AI Planning.
Planning-graph techniques.
Heuristic planning.

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Acknowledgements

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Outline

- History
- Motivation
- Reachability analysis
- The planning graph
  - Example
  - Mutual exclusion
  - Example (continued)
- The Graphplan algorithm
- Solution extraction
- Heuristics derived from planning graphs
- Discussion

History

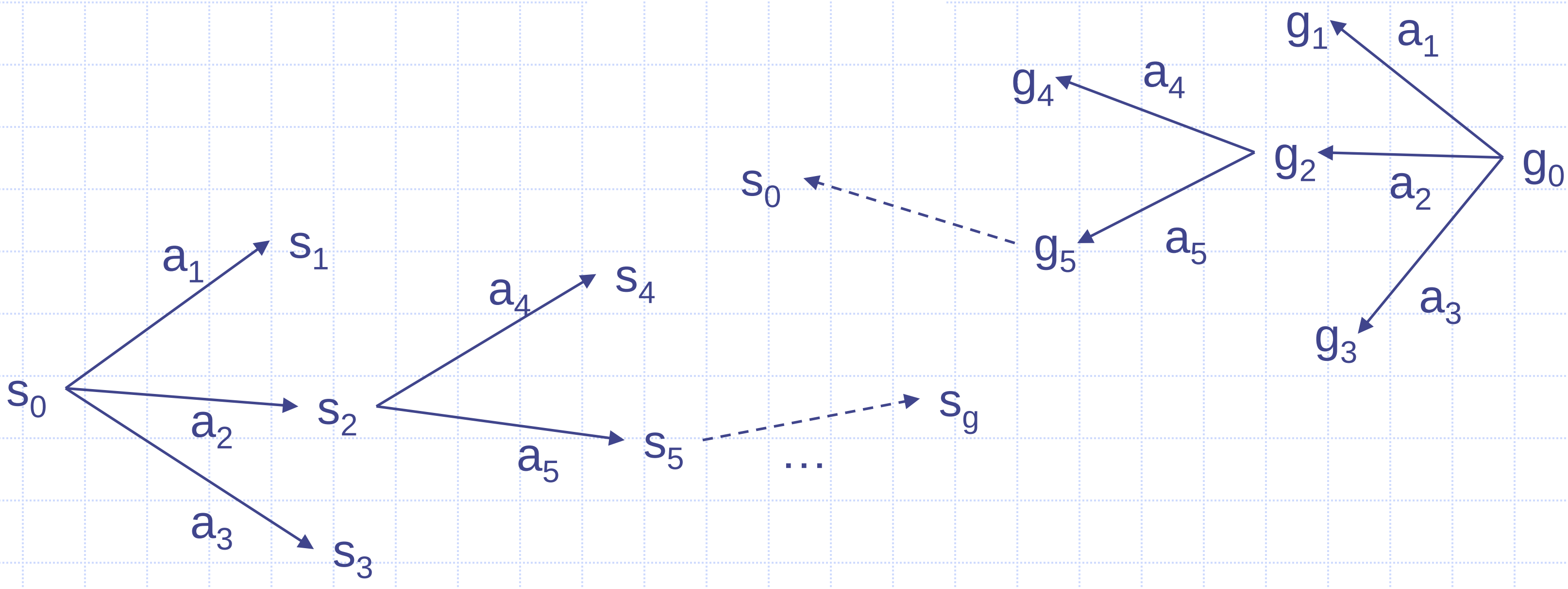
- Before Graphplan came out, most planning researchers were working on PSP-like planners
  - POP, SNLP, UCPOP, etc.

- 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

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
- and forward search may try lots of actions that do not reach the goal state



Motivation

- 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
    - actions that occur in the solutions to the relaxed problem will also occur in 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

Motivation

- State-space planners provide a plan as a sequence of actions
- Plan-space planning synthesize a plan as a partially ordered set of actions; any sequence that meets the constraints of the partial order is a valid plan
- Planning-graph approaches take a middle ground. Their output is a sequence of sets of actions, e.g. <{a1,a2},{a3,a4},{a5,a6,a7}>
- Plan-space planning: *least-commitment principle*

  Planning-graph approach: *strong commitment* while planning, actions are considered fully instantiated and at specific time steps; *least-commitment* with respect to the order of the actions at a time step
- Planning-graph approaches rely on the idea of ***relaxation of the reachability analysis***

Reachability analysis

- Analysis performed by planners to make sure the goals of the problem are reachable

- State reachability:
  - given a set **A** of actions, a state **s** is reachable from some initial state **s0** if there is a sequence of actions in **A** that defines a path from **s0** to **s**
  - Reachability analysis consists of analyzing which states can be reached from **s0** in some number of steps and how to reach them
  - Reachability can be computed *exactly* through a *reachability tree* => it cannot be computed in a tractable way
  - Reachability can be *approximated* through a *planning graph* => relaxation of the reachability analysis

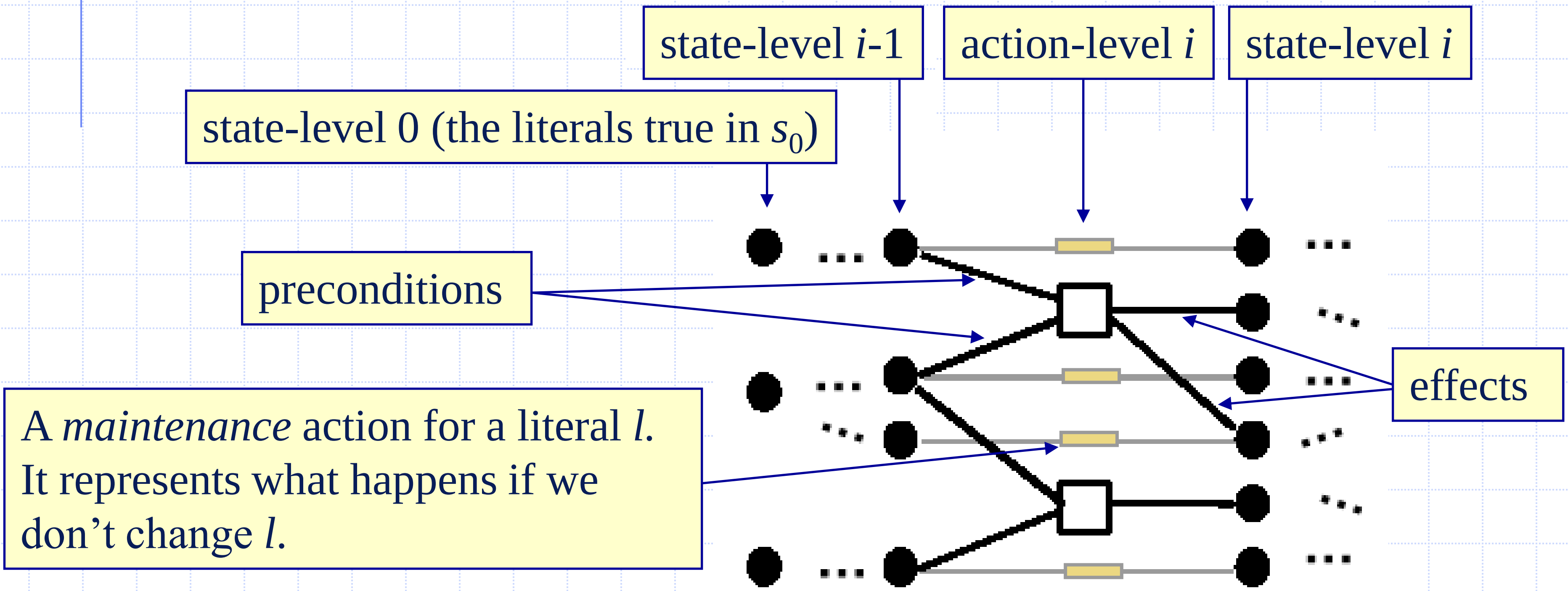
The planning graph (I)

