## Principles of AI Planning

Nondeterministic planning with partial observability

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February 7th, 2007

## Nondeterministic planning with partial observability

Planning with partial observability is harder than both the fully observable and unobservable cases:

- Memoryless plans (where the next action to take only depends on the current situation) as in the fully observable case are not sufficient.
- Of course, we cannot define a memoryless plan based on individual states because limited observability makes some states indistinguishable.
- It is also not sufficient to consider memoryless plans where the action to take is based on the current observation class.
- Conformant (i.e., non-branching) plans as in the unobservable case are also clearly not powerful enough.


## Strong planning

- We will (mostly) consider the strong planning problem.
- Generalizations to the strong cyclic planning are similar to the fully observable case.


## Algorithms

Similar to other variants of the planning problem, there are three major approaches to nondeterministic planning with partial observability:

- Reduction to another problem
- Forward search
- Backward search

We will consider one example for each of these.

## Algorithms

Three approaches

Reduction to another problem:

- Reduce to planning with full observability.

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Backward search (regression):

- Start from the set of goal states.
- Find state sets from which already generated state sets can be reached by applying operators and making observations.


## Reduction to fully observable case

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- Memoryless plans are not sufficient for the partially observable case because a plan must take into account the knowledge collected in previous observations etc.
- During plan execution, this knowledge is represented in the current belief state.

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## Reduction to fully observable case

State variables

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Let $\mathcal{T}=\langle A, I, O, G, V\rangle$ be the input task with state set $S$. We define the fully observable task $\mathcal{T}^{\prime}=\left\langle A^{\prime}, I^{\prime}, O^{\prime}, G^{\prime}, A^{\prime}\right\rangle$.

## State variables

- For each state $s \in S$, there is one state variable $v_{s} \in A^{\prime}$.
- Intuition: $v_{s}$ is true in a state of $\mathcal{T}^{\prime}$ iff it is possible that we are currently in $s$.
- Formally: $A^{\prime}:=\left\{v_{s} \mid s \in S\right\}$


## Reduction to fully observable case

Let $\mathcal{T}=\langle A, I, O, G, V\rangle$ be the input task with state set $S$.
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## Initial state formula

- The initial state of $\mathcal{T}^{\prime}$ is fully deterministic (in terms of $A^{\prime}$ ), as there is only one possible initial belief state in $\mathcal{T}$.
- For all states $s$ in the initial belief state of $\mathcal{T}$, variable $v_{s}$ is initially true. Other variables are initially false.
- Formally: $I^{\prime}:=\bigwedge_{s \in S, s \models I} v_{s} \wedge \bigwedge_{s \in S, s \not \models I} \neg v_{s}$.


## Reduction to fully observable case

Let $\mathcal{T}=\langle A, I, O, G, V\rangle$ be the input task with state set $S$.
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## Goal formula

- A goal belief state of $\mathcal{T}$ is one where all possible states satisfy $G$.
- This is equivalent to saying that no state in the current belief state violates $G$.
- We can express that by saying that none of the variables


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Summary $v_{s}$ for states $s$ violating $G$ are true.

- Formally: $G^{\prime}:=\bigwedge_{s \in S, s \not \models G} \neg v_{s}$.


## Reduction to fully observable case

Let $\mathcal{T}=\langle A, I, O, G, V\rangle$ be the input task with state set $S$.
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## Operators (preconditions)

- Each operator $o=\langle c, e\rangle \in O$ is translated to an operator
- To test whether operator $o$ is applicable, we must verify that all states in the current belief state satisfy $c$.
- Again, this is equivalent to saying that no state in the current belief state violates $c$.
- Formally: $c^{\prime}:=\bigwedge_{s \in S, s \notin c} \neg v_{s}$.


## Reduction to fully observable case

 Initial state formulaLet $\mathcal{T}=\langle A, I, O, G, V\rangle$ be the input task with state set $S$.
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## Operators (effects)

- Each operator $o=\langle c, e\rangle \in O$ is translated to an operator $o^{\prime}=\left\langle c^{\prime}, e^{\prime}\right\rangle \in O^{\prime}$.
- After applying operator $o$, we can possibly be in state $s \in S$ iff we were previously in some state in which $o$ is applicable and from which applying $o$ can lead to $s$.


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- This is modeled by an effect
- Formally: $e^{\prime}:=\bigwedge_{s \in S}\left(\left(\left(\bigvee_{t \in \text { preimg }_{o}(s)} v_{t}\right) \triangleright v_{s}\right) \wedge\right.$

$$
\left.\left(\neg\left(\bigvee_{t \in \operatorname{preimg}_{o}(s)} v_{t}\right) \triangleright \neg v_{s}\right)\right) .
$$

## Reduction to fully observable case

Done?

