Cyclophobic Reinforcement Learning

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Abstract

In environments with sparse rewards, finding a good inductive bias for exploration is crucial to the agent's success. However, there are two competing goals: novelty search and systematic exploration. While existing approaches such as curiosity-driven exploration find novelty, they sometimes do not systematically explore the whole state space, akin to depth-first-search vs breadth-first-search. In this paper, we propose a new intrinsic reward that is cyclophobic, i.e., it does not reward novelty, but punishes redundancy by avoiding cycles. Augmenting the cyclophobic intrinsic reward with a sequence of hierarchical representations based on the agent's cropped observations we are able to achieve excellent results in the MiniGrid and MiniHack environments. Both are particularly hard, as they require complex interactions with different objects in order to be solved. Detailed comparisons with previous approaches and thorough ablation studies show that our newly proposed cyclophobic reinforcement learning is more sample efficient than other state of the art methods in a variety of tasks.

1 Introduction

Exploration is one of reinforcement learning's most important problems. Learning success largely depends on whether an agent is able to explore its environment efficiently. Random exploration explores all possibilities but at great costs, since it possibly revisits states very often. More efficient approaches can use intrinsic rewards based on novelty (Ostrovski et al., 2017; Bellemare et al., 2016), where the occurrence of states is counted and some novelty metric is determined or can be based on curiosity where novelty in the representations is determined (Pathak et al., 2017; Burda et al., 2018; Raileanu & Rocktäschel, 2020; Zhang et al., 2021). This often leads to great results, but at the price of possibly not exploring all corners of the environment systematically. The latter also paradoxically end up being less sample efficient, when aleatoric uncertainty in the observations is not large enough to give an informative reward signal, such as in environments which are challenging from a combinatorial standpoint, but where the observations are simple (Parisi et al., 2021). Especially in environments where the task is complex we would ideally pursue both goals: novelty search and systematical exploration.

How can we favor novelty while ensuring that the environment is systematically explored? To achieve this, we propose *cyclophobic reinforcement learning* which is based on the simple idea of avoiding cycles during exploration. More precisely, we define a negative intrinsic reward, i.e., the cyclophobic intrinsic reward that penalizes redundancy in the exploration history. With this we ensure two things: first, the agent receives immediate feedback about which state-action pair to discourage. Second, by maximizing the agent's actions it is forced to take the next unexplored state-action pair since already explored state-action pairs will have a negative intrinsic reward. This approach is similar to optimistic initialization (Machado et al., 2014) where the value function is initialized with a high value and as the update rule is applied, the values will decrease for subsequent visits, thus forcing the agent to take the next unexplored action with highest remaining value. In this sense, the cyclopohobic intrinsic reward can be seen as a count-based extension of optimistic initialization.

The cyclophobic intrinsic reward is further enhanced by applying it to several cropped observations of the environment which we call hierarchical state representations. Furthermore, we call the single cropped views,

hierarchical views. The notion of redundancy can be defined relative to cropped views of the agent: while cycles in the global view induce cycles in a corresponding smaller view, the converse is not the case. E.g., a MiniGrid agent turning four times to the left produces a cycle in state space that we would like to avoid everywhere. This cycle occurrs in the global view, but penalizing it only in the global view does not avoid it in other locations. However, with a hierarchy of views, we record a cycle in some smaller view as well, which allows us to transfer this knowledge to any other location of the environment and to hereby avoid further cycles for parts in the environment that look the same. Similarly, cycles on a hierarchical level reveal structural properties about the environment. An interesting object such as a key, produces less cycles in a smaller view than some other object (since e.g. the key can be interacted with). Thus the probability of picking up the key increases, since other *less interesting* observations produce more cycles (e.g a wall). Overall, a hierarchy of cropped views is a state representation that is complementary to the cyclophobic intrinsic reward that does not require the learning of an inverse dynamics model as in other works (Pathak et al., 2017; Henaff et al., 2022). The approach of exploiting a prioproceptive inductive bias for the observations can also be seen in Parisi et al. (2021), where a 360° panoramic view of the environment is created, which enhances the information the intrinisic reward gives about the environment. An important aspect of exploration and another desirable property of hierarchical views is that they are task-agnostic (Parisi et al., 2021). That is, the cropped views of the environment can be transferred to other environments and are not task dependent. Thus, hierarchical state representations on one hand generalize cycles when learning about a task, but also represent task-agnostic knowledge when transferring knowledge to other tasks.

Contributions:

1. We introduce cyclophobic reinforcement learning for efficient exploration in environments with extremely sparse rewards and large action spaces. It is based on a cyclophobic intrinsic reward for systematic exploration applied to a hierarchy of views. Instead of rewarding novelty, we avoid redundancy by penalizing cycles, i.e., repeated state-action pairs in the exploration history. Our approach can be applied to any MDP for which a hierarchy of views can be defined.

2. In the sparse-reward setting of the MiniGrid and MiniHack environments we thoroughly evaluate cyclophobic reinforcement learning and can show that it achieves excellent results compared to existing methods, both for tabula-rasa and transfer learning.

3. In an ablation study we provide deeper insights into the interplay of the cyclophobic intrinsic reward and the hierarchical state representations. We provide insight into the role of learning representations for exploration. We show that exploration and therefore learning success depend greatly on the function approximator learning appropriate invariances that reduce the complexity of the state space.

Notation: We define an MDP as a tuple $(\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma)$, where the agent and the environment interact continuously at discrete time steps $t = 0, 1, 2, 3, \ldots$ We define the state an agent receives from the environment as a random variable $S_t \in \mathcal{S}$, where $S_t = s$ is some representation of the state from the set of states $\mathcal{S}$ at timestep t. From that state, we define a random variable for the agent selecting an action $A_t \in \mathcal{A}$ where $A_t = a$ is some action in the possible set of actions $\mathcal{A}$ for the agent at timestep t. This action is selected according to a policy $\pi(a \mid s)$ or $\pi(s)$ if the policy is deterministic. One time step later as a consequence of its action, the agent receives a numerical reward which is a random variable $R_{t+1} \in \mathbb{R}$, where $R_{t+1} = r$ is some numerical reward at timestep $t + 1$. Finally, the agent finds itself in a new state S_{t+1}. Furthermore we define a POMDP $(\mathcal{S}, \mathcal{A}, \mathcal{O}, \mathcal{P}, \mathcal{R}, \mathcal{Z}, \gamma)$ as a generalization of an MDP in the case the true state space $\mathcal{S}$ is unknown. That is, the agent sees the state $s \in \mathcal{S}$ through an observation $o \in \mathcal{O}$, where an observation function $\mathcal{Z} : \mathcal{S} \to \mathcal{O}$ maps the true state to the agent's observation.

2 Building Blocks

We begin by first defining the cyclophobic intrinsic reward and hierarchical state representations as they are the building blocks of our method. Finally, we define a policy which combines the intrinsic and extrinsic rewards together with the hierarchical state representations to form a global policy which the agent acts upon.

2.1 Cyclophobic Intrinsic Reward

For efficient exploration, redundancy must be avoided. A sign for redundancy is when states are repeatedly explored, with other words, when the agent encounters cycles in the state space instead of focusing on novel areas. To guide the exploration, we will penalize cycles using a cycle penalty, which we call cyclophobic intrinsic reward (a negative intrinsic reward). This avoids redundancy such that uninteresting parts of the state-action space are discarded quickly. For instance, if an agents gets stuck in some area, typically, it is facing numerous cycles. In such a situation we would like the agent to assign penalties to the repeating state-action pairs in order to focus on more promising parts of the state space that do not cause immediate repetition.

