Learning to Search for Targets
with Deep Reinforcement Learning

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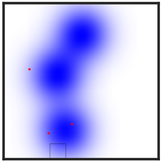
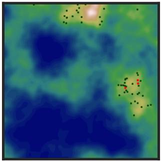
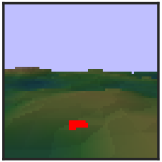






Outline

Description

Learned autonomous search for a set of targets in a visual environment with a camera.

- Camera perceives limited region of environment.
- Moving camera changes visible region.
- Detect when targets are visible.
- Locate targets in minimum time.
- Learn control from sample scenarios.
- Use deep reinforcement learning.
- Focus on search behavior, simple detection.

Problem Statement

- Searched scene $S \subset \mathbb{R}^d$.
- Perceived view $V \subset S$ in the form of an image.
- View can be transformed to new subspace at a cost.
- Targets in scene $\{t_0, \ldots t_n\}$, $t_i \in S$.
- Detect when targets are visible, i.e. $V \cap T \neq \varnothing$.
- Goal:
  - Maximize probability of finding all targets.
  - Minimize cost (time).
  - NP-complete [1].

Motivation

- Applications in search and rescue, surveillance, home assistance, etc.
- Autonomous systems may reduce cost and time.
- Learning vs. handcrafted systems:
  - May find better solutions (deep RL: Atari [2], Go [3], StarCraft II [4]).
  - Applicable as long as data is available.
  - Guarantees and understandability.

Aim

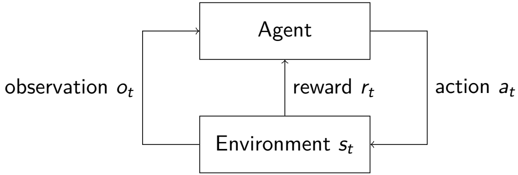
- Utilize structure in environments:
  - Books are in bookshelves, cars on roads...
  - Targets can be spread out/close together...
- Learn distribution of targets from training samples.
  - Realistically limited training samples available.
  - Generalize to similar unseen search scenarios.
- Remember features of explored environment to:
  - Avoid searching regions twice.
  - Prioritize promising regions.

Research Questions

1. How can an agent that learns to intelligently search for targets be implemented with deep reinforcement learning?
2. How does the learning agent compare to random, greedy, exhaustive and human searchers?
3. How well does the learning agent generalize from a limited number of training samples to unseen in-distribution search scenarios?

Reinforcement Learning I

- Learn from interaction how to achieve a goal.
- Partially Observable Markov Decision Process [5]:
    - *Agent* interacts with *environment* over discrete time steps $t = 0, 1, 2 \ldots, T$.
    - New state s_{t+1} depends on history $a_0, o_1, r_1, \ldots, a_{t-1}, o_t, r_t$.
    - Agent usually maintains internal state $\rightarrow$ memory.



Reinforcement Learning II

- Policy $\pi(a|s)$ is a mapping from states to action probabilities.
- Find policy that maximizes expected future reward $\mathbb{E}\left[\sum_{k=0}^{T} \gamma^{k-t-1} r_k\right]$.
- There are several different algorithms.
- Reward signal is often a design parameter.
- Deep reinforcement learning: approximate π with deep neural networks.

Related Work

- Visual attention:
  - Sequential focus points for foveated vision [6].
- Visual navigation:
  - Solve random mazes [7].
  - Find target object in indoor scenes [8].
- Object detection:
  - Region proposals for object localization [9].
  - Anatomical landmark detection in medical images [10].

Environments

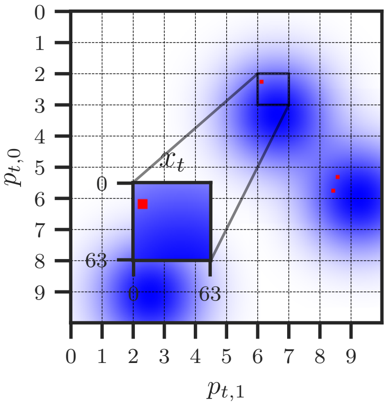
- Three simulated environments.
- Find three targets in less than 1 000 steps.
- There is some structure that can be utilized to find targets quicker.
- Procedurally generated, conditioned on seed.
- New seed after each finished search.

