cis32-ai — lecture # 22 — wed-26-apr-2006

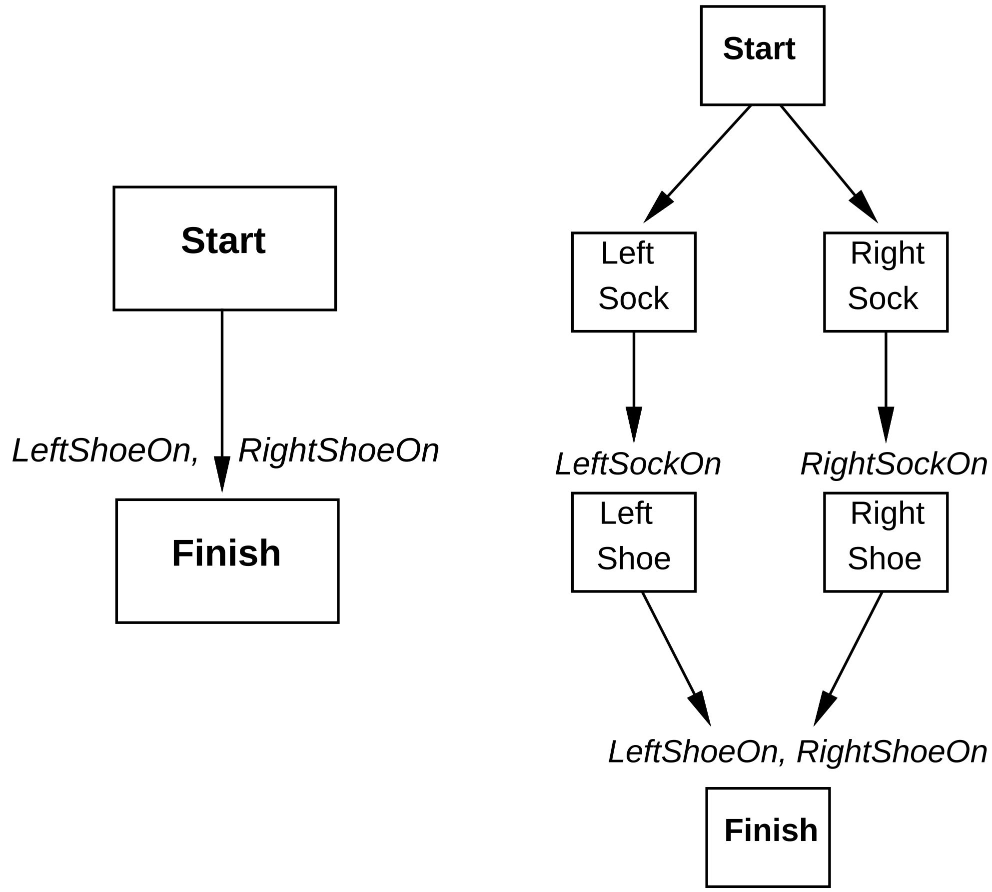
today's topics:

- partial-order planning
- decision-theoretic planning

Partial Order Planning

- The answer to the problem we ended the last lecture with is to use partial order planning.
- Basically this gives us a way of checking before adding an action to the plan that it doesn't mess up the rest of the plan.
- The problem is that in this recursive process, we don't know what the rest of the plan is.
- Need a new representation *partially ordered plans*.

