

# Building Opponent Model in Imperfect Information Board Games

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## Abstract

*In imperfect information problems, board game is a class of special problem that differs from card games like poker. Several characters make it a valuable test bed for opponent modeling, which is one of the most difficult problems in artificial intelligence decision systems. In card games, opponent modeling has proved its importance on improving agents' strength. In this paper, a method of building opponent models in imperfect information board games is introduced systematically. Formalized evaluation method of arrangement strength in board game is proposed. Risk dominance is suggested as the classified criterion of building opponent models and basing that, classified primary probability tables are built as opponent models. Last, Siguo game is chosen as the application for opponent modeling and shows its advantages in the experiments.*

**Keywords:** imperfect information, board game, opponent modeling

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## 1. Introduction

There has been a mount of researches on opponent modeling about perfect information games. In game theory, the question is known as the best response problem - looking for an optimal response to a given opponent model (Gilboa 1988). However, these works have not been widely applied in practice. For instance, Jansen [1] describes various positions in a game where different opponents' strategies should be considered. Lida, et. al. suggested other potential applications of opponent modeling [2, 3], and various other algorithms for opponent modeling have been suggested by Carmel and Markovitch [4], Korf [5], and Donkers et. al [6].

These results of research have not played an important role in perfect information games for mainly two reasons. One is about the effect of game tree pruning, which is the conclusion from Carmel and Markovitch's research. In their experiments in Checkers, they showed that while opponent modeling methods were superior given the same search depth, they weren't effective on dealing with the number of node expansions. This is because opponent modeling necessarily reduces the amount of pruning possible in a game tree. So, alpha-beta is able to overcome handicaps in opponent modeling due to its advantage in search depth.

However in imperfect information games, the efficiency of pruning algorithm can not do as well as in perfect information games. Moreover, decreasing the scale of possible worlds is another task as important as game tree pruning. This means that if good opponent modeling method can show its advantages on worlds scale decreasing, the imperfect information game problem can be more likely to be a success applied field of opponent modeling researches.

Another reason that why opponent modeling techniques haven't been widely applied is that the assumption of an optimal opponent in the perfect information game is adequate for most conditions. However, the conditions are quite different in imperfect information games in which the players can only hold partial or imprecise information of the game. In this case, if the definition of an optimal opponent is a player who plays a Nash equilibrium, imperfect information game player can not find best strategy to the unseen Nash equilibrium in most cases. In another perspective, basing on different information that the players hold, there can be different equilibriums for different players. This is another point that opponent modeling method is supposed can play its role in imperfect information game.

Researchers have gained some success in imperfect information card game problems. In 1998, D. Billings explained how they implemented both specific and generic opponent modeling in Loki [7]. This computer program was the first successful demonstration of opponent modeling improving the performance of a poker bot. Korb et al. [8] proposed a method which using Bayesian network to model opponents in 1999. In 2000, Davidson et al. applied ANN (artificial neural network) method on opponents modeling method [9]. And then, Southey (2005) and Ponsen (2008) proposed the further researches on this area [10, 11]. The researches on analysis of human behavior [12] are also becoming a raising topic in recent year.

Researches on applying opponent modeling method on board game are quite rare compared with those on card games. In 2009, Stankiewicz described a method to model the opponent in Stratego [13]. Basing on the analysis of the moves of the opponent, probability distributions can be derived in order to determine the most likely type of an unknown piece. Stankiewicz's work provides a prim exploration of using opponent modeling method on board game. However, his reasearch did not involve the modeling method of whole board arrangement strategies and formalized method to classify the factitious tendency of opponent patterns. Thus, some probable solutions are provided and these problems will be intensively studied in this paper.

The structure of this paper is as following. Section 2 gives some back ground and further motivates the practical meaning of our work. Section 3 provides our methods of building opponent models in board game which contains methods of arrangement strength evaluation, building general and classified primary models basing on opponent arrangement tendencies and prediction method basing on opponent models. The experiments and results adopting these methods are discussed in Section 4. Finally, Section 5 provides the conclusions and discusses the future research about our work.

