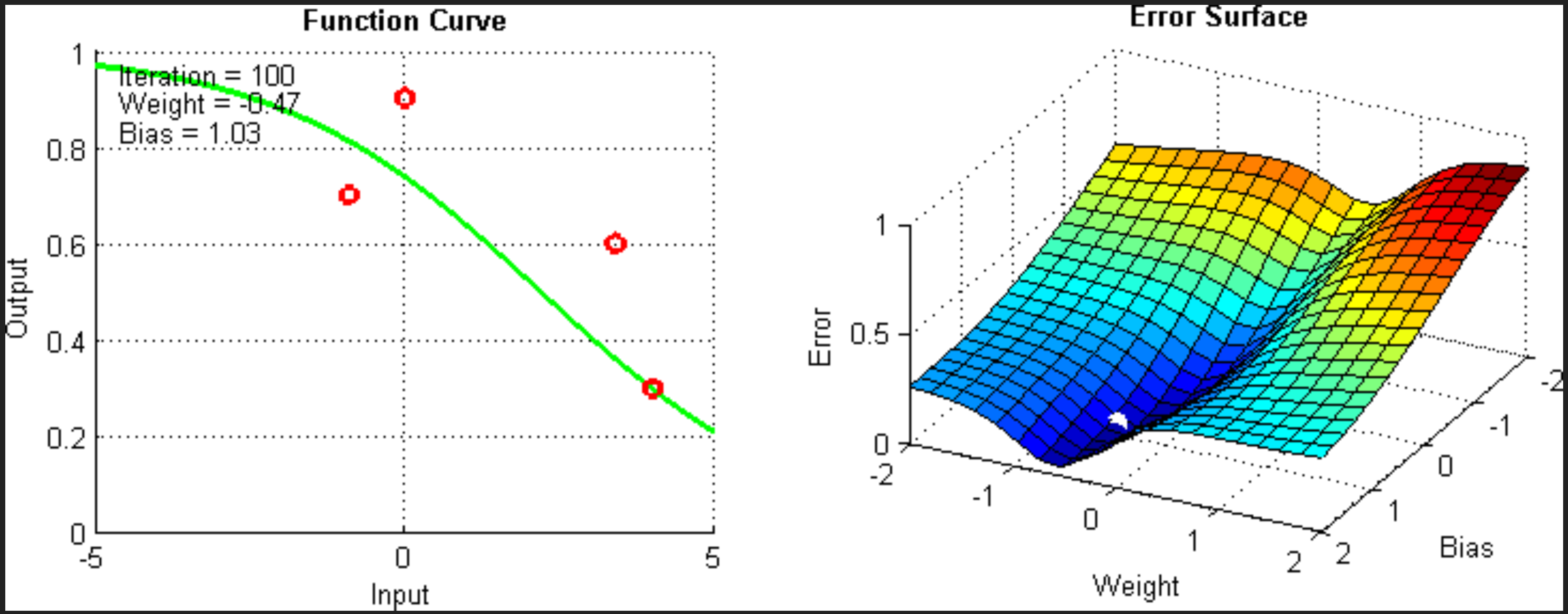
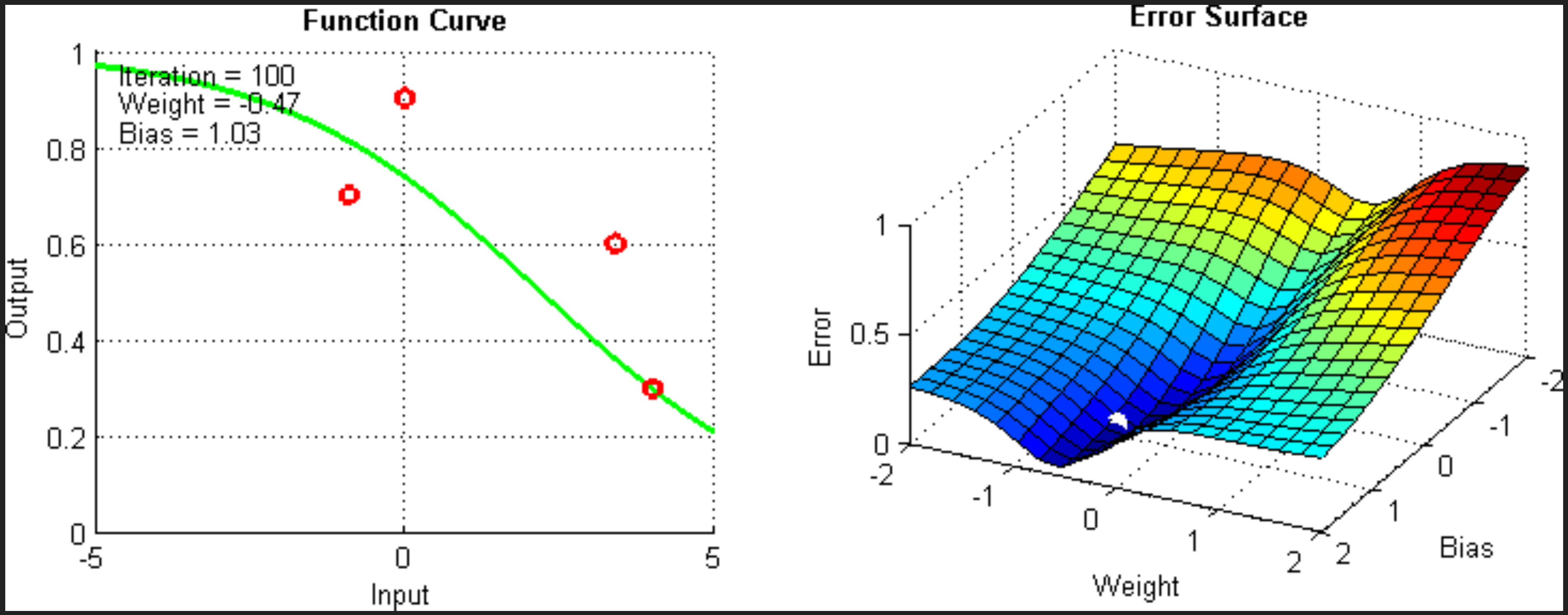


LOSSES, OPTIMISERS & ACTIVATIONS



LOSSES, OPTIMISERS & ACTIVATIONS

LOSS FUNCTIONS

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$$H(p,q) = -\sum_{x} p(x)\,\log q(x)$$

USECASES

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- CE Loss: Classification with target variable having multiple classes

OPTIMISERS

VANILLA GRADIENT DESCENT

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Function:

$$J(\theta_1, \theta_2) = {\theta_1}^2 + {\theta_2}^2$$

Objective:

$$\min_{\theta_1, \theta_2} J(\theta_1, \theta_2)$$

Update rules:

$$\theta_1 := \theta_1 - \alpha \frac{d}{d\theta_1} J(\theta_1, \theta_2)$$

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- First Order Differentiation
- Also called Batch Gradient Descent
- Running through ALL samples can be very computationally expensive!

