Neural Map

Structured Memory for Deep RL

Structured Memory for Deep RL

Background

Neural Map: Location-Aware Memory

Incorporating Prior Knowledge with Memory

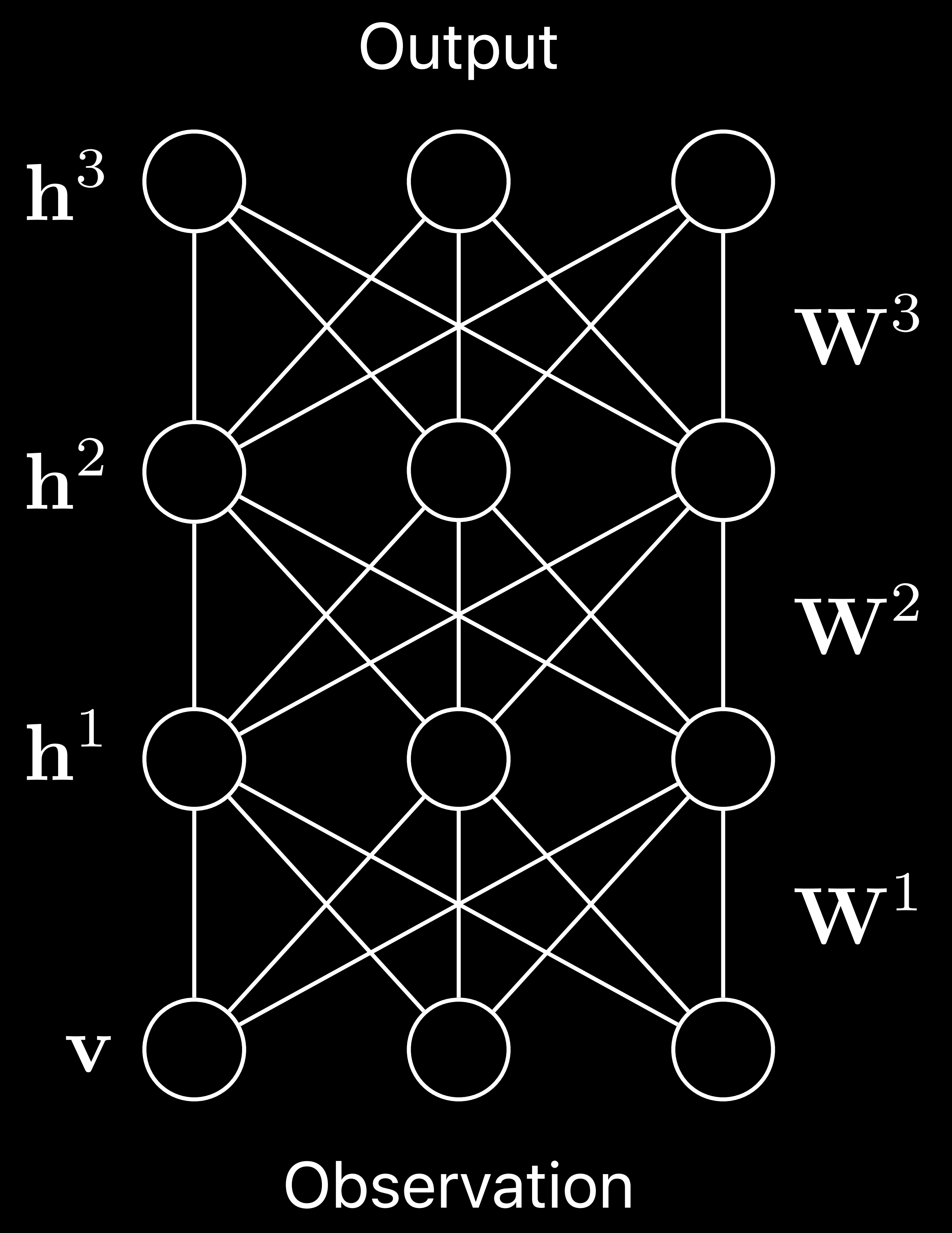
Background

Supervised Learning

- Most deep learning problems are posed as supervised learning problems: mapping and input to an output

- Environment is typically **static**

- Typically, outputs are assumed to be **independent** of each other



Environments for RL

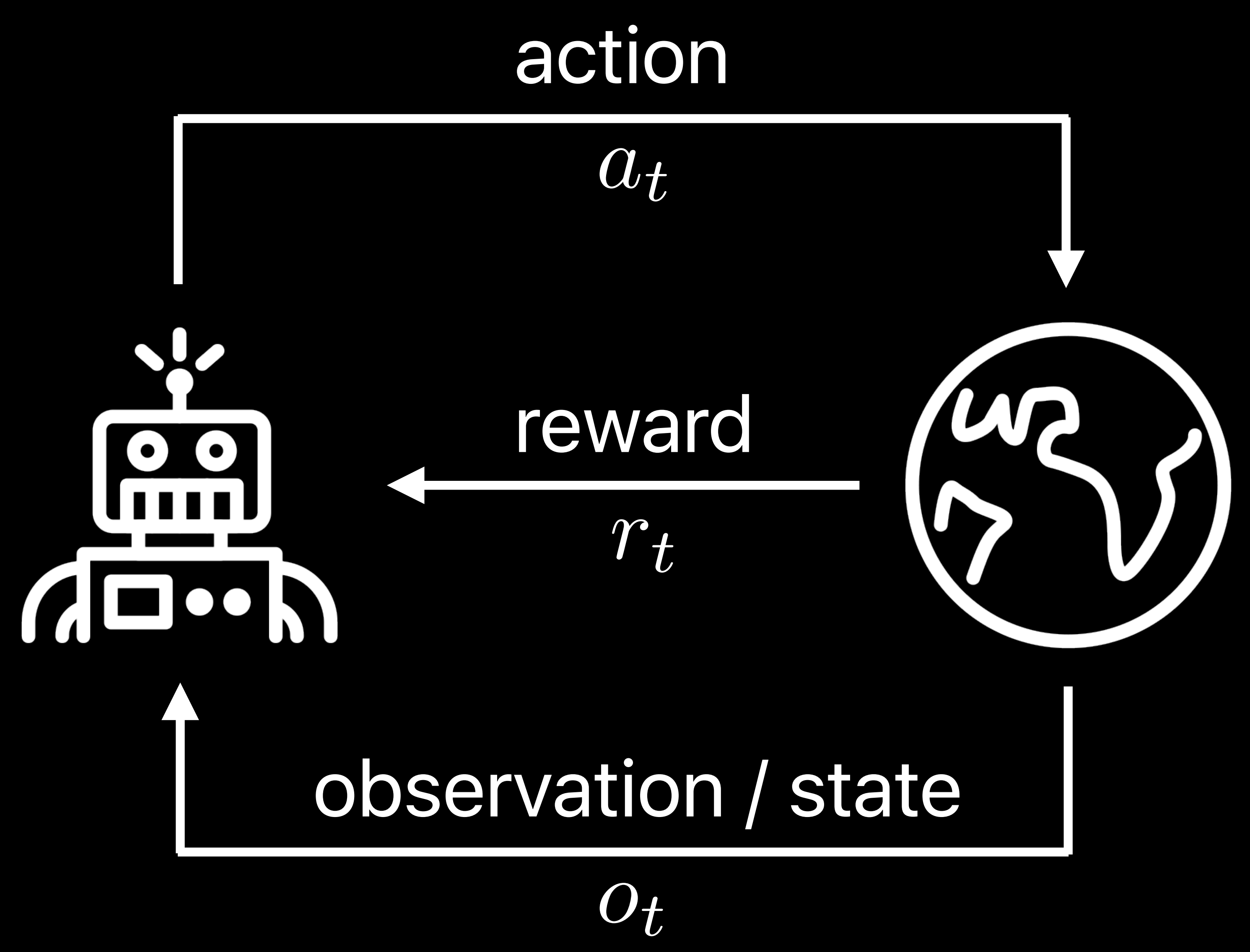
- **Environments are dynamic** and change over time

- **Actions can affect the environment** with arbitrary time lags

- **Labels can be expensive** or difficult to obtain

Reinforcement Learning

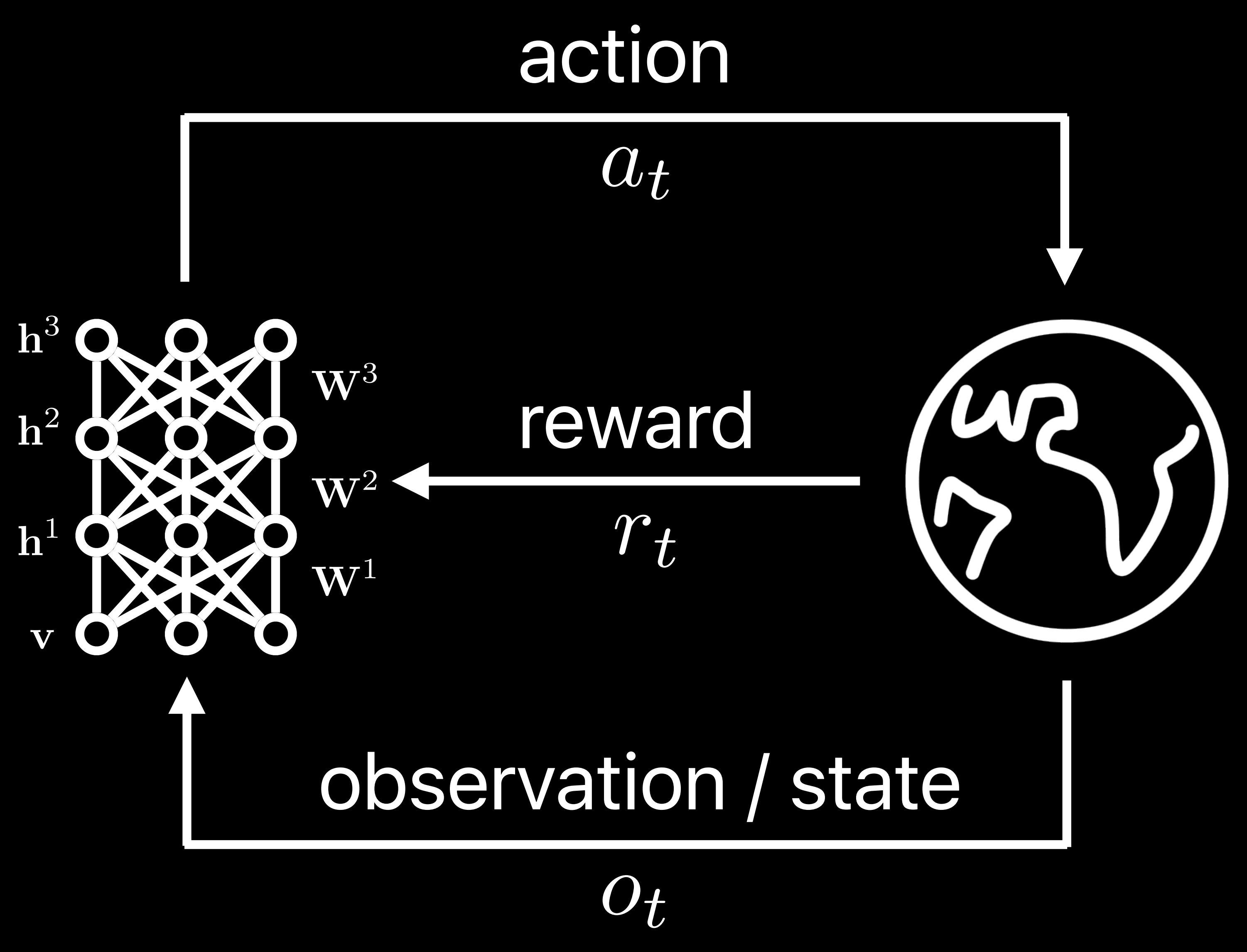
- Instead of a label, the agent is provided with a **reward signal**:
  - High reward == good behavior
- RL produces policies
  - Map observations to actions
  - Maximize long-term reward



- Allows learning purposeful behaviors in dynamic environments

Deep Reinforcement Learning

- Use a deep network to parameterize the policy
- Adapt parameters to maximize reward using:
  - Q-learning
  - Actor-Critic
  - Evolution Strategies



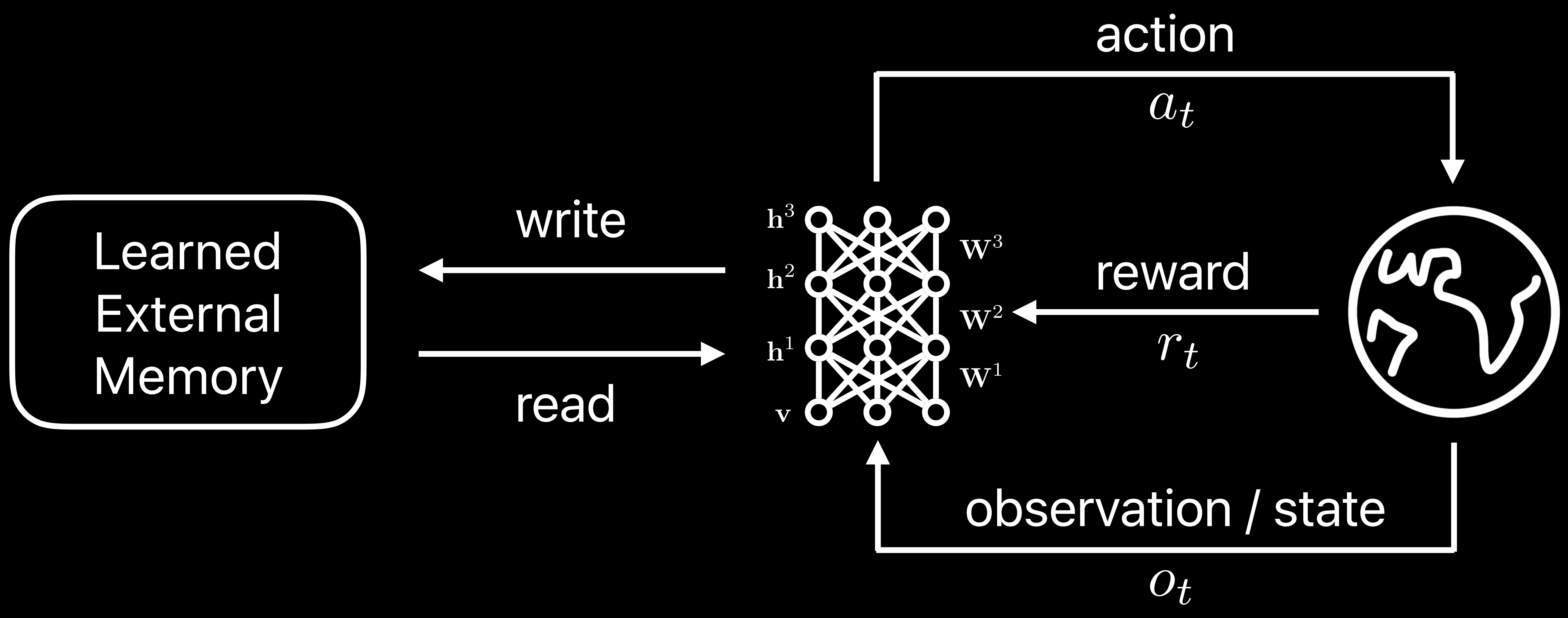
Learning 3-D game without memory

Chaplot, Lample, AAAI 2017

Reinforcement Learning: an Introduction, Sutton and Barto,2014
Deep Q-Networks, Mnih et al., 2013, Nature, 2015;
Asynchronous Methods for Deep RL, Mnih et al., ICML 2016
Evolution Strategies, Salimans et al., 2017
Playing FPS games with deep RL, Chaplot & Lample, AAAI 2017

