

# CSC311 Introduction to Machine Learning

## Vectorizing The Backpropagation Algorithm

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# Learning Outcomes

By the end of this lecture, students should be able to

- Derive vectorized expressions for quantities in the forward pass of the backpropagation algorithm for a small neural network.
- Derive vectorized expressions for gradients with respect to activations, pre-activations, and weights in the backward pass of the backpropagation algorithm for a small neural network.

# Outline

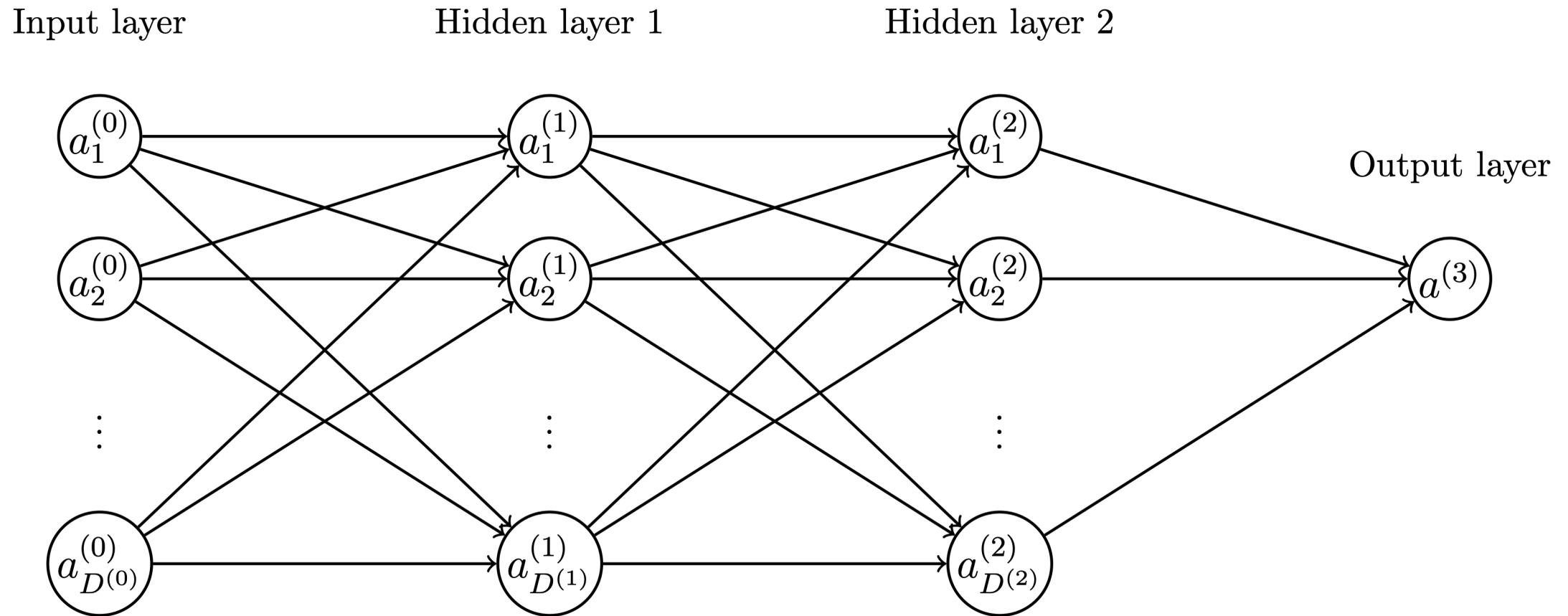
- Review of 3-Layer Neural Network
- Vectorizing Forward Pass
- Vectorizing Backward Pass



# Review: 3-Layer Neural Network

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# 3-Layer Neural Network



# Notation and Definitions

$L$ : number of layers

$\mathbf{a}^{(0)}$ : input to the model ( $\mathbf{x}$ )

$t$ : target output

$C$ : loss function  $C(\mathbf{a}^{(L)}, t)$

For each layer  $m$  where  $m \in [1, L]$

$D^{(m)}$ : dimensionality of layer  $m$

$\mathbf{W}^{(m)}$ : weight matrix for layer  $m$ ,  $\mathbb{R}^{D^{(m)} \times D^{(m-1)}}$

