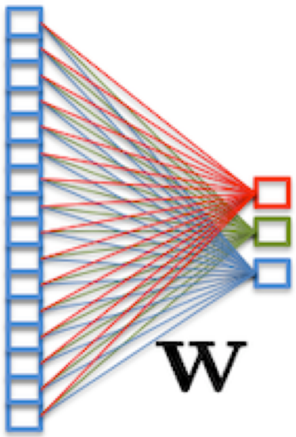
5IF - Deep Learning et Programmation Différentielle

5.3 Robot Navigation



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Lecture: Deep Learning and Differential Programming

5.4 Robot Navigation

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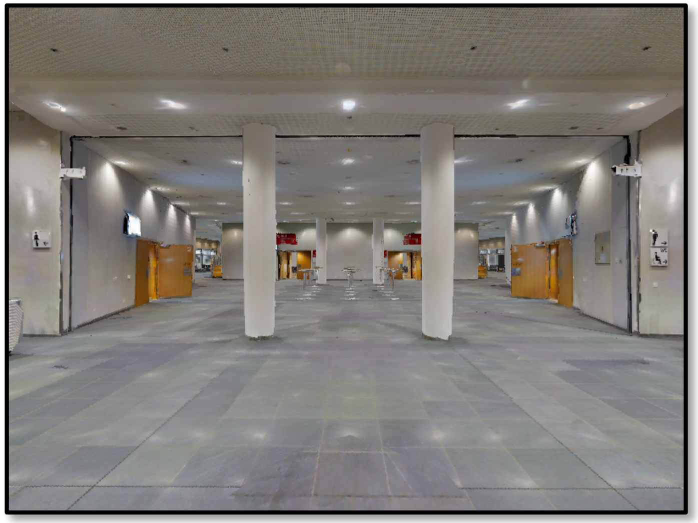
Robotics

Perception



Navigation

HCI

Compagnon robots

Learning to navigate in 3D environments

Purely geometrical mapping + planning

Adding semantics

Purely learned policies (Deep-RL)

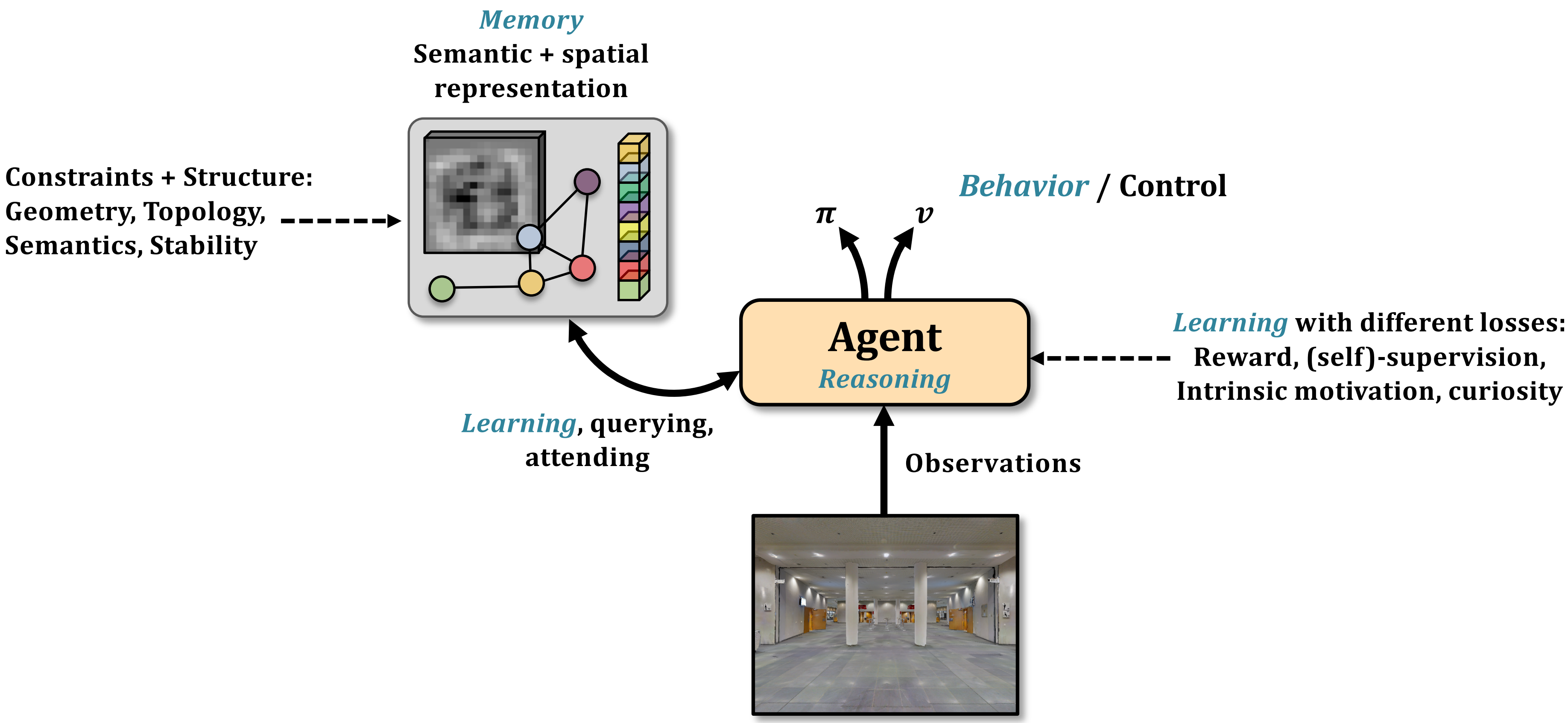
Inductive biases: Geometry, topology, stability etc.

+ Real world solutions
- Simple tasks and reasoning (eg. waypoint navigation)

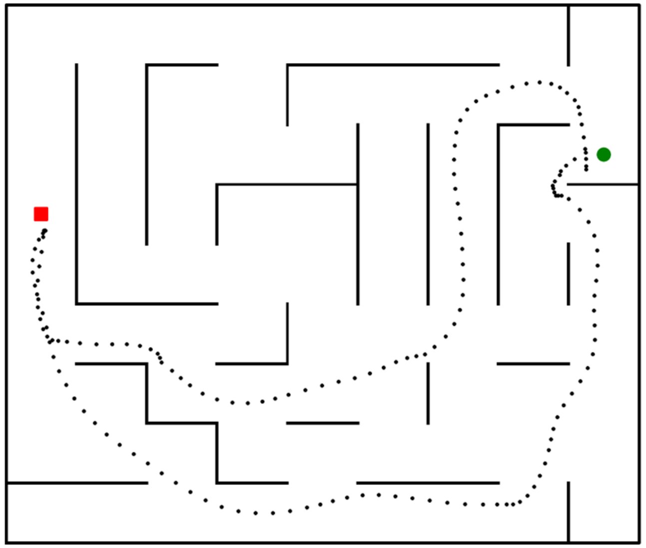
+ High-level reasoning
+ Discover tasks from reward
- Does not transfer to the real world

Question:

What kind of inductive bias can we create for learning navigation?

