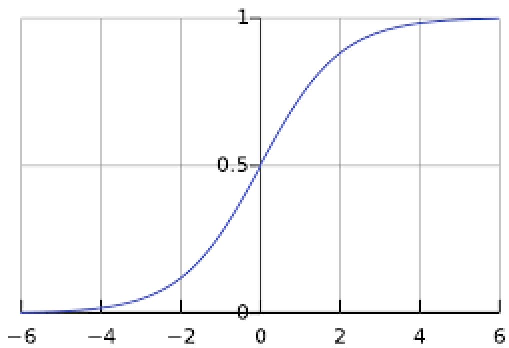
1. Sigmoid (Logistic) Activation Function

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



Advantages:

- **Smooth gradient**: Helps with gradient-based optimization methods.
- **Output range**: (0, 1), which can be interpreted as probabilities.

Disadvantages:

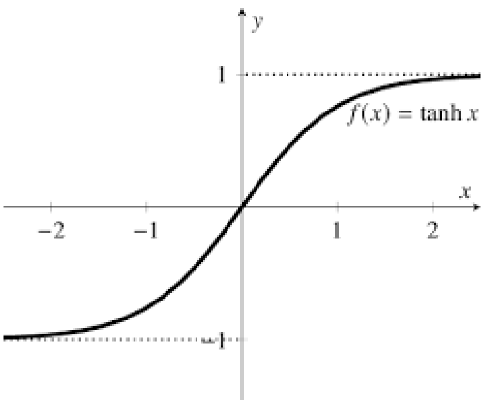
- **Vanishing gradient problem**: For very high or very low input values, the gradient becomes very small, which can slow down the training.
- **Outputs not zero-centered**: This can slow down convergence during gradient descent.

Usage Recommendations:

- **Sigmoid**: Historically used but less common now due to the vanishing gradient problem.

2. Hyperbolic Tangent (tanh) Activation Function

$f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$



Advantages:

- **Zero-centered**: The outputs range from -1 to 1, which can help with convergence.
- **Smooth gradient**: Like the sigmoid, it provides a smooth gradient.

Disadvantages:

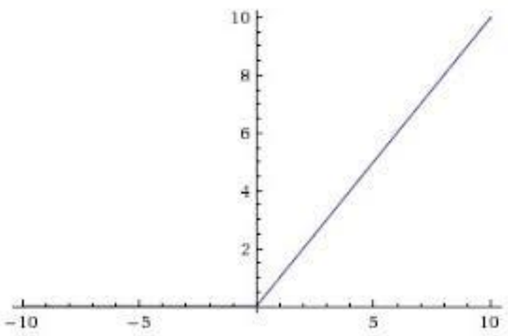
- **Vanishing gradient problem**: Similar to sigmoid, though less severe.

Usage Recommendations:

- **Tanh**: Historically used but less common now due to the vanishing gradient problem.

3. Rectified Linear Unit (ReLU) Activation Function

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



Advantages:

- **Computationally efficient**: Only requires a threshold at zero.
- **Sparse activation**: A portion of neurons are deactivated, promoting sparsity and efficient computation.
- **Alleviates vanishing gradient problem**: Increases the convergence rate of gradient descent.

Disadvantages:

- **Dying ReLU problem**: Neurons can sometimes get stuck during training and output zero for all inputs. This can be mitigated using variants like Leaky ReLU.

Usage Recommendations:

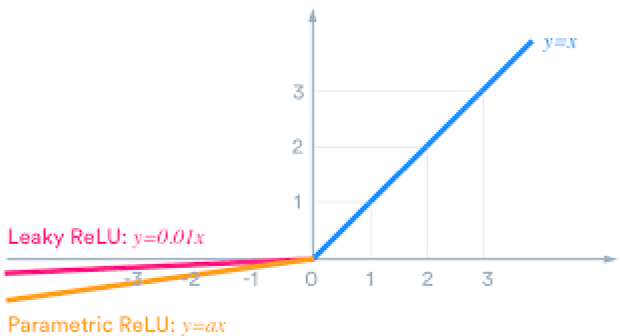
- **ReLU**: The default choice for most deep learning models due to its simplicity and effectiveness.

4. Leaky ReLU Activation Function

$$\begin{cases} x & \text{if } x \geq 0 \\ \alpha x & \text{if } x < 0 \end{cases}$$

f(x)=max (αx, x)

Where α is a small constant, typically 0.01.



