Imitation Learning in Games: Teaching AI by Mimicking Expert Human Players

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Abstract

AI transforms virtual gaming by creating more immersive and dynamic experiences through intelligent NPCs, personalized content, procedural generation, enhanced graphics, and adaptive storytelling. AI-driven advancements further amplify this impact, offering richer, more engaging virtual environments and fostering greater player engagement and retention. This paper explores the multifaceted role of AI in gaming, focusing on its capacity for personalization, intelligent non-player character (NPC) behaviour and improved game design. AI tailors gaming experiences to individual player preferences, dynamically adjusting difficulty levels and content recommendations. This paper concludes by emphasizing the transformative potential of AI in gaming, highlighting its role in shaping the future of user experience and engagement in the digital realm. In the field of artificial intelligence, teaching machines to learn and perform tasks has been a long-standing goal. One approach that has gained significant attention is imitation learning, a technique that enables machines to acquire skills by observing and mimicking human behaviour. This research explores the concept of imitation learning, its applications, and the challenges associated with this approach. We discuss the concept, applications, methodologies, and challenges of imitation learning in games and highlight its transformative potential for the future of digital entertainment.

Keywords: Imitation Learning, Artificial Intelligence, Gaming, Human player, Non-player character (NPC)

Introduction

Imitation learning is a machine learning paradigm that trains an AI agent to perform tasks by mimicking demonstrations from an expert, typically a human player. In video games, this technique is used to create realistic and engaging non-player characters (NPCs) that can replicate human-like playstyles, strategies, and behaviours without the need for extensive manual programming or reward-based reinforcement learning. AI enables non-player characters (NPCs) to exhibit more realistic, unpredictable, and adaptive behaviours, making interactions more engaging and lifelike. This can extend to dynamically adjusting game difficulty based on player performance, ensuring a balanced and challenging experience. AI systems analyse player behaviour and preferences to deliver tailored content. Integration of AI with gaming platforms allows for real-time adjustments in virtual environments, improving user interfaces and creating more deeply engaging and interactive experiences for players. AI allows NPCs to interpret player actions, voice commands, and gameplay decisions so that they respond dynamically.

Imitation learning has emerged as a powerful technique for teaching machines to learn from human expertise. By observing and mimicking the actions of expert demonstrators, agents can acquire complex skills and behaviours without the need for explicit programming. While imitation learning has shown promising results in various domains, it also faces challenges such as distribution shift and the reliance on high-quality demonstration data. To overcome these limitations, researchers are exploring the integration of imitation learning with other machine learning techniques, paving the way for more advanced and versatile AI systems. As imitation learning continues to advance, it holds the potential to revolutionize the way machines learn and interact with the world around them.AI-empowered avatars can imitate real human facial expressions and emotions in multiplayer interactions, which makes them more realistic.

There are certain challenges of imitation learning like Suboptimal demonstrations. The quality of the trained AI is limited by the quality of the expert demonstrations. Gathering enough high-quality, labelled human demonstrations can be expensive and time-consuming, particularly for complex tasks. The AI can struggle to generalize its learned behaviour to new environments or situations that were not represented in the training data.

In complex games with incomplete information, the AI cannot simply imitate the visible state. It must infer or model the hidden information that the human player is using. While imitation learning can be effective for specific behaviours, it is difficult to scale for games with many concurrent actions, such as real-time strategy games.

