

## AI Programming 복습 ③

## 지난목차

▶ Linear Algebra scalar vector matrix tensor

▶ Derivative

▶ Gradient Descent

▶ Back-propagation

▶ Gradient Descent of Loss Function

$\nabla_w \text{loss}$

$$\lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h}$$
 (공정 차이 / 임의 차이)

$$f(x) \rightarrow f(\vec{x})$$

$$\nabla f(\vec{x}) = \left[ \frac{\partial f}{\partial x_1}, \dots, \frac{\partial f}{\partial x_n} \right]^T$$

$$\vec{x} \leftarrow \vec{x} - \sigma \nabla f(\vec{x})$$

1

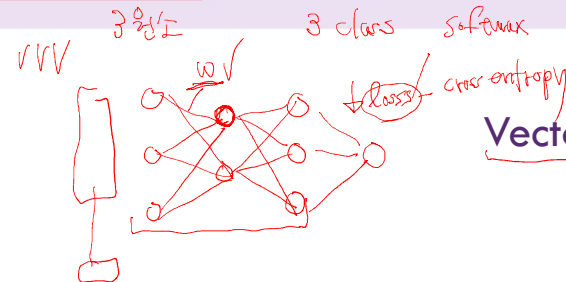
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## 목차

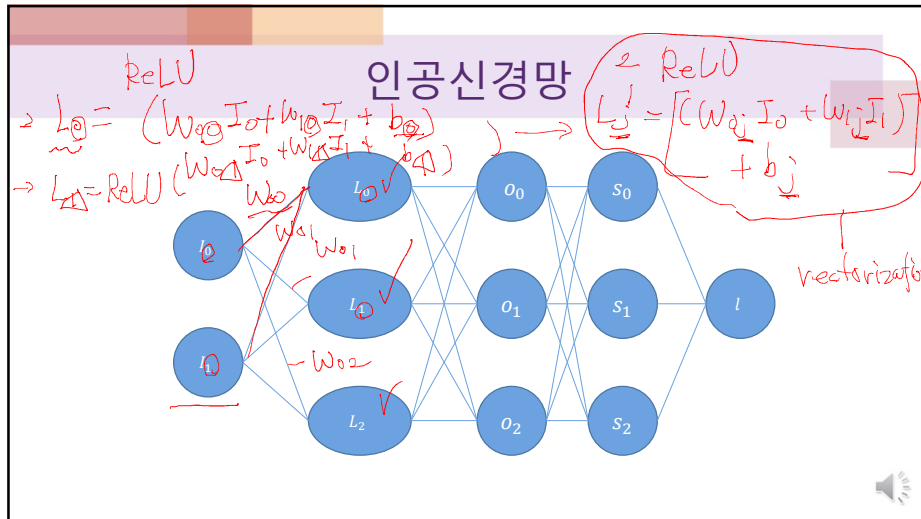
- ▶ Vectorization I
- ▶ Vectorization II
- ▶ Pytorch의 소개
- ▶ Class: 'torch.Tensor' 연산
- ▶ AUTOGRAD
- ▶ torch.nn
- ▶ PyTorch.nn의 응용 - model
- ▶ PyTorch.nn의 응용 - training

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## Vectorization I



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$$\begin{aligned}
 (A \cdot B)_j &= \sum_i^2 a_i b_{ij} & W^{(0)} &= \begin{bmatrix} w_{00} & w_{01} & w_{02} \\ w_{10} & w_{11} & w_{12} \\ w_{20} & w_{21} & w_{22} \end{bmatrix} &\longleftarrow (I \cdot W^{(0)})_j = \sum_{i=0}^2 I_i \cdot w_{ij}^{(0)} \\
 I &= \begin{bmatrix} I_0 \\ I_1 \\ I_2 \end{bmatrix} \\
 L_0 &= \text{ReLU}\left(\sum_{i=0}^2 w_{i0}^{(0)} \cdot I_i + B_0\right) & L_0 &= \sum_{i=0}^2 I_i \cdot w_{i0}^{(0)} \\
 L_1 &= \text{ReLU}\left(\sum_{i=0}^2 w_{i1}^{(0)} \cdot I_i + B_2\right) \longrightarrow L_1 = \sum_{i=0}^2 I_i \cdot w_{i1}^{(0)} \longrightarrow L_j = \sum_{i=0}^2 I_i \cdot w_{ij}^{(0)} \\
 L_2 &= \text{ReLU}\left(\sum_{i=0}^2 w_{i2}^{(0)} \cdot I_i + B_2\right) & L_2 &= \sum_{i=0}^2 I_i \cdot w_{i2}^{(0)}
 \end{aligned}$$

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$$\begin{aligned}
 W^{(0)} &= \begin{bmatrix} w_{00} & w_{01} & w_{02} \\ w_{10} & w_{11} & w_{12} \\ w_{20} & w_{21} & w_{22} \end{bmatrix} \\
 L &= [L_0 \quad L_1 \quad L_2] \\
 B &= [B_0 \quad B_1 \quad B_2]
 \end{aligned}$$

