Planning

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Planning

The Planning problem
Planning with State-space search
Partial-order planning
Planning graphs
Planning with propositional logic
Analysis of planning approaches

What is Planning

Generate sequences of actions to perform tasks and achieve objectives.
- States, actions and goals

Search for solution over abstract space of plans.

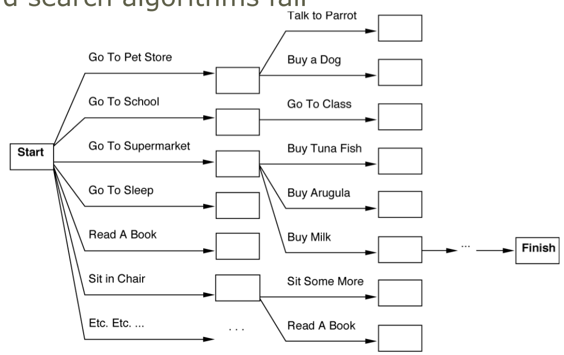
Classical planning environment: fully observable, deterministic, finite, static and discrete.

Assists humans in practical applications
- design and manufacturing
- military operations
- games
- space exploration

Why not standard search?

Consider the task get milk, bananas and a cordless drill

Standard search algorithms fail



Difficulty of real world problems

Assume a problem-solving agent using some search method …

- Which actions are relevant?
  - Exhaustive search vs. backward search
- What is a good heuristic functions?
  - Good estimate of the cost of the state?
  - Problem-dependent vs, -independent
- How to decompose the problem?
  - Most real-world problems are ***nearly*** decomposable.

Planning language

What is a good language?

- Expressive enough to describe a wide variety of problems.
- Restrictive enough to allow efficient algorithms to operate on it.
- Planning algorithm should be able to take advantage of the logical structure of the problem.

STRIPS and PDDL

General language features

Representation of states

- Decompose the world in logical conditions and represent a state as a *conjunction of positive literals.*
  - Propositional literals: *Safe* ∧ *HasGold*
  - FO-literals (grounded and function-free): *At(Plane1, Copenhagen)* ∧ *At(Plane2, Oslo)*
- Closed world assumption

Representation of goals

- Partially specified state and represented as a *conjunction of positive ground literals*
- A goal is *satisfied* if the state contains all literals in goal.

General language features

Representations of actions

- Action = PRECOND + EFFECT

  Action(Fly(p, from, to),
  PRECOND: At(p, from) ∧ Plane(p) ∧ Airport(from) ∧ Airport(to)
  EFFECT: ¬AT(p, from) ∧ At(p, to))

= action schema (p, from, to need to be instantiated)
  - Action name and parameter list
  - Precondition (conj. of function-free literals)
  - Effect (conjunction of function-free literals and P is True and not P is false)
- Add-list vs delete-list in Effect

Language semantics?

How do actions affect states?

– An action is applicable in any state that satisfies the precondition.
– For FO action schema applicability involves a substitution θ for the variables in the PRECOND.

At(P1, JFK) ∧ At(P2, SFO) ∧ Plane(P1) ∧ Plane(P2) ∧ Airport(JFK) ∧ Airport(SFO)

Satisfies : *At(p, from) ∧ Plane(p) ∧ Airport(from) ∧ Airport(to)*

With θ =*{p/P1, from/JFK, to/SFO}*

Thus the action is applicable.

Language semantics?

The result of executing action a in state s is the state s'

– s' is same as s except
  – Any positive literal *P* in the effect of *a* is added to *s'*
  – Any negative literal ¬*P* is removed from *s'*

EFFECT: ¬AT(p, from) ∧ At(p, to):

At(P1, SFO) ∧ At(P2, SFO) ∧ Plane(P1) ∧ Plane(P2) ∧ Airport(JFK) ∧ Airport(SFO)

– STRIPS assumption: (avoids representational frame problem)

every literal NOT in the effect remains unchanged

Expressiveness and extensions

STRIPS is simplified

– Important limit: function-free literals
  – Allows for propositional representation
  – Function symbols lead to infinitely many states and actions

Expressiveness extension: Planning Domain Description Language (PDDL)

