Persona-driven Dominant/Submissive Map (PDSM) Generation for Tutorials

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ABSTRACT
In this paper, we present a method for automated persona-driven video game tutorial level generation. Tutorial levels are scenarios in which the player can explore and discover different rules and game mechanics. Procedural personas can guide generators to create content which encourages or discourages certain playstyle behaviors. In this system, we use procedural personas to calculate the behavioral characteristics of levels which are evolved using the quality-diversity algorithm known as Constrained MAP-Elites. An evolved map’s quality is determined by its simplicity: the simpler it is, the better it is. Within this work, we show that the generated maps can strongly encourage or discourage different persona-like behaviors and range from simple solutions to complex puzzle-levels, making them perfect candidates for a tutorial generative system.

CCS CONCEPTS
• Applied computing → Computer games; • Mathematics of computing → Evolutionary algorithms.

KEYWORDS
procedural level generation, procedural persona, quality diversity, evolution, experience driven level generation

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1 INTRODUCTION
Most games include some form of tutorial that teaches you how to play the game. In particular, games often feature levels that teach the player various aspects of the game. It is very common for such tutorial content to occur at the beginning of the game, but also whenever new mechanics, NPC types or similar concepts are introduced. For example, when you find the grapple hook in one of the Zelda games, you can be certain to find a few puzzles nearby that requires you to use it so that you can learn by doing.

Many games contain some form of level generation, and procedural content generation for games is also an active research field [36]. In this context, the question of how to generate tutorials has attracted some attention recently [3, 13, 14, 16]. The reasons for wanting to generate tutorials are multiple: one might want to part-automate the tutorial creation process to free up game designers and developers to work on other topics; one might want to enable automatically generated games to have tutorials; and one might want to create tutorial-generating systems in order to better understand tutorials in general. But there is yet another reason for creating systems that generate tutorials: the ability to create experiences for specific player types, to fit their playstyle and/or capabilities. Such systems could create tutorials that are more engaging and effective for particular players, instead a one-size-fits-all approach that becomes more or less necessary with hand-crafted tutorials. These levels could encourage players to explore different playstyles and push their limits, depending on the intention of the game designer. In some of the research that this paper builds on, tutorial levels were generated that taught specific mechanics, in the sense that a player needed to use (or not use) those mechanics in order to finish the level [5, 14].

Generating tutorials to fit playstyles can be seen as a form of experience-driven procedural content generation (EDPCG) [44]. In the EDPCG paradigm, models of user experience (and potentially also player behavior) are used to guide content generation algorithms. In practice this can take the shape of fitness functions for evolutionary algorithms [34, 37, 38], rewards for reinforcement learning algorithms [31, 39], or constraints for constraint satisfaction algorithms karth2021wfc. For example, one could learn a predictor of engagement that uses playstyle characteristics and level characteristics as input; by keeping the playstyle constant, one could use evolutionary computation to search for levels that maximize engagement for a particular player [37, 38].

Following this paradigm, there are several ways in which one could create a tutorial level that is tailored to a specific playstyle. One way is to create a level that mandates the use of some mechanic (or in general, overcomes a specific type of challenge) and that
is winnable using the currently used playstyle. Another type of tutorial level is one that forces the player away from a certain behavior to win. In the latter case, the playstyle may be something the game wishes to teach in order to enable the player to enjoy more of the game. Also, the game can try to teach when to avoid a certain playstyle to help the player understand the strategic depth of the game.

In this paper, we investigate methods for generating tutorial levels tailored to playstyles in MiniDungeons 2 [22]. For this, we use the concept of procedural personas. A procedural persona is a generative model (i.e., a game-playing agent) of an archetypical playstyle [18, 19]. The three procedural personas used in this study – the runner, the monster killer, and the treasure collector – exemplify sharply different strategies of playing a game. We then use a quality-diversity algorithm, Constrained MAP-Elites, to find large sets of different levels. QD algorithms offer an advantage over single-objective optimization algorithms, in that they can illuminate level design space quickly. Previous research with mechanic-dependent level generation demonstrates this well [5, 25]. The levels generated in this paper systematically vary depending on which personas can perform well on them. Thus, the system can generate levels that can be played equally well by multiple playstyles, that encourage the use of a particular playstyle, or that discourage the use of a particular playstyle.

