Lecture slides for

Automated Planning: Theory and Practice

Chapter 9
Heuristics in Planning

Dana S. Nau
University of Maryland

3:08 PM   March 7, 2012

Planning as Nondeterministic Search

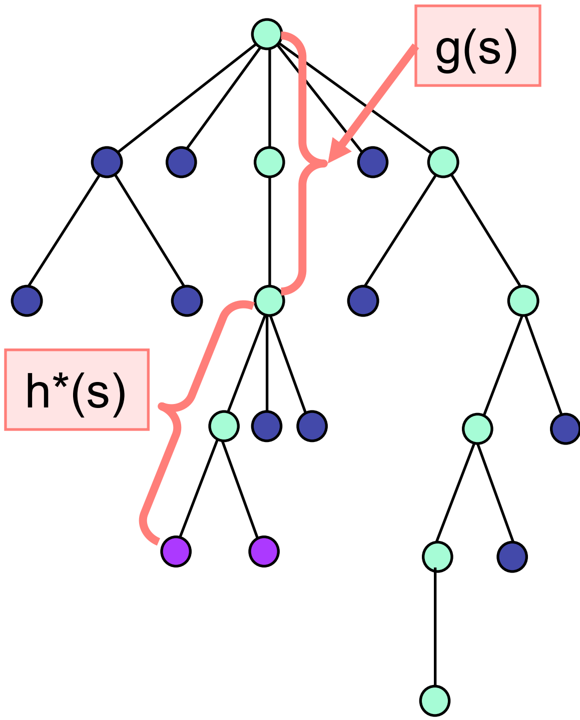
```
Abstract-search(u)
    if Terminal(u) then return(u)
    u ← Refine(u)              ;;    refinement step
    B ← Branch(u)              ;;    branching step
    B′ ← Prune(B)              ;;    pruning step
    if B′ = ∅ then return(failure)
    nondeterministically choose v ∈ B′
    return(Abstract-search(v))
end
```

Making it Deterministic

```
Depth-first-search(u)
    if Terminal(u) then return(u)
    u ← Refine(u)                ;;  refinement step
    B ← Branch(u)                ;;  branching step
    C ← Prune(B)                 ;;  pruning step
    while C ≠ ∅ do
        v ← Select(C)            ;;  node-selection step
        C ← C − {v}
        π ← Depth-first-search(v)
        if π ≠ failure then return(π)
    return(failure)
end
```

Digression: the A* algorithm (on trees)

- Suppose we're searching a **tree** in which each edge (s,s') has a cost $c(s,s')$
  - If p is a path, let $c(p)$ = sum of the edge costs
  - For classical planning, this is the length of p



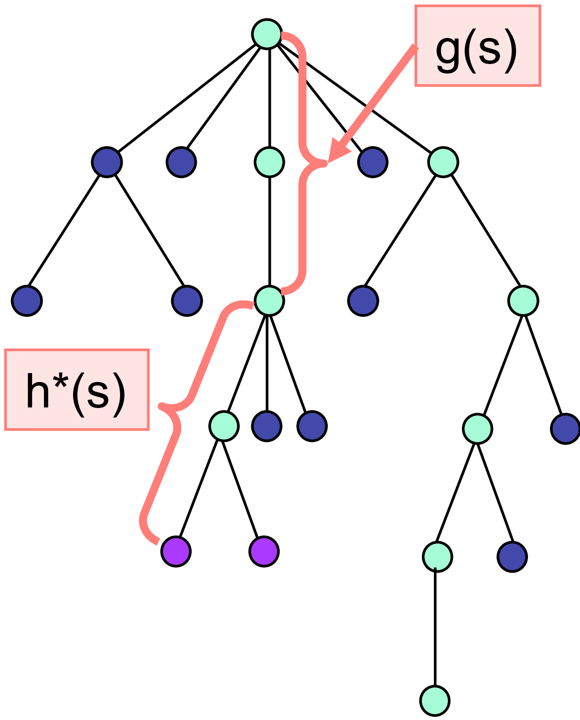
- For every state s, let
  - $g(s)$ = cost of the path from s_0 to s
  - $h^*(s)$ = least cost of all paths from s to goal nodes
  - $f^*(s) = g(s) + h^*(s)$ = least cost of all paths from s_0 to goal nodes that go through s

- Suppose $h(s)$ is an estimate of $h^*(s)$
  - Let $f(s) = g(s) + h(s)$
    - » $f(s)$ is an estimate of $f^*(s)$
  - h is *admissible* if for every state s, $0 \le h(s) \le h^*(s)$
  - If h is admissible then f is a lower bound on f^*