Action(Fly(p: Plane, from: Airport, to: Airport),
PRECOND: At(p, from) ∧ (from ≠ to)
EFFECT: ¬At(p, from) ∧ At(p, to))

Standardization : *now (since 2008) in its 3.1 version*

Example: air cargo transport

Init(At(C1, SFO) ∧ At(C2, JFK) ∧ At(P1, SFO) ∧ At(P2, JFK) ∧ Cargo(C1) ∧ Cargo(C2) ∧ Plane(P1) ∧ Plane(P2) ∧ Airport(JFK) ∧ Airport(SFO))

Goal(At(C1, JFK) ∧ At(C2, SFO))

Action(Load(c, p, a)
PRECOND: *At(c, a) ∧ At(p, a) ∧ Cargo(c) ∧ Plane(p) ∧ Airport(a)*
EFFECT: *¬At(c, a) ∧ In(c, p))*
Action(Unload(c, p, a)
PRECOND: *In(c, p) ∧ At(p, a) ∧ Cargo(c) ∧ Plane(p) ∧ Airport(a)*
EFFECT: *At(c, a) ∧ ¬In(c, p))*
Action(Fly(p, from, to)
PRECOND: *At(p, from) ∧ Plane(p) ∧ Airport(from) ∧ Airport(to)*
EFFECT: *¬At(p, from) ∧ At(p, to))*

[Load(C1, P1 ,SFO), Fly(P1, SFO, JFK), Load(C2, P2, JFK), Fly(P2, JFK, SFO)]

Example: Spare tire problem

Init(At(Flat, Axle) ∧ At(Spare, trunk))
Goal(At(Spare, Axle))
Action(Remove(Spare, Trunk)
  PRECOND: *At(Spare, Trunk)*
  EFFECT: *¬At(Spare, Trunk) ∧ At(Spare, Ground))*
Action(Remove(Flat, Axle)
  PRECOND: *At(Flat, Axle)*
  EFFECT: *¬At(Flat, Axle) ∧ At(Flat, Ground))*
Action(PutOn(Spare, Axle)
  PRECOND: *At(Spare, Groundp) ∧ ¬At(Flat, Axle)*
  EFFECT: *At(Spare, Axle) ∧ ¬At(Spare ,Ground))*
Action(LeaveOvernight
  PRECOND:
  EFFECT: *¬At(Spare, Ground) ∧ ¬At(Spare, Axle) ∧ ¬At(Spare, trunk) ∧ ¬At(Flat, Ground) ∧ ¬At(Flat, Axle))*

This example goes beyond STRIPS: negative literal in pre-condition (PDDL description)

Example: Blocks world

Init(On(A, Table) ∧ On(B, Table) ∧ On(C, Table) ∧ Block(A) ∧ Block(B) ∧ Block(C) ∧ Clear(A) ∧ Clear(B) ∧ Clear(C))

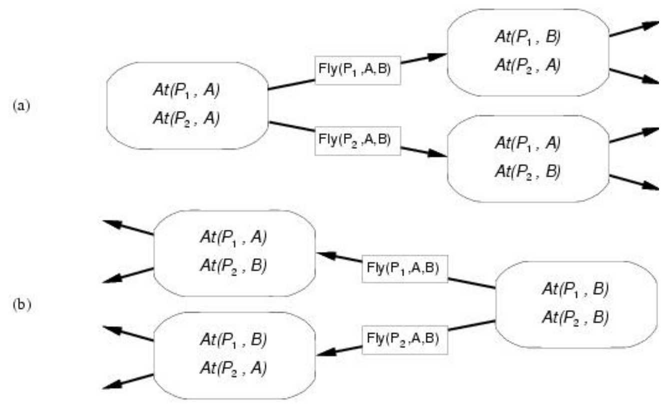
Goal(On(A, B) ∧ On(B, C))

Action(Move(b, x, y)
  PRECOND: *On(b, x) ∧ Clear(b) ∧ Clear(y) ∧ Block(b) ∧ (b ≠ x) ∧ (b ≠ y) ∧ (x ≠ y)*
  EFFECT: *On(b, y) ∧ Clear(x) ∧ ¬On(b, x) ∧ ¬Clear(y))*
Action(MoveToTable(b, x)
  PRECOND: *On(b, x) ∧ Clear(b) ∧ Block(b) ∧ (b ≠ x)*
  EFFECT: *On(b, Table) ∧ Clear(x) ∧ ¬On(b, x))*

Planning with state-space search

- Both forward and backward search possible
- Progression planners
  - forward state-space search
  - Consider the effect of all possible actions in a given state
- Regression planners
  - backward state-space search
  - To achieve a goal, what must have been true in the previous state.

