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DeCAIR

# Neural Networks

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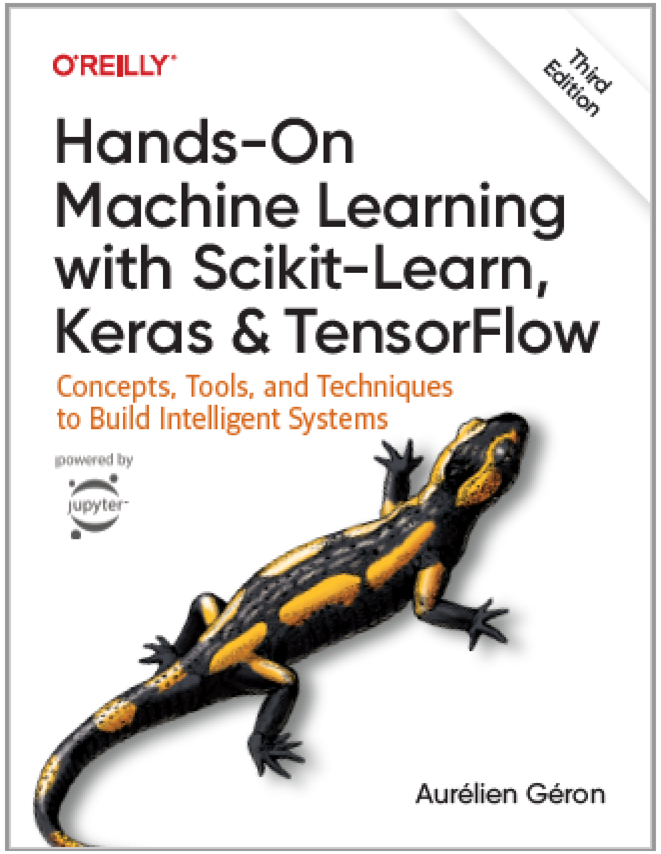
# Reference




- Chapter 10: **Introduction to Artificial Neural Networks with Keras**

- Aurélien Géron, **Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow**, O'Reilly, 3rd Edition, 2022
  - Material: https://github.com/ageron/handson-ml3

