

Lecture 13

Planning as CSP

Lecture Overview

• Recap of Lecture 12

- Planning as CSP
 - Details on CSP representation -
Solving the CSP planning problem
- Intro to Logic (time permitting)

Course Overview

Problem Type

Arc

Environment

Stochastic

Representation

Reasoning Technique

Deterministic

Consistency

Constraint Satisfaction

Vars + Constraints

Search

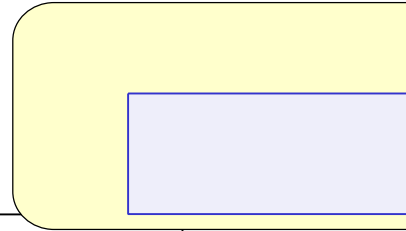
Static *Belief Nets*

Query

Logics

Search

Variable



Elimination

Sequential

STRIPS

Decision Nets Variable

Planning

Search

Elimination

We'll focus
on Planning

Markov Processes Value

Iteration

Planning Problem

- Goal
- Description of states of the world

- Description of available actions => when each action can be applied and what its effects are
- **Planning**: build a sequence of actions that, if executed, takes the agent from the current state to a state that achieves the goal

Standard Search vs. Specific R&R systems

- Constraint Satisfaction (Problems):
- **State**: assignments of values to a subset of the variables
- **Successor function**: assign values to a “free” variable
- **Goal test**: all variables assigned a value and all constraints satisfied?
- **Solution**: possible world that satisfies the constraints

- Heuristic function: none (all solutions at the same distance from start)

- Planning:

- State
- Successor function
- Goal test
- Solution
- Heuristic function

- Inference
- State
- Successor function
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Key Idea of Planning

- **Open-up** the representation of states, goals and actions
 - **Both** states and goals as set of **features**
 - Actions as **preconditions** and **effects** defined on state features

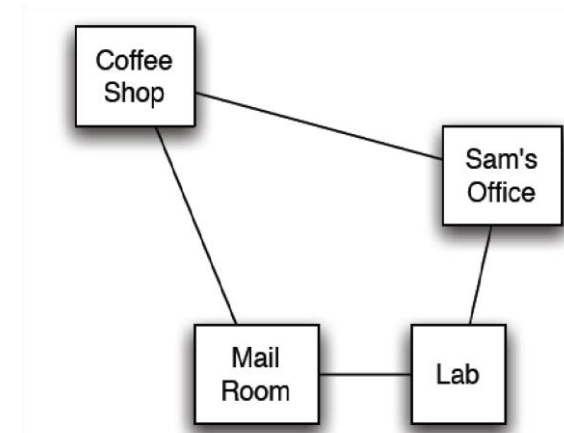


- agent can reason more deliberately about which actions to consider to achieve its goals.

Delivery Robot Example: features

- **RLoc** - Rob's location
- Domain: {coffee shop, Sam's office, mail room, lab} **short** {cs, off, mr, lab}
- **RHC** - Rob has coffee
- Domain: {true, false}. Alternatively notation for **RHC** = T/F:
rhc indicates that Rob has coffee, and \overline{rhc} that Rob doesn't have coffee
- **SWC** - Sam wants coffee {true, false}
- **MW** - Mail is waiting {true, false}
- **RHM** - Rob has mail {true, false}
- An example state is

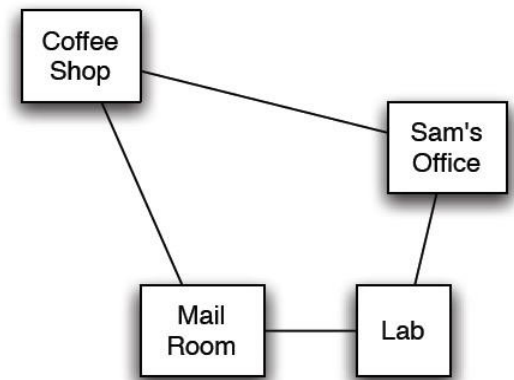
$\langle lab, \overline{rhc}, swc, \overline{mw}, rhm \rangle$



Rob is in the lab, it does not have coffee, Sam wants coffee, there is no mail waiting and Rob has mail

Delivery Robot Example:

Actions



The robot's **actions** are:

puc - Rob picks up coffee

- must be **at the coffee shop** and **not have coffee** **Preconditions for action application**

delC - Rob delivers coffee

- must be **at the office**, and must **have coffee** *pum* - Rob picks up

mail

- must be in the **mail room**, and **mail must be waiting** *delM* - Rob

delivers mail

- must be **at the office** and **have mail** *move* - Rob's move

actions – there are 8 of them

- move clockwise (*mc-x*), move anti-clockwise (*mac-x*) from location x (where x can be any of the 4 rooms)
- must be in **location x**

Modeling actions for planning

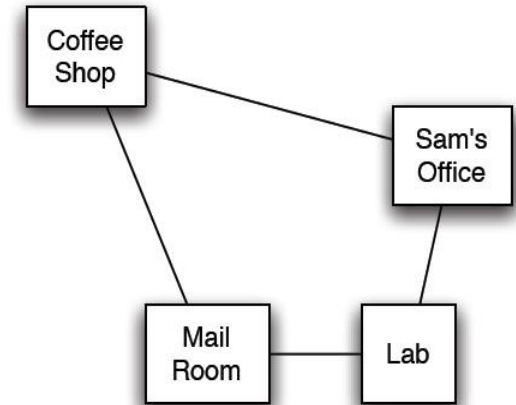
- The key to sophisticated planning is **modeling actions**
- Leverage a feature-based representation:
- Model when **actions are possible**, in terms of the values of the features in the current state

- Model **state transitions** caused by actions in terms of changes in specific features

STRIPS actions: Example

STRIPS representation of the action **pick up coffee**, puc:

- preconditionsLoc= cs and RHC= F
- effectsRHC= T **cs = coffee shop**



off = Sam's office
mr = mail rom

STRIPS representation of the action **deliver coffee**,
Del :

- preconditions Loc= off and RHC= T
- effects RHC = T and SWC = F

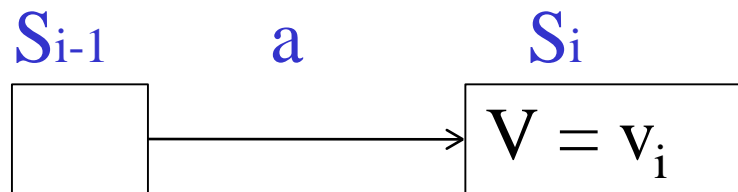
Note in this domain Sam doesn't have to want coffee for Rob to deliver it; one way or another, Sam doesn't want coffee after delivery.

STRIPS Actions (cont')

The STRIPS assumption:

all features not explicitly changed by an action stay unchanged

- So if the feature V has value v_i in state S_i , after action a has been performed,
- what can we conclude about a and/or the state of the world S_{i-1} immediately preceding the execution of a ?



