Learning to Search for Targets

with Deep Reinforcement Learning

Oskar Lundin

Linköping University

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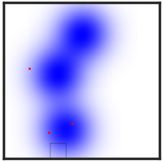

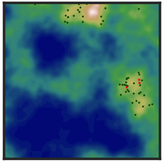

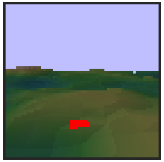

Outline

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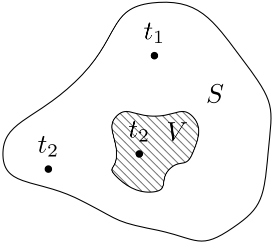

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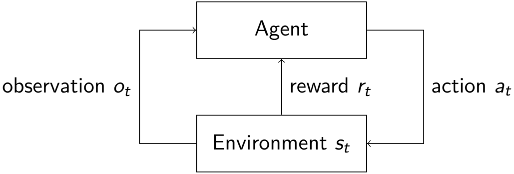

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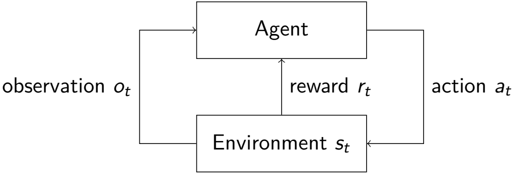

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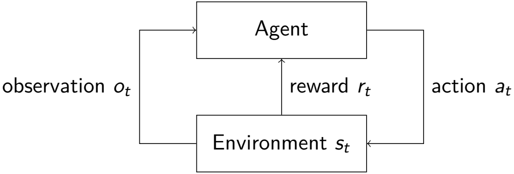

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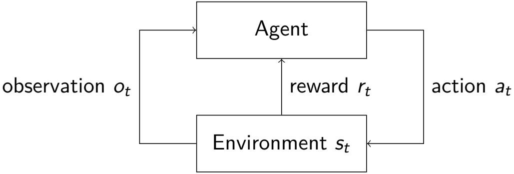

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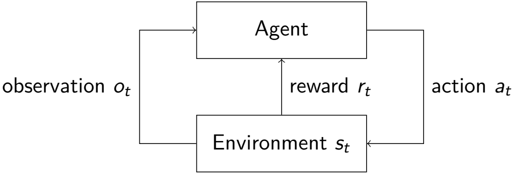
    - Agent usually maintains internal state $\rightarrow$ memory.



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- Deep reinforcement learning: approximate π with deep neural networks.

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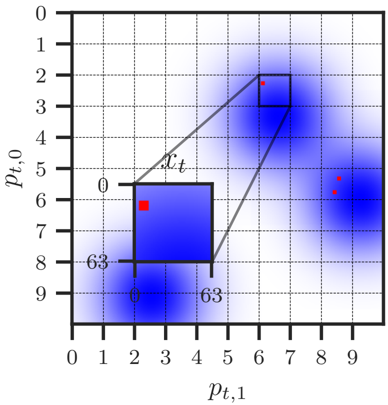

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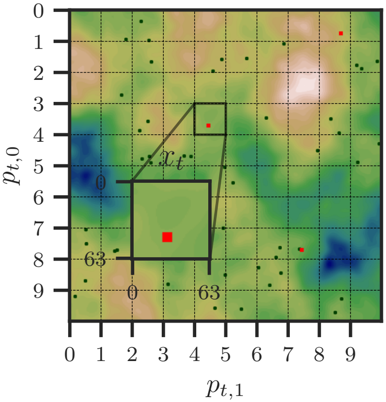

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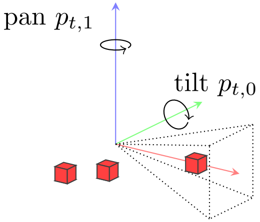

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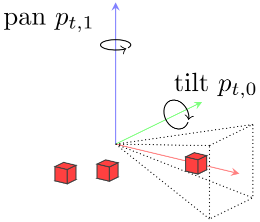

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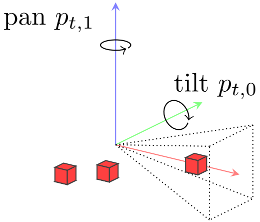

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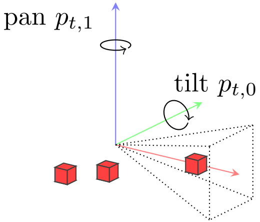

