

AI Strategy Approach Development on Baghchal using AlphaZero

Rajendra Bahadur Thapa
Gandaki College of Engineering and Science
Pokhara University.
rajendra@gces.edu.np

Laxmi Kanta Poudel
Gandaki College of Engineering and Science
Pokhara University
be2020se732@gces.edu.np

Article History:

Received: 30 July 2024

Revised: 24 August 2024

Accepted: 14 November 2024

Keywords—Baghchal, Tiger - Goat, Heuristic, AlphaZero, Monte Carlo Tree Search.

Abstract—Baghchal, a traditional Nepali board game, involves strategic moves between tigers and goats on a 5x5 grid. The inscribed game board can be found in wooden structures or stone slabs in public places. Like every traditional game Baghchal is available in computer games. This paper implies the heuristic method and its enhancement with AI strategy. The heuristic method focused on evaluating tiger positions, movement patterns, and blocking strategies. In contrast, the Monte Carlo Tree Search (MCTS) approach used probability outcomes from multiple game simulations to optimize moves. The efficacy of heuristic patterns is derived from experienced players' game-play and compared them with the computationally intensive approach of MCTS employed by AlphaZero. The findings indicate that while the heuristic approach can create a competitive bot, it has limitations in recognizing win/lose conditions early. The MCTS method provides a more robust strategy by averaging position evaluations over sub-trees. Through 20,000 simulated games, it is observed that tigers have an initial advantage, but optimal play can lead to draw. This dual approach offers comprehensive insights into Baghchal game-play, suggesting that combining heuristics with MCTS could enhance strategic decision-making in similar asymmetric board games.

I. INTRODUCTION

In most of the chautaris of hilly regions of Nepal, Baghchal game board is inscribed in the stone slab. The Baghchal board has 5x5 grids which are interconnected creating 25 intersection points where the game pieces are placed as in figure 1. The game pieces consist of four tiger pieces and 20 goat pieces which can move along the lines from one point to another. One player controls four tigers while the other player controls 20 goats. Baghchal is an asymmetric as the rivals use weapons with different characteristics, in a way used in the days of Roman gladiator combat [1].

The objective for the player who plays the tiger is to capture five goats by jumping over the goats while the objective for the player who controls the goats is to gridlock the tigers so that they do not have any legal moves left. Baghchal (bagh c⁻al, in Nepali language) also called dhun

ka⁻sa, in Newari or Nepal Bhasa. It shows the relationship between predator and prey. Tiger commonly called as king of jungle in asian countries [2]. Nowadays this game has gain certain attraction through mobile apps as well[3].

Baghchal with different board structure but similar pieces and legal move is observed in southern India, probably showing its diversity and evolution in different geological places. Baghchal can be a symbiotic between mathematics and culture. It could be a great tool to teach mathematical concepts like Pythagoras theorem, infinite series and centroid [4]. BaghChal is being approached from two corners of game theory. In Heuristic approach, game-play of different experienced players is analyzed and tried to model it into certain patterns out of their gameplay and configure it into a bot. And in Monte Carlo approach, probability of outcome of many game-play is calculated from game

point of view and made moves based upon the calculated values. Some dynamics of the game such as Asymmetry of board configuration as the game progresses, Win-Lose ratio, Adaptability and learning potential of two approaches and cost/efficiency of them is being analyzed.

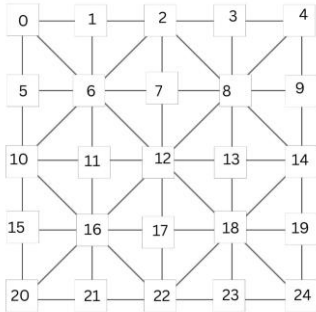


Fig. 1. Board structure of Baghchal with numeric positions

A. Rules:

- There are 4 tigers and 20 goats. Tigers are placed at 4 corners and goat is placed sequentially till 20 goats are placed in sequence. [1]
- Goat moves to its nearest adjacent position shown by the grid line.
- A tiger can slide from his current spot to any empty spot that is adjacent and connected by a line.
- If the landing area beyond the goat is empty, a tiger may leap in a straight line over any single neighboring goat, killing it i.e. removing it from the board [1].
- Goat wins when tigers have no legal move available.
- Tiger wins when 5 goats are killed.

