THAT ESCALATED QUICKLY: COMPOUNDING COMPLEXITY BY EDITING LEVELS AT THE FRONTIER OF AGENT CAPABILITIES

Anonymous authors
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ABSTRACT

Given a well-specified task, and enough samples, reinforcement learning (RL) algorithms can produce agents that achieve a high reward. However, a key challenge that limits the utility of RL agents for real-world problems is the agent's subsequent ability to generalize to unseen variations (or levels). To train more robust agents, the field of *Unsupervised Environment Design* (UED) seeks to update both the agent and the distribution over environments, producing a curriculum of increasingly complex levels. Recent progress in UED led to agents capable of systematic generalization within an environment, including transfer to human-designed levels, while also achieving theoretical convergence guarantees. However, learning environment adversaries remains a challenge, while prominent replay-based methods rely on the ability of a random generator to produce a sufficient number of levels with high learning potential. In this paper we instead propose to *evolve* a curriculum, by making edits to previously useful levels. Our approach, which we call *Adversarially Compounding Complexity by Editing Levels* (ACCEL), consistently produces incrementally challenging levels at the frontier of an agent's capabilities, resulting in curricula that start simple but become increasingly complex, leading to agents that can transfer to challenging out-of-distribution environments.

1 INTRODUCTION

Reinforcement learning (RL, Sutton & Barto (1998)) considers the problem of an agent learning from experience in an environment to maximize total (discounted) of reward. The past decade has seen a surge of interest in RL, with high profile successes in games (Vinyals et al., 2019; Berner et al., 2019; Silver et al., 2016; Mnih et al., 2013) and robotics (OpenAI et al., 2019; Andrychowicz et al., 2020). As such, there is tremendous excitement that RL may be a path towards generally capable agents (Silver et al., 2021). However, despite these impressive results, deploying RL agents in the real world remains a challenge (Dulac-Arnold et al., 2019). Notably, strong training performance in simulation may not result in policies that are robust to the many sources of variation in the real world.

Addressing this challenge on the agent side has become an active area of research (Zhang et al., 2021a; Agarwal et al., 2021a; Raileanu & Fergus, 2021), but in this paper we instead focus on the impact of the *training environment* itself, which often has a significant impact on agent performance (Co-Reyes et al., 2020). For example in locomotion tasks, Reda et al. (2020) found that the initial state distribution, survival bonus, reward structure and control frequency had a significant impact on the performance of an agent. Indeed, *curricula* over environments can also influence the generalization performance of the agent Jiang et al. (2021b). Throughout this paper we consider distributions of environments, referring to each individual sample as a *level*. Given a parameterized environment, the simplest approach one can consider is Domain Randomization (DR, Jakobi, 1997; Tobin et al., 2017; Sadeghi & Levine, 2017; Risi & Togelius, 2020; Peng et al., 2017), whereby an agent trains on individual levels uniformly sampled from an underlying environment distribution. It has been shown that training an agent with a DR-type approach can produce agents capable of complex real-world skills (OpenAI et al., 2019). However, the performance of DR is only as good as the sampling distribution available—thus it can be ineffective when the probability of sampling useful levels is low.

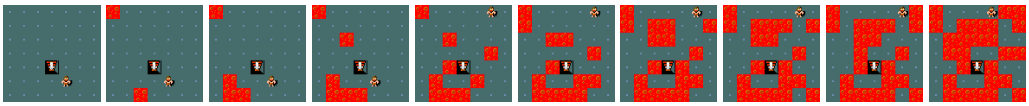


Figure 1: The evolution of a level: At first, the editor places blocks outside the trajectory of the optimal policy, which acts as an augmentation as the agent has a fully observable view. Then, the editor moves the agent further from the goal, before placing challenging obstacles in its path. Note that since the agent can move diagonally in this environment, the final level is solvable. Each level is a high Positive Value Loss at the time it is included in the level store, thus the level co-evolves with the agent over time.

Recently, the field of *Unsupervised Environment Design* (UED, Dennis et al., 2020) has emerged as a general approach to generating effective curricula. Given a parameterized environment, UED methods frame learning as a game between a *teacher* which generates a curriculum of environments, and a *student* agent seeking to maximize some notion of return. UED is a generalization of several other approaches, indeed, DR can be considered as a UED algorithm whereby the teacher generates environments uniformly at random from the environment distribution. Other approaches to UED consider learning a teacher agent (or generator), with a variety of adversarial objectives proposed (Dennis et al., 2020; Gur et al., 2021). However, it is often challenging to learn the generator, given the nonstationarity of the problem and the complexity of building entire environments with a sparse reward signal. Recent work showed it can be more effective to simply *curate* levels produced by DR (Jiang et al., 2021b;a; Matiisen et al., 2020), producing a curriculum of increasingly complex randomly generated levels. Despite the promise, these methods can only be as effective as the random levels they sample, which can be a limitation in high dimensional design spaces. Finally, another series of promising works seek to *evolve* populations of environments (Wang et al., 2019; 2020; Dharna et al., 2020), but these methods heavily rely on handcrafted heuristics while also using up to 20x more compute than training a single agent. In this paper we seek a general method harnessing the benefits of evolution to train a single agent. We posit the following: *Rather than generate levels from scratch, it may be more effective to edit previously curated levels*

Our primary contribution is to propose a new method which we call *Adversarially Compounding Complexity by Editing Levels*, or ACCEL. ACCEL can be seen as an evolutionary process, with levels constantly changing to remain at the frontier of the student agent's capabilities (see: Fig. 2).

As such, an emergent property of the levels generated is that they begin simple but quickly become more complex. This benefits both the beginning of training (Berthouze & Lungarella, 2004), as the student begins learning much faster, while it also facilitates the construction of complex structures (see Fig.1). We believe ACCEL provides the best of both worlds: a principled curation method coming with theoretical guarantees, alongside a mechanism to arbitrarily increase complexity beyond the confines of a fixed budget or parameterization. We evaluate ACCEL on a series of challenging procedurally generated grid world environments, where ACCEL demonstrates the ability to rapidly increase complexity while maintaining performance. Finally, we show that ACCEL makes it possible to train agents capable of transfer to mazes an order of magnitude larger than the training distribution, achieving over double the success rate of the next best baseline.

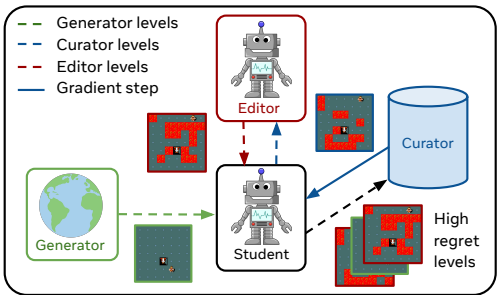


Figure 2: An overview of ACCEL. Levels are (randomly) sampled from a generator, and evaluated, with high regret levels added to the level store. The curator selects levels to replay, which are used to train the student agent. After training, the levels are passed to the editor and the edited levels are added to the level store if they are high regret.This diagram is a work in progress.

2 Background

2.1 From MDPs to Underspecified POMDPs

A Markov Decision Process (MDP) is defined as a tuple $\langle S, A, \mathcal{T}, \mathcal{R}, \gamma \rangle$ where S and A stand for the sets of states and actions respectively and $\mathcal{T} : S \times A \to \mathbf{\Delta}(S)$ is a transition function representing the probability that the system/agent transitions from a state $s_t \in S$ to $s_{t+1} \in S$ given action $a_t \in A$.

Each transition also induces an associated reward r_t generated by a reward function$\mathcal{R} : S \to \mathbb{R}$, and γ is a discount factor. When provided with an MDP, the goal of Reinforcement Learning (RL, Sutton & Barto, 1998) is to learn a policy π that maximizes expected discounted reward, i.e. $\mathbb{E}[\sum_{i=0}^{T} r_t \gamma^t]$.

Despite the generality of the MDP framework, it is often an unrealistic model for real world environments. First, it assumes full observability of the state, which is often impossible in practice. This is addressed in *partially observable* MDPs, or POMDPs, which include an observation function $\mathcal{I} : S \to O$ which maps the true state (which is unknown to the agent) to a (potentially noisy) set of observations O. Secondly, the traditional MDP framework assumes a single reward and transition function, which are fixed throughout learning. Instead, in the real world, agents may experience variations not seen during training, which makes it crucial that policies are capable of robust transfer.