The A* Algorithm

- A* on trees:

  loop
    choose the leaf node s such that $f(s)$ is smallest
    if *s* is a solution then return it and exit
    expand it (generate its children)

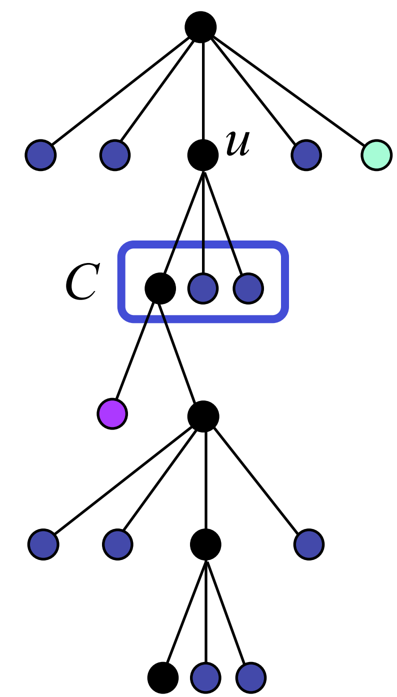


- On graphs, A* is more complicated
  - additional machinery to deal with multiple paths to the same node
- If a solution exists (and certain other conditions are satisfied), then:
  - If $h(s)$ is admissible, then A* is guaranteed to find an optimal solution
  - The more "informed" the heuristic is (i.e., the closer it is to h^*), the smaller the number of nodes A* expands
  - If $h(s)$ is within c of being admissible, then A* is guaranteed to find a solution that's within c of optimal

Hill Climbing

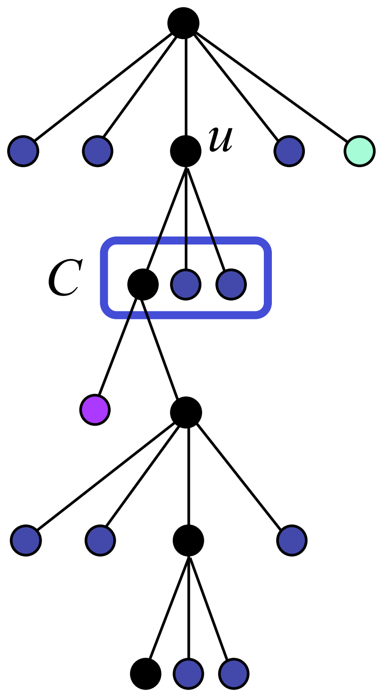
- Use h as a node-selection heuristic
  - Select the node v in C for which $h(v)$ is smallest
- Why not use f ?
- Do we care whether h is admissible?

```
Depth-first-search(u)
    if Terminal(u) then return(u)
    u ← Refine(u)           ;;  refinement step
    B ← Branch(u)           ;;  branching step
    C ← Prune(B)            ;;  pruning step
    while C ≠ ∅ do
        v ← Select(C)       ;;  node-selection step
        C ← C − {v}
        π ← Depth-first-search(v)
        if π ≠ failure then return(π)
    return(failure)
end
```



FastForward (FF)

- Depth-first search
- Selection heuristic: *relaxed Graphplan*
  - Let v be a node in C
  - Let P_v be the planning problem of getting from v to a goal
  - use Graphplan to find a solution for a relaxation of P_v
  - The length of this solution is a lower bound on the length of a solution to P_v

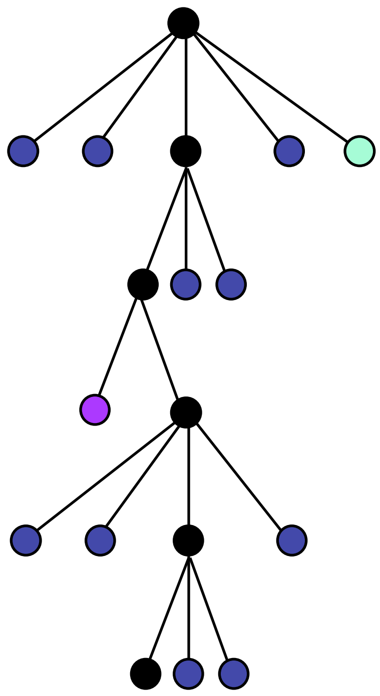


Selection Heuristic

- Given a planning problem P_v, create a relaxed planning problem P'_v and use GraphPlan to solve it
  - Convert to set-theoretic representation
    - No negative literals; goal is now a set of atoms
  - Remove the delete lists from the actions
  - Construct a planning graph until a layer is found that contains all of the goal atoms
  - The graph will contain no mutexes because the delete lists were removed
  - Extract a plan π' from the planning graph
    - No mutexes → no backtracking → polynomial time
- $|\pi'|$ is a lower bound on the length of the best solution to P_v

