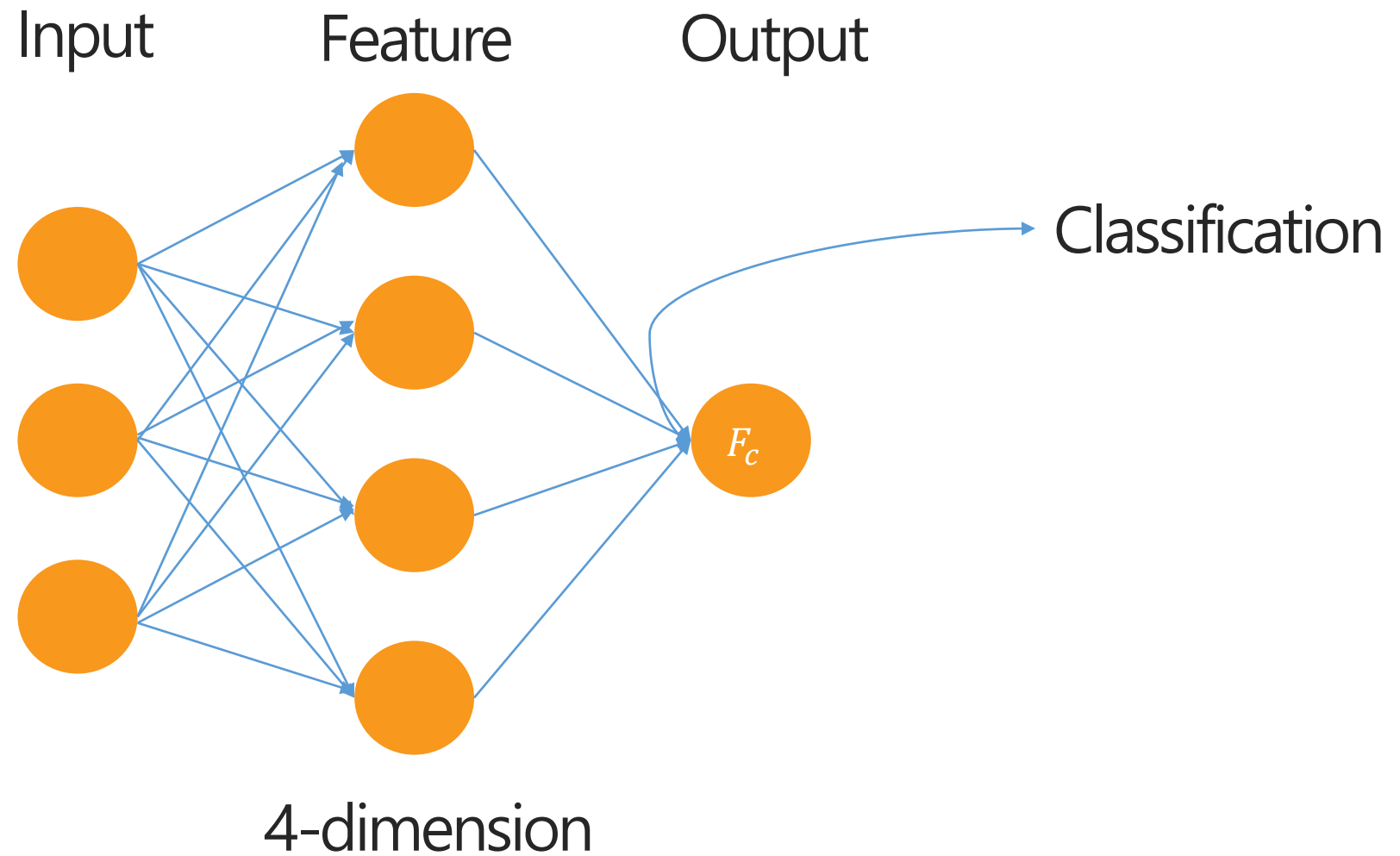


Dog=1

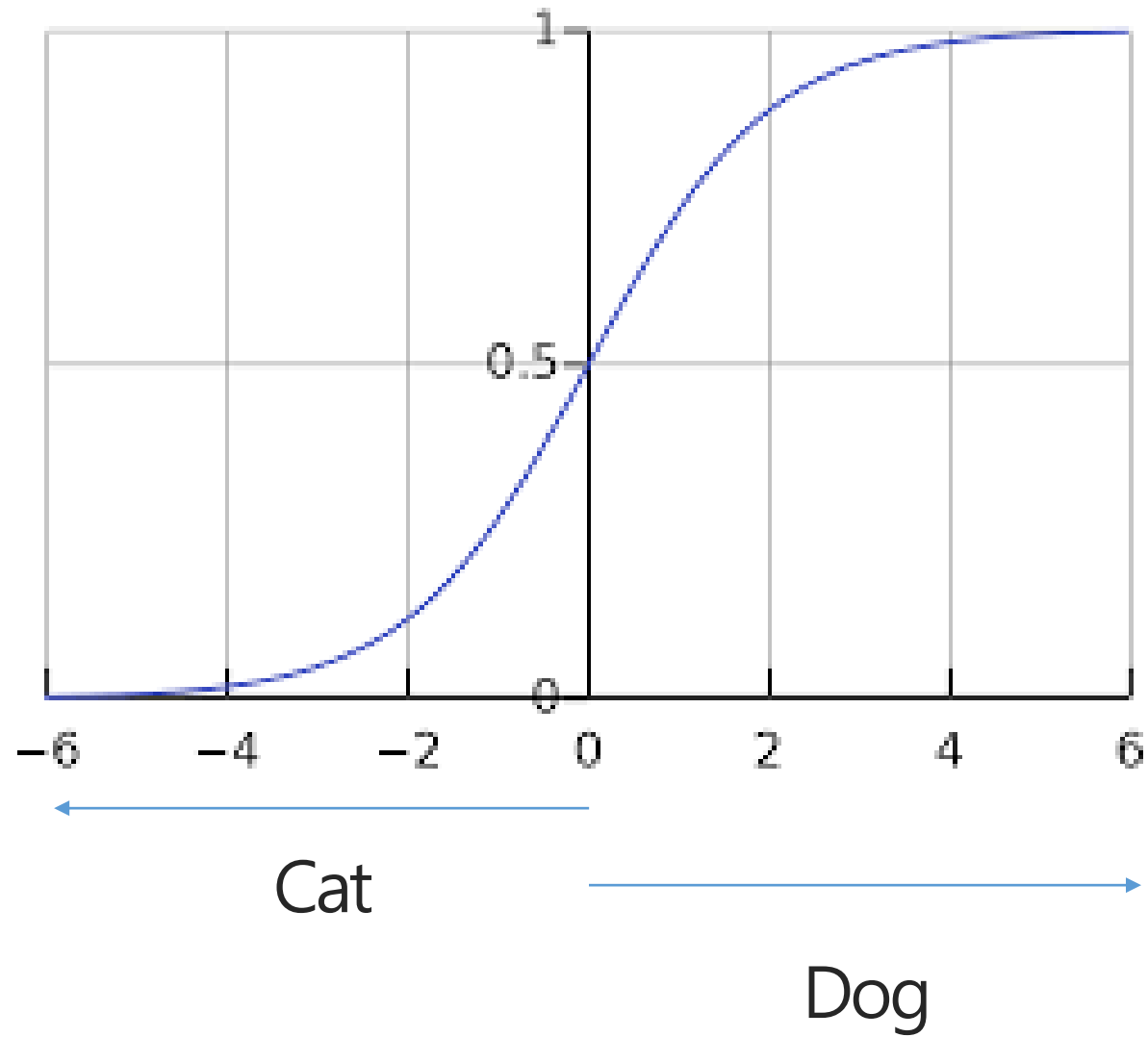
CAT 출처(URL) : <https://www.bbc.com/news/uk-england-stoke-staffordshire-52047832>

DOG 출처(URL) : <https://www.theguardian.com/science/2019/jun/17/how-dogs-capture-your-heart-evolution-puppy-dog-eyes>