Literature Review

Artificial Intelligence (AI) is rapidly becoming the cornerstone of innovation across various industries, and the gaming industry is no exception. The evolution of AI technologies has fundamentally altered the landscape of video games, driving unprecedented levels of interactivity, immersion, and personalization [1]. Historically, video games have been limited by static designs and pre-scripted behaviours, which, while effective, often resulted in predictable and repetitive gameplay experiences. However, the advent of AI has introduced dynamic elements that can adapt in real-time to player actions, creating a more engaging and immersive environment [2]. AI’s role in gaming encompasses a wide range of applications, from enhancing non-player character (NPC) behaviours to generating entire game worlds procedurally [3]. The ability of AI to learn and evolve based on player interactions by imitating opens up new possibilities for creating personalized experiences that can cater to individual player preferences. This personalization is crucial in an era where players seek unique and meaningful engagements rather than generic gameplay [4] Moreover, AI is instrumental in analysing vast amounts of player data to provide insights that can drive game design and development. This data-driven approach allows developers to fine-tune their games, ensuring they meet the evolving expectations of the gaming community [5]. The integration of AI in gaming is not just about making better games; it's about creating experiences that resonate on a deeper level with players. One of the most impactful applications of AI in gaming is adaptive difficulty, as exemplified by games like The Legend of Zelda: Breath of the Wild- In this game, adaptive difficulty is subtly implemented through a dynamic scaling system that adjusts the challenge based on the player's progression. As players defeat enemies and complete various tasks, the game tracks their achievements and gradually increases the strength and variety of enemies encountered, introducing tougher foes and more complex combat scenarios [6]. This ensures that the game remains challenging and engaging, regardless of the player's skill level or play style, fostering a sense of growth and mastery as players explore the vast open world of Hyrule. The balance between exploration, puzzle-solving, and combat is carefully maintained, allowing players to feel a sense of accomplishment without overwhelming them with difficulty spikes [7]. In a similar vein, Metal Gear Solid 5 demonstrates how AI can dynamically adjust challenges to match the player's skill level, ensuring a consistently engaging experience. The AI Director in the game monitors real-time metrics such as player health, stress levels, and success rates, making on-the-fly adjustments to enemy spawn rates and item placements [8]. This adaptability is key to maintaining player interest and satisfaction in increasingly competitive and complex gaming environments. By tailoring various game elements, from enemy behaviours to environmental challenges, the AI ensures that players remain challenged without being over whelmed, providing a tailored gaming experience that adapts to individual play styles [9]. Moreover, adaptive difficulty and personalization can significantly reduce frustration and enhance enjoyment, making games accessible to a broader audience, including those with varying skill levels [10]. For instance, Mortal Kombat vs. DC Universe dynamically adjusts the behaviour of opponents based on the player's performance, ensuring that matches remain challenging yet fair. This adaptability not only keeps players engaged by matching their skill level but also helps in maintaining a smooth learning curve, preventing both frustration for beginner sand boredom for advanced players [11].

Ultimately, as AI continues to evolve, it will undoubtedly keep transforming the gaming industry in profound ways [14]. By addressing the current challenges and exploring the potential of new AI technologies, developers and researchers can ensure that this transformation benefits all stakeholders and leads to a more exciting, inclusive, and responsible gaming future [15].

Games like Minecraft also use procedural content generation to create endless variations of worlds, encouraging creativity and exploration. The use of procedural algorithms ensures that no two game sessions are ever the same, providing a unique experience each time [15]. This capability allows for a high degree of player creativity and experimentation, as players can continually discover new landscapes and challenges [16].

