Motivation

- A big source of inefficiency in search algorithms is the *branching factor*
  - the number of children of each node
- E.g., a backward search may try lots of actions that can’t be reached from the initial state

Similarly, a forward search may generate lots of actions that do not reach to the goal
One way to reduce branching factor

- First create a relaxed problem
  - Remove some restrictions of the original problem
    - Want the relaxed problem to be easy to solve (polynomial time)
  - The solutions to the relaxed problem will include all solutions to the original problem

- Then do a modified version of the original search
  - Restrict its search space to include only those actions that occur in solutions to the relaxed problem
Outline

- The Graphplan algorithm
- Planning graphs
  - example
- Mutual exclusion
  - example (continued)
- Doing solution extraction
  - example (continued)
- Discussion
- Extract heuristic values from planning graph
- FF-plan
The Graphplan algorithm

**Graphplan**

procedure Graphplan:

- for $k = 0, 1, 2, \ldots$

  - *Graph expansion:*
    - create a "planning graph" that contains $k$ "levels"
    - Check whether the planning graph satisfies a necessary (but insufficient) condition for plan existence

  - If it does, then
    - *do solution extraction:*
      - backward search, modified to consider only the actions in the planning graph
      - if we find a solution, then return it

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The Planning Graph

- Search space for a relaxed version of the planning problem
- Alternating layers of ground literals and actions
  - Nodes at action-level $i$: actions that might be possible to execute at time $i$
  - Nodes at state-level $i$: literals that might possibly be true at time $i$
  - Edges: preconditions and effects
Due to Dan Weld (U. of Washington)

Suppose you want to prepare dinner as a surprise for your sweetheart (who is asleep)

\[ s_0 = \{ \text{garbage, cleanHands, quiet} \} \]
\[ g = \{ \text{dinner, present, } \neg \text{garbage} \} \]

<table>
<thead>
<tr>
<th>Action</th>
<th>Preconditions</th>
<th>Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>cook()</td>
<td>cleanHands</td>
<td>dinner</td>
</tr>
<tr>
<td>wrap()</td>
<td>quiet</td>
<td>present</td>
</tr>
<tr>
<td>carry()</td>
<td>none</td>
<td>\neg \text{garbage}, \neg \text{cleanHands}</td>
</tr>
<tr>
<td>dolly()</td>
<td>none</td>
<td>\neg \text{garbage}, \neg \text{quiet}</td>
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</tbody>
</table>

Also have the maintenance action: one for each literal
Example (continued)

- **state-level 0:**
  \[ \{ \text{all atoms in } s_0 \} \cup \{ \neg \text{negations of all atoms not in } s_0 \} \]

- **action-level 1:**
  \[ \{ \text{all actions whose preconditions are satisfied and non-mutex in } s_0 \} \]

- **state-level 1:**
  \[ \{ \text{all effects of all of the actions in action-level 1} \} \]

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Also have the maintenance action

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Mutual Exclusion

Two actions at the same action-level are mutex if
- *Inconsistent effects*: an effect of one negates an effect of the other
- *Interference*: one deletes a precondition of the other
- *Competing needs*: they have mutually exclusive preconditions

Otherwise, they don't interfere with each other.
- Both may appear in a solution plan.

Two literals at the same state-level are mutex if
- *Inconsistent support*: one is the negation of the other, or all ways of achieving them are pairwise mutex.

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Augment the graph to indicate mutexes

carry is mutex with the maintenance action for garbage (inconsistent effects)

dolly is mutex with wrap interference

∼quiet is mutex with present inconsistent support
each of cook and wrap is mutex with a maintenance operation

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Also have the maintenance action

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Mutual exclusion

Example

Example (continued)

- Check to see whether there’s a possible solution
- Recall that the goal is
  - \( \{ \neg \text{garbage}, \text{dinner}, \text{present} \} \)
- Note that in state-level 1,
  - All of them are there
  - None are mutex with each other
- Thus, there’s a chance that a plan exists
- Try to find it
  - Solution extraction
Recall what the algorithm does

procedure Graphplan:
  for $k = 0, 1, 2, \ldots$
    \begin{itemize}
      \item Graph expansion:
        \begin{itemize}
          \item create a "planning graph" that contains $k$ "levels"
        \end{itemize}
      \item Check whether the planning graph satisfies a necessary
          (but insufficient) condition for plan existence
      \item If it does, then
        \begin{itemize}
          \item do solution extraction:
            \begin{itemize}
              \item backward search, modified to consider only the actions in
                  the planning graph
              \item if we find a solution, then return it
            \end{itemize}
        \end{itemize}
    \end{itemize}
Solution Extraction

procedure Solution-extraction\((g, i)\)

if \(i=0\) then return the solution

for each literal \(l\) in \(g\)

non-deterministically choose an action to use in state \(s_{i-1}\) to achieve \(l\)

if any pair of chosen actions are mutex

then backtrack

\(g' := \{\text{the preconditions of the chosen actions}\}\)

Solution-extraction\((g', i-1)\)

end Solution-extraction
Example (continued)

- Two sets of actions for the goals at state-level 1
- Neither of them works
  - Both sets contain actions that are mutex
Recall what the algorithm does

procedure Graphplan:

- for $k = 0, 1, 2, \ldots$ \Rightarrow create next level
  - Graph expansion:
    - create a "planning graph" that contains $k$ "levels"
    - Check whether the planning graph satisfies a necessary (but insufficient) condition for plan existence
    - If it does, then
      - do solution extraction: \Rightarrow no solution found
        - backward search, modified to consider only the actions in the planning graph
        - if we find a solution, then return it
Example (continued)

