# *Chapters 8: Planning*

## *DIT410/TIN172 Artificial Intelligence*

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modifed from slides by Poole & Mackworth



1 April, 2015

# Outline

# *Planning*

- Planning is deciding what to do based on an agent's ability, its goals, and the state of the world.
- Initial assumptions:
  - The world is deterministic.
  - There are no exogenous events outside of the control of the robot that change the state of the world.
  - The agent knows what state it is in.
  - Time progresses discretely from one state to the next.
  - Goals are predicates of states that need to be achieved or maintained.
- The aim is to find a sequence of actions to solve a given goal.

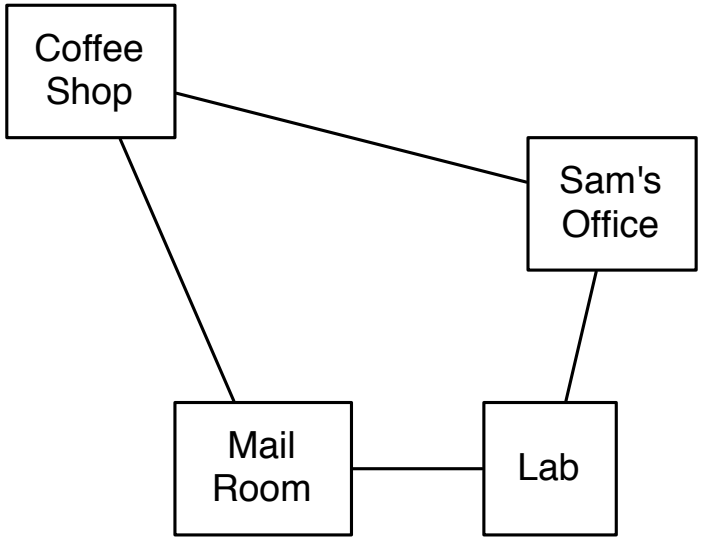
# *Classical planning*

- flat or modular or hierarchical
- explicit states or features or individuals and relations
- static or finite stage or indefinite stage or infinite stage
- fully observable or partially observable
- deterministic or stochastic dynamics
- goals or complex preferences
- single agent or multiple agents
- knowledge is given or knowledge is learned
- perfect rationality or bounded rationality

# Actions

- A deterministic action is a partial function from states to states.
- The preconditions of an action specify when the action can be carried out.
- The effect of an action specifies the resulting state.

# *Delivery robot example*




**Features:**

$RLoc = \{lab, mr, off, cs\}$ – Rob's location

$rhc$ – Rob has coffee

$swc$ – Sam wants coffee

$mw$ – Mail is waiting

$rhm$ – Rob has mail

**Actions:**

$mc$ – move clockwise

$mcc$ – move counterclockwise

$puc$ – pickup coffee

$dc$ – deliver coffee

$pum$ – pickup mail

$dm$ – deliver mail

# Outline

# *Explicit state-space representation*

| State | Action | Resulting State |
|---|---|---|
| $\langle lab, \neg rhc, swc, \neg mw, rhm \rangle$ | $mc$ | $\langle mr, \neg rhc, swc, \neg mw, rhm \rangle$ |
| $\langle lab, \neg rhc, swc, \neg mw, rhm \rangle$ | $mcc$ | $\langle off, \neg rhc, swc, \neg mw, rhm \rangle$ |
| $\langle off, \neg rhc, swc, \neg mw, rhm \rangle$ | $dm$ | $\langle off, \neg rhc, \neg swc, \neg mw, \neg rhm \rangle$ |
| $\langle off, \neg rhc, swc, \neg mw, rhm \rangle$ | $mcc$ | $\langle cs, \neg rhc, swc, \neg mw, rhm \rangle$ |
| $\langle off, \neg rhc, swc, \neg mw, rhm \rangle$ | $mc$ | $\langle lab, \neg rhc, swc, \neg mw, rhm \rangle$ |
| $\ldots$ | $\ldots$ | $\ldots$ |

This table will have $\#states \times \#actions$

$= (4 \cdot 2 \cdot 2 \cdot 2 \cdot 2) \times 6 = 384$ rows.