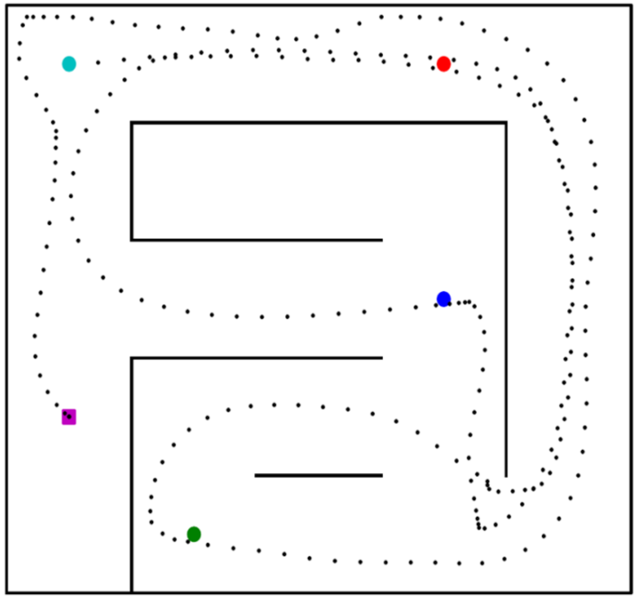

Memory
Semantic + spatial representation
Constraints + Structure:
Geometry, Topology,
Semantics, Stability
Behavior / Control
π
v
Agent
Reasoning
Learning with different losses:
Reward, (self)-supervision,
Intrinsic motivation, curiosity
Learning, querying,
attending
Observations

Experiments: Scenarios



Find and return

- Find an object in a maze and then returning to the starting point
- Sparse rewards:
  - 0.5 for finding the object
  - 0.5 for returning to the starting point



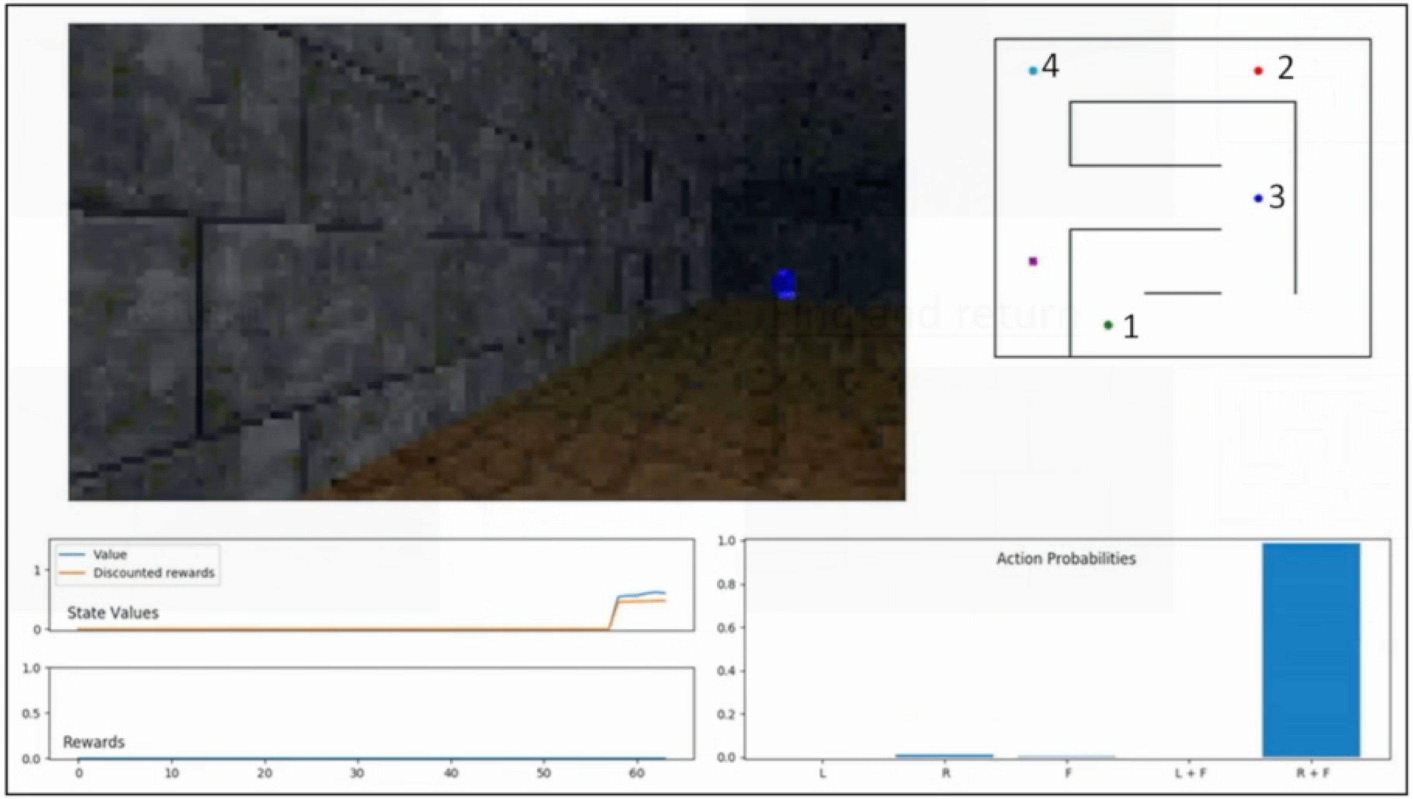
Ordered K-item

- Collect k items in a fixed order
- Sparse rewards:
  - 0.5 for each object collected

[Beeching et al., Arxiv 2018]

