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Combining Evolutionary Search with Behaviour Cloning for Procedurally Generated Content

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Abstract

In this work, we consider the problem of procedural content generation for video game levels. Prior approaches have relied on evolutionary search (ES) methods capable of generating diverse levels, but this generation procedure is slow, which is problematic in real-time settings. Reinforcement learning (RL) has also been proposed to tackle the same problem, and while level generation is fast, training time can be prohibitively expensive. We propose a framework to tackle the procedural content generation problem that combines the best of ES and RL. In particular, our approach first uses ES to generate a sequence of levels evolved over time, and then uses behaviour cloning to distil these levels into a policy, which can then be queried to produce new levels quickly. We apply our approach to a maze game and *Super Mario Bros*, with our results indicating that our approach does in fact decrease the time required for level generation, especially when an increasing number of valid levels are required.

1 Introduction

Procedural content generation (PCG) is used in a wide range of applications, ranging from testing autonomous robot software [1] to the generation of video game levels [3]. With a specific focus on video game design, PCG allows for automatic generation of various aspects of the game, such as level and terrain design [6]. As such, it is a powerful tool that can be used by designers to generate more content using fewer resources.

One of the most common ways of implementing PCG is through the use of evolutionary search, and more specifically genetic algorithms (GAs) [4]. GAs are particularly advantageous when it comes to level generation, since they have the ability to create diverse levels. However, GAs generate their results by intelligently modifying a population of candidate solutions until a suitable one is found. They are therefore often slow to generate a playable level, which may be problematic when real-time generation is required.

A more recent approach to procedurally generating video game levels is reinforcement learning (RL) [14], which frames the creation of a level as a sequential decision process and learns a *policy* that produces a sequence of actions to transform an initial randomly generated level into one that is playable and interesting [6]. Unfortunately, RL requires a reward function specified by a human designer to guide learning, and usually requires significant amounts of training time before a suitable level can be created. However, after a model has been trained, the generation of levels is fast.

In this work, we explore the possibility of combining ideas from both ES and RL to inherit the best of both methods. In particular, ES is capable of generating multiple diverse levels, while RL is capable of generating a single level quickly. We therefore propose an approach that learns a policy using the levels generated by ES, effectively distilling the results of ES into a policy that can be queried to generate new levels quickly. Importantly, these policies can be constructed without the extensive training time required by prior work [6].

We demonstrate our approach in a Maze game, as well as *Super Mario Bros.*, where results indicate that our approach is able to generate playable levels significantly faster than the competing GA.

2 Background

In this section, we discuss genetic algorithms and reinforcement learning, two optimisation techniques that have been used in the literature to develop PCG systems.

2.1 Genetic Algorithms

Genetic algorithms (GAs) seek to optimise a population of candidate solutions. Each individual in the population encodes a particular solution using a genetic representation, or *gene*. Individuals are evaluated using a *fitness function*, which is a task-specific function that evaluates the performance of an individual, and is used to decide how they should be modified.

There are several operators that can be applied to the population in order to increase the fitness of the individuals. The most common of these are *crossover*, where two high-performing (according to the fitness function) individuals are combined to form new individuals, and *mutation*, where an individual's gene is perturbed to encourage exploration of the solution space. Crossover and mutation are illustrated by Figure 1.

Starting with an initial randomly generated population, GAs modify the population to produce new individuals. Each iteration results in a new *generation* of candidate solutions, which are created using the above operations, and also often inherit the top performing individuals from the previous generation in a concept known as *elitism*. The GA continues for a given number of generations, or until individuals surpass some predefined fitness threshold.

2.2 Reinforcement Learning

In reinforcement learning (RL), an agent interacts with an environment in an attempt to solve a given task in a trial-and-error fashion. Typically, an environment is modelled as a Markov decision process $\langle S, A, P, R, \gamma \rangle$, where (i) S is the state space; (ii) A is the set of actions available to an agent; (iii) $P(s'|s,a)$ is the transition dynamics, specifying the probability of an agent finding itself in state s' after executing action a from state s; (iv) $R(s,a)$ is the reward function that specifies the reward an agent receives for executing action a in state s; and (iv) $\gamma \in [0,1)$ is used to discount future rewards.