Progression and regression



Progression algorithm

Formulation as state-space search problem:
- Initial state = initial state of the planning problem
  - Literals not appearing are false
- Actions = those whose preconditions are satisfied
  - Add positive effects, delete negative
- Goal test = does the state satisfy the goal
- Step cost = each action costs 1

No functions … any graph search that is complete is a complete planning algorithm.
- E.g. A*

Inefficient:
- (1) irrelevant action problem
- (2) good heuristic required for efficient search

Regression algorithm

How to determine predecessors?
- What are the states from which applying a given action leads to the goal?

  Goal state = *At(C1, B)* ∧ *At(C2, B)* ∧ … ∧ *At(C20, B)*
  Relevant action for first conjunct*: Unload(C1, p, B)*
  Works only if pre-conditions are satisfied.
  Previous state= *In(C1, p)* ∧ *At(p, B)* ∧ *At(C2, B)* ∧ … ∧ *At(C20, B)*
  Subgoal At(C1, B) should not be present in this state.

Actions must not undo desired literals (consistent)

Main advantage: only relevant actions are considered.
- Often much lower branching factor than forward search.

Regression algorithm

General process for predecessor construction
- Give a goal description G
- Let A be an action that is relevant and consistent
- The predecessors are as follows:
  - Any positive effects of A that appear in G are deleted.
  - Each precondition literal of A is added , unless it already appears.

Any standard search algorithm can be added to perform the search.

Termination when predecessor is satisfied by initial state.
- In FO case, satisfaction might require a substitution.

Heuristics for state-space search

Neither progression or regression are very efficient without a good heuristic.
- How many actions are needed to achieve the goal?
- Exact solution is NP hard, find a good estimate

Two approaches to find admissible heuristic:
- The optimal solution to the relaxed problem.
  - Remove all preconditions from actions
- The subgoal independence assumption:

  The cost of solving a conjunction of subgoals is approximated by the sum of the costs of solving the subproblems independently.

Partial-order planning

Progression and regression planning are *totally ordered plan search* forms.

– They cannot take advantage of problem decomposition.

  – Decisions must be made on how to sequence actions on all the subproblems

Least commitment strategy:

– Delay choice during search

Shoe example

Goal(RightShoeOn ∧ LeftShoeOn)

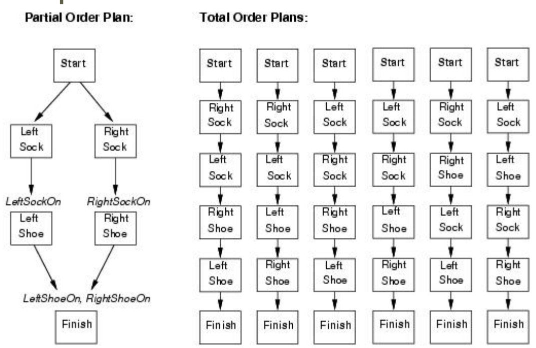
Init()

Action(RightShoe,	PRECOND: RightSockOn	EFFECT: RightShoeOn)
Action(RightSock,	PRECOND:	EFFECT: RightSockOn)
Action(LeftShoe,	PRECOND: LeftSockOn	EFFECT: LeftShoeOn)
Action(LeftSock,	PRECOND:	EFFECT: LeftSockOn)

Planner: combine two action sequences
(1) leftsock, leftshoe
(2) rightsock, rightshoe

Partial-order planning(POP)

Any planning algorithm that can place two actions into a plan without stating which comes first is a PO plan.



