Solving problems can vary greatly between humans and machines, as each approaches challenges with different strategies. One classic example is navigating a maze, which highlights the distinct problem-solving methods of humans compared to intelligent agents like those using deep Q-learning.

Firstly, Humans often rely on intuition, context, and strategies to navigate mazes. A common approach is to follow a constant path, such as taking every right turn and backtracking when no further turns are possible. Although this method is not efficient, humans understand intuitively that it guarantees reaching the exit is inevitable with this strategy. Also, humans utilize their short-term memory to recall paths explored, to avoid repeating the same mistake and avoiding hitting the same dead end again. Additionally, humans can visualize and create a mental map of the maze as they explore, using spatial recognition to detect if they are going in a loop are going to end up at a dead end. This mental map allows intuition to guide their decisions, ultimately optimizing their path to the exit over time. In my experience navigating mazes, this combination of spatial awareness and intuition is a crucial tool in aiding my foresight to come to educated decisions.

A Q-learning agent handles the maze in a different way. It breaks the maze into states and chooses actions in each state, getting rewards or penalties depending on how good the move is. Over time, it updates a Q-table, which keeps track of expected rewards for each action in each state. When you combine this with a neural network, the Q-values help the agent predict the reward for a move and improve its choices. The agent also balances exploring new moves and exploiting the best-known moves based on an exploration factor (Medium, 2018; Serengeti Tech, 2023). This helps it gradually figure out the best path.

Both use memory and the value of experiences to track past actions: humans use short-term memory, and agents use a Q-table (Medium, 2022). The big difference is that humans can use intuition, general knowledge, and context to adapt to new problems quickly, while agents need lots of training on the same problem to figure out an optimal strategy (Wang et al., 2025; Zheng et al., 2023). Humans don’t always find the perfect path, but we can still solve the problem efficiently, whereas agents aim to converge on the optimal solution after many trials.

Exploitation is when the agent picks the action it knows is the best from its Q-table, and exploration is when it tries random actions to find new possibilities. The right balance depends on the complexity of the maze and how far the agent is in training. Early on, more exploration is helpful; later, more exploitation helps refine the optimal path (Medium, 2018).

Reinforcement learning helps the agent figure out the path to the goal. For instance, in a maze with a “pirate” looking for treasure, the agent gets a reward for moving toward the treasure and a penalty for hitting walls. Over time, this encourages the agent to find the shortest path (Medium, 2022; CEUR-WS, 2023). Algorithms like deep Q-learning are great for complex problems because they can handle large state spaces and learn from repeated experience. I implemented deep Q-learning which let the agent improve over many episodes. Combining reinforcement learning with neural networks allows the agent to tackle mazes that would challenge a human (Zheng et al., 2023; Wang et al., 2025).

In conclusion, humans and machines approach problem-solving in very different ways. Humans rely on memory, intuition, and experience, while agents systematically learn from rewards and penalties. Both use experience to improve decisions, but humans can generalize and adapt faster. Reinforcement learning with deep Q-learning is a powerful way for machines to solve complex tasks like maze navigation, showing the strengths of computational approaches.

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