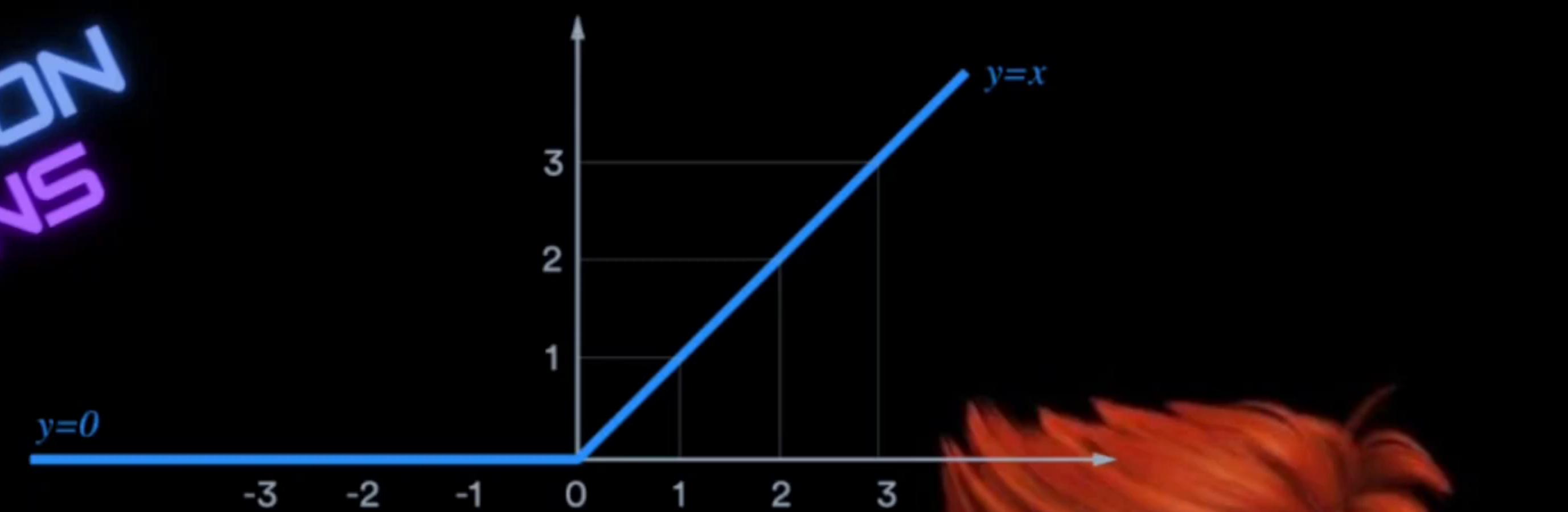


ACTIVATION
FUNCTIONS



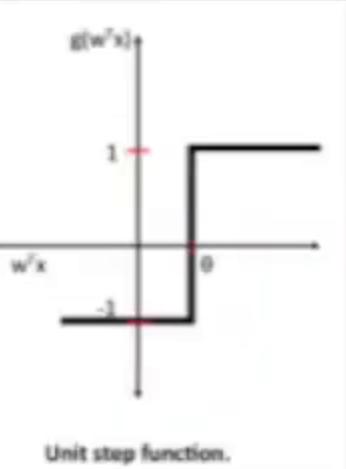
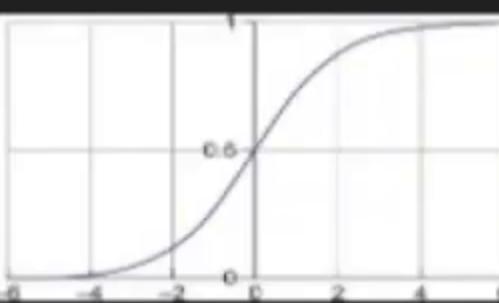
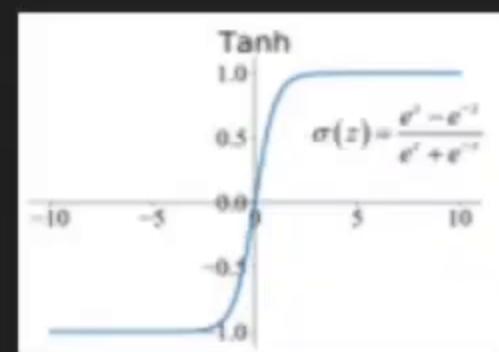
RELU ACTIVATION



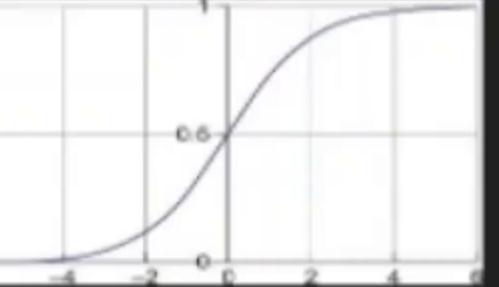
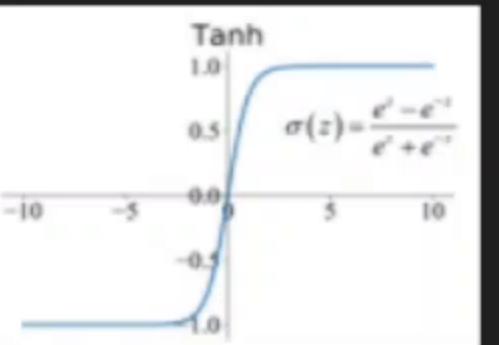
Programming



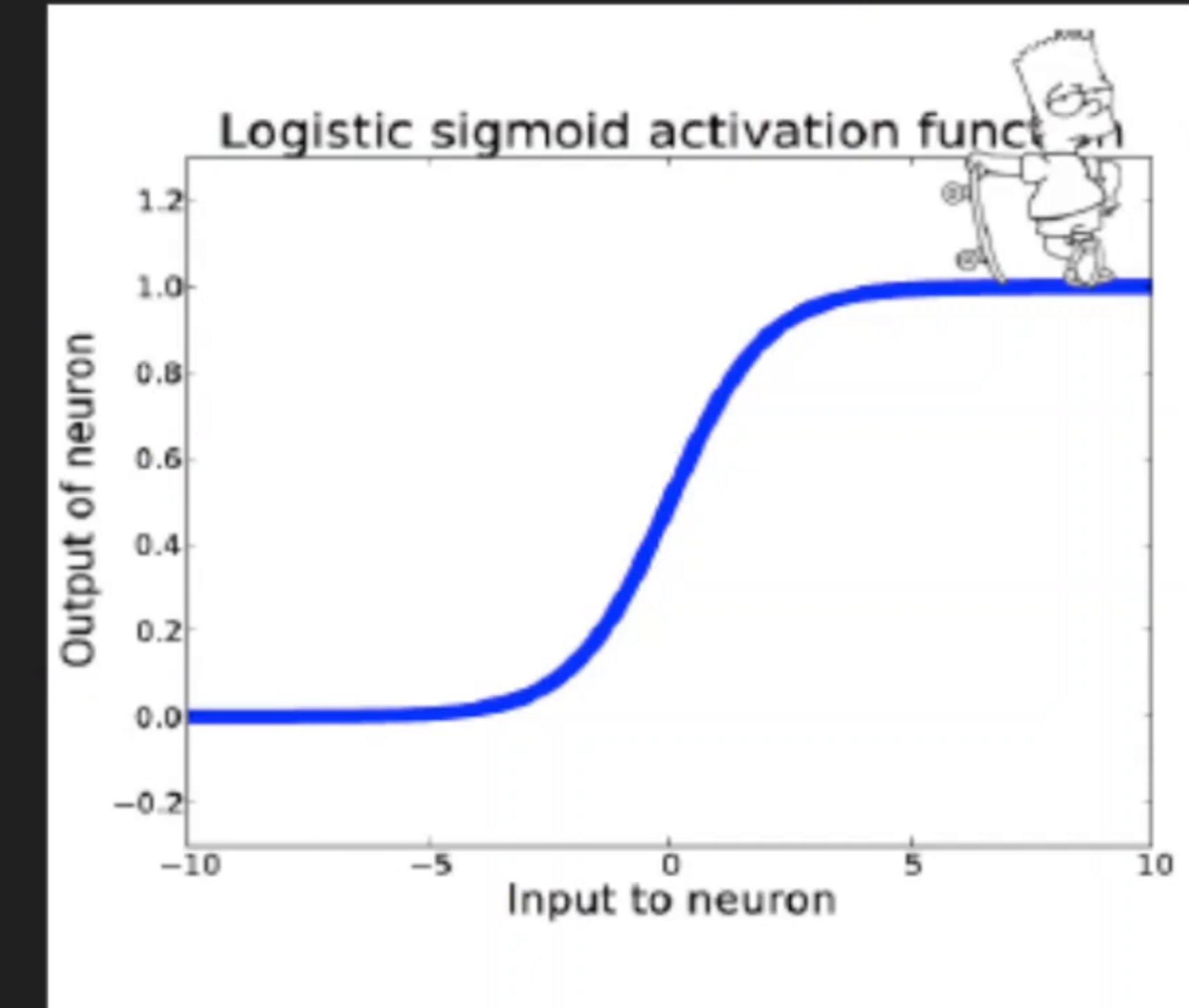
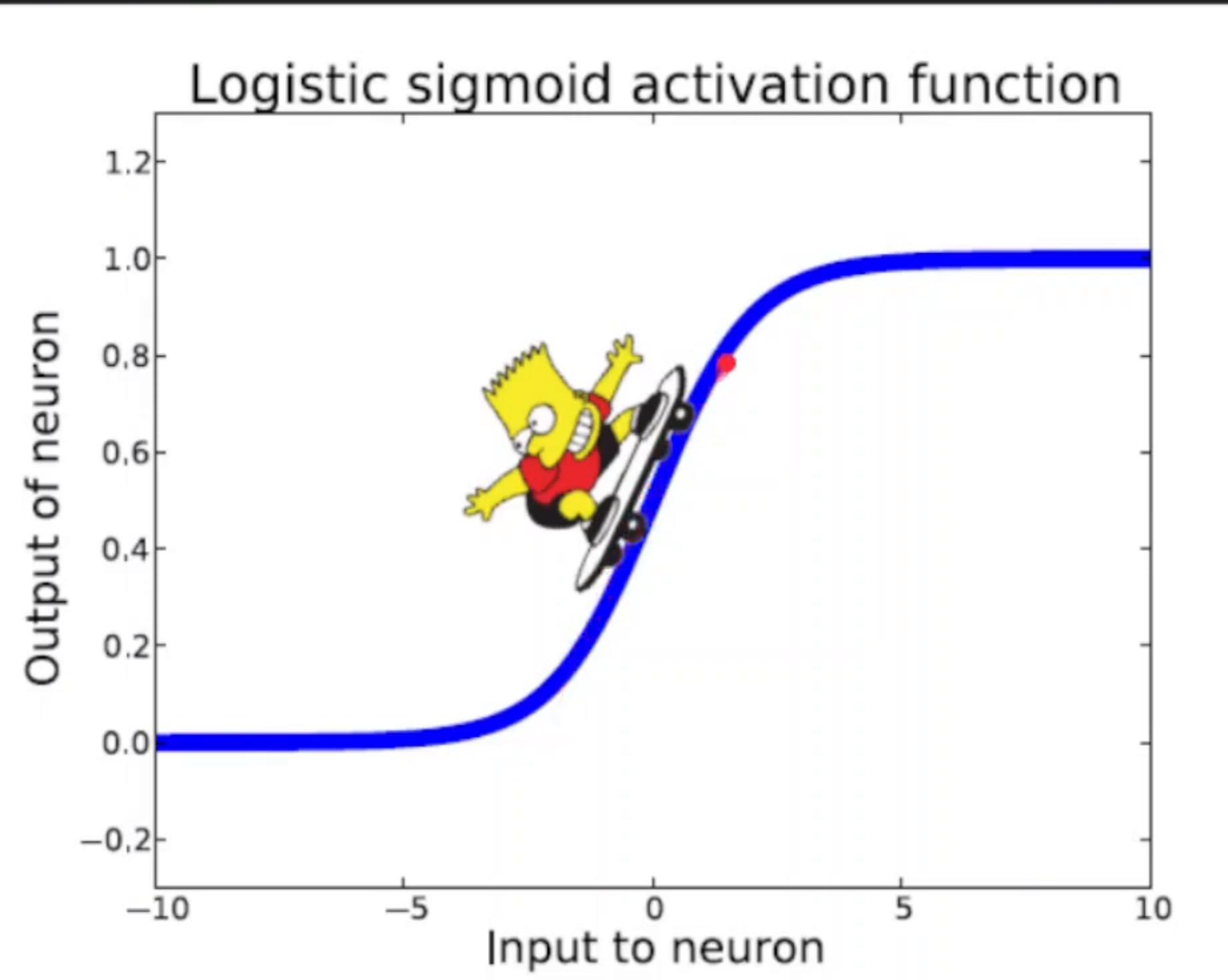
Recap

Step	<i>Binary step</i> $f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$	$f'(x)=0$	 Unit step function.	*Not used much *Binary
Sigmoid	$S(x) = \frac{1}{1 + e^{-x}}$	$f'(x) = f(x) * (1-f(x))$		* Binary * Preferred
Tanh	Tanh Function $a = \frac{e^z - e^{-z}}{e^z + e^{-z}}$	$f'(x) = 1 - f(x)^2$		* Binary * Better than Sigmoid * Hidden layers
Softmax	$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}}$	$\frac{\partial S(z_i)}{\partial z_j} = \begin{cases} S(z_i) \times (1 - S(z_i)) & \text{if } i = j \\ -S(z_i) \times S(z_j) & \text{if } i \neq j \end{cases}$		* Multi-class * Output layers

