Foundations of AI

15. Planning

The art and practice of thinking before acting

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What is Action Planning?

Planning Formalisms

Current Approaches to Planning

Iterative Deepening Planning

Heuristic Search Planning

Summary and Outlook
What is planning?

- Planning is the process of generating (possibly partial) representations of future behavior prior to the use of such plans to constrain or control that behavior:

  *Planning is the art and practice of thinking before acting* [Haslum]

- The outcome is usually a set of actions, with temporal and other constraints on them, for execution by some agent or agents.
Planning tasks

Given a **current state**, a set of possible **actions**, a specification of the **goal conditions**, which **plan** transforms the **current state** into a **goal state**?
Another planning task: *Logistics*

Given a road map, and a number of trucks and airplanes, make a plan to transport objects from their start to their goal destinations.
Domain-independent action planning

- Start with a **declarative specification** of the planning problem
- Use a **domain-independent planning** system to solve the planning problem

* Domain-independent planners are **generic problem solvers**

- **Issues:**
  - Good for evolving systems and those where performance is not critical
  - Running time should be comparable to specialized solvers
  - Solution quality should be acceptable
  - . . . at least for all the problems we care about
Planning problem classes

**Effects:** deterministic, non-deterministic, probabilistic

**Observability** of the environment: complete, partial, not observable

**Horizon:** finite, infinite

**Objective:** reach goal, maintain property, maximize probability of reaching a state, maximize expected reward

**Classical Planning:** deterministic actions, complete observability (in the beginning), finite horizon, reach goal

**Conditional Planning:** non-deterministic actions, complete observability, finite horizon, reach goal

**Markov Decision Processes (MDP):** probabilistic actions, complete obs., maximize expected reward

...
Action planning is not . . .

- **Problem solving by search**, where we describe a problem by a state space and then implement a program to search through this space
  - in action planning, we specify the problem declaratively (using logic) and then solve it by a general planning algorithm
- **Program synthesis**, where we generate programs from specifications or examples
  - in action planning we want to solve just one instance and we have only very simple action composition (i.e., sequencing, perhaps conditional and iteration)
- **Scheduling**, where all jobs are known in advance and we only have to fix time intervals and machines
  - instead we have to find the right actions and to sequence them

~~️ Of course, there is interaction with these areas!
The basic STRIPS formalism

STRIPS: Stanford Research Institute Problem Solver

- $S$ is a first-order signature and $\Sigma_S$ denotes the set of ground atoms over the signature (also called facts or fluents).
- $\Sigma_{S,V}$ is the set of atoms over $S$ using variable symbols from the set of variables $V$.
- A first-order STRIPS state $S$ is a subset of $\Sigma_S$ denoting a complete theory or model (using CWA).
- A planning task (or planning instance) is a 4-tuple $\Pi = \langle S, O, I, G \rangle$, where
  - $O$ is a set of operator (or action types)
  - $I \subseteq \Sigma_S$ is the initial state
  - $G \subseteq \Sigma_S$ is the goal specification
- No domain constraints (although present in original formalism)
Operators, actions & state change

- **Operator:**
  \[ o = \langle \text{para}, \text{pre}, \text{eff} \rangle, \]
  with \( \text{para} \subseteq V, \text{pre} \subseteq \Sigma_{S,V}, \text{eff} \subseteq \Sigma_{S,V} \cup \neg \Sigma_{S,V} \)
  (element-wise negation) and all variables in \( \text{pre} \) and \( \text{eff} \) are listed in \( \text{para} \).
  Also: \( \text{pre}(o), \text{eff}(o) \).
  \( \text{eff}^+ = \) positive effect literals
  \( \text{eff}^- = \) negative effect literals

- **Operator instance** or **action:** Operator with empty parameter list (**instantiated schema**)!

- **State change** induced by action:
  \[
  \text{App}(S, o) = \begin{cases} 
  S \cup \text{eff}^+(o) - \neg \text{eff}^-(o) & \text{if } \text{pre}(o) \subseteq S \land \\
  \text{undefined} & \text{otherwise}
  \end{cases} 
  \]
Example formalization: *Logistics*

- Logical atoms: $at(O, L)$, $in(O, V)$, $airconn(L1, L2)$, $street(L1, L2)$, $plane(V)$, $truck(V)$

- Load into truck: *load*
  - Parameter list: $(O, V, L)$
  - Precondition: $at(O, L)$, $at(V, L)$, $truck(V)$
  - Effects: $\neg at(O, L)$, $in(O, V)$

