Introducing CAL: Context-Aware Learning

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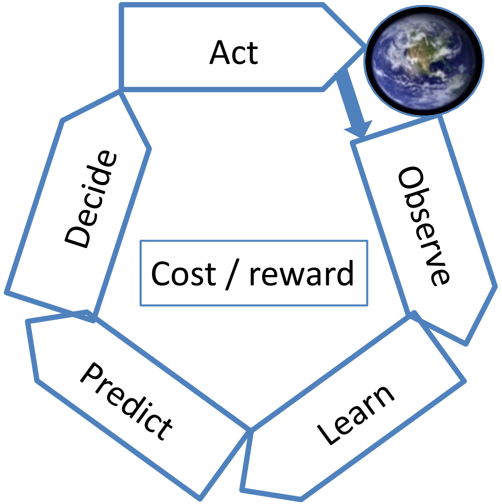
Goal: Design a robust system capable of learning by multimodal observation, continuously and unsupervised, predicting, (ultimately) making decisions and acting on them.

Outline

1. Architecture of network
2. Algorithms
3. Components: test and demo
    1. Static correlation
    2. Sequence memory
    3. Temporal pooling and correlation
    4. Feedback
4. Predicting chaos – double pendulum
5. Scaled network – auto-encoding of sequences
6. Summary



Summary of take-home messages

Design

- Neurological inspiration
  - Neurons in mini-columns, cortical *layers* (L-I .. L-VI) and hierarchy (*levels*)
  - Driving and modulating synapses, (modified) Hebbian updates
  - Stable network via homeostasis
  - Avoid catastrophic forgetting
- Simplicity
  - Binary neurons and synapses, sparse neural activity, sparse synapse connections
  - A few canonical functions: correlation, sequence learning, feed-forward with temporal pooling, feedback
- Importance of time
  - Learn to predict

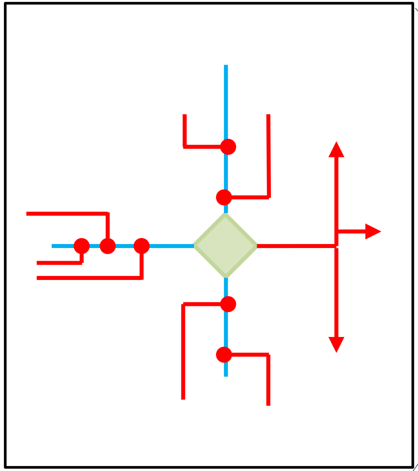
Results

- Emergent invariance
  - Invariant representations generated in higher levels of hierarchy

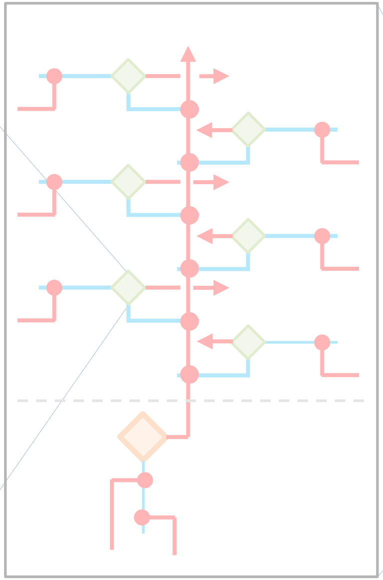
- Context for current (driving) input provided by modulating synapses

CAL architecture: biologiCAL

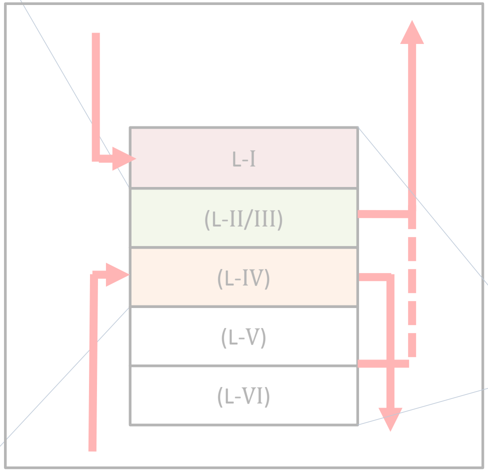
Cellular scale
- ~ 5 μm
- Neuron, axons, dendrites, synapses



