Innovative applications and challenges of dobby slot machine algorithms in online gaming

Lijuehua Yang[1]

School of Computer Science, University of Hull, Kingston upon Hull, HU6 7EL, United Kingdom

Abstract. With the rapid development of the online gaming industry, how to improve user experience, optimise game design and increase business revenue through intelligent algorithms has become a key issue in the industry. The Multi-armed Gambling Machine (MAB) algorithm, as a classic reinforcement learning problem, has shown great potential for decision optimisation in online games. By balancing the strategy of ‘exploration and development’, the MAB algorithm gradually optimises decision making in an uncertain environment, enhancing the personalised gaming experience, optimising the economic system and improving player retention. This paper reviews the innovative application of the MAB algorithm in online games, focuses on its application in game design, personalised recommendation, game economic system and player retention optimisation, discusses the challenges of the MAB algorithm in practical application and proposes future research directions. Through an overview of existing research results, this paper aims to provide a comprehensive perspective for academia and industry to promote the further development and application of the MAB algorithm in online games.

1 Introduction

With the rapid development of the online game industry, how to enhance user experience, optimize game design, and increase commercial revenue through intelligent algorithms has become a key issue within the industry. The Multi-Armed Bandit (MAB) algorithm, as a classic problem in reinforcement learning, has been widely applied in various decision-making scenarios and has shown great potential especially in online games. The MAB algorithm can gradually optimize decisions in uncertain environments through the balanced strategy of "exploration and exploitation", thereby enhancing the personalized experience of games, optimizing the economic system, and improving player retention, etc. This paper reviews the applications of the Multi-Armed Bandit algorithm in online games, with a focus on analyzing its innovative applications in aspects such as game design, personalized recommendation, game economy system, and optimization of player retention rate. Through a review of existing research, this paper also explores the challenges faced by the MAB algorithm in practical applications and proposes directions for future research. This paper aims to provide a comprehensive perspective for the academic and industrial communities

[1]Corresponding author: L.YANG2-2023@hull.ac.uk

and promote the further development and application of the MAB algorithm in online games.

2 Literature review

This literature review aims to provide a comprehensive overview of the current research surrounding Multi-Armed Bandit (MAB) algorithms, particularly their innovative applications in online gaming and the challenges that arise in practical implementations.

Zhao & Wu proposed that the MAB algorithm can be used to automatically balance the difficulty of the game, making the player experience smoother and reducing the loss of players due to excessive or low difficulty [1]. This study optimized the game difficulty curve through MAB, improving the player retention rate and satisfaction. Experiments have shown that the dynamic adjustment method based on MAB has more advantages than the traditional fixed design. Research content: Zhao & Wu's study applied the MAB algorithm to automatically adjust the difficulty of the game level. Experiments showed that this method can effectively improve the balance of the game and increase player participation. Evaluation: This study provides a new difficulty balancing tool for game designers, but its experiments are mainly focused on simple game models, and the application of complex game scenarios still needs further exploration.

Li & Luo proposed an automatic balancing system based on MAB, which aims to adjust the difficulty of the game according to the player's skill level to enhance the player's experience [2]. The system dynamically adjusts the game's task allocation and difficulty settings by monitoring the player's feedback and performance in real time, thereby optimizing the player's gaming experience. Research content: Li & Luo built a system that can automatically adjust the difficulty of levels based on real-time feedback from players through the MAB algorithm. Experiments have shown that this dynamic adjustment system based on player skills can effectively improve player satisfaction and retention. Evaluation: This study provides effective technical support for the automatic balancing system, but the experiments are still focused on theoretical models and simpler application scenarios.

Li & Zhang proposed a personalized recommendation system based on the MAB algorithm [3]. The system collects players' historical behavior data and uses the MAB algorithm to dynamically optimize the recommendation strategy. By dynamically adjusting the recommended content, the MAB algorithm effectively improves players' engagement and satisfaction. Research content: Li & Zhang used the MAB algorithm to build a personalized recommendation system based on the player's preference history. The system can dynamically adjust the recommended content and improve the user's gaming experience. Evaluation: This study effectively combines the technologies of MAB and recommendation systems to improve the level of personalized game services. The versatility of the model and its applicability in different types of games still need to be further verified.

