Graph-Based Next-Event Prediction Methods Considering the Interrelationships among Game Players' Memories: Focusing on a Card Game

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Abstract

This study aims to understand the process by which humans form a hierarchy of predictions when anticipating future developments of events and take actions accordingly. Predictions are not necessarily based on probabilistic judgments; rather, even in situations where probabilities cannot be quantitatively assessed, people make guesses by referring to their memory and constructing their own theories related to the current situation. In this study, we compare and examine three computational models that represent "relational values" to investigate how experience-based theory construction contributes to predicting future developments.

Keywords: Game, Rule, Cheating, *Ikasama*, Cognitive model

1. Introduction

In this first section, we discuss cheating and other foul play in video games and state the purpose of this study.

1.1. Background

In modern times, advances in computer technology have dramatically transformed gaming, with online games, where players can play against others over long distances via the Internet, becoming increasingly popular. However, players still violate the rules, and cheating and glitching continue to be prevalent in online games. Cheating is defined as "the act of exploiting a loophole in the game system to give players an advantage that would not otherwise be possible" [1]. The game system refers to the rules that determine victory conditions and restrict player actions in video games, as well as the program code itself, which strictly defines the actions players can take. Cheating is the act of a player using an external tool to circumvent the constraints imposed by these rules. Similarly, glitches also provide players with an advantage, but rather than relying on external means, they intentionally exploit bugs caused by flaws in the program code or hardware specifications of the game.[1]

All of these types of foul play give users an unfair advantage in the game; in other words, *Ikasama* play in Japanese. Although the word of *Ikasama* has a wide meaning than "cheating," the two words are almost equal in this study. In the following description, we distinguish between the two depending on the contexts.

Game publishers have implemented various measures to prevent, correct, and eliminate *Ikasama* to some extent. However, cheat creators continue to find loopholes in the publishers' measures. The relationship between game publishers and cheat creators has become a cat-and-mouse game.

Quago, a developer of anti-cheat tools, cited a report by Dutch software developer Irdeto, which found that 60% of online gamers experienced a negative impact on their multi-player gaming experience because of cheating. The report also noted that *Ikasama* play discourages players from purchasing in-game items and content and even leads to players abandoning the game altogether, resulting in

[1] Rules are an important element in defining games. In this study, we define a "game" as a form of "play" based on a set of rules. Huizinga distinguished between participants who openly break the established rules as "game breakers" and participants who appear to follow the rules on the surface but actually deviate from them as "cheaters." He also pointed out that the establishment and maintenance of play are closely linked to "fairness," and stated that "cheaters" ultimately contribute to the maintenance of play itself by maintaining a superficial sense of fairness [2].

negative financial impacts for game developers and publishers [3].

1.2. Objective

In this study, we consider that a core of the *Ikasama* play's problems is that it makes players feel uncomfortable. Based on this, we examined this point from the perspective of players' gaming experiences. We also consider the cognitive processes that exist before a player judges a certain game action to be "*Ikasama* play" or simply "*Ikasama*," and the effectiveness of countermeasures against *Ikasama* play by constructing a pseudo-player.

2. Problem Organization and an Approach

In Section 2, we summarize the subject matter of this study and describe our approach to the problem.

2.1. Problems

According to the EAA [4], cheating is a problem because it disrupts fairness, which is indeed true. However, the authors believe that this is not the direct cause of the observed results in this study. This is because it is the players, not the game system, who determine that fairness has been disrupted. For example, even if the game system determines that fairness has been disrupted, if the players do not, then there is no problem in the game. This is evident from the fact that actions that would be considered *Ikasama* (play) in multi-player games are not considered *Ikasama* (play) in single-player games. Therefore, *Ikasama* play disrupts fairness; however, for that to occur, other players must first perceive it as a disruption of fairness. The important difference here is that if a player determines that *Ikasama* play is oc.curring, it becomes a problem regardless of whether *Ikasama* (play) actually occurred.

2.2. Ikasama *(play) in this paper*

First, because *Ikasama* (play) is used to create an unfair advantage, the person who meets *Ikasama* play naturally feels at a disadvantage. This can also be described as *Zurui-koi* (behavior or act): an "unsportsmanlike conduct." So, is *Ikasama* (play) synonymous with *Zurui-koi*? However, this is not necessarily true. Consider the card game *Lose with the Joker* as an example. An *Ikasama* play in the *Lose with the Joker* could involve manipulating the cards dealt to you or switching cards. However, *Zurui-koi* can also involve a disruptive behavior, such as shouting. Thus, *Zurui-koi* includes non-cheating behaviors or *Ikasama* behaviors; in other words, *Ikasama* (play) is inherently included within *Zurui koi*. If we distinguish between *Ikasama* play and non-cheating behaviors, *Ikasama* (play) is always a violation of the rules, while non-cheating behaviors cannot necessarily be considered foul play; it seems that there are differences depending on the rules of the game. Because the goal of this study is to solve the *Ikasama* (play)'s problem, non-cheating behaviors will be not treated.