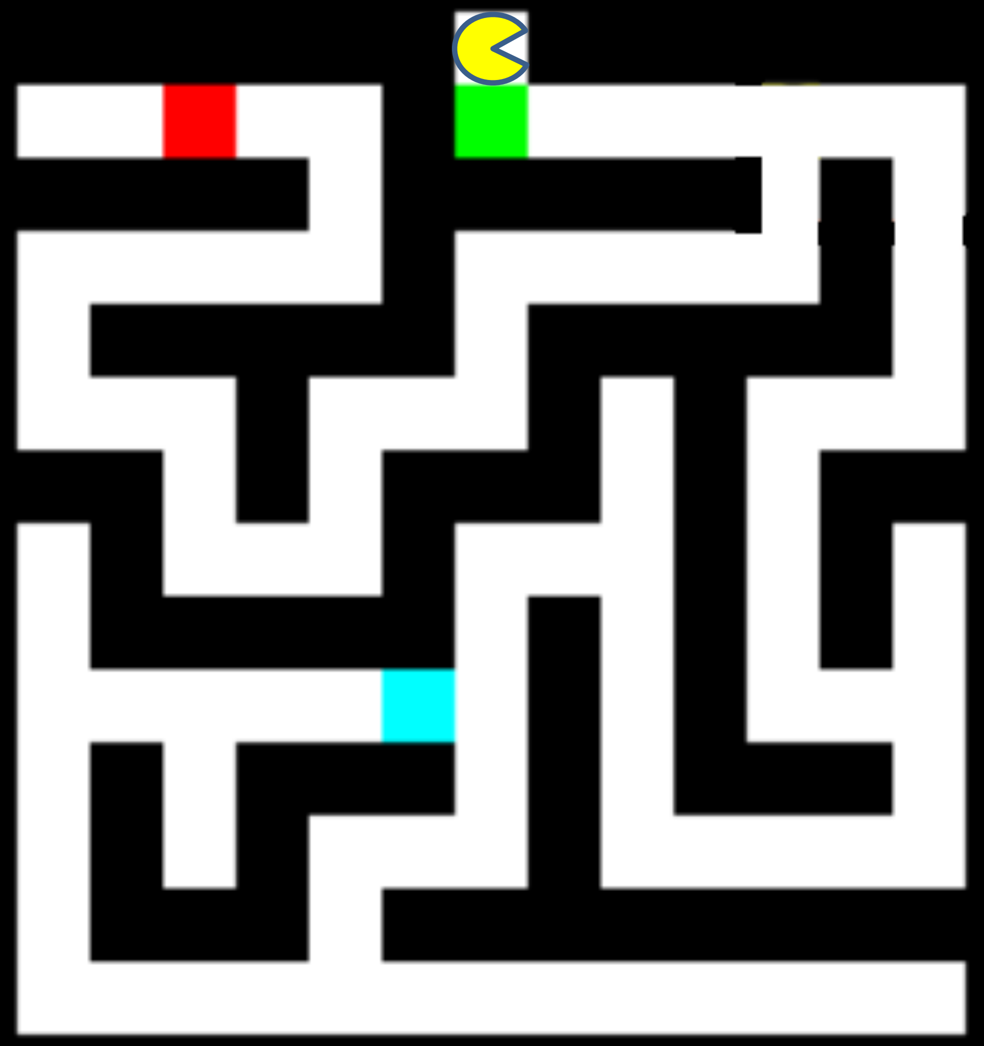
Deep Reinforcement Learning with Memory

- Can we learn an agent with a more advanced external memory?
  - Neural Turing Machines (Graves et al., 2014)
  - Differential Neural Computers (Graves et al., 2016)
- **Challenge**: Memory systems are difficult to train, especially using RL



Why is Memory Challenging?

- Suppose an agent is in a simple random maze:
  - Agent starts at top of map
  - An agent is shown an indicator near its initial state
  - The color of the indicator determines what the correct goal is



Oh et al, Control of Memory, Active Perception, and Action in Minecraft, ICML 2016

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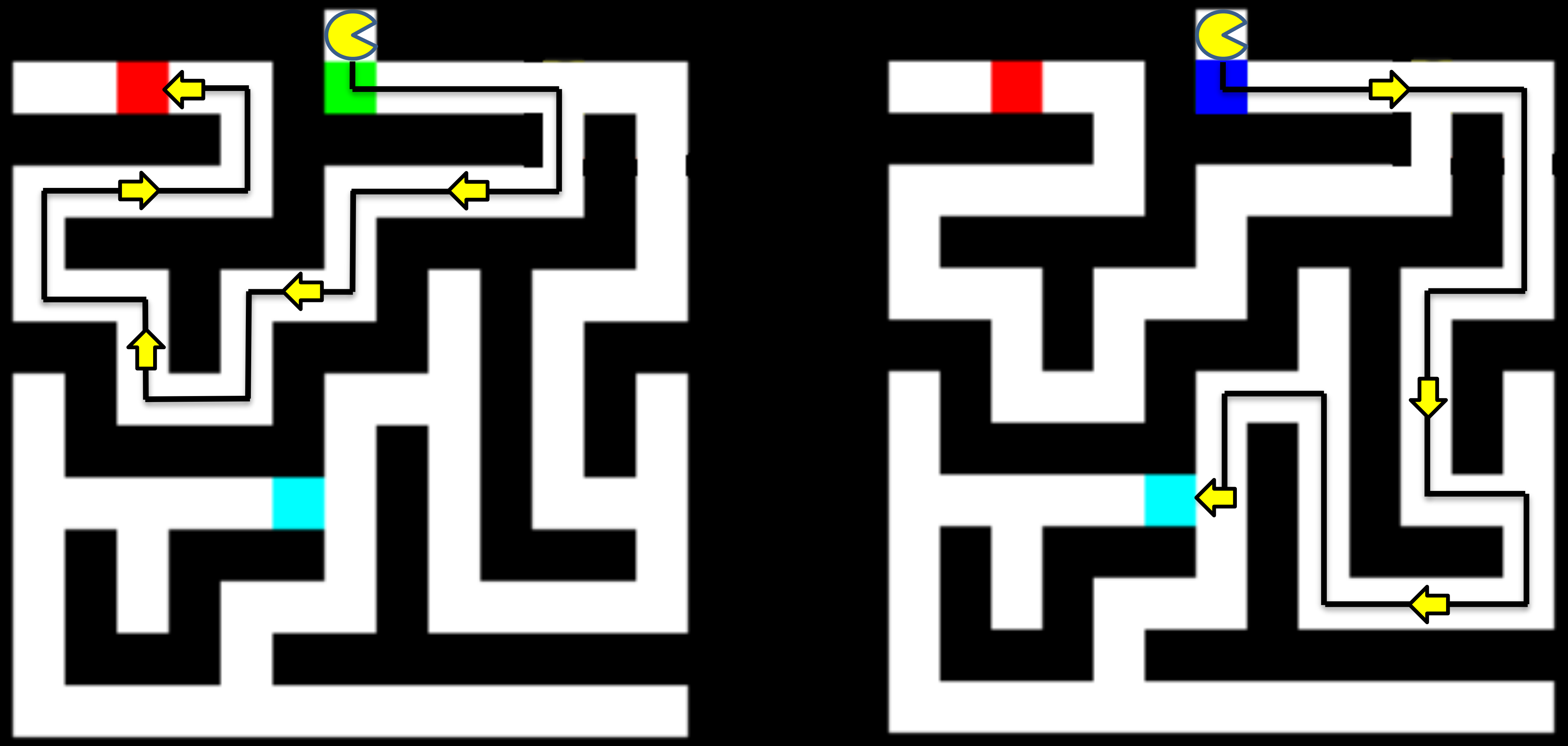
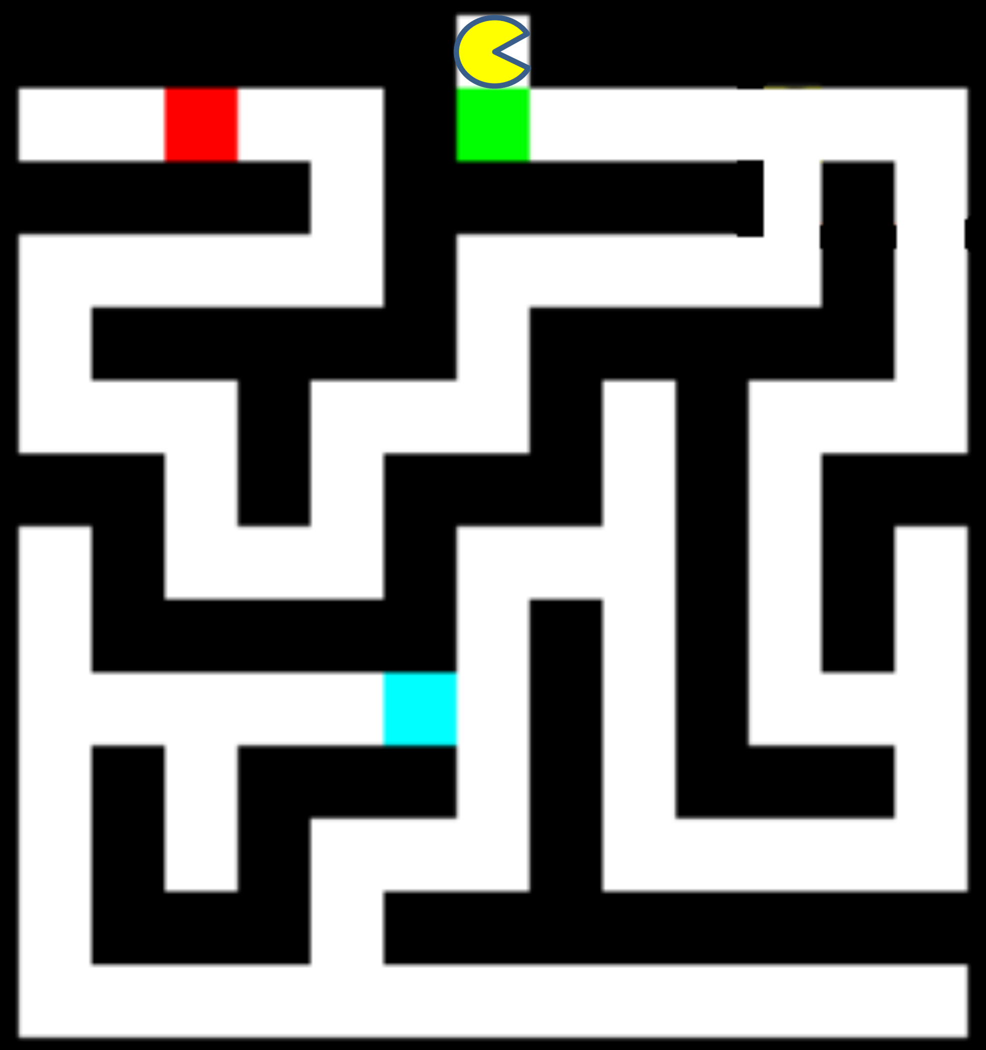


Oh et al, Control of Memory, Active Perception, and Action in Minecraft, ICML 2016

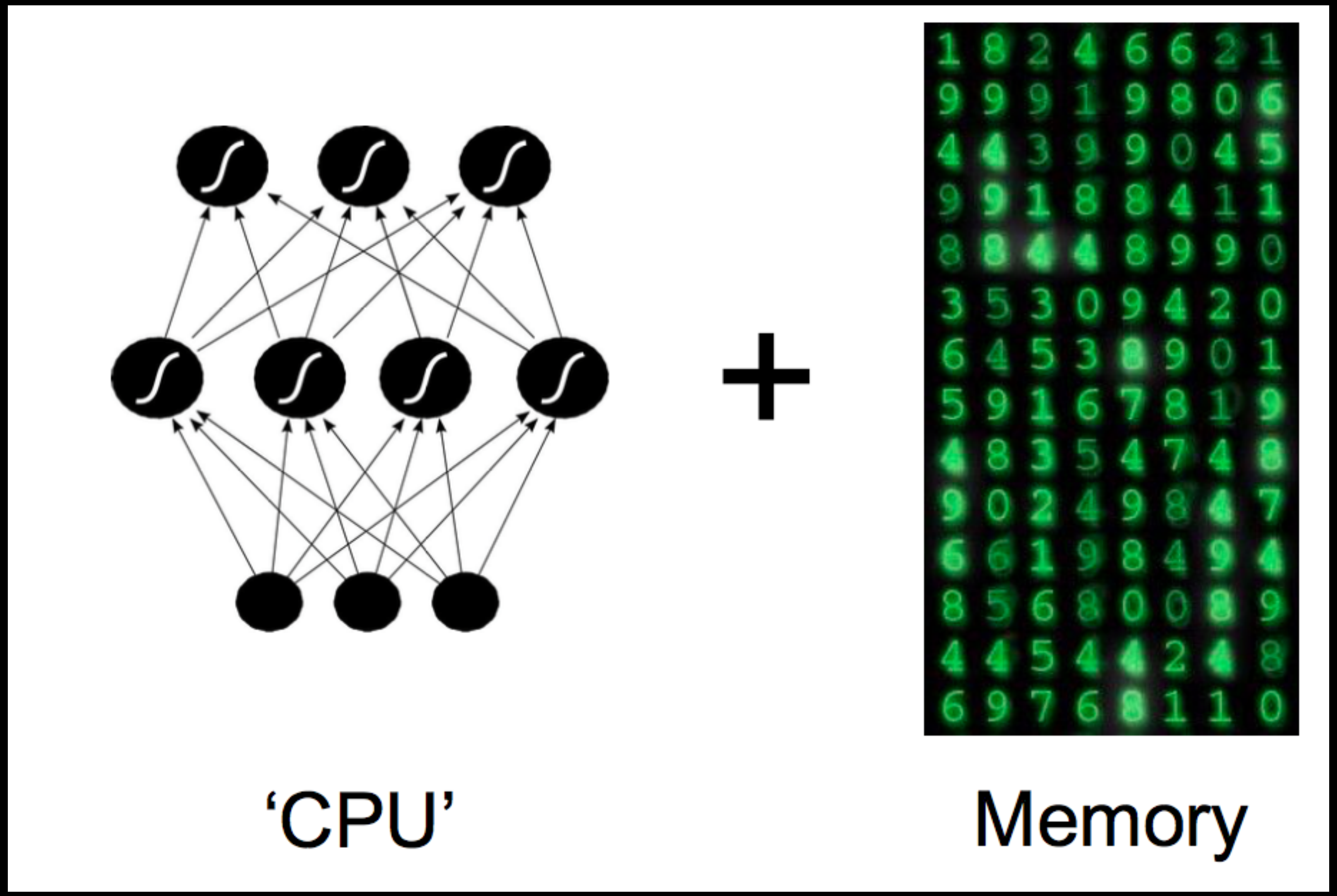
Why is Memory Challenging?