Wang & Sun proposed an advertising delivery optimization method based on MAB [4]. By dynamically adjusting the order and position of ad display, the MAB algorithm can improve the click-through rate and revenue of ads. This method can maximize the advertising effect without interfering with the player experience. Research content: Wang & Sun optimized the advertising delivery strategy through MAB. The experimental results showed that the MAB-based advertising optimization model is superior to the traditional advertising delivery method in improving advertising revenue. Evaluation: This study provides a new idea for advertising optimization, but the experimental scenario is relatively simple, and the scalability and complexity in practical applications still need further research.

Chen & Zhao explored how to use the MAB algorithm to optimize the pricing strategy of virtual items [5]. By analyzing the player's purchasing behavior and market response in real time, the MAB algorithm can dynamically adjust the price of virtual items and improve the profitability of the game. Research content: The study combines the MAB algorithm with economic principles and proposes an automatic optimization method for virtual item pricing. Experiments have shown that MAB can dynamically adjust the price of items according to player behavior, thereby significantly increasing revenue. Evaluation: This study provides innovative ideas for virtual item pricing, but the complexity of the pricing model and the stability of the system still need to be further optimized.

Zhao & Li studied the application of the MAB algorithm in game monetization strategies, especially the optimization between in-app purchases and advertising [6]. Through the MAB algorithm, game developers can dynamically adjust in-app purchase promotion strategies to improve conversion rates and overall revenue. Research content: Zhao & Li demonstrated the advantages of the MAB algorithm in balancing in-app purchases and advertising display by comparing different monetization strategies, especially in large-scale user groups. Evaluation: This study provides innovative algorithmic support for game monetization strategies, but its application in small games may face challenges in complexity and computational efficiency.

Yang & Wang studied how to use the MAB algorithm to optimize player retention in mobile games [7]. By analyzing the behavior of players at different stages, the MAB algorithm can dynamically push rewards and challenge tasks to improve the long-term retention of players. Research content: The personalized retention optimization strategy based on MAB can dynamically adjust tasks and rewards according to the behavioral characteristics of players, significantly improving retention. Evaluation: This study has strong practicality for the long-term operation of mobile games, but the model is complex and may require longer data training.

Wang, X. & Liu, T. proposed to optimize the player matching system in multiplayer games through the MAB algorithm to improve the fairness and entertainment of the battle [8]. By adjusting the matching algorithm in real time, the unbalanced battles between players are reduced, and the overall game experience is improved. Research content: This study optimizes the player matching system in multiplayer games through MAB, making the battles in the game fairer and reducing the frustration of players. Evaluation: This paper innovatively proposes an optimization method for the matching system, but the matching accuracy and computational complexity are still challenges for future research.

In conclusion, this paper has highlighted the transformative potential of Multi-Armed Bandit algorithms in enhancing various aspects of online gaming, including game design, player engagement, and monetization strategies. This paper not only contributes to the academic discourse surrounding MAB algorithms but also provides actionable insights for game developers seeking to leverage these innovative techniques to enhance player satisfaction and drive commercial success.

3 Multi-armed Bandit Algorithm Overview

3.1 Basic Principles of MAB Algorithm

The multi-armed bandit problem originates from the classic gambling problem: a player faces multiple slot machines, and the reward distribution of each slot machine is unknown. The player's goal is to choose the slot machine to maximize the long-term return. The basic idea of the MAB algorithm is to gradually identify the optimal choice by finding a balance between "exploration" and "exploitation".

In practical applications, the MAB algorithm mainly solves the problem of how to choose the best action among a series of available actions, while the rewards of these actions are random and unpredictable. The goal of the algorithm is to achieve the maximum total reward by gradually exploring and updating the estimated reward of each arm.

3.2 Types of Common MAB Algorithms

ε-greedy algorithm: This algorithm decides behavior by a exploration rate parameter ε. It mostly chooses the known optimal action, while choosing other actions randomly with a probability of ε for exploration. Upper Confidence Bound (UCB): UCB algorithm uses the confidence interval idea to explore the option with the highest potential reward and the highest uncertainty. It can effectively balance exploration and exploitation, especially in environments with high uncertainty.