To address both of these issues, we use the recently introduced *Underspecified* POMDP, or UPOMDP, given by $\mathcal{M} = \langle A, O, \Theta, S^{\mathcal{M}}, \mathcal{T}^{\mathcal{M}}, \mathcal{I}^{\mathcal{M}}, \mathcal{R}^{\mathcal{M}}, \gamma \rangle$. This definition is identical to a POMDP with the addition of Θ to represent the free-parameters of the environment. These parameters can be distinct at every time step and incorporated into the transition function $\mathcal{T}^{\mathcal{M}} : S \times A \times \Theta \to \mathbf{\Delta}(S)$. Following Jiang et al. (2021a) we define a *level* $\mathcal{M}_\theta$ as an environment resulting from a fixed θ. We define the value of π in $\mathcal{M}_\theta$ to be $V^\theta(\pi) = \mathbb{E}[\sum_{i=0}^{T} r_t \gamma^t]$ where r_t are the rewards achieved by π in $\mathcal{M}_\theta$. UPOMDPs benefit from their generality, since Θ can represent possible dynamics (for example in sim2real (Peng et al., 2017; OpenAI et al., 2019; Andrychowicz et al., 2020)), changes in observations, different reward functions or differing game maps in procedurally generated environments.

2.2 Methods for Unsupervised Environment Design

The goal of Unsupervised Environment Design (UED, Dennis et al., 2020) is to generate a series of levels that form a curriculum for a student agent, such that the student agent is capable of transfer, by maximizing some utility function $U_t(\pi, \theta)$. In the case of domain randomization, the utility function is simply:

$$U_t^U(\pi, \theta) = C \tag{1}$$

for any constant C. When learning a teacher, recent approaches proposed to use objectives seeking to maximize *regret*, defined as the difference between the expected return of the current policy and the optimal policy, ie:

$$U_t^R(\pi, \theta) = \underset{\pi^* \in \Pi}{\operatorname{argmax}}\{\textsc{Regret}^\theta(\pi^*, \pi)\} = \underset{\pi^* \in \Pi}{\operatorname{argmax}}\{V^\theta(\pi^*) - V^\theta(\pi)\} \tag{2}$$

Unlike other objectives, which may promote unsolvable environments, regret-based objectives have been shown to promote the simplest possible environments that the agent cannot currently solve (Dennis et al., 2020). However, since we do not have access to π^*, a key challenge in UED algorithms utilizing objectives inspired by Equation 2 is to *approximate* the regret. Recently, the *Prioritized Level Replay* (PLR, Jiang et al., 2021b;a) algorithm introduced an additional teacher agent in the form of a *curator*, forming a "dual curriculum game". The curator maintains a buffer of previously experienced levels and actively selects levels to be replayed by the student policy using objectives approximating regret. One of the objectives used by PLR is *Positive Value Loss*, given by:

$$\frac{1}{T}\sum_{t=0}^{T} \max\left(\sum_{k=t}^{T} (\gamma\lambda)^{k-t}\delta_k, 0\right) \tag{3}$$

where λ and γ are the GAE (Schulman et al., 2016) and MDP discount factors respectively, and δ_t, the TD-error at timestep t. Since Positive Value Loss approximates regret, if the student trains solely on curated levels (i.e. does not take gradient steps on levels from the generator), then PLR achieves robustness guarantees. More formally, if $S_t = \Pi$ is the strategy set of the student and $S_t = \Theta$ is the strategy set of the teacher (in this case the curator), then (by Corollary 1 of Jiang et al. (2021a)), in equilibrium the resulting student policy converges to a minimax regret policy, ie:

$$\pi \in \underset{\pi_A \in \Pi}{\operatorname{argmax}}\{\min_{\theta, \pi_B \in \Theta, \Pi}\{\textsc{Regret}^\theta(\pi_A, \pi_B)\}\} \tag{4}$$

PLR not only leads to robustness in equilibria but also empirically produces policies with strong generalization capabilities. Next, we introduce our new approach which seeks to leverage the curator to produce batches of high regret levels.

3 COMPOUNDING COMPLEXITY BY EDITING LEVELS

In this section we propose a new method that helps produce more effective curricula in complex design spaces, inspired by a variety of sources, including regret-based UED methods and evolution. Many previous works have emphasized the importance of training on levels at the "frontier" of difficulty (Wang et al., 2019; Jiang et al., 2021b; Zhang et al., 2020). This is often implemented via heuristics, for example, POET pre-filters levels using handcrafted criteria to have a reward in the range $[50, 300]$. Instead, we seek a more general approach and follow the *Value Correction Hypothesis* from Jiang et al. (2021b), using the Positive Value Loss to assess learning potential. To see the impact of PLR on a simple example, we include a visualization in 13 in the Appendix. Indeed, it is critically important that the agent experiences frontier levels to learn efficiently, which may be a challenge as the dimensionality of the design space increases—a problem we call "the curse of dimensionality in UED". However, if it is possible to *edit* levels, then it may be possible to produce an entire batch of useful levels from a single example.

We now introduce our new algorithm, which we call *Adversarially Compounding Complexity by Editing Levels*, or ACCEL. The key idea of ACCEL is to introduce an *editor*, which produces new levels for the agent by making edits to levels sampled by the curator. Indeed, ACCEL can be seen an evolutionary process, whereby the "fitness" function is (approximate) regret, since levels only stay in the "population" (or level replay buffer) if they meet the criteria for curation. Evolution has led to many successes in other domains (Stanley et al., 2019; Pugh et al., 2016), and even proven useful for UED with the POET algorithm. In contrast to POET, ACCEL only trains a *single agent*, compared to a population of twenty. This has the benefit of having $20\times$ lower computational cost while also producing a single generally capable agent. In addition, POET uses an approximate minimax adversarial objective (as opposed to minimax *regret*) which produces unsolvable environments (Dennis et al., 2020), and thus requires heuristics to succeed in the original paper.

Algorithm 1 ACCEL (changes vs. Robust PLR)

Input: Buffer size K, initial fill ratio ρ.
Initialize: Initialize policy $\pi(\phi)$, level buffer, Λ.
 # Initial Data Collection
Sample $K * \rho$ initial levels.
 # Main Training Loop
while *not converged* **do**
  Sample replay decision $d \sim P_D(d)$
  if $d = 0$ **then**
    Sample level θ from level generator
    Collect π's trajectory τ on θ, with a stop-gradient $\phi_\perp$
    Compute PLR score, $S^P = \textbf{score}(\tau, \pi)$
    Update Λ with θ using score S^P
  else
    Sample a replay level, $\theta \sim \Lambda$
    Collect policy trajectory τ on θ
    Update π with rewards $R(\tau)$
    Edit Levels, to produce θ'
    Collect π's trajectory τ on θ', with a stop-gradient $\phi_\perp$
    Compute PLR score, $S^P = \textbf{score}(\tau, \pi)$
    Update Λ with θ' using score S^P
    (Optionally) Update Editor using score S^P
  end
end

We consider both a learned editor, optimizing for Positive Value Loss (Equation 3), and a random one. Like with robust PLR from Jiang et al. (2021a) we do not take gradient steps on the edited level. Instead, we evaluate them and add them to the replay buffer for curation if they meet the threshold for the scoring function. Finally, we consider two criteria for editing levels, both applied to the most recent replay batch: "easy" where we edit the levels which have the highest return and lowest approximate regret, essentially those which the agent can solve with low future learning potential, and "batch" where we use the entire batch. The full procedure is shown in Algorithm 1.

We posit that editing is effective for two reasons. First, in some cases, a small incremental change to an environment can lead to dramatic changes in their characteristics (Sturtevant et al., 2020), which may move those that are currently too hard or too easy towards the frontier of the agent's capabilities. This may also prevent overfitting, for example in Fig.3 we see three levels generated by ACCEL in the MiniGrid environment. Each is an edit of the same level and requires the agent to explore in a different fashion. Training on these environments simultaneously will teach the agent to actively explore the environment, backtracking where necessary to find the goal. Second, making edits *outside* of the direct trajectory

Figure 3: Levels generated by ACCEL. Though all levels are evolved from the same DR level, they require different behaviors to solve. Left: the agent can go up or left and reach the goal. Middle: the goal is on the left, while on the right the left path is blocked so the agent must backtrack if it goes left.

of the agent can be seen as a form of data augmentation, which has been shown to improve sample efficiency in RL (Laskin et al., 2020; Kostrikov et al., 2021; Raileanu et al., 2020).

