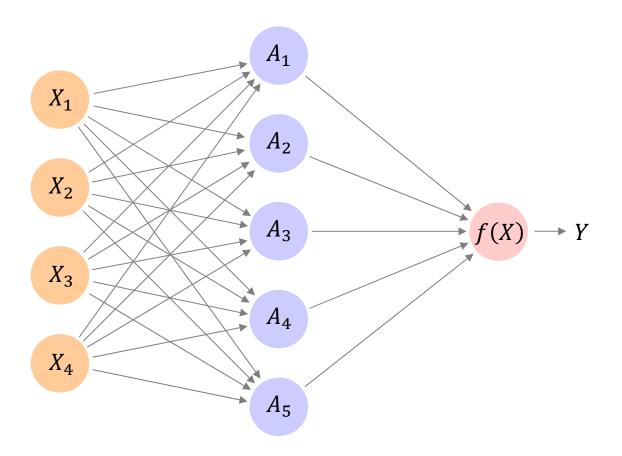
#### Today

- Neural networks and deep learning
  - Single layer neural networks
  - Multi-layer neural networks
  - Convolutional neural networks
  - U-net
  - Transformers

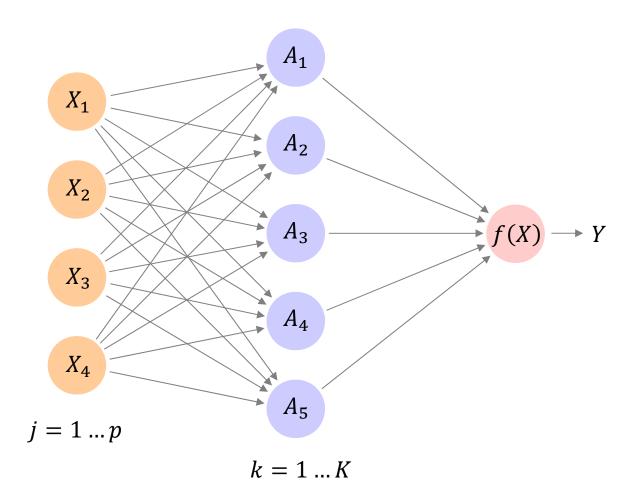
Input layer Hidden layer

Output layer



Input layer Hidden layer

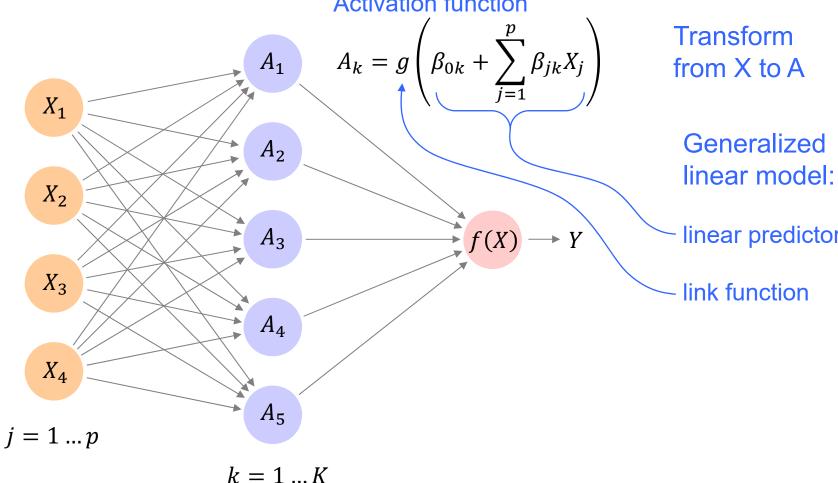
Output layer

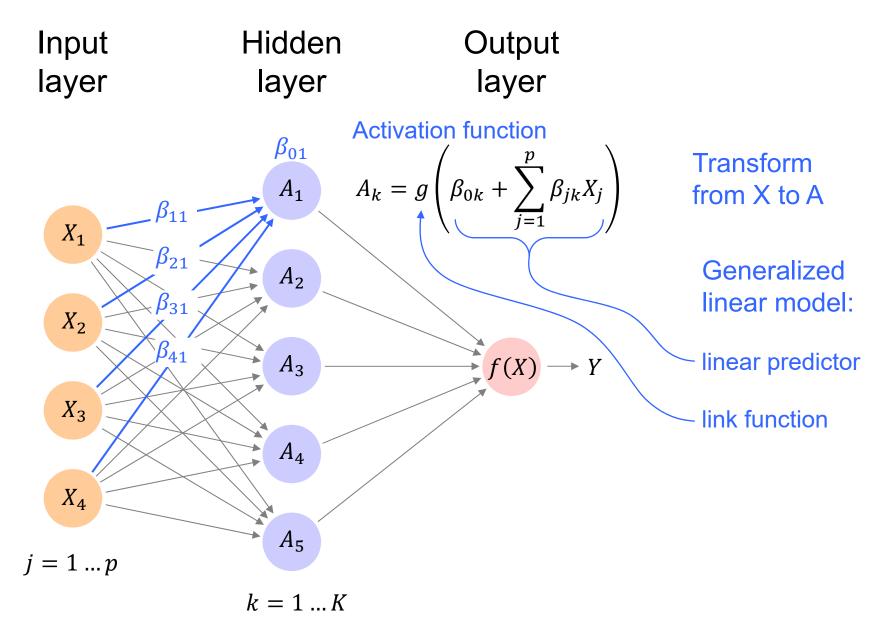


Input Hidden Output layer layer layer **Activation function** 

Generalized

linear predictor





Input Hidden Output layer layer layer **Activation function Transform**  $A_1$ from X to A  $X_1$  $\beta_{02}$  $\beta_{12}$ Generalized  $A_2$  $\beta_{22}$ linear model:  $X_2$  $\beta_{32}$ linear predictor  $A_3$ f(X) $\langle \beta_{42} \rangle$  $X_3$ link function  $A_4$  $X_4$  $A_5$ j = 1 ... pk = 1 ... K

Input Hidden Output layer layer layer **Activation function Transform**  $A_1$ from X to A  $X_1$ Generalized  $A_2$ linear model:  $X_2$ linear predictor  $A_3$ f(X) $\beta_{15}$  $X_3$ link function  $\beta_{25}$  $A_4$  $\beta_{35}$  $X_4$  $\beta_{05}$  $\beta_{45}$  $A_5$ j = 1 ... p