C. At least one of A and B

Solving planning problems

- STRIPS lends itself to solve planning problems either
 - As pure search problems
 - As CSP problems
- We will look at one technique for each approach

Forward planning

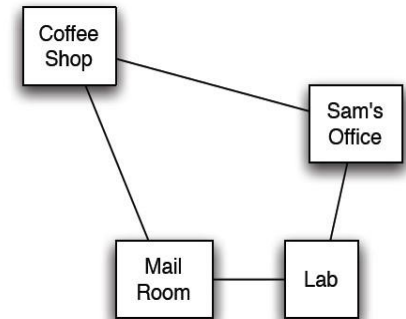
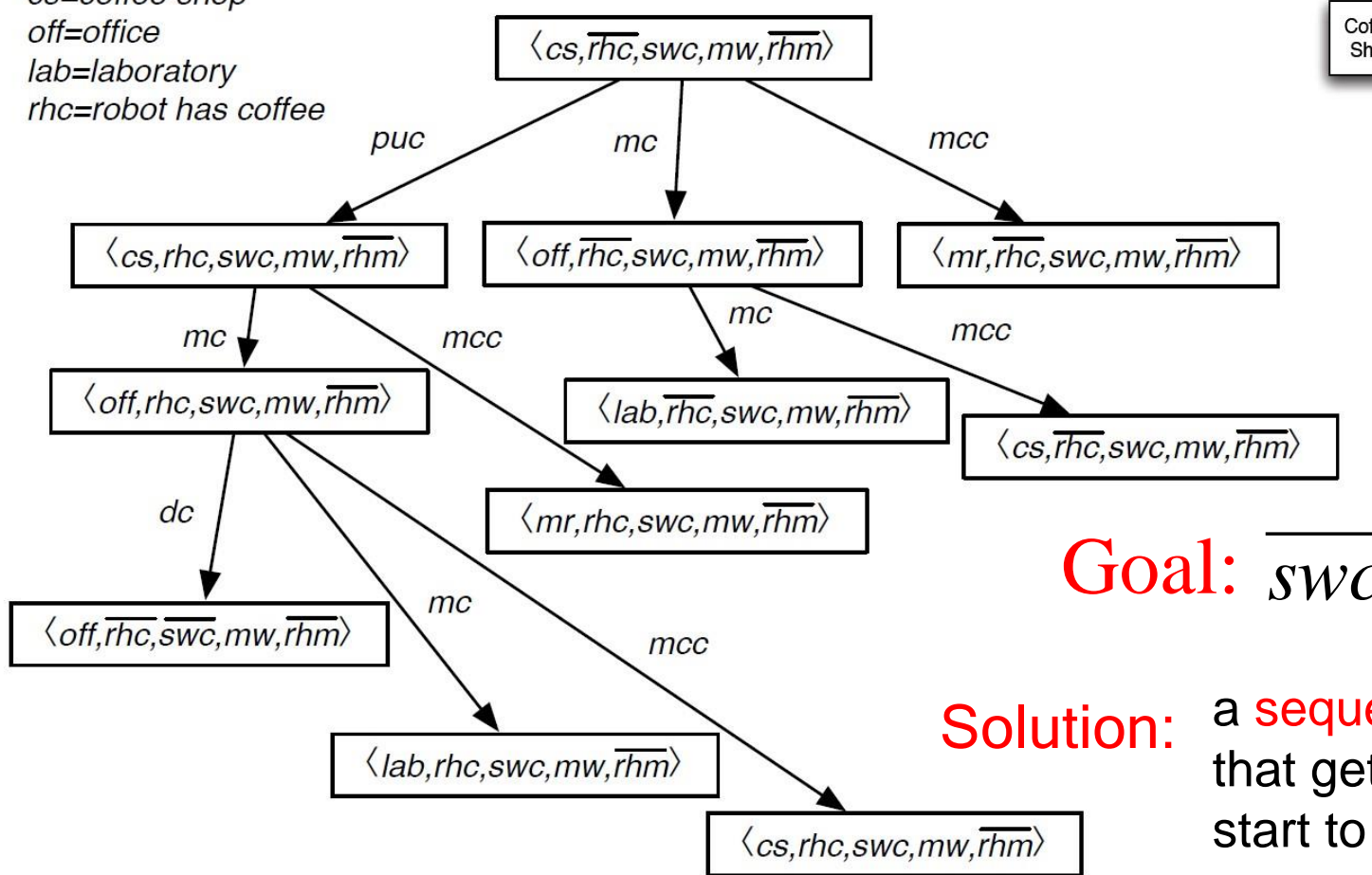
- To find a plan, a solution : search in the state-space graph
- The **states** are the **possible worlds**
 - ✓ full assignments of values to features
- The **arcs** from a state s represent all the **actions** that are **possible** in state s
- A **plan** is a path from the state representing the initial state to a state that satisfies the goal

Which actions **a** are possible in a state **s**?

B. Those where **a**'s preconditions are satisfied in **s**

Example for state space graph

cs=coffee shop
off=office
lab=laboratory
rhc=robot has coffee



Goal: \overline{swc}

Solution: a sequence of actions that gets us from the start to a goal

What is a solution to this planning problem?

D (puc, mc, dc)

Standard Search vs. Specific R&R systems

Constraint Satisfaction (Problems):

- **State:** assignments of values to a subset of the variables
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- **Solution:** possible world that satisfies the constraints
- **Heuristic function:** *none (all solutions at the same distance from start)*

Planning :

- **State:** full assignment of values to features
- **Successor function:** states reachable by applying actions with preconditions satisfied in the current state
- **Goal test:** partial assignment of values to features
- **Solution:** a sequence of actions
- **Heuristic function**

Inference

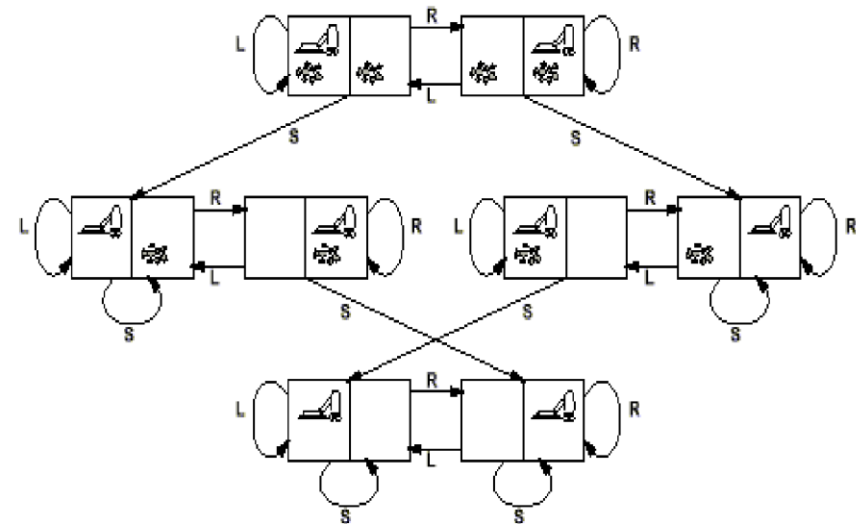
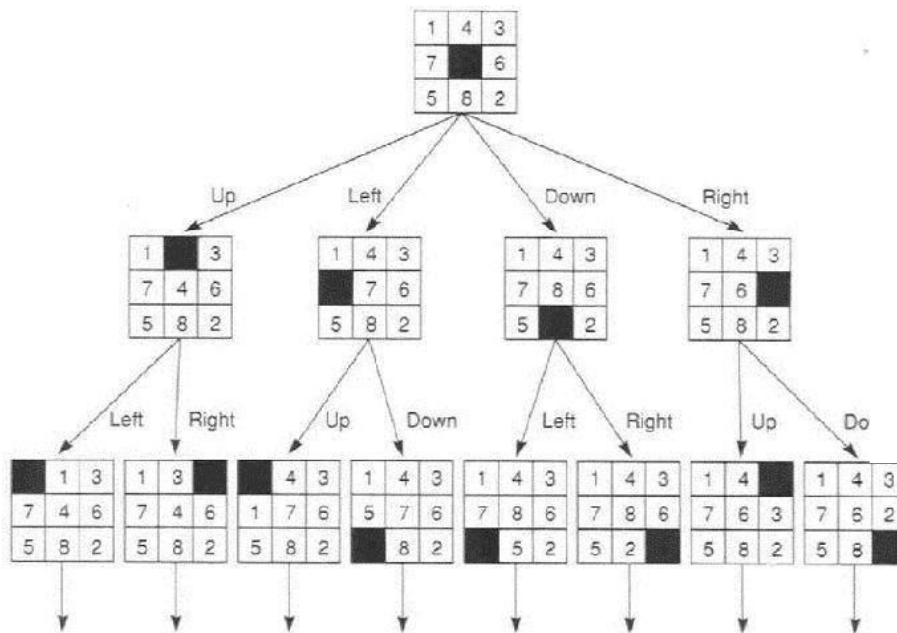
- **State**

