Modeling Cortical Layers

Progress in Cortical Modeling and Implications for Neuro HW

BrainScaleS
October 2, 2014

Jeff Hawkins
jhawkins@Numenta.com

Numenta

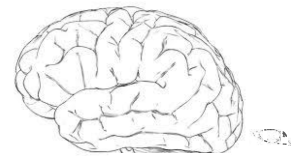
Numenta's Goals

1) Discover common operating principles of neocortex
2) Create Machine Intelligence technologies based on these principles

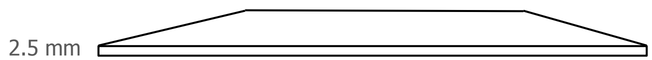
Talk Topics

- Cortical facts
- Cortical theory
- Applications
- HW implications

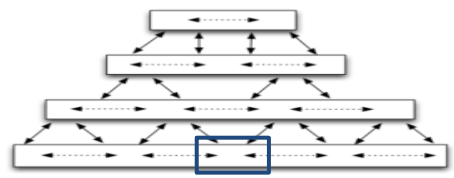
Cortical Facts



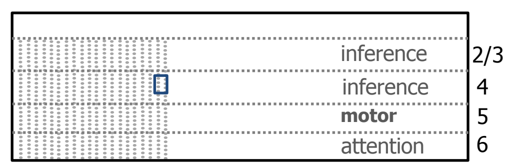
Sheet of cells



Remarkably uniform
- anatomically
- functionally

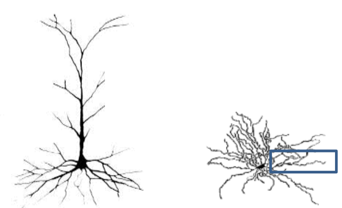


Hierarchy

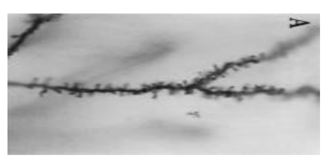


Cellular layers

Mini-columns



Neurons w/1000's of synapses
- 10% proximal
- 90% distal



Active distal dendrites

Synaptogenesis

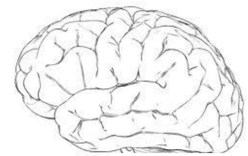
Cortical Theory

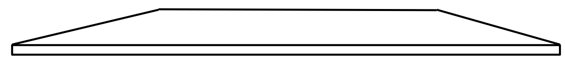
HTM
(Hierarchical Temporal Memory)

1) Hierarchy of identical regions
2) Each region learns sequences
3) Stability increases going up hierarchy if input is predictable
4) Sequences unfold going down

Questions

- What does a region do?
- What do the cellular layers do?
- How do neurons implement this?
- How does this work in hierarchy?





Sheet of cells

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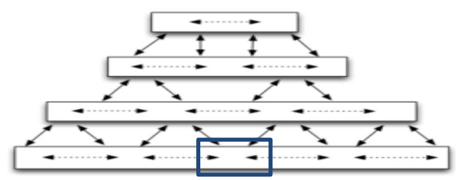
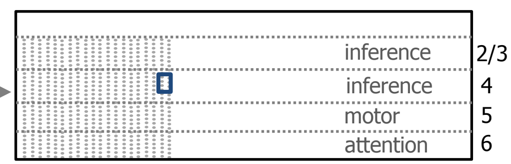


Hierarchy



Cellular layers

Mini-columns

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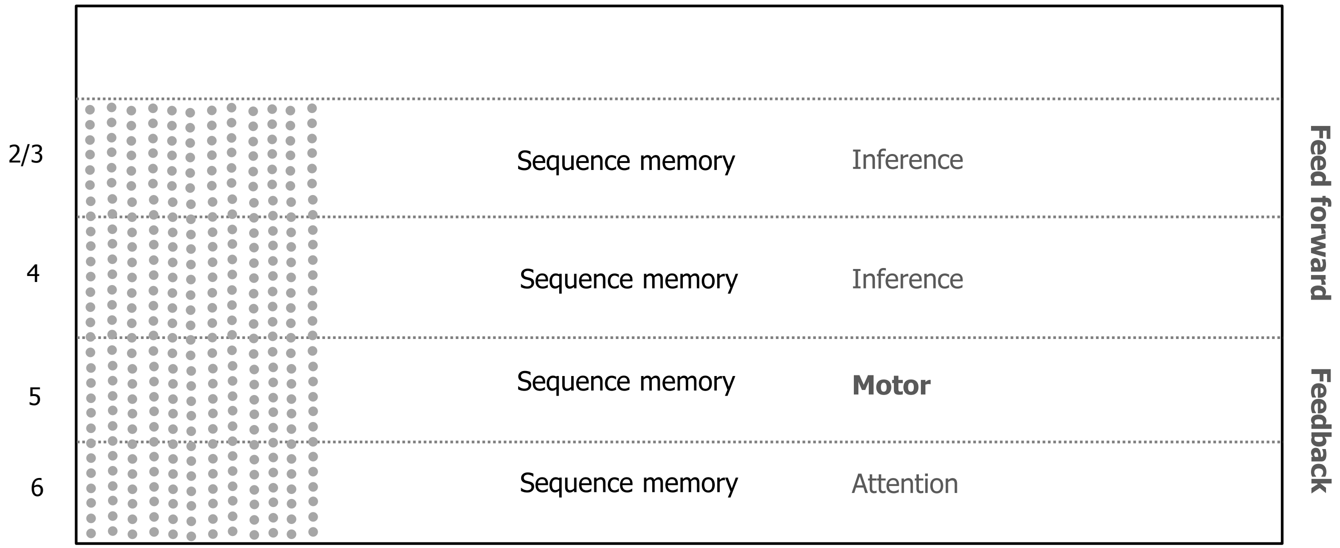
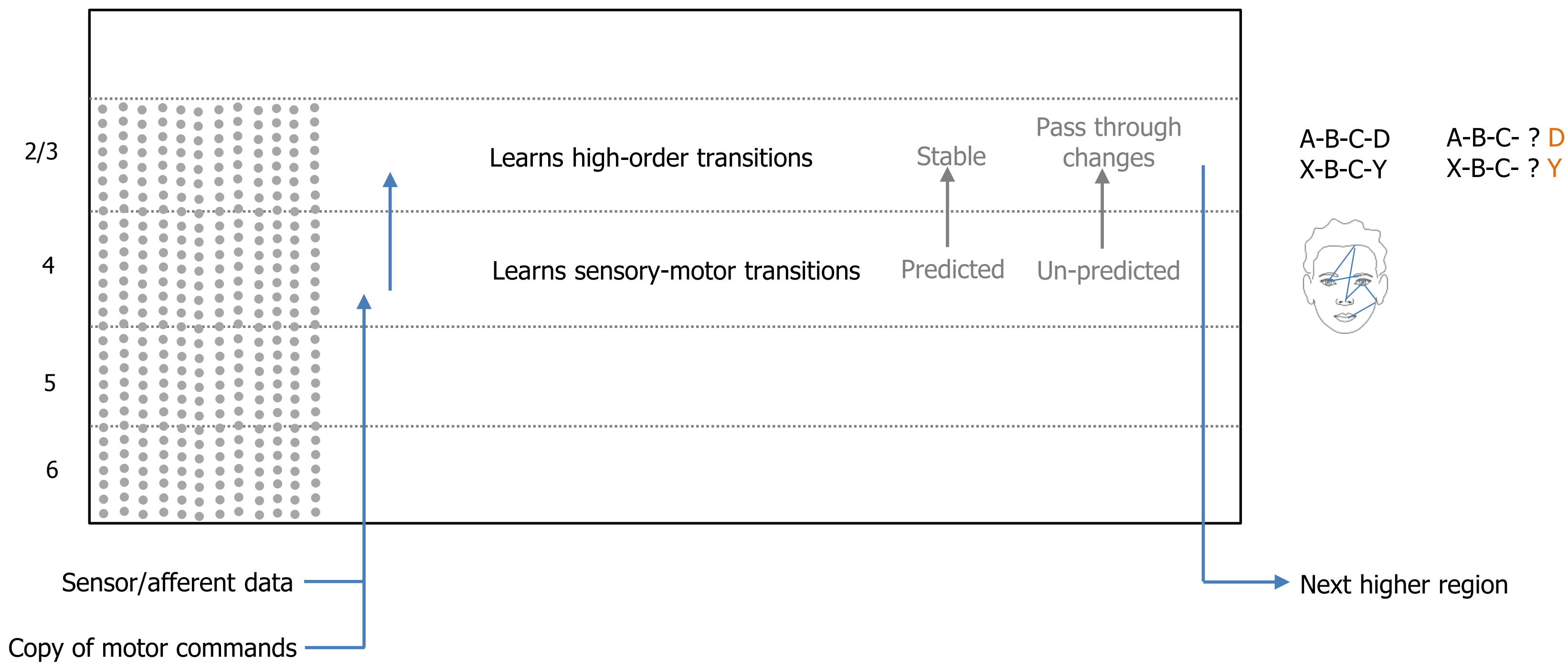
Cellular Layers