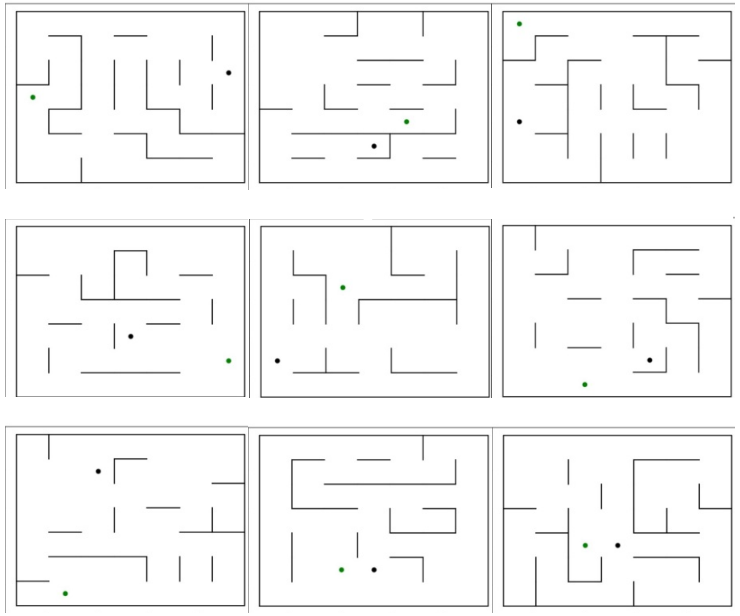
Scenarios: Ordered K-item

- Collect K items in a specific order
- Tests: Vision & memory

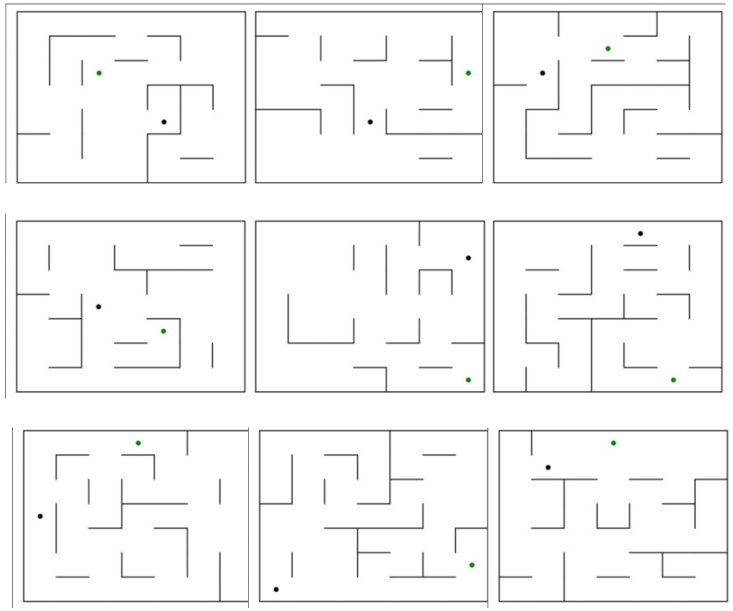


Generalization to unseen mazes

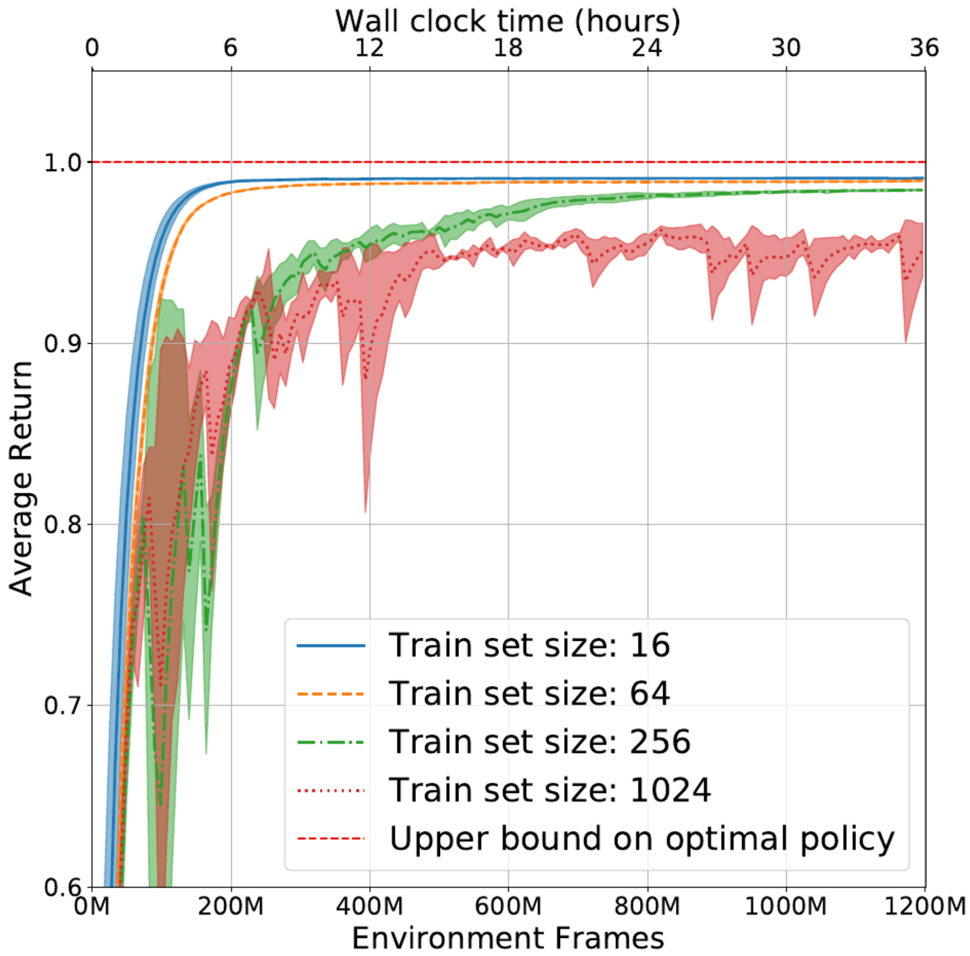