- At the start, **no a priori knowledge** to store color into memory
- The following must hold:
  - Write color to memory at the start of maze
  - Never overwrite memory of the color over *T* time steps
  - Find and enter the goal
- **Solution**: Write everything into memory



Neural Turing Machines (Graves et al., 2014)

- Basic Idea: Turn neural networks into 'differentiable computers' by giving them read-write access to external memory



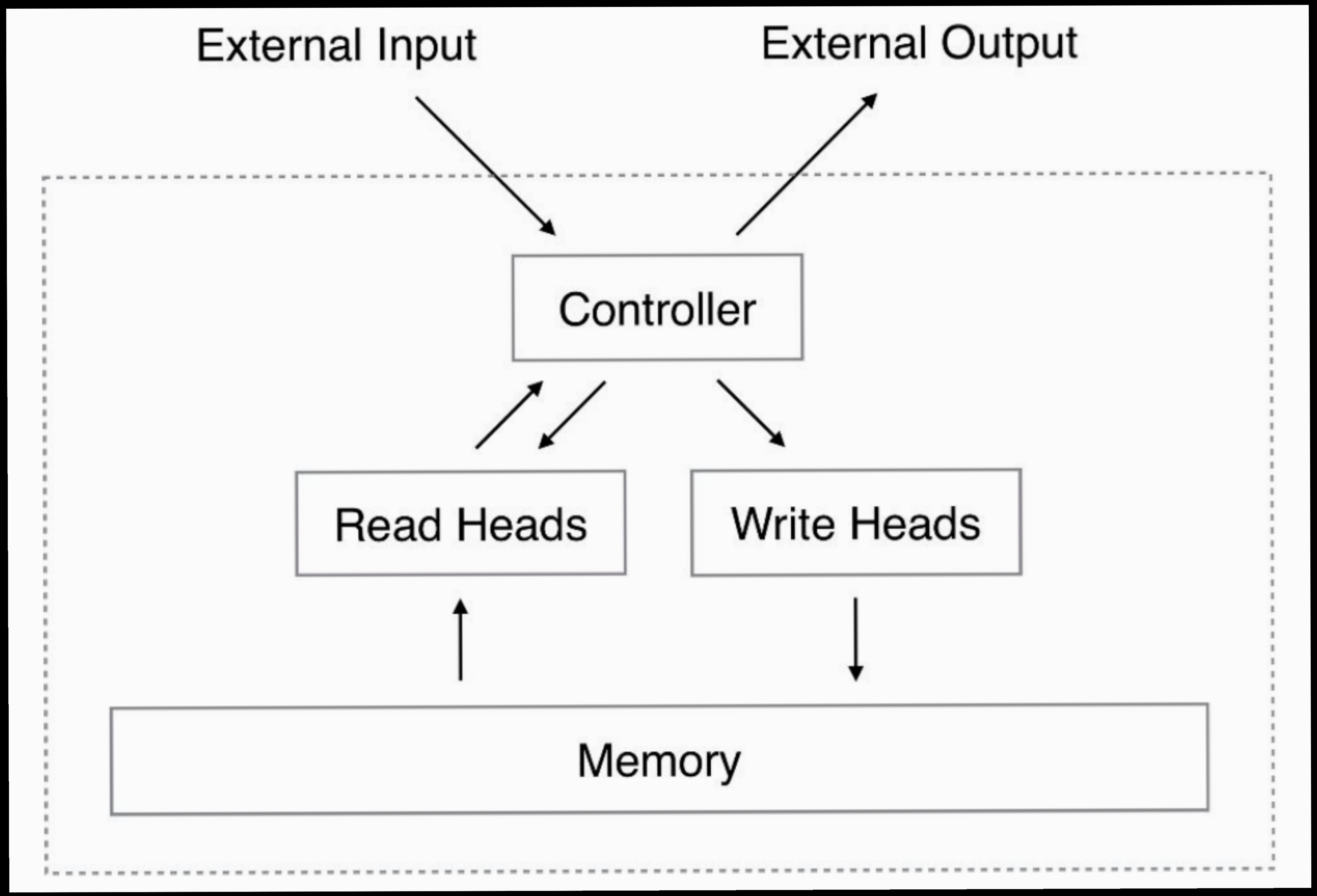
=

computer that learns programs from examples

(neural net that separates computation from memory)

Differentiable Neural Computer, Graves et al., Nature, 2016;
Neural Turing Machine, Graves et al., 2014

Architecture (Graves et al., 2014)



Everything is differentiable

- The Controller is a neural network (recurrent or feedforward)
- The Heads select portions of the memory and read or write to them
- The Memory is a real-valued matrix

Differentiable Neural Computer, Graves et al., Nature, 2016;
Neural Turing Machine, Graves et al., 2014

Selective Attention

- Want to focus on the parts of memory the network will read and write to: need an attention model
- Use the controller outputs to parameterize a distribution (weighting) over the rows (locations) in the memory matrix
- The weighting defines content-based attention mechanism.

Addressing by Content

- A key vector k is emitted by the controller and compared to
  - content of each memory location M[i]
  - using a similarity measure S(.,.), e.g. cosine distance
  - then normalized with a softmax

- A 'sharpness' parameter is used to narrow the focus:
  - Finds the memories "closest" to the key

$$\mathbf{w}[i] = \frac{\exp\left(\beta S(\mathbf{k}, \mathbf{M}[i])\right)}{\sum_j \exp\left(\beta S(\mathbf{k}, \mathbf{M}[j])\right)}$$

Addressing by Content

- Once the weightings are defined, each read head returns a read vector r as input to the controller at the next time step

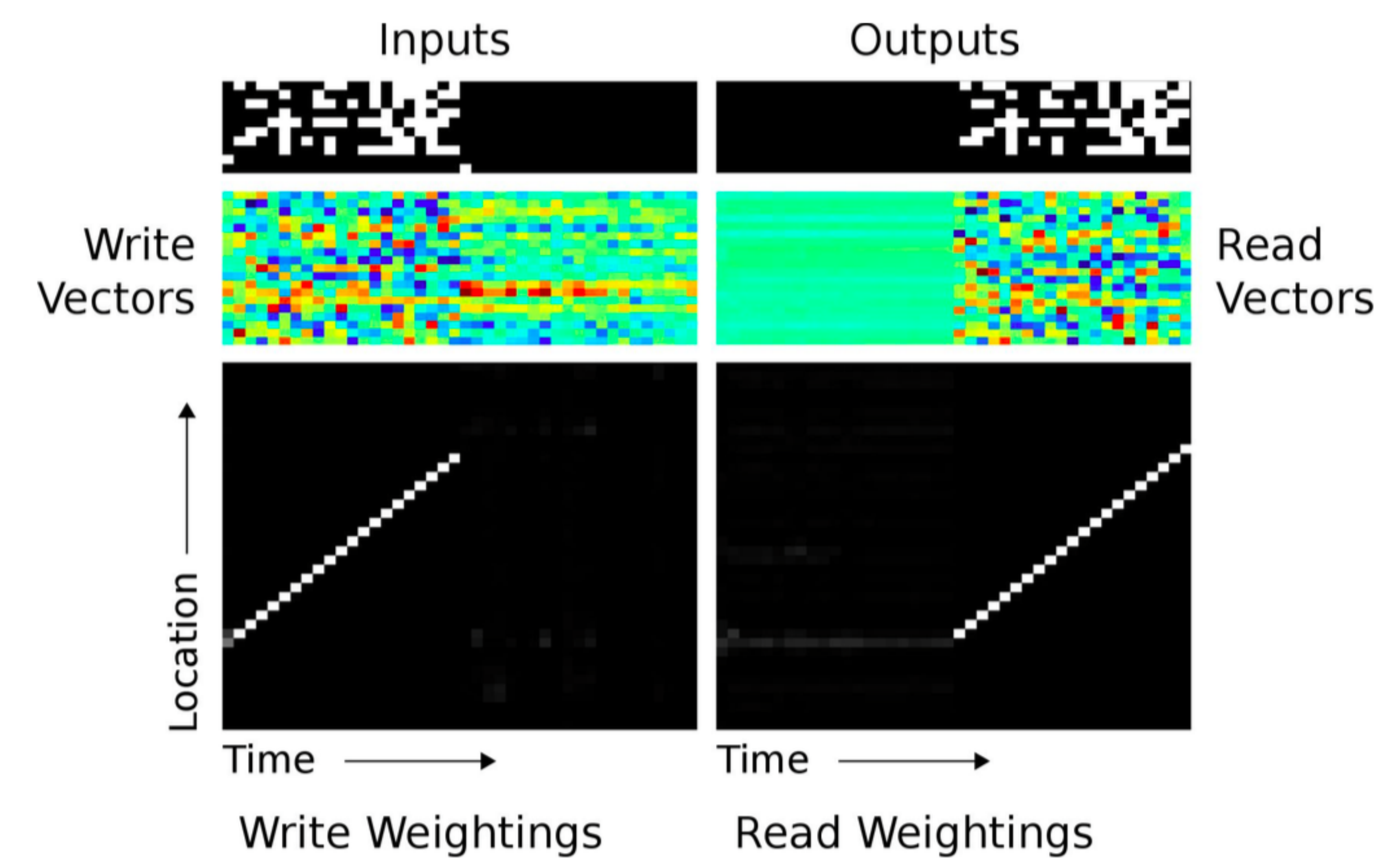
$$\mathbf{r} = \sum_i \mathbf{w}[i]\mathbf{M}[i]$$

- Each write head receives an erase vector e and adds vector a from the controller

  - and then writes to modify the memory (like LSTM)

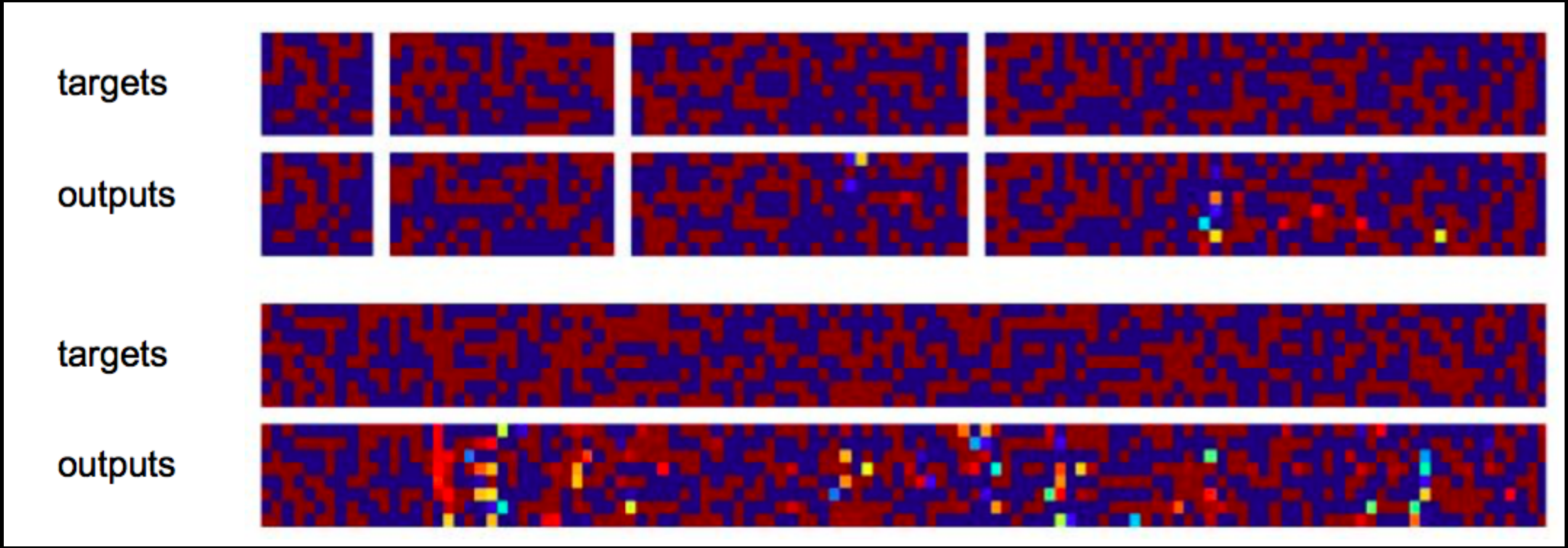
$$\mathbf{M}[i] \leftarrow \mathbf{M}[i](\mathbf{1} - \mathbf{w}[i]\mathbf{e}) + \mathbf{w}[i]\mathbf{a}$$

The NTM Copy Algorithm

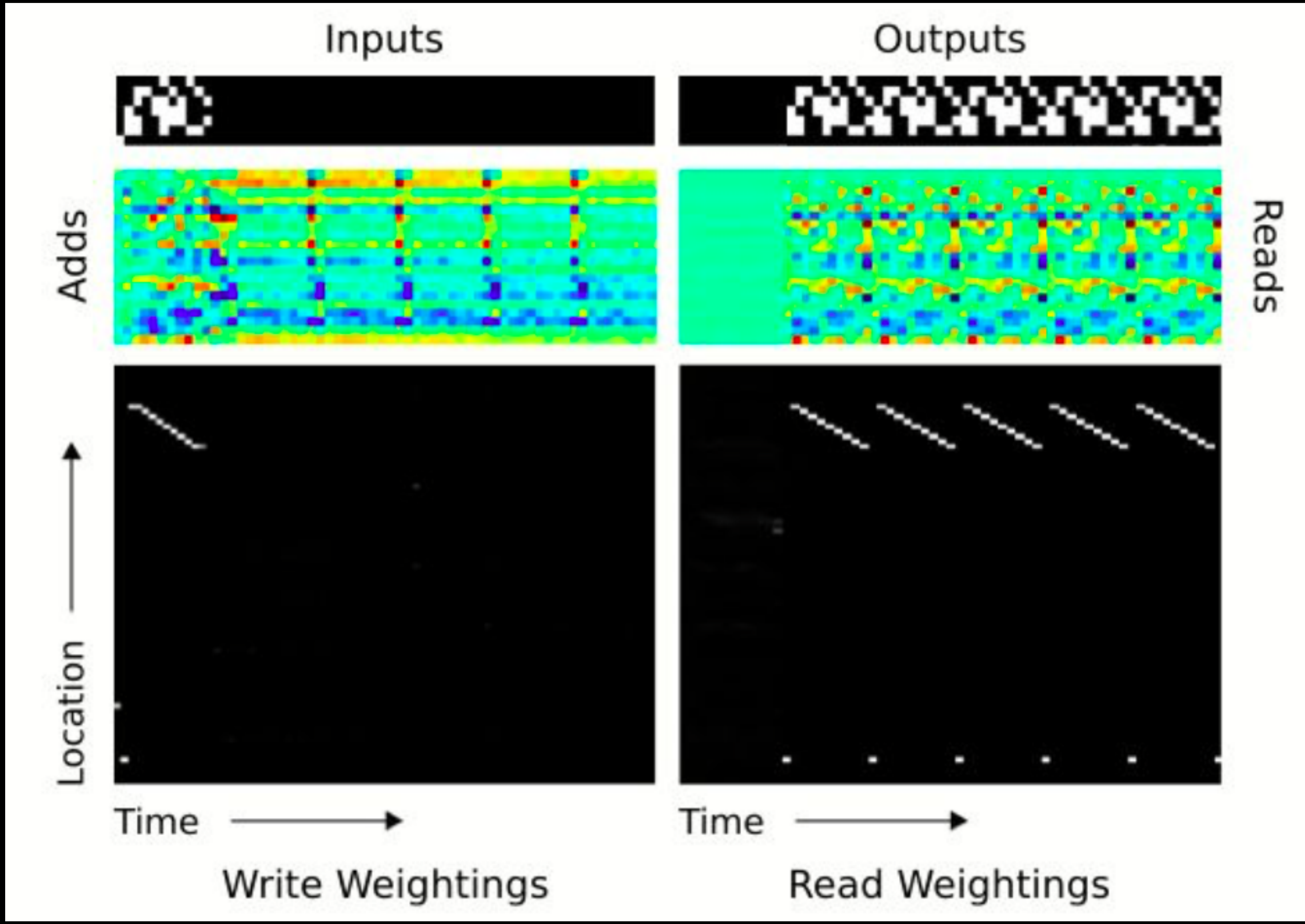


initialize: move head to start location
while input delimiter not seen **do**
  receive input vector
  write input to head location
  increment head location by 1
end while
return head to start location
while true **do**
  read output vector from head location
  emit output
  increment head location by 1
end while

NTM Generalization: length 10 to 120



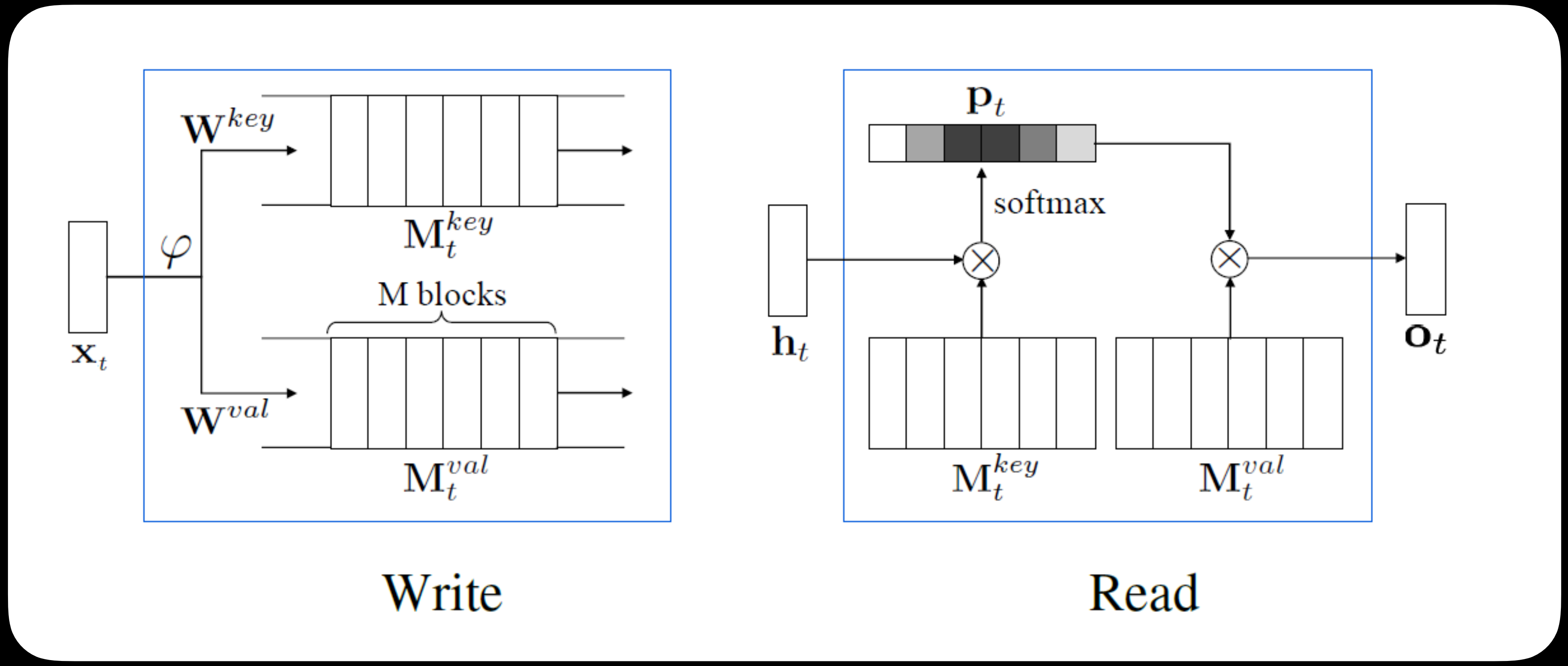
Copy N Times



- Learning For Loop using content to jump, iteration to step, and a variable to count to N