Observation, Action and Reward

- Observations $o_t = \langle x_t, p_t \rangle$, where
  - $x_t \in \mathbb{R}^{3\times 64\times 64}$ is an RGB image,
  - $p_t \in \{0,\dots,H\} \times \{0,\dots,W\}$ is the camera position.
- Actions $a_t \in \{\texttt{INDICATE}, \texttt{UP}, \texttt{DOWN}, \texttt{LEFT}, \texttt{RIGHT}\}$, where
  - `INDICATE` identifies targets, and
  - `UP`, `DOWN`, `LEFT`, `RIGHT` move camera.
- Reward $r_t = h - 0.01 + 0.005d + 0.005e$ where
  - $h = |T \cap V|$ if $a_t = \texttt{INDICATE}$, else 0.
  - $d = 1$ if a_t moves closer to nearest target, else 0.
  - $e = 1$ if a_t moves to new position, else 0.

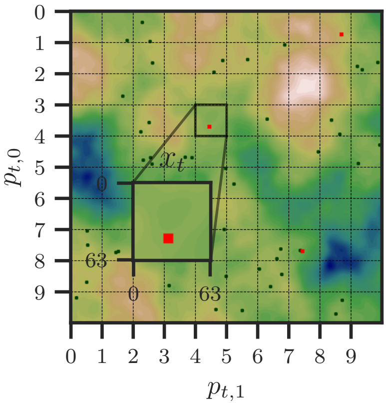
Environment I: Gaussian

- Three gaussian kernels with random center.
- Sum of three gaussian kernels = blue color intensity.
- More blue →higher target probability.
- Agent should prioritize blue regions.



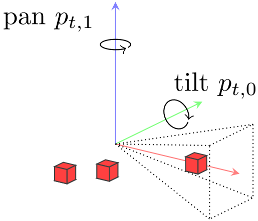
Environment II: Terrain

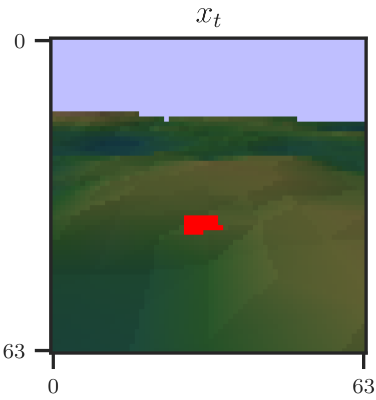
- Terrain seen from above (e.g. UAV).
- Targets between ocean and mountains.
- More realistic, higher variance.



Environment III: Camera

- Terrain seen from perspective projection camera.
- Variance in target appearance.
- Moving actions control pan and tilt.
  - 20 pan angle steps.
  - 10 tilt angle steps.

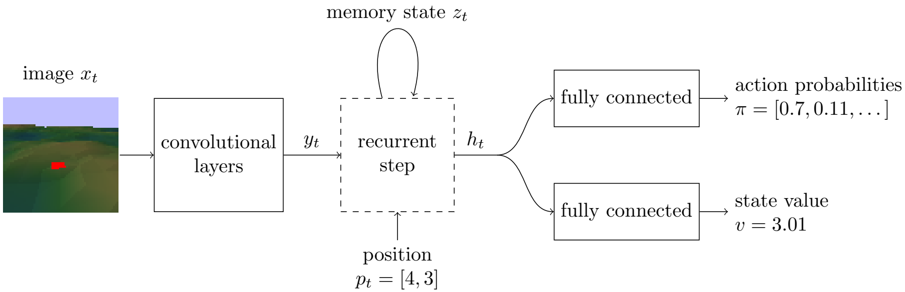




Approach

- Function approximation with deep neural networks.
  - Policy $\pi(a|s, \theta)$.
  - Value $v_\pi(s, \theta)$ (predicts future reward).
- Training procedure:
  1. Collect interactions with environment.
  2. Compute loss $\mathcal{L}(\theta)$.
  3. Optimize $\mathcal{L}$ wrt θ.
  4. Repeat...
- Use proximal policy optimization [11].
  - RL algorithm from 2017.
  - Stable performance, relatively little tuning [12].

Architecture



Memory

- *Agent should remember visual features and associate them with their spatial location.*
- Two memory variants:
  1. Temporal memory (long short-term memory [13]):
     - Previously applied successfully to tasks where memory is required [14, 15, 7, 16].
     - How long sequences can be remembered?
  2. Spatial memory (inspired by [17]):
     - Feature map with one slot per camera position.
     - Indexed with current position.
     - Stores image representation at each slot.
     - Read whole memory with convolutional layers.