# Outline

# *Feature-based representation of actions*

For each action:

- precondition is a proposition that specifies when the action can be carried out.

For each feature:

- causal rules that specify when the feature gets a new value, and
- frame rules that specify when the feature keeps its value.

# Example feature-based representation

Precondition of pick-up coffee ($Act = puc$):

$$RLoc = cs \wedge \neg rhc$$

Rules for when the robot has coffee ($rhc$):

$$\begin{array}{lcll} rhc' & \leftarrow & Act = puc & \text{(causal rule)} \\ rhc' & \leftarrow & rhc \wedge Act \neq dc & \text{(frame rule)} \end{array}$$

Rules for when the robot is in the coffee shop ($RLoc = cs$):

$$\begin{array}{lcll} RLoc' = cs & \leftarrow & RLoc = mr \wedge Act = mc & \text{(causal rule)} \\ RLoc' = cs & \leftarrow & RLoc = off \wedge Act = mcc & \text{(causal rule)} \\ RLoc' = cs & \leftarrow & RLoc = cs \wedge Act \neq cc \wedge Act \neq mcc & \text{(frame rule)} \end{array}$$

# Outline

# *STRIPS representation*

Divide the features into:

- primitive features
- derived features – there are rules specifying how they are derived from primitive features

For each action:

- precondition that specifies when the action can be carried out.
- effect a set of assignments of values to primitive features that are made true by this action.

*STRIPS assumption*:

- every primitive feature not mentioned in the effects is unaffected by the action.

# *Example STRIPS representation*

| | | |
|---|---|---|
| Pick-up coffee ($puc$): | | |
| precondition: | $[RLoc = cs, \neg rhc]$ | effect: $[rhc]$ |
| Deliver coffee ($dc$): | | |
| precondition: | $[RLoc = off, rhc]$ | effect: $[\neg rhc, \neg swc]$ |
| Move clockwise from mail room ($mc(mr)$): | | |
| precondition: | $[RLoc = mr]$ | effect: $[RLoc = cs]$ |
| Move clockwise from office ($mc(off)$): | | |
| precondition: | $[RLoc = off]$ | effect: $[RLoc = lab]$ |
| $\vdots$ | | |

# *Planning*

Given:

- A description of the effects and preconditions of the actions
- A description of the initial state
- A goal to achieve

Find a sequence of actions that is possible and will result in a state satisfying the goal.

