

# 머신러닝 강의 03

## 기초 모델 구현

# Perceptron

## Contents

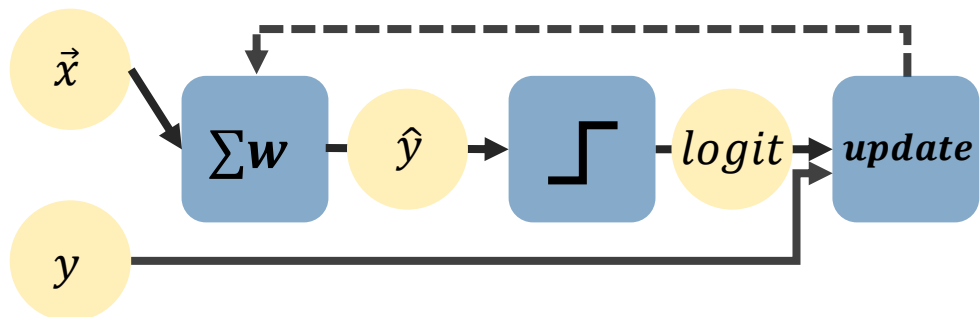
선형 함수

결정 함수

최적화

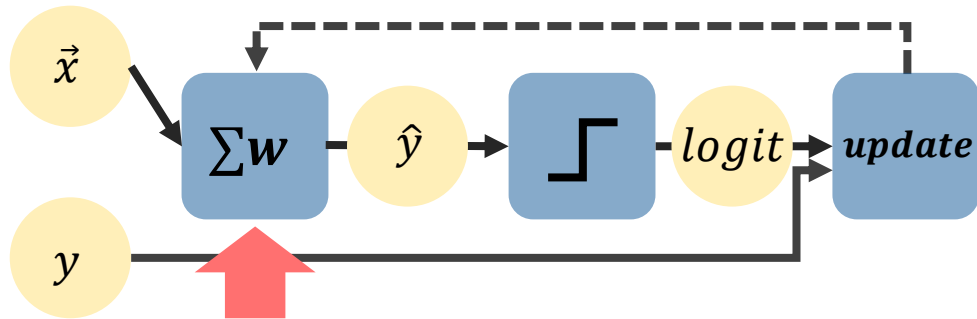
평가

# 소개



```
class Perceptron():  
    def __init__(self, lr=0.001, random_state=1):  
        self.lr=lr  
        self.seed = np.random.RandomState(random_state)
```

# 모델 구현 - 선형 함수

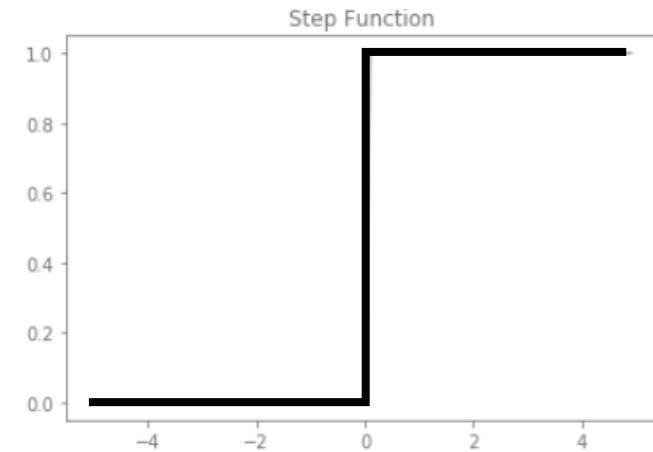
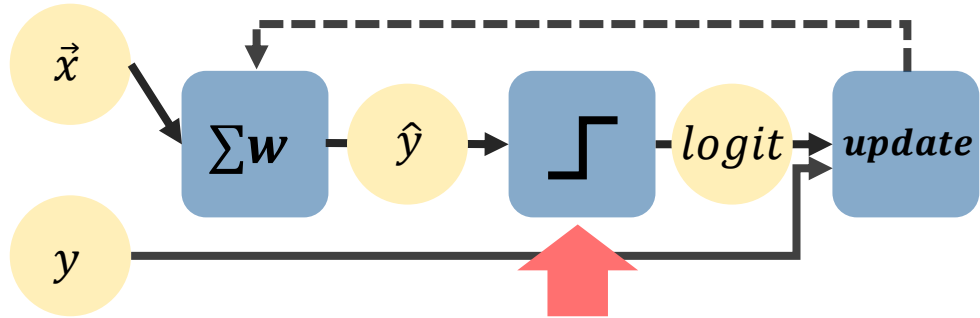


