Planning

Chapter 10, Sections 1–4

Outline

- ♢ Planning Domain Definition Language (PDDL)
- ♢ Forward and backward state-space search
- ♢ GraphPlan
- ♢ SatPlan
- ♢ Partial order planning

Automated Planning

Planning research has been central to AI from the beginning, partly because of practical interest but also because of the "intelligence" features of human planners.

♢ Large logistics problems, operational planning, robotics, scheduling etc.

♢ A number of international Conferences on Planning

♢ Bi-annual Planning competition

Automated Planning

The setting: a single agent in a fully observable, deterministic and static environment.

Propositional logic can express small domain planning problems, but becomes impractical if there are many actions and states (combinatorial explosion).

Example: In the wumpus world the action of a forward-step has to be written for all four directions, for all n^2 locations, and for each time step T.

The Planning Domain Definition Language (PDDL) is a subset of FOL and more expressive than propositional logic. It allows for factored representation.

Planning Domain Definition Language (PDDL)

PDDL is derived from the STRIPS planning language.

– Initial and goal states.
– A set of $\textsc{Actions}(s)$ in terms of preconditions and effects.
– Closed world assumption: Unmentioned state variables are assumed false.

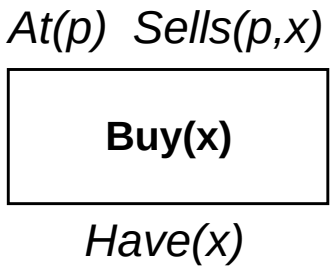
Example:

$\textsc{Action}$: Fly(from, to)
$\textsc{Precondition}$: At(p, from), Plane(p), Airport(from), Airport(to)
$\textsc{Effect}$: ¬At(p, from), At(p, to)

PDDL/STRIPS operators

Tidily arranged actions descriptions, restricted language

ACTION: Buy(x)
PRECONDITION: At(p), Sells(p, x)
EFFECT: Have(x)



[Note: this abstracts away many
important details of buying!]

Restricted language $\Rightarrow$ efficient algorithm
Precondition: conjunction of positive literals
Effect: conjunction of literals

A complete set of STRIPS operators can be translated
into a set of successor-state axioms

Example: Air cargo transport

A classical transportation problem: Loading and unloading cargo and flying between different airports.

Actions: Load(cargo, plane, airport), Unload(cargo, plane, airport),
Fly(plane, airport, airport)

Predicates: In(cargo, plane), At(cargo$\vee$plane, airport)

Example solution:
Load(C1, P1, SFO), Fly(P1, SFO, JFK), Unload(C1, P1, JFK),
Load(C2, P2, JFK), Fly(P2, JFK, SFO), Unload(C2, P2, SFO).

Example: The blocks world

Cube-shape blocks sitting on a table or stacked on top of each other.

Actions: PutOn(block, block), PutOnTable(block)

Predicates: On(block, block$\vee$table), Clear(block$\vee$table)

How difficult is planning?

Does there exist a plan that achieves the goal? PlanSat

Does there exist a solution of length at most k? Bounded PlanSat

PlanSat and Bounded PlanSat are PSPACE-complete.
– i.e., difficult!

PlanSat without negative preconditions and without negative effects is in P.
– i.e., solveable!

State-space search

♢ Forward (progression):
state-space search considers actions that are **applicable**

♢ Backward (regression):
state-space search considers actions that are **relevant**

Neither of them is efficient without good heuristics!

Heuristics for forward state-space search

For forward state-space search there are a number of domain-independent heuristics:

- ♢ Relaxing actions:
  - Ignore-preconditions heuristic
  - Ignore-delete-lists heuristic
- ♢ State abstractions:
  - Reduce the state space