Representation

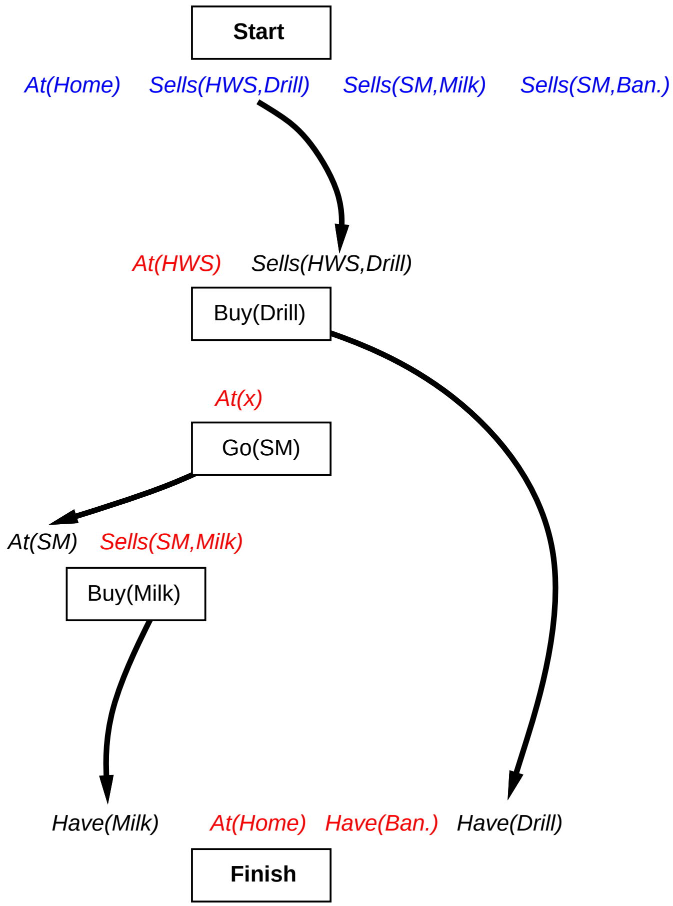


Partially ordered plans

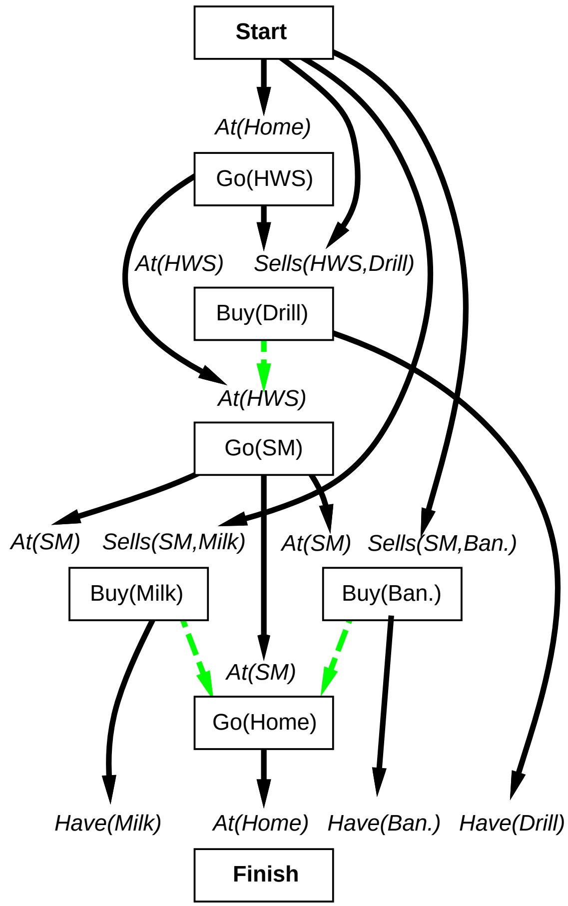
- *Partially ordered* collection of steps with
  - $Start$ step has the initial state description as its effect
  - $Finish$ step has the goal description as its precondition
  - *causal links* from outcome of one step to precondition of another
  - *temporal ordering* between pairs of steps
- *Open condition* $=$ precondition of a step not yet causally linked
- A plan is *complete* iff every precondition is achieved
- A precondition is *achieved* iff it is the effect of an earlier step and no *possibly intervening* step undoes it

Plan construction

Plan construction (2)



Plan construction (3)



Planning process

- Operators on partial plans:
  - *add a link* from an existing action to an open condition
  - *add a step* to fulfill an open condition
  - *order* one step wrt 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 unresolvable

POP algorithm

function POP (*initial, goal, operators*) returns *plan*
    plan $\leftarrow$ MAKE-MINIMAL-PLAN(*initial,goal*)
    loop do
        if SOLUTION?(*plan*) then return *plan*
        $S_{need}, c \leftarrow$ SELECT-SUBGOAL(*plan*)
        CHOOSE-OPERATOR(*plan,operators*,S_{need}, c)
        RESOLVE-THREATS(*plan*)
    end loop
end function

function SELECT-SUBGOAL(*plan*) returns S_{need}, c
    pick a plan step S_{need} from STEPS(*plan*)
        with a precondition c that has not been achieved
    return S_{need}, c
end function

