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# Evolving Curricula with Regret-Based Environment Design

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## Abstract

It remains a significant challenge to train generally capable agents with reinforcement learning (RL). A promising avenue for improving the robustness of RL agents is through the use of curricula. One such class of methods frames environment design as a game between a student and a teacher, using regret-based objectives to produce environment instantiations (or levels) at the frontier of the student agent’s capabilities. These methods benefit from their generality, with theoretical guarantees at equilibrium, yet they often struggle to find effective levels in challenging design spaces. By contrast, evolutionary approaches seek to incrementally alter environment complexity, resulting in potentially open-ended learning, but often rely on domain-specific heuristics and vast amounts of computational resources. In this paper we propose to harness the power of evolution in a principled, regret-based curriculum. Our approach, which we call *Adversarially Compounding Complexity by Editing Levels* (ACCEL), seeks to constantly produce levels at the frontier of an agent’s capabilities, resulting in curricula that start simple but become increasingly complex. ACCEL maintains the theoretical benefits of prior regret-based methods, while providing significant empirical gains in a diverse set of environments.

An interactive version of the paper is available at [accelagent.github.io](https://accelagent.github.io).

## 1 Introduction

Reinforcement Learning (RL, Sutton and Barto (1998)) considers the problem of an agent learning through experience to maximize reward in a given environment. 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; Hu and Foerster, 2020) and robotics (OpenAI et al., 2019; Andrychowicz et al., 2020), with some believing RL may be sufficient for producing generally capable agents (Silver et al., 2021). Despite the promise of RL, it is often a challenge to train agents capable of systematic generalization (Kirk et al., 2021).

This work focuses on the use of adaptive curricula for training more generally-capable agents. By adapting the training distribution over the parameters of an environment, adaptive curricula have been shown to produce more robust policies in fewer training steps (Portelas et al., 2019; Jiang et al., 2021b). For example, these parameters may correspond to friction coefficients in a robotics simulator or maze layouts for a navigation task. Each concrete setting of parameters results in an environment instance called a *level*. Indeed, adaptive curricula have played a key role in many prominent RL success, either over opponents (Vinyals et al., 2019), game levels (Team et al., 2021), or parameters of a simulator (OpenAI et al., 2019; Andrychowicz et al., 2020).

*Unsupervised Environment Design* (UED, Dennis et al. (2020)) formalizes the problem of finding adaptive curricula, whereby a teacher agent designs levels using feedback from a student, which seeks

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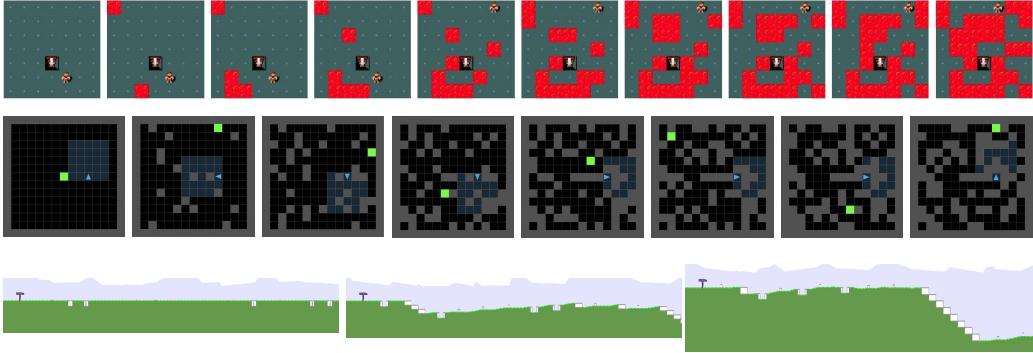


Figure 1: The evolution of a level in three different environments: MiniHack lava grids, MiniGrid mazes and BipedalWalker terrains. In each case, the far left shows a base level, acting as a parent for subsequent edited levels to the right. Each level along the evolutionary path has a high regret for the student agent at that point in time. Thus the level difficulty co-evolves with the agent’s capabilities. In each environment, we see that despite starting with simple levels, the pursuit of high regret leads to increasingly complex challenges. This complexity emerges entirely without relying on any environment-specific exploration heuristics. Note that since the agent can move diagonally in the lava environment, the final level is solvable.

to solve them. When using *regret* as feedback, [Dennis et al. \(2020\)](#) showed that if the system reaches equilibrium, then the student must follow a minimax regret strategy, i.e. the student would be capable of solving all solvable environments. Empirically, this approach produces student policies exhibiting impressive zero-shot transfer to challenging human designed environments ([Dennis et al., 2020; Jiang et al., 2021a; Gur et al., 2021](#)). However, training such an adversarial teacher remains a challenge, and so far, the strongest empirical results come from curating randomly sampled levels for high-regret, rather than learning to directly design such levels ([Jiang et al., 2021a](#)). Such a curatorial approach is unable to take advantage of any previously discovered level structures, and its performance can be expected to degrade as the size of the design space grows.

An important benefit of adaptive curricula is the possibility of open-ended learning ([Soros and Stanley, 2014](#)), given the curriculum can be steered toward constantly designing novel tasks for the agent to solve. While generating truly open-ended learning remains a grand challenge ([Stanley et al., 2017](#)), recent works in the evolutionary community have taken the first steps in this direction, through methods such as Minimal Criteria Coevolution (MCC, [Brant and Stanley \(2017\)](#)) and POET ([Wang et al., 2019, 2020](#)). These approaches show that evolving levels can effectively produce agents capable of solving a diverse range of challenging tasks. In contrast to prior UED works, these evolutionary methods directly take advantage of the most useful structures found so far in a constant process of mutation and selection. However, the key drawback of these methods is the reliance on domain specific heuristics, while also requiring vast computational resources, making it challenging for the community to make further progress in this direction.

In this work, we seek to harness the power and potential open-endedness of evolution in a principled regret-based curriculum. We introduce a new algorithm, called *Adversarially Compounding Complexity by Editing Levels*, or ACCEL. ACCEL evolves a curriculum by making small *edits* (e.g. mutations) to previously high-regret levels, thus constantly producing new levels at the frontier of the student agent’s capabilities (see: Figure 2). Levels generated by ACCEL begin simple but quickly become more complex. This benefits both the beginning of training ([Berthouze and Lungarella, 2004; Schmidhuber, 2013](#)), where the student begins learning much faster, while rapidly co-evolving the policy with the environment to solve increasingly complex levels (see Figure 1).

We believe ACCEL provides the best of both worlds: an evolutionary approach that can generate increasingly complex environments, combined with a regret-based curator that reduces the need for domain-specific heuristics and provides theoretical robustness guarantees in equilibrium. ACCEL leads to strong empirical gains in both sparse navigation tasks and a 2D bipedal locomotion task over challenging terrain. In both domains, ACCEL demonstrates the ability to rapidly increase level complexity while producing highly capable agents. ACCEL produces and solves highly challenging levels with a fraction of the compute of previous approaches, reaching comparable performance to POET while training on less than 0.05% of the total number of samples on a single GPU.

## 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  $\mathcal{T} : S \times A \rightarrow \Delta(S)$  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 induces an associated reward  $r_t$ , generated by a reward function  $\mathcal{R} : S \rightarrow \mathbb{R}$ , and  $\gamma$  is a discount factor. Given an MDP, the goal of Reinforcement Learning (RL, Sutton and Barto (1998)) is to learn a policy  $\pi$  that maximizes expected discounted reward, i.e.  $\mathbb{E}[\sum_{i=0}^T r_t \gamma^t]$ .

Despite its generality, the MDP framework is often an unrealistic model for real-world environments. First, it assumes full observability of the state, which is often impossible in practice. This limitation is addressed by *partially observable* MDPs (POMDPs), which include an observation function  $\mathcal{I} : S \rightarrow O$  mapping 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 training. Instead, in the real world, agents may experience variations not seen during training, making robust transfer crucial in practice.

To address these issues, we use the recently introduced *Underspecified* POMDP, or UPOMDP (Dennis et al., 2020), 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  $\Theta$  to represent the free parameters of the environment, similar to the context in a Contextual MDP (Modi et al., 2017). These parameters can be distinct at every time step and incorporated into the transition function  $\mathcal{T}^\mathcal{M} : S \times A \times \Theta \rightarrow \Delta(S)$ . Following Jiang et al. (2021a) we define a *level*  $\mathcal{M}_\theta$  as an environment resulting from a fixed  $\theta \in \Theta$ . We define the value of  $\pi$  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  $\pi$  in  $\mathcal{M}_\theta$ . UPOMDPs benefit from their generality, since  $\Theta$  can represent possible transition dynamics (for example in sim2real (Peng et al., 2017; OpenAI et al., 2019; Andrychowicz et al., 2020)), changes in observations, different reward functions, or world topology in procedurally generated environments.

### 2.2 Methods for Unsupervised Environment Design

Unsupervised Environment Design (UED, Dennis et al. (2020)) seeks to produce a series of levels that form a curriculum for a *student* agent, such that the student agent is capable of systematic generalization across all possible levels. UED typically views levels as produced by a generator (or *teacher*) maximizing some utility function,  $U_t(\pi, \theta)$ . For example DR corresponds to a teacher with a constant utility function, for any constant  $C$ :

$$U_t^U(\pi, \theta) = C. \quad (1)$$

Recent UED methods use teacher that maximize *regret*, defined as the difference between the expected return of the current policy and the optimal policy. The teacher's utility is then defined as

$$U_t^R(\pi, \theta) = \operatorname{argmax}_{\pi^* \in \Pi} \{\text{REGRET}^\theta(\pi, \pi^*)\} \quad (2)$$

$$= \operatorname{argmax}_{\pi^* \in \Pi} \{V^\theta(\pi^*) - V^\theta(\pi)\}. \quad (3)$$

Regret-based objectives are desirable, as they have been shown to promote the simplest possible levels that the student cannot currently solve (Dennis et al., 2020). More formally, if  $S_t = \Pi$  is the strategy set of the student and  $S_t = \Theta$  is the strategy set of the teacher, then if the learning process reaches a Nash equilibrium, the resulting student policy  $\pi$  provably converges to a minimax regret policy, defined as

$$\pi = \operatorname{argmin}_{\pi_A \in \Pi} \left\{ \max_{\theta, \pi_B \in \Theta, \Pi} \{\text{REGRET}^\theta(\pi_A, \pi_B)\} \right\}. \quad (4)$$

However, without access to  $\pi^*$ , UED algorithms must approximate the regret. PAIRED estimates regret as the difference in return attained by the main student agent and a second agent. By maximizing this difference, the teacher maximizes an approximation of the student's regret. Furthermore, multi-agent learning systems may not always converge in practice (Mazumdar et al., 2020). Indeed, the Achilles' heel of prior UED methods, like PAIRED (Dennis et al., 2020), is the difficulty of training the teacher, typically entailing an RL problem with sparse rewards and long-horizon credit assignment. An alternative regret-based UED approach is *Prioritized Level Replay* (PLR, Jiang et al. (2021b,a)).

