Supplementary Material: Discovering Reinforcement Learning Algorithms

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DeepMind

A Training Environments

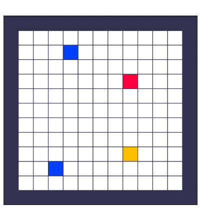
A.1 Tabular Grid World

When an agent collects an object, it receives the corresponding reward r, and the episode terminates with a probability of ϵ_{term} associated with the object. The object disappears when collected, and reappears with a probability of $\epsilon_{\text{respawn}}$ for each time-step. In the following sections, we describe each object type i as $\{N \times [r, \epsilon_{\text{term}}, \epsilon_{\text{respawn}}]\}_i$, where N is the number of objects with type i.

Observation Space In tabular grid worlds, object locations are randomised across lifetimes but fixed within a lifetime. Thus, there are only $p \times 2^{\text{m}}$ possible states in each lifetime, where p is the number of possible positions, and m is the total number of objects. An agent is simply represented by a table with distinct $\pi(a|s)$ and $y(s)$ values for each state without any function approximation.

Action Space There are two different action spaces. One version consists of 9 movement actions for adjacent positions (including staying at the same position) and 9 actions for collecting objects at adjacent positions. The other version has only 9 movement actions. In this version, an object is automatically collected when the agent visits it. We randomly sample either one of the action spaces for each lifetime during meta-training.

A.1.1 Dense



Component	Description
Observation	State index (integer)
Number of actions	9 or 18
Size	11×11
Objects	$2 \times [1, 0, 0.05]$, $[-1, 0.5, 0.1]$, $[-1, 0, 0.5]$
Maximum steps per episode	500

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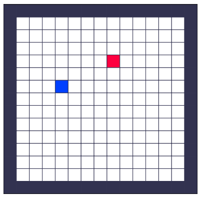
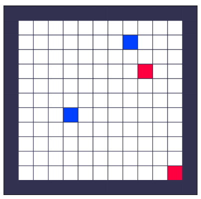
A.1.2 Sparse



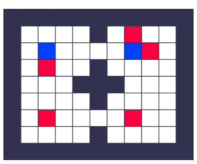
Component	Description
Observation	State index (integer)
Number of actions	9 or 18
Size	13×13
Objects	$[1, 1, 0]$, $[-1, 1, 0]$
Maximum steps per episode	50

A.1.3 Long Horizon



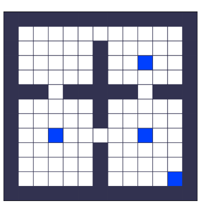
Component	Description
Observation	State index (integer)
Number of actions	9 or 18
Size	11×11
Objects	$2 \times [1, 0, 0.01]$, $2 \times [-1, 0.5, 1]$
Maximum steps per episode	1000

A.1.4 Longer Horizon



Component	Description
Observation	State index (integer)
Number of actions	9 or 18
Size	7×9
Objects	$2 \times [1, 0.1, 0.01]$, $5 \times [-1, 0.8, 1]$
Maximum steps per episode	2000

A.1.5 Long Dense

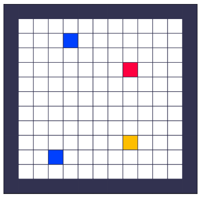


Component	Description
Observation	State index (integer)
Number of actions	9 or 18
Size	11×11
Objects	$4 \times [1, 0, 0.005]$
Maximum steps per episode	2000

A.2 Random Grid World

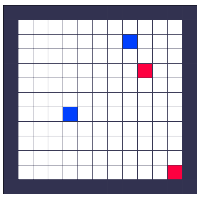
The random grid worlds are almost the same as the tabular grid worlds except that object locations are randomised within a lifetime. More specifically, object locations are randomly determined at the beginning of each episode, and objects re-appear at random locations after being collected. Due to the randomness, the state space is exponentially large, which requires function approximation to represent an agent. The observation consists of a tensor $\{0, 1\}^{N \times H \times W}$, where N is the number of object types, $H \times W$ is the size of the grid.