N - Training configurations

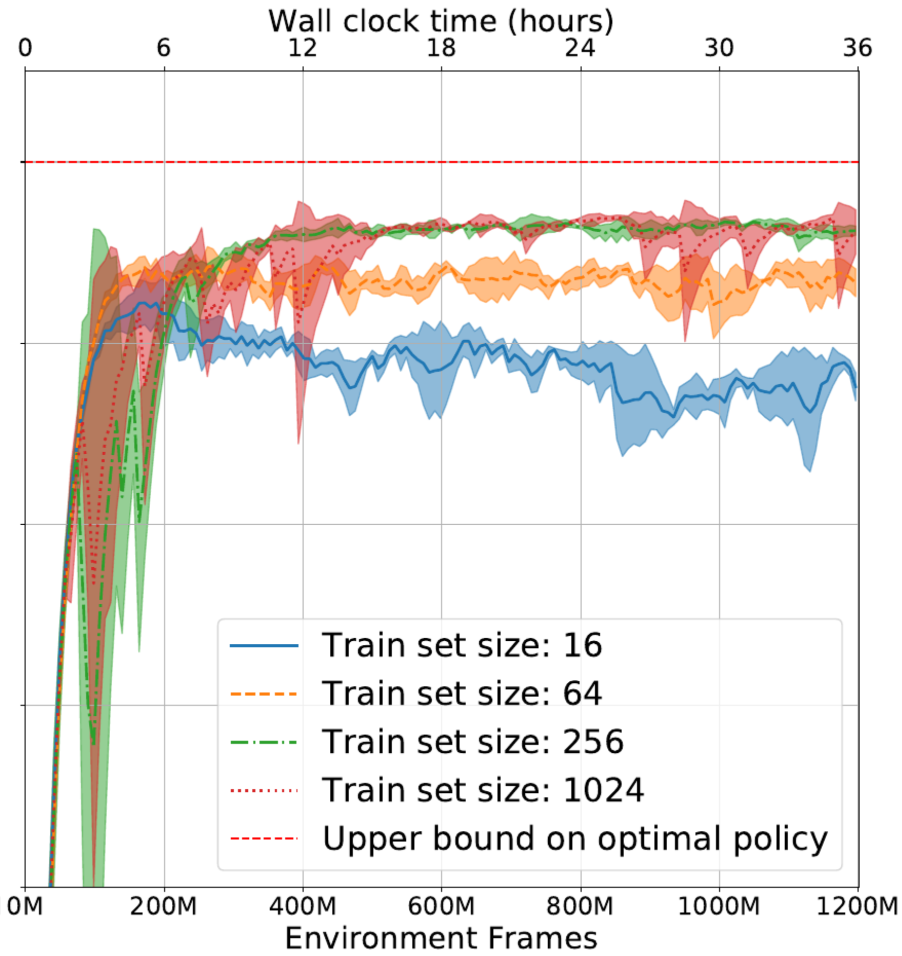


K - Testing configurations

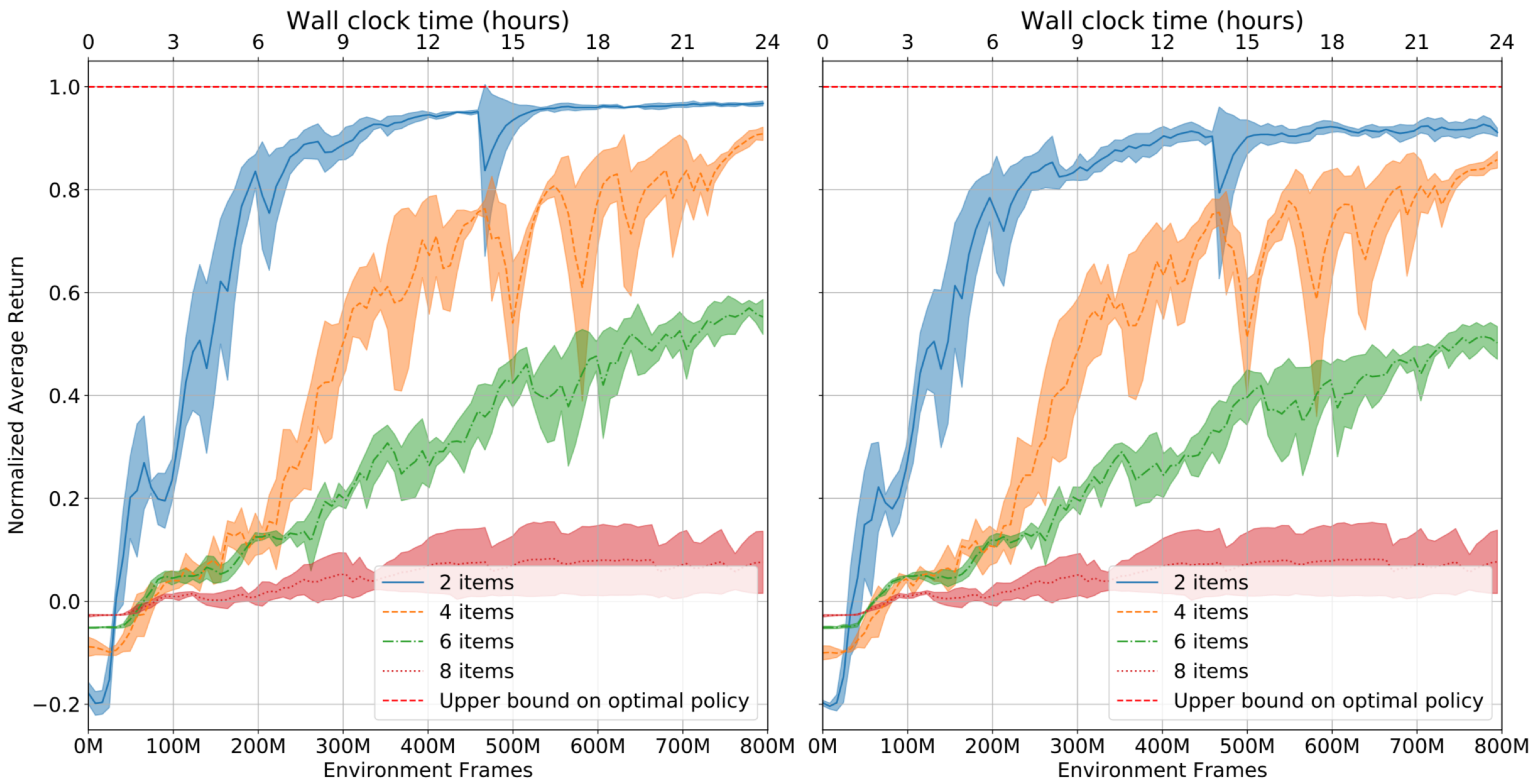


Generalization to unseen mazes





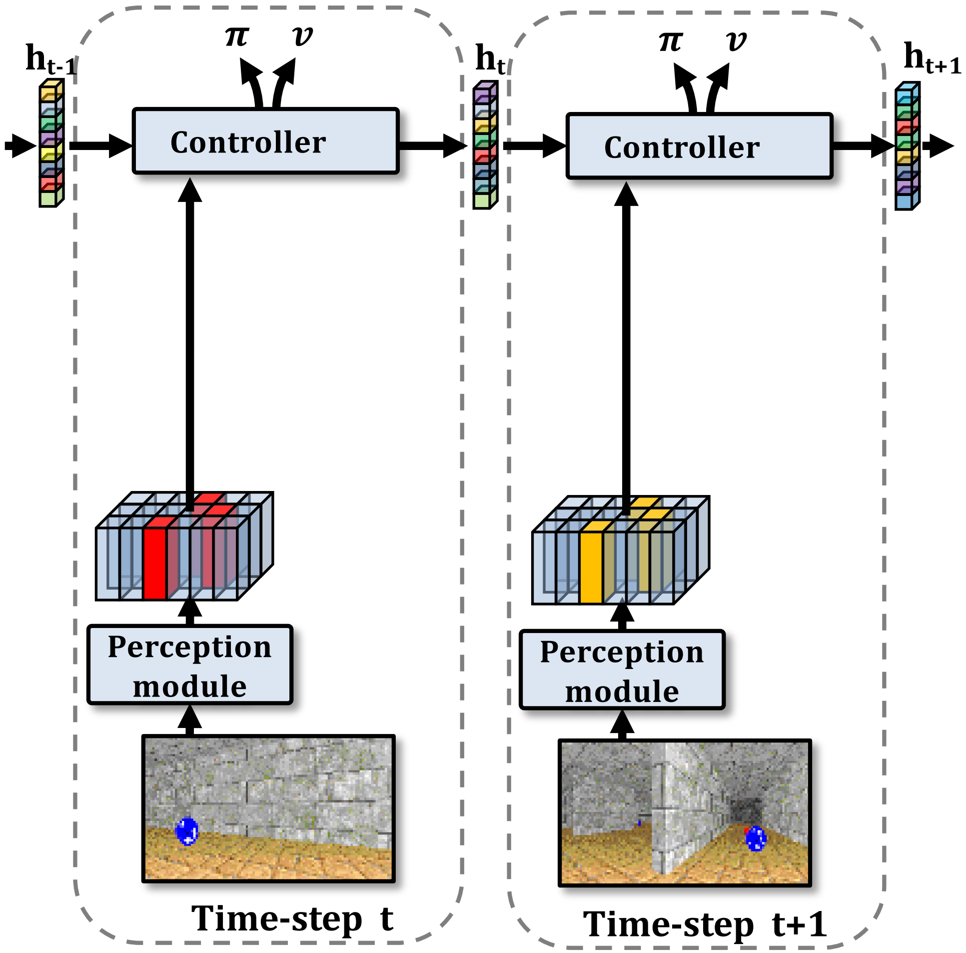
K-item scenario: recurrent agent (A3C)



