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Planning is the art and practice of thinking before acting: of reviewing the courses of action one has available and predicting their expected (and unexpected) results to be able to choose the course of action most beneficial with respect to one's goals.

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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)

Language for Classical Planning: SAS$^+$

A SAS$^+$ 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 $s \in S$ 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: $(a, s_i) \to s_{i+1} = s_i - Del(a) + Add(a)$ if $Pre(a) \subseteq s_i$,
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- In what follows: the benefit of the more informative model

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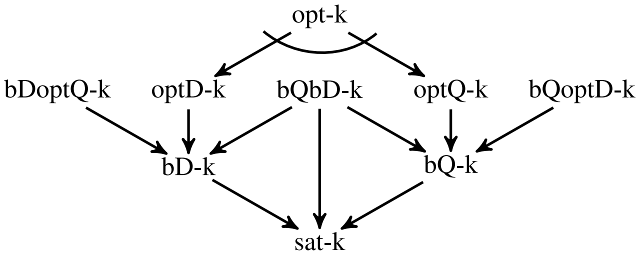
- Diverse planning: variety of problems, aiming at obtaining diverse set of plans, considering plan quality as well



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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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- 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)
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Potential Heuristics

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

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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,'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

All links