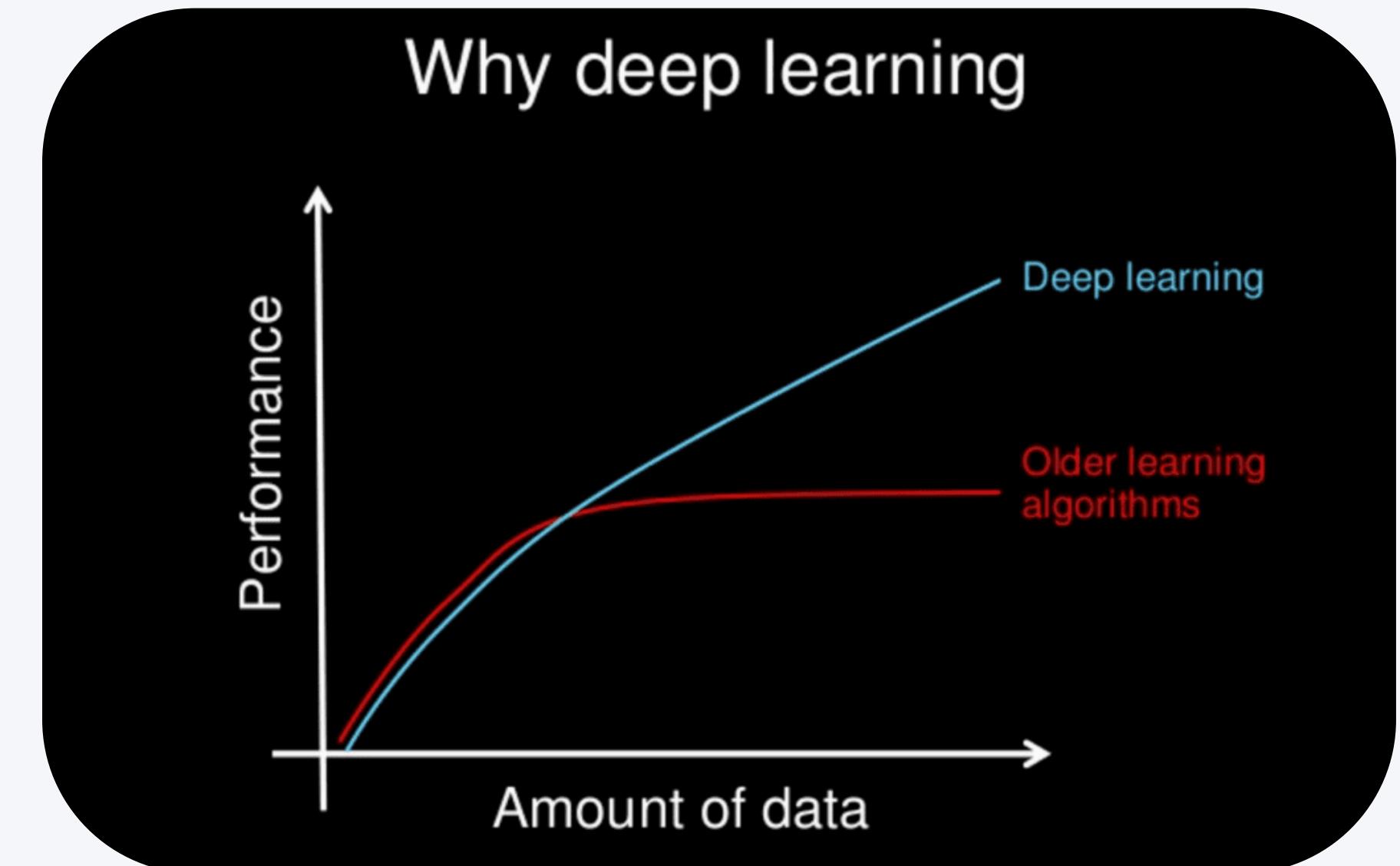


# **Introduction to Deep Learning**

# FROM MACHINE LEARNING TO DEEP LEARNING

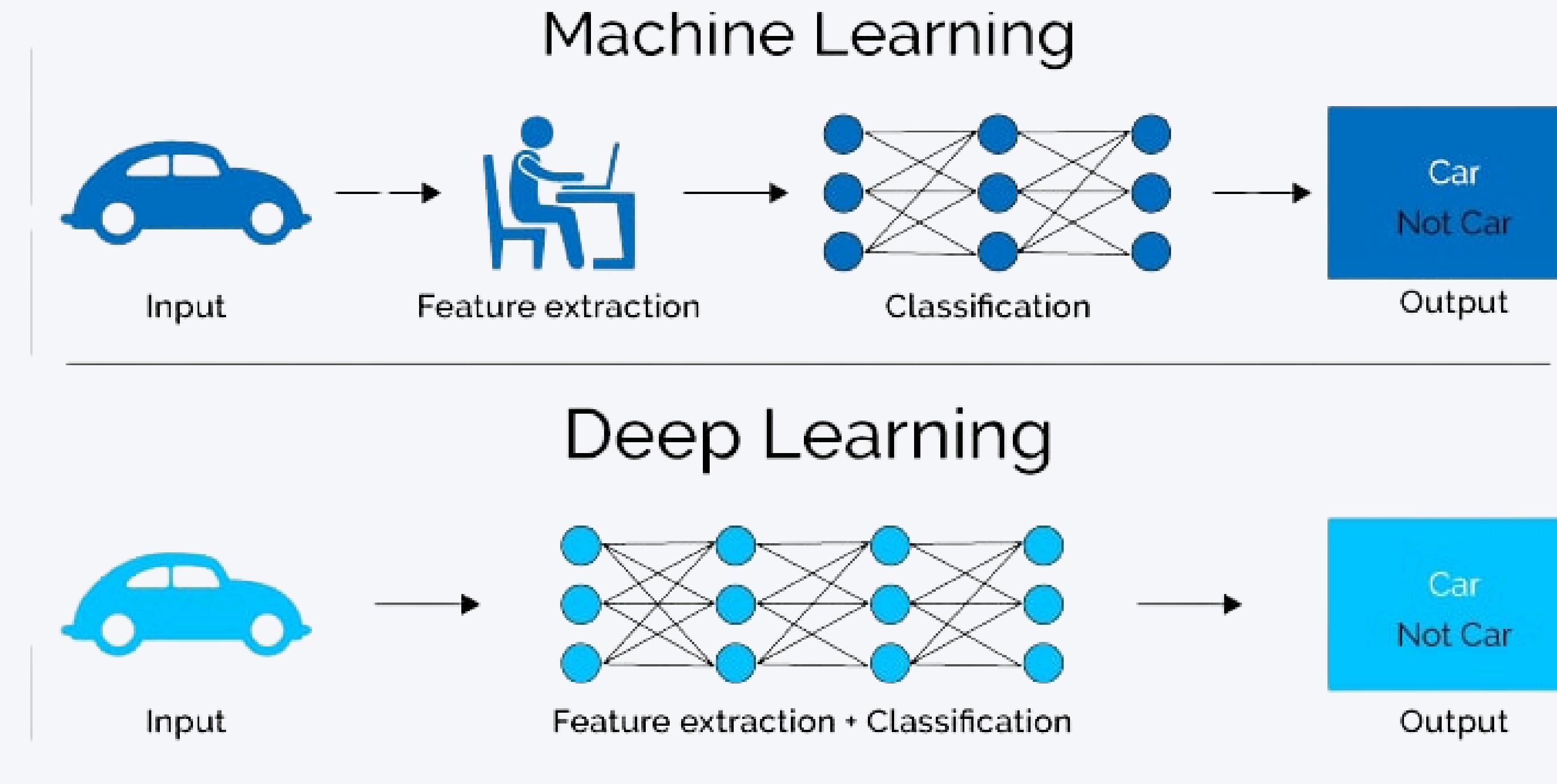
## Why ML Cannot Handle Large, Complex Data?

- **Scalability Issues:** Traditional ML models struggle to process massive datasets efficiently.
- **Feature Engineering Dependency:** Requires manual feature extraction, which becomes impractical with large, high-dimensional data like images or videos.
- **Unstructured Data Limitation:** ML models are not inherently designed for unstructured formats (e.g., audio, text, images).
- **Complex Relationships:** Fails to capture hierarchical or layered patterns effectively.



<https://machinelearningmastery.com/what-is-deep-learning/>

# FROM MACHINE LEARNING TO DEEP LEARNING



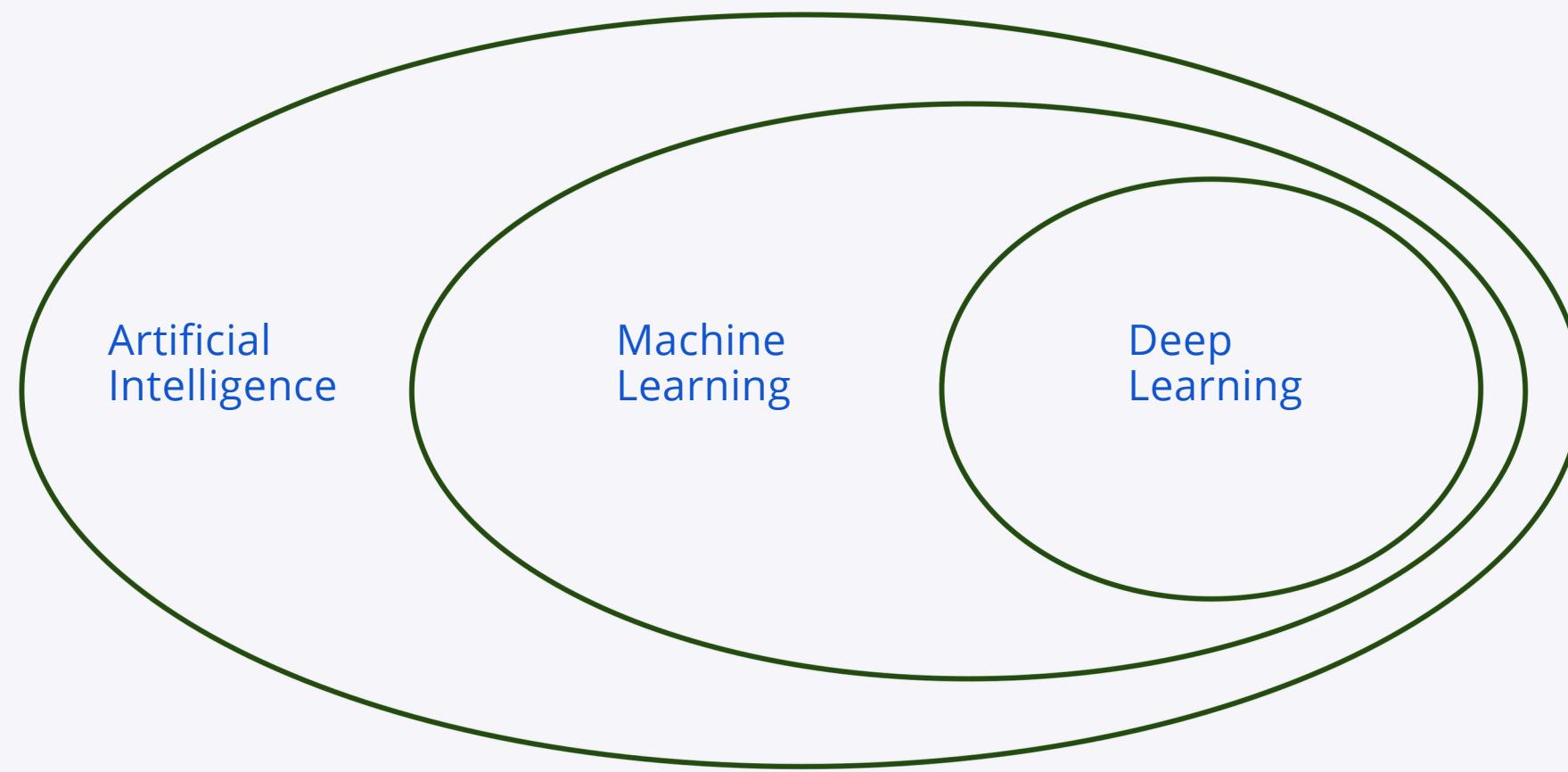
<https://levity.ai/blog/difference-machine-learning-deep-learning>

# DEEP LEARNING AS A SUBSET

- Deep learning is a subfield of ML based on artificial neural networks..

Deep learning itself is **not** new:

- Neural networks have been around since the 70s.

