

Forward Propagation of Neural Networks

Lecture.4
Loss Functions

Lecture.4 Loss Functions

- Cartesian Product for Predictions/Labels

$$\mathbb{R}$$

$$\mathbb{B} = \{0, 1\}$$

$$\mathbb{C} = \{c_1, c_2, \dots, c_K\}$$

$$\mathbb{P} = \{x \mid 0 \leq x \leq 1\}$$

$$\mathbb{B}_1^n = \left\{ (b_1, b_2, \dots, b_n)^T \mid \forall b_i \in \mathbb{B}, \sum_{i=1}^n b_i = 1 \right\}$$

Lecture.4 Loss Functions

- Mean Squared Error

Dataset for Regression

$$(\vec{x}^{(1)}) = \begin{pmatrix} x_1^{(1)} & x_2^{(1)} & \dots & x_{l_I}^{(1)} \end{pmatrix} \quad y^{(1)} \in \mathbb{R}$$

$$(\vec{x}^{(2)}) = \begin{pmatrix} x_1^{(2)} & x_2^{(2)} & \dots & x_{l_I}^{(2)} \end{pmatrix} \quad y^{(2)} \in \mathbb{R}$$

$$\vdots$$

$$(\vec{x}^{(N)}) = \begin{pmatrix} x_1^{(N)} & x_2^{(N)} & \dots & x_{l_I}^{(N)} \end{pmatrix} \quad y^{(N)} \in \mathbb{R}$$



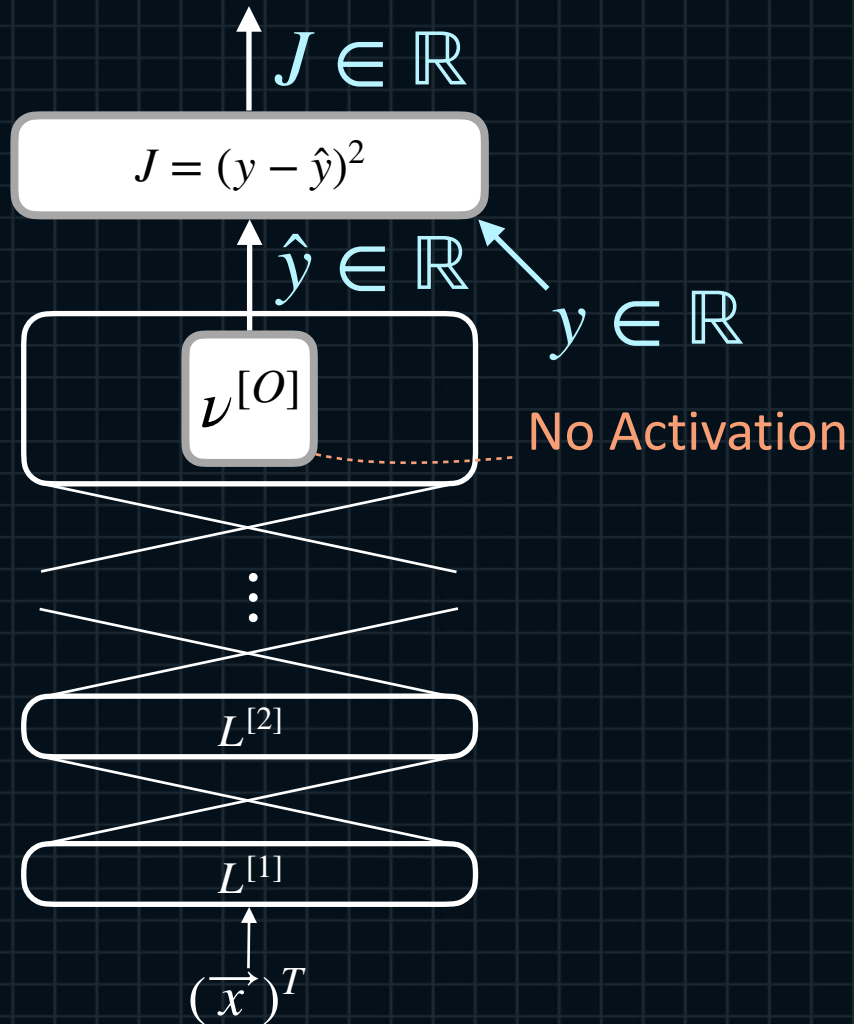
$$X^T = \begin{pmatrix} \leftarrow & \vec{x}^{(1)} & \rightarrow \\ \leftarrow & \vec{x}^{(2)} & \rightarrow \\ & \vdots & \\ \leftarrow & \vec{x}^{(N)} & \rightarrow \end{pmatrix} \in \mathbb{R}^{N \times l_I}$$

$$Y = \begin{pmatrix} y^{(1)} \\ y^{(2)} \\ \vdots \\ y^{(N)} \end{pmatrix} \in \mathbb{R}^{N \times 1}$$