$$\begin{aligned} f(x) &= \vec{w} \cdot \vec{x} + b \\ &= w_1x_1 + w_2x_2 + \dots w_mx_m + b \end{aligned}$$

```
def init_weights
```

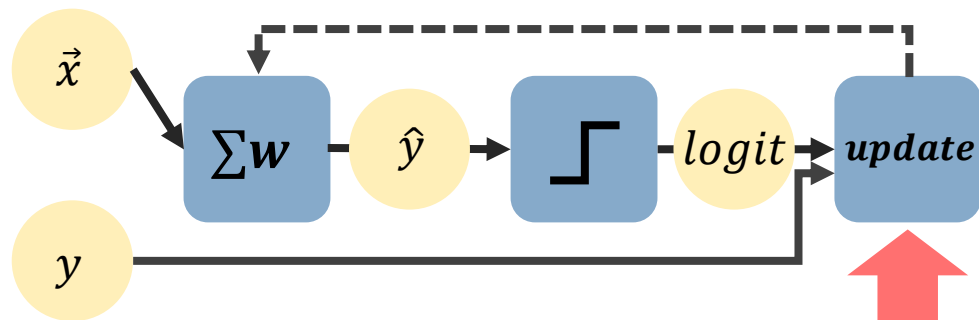
```
def model
```

# 모델 구현 - 결정 함수



```
def predict
```

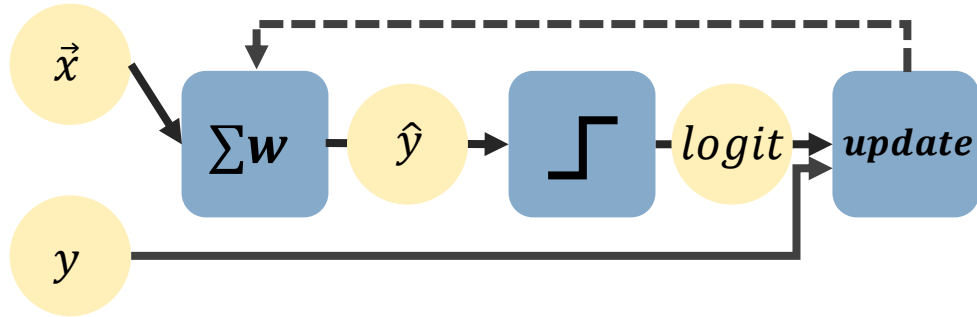
# 모델 구현 - 최적화



$$\begin{aligned} w_j &:= w_j + \Delta w_j \\ &= w_j + \eta(y^{(i)} - \text{logit}^{(i)})x_j^{(i)} \end{aligned}$$

```
def fit
```

# 모델 구현 - 평가



$$accuracy = \frac{\text{정답을 맞춘 데이터 수}}{\text{전체 데이터 수}}$$

```
def evaluate
```

```
def loss
```

```
def accuracy
```

