Learning to Search for Targets
with Deep Reinforcement Learning

Oskar Lundin

Linköping University

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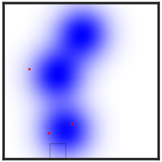
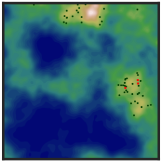
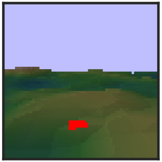

Outline

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- Patterns and cues may be subtle and difficult to pick up.

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- Handcrafted systems using domain knowledge are difficult to design.
- Subtle patterns and difficult planning decisions.
- Learning system applicable as long as data is available.

Design Challenges

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- Real-world tasks have limited number of training samples.

Research Questions

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2. How does the learning agent compare to random walk, exhaustive search, and a human searcher with prior knowledge of the searched scenes?
3. How well does the learning agent generalize from a limited number of training samples to unseen in-distribution search scenarios?

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Agent interacts with *environment* over discrete time steps. At each step $t = 0, 1, 2 \dots, T$:

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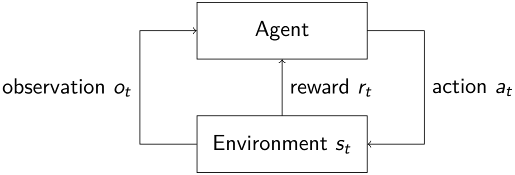

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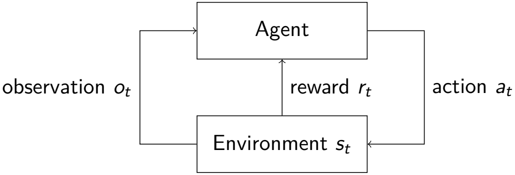

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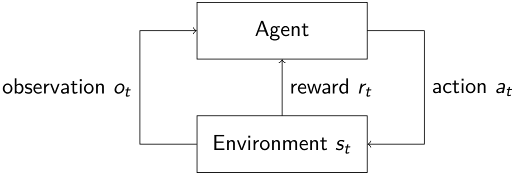

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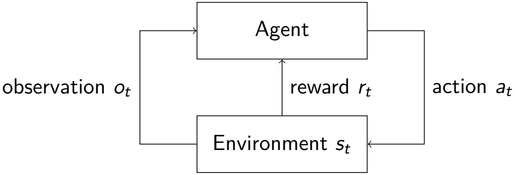

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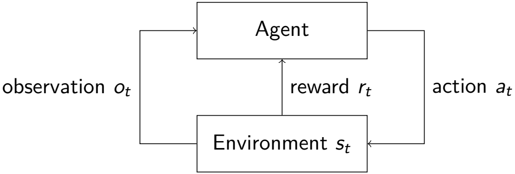

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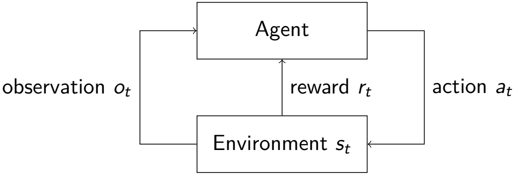
- State not available to agent, must maintain internal state $\rightarrow$ memory.



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Paradigm for learning from interactions how to achieve a goal.

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- Several algorithms with different pros and cons.

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Deep RL for similar tasks:

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Missing: how visual cues can guide search, overfitting and generalization from limited samples, rigorous performance evaluation.

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- Maximize the probability of finding all targets while minimizing cost in time (NP-complete [11]).

