Design Defense

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The difference in how we, human beings, and machines solve problems is similar in the basic aspects; gather data, process said data, and act upon the output of the processed data. However, we humans have all of this computing power contained with in our head, where as the machines are comprised of many processors, power supplies, I/O ports, ribbon cables and a plethora of other computer parts which makes for a rather large piece of equipment, compared to a modest three-pound hunk of grey matter. Yet our machines, can process at speeds we cannot even imagine. As an example, when running this game, the A.I. was able to play 15,000 rounds of the game in 24 minutes. Whereas a human, would have taken days, but probably more accurately weeks because we humans need things like sleep and food.

But we humans have another advantage to aid in our problem solving skills, we have built in sensors, eyesight, touch, smell, taste and hearing, as well as the ability to think abstractly and how past experiences might help us in a given situation and even out “gut instinct” plays a part in our decision making process. Whereas A.I. can only rely on empirical data, A.I. doesn’t have a gut feeling or makes a decision on a hunch. And because of this the A.I. cannot decide for itself, it must follow specific, logical steps to give it the ability to solve the pathfinding problem. Our A.I. must be given input data so that it is able to understand the problem at hand, and eventually enable it to solve the given problem. From there, algorithms, such as a depth first search algorithm or a shortest path algorithm, process the data and the A.I. decides which algorithm most efficiently solves the problem.

Once the algorithms have processed the data the A.I. makes a determination based on the information it has will be able to give the user an output. The biggest difference in this approach is that while the A.I. has to be “spoon fed” input data before it can process it, we can gather data. Another difference in our methods is that humans don’t not usually think of the rewards and penalties at each step throughout the problem-solving process, for us it’s basically “the ends justify the means.” Also, it is entirely possible that I could repeat the same path several times randomly or become distracted, bored or a thousand other things that would break my concentration and take my thoughts off the puzzle creating inefficiency. Yet, the A.I. thinks of the maximum reward and penalty at every step of the problem and constantly works to improve throughout the process. This allows the machine to learn from their mistakes faster and provide the solution within a drastically minimal amount compared to a human.

The biggest differences between exploitation and exploration are that in exploitation, the A.I. is searching the entire amount of sample inputs and testing for each for every possible combination to find solutions. While, exploration the A.I. is pursuing solutions by searching, testing, finding, and improving every possible combination to find solutions. The ideal proportion of exploitation and exploration for this treasure hunt problem, would probably lean more towards that of the exploitation path, as using the exploration path would be in essence how a human would progress, thus probably take longer, although given the A.I.’s speed, exploring would still be much faster than a human. And this helps cement reinforcement learning as it helps determine the path to the goal using trial and error. The A.I. is only able to discover the optimal path when using a testing method to solve the treasure hunting problem.

To implement the deep Q-learning, it was a matter of following the basic steps for using a neural network. First, I had to import libraries for the machine that where created for this specific type of learning. Second, I had to build an area for the machine so that it could be trained. Next, create a learning agent and also incorporate a reward system. Next, implement the use of an enhanced learning algorithm, then test it out to make sure that it was operating with the parameters of the specific environment. And lastly, review and adjust and tweak the code as necessary in ensure optimum results from the A.I.

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