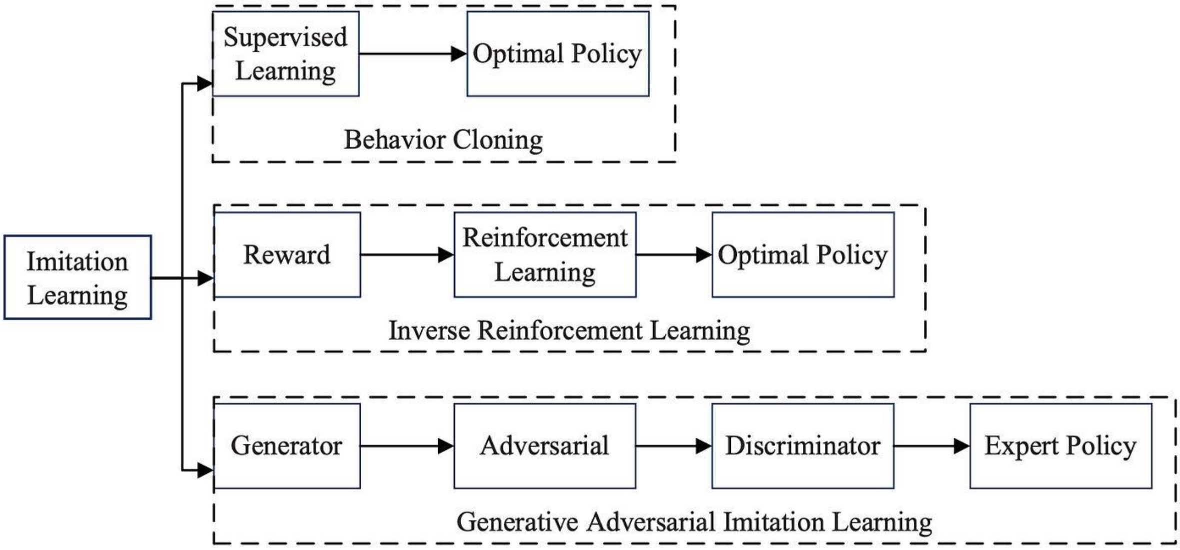
Dynamic storytelling relies on AI techniques such as natural language processing, decision trees, and machine learning to create adaptive narratives. These techniques enable the game to respond to player choices in real-time, creating a branching narrative that can lead to a multitude of outcomes [9]. This not only enhances the replay value of the game but also allows players to experience a story that feels uniquely their own [12]. Furthermore, dynamic storytelling can enhance emotional engagement by creating a sense of agency and consequence. When players feel that their choices have a meaningful impact on the story, they are more likely to become emotionally invested in the game [10]. This can lead to more memorable and impactful gaming experiences, as players are drawn into the narrative and motivated to explore different story paths [11] Artificial Intelligence is not just enhancing video games; it is transforming them. From adaptive difficulty and realistic NPCs to procedural content generation and dynamic storytelling, AI is revolutionizing every aspect of game design and player experience [1]. While challenges and ethical considerations must be addressed, the future of AI in gaming is bright [4]. Continued innovation and responsible development will lead to a new era of interactive entertainment that is more engaging, immersive, and inclusive than ever before [7]. For developers, the implications are clear: embracing AI can lead to more engaging and dynamic games but must be balanced with considerations of ethical design and user safety [3]. For researchers, the field of AI in gaming presents a fertile ground for further study, particularly in understanding the long-term impacts of these technologies on society [12]. Ultimately, as AI continues to evolve, it will undoubtedly keep transforming the gaming industry in profound ways [14]. By addressing the current challenges and exploring the potential of AI technologies, developers and researchers can ensure that this transformation benefits all stakeholders and leads to a more exciting, inclusive, and responsible gaming future [15]

Reinforcement learning and imitation learning are two widely-used methods to learn game AI [17] – [20]. For the former, AI model is required to interact with game environment to get current state, which is fed into neural network. Then, the network outputs the corresponding action and gets the reward from environment. The goal is to maximize the expected rewards. Comparing with reinforce learning which has no prior knowledge, imitation learning requires a set of manually recorded data. The goal of imitation learning is to output action similar with human behaviours.

Imitation learning [21]-[22] aims to complete a task based on expert demonstrations. There are mainly three kinds of methods: behaviour clone [23], inverse reinforcement learning [24] and generative adversarial imitation learning (GAIL) [18].

Methodology

There are various Core approaches to imitation learning in games. One is Behavioural Cloning (BC), where the AI agent learns a direct mapping from a given state to an expert's action. Behavioural cloning is a supervised learning approach where an AI agent learns to mimic the actions of an expert (like a human player) based on observed demonstration. An expert plays the game, and their actions are recorded along with the corresponding game state (e.g., screen captures, character coordinates, and in-game parameters). This creates a dataset of state-action pairs. The imitation task is converted into a supervised learning problem. The agent's goal is to predict the expert's action (the "label") given a specific game state (the "input"). A neural network is trained on the collected dataset. The model learns to map input states to expert actions by minimizing the difference between its predicted action and the expert's action. The trained model is deployed in the game. It observes the current game state and, based on its learned policy, executes the predicted action. However, the model has no inherent understanding of the long-term goal, making it susceptible to "distribution shift" errors if it encounters a state not seen during training. Sometime Behavioural Cloning can also suffer from "compounding errors" where small mistakes or deviations from the expert's training data can accumulate over time, leading to unpredictable and poor performance.



Inverse Reinforcement Learning (IRL) is a process where the AI infers the reward function through observation of expert human players, and then learns through reinforcement learning. Inverse Reinforcement Learning (IRL) is applied in gaming to understand and replicate human-like behaviour, design complex non-player characters (NPCs), and automate testing. Instead of manually defining a reward function for an agent, IRL infers the underlying goals and preferences directly from demonstrations of expert gameplay. Game developers often rely on scripted routines or simple state machines, which can lead to predictable and repetitive NPC behaviour. IRL allows NPCs to learn complex, dynamic behaviours by observing human player actions. For example, an NPC can learn an expert player's combat strategy, including when to attack aggressively or when to retreat, by observing replays of their matches. IRL can be used in multiplayer games to understand the reward functions of multiple agents, whether they are cooperating or competing. By inferring the objectives of different players, NPCs can then act more intelligently and form more complex strategies during gameplay.