- A layered graph
- Two kinds of layers alternate:
  - Literals (propositions) (shown with circles)
  - Actions (shown with squares)
- Every two layers correspond to a discrete time (time step)
- No variables as in action schemas

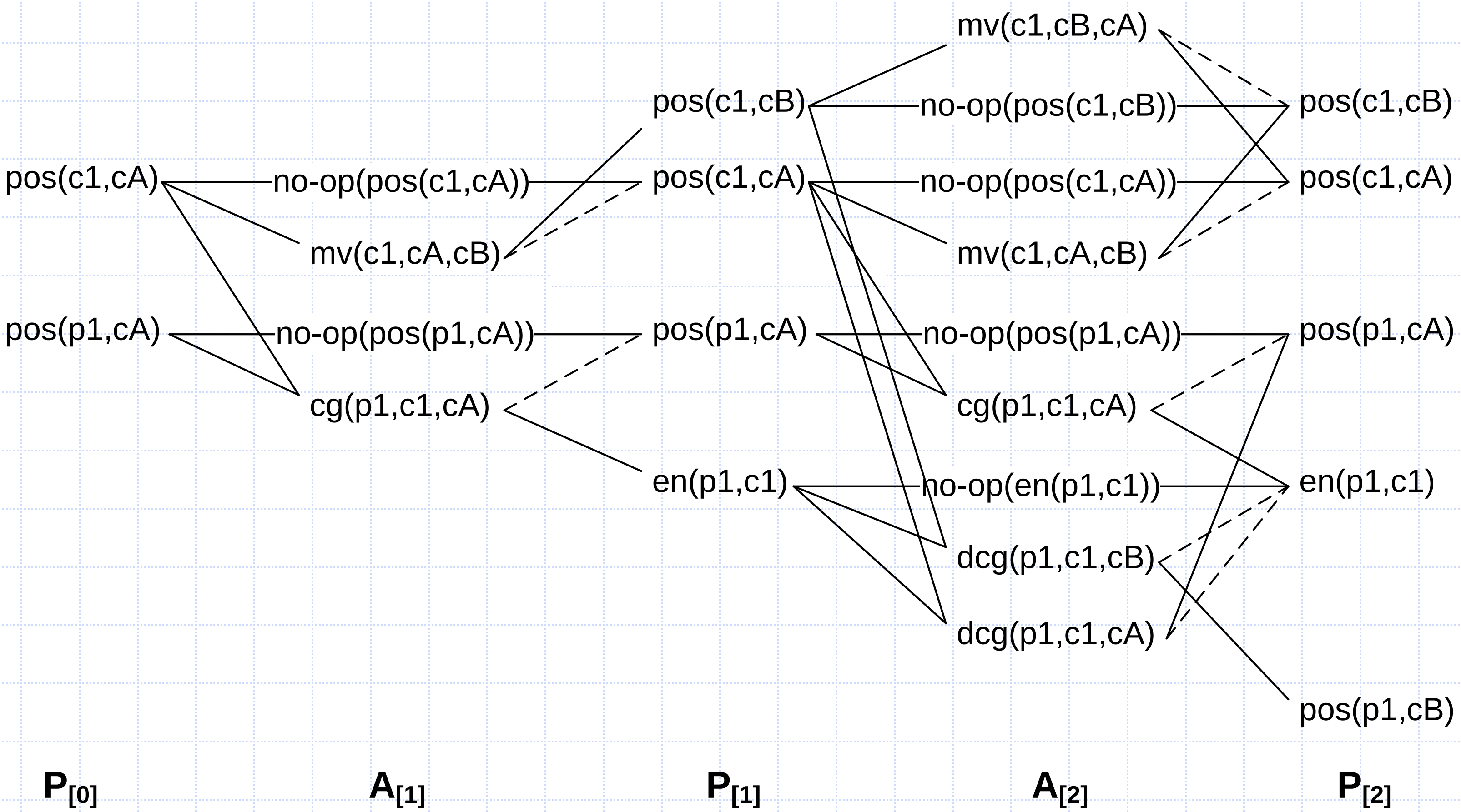
- The first layer is a literal layer which shows all the literals that are true in the initial state
- Every action has a link from each of its preconditions and a link to each of its effects.
- Straight lines between two literals at consecutive literal levels denote *NoOp*

The planning graph (II)

- 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

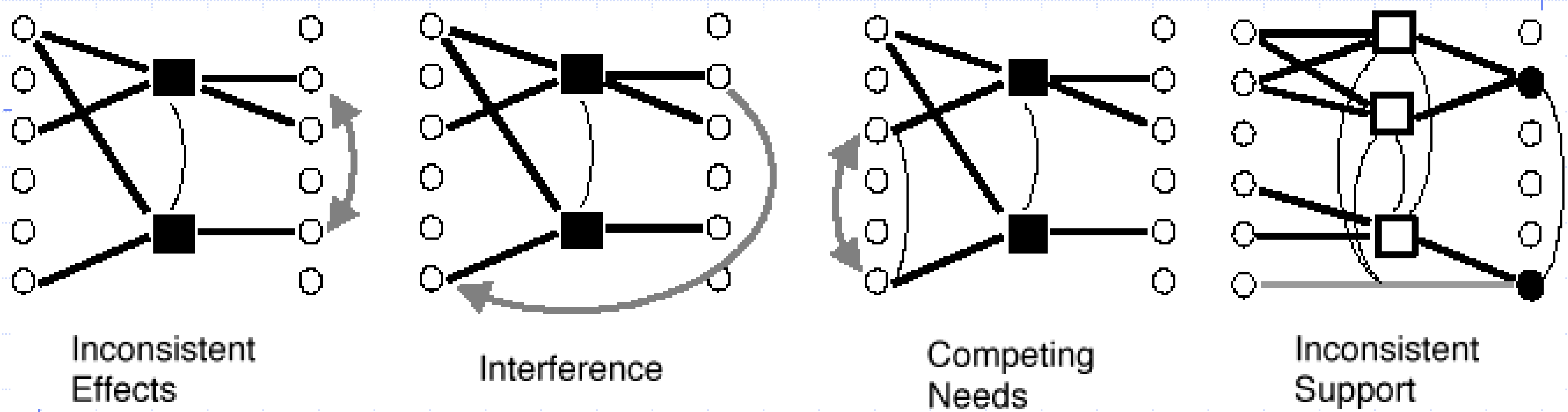


Example



mv(c1,cB,cA)
pos(c1,cB)
no-op(pos(c1,cB))
pos(c1,cB)
pos(c1,cA)
no-op(pos(c1,cA))
pos(c1,cA)
no-op(pos(c1,cA))
pos(c1,cA)
mv(c1,cA,cB)
mv(c1,cA,cB)
pos(p1,cA)
no-op(pos(p1,cA))
pos(p1,cA)
no-op(pos(p1,cA))
pos(p1,cA)
cg(p1,c1,cA)
cg(p1,c1,cA)
en(p1,c1)
no-op(en(p1,c1))
en(p1,c1)
dcg(p1,c1,cB)
dcg(p1,c1,cA)
pos(p1,cB)
P[0]
A[1]
P[1]
A[2]
P[2]

