A Framework for Generating Playstyles of Game AI with Clustering of Play Logs

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Abstract: Many attempts have been made to implement agents for playing games with particular playstyles. Most of these were aimed at generating agents with predetermined playstyles. To this end, they set the reward function to increase the reward as the agent acquires their intended playstyles. However, it is not easy to generate unexpected playstyles through this approach. In this study, we propose a framework to generate multiple playstyles without predefining them. The proposed framework first arranges a set of reward functions regarding the target game and repeats to select a function and make an agent learn with it. Each learned agent is made to play the game, and those whose scores are higher than a predetermined threshold are selected. Finally, each cluster obtained from clustering the play logs (i.e., metrics on the behavior in the game) of the selected agents is considered a playstyle. As a result, it is possible to generate playstyles that play the game well using this procedure. We also applied the proposed framework to a roguelike game, MiniDungeons, and observed that multiple playstyles were generated.

1 INTRODUCTION

With the rapid development of game AI technologies, agents (computer programs that play games) that surpass human professionals, such as AlphaZero (Silver et al., 2017), have appeared for perfect information games. More recently, there have been various studies to go beyond just playing the game well, such as the agents to play imperfect information games (Brown and Sandholm, 2019) and research to imitate human play by agents (Ortega et al., 2013).

Several attempts have also been made to implement agents for playing games with particular playstyles (Tychsen and Canossa, 2008; Holmgård et al., 2014; Holmgård et al., 2016; Holmgård et al., 2019; Ishii et al., 2018; Tampuu et al., 2017; Fan et al., 2019). Here, the playstyle means a set of characteristic behavior of a player (Tychsen and Canossa, 2008). For example, in the poker, some styles use bluffs and prefer stable wins. Most previous studies aimed at generating agents with specific and predetermined playstyles. To this end, they commonly introduced a reward function (a function for an agent to learn playing games) in advance to emerge the intended playstyle. However, it is not easy to generate unexpected playstyles using this approach.

In this study, we propose a framework to generate multiple playstyles (including unexpected ones) for playing games well without predefining the aimed styles and the corresponding reward functions. The proposed framework first arranges a set of reward functions regarding the target game and repeats to select a function and make an agent learn with it. As a result, various agents learned with different reward functions are generated. These learned agents are made to play the game and selected those whose scores (evaluated by the predetermined utility function for the game) are higher than a predetermined threshold. Finally, the play logs (the metrics recording the behavior in a game) of the selected agents are clustered, and the resulting clusters are regarded as the playstyles. Through the above procedure, it is possible to generate multiple characteristic styles for playing the game well.

To evaluate the performance of the proposed framework, we conducted an experiment to generate playstyles for the roguelike game called MiniDungeons (Holmgård et al., 2014). In the experiments, we use a genetic algorithm called NeuroEvolution of Augmenting Topologies (NEAT) (Stanley and Mi-

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ikkulainen, 2002) for agent learning. We created 96 functions from the set of reward functions using a grid search method. The utility function was defined to give a high score when the agent safely reached the exit in three evaluation stages. Under the above settings, the experimental results show that 41 agents trained on 41 reward functions, respectively, could obtain scores above the threshold. As a result, we obtained four playstyles.

There are various possible applications of the proposed framework. When conducting test play in game development using agents, it is useful to improve the game and remove bugs by testing in various styles and agents with a predetermined one. Additionally, the proposed framework is useful for analyzing the characteristics of games.

The remainder of the paper is organized as follows. Section 2 presents related work. Section 3 presents the formal description of our target problem. Section 4 describes the proposed framework. Section 5 presents the experimental results of the proposed framework. Finally, Section 6 presents the conclusion and future studies.

2 RELATED WORK

Tychsen et al. (Tychsen and Canossa, 2008) is one of the earliest studies on playstyle in games. They defined the notion of playstyle as a set of characteristic behavior of a player and analyzed the behavior of players in the game called *Hitman: Blood Money* by measuring various metrics of play logs, such as the player's position in the game field. Additionally, they reported that these metrics could range from high to low abstraction. They claimed that these are useful for analysis with proper preprocessing.