POP algorithm, continued

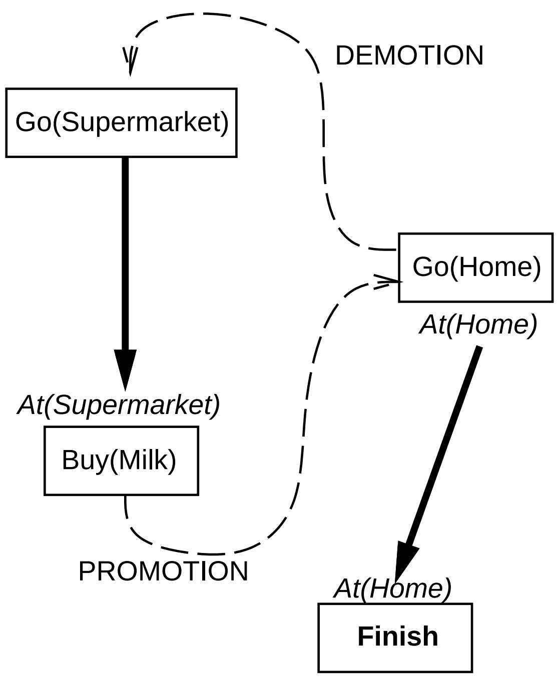
procedure CHOOSE-OPERATOR(*plan*,*operators*,S_{need}, c)
    choose a step S_{add} from *operators* or STEPS(*plan*) that has c as an effect
    if there is no such step then fail   add the causal link $S_{add} \xleftarrow{c} S_{need}$ to LINKS(*plan*)
    add the ordering constraint $S_{add} \prec S_{need}$ to ORDERINGS(*plan*)
    if S_{add} is a newly added step from *operators* then
        add S_{add} to STEPS(*plan*)
        add $Start \prec S_{add} \prec Finish$ to ORDERINGS(*plan*)
    end if
end procedure

POP algorithm, continued

procedure RESOLVE-THREATS(*plan*)
    for each S_{threat} that threatens a link $S_i \xleftarrow{c} S_j$ in LINKS(*plan*) do
        choose either
            Demotion: Add $S_{threat} \prec S_i$ to ORDERINGS(*plan*)
            Promotion: Add $S_j \prec S_{threat}$ to ORDERINGS(*plan*)
        if not CONSISTENT(*plan*) then fail
    end for each
end procedure

Clobbering

- A *clobberer* is a potentially intervening step that destroys the condition achieved by a causal link. E.g., $Go(Home)$ clobbers $At(Supermarket)$:



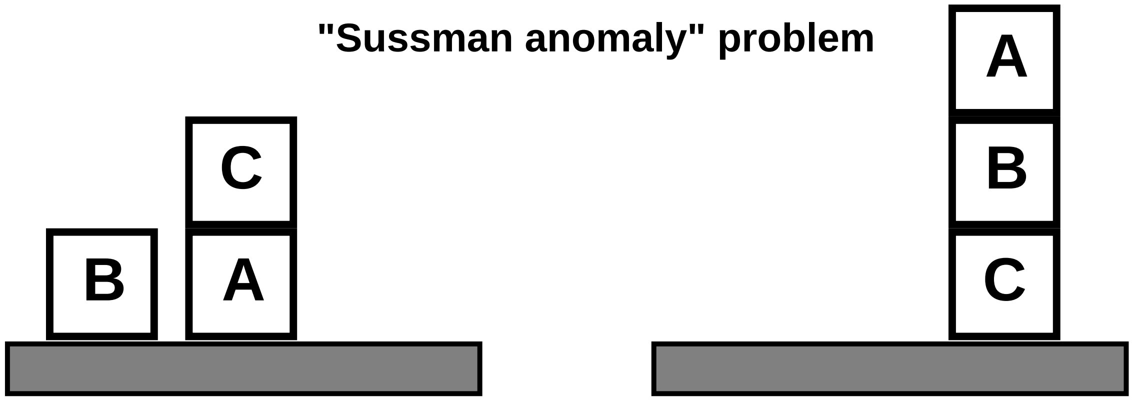
Demotion: put before $Go(Supermarket)$

Promotion: put after $Buy(Milk)$

Properties of POP

- Nondeterministic algorithm: backtracks at *choice* points on failure:
  - choice of S_{add} to achieve S_{need}
  - choice of demotion or promotion for clobberer
  - selection of S_{need} is irrevocable
- POP is sound, complete, and *systematic* (no repetition)
- Extensions for disjunction, universals, negation, conditionals
- Can be made efficient with good heuristics derived from problem description
- Particularly good for problems with many loosely related subgoals

Example



Start State

Goal State

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)

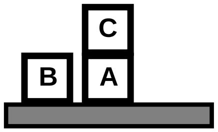
~On(x,z) Clear(z) On(x,Table)

+ several inequality constraints

Example (2)

