Project Two

CS 370

Benjamin Leanna

SNHU

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For project two, the focus was on creating a treasure hunt game where a pirate, represented by an AI agent, looks to locate the treasure in a maze before a human player can. I had the task of designing this agent by developing code for the Q-Training that would allow the agent to learn the best way to complete the game. I want to look at the differences between the human vs machine approaches and their similarities and differences, the purpose of the intelligent agent, exploitation vs exploration, reinforcement learning for goal achievement, evaluating algorithmic solutions, and finally the implementation of deep Q-Learning.

**1. Human vs. Machine Approaches:**

* *Human Approach*: In Nick Chater’s and Mike Oaksford’s book, “The Probabilistic Mind”, they say that when a person ventures into the maze, the cognitive process involves a dynamic interplay of visual observation, memory recall, and adept problem-solving skills. The individual visually scans the maze, mentally maps potential routes, and engages in decision-making predicated on spatial awareness and contextual cues.
* *Machine Approach*: In a large contrast, our intelligent agent adopts a sophisticated approach embedded in a deep Q-learning algorithm. The agent traverses the labyrinth through a process of systematic trial and error, learning from each encountered experience. This algorithmic approach involves the exploration of diverse paths, with the agent adapting its strategy based on the rewards or penalties gleaned from its interactions with the environment.

**2. Similarities and Differences:**

* *Similarities:* While these approaches may seem disparate on the surface, a common thread lies in their mutual reliance on exploration. Human navigation involves visual exploration, and the intelligent agent embarks on systematic exploration through algorithmically driven trial and error.
* *Differences:* Divergence emerges in the methodologies. The human approach, intuitive and visually informed, contrasts with the agent's methodical, data-driven learning. The agent gets better at making decisions by tweaking its approach using feedback from the environment. This makes it different from how humans naturally make choices.

**3. Purpose of the Intelligent Agent:**

* The reason our clever agent exists is crystal clear - it's like a cool guide in the game, expertly finding its way through the maze to grab the treasure before the human player does. But it's not just about moving around; it's like a smart creature that learns from every move, changing its game plan to make better decisions.

**4. Exploitation vs. Exploration:**

* *Exploitation vs. Exploration:* At the heart of effective maze navigation lies the reasoning between exploitation and exploration. Exploitation entails adhering to actions known to yield high rewards, while exploration involves venturing into uncharted territory to uncover potential rewards. Striking a nuanced balance between these two facets is super important for effective pathfinding.
* *Ideal Proportion:* In the initial stages, a higher proportion of exploration is favored for the agent to unveil optimal paths in the maze. As the agent accumulates knowledge, a gradual shift towards exploitation becomes the ideal trajectory, leveraging acquired insights for more targeted decision-making.

**5. Reinforcement Learning for Goal Achievement:**

* The backbone of the intelligent agent's journey is reinforcement learning, a model that propels the agent towards the treasure. Positive rewards accompany successful goal achievement, creating an associative link between actions and favorable outcomes. This iterative learning process progressively hones the agent's understanding of the optimal path through the maze.

**6. Evaluating Algorithmic Solutions:**

* The clever implementation of algorithms, with a primary focus on deep Q-learning complemented by neural networks, emerges as an instrumental strategy in navigating the complex maze. The iterative nature of reinforcement learning proves to be particularly adaptive, allowing the agent to dynamically adjust and optimize its decision-making based on accumulated experiences, making it exceptionally well-suited for dynamic and evolving environments.

**7. Implementation of Deep Q-learning:**

* The granular details of implementing deep Q-learning involve the seamless integration of neural networks. These neural architectures serve as the computational backbone, tasked with approximating the Q-function - the linchpin mapping states and actions to their associated values. Through a meticulous training process informed by the agent's experiences within the maze, the neural network undergoes iterative refinement, enhancing its predictive capabilities and steering the agent towards an increasingly effective path to the final goal, the treasure.

In conclusion, the intricate interplay between human intuition and algorithmically driven machine learning describes the multifaceted nature of maze navigation. The deliberate utilization of deep Q-learning, reinforcement learning, and neural networks serves as a evidence to the efficacy of algorithmic solutions in unraveling the complexities of pathfinding within the dynamic gaming domain. The synergistic integration of human and machine-centric methodologies point to a new frontier in intelligent navigation, emphasizing the transformative potential of artificial intelligence in the realm of problem-solving.

Petrenko, A. (2010). Nick Chater and Mike Oaksford, eds. The Probabilistic Mind: Prospects for Bayesian Cognitive Science . Reviewed by. *Philosophy in Review*, *30*(1), 16–19. <https://journals.uvic.ca/index.php/pir/article/download/205/221>

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