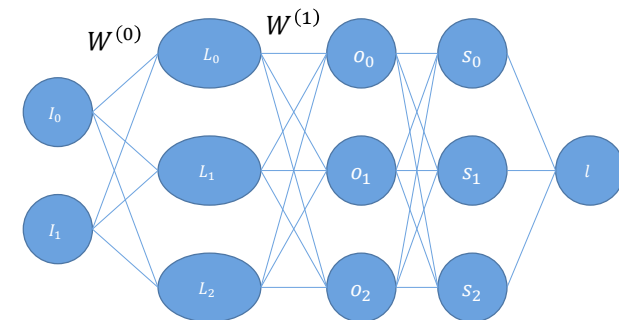
$$L_0 = \text{ReLU}\left(\sum_{i=0}^2 w_{i0}^{(0)} \cdot I_i + B_0\right)$$

$$L_1 = \text{ReLU}\left(\sum_{i=0}^2 w_{i1}^{(0)} \cdot I_i + B_1\right) \quad \longrightarrow \quad L = \text{ReLU}(I \cdot W^{(0)} + B)$$

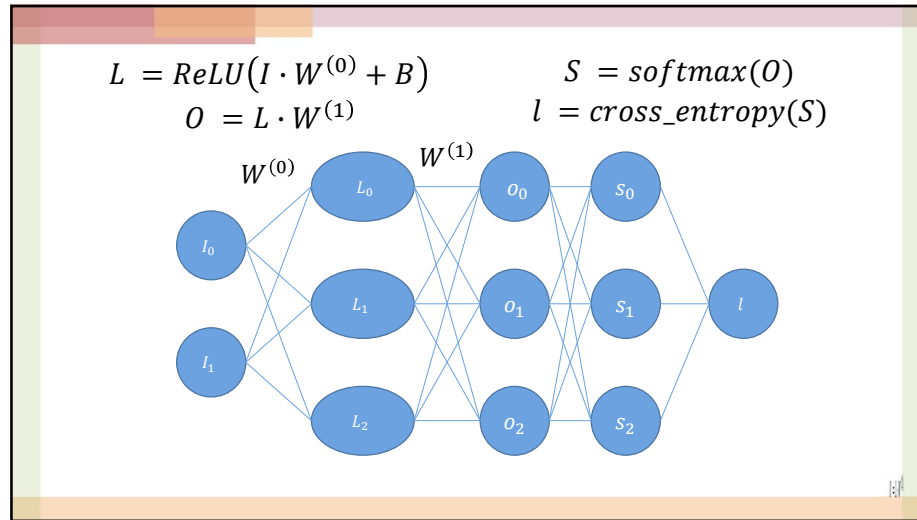
$$L_2 = \text{ReLU}\left(\sum_{i=0}^2 w_{i2}^{(0)} \cdot I_i + B_2\right)$$

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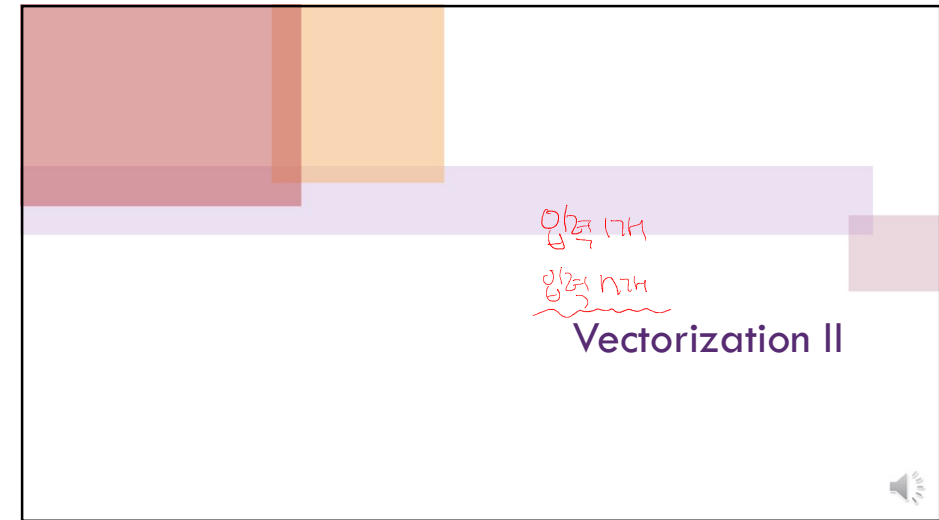
$$L = ReLU(I \cdot W^{(0)} + B) \quad O = L \cdot W^{(1)}$$