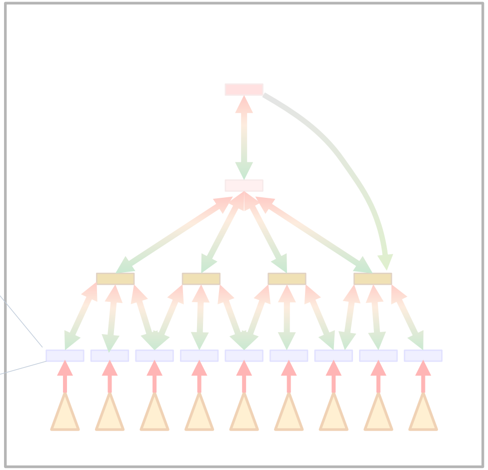
Micro scale
- ~ 100 μm
- Mini-column



Meso scale
- ~ 1 mm
- Region of cortical sheet
- Components are layered

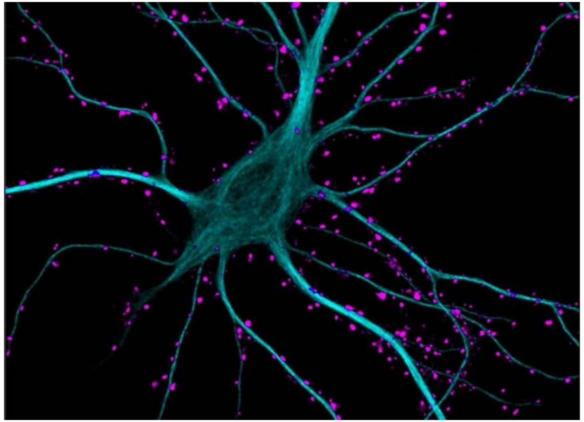


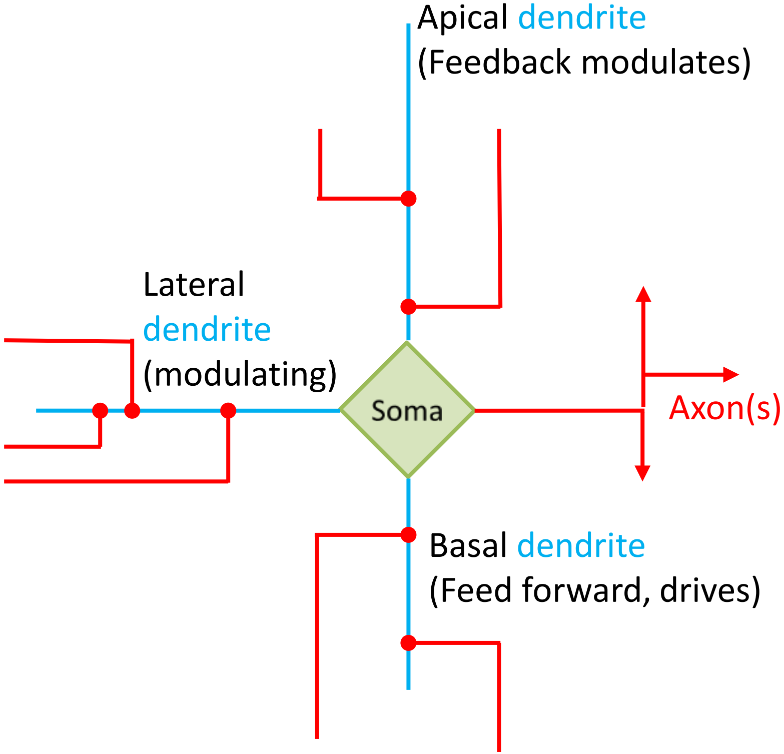
Macro scale
- ~ 10 cm
- Hierarchical network of cortical “regions”



Cellular scale – single neuron

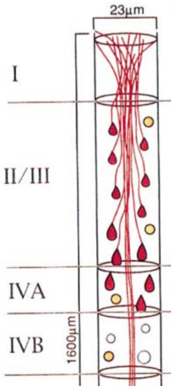
- Soma
- Dendrites (receive input)
  - Driving (basal)
  - Modulating (lateral and/or apical)
- Axons propagate output
- Synapses



