Informatics 2D – Reasoning and Agents

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Lecture 18 – Planning and Acting in the Real World I
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Where are we?

Last time ...

- Discussed planning with state-space search
- Identified weaknesses of this approach
- Introduced partial-order planning
  - Search in plan space rather than state space
  - Described the POP algorithm and examples

Today ...

- **Planning and acting in the real world I**

Planning/acting in Nondeterministic Domains

- So far only looked at **classical** planning, i.e. environments are fully observable, static, deterministic
- Also assumed that action descriptions are correct and complete
- Unrealistic in many real-world applications:
  - Don't know everything; may even hold incorrect information
  - Actions can go wrong
- Distinction: **bounded** vs. **unbounded** indeterminacy: can possible preconditions and effects be listed at all?
- Unbounded indeterminacy related to qualification problem

Methods for handling indeterminacy

- **Sensorless/conformant planning**: achieve goal in all possible circumstances, relies on coercion
- **Contingency planning**: for partially observable and non-deterministic environments; includes sensing actions and describes different paths for different circumstances
- **Online planning and replanning**: check whether plan requires revision during execution and replan accordingly

Example Problem: Paint table and chair same colour

Initial State: We have two cans of paint and table and chair, but colours of paint and of furniture is unknown:

$$Object(Table) \wedge Object(Chair) \wedge Can(C_1) \wedge Can(C_2) \wedge InView(Table)$$

Goal State: Chair and table same colour:

$$Color(Chair, c) \wedge Color(Table, c)$$

Actions: To look at something; to open a can; to paint.

Formal Representation of the Three Actions

Now we allow variables in preconditions that aren't part of the actions's variable list!

$$\begin{aligned}&Action(RemoveLid(can),\\&\quad \textsc{Precond}: Can(can)\\&\quad \textsc{Effect}: Open(can))\end{aligned}$$

$$\begin{aligned}&Action(Paint(x, can),\\&\quad \textsc{Precond}: Object(x) \wedge Can(can) \wedge Color(can, c) \wedge Open(can)\\&\quad \textsc{Effect}: Color(x, c))\end{aligned}$$

$$\begin{aligned}&Action(LookAt(x),\\&\quad \textsc{Precond}: InView(y) \wedge (x \neq y)\\&\quad \textsc{Effect}: InView(x) \wedge \neg InView(y))\end{aligned}$$

Sensing with Percepts

- A percept schema models the agent's sensors.
- It tells the agent what it knows, given certain conditions about the state it's in.

$$\begin{aligned}&Percept(Color(x, c),\\&\quad \textsc{Precond}: Object(x) \wedge InView(x))\end{aligned}$$

$$\begin{aligned}&Percept(Color(can, c),\\&\quad \textsc{Precond}: Can(can) \wedge Open(can) \wedge InView(can))\end{aligned}$$

- A fully observable environment has a percept axiom for each fluent with no preconditions!
- A sensorless planner has no percept schemata at all!

Planning

- One could coerce the table and chair to be the same colour by painting them both—a sensorless planner would have to do this!
- But a contingent planner can do better than this:
  1. Look at the table and chair to sense their colours.
  2. If they're the same colour, you're done.
  3. If not, look at the paint cans.
  4. If one of the can's is the same colour as one of the pieces of furniture, then apply that paint to the other piece of furniture.
  5. Otherwise, paint both pieces with one of the cans.
- Let's now look at these types of planning in more detail. . .

How to represent belief states

1. Sets of state representations, e.g.

$$\{(AtL \land CleanR \land CleanL), (AtL \land CleanL)\}$$

   (2^n states!)
2. Logical sentences can capture a belief state, e.g. $AtL \land CleanL$ shows ignorance about $CleanR$ by not mentioning it!
   - This often offers a more compact representation, but
   - Many equivalent sentences; need **canonical** representation to avoid general theorem proving; E.g:
     - All representations are ordered conjunctions of literals (under open-world assumption)
     - But this doesn't capture everything (e.g. $AtL \lor CleanR$)
3. Knowledge propositions, e.g. $K(AtR) \land K(CleanR)$ (closed-world assumption)

- Will use second method, but clearly loss of expressiveness

Sensorless Planning: The Belief States

- There are no *InView* fluents, because there are no sensors!
- There are unchanging facts: $Object(Table) \land Object(Chair) \land Can(C_1) \land Can(C_2)$
- And we know that the objects and cans have colours: $\forall x \exists c\, Color(x, c)$
- After skolemisation this gives an initial belief state:

$$b_0 = Color(x, C(x))$$

- A belief state corresponds exactly to the set of possible worlds that satisfy the formula—open world assumption.

