CS 188 Introduction to Artificial Intelligence
Summer 2023 Note 1

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Agents

In artificial intelligence, the central problem at hand is that of the creation of a rational **agent**, an entity that has goals or preferences and tries to perform a series of **actions** that yield the best/optimal expected outcome given these goals. Rational agents exist in an **environment**, which is specific to the given instantiation of the agent. Agents use sensors to learn about the environment and act on it using actuators. Take a simple checker's agent for example: the environment for a checkers agent is the virtual checkers board on which it plays against opponents, and its piece moves are the actions. Together, an environment and the agents that reside within it create a **world**.

A **reflex agent** is one that doesn't think about the consequences of its actions, but rather selects an action based solely on the current state of the world. These agents are typically outperformed by **planning agents**, which maintain a model of the world and use this model to simulate performing various actions. Then, the agent can determine hypothesized consequences of the actions and can select the best one. This is simulated "intelligence" in the sense that it's exactly what humans do when trying to determine the best possible move in any situation - by thinking ahead.

To define the task environment we use the **PEAS** (**P**erformance Measure, **E**nvironment, **A**ctuators, **S**ensors) description. The performance measure describes what utility the agent tries to increase. The environment summarizes where the agent acts and what affects the agent. The actuators and the sensors are the methods with which the agent acts on the environment and receives information from it.

The **design** of an agent heavily depends on the type of environment the agents acts upon. We can characterize the types of environments in the following ways.

- In *partially observable* environments, the agent does not have full information about the state and thus the agent must have an internal estimate of the state of the world. This is in contrast to *fully observable* environments, where the agent maintains full information about their state.
- *Stochastic* environments have uncertainty in the transition model, i.e. taking an action in a specific state may have multiple possible outcomes with varying associated probabilities. This is in contrast to *deterministic* environments, where taking an action in a state has a single outcome that is guaranteed to happen.
- In *multi-agent* environments the agent acts in the environments along with other agents. For this reason the agent might need to randomize its actions in order to avoid being "predictable" by other agents.
- If the environment does not change as the agent acts on it, then this environment is called *static*. This is in contrast to *dynamic* environments that change as the agent interacts with it.

- If an environment has *known physics*, then the transition model (even if stochastic) is known to the agent and it can use that when planning a path. If the *physics are unknown* the agent will need to take actions deliberately to learn the unknown dynamics.

Utility and Lotteries

Rational agents seek to maximize its expected utility given what it knows. This idea is known as the Principle of Maximum Expected Utility. They do this by evaluating different states via a utility function. Utility functions are functions that map outcomes or states of the agent's world to a real valued number that represents, in essence, their preference or desirability with that outcome. Higher numbers are associated with outcomes that are more aligned with the agent's goals. The agent can employ its utility function to evaluate and compare the varying choices it can make based on the expected utility. By maximizing this expected utility, the agent behaves rationally.

Lotteries are situations where the rewards or prizes aren't fixed or determined. Rather, they are uncertain and the outcomes may vary according to a probability distribution. Lotteries are used to model scenarios where the agent faces risk or uncertainty. A lottery may be represented as $L = [p, A; (1-p), B]$. Here, the agent would receive the prize A with probability p and prize B with probability $1-p$. For a given lottery $[p, S_1; \ldots; p_n, S_n]$ and a utility function $U(r)$, we can evaluative the expected utility of this lottery as $U([p, S_1; \ldots; p_n, S_n]) = \sum_{i=1}^{n} p_i U(S_i)$.

In order to reason about the prizes within lotteries, we assign preferences that provide order respective to the prizes themselves. For example, if we see the notation $A \succ B$, that means the agent prefers prize A over prize B. We can reasonably conclude that for this rational agent's utility function, $U(r), A \succ B \implies U(A) > U(B)$. Likewise, if we encounter the notation $A \sim B$, this tells us that the agent is indifferent between A and B. In other words, $A \sim B \implies U(A) = U(B)$. We can now introduce the notion of rational preferences. These are preferences that, if followed, allow an agent to behave rationally:

- Orderability: $(A \succ B) \vee (B \succ A) \vee (A \sim B)$.
- Transitivity: $(A \succ B) \wedge (B \succ C) \implies (A \succ C)$.
- Continuity: $(A \succ B \succ C) \implies \exists p : [p, A; 1-p, C] \sim B$.
- Sustainability: $(A \sim B) \implies [p, A; 1-p, C] \sim [p, B; 1-p, C]$.
- Monotonicity: $(A \succ B) \implies (p \geq q) \iff [p, A; 1-p, B] \geq [q, A; 1-q, B]$.

Summary

In this note, we discussed how an agent interacts with the environment through its sensors and its actuators. The agent function describes what the agent does in all circumstances. Rationality of the agent means that the agent seeks to maximize their expected utility. We discussed utility and lotteries, and how to reason about them. Finally, we defined our task environments using PEAS descriptions.