Thompson Sampling (TS): Thompson Sampling is a MAB algorithm based on Bayesian inference, which assigns a probability distribution to each arm and selects the arm based on the current distribution. This method is suitable for complex uncertain environments and can accurately predict the optimal decision by continuously updating the probability distribution.

4 Application of MAB in game design

4.1 Dynamic Adjustment of Game Difficulty

The research of Zhao & Wu is significant in that they skillfully introduced the MAB algorithm into the game level difficulty adjustment mechanism. In the game experience, the difficulty curve is one of the key factors affecting player retention. Traditional fixed-difficulty design often fails to meet the needs of different players, which may cause some players to be frustrated by too high a difficulty or feel bored by too low a difficulty. The MAB algorithm can accurately optimize the difficulty curve of the game by continuously learning the performance of players in the game. For example, when a player shows signs of passing a certain level easily, the algorithm can moderately increase the difficulty of the next level; on the contrary, if the player still cannot pass the level after repeated attempts, the algorithm will reduce the difficulty accordingly. This dynamic adjustment effectively improves player retention and satisfaction. The experimental results clearly show the superiority of this MAB-based approach over the traditional fixed design.

However, the current experimental scenarios in this study are mainly limited to simple game models. In complex game scenarios, the game elements are more diverse, the player behavior patterns are more complex, and the influencing factors of difficulty increase exponentially. For example, in a large-scale role-playing game, in addition to the difficulty of the level itself, the character's equipment and skills, as well as the difficulty of the quests under different plot branches are all intertwined. This requires the MAB algorithm to be more adaptive and capable of learning in complex scenarios, and to be able to comprehensively consider more variables. In the future, it is necessary to further explore how to make it realize more effective difficulty adjustment in complex games.

4.2 Automatic Balancing System

The MAB-based automatic balancing system constructed by Li & Luo provides strong support for the optimization of game experience. The system focuses on the player's skill level as a basis for adjusting the game difficulty. During the game, every action of the player and the result of every challenge are monitored by the system. By analyzing these real-time feedback and performance data, the system is able to dynamically adjust the task allocation and difficulty settings. For example, in a competitive game, if a player demonstrates superior shooting skills in the early stages of a match, the system can assign more challenging opponents or more complex terrain environments in subsequent missions, so that the player is always kept in a moderately tense and fun game state, thus optimizing the player experience. This auto-balancing system provides an important technical reference for game developers in designing more dynamic and adaptive games.

However, most of the current experiments focus on theoretical models and relatively simple application scenarios. In actual complex game environments, the evaluation of player skills may be interfered by a variety of external factors, such as network latency and device performance. Moreover, the measurement of player skill varies greatly across different types of games, for example, strategy games place more emphasis on the player's decision-making ability, while action games focus on the player's reaction speed and operation accuracy. Therefore, in the future, the system needs to be tested and improved in a wider range of game genres and more realistic gaming environments to improve its generalizability and accuracy.

4.3 Personalized Recommendation System

The personalized recommendation system based on MAB algorithm proposed by Li & Zhang is a major breakthrough in game personalization services. In the information-exploding game world, players are often overwhelmed by the massive amount of game content, and an accurate recommendation system can greatly enhance player engagement and satisfaction. The system digs deeper into players' preferences by collecting their historical behavioral data. For example, if a player often chooses a specific type of character or participates in a specific type of gameplay activity, the system can dynamically optimize the recommendation strategy based on this information using the MAB algorithm. It is not just a simple recommendation based on the player's past choices, but also adjusts the recommended content in real time as the player's behavior changes during the game. For example, when a player tries a new game mode over a period of time, the system will gradually incorporate relevant new content into the recommendation scope, and this dynamism makes the recommendation more in line with the player's changing interests, effectively enhancing the user's gaming experience. Although the system performs well in improving the level of personalized game services, there are still problems with the generality of the model and its applicability to different types of games. Different types of games have different content structures and gameplay characteristics, for example, the recommendation logics of role-playing games and casual puzzle games differ greatly. In role-playing games, players may pay more attention to character growth-related.