$\mathbf{b}^{(m)}$ : bias vector for layer  $m$ ,  $\mathbb{R}^{D^{(m)}}$

$\sigma^{(m)}$ : non-linearity for layer  $m$

$\mathbf{z}^{(m)}$ : pre-activations for layer  $m$

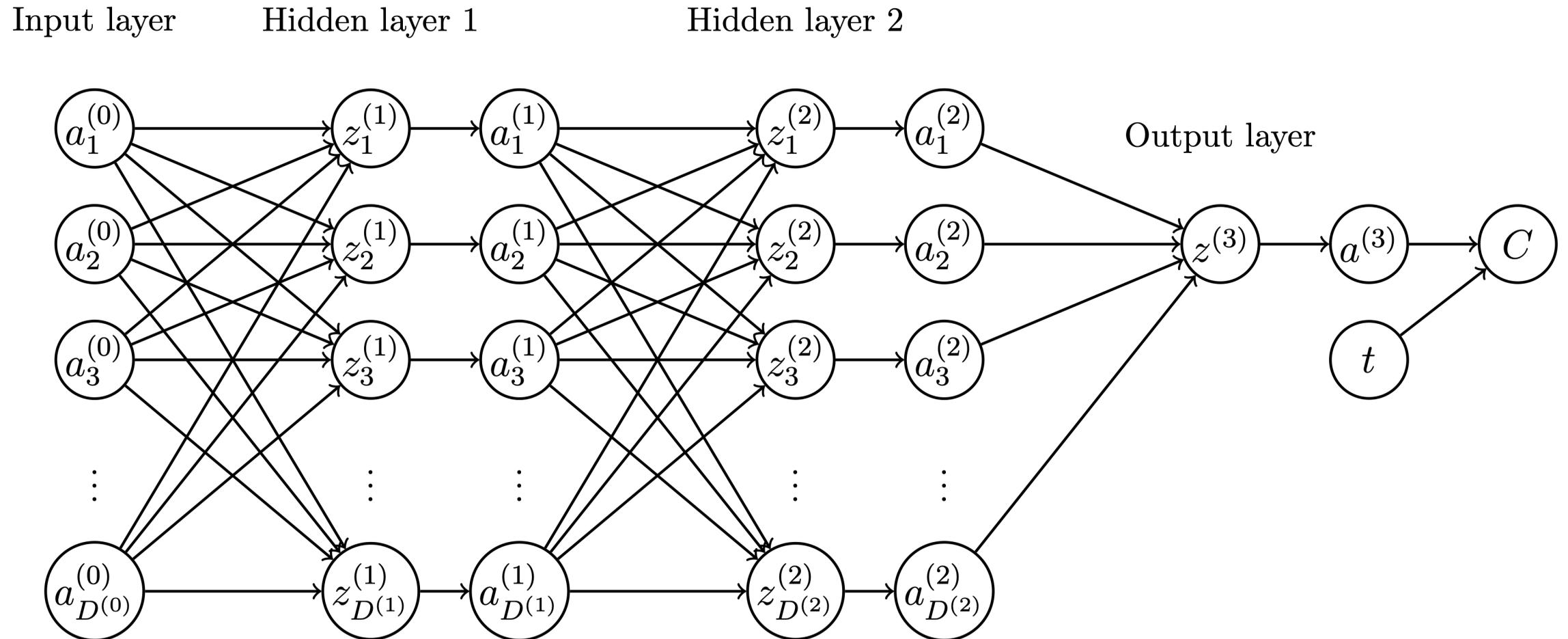
$\mathbf{a}^{(m)}$ : activations for layer  $m$

weights  
going into  
the  $m$ th  
layer

output input

$\mathbb{R}^{D^{(m)}}$   
 $\mathbb{R}^{D^{(m)}}$

# Computation Graph





# Vectorizing Forward Pass

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# Forward Pass Computations

layer 1:

$$z_i^{(1)} = \sum_{j=1}^{D^{(0)}} W_{ij}^{(1)} a_j^{(0)} + b_i^{(1)}$$

$$a_i^{(1)} = \sigma^{(1)}(z_i^{(1)})$$

layer 2:

$$z_i^{(2)} = \sum_{j=1}^{D^{(1)}} W_{ij}^{(2)} a_j^{(1)} + b_i^{(2)}$$

$$a_i^{(2)} = \sigma^{(2)}(z_i^{(2)})$$

layer 3:

$$z^{(3)} = \sum_{j=1}^{D^{(2)}} w_j^{(3)} a_j^{(2)} + b^{(3)}$$

$$a^{(3)} = \sigma^{(3)}(z^{(3)})$$

$$C = C(a^{(3)}, t)$$

# Vectorizing Forward Pass Computations

## Non-Vectorized

For each  $m = 1, \dots, L$ ,

$$z_i^{(m+1)} = \left( \sum_j W_{ij}^{(m+1)} a_j^{(m)} \right) + b_i^{(m+1)}$$

$$a_i^{(m+1)} = \sigma^{(m+1)} \left( z_i^{(m+1)} \right)$$

For output layer  $L$

$$C = C(a^{(L)}, t)$$

## Vectorized

For each  $m = 1, \dots, L$ ,

For output layer  $L$

$$C = C(a^{(L)}, t)$$

# Result of Vectorizing Weighted Sum

$$W^{(m+1)} \mathbf{a}^{(m)}$$

$D^{(m+1)} \times D^{(m)} \quad D^{(m)} \times 1$

all the weights going into the 1st unit in the (m+1)th layer

What is the vectorized expression for the following?