# Adaline

## Contents

선형 함수

결정 함수

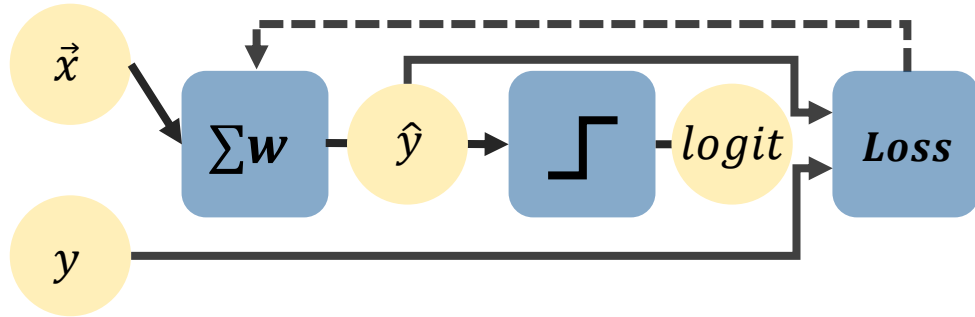
손실 함수

최적화

평가

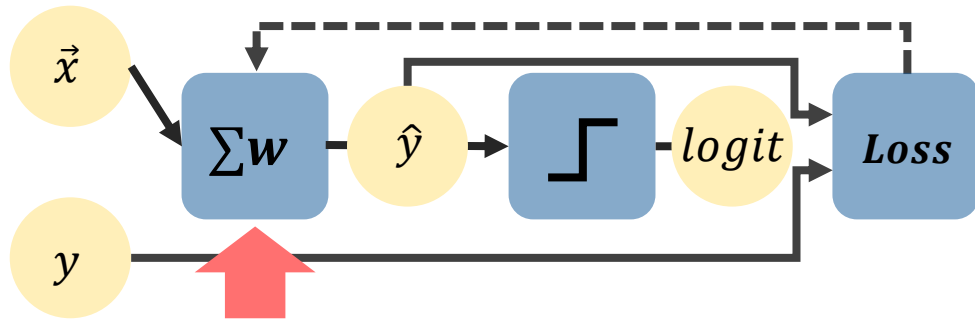


# 소개



```
class Perceptron():  
    def __init__(self, lr=0.001, random_state=1):  
        self.lr=lr  
        self.seed = np.random.RandomState(random_state)
```

# 모델 구현 - 선형 함수

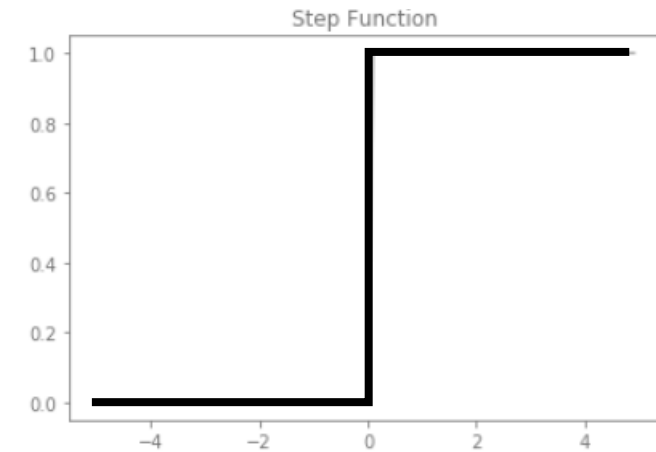
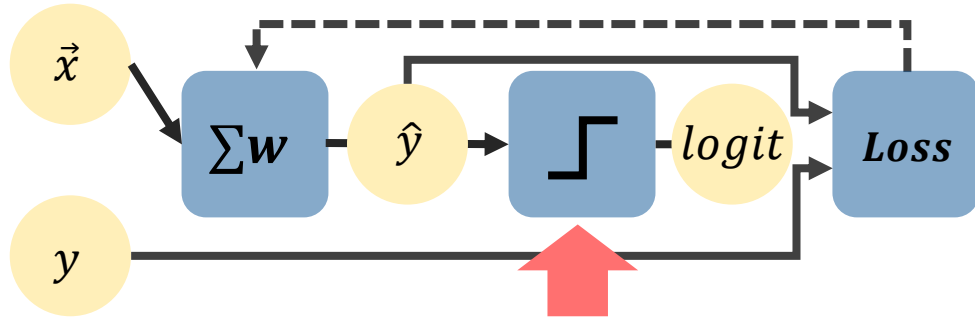


$$\begin{aligned} f(x) &= \vec{w} \cdot \vec{x} + b \\ &= w_1x_1 + w_2x_2 + \dots w_mx_m + b \end{aligned}$$

```
def init_weights
```

