Learning to Search for Targets
with Deep Reinforcement Learning

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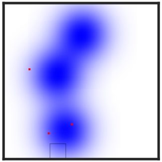
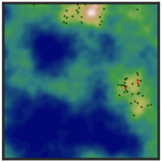
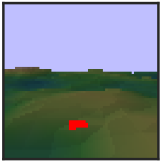
  

Outline

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.

Aspects

- Exhaustive search sufficient in small or random environments [1].
- Most real-world search tasks exhibit structure.
- Visual cues can be used to find targets quicker.
  - Books are in bookshelves, cars on roads...
  - Targets spread out/close together...

Motivation

- Applications in search and rescue, surveillance, home assistance, etc.
- Autonomous systems may reduce risk and cost.
- Handcrafted systems:
  - Difficult to design.
  - Communicate how to behave?
  - Redesign for new environments.
  - Subtle patterns.
  - May be suboptimal.
- Learning systems:
  - Applicable as long as data is available.
  - Can find subtle patterns.
  - May find better solutions.
  - Deep RL: Atari [2], Go [3], StarCraft II [4], etc.

Design Challenges

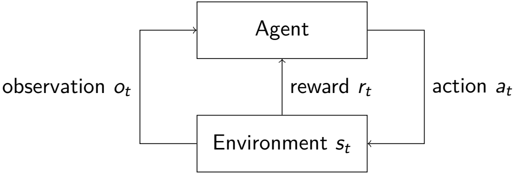
- Prioritize regions with high probability of targets based on previous experience.
- Learn correlations between scene appearance and target probability.
- Search exhaustively while avoiding searching the same region twice.
- Remember features of searched regions (avoid revisits, scene understanding).
- Real-world tasks have limited number of training samples.

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 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?

Partially Observable Markov Decision Process (POMDP)

- Formally description of environment.
- *Agent* interacts with *environment* over discrete time steps $t = 0, 1, 2 \ldots, T$
- Environment *state* s_t can not be observed.
- Only partial *observations*.
- Agent takes *action* a_t.
- Perceives partial *observation* o_t of state.
- Receives scalar reward r_t that indicates whether action is good or bad.
- New state s_{t+1} depends only on history of interactions.
- State not available to agent, must maintain internal state $\rightarrow$ memory.



Reinforcement Learning (RL)

Paradigm for learning from interactions how to achieve a goal.

- Policy $\pi(a|s)$ is a mapping from states to action probabilities.
- Find policy that maximizes cumulative reward $\mathbb{E}\left[\sum_{k=0}^{T} \gamma^{k-t-1} r_k\right]$.
- No inherent reward: design parameter!
-

Deep RL: Approximate π with deep neural networks.

Related Work

Deep RL for similar tasks:

- Visual attention:
  - Sequential focus points for foveated vision [5].
- Visual navigation:
  - Solve random mazes [6].
  - Find target object in indoor scenes [7].
- Object detection:
  - Region proposals for object localization [8].
  - Contextual reasoning over spatial layout in scenes [9].
  - Anatomical landmark detection in medical images [10].

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

Problem Statement

- Agent searches scene $S \subset \mathbb{R}^d$.
- Scene contains set of targets $\{t_0, \ldots t_n\}$, $t_i \in S$.
- Agent perceives view $V \subset S$.
- View can be transformed to new subspace.
- Indicate when targets are visible, i.e. $V \cup T \neq \varnothing$.
- Maximize the probability of finding all targets while minimizing cost in time (NP-complete [11]).