Each layer implements a variation of a common sequence memory algorithm.

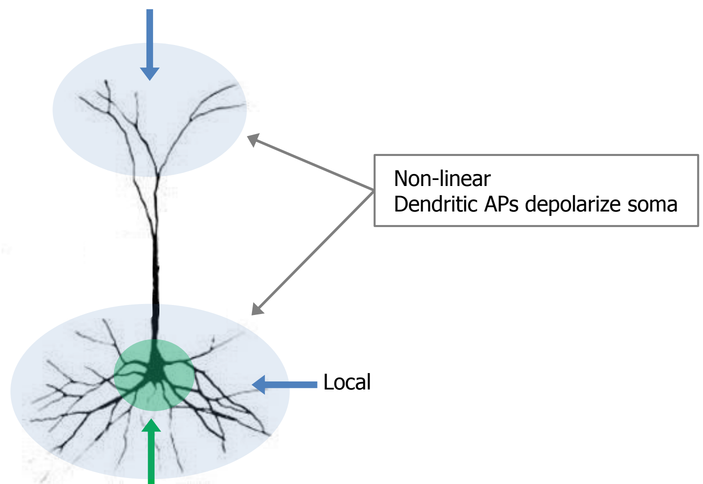
Two Types of Inference (L4, L2/3)

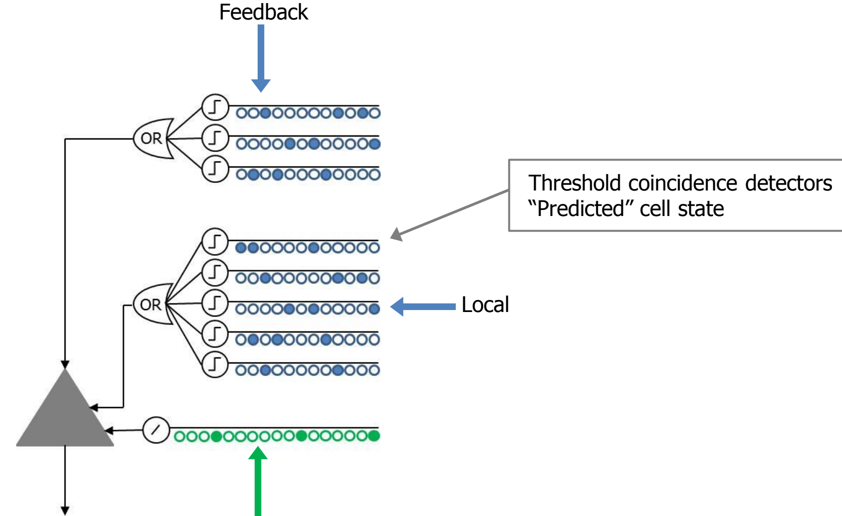


These are universal inference steps.
They apply to all sensory modalities.

Produces receptive field properties seen in cortex.

The Neuron





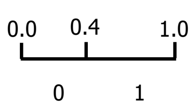
Biological neuron

HTM neuron

Learning is mostly formation of new synapses.

Synapses are low fidelity.

Biological Synapses

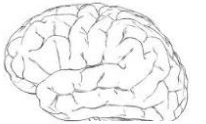


Scalar "permanence"

Binary weight

HTM Synapses

Sparse Distributed Representations (SDRs)



- Many bits (thousands)
- Few 1’s mostly 0’s
- Example: 2,000 bits, 2% active

  01000000000000000001000000000000000000000000000000000000000000000000000000000000000000000010000............01000

- Each bit has learned semantic meaning

SDR Properties

1) **Store and Compare**:
store indices of active bits

0100000000000000000001000000000000100000000000000000000000000010000............01000

Indices
1
2
3
4
5
|
40

subsampling is OK

0100000000000000000001000000000000100000000000000000000000000010000............01000

Indices
1
2
|
10

2) **Union membership**:

1) 0100000000000000000000100000000000000000000000000000000000000000010000............01000
2) 000000000000000000001000000000000000000010000000000000000000000000000000............00001 2%
3) 00001000000000000000000000000001000000000000000000000001000000000000............00000

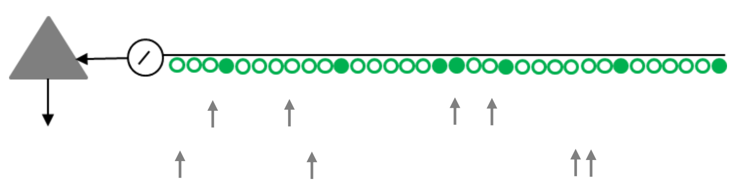
....