Holmgård et al. (Holmgård et al., 2014; Holmgård et al., 2016) presented a model of the evolution of player's decision-making and created five agents with different playstyles through learning. They generated agents specified by linear networks and used an evolutionary strategy to optimize agents. Here, they defined reward functions to emerge the predetermined playstyles in advance. For example, the reward function for the playstyle called Monster Killer was defined as the more monsters the agent kills, the bigger the reward.

Ishii et al. (Ishii et al., 2018) generated agents with two playstyles, called close-range and long-range attacks, on the fighting game platform FightingICE. Their idea was to use Monte Carlo tree search and measure the distance to the opponent and the number of actions suitable for the aimed playstyle when evaluating the agent's reward.

Tampuu et al. (Tampuu et al., 2017) generated the playstyles of cooperation and hostility on the hockey game called Pong of Atari 2600. These playstyles were implemented by defining two distinct reward functions based on deep Q-network (Mnih et al., 2013). The cooperation and hostility playstyles were generated by taking negative and positive rewards, respectively.

Fan et al. (Fan et al., 2019) developed an agent to entertain novice players of the game, Go using heuristics that selects different moves for different strategies. The heuristics were originally developed by (Ikeda and Viennot, 2013) based on the Monte Carlo tree search and applied it to the agent playing Go called Leela, which was based on AlphaGo Zero. Here, the strategies taken by the heuristics were developed by defining different rewards for the results of game play.

In the above studies, agents with specific styles were developed in common by predefining aimed playstyles and reward functions adjusted to the styles. As applications of these studies, there are attempts to automatically validate level design (Holmgård et al., 2014) and attract human players (Fan et al., 2019). However, it is not easy to generate playstyles that are unexpected in advance using the approach in the previous studies. On the other hand, the proposed method has the advantage of generating multiple playstyles to identify the potential playstyles without defining the playstyles in advance.

There have been many attempts at modeling cognitive, affective, and behavioral responses of players, predicting human experience and characteristics from gameplay inputs(Yannakakis et al., 2013). Drachen et al. (Drachen et al., 2009) collected play logs from over 1,000 players of the game called Tomb Raider: Underworld, and classified them into multiple player types. In (Drachen et al., 2009), six distinct features were picked out from the collected play logs and classified them with clustering and self-organizing maps. As a result, they clarified that there were four distinct types of players. This approach must collect a lot of data from human players for analyzing. In addition, game designers cannot have collected and analyzed data when they want to change the game mechanics through trial and error during game development, i.e. before release. Therefore, this study trains agents with many reward weights, generating agents with more behavioral patterns, instead of collecting human players' data.

3 PROBLEM DESCRIPTION

In this section, we give a formal definition of playstyles and the problem description of playstyle generation addressed in this paper.

First, we define games as the complete information extensive-form games in game theory (cf. (Osborne and Rubinstein, 1994; Leyton-Brown and Shoham, 2008)). An extensive-form game is a model where one or more players make consecutive decisions according to their policy and each player obtains a reward according to the result. However, for the sake of simplicity, we only consider games with a single player where there is no probabilistic choice of action.

Definition 1 (Game)**.** A game is a tree defined as a tuple (A,H,Z,χ,σ,u), where

- A is the set of actions;
- H is the set of non-terminal nodes of game tree;
- Z is the set of terminal nodes of game tree, disjoint from H;
- $\chi : H \rightarrow 2^A$ is the action function, which assigns to each choice node a set of possible actions;
- $\sigma : H \times A \rightarrow H \cup Z$ is the successor function, which maps a non-terminal node and an action to a new node;
- $u : Z \rightarrow \mathbb{R}$ is the utility function (where $\mathbb{R}$ denotes the set of real numbers).