k = 1 ... K

Input layer Hidden layer

Output layer

**Sigmoid** 

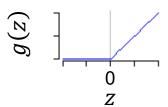


$$A_1 \qquad A_k = g\left(\beta_{0k} + \sum_{j=1}^p \beta_{jk} X_j\right)$$

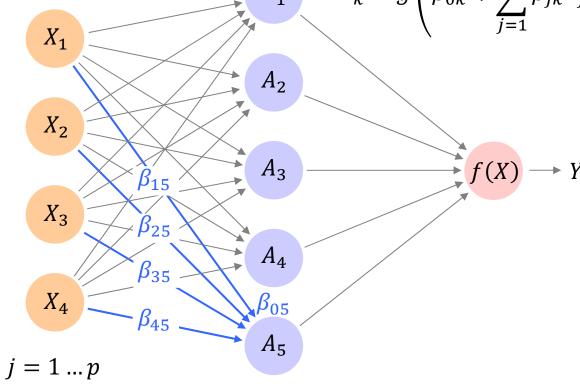
ReLU

aka

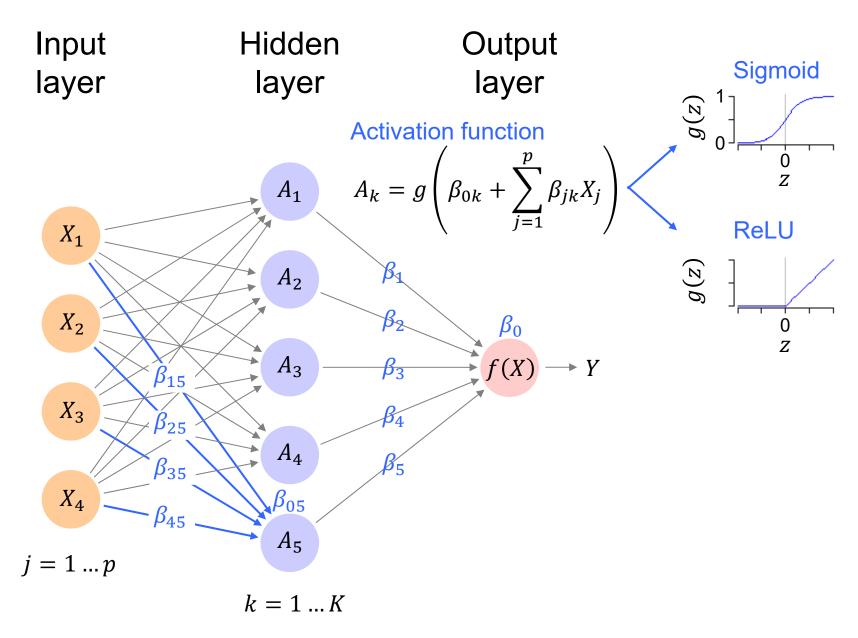
logit link

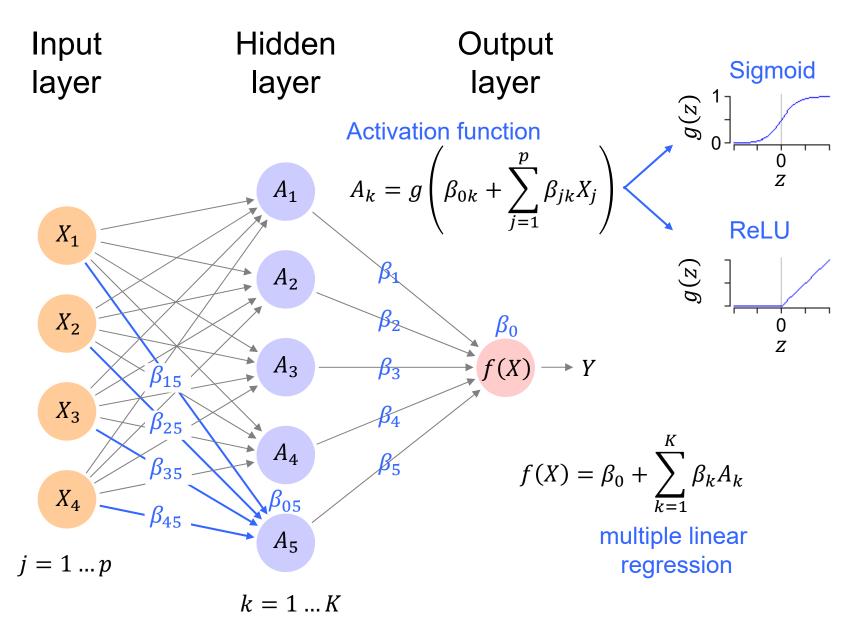