2 BACKGROUND

In this section, we discuss the usage of quality diversity algorithm for Procedural level generation and usage of player personas as content evaluators not only in MiniDungeons 2 (the game used in this research) but also in other games. We review recent research in experience-driven procedural content generation, touch upon different types of video game tutorial patterns, and describe the MiniDungeons 2 framework in detail.

2.1 Experience-driven PCG

Procedural Content Generation (PCG) [17, 36] is the process of using computer algorithms to produce content. PCG techniques have been utilized in games as far back as the level generation systems in Beneath the Apple Manor (Don Worth, 1978) and Rogue (Glenn Wichman, 1980), and continue to be used to generate maps in Spelunky (Derek Yu, 2008), terrain in Minecraft (Mojang, 2011), and worlds in Starbound (Chucklefish, 2016) and No Man’s Sky (Hello Games, 2016). Most PCG methods generate content for the general audience of the game in question. Experience-driven Procedural Content Generation [44] (EDPCG) generates content designed for a specific user experiences. EDPCG may use any of the methods specified in previous sections for a wide variety of applications such as generating levels [39], music [35], and therapeutic experiences [31]. Designing for a specific user experience can come in many forms, such as level difficulty (as measured by the player’s skill) [23], aesthetics [30], or letting users pick for themselves [29].

2.2 Quality-Diversity PCG

Quality diversity algorithms (QD) have become more popular for PCG recently, especially in level generation [11]. QD algorithms free the designer from having to code complex fitness functions. Instead, all the complexity can be moved towards the diversity component of the algorithm. QD algorithms can find diversity in level design space while maintaining high quality. For example, novelty search with local competition can generate a variety of The Sims (Maxis, 2000) houses such that a sim’s agent could live comfortably [6]. Garvina et al. [12] uses constrained surprise search to generate balanced weapons in Unreal Tournament III (Epic Games, 2007) such that the generated weapons have wildly diverse behavior.

One of the most well-known QD algorithms is MAP-Elites [32], which uses a multi-dimension grid instead of population to store evolved solutions. A set of distinct behavior characteristics determines where in the map a solution resides, while a solution’s fitness determines if it will be saved or thrown away. MAP-Elites has been used in many PCG projects such as generating Hearthstone Decks [10, 45], 2D and 3D objects [28, 33], and platformer levels [43]. Constrained MAP-Elites (CME) is a hybrid algorithm that combines MAP-Elites with the FI2-Pop algorithm [27] first introduced for bullet hell level generation [26]. CME has been used for other projects such as mixed-initiative generation of dungeon crawlers [1] and tutorial generation of levels that teach targeted game mechanics [5, 25].

2.3 Procedural Personas

Bartle [4] originally proposed a taxonomy of players and their personas based on how they interacted with the environment and other players with categories such as killers, socializers, achievers, and explorers. Typically, designers design levels to cater to a set of personas or to contain multiple paths that encourage different persona types. Unsupervised learning methods have been used to infer play personas using playtraces from Tomb Raider: Underworld [8] and Starcraft II [2]. Meanwhile supervised learning methods have been used to infer play personas [15] using either playtraces or game mechanics vectors in MiniDungeons 2.

Tykcsen and Canossa [42] introduced player personas through game metrics and triggered mechanics. These metrics could be used to recreate a specific player but may not give as much insight as to what a type of player might do on a general scale (i.e. how would the same player react in a game level they have never played before.) With automated and artificial personas, these agents can be inserted into the game to predict how a player may approach a game level, saving human and computation resources and speeding up the design process. Procedural agents developed via evolution [18, 19] and reinforcement learning [20] have shown to be accurate in emulating player behaviors in a game setting. These artificial personas can be used for automated playtesting and encapsulate a variety of behaviors which lead to a wider diversity of levels designed for players with different play personas.