## 2. Related Works and Siguo Game

In imperfect information game area, the main researches are focus on poker and bridge. The research about bridge can be traced back to 1960s. After 1998, Ginsberg's bridge program GIB got a great success and it has reached the level of human bridge master by now [14]. The upper two classes of imperfect information games are both cards game, which is quite different from board game. In recent years, a kind of "unseen" chess called Kriegspiel [15] become a new research game of imperfect information area. In China, a very popular board game, Siguo game is also a suitable platform for such researches and paper [16] provided a detailed introduction of the game. Another similar research as Siguo game is Stratego [17].

Board game differs from card game at the unknown information that player faces. The distribution of unknown pieces or cards in card game is following nature distribution besides in board game it is factitious. In another word, in card game player should guess which cards other opponents take while in board game player should guess how arranged of the opponents' pieces.

Comparing with card game, board games usually have larger scale of possible worlds' space. Basing on our research, the initial worlds' space of Siguo game is  $3.58 \times 10^6$ , far beyond the declarer player in bridge's  $1.04 \times 10^7$ . Table 1 shows the scale of the initial possible worlds' space of five classic imperfect information domains [18]. As the result, the methods that can effectively decrease the possible worlds' space are very significant in board games.

Table 1. Initial Possible Worlds' Number of Five Classic Imperfect Information Game Domains

	Initial possible worlds' space	Cards/pieces' distribution	The trend of Information changing
Bridge	$1.04 \times 10^7$ (declear)	Natural	decrease
Siguo Game	$7.1 \times 10^{17}$ (for one player)	Factitious	decrease
Texas hold'em (poker)	1225 (two players game)	Natural	decrease
Kriegspiel	1	Natural	increase
Stratego	$1.41 \times 10^{33}$	Factitious	decrease

As a class of imperfect information game, besides the provided meaning in former chapters, board game has at least three advantages to be studied for opponent modeling algorithms. Firstly, besides the nature distribution of initial player conditions, board game players can arrange their pieces as their wishes. The arrangement strategies of different players are typical opponents' models which follows players' subjective tendencies. Secondly, board game provide a static statement before the beginning of a round of game for player to choose their arrangement strategies, which means however the following game process, they can not change the initial arrangement. Basing on related studies, one of the troublesome problems is that players are changing among different models with the changing of game conditions. Modeling opponents' arrange strategies can guarantee the consistency of opponents' tendency at least in one round. In the end, correctly matched opponent model can play a more important role in imperfect information board game. No matter how game process, all moving pieces can be traced back from their initial positions on the board. This means if the computer agent can build a proper opponent model which can effectively predict the arrangement of other players, it will gain great dominance in any stage of the game. These points can be further observed in the following introduction Siguo game.

## 2.2. Introduction of Siguo game

Siguo game is a variation of Stratego, which was developed by Mogendorff in 1942 and first appeared in its present form in 1961. As a variant of Stratego, Siguo game has its special characters like 4-player, camp positions, more types of pieces and more abundant ways of movements. All of these make it more interesting and complex both as a game and a research plat form. In China, there are 6 million online players of Siguo game involved in Tencent company game platform [19], which is also the cooperated research platform of our work.

In Siguo game, each player has 25 pieces at his disposal to place in a 5\*6 area on the board. The detail introduction of pieces is listed as following Figure 1 and Table 2.

Figure 1. The Board and Positions of Siguo game

Table 2. Ranks of Pieces on the Board

Rank of Piece	Abbreviation	Quantity	Piece ID
Marshal	Ma	1	1
General	Ge	1	2
Major General	M. G	2	3
Brigadier General	B. G	2	4
Colonel	Co	2	5
Major	Mj	2	6
Captain	Ca	3	7
Lieutenant	Li	3	8
Sapper	Sa	3	9
Landmine	Mi	3	10
Bomb	Bo	2	11
Flag	F	1	12

The following Figure 1 and Table 2 show the board and pieces conditions of Siguo game for further demonstration of the upper standpoint. This game can be introduced as following aspects.

**Path:** Paths in Siguo game contains road and railway. Pieces may move one square on road or move to any position on a railway, horizontally or vertically.

