Analysis of different approaches to video game bots based on bot bowl competition

Jakub Stolarski, Piotr Olechno, Mateusz Gietka, Dr Krzysztof Hryniów

Warsaw University of Technology, Department of Elecrtical Engineering, Poland

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Abstract

The paper explores different solutions for implementing self-learning artificial intelligence (AI) competitive bots for the game Blood Bowl. The winners of the most of the previous competitions were scripted bots but in recent years bots based on machine learning started to outspace their competition. Blood Bowl is a two-player, turn-based, asymmetric board game that combines elements of American football with the Warhammer board game. Teams consist of eleven to sixteen players, each of them having varying configurations of five main statistics: move allowance, strength, agility, armor value, and passing. The main goal is to score a higher takedown number than the opponent. This paper's primary objective is to develop a sophisticated AI agent capable of participating in the Bot Bowl Tournament and competing against other state-of-the-art bots. The research focuses on exploring behavioral cloning solutions created by using an in-depth analysis of games played in previous tournaments to vastly improve both the win ratio and complexity of moves employed by the bot. Using wrappers and scripted actions enhances the efficiency and effectiveness of the AI's learning mechanisms. By leveraging insights acquired from past gameplay data and employing advanced machine learning techniques, this research seeks to contribute to the advancement of AI in competitive gaming environments.

1 Introduction

Artificial Intelligence (AI) has continually pushed the boundaries of what computers can achieve in various domains, and gaming serves as a particularly fertile ground for AI research and development. Games provide structured environments where AI algorithms can be tested, refined, and ultimately showcased. From classics like Chess and Go to modern video games, AI has made remarkable strides in mastering complex gaming scenarios. However, not all games are created equal in the eyes of AI. While some games may seem straightforward for AI to master, others present unique challenges that demand innovative approaches[1, 2]. That is why Blood Bowl, a captivating fusion of American football and the Warhammer universe, offers a fresh and intriguing challenge for AI enthusiasts. Blood Bowl is a fully-observable, stochastic, turn-based experience played on a grid-based board. Each player controls a team of eleven to sixteen players, each with its own set of statistics and abilities. The objective is to outmaneuver, outsmart, and outscore the opponent by skillfully navigating the chaos of the battlefield. The sheer complexity of Blood Bowl poses a significant challenge for traditional AI algorithms. The action space in Blood Bowl varies from 1 to 395, with coaches often selecting between dice results or squares on the board, and each player action involving choosing from adjacent squares or action types, resulting in a vast number of unique action sequences and an average turn-wise branching factor estimated at 10^{50}, surpassing those in Chess (30) and Go (300). The game's branching factor is staggering, with each turn offering countless possibilities for movement, strategy, and interaction. Furthermore, scoring points is rare and challenging, making it hard to create effective strategies or use typical reinforcement learning methods. In response to this challenge, our research endeavors to pioneer AI solutions capable of mastering Blood Bowl's intricacies and competing at the highest levels. Drawing inspiration from recent advancements in deep reinforcement learning and behavioral cloning, we aim to develop sophisticated AI agents primed for success in the Bot Bowl Tournament. Our approach leverages a fusion of machine learning techniques and analysis of past gameplay data. We aim to teach our AI agents the strategies of experienced Blood Bowl players, helping them make smart choices and perform complicated moves accurately. Central to our methodology is the utilization of behavioural cloning, which streamlines the learning process and enhance the efficiency of our AI's decision-making mechanisms. By analyzing a lot of gameplay data, we aim to make our AI agents smarter and more adaptable for them to excel in competitive gaming.