2.4 Video Game Tutorials

Previous work in automated tutorial generation has highlighted common tutorial patterns found across games. Instruction-based tutorials explain how to play the game by providing the player with a group of instructions to follow, similar to what is seen in boardgames. For example: strategy games, such as Starcraft (Blizzard, 1998), teach the player by taking them step by step towards understanding different aspects of the game. Demonstration-based
Any game character may move in one of the four cardinal directions to which it was thrown to pick it up in order to use it again. Treasures come in pairs and they teleport any character from one location to the other on the same turn. Traps deal 1 damage to any character moving through them. Levels also contain enemies, all of which desire to attack the player:

- **Goblins** move 1 tile towards the player if within line of sight. They have 1 HP and deal 1 damage upon collision.
- **Goblin Wizards** cast a 1 damage spell at the hero if they have line of sight within 5 tiles. If they are over 5 tiles but have line of sight, they will move 1 tile towards the player. Wizards have 1 HP and deal no damage on collision.
- **Blobs** move 1 tile towards a potion or the hero within line of sight. A blob colliding with a potion or another blob enables it to level-up into a more powerful blob. Blob starts with 1 HP and does 1 damage and increase by 1 HP and 1 damage for every level up with max of 3 HP and 3 damage.
- **Ogres** will move 1 tile towards either the hero or a treasure within line of sight. When an ogre collides with a treasure, they consume it. Ogres have 2 HP and deal 2 damage to anything they collide with.
- **Minitaurs** always move 1 tile along the shortest path to the hero, regardless of line of sight. Collision with the minitaurs deals 1 damage and stun it for 5 turns where the player can move through. A minitaur has no HP and is immortal.

3 PERSONA-DRIVEN LEVEL GENERATOR

We use the evolutionary search-based algorithm known as Constrained MAP-Elites (CME) [26] to generate levels. Similar to MAP-Elites, CME uses a multi-dimensional grid of cells to store the chromosomes instead of an actual population. Each chromosome is placed in the grid based on a set of distinct behavior characteristics, while its fitness determines if it will be saved or thrown away. The difference is that each cell in CME has three different types of chromosomes: elite, feasible, and infeasible (similar to FL2Pop algorithm[27]). Feasible and infeasible chromosomes are characterized by if they satisfy a group of constraints or not. If a chromosome satisfies these constraints, they are placed in the feasible population; otherwise they are placed in the infeasible one. The elite chromosome is the fittest chromosome in the feasible population. Chromosomes can be moved between cells if their behavior characteristic shifts and/or between different populations within their cell if they successfully outgrow their constraints or fail to do so.

The system's evolutionary pipeline consists of 5 distinct steps: initialization, evaluation, replacement, selection, and mutation. The system uses these steps in the following fashion to generate levels:

1. **Initialization**
   - Initialize a multi-dimensional grid of cells where each cell have 2 populations for the feasible and the infeasible chromosomes where each population of size “MAP_CELL_SIZE”.

2. **Generation**
   - Generate an initial population of chromosomes of size “POP_SIZE” using the Initialization step.

3. **Evaluation**
   - Evaluate the current population of chromosomes fitness and behavior characteristics using the Evaluation step.

4. **Replacement**
   - Insert the current population of chromosomes into the multi-dimensional grid using the Replacement step.
(5) Generate a new population of chromosomes of size “POP-SIZE”
   (a) Select a chromosome from the grid using the Selection
       step.
   (b) Make a new copy of the selected chromosome using the
       Mutation step.
   (6) Repeat steps 3 to 5 for number of iterations equal to “ITER-
       ATIONS”.

A chromosome (game level) is represented as a 2D array of size
(“LEVEL_WIDTH” x “LEVEL_HEIGHT”) where each tile can be any
of the possible tile types in MD2 (empty, solid, hero, potion, treasure,
trap, portal, goblin, goblin wizard, blob, ogre, and minitaur). Table 1
provides a description of all hyperparameters as they are referenced
in the previous steps and the following sections as well as their experiment values.

3.1 Initialization
The system initially creates blank maps (empty map with only
wall border) with a fixed width and height (“LEVEL_WIDTH” x
“LEVEL_HEIGHT”). In our experiments, level width and height are
fixed to a size of 10x10, in contrast to the traditional MD2 levels
which are 10x20. We selected this smaller size as it allows for faster
agent evaluation which is described in Section 4. This also makes
for smaller and simpler levels, which is inline with the primary
motivation of tutorial levels.

Every tile in the map (except the border tiles) is iteratively
changed to a random tile based on predefined probabilities where
empty and wall tiles have higher probabilities than other game
elements (empty probability and wall probabilities are defined in
Table 1 as “EMPTY_INIT_RATE” and “WALL_INIT_RATE” respec-
tively). After this step, the randomly initialized levels are repaired
such that these levels contain exactly one player, one exit, and either
exactly 2 or 0 portals. The algorithm repairs the generated levels
by either placing the missing tile at a random location or removes
the excessive tiles until the levels are fixed.