**Positions:** Positions in Siguo game contains normal pos, camp and base pos. There are 30 positions at each side that contain 5 camps, 2 bases and 23 normal poses. Pieces in camp can not be attacked. Bases are the only positions that players can arrange their flag in the beginning, and pieces will become immovable when they are arranged or moved in base positions.

**Pieces:** The ranks are listed in Table 2 from strongest to weakest, except the Bomb and landmine with special ranks. A player may attempt to capture an opponent's piece if the player's piece begins its turn to a position of opponent's piece. In general, a piece is captured if its rank is lower than the rank of the piece it is attacking or attacked by. If the rank of the two pieces is equal, both pieces are captured. There are some exceptions to these rules however.

The Sapper may move to any square while other pieces can only move a straight line along the railway. It is the only piece that can capture Landmine. The Landmine on the other hand, is invincible to other pieces but immovable.

When Bomb is attacked or attacks other pieces, whatever the other pieces are, both of them are captured. That is to say, Bomb is an important piece to overawe opponents' strong pieces.

Flag is most special piece that can only be arranged at base positions. Any other pieces can capture it and declare the loss of its player.

**Win the game:** The game contains 4 players, each gets a moving chance following a clockwise order. Players sit opposite are comrade and fight against those sit neighbor. In playing process, player can only see the ranks of his own pieces and others' pieces are shown as reverse side. The game ends when a player and his comrade's Flags are both captured or cannot make any more moves. In other words, players in this game should try to attack opponents Flag while protect his own Flag.

In this sense, Siguo game has several characters as a valuable test-bed of game research; such as risk management, opponent modeling, bluffing and cooperation, imperfect information and deception, multiplayer strategy. All of these are much like decision-making applications in the real world.

### **3. Building Opponent Models in Board Game**

This chapter will provide the method of building opponent models in board game. Actually speaking, what the opponent models contain is a probability table that predicts players' arrangement on each board positions. One way of build the table is according to statistics history arrangement data without classification of players. This probability can be concerned suit for all kinds of players. Besides this way, the purpose of this paper is to build several probability tables that suit for different types of players basing on their arrangement tendencies. These can be used to provide more precise prediction about special opponent's arrangement.

There are mainly two differences of building opponent models in board game and in card game. Firstly, it is hard to build special models for each individual player like methods introduced in poker game. This is because comparing with poker game, board games have much larger scale of possible arrangement conditions. This means opponent modeling method in board games can not update the probability table effectively in the re-weighting process. Thus, building primary classified models is the second best approach on this topic. Secondly, arrangement strategy in board game cannot be illustrated as clear and numerable actions, like (fold, call, raise) in Texas Hold'em. Arrangement tendency is an abstract concept that needs to be realized by a specific character of opponent's strategy. Considering about these, a series of methods are introduced as following:

1. Evaluation of arrangement strength: A formalized method of evaluating arrangement strategies. Risk dominance tendency is adopted as the specific character to realized opponents' tendency.

2. Building primary classified opponent models basing on history data: Opponents' arrangement strategies are classified into several primary models.

3. Prediction method basing on opponent models: How to use the primary opponent models to make a more precise prediction of opponent arrangement.

In the following of this chapter, Siguo game will be adopted to introduce the methods of modeling opponents in board game. Attention that the methods are general manner that not only suitable for Siguo game but for all board game problems.

**3.1. Evaluation of Arrangement Strength**

The first problem is building formalized method of evaluating strength of opponents' arrangement. Our previous researches on risk dominance and risk strategy decision in imperfect information games have gained some progress [10, 20]. Thus, the risk characters about the opponents' arrangement tendency in imperfect information conditions are used as the break point of realizing the concept of opponents' arrangement tendency in this paper.

A simple viewpoint of risk dominance theory is that the more payoffs you want to get, the more risk you will suffer. Embodying it in board game, attacking aggressively usually means high payoffs and high risks besides defense carefully means low payoffs and low risks. Basing on our former research, players of board game can be distinctly distinguished by their action tendency of attack or defensive priority basing on their risk perceive. Thus, a formalized method is provided firstly which evaluates the strength of an arrangement from two characters, the potential ability of attack and defensive.

In Siguo game, player could arrange their pieces (25 pieces with 12 different types) on the 25 available positions of the board. Figure 2 shows the pieces and positions on board in Siguo game.

