Avoiding Cross-Talk Interference during the Sequential Learning of Multiple Skills

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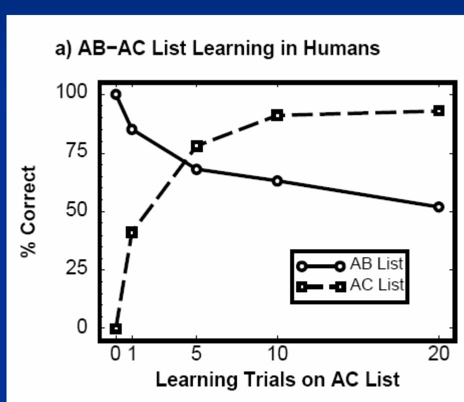
Savings in AB-AC List Learning



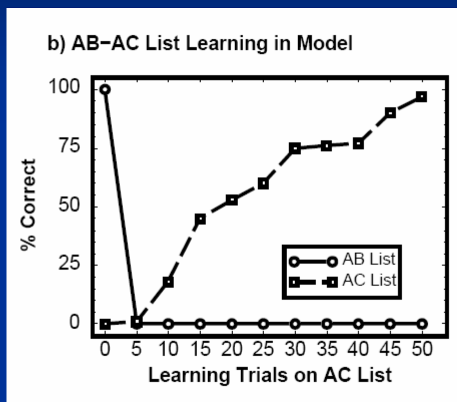
A – B list:

- Chair – Table
- Boy – Girl
- Head – Hand
- …

A – C list:

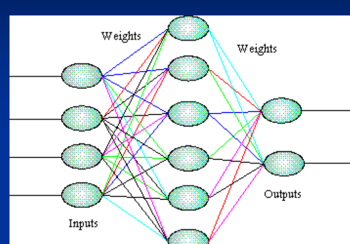
- Chair – Cushion
- Boy – Man
- Head – Hair
- …

Catastrophic Interference



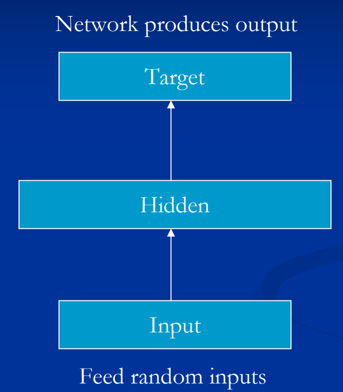
- Traditional artificial neural network models immediately and completely forget old information when trained on something new

Catastrophic interference in artificial neural networks



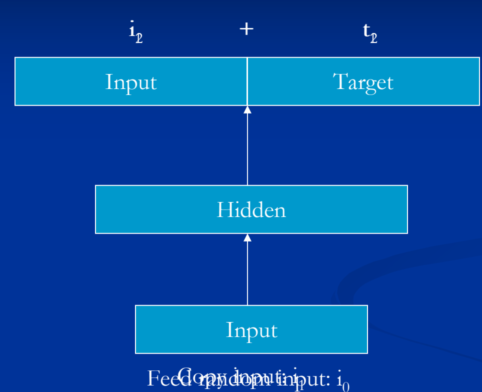
- Typically, any task is learned in terms of weights distributed across the entire network
- Weights change when the network is presented with a new input, making it abruptly and completely forget previous learning

Solution#1: Retraining



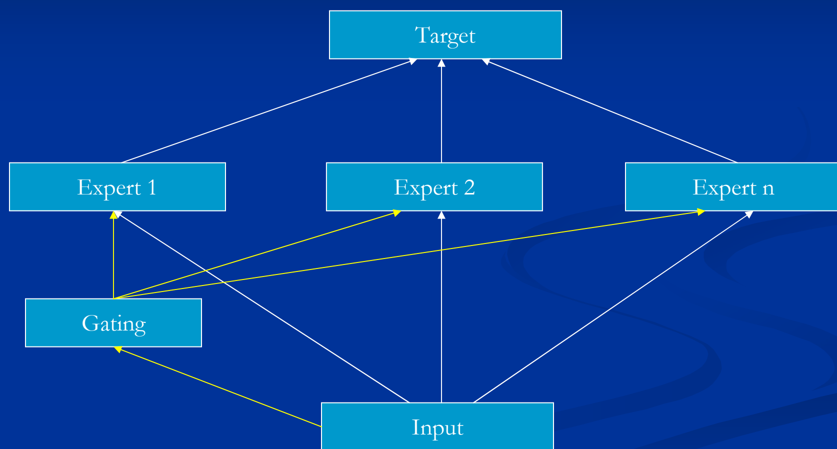
Random input and the network output could be used as a representative of the previous training data