II. METHODOLOGY

In chess, a standard metric for measuring player performance is the Elo rating system [5] [6]. However, in Baghchal, no widely accepted measurement techniques exist, and there is a lack of available gameplay data for training or benchmarking. To address this, we created random-playing algorithms for benchmarking. Heuristic-based strategies led to biases such as pre-programmed strategic bias, handcrafted feature bias, and over-fitting to specific scenarios. Random-playing algorithms helped reduce some of those biases. However, they still fail to simulate real-world decision-making. Random algorithms were simulated multiple times to minimize these biases in the study.

A. Heruistic Rules

Game-play of experienced players is analyzed and patterns are drawn which decides for the upcoming outcomes. Some of the questions analyzed are as follow:

- How many positions can a tiger oversee/influence directly or indirectly?

- How evenly tigers are distributed?
- How fast can they evenly distribute on board after they capture a goat?

Statistical analysis on these observation to produce a rule of thumb. Some of the metrics being used were:

- Frequency analysis.
- Sequential analysis (Markov Chain analysis or probabilities between states).
- Human observation.

B. Monte Carlo Tree Search (MCTS)

MCTS originally appeared as an algorithm for creating computer players in Go by Kocsis, Szepesvari, and Coulom. [7]. MCTS is a heuristic search algorithm for decision processes mainly popular in game theory. The method relies on intelligent tree search that balances exploration and exploitation [7]. It combines the precision of tree search with the generality of random sampling to explore the decision state space as shown in figure 2 [8]. The Upper Confidence Bounds for Tree(UCT) is given by equation (1).

$$UCT = \frac{w_i}{n_i} + c\sqrt{\frac{\ln N}{n_i}} \quad (1)$$

where:

- w_i is the number of wins for the node,
- n_i is the number of simulations for the node,
- N is the total number of simulations for the parent node,
- c is the exploration parameter (commonly set to $\sqrt{2}$)

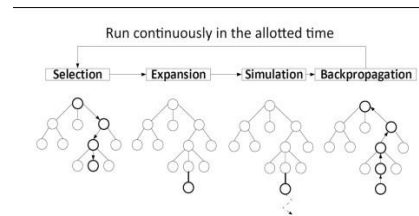


Fig. 2. Monte Carlo Tree Search [7].

C. AlphaZero

AlphaZero combines the value and policy or probability for each nodes in the upper confidence bound for trees with action functions as shown in equations 2, 3, 4, 5 and 6.

1. Value and Policy Network Outputs:

$$(\mathbf{p}, v) = f_{\theta}(s) \quad (2)$$

where:

- $\mathbf{p}$ is a vector of move probabilities.
- v is the estimated value of the position (probability of winning) [9].

2. Updated Upper Confidence Bound for Trees (UCB):

$$UCB = \frac{w_i}{n_i} + P_i c \sqrt{\frac{N}{1 + n_i}} \quad (3)$$

where:

w_i is the number of wins for the node,

n_i is the number of simulations for the node,

P_i is the prior probability from the policy network,

N is the total number of simulations for the parent node,

c is the exploration parameter.

3. Action-Value Function (Q-value) Update:

$$Q(s, a) \leftarrow \frac{1}{N(s, a)} \left(R(s, a) + \sum_{s'} \gamma V(s') \right) \quad (4)$$

where:

$R(s, a)$ is the reward for action a in state s ,

$V(s')$ is the value of the resulting state s' , γ is the discount factor.

4. Policy Improvement:

$$\pi(a|s) = \frac{N(s, a)}{\sum_b N(s, b)} \quad (5)$$

This target policy is used to update the neural network.

