

**Example of Single
Neuron with
Activation
Function**

EXAMPLE OF SINGLE NEURON WITH ACTIVATION FUNCTION

Problem Statement: Binary Classification for Insurance Purchase Prediction

Objective:

Given the age of a person, predict whether the person will buy insurance or not.

Input:

- A single feature: Age (numerical).
-

Output:

- A binary label:
 - 1: Person will buy insurance.
 - 0: Person will not buy insurance.

Age	Buys Insurance
22	0
25	0
47	1
52	0
46	1
56	1

EXAMPLE OF SINGLE NEURON WITH ACTIVATION FUNCTION

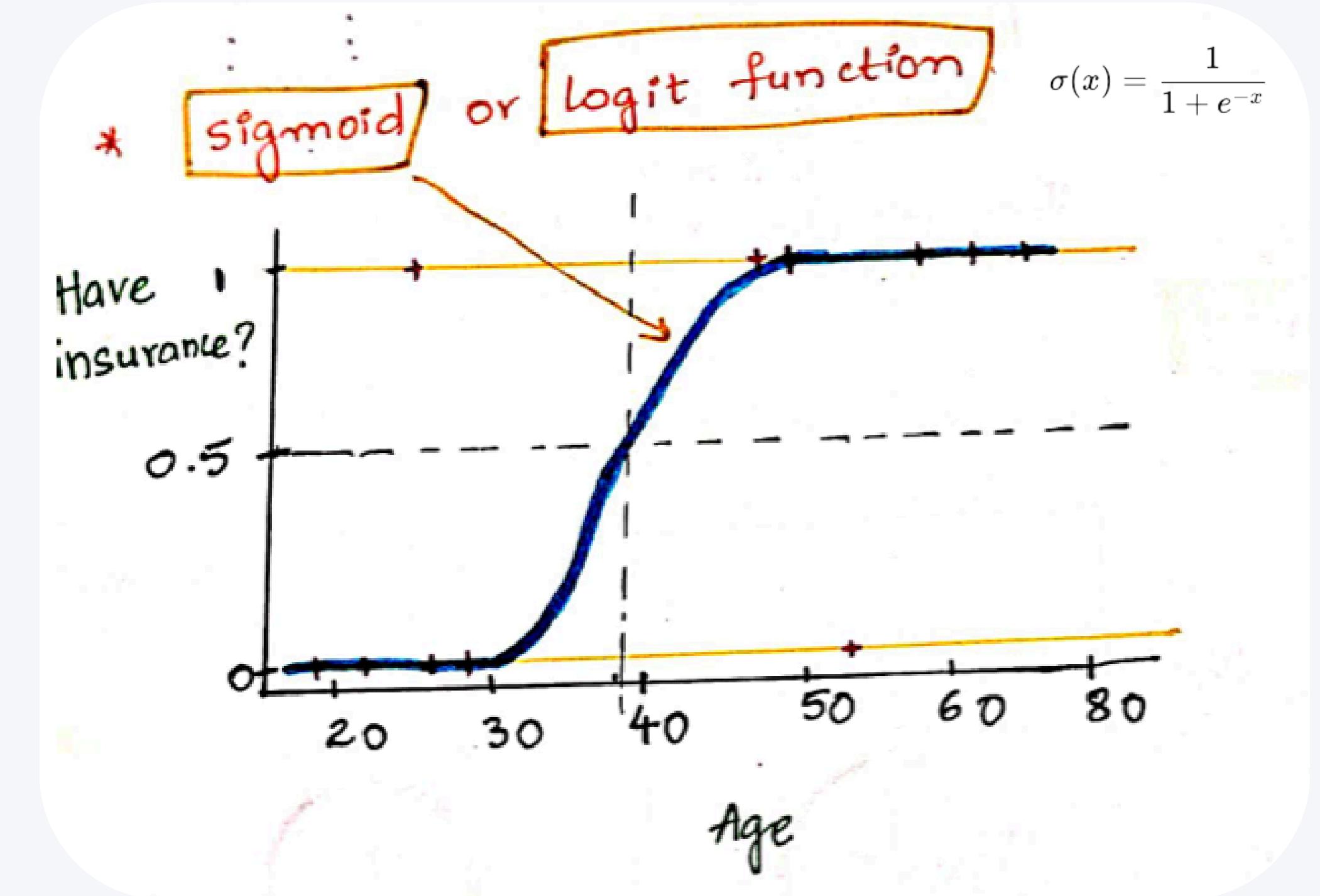
Let's consider a sigmoid activation function to solve the classification problem

Euler's Number (e): $e \approx 2.71828$.

$$\frac{1}{1 + e^{-200}} \approx \frac{1}{1 + 0} = 1$$

$$\frac{1}{1 + e^{200}} \approx \frac{1}{1 + \infty} = 0$$

The **Sigmoid** function converts any input into a range between 0 and 1, making it ideal for probability-based outputs

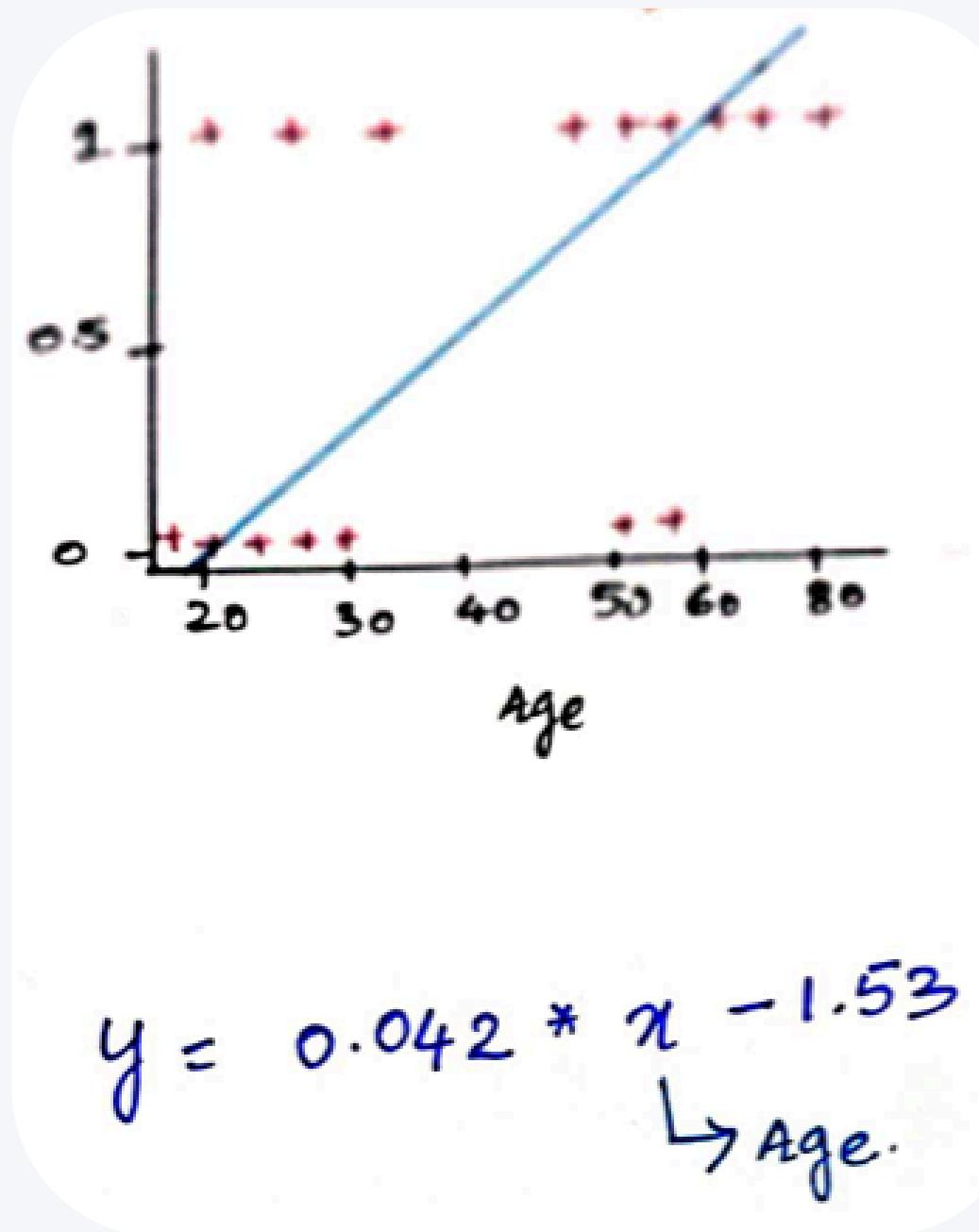


EXAMPLE OF SINGLE NEURON WITH ACTIVATION FUNCTION

Two Steps to solve the problem .. and this is the basic of NN with single neuron !!