Training

- Train for 25M time steps.
- Results reported across 3 training runs.
- Separate training and test sets.

Implementation

- OpenAI Gym environment interface.
- Custom proximal policy optimization implementation.
- PyTorch for models and automatic differentiation.
- Intel Core i9-10900X CPU.
- NVIDIA GeForce RTX 2080 Ti GPU.

Experiment I: Search Performance

- Compare to simple reference behaviors (baselines).
- Metrics:
  1. Average search path length.
  2. Average success rate.
  3. Success weighted by inverse path length (SPL) [18].
     With N test samples, S_i as a binary success indicator, p_i as the taken search path length l_i is the shortest search path length:

$$\text{SPL} = \frac{1}{N} \sum_{i=1}^{N} S_i \frac{l_i}{\max(p_i, l_i)}$$

Baselines

Random: randomly samples actions.

Greedy: greedily selects exploring actions (random if none).

Exhaustive: exhaustively covers search space with minimal revisits.

Human: human searcher with knowledge of environment.

Handcrafted: prioritize actions that lead to higher blue intensity (gaussian environment only).

Gaussian Environment

Agent	SPL	Success	Length
random	0.06 ± 0.01	0.92 ± 0.06	369.07 ± 24.93
greedy	0.17 ± 0.00	1.00 ± 0.00	147.12 ± 2.38
exhaustive	0.21 ± 0.00	1.00 ± 0.00	83.37 ± 2.88
handcrafted	0.33 ± 0.00	1.00 ± 0.00	65.20 ± 1.41
human	0.23 ± 0.03	1.00 ± 0.00	80.97 ± 13.49
temporal	0.24 ± 0.03	0.99 ± 0.01	101.25 ± 13.32
spatial	0.29 ± 0.02	0.99 ± 0.01	72.16 ± 5.97

`video 1`, `video 2`, `video 3`.

Terrain Environment

Agent	SPL	Success	Length
random	0.06 ± 0.01	0.89 ± 0.04	366.05 ± 26.96
greedy	0.17 ± 0.01	1.00 ± 0.00	141.01 ± 2.31
exhaustive	0.22 ± 0.00	1.00 ± 0.00	84.11 ± 0.84
human	0.26 ± 0.02	1.00 ± 0.00	76.73 ± 5.33
temporal	0.25 ± 0.02	1.00 ± 0.01	103.76 ± 11.69
spatial	0.27 ± 0.01	1.00 ± 0.00	79.60 ± 6.88

`video 1`, `video 2`, `video 3`.

Camera Environment

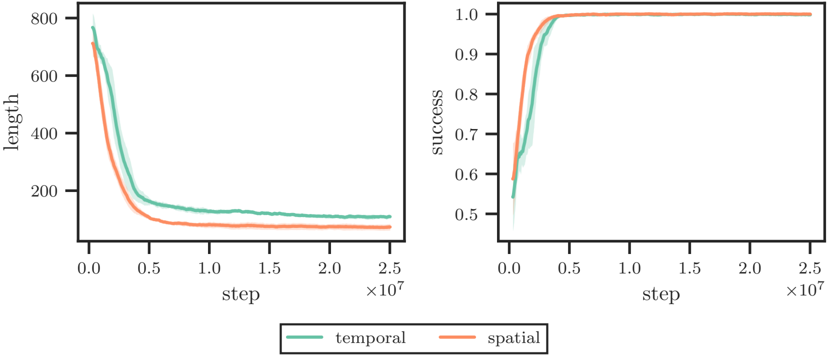
Agent	SPL	Success	Length
random	0.04 ± 0.00	0.62 ± 0.03	545.09 ± 56.25
greedy	0.12 ± 0.01	0.97 ± 0.01	255.60 ± 10.44
exhaustive	0.37 ± 0.00	1.00 ± 0.00	67.03 ± 0.00
human	0.68 ± 0.08	1.00 ± 0.00	38.10 ± 5.72
temporal	0.70 ± 0.02	1.00 ± 0.00	42.36 ± 2.05
spatial	0.66 ± 0.03	1.00 ± 0.00	42.90 ± 1.73

`video 1`, `video 2`, `video 3`.