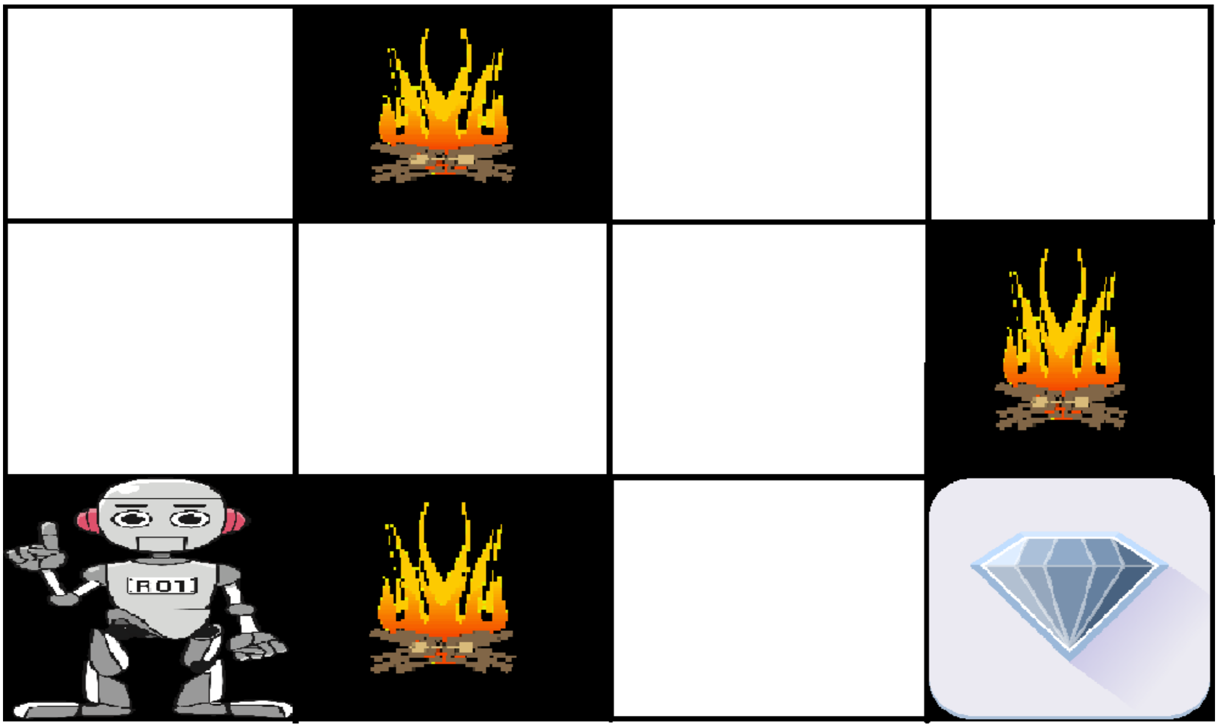
In Reinforcement Learning (RL), an agent learns to maximize a cumulative reward signal within an environment. The agent, environment, state space, action space, and a reward function must be defined. The reward function is manually created by a developer to incentivize desired behaviour agent observes the current state of the environment and selects an action based on its current policy. The environment transitions to a new state, and the agent receives a reward or penalty based on the outcome of its action. The agent uses this reward signal to update its policy through trial and error. It learns to favour actions that lead to higher rewards over time, even if the reward is delayed. This loop of observation, action, and reward continues for many iterations, during which the agent refines its policy to maximize its long-term cumulative reward. The process stops when the agent's policy converges, meaning its decision-making is stable and consistently leads to the maximum possible reward.

Reinforcement Learning Example: Navigating a Maze

Imagine a robot navigating a maze to reach a diamond while avoiding fire hazards. The goal is to find the optimal path with the least number of hazards while maximizing the reward:

- Each time the robot moves correctly, it receives a reward.
- If the robot takes the wrong path, it loses points.