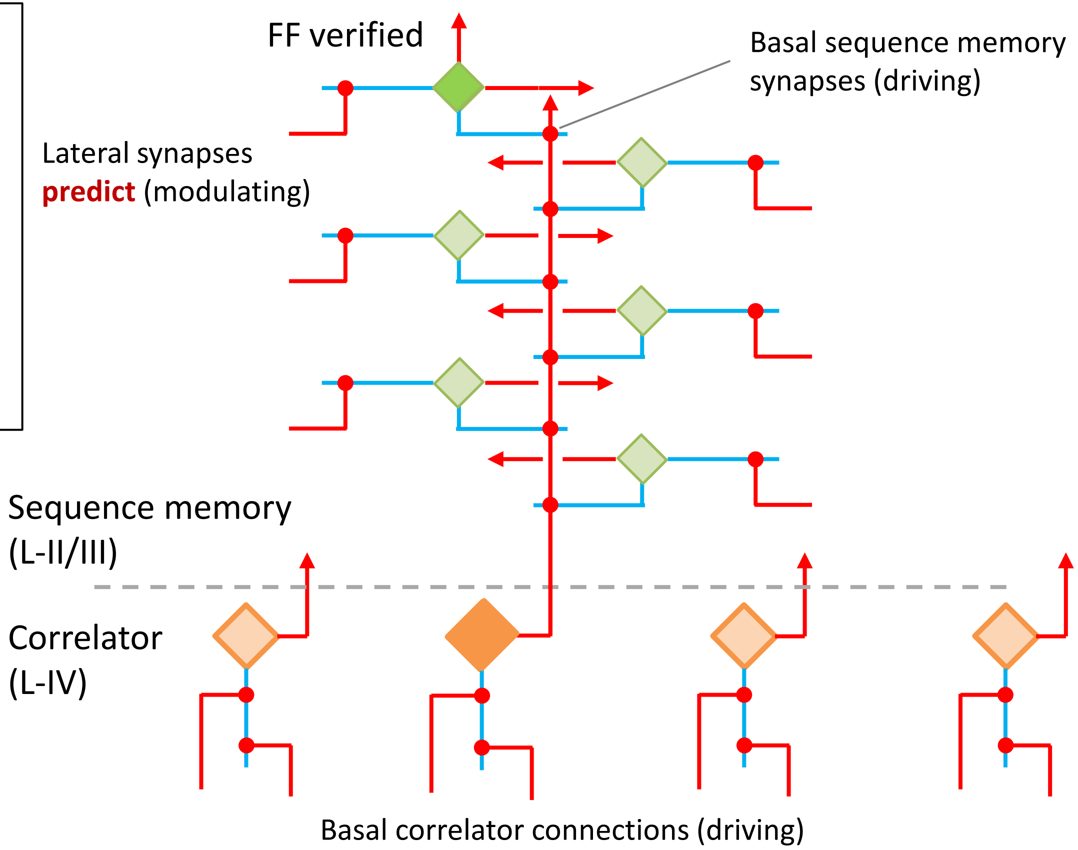


Micro scale – mini-column

- Basic neural "circuit"
- Correlator is (layer of) L-IV cells
  - Driven by synapses on basal dendrite
  - Drive L-II/III cells via their basal synapses
- Sequence memory is (layer of) mini-columns
  - Mini-column defined by common L-IV cell
  - L-II/III cells connect laterally to modulate

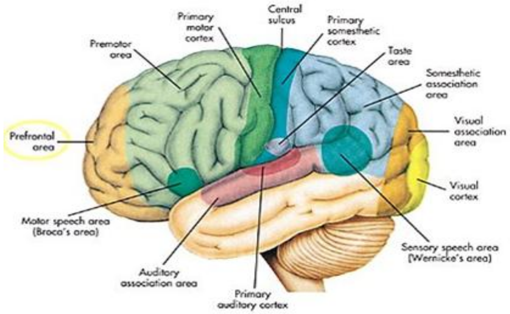


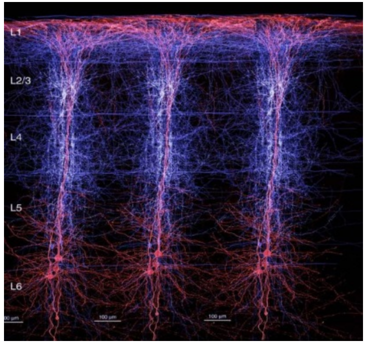
[From Mountcastle Brain, 1997]



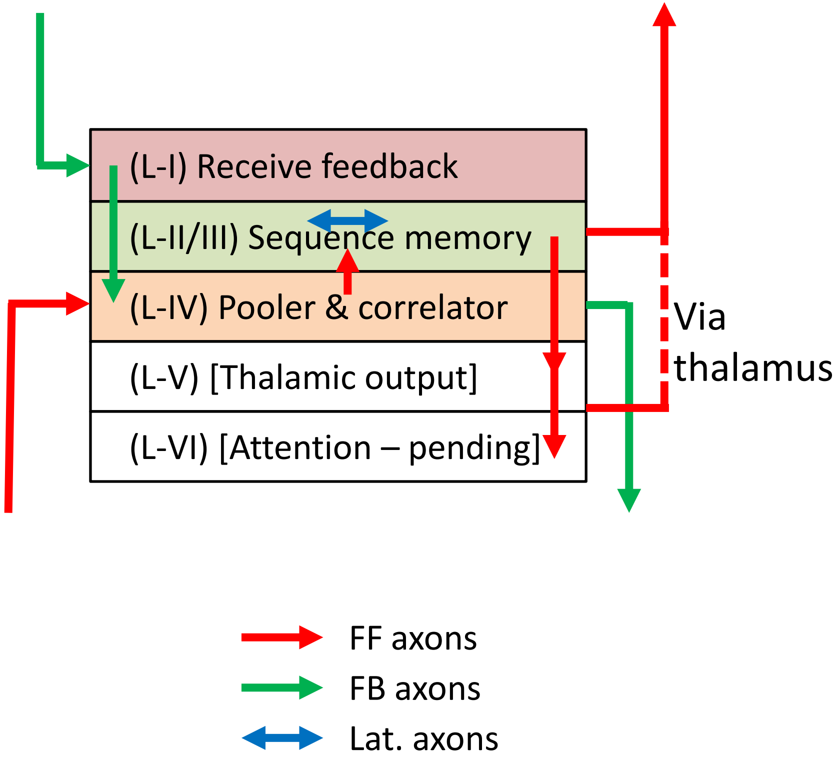
Meso scale – cortical region

- Region of cortical sheet
- Components are layered
  - Structural differences
  - Functional differences
  - (No universal agreement)
- Similar over entire cortex



