



# PEP 559

## Machine Learning in Quantum Physics

Dr. Chunlei Qu

Spring 2025

# Four Modules

- Model A: Machine Learning
- Module B: Deep Learning
- Module C: Quantum Information
- Module D: Machine Learning for Quantum Physics



# Three types of machine learning

## Supervised learning

- Labeled data
- Direct feedback
- Predict outcome/future

## Unsupervised learning

- No labels/targets
- No feedback
- Find hidden structure in data

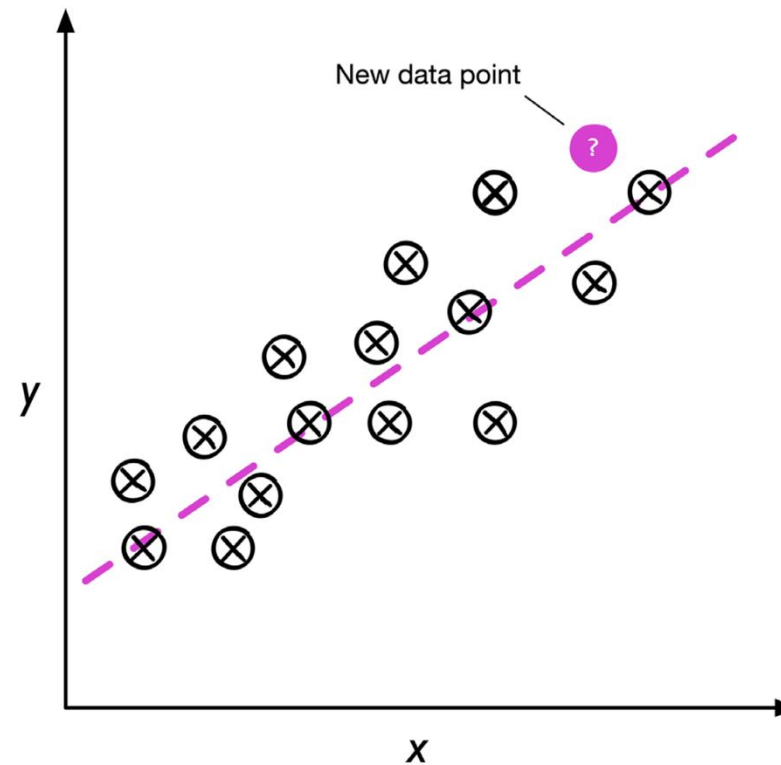
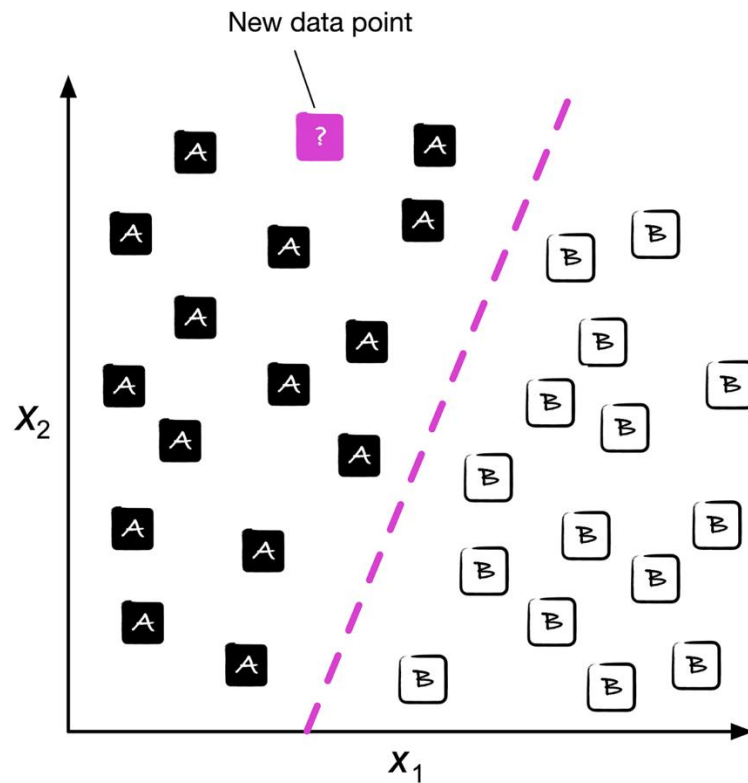
## Reinforcement learning