- Drive operation: *drive*
  - Parameter list: $(V, L1, L2)$
  - Precondition: $at(V, L1)$, $truck(V)$, $street(L1, L2)$
  - Effects: $\neg at(V, L1)$, $at(V, L2)$

- …

- Some constant symbols: $t1$, $s$, $c$, $p1$ with $truck(t1)$ and $street(s, c)$

- Action: $drive(t1, s, c)$
Plans & successful executions

- A **plan** $\Delta$ is a sequence of actions.
- State resulting from **executing a plan**:

  \[
  \text{Res}(S, \langle \rangle) = S
  \]

  \[
  \text{Res}(S, (o; \Delta)) = \begin{cases} 
  \text{Res}(\text{App}(S, o), \Delta) & \text{if } \text{App}(S, o) \\
  \text{undefined} & \text{otherwise}
  \end{cases}
  \]

- **Plan** $\Delta$ is **successful** or **solves** a planning task if $\text{Res}(I, \Delta)$ is defined and $G \subseteq \text{Res}(I, \Delta)$. 
A small *Logistics* example

**Initial state:** \( S = \{ \text{at}(p1, c), \text{at}(p2, s), \text{at}(t1, c), \text{at}(t2, c), \text{street}(c, s), \text{street}(s, c) \} \)

**Goal:** \( G = \{ \text{at}(p1, s), \text{at}(p2, c) \} \)

**Successful plan:** \( \Delta = \langle \text{load}(p1, t1, c), \text{drive}(t1, c, s), \text{unload}(p1, t1, s), \text{load}(p2, t1, s), \text{drive}(t1, s, c), \text{unload}(p2, t1, c) \rangle \)

Other successful plans are, of course, possible
Simplifications: Datalog- and propositional STRIPS

- STRIPS as described above allows for unrestricted first-order terms, i.e., arbitrarily nested function terms

→ Infinite state space

- Simplification: No function terms (only 0-ary = constants)

→ Datalog-STRIPS

- Simplification: No variables in operators (= actions)

→ Propositional STRIPS

→ used in planning algorithms nowadays (but specification is done using Datalog-STRIPS)
Beyond STRIPS

Even when keeping all the restrictions of classical planning, one can think of a number of *extensions* of the planning language.

- **General logical formulas as preconditions**: Allow all Boolean connectors and quantification

- **Conditional effects**: Effects that happen only if some additional conditions are true. For example, when *pressing the accelerator pedal*, the effects depends on which gear has been selected (no, reverse, forward).

- **Multi-valued state variables**: Instead of 2-valued Boolean variables, multi-valued variables could be used

- ...
PDDL: The planning domain description language

- Since 1998, there exists a bi-annual *scientific competition* for action planning systems.
- In order to have a common language for this competition, **PDDL** has been created (originally by Drew McDermott)
- Meanwhile, version 3.1 (IPC-2008) with most of the features mentioned.
- Sort of standard language by now.
- We will stick to STRIPS here.
Current Approaches to Planning

- In 1992, Kautz and Selman introduced planning as satisfiability

  Encode possible \( k \)-step plans as Boolean formulas and use an iterative deepening search

- In 1995, Blum and Furst introduced planning graphs

  iterative deepening approach that prunes the search space using a graph-structure

- In 1996, McDermott proposed to use (again) an heuristic estimator to control the selection of actions, similar to GPS

- Geffner (1997) followed up with a propositional, simplified version (HSP) and Hoffmann & Nebel (2001) with an extended version integrating strong pruning. (FF)

- Even better system is FD by Helmert

  Heuristic planners seem to be the most efficient sub-optimal planners these days
Iterative Deepening Search

1. Initialize $k = 0$
2. Try to construct a plan of length $k$ exhaustively
3. If unsuccessful, increment $k$ and goto step 2.
4. Otherwise return plan

~~> Finds shortest plan
~~> Needs to prove that there are no plans of length 1, 2, \ldots $k - 1$ before a plan of length $k$ is produced.
Planning as Satisfiability

- Take the dual perspective: Consider all models satisfying a particular formula as plans
- Similar to what is done in the generic reduction that shows NP-hardness of SAT (simulation of a computation on a Turing machine)
- Build formula for $k$ steps, check satisfiability, and increase $k$ until a satisfying assignment is found
- Use time-indexed propositional atoms for facts and action occurrences
- Formulate constraints that describe what it means that a plan is successfully executed:
  - Only one action per step
  - If an action is executed then their preconditions were true and the effects become true after the execution
  - If a fact is not affected by an action, it does not change its value (frame axiom)
Planning as Satisfiability: Example