5. Loss Function:

$$l(\theta) = (z - v)^2 - \pi^T \log \mathbf{p} + c \|\theta\|^2 \quad (6)$$

where:

z is the actual game outcome,

v is the value prediction from the network,

π is the target policy,

$\mathbf{p}$ is the policy prediction from the network,

$c \|\theta\|^2$ is an L_2 regularization term.

D. Game tree complexity analysis:

For each of a number of random paths from the root to a leaf, we evaluate the quantity

$$F = 1 + f_1 + f_1 f_2 + f_1 f_2 f_3 + \dots, \quad (7)$$

where f_j is the fan out, or the number of children, of the node at level j encountered along this path [1].

III. HEURISTIC OBSERVATION

Some heuristic rules of thumb observed were: Strength of tiger at different position: Tiger at central position (12) is highly advantageous towards the end of placement phase and sliding phase of the game. It can oversight eight different positions on the board.

- Tigers placed centrally along a the edge (location 2 and its symmetry) provide next advantageous position.
- Tigers placed at 6th, 8th and 4th position have similar positional advantages. Their advantages follow the same order.
- 1st position is considered the least favorable because it has limited visibility and can only monitor up to two positions on the board. Tigers are often observed to become trapped when positioned in this area of the board.

- 2) The observed findings indicate that consuming goats is primarily advantageous for tigers. This action not only reduces the number of goats but also augments the number of vacant positions on the board. Predominantly, consuming goats significantly elevates the tiger's chances of winning.
- 3) The second most favorable move for the tiger is to fork two goats to threaten. If tiger forks two goat for potential eat then it have a surety to eat at least one of them.
- 4) There is a sure eat condition. so it's better and more favorable for the tiger. It will sure eat the goat placed at 16th position.
- 5) Blockage using 4, 3 and 2 tigers: There are patterns of 4, 3 and 2 tigers to form a interlocking structure for goats. It not only influence the goat placement but also effect the sliding of goats. Representative conditions are shown in Fig. 3.
- 6) Goat is lost if the first move is not the central of an outside edge.
- 7) Goat's strategy sounds simple: first populate the borders, and when at full strength, try to advance in unbroken formation, in the hope of suffocating the tigers as in fig 5 [1].

A. Limitations:

- 1) For condition 2 described above, there are instances where capturing a goat can significantly diminish the likelihood of winning, and one of these situations is shown in the diagram below in fig 3.

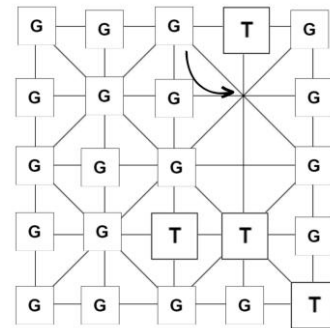


Fig. 3. Condition for baghchal game at last situation 1.

- 2) Under these circumstances, the tiger emerges victorious since the goat has no valid moves to execute. This stands as the sole constraint for the tiger's win through capturing all five goats. The straightforward and heuristic approach, when employed in such scenarios, fails to recognize the winning position for the tiger as shown in fig 4.

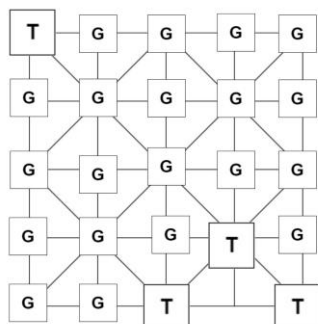


Fig. 4. Condition for baghchal game at last situation 2

- 3) Under this circumstance, the tiger faces defeat because when a goat is positioned in the center of the board, the tiger loses even before all 20 goats are placed. The straightforward and heuristic approach, when applied in such situations, does not have the capability to preemptively identify and prevent these types of scenarios.