Binary Classification



Binary Classification



How to Make

Binary Classification Cost Function

Cost Function

Cross Entropy

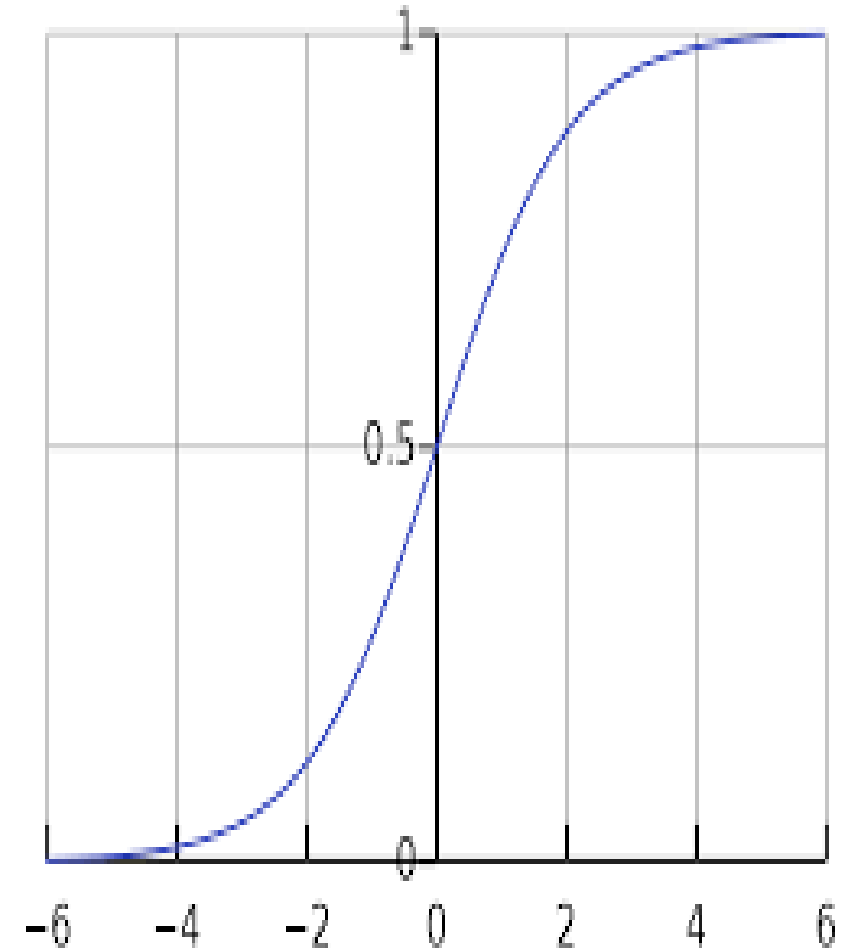
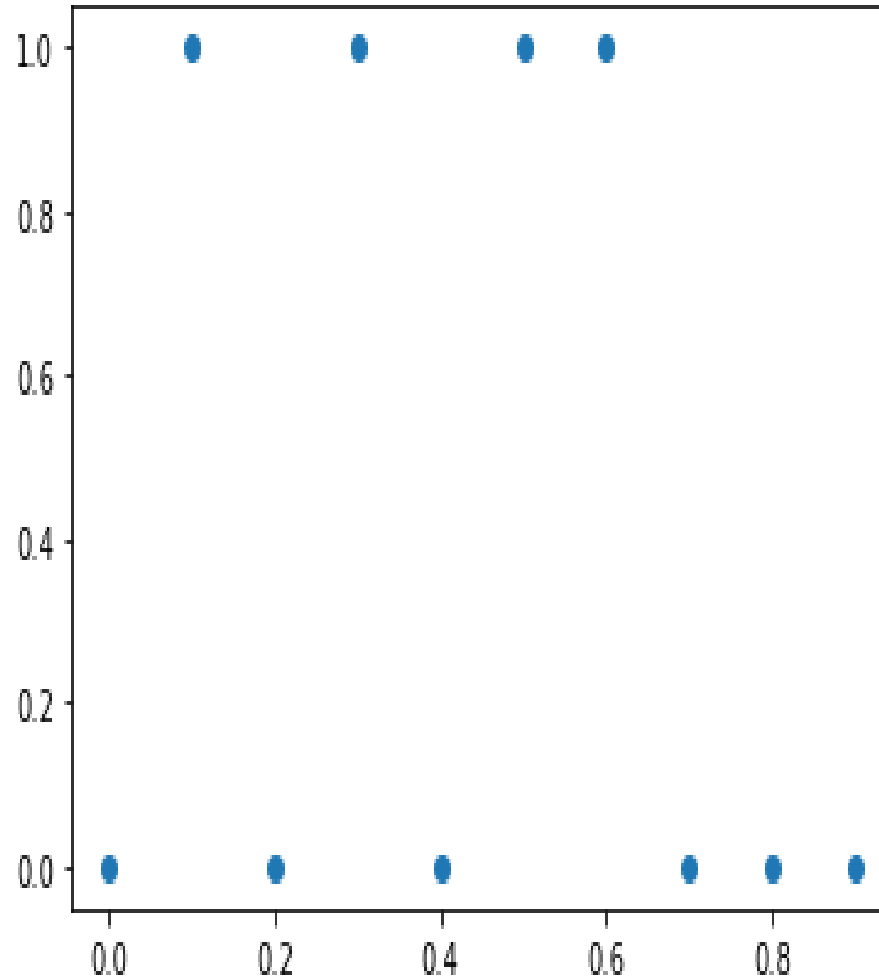
$Y \Rightarrow$ Discrete