Mutual Exclusion



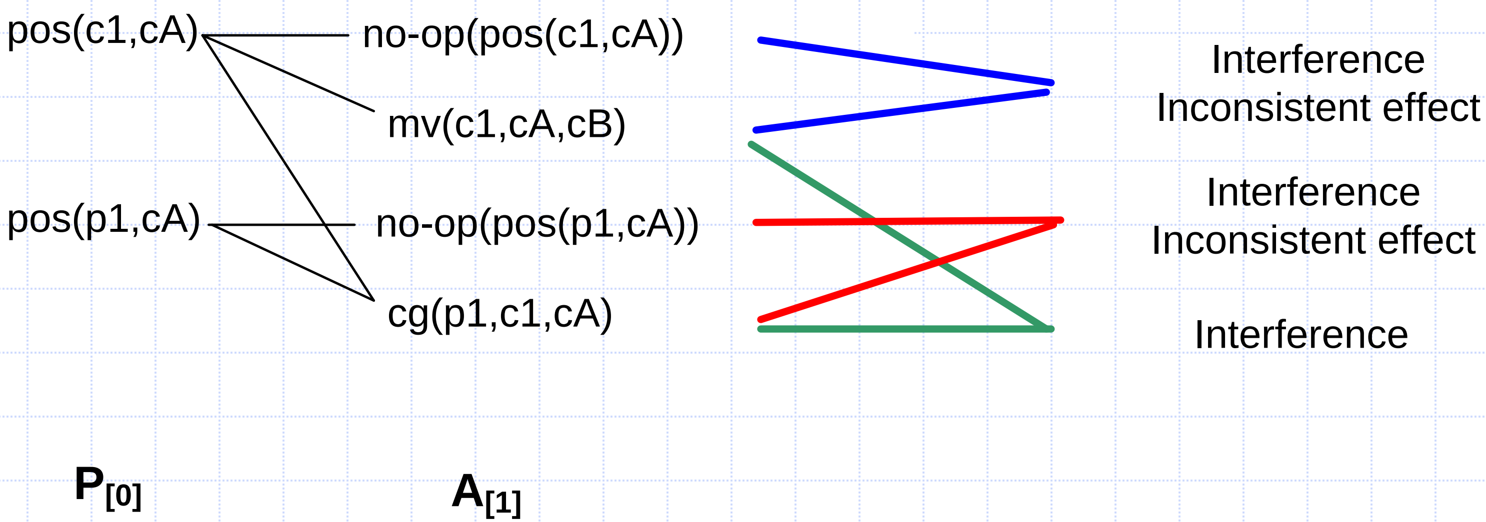
- Two actions at the same action-level are mutex if
  - *Inconsistent effects:* an effect of one negates an effect of the other
  - *Interference:* one deletes a precondition of the other
  - *Competing needs:* **they have mutually exclusive preconditions**
- Otherwise they don't interfere with each 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**

Recursive propagation of mutexes

Example (level A[1])

A[1]

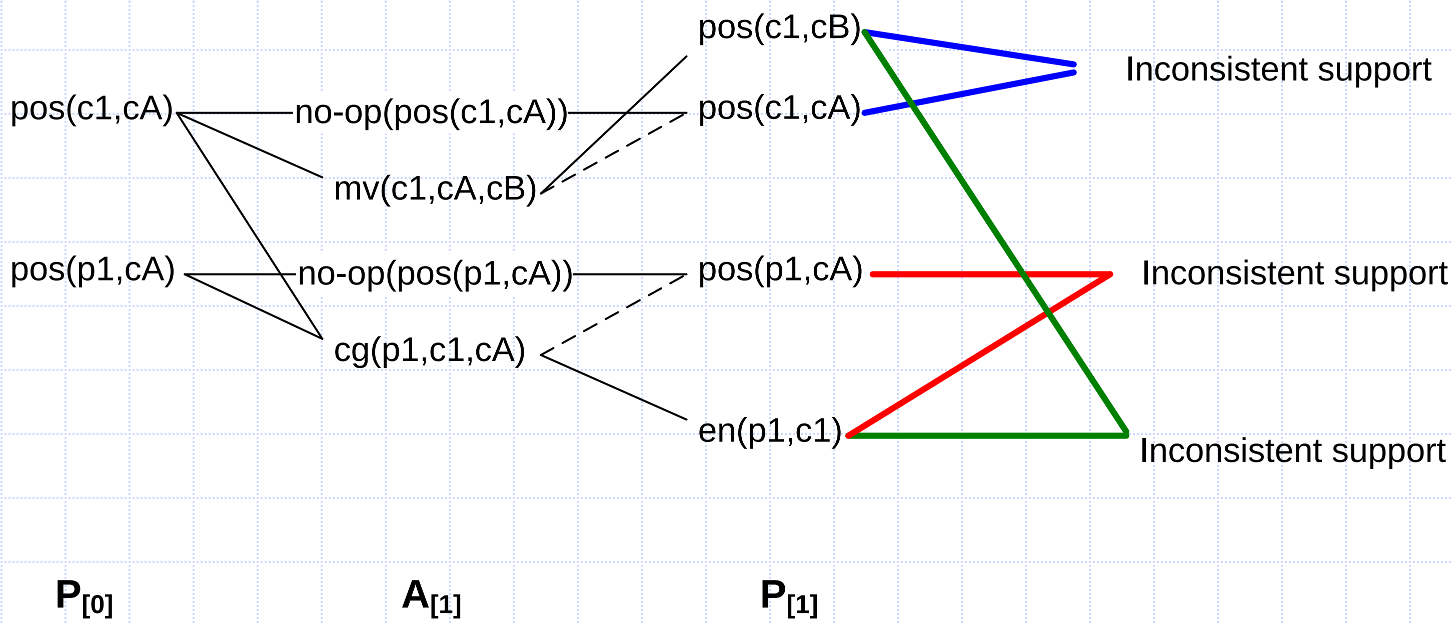
mv(c1,cA,CB) x {cg(p1,c1,cA), no-op(pos(c1,cA))}
cg(p1,c1,cA) x {no-op(pos(p1,cA)), mv(c1,cA,cB)}



