

Logistic regression to Feed-forward network

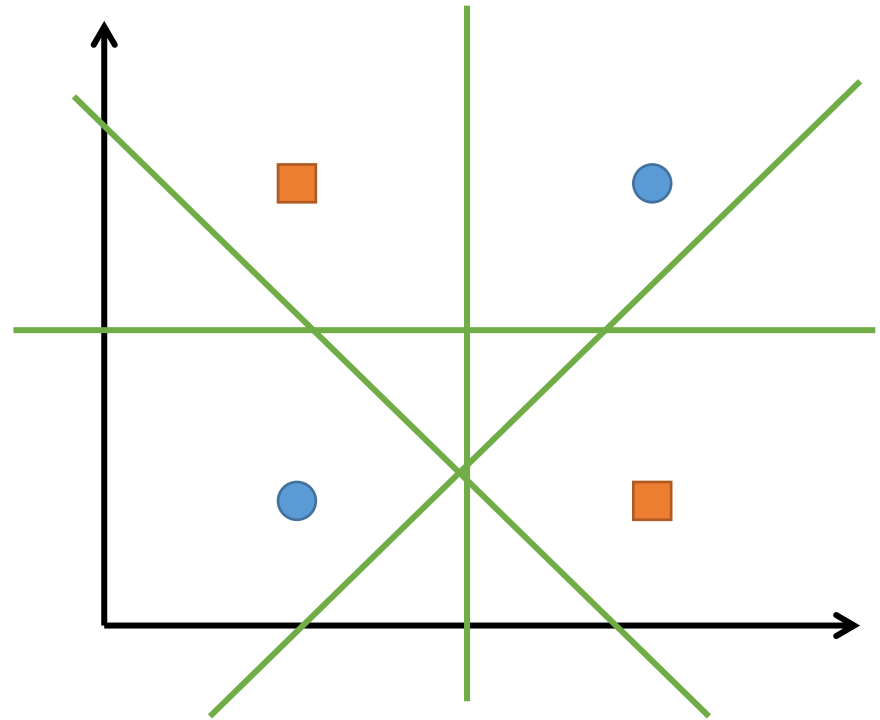
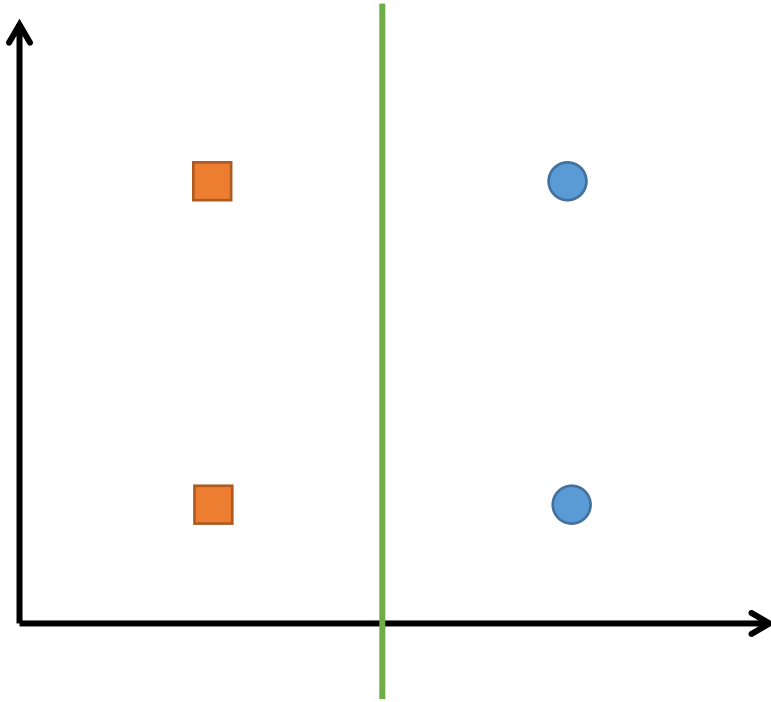
Taehoon Ko (thoon.koh@gmail.com)

목표

- Logistic regression의 분류 경계를 이해한다.
- Feed-forward network가 어떠한 원리로 비선형 분류 경계를 만들어내는지 이해한다.

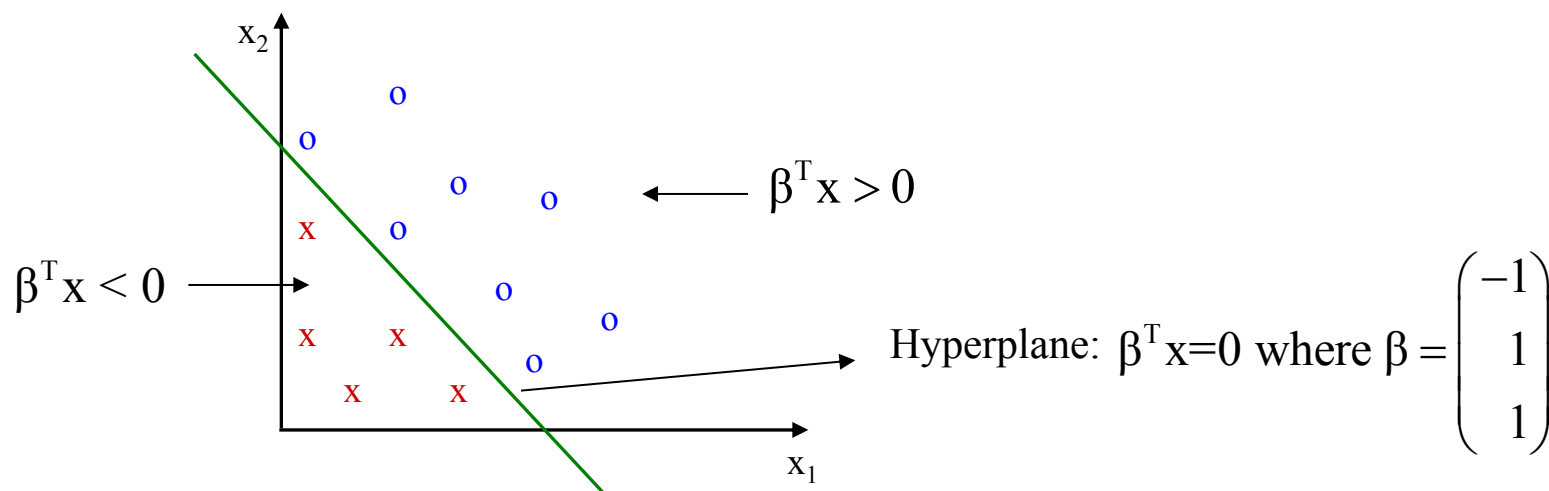
Limitation of linear models

- 단 하나의 직선을 그어서 파란색 원과 붉은색 사각형을 분류할 수 있는가?



Logistic regression (revisited)

- Logistic regression은 학습 알고리즘을 통해 2-class points를 분류하는 초평면(hyper-plane)을 찾는 것
- 선형적인 의사결정경계(linear decision boundary)만 생성 가능



Classifier

$$y = \frac{1}{(1 + \exp(-\beta^T \mathbf{x}))}$$

$$\begin{cases} y \rightarrow 1 & \text{if } \beta^T \mathbf{x} \rightarrow \infty \\ y = \frac{1}{2} & \text{if } \beta^T \mathbf{x} = 0 \\ y \rightarrow 0 & \text{if } \beta^T \mathbf{x} \rightarrow -\infty \end{cases}$$

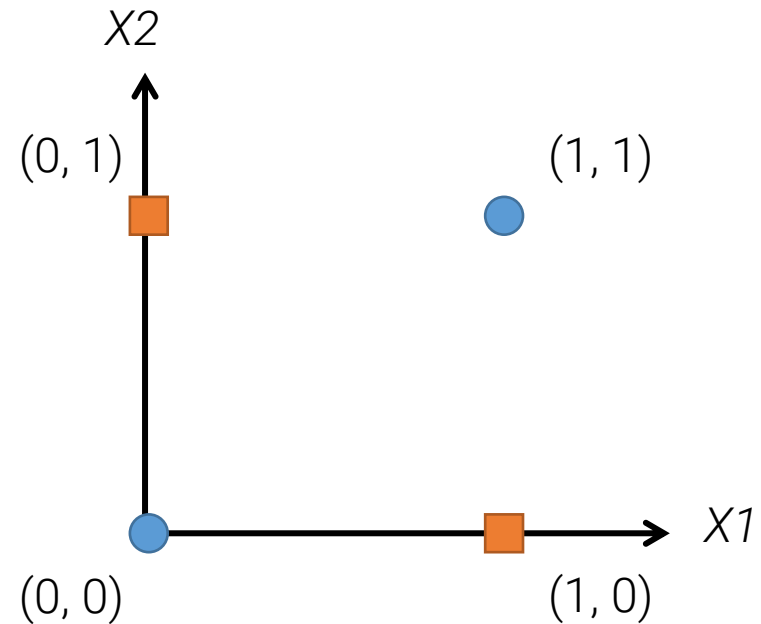
Exclusive OR (XOR) problem

- XOR

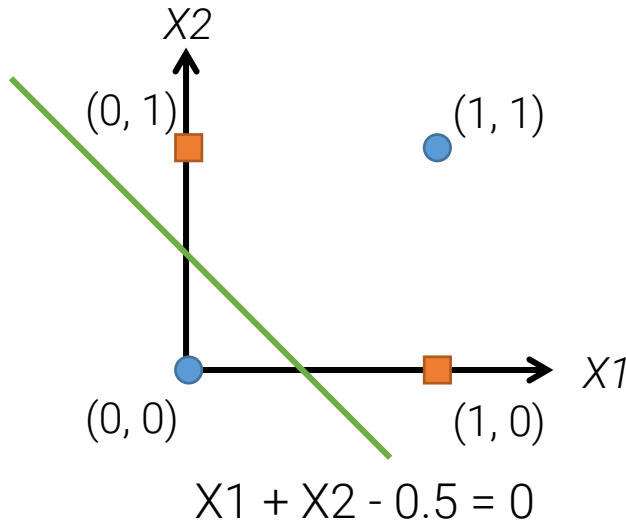
Exclusive-OR gate



A	B	Output
0	0	0 ●
0	1	1 ■
1	0	1 ■
1	1	0 ●



XOR classification by logistic regression model



$$\begin{aligned} y &= \Pr(class = 1) \\ &= \frac{1}{1 + e^{-(X_1 + X_2 - 0.5)}} \\ &= \sigma(X_1 + X_2 - 0.5) \end{aligned}$$