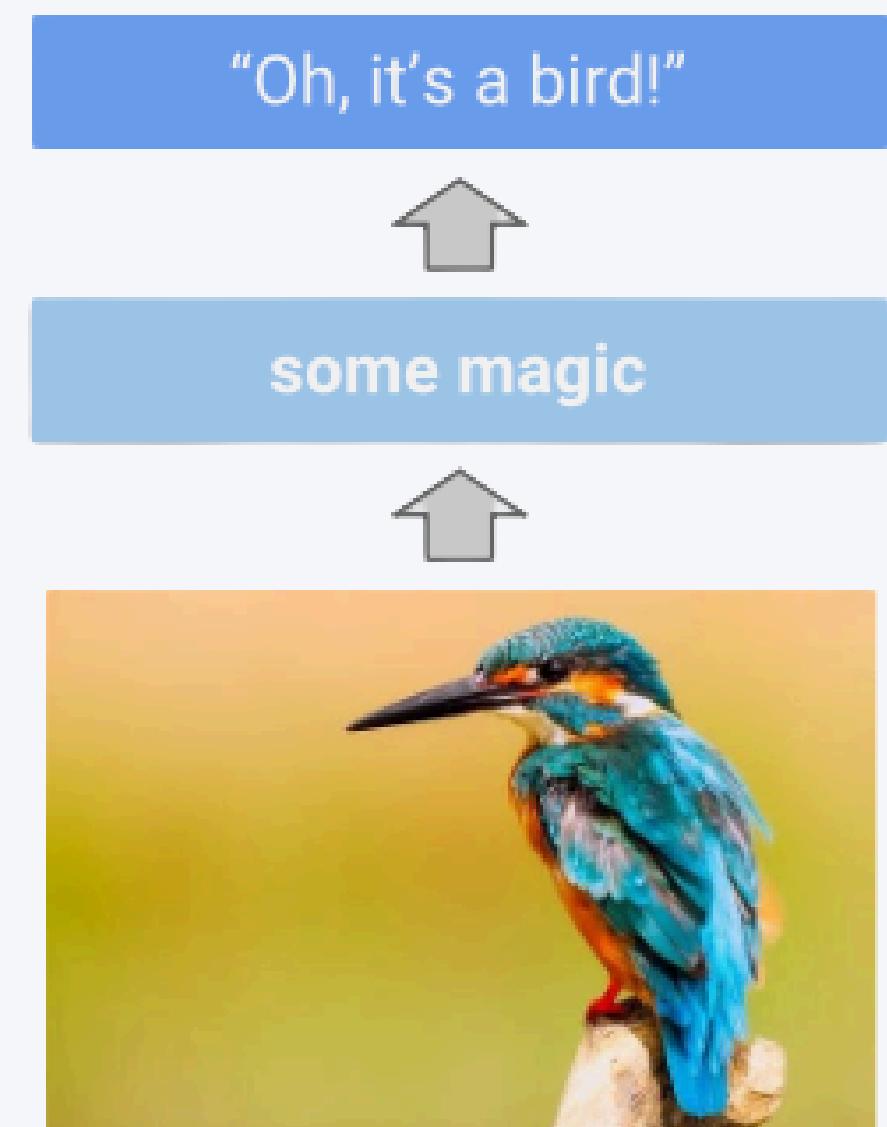
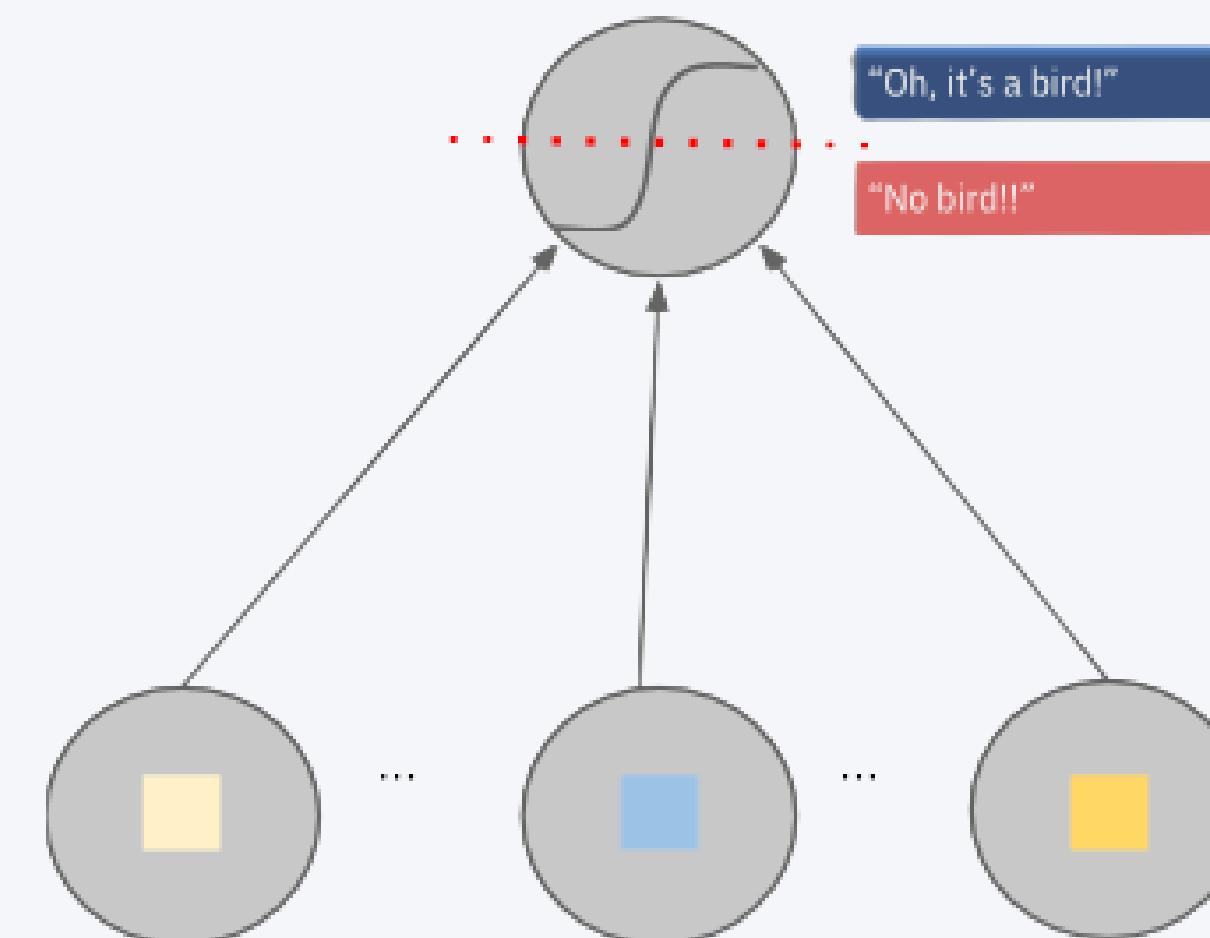


# FROM MACHINE LEARNING TO DEEP LEARNING

“Machine learning algorithms, inspired by the brain, based on learning multiple levels of representation/abstraction.”

- The algorithm is given an image, e.g., of a bird.

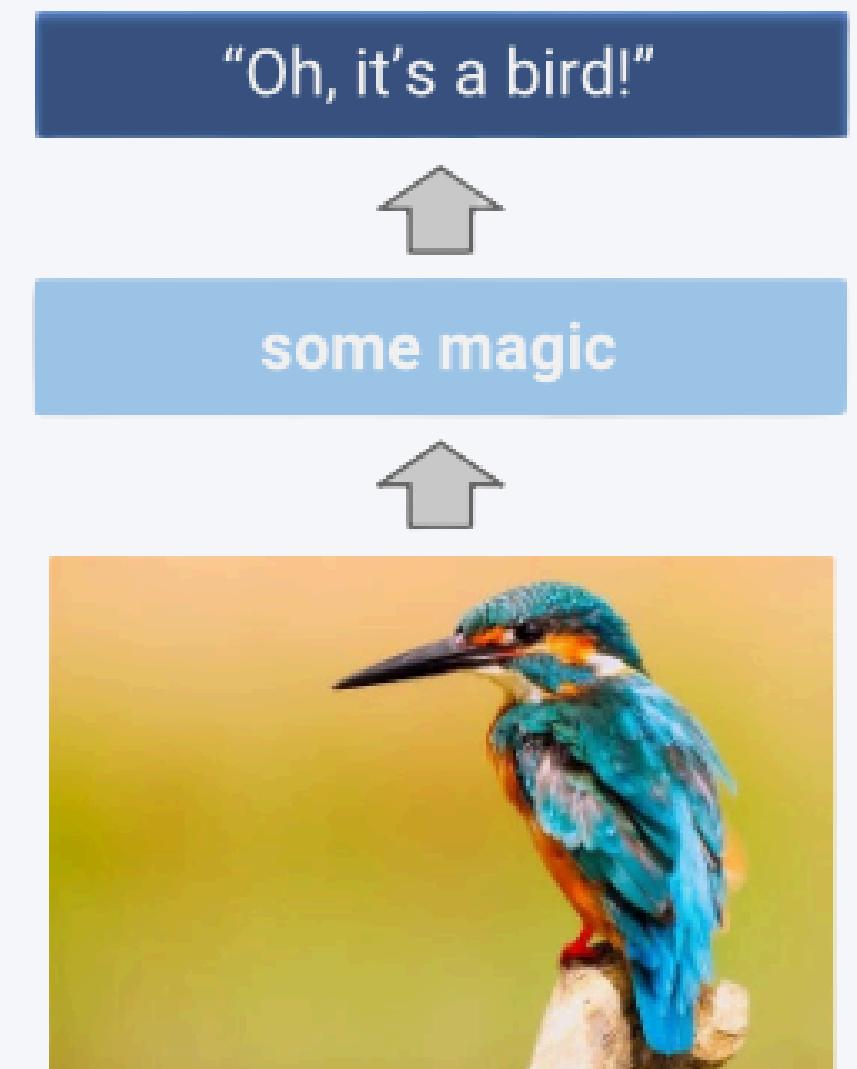
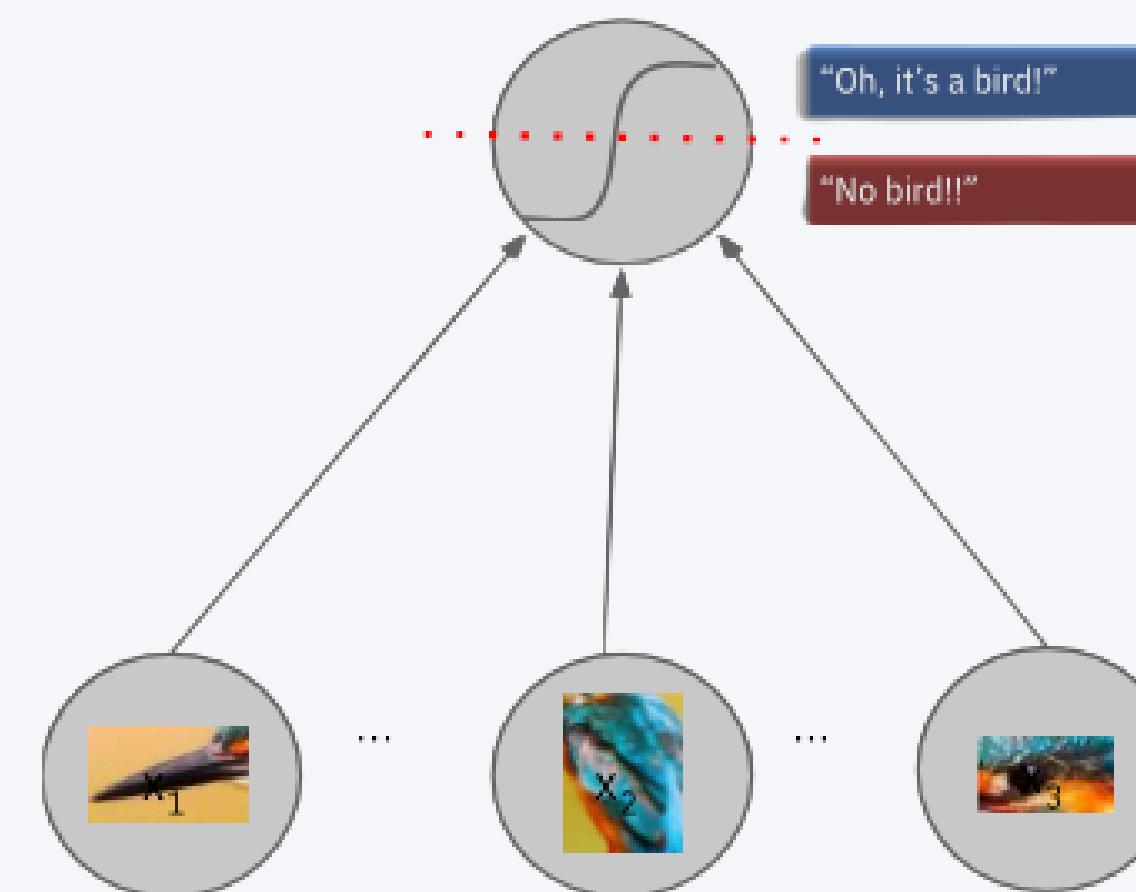
It begins by analyzing small, simple features, such as edges, corners, or textures from the input image.