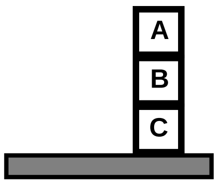
START

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

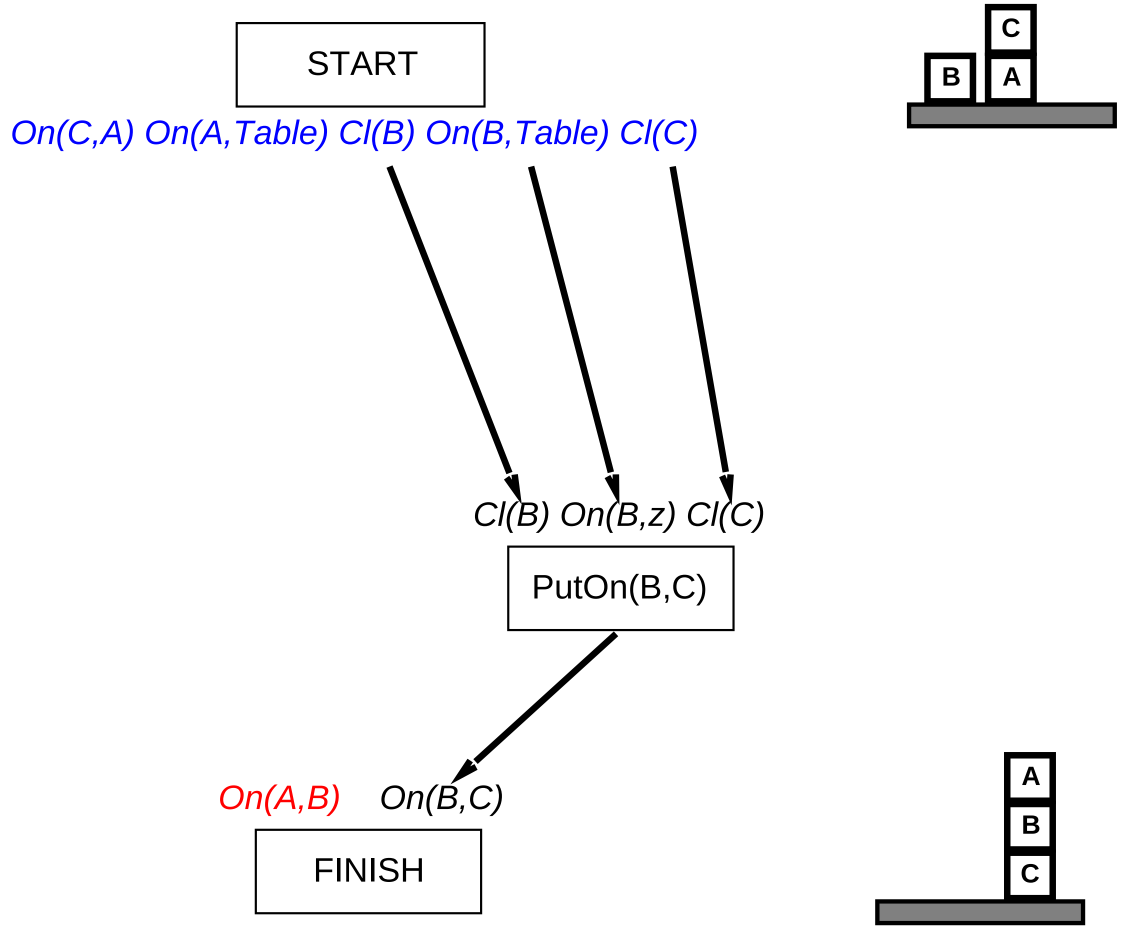


On(A,B) On(B,C)