- Successor function
- Goal test
- Solution
- Heuristic function

For generic search algorithms



For generic search algorithms



- **Actions** - left, right, suck
 - Successor states in the graph describe the effect of each action applied to a given state

Actions: blank moves left, right, up down

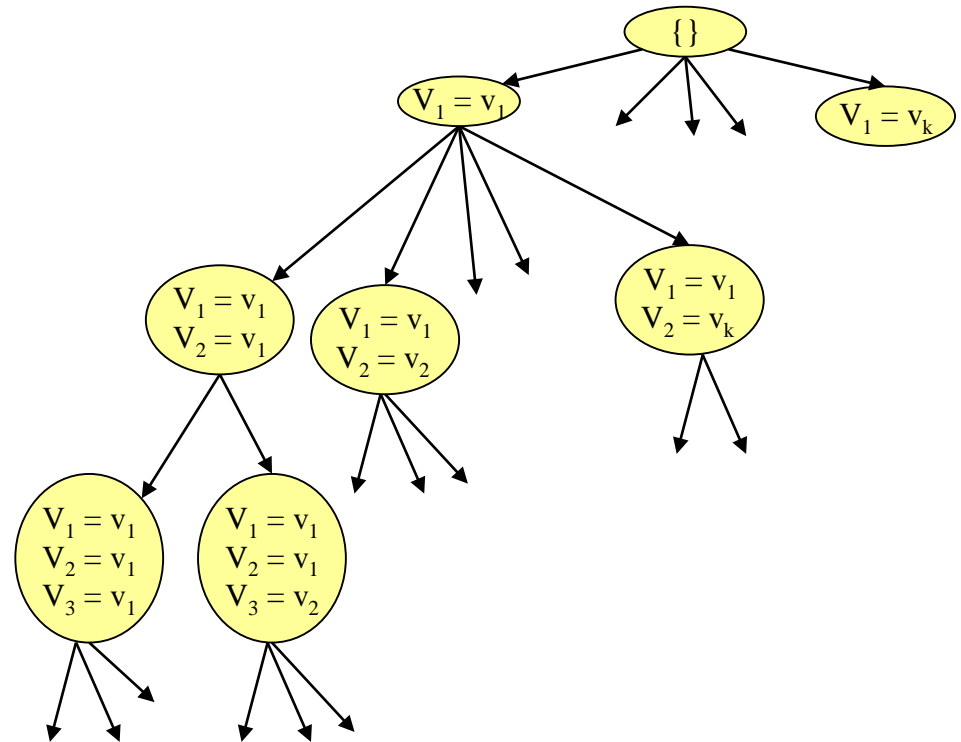
- **Possible Goal** - no dirt **Goal:** configuration with numbers in right sequence

Search Spaces Seen so Far

For solving CSP problems with Search

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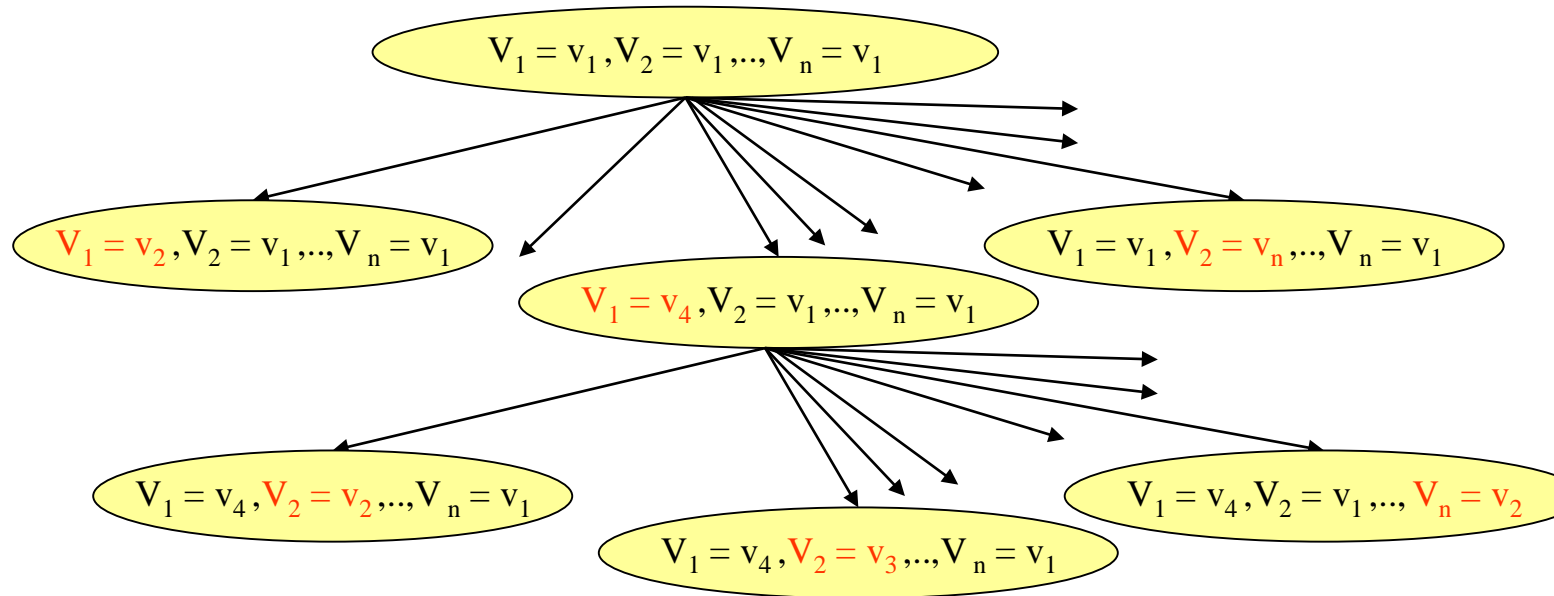


Search Spaces Seen so Far

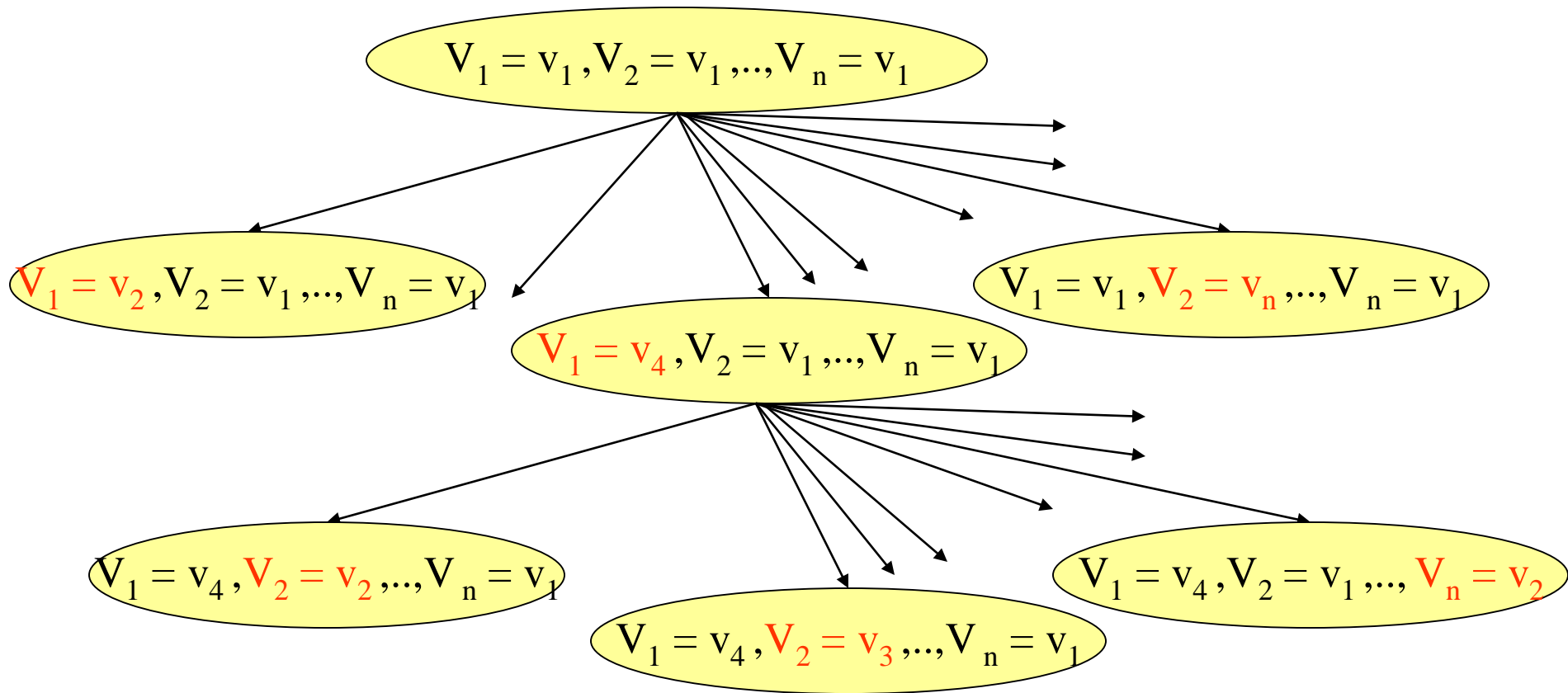
For solving CSP problems with Stochastic Local Search

