

Chapters 8: Planning

DIT410/TIN172 Artificial Intelligence

Peter Ljunglöf

modified from slides by Poole & Mackworth

(Licensed under Creative Commons BY-NC-SA v4.0)

1 April, 2015

Outline

1 *Representing actions (8.1)*

- State-space representation (8.1.1)
- Feature-based representation (8.1.2)
- STRIPS representation (8.1.3)

2 *Planning (8.2–8.4)*

- Forward planning (8.2)
- Regression planning (8.3)
- Planning as a CSP (8.4)

What is 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 external events outside 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.

Outline

1 *Representing actions (8.1)*

- State-space representation (8.1.1)
- Feature-based representation (8.1.2)
- STRIPS representation (8.1.3)

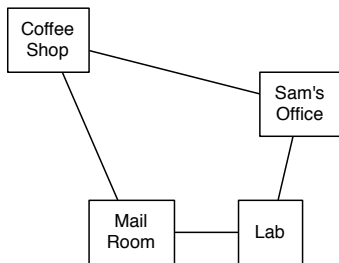
2 *Planning (8.2–8.4)*

- Forward planning (8.2)
- Regression planning (8.3)
- Planning as a CSP (8.4)

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

1 *Representing actions (8.1)*

- State-space representation (8.1.1)
- Feature-based representation (8.1.2)
- STRIPS representation (8.1.3)

2 *Planning (8.2–8.4)*

- Forward planning (8.2)
- Regression planning (8.3)
- Planning as a CSP (8.4)

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	$\langle lab, \neg rhc, swc, \neg mw, rhm \rangle$
...

This table will have $\#states \times \#actions$
 $= (4 \cdot 2 \cdot 2 \cdot 2 \cdot 2) \times 6 = 384$ rows.

Outline

1 *Representing actions (8.1)*

- State-space representation (8.1.1)
- **Feature-based representation (8.1.2)**
- STRIPS representation (8.1.3)

2 *Planning (8.2–8.4)*

- Forward planning (8.2)
- Regression planning (8.3)
- Planning as a CSP (8.4)

Feature-based representation of actions

Each action has a:

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

For each feature there are:

- **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 picking up coffee ($Act = puc$):

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

Rules for when the robot has coffee (rhc):

$$rhc' \leftarrow Act = puc \quad (\text{causal rule})$$

$$rhc' \leftarrow rhc \wedge Act \neq dc \quad (\text{frame rule})$$

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

$$RLoc' = cs \leftarrow RLoc = mr \wedge Act = mc \quad (\text{causal rule})$$

$$RLoc' = cs \leftarrow RLoc = off \wedge Act = mcc \quad (\text{causal rule})$$

$$RLoc' = cs \leftarrow RLoc = cs \wedge Act \neq cc \wedge Act \neq mcc \quad (\text{frame rule})$$

Outline

1 *Representing actions (8.1)*

- State-space representation (8.1.1)
- Feature-based representation (8.1.2)
- STRIPS representation (8.1.3)

2 *Planning (8.2–8.4)*

- Forward planning (8.2)
- Regression planning (8.3)
- Planning as a CSP (8.4)

STRIPS representation

Divide the features into:

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

Each action has:

- **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.

The 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

Outline

1 *Representing actions (8.1)*

- State-space representation (8.1.1)
- Feature-based representation (8.1.2)
- STRIPS representation (8.1.3)

2 *Planning (8.2–8.4)*

- Forward planning (8.2)
- Regression planning (8.3)
- Planning as a CSP (8.4)

Planning

Given:

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

We want to find a sequence of actions that is possible and will result in a state satisfying the goal.

Outline

1 *Representing actions (8.1)*

- State-space representation (8.1.1)
- Feature-based representation (8.1.2)
- STRIPS representation (8.1.3)

2 *Planning (8.2–8.4)*

- Forward planning (8.2)
- Regression planning (8.3)
- Planning as a CSP (8.4)

Forward Planning

Idea: search in the state-space graph.

- The nodes represent the states
- The arcs (neighbors) 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

Actions

mc: move clockwise

mac: move anticlockwise

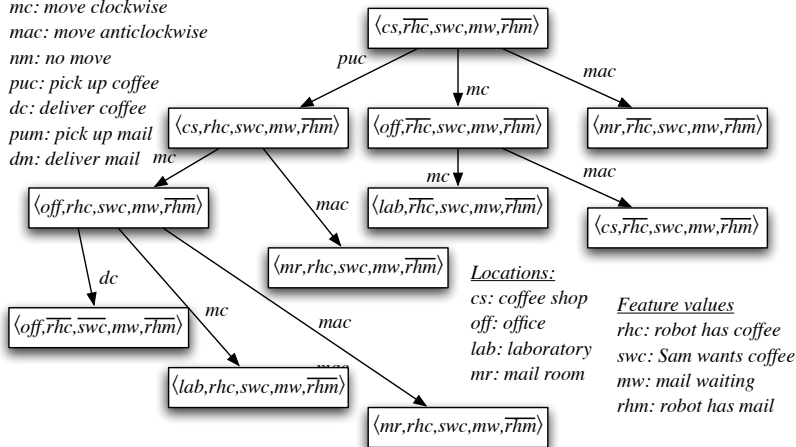
nm: no move

puc: pick up coffee

dc: deliver coffee

pum: pick up mail

dm: deliver mail



What are the errors?