An agent conducts consecutive decision-making on a game, and as a result, acquires some utility on a terminal node. The utility function u is a function determining the utility according to the result of game play. A game is designed so that maximization of the utility leads to the achievement of the game objective. For example, in Super Mario Bros., the utility is the score displayed in the upper right corner of a screen, and the more objectives a player achieves in the game, such as “getting to the goal faster” or “getting more coins,” the higher the utility it gains.

Next, we introduce the reward function. This function is used by agents to learn the game in our framework described in the next section. Here, the reason for providing the reward function separately from the utility function is that it is difficult to train the agents directly by the utility function.

Definition 2 (Reward Function)**.** A reward function $f_w : D_1 \times \cdots \times D_n \rightarrow \mathbb{R}$ for game play is defined as $f_w(d_1,\ldots,d_n) = \sum_{i=1}^{n} w_i \times d_i$, where w denotes the vector of weights to parameters and $w = (w_1,\ldots,w_n) \in W (= W_1 \times \cdots \times W_n)$. Also, let $D_i \subset \mathbb{R}, W_i \subset \mathbb{R}$.

Here, each parameter d_i of a reward function is a numerical value representing a certain feature of the agent’s behavior in the game. For example, in the case of Super Mario Bros., the number of coins acquired and the number of jumps may be parameter values. The reward for play is defined as the sum of each parameter d_i multiplied by a predefined weight w_i.

Next, we introduce the model that constitutes an agent. A model has parameters to infer the correct labels and optimizes them by learning datasets. That is, it takes non-terminal nodes as inputs and outputs the next action to be taken that maximizes the reward function. Originally, the model outputs values of all possible actions, but for the sake of simplicity, we assume that it takes an action with the largest value and omit the detailed descriptions.

Definition 3 (Model)**.** The model that constitutes an agent is defined as the function $m : H \rightarrow A$.

For example, an instance of the Deep Q-Network or NEAT correspondents to a model m. The set of models is denoted by M.

Next, we define the learned model. This represents the model learned by a reward function.

Definition 4 (Learned Model)**.** A model m trained by a reward function is denoted as the learned model $m^* : H \rightarrow A$. The set of learned models is denoted as M^*. Here, if $g : H \times A \rightarrow D$ is a function that returns a vector of measurements where an agent takes an action on a non-terminal node, then an action a on a non-terminal node h satisfies $a = \underset{a' \in \chi(h)}{\arg\max} f_w(g(h,a'))$.

For a given reward function f_w and a learned model m^*, we use $z[f_w,m^*]$ to denote the terminal node reached by an agent repeating to take actions so as to maximize its reward determined by f_w and m^* at each node. Here, note that the utility is defined as a part of the game, while the reward is a criterion for the agent to select the optimal action in the learning.

Next, we define the feasible solution, which is a pair (f_w,m^*) that leads to a utility exceeding a predefined threshold.

Definition 5 (Feasible Solution)**.** Let θ be a real number and called a threshold. For a given reward function f_w and a learned model m^*, if $u(z[f_w,m^*]) \geq \theta$, then the tuple of (f_w,m^*) is called a feasible solution. The set of feasible solutions (for a threshold θ) is denoted by E.

Thus, a feasible solution can be regarded as an agent which plays the game well.

Next, we define the play log. Intuitively, this is a real vector representation of a record of game play by an agent.

Definition 6 (Play Log)**.** A real vector recording of the occurrence of various events in game play by an agent based on a feasible solution (f_w, m^*) is called a play log. We define the function $pl : F_w \times M^* \to Y$ that returns the play log for a given feasible solution, where $Y = Y_1 \times \cdots \times Y_n$ for each $Y_i \subset \mathbb{R}$.

Next, we define the playstyle. Intuitively, the playstyle is a set of characteristic behaviors of an agent.

Definition 7 (Playstyle)**.** For a given set E $(= \cup_{i=1}^{k} E_i)$ of feasible solutions, a playstyle on granularity k is a set E_i (for $i = 1, \ldots, k$) if satisfies the following conditions.