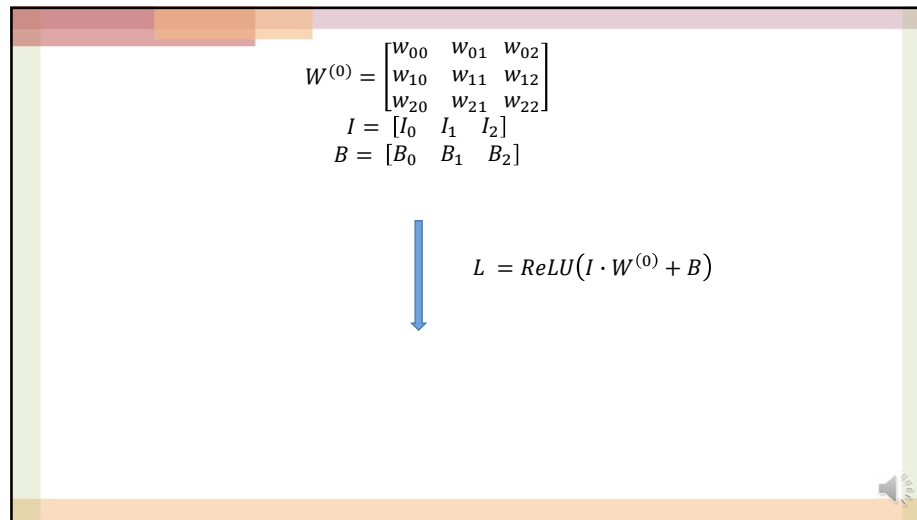
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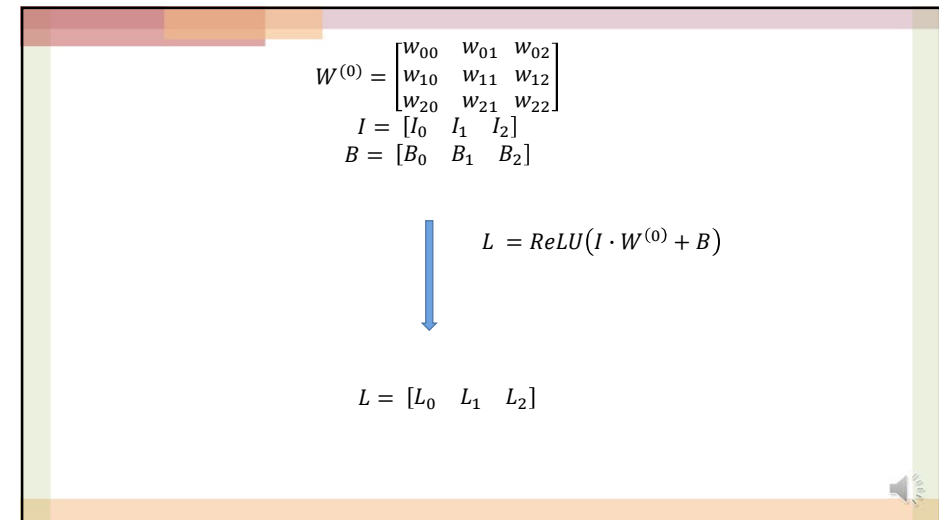
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$$W^{(0)} = \begin{bmatrix} w_{00} & w_{01} & w_{02} \\ w_{10} & w_{11} & w_{12} \\ w_{20} & w_{21} & w_{22} \end{bmatrix}$$

$$I = \begin{bmatrix} I_0 & I_1 & I_2 \end{bmatrix} \quad B = \begin{bmatrix} B_0 & B_1 & B_2 \end{bmatrix} \quad \rightarrow \quad I' = \begin{bmatrix} I_0 & I_1 & I_2 \\ I'_0 & I'_1 & I'_2 \end{bmatrix}$$

$$L = \text{ReLU}(I \cdot W^{(0)} + B)$$

$$W^{(0)} = \begin{bmatrix} w_{00} & w_{01} & w_{02} \\ w_{10} & w_{11} & w_{12} \\ w_{20} & w_{21} & w_{22} \end{bmatrix}$$

$$I = \begin{bmatrix} I_0 & I_1 & I_2 \end{bmatrix} \quad B = \begin{bmatrix} B_0 & B_1 & B_2 \end{bmatrix} \quad \rightarrow \quad I' = \begin{bmatrix} I_0 & I_1 & I_2 \\ I'_0 & I'_1 & I'_2 \end{bmatrix}$$

$$L = \text{ReLU}(I \cdot W^{(0)} + B)$$

$$L = \begin{bmatrix} L_0 & L_1 & L_2 \\ L'_0 & L'_1 & L'_2 \end{bmatrix}$$

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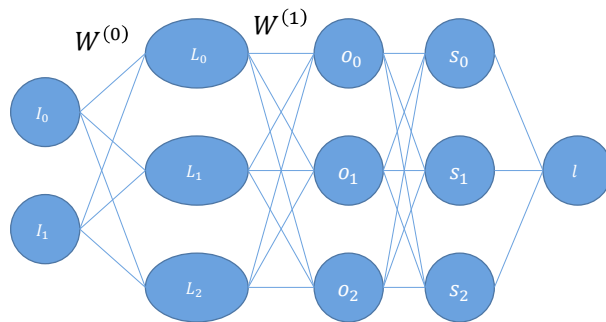
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$$L = \text{ReLU}(I \cdot W^{(0)} + B)$$

$$O = L \cdot W^{(1)}$$

$$S = \text{softmax}(O)$$

$$l = \text{cross\_entropy}(S)$$



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$$L = \text{ReLU}(I \cdot W^{(0)} + B)$$