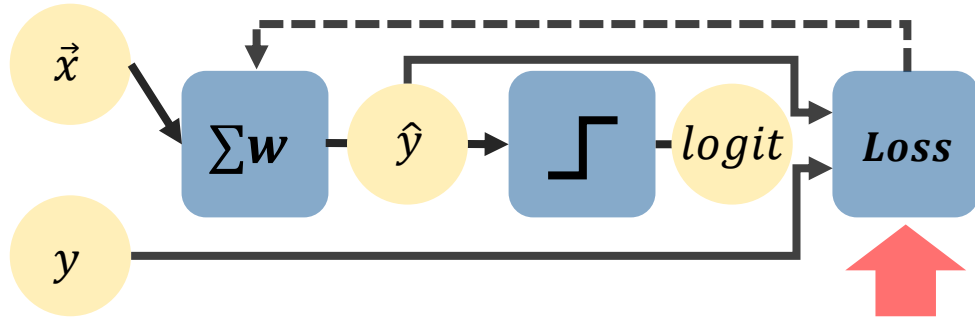
```
def model
```

# 모델 구현 - 결정 함수



```
def predict
```

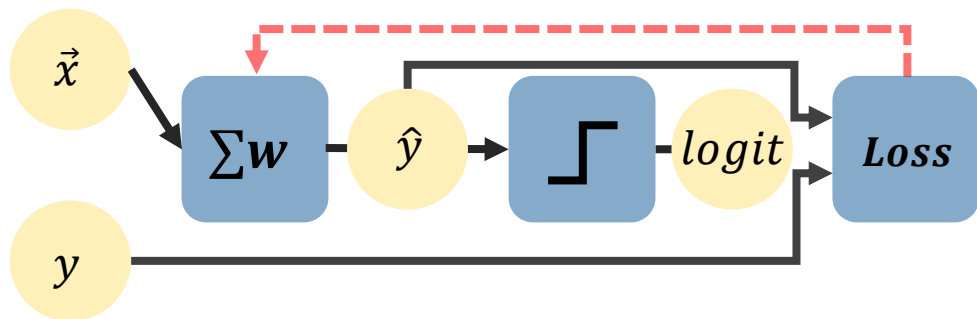
# 모델 구현 - 손실 함수



$$L(w) = \frac{1}{2} \sum_i (y^{(i)} - \hat{y}^{(i)})^2$$

```
def loss
```

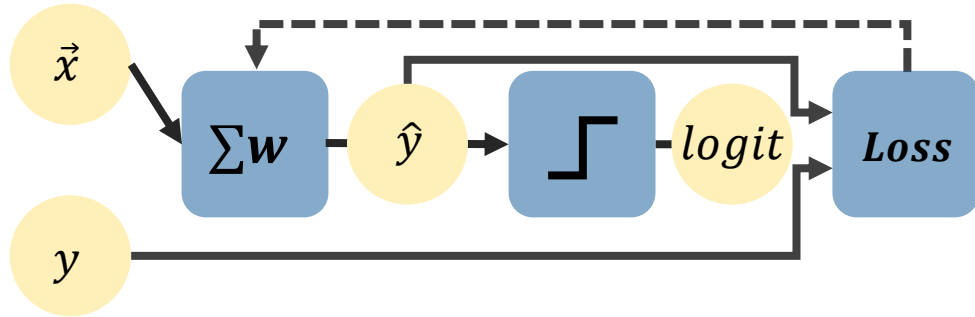
# 모델 구현 - 최적화



$$\begin{aligned} w_j &:= w_j + \Delta w_j \\ &= w_j - \eta \nabla L(w_j) \\ &= w_j + \eta \sum_i (y^{(i)} - \hat{y}^{(i)}) x_j^{(i)} \end{aligned}$$

```
def fit
```

