Planning with Biological Neurons and Synapses

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COATI

Inria
INVENTEURS DU MONDE NUMÉRIQUE

Joint work with

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Gran Sasso Science Institute

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Columbia University

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COATI, CNRS

Christos Papadimitriou
Columbia University

AAAI22
Virtual Event

Brain & Mind

How does the brain beget the mind?

How do intelligence, reasoning, languange (etc.) emerge from neurons and synapses?

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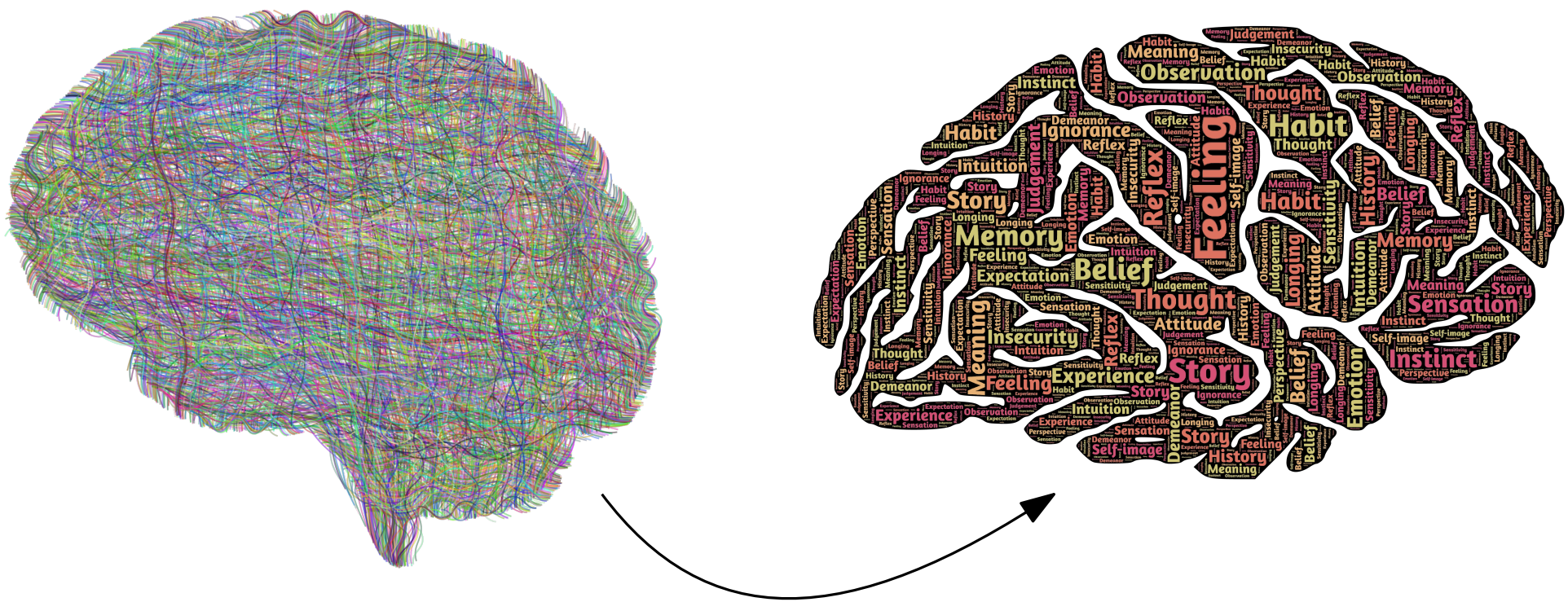

Brain & Mind

Despite tremendous advances over the past decades in our understanding of neural mechanisms, still very far from answering

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Nobel laureate Richard Axel: *We do not have a* **logic** *for the transformation of neural activity to thought and action. I consider discerning [this* **logic***] as the most important future direction in Neuroscience* [Axel, Neuron 2018]

The Assembly Calculus

Recently proposed formal computational system [Papadimitriou et al., PNAS 2020]

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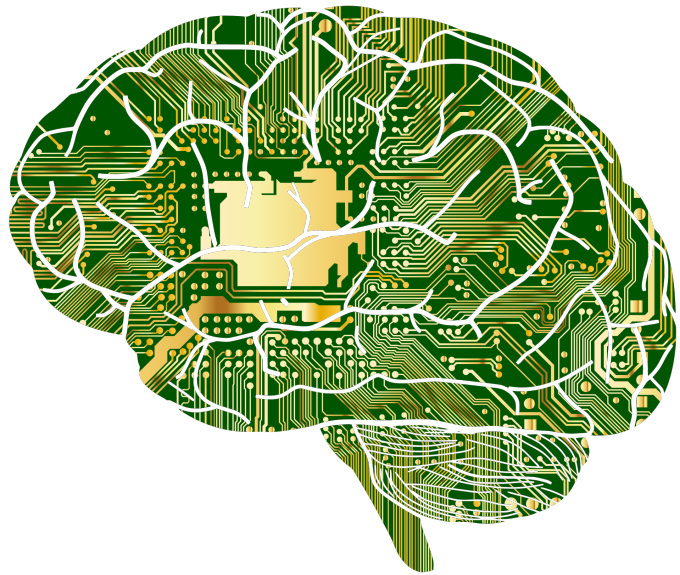
- bridging through computation the gap between neurons and intelligence



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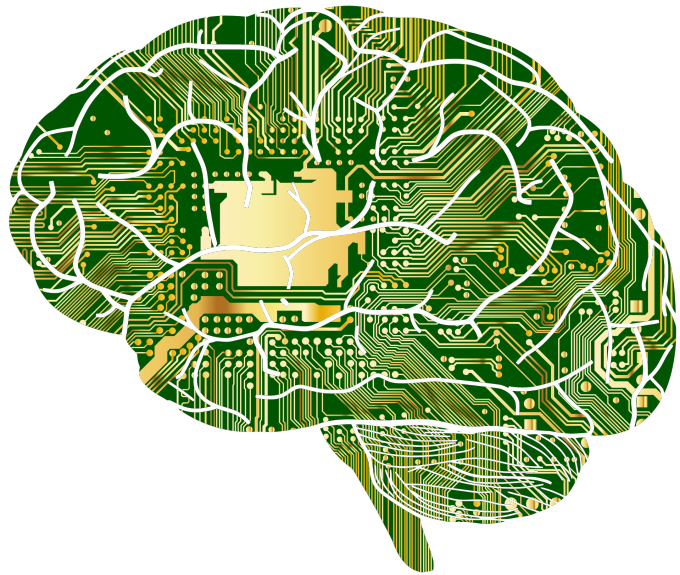
Components:

- *assemblies*
- *operations*



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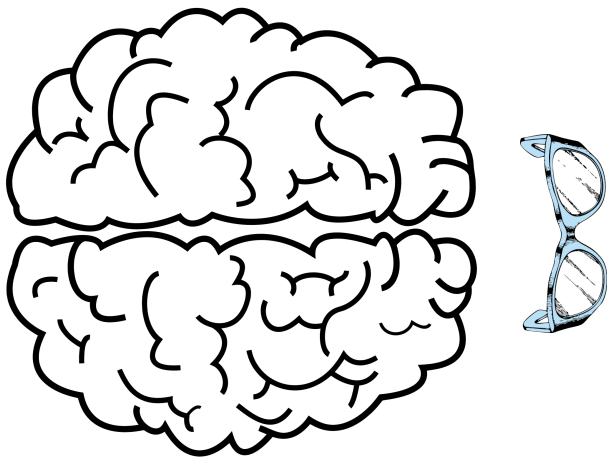

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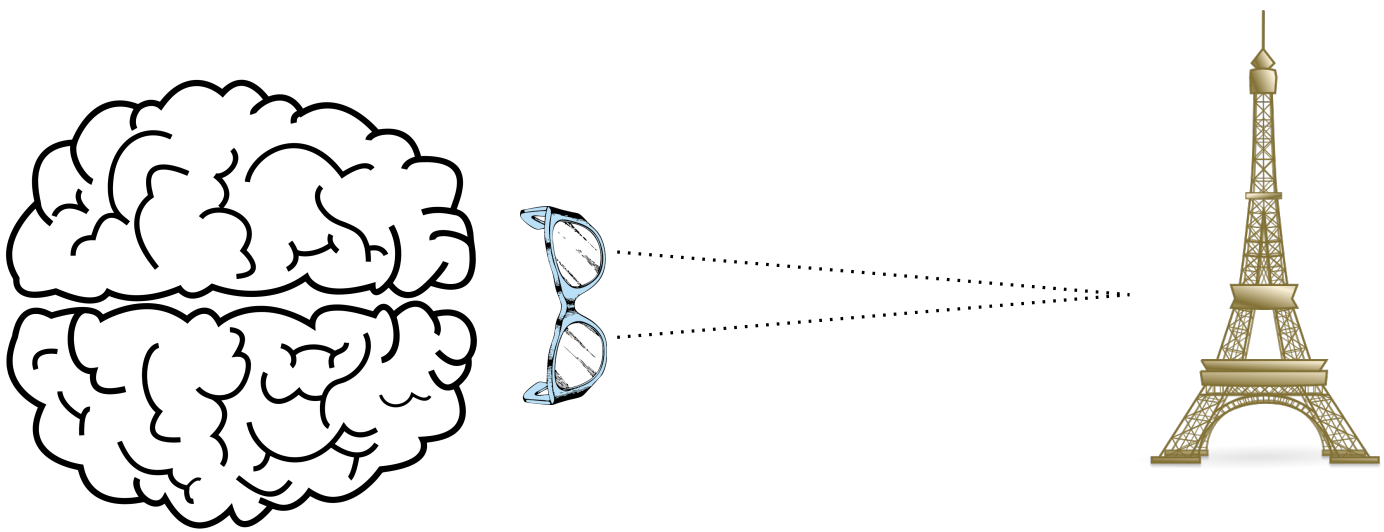

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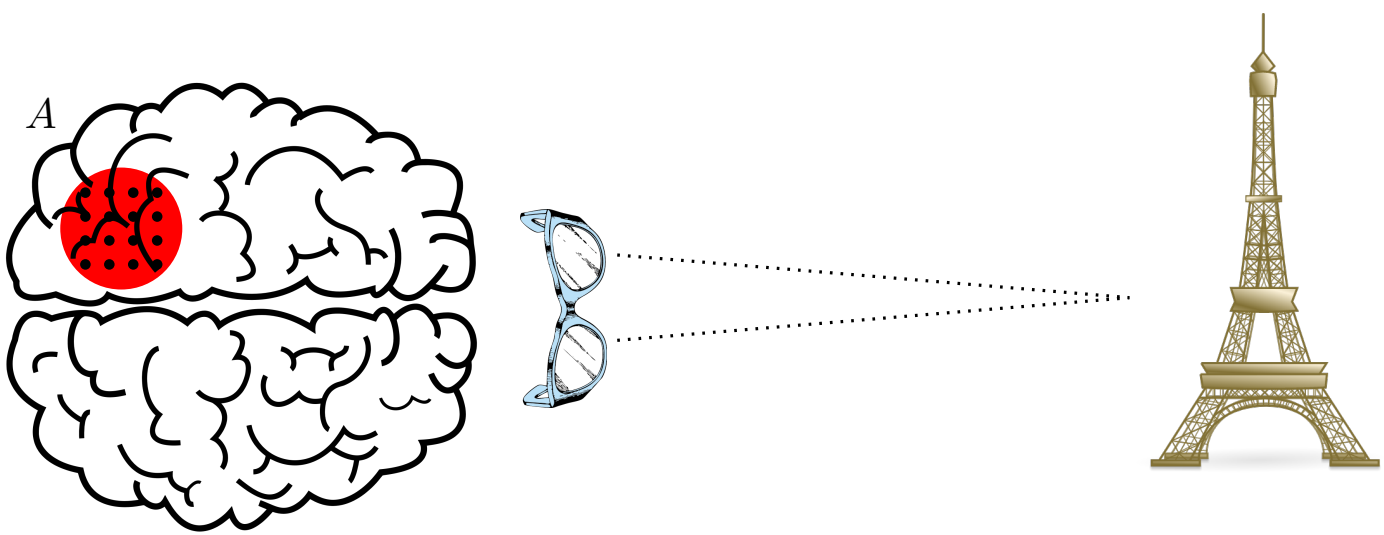

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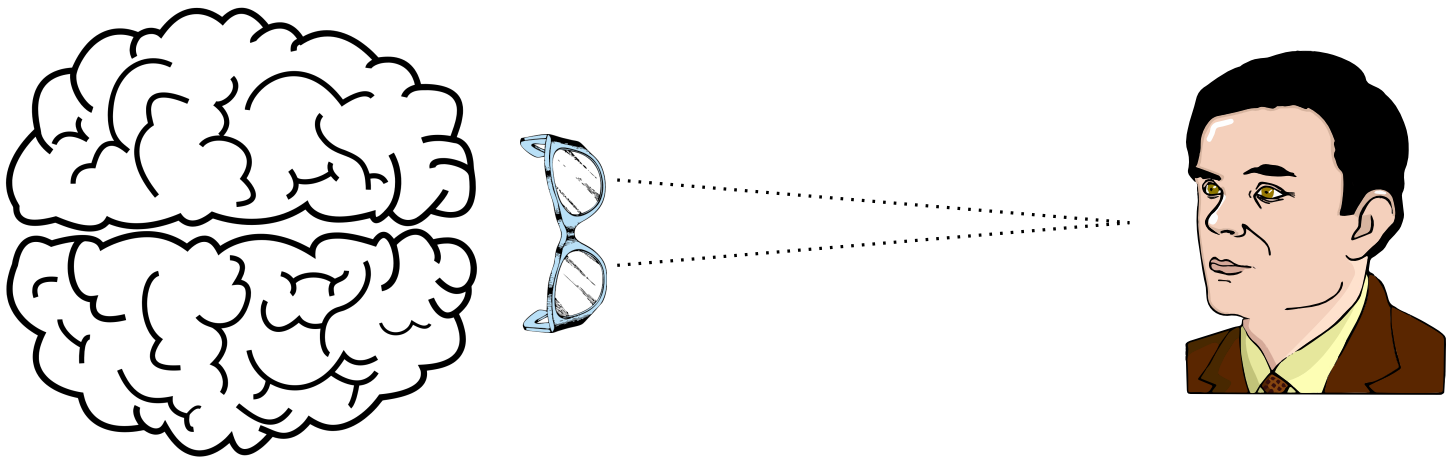

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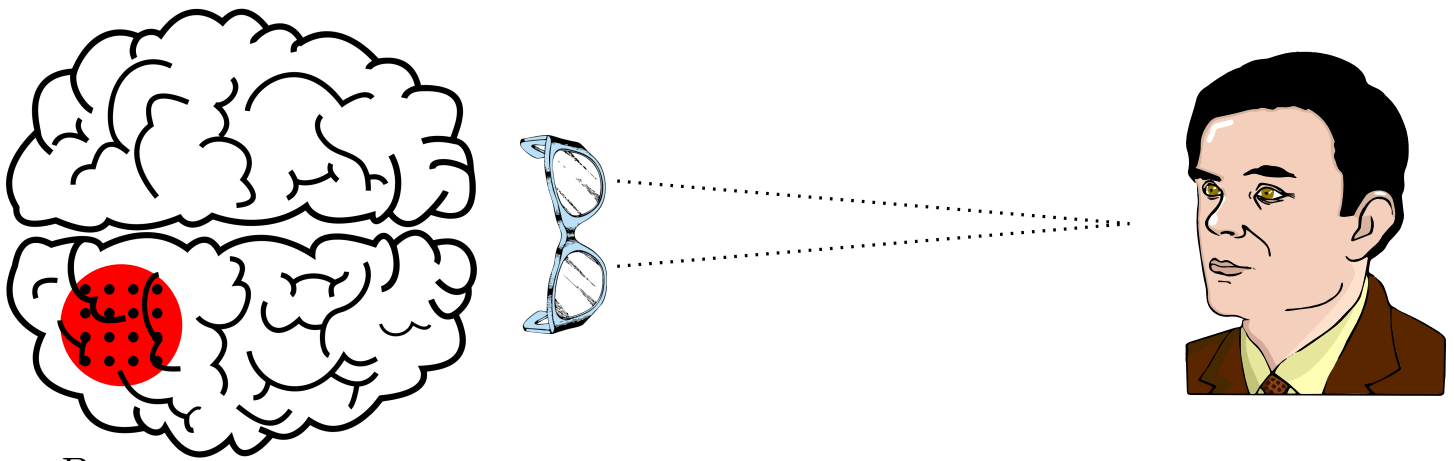
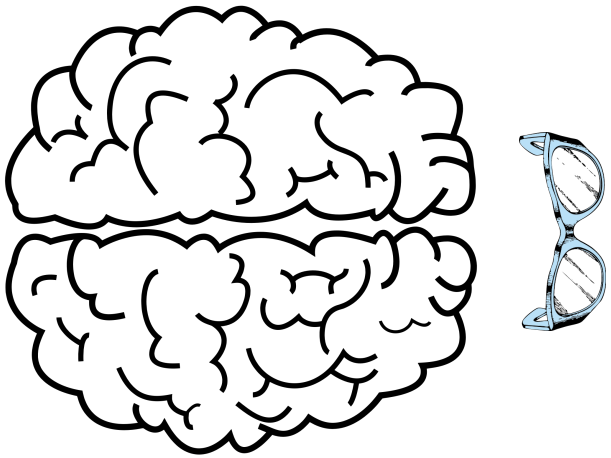


B

Operations with Assemblies

Experiment by [Ison et al., Neuron 2015]



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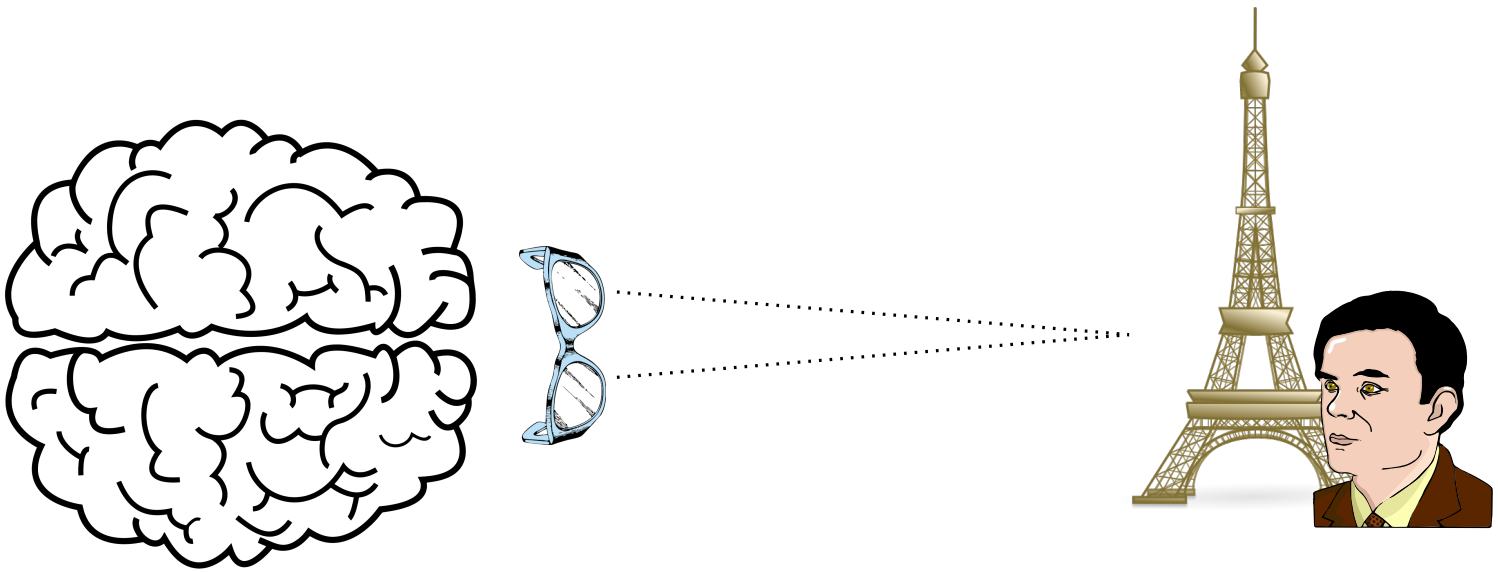

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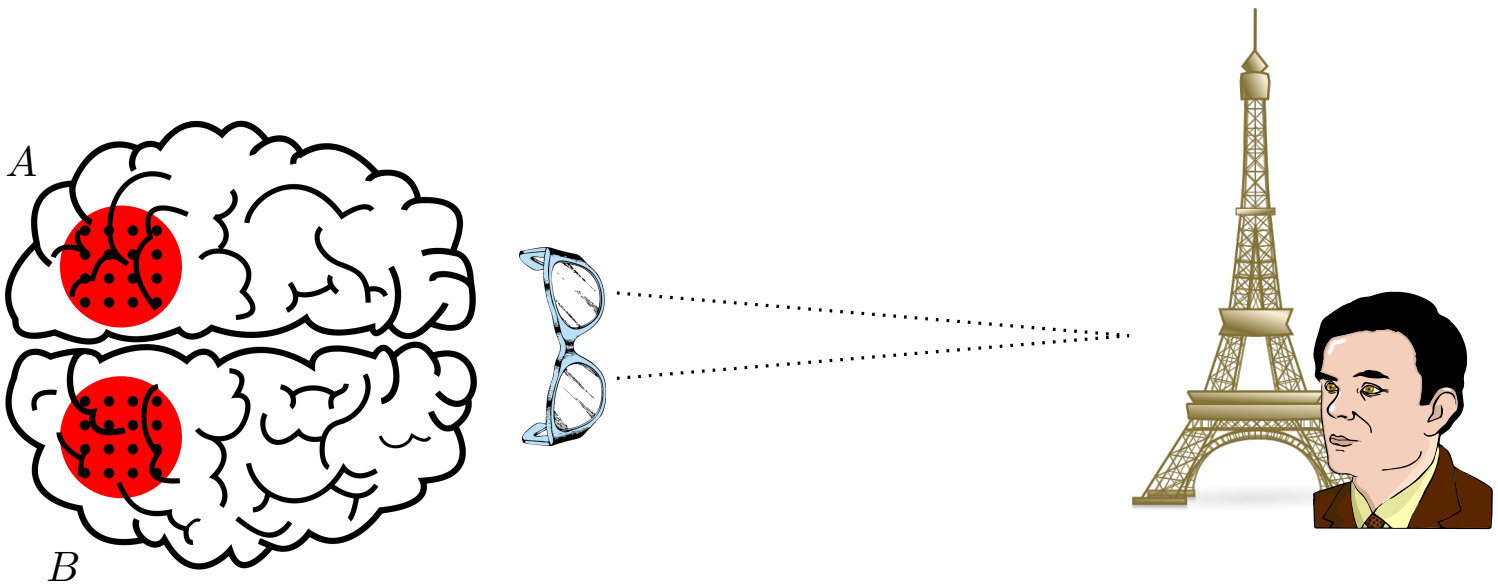