# Introduction

- YouTube Video: *But what *is* a Neural Network?* from 3Blue1Brown

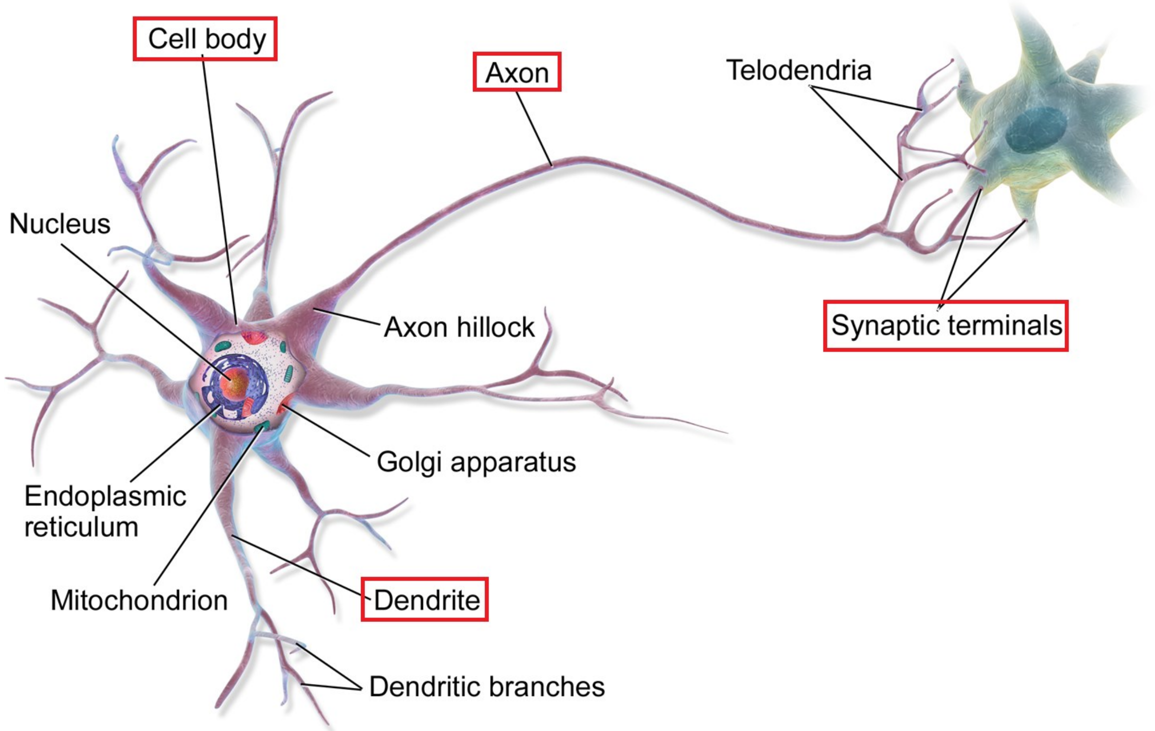
https://youtu.be/aircAruvnKk

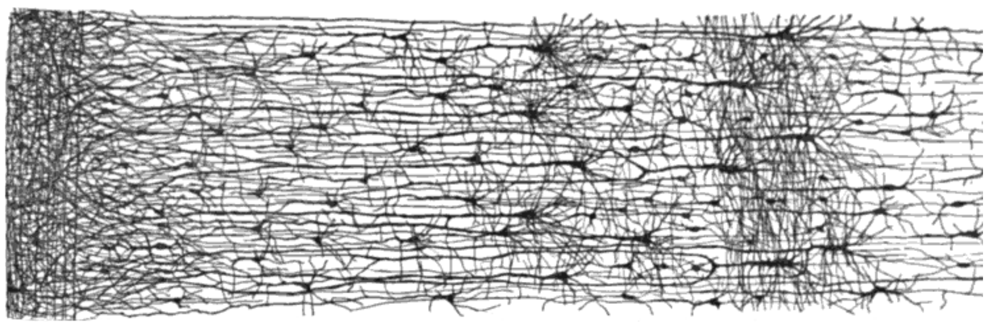
# Outline

1. Introduction
2. The perceptron
3. Multi-layer perceptron (MLP)
4. Regression MLPs
5. Classification MLPs

# 1. Introduction

- **Artificial neural networks** (ANNs) are inspired by the brain's architecture.
- First suggested in 1943. Is now **flourishing** due to the availability of:
  - Data
  - Computing power
  - Better algorithms