An agent interacts with its environment through a *policy* π, which maps states to actions. The utility of a given policy can be quantified by its *value function*, which captures the expected future rewards following π:

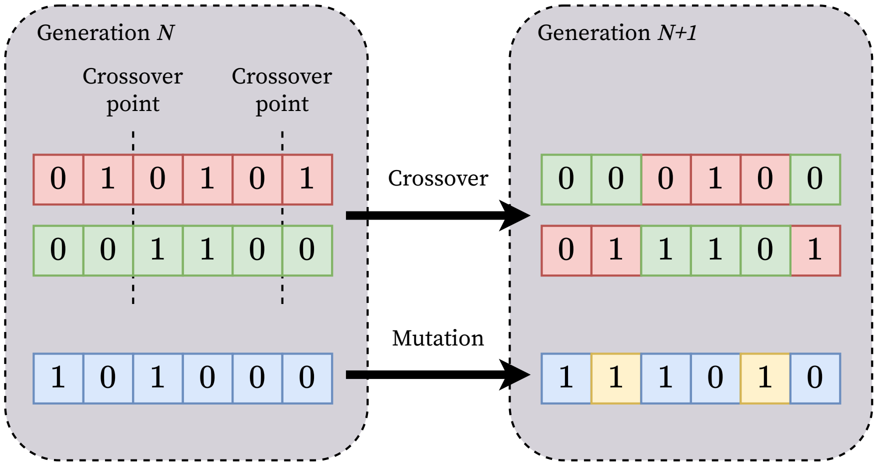


Figure 1: Illustration of crossover and mutation. Here, solutions are encoded as binary strings. The top row illustrates 2-point crossover, where two genes (red and green) are combined to create two new individuals. The bottom row illustrates mutation, where the genes of the blue individual are perturbed (by flipping a small number of its bits) to produce a new individual.

$$v_\pi(s) = \mathbb{E}_\pi \left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) | s_t = s \right].$$

The aim of an agent is to discover an optimal policy π^*, such that $\pi^* \in \arg\max_\pi v_\pi(s)$ for all s in S. This is often achieved through planning approaches such as policy iteration [5], or learning approaches such as Q-learning [17].

2.2.1 Learning from Demonstration

An alternate approach to compute a policy relies on an agent having access to the transition data of another agent, consisting of trajectories $\{s_0, a_0, s_1, a_1, \ldots, a_{n-1}, s_n\}$.

If these trajectories are generated by an expert, then an agent can use *behaviour cloning* to mimic the expert to learn a direct mapping between states and actions. This can be achieved by constructing a dataset $X = \{s_i\}_{i=0}^{n-1}$ with associated labels $Y = \{a_i\}_{i=0}^{n-1}$ and then applying any appropriate supervised learning method to train a model to predict Y given X. Once trained, this model can then be used directly as a policy, avoiding the need to learn a value function or policy from reward signal alone.

3 Related Work

While there have been many approaches to PCG, evolutionary methods are perhaps the most popular [15, 13]. For example, [4] use a simple genetic algorithm to generate video game levels, while [8] use a two-population genetic algorithm. This ensures that a high number of playable levels is generated by maintaining separate populations of feasible (playable) and non-feasible levels. Diverse levels are also encouraged through the use of novelty-based fitness functions

[7]. However, game-specific knowledge is also injected to repair unplayable levels, limiting its general applicability.

There has also been work on PCG that leverages the generalisability of neural networks. For example, [10] represent each collectable game item by a neural network, the weights and structure of which is evolved with a genetic algorithm, while [16, 12] train a generative adversarial network (GAN) on a collection of existing game levels. They then use evolutionary methods to search for a latent input vector to this GAN to generate a level. However, these approaches require significant amounts of training data and are biassed towards existing levels, which may be undesirable should new and interesting levels be required.

