



# Module 4.3 - Advanced NNs



# "Pooling"

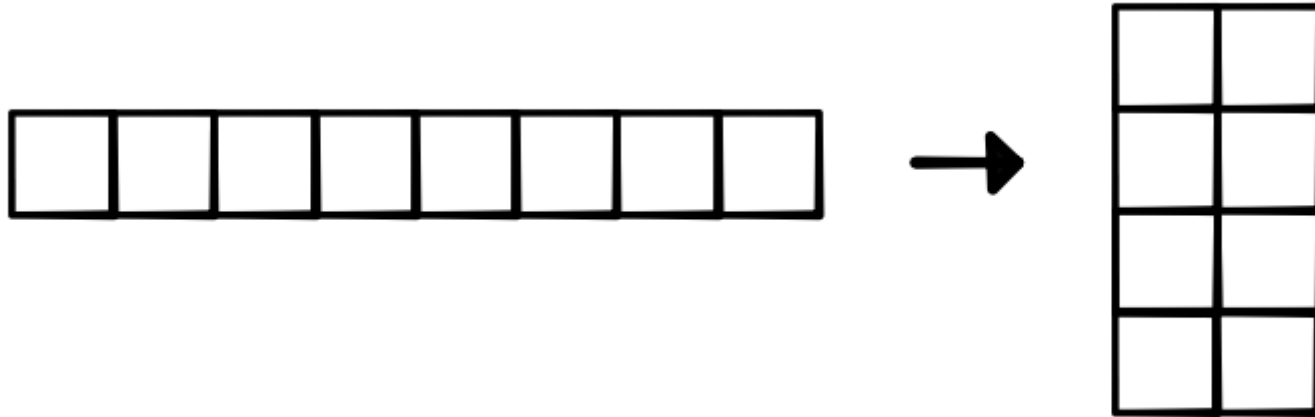
Reduction applied to each region:





# Simple Implementation

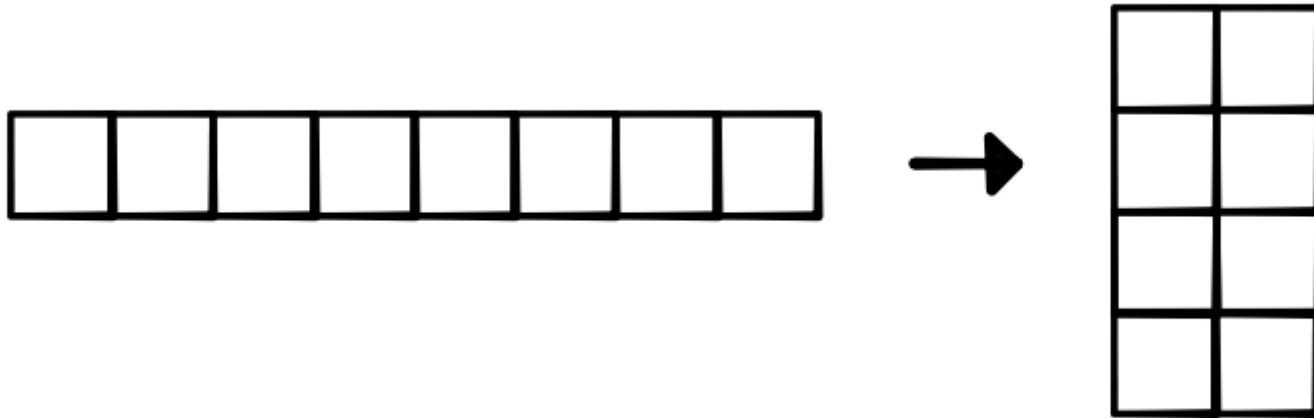
- Ensure that it is contiguous
- Use View to "fold" the tensor





# Why does folding work?

- View requires "contiguous" tensor
- View(4, 2) makes strides (2, 1)

