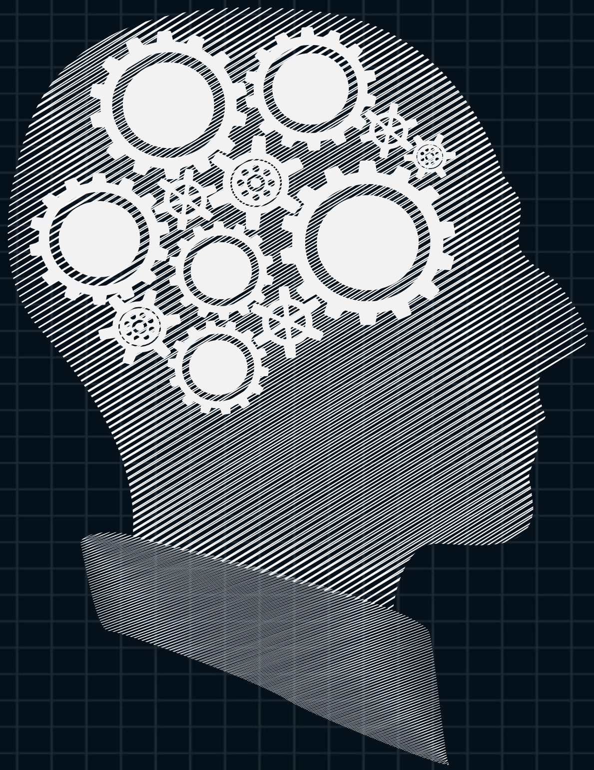


Backpropagation and Jacobian Matrices

Lecture.1
Why Backpropagation and Jacobians?

Lecture.1
Why Backpropagation
and Jacobians?

- Trainable Models and Params

Artificial Neurons

$$\hat{y} = xw + b$$

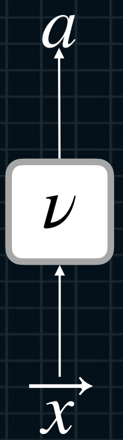
$$\hat{y} = \vec{x}^T \cdot \vec{w} + b$$

x가 n개라면,
w도 n개
b = 1

$$\hat{y} = g\left(\vec{x}^T \cdot \vec{w} + b\right)$$

sigmoid...

w : n
b : 1



$$\nu\left(\vec{x}; \vec{w}, b\right) = g\left((\vec{x})^T \vec{w} + b\right)$$

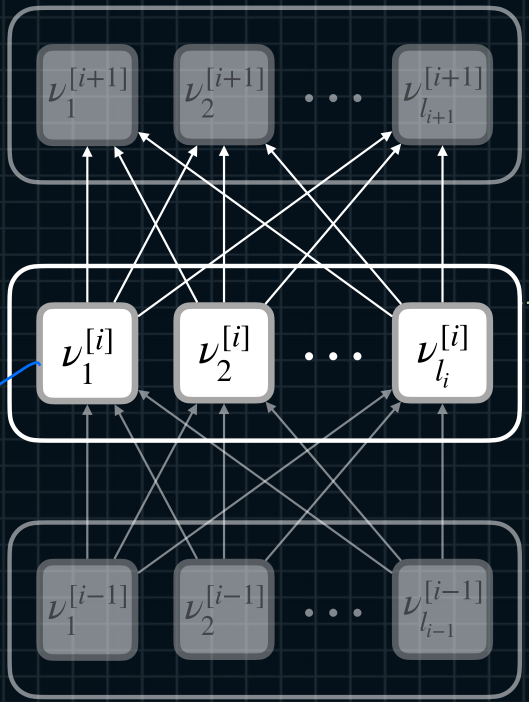
$$\vec{w} \in \mathbb{R}^{l_I \times 1}$$

$$b \in \mathbb{R}$$

Lecture.1
Why Backpropagation
and Jacobians?

- Trainable Models and Params

Dense Layers



각각 neuron들이

l_i개의 weight

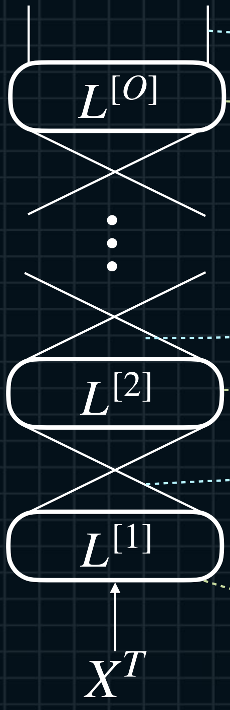
$$W^{[i]} = \begin{pmatrix} \uparrow & \uparrow & & \uparrow \\ \vec{w}_1^{[i]} & \vec{w}_2^{[i]} & \cdots & \vec{w}_{l_i}^{[i]} \\ \downarrow & \downarrow & & \downarrow \end{pmatrix} \in \mathbb{R}^{l_{i-1} \times l_i}$$

$$(\vec{b}^{[i]})^T = \begin{pmatrix} b_1^{[i]} & b_2^{[i]} & \ldots & b_{l_i}^{[i]} \end{pmatrix} \in \mathbb{R}^{1 \times l_i}$$

Lecture.1
Why Backpropagation
and Jacobians?

- Trainable Models and Params

Dense Layers



학습해야되는 변수의 수가 기하급수적으로 늘어남

$$W^{[O]} = \begin{pmatrix} \uparrow & \uparrow & & \uparrow \\ \vec{w}_1^{[O]} & \vec{w}_2^{[O]} & \cdots & \vec{w}_{l_O}^{[O]} \\ \downarrow & \downarrow & & \downarrow \end{pmatrix} \in \mathbb{R}^{l_{O-1} \times l_O}$$

$$(\vec{b}^{[O]})^T = \begin{pmatrix} b_1^{[O]} & b_2^{[O]} & \ldots & b_{l_O}^{[O]} \end{pmatrix} \in \mathbb{R}^{1 \times l_O}$$

$$\underset{\mathbb{R}^{N \times l_O}}{(A^{[O]})^T} = \underset{\mathbb{R}^{N \times l_{O-1}}}{(A^{[O-1]})^T}\underset{\mathbb{R}^{l_{O-1} \times l_O}}{W^{[O]}} + \underset{\mathbb{R}^{1 \times l_O}}{(\vec{b}^{[O]})^T}$$

$$W^{[2]} = \begin{pmatrix} \uparrow & \uparrow & & \uparrow \\ \vec{w}_1^{[2]} & \vec{w}_2^{[2]} & \cdots & \vec{w}_{l_2}^{[2]} \\ \downarrow & \downarrow & & \downarrow \end{pmatrix} \in \mathbb{R}^{l_1 \times l_2}$$

$$(\vec{b}^{[2]})^T = \begin{pmatrix} b_1^{[2]} & b_2^{[2]} & \ldots & b_{l_2}^{[2]} \end{pmatrix} \in \mathbb{R}^{1 \times l_2}$$

$$\underset{\mathbb{R}^{N \times l_2}}{(A^{[2]})^T} = \underset{\mathbb{R}^{N \times l_1}}{(A^{[1]})^T}\underset{\mathbb{R}^{l_1 \times l_2}}{W^{[2]}} + \underset{\mathbb{R}^{1 \times l_2}}{(\vec{b}^{[2]})^T}$$

$$\underset{\mathbb{R}^{N \times l_1}}{(A^{[1]})^T} = \underset{\mathbb{R}^{N \times l_I}}{X^T}\underset{\mathbb{R}^{l_I \times l_1}}{W^{[1]}} + \underset{\mathbb{R}^{1 \times l_1}}{(\vec{b}^{[1]})^T}$$

$$W^{[1]} = \begin{pmatrix} \uparrow & \uparrow & & \uparrow \\ \vec{w}_1^{[1]} & \vec{w}_2^{[1]} & \cdots & \vec{w}_{l_1}^{[1]} \\ \downarrow & \downarrow & & \downarrow \end{pmatrix} \in \mathbb{R}^{l_I \times l_1}$$