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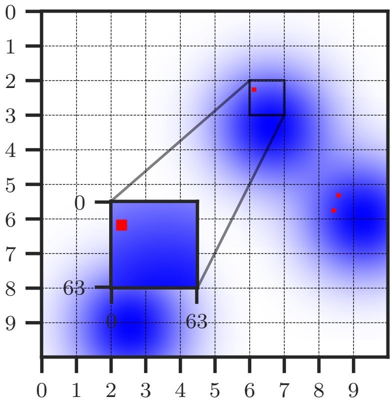

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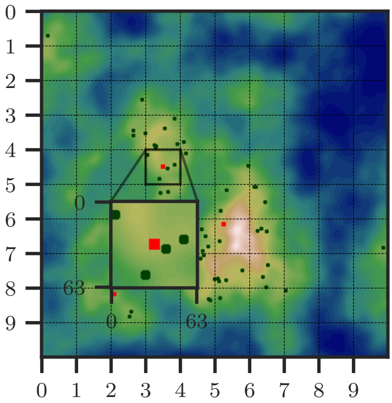

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- Height map from terrain environment turned into mesh, same appearance and target probability as before.
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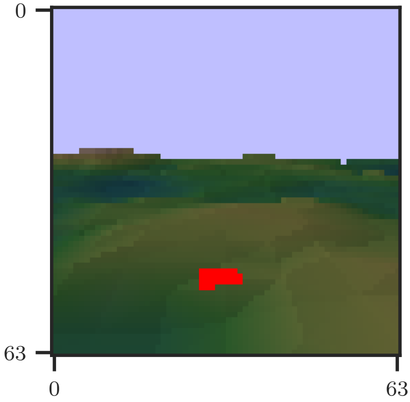

Approach

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- Loss function from proximal policy optimization [12].

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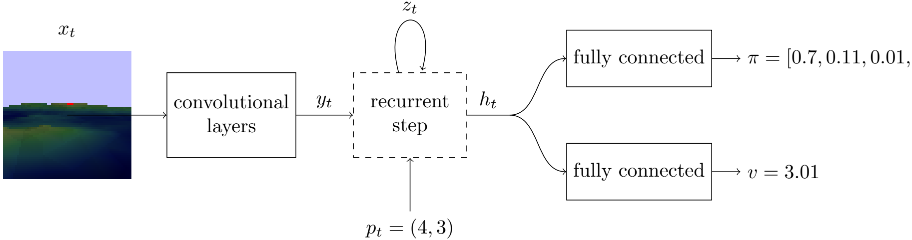

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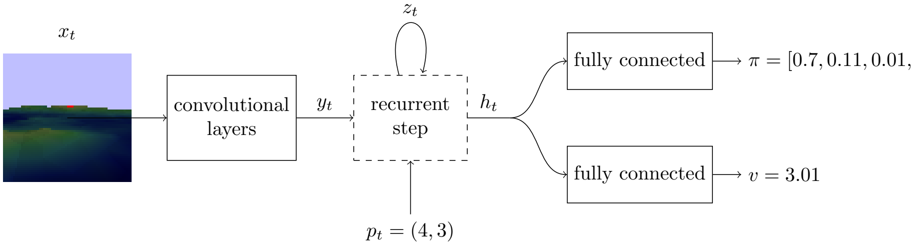

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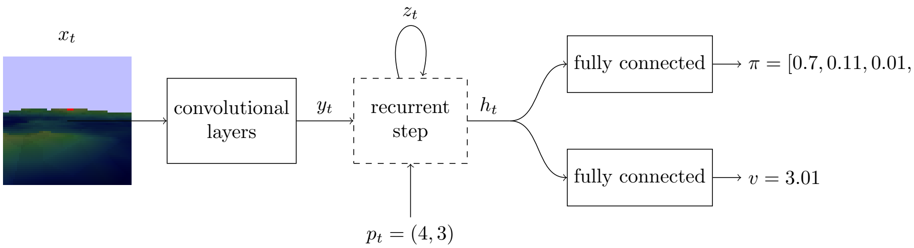

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- Two memory variants...

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   - Read whole memory with convolutional layers.

