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Master's Thesis

Gaming Entertainment Assessment:
Case Study Using Jump & Jump Game and Mafia Game

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Abstract

In recent years, the development of applets and the concept of metaverse has been evolved in our life. As time goes by, there are always new ideas are revolutionizing our understanding of life constantly. And the game element has become an integral part of these new ideas. In December 2017, at the beginning of the development of the applet, there was an arcade game based on the applet which is called Jump & Jump used to be all the rage. And in this paper, we will introduce the Jump & Jump game and the Mafia game respectively, as a summary of the research results during the master research.

About the Jump & Jump game, what is an arcade game launched on the WeChat platform (a social software in China) at the end of 2017 by Tencent company. It is a game on the WeChat applet platform for smartphones, which is operated via a touch screen. The purpose of this game is straightforward. The player controls an " i" -shaped villain, always jumping towards the box in front of it to accumulate more points.

There are two modes in this Jump & Jump game. One is the single-player mode, and another one is the multiplayer mode which supports up to 8 people. In single-player mode, the game performs according to the usual rules. In multiplayer mode, all players control the same “i”-shaped villain to jump, each player jumps for one time. Once a player fails, they can only watch the game. The next player can continue from the box where the previous player failed and persistently jumps to the end. The final player is the winner. After the game, the number of jumps will rank the players accordingly.

Since December 2017, the game has been released on the WeChat platform in China. The game was all the rage shortly after it was launched and became a hot topic for both users and media, which then later loses such spotlights just after a few months. It is found that the player’s number has been exploded in the short term. This caught our attention. We also found that the Jump & Jump game is an endless game. If the player does not fail, the game can go infinitely. Previously, based on the game refinement theory, there was no relevant research on this game. This aroused our interest. Hence, we decided to do major research with this arcade game. And our objective is to reveal the reasons for the Jump & Jump game to be phenomenal and downfall while finding its possible enhancement.

The entertainment assessment of the Jump & Jump game is performed by using the game refinement (GR) theory. The game refinement theory

has been proposed earlier to determine different levels of sophistication of games. Furthermore, it was proposed based on the concept of game progress and game information progress. It bridges a gap between board games and sports games. Many previous works on game refinement theory have shown that it is a reliable measurement tool for evaluating the game's entertainment where the sophistication of games can be determined. In our paper, we will briefly introduce the applications of the game refinement theory in different contexts.

After realizing the game progress model of the game refinement theory. We will apply the game refinement theory to analyze the game progress of the Jump & Jump game. It is believed that the Jump & Jump game is a kind of sports game, while it differs due to neither being time-limited nor score-limited sports. According to our investigation of GR's measure of different level players (the level of players is expressed by $L \in [0.1, 0.9]$), we can consider this game as the case where the task's difficulty level is fixed for players with various levels. And in each game of Jump & Jump, each jump attempts players made per game is considered as an independent experiment. Hence, it is assumed that there is a probability of success for each jump where p is the probability of successful jump action. Conversely, the probability of failure, equivalent to the risk rate of the player takes, is denoted as $m = 1 - p$. Then, a Binomial distribution is utilized to simulate the successful probability of the different states of the players' performance.

We simulate the Jump & Jump game progress through a program that is written in JavaScript. A cyclic Binomial distribution for simulating jump in the game is utilized with $\delta = 0.2$ (standard deviations). The simulation is conducted 1000 times, and the process repeats for every player level. Since each jump of players is a random independent experiment, another Binomial distribution is used to generate random probability to represent a realistic simulation of risk rate (m) and success probability (p).

Through analyzing our data based on the game refinement theory, we can realize that if players reach the $Lv7$ after some practice. They can feel strong engagement in this kind of situation. Such a situation implies that the game becomes easy to win and potentially becomes effortless. This result implies that if a player can reach this level quickly, it is easy for the player to feel dull in this game. And also, the game becomes fair in a subjective sense, which suggests that prolonged play at such a level could potentially cause addiction.

The game rule is given so that the game immediately fails once the player fails to jump to the next box. Such a situation resembles a kind of training because it does not allow failure in the game. Hence, it can be concluded that the Jump & Jump game is a game that gamified sports training. We can also get the result through the analysis from our data with game refinement theory. Similarly, it can also explain the reason why the Jump & Jump game is a phenomenal game.

For improving this kind of situation, some possible enhancements have been proposed by us based on the game refinement theory from the aspect of entertainment. It mainly includes two aspects: adding puzzle element and adding time limit. From these two aspects, the possible enhancements are established to improve the game as well as the potential design direction of an arcade game.

In the Jump & Jump game, we analyze the entertainment aspect of the Jump & Jump game for different levels of players by applying the game refinement theory. And it also identified the reason why players at earlier levels tend to be more exciting than higher-level players. Then we proposed potential enhancements to improve such drawbacks. It is believed that such improvements may provide further advancement in the design of arcade games and possibly maintain the popularity of the Jump & Jump game.

After introducing the Jump & Jump game, we will also introduce the case study on the Mafia game about the dynamics of minority versus majority behaviors. The game 'Mafia' is a logic puzzle that has been a top-rated party game played worldwide. Many studies have been dedicated to determining the best character combination to keep players engaged while analyzing the overall death toll. Although it has only two-sided plays, there are multiple combinations of characters in which each character's rules are different.

The Mafia game study explores the game's sophistication using the game refinement theory and motion in mind model while measuring the entertainment of each character's actions. It then focuses on the dynamics of minority versus majority behaviors during the game process. Computer simulations were conducted to collect the data of each character and assess the entertainment impacts. Moreover, the energy value of each character was computed based on the motion in mind model.

The results show that when the number of 'mafia' and the number of 'sheriff' are equal, the sophistication of each character is maximized. In addition, the data indicates the player engagement in the following order: $Mafia > Sheriff > Citizen$. Thus, it can be concluded that the actions of the Mafia character are the most complicated and significantly impact the game. It is expected that the results in the Mafia game study enable game designers to improve each character's perspective and examine possible enhancements from the viewpoint of entertainment.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background

In recent years, the development of applets and the concept of metaverse has been evolved in our life. As time goes by, there are always new ideas are revolutionizing our understanding of life constantly. And the game element has become an integral part of these new ideas. In December 2017, at the beginning of the development of the applet, there was an arcade game based on the applet which is called Jump & Jump used to be all the rage.

After introducing the Jump & Jump game, as a summary of the research results during the master research, we will also introduce the case study on the Mafia game about the dynamics of minority versus majority behaviors.

1.1.1 Jump & Jump game

Jump & Jump is a game on the WeChat applet platform for smartphones [1], which is operated via touch screen. The game has single-player mode and multiplayer mode which supports up to 8 people. The purpose of this game is very simple. The player control a “i”-shaped villain, constantly jumping towards the box in front, for accumulating more points.

Since December 2017, the game has been released on the WeChat platform in China. The game was all the rage shortly after it was launched and became a hot topic for both users and media, which then later loses such spotlights just after a few months. It is found that the player’s number has been exploded in the short term. This caught our attention. We also found that the Jump & Jump game is an endless game. If the player does not fail, the game can go infinitely. Previously, based on the game refinement theory, there was no relevant research on this game. This aroused our interest.

Hence, we decided to do major research with this arcade game. And our objective is to reveal the reasons for the Jump & Jump game to be phenomenal and downfall while finding its possible enhancement.

1.1.2 Mafia game

The Mafia game, a popular high logic party game around the world, was created for psychology research in the 1970s [10]. And it also can played on the Internet. A simple version of Mafia game contains two groups with three kinds of characters: (1) mafia and citizens, and (2) mafia, sheriffs and citizens. The game alternates between day and night round by round; players in different roles have their own functions. The game was suitable for analyzing the sophistication and energy exchange between players and the game itself since it is a multiplayer game.

As a top-rated party game played worldwide, many studies have been dedicated to determining the best character combination to keep players engaged while analyzing the overall death toll. Although it has only two-sided plays, there are multiple combinations of characters in which each character's rules are different.

Finally, as a result, our analysis shows that when the number of 'mafia' and the number of 'sheriff' are equal, the sophistication of each character is maximized. In addition, the data indicates the player engagement in the following order: $Mafia > Sheriff > Citizen$. Thus, it can be concluded that the actions of the Mafia character are the most complicated and significantly impact the game. It is expected that the results in the Mafia game study enable game designers to improve each character's perspective and examine possible enhancements from the viewpoint of entertainment.

1.2 Research objective

In the research of the Jump & Jump game, we would like to concentrate on the entertainment of the Jump & Jump game where it is analyzed using the game refinement theory, and the reasons for its phenomenal popularity that soon later losses its spotlights, are also revealed through the analysis of simulation results. Then, according to the game refinement theory, some possible enhancements are proposed to improve the game for making it popular again.

At first, we need to get the search popularity of the Jump & Jump game on the Internet for confirming that the Jump & Jump game is a phenomenal game. According to the search popularity graph, we can realize the specific data. So that, we can know how many people are still concentrating on this game and how many players remain. Then after confirming that the Jump & Jump game is a phenomenon game, we analyze the game progress of the Jump & Jump game through applying game refinement theory. To find out the factors which affect the entertainment of this game.

Then we port this game to the website by using JavaScript to capture the data we needed. After determining the data factors we need in the program. We can simulate the game process. And then, a large number of simulations were performed by the program to get the necessary data. After getting the data, we calculate and analyze the data by using game refinement theory. So that, we can get and confirm the factors that affect the entertainment of the game. Furthermore, we can reveal the reason why it becomes a phenomenal game.

Finally, based on the game refinement theory and our analysis of the data, we can consider the possible enhancement for Jump & Jump game. And further, simulate and analyze the data of our improved game. In the end, based on our data of the improved game, we can propose possible enhancements for this game from the perspective of a game designer. To achieve our objective of improving the Jump & Jump game.

In the study case of the Mafia game, Our research attempt to explore the game's sophistication using the game refinement theory and motion in mind model while measuring the entertainment of each character's actions. It then focuses on the dynamics of minority versus majority behaviors during the game process. Computer simulations were conducted to collect the data of each character and assess the entertainment impacts. Moreover, the energy value of each character was computed based on the motion in mind model.

1.3 Structure

The paper's organization is shown as follows:

In chapter 1, we will provide the overview of the Jump & Jump game and the Mafia game. Then our research objective is given in this chapter.

In chapter 2, the research of the Jump & Jump game will be provided in detail. It includes some related works, assessment methodology and simulation experiment. Finally, the analysis results will also be given in this chapter.

In chapter 3, the research of the Mafia game will be provided. We will analyze the Mafia game from the perspective of dynamics of minority versus majority behaviors based on the game refinement theory.

Finally, chapter 4 concludes the paper.

Chapter 2

Analysis of Jump & Jump Game and Its Possible Enhancement

This chapter is based on the integration, update, and abridgment of the following publication:

- H. Ri, M. N. Akmal Khalid and H. Iida,“Analysis of Jump & Jump Game and its Possible Enhancement”, 2020 International Conference on Advanced Information Technologies (ICAIT), 2020, pp. 82–87

2.1 Related works about the Jump & Jump game

As we know above, the Jump & Jump game is an arcade game on the WeChat applet platform and it is operated via touch screen. In this game, there is a certain distance between the boxes in the game, and the player only needs to press the screen to store power to ensure that such a jump accurately leaps to the next box. As the player successfully jumps on a box, the next one will appear. Suppose if the player jumps to the box successfully, the player is given one score point. For every successful consecutive jump, the player will obtain a linear increase of two points for each (up to 32 points of 16 consecutive jumps). After that, if the player continuously jumps, each jump will be 32 points. And if players stay on some boxes for a short period of time will also get bonus points. If the player jumps out of the box. This game will end and show the player's score. The size and spacing of the boxes are different. And the difficulty will gradually increase as the game progresses.[1]

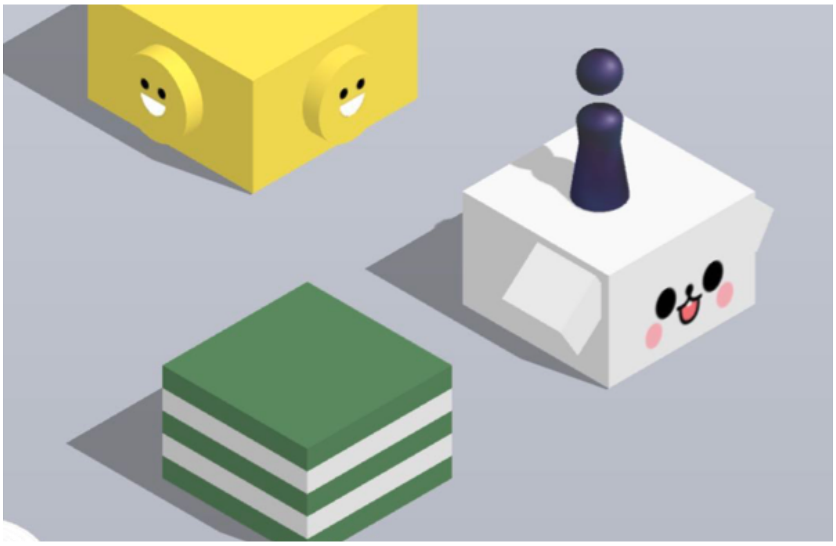

Figure 2.1: screenshot of Jump & Jump game

For a detailed introduction to the playing method, we would like to give some descriptions of the playing method as follows: The game is shown on the smartphone. On the screen, a small villain is standing on the box, and the distance is not certain between the boxes. The players need to control the small villain to make jump attempts with their fingers pressing on the screen based on their judgment.