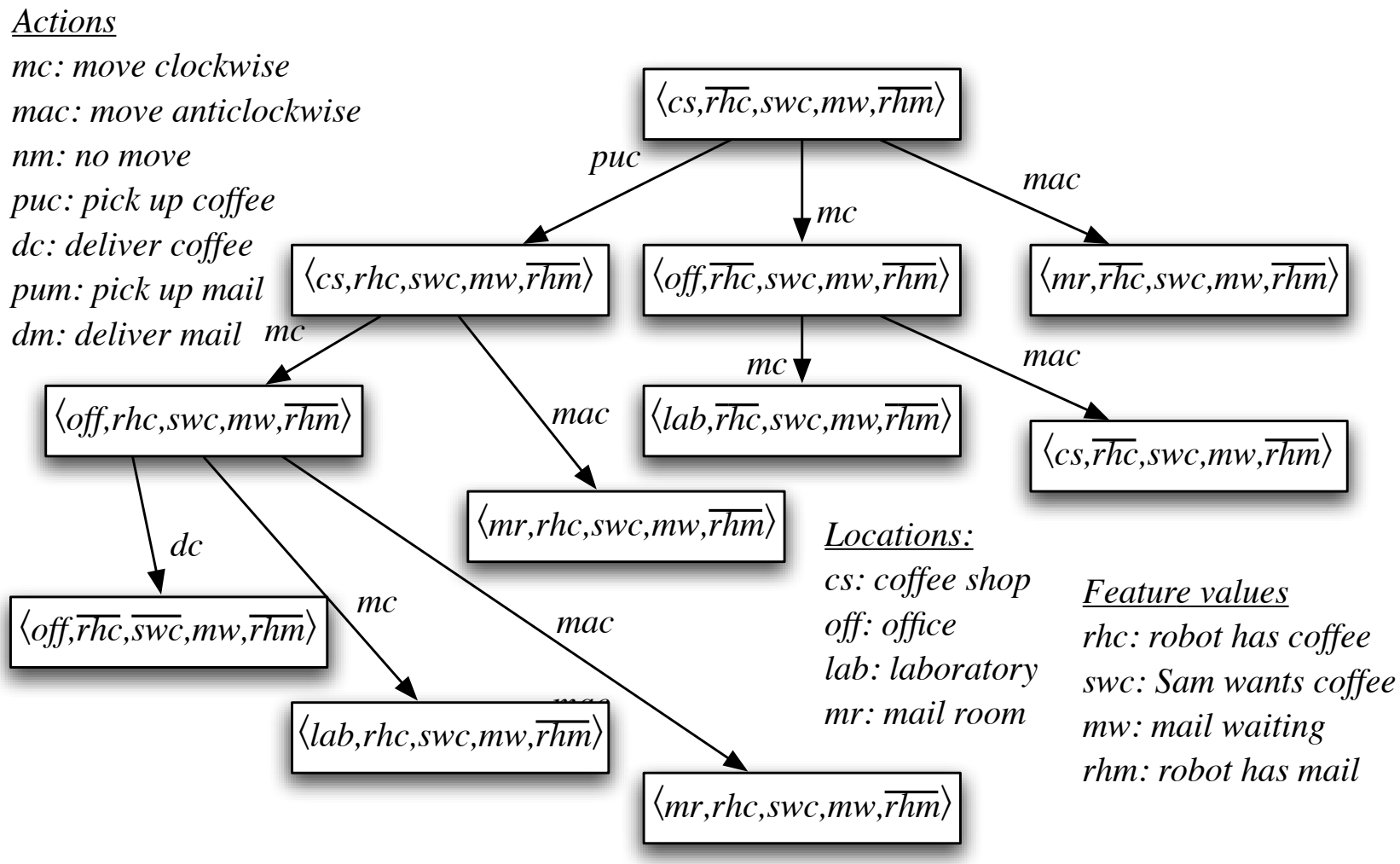
# Outline

# *Forward Planning*

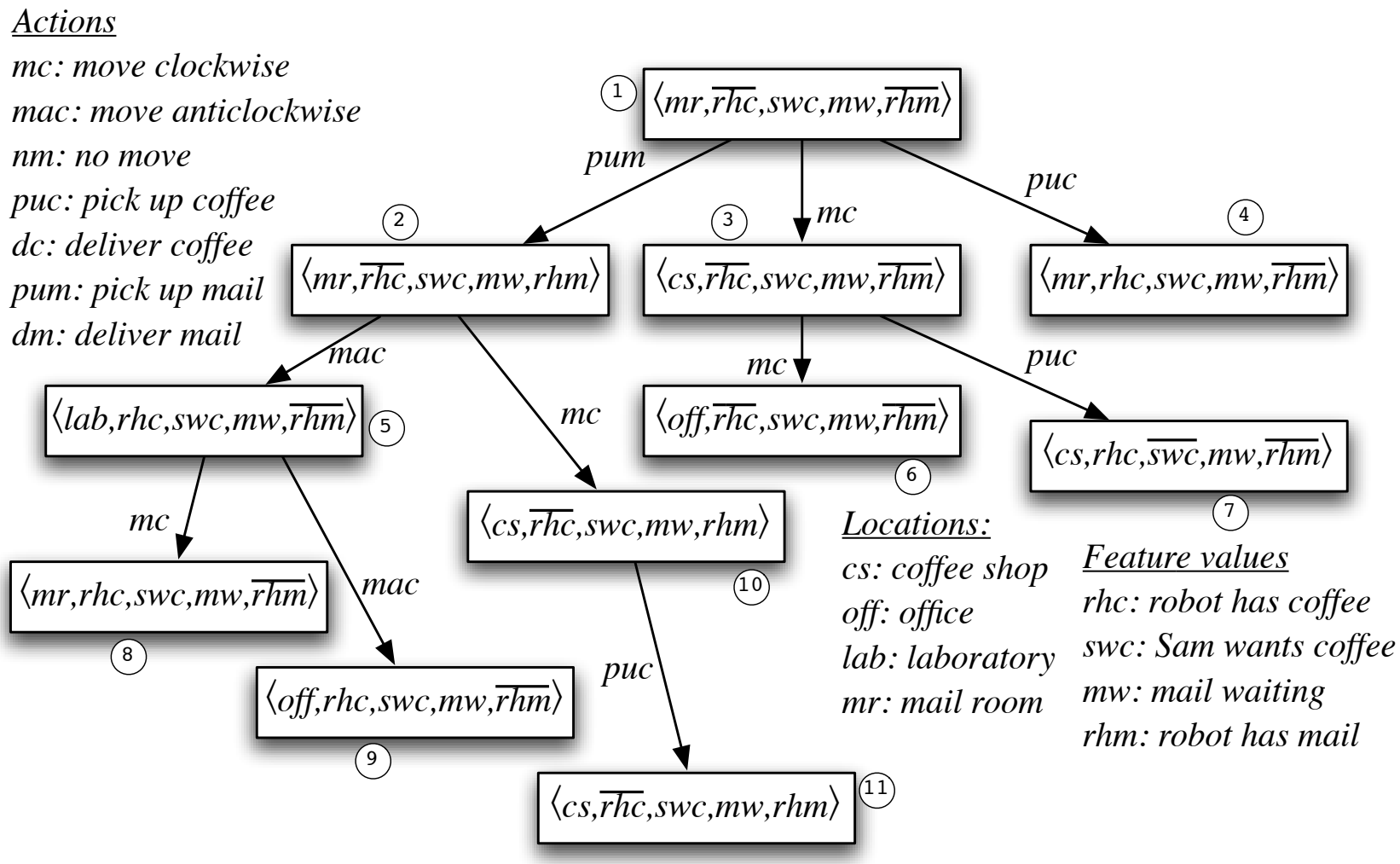
Idea: search in the state-space graph.

- The nodes represent the states
- The arcs correspond to the actions: The arcs from a state $s$ represent all of the actions that are legal in state $s$.
- A plan is a path from the state representing the initial state to a state that satisfies the goal.

# Example state-space graph



# What are the errors?



# *Forward planning representation*

- The search graph can be constructed on demand:
  it only constructs reachable states.
- To do a cycle check or multiple path-pruning,
  the planner needs to be able to find repeated states.
- There are a number of ways to represent states:
  - As a specification of the value of every feature
  - As a path from the start state

# *Improving search efficiency*

Forward search can use domain-specific knowledge specified as:

- a heuristic function that estimates the cost of achieving a goal
- domain-specific pruning of neighbors:
  - don't go to the coffee shop unless "Sam wants coffee" is part of the goal and Rob doesn't have coffee
  - don't pick-up coffee unless Sam wants coffee
  - unless the goal involves time constraints, don't do the "no move" action.

# Outline

# *Regression/backward planning*

Idea: search backwards from the goal description: nodes correspond to subgoals, and arcs to actions.

- Nodes are propositions: a formula made up of assignments of values to features
- Arcs correspond to actions that can achieve one of the goals
- Neighbors of a node $N$ associated with arc $A$ specify what must be true immediately before $A$ so that $N$ is true immediately after.
- The start node is the goal to be achieved.
- $goal(N)$ is true if $N$ is a proposition that is true of the initial state.