10) 0000000000000000100000000100000000000000000000000000000000010000000000000............00000

Union → 0100100000000001001010010000010000010000000000000101000000010000............01001 20%

Is this SDR a member? → 000010000000000000000000000000100000000000000000000000100000000000............00000

A cell can recognize many unique patterns on a single dendritic branch.

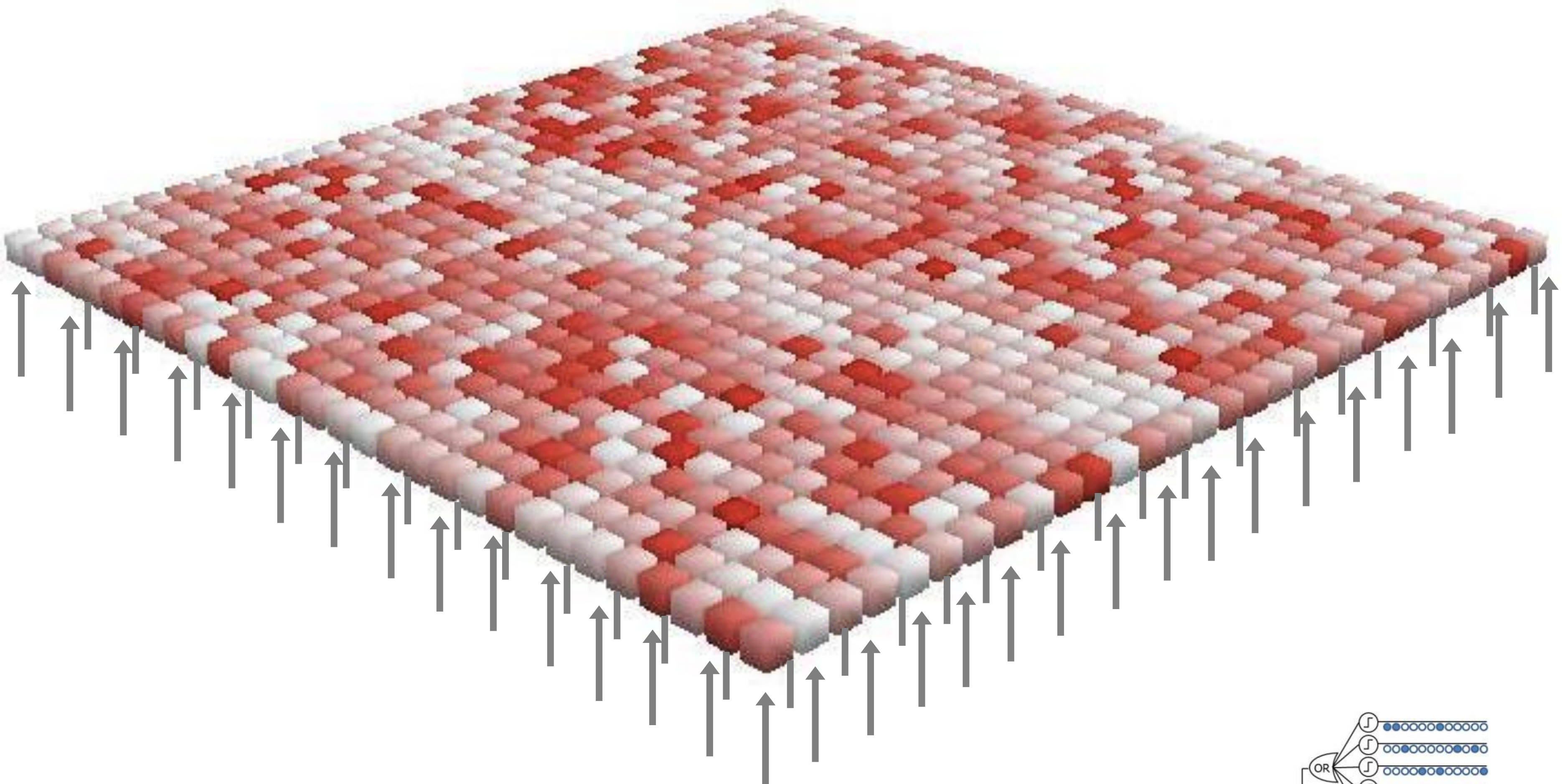


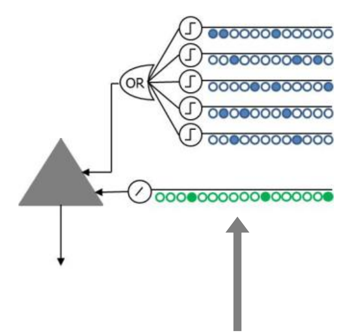
Ten synapses from Pattern 1

Ten synapses from Pattern N