Furthermore, if players stay on some boxes for a short time, they will also get bonus points. The game will end if the player jumps out of the box. This game will end and show the player's score. The size and spacing of the boxes are different. Also, the difficulty will gradually increase as the game progresses (see Figure 2.1).

There are two modes in the Jump & Jump game. One is the single-player mode, and another one is the multiplayer mode (supports up to 8 people). In single-player mode, the game performs according to the usual rules. In multiplayer mode, all players control the same "i"-shaped villain to jump, each player jumps for one time. Once a player fails, they can only watch the game. The next player can continue from the box where the previous player failed and persistently jumps to the end. The final player is the winner. After the game, the number of jumps will rank the players accordingly.

[1] Jump & Jump - wikipedia, https://zh.wikipedia.org/wiki/跳一跳, Last accessed 15 February 2020

For the single-player mode, this game has a ranking list, and players can check their friends' rankings. The ranking list is reset once a week [6]. In recent years, due to the development and influence of big data technology, the data of the Jump & Jump game from the website can be retrieved. Figure 2.2 illustrates the data recorded from January 2017 to March 2020, showing the search popularity of Jump & Jump game users.

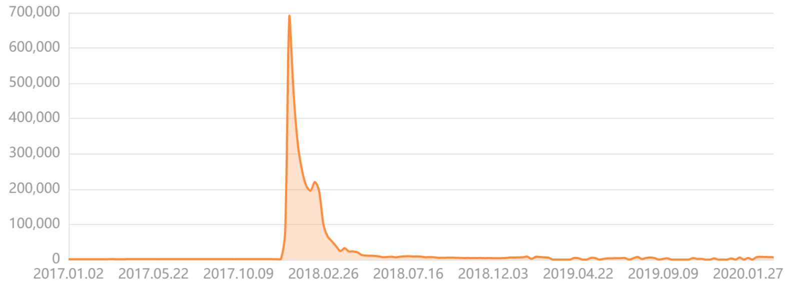

Figure 2.2: Search popularity of Jump & Jump game (http://data.chongbuluo.com/)

It can be observed that since the game was released in December 2017, game players' numbers exploded quickly. However, after just three months, it was no longer as attractive as before, and a few users remain in this game. Perhaps because some expert players have repeatedly played this game, the game becomes effortless and possibly dull. In addition, the game becomes fair in a subjective sense for some master players, which suggests that prolonged play at such a level could potentially cause addiction. With the adoption of game refinement theory, the reasons for such a downward trend demonstrated in Figure 2.2 may be reasonably explained for the Jump & Jump game popularity.

2.2 Assessment methodology

The traditional game theory was originated with the idea of the existence of mixed-strategy equilibria in two-person zero-sum game [2], which has been shown also a powerful tool in many fields such as political science, sports, psychology, and economics. However, from the game creator's point of view, there are few people analysis the attractiveness of games and its sophistication by using mathematical theory. An early work in this direction was done by Iida [3], in which a measure of game refinement was proposed based on the concept of game outcome uncertainty. It constructed a logistic model in the framework of game refinement theory.

The game refinement theory has been proposed earlier to determine different levels of sophistication of games. Furthermore, it was proposed based on the concept of game progress and game information progress [4]. It bridges a gap between board games and sports games [5]. Previous works on game refinement theory have shown that it is a reliable measurement tool for evaluating the game's entertainment where the sophistication of games can be determined. Hence, after realizing the game progress model of the game refinement theory. We will apply the game refinement theory to analyze the game progress of the Jump & Jump game.

As we said before, the previous works on game refinement theory have shown that it is a reliable measurement tool for evaluating the game's entertainment where the sophistication of games can be determined. So, we would like to introduce the game refinement theory in detail in this section.

In the game refinement theory, the various games can be represented through the game progress model, where there are two kinds of progress models: one kind is the game speed or scoring rate, while another one is game information progress that focuses on the game outcome. Several games are sophisticated by applying the GR measure (Table 2.1). These games include Chess and Go from the board game, basketball, soccer, and badminton from sports game and Dota from electronic sports game [8], where B/G is the branching factor or total goal, and the D/T is the game length or total shot attempts, respectively.

Game	B/G	D/T	GR
Chess [4] [9]	35	80	0.074
Go [9]	250	208	0.076
Basketball [7]	36.38	82.01	0.073
Soccer [7]	2.64	22	0.073
Badminton [7]	46.34	79.34	0.086
Dota 6.80 [8]	68.6	106.2	0.078

B/G: branching factor/total goal;
D/T: game length or total shot attempts;

Table 2.1: GR measure of several sophisticated games

From the table, it can be observed that those games have similar GR measures, which lie between 0.07 and 0.08. It indicated that these games have the same or similar game sophistication, which is quantified by the game refinement theory. In this condition, players enjoy the same level of engagement among various types of games.

Similarly, game refinement theory can also be applied to a non-game context that had been successful in evaluating the hotel loyalty programs [12]. The study of hotel loyalty explores a novel way to evaluate the benefit of gamified strategy in the business domain. A data-driven approach is proposed for discovering the patterns of different hotel loyalty programs. With the help of the game refinement measurement, it found that the selected comparison items of the hotel rewards highly relate to the number of customers.

In the education domain, as an application to the non-game context, the research of the gamified language learning platforms named MindSnacks and Duolingo can be found in paper [13]. In this comparative study, the differences in course structures between two language learning platforms (MindSnacks and Duolingo) are compared. Through the quantified attractiveness which is based on a mathematical model of game refinement theory, it showed the differences in learning achievement between the two platforms. However, due to insufficient categories of comparison platforms, it still needs further research in the domain of gamification in education.

After summarizing the above study cases, if we would like to analyze the Jump & Jump game through applying the game refinement theory, we should realize that the Jump & Jump game was initially a kind of jump sport in our real life, which is simulated in a game form. Hence, from our point of view, the game progress model in the sports game is considered.

2.2.1 Game Progress Model in Sports Game

As we said before, the Jump & Jump game is initially a kind of jump sport in our real life, which is simulated in a game style. And we would like to apply the game refinement theory to the Jump & Jump game. The game progress model in the sports game is considered. Hence, we would like to introduce the game progress model in the sports game in detail in this section.

In a sports game, some games are score-limited; others are time-limited. Hence, in a sports game (e.g., Soccer and Basketball), there are two factors for calculating the scoring rate. One is the goal in the game; another is the time or steps to achieve the goal. The game speed is given by the average number of successful shoots divided by the average number of total shoot attempts. For other sports games such as Volleyball and Tennis, the goal (i.e., score to win) is set in advance, where the average number of total points per game may correspond to the steps to achieve the goal.

The game progress represents the degree of certainty of a game's result in time or steps (t). By observing the whole situation of a game, the overall game is regarded as linear progress. Hence, the game progress $x(t)$ will be given as a linear function of the amount of uncertainty solving as given by (2.1), where parameter n (where $1 \leq n \in N$) is the number of possible options and $x(0) = 0$ and $x(T) = 1$.

$$x'(t) = \frac{n}{t}\ x(t) \tag{2.1}$$

However, during the in-game time, the result of the game is always uncertain. The result of the game is unknown until it is finished. As such, it is reasonable to render the game progress exponential where (2.2) gives a realistic model of the game progress model.

$$x(t) = \left(\frac{t}{T}\right)^n \tag{2.2}$$

In the game progress model, n is the rate of action that contributes to the goal of the game, and $(\frac{t}{T})$ is the percentage of game goal completion. Here n stands for a constant parameter which is given based on the perspective of an observer of the game considered. Then, the acceleration of game information progress (rate of uncertainty solving) is obtained by deriving (2.2) twice by solving it at $t \in [0, T]$, (2.3) is obtained.

$$x''(t) = \frac{n\ (n-1)}{T^n}\ t^{n-2}\ |_{t=T} \quad = \frac{n\ (n-1)}{T^2} \tag{2.3}$$

According to (2.3), we realize that game progress is happening in our minds. Since the physics of information in the brain is still unknown, the acceleration of information progress is likely subject to physics's forces and laws. The acceleration of velocity implies the difference in the rate of acquired information during game progress. A measure of game refinement (GR) is obtained as the root square of the second derivative. For a game with branching factor B and game length D (i.e., board game, approximated by utilizing an efficient $\alpha\beta$ algorithm in a MIN/MAX tree search structure), the GR can be approximated as in (2.4).

$$GR = \frac{\sqrt{n\ (n-1)}}{T} \approx \frac{\sqrt{B}}{D} \tag{2.4}$$

2.2.2 Modeling game progress of Jump & Jump game

It is believed that the Jump & Jump game is a kind of sports game, while it differs due to neither being time-limited nor score-limited sports. It is not the same as the usual sports game. And It has a serious rule. The game rule is given so that the game immediately fails once the player fails to jump to the next box. Such a situation resembles a kind of training because it does not allow failure in the game.

In each game of Jump & Jump, each jump attempts players made per game is considered as an independent experiment. Hence, it is assumed that there is a probability of success for each jump where p is the probability of successful jump action. Conversely, the probability of failure, equivalent to the risk rate of the player takes, is denoted as $m = 1 - p$.

For finding the comfortable steps in each game for every player's level, we assume that the game failure's risk varies linearly with the progress of the game ($y = vt$, where $v = p$). For realistic, based on the game refinement theory, the game progress model of the game can be given as the function $y = \frac{1}{2}at^2$ where $\sqrt{a} = GR$ (Figure 2.3). Hence, the natural progress of the game can be derived from the analogy between natural gravity.

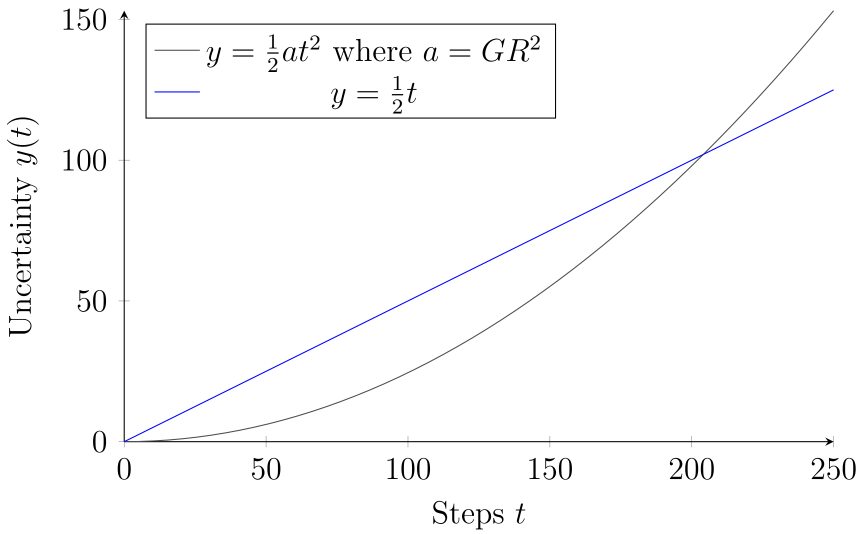

Figure 2.3: Game progress model in Jump & Jump game based on uncertainty solving rate

According to the previous works of the game refinement theory research, the GR measure of the most comfortable points for the sports games, such as table tennis and so on, with respect to $GR \in [0.07, 0.08]$ ("zone" area). $GR = 0.07$ and $GR = 0.08$ is the lower bound and upper bound of the game sophistication "zone", respectively. The games that are highly dependent on luck (larger win to total score ratio) are situated in areas greater than $GR = 0.08$, whereas games that are highly dependent on skill (smaller win to total score ratio) are situated in the area lesser than $GR = 0.07$.

