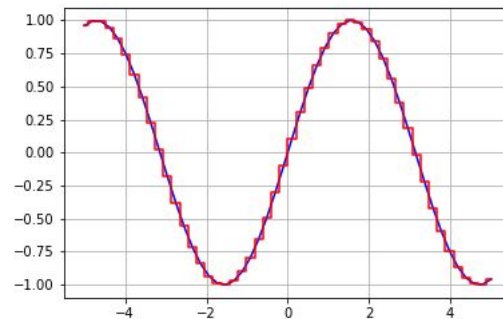
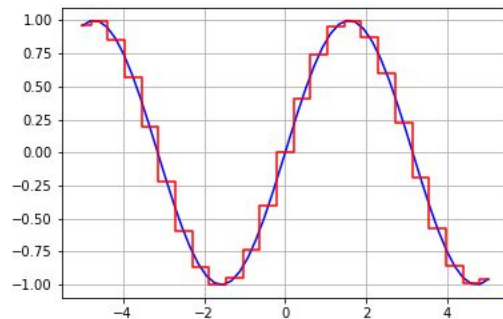
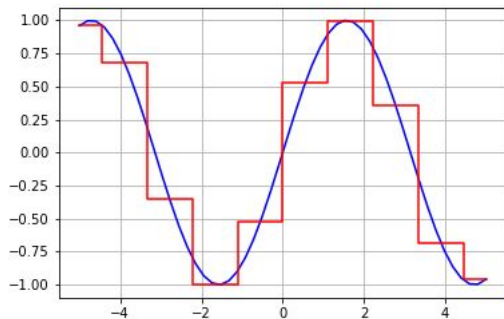


# Week 5

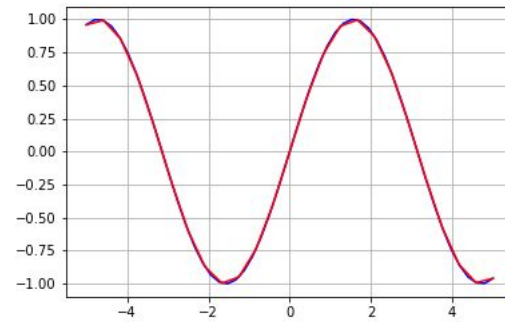
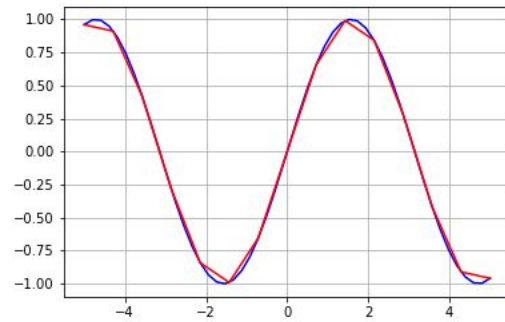
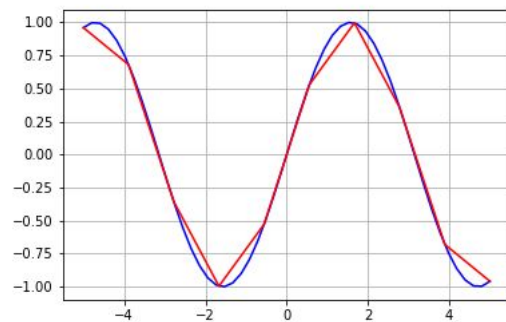
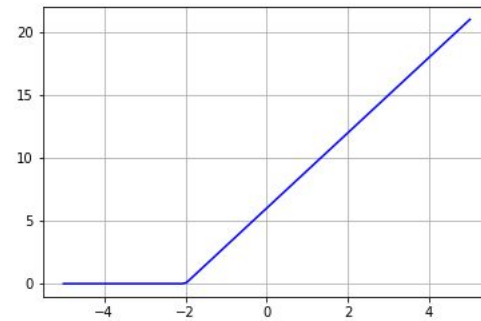
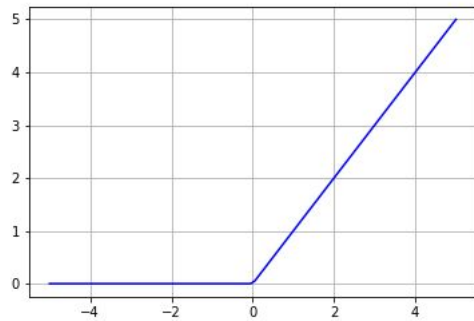
## Different Types of Activation Units

# Universal function approximation

- Non-linear function enables approximation to any function
- 
- Example: Unit step function
- Problem: The gradient of the unit step function is zero everywhere