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

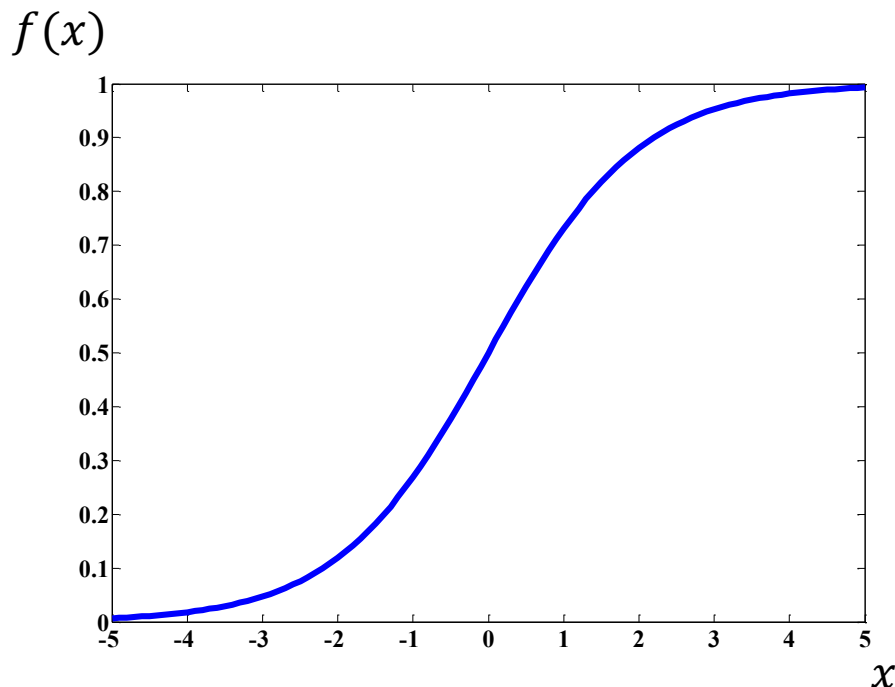
Logistic function
(a.k.a. softmax func., sigmoid function)

(Revisited) Logistic function

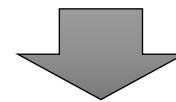
- Logistic function

- $-\infty < x < \infty$ 일 때, logistic function $f(x)$ 은 다음과 같이 정의됨.

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

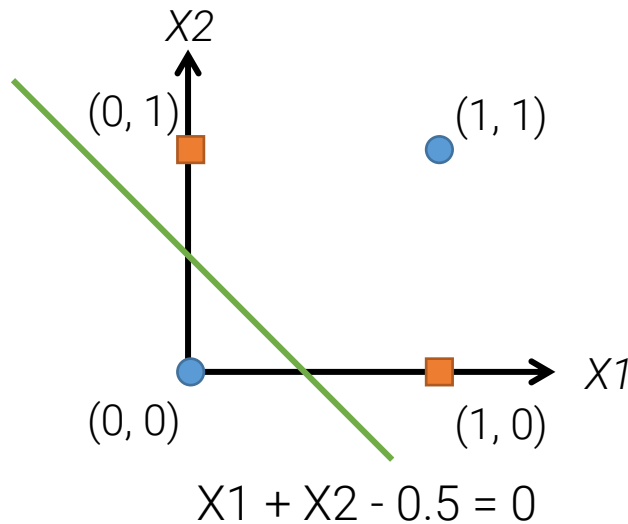


- $0 < f(x) < 1$
- $x = 0$ 일 때, 함수값은 $f(0) = 0.5$
- 위의 점을 기준으로 함수가 대칭 (symmetric)



$f(x)$ 는 특정사건이 일어날 확률과 매우 유사하므로, 확률을 logistic function으로 모델링하는 것이 가능함.

XOR classification by logistic regression model



$$y = \frac{1}{1 + e^{-(X_1 + X_2 - 0.5)}}$$
$$= \sigma(X_1 + X_2 - 0.5)$$

```
In [1]: import numpy as np
```

```
In [2]: def logistic(x):  
         return 1 / (1 + np.exp(-x))
```

```
In [3]: logistic(0 + 0 - 0.5)
```

```
Out [3]: 0.37754066879814541
```

```
In [4]: logistic(1 + 1 - 0.5)
```

```
Out [4]: 0.81757447619364365
```

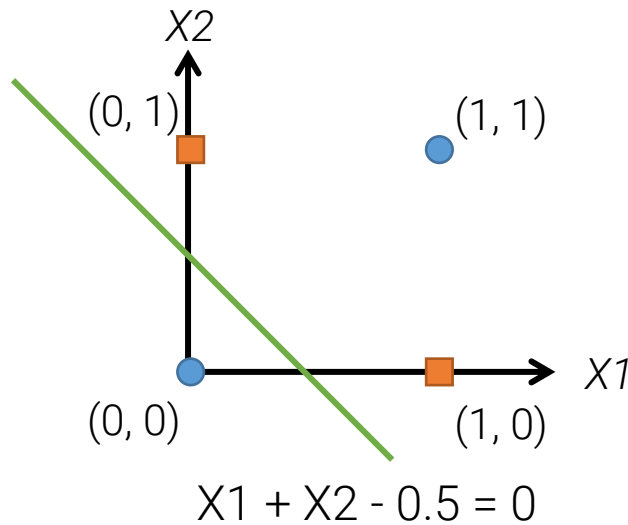
```
In [5]: logistic(0 + 1 - 0.5)
```

```
Out [5]: 0.62245933120185459
```

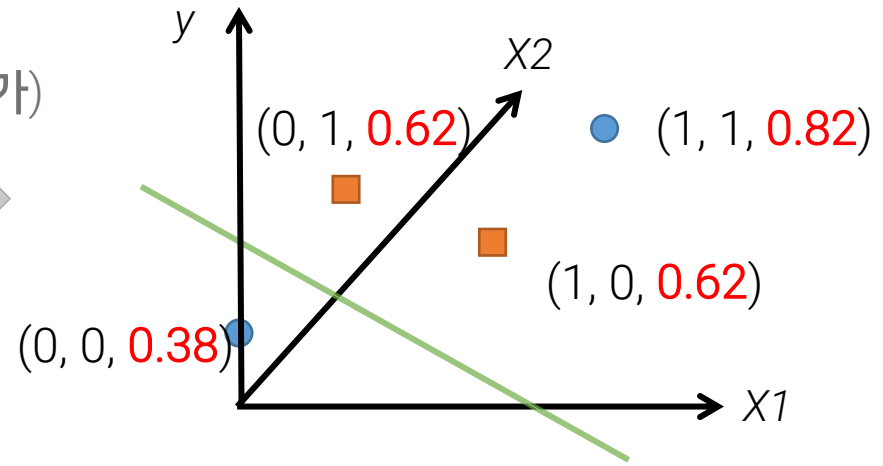
```
In [6]: logistic(1 + 0 - 0.5)
```

```
Out [6]: 0.62245933120185459
```

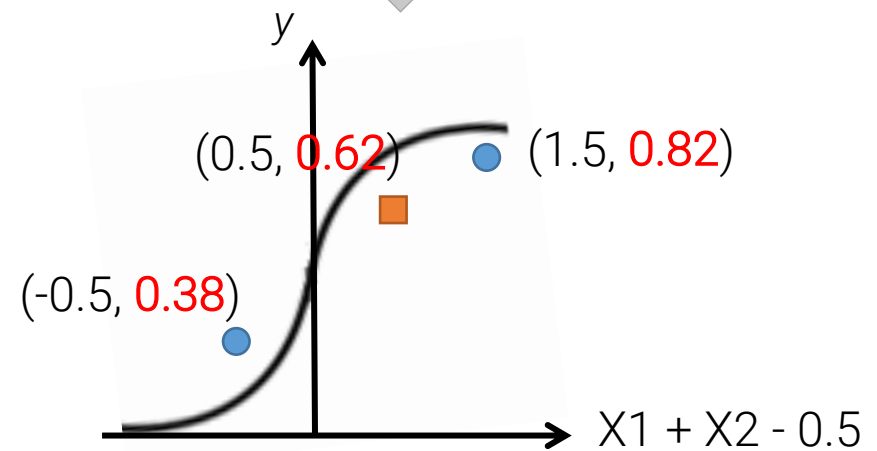

XOR classification by logistic regression model



(차원 추가)



(단면)