$$W^{(m+1)} = \begin{bmatrix} \omega_{11} & \omega_{12} & \dots & \dots \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix}$$

output  $D^{(m+1)}$   $\times$  input  $D^{(m)}$

$$\begin{bmatrix} z_1^{(m+1)} \\ z_2^{(m+1)} \\ \vdots \\ z_{D^{(m+1)}}^{(m+1)} \end{bmatrix}$$

$$z_i^{(m+1)} = \sum_{j=1}^{D^{(m)}} W_{ij}^{(m+1)} a_j^{(m)}, \quad i = 1, \dots, D^{(m+1)}$$

dim:  $D^{(m+1)} \times 1$

(A)  $(W^{(m+1)})^T \mathbf{a}^{(m)}$

(C)  $W^{(m+1)} \mathbf{a}^{(m)}$

(B)  $(\mathbf{a}^{(m)})^T W^{(m+1)}$

(D)  $\mathbf{a}^{(m)} W^{(m+1)}$

## Solution: Result of Vectorizing Weighted Sum

What is the vectorized expression for the following?

$$\sum_{j=1}^{D^{(m)}} W_{ij}^{(m+1)} a_j^{(m)}, \quad i = 1, \dots, D^{(m+1)}$$

(A)  $(\mathbf{W}^{(m+1)})^T \mathbf{a}^{(m)}$

(C)  $\mathbf{W}^{(m+1)} \mathbf{a}^{(m)}$  **(Correct)**

(B)  $(\mathbf{a}^{(m)})^T \mathbf{W}^{(m+1)}$

(D)  $\mathbf{a}^{(m)} \mathbf{W}^{(m+1)}$

Recall the dimensions  $\mathbf{W}^{(m+1)} \in \mathbb{R}^{D^{(m+1)} \times D^{(m)}}$ ,  $\mathbf{a}^{(m)} \in \mathbb{R}^{D^{(m)} \times 1}$

# Vectorizing Forward Pass Computations

## Non-Vectorized

For each  $m = 1, \dots, L$ ,

$$z_i^{(m+1)} = \sum_j W_{ij}^{(m+1)} a_j^{(m)} + b_i^{(m+1)}$$

$$a_i^{(m+1)} = \sigma^{(m+1)}(z_i^{(m+1)})$$

For output layer  $L$

$$C = C(a^{(L)}, t)$$

## Vectorized

For each  $m = 1, \dots, L$ ,

$$\mathbf{z}^{(m+1)} = \mathbf{W}^{(m+1)} \mathbf{a}^{(m)} + \mathbf{b}^{(m+1)}$$

$$\mathbf{a}^{(m+1)} = \sigma^{(m+1)}(\mathbf{z}^{(m+1)})$$

For output layer  $L$

$$C = C(a^{(L)}, t)$$



# Vectorizing Backward Pass

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# Backward Pass Computations

- ① Compute gradients for **output** layer  $\longrightarrow$  *this assumes a scalar output*

$$\frac{\partial \mathcal{C}}{\partial z^{(L)}} = \frac{\partial \mathcal{C}}{\partial a^{(L)}} \cdot \sigma^{(L)'}(z^{(L)})$$

- ② Compute gradients for each **hidden** layer recursively

$$\frac{\partial \mathcal{C}}{\partial z_j^{(m)}} = \left( \sum_i \frac{\partial \mathcal{C}}{\partial z_i^{(m+1)}} \cdot W_{ij}^{(m+1)} \right) \cdot \sigma^{(m)'}(z_j^{(m)}), \quad j = 1, \dots, D^{(m)}$$

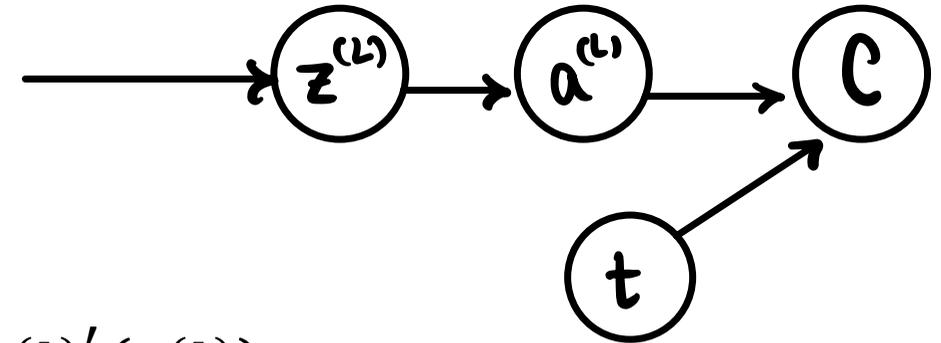
- ③ Compute gradients for the **weights**

$$\frac{\partial \mathcal{C}}{\partial W_{ij}^{(m)}} = \frac{\partial \mathcal{C}}{\partial z_i^{(m)}} \cdot a_j^{(m-1)}, \quad i = 1, \dots, D^{(m)}, j = 1, \dots, D^{(m-1)}$$

