

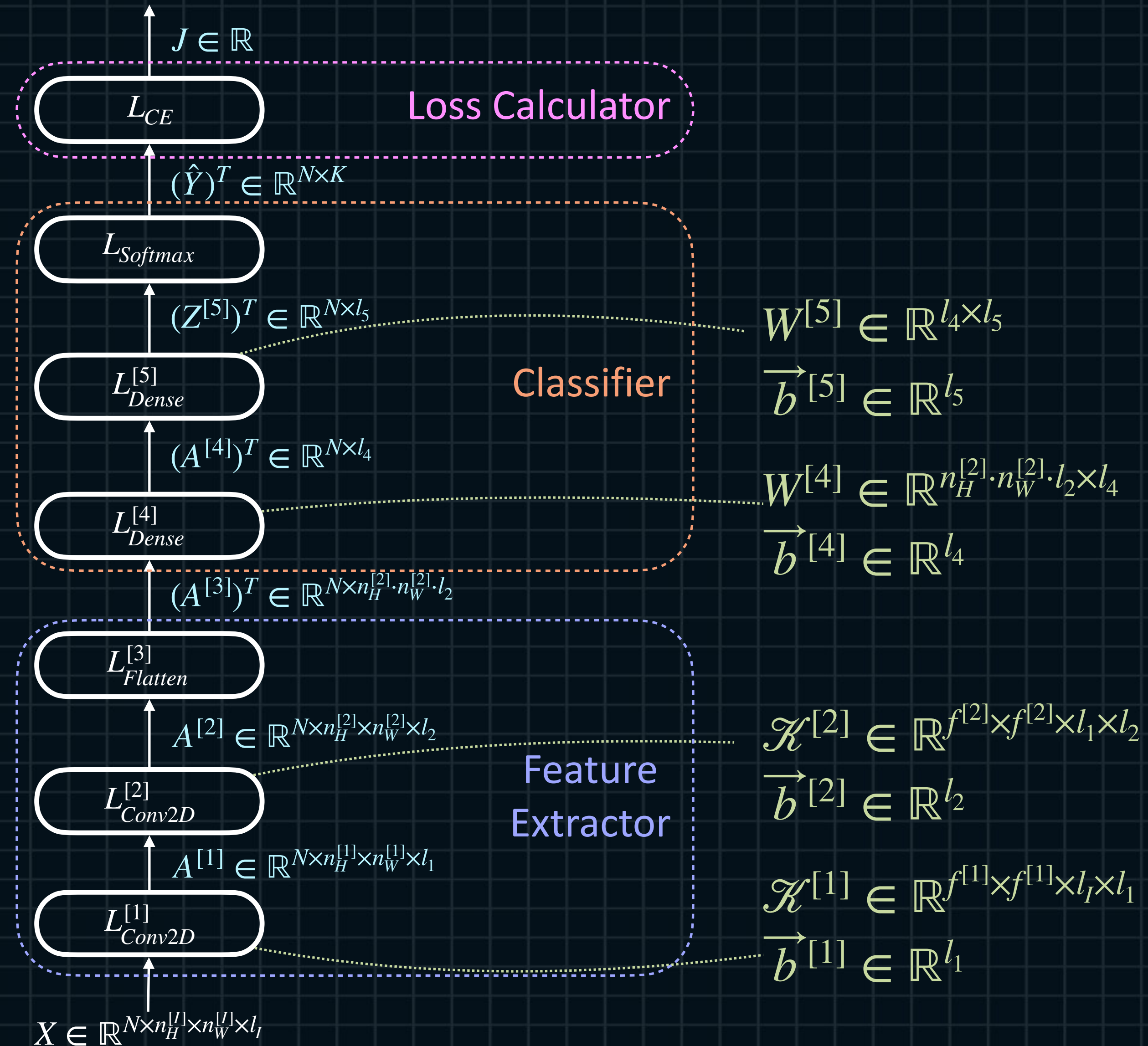
# Backpropagation and Jacobian Matrices

Lecture.0  
Orientation



# Lecture.0 Orientation

## - Previous Lecture



Lecture.0  
Orientation

- Backpropagation

Backpropagation  
for TRAINING neural networks

# Lecture.0 Orientation

## - Chain Rule and Backpropagation

Chain Rule

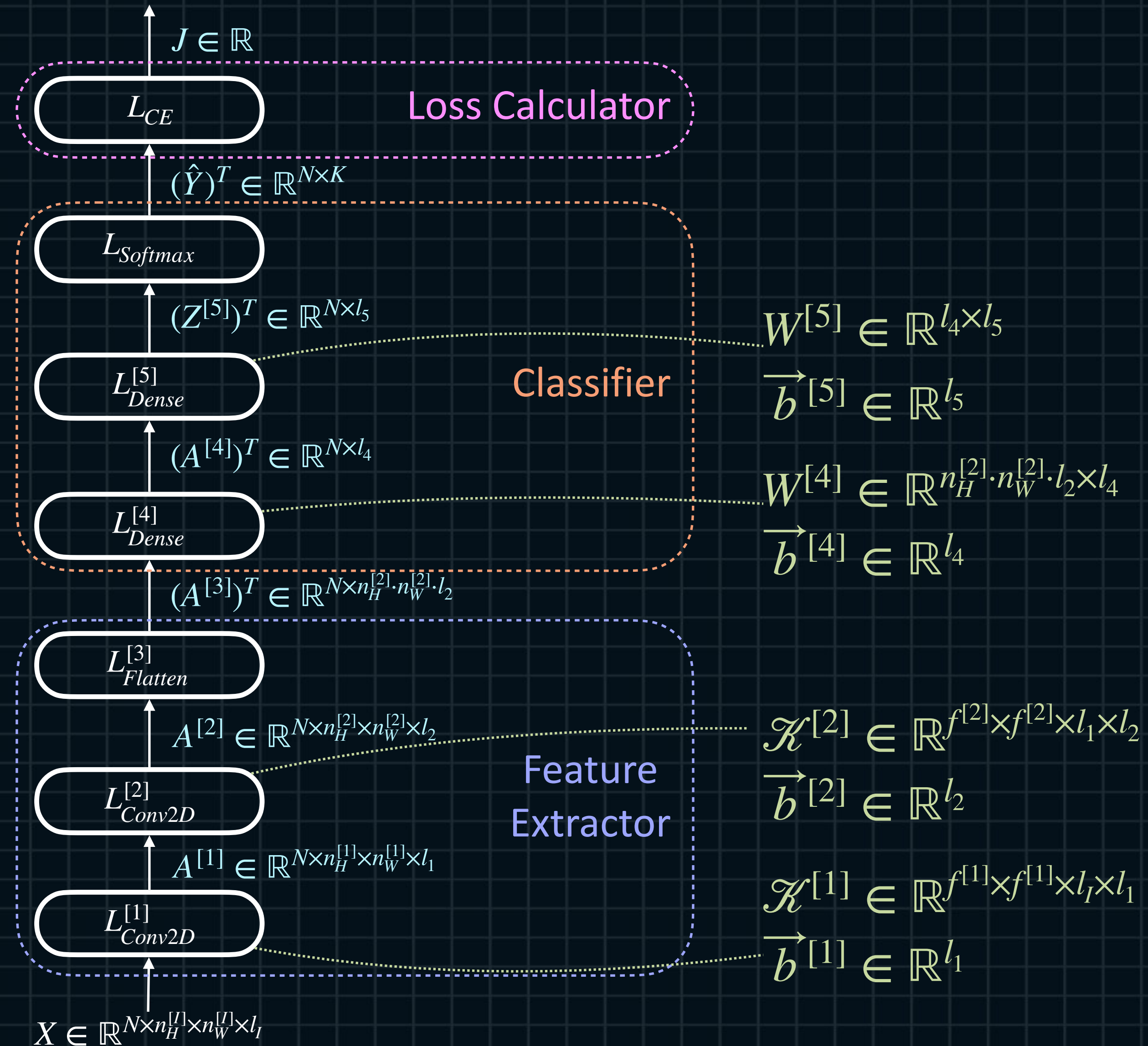


Backpropagation



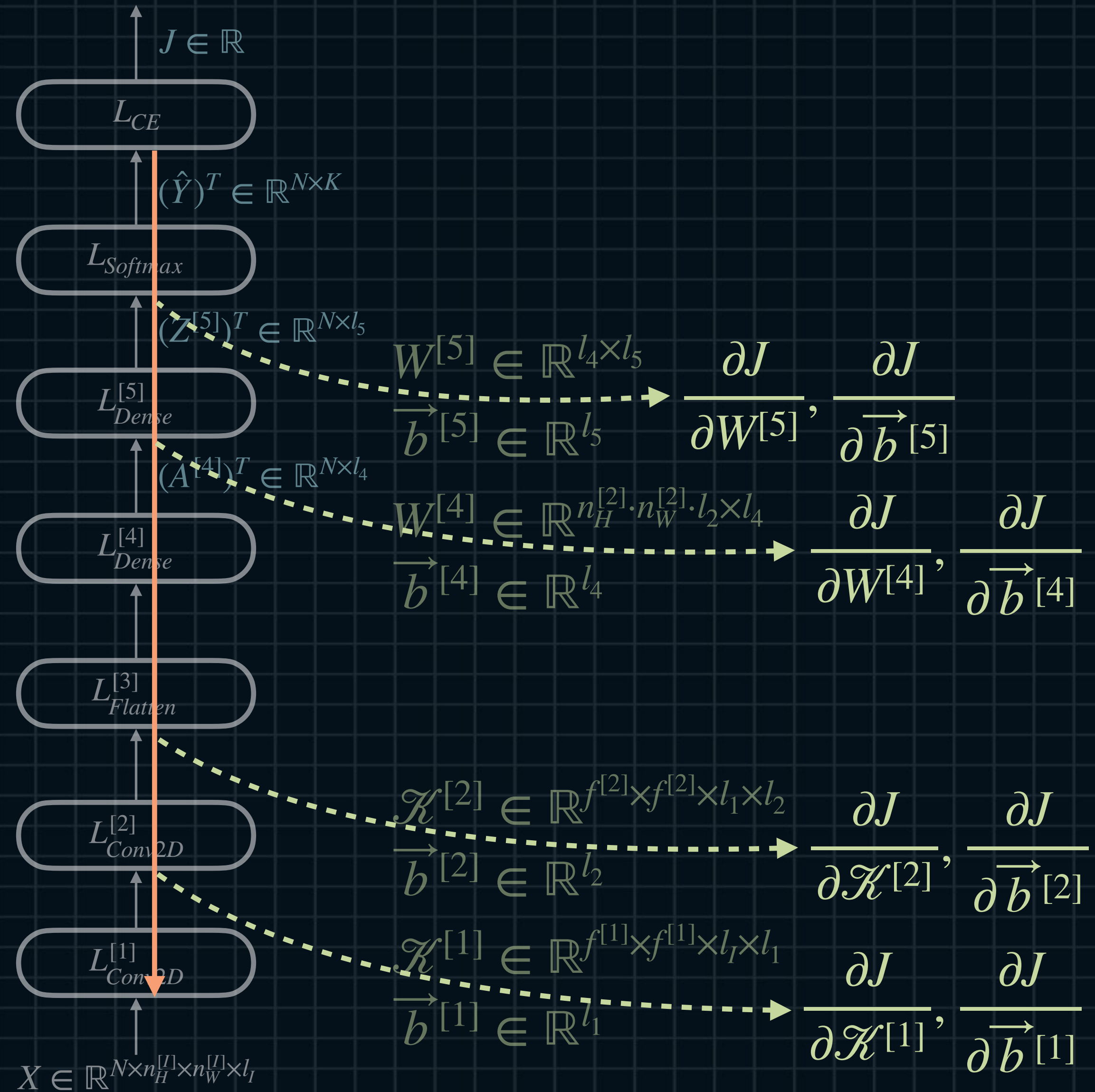