FastForward

- FF evaluates all the nodes in the set C of u's successors
- If none of them has a better heuristic value than u, FF does a breadth-first search for a state with a strictly better evaluation
- The path to the new state is added to the current plan, and the search continues from this state
- Works well because plateaus and local minima tend to be small in many benchmark planning problems



- Can't guarantee how fast FF will find a solution, or how good a solution it will find
  - However, it works pretty well on many problems

AIPS-2000 Planning Competition

- 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

2002 International Planning Competition

- 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

2004 International Planning Competition

- FastForward's author was one of the competition chairs
  - Thus FastForward did not participate

Plan-Space Planning

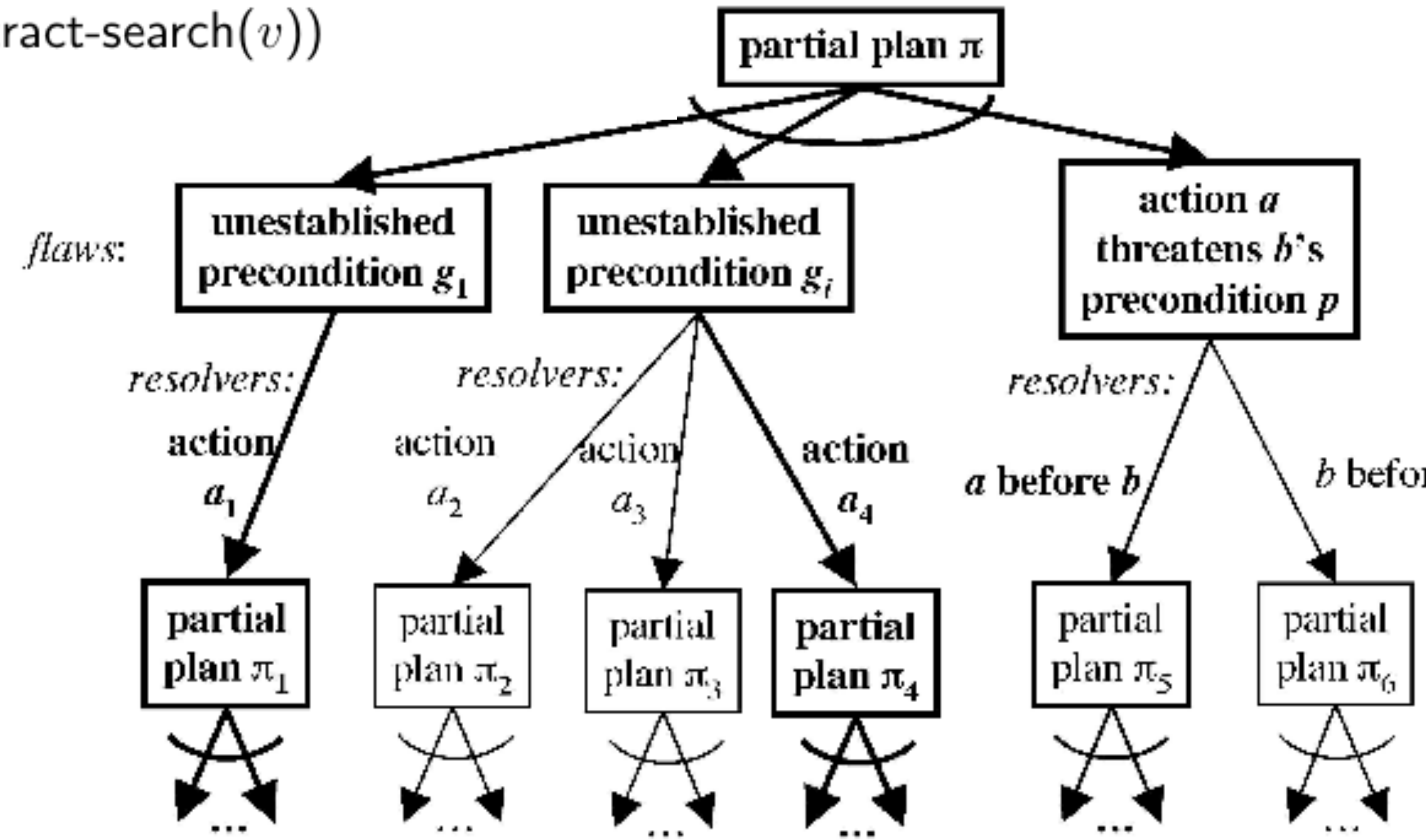
```
Abstract-search(u)
    if Terminal(u) then return(u)
    u ← Refine(u)              ;;  refinement step
    B ← Branch(u)              ;;  branching step
    B' ← Prune(B)              ;;  pruning step
    if B' = ∅ then return(failure)
    nondeterministically choose v ∈ B'
    return(Abstract-search(v))
end
```