# Gradients for the Output Layer

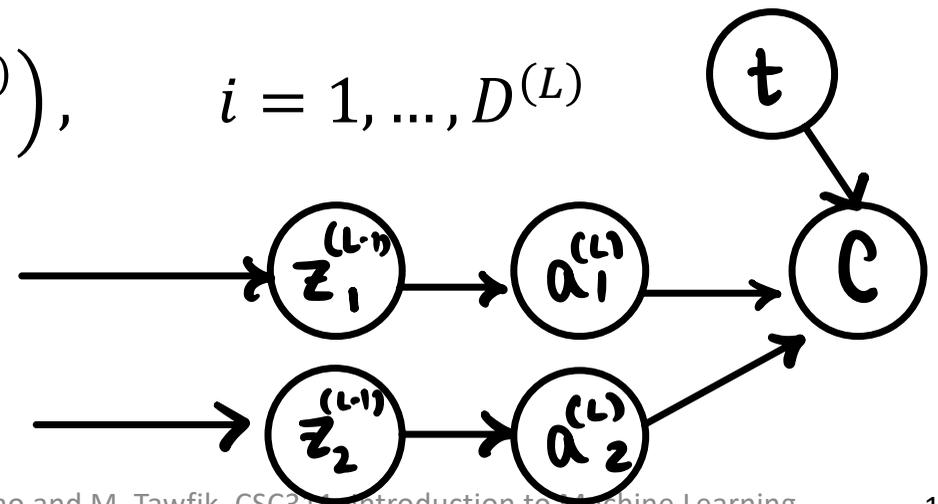
In our network,  $z^{(L)}, a^{(L)}, t \in \mathbb{R}$  are scalars.

$$\frac{\partial C}{\partial z^{(L)}} = \frac{\partial C}{\partial a^{(L)}} \cdot \frac{\partial a^{(L)}}{\partial z^{(L)}} = \frac{\partial C}{\partial a^{(L)}} \cdot \sigma^{(L)'}(z^{(L)})$$



In general,  $\mathbf{z}^{(L)}, \mathbf{a}^{(L)}, \mathbf{t} \in \mathbb{R}^{D^{(L)} \times 1}$  can be vectors. *e.g. multi-class classification*

$$\frac{\partial C}{\partial z_i^{(L)}} = \frac{\partial C}{\partial a_i^{(L)}} \cdot \frac{\partial a_i^{(L)}}{\partial z_i^{(L)}} = \frac{\partial C}{\partial a_i^{(L)}} \cdot \sigma^{(L)'}(z_i^{(L)}), \quad i = 1, \dots, D^{(L)}$$



# Exercise 1: Gradients for the Output Layer

What is the vectorized expression for the following?

$$\frac{\partial C}{\partial z_i^{(L)}} = \frac{\partial C}{\partial a_i^{(L)}} \cdot \sigma^{(L)'}(z_i^{(L)}), \quad i = 1, \dots, D^{(L)}$$

$\nabla_{\mathbf{a}^{(L)}} C$   
 $D^{(L)} \times 1$

$D^{(L)} \times 1$

(A)  $(\nabla_{\mathbf{a}^{(L)}} C)^\top (\sigma^{(L)'}(\mathbf{z}^{(L)}))$

(D)  $(\sigma^{(L)'}(\mathbf{z}^{(L)})) (\nabla_{\mathbf{a}^{(L)}} C)^\top$

(B)  $(\sigma^{(L)'}(\mathbf{z}^{(L)}))^\top (\nabla_{\mathbf{a}^{(L)}} C)$

(E)  $(\nabla_{\mathbf{a}^{(L)}} C) (\sigma^{(L)'}(\mathbf{z}^{(L)}))^\top$

**(C)**  $(\nabla_{\mathbf{a}^{(L)}} C) \odot (\sigma^{(L)'}(\mathbf{z}^{(L)}))$

$\left[ \frac{\partial C}{\partial z_1^{(L)}} \quad \frac{\partial C}{\partial z_2^{(L)}} \quad \dots \quad \frac{\partial C}{\partial z_{D^{(L)}}^{(L)}} \right]^\top$   
 $\nabla_{\mathbf{z}^{(L)}} C$   
 $D^{(L)} \times 1$

## Solution 1: Gradients for the Output Layer

What is the vectorized expression for the following?

$$\frac{\partial \mathcal{C}}{\partial z_i^{(L)}} = \frac{\partial \mathcal{C}}{\partial a_i^{(L)}} \cdot \sigma^{(L)'}(z_i^{(L)}), \quad i = 1, \dots, D^{(L)}$$

(A)  $(\nabla_{\mathbf{a}^{(L)}} \mathcal{C})^\top (\sigma^{(L)'}(\mathbf{z}^{(L)}))$