Learning Transitions

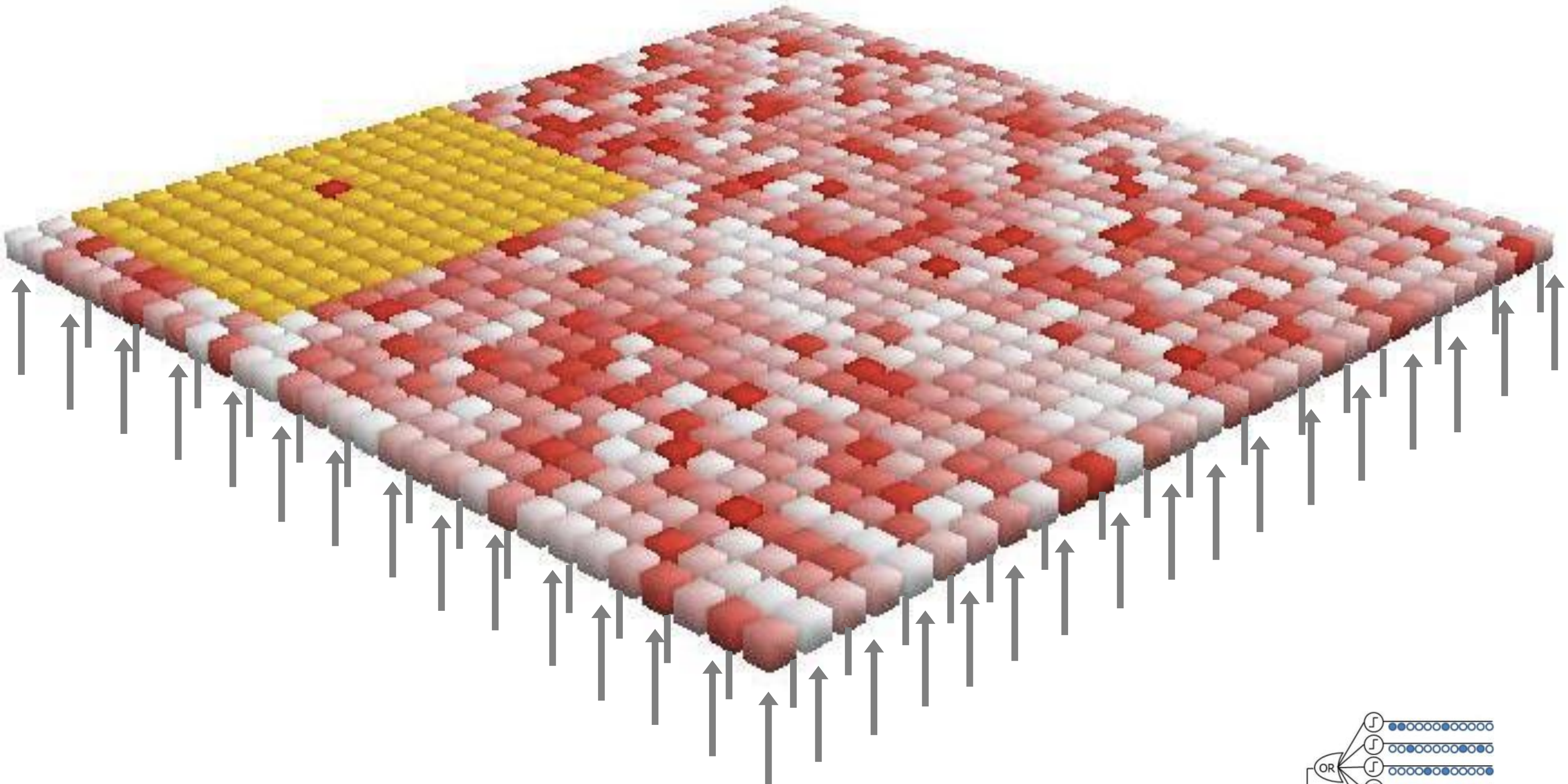
Feedforward activation

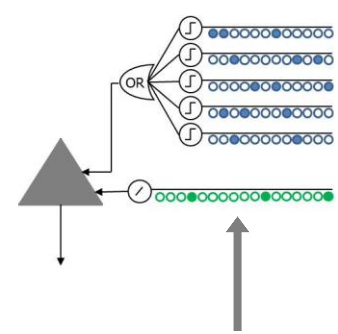




Learning Transitions

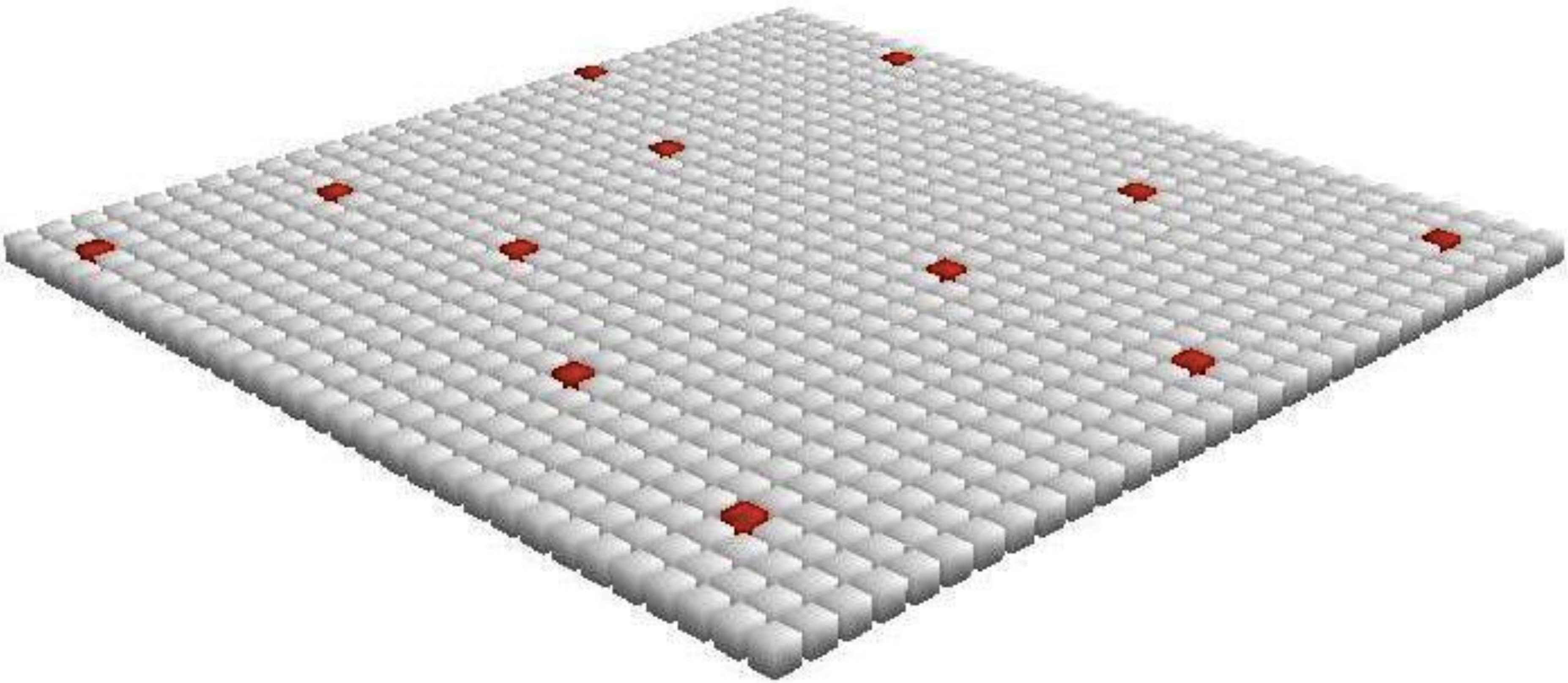
Inhibition





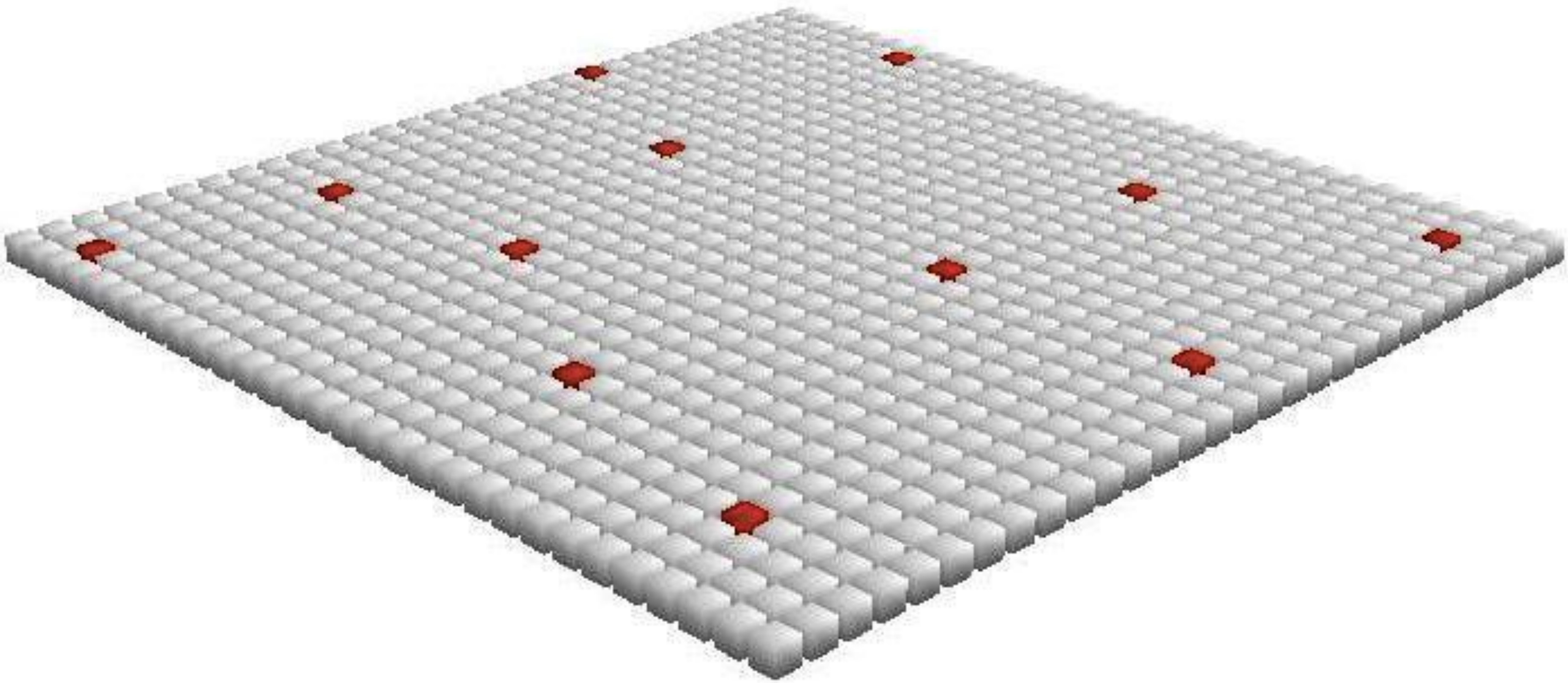