- Condition 1:

$$E_i \cap E_j = \emptyset \quad (\forall i, j \leq k \,\text{with}\, i \neq j).$$

- Condition 2:

$$\begin{aligned}&\| \tfrac{1}{|E_i|} \textstyle\sum_{(f_w, m^*) \in E_i} pl(f_w, m^*) \\ &\quad - \tfrac{1}{|E_j|} \textstyle\sum_{(f_w, m^*) \in E_j} pl(f_w, m^*) \| \geq \delta_b \quad (\forall i, j \leq k).\end{aligned}$$

- Condition 3:

$$\begin{aligned}&\forall (f_{w_a}, m_a^*) \in E_i,\ \forall (f_{w_b}, m_b^*) \in E_i \\ &\quad (\| pl(f_{w_a}, m_a^*) - pl(f_{w_b}, m_b^*) \| \leq \delta_i) \quad (\forall i \leq k).\end{aligned}$$

Here, $\delta_b \in \mathbb{R}$ is the threshold on the distances between playstyles and $\delta_i \in \mathbb{R}$ is the threshold on the distances between individuals in the playstyle.

Intuitively, Condition 1 means that each subset E_i of the feasible solutions is a partition of set E. Condition 2 means that the average distance of play logs of any two subsets E_i and E_j must be more than or equal to δ_b. Condition 3 means that the distance between any two play logs generated by feasible solutions in E_i must be less than or equal to δ_i.

Finally, we describe the problem of playstyle generation addressed in this study.

Definition 8 (Playstyle Generation Problem)**.** Playstyle generation problem is a problem to find a class $\{E_1 \ldots, E_k\}$ of playstyles for a given game G and a granurality k.

4 FRAMEWORK FOR PLAYSTYLE GENERATION

4.1 Procedure to Generate Playstyles

The procedure to generate playstyles using this framework is as follows. (See also Figure 1 for the graphical presentation.)

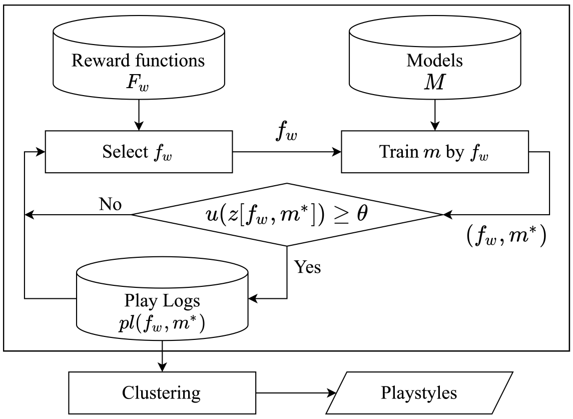


Figure 1: Procedure of the playsytle generation by the framework.

For a given game G, the framework first provides a set F_w of various types of reward functions for the agent to learn to play this game. It also determines the types of behavior of interest for the agent playing the game generated through this framework, and which features are recorded as play logs. That is, the function pl is defined. Furthermore, some parameters and variables, such as the threshold θ and k for clustering, are determined.

Next, the proposed framework makes agents learn with reward functions in F_w and selects only those satisfying $u(z[f_w, m^*]) \geq \theta$. Specifically, a reward function $f_w \in F_w$ is selected and generate a model m by learning with this function. Then, the learned agent is made to play the game. Play log whose utility exceeds the threshold θ is saved; otherwise, the agent is discarded. By repeating the above procedure, a set of logs that play the game well is obtained. Here, to efficiently obtain a model that plays the game well, it is necessary to select a reward function from F_w that is likely to generate such a model.

Finally, the collected play logs are classified into k clusters using some clustering technique; each is regarded as a playstyle playing game well.

4.2 Selection of Reward Functions

When selecting a function from a set of reward functions, it is necessary to efficiently and evenly select ones that are likely to generate agents that play well. As such a method, grid search is a brute force search for combination of input values. Since an advantage of the grid search is simple and easy to implement, our experiments adopt this method. Other methods include particle swarm optimization and Bayesian optimization. These methods are convenient for efficiently finding a plurality of semi-optimal solutions.