A.2.1 Dense



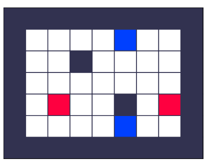
Component	Description
Observation	$\{0,1\}^{N\times H\times W}$
Number of actions	9 or 18
Size	11×11
Objects	$2 \times [1, 0, 0.05]$, $[-1, 0.5, 0.1]$, $[-1, 0, 0.5]$
Maximum steps per episode	500

A.2.2 Long Horizon



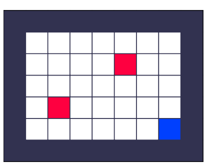
Component	Description
Observation	$\{0,1\}^{N\times H\times W}$
Number of actions	9 or 18
Size	11×11
Objects	$2 \times [1, 0, 0.01]$, $2 \times [-1, 0.5, 1]$
Maximum steps per episode	1000

A.2.3 Small



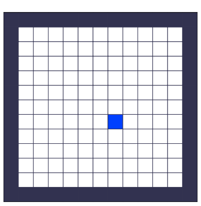
Component	Description
Observation	$\{0,1\}^{N\times H\times W}$
Number of actions	9 or 18
Size	5×7
Objects	$2 \times [1, 0, 0.05]$, $2 \times [-1, 0.5, 0.1]$
Maximum steps per episode	500

A.2.4 Small Sparse



Component	Description
Observation	$\{0,1\}^{N\times H\times W}$
Number of actions	9 or 18
Size	5×7
Objects	$[1, 1, 1]$, $2 \times [-1, 1, 1]$
Maximum steps per episode	50

A.2.5 Very Dense

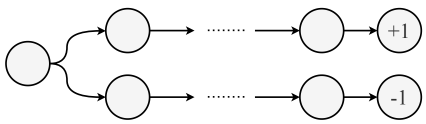


Component	Description
Observation	$\{0,1\}^{N\times H\times W}$
Number of actions	9 or 18
Size	11×11
Objects	$[1, 0, 1]$
Maximum steps per episode	2000

A.3 Delayed Chain MDP

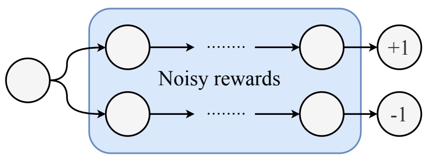
This environment is inspired by the *Umbrella* environment in Behaviour Suite [7]. The agent has a binary choice (a_0, a_1) for each time-step. The first action determines the reward at the end of the episode (1 or -1). The episode terminates after a fixed number of steps (i.e., chain length), which is sampled randomly from a pre-defined range for each lifetime and fixed within a lifetime. For each episode, we randomly determine which action leads to a positive reward and sample the corresponding chain MDP. There is no state aliasing because all states are distinct. Optionally, there can be noisy rewards $\{1, -1\}$ for the states in the middle that are independent of the agent's action.

A.3.1 Short



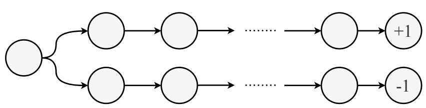
Component	Description
Observation	State index (integer)
Number of actions	2
Chain length	$[5, 30]$
Noisy rewards	No

A.3.2 Short and Noisy



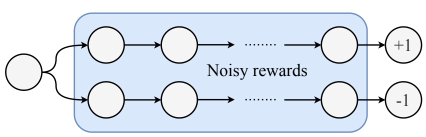
Component	Description
Observation	State index (integer)
Number of actions	2
Chain length	$[5, 30]$
Noisy rewards	Yes

A.3.3 Long



Component	Description
Observation	State index (integer)
Number of actions	2
Chain length	$[5, 50]$
Noisy rewards	No

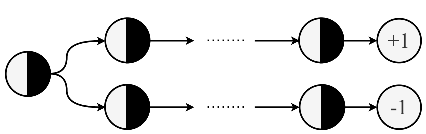
A.3.4 Long and Noisy



Component	Description
Observation	State index (integer)
Number of actions	2
Chain length	$[5, 50]$
Noisy rewards	Yes

A.3.5 State Distraction

In this delayed chain MDP, an observation $s_t \in \{0, 1\}^{22}$ consists of two relevant bits: whether a_0 is the correct action and whether the agent has chosen the correct action, and noisy bits $\{0, 1\}^{20}$ that are randomly sampled independently for all states. The agent is required to find out the relevant bits while ignoring the noisy bits in the observation.