Memory Networks

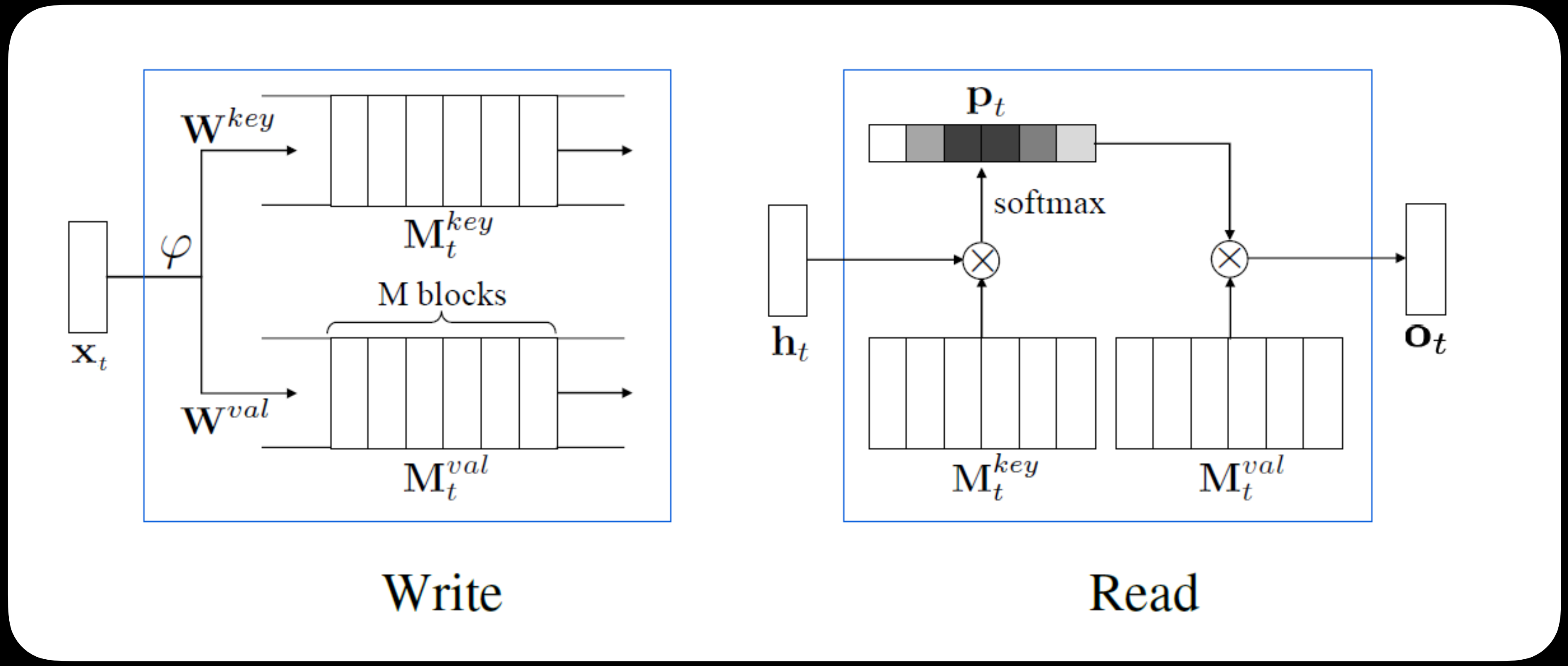
- Store (*key*, *value*) representations for the last *M* frames
- At each time step:
  - Perform a read operation over their memory database
  - Write the latest percept into memory



Weston et al, Memory Networks, ICLR 2015
Miller et al, Key-Value Memory Networks., EMNLP 2016
Oh et al, Control of Memory, Active Perception, and Action in Minecraft, ICML 2016

Memory Networks

- Easy to learn: Just store as much as possible!
- Can be inefficient:
  - We need *M* > time horizon of the task (can't know this *a priori*)
  - We might store a lot of useless/redundant data
- Time/space requirements increase with *M*



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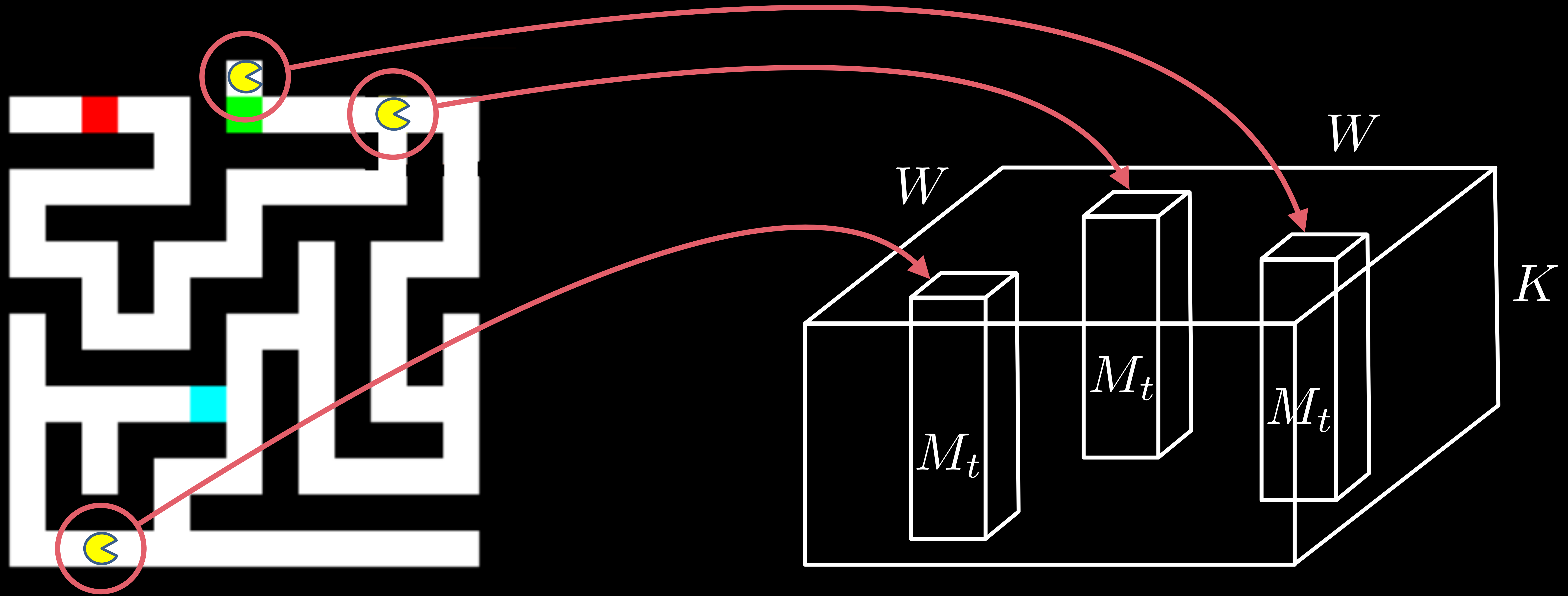
Neural Map: Location-Aware Memory

Neural Map (Location-Aware Memory)

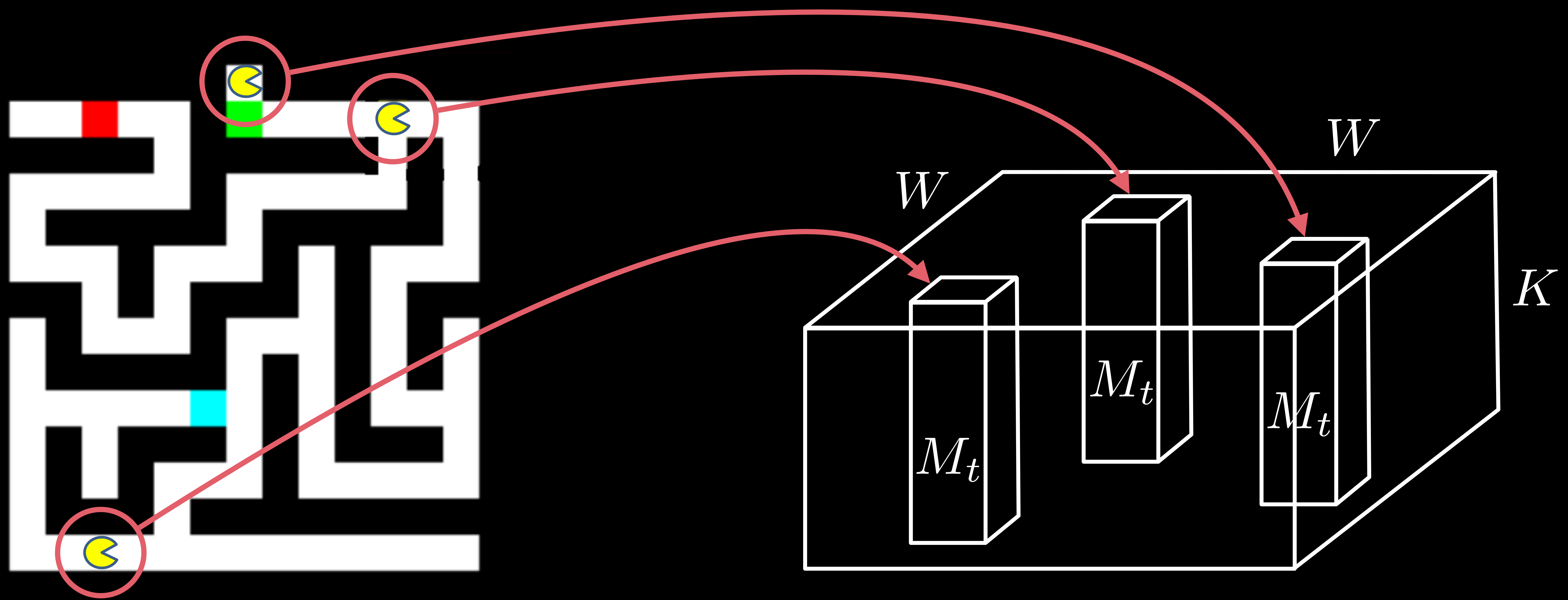
- Writable memory with a specific inductive bias:
  - Structure memory into $W \times W$ grid of K-dim cells
  - For every (x, y) position, write to (x', y') in the $W \times W$ grid



Parisotto, Salakhutdinov, ICLR 2018

Neural Map (Location-Aware Memory)

- Acts as a map that the agent fills out as it explores
- **Sparse Write**:
  - Inductive bias prevents the agent from overwriting its memory too often
  - Allow easier credit assignment over time



Parisotto, Salakhutdinov, ICLR 2018

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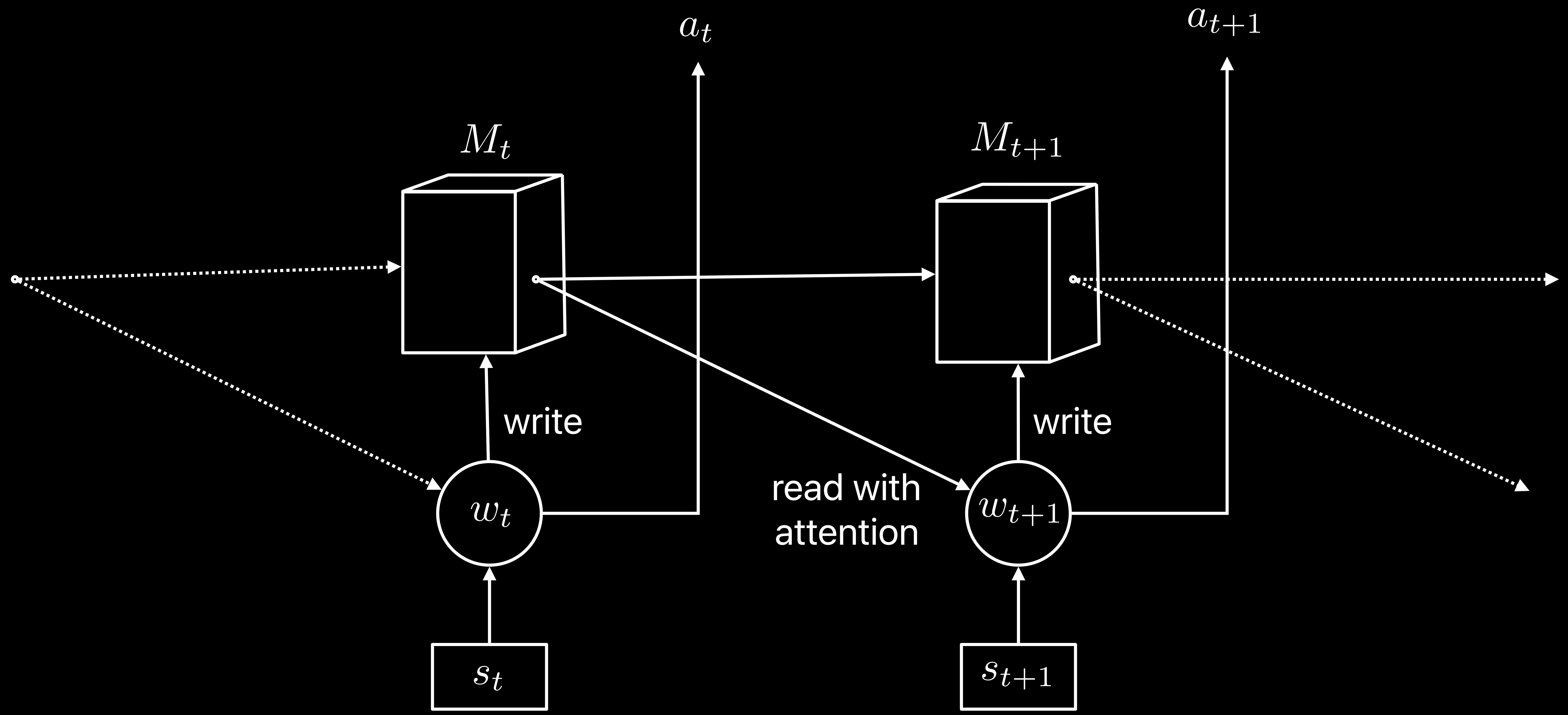


