Design and implementation of Bonanza Method for the Evaluation in the Game of Arimaa

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Abstract – Since the bonanza method had been discovered and proved to be required to make a strong Japanese chess program, the idea of applying it to the other 2-player perfect information game like Arimaa is proposed. In order to create a strong Arimaa program, the study aims to create the evaluation function that enables the accurate positional evaluation by using supervised learning algorithm called bonanza.

INTRODUCTION

Since the computer chess program had already reached the state of the art by beating the world champion human player in 1997, the new game called “Arimaa” founded in 2002 by Omar Syed was claimed to be the new way more challenge in the research of AI game. Like chess, Arimaa, the 2-player zero-sum perfect information game, was designed to be easy to play for human but hard for the computer. A move in arimaa is the combination of 4 piece movement called steps. Due to Arimaa piece can only move to the orthogonally adjacent positions, Arimaa piece move quite slow compared to chess. Therefore, this leads Arimaa deeper in strategy and wider in game tree search space. There are 6 types of piece ordered by the strongest piece which are Elephant, Camel, Horse, Dog, Cat, and Rabbit. The goal is to bring a weakest piece, (a rabbit), to the opposite side of the board. The game also ends when a player loses all his rabbit or when he repeatedly makes the same move for three times. Stronger piece may pull or push the weaker piece into trap and perform capturing.

Practically, with the high branching factor (16,000 possible move per position), Arimaa can be considered that it has the extremely large search space. That means it is impossible to do a full-width search within a limited time period. Fortunately, there was some study on tackling the Arimaa high branching factor effectively by using move-ordering heuristics [1]. Since 95% of expert moves were arranged in the top first 5% of the possible move list, the quality of alpha-beta search was proved to be more effective. For the evaluation of Arimaa position, the variety of technique such as hand-coded evaluation, reinforcement learning was applied to deal with the complicated in the evaluation. However, to evaluate position accurately, there still exist the way to improve the evaluation using the supervised machine learning technique called “bonanza”, which aims to evaluate the position like the way human does.

I. RELATED WORK

A. Monte-Carlo Tree Search based Arimaa program

Inspired from the highly effective in Computer Go, the Monte-Carlo Tree Search (MCTS) was managed to be used as the search algorithm in Arimaa by Tomas Kozelek [2]. The “as-is” Monte-Carlo playouts used in Computer Go was proved to provide a weak Arimaa player. Besides, the standard improvement in Go such as UCT-RAVE, UCB-tuned still provided no effect to the strength of the Arimaa program. Since the MCTS approach tends to provide the average strength program compared with the Alpha-Beta approach. That means the role of evaluation function was proved to be important. So, we chose to focus on the study of the evaluation function in Arimaa in order to create a strong Arimaa program.

B. Alpha-Beta Pruning Tree Search based Arimaa program

Most of the strong Arimaa program is based on the Alpha-Beta search algorithm. Like the winner of 2011 Computer Arimaa Championship, bot_sharp, was also the Alpha-Beta engine plus the standard improvement effectively used in Chess like the move ordering technique [1]. Move ordering enables the search to search on the expert-like move first, which means that it optimized the time usage in searching the principal variations. Bot_sharp evaluation function was tuned by using the reinforcement machine

![Figure 1: Example of Arimaa Position](image-url)
learning technique. The 4 different algorithms which are TD, TD-
Leaf, Treestrap, and Rootstrap were used to perform weight training.

B. The bonanza method

In the field of Japanese chess AI development, the bonanza method,
invented by Kunihito Hoki[3], was considered to be indispensable
for the good program. Bonanza is the name of the supervised
machine learning method that performs the evaluation function
weight training by using the expert human game play
(game record) as the training instance. The idea of the bonanza
technique is to find the objective function that can define how
advantages the move is, compared with the expert human move.

\[
J'(P_0, P_1, \ldots, P_{N-1}, v) = \sum_{n=0}^{N-1} l(P_n, v) \quad (1)
\]

Given an amount of sample data record which provides total N-1
number of recorded positions and the weight (v), the objective
function J’ returns minimum value when minimax search results
agree with the records. The function l(P, v) shown below describes
the actual activities of objective function J’.

\[
l(P, v) = \sum_{m=0}^{M} T[Eval(P_m, v) - Eval(P_m, 0)] \quad (2)
\]

Given the position P, for each of the possible moves \( P_m \)
the difference between evaluation value of the position \( P_m \)
and the evaluation value of the record position \( P_{m=0} \) is used as the input
to the function T. Where T represents the monotonic increasing
function, in this case, the sigmoid function is used. Then, given the
function l, the gradient \( \frac{\partial l(P_0, \ldots, P_{N-1}, v)}{\partial v} \) is calculated to be used in the
weight training process.

\[
\frac{\partial l(P_0, \ldots, P_{N-1}, v)}{\partial v} = T[x] \cdot T[1 - x] \cdot (g(P_m) - g(P_{m=0})) \quad (3)
\]

Where \( x = Eval(P_m, v) - Eval(P_{m=0}, v) \). The gradient is
then used as the update value in the weight training process.

\[
p_{\text{new}} = p_{\text{old}} - h\text{sign}\left[\frac{\partial l(P_0, \ldots, P_{N-1}, v)}{\partial v}\right] \quad (4)
\]

Where h is the learning rate, and the sign(x) function returns the
sign of x.