4.3 Generating Learning Models and Play Logs

Since the play logs identify the playstyle, the elements of the play log recorded as a vector are the numerical values of the events considered necessary for identifying the playstyle in the game. However, each reward function describes how the agent ought to behave in the game.

In our framework, the model used for agent training is independent of any specific method if it outputs the action that maximizes the value of a given reward function for the input state. Examples of such learning models include genetic algorithms (Srinivas and Patnaik, 1994) and deep reinforcement learning (Mnih et al., 2013).

5 EXPERIMENTS

5.1 Setting Game and Model

In this study, we conducted experiments with a rogue-like game to evaluate the effectiveness of the proposed framework. We used MiniDungeons (Holmgård et al., 2014; Holmgård et al., 2016), a model developed by Holmgård with Java, in this experiment. Here, we reimplemented this game with Python to run in the OpenAI Gym environment. We set multiple stages and parameters and domains of reward functions.

The agent in this game aims to move from the starting point to the goal without dying. This agent can repeatedly move one square up, down, left, and right. Each stage is a two-dimentional grid including some special types of cells indicating the starting point, blocks, treasures, monsters, potions, and exit. When the agent arrives at each treasure, monster potion, and exit, it receives a predetermined reward. Furthermore, a negative reward is obtained as a penalty for the passage of time for each movement.

In this experiment, we use NeuroEvolution of Augmenting Topologies (NEATs) as the learning model of agents. A reward function is initially set for each NEAT. Then, the individual, which is identical to its model, receives a state from the environment. Then, the agent evaluates the reward of the state or action by its reward function. Finally, it outputs an action selected by the network to the environment. These operations are repeated until the agent reaches the goal, the physical strength less than or equal to 0, or the specified number of turns has passed. After the play, the total rewards obtained during this play are set to the fitness of the agent, and the agent's play log is recorded. Agents optimized for the reward functions are generated so that individuals with high fitness survive by natural selection.

Table 1: Parameters of reward functions and weights.

Parameter	Weight
Movement	(-2, -1, 0)
Reaching the exit	(-100, 100)
Acquisition of a tresure	(-40, 40)
Acquisition of a potion	(-30, 30)
Defeating a monster	(-50, 50)
Death	(-100, 100)

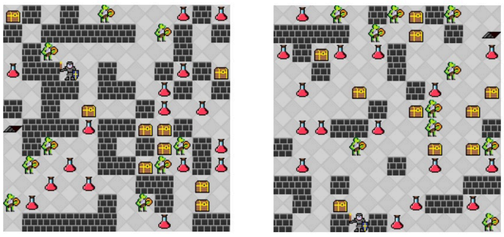
The input layer of the individual is set as eight neurons and receives information from the environment about the shortest distance to each object and the remaining health. Here, there are two possible distances: the distance when approaching the object safely avoiding monsters, and the distance without avoiding them. The action corresponding to the output neuron with the maximum value is selected at each decision point, and the agent moves one square toward the selected object.

5.2 Setting Framework

The utility function of MiniDungeons was set as "it returns 1 if the agent reaches the exit without dying within the time limit at all stages, and 0 otherwise." The threshold of the feasible solution was set as "reaching the exit without dying within the time limit at all stages (i.e., the value 1)."

Here, the reward functions have six parameters. Table 1 presents the types of values fed into parameters and weights. We set the reward functions so that the absolute value of the exit and death were equal, and the absolute values were in the order of monster, treasure, and potion. The values of reward functions were searched by grid search and direct product of weights on Table 1. Thus, the number of reward functions searched was $3 \times 2^5 = 96$. For example, if the weights of the reward functions parameters are $(-2, 100, 40, -30, -50, -100)$, and the measured values for each event are $(20, 1, 2, 0, 3, 0)$, then the reward is 10, the value of the inner product. The play log expressed in vector form is used for clustering when generating playstyles. This play log contains the number of visits to each cell.