And the figure 2.3 showed an example of a $m = 0.5$ curve and $GR = 0.07$ curves. According to the game refinement theory, once the steps are more significant than the intersection steps in the uncertainty progress model, the game may bore the players. Therefore, from the analysis of figure 2.3, the relationship between acceleration in our mind (GR^2) and game length (game steps) can be realized. Through simultaneous linear and quadratic functions, we can get

$$\frac{1}{2}at^2 = mt \tag{2.5}$$

Solving the cross point of $y = \frac{1}{2}at^2$ and $y = mt$, (2.6) is obtained.

$$a = \frac{2m}{t} \tag{2.6}$$

From equation (2.6), as the risk rate of game(m) changes, we can draw a plot of intersection trajectory, which is shown as figure 2.4. From figure 2.4, we can see the GR measure corresponding to the theoretical game length for different level's players. Hence, from the observation of the uncertainty progress model in this game, comfortable steps can be theoretically achieved. The comfortable steps were set temporarily in the simulation using the number of steps at the intersection of two functions. Then, the comfortable steps in our simulations are adjusted based on further observation and analysis.

Based on (2.6), the risk rate of game (m) is directly proportional to the $a = GR^2$ in this game. Hence, we can realize that the GR measure is different for all kinds of players in this game. Moreover, the outcome of each jump attempt in the game is binary (successfully jumping to the next box or falling). The failure probability of each jump attempt is $(\frac{1}{2})^t$ in each game (here t is the steps in the game). The risk rate was utilized to differentiate the player's levels in the simulation.

In general, we consider that the probability of success is great than 0.5 is safety for the player, otherwise, we regard this jump attempt as dangerous. When there is a safety jump, we think it does contribute to the goal of the game. Hence, we can regard the times of safety jump per game as G branching factor, total times of jump in per game as T branching factor respectively. According to game refinement theory, the GR measure of each level can be defined as $\frac{\sqrt{G}}{T}$.

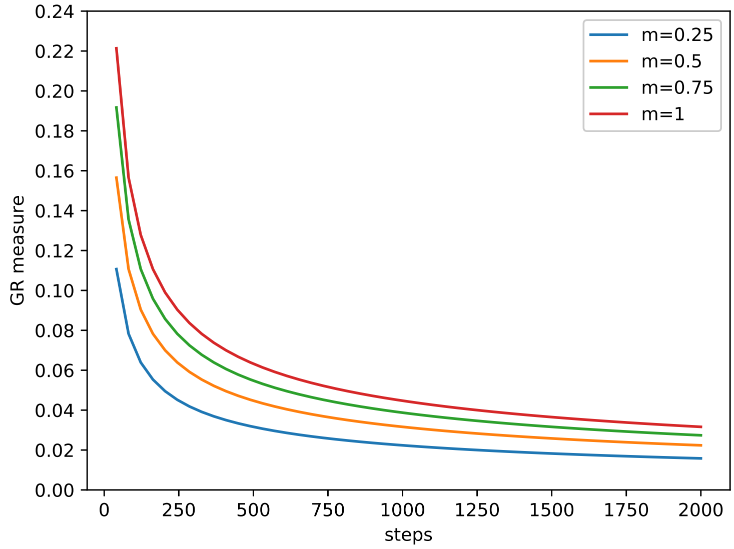

Figure 2.4: The GR measure corresponding to the theoretical game length

2.3 Experiment results

2.3.1 Simulation setup

After defining the GR measure per level in Jump & Jump game. We can consider our simulation experiment. We set nine levels of players. In our simulation, we represent players by setting nine levels. The level of players is expressed by 'L' from 0.1 to 0.9. The 0.1 stands for a novice and 0.9 a master in the game. On the contrary, the risk rate for different level players is from 0.9 to 0.1, which is shown in the brackets after the level in table 2.2.

From the analysis of the previous section, we regard each jump of players per game as a random independent experiment. And we can simulate the game progress by programming. To make simulation closer to a real person, we use the Binomial distribution for the random probability of a successful jump in simulation. Through the random probability to simulate each jump attempt for the player in each level. Finally, through simulation based on game refinement theory, we can analyze the entertainment of players at each level.

Since the Jump & Jump game has no time and scores limits, a comfortable game length for the simulation needs to be defined. As we know, the Jump & Jump game is a simple arcade game where players only need to press the screen for playing. Hence, we theoretically think that most players' GR measure would be higher than the one given by the GR measure (smaller game length), as illustrated in Figure 2.3. Finally, through considering of game progress of game refinement theory and our experience, we set a smaller game length in simulation than the length of intersection of the linear function and quadratic function in figure 2.3.

2.3.2 Simulation program

About the Algorithm 1, since the simulation time of the Jump & Jump game on the web page is too long, we could not get enough data in a short time. Hence, after we extract the essence think of our Jump & Jump game which is ported on the web page. A program to simulate the game progress of the Jump & Jump game using JavaScript is given in Algorithm 1. And the main code for Algorithm 1 and the ported remake Jump & Jump game on the web page will be shown in Appendix B.

In the listing of Algorithm 1, the player's level is set at 5, where the Binomial distribution simulates the successful probability of the different states of the players' performance. A cyclic Binomial distribution for simulating jump in the game is utilized with 0.2 standard deviations. Hence, the GR value of each round can be computed. The simulation is conducted 1000 times to obtain the average GR value for each game, and the process repeats for every player level.

And we will roughly explain some detailed information about the Algorithm 1 here. Firstly, we set the probability variable which obeys the uniform distribution for each jump attempt of players. We also set a hypothetical game length for this level. Then we use this variable to represent the jump process in the game. If it is greater than 0.5, we regard it as a safe attempt. Otherwise, we regard it as a risk. After making the loop 1000 times, we calculate the average number as the data for our simulation.

2.4 Discussion

2.4.1 Data analysis of GR measure

After the experiment of our simulation, we can collect some data in the program. Before this, we should clarify that the player levels are set to nine levels, expressed by $L \in [1, 9]$, where 1 and 9 stand for a novice and an expert player in the game, respectively (Table 2.2), along with the risk rate for different level players. Since each jump of players is a random independent experiment, a Binomial distribution is used to generate random

Algorithm 1: Jump & Jump simulation

```
p:= probability;
U:= uniform distribution variable;
S:= number of steps;
L := level number;
std := standard deviation;
f := game length variable;
F := game length array;
GR := game refinement variable;
aveGR := average game refinement variable;
arr := an array variable;
S ← 120;
L ← 0.9;
std ← 0.2;
U ← GenerateUniformDistribution();
for k to 1000 do            // Cyclic binomial distribution to
 simulate jump
    for i to S do
        p ← GetNormalDistribution(L, std);
        if p > 1 then  p ← 1;
        if p > 0.5 then  f += 1;
        GR ← MathSqrt(f)/S;
        if i := S then
            F ← f;
            f ← 0;
        end if
    end for
    arr ← GR;
end for
aveGR ← GetAverage(arr);
return aveGR;
```

probability to represent a realistic simulation of risk rate (m) and success probability ($p = 1 - m$). Hence, based on the simulation, the GR value of each player's level is calculated (Table 2.2). It can be observed that the GR value increases as the player's level increases but peaked at $L = 5$, which then reduces again, which then stabilizes at $GR = 0.09$.

L (risk)	G	T	GR
9 (0.1)	117.365	120	0.09
8 (0.2)	79.142	85	0.104
7 (0.3)	54.662	65	0.113
6 (0.4)	34.420	50	0.117
5 (0.5)	17.549	35	0.119
4 (0.6)	7.825	25	0.110
3 (0.7)	2.451	15	0.097
2 (0.8)	0.716	10	0.060
1 (0.9)	0.111	5	0.021

G: average number of safe jump;
T: average steps per game;

Table 2.2: GR measure of Jump & Jump game based on player levels

And also, the corresponding plot of table 2.2 is shown in Figure 2.5.

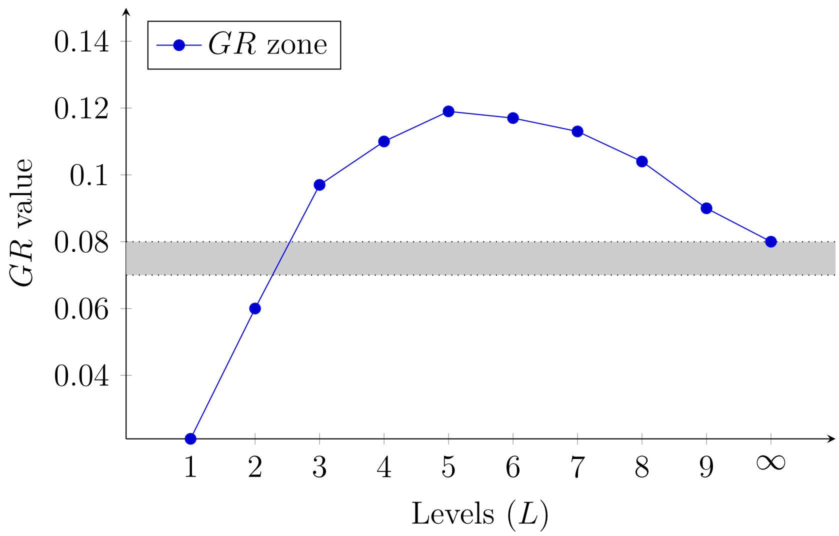

Figure 2.5: Changes of GR measures based on player's level

Most previous works found the GR value to be between 0.07 and 0.08 in various games, which provides a balance between the skill and the chance [4].

In other words, the game is the most engaged in this context. From the simulation results, we can know that when the L is between 2 and 3, the Jump & Jump game is most exciting and thrilling (situated on the border of GR zones). Furthermore, when L exceeds 9, the GR value stabilizes at 0.08, implying the game to be attractive to expert players and the repetitive nature of the game.

From another perspective, the game is the most enjoyable for players with L between 2 and 3, which implies that it is engaging to the novice players. This situation also explains the reasons why the game became popular quickly. As for whether this situation applies to all players. Here also some explanations are shown: Our simulation is supported by the mathematical theory of the uniform distribution, which can represent most of the players. Figure 2.2 is the big data of all the players in this game. Based on these conditions, we can know that our research applies to most players in this game.

2.4.2 Data analysis of motion in mind

After we analyze the GR measure in Jump & Jump game, we can realize that the Jump & Jump game is a kind of game that the task's difficulty level(m) is fixed for players with various levels (v). For the Jump & Jump game, the difficulty is fixed, it is supposed that the success rate of v will increase when a player's ability becomes higher. For some expert players, perhaps the Jump & Jump game have been repeatedly played, this game becomes effortless and possibly dull.

With the adoption of motion in mind measures, the downward trend demonstrated in Figure 2.2 may be also reasonably explained for the reduction of the popularity of the Jump & Jump game. Some detailed analysis can be found in paper [15]. We show some simple analysis here as a supporting corroboration.

In paper [15], the motion in mind measure has been calculated based on the game refinement theory. Table 2.3 shows the motion in mind measures over various levels in Jump & Jump game. Based on this table, Figure 2.6 illustrates the proposed measure of engagement ($\vec{p}_2$) over various players' ability levels according to their success rate (v).

According to Figure 2.6, two peak points of $\vec{p}_2$ can be observed, where $Lv3$ takes the strong impact of engagement ($v = 0.16$; high-tension engagement). It means that the players would feel highly engaged in the sense of competitiveness if they successfully arrive at this level from the very novice level($Lv1$).

In another word, the Jump & Jump game has the challenge(negative

Level	G	T	v	m	$\vec{p_1}$	E_p	$\vec{p_2}$
Lv9	117.37	120	0.98	0.02	0.0196	0.0384	0.0188
Lv8	79.14	85	0.93	0.07	0.0651	0.1211	0.0560
Lv7	54.66	65	0.84	0.26	0.2184	0.3669	**0.1485**
Lv6	34.42	50	0.69	0.31	0.2139	0.2952	0.0813
Lv5	17.55	35	0.50	0.50	0.2500	0.2500	**0**
Lv4	7.83	25	0.31	0.69	0.2139	0.1326	-0.0813
Lv3	2.45	15	0.16	0.84	0.1344	0.0430	**-0.0914**
Lv2	0.72	10	0.07	0.93	0.0651	0.0091	-0.0560
Lv1	0.11	5	0.02	0.98	0.0196	0.0008	-0.0188

G: average number of safe jump;
T: average steps per game;

Table 2.3: Motion in mind measures over various levels [15]

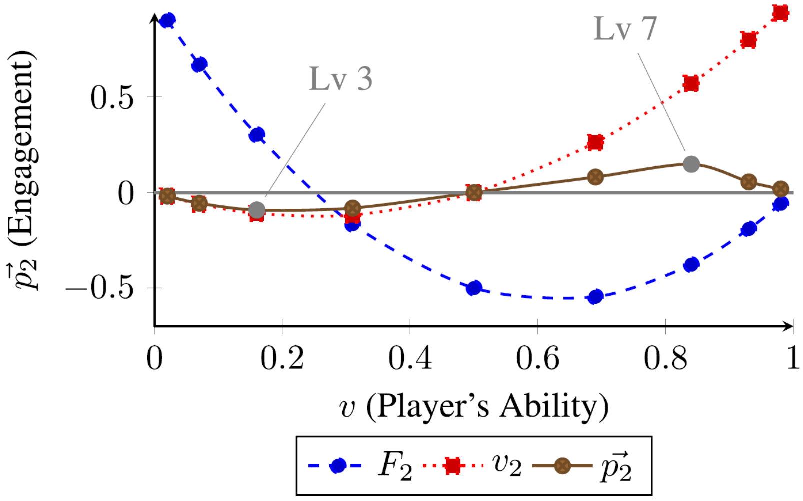

Figure 2.6: The motion in mind measures for Jump & Jump game of 9 levels of player's ability. Interplay of $\vec{p_2}$ and F_2 implies different engagement mechanism impacted the game enjoyment and continuity differently on $Lv3$ (high-tension engagement) and $Lv7$ (high-expectant engagement). [15]

$\vec{p_2}$) which need the player's ability to overcome it(positive F_2). And when a player is reaching $Lv3$, it also indicates that the player is close to the moment that borders the play satisfaction and works dedication($\vec{p_2} = F_2$; player satisfaction model). In this condition, it means that the $Lv3$ is the "turning point" from frustrating(work-like) to fascinating(more play-like) play experience. If players reach the $Lv7$ after some practice, they will feel strong engagement($v = 0.84$; win-expectant engagement). Such a situation implies that the game becomes easy to win (positive v_2) and potentially becomes effortless (negative F_2).

