Automated Planning

C1. Overview of Classical Planning Algorithms

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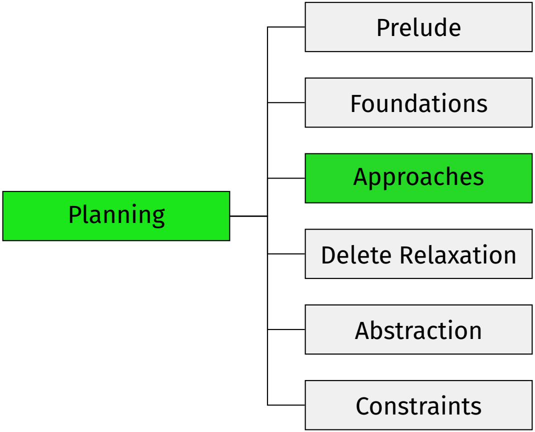
based on slides from the AI group at the University of Basel

Content of this Course



The Big Three

Classical Planning Algorithms

Let’s start solving planning tasks!

This Chapter

very high-level overview of classical planning algorithms

- bird’s eye view: no details, just some very brief ideas

The Big Three

Of the many planning approaches, three techniques stand out:

- explicit search
- SAT planning
- symbolic search

also: many algorithm portfolios

Satisficing or Optimal Planning?

must carefully distinguish:

- satisficing planning: any plan is OK (cheaper ones preferred)
- optimal planning: plans must have minimum cost

solved by similar techniques, but:

- details very different
- almost no overlap between best techniques for satisficing planning and best techniques for optimal planning
- many tasks that are trivial for satisficing planners are impossibly hard for optimal planners

Explicit Search

Explicit Search

You know this one already! (Hopefully.)

Reminder: State-Space Search

Need to Catch Up?

- We assume prior knowledge of basic search algorithms:
  - uninformed vs. informed (heuristic)
  - satisficing vs. optimal
  - heuristics and their properties
  - specific algorithms: e.g., breadth-first search, greedy best-first search, A*
- If you are not familiar with them, we recommend the relevant slides from the Artificial Intelligence course: `https://www.ida.liu.se/~TDDC17/`

Reminder: Interface for Heuristic Search Algorithms

Abstract Interface Needed for Heuristic Search Algorithms

- init() $\rightsquigarrow$ returns initial state
- is_goal(s) $\rightsquigarrow$ tests if s is a goal state
- succ(s) $\rightsquigarrow$ returns all pairs $\langle a, s' \rangle$ with $s \xrightarrow{a} s'$
- cost(a) $\rightsquigarrow$ returns cost of action a
- h(s) $\rightsquigarrow$ returns heuristic value for state s

Design Choice: Search Direction

How to apply explicit search to planning? $\rightsquigarrow$ many design choices!

Design Choice: Search Direction

- progression: forward from initial state to goal
- regression: backward from goal states to initial state
- bidirectional search

$\rightsquigarrow$ Chapter C2

Design Choice: Search Algorithm

How to apply explicit search to planning? $\rightsquigarrow$ many design choices!

Design Choice: Search Algorithm

- uninformed search:
  depth-first, breadth-first, iterative depth-first, ...
- heuristic search (systematic):
  greedy best-first, A^*, weighted A^*, IDA^*, ...
- heuristic search (local):
  hill-climbing, simulated annealing, beam search, ...

Design Choice: Search Control

How to apply explicit search to planning? $\rightsquigarrow$ many design choices!

Design Choice: Search Control

- heuristics for informed search algorithms
- pruning techniques: invariants, symmetry elimination, partial-order reduction, helpful actions pruning, …

How do we find good heuristics in a domain-independent way?

$\rightsquigarrow$ one of the main focus areas of classical planning research

SAT Planning

SAT Planning: Basic Idea

- formalize problem of finding plan with a given horizon (length bound) as a propositional satisfiability problem and feed it to a generic SAT solver
- to obtain a (semi-) complete algorithm, try with increasing horizons until a plan is found (= the formula is satisfiable)
- important optimization: allow applying several non-conflicting operators "at the same time" so that a shorter horizon suffices

SAT Encodings: Variables

- given propositional planning task $\langle V, I, O, \gamma \rangle$
- given horizon $T \in \mathbb{N}_0$

Variables of SAT Encoding

- propositional variables v^i for all $v \in V$, $0 \leq i \leq T$
  encode state after i steps of the plan
- propositional variables o^i for all $o \in O$, $1 \leq i \leq T$
  encode operator(s) applied in i-th step of the plan

Design Choice: SAT Encoding

Again, there are several important design choices.

Design Choice: SAT Encoding

- sequential or parallel
- many ways of modeling planning semantics in logic

$\rightsquigarrow$ main focus of research on SAT planning

Design Choice: SAT Solver

Again, there are several important design choices.