$$O = L \cdot W^{(1)}$$

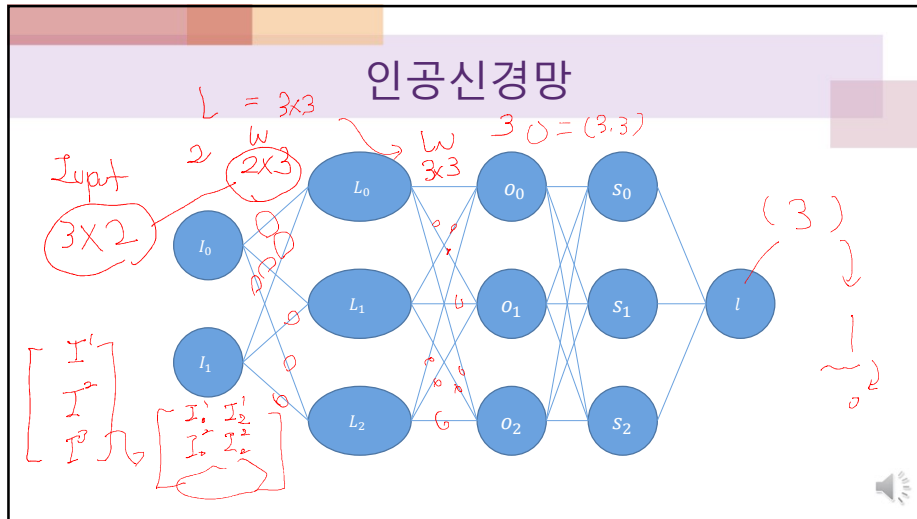
$$S = \text{softmax}(O)$$

$$l = \text{cross\_entropy}(S)$$

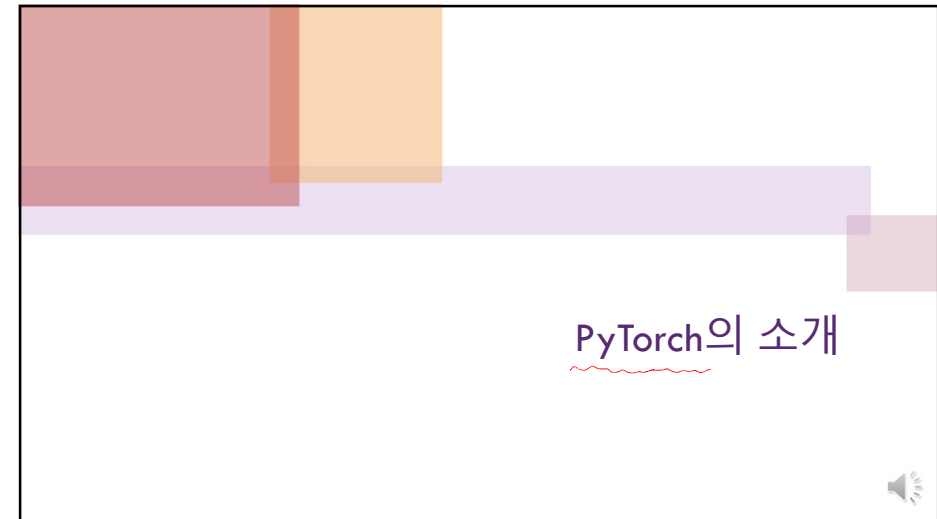
$$l = [l, l']$$

$$l_f = \frac{l + l'}{2}$$

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### PyTorch

PyTorch

- ▶ 프로그램 라이브러리
- ▶ Deep Learning 의 여러 계산을 편리하게 위한 라이브러리
- ▶ Feed-forward, Back propagation, etc.

```
import torch
```

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### PyTorch의 구성요소

- ▶ torch: Tensor를 생성하는 라이브러리
- ▶ torch.autograd: 자동 미분 기능을 제공
- ▶ torch.nn: 신경망 생성
- ▶ torch multiprocessing: 병렬처리

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## torch.Tensor

```
1 import torch
2
3 x = torch.empty(3)
4 print(x)
```

```
tensor([0.0000e+00, 4.6566e-10, 0.0000e+00])
```

- ▶ class → Tensor
- ▶ 객체
- ▶ Attribute 과 Methods



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## tensor: method() → size()

```
>>> x
tensor([[0.0944, 0.2820, 0.5201, 0.0791],
        [0.1943, 0.8991, 0.6799, 0.3343]])
>>> x.size()
torch.Size([2, 4])
```

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## tensor: view()

```
x = torch.randn(4, 5)
y = x.view(20)
z = x.view(5, -1)

print(x.size())
print(y.size())
print(z.size())
```

```
torch.Size([4, 5])
torch.Size([20])
torch.Size([5, 4])
```

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## tensor: indexing

```
>>> x
tensor([[0.0944, 0.2820, 0.5201, 0.0791],
        [0.1943, 0.8991, 0.6799, 0.3343]])
>>> x[0,0]
tensor(0.0944)
>>> x[1,1]
tensor(0.8991)
>>> x[0,0].item()
0.09443610906600952
```

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## tensor: indexing

```
>>> x[:,1]
tensor([0.2820, 0.8991])
>>> x[1,:]
tensor([0.1943, 0.8991, 0.6799, 0.3343])
>>> x[0:2]
tensor([[0.0944, 0.2820, 0.5201, 0.0791],
        [0.1943, 0.8991, 0.6799, 0.3343]])
>>> x[:,0:2]
tensor([[0.0944, 0.2820],
        [0.1943, 0.8991]])
```



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## Class: 'torch.Tensor' 연산



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## tensor + 숫자

```
>>> x
tensor([[0.0944, 0.2820, 0.5201, 0.0791],
        [0.1943, 0.8991, 0.6799, 0.3343]])
>>> x+1
tensor([[1.0944, 1.2820, 1.5201, 1.0791],
        [1.1943, 1.8991, 1.6799, 1.3343]])
>>> x*2
tensor([[0.1889, 0.5640, 1.0403, 0.1582],
        [0.3887, 1.7983, 1.3598, 0.6687]])
>>> x/2
tensor([[0.0472, 0.1410, 0.2601, 0.0396],
        [0.0972, 0.4496, 0.3400, 0.1672]])
```