# Lecture.0 Orientation

## - Chain Rule and Backpropagation



# Lecture.0 Orientation

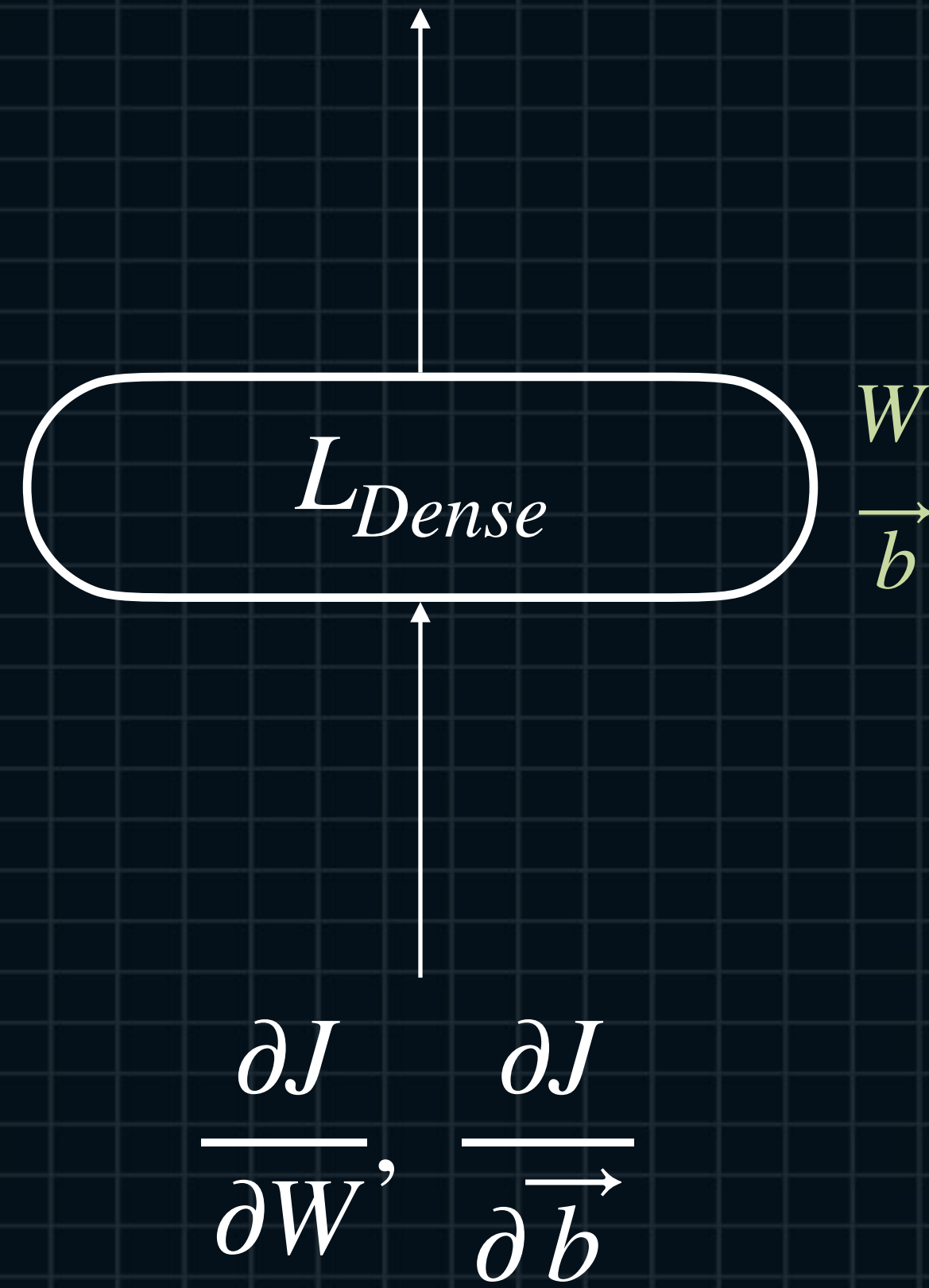
## - Chain Rule and Backpropagation





# Lecture.0 Orientation

## - Tensor Parameters



# Lecture.0 Orientation

## - Jacobian Matrices

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



# Lecture.0 Orientation

## - Purpose of This Lecture

- Basic principle of learning
- Basics for advanced techniques
- Improving math abilities