Advantages:

- **Solves dying ReLU problem**: Allows a small, non-zero gradient when the unit is not active.

Disadvantages:

- **Computationally slightly less efficient**: Due to the added multiplication.

Usage Recommendations:

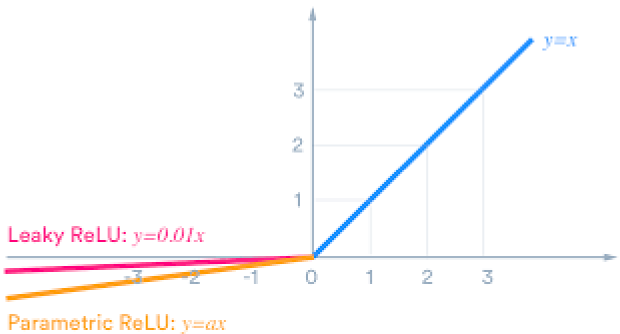
- **Leaky ReLU:** Used when the dying ReLU problem is encountered.

5. Parametric ReLU (PReLU) Activation Function

$$\begin{cases} x & \text{if } x \geq 0 \\ a_i x & \text{if } x < 0 \end{cases}$$

f(x)=max (α_i x, x)

Where α_i is a parameter learned during training.



Advantages:

- **Adaptive**: The parameter α\alphaα can be learned to best fit the data.

Disadvantages:

- **Increased computational cost**: Due to learning an additional parameter.

Usage Recommendations:

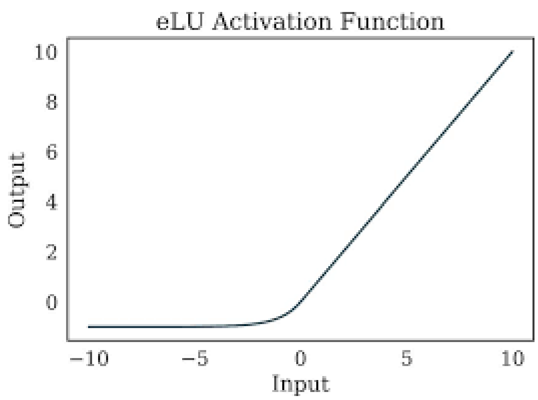
- **PReLU:** Used when the dying ReLU problem is encountered.

6. Exponential Linear Unit (ELU)

$$\begin{cases} x & \text{if } x \geq 0 \\ \alpha(e^x - 1) & \text{if } x < 0 \end{cases}$$

$f(x)=\max(\alpha(e^x - 1), x)$

where α is a positive constant that determines the value to which an ELU saturates for negative net inputs.



Advantages:

- **Improves learning characteristics**: Combines the benefits of ReLU and leaky ReLU.
- **Smooth gradient**: Reduces the vanishing gradient problem.

Disadvantages:

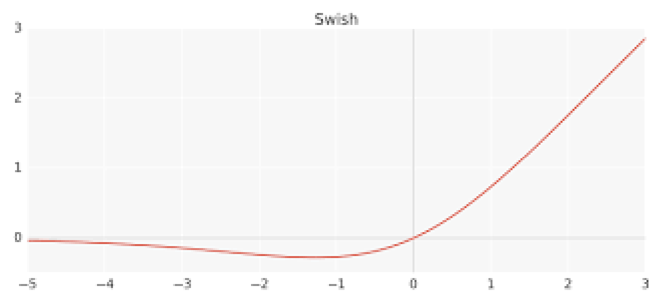
- **Computational cost**: More complex than ReLU.

Usage Recommendations:

- **ELU**: Can be used when additional performance is needed, and computational resources allowed.

7. Swish Activation Function

$$f(x) = x \cdot \text{sigmoid}(x) = \frac{x}{1+e^{-x}}$$



Advantages:

- **Smooth and non-monotonic**: Often outperforms ReLU on deep networks.

Disadvantages:

- **Computationally more expensive**: Due to the combination of multiplication and sigmoid function.

Usage Recommendations:

- **Swish**: Can be used when additional performance is needed, and computational resources allowed.

8. Usage Recommendations:

- **Sigmoid and Tanh**: Historically used but less common now due to the vanishing gradient problem.
- **ReLU**: The default choice for most deep learning models due to its simplicity and effectiveness.
- **Leaky ReLU / PReLU**: Used when the dying ReLU problem is encountered.
- **ELU and Swish**: Can be used when additional performance is needed and computational resources allow.