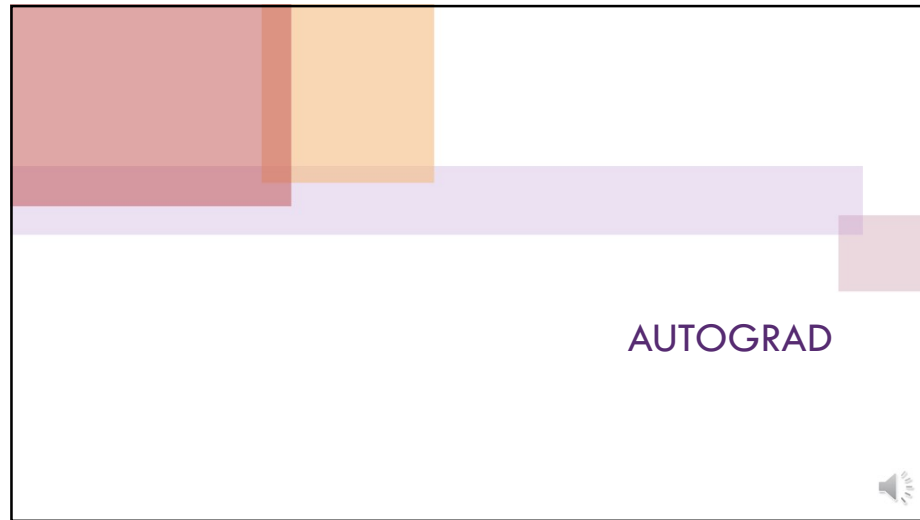
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## tensor + tensor

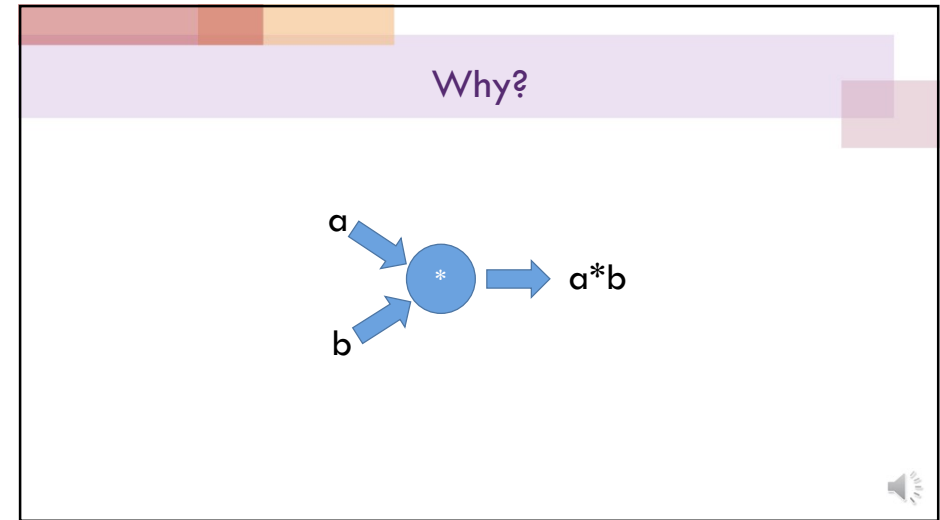
```
>>> x
tensor([[0.0944, 0.2820, 0.5201, 0.0791],
        [0.1943, 0.8991, 0.6799, 0.3343]])
>>> y
tensor([[ 0.8229, -0.4968, -0.6924, -0.2391],
        [ 0.5471,  0.7664, -0.1118, -0.8951]])
>>> x+y
tensor([[ 0.9174, -0.2148, -0.1722, -0.1600],
        [ 0.7414,  1.6655,  0.5681, -0.5607]])
>>> x*y
tensor([[ 0.0777, -0.1401, -0.3601, -0.0189],
        [ 0.1063,  0.6891, -0.0760, -0.2992]])
```



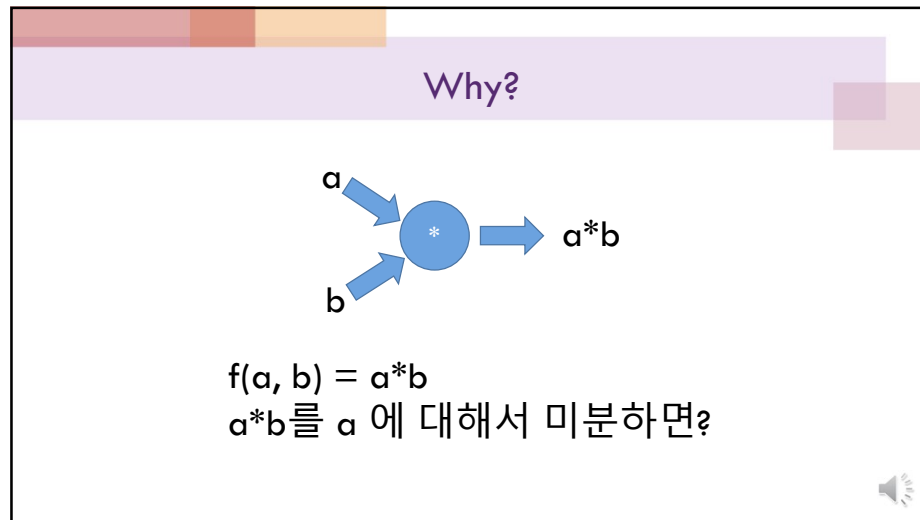
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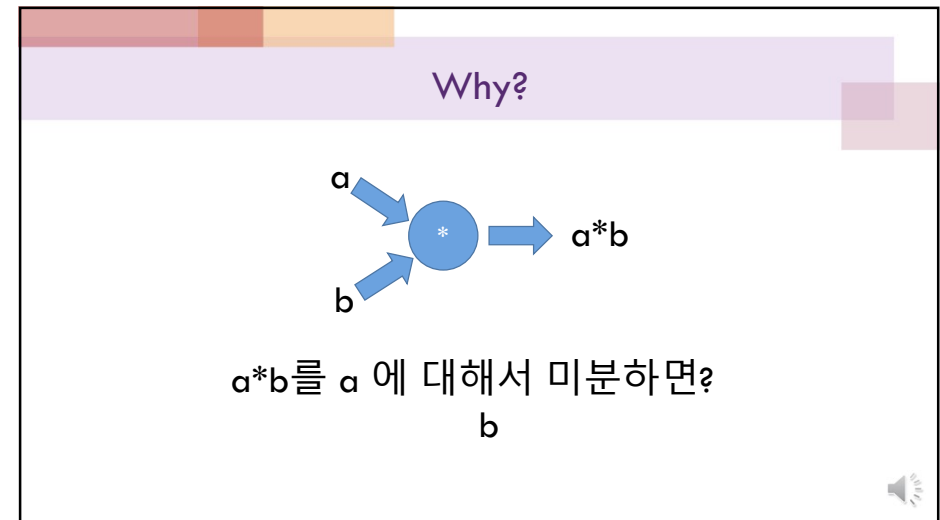
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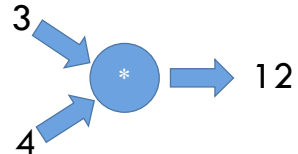
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Why?