$$H(X) = \frac{1}{1 + e^{uX}}$$

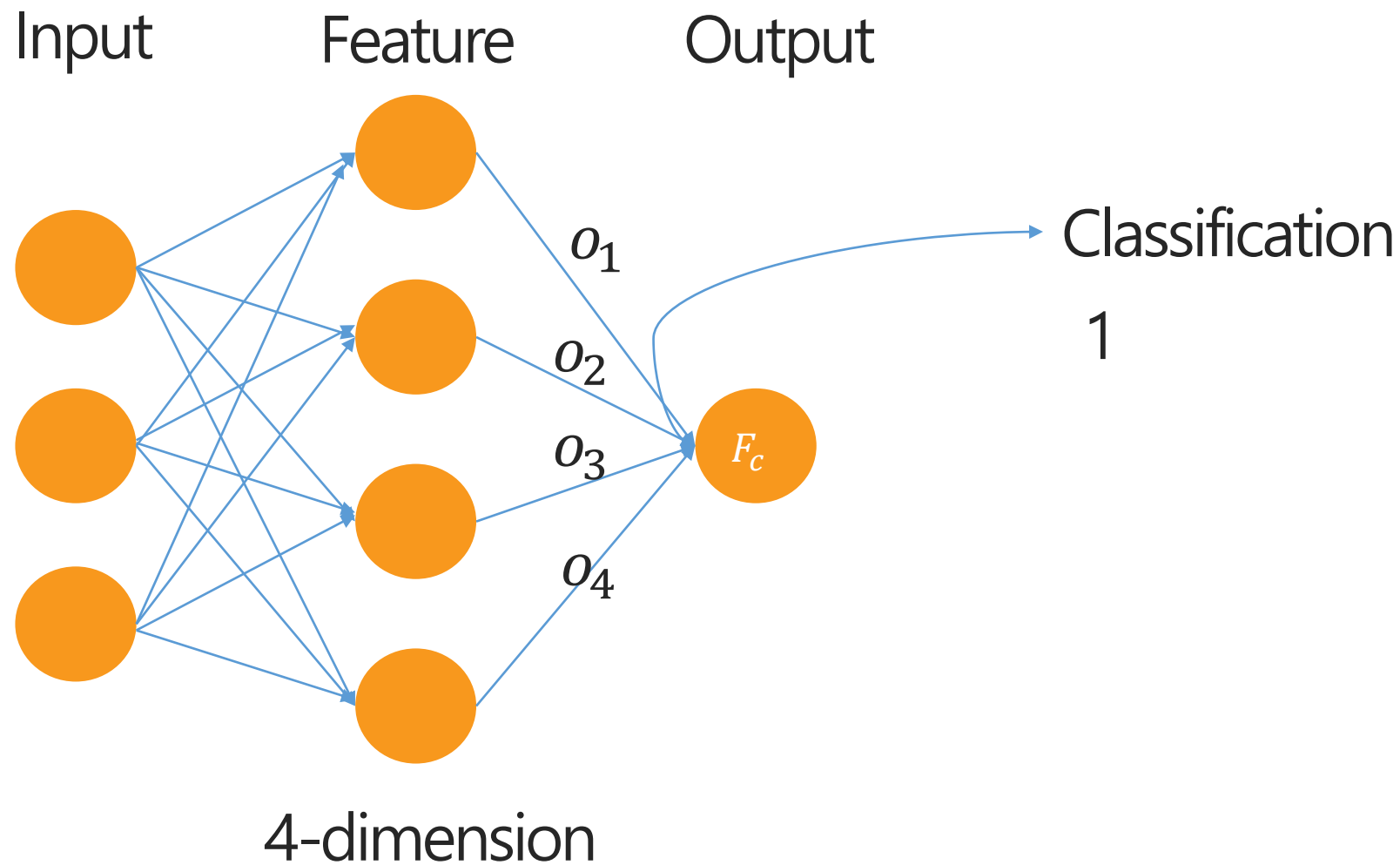
$$\text{cost}(W) = \frac{1}{m} \sum_{i=1}^m (H(X) - y^i)^2$$