For the above analysis of the Jump & Jump game based on the game refinement theory, if players can achieve a high level (such as $Lv7$) too quickly, the game would become effortless and possibly dull. In addition, the $v_2 = 0.5712$ at $Lv7$ implies that the game becomes fair in a subjective sense, which suggests that prolonged play at such a level could potentially cause addiction.

2.4.3 Summary

The Jump & Jump game reflects a form of training process where the jumping activity is a simulation of actual sports. Although the training makes players learn new skills (an element of uncertainty), it cannot break the game playing limit and impedes player growth. Therefore, the player may quickly lose interest in the game, which possibly explained the reason for its short-lived popularity (see Figure 2.2).

When the $L < 5$, especially $2 \leq L \leq 3$, each jump is considered adventurous to the players (high risk), which imposes an attractive challenge. In essence, the game builds a sense of thrills to the player via a training-like activity until the player reaches a certain point, in which the game becomes repetitive and loses its attractiveness.

From above, we can realize that Jump & Jump game is easy to attract novice players as a phenomenal game. After passing the novice period, most players' levels are reaching $Lv7$ or $Lv8$. It is difficult for these players to breakthrough in the Jump & Jump game. There are only a few expert players who can find their heat flow and immerse themselves in this game after $Lv9$, which is consistent with the data shown in figure 2.2.

In this section, we do some simulations and analyze the data with the help of game refinement theory. Then we revealed the reason why this game became a phenomenal game. We find that this game is attractive for novice players and becomes effortless quickly for most players. Only a few parts of expert players can immerse themselves in this game. Hence, to retain the attractiveness of the game and improve the game's popularity, possible enhancement is considered.

2.5 Possible enhancement

In the last chapter, we have introduced the reason why this game is a phenomenal arcade game. Currently, the number of players for the game had significantly declined (see Figure 2.2) as the game resembles training due to the game becoming monotonous, straightforward, and the player can quickly master the game. Naturally, the game length would become too long for most players. According to the game progress model in Figure 2.3, the game length should be shorter. In other words, we should increase the difficulty of this game, which generally makes the game be balanced between the skill and the chance.

Also, we can find direction to improve this game by comparing it with other games. There are a lot of previous works that have applied game refinement theory to analyze and improve games. Through comparing of game progress model with other games, We find that Jump & Jump game is a simple game as we already know. Based on the game progress model, we can realize that players can easily exceed the game length represented by the intersection of the linear function and the quadratic function. Then players find no target in the game and just jump ahead for high scores. Hence, we realize that we could do some possible enhancements to increase the difficulty of the Jump & Jump game and give some targets for players. Through this method, some possible enhancements can be found. The comparison of games progress model is shown in Figure 2.7. And the current situation of the Jump & Jump game's progress model is shown in Figure 2.8.

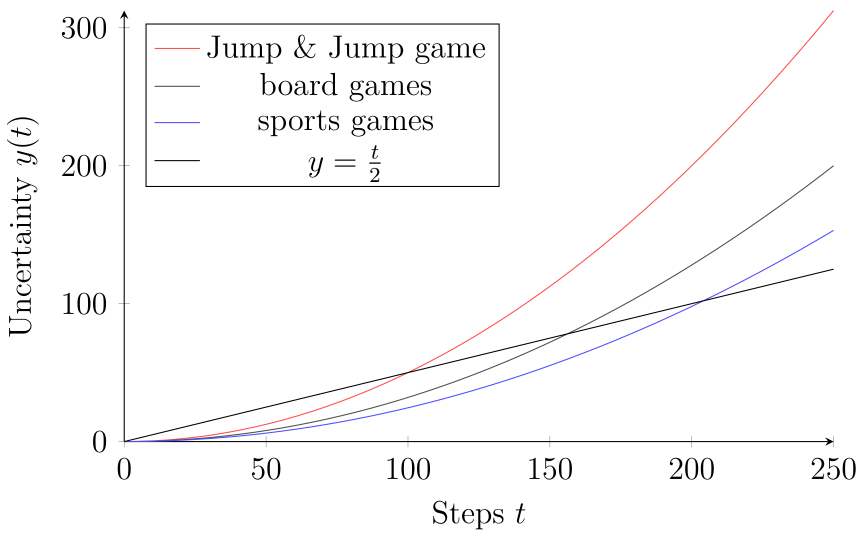

Figure 2.7: Comparison of game progress model over various games

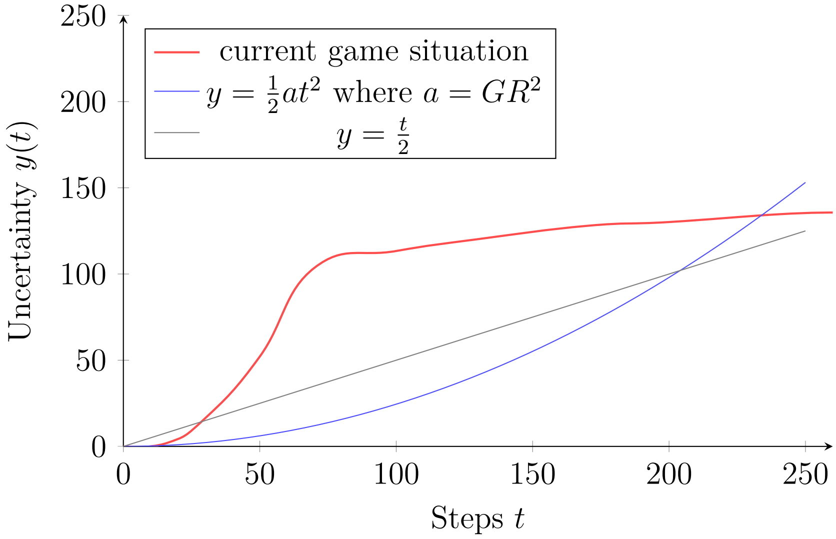

Figure 2.8: Current situation of game progress model in Jump & Jump game

And based on the previous simulation experiment, it was found that maintaining the difficulty of the game within the $GR \in [0.07, 0.08]$ may be invaluable to the game's popularity. For maintaining the difficulty, in other words, which is to limit the game length. We found some specific methods to implement it, which are to increase the difficulty and add randomness elements in this game.

Therefore, a few specific aspects can increase the game difficulty, such as adding time limits and incorporating puzzle elements. The main focus is to increase the tension and excitement in the game and let players eager to jump further to increase difficulty.

Hence, the improved version of the game is analyzed by using the game refinement theory, where the result is discussed. The improved version of the Jump & Jump game is implemented using JavaScript. Nine different levels of players were simulated for the enhanced version of the Jump & Jump game. Similar simulation settings were adopted as the previous experiment, where adjustments are conducted by simulating the real situation of different distances made by the players. The box of the enhanced version of the Jump & Jump game has the length and width of 4, where the generated random jump distance for the player is added with a random range between $[-2, 2]$ to indicate unstable play.

2.5.1 Adding puzzle elements

In this section, we would like to introduce a method through adding puzzle elements into the Jump & Jump game. The rules of our new game are based on the original game. And there are boxes in both directions in our new game. The puzzle element in the Jump & Jump game requires players to answer a small quiz each time they jump. Correctly answered puzzles allowed them to jump in any direction by themselves correctly. Conversely, they are given dual choices called 'panda help' and 'AI help.' 'Panda help' means that the direction of the player's jump is correct but with random distance, while 'AI help' means the distance of the jump is correct but with random direction. The random rate of those choices is equal (risk rate of 0.5).

We simulated 9 different levels of players in our ported remake game. And add the puzzle elements we mentioned above to our remake game. The core code will be shown in Appendix B. In our simulation, we also use Binomial distribution to generate the risk rate of players. A similar analysis based on the game refinement theory will be implemented as before. If the successful probability is greater than 0.5, we regard this jump attempt as safety, otherwise we regard this jump attempt as an adventure.

For exploring the impact under new game context, at each player level, their choice (set as one initially) is incremented by one for every tenth jump made. For the example, we consider setting each level player to make 1 choice in every 10 jumps. Once the game length is bigger than 20, there will be 2 choices in every 10 jumps. After 30, there will be 3 choices..., and so on. And risk-taking is emulated by random puzzle choices made by the player in the simulation. We regard this choice as taking a risk in the simulation.

Through computer self-play in our remake game, we choose different level computers to represent different level players in the game. And we help computers do choice randomly in puzzle choices. Hence, we can collect the data of the new game context. To stabilize the data, we will take the average of game length which is obtained from ten rounds of self-playing in this new game context. Then we perform this average game length in Algorithm 1. After 1000 time simulations, we can get the GR measure of this level's players. So that, after reducing the number of choices we consider risky, we can get the GR measure for each level's players. Hence, the data of our new puzzle jump game is shown in table 2.4.

As we can see in table 2.4, we find that because of the puzzle elements the game length is shorted. From the previous works and our analysis, we already know that the GR measure of a game is between 0.07 and 0.08, the game will achieve a balance between the skill and the chance [4]. In table 2.4, level 4 and level 5 as a middle level in players has reached this situation. And when the GR measure is greater than 0.08, the game that highly dependent on luck, when the GR measure is lesser than 0.07, the game that highly

level(risk)	G	T	GR measure
9(0.1)	31.493	45	0.125
8(0.2)	26.311	42	0.122
7(0.3)	19.248	38	0.115
6(0.4)	15.211	36	0.108
5(0.5)	8.577	35	0.083
4(0.6)	5.047	30	0.074
3(0.7)	1.278	20	0.057
2(0.8)	0.203	11	0.041
1(0.9)	0.157	7	0.021

G: average number of safe jump;
T: average steps per game;

Table 2.4: GR measure of enhanced Jump & Jump game based on player levels(puzzle elements)

dependent on skill. After comparing with table 2.2, we can see that the GR measure become greater than before.

Two reasons can explain this condition. One is that the randomness of the puzzle elements is strong, it's highly dependent on the luck of players. Another is that the uncertainty of the puzzle element makes game length short. As our experience, when the sports game length becomes shorter, the game will be more dependent on luck than before. Hence, we can realize that this kind of puzzle method is highly dependent on luck. Through these methods, it can increase the excitement and entertainment of the game. And this result also embodies the reliability of the game refinement theory.

2.5.2 Adding time limits

There is another method to increase the difficulty of this game, which is by adding time limits to this game. In a typical game situation, the time limit plays a role in urging players to make jump attempts. To some extent, the probability of player jumping failure is increased, thus achieving the purpose of increasing the difficulty of the game. It is conjectured that time limits may shorten the simulation's length instead of having a realistic emulation of the player being under pressure. As such, a timer is incorporated into the enhanced version of the Jump & Jump game to fix the game time. The time limit is set as 60 seconds for each round of the game. By adding a total time limit of the game, we can know the game length for each level's players in a fixed period.

Similar to adding puzzle elements, we also collect data through our remake game. This time we add a timer to the program to fix the game time. As we mentioned before, we know that the time limits will affect the players. However, the time for computer jump is fixed. Hence, the time limit just shortens the game length of the simulation. However, in reality, players are affected by time. So, we should realize that our programming is only a simulation, which tries to simulate the real situation of players.