12를 4에 대해서 미분하면?  
3

autograd

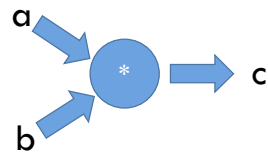
```

>>> a = torch.tensor(3, dtype=torch.float, requires_grad=True)
>>> a
tensor(3., requires_grad=True)
>>> b = torch.tensor(4, dtype=torch.float, requires_grad=True)
>>> c = a*b
>>> c.backward()
>>> a.grad
tensor(4.)
>>> b.grad
tensor(3.)
  
```

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Why?



$\frac{\partial c}{\partial a} \rightarrow a.grad$        $\frac{\partial c}{\partial b} \rightarrow b.grad$

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```

>>> a = torch.ones(3, requires_grad = True)
>>> b = a + 1
>>> c = b*b
>>> a.grad
2
>>> a.grad_fn
<AddBackward0 object at 0x000001EE4C8148C8>
>>> b.grad
2
>>> b.grad_fn
<MulBackward0 object at 0x000001EE4C803F08>
>>> c.grad
4
>>> c.grad_fn
<MulBackward0 object at 0x000001EE4C803F08>
>>> d = c.sum()
>>> d.backward()
4
>>> a.grad
4
>>> b.grad
8
  
```

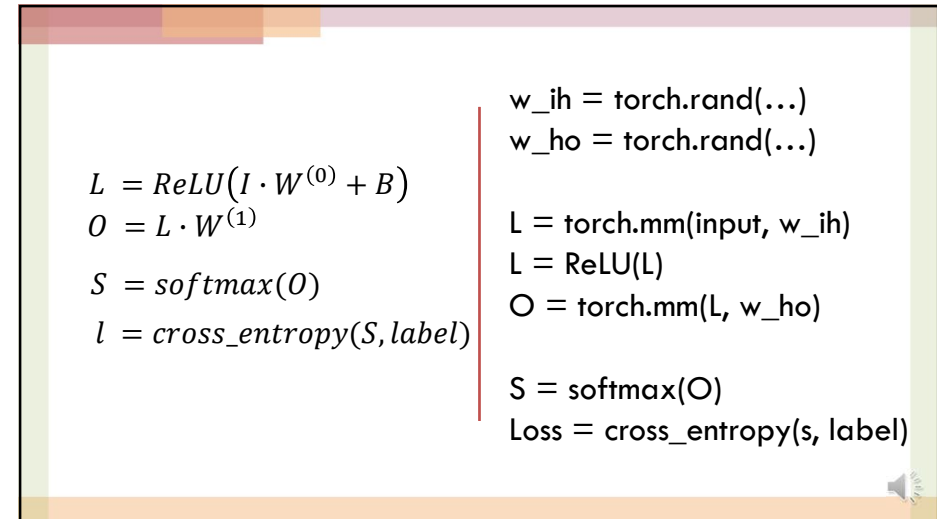
Handwritten notes on the right side of the slide:

- Diagram showing the flow of gradients:  $a \rightarrow b \rightarrow c \rightarrow d$ . Each node is circled, and arrows indicate the backward pass.
- Checkmarks next to the values:  $\checkmark (1, 1, 1)$ ,  $\checkmark (2, 2, 2)$ ,  $\checkmark (4, 4, 4)$ .
- Text: "loss" with an arrow pointing to the final value 4.
- Text:  $\checkmark d = 12 \rightarrow \text{scalar}$ .
- Text:  $\checkmark 4 \rightarrow 1.4$  (with a checkmark).

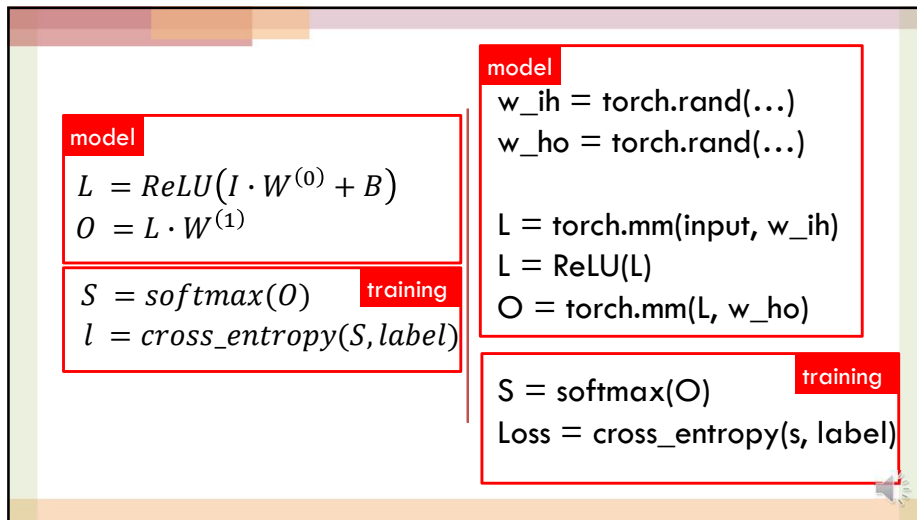
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## Pytorch의 구성요소

- ▶ torch: Tensor를 생성하는 라이브러리
- ▶ torch.autograd: 자동 미분 기능을 제공
- ▶ **torch.nn: 신경망 생성**
- ▶ torch.multiprocessing: 병렬처리



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## Pytorch

torch.nn

- ▶ CLASS 로 인공지능망의 모델 구현을 위한 라이브러리
- ▶ FC Layer, CNN, RNN, Transformers 등의 구조가 미리 입력



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## PyTorch.nn의 응용 – model



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model

$$L = \text{ReLU}(I \cdot W^{(0)} + B)$$

$$O = L \cdot W^{(1)}$$

model

MODULE

CLASS torch.nn.Module [SOURCE]

Base class for all neural network modules.

Your models should also subclass this class.