Rectified linear unit



k = 1 ... K





#### Model algorithm

define g(z) load  $x_i$ 

oot V

set K

set parameters:  $\beta_{..}$ 

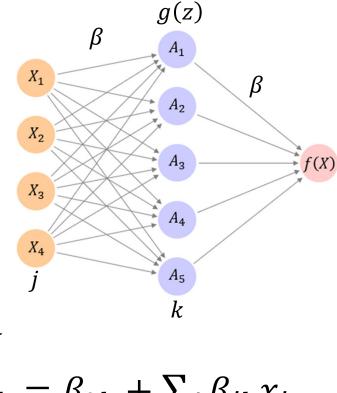
for each activation unit k in 1:K

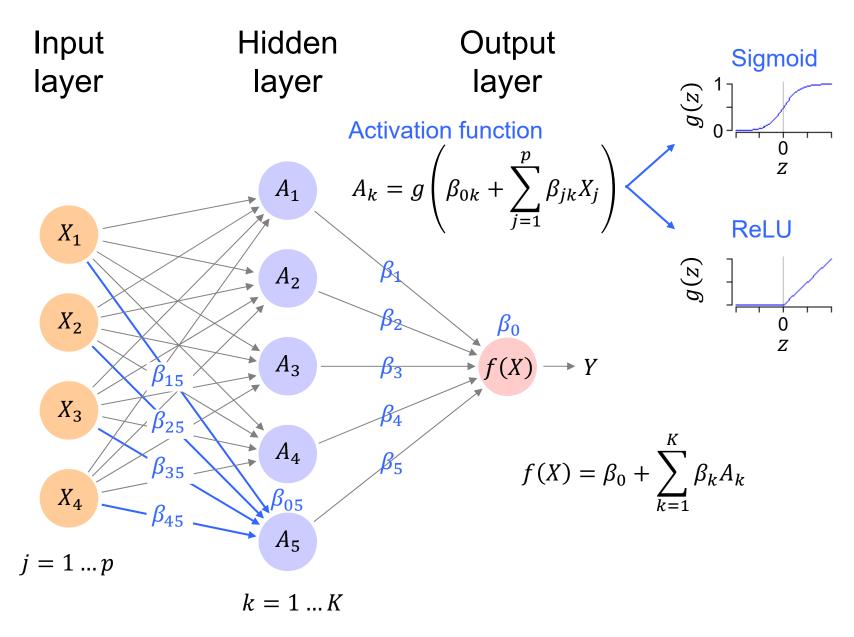
calculate linear predictor:  $z_k = \beta_{0k} + \sum_j \beta_{jk} x_j$ 