A key benefit in comparison to prior work is that since we are building upon the robust version of PLR (Jiang et al., 2021a), our approach maintains the same theoretical guarantees:

Remark 1. *If the procedure described in Algorithm 1 finds a Nash equilibrium, then the student policy is following a minimax regret strategy.*

Note that this is a somewhat trivial remark: since we do not train on levels produced by the editor, the procedure resembles PLR$^{\perp}$ from Jiang et al. (2021a), thus inherits the guarantees from Corrollary 3.3 (in Jiang et al. (2021a)). Nonetheless, this is in stark contrast with other evolutionary approaches, which rely solely on empirical results. We are now ready to test ACCEL in practice.

4 Experiments

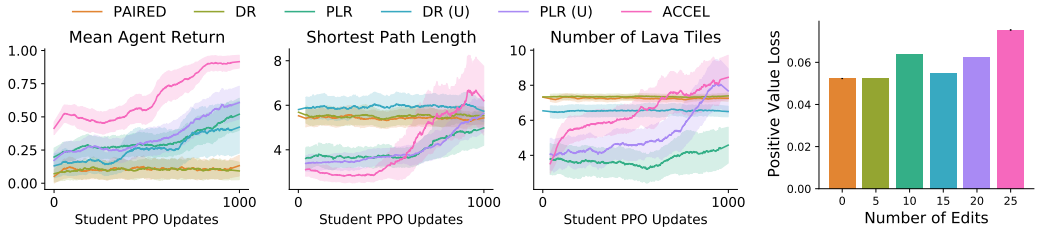
In our experiments we seek to answer the following two questions: 1) Can ACCEL lead to sample efficient learning in complex design spaces? 2) Can ACCEL compound complexity to asymptotically produce agents capable of solving challenging human-designed environments? We conduct a series of experiments in grid world environments, as have been used in previous UED works (Dennis et al., 2020; Jiang et al., 2021a). These environments are made challenging by high dimensional observations and sparse rewards, thus they are often used to test state-of-the-art exploration methods (Raileanu & Rocktäschel, 2020; Zhang et al., 2021b; Flet-Berliac et al., 2021).

In all cases, we seek to train a student agent via Proximal Policy Optimization (PPO, Schulman et al., 2016-2018), with a ResNet policy (He et al., 2016) as originally proposed in Espeholt et al. (2018). To evaluate the quality of the curricula, we show all performance with respect to the number of student gradient updates as opposed to total environment interactions, which is often comparable for PLR and ACCEL. For a full list of hyperparameters for each experiment please see Table 6 in Section B.3. As baselines we consider the following:

- **Domain Randomization (DR)**: Randomly sampling from a parameterized distribution.
- **Prioritized Level Replay (PLR)**: We use Robust PLR from Jiang et al. (2021a).
- **PAIRED**: Placing a given number of blocks, using the algorithm described in Dennis et al. (2020).
- **Minimax Adversarial**: Placing blocks using an adversarial objective seeking to minimize return.

As in Dennis et al. (2020) we use a single minimax agent to demonstrate the flaws in the POET objective when it is not combined with hand-coded constraints on the levels generated. We leave the comparison to population-based methods to future work due to the computational expense.

4.1 Learning with Lava



(a) **Training Complexity** (b) **Edit Efficacy**

Figure 4: Lava grid training data. a) Left to right: mean agent return on training levels, the shortest path length and the number of lava tiles, plots show mean and sem. b) Positive Value Loss by number of edits for ACCEL.

We begin with a simple grid environment, whereby the agent must navigate to a goal in the presence of lava blocks. The grid is small, only 7x7, however, it is challenging for RL agents since exploring with random actions often leads to instant death, which makes it challenging to receive feedback via the sparse reward. Indeed, this makes the choice of DR parameterization crucial, since sampling too

many blocks early on will be prohibitive for learning. We compare two different parameterizations: "Binomial" where the agent samples from {lava, none} for 20 steps, and "Uniform" where the agent samples the number of tiles to place from the range [0,20]. For ACCEL, we use a generator that produces empty rooms and then proceed to edit the levels to add (or remove) lava blocks. The environment is built with MiniHack, thus the agent has a global observation (details in the Appendix, Section: B.1). We ran each method for five seeds, showing the results in Fig 4.

As we see, ACCEL quickly produces levels with more lava than the other methods, while also getting near-perfect return on its training distribution. Interestingly, with the Uniform parameterization, we see that PLR is able to produce a similar training profile to ACCEL, but achieves a lower value in every individual metric. The methods with learned generators (PAIRED and minimax) fail to learn anything, thus are unable to form a curriculum (Fig. 4). Finally on the right we took a snapshot of the level replay buffer for ACCEL, where we clearly see that the levels which have been edited more have higher approximate regret. After one thousand PPO updates (around 20M timesteps) we tested each agent on a series of test tasks, which we show in the Appendix (see Section A.2). We thus have answered our first question: in a design space with a high proportion of challenging levels, ACCEL is able to build an effective curriculum which quickly facilitates learning on the full distribution.

4.2 Partially Observable Navigation

To answer the second question, we now scale to a larger environment, using the MiniGrid (Chevalier-Boisvert et al., 2018) setting originally introduced in Dennis et al. (2020). Despite being a conceptually simple environment, this is a large scale experiment: our agents train for 20k updates (around 350M steps, see Table5), learning a recurrent policy with a 147 dimension partially observable observation. As such, the maze environment has become a prominent benchmark for UED algorithms (Dennis et al., 2020; Jiang et al., 2021a). In previous works, DR used the "fixed" parameterization, which Jiang et al. (2021a) showed that DR is particularly sensitive to the number of blocks placed. Instead, we use the Uniform parameterization which first samples the number of blocks to place, ranging from zero (an empty room) to sixty. We use the same generator for DR, PLR and ACCEL. We also consider a version of which begins with empty rooms, as in the lava environment. For both versions of ACCEL we edit the block locations (adding or removing them) as well of the goal location. After replay, we edit the "easy" levels, essentially moving levels back to the frontier once their learning potential has been reduced.

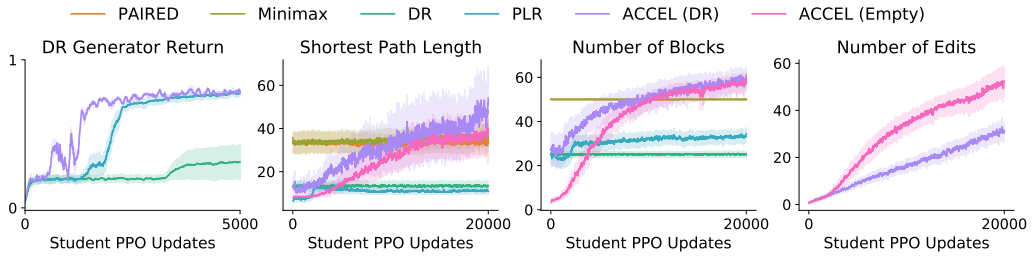


Figure 5: MiniGrid training data. From left to right: the performance of all agents on the DR generator, the shortest path length and number of blocks on training levels, and the weighted number of edits in the buffer for ACCEL. Plots show the mean and standard error across five runs.

In Fig.5 we show the training performance, where ACCEL does exactly as intended—it compounds initial complexity to quickly train agents capable of performing well on the full distribution. Indeed, ACCEL learns more efficiently on the DR distribution than DR and PLR, the agents that explicitly train on it. Meanwhile, ACCEL produces more levels with more blocks and longer paths to the goal. Inevitably, we see that the edited levels take an increasing share of the replay buffer. After 20k training steps, we evaluate the agents zero-shot on a series of held-out environments as used in prior works (see Fig.12), with the performance shown in Fig.6. We include bars showing the mean and sem for each envronment, as well as the aggregate performance using the recently introduced `rliable` Agarwal et al. (2021b). As we see, both versions of ACCEL performs at least as well as the next best baseline in almost all settings, with notable outperformance on the more complex Labyrinth and Maze environments. This translates to significantly stronger performance at the aggregate level, with an IQM near 100% solved rate compared to below 80% for all baselines.