(D)  $(\sigma^{(L)'}(\mathbf{z}^{(L)})) (\nabla_{\mathbf{a}^{(L)}} \mathcal{C})^\top$

(B)  $(\sigma^{(L)'}(\mathbf{z}^{(L)}))^\top (\nabla_{\mathbf{a}^{(L)}} \mathcal{C})$

(E)  $(\nabla_{\mathbf{a}^{(L)}} \mathcal{C}) (\sigma^{(L)'}(\mathbf{z}^{(L)}))^\top$

(C)  $(\nabla_{\mathbf{a}^{(L)}} \mathcal{C}) \odot (\sigma^{(L)'}(\mathbf{z}^{(L)}))$  **(Correct)**

Recall the dimensions:  $\nabla_{\mathbf{a}^{(L)}} \mathcal{C}, \sigma^{(L)'}(\mathbf{z}^{(L)}), \nabla_{\mathbf{z}^{(L)}} \mathcal{C} \in \mathbb{R}^{D^{(L)} \times 1}$

# Vectorizing Gradients for the Output Layer

Non-vectorized:

$$\frac{\partial \mathcal{C}}{\partial z_i^{(L)}} = \frac{\partial \mathcal{C}}{\partial a_i^{(L)}} \cdot \frac{\partial a_i^{(L)}}{\partial z_i^{(L)}} = \frac{\partial \mathcal{C}}{\partial a_i^{(L)}} \cdot \sigma^{(L)'}(z_i^{(L)}), \quad i = 1, \dots, D^{(L)}$$

Vectorized:

## Solution: Vectorizing Gradients for the Output Layer

Non-vectorized:

$$\frac{\partial \mathcal{C}}{\partial z_i^{(L)}} = \frac{\partial \mathcal{C}}{\partial a_i^{(L)}} \cdot \frac{\partial a_i^{(L)}}{\partial z_i^{(L)}} = \frac{\partial \mathcal{C}}{\partial a_i^{(L)}} \cdot \sigma^{(L)'}(z_i^{(L)}), \quad i = 1, \dots, D^{(L)}$$

Vectorized:

$$\nabla_{\mathbf{z}^{(L)}} \mathcal{C} = (\nabla_{\mathbf{a}^{(L)}} \mathcal{C}) \odot \left( \sigma^{(L)'}(\mathbf{z}^{(L)}) \right)$$

# Backward Pass Computations

- ✓ 1. Compute gradients for **output** layer

$$\nabla_{\mathbf{z}^{(L)}} \mathcal{C} = (\nabla_{\mathbf{a}^{(L)}} \mathcal{C}) \odot \left( \sigma^{(L)'}(\mathbf{z}^{(L)}) \right)$$

2. Compute gradients for each **hidden** layer recursively

$$\frac{\partial \mathcal{C}}{\partial z_j^{(m)}} = \left( \sum_i \frac{\partial \mathcal{C}}{\partial z_i^{(m+1)}} \cdot W_{ij}^{(m+1)} \right) \cdot \sigma^{(m)'}(z_j^{(m)}), \quad j = 1, \dots, D^{(m)}$$

3. Compute gradients for the **weights**

$$\frac{\partial \mathcal{C}}{\partial W_{ij}^{(m)}} = \frac{\partial \mathcal{C}}{\partial z_i^{(m)}} \cdot a_j^{(m-1)}, \quad i = 1, \dots, D^{(m)}, j = 1, \dots, D^{(m-1)}$$

# Vectorizing the Recursive Step

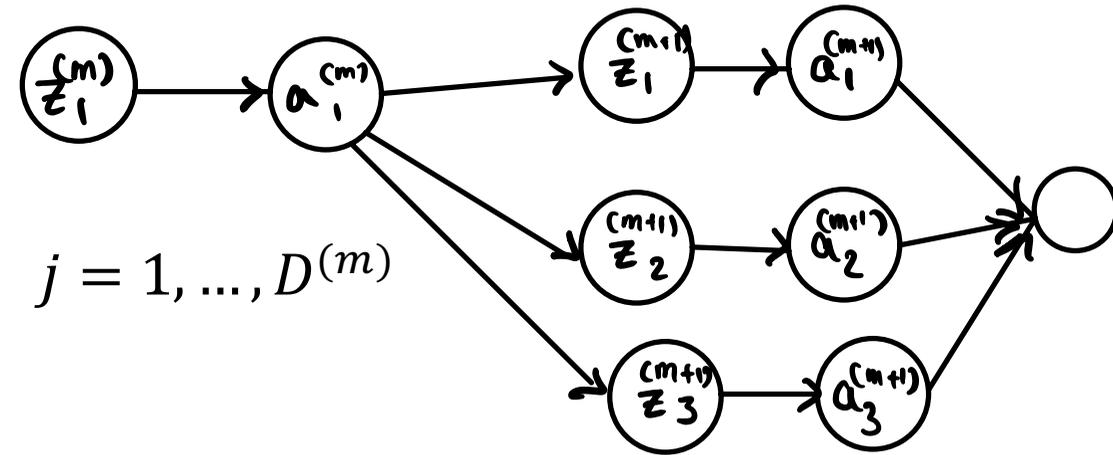
$$\frac{\partial \mathcal{C}}{\partial z_j^{(m)}} = \left( \sum_{i=1}^{D^{(m+1)}} \left( \frac{\partial \mathcal{C}}{\partial z_i^{(m+1)}} \cdot W_{ij}^{(m+1)} \right) \right) \cdot \sigma^{(m)'} \left( z_j^{(m)} \right), \quad j = 1, \dots, D^{(m)}$$