# 모델 구현 - 평가



$$accuracy = \frac{\text{정답을 맞춘 데이터 수}}{\text{전체 데이터 수}}$$

```
def evaluate
```

# 선형회귀

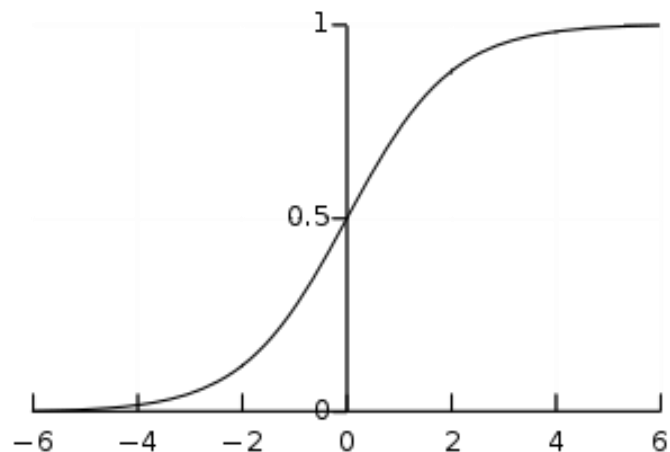
## Contents

Linear regression

Logistic regression

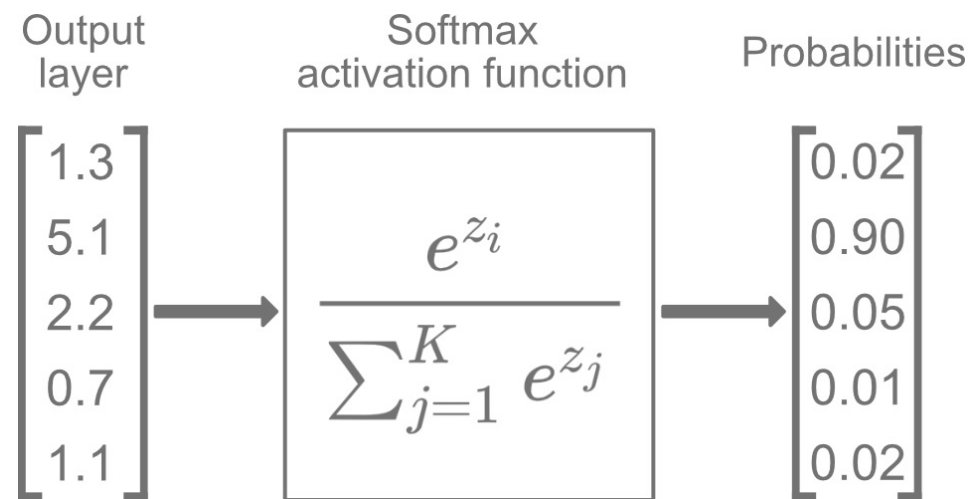
Softmax regression

# 모델 구현 - 평가



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

```
def sigmoid
```



```
def softmax
```