# FROM MACHINE LEARNING TO DEEP LEARNING

“Machine learning algorithms, inspired by the brain, based on learning multiple levels of representation/abstraction.”

- The algorithm combines these simple features (e.g., edges) to recognize slightly more complex patterns, such as shapes or contours.
- Each layer learns to represent the input data at a higher level of abstraction

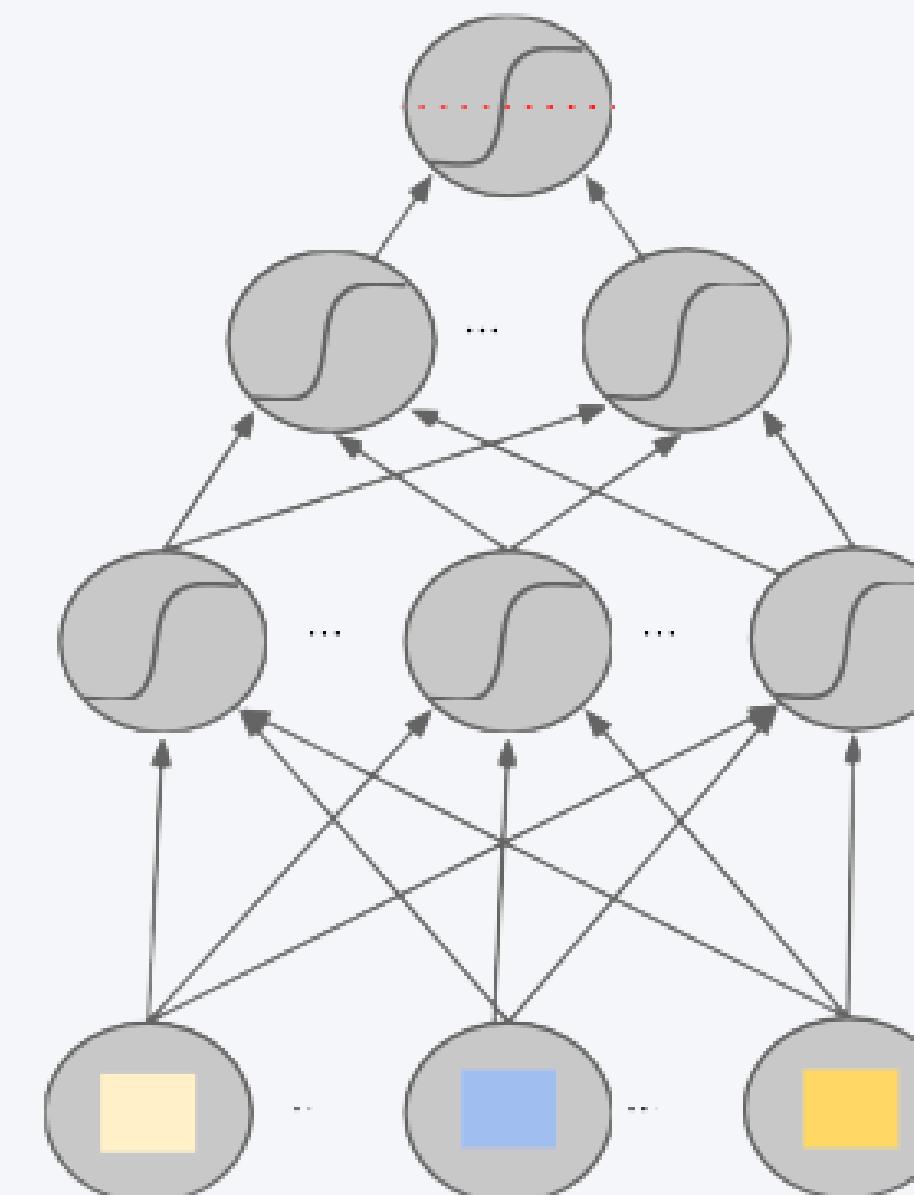


# FROM MACHINE LEARNING TO DEEP LEARNING

“Machine learning algorithms, inspired by the brain, based on learning multiple levels of representation/abstraction.”

## Deeper Layers

- Further layers combine the learned patterns to identify more significant features, like parts of the bird (e.g., wings, beak, or feathers).
- At this stage, the algorithm can identify complex structures from the input.

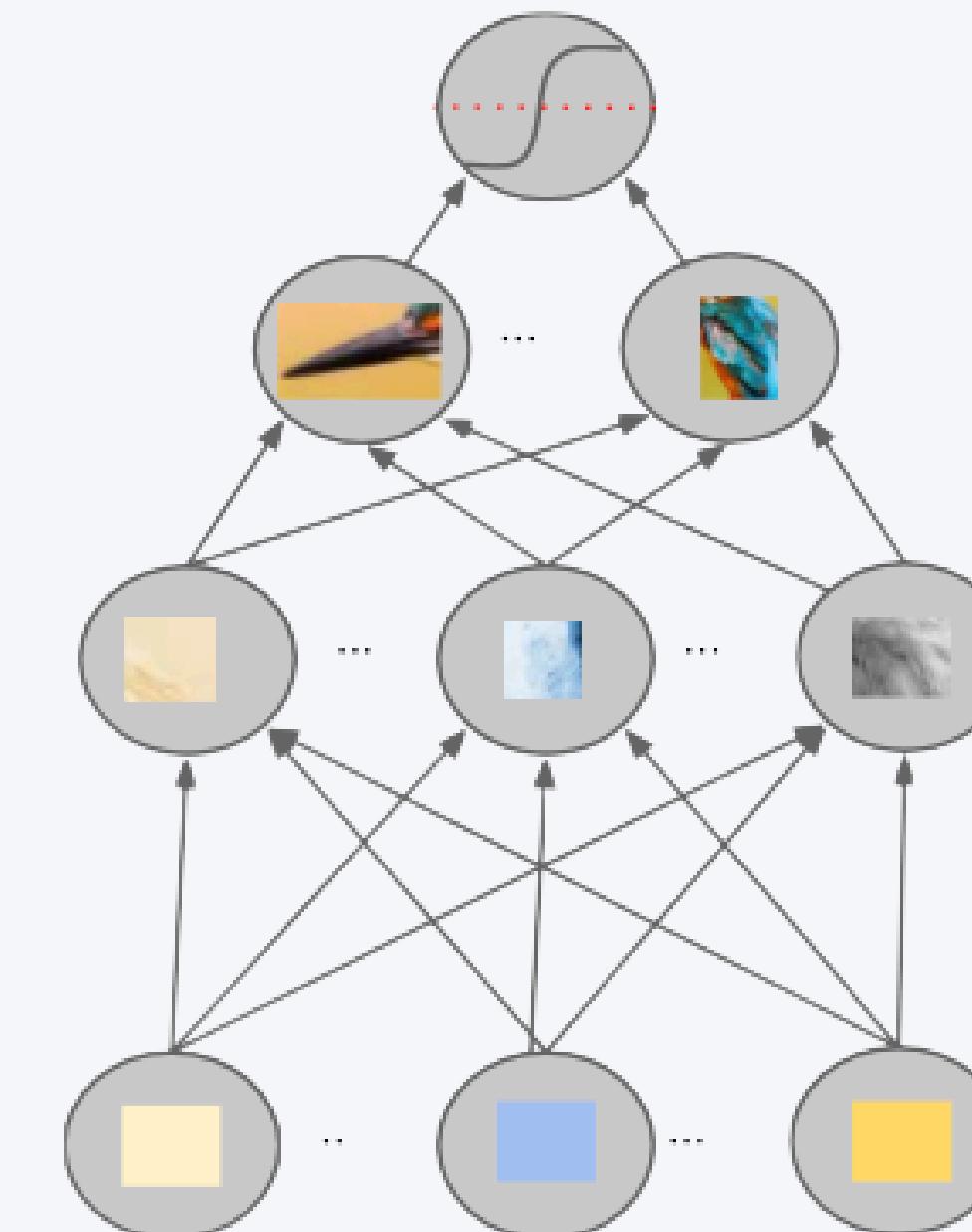


# FROM MACHINE LEARNING TO DEEP LEARNING

“Machine learning algorithms, inspired by the brain, based on learning multiple levels of representation/abstraction.”

## Output

- At the highest level, the algorithm understands the image as a whole and determines the final classification: "Oh, it's a bird!"
- The "magic" refers to the layers of abstraction (neural networks) that learn from raw data without human intervention.



# POSSIBLE USE-CASES

Deep learning can be extremely valuable if the data has these properties:

- It is high dimensional.
- Each single feature itself is not very informative but only a combination of them might be.
- There is a large amount of training data.

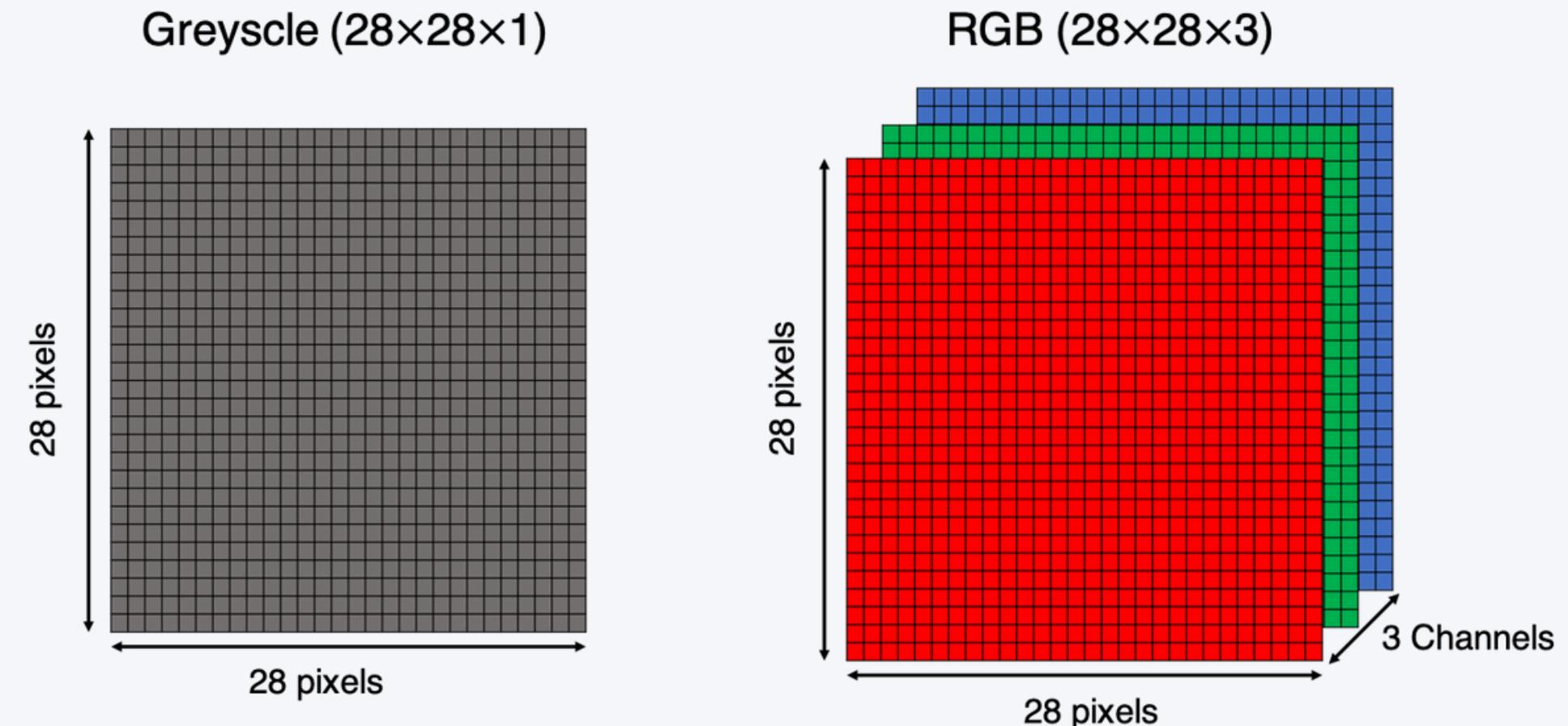
This implies that for tabular data, deep learning is rarely the correct model choice.

- Without extensive tuning, models like random forests or gradient boosting will outperform deep learning most of the time.
- One exception is data with categorical features with many levels.