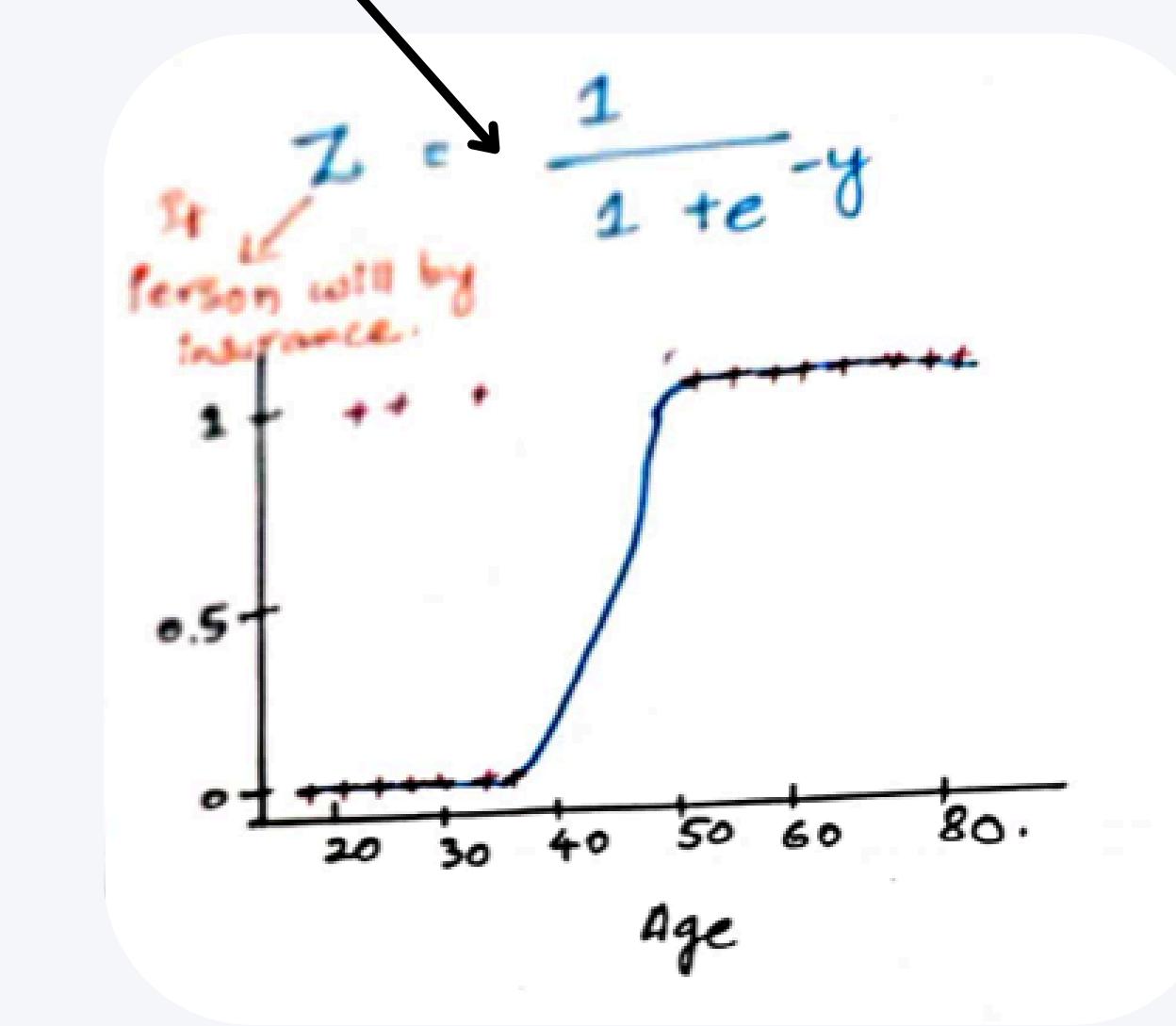
STEP#1

$y = wx+b$ | Transformation



STEP#2

$Z = \dots$ | Activation



EXAMPLE OF SINGLE NEURON WITH ACTIVATION FUNCTION

Two Steps to solve the problem .. and this is the basic of NN with single neuron !!

1. Linear Equation Setup:

$$y = 0.042 \cdot \text{age} - 1.53$$

2. Sigmoid Activation:

The linear output (y) is passed through the sigmoid function:

$$z = \frac{1}{1 + e^{-y}}$$

Threshold Decision:

- $z < 0.5$: Person will **not** buy insurance.
- $z \geq 0.5$: Person **will** buy insurance.

• For Age = 35:

$$y = 0.042 \cdot 35 - 1.53 = -0.06$$

$$z = \frac{1}{1 + e^{0.06}} \approx 0.48$$

Decision: Will not buy insurance.

• For Age = 43:

$$y = 0.042 \cdot 43 - 1.53 = 0.276$$

$$z = \frac{1}{1 + e^{-0.276}} \approx 0.568$$

Decision: Will buy insurance.

Generalized Formula for Multiple Features:

For multiple features such as **age**, **income**, and **education**, the linear equation becomes:

$$y = w_1 \cdot x_1 + w_2 \cdot x_2 + w_3 \cdot x_3 + b$$

Where:

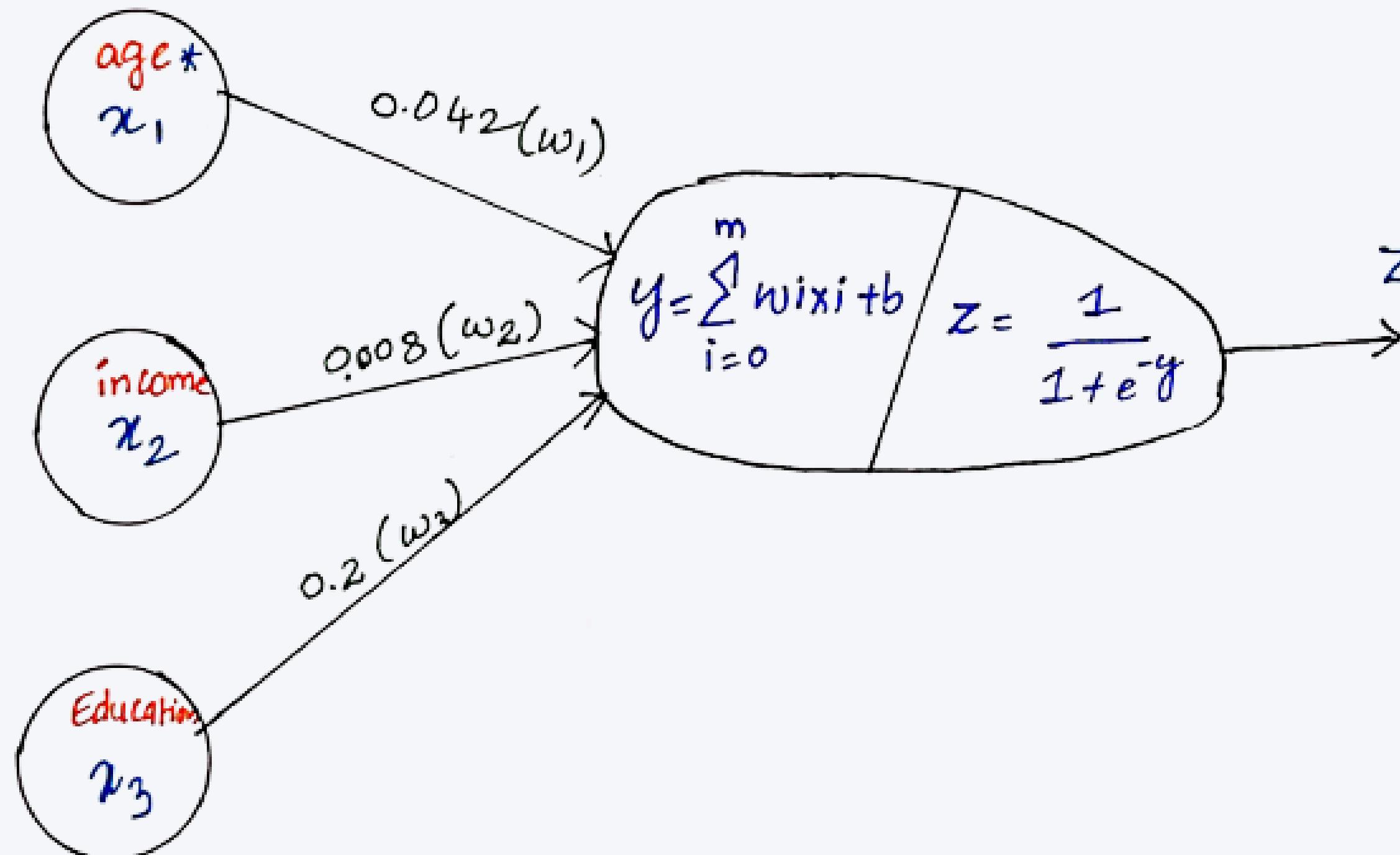
- w_1, w_2, w_3 : Weights for each feature.
- x_1, x_2, x_3 : Feature values.
- b : Bias term.

