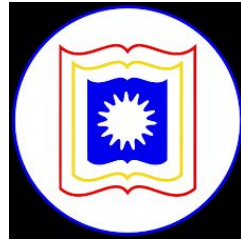


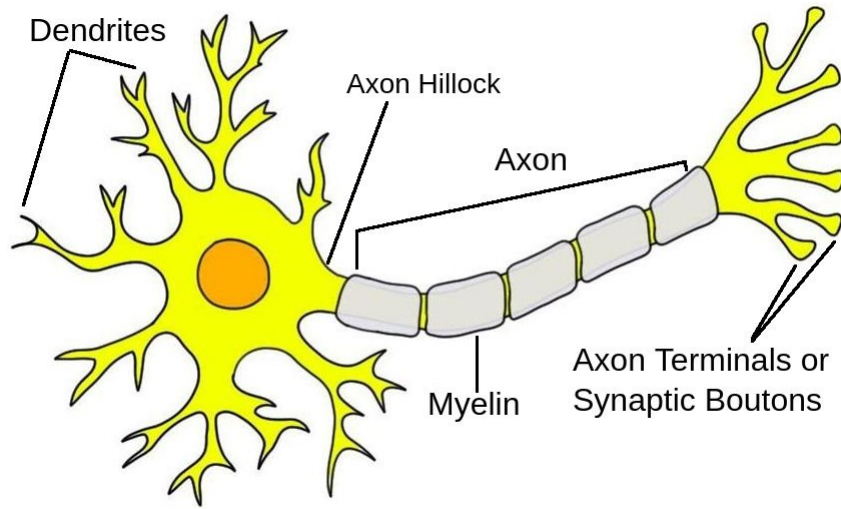
# CSE4261: Neural Network and Deep Learning

Lecture: 21.05.2025

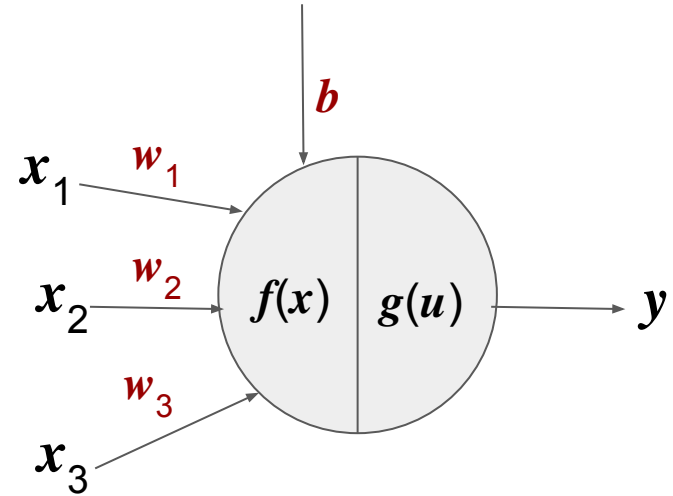


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# Biological Neuron Vs. Artificial Neuron



Biological Neuron



Artificial Neuron

# Steps of Traditional Machine Learning

## 1. Data Preparation:

- a. Data Collection
- b. Data Splitting

## 2. Data pre-processing

- a. Data Cleaning
- b. Data Transformation

## 3. Feature Extraction:

- a. Identify Relevant Features
- b. Extract and Transform Features

## 4. Training Classifier:

- a. Model selection
- b. Searching for optimum parameters

## 5. Evaluation

- a. Estimate metrics using test set

# End-to-End Learning

End-to-end learning or end-to-end training, is a machine learning model that:

- learns directly from raw input data to produce a desired output, without the need for manual feature engineering or pre-processing steps.
- gets popularity in deep learning.
- bypasses few steps of traditional learning such as data pre-processing, feature extraction.