Lecture.4 Loss Functions

- Mean Squared Error

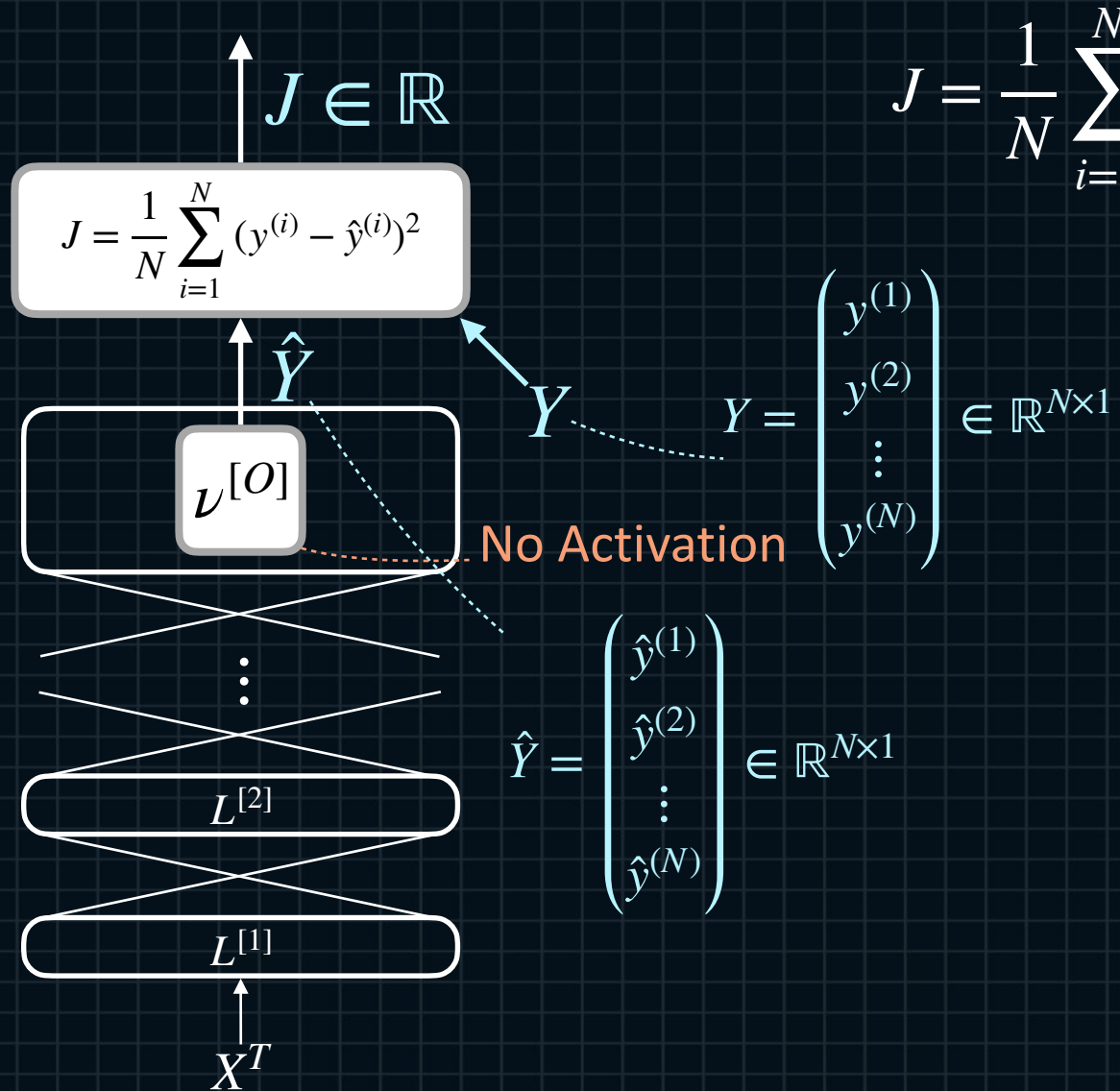
Squared Error



$$J = (y - \hat{y})^2$$

Lecture.4 Loss Functions

- Mean Squared Error



$$J = \frac{1}{N} \sum_{i=1}^N (y^{(i)} - \hat{y}^{(i)})^2$$

Lecture.4 Loss Functions

- Binary Cross Entropy

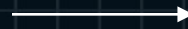
Dataset for Binary Classification

$$(\vec{x}^{(1)}) = \begin{pmatrix} x_1^{(1)} & x_2^{(1)} & \dots & x_{l_I}^{(1)} \end{pmatrix} \quad y^{(1)} \in \mathbb{B}$$

$$(\vec{x}^{(2)}) = \begin{pmatrix} x_1^{(2)} & x_2^{(2)} & \dots & x_{l_I}^{(2)} \end{pmatrix} \quad y^{(2)} \in \mathbb{B}$$