```
class Model(nn.Module):
    def __init__(self):
        super(Model, self).__init__()

    def forward(self, x):
        return x
```



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**model**

## MODULE

CLASS torch.nn.Module [SOURCE]

Base class for all neural network modules.  
Your models should also subclass this class.

`train(mode=True)` [SOURCE]

Sets the module in training mode.

`eval()` [SOURCE]

Sets the module in evaluation mode.

`cpu()` [SOURCE]

Moves all model parameters and buffers to the CPU.

`cuda(device=None)` [SOURCE]

Moves all model parameters and buffers to the ~~CPU~~ GPU.

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**model**

`w_ih = torch.rand(784,100)`  
`w_ho = torch.rand(100,10)`

**model**

## LINEAR

CLASS torch.nn.Linear(in\_features, out\_features, bias=True, device=None, dtype=None) [SOURCE]

Applies a linear transformation to the incoming data:  $y = xA^T + b$

```
class Model(nn.Module):
    def __init__(self):
        super(Model, self).__init__()
        self.fc1 = nn.Linear(784, 100)
        self.fc2 = nn.Linear(100, 10)
        self.relu = nn.ReLU()

    def forward(self, x):
        x = self.fc1(x)
        x = self.relu(x)
        x = self.fc2(x)
        return x
```

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**model**

`w_ih = torch.rand(784,100)`  
`w_ho = torch.rand(100,10)`

**model**

## LINEAR

CLASS torch.nn.Linear(in\_features, out\_features, bias=True, device=None, dtype=None) [SOURCE]

Applies a linear transformation to the incoming data:  $y = xA^T + b$

```
class Model(nn.Module):
    def __init__(self):
        super(Model, self).__init__()
        self.fc1 = nn.Linear(784, 100)
        self.fc2 = nn.Linear(100, 10)
        self.relu = nn.ReLU()

    def forward(self, x):
        x = self.fc1(x)
        x = self.relu(x)
        x = self.fc2(x)
        return x
```

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**model**

`L = torch.mm(input, w_ih)`  
`L = ReLU(L)`  
`O = torch.mm(L, w_ho)`

**model**

## RELU

CLASS torch.nn.ReLU(inplace=False) [SOURCE]

Applies the rectified linear unit function element-wise:  
 $\text{ReLU}(x) = (x)^+ = \max(0, x)$

```
class Model(nn.Module):
    def __init__(self):
        super(Model, self).__init__()
        self.fc1 = nn.Linear(784, 100)
        self.fc2 = nn.Linear(100, 10)
        self.relu = nn.ReLU()

    def forward(self, x):
        x = self.fc1(x)
        x = self.relu(x)
        x = self.fc2(x)
        return x
```

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## PyTorch.nn의 응용 - training

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training

```
S = softmax(O)
Loss = cross_entropy(s, label)
```

```
cls_loss = nn.CrossEntropyLoss()
loss = cls_loss(outputs, label)
```

training

### CROSSENTROPYLOSS

```
CLASS torch.nn.CrossEntropyLoss(weight=None, size_average=None,
    ignore_index=-100, reduce=None, reduction='mean',
    label_smoothing=0.0) [SOURCE]
```

This criterion computes the cross entropy loss between input and target.

!! 주의 !!  
softmax + cross\_entropy  
+ one\_hot

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training

```
loss.backward()
```

$$W = W - lr * W.grad$$

training

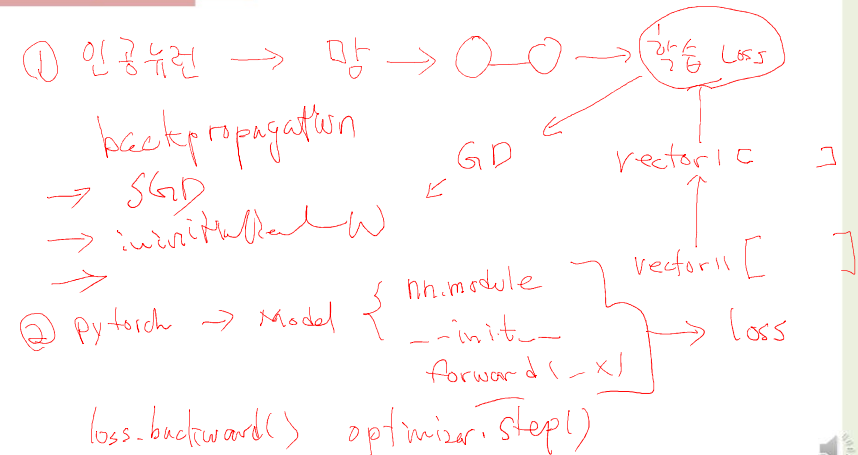
```
CLASS torch.optim.Optimizer(params, defaults) [SOURCE]
```

Base class for all optimizers.