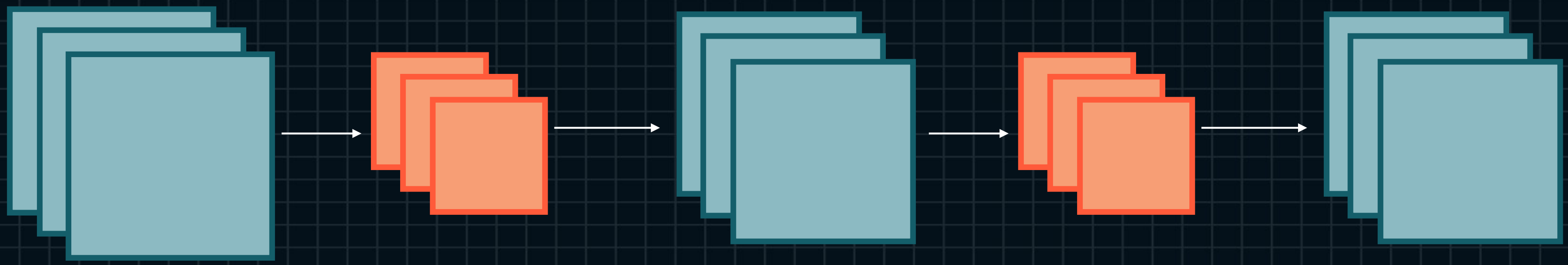
$$(\vec{b}^{[1]})^T = \begin{pmatrix} b_1^{[1]} & b_2^{[1]} & \ldots & b_{l_1}^{[1]} \end{pmatrix} \in \mathbb{R}^{1 \times l_1}$$

각 Layer마다 W와 b가 존재

Lecture.1
Why Backpropagation
and Jacobians?

- Trainable Models and Params

Conv Layers



$X \in \mathbb{R}^{n_H^{[I]} \times n_W^{[I]} \times l_I}$

$\mathscr{K}^{[1]} \in \mathbb{R}^{f^{[1]} \times f^{[1]} \times l_I \times l_1}$
$\vec{b}^{[1]} \in \mathbb{R}^{l_1}$

$A^{[1]} \in \mathbb{R}^{n_H^{[1]} \times n_W^{[1]} \times l_1}$

$\mathscr{K}^{[2]} \in \mathbb{R}^{f^{[2]} \times f^{[2]} \times l_1 \times l_2}$
$\vec{b}^{[2]} \in \mathbb{R}^{l_2}$

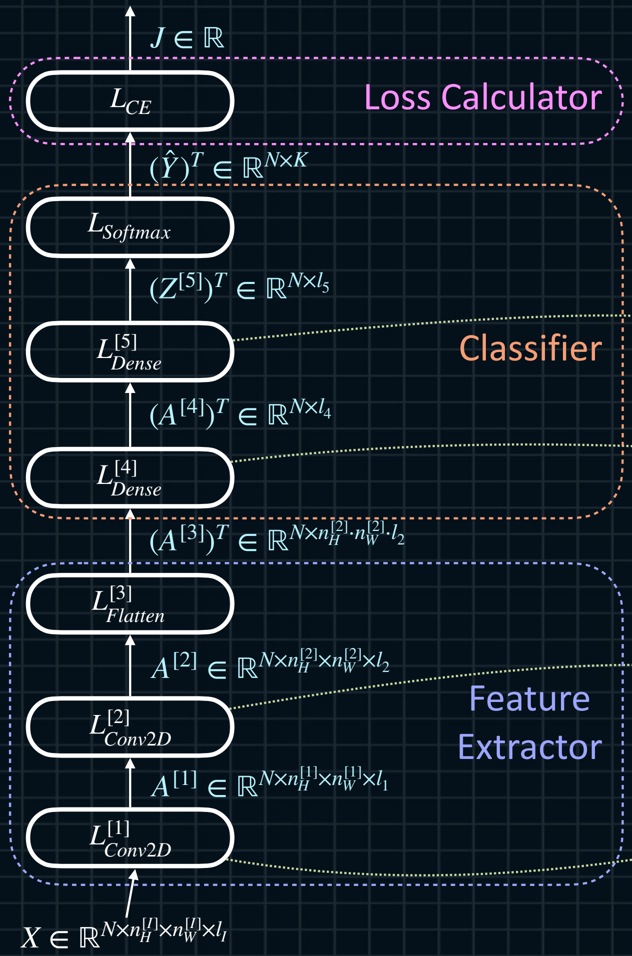
$A^{[2]} \in \mathbb{R}^{n_H^{[2]} \times n_W^{[2]} \times l_2}$

Output size filter 형상이 따라
Kernel (Tensor)의 형태 또는 bias vec. 결정

Lecture.1
Why Backpropagation
and Jacobians?

- Trainable Models and Params

CNNs



파라미터들 [illegible] 형태가
Matrix | vector | 고차원의 Tensor

$W^{[5]} \in \mathbb{R}^{l_4\times l_5}$

$\vec{b}^{[5]} \in \mathbb{R}^{l_5}$

$W^{[4]} \in \mathbb{R}^{n_H^{[2]}\cdot n_W^{[2]}\cdot l_2\times l_4}$

$\vec{b}^{[4]} \in \mathbb{R}^{l_4}$

$\mathcal{K}^{[2]} \in \mathbb{R}^{f^{[2]}\times f^{[2]}\times l_1\times l_2}$

$\vec{b}^{[2]} \in \mathbb{R}^{l_2}$

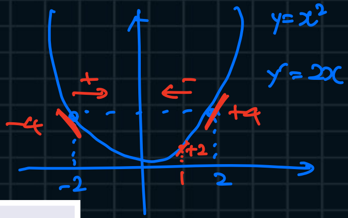
$\mathcal{K}^{[1]} \in \mathbb{R}^{f^{[1]}\times f^{[1]}\times l_I\times l_1}$

$\vec{b}^{[1]} \in \mathbb{R}^{l_1}$

Lecture.1
Why Backpropagation and Jacobians?

