

# # Softmax Regression

Classify data into multiple classes (e.g., 3 classes: 0, 1, 2)  
we want a function that gives class probabilities.

## 1. Linear Model

For every class  $j$ :

$$z_j = W_j^T \cdot x + b_j$$

Where:

- $x$  = input features (2D here)
- $W_j$  = weights for class  $j$
- $b_j$  = bias for class  $j$

This gives raw scores (Logits), not probabilities.

## 2. Softmax Function (converts scores $\rightarrow$ probabilities)

$$\text{Softmax}(z_j) = \frac{e^{z_j}}{\sum_{k=1}^C e^{z_k}}$$

Where:

- $C$  = number of classes

✓ Output of Softmax:

- Every class gets a probability
- Probabilities sum to 1

## 3. Loss Function: Cross Entropy

Measures how wrong model ~~pred~~ predictions are.

For each example:

$$L = - \sum_{j=1}^C y_j \log(\hat{y}_j)$$

Where:

- $y_j$  = true label (one-hot)
- $\hat{y}_j$  = Predicted Probability

Total loss:

$$J = \frac{1}{N} \sum_{i=1}^N L_i$$

Lower loss  $\rightarrow$  better model.

#### 4. Gradient Descent (Optimization)

We update weights in the direction that reduces loss.

Gradients:

$$\frac{\partial J}{\partial W} = \frac{1}{N} X^T (\hat{Y} - Y)$$

$$\frac{\partial J}{\partial b} = \frac{1}{N} \sum_{i=1}^N (\hat{y}_i - y_i)$$

Update Rules:

$$W := W - \alpha \frac{\partial J}{\partial W}$$

$$b := b - \alpha \frac{\partial J}{\partial b}$$

Where:

$\alpha$  = learning rate (small step size)

#### 5. Prediction

Pick the class with ~~least~~ highest probability.

$$\hat{y} = \arg \max_j (\hat{y}_j)$$

✓ Gives final class label (0, 1, 2, ...)

## • Full Concept in 4 Lines

Step	Action	Math Output
1.	Linear Junction	Raw scores $z$
2.	Softmax	Probabilities
3.	Cross entropy	Loss
4.	Gradient descent	Improve weights

## • Intuition

Model draws decision boundaries between groups.

Softmax gives confidence for each class.

Training improves boundaries until most points are classified correctly.