Formally, let us assume that we have per episode a history of previous state-action pairs $\mathcal{H}_{\text{episodic}} = \{(s_1, a_1), (s_2, a_2), \ldots, (s_t, a_t)\}$ and we are currently at the state-action pair (s_{t+1}, a_{t+1}). We say that we have encountered a cycle if the state in the current state-action pair appeared already in the history, i.e. $(s_{t+1}, a_{t+1}) \in \mathcal{H}_{\text{episodic}}$. For its first repeated occurrence, we will penalize the state-action pair (s_t, a_t) (just before the cycle) by negative one,

$$r_{\text{cycle}}(s, a; \mathcal{H}_{\text{episodic}}) = -1. \tag{1}$$

Note that the cycle penalty as a function depends on the episodic history $\mathcal{H}_{\text{episodic}}$. If a cycle is encountered multiple times, e.g. l times, the overall cycle penalty for a state-action pair is $-l$. That is, during exploration the cycle penalty can penalize indefinitely. However, note that every single repeated encounter is penalized with -1. For pairs (s, a) that have not created a cycle, $r_{\text{cycle}}(s, a; \mathcal{H}_{\text{episodic}}) = 0$.

Learning with cycle penalties. In principle, the cycle penalty can be combined with any reinforcement learning algorithm. However, we explain how it can be built into the SARSA update rule, since the latter will propagate the penalty across the trajectory. This is important as we want the cycle discouragement to happen on-policy, i.e., the state-action pair before the cycle should be penalized. Eventually, through the SARSA updates this information will propagate to other state-action pairs. To learn the Q-function, we are employing the standard SARSA update rule,

$$Q(s, a) \leftarrow (1 - \eta)\, Q(s, a) + \eta\big[r(s, a) + \gamma\, Q(s', a')\big] \tag{2}$$

with $(s, a, r_{\text{ex}}, s', a')$ being a transition, η being step size and where the total reward $r(s, a)$ for the state-action pair (s, a) is the weighted sum of the extrinsic reward from the environment r_{ex} and the cyclophobic intrinsic reward r_{cycle} defined above,

$$r(s, a) = \rho\, r_{\text{ex}}(s, a) + r_{\text{cycle}}(s, a; \mathcal{H}_{\text{episodic}}). \tag{3}$$

where ρ trades off extrinsic and intrinsic rewards.

2.2 Hierarchical State Representations

Besides penalizing cycles, the second key idea of this paper is to consider a hierarchy of state representations. For this, we repeatedly crop the agent's observations to induce additional partially observable Markov decision processes (POMDPs). In general, restricting the view leads to ignoring information about the environment, however in combination with the cyclophobic intrinsic reward we gain additional information about the structure of the environment as we get different Q-functions for different POMDP's. The relevant insight is that on limited views lower down the hierarchy, trajectories can contain cycles that have not been experienced on views higher up the hierarchy. These cycles in smaller views represent transferable knowledge about the structure of the environment. E.g. in the MiniGrid environment (see Section B.1) encountering a wall in the smallest view will cause a cycle, capturing that running into a wall is counterproductive. On larger views this knowledge is only available directly, if we tried all walls everywhere. So, the smaller views capture relevant invariances that also apply to the larger views. Hierarchical state representations also enable task-agnostic learning (Parisi et al., 2021). That is, when learning an exploration policy we want to learn a policy that together with its representations can be transferred to other environments. By definition, the hierarchical

state representations allow us to transfer learned invariances in smaller views to other environments by simply keeping these views for transfer learning. In general MDPs, it might not be obvious how to define hierarchical state representations. Ideally, the agent has some sort of sense of "location" to allow cropped views to be meaningful. In general, for grid world-like environments, the hierarchical state representations are easily definable, since the agent has a defined location that can be used to define smaller neighborhoods typically corresponding to limited views around the agent or from the agent's view.

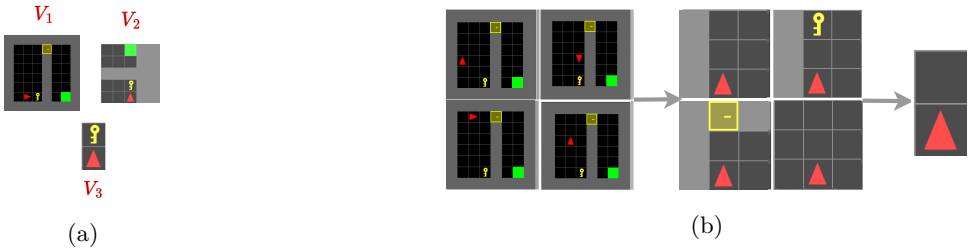

Figure 1: **Hierarchical views allow us to transfer relevant invariances about the environment.** (a) The three different representations are obtained by cropping the observation for each state-action pair (s, a). V_1 is the full view where the agent sees the whole environment or the largest portion of it. V_2 is an intermediate cropped representation of the agent's view that helps the agent generalize by reusing familiar observations . V_3 is the most restricted view where the agent only sees what is immediately in front of it. (b) Through the views V_1 to V_k the amount of cycles continuously increases as the observations in the higher views can be mapped multiple times to the same observation in the lower view. This naturally leads to each view being a separate POMDP describing the true MDP.

To discuss the roles of the different views more precisely, let's consider three such cropped views which consist of the global view V_1, the intermediate view V_2 and the smallest possible view V_3 (see Figure 1a). Each view gives a new, typically more limited, perspective of the true state. As shown in Figure 1b, each view induces a different set of cycles, for instance a sequence of actions which do not lead to a cycle in the full view V_1, might lead to a cycle in a smaller view V_3, because in the latter, more states are mapped to the same observation. Thus, the different views provide different types of information which are useful for learning and allow the agent to focus on different properties of the environment.

In general, we can have an arbitrary number of views. Each view V_i induces a POMDP

$$\mathcal{V}_i = (\mathcal{S}, \mathcal{A}, \mathcal{O}^{V_i}, \mathcal{P}, \mathcal{R}, \mathcal{Z}^{V_i}, \gamma) \tag{4}$$

each having their own set of observations $\mathcal{O}^{V_i}$ and observation function $\mathcal{Z}^{V_i} : \mathcal{S} \to \mathcal{O}^{V_i}$. All POMDP's $\mathcal{V}_1, \mathcal{V}_2, \ldots$ operate on the same state space $\mathcal{S}$, however they have different sets of observations $\mathcal{O}$ and corresponding observation functions. General POMDPs can have a probabilistic observation function. In our case, the observations are deterministic functions of the full view, e.g. the observations for the ith POMDP of state s is

$$o^{V_i} = \mathcal{Z}^{V_i}(s) \tag{5}$$

which corresponds to the cropping for the view V_i. Hereby we create partial representations of the state space that allow us to identify invariances in the environment by looking at the same true state s through different perspectives.