- **Fact atoms:**
  \[ at(p1, s)_i, at(p1, c)_i, at(t1, s)_i, at(t1, c)_i, in(p1, t1)_i \]

- **Action atoms:**
  \[ move(t1, s, c)_i, move(t1, c, s)_i, load(p1, s)_i, \ldots \]

- **Initial state:** \[ at(p1, c)_1, at(p2, s)_1, at(t1, c)_1 \]

- **Only one action per step:**
  \[ \bigwedge_{i,x,y} \neg (unload(t1, p1, x)_i \land load(p1, t1, y)_i) \land \ldots \]

- **Preconditions:**
  \[ \bigwedge_{i,x} (unload(p1, t1, x)_i \rightarrow in(p1, t1)_{i-1}) \land \ldots \]

- **Effects:**
  \[ \bigwedge_{i,x} (unload(p1, t1, x)_i \rightarrow \neg in(p1, t1)_i \land at(p1, x)_i) \land \ldots \]

- **Frame axioms:**
  \[ \bigwedge_{i,x,y,z} (\neg move(t1, x, y)_i \rightarrow (at(t1, z)_{i-1} \leftrightarrow at(t1, z)_i)) \land \ldots \]

\[ \leadsto \] A satisfying truth assignment corresponds to a **plan** (use the true action atoms)
Advantages of the Approach

- Flexible search strategy
- Can make use of SAT solver technology
- ... and automatically profits from advances in this area
- Can express constraints on intermediate states
- Can use logical axioms to express additional constraints, e.g., to prune the search space
Planning Based on Planning Graphs

Main ideas:

- Describe *possible* developments in a graph structure (use only positive effects)
  - Layered graph structure with fact and action levels
  - **Fact level (F level):** positive atoms (the first level being the initial state)
  - **Action level (A level):** actions that can be applied using the atoms in the previous fact level
  - **Links:** precondition and effect links between the two layers

- Record **conflicts** caused by negative effects and propagate them

- **Extract a plan** by choosing only non-conflicting parts of the graph (allowing for parallel actions)

- Parallelism (for non-conflicting actions) is a great boost for the efficiency.
Example Graph

\[ I = \{ \text{at}(p1, c), \text{at}(p2, s), \text{at}(t1, c) \}, \quad G = \{ \text{at}(p1, s), \text{in}(p2, t1) \} \]
Example Graph

- $I = \{ \text{at}(p_1, c), \text{at}(p_2, s), \text{at}(t_1, c) \}$, $G = \{ \text{at}(p_1, s), \text{in}(p_2, t_1) \}$
- All applicable actions are included
Example Graph

- \( I = \{ at(p1, c), at(p2, s), at(t1, c) \} \), \( G = \{ at(p1, s), in(p2, t1) \} \)
- All applicable actions are included
- In order to propagate unchanged properties, use *noop* action, denoted by *
Example Graph

- $I = \{at(p1, c), at(p2, s), at(t1, c)\}$, $G = \{at(p1, s), in(p2, t1)\}$
- All applicable actions are included
- In order to propagate unchanged properties, use *noop* action, denoted by *
- Expand graph
Example Graph

- $I = \{ at(p_1, c), at(p_2, s), at(t_1, c) \}$,
- $G = \{ at(p_1, s), in(p_2, t_1) \}$
- All applicable actions are included
- In order to propagate unchanged properties, use *noop* action, denoted by *
- Expand graph as long as not all goal atoms are in the fact level
Plan Extraction

- Start at last fact level with goal atoms
- Select a minimal set of **non-conflicting actions** that generate the goal atoms
  - Two actions are **conflicting** if they have complementary effects or if one action deletes or asserts a precondition of the other action
- Use the preconditions of the selected actions as **(sub-)goals** on the next lower fact level
- **Backtrack** if no non-conflicting choice is possible
- If all possibilities are exhausted, the graph has to be **extended** by another level.
Extracting From the Example Graph

Start with \textit{goals} at highest fact level
Extracting From the Example Graph

Select minimal set of actions & corresponding subgoals
Wrong choice leading to conflicting actions
Extracting From the Example Graph

*Other choice*, but no further selection possible
Extracting From the Example Graph

Final selection
Propagation of Conflict Information: Mutex pairs

**Idea:** Try to identify as many pairs of conflicting choices as possible in order to **prune** the search space.

- Any pair of conflicting actions is **mutex** (mutually exclusive).
- A pair of atoms is **mutex** at F-level $i > 0$ if all ways of making them true involve actions that are **mutex** at the A-level $i$.
- A pair of actions is also **mutex** if their preconditions are.
- ... Actions that are **mutex** cannot be executed at the same time.
- Facts that are **mutex** cannot be both made true at the same time.
- Never choose **mutex pairs** during **plan extraction**.