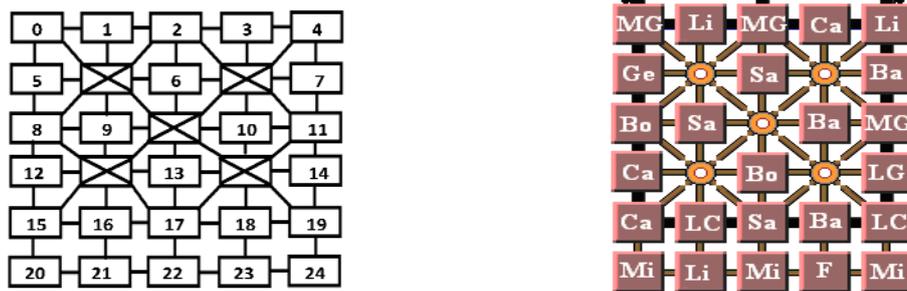


Figure 2. Available Arrangement Positions of One Player in Siguo Game and an Example of Arrangement

In Siguo game, arrangement means a combination of pieces and positions. Formula 1 provides a method of evaluating the pieces' static values.  $F$  is a matrix of  $12 \times 12$  that calculated by two matrix. The first matrix means the payoffs that one kind of pieces attacks another. For example,  $f_{1,2}$  means when piece type 1 (Ma) attacks type 2 (Ge), player with type 1 will get  $f_{1,2}$  payoffs from this step. The second matrix records the statistics data that the probability of one kind of pieces meets another. For example,  $p_{1,2}$  means the probability that Ma meets Ge. Thus, the static strength of all 12 types of pieces can be calculated from the diagonal line of  $F$ , which is recorded in  $F_s$  as formula 2 shows.

$$F = \begin{bmatrix} f_{1,1} & f_{1,2} & \dots & f_{1,12} \\ f_{2,1} & f_{2,2} & \dots & f_{2,12} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ f_{12,1} & f_{12,2} & \dots & f_{12,12} \end{bmatrix} \times \begin{bmatrix} p_{1,1} & p_{1,2} & \dots & p_{1,13} \\ p_{2,1} & p_{2,2} & \dots & p_{2,13} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ p_{12,1} & p_{12,2} & \dots & p_{12,13} \end{bmatrix} \tag{1}$$

$$F_S = [F_{1,1}, F_{2,2}, \dots, F_{12,12}] \quad (2)$$

Basing on static value matrix  $F_S$ , the static value of an opponent's arrangement, using  $B_S$  donates it, can be calculated by formula (3).

$$B_S = F_S \times B_i = [F_{1,1}, F_{2,2}, \dots, F_{12,12}] \times \begin{bmatrix} b_{1,1} & b_{1,2} & \dots & b_{1,25} \\ b_{2,1} & b_{2,2} & \dots & b_{2,25} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ b_{12,1} & b_{12,2} & \dots & b_{12,25} \end{bmatrix} \quad (3)$$

In formula 3,  $B_i$  is a  $\{0,1\}$  matrix which is used to record the arrangement of opponent's board. When opponent arranges piece  $i$  at position  $j$ ,  $b_{ij}=1$  and others are set 0. By this method,  $B_S$  can be built as a  $1*25$  matrix that records the static strength of an arrangement of the board.

Next, the static strength of pieces will be weighting by an influence matrixes  $I_{AD}$  which evaluates their positions' influence on aggressive and defensive.

$$I_{AD} = \begin{bmatrix} A_1 & D_1 \\ A_2 & D_2 \\ \cdot & \cdot \\ \cdot & \cdot \\ \cdot & \cdot \\ A_{25} & D_{25} \end{bmatrix} \quad (4)$$

Just as formula 4 shows, the aggressive and defensive factor of pieces on positions are evaluated separately. Generally speaking, the positions on front line provide more aggressive influence and positions provide more defensive influence on back line. Positions will provide both more influence of aggressive and defensive when convenient to transport. The value of  $I_{AD}$  can be studied and trained in history game records. The method and process of training of  $I_{AD}$  is not trivial which is also one of our study topics [20]. In this paper, it is sufficient to know that the training is based primarily on three things:

1. When a piece captures other pieces in self-area on the board, the defensive coefficient of its initial position will be increased. Otherwise, the aggressive coefficient of its initial position will be increased.
2. When a piece is captured by other pieces in self-area on the board, the defensive coefficient of its initial position will be decreased. Otherwise, the aggressive coefficient of its initial position will be decreased.
3. The coefficients are also influenced by the adjacent positions and its convenience for pieces transportation.