- *Refine* = select next flaw to work on
- *Branch* = generate resolvers
- *Prune* = remove some of the resolvers
- *nondeterministic choice* = resolver selection

```
Abstract-search(u)
    if Terminal(u) then return(u)
    u ← Refine(u)          ;;   refinement step
    B ← Branch(u)          ;;   branching step
    B′ ← Prune(B)          ;;   pruning step
    if B′ = ∅ then return(failure)
    nondeterministically choose v ∈ B′
    return(Abstract-search(v))
end
```

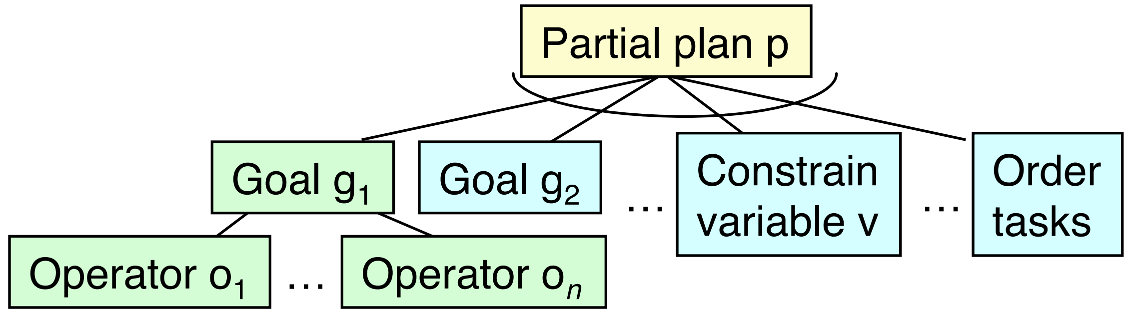
Flaw Selection

- Must eventually resolve all of the flaws, regardless of which one we choose first
  - an "AND" branch