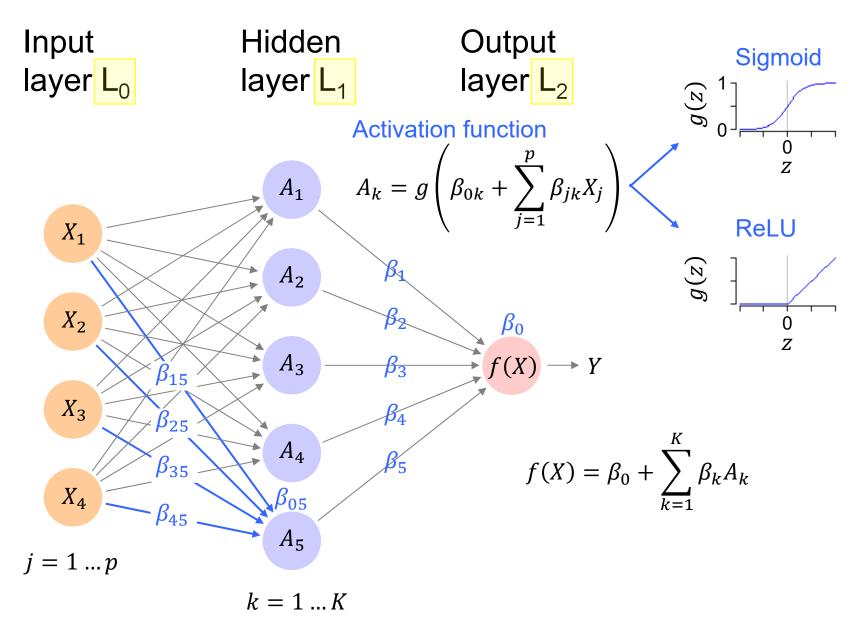
calculate nonlinear activation:  $A_k = g(z_k)$ 

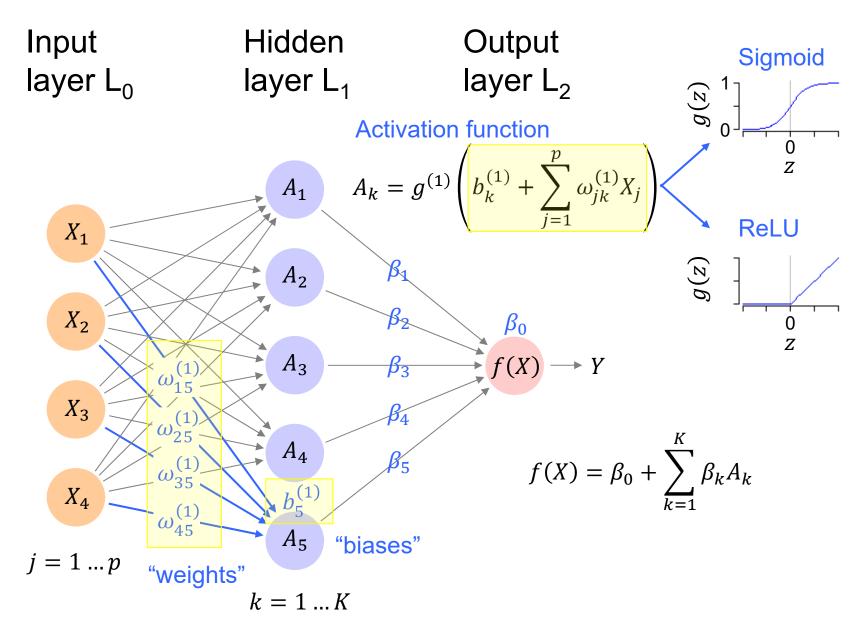
calculate linear model:  $f(x) = \beta_0 + \sum_k \beta_k A_k$ 