2 Previous solutions

Before the explosion of popularity of AI solutions, the primary method for developing Blood Bowl bots was through the creation of scripted game logic by knowledgable game masters with profound understanding of the game nuances. This traditional approach relied on scripts, heuristics, and occasionally, reinforcement learning[3]. A good example of such methodology was Grodbot, a scripted bot slightly surpassing a rookie player's capabilities. Grodbot meticulously evaluated moves based on success probabilities, employing pathfinding and heuristic values to determine actions such as receiving, defense, and fouling. In a head-to-head assessment against a random bot, GrodBot emerged victorious in all ten games, while its counterpart failed to score a single touchdown. An alternative path in the development of Blood Bowl bots involved the exploration of search-based algorithms, notably employing Monte Carlo search[4, 5]. Despite their potential, these methods failed to gather bigger publicity. Furthermore, reinforcement learning emerged as a promising way for addressing the limitations of previous bot designs and harnessing the prowess of AI to create the ultimate bot. Initially, reinforcement learning solutions struggled to compete with other bot variants. However, this changed with the publication of Mimicbot, which harnessed the innovative approach of behavioral cloning. Mimicbot swiftly established itself as the most promising bot solution, outclassing its predecessors with unparalleled game skill and accuracy.

3 Metodology

In our study, in addition to leveraging the successes of MimicBot, we implemented several key modifications to enhance the performance and efficiency of our bot. One such adaptation involved adjusting the rewards and punishments within our reinforcement learning routine. We adjusted rewards to encourage positive actions more, creating a better learning environment for our bot. We also simplified decision-making by adding a scripted action wrapper to handle routine actions tasks that were deemed less critical, such as rerolling the dice or determining starting positions. This allowed the bot to focus its cognitive resources on more substantial strategic considerations. By simplifying the action space in this manner, we aimed to speed up the learning process and enhance overall performance. Moreover, we incorporated an enemy switching mechanism into our training program to diversify and intensify the learning experience. This mechanism involved alternating between different adversaries during training sessions, including a scripted bot, a random bot, and previous iterations of our own bot. By exposing our bot to a range of opponents with varying degrees of complexity and unpredictability, we sought to cultivate robust adaptability and decision-making capabilities. Through these strategic adjustments and iterative refinements, our methodology evolved into a comprehensive framework poised to tackle the challenges inherent in the task at hand. By integrating insights from MimicBot's successes and implementing innovative adaptations, we allowed our bot to achieve optimal performance and surpass existing benchmark bots within the Blood Bowl domain.

4 Results

The baseline bot exhibited limited proficiency in the task of full-board gameplay, struggling to acquire points irrespective of adjustments made to reward values. Despite occasional successes, its performance fell short to satisfactory levels, indicating the need for further research. Expanding the neural network architecture caused positive improvements in the bot's performance. While it demonstrated an increased ability to score points, its effectiveness remained constrained within certain bounds, failing to achieve optimal results. Incorporating a novel learning methodology, we engaged in match play with opponents, alternating between random and scripted bot adversaries. The graphs below show the win and touchdown rates attained during the training cycle of this bot iteration.

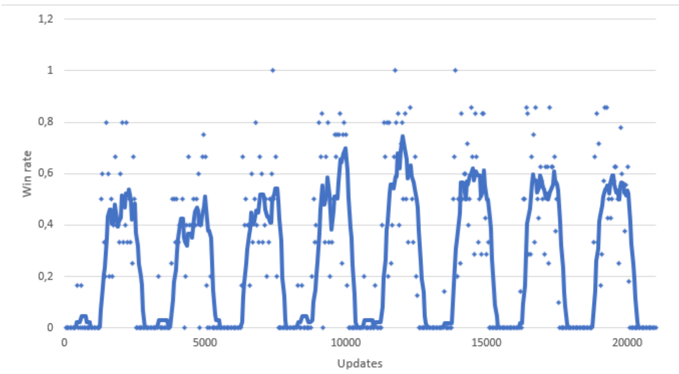

Figure 1. Win rate with alternating opponents.