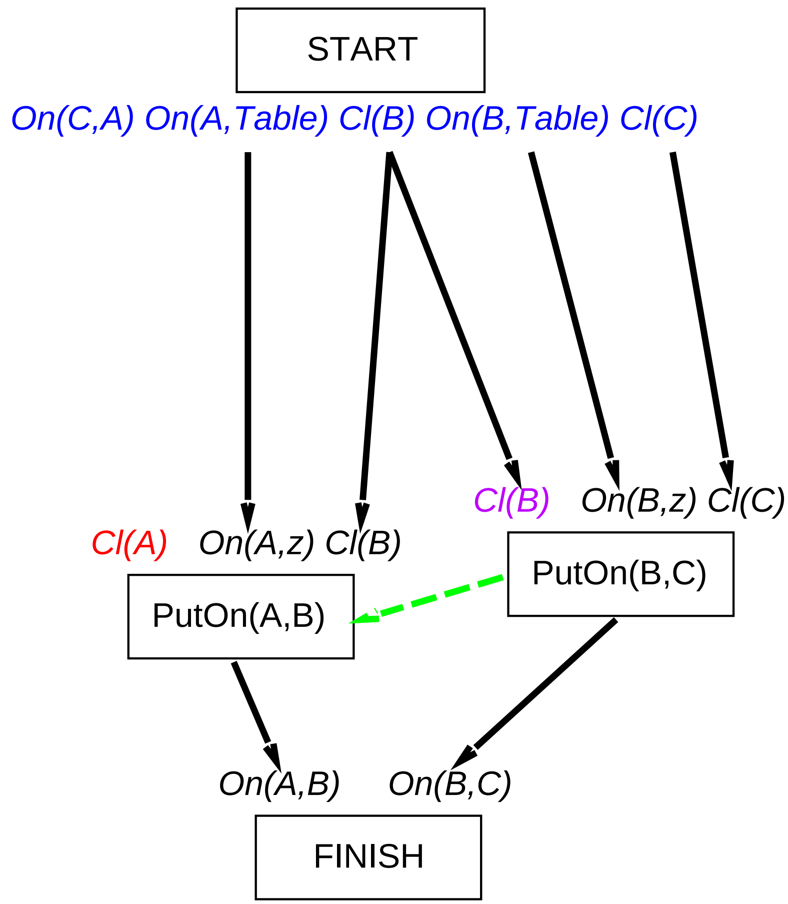
FINISH

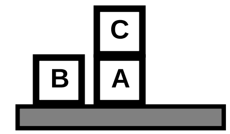


Example (3)

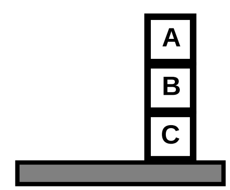

START
On(C,A) On(A,Table) Cl(B) On(B,Table) Cl(C)
Cl(B) On(B,z) Cl(C)
PutOn(B,C)
On(A,B) On(B,C)
FINISH
C
B A
A
B
C

Example (4)

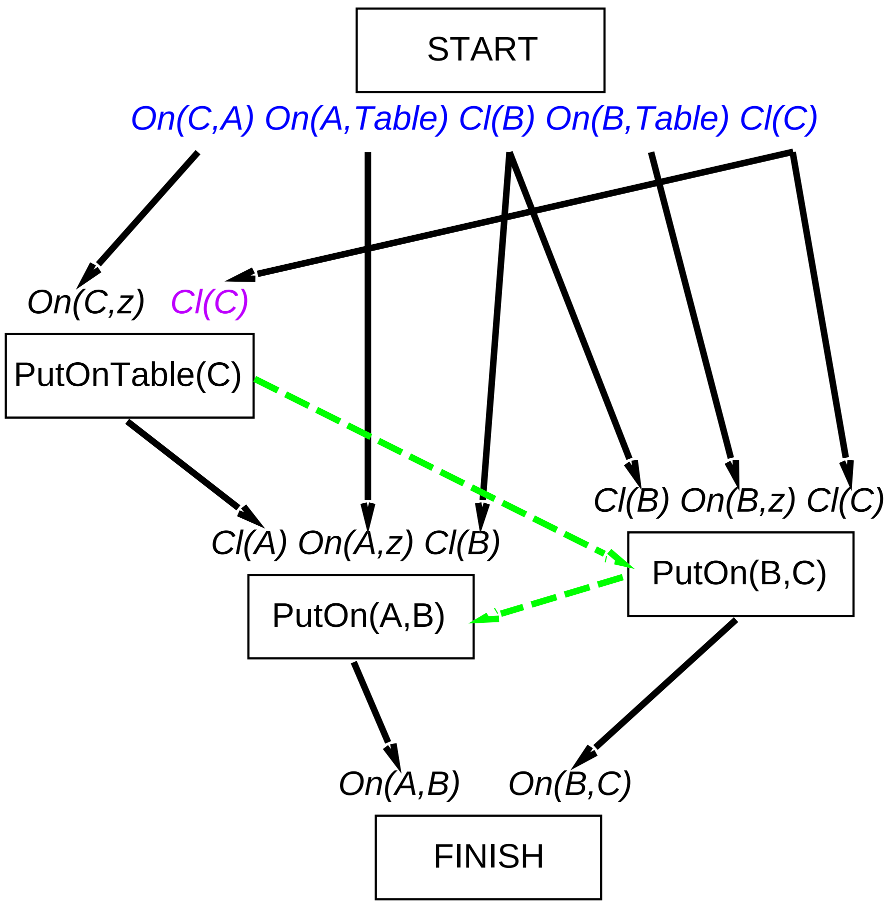


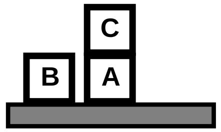


PutOn(A,B)
clobbers Cl(B)
=> order after
PutOn(B,C)



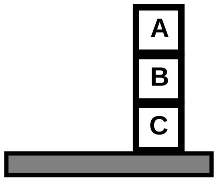
Example (5)





