Planning

CPS 570

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Some Actual Planning Applications

- Used to fulfill mission objectives in Nasa's Deep Space One (Remote Agent)
  - Particularly important for space operations due to latency
- Also used for Rovers
  - Finally(!) used onboard on curiosity:
    http://www.jpl.nasa.gov/news/news.php?release=2013-259&rn=news.xml&rst=3884
- Aircraft assembly schedules
- Logistics for the U.S. Navy
- Observation schedules for Hubble space telescope
- Scheduling of operations in an Australian beer factory

Scheduling

- Many "planning" problems are scheduling problems
- Scheduling can be viewed as a generalization of the planning problem to include resource constraints
  - Time & Space
  - Money & Energy
- Many principles from regular planning generalize, but some extensions (not discussed here) are used

Characterizing Planning Problems

- Start state (group of states)
- Goal – almost always a group of states
- Actions
- Objective: Plan = A sequence of actions that is ***guaranteed*** to achieve the goal.
- Like everything else, can view planning as search…
- So, how is this different from generic search?

What makes planning special?

- States typically specified by a set of relations or propositions:
  - On(solar_panels, cargo_floor)
  - arm_broken
- Goal is almost always a set
  - Typically care about a small number of things:
    - at(Ron, airport),
    - parked_in(X, car_of(Ron))
    - airport_parking_stall(X)
  - Many things are irrelevant
    - parked_in(Y, car_of(Bill))
    - adjacent(X,Y)
- Branching factor is large

Planning Algorithms

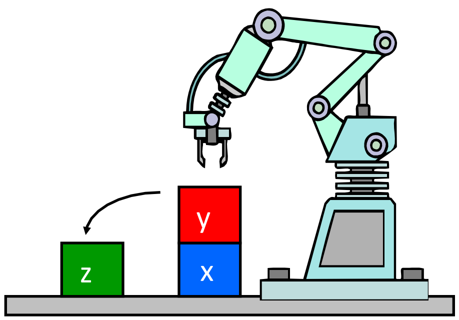
- Extremely active and rapidly changing area
- Regular competitions pit different algorithms against each other on suites of challenge problems
- Algorithms compete in different categories
  - General vs. Domain specific
  - Optimal vs. Satisficing
- No clearly superior method has emerged

PDDL – A Language for Planning Problems

- Actions have a set of preconditions and effects
- Think of the world as a database
  - Preconditions specify what must be true in the database for the action to be applied
  - Effects specify which things will be changed in the database if the action is taken
- NB: PDDL supersedes an earlier, similar representation called STRIPS

move(obj,from,to)

- Preconditions
  - clear(obj)
  - on(obj,from)
  - clear(to)
- Effects
  - Add
    - on(obj,to)
    - clear(from)
  - Delete
    - on(obj,from)
    - clear(to)



move(y,x,z)

Limitations of PDDL

- Assumes that a small number of things change with each action
  - Dominoes ☹
  - Pulling out the bottom block from a stack ☹
- Preconditions and effects are conjunctions
- No quantification
- Closed world assumption (negation in implemented as deletion, no negated preconditions)

How hard is planning?

- Planning is NP hard
- How can we prove this?
  - Use Planning to solve 3SAT
  - Any 3SAT instance can be converted to a planning problem in polynomial time
  - Polynomial time planning algorithm would imply polynomial time solution to 3SAT

Planning Reduction

- Introduce a predicate for whether a clause is satisfied or unsatisfied
- Goal: satisfied_c_1 AND satisfied_c_2…AND satisfied_c_m
- Initial state: unsatisfied_c_1 AND unsatisfied_c_2…AND unsatisfied_c_m, unassigned(x_1) AND unassigned(x_2) AND …unassigned(x_n)

set(x_i,value)

- Preconditions:
  - unassigned(x_i)
- Effects
  - Add
    - assigned(x_i)
    - set(x_i,value)
  - Delete
    - unassigned(x_i)

Satisfy_c_i

- Preconditions
  - Unsatisfied_c_i
  - Set(x_j,$v_i(x_j)$) OR set(x_k,$v_i(x_k)$) OR set(x_l,$v_i(x_l)$)
- Effects
  - Add
    - Satisfied_c_i
  - Delete
    - {}

$v_i(x_j)$ = truth value needed by variable j in clause i

How expensive is this reduction?

- How many predicates/propositions are introduced?
- How many actions are introduced?
- What does the plan do?
- What prevents the planner from making inconsistent assignments?

Is planning NP-complete?

