Hippocampal indexing and cortical hierarchies: the drivers of quasi-continuous learning

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Driving Applications: Lifelong Learning Machines (L2M)

Introduction

- Existing Artificial Intelligence (AI) systems are generally unable to adapt beyond what they have been trained in advance to do
- Animals and humans are capable of learning from experience, quick adaption to new tasks and effective combination of the past and recent knowledge for effective task solving
- To understand critical principles behind brain inspired continuous learning, we apply a combination of state of the art experimental techniques and advanced modeling

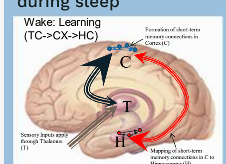
Objectives

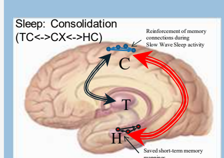
Our overall goal is to address L2M objectives by developing new machine learning mechanisms capable of continuous learning and quick adaptation to new tasks and situations based on principles utilized by the brain plastic nodal (neuronal) networks (PNNs). To accomplish it, we plan:

- To test experimentally and implement in computer models critical elements of the neuronal PNNs – reward driven selective plasticity, off-line memory consolidation, hierarchical memory structure
- To apply these principles to demonstrate (a) Continual learning and Adapting to new tasks based on the PNN ability to apply knowledge learned for one memory category to the other recently learned memory categories; (b) Selective plasticity taking advantage of hierarchical memory structure allowing to keep stable primitive memory categories and to modify higher level categories to balance stability and plasticity
- To test and implement memory retrieval mechanisms based on neuronal network attractor dynamics as a solution for fast and efficient Goal driven perception

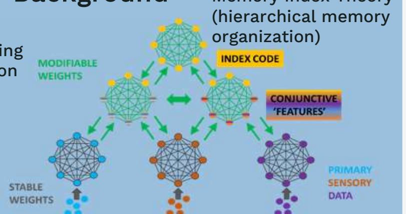
Background

Two stage theory of memory formation: learning in awake and consolidation during sleep

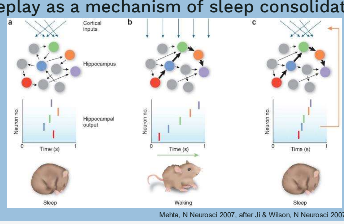




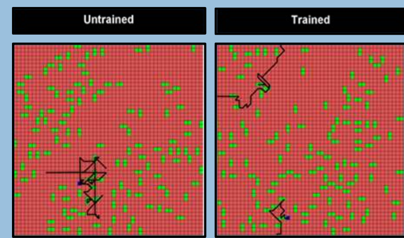
Memory Index Theory (hierarchical memory organization)

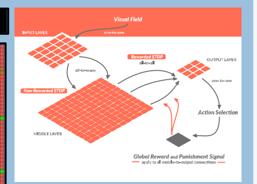


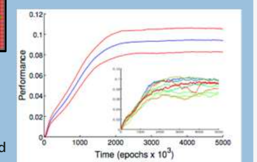
Replay as a mechanism of sleep consolidation



Classic Reinforcement Learning Task: Simple foraging in 2D environment

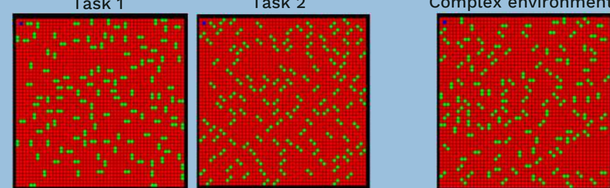






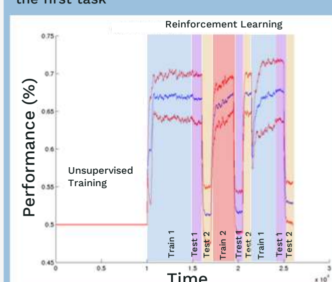
- Network design is based on spiking neurons and implements various plasticity mechanisms
- Input layer: Unsupervised training in spiking neural network with STDP performs basic convolution task, similar to input layers of CNN
- Hidden layer: Reinforcement Learning based on rewarded STDP assigns "value" to specific input patterns to drive successful learning