The bonanza method had become the “must have” and proved to
be useful in the modern Japanese chess program. In the other game
designed to be challenge for the computer to play like Arimaa, the
effectiveness of bonanza method against the Arimaa evaluation
function will be shown in this work.

II. PROPOSED METHOD

The idea to apply the bonanza method to improve the evaluation
function of Arimaa game was purposed for the attempt to create a
strong Arimaa program. In order to deal with the difficulty in
evaluation position in Arimaa, we suggest the evaluation function
that all the weights were automatically trained based on the
bonanza method which is hypothesized to be able to create a good
evaluation function.

In this work, we started from the small set of feature. Only the
piece position and the piece type had been used as the feature
vector. The actual feature vector is as shown below

weight [piece type][x position][y position]

The piece in Arimaa consists of 6 types and each has the
different value depended on the piece strength. The position in
Arimaa consists of 64 positions (8x8). Therefore, Total 384
features were used to create the evaluation feature.

With these simple set of features, the program is expected to be
able to evaluate how advantage to move the piece to a position, and
the material advantage of a given position.

III. IMPLEMENTATION

A. Game Record Preparing

The game records from the Arimaa website[4] were downloaded
and pre-processed to be able to use in evaluation function weight
training. The online game records since the game was invented are
available for download. The game record with rating more than
1800 was assumed to be a good game and being used as the
training instance.

B. Arimaa Game Engine

In this work, the program was developed based on the program
called “Bot_Faerie” available on Arimaa website to be used as a
starter Arimaa game engine. Bot_Faerie was written in C. It
consists of most of the useful features such as Generate possible
moves, simple Alpha-Beta Pruning Search, and a simple evaluation
function (material value). Besides, it also keep the position hash
value in order to avoid the search at the previously search position.
Therefore, it would be a right choice to realize evaluation function
weight training with the bonanza method based on the Bot_Faerie
engine.

C. Weight Training

Before the weight training was performed, the initial weight was
set to the initial piece values which are 20000 for Elephant, 5000
for camel, 3000 for horses, 1800 for dogs, 1500 for cats, 1000 for
rabbits. In this work, the update was done by the policy
Where $h$ is the learning rate which better be set to the small number. In this work it was set to 1.0. And, the actual weight updates was used as the weight updates instead of the sign function used in the original work by Kumiho Hoki. The weight was trained by using 700 recorded positions from several game records. The result of bonanza weight training was shown in the table below.

**TABLE I**

<table>
<thead>
<tr>
<th>Rabbit PIECE</th>
<th>481</th>
<th>917</th>
<th>941</th>
<th>879</th>
<th>990</th>
<th>1009</th>
<th>1082</th>
<th>1062</th>
<th>1133</th>
<th>902</th>
<th>1201</th>
<th>1066</th>
<th>1091</th>
<th>924</th>
<th>867</th>
<th>839</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cat PIECE</td>
<td>991</td>
<td>990</td>
<td>846</td>
<td>401</td>
<td>1053</td>
<td>1037</td>
<td>1089</td>
<td>593</td>
<td>972</td>
<td>1974</td>
<td>837</td>
<td>1227</td>
<td>993</td>
<td>995</td>
<td>860</td>
<td>1142</td>
</tr>
<tr>
<td>Dog PIECE</td>
<td>1029</td>
<td>986</td>
<td>1044</td>
<td>913</td>
<td>1086</td>
<td>987</td>
<td>986</td>
<td>1005</td>
<td>874</td>
<td>1020</td>
<td>510</td>
<td>871</td>
<td>989</td>
<td>868</td>
<td>1001</td>
<td>1118</td>
</tr>
<tr>
<td>Elephant PIECE</td>
<td>1008</td>
<td>1227</td>
<td>825</td>
<td>1014</td>
<td>922</td>
<td>1020</td>
<td>1031</td>
<td>1096</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**TABLE II**