POP as a search problem

States are (mostly unfinished) plans.

– The empty plan contains only start and finish actions.

Each plan has 4 components:

– A set of actions (steps of the plan)

– A set of ordering constraints: A < B (A before B)

  – Cycles represent contradictions.

– A set of causal links $A \xrightarrow{p} B$

  – The plan may not be extended by adding a new action C that conflicts with the causal link. (if the effect of C is ¬p and if C could come after A and before B)

– A set of open preconditions.

  – If precondition is not achieved by action in the plan.

Example of final plan

Actions={Rightsock, Rightshoe, Leftsock, Leftshoe, Start, Finish}

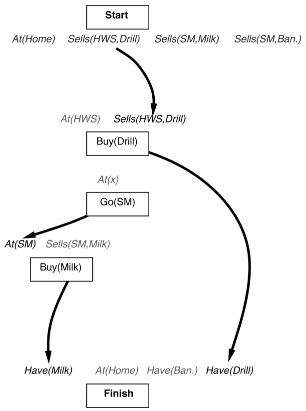
Orderings={Rightsock < Rightshoe; Leftsock < Leftshoe}

Links={Rightsock->Rightsockon -> Rightshoe, Leftsock->Leftsockon-> Leftshoe, Rightshoe->Rightshoeon->Finish, …}

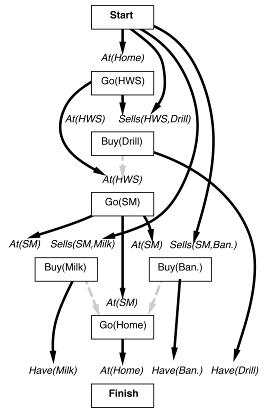
Open preconditions={}

Shopping list example

Shopping list example



Shopping list example



POP as a search problem

A plan is *consistent* iff there are no cycles in the ordering constraints and no conflicts with the causal links.

A consistent plan with no open preconditions is a *solution*.

A partial order plan is executed by repeatedly choosing *any* of the possible next actions.

- This flexibility is a benefit in non-cooperative environments;
- Gives rise to emergent behaviours.

Solving POP

Assume propositional planning problems:

- The initial plan contains *Start* and *Finish*, the ordering constraint *Start* < *Finish*, no causal links, all the preconditions in *Finish* are open.
- Successor function :
  - picks one open precondition *p* on an action *B* and
  - generates a successor plan for every possible consistent way of choosing action *A* that achieves *p*.
- Test goal

Enforcing consistency

When generating successor plan:

- The causal link *A->p->B* and the ordering constraint A < B is added to the plan.
  - If A is new also add start < A and A < B to the plan
- Resolve conflicts between new causal link and all existing actions
- Resolve conflicts between action A (if new) and all existing causal links.

Process summary

Operators on partial plans

- Add link from existing plan to open precondition.
- Add a step to fulfill an open condition.
- Order one step w.r.t another to remove possible conflicts

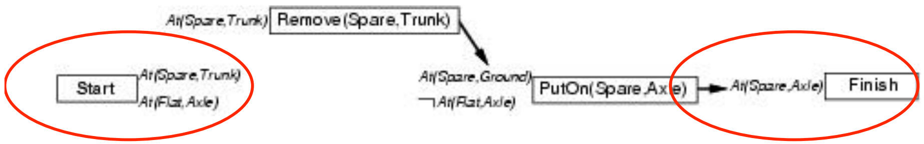
Gradually move from incomplete/vague plans to complete/correct plans

Backtrack if an open condition is unachievable or if a conflict is irresolvable.