3.2 Evaluation
The maps are placed into a Constrained MAP-Elites grid with each
cell in the matrix containing two populations: feasible and infeas-
ible. The feasibility of the map is determined by calculating a
constraint value. The constraint value for the maps are based on the
connectivity of the map. A breadth-first algorithm is conducted on
every non-wall tile in the map starting from the player’s initial
position, and if every non-wall tile is reached the constraint value
is 1 and the map is considered feasible. Infeasible maps contain
disconnected non-wall tiles and the constraint value is based on the
ratio between reachable tiles (t\text{reach}) and all non-wall tiles (t\text{total})
as shown in the following equation:

\[ S = \frac{t_{\text{reach}}}{t_{\text{total}}} \quad (1) \]

The fitness function measures the simplicity of the levels. To
calculate simplicity of the generated levels, we calculate the entropy
of the different tiles in the generate level similar to Charity et al. [5].
With this fitness, the generator will try to evolve levels that have
uniform tile types which makes levels look less noisy. Equation 2
displays the map fitness equation, where \( p_i \) is the percentage of
a specific tile \( i \) existing on the level and \( n \) is the total number of
distinct tiles in MD2.

\[ \text{fitness} = 1 + \sum_{i=0}^{n} p_i \cdot \log(p_i) \quad (2) \]

In order to place a newly generated level in the CME grid, its
behavior characteristics need to be calculated. In this work, the
behavior characteristics are the hero’s remaining health after level
completion by each persona, ranging from 0 (death) to 10 (full
health). The health is divided into buckets of 10/\text{BUCKET} health
where “\text{BUCKET}” is the hyperparameter that determines the size
of each dimension. With multiple different personas, the size of the
MAP-Elites matrix will be \text{BUCKET}_\text{PERSONAS} cells, where “\text{PER-
SONAS}” is a hyperparameter that determines the number of used
personas. In our experiments, we use 3 different personas which are
runner, monster killer, and treasure collector; and 5 buckets per
dimension. More information about the different personas will be
described in Section 4.

3.3 Replacement
The elites of this matrix are defined as the levels with the highest
fitness values in the feasible population of the cells. Each cell has
a limit to the size of the population (“\text{MAP\_CELL\_SIZE}”). When a
new generated level has a better fitness or constrained value than
levels in the current cell’s feasible or infeasible population, the
least fit level in that population is replaced by the new level. In the
case of the feasible population, if the new level has better fitness
than the least fit level in this population, the new level is inserted
and the least fit level will be moved to the infeasible population
instead of being completely deleted. On the other hand, if the new
level is going to be inserted in the infeasible population, it must be
better than the least performing level to replace it. After a couple of
iterations, the infeasible population will contain substantially fewer
maps with low constraint values as more fitted individuals are being
pushed into the cell. This “survival of the fittest” replacement for
the feasible and infeasible populations maintains the quality of the
matrix and all of the maps contained in the cells while providing
better selection possibilities for future populations.

3.4 Selection
In the selection step, it is important to note that behavioral charac-
teristics are not considered at all. Every elite level from the matrix is
added into an elite selection pool indiscriminately. Members of the
feasible and infeasible populations are added to their own respec-
tive pools. Elites are given the highest probability (“\text{ELITE\_PROB}”)
to be selected, then feasible (“\text{FEAS\_PROB}”), and lastly infeasible
(1 – \text{ELITE\_PROB} – \text{FEAS\_PROB}). When a set is chosen, a chromo-
some is selected randomly from the set to be mutated (explained in
Section 3.5) before being added to the next generation’s population.