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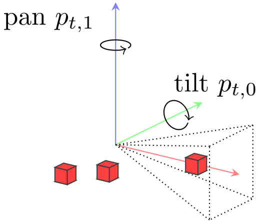

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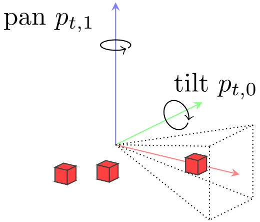

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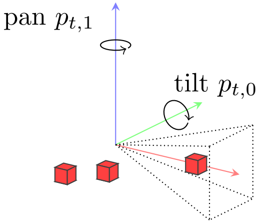

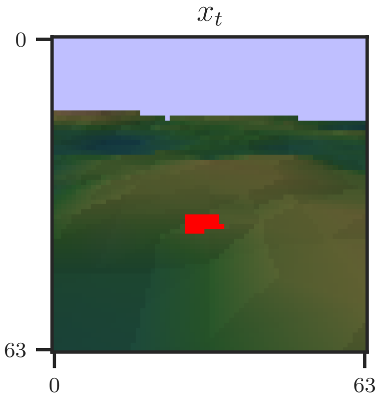

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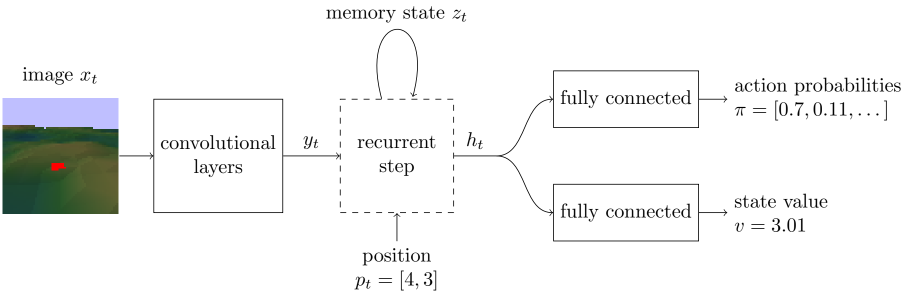
  - Relatively new algorithm.
  - Stable performance with little tuning [12].

Architecture



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     - Read whole memory with convolutional layers.

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- 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:

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

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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

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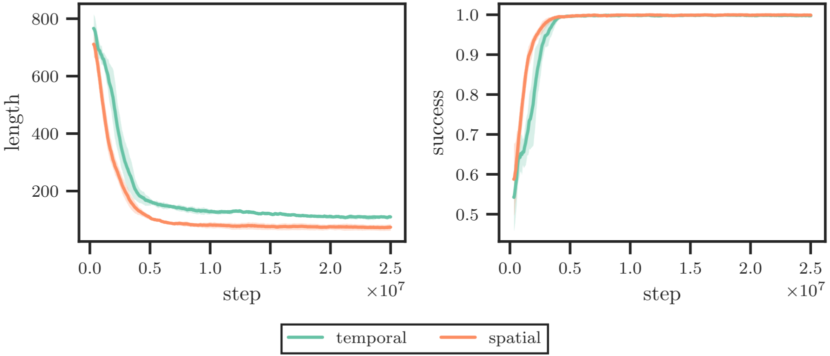
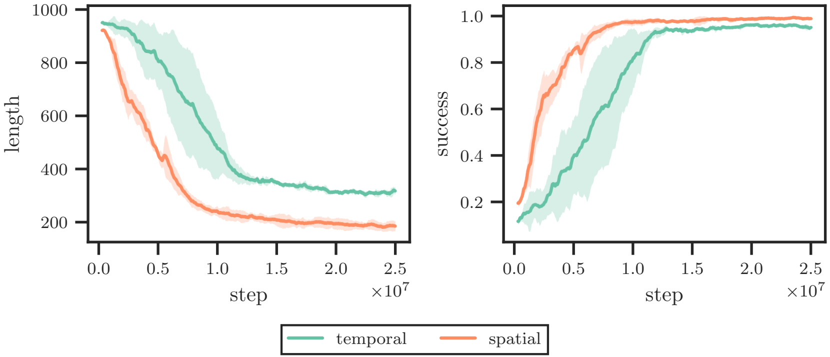
  - Remember appearance of environment.
- Compare memories on 10×10, 15×15, and 20×20 versions of gaussian environment.