Compact form:

$$y = \sum_{i=1}^m (w_i \cdot x_i) + b$$

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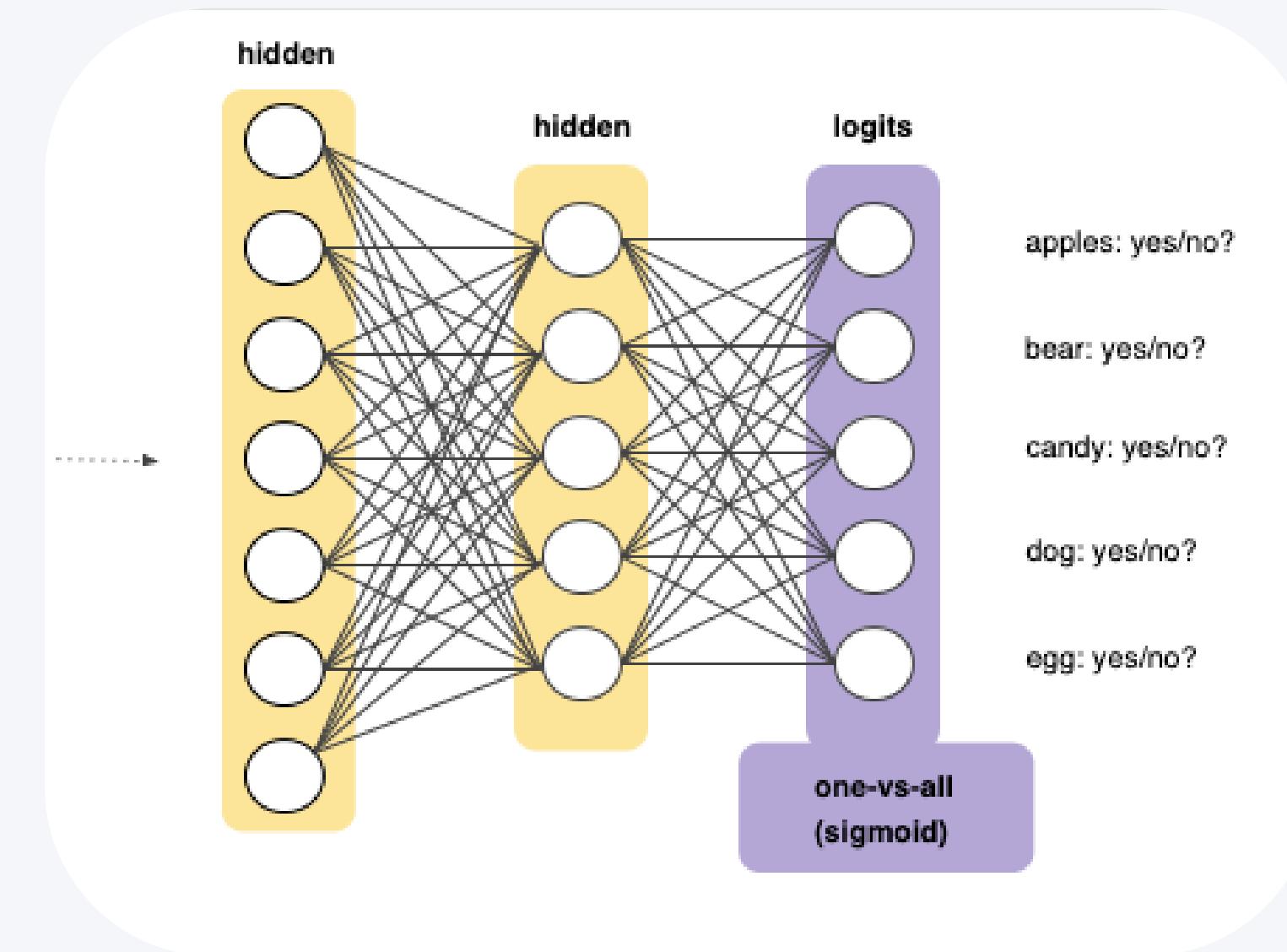


Layer Networks for Multi-Class Classification

LAYER NETWORKS FOR MULTI-CLASS CLASSIFICATION

What About Multi-Class Classification ?

- We have only considered regression and binary classification problems so far.
- How can we get a neural network to perform multiclass classification?