Experiment II: Scaling to Larger Search Spaces

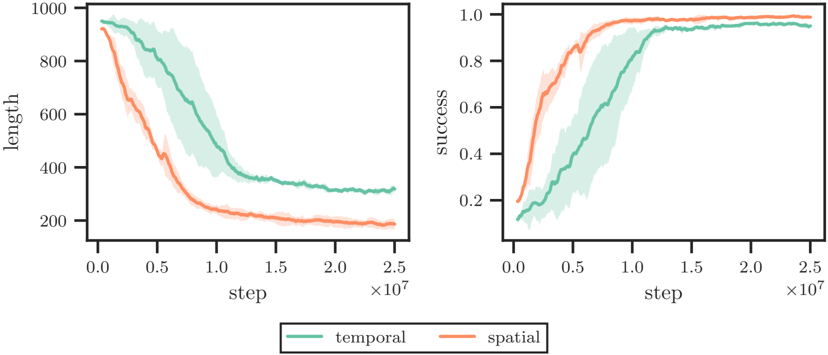
- Larger search spaces are more difficult.
- Stronger demands on memory:
    - Remember visited positions.
    - Remember appearance of environment.
- Compare memories on 10×10, 15×15, and 20×20 versions of gaussian environment.

10×10



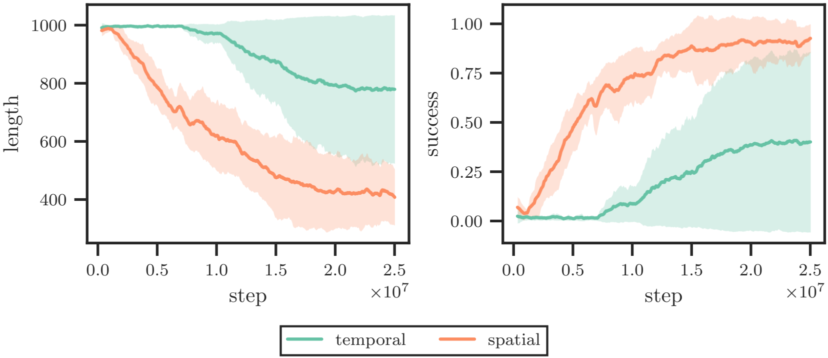
length
800
600
400
200
0.0
0.5
1.0
1.5
2.0
2.5
step
×10^7
success
1.0
0.9
0.8
0.7
0.6
0.5
temporal
spatial

15×15



1000
800
600
400
200
length
0.0
0.5
1.0
1.5
2.0
2.5
step
$\times 10^7$
1.0
0.8
0.6
0.4
0.2
success
0.0
0.5
1.0
1.5
2.0
2.5
step
$\times 10^7$
temporal
spatial

20×20

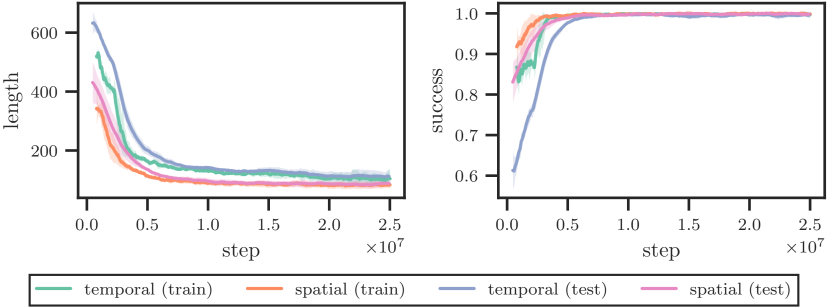


length
1000
800
600
400
0.0
0.5
1.0
1.5
2.0
2.5
step
$\times 10^7$
success
1.00
0.75
0.50
0.25
0.00
0.0
0.5
1.0
1.5
2.0
2.5
step
$\times 10^7$
temporal
spatial

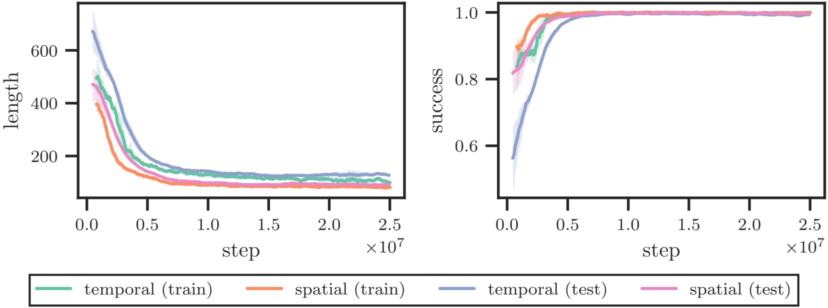
Experiment III: Generalization From Limited Samples

- Real-world tasks usually have limited training samples.
- Train on 500, 1 000, 5 000 and 10 000 samples of terrain environment.
- Test on held out samples from full distribution.