- Given the set of variables $\{V_1, \dots, V_n\}$, each with domain $\text{Dom}(V_i)$
- States are full assignments of values to variables

- The start node is any assignment $\{V_1 / v_1, \dots, V_n / v_n\}$.
- The **neighbors** of node with assignment
 $A = \{V_1 / v_1, \dots, V_n / v_n\}$ are nodes with assignments that **differ from A for one value only**



Search Space



- Only the current node is kept in memory at each step.
- Very **different from** the **systematic tree search** approaches we have seen so far!

- Local search does **NOT** backtrack!

Anything else

Another formulation of CSP as search

Arc consistency with domain splitting

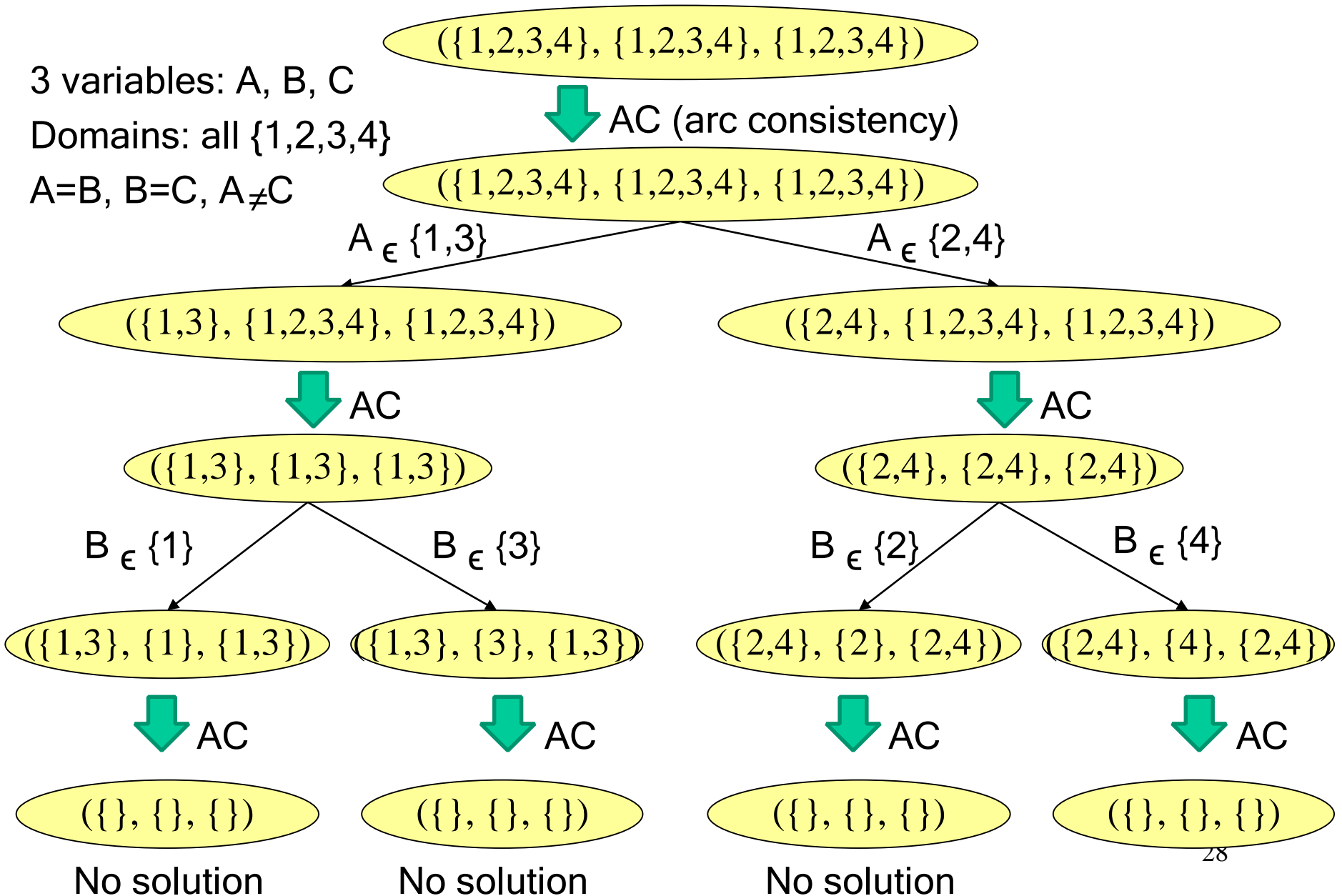
- States: **vector $(D(V_1), \dots, D(V_n))$ of remaining domains**, with $D(V_i) \subseteq \text{dom}(V_i)$ for each V_i
- Start state: vector of original domains $(\text{dom}(V_1), \dots, \text{dom}(V_n))$
- Successor function:
- **reduce one of the domains + run arc consistency**
- Goal state: vector of unary domains that satisfies all constraints
- That is, only one value left for each variable
- The assignment of each variable to its single value is a **model**
- Solution: that assignment

Arc consistency + domain splitting: example

3 variables: A, B, C

Domains: all $\{1,2,3,4\}$

$A=B$, $B=C$, $A \neq C$



Forward Planning

- Any of the search algorithms we have seen can be used in Forward Planning
- Problem?
- Complexity is defined by the branching factor, e.g....
Number of applicable actions to a state
- Can be very large

- Solution?