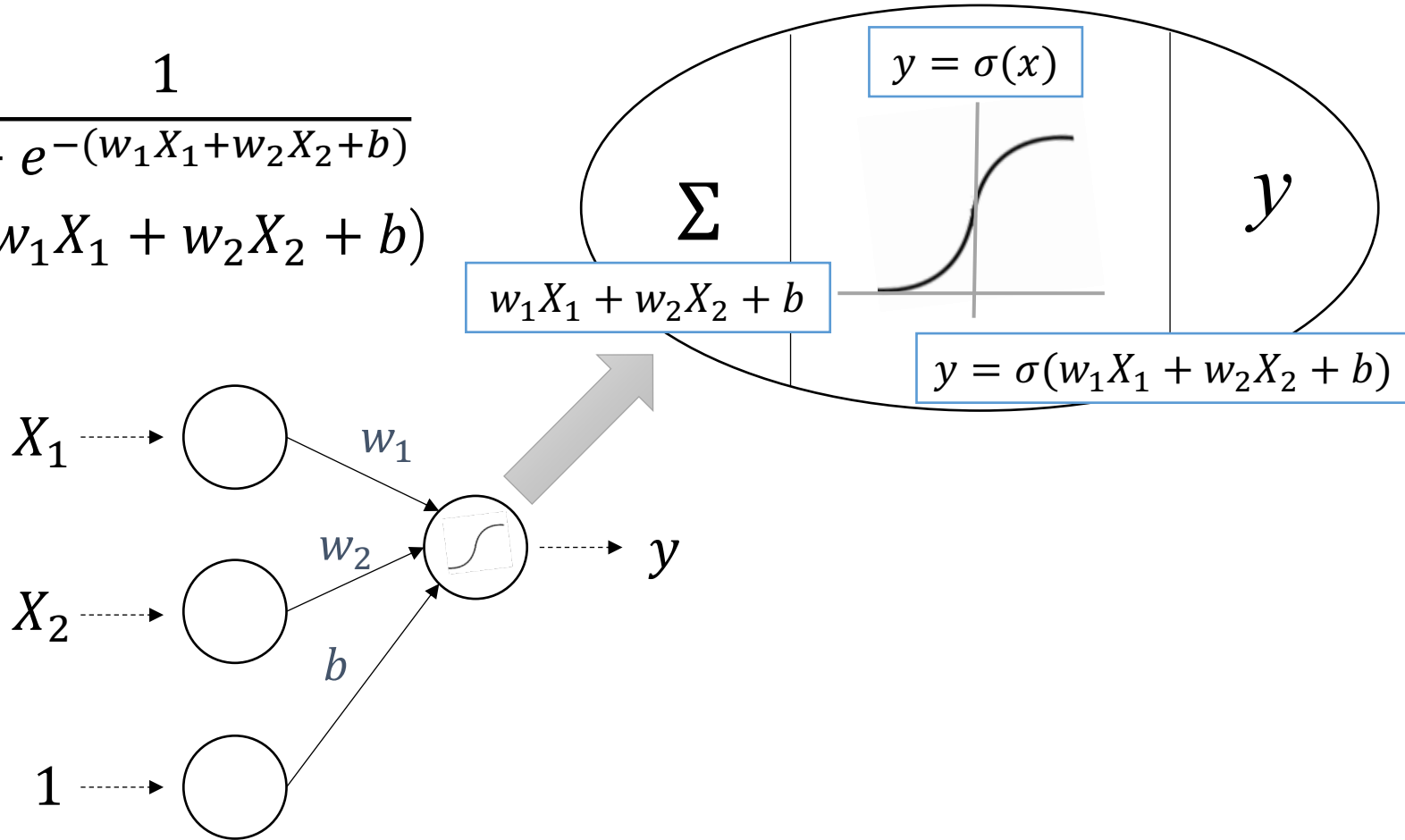


$$y = \frac{1}{1 + e^{-(X_1 + X_2 - 0.5)}} \\ = \sigma(X_1 + X_2 - 0.5)$$

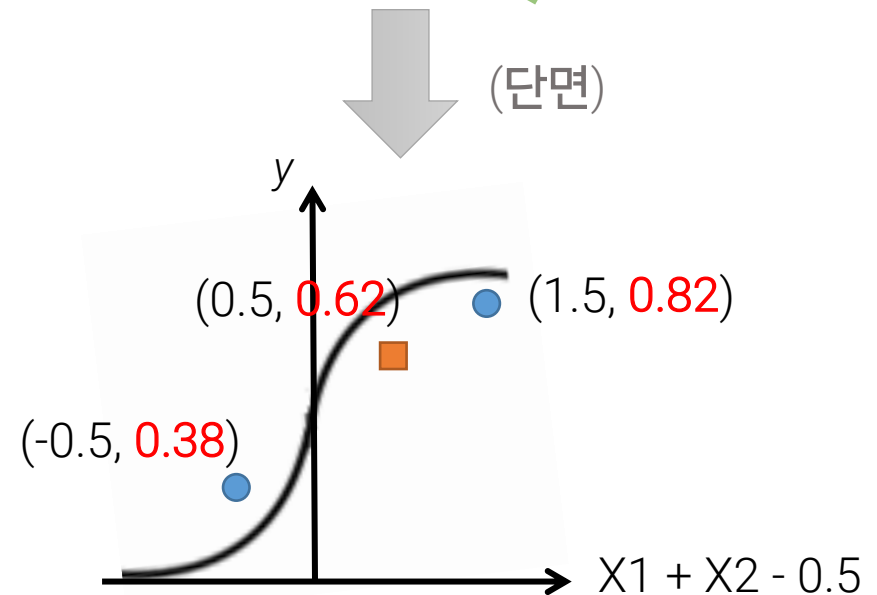
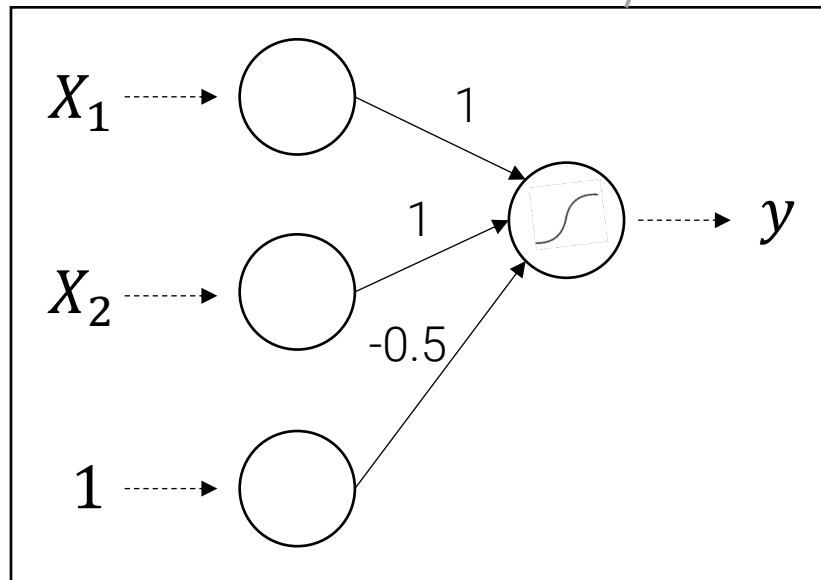
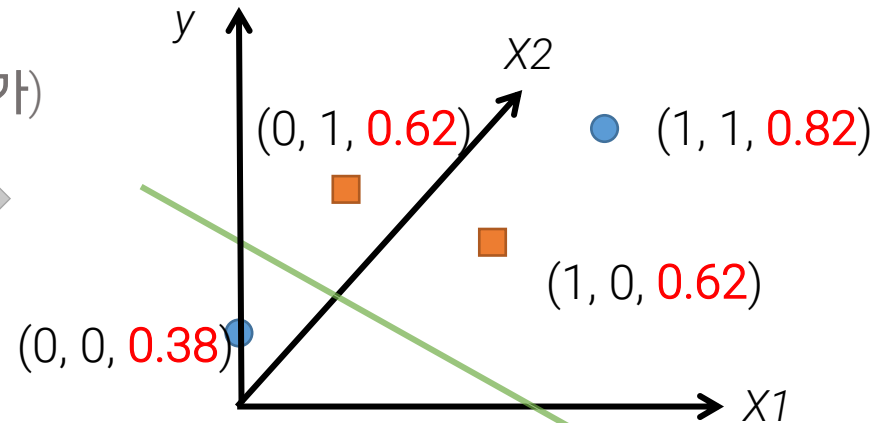
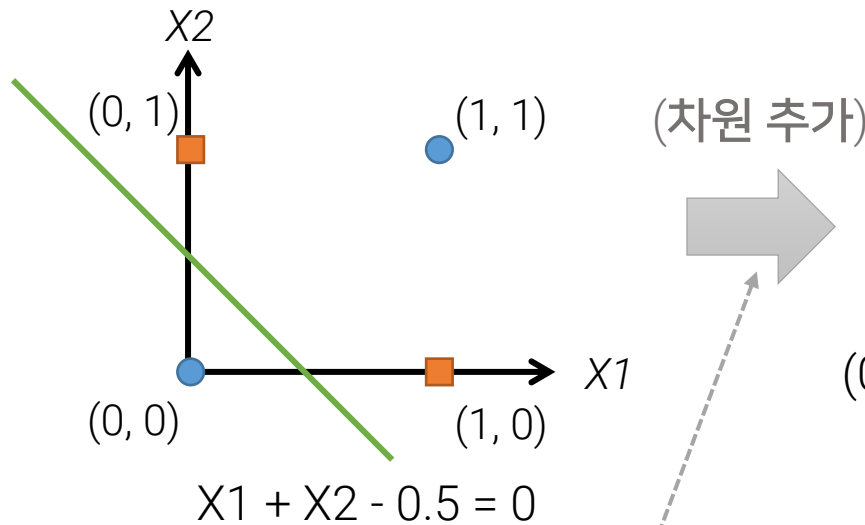
Logistic regression as a network

- Logistic regression을 network로 표현하면 다음과 같다.

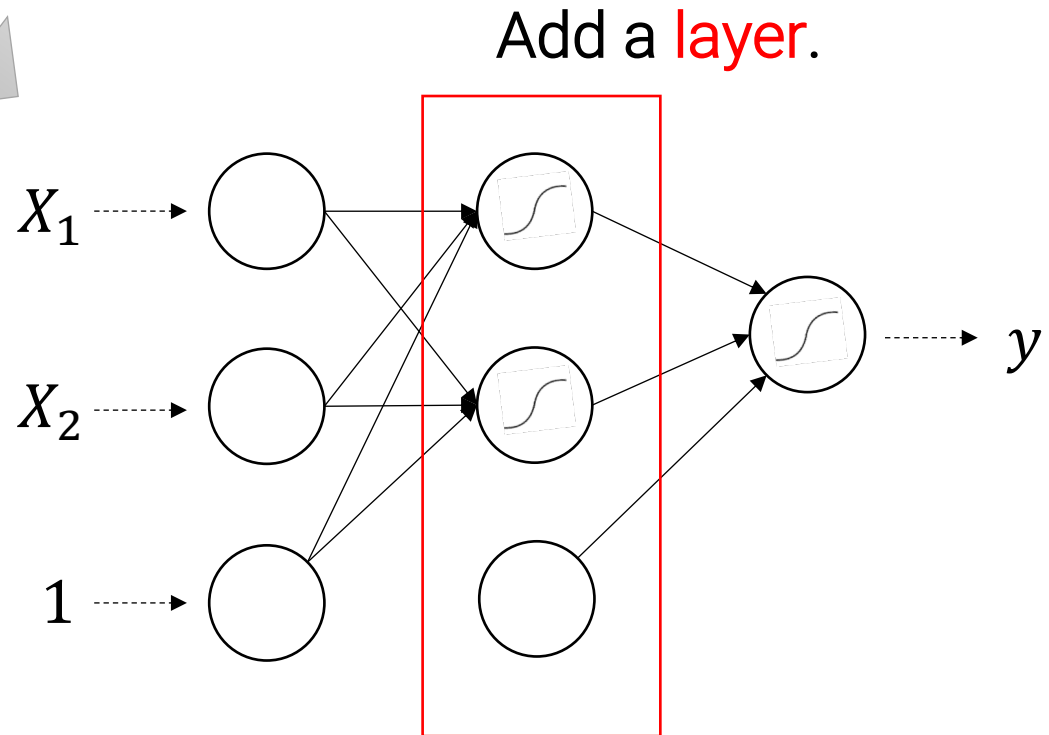
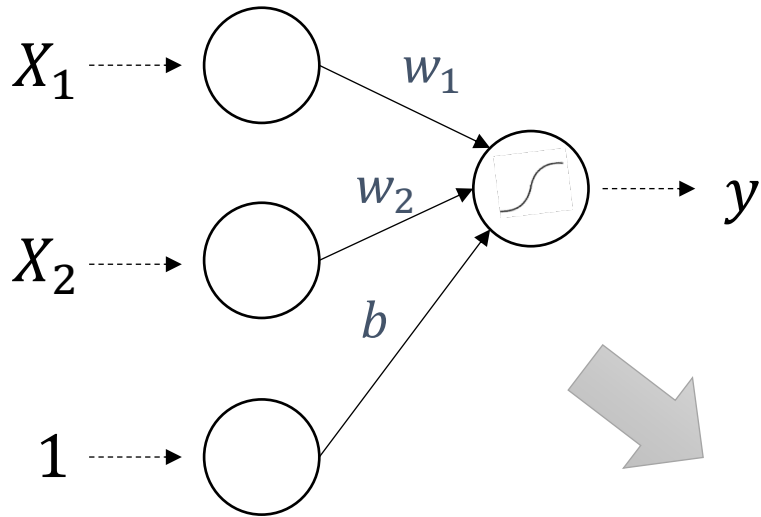
$$y = \frac{1}{1 + e^{-(w_1X_1 + w_2X_2 + b)}} \\ = \sigma(w_1X_1 + w_2X_2 + b)$$