## 1. Vectorizing

$$\frac{\partial \mathcal{C}}{\partial a_j^{(m)}} = \sum_i \left( \frac{\partial \mathcal{C}}{\partial z_i^{(m+1)}} \cdot W_{ij}^{(m+1)} \right), \quad j = 1, \dots, D^{(m)}$$

## 2. Vectorizing

$$\frac{\partial \mathcal{C}}{\partial z_j^{(m)}} = \frac{\partial \mathcal{C}}{\partial a_j^{(m)}} \cdot \sigma^{(m)'} \left( z_j^{(m)} \right), \quad j = 1, \dots, D^{(m)}$$



## Exercise 2: Loss Derivative with respect to Activations

What is the vectorized expression for the following?

$$\nabla_{\vec{a}^{(m)}} C \leftarrow \frac{\partial C}{\partial a_j^{(m)}} = \sum_{i=1}^{D^{(m+1)}} \left( \frac{\partial C}{\partial z_i^{(m+1)}} \cdot W_{ij}^{(m+1)} \right), \quad j = 1, \dots, D^{(m)}$$

Handwritten annotations:  $\nabla_{\vec{z}^{(m+1)}} C$  (blue),  $D^{(m+1)} \times 1$  (red),  $D^{(m)} \times 1$  (red),  $W^{(m+1)}$  (blue),  $D^{(m+1)} \times D^{(m)}$  (red).

(A)  $(\mathbf{W}^{(m+1)})^\top (\nabla_{\mathbf{z}^{(m+1)}} C)$

(C)  $\mathbf{W}^{(m+1)} (\nabla_{\mathbf{z}^{(m+1)}} C)$

$D^{(m+1)} \times D^{(m)}$

(B)  $(\nabla_{\mathbf{z}^{(m+1)}} C)^\top \mathbf{W}^{(m+1)}$

(D)  $(\nabla_{\mathbf{z}^{(m+1)}} C) \mathbf{W}^{(m+1)}$

## Solution 2: Loss Derivative with respect to Activations

What is the vectorized expression for the following?

$$\frac{\partial \mathcal{C}}{\partial a_j^{(m)}} = \sum_{i=1}^{D^{(m+1)}} \left( \frac{\partial \mathcal{C}}{\partial z_i^{(m+1)}} \cdot W_{ij}^{(m+1)} \right), \quad j = 1, \dots, D^{(m)}$$

(A)  $(\mathbf{W}^{(m+1)})^\top (\nabla_{\mathbf{z}^{(m+1)}} \mathcal{C})$  **(Correct)**

(C)  $\mathbf{W}^{(m+1)} (\nabla_{\mathbf{z}^{(m+1)}} \mathcal{C})$

(B)  $(\nabla_{\mathbf{z}^{(m+1)}} \mathcal{C})^\top \mathbf{W}^{(m+1)}$

(D)  $(\nabla_{\mathbf{z}^{(m+1)}} \mathcal{C}) \mathbf{W}^{(m+1)}$

Recall the dimensions:  $\mathbf{W}^{(m+1)} \in \mathbb{R}^{D^{(m+1)} \times D^{(m)}}$ ,  $\nabla_{\mathbf{z}^{(m+1)}} \mathcal{C} \in \mathbb{R}^{D^{(m+1)} \times 1}$

## Exercise 3: Loss Derivative with respect to Pre-activations

What is the vectorized expression for the following?

$$\nabla_{\mathbf{z}^{(m)}} C \leftarrow \frac{\partial C}{\partial z_j^{(m)}} = \frac{\partial C}{\partial a_j^{(m)}} \cdot \sigma^{(m)'}(z_j^{(m)}), \quad i = 1, \dots, D^{(m)}$$

← →

(A)  $(\nabla_{\mathbf{a}^{(m)}} C)^\top (\sigma^{(m)'}(\mathbf{z}^{(m)}))$

(D)  $(\sigma^{(m)'}(\mathbf{z}^{(m)})) (\nabla_{\mathbf{a}^{(m)}} C)^\top$

(B)  $(\sigma^{(m)'}(\mathbf{z}^{(m)}))^\top (\nabla_{\mathbf{a}^{(m)}} C)$

(E)  $(\nabla_{\mathbf{a}^{(m)}} C) (\sigma^{(m)'}(\mathbf{z}^{(m)}))^\top$

**(C)**  $(\nabla_{\mathbf{a}^{(m)}} C) \odot (\sigma^{(m)'}(\mathbf{z}^{(m)}))$

## Solution 3: Loss Derivative with respect to Pre-activations

What is the vectorized expression for the following?