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

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



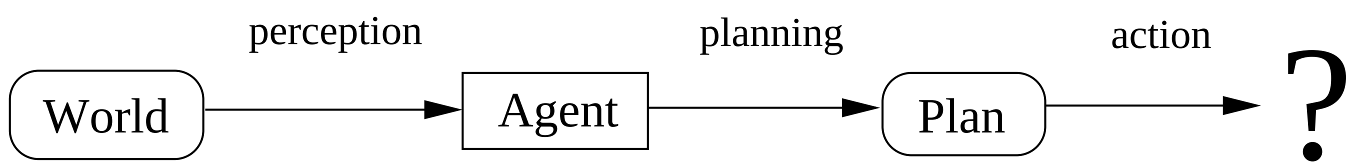
Decision-theoretic planning

- Closed loop planning
- The central question in designing an agent is building it so that it can figure out what to do next.
- That is finding a set of actions which will lead to a goal.
- Previously we studied a traditional approach to planning from AI.
- This was the use of means-ends analysis along with the STRIPS representation.

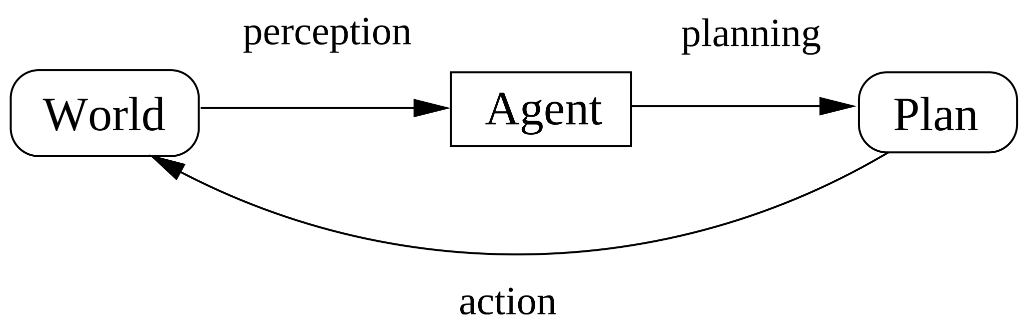
- STRIPS:
  - add condition;
  - delete condition; and
  - precondition.
- Algorithms use:
  - Use precondition to decompose goals;
  - Use add condition to select actions; and
  - Use delete condition to constrain order on actions.

- The main limitations of this approach are:
  - Efficiency (doesn't scale)
  - Robustness
- The second of these is what interests us here.
- The problem is:
  - Plan is linear
  - Planning is separated from acting
  - Actions are non-deterministic
- Though partial-order planning is an improvement on simple means-ends analysis, it still can't cope with non-determinism.

- One way of thinking about this is in terms of *closed loop* planning.
- Classical planning has:



- While close loop planning has actions which are dependent on what is observed in the world:



- Clearly this is the kind of planning that better fits agents.

- Conditional planning is one approach to closed-loop planning.
- Conditional plans are allowed to have branches and loops where control choices depend upon observations.
- For example:
  1. pick up block A
  2. while block A not held
     pick up block A.
  3. if block C clear
     put block A on block C.
  4. else clear block C.
- However, the situation gets more complex with unreliable sensors.

- To deal with unreliable sensors we need to bring in decision theory.
- (Just as we did to take account of dice rolls in game playing).
- A problem with using classical decision theory in the context of intelligent agents is that it is a one-shot process.
- The process only takes into account the current state and the one the decision will lead to.
- This is fine if the next state is the goal state.
- In contrast, what we are often interested in is determining a sequence of actions which take us through a series of states, especially when the choice of actions varies from state to state.

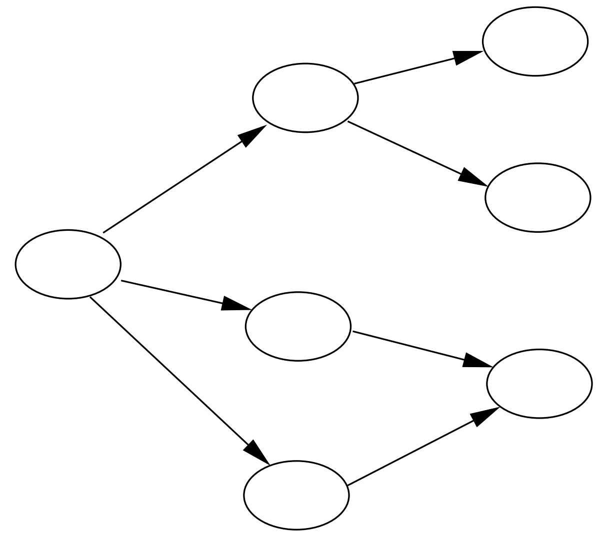
- We do this through the use of *decision theoretic planning* models.
- We will cover two closely related types of these models here:
  - Markov decision processes.
  - Partially observable Markov decision processes.
- Both are close in many ways to the kind of search models we studied earlier.
- The big change is that actions can have more than one outcome.
- So we start by considering planning as search.