Next, *Ikasama* play is distinguished by rules, but the definition of these rules varies from player to player. Therefore, it is not possible to define the point at which/what point an act constitutes a violation of the rules or *Ikasama* (play).

From the above, it can be seen that the *Ikasama* (play) dealt with in this study is clearly a violation of the rules, but is something that has not been detected or eliminated by the measures taken by game developers and game publishers.

2.3. Approaching the problem

In this study, we focus on the fact that cheating is a tool that enables behaviors that would otherwise be impossible and assumed that players would be surprised when they discovered *Ikasama* (play). Therefore, by determining that players were surprised, it would be possible to identify moments when they may have encountered *Ikasama* (play). By extracting the level of surprise at each moment, it is possible to evaluate the reliability of each extracted moment. Surprise refers to something unexpected, which can also be rephrased as a large information gain (the greater the information gain, the lower the uncertainty). Based on this, the author hypothesized that the level of surprise could be extracted by considering how well players predict the next development in the game.

To consider how well players predicted what would happen next, we first needed to clarify how they played the game.

Players improve as they continue playing a game and can adapt quickly when playing other games of the same type. This shows that players understand a game not from rules or clear systems but from their gameplay experience. We can also assume that players use this understanding of the game to make various decisions while they are playing. Therefore, when a player plays a game, we need to consider it as being divided into how they understand the game and how they use that understanding to play the game.

Therefore, we devised the following cognitive model (Figure 1), which considers how inferences that determine human behavior and attention can be made from information obtained from the sensory organs.

- **Information from sensory organs**: Sound and light obtained through vision and hearing
- **Memory**: Experience with the target game
- **Interpretive facts**: Semantic understanding of information from sensory organs
- **Situation Network**: A network model that explains the current situation
- **Conjecture group**: What is conjectured as the next step
- **Concern Bias**: The degree to which things cannot be ignored
- **Guessing probability distribution**: The probability of occurrence of the guessing group plus concern bias

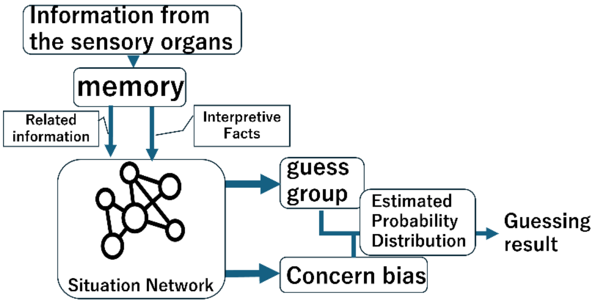

Figure 1 Assumed cognitive model.

The information acquired through the sensory organs is simply color arrangement and wavelength and is therefore meaningless in this state. In this model, the memory assumed to contain information from the sensory organs is the memory for the target game. This consists of each player's unique understanding of the game rules. Understanding the game rules is the basis for explaining the explicit rules of the target game as a solution to the problem. These rules also explain the conditions for victory and how to win. This memory allows the information from the sensory organs is given a way to be handled in the game. In this study, this transformation into a meaningful form is referred to as an interpretive fact. This is an interpretation given by the individual's memory of the information from the sensory organs that everyone receives equally in the same situation. However, this interpretation is not treated as an interpretation by the individual; it is subjective and treated as objective data. Information related to the interpretive fact is then retrieved from memory through involuntary recall. The interpretive facts and retrieved information are linked to form a network. This network represents a subjective understanding of the situation, and individuals treat this network as an interpretation. This model then derives a possible guess set and concern bias from the situation network. The guess set is the probability of each possible next development from the situation, and the concern bias is a biased guess set probability, such as a loss in gameplay. The guess result is determined based on the probability of the guess set plus the biased-guess probability distribution.

Focusing on the fact that cheating is a tool that enables behaviors that would otherwise be impossible, we assumed that players would be surprised when they discovered *Ikasama* (play). Surprise means that something is unexpected, which can also be rephrased as a large information gain. Based on this, we thought that this model could evaluate the suspiciousness of the next development based on how unlikely it was to occur in the estimated probability distribution.

3. Attempts at Model Construction

Here, when constructing a pseudo-player, we consider an appropriate model using the card game *Coyote* as an example of a card game.

3.1. Memory association verification

We used *Coyote* as a subject and considered the relevance of cards using three analytical methods to examine how players understand the game, how they extract relevant information using interpretive facts, and what information can be considered appropriate for constructing a situation network.

First, the focus is on card games because there is little impact if we ignore the transformation process from information acquired by the sensory organs to interpretative facts. Because card games involve using cards, positional information is not relevant to the game, and only symbolic information on the cards is required to play the game. In addition, because card games are divided into turns, it is easy to define the next development step.

Coyote, each player is dealt a numbered card, and players can only see the cards of other players (Figure 2).