- Decision process
- Reward system
- Learn series of actions



# Supervised learning

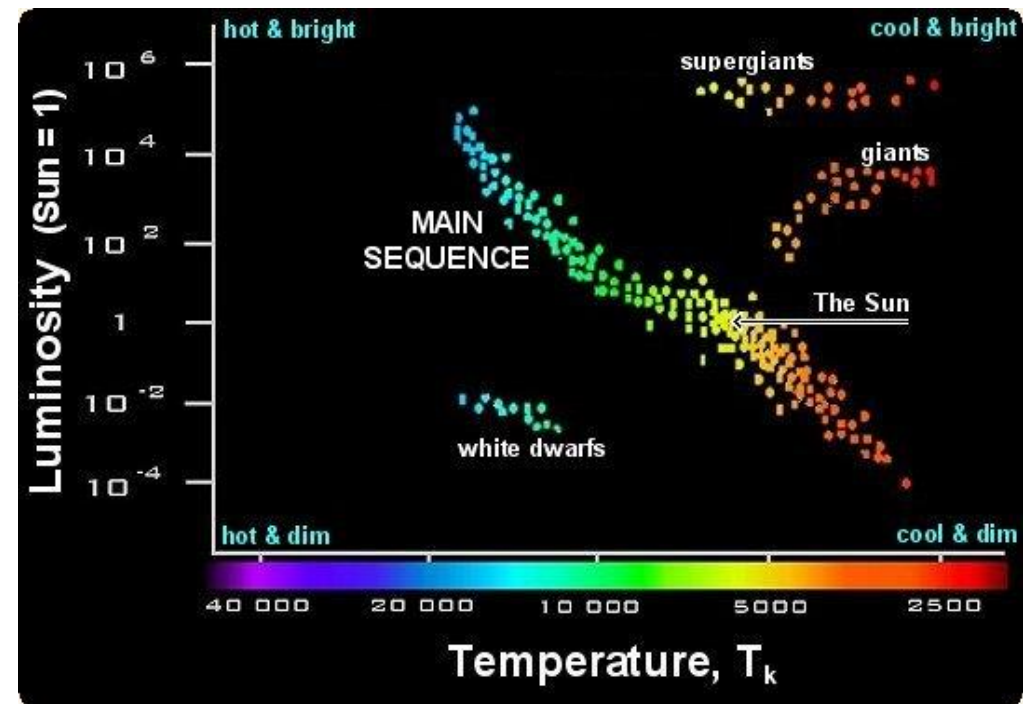
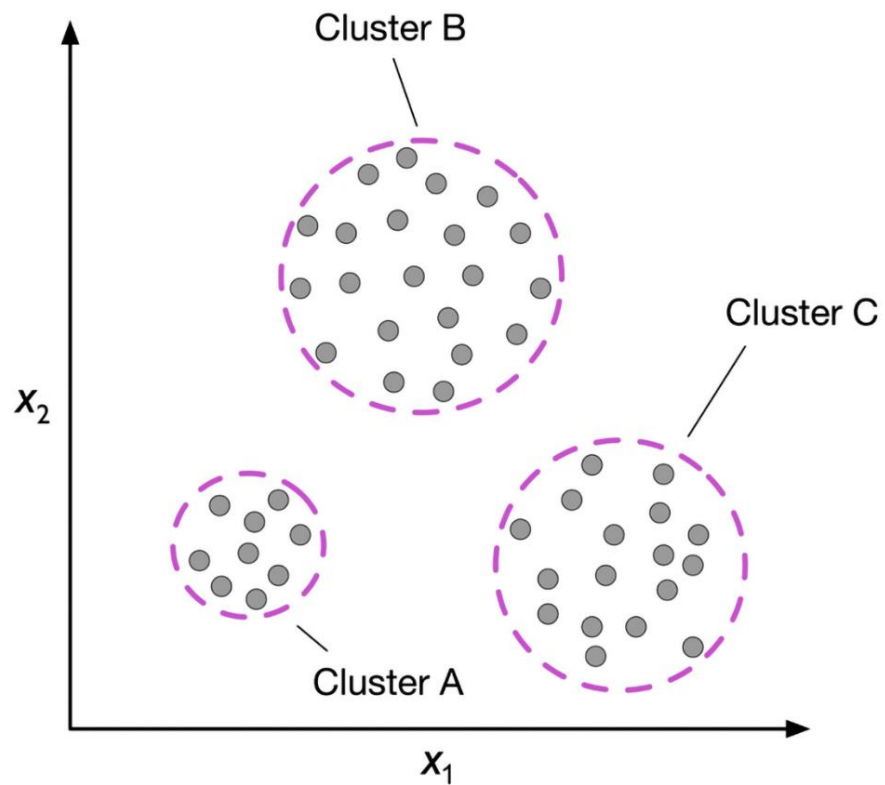
- **Classification:** labels are **discrete**, e.g., email spam detection is a binary classification task
- **Regression:** labels are **continuous**, e.g., house price vs. size