Note that, POMDPs are normally used to model uncertain observations. That is, they are a generalization of MDPs where the true state is not observable. Here, the POMDP idea is used to model different views of a fully observable state space. Therefore, we do not seek to solve a POMDP problem, but rather we extend a regular MDP to get redundant hierarchical representations.

2.3 A cyclophobic policy for hierarchical state representations

In the following, we describe how the cyclophobic intrinsic reward and the hierarchical state representations can be combined into a policy that exploits the cyclophobic inductive bias. For this, we define several Q-functions along the views, and combine them as a weighted sum. The weights are determined by counts of the observations in each observation set $\mathcal{O}^{V_i}$ which we explain next.

Mixing coefficients. Many strategies for defining mixing coefficients are possible. For concreteness, in this paper we follow a simple schema, where we determine the weights from the observation counts, which are obtained from the history of states visited throughout training,

$$\mathcal{H}_{\text{all}} = \{s_1, s_2, \ldots, s_T\}. \tag{6}$$

Note that $\mathcal{H}_{\text{all}}$ contains all states that have been visited in the training so far, which is different from the states in the episodic history $\mathcal{H}_{\text{episodic}}$ that was used in Sec. 2.1 to define cycles. Denoting the corresponding views of the history as $o_t^{V_i} = \mathcal{Z}^{V_i}(s_t)$, the counts for view V_i are

$$N(o_1^{V_i}), N(o_2^{V_i}), \ldots, N(o_T^{V_i}). \tag{7}$$

where N counts the number of times the observation $o_t^{V_i}$ has been encountered. The raw counts are normalized by their maximum (maximum for simplicity, other normalizations are possible), because the smaller views have higher counts than the bigger views. The weights should be large for states that have been seen less often, so we subtract the normalized counts from one,

$$\alpha_*^{V_i}(o_t^{V_i}) = 1 - \frac{N(o_t^{V_i})}{\max(N(o_1^{V_i}), N(o_2^{V_i}), \ldots, N(o_T^{V_i}))}. \tag{8}$$

The previous formula allows us to compute the weights for each respective view V_i for a single state s_t,

$$\alpha_*(s_t) = [\alpha_*^{V_1}(\mathcal{Z}^{V_1}(s_t)), \ldots, \alpha_*^{V_k}(\mathcal{Z}^{V_k}(s_t))] = [\alpha_*^{V_1}(o_t^{V_1}), \ldots, \alpha_*^{V_k}(o_t^{V_k})] \tag{9}$$

where $\alpha_*(s_t)$ is a vector. Finally, the softmax operator turns these weights into a vector of probabilities,

$$\alpha(s_t) = \text{softmax}(\alpha_*(s_t)) = [\alpha_1(s_t), \ldots, \alpha_k(s_t)]. \tag{10}$$

The entries of this vector are denoted by $\alpha_i(s_t)$ and are used to define the cyclophobic Q-function in the next section. The definition of α can be extended to all state s by setting it to zero for unseen states, i.e. $\alpha(s) = 0$ (zero-vector) for $s \notin \mathcal{H}_{\text{all}}$.

In general, larger views in the hierarchy will have bigger entries in $\alpha(s_t)$ as the observations repeat less often than in the smaller views. Thus $\alpha(s_t)$ gives more weight to the larger views than the smaller ones. However, the converse is true for the cyclophobic intrinsic reward, since in the smaller views the cyclophobic penalty is given far more often than in the larger views and thus the q-values in smaller views will be higher than in the larger views.

Cyclophobic Q-function. To combine all views into a single global policy we define a mixture over the different Q-functions learned with the cyclophobic intrinsic reward as defined in Section 2.1. For view V_i, we define Q-function as

$$Q(o^{V_i}, a) \leftarrow (1-\eta)\; Q(o^{V_i}, a) + \eta\big[r(o^{V_i}, a) + \gamma Q(o'^{V_i}, a')\big]. \tag{11}$$

This follows from our argumentation in Section 2.2, where we replace the state s in Equation 2 by the observations o^{V_i} in their respective views. Then we can define cyclophobic Q-function as the mixture of the Q-functions of each view,

$$Q_{\text{cycle}}\big(s, a\big) = \sum_i \alpha_i(s)\, Q(\mathcal{Z}^{V_i}(s), a) = \sum_i \alpha_i(s)\, Q(o^{V_i}, a). \tag{12}$$

Note that the mixing coefficients $\alpha_i(s_t)$ are only non-zero for states s_t that appeared in the global history $\mathcal{H}_{\text{all}}$. Thus the cyclophobic Q-function is zero for states $s \notin \mathcal{H}_{\text{all}}$ not encountered.

Cyclophobic policy. Finally, the cyclophobic policy is defined as the greedy action for the cyclophobic Q-function, i.e.

$$\pi(s) = \arg\max_a Q_{\text{cycle}}\big(s, a\big) = \arg\max_a \sum_i \alpha_i(s) Q(o^{V_i}, a). \tag{13}$$

Having normalized the counts within each view ensures comparability of the counts. This ensures that Q-values from rare i.e more salient observations have a larger effect on deciding the action for the policy π. In an ablation study in Section 3 we show that the combination of the cyclophobic intrinsic reward and hierarchical state representations is crucial to the method's success.

3 Experiments

Our experiments are inspired by Parisi et al. (2021) and Samvelyan et al. (2021). We test in environments where the causal structure is complex and the binding problem (Greff et al., 2020), (van Steenkiste et al., 2019) arises. That is, where some form of disentangled representation of the environments plays an important role for efficiently finding solutions.

Environments: We test our method on the MiniGrid and MiniHack environments:

- The MiniGrid environment (Chevalier-Boisvert et al., 2018) consists of a series of procedurally generated environments where the agent has to interact with several objects to reach a specific goal. The MiniGrid environments pose currently a benchmark for the sparse reward problem, since a reward is only given when reaching the final goal state.
- The MiniHack environment (Samvelyan et al., 2021) is a graphical version of the NetHack environment (Küttler et al., 2020). We select environments from the *Navigation* and *Skill* tasks. The MiniHack environment has a richer observation space by containing more symbols than the MiniGrid environments and a richer action space with up to 75 different actions. While not necessarily tailored to the sparse reward problem as the MiniGrid environment, the high state-action complexity makes it one of the most difficult environments for exploration.

State encoding: For both environments we choose five croppings of the original full view. The views V_1, V_2, V_3, V_4, V_5 are of grid size 9×9, 7×7, 5×5, 3×3 and 2×1. In principle we could also include the full view. However, in the experiments the performance was much better when we limit ourselves to the partial views. Furthermore, every part of the grid that is behind of the wall from the agent's perspective is occluded (note that this is not the case in Figure 1a for visualization purposes). Intuitively, limiting the views allows the agent to ignore irrelevant details that are far away.

Next, the views are mapped to hashcodes (we use the open source *xxhash* library). That is, we have a hash function g that maps observation $o_t^{V_i}$ to a hashcode $h_t^{V_i} = g(o_t^{V_i})$. This helps us to quickly check for cycles as we only need to check whether two hashcodes are equal. For the MiniHack environment, a text prompt is an integral part of the current state. So, for MiniHack, the hashcode for a state is the concatenation of the hashcodes of the observation $o_t^{V_i}$ and the text prompt m_t, where $m_t \in \mathbb{R}^k$ is an encoding of a string of length k, i.e.

$$h_t = g(o_t) + g(m_t). \qquad \text{("+" denoting concatenation)} \tag{14}$$

Overall, while the observations in the MiniGrid and MiniHack environments are more simple than in for instance Atari (Bellemare et al., 2012) or Habitat Savva et al. (2019), the action-space and task that have to be solved are more complex in the MiniGrid and MiniHack environments.