PLR trains the student on challenging levels found by curating a rolling buffer of the highest-regret levels surfaced through random search over possible level configurations. In practice, PLR has been found to outperform other UED methods that directly train a teacher. PLR approximates regret using the *positive value loss*, given by

$$\frac{1}{T} \sum_{t=0}^T \max \left( \sum_{k=t}^T (\gamma \lambda)^{k-t} \delta_k, 0 \right) \quad (5)$$

where  $\lambda$  and  $\gamma$  are the Generalized Advantage Estimation (GAE, Schulman et al. (2016)) and MDP discount factors respectively, and  $\delta_t$ , the TD-error at timestep  $t$ . Equipped with this method for approximating regret, Corollary 1 in Jiang et al. (2021a) finds that if the student agent only trains on curated levels, then it will follow a minimax regret strategy at equilibrium. Thus, counterintuitively, the student learns more effectively by training on less data.

Empirically PLR has been shown to produce policies with strong generalization capabilities, but remains limited in being able to only curate randomly sampled levels. PLR’s inability to build off of previously discovered structures may make it challenging to sample complex structures with the frequency required to train agents capable of solving them. Further, random search will suffer from the curse-of-dimensionality in higher-dimensional design spaces, where randomly encountering levels at the frontier of the agent’s current capabilities can be highly unlikely.

### 3 Adversarially Compounding Complexity

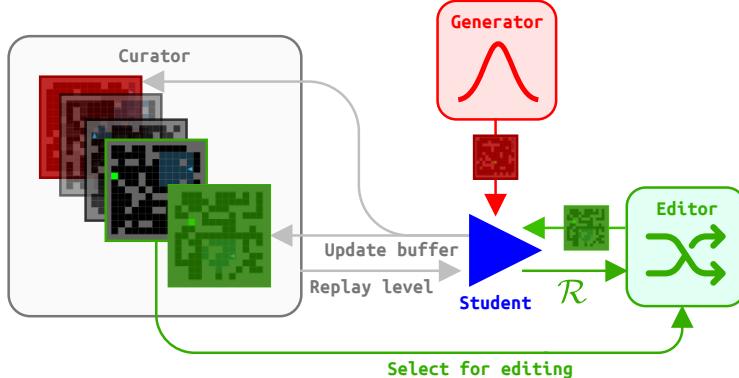


Figure 2: An overview of ACCEL. Levels are randomly sampled from a generator and evaluated, with high-regret levels added to the level replay buffer. The curator selects levels to replay, and the student only trains on replay levels. After training, the replayed levels are edited and evaluated again to compute regret for level replay.

In this section we introduce a new algorithm for UED, combining an evolutionary environment generator with a principled regret-based curator. Unlike PLR which relies on random sampling to produce new batches of training levels, we instead propose to make *edits* (e.g. mutations) to previously curated ones. Evolutionary methods have been effective in a variety of challenging optimization problems (Stanley et al., 2019; Pugh et al., 2016), yet typically rely on handcrafted, domain-specific rules. For example, POET manually filters BipedalWalker levels to have a return in the range [50, 300]. The key insight in this work is that regret serves as a domain-agnostic fitness function for evolution, making it possible to consistently produce batches of levels at the frontier of agent capabilities across domains. Indeed, by iteratively editing and curating the resulting levels, the levels in the level replay buffer quickly increase in complexity. As such, we call our method *Adversarially Compounding Complexity by Editing Levels*, or ACCEL.

ACCEL does not rely on a specific editing mechanism, which could be any mutation process used in other open-ended evolutionary approaches (Soros and Stanley, 2014). In this paper, editing involves making a handful of changes (e.g. adding or removing obstacles in a maze), which can operate directly on environment elements within the level or on a more indirect encoding such as the latent-space representation of the level under a generative model of the environment. In general, editing may rely

on more advanced mechanisms, such as search-based methods, but in this work we predominantly make use of simple, random mutations. ACCEL makes the key assumption that regret varies smoothly with the environment parameters  $\Theta$ , such that the regret of a level is close to the regret of others within a small edit distance. If this is the case, then small edits to a single high-regret level should lead to the discovery of entire batches of high-regret levels—which could be an otherwise challenging task in high-dimensional design spaces.

Following PLR (Jiang et al., 2021a), we do not immediately train on edited levels. Instead, we first evaluate them and only add them to the level replay buffer if they have high regret, estimated by positive value loss (Equation 5). We consider two different criteria for selecting which replayed levels to edit: Under the “easy” criterion, we edit those levels which the agent can currently solve with low regret, approximated as the agent’s return minus its regret. Under the “batch” criterion, we simply edit the entire batch of replayed levels. The full procedure is shown in Algorithm 1.

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**Algorithm 1** ACCEL

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**Input:** Buffer size  $K$ , initial fill ratio  $\rho$ , level generator.  
**Initialize:** Initialize policy  $\pi(\phi)$ , level buffer  $\Lambda$ .  
*# 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**  
         *# Evaluate DR levels but do not update*  
         Sample level  $\theta$  from level generator  
         Collect  $\pi$ ’s trajectory  $\tau$  on  $\theta$ , with a stop-gradient  $\phi_\perp$   
         Compute approximate regret  $S$ , using Equation 5  
         Add  $\theta$  to  $\Lambda$  if score  $S$  meets threshold  
     **else**  
         *# Train student agent on curated high regret levels*  
         Sample a replay level,  $\theta \sim \Lambda$   
         Collect policy trajectory  $\tau$  on  $\theta$   
         Update  $\pi$  with rewards  $R(\tau)$   
         *# Edit previously high regret levels and evaluate*  
         Edit  $\theta$  to produce  $\theta'$   
         Collect  $\pi$ ’s trajectory  $\tau$  on  $\theta'$ , with a stop-gradient  $\phi_\perp$   
         Compute approximate regret  $S$ , using Equation 5  
         Add  $\theta'$  to  $\Lambda$  if score  $S$  meets threshold  
         (Optionally) Update Editor using score  $S$   
     **end**  
**end**

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ACCEL can be seen as a UED algorithm taking a step toward open-ended evolution (Stanley et al., 2017), where the evolutionary fitness is estimated regret, as levels only stay in the population (that is, the level replay buffer) if they meet the high-regret criterion for curation. However, ACCEL avoids some important weaknesses of evolutionary algorithms such as POET: First, ACCEL maintains a population of levels, but not a population of agents. Thus, ACCEL requires only a single desktop GPU for training. In contrast, evolutionary approaches typically require a CPU cluster. Moreover, forgoing an agent population allows ACCEL to avoid the agent selection problem. Instead, ACCEL directly trains a single generally-capable agent. Finally, since ACCEL uses a minimax *regret* objective (rather than minimax as in POET), it naturally promotes levels at the frontier of agent’s capabilities, without relying on domain-specific knowledge (such as reward ranges). Training on high regret levels also means that ACCEL inherits the robustness guarantees in equilibrium from PLR (Corollary 1 in Jiang et al. (2021a)):

**Remark 1.** *If ACCEL reaches a Nash equilibrium, then the student follows a minimax regret strategy.*

In stark contrast, other evolutionary approaches primarily justify their applicability solely via empirical results on specific domains. As we will show next, a key strength of ACCEL is its generality, as it can produce highly capable agents in a diverse range of environments, without domain knowledge.

## 4 Experiments

In our experiments we seek to compare agents trained with ACCEL with several of the best-performing UED baselines. In all cases, we train a student agent via Proximal Policy Optimization (PPO, Schulman et al. (2018)). To evaluate the quality of the resulting curricula, we show all performance with respect to the number of gradient updates for the student policy, as opposed to total number of environment interactions, which is, in any case, often comparable for PLR and ACCEL (see Table 10). For a full list of hyperparameters for each experiment please see Table 11 in Section B.3. Our primary baseline is Robust PLR (Jiang et al., 2021a), which combines the random generator with a regret-based curation mechanism. The other baselines are domain randomization (DR), PAIRED (Dennis et al., 2020), and a minimax adversarial teacher. The minimax baseline corresponds to the objective used in POET without the hand-coded constraints. We leave the comparison to population-based methods to future work due to the computational expense required. We report results in a consistent manner across environments—in each case, we show the emergent complexity during training and report test performance in terms of the aggregate inter-quartile mean (IQM) and optimality gap using the recently introduced `rliable` library (Agarwal et al., 2021b).

We begin with a simple proof-of-concept environment, where a large proportion of levels are not conducive to learning. We then scale to a larger partially-observable navigation environment, where we test our agents on challenging out-of-distribution environments. Finally, we compare each method on the continuous-control environment from Wang et al. (2019), featuring a highly challenging distribution of training levels that requires the agent to master multiple behaviors to achieve strong performance.

### 4.1 Learning with Lava

We begin with a simple proof of concept: a grid environment, where the agent must navigate to a goal in the presence of lava blocks. The grid is only  $7 \times 7$ , but remains challenging as the episode terminates with zero reward if the agent touches the lava. This dynamic makes exploration more difficult by penalizing random actions. While toy, such challenges may be relevant in real-world, safety-critical settings, where agents may wish to avoid events causing early termination during training. For DR and PLR, the random generator samples the number of lava tiles to place from the range [0,20]. For ACCEL, we use a generator that produces empty rooms and then proceeds to edit the levels by adding or removing lava tiles. The environment is built with MiniHack (Samvelyan et al., 2021), in which the agent has full observability with a high dimensional input. The full environment details are provided in Appendix B.1).

Figure 3 shows the results of running each method over 5 random seeds. Despite starting with empty rooms ACCEL quickly produces levels with more lava than the other methods, while also attaining higher training returns, reaching near-perfect performance on its training distribution. This behavior is entirely driven by the pursuit of high-regret levels, which constantly seeks the frontier of the agent’s capabilities. PLR is able to produce a similar training profile to ACCEL, but achieves lower values for each complexity metric.

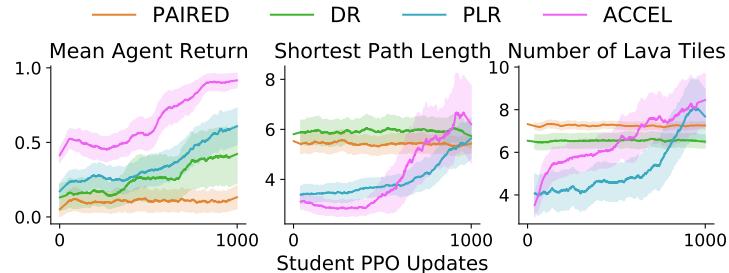


Figure 3: Training return and emergent complexity in Lava Grid. The plots report the mean and standard error over 5 seeds.

We evaluate each agent on a series of test levels after 1000 PPO updates (approximately 20M timesteps), and report the aggregate results in Figure 4, where we see that ACCEL is the best performing method. Extended results are shown in Appendix A.3). This experiment demonstrates

that ACCEL can facilitate learning in settings where the student agent is likely to suffer from instant death, and therefore struggle to learn, in a high proportion of training levels.