# Kernel

- In computer vision, kernel is a (usually) small matrix of numbers that is used in image convolutions.
- Different sized kernels containing different patterns of numbers produce different results under convolution.
- Generally, small odd numbers such as 3, 5, or 7 are used as the size of a kernel.
- Popular human-decided kernels:
  - Gaussian Blur Kernel
  - Laplacian Kernel
  - Prewitt Kernel
  - Sobel Kernel

# Sobel Kernel

$$K_{\text{Vertical}} = \begin{array}{|c|c|c|} \hline -1 & 0 & 1 \\ \hline -2 & 0 & 2 \\ \hline -1 & 0 & 1 \\ \hline \end{array}$$

$$K_{\text{Left Diagonal}} = \begin{array}{|c|c|c|} \hline 0 & 1 & 2 \\ \hline -1 & 0 & 1 \\ \hline -2 & -1 & 0 \\ \hline \end{array}$$

$$K_{\text{Horizontal}} = \begin{array}{|c|c|c|} \hline 1 & 2 & 1 \\ \hline 0 & 0 & 0 \\ \hline -1 & -2 & -1 \\ \hline \end{array}$$

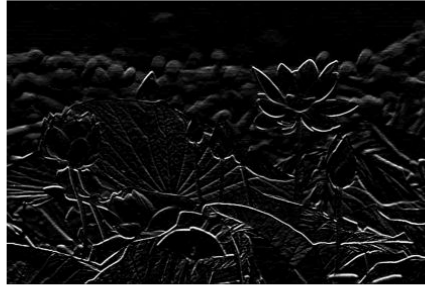
$$K_{\text{Right Diagonal}} = \begin{array}{|c|c|c|} \hline -2 & -1 & 0 \\ \hline -1 & 0 & 1 \\ \hline 0 & 1 & 2 \\ \hline \end{array}$$

# Effect of Well-Known Sobel Kernel

Grayscale



Horizontal Convolution



Vertical Convolution



Left-Diagonal Convolution



Right-Diagonal Convolution



# Feature Map

A feature map:

- is a 2D matrix in a hidden layer
- represents the output of a convolutional layer
- captures specific features or patterns in the input data.

In a CNN:

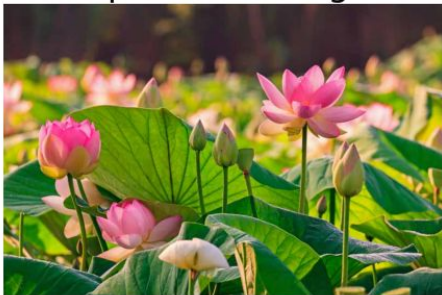
- Instead of human-decided kernels/filters, different automatically learned kernels/filters are used to generate different feature maps