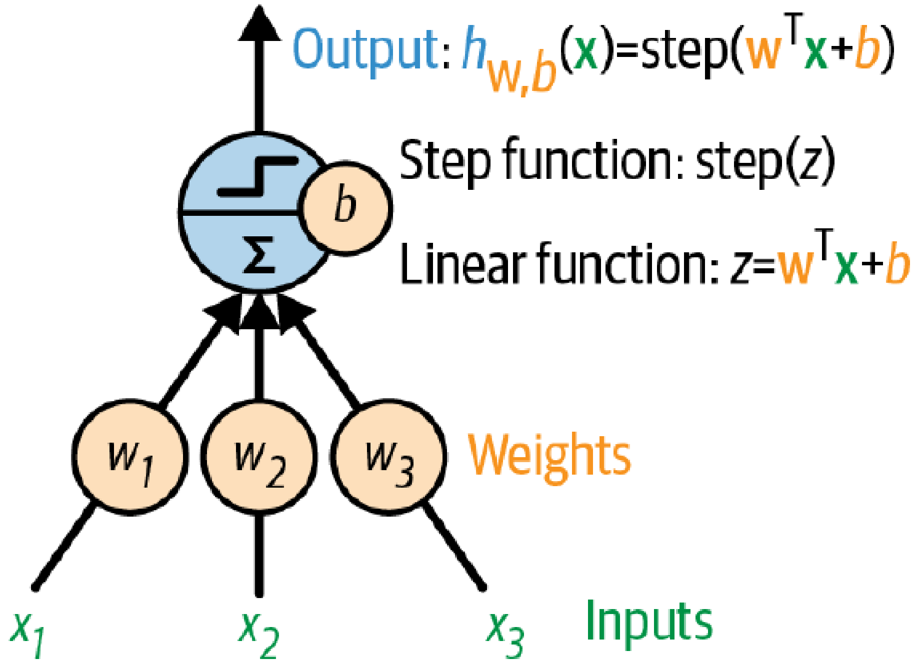


# 2. The Perceptron

- The **Perceptron** is a simple ANN, invented in 1957 and can perform linear binary classification or regression.

**Linear threshold unit (LTU)**



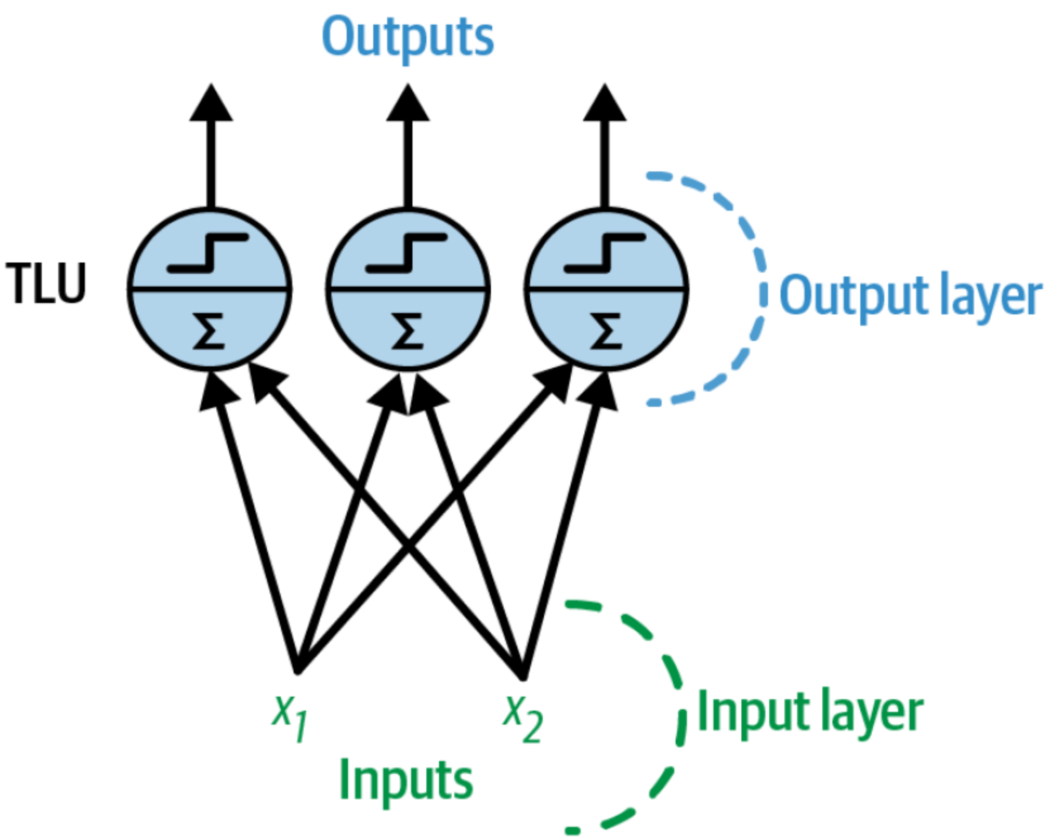

- Common **step function**:

$$\text{heaviside}(z) = \begin{cases} 0 & \text{if } z < 0 \\ 1 & \text{if } z \geq 0 \end{cases} \qquad \text{sgn}(z) = \begin{cases} -1 & \text{if } z < 0 \\ 0 & \text{if } z = 0 \\ +1 & \text{if } z > 0 \end{cases}$$