- Gradient-based Learning

Differential Coefficient in DL



$y = x^2$

$y' = 2x$

부호/크기

$y'|_{x=2} = +4$

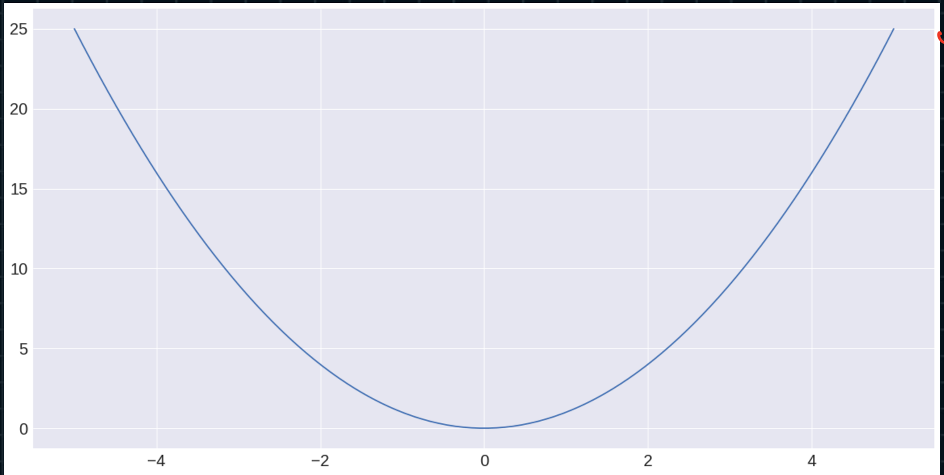
$y'|_{x=-2} = -4$

y 값을 낮추려면?

y'(미분계수) 부호의 역순으로 진행

x값이 움직여야 하는 방향

움직여야 하는 방향 $= -\frac{dy}{dx}$



$$y' = 2x$$
$$y'|_{x=2} = 2 \cdot 2 = +4$$
$$y'|_{x=-2} = 2 \cdot (-2) = -4$$

$$y' = 2x$$
$$y'|_{x=1} = 2 \cdot 1 = +2$$
$$y'|_{x=2} = 2 \cdot 2 = +4$$

- Gradient-based Learning

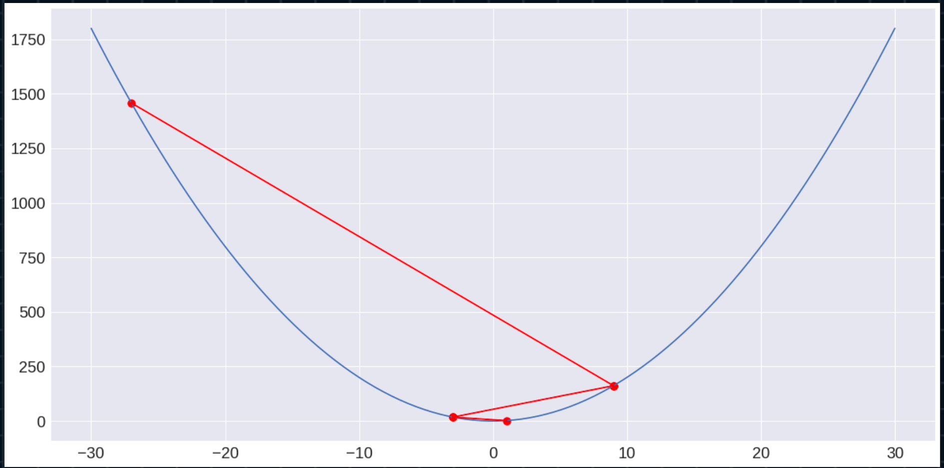
Update Notation

$$\underbrace{x :=}_{\text{update}} x + a$$

update e.g $x = x+2$

- Gradient-based Learning

Effectiveness of Gradients



프로그래밍 상의 문제!?

$$x := x - \underline{f'(x)} = -\frac{dy}{dx}$$
$$= x - 4x$$
$$= -3x$$

$$x := -3 \cdot 1 = -3$$
$$x := -3 \cdot (-3) = 9$$ → 오히려 반복할수록 멀어짐
$$x := -3 \cdot 9 = -27$$

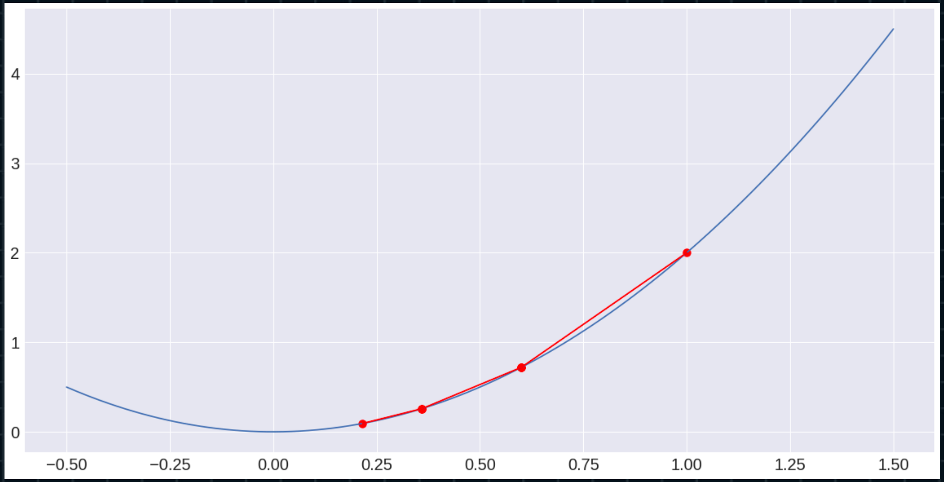
Lecture.1
Why Backpropagation
and Jacobians?

- Gradient-based Learning

ex) like. 미분계수

위 상태에서의 한계극복!

Learning Rate and Gradient-based Learning



$$x := x - \alpha f'(x)$$

└> 미분계수를 조절해주는 역할 (supressed)

$$x := x - 0.1 \cdot f'(x)$$
$$= x - 0.4x$$
$$= 0.6x$$

α = 하이퍼 파라미터 (사람이 조정)

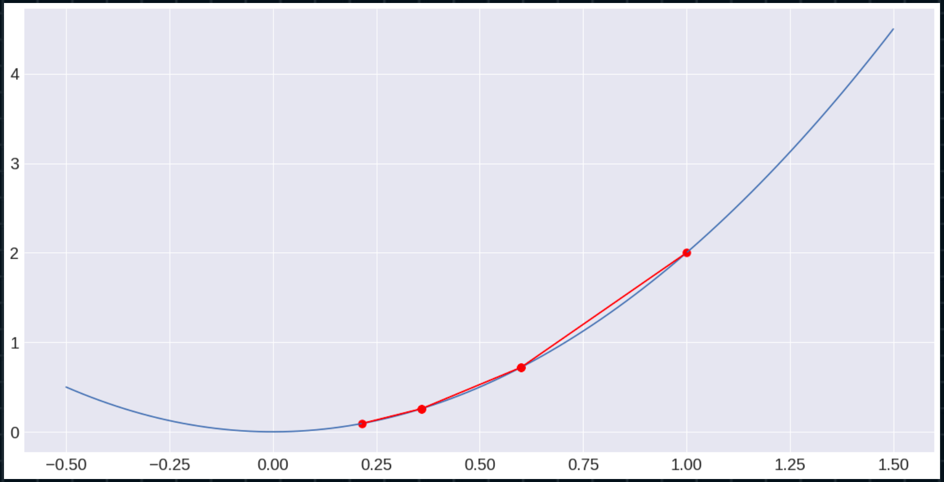
$$x := 0.6x$$

$$x := 0.6 \cdot 1 = 0.6$$
$$x := 0.6 \cdot 0.6 = 0.36$$
$$x := 0.6 \cdot 0.36 = 0.216$$