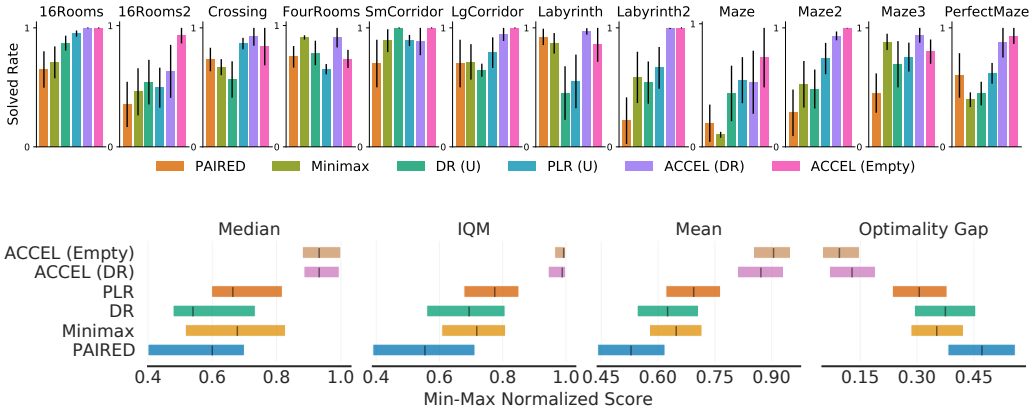
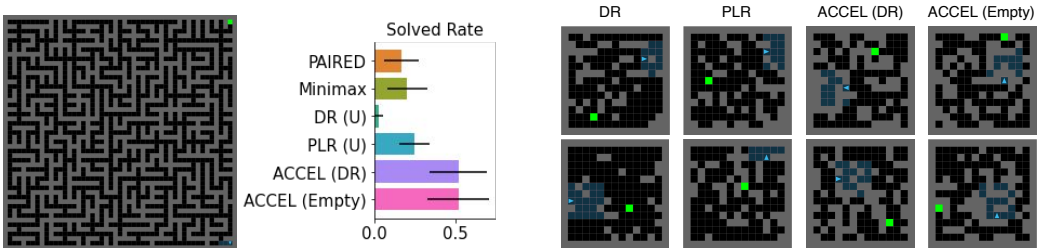


Figure 6: Zero-shot transfer results after 20k PPO updates. Agents are evaluated for 100 episodes on a series of human designed mazes. Top row: mean and standard error for each environment, across five runs. Bottom row: aggregate performance metrics.



(a) **PerfectMazeLarge** (b) **Example Levels**

Figure 7: a) Zero-shot performance on a large procedurally-generated maze environment. Agents are evaluated for 100 episodes, bars show mean and standard error. b) Example levels produced by each UED algorithm.

Next we consider a significantly more challenging environment—we use a larger version of the "PerfectMaze", a procedurally-generated maze environment, shown in Fig.7.a). The maze is a 51x51 grid, an order of magnitude larger than the training environments, and we use a maximum episode length of over 5k steps. This represents a daunting navigation challenge, requiring extensive use of memory so as not to get lost in a loop of repeatedly exploring the same paths. We evaluate the agents at the 20k checkpoint, testing each seed for 100 episodes, showing the mean and standard error in Fig.7.a). As we see, ACCEL significantly outperforms all baselines, achieving 52% success rate compared to the next best 25% for PLR.

In Fig.7.b) we show example levels from each method, where we see that ACCEL produces more complex mazes with higher block count, regardless of the DR generator used.[1] Note that PLR is capable of sampling 60 block levels, but it will infrequently sample those that also contain a useful (solvable) path to the goal, whereas ACCEL can produce entire batches of challenging levels by editing previously complex ones. For additional ablations see the Appendix (see Section A.3).

4.3 Discussion and Limitations

In our experiments we have demonstrated that ACCEL is capable of forming highly effective curricula in two challenging navigation environments. In the first, we showed ACCEL can facilitate learning in challenging design space with a high proportion of hard levels, which could have an impact in improving exploration in safety-critical settings. In the second, we showed it is possible to produce complex mazes which facilitate generalization to human-designed ones, scaling to mazes an order of magnitude larger than the training levels. We thus believe ACCEL would be an effective method for training agents in more open-ended UED design spaces.

However, as with any method, ACCEL comes with limitations. In the lava experiments, our approach includes an inductive bias with the ability to begin with a simple base case (an empty room). This

[1]For more details see `https://sites.google.com/view/compoundingcomplexity`

may not always be possible in practice, while in some cases the simple case (in terms of entities placed in the environment) may actually be a more difficult environment to solve (for example in a Hide and Seek game). In addition, our experiments thus far only consider navigation tasks. The MiniGrid experiments we include here are one of the largest settings used in UED, but for the field more broadly to become useful for real-world problems it will be necessary to test new environments.

On the algorithmic side, a potential limitation of ACCEL is that there may be a lack of diversity in the level replay buffer. In this work we do not explicitly optimize for diversity, but instead, seek to reduce the impact through changing level replay hyperparameters. For example, we continue to sample DR levels during training and for the lava experiments we also use a larger buffer. We demonstrate the impact of these design choices in the Appendix (see: Fig 15). We thus believe in order to scale ACCEL further it will be crucial to include a mechanism to encourage diversity.

5 Related Work

Our work straddles a variety of interrelated fields, which we discuss in this section. For a summary of the most closely related methods see Table 1. Our paper focuses on testing agents on distributions of environments, which has long been known to be crucial to evaluate the generalization capability of RL agents (Whiteson et al., 2009). The failure of agents in this setting has recently drawn considerable attention (Packer et al., 2019; Igl et al., 2019; Cobbe et al., 2020; Agarwal et al., 2021a; Zhang et al., 2018b; Ghosh et al., 2021), with policies often failing to adapt to changes in the observation (Song et al., 2020), dynamics (Ball et al., 2021) or reward (Zhang et al., 2018a). In this work, we seek to provide agents with a set of training levels to produce a policy that is robust to these variations.

In particular, we focus on the *Unsupervised Environment Design* (UED, Dennis et al., 2020) paradigm, which shifts from designing agents that can generalize from a fixed distribution of environments towards designing the environments themselves. The most popular method for UED is Domain randomization (DR, Jakobi, 1997; Sadeghi & Levine, 2017) which has been particularly successful in areas such as robotics (Tobin et al., 2017; James et al., 2017; Andrychowicz et al., 2020; OpenAI et al., 2019). This work directly extends *Prioritized Level Replay* (PLR, Jiang et al., 2021b;a), a method for curating DR levels such that those with high learning potential can be replayed a student agent. PLR is related to TSCL (Matiisen et al., 2020), self-paced learning (Klink et al., 2019; Eimer et al., 2021) and ALP-GMM Portelas et al. (2019), which seek to maintain and update distributions over environment parameterizations. Very recently it was shown that with a smooth task space, a method similar to PLR is capable of producing generally capable agents in a simulated game world (Team et al., 2021), using large scale compute and Population-Based Training (Jaderberg et al., 2017). However, this work relied on a highly optimized task design space, which is rarely present in practice.

Dennis et al. (2020) introduced the PAIRED algorithm, an elegant approach for UED, whereby an environment adversary optimizes for *minimax regret* (Savage, 1951), defined as the difference in performance between an antagonist agent (colluding with the adversary) and the protagonist. This guarantees the adversary produces solvable mazes, which allows the protagonist to transfer to unseen environments and even learn to navigate the web (Gur et al., 2021). Adversarial objectives have also been considered in robotics (Pinto et al., 2017). POET (Wang et al., 2019; 2020) considers evolving a *population* of environments, each paired with an agent, using an objective similar to minimax adversarial, which needs to be combined with domain-specific rules to prevent unsolvable environments from being proposed. We take inspiration from the evolutionary nature of POET but train a *single agent*, which is beneficial as it takes significantly fewer resources, while also removing the agent selection problem.