Training scenarios

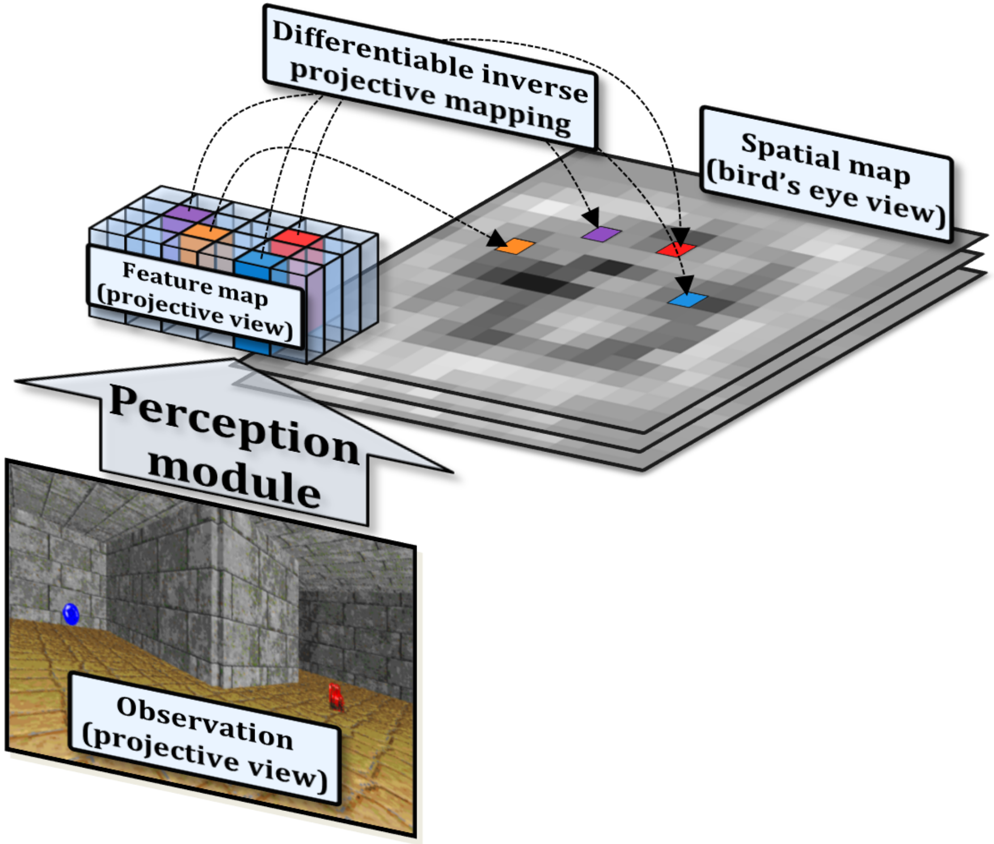
Testing scenarios

Learning agent control/behavior



Projective mapping

$$s_t = f_p(I_t; \theta_p)$$



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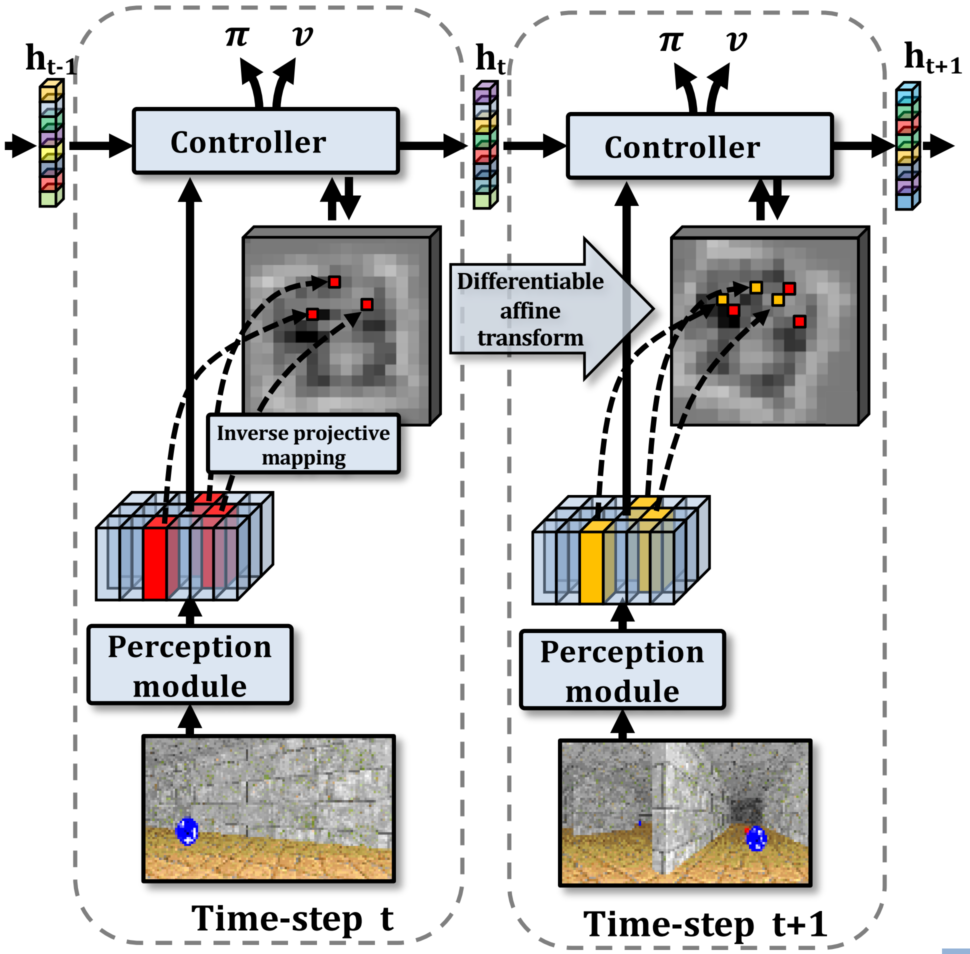
Learning agent control/behavior



[Beeching, Dibangoye, Simonin, Wolf, Under review]

A single forward pass

1. Transform the map to the agent's egocentric frame of reference

$$\hat{M}_t = \text{Affine}(M_{t-1}, dx_t, dy_t, d\phi_t)$$

2. Update the map to include new observations

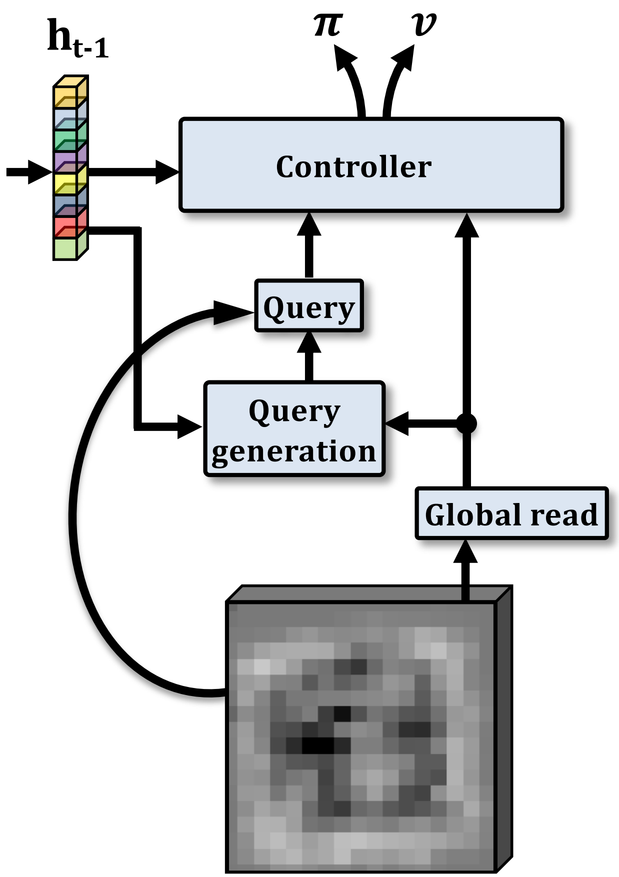
$$\tilde{M}_t = \text{InverseProject}(s_t, D_t) \qquad M'_t = \text{Combine}(\hat{M}_t, \tilde{M}_t)$$

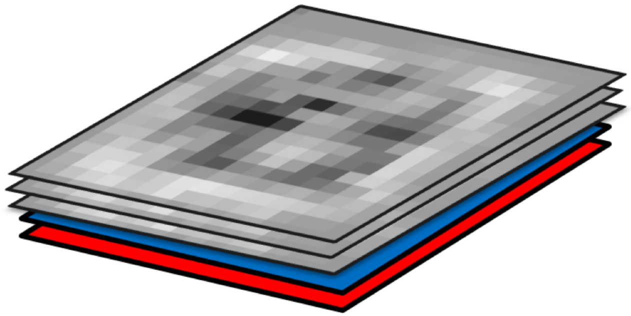
3. Perform a global read and attention based read,

