



Understanding Logistic Regression

A Supervised Learning Algorithm for Binary Classification

💡 What is Logistic Regression?

🎓 **Supervised learning algorithm** used for binary classification

🔌 Output values (Y) are either:

- 0 (No)
- 1 (Yes)

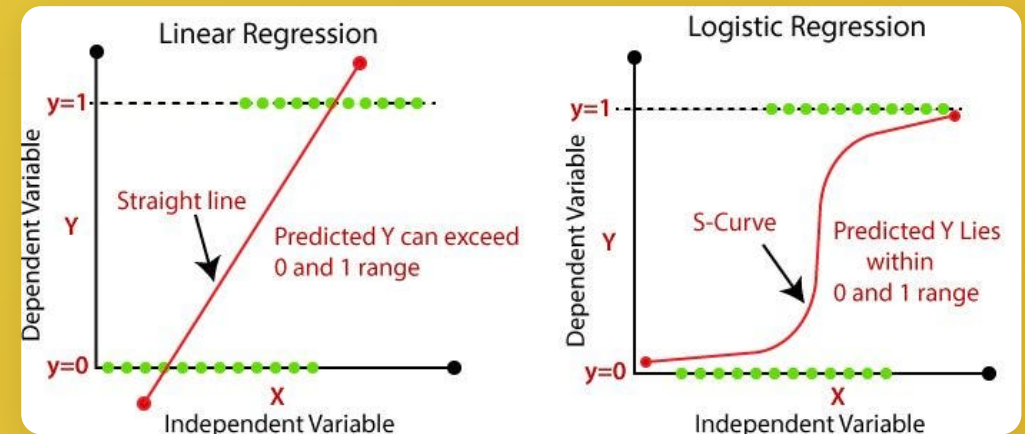
Example:



Cat in image?
Yes → 1



Cat in image?
No → 0



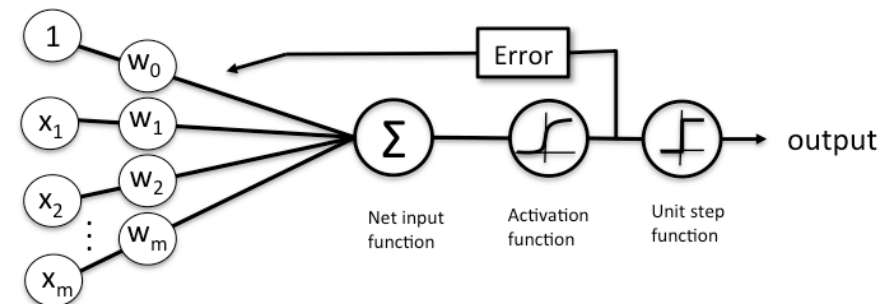
💡 What Are We Trying to Do?

- ➡ We have an **input X** (e.g., a digital image)
- ➡ We want to **calculate the probability** that this image is of a cat
- Σ This probability is denoted by **\hat{Y} (Y hat)**, our prediction of Y

$$P(Y = 1 \mid X)$$



We want to know the probability that **$Y = 1$** given **X**



Schematic of a logistic regression classifier.

🔑 Components of the Model



X: Feature Vector

The input data, such as pixel values of an image



W: Weight Vector

Has the same dimensions as X

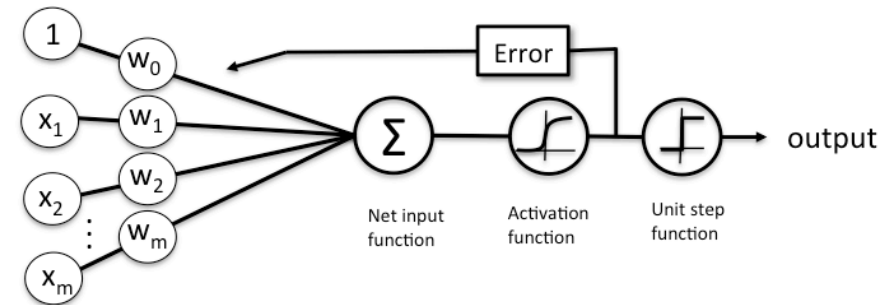


b: Bias

A single real number



Goal: Use **X**, **W**, and **b** to produce \hat{Y} (the predicted output)



Schematic of a logistic regression classifier.



