7-3 Project Two: Design Defense Document

CS – 370

Southern New Hampshire University

Daniel Taylor

02/25/2024

The task of navigating a maze represents a quintessential problem, and both humans and machines approach it with distinct methodologies. This design defense elucidates the approach taken to solve the maze navigation problem using an intelligent agent based on deep Q-learning. It delves into the differences between human and machine approaches, outlines the steps each would take, evaluates the purpose of the intelligent agent, and explores the role of exploration and exploitation in the learning process.

Humans and machines exhibit disparate problem-solving approaches. Humans rely on intuition, heuristics, and experience. In contrast, machines, embodied by intelligent agents, use algorithms and computational models. While humans visualize the maze and adapt strategies based on real-time feedback, the intelligent agent processes information mathematically, exploring possibilities and learning from experience.

Humans approach maze navigation through a sequence of steps. They observe the maze, identify the goal and obstacles, mentally plan a route, and physically navigate through the maze. Importantly, humans adapt their strategies based on real-time feedback and environmental cues.

The intelligent agent follows a systematic process:

1. **Observation and State Representation:** The agent observes the maze and represents the current state as a vector, a flattened representation of the maze.
2. **Exploration-Exploitation:** The agent balances exploration (trying new actions) and exploitation (choosing known, optimal actions). It decides actions based on Q-values, guiding it toward the goal.
3. **Learning:** The agent learns from rewards and updates Q-values, which represent the expected cumulative reward for taking a specific action in a specific state. Experience replay is employed to stabilize the learning process.

Both humans and the intelligent agent employ planning to reach the goal and adapt their strategies based on feedback. However, the agent's decisions are purely algorithmic, lacking the intuitive and heuristic reasoning that humans employ.

The primary purpose of the intelligent agent is pathfinding. It navigates the maze efficiently, seeking to optimize its path by learning from trial and error. The agent's decisions are guided by the goal of reaching the treasure cell.

Exploitation involves choosing known optimal actions, while exploration entails trying new actions to discover potentially better strategies. The ideal proportion of exploitation and exploration evolves over time. Initially, a higher exploration rate encourages the discovery of the maze, and as the agent learns, the exploration rate decreases to favor exploitation of the learned optimal path.

Reinforcement learning, specifically Q-learning, plays a pivotal role in determining the path to the goal. The agent learns the value of actions in different states and utilizes Q-values to make decisions. The reinforcement learning process involves receiving rewards for actions taken and adjusting the agent's strategy accordingly.

The implementation involves deep Q-learning using neural networks. A neural network approximates Q-values, and the model is trained using experience replay to enhance stability. This approach allows the agent to generalize its learning and make informed decisions in novel situations.

The intelligent agent's approach to maze navigation, rooted in deep Q-learning, demonstrates the synergy of algorithmic decision-making and computational power. While it lacks human intuition, it excels in systematic exploration and exploitation of the environment. The interplay between reinforcement learning, neural networks, and experience replay empowers the agent to learn efficient pathfinding strategies. This design defense showcases the potential of intelligent agents in solving complex problems, offering insights into the convergence of artificial and human intelligence in problem-solving domains.

References:

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