Sampling from input distribution

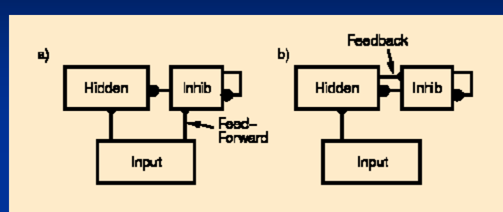


Attractor state input and the corresponding output could be used as a representative of the previous training data

Solution#2: Modular Architecture



Lateral inhibition…



- About 15% of the neurons in any area of the brain are inhibitory
- Give rise to set point type behavior
- Inhibition is fast

(O'Reilly and Munakata, 2000)

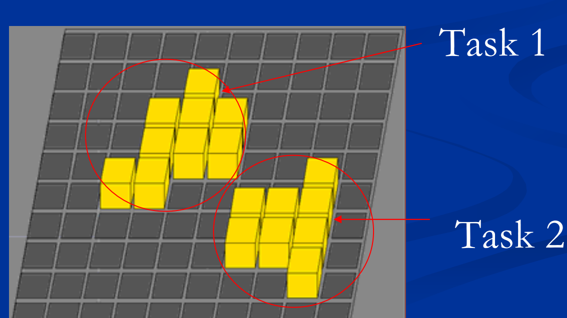
Lateral Inhibition

- Leabra (Local Error driven and Associative Biologically Realistic Algorithm) uses kWTA (k-Winners-Take-All) function to capture the effects of lateral inhibition

- The probability that the k units used to learn the first task will be different from the second task increases as k becomes smaller

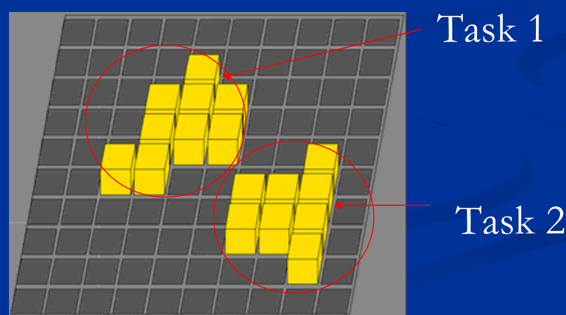
Solution#3: sparse representation…

- A small subset of neurons are used encode the knowledge of a particular task
- Subsequent tasks use a largely different set of neurons



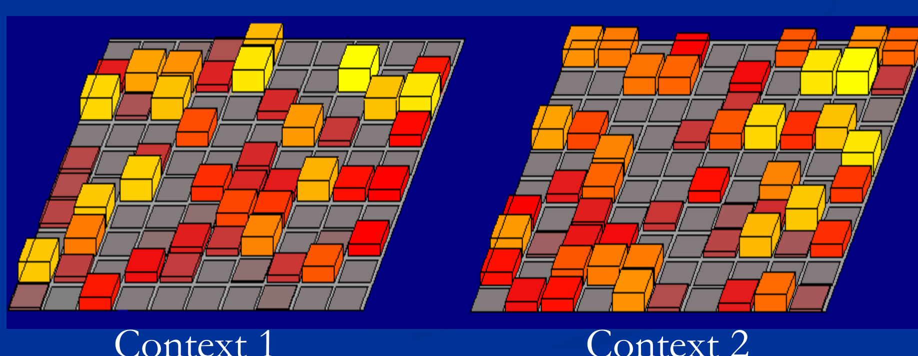
…Savings via sparse representation…

- Weights from previously learned task are not tweaked while learning the new task



Contextual cues

- Usually, there are distinct sensory or internal control cues that are associated with different tasks



Strengths and weaknesses of various approaches

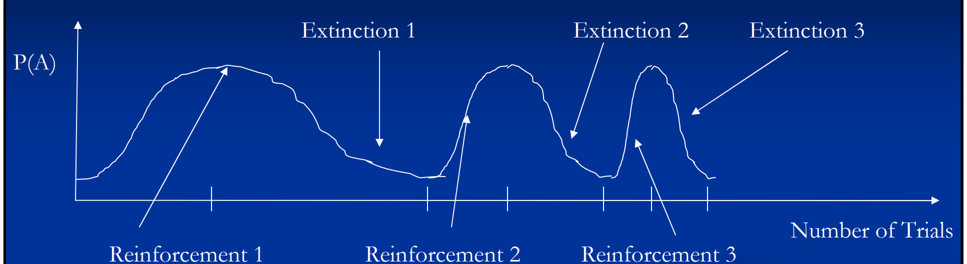
	Pseudo-patterns	Sparse Representation	Modular Architecture
Savings	Good	Good	Good
Space	None	None	None
Continuous Valued Data	Works	Works	Works
Biology	Plausible	Plausible	Questionable
Generalization	-	Limited	Limited
Scalability	-	To be tested	Best