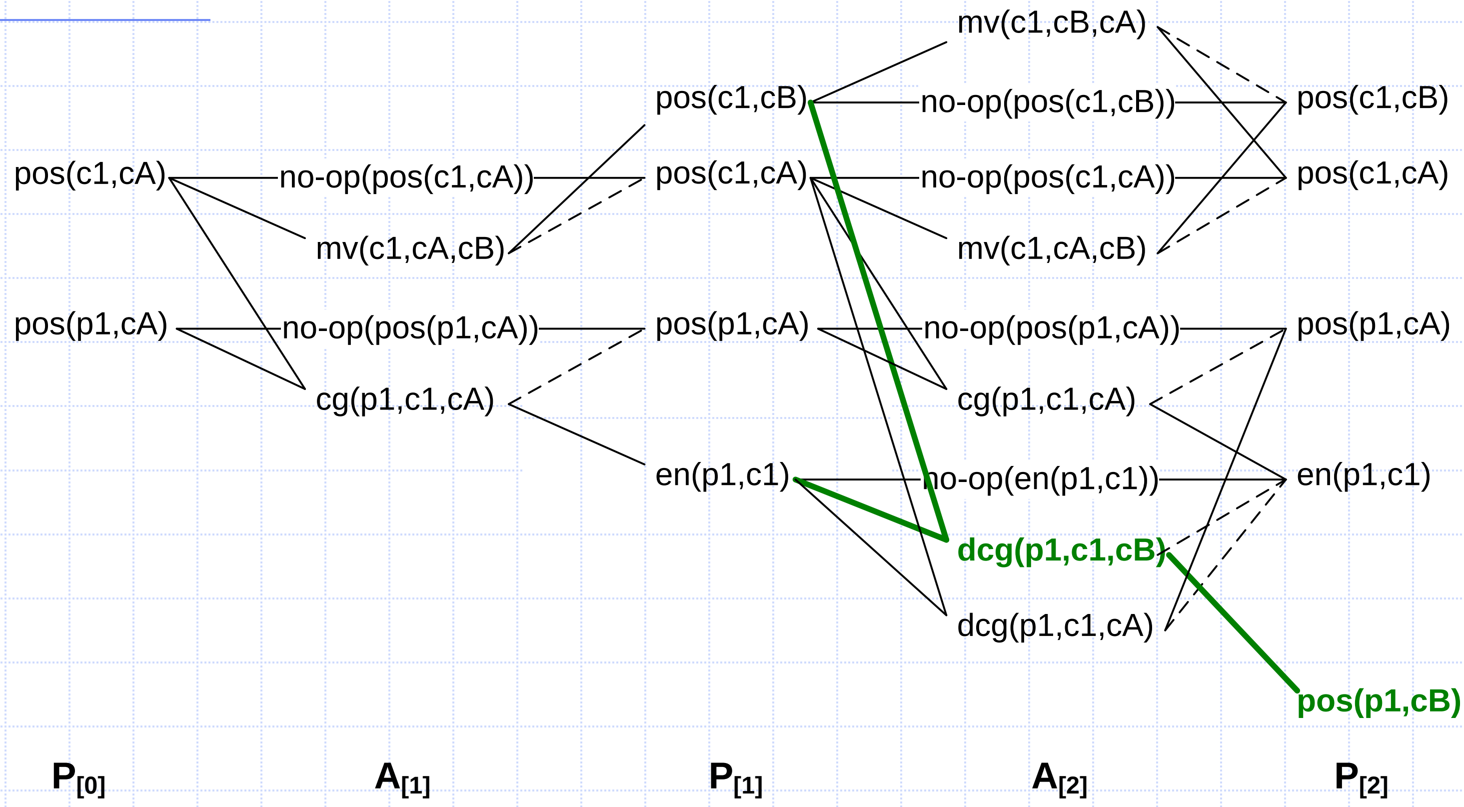
Example (level P[1])

P[1]

en(p1,c1) x {pos(p1,cA), pos(c1,cB)}
pos(c1,cA) x {pos(c1,cB)}
pos(c1,cB) x {en(p1,c1), pos(c1,cA)}



Example (level A[2])



Action **dcg(p1,c1,cB)** would not appear in **A[2]** because its preconditions are inconsistent. Consequently, literal pos(p1,cB) would not appear in **P[2],** which is an indication that the goal cannot be achieved at level **P[2]** and so the graph must be extended one more level (**A[3], P[3])**

Example (level A[2])

A[2]

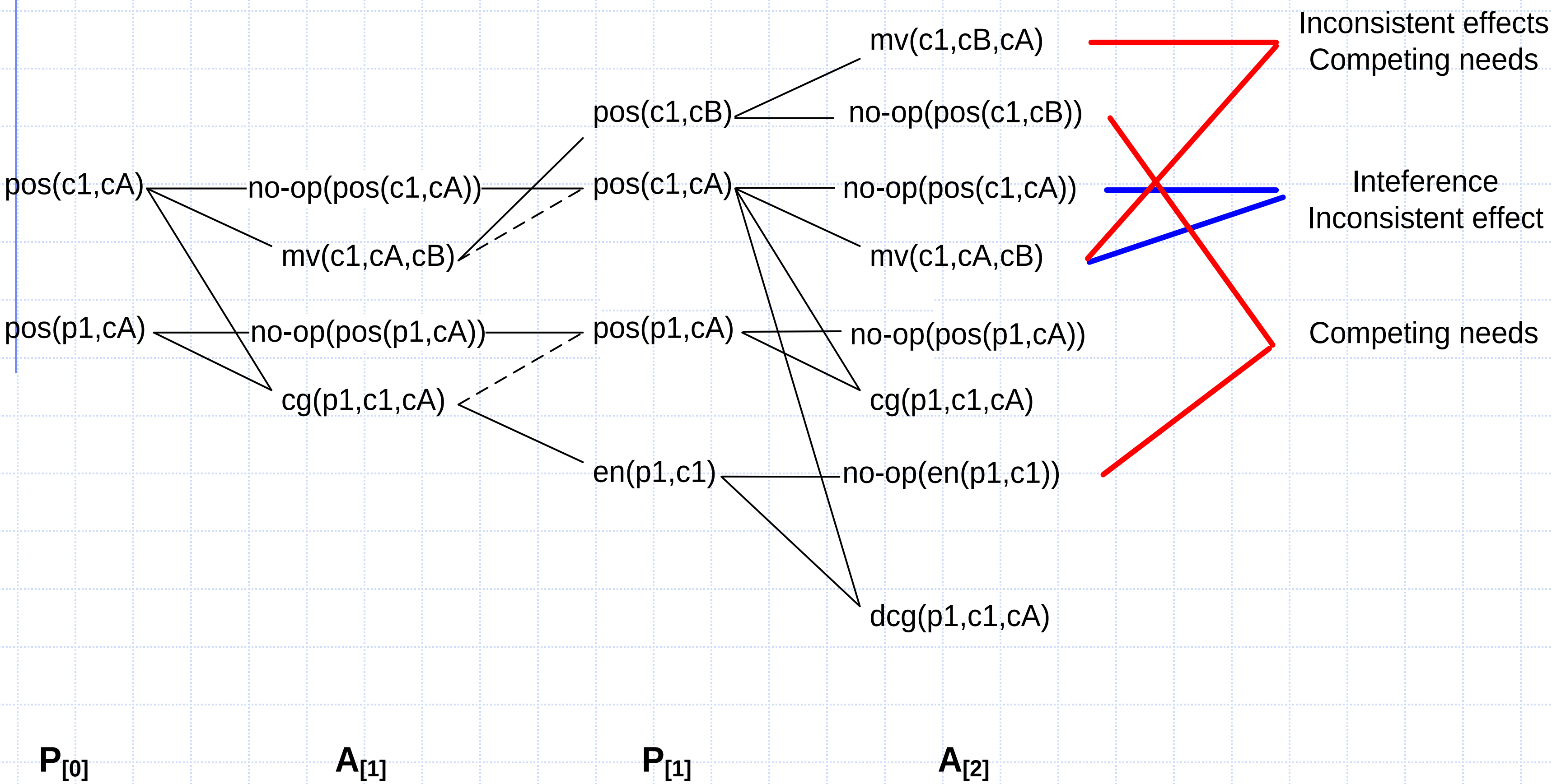
mv(c1,cA,cB) x
{mv(c1,cB,cA), cg(p1,c1,cA), dcg(p1,c1,cA), no-op(pos(c1,cA)), no-op(pos(c1,cB))}

mv(c1,cB,cA) x
{no-op(pos(c1,cB)), no-op(en(p1,c1)), no-op(pos(c1,cA)), cg(p1,c1,cA), dcg(p1,c1,cA), mv(c1,cA,cB)}

cg(p1,c1,cA) x
{no-op(pos(p1,cA)), mv(c1,cA,cB), mv(c1,cB,cA), no-op(pos(c1,cB)), dcg(p1,c1,cA), no/op(en(p1,c1))}

dcg(p1,c1,cA) x
{cg(p1,c1,cA), no-op(en(p1,c1)), mv(c1,cB,cA), no-op(pos(c1,cB)), mv(c1,cA,cB), no-op(pos(p1,cA))}