STOCHASTIC GRADIENT DESCENT

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Require: Learning rate schedule $\epsilon_1, \epsilon_2, \dots$
Require: Initial parameter $\boldsymbol{\theta}$
$k \leftarrow 1$
while stopping criterion not met **do**
Sample a minibatch of m examples from the training set $\{\boldsymbol{x}^{(1)}, \dots, \boldsymbol{x}^{(m)}\}$ with corresponding targets $\boldsymbol{y}^{(i)}$.
Compute gradient estimate: $\hat{\boldsymbol{g}} \leftarrow \frac{1}{m} \nabla_{\boldsymbol{\theta}} \sum_i L(f(\boldsymbol{x}^{(i)}; \boldsymbol{\theta}), \boldsymbol{y}^{(i)})$
Apply update: $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \epsilon_k \hat{\boldsymbol{g}}$
$k \leftarrow k + 1$
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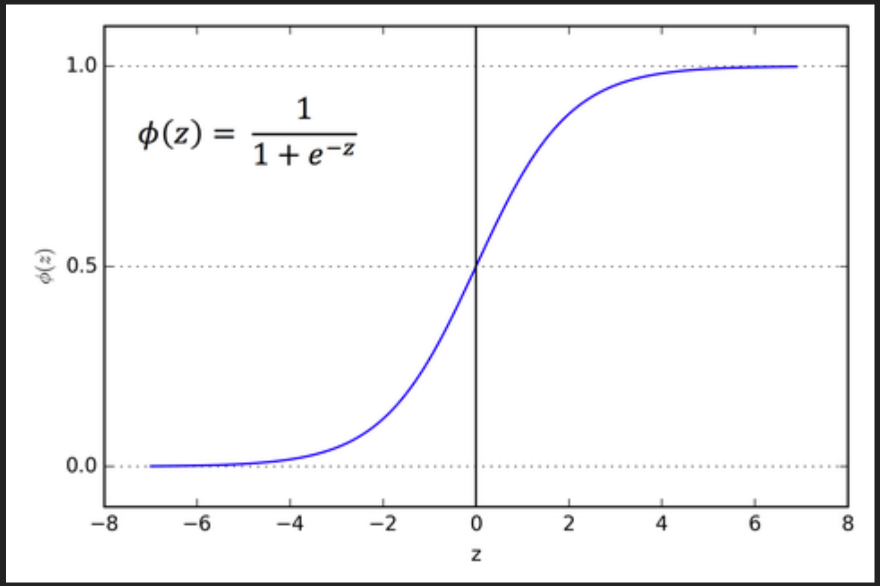
- Mini-batch of m examples
- Iterative
- First Order Differentiation
- Regularisation effect due to mini-batch

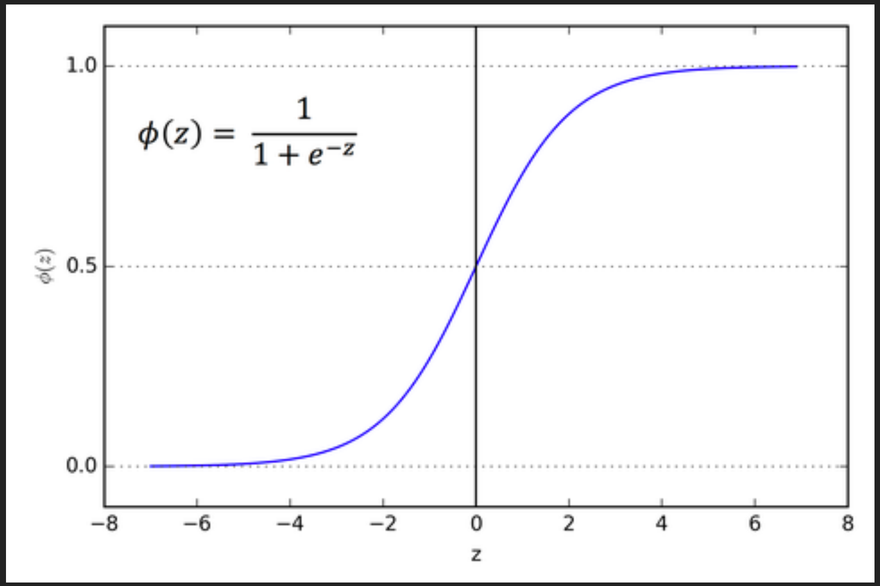
ACTIVATIONS

ACTIVATIONS – SIGMOID



ACTIVATIONS - SIGMOID

- Good for Binary Classification



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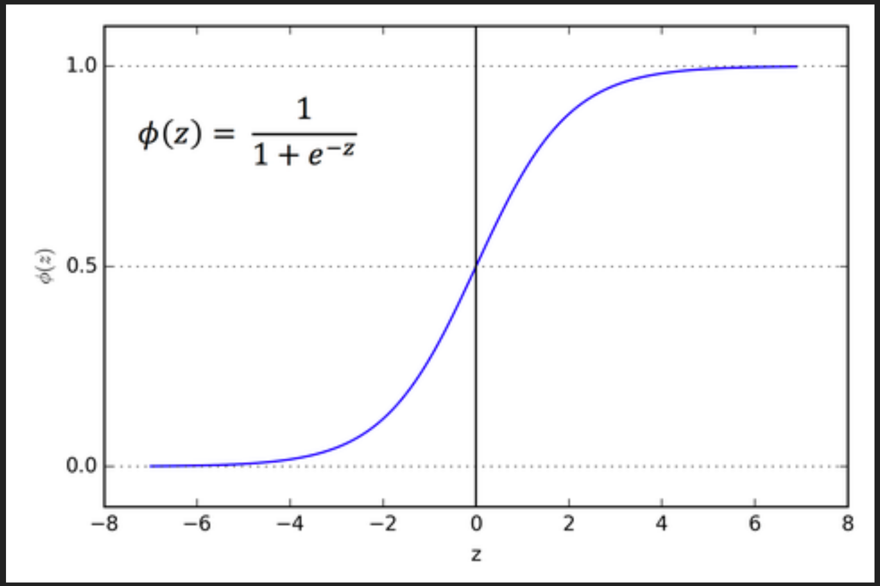

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- Softmax - Extension to Multi Class Classification

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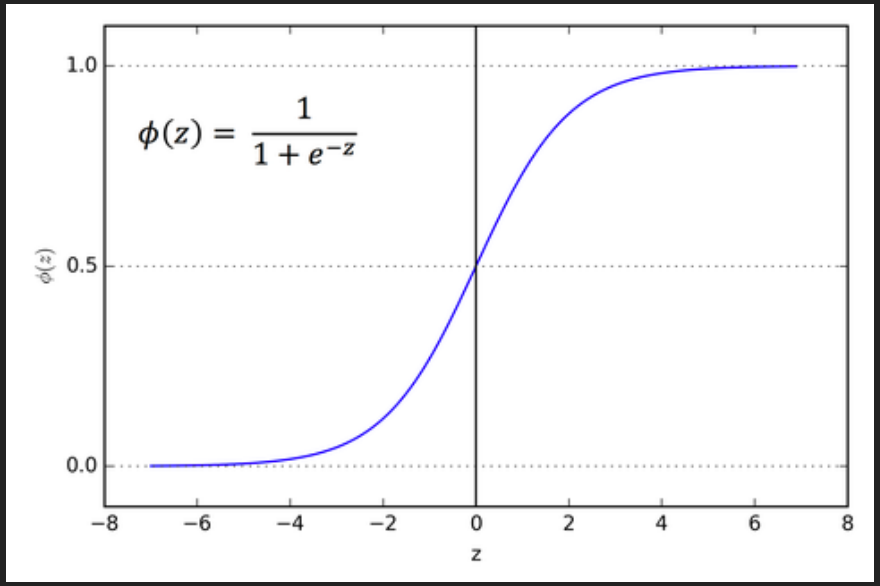