Component	Description
Observation	$\{0, 1\}^{22}$
Number of actions	2
Chain length	$[5, 30]$
Noisy rewards	No

B Implementation Details

B.1 Meta-Training

We trained LPGs by simulating 960 parallel lifetimes (i.e., batch size for meta-gradients), each of which has a learning agent interacting with a sampled environment, for approximately 10^{10} steps of interactions in total. In each lifetime, the agent updates its parameters using a batch of trajectories generated from 64 parallel environments (i.e., batch size for agent). Each trajectory consists of 20 steps. Thus, each parameter update consists of 64×20 steps. The meta-hyperparameters used for meta-training is summarised in Table 1.

Details of LPG Architecture The LPG network takes $x_t = [r_t, d_t, \gamma, \pi(a_t|s_t), y_\theta(s_t), y_\theta(s_{t+1})]$ at each time-step t, where r_t is a reward, d_t is a binary value indicating episode-termination, and γ is a discount factor. $y_\theta(s_t)$ and $y_\theta(s_{t+1})$ are mapped to a scalar using a shared embedding network (φ): Dense(16)-Dense(1). A backward LSTM with 256 units takes $[r_t, d_t, \gamma, \pi(a_t|s_t), \varphi(y_\theta(s_t)), \varphi(y_\theta(s_{t+1}))]$ as input and produces $\hat{\pi}$ and $\hat{y}$ as output. We slightly modified the LSTM core such that the hidden states are reset for terminal states ($d_t = 0$), which blocks information from flowing across episodes. In our preliminary experiment, this improved generalisation performance by making it difficult for LPG to exploit environment-specific patterns. Rectified linear unit (ReLU) was used as activation function throughout the experiment.

Details of LPG Update In Section 3.3, the meta-gradient for updating LPG is described as the outcome of REINFORCE for simplicity. In practice, however, we used advantage actor-critic (A2C) [6] to calculate the meta-gradient, which requires learning value functions for bootstrapping. Note that value functions were trained only to reduce the variance of meta-gradient. LPG itself has no access to value functions during meta-training and meta-testing. In principle, the *outer* algorithm used for discovery can be any RL algorithm, as long as they are designed to maximise cumulative rewards.

Details of Hyperparameter Balancing As described in Section 3.4, we trained a bandit $p(\alpha|\mathcal{E})$ to automatically sample better agent hyperparameters for each environment to make meta-training more stable. More specifically, the bandit samples hyperparameters at the beginning of each lifetime according to:

$$p(\alpha|\mathcal{E}) \propto \exp\left(\frac{R(\alpha, \mathcal{E}) + \rho/\sqrt{N(\alpha, \mathcal{E})}}{\tau}\right), \tag{1}$$

where $R(\alpha, \mathcal{E})$ is the final return at the end of the agent's lifetime with hyperparameters α in environment $\mathcal{E}$, which is averaged over the last 10 lifetimes. $N(\alpha, \mathcal{E})$ is the number of lifetimes simulated. τ is a constant temperature, and ρ is a coefficient for exploration bonus. Intuitively, we keep track of how well each α performs and sample hyperparmeters that tend to produce a larger final return with exploration bonus. In our experiments, α consists of two hyperparameters: learning rate (α_{lr}) and KL cost (α_y) for updating the agent's predictions. Table 2 shows the range of hyperparameters searched by the bandit. Note that this hyperparameter balancing requires multiple lifetimes of experience, which can be done only during meta-training. During meta-testing on unseen environments, α needs to be manually selected.

Preventing Early Divergence We found that meta-training can be unstable especially early in training, because the randomly initialised update rule (η) tends to make agents diverge or deterministic, which eventually causes exploding meta-gradients. To address this issue, we reset the lifetime whenever the entropy of the policy becomes 0, which means the policy becomes deterministic. We observed that this is triggered a few times early in training but eventually is not triggered later in training as the update rule improves.

Table 1: Meta-hyperparameters for meta-training.