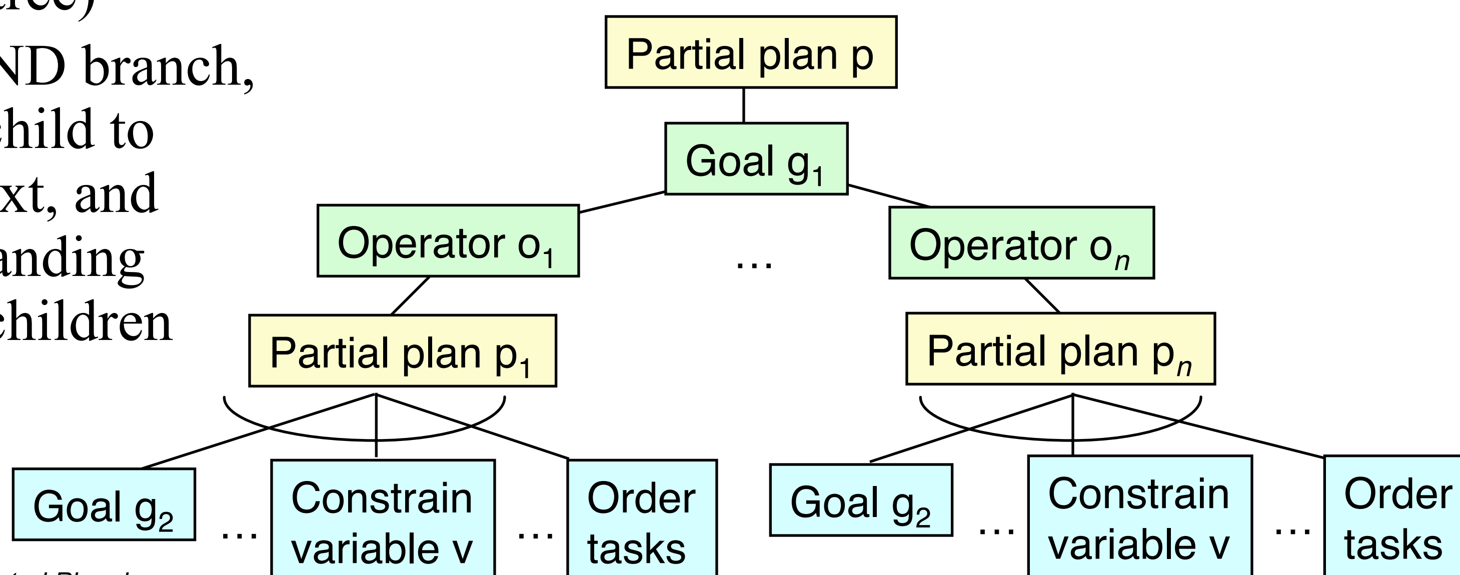


Serializing and AND/OR Tree

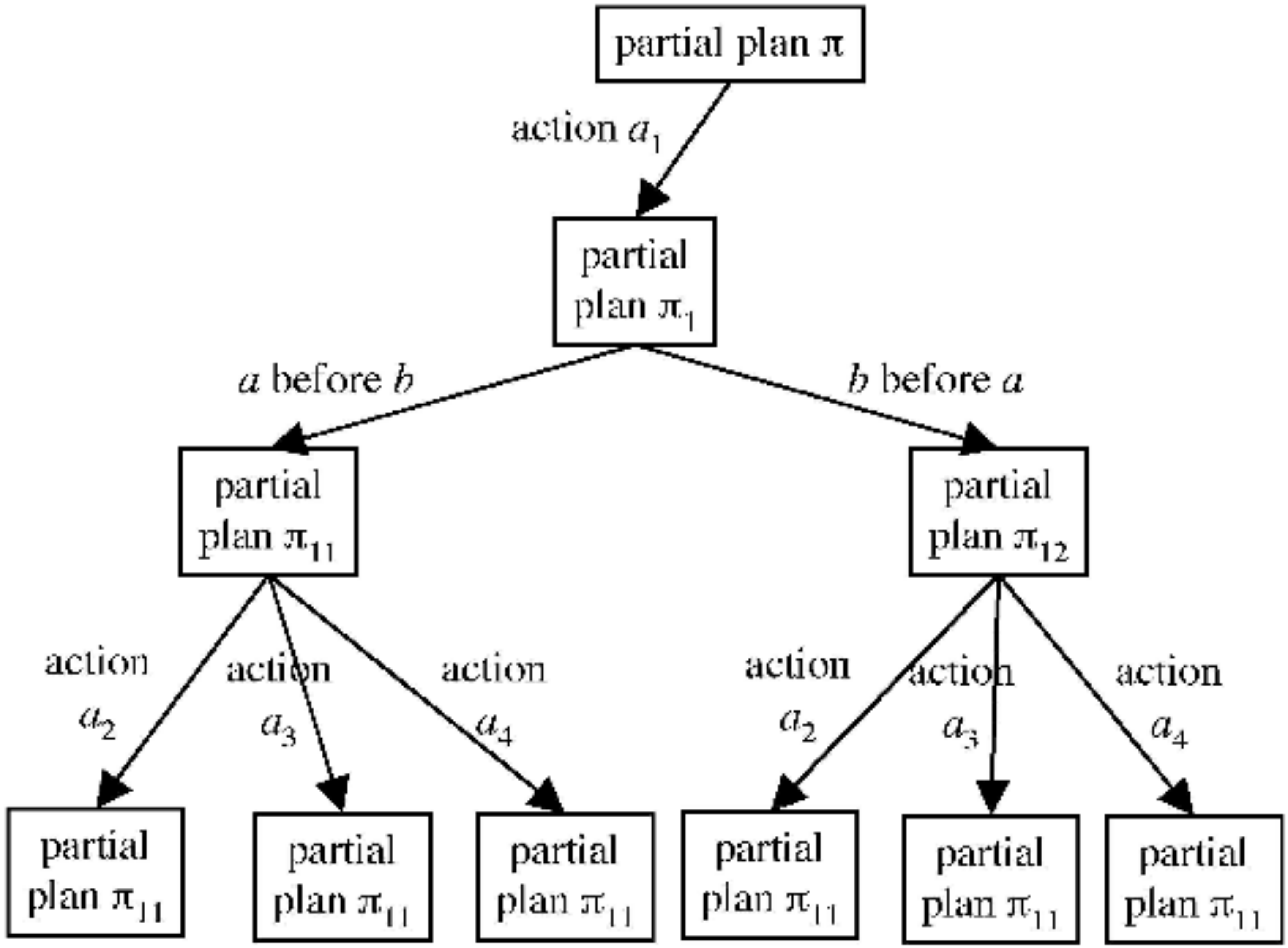
- The search space is an AND/OR tree



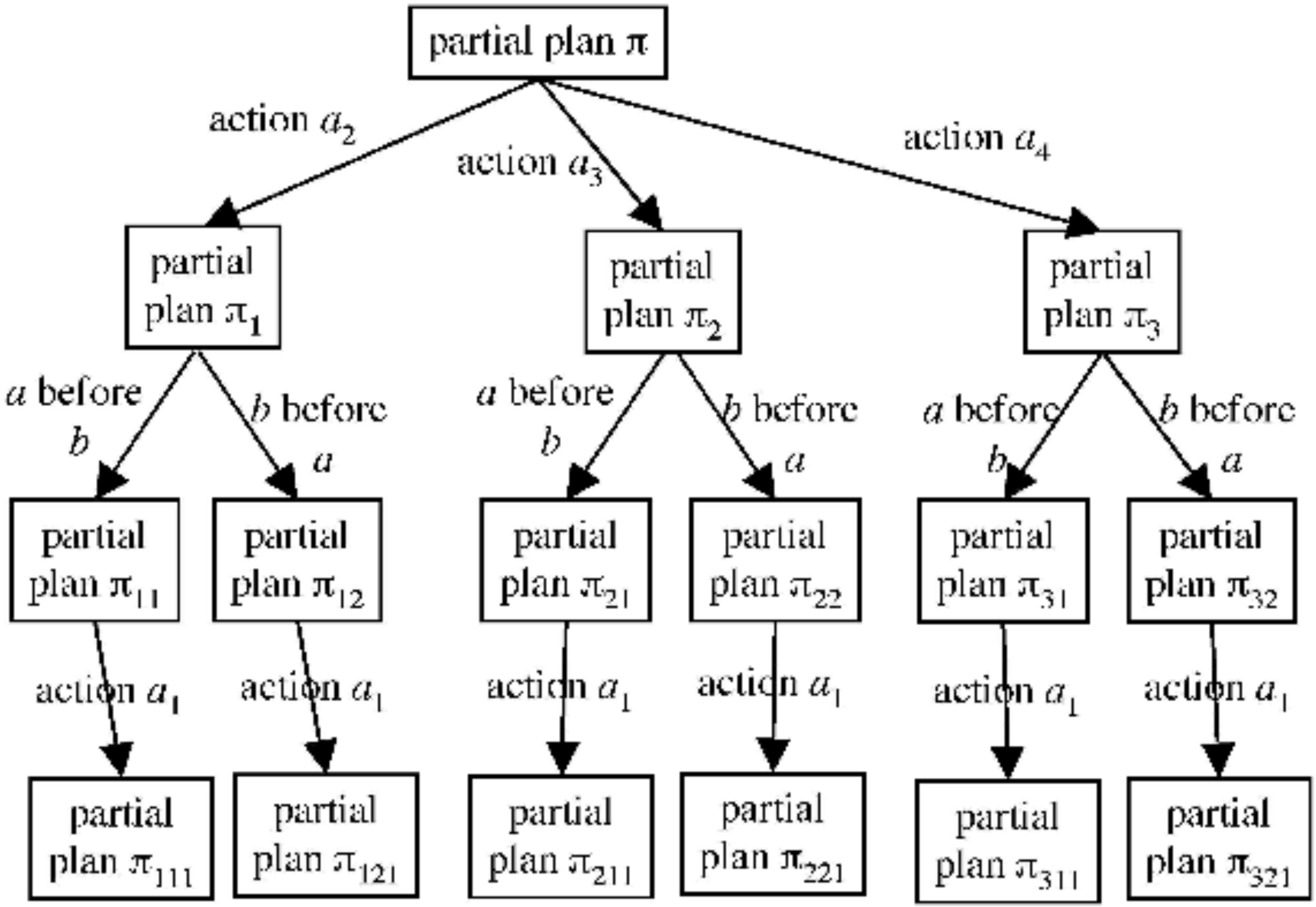
- Deciding what flaw to work on next = *serializing* this tree (turning it into a state-space tree)
  - at each AND branch, choose a child to expand next, and delay expanding the other children