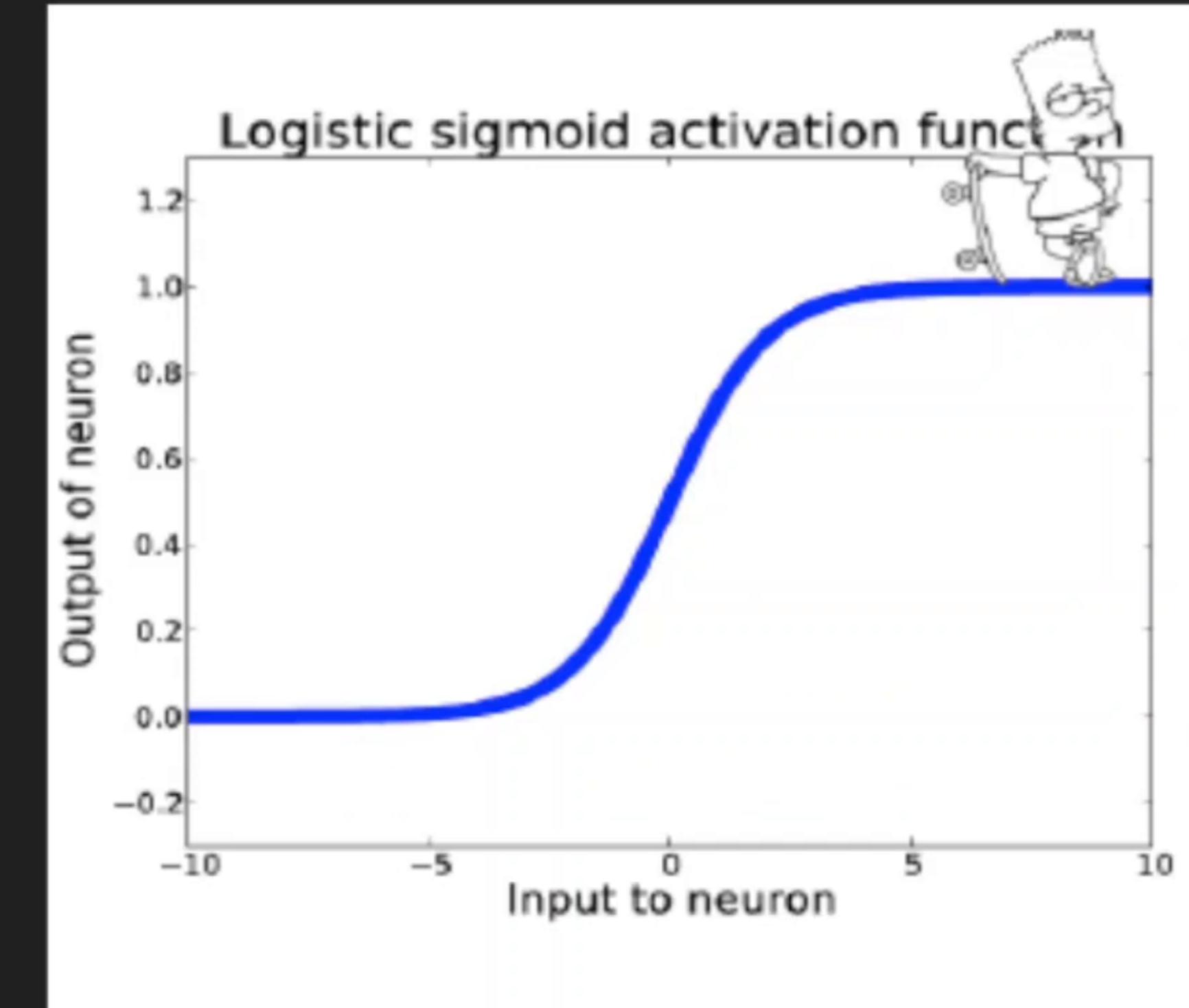
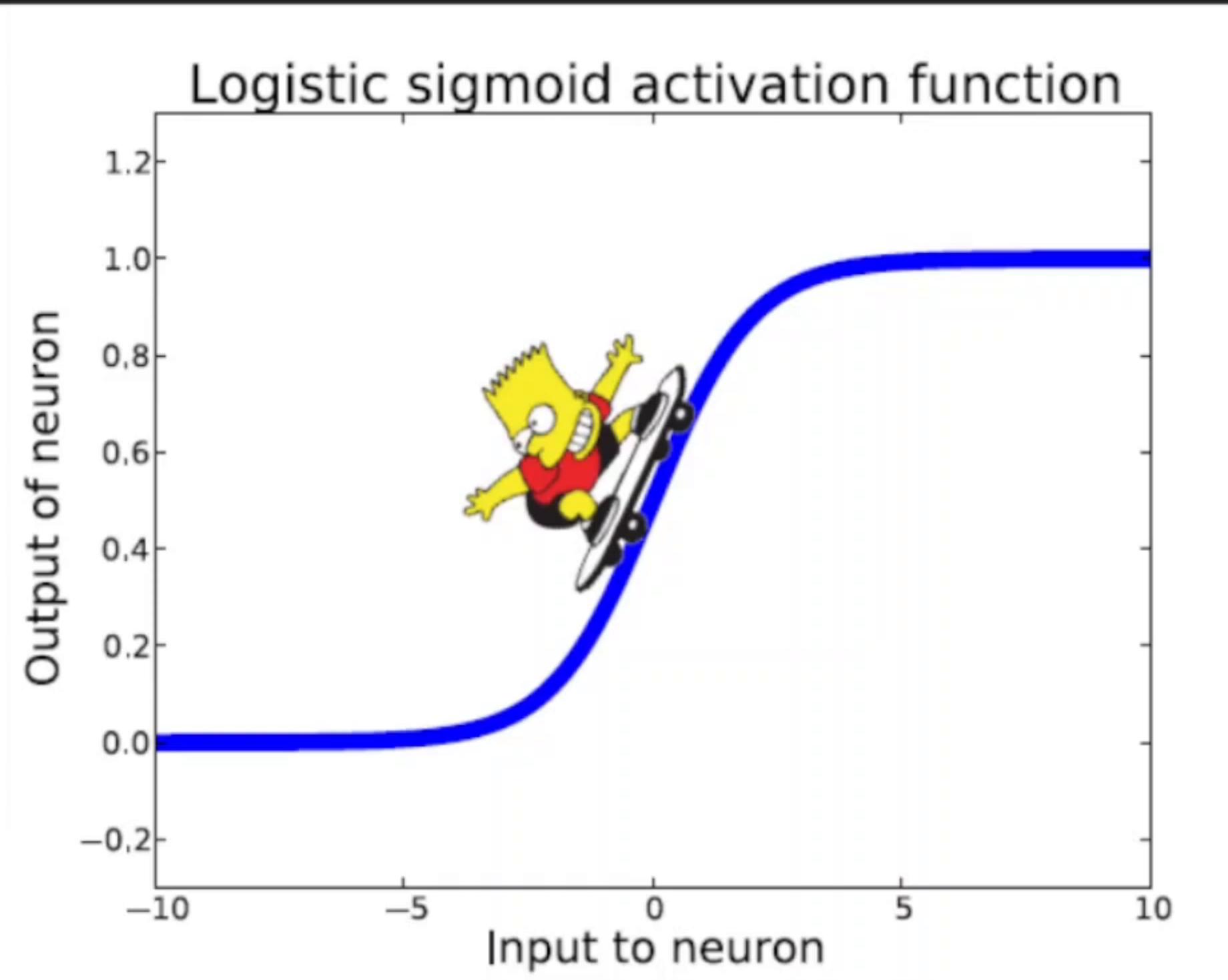
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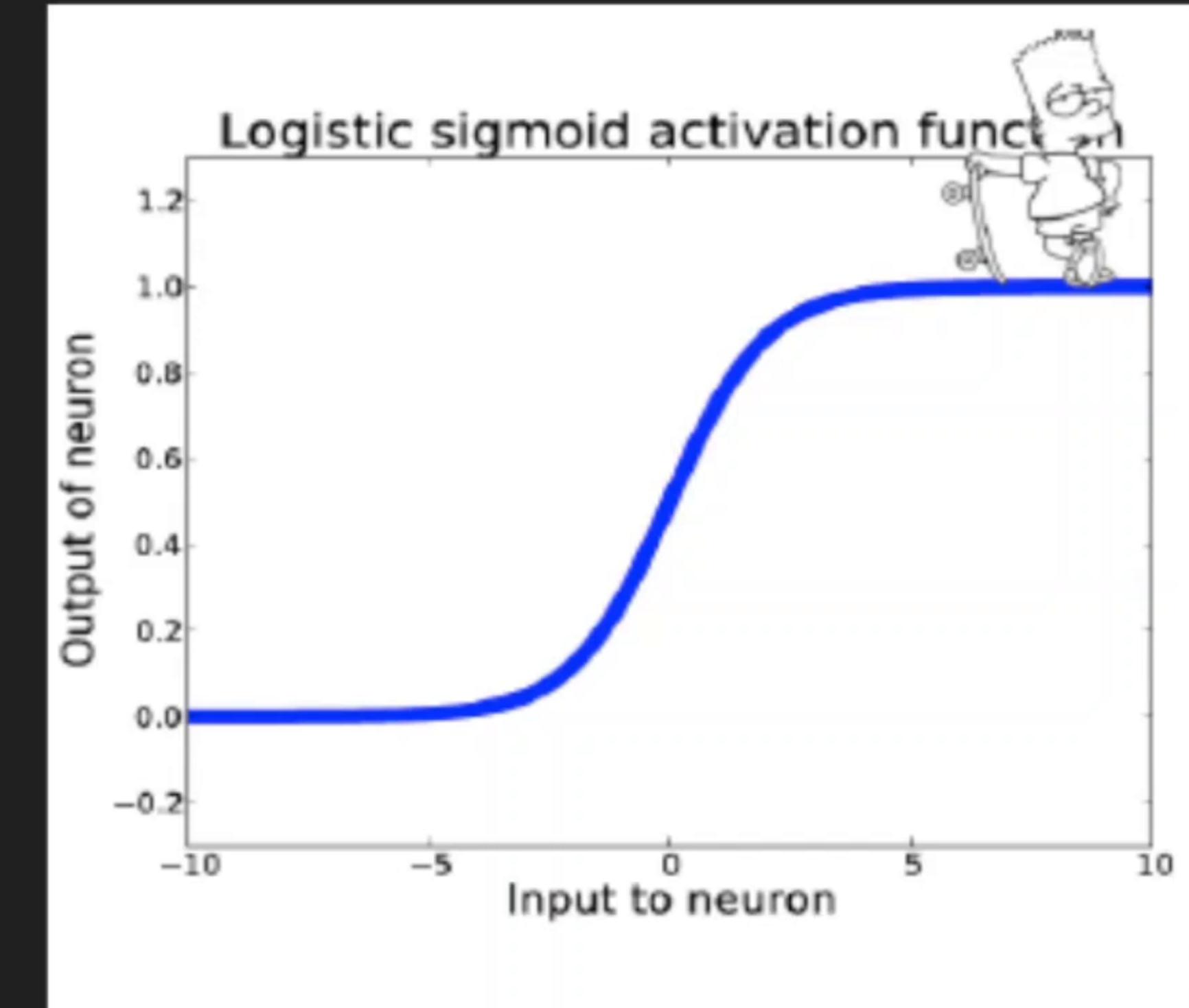
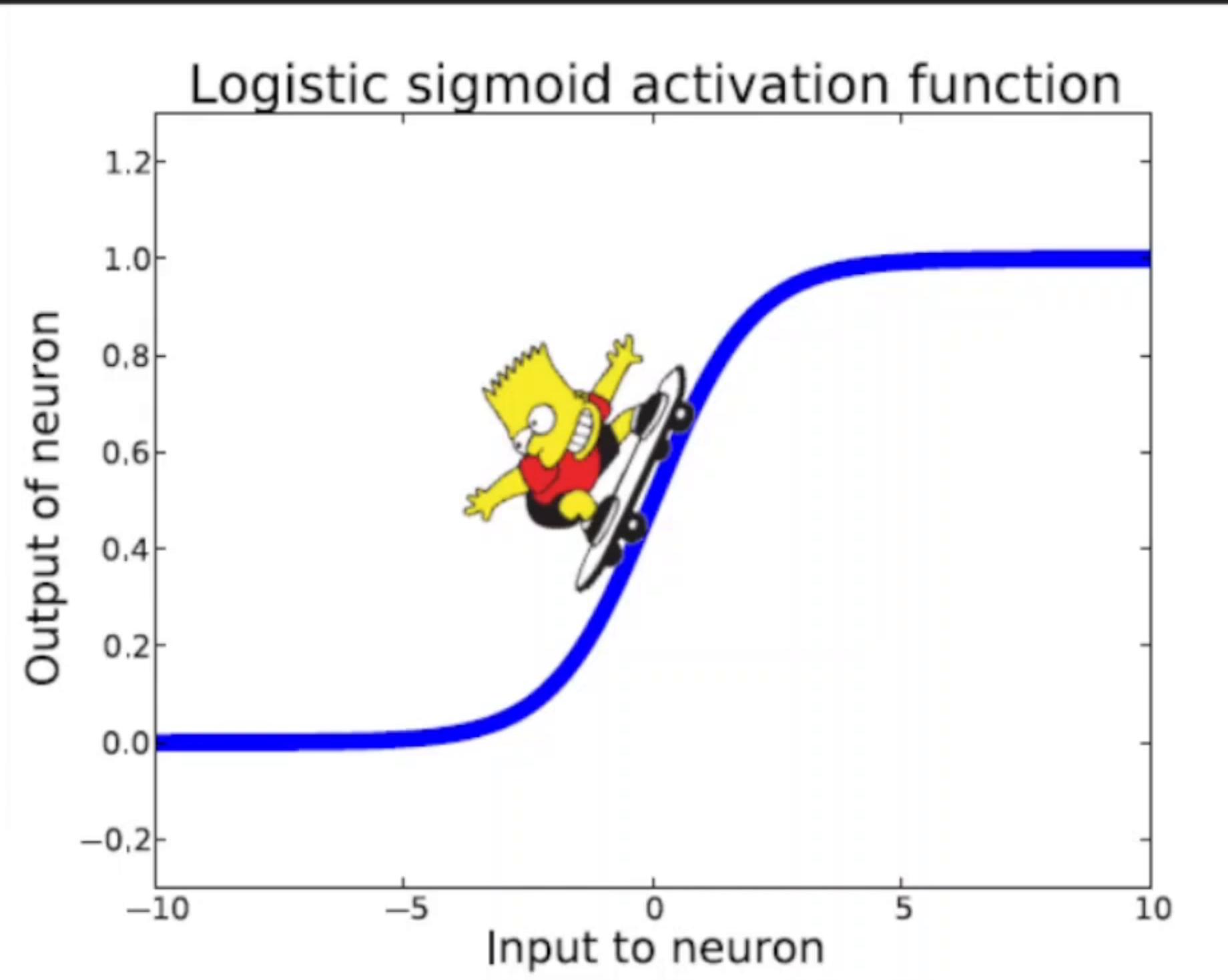
Vanishing Gradient



Vanishing Gradient

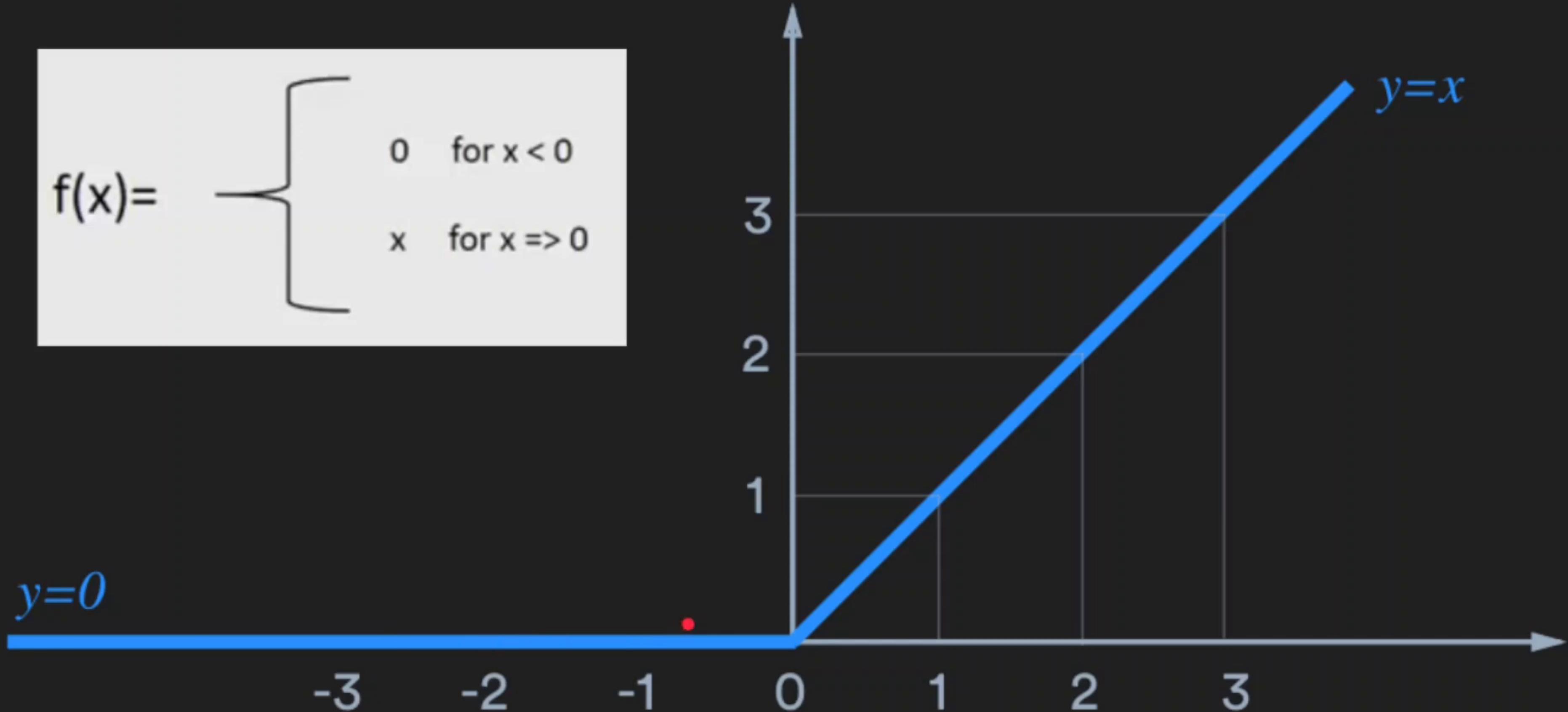


Vanishing Gradient



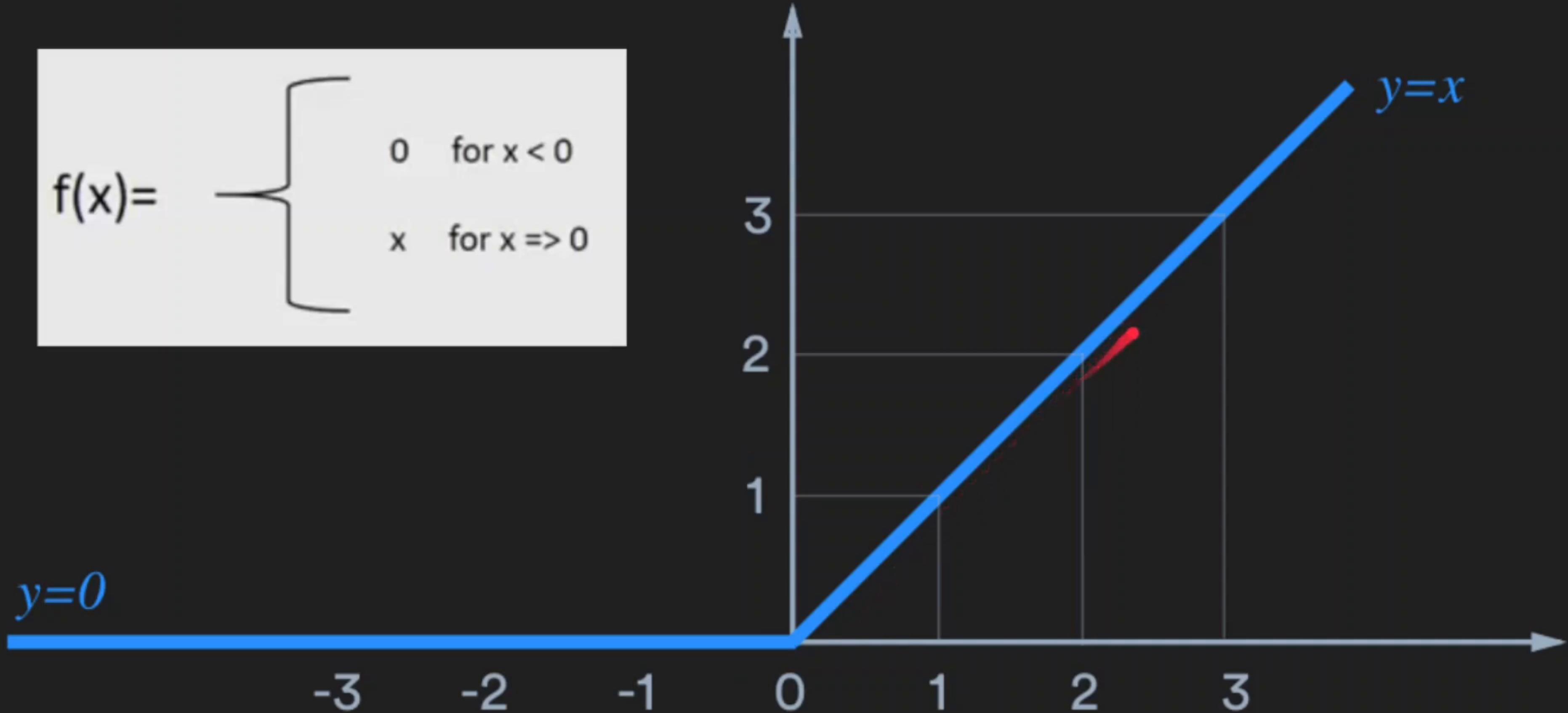
ReLU

$$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$$



ReLU

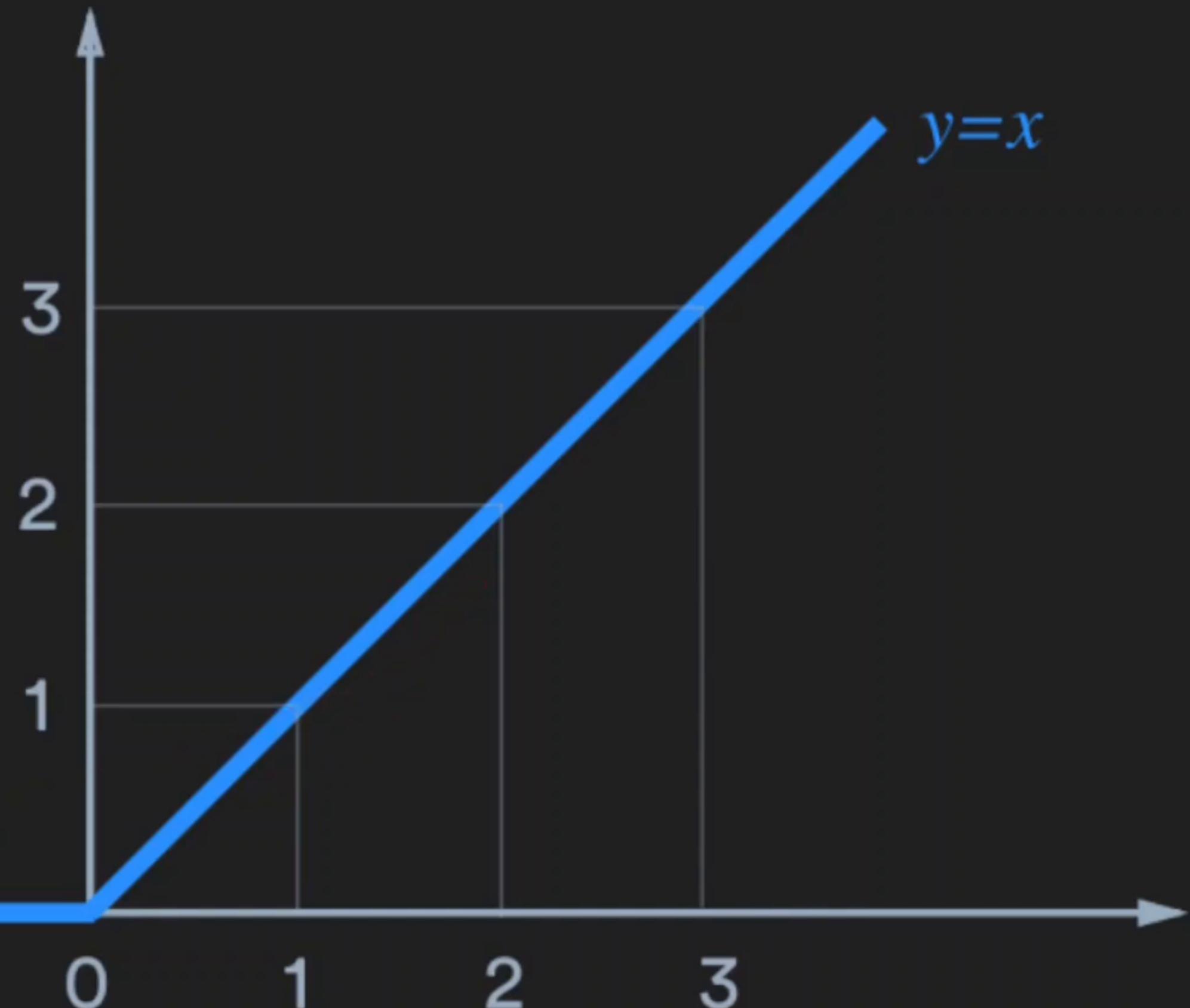
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ReLU