# POSSIBLE USE-CASE: IMAGES

## What is an Image ?

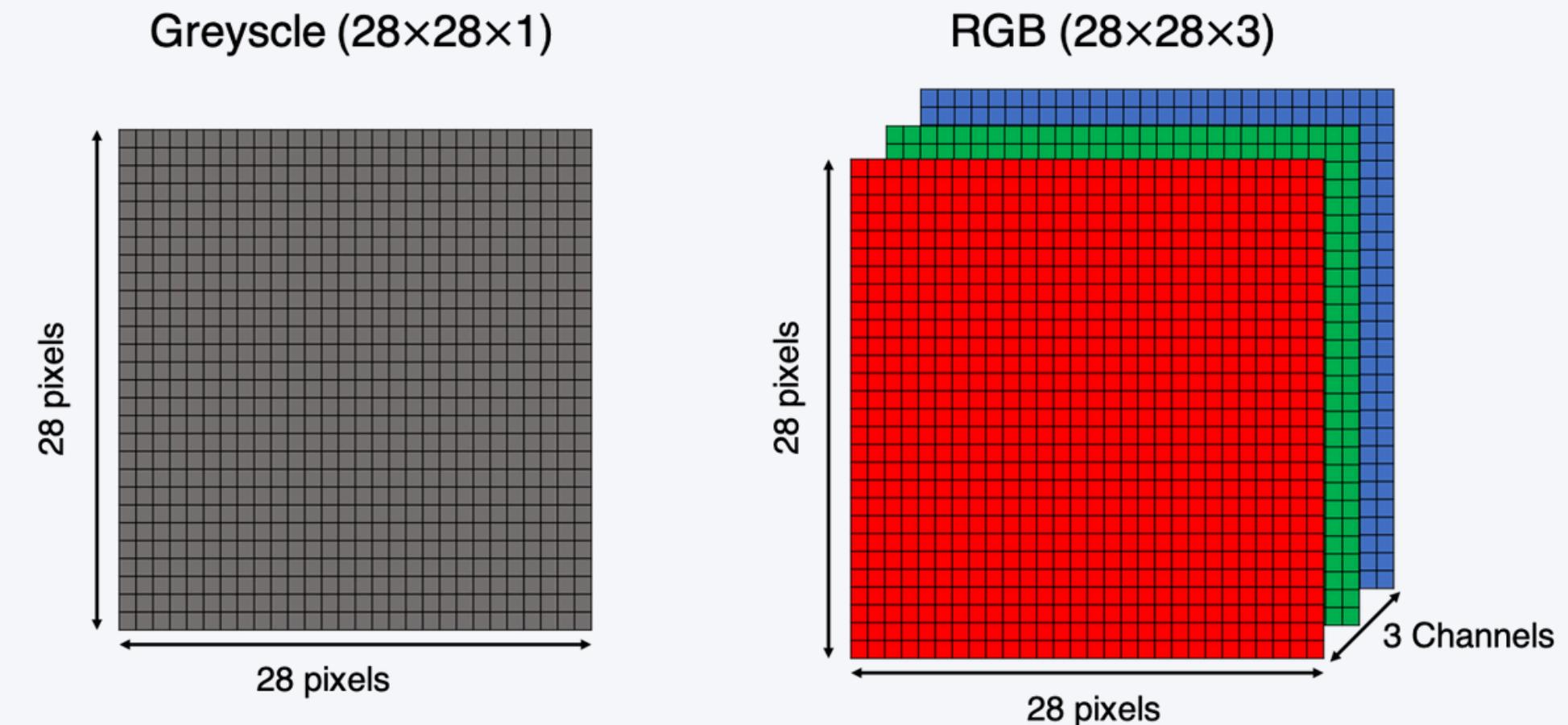
- An image is made up of tiny squares called pixels. Each pixel has a color value (e.g., red, green, blue).
- A 100x100 image has 10,000 pixels, and if it's a color image, each pixel has 3 values (R, G, B), giving us 30,000 values to analyze.



# POSSIBLE USE-CASE: IMAGES

## What is Pixel ?

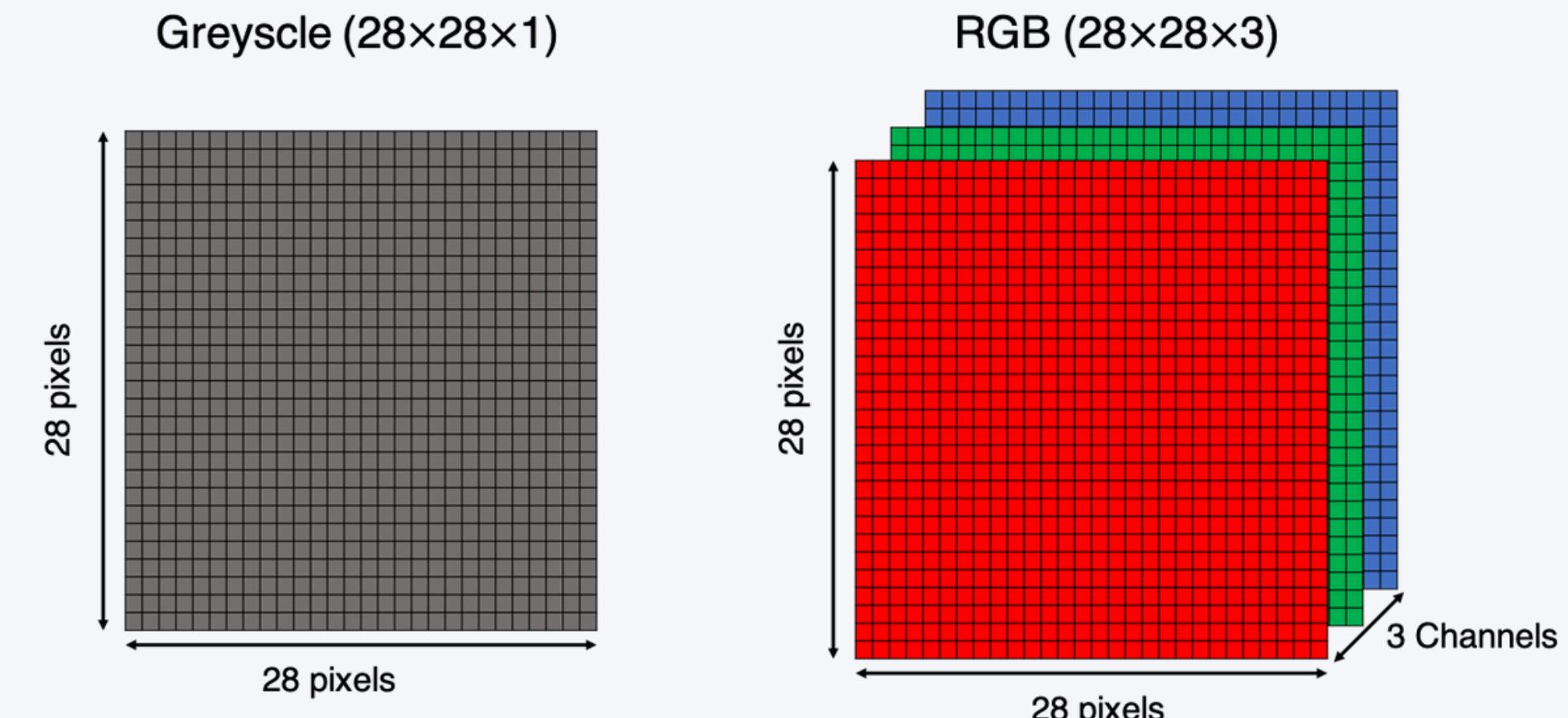
- A single pixel alone doesn't tell us much.  
But if we look at groups of pixels, we start seeing patterns like edges, shapes, or textures.
- Imagine zooming out from pixels in a photo of a bird. First, you see feathers, then the shape of wings, and finally the whole bird.



# POSSIBLE USE-CASE: IMAGES

## How Does Deep Learning Process Images?

- **Input:** The image is fed into a deep learning model, like a Convolutional Neural Network (CNN).
- **Early Layers:** Detect simple patterns (e.g., edges or small shapes).
- **Middle Layers:** Combine these patterns into meaningful parts (e.g., wings, beak).
- **Final Layers:** Recognize the whole object (e.g., “It’s a bird!”).



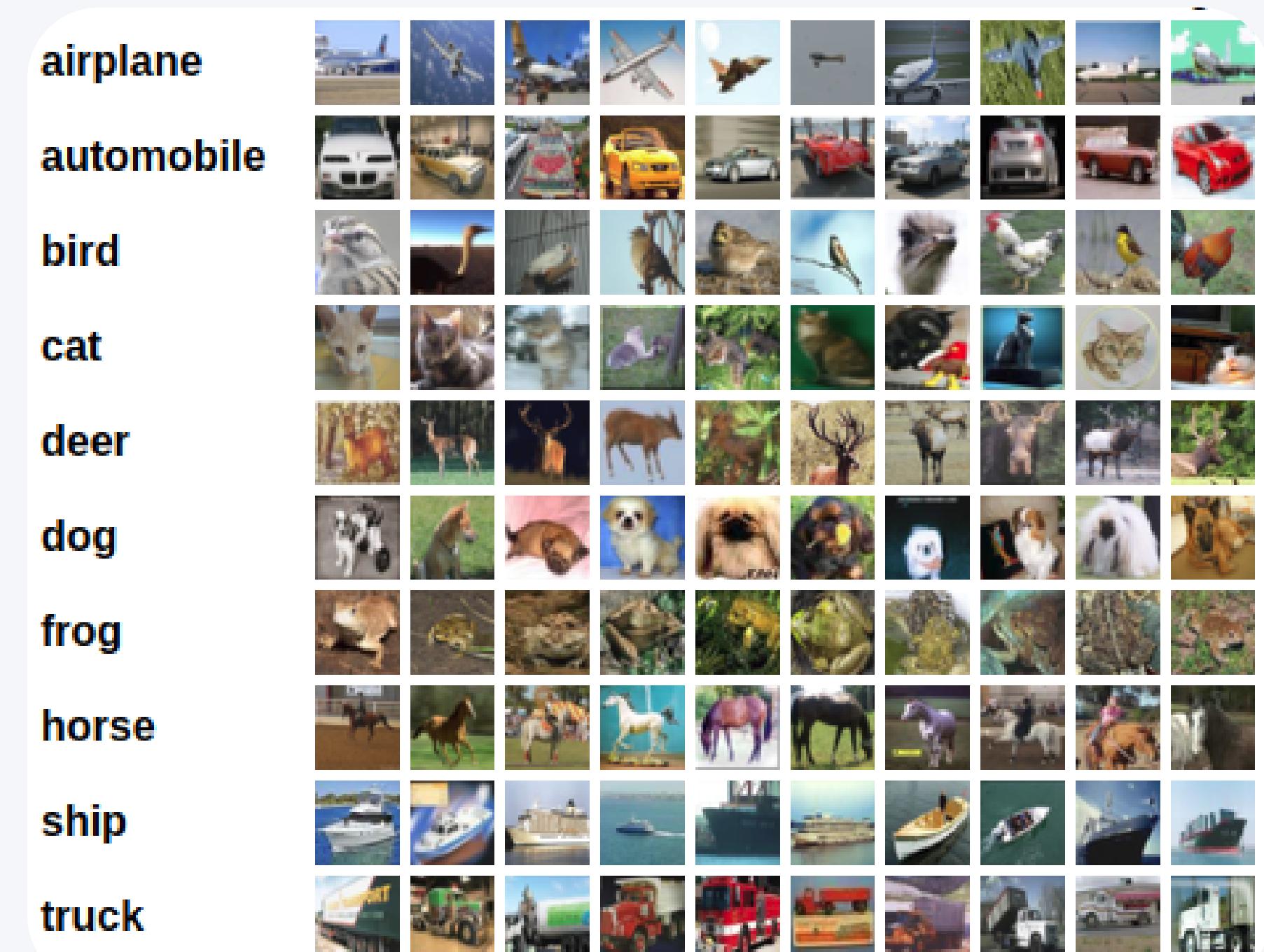
# POSSIBLE USE-CASE: IMAGES

## Image Classification with CIFAR-10

CIFAR-10 is a popular dataset used for training and evaluating image classification models.

- It contains 60,000 color images.
- Each image is 32x32 pixels in size (small and low resolution).
- There are 10 object classes, such as airplanes, cars, birds, and cats.
- Each class has 6,000 images.