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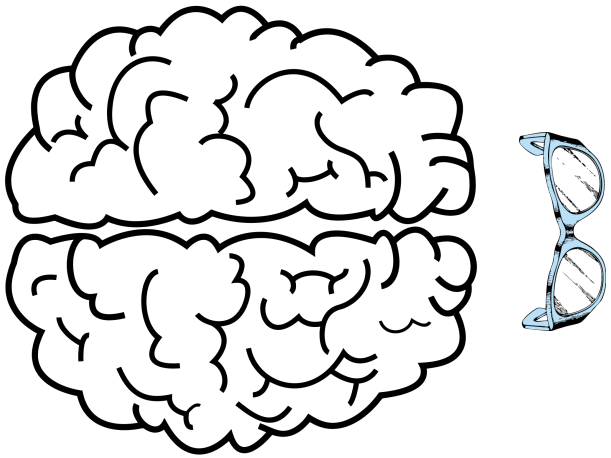

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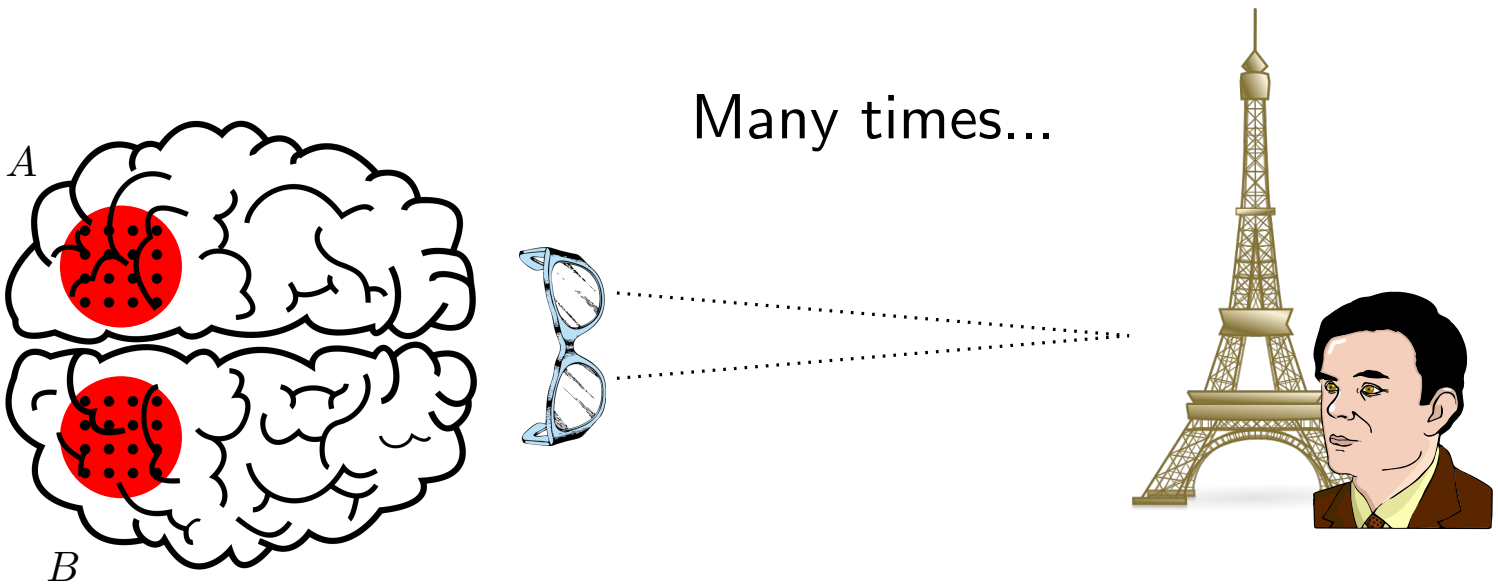

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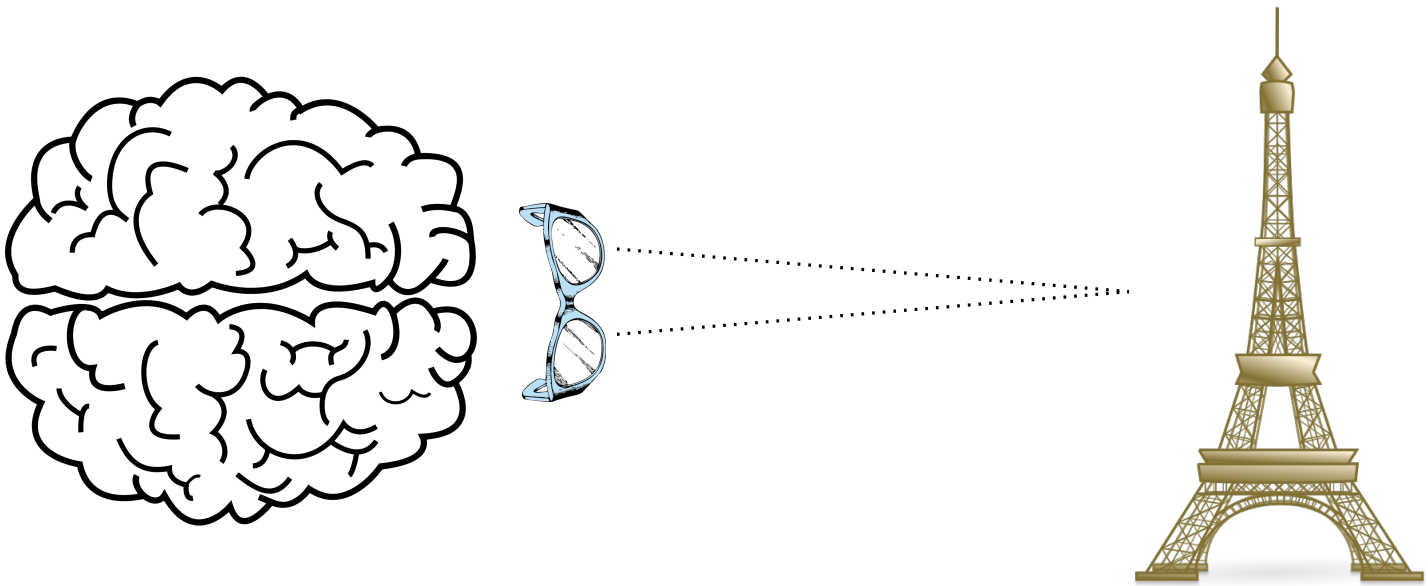

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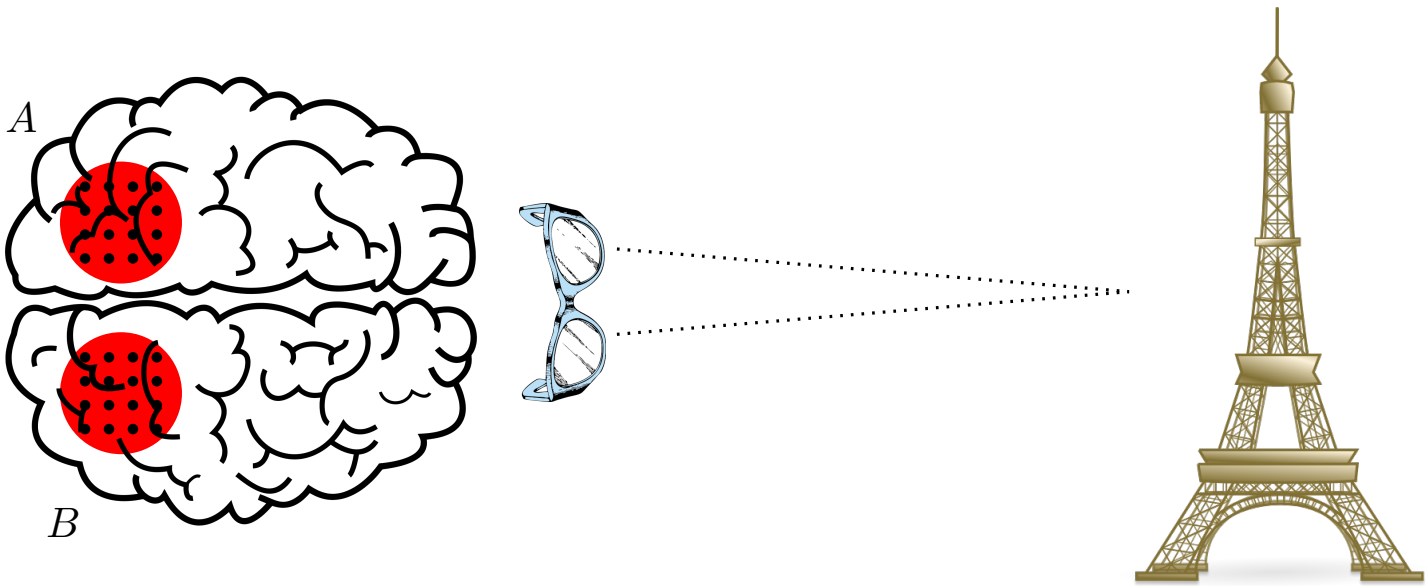

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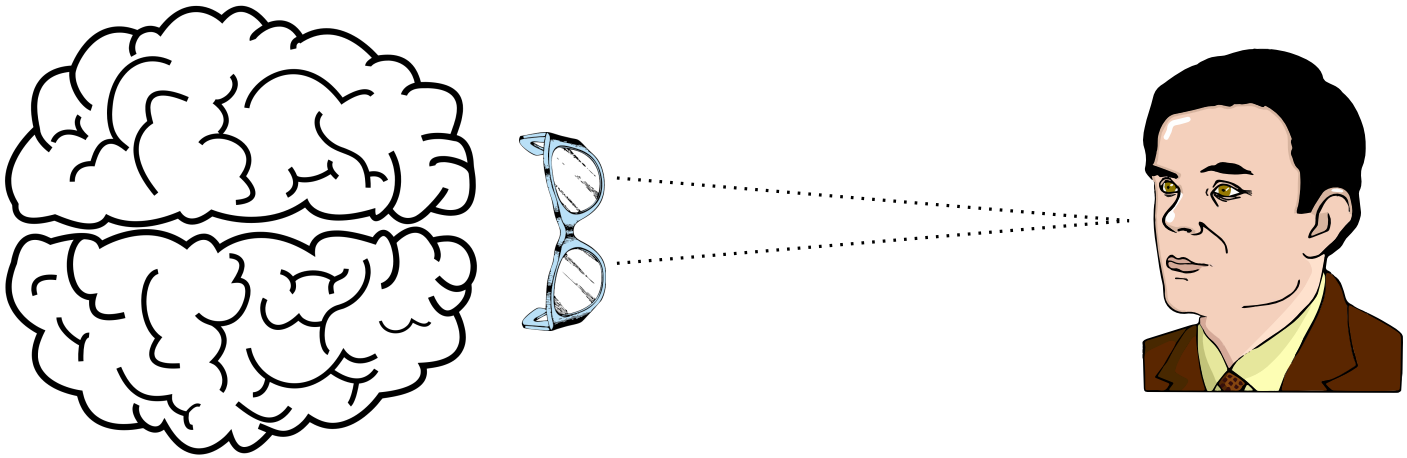

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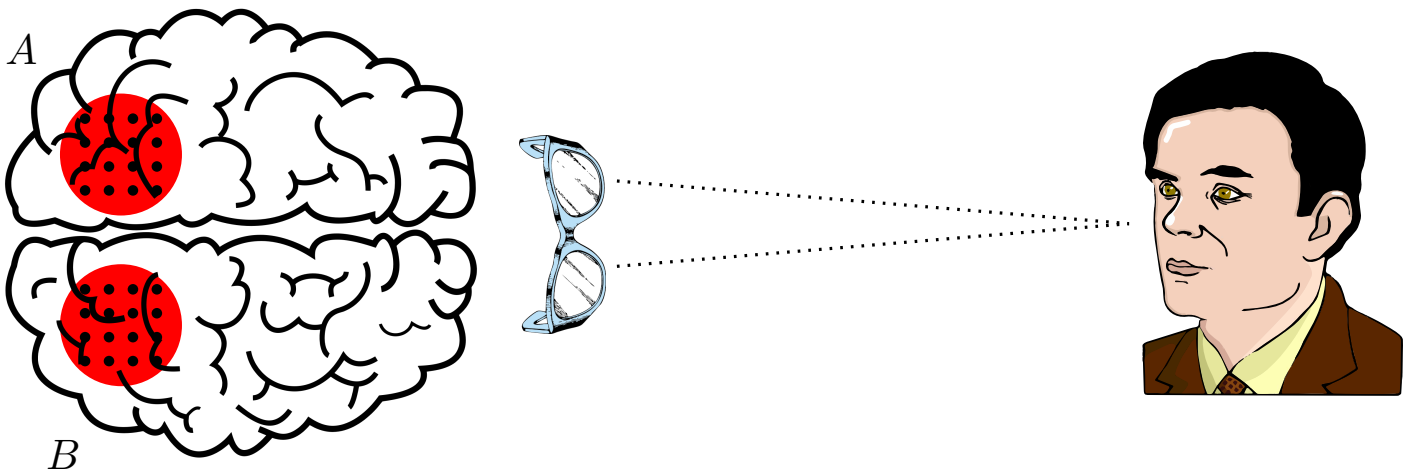

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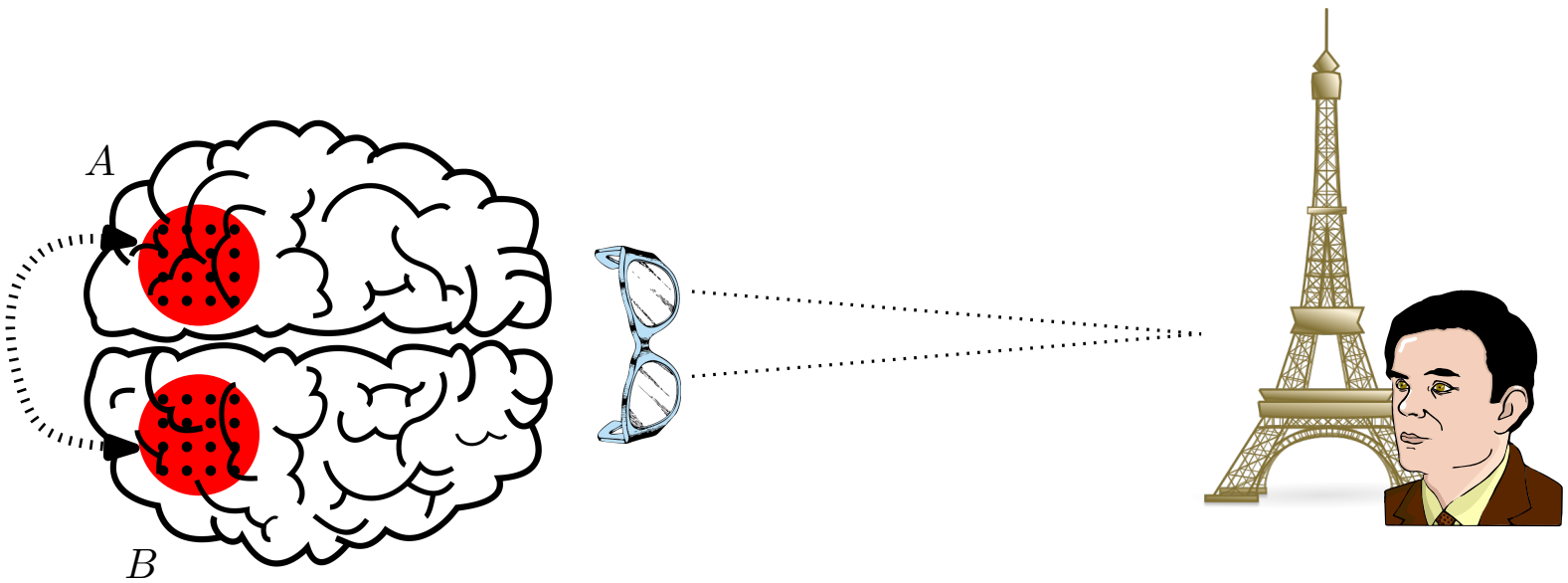

Association of assemblies (and others...)

The Model

- **Brain area**: $A = G_{n_A, p_A}$ Erdös Rényi graph

- *Recall* $G_{n,p} = (V, E)$:
  - $|V| = n$
  - $\forall x, y \in V$, $(x, y) \in E$ with probability p

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- *Recall* $G_{n,p} = (V, E)$:
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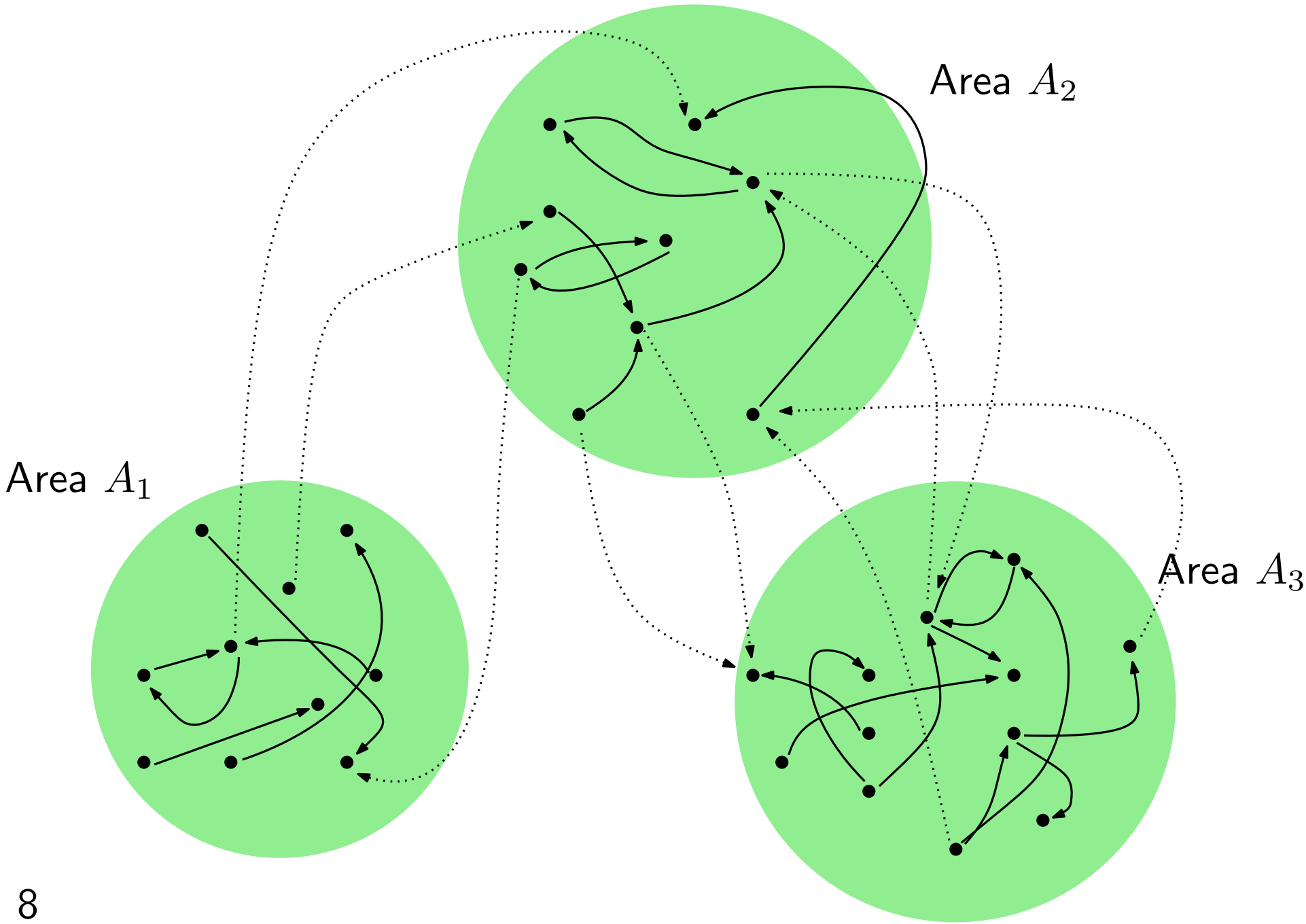
- set of brain areas $\mathcal{S} = \{A_1, A_2, \ldots, A_m\}$
- $\mathcal{C} \subseteq \mathcal{S} \times \mathcal{S}$ set of ordered pairs of brain areas

- **The Brain**: $\mathcal{B} = (V_{\mathcal{B}}, E_{\mathcal{B}})$ with
  - $V_{\mathcal{B}} = V_{A_1} \cup \cdots \cup V_{A_m}$
  - $E_{\mathcal{B}} = E \cup E_{A_1} \cup \ldots E_{A_m}$
  - E: $\forall (A, B) \in \mathcal{C}$, $\forall x \in A, y \in B$, $(x, y) \in E$ with probability $p_{A,B}$

Example of a Brain



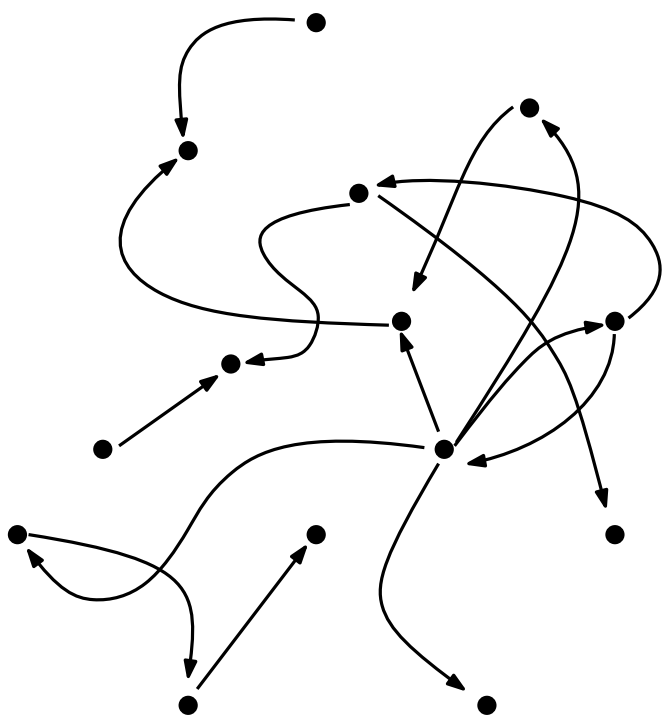
The Dynamics

Synchronous rounds

Neuron $=$ vertex **Fiber** $=$ edge

k-CAP: in each area, only the k neurons with the highest input fire simultaneously (ties broken u.a.r.)