$$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$$

$$y=0$$



ReLU Layer

Filter 1 Feature Map

9	3	5	-8
-6	2	-3	1
1	3	4	1
3	-4	5	1



9	3	5	0
0	2	0	1
1	3	4	1
3	0	5	1

ReLU Layer

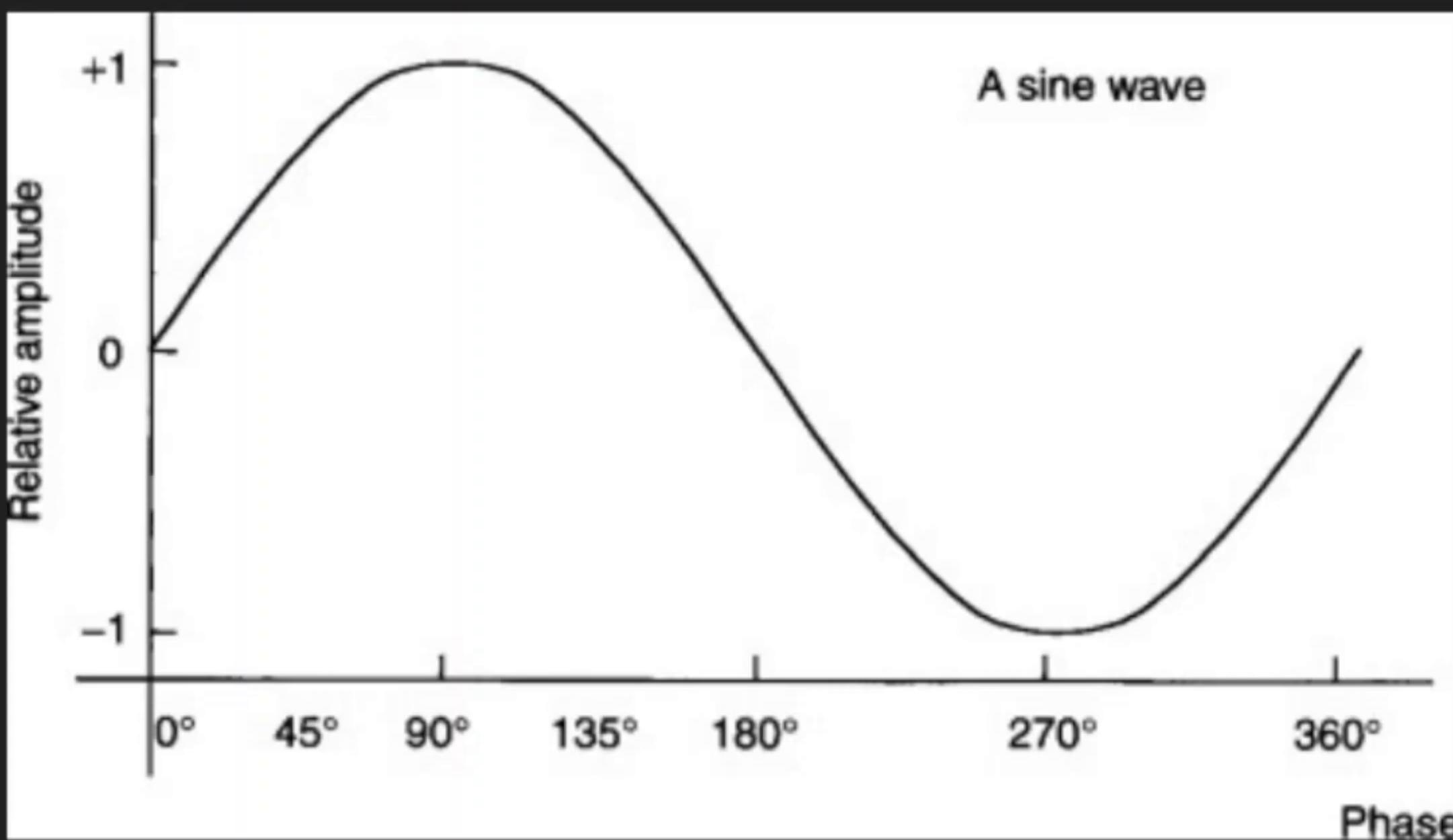
Filter 1 Feature Map

9	3	5	-8
-6	2	-3	1
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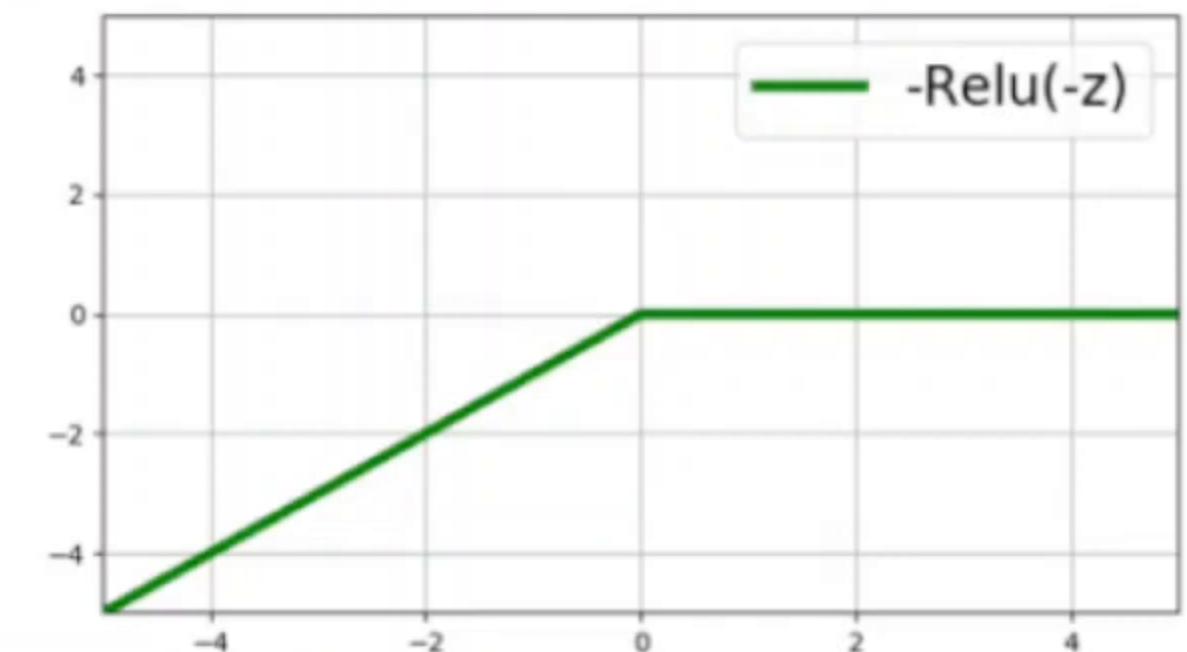
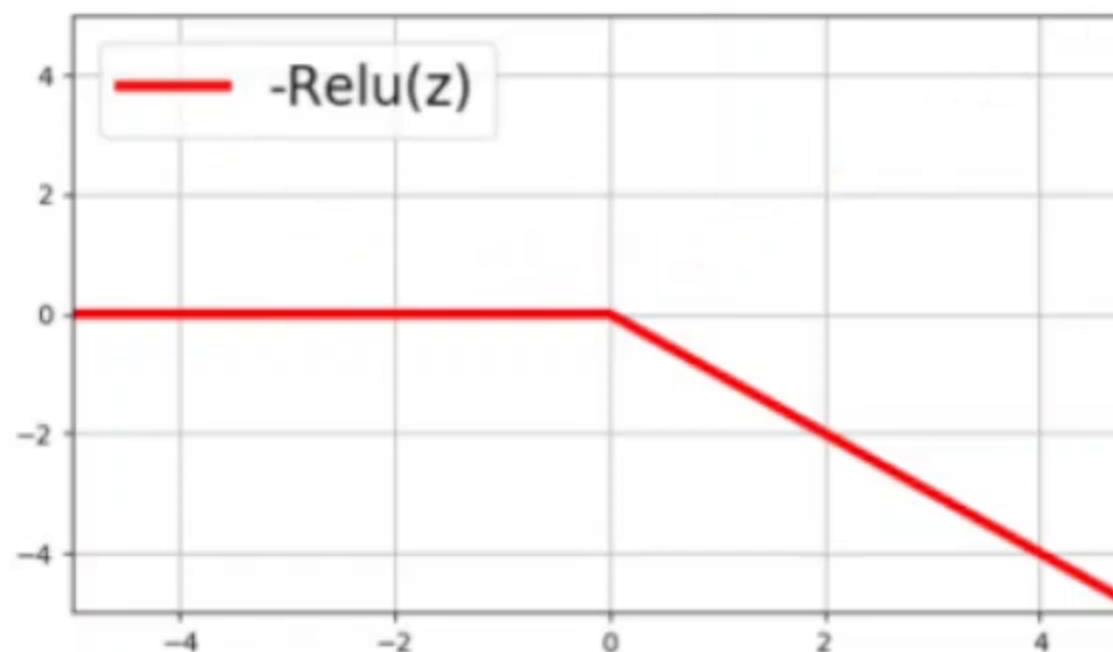
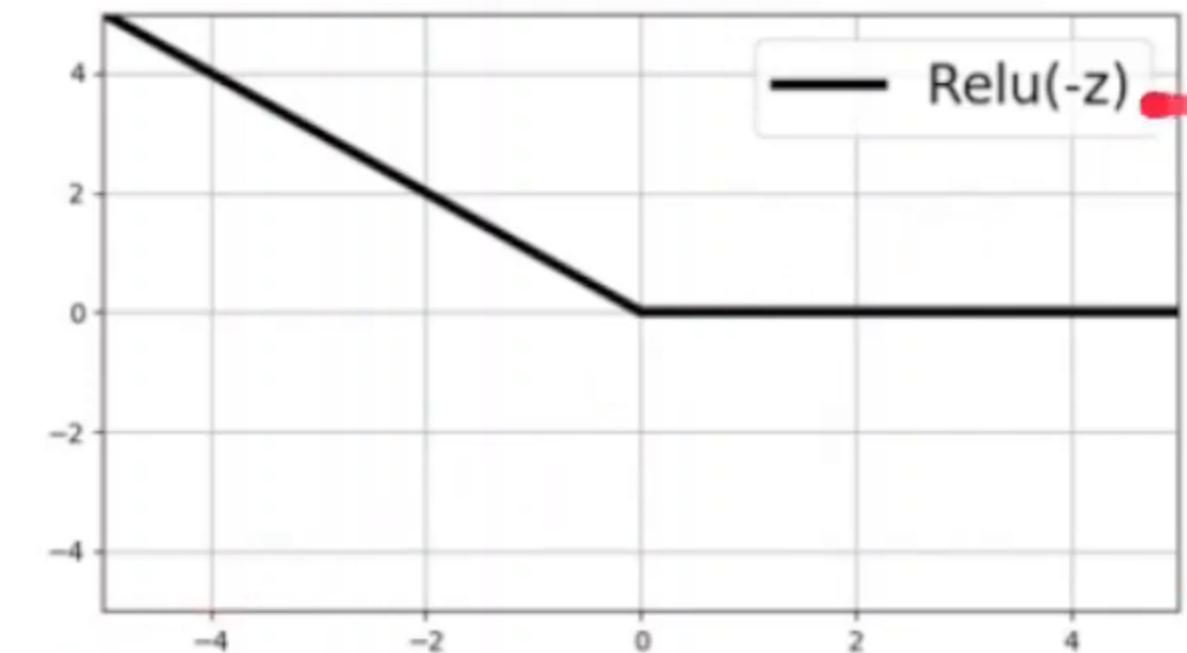
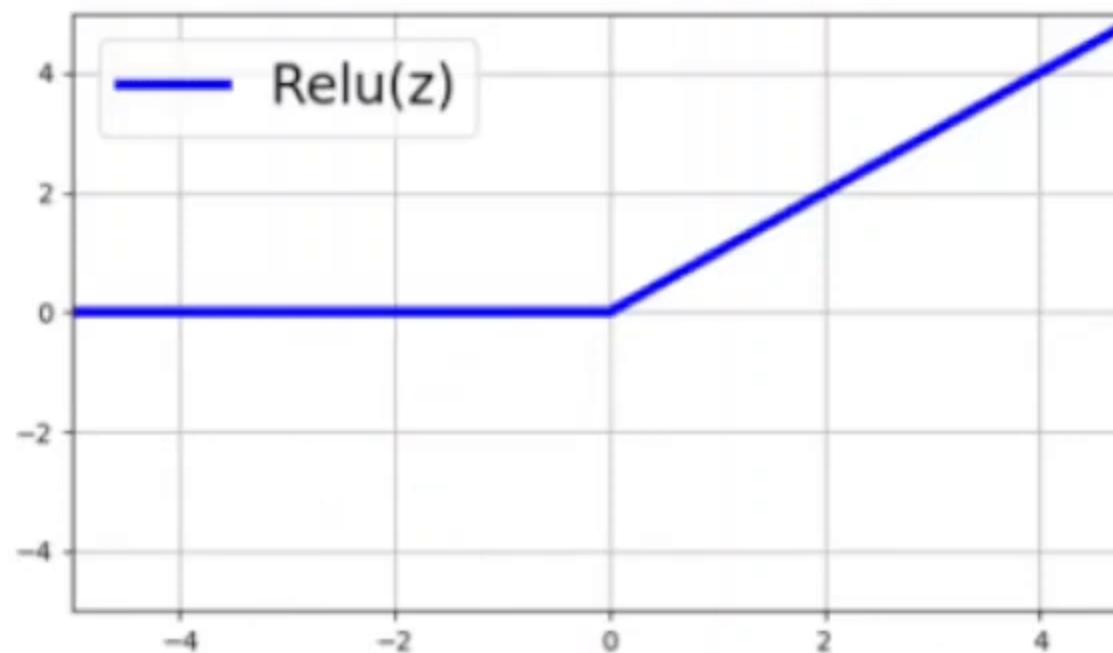
9	3	5	0
0	2	0	1
1	3	4	1
3	0	5	1

