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Problem-Solving Approaches in Maze Navigation: Human vs. Machine

Human Perspective: When people approach a maze-solving assignment, they frequently begin by surveying the entire maze and planning a route toward the objective, sometimes going backward from the goal to the start. Humans use pattern recognition to detect pathways, shortcuts, and dead ends. They use a trial-and-error technique in complicated mazes, making judgments at intersections based on memory and visual inputs. Humans can change their strategy based on progress, such as shifting pathways when they reach a dead end.

Machine method: An alternative method is used by an intelligent agent, such as the one employed in maze navigation. It is based on exploration (trying out random pathways) and exploitation (making educated judgments based on learned experiences). The agent learns through a reward-based system, getting rewards or penalties for its behaviors, which aids in developing a reward-maximizing strategy. Unlike humans, the agent makes judgments based on its present condition and acquired experience rather than having an overall picture of the maze. Its learning method is iterative, with improvements achieved through repeated trials.

Humans and intelligent agents both use trial and error to change their methods over time, depending on experience. Conversely, humans employ global strategy and intuitive pattern identification, whereas agents rely on local knowledge and methodical, data-driven learning.

The Intelligent Agent's Role in Pathfinding

The primary aim of an intelligent agent in pathfinding is to locate the most efficient way through the labyrinth to the destination, ideally with as little human involvement as possible. The agent develops and refines its strategy based on experiences and the rewards of those encounters.

Pathfinding Exploration vs. Exploitation

Exploration entails the agent attempting new actions and courses in order to gain more information about the labyrinth. In contrast, exploitation is making decisions based on prior knowledge, such as picking paths that have previously led to more significant rewards. The intricacy of the maze determines the appropriate balance of exploration and exploitation. Initially, greater exploration is desirable in order to get diverse experiences. As learning continues, increased exploitation is beneficial in using the gained information. This ratio is frequently dynamically modified throughout the learning process.

Determining the Path to the Goal Using Reinforcement Learning

In the context of this maze-solving activity, reinforcement learning allows the agent (the pirate) to learn the optimum path to the objective (the treasure) through trial and error. The agent builds its strategy depending on the consequences of its activities, which are governed by a reward system. It does not require a pre-determined path but rather learns the best way by constantly improving its judgments depending on the rewards gained for various acts.

Algorithm Evaluation in Complex Problem Solving

Algorithms, particularly those used in AI and machine learning, address complicated issues effectively. They can manage vast amounts of data, find patterns, and make choices on their own. The efficiency of these algorithms is determined by the quality of the data, the model's suitability for the job, and its flexibility in new scenarios. While algorithms excel at methodical and rule-based activities, they may lack human-like intuitive and creative problem-solving abilities.

Deep Q-Learning with Neural Networks Implementation

Deep Q-learning was applied in the game using a neural network. In each state, this neural network model calculates the value of each action (Q-value). The Q-values guide the agent's decisions, with the network's weights repeatedly changing depending on the rewards received and expected future benefits. This technique combines the concepts of Q-learning with the pattern recognition skills of deep learning, allowing the agent to improve its decision-making over time.

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