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1 INTRODUCTION

Explainability and interpretability of solutions generated by AI products are getting more and more important as AI solutions enter safety-critical products. As, in the long term, such explanations are the key to gaining users' acceptance of AI-based systems' decisions [4].

We report on the application of a model-driven optimisation to search for an interpretable and explainable policy that solves the game *2048*. This paper describes a solution to the *Interpretable Control Competition* [6]. We focus on solving the discrete *2048* game challenge using the open-source software EvoAL [2, 8] and aimed to develop an approach for creating interpretable policies that are easy to adapt to new ideas. We use a model-driven optimisation approach [5] to describe the policy space and use an evolutionary approach to generate possible solutions. Our approach is capable of creating policies that win the game, are convertible to valid Python code, and are useful in explaining the move decisions.

2 APPROACH

The proposed solution builds on EvoAL—a Java-based data-science research tool—which allows users to express optimisation problems using domain-specific languages (DSLs) and offers a rich extension API for problem-specific extensions. EvoAL offers different optimisation algorithms, such as evolutionary algorithms, genetic programming, and model-driven optimisation.

Normally, EvoAL uses two DSLs to configure an optimisation problem. Using the *data description language*, a user can specify the problem-specific data. The mapping to an optimisation algorithm and the algorithm configuration is done by using the *optimisation language*. As we aim to use a model-driven approach, we use a third DSL of EvoAL—the *definition language*—to describe the abstract syntax [3] of the policy. The generated model is then turned into Python code by using model-to-text concepts.

Figure 1 shows a sketch of our approach. We provide three DSL files to EvoAL, the data description, optimisation configuration, and the policy model. The policy model is linked to the Python module (*game.py*), which implements game state queries the policy can use. Furthermore, we implement EvoAL extensions for the fitness calculation and additional problem-specific operators for the evolutionary algorithm, which is part of EvoAL. The fitness calculation generates a Python module (*policy.py*) for each individual that implements its policy. Then, the Python interpreter runs a configurable number of games and writes the results to log files (*protocol.json*), which are then read by the fitness calculation and passed to the EA.

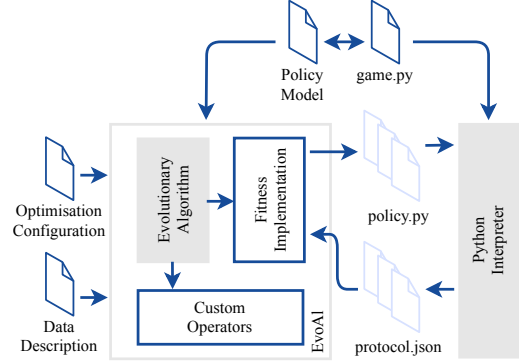


Figure 1: Depiction of our generation process

Our policy model builds upon the idea that a game is in a state, which influences the action taken. The state can be queried by simple functions, such as *Is a certain move valid?*, or *What is the gain of a specific move?*. A policy then combines these functions into boolean expressions, which are checked to determine if a specific action should be executed. Figure 2 shows an excerpt of the abstract syntax of our policy model, which we describe for EvoAL using the mentioned *description language*. By using this approach, it is possible to add new query functions by a) implementing the Python code and b) extending the description file. It is not necessary to adapt EvoAL or our Java-based extension to do so.

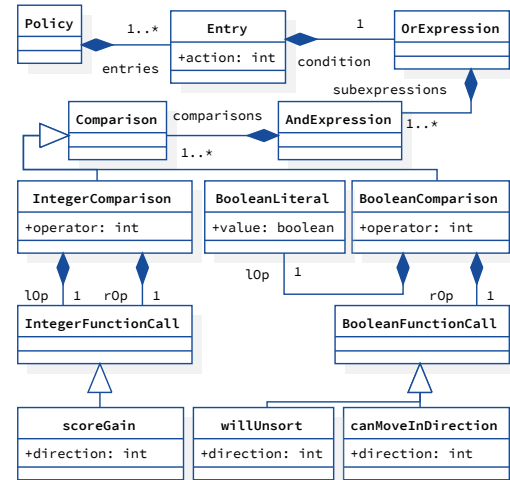


Figure 2: Excerpt of our policy model

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Initial Population The initial population contains random policies containing a single element in array-like references, c.f. Figure 2. Thus, the policies start with simple conditions that need to be mutated into more and more complex ones.

Operators We mainly employ general (not specialised for the problem) operators. We use a mutator that changes values (numbers, and boolean values), a mutator that changes array sizes (by removing or adding elements), a mutator that changes the order of arrays, and a custom mutator that rotates a given policy. We limit the number of mutators applied to an offspring to one, to reduce the changes in a policy. Additionally, we use a standard recombination operator, that swaps subtrees of two provided policies.

Fitness Our fitness function executes a policy a configurable number of times and calculates different statistical information, such as the minimum, maximum, and average of these runs. For one run, we store the maximum tile value and the overall score. This allows us to focus on searching for robust algorithms. We use a priority-ordered pareto-comparison as a fitness comparator.