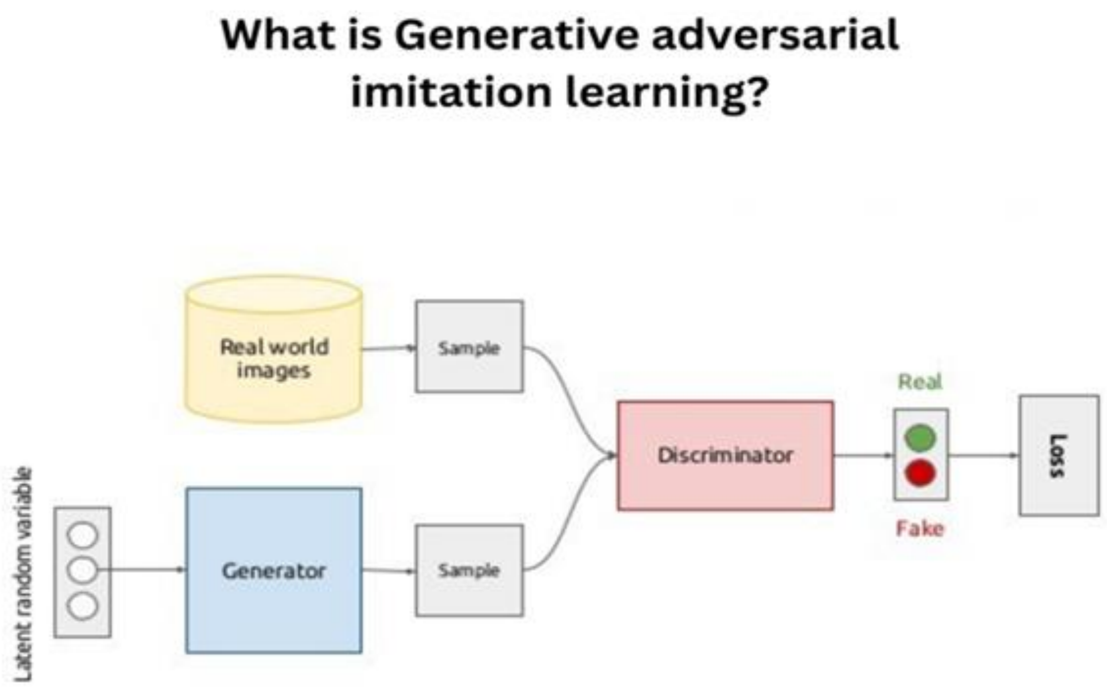
The robot learns by exploring different paths in the maze. By trying various moves, it evaluates the rewards and penalties for each path. Over time, the robot determines the best route by selecting the actions that lead to the highest cumulative reward.



The robot's learning process can be summarized as follows:

1. **Exploration**: The robot starts by exploring all possible paths in the maze, taking different actions at each step (e.g., move left, right, up, or down).
2. **Feedback**: After each move, the robot receives feedback from the environment:
   - A positive reward for moving closer to the diamond.
   - A penalty for moving into a fire hazard.
3. **Adjusting Behaviour**: Based on this feedback, the robot adjusts its behavior to maximize the cumulative reward, favouring paths that avoid hazards and bring it closer to the diamond.
4. **Optimal Path**: Eventually, the robot discovers the optimal path with the least number of hazards and the highest reward by selecting the right actions based on past experiences.

Generative Adversarial Imitation Learning (GAIL) uses an adversarial training process to produce more realistic behaviours. An adversarial training process is one where the model is trained with both normal and “adversarial” (i.e. malicious/designed to trick the model) data. It involves two neural networks: a generator and a discriminator. A set of expert demonstrations (state-action pairs) is collected from human players. A generator network is initialized with the goal of producing actions that are similar to the expert's policy. The agent uses this policy to interact with the game environment. A discriminator network is initialized. Its job is to act as a reward function by distinguishing between state-action pairs generated by the agent and those from the expert demonstrations. The generator and discriminator train in an alternating cycle. The discriminator is trained to become better at identifying fake (agent-generated) versus real (expert) state-action pairs. It is given a positive reward for correctly identifying an expert's move and a negative reward for an agent's move. The generator is trained to "fool" the discriminator into believing its actions is real. The better the generator is at convincing the discriminator, the higher its reward. Once the generator is sufficiently trained, it can be deployed as the agent's policy. The resulting behaviour is highly effective and difficult to distinguish from human play. It generates more realistic and diverse behaviours.