Experiments

1. Search Performance

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2. Scaling to Larger Search Spaces

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Definition

SPL with N as the number of test samples, S_i indicating success, p_i as the number of steps and l_i as the shortest path length:
$\mathrm{SPL} = \frac{1}{N} \sum_{i=1}^{N} S_i \frac{l_i}{\max(p_i, l_i)}$

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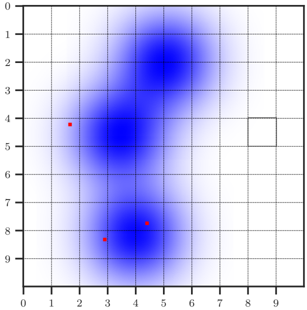
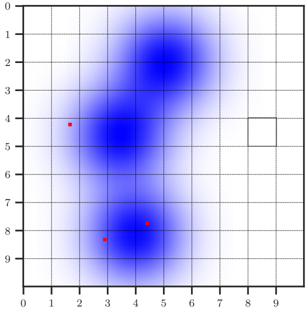
- Human: human searcher with prior knowledge of environment characteristics.
- Handcrafted (gaussian environment): prioritize actions that lead to higher blue intensity.

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



Environment sample



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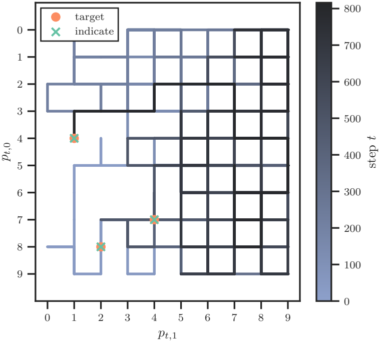
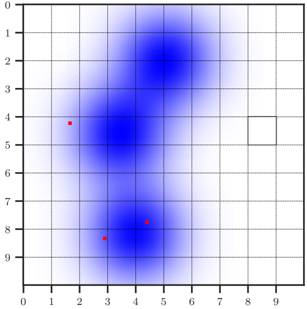


Random baseline



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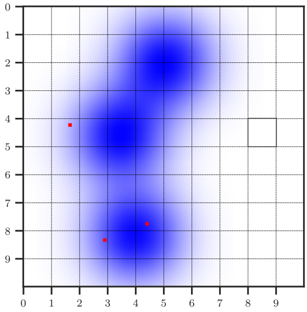

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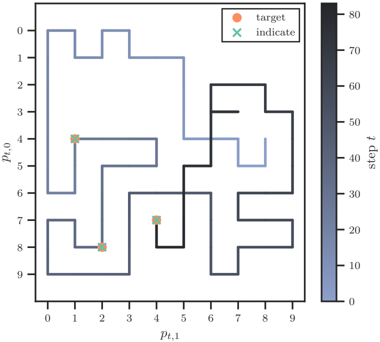
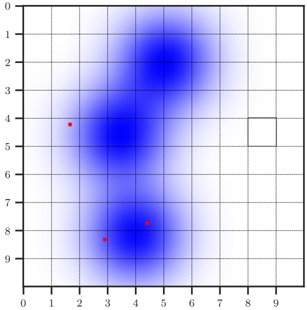


Greedy baseline



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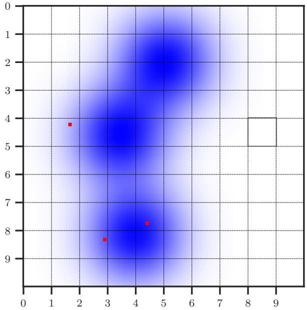

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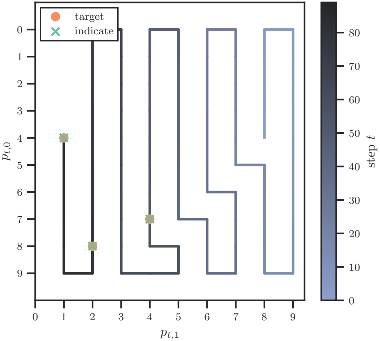
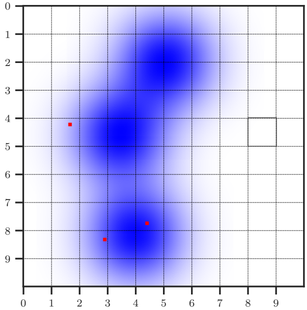


