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**Creating a Robust System for Intelligent Agent Navigation in Treasure Maze**

When solving a maze in a real-life scenario, I rely on intuition, reasoning, and past experiences. I use my sight to identify patterns, remember paths I’ve taken, and backtrack when I hit a dead end. This process feels natural, a mix of logic and creativity, and often doesn’t feel like following rigid instructions. Machines, on the other hand, are not naturally creative problem solvers. While they’re fast and reliable at executing tasks, they lack the creative reasoning that humans bring to problem-solving. Simulating this kind of creativity is the goal of artificial intelligence (AI). Unlike my heuristic approach, machines need structured programming to navigate problems like mazes.

In this project, the intelligent agent starts by identifying its position in the maze and analyzing its surroundings. It uses an ε-greedy strategy to make decisions, balancing exploration of random moves to learn about the maze and exploitation of the best-known moves to progress efficiently. After every move, the agent updates its understanding of the maze by evaluating the result of its actions. This step-by-step learning helps the agent build an optimal path from the start to the treasure.

Humans and machines solve problems differently, though there are similarities. Both rely on trial and error and learn from mistakes. For me, this learning happens in my memory, where I store experiences and use intuition to guide decisions. Machines, however, use replay buffers to store and analyze past actions. This allows them to refine their strategies, similar to how I improve through practice. But unlike me, machines can’t rely on intuition—they follow a structured learning process. In this project, the agent learns through reinforcement learning, gradually building a reliable strategy to reach its goal.

The main objective for the intelligent agent is to find the treasure quickly and efficiently. To achieve this, the agent uses reinforcement learning, a method that rewards good decisions and penalizes bad ones. For example, if the agent moves closer to the treasure, it gets a positive reward. If it hits a wall or moves away, it receives a negative signal. These rewards guide the agent to reinforce good actions and avoid bad ones. This feedback loop helps the agent improve over time, just like I learn from feedback in real life.

Reinforcement learning depends on two key ideas: exploration and exploitation. Exploration is when the agent tries different actions to gather information about the maze. Exploitation happens when the agent uses what it has learned to make the best possible moves. Balancing these two is crucial. If the agent explores too much, it wastes time. If it exploits too early, it might miss better paths. For this maze problem, the balance ensures the agent discovers the most efficient route without getting stuck in poor strategies.

The agent’s ability to solve the maze is powered by deep Q-learning, which uses neural networks to estimate Q-values. A Q-value represents how good a specific action is in a given state. In the maze, each grid cell is a state, and the agent’s position determines its current state. The neural network processes this state and predicts the Q-values for possible moves. Based on these predictions, the agent chooses the best action. Through repeated training, the neural network refines its predictions, allowing the agent to navigate the maze efficiently and consistently.

In conclusion, this project highlights how reinforcement learning and deep Q-learning enable an intelligent agent to solve a maze. By mimicking my trial-and-error methods and following a structured approach, the agent balances exploration and exploitation to optimize its performance. This demonstrates the potential of AI to tackle complex problems by learning and adapting, much like humans do but with its own systematic precision.

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