Strengths and weaknesses of various approaches

	Pseudo-patterns	Sparse Representation	Modular Architecture
Training Time	Slowest	Fast	Fast
Processing Requirements	-	-	Maximum
Noisy Data	-	Good noise resistance	-
Conflicting patterns	Fails	Works	Works

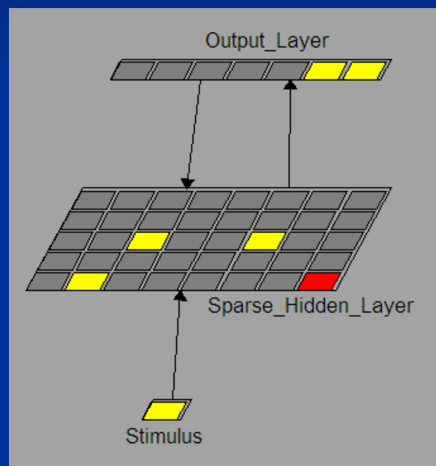
Thanks!

Savings in Conditioning

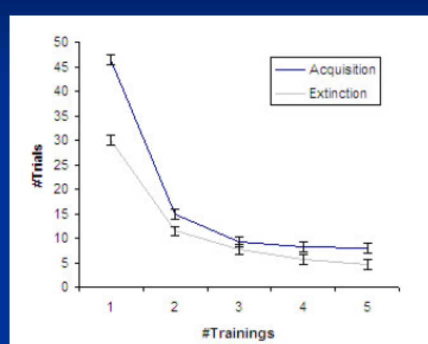


The Network

Acquisition



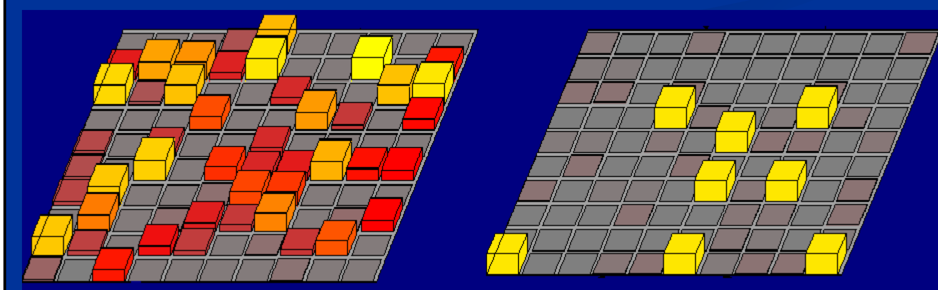
Simulation Results



- The neurons in the two pathway suppress each other via lateral inhibition
- Hence, the plasticity in the two pathways is

Measure of Sparsity

- Percentage of active units in a layer
- Smaller percentage implies greater sparsity

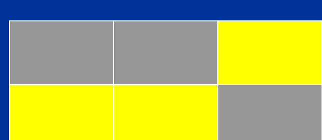


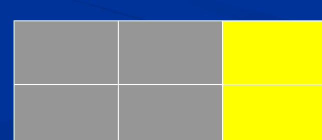
Not Sparse   Sparse

Measure of Segregation between representation

- Compute the percentage of common active units for the two tasks
- Take the maximum of the two values
- A smaller value signifies more segregation

$$\% \text{ common} = \frac{\text{common active units}}{\text{total number of active units}} \times 100$$

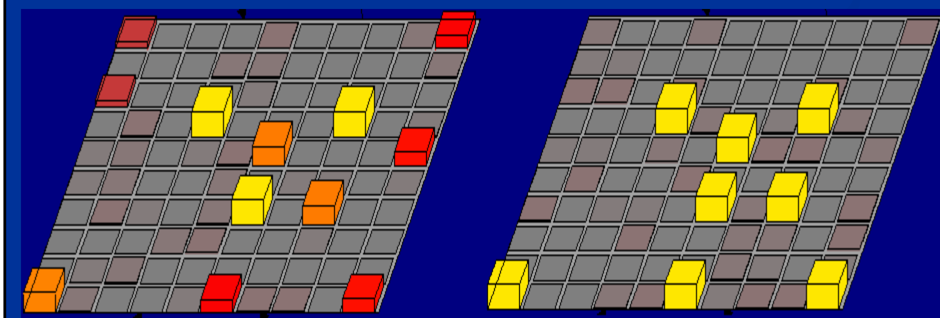




% common = (1/3) x 100 = 33%   % common = (1/2) x 100 = 50%

Extensive training

- Due to Hebbian learning along with lateral inhibition, over-training causes some of the units to strengthen their weights and suppress the activity of other units
- This results in sparser representation and greater savings



Learned to criterion   Over-learned