Standard Search vs. Specific R&R systems

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Inference

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Heuristics for Forward Planning


Not in textbook, but you can see details in Russel&Norvig,
10.3.2

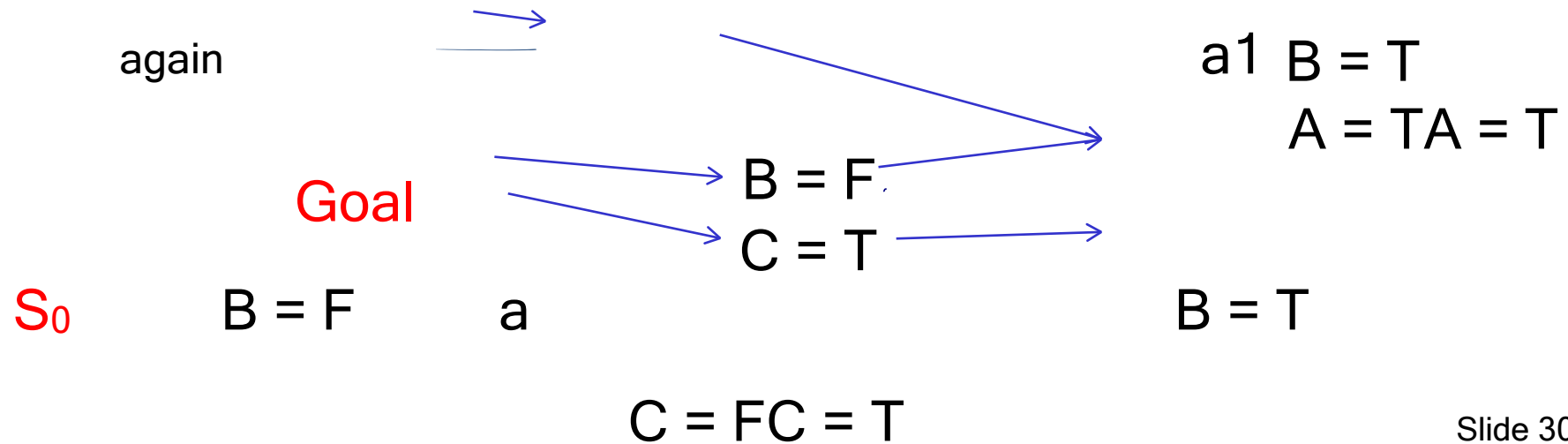
- Heuristic function: estimate of the **distance** from a state to the goal
- In planning this distance

is the.....B. # of actions
needed to get from s to
the goal

- Finding a good heuristics is what makes forward planning feasible in practice
- **Factored representation** of states and actions allows for definition of **domain-independent heuristics**
- We will look at one example of such domain-independent heuristic that has proven to be quite successful in practice

Heuristics for Forward Planning: ignore delete-list

- One strategy to find an admissible heuristics is
- to relax the original problem
- One way : remove all the effects that make a variable = F.
Action aeffects (B=F, C=T) 
- If we find the path from the initial state to the goal using this relaxed version of the actions:
- the length of the solution is an underestimate of the actual solution length
- Why? In the original problem, one action (e.g. aabove) might undo an already achieved goal (e.g. by a1 below). It would have to be achieved



Slide 30

Heuristics for Forward Planning: ignore delete-list

But how do we compute the actual heuristics values for **ignore delete-list**?

- To compute $h(s_i)$, run forward planner with
- s_i as start state

- Same goal as original problem
- Actions without “delete list”
- Often fast enough to be worthwhile
 - ✓ Planning is PSPACE-hard (that’s really hard, includes NP-hard)
 - ✓ Without delete lists: often very fast

Slide 31

Can you think of another way of deriving a domain-independent **admissible** heuristic for planning?

- Let’s stay in the robot domain • But say our robot has to bring coffee to Bob, Sue, and Steve:

- $G = \{\text{bob_has_coffee}, \text{sue_has_coffee}, \text{steve_has_coffee}\}$
- They all sit in different offices

A. Count Number of satisfied sub-goals

B. Count Number of unsatisfied sub-goals

C. Plan by ignoring action preconditions

Slide 32

Can you think of another way of deriving a domain independent **admissible** heuristic for planning?

- Let's stay in the robot domain • But say our robot has to bring coffee to Bob, Sue, and Steve:
- $G = \{\text{bob_has_coffee}, \text{sue_has_coffee}, \text{steve_has_coffee}\}$

D. None of the above

- They all sit in different offices

- BOTH **B. Count Number of unsatisfied sub-goals**

C. Plan by ignoring action preconditions

- ✓ in this domain, and for this goal, because one cannot achieve more than one subgoal with a single action
- ✓ In general, only C; B might be an overestimate of the actual cost when actions can achieve multiple subgoals Slide 33

Example

- Let's stay in the robot domain • But say our robot has to bring coffee to Bob, Sue, and Steve:
- $G = \{\text{bob_has_coffee}, \text{sue_has_coffee}, \text{steve_has_coffee}\}$

- They all sit in different offices
- **Admissible heuristic: ignore preconditions:**
- Can simply apply “Deliver Coffee(person)” action for each person (since there is no need to have coffee to deliver it)

Slide 34

Solving planning problems


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- As CSP problems

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Slide 35

Lecture Overview

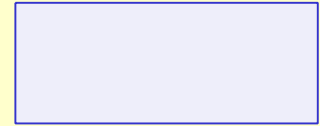
- Recap of Lecture 12
-  Planning as CSP

- Details on CSP representation -
- Solving the CSP planning problem
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Course Overview

Problem Type

Arc Environment Stochastic



Representation Reasoning Technique

Deterministic

Consistency

Constraint Satisfaction *Vars + Constraints* Search

Static *Belief Nets*

Query

Logics

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Variable



Elimination

Sequential

STRIPS

Decision Nets Variable

Planning

Search

Elimination

Markov Processes

Value

Iteration

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Planning as a CSP

- We simply reformulate a STRIPS model as a set of variables and constraints
- Give it a try: please work in groups of two or three for a few minutes and try to define what would you chose as

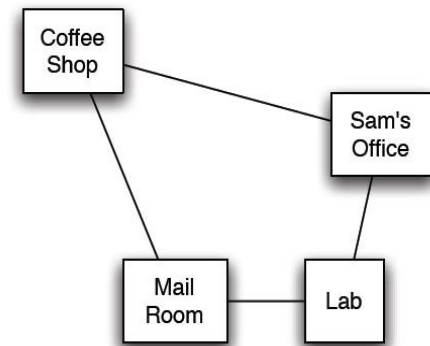
- Variables
- Constraints
- Use the Rob Delivery World as a leading example

Slide 38

What will be the CSP variables and constraints?

- Features change over time
- Might need more than one CSP variable per feature

- Initial state constraints
- Goal state constraints



- STRIPS example actions
- STRIPS representation of the action **pick up coffee**, PUC:
 - ✓ **preconditions** Loc = cs and RHC \overline{rhc}
 - ✓ **effects** RHC = rhc
- STRIPS representation of the action **deliver coffee**, DelC:
 - ✓ **preconditions** Loc = off and RHC = rhc
 - ✓ **effects** RHC = \overline{rhc} and SWC \overline{swc}