Hyperparameter	Value	Searched values
Optimiser	Adam	-
Learning rate	0.0001	{0.0005, 0.0001, 0.00003}
Discount factor (γ)	{0.995, 0.99}	-
Policy entropy cost (β_0)	{0.01, 0.02}	-
Prediction entropy cost (β_1)	0.001	{0.001, 0.0001}
L2 regularisation weight for $\hat{\pi}$ (β_2)	0.001	{0.01, 0.001}
L2 regularisation weight for $\hat{y}$ (β_3)	0.001	{0.01, 0.001}
Bandit temperature (τ)	0.1	{1, 0.1}
Bandit exploration bonus (ρ)	0.2	{1, 0.2}
Number of steps for each trajectory	20	-
Number of parameter updates (K)	5	-
Number of parallel lifetimes	960	-
Number of parallel environments per lifetime	64	-

Discount factor and policy entropy cost are randomly sampled from the specified range for each lifetime.

Table 2: Agent hyperparameters for each training environment.

Environment	Architecture	Optimiser	Learning rate (α_{lr})	KL cost (α_y)	Lifetime
`dense`	Tabular	SGD	$\{20, 40, 80\}$	$\{0.1, 0.5, 1\}$	3M
`sparse`	Tabular	SGD	$\{20, 40, 80\}$	$\{0.1, 0.5, 1\}$	3M
`long_horizon`	Tabular	SGD	$\{20, 40, 80\}$	$\{0.1, 0.5, 1\}$	3M
`longer_horizon`	Tabular	SGD	$\{20, 40, 80\}$	$\{0.1, 0.5, 1\}$	3M
`long_dense`	Tabular	SGD	$\{20, 40, 80\}$	$\{0.1, 0.5, 1\}$	3M
`dense`	C(16)-D(32)	Adam	$\{0.0005, 0.001, 0.002, 0.005\}$	$\{0.1, 0.5, 1\}$	30M
`long_horizon`	C(16)-D(32)	Adam	$\{0.0005, 0.001, 0.002, 0.005\}$	$\{0.1, 0.5, 1\}$	30M
`small`	D(32)	Adam	$\{0.0005, 0.001, 0.002, 0.005\}$	$\{0.1, 0.5, 1\}$	30M
`sparse`	D(32)	Adam	$\{0.0005, 0.001, 0.002, 0.005\}$	$\{0.1, 0.5, 1\}$	30M
`very_dense`	C(32-16-16)-D(256)	Adam	$\{0.0005, 0.001, 0.002, 0.005\}$	$\{0.1, 0.5, 1\}$	30M
`short`	Tabular	SGD	$\{20, 40, 80\}$	$\{0.1, 0.5, 1\}$	1M
`short_noisy`	Tabular	SGD	$\{20, 40, 80\}$	$\{0.1, 0.5, 1\}$	1M
`long`	Tabular	SGD	$\{20, 40, 80\}$	$\{0.1, 0.5, 1\}$	1M
`long_noisy`	Tabular	SGD	$\{20, 40, 80\}$	$\{0.1, 0.5, 1\}$	1M
`distractor`	D(16)	Adam	$\{0.002, 0.005, 0.01\}$	$\{0.1, 0.5, 1\}$	2M

'C(N1-N2-...)' represents convolutional layers with N1, N2, ... filters for each layer.
'D(N)' represents a dense layer with N units.
Lifetime is defined as the total number of steps.

B.2 Meta-Testing

We selected the best update rule (η) and hyperparameters according to the validation performance on two Atari games (`breakout, boxing`), and used them to evaluate across all 57 Atari games. We found that subtracting a baseline slightly improves the performance on Atari games as follows:

$$\Delta\theta \propto \mathbb{E}_{\pi_\theta}\left[\nabla_\theta \log \pi_\theta(a|s)(\hat{\pi} - f_\theta(s)) - \alpha_y \nabla_\theta D_{\mathrm{KL}}(y_\theta(s)\|\hat{y}) - \frac{1}{2}||f_\theta(s) - \hat{\pi}||^2\right], \qquad (2)$$

where $f_\theta(s)$ is an action-independent baseline function. The hyperparameters are summarised in Table 3, and the learning curves are shown in Figure 1.

B.3 Computing Infrastructure

Our implementation is based on JAX [1], RLAX [2], Optax [4], Haiku [3] using TPUs [5]. The training environments are also implemented in JAX, which enables running on TPU as well. It took approximately 24 hours to converge using a 16-core TPU-v2.

Table 3: Hyperparameters used for meta-testing on Atari games.