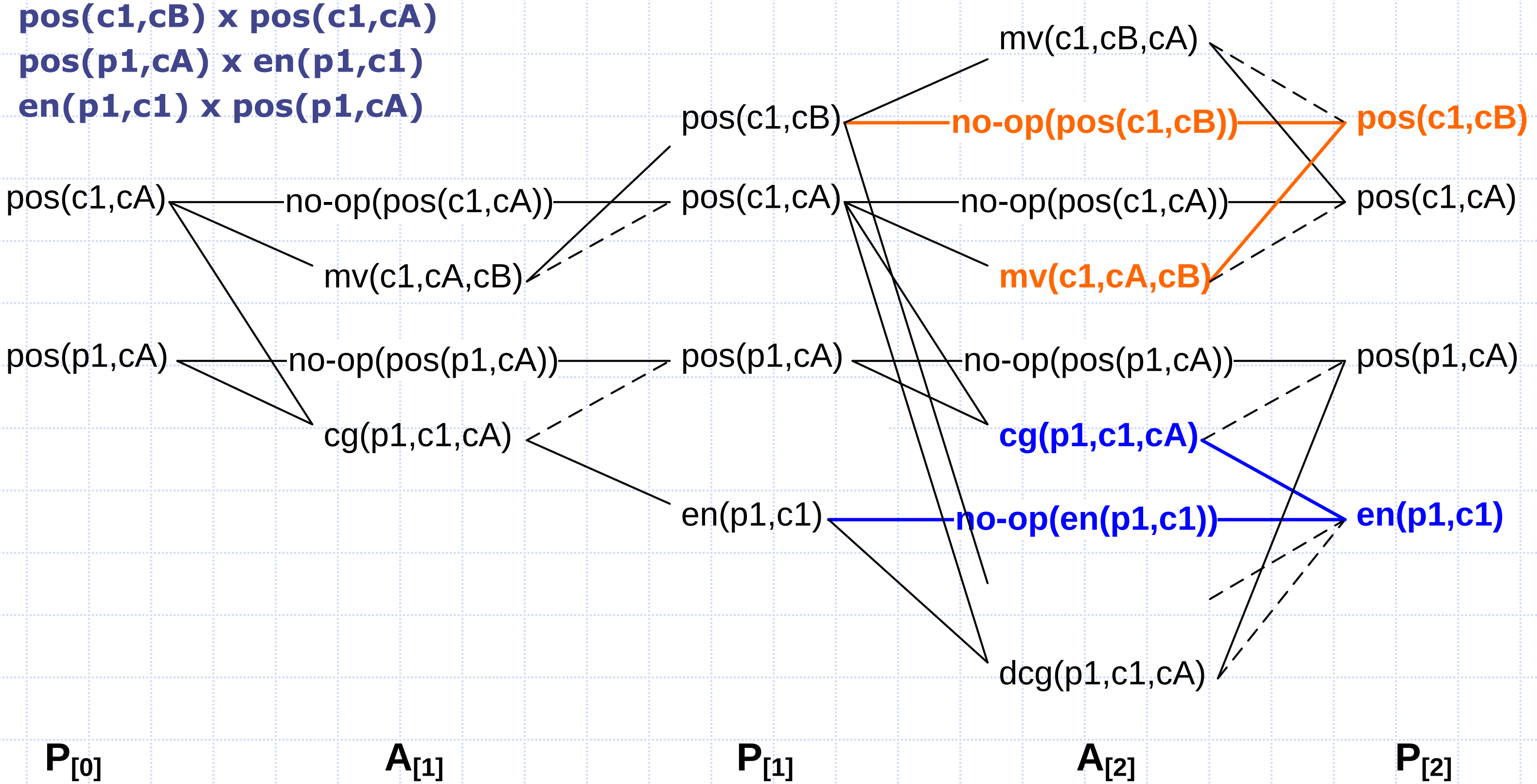
Example (level A[2])



Example (level P[2])

P[2]

pos(c1,cA) x pos(c1,cB)
pos(c1,cB) x pos(c1,cA)
pos(p1,cA) x en(p1,c1)
en(p1,c1) x pos(p1,cA)



pos(c1,cB) and **en(p1,c1)** are no longer mutex because now not all ways of achieving **pos(p1,cB)** are pairwise mutex with all ways of achieving **en(p1,c1)**

Example (level P[2])

Literals in P[2]

pos(c1,cB)

en(p1,c1)

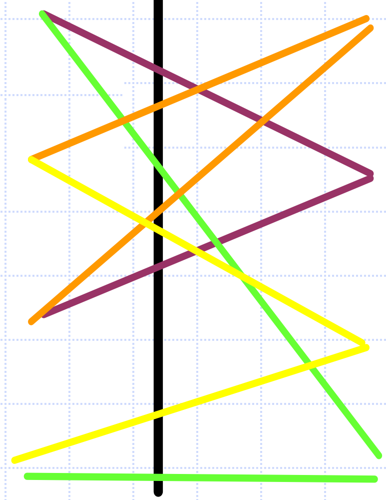
Actions in A[2] achieving the literals

no-op(pos(c1,cB))

mv(c1,cA,cB)

no-op(en(p1,c1))

cg(p1,c1,cA)



Mutex relations

Non-mutex

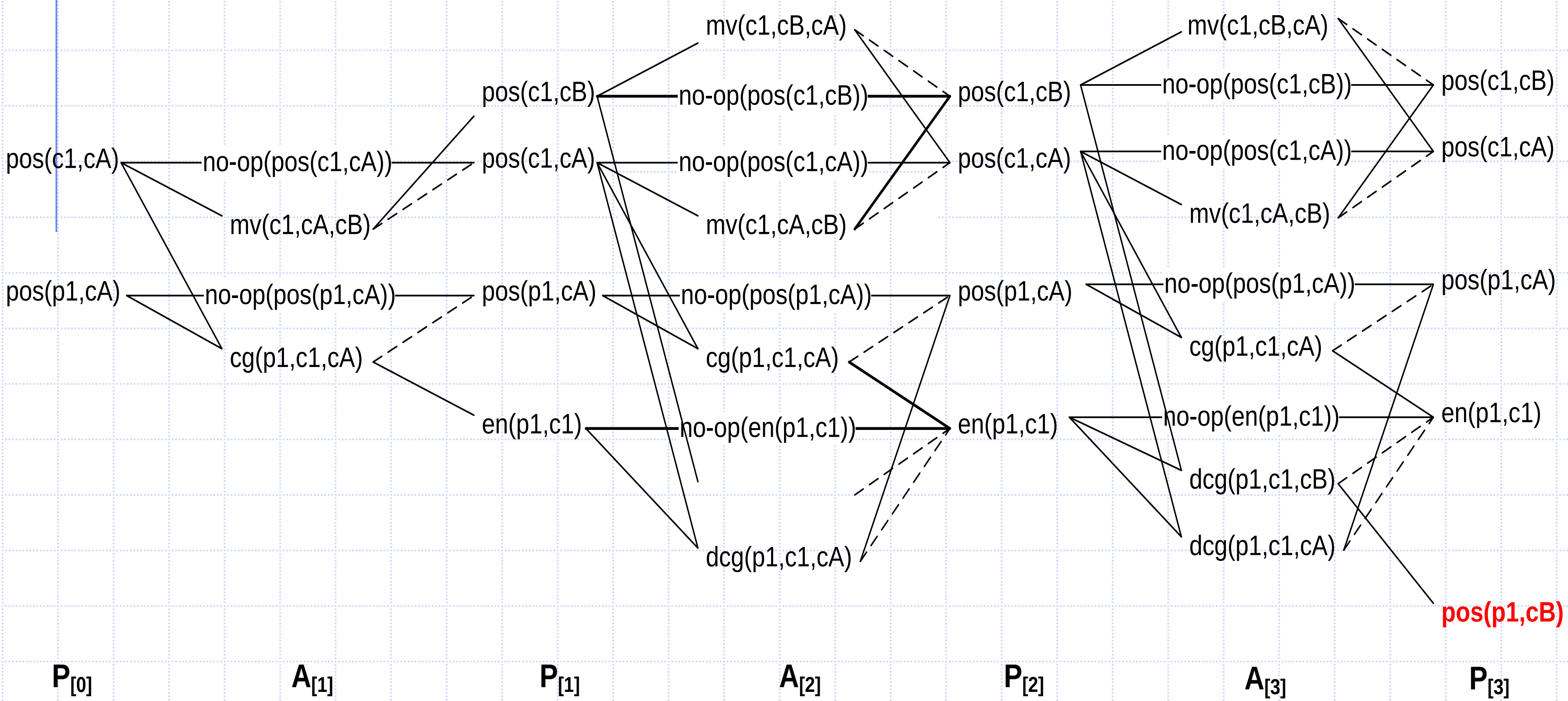
Competing needs in A[2]

