Andrew J Miller
Udacity – Artificial Intelligence Nanodegree
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Research Review

Bayesian Networks:

      Bayesian Networks are probabilistic belief models that help us plan for situations that do not have definitive choices or outcomes for each node. Instead the outcome for each node is defined by Bayesian probability. These planning processes are awesome because a lot of the time we plan or things to happen and the strangest outcomes occur. However, at each point, it's easy (sometimes) to see all of the possible actions for each outcome. They're also good when dealing with adversaries who operate on models that we have no vision of. If we do not know what our enemies value, and only what they might value, then Bayesian networks help us view our planning graph in a way where we define an adversaries action by things they may or may not want. Bayesian probability is used as the statistical model for these methods because they better define the possibilities and outcomes of than other probabilistic outcomes. For me, I think the they might be great for a time series simulation where your limited on the amount of searchable space. So valuing decisions based on what is most likely to occur could be useful.

Markov Decision Processes:

      Markov decision processes are processes by which machines plan and act. They are defined by objective functions and policies. The processes contain a set of all possible states, a set of actions at each state, a value reward function, and a transition that describes the effect that each action has on all other states. The idea is that states can be become valuable depending on where the agent is at in the space. So, acting could make your next action more (or less) valuable if that action affects the entire environment or game. It's like if you're trying to make a lot of money, you could sell a ton of capital, and that would get you the most reward the fastest. However, you should probably keep your capital because it might be able to make you more money in the long run and this would give your future states more utility than if you just sold it all. Which is great because it gives agents a sort of pseudo will-power. This relates directly to search and planning because it's another way we can think about cost and the way we define the value of each state when defining/ constraining the search space.

Action/ Consequence discovery & Reinforcement Learning:

      Part of planning and searching is dealing with problems that have inputs and actuations that have no known consequences. To generalize your Reinforcement learning must be involved so that an agent can successfully identify the value of the current state that they are in along with their future states. They do this by learning and assigning values to their states based on their senses. Machines begin to associate the value of their senses with certain actions, and ultimately outcomes. They also keep track of past actions to keep from searching the same space again. Google's DeepMind is a good example of this method. Nearly all of their methods revolve around discovery and some sort of statistical method to pick what state the agent believes it's in and what action it believes it should take. In this specific example, the agent is given a visual input, motor actuators, and a set of instructions. The agent must figure out the meaning of the command and execute actions which navigate it toward an object. The search space is the meaning of the words, coupled with how the agent defines what it sees. What I found most interesting is that the agent could navigate towards an object that needed to be next to another specific object. Which I thought was very impressive.

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Works referenced:

AC/RL: https://arxiv.org/pdf/1706.06551.pdf

Bayes/Markov: https://www.cs.rice.edu/~vardi/dag01/givan1.pdf

Bayes: http://www0.cs.ucl.ac.uk/staff/d.silver/web/Publications_files/bafa.pdf

Bayes/ Markov: https://web.stanford.edu/group/nasslli/courses/boutilier/Lecture1.pdf