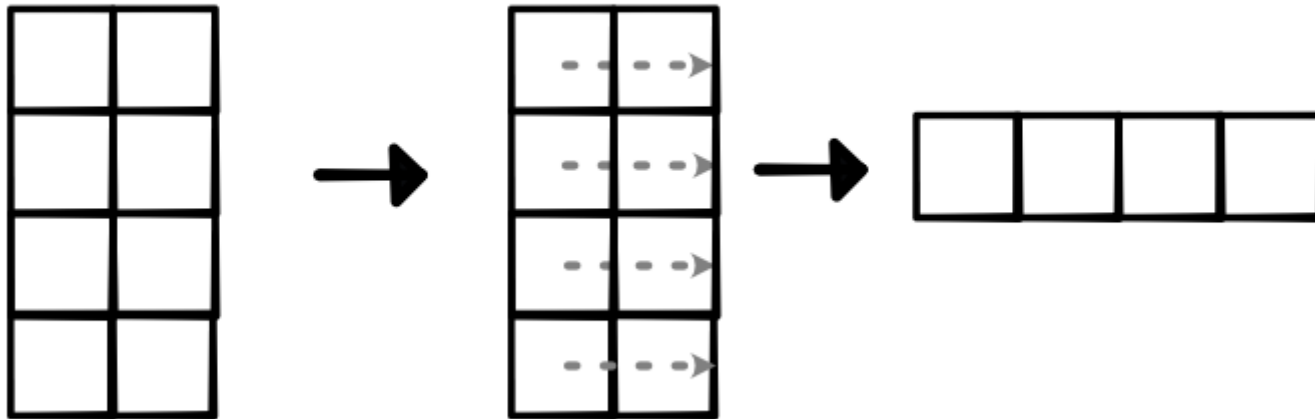






# Simple Implementation

- Reduce along created fold





# Quiz



# Gradient Flow

- Layers that are used get more updates
- Gradient signals which aspect was important
- Can have extra layers



# More Reductions

- Heading for a `max` reduction
- Heading for a `softmax` output
- Quick detour





# ReLU, Step, Sigmoid



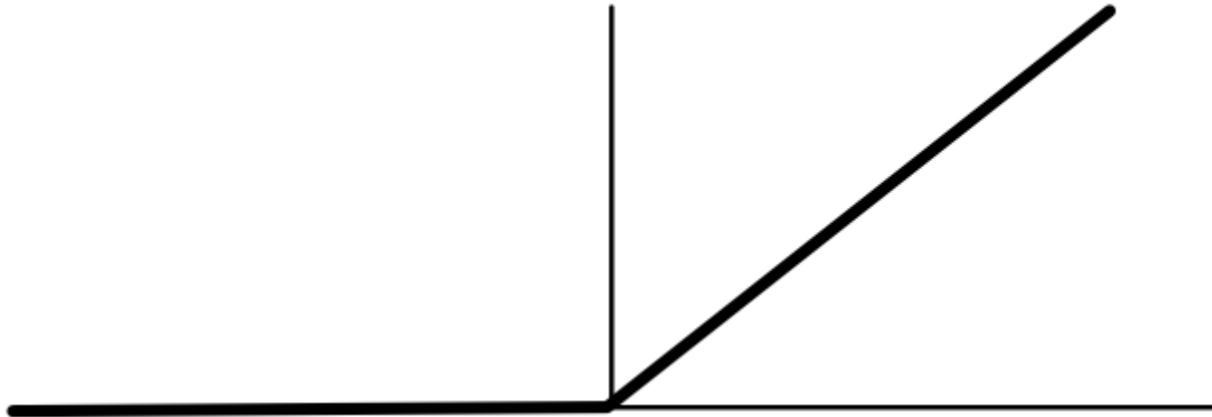
# Basic Operations

- Introduced in Module-0
- Widely used in ML
- What is it?