Similar to before, we also take the average of game length and G branching factors which are obtained from ten rounds of self-play. After getting data, we take the game length to the Algorithm 1 for comparing the GR measure. So that, we can get more reasonable data. Finally, these data are shown in table 2.5.

level(risk)	G	T	GR measure
9(0.1)	30.275	31	0.177
8(0.2)	29.008	31	0.174
7(0.3)	25.137	30	0.166
6(0.4)	15.3	29	0.135
5(0.5)	8.1	25	0.113
4(0.6)	4.8	20	0.109
3(0.7)	1.930	12	0.104
2(0.8)	0.726	10	0.061
1(0.9)	0.157	7	0.021

G: average number of safe jump;
T: average steps per game;

Table 2.5: GR measure of enhanced Jump & Jump game based on player levels(time limit)

From the data in table 2.5, we can see that the game length of players above level 5 is limited to around 30. Through comparing with table 2.2, we find that the GR measures of the players above level 5 are higher than the data in table2.2 and below level 5 are similar to the data in table2.2. We can know that the reason for this condition is caused by adding a time limit. Hence, we can realize that shortening the game length will increase the randomness of the game and also increase the excitement in sports games.

Through increasing difficulty and reducing the length of the game, the GR measure has increased significantly, which makes expert players have a higher acceleration to the Jump & Jump game. However, according to the game refinement theory, it means that the game highly depends on luck rather than skill. This deviates from our original purpose for making the game popular again. Therefore, we should understand that the game needs a perfect combination of skill and luck, which is also the key point of game refinement theory. And its external expression is that the GR measure is between 0.07 and 0.08.

2.5.3 Discussion

The results based on the puzzle jump (1000 simulations) and time limit (10 simulations) for each level of the players are given in Table 2.4 and Table 2.5. It can be observed that the randomness of the puzzle elements makes the game dependent on chance, and the uncertainty of the puzzle element reduces the game length. This method increases the excitement and entertainment of the game. Meanwhile, it can be observed that adding a time limit to the game length for players of $L \geq 5$ reduces it to about 30. This condition is the consequence of the reduced game length, which increases randomness and the game's expected excitement.

The GR measures for the enhanced Jump & Jump game (Figure 2.9) for the players $L \geq 5$ are higher while $L < 5$ are roughly similar when compared to the original version (see also Table 2.2). Based on the two enhancements considered, the GR measure increased significantly, where the players felt greater informational acceleration to the game. This situation implies that the game highly depends on luck rather than skill. It is different from our initial purpose to improve this game.

Therefore, a sophisticated game requires a harmonic balance between skill and luck, an essential component of the game refinement theory. Between the two enhancements, we can see that the method of adding puzzle elements is better than simply adding the time limits. Its data can also explain the problem. After comparing the data of table 2.4 and table 2.5, where the GR measure is relatively close to the "zone" value ($GR \in [0.07, 0.08]$) for the mid-levelled players ($L \in \{4, 5\}$), which is what we would like to see.

Based on the two enhancements and our analysis above, we realize that if we would like to retain the attractiveness of the game and improve the game' s popularity, we need to keep the game balance between skill and luck by revising the game from some specific aspects. Therefore, to stabilize the GR measure of mid-leveled players within the "zone" ($GR \in [0.07, 0.08]$), which should be considered.

2.6 Chapter conclusion

In this section, we will give a chapter conclusion of this chapter. At the beginning of this chapter, the play method and some related works of the

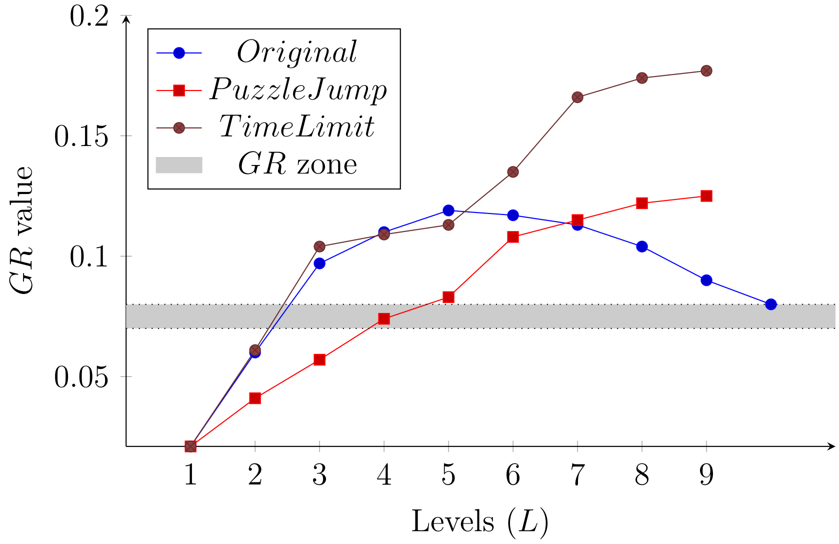

Figure 2.9: Changes of GR measures based on player's level and different enhancements of the game

Jump & Jump game are provided. Then, we introduced the mechanism of the game refinement theory which can be applied to the Jump & Jump game. Because the Jump & Jump game is a gamified sports game, we introduced the game progress model in the sports game in detail. Then the modeling game progress of the Jump & Jump game is given in section 2.2. After deciding our assessment methodology, we gave out our simulation and the analysis of its results.

Finally, according to our analyses of the GR measure and motion in mind model, we realized that the Jump & Jump game needs to be improved. Hence, we proposed some possible enhancements for the Jump & Jump game from the aspect of increasing difficulty. Although we reduce the game length and increase the randomness of the game through these methods. It also increases the excitement of the game. It is believed that through these methods of improving the game, the data in figure 2.2 will be improved.

Chapter 3

Dynamics of Minority versus Majority Behaviors: Case Study on Mafia Game

We have briefly introduced the Mafia game and shown our research objective in chapter 1. And this chapter will introduce the study on the Mafia game in detail.

3.1 Related works about the Mafia game

In this section, a brief sketch of the Mafia game is given, and an overview of research development with the game is presented.

The Mafia game is a party game and can be played both offline and online on the Internet. The moderator divides the players into two secret teams: the mafias and the citizens. Then, the moderator sends the identity cards to each player. The mafias' goal is to kill all of the citizens before being discovered. The citizens' goal is to identify the mafias and vote to lynch them —the game cycles between day and night.

During the night in the game, everyone closes their eyes except the mafias. The mafias will silently decide which player they want to kill and signal their choice to the judge. Once they have made their choice, the judge asks everyone to open their eyes and announces who was killed. Then everyone is free to say or do anything to guess who the mafias are and vote to lynch someone they suspect. That player reveals their identity, and if there are any surviving mafia, the night begins again. The standard edition Mafia game contains "Judge," "Mafias," "Sheriffs," and "Citizens." The game is based on the "kill all the Citizens and Sheriffs, or all the Mafias" rule.

The paper [16] had conducted a study with a focus on the use of the Mafia game in linguistic classrooms based on self-report and a set of semi-structured interviews administered to 137 undergraduate students and 12 facilitators. The findings revealed that learners participated and mitigated anxiety in learning English since the game required interrogate and team-driven decision-making. However, careful consideration of the level of linguistic ability relative to the game implementation as an instructional tool can be learner-specific. Meanwhile, [17] reported on the implementation of student-centered applied-learning activity using the game Werewolf[1], where learners engaged with symbolic interaction theory and analyzed everyday life experiences. Such an implementation aimed to incorporate more active learning approaches to social theory by outlining an applied-learning activity based on the role-playing game Werewolf as an alternative pedagogical tool that demonstrated heightened understanding of the underlying concepts.

From the perspective of natural language processing and automating AI negotiation, complex negotiation involves an uncooperative situation requiring an agent's ability to hide information and infer intention from communication between AI agents [18]. Such feat had been achieved by designing the protocol between agents, which was analyzed from the agent communication in the Werewolf game. This situation includes features such as the absence of objectivity, reasoning, and persuasion were derived from the lack of objectivity, modeling of others' self from the viewpoint of others. Another study by [19] involves analyzing conversations in-game logs where cooperation between werewolves via measure of the number of "whispers" (werewolves' private chat) and its influence on the percentage of winning. The study found that the winning percentage of werewolves is higher when two werewolves have established frequent dialogues or a high number of whispers occurred.

Recently, [20] proposed a simulator that can simulate various characters' actions more realistically by adding a weight of credibility, which changes continuously as the game progresses and clearly distinguishes the identity of each player. In addition, the study also analyzed the simulation to find the best combination solution dynamically as the change of the total number of players relative to two theories: (1) simple asymptotic formula for the mafia-winning chance, and (2) game refinement (GR) theory. Since deceptive games such as the Mafia game require developing strategies (deceivers draw in unknown bystanders and bystanders detecting falsehoods), a study by [21] developed a computational classifier to identify mafia from text-based role-playing behaviors of the characters with up to 70% accuracy. The study's finding suggests that understanding the systematic features that define hon-

[1] a similar variant of Mafia game with additional roles or characters

est and deceptive players advances the ability to automate the detection of online deceit and grasp group dynamics in real-world collaboration.

From the information science perspective, manipulating and exploiting the game rules and settings change the complexity of the Mafia game which ultimately, could also influence its entertainment impact. However, limited studies were conducted to quantify and determine such criteria while maintaining the relative balance of 'chance' and 'skill' in the game itself. Analyzing game sophistication via the GR theory has been successfully applied for such purposes to various board games [22] and sports games [23, 24]. However, the Mafia game, focusing on psychology research between an informed minority and uninformed majority, provides different dynamics of interactions between multiple players that pose unique challenges by themselves [10]. From the macro-level analysis and application of Nash equilibrium, [11] found that the optimal combinations of characters directly influenced the sophistication of the Mafia game. Nevertheless, such a situation assumed that the behaviors of each character were always optimal, but in reality, they were not always optimal. As such, our study attempts to focus on each character's actions and assess their entertainment impact by applying the GR theory and motion in mind model [25].

3.2 Assessment methodology

Game refinement (GR) theory has been proposed earlier to determine different levels of sophistication of games. Furthermore, it was proposed based on the concept of game progress and game information progress [4]. We have introduced the game progress model of the game refinement theory in previous chapter. Hence, we do not repeat here. And the method for applying the GR theory in the Mafia game is provided in this section.

3.2.1 Game refinement theory in Mafia game

In order to analyze the Mafia according to the possible actions, we need to first clarify the actions of each character in the game (four characters in the Mafia game; Judge, Mafias, Citizens, Sheriffs).

- Judge: Hosts the game, not participating with any team.
- Mafias: Kills one character (except the mafia) every night and pretend to be a player during the daytime.
- Citizens: Votes to lynch someone during the daytime.

- Sheriffs: Each night, the sheriff can discover the real identity of a player (except the sheriff).

From the actions of each character in the game, it can observed that there are a number of different ways the mafias can kill the citizens. For the mafias, they can kill the citizen at night, or induce other players to lynch someone during the daytime. The citizens take into account the statements of the others and the results of each round, then choose the player they believe to be guilty to lynch them. Therefore, to analyze the sophistication of each character, the value for B can be defined differently in (2.4) for each character.

- Mafias: Let B_m be the sum of the Sum_a and Sum_b, where Sum_a indicates the average of the number of killing actions at night, and Sum_b indicates the number of players who are lynched by voting with mafias during the daytime.
- Citizens: Let B_c be the average of the number of mafias who are lynched by citizen voting.
- Sheriffs: Let B_s be the average of the number of mafias with their identity confirmed by the sheriffs and then be lynched by voting.

For assessing the entertainment of this game, the branching factor (B) analyzed above is regarded as the contribution to the game goal in the game progress for each character. Then, D in (2.4) is the average of the sum of all the actions, during the life of each character in this game. Thus, the final form of game refinement measures in the Mafia game is given by function (3.1).

$$GR = \frac{\sqrt{B}}{D} \tag{3.1}$$

3.2.2 Motion in mind model

The notion of "motion" in game-playing relies on the rate of the information representing the "progress" of the gaming process, constituting the speed or "velocity" of the game, defined as the success rate (v) [25]. In contrast, the challenge or difficulty of reaching such a success rate would constitute the weight or "mass" of a game that can be generally defined as the difficulty rate ($m = 1 - v$). In the context of games, given one part of m and one part of v, the fundamental assumptions of zero-sum game-playing condition where gain or loss utility of one player is exactly balanced by the losses or gains of the utility of its opponent [15, 26].

In the study of the Mafia game, the focus is shifted towards the potential energy (E_p) and momentum ($\vec{p}$) in the game, where the former is defined as the game playing potential or the expected game information required to finish a game, while the latter refers to the competitive balance of a game involving the degree of challenge needed (m) and effort given (v) to drive the game progression. Since $v = 1 - m$ and $\vec{p} = mv = m \cdot (1 - m)$, it can be observed that $\vec{p} \leq \frac{1}{4}$. This implies that momentum is maximized when $m = \frac{1}{2}$ [25]. With respect to the study conducted on player satisfaction model by [27], the reward system (N) was incorporated to better represent the motion in mind model, given by (3.2) and (3.3) for the E_p and $\vec{p}$, respectively.

$$E_p = 2mv^2 = \frac{2(N-1)}{N^3} \tag{3.2}$$

$$\vec{p} = mv = \frac{(N-1)}{N^2} \tag{3.3}$$

3.3 Experiment results and its analysis

In this section, simulation design with AI and its results of data analysis are shown.