# 2. The Perceptron

- The Perceptron has an **input layer** with **bias** and **output layer**.
- With **multiple output nodes**, it can perform multiclass classification.
- Hebbian learning "**Cells that fire together, wire together**."

$$\boxed{w_{i,j}^{(\text{next step})} = w_{i,j} + \eta\left(y_j - \hat{y}_j\right)x_i}$$



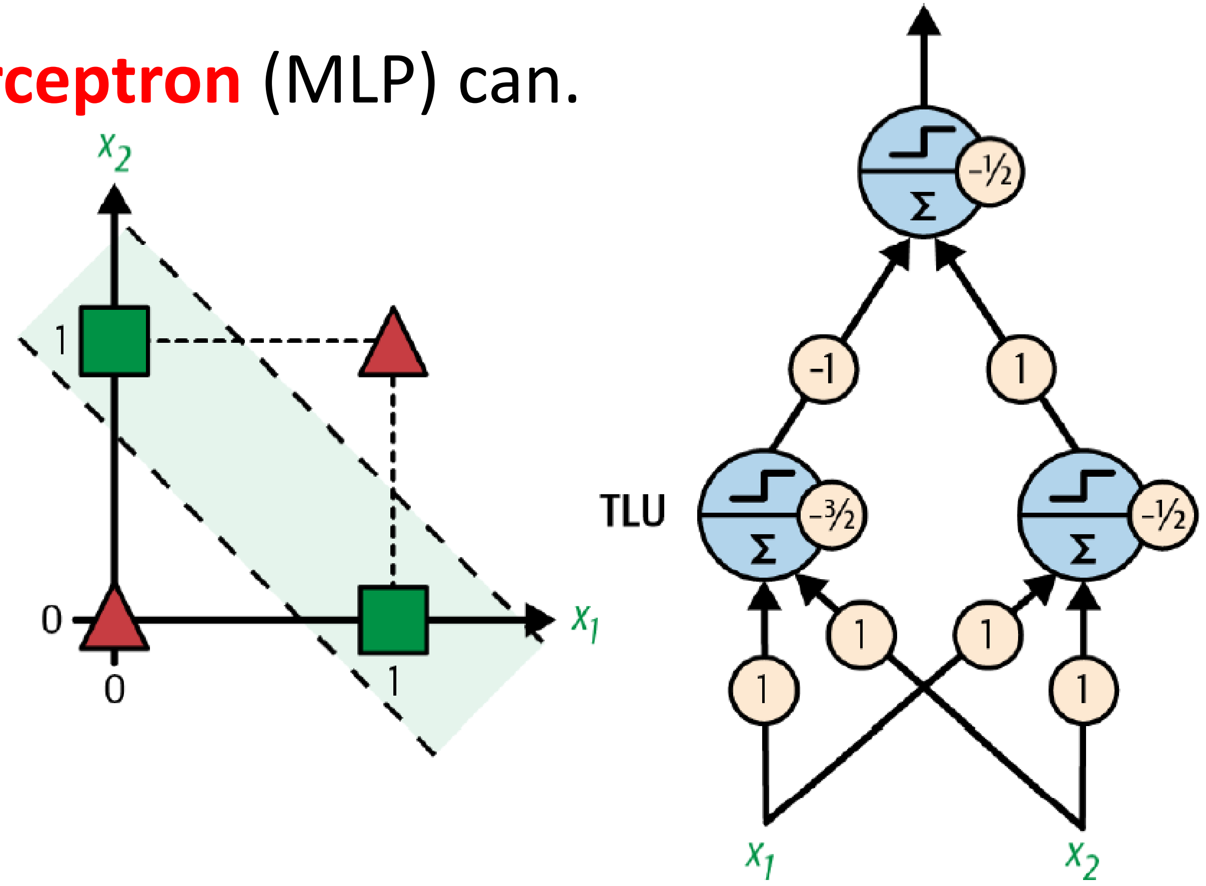
# 2. The Perceptron

- Scikit-Learn provides a **Perceptron** class.

```
import numpy as np
from sklearn.datasets import load_iris
from sklearn.linear_model import Perceptron

iris = load_iris(as_frame=True)
X = iris.data[["petal length (cm)", "petal width (cm)"]].values
y = (iris.target == 0)  # Iris setosa

per_clf = Perceptron(random_state=42)
per_clf.fit(X, y)

X_new = [[2, 0.5], [3, 1]]
y_pred = per_clf.predict(X_new)  # predicts True and False for these 2 flowers
```