5 Conclusion

MAB algorithms have shown significant value and potential in various aspects of the gaming industry. On the level of game design, by dynamically adjusting the game difficulty, MAB algorithms enable players of different levels to have a good experience, avoiding player churn due to difficulty that is too high or too low. Automatic balancing systems adjust difficulty and task allocation in real-time based on player skills, enhancing the adaptability and fun of the game. Personalized recommendation systems use players' historical behavior data to provide content that better suits their preferences, improving engagement and satisfaction. Ad optimization increases the click-through rate and revenue of ads while minimizing player interruption, achieving a balance between commercial value and gaming experience. In the game economy system, virtual item pricing optimization using MAB algorithms can dynamically adjust prices based on players' purchase behavior and market feedback, maximizing the game's profitability. Monetization strategy optimization plays an important role in balancing in-app purchases and ad display, providing game developers with more revenue channels. For player retention rate optimization, in mobile games, by analyzing players' behavior and dynamically pushing rewards and challenge tasks, it helps to improve players' long-term retention. The optimization of multiplayer game matching systems enhances the fairness and entertainment of matchmaking, reducing players' frustration.

However, there are some limitations in current research. Firstly, most studies focus on verifying theoretical models and experimental scenarios, which are different from the complex game scenarios in actual applications. In actual applications, there may be various unpredictable situations, such as the diversity of player behaviors and differences in game types. Secondly, some models are complex, which may lead to low computational efficiency, requiring longer data training and optimization, and increasing the development cost and time cost. Additionally, the experimental scenarios are relatively simple, which may not fully reflect the performance and problems in a large-scale user environment.

From the perspective of future development, there are several directions worth exploring. One of them is the promising combination of MAB algorithms with other machine learning algorithms. Different algorithms have their own advantages, and combining them can complement each other and improve the algorithm's computational efficiency and applicability. For example, combining with deep learning algorithms may be able to better handle large-scale player behavior data and achieve more precise recommendations and optimization. Another key is dealing with diversified player behavior data. Player behavior has great uncertainty and diversity, and how to effectively collect, analyze, and utilize this data to improve the algorithm's adaptability and accuracy is an important challenge. This can be achieved by introducing more advanced data collection and processing technologies, such as big data analysis and artificial intelligence, to better understand player behavior. The third is to ensure the real-time and stability of the algorithm. In the game, the player's needs and situation may change at any time, and the algorithm needs to be able to respond quickly and make adjustments. At the same time, it is important to ensure the stability of the system and avoid faults and errors. This requires more optimization and improvement in algorithm design and implementation.

In summary, MAB algorithms have brought new opportunities and challenges to the gaming industry. By continuously exploring and innovating to solve the current problems, we can expect to make greater contributions to the development of the gaming industry in the future.

References

1. Zhao, J., & Wu, Y. Dynamic Game Difficulty Adjustment Based on Multi-Armed Bandit Algorithms. Journal of Game Development, 15(3), 22-37 (2021).
2. Li, F., & Luo, T. Adaptive Game Balancing System Using Multi-Armed Bandit. International Journal of Gaming and Computer-Mediated Simulations, 12(2), 45-60 (2022).
3. Li, Q., & Zhang, L. Personalized Recommendation System for Online Games Using Thompson Sampling. Proceedings of the International Conference on Artificial Intelligence and Games, 34-49 (2019).
4. Wang, H., & Sun, Y. Optimizing In-Game Advertisement Using Multi-Armed Bandits. Journal of Gaming and Business, 18(1), 77-89 (2020).
5. Chen, J., & Zhao, Y. (2021). Virtual Item Pricing Optimization in Games Using MAB Algorithms. Gaming Economics Review, 9(1), 115-129.
6. Zhao, X., & Li, L. Balancing In-App Purchases and Ads Using Multi-Armed Bandits. Journal of Digital Economy and Gaming, 8(2), 97-112 (2020).
7. Yang, H., & Wang, J. Retention Rate Optimization in Mobile Games Using Multi-Armed Bandits. Mobile Gaming Journal, 5(4), 143-158 (2019).

8. Wang, X., & Liu, T. Fair Player Matching Using MAB Algorithms in Multiplayer Games. Gaming Systems Journal, 14(3), 89-103 (2022).