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Problem of Action Selection

Approaches in AI to Problem of Action Selection

1. Programming: specify control by hand
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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

$$s' = f(a, s) \text{ for } a \in A(s)$$

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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)

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 $s \in S$ 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 Π

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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- In what follows: the benefit of the more informative model

Classical Planning: Computational problems

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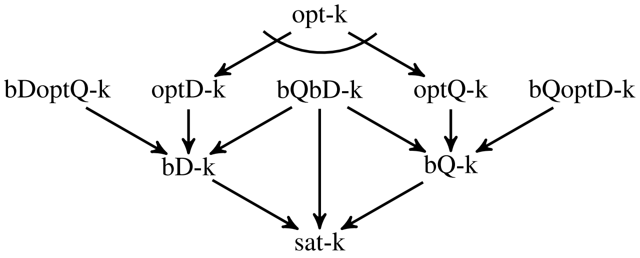
- Diverse planning: variety of problems, aiming at obtaining diverse set of plans, considering plan quality as well



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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- Some state-of-the-art planners still rely on Π^+ ...

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 $h^{1} \equiv h^{max}$

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Abstractions

- PDBs (Edelkamp, '01; Haslum et al., '05, '07)
- Merge & Shrink (Helmert et al., '07,'14; Katz et al, '12; Sievers et al., '14)
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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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- 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,b)
- 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

All links