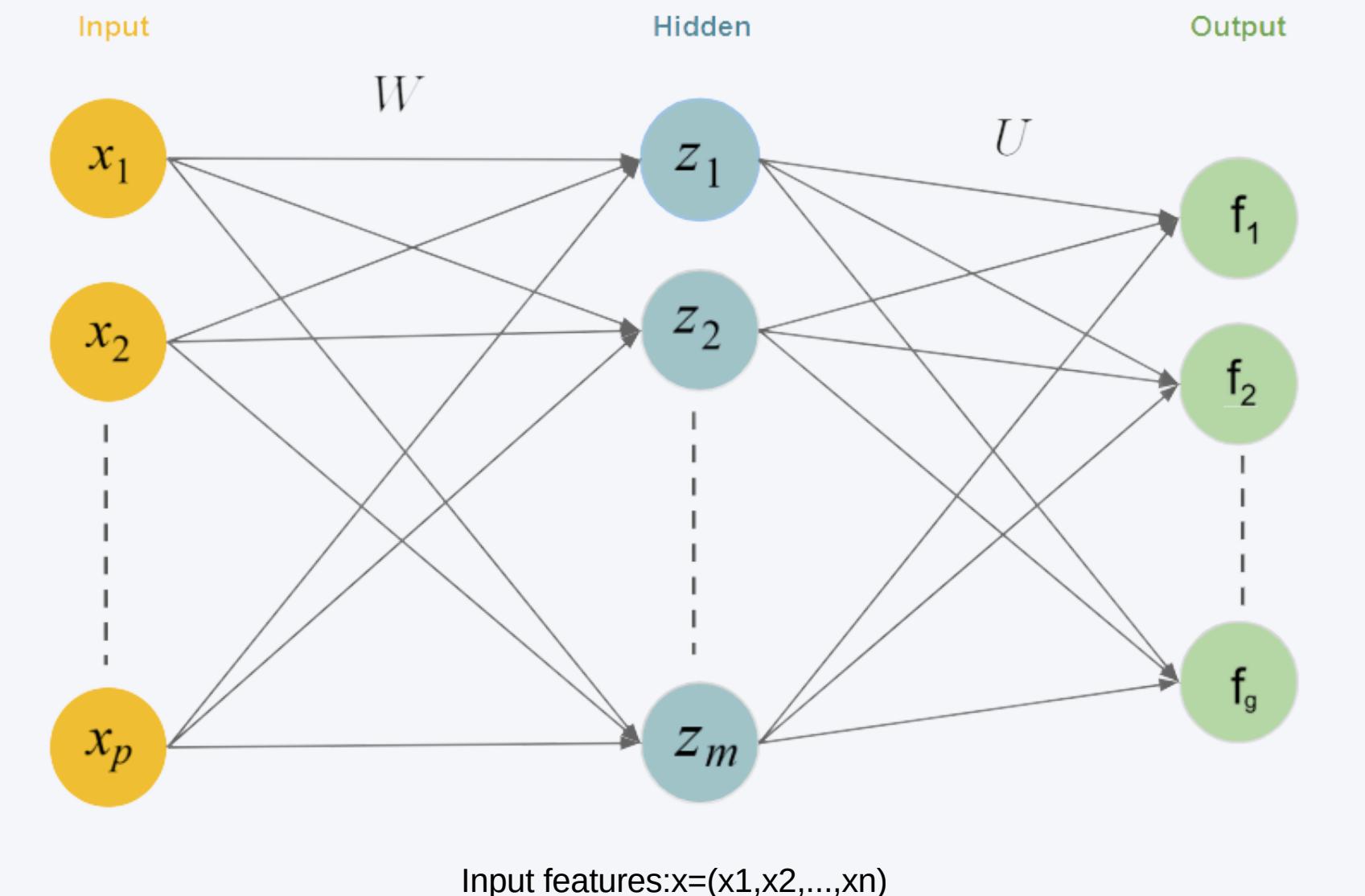


<https://www.google.com/url?sa=i&url=https%3A%2F%2Faman.ai%2Fprimers%2Fai%2Fmulticlass-vs-multilabel-classification%2F&psig=AOvVaw0J39FfDxrr6WGkBu7bzvo3&ust=1736691083883000&source=images&cd=vfe&opi=89978449&ved=0CBcQjhxqFwoTCMDA7czs7YoDFQAAAAAdAAAAABAT>

LAYER NETWORKS FOR MULTI-CLASS CLASSIFICATION

How does it work ?

- The first step is to add additional neurons to the output layer.
 - Each neuron in the layer will represent a specific class
 - Number of neurons in the output layer = number of classes.



Hidden neurons: Derived features from the hidden layer are represented as $z=(z_1, z_2, \dots, z_m)$.

Weights:

- W_j : Weights for connections between input and hidden layer.
- U_k : Weights for connections between hidden layer and output layer.

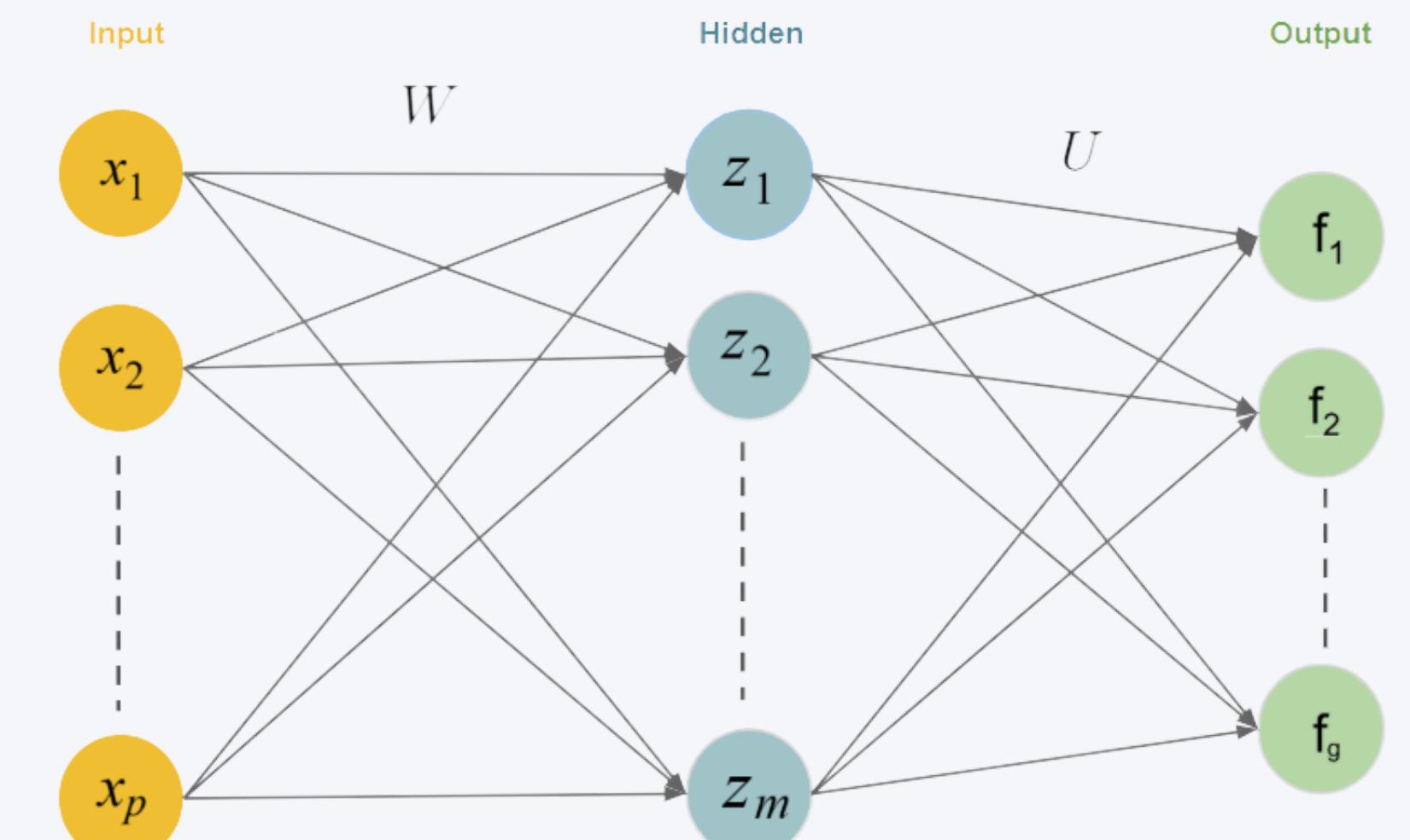
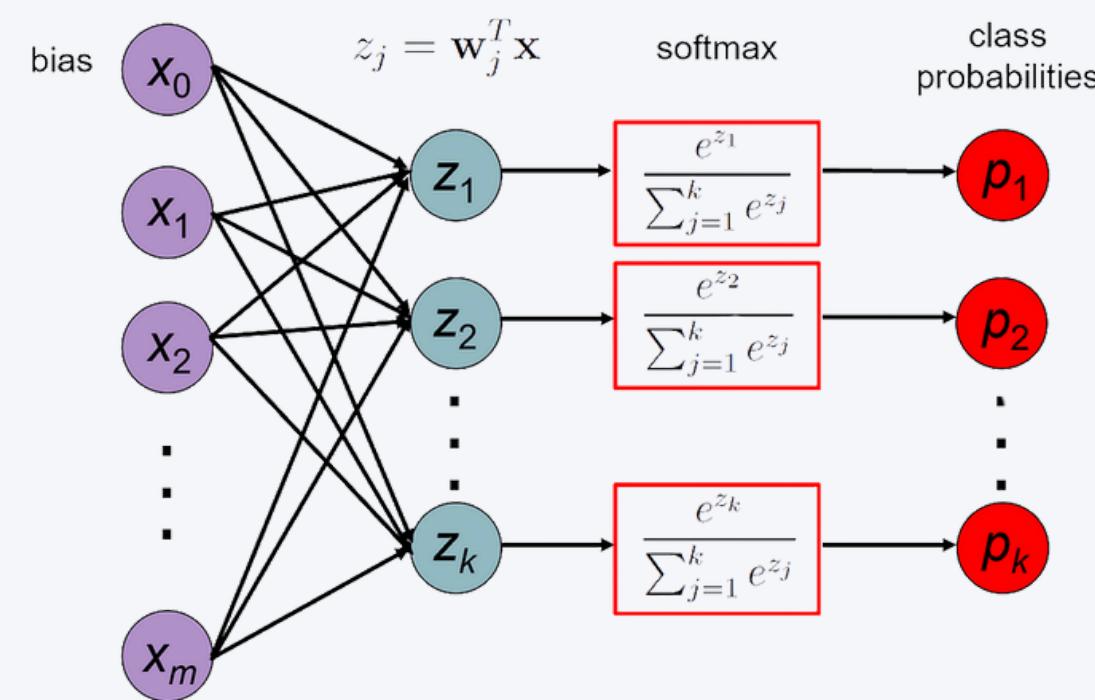
LAYER NETWORKS FOR MULTI-CLASS CLASSIFICATION

How does it work ?