How Do We Calculate the Prediction?



First compute $Z = W^T X + b$



Problem: Z might be **greater than 1** or **negative**



This doesn't make sense for a **probability** (must be between 0 and 1)



Solution: Pass Z through the **Sigmoid Function**

Linear Combination

$$\begin{array}{ccccccc} \mathbf{W}^T & \times & \mathbf{X} & + & \mathbf{b} & = & \mathbf{Z} \\ \text{Weights} & & \text{Features} & & \text{Bias} & & \text{Output} \end{array}$$

$$\mathbf{Z} = \mathbf{W}^T \mathbf{X} + \mathbf{b}$$

But Z can be any real number, not a valid probability

Σ The Sigmoid Function



Takes **any real number (Z)** and converts it to a value **between 0 and 1**

Formula

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



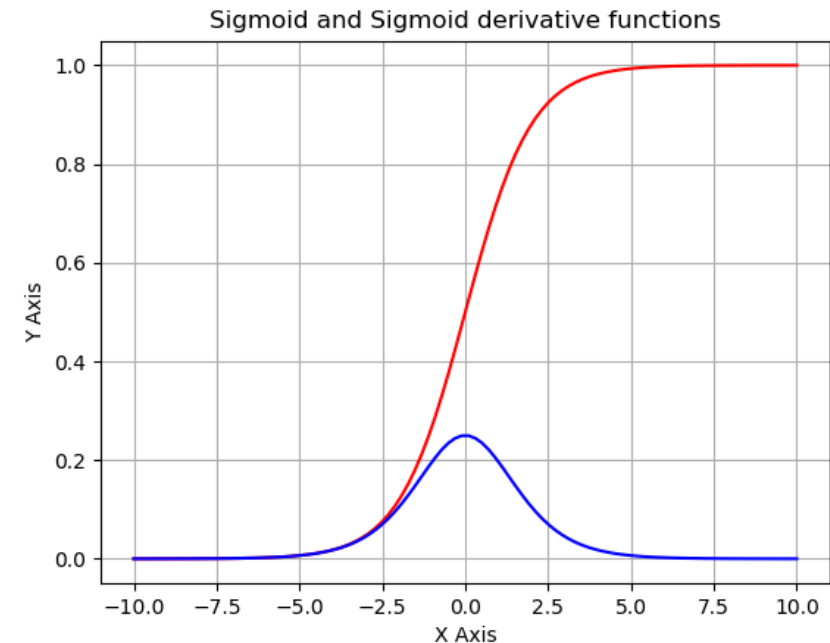
When **Z** is very large →
output \approx **1**



When **Z** is very small
(negative) → output \approx **0**



Transforms **linear values** into **meaningful probabilities**



🔗 The Complete Relationship in the Model

Complete Formula

$$\hat{Y} = \sigma(W^T X + b)$$

- 1 Compute $Z = W^T X + b$
- 2 Pass Z through the **sigmoid function**
- 3 Get \hat{Y} between 0 and 1 \rightarrow probability that $Y = 1$

Logistic Regression Model

$$W^T \times X + b = Z$$

$$Z \rightarrow \sigma(Z) \rightarrow \hat{Y}$$

\hat{Y} represents the probability that $Y = 1$ given X

What Are We Trying to Learn?



Learn the values of **W** (weights) and **b** (bias)



Make predicted value \hat{Y} as close as possible to actual value **Y**



Minimize the difference between predictions and true labels



Build a model that accurately predicts whether an image contains a **cat** or not

Learning Process

W, b



$\hat{Y} = \sigma(W^T X + b)$

\hat{Y}



Y

Through optimization, we find the best W and b values

Summary

Key Points About Logistic Regression



Binary classification algorithm for 0/1 outputs



Uses **sigmoid function** to convert linear output to probability



Learns **weights (W)** and **bias (b)** to make accurate predictions



Final output: **Probability** that $Y = 1$ given X

Complete Logistic Regression Formula

$$\hat{Y} = \sigma(W^T X + b)$$

Where σ is the sigmoid function that transforms any real number into a probability between 0 and 1