Design Choice: SAT Solver

- out-of-the-box like MiniSAT, Glucose, Lingeling
- planning-specific modifications

Design Choice: Evaluation Strategy

Again, there are several important design choices.

Design Choice: Evaluation Strategy

- always advance horizon by +1 or more aggressively
- possibly probe multiple horizons concurrently

Symbolic Search

Symbolic Search Planning: Basic Ideas

- search processes sets of states at a time
- operators, goal states, state sets reachable with a given cost etc. represented by binary decision diagrams (BDDs) (or similar data structures)
- hope: exponentially large state sets can be represented as polynomially sized BDDs, which can be efficiently processed
- perform symbolic breadth-first search (or something more sophisticated) on these set representations

Symbolic Breadth-First Progression Search

prototypical algorithm:

Symbolic Breadth-First Progression Search

def bfs-progression(V, I, O, γ):
    $goal\_states := models(\gamma)$
    $reached_0 := \{I\}$
    $i := 0$
    loop:
        if $reached_i \cap goal\_states \neq \emptyset$:
            return solution found
        $reached_{i+1} := reached_i \cup apply(reached_i, O)$
        if $reached_{i+1} = reached_i$:
            return no solution exists
        $i := i + 1$

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$\rightsquigarrow$ If we can implement operations *models*, $\{I\}$, $\cap$, $\neq \emptyset$, $\cup$, *apply* and $=$ efficiently, this is a reasonable algorithm.

Design Choice: Symbolic Data Structure

Again, there are several important design choices.

Design Choice: Symbolic Data Structure

- BDDs
- ADDs
- EVMDDs
- SDDs

Other Design Choices

- additionally, same design choices as for explicit search:
  - search direction
  - search algorithm
  - search control (incl. heuristics)
- in practice, hard to make heuristics and other advanced search control efficient for symbolic search
  $\rightsquigarrow$ rarely used

Planning System Examples

Planning Systems: FF

FF (Hoffmann & Nebel, 2001)

- problem class: satisficing
- algorithm class: explicit search
- search direction: forward search
- search algorithm: enforced hill-climbing
- heuristic: FF heuristic (inadmissible)
- other aspects: helpful action pruning; goal agenda manager

$\rightsquigarrow$ breakthrough for heuristic search planning;
winner of IPC 2000

Planning Systems: LAMA

LAMA (Richter & Westphal, 2008)

- problem class: satisficing
- algorithm class: explicit search
- search direction: forward search
- search algorithm: restarting Weighted A* (anytime)
- heuristic: FF heuristic and landmark heuristic (inadmissible)
- other aspects: preferred operators; deferred heuristic evaluation; multi-queue search

$\rightsquigarrow$ still one of the leading satisficing planners;
winner of IPC 2008 and IPC 2011 (satisficing tracks)

Planning Systems: Fast Downward Stone Soup

Fast Downward Stone Soup (Helmert et al., 2011)

- problem class: optimal
- algorithm class: (portfolio of) explicit search
- search direction: forward search
- search algorithm: A^*
- heuristic: LM-cut; merge-and-shrink; landmarks; blind (admissible)

$\rightsquigarrow$ winner of IPC 2011 (optimal track)

Planning Systems: Madagascar-pC

Madagascar (Rintanen, 2014)

- problem class: satisficing
- algorithm class: SAT planning
- encoding: parallel ∃-step encoding
- SAT solver: using planning-specific action variable selection
- evaluation strategy: exponential horizons, parallelized probing
- other aspects: invariants

⇝ second place at IPC 2014 (agile track)

Planning Systems: SymBA*

SymBA* (Torralba, 2015)

- problem class: optimal
- algorithm class: symbolic search
- symbolic data structure: BDDs
- search direction: bidirectional
- search algorithm: mixture of (symbolic) Dijkstra and A*
- heuristic: perimeter abstractions/blind

$\rightsquigarrow$ winner of IPC 2014 (optimal track)

Planning Systems: Ragnarok

Ragnarok (Drexler et al., 2023)

- problem class: optimal
- algorithm class: portfolio of explicit and symbolic search
- search direction: forward and bidirectional search
- search algorithm: A^*, uniform cost search, decoupled search
- heuristic: saturated cost partitioning, post-hoc optimization

$\rightsquigarrow$ winner of IPC 2023 (optimal track)

Summary

Summary

big three classes of algorithms for classical planning:

- explicit search
  - design choices: search direction, search algorithm, search control (incl. heuristics)
- SAT planning
  - design choices: SAT encoding, SAT solver, evaluation strategy
- symbolic search
  - design choices: symbolic data structure + same ones as for explicit search