Artificial Intelligence

13. Introduction to Planning

How to Describe Arbitrary Search Problems

Prof Sara Bernardini
bernardini@diag.uniroma1.it
www.sara-bernardini.com

SAPIENZA
UNIVERSITÀ DI ROMA

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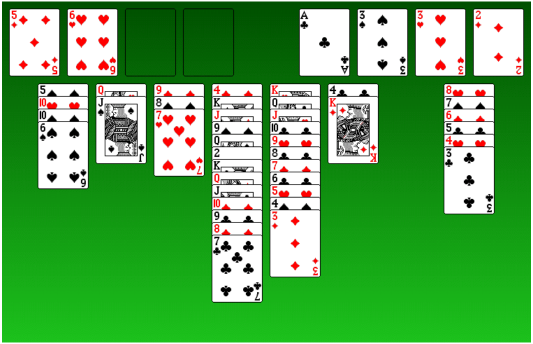
Agenda

1. Introduction
2. The History of Planning
3. The STRIPS Planning Formalism
4. Why Complexity Analysis?
5. Planning Complexity
6. Conclusion

Reminder: Classical Search Problems (Chapters 3 & 4)



- States: Card positions (*position_Jspades=Qhearts*).
- Actions: Card moves (*move_Jspades_Qhearts_freecell4*).
- Initial state: Start configuration.
- Goal states: All cards "home".
- Solution: Card moves solving this game.

Planning

Ambition:

Write one program that can solve all classical search problems.

Types of description

- The **blackbox description** of a problem Π is an API (a programming interface) providing functionality allowing to construct the state space: InitialState(), GoalTest(s), ...

  $\rightarrow$ "Specifying the problem" $=$ programming the API.

- The **declarative description** of Π comes in a problem description language. This allows to implement the API, and much more.

  $\rightarrow$ "Specifying the problem" $=$ writing a problem description.

$\rightarrow$ Here, "problem description language" $=$ planning language.

"Planning Language"?

How does a planning language describe a problem?

- A *logical description* of the possible states (vs. Blackbox: data structures). E.g.: predicate $Eq(.,.)$.
- A *logical description* of the initial state I (vs. data structures). E.g.: $Eq(x, 1)$.
- A *logical description* of the goal condition G (vs. a goal-test function). E.g.: $Eq(x, 2)$.
- A *logical description* of the set A of actions in terms of preconditions and effects (vs. functions returning applicable actions and successor states).
  E.g.: "increment x: pre $Eq(x, 1)$, eff $Eq(x, 2) \wedge \neg Eq(x, 1)$".

$\rightarrow$ Solution (plan) $=$ sequence of actions from A, transforming I into a state that satisfies G. E.g.: "increment x".

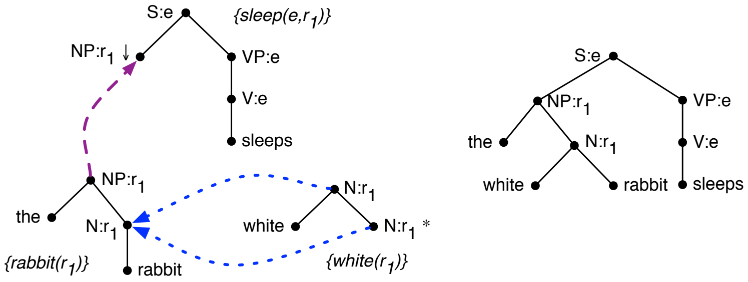
"Planning Language"?

Disclaimer:

→ Planning languages go way beyond classical search problems. There are variants for inaccessible, stochastic, dynamic, continuous, and multi-agent settings.

- We focus on classical search for simplicity (combined with practical relevance).
- For a comprehensive overview, see [Ghallab *et al.* (2004)].