- We have translated state variables, initial state formula, goal formula and operators.

Is that it?

- So far, our translation is independent of the set of observable variables $V$ !
- Moreover, the resulting planning task is deterministic!

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Is there an error in our modeling?

## Reduction to fully observable case

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## Reduction to fully observable case

Not done

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Is there an error in our modeling?

- No, but it is not complete yet: There are solvable partially observable tasks $\mathcal{T}$ for which $\mathcal{T}^{\prime}$ (as defined so far) is unsolvable.
- The reason for this is that he have not yet modeled the possibility of observing state variables.

Modeling observations requires introducing nondeterminism in

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Modeling observations requires introducing nondeterminism in $\mathcal{T}^{\prime}$.


## Reduction to fully observable case

Let $\mathcal{T}=\langle A, I, O, G, V\rangle$ be the input task with state set $S$.
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- If we observe $u$ in a belief state $b$, we can end up in two different belief states: one containing exactly the states of $b$ where $u$ is true, and one containing exactly the states of $b$ where $u$ is false.
- In other words, either the belief states where $u$ is false or the belief states where $u$ is true are ruled out.
- Formally: Translate observation of $u \in V$ into an operator $\left\langle\top, e_{u}^{\prime}\right\rangle \in O^{\prime}$ with $e_{u}^{\prime}:=\left(\bigwedge_{s \in S, s \mid \vDash u} \neg v_{s}\right) \mid\left(\bigwedge_{s \in S, s \mid=u} \neg v_{s}\right)$.


## Reduction to fully observable case

- Note that the reduction works both for strong and for strong cyclic planning.
- The reduction has a significant drawback: Since it introduces as many state variables as there are states in the original task, the resulting problem is exponentially larger than the original one.
- This will usually not be practical.
- On the other hand, there does not really exist any truly "practical" algorithm for nondeterministic planning with partial observability.


## Reduction to fully observable case

Complexity result

- Using an exponential-time planning algorithm for fully observable planning, $\mathcal{T}^{\prime}$ can be solved in time $O\left(c^{\left\|\mathcal{T}^{\prime}\right\|}\right)$, and $\left\|\mathcal{T}^{\prime}\right\|=O\left(c^{\|\mathcal{T}\|}\right)$.
- Thus, we have a double-exponential $\left(O\left(c^{c^{\|I\|}}\right)\right)$ algorithm
for nondeterministic planning for partial observability.
- We will later prove that this is worst-case optimal.

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## Search in AND/OR trees

In forward search, plans are represented as trees whose nodes represent the situations arising during plan execution.

- The root node represents the initial situation.
- OR nodes correspond to choosing and applying operators.
- Note how these relate to operators in $\mathcal{T}^{\prime}$ in the earlier reduction.
- AND nodes correspond to making observations.
- Note how these relate to nondeterminism in $\mathcal{T}^{\prime}$ in the earlier reduction.


## Search in AND/OR trees

## Example



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## AND/OR trees

Formal definition

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## Definition

An AND/OR tree is a labeled rooted tree where

- internal nodes are labeled with $(\wedge)$ or $(\vee)$ (AND nodes/OR nodes), and
- leaves are labeled with $(T)$ or $(\perp)$

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Algorithm (true leaves/false leaves).

## AND/OR trees

Truth value

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## Definition

An AND/OR tree evaluates to true iff

- it is a true leaf,
- it is an OR node with a child that evaluates to true, or
- it is an AND node whose children all evaluate to true.


## Partial plan trees

## Definition

A partial plan tree for a nondeterministic planning task following properties:

- Each node $n$ has an associated belief state $b(n)$.
- If $n$ is the root node, then $b(n)=\{s \in S|s|=I\}$.

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- A leaf node $n$ is labeled with ( $T$ ) iff $b(n) \models G$. In this case it is called a goal node, otherwise an open node.


## Partial plan trees

## Definition (ctd.)

A partial plan tree for a nondeterministic planning task $\langle A, I, O, G, V\rangle$ with state set $S$ is an AND/OR tree with the
following properties:

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- An OR node $n$ (also called an operator node) has one child $n_{o}$ for each operator $o \in O$ applicable in $b(n)$, with associated belief state $b\left(n_{o}\right)=a p p_{o}(b(n))$.
- An AND node $n$ (also called an observation node) has an associated formula $\varphi(n)$ over $V$. It has two children:
- $n^{\top}$ with $b\left(n^{\top}\right)=\{s \in b(n) \mid s \models \varphi\}$
- $n^{\perp}$ with $b\left(n^{\perp}\right)=\{s \in b(n) \mid s \not \vDash \varphi\}$.