Finally, [6] frame the problem of level generation as a Markov decision process, and use standard RL techniques to learn a policy that generates new levels. Here, actions involve changing a single tile of a 2D map. After to training, generation is fast, and their approach does not rely on prior training data. However, the approach requires a handcrafted reward function, and the training time is extensive (on the order of 100 million timesteps), which is limiting in more complex environments.

4 Genetic Algorithms with Behaviour Cloning for PCG

In Section 2, we described two approaches that have previously been used for PCG. GAs have been shown to be capable of generating interesting playable levels [4], but the search procedure must be executed whenever a new level is required. By contrast, a policy learned through RL can generate new levels quickly, but the training of such policies is complex and time-consuming. Policies can also be computing from demonstration data, but this assumes access to expert trajectories, which is not often the case.

In this section, we describe a novel framework for PCG that addresses the above issues. The main idea here is to execute a GA to generate levels, and then treat the data generated during the search procedure as the output of an "expert" to which behaviour cloning can be applied. As a result, our approach produces a policy that can be used to generate new levels quickly, while avoiding the requirement for expensive training or complex, handcrafted reward functions.

In the rest of this paper, we will limit ourselves to 2D tile-based games, where a level is made up of a grid of 2D tiles or cells, each of which takes a specific type (e.g., empty, obstacle, etc). Similarly to [6], an action is represented as the tuple $\langle x, y, t \rangle$, which indicates that the tile at location (x, y) should be modified to type t.

4.1 Phase 1: Evolutionary Search

We first implement a GA similarly to [11] to generate playable levels. The initial population consists of randomly generated levels, which subsequently undergo both crossover and mutation to create the next generation. We also use elitism, retaining a number of high-performing individuals from the previous population. After each new generation is formed, we consider the top levels (according to the fitness function) and determine whether they have reached an "acceptable" threshold of performance. If this is the case, the GA terminates, but otherwise continues until a sufficient number of "acceptable" levels have been created. This process is illustrated by Figure 2.

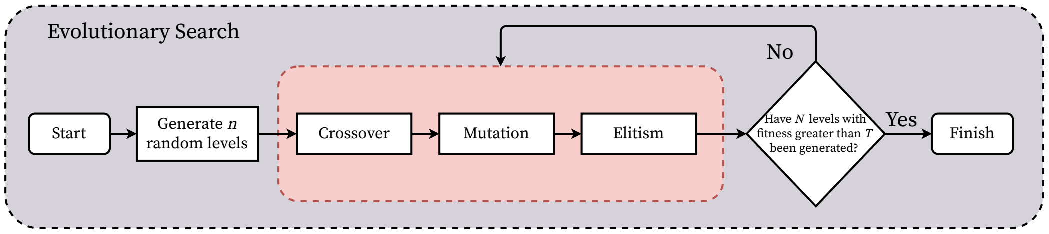

Evolutionary Search
No
Start
Generate n random levels
Crossover
Mutation
Elitism
Have N levels with fitness greater than T been generated?
Yes
Finish

Figure 2: The process of generating a set of playable levels using a GA. The GA continues until it has produced a sufficient number of levels whose fitness exceeds some threshold.

4.2 Phase 2: Policy Creation through Behaviour Cloning

The output of Phase 1 is a set of playable levels, as well as the random levels that were initially created. We consider all initial and final levels, and compute the changes in tiles necessary to transform an initial level into the final one. To generate the data that will be used to fit a policy, we consider each start level S_i, end level E_i and set of changes between the two Δ_i. Note that because of our action formulation, Δ_i is equivalently a sequence of actions necessary to transform S_i into E_i.

We then follow the approach in Algorithm 1 to generate the data. This begins using the state of the initial level, s_0 and computing the first action from Δ_i to apply, a_0. The tuple (s_0, a_0) is saved to a buffer, and a_0 is applied to s_0 to produce a new state s_1. This process is repeated until all actions in Δ_i have been applied. All of the above is applied to each start and end level to produce a set of state-action pairs that implicitly represents a policy.