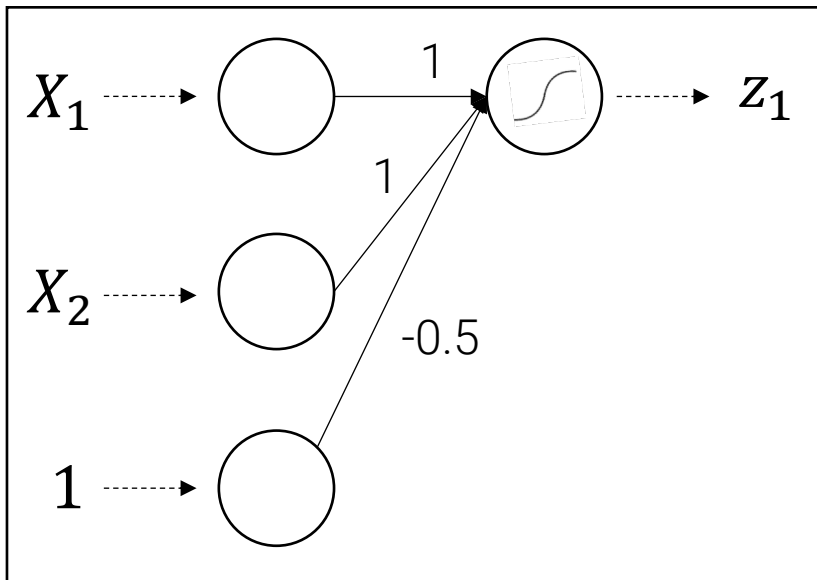
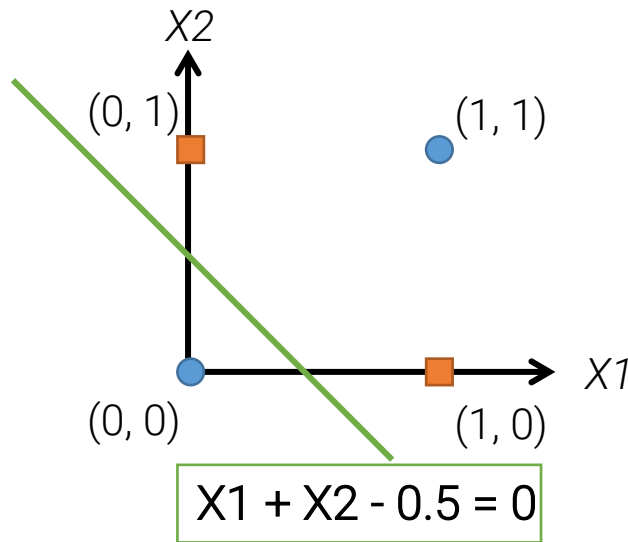
XOR classification by logistic regression model



How about this model? → Feed-forward network



XOR classification by feed-forward network model



```
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Out [3]: 0.37754066879814541
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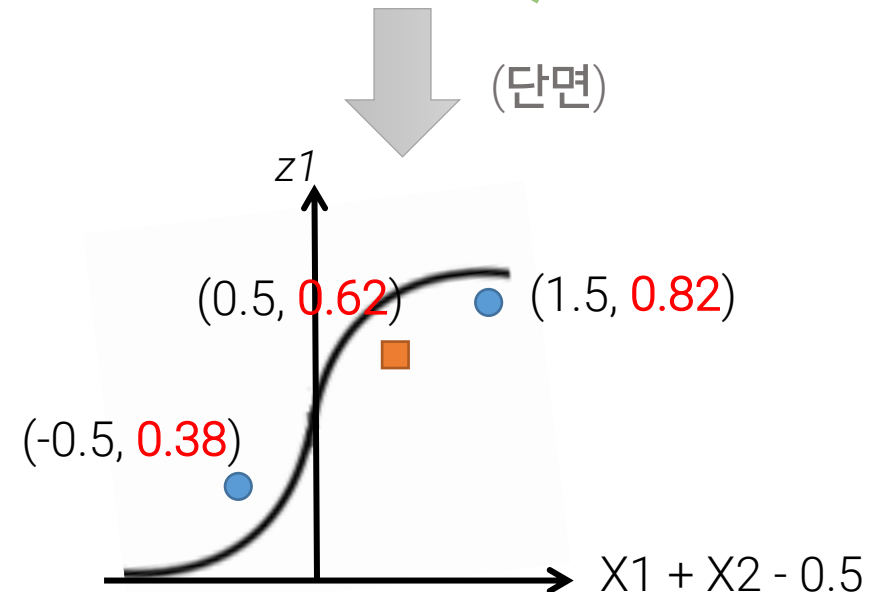
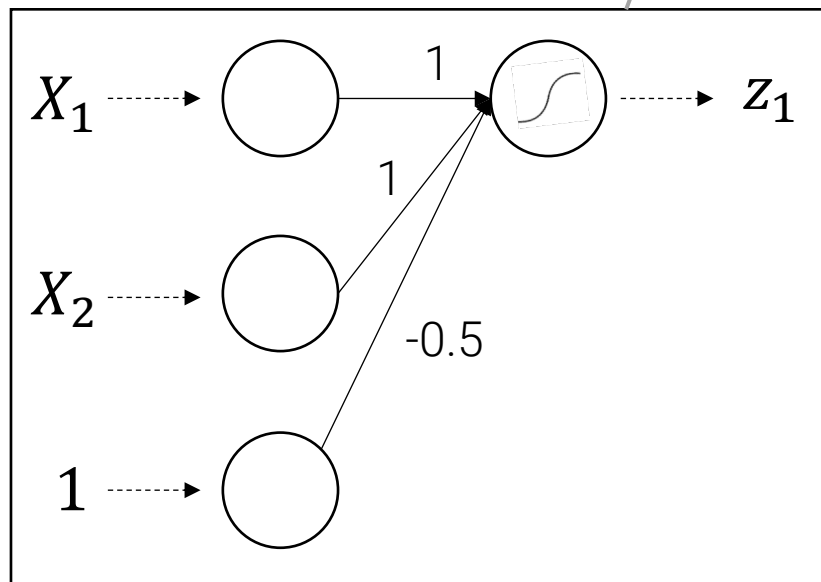
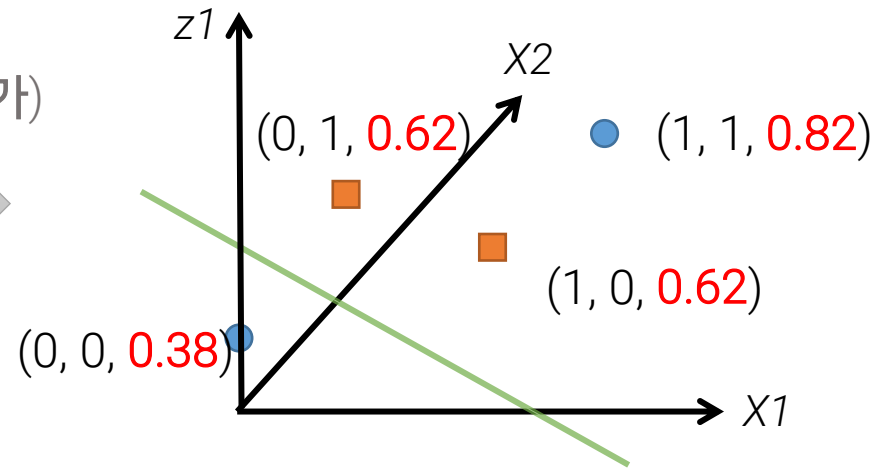
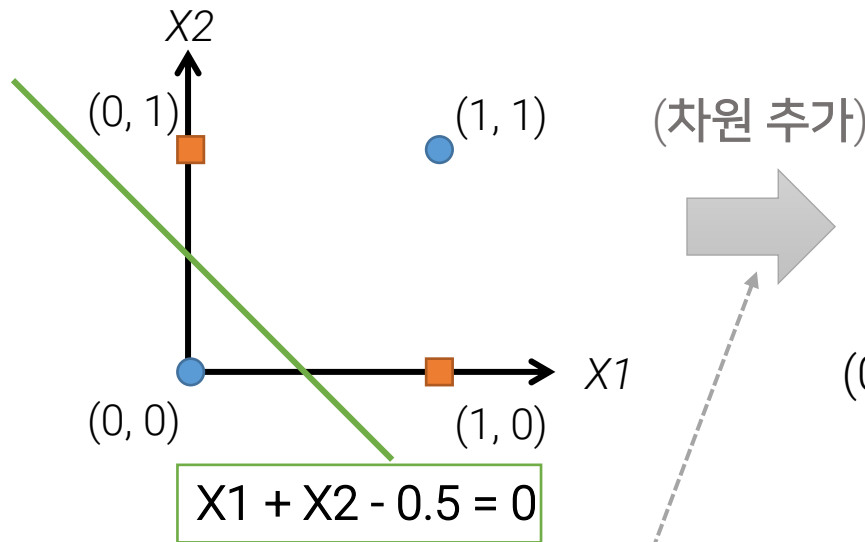
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In [5]: logistic(0 + 1 - 0.5)
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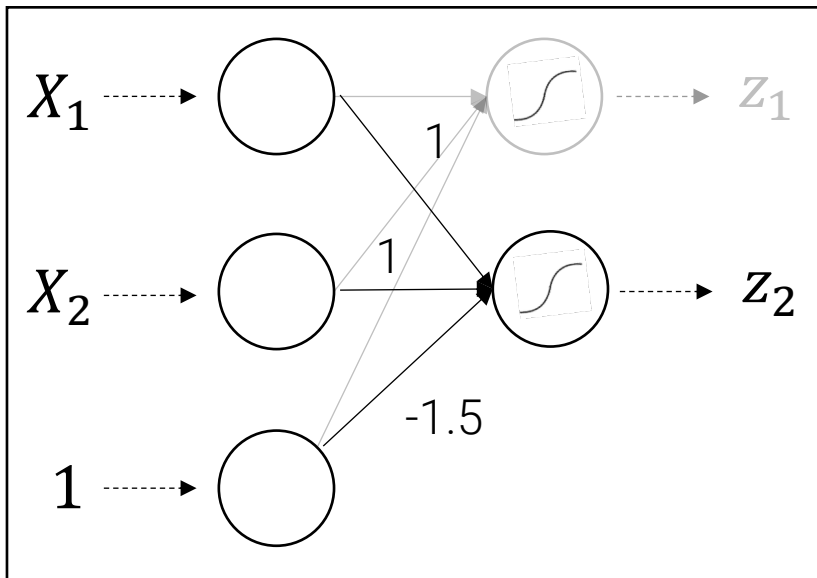
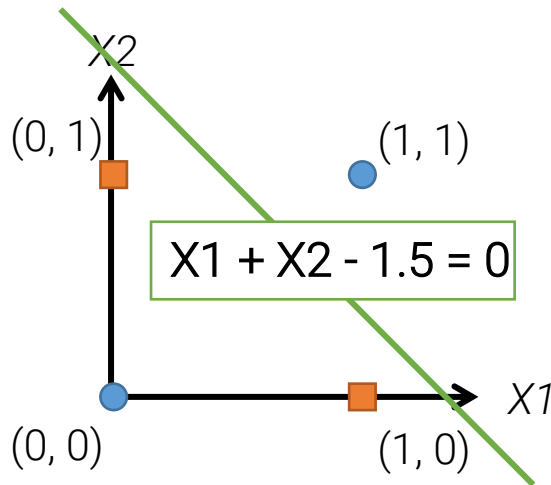
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In [6]: logistic(1 + 0 - 0.5)
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XOR classification by feed-forward network model



XOR classification by feed-forward network model