The second step is to apply a **softmax activation function** to the output layer.

Softmax provides a **probability distribution** over multiple classes, enabling multi-class predictions.

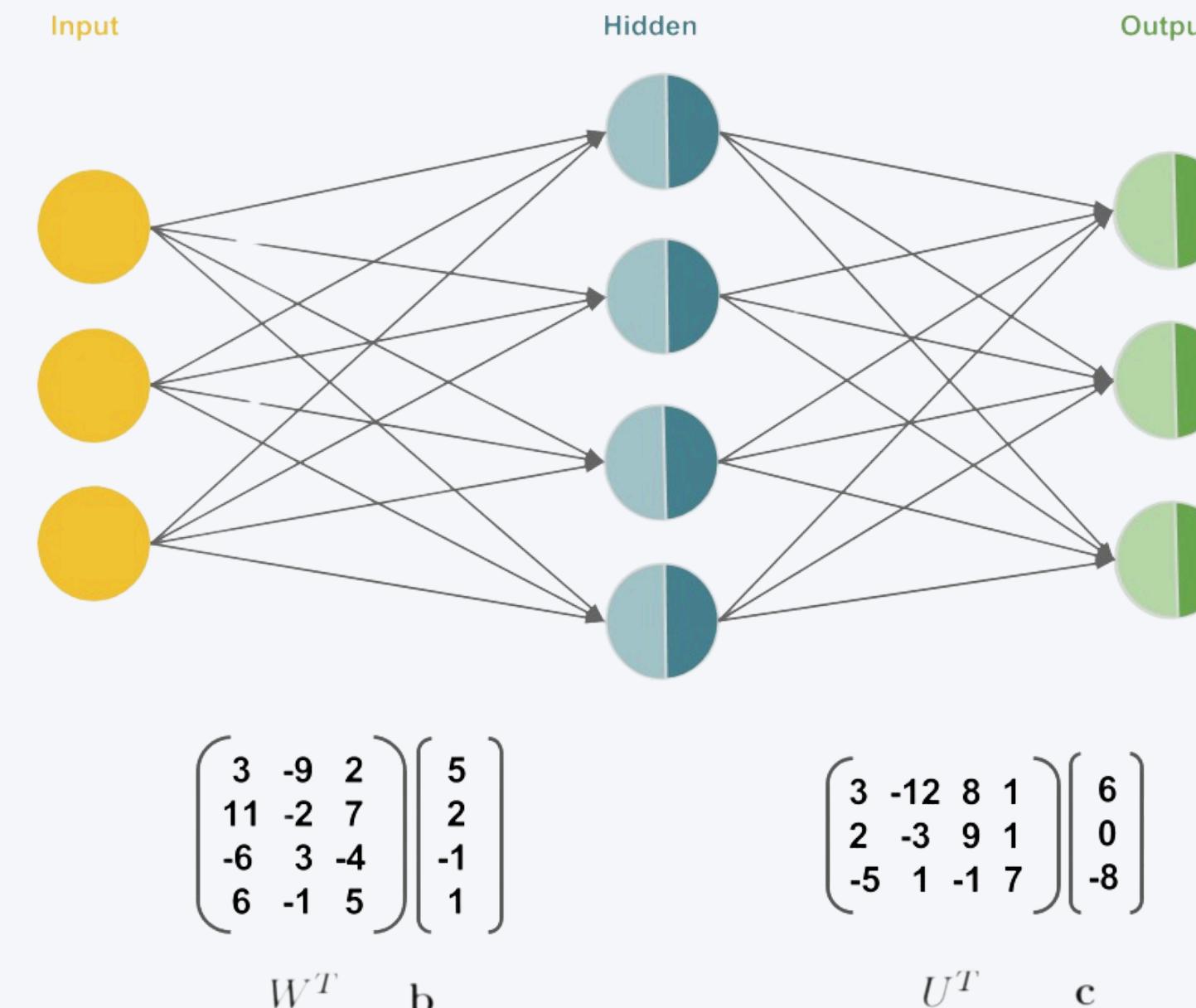
- Converts the model's output into probabilities for each class.
- Ensures all probabilities sum to 1.



LAYER NETWORKS FOR MULTI-CLASS CLASSIFICATION

Example on MULTI-CLASS CLASSIFICATION

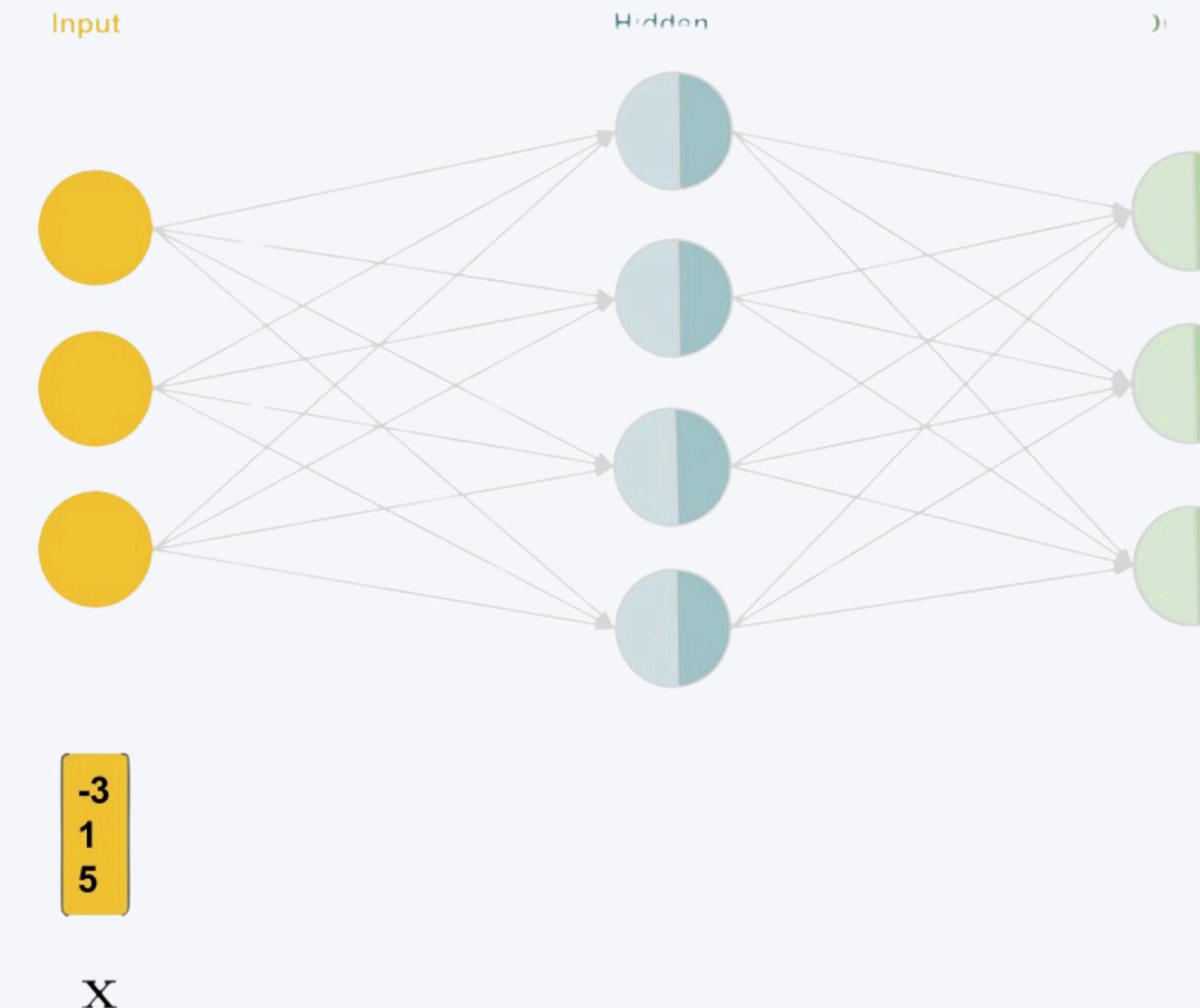
Forward pass (Hidden: Sigmoid, Output: Softmax).