The increase and decreased range is influenced by the temporal game conditions and the following tables show our primary results.

Table 3. Aggressive Influence Coefficient on Siguo Board

row/column	1	2	3	4	5
1	2.053	0.512	2.109	0.497	2.001
2	0.962		0.470		1.216
3	0.533	0.049		0.113	0.503
4	0.325		-0.591		0.141
5	0.331	0.291	0.152	0.092	0.410
6	-0.179	0	0	0	-0.211

Table 4. Defensive Influence Coefficient on Siguo Board

row\column	1	2	3	4	5
1	-0.251	0.011	0.203	-0.387	-0.196
2	0.305		0.587		0.411
3	0.125	2.007		2.146	0.069
4	0.488		0.230		0.398
5	2.144	0.431	-0.015	0.505	2.122
6	0.106	0	0	0	0.109

Table 3 and 4 show our training result on aggressive and defensive influence coefficient on Siguo board. It can be observed that there are several crucial positions for aggressive and defensive. For example, arranging strong piece at positions row 1, column 1\3\5 will greatly increase the attack ability of the arrangement. On the other side, arranging them at row 5, column 2, 4 will form an effective defensive arrangement.

In this sense, the finally evaluating result of arrangement can be represented by a binary group  $B_{AD}$ , which can be calculated as formula 5. In this formula, the first term of  $B_{AD}$  donates the aggressive strength of the arrangement and the second term donates the defensive strength. Both of them are calculated by the sum of corresponding term of matrix  $B_S$  and  $I_{AD}$ . Thus far, the method of evaluation arrangement strength in our research has been introduced.

$$B_{AD} = B_S \times I_{AD} = \left[ \sum_{i=1}^{25} A_i B_{si}, \sum_{j=1}^{25} D_j B_{sj} \right] \quad (5)$$

### 3.2. Opponents' Classification and Building Special Opponent's Models

Basing on upper method, History data of Siguo game can be analyzed to explore the arrangement tendency of opponents. Figure 3 shows parts of results.

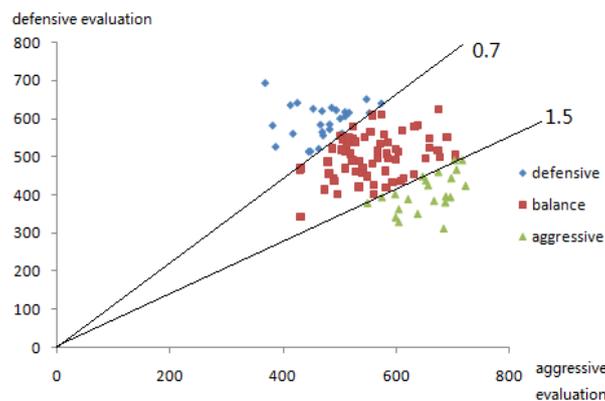


Figure 3. Board Weighting Results for 200 Rounds Basing on A&amp;D Method

Figure 3 shows arrangement evaluation results for 200 rounds Siguo game. Using the ratio of aggressive term and defensive term of  $B_{AD}$ , the arrangement of players can be classified as three classifications: aggressive, balance and defensive. The oblique line in the figure shows the boundage ratio of the three opponent models. In our statistics result of 5000 rounds, setting boundage ratio as 0.7 and 1.5, the opponents that modeled as aggressive type are about 22 percent. Opponents that modeled as defensive type are about 27 percent of all and the others are modeled balance type.

The next step is building primary opponent models basing on the upper results of opponent classification. In imperfect information problems, the opponent models is actually probability tables which is the data resource for strategy decision methods, such as PIMC [21] (Perfect Information Monte-Carlo Method). In former research of board game, the probability table are built basing on the history data without classification, which can be concerned as a general model that suit for all kinds of opponents. In our research, history data are classified

firstly basing on the arrangement tendency. And then, three classified primary models are built separately to better illustrate the characters of different arrangement tendency.