Parisotto, Salakhutdinov, ICLR 2018

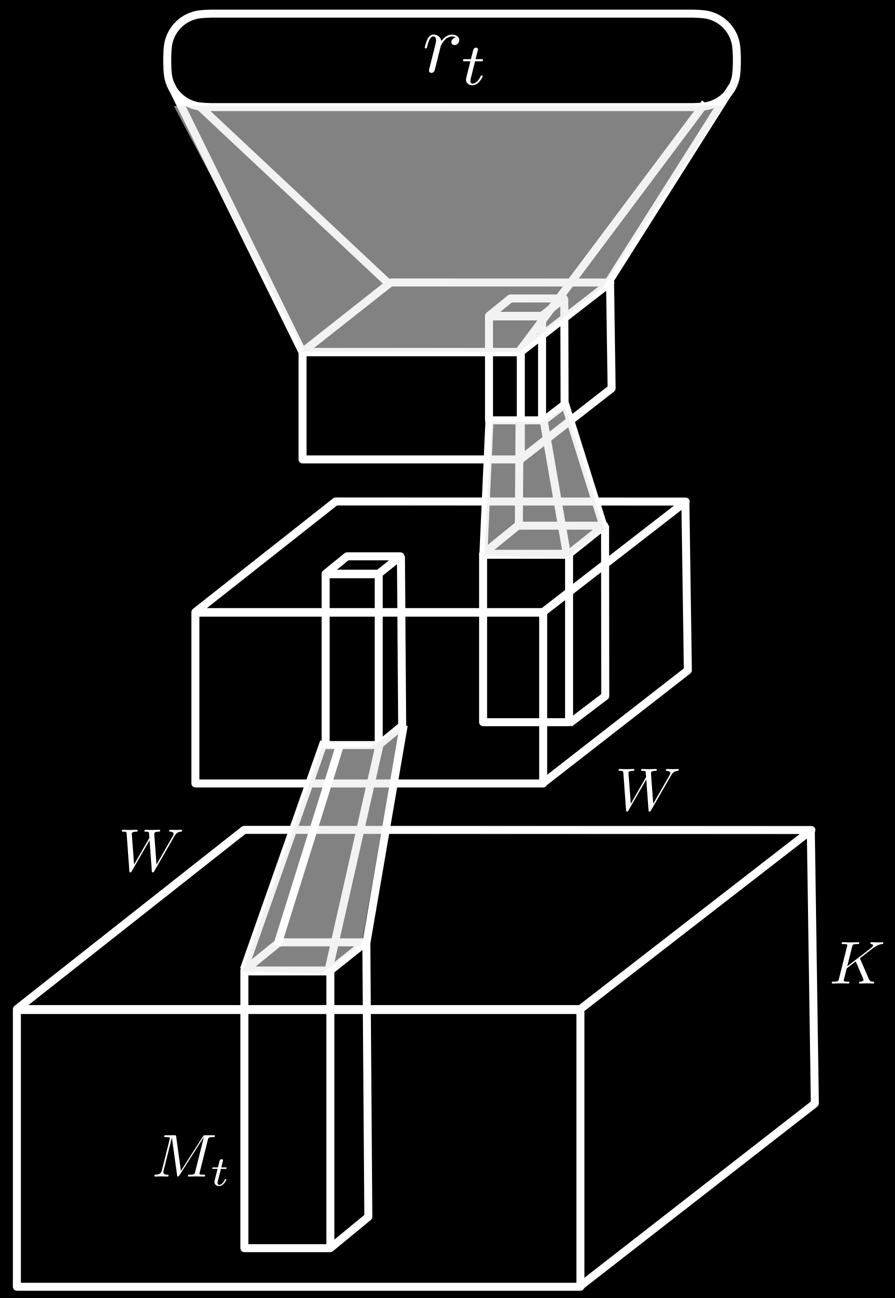
Neural Map: Operations

- Two read operations:
  - Global summarization
  - Context-based retrieval
- Sparse write only to agent position
- Both read and write vectors are used to compute policy

$$
\begin{aligned}
r_t &= read(M_t) \\
c_t &= context(M_t, s_t, r_t) \\
w_{t+1}^{(x_t,y_t)} &= write(s_t, r_t, c_t, M_t^{(x_t,y_t)}) \\
M_{t+1} &= update(M_t, w_{t+1}^{(x_t,y_t)}) \\
o_t &= [r_t, c_t, w_{t+1}^{(x_t,y_t)}] \\
\pi_t(a|s) &= \mathrm{Softmax}(f(o_t))
\end{aligned}
$$

Neural Map: Global Read

- Reads from the entire neural map using a deep convolutional net
- Produces a vector that provides a global summary



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\end{aligned}
$$

Neural Map: Context Read

- Read operation using attention

$$q_t = W[s_r, r_t]$$
$$a_t^{(x,y)} = q_t \cdot M_t^{(x,y)}$$
$$\alpha_t^{(x,y)} = \frac{e^{a_t^{x,y}}}{\sum_{(w,z)} e^{a_t^{(w,z)}}}$$
$$c_t = \sum_{(x,y)} \alpha_t^{(x,y)} M_t^{(x,y)}$$

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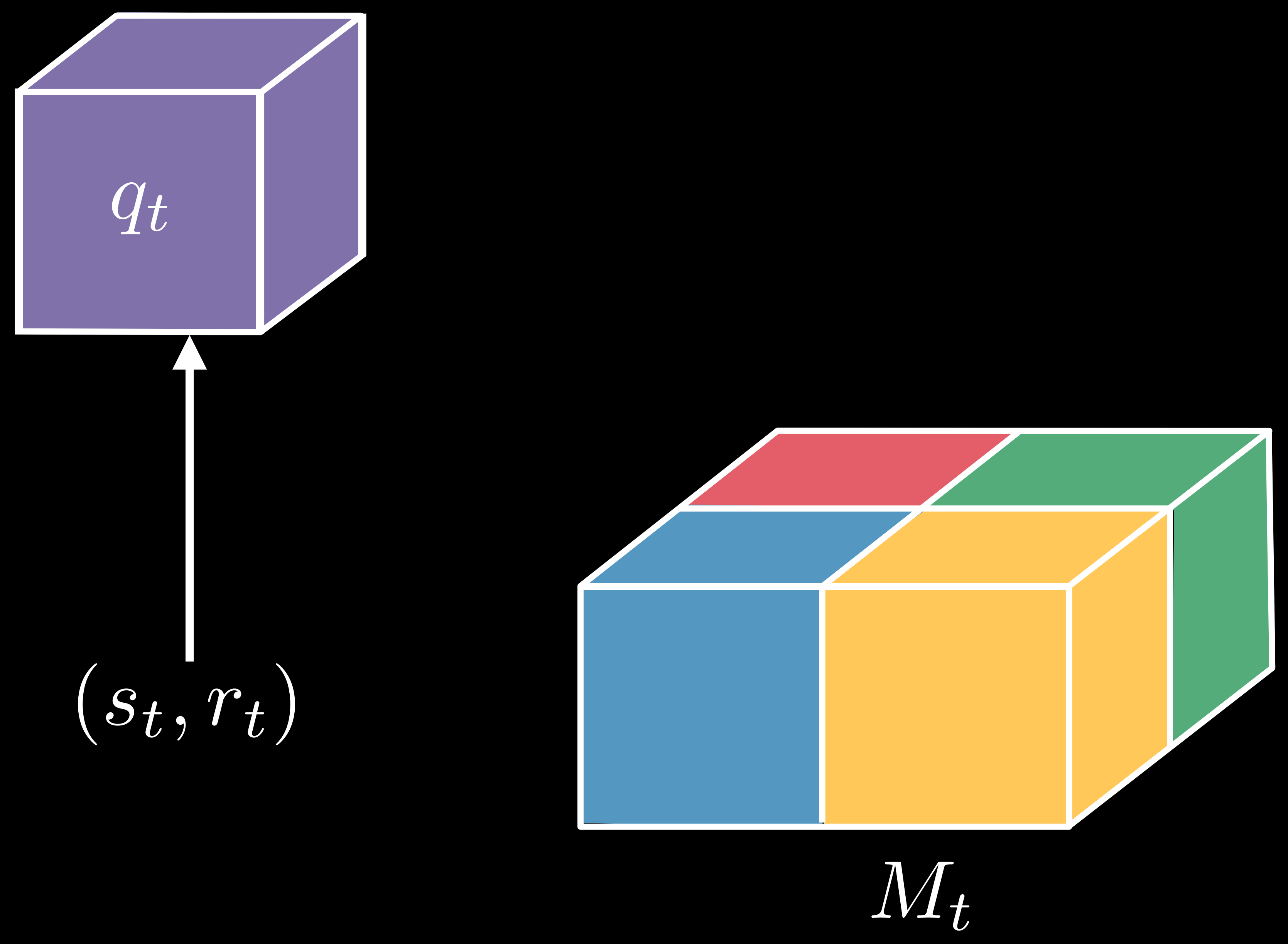
Bahdanau et al., Neural Machine Translation by Jointly Learning to Align and Translate, ICLR 2015
Xu et al., Caption Generation with Visual Attention, ICML 2015

Neural Map: Context Read

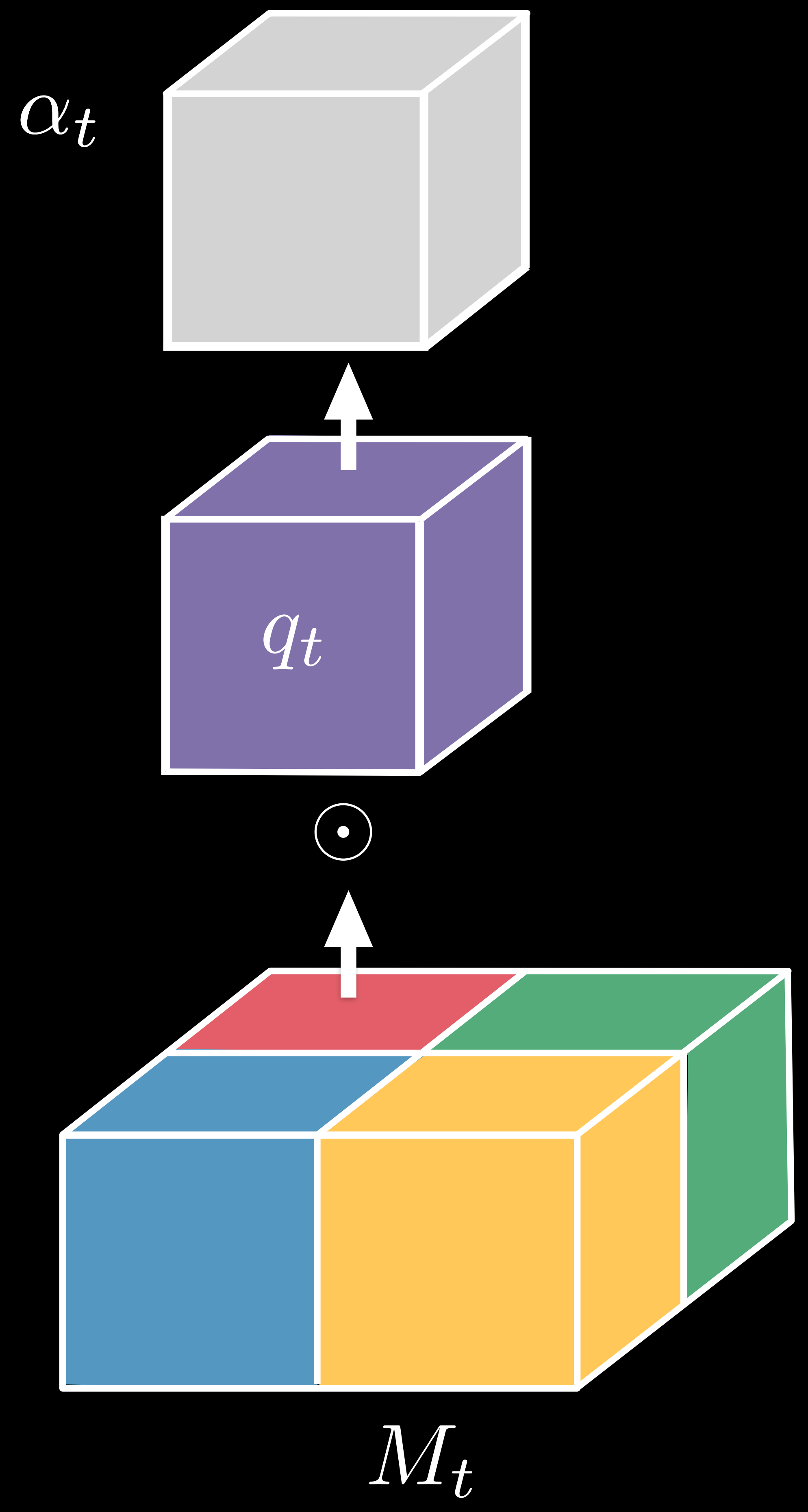
- Read operation using attention

- Simple 2x2 memory M_t
- Obtain query vector q_t from state s_t and global read r_t



Neural Map: Context Read

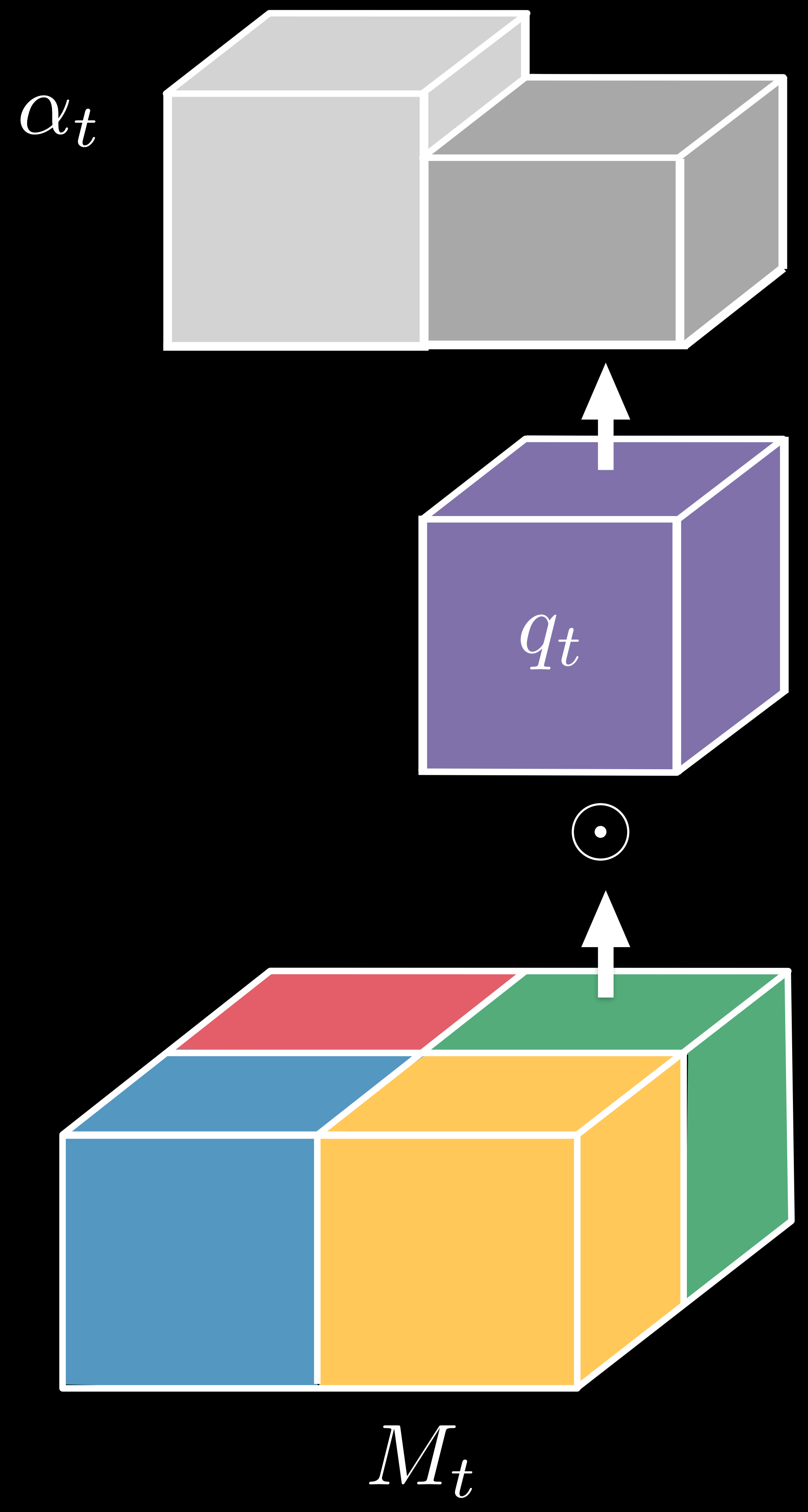
- Read operation using attention



- Dot product between query vector q_t and every memory cell
- Produces a similarity α_t