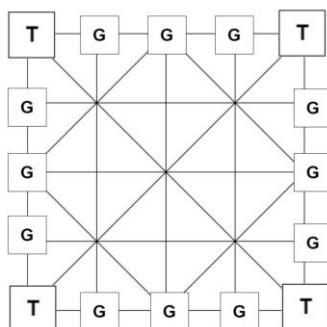


Fig. 5. Goats positioning at the borders.

IV. RESULTS AND FINDINGS

some assumptions and scenarios of heuristic vs human study:

- Program was exhibited at 9th IT EXPO of Gandaki College Of Engineering and Science [13].
- People trying were average in their game-play, mostly comprised of +2 students, Engineering students and visitors at EXPO.
- When people were introduced to MCTS bot, none of them were able to make a win, some were able to force draw the computer bot. The result of the game-play between human vs heuristic bot is shown in table I. Out of 350 game-play, bot won 52%, 34% was draw and only 13% human won the game-lay.

TABLE I AVERAGE HUMAN VS HEURISTIC BOT.

Total games played	bot win	draw	bot loose
350	183	119	48

When developing a bot with moderate performance expectations, instead of employing a computationally intensive method and fine-tuning it, we can opt for a trade-off by choosing a slightly less resource demanding heuristic method. This allows us to balance a satisfactory level of quality while simultaneously saving both time and computational resources. On head-to-head with heuristic and MCTS, on every encounter MCTS made a wide-margin win.

- Placing a goat else than center of edge for the first move always leads to the capture.
- When played optimally tiger can force a capture at placement phase and force another capture at starting of sliding phases.
- On analysis on heuristic approach, it can be concluded that winning of goat drastically decreases when 3 or more goats are capture. There still remains the chances of repeated movement in cantonment (empty area surrounded by goat and goat can make a movement in this area to escape immediate capture by tiger) area to prevent further loss and force to draw. This is only possible if the center of the board is captured by goat.
- When 4 goats are captured (in some cases 3 goats) there will be enough spaces in board to make a movement for goat and tigers can not make pressure to each and every vacant position available. Although Tiger is in upper hand in these kind of scenario but goat still have chances to draw, the best move for tigers in these kind of situation will be to let goat form a cantonment in position like 1 or its symmetrical position with central position captured by tiger.

Over 20,000 games were played to analyze the winloss ratio. The percentages were rounded to their nearest stable values and then plotted. A specific random board position, along with the number of goats captured, was provided, and the gameplay was simulated from that point. Higher-order goat captures were generated and simulated based on this board setup, rather than forcing

Probability and plotting

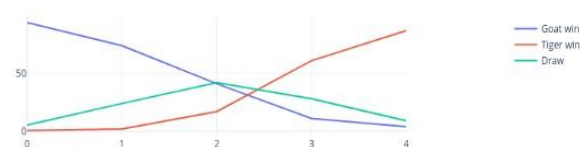


Fig. 6. Game-play win status with respect to the number of goats killed

the game to create such structures. The forced draw bias condition was minimized, as it would result in frequent draws due to gameplay in the cantonment areas. The results are summarized in Table II below:

TABLE II RESULT OF GAMEPLAY WITH ALPAZERO BOT

Number of goat captured	Tiger win	Draw	goat win
0	0.6%	5.4%	94%
1	2%	24%	74%
2	21%	42%	37%
3	61%	28%	11%
4	87%	9%	4%

It is observed that tiger is slightly powerful in initial state of game-play because it can force 2 goat capture. But analyzing the above table, we can conclude that tiger's win, draw and loose is 21%,42% and37% respectively on 2 goats capture. So the position of tigers and central area governance play the vital role in determining the win and loose of the game.

When played optimally there is always a option to force draw. Tiger can force two captures while placing phase and starting of sliding phase which is shown in fig 6. It is seen that after 2 goats are being killed the probability's of tiger and goat will be 50-50. The more goats being killed,probability of winning of goat decreases. Alternatively,there will be increase in the tiger winning probability.