Available Functions We aimed at using query functions that are simple and do not implement complex board situations. In total, we provide ten different query functions, such as *canMoveInDirection* allows the policy to query if a single move into a direction is possible, whereas *canMoveInDirections* checks for two subsequent moves. *scoreGain* will calculate the score improvement gained by a single move, whereas *scoreGains* checks two subsequent moves. The complete list of functions can be found in the policy model, which is specified in the file *model.dl*.

Pipeline The pipeline configuration is stored in the aforementioned DSL files, which can be found in the folder *evoal-configuration* of the supplemental repository [1]. The files can be read with a text editor. EvoAl’s Eclipse-based DSL editors provide additional syntax highlighting and cross-referencing. The pipeline has been tested on Linux and MacOS using a *Java 17 JRE*. To run the pipeline, it is necessary to checkout the repository, set up the Python environment, download an EvoAl release [7] and extract it to the folder *evoal-release* in the repository and execute the script file *01-run-search.sh*.

3 EXPERIMENTAL RESULTS

The allowed budget contains 200.000 evaluations of the game. We configured the EA to use a population size of 100 individuals. For a fitness evaluation, we decided to simulate six games with the same policy, resulting in $\frac{200000}{100 \cdot 6} = 333$ generations that can be executed.

Best Policy Figure 3 shows the development of the highest tile reached during the evolution process. As a policy run simulates six games, the data points in dark blue show the best highest tile value of a policy run and the light blue data points show the average value of the highest tile of a policy run. The filled data points represent the best individual of a generation, while the non-filled data points represent the average result of a generation. The depiction shows that whenever the process succeeds in generating a new best highest tile, the average highest tile first improves (the policies are getting more stable) before the best highest tile can reach the next level.

The result of the optimisation run is a policy that reached a *max(highest-tile)* of 2.048, an *average(highest-tile)* of 1.276, and

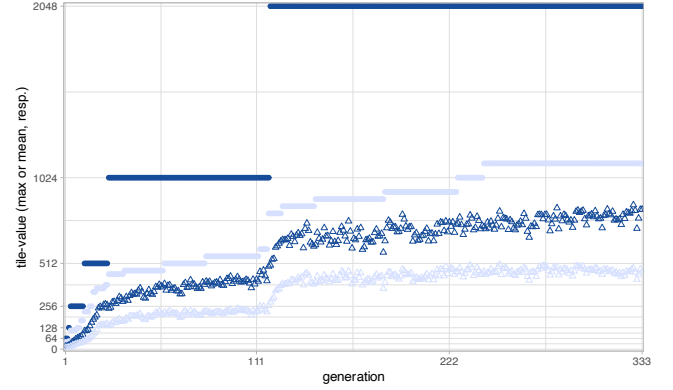


Figure 3: Overview of the fitness values over time

an *average (total-score)* of 14.093. The policy is, during the optimisation, an instantiation graph of the model shown in Figure 2, which can be converted into a graphical representation or a textual representation. Nevertheless, Listing 1 shows the best policy after converting it into a Python program as this is the executable policy.

Listing 1 Best policy after 333 generations

```
1 import numpy as np
2 import evoal.game as game
3
4
5 def control(observation: np.ndarray) -> int:
6     """Generated policy function for the game 2048"""
7
8     if game.scoreGains(observation, direction1 = 2, direction2 = 3) >
9         ↳ game.scoreGains(observation, direction1 = 1, direction2 = 0) or
10         ↳ game.scoreGains(observation, direction1 = 2, direction2 = 2) >
11         ↳ game.scoreGains(observation, direction1 = 3, direction2 = 2):
12         return game.toAction(2)
13
14     if game.scoreGains(observation, direction1 = 1, direction2 = 0) <
15         ↳ game.scoreGains(observation, direction1 = 3, direction2 = 2) or not
16         ↳ game.canMoveInDirection(observation, direction = 1):
17         return game.toAction(3)
18
19     if game.scoreGains(observation, direction1 = 2, direction2 = 3) >
20         ↳ game.scoreGains(observation, direction1 = 1, direction2 = 1) or
21         ↳ game.scoreGains(observation, direction1 = 2, direction2 = 1) >
22         ↳ game.scoreGains(observation, direction1 = 0, direction2 = 1):
23         return game.toAction(2)
24
25     return game.toAction(1)
```

The shown policy focuses on increasing the score gain and chooses to go in the direction that promises higher score gain. The remaining queries, such as *willBeSorted*, are part of some policies but did not make it into the best policy. At the same time, the policy only uses three out of four directions, which might leave room for further improvement, but we assume that the situation where the board would have to be moved into the fourth direction occurs very seldom.

Having a given board situation, the policy allows one to explain precisely why a certain move was made. On the one hand, the state queries are easy to understand and, on the other hand, they can be calculated for a given board to show the decision process. While being explainable, our approach is flexible and can easily be extended with additional queries without having to change the optimisation process.

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