Neural Map: Context Read

- Read operation using attention



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Neural Map: Context Read

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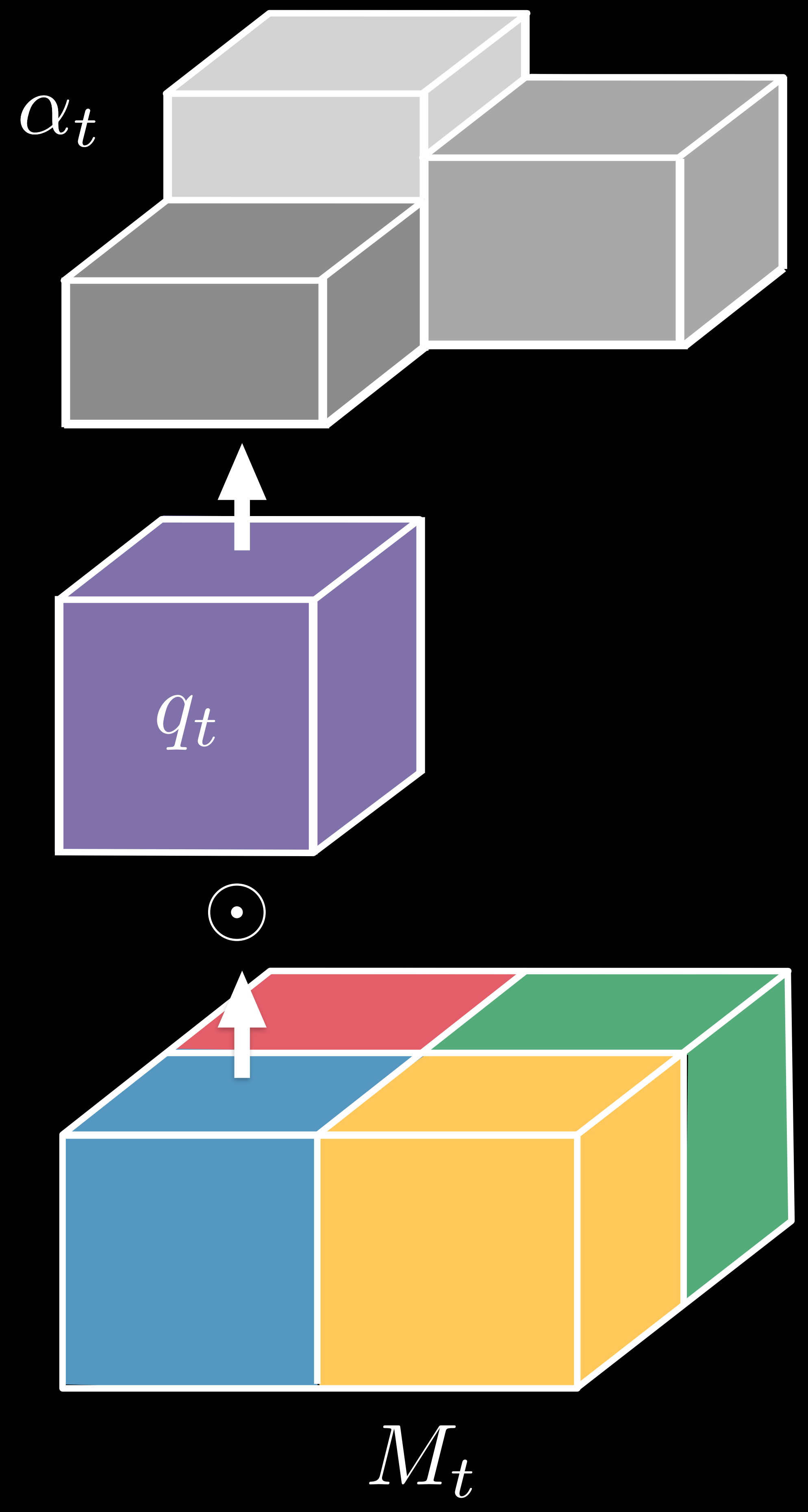

- Dot product between query vector q_t and every memory cell
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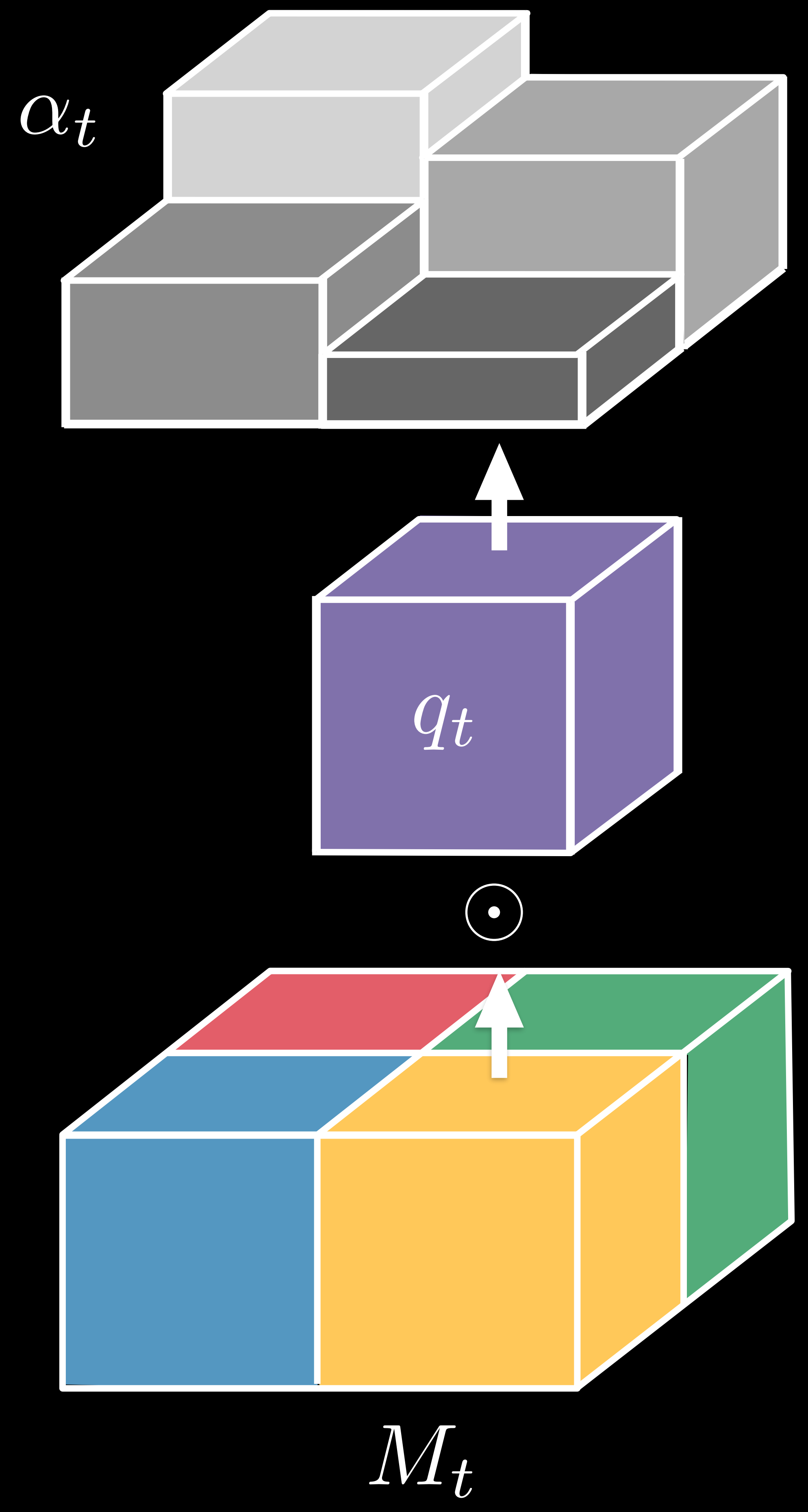
Neural Map: Context Read

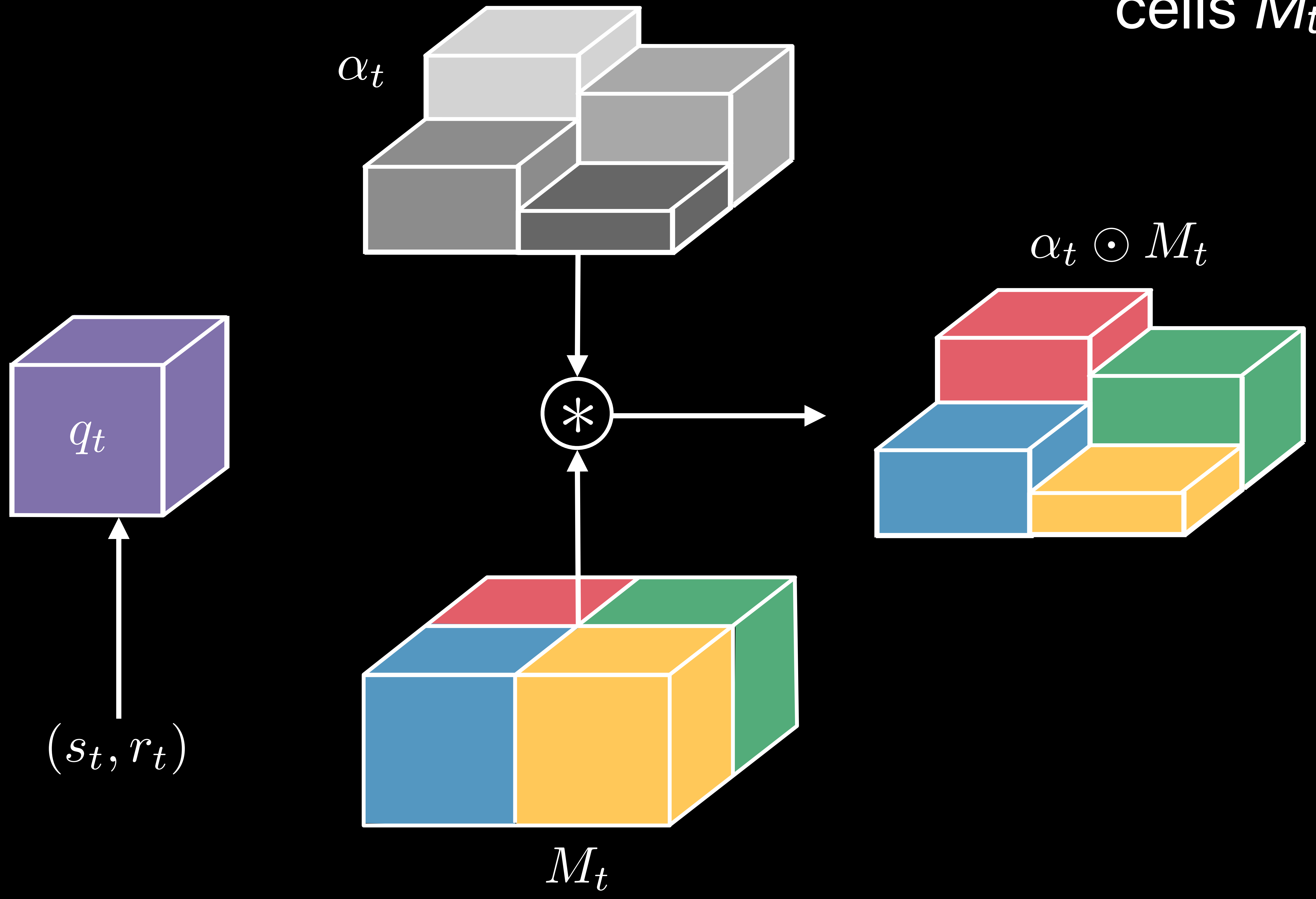
- Read operation using attention



- Dot product between query vector q_t and every memory cell
- Produces a similarity α_t

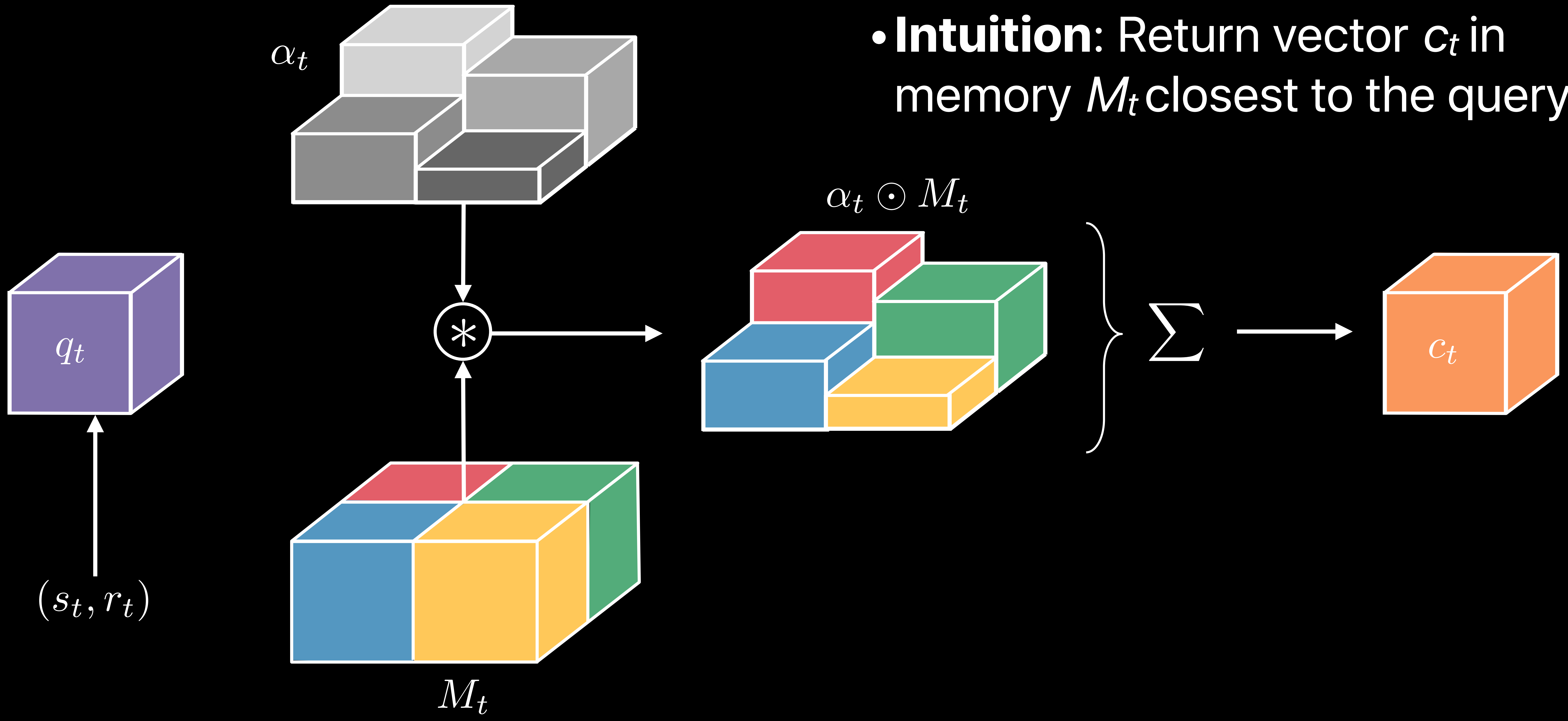
Neural Map: Context Read

- Read operation using attention
- Element-wise product between query similarities α_t and memory cells M_t