3.3.1 Simulation setup and analysis

The simulation was conducted to imitate real human behaviors such as in-group cooperation and competition using a simulator engine that considers preset actions of each character adopted by AI agents. Each action is generated randomly for each character, and some actions use weighting for specific cases. For each character, their condition is shown as follows:

- Sheriff (S): Generally, after the sheriffs discovered that a player's identity is a "mafia," they will vote for the player with a high probability in the next voting, and they also will induce other citizens to vote for this player. Therefore, we set a parameter to indicate the possibility of exposing the identity of mafia.

- Mafia (M): The mafias kill the citizens randomly except that one of them has been exposed by any sheriff. At this time, the sheriff that revealed them would be the target of them.

- Citizen (C): Because all the citizens do not know the identity of each player, there is no guarantee that all citizens will believe in sheriff's speech. There, we set a parameter for each citizen to indicate that possibility of believing in sheriff.

Based on the probabilities of each character's action, it can imitate the "identity hiding" behavior of a real player in the game; thus, making the simulator close to reality helps us analyze each character's sophistication. Hence, we create a program to simulate the Mafia game by using C++ for collecting the action data. The process of the simulator is shown in Algorithm 2 where it describes the overall process of the simulator. In general, the process first starts with the mafia choosing the player to kill which then the identity of all players is checked by the sheriff. Then, players discuss which of the player will be lynched out. Finally, the game continues if the number of mafia is smaller than the total number of the sheriff and citizens ($M \leq S + C$), or one mafia still exists ($M \neq 0$).

Algorithm 2: Mafia simulation

S:= Count of Sheriff;
C:= Count of Citizen;
M:= Count of Mafia;
V:= Voting Result;
do
    `MafiaKilling(`C,S`)`;
    `SheriffChecking()`;
    `SheriffVoting()`;
    `MafiaVoting()`;
    `CitizenVoting()`;
    V $\leftarrow$ `JudgeStatistics()` ;
    `Lynch(`V`)`;
while $M \leq S + C$ *and* $M! = 0$;

Each of the functions was as follows. The `MafiaKilling(C,S)` function involves the mafia randomly selecting the target to kill. If the mafia feels that the sheriff is marking them, the priority is given to targeting the sheriff. In the `SheriffChecking()` function, only the sheriff can check the identity of the players. Firstly, they choose a random target to check the identity, and a threshold value determines the possibility of exposing the identity of the mafia. If they identify the mafia, the mafia will be marked.

In voting, the `SheriffVoting()` function determines if there is any mafia is marked by them. If there is, then a priority vote is given to that mafia while persuading other players to vote together. If there is no marked mafia, they will randomly select a player to vote instead. Meanwhile, the `MafiaVoting()` function involves voting a player randomly. For the `CitizenVoting()` function, the voting is determined based on their judgment of other players. This condition is determined by using a threshold value, where they will mark a player as a mafia when over the threshold while choosing a random target to vote when under the threshold. For the `JudgeStatistics(V)` function, the judge find the player who accumulated the most votes and shows the result. Then, the player who accumulated the most vote will be out of the game, given by `Lynch(V)` function.

3.3.2 Results analysis of GR

A total of 648 combinations of each game character were simulated, in which the game was run 10,000 times to ensure the result reliability. Table 3.1 showed ten sets of data to observe the trend of our data. From the table, 'S,' 'C,' 'M' showed the number of players for "Sheriff," "Citizen," and "Mafia," respectively. In addition, "C_win" and "M_win" represented the number of wins in their respective roles (Citizen and Mafia) for the 10,000 games. Here, it can be noted that when the number of the mafia is greater than one-fifth of the total number, the mafias will win overwhelmingly. The average number of actions, the average number of effective actions, and the GR measure for each combination will be shown for each character. According to the table, it can be noted that for each character, as the number of players increases, more changes will happen while decreasing the GR value (For instance, the parameter $(S = 7, C = 15, M = 7)$ and $(S = 9, C = 15, M = 10)$).

For the sheriff and the mafia, because they were constrained by each other when the number of players is small, the players can choose fewer operations, resulting in a more considerable GR value (For instance, the parameter $(S = 2, C = 4, M = 2)$ and $(S = 2, C = 14, M = 2)$). In contrast, for the citizens, due to the high randomness of the actions, if the player number is large, the effective actions will be small, resulting in a long game and a lower GR measure (For instance, the parameter $(S = 2, C = 10, M = 2)$ and $(S = 10, C = 15, M = 10)$).

For finding the best choice combination, the GR measure of each character was assessed. Most previous works found that $GR \in [0.07, 0.08]$ is the 'zone' value in various games that provide a balance between skill and chance [4]. In other words, the game is the most engaged in this context. Ideally, all the assessment of GR values in our study should conform to this 'zone' value. However, it is hard to be achieved because of their mutual restraint. Alternatively, its variance from 0.07 could help us select the

$Com(S,C,M)$	C_{win}	M_{win}	$GR(S)$	$GR(C)$	$GR(M)$	Var
2,4,2	2275	7725	0.3439	0.2134	0.2946	0.146
2,8,3	825	9175	0.2613	0.092	0.1913	0.0518
2,10,2	2901	7099	0.2296	0.0722	0.1997	0.0423
2,10,5	125	9875	0.2503	0.0621	0.1257	0.0357
2,14,2	5871	4129	0.1966	0.0459	0.1804	0.0288
5,10,5	2170	7830	0.1145	0.0550	0.1058	0.0035
4,15,2	7059	2941	0.1235	0.0394	0.1683	0.0135
7,15,7	2138	7862	0.071	0.0318	0.0674	0.0015
9,15,10	365	9635	0.0571	0.0301	0.0453	0.0024
10,15,10	630	9370	0.0506	0.0302	0.0444	0.0026

$Com(S,C,M)$: The parameter combination;
C_{win}: The game citizen win, M_{win} for mafia;
$GR(S)$: The GR measure for Sheriff, Similar to mafia and citizen;
Var: The variance among GR measure of characters;

Table 3.1: GR measure of Mafia characters based on various setting

best combination to indicate relative closeness to the 'zone' value. From the simulation results, when the number of mafias is equal to the number of the sheriff, each character's average sophistication is the highest. However, considering the most balanced case of all of the results, the parameters of $(S = 5, C = 10, M = 5)$ and $(S = 7, C = 15, M = 7)$ were the optimal choices.

3.3.3 Result analysis of E_p

Having the GR measure among various characters, further analysis is conducted to determine the players' potential energy using the potential energy (E_p) measure of the motion in mind model. Although the rules of Mafia game constitute three or more characters, the game essentially still is two-sided. As such, the energy for each character is defined as (3.4), (3.5) and (3.6), where the results is given in Table 3.2. From the table, 'S,' 'C,' 'M' showed the number of players for "Sheriff," "Citizen," and "Mafia," respectively. In addition, "C_win" and "M_win" represented the number of wins in their respective character (Citizen and Mafia) for the 10,000 game run.

$$E_p \text{ for Sheriff} = 2 * m_c * v_s^2 = 2 * m_c * (\frac{G_s}{T_s})^2 \tag{3.4}$$

$$E_p \text{ for Citizens} = 2 * m_c * v_c^2 = 2 * m_c * (\frac{G_c}{T_c})^2 \tag{3.5}$$

$$E_p \text{ for Mafia} = 2 * m_f * v_f^2 = 2 * m_f * (\frac{G_f}{T_f})^2 \tag{3.6}$$

$Com(S,C,M)$	C_{win}	M_{win}	$E_p(S)$	$E_p(C)$	$E_p(M)$	$E_p(Var)$
2,4,2	2275	7725	0.190	0.035	0.635	0.097
4,4,2	5257	4743	0.243	0.078	0.323	0.016
2,8,3	825	9175	0.053	0.004	0.473	0.067
2,10,2	2901	7099	0.180	0.014	0.529	0.069
2,10,5	125	9875	0.009	0.0003	0.258	0.021
2,12,6	12	9988	0.0006	2.279E-05	0.178	0.010
5,10,5	2170	7830	0.067	0.008	0.214	0.011
4,15,2	7059	2941	0.225	0.015	0.181	0.012
4,15,4	3286	6714	0.110	0.007	0.214	0.011
7,15,7	2138	7862	0.038	0.004	0.122	0.003

$Com(S,C,M)$: The setting combination;
C_{win}: The game citizen win, M_win for mafia;
$E_p(S)$: The potential energy for Sheriff, similar to mafia and citizen;
$E_p(Var)$: The variance for the potential energy;

Table 3.2: Potential energy of Mafia characters based on various settings

3.4 Discussion

Various games considered in the study constitute three distinct sports landscapes: mind (or m-sports; e.g., board game or abstract games such as Go, Shogi, and Chess), physical (or p-sports; e.g., Basketball, Soccer, Table Tennis, and Badminton), and electronic (or e-sports; e.g., DoTA and action games), as depicted in Figure 3.1 (adapted with permission from paper [27]). Since N values were related to the reward ratio for a player in the game-playing process, in the context of the Mafia game study, the N value is determined as $\frac{1}{v}$ (v is the game speed defined by the ratio of $\frac{G}{T}$).

The energy changes of each character in the Mafia game had been given in Figure 3.2, where the x-axis is the N value and the y-axis is the variance of the energy. It can be observed that the $N \in [2, 6]$ for Sheriff and Mafia, while $N \in [3, 14]$ for the Citizen. This situation describes that Mafia and Sheriff always remain hidden in the game (minority) but represent a compelling character. Depending on their roles, they often have to complete their tasks in secret (such as identifying their partner or avoiding being a target of lynching). Therefore, according to their N value, Sheriff and Mafia requires being more competitive and typically dealing with a more stable condition

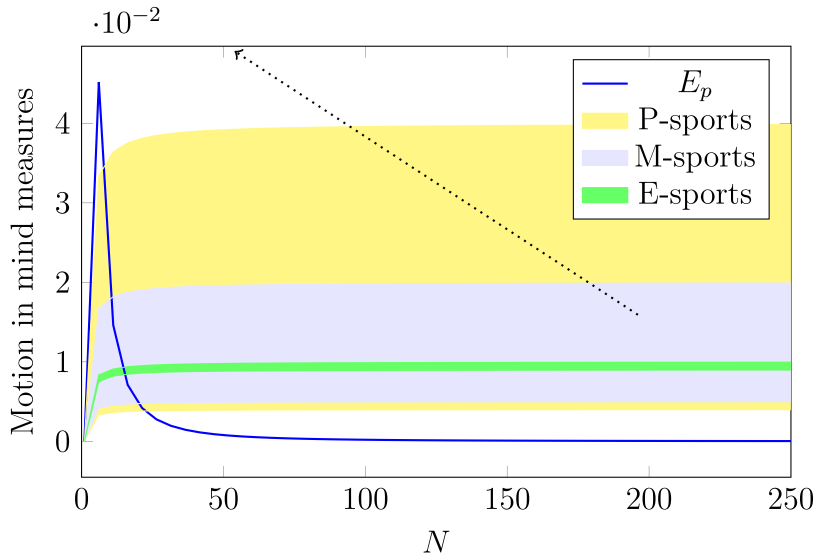

Figure 3.1: The convergence of p-sports, m-sports, and e-sports based on the a indicators, relative to the physics in mind measures

(lower range of N values). In addition, compared to Mafia, Sheriff could not directly control the game results based on their role but can help Citizens, making them need more energy when N is small. In contrast, Citizen has a larger range of N values; thus, reflecting their unstable condition and relying on high ability, motivation, and effort, but less competitive than the other two characters. Thus, ranking the engagement experience, the ordering was $Mafia > Sheriff > Citizen$. As for the rank of game effort, the ordering was $Sheriff > Mafia > Citizen$.