<table>
<thead>
<tr>
<th>Cat PIECE</th>
<th>1500</th>
<th>1500</th>
<th>1474</th>
<th>1498</th>
<th>1500</th>
<th>1490</th>
<th>1500</th>
<th>1500</th>
<th>1500</th>
<th>1500</th>
<th>1500</th>
<th>1500</th>
<th>1500</th>
<th>1500</th>
<th>1500</th>
<th>1500</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dog PIECE</td>
<td>1500</td>
<td>1500</td>
<td>1467</td>
<td>1502</td>
<td>1495</td>
<td>1592</td>
<td>1501</td>
<td>1500</td>
<td>1500</td>
<td>1500</td>
<td>1500</td>
<td>1500</td>
<td>1500</td>
<td>1500</td>
<td>1500</td>
<td></td>
</tr>
<tr>
<td>Elephant PIECE</td>
<td>1500</td>
<td>1498</td>
<td>1512</td>
<td>1485</td>
<td>1624</td>
<td>1521</td>
<td>1500</td>
<td>1500</td>
<td>1500</td>
<td>1500</td>
<td>1500</td>
<td>1500</td>
<td></td>
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</tr>
</tbody>
</table>

The weight training result for showed in TABLE I did not clarify the trend to move rabbit since it is generally used as the wall to defend the goal for the long time in a game. So, the trained weight reveals the trend for the rabbit is not to move forward. And, this can lead to the poor effectiveness in attacking the goal.

From TABLE II and III, Cats and dogs piece were likely to be a defense pieces because of their weakness. The trained weights showed the trend that cats and dogs value was relatively high when they are next to the trap. This maybe because players usually use cats and dogs to grant controls the trap of their own side to prevent capturing threat when the strong pieces are attacking.

Horses, Camels, and Elephant were classified as the attacker class due to the strength. The result of weight training from TABLE IV,V,VI may not obviously showed how the pieces were likely to be moved but it can be considered that those attacking pieces were played in the center of the board. The values of weight on the edges of the board were not changed compared to the center.

Since the weight training process consumes an enormous amount of time until finish, with the specified period of time, only few data were used for the weight training. So, the limited data amount leads to the result which may not reveal some significant meaning and still far from our expectation. However, we believed that with the bonanza method, the increasing amount of data trained will lead to the better evaluation function. Also, the more pattern or strategy can still achievable.

**D. Match Test**

After the weight training was finished, the locally arranged Arimaa game was performed in order to test whether how the evaluation really does and how it affects the game play.

The original Bot_Faerie was selected to be a competitor to our developed program. The match was performed locally with no time
limit for thinking. On the Arimaa website, Bot_Faerie with the alpha-beta-Search and the piece material evaluation function was rated as the average beginner player level.

At the start of the match, Bot_Faerie pretended to make moves that scatter the piece to many directions. The pieces were move into the opponent side by greatly distance. On the other hand, our own developed program were not pretended to advance pieces toward the opponent side, instead the pieces move like a group.

Unfortunately, due to our bonanza evaluation function was way too early to be used the match result in the lost to Bot_Faerie. See in the figure 4, the late game state of our developed program was not really changed compared to the start position. Besides, the rabbit pieces always stayed in own side and are not going to attack the goal as the enemy did. Despite the poor attack, our own developed program had done well on the defense against the opponent rabbits. Still, with only defense, it cannot surpass the Bot_Faerie at this time. This maybe because the weight was not appropriated trained yet. It required more game training. We think that given a certain amount of recorded data trained, bonanza method can be able to evaluate position more accurately and can surpass Bot_Faerie in the future.

IV. CONCLUSION

The idea of the bonanza method known as the state of the art machine learning algorithm in Japanese chess field, was studied the possibility to apply to capable with the game of Arimaa which required the more sophisticated evaluation function due to its deep in strategy. The idea is to find the evaluation function that can evaluate the quality of a move compared to the move the human expert does. Using a set of feature, (in this work, piece position, type) the weight of the evaluation function were trained based on the game recorded of the professional player. The process of training consumes time and certain amount of data in order to create a good evaluation function.

Using the bonanza method, the well-trained Arimaa program was expected to be able to determine whether moving a piece to given position is advantage or not. This includes the material advantage and position advantage.

With the limited time constraint, our Arimaa program using bonanza supervised machine learning algorithm for the evaluation was unable to win against the test program. However, with the certain amount of game record trained we think our own developed program can surpasses the test program and given the preferable result using the designed feature.

There are many ways to improve our own developed program. For example, the feature used in the program can be extended to the 2 pieces relationship, 3 pieces relationship. With the same set of train data, considering relation between pieces has the higher expectation to be way to improve the evaluation.

Some search improvement like probcut \cite{6}, etc. can be added into the program in order to reduce the time in searching positions by pruning the sub tree that does not affect the minimax value.

V. REFERENCE


\[4\] Arimaa Game Archive, Retrieve 2012/01/09, From “www.arimaa.com/arimaa/”

\[5\] Arimaa Sample C Bot (bot_faerie), Retrieve 2012/01/09, From “www.arimaa.com/arimaa/”