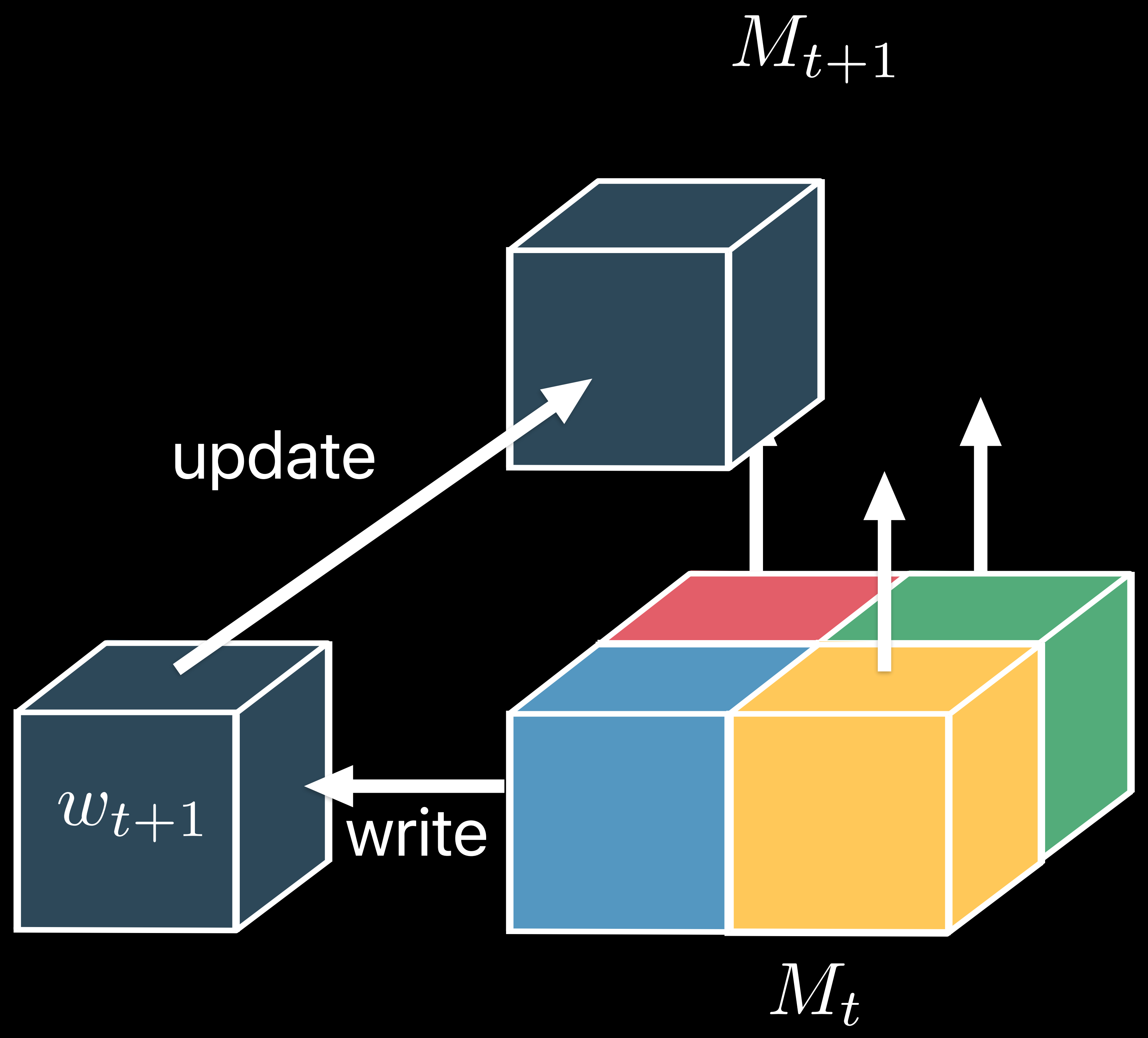
Neural Map: Context Read

- Read operation using attention
- Sum over all positions to obtain context read vector c_t
- **Intuition**: Return vector c_t in memory M_t closest to the query q_t



Neural Map: Write

- Creates a new *k*-dim vector to write to the current position in the map
- Update the neural map at the current position with this new vector



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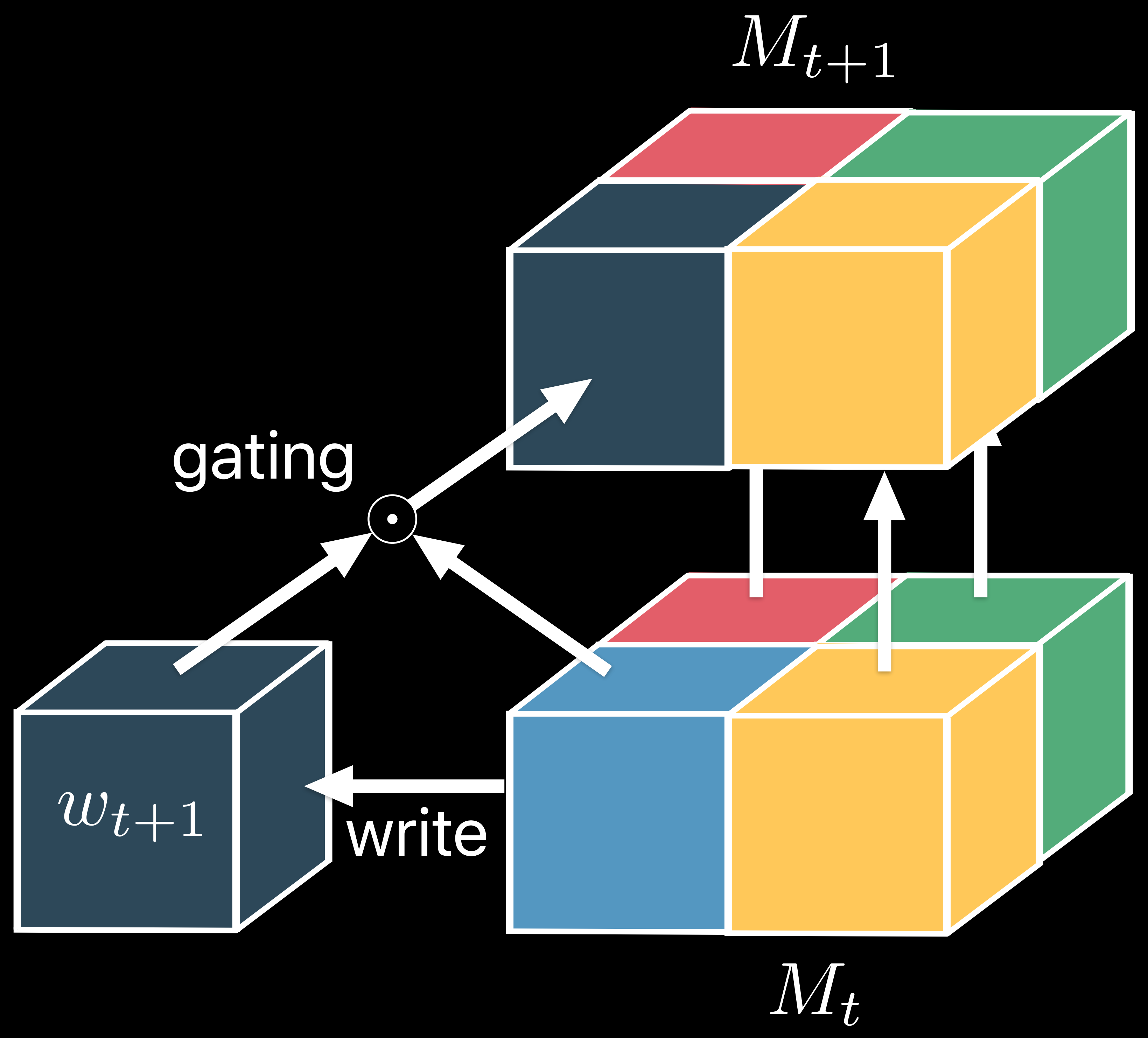
Neural Map: GRU Write Update

- Creates a new *k*-dim vector to write to the current position in the map
- Update the neural map at the current position with this new vector



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Chung et al.,Gated Recurrent Neural Networks , 2014

Neural Map: Output

- Output the read vectors and what we wrote
- Use those features to compute a policy

$$
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r_t &= read(M_t) \\
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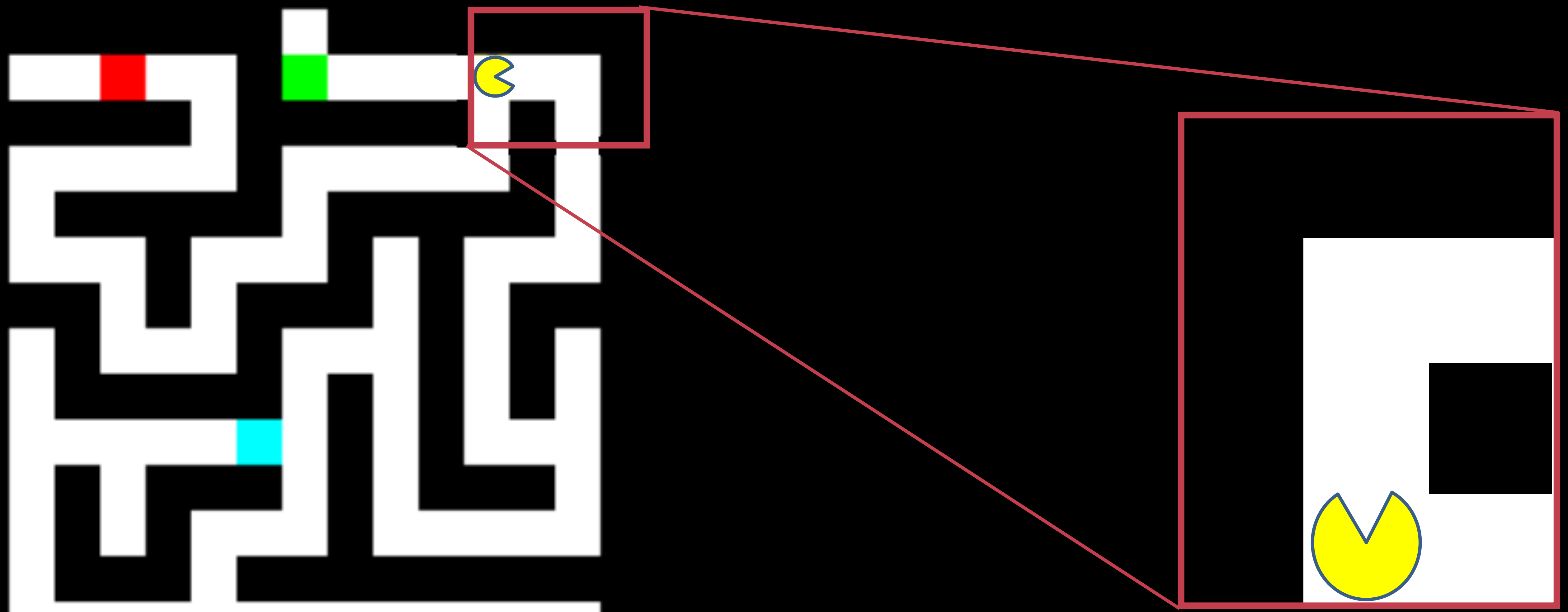
\end{aligned}
$$

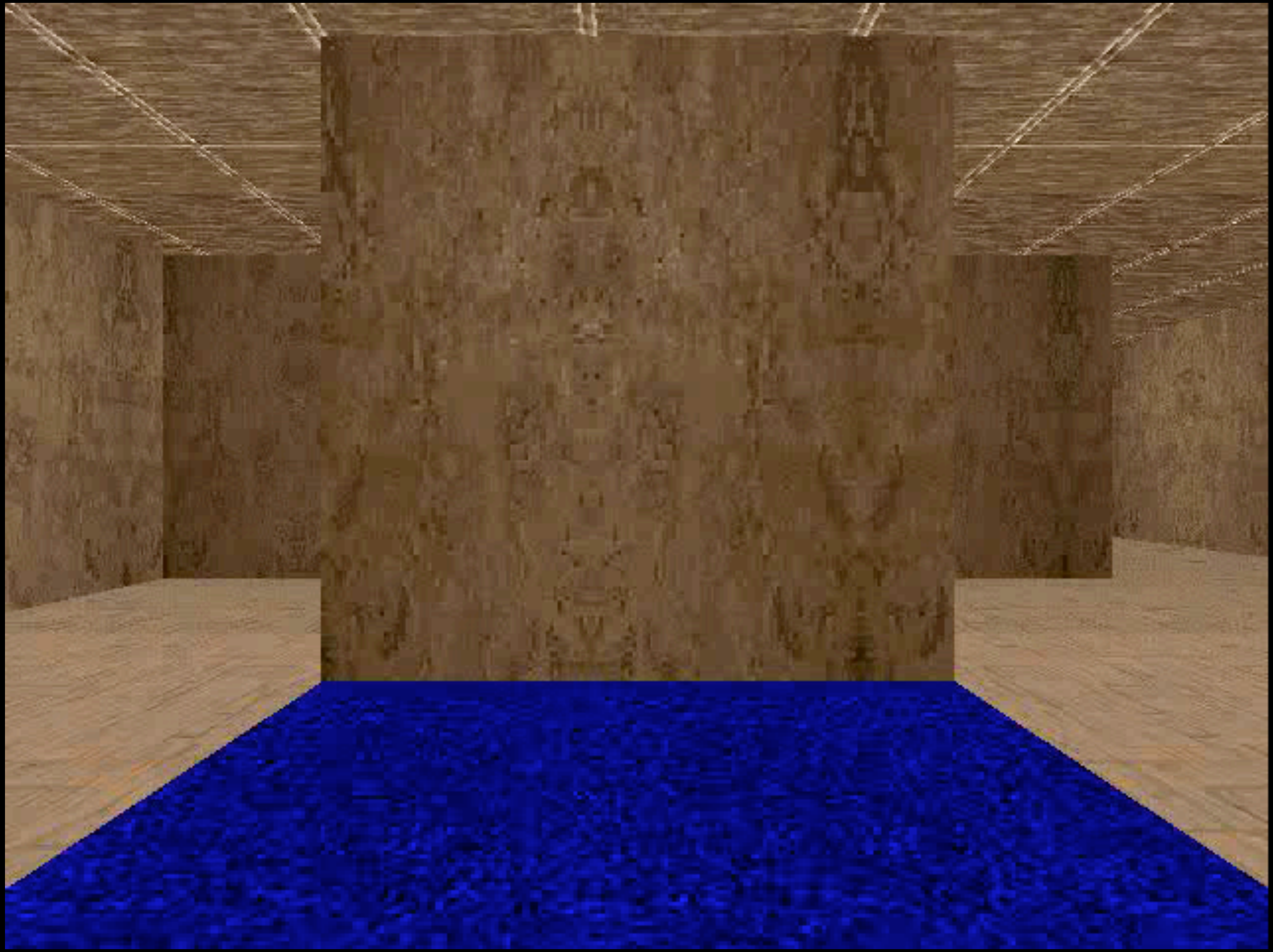
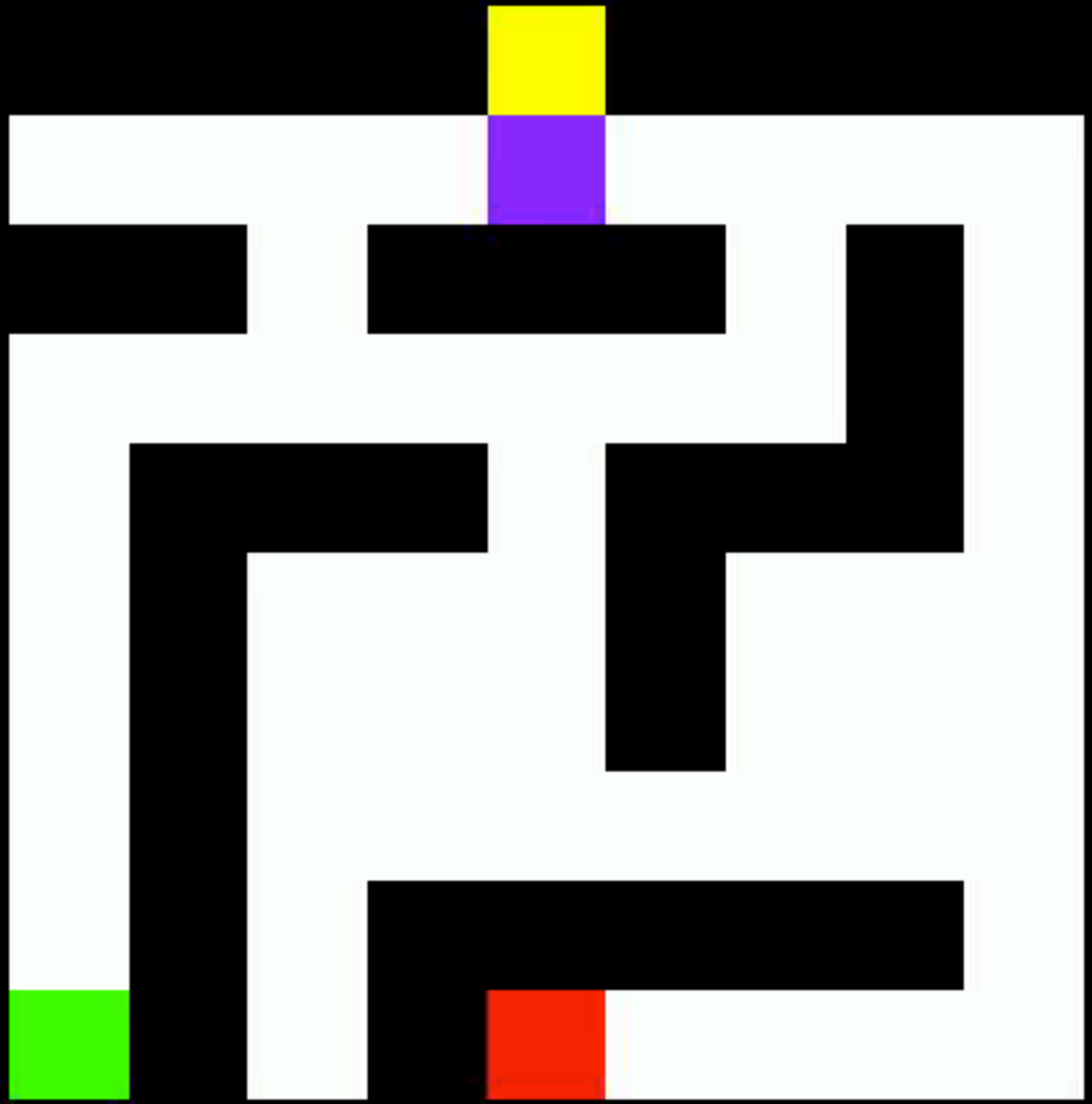
Random Maze with Indicator

