Informatics 1 Cognitive Science

Lecture 23: Learning and Memory Part 3

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Overview

Learning

Learning

Learning is an adaptive change in the nervous system that supports the acquisition, storage, and updating of knowledge, skills, and behaviors.

Non-associative learning Changes due to repeated exposure, habituation and sensitisation.

Associative learning Relationships between stimuli or actions and outcomes, e.g. classical and operant conditioning.

Statistical learning Detecting regularities, transition probabilities or co-occurrences.

Concept formation Building explicit representations of categories, rules, and abstract relationships.

Reinforcement learning Learning to act based on rewards and punishments.

Observational and social learning Modelling and imitation, may involve vicarious reinforcement.

Supervised Learning

- Assumes a teaching signal exists: Memory representations are modified according to an error or objective function (e.g. data labels, a desired task outcome and so on).
- Example: The perceptron rule or the backprop algorithm with error function.
- Powerful but requires careful specification of the objective, and brain circuits dedicated to computing it.

Unsupervised Learning

- A learning rule that builds useful representations from data ("structure from data", e.g. from sensory inputs).
- Examples: Principal Component Analysis, clustering and density estimation more generally.
- Recent ML methods: self-supervised learning, contrastive learning, generative models.
- Thought to underlie development of early sensory representations in the cortex.

It is currently unclear how much the brain can/does learn in a purely unsupervised manner.

Hebbian Plasticity

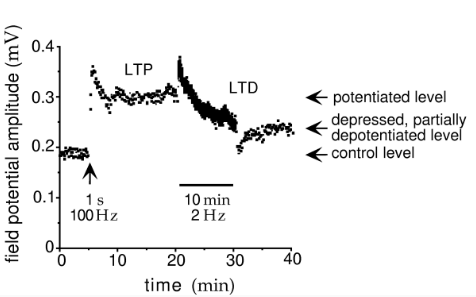
The basis of (most) learning: Hebbian Plasticity

In 1949 Donald Hebb, who was thinking about reverberating loops in networks of neurons, postulated that:

“When an axon of cell A is near enough to excite cell B or repeatedly or consistently takes part in firing it, some growth or metabolic change takes place in one or both cells such that A’s efficiency, as one of the cells firing B, is increased.”

“Cells that fire together wire together”

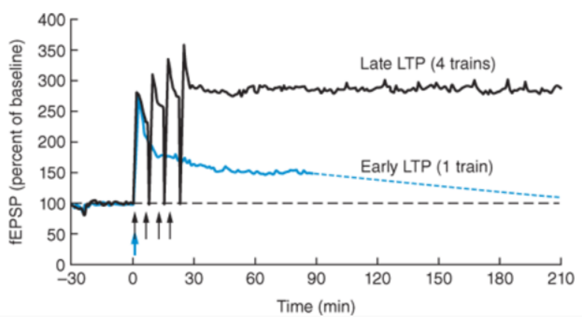
Synaptic Plasticity, the Basis of Memory



Depending on the input and activity of a neuron, a synapse can either show *long term potentiation* (LTP) or *long term depression* (LTD). These changes can persist for a long time (at least for months).

Discovered by: Bliss, T.V.P. and Lomo, T., J. Physiol. 232 (1973), pp. 331–56.

Early and Late LTP



A weak stimulus causes short-lasting LTP, while a strong stimulus causes permanent LTP (depends on protein synthesis).

A Model of neural Hebbian plasticity

A simple mathematical model of Hebbian Plasticity

Idea: “Neurons that fire together, wire together.”

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Activity of a neuron (e.g. firing rate):

$$y = f\left(\sum_{j=1}^{N} w_j x_j\right) = f(\mathbf{w} \cdot \mathbf{x})$$

where **w** are synaptic weights and **x** are input activities.

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Weight changes:

$$\begin{aligned}\Delta w_i &= \epsilon y x_i \\ &= \epsilon x_i \sum_{j=1}^{N} w_j x_j\end{aligned}$$

where ϵ is a small constant learning rate.

Is this model sufficient to explain learning?

The weights simply track the correlations between inputs and output activity:

$$\Delta w_i \quad = \quad \epsilon y x_i$$

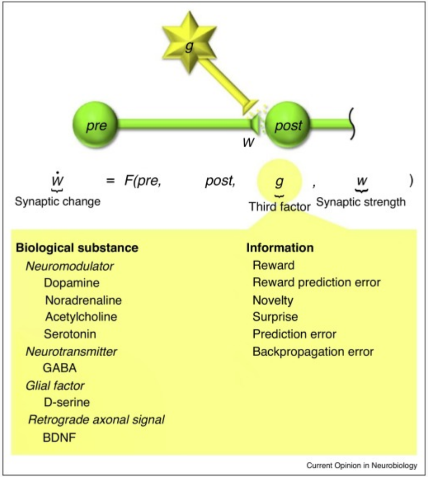
Problems:

- Learning is unstable: Potentiation causes more potentiation, weights and activity grow to infinity.
- The learning rate ϵ determines the speed of learning. If large (e.g. for very fast, one-shot learning), learning is fast, but even more unstable.