Environments

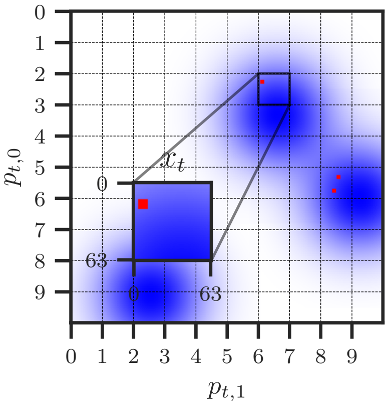
- Three simulated environments used for experiments.
- Search space discretized into $H \times W$ camera positions.
- Each camera position has a unique view $V \subset S$.
- Three targets in all scenes.
- Target probability correlated with scene appearance.
- Possible to do better than exhaustive search on average.
- Scenes procedurally generated:
  - Pseudorandom seed determines scene appearance and target positions.
  - Gives control over difficulty to solve.
  - Can vary training and test set sizes by limiting seed pool.

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 RGB image,
  - $p_t \in \{0, \dots, H-1\} \times \{0, \dots, W-1\}$ is camera position.
- Actions $a_t \in \{\mathtt{INDICATE}, \mathtt{UP}, \mathtt{DOWN}, \mathtt{LEFT}, \mathtt{RIGHT}\}$, 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 $a_t = \mathtt{INDICATE}$, 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.

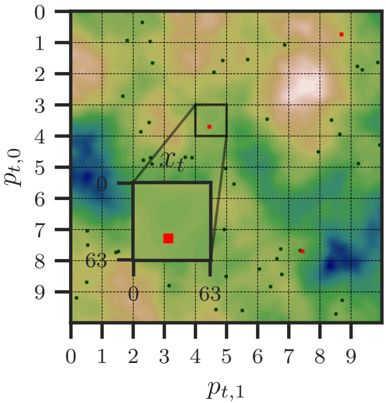
Environment I: Gaussian

- Three gaussian kernels with random center.
- Sum of kernels = blue color intensity, probability of targets.
- Agent should prioritize blue regions.



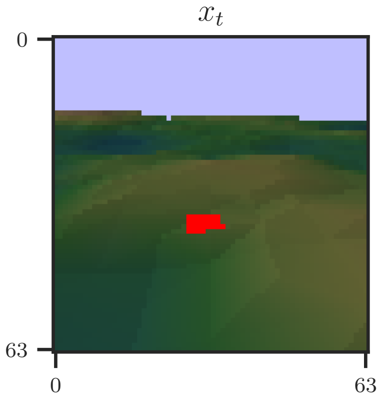
Environment II: Terrain

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



Environment III: Camera

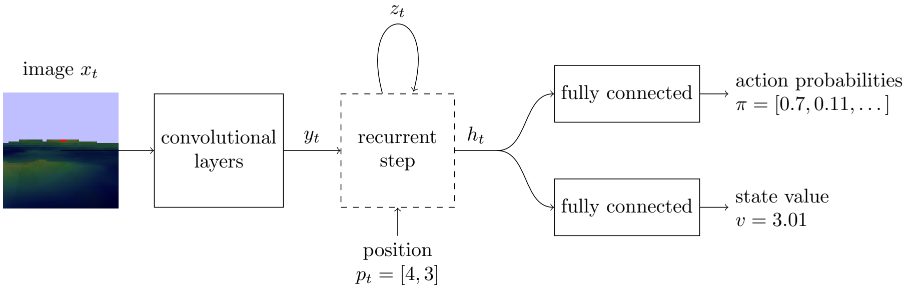
- Terrain seen from perspective projection camera.
- Moving actions control pan and tilt.
- Visually complex, difficult to interpret.



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...
- Loss function from proximal policy optimization [12].
  - Relatively new RL algorithm.
  - Stable performance, little hyperparameter tuning [13]
  - May lead to non-global optima...

Architecture



Memory

- **Agent should remember visual features and associate them with their spatial location**.
- Two memory variants:
  1. Temporal memory (long short-term memory [14]):
     - Previously applied to POMDPs [15, 16, 6, 17].
     - May struggle with remembering over many time steps.
     - Important for exhaustive search and scene understanding.
  2. Spatial memory (inspired by [18]):
     - Map with one slot per camera position.
     - Write image representation to current position memory.
     - Read whole memory with convolutional layers.