Exhaustive baseline



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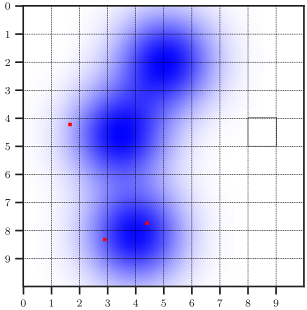

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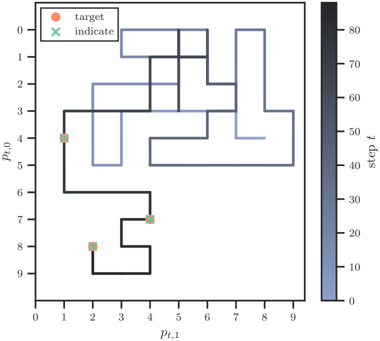
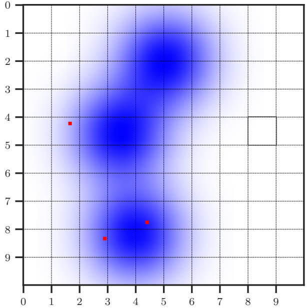


Handcrafted baseline



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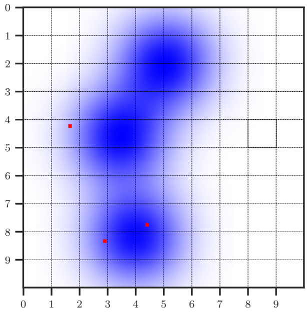

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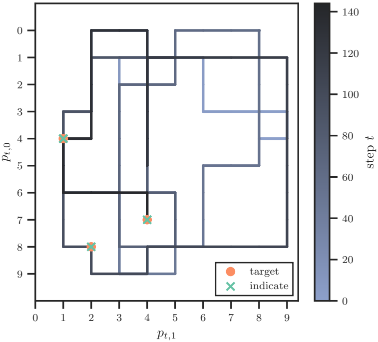
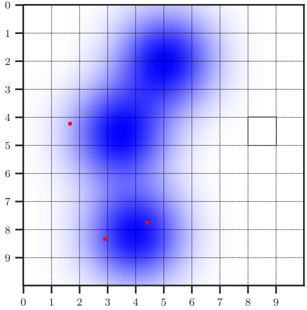


Temporal memory



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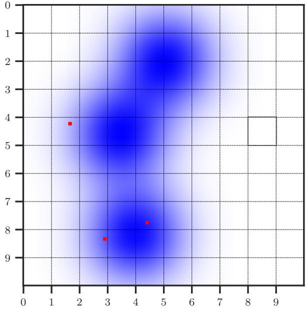

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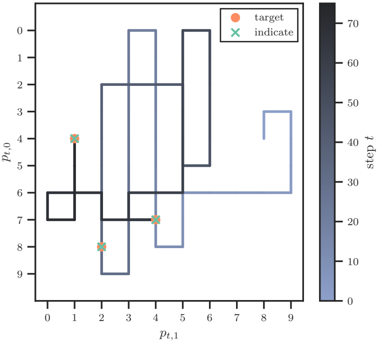
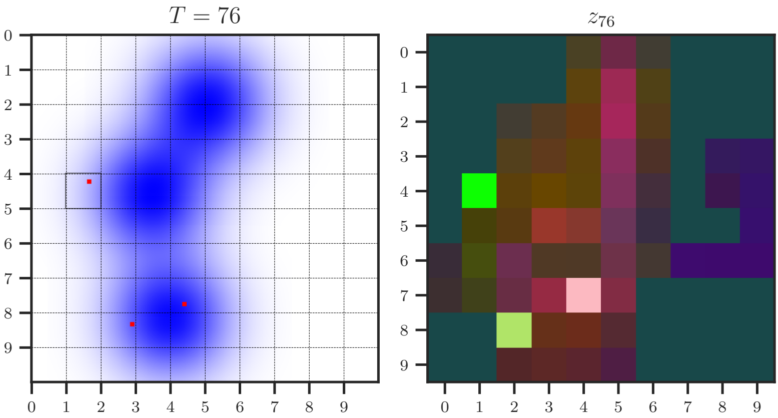


Spatial memory



PCA decomposition of spatial memory after episode.