Hyperparameter	Value	Searched values
Optimiser	Adam	-
Network architecture	C(32)-C(64)-C(64)-D(512)	-
Learning rate (α_{lr})	0.0005	{0.001, 0.0005, 0.0003}
KL cost (α_{y})	0.5	{1, 0.5, 0.1}
Discount factor (γ)	0.995	-
Number of steps for each trajectory	20	-
Number of parallel environments (batch size)	30	-

C Generalisation to Atari Games

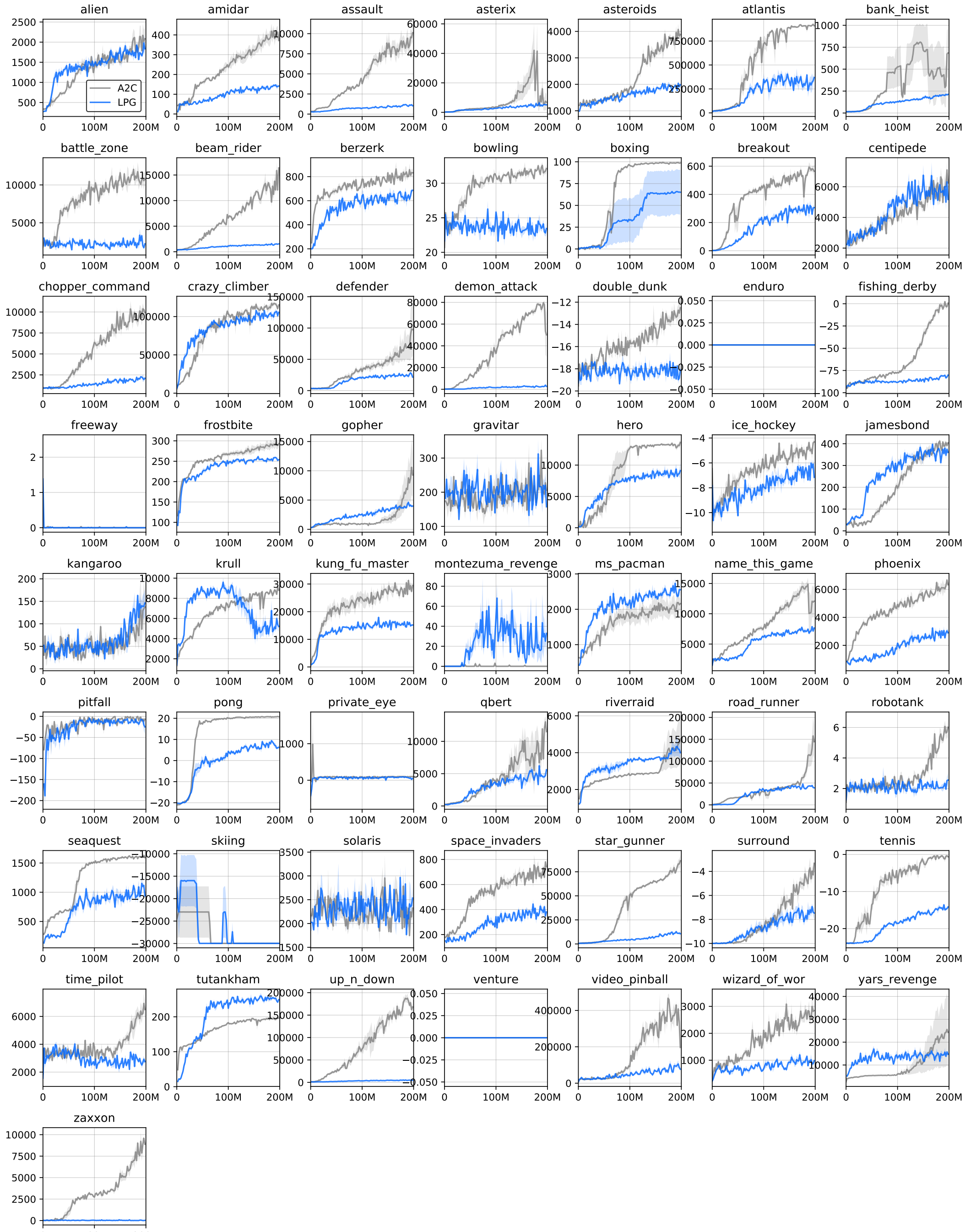


Figure 1: Learning curves on Atari games. X-axis and y-axis represent the number of frames and episode return respectively. Shaded areas show standard errors from 3 independent runs.

References

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