Algorithm 1 Build policy dataset

```
Require: $InitialLevels \leftarrow$ initial randomly generated levels
Require: $FinalLevels \leftarrow$ final levels generated by GA
  $Changes \leftarrow \varnothing$
  for all $(S_i, E_i) \in InitialLevels \times FinalLevels$ do
      $s \leftarrow \text{STATE}(S_i)$
      $\Delta \leftarrow \text{COMPUTEDIFFS}(S_i, E_i)$        ▷ difference in tiles between start and end levels
      for all $a \in \Delta$ do
          $Changes \leftarrow Changes \cup \{(s, a)\}$
          $s \leftarrow \text{NEXTSTATE}(s, a)$
  Return $Changes$
```

4.3 Phase 3: Policy Execution

To generate a new level, we begin with a randomly created one and must apply our policies, computed in the previous phase, to produce a playable level. One issue is that our policy should generalise to unseen states, and while there are many approaches to doing so, here we use a simple approach based on the nearest neighbours algorithm, implemented in SCIKIT-LEARN [9].

Given an initial randomly generated state, the policy is applied as follows. First, the state is passed to the nearest neighbour algorithm to find the most similar state observed in Phase 2. The action corresponding to this state is then returned and executed. However, in practice we found that applying a single action to the state does not change it significantly; as a result, the policy may find itself applying the same action in an infinite loop, since the nearest neighbour algorithm continues to return the same state.

We therefore take inspiration from prior work [2] and execute several actions in sequence before computing the next state. This can be seen as executing a temporally extended action for n timesteps. Since the buffer created in the previous phase is sequential, we simply execute action a_i, and then subsequently $a_{i+1}, \dots a_{i+n}$. In practice, instead of using a fixed value of n, we instead use hyperparameter p, which represents the proportion of the total changes that should be made, $|\Delta_i|$, and compute $n = |\Delta_i|/p$.

The above process is repeated until one of two conditions are met: either a maximum number of steps is reached, or an acceptable level (according to the fitness function) is generated. In the former case, the algorithm restarts with a new random level. This entire procedure is illustrated by Figure 3.

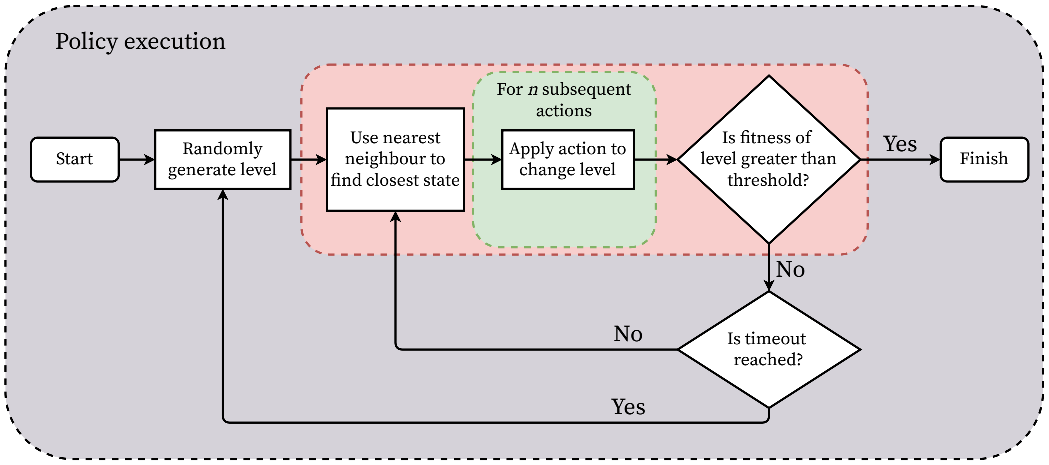

Policy execution
Start
Randomly generate level
Use nearest neighbour to find closest state
For n subsequent actions
Apply action to change level
Is fitness of level greater than threshold?
Yes
Finish
No
Is timeout reached?
No
Yes

Figure 3: Applying our policy to transform an initial random level into a playable one.

5 Experiments

We apply our framework to two tile-based environments: a Maze domain, where an agent is required to navigate from the top left to the botton right of a maze consisting of free space and walls, and the video game *Super Mario Bros*. We use the AMIDOS2006 MARIO AI framework[1] to generate *Super Mario Bros* levels of size 101×16 tiles and to evaluate the fitness of these levels.