# Lecture.0 Orientation

## - The MOST Important Thing

$$\frac{\partial J}{\partial \vec{J}_0} = \begin{pmatrix} \frac{1}{N} & \frac{1}{N} & \dots & \frac{1}{N} \end{pmatrix}$$

$$\frac{\partial \vec{J}_0}{\partial \hat{y}} = \begin{pmatrix} -2(y^{(1)} - \hat{y}^{(1)}) & 0 & \dots & 0 \\ 0 & -2(y^{(2)} - \hat{y}^{(2)}) & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & -2(y^{(N)} - \hat{y}^{(N)}) \end{pmatrix}$$

$$\begin{aligned} \frac{\partial J}{\partial \hat{y}} &= \frac{\partial J}{\partial \vec{J}_0} \frac{\partial \vec{J}_0}{\partial \hat{y}} = \begin{pmatrix} \frac{1}{N} & \frac{1}{N} & \dots & \frac{1}{N} \end{pmatrix} \begin{pmatrix} -2(y^{(1)} - \hat{y}^{(1)}) & 0 & \dots & 0 \\ 0 & -2(y^{(2)} - \hat{y}^{(2)}) & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & -2(y^{(N)} - \hat{y}^{(N)}) \end{pmatrix} \\ &= -\frac{2}{N} \begin{pmatrix} (y^{(1)} - \hat{y}^{(1)}) & (y^{(2)} - \hat{y}^{(2)}) & \dots & (y^{(N)} - \hat{y}^{(N)}) \end{pmatrix} \end{aligned}$$