$$r_t = \text{Read}(M'_t) \qquad c_t = \text{Context}(M'_t, s_t, r_t)$$

Querying spatial memory

The network learns to query for specific content

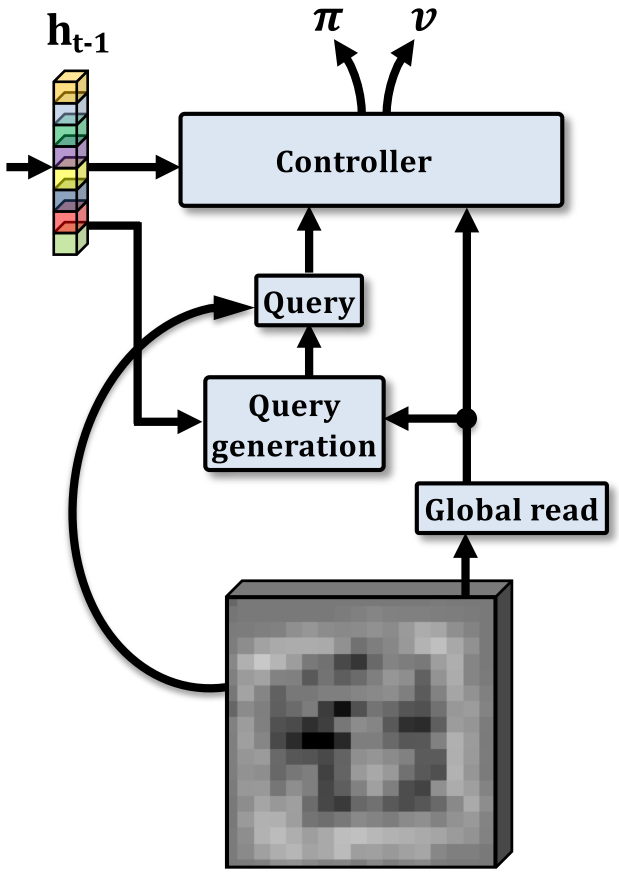


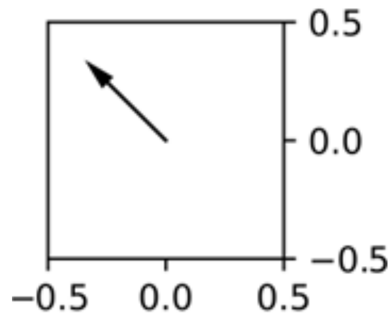


Ease localization with coordinate planes

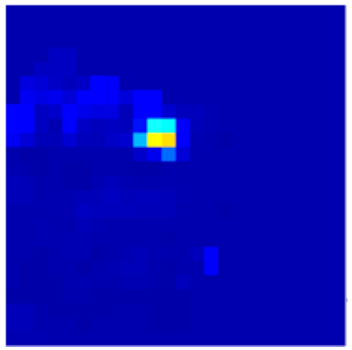
Querying spatial memory

The network learns to query for specific content





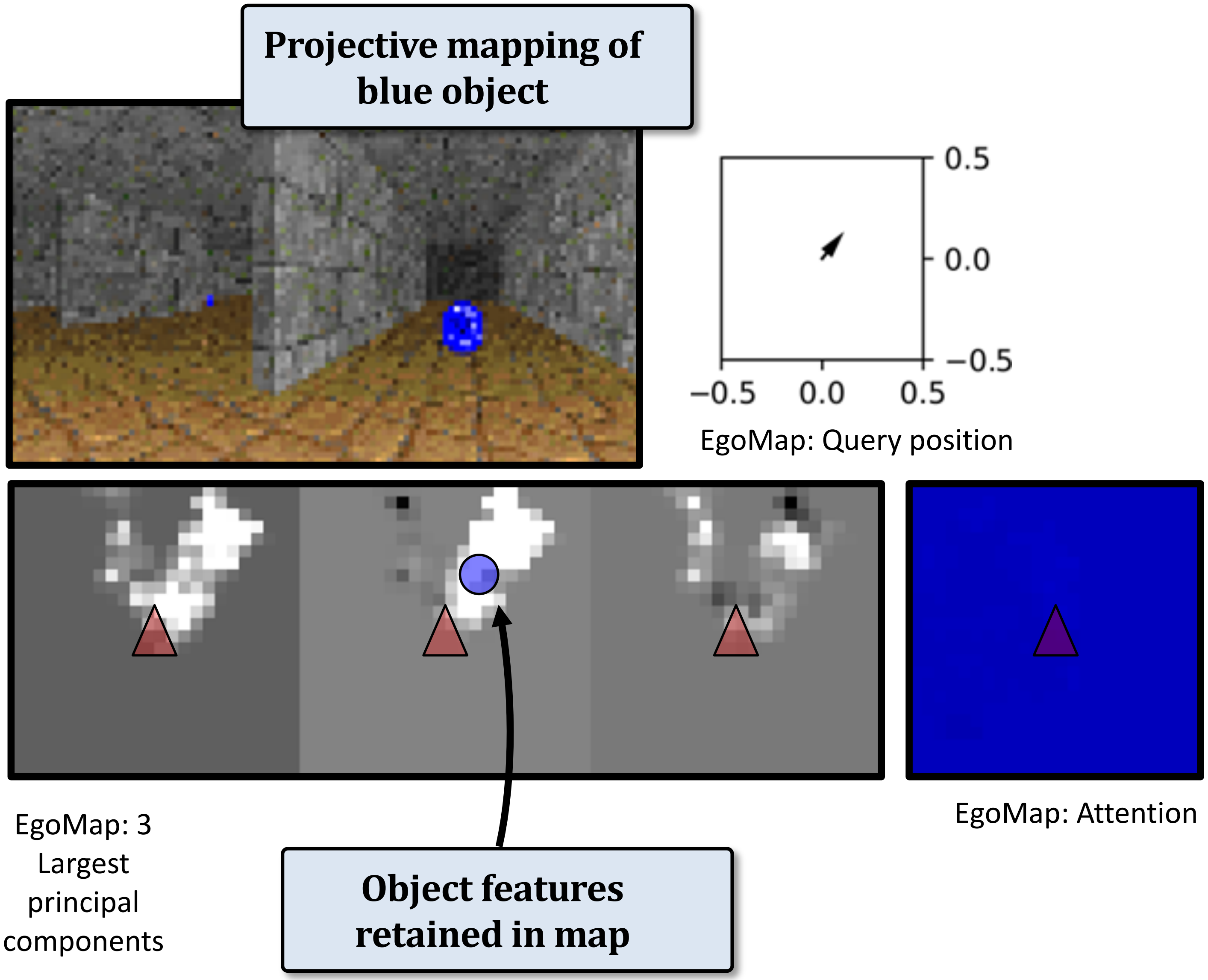
Attention: Spatial direction



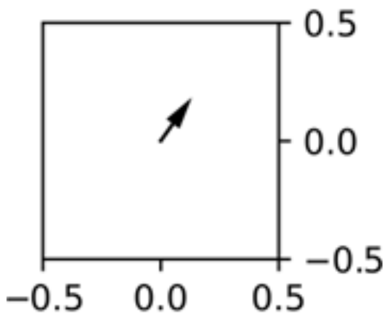
Attention distribution

[Beeching, Dibangoye, Simonin, Wolf, Under review]