Plausible solutions:

- A bounded w_{ij}.
- Weight decay: $\Delta w_i = -\epsilon(yx_i - w_i)$.
- Covariance rule: $(y- < y >)(x_i- < x_i >)$.

Supervised learning: three-factor leading



A third factor in a learning rule can be added to act as supervisory signal.

Hebbian Assemblies

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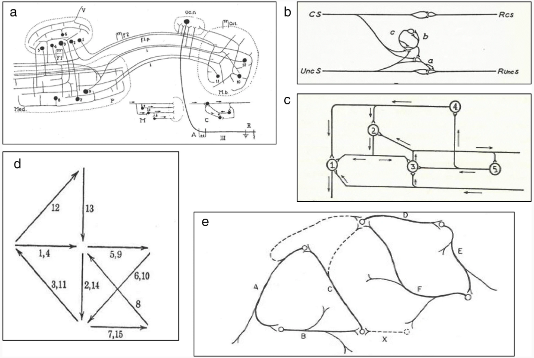
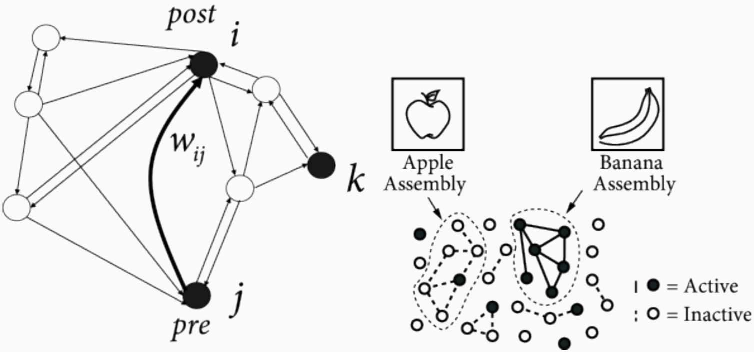


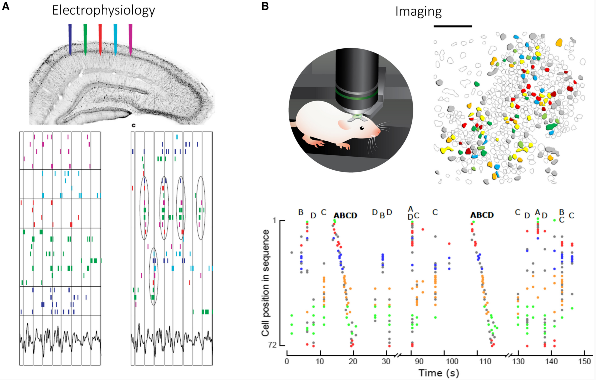
Hebb suggested reverberatory activity underlies learning and memory (1949): (a) Oculo-motor circuits, (b) simple conditioning circuit model, (d) a reverberating circuit, (d) schematics of a reverberating circuit (a Hebbian assembly) (e) two assemblies A-B-C and D-E-F (in an association cortex), where synapse strengthening leads to reverberation in the circuit.

Hebbian Assemblies



Assemblies can arise from stimulation of a subset of input neurons, where plasticity leads to a stable representation of the input by recruiting additional neurons.

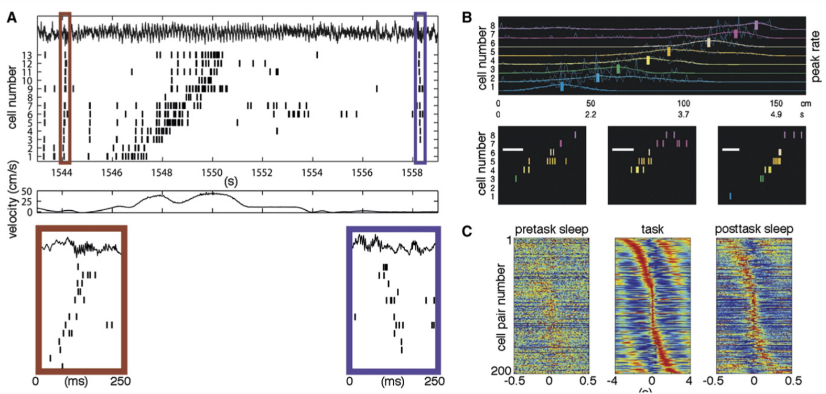
Hebbian Assemblies in Hippocampus



Hippocampal activity during spatial exploration (colours code for recording locations), assemblies become visible by re-arraigning the activity patterns.

Yuste, R., Cossart, R., & Yaksi, E. (2024). Neuronal ensembles: Building blocks of neural circuits. Neuron.

Hebbian Assemblies in Hippocampus



Sequences of place cells during navigation are replayed during rest (A) or sleep (B).

Buzsáki, G. (2010). Neural syntax: cell assemblies, synapsembles, and readers. Neuron, 68(3), 362-385.

Summary

- Learning takes many forms: supervised, unsupervised, reinforcement, statistical, etc.
- A key neural mechanism is synaptic plasticity (LTP/LTD): connections change with activity correlations
- Hebbian plasticity can support the formation of cell assemblies and replay-like dynamics linked to memory.