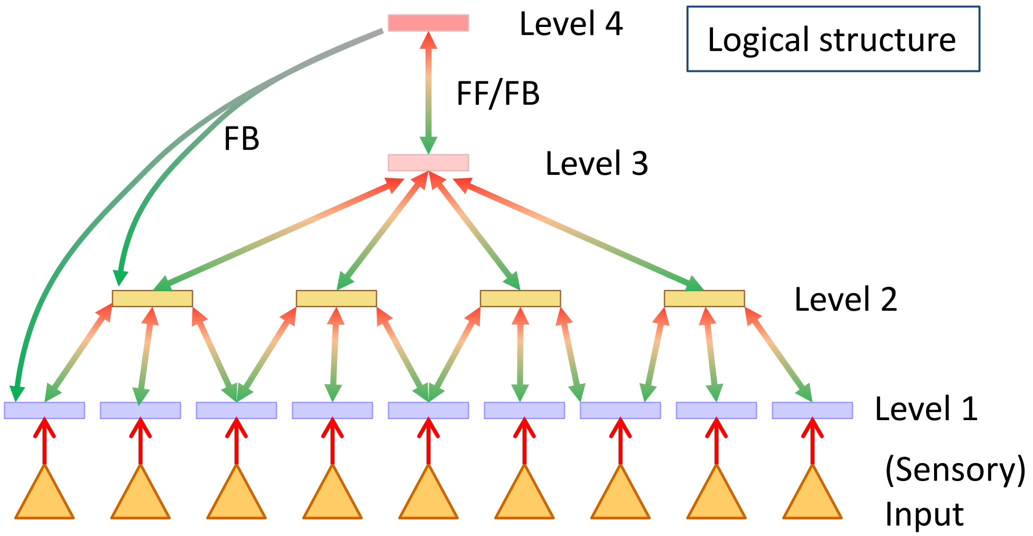


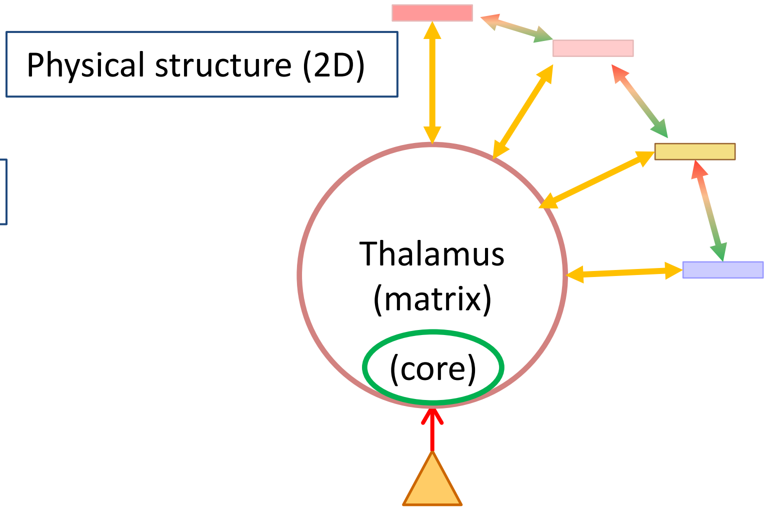
Cortex cross-section
[R. Friedman Biomed. Comp. Rev. 2009]



Macro scale - cortex

- Hierarchical network of "regions"
- Connected by fibers (bundles of axons)
  - Feed-forward and feedback
  - Direct or routed via thalamus
- FF to next highest level
- FB to any lower level





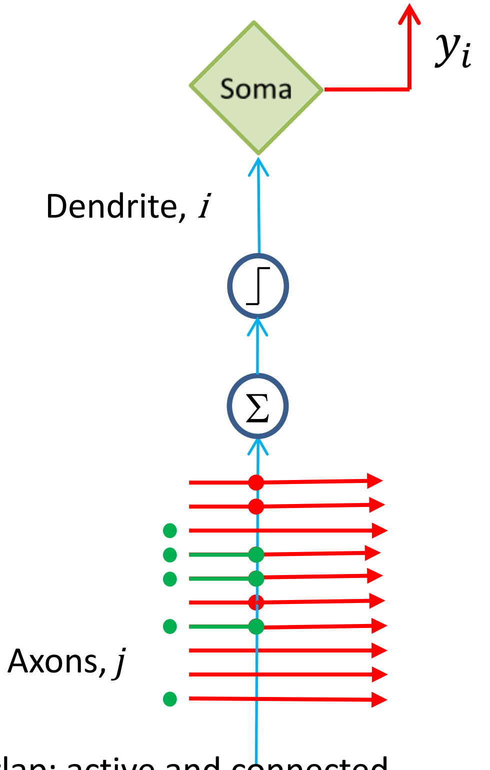
Cortico-cortical and trans-thalamic pathways

CALgorithms: MathematiCAL

Input is axon activity, $\boldsymbol{x}$, a sparse binary vector (sbv).
Connectivity $\boldsymbol{C}$ is sparse binary matrix

Output is dendrite activity, $\boldsymbol{y}$, also sbv
multiply (axon active and connected)
accumulate, (sum is "overlap")
threshold:

$$y_i = \left(\sum_j c_{ij} x_j\right) \geq \tau$$



Overlap: active and connected
$\Sigma = 3$

Self-adjusting threshold & *k*-winners-take-all

$$\boldsymbol{y} = \boldsymbol{C}\boldsymbol{x} \geq \tau; \;\; \tau \text{ such that } |\boldsymbol{y}| = k$$

Threshold modulation – provides context

Lateral activity (overlap $\Sigma^{(L)}$)
provides context of current sequence (e.g. '...ABC')