Learning Transitions

Sparse cell activation

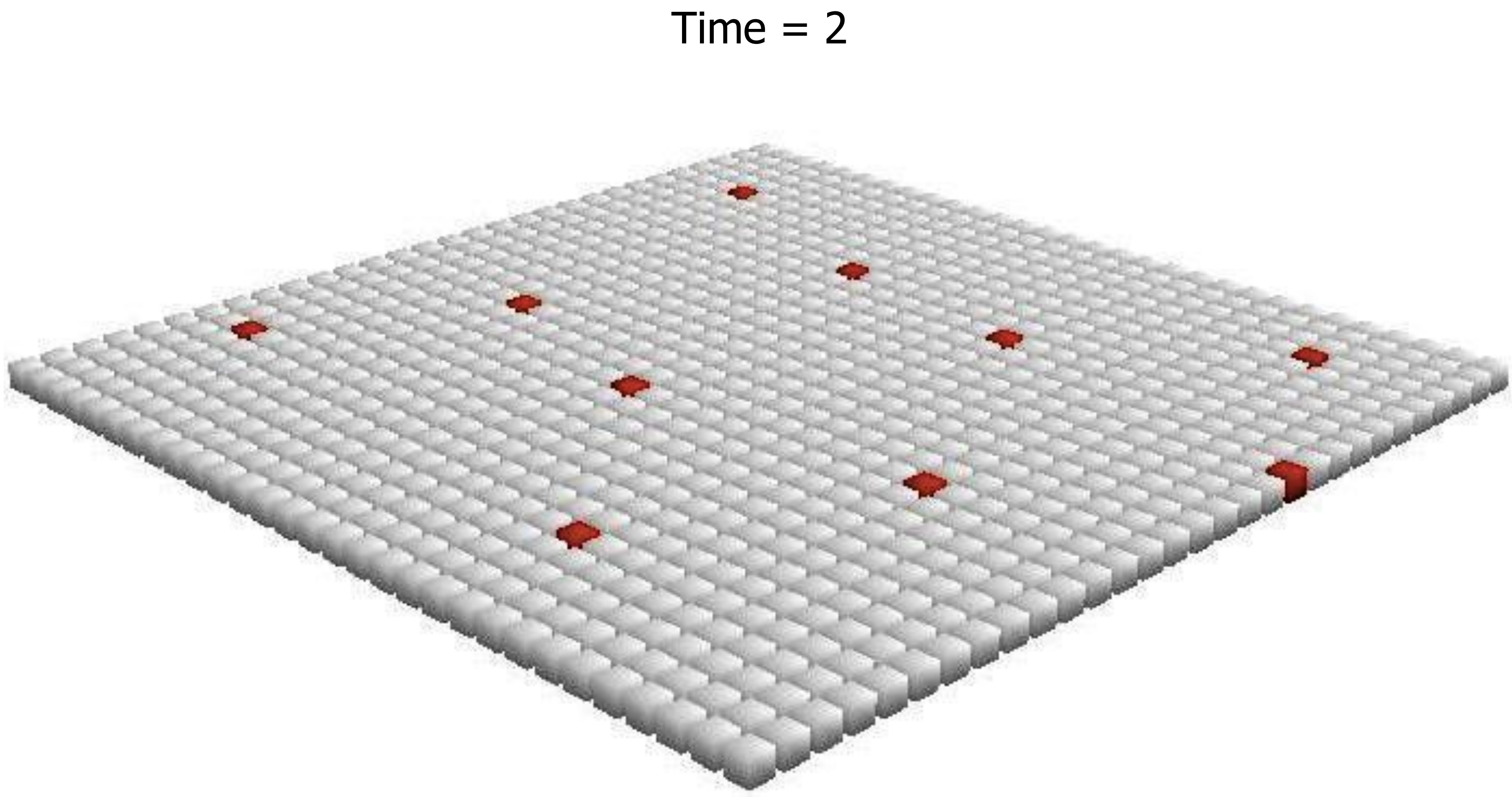


Learning Transitions

Time = 1



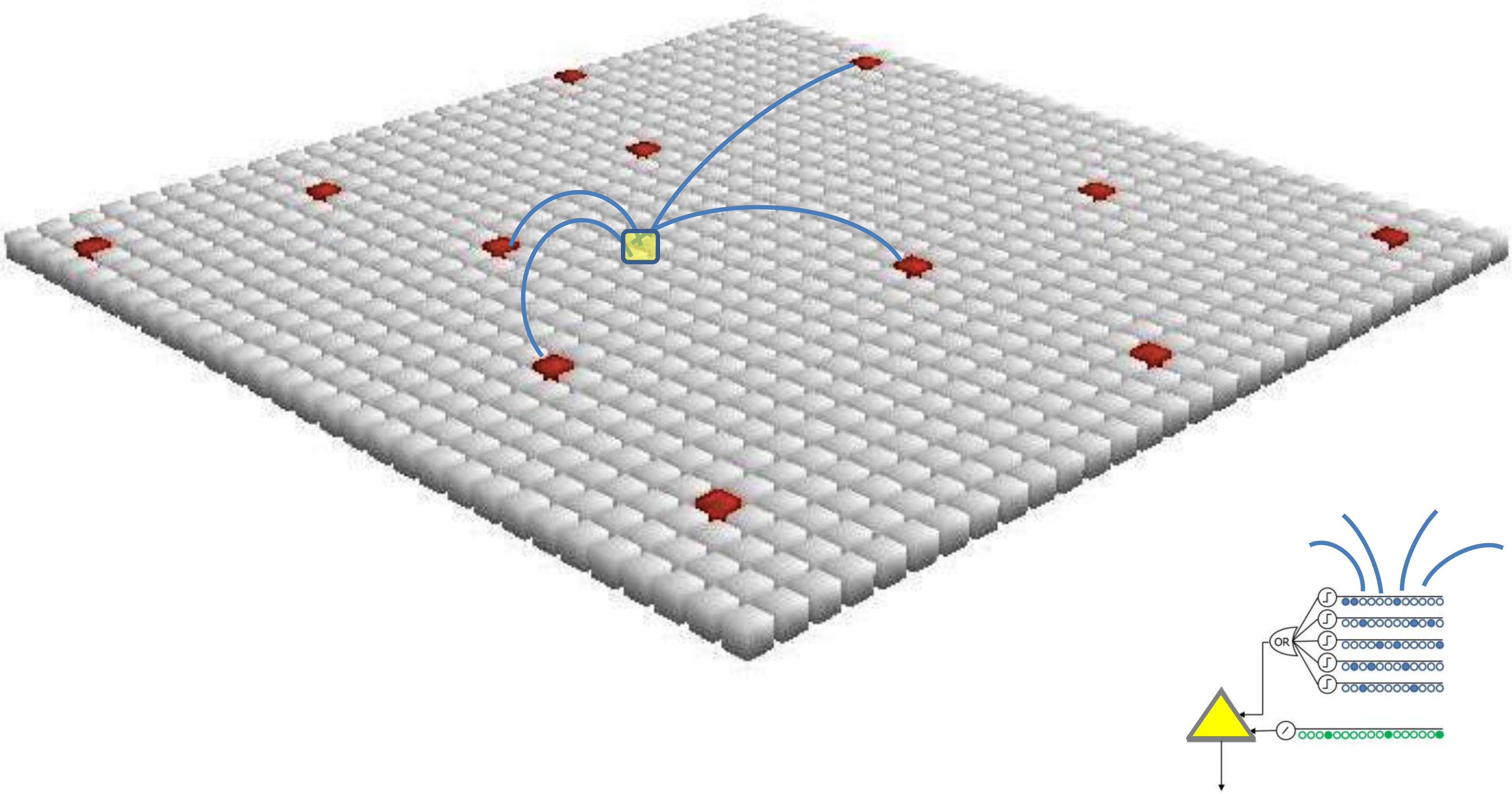
Learning Transitions



Learning Transitions

Form connections to previously active cells.