All fiber weights initialized to be 1



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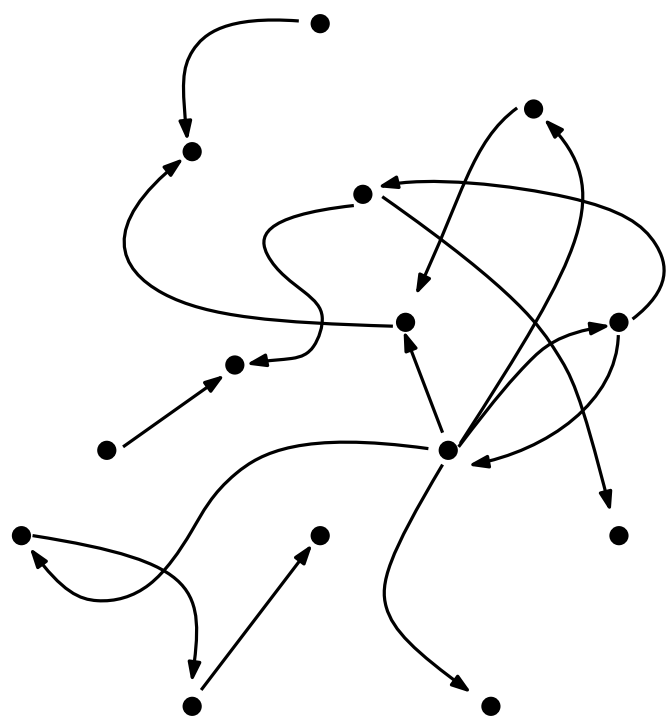

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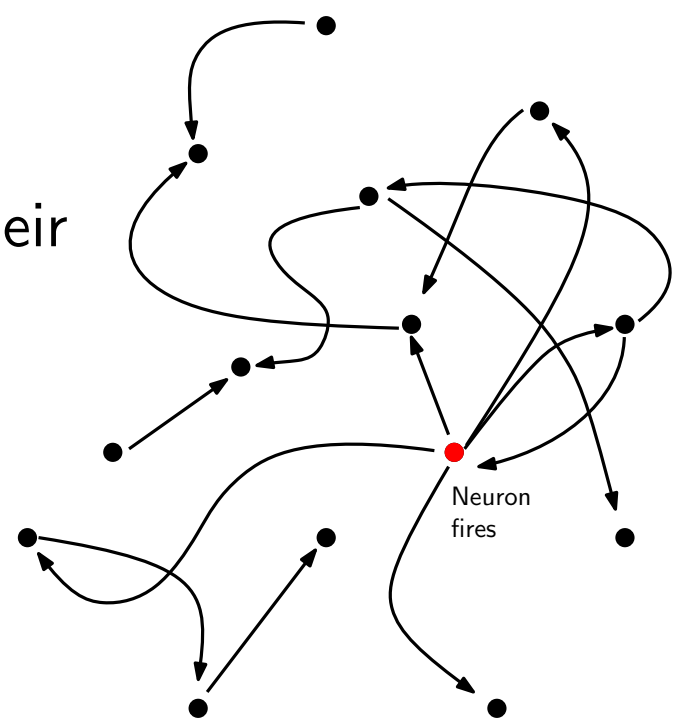
- edges whose endpoints have fired update their weights: $w_{\text{new}}(xy) = w_{\text{old}}(xy)(1+\beta)$

  Hebbian plasticity: β is a constant



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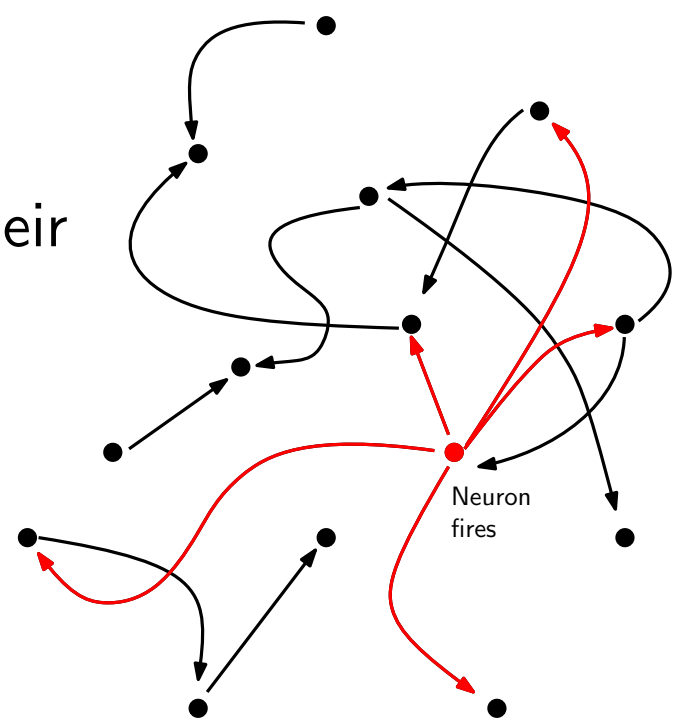

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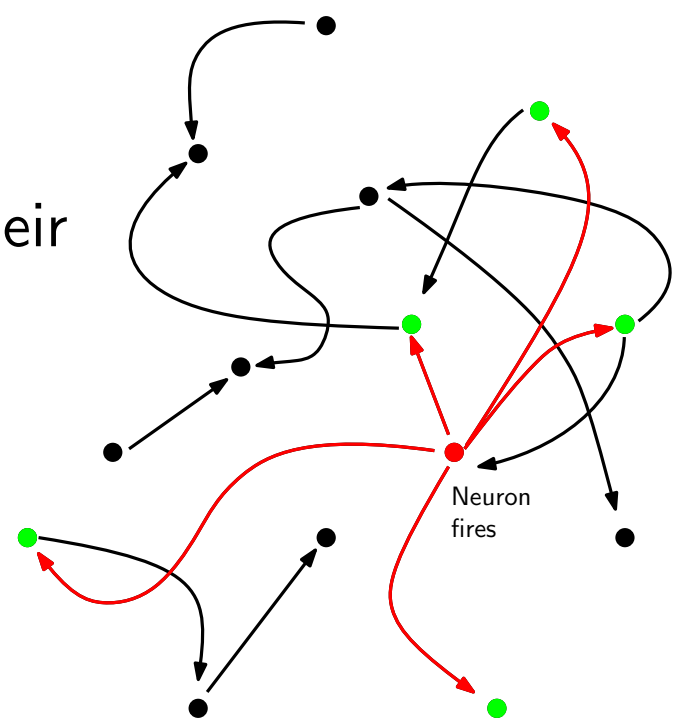

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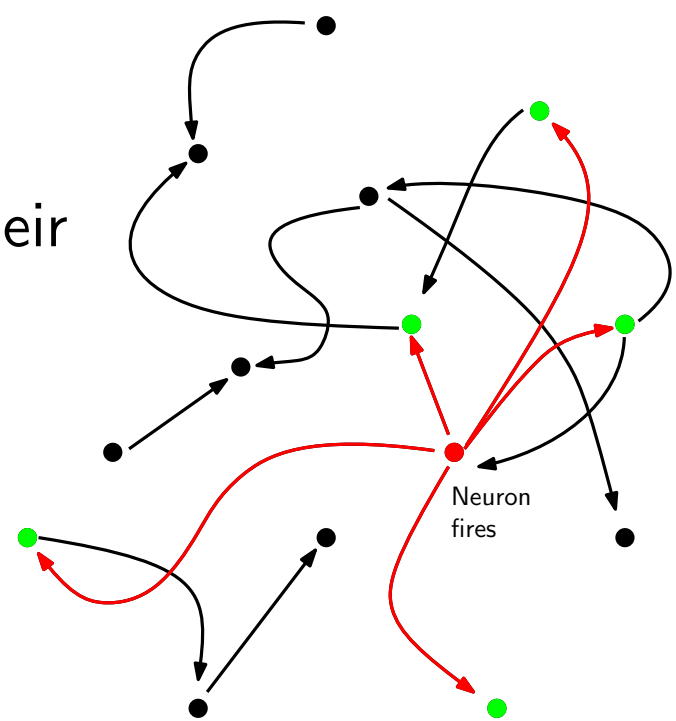
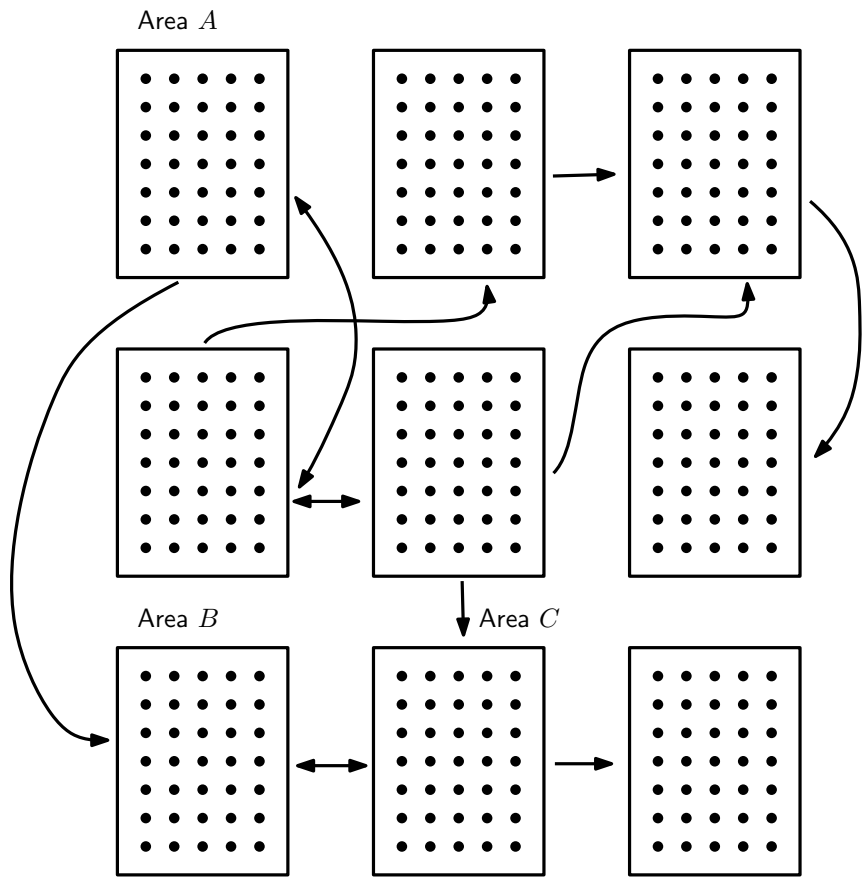
Assembly: stable set of k neurons firing



Operations

The brain and its areas

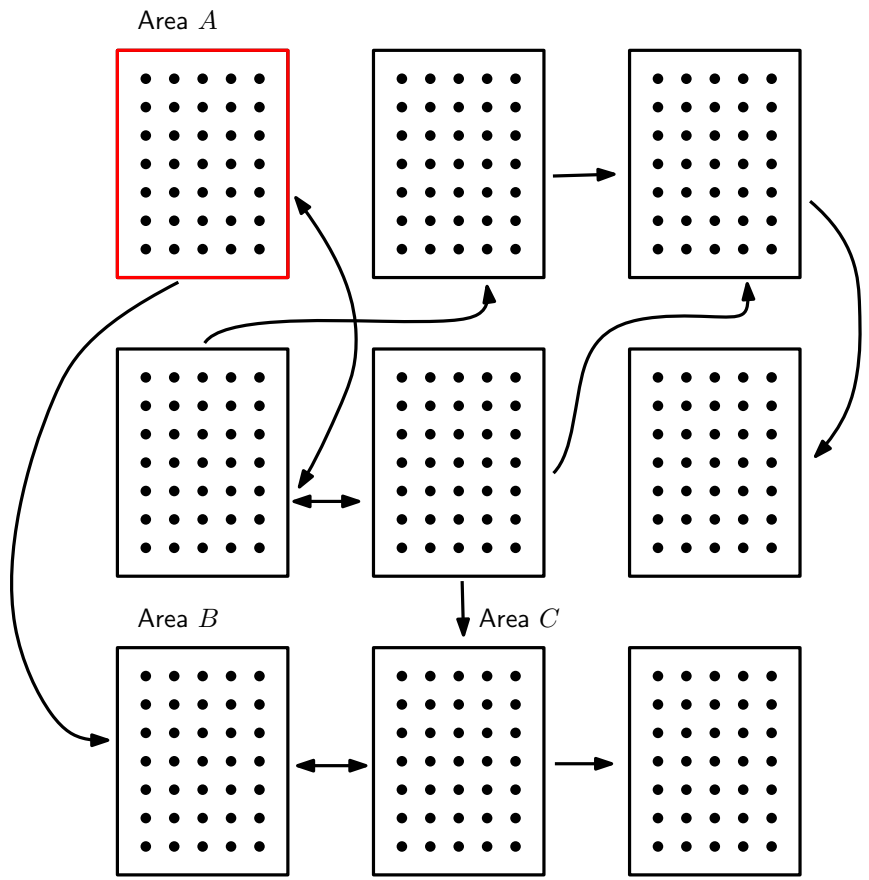


Operations

- **Inhibition**: an area can be inhibited, that is, its neurons cannot fire

Inhibition is accomplished through populations of inhibitory neurons, whose firing prevents other neurons from firing [Mitropolsky et al., TACL 2021]

The brain and its areas



For areas A, B, C:

- `inhibitArea` (A)

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- **Disinhibition**: an inhibited area can be disinhibited, that is, its neurons can now fire

Disinhibition inhibits a population of inhibitory neurons, which currently inhibit the area [Mitropolsky et al., TACL 2021]

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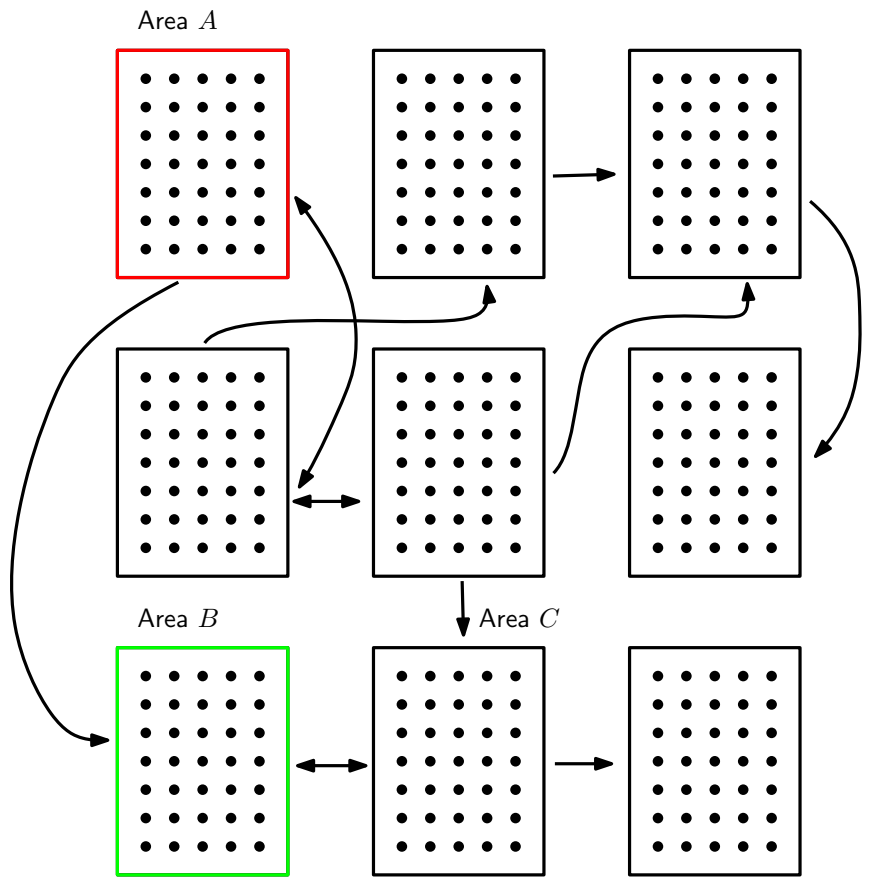

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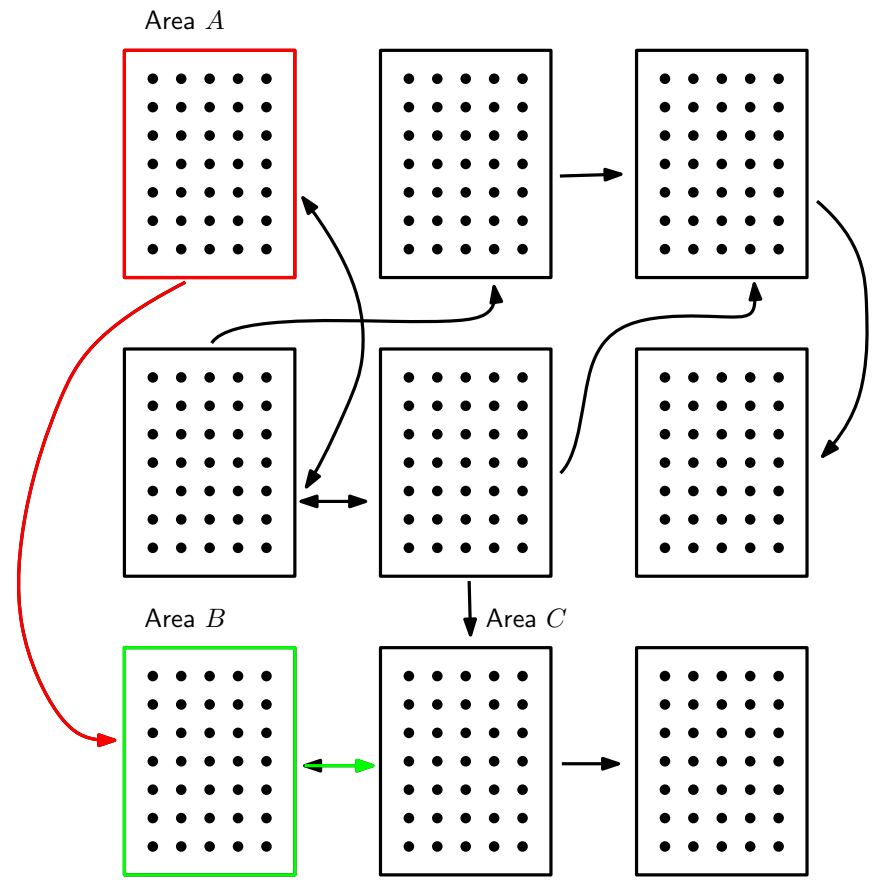


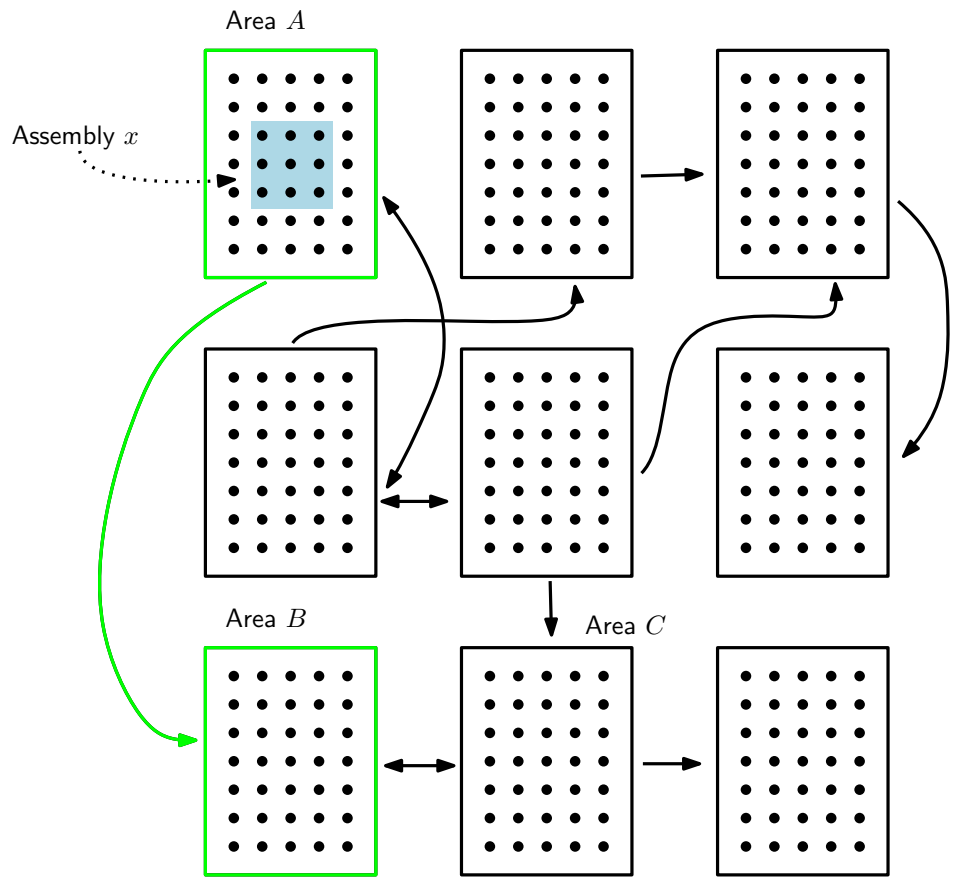
We assume we can do the same with fibers

For areas A, B, C:

- `inhibitArea` (A)
- `inhibitFiber` (A, B)
- `disinhibitArea` (B)
- `disinhibitFiber` (B, C)

Operations

The brain and its areas

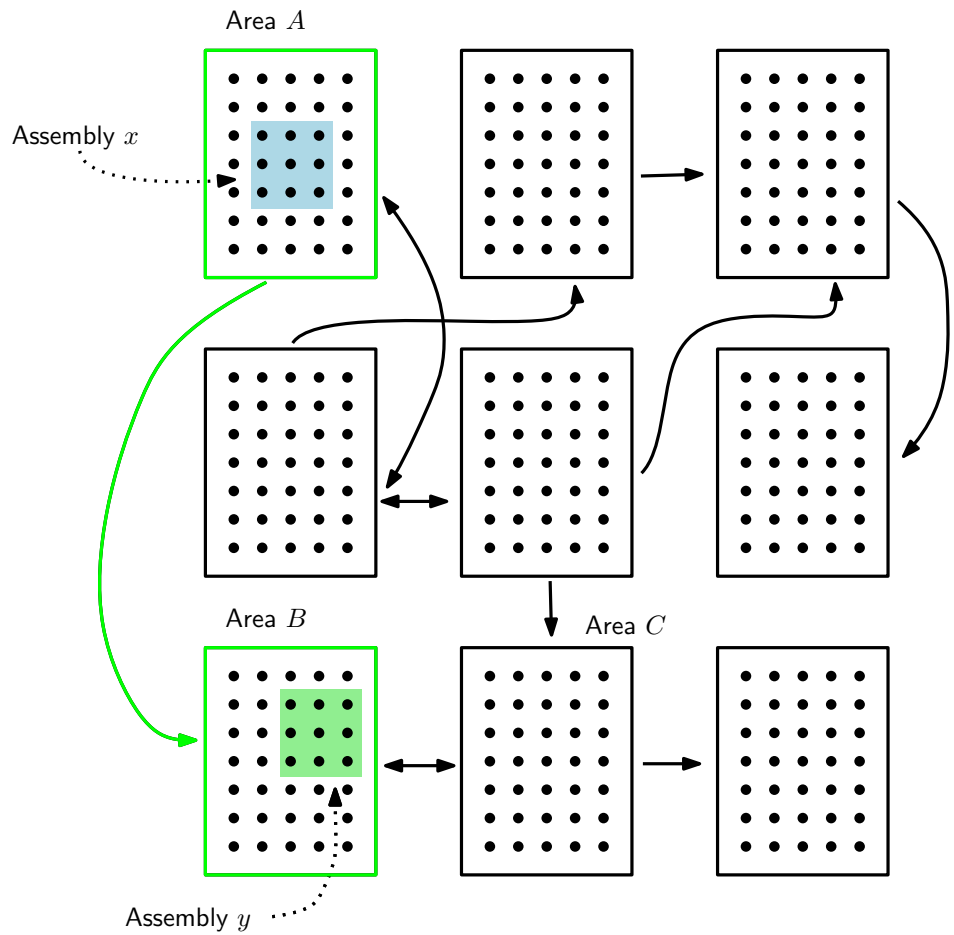


Operations

- **Projection**: the last active assembly x in area A starts firing repeatedly into area B until an assembly y is formed

This process eventually converges under a wide range of parameters w.h.p. [Papadimitriou et Vempala, ITCS 2019]