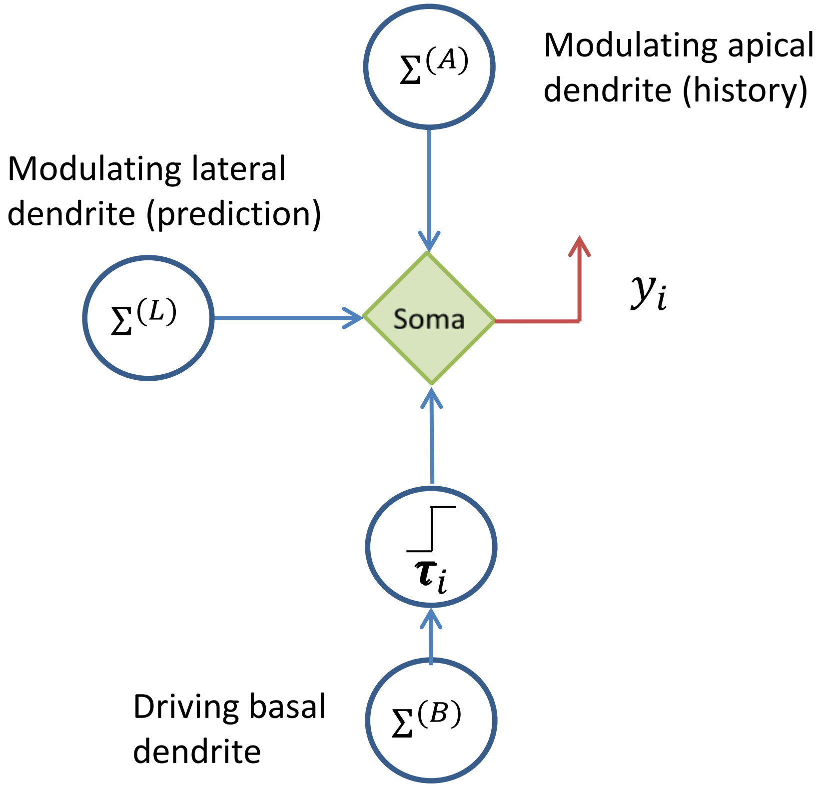
Prediction via reduction of basal threshold of
'D' mini-columns

$$\tau_i = \tau / g_i^{(L)}; \quad \text{"gain"} \;\; g_i^{(L)} \sim \Sigma^{(L)}$$

Lower threshold is equivalent to higher overlap

$$y_i = \Sigma^{(B)} \geq \tau_i \qquad \Rightarrow y_i = \left(g_i^{(L)} \Sigma^{(B)} \right) \geq \tau$$

Similarly apical overlap.
Feedback provides prior context, to sustain basal activity.



Synapse update – following Hebb

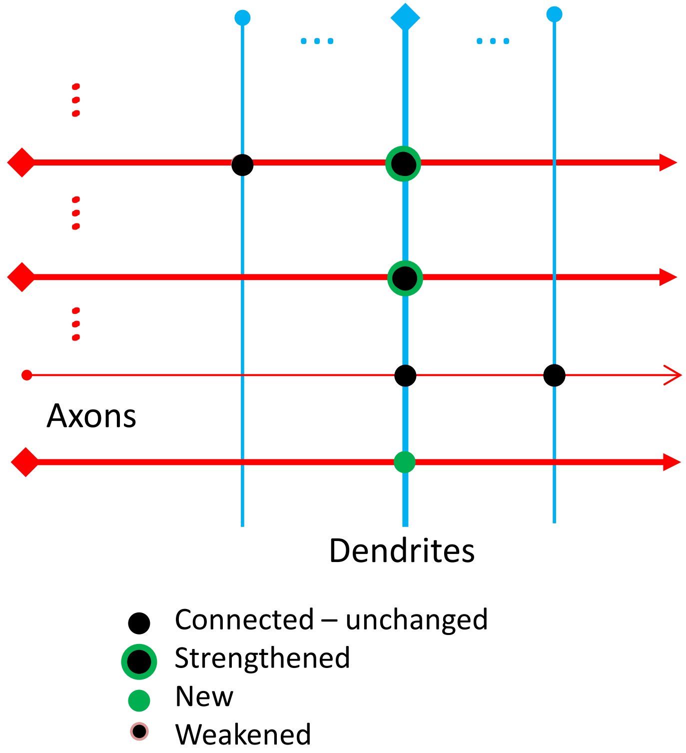
- Synapse “permanence” is scalar property
- Connectivity (weight) is binarized permanence (*cf*. Numenta HTM)

Hebb

- Both pre- and post-synaptic neurons active: strengthen (increase permanence) or create new one
- Only one active: weaken (decrease permanence)

Correlation

- When two axons are often active simultaneously, they connect to the same dendrite
- When two axons are rarely active simultaneously, they connect to different dendrites



Maintain a balance – homeostasis

Dendrite sensitization

- Lower threshold (increase gain) for dendrites with few connections

"Proportional Hebb"

- Increase/decrease in inverse proportion to number being updated
  i.e. maintain roughly constant mean permanence

"Conditional Hebb"

- If axon or dendrite has excess connections, do not strengthen
- If axon or dendrite has too few connections, do not weaken
  i.e. maintain roughly equal number of connected synapses

"Pruning"

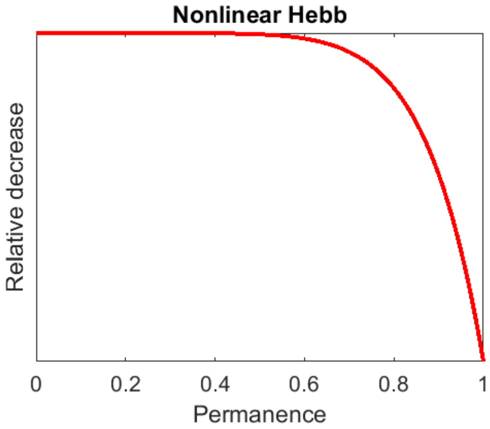
- Remove excess weak synapses
  cf. mechanism during sleep