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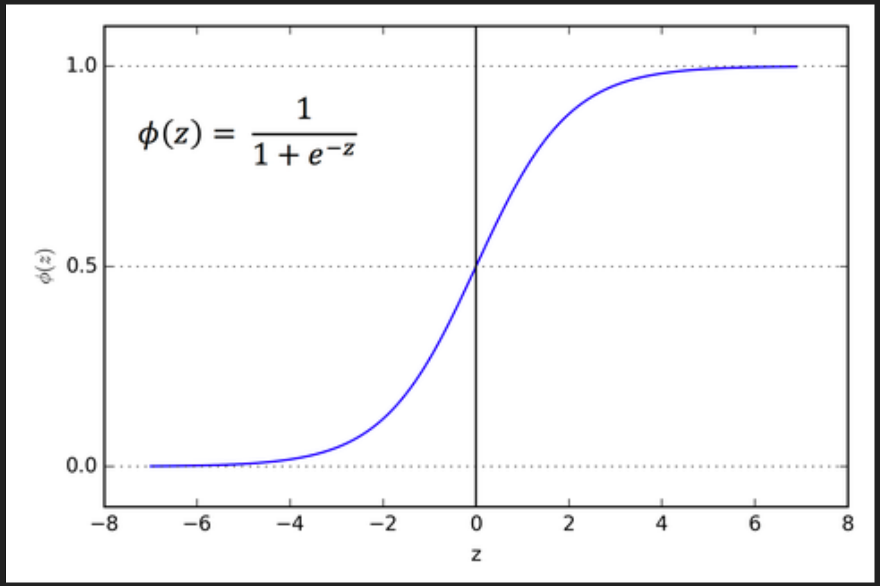

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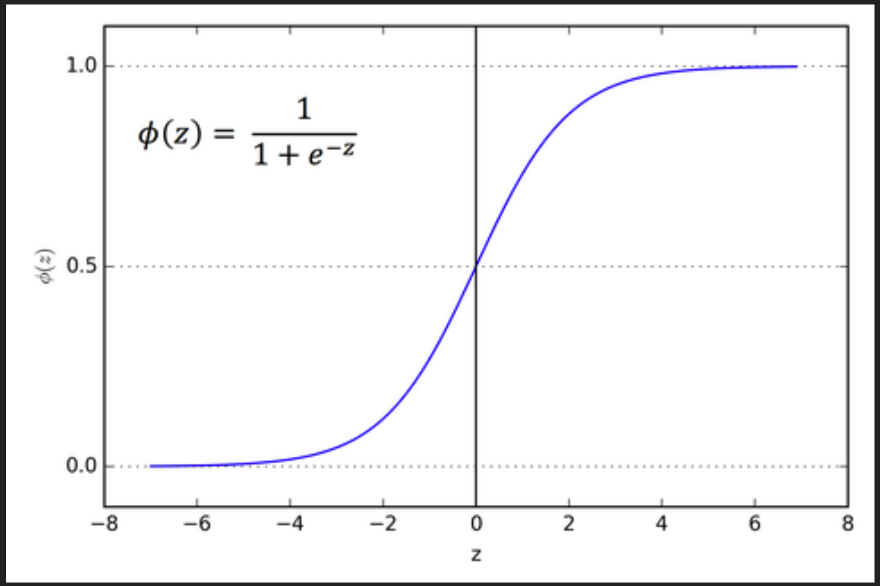

- Good for Binary Classification
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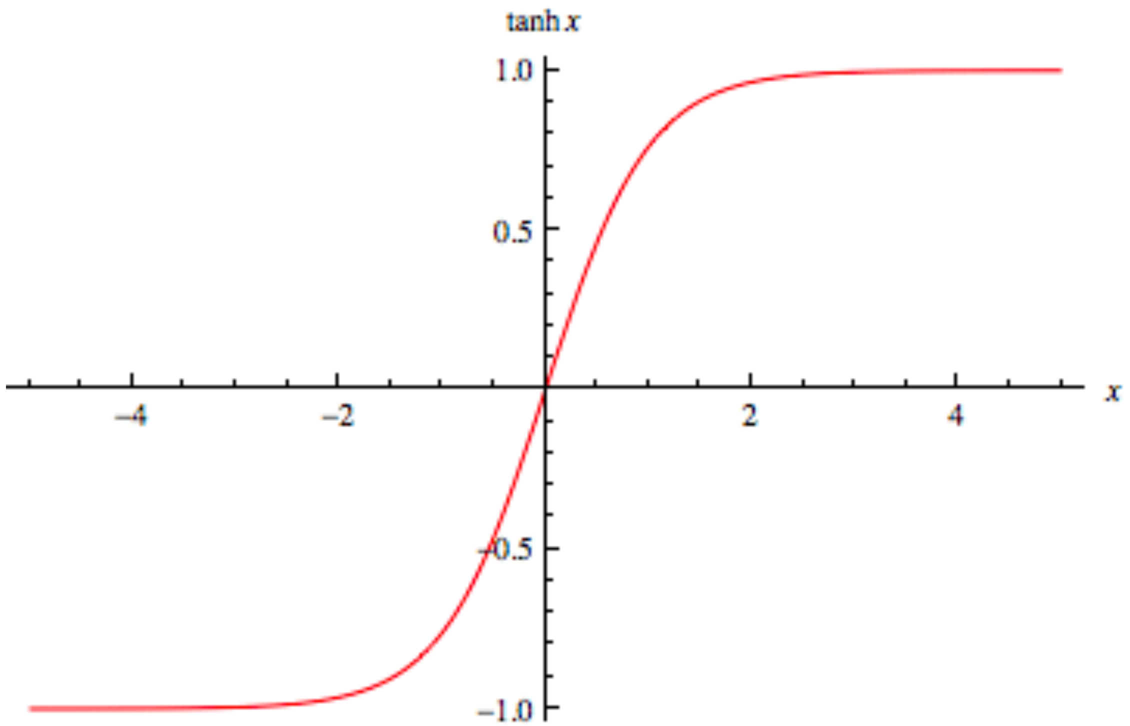
- Not zero centered
- Exp() - Computationally expensive