$$\vdots$$

$$(\vec{x}^{(N)}) = \begin{pmatrix} x_1^{(N)} & x_2^{(N)} & \dots & x_{l_I}^{(N)} \end{pmatrix} \quad y^{(N)} \in \mathbb{B}$$

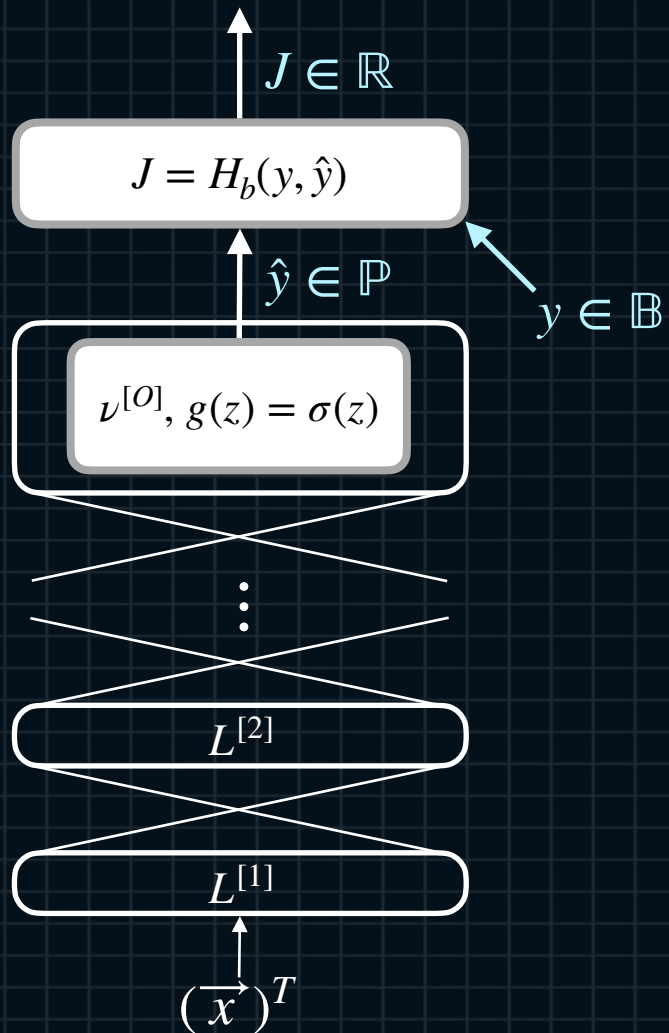


$$X^T = \begin{pmatrix} \leftarrow & \vec{x}^{(1)} & \rightarrow \\ \leftarrow & \vec{x}^{(2)} & \rightarrow \\ & \vdots & \\ \leftarrow & \vec{x}^{(N)} & \rightarrow \end{pmatrix} \in \mathbb{R}^{N \times l_I}$$

$$Y = \begin{pmatrix} y^{(1)} \\ y^{(2)} \\ \vdots \\ y^{(N)} \end{pmatrix} \in \mathbb{B}^{N \times 1}$$