UED is inherently related to the field of *Automatic Curriculum Learning* (ACL, Portelas et al., 2020; Florensa et al., 2017; Baranes & Oudeyer, 2009), which seeks to provide a curriculum of increasingly challenging tasks or goals given a (typically) fixed environment. A canonical approach is Hindsight Experience Replay (Andrychowicz et al., 2017) which was shown to be effective for sparse reward tasks. Asymmetric Self Play (Sukhbaatar et al., 2018) takes the form of one agent proposing goals for another, which was shown to be effective for challenging robotic manipulation tasks (OpenAI et al., 2021). AMIGo (Campero et al., 2021) and APT-Gen (Fang et al., 2021) provide solutions to problems where the target task is known, providing a curriculum of increasing difficulty. Indeed, many ACL methods emphasize learning to reach goals or states with high uncertainty (Racaniere et al., 2020; Pong et al., 2020; Zhang et al., 2020), either using generative (Florensa et al., 2018) or

Table 1: The components of related approaches. Like POET, we evolve levels, but use a single agent rather than a population, while also using a minimax regret objective, which ensures the environments generated are solvable. PAIRED uses minimax regret for the generator, which is often challenging to optimize, while it does not replay levels so may suffer from cycling. Finally, PLR curates levels using minimax regret, but relies solely on domain randomization for generation.

Algorithm	**Generation Strategy**	**Generator Obj**	**Curation Obj**	**Setting**
POET (Wang et al., 2019)	Evolution	Minimax	MCC	Population-Based
PAIRED (Dennis et al., 2020)	Reinforcement Learning	Minimax Regret	None	Single Agent
PLR (Jiang et al., 2021b;a)	Random Search	None	Minimax Regret	Single Agent
ACCEL	Evolution	Minimax Regret	Minimax Regret	Single Agent

world models (Mendonca et al., 2021). Unlike these methods, UED approaches seek to fully specify environments, rather than just goals within a fixed environment.

In the symbolic AI community, *environment design* has been considered as a means to alter an environment to influence an agent's decisions (Zhang & Parkes, 2008; Zhang et al., 2009). This was extended with automated design (Keren et al., 2017; 2019), which seeks to redesign environments given the limitations of agents, to improve their performance. Unlike these works, ACCEL seeks to automatically design environments in order to produce a curriculum for a learned agent.

Our work also closely relates to the field of *Procedural Content Generation* (PCG, Risi & Togelius, 2020; Justesen et al., 2018), where levels are sampled from a distribution. Popular PCG settings include the Procgen Benchmark (Cobbe et al., 2020), MiniGrid (Chevalier-Boisvert et al., 2018), Obstacle Tower (Juliani et al., 2019), GVGAI (Perez-Liebana et al., 2019) and the NetHack Learning Environment (Küttler et al., 2020). This work uses the recently proposed MiniHack environment (Samvelyan et al., 2021), which provides a flexible framework for creating diverse environments. Within the PCG community, automatically generating game levels has been of interest for more than a decade (Togelius & Schmidhuber, 2008). More recently, machine learning has proven to be effective (Summerville et al., 2018; Bhaumik et al., 2020; Liu et al., 2021). Related to our work, PCGRL (Khalifa et al., 2020; Earle et al., 2021a) framed level design as an RL problem, designing environments by making incremental changes. However, it makes use of hand-designed dense rewards, and focuses on the design of levels for *human* players. By contrast, ACCEL seeks to train a student agent and does not require domain-specific feedback.

6 Conclusion and Future Work

In this paper we proposed a new method for Unsupervised Environment Design (UED), ACCEL, which evolves a curriculum by *editing* previously curated levels. This makes it possible to constantly generate a wide variety of environments at the frontier of the agent's capabilities, producing curricula that start simple and quickly compound. We believe ACCEL offers the best of both worlds: a principled regret-based curriculum that does not require domain-specific heuristics, alongside an evolutionary process that produces a broad spectrum of complexity catering to the agent's current capabilities. In our experiments we showed that ACCEL is capable of efficiently training agents that can transfer to a series of human-designed environments, outperforming competitive baselines.

For future work, it may be possible to use ideas from Neural Cellular Automata to enhance the editing process (Earle et al., 2021b), possibly making use of controllable editors that can boost specific properties of levels (Earle et al., 2021a). We could also consider generative modelling approaches to level editing, training on PLR levels to produce new frontier levels. We did not explore methods to encourage levels to be diverse, but this would likely be important for larger-scale experiments. Another possibility is to actively seek levels which have high "Evolvability" (Gajewski et al., 2019). This could be increased by introducing so-called "extinction events" (Raup, 1986), which have been shown to increase Evolvability (Lehman & Miikkulainen, 2015) and are believed to play a crucial role in natural evolution. Equipped with some of these ideas, we could go significantly further towards open-endedness (Earle et al.). We believe it may be possible to increase the search space such that MiniHack can make broader use of the richness of the NetHack world, possibly aiding us in making progress in the full game of Nethack—a grand challenge in reinforcement learning.

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A ADDITIONAL EXPERIMENTAL RESULTS

A.1 LEVEL EVOLUTION

In Fig 8 and 9 and we show additional levels produced by ACCEL for the MiniHack lava environment and MiniGrid mazes respectively. Note that in all cases, each incremental step along the evolutionary process produces a level that has high learning potential *at that point in time*.

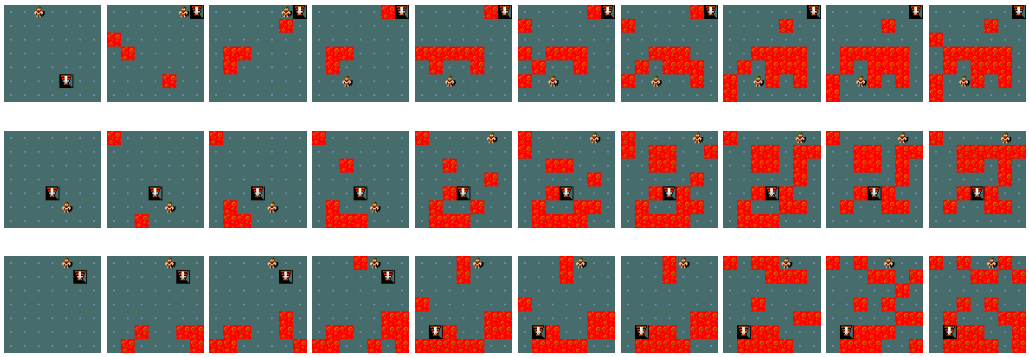

Figure 8: Levels generated by ACCEL. Note that in all cases, each individual level along the evolutionary path is at the frontier for the student agent at that stage of training. As we can see, the edits compound to produce a series of challenges: in the first level the lava gradually surrounds the agent, such that they can initially explore in multiple directions but at the end the task can only be solved by going down and to the right. In the middle row we see a level where the agent always has a direct run at the goal, but a corridor is evolved over time to become increasingly narrow, before being filled in so the agent has to go around. Finally in the bottom row the level begins with simple augmentations before moving the agent behind a barrier, which results in a challenging task where the agent has to move in a diagonal direction to escape the lava.