ACTIVATIONS – TANH



ACTIVATIONS – TANH

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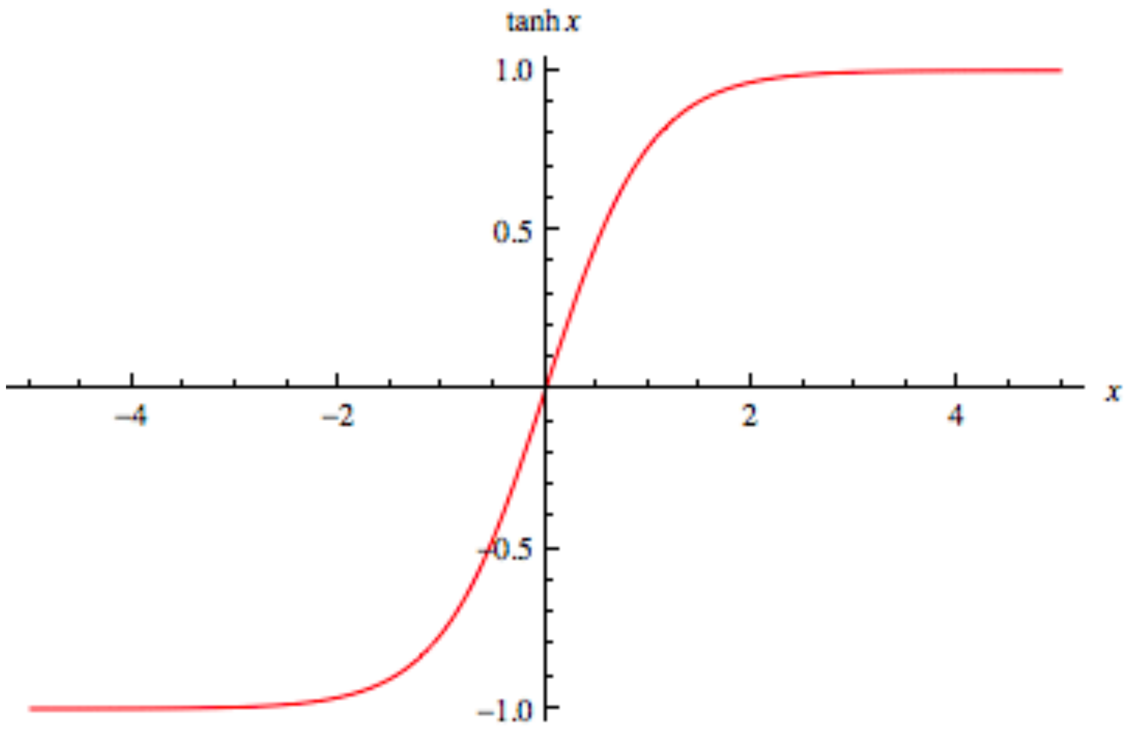
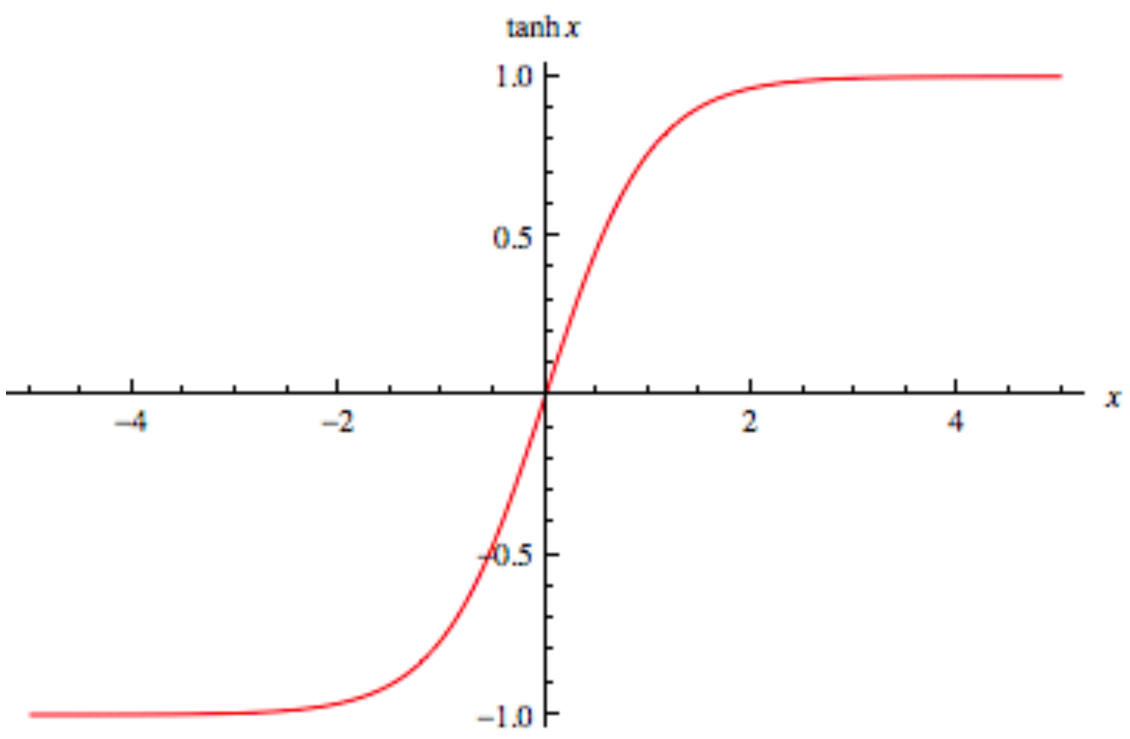


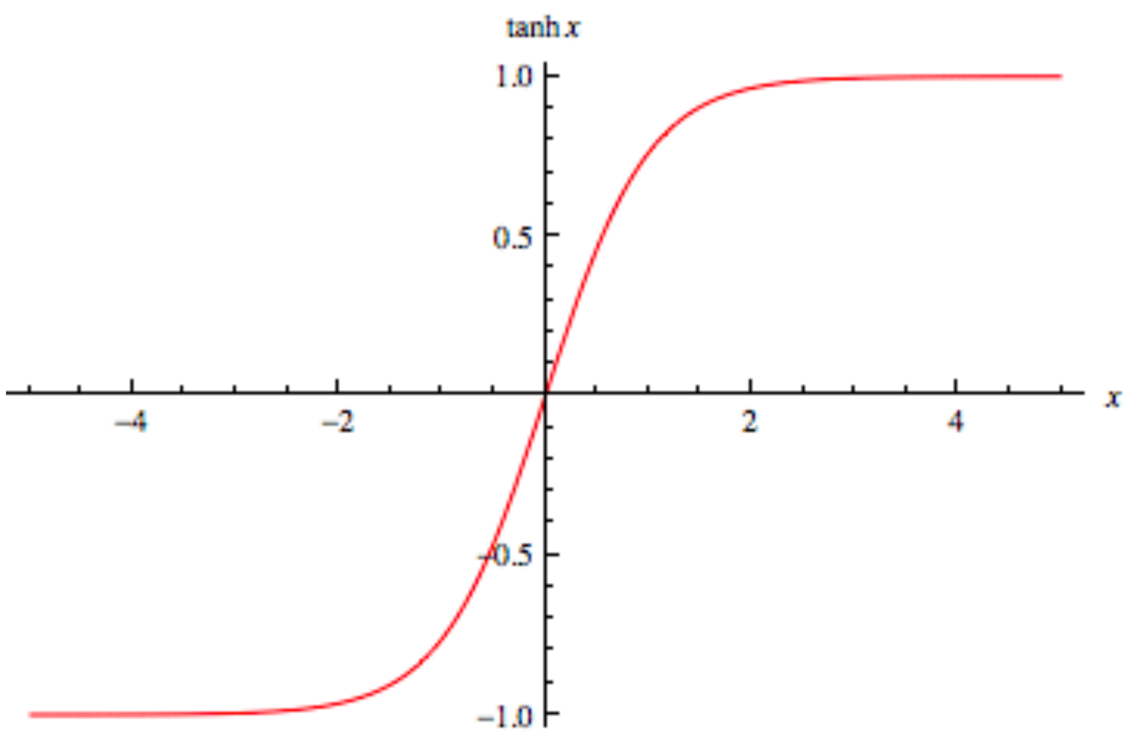
ACTIVATIONS – TANH

- Zero - centered
- Used in Recurrent Neural Networks

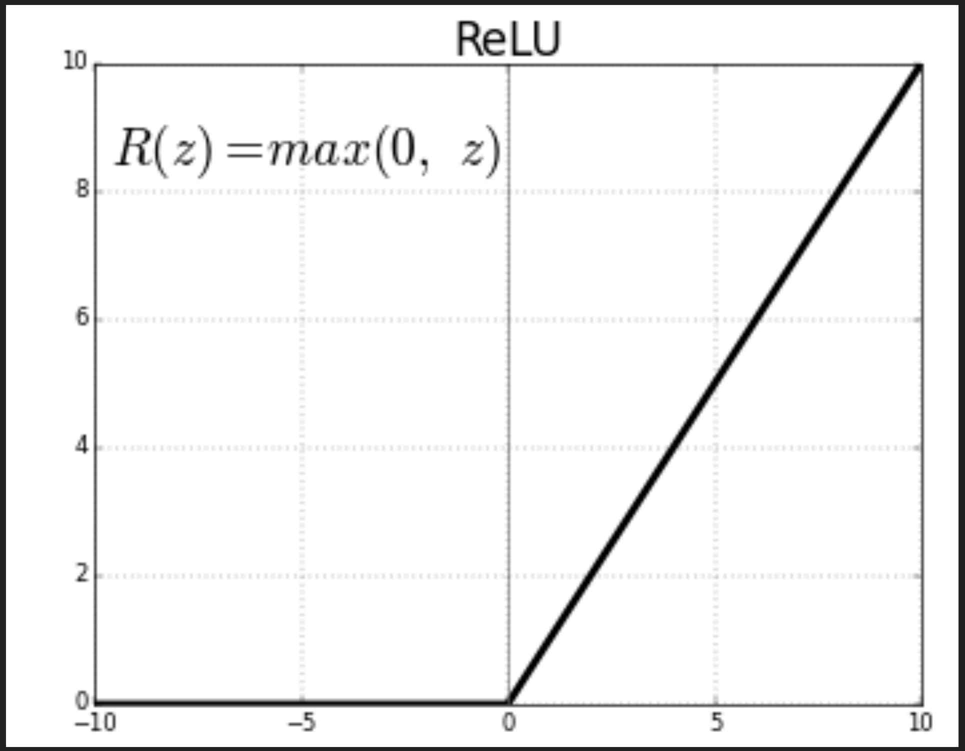


ACTIVATIONS – TANH

- Zero - centered
- Used in Recurrent Neural Networks
- Saturated Neurons - Kill gradients