Lecture.4 Loss Functions

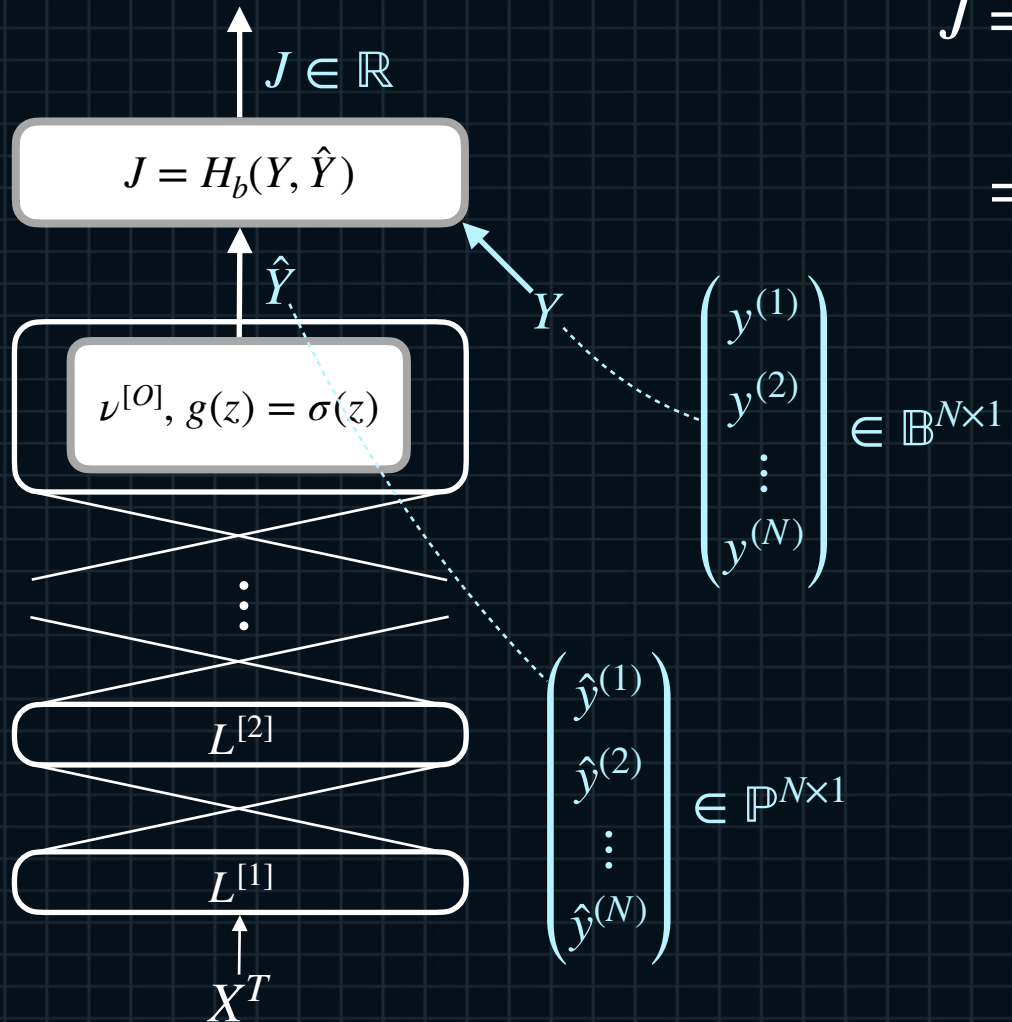
- Binary Cross Entropy



$$H_b(y, \hat{y}) = - [y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})]$$

Lecture.4 Loss Functions

- Binary Cross Entropy



$$J = H_b(Y, \hat{Y})$$

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

Lecture.4 Loss Functions

- Categorical Cross Entropy

Dataset for Multi-class Classification

$$\mathbb{C} = \{c_1, c_2, \dots, c_K\}$$

$$(\vec{x}^{(1)}) = \begin{pmatrix} x_1^{(1)} & x_2^{(1)} & \dots & x_{l_I}^{(1)} \end{pmatrix} \quad y^{(1)} \in \mathbb{C}$$

$$(\vec{x}^{(2)}) = \begin{pmatrix} x_1^{(2)} & x_2^{(2)} & \dots & x_{l_I}^{(2)} \end{pmatrix} \quad y^{(2)} \in \mathbb{C}$$

$$\vdots$$

$$(\vec{x}^{(N)}) = \begin{pmatrix} x_1^{(N)} & x_2^{(N)} & \dots & x_{l_I}^{(N)} \end{pmatrix} \quad y^{(N)} \in \mathbb{C}$$