Interferences in A[2]

Competing needs in A[2]

Example (layers A[3], P[3])

- The planning graph is extended level by level until the goals are achieved (necessary but not sufficient condition)

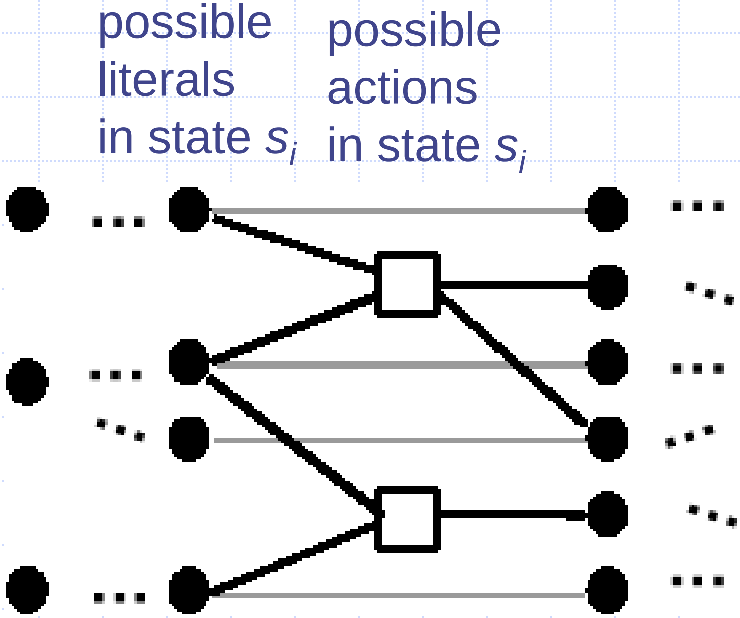


The Graphplan algorithm

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

relaxed problem



Solution extraction

- Check to see whether there's a possible solution
  - All of the goals appear at a proposition level
  - None are mutex with each other
- Thus, there's a chance that a plan exists

Solution Extraction

The set of goals we are trying to achieve

The level of the state s_j

A real action or a maintenance action

procedure Solution-extraction(g,j)

if $j=0$ then return the solution

for each literal l in g

nondeterministically choose an action to use in state s_{j-1} to achieve l

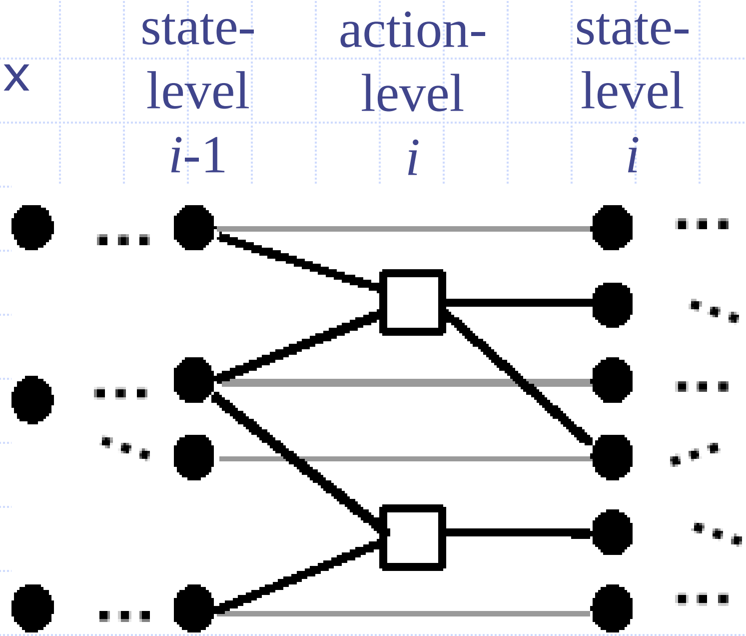
if any pair of chosen actions are mutex

then backtrack

g' := {the preconditions of the chosen actions}

Solution-extraction(g', $j-1$)

end Solution-extraction



Solution extraction

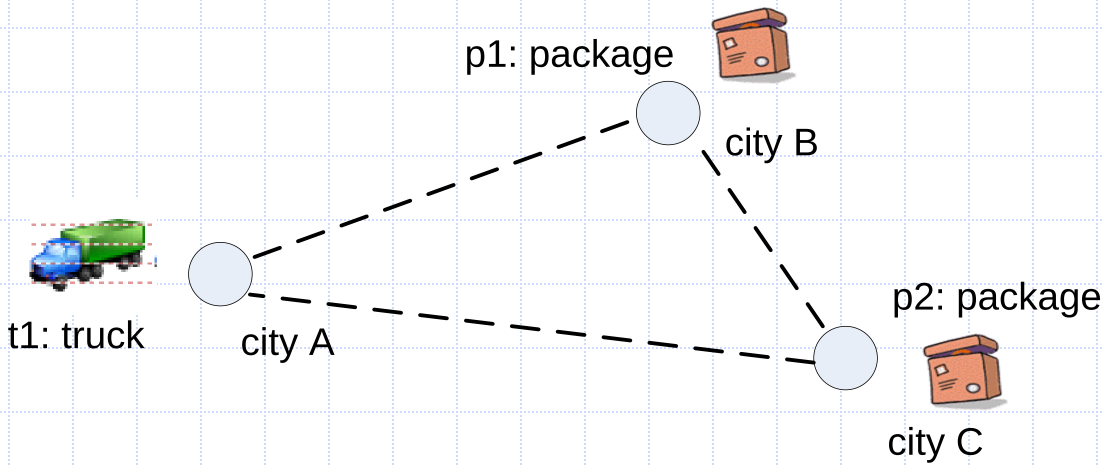
- If any pair of chosen actions are mutex then backtrack:
  - Choose another action for a literal so that the pair is not mutex
- If all sets of actions (combinations of actions) in level A_i for the literals at level P_i contain mutex actions then go back and do more graph expansion => generate another action level and another proposition level
- Termination of Graphplan:
  - Literals increase monotonically
  - Actions increase monotonically
  - Mutexes decrease monotonically
  - The graph levels off in a finite number of steps (two subsequent proposition levels are identical)

Solution extraction and mutex relations

- The mutual exclusion rules do not guarantee to find *all* mutual exclusion relationships, but usually find a large number of them (in fact, determining *all* mutual exclusion relationships can be as hard as finding a plan).