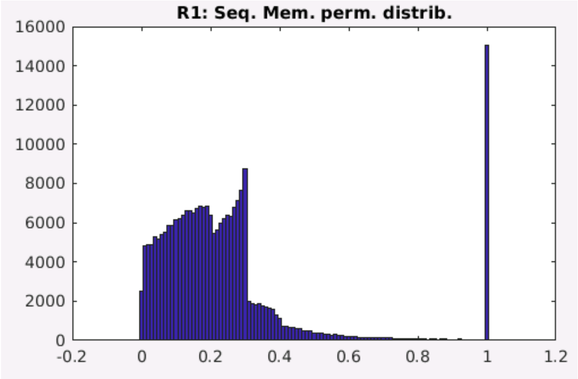
Do not forget - long term memory

"Nonlinear Hebb" to avoid "catastrophic forgetting"

- Reduce permanence decrements for well established synapses

$$\delta p \sim (1 - p^{\gamma}), \qquad \gamma > 5$$





Results in two populations of synapses: plastic and permanent

Temporal pooling and correlation (towards invariance)

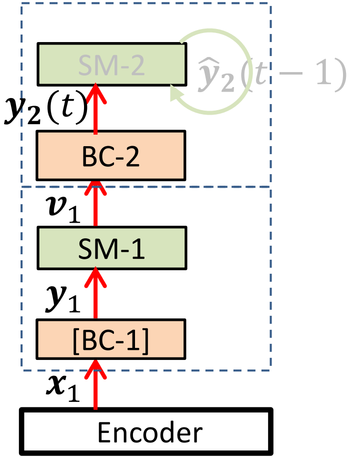
Feed forward from SM-1 to BC-2 verified neurons :

$\boldsymbol{v}_1(t)$ predicted at t-1, active at t

Pool by union of consecutive FF inputs:

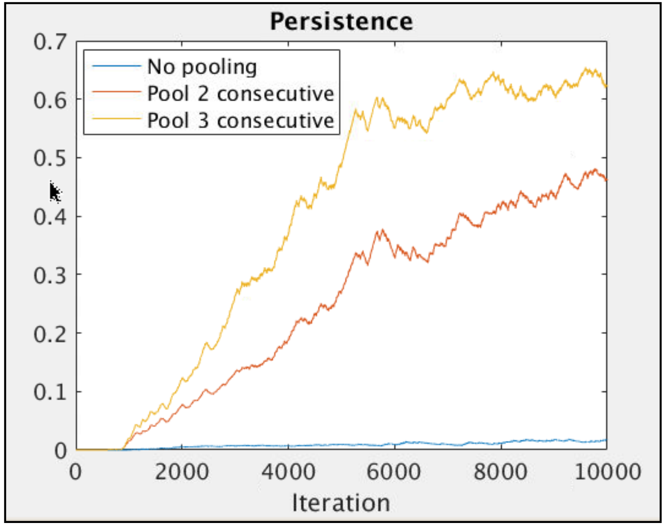
$$\boldsymbol{x}_2(t) = \boldsymbol{v}_1(t) \cup \boldsymbol{v}_1(t-1) \cup \boldsymbol{v}_1(t-2) \ldots$$

Network: 2 regions (1-1)



Metric: persistence
(fraction of bits that remain
on in two consecutive iterations)

$$\Pi(t) = \frac{|\boldsymbol{y}_2(t-1) \cap \boldsymbol{y}_2(t)|}{|\boldsymbol{y}_2(t-1)|}$$