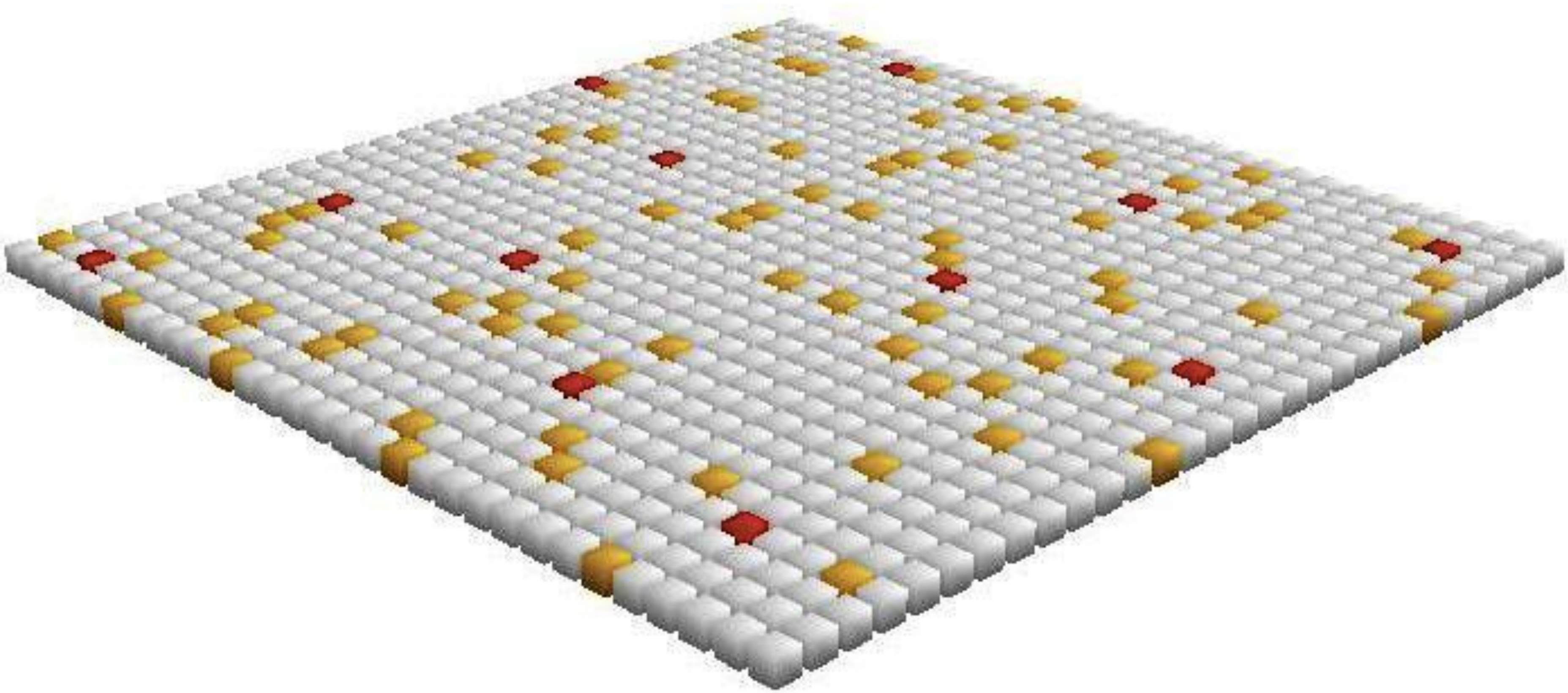
Predict future activity.



Learning Transitions

Multiple predictions can occur at once.

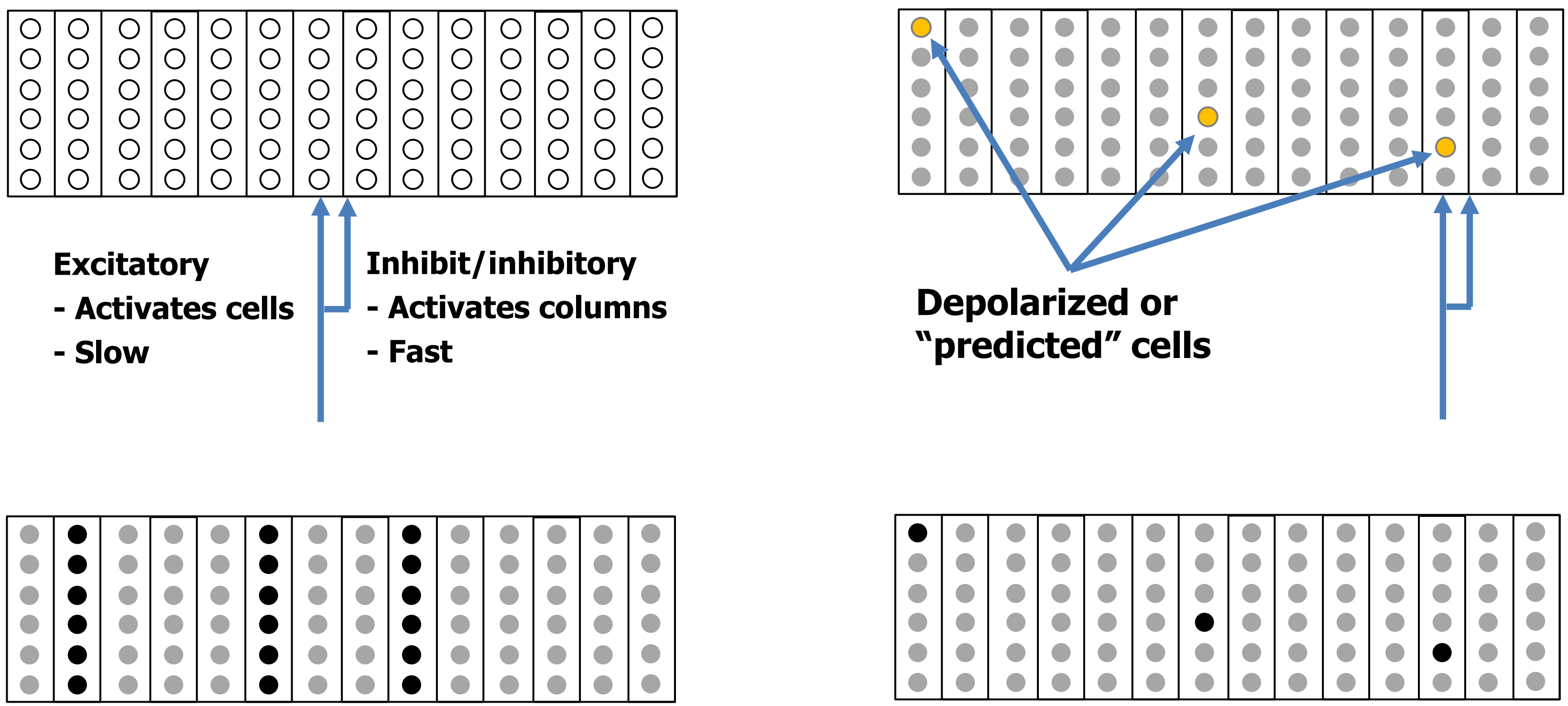
A-B A-C A-D



- This is a first order sequence memory.
- It cannot learn A-B-C-D vs. X-B-C-Y.

- Mini-columns turn this into a high-order sequence memory.