Training

- Train for 25M time steps.
- Results reported across 3 runs with different seeds.
- Separate training and test sets.
- Same hyperparameters in all runs.

Implementation

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

Experiment I: Search Performance

- Compare to baselines.
- Simple reference behaviors.
- Use held out samples as test set.
- Average number of steps on test set.
- Success weighted by inverse path length (SPL) metric [19].

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

Baselines

Random: randomly samples actions.

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

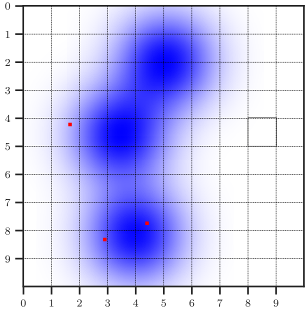
Exhaustive: exhaustively covers search space with minimal revisits.

Human: human searcher with knowledge of environment characteristics.

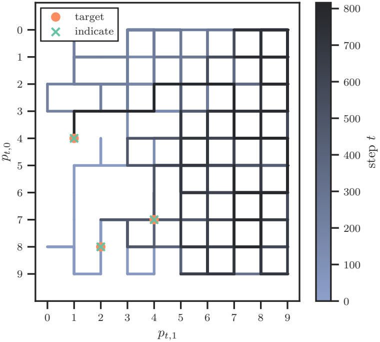
Handcrafted: prioritize actions that lead to higher blue intensity (gaussian environment only).

Gaussian Environment

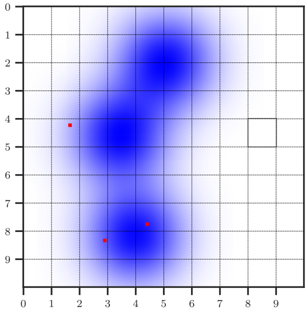
Agent	SPL	Success	Length
random	0.06 ± 0.01	0.92 ± 0.06	369.07 ± 24.93
greedy	0.17 ± 0.00	1.00 ± 0.00	147.12 ± 2.38
exhaustive	0.21 ± 0.00	1.00 ± 0.00	83.37 ± 2.88
handcrafted	0.33 ± 0.00	1.00 ± 0.00	65.20 ± 1.41
human	0.23 ± 0.03	1.00 ± 0.00	80.97 ± 13.49
temporal	0.24 ± 0.03	0.99 ± 0.01	101.25 ± 13.32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