# Feature Maps of Pre-trained VGG16

- Layer: block3\_conv1

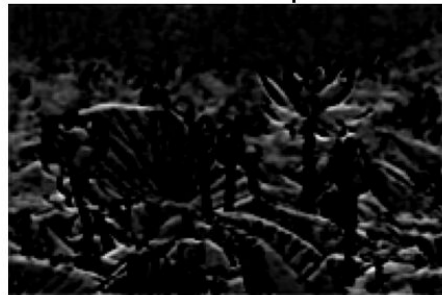
Input RGB Image



FeatureMap-1



FeatureMap-2



FeatureMap-3



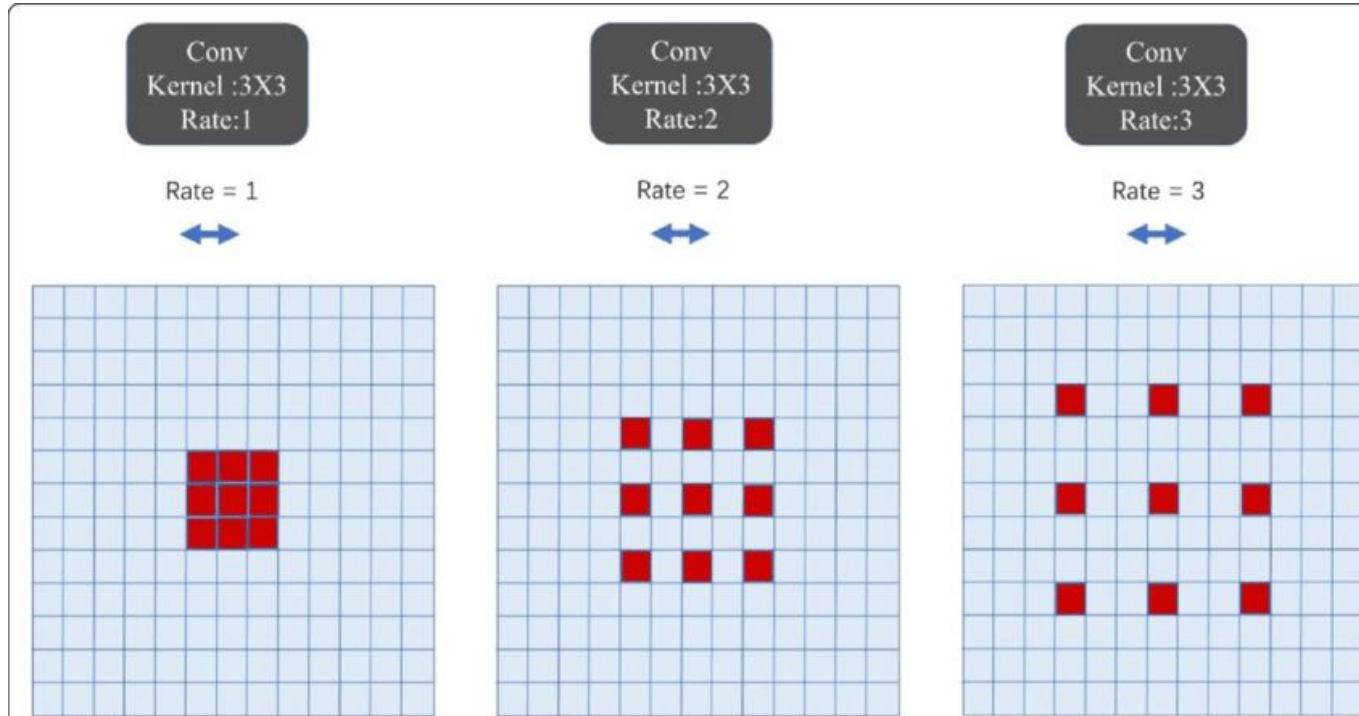
FeatureMap-4



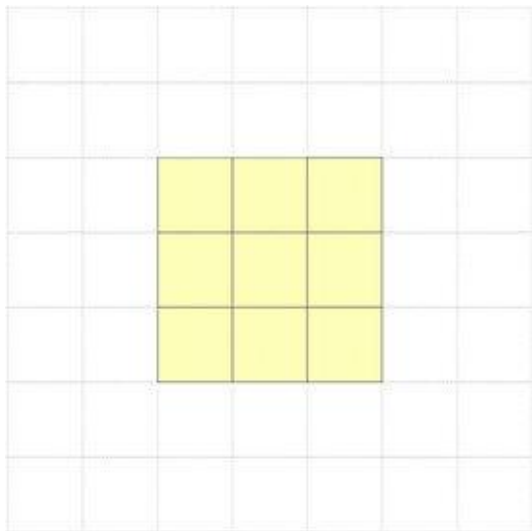
FeatureMap-5



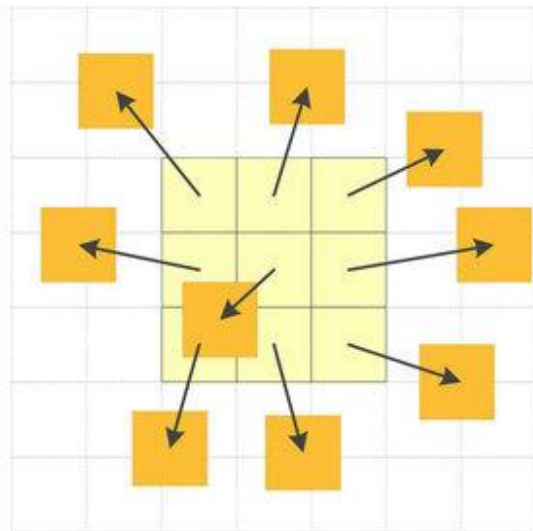
# Atrous or Dilated Kernel



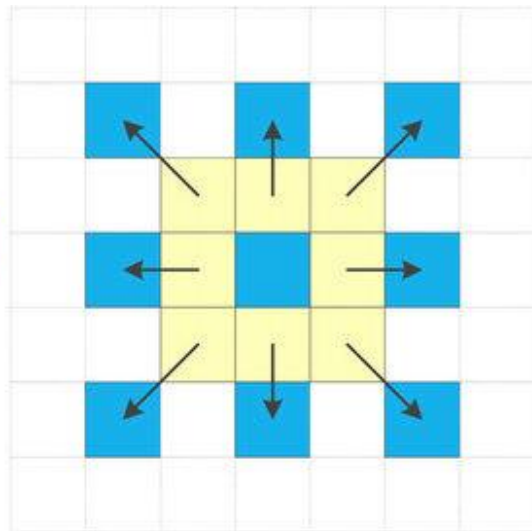
# Deformable Kernel



(a) Ordinary Kernel



(b) Deformable Kernel

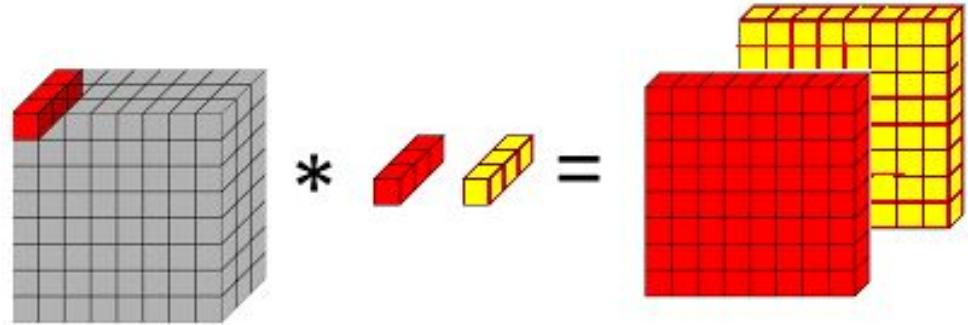
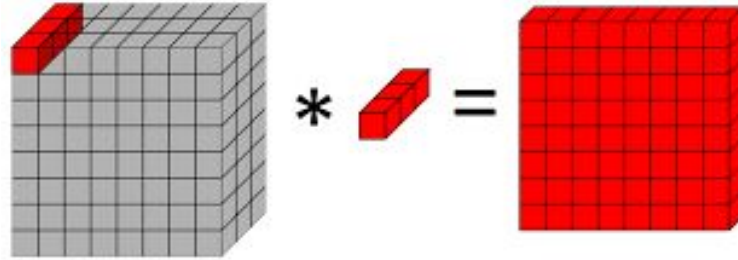


(c) Special Case of  
Deformable Kernel

# Point-Wise convolution

1 x 1 kernel is used for point-wise convolution.

**Advantage:** Increase or reduce the depth (or number of channels) of an image.



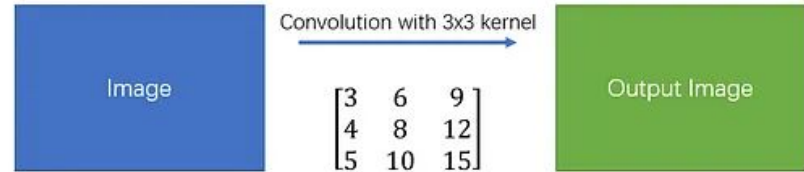
# Spatial Separable Convolution

A spatial separable convolution simply divides a kernel into two, smaller kernels.

**Advantage:** Less parameters, less memory and less computations than regular convolution

**Limitations:** Not all kernels can be spatially “separated”

## Simple Convolution



## Spatial Separable Convolution



# Depthwise Convolution

Each input channel is convolved with a different kernel (called a depthwise kernel).