V. CONCLUSION

Baghchal game has many symmetric position like 4 corners ,8 next to corners, etc. except the central position. But for the moves, central position also involves 8 similar moves. Unlike other games like chess, baghchal can be easily tweaked by computational intelligence. Heuristic approach could not decide win or loose in advance but are efficient in computational resources. The result based on AI approach using MTCS powered by AlphaZero implementation showed after 2 goats captured, the probability of tiger and goat wining will be 50-50. The more goats being captured, the probability of winning of goat decreases as tiger win will be declared after 5 goats being captured. On simple and moderate game mode,heuristic method will be recommended whereas AI strategy like AlphaZero in advanced mode of game-play.

VI. LIMITATIONS AND FURTHER WORK

limitation of this study is that we were unable to create a completely bias-free benchmarking system, as discussed in the methodology section. Although MCTS demonstrates positional play, where the tiger prioritizes a stronger board position over immediate actions like capturing a goat and employs both strategic sacrifices (delaying immediate gains like capturing a goat to achieve a greater long-term

advantage) and positional sacrifices (foregoing short-term actions to improve overall control of the board for future moves), these factors were not accounted for in our statistical and mathematical analysis.

REFERENCES

- [1] L. Y. Jin and J. Nievergelt, "Tigers and Goats is a draw"Games of No Chance III, Proc. BIRS Workshop on Combinatorial Games"pp.163176, 2005.
- [2] C. S. Gutierrez-Perera, et al." Play in Scientific and Mathematical' Non-Formal Education. Bagh Chal, a Tigers-and-Goats Game"European Proceedings of Social and Behavioural Sciences",Future Academy 2016.
- [3] P. Shouthiri, "Tigers and goats a board game for android"International Journal of Scientific and Research Publications" vol 7,no. 10, pp 59-64, 2017.
- [4] J. B. Pradhan,"Symbiosis between mathemaCCCs and cultural game: A Nepalese experience,"Retrieved from Research Gate: <https://www.researchgate.net/publication/331233688>,"2019.
- [5] M. E. Glickman and A. C. Jones "Rating the chess rating system, "CHANGBERLIN THEN NEW YORK, "SPRINGER INTERNA TIONAL, vol 12, pp 228, 1999.
- [6] A. Berg, "Statistical analysis of the elo rating system in chess, "Chance, ", Taylor & Francis," vol 33, pp 3438, 2020.
- [7] M. Swiechowski, et al. "Monte Carlo tree search: A review of recent modifications and applications, " Artificial Intelligence Review, Springer, vol 56, no. 3, pp 2497-2562, 2023.
- [8] C. Browne, et al. "A Survey of Monte Carlo Tree Search Methods, "IEEE Transactions on Computational Intelligence and AI in Games," vol 4:1, pp 1-43, 2012 doi 10.1109/TCIAIG.2012.2186810.
- [9] D. Silver, et al.,"Mastering the game of Go with deep neural networks and tree search,"nature,"Nature Publishing Group," vol 529, pp 484 - 489, 2016.
- [10] D. Silver, H. Thomas, et al.,"Mastering chess and shogi by selfplay with a general reinforcement learning algorithm" arXiv preprint arXiv:1712.01815" 2017.
- [11] S. Agarwal and I. Hiroyuki,"Analyzing Thousand Years Old Game Tigers and Goats is Still Alive"Asia-Pacific Journal of Information Technology and Multimedia"2018.
- [12] C. B. Browne, et. al"A survey of monte carlo tree search methods"IEEE Transactions on Computational Intelligence and AI in games,"IEEE, vol 4, pp 1-43, 2012.
- [13] collegenp.com, "Ninth GCES IT Exp2080: Showcasing Talent and Creativity in Information Technology," 2023 -06-09," <https://www.collegenp.com/event/ninth-gces-it-expo-2080-showcasingtalent-and-creativity-in-information-technology/>.