Training setup and baselines: We train each agent for three runs using different seeds for every run. For transfer learning, we use the "DoorKey-8x8" and MultiEnv("MultiRoom-N4-S5", "KeyCorridorS3R3", "BlockedUnlockPickup") setups for pretraining. For each environment we pretrain for 5 million steps. For the

MultiEnv setup this means that we pretrain for a total of 15 millions steps which is less than Parisi et al. (2021)'s 40 million steps. For transfer learning, during pretraining we save the extrinsic rewards in a second separate Q-table in addition to the main Q-table which contains values of equation 2. These extrinsic rewards in the second Q-table are then used at the beginning of transfer learning for each environment, while we continue to use the cyclophobic intrinsic reward when doing transfer learning. The baselines for the MiniGrid experiments are provided by Parisi et al. (2021) and allow us to compare our method to C-BET (Parisi et al., 2021), Random Network Distillation (Ostrovski et al., 2017), RIDE (Raileanu & Rocktäschel, 2020) and Curiosity-driven exploration (Pathak et al., 2017). Furthermore, we also compare to NovelD Zhang et al. (2021). For the MiniHack environment we compare our results to the baselines presented by Samvelyan et al. (2021) which include IMPALA (Espeholt et al., 2018), RIDE (Raileanu & Rocktäschel, 2020) and Random Network Distillation (Burda et al., 2018). For the skill tasks the only available baseline is IMPALA (Espeholt et al., 2018).

Evaluation metric: While during learning the intrinsic reward based on cyclophobia plays the essential role, the ultimate goal is to maximize the extrinsic reward that is provided by the environment. Thus for comparison, we have to plot the extrinsic reward the agent receives for each episode. The reward ranges from 0 to 1.

3.1 MiniGrid

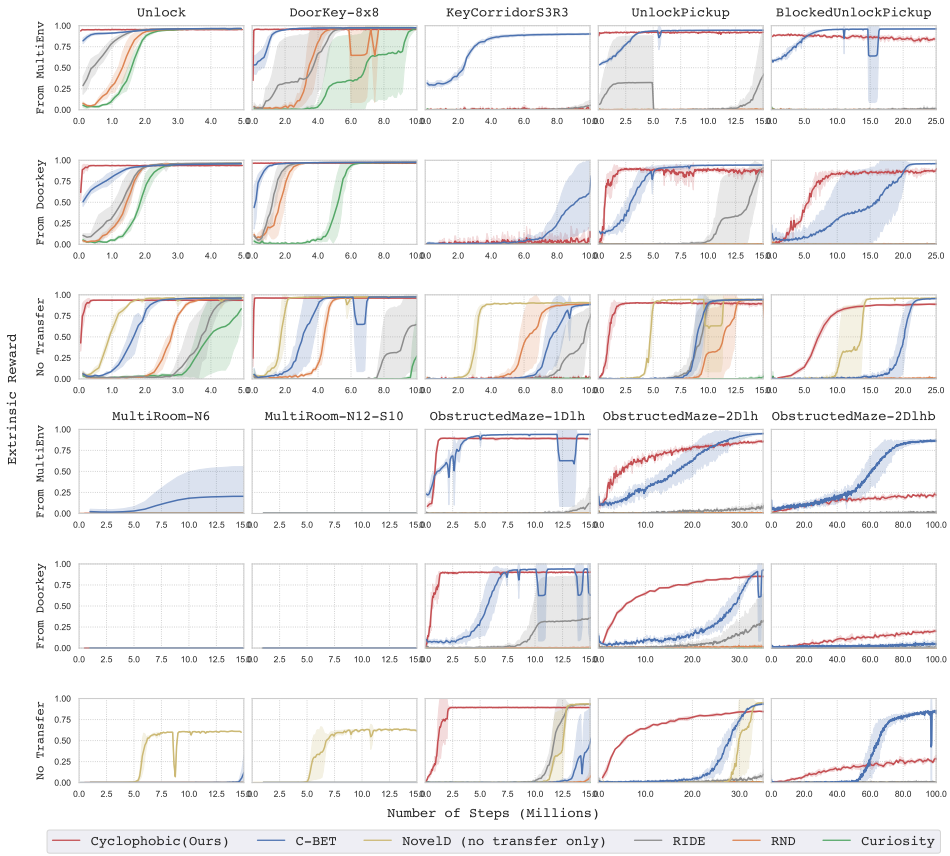

Figure 2: **MiniGrid:** We converge faster than C-BET (Parisi et al., 2021) in many MiniGrid environments with and w/o pretraining. We also converge faster than NovelD Zhang et al. (2021) which we compare to in the "no transfer" setting only. The hierarchical state representations and cyclophobic intrinsic reward is extremely quick to converge which shows efficient exploration and the usefulness of the cropped representations, since we are also able to transfer knowledge by pretraining on other environments.

To test our method in the MiniGrid environment we choose the same training setup of Parisi et al. (2021). That is, we determine the performance of the agent with no pretraining and when pretraining from other environments as explained in the previous section. Figure 2 shows the agent's performance when training from scratch (rows three and six) and when transferring knowledge from pretrained environments (bottom three rows).

- **Learning from scratch** (rows three and six): In three out of six environments, our proposed method converges much faster than the competitors, including C-BET (Parisi et al., 2021) and NovelD Zhang et al. (2021). Only "KeyCorridorS3R3", "MultiRoom" and "ObstructedMaze-2Dlhb" pose significant challenges to our approach, because our method is tabular and thus cannot deal with too many object variations in the environment (e.g. random color changes). This is discussed in Section 5.1. Furthermore, the "MultiRoom" environment proves challenging for all environments with only C-BET and NovelD managing to reach convergence, while we are able to fetch some rewards. This is due to the large amount of observations the different corridors produce. Note that we were not able to reach convergence in "ObstructedMaze-2Dlhb" with NovelD. In Figure 6 our approach also excels in the "KeyCorridorS3R3" and more difficult environments once we remove the colors, e.g. "KeyCorridorS4R3", "KeyCorridorS5R3", "KeyCorridorS6R3".
- **Transferring knowledge** (rows one, two, four and five): Having trained on one environment can we transfer knowledge to a different one? In some environments the transfer even improved the results from the "no transfer" setup (see "Unlock", "Doorkey", "UnlockPickup", "BlockedUnlockPickup", "ObstructedMaze-1Dlh") and never deteriorated performance.