The brain and its areas



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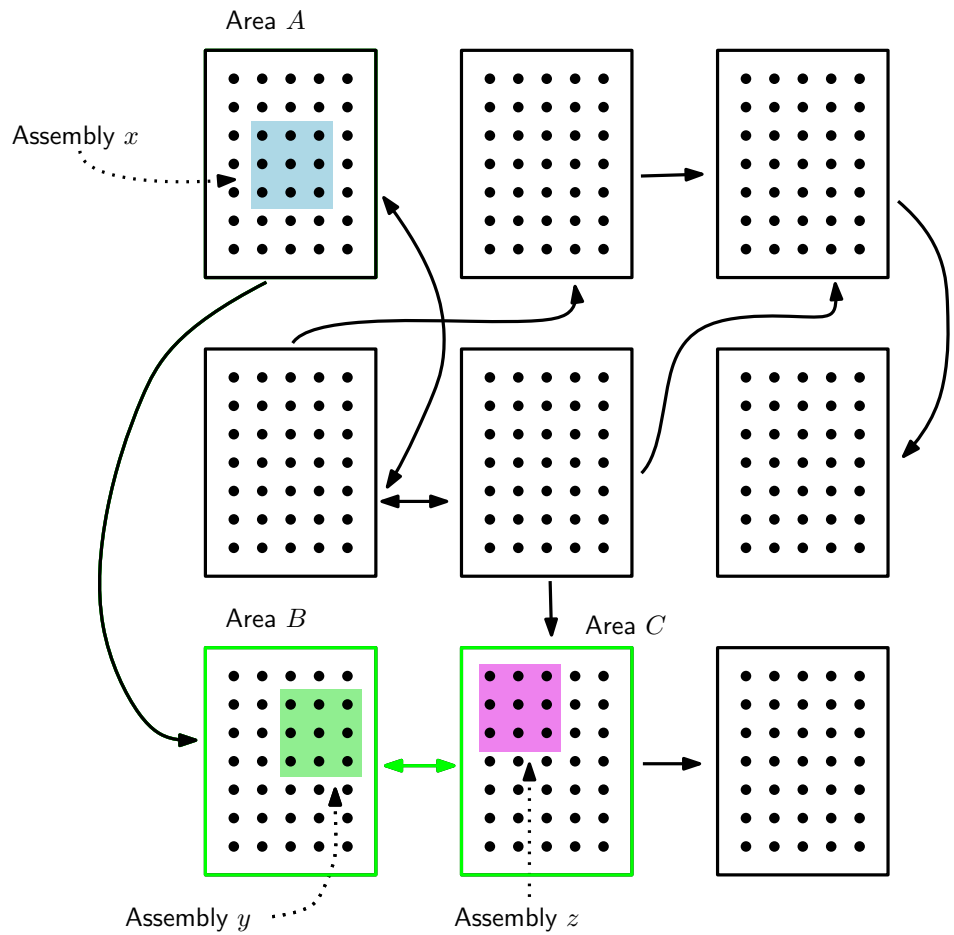

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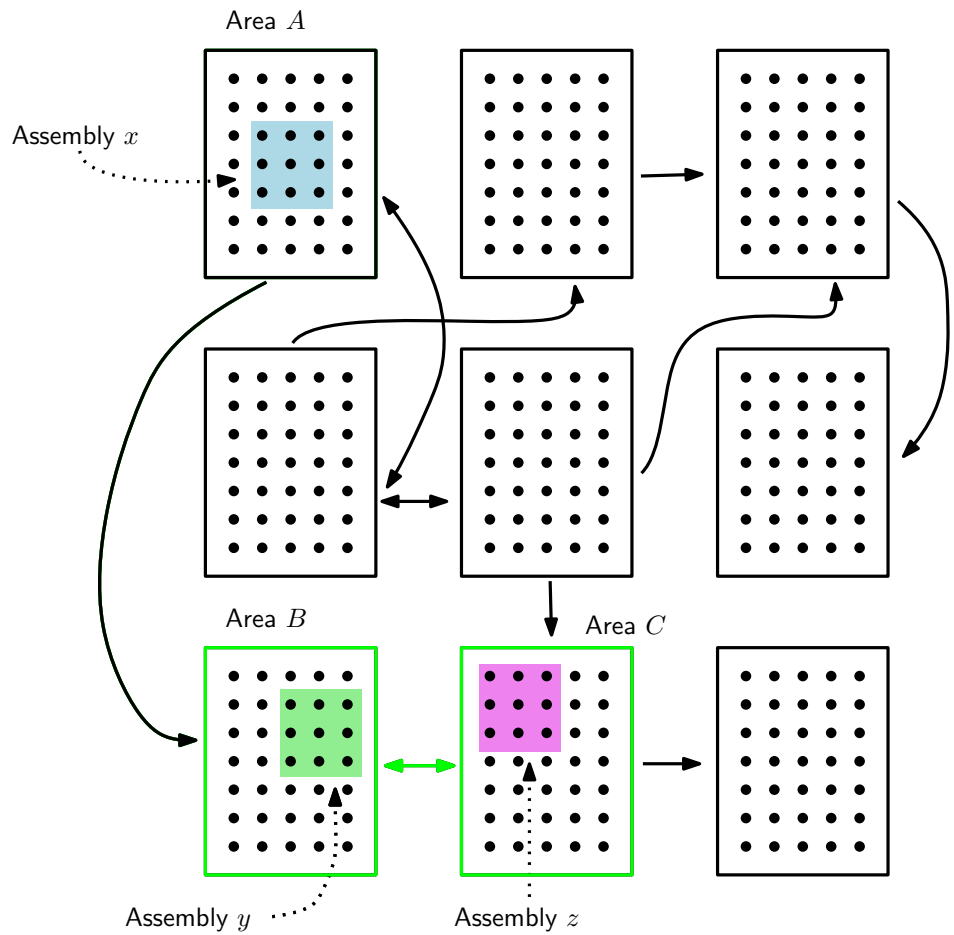
- **Association**: last active assemblies y in area B and z in area C fire simultaneously until they're linked

Linked: the firing of one results into the firing of the other

The brain and its areas



For areas A, B, C:

- `project` (A, B)
- `associate` (B, C)

Remember?

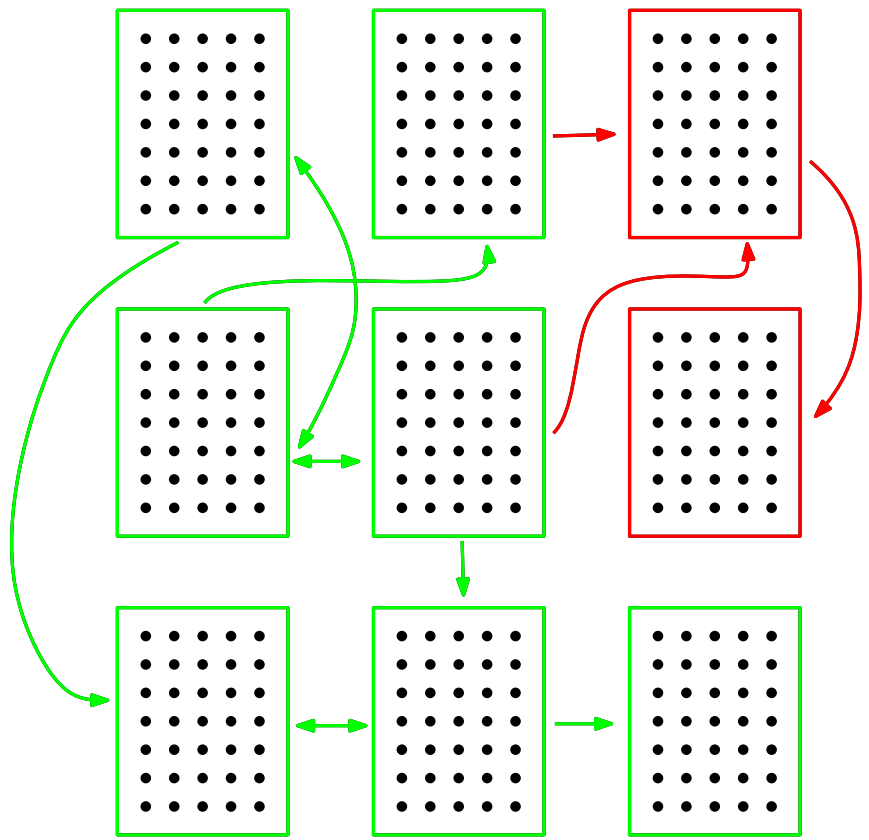
Operations

- **Strong projection**: enhancement of the projection operation

Dynamics on the subgraph induced by all disinhibited areas and fibers:

- all active assemblies start projecting in adjacent areas, forming new assemblies, and so on, until stability

The brain and its areas



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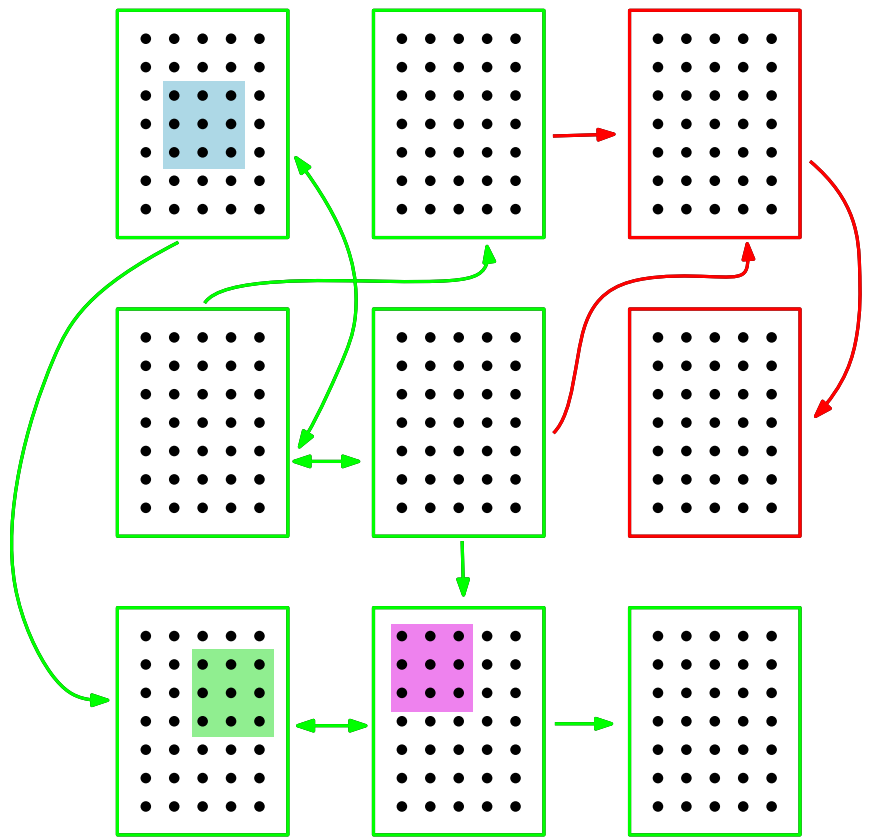

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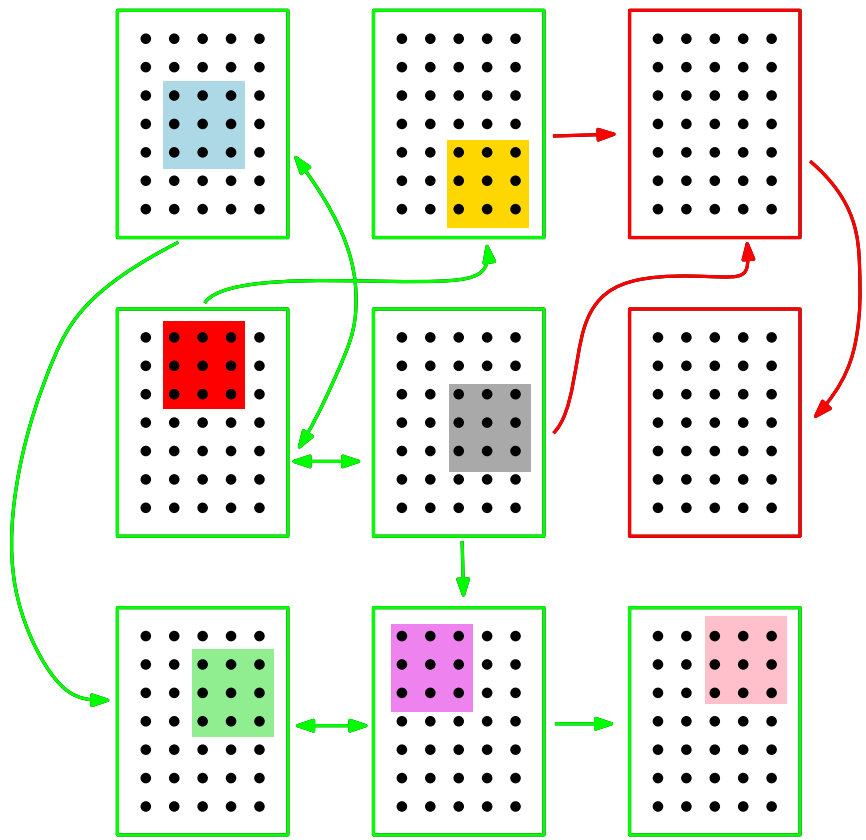

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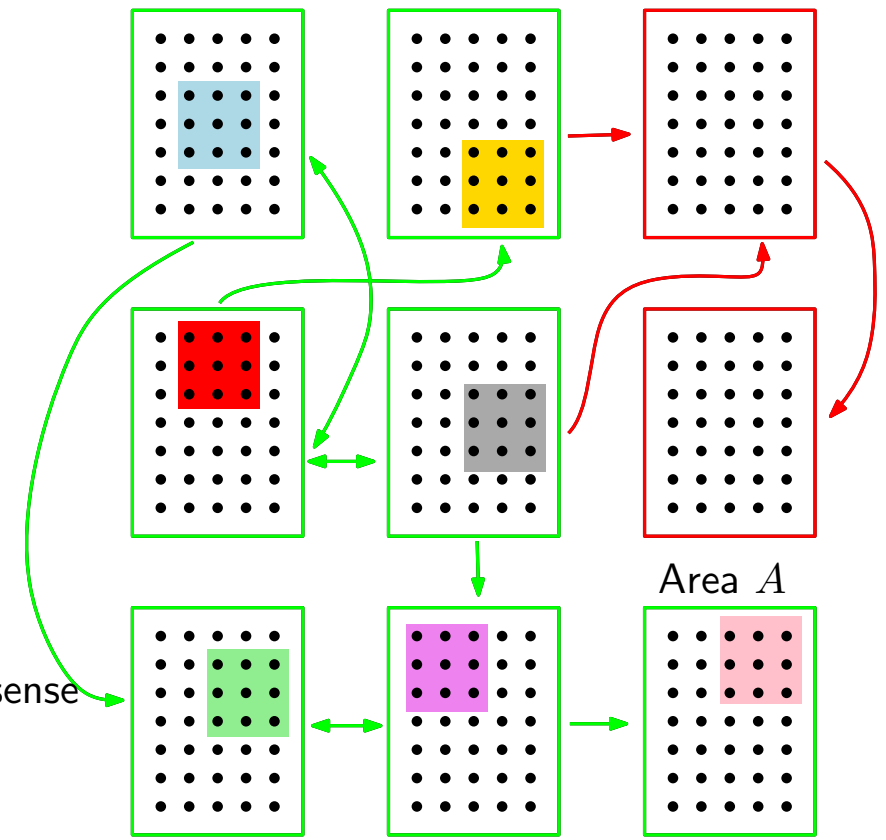
- **Read**: identifies whether in a given area an assembly has fired

[Buzsáki, Neuron 2010] proposes that, for assemblies to be functionally useful, readout mechanisms must exist that sense the current state of the assembly system and trigger appropriate further action

- returns a boolean

The brain and its areas



We write `strongProject()` and `read`(A) for a brain area A

Related Works

- [Legenstein et al., ITCS 2018] shows analytically how assemblies emerge from stimula

- [Papadimitriou et Vempala, ITCS 2019] analyzes the convergence of processes defined by operations with assemblies

- [Papadimitriou et al., PNAS 2020] introduces the formal model of the assembly calculus and proves it's Turing complete
  - gives a Python code which simulates the model
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- [Mitropolsky et al., TACL 2021] proposes a parser for the English language in the assembly calculus

Our Contribution

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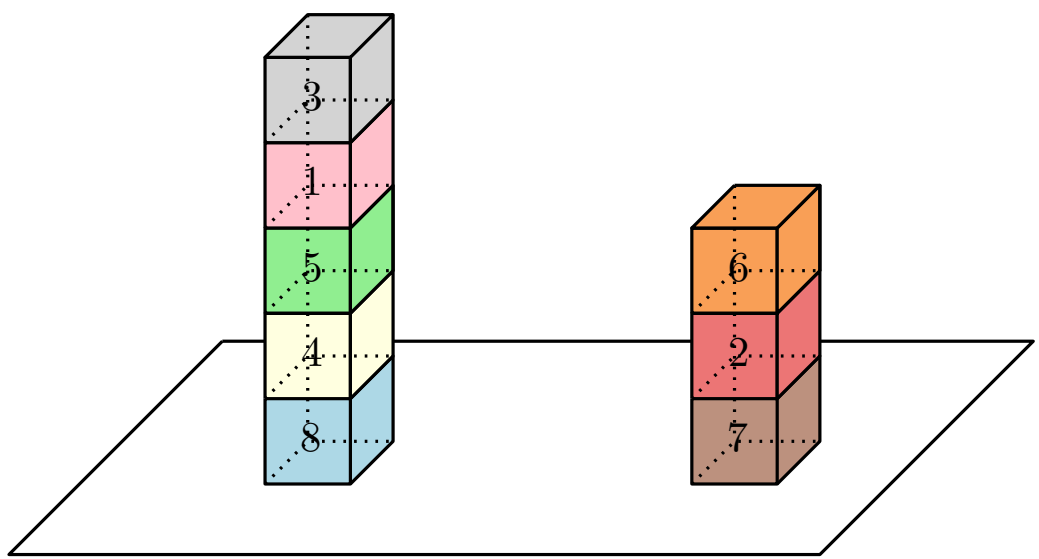

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- set of stacks $\{S_i\}_i$
- each stack is a sequence of blocks $S_i = (b_1^{(i)}, \ldots, b_{k_i}^{(i)})$
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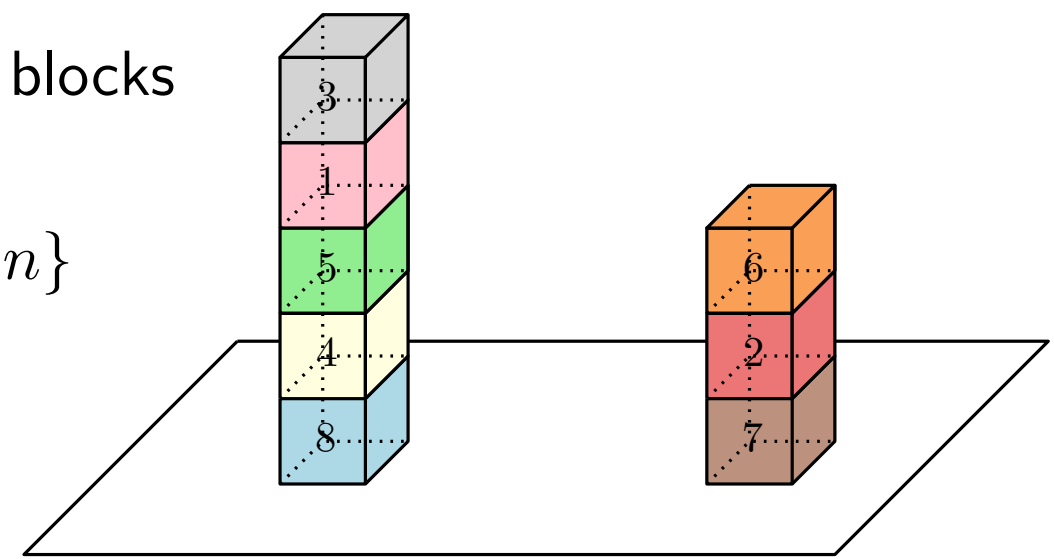

The Planning Task

Possible moves:

- move a block from the top of a stack to the table
- move a block from the top of a stack to the top of another stack
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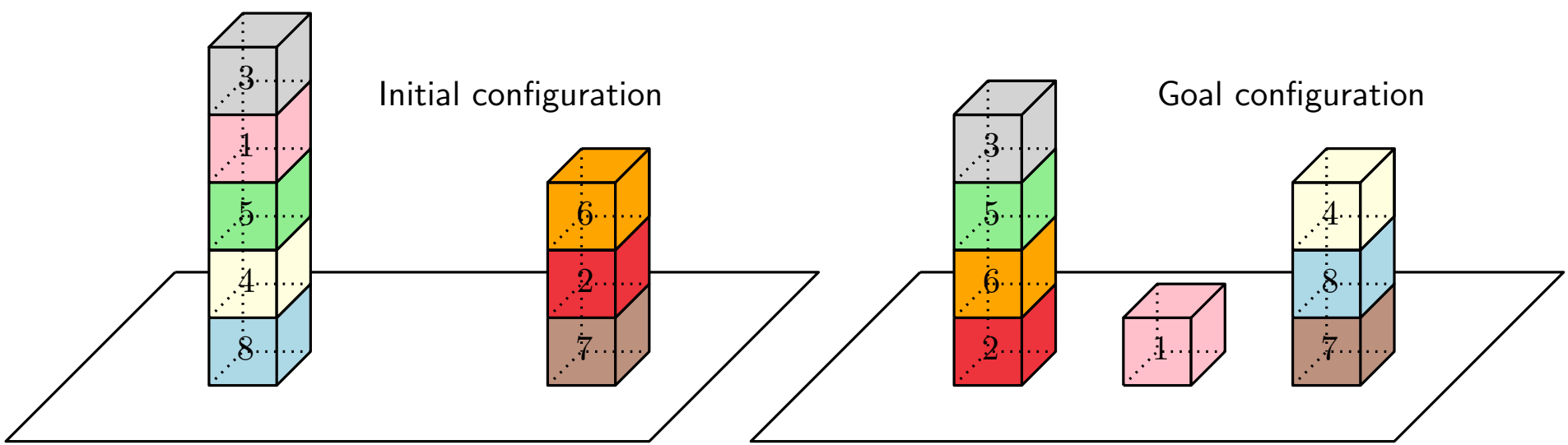

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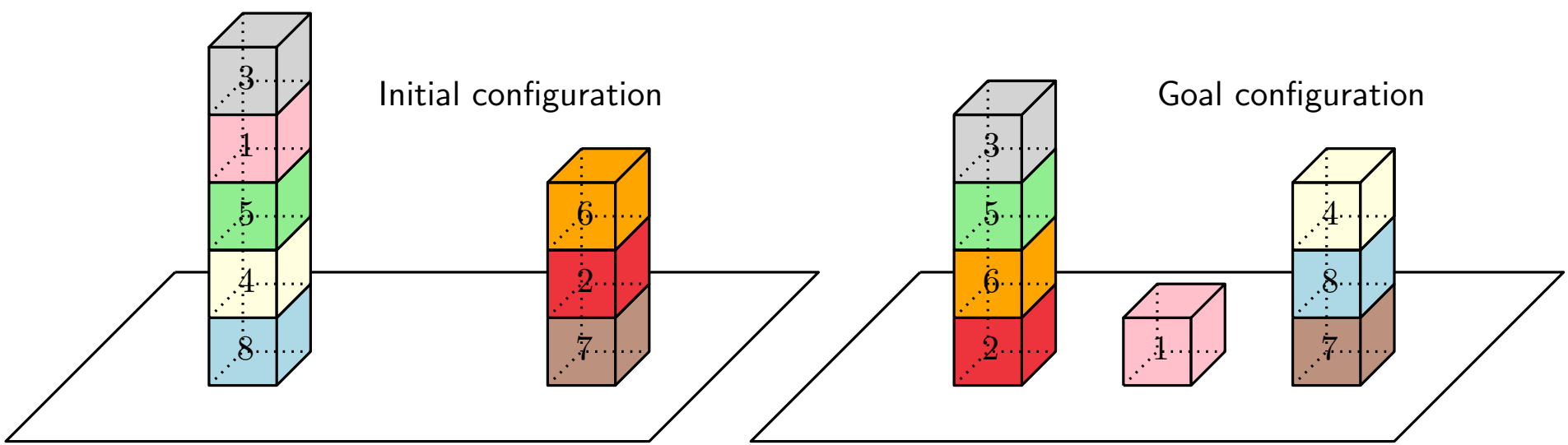
Output:
- the sequence of moves



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We implement both of them...