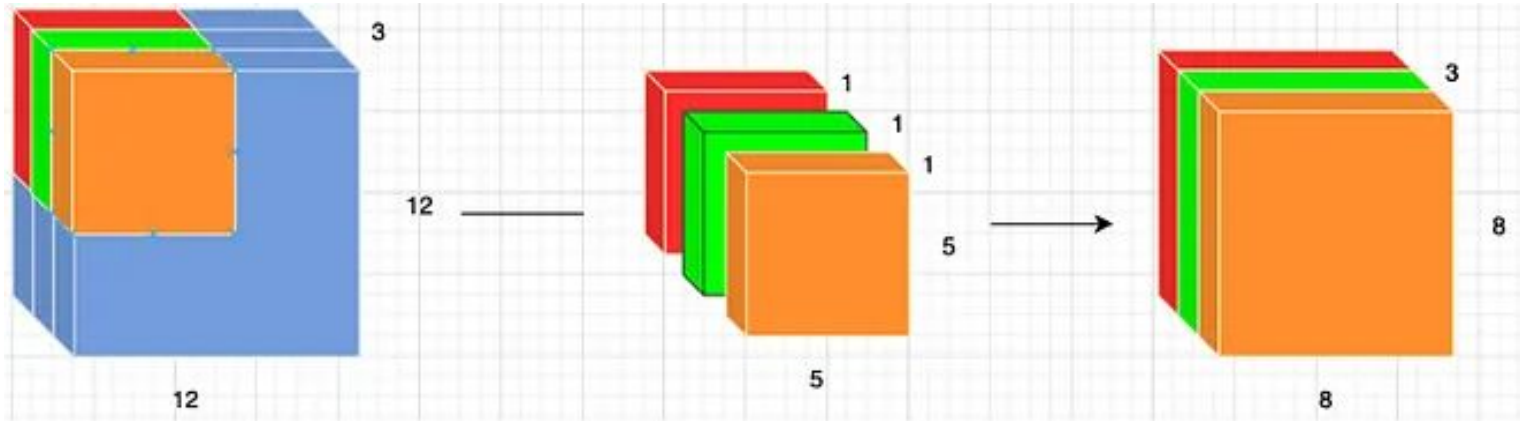


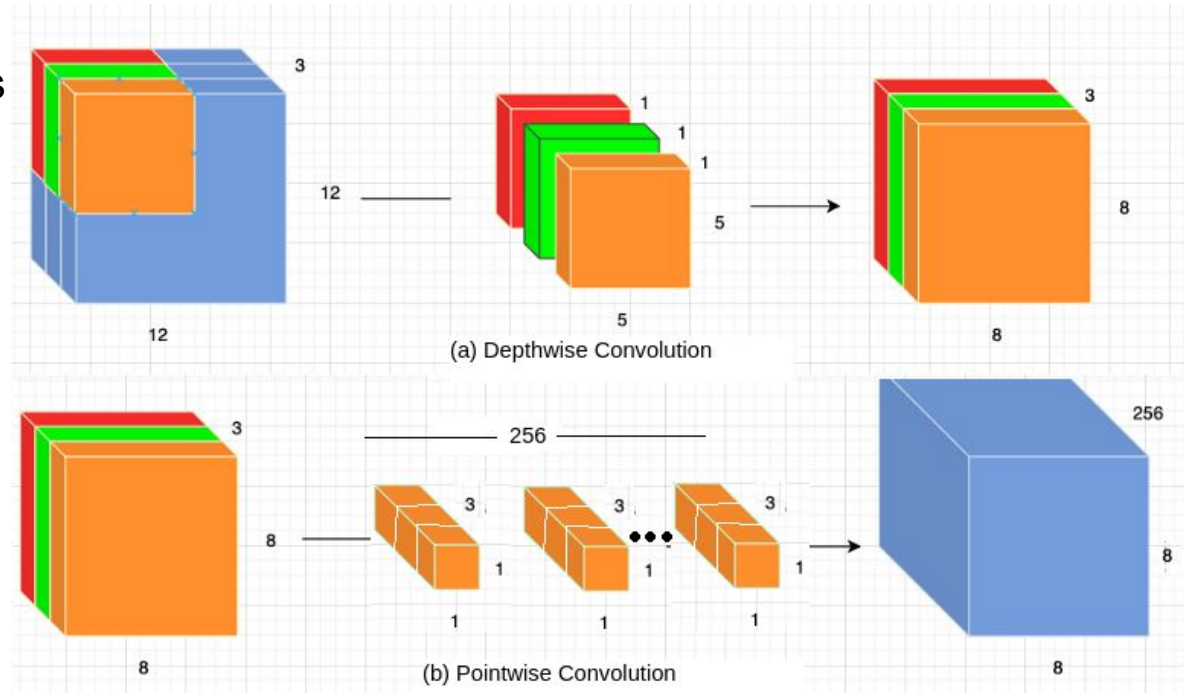
Image Source: Google Search Engine

# Depthwise Separable Convolution

A Depthwise Convolution follows Pointwise Convolution.

For standard Convolution, number of multiplications:  
 $8 \times 8 \times 5 \times 5 \times 3 \times 256 = 1228800$

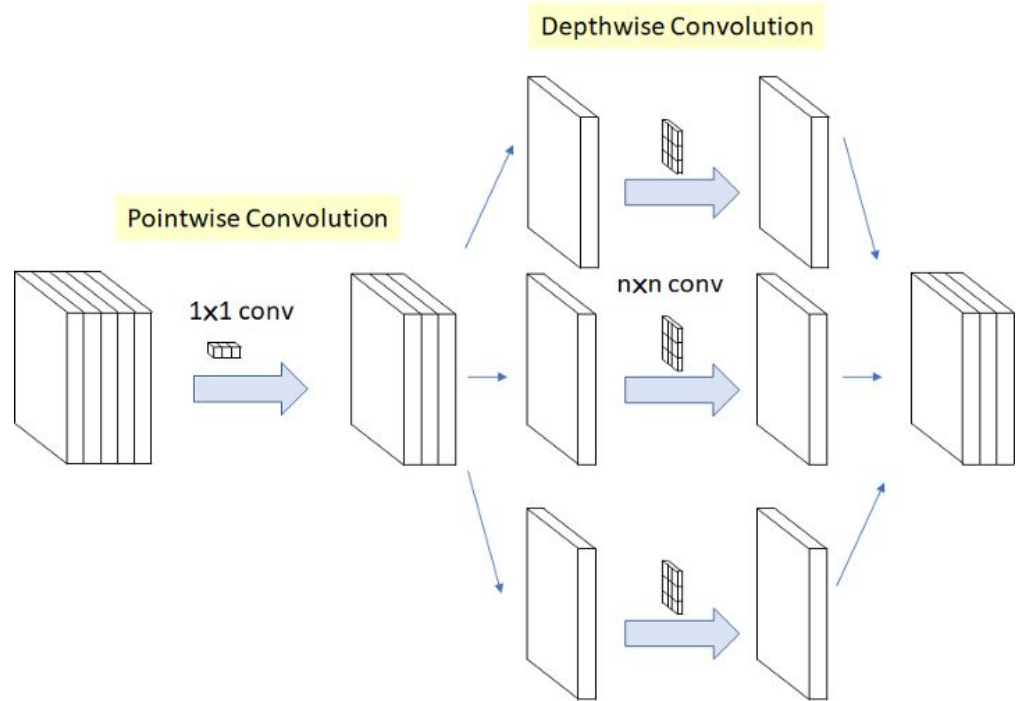
For Depthwise Separable Convolution, number of multiplications:  
 $8 \times 8 \times 5 \times 5 \times 3 + 256 \times 1 \times 1 \times 3 \times 8 \times 8 = 53952$



# Modified Depthwise Separable Convolution

In a Modified Depthwise Separable Convolution is the **pointwise convolution** followed by a **depthwise convolution**.

Xception Network uses Modified Depthwise Separable Convolution.