값이 작아지는 형태

- Gradient-based Learning

Descending Without a Map



실제 DL에서는 $y=x^2$와 같은
함수 형상은 알 수 X

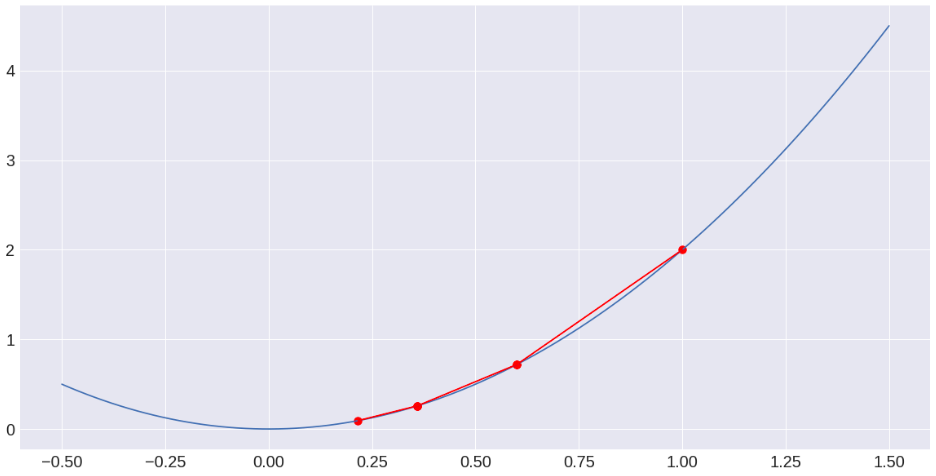
$$x := x - \alpha f'(x)$$

미분을 하는 이유?

- 함수값을 최소로 하는 x값을 찾기 위함
- 미분계수의 반대 방향으로 진행 필요

- Gradient-based Learning

Target of Gradient



왜 함수 값을 줄여야 하는가?

→ Loss ↓

MSE (Mean Squ—)
BCEE (Binary Cross —)
CCEE (Categorical —)

$$J = \mathscr{L}(y, \hat{y}) = \frac{\partial J}{\partial x}$$

Loss

$$x := x - \alpha \mathscr{L}'(x)$$

Loss를 줄이기 위해 x 값을 어떻게 조정해야 하는가?

- Backpropagation

각층의 w, b 를 조정해서
J(loss)가 최소로 되는 값 찾음

Chain Rule

큰 합성함수 형태

$$y = f_4(f_3(f_2(f_1(x))))$$

각각 합성함수 형태

Forward

Backward

$$y = f_4(u_3) \qquad \frac{\partial y}{\partial u_3}$$

각 단계별 편미분

∂y → 출력

∂u_3 → 입력

$$u_3 = f_3(u_2) \qquad \frac{\partial u_3}{\partial u_2} \qquad \frac{\partial y}{\cancel{\partial u_3}} \frac{\cancel{\partial u_3}}{\partial u_2} = \frac{\partial y}{\partial u_2}$$

실제 미분값이 복잡해지는 대신
이전 값이 처리 가능

$$u_2 = f_2(u_1) \qquad \frac{\partial u_2}{\partial u_1} \qquad \frac{\partial y}{\cancel{\partial u_2}} \frac{\cancel{\partial u_2}}{\partial u_1} = \frac{\partial y}{\partial u_1}$$

$$u_1 = f_1(x) \qquad \frac{\partial u_1}{\partial x} \qquad \frac{\partial y}{\cancel{\partial u_1}} \frac{\cancel{\partial u_1}}{\partial x} = \frac{\partial y}{\partial x}$$

- Backpropagation

Chain Rule

$$y = f_4(f_3(f_2(f_1(x))))$$

$$y = f_4(u_3)$$

$$u_3 = f_3(u_2)$$

$$u_2 = f_2(u_1)$$

$$u_1 = f_1(x)$$

$$\frac{\partial y}{\partial x}$$

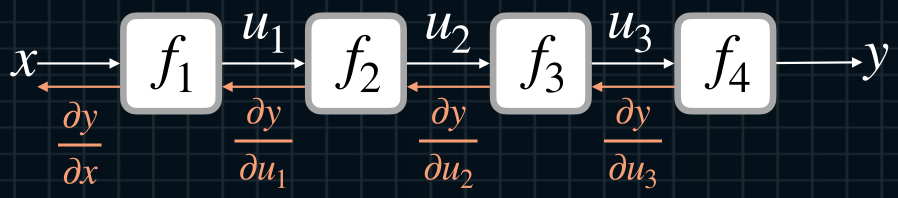
$$\frac{\partial y}{\partial u_1}$$

$$\frac{\partial y}{\partial u_2}$$

Forward Backward

- Backpropagation

Chain Rule



해당 값이 주어져야만

이 값을 구할 수 있음

의존적!