**Plan graph search** and **mutex propagation** make planning 1–2 orders of magnitude more **efficient** than conventional methods.
Disadvantages of Iterative Deepening Planners

- If a domain contains many symmetries, proving that there is no plan up to length of $k - 1$ can be very costly.
- Example: *Gripper* domain:
  - there is one robot with two grippers
  - there is room $A$ that contains $n$ balls
  - there is another room $B$ connected to room $A$
  - the goal is to bring all balls to room $B$

- Obviously, the plan must have a length of at least $n/2$, but ID planners will try out all permutations of actions for shorter plans before noting this.

⇒ Give better *guidance*
Heuristic Search Planning

- Use an **heuristic estimator** in order to select the next action or state
- Depending on the **search scheme** and the **heuristic**, the plan might not be the shortest one
  - It is often easier to go for **sub-optimal** solutions (remember **Logistics**)

![Graph comparing heuristic search planner vs. iterative deepening on Gripper](image)
Deriving Heuristics: Relaxations

- General principle for deriving heuristics:
  - Define a simplification (relaxation) of the problem and take the difficulty of a solution for the simplified problem as an heuristic estimator
- Example: *straight-line distance* on a map to estimate the travel distance
- Example: *decomposition* of a problem, where the components are solved ignoring the interactions between the components, which may incur additional costs
- In planning, one possibility is to ignore *negative effects*
Ignoring Negative Effects: Example

- In **Logistics**: The negative effects in *load* and *drive* are ignored:
  - **Simplified** load operation: $load(O, V, P)$
    - Precondition: $at(O, P), at(V, P), truck(V)$
    - Effects: $\neg at(O, P), in(O, V)$
  - After loading, the package is still at the place and also inside the truck
  - **Simplified** drive operation: $drive(V, P1, P2)$
    - Precondition: $at(V, P1), truck(V), street(P1, P2)$
    - Effects: $\neg at(V, P1), at(V, P2)$
  - After driving, the truck is in two places!
  - We want the length of the shortest *relaxed* plan $\sim h^+(s)$
  - How difficult is *monotonic* planning?
Monotonic Planning

Assume that all effects are positive

- finding **some plan** is easy:
  - Iteratively, execute all actions that are *executable* and have not all their effects made true yet
  - If no action can be executed anymore, check whether the goal is satisfied
  - If not, there is no plan
  - Otherwise, we have a plan containing each action only once

- Finding the **shortest plan**: easy or difficult?
  \( \rightarrow \) NP-hard
  \( \sim \) Consider approximations to \( h^+ \).
The FF Heuristic

- Use the *planning graph method* to construct a plan for the monotone planning problem
- Can be done in poly. time (and is *empirically very fast*)
- Generates an *optimal parallel plan* that might not be the best sequential plan
  - The number of actions in this plan is used as the heuristic estimate (more *informative* than the parallel plan length, but not *admissible*)
  - Appears to be a good approximation
The FF System

- **FF** (*Fast Forward*) is a *heuristic search planner* developed in Freiburg.

- **Heuristic**: Goal distances are estimated by *solving a relaxation* of the task in every search state (ignoring negative effects) – the solution is *not minimal*, however!

- **Search strategy**: *Enforced hill-climbing*

- **Pruning**: Only a fraction of each states successors are considered: only those *successors* that would be *generated by the relaxed solution* – with a fall-back strategy considering all successors if we are unsuccessful

⇒ FF used to be one of the fastest planners around

→ Meanwhile, there is FD, which contains more domain analysis and which is faster because of this
Runtime: *Logistics* in the 2000 competition
Summary and Outlook

- Planning generates representation of future behavior
- Classical planning assumes full observability and deterministic actions
- Compared with MDPs, one can deal with much larger state spaces
- Current algorithmic approaches are
  - planning as satisfiability
  - planning graphs
  - heuristic search planning, which seems to be the most promising approach for satisficing planning
- Many possible extensions . . .
- Applications in robotic, video games, . . .

⇒ Come to the Foundations of AI group, if you are interested in pursuing research in this area