```
In [1]: import numpy as np
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```
In [2]: def logistic(x):  
        return 1 / (1 + np.exp(-x))
```

```
In [3]: logistic(0 + 0 - 1.5)
```

```
Out [3]: 0.18242552380635635
```

```
In [4]: logistic(1 + 1 - 1.5)
```

```
Out [4]: 0.62245933120185459
```

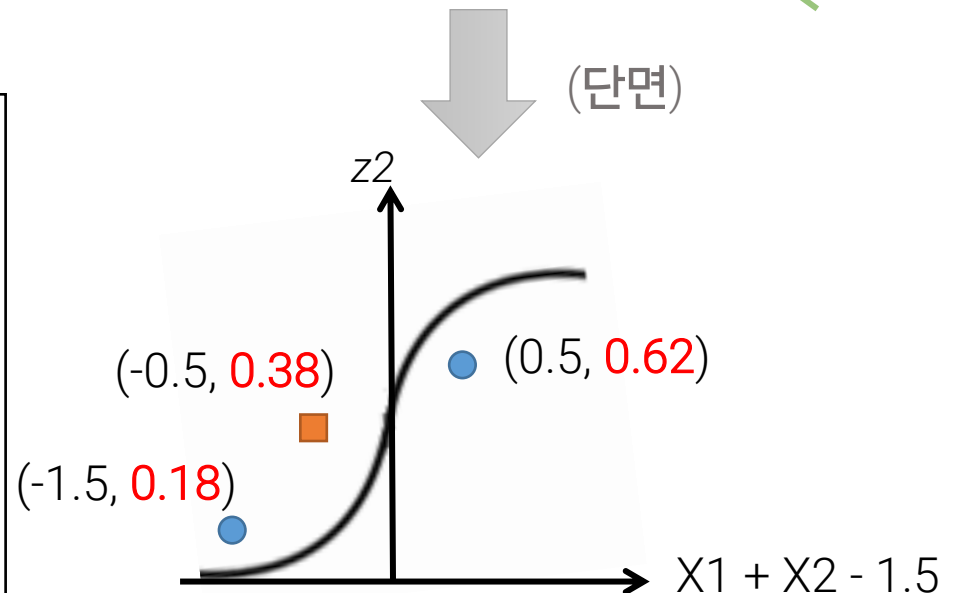
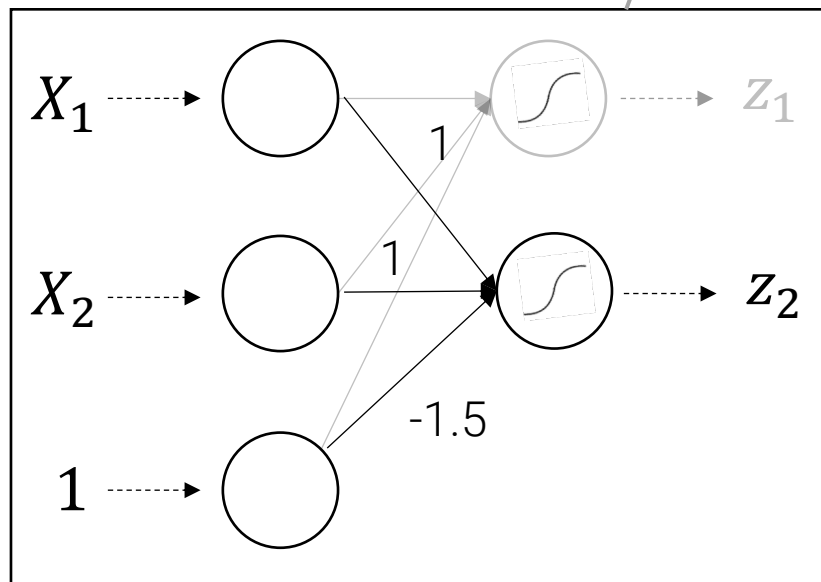
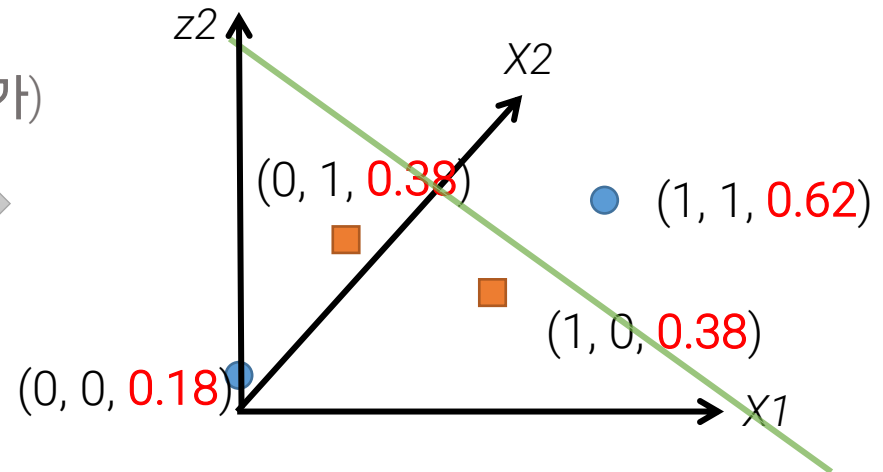
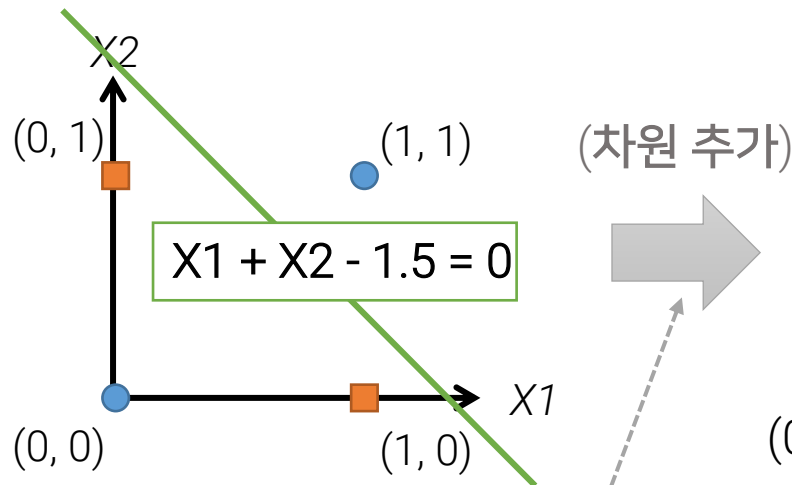
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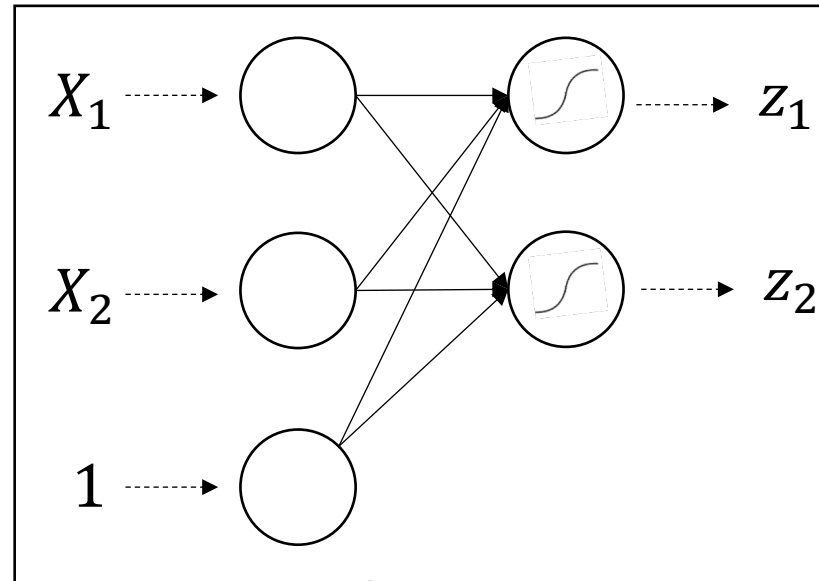
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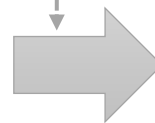
XOR classification by feed-forward network model



FFN changes data representation

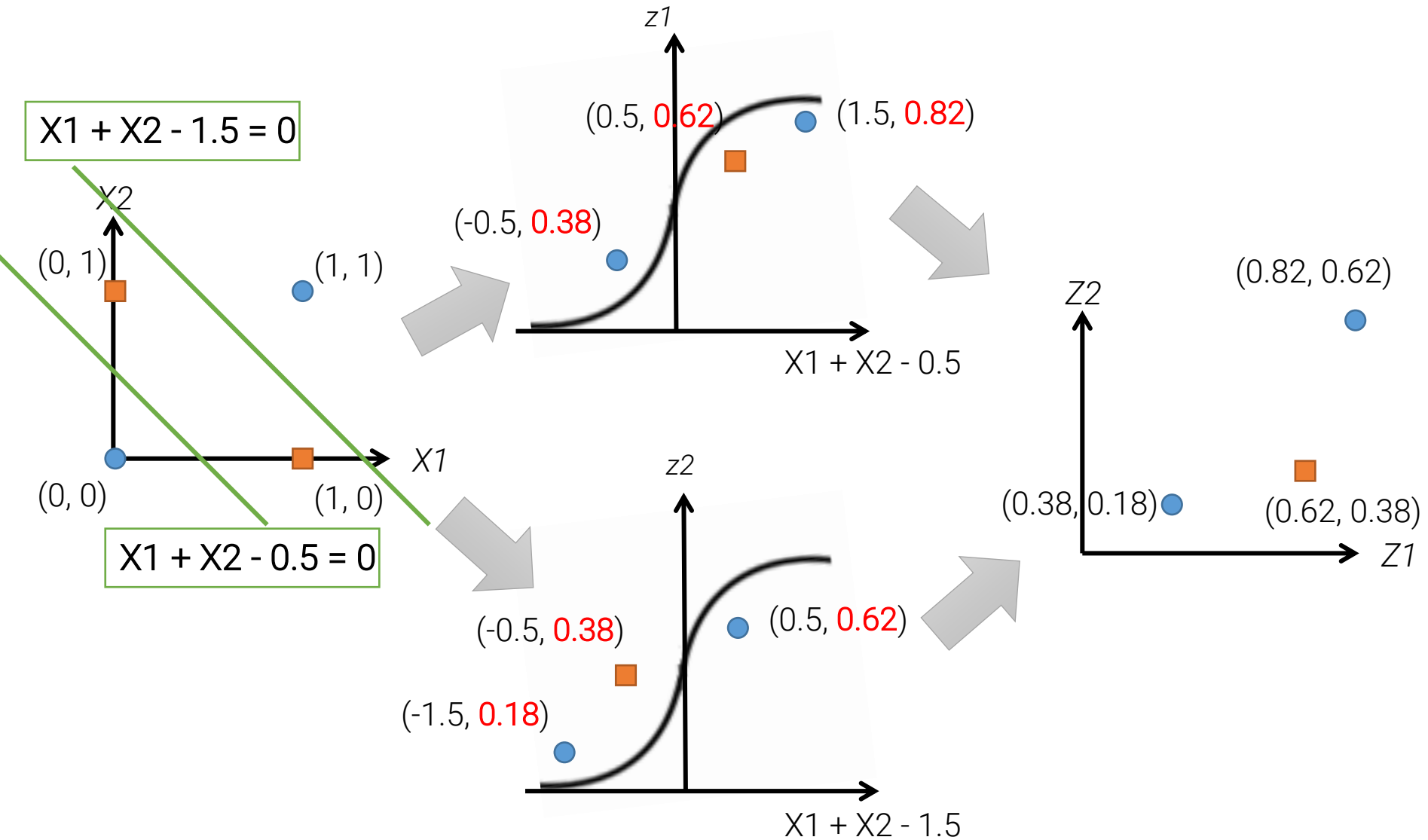