10×10

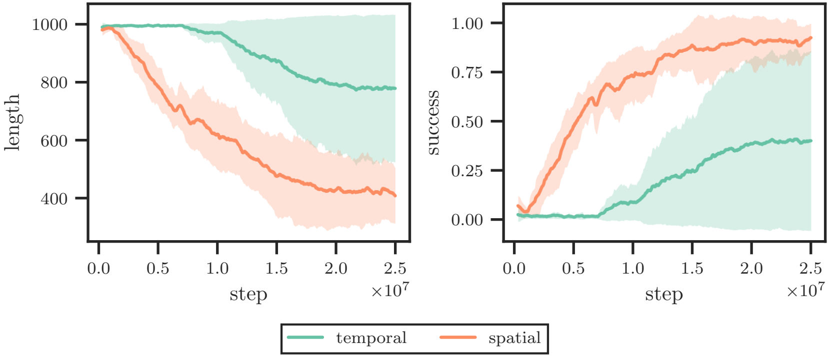


length
800
600
400
200
0.0
0.5
1.0
1.5
2.0
2.5
step
×10^7
success
1.0
0.9
0.8
0.7
0.6
0.5
temporal
spatial

15×15


1000
800
600
400
200
length
0.0
0.5
1.0
1.5
2.0
2.5
step
×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
×10^7
temporal
spatial

20×20



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

Experiment III: Generalization From Limited Samples

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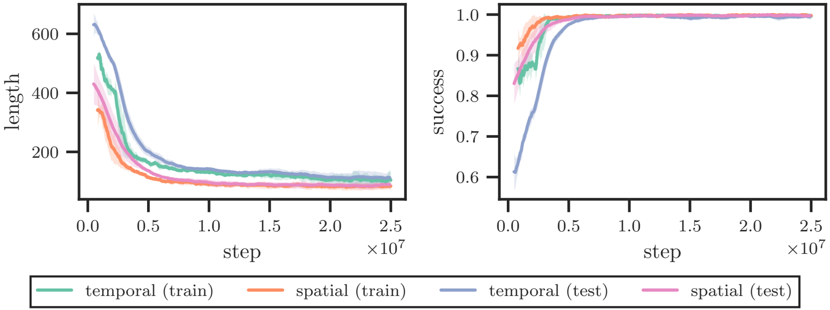
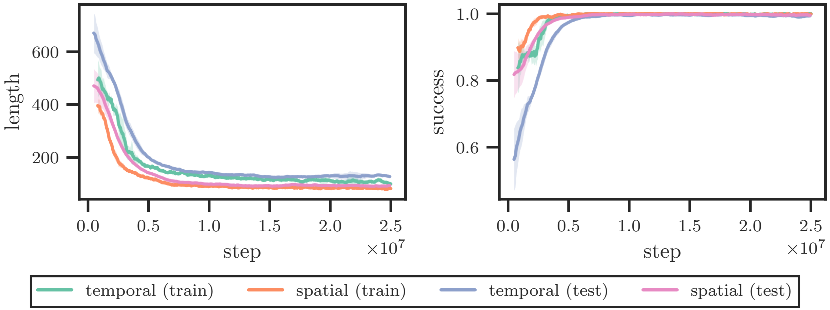
- Test on held out samples from full distribution.

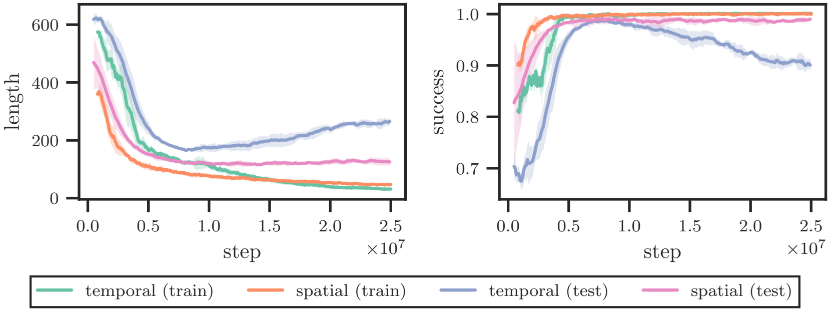
10000 samples



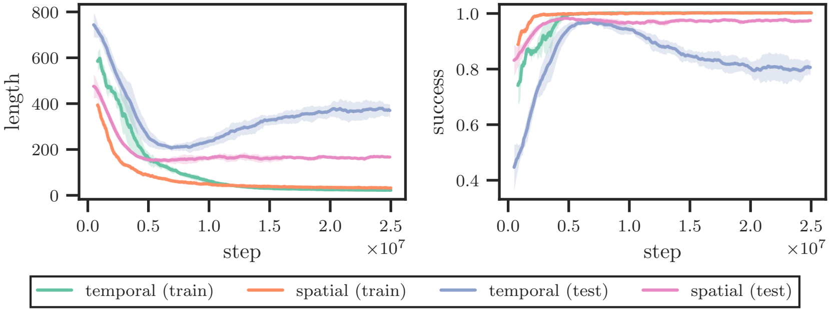
5000 samples



1000 samples



500 samples



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

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  - Sample efficiency: relatively many samples needed even for simple environments.