5.1 Maze Domain

We use the Maze domain as a test-bed with which to validate our framework. A Maze level is considered "playable" if there exists a valid path from the top left to the bottom right corner. Maze levels are generated by randomly placing walls within the bounds of the maze, and a given level is represented by the xy-coordinates of each wall.

[1] https://github.com/amidos2006/Mario-AI-Framework

Fitness function The fitness function for the generated mazes takes into account whether or not the level is playable, the spread of blocks within the maze, and the length of the shortest path from the start to the goal. The first component ensure the maze is solvable, while the second favours mazes with an equal spread of vertical and horizontal walls. Finally, longer optimal solutions are given higher fitness to promote difficult, interesting mazes. The exact fitness function is

$$f(x) = 0.7 \times Finishable + 0.2 \times RatioX + 0.2 \times RatioY + 0.0001 \times PathLength$$

where (i) $Finishable$ is 1 if a solution exists, and 0 otherwise; (ii) $RatioX$ is the number of walls in the left half of the level divided by the total number of walls; (iii) $RatioY$ is the number of walls in the top half of the level divided by the total number of walls; and (iv) $PathLength$ is the length of optimal path. We apply the framework described in Section 4 to the Maze domain with the hyperparameters and experimental settings described in Table 1.

Hyperparameter	Description	Value
Initial population size	Number of levels to be generated and evaluated for initial batch of levels	50
Size of child list	Size of list of levels with the best fitnesses to determine whether to terminate	20
Crossover points	Number of segments each chromosome should be split for crossover	50
Mutation rate	Percentage of chromosome to mutate	0.05
Maximum iterations	Maximum number of iterations for genetic algorithm	1000
p	Parameter that controls the length of the temporally extended action	0.06
D	Size of the mazes	10 – 50
Number of walls	Number of walls for in each level	$0.15D^2$

Table 1: Maze domain hyperparameters and experimental settings.

We evaluate our approach against a genetic algorithm to determine the time taken to generate the same number of playable levels. We first note that even though the policy is created from levels generated by a GA, the final levels differ between the two approaches. Figures 4 and 5 illustrate a subset of these levels.

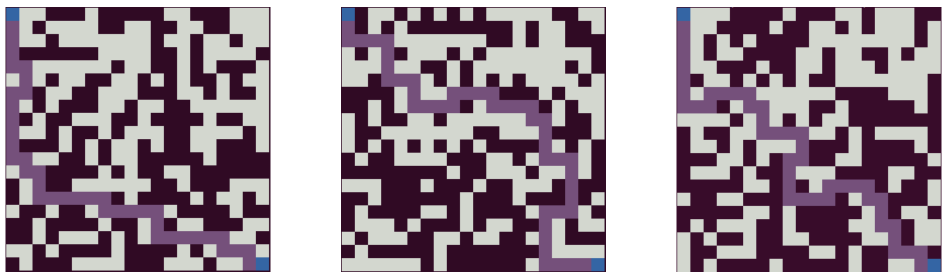


Figure 4: Maze levels of size 20 × 20 generated by a genetic algorithm. Purple indicates the optimal path from the start to the goal location.