Text input: 3 sentences, selected in random order. Total of 10,000 characters

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The quick brown fox jumps over a lazy dog.
The 1990s saw the emergence of cognitive models.
CAL is built on several fundamental principles.
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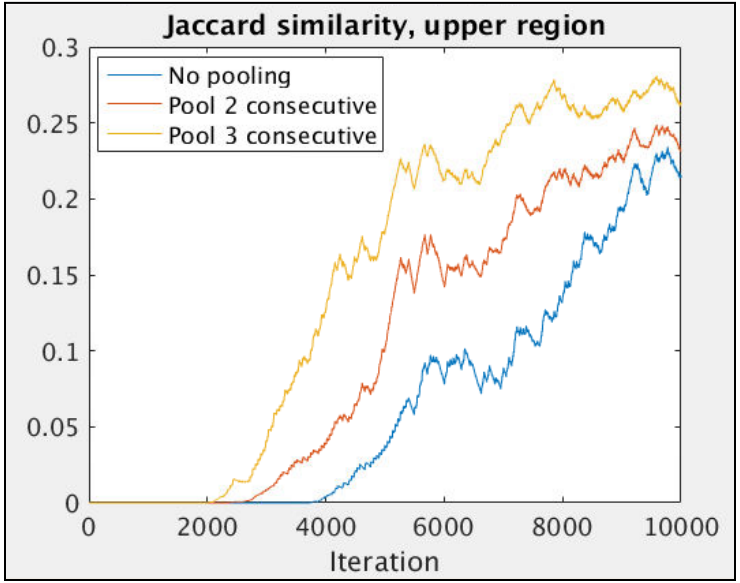
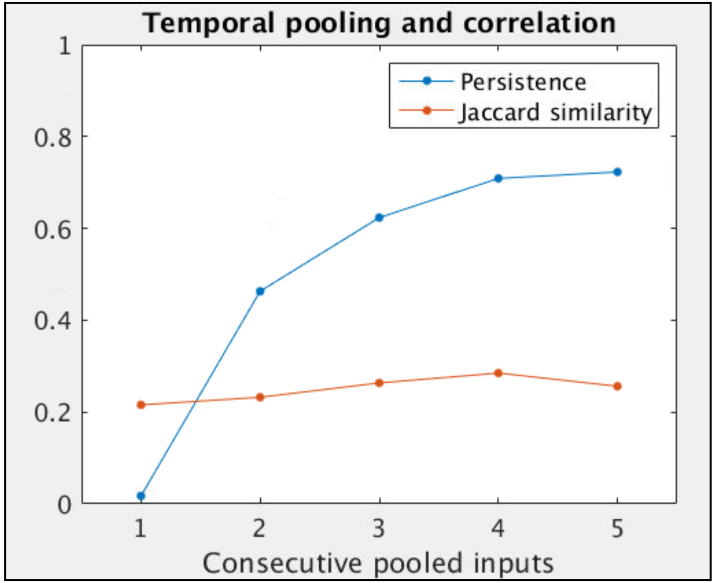
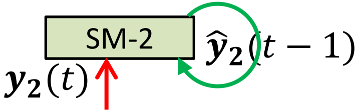
Temporal pooling (cont.) – Learning rate, persistence





Jaccard similarity: normalized match of previous prediction and current "truth" $J = \frac{|\hat{\boldsymbol{y}}_2\,(t-1) \cap \boldsymbol{y}_2(t)|}{|\hat{\boldsymbol{y}}_2\,(t-1) \cup \boldsymbol{y}_2(t)|}$

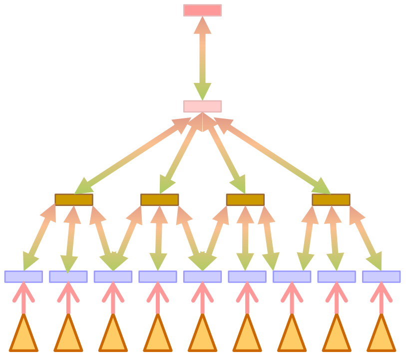


Temporal pooling (union of consecutive inputs)

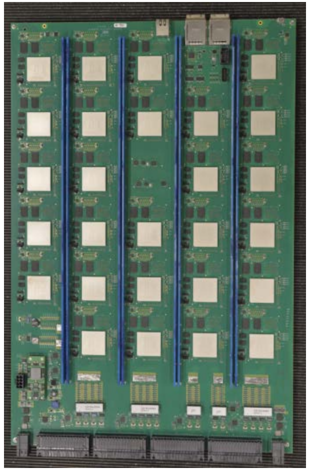
- generates increasing stability of representation
- accelerates learning

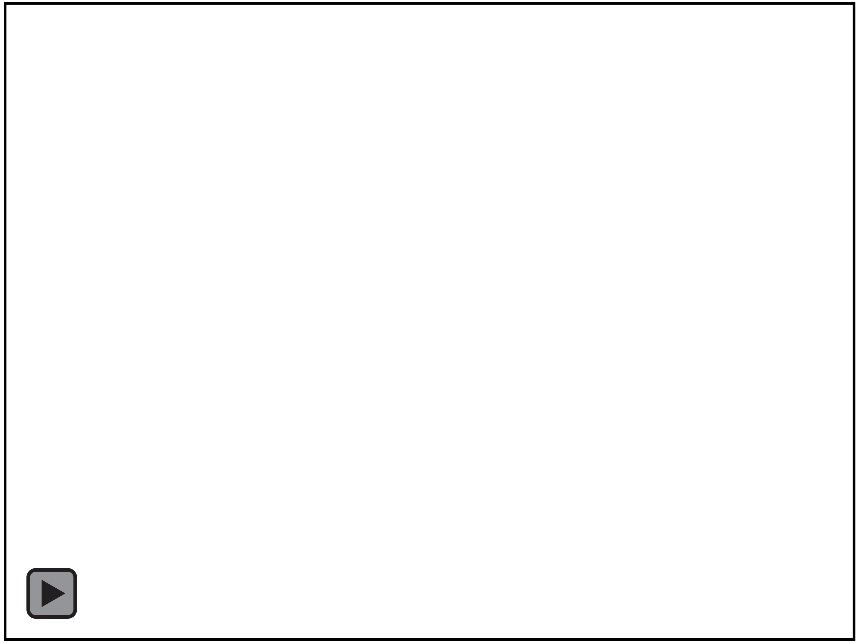
Scaling the hierarchy – video sequences

Network (9-4-1-1)

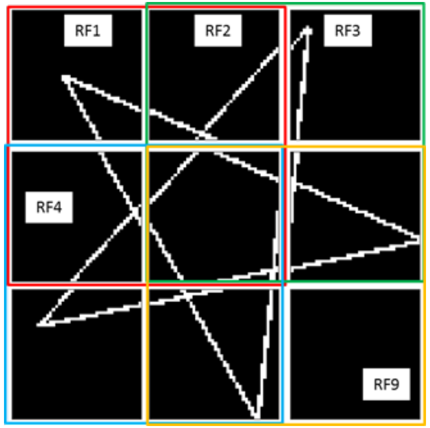


ESCAPE
27 CPUs
1 GB each
FPGAs





Input:
rotating binary images,
7 different shapes.