LAYER NETWORKS FOR MULTI-CLASS CLASSIFICATION

Example on MULTI-CLASS CLASSIFICATION

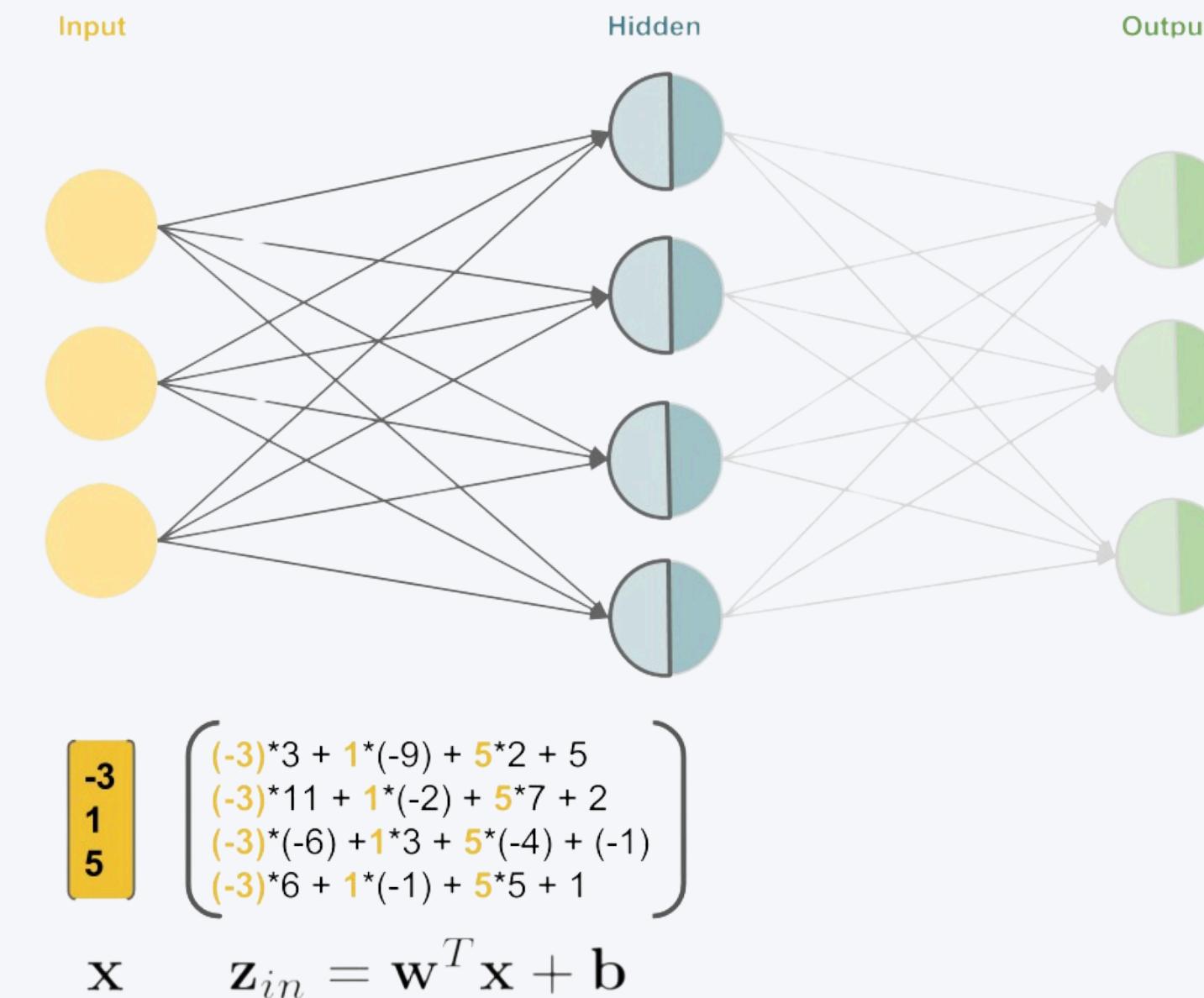
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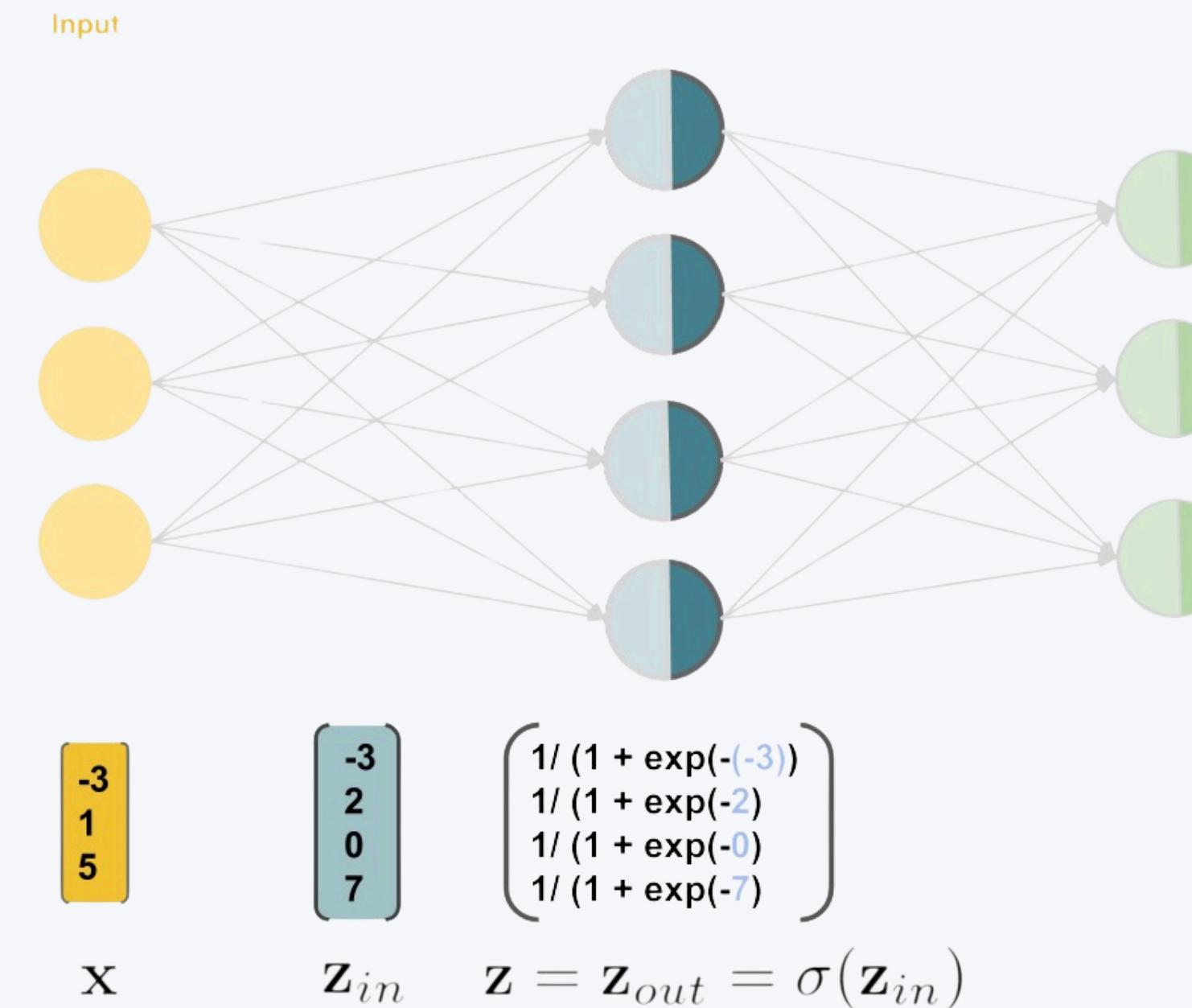
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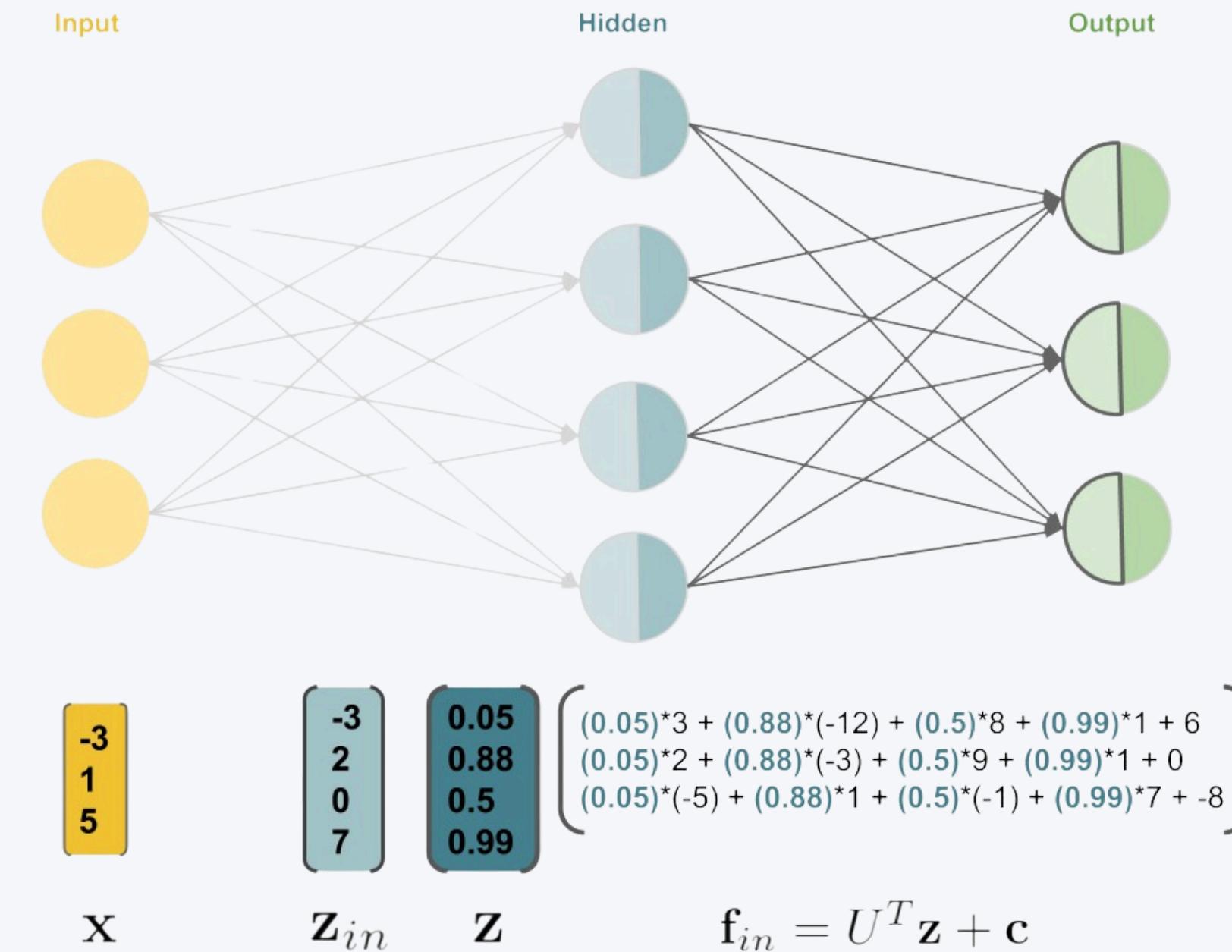
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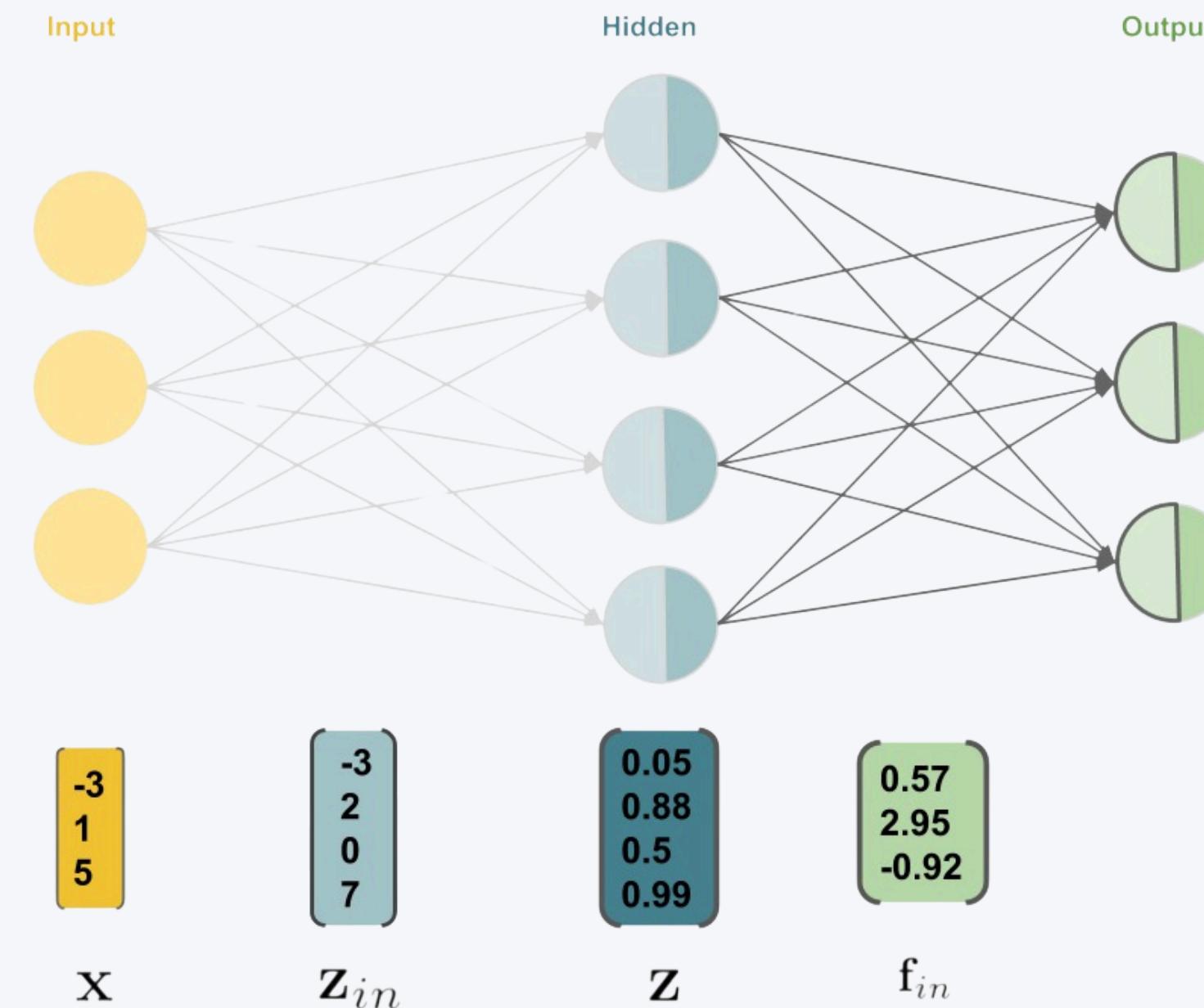
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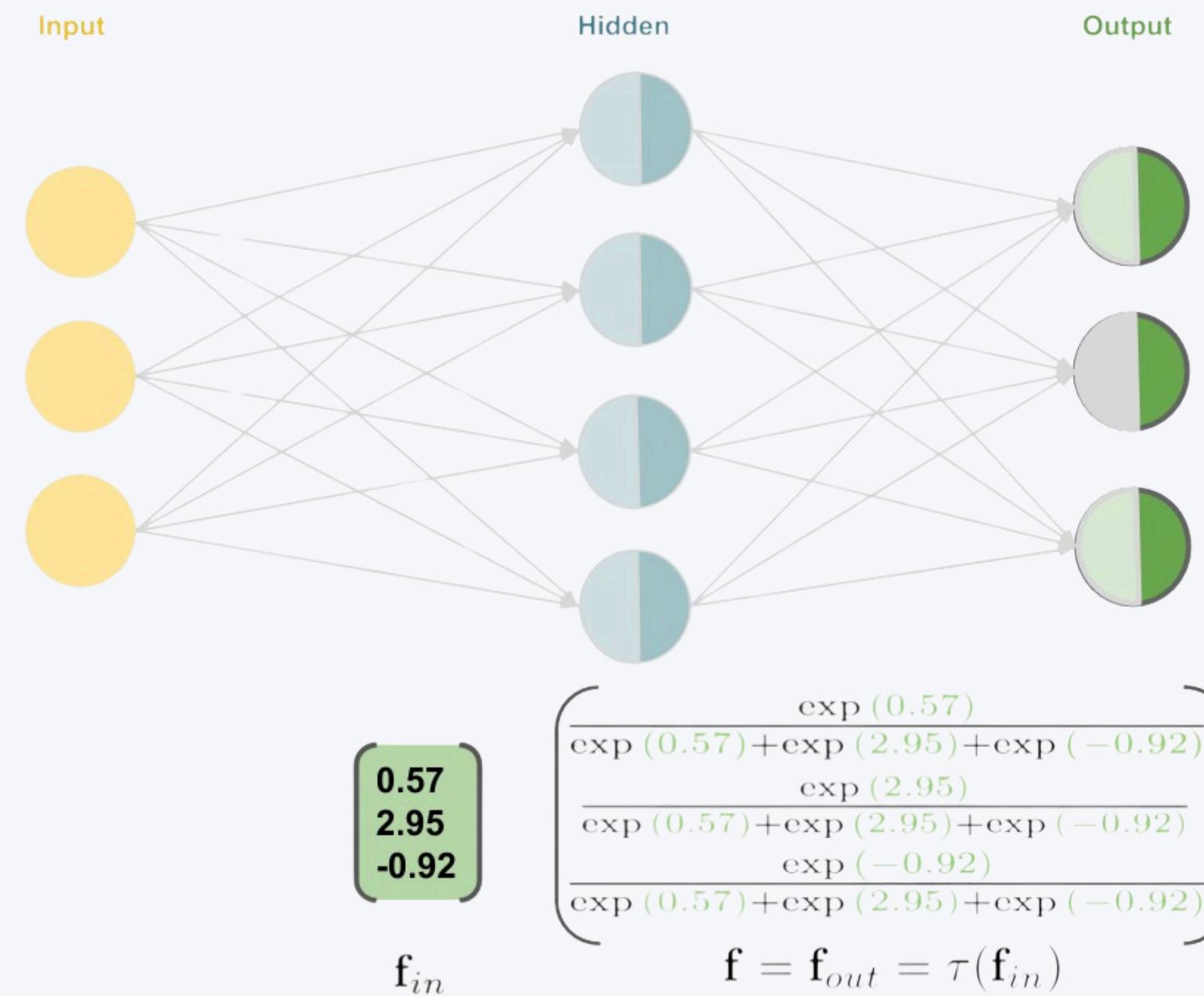