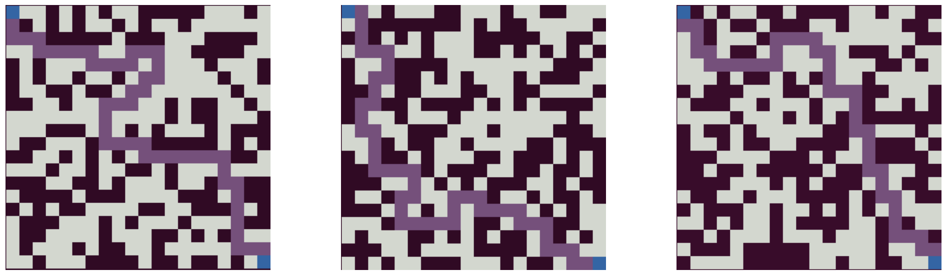
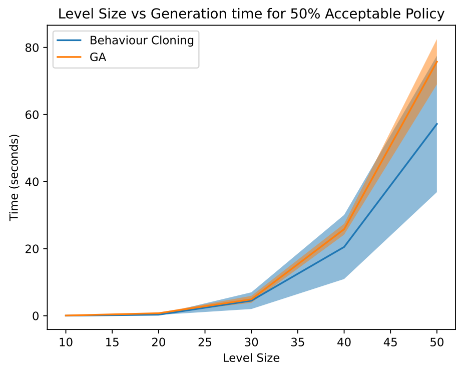
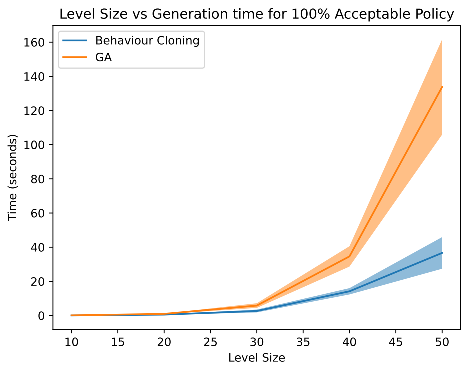


Figure 5: Maze levels of size 20 × 20 generated by our approach. Purple indicates the optimal path from the start to the goal location.

Our initial tests indicated that applying behaviour cloning to the output of a GA that terminates when at least one individual passes the threshold resulted in poor performance. However, when at least half of the GA's individuals were deemed acceptable (i.e. 50% of the final generation had a fitness greater than the threshold), applying our approach resulted in good performance. Moreover, when requiring that the final generation of the GA consist of only acceptable levels, our approach vastly outperforms it, especially as the size of the Maze level increases. Figure 6 illustrates that increasing the quality of the GA's output has a positive effect on our framework. The results also indicate that our method is able to better scale to larger domains when compared to GAs.



(a) Maze generation with 50% acceptable levels produced by the GA.



(b) Maze generation with 100% acceptable levels produced by the GA.

Figure 6: A wall-clock comparison of our approach with a genetic algorithm on the Maze domain of various sizes. Lower is better. Mean and standard deviation over 10 random seeds are shown.

5.2 *Super Mario Bros* Domain

We now apply our framework to a significantly more challenging video game environment. In *Super Mario Bros.*, the agent traverse the level from left to right while avoiding enemies and obstacles. Since there are multiple tile types, each level is represented by the xy-position of each tile, as well as its specific type. To generate a random level, we randomly place tiles within the level, but assign higher probability to "air" tiles (which can be passed through) to assist the GA in producing playable levels. A randomly generated level is illustrated by Figure 7.

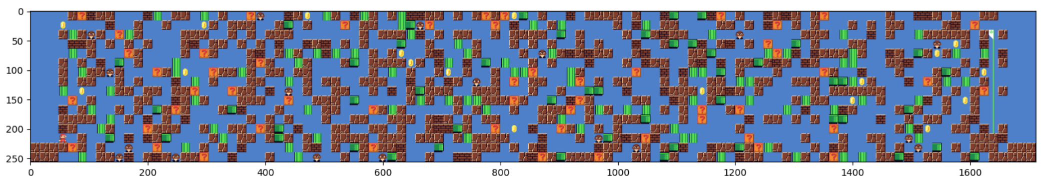


Figure 7: Randomly generated *Super Mario Bros* level.

Fitness function For *Super Mario Bros*, we implement a fitness function that includes whether the agent timed out, won or lost the current level (based on behaviour generated by AMIDOS2006 MARIO AI). The fitness function also includes the percentage of the level the agent was able to complete before the end state, and the agent's state (whether the agent acquired upgrades within the level). Specifically, the fitness function is

$$f(x) = WinState + 2 \times CompletionPercentage + 0.5 \times MarioState,$$

where (i) $WinState$ takes the value 0.1 if a timeout occurs, 0.4 if the agent loses and 1 if it succeeds; (ii) $CompletionPercentage$ is the percentage of the screen the agent is able to traverse to the right; and (iii) $MarioState$ is 1 if any power-ups were collected, and 0 otherwise.