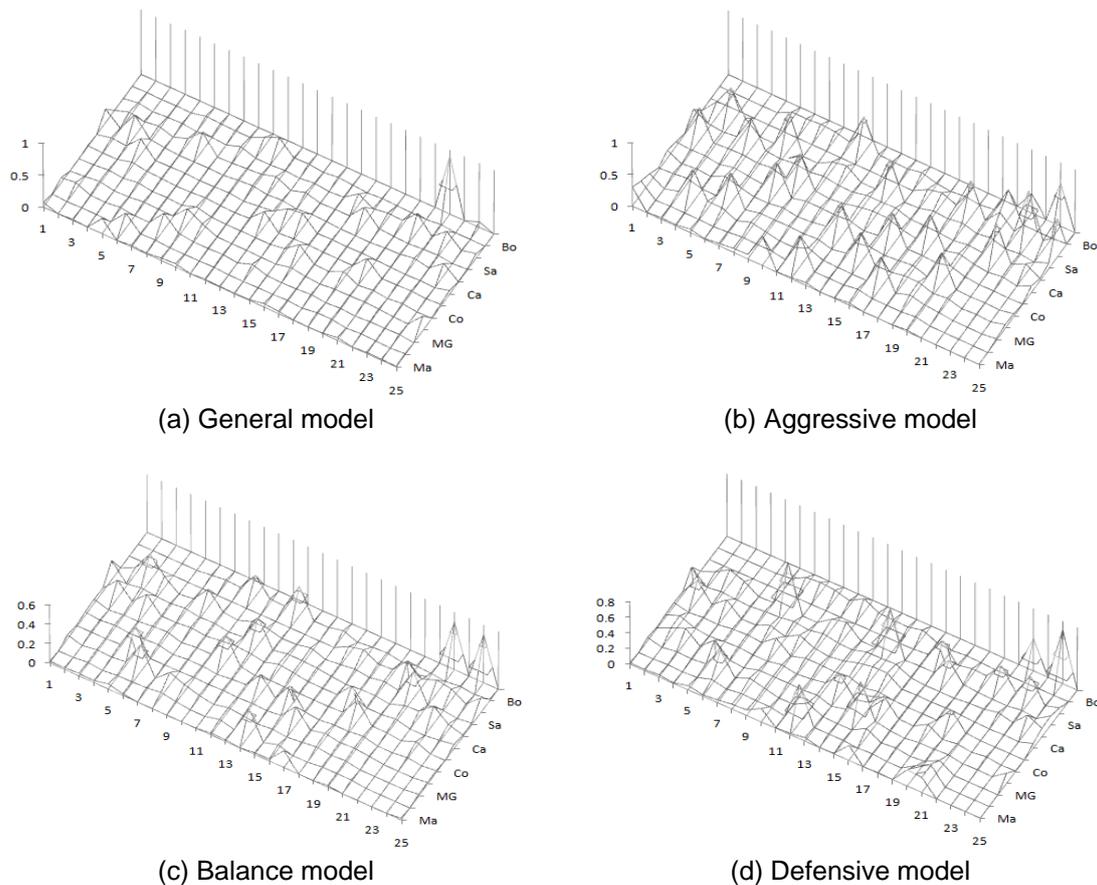


Figure 4. Classified Primary Models of Siguó Game

Figure 4 shows statistics probability of arrangement distribution of classified primary models of Siguó game. In program, it is recorded by table manner and in this paper shows as graphs for clearly. Basing on these models, once a player is modeled, this table can provide more precise sample set to predict his arrangement. Take the distribution of piece “Ma” for example, just as Figure 4 shows, it has a higher probability to be arranged at position 0 in aggressive model, which is a typical “aggressive position”. However in defensive model, it can be observed that it is mainly arranged at position 15 and 19, which are both good position for defense.

### 3.3. Prediction Method Basing on Opponent Models

Basing on primary opponent models, more precise prediction of opponents' arrangement can be processed. The last problem is that how to map a new opponent to models basing on the gained information with the game processing. The current mapping strategy in our Siguó System is unsophisticated and can be improved. Thus, a simple method is adopted and a briefly introduce is provided here.