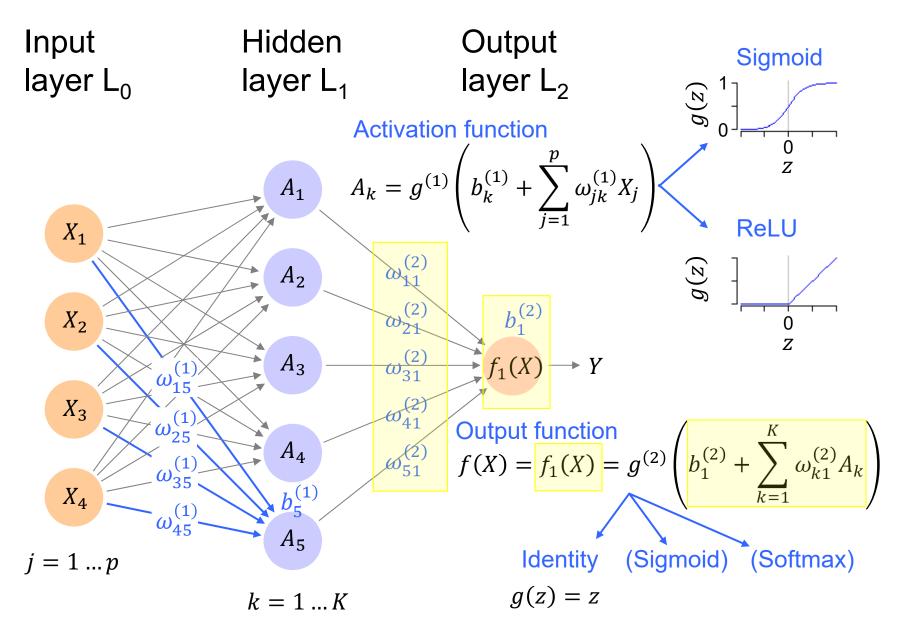
return f(x)