Fit the Sine wave



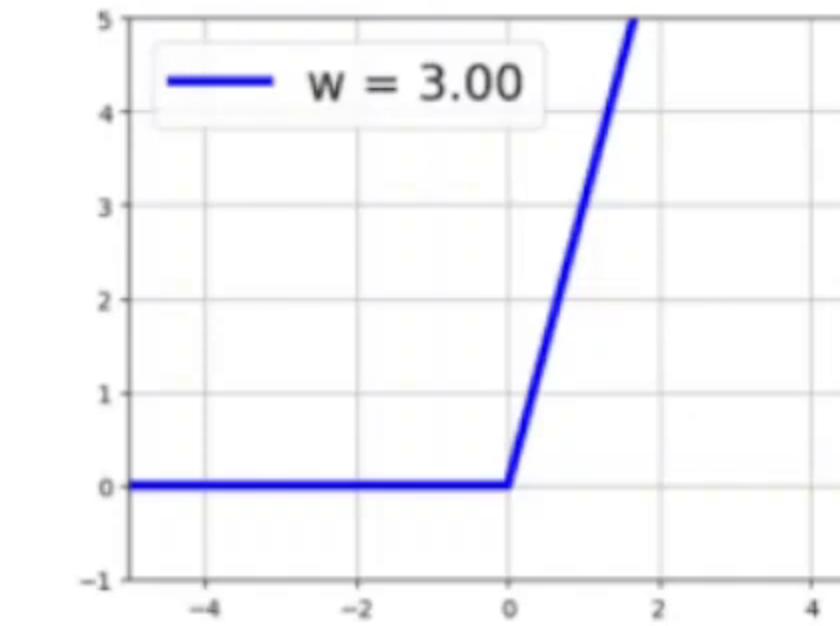
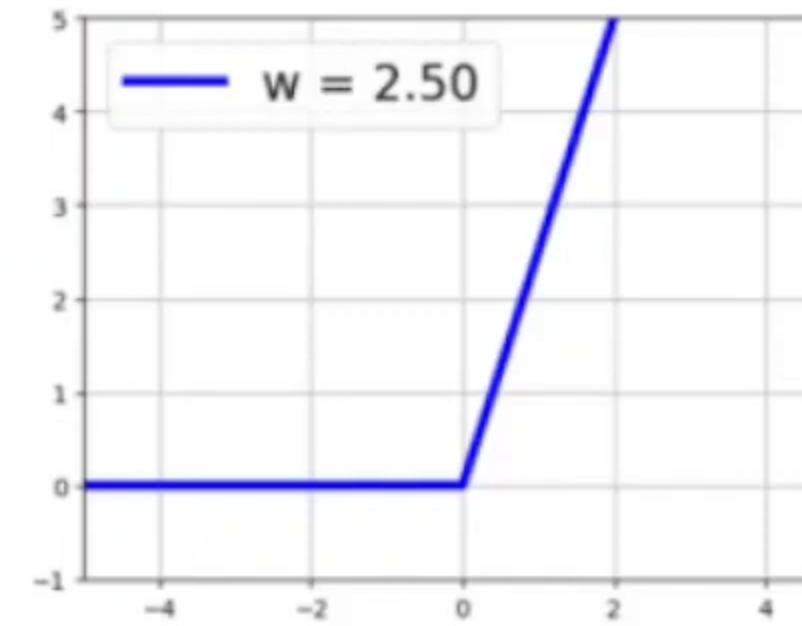
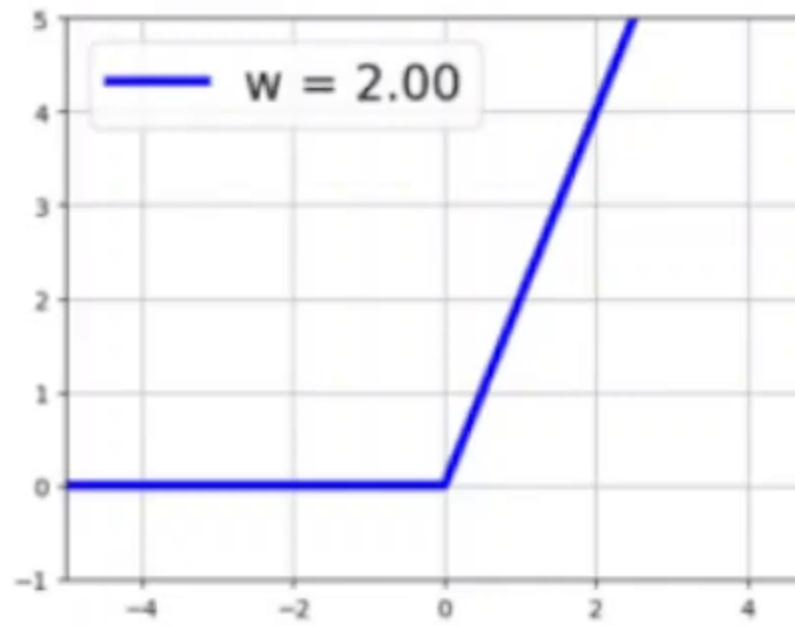
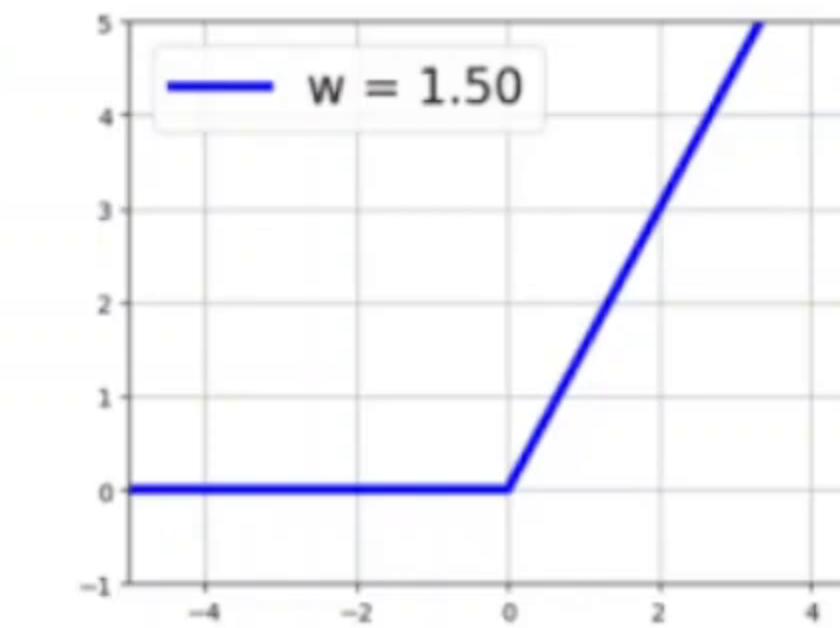
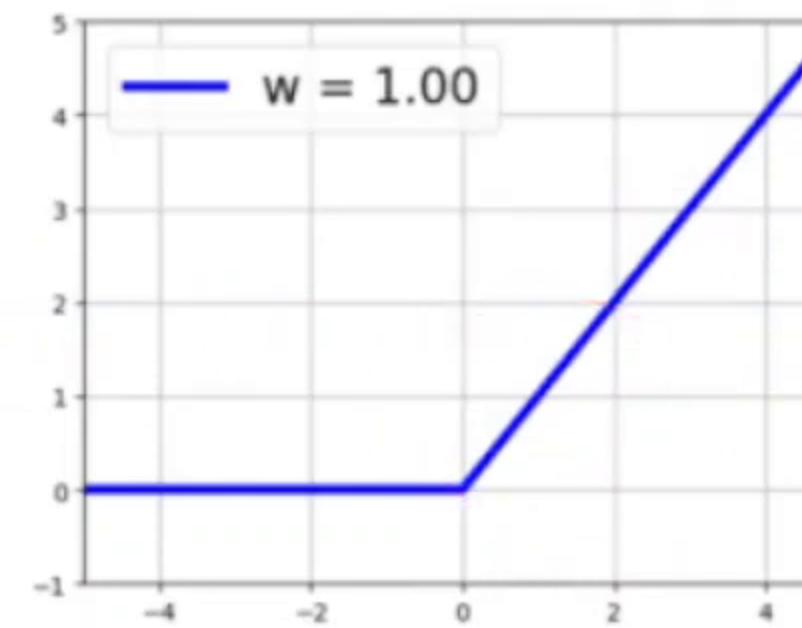
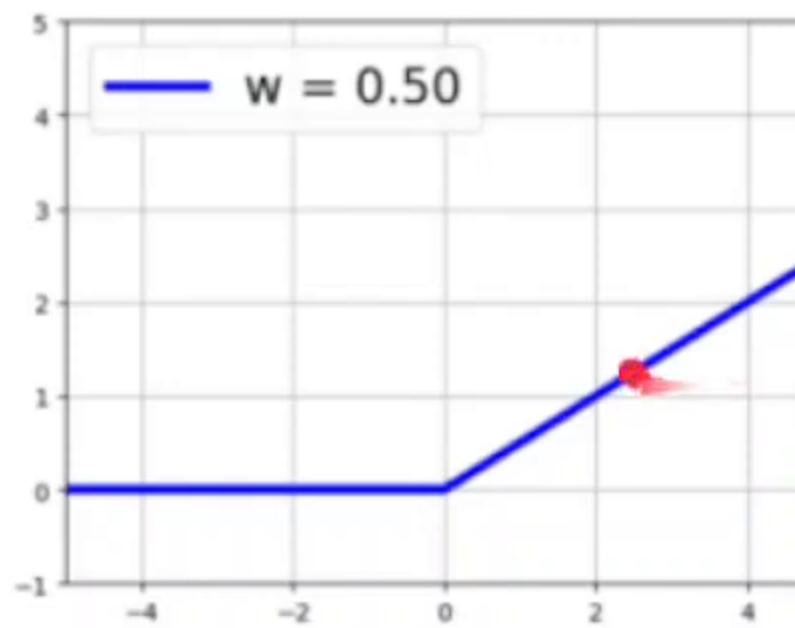
ReLU function variations - Negative inputs

The Flexibility of $\text{Relu}(z)$



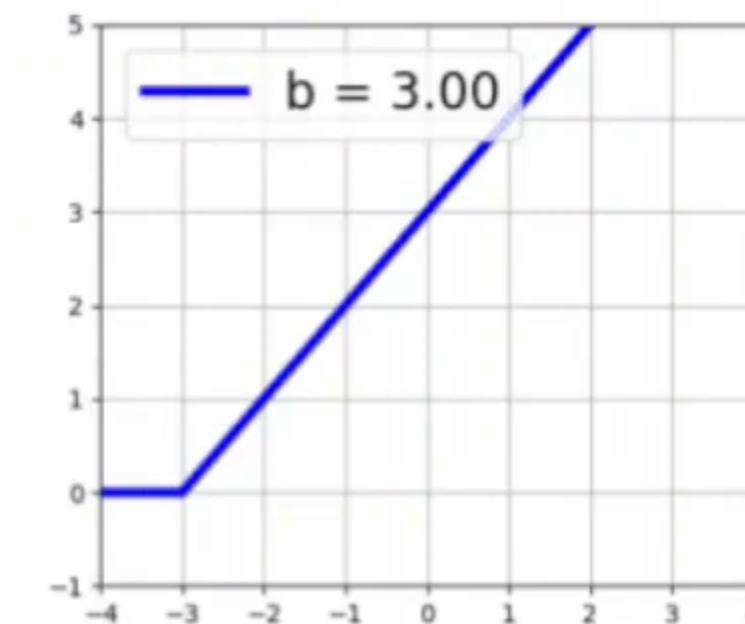
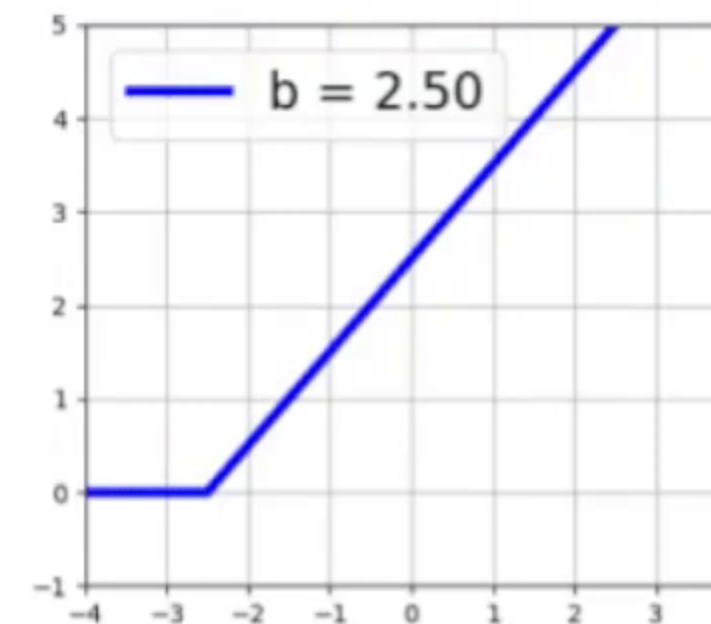
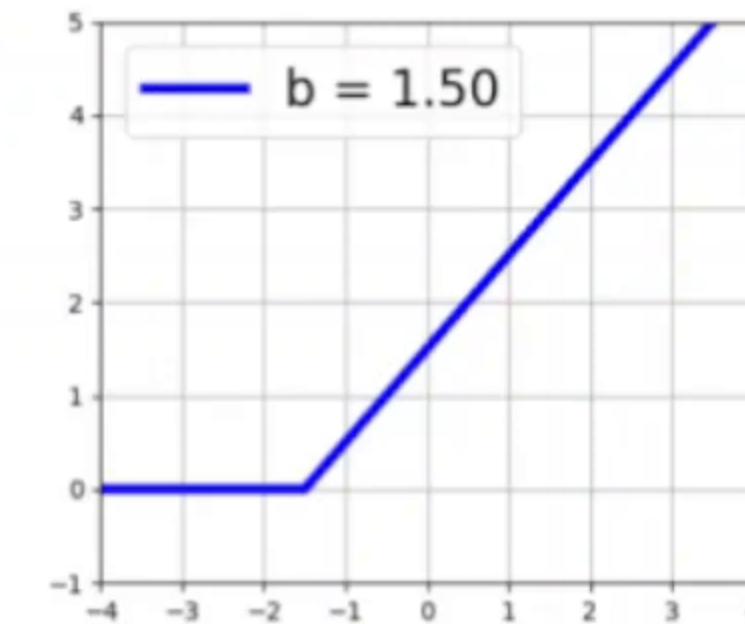
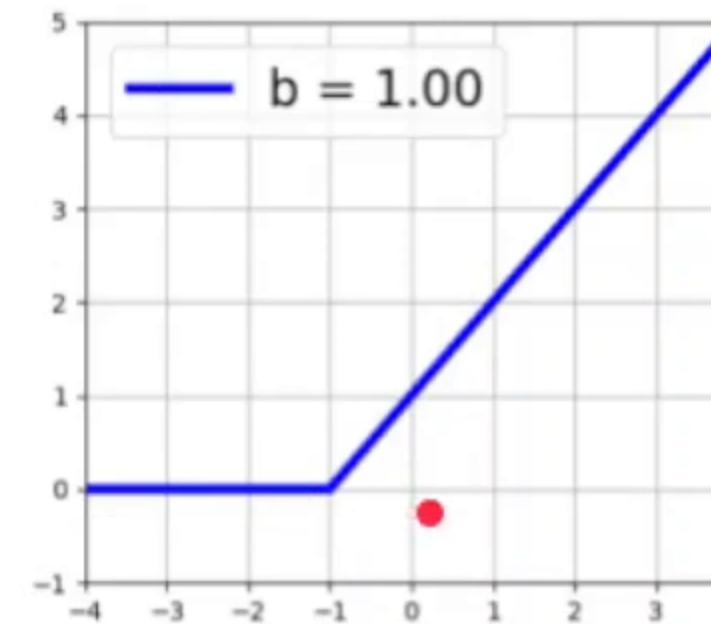
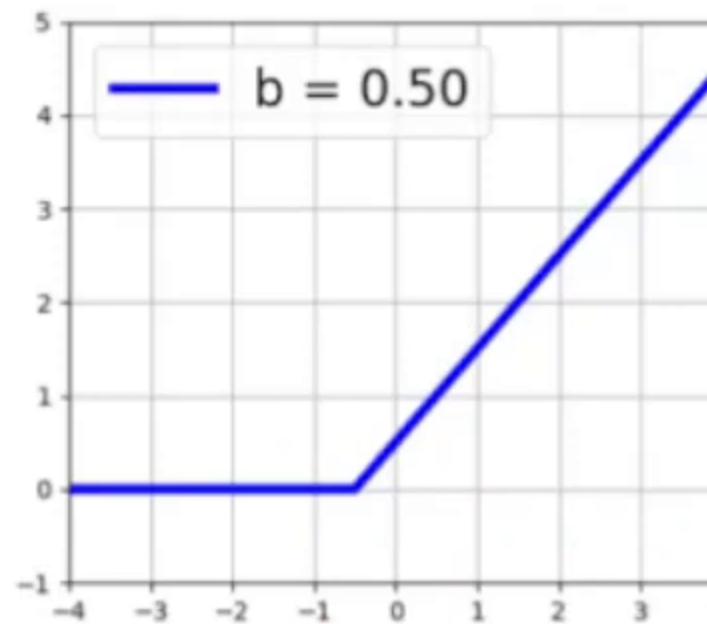
Changing Slope

Changing the slope of $\text{Relu}(w \cdot z)$ using a coefficient w

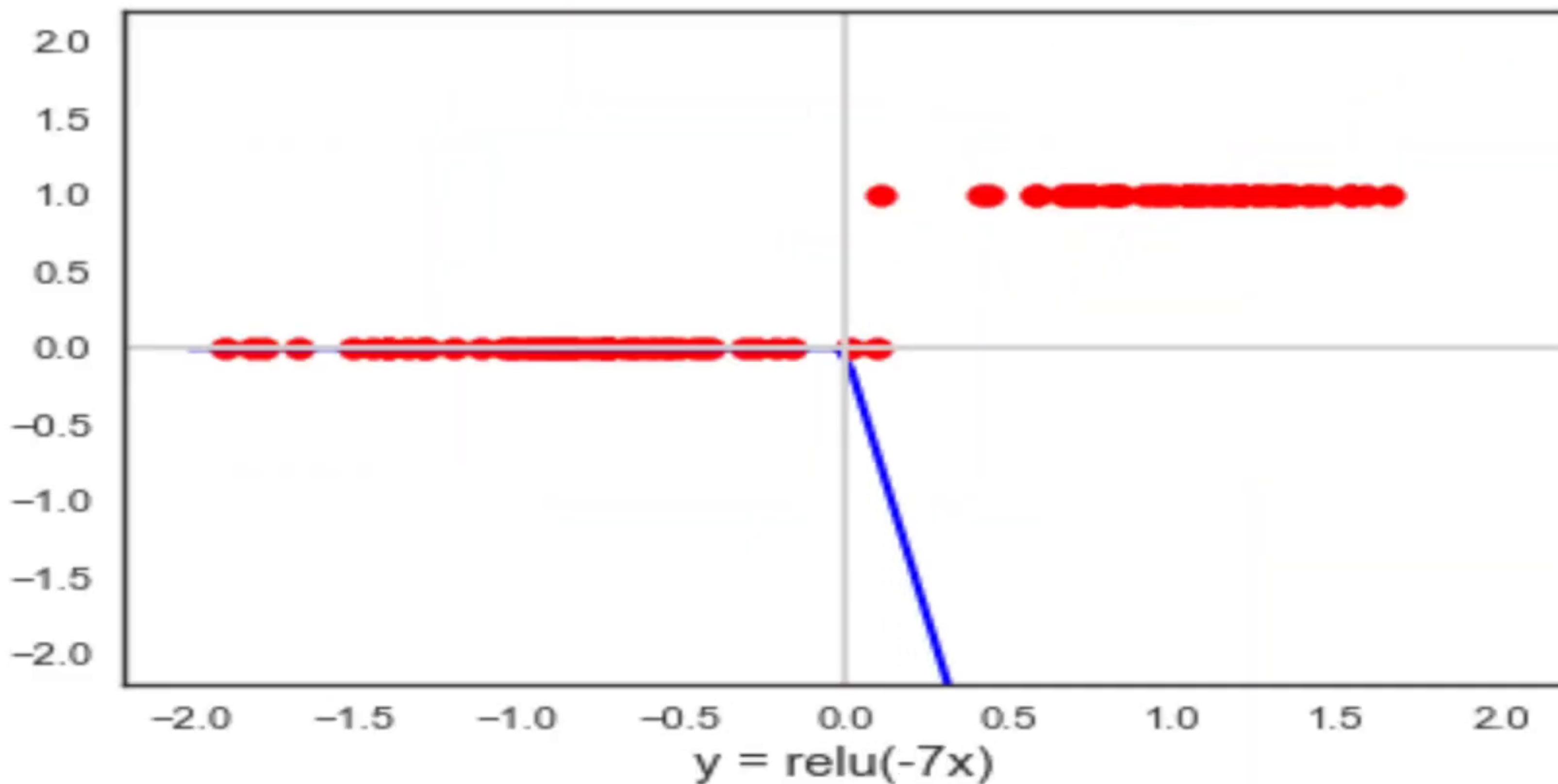


Changing Bias - Horizontal

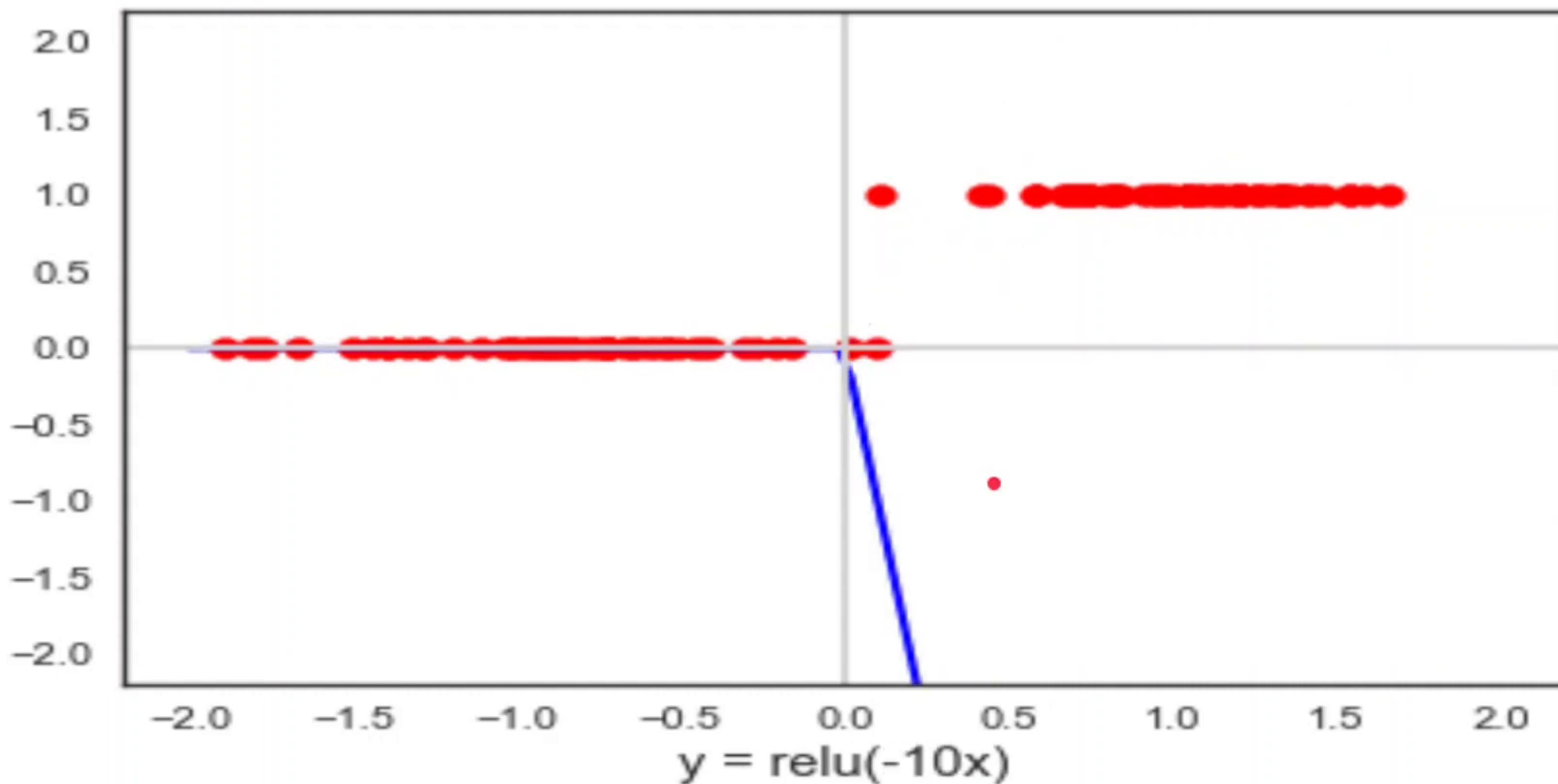
Shifting $\text{Relu}(z+b)$ horizontally using a bias term b inside $\text{Relu}()$