→

$$X^T = \begin{pmatrix} \leftarrow & \vec{x}^{(1)} & \rightarrow \\ \leftarrow & \vec{x}^{(2)} & \rightarrow \\ & \vdots & \\ \leftarrow & \vec{x}^{(N)} & \rightarrow \end{pmatrix} \in \mathbb{R}^{N \times l_I}$$

$$Y = \begin{pmatrix} y^{(1)} \\ y^{(2)} \\ \vdots \\ y^{(N)} \end{pmatrix} \in \mathbb{C}^{N \times 1}$$

Lecture.4 Loss Functions

- Categorical Cross Entropy

Dataset for Multi-class Classification + One-hot Encoding

$$(\vec{y}^{(i)})^T \in \mathbb{B}_1^{1 \times K}$$

$$(\vec{y}^{(1)})^T = (1 \ 0 \ \dots \ 0), \alpha = 1$$

$$(\vec{y}^{(2)})^T = (0 \ 1 \ \dots \ 0), \alpha = 2$$

$$\vdots$$

$$(\vec{y}^{(K)})^T = (0 \ 0 \ \dots \ 1), \alpha = K$$

$$(\vec{y}^{(1)})^T \in \mathbb{B}_1^{1 \times K}$$

$$(\vec{y}^{(2)})^T \in \mathbb{B}_1^{1 \times K}$$

$$\vdots$$

$$(\vec{y}^{(N)})^T \in \mathbb{B}_1^{1 \times K}$$

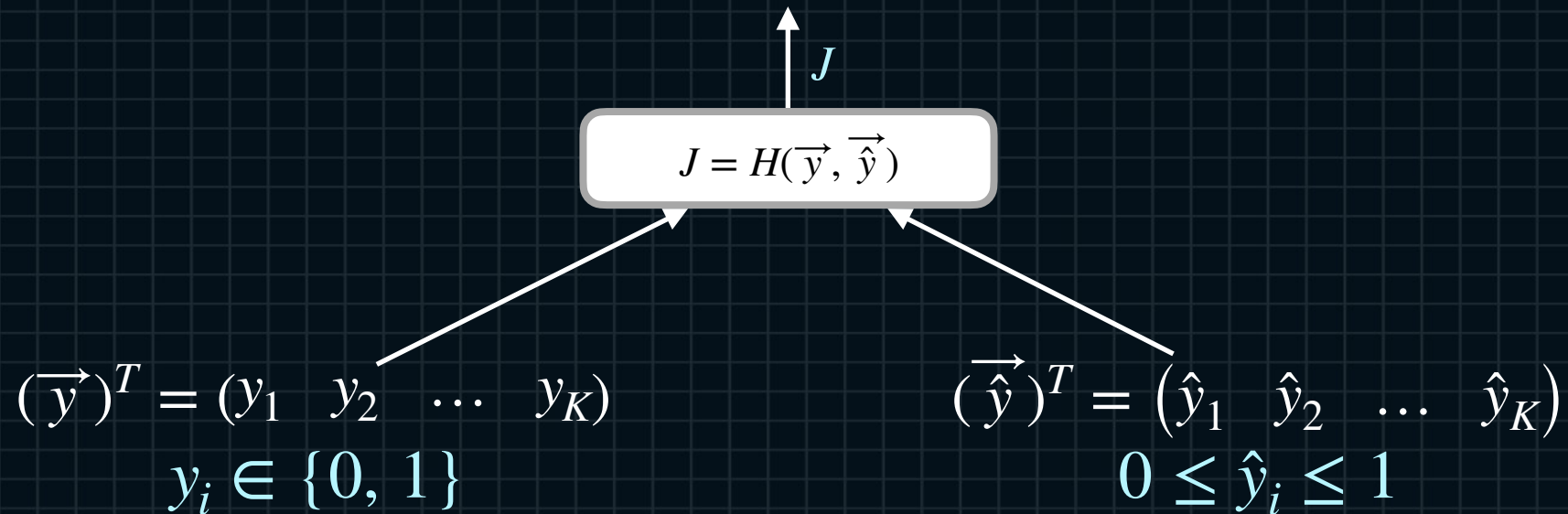
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$$Y^T = \left(\begin{array}{ccc} \leftarrow & (\vec{y}^{(1)})^T & \rightarrow \\ \leftarrow & (\vec{y}^{(2)})^T & \rightarrow \\ & \vdots & \\ \leftarrow & (\vec{y}^{(N)})^T & \rightarrow \end{array} \right) \in \mathbb{B}_1^{N \times K}$$