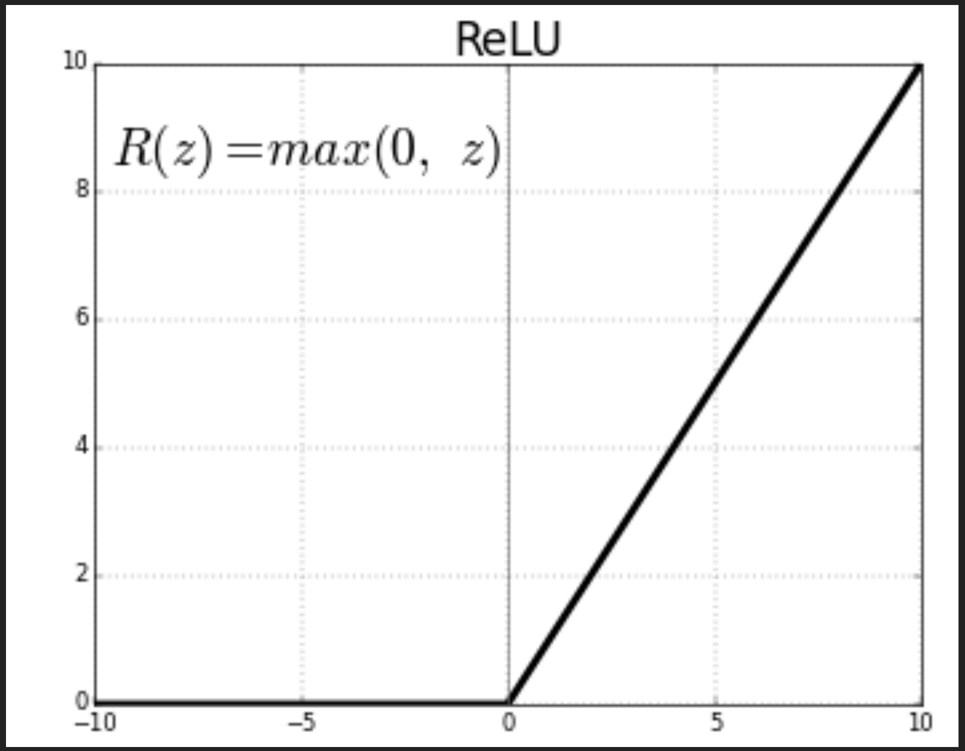


ACTIVATIONS – RECTIFIED LINEAR UNIT(RELU)



ACTIVATIONS – RECTIFIED LINEAR UNIT(RELU)

- Neurons do not get saturated. Faster Convergence. Computationally efficient.



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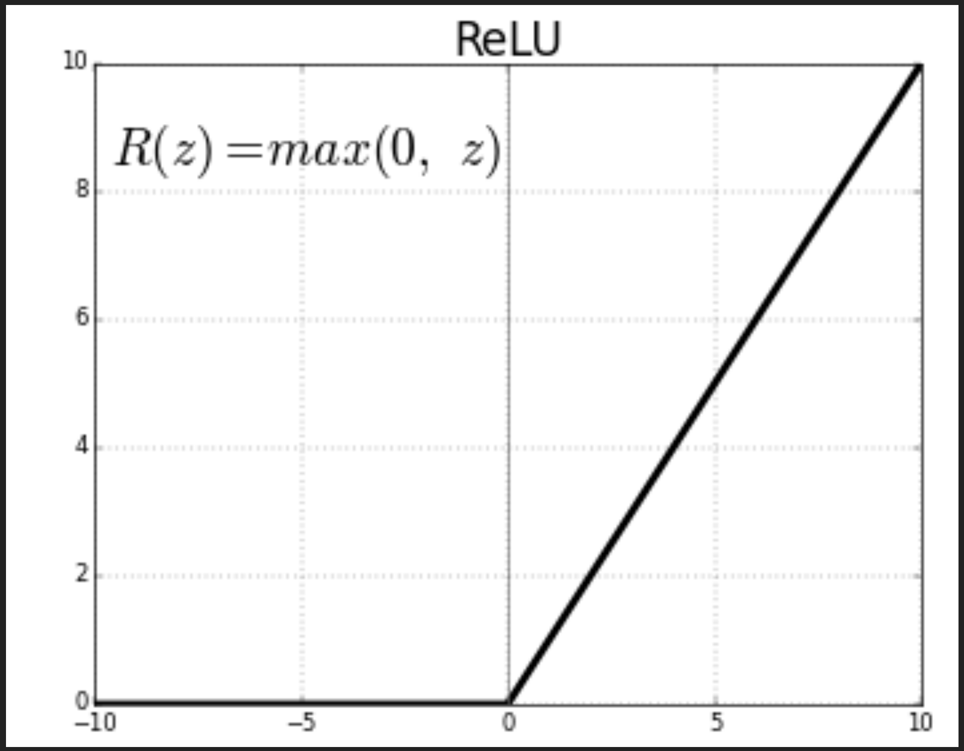

ACTIVATIONS – RECTIFIED LINEAR UNIT(RELU)

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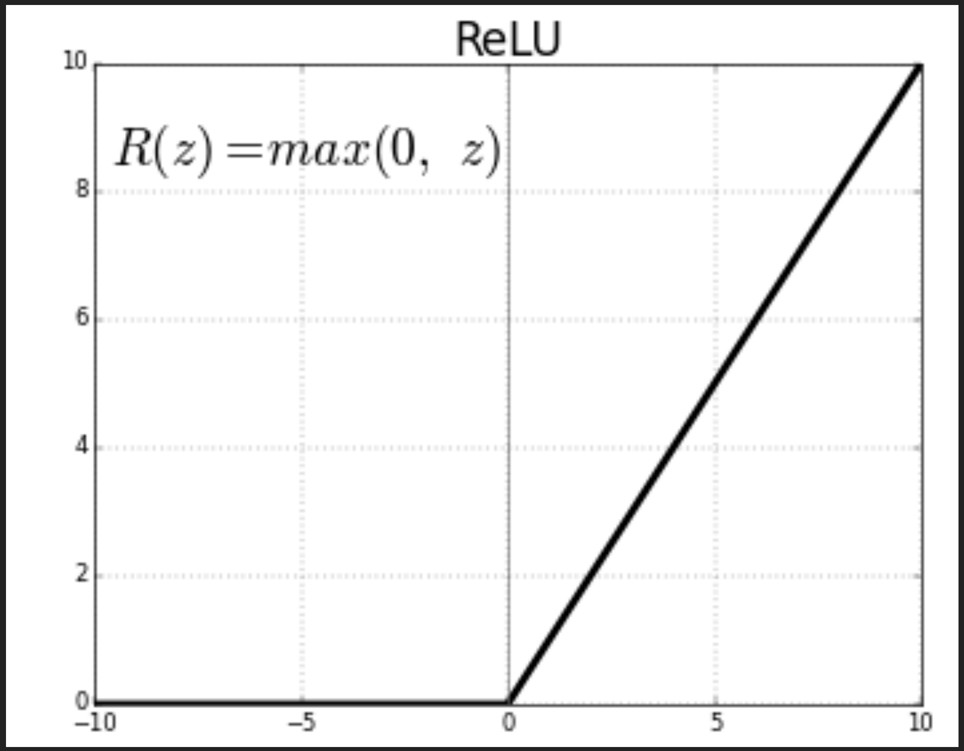
- Not zero-centered
- Gradient is 0 for x<0