Back to the Brain: Assumptions

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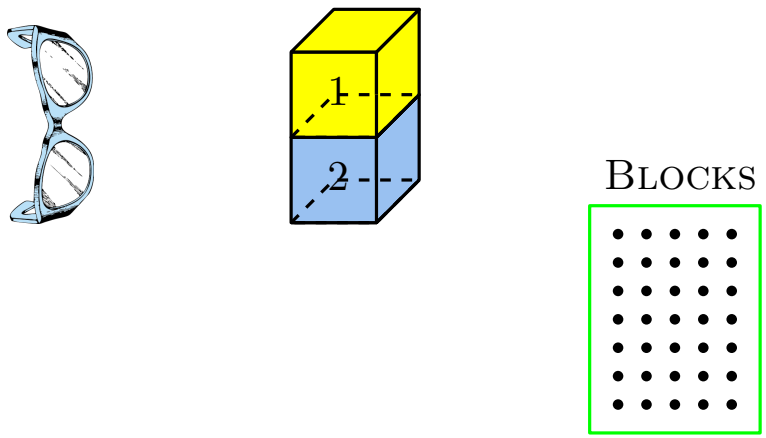

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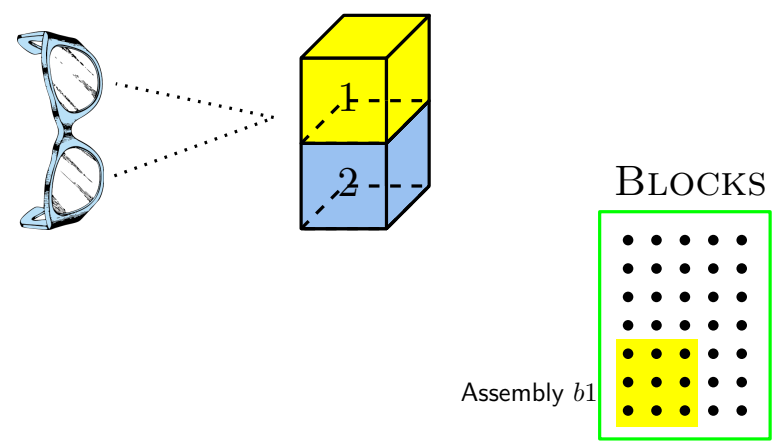

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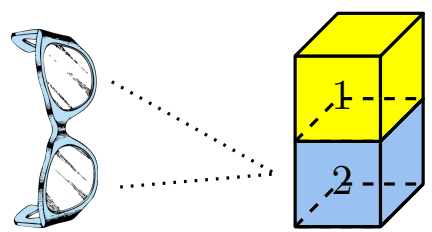

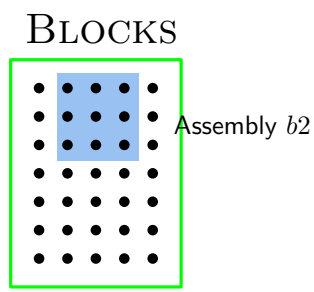

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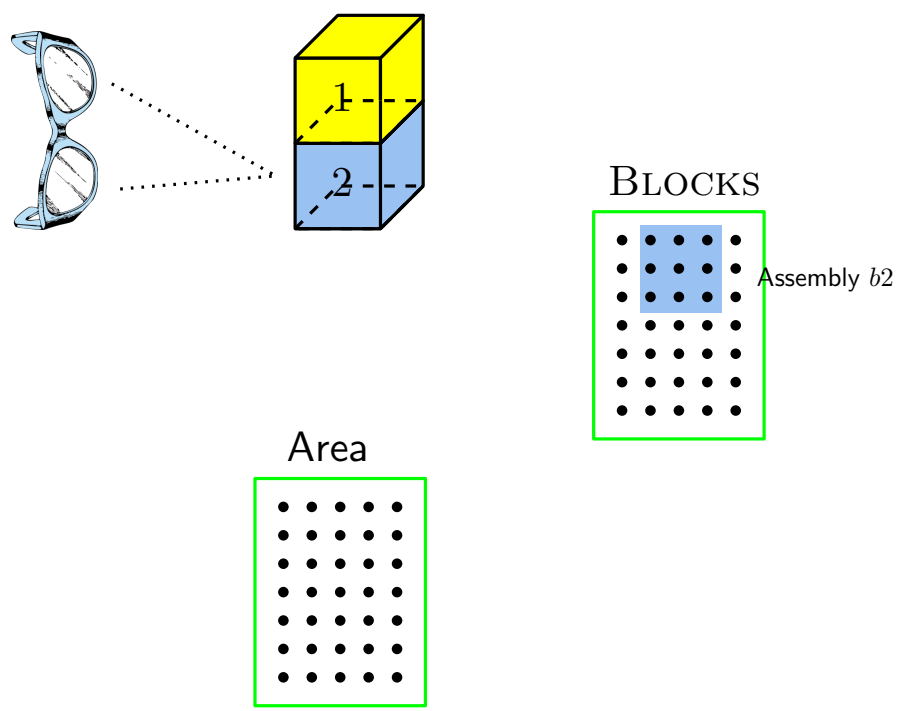

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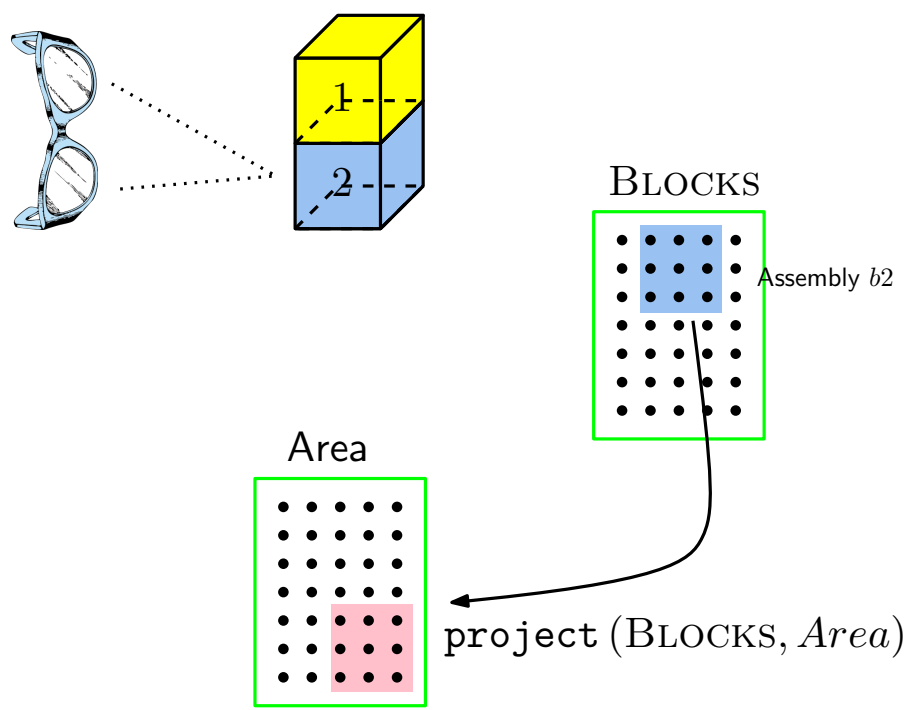

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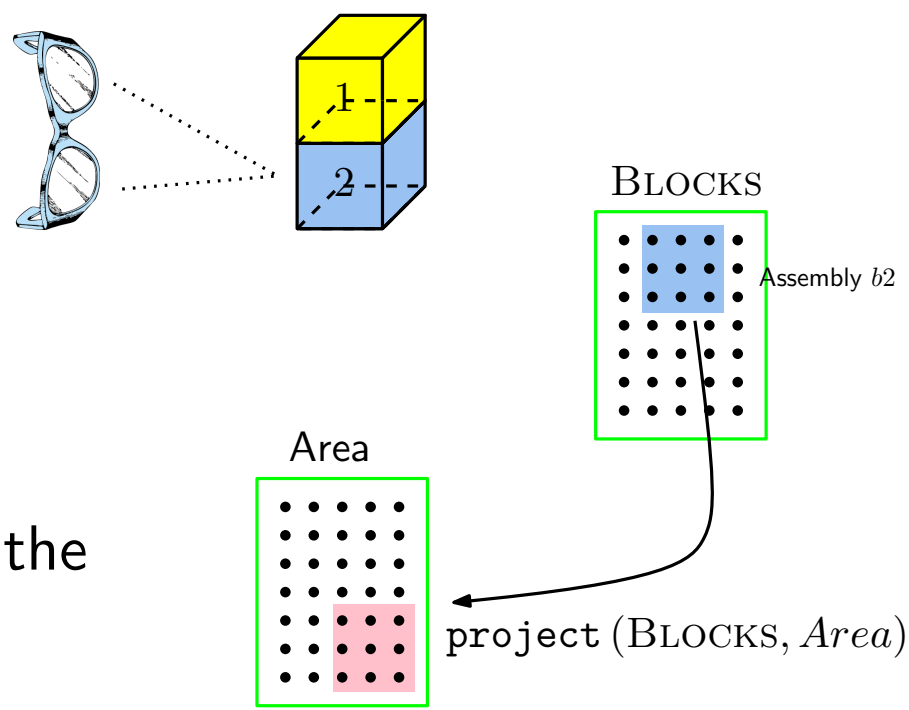
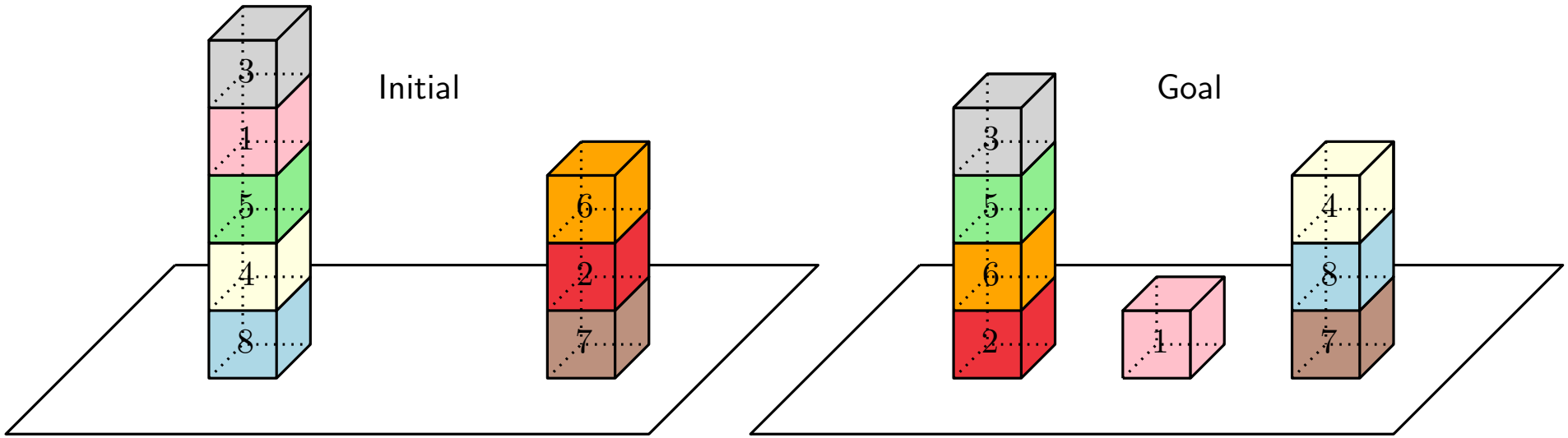


Further assumptions: each area has n neurons, the same Erdös-Renyi prob. p, the same k as the CAP

Back to the Planning Problem



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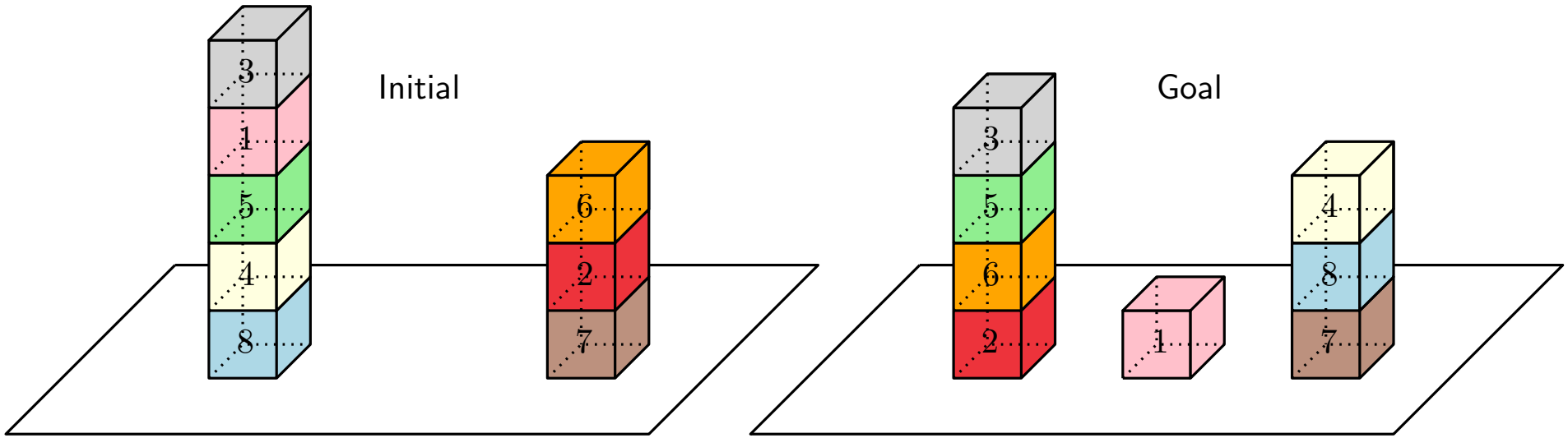

- **First**: way to represent the initial and the goal stacks in the brain

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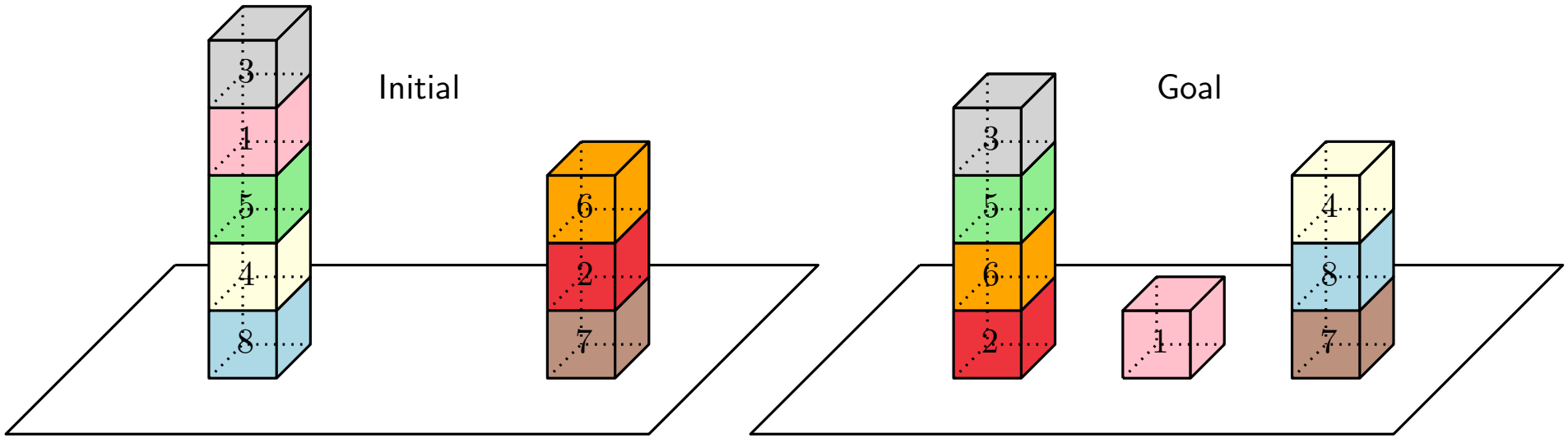

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A Parser

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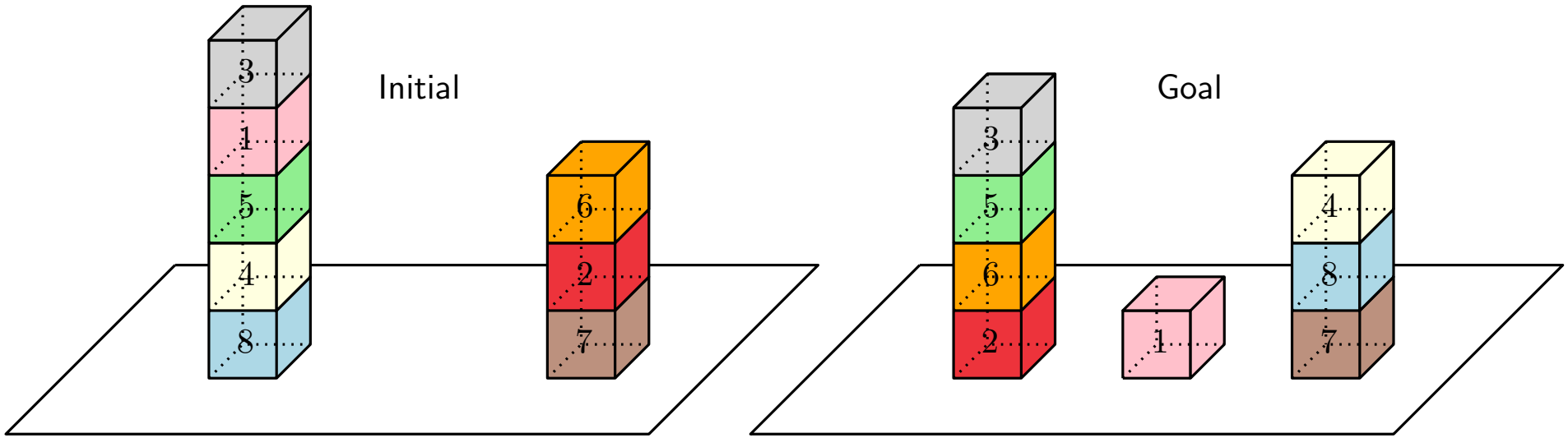


- **First**: way to represent the initial and the goal stacks in the brain

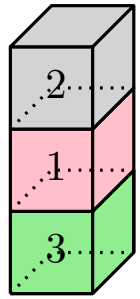
A Parser

- **Second**: way to implement actions and represent them

The Parser

Assumptions:

- single stack
- brain as undirected graph
- 5 brain areas, BLOCKS, NODE_0, NODE_1, NODE_2, HEAD



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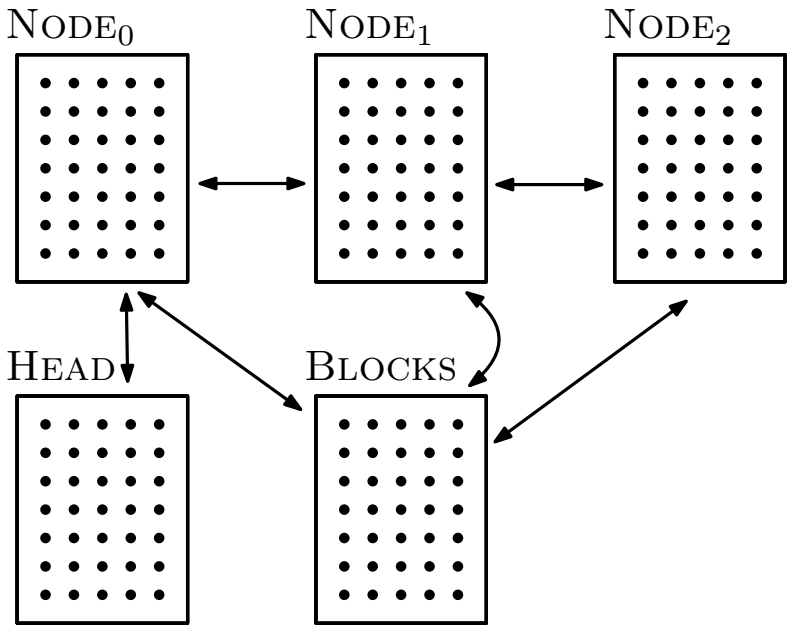

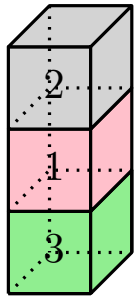

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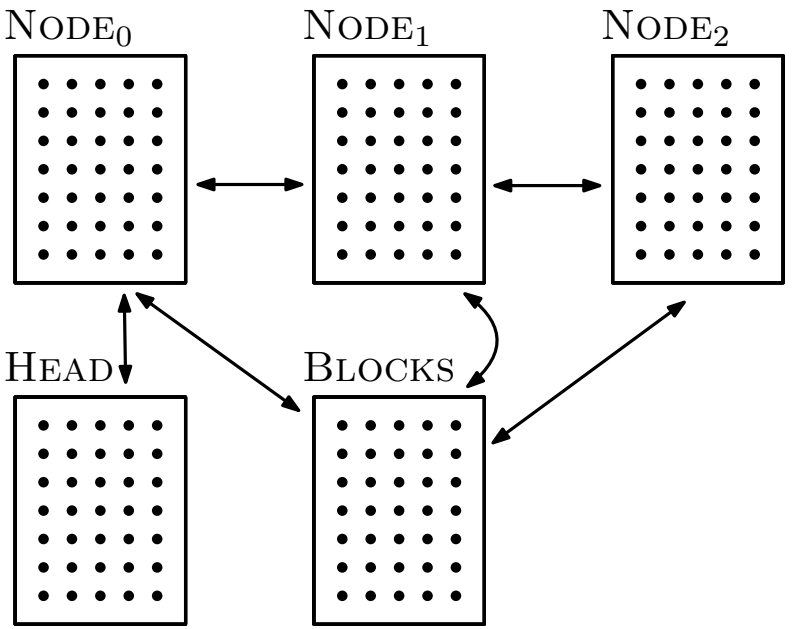