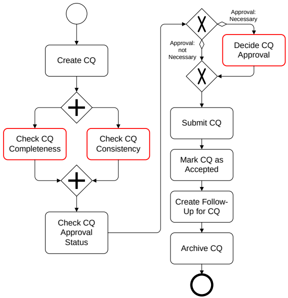
Application: Natural Language Generation



- **Input:** Tree-adjoining grammar, intended meaning.
- **Output:** Sentence expressing that meaning.

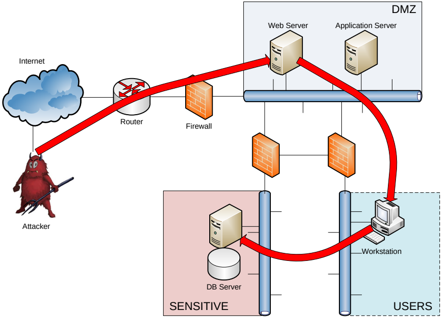
Application: Business Process Templates at SAP

Action name	precondition	effect
Check CQ Completeness	CQ.archiving:notArchived	CQ.completeness:complete OR CQ.completeness:notComplete
Check CQ Consistency	CQ.archiving:notArchived	CQ.consistency:consistent OR CQ.consistency:notConsistent
Check CQ Approval Status	CQ.archiving:notArchived AND CQ.approval:notChecked AND CQ.completeness:complete AND CQ.consistency:consistent	CQ.approval:necessary OR CQ.approval:notNecessary
Decide CQ Approval	CQ.archiving:notArchived AND CQ.approval:necessary	CQ.approval:granted OR CQ.approval:notGranted
Submit CQ	CQ.archiving:notArchived AND (CQ.approval:notNecessary OR CQ.approval:granted)	CQ.submission:submitted
Mark CQ as Accepted	CQ.archiving:notArchived AND CQ.submission:submitted	CQ.acceptance:accepted
Create Follow-Up for CQ	CQ.archiving:notArchived AND CQ.acceptance:accepted	CQ.followUp:documentCreated
Archive CQ	CQ.archiving:notArchived	CQ.archiving:archived



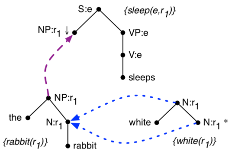
- **Input:** SAP-scale model of behavior of activities on Business Objects, process endpoint.
- **Output:** Process template leading to this point.

Application: Automatic Hacking

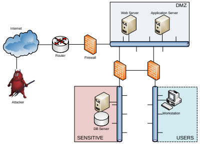


- **Input:** Network configuration, location of sensible data.
- **Output:** Sequence of exploits giving access to that data.

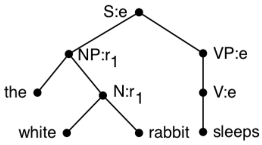
Planning!

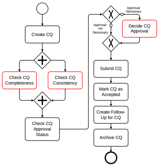


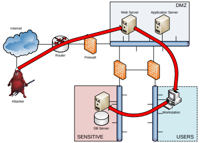
Action name	precondition	effect
Check CQ Completeness	CQ.archiving:notArchived	CQ.completeness:complete OR CQ.completeness:notComplete
Check CQ Consistency	CQ.archiving:notArchived	CQ.consistency:consistent OR CQ.consistency:notConsistent
Check CQ Approval Status	CQ.archiving:notArchived AND CQ.approval:notChecked AND CQ.completeness:complete AND CQ.consistency:consistent	CQ.approval:necessary OR CQ.approval:notNecessary
Decide CQ Approval	CQ.archiving:notArchived AND CQ.approval:necessary	CQ.approval:granted OR CQ.approval:notGranted
Submit CQ	CQ.archiving:notArchived AND (CQ.approval:notNecessary OR CQ.approval:granted)	CQ.submission:submitted
Mark CQ as Accepted	CQ.archiving:notArchived AND CQ.submission:submitted	CQ.acceptance:accepted
Create Follow-Up for CQ	CQ.archiving:notArchived AND CQ.acceptance:accepted	CQ.followUp:documentCreated
Archive CQ	CQ.archiving:notArchived	CQ.archiving:archived