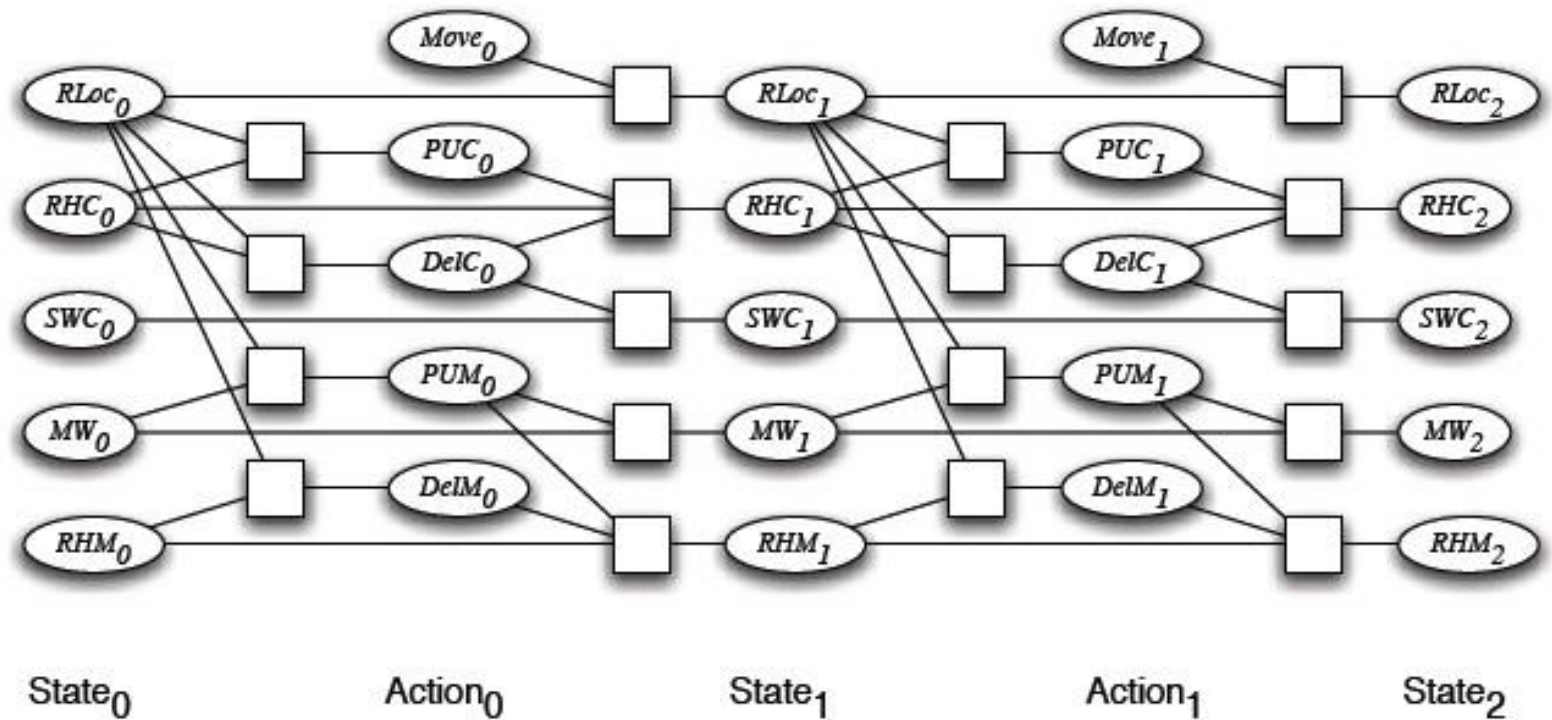
Have to capture these conditions as **constraints**

Planning as a CSP: General Idea

- Action preconditions and effects are virtually **constraints** between
- the action,
- the states in which it can be applied
- the states that it can generate
- Thus, we can make both **states** and **actions** into the **variables** of our CSP formulations
- However, constraints based on action preconditions and effects relate to states at a given time t , the corresponding valid actions and the resulting states at $t + 1$
- need to have as many **state** and **action variables** as there are **planning steps**

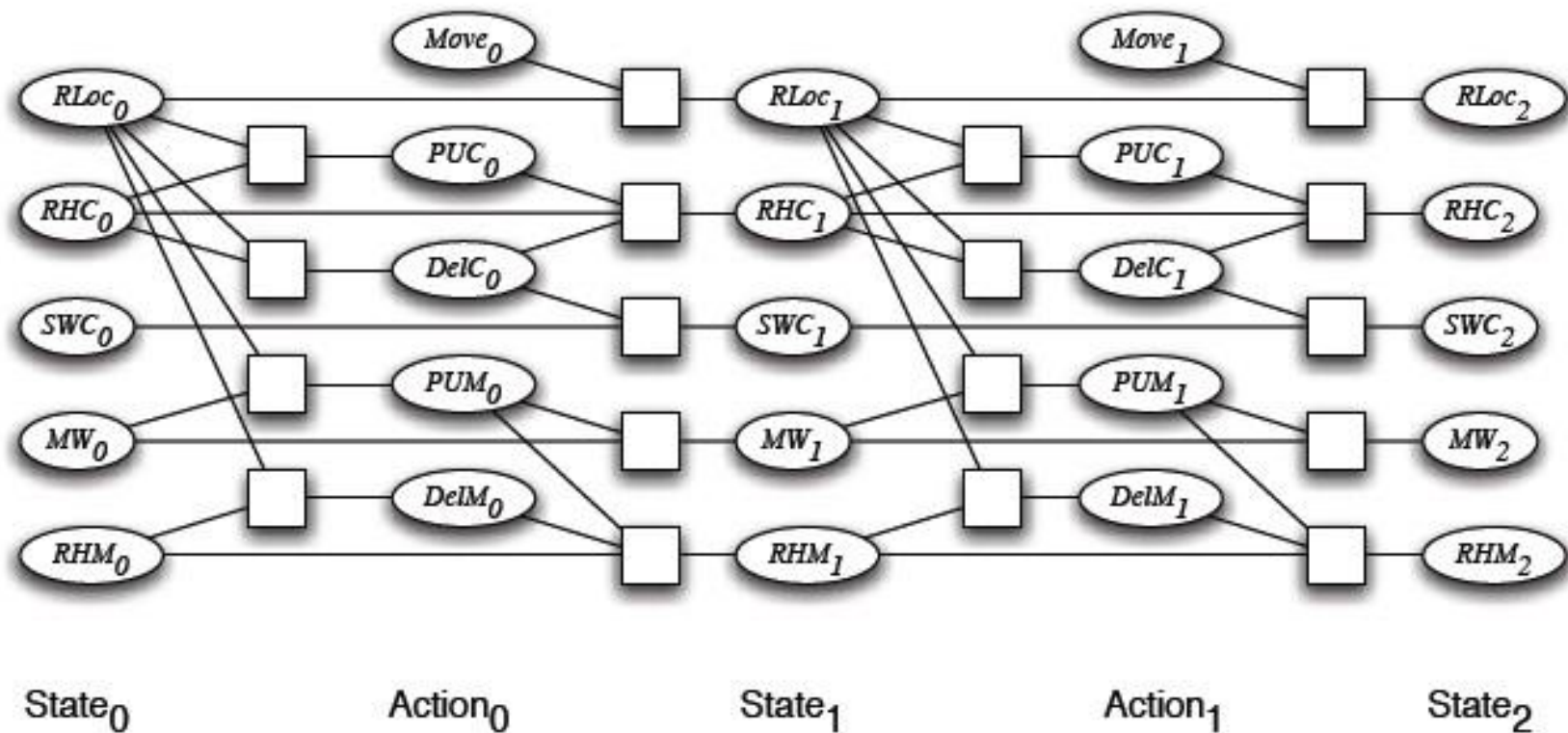
Planning as a CSP: General Idea

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Planning as a CSP: General Idea