Example: Spare tire problem

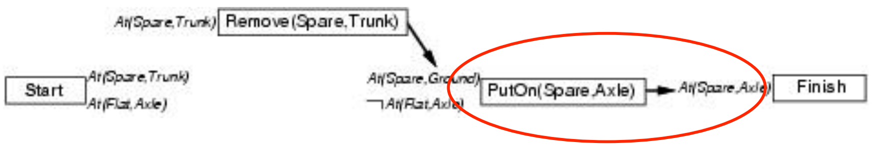
Init(At(Flat, Axle) ∧ At(Spare, trunk))
Goal(At(Spare, Axle))
Action(Remove(Spare, Trunk)
PRECOND: *At(Spare, Trunk)*
EFFECT: *¬At(Spare, Trunk) ∧ At(Spare, Ground))*
Action(Remove(Flat, Axle)
PRECOND: *At(Flat, Axle)*
EFFECT: *¬At(Flat, Axle) ∧ At(Flat, Ground))*
Action(PutOn(Spare, Axle)
PRECOND: *At(Spare, Groundp) ∧ ¬At(Flat, Axle)*
EFFECT: *At(Spare ,Axle) ∧ ¬At(Spare, Ground))*
Action(LeaveOvernight
PRECOND:
EFFECT: *¬At(Spare, Ground) ∧ ¬At(Spare, Axle) ∧ ¬At(Spare, trunk) ∧ ¬At(Flat, Ground) ∧ ¬At(Flat, Axle))*

Solving the problem



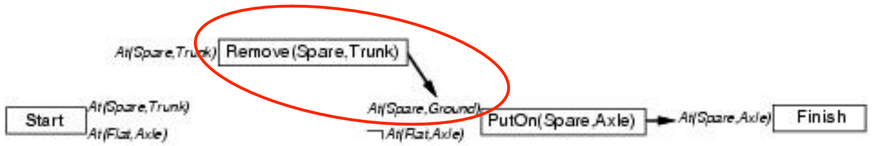
Initial plan: Start with EFFECTS and Finish with PRECOND.

Solving the problem



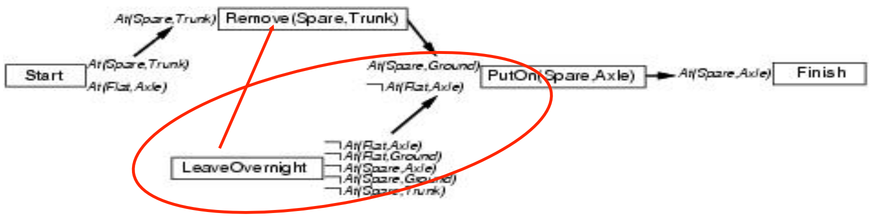
Initial plan: Start with EFFECTS and Finish with PRECOND.
Pick an open precondition: *At(Spare, Axle)*
Only *PutOn(Spare, Axle)* is applicable
Add causal link: $PutOn(Spare,Axle) \xrightarrow{At(Spare,Axle)} Finish$
Add constraint : *PutOn(Spare, Axle) < Finish*

Solving the problem



Pick an open precondition: *At(Spare, Ground)*
Only *Remove(Spare, Trunk)* is applicable
Add causal link: $Remove(Spare,Trunk) \xrightarrow{At(Spare,Ground)} PutOn(Spare,Axle)$
Add constraint : *Remove(Spare, Trunk) < PutOn(Spare,Axle)*