It is widely used for building and testing models that classify images into one of the 10 categories



**Figure:** Example for image classification (Krizhevsky, 2009)

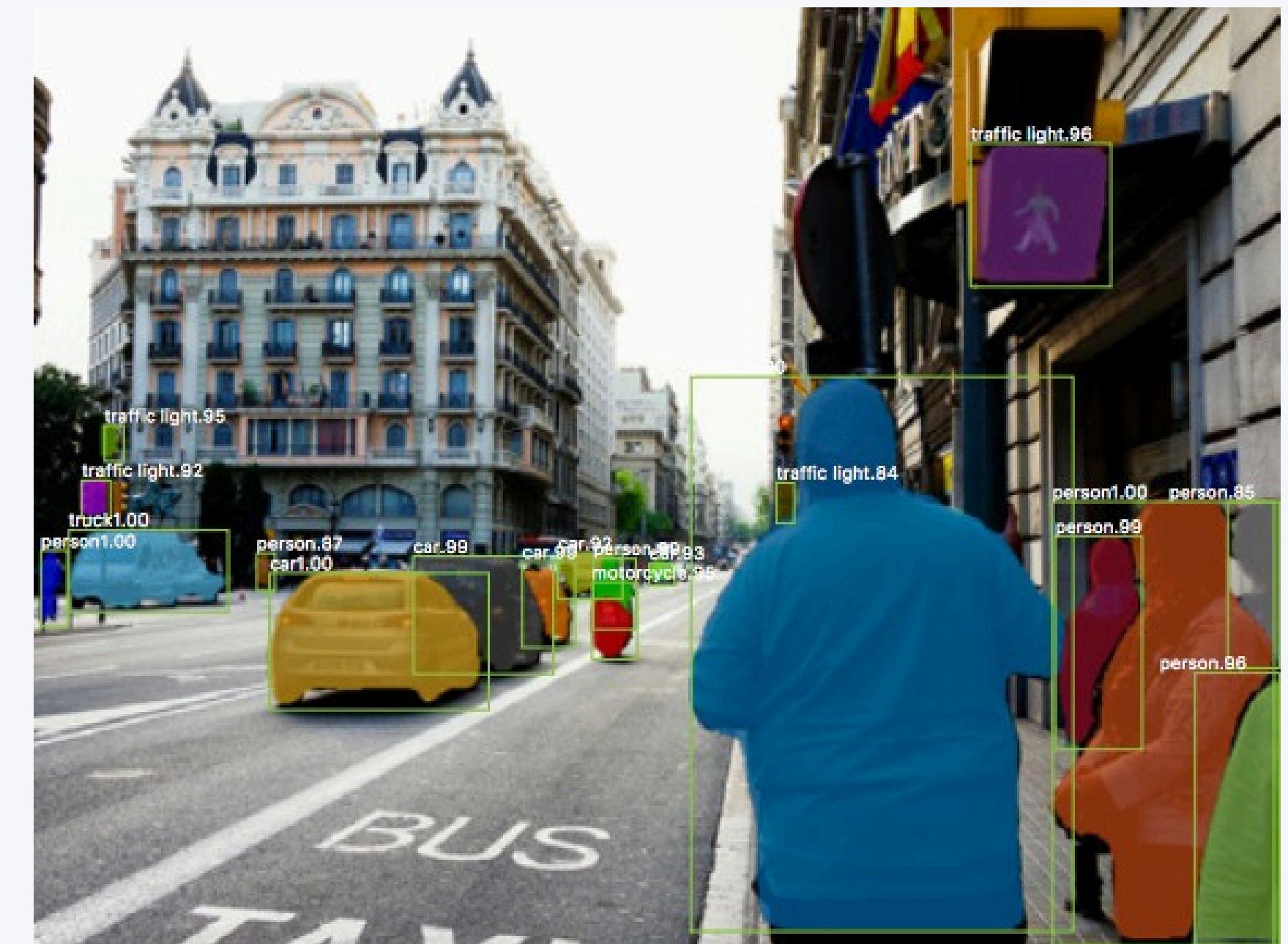
# POSSIBLE USE-CASE: IMAGES

## Object Detection with Mask R-CNN

**Mask R-CNN is a powerful framework for object detection and instance segmentation.**

- Detects Objects: Identifies and locates multiple objects in an image.
- Segmentation Mask: Creates a detailed mask (outline) for each object, showing its exact shape and boundaries.

It combines object detection with precise instance segmentation, making it useful for tasks that require detailed understanding of each object in the image.



**Figure:** Example for object detection (He et al., 2017)

# POSSIBLE USE-CASE: IMAGES

## Image Segmentation

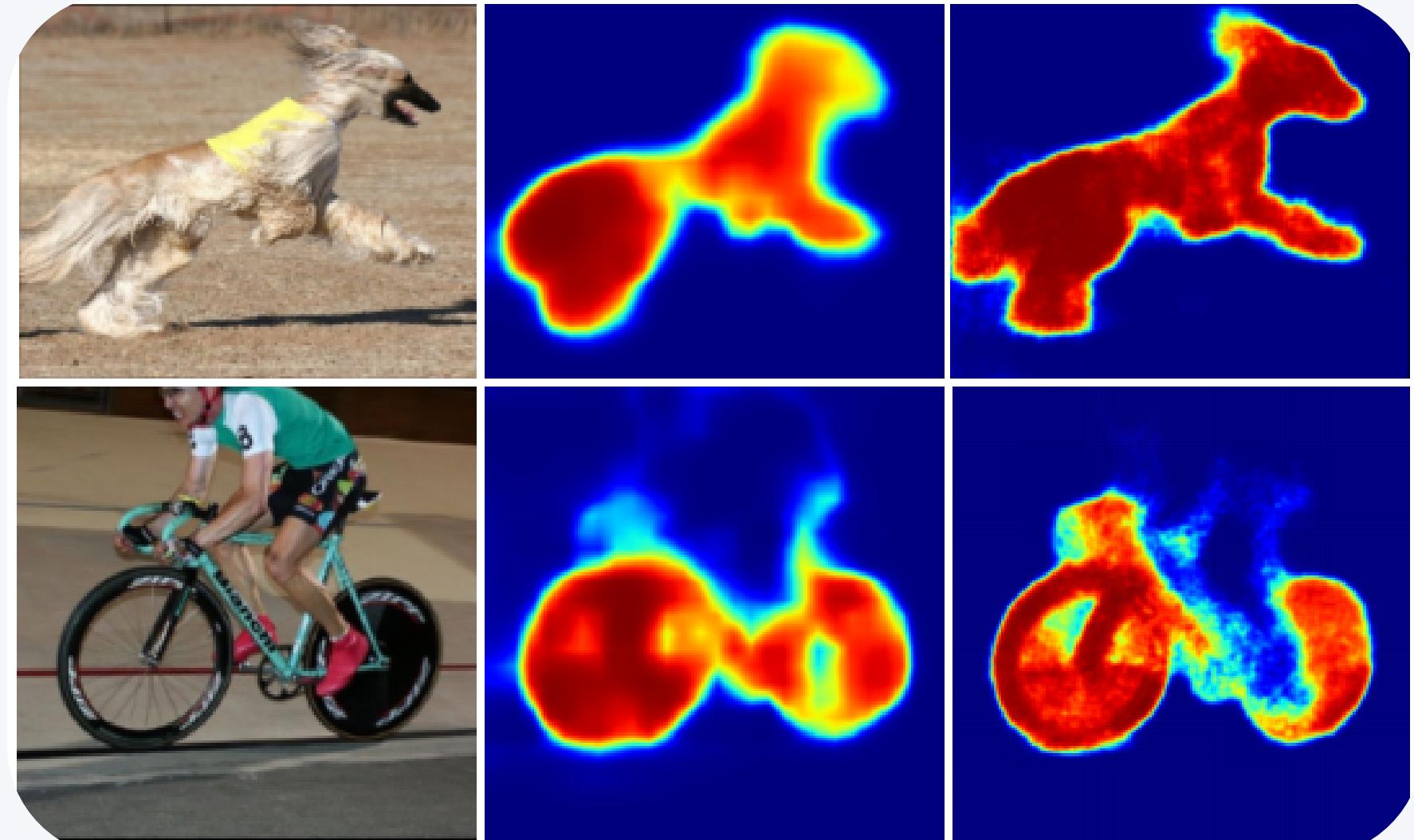
Image segmentation is a process that divides an image into multiple segments or regions, making it easier to analyze and understand.

- Partitions the image into meaningful sections, like objects, backgrounds, or specific regions of interest.
- Helps identify boundaries and shapes of objects within the image.

- **Types of Segmentation:**

- a. Semantic Segmentation: Labels each pixel in the image with a class (e.g., sky, road, car).

- b. Instance Segmentation: Separates individual objects of the same class (e.g., two cars are segmented separately).



**Figure:** Example for image segmentation (Noh et al., 2015))

# POSSIBLE USE-CASE: TEXTS

## Texts in Deep Learning

### High Dimensional:

- In text data, each word can be treated as a feature.
- For example, the German language has over 300,000 words, making text highly complex to process.

### Informative:

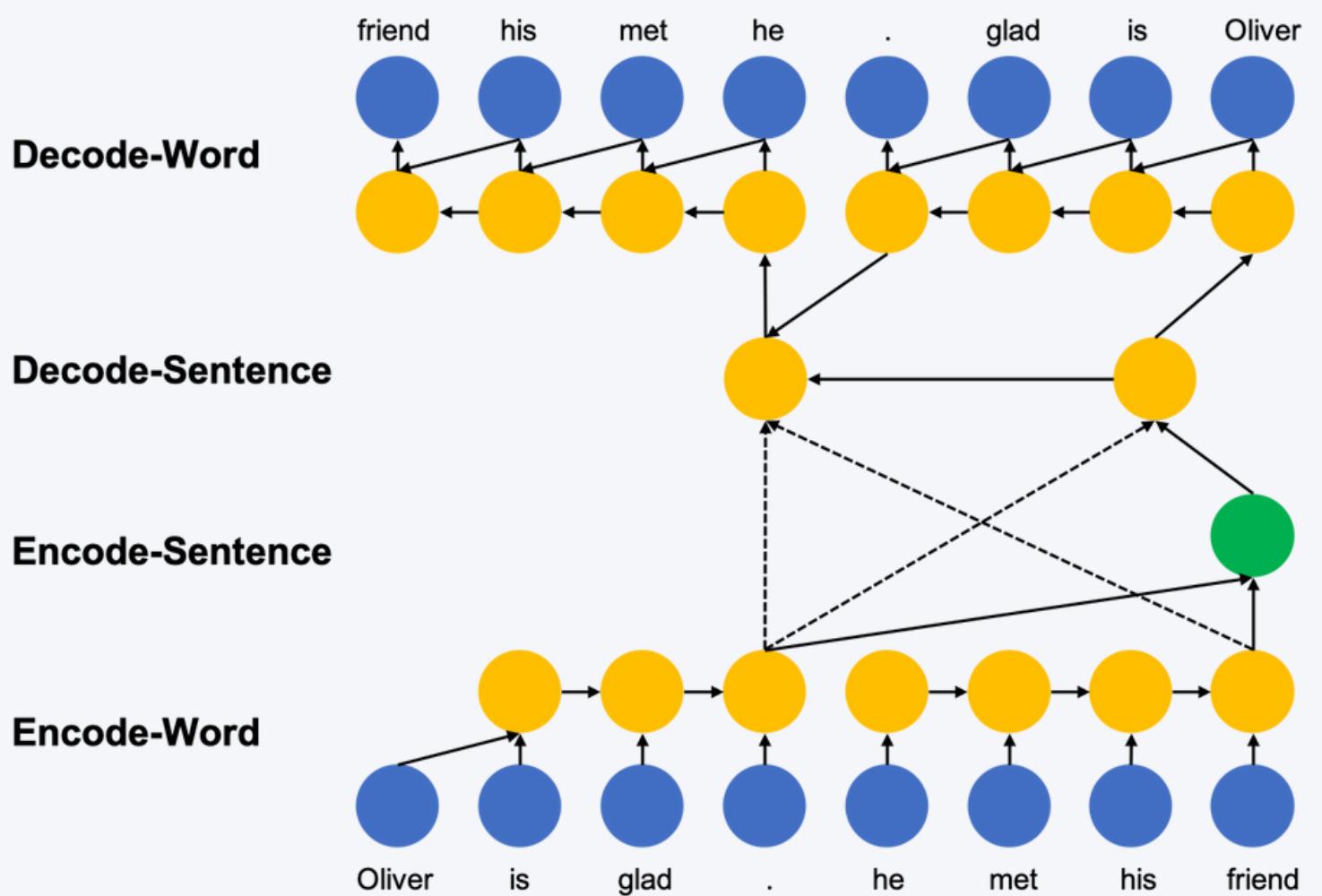
- A single word alone doesn't convey much meaning.
- Context from surrounding words or sentences is crucial for understanding.

### Training Data:

- There is an abundance of text data available, from books, articles, social media, etc., providing rich material for training models.

### Architecture:

- Recurrent Neural Networks (RNNs):
  - Specialized models for handling sequential data like text.
  - They process words in sequence and retain context from earlier words to understand the meaning better.