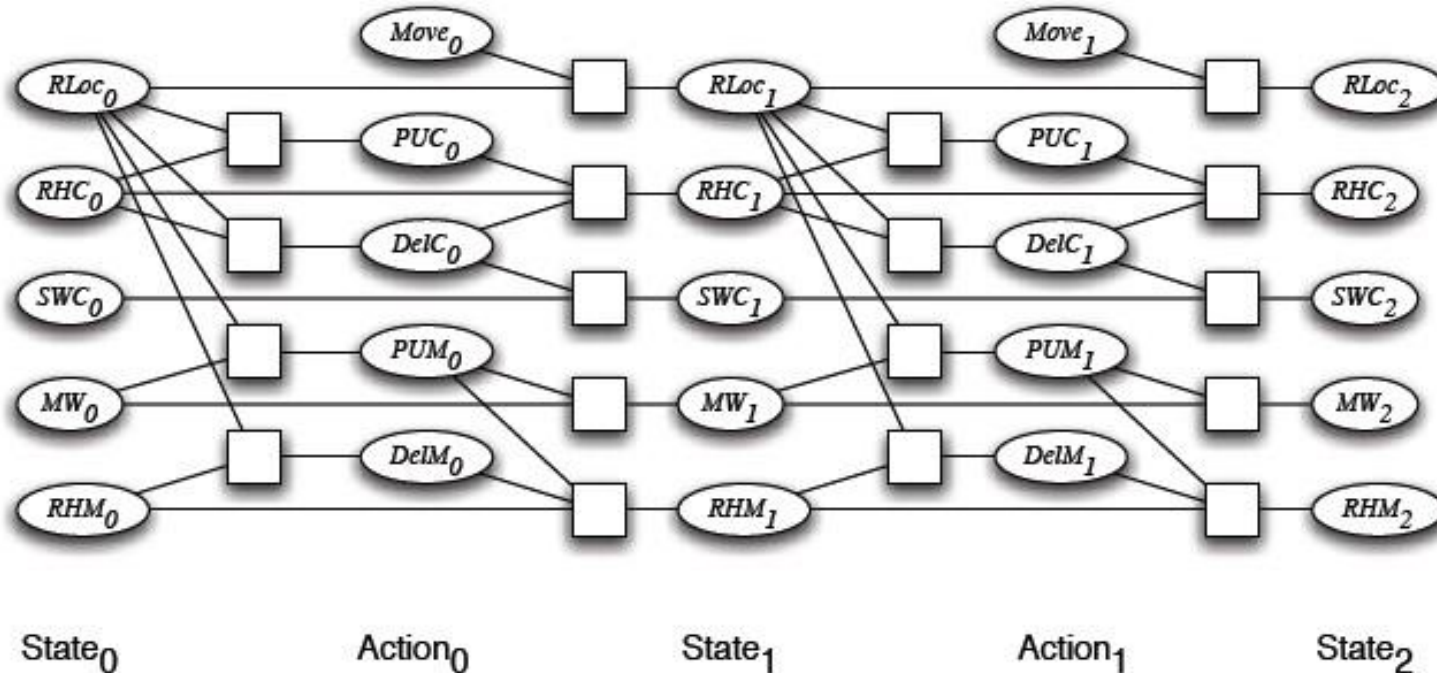
- These action constraints relate to **states at a given time t** , the corresponding valid **actions** and the **resulting states** at $t + 1$
- we need to have as many state and action variables as we have planning steps



Planning as a CSP: Variables

- We need to 'unroll the plan' for a fixed number of steps: this is called the **horizon k**
- To do this with a horizon of k:


- construct a **CSP variable** for each **STRIPS state variable** at each time step from 0 to k
- construct a **Boolean CSP variable** for each **STRIPS action** at each time step from 0 to k - 1.



Lecture Overview

- Recap of Lecture 12

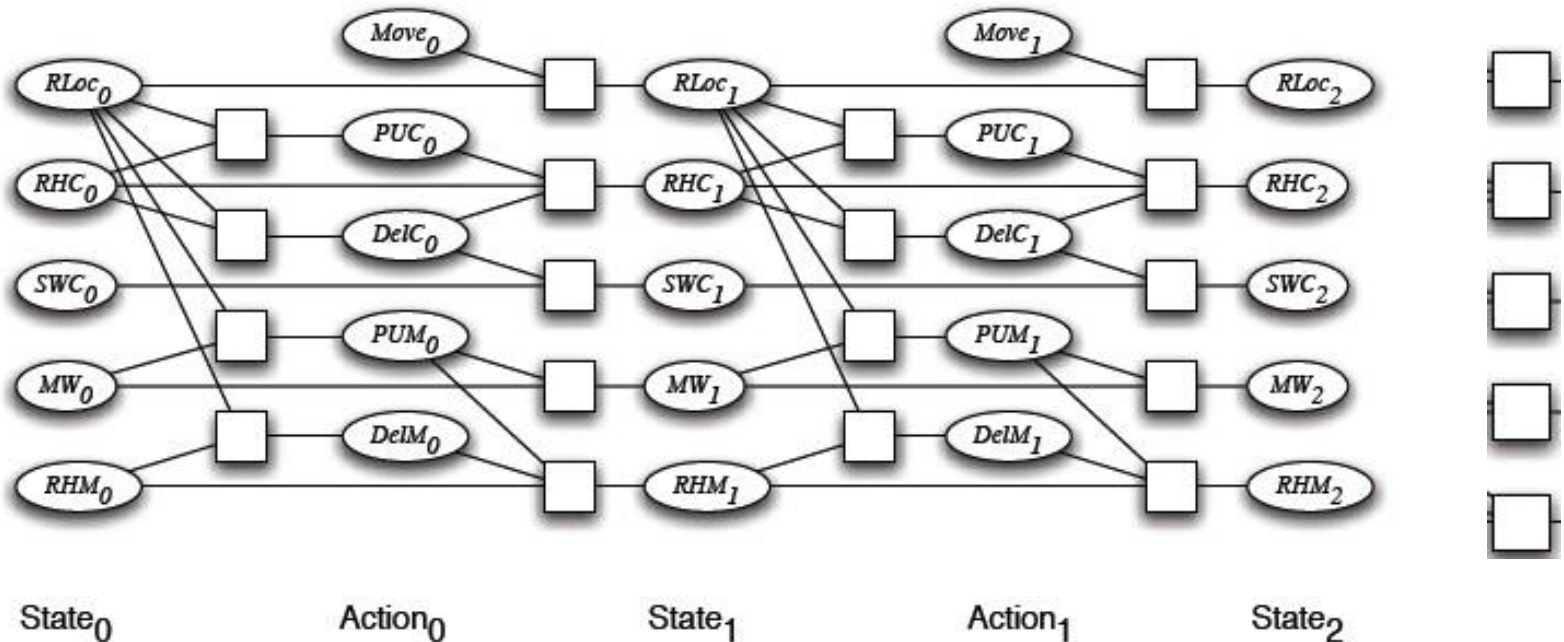
- Planning as CSP

 - Details on CSP representation - Solving the CSP planning problem

- Intro to Logic (time permitting)

Initial State(s) and Goal(s)

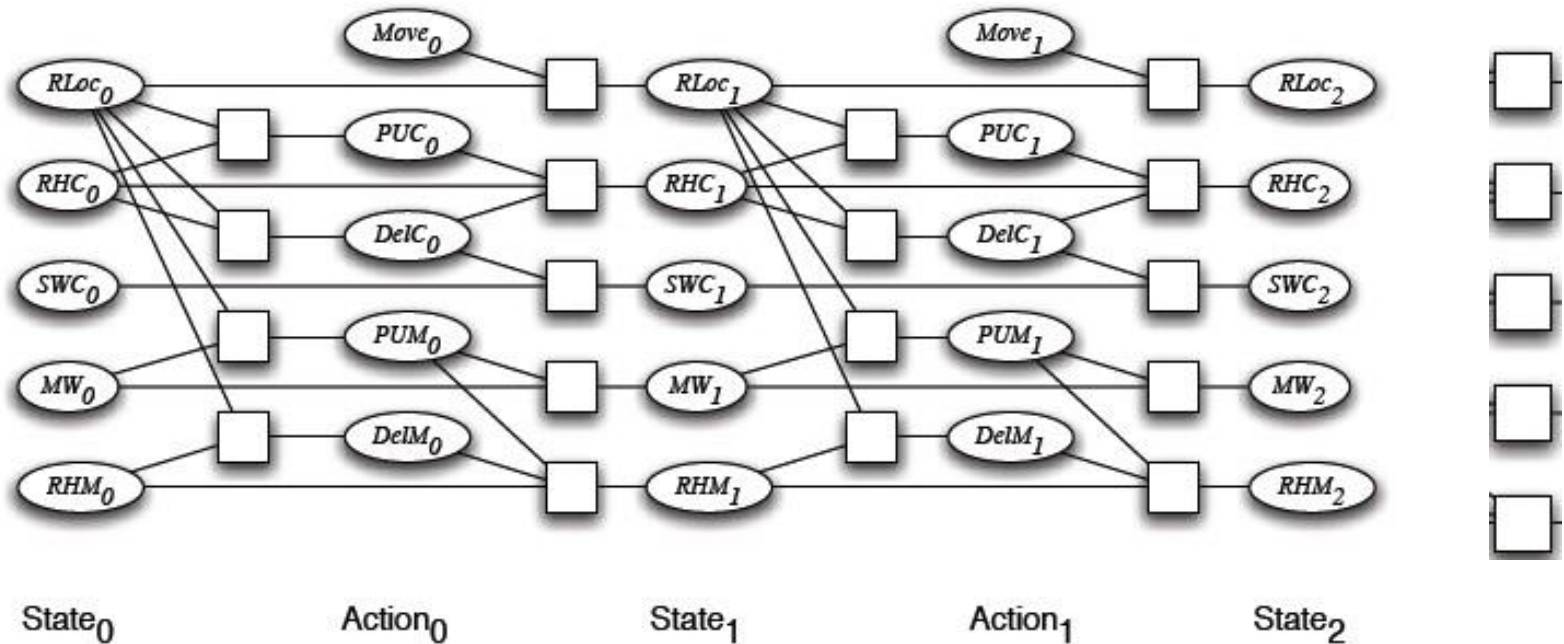
- How can we represent the initial state(s) and the goal(s) with this representation? E.g.,
 - ✓ Initial state with Sam wanting coffee and Rob at the coffee shop, with no coffee
 - ✓ Goal: Sam does not want coffee