Lecture.4 Loss Functions

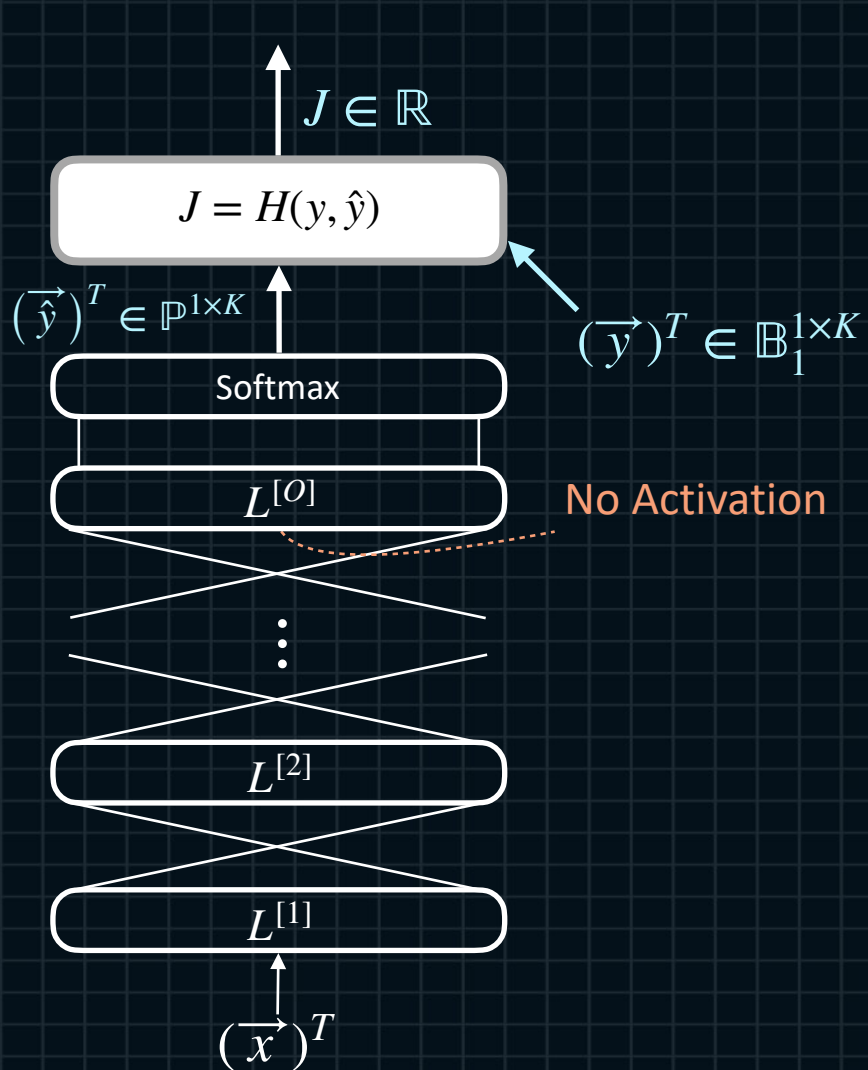
- Categorical Cross Entropy

$$H(\vec{y}, \vec{\hat{y}}) = - \sum_{i=1}^K y_i \log(\hat{y}_i)$$



Lecture.4 Loss Functions

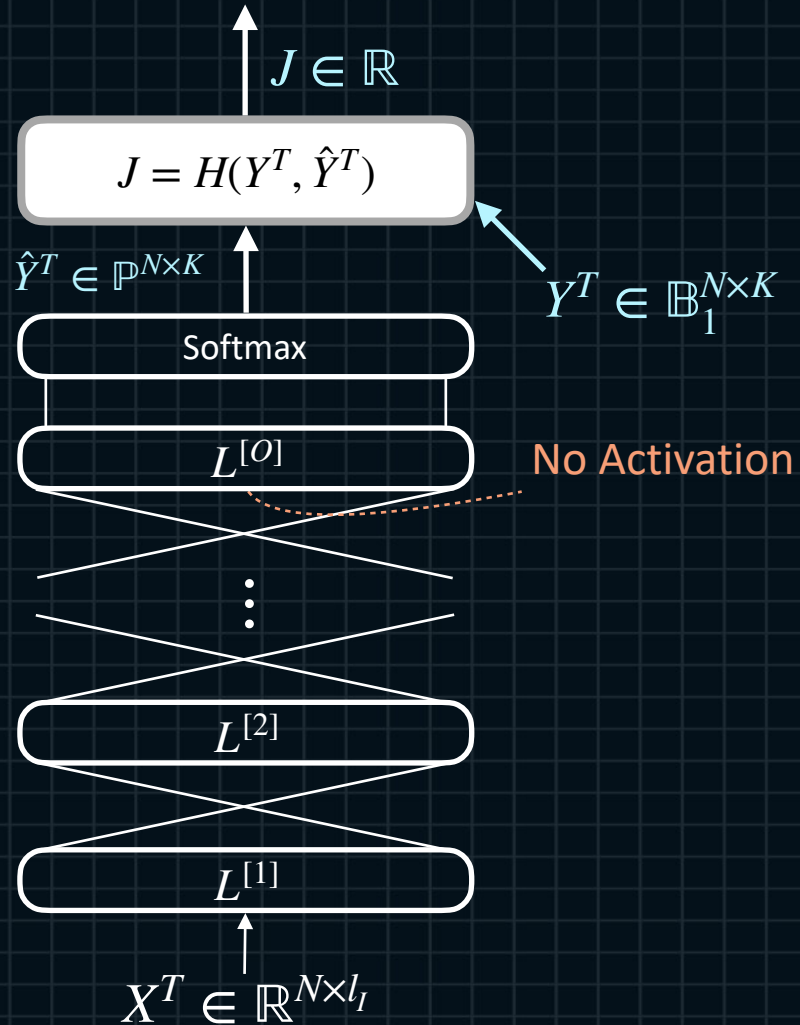
- Categorical Cross Entropy