$$\frac{\partial \mathcal{C}}{\partial z_j^{(m)}} = \frac{\partial \mathcal{C}}{\partial a_j^{(m)}} \cdot \sigma^{(m)'}(z_j^{(m)}), \quad i = 1 \dots, D^{(m)}$$

(A)  $(\nabla_{\mathbf{a}^{(m)}} \mathcal{C})^\top (\sigma^{(m)'}(\mathbf{z}^{(m)}))$

(D)  $(\sigma^{(m)'}(\mathbf{z}^{(m)})) (\nabla_{\mathbf{a}^{(m)}} \mathcal{C})^\top$

(B)  $(\sigma^{(m)'}(\mathbf{z}^{(m)}))^\top (\nabla_{\mathbf{a}^{(m)}} \mathcal{C})$

(E)  $(\nabla_{\mathbf{a}^{(m)}} \mathcal{C}) (\sigma^{(m)'}(\mathbf{z}^{(m)}))^\top$

(C)  $(\nabla_{\mathbf{a}^{(m)}} \mathcal{C}) \odot (\sigma^{(m)'}(\mathbf{z}^{(m)}))$  **(Correct)**

Recall the dimensions:  $\nabla_{\mathbf{a}^{(m)}} \mathcal{C}, \sigma^{(m)'}(\mathbf{z}^{(m)}) \in \mathbb{R}^{D^{(m)} \times 1}$

# Vectorizing the Recursive Step

Non-vectorized:

$$\frac{\partial \mathcal{C}}{\partial z_j^{(m)}} = \left( \sum_{i=1}^{D^{(m+1)}} \left( \frac{\partial \mathcal{C}}{\partial z_i^{(m+1)}} \cdot W_{ij}^{(m+1)} \right) \right) \cdot \sigma^{(m)'} \left( z_j^{(m)} \right), \quad i = 1 \dots, D^{(m)}$$

Vectorized:

# Vectorizing the Recursive Step

Non-vectorized:

$$\frac{\partial \mathcal{C}}{\partial z_j^{(m)}} = \left( \sum_{i=1}^{D^{(m+1)}} \left( \frac{\partial \mathcal{C}}{\partial z_i^{(m+1)}} \cdot W_{ij}^{(m+1)} \right) \right) \cdot \sigma^{(m)'}(z_j^{(m)}), \quad i = 1 \dots, D^{(m)}$$

Vectorized:

$$\nabla_{\mathbf{z}^{(m)}} \mathcal{C} = \left( (\mathbf{W}^{(m+1)})^\top (\nabla_{\mathbf{z}^{(m+1)}} \mathcal{C}) \right) \odot \left( \sigma^{(m)'}(\mathbf{z}^{(m)}) \right)$$

# Backward Pass Computations

- ✓ 1. Compute gradients for **output** layer

$$\nabla_{\mathbf{z}^{(L)}} \mathcal{C} = (\nabla_{\mathbf{a}^{(L)}} \mathcal{C}) \odot \left( \sigma^{(L)'}(\mathbf{z}^{(L)}) \right)$$

- ✓ 2. Compute gradients for each **hidden** layer recursively

$$\nabla_{\mathbf{z}^{(m)}} \mathcal{C} = \left( (\mathbf{W}^{(m+1)})^\top (\nabla_{\mathbf{z}^{(m+1)}} \mathcal{C}) \right) \odot \left( \sigma^{(m)'}(\mathbf{z}^{(m)}) \right)$$

3. Compute gradients for the **weights**

$$\frac{\partial \mathcal{C}}{\partial W_{ij}^{(m)}} = \frac{\partial \mathcal{C}}{\partial z_i^{(m)}} \cdot \frac{\partial z_i^{(m)}}{\partial W_{ij}^{(m)}} = \frac{\partial \mathcal{C}}{\partial z_i^{(m)}} \cdot a_j^{(m-1)}$$

# Exercise 4: Loss Derivative with respect to Weights

$$\begin{bmatrix} \frac{\partial C}{\partial z_1^{(m)}} \\ \frac{\partial C}{\partial z_2^{(m)}} \\ \vdots \end{bmatrix} \quad \nabla_{\mathbf{z}^{(m)}} C$$

$D^{(m)} \times 1$

What is the vectorized expression for the following?

$$\frac{\partial C}{\partial W_{ij}^{(m)}} = \frac{\partial C}{\partial z_i^{(m)}} \cdot a_j^{(m-1)}, \quad i = 1, \dots, D^{(m)}, j = 1, \dots, D^{(m-1)}$$