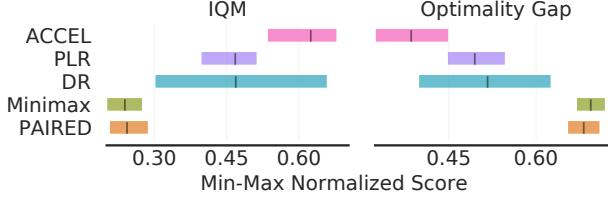


Figure 4: Lava Grid aggregate test performance.

#### 4.2 Partially Observable Navigation

We now scale ACCEL to a maze navigation environment based on MiniGrid (Chevalier-Boisvert et al., 2018), originally introduced in Dennis et al. (2020). Despite being a conceptually simple environment, training robust agents in this domain requires a large-scale experiment: Our agents train for 20k updates ( $\approx 350M$  steps, see Table 10), learning an LSTM-based policy with a 147-dimensional partially-observable observation. Our DR baseline samples between 0 and 60 blocks to place, providing a sufficient range for PLR to form a curriculum. For ACCEL we begin with empty rooms and randomly edit the block locations (by adding or removing blocks), as well as the goal location. After replay, we edit levels selected via the “easy” criterion—essentially moving levels back to the learning frontier once their learning potential has been reduced. In Figure 5, we report training performance and complexity metrics. We see that ACCEL rapidly compounds complexity, leading to training levels with significantly higher block count and longer solution paths than other methods.

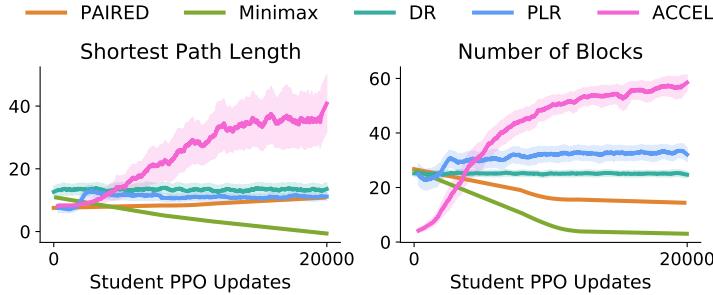


Figure 5: Emergent complexity metrics for maze navigation levels during training. Plots show the mean and standard error across 5 training seeds.

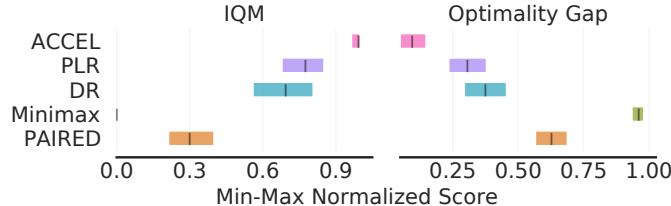


Figure 6: Aggregate test performance on maze navigation environments.

We evaluate the zero-shot transfer performance of each method on a series of held-out test environments, as done in prior works. For DR, PLR, and ACCEL, evaluation occurs after 20k student PPO updates, focusing the comparison on the effect of the curriculum. The minimax and PAIRED results are those reported in Jiang et al. (2021a) at 250M training steps ( $\approx 30k$  updates). As we see, ACCEL performs at least as well as the next best method in almost all test environments, with particularly strong performance in Labyrinth and Maze. As reported in Figure 6, ACCEL achieves drastically stronger performance than all other methods in aggregate across all test environments: its IQM approaches a perfect solved rate compared to below 80% for the next best method, PLR, with an 80.2% probability of improvement over PLR. Detailed, per environment test results are provided in Figures 23) and 26 in Appendix A.3. Example levels generated by each method are shown in Figure 7, where we see ACCEL produces more structured mazes than the baselines.

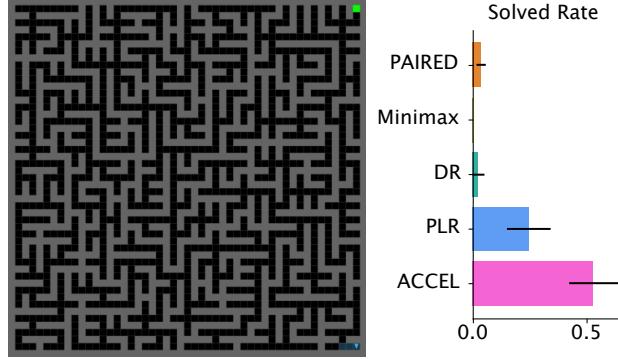


Figure 8: Zero-shot performance on a large procedurally-generated maze environment. The bars show mean and standard error over 5 training seeds, each evaluated over 100 episodes. ACCEL achieves over double the success rate of the next best method, despite beginning with empty rooms.

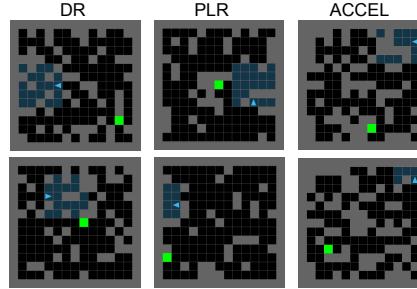


Figure 7: Example levels generated by DR, PLR and ACCEL.

Next, we consider an even more challenging setting—we use a larger version of “PerfectMaze”, a procedurally-generated maze environment, shown in Figure 8. Each randomly-generated maze has  $51 \times 51$  tiles, an order of magnitude larger than training levels, with a maximum episode length of over 5k steps. We evaluate each agents for each training seed for 100 episodes, using the same checkpoints used to produce Figure 6. The evaluation results in Figure 8 show ACCEL significantly outperforms all baselines, achieving a success rate of 53% compared to the next best method, PLR, which attains a success rate of 25%, while all other methods fail. Notably, ACCEL learns to approximately follow the “left-hand” rule for solving single-component mazes.

We seek to understand the key drivers of ACCEL’s outperformance: Incremental changes to a level can lead to a diverse batch of new ones (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 diversity may prevent overfitting. For example, in Figure 9, we see three edits of the same level produced by ACCEL. Each has a similar initial observation, yet requires the agent to explore in different directions to reach the goal, thereby pressuring the agent to actively explore the environment. Making edits such as these *outside* of the direct trajectory of the agent can also be seen as a form of data augmentation that changes the observation but not the optimal policy. Such data augmentations have been shown to improve sample efficiency and robustness in RL (Laskin et al., 2020; Kostrikov et al., 2021; Raileanu et al., 2020).

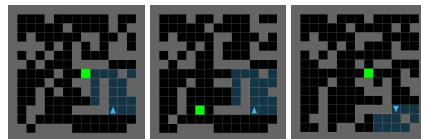


Figure 9: Despite sharing a common ancestor, each of these levels require different behaviors to solve. Left: the agent can go up or left and reach the goal. Middle: the goal is on the left, while on the right the left path is blocked.

### 4.3 Walking in Challenging Terrain

Finally, we evaluate our approach on a continuous-control environment with dense rewards, using the BipedalWalker environment from Wang et al. (2019). As in Wang et al. (2019) we use a modified version of the BipedalWalkerHardcore environment from OpenAI Gym (Brockman et al., 2016). We include all eight parameters in the design space, rather than the subset used in Wang et al. (2019), making more complex. This environment is detailed at length in Appendix B.1. We run all baselines from previous experiments, alongside an additional baseline, ALP-GMM (Portelas et al., 2019), which was originally tested on BipedalWalker. We train agents for 30K student updates, equivalent to between 1B to 2B total environment steps, depending on the method (see Table 10). During training we evaluate agents on both the simple BipedalWalker and more challenging BipedalWalker-Hardcore environments, in addition to four environments testing the agent’s effectiveness against specific, isolated challenges otherwise present to varying degrees in training levels: {Stump, PitGap, Stairs, Roughness}, shown in Figure 10.

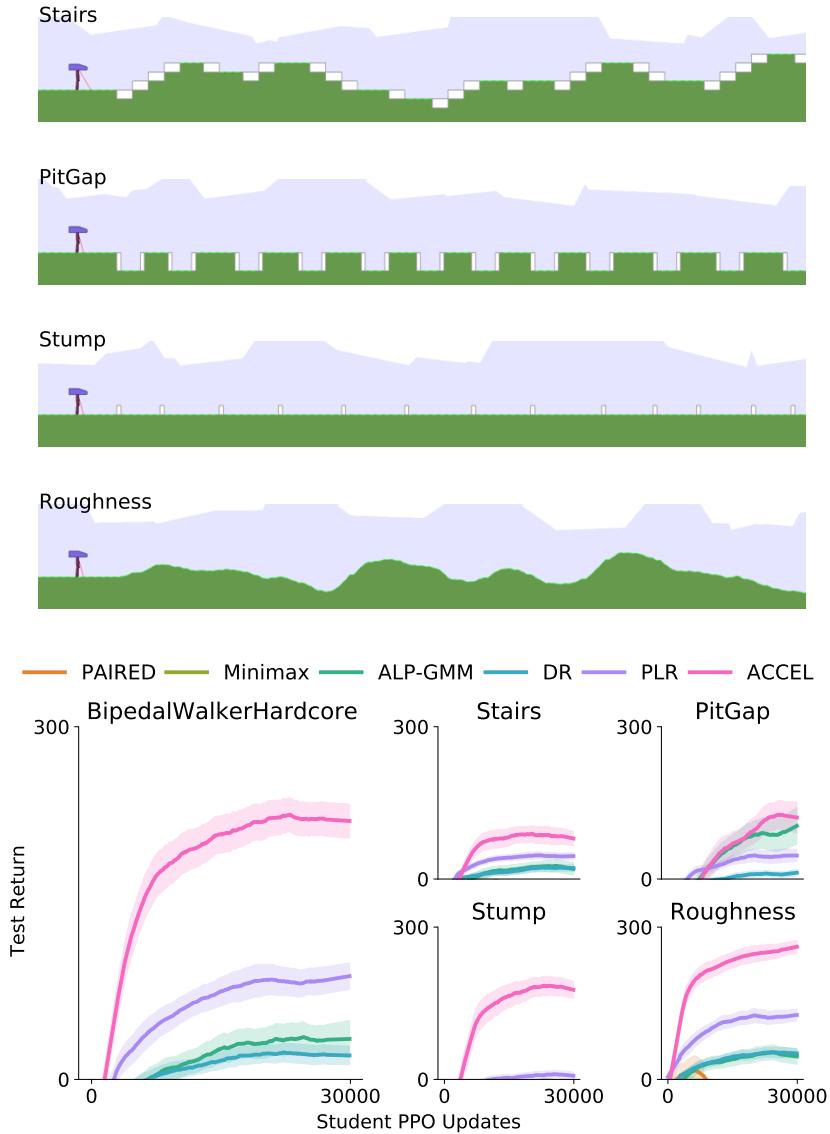


Figure 10: Top: Examples of the four individual challenges in BipedalWalker, **Bottom:** Performance on BipedalWalker test environments during training. Results show mean and standard error. Returns below zero are omitted.

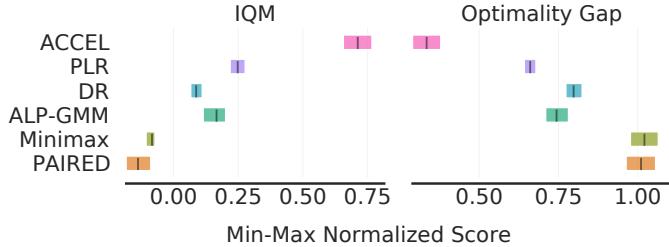


Figure 11: Aggregate performance across BipedalWalker test environments.