Planning Domain Definition Language (PDDL) $\mapsto$ Planning System







Reminder: General Problem Solving, Pros and Cons

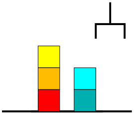
- **Powerful:** In some applications, generality is absolutely necessary. (E.g. SAP)
- **Quick:** Rapid prototyping: 10s lines of problem description vs. 1000s lines of C++ code. (E.g. language generation)
- **Flexible:** Adapt/maintain *the description*. (E.g. network security)
- **Intelligent:** Determines automatically how to solve a complex problem effectively! (The ultimate goal, no?!)

- **Efficiency loss:** Without any domain-specific knowledge about Chess, you don't beat Kasparov . . .

  → Trade-off between "automatic and general" vs. "manualwork but effective".

How to make fully automatic algorithms effective?

ps. “Making Fully Automatic Algorithms Effective”



- n blocks, 1 hand.
- A single action either takes a block with the hand or puts a block we're holding onto some other block/the table.

blocks	states
1	1
2	3
3	13
4	73
5	501
6	4051
7	37633
8	394353

blocks	states
9	4596553
10	58941091
11	824073141
12	12470162233
13	202976401213
14	3535017524403
15	65573803186921
16	1290434218669921

$\rightarrow$ State spaces typically are huge even for simple problems.

$\rightarrow$ In other words: Even solving “simple problems” automatically (without help from a human) requires a form of intelligence. With blind search, even the largest super-computer in the world won't scale beyond 20 blocks!

Algorithmic Problems in Planning

Satisficing Planning

Input: A planning task Π.
Output: A plan for Π, or "unsolvable" if no plan for Π exists.

Optimal Planning

Input: A planning task Π.
Output: An *optimal* plan for Π, or "unsolvable" if no plan for Π exists.

$\rightarrow$ The techniques successful for either one of these are almost disjoint. And satisficing planning is *much* more effective in practice.

$\rightarrow$ Programs solving these problems are called (optimal) planners, planning systems, or planning tools.

In the Beginning . . .

. . . Man invented Robots:

"Planning" as in "the making of plans by an autonomous robot".

In a little more detail:

- Newell and Simon (1963) introduced general problem solving.
- *. . . not much happened (well not much we still speak of today) . . .*
- Stanford Research Institute developed a robot named "Shakey".
- They needed a "planning" component taking decisions.
- They took inspiration from general problem solving and theorem proving, and called the resulting algorithm "STRIPS" (Stanford Research Institute Problem Solver).

And then:

History of Planning Algorithms

Compilation into Logics/Theorem Proving:

- **Popular when:** Stone Age – 1990.
- **Approach:** *From planning task description, generate FOL formula φ that is satisfiable iff there exists a plan; use a theorem prover on φ.*
- **Keywords/cites:** Situation calculus, frame problem, ...

Partial-Order Planning:

- **Popular when:** 1990 – 1995.
- **Approach:** *Starting at goal, extend partially ordered set of actions by inserting achievers for open sub-goals, or by adding ordering constraints to avoid conflicts.*
- **Keywords/cites:** UCPOP [Penberthy and Weld (1992)], causal links, flaw-selection strategies, ...

History of Planning Algorithms, ctd.

GraphPlan:

- **Popular when:** 1995 – 2000.
- **Approach:** *In a forward phase, build a layered "planning graph" whose "time steps" capture which pairs of actions can achieve which pairs of facts; in a backward phase, search this graph starting at goals and excluding options proved to not be feasible.*
- **Keywords/cites:** [Blum and Furst (1995, 1997); Koehler *et al.* (1997)], action/fact mutexes, step-optimal plans, . . .

