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**Design Defense: Deep Q-Learning for Pathfinding in a Treasure Maze**

In the realm of artificial intelligence, the successful fusion of human and machine strategies is necessary to solve complex problems. This paper provides a thorough design argument for an intelligent agent that uses deep Q-learning to navigate a challenging maze with the overall goal of discovering a hidden prize. We acquire important insights into the capabilities and limitations of AI in complex tasks by analyzing the differences between human and machine problem-solving strategies, illuminating the stepwise processes used by both entities, and critically assessing the selected method.

**Human vs. Machine Problem Solving:**

Due to their different cognitive structures, human and machine problem-solving methods fundamentally differ from one another. To get around the maze, humans need cognitive abilities like pattern identification, perception, decision-making, and memory retrieval. They create a mental map of the maze, select routes based on visual signals, and iteratively hone their tactics through trial and error. In contrast, the intelligent agent uses the machine learning algorithm deep Q-learning to enhance its decision-making. Through a careful mix of exploration and exploitation, this algorithm enables the agent to acquire optimal actions that result in a successful navigation strategy (Simplilearn, 2022; Reuell, 2015).

**Steps for Human Problem Solving:**

A human observer would carefully examine the environment, pinpoint potential pathways, and make choices based on sensory inputs to find their way through the maze. Individuals gradually improve their strategy with each choice they make by learning from their past mistakes, ultimately perfecting their pathfinding skills (Reuell, 2015).

**Steps for Intelligent Agent Problem Solving:**

The intelligent agent follows a set of predetermined steps while functioning according to the deep Q-learning paradigm. It begins by setting up the maze environment, choosing a starting point, and assessing the current situation. By using an epsilon-greedy strategy, the agent skillfully switches between discovering new paths and using the information at hand to influence decisions. The agent obtains rewards and enters a new state because of an activity. These encounters are carefully remembered and used to train a neural network. The network gradually converges over repeated cycles to an ideal Q-value function, honing decision-making skills and enabling expert maze traversal (Simplilearn, 2022).

**Similarities and Differences:**

The goal of both human and automated problem-solving efforts is to find the best paths by combining exploration and learning. The difference between people and agents, though, is that humans rely on cognitive abilities, whereas agents use algorithms and neural networks. Notably, even though both entities modify their methods in response to input, the agent's learning process is distinct from human intuition in that it is data driven (Reuell, 2015).

**Assessing the Intelligent Agent's Purpose:**

Finding the most effective route to the hidden prize within the maze is the intelligent agent's primary goal. The agent achieves this by carefully balancing the use of its current knowledge with exploration of previously unexplored domains, ultimately driving it towards the achievement of its goal (Simplilearn, 2022).

**Exploration vs. Exploitation and Reinforcement Learning:**

Exploration involves consciously engaging in novel acts to gather knowledge, whereas exploitation involves making decisions about which actions to take based on acquired Q-values. The ideal balance between exploration and exploitation is crucial for this pathfinding problem. Exploration should be prioritized in the early phases because it helps uncover the best routes. The balance swings toward exploitation as the agent gains knowledge to capitalize on the new insights (Simplilearn, 2022).

**Reinforcement Learning's Role:**

The agent's path to achieving the goal is determined in large part by reinforcement learning. The agent iteratively changes its Q-values based on rewards accumulated from its activities by carefully balancing exploration and exploitation. The Q-value estimates are improved over time by this iterative process, allowing the agent to predict actions leading to the treasure with more accuracy (Simplilearn, 2022).

**Algorithms for Complex Problems**:

By automating the decision-making process, algorithms play a crucial part in finding solutions to complex problems. In this situation, a powerful method for the intelligent agent to internalize the best course of action and accurately navigate the maze comes from the synergy of deep Q-learning and neural networks. The neural network of the agent is carefully honed to approximate Q-values, enabling adaptive judgments based on the changing dynamics of the maze (Simplilearn, 2022).

In conclusion, this design defense thoroughly explains how deep Q-learning can be used to resolve the pathfinding difficulty in a treasure maze. We identify the potential of AI in solving complicated problems by outlining the differences between human and machine techniques, clarifying their procedural trajectories, and gauging the effectiveness of the algorithm. This methodology is positioned as a powerful tool for solving complex puzzles thanks to the subtle orchestration of exploration and exploitation inside deep Q-learning, supplemented with reinforcement learning, underscoring its applicability in future applications.

**References:**

Reuell, P. (2015, October 5). How the brain builds new thoughts. Harvard Gazette. https://news.harvard.edu/gazette/story/2015/10/how-the-brain-builds-new-thoughts/

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