The Plan

$$[RemoveLid(C_1), Paint(Chair, C_1), Paint(Table, C_1)]$$

Rules:

- You can only apply actions whose preconditions are satisfied by your current belief state b.
- The update of a belief state b given an action a is the set of all states that result (in the physical transition model) from doing a in each possible state s that satisfies belief state b:
  $b' = \text{Result}(b, a) = \{s' : s' = \text{Result}_P(s, a) \land s \in b\}$

Or, when a belief b is expressed as a formula:

1. If action adds l, l becomes a conjunct of the formula b' (and the conjunct $\neg l$ removed, if necessary); so $b' \models l$
2. If action deletes l, $\neg l$ becomes a conjunct of b' (and l removed).
3. If action says nothing about l, it retains its b-value.

Showing the Plan Works

$$\begin{aligned}
b_0 &= Color(x, C(x)) \\
b_1 &= \text{Result}(b_0, RemoveLid(C_1)) \\
&= Color(x, C(x)) \land Open(C_1) \\
b_2 &= \text{Result}(b_1, Paint(Chair, C_1)) \\
&\quad (\text{binding } \{x/C_1, c/C(C_1)\} \text{ satisfies } \text{Precond}) \\
&= Color(x, C(x)) \land Open(C_1) \land Color(Chair, C(C_1)) \\
b_3 &= \text{Result}(b_2, Paint(Table, C_1)) \\
&= Color(x, C(x)) \land Open(C_1) \land \\
&\quad Color(Chair, C(C_1)) \land Color(Table, C(C_1))
\end{aligned}$$

Conditional Effects

- So far, we have only considered actions that have the same effects on all states where the preconditions are satisfied.
- This means that any initial belief state that is a conjunction is updated by the actions to a belief state that is also a conjunction.
- But some actions are best expressed with conditional effects.
- This is especially true if the effects are non-deterministic, but in a bounded way.

Extending action representations

- Disjunctive effects: $Action(Left, \textsc{Precond}{:}AtR, \textsc{Effect}{:}AtL \vee AtR)$
- Conditional effects:

  $Action(Vacuum,$
  $\textsc{Precond}{:}$
  $\textsc{Effect}{:}(\textbf{when } AtL: \ CleanL) \wedge (\textbf{when } AtR: \ CleanR))$

- Combination:

  $Action(Left,$
  $\textsc{Precond}{:}AtR$
  $\textsc{Effect}{:}AtL \vee (AtL \wedge (\textbf{when } CleanL: \ \neg CleanL)))$

- Conditional steps: **if** $AtL \wedge CleanL$ **then** *Right* **else** *Vacuum*

Contingent Planning: Using the Percepts

The formal representation of the plan we saw earlier:

$[LookAt(Table), LookAt(Chair)$
if $Color(Table, c) \wedge Color(Chair, c)$ **then** $NoOp$
else $[RemoveLid(C_1), LookAt(C_1), RemoveLid(C_2), LookAt(C_2),$
if $Color(Chair, c) \wedge Color(can, c)$ **then** $Paint(Table, can)$
else if $Color(Table, c) \wedge Color(can, c)$ **then** $Paint(Chair, can)$
else $[Paint(Chair, C_1), Paint(Table, C_1)]]]$

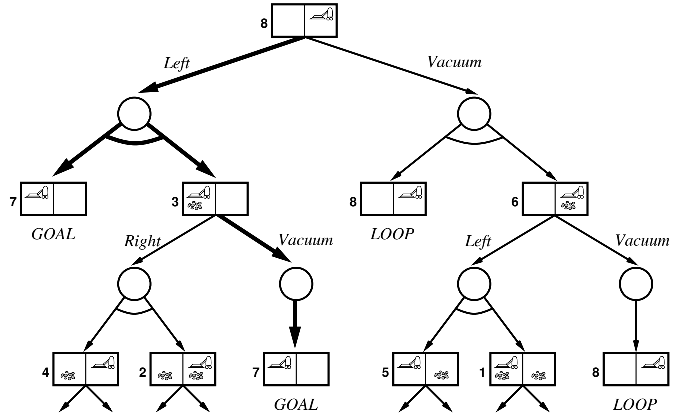
- Variables (e.g., c) are existentially quantified.