Programs that has won the bi-annual Planning competition has often used

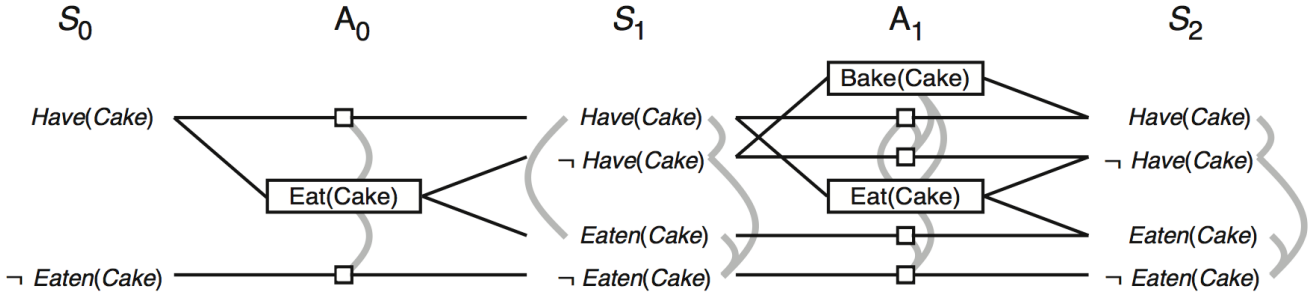
- FF (fast forward) search with heuristics, or
- planning graphs, or
- SAT.

Planning graphs

The main disadvantage of state-space search is the size of the search tree (exponential). Also, the heuristics are not admissible in general.

The planning graph is a polynomial size approximation of the complete tree. Search on this graph is an admissible heuristic.

The planning graph is organized in alternating levels of possible states S_i and applicable actions A_i. Links between levels represent preconditions and effects whereas links within the levels express conflicts (mutex-links).



Planning graphs

A planning problem with l literals and a actions has a polynomial size planning graph:

– Levels S_i contain at most l nodes and l^2 mutex links
– Levels A_i contain at most $a + l$ nodes and $(a + l)^2$ mutex links
– At most $2(al + l)$ links between levels for preconditions and effects
– Therefore, a graph with n levels has size $O(n(a + l)^2)$

The GraphPlan algorithm

The GraphPlan algorithm expands the graph with new levels S_i and A_i until there are no mutex links between the goals. To extract the actual plan, the algorithm searches backwards in the graph.

The plan extraction is the difficult part and is usually done with greedy-like heuristics.

SatPlan and CSP

Translate the PDDL description into a SAT problem or a CSP (constraint satisfaction problem).

The goal state as well as all actions have to be propositionalized. Action schemas have to be replaced by a set of ground actions, variables have to be replaced by constants, fluents need to be introduced for each time step, etc.

$\Rightarrow$ combinatorial explosion

In other words, we remove a part of the benefits of the expressiveness of PDDL to gain access to efficient solution methods for SAT and CSP solvers.

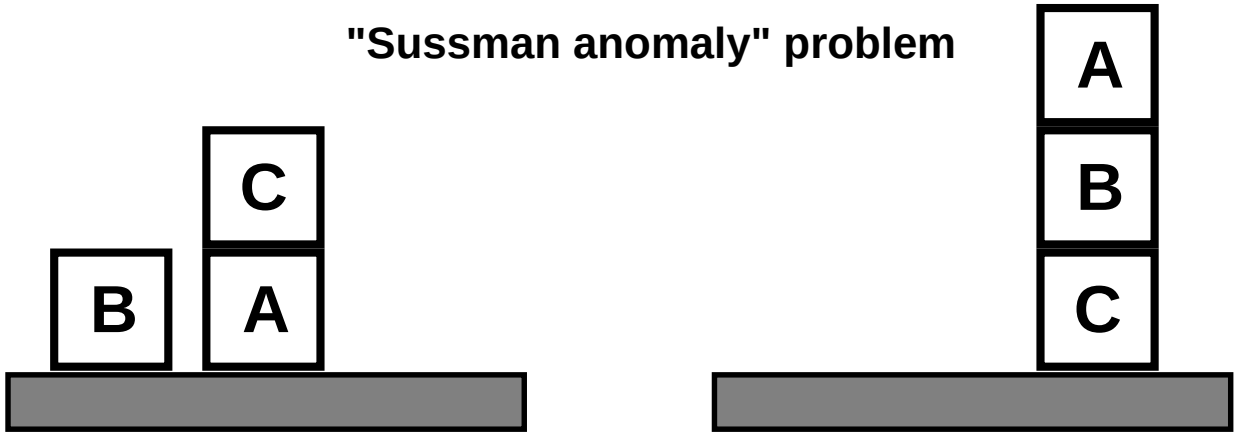
Historical remark: Linear planning

Planners in the early 1970s considered totally ordered action sequences
- problems were decomposed in subgoals
- the resulting subplans were stringed together in some order
- this is called linear planning