After 30k PPO updates, we conduct a more rigorous evaluation, using 100 test episodes in each test environment, and report the aggregate results in Figure 11 (normalized assuming a return range of {0,300}). ACCEL significantly outperforms all baselines, achieving close to 75% of optimal performance, almost three times the next best baseline (PLR). All other baselines struggle, likely due to the challenging environment design space containing a high proportion of levels that are not conducive to learning. Faced with such challenging levels, agents may learn to resort to the locally optimal behavior of preventing itself from falling (avoiding a -100 penalty), rather than attempt forward locomotion. Finally, we see ALP-GMM was unable to perform well when the design space was increased from 2D (as in Portelas et al. (2019)) to 8D.

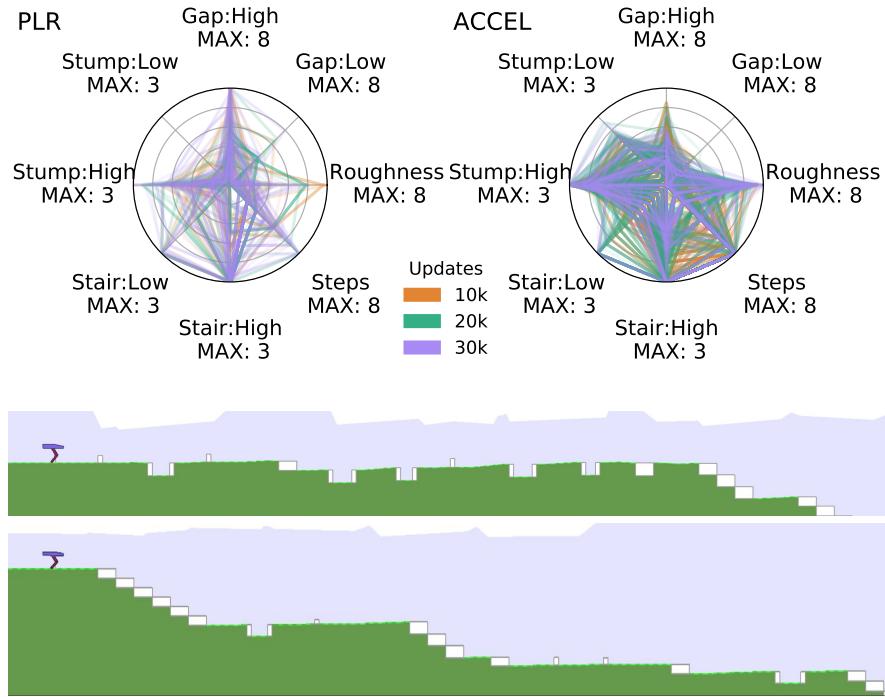


Figure 12: Emergent Complexity in BipedalWalker. Top: Rose plot of complexity metrics of BipedalWalker levels discovered by PLR and ACCEL. Each line represents a solved level from the associated checkpoint. All levels are among the top-100 highest regret levels for the given checkpoint. Bottom: Two levels created and solved by ACCEL.

Next we seek to understand the properties of the evolving distribution high regret levels. We include all *solved levels* from the top 100 regret levels after 10k, 20k and 30k student updates. For each level we show all eight parameters in Figure 12 (top), with the PLR agent as a comparison. As we see, ACCEL solves a vast quantity of difficult levels, of comparable difficulty with other methods such as POET, but using a fraction of the compute. For comparison, ACCEL used 2.07B timesteps to get to 30k student updates, which is less than 0.5% of what is used in Wang et al. (2019). In the next section we seek a more direct comparison with results from POET.

#### 4.4 POET Comparison

For a more direct comparison with POET, we ran an experiment using the smaller 5D BipedalWalker environment encoding used in Wang et al. (2019). We train each method for ten independent runs for 50k student PPO updates. For evaluating the difficulty of generated levels, we use the thresholds provided in Wang et al. (2019), summarized in Table 1. A level meeting none of these thresholds is considered “Easy”, while meeting one, two or three is considered “Challenging”, “Very Challenging” or “Extremely Challenging” respectively.

Table 1: Environment encoding thresholds for 5D BipedalWalker.

Stump Height (High)	Pit Gap (High)	Ground Roughness
$\geq 2.4$	$\geq 6$	$\geq 4.5$

In Figure 13, we show the composition of the ACCEL level replay buffer during training. As we see, ACCEL produces an increasing number of “Extremely Challenging” levels as training progresses. This is a significant achievement given that Wang et al. (2019) showed it was not possible to create levels in this category with their evolutionary curriculum, without including a complex stepping stone procedure. We thus see regret-based UED offers a computationally cheaper alternative to producing such levels. Moreover, POET explicitly encourages the environment parameters to reach high values through an explicit novelty bonus, whereas the complexity discovered by ACCEL is completely emergent, arising purely through the pursuit of high-regret levels.

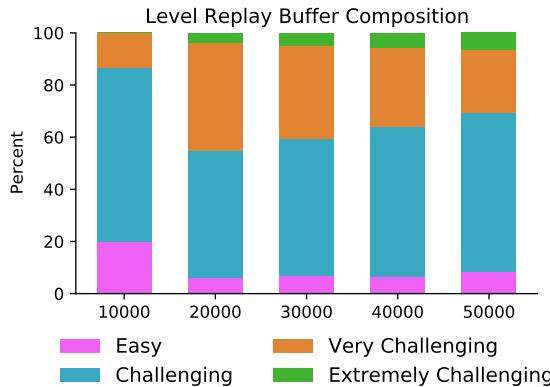


Figure 13: Percentage of the ACCEL level replay buffer falling into each difficulty category. Note the complexity is purely emergent in the pursuit of high-regret levels.

We further evaluate agents trained in the 5D BipedalWalker environment on the settings outlined in Figure 10, and report the results in Table 2. Note that the Stairs environment is now out-of-distribution, as the agent never experiences stairs during training. As we saw in the higher dimensional setting, the ACCEL agent is able to perform well across all settings, outperforming both baselines.

Table 2: Test solved rate after 50k updates: all ten runs of each method are evaluated on held out environments for 100 episodes. Extremely Challenging evaluations use 1000 episodes due to the diversity of the levels produced. Mean and sem shown. Bold indicates within a standard error of the best mean.

	PLR	ALP-GMM	ACCEL
Stump	$0.04 \pm 0.02$	$0.07 \pm 0.02$	<b><math>0.44 \pm 0.08</math></b>
PitGap	$0.2 \pm 0.09$	<b><math>0.58 \pm 0.08</math></b>	<b><math>0.61 \pm 0.08</math></b>
Roughness	$0.23 \pm 0.04$	$0.13 \pm 0.03$	<b><math>0.73 \pm 0.03</math></b>
Stairs	$0.02 \pm 0.0$	$0.01 \pm 0.0$	<b><math>0.12 \pm 0.02</math></b>
Hardcore	$0.21 \pm 0.04$	$0.2 \pm 0.04$	<b><math>0.65 \pm 0.02</math></b>
Extreme	$0.01 \pm 0.01$	$0.02 \pm 0.01$	<b><math>0.12 \pm 0.02</math></b>

Taking our evaluation one step further, we also test all methods on a held out distribution of “Extremely Challenging” levels. In this case, each time the environment is reset we resample the parameters,

such that they meet all three criteria in Table 1. This inevitably leads to a highly diverse set of test levels. To mitigate the risk of stochasticity influencing the outcome, we evaluate each method for 1000 episodes. We compare the solved rate for each method in Table 2. Finally, we seek to evaluate our agents on specific levels produced by POET. We used the rose plots in Wang et al. (2019) to create six “Extremely Challenging” environments, each solved by one of the three POET runs. Unsurprisingly our agents found these levels challenging, with low success rates. We note that this is not a perfect comparison—POET fixes the environment seed, thereby solving one level from each parameterization, while we repeatedly sample from the same distribution. However, despite this, 9 out of 10 of our independent runs solved at least one of the six environments at least once out of 100 trials per run. See the Appendix (Table 7) for more detail on this experiment.

To summarize, we believe ACCEL is capable of producing levels of comparable complexity to POET, without a novelty bonus or hand-coded heuristics, and using a fraction of the computational cost. Moreover, we train a single agent that is robust across environment challenges, while POET selects multiple agents, each tailored to individual challenges. Therefore, we believe our method produces agents that are more robust, and thus, more generally capable.

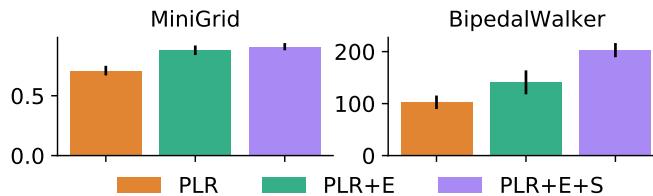


Figure 14: Aggregate returns for Editing ablations in MiniGrid and BipedalWalker. E=editing, S=start simple.

**Do we need to start simple?** To provide a better understanding of ACCEL, we conduct a simple ablation study to test the importance of the editing mechanism and the inductive bias of starting simple. In Figure 14 we show the performance of three approaches: PLR (sample and replay DR levels), PLR+E (sample, replay and edit DR levels) and finally PLR+E+S (i.e. ACCEL). As we see, editing levels leads to improved performance, while starting simple is more important in the BipedalWalker environment.

#### 4.5 Discussion and Limitations

In our experiments we have demonstrated that ACCEL is capable of forming highly effective curricula in three challenging and diverse environments. In the lava experiment, we showed ACCEL can facilitate learning in a design space with a high proportion of hard levels, which could have an impact in improving exploration in safety-critical settings. In MiniGrid, we showed it is possible to produce complex mazes which facilitate zero-shot transfer to human-designed ones, scaling to environments an order of magnitude larger than the training environment. Finally in the BipedalWalker setting we were able to match the complexity of POET using a single agent, with a small fraction of the computational cost. We thus believe we have shown evidence that ACCEL would be an effective method for training agents in more open-ended UED design spaces.

Importantly, the goal of our work differs from Wang et al. (2019). The primary motivation of ACCEL is to produce a single robust agent that can solve a wide range of challenges. ACCEL’s regret-based curriculum seeks to prioritize the simplest levels that the agent cannot currently solve. In contrast, POET co-evolves agent-environment pairs in order to find specialized policies for solving a single highly specialized task. POET’s specialized agents may likely learn to solve challenging environments outside the capabilities of ACCEL’s generalist agents, but at the cost of potentially overfitting to their paired levels. Thus, unlike ACCEL, the policies produced by POET should not be expected to be robust across the full distribution of levels. The relative merits of POET and ACCEL thus highlight an important trade-off between specialization and generalization.

While ACCEL’s simplicity is appealing, it is possible that larger design spaces will require additional mechanisms, such as actively encouraging diversity in the level space. In addition, ACCEL includes

an inductive bias with the ability to begin with a simple base case (e.g. an empty room). This may not always be possible in practice, as in some settings the simplest example (in terms of the entities placed in the environment) may actually be a more difficult environment to solve, for example, in a Hide and Seek game.