- Results are robust with respect to small noise in the (x, y)-position of the agent



complete map
(not visible)

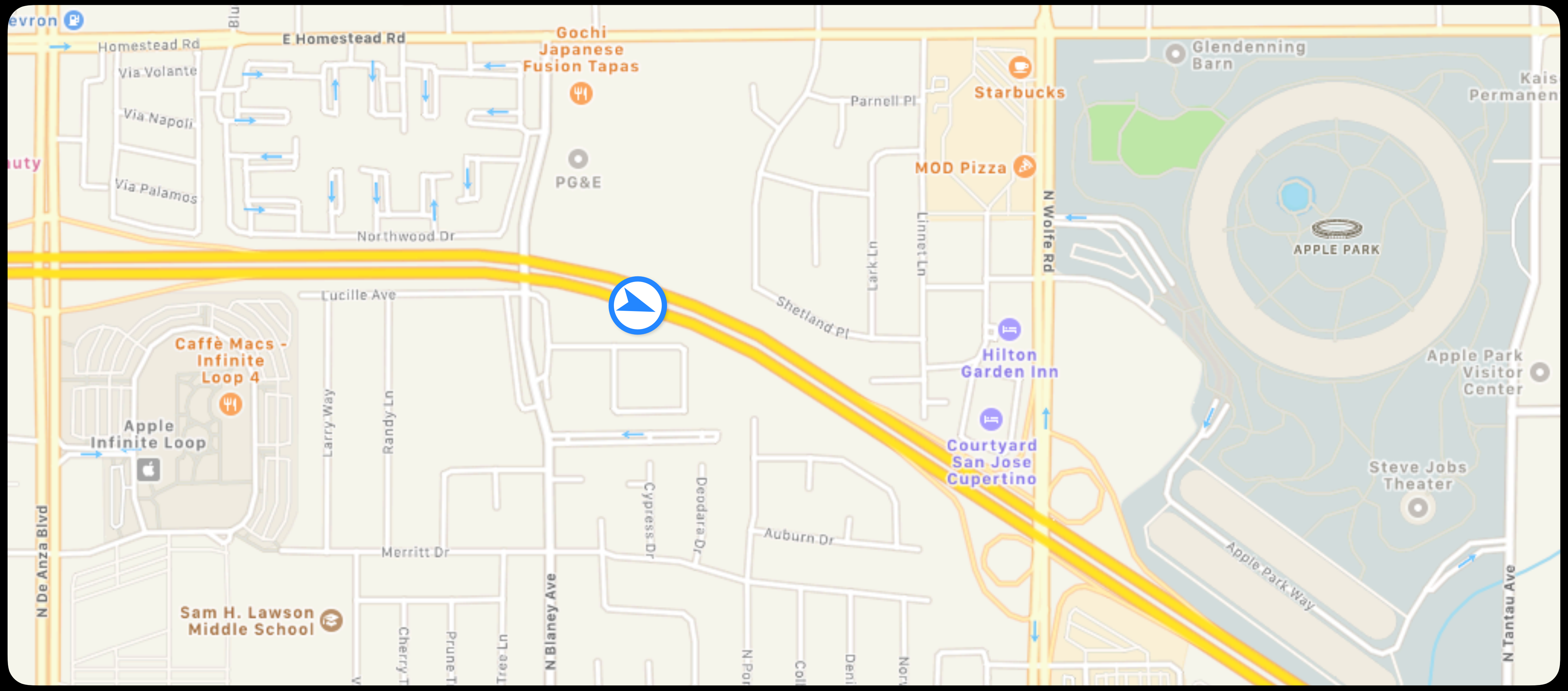
input state
(partially observable)

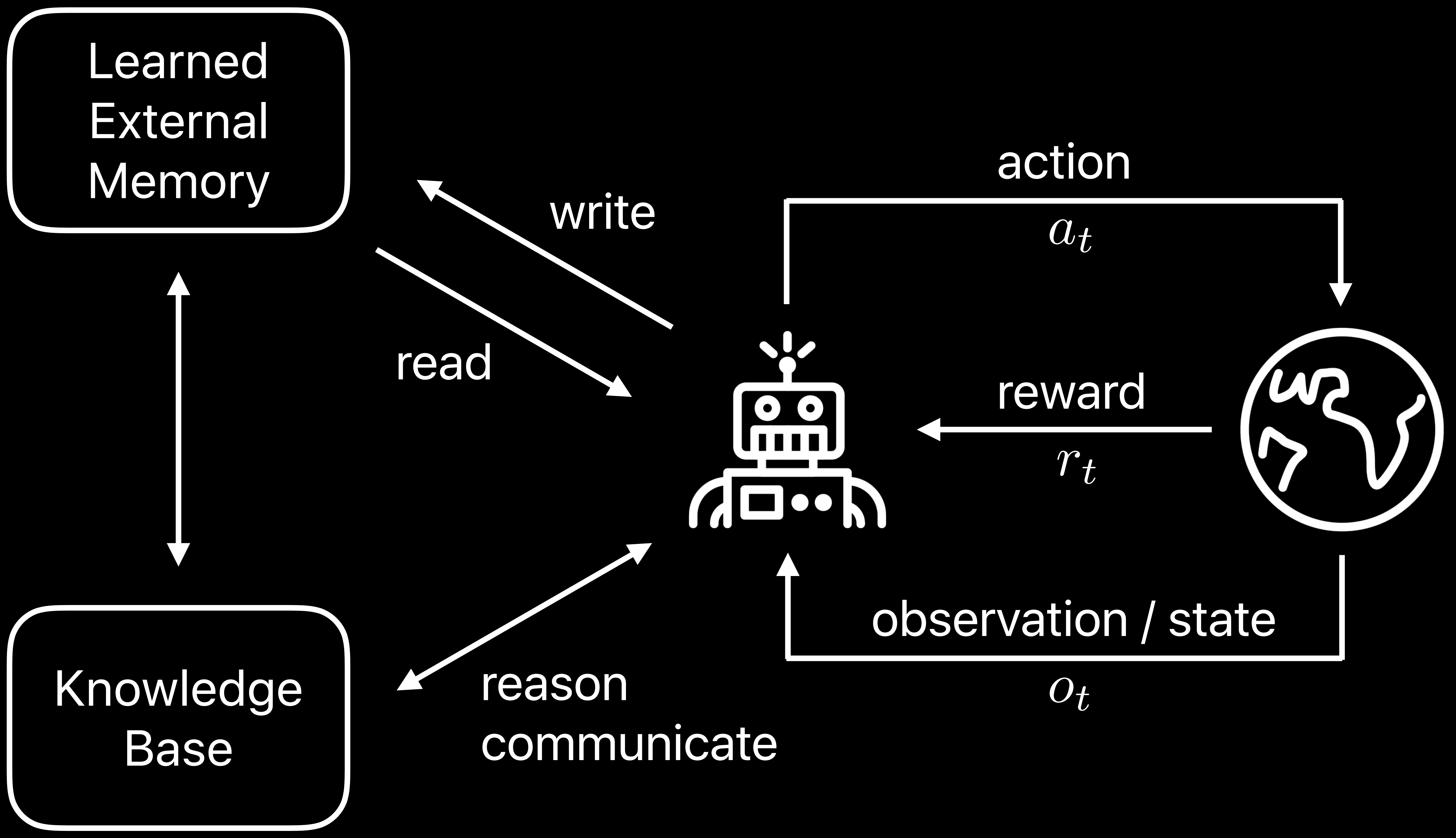
Random Maze with Indicator

Egocentric Neural Map

- Problem with Neural Map: it requires mapping from (x,y) to (x',y')
  - We need to have already solved localization
- Obtain a map which is egocentric:
  - The agent always writes to the center of the map
  - When the agent moves, the entire map moves by the opposite amount

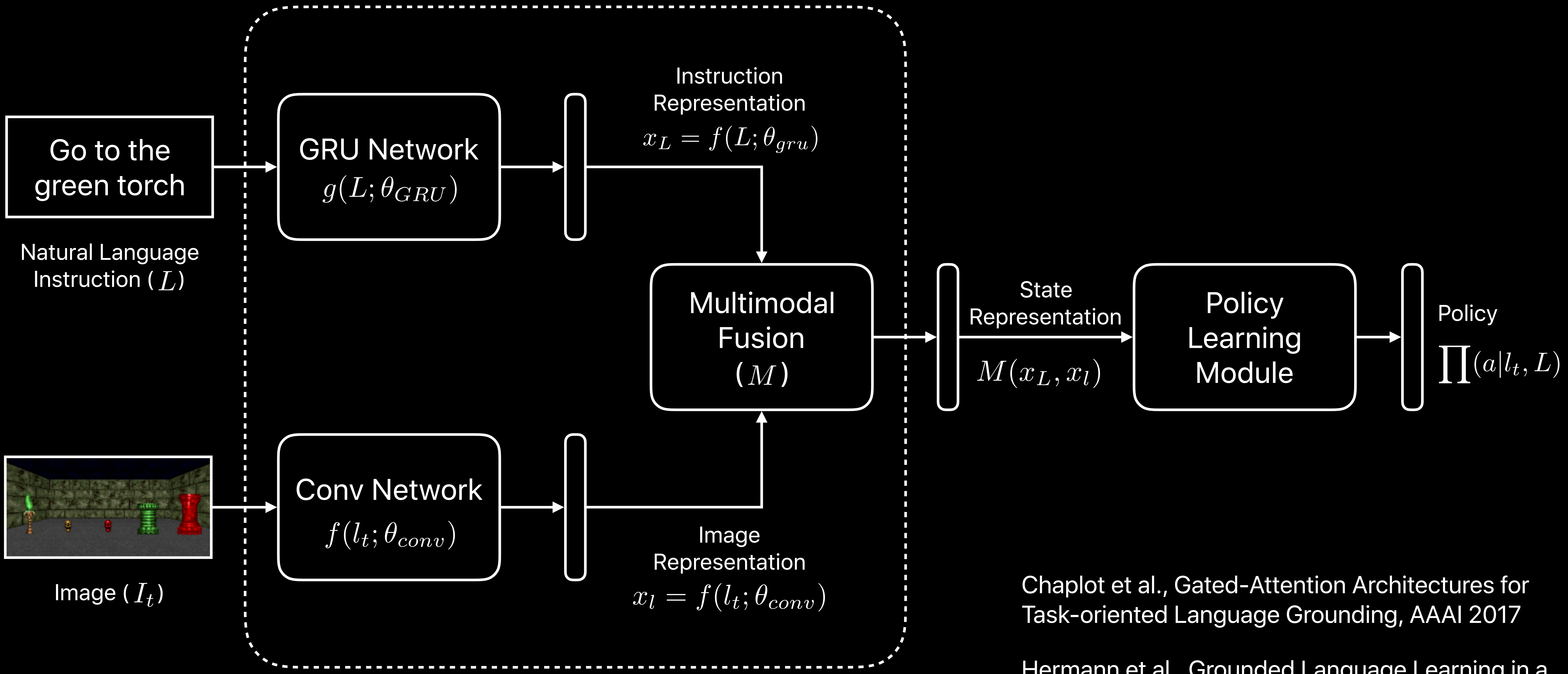


Intelligent Agents



Go to the red short torch

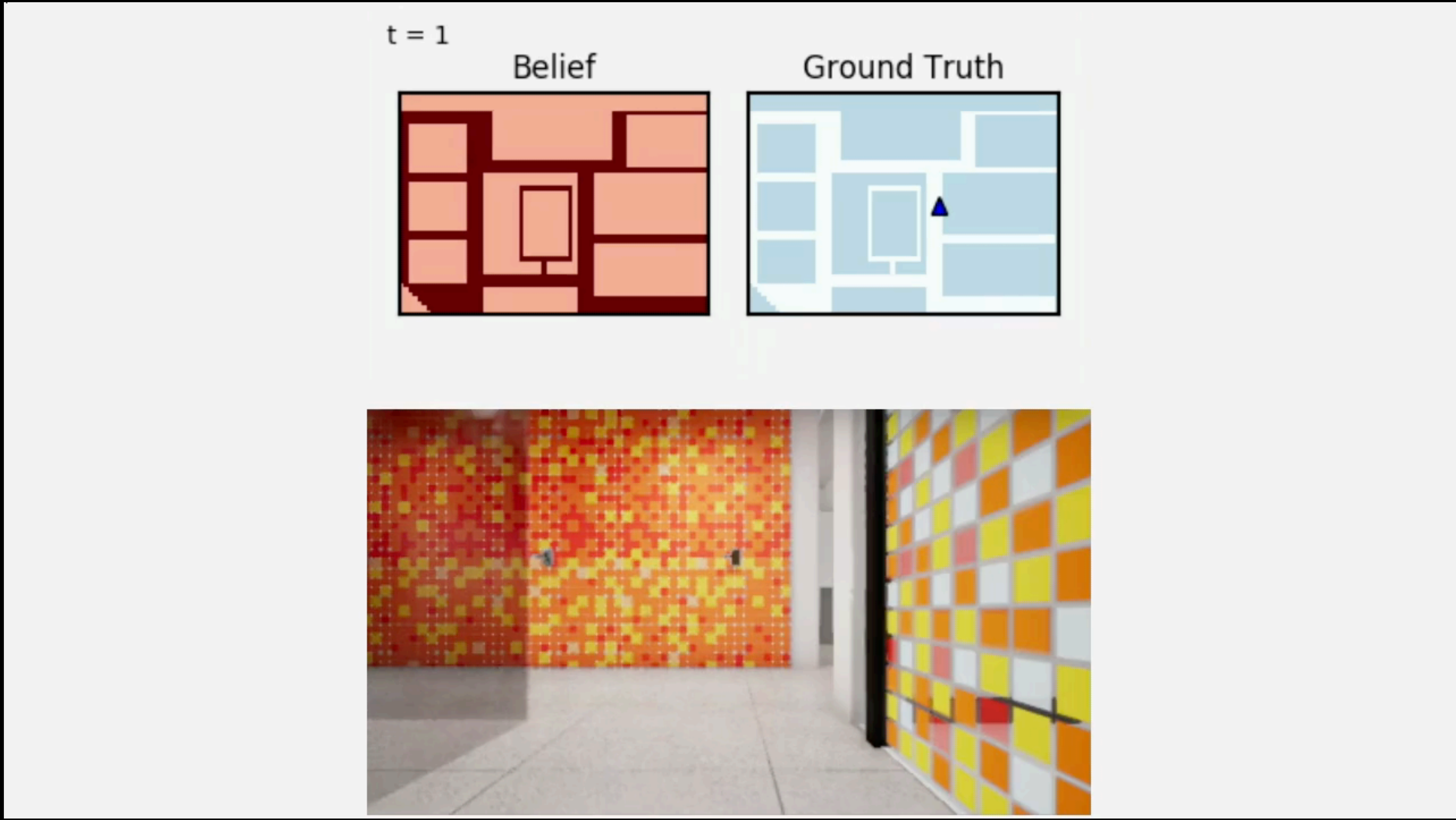
Learning to Execute Instructions



Chaplot et al., Gated-Attention Architectures for Task-oriented Language Grounding, AAAI 2017

Hermann et al., Grounded Language Learning in a Simulated 3-D world, 2017

Active Neural Localization



Chaplot, Parisotto, Salakhutdinov, ICLR 2018

Discussion

- Can we extend to multi-agent domains?
  - Multiple agents communicating through shared memory.
- Can we train an agent to learn how to simultaneously localize and map its environment using the Neural Map?
  - Solves problem of needing an oracle to supply (x, y) position
- Can we structure neural maps into a multi-scale hierarchy?
  - Each scale will incorporate longer range information

Thank you