Binary

X	Y
0	0
0.1	1
0.2	0
0.3	1
0.4	0
0.5	1
0.6	1
0.7	0
0.8	0
0.9	0



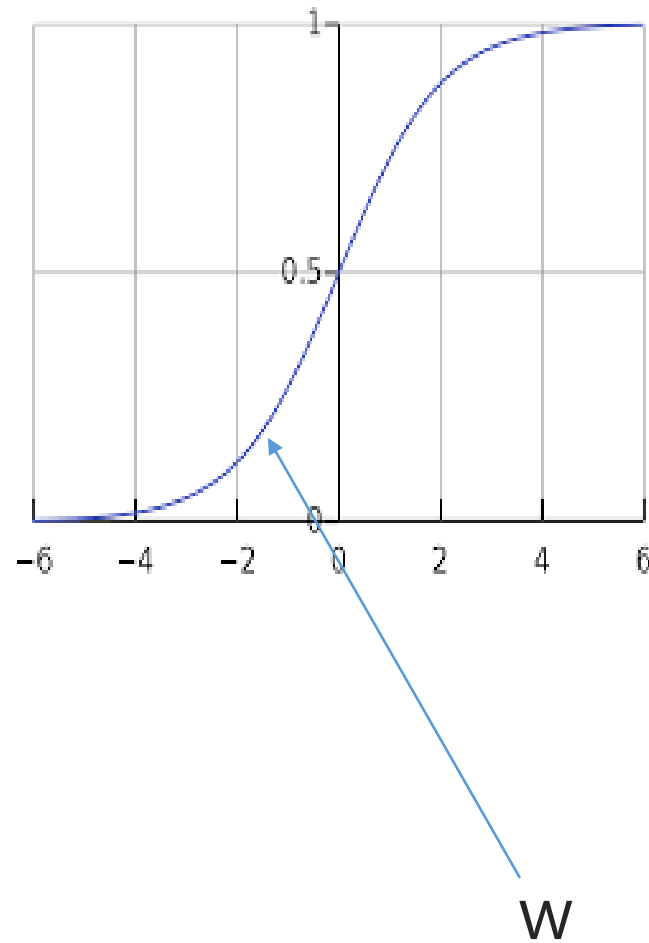
Binary



Binary

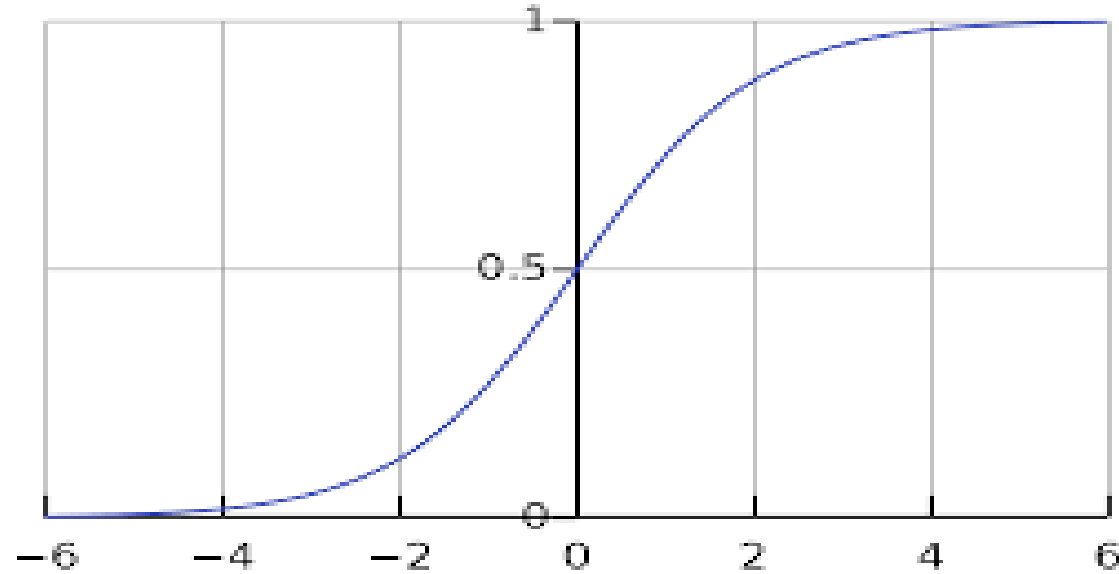
$$H(o) = \frac{1}{1 + e^{ou}}$$

$$O = o_1 + o_2 + o_3 + o_4$$



Binary

MSE, ABS Problem



If) $w \Rightarrow (-2 \sim 0) \Rightarrow y=1$ MSE $\Rightarrow 0.5$ 로 수렴