$$H(\vec{y}, \hat{\vec{y}}) = - \sum_{i=1}^K y_i \log(\hat{y}_i)$$

Lecture.4 Loss Functions

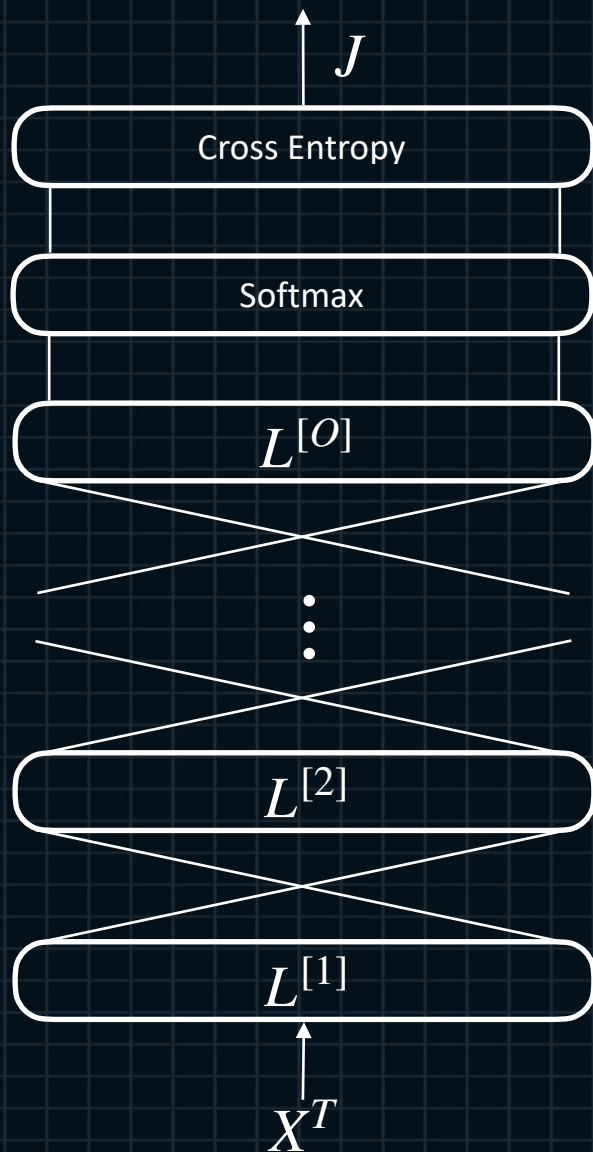
- Categorical Cross Entropy

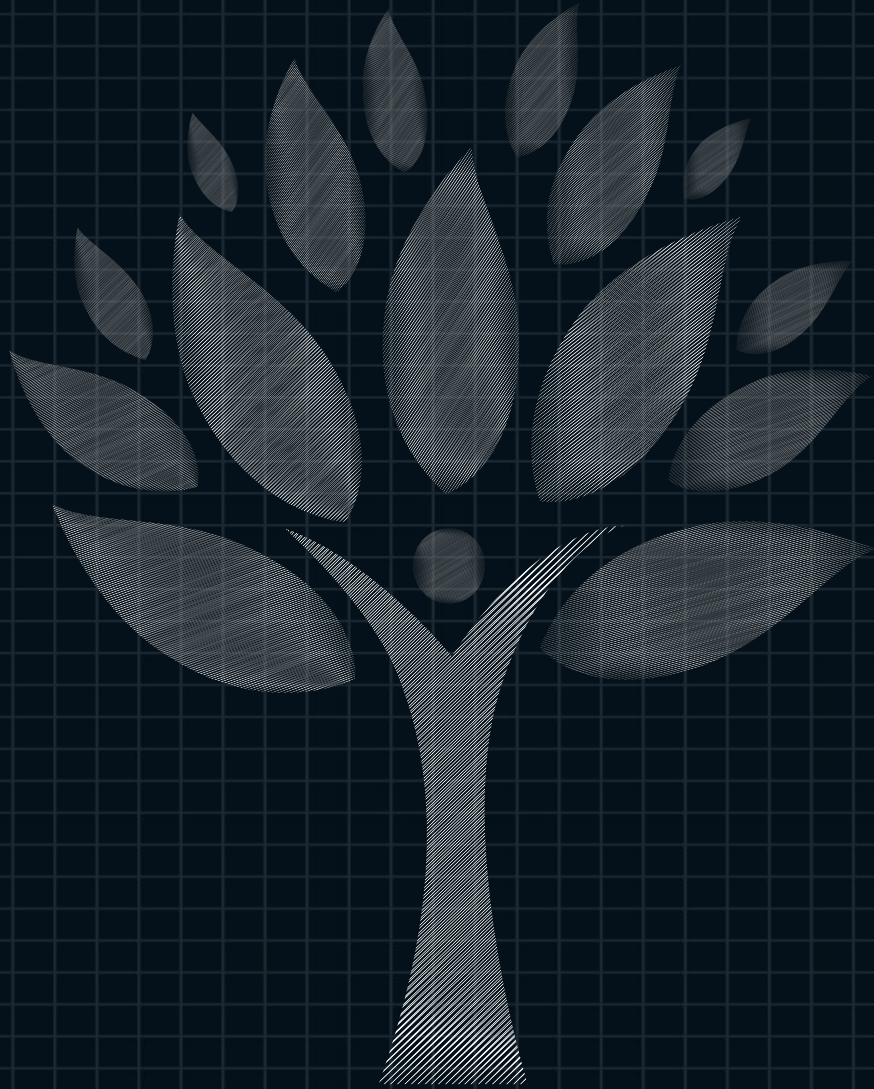


$$\begin{aligned} H(Y^T, \hat{Y}^T) &= \frac{1}{N} \sum_{i=1}^N H(\vec{y}^{(i)}, \vec{\hat{y}}^{(i)}) \\ &= -\frac{1}{N} \sum_{i=1}^N \sum_{j=1}^K y_j^{(i)} \log(\hat{y}_j^{(i)}) \end{aligned}$$

Lecture.4 Loss Functions

- from Feature to Loss





Forward Propagation of Neural Networks

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