Planning as SAT:

- **Popular when:** 1996 – today.
- **Approach:** *From planning task description, generate propositional CNF formula φ_k that is satisfiable iff there exists a plan with k steps; use a SAT solver on φ_k, for different values of k.*
- **Keywords/cites:** [Kautz and Selman (1992, 1996); Rintanen *et al.* (2006); Rintanen (2010)], SAT encoding schemes, BlackBox, . . .

History of Planning Algorithms, ctd.

Planning as Heuristic Search:

- **Popular when:** 1999 – today.
- **Approach:** Devise a method $\mathcal{R}$ to simplify ("relax") any planning task Π; given Π, solve $\mathcal{R}(\Pi)$ to generate a heuristic function h for informed search.
- **Keywords/cites:** [Bonet and Geffner (1999); Haslum and Geffner (2000); Bonet and Geffner (2001); Hoffmann and Nebel (2001); Edelkamp (2001); Gerevini *et al.* (2003); Helmert (2006); Helmert *et al.* (2007); Helmert and Geffner (2008); Karpas and Domshlak (2009); Helmert and Domshlak (2009); Richter and Westphal (2010); Nissim *et al.* (2011); Katz *et al.* (2012); Keyder *et al.* (2012); Katz *et al.* (2013); Domshlak *et al.* (2015)], critical path heuristics, ignoring delete lists, relaxed plans, landmark heuristics, abstractions, partial delete relaxation, . . .

The International Planning Competition (IPC)

Competition?

"Run competing planners on a set of benchmarks devised by the IPC organizers. Give awards to the most effective planners."

- 1998, 2000, 2002, 2004, 2006, 2008, 2011, 2014, 2018, 2023
- PDDL [McDermott *et al.* (1998); Fox and Long (2003); Hoffmann and Edelkamp (2005); Gerevini *et al.* (2009)]
- ≈ 50 domains, $\gg 1000$ instances, 74 (!!) planners in 2011
- Optimal track vs. satisficing track
- Various others: uncertainty, learning, ...

`http://ipc.icaps-conference.org/`

Winners of the IPC

Edition	Satisficing track	Optimal track
IPC'00:	FF, heuristic search	–
IPC'02:	LPG, heuristic search	–
IPC'04:	SGPlan, heuristic search	SATPLAN, SAT compilation
IPC'06:	SGPlan, heuristic search	SATPLAN, SAT compilation
IPC'08:	LAMA, heuristic search	Gamer, symbolic search
IPC'11:	LAMA, heuristic search	Fast-Downward, heuristic search
IPC'14:	IBACoP, portfolio	SymBA*, symbolic search
IPC'18:	FDSS, portfolio (HS)	Delfi portfolio (symbolic + HS)
IPC'23:	Scorpion-Maidu, portfolio (HS) Levitron, portfolio (HS)	Ragnarok portfolio (HS)

→ For the rest of this chapter, we focus on planning as heuristic search.

→ This is a VERY short summary of the history of the IPC! There are many different categories, and many different awards.

Questionnaire

Question!

If planners x, y both compete in IPC'YY, and x wins, is x "better than" y?

(A): Yes. (B): No.

→ Yes, but only on the IPC'YY benchmarks, and only according to the criteria used for determining a "winner"! On other domains and/or according to other criteria, you may well be better off with the "loser".

→ It's complicated, over-simplification is dangerous. (But, of course, nevertheless is being done all the time).

"STRIPS" Planning

- STRIPS = Stanford Research Institute Problem Solver.

  STRIPS is the simplest possible (reasonably expressive) logics-based planning language.

- STRIPS has only Boolean variables: propositional logic atoms.
- Its preconditions/effects/goals are as canonical as imaginable:
  - Preconditions, goals: conjunctions of positive atoms.
  - Effects: conjunctions of literals (positive or negated atoms).
- We use the common special-case notation for this simple formalism.
- I'll outline some extensions beyond STRIPS later on, when we discuss PDDL.

