COMP219:
Artificial Intelligence

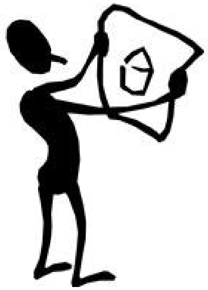
Lecture 23: Classical Planning

Overview

- Last time
  - Resolution in first-order logic; relating Prolog, FO logic and resolution
- Today
  - Overview of classical planning
  - Representing planning problems
    - Planning Domain Definition Language (PDDL)
  - State space linear planning
- Learning outcomes covered today:

  Identify or describe approaches used to solve planning problems in AI and apply these to simple examples

What is planning?



- “Devising a plan of action to achieve one’s goals”

  Planning = How do I get from here to there?

- Planning systems are problem-solving algorithms that operate on explicit propositional or relational representations of states and actions
- Planning problem: find a plan that is guaranteed (from any of the initial states) to generate a sequence of actions that leads to one of the goal states
- Planning problems often have large state spaces

Automated Planning

- We will look at two popular and effective current approaches to automated classical planning:
  – Forward state-space search with heuristics
  – Translating to a Boolean satisfiability problem

- There are also other approaches
  – e.g. planning graphs: data structures to give better heuristic estimates than other methods, and also used to search for a solution over the space formed by the planning graph

Representing Planning Problems

- Recall search based problem-solving agents
  – Find sequences of actions that result in a goal state BUT deal with *atomic* states so need good domain-specific heuristics to perform well
- Planning represented by factored representation
  – Represent a state by a collection of variables
- **Planning Domain Definition Language (PDDL)**
  – Allows expression of all actions with one schema
  – Inspired by earlier STRIPS planning language

Defining a Search Problem

- Define a search problem through:
  1. Initial state
  2. Actions available in a state
  3. Result of action
  4. Goal test

PDDL – Representing States (I)

- A state is represented by a conjunction of fluents
- These are ground, functionless atoms
  - Example: `At(Truck1,Manchester)` ∧ `At(Truck2,Warrington)`
- Closed world assumption (no facts = false)
- Unique names assumption (`Truck1` distinct from `Truck2`)

PDDL – Representing States (II)

- Not allowed:

  `At(x,y)` non-ground (i.e. variables alone)

  `¬ Poor` negation

  `At(Father(Fred),Liverpool)` uses function

- A state is treated as either
  - *conjunction* of fluents, manipulated by logical inference
  - *set* of fluents, manipulated with set operations

PDDL – Representing Actions

- Actions described by a set of action schemas that implicitly define `Actions(s)` and `Result(s,a)` functions
- Classical planning: most actions leave most states unchanged
  - Relates to the Frame Problem: issue of what changes and what stays the same as a result of actions
- PDDL specifies the result of an action in terms of *what changes* – don’t need to mention everything that stays the same

Action Schema (I)

- Represents a set of ground actions
- Contains action name, list of variables used, precondition and effect
- Example: action schema for flying a plane from one location to another

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

Action Schema (II)

- Free to choose whatever values we want to instantiate variables
- Precondition and effect of an action are each conjunctions of literals (positive or negated atomic sentences)
  - Precondition defines states in which action can be executed
  - Effect defines result of action
- Sometimes we want to *propositionalise* a PDDL problem (replace each action schema with a set of ground actions) and use a propositional solver (e.g. SATPLAN) to find a solution
  - More on this later…

Action Schema (III)

- Action a can be executed in state s if s entails the precondition of a

  $(a \in \mathtt{Actions}(s)) \Leftrightarrow s \models \mathtt{Precond}(a)$

  where any variables in a are universally quantified

- Example:

  $\forall \mathtt{p,from,to}\ (\mathtt{Fly(p,from,to)} \in \mathtt{Actions}(s)) \Leftrightarrow$
  $\mathtt{s} \models (\mathtt{At(p,from)} \wedge \mathtt{Plane(p)} \wedge \mathtt{Airport(from)}$
  $\wedge\ \mathtt{Airport(to)})$

- We say that a is applicable in s if the preconditions are satisfied by s

Action Schema (IV)

- Result of executing action a in state s (s')

  `Result(s,a)=(s-Del(a))` $\bigcup$ `Add(a)`

- Delete list (`Del(a)`): fluents that appear as negative literals in action's effect
- Add list (`Add(a)`): fluents that appear as positive literals in action's effect