3.2 MiniHack

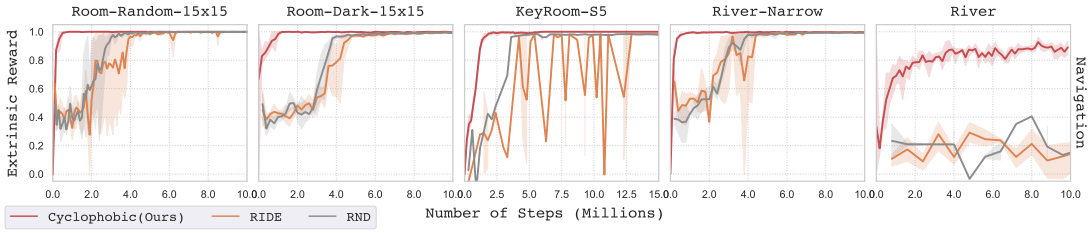

Figure 3: **MiniHack Navigation:** The agent converges quicker in the *Navigation* task than the intrinsic curiosity baselines such as RIDE (Raileanu & Rocktäschel, 2020) and Random Network Distillation (Burda et al., 2018). This corroborates our hypothesis, that avoiding cycles is essential for quick exploration.

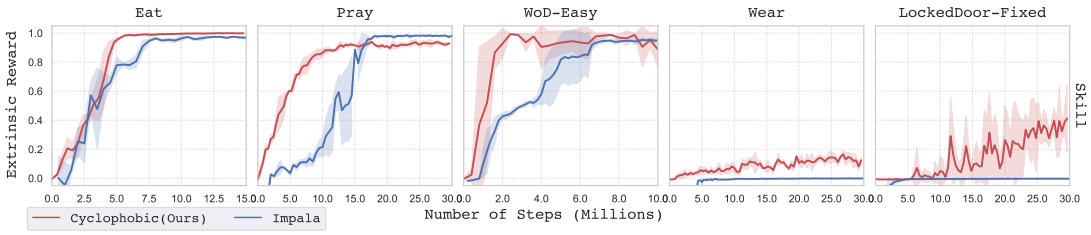

Figure 4: **MiniHack Skill:** We converge quicker than IMPALA (Espeholt et al., 2018) in the *Skill* task. The *Skill* task defines over 75 different actions the agent must learn to use making it one of the most difficult sets of environments of the MiniHack suite.

To push our approach to its limits, we also tackle some of the MiniHack environments which requires the agent to learn a large skill set.

- **Navigation task:** For the simpler navigation tasks shown in Figure 3, our method converges quicker than intrinsic curiosity driven methods such as RIDE and RND. Especially, in the "River"

environment, only our cyclophobic agent is able to converge and solve the environment. However, of course there are environments such as "RoomUltimate" where our approach fails due to its tabular style, which limits the complexity of the environment.

- **Skill task:** For the *Skill* task the only available baseline is IMPALA which is not based on intrinsic curiosity. Here we are also vastly superior, even collecting extrinsic rewards when the baseline can not ("Wear" and "LockedDoor-Fixed").

3.3 Ablation Study

We analyze several aspects of cyclophobic reinforcement learning in our ablation study. We first take a look at the impact of hierarchical state representations on the performance of cyclophobic reinforcement learning (see Figure 5). Furthermore, we study how observational complexity affects exploration by ablating a reward-independent observational feature in the observations, that is we reduce the number of different colors for objects in the "KeyCorridor" environment (see Figure 6). Finally, we also analyze how efficiently the cyclophobic intrinsic reward explores the environment by visualizing state visitation counts (see Figure 7).

Impact of hierarchical views: In Figure 5 we analyze the impact of the hierarchical state representations on the agent's performance. The training setup is described in section C.3. We ablate the hierarchical views in 3 ways. (i) In the first two figures we measure performance of cylophobic reinforcement learning and optimistic initialization with and without the hierarchical views. Both for optimistic initialization and for cyclophobic reinforcement learning the hierarchical views improve performance. (ii) In the middle two figures we measure the effect of weighting the different views according to their visitation counts. We see that for "River" the performance is improved while for "UnlockPickup" both weighted and unweighted variants perform the same. Overall the effect of weighting the different views is not very pronounced. (iii) Finally in the last two figures we toggle the largest, intermediate and smallest views. Only using single views performs the worse. Combining the largest and smallest views improves performance, especially for "River". However, the best performance is achieved when combining largest, intermediate and smallest views together.

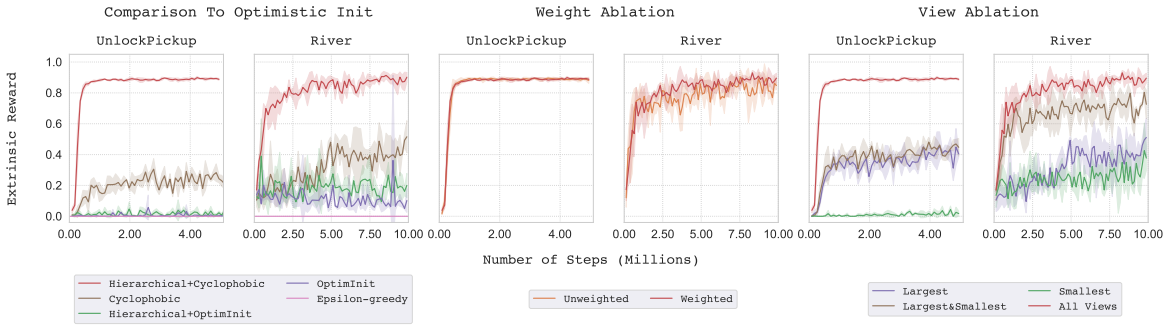

Figure 5: **Hierarchical state representations ablation:** Hierarchical state representations are crucial to performance in cyclophobic reinforcement learning. In the first two figures we compare cyclophobic reinforcement learnign to optimistic initialization with and without hierarchal views and see that hierarchical views improve performance for both the optimisitic initialization and cyclophobic agent. In the two middle figures we measure the effect of weighting the different views. In the last two figures we toggle between the largest, intermediate and smallest views. We see that all 3 types of views deliver the best performance.

Importance of state representations: We demonstrated the impact of learning or imposing a state representation for an agent with hierarchical state representations. We now analyze how much of the success in exploration is due to the function approximator learning observational invariances as described in Section 5.1. In Figure 6 (white), we fix the color of objects in the environment to only one color and compare our method to NovelD (Zhang et al., 2021), since it is able to solve all MiniGrid environments. We see that in "KeyCorridorS4R3" and "KeyCorridorS5R3" our method is more sample efficient than NovelD. Only in the "KeyCorridorS6R3" the large state space reduces performance (see Figure 6 (pink left)). In general, we see

that when the environment is observationally less complex (e.g by removing colors (see Figure 6 (pink right)), the cyclophobic agent is more sample efficient than NovelD. However, as soon as observational complexity increases NovelD takes the upper hand.

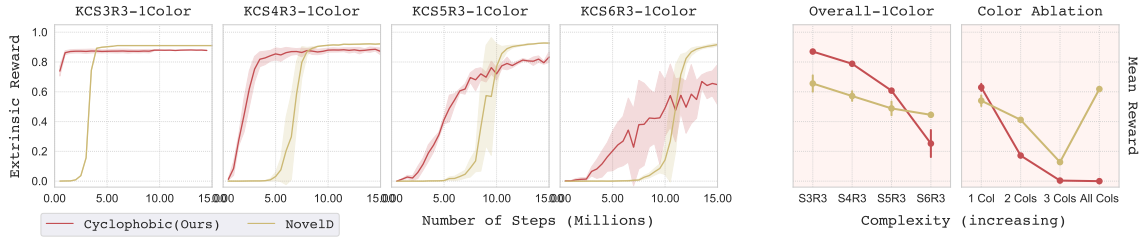

Figure 6: **Observational complexity ablation study (reducing colors):** The cyclophobic agent can gather rewards successfully in large "KeyCorridor" environments when reducing colors, showing that the exploration mechanism is very strong. Generally, the more distinct i.e. complex the observations in the environment are, the more the learned invariances from the neural network matter.