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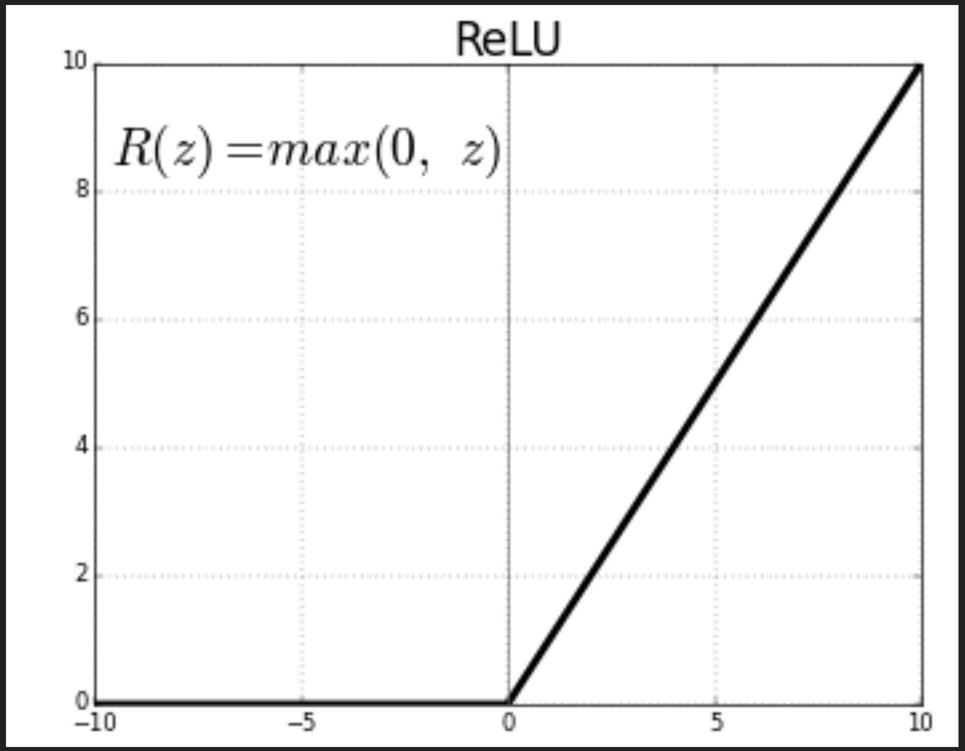
- Regularisation effect



ACTIVATIONS - RECTIFIED LINEAR UNIT(RELU)

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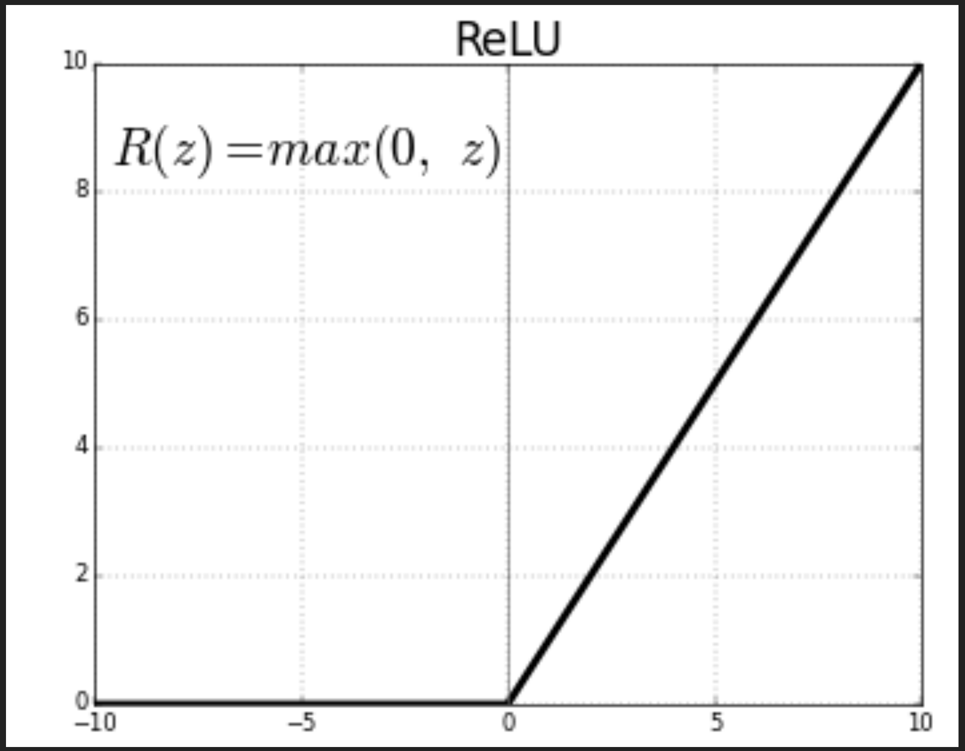
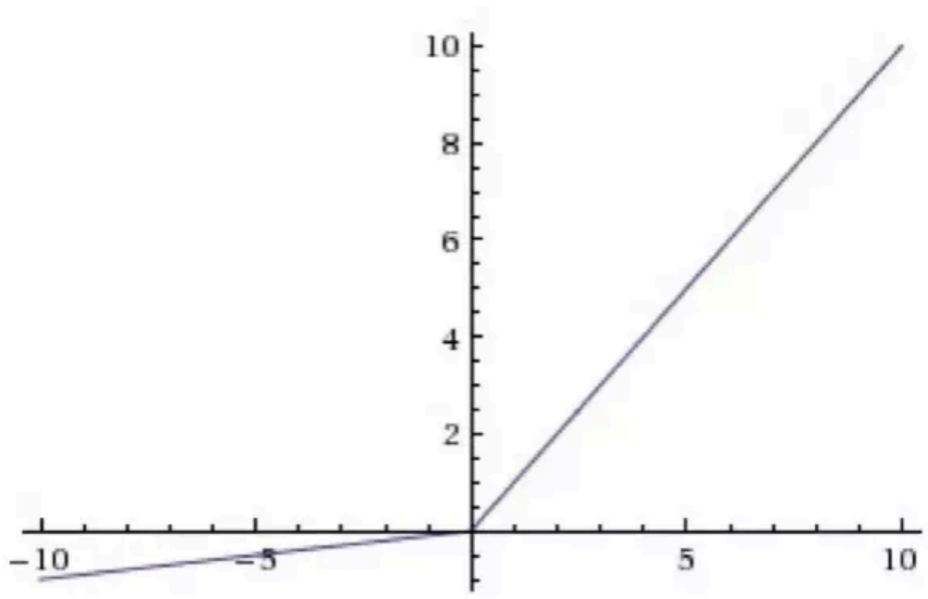
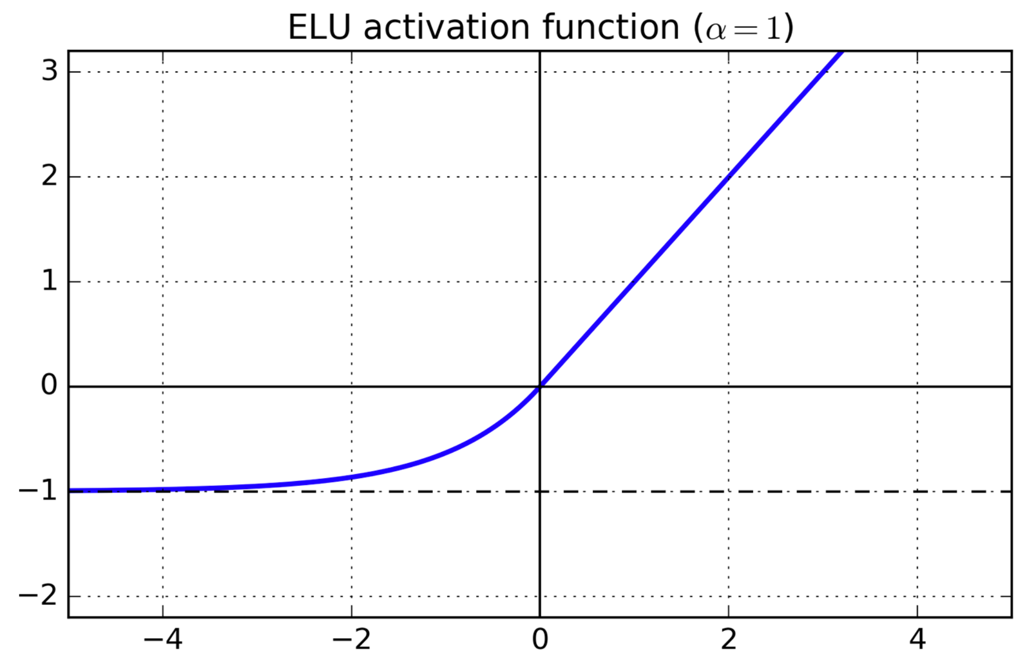
- Not zero-centered
- Gradient is 0 for x<0
- Regularisation effect
- More biologically plausible than Sigmoid