# POSSIBLE USE-CASE: TEXTS

## TEXT CLASSIFICATION

**Sentiment Analysis is the application of natural language processing to systematically identify the emotional and subjective information in texts.**



**Positive**

Great job! Your customer support is fantastic.



**Neutral**

Not bad, but it should be improved in the future.



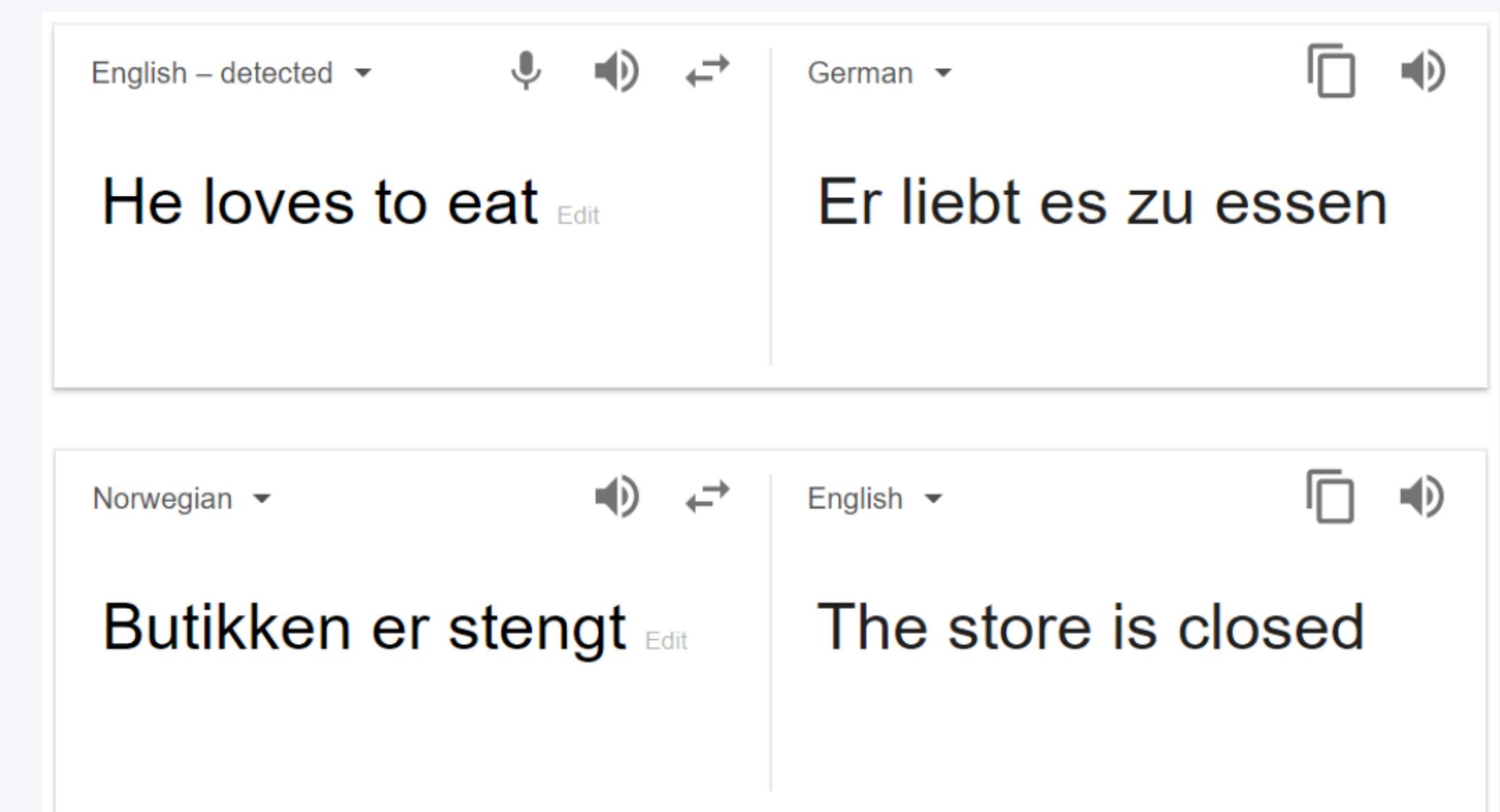
**Negative**

The worst customer service I have ever seen.

# POSSIBLE USE-CASE: TEXTS

## Machine Translation

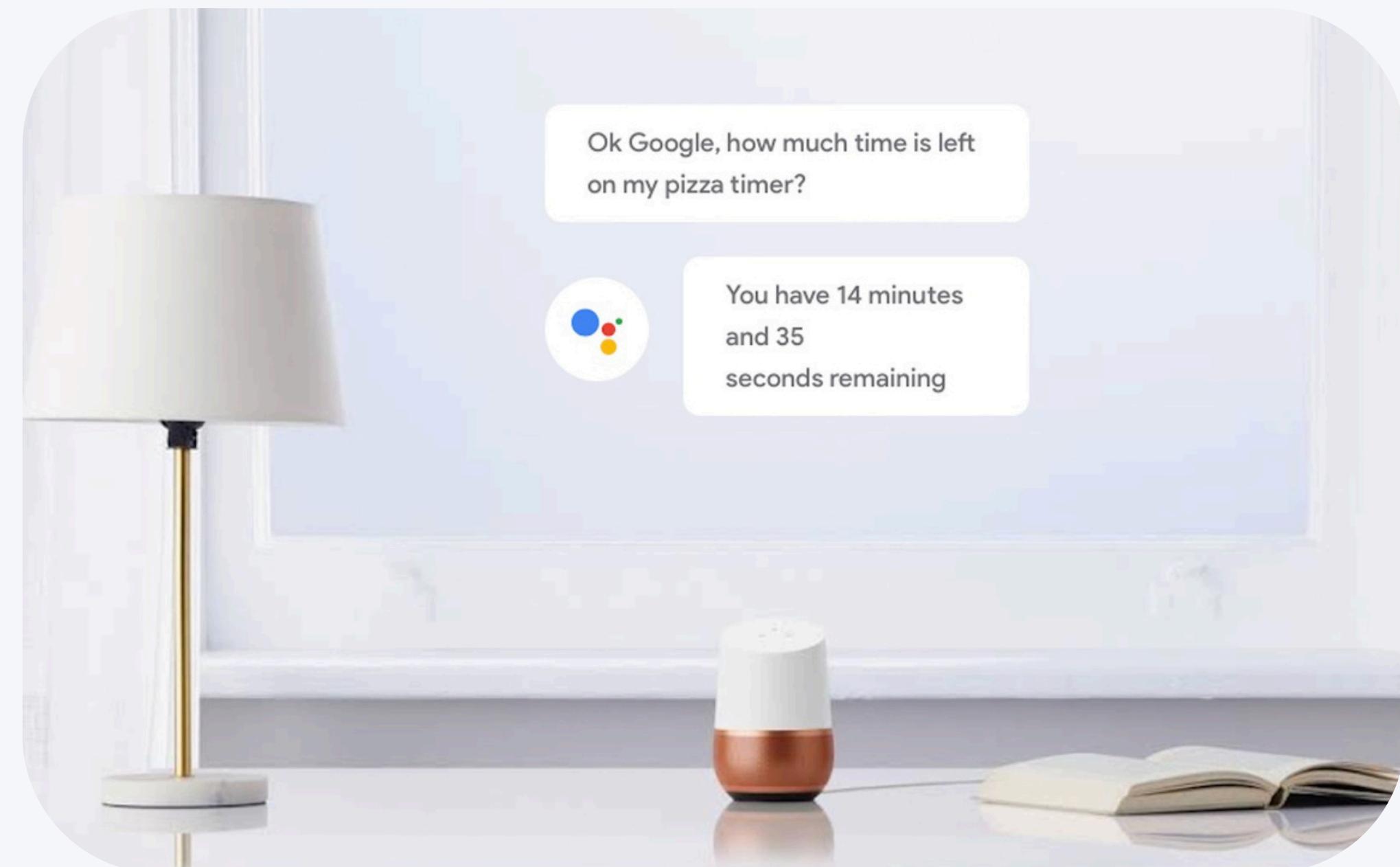
Machine Translation (e.g. google translate) Neural machine translation exploits neural networks to predict the likelihood of a sequence of words, typically modeling entire sentences in a single integrated model.



# POSSIBLE USE-CASE: SPEECH

## Speech Recognition and Generation

Speech Recognition and Generation (e.g. google assistant) Neural network extracts features from audio data for downstream tasks, e.g., to classify emotions in speech.

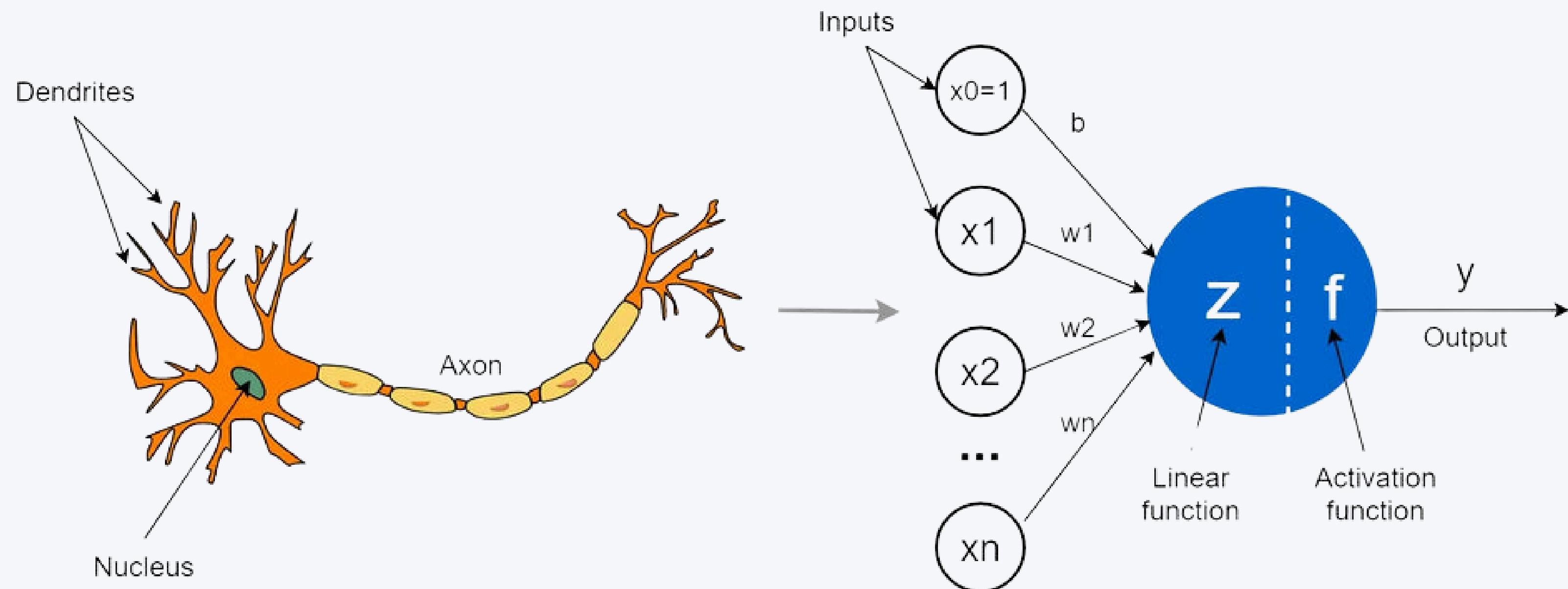


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# Single Neuron

# SINGLE NEURON



<https://www.lucentinnovation.com/blogs/technology-posts/understanding-the-perceptron>