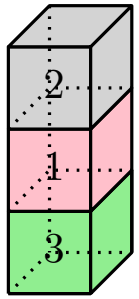

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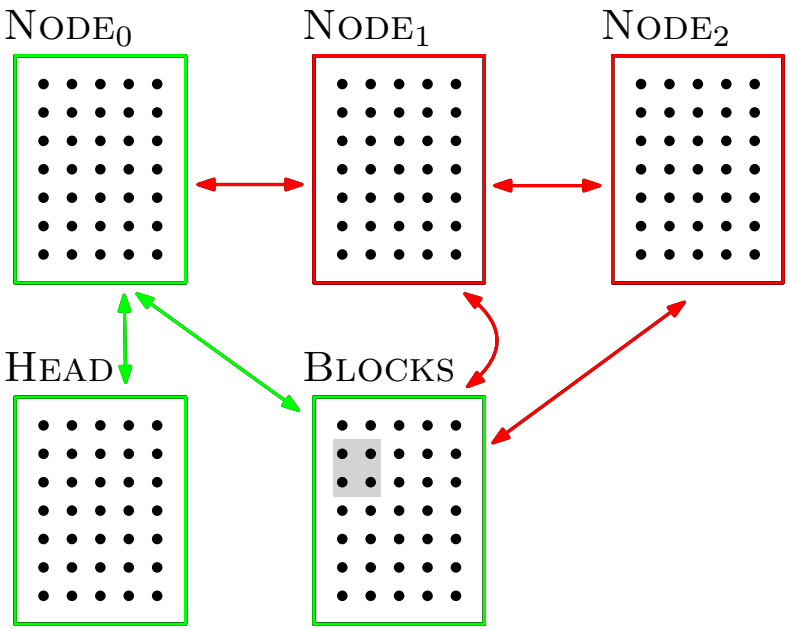

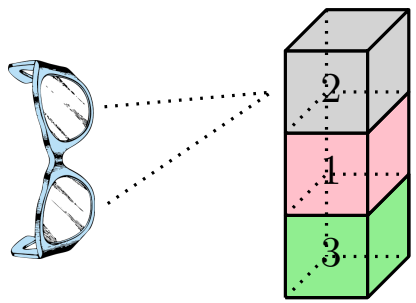

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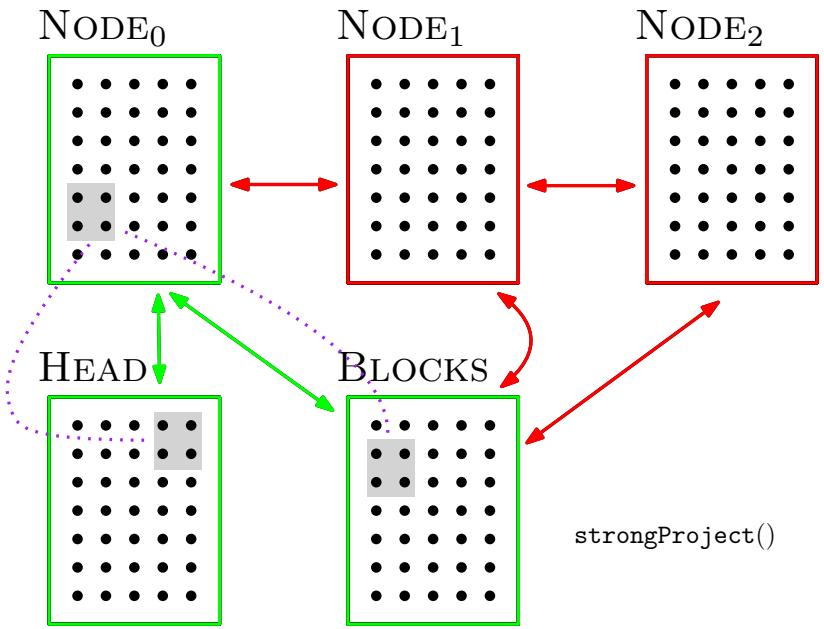

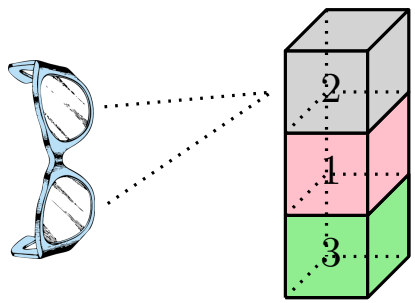

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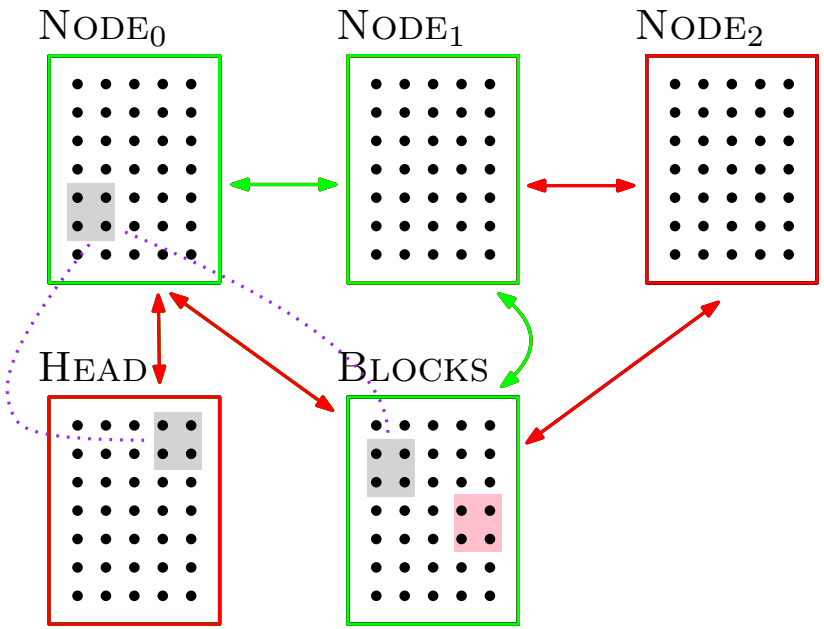

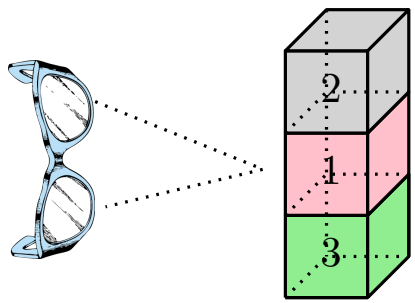

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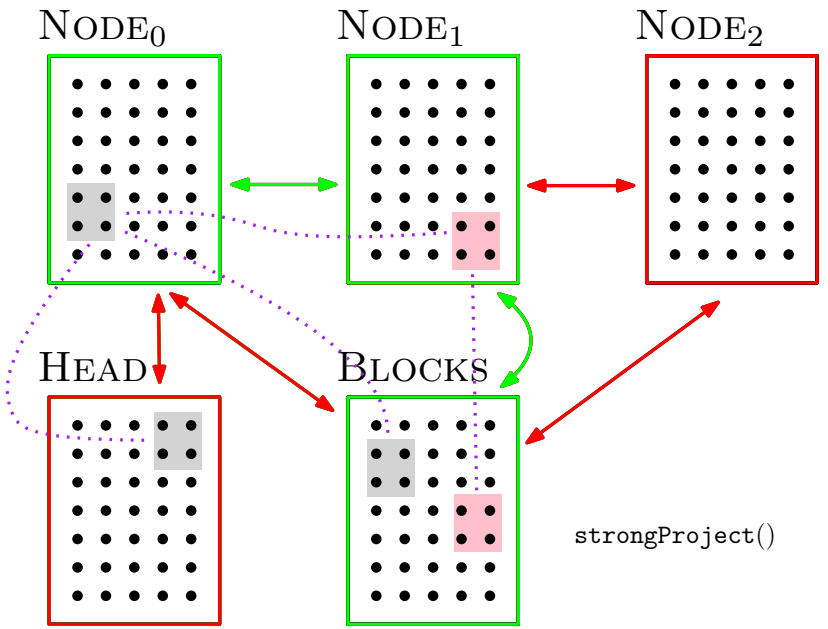

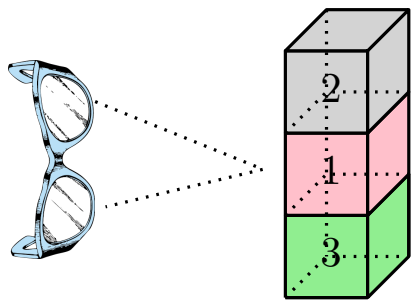

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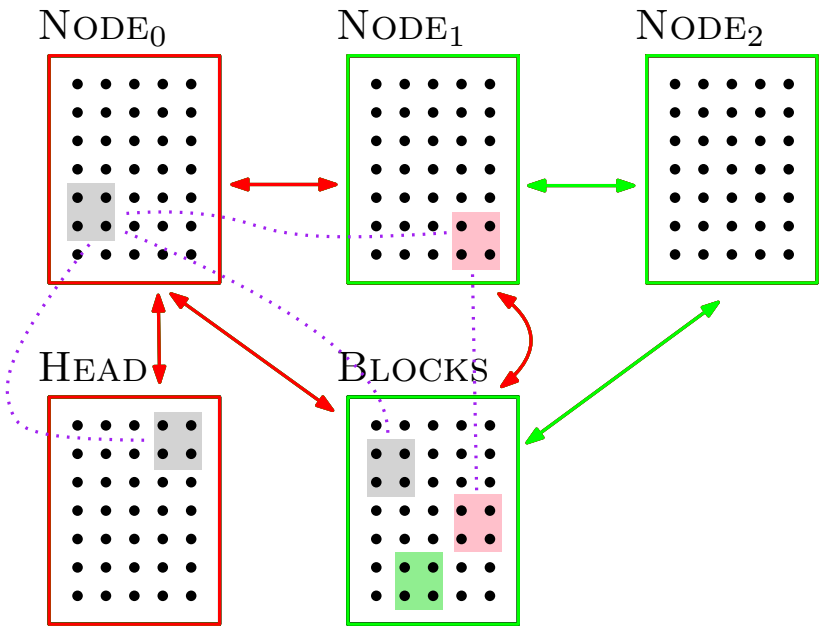

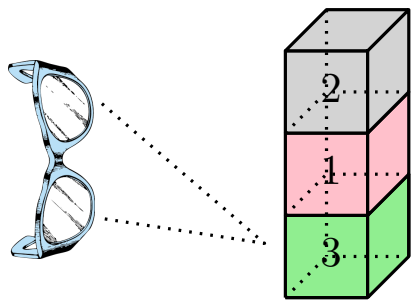

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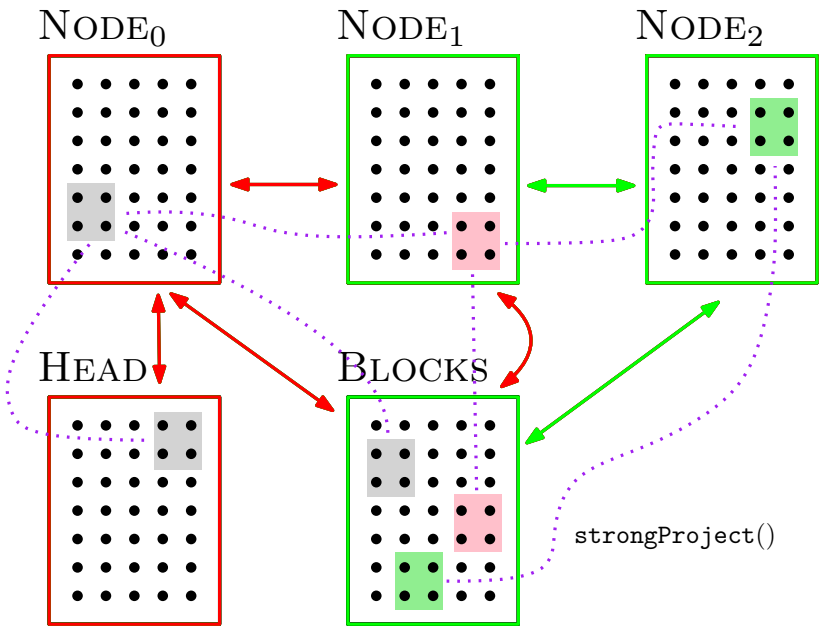

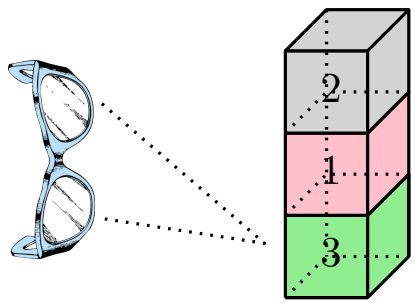

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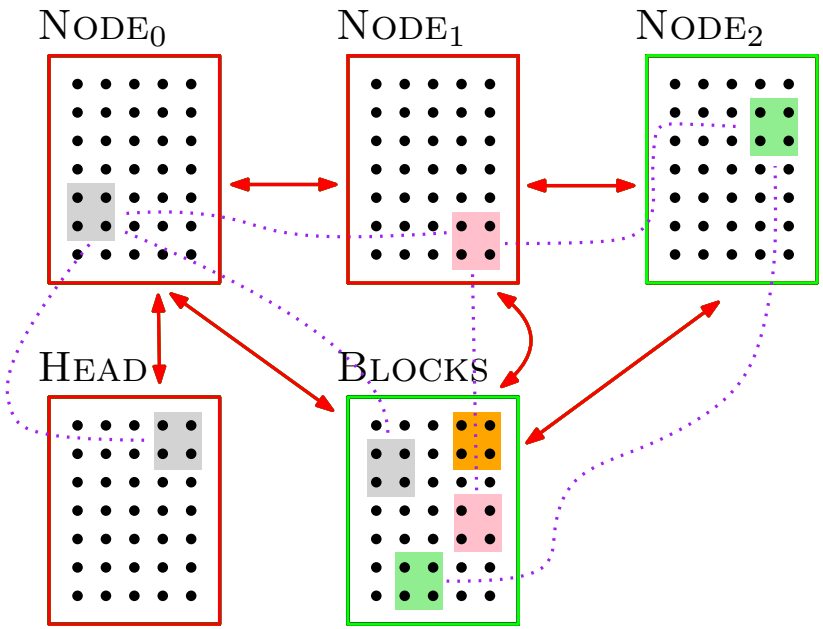

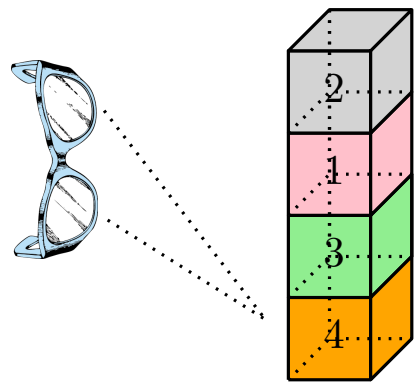

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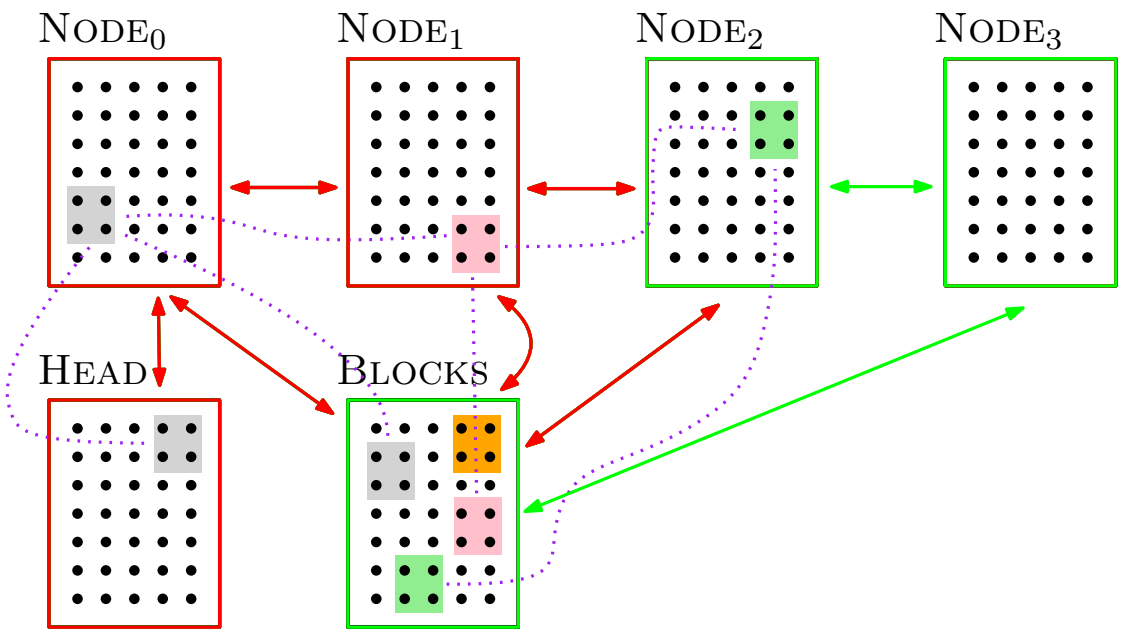

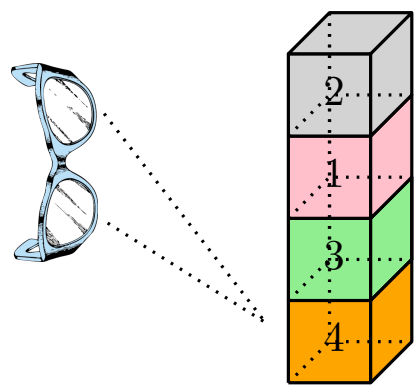

As many areas as the number of blocks... :(

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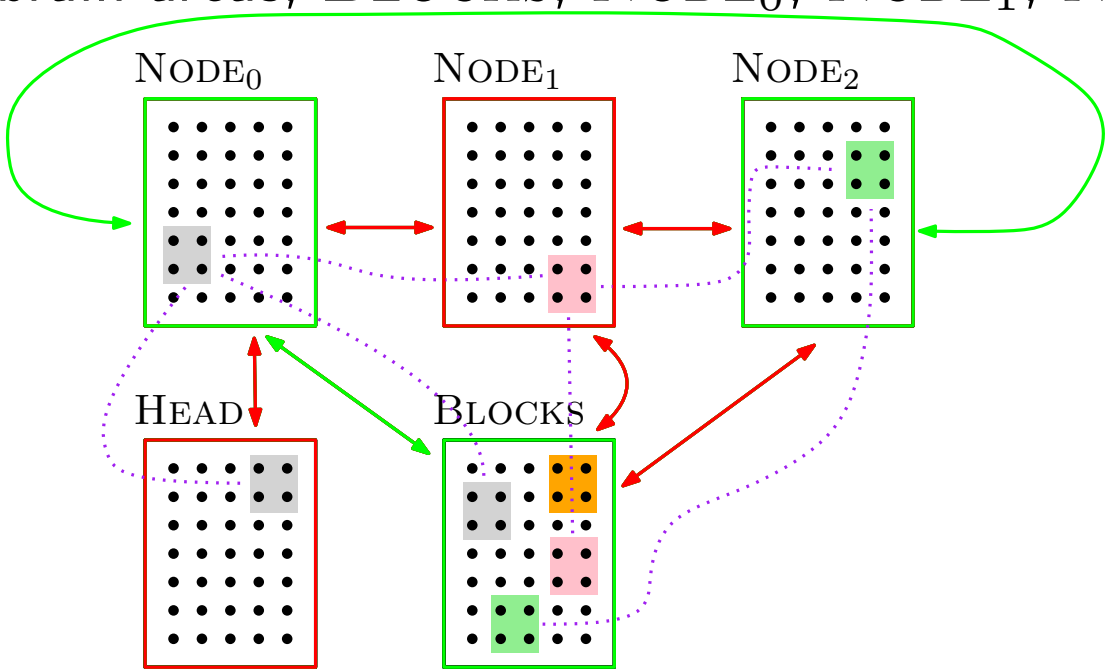

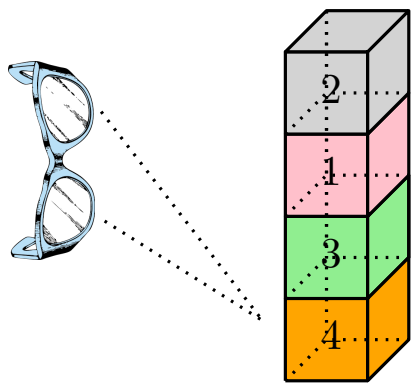

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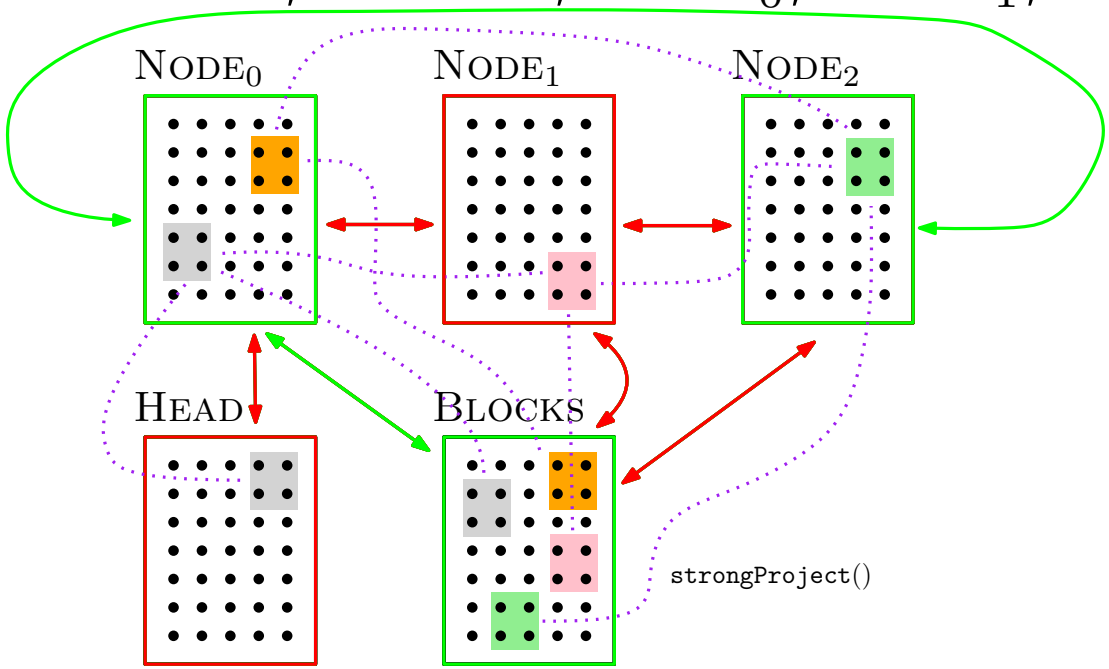