ID	class	X1	X2
1	0 ●	0	0
2	1 ■	0	1
3	1 ■	1	0
4	0 ●	1	1

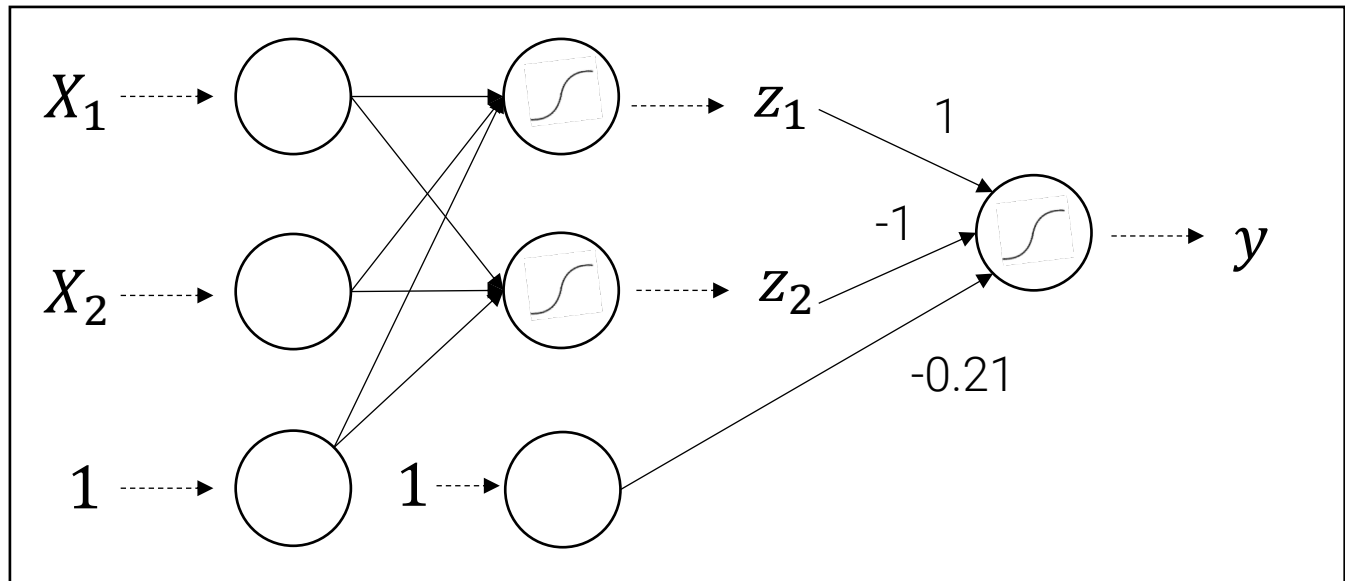
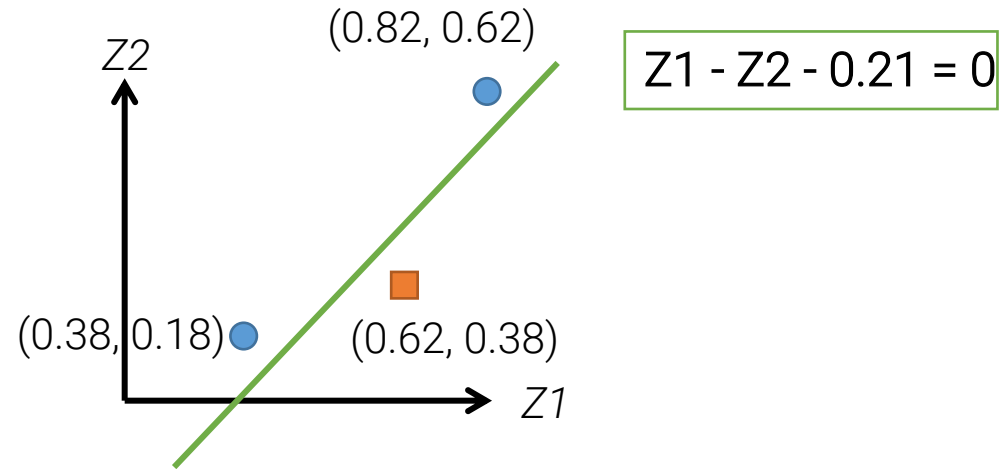


ID	class	Z1	Z2
1	0 ●	0.38	0.18
2	1 ■	0.62	0.38
3	1 ■	0.62	0.38
4	0 ●	0.82	0.62

FFN changes data representation



XOR classification by feed-forward network model

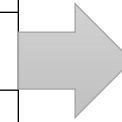


XOR classification by feed-forward network model

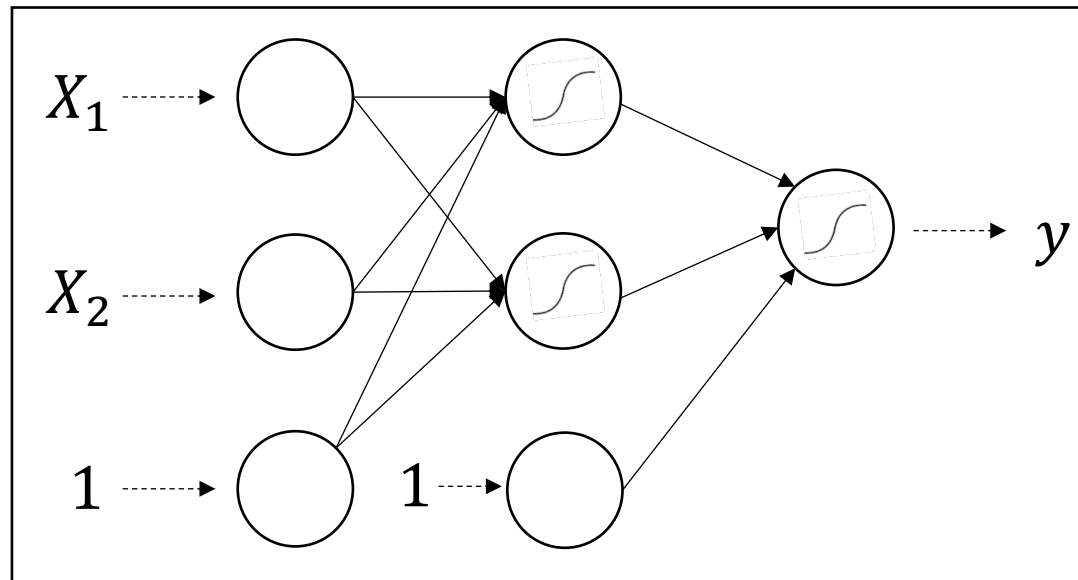
ID	class		X1	X2
1	0	●	0	0
2	1	■	0	1
3	1	■	1	0
4	0	●	1	1



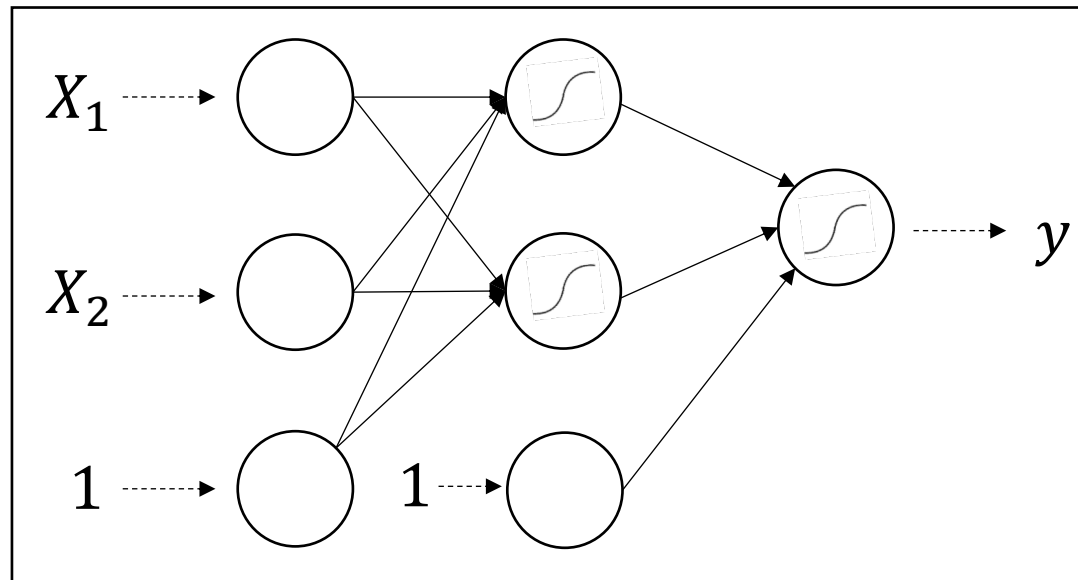
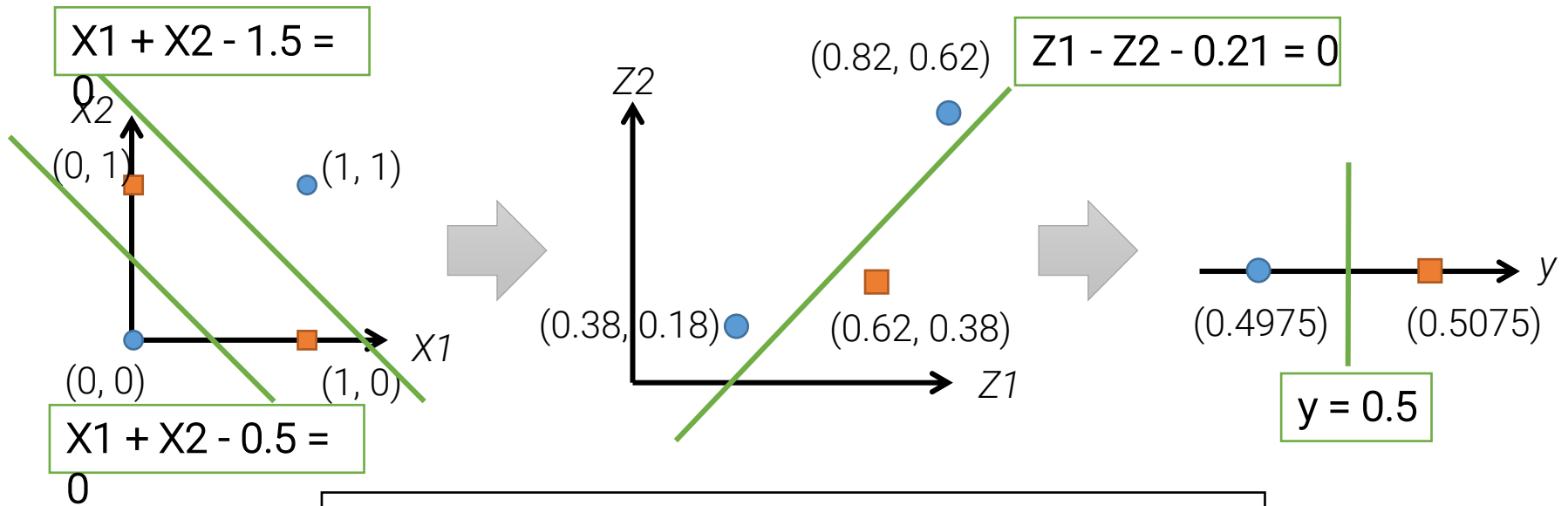
ID	class		Z1	Z2
1	0	●	0.38	0.18
2	1	■	0.62	0.38
3	1	■	0.62	0.38
4	0	●	0.82	0.62



ID	class		y
1	0	●	0.4975
2	1	■	0.5075
3	1	■	0.5075
4	0	●	0.4975

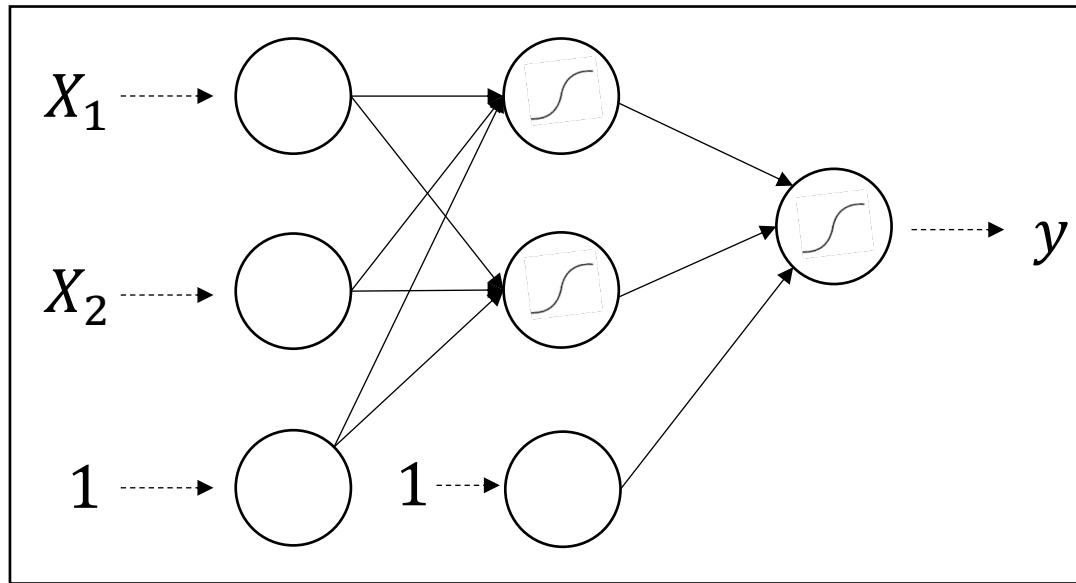