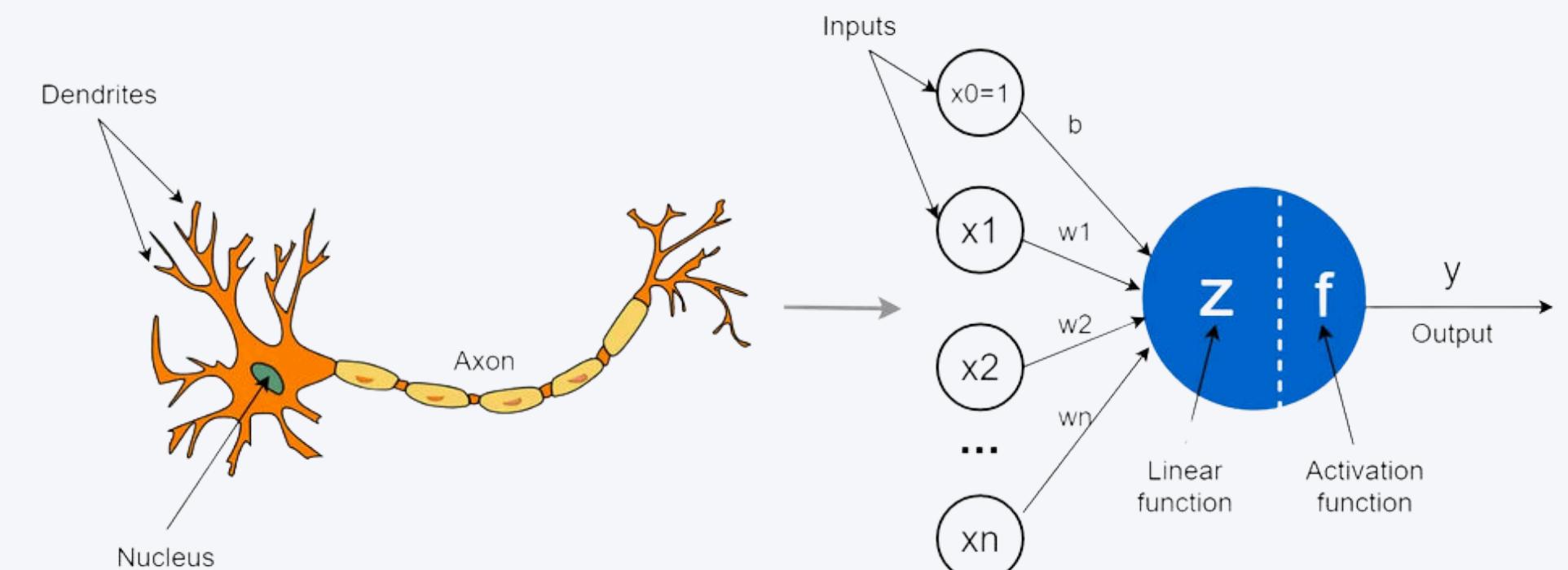
# SINGLE NEURON

## What is a Perceptron?

In the domain of artificial intelligence and machine learning, the term "**perceptron**" is frequently used. The fundamental building block of artificial neural networks, the perceptron is the most fundamental part of machine learning and deep learning technologies.

A single-layer neural network linear or machine learning approach called a **perceptron** is used to learn different binary classifiers under supervision.

- Perceptron is a **linear classifier (binary)** and is a collection of straightforward logical assertions that combine to form a neural network, which is an array of sophisticated logical assertions. It is employed in supervised learning as well. Classifying the provided input data is helpful.



<https://www.lucentinnovation.com/blogs/technology-posts/understanding-the-perceptron>

# SINGLE NEURON

## How Perceptrons Are Inspired by Biological Neurons?

### Inputs (Dendrites):

- **Biological Neurons:** Dendrites receive signals from other neurons.
- **Perceptrons:** Inputs (numbers) act like dendrites, receiving data from other perceptrons.

### Connections (Synapses):

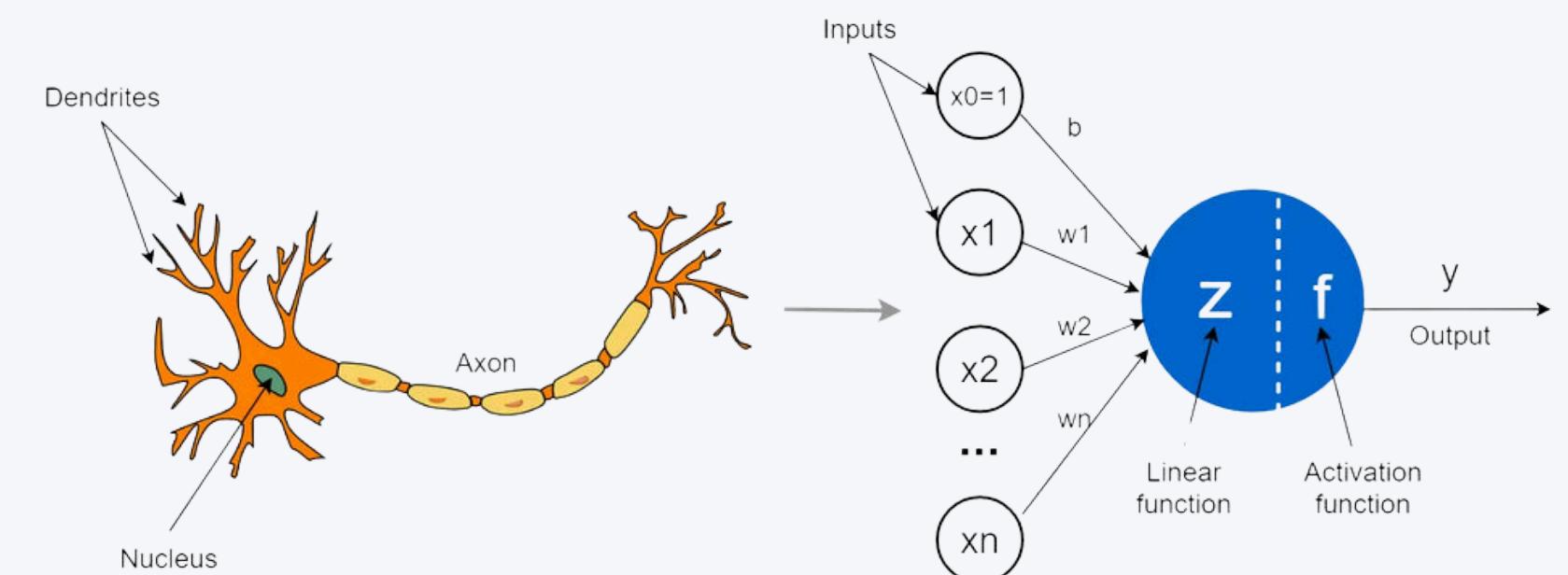
- **Biological Neurons:** Synapses connect dendrites to neurons and determine signal strength.
- **Perceptrons:** Weights represent the importance of each input, similar to synapse strength.

### Processing (Nucleus):

- **Biological Neurons:** The nucleus processes input signals to generate an output.
- **Perceptrons:** A mathematical function (nucleus) processes inputs to produce an output value.

### Output (Axon):

- **Biological Neurons:** Axons carry the output signal to other neurons.
- **Perceptrons:** The output value serves as input for the next perceptron.



<https://www.lucentinnovation.com/blogs/technology-posts/understanding-the-perceptron>

# SINGLE NEURON

## How Does the Perceptron Work?

The perceptron is a simple model for solving binary classification problems (e.g., output 0 or 1).

### 1. Key Components:

- **Inputs** ( $x_1, x_2, x_3$ ): Data features passed into the model.
- **Weights** ( $w_1, w_2, w_3$ ): Represent the importance of each input.
- **Threshold**: A value used to decide if the output is 0 or 1 based on the weighted sum of inputs.

### 2. Working Mechanism:

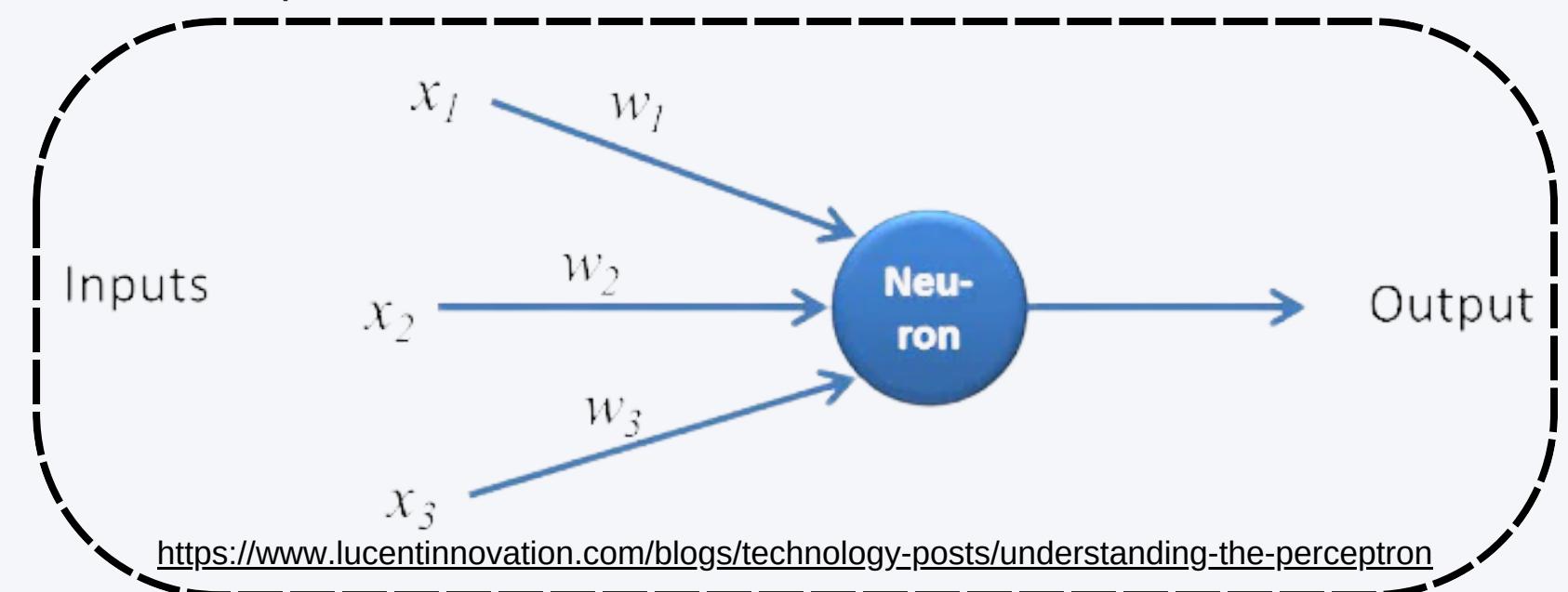
- **Compute the weighted sum:** 
$$z = w_1x_1 + w_2x_2 + w_3x_3 + \text{bias}$$
- Apply the threshold:
  - If  $z > \text{threshold}$ , output = 1.
  - If  $z \leq \text{threshold}$ , output = 0.

### 3. Learning Process:

- **Adjust Weights:**
  - The perceptron modifies the weights during training to minimize the error between the expected and actual outputs.
- **Iterative Updates:**
  - This process is repeated until the weights converge to a stable solution.

### 4. Binary Classifier:

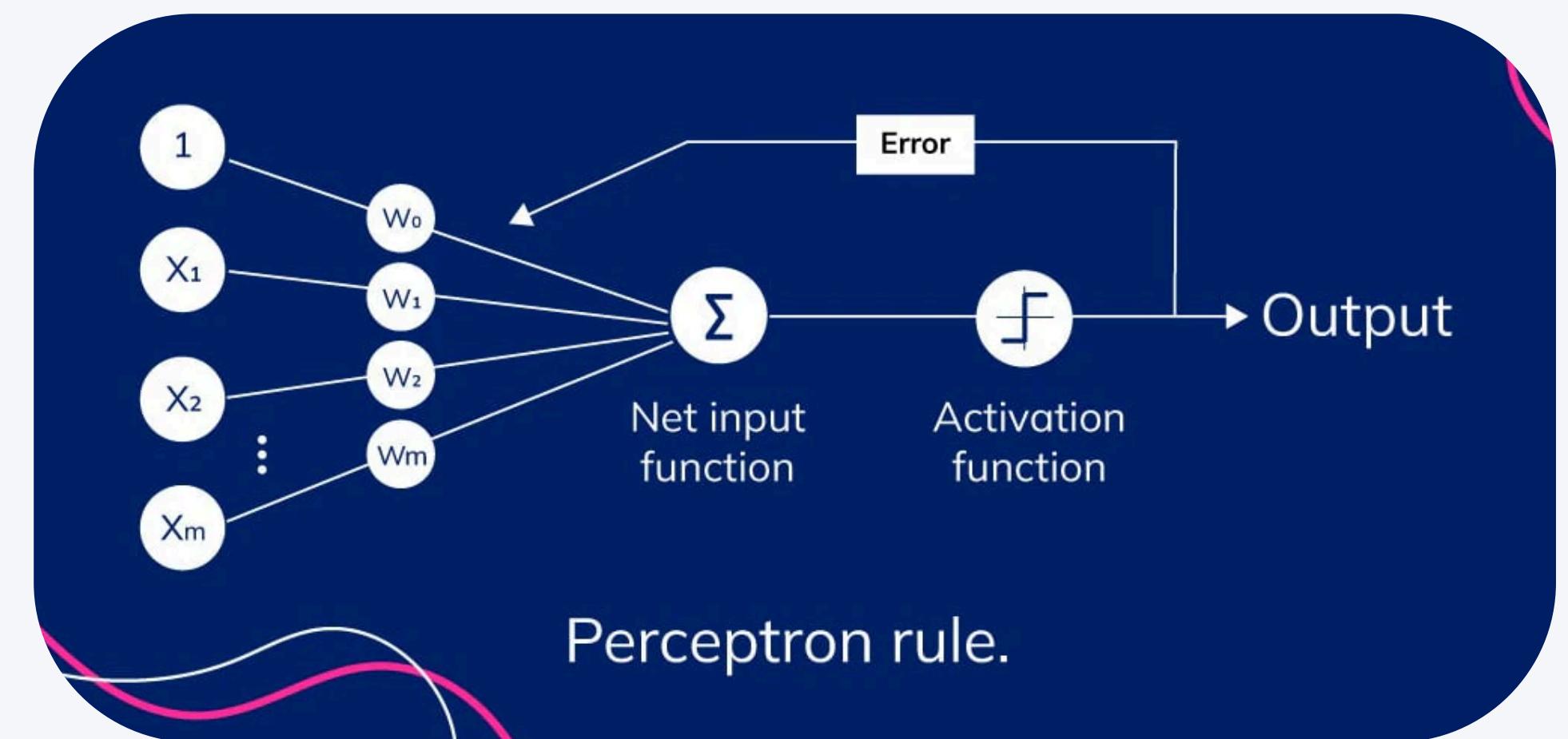
- The perceptron classifies data into two categories (e.g., 0 or 1).