backward

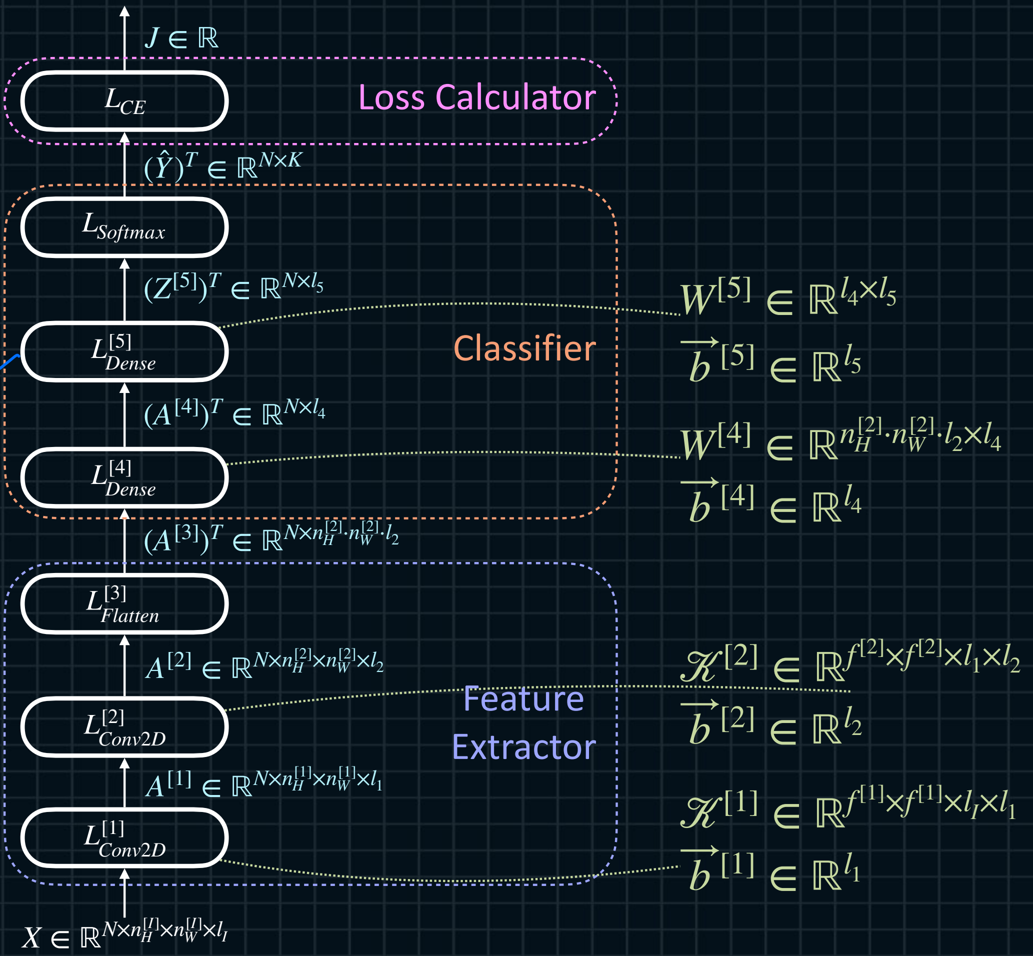
- Backpropagation

Chain Rule in Deep Learning

$$\frac{\partial J}{\partial \hat{y}} \qquad \frac{\partial \hat{y}}{\partial z^{[5]}}$$

$$Z^{[5]} = A^{[4]} \cdot W^{[5]} + (\vec{b}^{[5]})^T$$

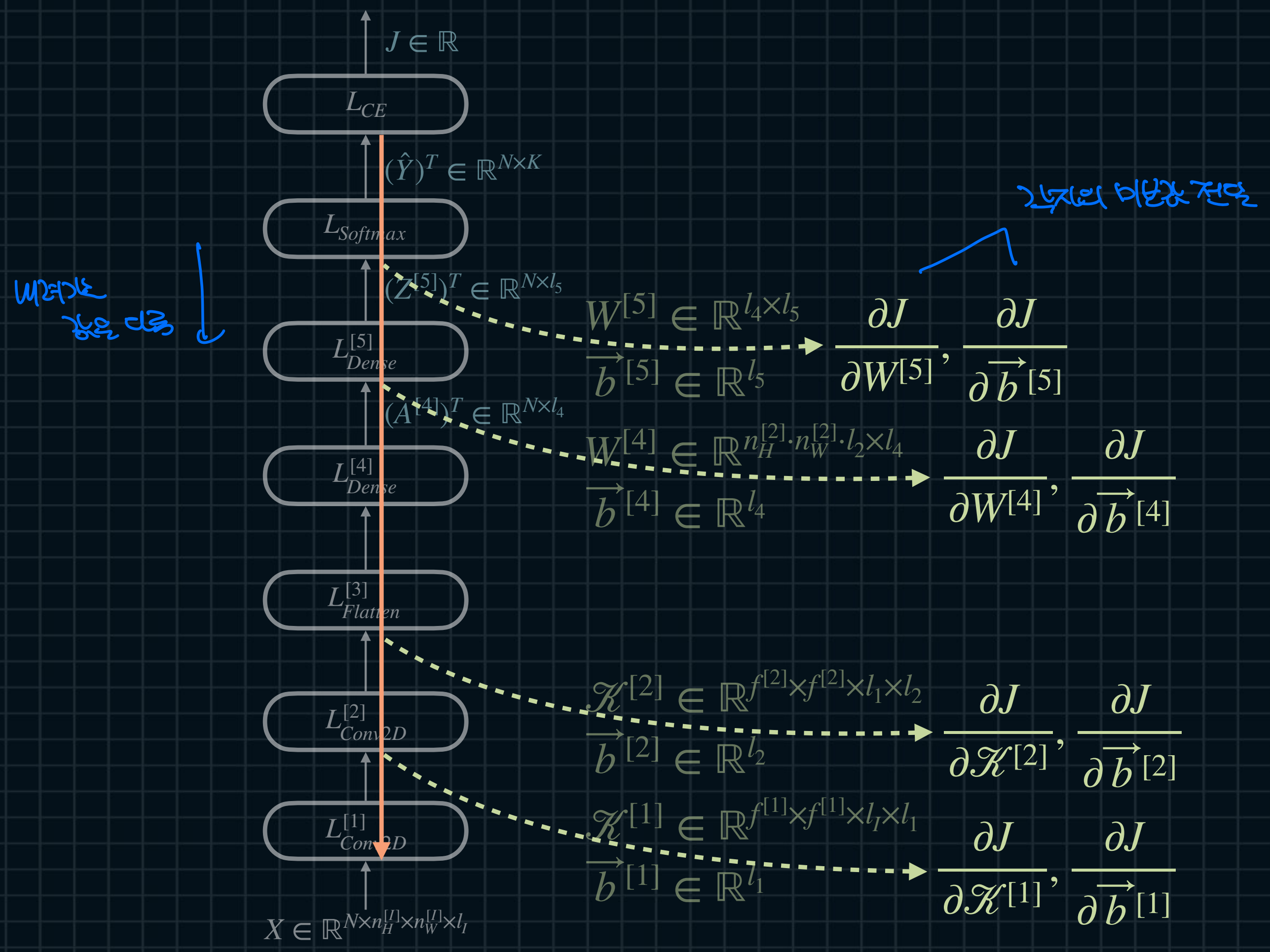
$$\frac{\partial Z^{[5]}}{\partial A^{[4]}} \qquad \frac{\partial Z^{[5]}}{\partial W^{[5]}} \qquad \frac{\partial Z^{[5]}}{\partial \vec{b}^{[5]}}$$



Lecture.1
Why Backpropagation and Jacobians?

- Backpropagation

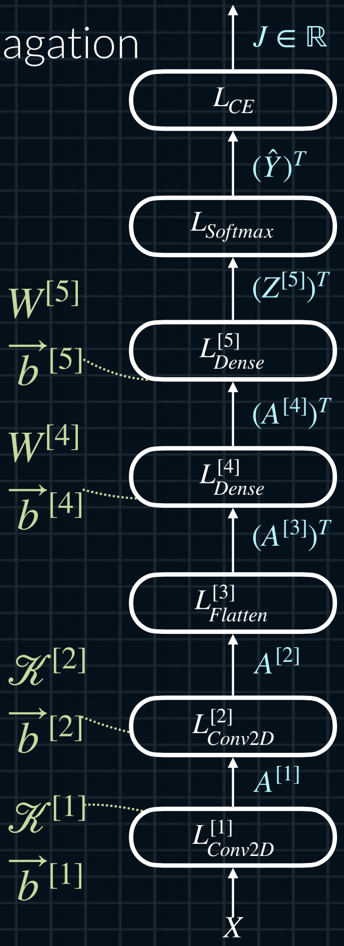
Backpropagation



Lecture.1
Why Backpropagation
and Jacobians?