# 2. The Perceptron

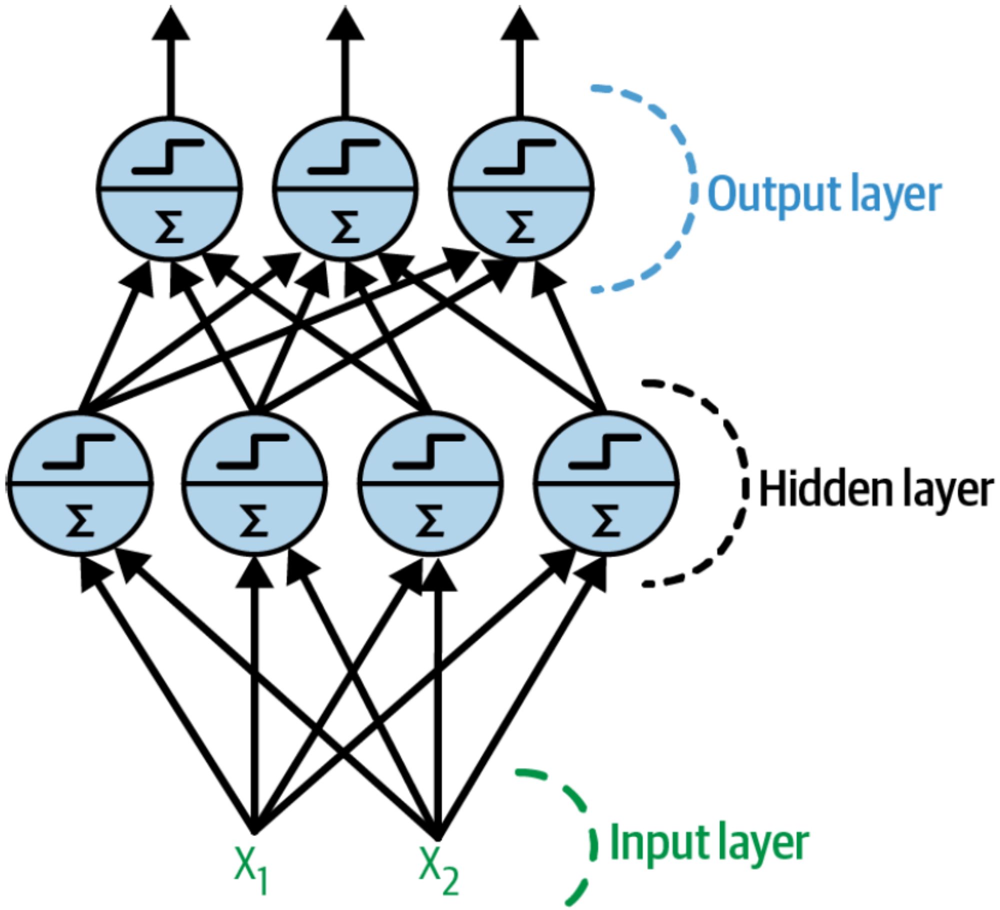
- The perceptron **cannot solve non-linear problems** such as the XOR problem.
- The **Multi-Layer Perceptron** (MLP) can.