# Defining nodes and arcs

- A node $N$ can be represented as a set of assignments of values to variables:

  $$[X_1 = v_1, \ldots, X_n = v_n]$$

  This is a set of assignments you want to hold.
- The last action is one that achieves one of the $X_i = v_i$, and does not achieve $X_j = v'_j$ where $v'_j$ is different to $v_j$.
- The neighbor of $N$ along arc $A$ must contain:
  - The prerequisites of action $A$
  - All of the elements of $N$ that were not achieved by $A$

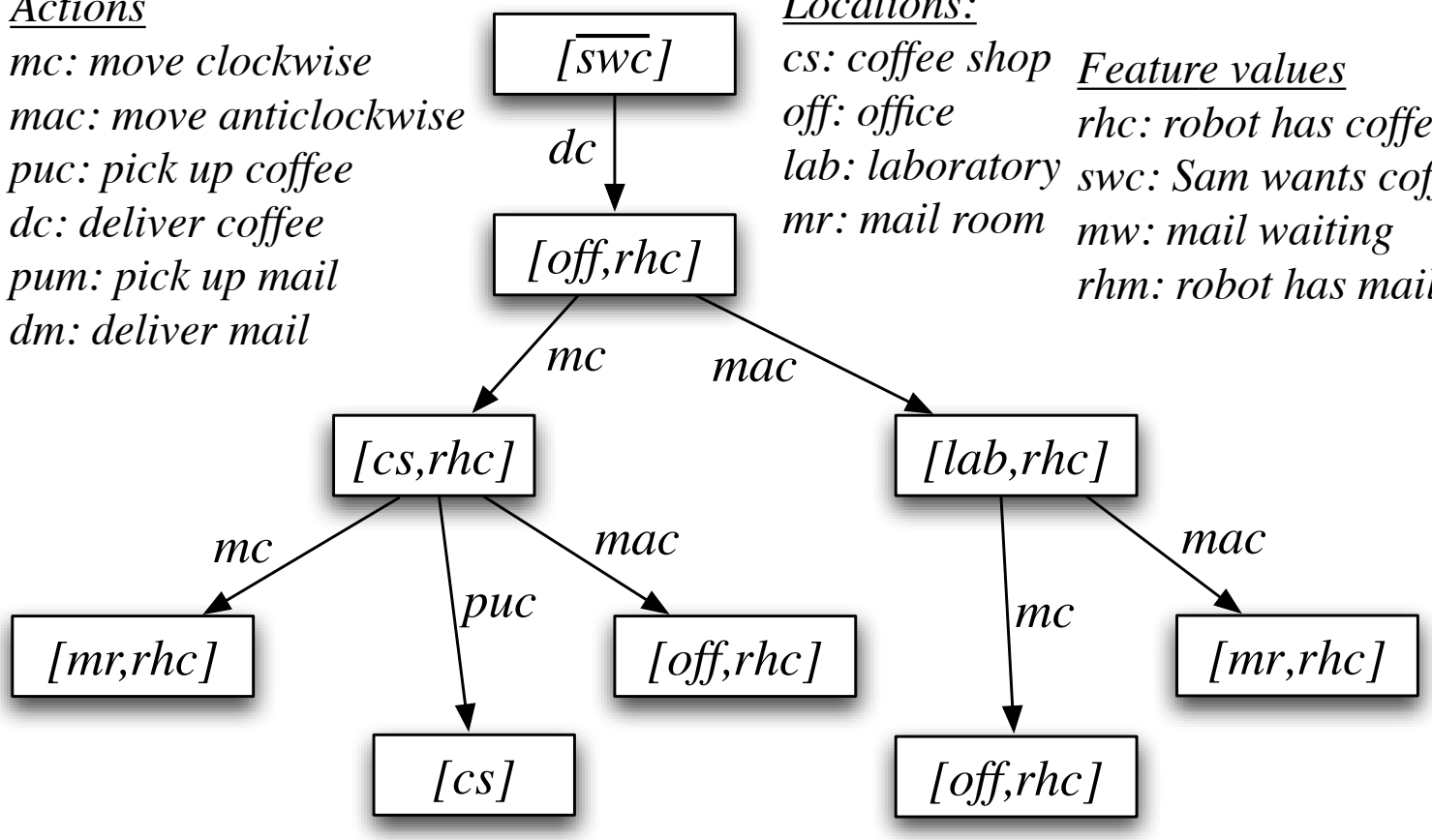
  $N$ must be consistent.