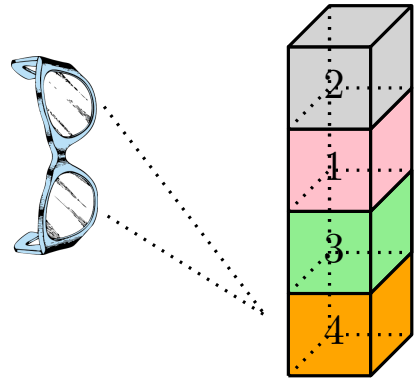

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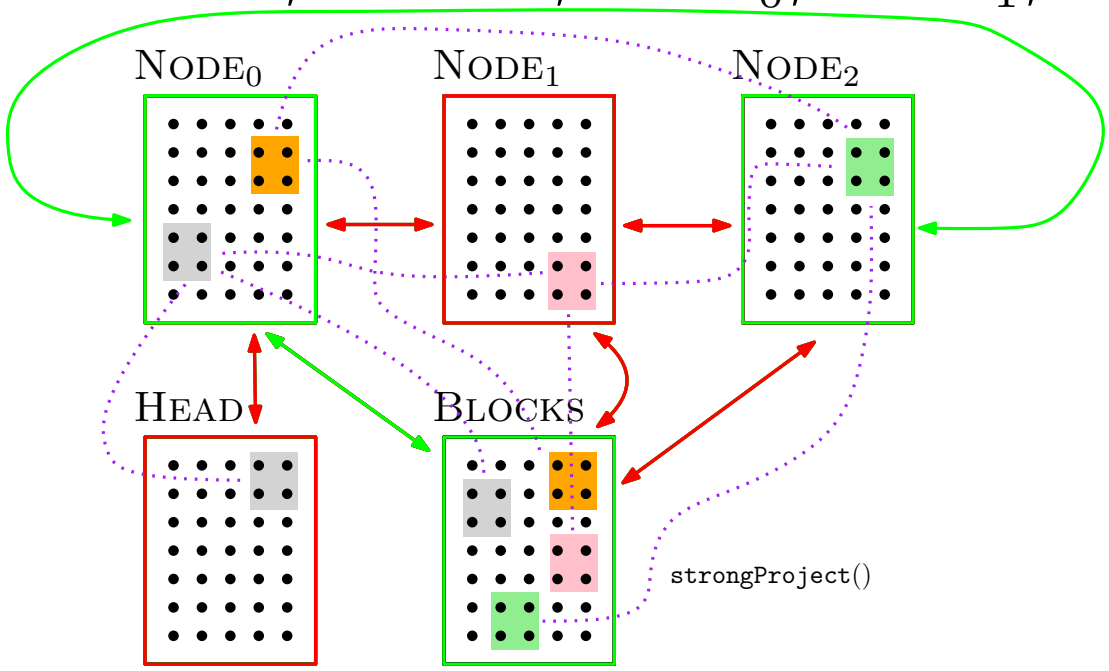
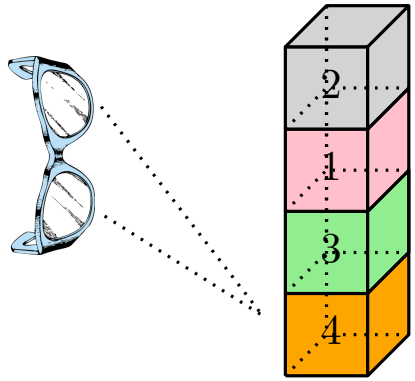




Chaining: novelty. Number of blocks represented depends only on n (number of neurons per area) and k (the CAP)

Parser Code

Algorithm 1: $\textsc{Parser}\,(S)$

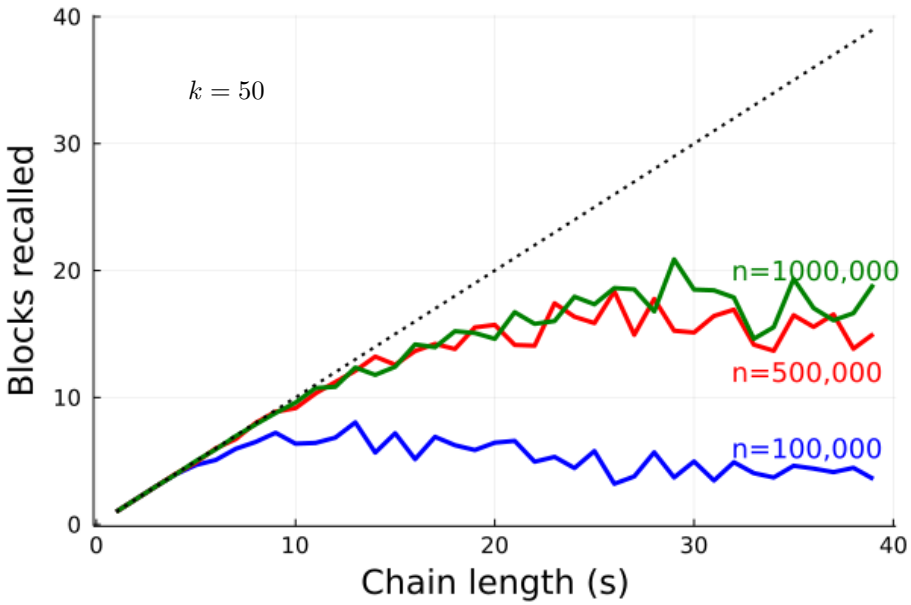
input: a stack S of blocks $b_1, b_2, \ldots, b_s$.

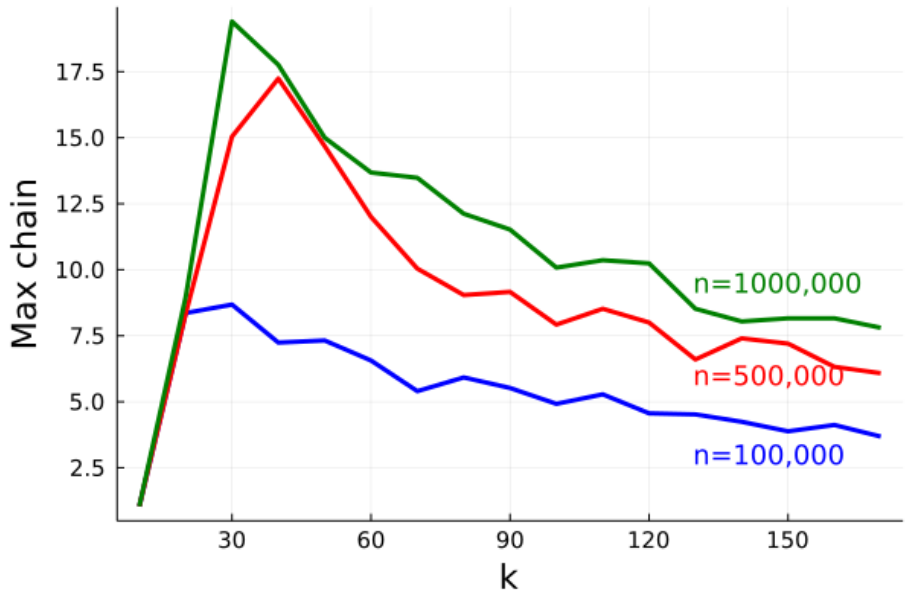
```
1  disinhibitArea ({Blocks, Head, Node_0});
2  disinhibitFiber ({(Head, Node_0) , (Node_0, Blocks)});
3  fire (b_1);
4  strongProject();
5  inhibitArea ({Head});
6  inhibitFiber ({(Head, Node_0) , (Node_0, Blocks)});
7  foreach i with 2 ≤ i ≤ s do
8  |   p = (i − 2) mod 3; c = (i − 1) mod 3;
9  |   disinhibitArea ({Node_c});
10 |   disinhibitFiber ({(Node_p, Node_c) , (Node_c, Blocks)});
11 |   fire (b_i);
12 |   strongProject();
13 |   inhibitArea ({Node_p});
14 |   inhibitFiber ({(Node_p, Node_c) , (Node_c, Blocks)});
15 end
16 inhibitArea ({Blocks, Node_(s−1) mod 3});
```

Chaining Experiments

Due to overlap of assemblies, chaining may fail

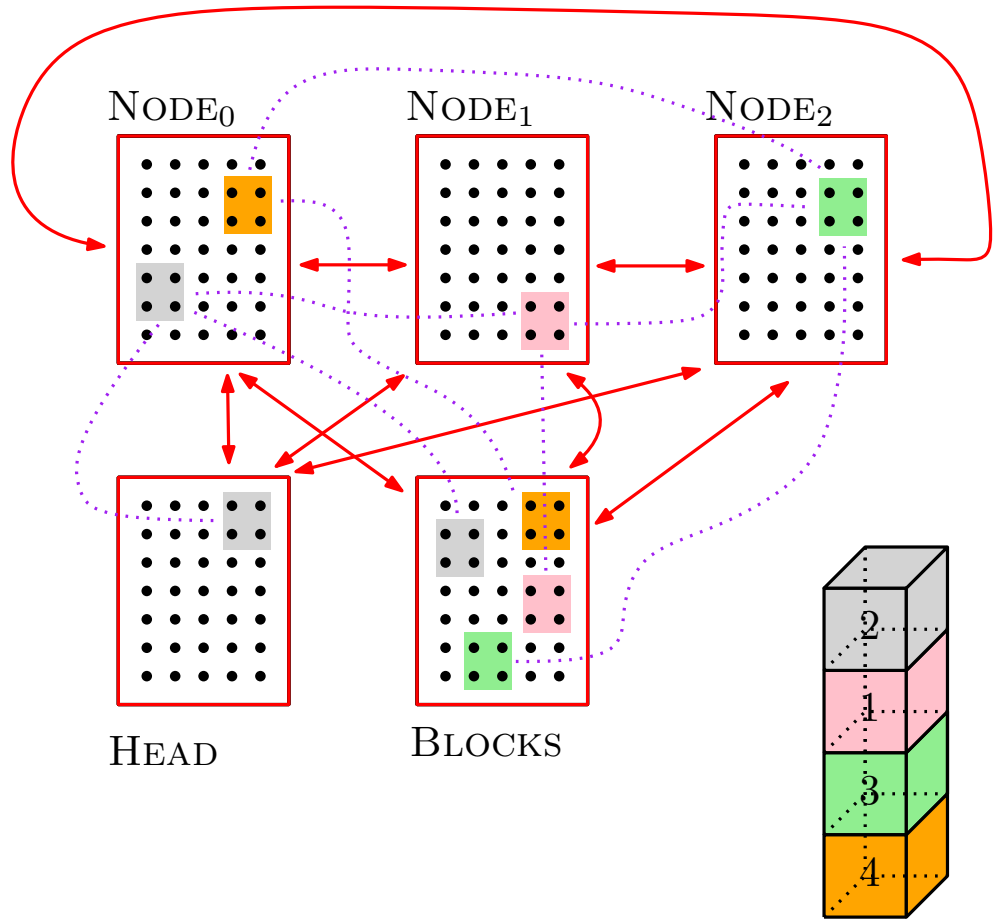
Experiments conducted averaging over 50 trials





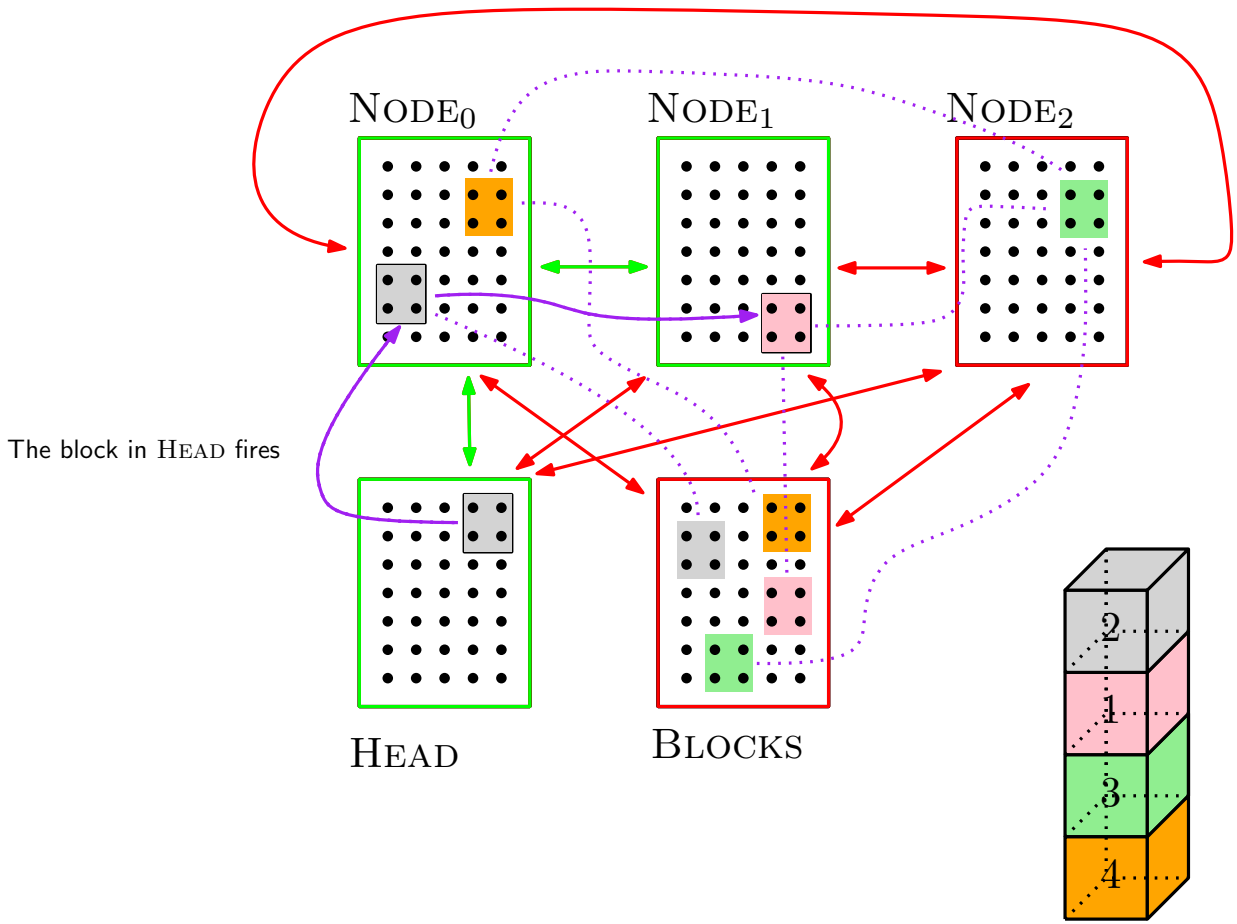
Actions

- *Removing the top block*



Actions

- *Removing the top block*



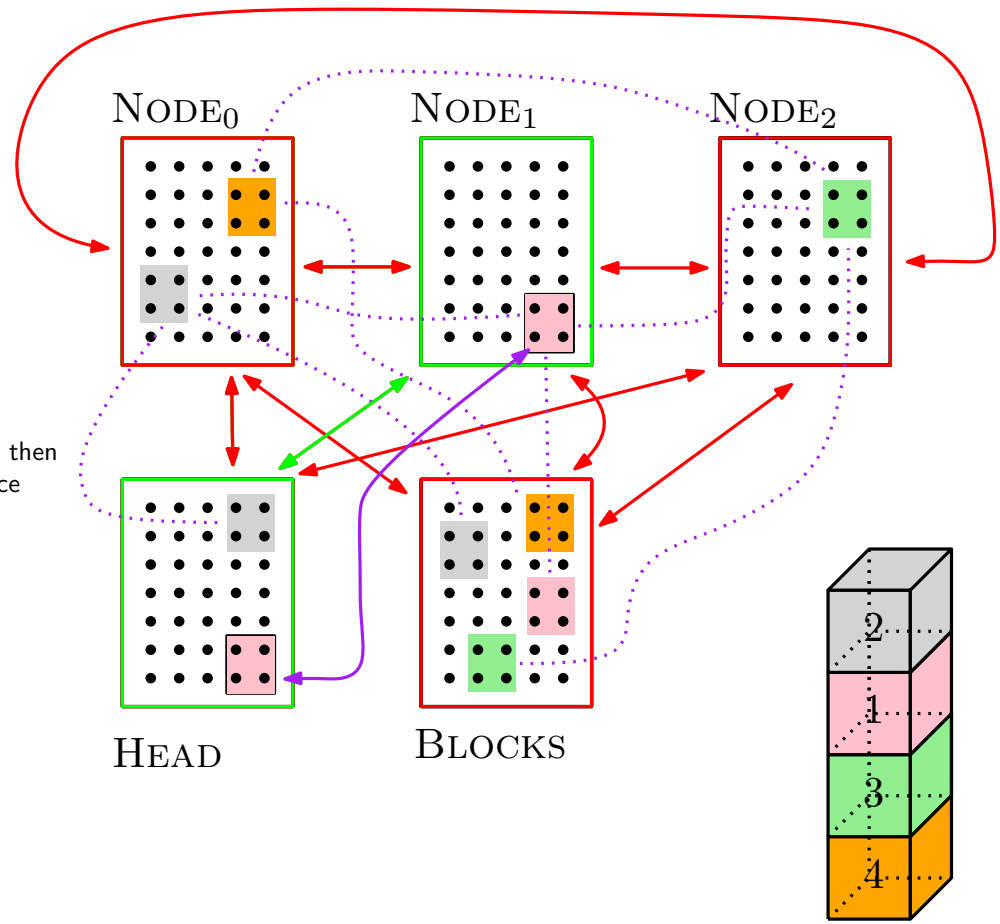
Actions

- *Removing the top block*

The last active assembly in HEAD will point to the new top

The model doesn't forget old connections, it simply doesn't use them again

Now, `project` $(\text{NODE}_1, \text{HEAD})$ and then `project` $(\text{HEAD}, \text{NODE}_1)$ to reinforce



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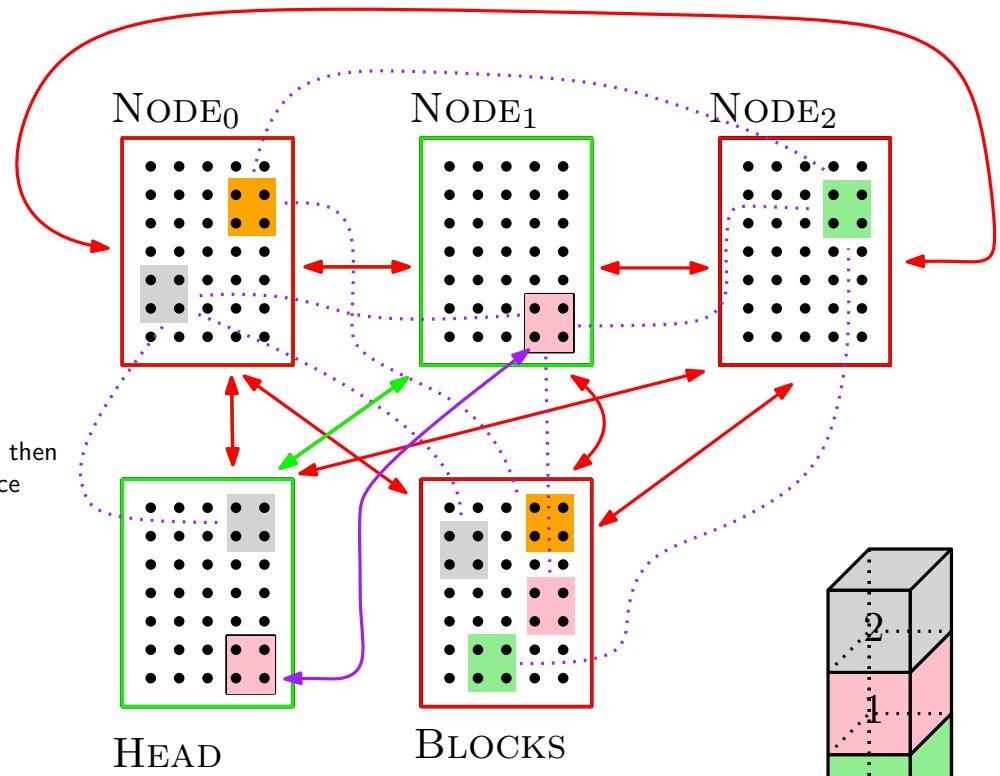
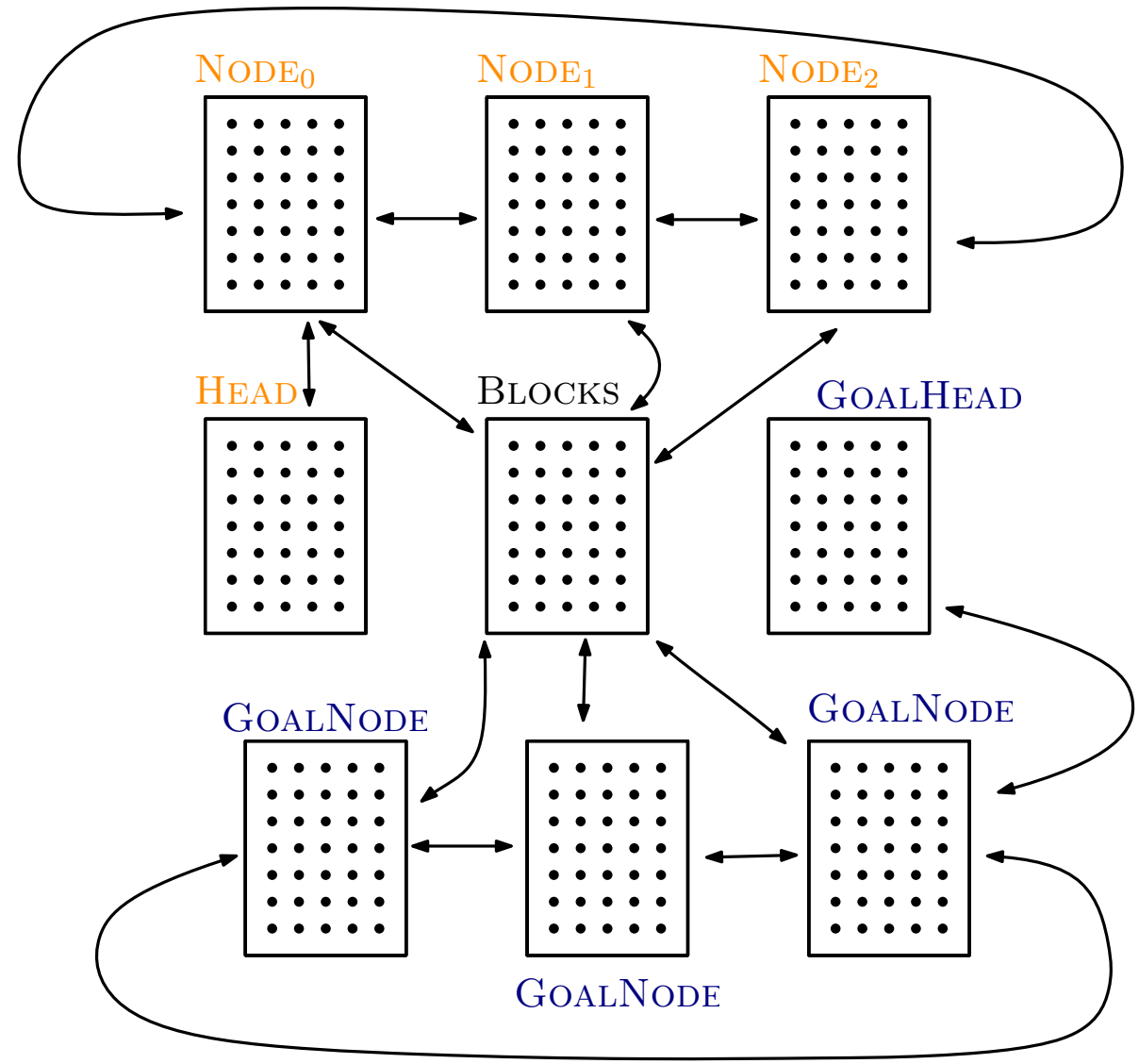