Solving the problem



Pick an open precondition: *¬At(Flat, Axle)*

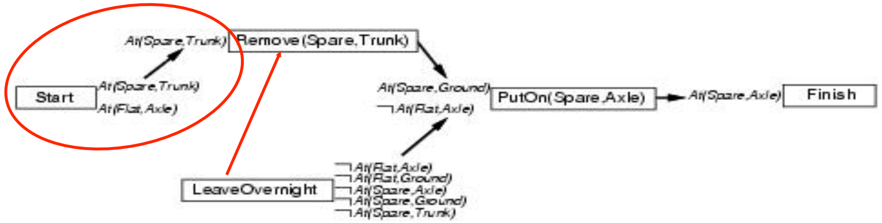
LeaveOverNight is applicable

conflict: *LeaveOverNight* also has the effect ¬ *At(Spare,Ground)*

$$Remove(Spare,Trunk) \xrightarrow{At(Spare,Ground)} PutOn(Spare,Axle)$$

To resolve, add constraint : *LeaveOverNight < Remove(Spare, Trunk)*

Solving the problem



Pick an open precondition: *At(Spare, Trunk)*

Only *Start* is applicable

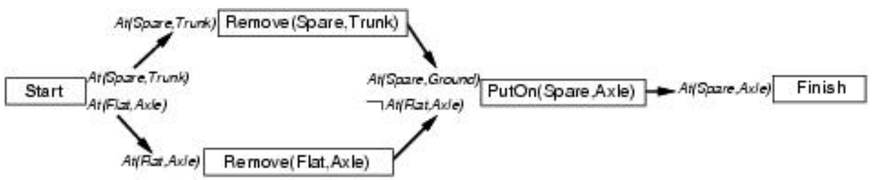
Add causal link: $Start \xrightarrow{At(Spare,Trunk)} Remove(Spare,Trunk)$

Conflict: of causal link with effect *¬At(Spare,Trunk)* in *LeaveOverNight*

- *No re-ordering solution possible.*

backtrack

Solving the problem



Remove *LeaveOverNight*, *Remove(Spare, Trunk)* and causal links

Repeat step with Remove(Spare,Trunk)

Add also RemoveFlatAxle and finish

Some details …

What happens when a first-order representation that includes variables is used?

- Complicates the process of detecting and resolving conflicts.
- Can be resolved by introducing inequality constraint.

CSP's most-constrained-variable heuristic can be used for planning algorithms to select a PRECOND.

Planning graphs

Used to achieve better heuristic estimates.

- A solution can also be directly extracted using GRAPHPLAN.

Consists of a sequence of levels that correspond to time steps in the plan.

- Level 0 is the initial state.
- Each level consists of a set of literals and a set of actions.
  - *Literals* = all those that *could* be true at that time step, depending upon the actions executed at the preceding time step.
  - *Actions* = all those actions that *could* have their preconditions satisfied at that time step, depending on which of the literals actually hold.

Planning graphs

"Could"?

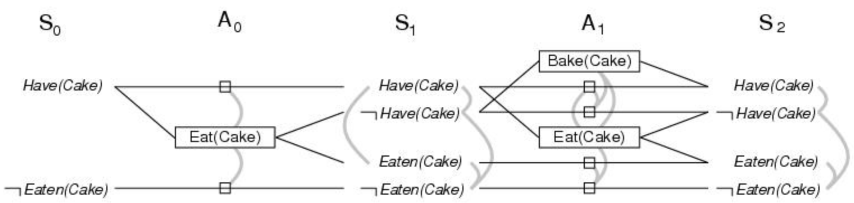
- Records only a restricted subset of possible negative interactions among actions.

They work only for propositional problems.

Example:

Init(Have(Cake))
Goal(Have(Cake) ∧ Eaten(Cake))
Action(Eat(Cake), PRECOND: Have(Cake)
EFFECT: ¬Have(Cake) ∧ Eaten(Cake))
Action(Bake(Cake), PRECOND: ¬ Have(Cake)
EFFECT: Have(Cake))

Cake example



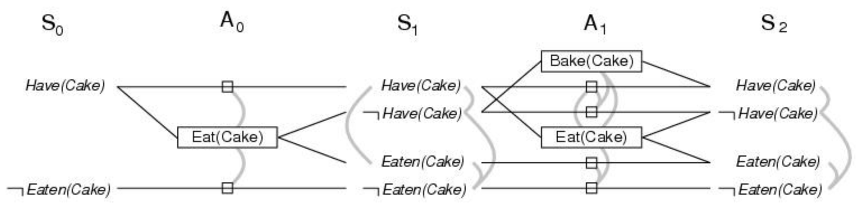
Start at level S_0 and determine action level A_0 and next level S_1.

- A_0 >> all actions whose preconditions are satisfied in the previous level.
- Connect precond and effect of actions S_0 --> S_1
- Inaction is represented by *persistence actions*.