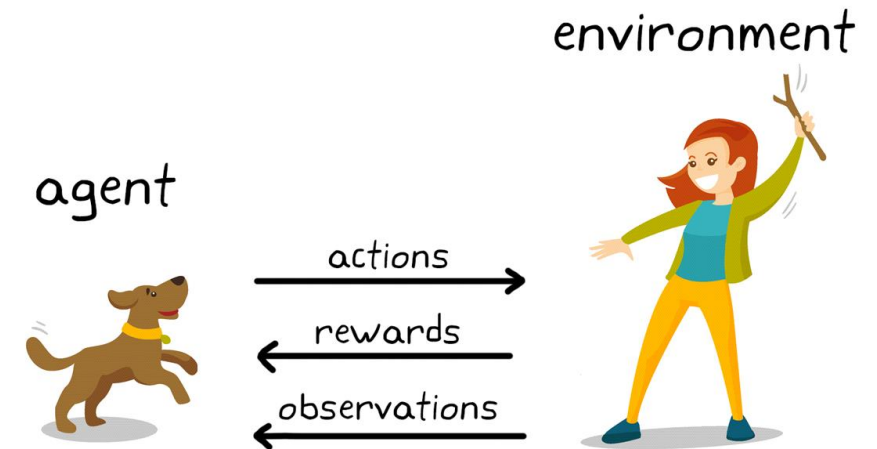
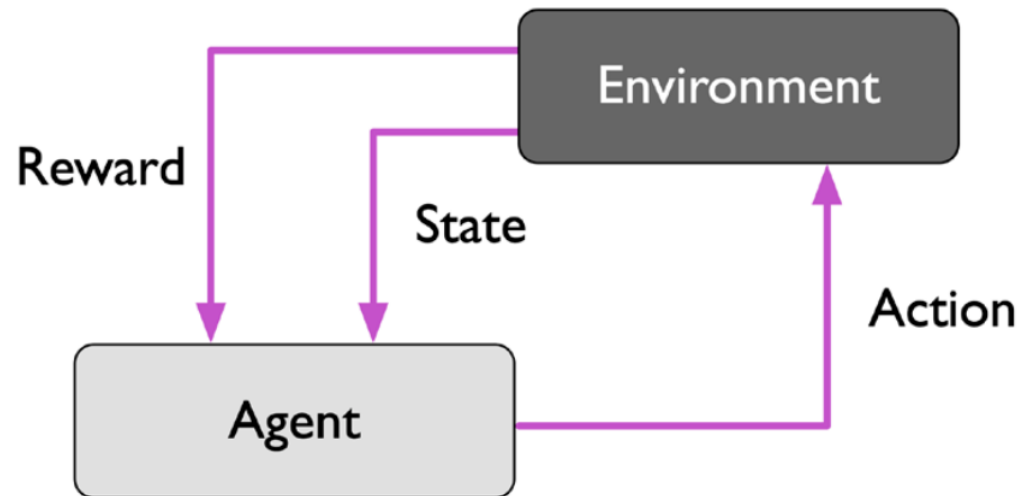
# Unsupervised learning

- **Clustering:** Discovering hidden structure of **unlabeled** data
- For example, the **Hertzsprung-Russell diagram** groups stars by temperature and luminosity



# Reinforcement learning

- To develop a system (**agent**) that improves its performance based on interactions with the environment



# Notation and Terminology

**Samples**  
(instances, observations)

	Sepal length	Sepal width	Petal length	Petal width	Class label
1	5.1	3.5	1.4	0.2	Setosa
2	4.9	3.0	1.4	0.2	Setosa
...					
50	6.4	3.5	4.5	1.2	Versicolor
...					
150	5.9	3.0	5.0	1.8	Virginica

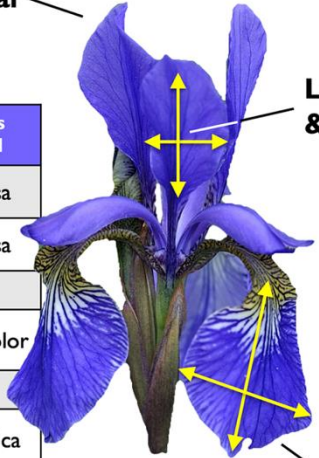
**Features**  
(inputs, attributes, measurements, dimensions)

**Petal**

**Length & width**

**Sepal**

**Class labels**  
(targets, outcomes)



## The Iris DataSet

- **4 Features:** Sepal length, Sepal width, Petal length, Petal width
- **150 Samples** or instances or observations, etc.
- **Class labels:** Setosa, Versicolor, Virginica.