The formatted expression and preconditions of the problem are as following:

- 1) Opponent models:  $O$  is the set of opponent models which contains three different models as  $\{A, B, D\}$ .
- 2) Player strategy set:  $X, Y, Z$  are the strategy sets of different types of players' tendency. The whole strategy set is  $\{X, Y, Z, \dots\}$ .  $X$  means arrange piece  $i$  at position  $j$ .
- 3) Prior probability: Player  $i$  has a prior probability  $P$  to choose his tendentious strategy which is

recorded in different models. For example,  $P(X|A)$  means if player  $i$  is a  $A$  type player, he has a probability of  $P(X|A)$  to choose arrange strategies that belongs to  $X$ .

- 4) History record: a history record  $h$  is a  $n$  dimension group that records the gained information of opponent's arrangement. For example,  $h\{X, Y, Z\}$  means the information of three pieces and their arrangement positions have been gained and recorded. In Siguo game, history record can be analyzed with the game processing. For example, if a  $Ge$  is captured by an unknown piece, it can be confirmed as a  $Ma$ . Tracing the move record of this piece, the information that which position opponent arranges the  $Ma$  can be recorded.
- 5) In this case, method of map an opponent to opponent models basing on a series of his recorded information of arrangement can be described as following:  
Given a player  $i$ 's history record  $h$ , the probability that player  $i$  is a type  $A$  player is:

$$P(A|h) = \frac{P(h|A)P(A)}{P(h)} = \frac{P(h|A)P(A)}{P(h|A) + P(h|B) + P(h|D)} \quad (6)$$

Attention that  $P(A)$  in formula 6 is the history distribution of three types of players. It can be updated if multi-rounds of game are played with same players. The probability of  $P(h|A)$ ,  $P(h|B)$ ,  $P(h|D)$  are recorded in the three models' probability tables. Thus, the probability of player  $i$ 's type can be expressed as a three terms like ( $P(A|h)$ ,  $P(B|h)$ ,  $P(D|h)$ ). Basing on upper calculations and primary models, at least two methods can be used to predict opponent's arrangement. Firstly, a simple way is to treat player as a certain type which shows the highest probability. And then, the probability table of this type's model can be adopted as the basement of further prediction. The second method is to adopt a mix probability approach, which is also applied in our system. As an example, the probability of piece  $i$  arranged at position  $j$  can be calculated as formula 7:

$$P(i, j) = P(i, j|A)P(A|h) + P(i, j|B)P(B|h) + P(i, j|D)P(D|h) \quad (7)$$

#### 4. Experiments

In this part, Siguo game is chosen as the sample domain of our research while the introduced methods in this paper are also appropriate for all imperfect information board games. In our experiments, the agents are classified as two characters, which are the tendency of their arrangement and whether they adopt classified opponent modeling method. Agent of random and general (PRG) is set as the previous best version of Siguo game agent which has been exhibited in 2012 2nd IEEE International Conference on Cloud Computing and Intelligence Systems [22]. In our experiments, it is basically set to adopt random arrangement strategy and does not adopt classified opponent modeling method but using a general opponent model as prediction probability table. It represents the classic agent without methods discussed in this paper. Then, agent of random and classified (PRC) is adopt random arrangement strategy and using classified primary opponent modeling discussed in previous chapters. And following, six different agents (PAG, PAC, PBG, PBC, PDG and PDC) are set as the combination of character {aggressive, balance, defensive} arrangement strategy and {general, classified} opponent modeling.

Table 5. Agents' Set in Experiments

Player Types	Arrangement tendency	Prediction methods
PRG	random	General OM
PRC	random	Classified OM
PAG	aggressive	General OM
PAC	aggressive	Classified OM
PBG	balance	General OM
PBC	balance	Classified OM
PDG	defensive	General OM
PDC	defensive	Classified OM

Table 6 shows the prediction precision of agents with or without the help of classified primary opponent models. The percentage in the table means the average rate of correct pieces' prediction in different stage of one round. Agents with or without classified opponent models performs a similar correct rate of prediction in the beginning stage of the game. That is because in the initial stage of Siguo game, players have almost no exact information besides themselves. All of the agent's prediction are actually basing on general model for that method of formula 7 shows probability results much as same comparing with general model. However, when game processes to middle and end stage, agents with classified models shows some advantages then those with general model. The correct prediction rate is improved around 6~11 percentage point in middle stage and 3~6 percentage point in the end stage. The improvement is strictly reflected by the better performance of agents with classified models just as Figure 4 shows.