# Outline

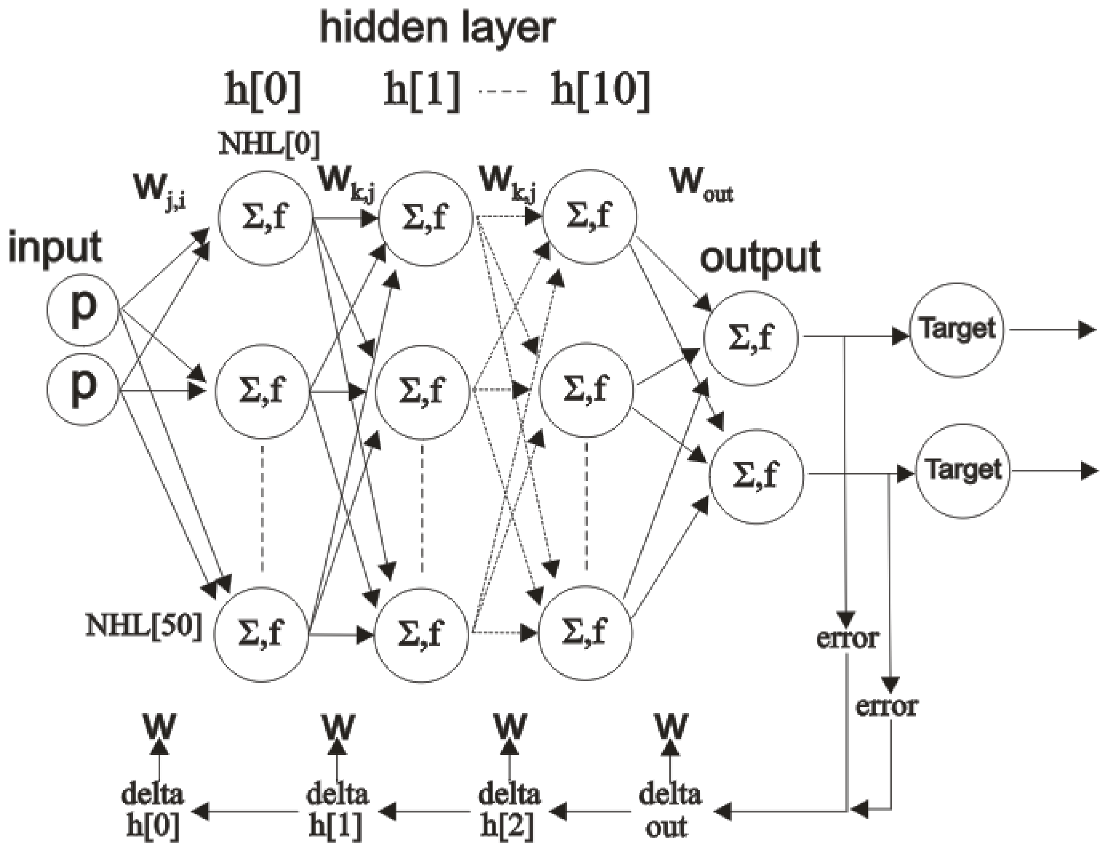
# 3. Multi-Layer Perceptron (MLP)

- An MLP is composed of a (pass-through) **input layer**, one or more layers of LTUs, called **hidden layers**, and a final layer of LTUs called the **output layer**.
- When an ANN has **two or more** hidden layers, it is called a **deep neural network** (DNN).



# 3. Multi-Layer Perceptron (MLP)

- Trained using the **backpropagation training algorithm**.
  - For each training instance the algorithm first makes a prediction (**forward pass**), measures the error,
  - then goes through each layer in reverse to measure the error contribution from each connection (**reverse pass**),
  - and finally slightly tweaks the connection weights to reduce the error (**Gradient Descent step**).