When observing the change in player number (Figure 3.3), it was found that as the player number increases, the energy decreases, which reflects that player would need less energy for playing the game. This condition describes that as the number of players increases, the game 'pressure' for each character in the Mafia game will not be as much since the thrill of engagement was less often and evident due to being rarely suspected or targeted. The further analysis reflected that when an increase in the proportion of Mafia decreases the energy of Mafia, as shown in Figure 3.4. This condition means that the game will be easier when the Mafia number increases. In contrast, when the proportion of Sheriff increases, their energy increases which shows that it is more difficult to be engaged when a larger proportion of the player is the Sheriff. For Citizen, no direct impact was observed when its proportion changes due to less functionality were expected from the Citizen role (such as the most straightforward character to play and they usually cannot know

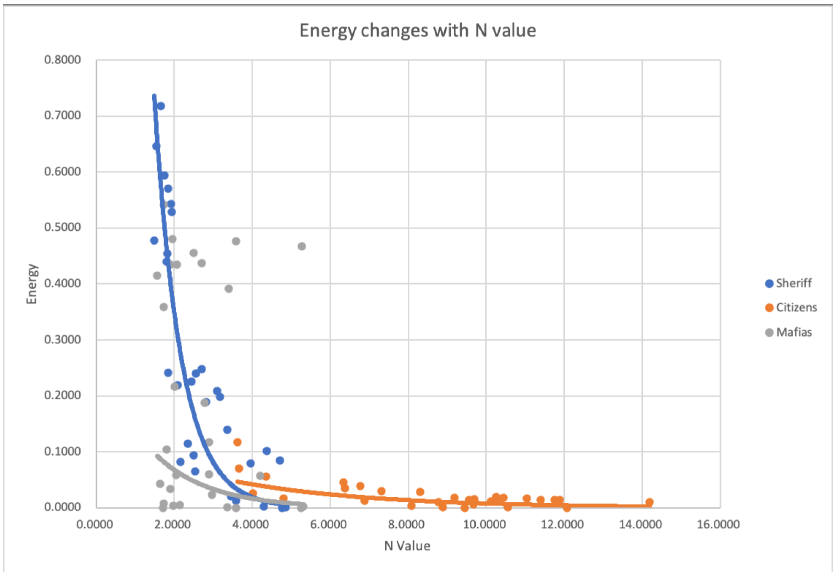

Figure 3.2: Energy changes of each character

more about other characters' information), which does not change the energy. As such, they were stable in any of the settings.

3.5 Chapter conclusion

The chapter conclusion of the Mafia game study will be given in this section. In this chapter, we gave out a brief sketch of the Mafia game at first. Then an overview of research development with the Mafia game is provided.

The Mafia game is a top-rated party game played worldwide. A typical analysis is proposed to determine the best character combination by analyzing the overall death toll based on the game refinement theory in paper [11]. However, we found that because of the mutual restraint between the characters, it is difficult for all the players to feel the same entertainment in this game. Hence, from the aspect of dynamics of minority versus majority behaviors, our assessment methodology is given based on the game refinement theory and motion in mind model. Then, the game simulation and its result analyses of the GR measure and E_p are provided.

According to our analyses, we found several optimal combinations that the sophistication of each character is maximized as a result. In addition, the data of E_p indicates the player engagement in the following order: $Mafia > Sheriff > Citizen$. Hence, we conclude that the actions of the Mafia impact this game most.

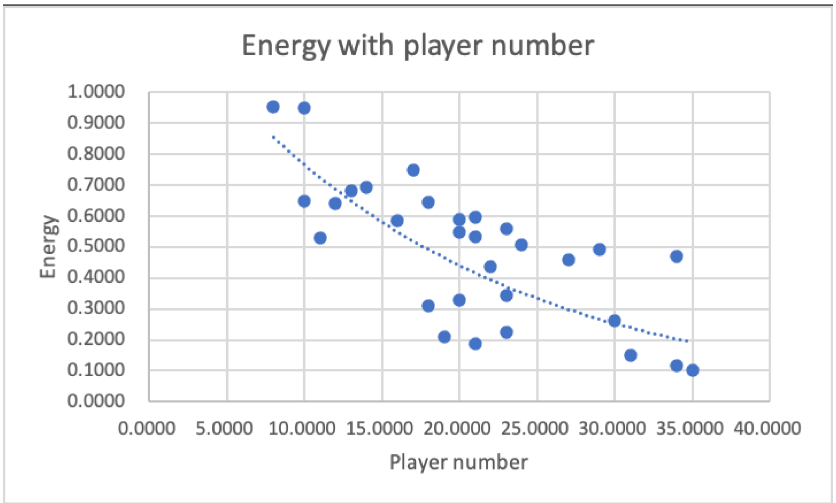

Figure 3.3: Energy changes with player number

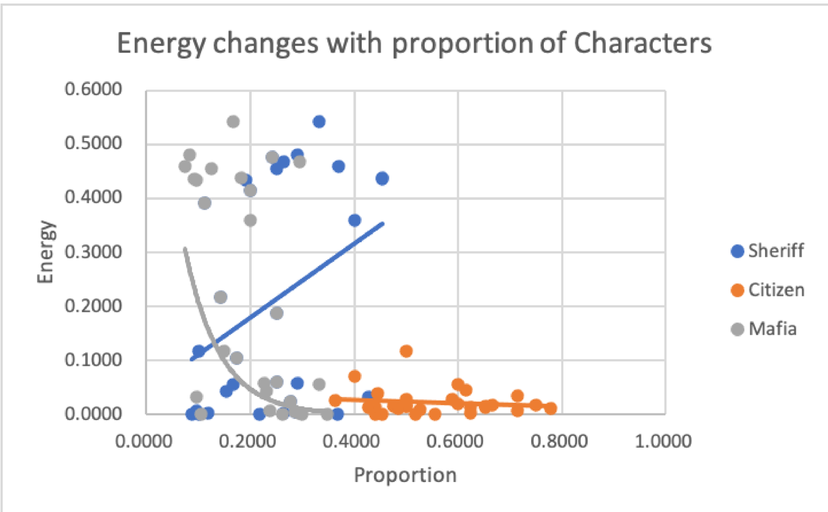

Figure 3.4: Energy changes with proportion of characters

Although, we potentially described the dynamics of minority versus majority behaviors in the Mafia game. We could not estimate the behavior of players in reality after all. The reality behavior of players is much more complex than we imagine. And the game is also evolving. Hence, future research direction can be determined as the comparison of simulation results with actual player behavior. And also, the study on the Mafia game can contribute to some extent to the improvement of this game from the perspective of game designers.

Chapter 4

Conclusion

In this chapter, we will provide a conclusion of this paper. As a summary during the master research, from the perspective of the game progress model and motion in mind model, we analyzed the Jump & Jump game and the Mafia game based on the game refinement theory. Hence, we will give the conclusion of the Jump & Jump game research and the Mafia game research, respectively.

4.1 Conclusion of the Jump & Jump game research

The Jump & Jump is a rage arcade game after it was launched at the end of 2017, primarily due to its simple mechanics. As a simple arcade game, it was all the rage shortly.

Due to such a reason(only need to press the screen), however, the game's tricks are quickly grasped by most players. When they are reaching a high level in Jump & Jump game, they could not break through in a short time. According to our research results, the game becomes a kind of training where the play becomes dull and loses its attractiveness over time. Hence, it is natural for these players to no longer pay attention to the game after a period. And there are only a few true expert players who can find their heart flow in the Jump & Jump game.

Although some works from the game operators had been proposed. Such as bonus points, weekly rankings among the player's social network based on the WeChat platform, and so on, which are integrated into the game to improve the player's engagement [14]. However, the game mechanics did not change, which makes the game challenging to retain players' interest, causing it to lose its popularity.

The Jump & Jump game research analyzes the entertainment aspect of the Jump & Jump game for different levels of players by applying the game refinement theory. And with the help of the GR measure and motion in mind, it also identified the reason why players at earlier levels tend to be more exciting than higher-level players.

Further, we reveal the reason for the phenomenal game(no longer popular after a short time). Then we proposed potential enhancements to improve such drawbacks. Such improvements may provide further advancement in the design of arcade games and possibly maintain the popularity of the Jump & Jump game. It is believed that these ideas may make further improvements in future research that possibly make the Jump & Jump game popular again.

4.2 Conclusion of the Mafia game study

The Mafia game study proposed methods to analyze the sophistication of character roles in Mafia game using the GR theory, while expanding the analysis to its game-playing experience using the motion in mind model via the reward ratio to determine their potential energy. Typical analysis of such a game involves determining the best character combination by analyzing the overall death toll [11]. Our study is interested in observing how the combinations of the character affect the game-playing experience and impact it overall expected entertainment which originated from the mutual restraint between the characters. A total of 6,480,000 game run were analyzed from the simulator of the Mafia game implemented using C++ program.

Based on the analysis of the GR value, several optimal character combinations in the Mafia game were identified, which helps balance the game experience in terms of ability and chance while providing enough sophistication to be entertaining when using any of the characters. Analysis from the energy in mind perspective, the relationship between reward ratio (N) and proportion of character roles, was also explored. The N value and the number of the character's proportion affect the player experience on Mafia and Sheriff, while Citizen always has a stable engagement experience.

The Mafia game study potentially describes dynamics of minority versus majority behaviors in a party game setting of the Mafia game, which had been analyzed by theoretical quantification methods of GR value and motion in mind model. Nevertheless, it does not claim that such a method could perfectly describe players' actual behaviors in game-playing settings but rather estimate the possibility of such behavior and approximate the optimal entertainment expectation from it. In addition, the game designer can also improve the character roles and functionality in the minority or majority group to enhance the game-playing experience while improving its entertainment aspects. Therefore, future studies could be conducted to compare, on a large scale, how the current simulation results hold against actual human behaviors while further verifying the effectiveness of such quantification method. Similarly, such a quantification method could also be adapted to determine the educational potential of the Mafia game, which had been previously hinted to be an essential tool that was useful in such endeavors.

Appendix A

Screenshots

A.1 Some screenshots of our Jump & Jump remake game

Some screenshots of our remake game is shown here. And a part of core code will be shown in Appendix B.

The figure which is shown in Figure A.1 is the normal model of our remake Jump & Jump game on the web page. The screenshot of choosing player's level under the normal model is shown in Figure A.2. And the screenshot of the scoreboard under the normal model is given in Figure A.3.

The enhanced model of our remake game is shown in Figure A.4. And the falling down situation with wrong direction and the wrong distance will be shown in Figure A.5 and Figure A.6, respectively as follows:

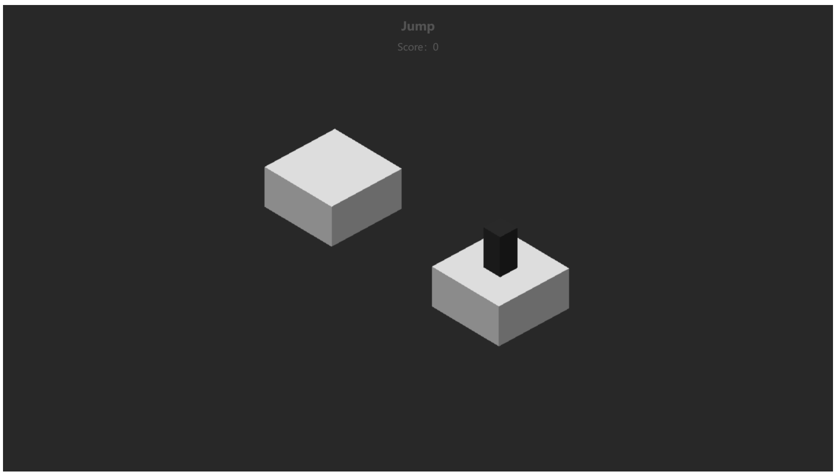

Figure A.1: Normal model of the remake game

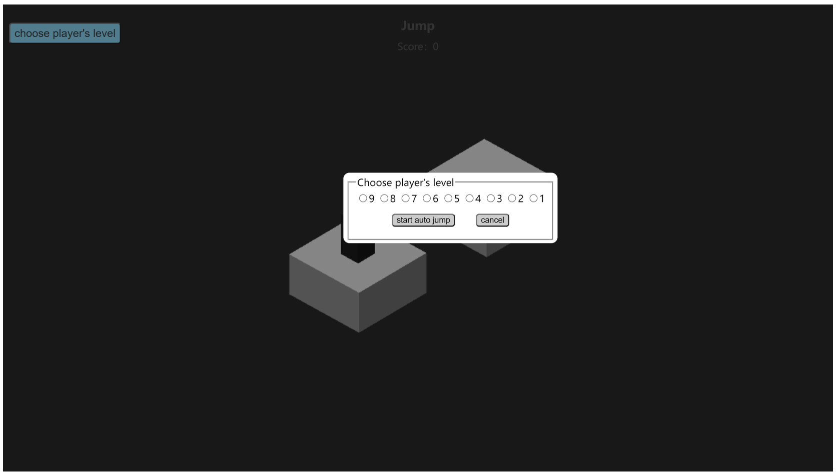

Figure A.2: Choosing player's level under normal model

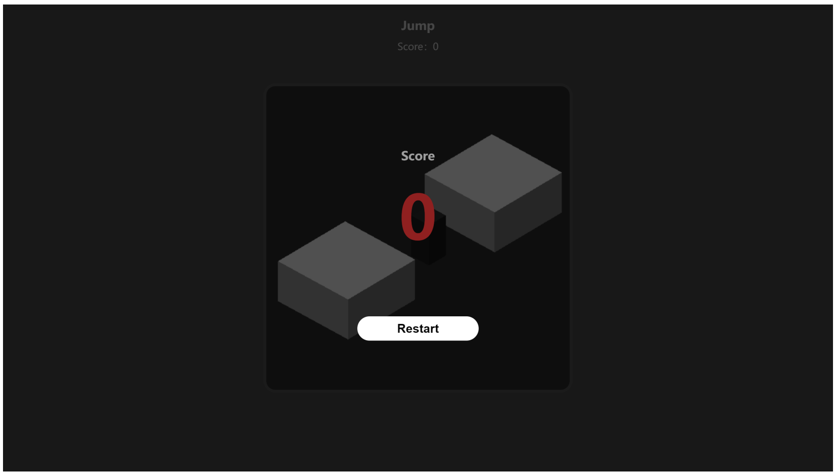

Figure A.3: The scoreboard under normal model

A.2 The screenshots of the Mafia game

The screenshots of the Mafia game card (offline version) and werewolf game (online version) are given here.