# Data Matrix

- Superscript = **sample** index = row index
- Subscript = **feature** index = column index

$$\mathbf{X} \in \mathbb{R}^{150 \times 4}$$

$$\begin{bmatrix} x_1^{(1)} & x_2^{(1)} & x_3^{(1)} & x_4^{(1)} \\ x_1^{(2)} & x_2^{(2)} & x_3^{(2)} & x_4^{(2)} \\ \vdots & \vdots & \vdots & \vdots \\ x_1^{(150)} & x_2^{(150)} & x_3^{(150)} & x_4^{(150)} \end{bmatrix}$$

sample  
vector

feature vector



# Terminology

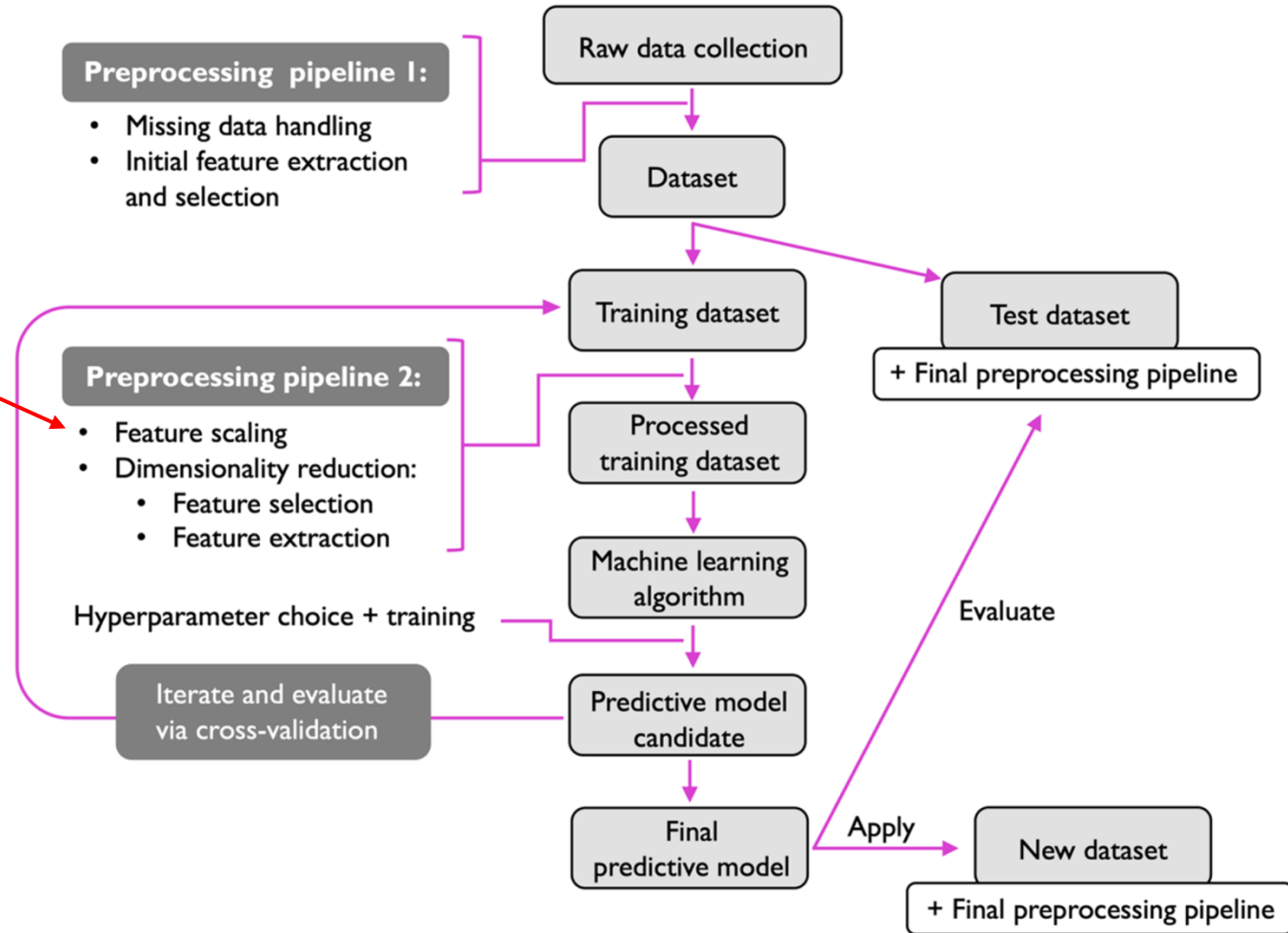
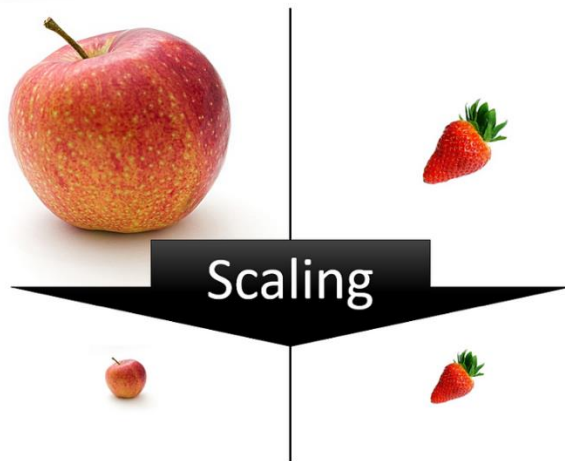
- **Training example:** a row in the data matrix, also known as an observation, record, instance, or sample
- **Feature:** a column in the data matrix, also known as predictor, variable, input, attribute
- **Target:** also known as class label, ground truth, outcome, output, etc.
- **Loss function:** also known as cost function or error function