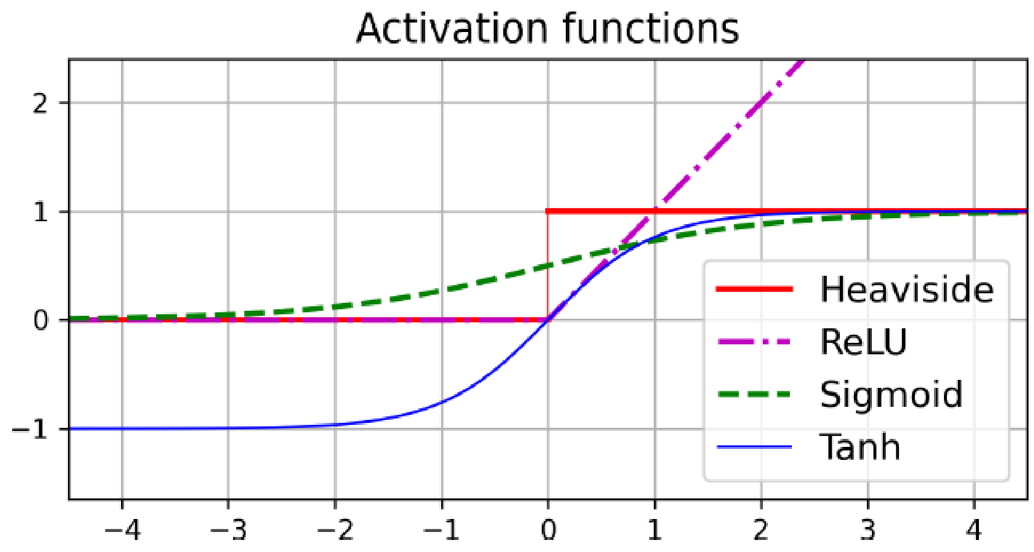
# 3. Multi-Layer Perceptron (MLP)

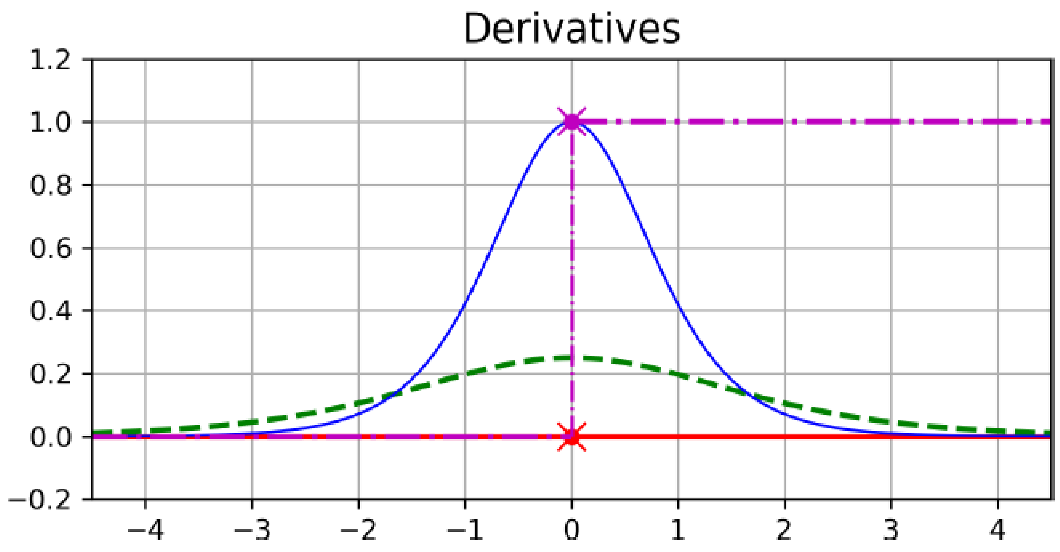
- **Common activation functions**: **logistic**, **hyperbolic tangent**, and **rectified linear unit**.