 $w \Rightarrow (0 \sim 2) \Rightarrow y=0$ Local Minimum 빠지기 쉽다.

Cross Entropy

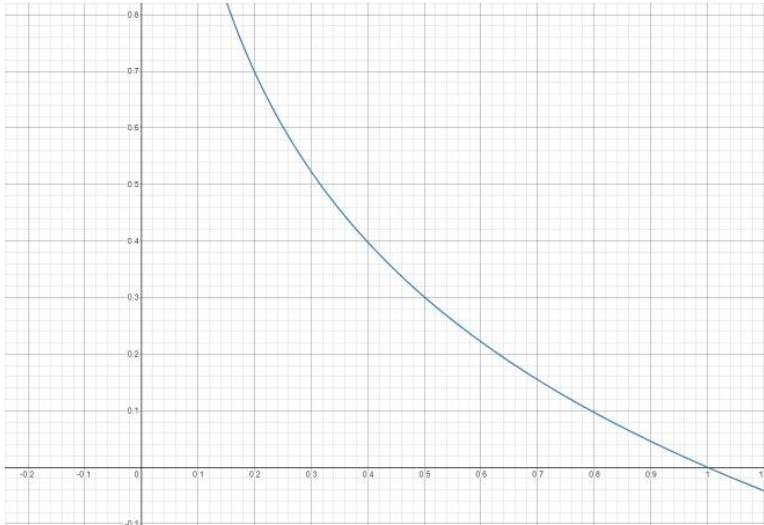
$$H(P, Q) = -\sum P(x) \log(Q(x))$$

$$c(H(x), y) = \begin{cases} -\log(H(x)) & : y = 1 \\ -\log(1 - H(x)) & : y = 0 \end{cases}$$

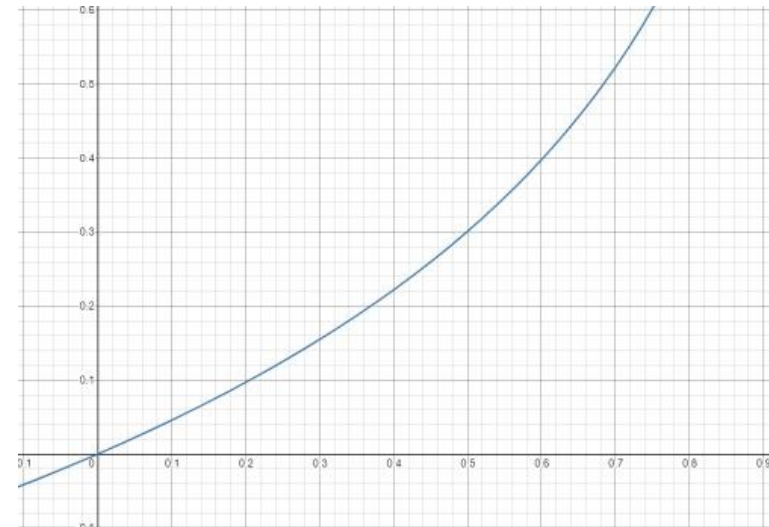
$$c(H(x), y) = -y \log(H(x)) - (1 - y) \log(1 - H(x))$$