We apply or approach to *Super Mario Bros* with the hyperparameters and experimental settings described in Table 2.

Hyperparameter	Description	Value
Initial population size	Number of levels to be generated and evaluated for initial batch of levels	100
Size of child list	Size of list of levels with the best fitnesses to determine whether to terminate	20
Crossover points	Number of segments each chromosome should be split for crossover	101
Mutation rate	Percentage of chromosome to mutate	0.05
Maximum iterations	Maximum number of iterations for genetic algorithm	1000
p	Parameter that controls the length of the temporally extended action	0.05

Table 2: *Super Mario Bros* hyperparameters and experimental settings.

As in the Maze domain, we again note that there is a large difference between the output of the GA and our approach, despite the latter being trained on levels produced by the former. This is illustrated by Figures 8 and 9.

Finally, we quantitatively compare our approach to a GA to measure how long it takes to generate a given number of playable levels. The results in Figure 10 clearly indicate that once a policy has been trained on the output of a GA, the creation of subsequent levels is significantly faster than repeatedly executing the GA to produce more levels.

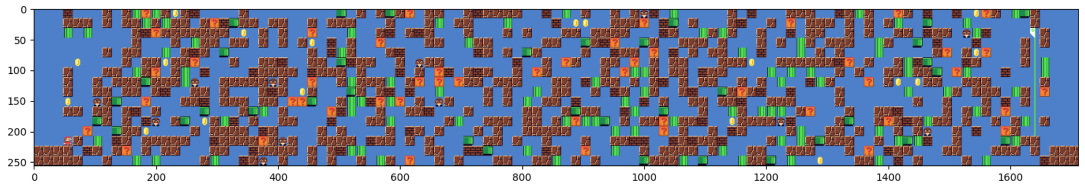


Figure 8: *Super Mario Bros* level generated by a genetic algorithm.

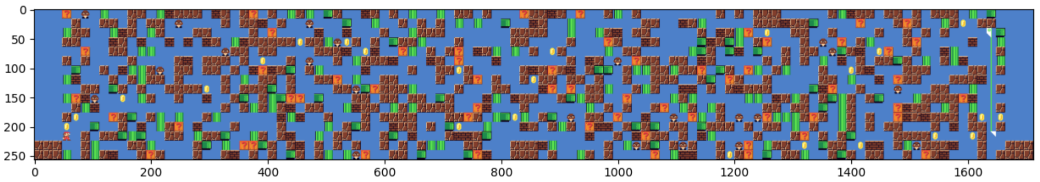


Figure 9: *Super Mario Bros* level generated by our approach.

6 Conclusion

We have proposed an approach to procedural content generation for video games that relies on a combination of evolutionary search and behaviour cloning. Our approach allows an agent to derive a policy capable of generating new levels quickly, without the need for expensive training or complex, handcrafted reward functions. Our results on two domains, including a complex video game, indicate that our approach outperforms genetic algorithms.

Our framework is agnostic to the exact details of both the genetic algorithm and the method of behaviour cloning. We adopted a simple, naïve approach here, but promising future work would be to incorporate more sophisticated algorithms and techniques, such as deep neural networks and more advanced search strategies. More generally, the combination of evolutionary search with reinforcement may be a productive avenue for deploying PCG in the real world.

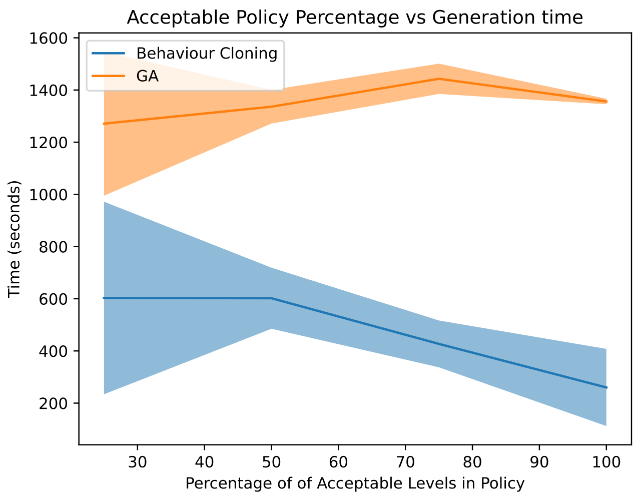


Figure 10: A wall-clock comparison of our approach with a genetic algorithm on the *Super Mario Bros* domain as a function of the number of levels required by the GA to be acceptable. Lower is better. Mean and standard deviation over 10 random seeds are shown.