Initial State(s) and Goal(s)

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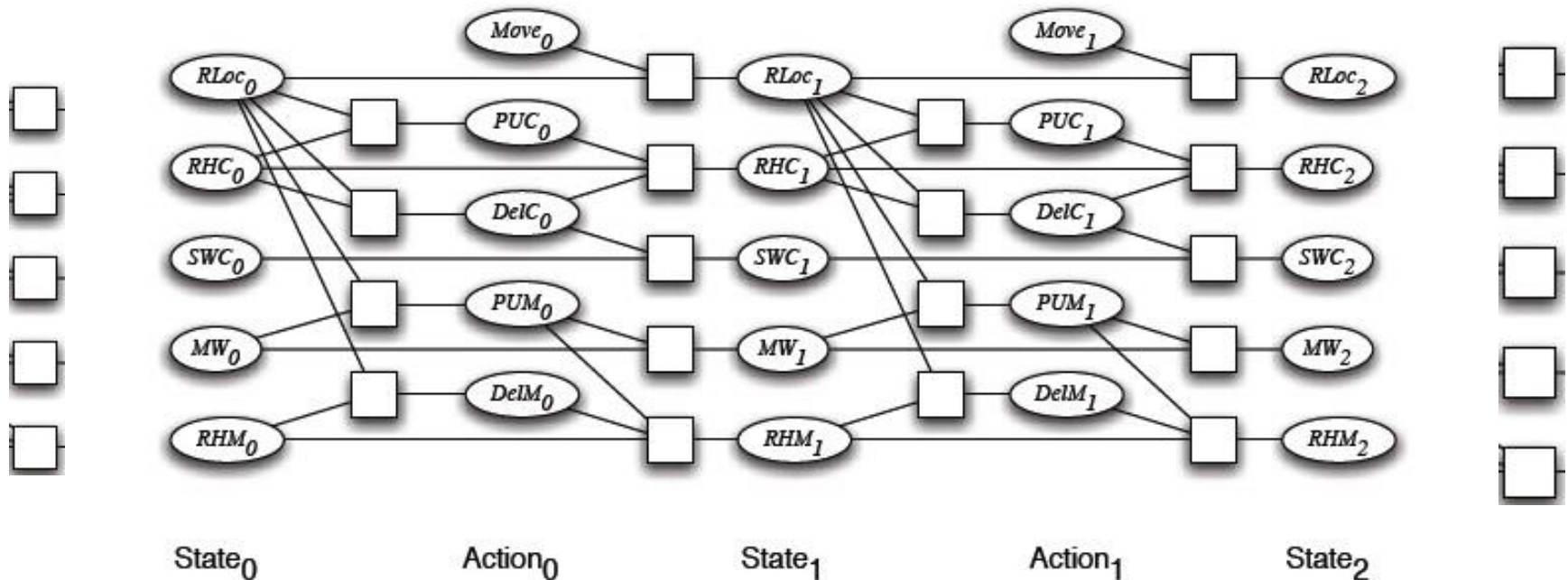
✓ Goal: Sam does not want coffee



Initial and Goal Constraints

- initial state constraints: unary constraints on the values of the state variables at time 0

- goal constraints: unary constraints on the values of the state variables at time k



CSP Planning: Precondition Constraints

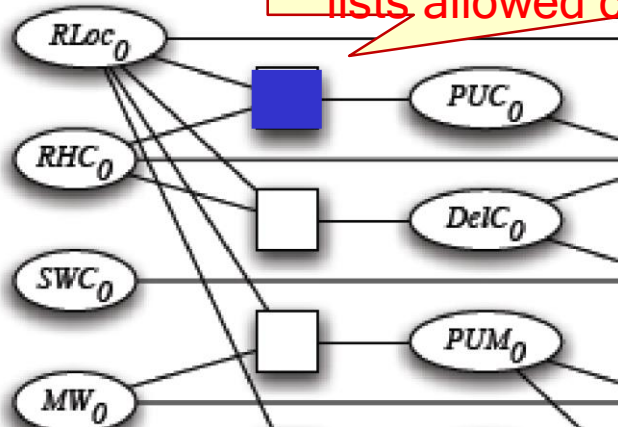
precondition constraints

- between state variables at time t and action variables at time t
- specify when actions may be taken. E.g.,
 - ✓ robot can only pick up coffee when $Loc=cs$ (coffee shop) and

RHC = false (don't have coffee already)

RLoc ₀	RHC ₀	PUC ₀
CS	T	
CS	F	
CS	F	
mr	T/F	
lab	T/F	

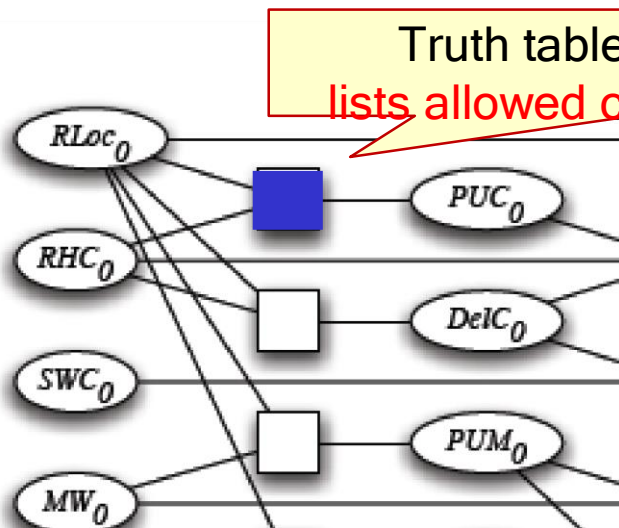
Truth table for this constraint:
lists allowed combinations of values



CSP Planning: Precondition Constraints

precondition constraints

- between state variables at time t and action variables at time t



Truth table for this constraint:
lists allowed combinations of values

$RLoc_0$	RHC_0	PUC_0
CS	T	F
CS	F	T
CS	F	F
mr	*	F
lab	*	F
off	*	F

Need to allow for the option of *not* taking an action even when it is valid

- specify when actions may be taken. E.g.,
 - ✓ robot can only pick up coffee when $Loc=cs$ (coffee shop) and $RHC = false$ (don't have coffee already)

Learning Goals for Planning

- STRIPS
 - Represent a planning problem with the STRIPS representation
 - Explain the STRIPS assumption
 - Forward planning
 - Solve a planning problem by search (forward planning). Specify states, successor function, goal test and solution
- INCLUDED IN THE MIDTERM UP TO HERE
- Construct and justify a heuristic function for forward planning

- CSP planning
- Translate a planning problem represented in STRIPS into a corresponding CSP problem (and vice versa)
- Variables 51