ACTIVATIONS – LEAKY RELU AND ELU





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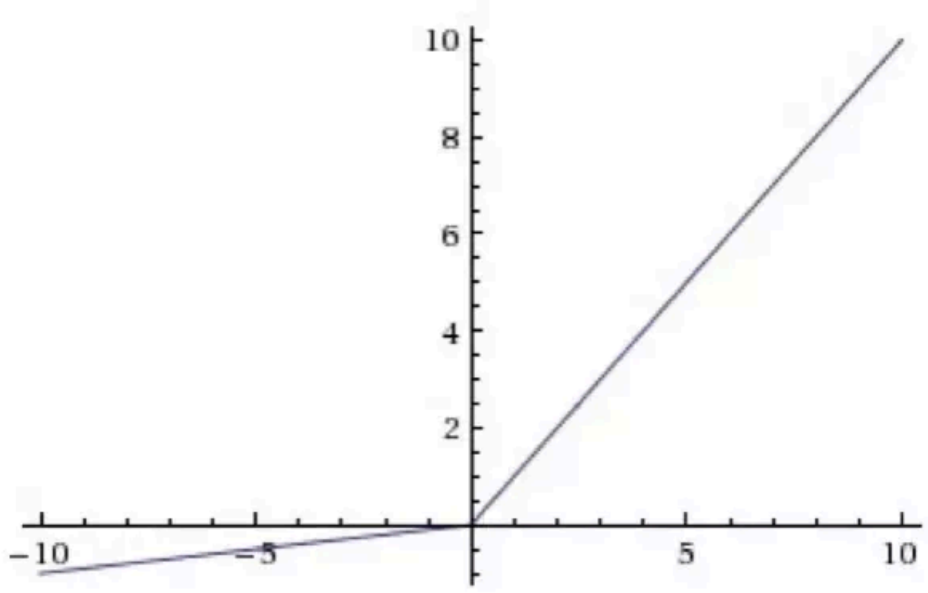