- Note that time is implicit: preconditions have time `t`, effects have `t+1`

Planning Domain

- A set of action schemas defines a planning domain
- A specific problem within a domain is defined by adding initial state and goal
  - Initial state: conjunction of ground atoms
  - Goal: conjunction of literals (positive or negative) that may contain variables
    - e.g. `At(p,LPL) ∧ Plane(p)`
- Problem solved when we find sequence of actions that end in a state that entails the goal
  - e.g. $\texttt{Plane(Plane}_1\texttt{)} \wedge \texttt{At(Plane}_1\texttt{,LPL)}$ entails the goal `At(p,LPL) ∧ Plane(p)`

Example: Air Cargo Transport

$Init(At(C_1,SFO) \land At(C_2,JFK) \land At(P_1,SFO) \land At(P_2,JFK) \land$
$Cargo(C_1) \land Cargo(C_2) \land Plane(P_1) \land Plane(P_2) \land$
$Airport(JFK) \land Airport(SFO))$

$Goal(At(C_1,JFK) \land At(C_2,SFO))$

Example from Chapter 10 of AIAMA

Example: Air Cargo Transport

Init($At(C_1,SFO) \land At(C_2,JFK) \land At(P_1,SFO) \land At(P_2,JFK) \land$
$Cargo(C_1) \land Cargo(C_2) \land Plane(P_1) \land Plane(P_2) \land$
$Airport(JFK) \land Airport(SFO)$)

Goal($At(C_1,JFK) \land At(C_2,SFO)$)

Action($Load(c,p,a)$,
PRECOND: $At(c,a) \land At(p,a) \land Cargo(c) \land Plane(p) \land$
$Airport(a)$
EFFECT: $\neg At(c,a) \land In(c,p)$)

Example from Chapter 10 of AIAMA

Example: Air Cargo Transport

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$Airport(a)$
EFFECT: $\neg At(c,a) \land In(c,p))$

$Action(Unload(c,p,a),$
PRECOND: $In(c,p) \land At(p,a) \land Cargo(c) \land Plane(p) \land$
$Airport(a)$
EFFECT: $At(c,a) \land \neg In(c,p))$

Example from Chapter 10 of AIAMA

Example: Air Cargo Transport

Init($At(C_1,SFO) \land At(C_2,JFK) \land At(P_1,SFO) \land At(P_2,JFK) \land$
$Cargo(C_1) \land Cargo(C_2) \land Plane(P_1) \land Plane(P_2) \land$
$Airport(JFK) \land Airport(SFO)$)

Goal($At(C_1,JFK) \land At(C_2,SFO)$)

Action(*Load*(c,p,a),
PRECOND: $At(c,a) \land At(p,a) \land Cargo(c) \land Plane(p) \land Airport(a)$
EFFECT: $\neg At(c,a) \land In(c,p)$)

Action(*Unload*(c,p,a),
PRECOND: $In(c,p) \land At(p,a) \land Cargo(c) \land Plane(p) \land Airport(a)$
EFFECT: $At(c,a) \land \neg In(c,p)$)

Action(*Fly*($p,from,to$),
PRECOND: $At(p,from) \land Plane(p) \land Airport(from) \land Airport(to)$
EFFECT: $\neg At(p,from) \land At(p,to)$)

Example from Chapter 10 of AIAMA

Example: Air Cargo Transport

- Problem defined with 3 actions
- Actions affect 2 predicates
- When a plane flies from one airport to another, all cargo inside goes too
  - in PDDL we have no explicit universal quantifier to say this as part of the `Fly` action
  - so instead we use the load/unload actions:
    - cargo seizes to be `At` the old airport when it is loaded
    - and only becomes `At` the new airport when it is unloaded

- A solution plan:

  $[Load(C_1,P_1,SFO), Fly(P_1,SFO,JFK), Unload(C_1,P_1,JFK),$
  $Load(C_2.P_2.JFK), Fly(P_2,JFK,SFO), Unload(C_2,P_2,SFO)].$
- Problem – spurious actions like $Fly(P_1,JFK,JFK)$ have contradictory effects
  - Add inequality preconditions $\wedge$ $(from \neq to)$

Planning as State-Space Search

- Forward (progression) state-space search
  - Prone to exploring irrelevant actions
  - Uninformed forward-search in large state spaces is too inefficient to be practical
  - Need heuristics to make forward search feasible