- Mutual exclusion rules only find binary mutex but there also exists other higher-order mutex, eg. *ternary* mutex …

- Example:



Goals: (at p1 cityA) and (at p2 cityA)

Solution extraction and mutex relations

- Shortest solution plan involves six steps:
  - {move (t1,cityA,cityB)}
  - {load (t1,p1,cityB)}
  - {move (t1,cityB,cityC)}
  - {load (t1,p2,cityC)}
  - {move (t1,cityC,cityA)}
  - {unload (t1,p1,cityA), unload (t1,p2,cityA)}

- However, Graphplan infers that the goals can be achieved together by level 5 of the graph. This is because **(in p1 t1) (in p2 t1)** and **(at t1 cityA)** are achieved by level 4 of the graph and Graphaplan will not find any mutex relation between any pair of literals:

Solution extraction and mutex relations

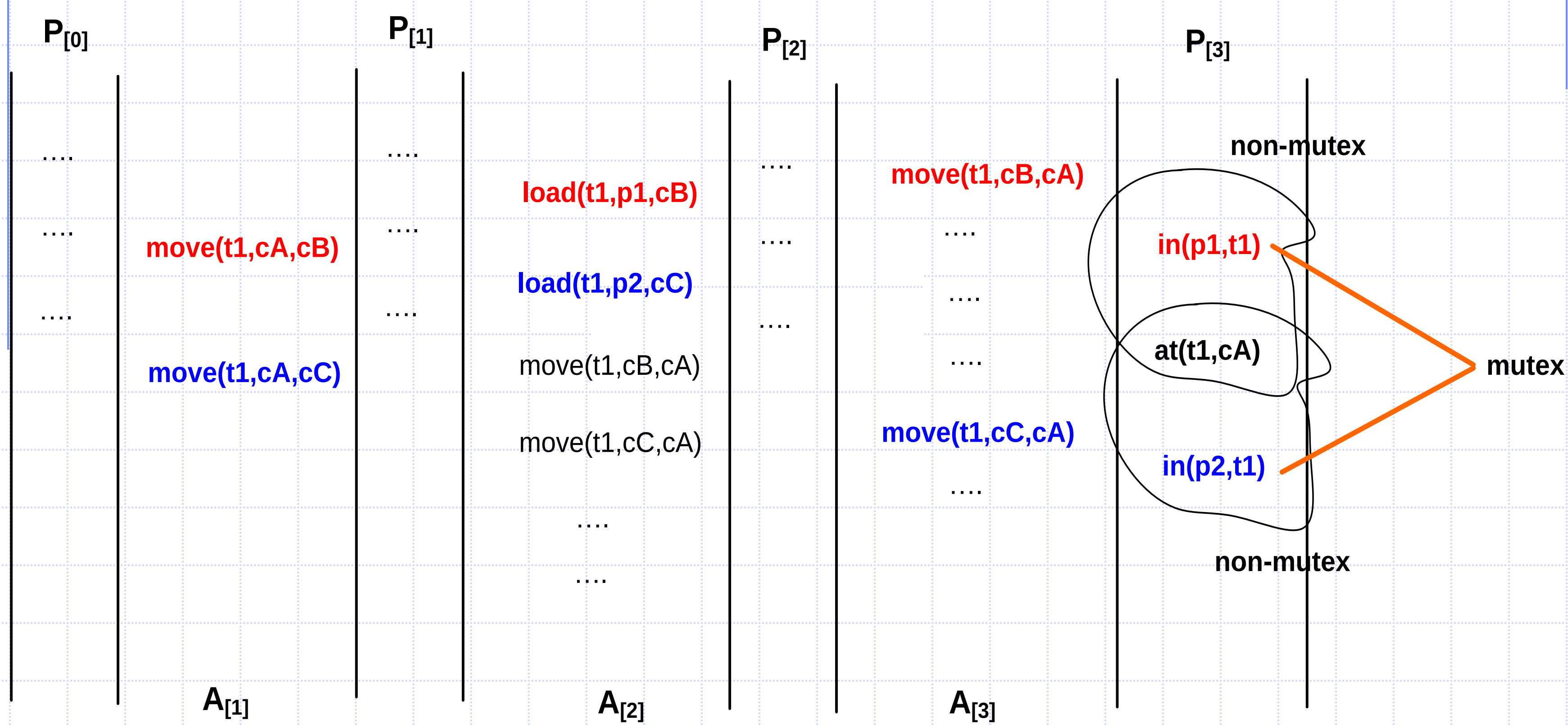
- the pairs **{(in p1 t1),(at t1 cityA)}** and **{(in p2 t1),(at t1 cityA)}** are not mutex at level 4 because there is a 3-step plan which will get the truck loaded with either package to the destination; and when two literals are found non-mutex, they can never subsequently become mutex since if they can occur in the same state then they will always be able to appear in the same state

- the pair **{(in p1 t1),(in p2 t1)}** is also not mutex at level 5 because there is a 4-step plan which will have the truck loaded with both packages although not at the destination

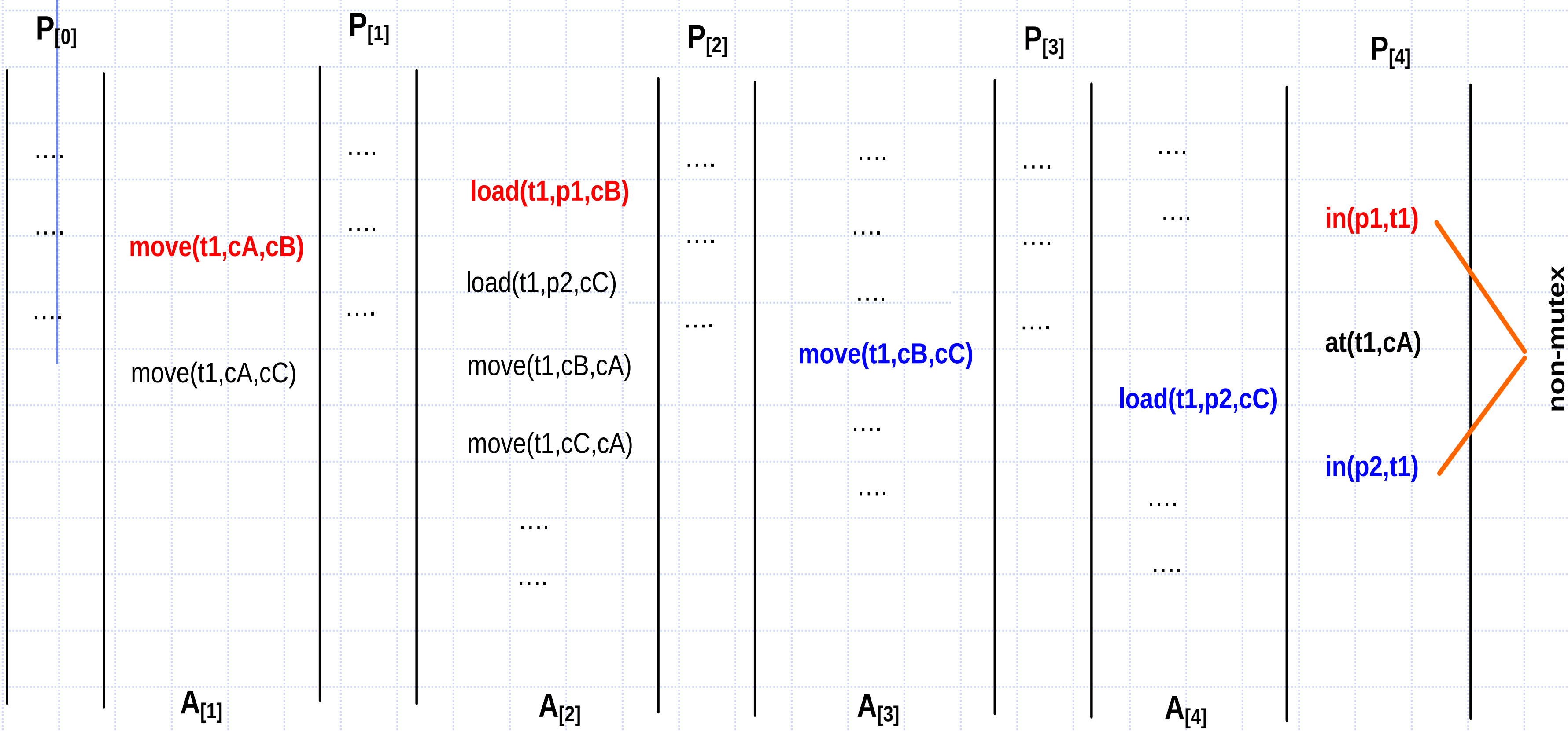
- then, no *binary* mutex relation is found with the three literals by level 4 although there is a mutex among the three literals