XOR classification by feed-forward network model



XOR classification by feed-forward network model

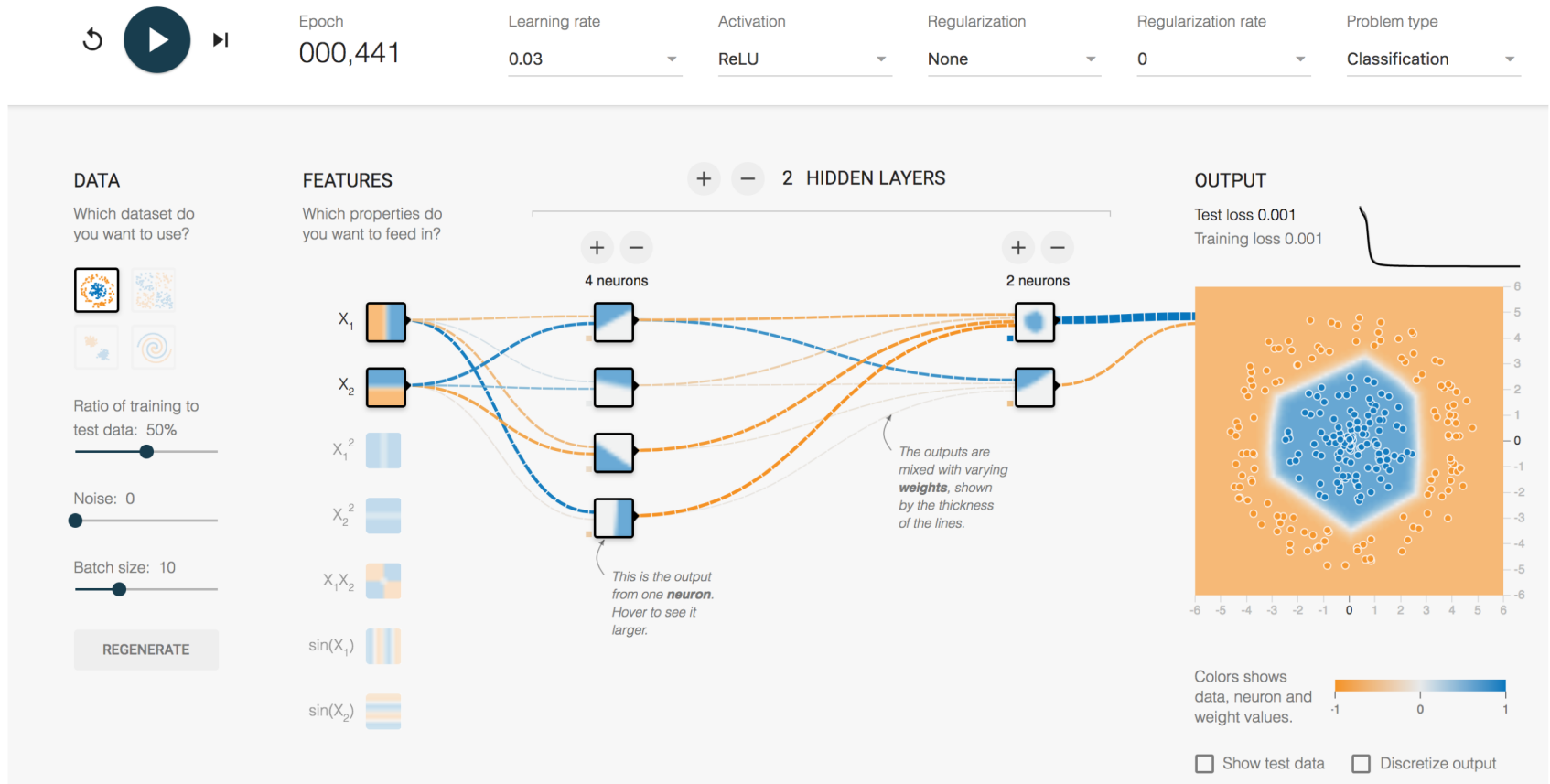
- 쉽게 말로 풀어서 쓰자면,
 - 관측된 (X_1, X_2) 라는 포인트들이
 - 네트워크의 다음 층(layer)에서 (Z_1, Z_2)의 형식으로 표현이 바뀐 후,
 - 마지막 층에서 클래스가 분류되었다.



A Neural network playground (by TensorFlow)

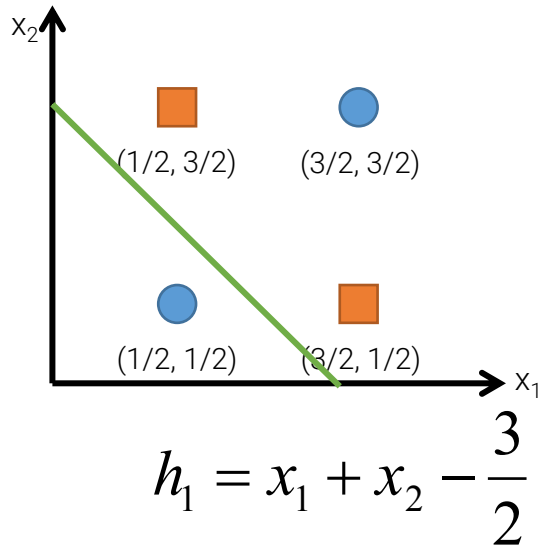
- <http://playground.tensorflow.org/>

Tinker With a **Neural Network** Right Here in Your Browser.
Don't Worry, You Can't Break It. We Promise.

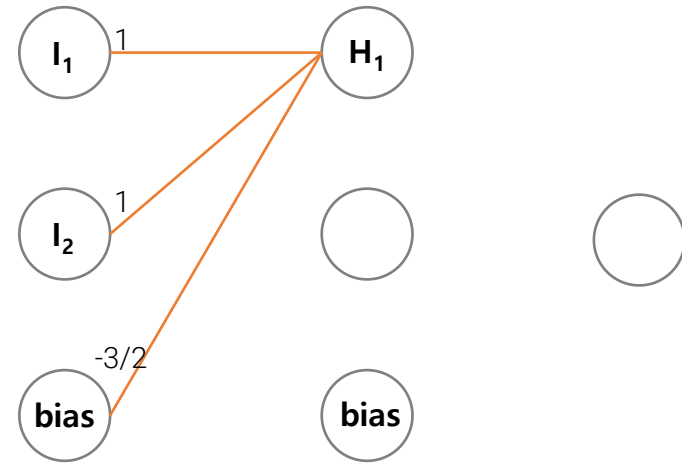


XOR classification by feed-forward network model

- XOR Problem: Revisited



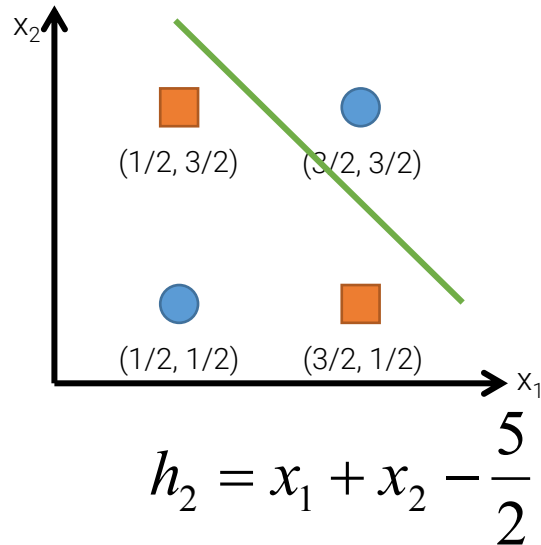
$$z_1 = g(h_1) = \begin{cases} 1 & \text{if } h_1 \geq 0 \\ -1 & \text{if } h_1 < 0 \end{cases}$$



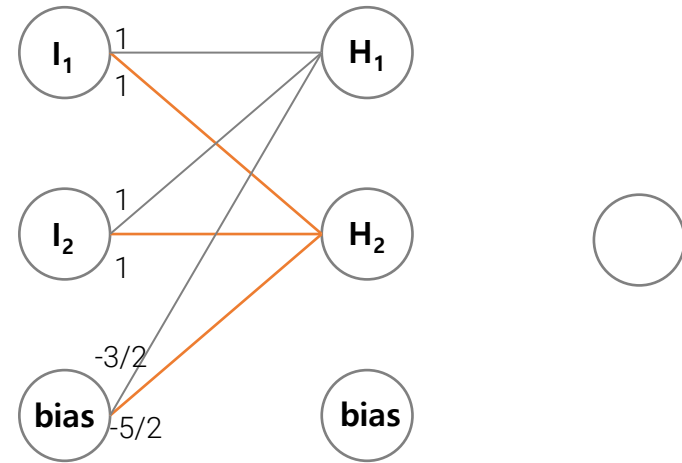