But, linear planning is **incomplete**!
- there are some very simple problems it cannot handle
- e.g., the Sussman anomaly
- a complete planner must be able to interleave subplans

Enter partial-order planning, state-of-the-art during the 1980s and 90s
- today mostly used for specific tasks, such as operations scheduling
- also used when it is important for humans to understand the plans
- e.g., operational plans for spacecraft and Mars rovers are checked by human operators before uploaded to the vehicles

Example: The Sussman anomaly



Clear(x) On(x,z) Clear(y)

PutOn(x,y)

~On(x,z) ~Clear(y)
Clear(z) On(x,y)

Clear(x) On(x,z)

PutOnTable(x)

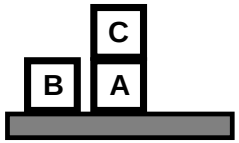
~On(x,z) Clear(z) On(x,Table)

+ several inequality constraints

Example contd.

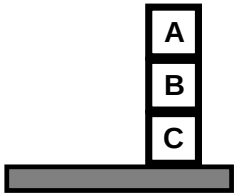
START

On(C,A) On(A,Table) Cl(B) On(B,Table) Cl(C)

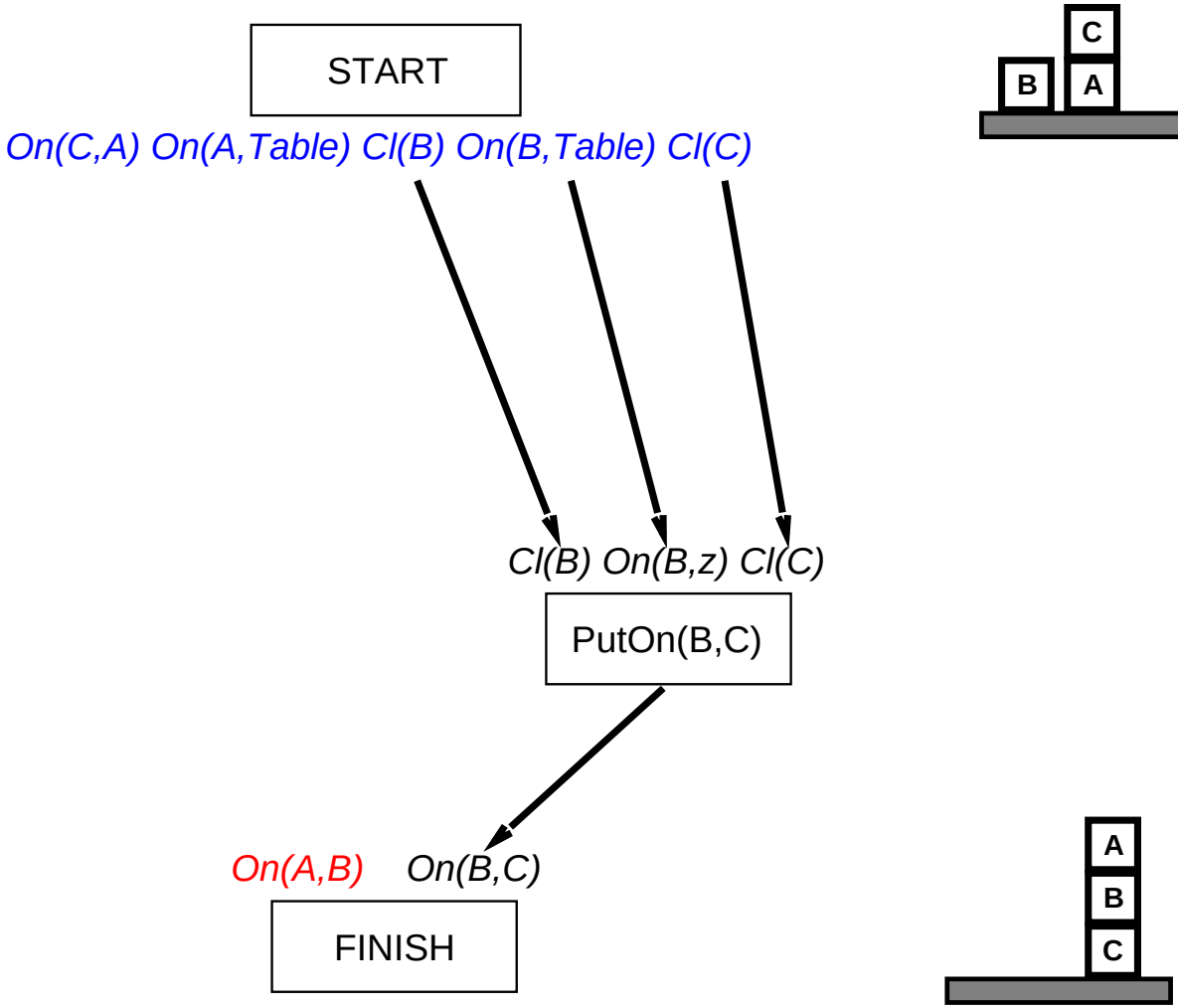


On(A,B) On(B,C)