# ML typical workflow

- **Feature scaling**

The features should be on the same scale for optimal performance. Normally, we transform it to a standard distribution with zero mean and unit variance.

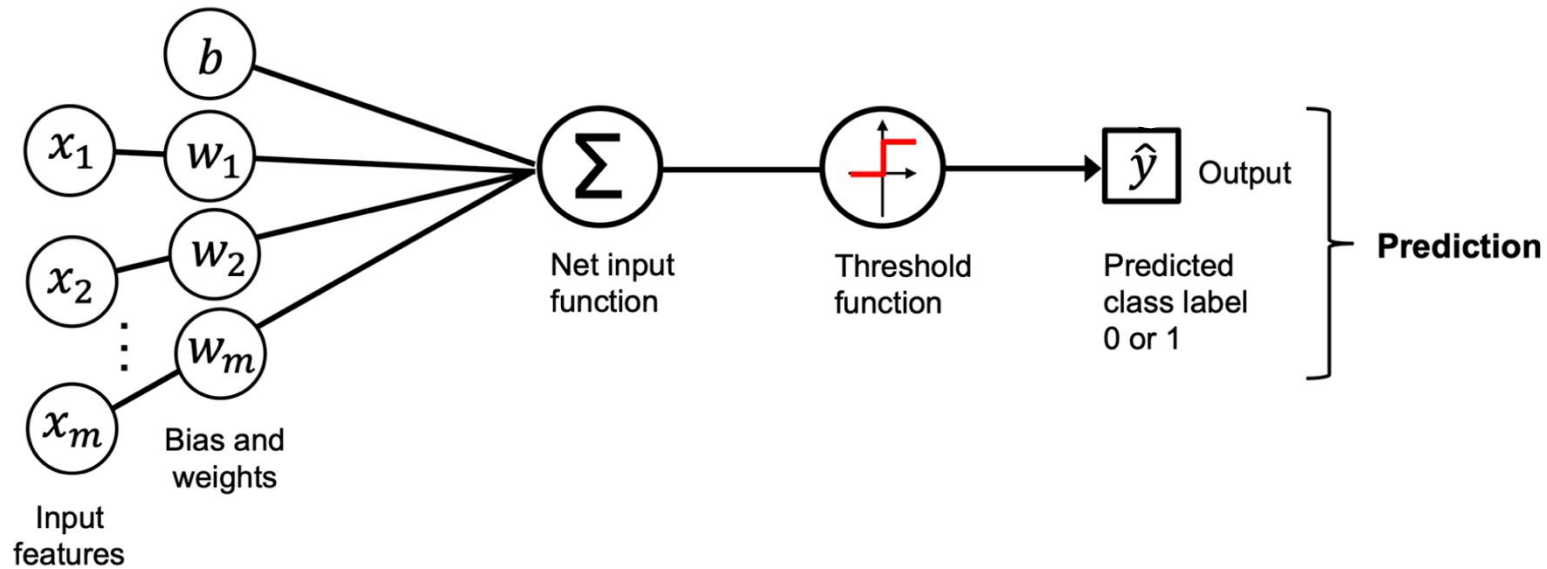


# Python

- See Jupyter Notebook

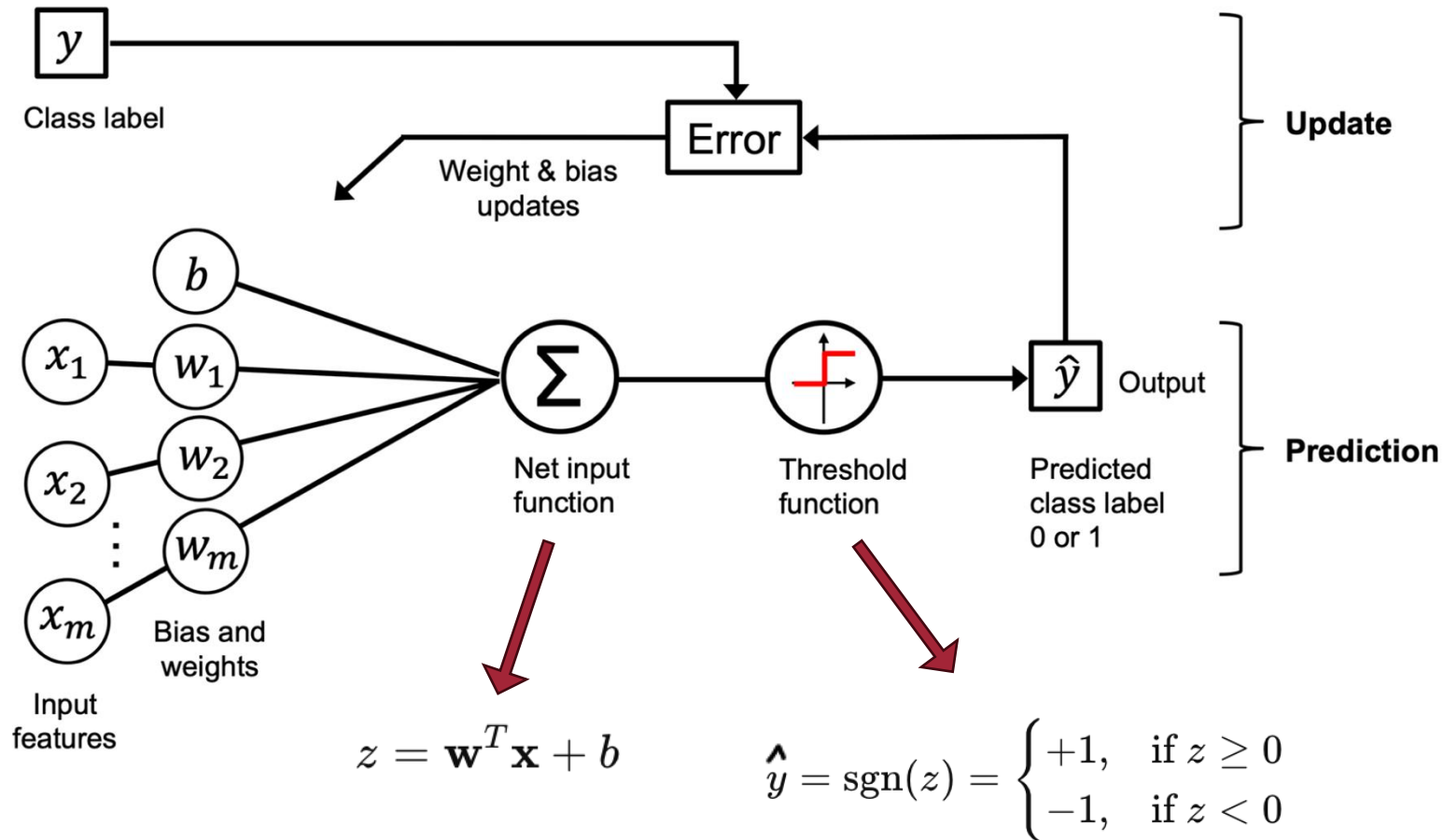