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  - Noise and higher variance.

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Search Paths I

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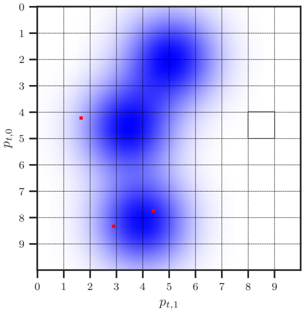
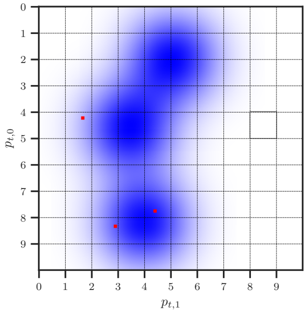
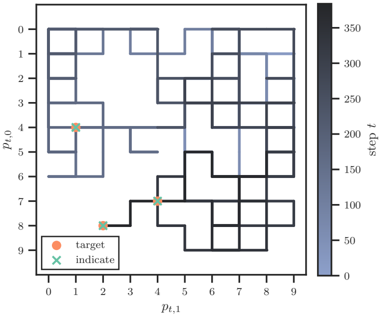


Environment sample

Search Paths I



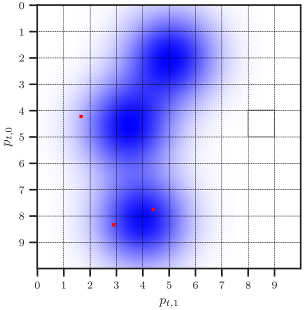
Environment sample



Random baseline

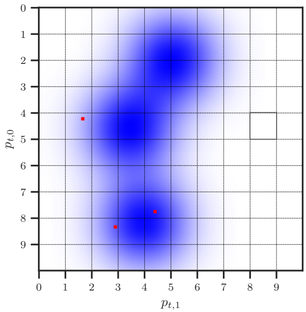
Search Paths II

Search Paths II

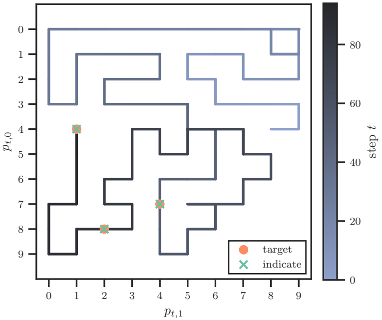


Environment sample

Search Paths II



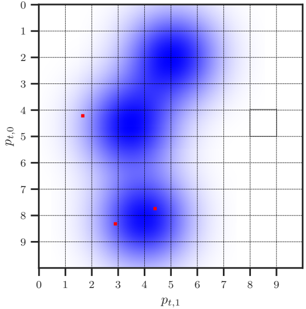
Environment sample



Greedy baseline

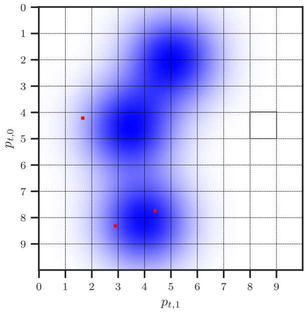
Search Paths III

Search Paths III

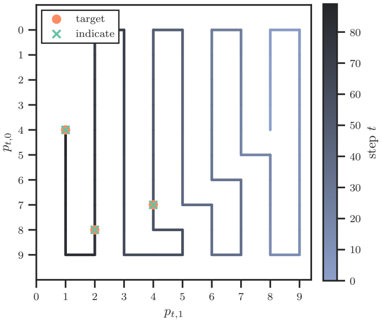


Environment sample

Search Paths III