Figure 2 shows examples of the training and evaluation stages used in the experiments. Three training stages were used for training individuals of NEAT. The individual's utility with the highest fitness was examined to exceed the threshold in three evaluation stages. It was judged that the agent played the game



(a) (b)

Figure 2: Examples of training stage (a) and evaluation stage (b).

Table 2: Parameter settings.

Paramerter	Value
Initial Health	30
Health required to defeat a monster	10
Health recovered by a potion	10
Maximum number of movements	200
Number of individuals of population	75
Number of populations	50

well if it reached the exit without dying in all evaluation stages. Separating used stages makes it possible to select reward functions that more generally satisfy the rule of the game. These stages were randomly generated according to a predetermined appearance ratio of objects.

Table 2 presents the parameters of MiniDungeons and NEAT. Each population of NEAT consists of 50 individuals and 75 populations were trained. Thus, 360,000 individuals were trained and 96 candidates were generated, and only those with utilities exceeded the threshold were used to create playstyles.

5.3 Results for the Framework

Under the above settings, the experimental results show that 48 out of 96 individuals optimized on 96 reward functions satisfied the condition of the evaluation stages. The 48 feasible solutions were classified into 11 clusters with x-means (Pelleg and Moore, 2000). Here, the play logs of three evaluation stages were used as the criterion for classification. The x-means automatically estimates the number of clusters; however, the number of estimated clusters varies depending on random numbers. Thus, x-means were repeated 1000 times, and 11, the number of clusters that appeared most frequently, was adopted.

7 out of 11 clusters were excluded because their sizes were less than 4, being difficult to analyze playstyles. Table 3 shows the detail of four clusters whose sizes are greater than or equal to 5. Each cluster 5, 7, 9, and 10 have a size greater than or equal to 5 and accounts for 75% of the total.

Table 3: Generated clusters.

ID	Size	Name
5	11	Runner
7	11	Consumer
9	10	Treasure Collector
10	5	Coward

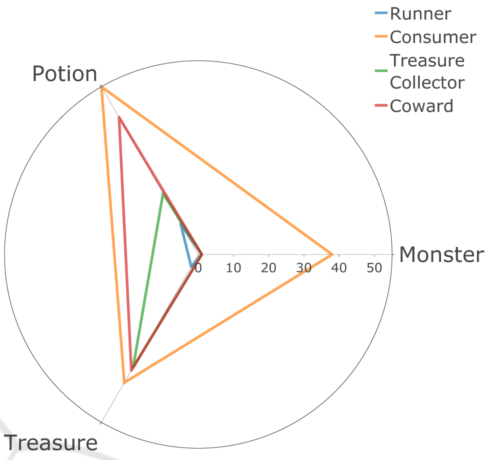


Figure 3: Comparison of behavioral characteristics between cluster (by measuring play logs).

Cluster 5 (named Runner) was negatively rewarded by treasures on all reward functions and was negatively rewarded by either monster, treasure, or both. Thus, it gave priority to the exit and avoids other objects as much as possible. Cluster 7 (Consumer) was positively rewarded with curiosity by treasures, potions, and monsters on all reward functions. Cluster 9 (Treasure Collector) was positively rewarded by treasures on all reward functions. Cluster 10 (Coward) was positively rewarded by potions and treasures; however, it was negatively rewarded by monsters.

We analyzed the events measured by agents on three evaluation stages for each cluster to investigate the characteristics of these clusters. Figure 3 shows the radar chart of the event logs. The events measured were the number of monsters killed and the number of potions and treasures obtained. Figure 3 shows the plot of the average of the measured logs for all reward functions in each cluster.

The shape of the cluster 5 (Runner) is smaller than the other clusters. The reason is that agents disliked other objects and immediately headed for the exit. It is considered that agents acquired some potions and treasures along the way to reach the exit in the shortest path. Cluster 7 (Consumer) has the largest shape and is close to an equilateral triangle. Agents of this cluster killed monsters instead of other clusters and

Table 4: Variance of logs per cluster for play logs.