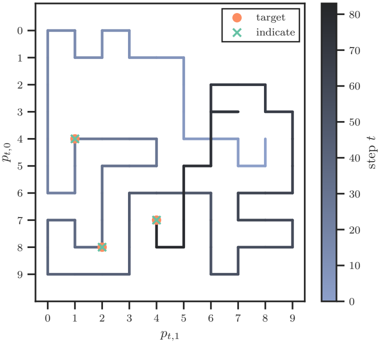
Environment sample



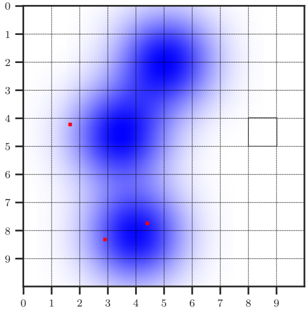
Random baseline



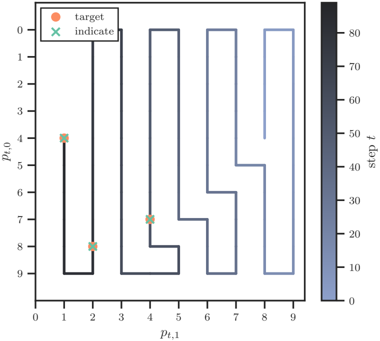
Environment sample



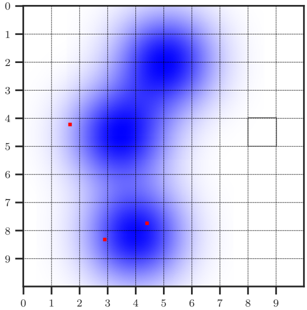
Greedy baseline



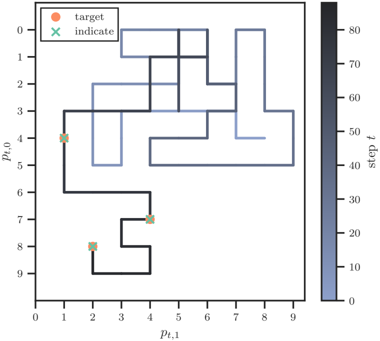
Environment sample



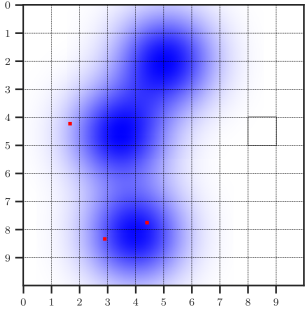
Exhaustive baseline



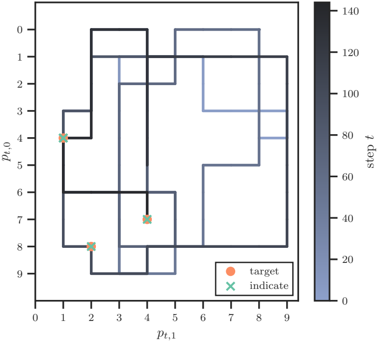
Environment sample



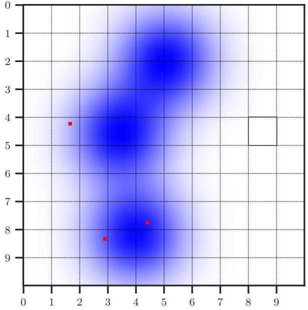
Handcrafted baseline



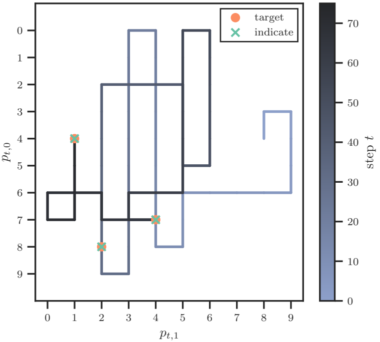
Environment sample



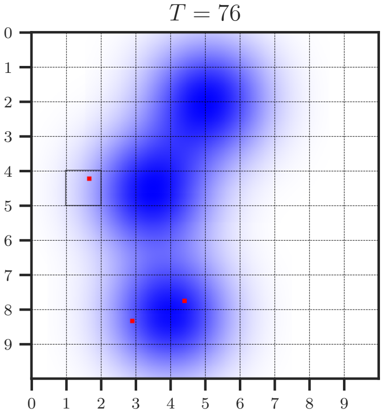
Temporal memory

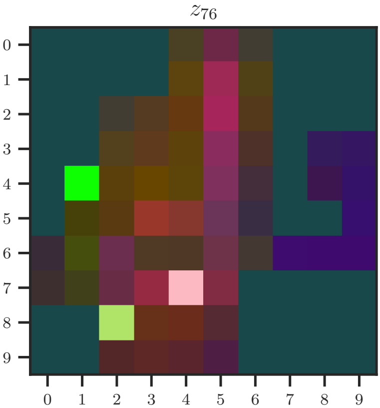


Environment sample



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

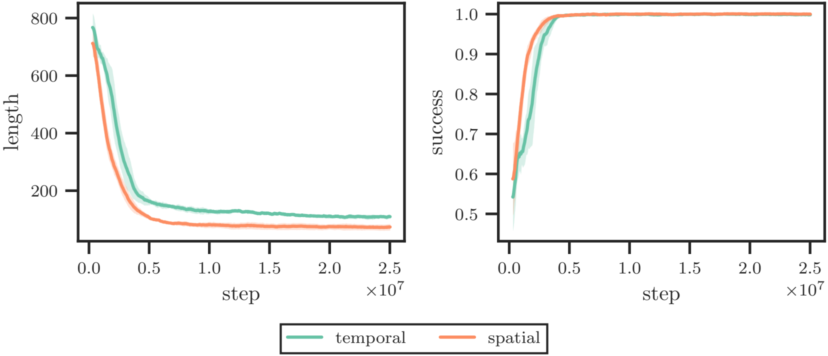
Agent	SPL	Success	Length
random	0.04 ± 0.00	0.62 ± 0.03	545.09 ± 56.25