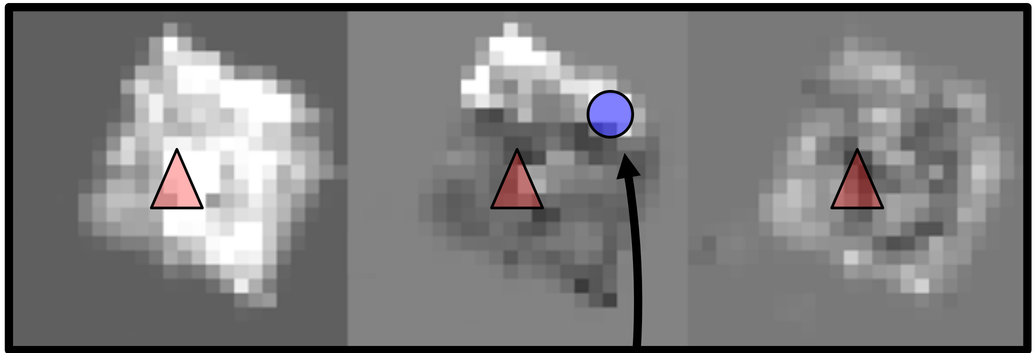
6 item scenario: time-step 005

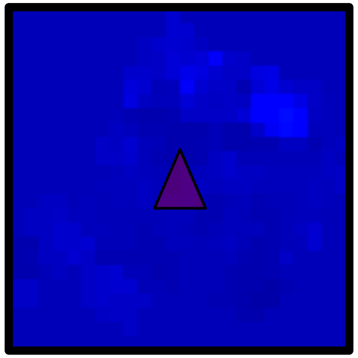


6 item scenario: time-step 105



EgoMap: Query position



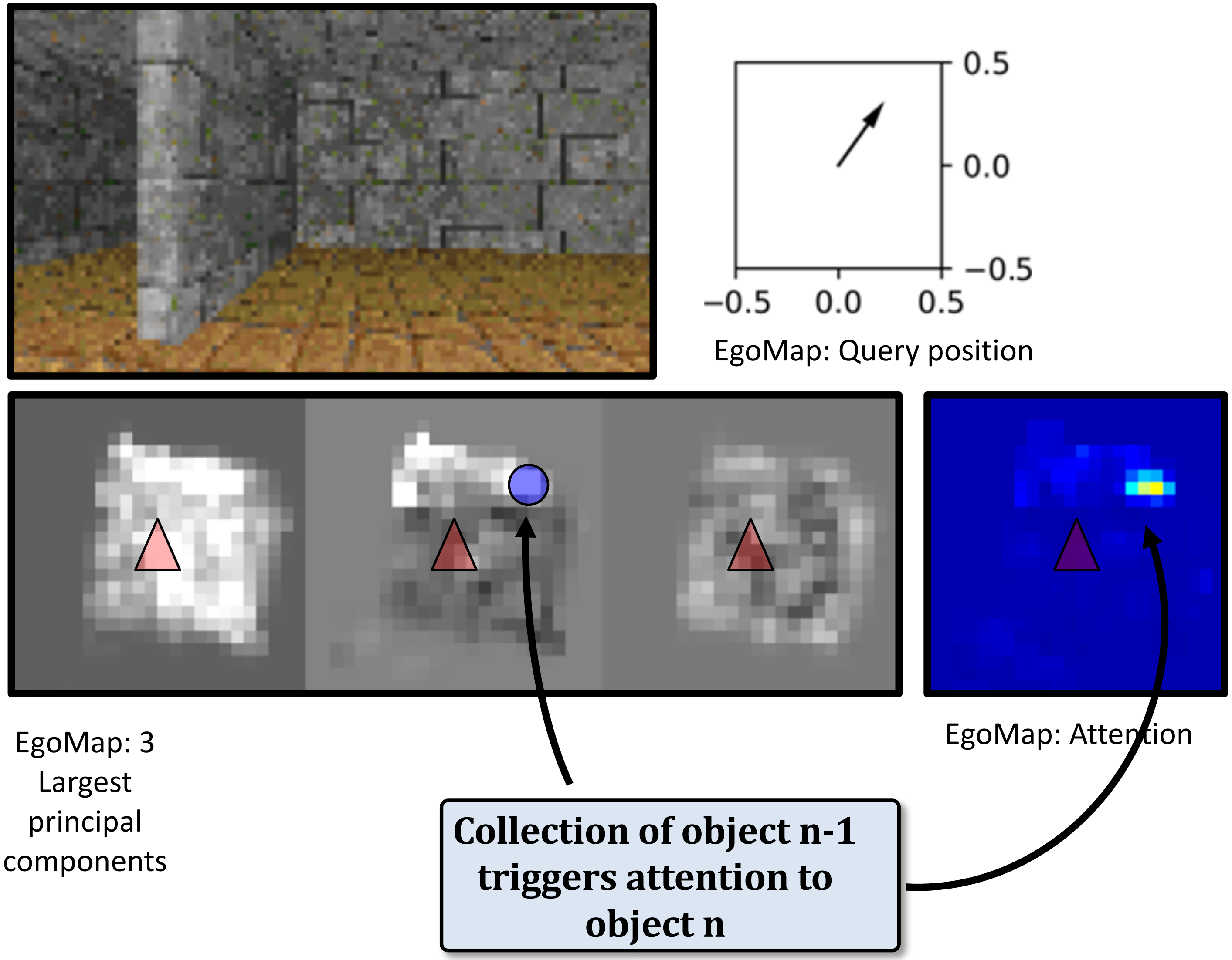


EgoMap: 3 Largest principal components

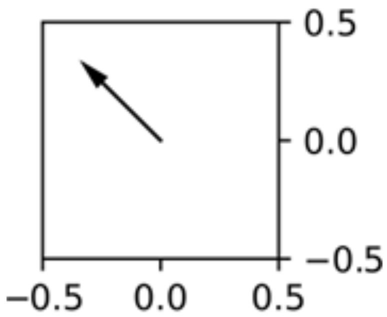
Object features retained in map

EgoMap: Attention

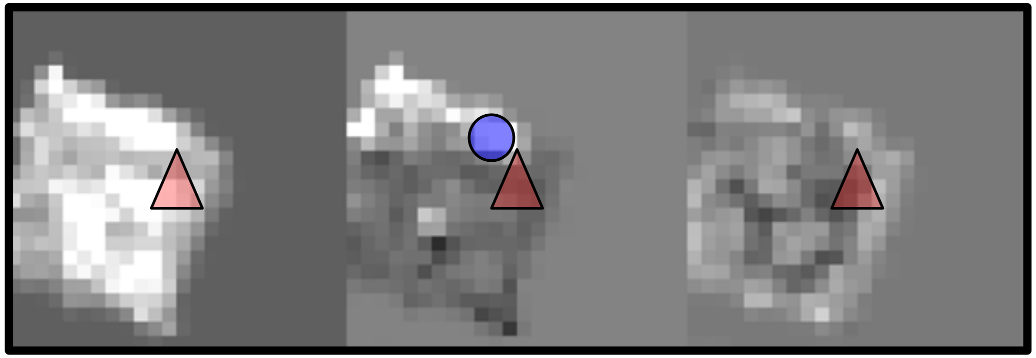
6 item scenario: time-step 108

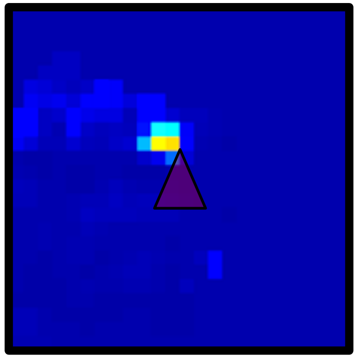


6 item scenario: time-step 134



EgoMap: Query position

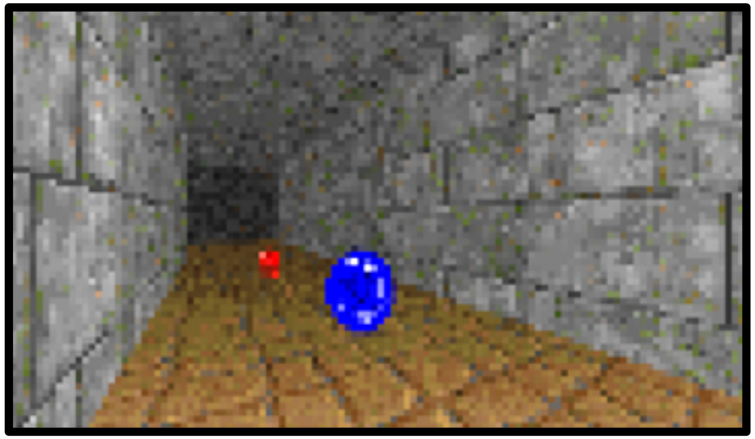


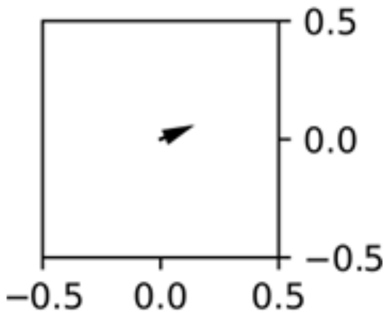


EgoMap: 3 Largest principal components

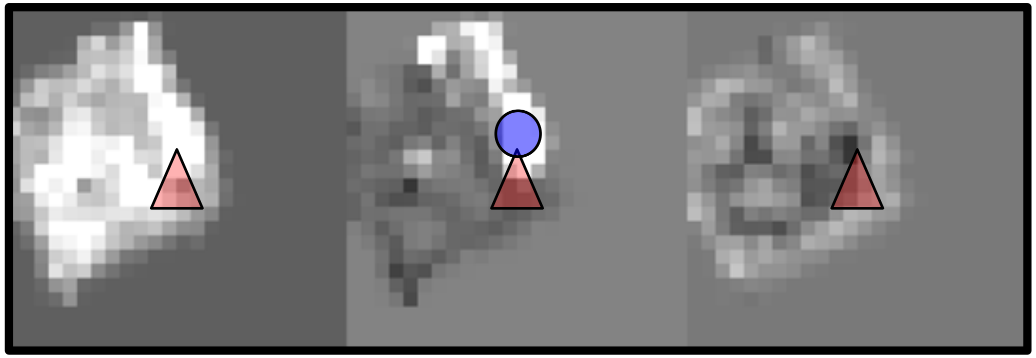
EgoMap: Attention

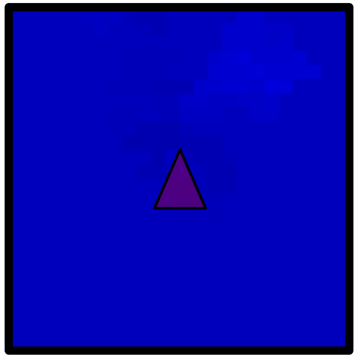
6 item scenario: time-step 140





EgoMap: Query position



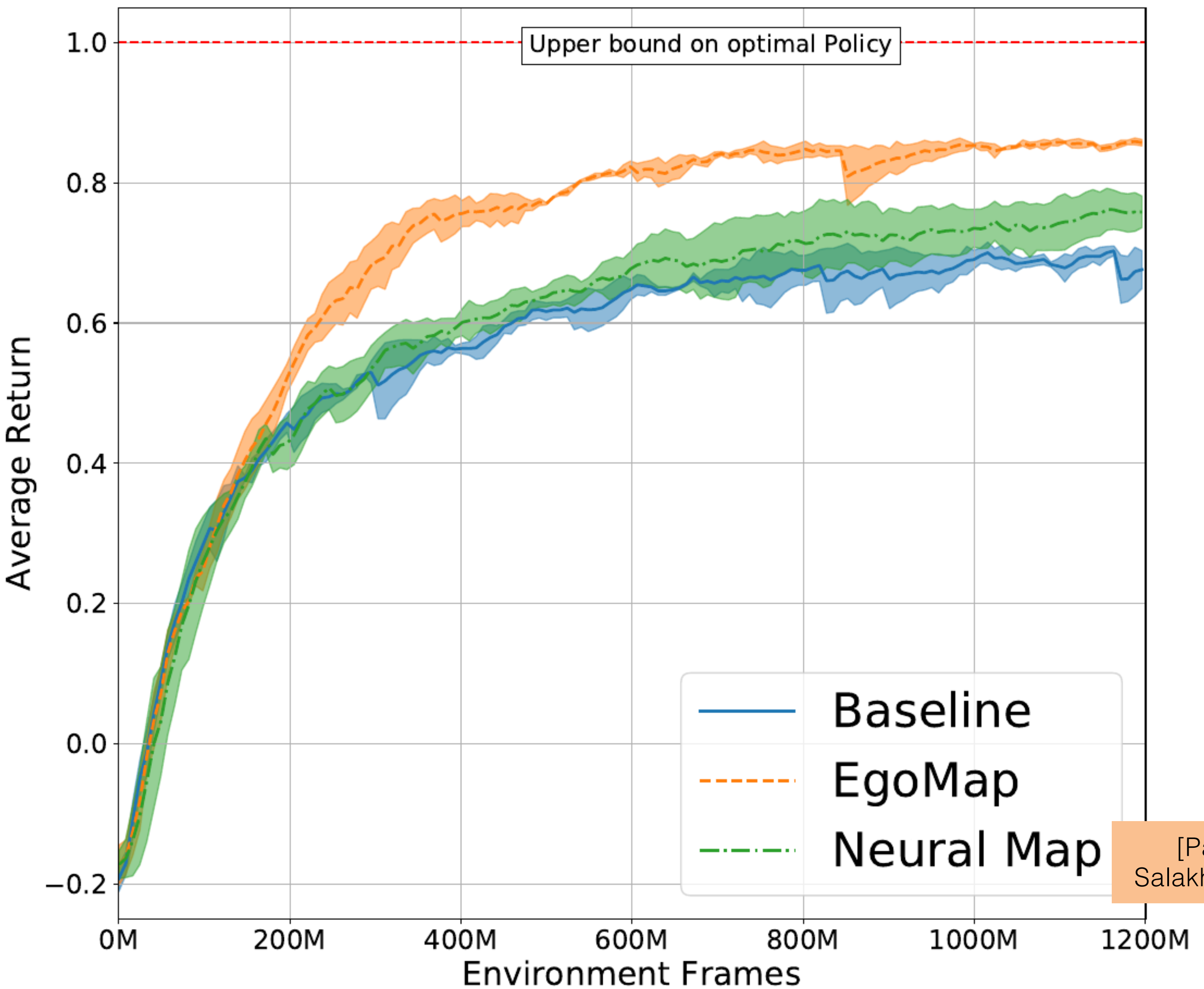


EgoMap: 3 Largest principal components

EgoMap: Attention

When the object is not occluded, the agent does not attend to it

Results



[Parisotto and Salakhutdinov, 2018]

[Beeching, Dibangoye, Simonin, Wolf, Under review]

Quantitative results

	Scenario							