Application

There are various applications and case studies in games which are used to train AI. A 2008 study demonstrated that imitation learning could be used to train AI agents in a simulated "Robosoccer" game to mimic human playstyles for low-level behaviours like ball-handling. A Robosoccer game involves two teams of robots playing a modified version of soccer on a designated field. These competitions can be either autonomous (with AI-driven robots) or remote controlled. This game generally includes aspects like robot size and weight limitations, gameplay duration, rules against interfering with the opponent, and a focus on intelligent multi-agent control and cooperation. In Autonomous Robosoccer game, Robots are controlled by artificial intelligence (AI), making it a test of advanced robotic control and coordination. In Robosoccer Games, two teams compete, with each team typically using three robots. The game is played on a defined field, which can vary in size, and uses a standardized ball (often a golf ball). Robots must adhere to specific size, weight, and height constraints. In game matches are divided into halves, with a set duration for each. The game involves chasing, kicking, and scoring goals with the ball. Intentionally pushing or fighting with an opponent's robot without the ball can result in a penalty. A referee oversees the game to enforce rules and ensure fair play. Penalties can be given for various infractions, such as being late for the match or for illegal interference. This game gives the opportunity to solve robotic challenges and build creative learning in science, technology, engineering, and math.

In Racing games, Researchers have used imitation learning, often combined with reinforcement learning, to create diverse AI opponents for car racing games. In car racing games, AI provides opponents by implementing decision-making and movement algorithms to control Non-Player Character (NPC) cars, ensuring they follow a track, avoid obstacles, and strategically compete with human players. The AI learns from the player's actions and gameplay data, adapting its speed and driving lines to create a challenging, engaging, and realistic experience by mimicking human-like behaviours such as intelligent overtaking, defensive driving, and even making mistakes. These AI opponents learn to mimic the racing styles of human players of varying skill levels.

For real-time strategy games like Star Craft II, projects have applied imitation learning with deep neural networks to tackle complex, concurrent strategies and incomplete information. While this has shown potential, capturing the full complexity of human strategy remains challenging. StarCraft II, released in 2010, involves the player viewing the events as a military commander for each of the three species. StarCraft II multi-player gameplay spawned a separate esports competition that later drew interest from companies. StarCraft II has been used in the field of multi-agent reinforcement learning. A proof-of-concept to show that modern reinforcement learning algorithms can compete with professional human players. In December 2018, DeepMind's StarCraft II bot, called Alpha Star, defeated professional StarCraft II players in the game for the first time. It beat the player MaNA 5–0, albeit under conditions some deemed to be unfair. A fairer version of Alpha Star attained Grandmaster status in August 2019, an accomplishment called a "landmark achievement" for the field of artificial intelligence.

In First-person shooter (FPS) games AI agents have been trained using imitation learning to master FPS games. In PC first-person shooter (FPS) games, AI (Artificial Intelligence) primarily acts as enemy NPCs in single-player campaigns and cooperative modes, providing tactical challenges and creating immersive environments. AI also plays a crucial role in developing and testing advanced algorithms for the games themselves, improving gameplay mechanics and realism. Furthermore, AI powers companion characters in some games, enhancing the solo player experience with teamwork and coordination. As for Enemy Non-Player Characters (NPCs)**:** Enemies in single-player campaigns, such as in Borderlands 2 or

Doom Eternal, behave intelligently, using tactics, cover, and flanking manoeuvres to challenge the player. In AI Companions/Teammates games like Left 4 Dead 2 and Ready or Not, AI teammates assist the player in solo campaigns, providing tactical support and improving the solo experience. AI is also emerging to create more realistic and responsive companions. FPS environments offer a vast playground for AI development and testing. Advances in AI allow developers to create more sophisticated gameplay, more dynamic environments, and better player experiences. AI is used to balance game difficulty, ensuring a consistent challenge for players of varying skill levels. For Automated game testing Imitation learning is being used to train AI agents to play a game autonomously to test its design. This is particularly valuable for complex games where manual testing is slow and inefficient. Non-player character (NPC) behaviour-In the Unity ML-Agents toolkit, imitation learning can be used to train NPCs to act believably by leveraging human gameplay logs.

Discussion

Artificial Intelligence (AI) plays a crucial role in game development. It holds a significant position across all genres of games, enabling developers to craft immersive worlds. By analysing player actions, AI helps uncover unique properties within the game environment. Moreover, it simplifies enhancing the intelligence of non-player characters (NPCs), whether they are friendly or antagonistic. In many games, AI-controlled characters dynamically respond to real players' actions, often governed by intricate behavioural rules. The industry increasingly emphasizes creating NPCs that feel believable, enhancing player immersion and directly impacting enjoyment. Positive player reception translates to increased game sales, making AI an essential pillar for successful game design.