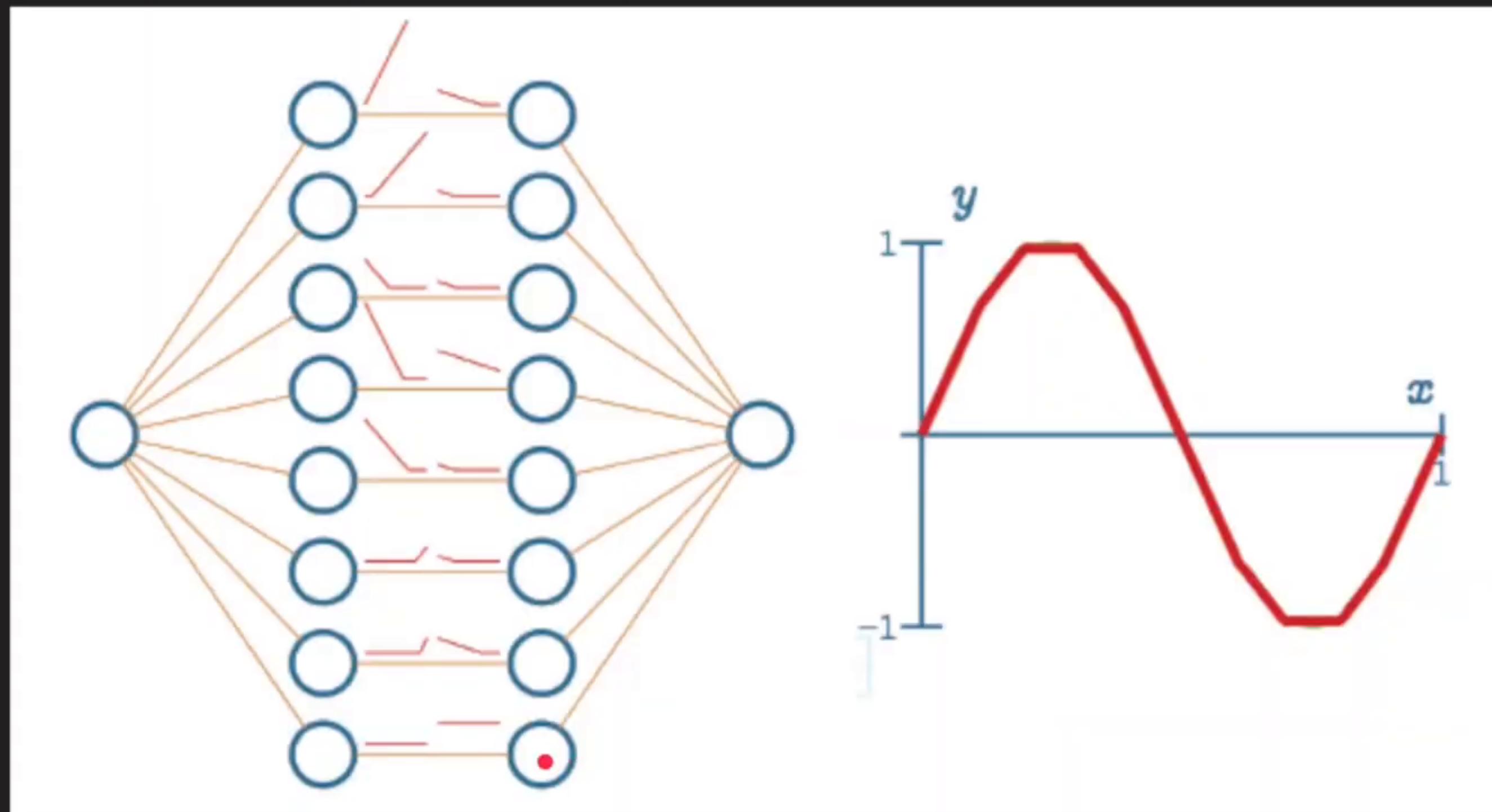
ReLU in Action



ReLU in Action

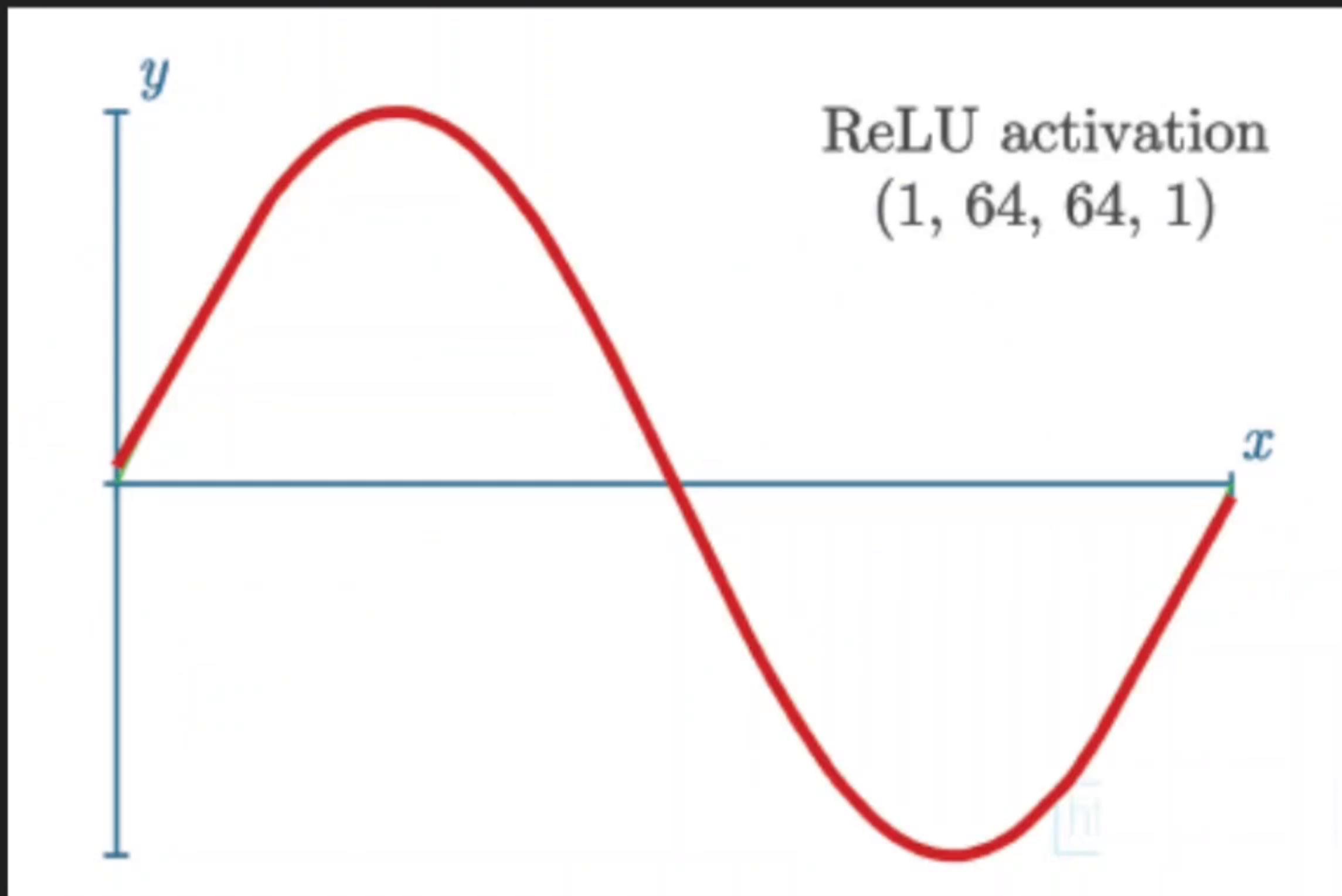


Sine wave Approximation



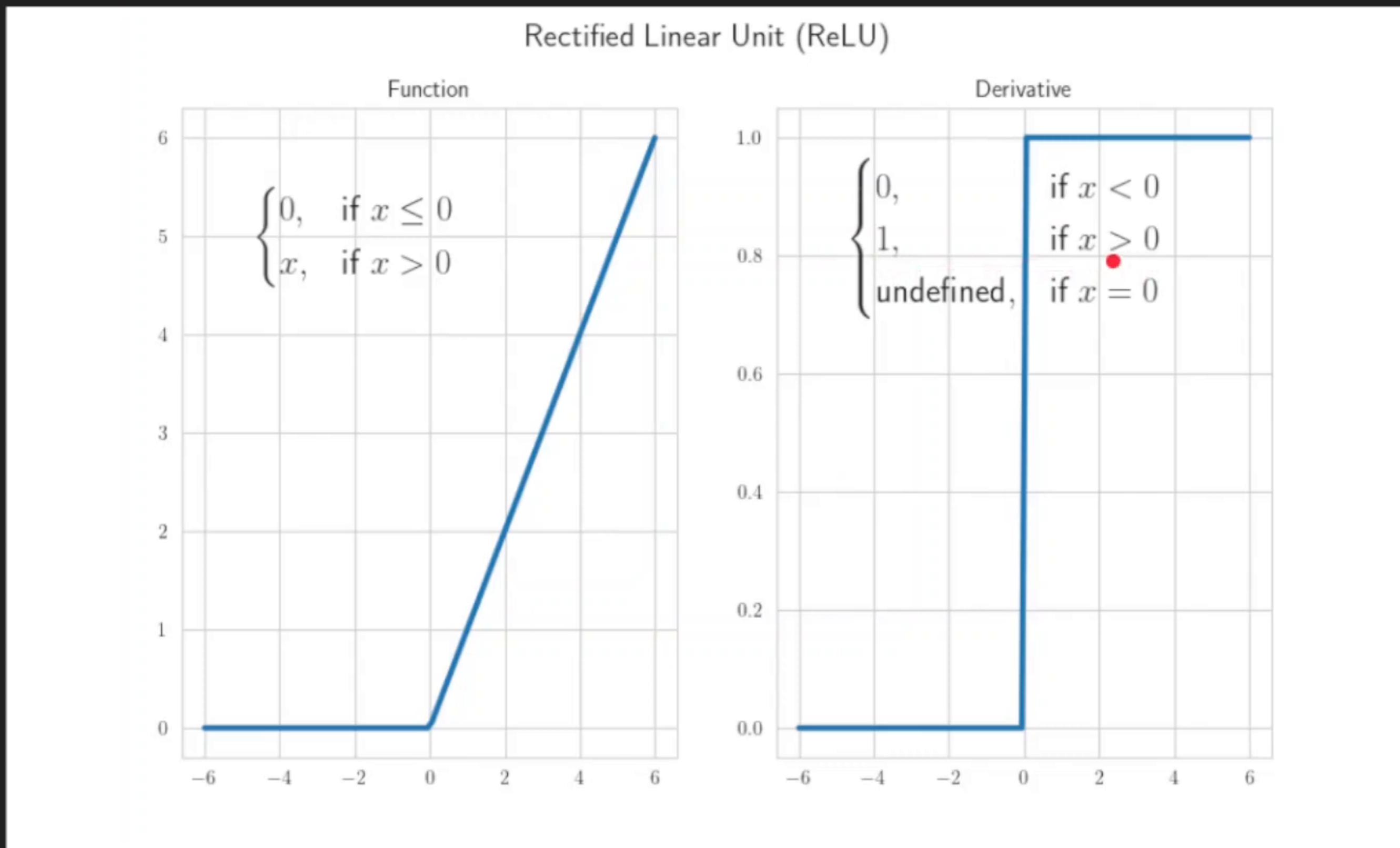
Arch - (1,8,8,1)

Sine wave Approximation

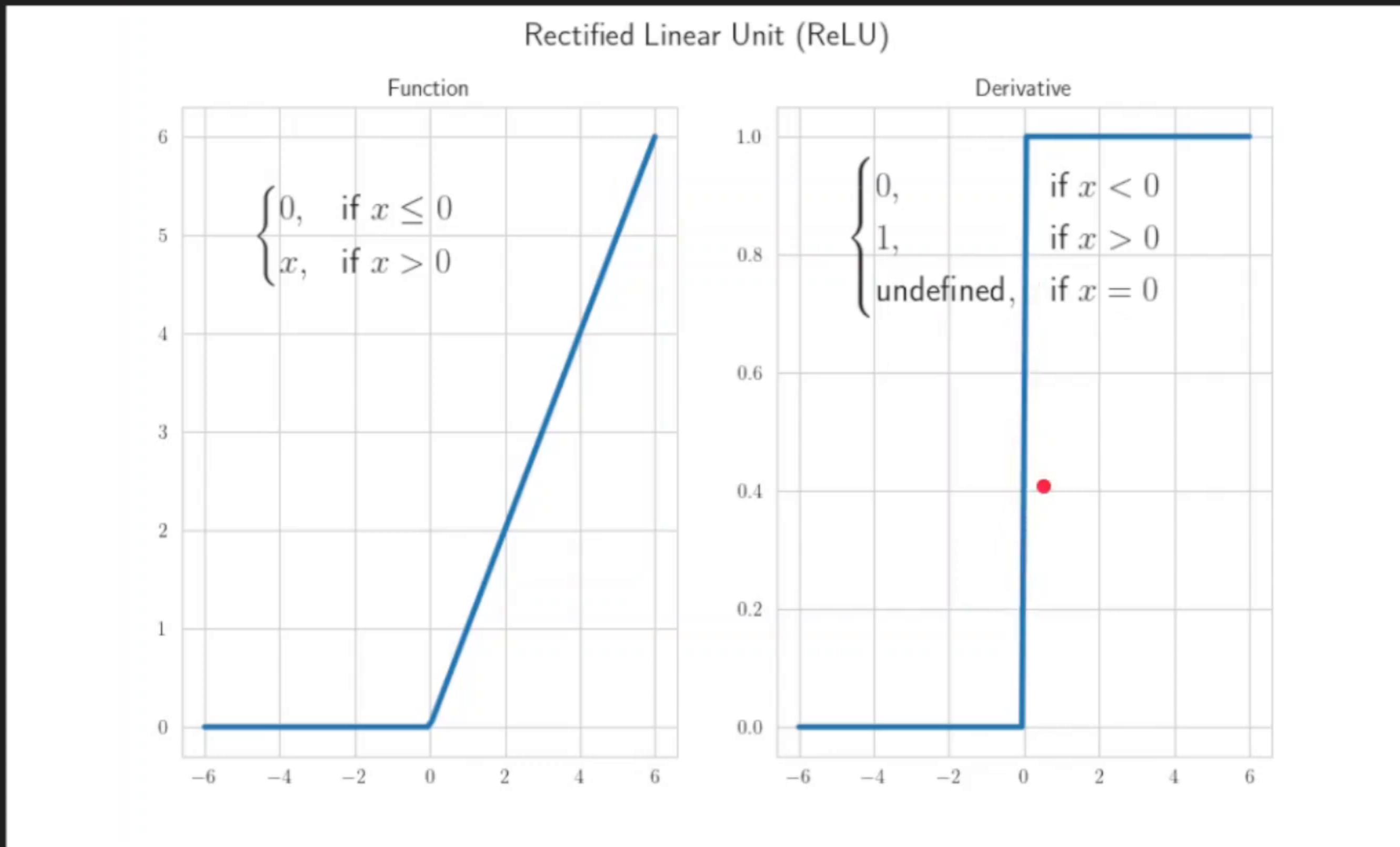


Arch - (1,64,64,1)