Actions

mc: move clockwise

mac: move anticlockwise

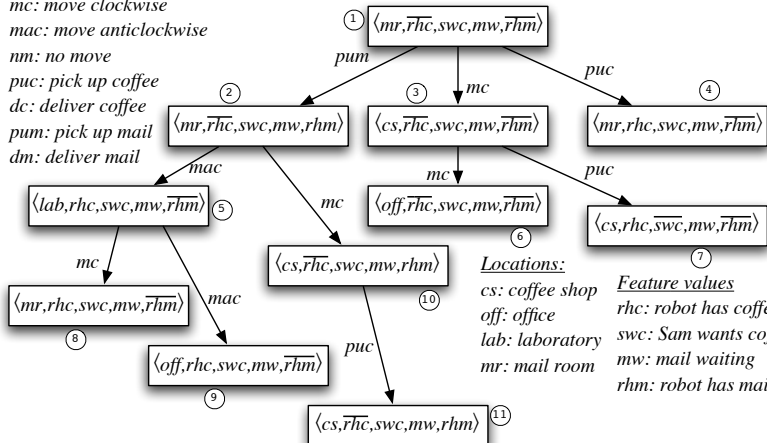
nm: no move

puc: pick up coffee

dc: deliver coffee

pum: pick up mail

dm: deliver mail



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

1 *Representing actions (8.1)*

- State-space representation (8.1.1)
- Feature-based representation (8.1.2)
- STRIPS representation (8.1.3)

2 *Planning (8.2–8.4)*

- Forward planning (8.2)
- **Regression planning (8.3)**
- Planning as a CSP (8.4)

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:

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

- ▶ This is a set of assignments you want to hold.
 - ▶ *Note:* The assignment is on a *subset* of all variables.
 - 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

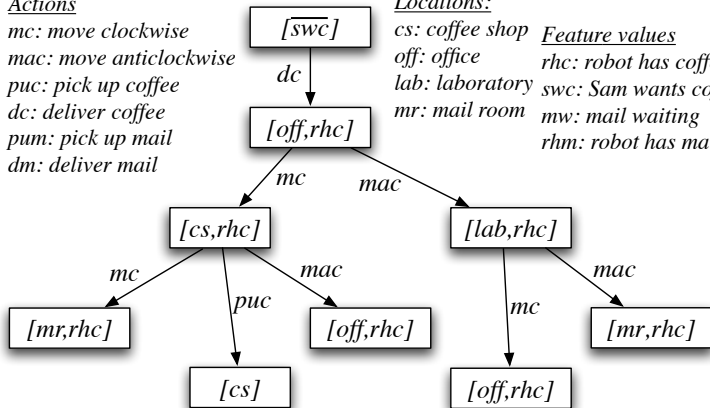
mc: move clockwise
mac: move anticlockwise
puc: pick up coffee
dc: deliver coffee
pum: pick up mail
dm: deliver mail

Locations:

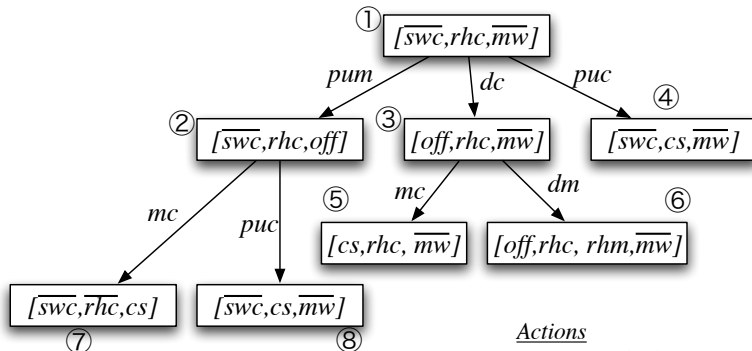
cs: coffee shop
off: office
lab: laboratory
mr: mail room

Feature values

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



Find the errors



Locations:

cs: coffee shop

off: office

lab: laboratory

mr: mail room

Feature values

rhc: robot has coffee

swc: Sam wants coffee

mw: mail waiting

rhm: robot has mail

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 $[X_1 = v_1, \dots, X_n = v_n]$, then