→ **Historical note:** STRIPS [Fikes and Nilsson (1971)] was originally a planner (cf. Shakey), whose language actually wasn't quite that simple.

STRIPS Planning: Syntax

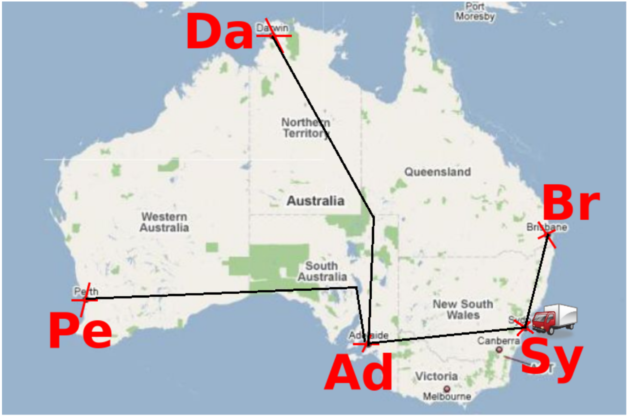
Definition (STRIPS Planning Task). *A STRIPS planning task, short planning task, is a 4-tuple $\Pi = (P, A, I, G)$ where:*

- *P is a finite set of facts (aka propositions).*
- *A is a finite set of actions; each $a \in A$ is a triple $a = (pre_a, add_a, del_a)$ of subsets of P referred to as the action's precondition, add list, and delete list respectively; we require that $add_a \cap del_a = \emptyset$.*
- *$I \subseteq P$ is the initial state.*
- *$G \subseteq P$ is the goal.*

We will often give each action $a \in A$ a name (a string), and identify a with that name.

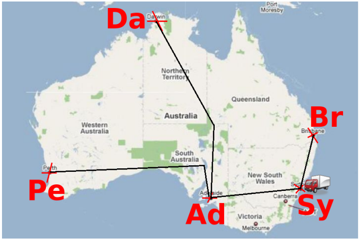
Note: We assume, for simplicity, that every action has cost 1. (Unit costs, cf. Chapter 3.)

"TSP" in Australia



[→ Strictly speaking, this is not actually a **TSP** problem instance; simplified/adapted for illustration.]

STRIPS Encoding of "TSP"



- Facts P: $\{at(x), visited(x) \mid x \in \{Sydney, Adelaide, Brisbane, Perth, Darwin\}\}$.
- Initial state I: $\{at(Sydney), visited(Sydney)\}$.
- Goal G:
  $\{at(Sydney)\} \cup \{visited(x) \mid x \in \{Sydney, Adelaide, Brisbane, Perth, Darwin\}\}$.
- Actions $a \in A$: $drive(x, y)$ where x, y have a road.
  Precondition pre_a: $\{at(x)\}$.
  Add list add_a: $\{at(y), visited(y)\}$.
  Delete list del_a: $\{at(x)\}$.
- Plan: $\langle drive(Sydney, Brisbane), drive(Brisbane, Sydney), drive(Sydney, Adelaide),$ $drive(Adelaide, Perth), drive(Perth, Adelaide), drive(Adelaide, Darwin),$ $drive(Darwin, Adelaide), drive(Adelaide, Sydney)\rangle$.

STRIPS Planning: Semantics

Definition (STRIPS State Space). *Let $\Pi = (P, A, c, I, G)$ be a STRIPS planning task. The state space of Π is $\Theta_\Pi = (S, A, T, I, S^G)$ where:*

