

Planning and Optimization

C1. Overview of Classical Planning Algorithms

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C1.1 The Big Three

C1.2 Explicit Search

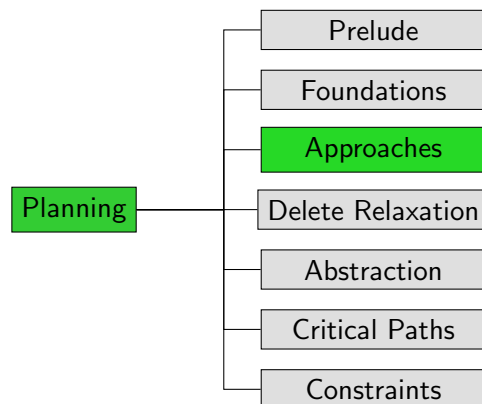
C1.3 SAT Planning

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Content of this Course



C1.1 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** ~↔ Chapters C2–C3, Parts D–G
- ▶ **SAT planning** ~↔ Chapters C4–C5
- ▶ **symbolic search** ~↔ Chapters C6–C7

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

C1.2 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 Ch. 5–19 of the [Foundations of Artificial Intelligence](https://dmi.unibas.ch/de/studium/computer-science-informatik/lehrangebot-fs23/lecture-foundations-of-artificial-intelligence-1/) course:
<https://dmi.unibas.ch/de/studium/computer-science-informatik/lehrangebot-fs23/lecture-foundations-of-artificial-intelligence-1/>

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

\rightsquigarrow Foundations of Artificial Intelligence course, Chapters 6 and 13

State Space vs. Search Space

- ▶ Planning tasks induce transition systems (a.k.a. state spaces) with an initial state, labeled transitions and goal states.
- ▶ State-space search searches state spaces with an initial state, a successor function and goal states.
- \rightsquigarrow looks like an obvious correspondence
- ▶ However, in planning as search, the state space being searched **can be different** from the state space of the planning task.
- ▶ When we need to make a distinction, we speak of
 - ▶ the **state space** of the planning task whose states are called **world states** vs.
 - ▶ the **search space** of the search algorithm whose states are called **search states**.

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 Chapters C2–C3

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

\rightsquigarrow Parts D–G

C1.3 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

↔ 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

C1.4 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( $V, I, O, \gamma$ ):
     $goal\_states := models(\gamma)$ 
     $reached_0 := \{I\}$ 
     $i := 0$ 
    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
         $i := i + 1$ 
  
```

↔ 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
 - ↪ rarely used

C1.5 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

↪ 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

↪ 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)

↪ winner of IPC 2011 (optimal track)

Planning Systems: Madagascar-pC

Madagascar (Rintanen, 2014)

- ▶ **problem class:** satisficing
- ▶ **algorithm class:** SAT planning
- ▶ **encoding:** parallel \exists -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

↪ winner of IPC 2014 (optimal track)

C1.6 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