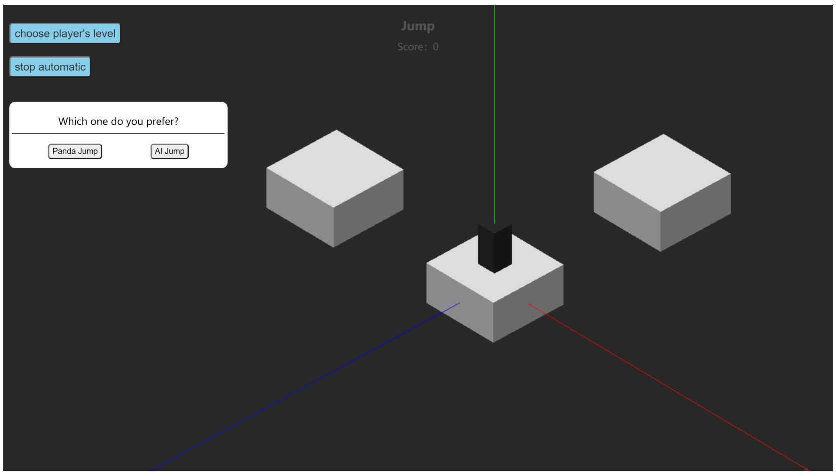

Figure A.4: Enhanced model of the remake game

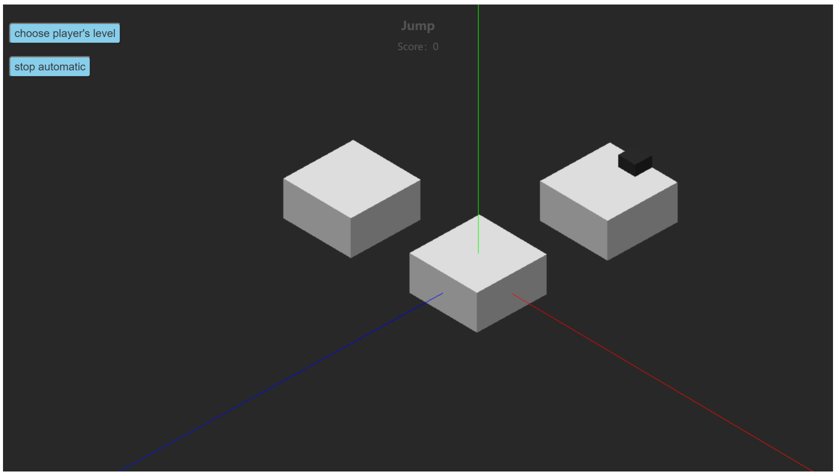

Figure A.5: Falling down with wrong direction

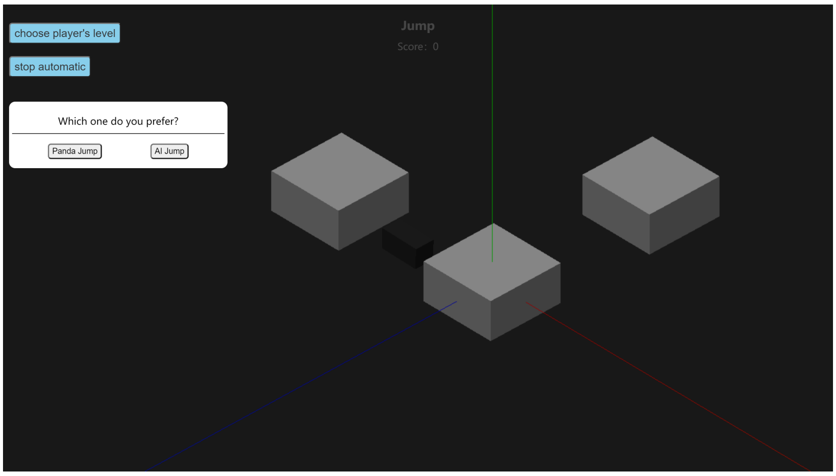

Figure A.6: Falling down with wrong distance

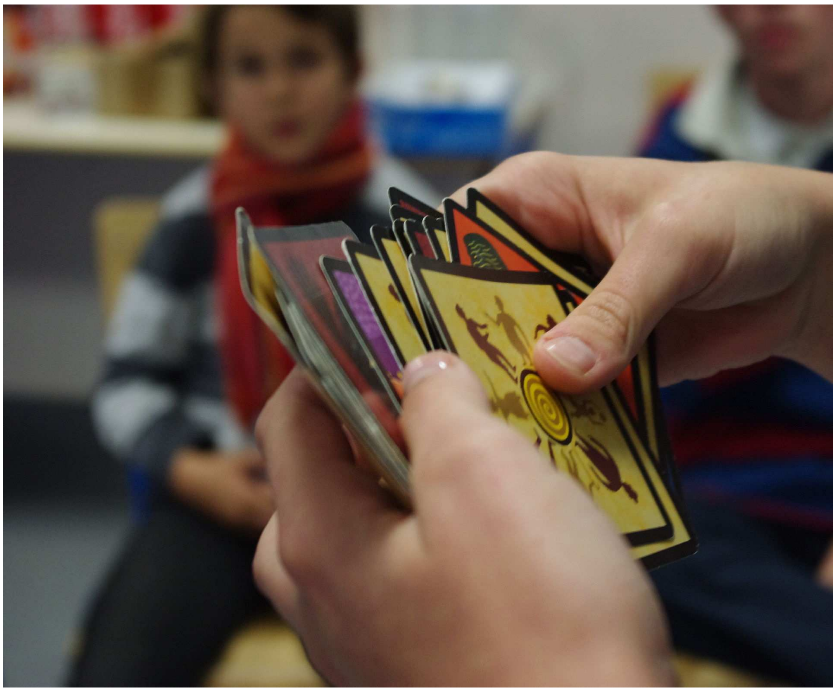

Figure A.7: The screenshot of the Mafia game card

Figure A.8: A screenshot of online werewolf game

Appendix B

Part of Core Code

In Appendix B, we will give a part of the core code of our programming. Algorithm.1 is the simulation of our remake Jump & Jump game, which is used to implement the Binomial distribution and calculate the GR measures for each level player. The $Lv5$ is shown as an example in the code.

```
--------------------------------------------------------
Algorithm.1
--------------------------------------------------------
//Binomial distribution
var uniform={
  getNumberInNormalDistribution: function(mean,std_dev){
    var finalNum = mean+(uniform.uniformNormalDistribution()*
       std_dev);
    return finalNum;
  },
  uniformNormalDistribution: function(){
      var sum=0.0;
      for(var i=0; i<12; i++){
          sum=sum+Math.random();
      }
      return sum-6.0;
  }
}

var prob = 0,
  bfactor = 0,
  GRvalue = 0,
  aveGR = 0,
  sumArr = 0;
var arrGR = [];
var steps = 50,
  level = 0.5;
var std_dev = 0.20;
//Cyclic Binomial distribution for simulating jump
```

```
for(var k=0;k<=1000;k++){
  for(var i=1;i<=steps;i++){
    prob = uniform.getNumberInNormalDistribution(level,
        std_dev);
    if(prob>1){prob = 1}
    // if(prob<0){prob = 0.001}
    if(prob>0.5){
      bfactor++;
    }
    GRvalue = Math.sqrt(bfactor)/steps;
    if(i == steps){bfactor = 0}
  }
  arrGR.push(GRvalue);
}
for(var j=0;j<arrGR.length;j++){
  sumArr +=arrGR[j];
}
aveGR = sumArr/arrGR.length;
console.log(aveGR+'sumArr');
```

Algorithm.2 shows a part of the core code for our enhanced Jump & Jump game. The core logic of puzzle elements is shown as follows.

```
-------------------------------------------------------
Algorithm.2
-------------------------------------------------------
var autoJump = {
  timer1: null,
  timer2: null,
  playerLevel: null,
    successProb: null,
  clickTimes: 0,
  jumpTime: 0,
  bFactor:0,
  calculateTime:function(){
        if(game.fallconfig.dir == 'left'){
            game.fallconfig.nextJumpTime = Math.abs(
                game.fallconfig.posNext)-Math.abs(
                game.jumper.position.x);
        }else{
            game.fallconfig.nextJumpTime = Math.abs(
                game.fallconfig.posNext)-Math.abs(
                game.jumper.position.z);
        }
        var nextDistance = game.fallconfig.nextJumpTime;
        var ramTime = autoJump.successProb>0.5?true:false;
        if(ramTime){
          nextDistance = nextDistance;
        }else{
```

```
          nextDistance = nextDistance+(Math.random()*(2-(-2))+(-2));
        }
        autoJump.jumpTime = 9.78046*Math.sqrt((nextDistance*(1000/60))/0.06);
        // 9.78046 is acceleration of gravity in game world
  },
  jumpFun: function(){
    game._handlemousedown();
    autoJump.timer1 = setTimeout(function(){
      clearTimeout(autoJump.timer1);
      game._handlemouseup();
    }, autoJump.jumpTime)
  },
  stopFun: function(){
    clearInterval(autoJump.timer2);
  },
  calSuccessProb: function(){
    var distribution={
      finalProb: 0,
      getNumberInNormalDistribution: function(mean,std_dev){
        var meanNum = Number(mean);
        return meanNum+distribution.uniformToNormalDistribution()*std_dev;
      },
      uniformToNormalDistribution: function(){
          var sum=0.0;
          for(var i=0; i<12; i++){
              sum=sum+Math.random();
          }
          return sum-6.0;
      }
    }
    if(autoJump.playerLevel != null){
      distribution.finalProb = distribution.getNumberInNormalDistribution(autoJump.playerLevel,0.2);
      if(distribution.finalProb>1){
        distribution.finalProb = 1;
      }else if(distribution.finalProb<0){
        distribution.finalProb = 0.001;
      }
    }else{
      return;
    }
    autoJump.successProb = distribution.finalProb;
  }
}
```

```
var visionControl = {
  flag: true,
  contrFun: function(){
    if(this.flag == true){
      $('.pandaOrAi').css({display:'block'});
    }else{
      $('.pandaOrAi').css({display:'none'});
    }
  }
}

// puzzle for jump
$(function(){
  // after choosing
  $('#panda, #computer').click(function(){
    visionControl.flag = false;
    visionControl.contrFun();
  })
  $('#panda').click(function(){
    pandaHelp.pandaJump();
  })
  $('#computer').click(function(){
    computerHelp.computerJump();
  })
  visionControl.contrFun();

  var pandaHelp = {
    pandaJump: function(){
          if(game.fallconfig.dir == 'left'){
              game.fallconfig.nextJumpTime = Math.abs(game.fallconfig.posNext)-Math.abs(game.jumper.position.x);
          }else{
              game.fallconfig.nextJumpTime = Math.abs(game.fallconfig.posNext)-Math.abs(game.jumper.position.z);
          }
          var nextDistance = game.fallconfig.nextJumpTime;
            // distance random
          var random = Math.random();
      var distanceFlag = random<0.5?true:false;
      console.log(distanceFlag,'distanceFlag');
          if(distanceFlag){
            nextDistance = nextDistance+(Math.random()*(2-(-2))+(-2));
          }else{
            nextDistance = nextDistance;
          }
```

```
            autoJump.jumpTime = 9.78046*Math.sqrt((nextDistance
                *(1000/60))/0.06);
            autoJump.jumpFun();
        }
    }
    var computerHelp = {
        computerJump: function(){
            // direction ramdom
            var flagRandom = Math.random();
            dirFlag = flagRandom<0.5?true:false;
            var random = Math.random();
            if(dirFlag){
          game.fallconfig.dir = random>0.5?'left':'right';
            }
      // console.log(game.fallconfig.dir,'newdir');
            autoJump.jumpFun();
        }
    }
})
```

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