Common Activation Functions

This is a **comprehensive, beginner-friendly table** summarizing the **most common activation functions** used in neural networks.
Each row shows the **name**, **mathematical equation**, **derivative**, **output range**, and **typical usage** (regression/classification).

🔢 Common Activation Functions

Name	Equation (f(x))	Derivative (f'(x))	Range	Common Usage
1. Linear (Identity)	$f(x) = x$	$f'(x) = 1$	$(-\infty, +\infty)$	Output layer for **regression**
2. Binary Step (Threshold)	$f(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}$	Not differentiable	$0, 1$	Simple logic gates, **no learning** (used in perceptron)
3. Sigmoid (Logistic)	$f(x) = \frac{1}{1+e^{-x}}$	$f'(x) = f(x)(1 - f(x))$	$(0, 1)$	**Binary classification**, hidden layers (older models)
4. Tanh (Hyperbolic Tangent)	$f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$	$f'(x) = 1 - f(x)^2$	$(-1, 1)$	Hidden layers (centers around 0, better than sigmoid)
5. ReLU (Rectified Linear Unit)	$f(x) = \max(0, x)$	$f'(x) = \begin{cases} 1 & x > 0 \\ 0 & x \leq 0 \end{cases}$	$[0, \infty)$	Most common for **hidden layers** (deep learning)
6. Leaky ReLU	$f(x) = \begin{cases} x & x > 0 \\ \alpha x & x \leq 0 \end{cases}$	$f'(x) = \begin{cases} 1 & x > 0 \\ \alpha & x \leq 0 \end{cases}$	$(-\infty, \infty)$	Hidden layers (solves "dead

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				ReLU" problem)
7. Parametric ReLU (PReLU)	$f(x) = \begin{cases} x & x > 0 \\ ax & x \leq 0 \end{cases}$	Same as above (a is learned)	$(-\infty, \infty)$	Hidden layers (adaptive negative slope)
8. Softplus	$f(x) = \ln(1 + e^x)$	$f'(x) = \frac{1}{1+e^{-x}} = \text{sigmoid}(x)$	$(0, \infty)$	Smooth version of ReLU
9. ELU (Exponential Linear Unit)	$f(x) = \begin{cases} x & x > 0 \\ \alpha(e^x - 1) & x \leq 0 \end{cases}$	$f'(x) = \begin{cases} 1 & x > 0 \\ f(x) + \alpha & x \leq 0 \end{cases}$	$(-\alpha, \infty)$	Hidden layers (smooth and avoids dead neurons)
10. SELU (Scaled ELU)	$f(x) = \lambda \begin{cases} x & x > 0 \\ \alpha(e^x - 1) & x \leq 0 \end{cases}$	$f'(x) = \lambda \begin{cases} 1 & x > 0 \\ f(x) + \alpha & x \leq 0 \end{cases}$	$(-\lambda \cdot \alpha, \infty)$	**Self-normalizing networks** (advanced deep nets)
11. Softmax	$f(x_i) = \frac{e^{x_i}}{\sum_j e^{x_j}}$	$f'(x_i) = f(x_i)(1 - f(x_i))$ (for each class)	$(0, 1)$, sums to 1	Output layer for **multi-class classification**
12. Swish	$f(x) = x \cdot \sigma(x) = \frac{x}{1+e^{-x}}$	$f'(x) = f(x) + \sigma(x)(1 - f(x))$	$(-\infty, \infty)$	Hidden layers (smooth & performs well)
13. Mish	$f(x) = x \tanh(\ln(1 + e^x))$	$f'(x) = \tanh(\text{softplus}(x)) + x \cdot \text{sech}^2(\text{softplus}(x)) \cdot \sigma(x)$	$(-\infty, \infty)$	Hidden layers (newer, smooth like Swish)

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14. Gaussian (Radial Basis)	$f(x) = e^{-x^2}$	$f'(x) = -2xe^{-x^2}$	$(0, 1]$	Used in **RBF networks**
15. Exponential Linear (ExpLU)	$f(x) = e^x - 1$	$f'(x) = e^x$	$(-1, \infty)$	Rare, sometimes used in experimental deep nets

