Part V

Planning under Uncertainty

Classical planning relies on several restrictive assumptions (see the conceptual model described in Chapter 1), among which are the following.

1. *Determinism:* Actions have deterministic effects, i.e., each action, if applicable in a state, brings to a single new state.
2. *Full observability*: The controller has complete knowledge about the current state of the system, i.e., observations result in a single state, the current state of the system.
3. *Reachability goals*: Goals are sets of states, i.e., the objective is to build a plan that leads to one of the goal states.

As a consequence, plans in classical planning are sequences of actions, and feedback provided by observations is not necessary. In this part of the book, we relax these assumptions.

Nondeterminism. Determinism is a simplified view of the world that assumes it to evolve along a single fully predictable path. The world dynamic is supposed to be entirely "determined" and fixed along that path. In some cases, a model of a system as such a deterministic path can be a useful abstraction, e.g., to reason about nominal cases of behaviors. However, determinism claims that we just need to properly extend a model to predict all that may happen. With a perfect model, the throw of a die would be fully determined. This is, however, a rather unrealistic and impractical assumption because we know that it is impossible to predict everything.

Nondeterminism takes a more realistic stand. Perfect models are, in principle, unachievable. It is much more useful to model all six possible outcomes of the throw of the die and to reason about several possibilities, none of which are certain. It may be useful to model the fact that a component may stop or fail and to plan for "exception handling" or recovering mechanisms.

Even when the obvious model is nondeterministic, classical planning assumes that the nominal case accounted for by a deterministic model is highly frequent, positing that cases not taken into account are marginal and/or can be easily dealt with at the controller level. However, in several applications such an assumption does not hold.

- Nonnominal outcomes of actions are important and sometimes highly critical. They should be modeled at planning time as well as nominal outcomes. For instance, it is very important to model the possible failures of an action that moves a railway switch or that sets the signals of a railroad crossing.
- Sometimes nominal outcomes do not exist, e.g., when we throw dice or toss a coin. This is the case also of actions that ask the user for information, that query a database, or that model web services.

Planning with nondeterministic domains leads to the main difficulty that a plan may result in many different execution paths. Planning algorithms need efficient ways to analyze all possible action outcomes and generate plans that have conditional behaviors and encode trial-and-error strategies.

Nondeterminism can be modeled by associating probabilities to the outcomes of actions. This allows us to model the fact that some outcomes are more likely to happen than others. For instance, nonnominal outcomes may have a lower probability than nominal outcomes.

Partial Observability. In several applications, the state of the system is only partially visible at run-time, and as a consequence different states of the system are indistinguishable for the controller. Indeed, in many applications, we have the following situations.

- Some variables of the system may never be observable by the controller. This is the case in the "home sequencing" problem, i.e., the problem of how to reinitialize a microprocessor by executing some commands without having access to its internal registers.
- Some variables can be observable just in some states or only after some "sensing actions" have been executed. For instance, a mobile robot in a room may not know whether the door in another room is open until it moves to that room. A planner that composes web services for a travel agency cannot know whether there will be seats available until it queries the web services.

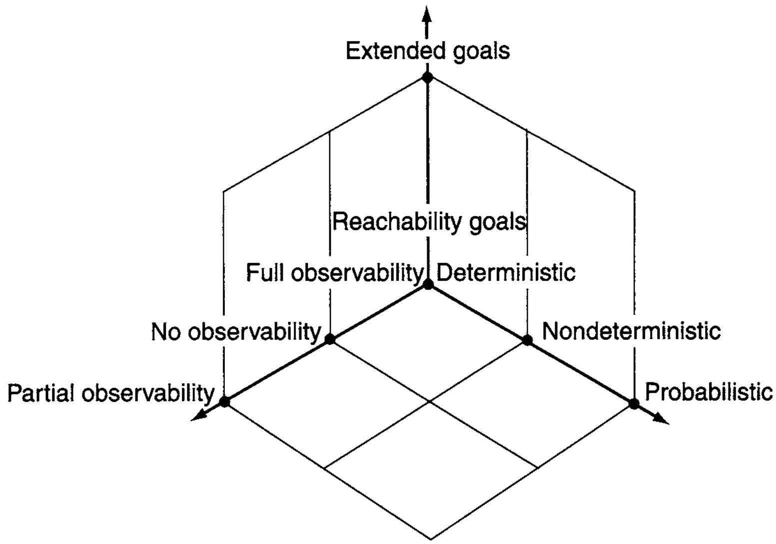

Figure V.1 Different dimensions of uncertainty.

Planning under partial observability has been shown to be a hard problem, both theoretically and experimentally. The main technical consequence of partial observability is that observations return sets of states rather than single states. This makes the search space no longer the set of states of the domain but its power set. Moreover, in the case of planning with probabilities, observations return probability distributions over sets of states. This makes the search space infinite.

Extended Goals. In nondeterministic domains, goals need to specify requirements of different strengths that take into account nondeterminism and possible failures. For instance, we might require that the system "tries" to reach a certain state, and if it does not manage to do so, it guarantees that some safe state is maintained. As an example, we can require that a mobile robot tries to reach a given location but guarantees to avoid dangerous rooms all along the path. Or we can require that the robot keeps moving back and forth between location A, and, if possible, location B. We thus specify that the robot must pass through location A at each round, while it should pass through location B just if possible: the strengths of the requirements for the two locations are different. This can be done with both simple goals like reachability goals and with more complex goals involving temporal conditions, e.g., conditions to be maintained rather than reached.

Extended goals of this kind can be represented in different ways. One approach is to represent extended goals with utility functions (e.g., costs and rewards). In this case, planning consists of searching for a plan that maximizes a utility function. An alternative approach is to represent extended goals with formulas in temporal logic. In this case, planning consists of generating a plan whose behaviors in the domain satisfy the temporal formula. In both cases, planning under uncertainty with extended goals is a challenging problem because extended goals add further complexity to an already complicated problem.

Outline of the Part. The problem of how to plan under uncertainty can thus be addressed along the different dimensions of nondeterminism, of partial observability, and of extended goals (see Figure V.1). In this part, we first describe two main approaches to planning under uncertainty along these three dimensions: planning based on Markov Decision Processes (Chapter 16) and planning by model checking (Chapter 17). We then discuss some further approaches originally devised for classical planning that have been extended to deal with some forms of uncertainty, e.g., state-space and plan-space planning, heuristic search, planning graphs, and planning as satisfiability (Chapter 18).