Overall, we observe that exploration success is not necessarily due to the intrinsic reward itself, but can also largely be attributed to the learned representations. Thus, when complexity in the observations increases, better performance in neural networks can be attributed to the learned invariances reducing observational complexity and not necessarily to a more efficient exploration strategy. This can be seen in the tabular cyclophobic agent as well, since the hierarchical state representations are crucial to solving the environments.

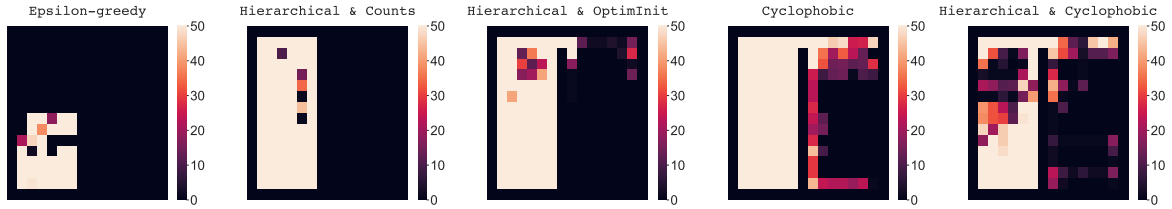

Figure 7: **Exploration behaviour(visitation counts for "DoorKey-16x16"):** The cyclophobic Q-function explores the environment more efficiently than the optmistic initialization, count and epsilon-greedy based counterparts. We record visitation counts for several variations of intrinsic reward and hierarchical state representations. Hierarchical state representations together with the cyclophobic intrinsic reward are the most efficient.

Exploration behavior: To show the effectiveness of the cyclophobic intrinsic reward and the hierarchical state representations, we perform an ablation study. Figure 7 shows state counts as a heat map after 10,000 steps of training. We distinguish four cases: **(i) epsilon-greedy:** Plain epsilon greedy exploration fails to find the goal in the bottom right. **(ii) hierarchical & counts:** We replace the cyclophobic intrinsic reward in equation (3) with a count-based intrinsic reward similar to Strehl & Littman (2008) defined by $N(o_T^{V_i})^{-\frac{1}{2}}$, for view V_i. This improves the results but still fails. **(iii) hierarchical & optimistic initialization:** We use optimistic initialization to let the agent try all possible actions. We initialize the q-table with a value of two. Optimistic initialization manages to enter the second room but just fails at getting a reward within 10,000 steps. **(iv) cyclophobic:** Having a cyclophobic intrinsic reward calculated only on the largest view finds the goal. **(v) cyclophobic & hierarchical:** The combination of hierarchical views and cyclophobic intrinsic rewards (as explained in Sec. 2.3) explores even more efficiently as can be seen in the left room where fewer steps are needed to leave it.

4 Related Work

Breadth-first-search vs depth-first-search exploration: The way different exploration methods explore the state-action space is an important aspect of designing exploration methods. We characterize this by

determining how an exploration method explores on the MDP-level. That is, the way the next action is chosen and the visited states-action pairs that result from the instrinsic reward. With count-based exploration (Ostrovski et al., 2017; Bellemare et al., 2016) where instrinsic reward are usually inverse visitation counts $N(o_T^{V_i})^{-\frac{1}{2}}$, the more a state is visited the less reward it will receive. In the short term, the agent will choose the same state-action pair on its next visit (since it has been given an intrinsic reward for being seen), until a random state-action pair is chosen. While this encourages the agent to revisit previously seen states, this also leads to a depth first approach to exploring the MDP and other action are only considered after randomly being chosen by ϵ-greedy. Another way to explore the environment is by exploiting prioproceptive information in the representations. Methods that use change based counts (Parisi et al., 2021; Zhang et al., 2021) or prediction error (Raileanu & Rocktäschel, 2020; Pathak et al., 2017; Burda et al., 2018; Henaff et al., 2022) as intrinsic reward give the highest intrinsic rewards to observations that are novel and have not been seen before. In this case, the resulting exploration heuristic is based on pursuing the most novel state-action pairs. This may also be problematic when the stochasticity in the observations is not necessarily aligned with the task at hand. Overall, this also equates to a depth-first-search on the MDP-level, since the agent will be enticed to pursue the most novel transition instead of exploring other local options.

In contrast, optimistic initialization (Machado et al., 2014; Choshen et al., 2018) systematically forces exploration on state-action pairs that have not been tried yet by the agent. The idea of optimistic initialization is to initialize the value function by a value larger than the expected reward. As the agent performs updates on the value function it will be forced to choose the next unexplored action since the value-function update for other state-action pairs will have decreased their value. Methods like Never Give Up (NGU) (Puigdomènech Badia et al., 2020) try to combine both depth-first-search and bread-first-search. NGU is composed of two networks where one network will look for novel state transitions and another network tries to give an intrinsic reward when a similar state is visited again to encourage revisiting of states by doing a nearest-neighbor search. While NGU's focus is more based on mitigating the lack of breadth-first-exploration in prediction error based methods, cyclophobic reinforcement learning can be seen as an extension of optmistic initialization where we incorporate more depth-first-search into optimistic initialization with the hierarchical state representations. Other methods such as RAM (Seurin et al., 2021), also attempt this by defining an instrinsic reward based on the saliency of actions in different states.

Loop closure, generalization and transfer learning: Mirowski et al. (2016) define loop closure as an auxiliary loss for exploration in 3D mazes in addition to a depth measure. The authors detect loop closure by checking whether the agent has been near a previously visited position. To get position information the authors integrate velocity information over time. Furthermore, NovelD (Zhang et al., 2021) can also be seen as indirectly detecting loops as it part of its intrinsic reward is based on only rewarding states when they have not been visited before. Learning representations of the environment that are reusable and can be transferred has been explored previously. Learning successor representations (Barreto et al., 2016) requires learning local environment dynamics that can be reused when the environment, i.e. the original distribution, is changed. (Schaul et al., 2015) use Singular Value Decomposition on the learned action-value function to obtain a canonical representation of the environment which can be transferred to other situations. More recently, Parisi et al. (2021) learn an exploratory policy which is then combined with a task specific policy at transfer time. Our method likewise contains a task-agnostic component given by the hierarchical state representations and a task-specific component given by the cyclophobic intrinsic reward.

5 Discussion

5.1 Limitations

In some environments with a big number of different objects our method struggles to converge. The tabular agent does not have the observational invariances that methods based on function approximation learn and exploit (e.g. with CNNs). For instance, for these environments learned invariances allow them to handle differently colored objects. While the tabular agent is able to avoid redundancy through the cyclophobic intrinsic reward and generalize this to other parts of the environment through the hierarchical state representations, it does not learn the kind of observational invariances neural networks do, which

are sometimes necessary. However, note that we can show that reducing the number of colors for the "KeyCorridor" environment improves our performance dramatically (see Figure 6). Also, preliminary results show a cyclophobic PPO agent (see Appendix A.1) solving "KeyCorridor", further supporting our theory. We explore this in our ablation study. An additional limitation that results from our tabular approach is that the entire observation history $\mathcal{H}_{\text{all}}$ has to be recorded. This however can be mitigated by using an unweighted sum of the q-values for all views as we show in the ablation study.