Now, `project` (NODE$_1$, HEAD) and then `project` (HEAD, NODE$_1$) to reinforce

- *Put a block from the table to the top of a stack*

Comparisons

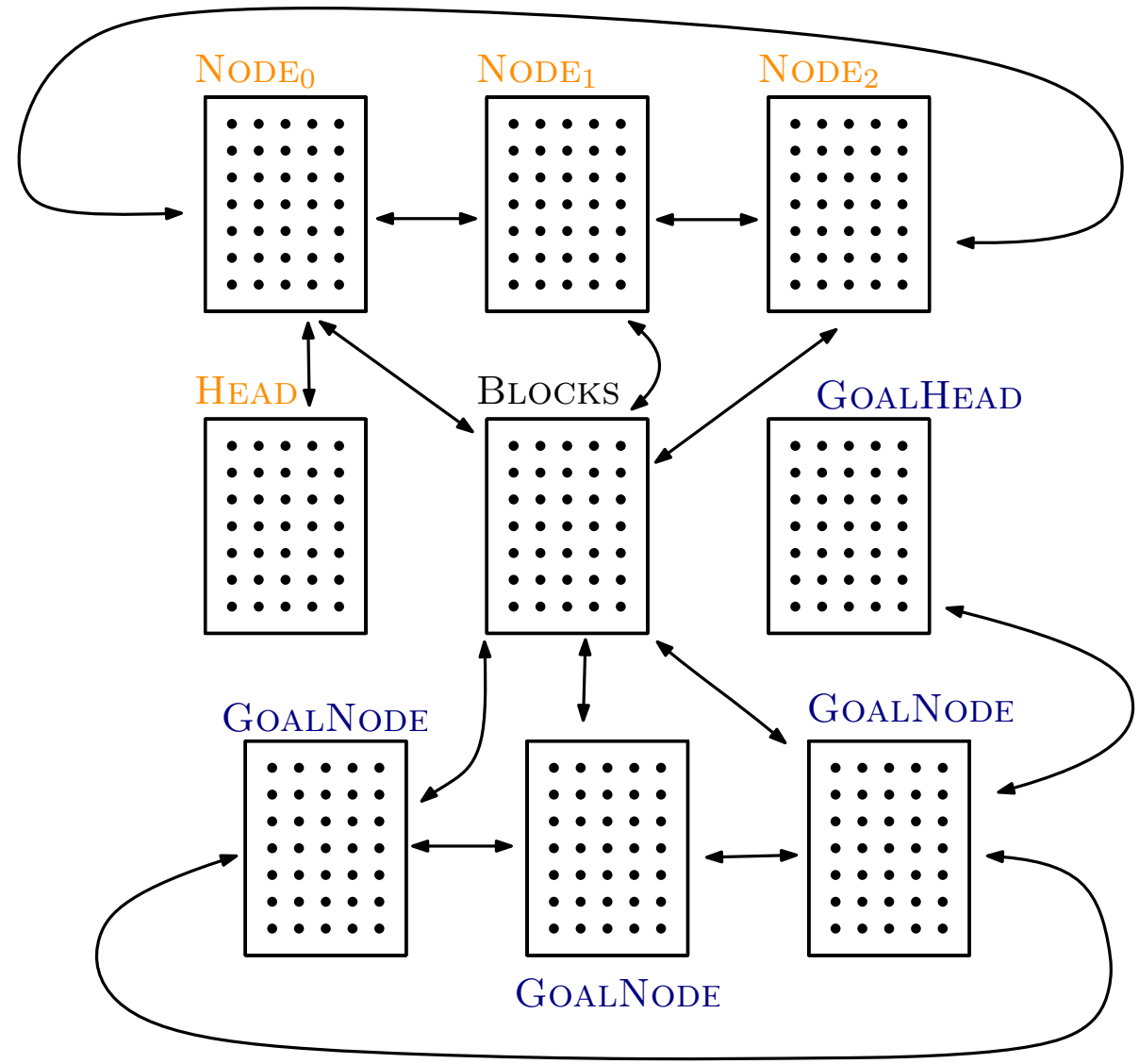
We have to save both the initial configuration and the goal configuration



Comparisons

We have to save both the initial configuration and the goal configuration

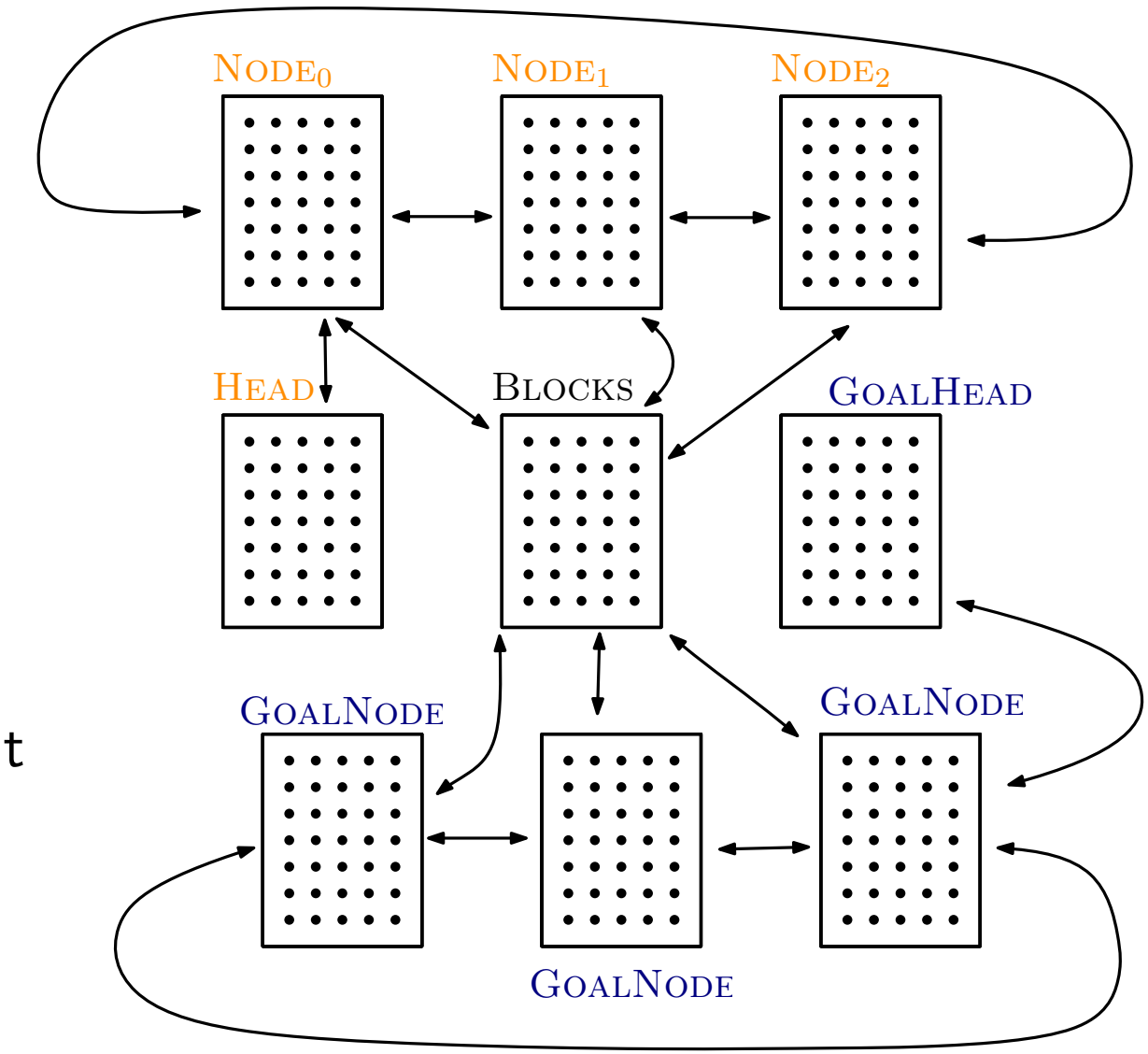
- *Intersect*: scrolls down the two stacks until reaching the last block, then starts comparing each pair of blocks by scrolling up



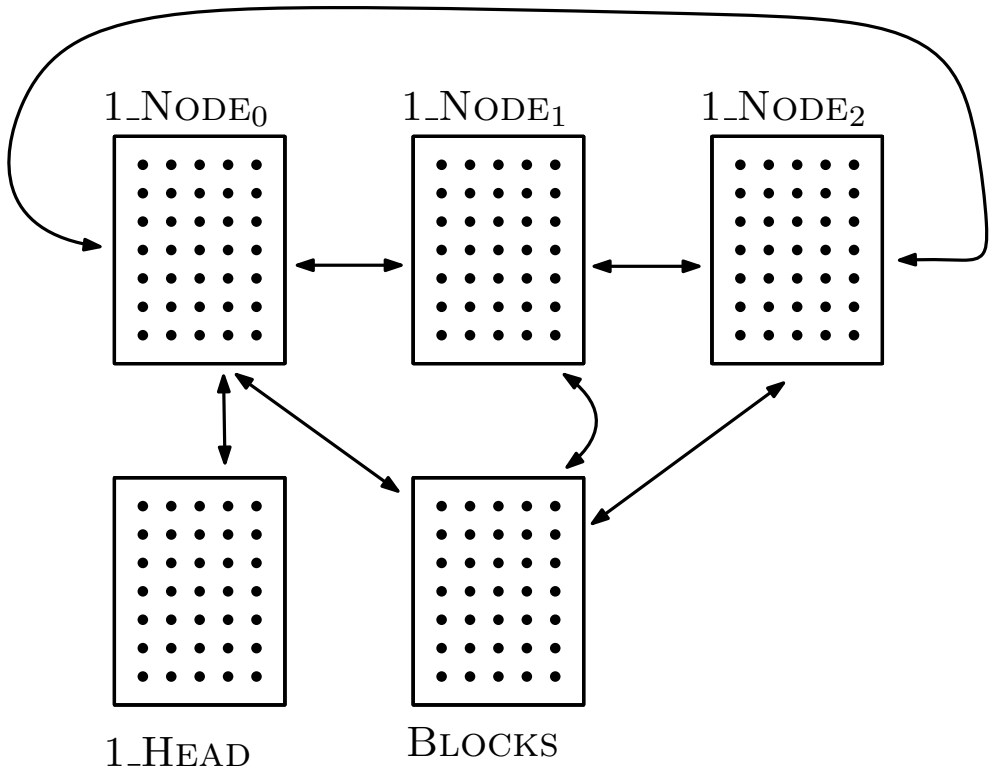
Comparisons

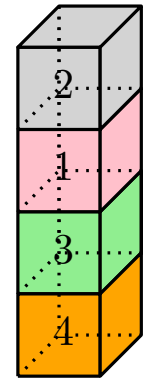
We have to save both the initial configuration and the goal configuration

- *Intersect*: scrolls down the two stacks until reaching the last block, then starts comparing each pair of blocks by scrolling up
- By combining these operations we implement the planning strategies

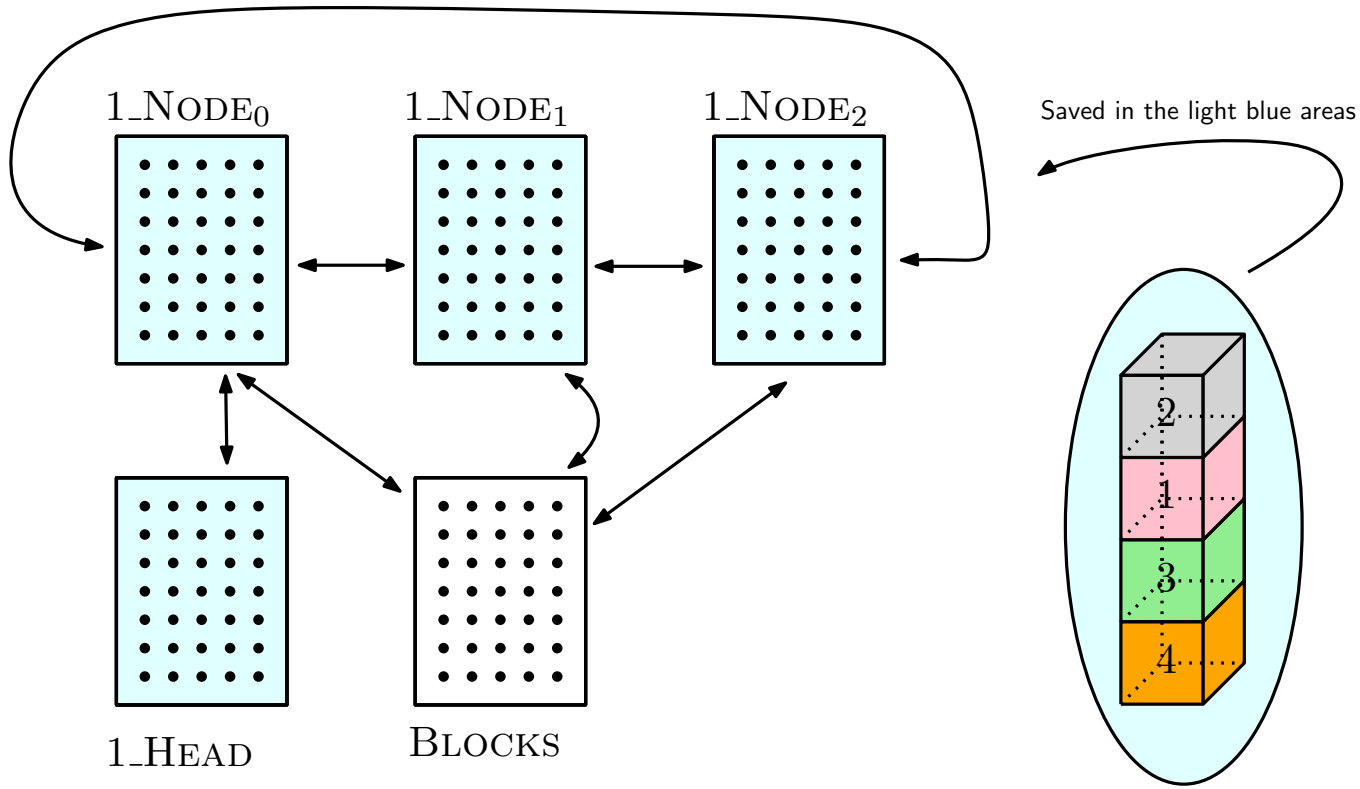


Multiple Stacks Case

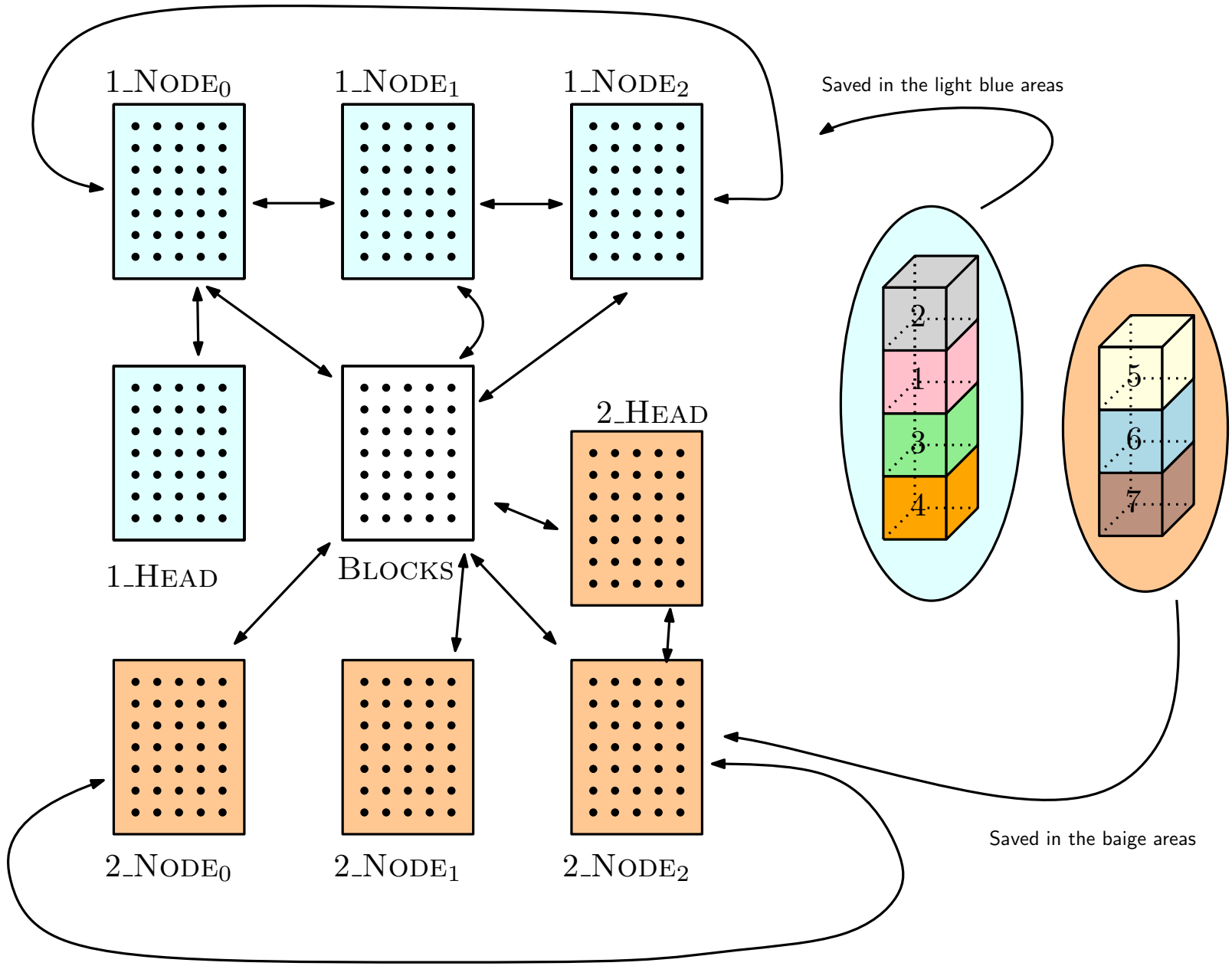




Multiple Stacks Case

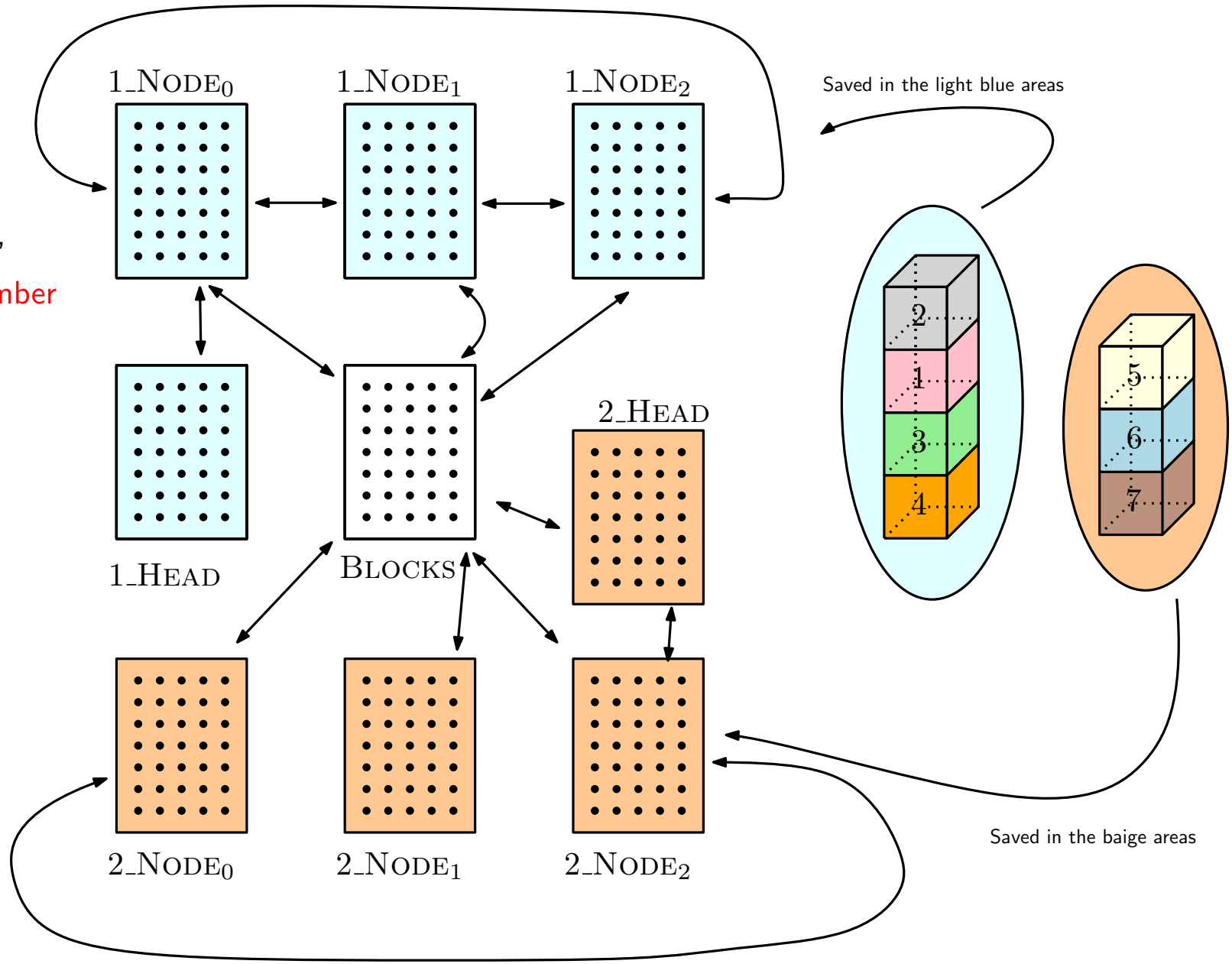


Multiple Stacks Case



Multiple Stacks Case

As many "parsing' regions as the number of stacks: **to be improved** (like chaining)



Discussion

- Demonstrated experimentally that reasonably large and complex programs in the assembly calculus can execute correctly and reliably
- Shown the realization of a *list-like data structure* which makes use of a *constant* number of brain regions
- Shown how simple manipulations of the data structure (removing or putting a block) can be realized by making use of a *constant* number of brain regions
- **Bottleneck**: the parsing. Its reliability depends on the ratio between the number of neurons and the size of the assemblies in each region
  - Must be the object of further investigation

Open problems: microscopic level

Missing items to make the model more solid.

Distributed computing:

- *k-winners take all*: looking for a plausible neuronal dynamics which implement the k-CAP. Inhibitory neurons firing may be useful [Kriener et al., PNAS 2020].

- *(Dis)inhibition of areas and fibers*: providing a model of how to accomplish (dis)inhibition. For now, just hypotheses.

Other directions: macroscopic level

After syntactic analysis in language [Mitropolsky et al., TACL 2021] and blocks world planning, what comes **next** as a compelling stylized cognitive function, which could be implemented in the AC?

- *Reasoning*
- *Planning and problem solving* in less specialized domains
- *Deductive tasks* in the context of logical and constraint-based formalisms

The End