- Backpropagation

Backpropagation



$$\frac{\partial J}{\partial \hat{Y}}$$

$$\frac{\partial \hat{Y}}{\partial Z^{[5]}}$$

$$\frac{\partial Z^{[5]}}{\partial A^{[4]}}, \frac{\partial Z^{[5]}}{\partial W^{[5]}}, \frac{\partial Z^{[5]}}{\partial \vec{b}^{[5]}}$$

$$\frac{\partial A^{[4]}}{\partial A^{[3]}}, \frac{\partial A^{[4]}}{\partial W^{[4]}}, \frac{\partial A^{[4]}}{\partial \vec{b}^{[4]}}$$

$$\frac{\partial A^{[3]}}{\partial A^{[2]}}$$

$$\frac{\partial A^{[2]}}{\partial A^{[1]}}, \frac{\partial A^{[2]}}{\partial \mathscr{K}^{[2]}}, \frac{\partial A^{[2]}}{\partial \vec{b}^{[2]}}$$

$$\frac{\partial A^{[1]}}{\partial \mathscr{K}^{[1]}}, \frac{\partial A^{[1]}}{\partial \vec{b}^{[1]}}$$

$$\frac{\partial J}{\partial \hat{Y}} \frac{\partial \hat{Y}}{\partial Z^{[5]}} = \frac{\partial J}{\partial Z^{[5]}}$$

$$\frac{\partial J}{\partial Z^{[5]}} \frac{\partial Z^{[5]}}{\partial A^{[4]}} = \frac{\partial J}{\partial A^{[4]}} \qquad \frac{\partial J}{\partial Z^{[5]}} \frac{\partial Z^{[5]}}{\partial W^{[5]}} = \frac{\partial J}{\partial W^{[5]}} \qquad \frac{\partial J}{\partial Z^{[5]}} \frac{\partial Z^{[5]}}{\partial \vec{b}^{[5]}} = \frac{\partial J}{\partial \vec{b}^{[5]}}$$

$$\frac{\partial J}{\partial A^{[4]}} \frac{\partial A^{[4]}}{\partial A^{[3]}} = \frac{\partial J}{\partial A^{[3]}} \qquad \frac{\partial J}{\partial A^{[4]}} \frac{\partial A^{[4]}}{\partial W^{[4]}} = \frac{\partial J}{\partial W^{[4]}} \qquad \frac{\partial J}{\partial A^{[4]}} \frac{\partial A^{[4]}}{\partial \vec{b}^{[4]}} = \frac{\partial J}{\partial \vec{b}^{[4]}}$$

$$\frac{\partial J}{\partial A^{[3]}} \frac{\partial A^{[3]}}{\partial A^{[2]}} = \frac{\partial J}{\partial A^{[2]}}$$

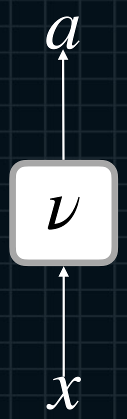
→ 학습변수가 없기때문에 W, $\vec{b}$에 대해선 내용X

$$\frac{\partial J}{\partial A^{[2]}} \frac{\partial A^{[2]}}{\partial A^{[1]}} = \frac{\partial J}{\partial A^{[1]}} \qquad \frac{\partial J}{\partial A^{[2]}} \frac{\partial A^{[2]}}{\partial \mathscr{K}^{[2]}} = \frac{\partial J}{\partial \mathscr{K}^{[2]}} \qquad \frac{\partial J}{\partial A^{[2]}} \frac{\partial A^{[2]}}{\partial \vec{b}^{[2]}} = \frac{\partial J}{\partial \vec{b}^{[2]}}$$

$$\frac{\partial J}{\partial A^{[1]}} \frac{\partial A^{[1]}}{\partial \mathscr{K}^{[1]}} = \frac{\partial J}{\partial \mathscr{K}^{[1]}} \qquad \frac{\partial J}{\partial A^{[1]}} \frac{\partial A^{[1]}}{\partial \vec{b}^{[1]}} = \frac{\partial J}{\partial \vec{b}^{[1]}}$$

- Why Jacobians?

Derivatives of Scalars



$$\nu(x; w, b) = g(xw + b)$$

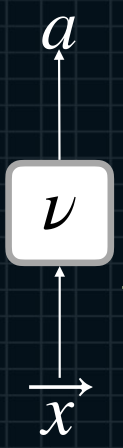
$w \in \mathbb{R}$

$b \in \mathbb{R}$

$$w := w - \alpha \frac{\partial J}{\partial w} \qquad b := b - \alpha \frac{\partial J}{\partial b}$$

- Why Jacobians?

Derivatives of Vectors



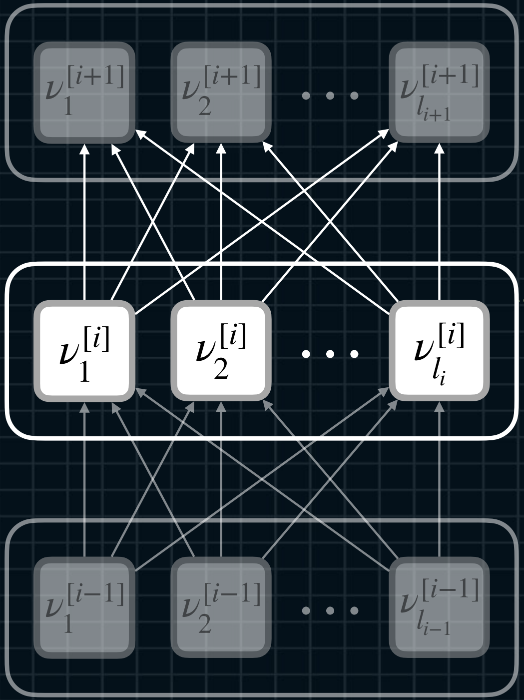
$$\nu\left(\vec{x};\vec{w},b\right)=g\left((\vec{x})^T\vec{w}+b\right)$$

$$\vec{w}\in\mathbb{R}^{l_I\times 1}$$
$$b\in\mathbb{R}$$

$$\vec{w}:=\vec{w}-\alpha\frac{\partial J}{\partial\vec{w}} \qquad b:=b-\alpha\frac{\partial J}{\partial b}$$

- Why Jacobians?