5.2 Contribution to existing literature

At a first glance, cyclophobic reinforcement learning can be seen as another count-based method where equal states are counted as cycles. Then instead of giving an intrinsic reward which is the inverse of visitation counts, the intrinsic reward is a fixed penalty given everytime a cycle is encountered i.e. a state is counted. As explained in Section 4, the cycle penalty encourages an exploration behaviour that explores all actions within a state first instead of pursuing the least visited, i.e., most novel states. This is inherently different from other count-based approaches. In this sense, the cyclophobic intrinsic reward behaves like optimistic initialization where the focus of exploration is placed on the actions instead of the states. Moreover, the hierarchical state representations contrast the breadth-first exploration by learning multiple value functions which are expressive due to the different contents in the hierarchical views. Only few other works such as NGU have followed this approach of balancing breadth-first and depth-first exploration as described in Section 4.

5.3 Extension to high-dimensional state spaces

So far we have tested cyclophobic reinforcement learning on the MiniGrid and MiniHack environments. While the state-action space of these environments is combinatorially complex to solve from an exploration standpoint, the observations are simple compared to other environments such as Atari (Bellemare et al., 2012) or Habitat (Savva et al., 2019) where the exploration task may not be as complex, but the observations are noisy and high-dimensional. Since cyclophobic reinforcement learning is a count-based method, we propose to extend cyclophobic reinforcement learning to high dimensional observations by using density estimation techniques as in Ostrovski et al. (2017); Bellemare et al. (2016). For the hierarchical state representations a PixelCNN (van den Oord et al., 2016) or VQ-VAE (van den Oord et al., 2017) could be used to estimate the density of the observations. With smaller views we expect these densities to get easier to estimate as they contain less observational detail. For the cyclophobic penalty, a pseudo count could be introduced as in Ostrovski et al. (2017); Bellemare et al. (2016). Another approach would be to define an embedding network as in NGU (Puigdomènech Badia et al., 2020) and searching for nearest neighbors in the episodic history to detect cycles. Note that in NGU's case the embedding network is used to revisit states while in our case it would be used to detect cycles in order to discourage visiting these states. Overall, we leave the extension to high-dimensional state spaces for future work.

5.4 Conclusion

Avoiding cycles allows the agent to quickly and systematically discard uninteresting state-action pairs which are repeated often. This makes our cyclophobic intrinsic reward a good inductive bias towards novelty that simultaneously encourages systematic exploration. The ablation studies show that the cyclophobic intrinsic reward just for a single view is already powerful enough to solve complex environments. Adding hierarchical state representations leads to even better performance, as can be seen in the MiniGrid experiments. Moreover, the experiments in MiniGrid confirm the transferability of the learned bias to new environments. Here, the hierarchical state representations are crucial since we detect cycles in smaller views that can be generalized to larger ones. In addition, the policy is task-agnostic since the cropped views can be easily transferred to other environments. Due to the tabular approach, environments with higher observational complexity lead to convergence problems with our method. Neural networks, learn invariances that reduce the complexity of the state space. To address the convergence problems, future work will therefore focus on incorporating cyclophobic reinforcement learning into a neural network based architecture.

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A Further Ablation Studies

For all plots in the ablation studies we use the same setup as in the main experiments. We refer to section C.3 for this.

A.1 Preliminary results with PPO

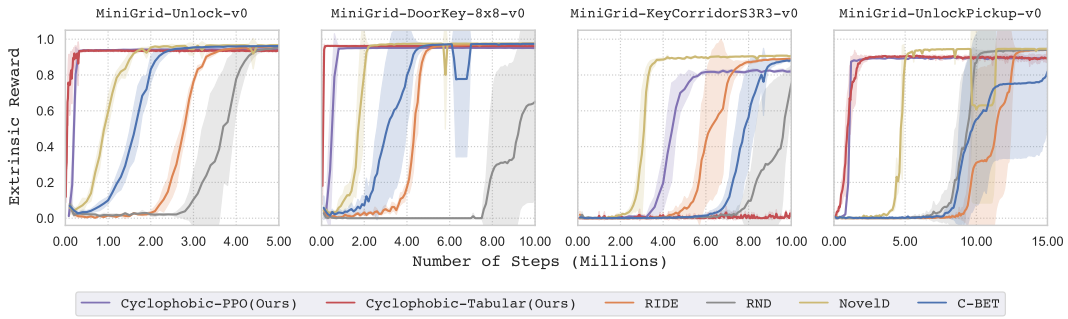

Figure 8: Using PPO together with only the cyclophobic intrinsic reward also converges far quicker than C-BET. Moreover, we are able to converge in KeyCorridorS3R3 confirming our theory in Section 5.1.

We train a PPO agent using only the cyclophobic intrinsic reward. Figure 8 shows that for the given environments the PPO agent also explores more efficiently than C-BET. Furthermore, our theory about observation complexity from 5.1 is supported as the PPO agent is able to solve the "KeyCorridor" environment. Note that these are preliminary results. In future work we seek to implement the hierarchical state representations for the neural agent.

B Environment Details

B.1 MiniGrid Experiments

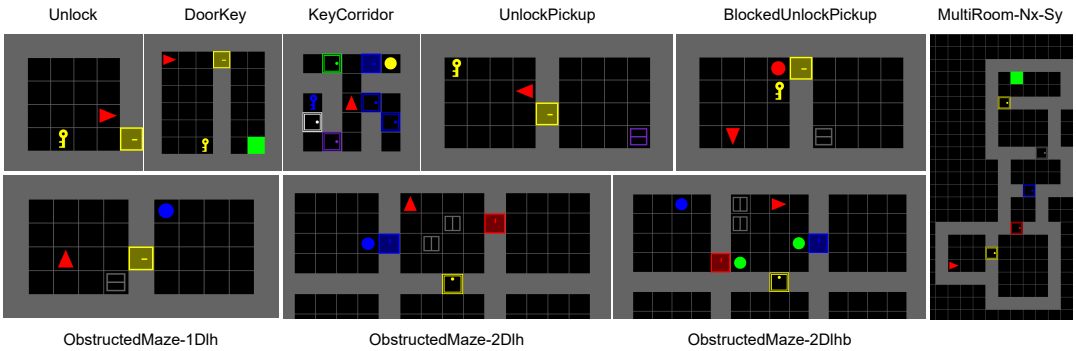

Figure 9: An overview of the MiniGrid environments used in this paper.

We test on some of the same environments as Parisi et al. (2021). In the following we describe the environments as Parisi et al. (2021) and add our own comments where relevant.

- **Unlock**: pick up the key and unlock the door. (288 steps per episode)
- **DoorKey-8x8:** pick up the key, unlock the door, and go to green goal (640 steps per episode)
- **KeyCorridorS3R3:** pick up the key, unlock the door, and pick up the ball (only the door before the ball is locked) (270 steps per episode).