One Serialization



Another Serialization



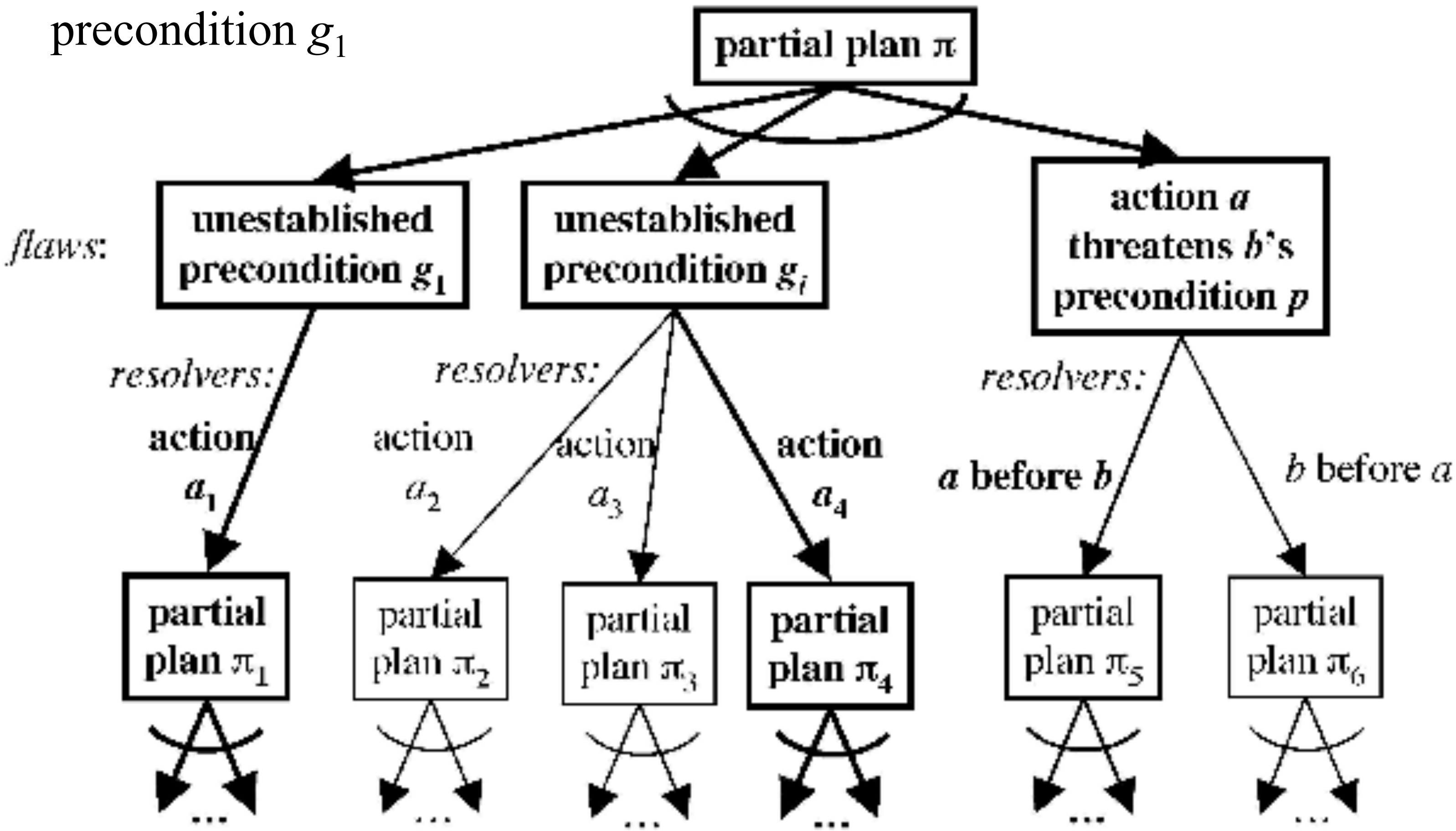
Why Does This Matter?

- Different refinement strategies produce different serializations
  - the search spaces have different numbers of nodes
- In the worst case, the planner will search the entire serialized search space
- The smaller the serialization, the more likely that the planner will be efficient

- One pretty good heuristic: fewest alternatives first

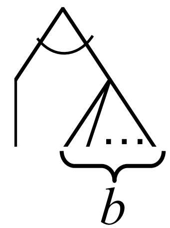
A Pretty Good Heuristic

- Fewest Alternatives First (FAF)
  - Choose the flaw that has the smallest number of alternatives
  - In this case, unestablished precondition g_1

