

# What is planning?

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Problem of Action Selection

# Approaches in AI to Problem of Action Selection

- ① **Programming:** specify control by hand
- ② **Learning:** learn control from experience
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Planning is the **model-based** approach to action selection: produces the behavior from the model (**solves** the model)

Other famous model-based techniques: **SAT**, **CSP/COP**, **MILP**

# Classical Planning Model

**Classical planning model** is a tuple  $\mathcal{S} = \langle S, s_0, S_G, A, f, c \rangle$ , where

- Finite and discrete state space  $S$
- A **known initial state**  $s_0 \in S$
- A set  $S_G \subseteq S$  of **goal states**
- Actions  $A(s) \subseteq A$  applicable in each  $s \in S$
- A **deterministic transition function**  
$$s' = f(a, s) \text{ for } a \in A(s)$$
- Non-negative action costs  $c(a, s)$

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Different **models** obtained by relaxing assumptions in **blue**: planning with preferences, conformant planning, contingent planning, FOND, MDPs, POMDPs, ...



# Language for Classical Planning: STRIPS

A STRIPS **Planning task** is 5-tuple  $\Pi = \langle F, O, c, I, G \rangle$ :

- $F$ : finite set of **atoms** (boolean variables)
- $O$ : finite set of **operators** (actions) of form  $\langle Add, Del, Pre \rangle$   
(Add/Delete/Preconditions; subsets of atoms)
- $c : O \mapsto \mathbb{R}^{0+}$  captures **operator cost**
- $I$ : **initial state** ( subset of atoms )
- $G$ : **goal description** ( subset of atoms )

# Language for Classical Planning: SAS<sup>+</sup>

- A SAS<sup>+</sup> **Planning task** is 5-tuple  $\Pi = \langle V, O, c, I, G \rangle$ :
- $V$ : finite set of **finite-domain multi-valued variables**
  - $O$ : finite set of **operators** (actions) of form  $\langle pre, eff \rangle$   
(Preconditions/Effects; partial variable assignments)
  - $c : O \mapsto \mathbb{R}^{0+}$  captures **operator cost**
  - $I$ : **initial state** ( variable assignment )
  - $G$ : **goal description** ( partial variable assignment )

**Plan**: sequence of applicable actions that maps  $I$  into a state consistent with  $G$

# From Language to Models

A STRIPS **Planning task**  $\Pi = \langle F, O, c, I, G \rangle$  determines state model  $\mathcal{S}(\Pi)$  where

- the states  $s \in \mathcal{S}$  are **collections of atoms** from  $F$
- the initial state  $s_0$  is  $I$
- the goal states  $s$  are such that  $G \subseteq s$
- the actions  $a$  in  $A(s)$  are ops in  $O$  s.t.  $Pre(a) \subseteq s$
- the next state is  $s' = s - Del(a) + Add(a)$
- action costs  $c(a, s) = c(a)$

♠ **Solutions** of  $\mathcal{S}(\Pi)$  are **plans** of  $\Pi$

# Planning and Model-based Reinforcement Learning

- **Forward model:**  $(a, s_i) \rightarrow s_{i+1} = s_i - Del(a) + Add(a)$  if  $Pre(a) \subseteq s_i$ ,  
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- Rewards approximate  $-c^*(s_{i+1})$ , the negative true cost of reaching the goal  
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- Non-deterministic setting is (slightly) more complicated
- In what follows: the benefit of the more informative model

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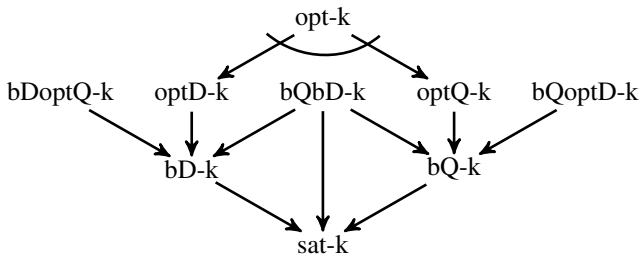
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- **Diverse** planning: variety of problems, aiming at obtaining diverse set of plans, considering plan quality as well



## Beyond Classical Planning: Some computational problems

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- **Temporal** planning: find which actions to execute and their consistent schedule
- **Probabilistic** planning: find a policy, mapping of states to actions, optimizing, e.g.
  - expected total rewards over a finite horizon
  - expected average rewards over an infinite horizon
  - expected discounted rewards over an infinite horizon

# Why is planning difficult?

- Solutions to classical planning problems are **paths from an initial state to a goal state** in the **transition graph**
  - Efficiently solvable by Dijkstra's algorithm in  $O(|V| \log |V| + |E|)$  time
  - Why don't we solve all planning problems this way?
- State spaces may be **huge**:  $10^{100}$  states is not uncommon
  - Constructing the transition graph is infeasible!
  - Planning algorithms try to **avoid constructing whole graph**, use concise representation for many transitions as a single action
  - Complexity measured in terms of (concise) input size: simplest case is PSPACE-complete
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- **Model Checking Planning** (1998 - ...): search state space  $\mathcal{S}(P)$  with 'symbolic' BrFS where sets of states represented by formulas implemented by BDDs

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- Most common relaxation in planning,  $\Pi^+$ , obtained by **dropping delete-lists** from ops in  $\Pi$ . If  $c^*(\Pi)$  is optimal cost of  $\Pi$ , then

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- Some state-of-the-art planners still rely on  $\Pi^+$  ...

