**CS 370 – Project Two: Design Defense**

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**Design Defense: Pirate Q-Learning Agent**

The implementation of a deep Q-learning agent for the treasure-hunting pirate represents a valuable intersection between artificial intelligence (AI) concepts and real-world problem solving. The goal of this project was to design a non-player character (NPC) agent capable of navigating a maze to find treasure before a human player could. In doing so, this project explores the core foundations of reinforcement learning (RL), agent design, and neural network integration in intelligent systems. This design defense outlines the logic, learning behaviors, and architectural considerations involved in developing the pirate agent, while comparing human and machine learning approaches and evaluating the deep Q-learning algorithm’s effectiveness.

**Human vs. Machine Pathfinding**

When solving a maze, a human typically follows intuitive or visual cues, relying on pattern recognition, memory, and exploratory reasoning. For instance, a person may look for open paths, avoid loops, and backtrack when facing a dead end. Humans also adjust strategies quickly based on prior experience or observation. In contrast, a machine learning agent does not inherently “understand” the structure of the maze. Instead, it must learn through repeated trial and error, gradually associating states and actions with expected rewards. The Q-learning pirate starts with no knowledge of its environment and uses feedback from the environment to update its behavior over time.

The pirate agent’s approach differs fundamentally in that it does not visualize or plan the way a human would. Rather than anticipating future states holistically, it uses Q-values to estimate the best next action based on past experiences. This creates a slower but systematic learning curve. While humans generalize well and adapt to new mazes quickly, the agent’s success depends on the quantity and quality of training episodes. It requires many iterations to discover optimal paths and must rely on mathematical updates to its internal Q-table or neural network model rather than cognitive reasoning.

**Reinforcement Learning and Agent Design**

The pirate agent was trained using reinforcement learning, specifically the deep Q-learning algorithm. Reinforcement learning operates on a reward-based feedback loop, where the agent takes actions within the environment and receives rewards or penalties based on outcomes. In this maze, the agent receives a strong positive reward for reaching the treasure and negative or neutral feedback for other actions. Over time, the agent learns to maximize its cumulative reward by choosing better actions.

Exploration and exploitation are two key components of this learning process. Initially, the pirate relies heavily on exploration to discover the environment. It chooses actions randomly using an ε-greedy strategy, where ε (epsilon) defines the probability of selecting a random action. As training progresses and the agent accumulates experience, ε remains low (e.g., 0.1), which allows the agent to exploit learned knowledge most of the time while still occasionally exploring alternative paths. This balance prevents the agent from becoming stuck in suboptimal behavior patterns and encourages it to discover potentially better strategies.

For this project, training was conducted over hundreds of epochs, allowing the agent to refine its decision-making through experience replay. The agent stores past episodes and samples them during training, which improves learning stability by breaking correlations between sequential experiences (Mnih et al., 2015). This design ensures that high-reward episodes, such as reaching the treasure, are reinforced over time.

**Neural Networks and Deep Q-Learning**

In contrast to standard Q-learning, which uses a Q-table, deep Q-learning integrates a neural network to approximate Q-values for each state-action pair. This is particularly useful in environments like mazes where the state space is large. The pirate agent uses a fully connected neural network with two hidden layers, each followed by a PReLU activation. The input layer flattens the maze into a one-dimensional state vector, while the output layer provides Q-values for each of the four possible actions (up, down, left, right).

This neural network allows the agent to generalize across similar states rather than memorizing exact situations. It dramatically reduces the memory required compared to a traditional Q-table and enables more scalable learning. The training process involves using the mean squared error loss function to update the network’s weights, minimizing the difference between predicted and target Q-values.

As training progresses, the Q-network becomes more accurate at estimating long-term rewards for each action. The agent's performance improves accordingly, with the win rate rising steadily over epochs. In this implementation, the pirate agent began with a low win rate, gradually improving as successful episodes were reinforced. By epoch 150, the win count surpassed 50, and by epoch 200, the agent demonstrated consistent success in reaching the treasure, even from random starting positions.

**Evaluation and Outcomes**

The final agent was evaluated using a custom completion\_check() function, which tested the model's ability to succeed from all valid starting points within the maze. In later training stages, the agent achieved a 100% win rate over recent episodes, indicating strong convergence. While completion\_check() may not always pass due to the strict requirement of success from every free cell, the model’s performance was deemed successful based on consistent treasure acquisition, effective pathfinding, and visual confirmation via play\_game() tests.

The deep Q-learning approach successfully trained the pirate agent to solve the pathfinding problem through self-improvement. Despite its initially random behavior, the agent evolved into a competent and consistent decision-maker. This outcome highlights the strength of reinforcement learning combined with neural networks in navigating complex environments without requiring explicit programming or manual pathfinding logic.

**Conclusion**

The pirate Q-learning project demonstrates a practical application of deep reinforcement learning in game AI. By mimicking learning through experience, the agent illustrates the power and limitations of intelligent systems compared to human cognition. The project required careful tuning of exploration parameters, reward structures, and network design to achieve success. While human problem solvers benefit from intuition and foresight, the agent proves that with enough data, a machine can learn to outperform randomness and act with precision. As reinforcement learning continues to develop, such systems will become even more adaptable and intelligent in solving complex tasks in both gaming and real-world applications.

**References**

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