Games against nature

- Conditional plans should succeed regardless of circumstances
- Nesting conditional steps results in trees
- Similar to adversarial search, **games against nature**
- Game tree has state nodes and chance nodes where nature determines the outcome
- Definition of solution: A subtree with
  - a goal node at every leaf
  - specifies one action at each state node
  - includes every outcome at chance node
- AND-OR graphs can be used in similar way to the minimax algorithm (basic idea: find a plan for every possible result of a selected action)

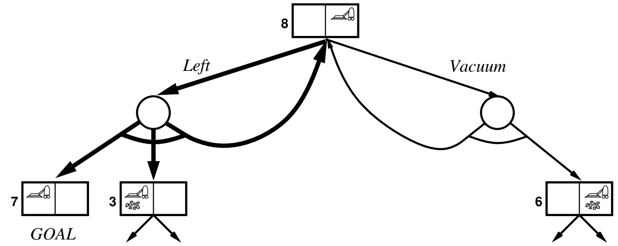
Example: “double Murphy” vacuum cleaner

- This wicked vacuum cleaner sometimes deposits dirt when moving to a clean destination or when vacuuming in a clean square
- Solution: [*Left*, **if** *CleanL*; **then** [] **else** *Vacuum*]



Acyclic vs. cyclic solutions

- If identical state is encountered (on same path), terminate with failure (if there is an acyclic solution it can be reached from previous incarnation of state)
- However, sometimes all solutions are cyclic!
- E.g., “triple Murphy” (also) sometimes fails to move.
- Plan [*Left*, **if** *CleanL* **then** [] **else** *Vacuum*] doesn’t work anymore
- Cyclic plan:
  [*L* : *Left*, **if** *AtR* **then** *L* **elseif** *CleanL* **then** [] **else** *Vacuum*]

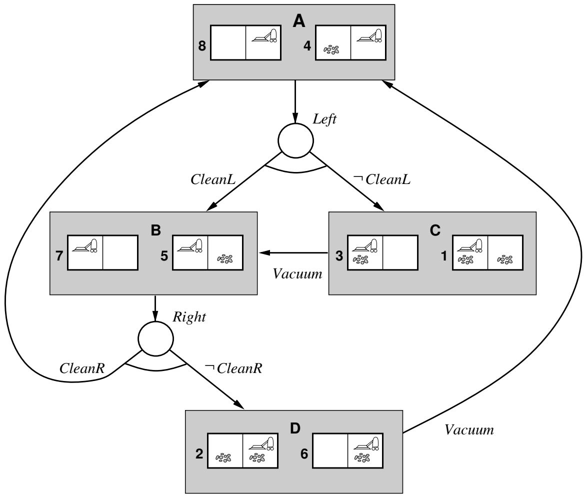


Nondeterminism and partially observable environments

“alternate double Murphy”:

- Vacuum cleaner can sense cleanliness of square it’s in, but not the other square, and
- dirt can sometimes be left behind when leaving a clean square.
- Plan in fully observable world: “Keep moving left and right, vacuuming up dirt whenever it appears, until both squares are clean and in the left square”
- But now goal test cannot be performed!

Housework in partially observable worlds



Conditional planning, partial observability

- Basically, we can apply our AND-OR-search to belief states (rather than world states)
- Full observability is special case of partial observability with singleton belief states
- Is it really that easy?
- Not quite, need to describe
  - representation of belief states
  - how sensing works
  - representation of action descriptions

Summary

- Methods for planning and acting in the real world
- Dealing with indeterminacy
- Contingent planning: use percepts and conditionals to cater for all contingencies.
- Fully observable environments: AND-OR graphs, games against nature
- Partially observable environments: belief states, action and sensing
- Next time: **Planning and acting in the real world II**