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 (spatial)

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 (temporal)

Experiment II: Scaling to Larger Search Spaces

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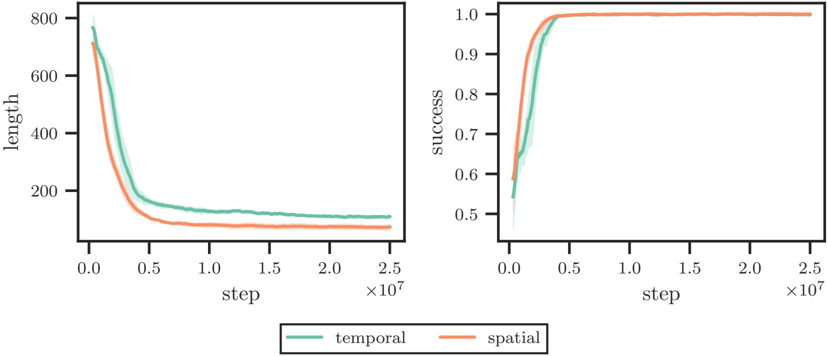
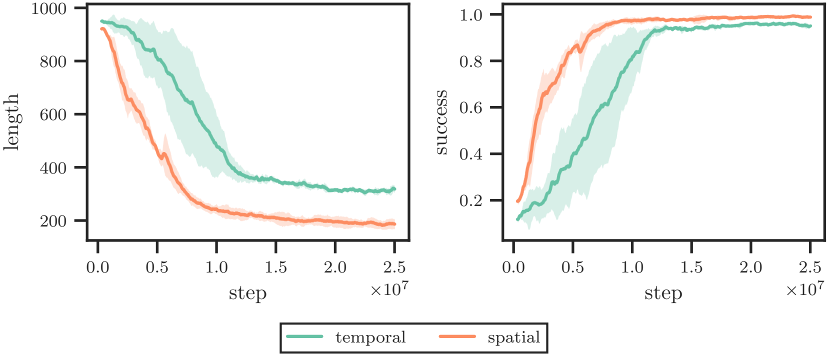
  - Stronger demands on memory (remember searched positions, scene understanding).
- Investigate impact by comparing agents on 10×10, 15×15, and 20×20 versions of gaussian environment.

10×10

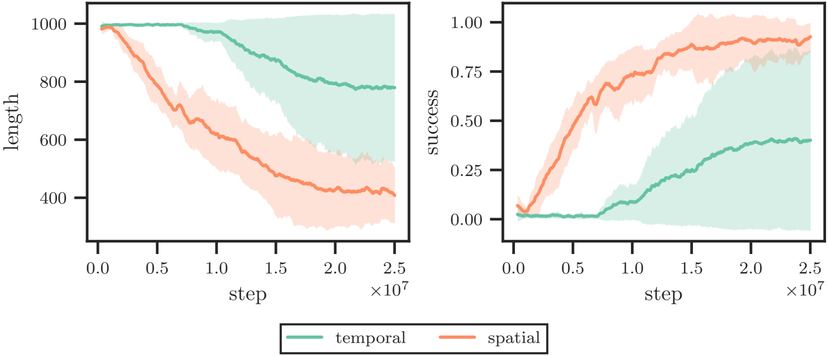

length
800
600
400
200
0.0
0.5
1.0
1.5
2.0
2.5
step
×10^7
success
1.0
0.9
0.8
0.7
0.6
0.5
temporal
spatial

15×15



length
1000
800
600
400
200
0.0
0.5
1.0
1.5
2.0
2.5
step
×10^7
success
1.0
0.8
0.6
0.4
0.2
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

- Limit number of scene samples seen during training to 500, 1 000, 5 000, 10 000.

