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**Design Defense: Pathfinding Intelligent Agent for Treasure Hunt Game**

**Introduction**

* In this design defense, I will discuss the development of an intelligent agent for a treasure hunt game using deep Q-learning. The agent, representing a pirate, navigates through a maze to find the treasure. I’ll analyze human and machine approaches, describe steps in maze solving, assess the agent's purpose, explain exploitation and exploration, evaluate reinforcement learning, and discuss deep Q-learning implementation.

**Human vs. Machine Approaches**

* Humans rely on cognitive processes and subjective decision-making, while machines follow algorithms and data-driven approaches. Humans plan routes, navigate, and adjust strategies, whereas machines initialize environments, explore/exploit, navigate, learn, and repeat.

**Steps in Maze Solving**

* Humans observe their surroundings to gather information about the maze layout, plan their route by mentally simulating possible paths, navigate through the maze based on their plan while making adjustments as needed, and adapt their strategy if they encounter obstacles or dead ends. Machines, on the other hand, initialize the maze environment, explore different paths through trial and error, navigate based on learned policies or heuristics, learn from experiences through reinforcement learning techniques, and iterate this process to improve performance over time.

**Purpose of Intelligent Agent**

* The purpose of the intelligent agent is to autonomously navigate the maze environment, mimicking human-like decision-making processes to maximize rewards (finding the treasure) while minimizing penalties (avoiding obstacles and dead ends). By simulating human-like decision-making, the agent can effectively explore the maze, adapt its strategy to changing conditions, and learn from its experiences to improve performance over time.

**Exploitation vs. Exploration**

* In pathfinding, exploitation involves maximizing immediate rewards by following known paths or policies, while exploration entails discovering new paths or strategies to potentially improve long-term rewards. An ideal balance between exploitation and exploration is crucial for effective maze solving. Initially, the agent may prioritize exploration to discover new paths and learn about the maze environment. As it gains more experience and knowledge, it can gradually shift towards exploitation to exploit the most promising paths and maximize rewards.

**Reinforcement Learning in Pathfinding**

* Reinforcement learning enables the agent to determine optimal paths by learning from interactions with the environment. Through trial and error, the agent receives rewards or penalties based on its actions, allowing it to update its policies or strategies accordingly. By adjusting its behavior based on received rewards and punishments, the agent can gradually learn to navigate the maze more effectively and find the optimal path to the goal (the treasure).

**Evaluation of Deep Q-Learning**

* Deep Q-learning proves effective for tackling complex problems by leveraging neural networks to learn and represent state-action values (Q-values) from raw input data. This approach enables the model to capture intricate relationships within the environment, generalize across similar states, approximate non-linear functions, and optimize actions based on temporal difference errors.
* The implementation of deep Q-learning for this game involves constructing a neural network model using TensorFlow and Keras, comprising multiple layers to approximate Q-values. Experience replay buffers store episodes, enabling the agent to learn from past experiences, while a separate target network stabilizes training. The model is iteratively trained using batches of experiences sampled from the replay buffer, minimizing the mean squared error between predicted and target Q-values to enhance performance over time.

**Conclusion**

* The intelligent pathfinding agent combines principles of reinforcement learning, specifically deep Q-learning, to navigate through a maze environment efficiently. By analyzing human and machine approaches, understanding maze-solving steps, assessing the agent's purpose, explaining exploitation and exploration, evaluating reinforcement learning, and discussing deep Q-learning implementation, it will create effective computational models for autonomous problem-solving.

**References:**

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