

Planning and Optimization

B1. Overview of Classical Planning Algorithms

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— B1. Overview of Classical Planning Algorithms

B1.1 The Big Three

B1.2 Explicit Search

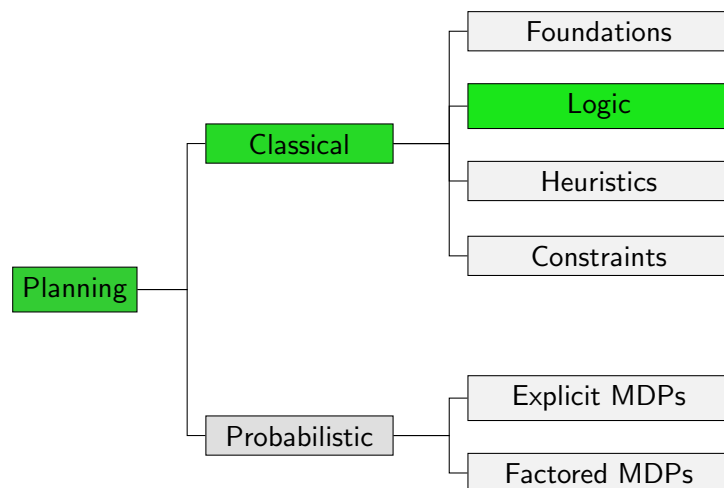
B1.3 SAT Planning

B1.4 Symbolic Search

B1.5 Planning System Examples

B1.6 Summary

Content of this Course



B1.1 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 B2–B4, Parts C–F
- ▶ **SAT planning** ~↔ Chapters B5–B6
- ▶ **symbolic search** ~↔ Chapters B7–B8

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

B1.2 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/en/academics/computer-science/courses-in-spring-semester-2020/lecture-foundations-of-artificial-intelligence/) course:
<https://dmi.unibas.ch/en/academics/computer-science/courses-in-spring-semester-2020/lecture-foundations-of-artificial-intelligence/>

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 B2–B4

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 C–F

B1.3 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

B1.4 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

B1.5 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: 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)

B1.6 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