Level A_0 contains the actions that could occur

- Conflicts between actions are represented by *mutex* links

Cake example



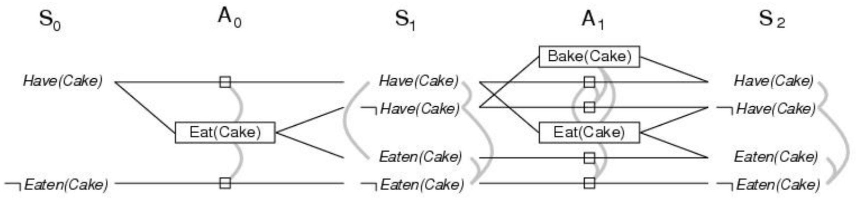
Level S_1 contains all literals that could result from picking any subset of actions in A_0

- Conflicts between literals that can not occur together (as a consequence of the selection action) are represented by mutex links.
- S_1 defines multiple states and the mutex links are the constraints that define this set of states.

Continue until two consecutive levels are identical: *leveled off*

- Or contain the same amount of literals

Cake example



A mutex relation holds between **two actions** when:

- *Inconsistent effects*: one action negates the effect of another.
- *Interference*: one of the effects of one action is the negation of a precondition of the other.
- *Competing needs*: one of the preconditions of one action is mutually exclusive with the precondition of the other.

A mutex relation holds between **two literals** when (*inconsistent support*):

- If one is the negation of the other OR
- if each possible action pair that could achieve the literals is mutex.

PG and heuristic estimation

PG's provide information about the problem

- A literal that does not appear in the final level of the graph cannot be achieved by any plan.
  - Useful for backward search (cost = inf).
- Level of appearance can be used as cost estimate of achieving any goal literals = *level cost*.
- Small problem: several actions can occur
  - Restrict to one action using serial PG (add mutex links between every pair of actions, except persistence actions).
- Cost of a conjunction of goals? Max-level, sum-level and set-level heuristics.

PG is a relaxed problem.

The GRAPHPLAN Algorithm

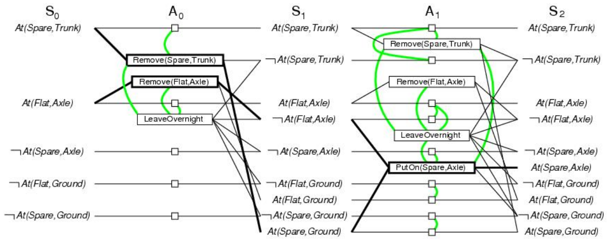
How to extract a solution directly from the PG

function GRAPHPLAN(*problem*) **return** *solution* or failure
    graph ← INITIAL-PLANNING-GRAPH(*problem*)
    goals ← GOALS[*problem*]
    loop do
        if *goals* all non-mutex in last level of graph **then do**
            solution ← EXTRACT-SOLUTION(*graph, goals,* LENGTH*(graph)*)
            if *solution* ≠ failure **then return** *solution*
            else if NO-SOLUTION-POSSIBLE(*graph*) **then return** failure
        graph ← EXPAND-GRAPH(*graph, problem*)

Example: Spare tire problem

Init(At(Flat, Axle) ∧ At(Spare, trunk))
Goal(At(Spare, Axle))
Action(Remove(Spare, Trunk)
    PRECOND: *At(Spare, Trunk)*
    EFFECT: *¬At(Spare, Trunk) ∧ At(Spare, Ground))*
Action(Remove(Flat, Axle)
    PRECOND: *At(Flat, Axle)*
    EFFECT: *¬At(Flat, Axle) ∧ At(Flat, Ground))*
Action(PutOn(Spare, Axle)
    PRECOND: *At(Spare, Groundp) ∧ ¬At(Flat, Axle)*
    EFFECT: *At(Spare, Axle) ∧ ¬At(Spare, Ground))*
Action(LeaveOvernight
    PRECOND:
    EFFECT: *¬At(Spare, Ground) ∧ ¬At(Spare, Axle) ∧ ¬At(Spare, trunk) ∧ ¬At(Flat, Ground) ∧ ¬At(Flat, Axle))*

GRAPHPLAN example



Initially the plan consist of 5 literals from the initial state and the CWA literals (S_0).

