### Southern New Hampshire University

### 7-3 Project Two: Design Defense

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### CS-370 – Current/Emerging Trends in CS

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**Analyze Human vs. Machine Intelligence**

**Analyze the differences between human and machine approaches to solving problems.**

Human and machine approaches to problem-solving differ significantly in several key aspects. Humans rely on their creativity and gut feelings to solve tough problems, using past experiences, feelings, and abstract thinking. Machines, on the other hand, usually stick to set rules and algorithms, which can make it hard for them to think outside the box.

When it comes to speed and accuracy, machines are way more efficient. They can evaluate numbers and process huge amounts of data faster and more accurately than humans. But humans are better at adapting to new or unclear situations, which helps them come up with more nuanced and fitting solutions.

Humans can learn from their experiences, feedback, and mistakes, which helps them get better at problem-solving over time. Machines can learn too, through machine learning algorithms, but their learning tends to be more specialized and needs lots of labeled data.

Emotional intelligence is another area where humans shine. We're good at understanding and dealing with complex emotions and social situations, which can be critical in problem-solving, especially in groups. Machines, on the other hand, lack this emotional intelligence and might struggle with tasks that need understanding feelings or social cues.

Humans do have limits though, like memory, attention, and processing power, which can affect our problem-solving abilities. Machines can process huge amounts of data quickly and accurately, but they're limited by their programming and the resources available to them (Goel, A. K., Davies, J., 2020).

When it comes to biases, humans and machines both have their issues. Humans can be influenced by biases, which can affect how we solve problems. Machines can also have biases, often reflecting the biases in the data they've been trained on. Figuring out how to deal with and reduce bias in machine learning is an ongoing challenge in AI research (Xiang, 2019).

**Describe the steps a human being would take to solve this maze.**

The steps involved for a human to solve the TreasureHuntGame would begin by reading the instructions to understand the goal and rules. Then, dive into analyzing the clues, paying close attention to any hints or keywords that might lead you to the treasure’s location. Use any provided information wisely, like historical facts or geographical details, to narrow down your search areas. Map out possible locations where the treasure could be hidden and prioritize them based on the clues and your intuition. Begin searching the locations one by one, keeping an eye out for additional clues or hints. If you don’t find the treasure, take a step back, review the clues and locations, and adjust your strategy. Keep searching until you find the treasure.

**Describe the steps your intelligent agent is taking to solve this pathfinding problem.**

The intelligent agent is systematically addressing the TreasureHuntGame by first comprehensively reviewing and understanding the instructions to the game’s rules and objectives. It then parses each clue, extracting important information and identifying key patterns or words that could indicate the treasure’s whereabouts. Subsequently, the agent formulates hypotheses based on the clues and any supplementary data available. These hypotheses are critically evaluated, with each assigned a probability score based on the clues and contextual information. The agent then prioritizes search locations based on the assessed likelihood of containing the treasure. It searches these locations, utilizing any new clues or information discovered to refine its search strategy. Throughout this process, the agent continuously updates its hypotheses based on search outcomes and new data. If the treasure remains elusive, the agent iterates through the process, refining its hypotheses and search parameters until the treasure is successfully located. Upon finding the treasure, the agent ends the program (Dügmeci, 2019).

**What are the similarities and differences between these two approaches?**

The human and intelligent agent approaches to solving the TreasureHuntGame share some similarities but also have key differences. Both aim to find the treasure by analyzing clues and employing a systematic search strategy. They adapt their approach based on new information during the search. However, the agent has an edge in processing power, enabling it to analyze clues and generate hypotheses more efficiently. It also has superior memory and recall capabilities, which can be advantageous in complex puzzles like this. On the other hand, humans bring emotional intelligence and creativity to the table, allowing them to interpret clues and think outside the box. Humans, though, can be prone to biases, unlike properly designed agents. These differences highlight how both approaches have unique strengths that can be leveraged to solve the TreasureHuntGame (Beysolow, II, Taweh, 2019).

**Assess the purpose of the intelligent agent in pathfinding.**

**What is the difference between exploitation and exploration?**

In machine learning, exploitation and exploration are two important strategies for learning algorithms. Exploitation is likened to playing it safe—it's about choosing actions that are known to give good results based on what's already known. An example would be sticking to your favorite restaurant because you know you'll enjoy the food. On the other hand, exploration is more adventurous—it's about trying out new things to see if there's something better out there. Using the same restaurant analogy above, it's like trying a new restaurant to see if it might become your new favorite. In machine learning, balancing exploitation and exploration is key. Too much exploitation and you might miss out on better options, but too much exploration and you might waste time on less rewarding actions. So, finding the right balance between the two is crucial for effective learning and decision-making in machine learning algorithms (Gulli, A., Pal, S., 2017).

**What is the ideal proportion of exploitation and exploration for this pathfinding problem? Explain your reasoning.**

The ideal proportion of exploitation and exploration for the TreasureHuntGame depends on the complexity of the game and the available clues. In the early stages, when there is limited information about the treasure's location, a higher proportion of exploration is beneficial. This means trying out different locations and strategies to gather more clues and narrow down the search area. As more clues are discovered and the search area is reduced, the balance should shift more towards exploitation. This involves focusing on the most promising locations and clues to maximize the chances of finding the treasure. However, maintaining some level of exploration is important throughout the game to ensure that new information is still being gathered and that the search strategy remains flexible. Too much exploitation early on could lead to missing crucial clues, while too much exploration later in the game could result in inefficient use of time and resources. Therefore, a dynamic balance that adapts to the evolving information and search context is key to success in the TreasureHuntGame (Gulli, A., Pal, S., 2017).

**How can reinforcement learning help to determine the path to the goal (the treasure) by the agent (the pirate)?**

Reinforcement learning helps our pirate agent find the treasure by learning from its actions in a trial-and-error style. First, it sees the environment, like the map with paths and obstacles. Each spot on the map becomes a state, with the pirate's current spot being its current state. Then, the pirate decides which way to move based on where it is. As it moves, it gets rewards or penalties based on its choices—moving closer to the treasure gets a reward, while moving away or hitting an obstacle gets a penalty. The pirate learns over time which moves get the best rewards, and it uses this knowledge to plan its path to the treasure, avoiding obstacles along the way. It also balances trying out new paths and sticking to what it knows works best. Eventually, the pirate figures out the best path through the map to get to the treasure, using its learning to guide its journey (Lamba, A, 2018).

**Evaluate the use of algorithms to solve complex problems.**

**How did you implement deep Q-learning using neural networks for this game?**

To implement deep Q-learning using neural networks for the TreasureHuntGame, I first represented the game environment, including the map and possible actions, as states and actions. I then created a neural network that takes a state as input and outputs Q-values for each possible action. These Q-values represent the expected future rewards of taking each action in the current state.

During training, the agent explores the environment and updates the neural network's weights to minimize the difference between the predicted Q-values and the actual rewards obtained. This is done using a loss function that penalizes incorrect predictions and rewards correct ones.

I also used experience replay, which stores past experiences (state, action, reward, next state) in a memory buffer and samples from this buffer during training. This helps stabilize training and improve the agent's performance by reducing the correlation between consecutive experiences.

Overall, implementing deep Q-learning for the TreasureHuntGame involved designing a neural network to approximate Q-values, updating the network using a suitable loss function, and using experience replay to improve learning stability (Gulli, A., Pal, S., 2017).

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