# SINGLE NEURON

## Basic Components of a Perceptron

- **Inputs ( $x_1, x_2, \dots, x_m$ ):**
  - Represent characteristics of the data.
  - Can be binary values or real numbers.
  - Inputs are often expressed as a vector.
- **Weights ( $w_1, w_2, \dots, w_n$ ):**
  - Assigned to each input to determine its importance.
  - Initially random and updated during training.
- **Summation Function:**
  - Computes the weighted sum:  $z = w_1x_1 + w_2x_2 + \dots + w_nx_n$
  - Represents the dot product of the input vector and the weight vector.
- **Activation Function ( $f(z)$ ):**
  - Adds non-linearity to the output.
  - Examples: Sigmoid, ReLU, Step, Tanh, Softmax.
  - Determines whether the perceptron activates or remains dormant.
- **Bias ( $b$ ):**
  - A constant added to the weighted sum to adjust the output.
  - Allows learning even when inputs are zero.
- **Output ( $y$ ):**
  - The final output of the perceptron:  $y = f(z+b)$
  - Represents the prediction or decision made based on inputs.



<https://www.lucentinnovation.com/blogs/technology-posts/understanding-the-perceptron>

Let's Do  
Some Math

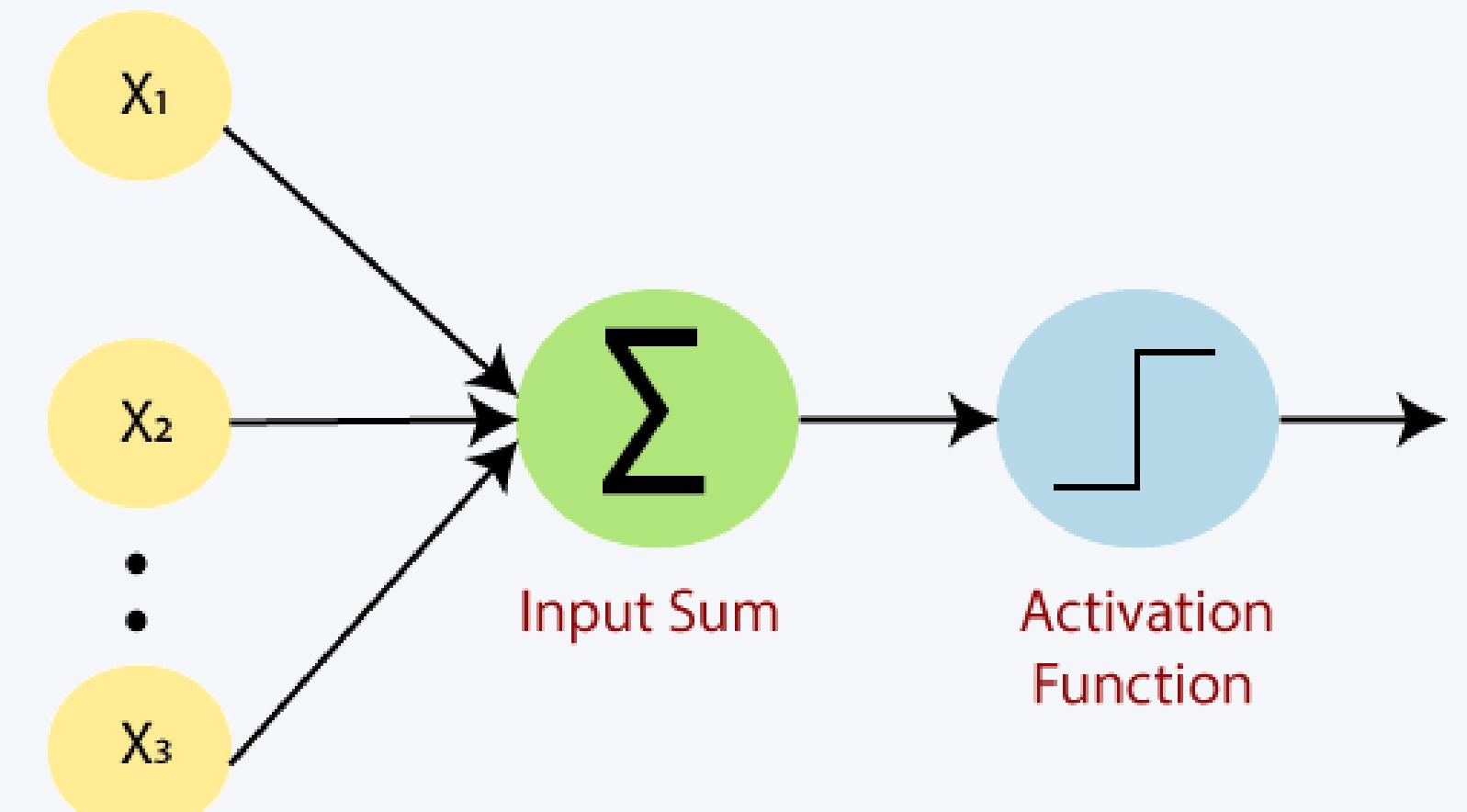
# SINGLE NEURON

## Types of Perceptron:

- The Perceptron can be categorized into two primary types:
  - Single-layer Perceptron
  - Multi-layer Perceptron.

### Single layer Perceptron

- The single-layer Perceptron is made up of a single layer of neurons that adds up all of the inputs and uses an activation function to determine the output.
- It works especially well for issues that can be solved linearly, or in which a straight line may divide the input data into two categories.



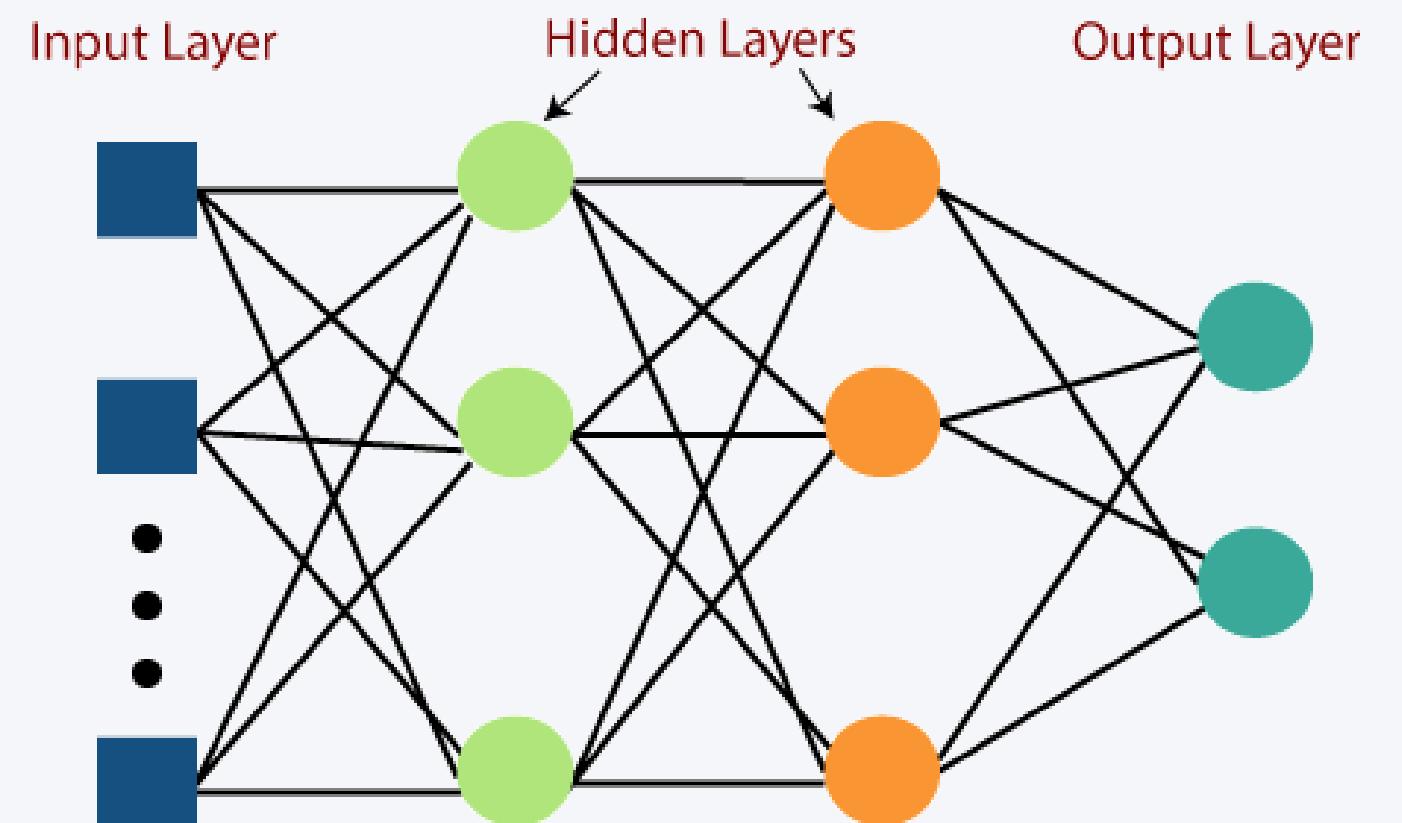
<https://www.lucentinnovation.com/blogs/technology-posts/understanding-the-perceptron>

# SINGLE NEURON

## Types of Perceptron:

### Multi-layer Perceptron

- A **multi-layer perceptron**, in contrast to a single-layer perceptron, consists of multiple layers of neurons, with one or more hidden layers positioned between the input and output layers.
- The model's hidden layers enable it to identify more complex patterns in the input data, which makes it suitable for handling problems that are not linearly separable.



<https://www.lucentinnovation.com/blogs/technology-posts/understanding-the-perceptron>

# SINGLE NEURON

## Strengths of Perceptron

### 1. Versatility:

- Multi-layer perceptrons can solve complex, non-linear problems.
- Works with both small and large datasets efficiently.

### 2. Quick Predictions:

- Provides fast predictions once the model is trained.

### 3. Linearly Separable Data:

- Effective for problems where classes can be separated by a straight line (or hyperplane).

### 4. Supervised Learning:

- Uses labeled data and adjusts weights to minimize errors.

### 5. Efficient Online Learning:

- Updates weights after analyzing each input, making it suitable for large datasets.

# SINGLE NEURON

## Limitations of Perceptron

- **Linearly Separable Only:**
  - Cannot handle non-linear problems; requires advanced models like support vector machines or multi-layer perceptrons.
- **Non-Convergence:**
  - Fails to converge if data cannot be split linearly, leading to endless weight updates.
- **Bias-Variance Trade-off:**
  - Increasing complexity can lead to overfitting or underfitting.
- **No Probabilistic Outputs:**
  - Does not provide probabilities for predictions, limiting its use in probabilistic decision-making.
- **Training Dependency:**
  - Performance heavily depends on the quality of training data.

# SINGLE NEURON

## Applications of Perceptron

- **Foundation for Neural Networks:**
  - Forms the building blocks of more advanced neural network architectures.
- **Educational Use:**
  - Helps teach the basics of machine learning and neural networks.
- **Simple Classification Tasks:**
  - Useful for straightforward problems with linearly separable data.
- **Future Potential:**
  - Predicted to evolve with advancements in computing and technology.
  - Potential to impact industries like healthcare, finance, and robotics through explainable AI and intelligent systems.

# Let's Code

Single Neuron (Linear Unit) in Keras