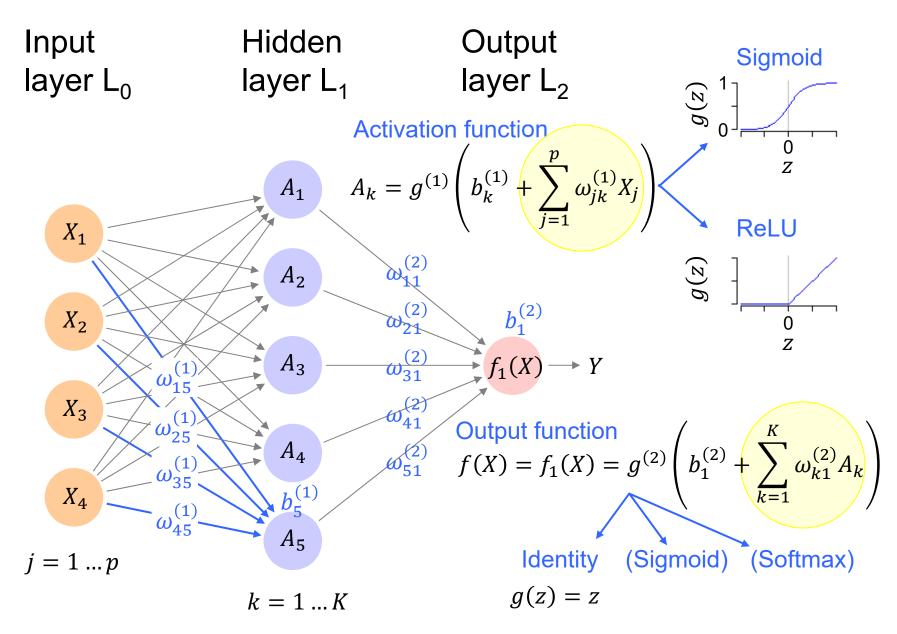


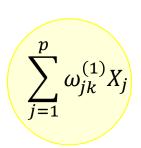






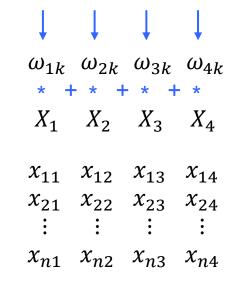






data rows i = 1...n

# multiply down columns then add across rows

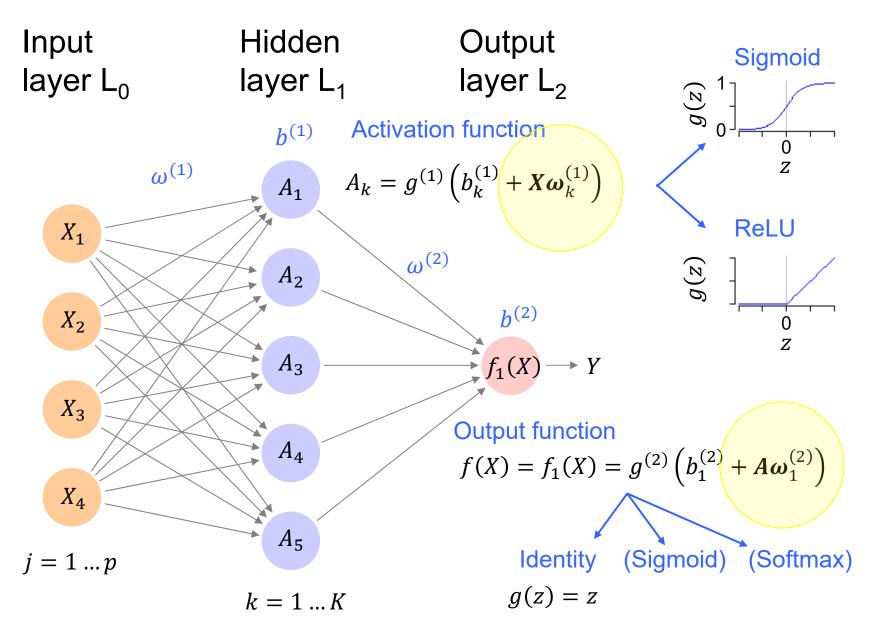


data columns j = 1...p

#### Matrix multiplication

$$X\omega_k$$

R: x % \* % w

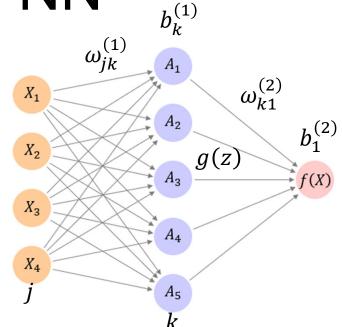


#### Model algorithm

define g(z)load and prepare  $x_j$ set Kset  $\omega_{jk}^{(1)}$ ,  $b_k^{(1)}$ ,  $\omega_{k1}^{(2)}$ ,  $b_1^{(2)}$ 

for each activation unit k in 1:K

calculate linear predictor:  $z_k = b_k^{(1)} + \boldsymbol{X}\boldsymbol{\omega}_k^{(1)}$  calculate nonlinear activation:  $A_k = g(z_k)$  calculate linear model:  $f(x) = b_1^{(2)} + \boldsymbol{A}\boldsymbol{\omega}_1^{(2)}$  return f(x)



#### Training algorithm

#### Loss function (MSE)

$$MSE(\theta) = \frac{1}{n} \sum_{i=1}^{n} (y_i - f_{\theta}(x_i))^2 \qquad \theta = \frac{\beta_1}{\beta_{10}} \beta_{11}$$

#### Training algorithm

```
Stochastic gradient descent guess \theta (typically random) set \lambda (learning rate) for iterations (e.g. until MSE(\theta) stops decreasing) randomly sample the data calculate gradient of MSE(\theta): \frac{\delta \text{MSE}(\theta)}{\delta \theta} Method: back propagation \theta \leftarrow \theta - \lambda \; \frac{\delta \text{MSE}(\theta)}{\delta \theta}
```

#### Training algorithm

```
Stochastic gradient descent (mini batch) guess \theta (typically random) set \lambda (learning rate) for many epochs randomly partition data into batches for each batch calculate gradient of \text{MSE}(\theta): \frac{\delta \text{MSE}(\theta)}{\delta \theta} \theta \leftarrow \theta - \lambda \; \frac{\delta \text{MSE}(\theta)}{\delta \theta}
```