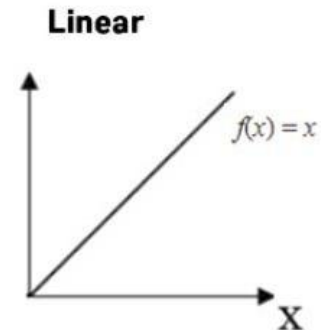
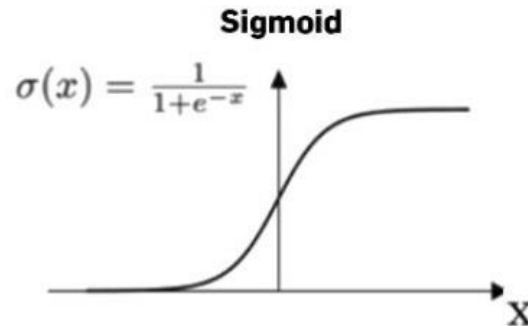
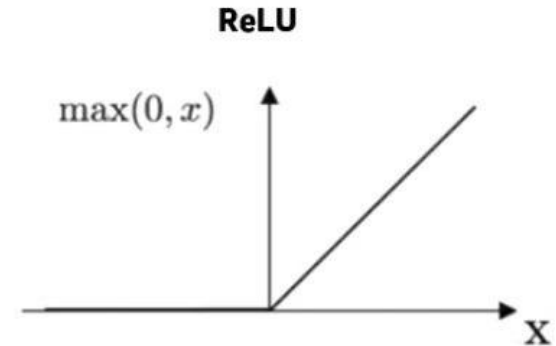
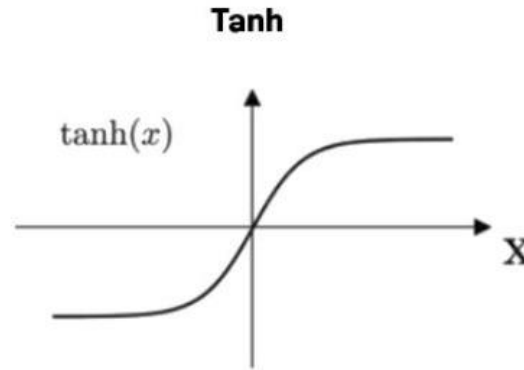


# Activation Function

- An activation function is a mathematical equation that determines how much data should be passed from a neuron to the next neuron.
- It is the function that is applied on the weighted sum of the input of the neuron, i.e., it is  $g(u)$ .
- Generally, it is a nonlinear function for a neuron in the hidden layer and linear/non-linear function for neurons in the output layer.
- A linear activation function, also known as "no activation" or "identity function," is directly proportional to the input.
- Popular non-linear activation functions are:
  - Sigmoid, Tanh, ReLU, ELU, Softmax

# Activation Functions

- Linear activation function in the output layer generally used for regression problem.
- Depending on the range of output values, we need to choose activation function.



# Some Popular Activation Functions

- **Sigmoid**
  - a. Also known as the logistic activation function
  - b. Often used for models that predict probability as an output.
  - c. Its curve looks like an S-shape and exists between 0 and 1.
  - d. Suffers from saturating gradients problem.
- **Hyperbolic tangent (Tanh)**
  - a. Has stronger gradients than the sigmoid function, and its output ranges from -1 to +1.
  - b. Helps the learning algorithm converge faster.
- **Rectified linear unit (ReLU)**
  - a. A non-saturating function, meaning it doesn't become flat at the extremes of the input range.
  - b. It is faster than sigmoid and tanh.
- **Softmax**
  - a. Converts vectors of real numbers into a probability distribution.
  - b. Each output value represents the probability that the input belongs to a specific class.

# Activation Functions for Classification

In output layer, generally:

- Sigmoid is used for binary classification
- Softmax is used for multi-class classification

Both generate values in the range of 0-1.

Summation of softmax values is 1.

Summation of sigmoid values in a classifier does not need to be 1.

$$\text{sigmoid}, y_i = \frac{e^{x_i}}{1 + e^{x_i}}$$

$$\text{softmax}, y_i = \frac{e^{x_i}}{\sum_{j=1}^k e^{x_j}}$$