$$\sigma(z) = 1 / (1 + \exp(-z))$$

$$tanh\ (z) = 2\sigma(2z) - 1$$

$$\mathrm{ReLU}\ (z) = \max\ (0, z)$$



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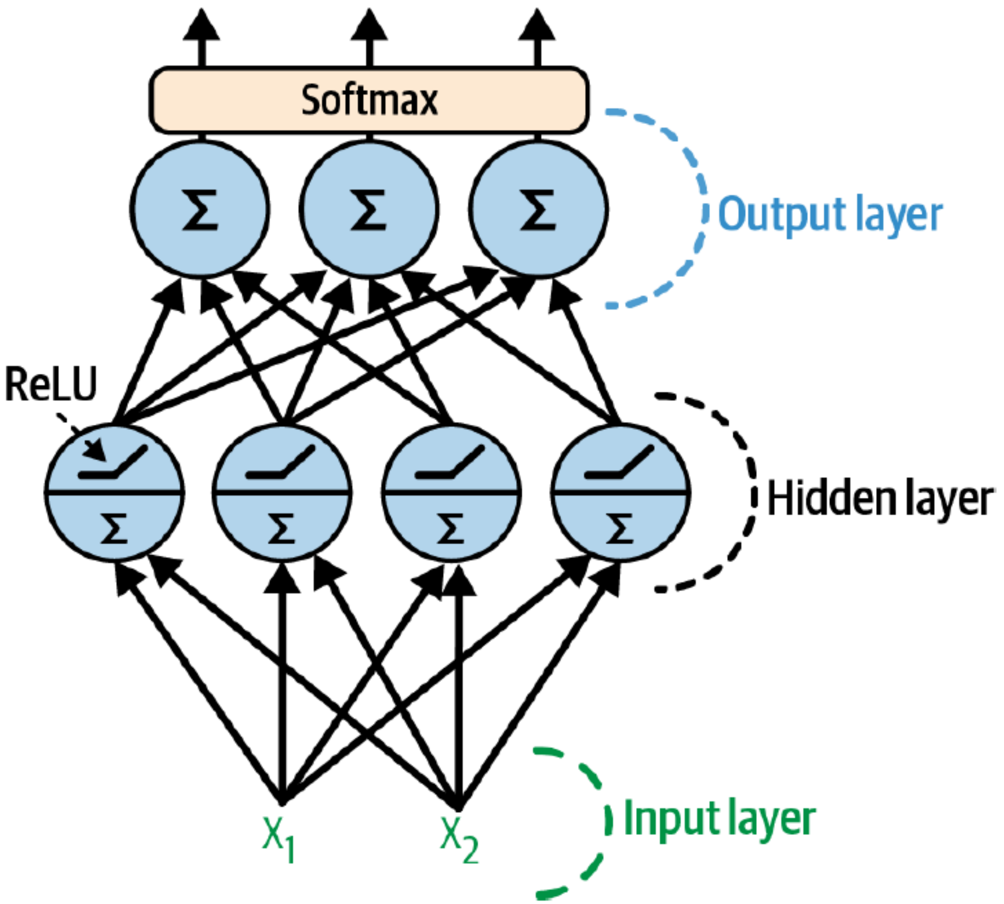
# 4. Regression MLPs

- Typical MLP architecture for **regression**:

| Hyperparameter | Typical value |
|---|---|
| # hidden layers | Depends on the problem, but typically 1 to 5 |
| # neurons per hidden layer | Depends on the problem, but typically 10 to 100 |
| # output neurons | 1 per prediction dimension |
| Hidden activation | ReLU |
| Output activation | None, or ReLU/softplus (if positive outputs) or sigmoid/tanh (if bounded outputs) |
| Loss function | MSE, or Huber if outliers |

# 5. Classification MLPs

- For **classification**, the output layer uses the **softmax function**.
- The output of each neuron corresponds to the **estimated probability** of the corresponding class.




$$\hat{p}_k = \sigma(\mathbf{s}(\mathbf{x}))_k = \frac{\exp\left(s_k(\mathbf{x})\right)}{\sum_{j=1}^{K} \exp\left(s_j(\mathbf{x})\right)}$$

$$\hat{y} = \underset{k}{\operatorname{argmax}}\ \sigma(\mathbf{s}(\mathbf{x}))_k$$

# 5. Classification MLPs

- Typical MLP architecture for **classification**:

| Hyperparameter | Binary classification | Multilabel binary classification | Multiclass classification |
|---|---|---|---|
| # hidden layers | Typically 1 to 5 layers, depending on the task | | |
| # output neurons | 1 | 1 per binary label | 1 per class |
| Output layer activation | Sigmoid | Sigmoid | Softmax |
| Loss function | X-entropy | X-entropy | X-entropy |

# Summary

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