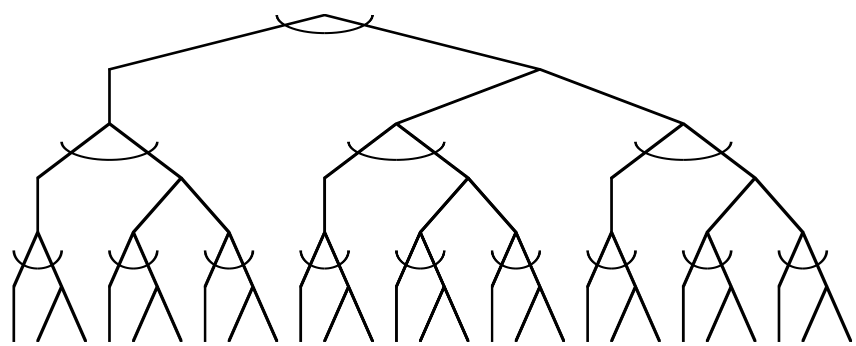


How Much Difference Can the Refinement Strategy Make?

- Case study: build an AND/OR graph from repeated occurrences of this pattern:

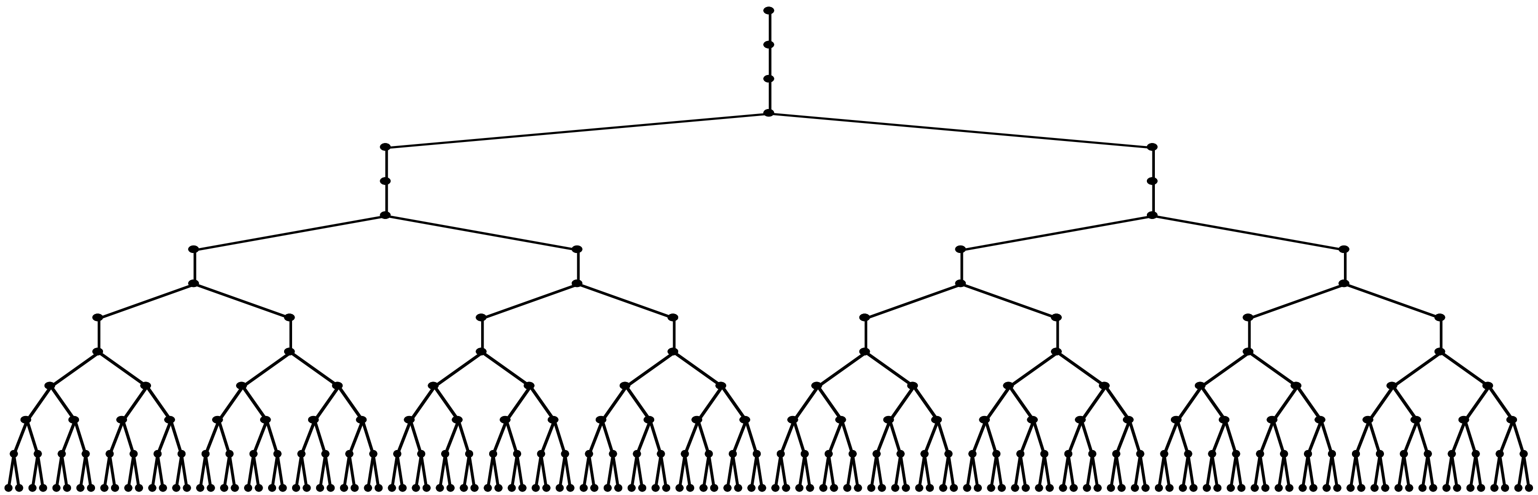


- Example:
  - number of levels $k = 3$
  - branching factor $b = 2$



- Analysis:
  - Total number of nodes in the AND/OR graph is $n = \Theta(b^k)$
  - How many nodes in the best and worst serializations?

Case Study, Continued



- The best serialization contains $\Theta(b^{2^k})$ nodes
- The worst serialization contains $\Theta(2^k b^{2^k})$ nodes
  - The size differs by an exponential factor
  - But both serializations are *doubly* exponentially large
- This limits how good *any* flaw-selection heuristic can do
  - To do better, need good ways to do node selection, branching, pruning

Resolver Selection

Abstract-search(u)
  if Terminal(u) then return(u)
  $u \leftarrow$ Refine(u) ;; *refinement step*
  $B \leftarrow$ Branch(u) ;; *branching step*
  $B' \leftarrow$ Prune(B) ;; *pruning step*
  if $B' = \emptyset$ then return(failure)
  nondeterministically choose $v \in B'$
  return(Abstract-search(v))
end

- This is an "or" branch