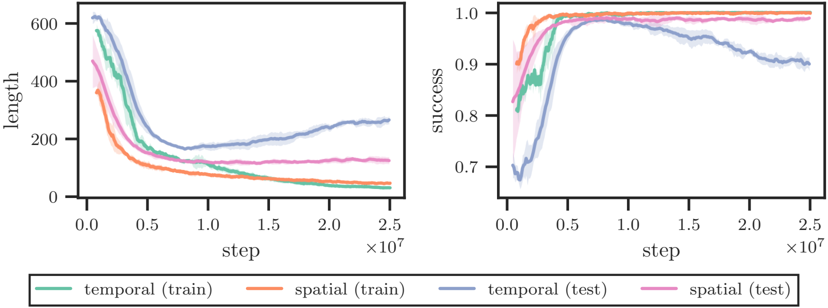
10000 samples



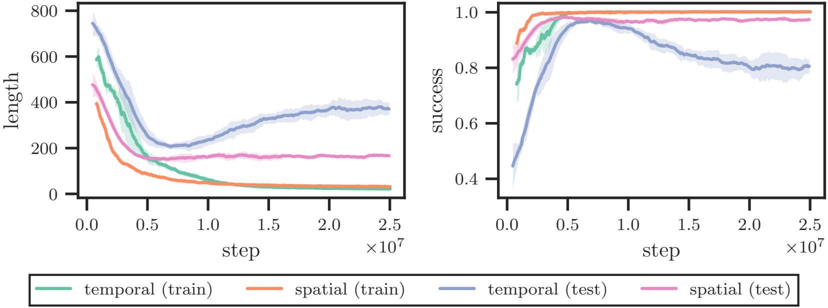
5000 samples



1000 samples



500 samples


length
800
600
400
200
0
0.0
0.5
1.0
1.5
2.0
2.5
step
$\times 10^7$
success
1.0
0.8
0.6
0.4
0.0
0.5
1.0
1.5
2.0
2.5
step
$\times 10^7$
temporal (train)
spatial (train)
temporal (test)
spatial (test)

Conclusion

- Architecture:
  - Spatial memory architecture scales to larger search spaces and generalizes better.
  - Temporal memory sufficient (and better) for smaller search spaces.
- Approach:
  - Better than simple baselines.
  - Comparable to human performance.
  - Worse than handcrafted baseline.
    - Why? Stochasticity, local optima, conditions...

Future Work

- Improvements to approach.
  - Neural network architecture.
  - Reinforcement learning algorithm.
  - Reward signal design.
- Realistic search scenarios.
- Formal verification (for security-critical applications).

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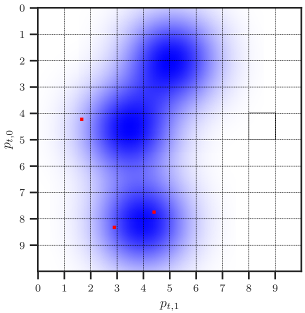
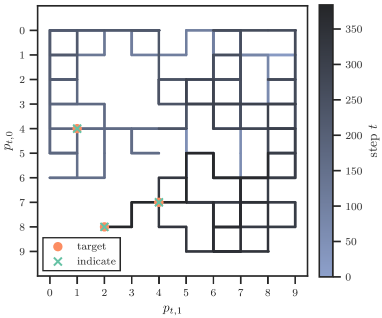
Search Paths I