3.5 Mutation
During the mutation step, every tile of a selected map is given
a chance of mutating as controlled by the rate of tile mutation
(“\text{MUTATION\_RATE}”). If a tile is set to mutate, it may change itself
into any tile in the game with equal probability except for an empty
tile, which has a higher chance to be selected as the end mutation.
| Parameter | Description |
|-----------|-------------|
| BUCKET    | Bucket size of the MAP-Elites matrix |
| PERSONAS | Number of dimensions that is used for the MAP-Elites matrix |
| MAP_CELL_SIZE | Maximum number of members allowed to be stored in a cell for the feasible/infeasible population |
| LEVEL_WIDTH | The width in tiles of evolved MD2 levels |
| LEVEL_HEIGHT | The height in tiles of evolved MD2 levels |
| ITERATIONS | How many times to evolve (evaluate, select, mutate) a population |
| POPTIZE | Maximum size of the population. Members may be removed if they are invalid to be evaluated |
| EMPTY_INIT_RATE | Probability to place an empty tile in the initialization phase of the map |
| WALL_INIT_RATE | Probability to place a wall tile in the initialization phase of the map |
| EMPTY_MUT_RATE | Probability to place an empty tile in the mutation phase of the map |
| MUTATION_RATE | The probability to mutate the current tile (iterates over every tile in the map excluding borders) |
| ELITE_PROB | Probability to select a sample from the elite population |
| FEAS_PROB | Probability to select a sample from the feasible population |
| C | Weight constant for agent’s utility cost |
| K | Weight constant for agent’s death cost |

Table 1: Hyperparameter descriptions and experimental values

("EMPTY_MUT_RATE"). All the other tiles have equal probability to be selected. We have the empty tile with higher probability than the rest to encourage the evolution to erase more often than adding. The same repair function from the initialization phase is used to ensure there is only 1 player, 1 exit, and 2 or 0 portals (see Section 3.1). If a mutation makes it physically impossible for the player to ever reach the exit, the level will be removed and will be inserted back to the CME grid. Since they are unplayable, these levels cannot allow agents to determine their behavior characteristics. Consequently, a generation may contain less chromosomes than the predefined size ("POPSIZE"), however all of the levels will be guaranteed to be playable.

4 PROCEDURAL PERSONAS

Our experiments use an online-planning best-first search agent to evaluate levels. Each turn, the agent is limited to building a 500 node tree to plan their next action. 500 is chosen after preliminary experiments suggest that a best-first search agent can play well but still be deceived with the resulting limited planning horizon. In theory, this could be varied to approximate player skill [24], however we do not perform that in this paper. The best-first search agent plays every level three times using three different playstyles (personas). The results of these three runs determine that level’s behavioral characteristics. Best-first search does not need to play the level more than once per persona due to the deterministic nature of both the game and the algorithm.

As mentioned in Section 3.2, the behavior characteristics of a level correspond to the remaining health of the different personas after completing the tested level. In previous work by Holmggaard et al. [18, 21], three main personas are identified for MD2:

1. **Runner (R):** complete the level as fast as possible.
2. **Monster Killer (MK):** slay as many monsters as possible before completing the level.
3. **Treasure Collector (TC):** open as many chests as possible before completing the level.

Each of these personas use a utility function which influences their behavior. Depending on the persona, the agent uses one of the following heuristics and cost functions. In the following equations, $h_{persona}$ and $g_{persona}$ denote the heuristic function and cost function respectively for a specific player persona ($persona$). The personas are delineated as runner ($r$), monster killer ($mk$), or treasure collector ($tc$).

A Runner agent ($R$) tries to get to the exit in the fewest amount of steps as possible. Equation 3 displays the heuristic ($h_r$) and cost ($g_r$) function of the runner agent.

$$h_r = \text{dist}_{exit}$$
$$g_r = -\text{steps}$$

where $\text{dist}_{exit}$ is the distance from the current player location to the exit, and $\text{steps}$ is the amount of steps taken since the start.

A Monster Killer agent (MK) tries to find the shortest path to the closest monster, killing all monsters while attempting not to die, and getting to the exit when all monsters have been slain. Equation 4 shows the heuristic ($h_{mk}$) and the cost ($g_{mk}$) functions of the monster killer agent.

$$h_{mk} = \begin{cases} 
\min(\text{dist}_{monster}) & N_{monster} > 0 \\
\text{dist}_{exit} & N_{monster} = 0 
\end{cases}$$
$$g_{mk} = c \cdot N_{monster} + k \cdot \text{Dead}$$

where $c$ and $k$ are constants (see Table 1 for used values), $\text{dist}_{exit}$ is the distance between the player and the exit, $\min(\text{dist}_{monster})$ is the distance to the closest monster from the player location, $N_{monster}$ is the number of alive monsters in the level, and $\text{Dead}$ is a binary value that is equal to 1 if the player is dead and 0 otherwise.