$$\begin{aligned} \frac{\partial J}{\partial w} &= \frac{\partial J}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial w} = -\frac{2}{N} \begin{pmatrix} (y^{(1)} - \hat{y}^{(1)}) & (y^{(2)} - \hat{y}^{(2)}) & \dots & (y^{(N)} - \hat{y}^{(N)}) \end{pmatrix} \begin{pmatrix} x^{(1)} \\ x^{(2)} \\ \vdots \\ x^{(N)} \end{pmatrix} \\ &= -\frac{2}{N} \sum_{i=1}^N x^{(i)} (y^{(i)} - \hat{y}^{(i)}) \end{aligned}$$

$$\begin{aligned} \frac{\partial J}{\partial b} &= \frac{\partial J}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial b} = -\frac{2}{N} \begin{pmatrix} (y^{(1)} - \hat{y}^{(1)}) & (y^{(2)} - \hat{y}^{(2)}) & \dots & (y^{(N)} - \hat{y}^{(N)}) \end{pmatrix} \begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{pmatrix} \\ &= -\frac{2}{N} \sum_{i=1}^N (y^{(i)} - \hat{y}^{(i)}) \end{aligned}$$

$$\frac{\partial J}{\partial l_j^{(i)}} = \frac{\partial J}{\partial \hat{y}_1^{(i)}} \frac{\partial \hat{y}_1^{(i)}}{\partial l_j^{(i)}} + \frac{\partial J}{\partial \hat{y}_2^{(i)}} \frac{\partial \hat{y}_2^{(i)}}{\partial l_j^{(i)}} + \dots + \frac{\partial J}{\partial \hat{y}_j^{(i)}} \frac{\partial \hat{y}_j^{(i)}}{\partial l_j^{(i)}} + \dots + \frac{\partial J}{\partial \hat{y}_K^{(i)}} \frac{\partial \hat{y}_K^{(i)}}{\partial l_j^{(i)}}$$

$$= d\hat{y}_1^{(i)} \frac{\partial \hat{y}_1^{(i)}}{\partial l_j^{(i)}} + d\hat{y}_2^{(i)} \frac{\partial \hat{y}_2^{(i)}}{\partial l_j^{(i)}} + \dots + d\hat{y}_j^{(i)} \frac{\partial \hat{y}_j^{(i)}}{\partial l_j^{(i)}} + \dots + d\hat{y}_K^{(i)} \frac{\partial \hat{y}_K^{(i)}}{\partial l_j^{(i)}}$$

$$= d\hat{y}_1^{(i)} \cdot (-\hat{y}_1^{(i)} \hat{y}_j^{(i)}) + d\hat{y}_2^{(i)} \cdot (-\hat{y}_2^{(i)} \hat{y}_j^{(i)}) + \dots + d\hat{y}_j^{(i)} \cdot (\hat{y}_j^{(i)} (1 - \hat{y}_j^{(i)})) + \dots + d\hat{y}_K^{(i)} \cdot (-\hat{y}_K^{(i)} \hat{y}_j^{(i)})$$

$$= d\hat{y}_j^{(i)} \hat{y}_j^{(i)} + d\hat{y}_1^{(i)} \cdot (-\hat{y}_1^{(i)} \hat{y}_j^{(i)}) + d\hat{y}_2^{(i)} \cdot (-\hat{y}_2^{(i)} \hat{y}_j^{(i)}) + \dots + d\hat{y}_j^{(i)} \cdot (-\hat{y}_j^{(i)} \hat{y}_j^{(i)}) + \dots + d\hat{y}_K^{(i)} \cdot (-\hat{y}_K^{(i)} \hat{y}_j^{(i)})$$

$$= d\hat{y}_j^{(i)} \hat{y}_j^{(i)} - \hat{y}_j^{(i)} \sum_{k=1}^K d\hat{y}_k^{(i)} \cdot \hat{y}_k^{(i)}$$

