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**7-3 Project Two Submission**

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March 19, 2024

**Introduction**

In the rapidly evolving field of artificial intelligence, understanding the intricacies of how intelligent agents are designed and implemented to solve problems is important. This analysis dives into the different approaches that humans and machines take towards problem-solving, with a specific focus on navigating mazes. It highlights the procedural steps taken by both entities, assesses the functionality of intelligent agents in pathfinding, explores the concepts of exploitation versus exploration in algorithmic learning, and discusses the implementation of deep Q-learning through neural networks. By comparing human and machine methods, we aim to elucidate the distinctive capabilities and limitations of each approach, providing insights that are grounded in current cognitive science and AI research.

**Differences Between Human and Machine Approaches to Problem Solving**

Humans and machines approach problem solving from fundamentally different perspectives. Humans rely on intuition, experience, and heuristic methods, particularly in complex environments like mazes. For example, a person might use visual cues and memory to make decisions at junctions within a maze (Lieberman, 2010). In contrast, machines utilize algorithms to determine the optimal path through a problem space. An intelligent agent solving a maze, for example, would systematically apply algorithms to explore and evaluate all possible routes to find the most efficient path (Russell & Norvig, 2016).

**Steps in Human Maze Solving**

When solving a maze, a human typically follows a series of intuitive steps: observing the layout, making decisions based on visible paths, and using memory to backtrack when dead ends are encountered. Common strategies like the "left-hand rule" where the solver always keeps their left hand on the wall, exemplify the heuristic approaches humans might use (Lieberman, 2010).

**Intelligent Agent's Approach to Pathfinding**

Conversely, an intelligent agent's approach to solving a maze is grounded in algorithmic processing. Depending on the agent’s programming, it might use pathfinding algorithms such as A\*, Dijkstra's, or reinforcement learning techniques to process and evaluate possible paths from start to finish. These decisions are based on the calculated efficiency of each route, with adjustments made based on learned experiences from the environment (Russell & Norvig, 2016).

**Comparison of Human and Machine Problem-Solving Approaches**

Both humans and intelligent agents start by observing their environment; however, their decision-making processes diverge significantly. Humans rely more on intuitive and experiential decision-making, whereas agents rely on programmed algorithms and logic to make decisions. These differences highlight the unique strengths and weaknesses of each approach in terms of flexibility, efficiency, and scalability (Russell & Norvig, 2016).

**Purpose and Strategy of Intelligent Agents in Pathfinding**

The primary purpose of an intelligent agent in pathfinding is to navigate through a maze with minimal human intervention, maximizing efficiency and reliability. The balance between exploration (trying new paths) and exploitation (using known successful paths) is crucial. Initially, an agent might explore extensively to gather as much information as possible, but as it learns, it shifts towards exploiting known paths to maximize efficiency (Sutton & Barto, 2018).

**Reinforcement Learning in Pathfinding**

Reinforcement learning plays an important role in how an intelligent agent learns to navigate a maze. By receiving rewards for beneficial actions and penalties for poor choices, the agent (e.g., a simulated pirate) learns to navigate towards a goal (e.g., treasure) efficiently. This trial-and-error method allows the agent to optimize its path over time based on feedback from the environment (Sutton & Barto, 2018).

**Implementation of Deep Q-Learning**

In the context of maze navigation, deep Q-learning involves using neural networks to approximate the Q-value function, which helps the agent determine the best actions to take at each state. This method allows the agent to learn and improve its policy based on the rewards associated with each action, continually updating its strategy to achieve the best possible outcomes (Mnih et al., 2015).

**Conclusion**

The exploration of human and machine problem-solving strategies provides insights into the capabilities and limitations inherent in both approaches. While humans bring intuition and adaptability to problem-solving, machines offer precision, consistency, and the ability to leverage complex algorithms effectively. In the domain of artificial intelligence, the synergy between human cognitive strategies and machine efficiency could lead to the development of more sophisticated, responsive, and capable AI systems. As technology advances, the integration of human-like problem-solving capabilities in machines will continue to be a significant focus of AI research and development, promising ever more innovative solutions to complex problems.

**References**

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