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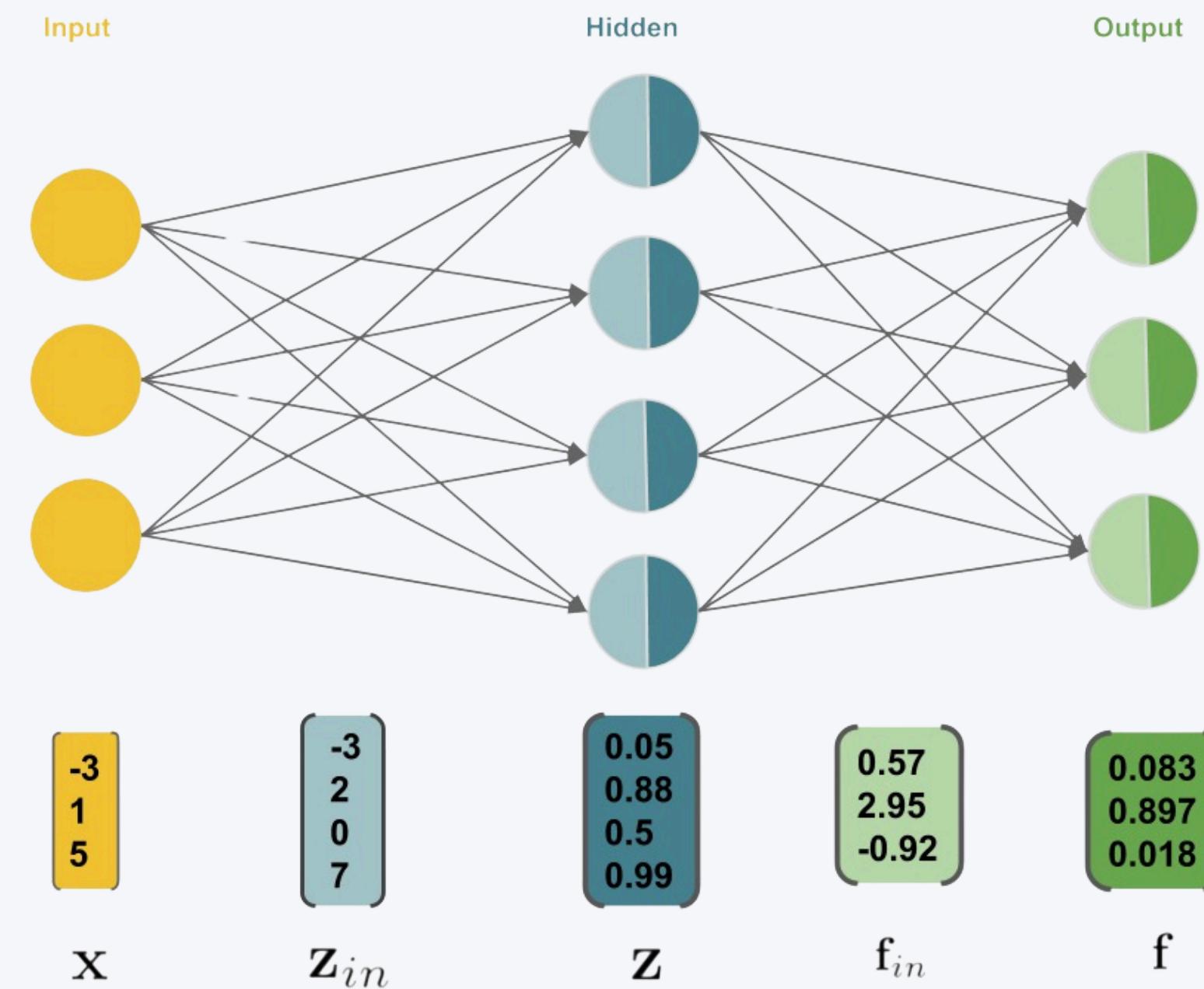
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Example on MULTI-CLASS CLASSIFICATION

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LAYER NETWORKS FOR MULTI-CLASS CLASSIFICATION

Cross-Entropy Loss

Revising: Squared Error:

- Measures the difference between predicted and true values by squaring the error.
- Works well for regression or simple problems but not ideal for classification.
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Introducing: Cross-Entropy Loss:

- Used in multi-class classification.
- Measures how far the predicted probability is from the correct class.
- Example: If the true class is 3, it compares the predicted probability for class 3 to 1 (perfect match).

$$L = - \sum (\text{True Label}) \times \log(\text{Predicted Probability})$$

Why Cross-Entropy?

- It penalizes wrong predictions more effectively by focusing on the probabilities assigned to the correct class.

Let's Code

Implementing Multi-Class Classification Problem with Keras