- NO!
- Consider the towers of Hanoi:
  - http://www.mazeworks.com/hanoi/index.htm
  - PDDL actions are the block moving actions
- Requires exponential number of moves
- Planning is actually PSPACE complete
- Planning with bounded plans is NP-complete

Should plan size worry us?

- What if you have a problem with an exponential length solution?
- Impractical to execute (or even write down) the solution, so maybe we shouldn't worry
- Sometimes this may just be an artifact of our action representation
  - Towers of Hanoi solution can be expressed as a simple recursive program
  - Nice if planner could find such programs

Planning Using Search

- Forward Search:
  - Blind forward search is problematic because of the huge branching factor
  - Some success using this method with carefully chosen action pruning heuristics (not covered in class)
- Backward Search:
  - Tends to focus search on relevant terms
  - Called "Goal Regression" in the planning context

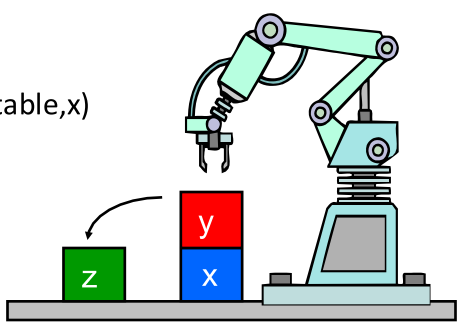
Goal Regression

- Goal regression is a form of backward search from goals
- Basic principle goes back to Aristotle
- Embodied in earliest AI systems
  - GPS: General Problem Solver by Newell & Simon
- Cognitively plausible
- Idea:
  - Pick actions that achieve (some of) your goal
  - Make preconditions of these actions your new goal
  - Repeat until the goal set is satisfied by start state

Goal Regression Example

Regress on(x,z)
through move(z,table,x)

New goal:
clear(x)

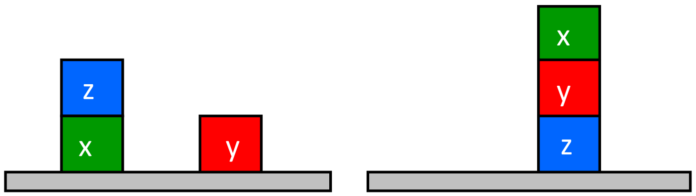


Goal: on(x,z)

Greed, decomposition in planning

- Does a greedy approach work for planning?
- Idea:
  - Pick actions that satisfy as many parts of the goal as possible
  - If no single action satisfies any part of the goal, break up the goal into pieces and plan to solve each of them individually
- Bad news: This works poorly in general

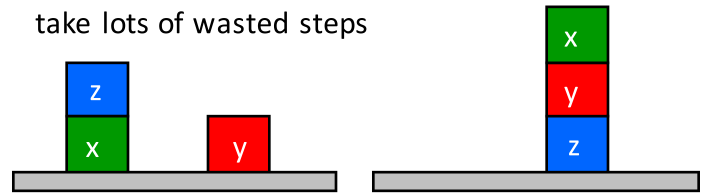
The Sussman Anomaly



Goal: on(x,y), on(y,z)

Problems with naïve subgoaling

- The number of conjuncts satisfied may not be a good heuristic
- Achieving individual conjuncts in isolation may actually make things harder
- Causes simple planners to go into loops and/or take lots of wasted steps



Summary of Traditional Planners

- Backward search methods are were more focused, with careful construction these could be sound and complete generic planners
- Forward search methods worked well when:
  - Search space was very narrow (only a small number of reasonable things to do, which prevented exponential growth in reachable search space)
  - Domain-specific knowledge could be used to narrow the search space

Modern Planners

- One family uses sophisticated heuristics (graphplan)
  - Uses various tricks to narrow search space
  - May use forward or backward planning
- Another family uses forward chaining with domain specific tricks to prune the search space
- Snother family converts everything into a giant SAT problem and runs a highly optimized SAT solver (SATPlan)

What's Missing?

- As described, plans are "open loop"
- No provisions for:
  - Actions failing
  - Uncertainty about initial state
  - Observations
- Solutions:
  - Plan monitoring, replanning
  - Conformant/Sensorless planning
  - Contingency planning

Planning Under Uncertainty

- What if there is a probability distribution over possible outcomes?
  - Called: Planning under uncertainty, decision theoretic planning, Markov Decision Processes (MDPs)
  - Much more robust: Solution is a "universal plan", i.e., a plan for all possible outcomes (monitoring and replanning are implicit)
  - Much more difficult computationally
- What if observations are unreliable?
  - Called: "Partial Observability", Partially Observable MDPs (POMDPs)
  - Applications to medical diagnosis, defense, sensor planning
  - Way, way harder computationally