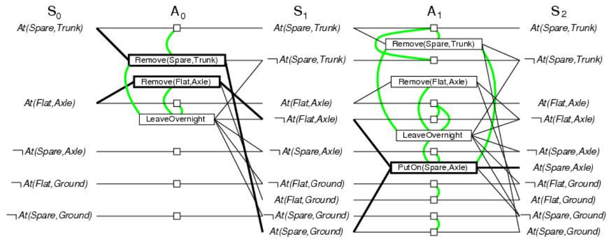
Add actions whose preconditions are satisfied by EXPAND-GRAPH (A_0)

Also add persistence actions and mutex relations.

Add the effects at level S_1

Repeat until goal is in level S_i

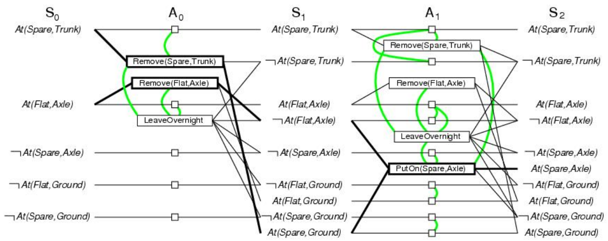
GRAPHPLAN example



EXPAND-GRAPH also looks for mutex relations

- Inconsistent effects
  - E.g. Remove(Spare, Trunk) and LeaveOverNight due to At(Spare, Ground) and **not** At(Spare, Ground)
- Interference
  - E.g. Remove(Flat, Axle) and LeaveOverNight At(Flat, Axle) as PRECOND and **not** At(Flat, Axle) as EFFECT
- Competing needs
  - E.g. PutOn(Spare, Axle) and Remove(Flat, Axle) due to At(Flat. Axle) and **not** At(Flat, Axle)
- Inconsistent support
  - E.g. in S_2, At(Spare, Axle) and At(Flat, Axle)

GRAPHPLAN example



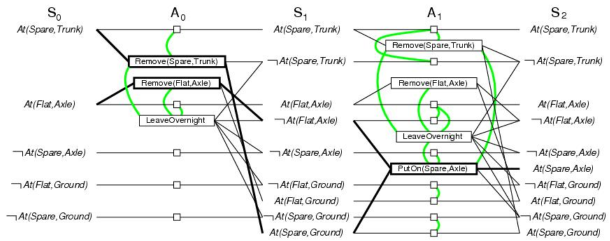
In S_2, the goal literals exist and are not mutex with any other

- Solution might exist and EXTRACT-SOLUTION will try to find it

EXTRACT-SOLUTION can use Boolean CSP to solve the problem or a search process:

- Initial state = last level of PG and goal goals of planning problem
- Actions = select any set of non-conflicting actions that cover the goals in the state
- Goal = reach level S_0 such that all goals are satisfied
- Cost = 1 for each action.

GRAPHPLAN example



Termination? YES

PG are monotonically increasing or decreasing:

- Literals increase monotonically
- Actions increase monotonically
- Mutexes decrease monotonically

Because of these properties and because there is a finite number of actions and literals, every PG will eventually level off !

Planning with propositional logic

Planning can be done by proving theorem in situation calculus.
Here: test the *satisfiability* of a logical sentence:

$$\textit{initial state} \wedge \textit{all possible action descriptions} \wedge \textit{goal}$$

Sentence contains propositions for every action occurrence.

- A model will assign true to the actions that are part of the correct plan and false to the others
- An assignment that corresponds to an incorrect plan will not be a model because of inconsistency with the assertion that the goal is true.
- If the planning is unsolvable the sentence will be unsatisfiable.

Analysis of planning approach

Planning is an area of great interest within AI

- Search for solution
- Constructively prove a existence of solution

Biggest problem is the combinatorial explosion in states.

Efficient methods are under research

- E.g. divide-and-conquer

Planning vs. scheduling

Classical planning:

What to do? In what order?

But not:

How long? When? Using what resources?

Normally:

Plan first, schedule later.

Representation

Job-shop scheduling problem:

- A set of jobs
- Each job is a collection of ACTIONS with some ORDERING CONSTRAINTS
- Each action has a DURATION and a set of RESOURCE CONSTRAINTS

resources may be CONSUMABLE or REUSABLE

Solution:

Start times for all actions, obeying all constraints