- **UnlockPickup:** pick up the key, unlock the door, and open the box (288 steps per episode).
- **BlockedUnlockPickup:** pick up the ball in front of the door, drop it somewhere else, pick up the key, unlock the door, and open the box (576 steps per episode).
- **ObstructedMaze-1Dlh:** open the box to reveal the key, pick it up, unlock the door, and pick up the ball (288 steps per episode).
- **ObstructedMaze-2Dlh:** same as above, but with two doors to unlock (576 steps per episode).
- **ObstructedMaze-2Dlhb:** same as above, but with two balls in front of the doors (like in BlockedUnblockPickup) (576 steps per episode).
- **MultiRoom-N6:** navigate through six rooms of maximum size ten and go to the green goal (all doors are already unlocked) (120 steps per episode).
- **MultiRoom-N12-S10:** navigate through twelve rooms of maximum size ten and go to the green goal (all doors are already unlocked) (120 steps per episode).

B.2 MiniHack Experiments

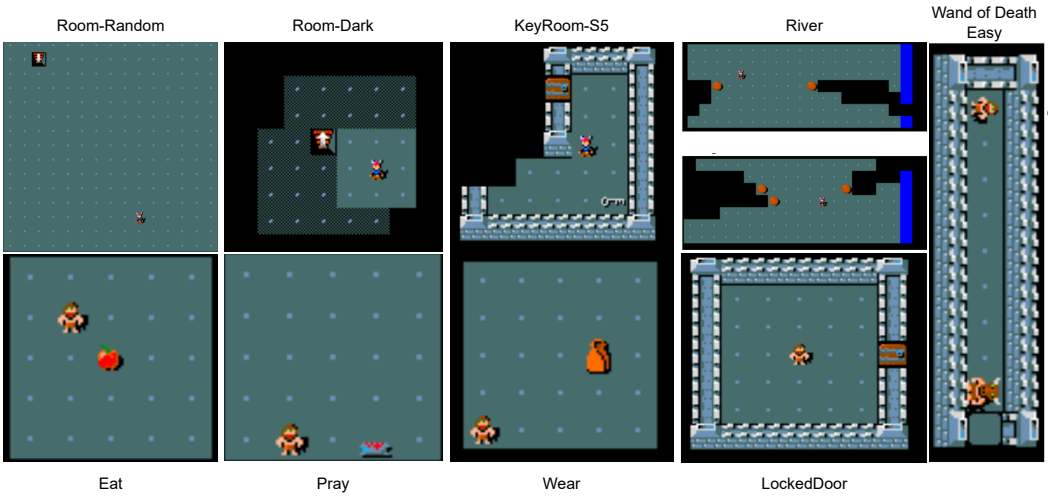

Figure 10: An overview of the Minihack environments tested in this paper. The top row shows the *Navigation* tasks, while the bottom row shows the *Skill* tasks.

We perform experiments inspired by the baselines from Samvelyan et al. (2021). Here, Samvelyan et al. (2021) define a set of navigation and skill acquisition tasks. The navigation tasks range from requiring the agent to navigate an empty room or maze, up to navigating environments with monsters and hazards. The skill acquisition tasks require the agent to perform a certain set of skills to be able to solve the environments.

B.2.1 Navigation tasks

In the following we describe the environments used from the navigation task.

- **Room-Random-15x15:** This task is set in a single square room, where the goal is to reach the staircase down. In the random version of this task, the start and goal positions are randomized.
- **Room-Dark-15x15:** Same as Room-Random, but the agent only sees parts of the environment it has already discovered.

- **KeyRoom-S5:** These tasks require an agent to pick up a key, navigate to a door, and use the key to unlock the door, reaching the staircase down within the locked room. The locations of the door, key and starting position are randomized.

- **River:** The river environment requires the agent to cross a river using boulders. When pushed into the water, they create a dry land to walk on, allowing the agent to cross it.

B.2.2 Skill tasks

The nature of commands in NetHack requires the agent to perform a sequence of actions so that the initial action, which is meant for interaction with an object, has an effect. The exact sequence of subsequent can be inferred by the in-game message bar prompts. Overall, in each of the following tasks the agent has to perform a sequence of actions that allow the agent to perform the required skill.

- **Eat:** The agent has to navigate and eat an apple. Doing so requires a sequence of actions and confirming a prompt to eat the appe.

- **Pray:** The agent has to pray on an altar. This is more complex than eating an apple as praying requires the agent to confirm more prompts.

- **Wear:** The agent has to wear armor. This is a more difficult task than the previous tasks.

- **LockedDoor-Fixed:**The agent has to kick a locked door.

- **Wand of Death-Easy:** The agent starts with a wand of deatch in its inventory and has to zap it towards a sleeping monster. That is, the agent needs to equip the wand of death walk to the monster and zap it.

In all of these environments the positions of the agent and of the object that has to be interacted with are randomised. Furthermore, the complexity is also increased by the confirmation prompts the agent has to answer in order to perform a certain action.

C Experimental Details

C.1 Hyperparameters

Common hyperparameters: In the following we present a table with all hyperparameters used for training the environments. In general, our method has very few hyperparameters. In this case the only really tunable hyperparameters are the step size η, the random action selection coefficient ϵ for epsilon-greedy exploration and the discount γ:

η	γ	Num. views
0.2	0.99	5

In our case we determined experimentally that 5 views is a good number of views for training an agent.

Epsilon-greedy parameter ϵ: While learning with the cyclophobic intrinsic reward we still perform random action from time to time by having an epsilon-greedy action selection. That is, the agent samples a value n from a uniform distribution and selects a random action if this $n < \epsilon$. These are the settings for ϵ for the respective environments:

Environments	ϵ
Unlock	0.1
DoorKey	0.1
KeyCorridor	0.1
UnlockPickup	0.3
MultiRoom-N6	0.1
MultiRoom-N12-S10	0.1
BlockedUnlockPickup	0.3
ObstructedMaze-1Dlh	0.3
ObstructedMaze-2Dlh	0.1
ObstructedMaze-2Dlhb	0.3
All MiniHack	0.3

Intrinsic reward tradeoff ρ: The intrinsic reward tradeoff ρ has the effect that the extrinsic reward gets propagated more when the agent encounters it, which is necessary for more complex environments. ρ is a hyperparameter that can be defined for each environment for best performance.

Environments	ρ
Unlock	1.0
DoorKey	1.0
KeyCorridor	1.0
UnlockPickup	2.0
MultiRoom-N6	2.0
MultiRoom-N12-S10	2.0
BlockedUnlockPickup	5.0
ObstructedMaze-1Dlh	2.0
ObstructedMaze-2Dlh	5.0
ObstructedMaze-2Dlhb	5.0
River	5.0
WOD-Easy	5.0
Eat	2.0
Pray	2.0
Rest of MiniHack	2.0

C.2 PPO Hyperparameters

GAE-*lambda*	0.95
γ	0.99
Batch size	256
Learning rate	0.001
Entropy coefficient	0.01
Value loss coefficient	0.5
Max Grad Normt	0.5
Clipping-ϵ	0.2
RMSProp-ϵ	1e-8
RMSProp-α	0.99

C.3 Plot smoothing

For all 3 runs we show the mean reward and standard deviation smoothed over a sliding window. For our and Samvelyan et al. (2021)'s experiments we use a sliding window of 50000 steps. For the experiments in Parisi et al. (2021) we use a sliding window of 96000 steps as per their experimental setup. The shaded areas are the standard deviation of the mean for 3 runs.