

# Derivative of the Sigmoid Function

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## 1. What is the Sigmoid Function?

The sigmoid function is:

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

It takes any real number and “squashes” it into the range **(0, 1)**.

This is why it's so popular in logistic regression — the output can be interpreted as a probability.

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## 2. Why Do We Need the Derivative?

In optimization (e.g., gradient descent), we need the **slope** of the function to update weights.

The derivative tells us **how much a small change in input changes the output**.

For sigmoid, the derivative is **beautifully simple** and that's why it's so convenient for machine learning.

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## 3. Step-by-Step Derivation

1. Start with:

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

2. Differentiate using the chain rule:

- Denominator:  $(1 + e^{-x})$
- Use the quotient rule or rewrite first:

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

- Derivative:

$$\sigma'(x) = -1 \cdot (1 + e^{-x})^{-2} \cdot (-e^{-x})$$

3. Simplify:

$$\sigma'(x) = \frac{e^{-x}}{(1 + e^{-x})^2}$$

#### 4. Now, the magic trick:

- We know  $\sigma(x) = \frac{1}{1+e^{-x}}$
- And  $1 - \sigma(x) = \frac{e^{-x}}{1+e^{-x}}$

Multiply them:

$$\sigma(x) \cdot (1 - \sigma(x)) = \frac{1}{1 + e^{-x}} \cdot \frac{e^{-x}}{1 + e^{-x}} = \frac{e^{-x}}{(1 + e^{-x})^2}$$

That matches our derivative expression.

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#### 4. Result

The derivative of the sigmoid function is:

$$\sigma'(x) = \sigma(x) \cdot (1 - \sigma(x))$$

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#### 5. Why This is Useful

- No exponentials are needed after computing  $\sigma(x)$  the derivative reuses the sigmoid value.
  - For logistic regression and neural networks, this saves computation and avoids messy math.
  - It also shows that:
    1. When  $\sigma(x)$  is near **0** or **1**, the derivative is small  $\rightarrow$  gradient updates are tiny (this is why sigmoid can cause the vanishing gradient problem).
    2. When  $\sigma(x) = 0.5$ , the derivative is largest (0.25)  $\rightarrow$  learning is fastest here.
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