# Simple Function: ReLU

Main "activation" function



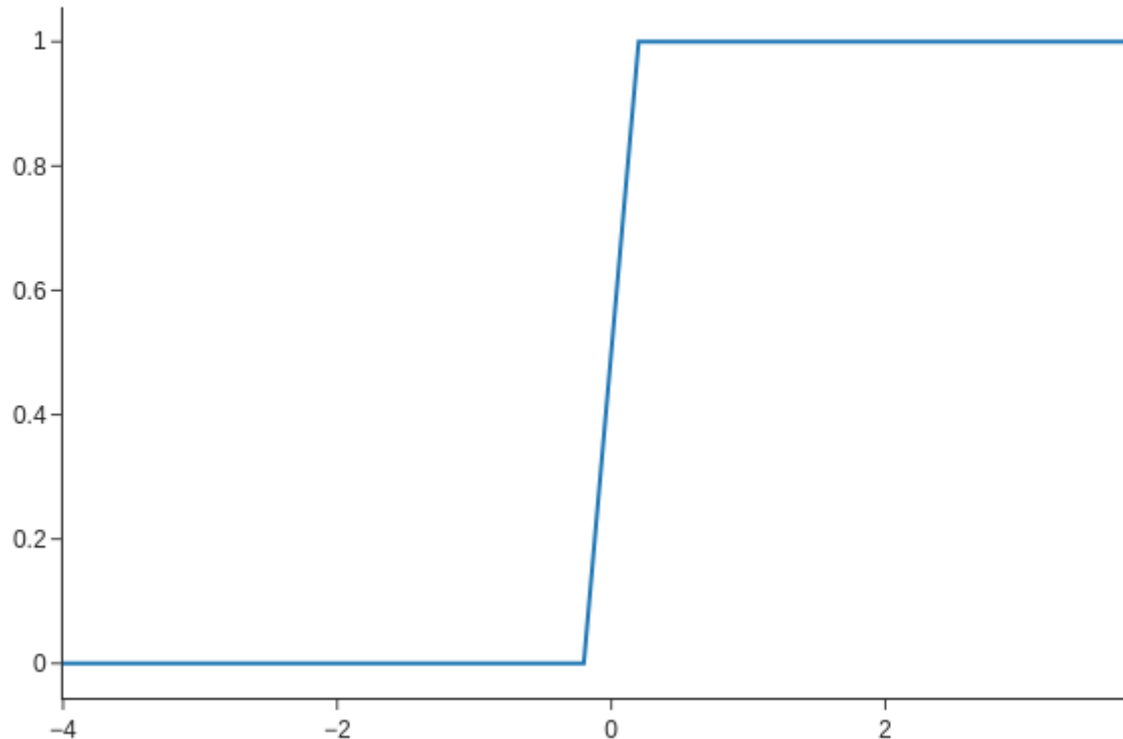
Primarily used to split the data.



# Simple Function: Step

Step function  $f(x) = x > 0$  determines correct answer

Derivative of ReLU







# ReLU

Mathematically,

$$\text{ReLU}(x) = \max$$

Simplest **max** function.



# Step

Mathematically,

$$\text{step}(x) = x > 0 = \arg\max\{0, x\}$$

Simplest `argmax` function.

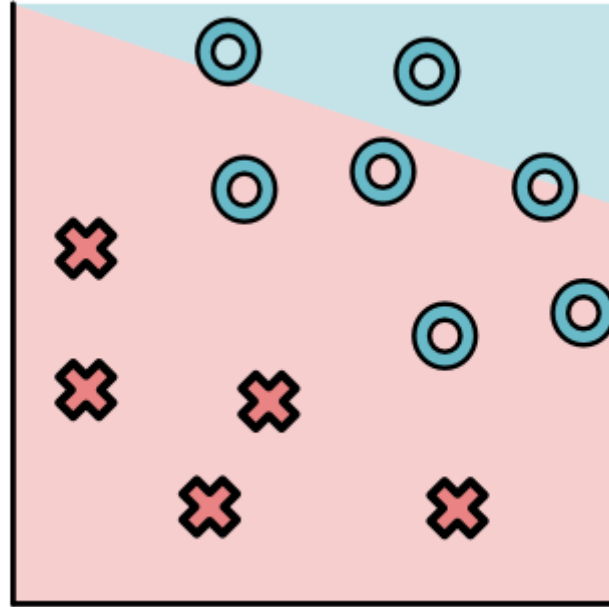


# Relationship

Step is derivative of ReLU

$$\text{ReLU}'(x) = \begin{cases} 0 & \text{if } x \leq 0 \\ 1 & \text{ow} \end{cases}$$
$$\text{step}(x) = \text{ReLU}'(x)$$





Loss of step tells us how many points are wrong.