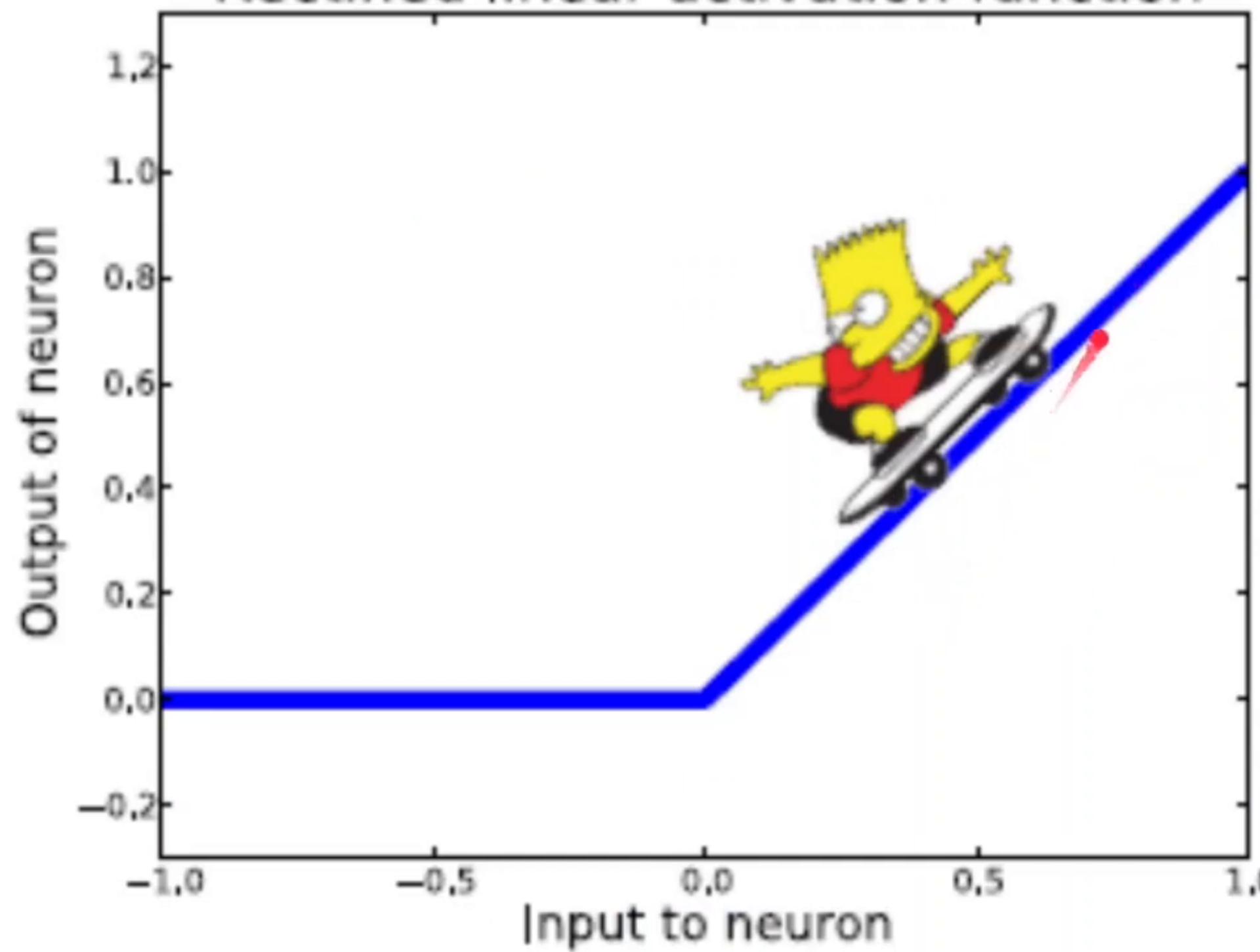
Derivative



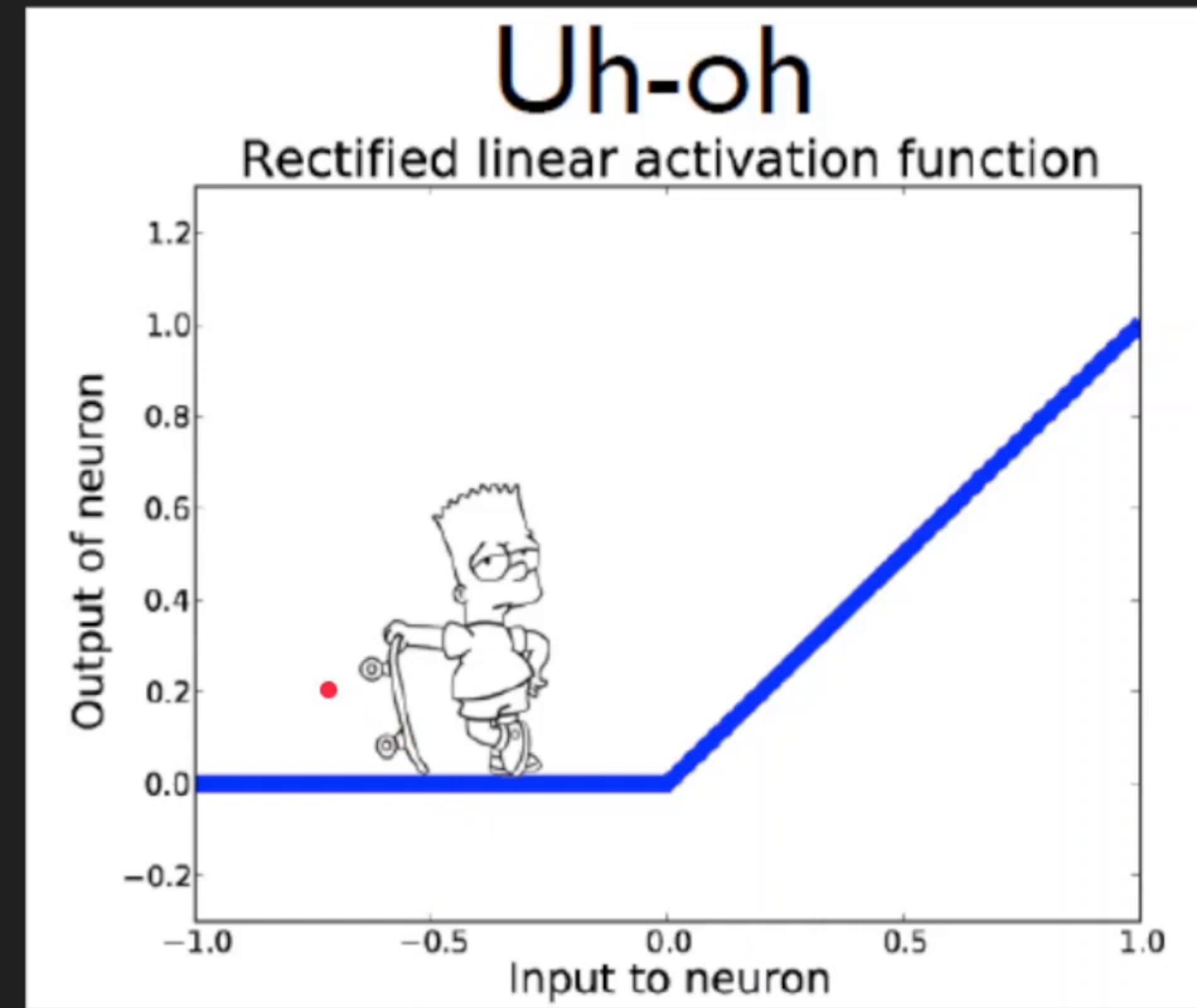
Derivative



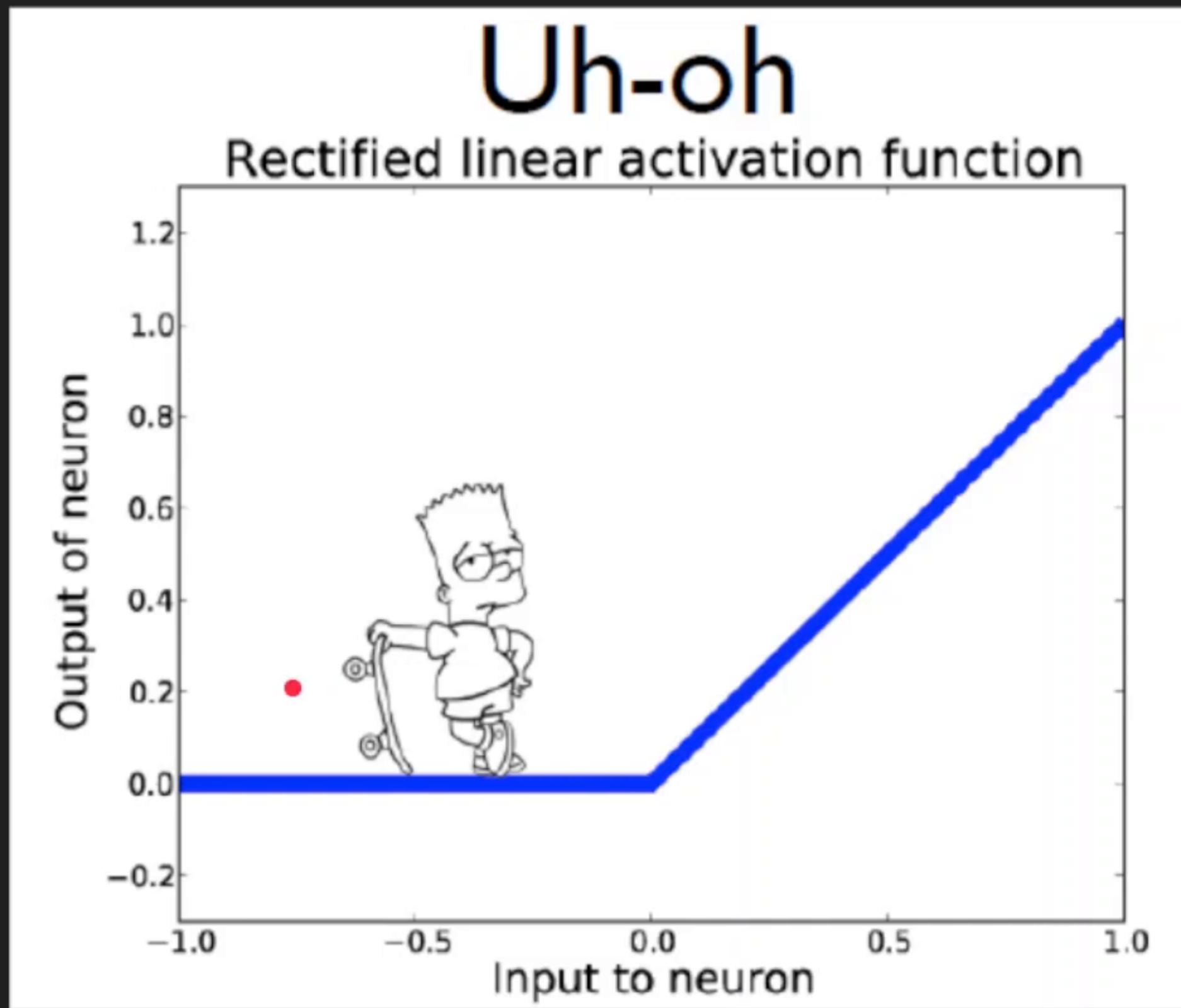
Rectified linear activation function



Dead Neurons

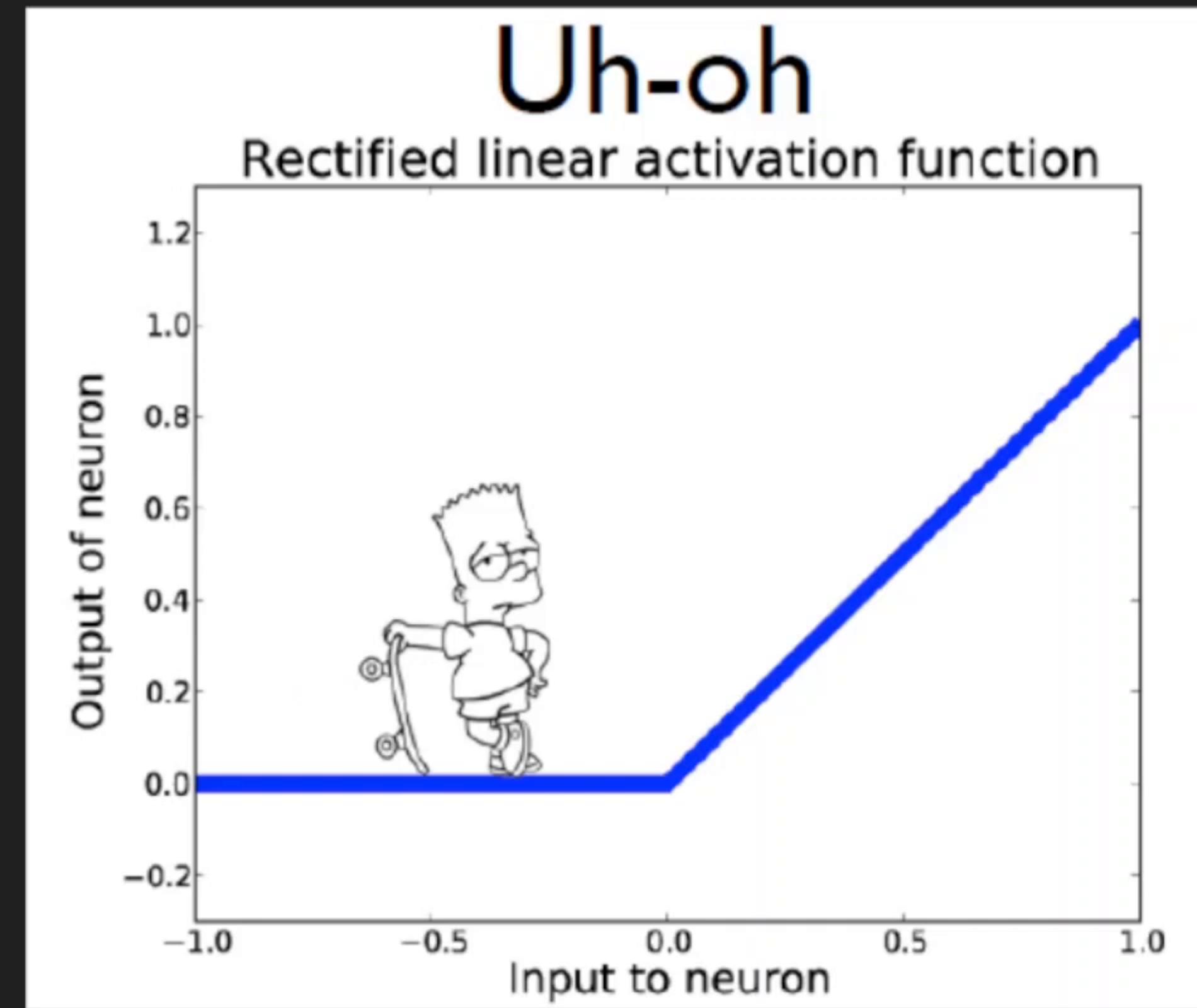
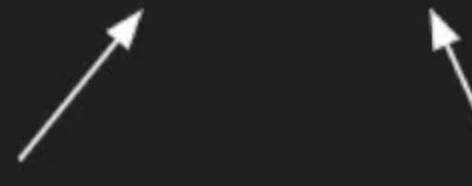


Dead Neurons



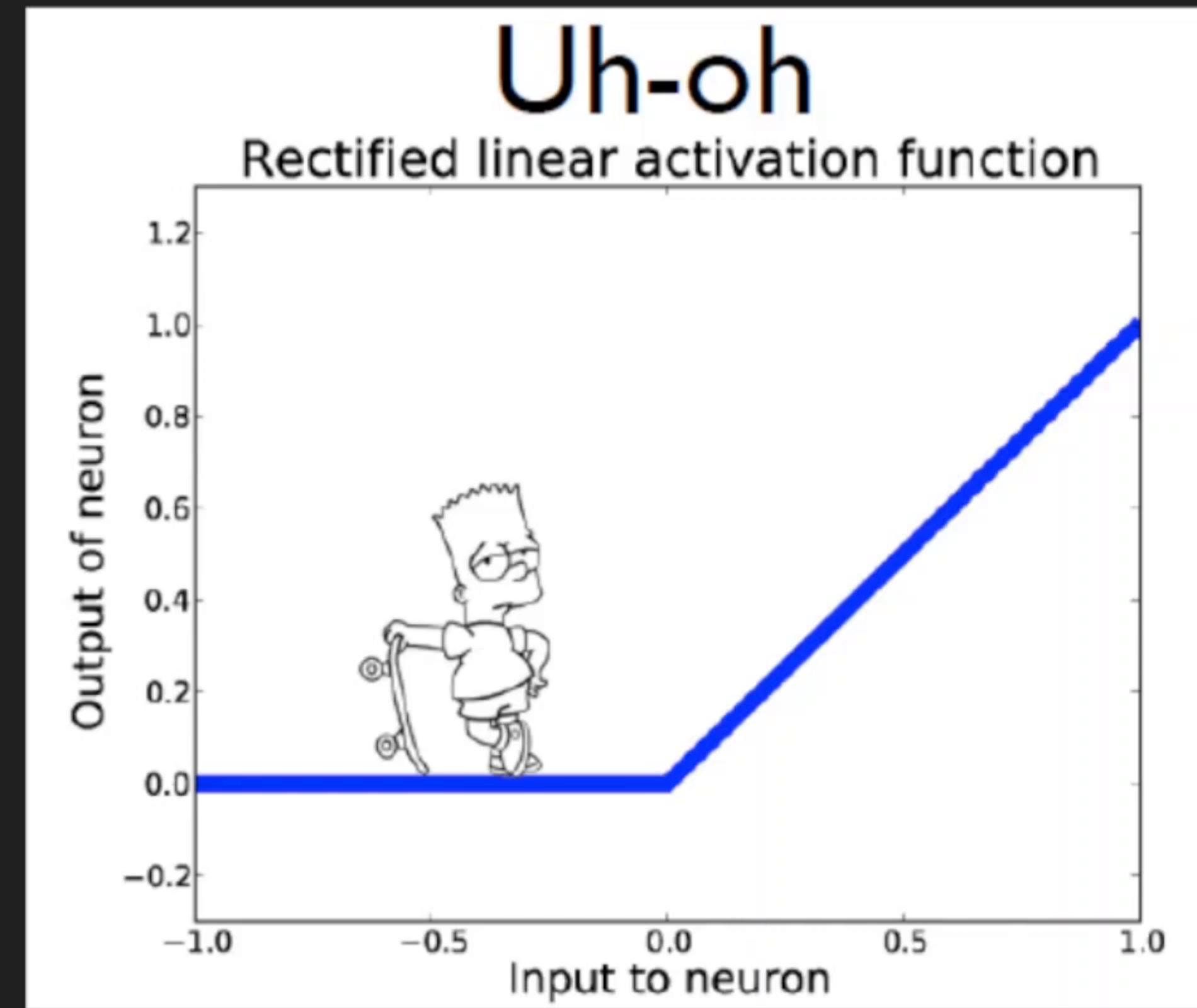
Dead Neurons

$$Y = \text{ReLU}(W^*X + b)$$



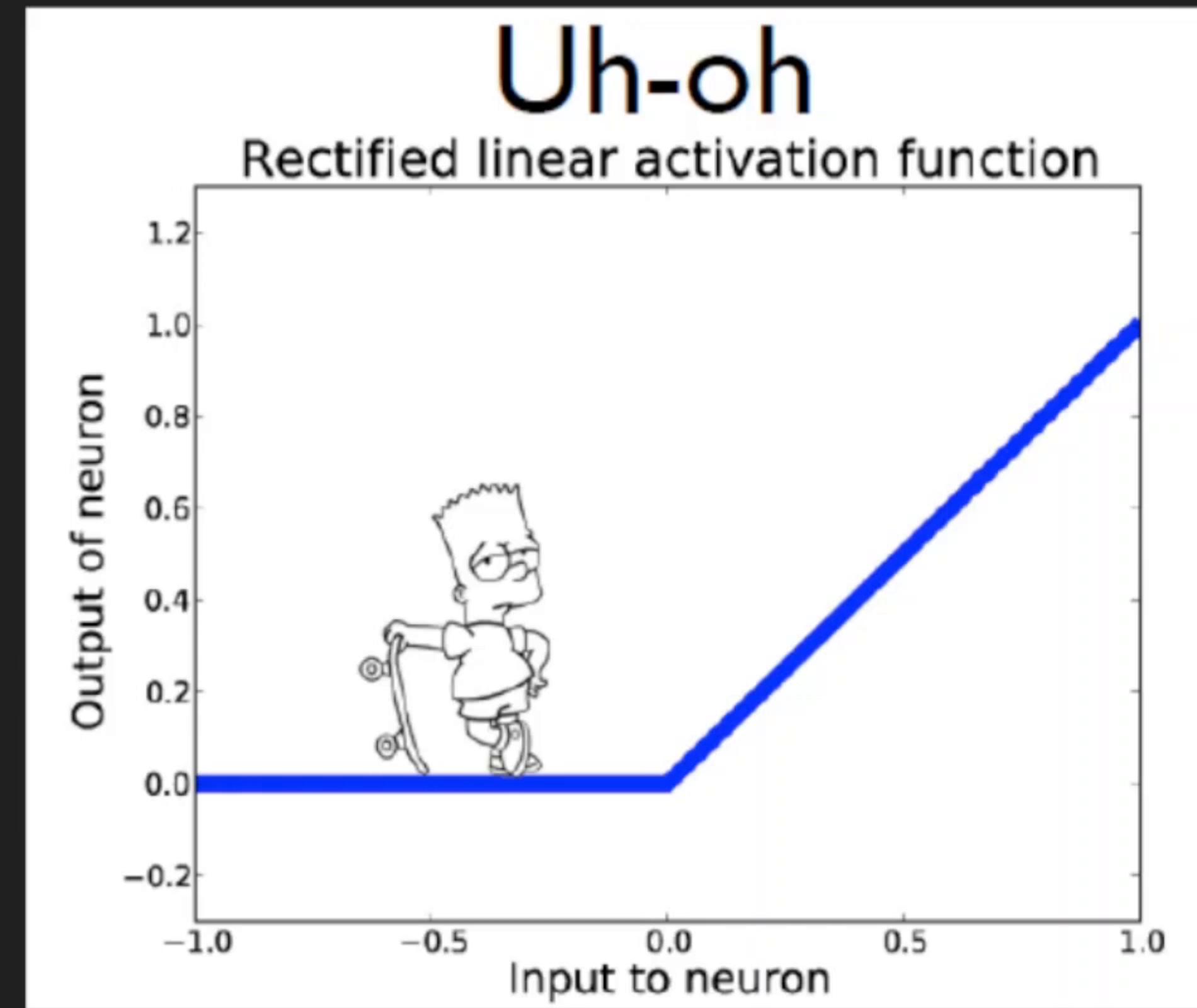
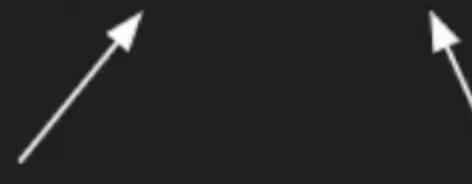
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Advantages