Example: Air Cargo Problem

- Consider this air cargo problem:
  - 10 airports: each has 5 planes and 20 pieces of cargo
  - Goal: Move all cargo at airport A to airport B
  - Simple solution: Load 20 cargo onto $plane_1$ at airport A, fly to airport B, unload cargo
  - Average branching factor is huge:
    - Each of 50 planes can fly to 9 airports
    - 200 cargo can be unloaded/loaded onto any plane at its airport
    - In any state min. 450 actions, max. 10,450 actions
  - If we take average 2000 possible actions per state, search graph up to obvious solution has 2000^{41} nodes

Backward (Regression) Relevant-States Search (I)

- Start at the goal, apply actions backwards until reach initial state
- Only consider actions that are relevant to the goal (or current state), i.e.
  - Action must contribute to the goal
  - Must not have any effect which negates an element of the goal
- Consider a set of relevant states at each step, not just a single state (*cf*. belief state search)

Backward (Regression) Relevant-States Search (II)

- We must know how to regress from a state description to a predecessor state
  - PDDL description makes it easy to regress actions:
    - Effects added by action need not have been true before
    - Preconditions must have been true before
    - Do not consider `Del(a)` as we don't know whether or not fluents were true before
- Need to deal with partially uninstantiated actions and states, not just ground ones
- Backward search keeps branching factor lower than forward search BUT using state sets means it's harder to define good heuristics – so most current systems favour forward search

Exercise

- Consider the following air cargo problem

- Goal: deliver a specific piece of cargo to SFO
  $At(C_2, SFO)$

- Which action does this suggest that will lead to this goal?

Exercise

- Consider the following air cargo problem

- Goal: deliver a specific piece of cargo to SFO $At(C_2, SFO)$
- Suggests the action

$$Action(Unload(C_2, p', SFO), \\ \text{PRECOND: } In(C_2, p') \land At(p', SFO) \land Cargo(C_2) \land Plane(p') \land Airport(SFO) \\ \text{EFFECT: } At(C_2, SFO) \land \neg In(C_2, p'))$$

unloading from an unspecified plane p' at SFO

- What is the regressed state description?

Exercise

- Goal: $At(C_2, SFO)$

  $Action(Unload(C_2,\ p',\ SFO),$

  PRECOND: $In(C_2,\ p') \land At(p',\ SFO) \land$
  $Cargo(C_2) \land Plane(p') \land$
  $Airport(SFO)$

  EFFECT: $At(C_2,\ SFO) \land \neg\ In(C_2,\ p'))$

- Regressed state description is

  $g' = In(C_2,\ p') \land At(p',\ SFO) \land Cargo(C_2)$
  $\land\ Plane(p') \land Airport(SFO)$

Heuristics for Planning

- As planning uses factored representation of states (rather than atomic states), it is possible to define good domain-independent heuristics
- An admissible heuristic (i.e. does not overestimate distance to goal) can be derived by defining a *relaxed problem* that is easier to solve
  - Can then make use of A* search to find optimal solutions
- The exact cost of a solution to this easier problem becomes a heuristic for the original problem
- Examples of heuristics: ignore preconditions, state abstraction, problem decomposition…

Planning as Boolean Satisfiability

- Reduces planning problem to classical propositional SAT problem
- SAT problem: is this propositional formula satisfiable? (- is there an assignment that makes it true?)
- Making plans by logical inference
- To use SATPlan, PDDL planning problem description needs first to be translated to propositional logic

SATPlan

- SATPLAN is the question of whether there exists any plan that solves a given planning problem
  - SATPLAN is about satisficing (want any solution, not necessarily the cheapest or the shortest)
- *Bounded* SATPLAN is the question of whether there exists a plan of length *k* or less
  - Bounded SATPLAN can be used to ask for the optimal solution
- If in the PDDL language we do not allow functional symbols, both problems are decidable

SATPlan Algorithm

1. Construct a propositional sentence that includes
   (a) description of the initial state
   (b) description of the planning domain (precondition axioms, successor state axioms, mutual exclusion of actions) up to some maximum time t_n
   (c) the assertion that the goal is achieved at time t_n
2. Call SAT solver to return a model for the sentence from 1.
3. If a model exists, extract the variables that represent actions at each time from t_0 to t_n and are assigned true, and present them in order of times as a plan

Summary

- Planning systems are problem-solving algorithms that operate on explicit propositional or relational representations of states and actions
  - PDDL describes
    - initial and goal states as conjunctions of literals
    - actions in terms of preconditions and effects
- State-space search in forward or backward direction
- Can get effective heuristics by relaxing the planning problem
- Can make plans by logical inference
  - Boolean satisfiability and SATPLAN

- Next time
  - Planning in complex environments