# Derivative of Step?

Mathematically,

$\text{step}'(x) =$

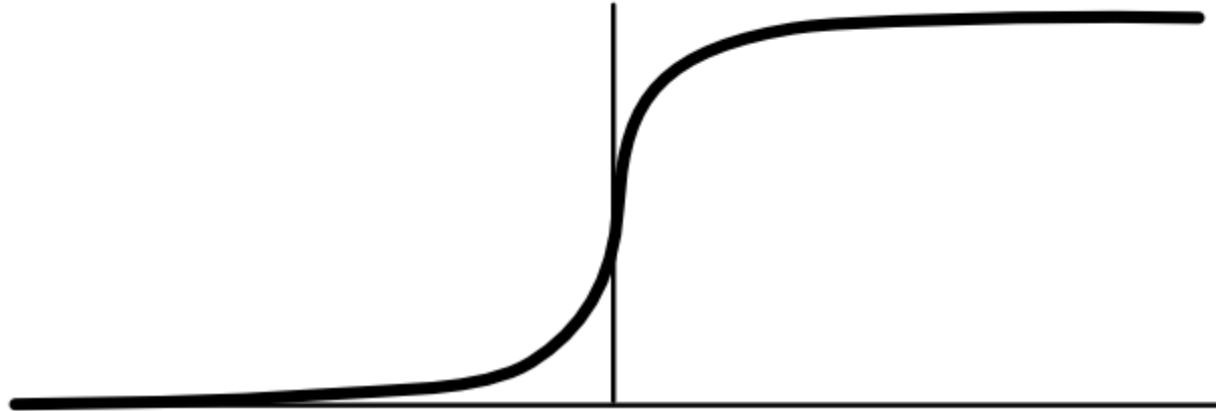
$$\begin{cases} 0 & \text{if } x \leq 0 \\ 0 & \text{ow} \end{cases}$$

Not a useful function to differentiate

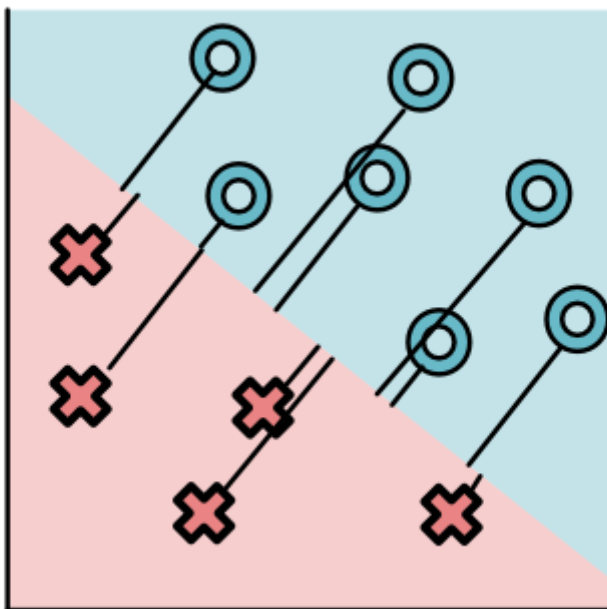


# Alternative Function: Sigmoid

Used to determine the loss function









# Soft (arg)max?

Would be nice to have a version that with a useful derivative

$\text{sigmoid}(x) = \text{softmax}\{0, x\}$

Useful soft version of argmax.





# Max, Argmax, Softmax



# Challenge

How do we generalize sigmoid to multiple outputs?





# Max reduction

- Max is a binary associative operator
- $\max(a, b)$  returns max value
- Generalized  $\text{ReLU}(a) = \max(a, 0)$



# Max Pooling

- Common to apply pooling with max
- Sets pooled value to "most active" in block
- Forward code is easy to implement





# Max Backward

- Unlike sum, max throws away other values
- Only top value gets used
- Backward needs to know this.



# Argmax

- Function that returns `argmax`, one-hot
- Generalizes step





# Max Backward

- First compute `argmax`
- Only send gradient to `argmax` gradinput
- Everything else is 0



# Ties

- What if there are two or more argmax's?
- Max is non-differentiable, like  $\text{ReLU}(0)$ .
- Short answer: Ignore, pick one





# HW

- When writing tests for max, ties will break finite-differences
- Suggestion: perturb your input by adding a small amount of random noise.