- Computationally Simple
- Representational Sparsity
- Linear Behaviour
- Train deeper networks

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$$f(x) = \max(0, x)$$



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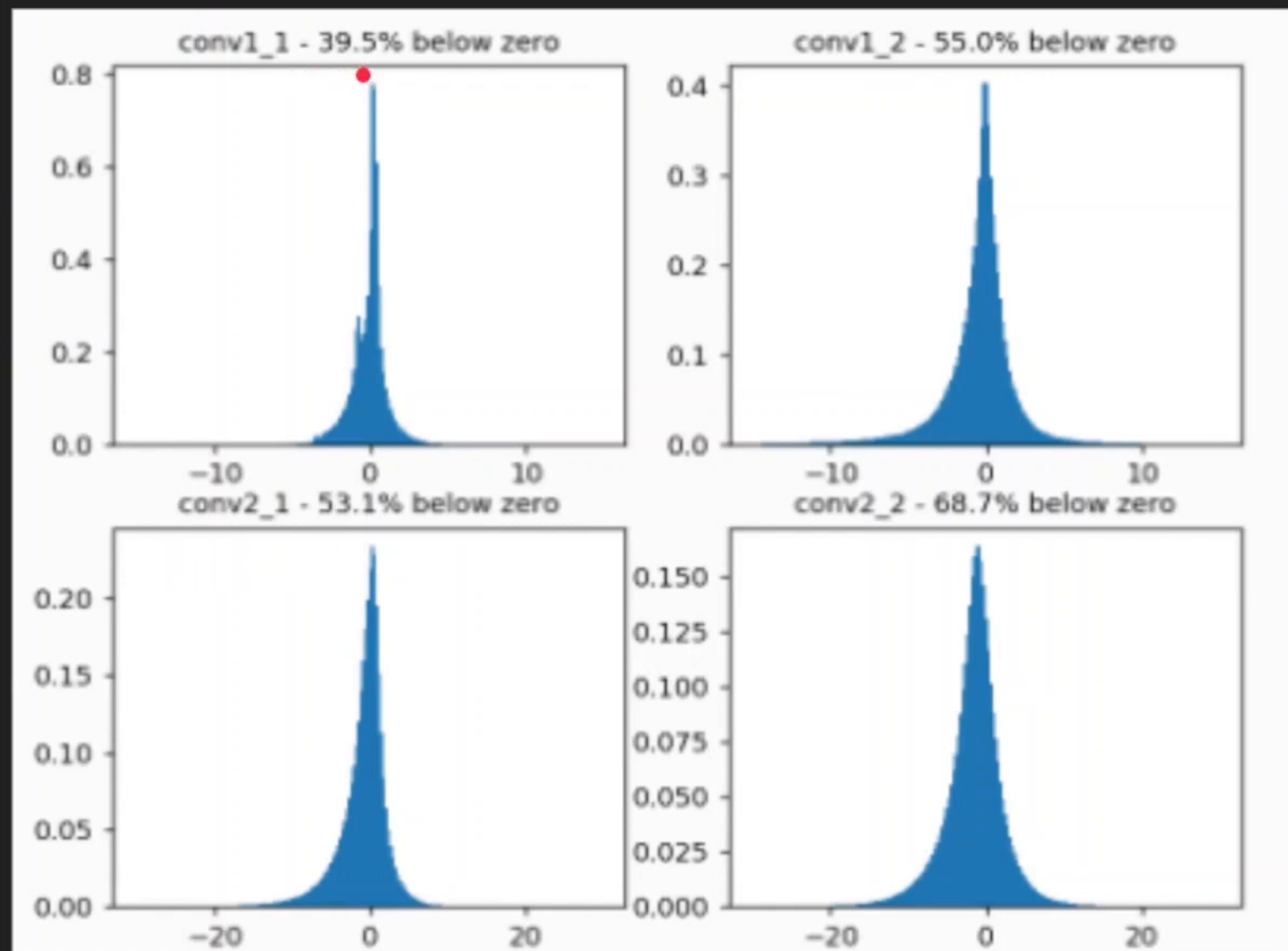
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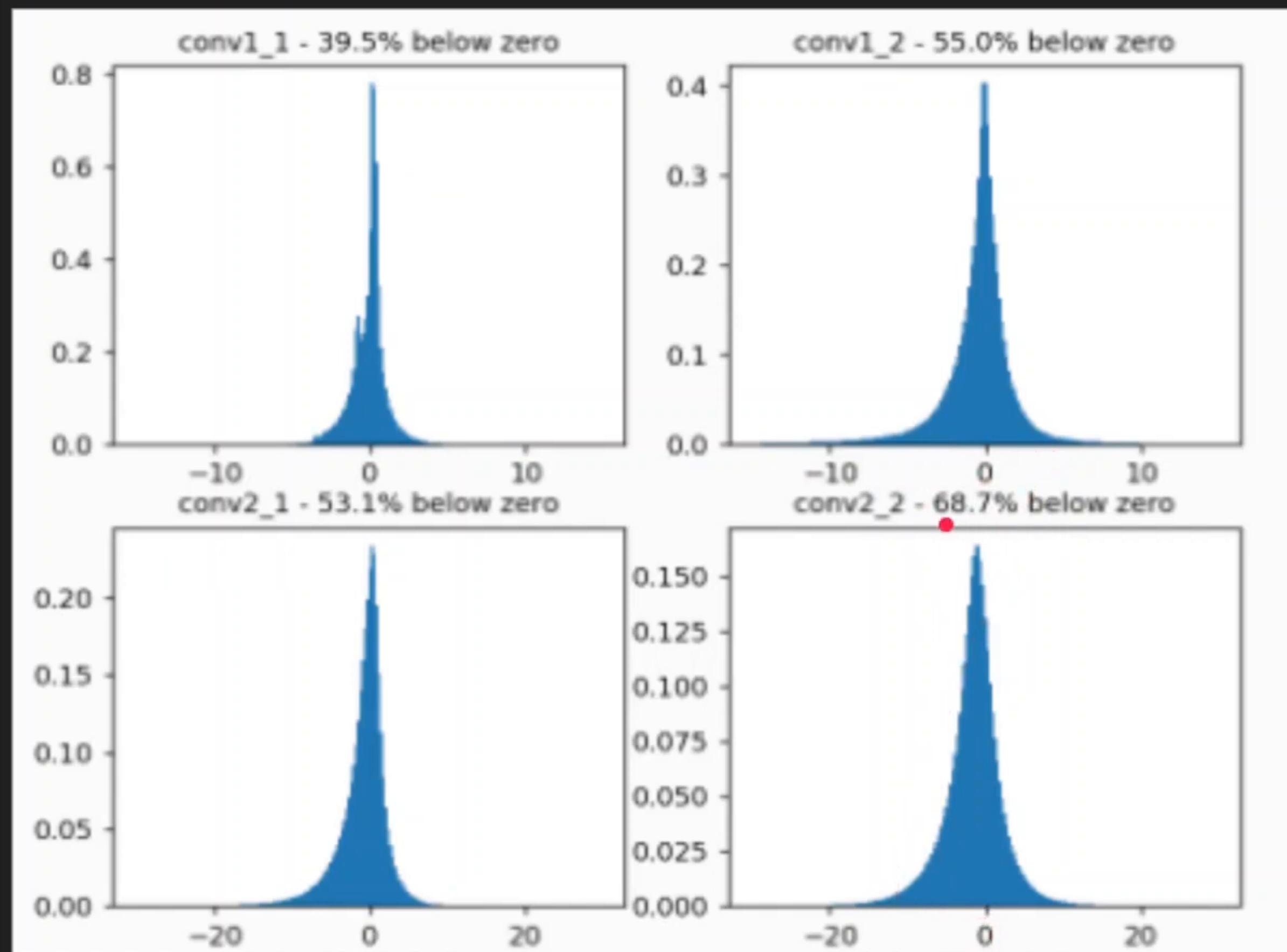
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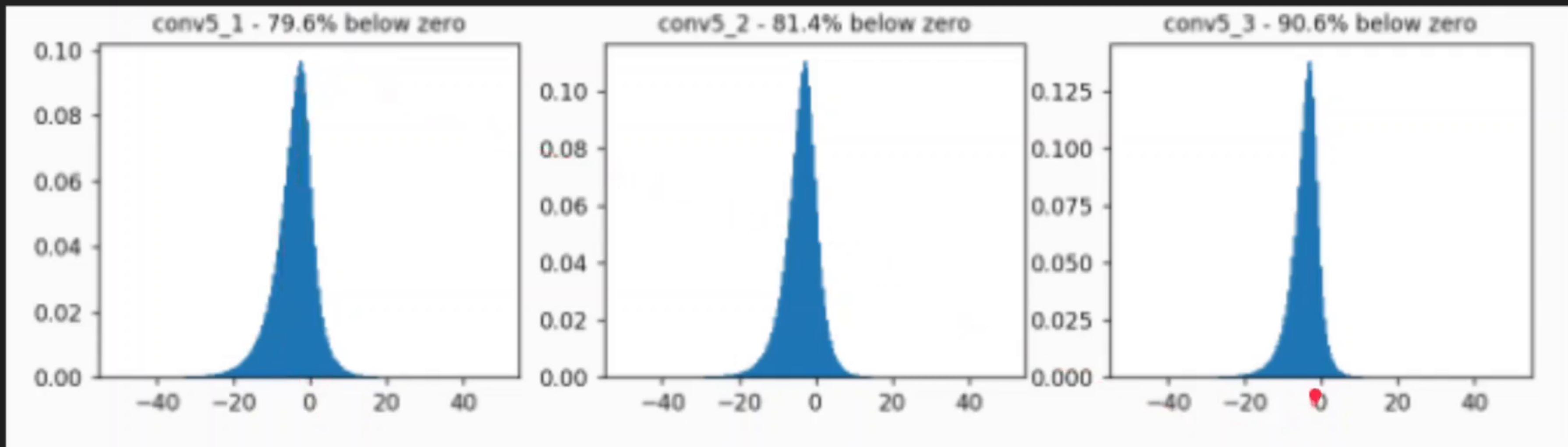
Negative inputs to Activation



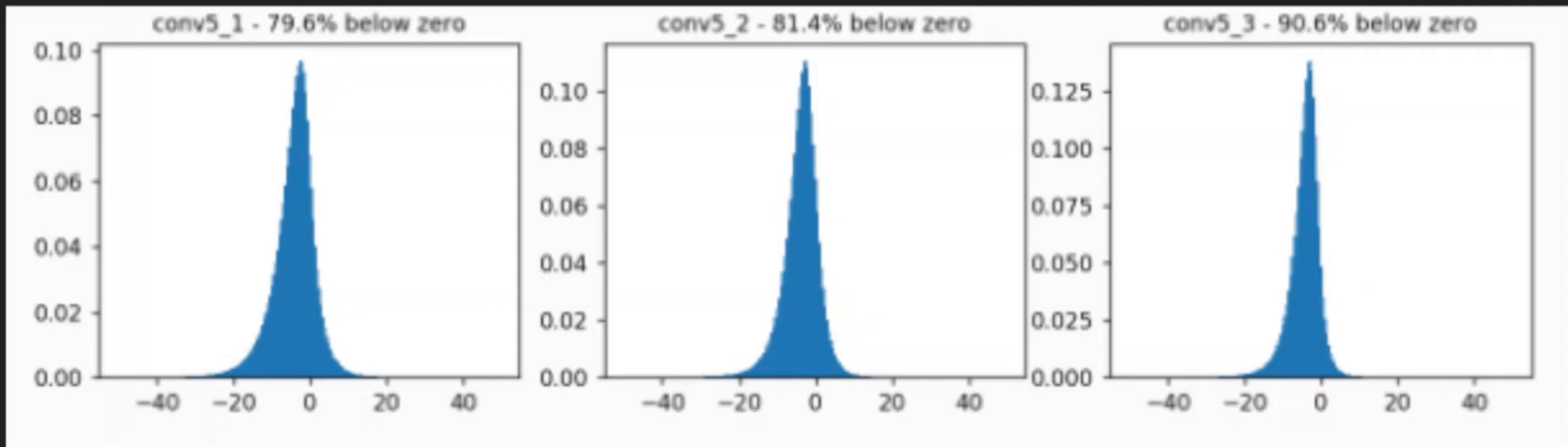
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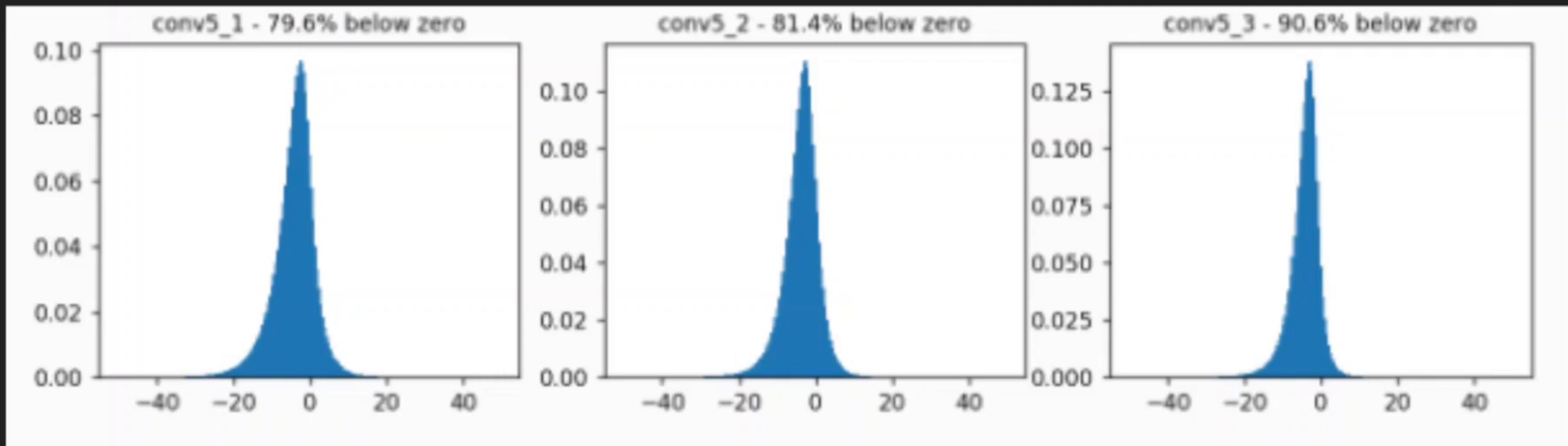
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Drawbacks

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- Dead Neurons

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$$W_{new} = W_{old} - \eta \Delta W$$


Learning rate

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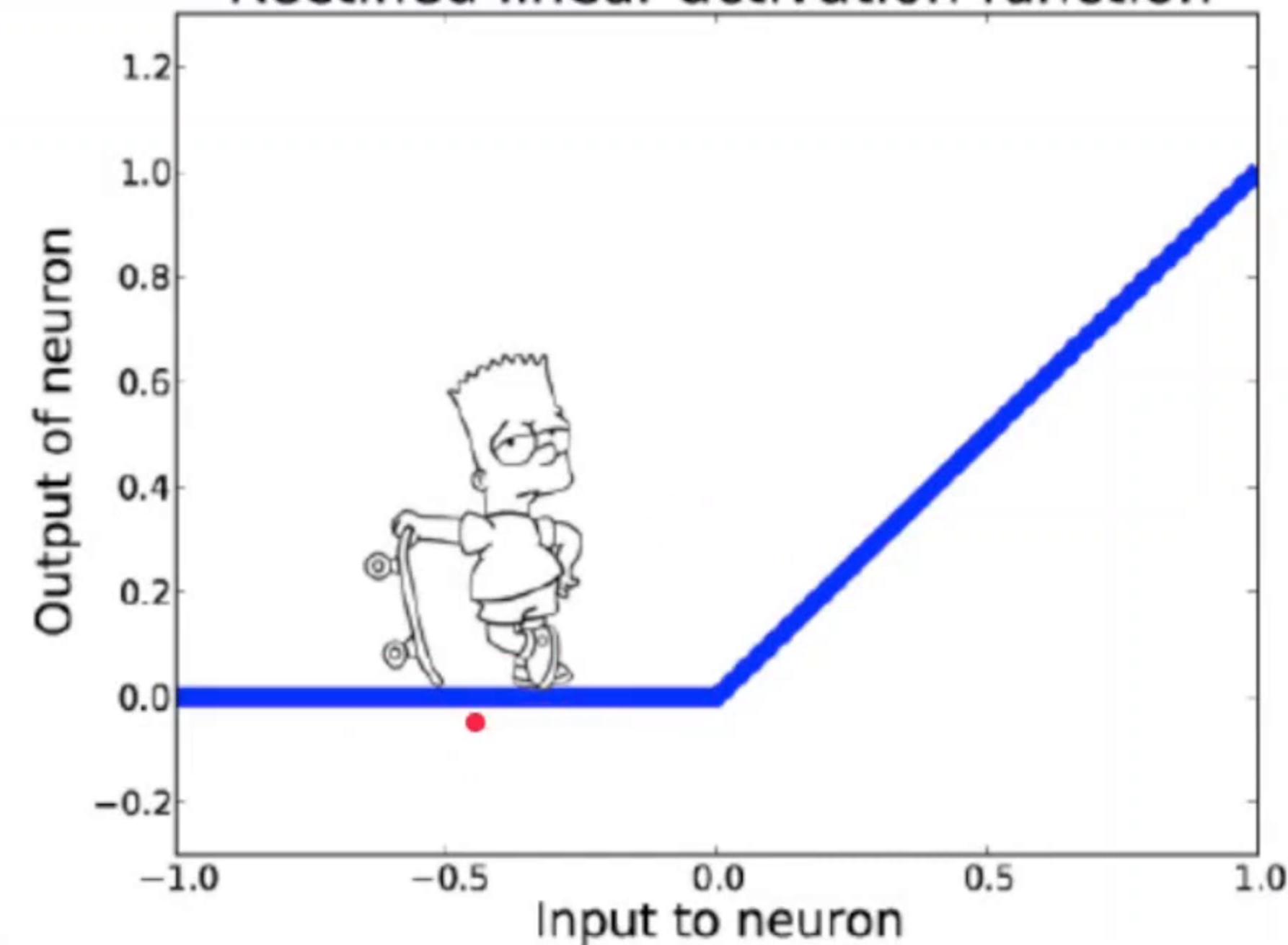