Planning as search

- The earliest search models we looked at are a form of planning.
- In the sheep and dogs example, a solution was:
  - A sequence of actions;
  - Which led to a goal
- This is just a plan.
- Adding in a heuristic function gives us an idea of optimality:
- An optimal plan is:
  - A sequence of actions;
  - Which leads to a goal;
  - With minimum cost.

- We can describe a state space search model as:
  - a state space S;
  - an initial state s_0;
  - a set of actions, $A(s) \subseteq A$, applicable in each state $s \in S$;
  - transition function $f(s, a)$ for $s \in S$ and $a \in A$;
  - action costs $c(a, s) > 0$; and
  - a set of goal states $G \subseteq S$

- This gives us a problem space that looks like:



- A solution is a path through this space from initial state to a goal state.

- There are lots of ways of searching this space.
- One simple way is greedy search:
  1. Evaluate each action a which can be performed in the current state:

     $$Q(a, s) = c(a, s) + h(s_a)$$

     where s_a is the next state.
  2. Apply action a that minimises $Q(a, s)$;
  3. If s_a is the goal, exit
     else $s := s_a$, goto 1.
- This just picks the cheapest move at each point.

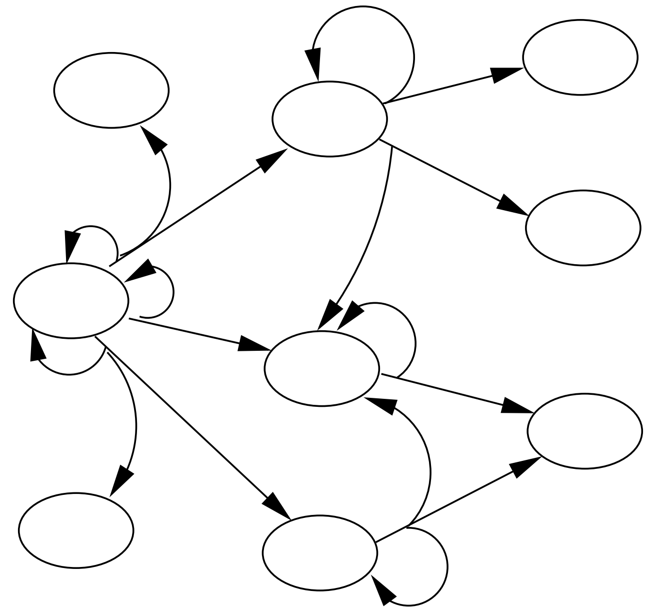
- This is a simple approach that uses little (and constant) memory.
- It can be easily adapted to give a closed-loop version:
  - Instead of s_a being the state we expect to get, make it the one we observe.
- Like any depth first approach, it isn't optimal.
- It might not even find solutions.
- (But we know how to use learning to ensure that it gets better over time).

Markov decision processes

- So far, there is nothing really new here.
- But it is only a small step to a much better representation.
- In a non-deterministic environment, we don't have a simple transition function.
- Instead an action can lead to one of a number of states.
- When we can tell which state we are in, then we have a Markov decision process (MDP)

- An MDP has the following formal model:
  - a state space S;
  - a set of actions, $A(s) \subseteq A$, applicable in each state $s \in S$;
  - transition probabilities $\mathrm{Pr}_a(s' \mid s)$ for $s, s' \in S$ and $a \in A$;
  - action costs $c(a, s) > 0$; and
  - a set of goal states $G \subseteq S$
- Thus for each state we have a set of actions we can apply, and these take us to other states with some probability.
- We don't know which state we will end up in, but we know which one we are in after the action (we have *full observability*).

- This gives us a problem space that looks like:



- A solution is now choice of action in every possible state that the agent might end up in.