References

[1] James Arnold and Rob Alexander. Testing autonomous robot control software using procedural content generation. In *International Conference on Computer Safety, Reliability, and Security*, pages 33–44. Springer, 2013.

[2] Will Dabney, Georg Ostrovski, and Andre Barreto. Temporally-extended ε-greedy exploration. In *International Conference on Learning Representations*, 2020.

[3] Lucas Ferreira, Leonardo Pereira, and Claudio Toledo. A multi-population genetic algorithm for procedural generation of levels for platform games. *Proceedings of the Companion Publication of the 2014 Annual Conference on Genetic and Evolutionary Computation*, 07 2014.

[4] Lucas Ferreira, Leonardo Pereira, and Claudio Toledo. A multi-population genetic algorithm for procedural generation of levels for platform games. In *Proceedings of the Companion Publication of the 2014 Annual Conference on Genetic and Evolutionary Computation*, pages 45–46, 2014.

[5] Ronald Howard. *Dynamic programming and Markov processes.* John Wiley, 1960.

[6] Ahmed Khalifa, Philip Bontrager, Sam Earle, and Julian Togelius. Pcgrl: Procedural content generation via reinforcement learning. *Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*, 16:95–101, 10 2020.

[7] Joel Lehman and Kenneth O Stanley. Abandoning objectives: Evolution through the search for novelty alone. *Evolutionary Computation*, 19(2):189–223, 2011.

[8] Antonios Liapis, Georgios N Yannakakis, and Julian Togelius. Constrained novelty search: A study on game content generation. *Evolutionary computation*, 23(1):101–129, 2015.

[9] Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, et al. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.

[10] Sebastian Risi, Joel Lehman, David B D'Ambrosio, Ryan Hall, and Kenneth O Stanley. Petalz: Search-based procedural content generation for the casual gamer. *IEEE Transactions on Computational Intelligence and AI in Games*, 8(3):244–255, 2015.

[11] Aykut Burak Safak, Erkan Bostanci, and Ali Emre Soylucicek. Automated maze generation for ms. pac-man using genetic algorithms. *International Journal of Machine Learning and Computing*, 6(4):226–240, 2016.

[12] Jacob Schrum, Vanessa Volz, and Sebastian Risi. Cppn2gan: Combining compositional pattern producing networks and gans for large-scale pattern generation. In *Proceedings of the 2020 Genetic and Evolutionary Computation Conference*, pages 139–147, 2020.

[13] Adam Summerville, Sam Snodgrass, Matthew Guzdial, Christoffer Holmgård, Amy K Hoover, Aaron Isaksen, Andy Nealen, and Julian Togelius. Procedural content generation via machine learning (pcgml). *IEEE Transactions on Games*, 10(3):257–270, 2018.

[14] Richard Sutton and Andrew Barto. *Reinforcement learning: An introduction.* MIT press, 2018.

[15] Julian Togelius, Georgios N Yannakakis, Kenneth O Stanley, and Cameron Browne. Search-based procedural content generation: A taxonomy and survey. *IEEE Transactions on Computational Intelligence and AI in Games*, 3(3):172–186, 2011.

[16] Vanessa Volz, Jacob Schrum, Jialin Liu, Simon M Lucas, Adam Smith, and Sebastian Risi. Evolving mario levels in the latent space of a deep convolutional generative adversarial network. In *Proceedings of the genetic and evolutionary computation conference*, pages 221–228, 2018.

[17] Christopher Watkins. *Learning from delayed rewards.* PhD thesis, Cambridge University, 1989.