A Treasure Collector agent (TC) tries to find the shortest path to the nearest treasure, collecting all treasures while attempting not to die, and getting to the exit when all treasures have been collected. It uses a similar equation to 4 but replacing $\min(\text{dist}_{monster})$ with $\min(\text{dist}_{treasure})$ (the distance to the closest treasure from the player location) and $N_{monster}$ with $N_{treasure}$ (number of unopened treasures in the level).

5 RESULTS

In this section, we review the results from CME over five runs. When we refer to a level’s behavioral characteristics, we refer to its bucketed values in order of runner, treasure collector, and monster
killer HP results. Buckets are numbered 0 to 4, totaling 5 buckets. For example, a level with dimensions of 444 means that the agent finished the level in the 4th bucket (the highest amount of HP) with every persona. We divide the levels into 3 major types:

- **Balanced**: These are levels where all three personas complete the level with approximately the same HP. These are the diagonal cells in the CME matrix (000, 111, 222, 333, and 444).
- **Dominant**: These are levels where a certain persona (R, TC, or MK) completes the level with more HP than the other two personas. We call them Runner dominant, Monster Killer dominant, and Treasure Collector dominant levels.
- **Submissive**: These are levels where a certain persona (R, TC, or MK) completes the level with less HP than the other two persona. We call them Runner submissive, Monster Killer submissive, and Treasure Collector submissive levels.

By differentiating levels this way, we can better analyze a level’s ability to encourage or discourage a player to behave as a specific persona. First, we analyze the resulting MAP-Elite matrix, focusing on the elite coverage. We then analyze the levels in terms of their persona HP outcomes, as defined in the paragraph above.

### 5.1 Elite Matrix

The elite map contains 5x5x5 cells, or 125, since each dimension is made of 5 buckets. If we aggregate the five runs, CME fills an average 34.2 cells (27.36%) with standard deviation of 4.82. Figure 2 displays the elite map of populated cells across 5 experimental runs. Higher runner health seems to correlate to higher cell coverage. This is likely to be because monster killer and treasure collector heuristics will default to runner heuristics (get to the exit) once their primary objectives are completed. Generating a level where a runner persona loses health while other algorithms loses less health in comparison is difficult to do, as it is not easy to deceive a runner without also deceiving the other two personas. The runner’s final health tends to act as an upper bound for the final health of the other agents. Although there are maps where TC and MK personas complete the level with higher health, they are less likely to be found.

To understand more about the ability of CME to generate different types of levels, we analyze the number of dominant and submissive level types across 5 experimental runs as shown in Table 2. The runner persona tends to dominate the other two personas more often than it is submissive. As mentioned before, both treasure collector and monster killer personas behave similar to the runner when there are no treasures or monsters respectively. In contrast, balanced levels seem relatively easy to discover, as on average 4 levels are found out of a maximum of five per experimental run. If both treasure and monsters are placed along or nearby the shortest path to the exit, all three personas tend to behave the same and therefore have identical HP outcomes. It is also relatively simple to create impossible levels by placing lots and lots of monsters near the exit (see Figure 3a).

### 5.2 Balanced Levels

Balanced levels are the levels in which all three personas finish with a similar health percentage. These levels have behavior characteristics of either 000, 111, 222, 333, or 444. A level with a behavior characteristic of 444, means that the agent finished the level with at least 8 or more HP remaining with every persona.

![Figure 2: The probability of an elite being found for each cell over 5 different runs.](image)

![Figure 3: Simplest generated balanced levels across 5 runs.](image)
Figure 3 displays 3 example levels for 3 different balanced levels values: 000, 222, and 444. The 444 levels (Figure 3c) are levels in which all 3 personas finish with nearly all of their HP. These are the simplest, easiest possible levels, consisting of just the hero and the exit. The only difference between these levels is the position of the player and exit location. Since the system has no constraint on the solution length, a level where the player starts next to an exit is scored similar to a level that requires the player to learn how to move and navigate a maze. However, the simplicity-based fitness function will pressure the generator to evolve empty levels since they will have higher fitness. We did not include path length as part of the constraints or fitness, since we wanted these levels to encourage a user to play as a certain persona and not how to move personas die or have very low health (000 levels). Placing lots of enemies along the shortest path towards the exit quickly obliterates HP regardless of the persona. Figure 3b displays levels where all 3 persona have medium amount of health (between 4 to 6 HP). Levels such as these tend to have a small amount of monsters that will deal some damage to the player. Similar to the hard levels in Figure 3a, the enemies are close to shortest path towards the exit.