## 5 Related Work

In this section we discuss related work, with a summary of the most closely related methods in Table 3. Our paper focuses on testing agents on distributions of environments, which has long been known to be crucial for evaluating the generality of RL agents (Whiteson et al., 2009). The inability of deep RL agents to reliably generalize has 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 aims to design environment directly, such that they induce experiences that result in learning the more robust policies. Domain Randomization (DR, Jakobi (1997); Sadeghi and Levine (2017)) can be viewed as the most basic form of UED. DR 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), with extensions proposing to actively update the DR distribution (Mehta et al., 2020; Raparthy et al., 2020). This paper 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 revisited by the student agent for training. 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 based on the recent performance of the agent. Recently, a method similar to PLR was shown to be capable of producing generally capable agents in a simulated game world with a smooth space of levels (Team et al., 2021).

Table 3: The components of related approaches. Like POET, ACCEL evolves levels, but uses a single agent rather than a population, and also uses a minimax regret objective ensuring generated environments are solvable. PAIRED uses minimax regret to train 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	None	Minimax Regret	Single Agent
ACCEL	Random + Evolution	None	Minimax Regret	Single Agent

Dennis et al. (2020) first formalized UED and introduced the PAIRED algorithm, a minimax regret (Savage, 1951) UED algorithm whereby an environment adversary learns to present levels that maximize regret, approximated as the difference in performance between the main student agent and a second agent. PAIRED produces agents with improved zero-shot transfer to unseen environments and has been extended to train agents that can robustly navigate websites (Gur et al., 2021). Adversarial objectives have also been considered in robotics (Pinto et al., 2017) and in directly searching for situations in which the agent sees the weakest performance (Everett et al., 2019). POET (Wang et al., 2019, 2020) considers co-evolving a *population* of minimax environments and agents that solve them. 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 eliminating 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 and Oudeyer (2009)), which seeks to provide an adaptive curriculum of increasingly challenging tasks or goals given a (typically) fixed environment (Andrychowicz et al., 2017). This setting differs from a general UPOMDP, where a task or goal specifier is not provided. Furthermore, UED approaches seek to *fully specify* environments, rather than just goals within a

fixed environment. In Asymmetric Self-Play (Sukhbaatar et al., 2018) one agent proposes goals for another, leading to effective curricula for challenging robotic manipulation tasks (OpenAI et al., 2021). AMIGo (Campero et al., 2021) and APT-Gen (Fang et al., 2021) provide adaptive curricula for hard-exploration, goal-conditioned problems. 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 world models (Mendonca et al., 2021).

Automatic environment design has also been considered in the symbolic AI community as a means to shape an agent’s decisions (Zhang and Parkes, 2008; Zhang et al., 2009) Automated environment design (Keren et al., 2017, 2019) seeks to redesign specific levels to improve the agent’s performance within them. In contrast, UED adapts curricula that improves performance across levels.

Our work also relates to the field of *procedural content generation* (PCG, Risi and Togelius (2020); Justesen et al. (2018)), which seeks to algorithmically generate diverse levels. Popular PCG environments used in RL 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 and Schmidhuber, 2008), with recent methods making use of machine learning (Summerville et al., 2018; Bhaumik et al., 2020; Liu et al., 2021). PCGRL (Khalifa et al., 2020; Earle et al., 2021a) frames level design as an RL problem, whereby the design policy makes incremental changes to the level to maximize some arbitrary objective subject to game-specific constraints. Unlike ACCEL, it makes use of hand-designed dense rewards and focuses on the design of levels for human players, rather than as an avenue to training highly-robust agents.

## 6 Conclusion and Future Work

We proposed ACCEL, a new method for unsupervised environment design (UED), that evolves a curriculum by *editing* previously curated levels. Editing induces an evolutionary process that leads to a wide variety of environments at the frontier of the agent’s capabilities, producing curricula that start simple and quickly compound in complexity. Thus, ACCEL provides a principled regret-based curriculum that does not require domain-specific heuristics, alongside an evolutionary process that produces a broad spectrum of complexity matched to the agent’s current capabilities. In our experiments, we showed that ACCEL is capable of training robust agents in a series of challenging design spaces, where ACCEL agents outperform the best-performing baselines.

We are excited by the many possibilities for extending how ACCEL edits and maintains its population of high-regret levels. The editing mechanism could encompass a wide variety of approaches, such as Neural Cellular Automata (Earle et al., 2021b), controllable editors (Earle et al., 2021a), or perturbing the latent space of a generative model (Fontaine et al., 2021). Another possibility is to actively seek levels which are likely to produce useful levels in the future (Gajewski et al., 2019). Moreover, ACCEL’s evolutionary search may be expedited by introducing so-called “extinction events” (Raup, 1986; Lehman and Miikkulainen, 2015), believed to play a crucial role in natural evolution. We did not explore methods to encourage level diversity, but such diversity is likely important for larger design spaces, such as 3D control tasks that transfer more directly to the real world. It remains an open question whether producing sufficient diversity would require a population, for example using the domain-agnostic, population-based novelty objective in Enhanced POET (Wang et al., 2020). We believe such ideas at the intersection of evolution and adaptive curricula can take us closer to producing a truly open-ended learning process between the agent and the environment (Stanley et al., 2017). Finally, we note that while ACCEL may be an effective approach for automatically generating an effective curriculum, it may still be necessary to likewise adapt the agent configuration (Parker-Holder et al., 2022) to most effectively train agents in open-ended environments.

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## A Additional Experimental Results

### A.1 Level Evolution

In Fig 15 and 16 and we show levels produced by ACCEL for the MiniHack lava environment and MiniGrid mazes respectively. Each step along the evolutionary process produces a level that has high learning potential *at that point in time*.

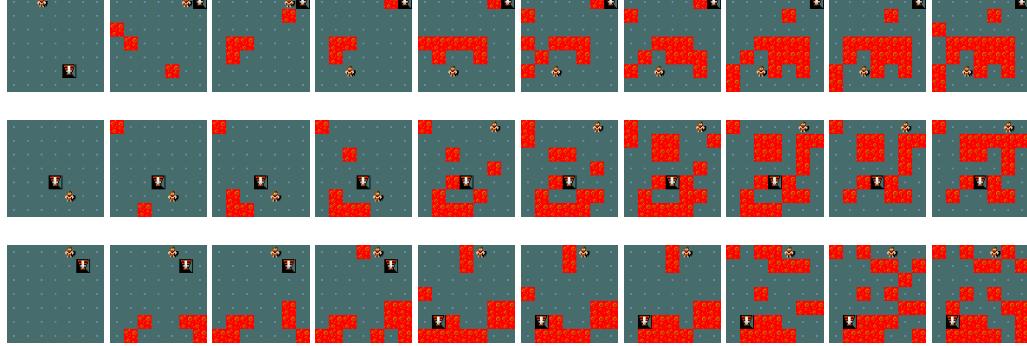


Figure 15: Levels generated by ACCEL. Each level along the evolutionary path is at the frontier for the student agent at that stage of training. As we can see, the edits compound to produce a series of challenges: in the first level the lava gradually surrounds the agent, such that they can initially 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.

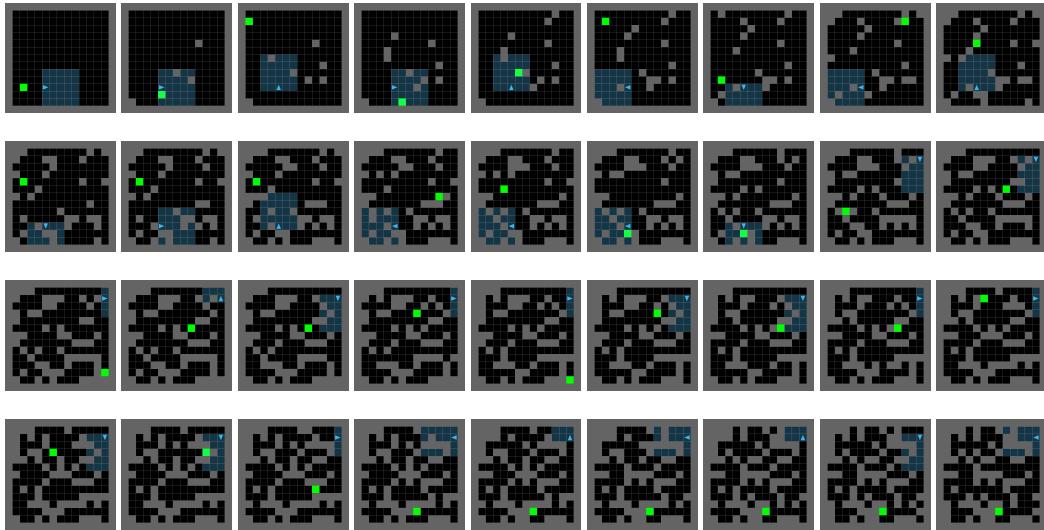


Figure 16: A single level evolved in the MiniGrid environment, starting from top left, ending bottom right. Throughout the process the agent experiences a diverse set of challenges.

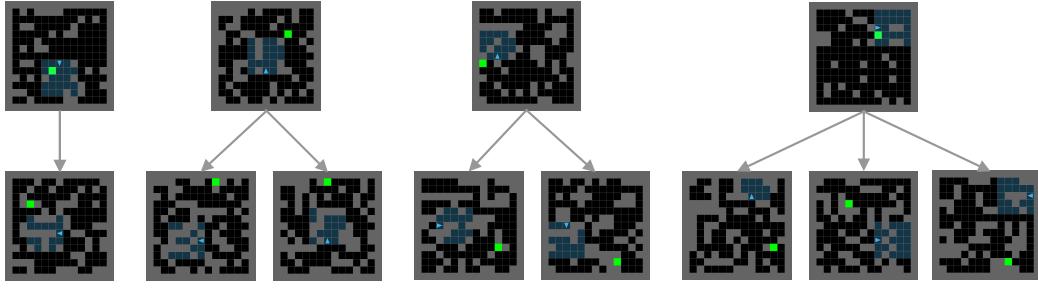


Figure 17: Maze evolution. Top shows starting levels, originally included in the replay buffer due to having high positive value loss. After many edits (up to 40), they produce the bottom row, which were all chosen to be in the highest 50 replay scores after 10k gradient steps. As we see, the same level can produce distinct future levels, in some cases multiple high regret levels.

