**7-3 Project Two**

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**Human vs. Machine Problem-Solving Approaches**

In considering the differences between human and machine approaches to problem-solving, it's essential to recognize the distinct cognitive processes involved. Humans often rely on intuition, pattern recognition, and past experiences to navigate challenges (Gulli & Pal, 2017). Conversely, machines follow predetermined algorithms and rules, leveraging computational power and vast datasets to arrive at solutions (Beysolow, 2019). While humans may exhibit flexibility and adaptability in uncertain or dynamic environments, machine decisions are deterministic and based on predefined rulesets (Tao & Couzin, 2019).

**Human Steps to Solve the Maze**

When considering how a human might approach solving the maze presented, it becomes evident that visual inspection, spatial reasoning, and trial and error play pivotal roles (Lamba, 2018). A human observer would visually inspect the maze, identify potential paths, and make decisions based on spatial reasoning and memory. Through trial and error, they would navigate the maze, adapting their strategy based on feedback from previous attempts.

**Steps of the Intelligent Agent**

Conversely, the intelligent agent in this scenario utilizes a deep Q-learning algorithm to navigate the maze (Samyzaf, 2021). This involves initializing a Q-table or Q-network to represent the action-value function and updating Q-values based on rewards obtained from interactions with the environment (Lamba, 2018). The agent must balance exploitation (choosing actions with known high rewards) and exploration (trying new actions to discover potentially better strategies) to optimize its pathfinding.

**Similarities and Differences**

While both approaches involve elements of exploration and exploitation, the intelligent agent's decisions are based on computational algorithms rather than human intuition (Gulli & Pal, 2017). The agent learns from its interactions with the environment to refine its decision-making process over time.

**Purpose of the Intelligent Agent**

The primary purpose of the intelligent agent in pathfinding is to efficiently navigate the maze to reach the goal (the treasure) while maximizing rewards and minimizing penalties (Tao & Couzin, 2019). Through reinforcement learning, the agent learns optimal policies through trial and error, receiving positive reinforcement for reaching the treasure and negative reinforcement for encountering obstacles or taking longer routes.

**Implementation of Deep Q-Learning**

Deep Q-learning, the algorithm employed in this scenario, utilizes neural networks to approximate the Q-values of state-action pairs (Beysolow, 2019). By training a neural network to predict Q-values based on the current state and action, the agent learns optimal strategies through a combination of supervised learning and reinforcement learning techniques, such as gradient descent and temporal difference learning.

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