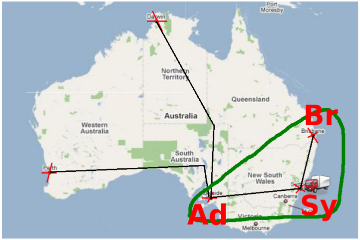
- *The states (also world states) $S = 2^P$ are the subsets of P.*
- *A is Π's action set.*
- *The transitions are $T = \{s \xrightarrow{a} s' \mid pre_a \subseteq s, s' = ([\![s]\!], a)\}$.*
  If $pre_a \subseteq s$, then a is applicable in s and $([\![s]\!], a) := (s \cup add_a) \setminus del_a$. If $pre_a \not\subseteq s$, then $([\![s]\!], a)$ is undefined.
- *I is Π's initial state.*
- *The goal states $S^G = \{s \in S \mid G \subseteq s\}$ are those that satisfy Π's goal.*

An (optimal) plan for $s \in S$ is an (optimal) solution for s in Θ_Π, i.e., a path from s to some $s' \in S^G$. A solution for I is called a plan for Π. Π is solvable if a plan for Π exists.

For $\vec{a} = \langle a_1, \dots, a_n \rangle$, $([\![s]\!], \vec{a}) := ([\![\dots]\!]([\![]\!][\![(]\!]s, a_1), a_2) \dots, a_n)$ if each a_i is applicable in the respective state; else, $([\![s]\!], \vec{a})$ is undefined.

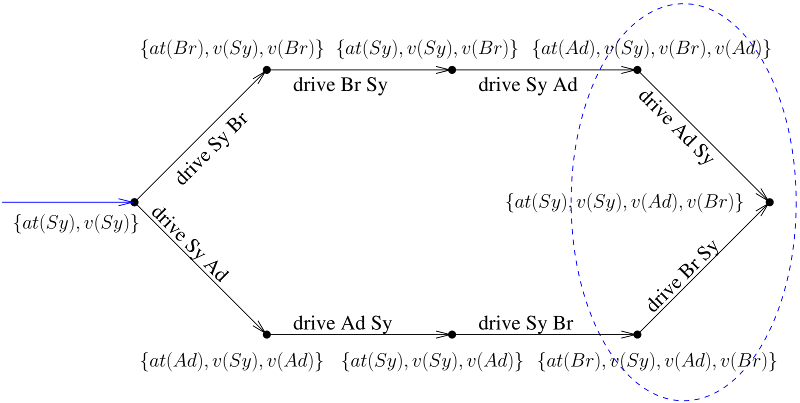
Note: This is exactly like the state spaces of **Chapter 3**, without a cost function. Solutions are defined as before (paths from I to a state in S^G).

STRIPS Encoding of Simplified “TSP”



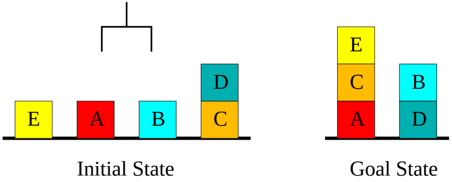
- Facts P: $\{at(x), visited(x) \mid x \in \{Sydney, Adelaide, Brisbane\}\}$.
- Initial state I: $\{at(Sydney), visited(Sydney)\}$.
- Goal G: $\{visited(x) \mid x \in \{Sydney, Adelaide, Brisbane\}\}$. (Note: no “$at(Sydney)$”.)
- Actions $a \in A$: $drive(x, y)$ where x, y have a road.
  Precondition pre_a: $\{at(x)\}$.
  Add list add_a: $\{at(y), visited(y)\}$.
  Delete list del_a: $\{at(x)\}$.

STRIPS Encoding of Simplified "TSP": State Space



→ Is this actually the state space? No, only the reachable part. E.g., Θ_Π also includes the states $\{v(Sy)\}$ and $\{at(Sy), at(Br)\}$.

(Oh no it's) The Blocksworld



- Facts: $on(x, y)$, $onTable(x)$, $clear(x)$, $holding(x)$, $armEmpty()$.
- Initial state: $\{onTable(E), clear(E), \dots, onTable(C), on(D, C), clear(D), armEmpty()\}$.
- Goal: $\{on(E, C), on(C, A), on(B, D)\}$.
- Actions: $stack(x, y)$, $unstack(x, y)$, $putdown(x)$, $pickup(x)$.
- $stack(x, y)$? $pre : \{holding(x), clear(y)\}$
  $add : \{on(x, y), armEmpty()\}$
  $del : \{holding(x), clear(y)\}$.