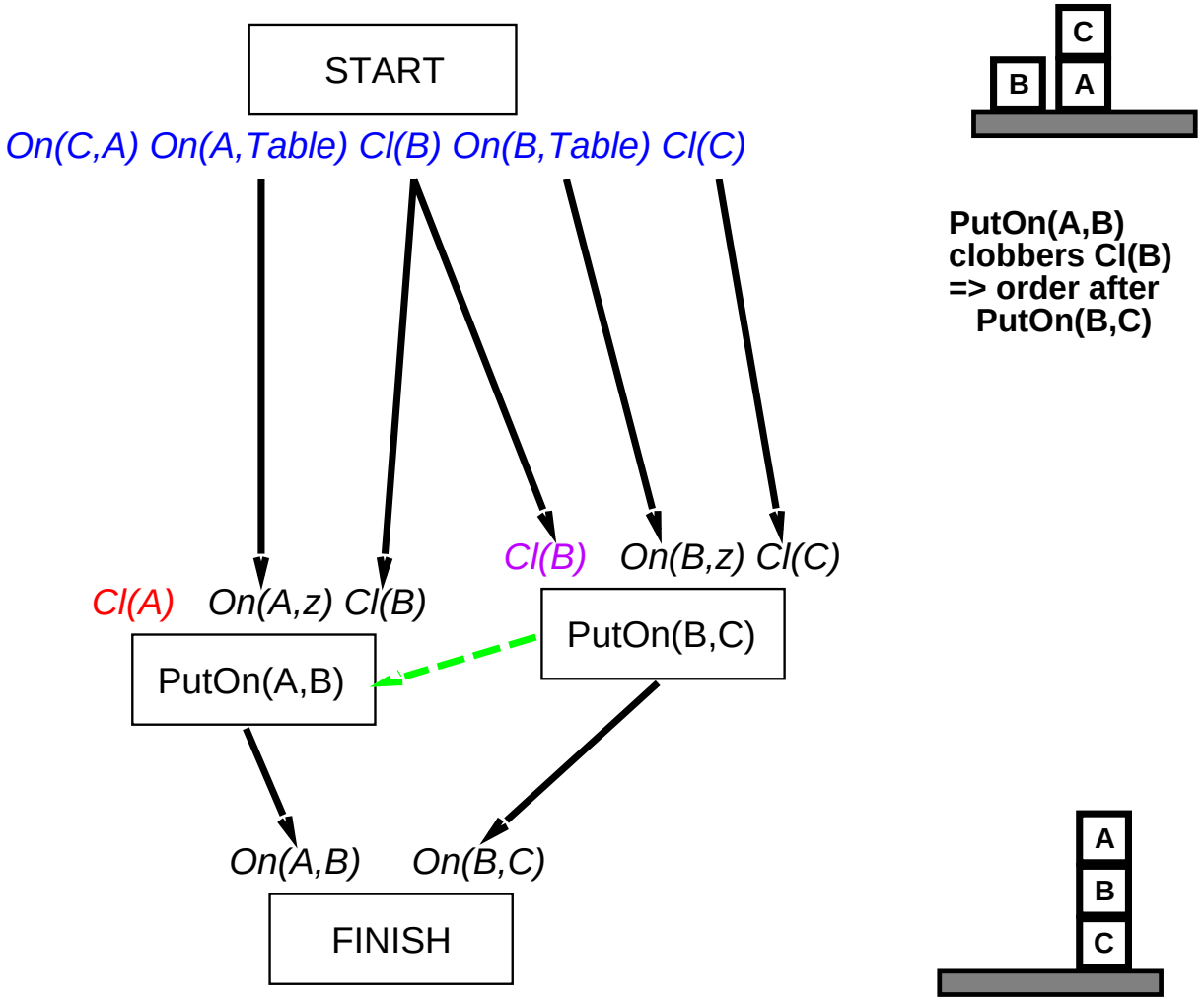
FINISH



Example contd.



Example contd.



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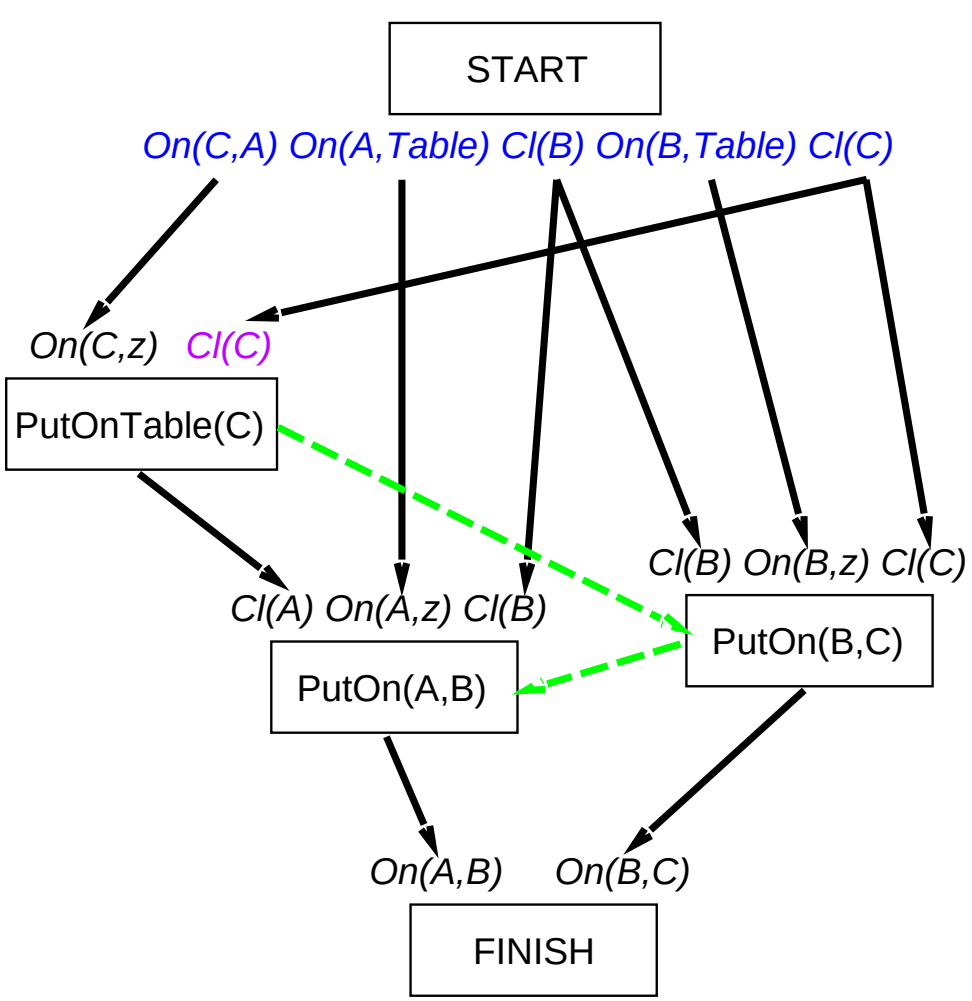

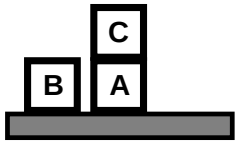

PutOn(A,B) clobbers Cl(B) => order after PutOn(B,C)

PutOn(B,C) clobbers Cl(C) => order after PutOnTable(C)