- Consequently, Graphplan begins searching for a plan from level 5 when it is impossible for one to be found until level 6 has been constructed.

Solution extraction and mutex relations



Solution extraction and mutex relations



Discussion

- 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

Heuristics derived from planning graphs

- Recall how GraphPlan works:

loop

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:

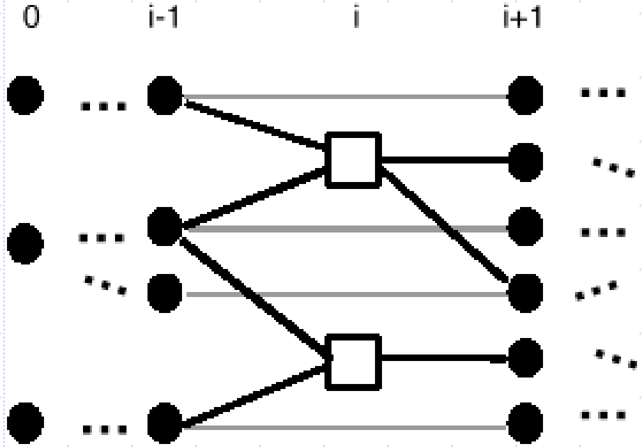
this takes exponential time

search backward from the goal, looking for a correct plan

if we find one, then return it

repeat

Heuristics derived from planning graphs



- 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***
- **$h(g_i)$:** estimate to achieve **g_i** from **s**
- **$h(g_i)$=** level of the first layer that "possibly achieves" **g_i**

Heuristics derived from planning graphs

- Heuristics for a set of goal **G**={pos(p1,cB),pos(c1,cA)}:
  - The ***max level heuristic*** takes the maximum level cost of any of the goals (admissible, not very accurate).
    $hmax(G)=max_{g \in G}\ h(g)$ // $hmax(G)=max(0,3)=3$
  - The sum ***level heuristic*** returns the sum of the level costs of the goals (inadmissible, works well in practice)
    $hsum(G)=\sum g \in G\ h(g)$ // $hsum(G)=0+3=3$
  - The ***max$_2$ level heuristic*** takes the maximum level at which coexist any pair of goals.
    $hmax_2(G)=_{max\{g1,g2\} \in G}\ h(g1 \wedge g2)$ // $hmax_2(G)= max(4)=4$
  - The ***max$_k$ level heuristic*** takes the maximum level at which coexist any *k* goals. $hmax_k(G)=_{max\{g1,g2,\ ..,\ gk\} \in G}\ h(g1 \wedge g2 \wedge \ldots \wedge gk)$

Heuristics derived from planning graphs

- Heuristics used by forward state-space planners (like FF)
- Application of the heuristic over each state in the tree
- Planning graph + mutex calculation over each state => very costly process
- Computing heuristics on a **relaxed planning graph (RPG):**
  - Ignoring negated effects
  - No mutex calculation
  - Slide 11 shows an example on how the RPG will look like
- hmax(G)=max(0,2)=2
- hsum(G)=0+2=2
- $hmax_2$(G)= max(2)=2

Heuristics derived from planning graphs

- **Relaxed Planning Graph**:
  - No delete effects
  - No mutex
  - No no-op actions because we are only interested in the first appearance of any action/proposition
- Relaxed plan heuristic: extract a plan from a **RPG**
- See examples of the blocks-world domain

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)

The FastForward Planner

- Use a heuristic function *h*(*s*) = relaxed plan
- Don't want an A*-style search (takes too much memory)
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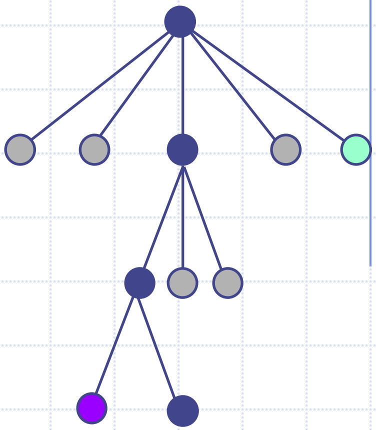
The FastForward Planner



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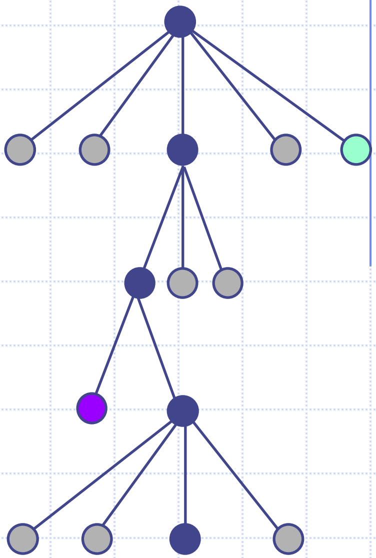
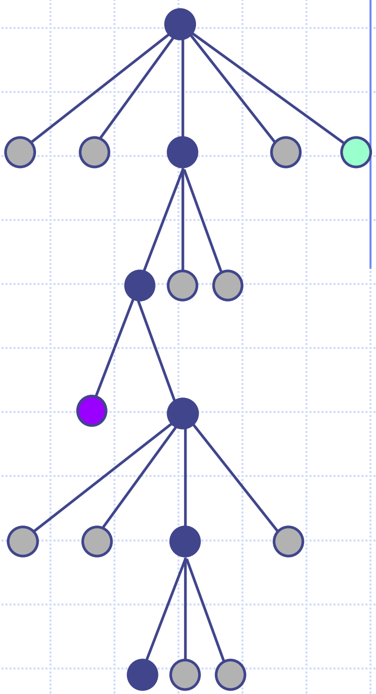


The FastForward Planner



- Use a heuristic function similar to $h(s)$ = relaxed plan
- 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 FF improves on this
  - e.g. a way to escape from local minima
    - breadth-first search, stopping when a node with lower cost is found

- 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