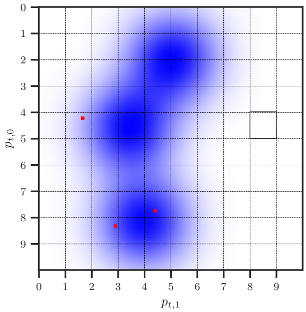
Environment sample



Exhaustive baseline

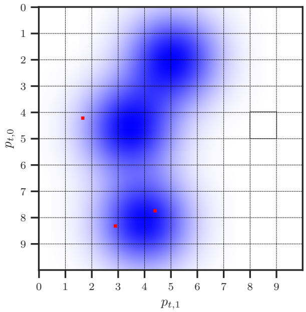
Search Paths IV

Search Paths IV

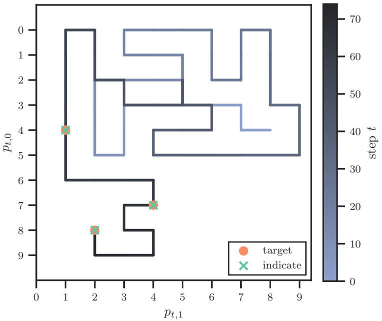


Environment sample

Search Paths IV



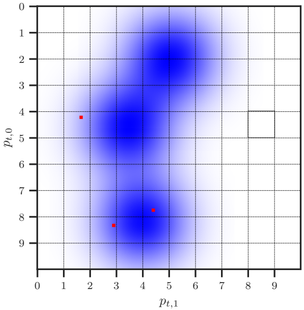
Environment sample



Handcrafted baseline

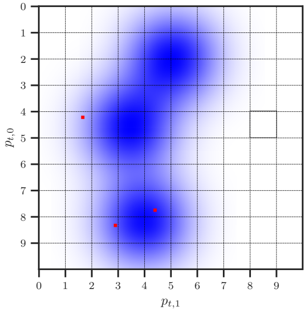
Search Paths V

Search Paths V

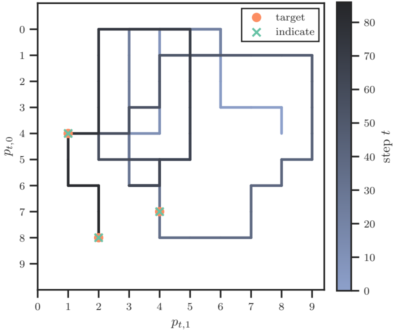


Environment sample

Search Paths V



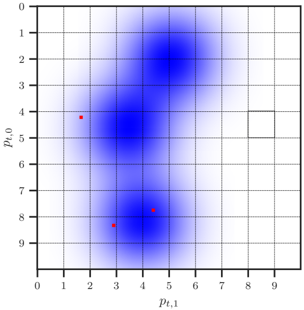
Environment sample



Temporal memory

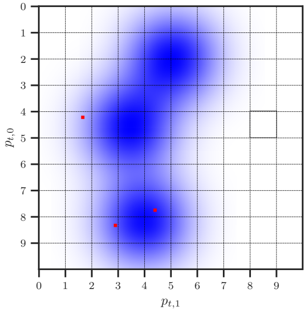
Search Paths VI

Search Paths VI

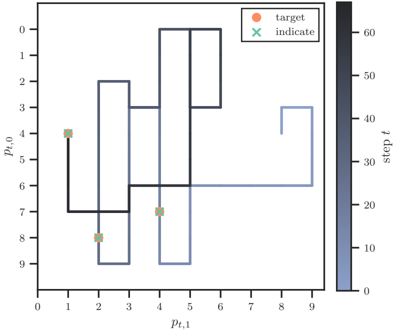


Environment sample

Search Paths VI

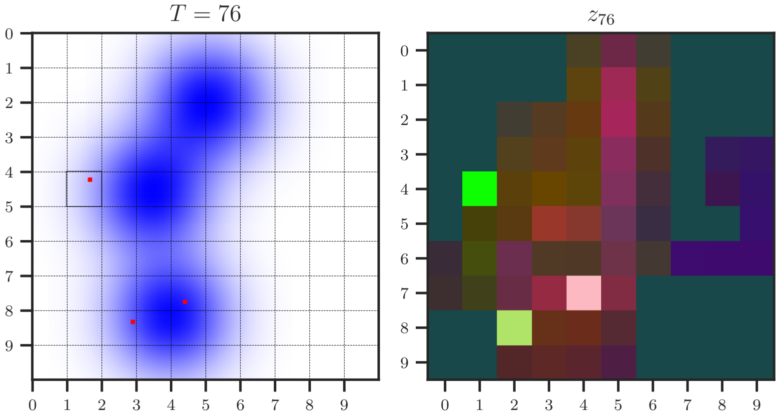


Environment sample



Spatial memory

Memory Viualization



PCA decomposition of spatial memory after episode.