Cost Function

$$c(H(x), y) = \begin{cases} -\log(H(x)) & : y = 1 \\ -\log(1 - H(x)) & : y = 0 \end{cases}$$



$-\log(x)$

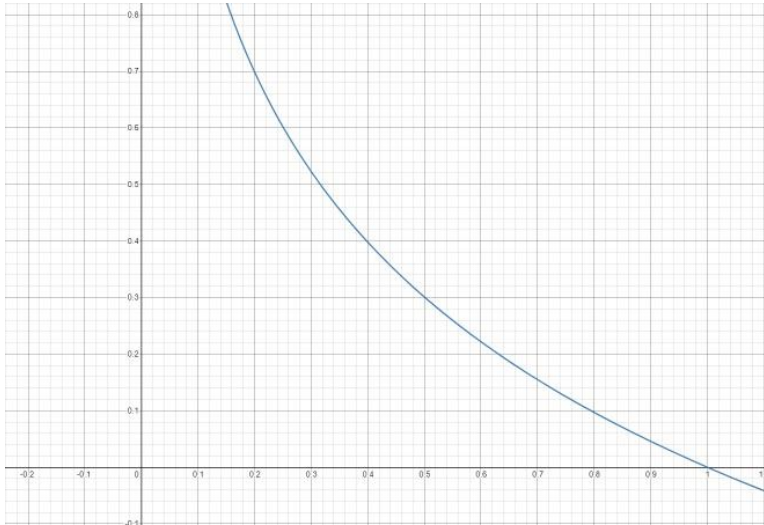


$-\log(1-x)$

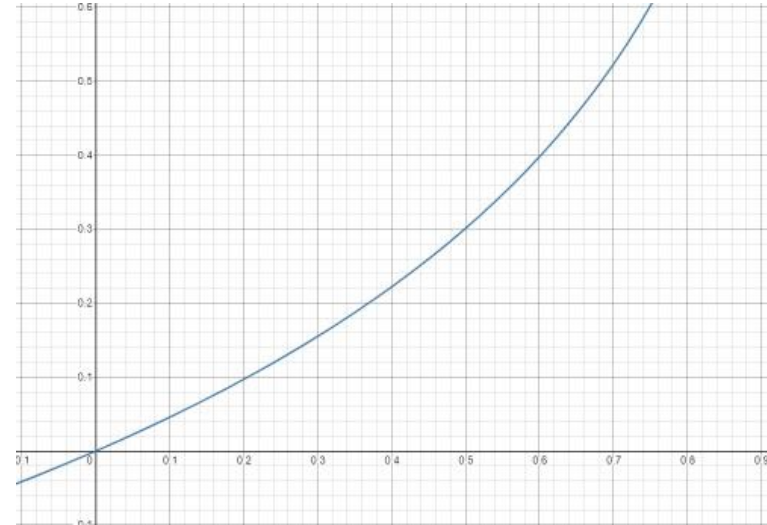
Cost Function

$$H(o) = \frac{1}{1 + e^{ou}}$$

$$O = o_1 + o_2 + o_3 + o_4$$



$-\log(x)$



$-\log(1-x)$

Cost Function

$$H(o) = \frac{1}{1 + e^{-ou}}$$

$$o = o_1 + o_2 + o_3 + o_4$$

$$o_1 = 0.1, o_2 = 0.2, o_3 = 2.5, o_4 = -2$$

$$o = 0.7, \text{predict } y \Rightarrow 1 \quad \text{But } y = 0$$

$$o_1 \Rightarrow 0.02, o_2 \Rightarrow 0.1, o_3 \Rightarrow 1.5, o_4 \Rightarrow -2.3$$

$$o = -2.3 + 1.62$$

$$o_1 \Rightarrow 0.2, o_2 \Rightarrow 0.4, o_3 \Rightarrow -0.5, o_4 \Rightarrow -0.3$$

$$o = -0.2, \text{predict } y \Rightarrow 0 \quad \text{But } y = 1$$

각, o_i 의 역할들이 점점 생긴다.

Next

Multinomial Classification

감사합니다

THANK YOU