Derivatives of Matrices



$$W^{[i]} = \begin{pmatrix} \uparrow & \uparrow & & \uparrow \\ \vec{w}_1^{[i]} & \vec{w}_2^{[i]} & \cdots & \vec{w}_{l_i}^{[i]} \\ \downarrow & \downarrow & & \downarrow \end{pmatrix} \in \mathbb{R}^{l_{i-1} \times l_i}$$

$$(\vec{b}^{[i]})^T = \begin{pmatrix} b_1^{[i]} & b_2^{[i]} & \dots & b_{l_i}^{[i]} \end{pmatrix} \in \mathbb{R}^{1 \times l_i}$$

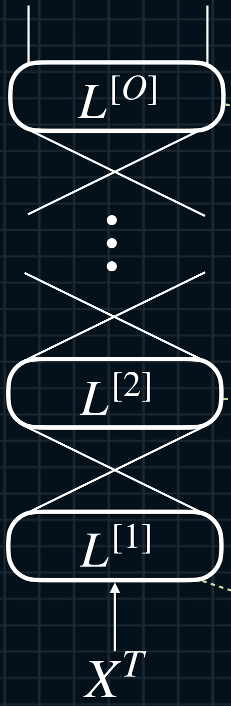
$$W^{[i]} := W^{[i]} - \alpha \frac{\partial J}{\partial W^{[i]}}$$

$$\vec{b}^{[i]} := \vec{b}^{[i]} - \alpha \frac{\partial J}{\partial \vec{b}^{[i]}}$$

Lecture.1
Why Backpropagation
and Jacobians?

- Why Jacobians?

Derivatives of Matrices



$$W^{[O]} = \begin{pmatrix} \uparrow & \uparrow & & \uparrow \\ \vec{w}_1^{[O]} & \vec{w}_2^{[O]} & \cdots & \vec{w}_{l_O}^{[O]} \\ \downarrow & \downarrow & & \downarrow \end{pmatrix} \in \mathbb{R}^{l_{O-1} \times l_O}$$

$$(\vec{b}^{[O]})^T = \begin{pmatrix} b_1^{[O]} & b_2^{[O]} & \dots & b_{l_O}^{[O]} \end{pmatrix} \in \mathbb{R}^{1 \times l_O}$$

$$W^{[2]} = \begin{pmatrix} \uparrow & \uparrow & & \uparrow \\ \vec{w}_1^{[2]} & \vec{w}_2^{[2]} & \cdots & \vec{w}_{l_2}^{[2]} \\ \downarrow & \downarrow & & \downarrow \end{pmatrix} \in \mathbb{R}^{l_1 \times l_2}$$

$$(\vec{b}^{[2]})^T = \begin{pmatrix} b_1^{[2]} & b_2^{[2]} & \dots & b_{l_2}^{[2]} \end{pmatrix} \in \mathbb{R}^{1 \times l_2}$$

$$W^{[1]} = \begin{pmatrix} \uparrow & \uparrow & & \uparrow \\ \vec{w}_1^{[1]} & \vec{w}_2^{[1]} & \cdots & \vec{w}_{l_1}^{[1]} \\ \downarrow & \downarrow & & \downarrow \end{pmatrix} \in \mathbb{R}^{l_I \times l_1}$$

$$(\vec{b}^{[1]})^T = \begin{pmatrix} b_1^{[1]} & b_2^{[1]} & \dots & b_{l_1}^{[1]} \end{pmatrix} \in \mathbb{R}^{1 \times l_1}$$

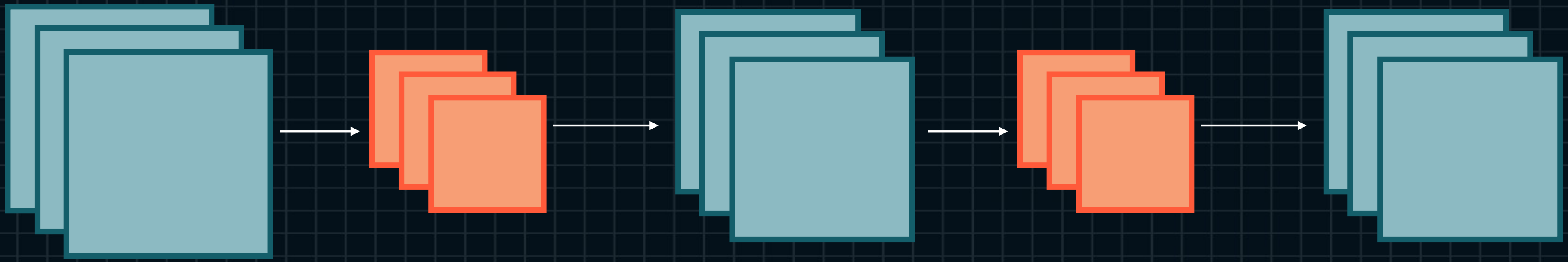
$$W^{[O]} := W^{[O]} - \alpha \frac{\partial J}{\partial W^{[O]}} \qquad \vec{b}^{[O]} := \vec{b}^{[O]} - \alpha \frac{\partial J}{\partial \vec{b}^{[O]}}$$

$$W^{[2]} := W^{[2]} - \alpha \frac{\partial J}{\partial W^{[2]}} \qquad \vec{b}^{[2]} := \vec{b}^{[2]} - \alpha \frac{\partial J}{\partial \vec{b}^{[2]}}$$

$$W^{[1]} := W^{[1]} - \alpha \frac{\partial J}{\partial W^{[1]}} \qquad \vec{b}^{[1]} := \vec{b}^{[1]} - \alpha \frac{\partial J}{\partial \vec{b}^{[1]}}$$

- Why Jacobians?

Derivatives of Tensors



$X \in \mathbb{R}^{n_H^{[I]} \times n_W^{[I]} \times l_I}$

$\mathscr{K}^{[1]} \in \mathbb{R}^{f^{[1]} \times f^{[1]} \times l_I \times l_1}$

$\vec{b}^{[1]} \in \mathbb{R}^{l_1}$

$A^{[1]} \in \mathbb{R}^{n_H^{[1]} \times n_W^{[1]} \times l_1}$

$\mathscr{K}^{[2]} \in \mathbb{R}^{f^{[2]} \times f^{[2]} \times l_1 \times l_2}$

$\vec{b}^{[2]} \in \mathbb{R}^{l_2}$

$A^{[2]} \in \mathbb{R}^{n_H^{[2]} \times n_W^{[2]} \times l_2}$

$$\mathscr{K}^{[1]} := \mathscr{K}^{[1]} - \alpha \frac{\partial J}{\partial \mathscr{K}^{[1]}}$$

$$\vec{b}^{[1]} := \vec{b}^{[1]} - \alpha \frac{\partial J}{\partial \vec{b}^{[1]}}$$

$$\mathscr{K}^{[2]} := \mathscr{K}^{[2]} - \alpha \frac{\partial J}{\partial \mathscr{K}^{[2]}}$$