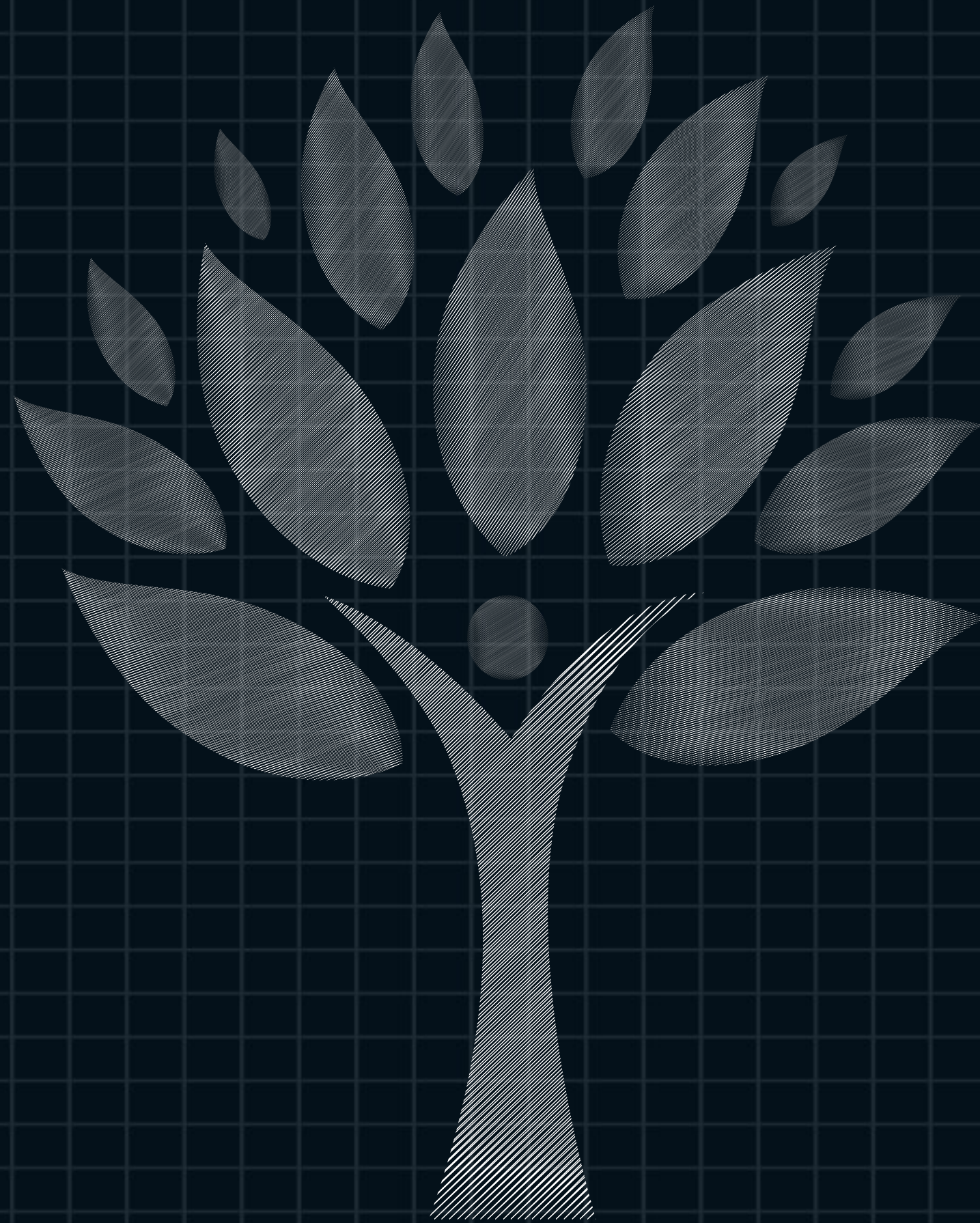
$$= -\frac{1}{N} \left[ \frac{y_j^{(i)}}{\hat{y}_j^{(i)}} \cdot \hat{y}_j^{(i)} - \hat{y}_j^{(i)} \sum_{k=1}^K \frac{y_k^{(i)}}{\hat{y}_k^{(i)}} \cdot \hat{y}_k^{(i)} \right]$$

$$= -\frac{1}{N} \left[ y_j^{(i)} - \hat{y}_j^{(i)} \sum_{k=1}^K y_k^{(i)} \right]$$

$$= -\frac{1}{N} \left[ y_j^{(i)} - \hat{y}_j^{(i)} \right]$$

$$\frac{\partial J}{\partial L} = -\frac{1}{N} (Y - \hat{Y})$$





# Backpropagation and Jacobian Matrices

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