# Heuristics for Classical Planning – Overview

## Delete-relaxation

- $h^+$  (Hoffmann & Nebel, '01)
- $h^{max}$  and  $h^{add}$  (Bonet & Geffner, '01)
- $h^{FF}$  (Hoffmann & Nebel, '01)
- $h^{pmax}$  (Mirkis & Domshlak, '07)
- $h^{sa}$  (Keyder & Geffner, '08)
- Semi-Relaxed Plan Heuristics (Keyder et al., '12,'14; Haslum '13; Hoffman et al., '14)
- Red-black Planning Heuristics (Katz et al., '13a,b; Katz & Hoffman '14; Domshlak et al., '15; Gnad & Hoffman, '15; Speicher et al., '17; Katz '19; Fiser et al, '21)

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## Critical path

- $h^m$  (Haslum & Geffner, '00) with  $h^1 \equiv h^{max}$

# Heuristics for Classical Planning – Overview

## Abstractions

- [PDBs](#) (Edelkamp, '01; Haslum et al., '05, '07)
- [Merge & Shrink](#) (Helmert et al., '07,'14; Katz et al, '12; Sievers et al., '14)
- [Implicit Abstractions](#) (Katz & Domshlak, '08, '10)
- [Counterexample-guided Abstraction Refinement \(CEGAR\)](#) (Seipp & Helmert, '13, '14, '18)

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## Landmarks

- Landmark count (Hoffmann et al., '04)
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## Potential Heuristics

- $h^{pot}$  (Pommerening et al., '15; Seipp et al., '15)

# Search Pruning Techniques

Partial Order Reduction (Alkhazraji et al., '12; Wehrle et al., '13; Wehrle & Helmert, '14; Roeger et al., '20)

- Exploit independence of operators
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Each of these techniques can lead to exponential reduction of the search space

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- Winners get all the glory! (and some cash prizes)
- Huge driver for research in planning for the last 20+ years.

# Famous Planners: IPC Top Performers

- Cost-optimal:
  - FDSS (IPC'11)
  - SymBA\* (IPC'14)
  - Delfi (IPC'18)
- Satisficing:
  - LAMA (IPC'08,11)
  - IBaCoP (IPC'14)
  - Mercury (IPC'14)
  - FDSS (IPC'18)
  - LAPKT-DUAL-BFWS (IPC'18)
- Probabilistic:
  - Prost (Since 2014)
  - Prost-DD (IPC'18)
  - Random-Bandit (IPC'18)
- Temporal:
  - YAHSP3-MT (IPC'14)
  - Temporal-FD (IPC'14)



# Major Planning Toolkits/Systems/Families

- Fast-Forward (better known as FF): Classical satisficing, numeric, conformant, contingent planners (Hoffmann & Nebel, '01)
- Fast Downward: Classical cost-optimal, satisficing, agile, cost-bounded. Variants built on top of Fast Downward include: OSP, FOND, probabilistic, temporal, ... (Helmert, '06)
- Lightweight Automated Planning ToolKiT (LAPKT): Classical cost-optimal, satisficing, agile (Ramirez, Lipovetzky, and Muise, '15)
- LPG: Classical satisficing, numeric, temporal, diverse, ... (Gerevini & Serina, '02)
- SHOP2: HTN planning (Nau et al., '03)
- OPTIC: Temporal planning (Benton et al., '12)
- Many many more ...

# Non-IPC Planners and Tools

- Planning service (and docker) for cost-optimal, agile, satisficing, top-k, top-quality, diverse planning (by Katz et al.)
- Planner in the cloud, collection of tools and APIs (by Muise et al.)
- Forbid-Iterative Collection of planners for top-k, top-quality, diverse planning (Katz & Sohrabi, '20; Katz et al., '20a,'20b,'22)
- Top-k planners:  $K^*$  (Katz et al., '18) and SymK (Speck et al., '20)
- OSP planners (Katz et al., '19; Katz & Keyder, '19; Speck & Katz, '21)
- FOND planner PRP (Muise et al., '12,'14a,b)
- Pyperplan: Lightweight python-based planner developed for educational purposes (Alkhazraji et al., '20)

## Other Major Community Efforts

- Slack workspace
- ICAPS web site
- Community GitHub
- PlanUtils: General library for setting up linux-based environments for developing, running, and evaluating planners
- Planning Wiki (initial effort), including a list of planners