# Regression example

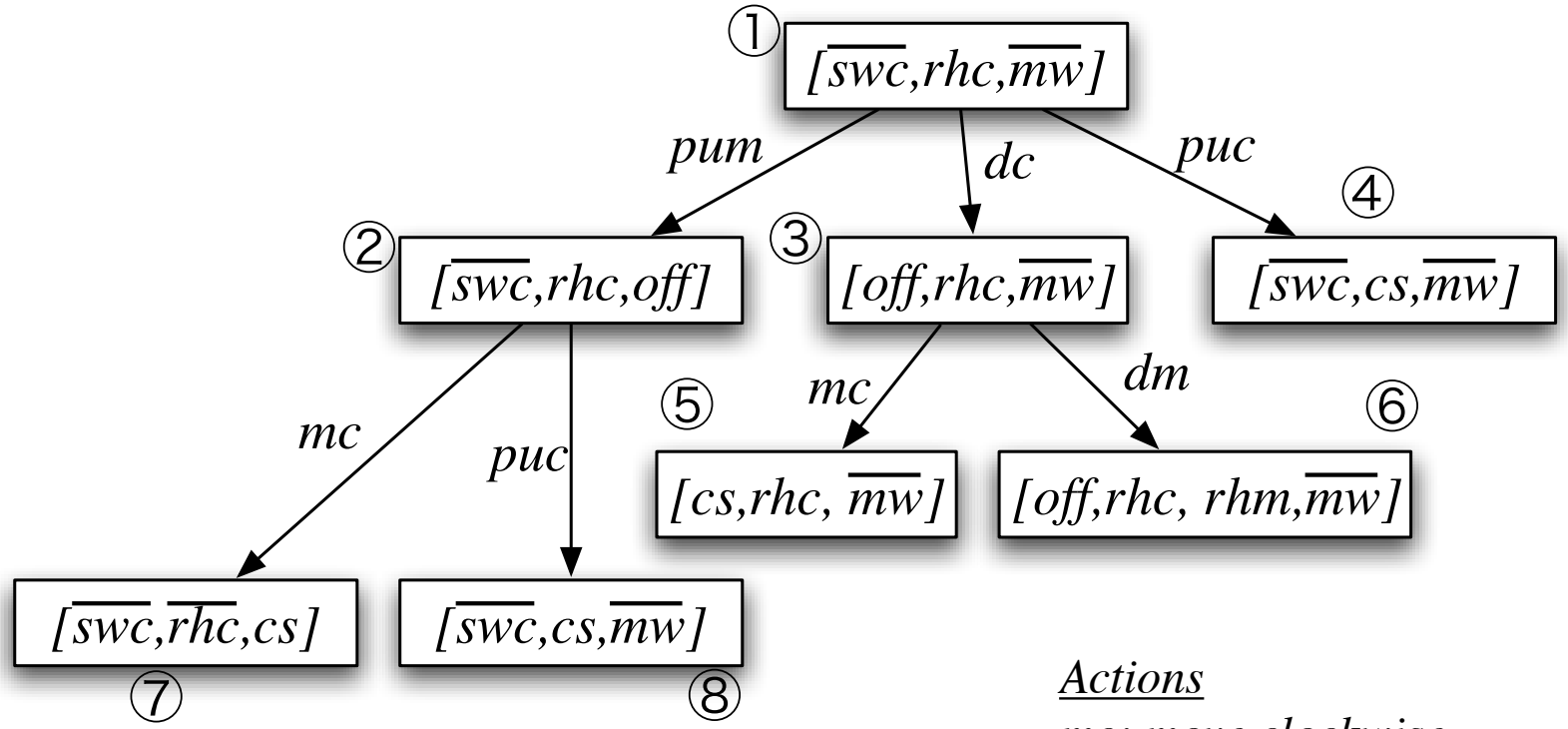
*Actions*
*mc: move clockwise*
*mac: move anticlockwise*
*puc: pick up coffee*
*dc: deliver coffee*
*pum: pick up mail*
*dm: deliver mail*