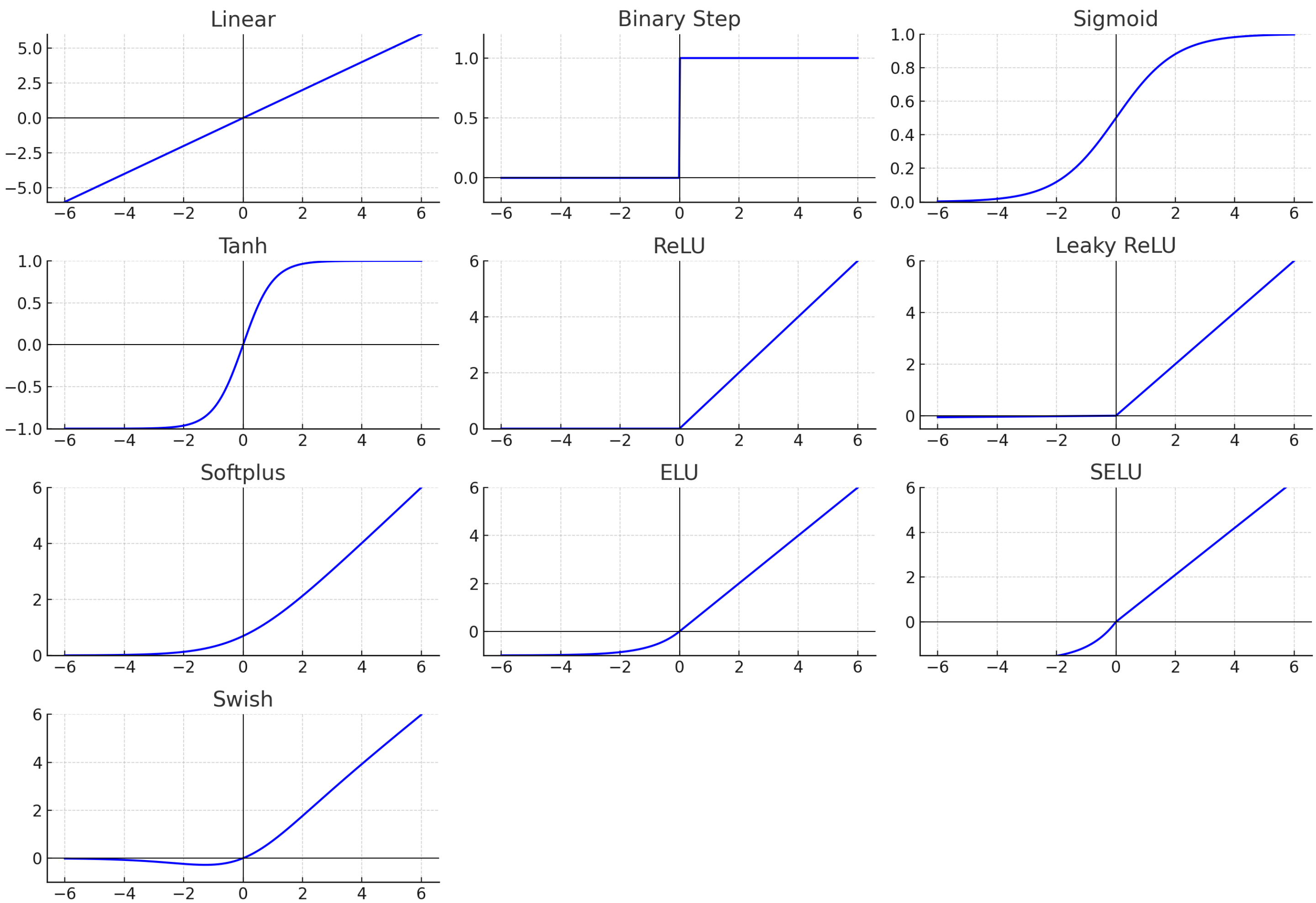
🧭 Quick Guide: Which to Use?

Goal	Recommended Activation
Regression output	**Linear**
Binary classification output	**Sigmoid**
Multi-class classification output	**Softmax**
Hidden layers (most networks)	**ReLU**, **Leaky ReLU**, or **Swish**
When input varies a lot / needs normalization	**SELU** or **ELU**