(A)  $(\nabla_{\mathbf{z}^{(m)}} C)^\top (\mathbf{a}^{(m-1)})$

(D)  $(\mathbf{a}^{(m-1)}) (\nabla_{\mathbf{z}^{(m)}} C)^\top$

(B)  $(\mathbf{a}^{(m-1)})^\top (\nabla_{\mathbf{z}^{(m)}} C)$

(E)  $(\nabla_{\mathbf{z}^{(m)}} C) (\mathbf{a}^{(m-1)})^\top$

(C)  $(\nabla_{\mathbf{z}^{(m)}} C) \odot (\mathbf{a}^{(m-1)})$

outer products

$$\mathbf{a}^{(m-1)}$$

$D^{(m-1)} \times 1$

$D^{(m)} \times D^{(m-1)}$

$$\begin{bmatrix} \frac{\partial C}{\partial \omega_{11}} & \frac{\partial C}{\partial \omega_{12}} & \dots & \frac{\partial C}{\partial \omega_{1D}^{(m-1)}} \\ \vdots & \vdots & & \vdots \end{bmatrix}$$

output  $\times$  input

weights into the 1st unit in the m<sup>th</sup> layer

## Solution 4: Loss Derivative with respect to Weights

What is the vectorized expression for the following?

$$\frac{\partial C}{\partial W_{ij}^{(m)}} = \frac{\partial C}{\partial z_i^{(m)}} \cdot a_j^{(m-1)}, \quad i = 1, \dots, D^{(m)}, j = 1, \dots, D^{(m-1)}$$

(A)  $(\nabla_{\mathbf{z}^{(m)}} C)^\top (\mathbf{a}^{(m-1)})$

(D)  $(\mathbf{a}^{(m-1)}) (\nabla_{\mathbf{z}^{(m)}} C)^\top$

(B)  $(\mathbf{a}^{(m-1)})^\top (\nabla_{\mathbf{z}^{(m)}} C)$

(E)  $(\nabla_{\mathbf{z}^{(m)}} C) (\mathbf{a}^{(m-1)})^\top$  **(Correct)**

(C)  $(\nabla_{\mathbf{z}^{(m)}} C) \odot (\mathbf{a}^{(m-1)})$

Recall the dimensions:  $\nabla_{\mathbf{z}^{(m)}} C \in \mathbb{R}^{D^{(m)} \times 1}$ ,  $\mathbf{a}^{(m-1)} \in \mathbb{R}^{D^{(m-1)} \times 1}$ ,  $\nabla_{\mathbf{W}^{(m)}} C \in \mathbb{R}^{D^{(m)} \times D^{(m-1)}}$

# Vectorizing the Gradients for the Weights

Non-vectorized:

$$\frac{\partial C}{\partial W_{ij}^{(m)}} = \frac{\partial C}{\partial z_i^{(m)}} \cdot \frac{\partial z_i^{(m)}}{\partial W_{ij}^{(m)}} = \frac{\partial C}{\partial z_i^{(m)}} \cdot a_j^{(m-1)}, \quad i = 1, \dots, D^{(m)}, j = 1, \dots, D^{(m-1)}$$

Vectorized:

## Solution: Vectorizing the Gradients for the Weights

Non-vectorized:

$$\frac{\partial C}{\partial W_{ij}^{(m)}} = \frac{\partial C}{\partial z_i^{(m)}} \cdot \frac{\partial z_i^{(m)}}{\partial W_{ij}^{(m)}} = \frac{\partial C}{\partial z_i^{(m)}} \cdot a_j^{(m-1)}, \quad i = 1, \dots, D^{(m)}, j = 1, \dots, D^{(m-1)}$$

Vectorized:

$$\nabla_{\mathbf{W}^{(m)}} C = (\nabla_{\mathbf{z}^{(m)}} C) (\mathbf{a}^{(m-1)})^\top$$

# Backward Pass Computations

- ✓ 1. Compute gradients for **output** layer

$$\nabla_{\mathbf{z}^{(L)}} \mathcal{C} = (\nabla_{\mathbf{a}^{(L)}} \mathcal{C}) \odot \left( \sigma^{(L)'}(\mathbf{z}^{(L)}) \right)$$

- ✓ 2. Compute gradients for each **hidden** layer recursively

$$\nabla_{\mathbf{z}^{(m)}} \mathcal{C} = \left( (\mathbf{W}^{(m+1)})^T (\nabla_{\mathbf{z}^{(m+1)}} \mathcal{C}) \right) \odot \left( \sigma^{(m)'}(\mathbf{z}^{(m)}) \right)$$

- ✓ 3. Compute gradients for the **weights**

$$\nabla_{\mathbf{W}^{(m)}} \mathcal{C} = (\nabla_{\mathbf{z}^{(m)}} \mathcal{C}) (\mathbf{a}^{(m-1)})^T$$