

Planning and Optimization

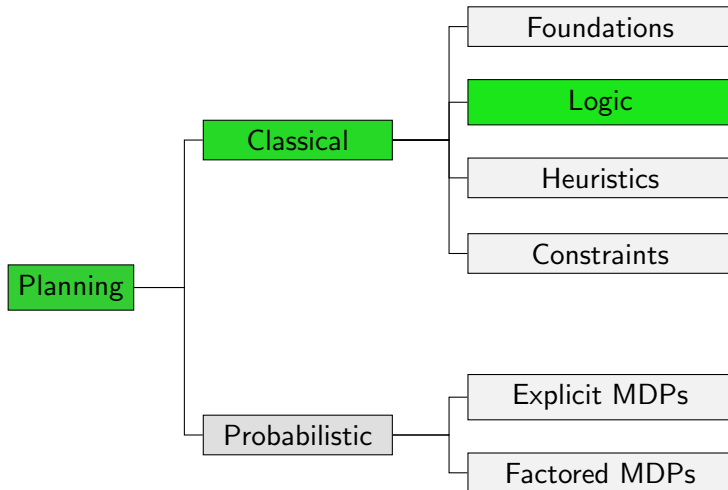
B1. Overview of Classical Planning Algorithms

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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** ~→ 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

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** course:
<https://dmi.unibas.ch/en/academics/computer-science/courses-spring-semester-2019/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.

~> 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

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 actions “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

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  
         $i := i + 1$ 
```

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            return no solution exists  
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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
 ~> 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

↪ 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)

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