Multiple Tasks Learning

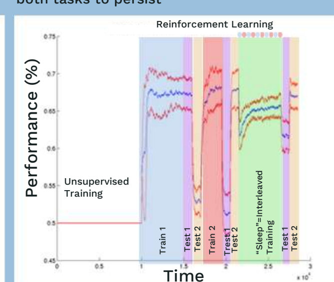


Task 1 goal is to acquire "–" and avoid "|". Task 2 goal is to acquire "/" and avoid "\"

Catastrophic Forgetting: The network is able to learn a task but when a second task is introduced there is complete forgetting of the first task

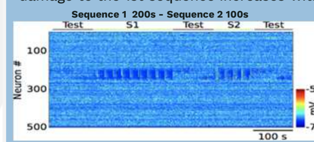


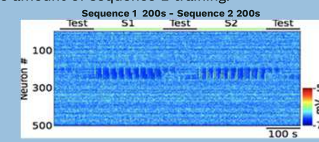
Simulated Sleep Replay (Interleaved Training): Sleep simulated through interleaved training allows for memories of both tasks to persist



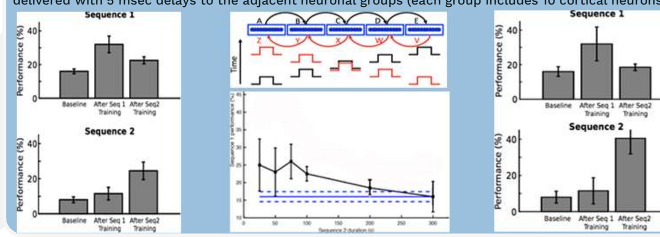
Biophysical Model of Sleep Consolidation in Thalamocortical Network

Training new memory damages old memories ("catastrophic forgetting"): For completely overlapping two sequences trained in the opposite network directions, learning second sequence (S2) causes damage of the first sequence (S1). The amount of damage to the 1st sequence increases with the amount of sequence 2 training.



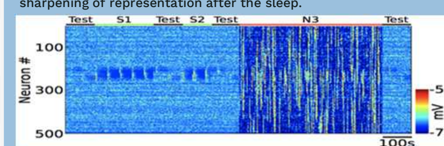


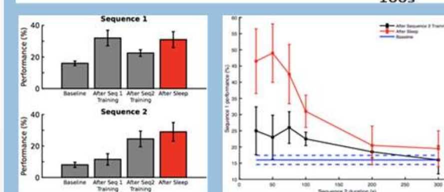
Two memory sequences (ABCDE and VWXYZ) are trained in the opposite network directions and include overlapping groups of neurons. Training - ordered sequence of stimuli (red or black pulses below) delivered with 5 msec delays to the adjacent neuronal groups (each group includes 10 cortical neurons).

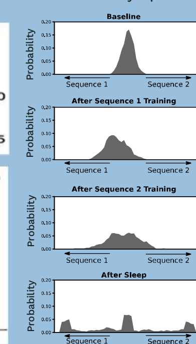


Sleep can recover damage during multiple tasks training: A period of deep sleep (N3) after training can recover damage of Task 1 (S1) memory, but only if it remains above some threshold before entering sleep. Sleep improves performance of both Task 1 and Task 2 memories. Sleep leads to fine synaptic weights tuning to maximize separation between two memories.

Below Right: Distribution of synaptic weights for all pairs of neurons from trained region. X axis – relative strength of S1 or S2 synapses for each pair of neurons. Middle of X axis represents pairs with equal strength of S1 and S2 synapses. Extreme left (right) are pairs with unidirectional synapses. Note sharpening of representation after the sleep.

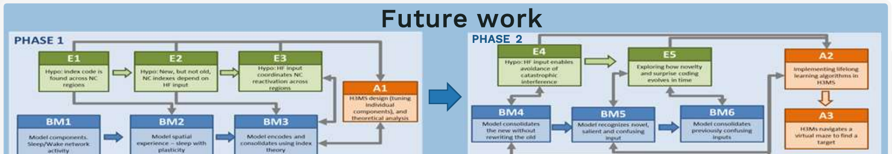






Synaptic weights separation may lead to formation of the state attractors. Inputs falling within an event horizon (green ball) lead to "pattern completion' and recall.

Future work



Conclusions from pilot studies

- Sleep replay of old and new memories helps to avoid damaging old memories. This suggest a solution for catastrophic forgetting problem
- Sleep replay is local which allows only specific (relevant to the new learning) sets of neurons and synapses to participate in synaptic changes

THE ELECTRONICS RESURGENCE INITIATIVE

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