Table 6. The Result of Average Correct Prediction Rate of Different Agents

Round stages	Agents with classified opponent models			Agents with general opponent models		
	Step 1~40	Step 41~120	Step 121~end	Step 1~40	Step 41~120	Step 121~end
Vs agents of Aggressive	12.13%	32.59%	55.31%	13.05%	24.56%	51.28%
Vs agents of Balance	14.98%	29.16%	48.15%	12.69%	23.41%	45.20%
Vs agents of Defensive	12.15%	31.34%	47.65%	10.65%	20.55%	41.13%
Vs agents of Random	11.96%	30.05%	42.54%	12.03%	24.65%	40.28%

Figure 5 shows the experiment results of self-play simulations among the eight versions of agents. Each of the agents are tested 100 rounds and the performance of each round are evaluated from -100~100. The performance of each agent is expressed as the accumulated points and the changing tendency with the experiments process.

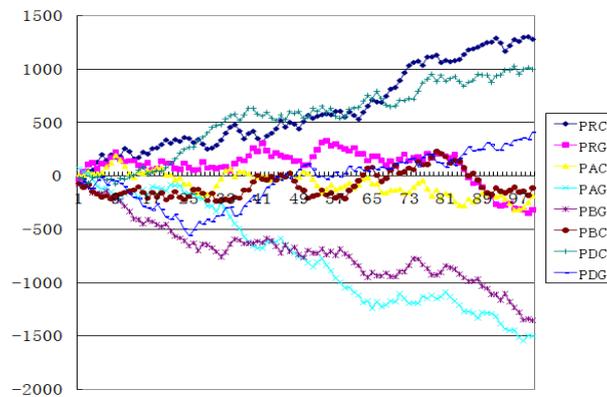


Figure 5. Experiment Results of 8 Versions of Agents in 100 Round Games

Observing the performance of the different agents, at least two points can be concluded. Firstly, the agents adopt classified opponent model performs comparatively better than those adopt same arrangement strategy but general opponent models. For example, agent PRS performs better than PRG and agent PBS performs better than PBG. Secondly, the agents adopt "aggressive tendency" arrangement strategy shows weakness as more obvious as the game process. This implies that playing with agents that adopts opponent modeling methods, aggressive players are more likely to expose flawed strategies once be modeled by their opponents. In this sense, adopting more cautious defensive arrangement strategies or random strategies to reduce the probability to be precisely modeled are better choice in imperfect information games.

## 5. Conclusion

In our research, agents adopts classified primary opponent models provide improved performance, both in the aspect of correct prediction rate of board arrangement and the whole gaming strength of agents. In this sense, at least two points can be concluded. Firstly, the opponent modeling method provided in this paper is proved its feasibility and effectivity. This is also the demonstration of beneficial opponent modeling method applied in imperfect information board games. Secondly, it can also be sustained that imperfect information board game, besides poker, is a valuable research area of the application on opponent modeling methods.

Besides the progress of works in this paper, there are at least two insufficient points in our research, which is also our study emphasis in future. Firstly, the method of opponent modeling dose not necessarily follow that it is just as successful in games against human players as it was against computer agents. Human player has much more strength of molding players and usually has a changing tendency of strategy decision. This requires the further investigation on the acceleration and precise of modeling process. And also, mix strategies should be considered to prevent computer agents from being modeled easily by their opponents. Secondly, diversified methods of collecting and applying statistics history data should be studied. In our research, much relevant context was ignored for simplicity such as contact between arrangement and opponents' pieces' movements. Applying data mining methods on this point can make a probable improvement about opponent modeling method.

In a word, more efforts will be kept on upper points, and opponent modeling will be continuous investigated in our future works.

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