greedy	0.12 ± 0.01	0.97 ± 0.01	255.60 ± 10.44
exhaustive	0.37 ± 0.00	1.00 ± 0.00	67.03 ± 0.00
human	0.68 ± 0.08	1.00 ± 0.00	38.10 ± 5.72
temporal	0.70 ± 0.02	1.00 ± 0.00	42.36 ± 2.05
spatial	0.66 ± 0.03	1.00 ± 0.00	42.90 ± 1.73

video 1, video 2, video 3 (temporal)

Experiment II: Scaling to Larger Search Spaces

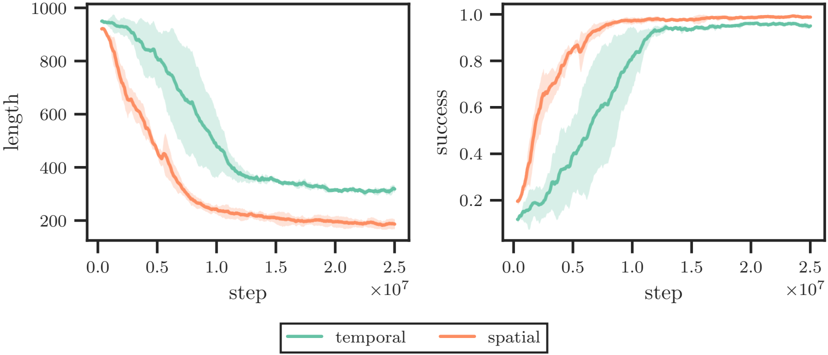
- Real-world search often in large environments.
- Larger search spaces more difficult.
- Stronger memory demands:
  - More positions to remember.
  - Avoid revisits.
- Compare memories on 10×10, 15×15, and 20×20 versions of gaussian environment.

10×10



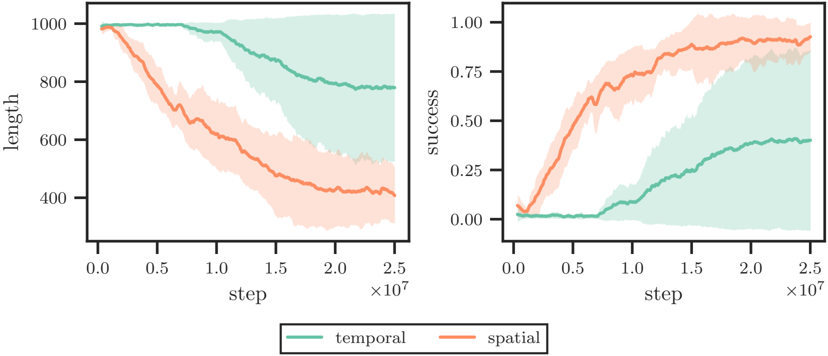
length
800
600
400
200
0.0
0.5
1.0
1.5
2.0
2.5
step
$\times 10^7$
success
1.0
0.9
0.8
0.7
0.6
0.5
temporal
spatial

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
0.0
0.5
1.0
1.5
2.0
2.5
step
×10^7
temporal
spatial