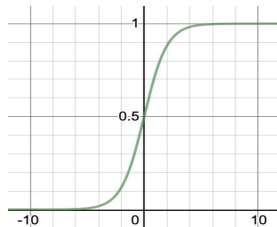
## Ex: ReLU



# Comparison of Activation Units

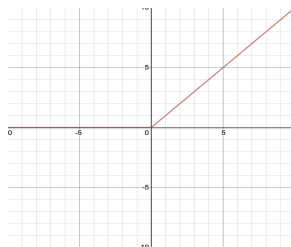
- Sigmoid

$$f(z) = \frac{1}{1 + e^{-z}}$$



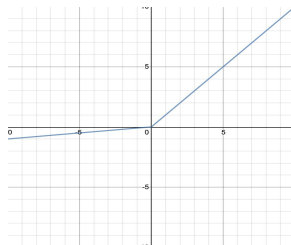
- ReLU

$$f(z) = \begin{cases} z & \text{if } z \geq 0, \\ 0 & \text{else.} \end{cases}$$



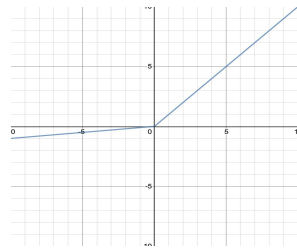
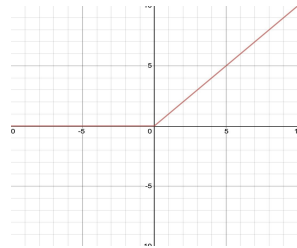
- Parametric ReLU

$$f(z) = \begin{cases} z & \text{if } z \geq 0, \\ az & \text{else.} \end{cases}$$



# ReLU

- ReLU doesn't saturate when  $z$  approaches infinity
  - First derivative has constant 1 when  $z > 0$
  - Less likely to have vanishing gradient
- ReLU dies when  $z < 0$ 
  - Doesn't solve the vanishing gradient problem in the  $z < 0$  region
- Parametric ReLU
  - First derivative has non zero value everywhere
  - Solves the dying ReLU problem



# Swish and Mish

- Latest state of the art activation functions
- Swish

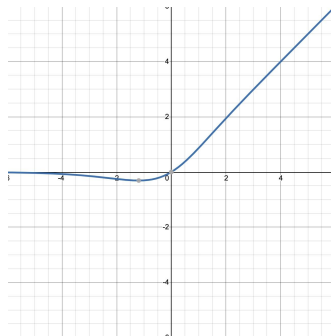
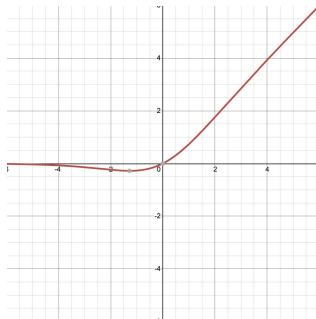
$$f(z) = \frac{z}{1 + e^{-\beta z}}$$

1. Unbounded above, bounded below
2. Non-monotonicity
3. Differentiable everywhere

- Mish -- Improve upon swish

$$f(z) = z \tanh(\ln(1 + e^z))$$

1. First derivative is preconditioned



# Gradient Vanishing/Exploding

- Recall back-propagation

$$\nabla_{\mathbf{W}^{(l)}} \mathcal{L} = \delta^{(l)} \mathbf{a}^{(l-1)T}$$

- Gradients are proportional to the multiplication of derivatives of activation functions and weight matrices in the following layers

$$\begin{aligned} \delta^{(l)} &= \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{(l)T}} \\ &= \text{diag}(\sigma'(\mathbf{z}^{(l)})) \mathbf{W}^{(l+1)T} \text{diag}(\sigma'(\mathbf{z}^{(l+1)})) \dots \mathbf{W}^{(L)T} \text{diag}(\sigma'(\mathbf{z}^{(L)})) \frac{\partial \mathcal{L}}{\partial \mathbf{y}^T} \end{aligned}$$

# Gradient Vanishing/Exploding

- Happens when
  - the there are too many cascaded layers ( $0.9^{100} \approx 0$  or  $1.1^{100} \approx \infty$ )
  - the model is poorly initialized ( $0.1^{10} \approx 0$  or  $1.1^{100} \approx \infty$ )
  - nonlinear functions are inappropriate ( $0.1^{10} \approx 0$  or  $1.1^{100} \approx \infty$ )
  - activations / inputs are inappropriate ( $0.1^{10} \approx 0$  or  $1.1^{100} \approx \infty$ )
  - ...
- Solve it from the source
  - use fewer layers (?)
  - design suitable initialization methods (Xavier, Kaiming, etc)
  - change activation units
  - batch normalization
  - ...