*Locations:*
*cs: coffee shop*
*off: office*
*lab: laboratory*
*mr: mail room*

*Feature values*
*rhc: robot has coffee*
*swc: Sam wants coffee*
*mw: mail waiting*
*rhm: robot has mail*



# Find the errors




*Locations:*
*cs: coffee shop*
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*Feature values*
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*Actions*
*mc: move clockwise*
*mac: move anticlockwise*
*puc: pick up coffee*
*dc: deliver coffee*
*pum: pick up mail*
*dm: deliver mail*

# *Formalizing arcs using STRIPS notation*

Assume that $G$ is $[X_1 = v_1, \ldots, X_n = v_n]$, then

$$\langle G, A, N \rangle$$

is an arc if:

- $\exists i \; X_i = v_i$ is on the effects list of action $A$
- $\forall j \; X_j = v'_j$ is not on the effects list for $A$, where $v'_j \neq v_j$
- $N$ is $\mathit{preconditions}(A) \cup \{X_k = v_k : X_k = v_k \notin \mathit{effects}(A)\}$ and $N$ is consistent in that it does not assign different values to any variable.

# *Loop detection and multiple-path pruning*

- Goal $G_1$ is simpler than goal $G_2$ if $G_1$ is a subset of $G_2$.
  - It is easier to solve $[cs]$ than $[cs, rhc]$.
- If you have a path to node $N$ have already found a path to a simpler goal, you can prune the path $N$.

# *Improving efficiency*

- A search can use a heuristic function that estimates the cost of solving a goal from the initial state.
- You can use domain-specific knowledge to remove impossible goals.
  - E.g., it is often not obvious from an action description to conclude that an agent can only hold one item at any time.

# *Comparing forward and regression planners*

- Which is more efficient depends on:
  - The branching factor
  - How good the heuristics are
- Forward planning is unconstrained by the goal (except as a source of heuristics).
- Regression planning is unconstrained by the initial state (except as a source of heuristics)

# Outline

# *Planning as a CSP*

- Search over planning horizons.
- For each planning horizon, create a CSP constraining possible actions and features
- Also factor actions into action features.

# Action Features

- $PUC$: Boolean variable, the agent picks up coffee.
- $DelC$: Boolean variable, the agent delivers coffee.
- $PUM$: Boolean variable, the agent picks up mail.
- $DelM$: Boolean variable, the agent delivers mail.
- $Move$: variable with domain $\{mc, mcc, nm\}$ specifies whether the agent moves clockwise, counterclockwise or doesn't move