Group	ID	Move	Monster	Potion	Treasure
PlayLog	5	91.7	0.6	45.8	0.3
	7	775.3	0	0	0
	9	411.4	0.81	30.0	1.6
	10	299.3	0.6	0	0.2
RewardWeights	4	8425.4	0	202.6	250
	5	20087.2	248.5	467.8	241.3
	6	6303.8	0.41	229.8	183.4
	9	7557.6	1.3	134.0	260.8
	10	3442.1	0	27.2	50.1

acquired potions and treasures at the same rate. In cluster 9 (Treasure Collector), the percentage of the number of treasures acquired is large. Only the number of monsters killed is small in cluster 10 (Coward). This tendency is also seen in Treasure Collector; however, there is the difference that agents take more potions to heal and put their safety first.

The generated playstyles have different priorities for objects; thus, behaving differently on stages. Therefore, the reward functions are considered to change the personality and preferences of agents. Thus, it is considered that the framework could generate playstyles without predefining playstyles and reward functions by searching these reward functions and clustering on only the feasible solutions.

5.4 Comparison with Clustering for Reward Functions

As an auxiliary evaluation, we also confirmed whether a similar playstyle could be obtained by clustering the vectors of weights for the parameters of the reward functions, instead of clustering play logs.

In the experiment, 48 reward functions whose utilities exceed the threshold were classified by the x-means based on the weights for the parameters. They were classified into 11 clusters, five of which have sizes greater than or equal 6. This result indicates that the individuals in the same cluster behaved similarly due to the similarity of the reward functions. However, compared to clustering play logs, the individuals in the same cluster often behaved differently. As an illustration of this result, Figure 4 shows the measurement of logs when clustering on reward functions. Clusters 4, 6, and 9, on average, avoided monsters, and Clusters 5 and 10, on average, were interested in all objects. The reason is that individuals with different behavior were mixed in the same cluster, averaging behavior. Table 4 summarizes the variance of logs per cluster for play logs and reward functions. In the cluster generated by values of reward functions, each individual behaves differently, increasing variances. These results suggest that when generating playstyles, it is better to convert reward functions into play logs by playing games and then classify play logs with clustering. The reason is that playstyles are identified based on information of events in games that can be observed by humans and machines.

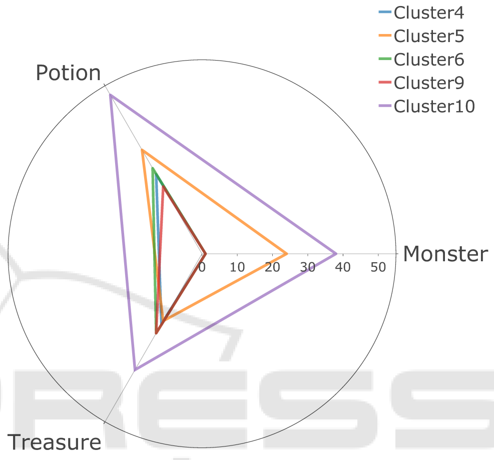


Figure 4: Comparison of behavioral characteristics between cluster (by measuring reward functions).

6 CONCLUSIONS AND FUTURE WORK

In this study, we proposed a framework for generating multiple playstyles for playing games well without predefining the aimed styles and the corresponding reward functions. The basic idea was to classify the play logs of agents who learned the game using different reward functions and who could play the game well. The proposed framework makes agents train by reward functions and select those whose scores exceed the threshold. Then, play logs of the selected agents are classified with clustering, generating playstyles. We applied our proposed framework to the roguelike game and demonstrated that multiple playstyles were generated.

In future studies, we will verify the effectiveness of the proposed framework by adopting it on more complex games, such as Super Mario Bros., consisting of many possible actions and states. We are also interested in using a genetic algorithm called Quality Diversity (Pugh et al., 2016) in our framework to make more effective and expressive the playstyle generation, especially MAP-Elites (Mouret and Clune, 2015).

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