```
learning_rate = 0.01
optimizer = optim.SGD(network.parameters(), lr=learning_rate)

optimizer.zero_grad()
loss.backward()
optimizer.step()
```

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## 목차

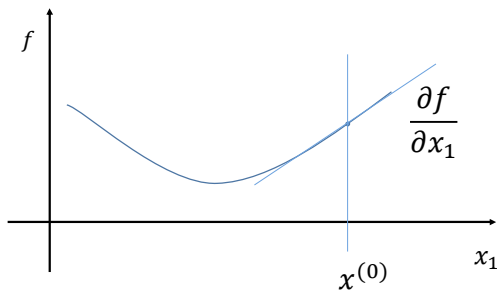
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## Gradient Descent & Vectorization II

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## Gradient Descent



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## Gradient Descent

$$f(X)$$

$f(X)$ 의 값을 줄이기 위한  $X$ 의 방향은?

$$X \leftarrow X - \eta \nabla_X f$$

$$X = [x_1, x_2, x_3, x_4]$$

$$\nabla X = \left[ \frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \frac{\partial f}{\partial x_3}, \frac{\partial f}{\partial x_4} \right]$$

$$x_1 \leftarrow x_1 - \eta \frac{\partial f}{\partial x_1}$$

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## Gradient Descent

$$loss(x; W)$$

$loss$ 의 값을 줄이기 위한  $W$ 의 방향은?

$$W \leftarrow W - \eta \nabla_W loss$$

$$W = [w_{11}^{(0)}, w_{12}^{(0)}, \dots, w_{nm}^{(l)}]$$

$$w_{11}^{(0)} \leftarrow w_{11}^{(0)} - \eta \frac{\partial f}{\partial w_{11}^{(0)}}$$

$$x?$$

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## Gradient Descent

$$loss(x; W)$$

$loss$ 의 값을 줄이기 위한  $W$ 의 방향은?

$$W \leftarrow W - \eta \nabla_W loss$$

$$W = [w_{11}^{(0)}, w_{12}^{(0)}, \dots, w_{nm}^{(l)}]$$

$$w_{11}^{(0)} \leftarrow w_{11}^{(0)} - \eta \frac{\partial f}{\partial w_{11}^{(0)}}$$

$$x \leftarrow x_1, x_2, \dots, x_m$$

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## Stochastic Gradient Descent

## Gradient Descent

$$loss(x; W)$$

$loss$ 의 값을 줄이기 위한  $W$ 의 방향은?

$$W \leftarrow W - \eta \nabla_W W$$

$$W = [w_{11}^{(0)}, w_{12}^{(0)}, \dots, w_{nm}^{(l)}]$$

$$w_{11}^{(0)} \leftarrow w_{11}^{(0)} - \eta \frac{\partial f}{\partial w_{11}^{(0)}}$$

$$x \leftarrow x_1, x_2, \dots, x_m$$

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## Gradient Descent

$$\text{loss}(x; W)$$

$$x \leftarrow x_1, x_2, \dots, x_{100}$$

loss 계산 후

$$w_{11}^{(0)} \leftarrow w_{11}^{(0)} - \eta \frac{\partial f}{\partial w_{11}^{(0)}}$$

$$x \leftarrow x_{101}, x_{102}, \dots, x_{200}$$

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## Gradient Descent

$$\text{loss}(x; W)$$

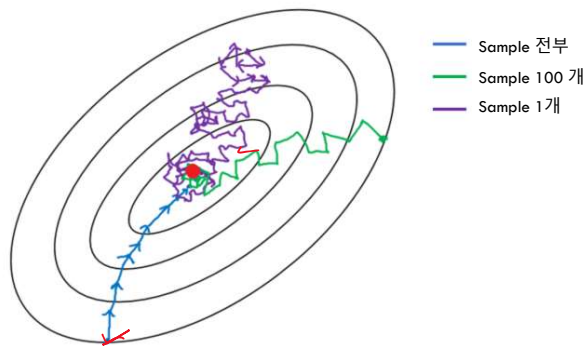
$$x \leftarrow x_{101}, x_{102}, \dots, x_{200}$$

loss 계산 후

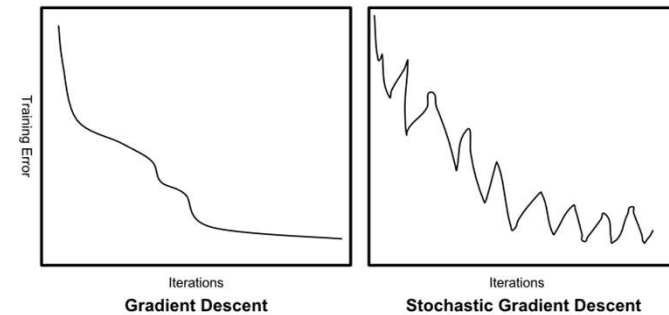
$$w_{11}^{(0)} \leftarrow w_{11}^{(0)} - \eta \frac{\partial f}{\partial w_{11}^{(0)}}$$

$x \leftarrow x_{201}, x_{202}, \dots, x_{300}$

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