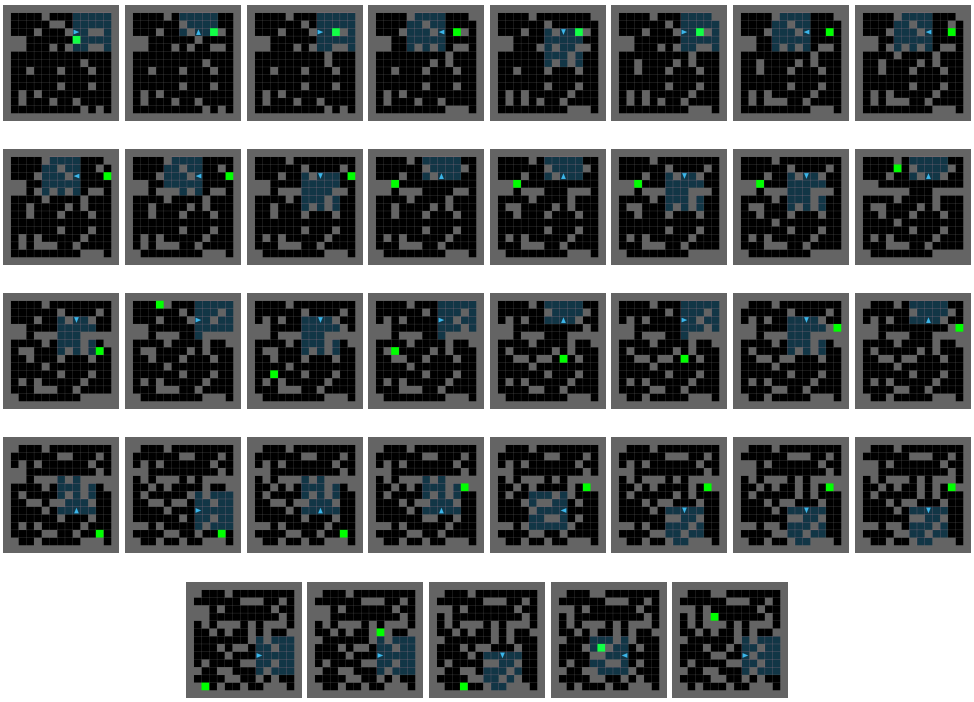

Figure 9: A single level evolved in the MiniGrid environment, starting from top left, ending bottom right. Note that in this setting we begin with levels sampled from the Uniform DR distribution.

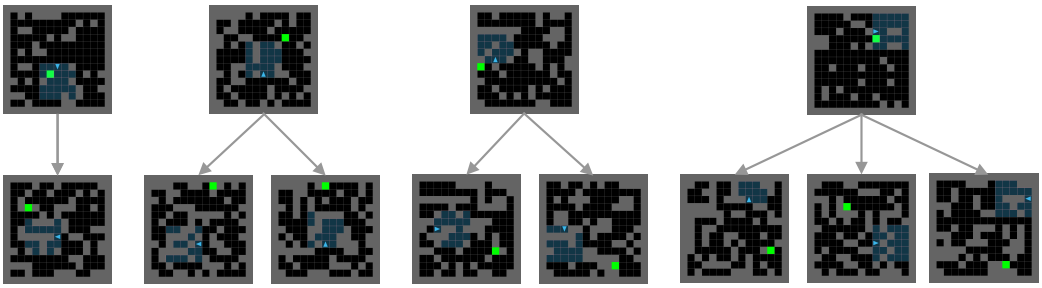

Figure 10: Maze evolution. Top row shows starting DR levels, originally included in the replay buffer due to having high positive value loss. After many edits (up to 40), they produce the bottom row, which were all chosen to be in the highest 50 replay scores after 10k gradient steps. As we see, the same DR level can produce distinct future levels, in some cases multiple high regret levels.

A.2 Full Experimental Results

Lava Grid Extended Results In Table 2 and Fig. 11 we include the full results for the MiniHack lava experiments. The first three (Empty, 10 Tiles and 20 Tiles) evaluate the performance of the agent within its training distribution, while we also include a held-out human designed environment, LavaCrossing S9N1, ported from MiniGrid Chevalier-Boisvert et al. (2018). As we see, ACCEL performs best on all of the in sample environments, while also being only one of two approaches to get meaningfully above zero in the human designed task.

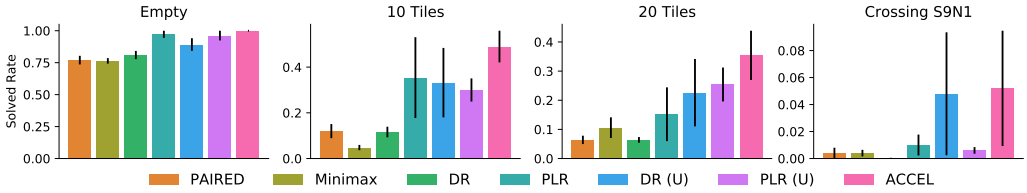

Figure 11: Test performance, both in distribution (Empty, 10 and 20 Tiles) and out of distribution (Crossing S9N1). Each evaluation is conducted for 100 trials. Plots show the mean and standard error across five runs.

Table 2: Test performance in four environments. Each data point corresponds to the mean (and standard error) of five independent runs, where each run is evaluated for 100 trials on each environment. † indicates the generator distribution is a Binomial, whereby the generator can place 20 blocks, each is either a lava tile or empty. ‡ indicates the generator first samples the number of lava tiles to place, between zero and 20, then places that many. Bold indicates being within one standard error of the best mean.

Test Environment	PAIRED	Minimax	DR†	PLR†	DR‡	PLR‡	ACCEL
Empty	0.77 ± 0.03	0.76 ± 0.02	0.81 ± 0.03	0.97 ± 0.03	0.89 ± 0.05	0.96 ± 0.04	$\mathbf{1.0 \pm 0.0}$
10 Tiles	0.12 ± 0.03	0.05 ± 0.01	0.12 ± 0.02	0.35 ± 0.18	0.33 ± 0.15	0.3 ± 0.05	$\mathbf{0.49 \pm 0.07}$
20 Tiles	0.06 ± 0.01	0.11 ± 0.04	0.06 ± 0.01	0.15 ± 0.09	0.23 ± 0.12	0.25 ± 0.06	$\mathbf{0.35 \pm 0.08}$
LavaCrossing S9N1	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.01 ± 0.01	$\mathbf{0.05 \pm 0.05}$	0.01 ± 0.0	$\mathbf{0.05 \pm 0.04}$

Partially-Observable Navigation Next we show the extended results for the MiniGrid experiments. We use a series of challenging zero-shot environments (see Fig. 12), introduced in the UED literature (Dennis et al., 2020; Jiang et al., 2021a). We include a full table of zero-shot transfer performance for both 10k and 20k PPO updates in Table 3.

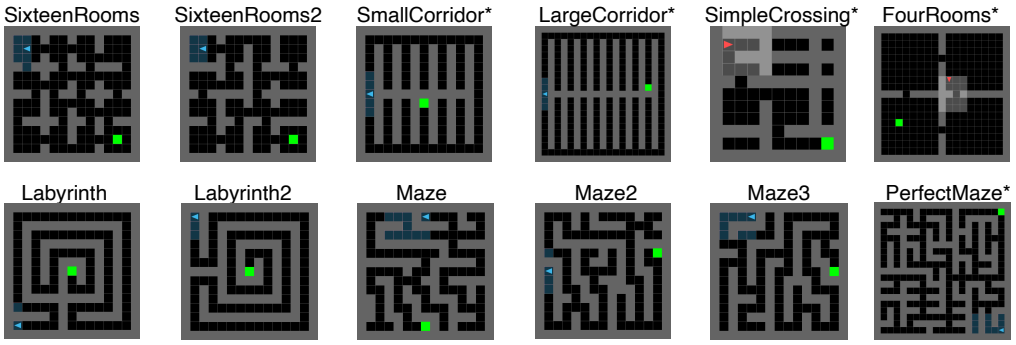

Figure 12: MiniGrid Zero-Shot Environments. Those with an asterisk are procedurally generated: For Small and Large Corridor, the position of the goal can be in any of the corridors, for SimpleCrossing and Four Rooms see Chevalier-Boisvert et al. (2018) and for PerfectMaze see Jiang et al. (2021a).

Table 3: Zero-Shot transfer to human-designed environments. Each data point corresponds to the mean (and standard error) of five independent runs, where each run is evaluated for 100 trials on each environment. † indicates the generator first samples the number of blocks to place, between zero and sixty, then places that many. ‡ indicates the generator produces empty rooms. Bold indicates being within one standard error of the best mean. $\star$ indicates $p < 0.05$ in Welch's t-test against PLR.