	4 item		6 item		Find and Return		Labyrinth	
Agent	Train	Test	Train	Test	Train	Test	Train	Test
Random	-0.179	-0.206	-0.21	-0.21	-0.21	-0.21	-0.115	-0.086
Baseline	2.341 ± 0.026	2.266 ± 0.035	2.855 ± 0.164	2.545 ± 0.226	0.661 ± 0.003	0.633 ± 0.027	0.73 ± 0.02	0.694 ± 0.009
Neural Map	2.339 ± 0.038	2.223 ± 0.040	2.750 ± 0.062	2.465 ± 0.034	0.825 ± 0.070	0.723 ± 0.026	$\mathbf{0.769 \pm 0.042}$	0.706 ± 0.018
EgoMap	$\mathbf{2.398 \pm 0.014}$	$\mathbf{2.291 \pm 0.021}$	$\mathbf{3.214 \pm 0.007}$	$\mathbf{2.801 \pm 0.048}$	$\mathbf{0.893 \pm 0.007}$	$\mathbf{0.848 \pm 0.017}$	0.753 ± 0.002	$\mathbf{0.732 \pm 0.016}$
Optimum	2.5	2.5	3.5	3.5	1	1	1	1

Mapping objects required

Not required

[Beeching, Dibangoye, Simonin, Wolf, Under review]

Results: ablation study

Ablation	**Train**	**Test**
Baseline	0.668 ± 0.028	0.662 ± 0.036
No global read	0.787 ± 0.007	0.771 ± 0.029
No query	0.838 ± 0.003	0.811 ± 0.013
No query temperature	0.845 ± 0.014	0.815 ± 0.019
No query position	0.839 ± 0.007	0.814 ± 0.008
Cosine query	0.847 ± 0.011	0.814 ± 0.017
L1 query	$\mathbf{0.851 \pm 0.014}$	$\mathbf{0.828 \pm 0.011}$

[Beeching, Dibangoye, Simonin, Wolf, Under review]