Visual comparison of the most common **activation functions** —

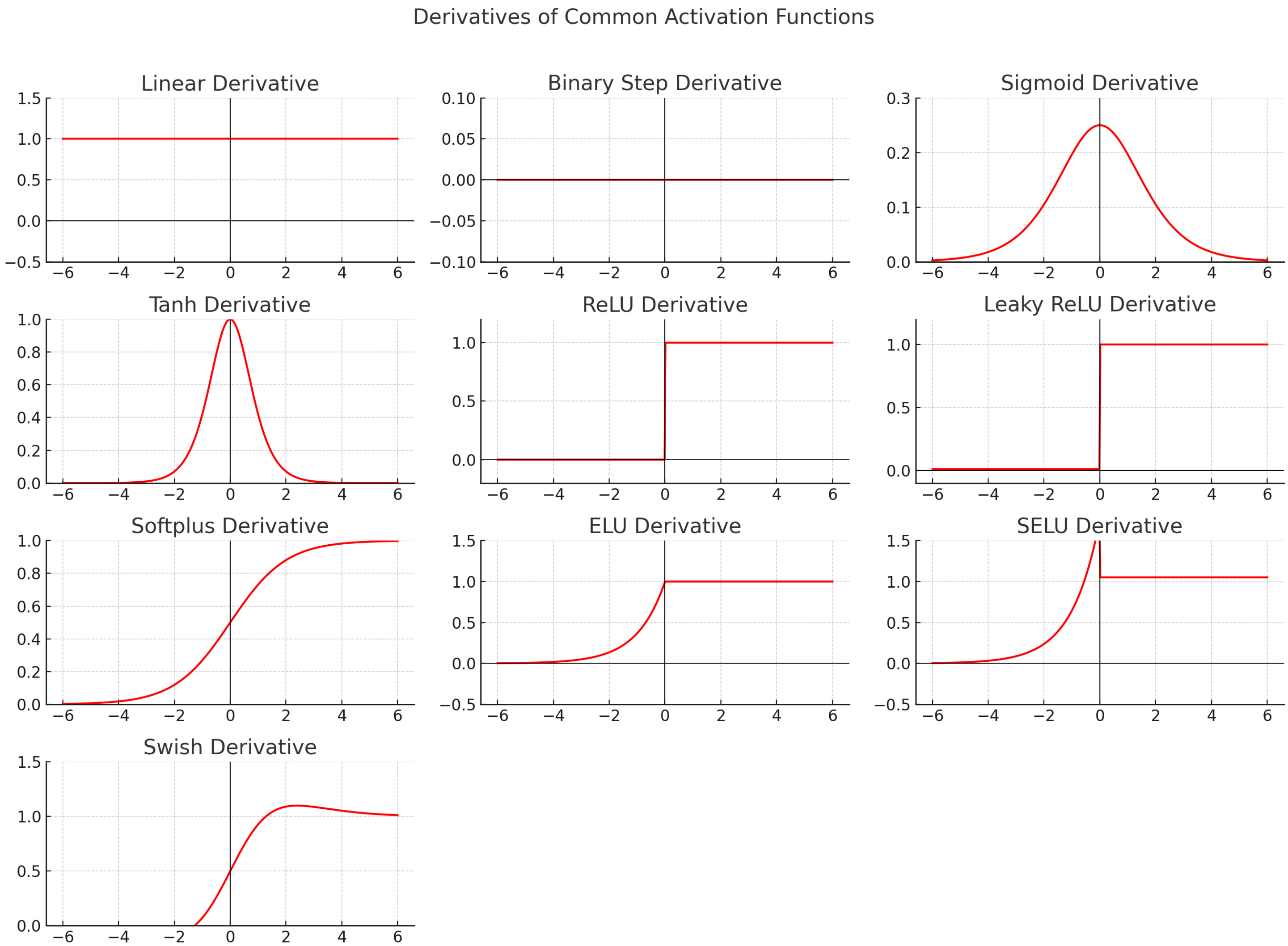
you can see how each one transforms input values:

Common Activation Functions — Shapes and Ranges



- **Linear** is a straight line (no activation).
- **Binary Step** sharply switches between 0 and 1.
- **Sigmoid** smoothly transitions from 0 to 1.
- **Tanh** is similar but ranges from -1 to 1.
- **ReLU** outputs 0 for negatives and linear for positives.
- **Leaky ReLU** allows small negative values.
- **Softplus** is a smooth version of ReLU.
- **ELU**, **SELU**, and **Swish** combine smoothness with nonlinearity for better gradient flow.

comparison of derivatives for the same activation functions:



You can see how each derivative behaves — for example:

- **Sigmoid** and **tanh** derivatives peak in the center but vanish at the extremes (causing vanishing gradients).
- **ReLU** has a constant derivative (1 for x>0, 0 for x<0), making it efficient for deep networks.
- **Leaky ReLU**, **ELU**, and **Swish** maintain small gradients even for negative inputs, helping learning stability.