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

is an arc if:

- $X_i = v_i$ is on the effects list of action A
(for some $1 \leq i \leq n$)
- $X_j = v'_j$ is not on the effects list for A
(for all $1 \leq j \leq n$ and all $v'_j \neq v_j$)
- $N = \{X_k = v_k \mid 1 \leq k \leq n \wedge X_k = v_k \notin effects(A)\}$
 $\cup preconditions(A)$
 and N is consistent
 (in that it does not assign conflicting 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

1 *Representing actions (8.1)*

- State-space representation (8.1.1)
- Feature-based representation (8.1.2)
- STRIPS representation (8.1.3)

2 *Planning (8.2–8.4)*

- Forward planning (8.2)
- Regression planning (8.3)
- Planning as a CSP (8.4)

Planning as a CSP

- We search over *planning horizons*.
- For each planning horizon, we create a CSP that constrains possible actions and features.
- We also have to factor the actions into *action features*.

Example: 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

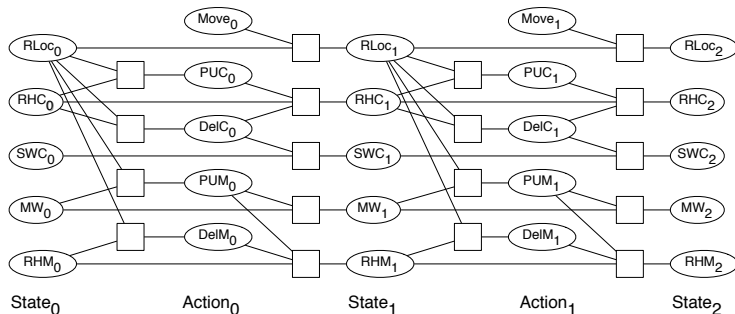
First we choose a planning horizon k :

- 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** are constraints between variables at the same time step.
- **precondition constraints** (between state variables at time t and action variables at time t), 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 $t + 1$), encode the effects of a rule.
- **action constraints** specify which actions cannot co-occur. Sometimes they are called mutual exclusion or mutex constraints.
- **initial state constraints** are usually domain constraints on the initial state (at time 0).
- **goal constraints** constrains the final state to be a state that satisfies the goals that are to be achieved.

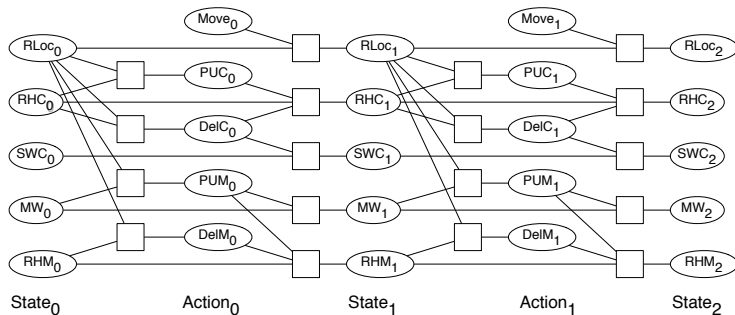
Example CSP for the delivery robot



$RLoc_i$ — 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

Example precondition constraints



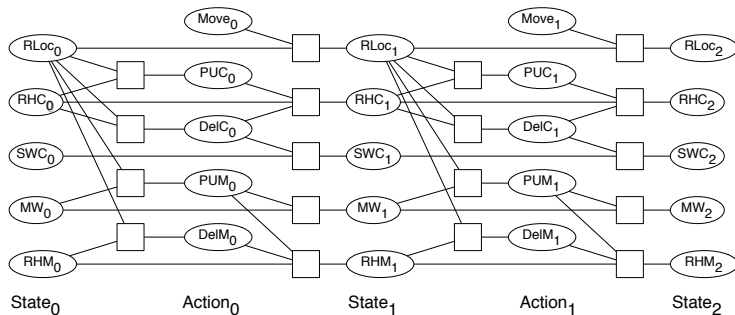
$$PUC_i \rightarrow (RLoc_i = cs) \wedge \neg RHC_i$$

$$DelC_i \rightarrow (RLoc_i = off) \wedge RHC_i$$

$$PUM_i \rightarrow (RLoc_i = mr) \wedge MW_i$$

$$DelM_i \rightarrow (RLoc_i = off) \wedge RHM_i$$

Example effect constraints



$$RHC_{i+1} \leftrightarrow PUC_i \vee (RHC_i \wedge \neg DelC_i)$$

$$SWC_{i+1} \leftrightarrow SWC_i \wedge \neg DelC_i$$

$$MW_{i+1} \leftrightarrow MW_i \wedge \neg PUM_i$$

$$RHM_{i+1} \leftrightarrow PUM_i \vee (RHM_i \wedge \neg DelM_i)$$