5.3 Dominant Levels

Dominant levels are levels where one persona completes the level with higher HP than the other two personas. For example, a 321 level is a runner dominant level, while a 242 level is a treasure collector dominant level, and a 024 level is a monster killer dominant level. Since the dominant levels cover 25% (30 cells out 125 cells as shown in table 2) of the map, we will focus on the dominant levels that have the highest fitness in the elite map. Figure 4 displays expressive range analysis of all the discovered dominant levels across 5 runs. Runner dominant levels (Figure 4a) tend to have at least 1 treasure or more and consistently have short distances to the exit. Monster killer dominant levels (Figure 4c) have longer paths to exit with fewer monsters than the runner dominant levels. There are not many treasure collector dominant levels as they appear to be difficult to discover (only 9 levels across 5 runs). We believe this is because of the difficulty of using treasures to guide the treasure collector down a different path where they do not take damage while the runner does. Figure 5 show the highest fittest levels where runner, treasure collector, and monster killer dominates respectively. The runner dominant levels (Figure 5a) contain short direct paths to the exit with a few enemies nearby. A treasure chest is sometimes placed while the runner does.

Figure 4: Expressive range analysis for the different dominant levels across 5 runs.

Figure 5: Simplest generated dominant levels where a certain persona ends with higher level than the other two.
4b). We show two of the simplest maps that do not have treasure yet the treasure collector manages to avoid taking much damage anyway, again due to the nuances of the collector’s heuristic and cost functions. We did not expect this type of behavior from treasure collectors, and we want to review the heuristic and cost functions of collectors in future work in order to generate more treasure collector dominant levels with treasures in them.

5.4 Submissive Levels

Submitive levels are levels where one of the personas finishes with lower HP than the other two. For example, a 143 level is a runner submissive level, a 301 level is a treasure collector submissive level, and a 241 is a monster killer submissive level. Figure 6 displays the expressive range analysis for the submissive levels. Runner submissive levels (Figure 6a) are difficult to find (10 levels across 5 runs), which is expected as it is difficult to make a runner persona lose health without the other personas also losing health (monster killers especially). Treasure collector submissive levels (Figure 6b) tend to have at least one treasure chest, usually in proximity of monsters who attacks the nearby collector. Also, these levels usually have a short path to the exit allowing runner to run to exit with less taken damage. Monster killer submissive levels (Figure 6c) tend to have 0 or 1 treasures and small amount of monsters with short to decent distance to exit. Not having a lot of treasures influences the collector and runner personas to move towards the exit without battling with monsters while monster killer will always go to battle them and lose health.

Similar to the dominant levels, we show the highest fitness level for each submissive persona in Figure 7. Looking at Table 2 and Figure 6, monster killer or treasure collector submissive levels seem to be easier to discover than runner submissive ones. The treasure collector submissive levels (Figure 7b) place treasure and wizards in such a way that the runner can go directly to the exit without taking damage while the treasure collector gets hit by a wizard. In the runner submissive level (Figure 7a), an enemy is placed close to the shortest path to the exit so it damages the runner on its way to the exit. Sometimes treasure is placed so that a treasure collector is guided away from the shortest path. The monster killer submissive levels (Figure 7c) place monsters in such a formation that the runner and treasure collector do not have to engage them to win the level. The monster killer will engage them and take damage.

