Your Name

October 5, 2025

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- They determine whether a neuron should be activated or not based on the input.
- Essential for learning complex patterns and enabling deep learning models to solve non-linear problems.
- Mathematically, an activation function $f(x)$ transforms the input signal into an output signal.

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- Without activation functions, neural networks would behave like linear regression models.
- Help in **gradient-based optimization** by providing differentiable outputs.
- Different activation functions suit different types of problems and architectures.

Common Types of Activation Functions

- Sigmoid

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Note: Each has unique properties, making them suitable for specific tasks.

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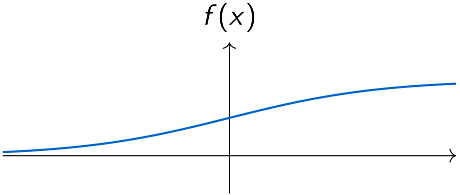

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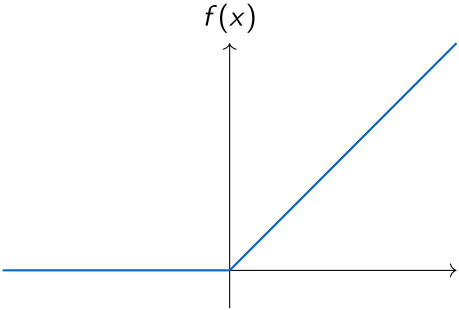

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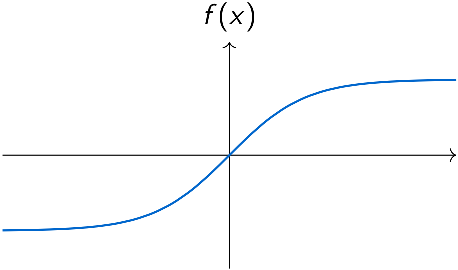

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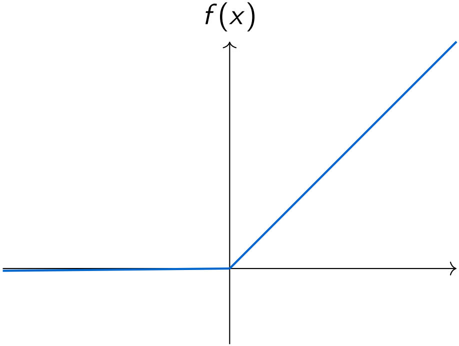

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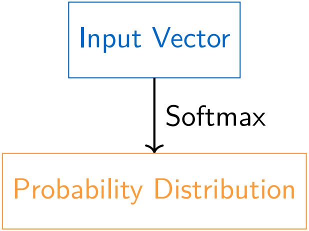

Comparison of Activation Functions

Function	**Output Range**	**Pros**	
Sigmoid	(0, 1)	Probabilistic output	V
ReLU	$[0, \infty)$	Fast, avoids vanishing gradient	
Tanh	(-1, 1)	Zero-centered	V
Leaky ReLU	$(-\infty, \infty)$	Prevents dying ReLU	
Softmax	(0, 1)	Probabilistic, multi-class	Comp

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- Choose the activation function based on the task:
  - Binary classification: Sigmoid
  - Deep networks: ReLU or Leaky ReLU
  - Multi-class classification: Softmax
  - Hidden layers: Tanh or ReLU variants
- Experimentation is key to finding the best activation function for your model!

Thank You!

Questions?

Contact: Your Name (your.email@example.com)