# 함수의 인풋과 아웃풋

linear

sigmoid

softmax

# 회귀

linear

sigmoid

softmax

Linear regression

# 이진분류

linear

sigmoid

softmax

\_\_\_\_\_ regression

# 다중 클래스 분류

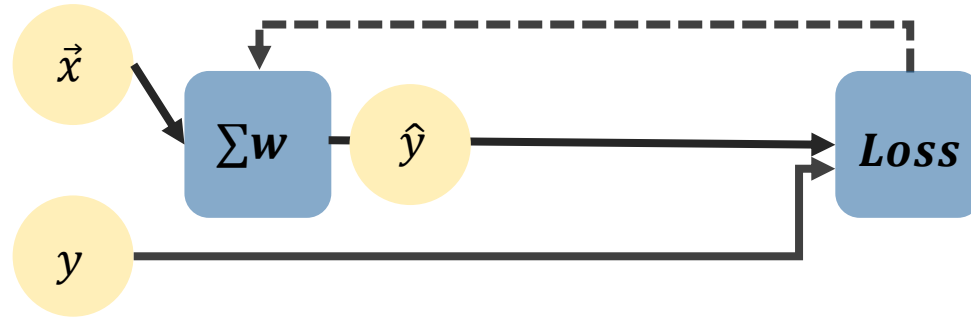
linear

sigmoid

softmax

\_\_\_\_\_ regression

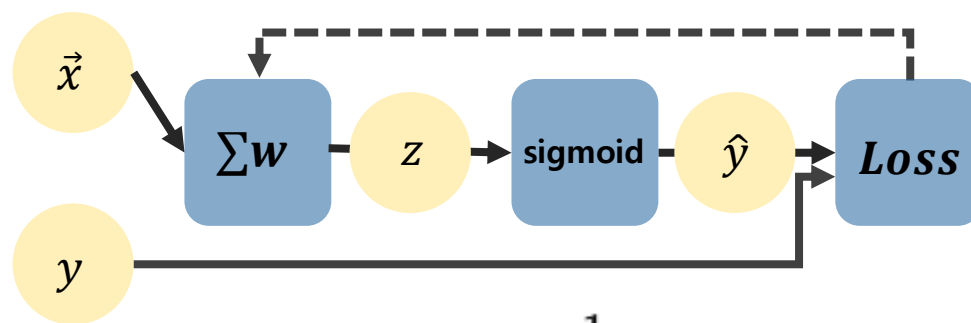
# 모델 구현 – linear regression



$$\begin{aligned} f(x) &= \vec{w} \cdot \vec{x} + b \\ &= w_1x_1 + w_2x_2 + \dots w_mx_m + b \end{aligned}$$

$$L(w) = \frac{1}{2} \sum_i (y^{(i)} - \hat{y}^{(i)})^2$$

# 모델 구현 – logistic regression

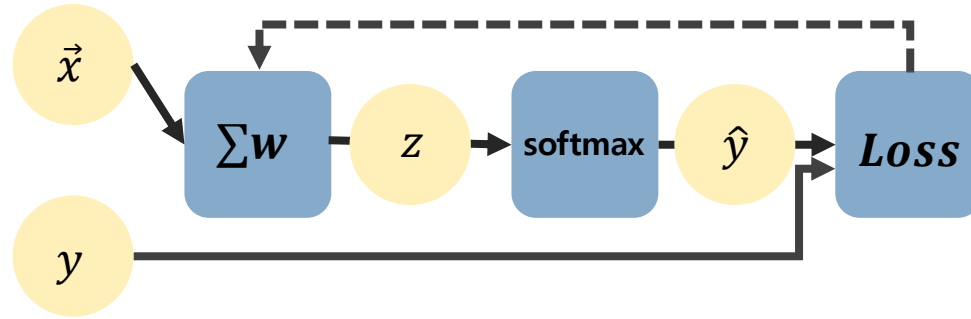


$$\begin{aligned} f(x) &= \vec{w} \cdot \vec{x} + b \\ &= w_1x_1 + w_2x_2 + \dots w_mx_m + b \end{aligned}$$

$$\frac{1}{1 + e^{-x}}$$

$$L = -\frac{1}{n} \sum_{i=1}^n [y^{(i)} \log \hat{y} + (1 - y^{(i)}) \log(1 - \hat{y})]$$

# 모델 구현 – softmax regression



$$\begin{aligned} f(x) &= \vec{w} \cdot \vec{x} + b \\ &= w_1 x_1 + w_2 x_2 + \dots w_m x_m + b \end{aligned}$$

$$\frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}}$$

$$L = -\frac{1}{n} \sum_{i=1}^n \sum_{j=1}^k y_j^{(i)} \log(p_j^{(i)})$$