Updates	**Environment**	PAIRED	Minimax	DR†	PLR†	ACCEL†	ACCEL‡
10k	16Rooms	0.66 ± 0.17	0.37 ± 0.16	0.34 ± 0.2	0.93 ± 0.04	$\mathbf{1.0 \pm 0.0}$	0.94 ± 0.05
	16Rooms2	0.17 ± 0.06	0.11 ± 0.06	0.02 ± 0.02	$\mathbf{0.52 \pm 0.12}$	$\mathbf{0.51 \pm 0.28}$	$\mathbf{0.64 \pm 0.14}$
	SimpleCrossing	0.5 ± 0.12	0.63 ± 0.14	0.36 ± 0.07	$\mathbf{0.85 \pm 0.04}$	$\mathbf{0.8 \pm 0.05}$	$\mathbf{0.83 \pm 0.08}$
	SmallCorridor	0.82 ± 0.16	0.63 ± 0.2	0.39 ± 0.18	$\mathbf{0.96 \pm 0.02}$	0.72 ± 0.1	0.58 ± 0.13
	LargeCorridor	0.8 ± 0.18	0.59 ± 0.21	0.26 ± 0.19	$\mathbf{0.94 \pm 0.02}$	$\mathbf{0.91 \pm 0.05}$	0.56 ± 0.15
	Labyrinth	0.03 ± 0.02	0.27 ± 0.18	0.18 ± 0.18	0.53 ± 0.17	$\mathbf{0.98 \pm 0.02}$	0.61 ± 0.24
	Labyrinth2	0.13 ± 0.07	0.0 ± 0.0	0.0 ± 0.0	0.66 ± 0.17	$\mathbf{0.97 \pm 0.03}$	0.62 ± 0.24
	Maze	0.45 ± 0.18	0.0 ± 0.0	0.0 ± 0.0	0.31 ± 0.09	$\mathbf{0.78 \pm 0.21}$	0.51 ± 0.15
	Maze2	0.03 ± 0.03	0.01 ± 0.01	0.0 ± 0.0	$\mathbf{0.41 \pm 0.14}$	$\mathbf{0.5 \pm 0.24}$	$\mathbf{0.47 \pm 0.18}$
	Maze3	0.22 ± 0.2	0.19 ± 0.1	0.17 ± 0.11	$\mathbf{0.83 \pm 0.07}$	$\mathbf{0.79 \pm 0.14}$	$\mathbf{0.75 \pm 0.11}$
	PerfectMaze (M)	0.45 ± 0.17	0.27 ± 0.16	0.1 ± 0.08	$\mathbf{0.57 \pm 0.04}$	$\mathbf{0.64 \pm 0.12}$	$\mathbf{0.62 \pm 0.1}$
	Mean	0.41 ± 0.05	0.3 ± 0.05	0.2 ± 0.04	0.67 ± 0.04	$\mathbf{0.79 \pm 0.04}^\star$	0.66 ± 0.04
20k	16Rooms	0.65 ± 0.15	0.71 ± 0.13	0.87 ± 0.06	0.95 ± 0.03	$\mathbf{1.0 \pm 0.0}$	$\mathbf{1.0 \pm 0.0}$
	16Rooms2	0.35 ± 0.19	0.45 ± 0.19	0.53 ± 0.18	0.49 ± 0.17	0.62 ± 0.22	$\mathbf{0.92 \pm 0.06}$
	SimpleCrossing	0.73 ± 0.1	0.67 ± 0.07	0.57 ± 0.15	$\mathbf{0.87 \pm 0.05}$	$\mathbf{0.92 \pm 0.08}$	$\mathbf{0.84 \pm 0.16}$
	FourRooms	0.74 ± 0.09	$\mathbf{0.9 \pm 0.02}$	0.77 ± 0.1	0.64 ± 0.04	$\mathbf{0.9 \pm 0.08}$	0.72 ± 0.07
	SmallCorridor	0.7 ± 0.2	0.89 ± 0.1	$\mathbf{1.0 \pm 0.0}$	0.89 ± 0.05	0.88 ± 0.11	$\mathbf{1.0 \pm 0.0}$
	LargeCorridor	0.7 ± 0.2	0.71 ± 0.15	0.64 ± 0.05	0.79 ± 0.13	0.94 ± 0.05	$\mathbf{1.0 \pm 0.0}$
	Labyrinth	0.92 ± 0.07	0.87 ± 0.09	0.45 ± 0.23	0.55 ± 0.23	$\mathbf{0.97 \pm 0.03}$	0.86 ± 0.14
	Labyrinth2	0.22 ± 0.2	0.58 ± 0.22	0.54 ± 0.18	0.66 ± 0.18	$\mathbf{1.0 \pm 0.01}$	$\mathbf{1.0 \pm 0.0}$
	Maze	0.19 ± 0.15	0.1 ± 0.02	0.43 ± 0.23	$\mathbf{0.54 \pm 0.19}$	$\mathbf{0.52 \pm 0.26}$	$\mathbf{0.72 \pm 0.24}$
	Maze2	0.29 ± 0.2	0.53 ± 0.2	0.49 ± 0.16	0.74 ± 0.13	0.93 ± 0.04	$\mathbf{1.0 \pm 0.0}$
	Maze3	0.45 ± 0.17	$\mathbf{0.88 \pm 0.07}$	0.69 ± 0.19	0.75 ± 0.12	$\mathbf{0.94 \pm 0.06}$	0.8 ± 0.1
	PerfectMaze (M)	0.6 ± 0.19	0.4 ± 0.06	0.45 ± 0.1	0.62 ± 0.09	$\mathbf{0.88 \pm 0.12}$	$\mathbf{0.93 \pm 0.07}$
	Mean	0.55 ± 0.05	0.64 ± 0.04	0.62 ± 0.05	0.71 ± 0.04	$\mathbf{0.88 \pm 0.04}^\star$	$\mathbf{0.9 \pm 0.03}^\star$

A.3 Additional Experiments

The Sensitivity of Domain Randomization Consider a simple parameterized grid world environment where an agent has to navigate towards a goal. Each level varies in terms of the location of the agent, goal and placement of obstacles. When these obstacles are *walls* the agent is able to learn quickly, achieving high performance on the training distribution. However, when these obstacles are *lava*, which causes instant death on collision, the agent is unable to learn (Fig. 13.a), left). If we change the DR parameterization to not only sample the locations of the lava tiles, but the *number of tiles to place*, then the agent does indeed learn (Fig. 13.a), right). This subtle change illustrates the sensitivity of DR to the environment parameterization. We refer to this problem as "curse of

(a) **Training Performance** (b) **Test Return** (c) **Level Profile**

Figure 13: Small grid results: a) On the left, we compare training with DR, randomizing obstacles that can be walls or lava, on the right we see that when the obstacles are lava the choice of DR parameterization has a significant impact on performance. In b) we see the test performance of these agents after 1k updates, PLR applied to the Binomial (Bin) levels is able to produce a strong agent, why? In c) we see a density plot of DR and PLR levels, showing frequency by Return and Positive Value Loss, which shows PLR curates solvable levels where the agent receives a learning signal.

dimensionality for UED", whereby increasing the design space leads to a crowding out of levels that are effective for learning.

In Fig.13.b) we show the test performance for the three DR agents at the same checkpoint (1000 updates), as well as a PLR agent using the Binomial DR levels. Despite the poor performance for the DR agent, PLR is able to achieve strong performance, outperforming even the Uniform DR agent. To see how this is possible, in Fig. 13.c) we compare the density of levels sampled by DR vs. those in the PLR buffer, sorted by Return and Positive Value Loss. Notably, the levels chosen by PLR are inherently higher return levels, thus, we see that PLR is able to find the frontier without handcrafted heuristics. This example illustrates the importance of having a sufficient quantity of frontier levels. Indeed, the success of PLR hinges on the ability to reliably sample new levels at the ever-changing frontier of the agent's capabilities. This is the key motivation for .

Next, in Fig.14 we show the performance of the three DR agents when tested on each other's training distributions after one thousand training steps. All agents perform worst on the Fixed levels, slightly better on the Binomial ones, with the best performance on Uniform. Notably, even the Fixed agent, the weakest of the three, is able to see almost double the performance on the Uniform levels. This indicates that a key ingredient to learning potential is having a sufficient number of easier levels to generate learning signal. Indeed, this was noted in Jiang et al. (2021b) in their MiniGrid experiments.