The advancement of AI research, along with the growth of the video game industry, has increasingly driven the development of believable non-player characters (NPCs). In recent years, Imitation Learning (IL) has been explored as an efficient and intuitive approach to programming autonomous behaviour. Foundational perspectives on IL include algorithmic overviews and theoretical frameworks as well as studies addressing challenges such as causal confusion in learning from demonstrations.

A variety of IL methods have been developed, establishing the field as a prominent area of research. In the context of video games, several approaches have aimed to produce believable NPCs across different genres. For instance, IL has been applied to generate human-like bots using provenance data to imitate player styles in platform games such as Super Mario Bros. and to adapt Monte Carlo Tree Search (MCTS) for more human-like decision making. Efforts have also been made to personalize content generation based on player behaviour.

Conclusion

Immersion is one of the key experiences a player should have when playing a game and NPC behaviour holds an important role in the field. Modern serious AI games must satisfy a number of requirements: aimed at problem-solving, must have a spirit of innovation, take into account the personal needs and preferences of the player and his goals, improve cognitive, analytical, mathematical, communication skills, promote the development of new technologies, develop creativity and skills management, ability to take initiative, etc. Various researches considered the characteristics that attract and retain the users in the games and how such characteristics can be used for the development of educational games. In gaming, it was revealed that realistic graphics, different levels of difficulty, and feedback in the form of scoring are important for the players. Various the qualitative characteristics like game design, user’s satisfaction, usability, usefulness, understandability, motivation, performance, playability, pedagogical aspects, learning outcomes, engagement, user's experience, efficacy, social impact, cognitive behaviour enjoyment, acceptance, user interface) of serious games in the field of education with the help of game for the teaching .Important features of the development of serious games are the focus on obtaining certain knowledge and skills from students. The development of serious games requires the use of machine learning methods to solve such practically important problems as image recognition, speech-based text recognition, etc. The recognition of the players' emotions is of particular importance, as it makes it possible to track those parts of the game that cause boredom, fear, etc. Recognition of players' emotions can be used to personalize content in educational games, and the natural language processing techniques in conjunction with neural networks are used to develop dialogues with the learners in real-time and create the effect of the tutor presence for support organization during learning. Research demonstrates progress in hybridizing IL with reinforcement learning, integrating provenance data, and adapting tree search methods for more human-like decisions. These advances point to a future of increasingly believable and adaptive NPCs. Immersive NPC behaviour is essential to modern games. Imitation learning offers a powerful avenue for creating adaptive, realistic, and educational experiences, from entertainment to serious games. Future developments should focus on emotion recognition, natural language processing for dynamic dialogue, and ethical design to ensure inclusive, safe, and engaging gameplay.

Reference

1. Togelius, J., Justinussen, T., & Hartzen, A. (2012). Compositional procedural content generation. In Proceedings of the third workshop on Procedural Content Generation in Games (PCG'12) (pp.14). Association for Computing Machinery.

2. Yanna kakis, G. N., & Togelius, J. (2018). Artificial Intelligence and Games. Springer. Https://doi.org/10.1007/978-3-319-63519-4.

3. Spronck, P., Ponsen, M., Sprinkhuizen-Kuyper, I., & Postma, E. (2006). Adaptive game AI with dynamic scripting. Machine Learning, 63(3), 217–248.

4. Khalifa, A., Bontrager, P., Earle, S., & Togelius, J. (2020). PCGRL: Procedural content generation via reinforcement learning. Proceedings of the 16th AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment (AIIDE2020). https://doi.org/10.1609/aiide.v16i1.7416.

5. Jaderberg, M., Mnih, V., Czarnecki, W. M., & Silver, D. (2019). Human-level performance in multiplayer games with deep reinforcement learning.Science, 364(6443),859_865.https://doi.org/10.1126/science.aau6249.

6. Wake, I., & Lee, N. (2024). Legend of Zelda Breath of the Wild and the lens of curiosity. In N. Lee (Ed.), Encyclopaedia of computer graphics and games(pp.343). Springer. https://doi.org/10.1007/978-3-031-23161-2 343

7. Domingues, J. M., Filipe, V., Carita, A. & Carvalho, V. (2024). Understanding the impact of perceived challenge on narrative immersion in video games: The role-playing game genre as a case study. Information, 15(6), 294.

