Innovative AI in Gaming: Deep Q-Learning for Pathfinding

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**Introduction**

The integration of Artificial Intelligence (AI) in gaming has revolutionized the way we interact with and experience games. In the realm of strategic and problem-solving games, AI plays a pivotal role in enhancing gameplay and providing dynamic challenges. A prime example of this integration is the use of deep Q-learning in pathfinding within games. Deep Q-learning, a sophisticated form of reinforcement learning, allows an AI agent, such as a pirate in a treasure hunt game, to navigate complex environments and achieve objectives efficiently. Unlike traditional AI approaches that follow predefined rules, deep Q-learning enables the agent to learn from its environment and improve over time, akin to human learning processes (AI Summer, n.d.; OpenAI, n.d.).

**Deep Q-Learning in AI Agents**

The core of the agent's learning process lies in the Q-learning algorithm. This technique involves learning a Q-value function that estimates the worth of actions in each state, guiding the agent towards the goal. It's crucial because it balances the need to explore new paths (exploration) and the need to exploit known paths (exploitation). This balance is achieved through the epsilon parameter, which is gradually adjusted to shift from exploration to exploitation as the agent learns from its environment (AI Summer, n.d.).

**Technical Implementation**

"The agent learns to achieve a goal in an uncertain, potentially complex environment. In reinforcement learning, an artificial intelligence faces a game-like situation" (OpenAI, n.d.). The implementation of deep Q-learning in this project involves building a neural network that approximates the Q-value function. It's structured to take the state of the game as input and output a Q-value for each possible action. The network updates its weights based on the agent's experiences, refining its action-prediction capability over time. As the agent interacts with the environment, it accumulates experiences, which are then used to update the model, refining its ability to predict the most rewarding actions. This iterative learning process embodies the core of deep Q-learning, enabling the agent to evolve its strategy over time.

**Human vs. AI Problem-Solving**

Unlike humans who rely on a combination of cognitive skills, intuition, and experience, the AI agent's decision-making process is driven by algorithmic predictions and learning from environmental feedback. While both humans and AI agents engage in exploration and learning from past actions, the AI agent does this through a structured mathematical framework, lacking the intuitive and adaptive nature of human cognition.

**Balancing Exploration and Exploitation**

Exploitation in AI, particularly in pathfinding, involves using existing knowledge to make decisions, optimizing actions based on learned strategies (Sutton & Barto, 2018). This approach is critical for efficiently navigating familiar paths in a gaming environment. Exploration, conversely, entails trying new actions to discover potentially superior solutions, essential for adapting to new or evolving environments (Mnih et al., 2015). The ideal balance between exploitation and exploration is dependent on the specific problem and learning stage of the agent. Initially, a higher rate of exploration is beneficial for accumulating diverse experiences. As the agent acquires knowledge, gradually shifting towards exploitation is advantageous. (AI Summer, n.d.).

**Application in Pathfinding**

In the context of the game, the agent uses reinforcement learning to navigate the maze. The agent receives feedback (rewards or penalties) based on its actions, which helps it determine the most effective paths to the goal. Over time, the agent learns to optimize its pathfinding strategy, improving its efficiency in reaching the treasure.

**Conclusion**

In conclusion, the application of deep Q-learning in gaming AI, specifically in pathfinding scenarios like the treasure hunt game, marks a significant advancement in the field of AI. This technology not only enhances game complexity and engagement but also provides insights into AI learning processes, mirroring aspects of human cognition. As the AI agent learns to navigate through challenges, it showcases the potential of machine learning in interactive environments. The continuous evolution of AI techniques like deep Q-learning promises to further revolutionize gaming experiences, paving the way for more intelligent and adaptive game design.

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