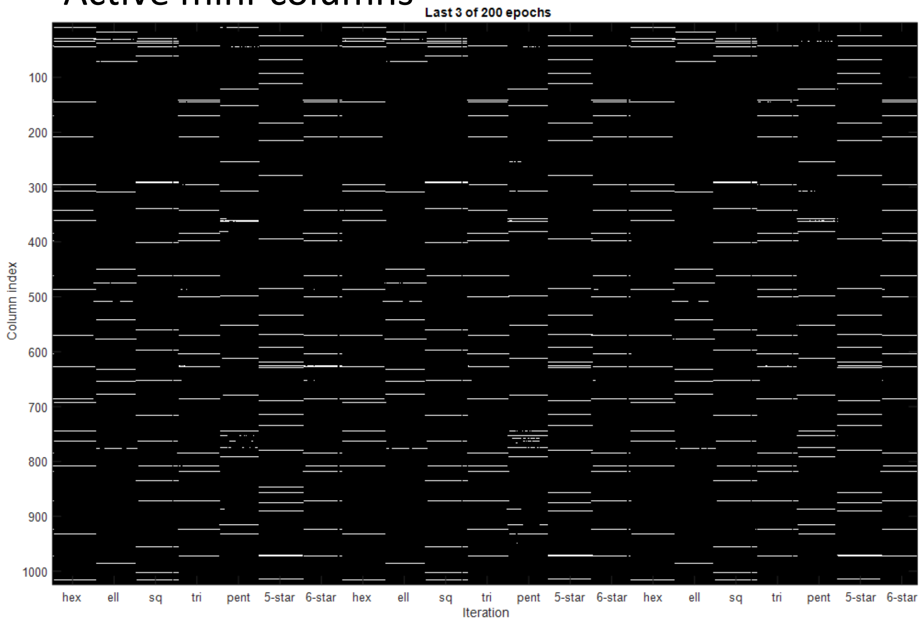


9 receptive fields
Feed 9 regions on level-1
Pool to 4 regions on level-2
1 region on levels 3, 4

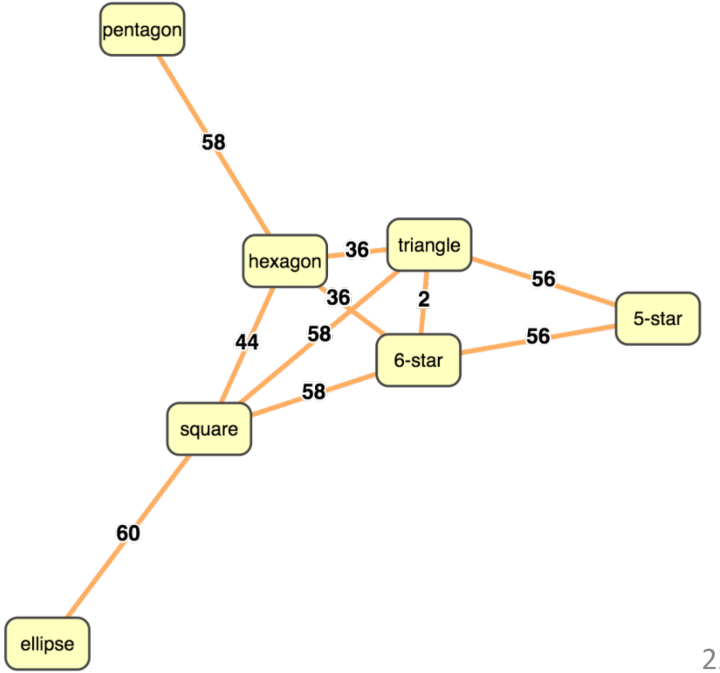
Building the hierarchy – auto-encoding of sequences

Representations ($\boldsymbol{y}_{4,1}$) in top region are stable for each shape

Active mini-columns



Hamming distances (max. 64) between representations as "force" diagram (Blank edges are orthogonal, d = 64)



Summary - pedagogiCAL

Design

- Neurological inspiration
  - Neurons in mini-columns, cortical **layers** (L-I .. L-VI) and hierarchy (**levels**)
  - Driving and modulating synapses, (modified) **Hebb**ian updates
  - Stable network via **homeostasis** (dendrite sensitization, proportional, conditional Hebb)
  - Avoid catastrophic forgetting (nonlinear Hebb)
- Simplicity
  - **Binary** neurons and synapses, sparse neural activity, sparse synapse connections
  - Active axons and connected synapses (**overlap**) and **floating threshold**
  - A few canonical functions:
(so far) **correlation**, **sequence** learning, feed-forward with **temporal pooling**, feedback
- Importance of time
  - Learn to predict

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Results

- Emergent invariance
  - Invariant representations generated in upper levels of hierarchy
- Context for current (**driving**, basal) input provided by **modulating** (lateral, apical) synapses

Acknowledgments

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