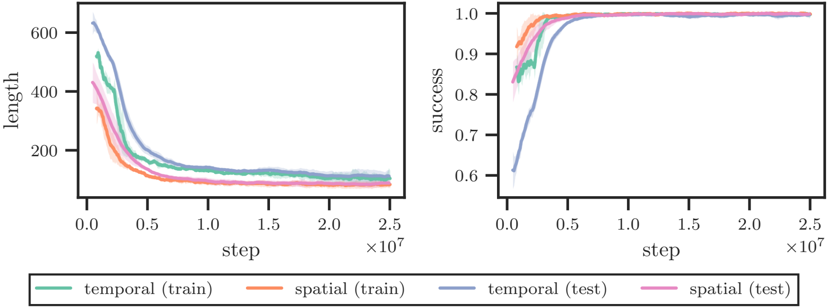
20×20


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
0.0
0.5
1.0
1.5
2.0
2.5
step
×10^7
temporal
spatial

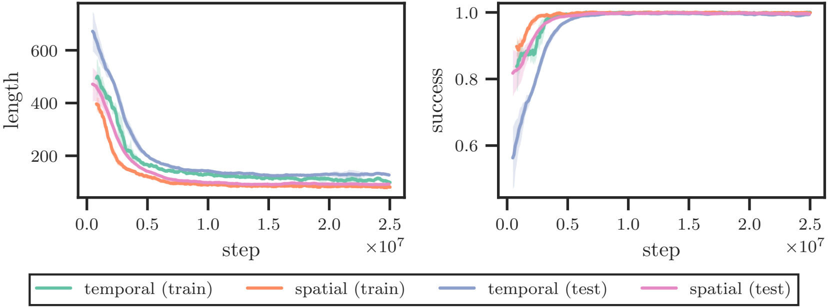
Experiment III: Generalization From Limited Samples

- Limit number of scene samples seen during training to 500, 1 000, 5 000, 10 000.
- Test on held out scenes from full distribution.
- Use terrain environment, high appearance variance and somewhat realistic.
- Fix seed pool used to generate scenes seen during training.
- Train agents until convergence (or for a fixed number of time steps).

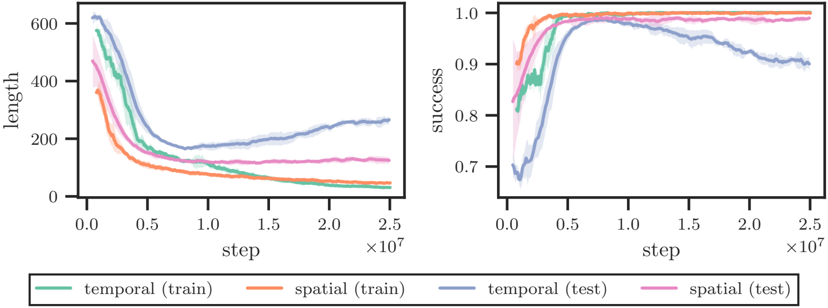
10000 samples



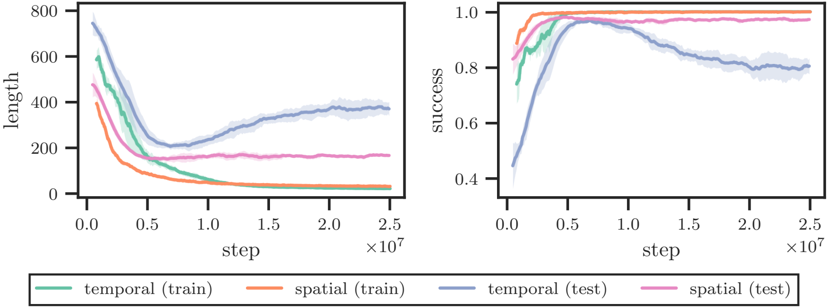
5000 samples



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)

Conclusion

- Proposed a method for solving visual search with reinforcement learning.
- Three environments for evaluating visual search agents.
- Compared two neural network architectures with different strengths.
- Specialized architectures can provide better performance and generalization.
- RL is not guaranteed to converge to optimal solutions.

Future Work

- Real-world scenarios (training data?).
- Formal verification (for security-critical applications).
- Hyperparameter tuning (expensive!).
- Other RL algorithms.

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