8. Romero-Mendez, E. A., Santana-Mancilla, P. C., Garcia-Ruiz, M., Montesinos-López, O. A., & Anido-Rifón, L. E. (2023). The use of deep learning to improve player engagement in a video game through a dynamic difficulty adjustment based on skills classification. Applied Sciences,13(14), 8249.

9. Arif, S., Arif, T., Haroon, M. S., Khan, A. J., Raza, A. A., & Athar,A. (2024). The art of storytelling: Multi-agent generative AI for dynamic multimodal narratives. https://doi.org/10.48550/arXiv.2409.11261.

10. Streicher, A., & Smeddinck, J. D. (2016). Personalized and adaptive serious games. In R. Dörner, S. Göbel, M. Kickmeier-Rust, M. Masuch, & K. Zweig (Eds.), Entertainment computing and serious games (Vol. 9970, pp. 332-377). Springer, Cham.

11. Švelch, J. (2020). Should the monster play fair? : Reception of artificial intelligence in alien: isolation. Game Studies, 20(2), 243-260.

12. Mortazavi, F., Moradi, H., & Vahabie, A. H. (2024). Dynamic difficulty adjustment approaches in video games: A systematic literature review. Multimedia Tools and Applications. Https://doi.org/10.1007/s11042-024-18768-x.

13. Saranya Rubini, S., Ram, R. V., Narasiman, C. V., Umar, J. M. & Naveen, S. (2023). Behaviours of modern game non-playable characters. In V. Bindhu, J. M. R. S. Tavares, & C. Vuppalapati (Eds.), Proceedings of Fourth International Conference on Communication, Computing and Electronics Systems (Vol. 977, pp. 345–356). Springer, Singapore. Https://doi.org/10.1007/978-981-19-7753-4_27.

14. Bormann, D., & Greitemeyer, T. (2020). Video games to foster empathy: A critical analysis of the potential of Detroit: Become Human and The Walking Dead. In Universal Access in Human-Computer Interaction. Applications and Practice (pp.212_228). Springer. https://doi.org/10.1007/978-3-030-49108-6.

15. Jaderberg, M., Czarnecki, W. M., Dunning, I., Marris, L., Lever, G., Castaneda, A. G., ... & Silver, D. (2019). Human-level performance in 3D multiplayer games with population-based reinforcement learning. Science, 364(6443), 859-865.

16. Fronek, R., Göbl, B., & Hlavacs, H. (2020). Procedural Creation of Behavior Trees for NPCs.In:Nunes, N.J., Ma, L.,Wang, M., Correia N., Pan,Z.(eds)Entertainment Computing

ICEC2020. Lecture Notesin Computer Science, vol12523.Springer, Cham. https://doi.org/10.1007/978-3-030-65736-9_26.

17. J. Oh, Y. Guo, S. Singh, and H. Lee, “Self-imitation learning,” arXiv preprint arXiv:1806.05635, 2018.

18. J. Ho and S. Ermon, “Generative adversarial imitation learning,” in Advances in neural information processing systems, 2016, pp. 4565– 4573.

19. T. P. Lillicrap, J. J. Hunt, A. Pritzel, N. Heess, T. Erez, Y. Tassa, D. Silver, and D. Wierstra, “Continuous control with deep reinforcement learning,” arXiv preprint arXiv:1509.02971, 2015.

20. L. Zhang, H. Pan, Q. Fan, C. Ai, and Y. Jing, “Gbdt, lr & deep learning for turn-based strategy game ai,” in 2019 IEEE Conference on Games (CoG). IEEE, 2019, pp. 1–8.

21. Y. Duan, M. Andrychowicz, B. Stadie, O. J. Ho, J. Schneider, I. Sutskever, P. Abbeel, and W. Zaremba, “One-shot imitation learning,” in Advances in neural information processing systems, 2017, pp. 1087– 1098.

22. S. Ross and D. Bagnell, “Efficient reductions for imitation learning,” in Proceedings of the thirteenth international conference on artificial intelligence and statistics, 2010, pp. 661–668.

23. S. Shalev-Shwartz and S. Ben-David, Understanding machine learning: From theory to algorithms. Cambridge university press, 2014.

24. P. Sermanet, K. Xu, and S. Levine, “Unsupervised perceptual rewards for imitation learning,” arXiv preprint arXiv:1612.06699, 2016.