## Forward planning as search in partial plan trees

- Clearly, a partial plan tree represents a strategy.
- This strategy is a strong plan iff the tree evaluates to true.

We thus obtain a (nondeterministic) forward search algorithm:
Forward search in partial plan trees def expand-tree $(\mathcal{T})$ :

Set $T$ to the partial plan tree for $\mathcal{T}$ that consists of a single leaf, labeled with the initial belief state. while $T$ evaluates to false:

Choose some open leaf $n$ in $T$.
Replace $n$ by an operator or observation node, adding the necessary children to $T$.

## Search in AND/OR trees

Issues

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- There is a conflict between plan size and observing:
- With many observations, plans become very big.
- With few observations, it may be impossible to find a plan.

Trying out all possible ways to branch is not feasible. No good general solutions to this problem exist.

- AND-OR search algorithms use heuristics for making branching decisions.
- But they do not really work well. . .


## Backward search algorithms

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- Backward search algorithms are similar in flavour to the ones for fully observable problems.
- Backward steps with operator application:
- Compute strong preimages.
- Backward steps with observations:
- Compute union of belief states from disjoint observational classes.
- Note: Can always take subsets of solved belief states to make them disjoint.


## Backward search algorithms

Regression: strong preimages

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## Observations in backward search

- Let $C_{1}, \ldots, C_{n}$ be different observational classes.
- Let $B_{1}, \ldots, B_{n}$ be belief states with $B_{i} \subseteq C_{i}$ for all $i=1, \ldots, n$ for which we have a solution plan.
- Then we can find a plan for $B=B_{1} \cup \cdots \cup B_{n}$ by first observing in which class $C_{i}$ we are and then applying the corresponding plan for $B_{i}$.

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## Observations in backward search

## Example: Combining two belief states



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## Observations in backward search

## Example: Combining two belief states, option 1



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## Observations in backward search

## Example: Combining two belief states, option 2



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## Observations in backward search

## Example: Combining two belief states, option 3



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## Observations in backward search

## Example: Combining two belief states, option 4



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## No observability $\Rightarrow$ no branching

Only one observational class: no choice between subplans

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## No observability $\Rightarrow$ no branching

No choice between subplans during execution: option 1


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## No observability $\Rightarrow$ no branching

No choice between subplans during execution: option 2

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## Full observability $\Rightarrow$ arbitrary branching

A different plan can be used for every state


## A systematic backward algorithm

Idea: always split belief states into all observational classes.
Initially, the set of solved belief states includes the set $b_{G} \cap C_{i}$ for each observational class $C_{i}$, where $b_{G}$ is the belief state containing all states satisfying the goal.

Then iterate the following steps:
(1) Pick one belief state $b_{i}$ for each observational class and compute their union $b$.
(2) If $b$ includes all initial states $\rightsquigarrow$ solution.
(3) Otherwise, compute the strong preimage of $b$ with respect to some operator $o$.
(1) Split the resulting set of states to belief states for different observational classes and add them to the set of solved belief states.

## Backward search <br> Example

- Blocks world with three blocks
- Goal: all blocks are on the table
- Only the variables clear( $X$ ) are observable.
- A block can be moved onto the table if the block is clear.
- 8 observational classes corresponding to the 8 valuations of $\{$ clear(A), clear(B), clear(C)\} (one of the valuations does not correspond to a blocks world state).


## Plan construction by backward search

## Example: goal belief state



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## Plan construction by backward search

Example: backward step with red-block-onto-table


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## Plan construction by backward search

Example: backward step with green-block-onto-table


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## Plan construction by backward search

## Example: backward step with blue-block-onto-table



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## Plan construction by backward search

Example: backward step with red-block-onto-table


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## Plan construction by backward search

Example: backward step with green-block-onto-table


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## Plan construction by backward search

Example: backward step with blue-block-onto-table


## Plan construction by backward search

Example: backward step with red-block-onto-table


## Plan construction by backward search

Example: backward step with green-block-onto-table


## Plan construction by backward search

Example: backward step with blue-block-onto-table


## Summary

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- Planning with partial observability in general requires more general classes of plans than the fully observable and unobservable special cases.
- It appears to be significantly harder.
- Algorithmic ideas are similar to the simpler cases:
- Reduction to full observability by viewing belief states as states.
- Forward search in AND/OR trees.
- Dynamic-programming style backward construction of solvable belief states, starting from goal belief states.