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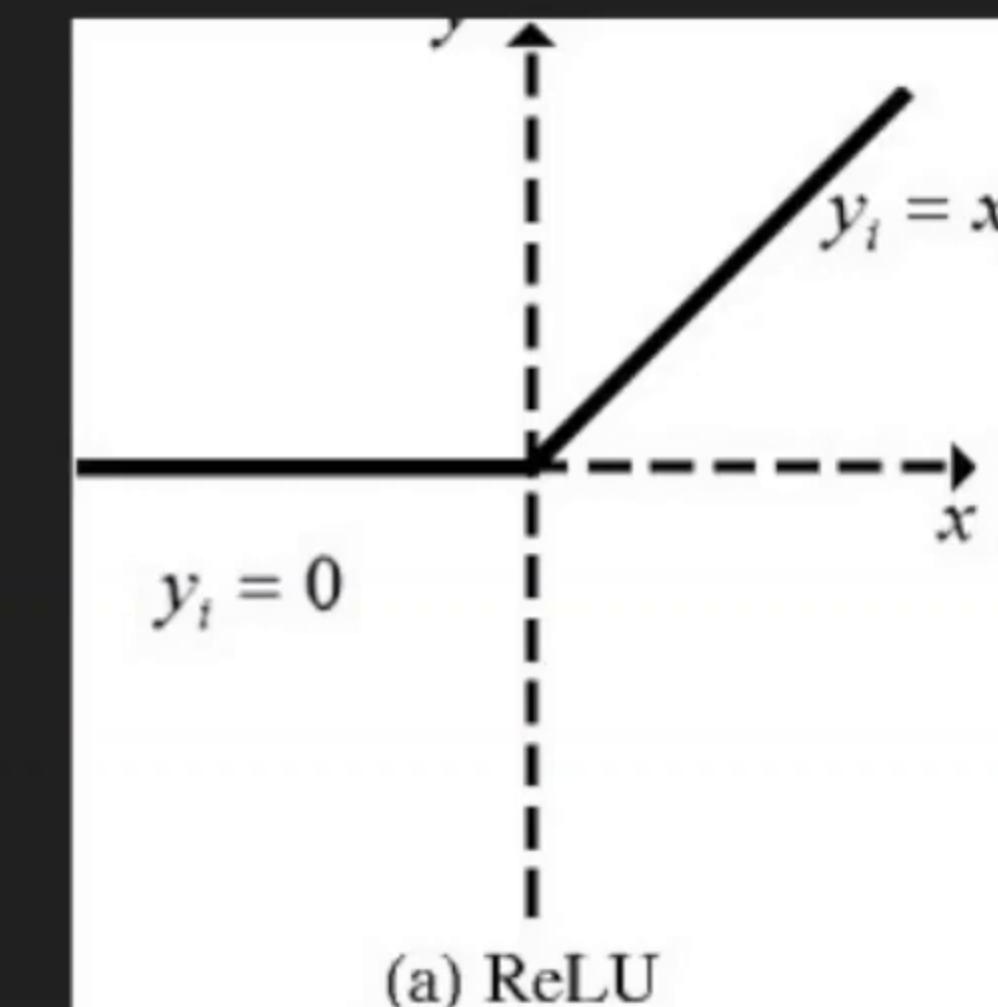
Uh-oh

Rectified linear activation function

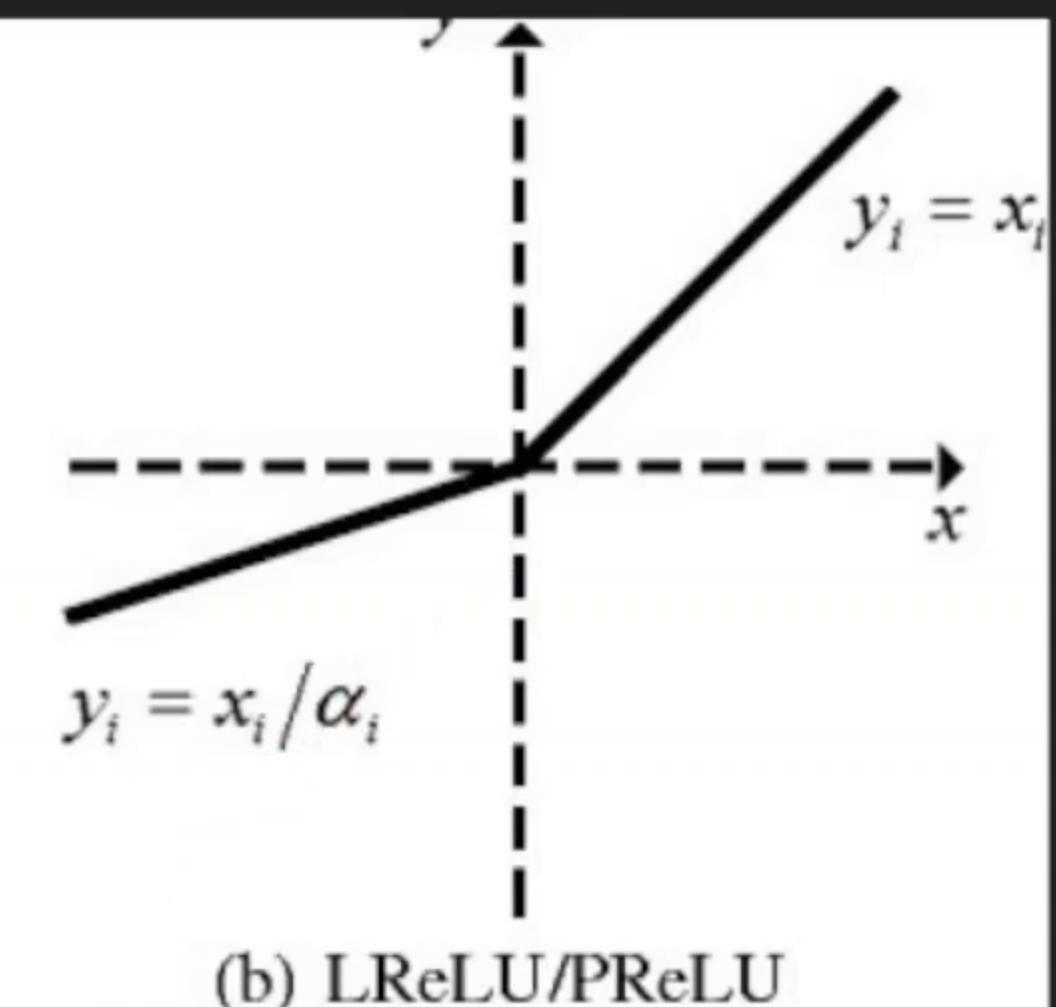


Drawbacks

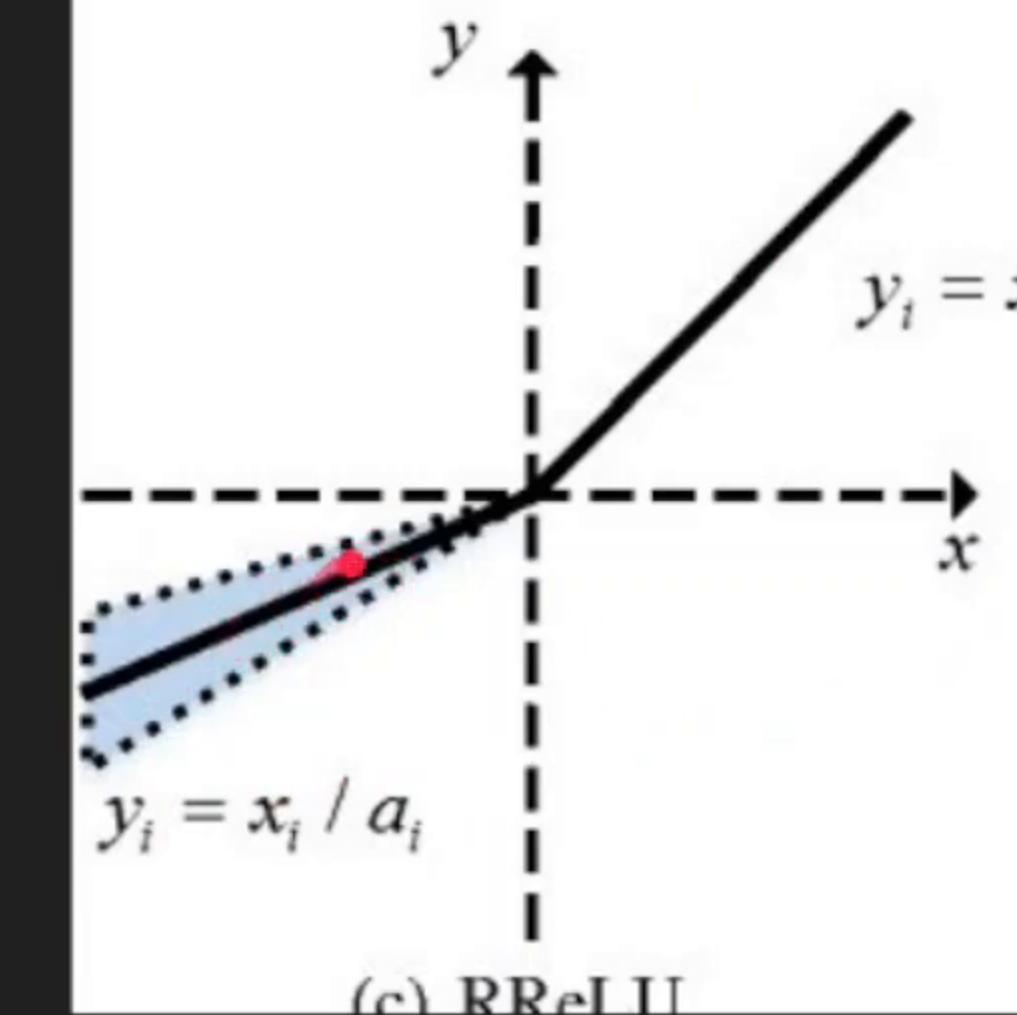
- Exploding Gradient
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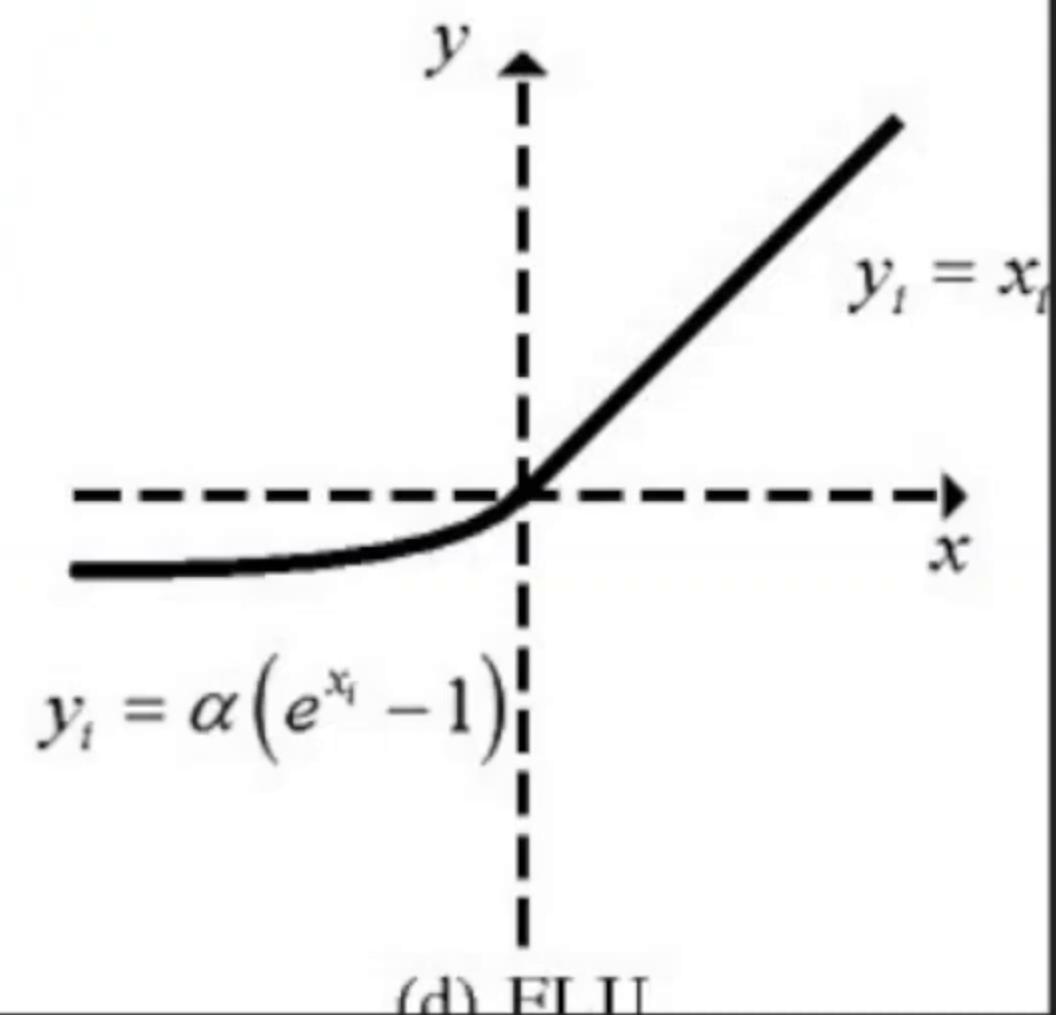
(a) ReLU



(b) LReLU/PReLU



(c) RReLU



(d) ELU

Tips

- Default Activation
- Smaller bias values
- He Weight Initialization
- Scale input data
- Weight penalty

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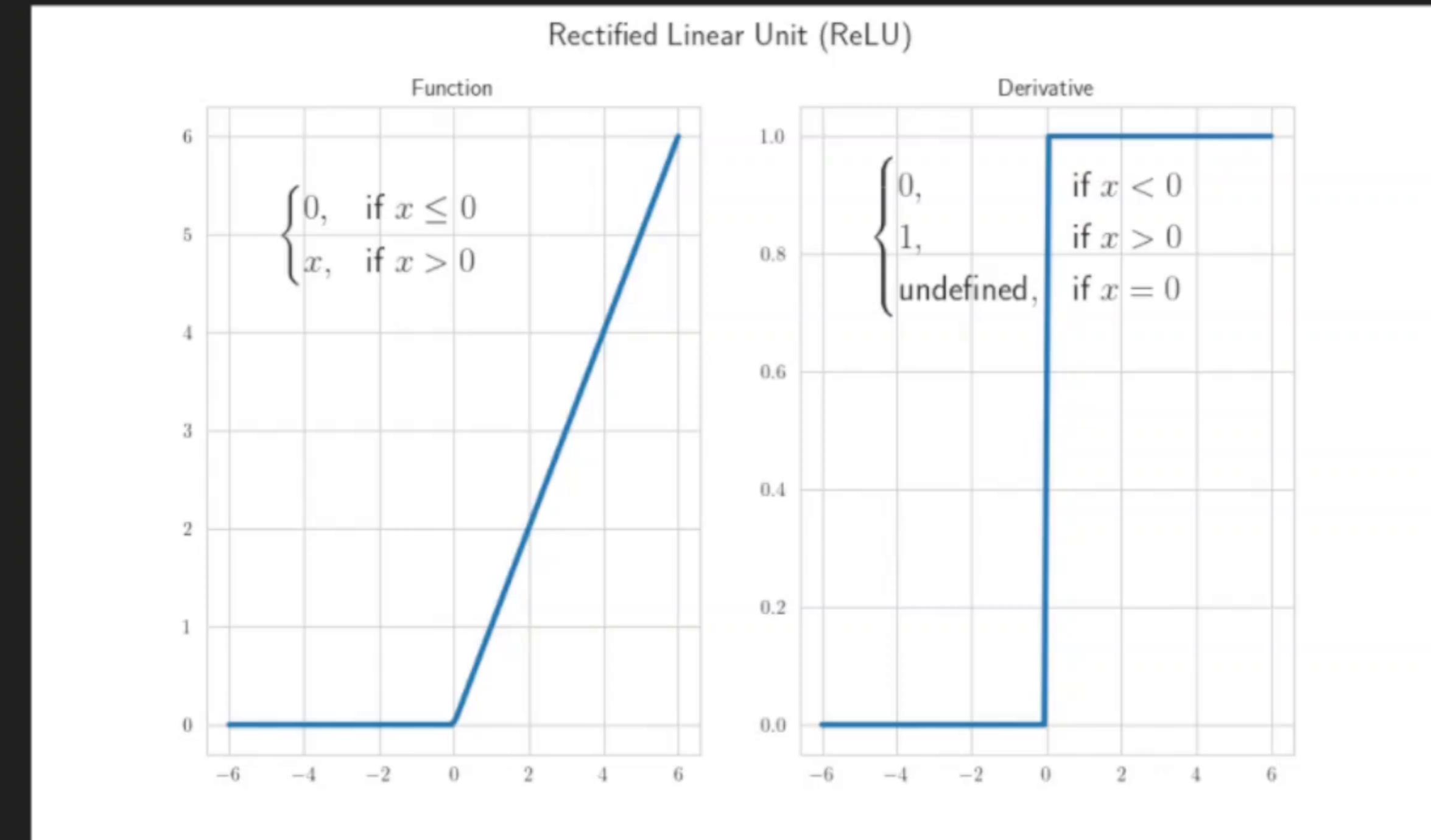
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Python Implementation

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def relu(x):  
    return max(0,x)
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Derivative:
if x>0:
 return 1
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