# McCulloch-Pitts (MCP) neuron model

- Pre-determined weights, no learning capability



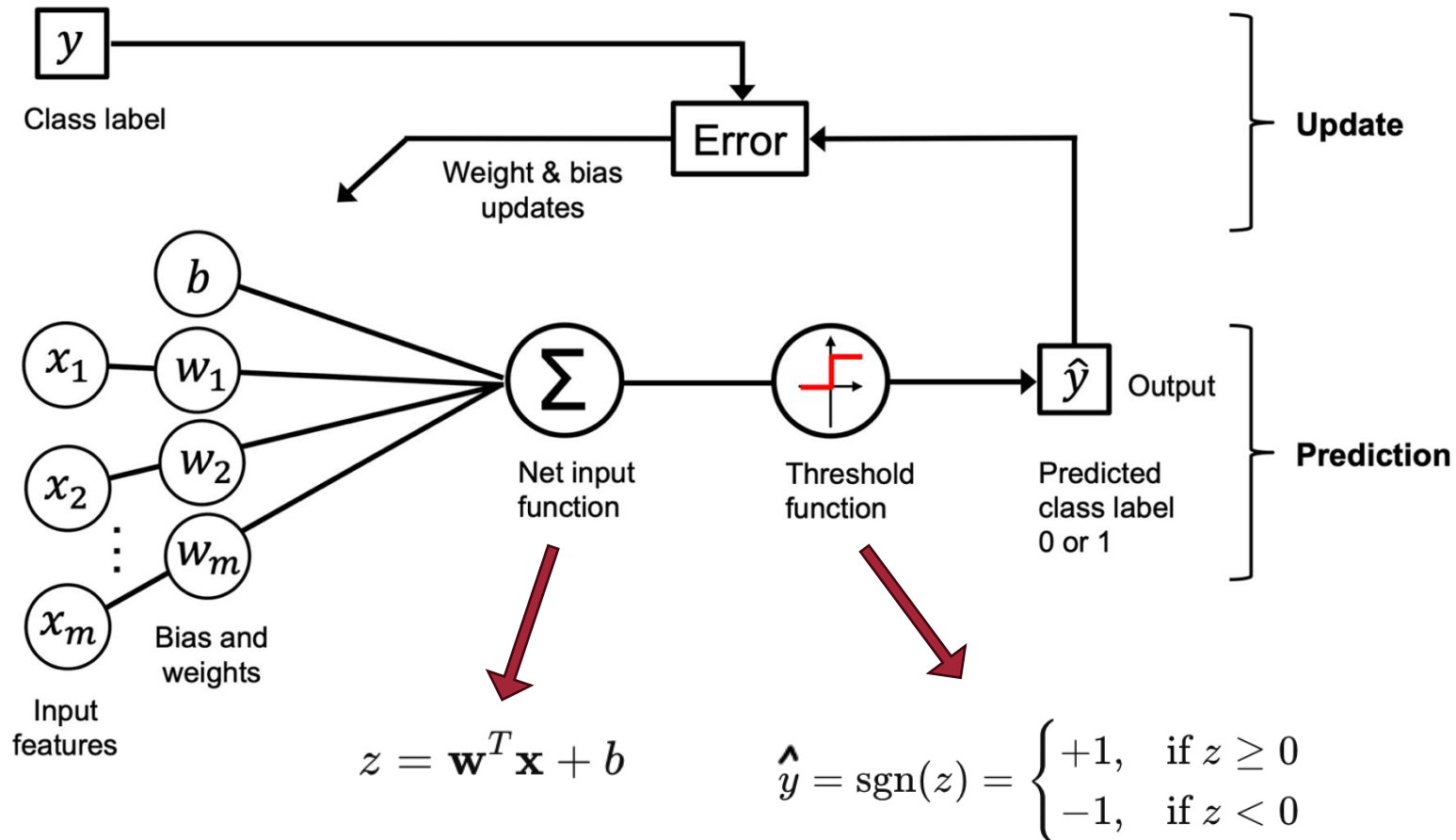
# Rosenblatt's perceptron model

- Proposed an algorithm that would automatically **learn the optimal weight** coefficients



# Key idea to adjust the weight (and bias)

- If predicted label is 1, but the actual label is 0, we want to reduce the weight
- If predicted label is 0, but the actual label is 1, we want to enhance the weight





# The perceptron learning rule

1. Initialize the weights and bias unit to 0 or small random numbers
2. For each training example,  $x^{(i)}$ :
  - a. Compute the output value,  $\hat{y}^{(i)}$
  - b. Update the weights and bias unit