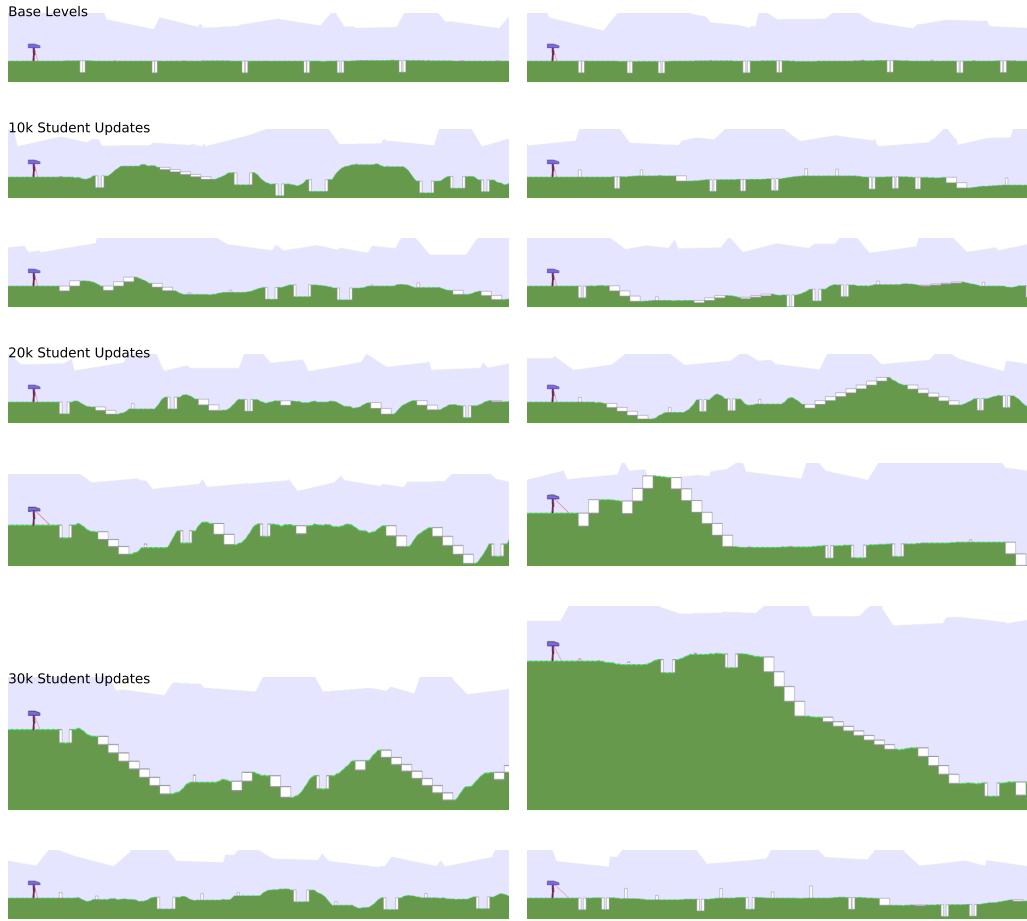


Figure 18: levels created and solved by ACCEL in the BipedalWalker environment. At the beginning (top row) levels are initialized with low values for each parameter. After several edits, we end up with challenging scenarios like steep staircases or high stumps. By the end of training, we see a diverse combination of multiple challenges.

## A.2 The Expanding Frontier

Here we analyze the performance of agents on levels produced by ACCEL. We have four agent checkpoints, from 5k, 10k, 15k and 20k student gradient updates. In Figure 19 we show four generations of a level, where we see that the later generations become harder for the 5k checkpoint, while the 20k checkpoint gets the highest learning signal (Positive Value Loss) from Generation 63.

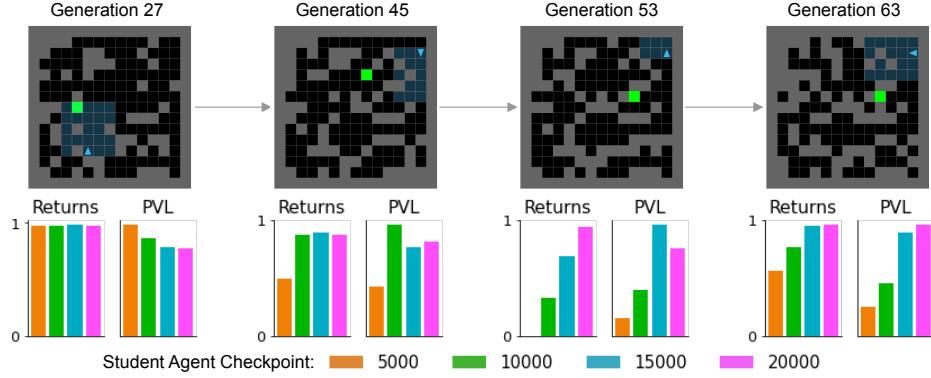


Figure 19: The Evolving Frontier. The top row shows four levels from the same lineage, at generations 27, 45, 53 and 63. Underneath each is a bar plot showing the Return and Positive Value Loss (PVL) for four different ACCEL policies, saved after 5k, 10k, 15k and 20k updates. At generation 27, all four checkpoints can solve the level, but the 5k checkpoint has the highest learning potential (PVL). On the right we see that by generation 63, only the 15k and 20k checkpoints are able to achieve a high return on the level.

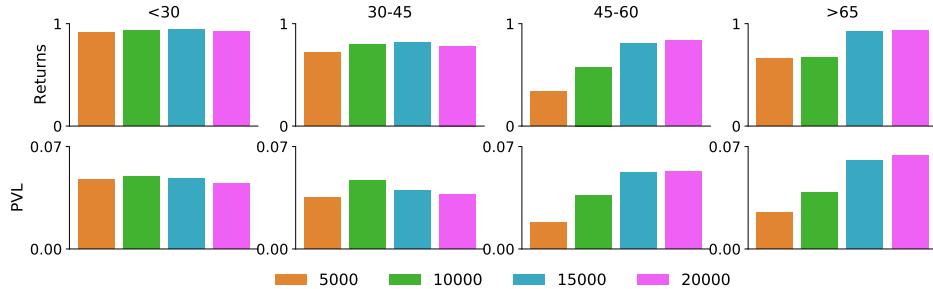


Figure 20: Aggregate metrics for each band of generations. For example, “30-45” refers to all the levels between generation 30-45. The later generation levels are harder for the early agents to solve, while the early agents have higher return and PVL for the earlier levels.

In Figure 20 we show all generations for the level included in Figure 19, grouped by generation. We then show the mean Return and Positive Value loss (PVL) for all four agent checkpoints. It is clear to see that the later generations have the highest learning potential for the 20k checkpoint, with the lowest return for the 5k checkpoint.

Next in Figure 21 we show data for all generations of 20 levels, chosen as those which were present in the 20k checkpoint replay buffer but also had ancestors in the 5k checkpoint buffer. For each checkpoint we plot all levels along the dimensions of Number of Blocks and Shortest Path, with the color corresponding to the solved rate. On the left, the 5k checkpoint agent can only repeatedly solve the shorter path levels with low block count. Later on, the 20k checkpoint agent performs well across the entire space.

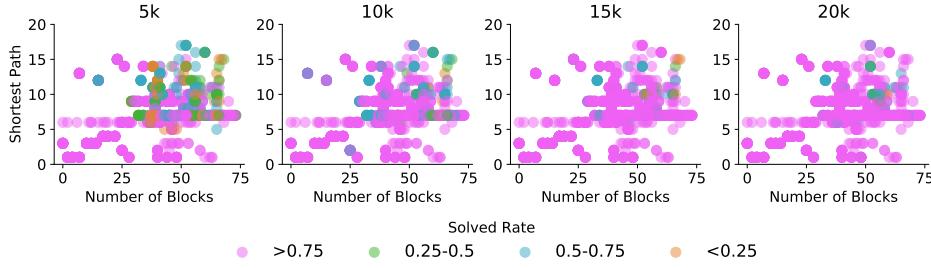


Figure 21: How do complexity metrics relate to difficulty? The plot shows the block count and shortest path length. From left to right we evaluate the agents at four checkpoints: 5k, 10k, 15k, 20k PPO updates. The color represents the solved rate. As we see, the 5k agent is unable to solve the levels with higher block count and longer paths to the goal, while the 20k agent is able to solve almost all levels.

### A.3 Full Experimental Results

**Lava Grid Extended Results** In Table 4 and Figure 22 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.

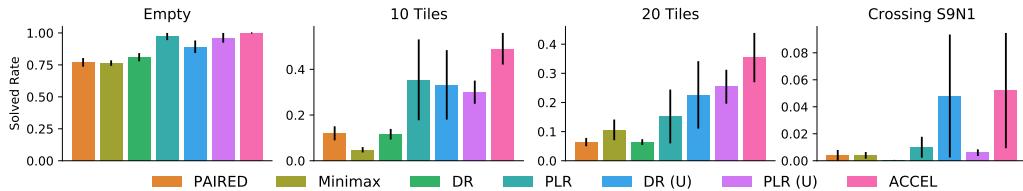


Figure 22: Test performance, both in distribution (Empty, 10 and 20 Tiles) and out of distribution (Crossing S9N1). Each evaluation is conducted for 100 trials. Plots show the mean and standard error across five runs.

Table 4: 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.  $\dagger$  indicates the generator distribution is a Binomial, whereby the generator can place 20 blocks, each is either a lava tile or empty.  $\ddagger$  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 $\dagger$	PLR $\dagger$	DR $\ddagger$	PLR $\ddagger$	ACCEL
Empty	$0.77 \pm 0.03$	$0.76 \pm 0.02$	$0.81 \pm 0.03$	$0.97 \pm 0.03$	$0.89 \pm 0.05$	$0.96 \pm 0.04$	$1.0 \pm 0.0$
10 Tiles	$0.12 \pm 0.03$	$0.05 \pm 0.01$	$0.12 \pm 0.02$	$0.35 \pm 0.18$	$0.33 \pm 0.15$	$0.3 \pm 0.05$	$0.49 \pm 0.07$
20 Tiles	$0.06 \pm 0.01$	$0.11 \pm 0.04$	$0.06 \pm 0.01$	$0.15 \pm 0.09$	$0.23 \pm 0.12$	$0.25 \pm 0.06$	$0.35 \pm 0.08$
LavaCrossing S9N1	$0.0 \pm 0.0$	$0.0 \pm 0.0$	$0.0 \pm 0.0$	$0.01 \pm 0.01$	$0.05 \pm 0.05$	$0.01 \pm 0.0$	$0.05 \pm 0.04$

**Partially-Observable Navigation** Next we show the extended results for the MiniGrid experiments. We use a series of challenging zero-shot environments (see Figure 23), introduced in the UED literature (Dennis et al., 2020; Jiang et al., 2021a). We include the full results in Table 5 and bar plots of the same data in Figure 26.

We also include an additional version of ACCEL using a the same generator as the DR and PLR baselines, thus editing more complex base levels. This removes the prior that it is beneficial to begin with simple empty rooms. As we see, both versions of ACCEL significantly outperforms the

baselines. Particularly in the more complex environments like Labyrinth we see large gains vs. the baselines. Also note that PLR outperforms all other baselines, and ACCEL outperforms PLR. We show this in the Table with a statistically significant point estimate, but also using the more robust metrics in `rliable` (Agarwal et al., 2021b), for example the “probability of improvement” shown in Figure 25.