- Go back and do more graph expansion
- Generate another action-level and another state-level

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Solution extraction

Twelve combinations at level 4

- Three ways to achieve $\neg\text{garb}$
- Two ways to achieve dinner
- Two ways to achieve present

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Several of the combinations look OK at level 2

Here’s one of them
Example (continued)

- Call Solution-Extraction recursively at level 2
- It succeeds
- Solution whose parallel length is 2

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Properties of GraphPlan

- GraphPlan is sound and complete
  - If Graphplan returns a plan, then that plan is a solution to the planning problem
  - If there are solutions to the planning problem, then GraphPlan returns one of them

- The size of the planning graph GraphPlan generates is polynomial in the size of the planning problems

- The planning algorithm always terminates
  - There is a fix-point on the number of levels of the planning graphs such that the algorithm either generates a solution or returns failure

- GraphPlan is a **partial order** planner
  - Actions located at the same level which are not mutex are given as ”simultaneously”
  - A total order plan can be generated by constructing an arbitrary sequence from the parallel actions
**History**

- **GraphPlan** was the first planner that used planning-graph techniques.

- Before GraphPlan came out, most planning researchers were working on PSP-like planners (POP, SNLP, UCPOP, etc.).

- The size of the planning graph GraphPlan generates is polynomial in the size of the planning problems.

- GraphPlan caused a sensation because it was so much faster.

- Many subsequent planning systems have used ideas from it:
  - IPP, STAN, GraphHTN, SGP, Blackbox, Medic, TGP, LPG
  - Many of them are much faster than the original Graphplan.
Comparison with Plan-Space Planning

- **Advantage:**
  - The backward-search part of Graphplan - which is the hard part - will only look at the actions in the planning graph smaller search space than PSP; thus faster

- **Disadvantage:**
  - To generate the planning graph, Graphplan creates a huge number of ground atoms
  - Many of them may be irrelevant

- Can alleviate (but not eliminate) this problem by assigning data types to the variables and constants
  - Only instantiate variables to terms of the same data type

- For classical planning, the advantage outweighs the disadvantage
  - GraphPlan solves classical planning problems much faster than PSP
Getting Heuristic Values from a Planning Graph

- Planning graphs can be used to get heuristic values for heuristic search planning.
- Recall how GraphPlan works:
  
  **Graph expansion:** this takes polynomial time
  
  extend a ”planning graph” forward from the initial state until we have achieved a necessary (but insufficient) condition for plan existence

  **Solution extraction:** this takes exponential time
  
  search backward from the goal, looking for a correct plan if we find one, then return it

repeat
**Using Planning Graphs to Compute h(s)**

- In the graph, there are alternating layers of ground literals and actions.
- The number of "action" layers is a lower bound on the number of actions in the plan.
- Construct a planning graph, starting at \( s \).
- \( \Delta^g(s, p) = \) level of the first layer that "possibly achieves" \( p \).
- \( \Delta^g(s, g) \) is very close to \( \Delta_2(s, g) \):
  - \( \Delta_2(s, g) \) counts each action individually.
  - \( \Delta^g(s, g) \) groups together the independent actions in a layer.

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The FastForward Planner

- Use a heuristic function similar to \( h(s) = \Delta^g(s, g) \)
  - Some ways to improve it (I’ll skip the details)
- Don’t want an A*-style search (takes too much memory)
- Instead, use a greedy procedure:

  until we have a solution, do
  
  expand the current state \( s \)
  
  \( s := \) the child of \( s \) for which \( h(s) \) is smallest
  
  (i.e., the child we think is closest to a solution)

- There are some ways to improve this (I’ll skip the details)
- Can’t guarantee how fast it will find a solution, or how good a solution it will find
  - However, it works pretty well on many problems

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FastForward did quite well

In the this competition, all of the planning problems were classical problems

Two tracks:
- "Fully automated" and "hand-tailored" planners
- FastForward participated in the fully automated track
  - It got one of the two "outstanding performance" awards
- Large variance in how close its plans were to optimal
  - However, it found them very fast compared with the other fully-automated planners
Among the automated planners, *FastForward* was roughly in the middle. LPG (graphplan + local search) did much better, and got a ”distinguished performance of the first order” award.

It’s interesting to see how *FastForward* did in problems that went beyond classical planning:

- Numbers, optimization

**Example: Satellite domain, numeric version**

- A domain inspired by the Hubble space telescope (a lot simpler than the real domain, of course)
  - A satellite needs to take observations of stars
  - Gather as much data as possible before running out of fuel
- Any amount of data gathered is a solution
  - Thus, *FastForward* always returned the null plan

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2004 International Planning Competition

- *FastForward’s* author was one of the competition chairs
  - Thus FastForward did not participate
Summary

- Graphplan is an efficient algorithm for domain-independent planning
- Graphplan works in two steps: Graph expansion and solution extraction
- Introducing mutex relations helps to restrict search by eliminating not admissible combinations of literals
- Graphplan is a partial order planner: actions which are independent can be in parallel, a total order plan can be generated from the partial-order solution
- The introduction of Graphplan in 1997 was a break-through in planning research: A. Blum and M. Furst (1997). Fast Planning Through Planning Graph Analysis.
- Graphplan was inspired by dynamic programming algorithms, especially dealing with network flow problems
- Graphplan was followed by many new algorithms which either built on Graphplan or proposed applications of other efficient algorithms to planning (e.g., SAT-Planning)