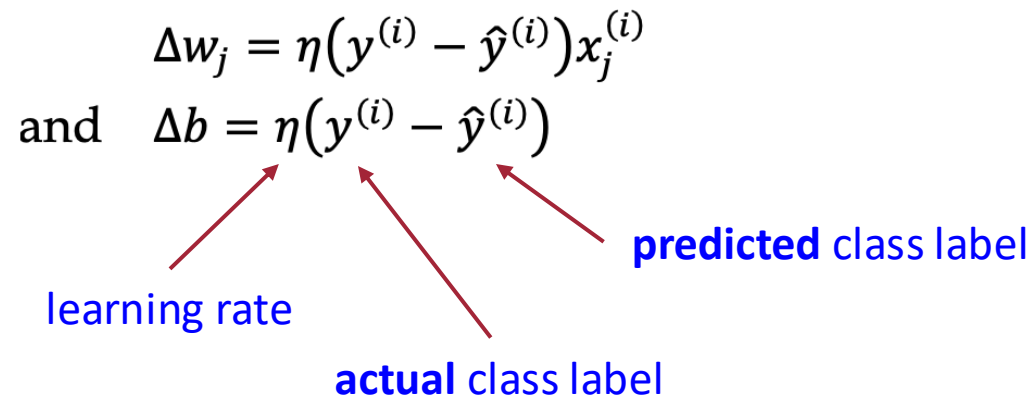
$$w_j := w_j + \Delta w_j$$

and  $b := b + \Delta b$

The update values (“deltas”) are computed as follows:

$$\Delta w_j = \eta(y^{(i)} - \hat{y}^{(i)})x_j^{(i)}$$

and  $\Delta b = \eta(y^{(i)} - \hat{y}^{(i)})$



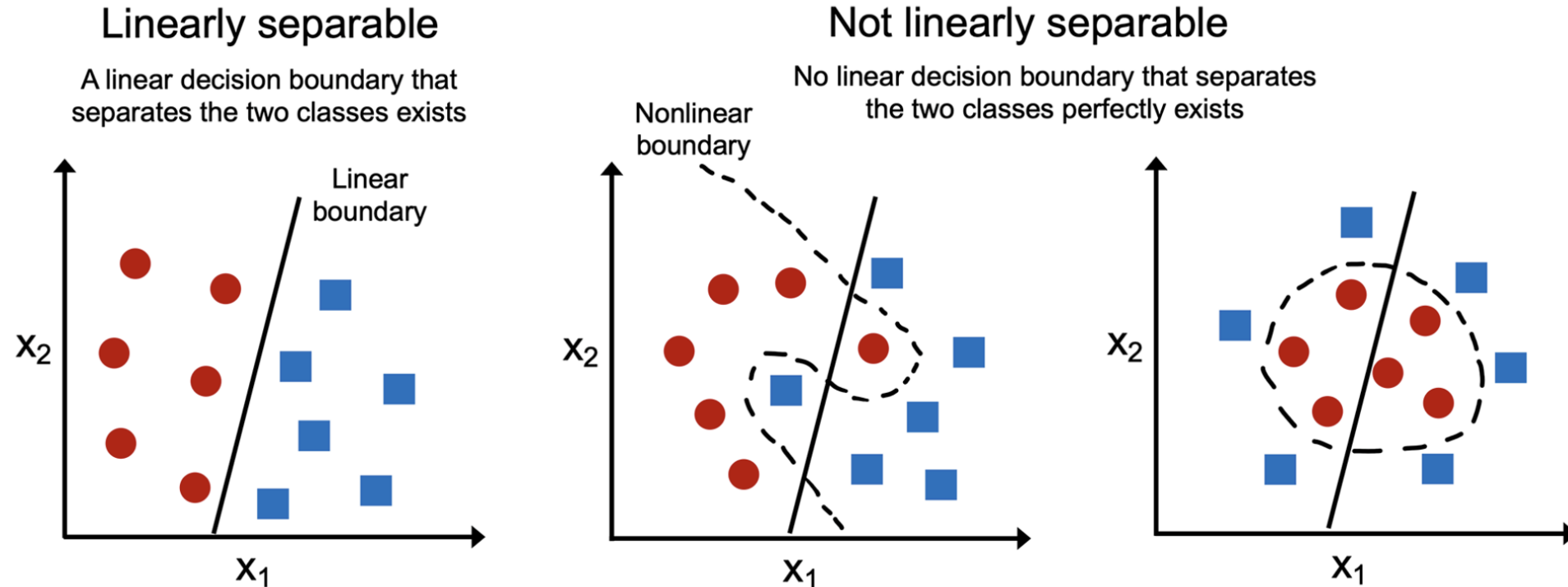
learning rate

actual class label

predicted class label

# Applicable to linearly separable data only

- The algorithm finds the linear decision boundary after certain number of iterations (**epochs**)



# Implementation

- See jupyter notebook

