BC Description and Visualization

I. Level Evaluation

We used Mario AI Framework to evaluate each level generated by the GAN. According to the AI agent's result, we assigned a fitness value f to each level. We defined f to be the percentage of completion, as Equation 1 shows:

$$f = \frac{d_{completed}}{d_{level}} \tag{1}$$

where $d_{completed}$ was the distance that the AI agent went through and d_{level} was the full distance of that level.

To map the latent vector onto the elite map, we also extracted Behavioral Characteristics (BCs) from each level. These BCs corresponded to the dimensions of the elite maps, and were either *static* (could be observed before the AI agent played it), such as the number of enemies in a level, or *dynamic* (were obtained from the AI agent's actions), such as whether the agent jumped while playing the level. We tried 3 sets of BCs as dimensions of our elite maps, and next we would discuss each set of BCs selected.

A. Mario GAN BCs

In this setting, We used two BCs to describe the "style" of a Mario level: the number of tiles in the sky and the number of enemies. Both of them were static and were observed before the AI agent started to play the level.

"Tiles in the sky" referred to all game objects (**i.e.** normal blocks, question blocks, coins) that could only be reached if Mario jumped. We assumed that a large value meant that there were many game elements above the ground and the player was encouraged jump to higher levels, while a small value implied that player would stay on the ground most of the time.

"Number of enemies" was the number of enemies in the whole level. Our GAN could generate 4 types of enemies: Spiky, Goomba, Green Goomba and Red Goomba. We assumed that this value reflected the intenseness of a level.

B. 8 Binary BCs

This setting corresponded to the "Constrained Map-Elites' dimensions" in previous work (Citaion Needed). We collected 8 BCs according to the AI agent's actions while playing. In other words, all the 8 BCs were *dynamic*. In addition, each BC was binary, representing whether the AI agent performed the action or satisfied certain condition. In this way, our elite map had 8 binary dimensions and 2^8 cells. Table I described the 8 BCs we used.

BC	Description
Jump	1 if the agent jumped at least once in this level, 0 otherwise.
High Jump	1 if the agent had stayed in air more than a certain amount of time during one jump (meaning that it travelled more than a certain distance vertically within one jump), 0 otherwise.
Long Jump	1 if the agent had travelled more than a certain distance horizontally within one jump, 0 otherwise.
Stomp Kill	1 if the agent killed at least one enemy by stompping (jumped onto it from above), 0 otherwise.
Shell Kill	1 if the agent killed at least one enemy using koopa shell, 0 otherwise.
Fall Kill	1 if there was at least one enemy that was killed because of falling out of the map, 0 otherwise.
Mushroom	1 if the agent collected at least one mushroom, 0 otherwise.
Coin	1 if the agent collected at least one coin, 0 otherwise.

TABLE I: Descriptions of the 8 BCs used in the 8 Binary BCs setting.

C. KL Divergent BCs

Under this setting, we selected two scenes from two different **original** Mario levels, as shown in Figure 1. The two BCs of a newly generated level were given by its KL Divergent values with each of the two original scenes. We then used the two KL Divergent values to map the new level onto our elite map.

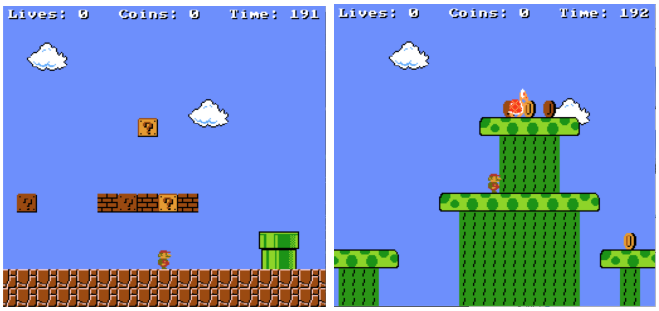
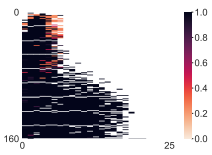


Fig. 1: These are the two scenes from the original Mario levels that we used to calculate KL Divergent.

II. Visualization

For each of the 5 searching algorithms (CMA-ME, CMA-ES, MAP-ELITE, ISOLine-DD, random search), we made simulations on all 3 BC settings discussed in Section I. Figure 2 showed the elite maps of all 5 searching algorithms under the MarioGAN BC setting.



CMA-ME CMA-ES MAP-ELITE Random ISOLine-DD

Fig. 2: These were the elite maps of the 5 searching algorithms using MarioGAN BC settings.