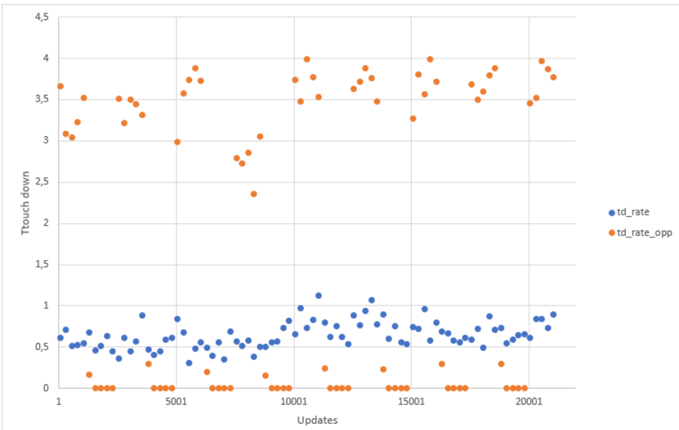

Figure 2. Touchdown rate with alternating opponents.

The graphs illustrate our bot's notable success in confrontation with random bot. However, it also shows considerable challenges in achieving victories when confronted with scripted adversary. The problem was addressed by incorporating behavioral cloning to the training routine. With that the bot rapidly acquired solid set of gameplay skills allowing it to increase the win rate while playing the scripted bot to about 0.33 which was shown on the graphs below.

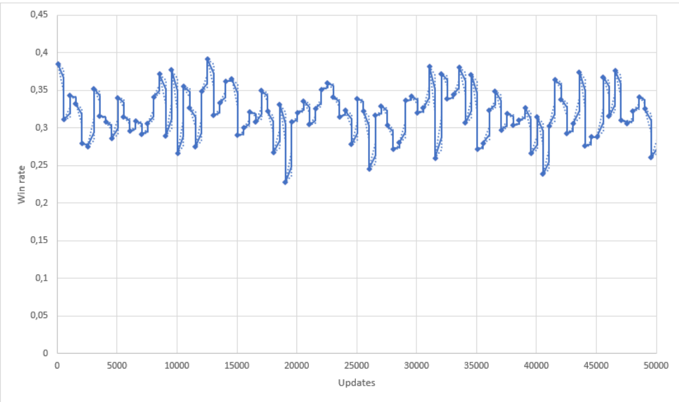

Figure 3. Win rate with scripted bot after behavioral cloning.

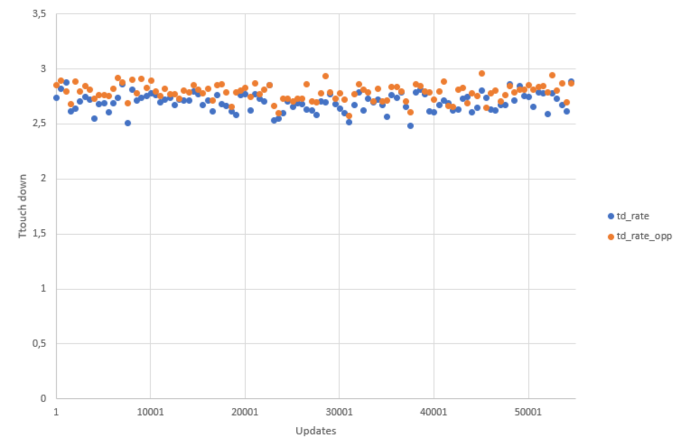

Figure 4. Touchdown rate with scripted bot after behavioral cloning.

The 5:1 ratio of behavioural cloning during the reinforcement learning allowed the bot swiftly reach success with the scripted opponent. Assigning it to more and more difficult challenges revealed its capacity for continuous improvement, particularly when confronted with challenges such as descending point-scoring opportunities during training. Overall, our findings underscore the importance of a holistic approach to reinforcement learning, where methodological innovations play a crucial role in improving the bot performance. Through strategic adaptation and iterative refinement, our bot not only mastered the fundamentals of gameplay but also demonstrated resilience and adaptability in evolving environments. These results signify a major advancement in the domain, laying the groundwork for further exploration and innovation in reinforcement learning methodologies. The research highlighted how different learning methods can affect game bots performance, emphasizing the importance of innovative methods in improving AI capabilities and paving the way for future advancements in artificial intelligence.

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