Forming High Order Representations



Unpredicted input => burst activation

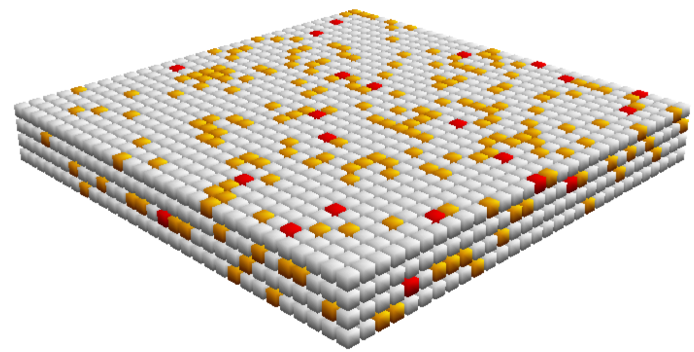
Predicted input => sparse activation

Unique high-order representation in context

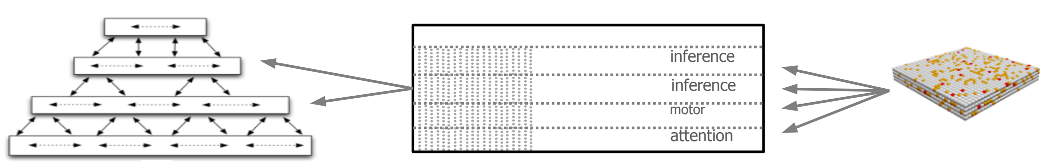
HTM Transition Memory (aka Cellular Layer)

Converts input to sparse activation of columns
Learns, recognizes, and recalls high-order sequences

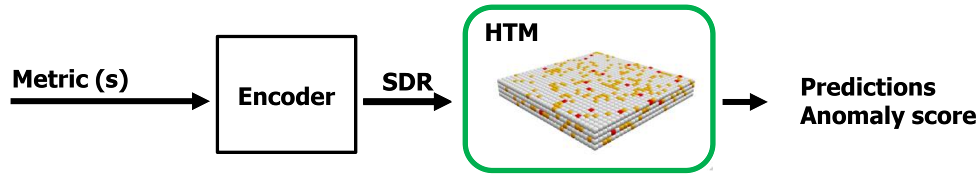
- Continuous learning
- High capacity
- Local learning rules
- Fault tolerant
- No sensitive parameters
- Generalizes

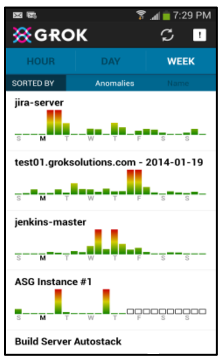


Basic building block of neocortex/machine intelligence



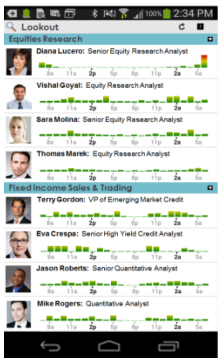
Application Examples



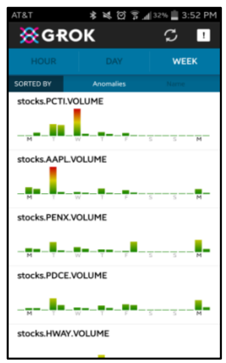


GROK
Server anomalies

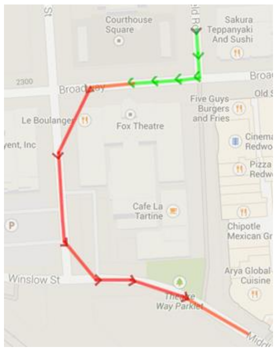
Available on AWS marketplace



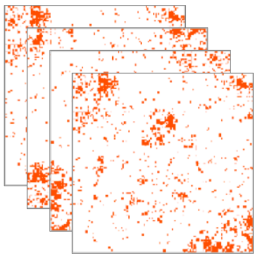
Rogue human behavior



Stock volume anomalies



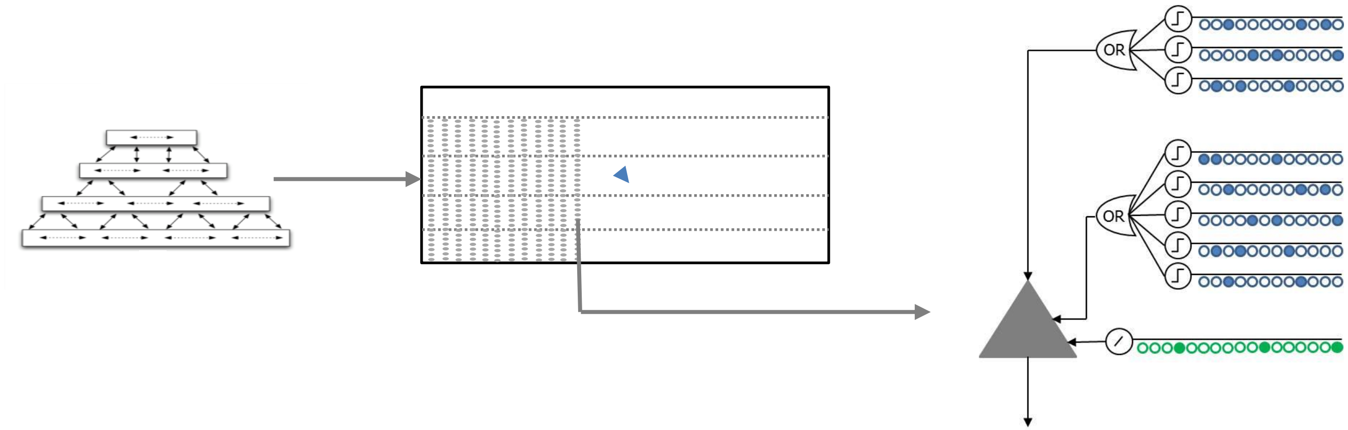
Geospatial tracking



Natural language search/prediction

All Use the Same HTM Code Base

HTM Implications for Neuromorphic HW



Challenges

Dendritic regions

Active dendrites

1,000s of synapses

10,000s of potential synapses

Continuous learning

Opportunities

Low precision synapses (memory)

Fault tolerant
- **memory**
- **connectivity**
- **neurons**
- **natural recovery**

Simple activation states
(no spikes, rhythms, channels)

Connectivity
- **very sparse, topological**

Numenta’s Approach to Research and Development

Open and transparent

Algorithms are documented

Software is open source (GPLv3)

NuPIC   www.Numenta.org

Active discussion groups for theory and implementation

Research code is posted daily

Collaborations

IBM Almaden Research, San Jose, CA
DARPA, Washington D.C
Cortical.IO, Austria

Jhawkins@numenta.com