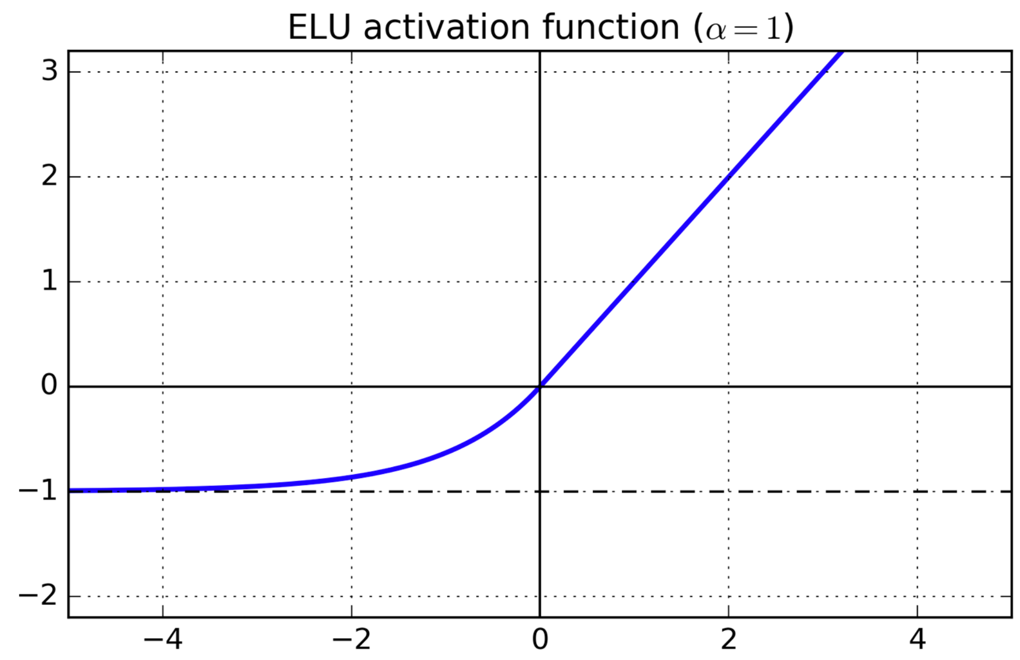

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- No Saturation.
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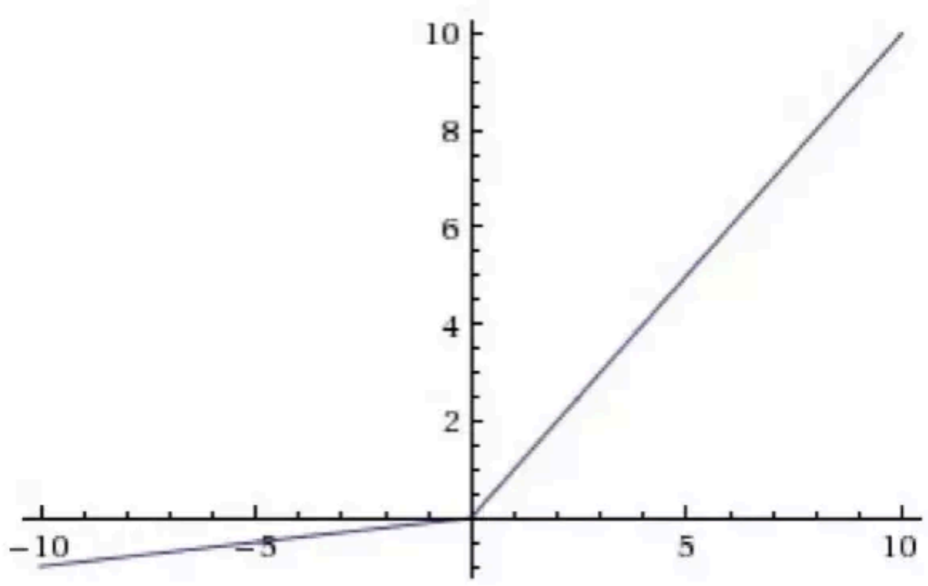
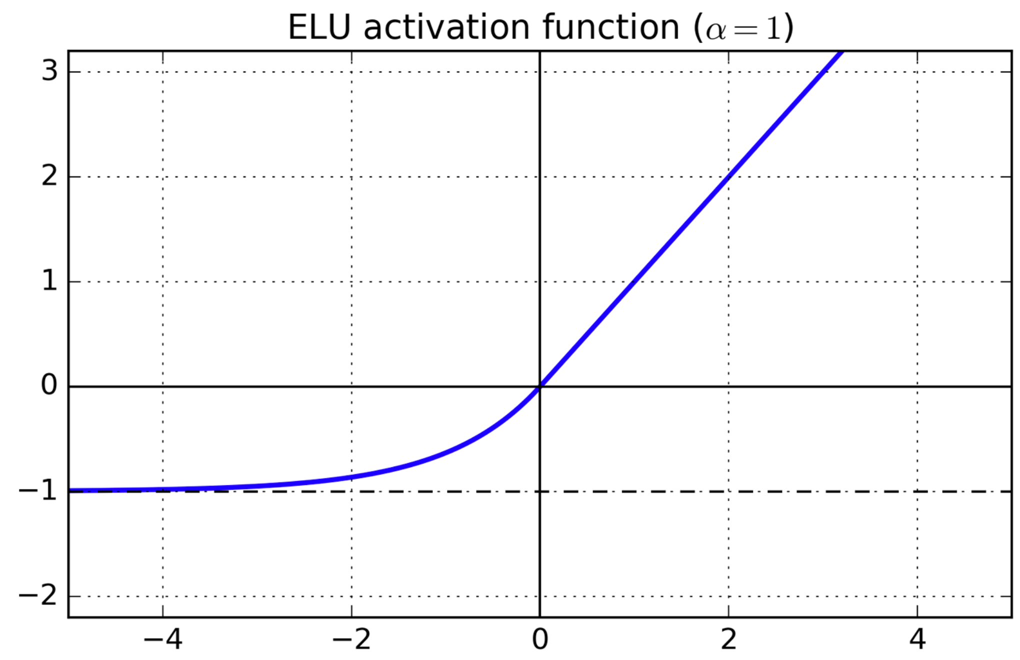
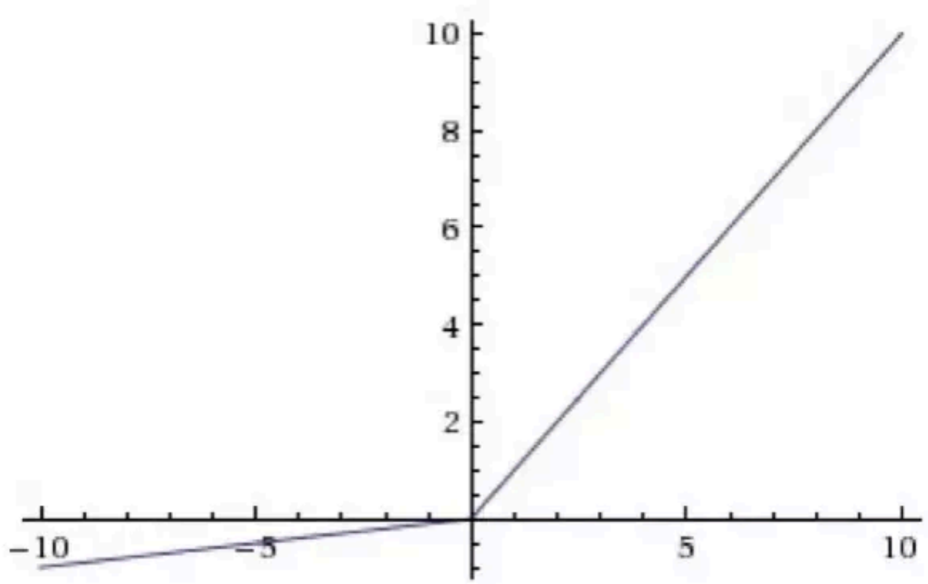
- Gradient is not 0 for x<0

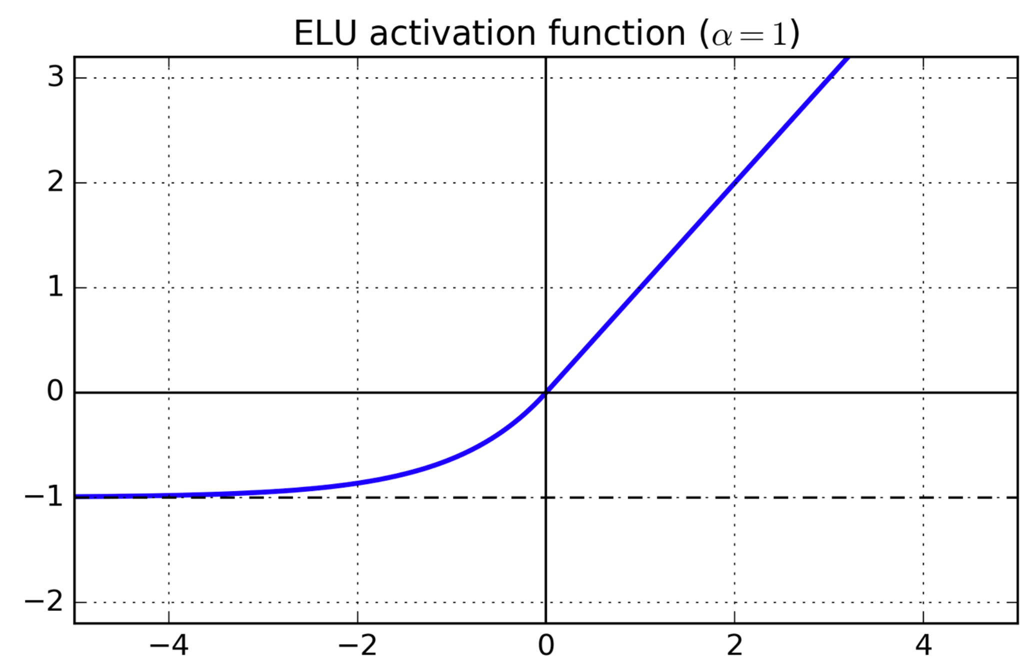




ACTIVATIONS – LEAKY RELU AND ELU

- No Saturation. Computationally efficient
- Closer to zero-entered than other activations
- Gradient is not 0 for x<0





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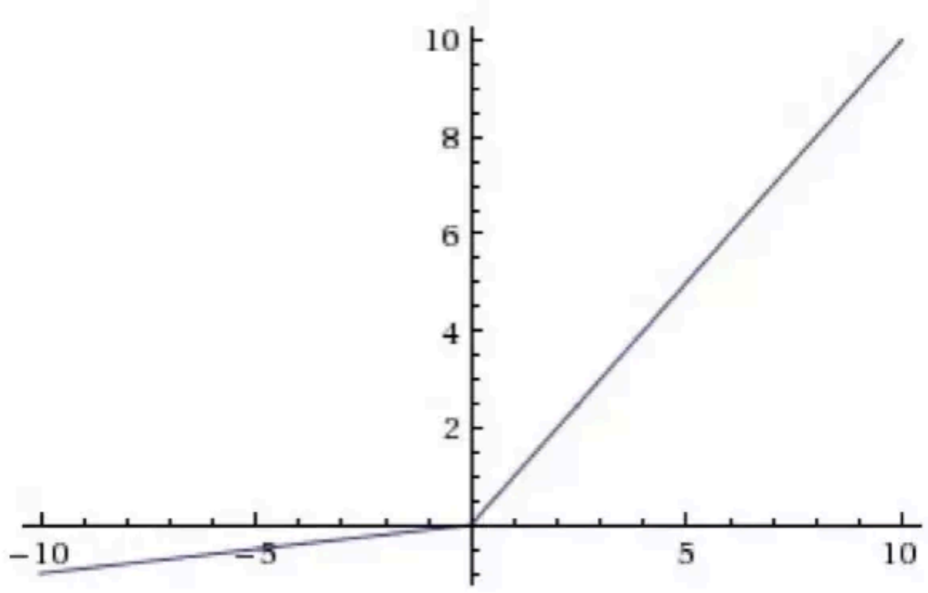

- Closer to zero-entered than other activations
- Negative Saturation adds noise hence robustness