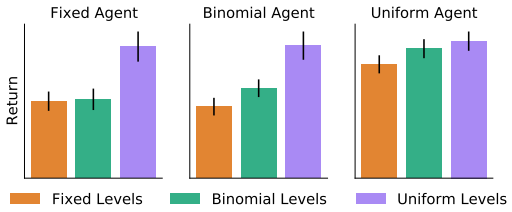

Figure 14: Performance of agents trained on different level distributions when tested on each of the distributions. It is clear to see the Uniform distribution contains more solvable levels—all three agents perform better on it.

Ablation Studies To investigate the design choices that led to the success of ACCEL, we consider a variety of ablations:

- **ACCEL** The main result included in the paper.
- **Edit Batch** The same ACCEL algorithm but editing the entire replay batch rather than the "easy" levels from the batch.
- **Learned Editor** The same algorithm changing only the editor, which is optimized for positive value loss.
- **No Editor** This is an ablation on the algorithm structure, we use Algorithm 1 but sample more DR levels instead of editing.

Each of these uses the same exact structure, sampling levels from the DR distribution 10% of the time, and editing levels after replaying from the curator. For the first, we edit the entire replay batch,

rather than just the top four easiest (high return minus positive value loss) that we use in the main experiments. The results after 10k updates are shown in Table4. As we see, Editing the batch levels performs slightly worse than easy, while there is also a decrease in performance for the learned editor. Note however that all of these ablations still outperform the next best baseline (PLR, mean = 0.69). Finally, the ablation using additional DR levels instead of edited ones performs poorly, showing the strong performance for ACCEL comes from editing rather than the structure of the algorithm.

Table 4: Zero-Shot transfer to human-designed environments. Each data point corresponds to the mean (and standard error) of five independent runs, where each run is evaluated for 100 trials on each environment. All methods use a DR generator which places between zero and sixty blocks.

Test Environment	ACCEL	Edit Batch	Learned Editor	No Editor
16Rooms	1.0 ± 0.0	0.76 ± 0.19	0.9 ± 0.07	0.84 ± 0.06
16Rooms2	0.51 ± 0.28	0.23 ± 0.16	0.41 ± 0.19	0.68 ± 0.18
SimpleCrossing	0.8 ± 0.05	1.0 ± 0.0	0.9 ± 0.1	0.75 ± 0.05
FourRooms	0.85 ± 0.05	0.85 ± 0.06	0.88 ± 0.04	0.88 ± 0.05
SmallCorridor	0.72 ± 0.1	0.74 ± 0.1	0.6 ± 0.17	0.7 ± 0.18
LargeCorridor	0.91 ± 0.05	0.75 ± 0.08	0.56 ± 0.18	0.63 ± 0.18
Labyrinth	0.98 ± 0.02	0.85 ± 0.11	0.99 ± 0.01	0.67 ± 0.19
Labyrinth2	0.97 ± 0.03	0.83 ± 0.11	0.7 ± 0.15	0.48 ± 0.2
Maze	0.78 ± 0.21	0.87 ± 0.05	0.57 ± 0.18	0.15 ± 0.08
Maze2	0.5 ± 0.24	0.67 ± 0.18	0.65 ± 0.15	0.23 ± 0.15
Maze3	0.79 ± 0.14	0.9 ± 0.08	0.95 ± 0.05	0.56 ± 0.17
Mean	0.79 ± 0.04	0.76 ± 0.04	0.74 ± 0.04	0.58 ± 0.05

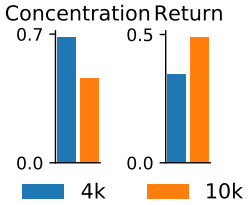

Figure 15: Replay buffer diversity vs. return.

Diversity of the Level Buffer we compare a buffer of size 4k with no DR sampling against our method with a buffer size of 10k and 10% sampling. The plots show the proportion of the top 200 levels produced by just ten initial generator levels, with a significant increase for the smaller buffer. We also compare the performance of the two agents on test levels with ten tiles, showing clear outperformance for the lower concentration agent.

B Implementation Details

In this section we detail the training procedure for all our experiments. Training for all methods is conducted on a single V100 GPU, using ten CPUs. The codebase is built on top of open source repos. Notably, for PAIRED and Minimax we use the PyTorch implementation: `https://github.com/ucl-dark/paired`.

B.1 Environment Details

Learning with Lava The MiniHack environment is an open-source Gym (Brockman et al., 2016) environment which provides a wrapper around the full game of NetHack via the NetHack Learning Environment Küttler et al. (2020). MiniHack allows users (or agents) the ability the fully specify environments leveraging the full game engine from NetHack. For our experiments we use a simple 7x7 grid, and allow the agent to place lava tiles in any location of their choice. We considered three different DR parameterizations in Fig.13. These are: "Fixed" which always places ten lava blocks, "Binomial" which places twenty blocks, with a 50-50 chance of the block being lava or nothing, and

"Uniform" which selects the number of lava blocks to place from the range $[0, 20]$. The reward is sparse, with the agent receiving +1 for reaching the goal, with a per timestep penalty of 0.01.

Partially-Observable Navigation Each maze consists of a 15×15 grid, where each cell can contain a wall, the goal, the agent, or navigable space. The student agent receives a reward of $1 - T/T_{\text{max}}$ upon reaching the goal, where T is the episode length and T_{max} is the maximum episode length (set to 250). Otherwise, the agent receives a reward of 0 if it fails to reach the goal.

Table 5: Total number of environment interactions for 20k PPO updates.

PPO Updates	PLR	ACCEL (DR)	ACCEL (Empty)
20k	327M	347M	369M

B.2 Environment Design Procedure

The environment design procedure works as follows: at each timestep the adversary agent receives an observation consisting of a map of the entire level and then takes a two dimensional action, consisting of an object and a location, which can be anywhere in the grid. This is similar to several recent works Dennis et al. (2020); Jiang et al. (2021b;a); Khalifa et al. (2020). For MiniGrid the object is always a wall. For both methods, the goal and agent location are placed in the final two steps.

When editing, the editor has five steps to alter the environment. For the lava environment we only edit to add or remove walls, while for MiniGrid we allow the editor to also change the goal location. If lava or walls are placed in the current location of the goal or agent, then these replace the goal or agent, which must then be relocated in the final two steps of the editing episode. If the editor attempts to remove the goal or agent location in the final two steps then the action is void.

B.3 Hyperparameters

The majority of our hyperparameters are inherited from previous works such as Dennis et al. (2020); Jiang et al. (2021b;a), with a few small changes. The first, for MiniHack we use the agent model from the NetHack paper (Küttler et al., 2020), using the `glyphs` and `blstats` as observations. The agent has both a global and a locally cropped view (produced using the coordinates in the `blstats`).

For MiniHack we conduct a grid search across the level replay buffer size $\{4000, 10000\}$ for both PLR and ACCEL, and for ACCEL we sweep across the edit method from {random, positive value loss} where positive value loss equates to a learned editor. For MiniGrid we maintain the replay buffer size from Jiang et al. (2021a) and only conduct the ACCEL grid search over the edit objective, again running both {random, positive value loss}, as well as the levels to edit from {easy, batch}. The final hyperparameters chosen are shown in Table 6.

Table 6: Hyperparameters used for training each method in the maze and car racing environments.

Parameter	MiniHack (Lava)	MiniGrid
PPO		
γ	0.995	0.995
λ_{GAE}	0.95	0.95
PPO rollout length	256	256
PPO epochs	5	5
PPO minibatches per epoch	1	1
PPO clip range	0.2	0.2
PPO number of workers	32	32
Adam learning rate	1e-4	1e-4
Adam ϵ	1e-5	1e-5
PPO max gradient norm	0.5	0.5
PPO value clipping	yes	yes
return normalization	no	no
value loss coefficient	0.5	0.5
student entropy coefficient	0.0	0.0
generator entropy coefficient	0.0	0.0
ACCEL		
Edit rate, q	1.0	1.0
Replay rate, p	0.9	0.9
Buffer size, K	10000	4000
Scoring function	positive value loss	positive value loss
Edit method	positive value loss	random
Levels edited	batch	easy
Prioritization	rank	rank
Temperature, β	0.3	0.3
Staleness coefficient, ρ	0.5	0.5
PLR		
Scoring function	positive value loss	positive value loss
Replay rate, p	0.5	0.5
Buffer size, K	10000	4000