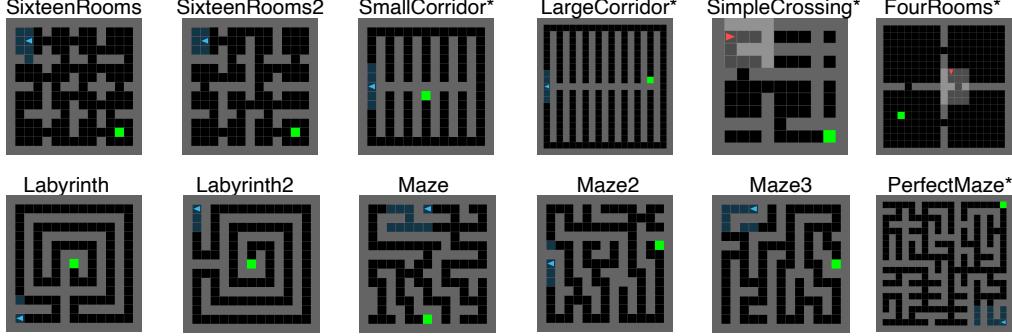


Figure 23: MiniGrid Zero-Shot Environments. Those with an asterisk are procedurally generated: For Small and Large Corridor, the position of the goal can be in any of the corridors, for Simple-Crossing and Four Rooms see Chevalier-Boisvert et al. (2018) and for PerfectMaze see Jiang et al. (2021a).

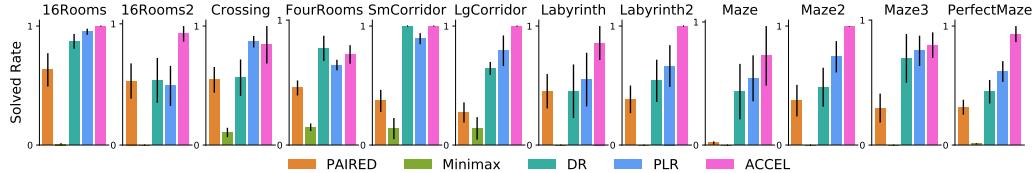


Figure 24: Zero-shot transfer results. Agents are evaluated for 100 episodes on a series of human designed mazes, plots show mean and standard error for each environment, across five runs.

Table 5: 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. \* indicates  $p < 0.05$  in Welch’s t-test against PLR. Note that all methods are evaluated after 20k student updates, aside from PAIRED and Minimax which have 30k updates.

Environment	PAIRED	Minimax	DR†	PLR†	ACCEL†	ACCEL‡
16Rooms	$0.63 \pm 0.14$	$0.01 \pm 0.01$	$0.87 \pm 0.06$	$0.95 \pm 0.03$	<b><math>1.0 \pm 0.0</math></b>	<b><math>1.0 \pm 0.0</math></b>
16Rooms2	$0.53 \pm 0.15$	$0.0 \pm 0.0$	$0.53 \pm 0.18$	$0.49 \pm 0.17$	$0.62 \pm 0.22$	<b><math>0.92 \pm 0.06</math></b>
SimpleCrossing	$0.55 \pm 0.11$	$0.11 \pm 0.04$	$0.57 \pm 0.15$	<b><math>0.87 \pm 0.05</math></b>	<b><math>0.92 \pm 0.08</math></b>	<b><math>0.84 \pm 0.16</math></b>
FourRooms	$0.46 \pm 0.06$	$0.14 \pm 0.03$	$0.77 \pm 0.1$	$0.64 \pm 0.04$	<b><math>0.9 \pm 0.08</math></b>	$0.72 \pm 0.07$
SmallCorridor	$0.37 \pm 0.09$	$0.14 \pm 0.09$	<b><math>1.0 \pm 0.0</math></b>	$0.89 \pm 0.05$	$0.88 \pm 0.11$	<b><math>1.0 \pm 0.0</math></b>
LargeCorridor	$0.27 \pm 0.08$	$0.14 \pm 0.09$	$0.64 \pm 0.05$	$0.79 \pm 0.13$	$0.94 \pm 0.05$	<b><math>1.0 \pm 0.0</math></b>
Labyrinth	$0.45 \pm 0.14$	$0.0 \pm 0.0$	$0.45 \pm 0.23$	$0.55 \pm 0.23$	<b><math>0.97 \pm 0.03</math></b>	$0.86 \pm 0.14$
Labyrinth2	$0.38 \pm 0.12$	$0.0 \pm 0.0$	$0.54 \pm 0.18$	$0.66 \pm 0.18$	<b><math>1.0 \pm 0.01</math></b>	<b><math>1.0 \pm 0.0</math></b>
Maze	$0.02 \pm 0.01$	$0.0 \pm 0.0$	$0.43 \pm 0.23$	<b><math>0.54 \pm 0.19</math></b>	<b><math>0.52 \pm 0.26</math></b>	<b><math>0.72 \pm 0.24</math></b>
Maze2	$0.37 \pm 0.13$	$0.0 \pm 0.0$	$0.49 \pm 0.16$	$0.74 \pm 0.13$	$0.93 \pm 0.04$	<b><math>1.0 \pm 0.0</math></b>
Maze3	$0.3 \pm 0.12$	$0.0 \pm 0.0$	$0.69 \pm 0.19$	$0.75 \pm 0.12$	<b><math>0.94 \pm 0.06</math></b>	$0.8 \pm 0.1$
PerfectMaze (M)	$0.32 \pm 0.06$	$0.01 \pm 0.0$	$0.45 \pm 0.1$	$0.62 \pm 0.09$	<b><math>0.88 \pm 0.12</math></b>	<b><math>0.93 \pm 0.07</math></b>
<b>Mean</b>	$0.39 \pm 0.03$	$0.05 \pm 0.01$	$0.62 \pm 0.05$	$0.71 \pm 0.04$	<b><math>0.88 \pm 0.04^*</math></b>	<b><math>0.9 \pm 0.03^*</math></b>

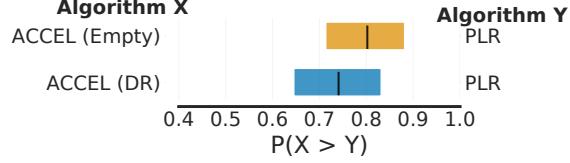


Figure 25: Probability of improvement of ACCEL vs. PLR across all the benchmark environments in Figure 23, using the open source notebook from Agarwal et al. (2021b). The probability of improvement represents the probability that Algorithm X outperforms Algorithm Y on a new task from the same distribution.

**BipedalWalker** For the BipedalWalker environment we test agents on each of the individual challenges from the environment parameterization. Concretely, we use the following four environments:

- **Stairs**: the stair height parameters are set to [2,2] with the number of steps set to 5.
- **PitGap**: the PitGap parameter is set to [5,5].
- **Stump**: the Stump parameter is set to [2,2].
- **Roughness**: the Roughness parameter is set to 5.

Each of these is visualized in the main body of the paper, in Figure 10. We also test agents on the simple BipedalWalker-v3 environment and the more challenging BipedalWalkerHardcore-v3 environment. For the “Hardcore” version, we note that none of our agents *officially* solve the environment, which is considered to be a reward over 300 for 100 independent evaluations. To test whether it is possible with our setup, we trained an identical PPO agent directly on the environment for 1B steps. The reward achieved was 239—indistinguishable from what is achieved by ACCEL using a far more challenging design space. In addition, the ACCEL agent is robust to individual challenges.

Table 6: Test performance on a variety of challenges. Each data point corresponds to the mean (and standard error) of ten independent runs, where each run is evaluated for 100 trials on each environment.  $\dagger$  indicates the generator first samples the number of blocks to place, between zero and sixty, then places that many.  $\ddagger$  indicates using the low value generator. Bold indicates being within one standard error of the best mean. All methods are evaluated after 30k updates.

Environment	PAIRED	Minimax	ALP-GMM	DR $\dagger$	PLR $\dagger$	ACCEL $\dagger$	ACCEL $\ddagger$
Basic	206.5 $\pm$ 30.3	154.3 $\pm$ 59.2	301.5 $\pm$ 11.6	261.9 $\pm$ 19.3	304.1 $\pm$ 1.8	316.9 $\pm$ 2.1	<b>318.1 <math>\pm</math> 1.0</b>
Hardcore	-47.2 $\pm$ 10.6	-44.3 $\pm$ 1.6	29.7 $\pm$ 9.9	23.8 $\pm$ 8.3	82.6 $\pm$ 8.5	163.3 $\pm$ 30.9	<b>236.0 <math>\pm</math> 8.9</b>
Stairs	-27.4 $\pm$ 12.1	-2.6 $\pm$ 2.6	22.1 $\pm$ 6.3	23.3 $\pm$ 4.4	48.0 $\pm$ 4.3	59.4 $\pm$ 10.5	<b>91.7 <math>\pm</math> 8.9</b>
PitGap	-68.2 $\pm$ 9.7	-79.3 $\pm$ 0.5	<b>98.8 <math>\pm</math> 24.9</b>	11.0 $\pm$ 7.6	46.2 $\pm$ 11.3	49.6 $\pm$ 12.6	<b>133.3 <math>\pm</math> 39.1</b>
Stump	-76.0 $\pm$ 10.3	-65.0 $\pm$ 18.4	-22.4 $\pm$ 17.2	-5.4 $\pm$ 5.5	7.5 $\pm$ 6.4	44.6 $\pm$ 49.8	<b>188.8 <math>\pm</math> 10.9</b>
Roughness	-5.1 $\pm$ 25.9	-1.2 $\pm$ 7.7	44.7 $\pm$ 11.6	52.3 $\pm$ 9.0	126.7 $\pm$ 7.3	211.7 $\pm$ 21.5	<b>248.9 <math>\pm</math> 12.3</b>
Mean	-2.9 $\pm$ 14.5	-6.3 $\pm$ 24.6	79.1 $\pm$ 17.5	61.1 $\pm$ 12.6	102.5 $\pm$ 13.0	140.9 $\pm$ 23.0	<b>202.8 <math>\pm</math> 13.6</b>

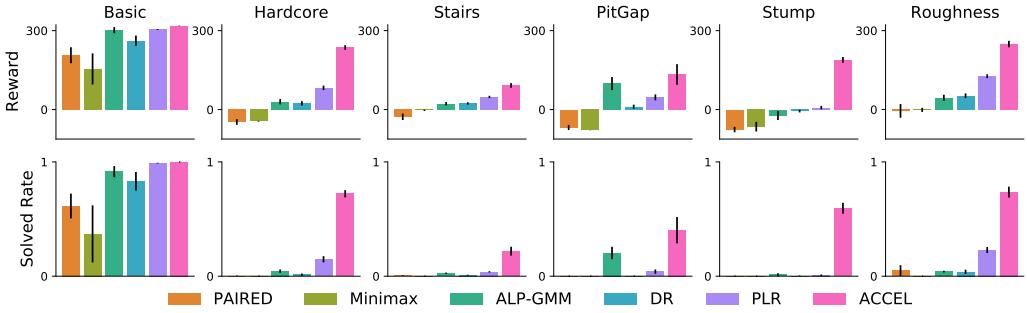


Figure 26: Test results. Agents are evaluated for 100 episodes on a series of individual challenges, plots show mean and standard error for each environment, across ten runs.