- We can think of this solution as a function π which maps states into applicable actions, $\pi(s_i) = a_i$.
- This function is called a *policy*.
- What a policy allows us to compute is a probability distribution across all the trajectories from a given initial state.
- This is the product of all the transition probabilities, $\Pr_{a_i}(s_{i+1} \mid s_i)$, along the trajectory.
- Goal states are taken to have no cost, no effects, so that if $s \in G$:
  - $c(a, s) = 0$
  - $\Pr(s \mid s) = 1$

- We can then calculate the expected cost of a policy starting in state s_0.
- This is just the probability of the policy multiplied by the cost of traversing it:

$$\sum_{i=0}^{\infty} c(\pi(s_i), s_i)$$

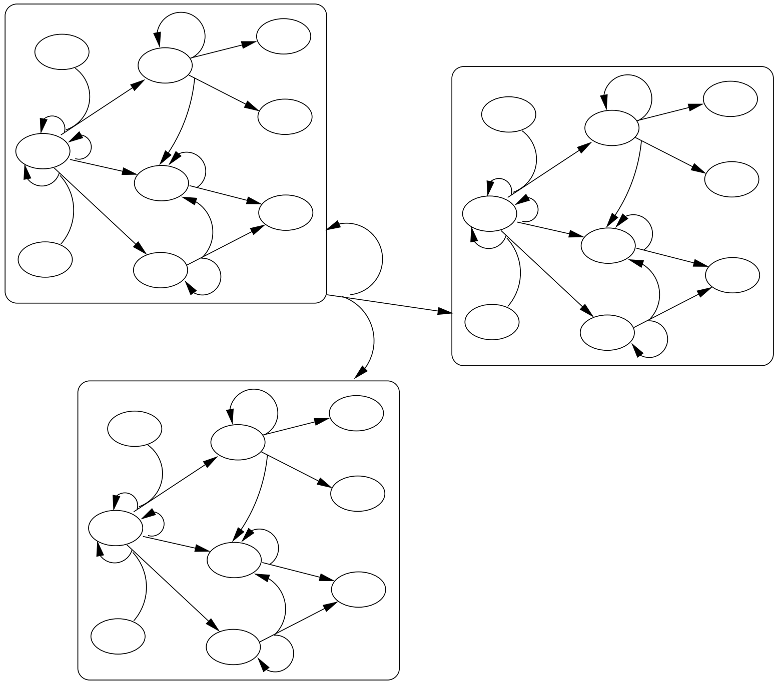
- An optimal policy is then a π^* that has minimum expected cost for all states s.
- As with the search version of the problem, we can solve this by searching, albeit through a much larger space.
- Later we will look at ways to do this search.

Partially observable MDPs

- Full observability is a big assumption (it requires an accessible environment). Much more likely is *partial observability*.
- This means that we don't know what state we are in, but instead we have some set of beliefs about which state we are in.
- We represent these beliefs by a probability distribution over the set of possible states.
- These probabilities are obtained by making observations.
- The effect of observations are modelled as probabilities $\Pr_a(o \mid s)$, where o are observations.

- Formally a POMDP is:
  - a state space S;
  - a set of actions, $A(s) \subseteq A$, applicable in each state $s \in S$;
  - transition probabilities $\Pr_a(s' \mid s)$ for $s, s' \in S$ and $a \in A$;
  - action costs $c(a, s) > 0$;
  - a set of goal states, G;
  - an initial belief state b_0;
  - a set of final belief states b_F;
  - observations o after action a with probabilities $\Pr_a(o \mid s)$

- So we have a situation which looks like:



- This is just an MDP over belief states.

- The goal states of an MDP are just replaced by, for example, states in which we are pretty sure we have reached a goal:

$$\sum_{s \in G} b(s) > 1 - \epsilon$$

- We solve a POMDP by looking for a function which maps belief states into actions, where belief states b are probability distributions over the set of states S.
- Given a belief state b, the effect of carrying out action a is:

$$b_a(s) = \sum_{s' \in S} \Pr_a(s \mid s') b(s')$$

- If we carry out a in b and then observe o, we get to state b_a^o:

$$b_a^o(s) = \frac{\Pr_a(o \mid s) b_a(s)}{\sum_{s' \in S} \Pr_a(o \mid s') b_a(s')}$$

- The term on the bottom is the probability of observing o after doing a in b.
- Thus actions map between belief states with probability:

$$b_a(o) = \sum_{s' \in S} \Pr_a(o \mid s') b_a(s')$$

  and we want to find a trajectory from b_0 to b_F at minimum cost.

Summary

- This lecture has looked at two more advanced approaches to planning:
  - partial order planning
  - decision theoretic planning
- partial order planning requires a new way of looking at the world, but the payoff is a more robust approach.
- we also looked at the POP algorithm, . . .
- . . . and saw how it could solve the Sussman anomaly.
- Starting from the notion of planning as search, we introduced the Markov decision process (MDP) representation.
- A solution to an MDP is a *policy*, a choice of what action to take in *every* state.