Principles of Machine Learning

THE PERCEPTRON: A MODEL FOR INFORMATION STORAGE AND ORGANIZATION IN THE BRAIN

Parsa Inanloo

Sharif University of Technology
Dept. of Aerospace Engineering

March 4, 2025

Table of Contents

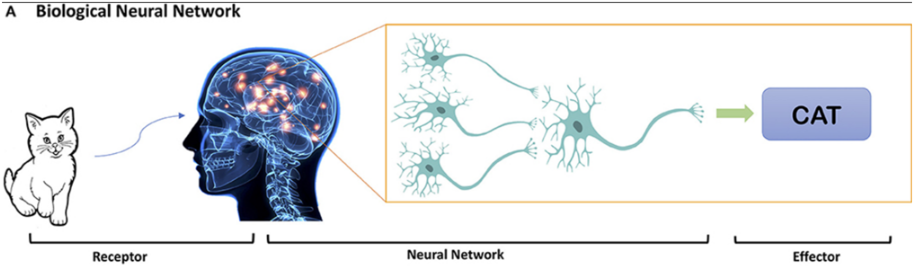
Outline

Fundamental Questions in Neural Information Processing

- **Sensing:** How are physical stimuli (e.g., light, sound) detected by our sensory organs?
- **Storage:** In what form is the sensory information stored in the brain?
- **Influence on Behavior:** How does stored information affect recognition and guide our behavior?

These questions set the stage for understanding neural network models.

Information Processing

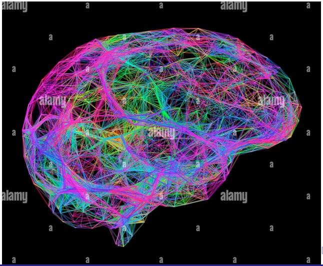


Representational (Coded) Memory Model

- **Concept:** Each stimulus is stored as an exact “picture” or code.
- **Mathematical Representation:** Think of it as storing a function or vector $\mathbf{x}$ that represents the stimulus.
- **Advantages:**
  - Direct matching between input and stored representation.
- **Challenges:**
  - Requires an exact one-to-one mapping.
  - Highly sensitive to noise and variations.

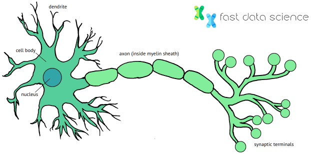
Connectionist (Associative) Memory Model

- **Concept:** Information is stored in the strengths of connections between neurons.
- **Neural Representation:** Instead of an exact code, the stimulus is represented by a pattern of activity over many neurons.
- **Advantages:**
  - Robust to noise and minor variations.
  - Better generalization for similar but not identical inputs.
- **Mechanism:** Learning occurs by adjusting connection weights via reinforcement (positive or negative).

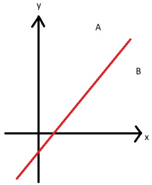


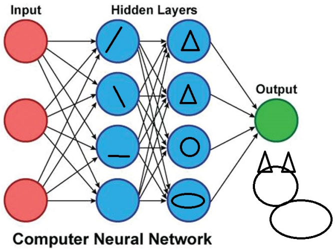
Why the Perceptron?

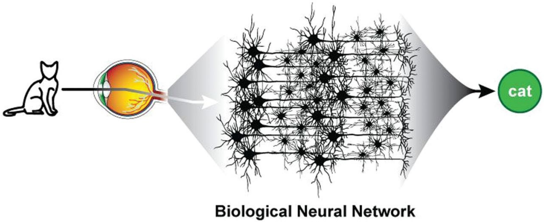
- The Perceptron integrates the ideas of the connectionist model.
- It provides a simple yet powerful framework for classification:
  - Inputs (from the sensory layer) are processed by an intermediate layer.
  - The network adjusts its connection weights based on experience (reinforcement learning).
  - A final decision (classification) is produced by the response units.
- It overcomes the limitations of the representational approach by being more flexible and robust.