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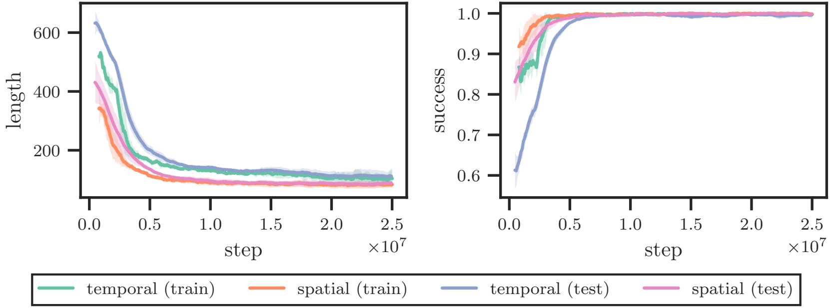
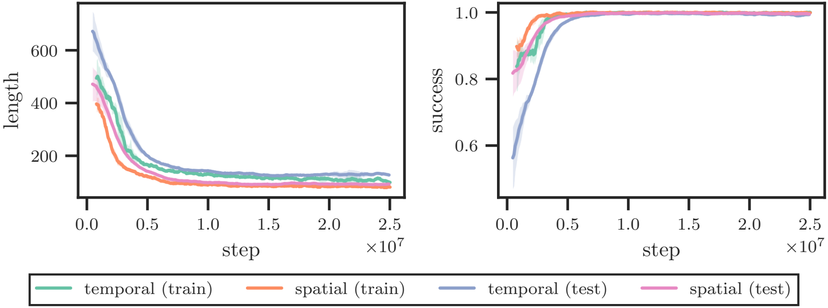
- Fix seed pool used to generate scenes seen during training.
- Train agents until convergence (or for a fixed number of time steps).

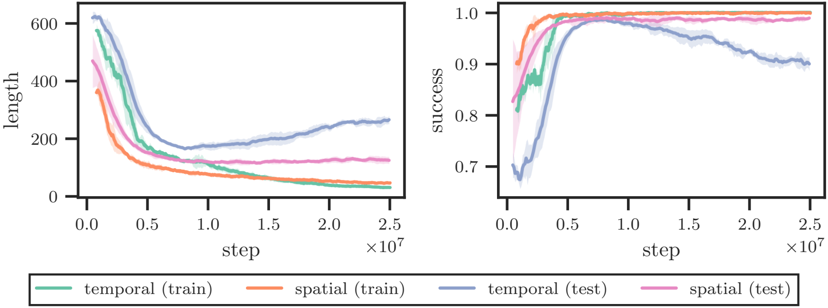
10000 samples



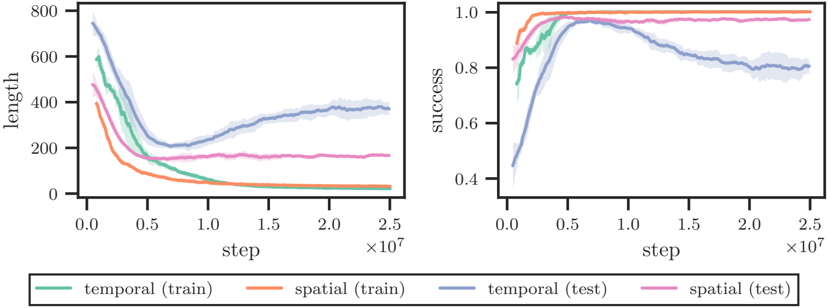
5000 samples



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
temporal (train)
spatial (train)
temporal (test)
spatial (test)

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- Proposed a method for solving visual search with reinforcement learning.

Problems with RL, future work, etc.

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- Three environments for evaluating visual search agents.
- Compared two neural network architectures with different strengths.
- Specialized architectures can provide better performance and generalization.

Problems with RL, future work, etc.

References I

[1] K. Nakayama and P. Martini, "Situating visual search," vol. 51, no. 13, pp. 1526–1537.

References II

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