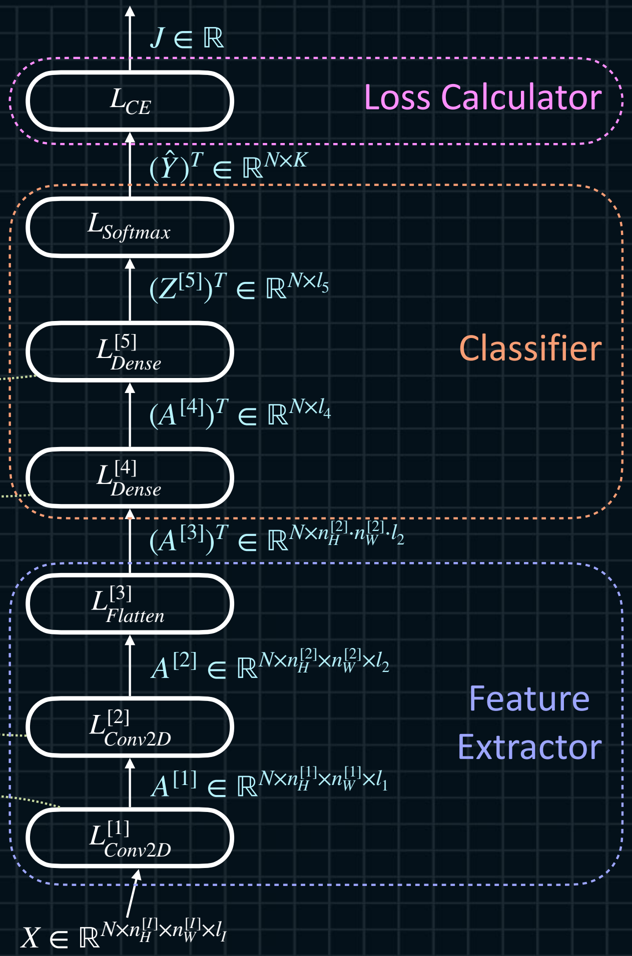
$$\vec{b}^{[2]} := \vec{b}^{[2]} - \alpha \frac{\partial J}{\partial \vec{b}^{[2]}}$$

Lecture.1 Why Backpropagation and Jacobians?

- Why Jacobians?

Derivatives of Tensors

$$W^{[5]} \in \mathbb{R}^{l_4 \times l_5}$$
$$\vec{b}^{[5]} \in \mathbb{R}^{l_5}$$
$$W^{[4]} \in \mathbb{R}^{n_H^{[2]} \cdot n_W^{[2]} \cdot l_2 \times l_4}$$
$$\vec{b}^{[4]} \in \mathbb{R}^{l_4}$$
$$\mathscr{K}^{[2]} \in \mathbb{R}^{f^{[2]} \times f^{[2]} \times l_1 \times l_2}$$
$$\vec{b}^{[2]} \in \mathbb{R}^{l_2}$$
$$\mathscr{K}^{[1]} \in \mathbb{R}^{f^{[1]} \times f^{[1]} \times l_I \times l_1}$$
$$\vec{b}^{[1]} \in \mathbb{R}^{l_1}$$



$$W^{[5]} := W^{[5]} - \alpha \frac{\partial J}{\partial W^{[5]}} \qquad \vec{b}^{[5]} := \vec{b}^{[5]} - \alpha \frac{\partial J}{\partial \vec{b}^{[5]}}$$

$$W^{[4]} := W^{[4]} - \alpha \frac{\partial J}{\partial W^{[4]}} \qquad \vec{b}^{[4]} := \vec{b}^{[4]} - \alpha \frac{\partial J}{\partial \vec{b}^{[4]}}$$

$$\mathscr{K}^{[2]} := \mathscr{K}^{[2]} - \alpha \frac{\partial J}{\partial \mathscr{K}^{[2]}} \qquad \vec{b}^{[2]} := \vec{b}^{[2]} - \alpha \frac{\partial J}{\partial \vec{b}^{[2]}}$$

$$\mathscr{K}^{[1]} := \mathscr{K}^{[1]} - \alpha \frac{\partial J}{\partial \mathscr{K}^{[1]}} \qquad \vec{b}^{[1]} := \vec{b}^{[1]} - \alpha \frac{\partial J}{\partial \vec{b}^{[1]}}$$

- Theoretical and Practical Jacobians

Upgrades of Derivatives(Jacobians)

$$\frac{\partial f}{\partial x} \longrightarrow \frac{\partial f}{\partial \vec{x}} \longrightarrow \frac{\partial \vec{f}}{\partial x} \longrightarrow \frac{\partial \vec{f}}{\partial \vec{x}} \longrightarrow \frac{\partial f}{\partial X}$$

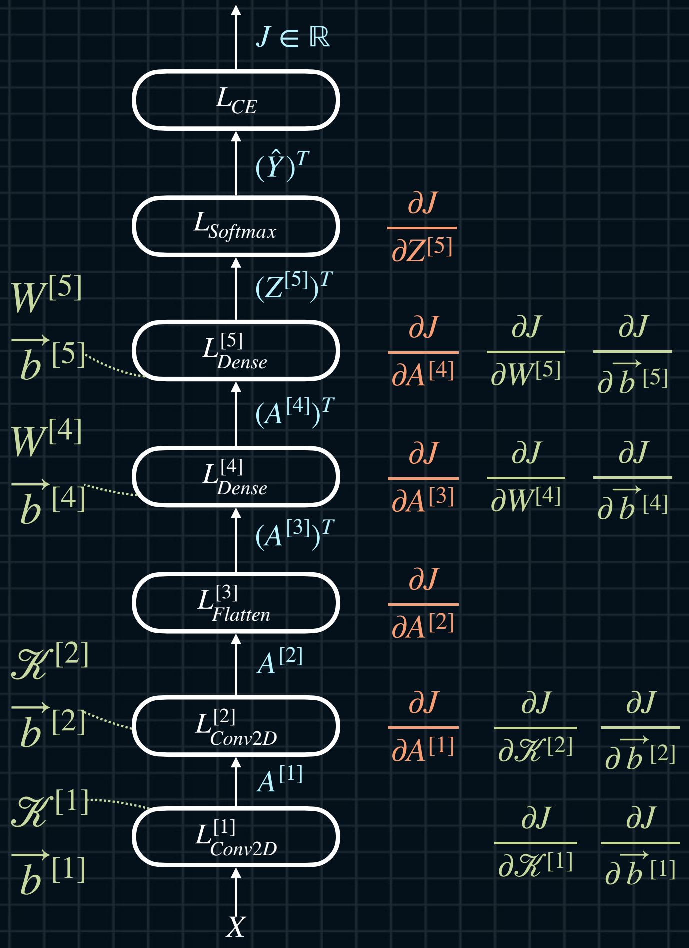
Theoretical Jacobians

$$
\begin{array}{c|c|c}
 & x & \vec{x} \\
\hline
f & \dfrac{\partial f}{\partial x} & \dfrac{\partial f}{\partial \vec{x}} \\
\hline
\vec{f} & \dfrac{\partial \vec{f}}{\partial x} & \dfrac{\partial \vec{f}}{\partial \vec{x}}
\end{array}
$$

Lecture.1
Why Backpropagation
and Jacobians?

- Theoretical and Practical Jacobians

Practical Jacobians



Backpropagation and Jacobian Matrices

Lecture.1
Why Backpropagation and Jacobians?