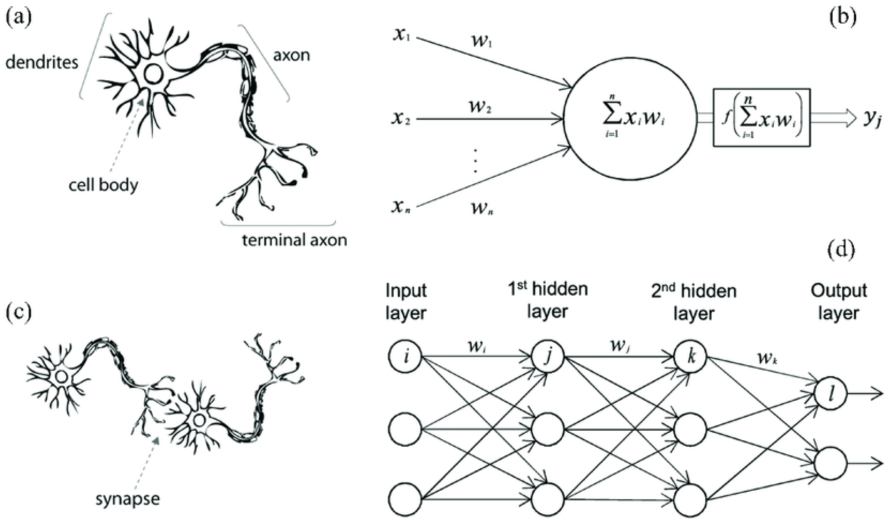
How Perceptron works







Mathematical and Neural View of the Perceptron



Five Fundamental Assumptions Underlying the Perceptron

- **1. Random Initial Connectivity:**
  Initially, the neural connections are largely random (subject to basic genetic constraints).
- **2. Neuronal Plasticity:**
  Neurons are capable of change—the connections adjust with activity and experience.
- **3. Formation of Common Pathways for Similar Stimuli:**
  With repeated exposure, similar stimuli tend to activate common groups of neurons, while dissimilar stimuli activate different pathways.
- **4. Role of Positive and Negative Reinforcement:**
  Reinforcement (reward or punishment) modulates the strength of connections, guiding the learning process.
- **5. Relative Definition of Similarity:**
  Similarity is not inherent only in the stimuli's physical features but also depends on how the neural system organizes and processes these features over time.

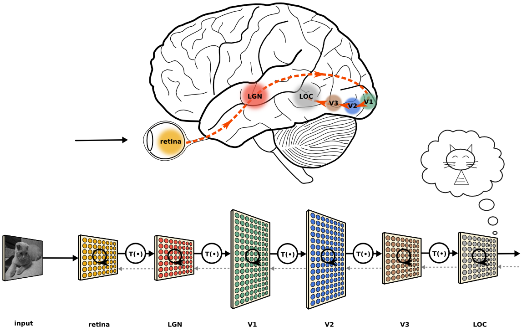
Outline

Overview of the Perceptron Architecture

- The Perceptron is designed to mimic basic properties of biological neural networks.
- It processes sensory input, performs intermediate processing, and finally produces a decision.
- Key components include:
    - Sensory Layer (S-Points)
    - Projection / First Association Stage (A-units)
    - (Optional) Second Association Stage (A2)
    - Response Units (R-units)
    - Feedback mechanisms for competitive decision-making

Sensory Layer (S-Points)

- **Role:** Detect raw stimuli (e.g., light on a retina).
- **Response:** Operates in an all-or-none (binary) fashion, or sometimes proportional to stimulus intensity.
- **Output:** Provides the initial input signals to the network.



Projection Area / First Association Stage (A-units)

- **Role:** Acts as the first processing stage where sensory inputs are integrated.
- **Connectivity:**
  - Each A-unit receives inputs from a subset of S-points.
  - Connections are spatially clustered; the number of inputs decreases with distance from a central receptive field.
- **Function:** This clustering aids in detecting features such as edges or contours.

Second Association Stage (Optional A2)

- In more complex models, a second association area further processes the outputs of the first A-units.
- **Connectivity:**
  - Connections between A1 and A2 are random, helping to distribute the information and improve robustness.
- **Note:** Many initial analyses combine these stages for simplicity.

Response Units (R-Units)

- **Role:** Produce the final output or decision of the network.
- **Input:** Each R-unit receives inputs from a specific group of A-units (its source-set).
- **Mutual Exclusivity:** R-units are organized such that when one becomes active, it suppresses the activity of others.
- **Outcome:** Only one response emerges as dominant, representing the system's decision.

Simplified (Two-Layer) Perceptron Model

- To simplify analysis, a version of the Perceptron is often used with only one association stage directly connected to the response units.
- **Structure:**
  - Sensory units (S) connect directly to A-units.
  - A-units then connect to R-units.
- **Feedback:** Even in this simpler model, feedback (especially inhibitory) is crucial to select a single dominant response.
- **Key Idea:** The simplification still preserves the essential features of distributed representation and competitive decision-making.

Key Points Recap

- **Feedforward Processing:** Information flows from S-points $\rightarrow$ A-units $\rightarrow$ R-units.
- **Local Receptive Fields:** A-units receive inputs from clustered regions of the sensory layer, aiding feature detection.
- **Feedback and Competition:** Inhibitory feedback among R-units ensures that only one response is ultimately activated.
- **Distributed Memory:** Memory is not stored in a single unit but across many A-units, making the system robust against noise and damage.

Conclusion of the Architecture Section

- The Perceptron architecture illustrates how a network with simple binary units and random initial connections can learn to recognize patterns.
- It combines both feedforward and feedback processes to achieve a stable, dominant response.
- This model laid the foundation for modern neural network research and continues to influence machine learning.