6 DISCUSSION

In this section, we discuss the results through the lens of the motivation for this paper: tutorial levels. Our original goal is to generate levels which encourage or discourage a player in following the behavioral patterns of a certain persona. Below, we analyze levels that spotlight situations in which some persona tactics end in success and others more likely failure. We also discuss the correlation of behavioral characteristics and difficulty, arguing a level’s difficulty is not determined solely from behavioral characteristics but that it does play a role.
6.1 Tutorial Levels

A notable subset of elites — especially levels where the runner finishes with the most health out of the 3 personas — generated levels that placed the player right next to the exit but had multiple monsters and/or treasures placed throughout the map (see Figure 5a). These levels present a great example of encouraging certain playstyles for players - particularly for the runner persona. The monster killers will attempt to kill all of the monsters on the map and the treasure collector will try to get all of the treasure. But because of the overwhelming number of enemies, both personas either make it to the exit with very low health or die. However, the runner persona will only have to move a few steps to reach the exit, typically without facing any danger from traps or monsters. While these levels may not necessarily kill a player who plays however they want, they show that not every persona’s strategy is easy, and they encourage a specific playstyle while punishing others.

Some of the levels encourage the player to use specific mechanics. For example, the monster killer dominant level shown in Figure 5c nudges the player towards throwing the javelin to avoid losing health. These levels may encourage the player to perform these mechanics but does not outright force them. If a designer wanted to force mechanic usage, they could simply change the player starting health. For example, if the player begins with only 2 HP in the monster killer dominant level (Figure 5c) then the level will force the player to learn that the only way to win is to throw the javelin.

Similarly, submissive levels are good at encouraging players to avoid certain behaviors. For example, treasure collector submissive levels (Figure 7b) may teach the player that not every treasure is safe to acquire since that there might be enemies protecting it. We can again make any submissive level an extreme variant by decreasing the player’s starting HP to make these situations even more dangerous. The player will either need to learn to avoid the enemies with the javelin to acquire the treasure (learning to be a monster killer) or avoid the treasure and run to the exit (learning to be a runner).

6.2 Correlation to Difficulty

Having a large amount of HP leftover for a persona does not always necessarily mean the level is “easy” for that persona. It does, however encourage the player to adopt the mindset of that persona style in order to maximize their ending HP. On the other hand, having a small amount (or hardly any) HP leftover for a persona typically does mean that playing is difficult.

One way to think about HP in MD2 is as a currency the player can spend. Some levels may require a player to spend more HP than others. On levels that require more spending, the player has less leeway in choosing when and how to spend that currency. In rogue-like game design literature, this concept is often referred to as “strategic headroom” [40]. Typically levels that have more headroom are easier for the player to win (more options for the player to use) than levels that have less headroom. In MD2, levels that require less HP spending can offer the player more options to take (Figure 3b) and therefore provide more headroom. Levels like the ones in Figure 3a afford very little headroom and are therefore very difficult.

6.3 Limitations and Future Work

The scope of this project begins and ends with level generation. It does not venture into tutorial level sequencing, nor does it investigate how to classify players’ persona styles and how to use that to feed them relevant content. The method in this paper utilizes a simplicity as a fitness metric; perhaps we could integrate path length that could encourage more interesting levels with longer solutions. Previous research in sequential tutorial level generation [16] stitches together minilevels which showcase different mechanics in order to mechanically replicate target levels in Mario. This would be a good target for future work here as well: building level curriculums based on persona-behavioral patterns. Recent research in automated play persona classification [15] provides an opportunity to use persona-driven level generators in a personalized level pipeline (see Figure 8). A classifier can identify a particular player's play persona. A persona-driven generator will generate personalized levels that can then be given to an automated “director” system, which then decides what levels to present to the player next, like in Endless Web [41]. This work also requires the use of procedural personas, which the Minidungeons 2 framework comes with. What if there are no tree-search agent personas available? Or maybe developers do not yet know all of the personas that could exist in the game. Automatically searching for new personas is a relatively unexplored area and is a good space for future work.

7 CONCLUSION

This paper describes the development and results of a persona-driven tutorial level generation system that uses quality diversity in order to find and improve levels catered towards a specific playstyle. A set of generated elite levels are found in the solution space which address a broad range of playstyles. These levels can encourage a player towards trying a specific strategy ranging in difficulty or allow multiple playstyle types to succeed in a single level through their own strategy. While this system uses the domain of MD2, a deterministic dungeon crawler game, our pipeline could be applied to other games so long as it has a clearly defined mechanic space allowing for a range of different playstyles. Our intention is to incorporate this system into a persona-adaptive tutorial sequencer so that players may learn to adapt to different playstyles as the
level context and difficulty changes. Tutorial generation is an exciting new paradigm, and the development of systems such as this one moves us closer toward fully automated video game tutorial generation.

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