**POET Generated Levels** We also evaluated our agents on the six “Extremely Challenging” environments highlighted in the original POET paper. These represent some of the most difficult environment

parameterizations produced by POET. Since each run of POET has a population of 20 agents, it is not clear if a single agent from any of their runs can solve more than one of these challenges. In addition, POET only solves a single fixed seed of these environments. Instead, we report the mean performance over a hundred random samples for each given parameterization, for all ten runs of ACCEL with the mean and max performance (across seeds) shown in Table 7.

Table 7: Test performance on levels produced by POET. In each case we run 100 trials with different random seeds. Mean shows the mean performance across all ten ACCEL runs. Max shows the best from the ten runs per environment.

	1a	1b	2a	2b	3a	3b
Mean	0.01	0.01	0.00	0.03	0.01	0.12
Max	0.03	0.05	0.00	0.08	0.03	0.31

#### A.4 Testing the Limits of Current Approaches

In the experimental section we showed the results for a large procedurally generated maze, of size 51x51. ACCEL averaged a 53% and 52% success rate when using the empty or DR generator respectively, vs. a next best PLR with 25%. Now we consider going even further. We tested both versions of ACCEL, as well as DR and PLR, on an even larger maze, this time 101x101, shown in Figure 27. Note that this would be challenging even for human players, since the agent has a partially observable view. The performance of all methods is significantly weaker, with DR and PLR achieving a mean of 4% success rate. However, ACCEL still outperforms, achieving 7% and 8% success rate with the DR and empty generators respectively. We believe at this point the bottleneck for further improvement may not be the curriculum, but instead the LSTM-based policy which has to remember all previous paths, to solve the maze in the allotted 20,402 steps.

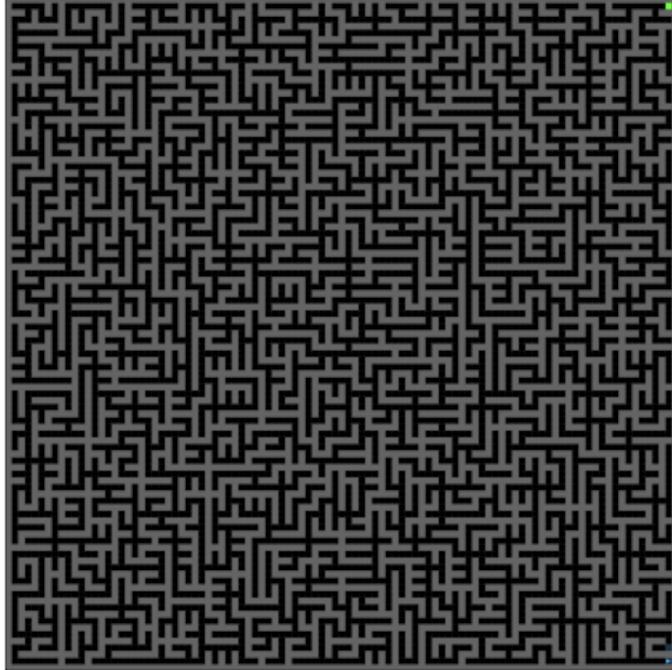


Figure 27: PerfectMazesXL. A 101x101 procedurally-generated MiniGrid environment. The agents have to transfer zero-shot from training in a 15x15 grid. This environment is challenging even for humans, since the agent only has a partially observable view, it requires memorizing the current location at all times to ensure exploring all corners of the grid.

## A.5 Additional Experiments

In this section we show a series of additional experiments to understand the performance of ACCEL.

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

- **ACCEL** Using the DR generator.
- **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.

Table 8: 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	$1.0 \pm 0.0$	$0.76 \pm 0.19$	$0.9 \pm 0.07$	$0.84 \pm 0.06$
16Rooms2	$0.51 \pm 0.28$	$0.23 \pm 0.16$	$0.41 \pm 0.19$	$0.68 \pm 0.18$
SimpleCrossing	$0.8 \pm 0.05$	$1.0 \pm 0.0$	$0.9 \pm 0.1$	$0.75 \pm 0.05$
FourRooms	$0.85 \pm 0.05$	$0.85 \pm 0.06$	$0.88 \pm 0.04$	$0.88 \pm 0.05$
SmallCorridor	$0.72 \pm 0.1$	$0.74 \pm 0.1$	$0.6 \pm 0.17$	$0.7 \pm 0.18$
LargeCorridor	$0.91 \pm 0.05$	$0.75 \pm 0.08$	$0.56 \pm 0.18$	$0.63 \pm 0.18$
Labyrinth	$0.98 \pm 0.02$	$0.85 \pm 0.11$	$0.99 \pm 0.01$	$0.67 \pm 0.19$
Labyrinth2	$0.97 \pm 0.03$	$0.83 \pm 0.11$	$0.7 \pm 0.15$	$0.48 \pm 0.2$
Maze	$0.78 \pm 0.21$	$0.87 \pm 0.05$	$0.57 \pm 0.18$	$0.15 \pm 0.08$
Maze2	$0.5 \pm 0.24$	$0.67 \pm 0.18$	$0.65 \pm 0.15$	$0.23 \pm 0.15$
Maze3	$0.79 \pm 0.14$	$0.9 \pm 0.08$	$0.95 \pm 0.05$	$0.56 \pm 0.17$
<b>Mean</b>	$0.79 \pm 0.04$	$0.76 \pm 0.04$	$0.74 \pm 0.04$	$0.58 \pm 0.05$

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 Table 8. 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.

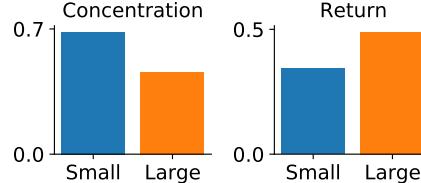


Figure 28: Replay buffer diversity vs. return in the lava environment. On the left we show the concentration of the replay buffer, measured as the percentage of the top 100 high-regret levels that can be produced by just ten parents. On the right we compare the average return on ten-tile test environments. “Small” corresponds to a buffer of size 4k, with no generator, while “Large” indicates a buffer of size 10k, using a generator 10% of the time.

**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. It is likely that hyperparameters alone will not be sufficient if we want to scale ACCEL to more open-ended problems, which we leave to future work.

## 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. For PAIRED and Minimax in the partially-observable navigation environment we use results from the authors of [Jiang et al. \(2021a\)](#).

### 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 to 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. The DR agent samples the number of blocks between [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  $15 \times 15$  grid, where each cell can contain a wall, the goal, the agent, or navigable space. The student agent receives a reward of  $1 - T/T_{\max}$  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.

**BipedalWalker** The BipedalWalker environment we use is a modified version of the BipedalWalkerHardcore environment from OpenAI Gym. The agent learns from a proprioceptive state with 24 dimensions consisting of lidar sensors, angles and contacts but notably the agent does not have access to its map coordinates. The action space is four continuous values controlling the torques of its 4 motors. The environment design space is shown in Table 9, where we show the value of the initialization for ACCEL, the edit size, and the maximum values. DR levels are sampled between zero and the maximum value. For PLR, we combine the environment parameterization with the specific seed of the sampled level, making the replay deterministic. For ACCEL we make an edit by randomly sampling one of the eight parameters and then adding or subtracting the quantity shown in the “Edit Size” row of Table 9.

Table 9: Environment design space for the BipedalWalker environment. Where values are shown as ranges, both the low and high end of the range are learned parameters, and when the level is created each obstacle size is sampled from the range.

	Stump Height	Stair Height	Stair Steps	Roughness	Pit Gap
<b>Easy Init</b>	[0,0.4]	[0,0.4]	1	Unif(0.6)	[0,0.8]
<b>Edit Size</b>	0.2	0.2	1	Unif(0.6)	0.4
<b>Max Value</b>	[5,5]	[5,5]	9	10	[10,10]

Table 10: Total number of environment interactions for a given number of student PPO updates.

Environment	PPO Updates	PLR	ACCEL
MiniGrid	20k	327M	369M
BipedalWalker	30k	1.96B	2.07B

## 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 lava tiles, while for MiniGrid we allow the editor to also change the goal location. If lava or walls (or lava) 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. For the lava grid in 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  $\{\text{random, positive value loss}\}$  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  $\{\text{random, positive value loss}\}$ , as well as the levels to edit from  $\{\text{easy, batch}\}$  and replay rate from  $\{0.8, 0.9\}$ . For MiniGrid, we follow the protocol from [Jiang et al. \(2021a\)](#) and select the best hyperparameters using the validation levels  $\{16\text{Rooms, Labyrinth, Maze}\}$ . The final hyperparameters chosen are shown in Table 11.

For BipedalWalker we used the continuous control policy from the open source implementation of PPO from [Kostrikov \(2018\)](#), as well as many of the hyperparameters used in the recommended settings for MuJoCo. This involves a simple feedforward neural network with two hidden layers of size 64 and Tanh activations. We tuned the hyperparameters for our base agent using domain randomization, and conducted a sweep over the learning rate  $\{3e-4, 3e-5\}$ , PPO epochs  $\{5, 20\}$ , entropy coefficient  $\{0, 1e-3\}$  and number of minibatches  $\{4, 32\}$ , using the validation performance on BipedalWalkerHardcore. We then used these base agent configurations for all UED algorithms. For PLR we further conducted a sweep over the buffer size  $\{1000, 5000\}$ , replay rate  $\{0.9, 0.5\}$  and staleness coefficient  $\{0.3, 0.5, 0.7\}$ , using the same settings found for both PLR and ACCEL. Finally, for ACCEL we tuned both the number of edits  $\{1, 2, 3, 4\}$  and whether to edit the easy or batch levels.

Table 11: Hyperparameters used for training each method in the maze and car racing environments.

Parameter	MiniHack (Lava)	MiniGrid	BipedalWalker
<i>PPO</i>			
$\gamma$	0.995	0.995	0.99
$\lambda_{\text{GAE}}$	0.95	0.95	0.9
PPO rollout length	256	256	2000
PPO epochs	5	5	5
PPO minibatches per epoch	1	1	32
PPO clip range	0.2	0.2	0.2
PPO number of workers	32	32	16
Adam learning rate	1e-4	1e-4	3e-4
Adam $\epsilon$	1e-5	1e-5	1e-5
PPO max gradient norm	0.5	0.5	0.5
PPO value clipping	yes	yes	no
return normalization	no	no	yes
value loss coefficient	0.5	0.5	0.5
student entropy coefficient	0.0	0.0	1e-3
generator entropy coefficient	0.0	0.0	0.0
<i>ACCEL</i>			
Edit rate, $q$	1.0	1.0	1.0
Replay rate, $p$	0.9	0.8	0.9
Buffer size, $K$	10000	4000	1000
Scoring function	positive value loss	positive value loss	positive value loss
Edit method	positive value loss	random	random
Levels edited	batch	easy	easy
Prioritization	rank	rank	rank
Temperature, $\beta$	0.3	0.3	0.1
Staleness coefficient, $\rho$	0.5	0.5	0.5
<i>PLR</i>			
Scoring function	positive value loss	positive value loss	positive value loss
Replay rate, $p$	0.5	0.5	0.5
Buffer size, $K$	10000	4000	1000