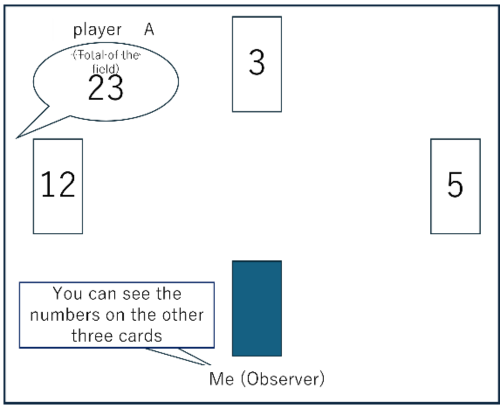

Figure 2 Coyote game board.

In this test, 52 cards were dealt, ranging from 1–13. Subsequently, without knowing what cards they had, players took turns declaring what they thought was the total number of cards on the table, and the player who guessed correctly won the game.

Unlike *Uno*, *Coyote* does not have many cards in the player's hand, and the only thing you know is your own cards; therefore, it has very few variables. Additionally, it is not a game of pure luck like blackjack, but there is some strategy involved; therefore, it was deemed an appropriate game to target in this study.

Three analytical techniques were used: association analysis, collaborative filtering, and self-organizing models.

Association analysis [5] is a type of data mining that uses the frequency of appearance of object A and the frequency of simultaneous appearance of A and B to calculate the correlation between A and B and search for highly relevant combinations in the data. Co-filtering [6] is a method for recommending something to object X by determining the recommended object based on the selection of object Y, which has made selections similar to that of X. This method calculates similarities, such as cosine similarity, and recommends items similar to a specific object. A self-organizing model autonomously acquires the topology and distribution of the input data without supervision.

Although the purposes of these three analytical methods are different, they are all models that determine and use some kind of relationship value between items in the derivation process.

3.2. *Correct answer rate*

The number declared by “me” in Figure 2 was determined using the analysis method explained in Section 3.1, and the accuracy rates were compared. In this comparison, “me” was the first among the four players to declare a number. The accuracy rates were evaluated when “me” recommended the card I held based on information about the three cards other than my own using the three models and when a random number was used as the answer. Table 1 presents the accuracy rates of the models.

Table 1 Correct answer rate for each model.

Random prediction	Association analysis	Co-tuning Filtering	Self-organization model
0.067000	0.073555	0.076111	0.075111

As shown in Table 1, the accuracy rates of the three models were almost the same, with the maximum difference being less than 0.01. From these results, it was not possible to confirm any significant differences between the models, at least on the scale of this study.

3.3. *Trend analysis*

The accuracy rate was verified based on whether the correct number was recommended in the first place, and the percentage of times that was considered the accuracy rate. Next, we verified whether these three models tended to recommend each number. For verification, the recommended ranking of each number was recorded from the list of number recommendation rankings for the test data, which is the output when the test data are given to each model, and a chi-square test was performed on the records of the recommendation rankings. The null hypothesis of the chi-square test was “the appearance ranking is uniformly distributed,” and the alternative hypothesis was “there is some kind of bias,” with a significance level of 95%.

Table 2 summarizes the results of the trend analysis using the chi-square test, showing whether there was a trend for each of the four methods and for each number.

As shown in Table 2, the rankings were uniform in the random case, but there was a bias in the rankings in all three models.

Table 2 Correct answer rate for each model (Asso: Association analysis; Co: Collaborative filtering; Self: Self-organizing models.).

	Random	*Asso*	*Co*	*Self*
1	0.3618	0.7300	0.8496	0.5949
2	0.0000	0.0000	0.0000	0.0000
3	0.0000	0.0000	0.0000	0.0000
4	0.0000	0.0000	0.0000	0.0000
5	0.3618	0.7300	0.8496	0.5949
6	0.0000	0.0000	0.0000	0.0000
7	0.0000	0.0000	0.0000	0.0000
8	0.0000	0.0000	0.0000	0.0000
9	0.3618	0.7300	0.8496	0.5949
10	0.0000	0.0000	0.0000	0.0000
11	0.0000	0.0000	0.0000	0.0000
12	0.0000	0.0000	0.0000	0.0000
13	0.3618	0.7300	0.8496	0.5949

Table 3 shows the 1st and 13th most likely numbers to recommend for each model. The numbers in parentheses indicate the likelihood of the number appearing in that rank compared with other ranks.

Table 3 Values that are easy and difficult to recommend for each model (Asso: Association analysis; Co: Collaborative filtering; Self: Self-organizing models.).

	Asso	*CO*	*Self*
1st place	5 (+19)	2 (+62)	11 (+21)
13st place	7 (+48)	5 (+50)	7 (+44)

Differences between models were also confirmed, such as the number 5, which is likely to be recommended as number 1 in association analysis, being recommended as 13 in emphasis filtering.

4. Conclusion

The results of this study did not confirm that the models used had an advantage in accuracy when predicting the fourth card from three cards, but they did show that each model tended to recommend certain numbers.

In the future, we will verify whether the accuracy rate increases when biased test data are used. We also need to consider how to express relationships when including the declarations of other players. Furthermore, we need to focus on the simplicity of the game rules and verify the differences in the boundaries that lead to overfitting for each game.

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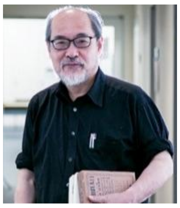
Prof. Takashi Ogata



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