# Soft argmax?

- Need a soft version of argmax.
- Generalizes sigmoid for our new loss function
- Standard name -> softmax



# Softmax

$$\text{softmax}(\mathbf{x}) = \frac{\exp \mathbf{x}}{\sum_i \exp x_i}$$



# Sigmoid is Softmax

$$\text{softmax}([0, x])[1] = \frac{\exp x}{\exp x + \exp 0} = \sigma(x)$$





# Softmax

## Softmax





# Review

- ReLU -> Max
- Step -> Argmax
- Sigmoid -> Softmax

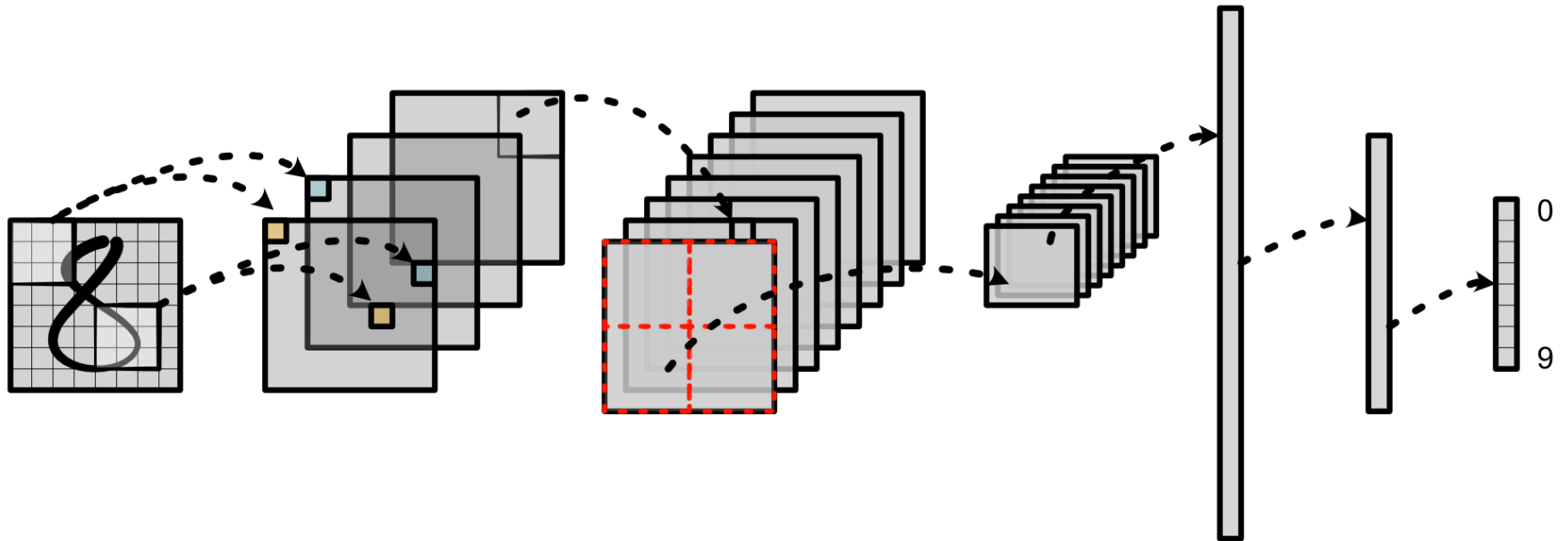


# Softmax



# Network

## Network







# Softmax Layer

- Produces a probability distribution over outputs (Sum to 1)
- Derivative similar to sigmoid
- Lots of interesting practical properties



# Softmax in Context

- Not a map!
- Gradient spreads out from one point to all.



# Softmax

- (Colab)

[[https://colab.research.google.com/drive/1EB7MI\\_3gzAR1g](https://colab.research.google.com/drive/1EB7MI_3gzAR1g)]

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# Soft Gates





# New Methods

- Sigmoid and softmax produce distributions
- Can be used to "control" information flow



# Example

Returns a combination of x and y  $f(x, y, r) = x * \sigma(r) + y * (1 - \sigma(r))$



# Gradient is controlled

$$f'_x(x, y, r) = \sigma(r)$$

$$f'_y(x, y, r) = (1 - \sigma(r))$$

$$f'_r(x, y, r) = (x - y)\sigma'(r)$$



# Neural Network Gates

Learn which one of the previous layers is most useful.

$$r = NN_1$$

$$x = NN_2$$

$$y = NN_3$$





# Gradient Flow

- Layers that are used get more updates
- Gradient signals which aspect was important
- Can have extra layers



# Selecting Choices

- Gating gives us a binary choice
- What if we want to select between many elements?
- Softmax!



# Softmax Gating

Combines many elements of  $X$  based on  $R$

$$f(X, R) = X \times \text{softmax}(R)$$



# Softmax Gating

- Brand name: Attention





# Example: Translation

- Show example



# Example: GPT-3

- Show example



QA