	x_1	x_2	h_1	z_1
●	1/2	1/2	-1/2	-1
■	3/2	1/2	1/2	1
■	1/2	3/2	1/2	1
●	3/2	3/2	3/2	1

XOR classification by feed-forward network model

- XOR Problem: Revisited



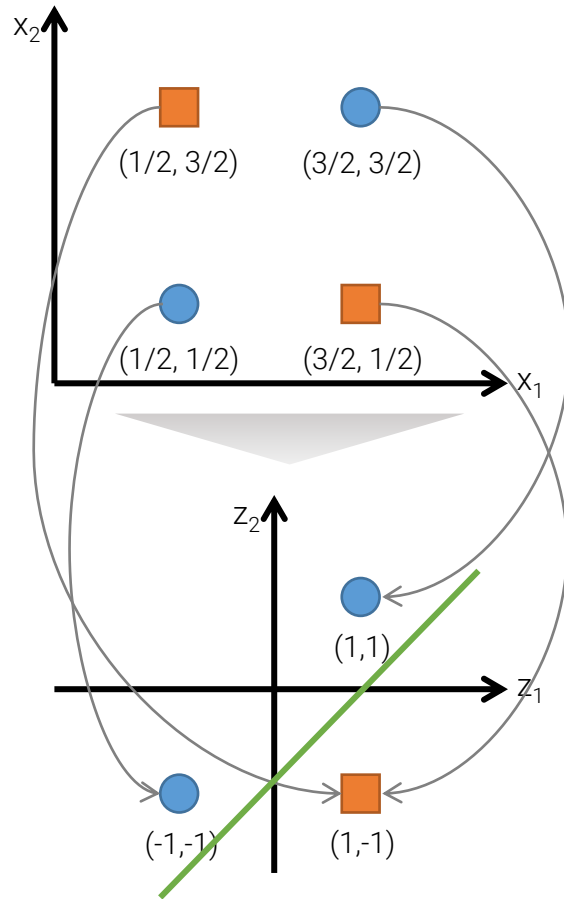
$$z_2 = g(h_2) = \begin{cases} 1 & \text{if } h_2 \geq 0 \\ -1 & \text{if } h_2 < 0 \end{cases}$$



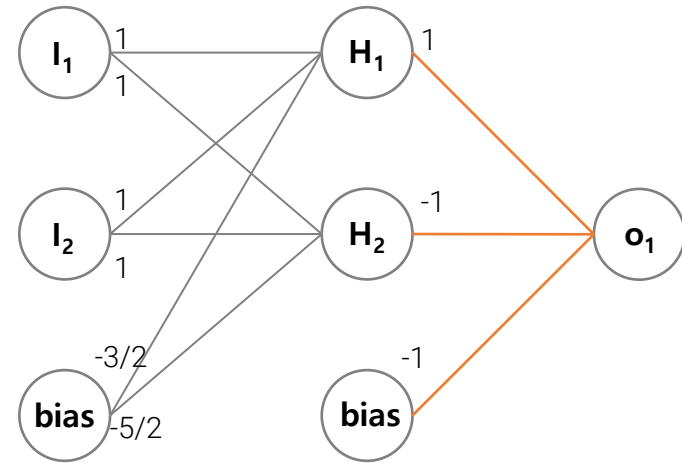
	x_1	x_2	h_2	z_2
●	1/2	1/2	-3/2	-1
■	3/2	1/2	-1/2	-1
■	1/2	3/2	-1/2	-1
●	3/2	3/2	1/2	1

XOR classification by feed-forward network model

• XOR Problem: Revisited



$$o_1 = z_1 - z_2 - 1$$



	x_1	x_2	h_1	z_1	h_2	z_2	o_1	z
●	1/2	1/2	-1/2	-1	-3/2	-1	-1	-1
■	3/2	1/2	1/2	1	-1/2	-1	1	1
■	1/2	3/2	1/2	1	-1/2	-1	1	1
●	3/2	3/2	3/2	1	1/2	1	-1	-1

$$z = g(o_1) = \begin{cases} 1 & \text{if } o_1 \geq 0 \\ -1 & \text{if } o_1 < 0 \end{cases}$$