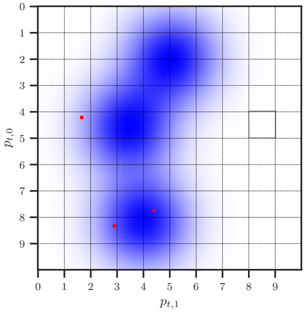


Environment sample

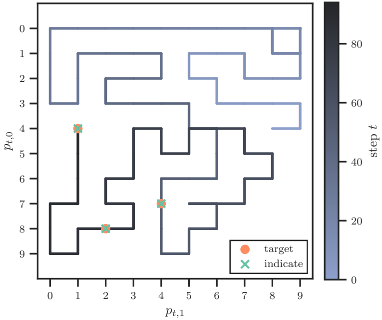


Random baseline

Search Paths II

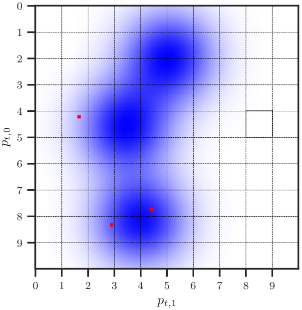


Environment sample

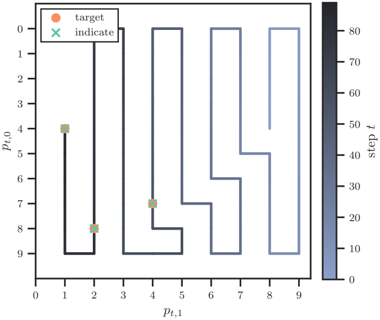


Greedy baseline

Search Paths III

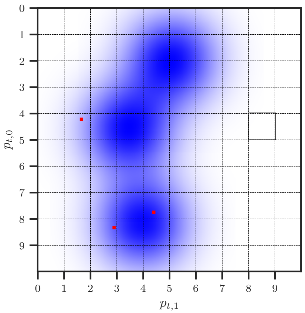


Environment sample

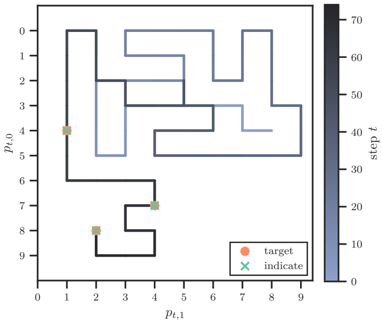


Exhaustive baseline

Search Paths IV

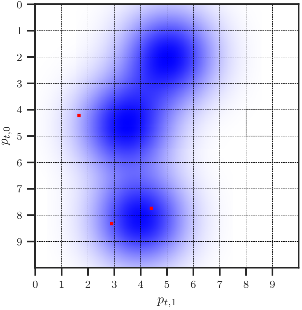


Environment sample

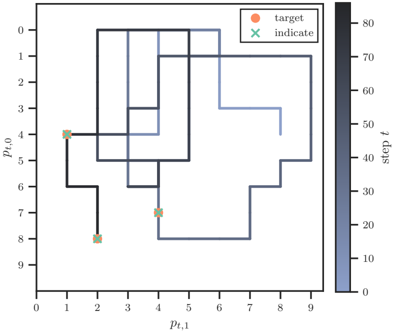


Handcrafted baseline

Search Paths V

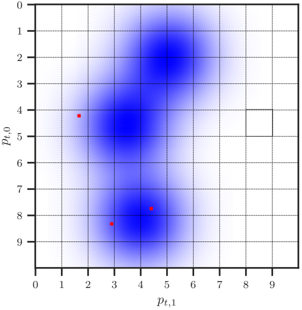


Environment sample

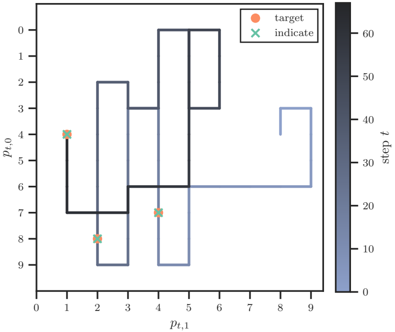


Temporal memory

Search Paths VI

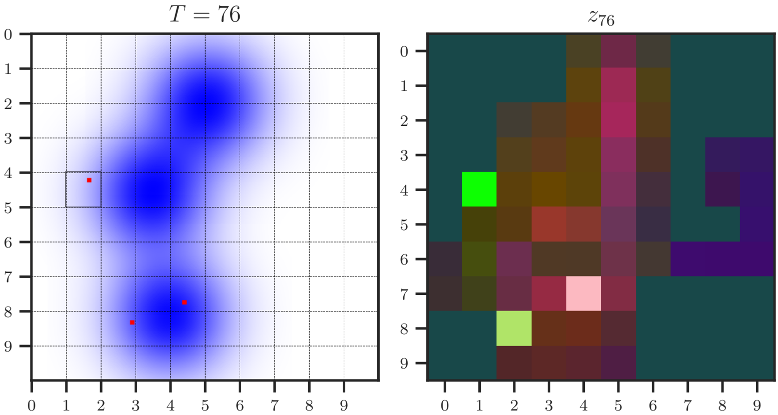


Environment sample



Spatial memory

Memory Viualization



PCA decomposition of spatial memory after episode.