# CSP variables

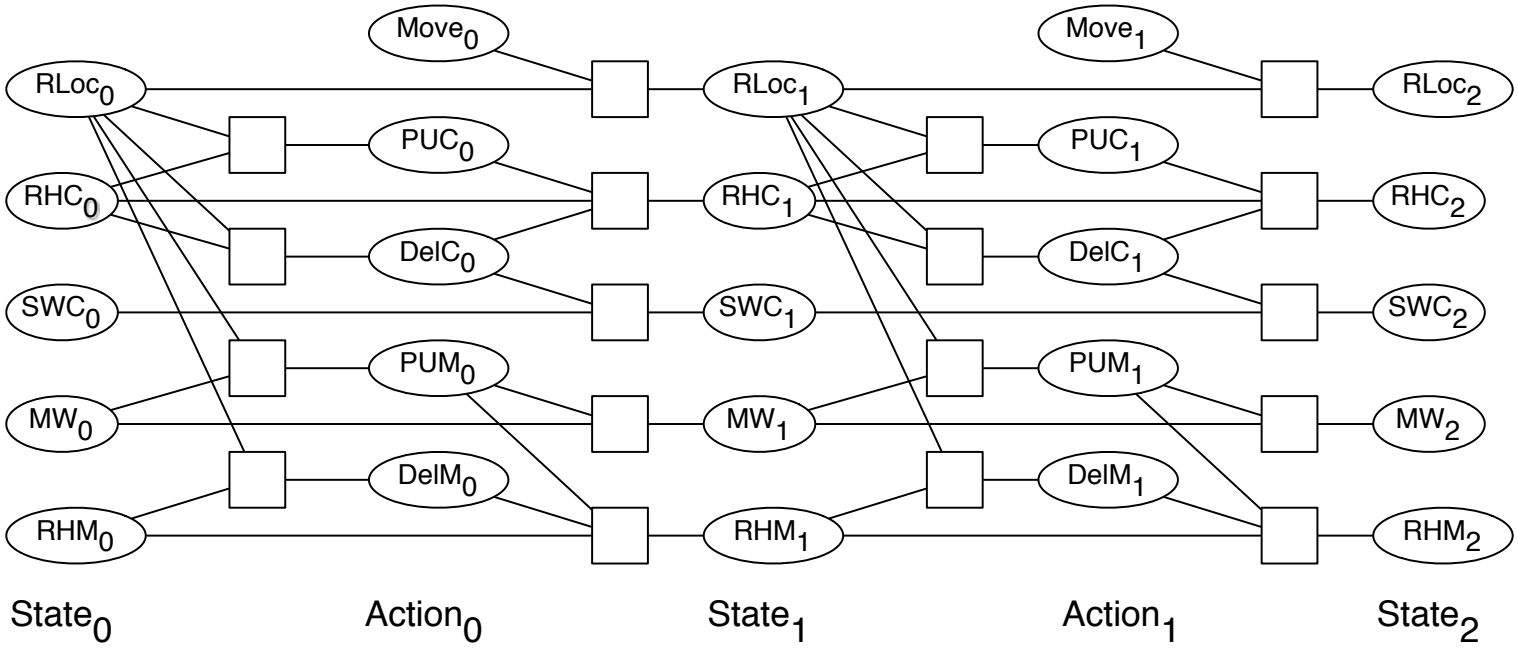
Choose a planning horizon $k$.

- Create a variable for each state feature and each time from 0 to $k$.
- Create a variable for each action feature for each time in the range 0 to $k - 1$.

# Constraints

- state constraints that are constraints between variables at the same time step.
- precondition constraints between state variables at time $t$ and action variables at time $t$ that specify constraints on what actions are available from a state.
- effect constraints between state variables at time $t$, action variables at time $t$ and state variables at time $t + 1$.
- action constraints that specify which actions cannot co-occur. These are sometimes called mutual exclusion or mutex constraints.
- initial state constraints that are usually domain constraints on the initial state (at time 0).
- goal constraints that constrains the final state to be a state that satisfies the goals that are to be achieved.

# CSP for delivery robot




$RLoc_i$ — Rob's location
$RHC_i$ — Rob has coffee
$SWC_i$ — Sam wants coffee
$MW_i$ — Mail is waiting
$RHM_i$ — Rob has mail

$Move_i$ — Rob's move action
$PUC_i$ — Rob picks up coffee
$DelC$ — Rob delivers coffee
$PUM_i$ — Rob picks up mail
$DelM_i$ — Rob delivers mail

# *Effect constraint*

| $RHC_i$ | $DelC_i$ | $PUC_i$ | $RHC_{i+1}$ |
|---|---|---|---|
| true | true | true | true |
| true | true | false | false |
| true | false | true | true |
| true | false | false | true |
| false | true | true | true |
| false | true | false | false |
| false | false | true | true |
| false | false | false | false |