Questionnaire

Question!

Which are correct encodings (ones that are part of some correct overall model) of the STRIPS Blocksworld $pickup(x)$ action schema?

(A): $(\{onTable(x), clear(x), armEmpty()\}, \{holding(x)\}, \{onTable(x)\})$.

(B): $(\{onTable(x), clear(x), armEmpty()\}, \{holding(x)\}, \{armEmpty()\})$.

(C): $(\{onTable(x), clear(x), armEmpty()\}, \{holding(x)\}, \{onTable(x), armEmpty(), clear(x)\})$.

(D): $(\{onTable(x), clear(x), armEmpty()\}, \{holding(x)\}, \{onTable(x), armEmpty()\})$.

→ (A): No, must delete $armEmpty()$. (B): No, must delete $onTable(x)$. (C), (D): Both yes: We can, but don't have to, encode the *single-arm* Blocksworld so that the block currently in the hand is not clear. (For (C), $stack(x, y)$ and $putdown(x)$ need to add $clear(x)$, so the encoding on the previous slide does not work.)

Why Complexity Analysis?

Why? Why?

Two very good reasons:

1. It saves you from spending lots of time trying to invent algorithms that do not exist.
2. Killer app in planning: tractable fragments for heuristic functions.

   → Identify special cases that can be solved in polynomial time.

   → Relax the input into the special case to obtain a heuristic function!

→ I'll next remind you of the basic terms, then I'll illustrate both with an example. Afterwards we'll have a brief look at the complexity of the main decision problems in STRIPS planning.

Reminder (?): **NP** and **PSPACE**

Def Turing machine: Works on a tape consisting of tape cells, across which its R/W head moves. The machine has internal states. There are transition rules specifying, given the current cell content and internal state, what the subsequent internal state will be, how what the R/W head does (write a symbol and/or move). Some internal states are accepting.

Def NP: Decision problems for which there exists a *non-deterministic* Turing machine that runs in *time* polynomial in the size of its input. Accepts if *at least one* of the possible runs accepts.

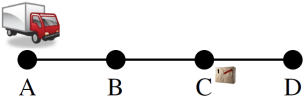
Def PSPACE: Decision problems for which there exists a *deterministic* Turing machine that runs in *space* polynomial in the size of its input.

Relation: Non-deterministic polynomial space can be simulated in deterministic polynomial space. Thus **PSPACE** $=$ **NPSPACE**, and hence (trivially) **NP** $\subseteq$ **PSPACE**. It is commonly believed that **NP** $\not\supseteq$ **PSPACE** (similar to **P** $\subseteq$ **NP**).

$\rightarrow$ For comprehensive details, please see a text book. My personal favorite is [Garey and Johnson (1979)]. (On the first 3 pages, they explain why knowing about **NP**-hardness will help you talk to your future boss.)

The "Only-Adds" Relaxation

Example: "Logistics"



- Facts P: $\{truck(x) \mid x \in \{A, B, C, D\}\} \cup \{pack(x) \mid x \in \{A, B, C, D, T\}\}$.
- Initial state I: $\{truck(A), pack(C)\}$.
- Goal G: $\{truck(A), pack(D)\}$.
- Actions A: (Notated as "precondition ⇒ adds, ¬ deletes")
  - $drive(x, y)$, where x, y have a road: "$truck(x) \Rightarrow truck(y), \neg truck(x)$".
  - $load(x)$: "$truck(x), pack(x) \Rightarrow pack(T), \neg pack(x)$".
  - $unload(x)$: "$truck(x), pack(T) \Rightarrow pack(x), \neg pack(T)$".

Only-Adds Relaxation: Drop the preconditions and deletes.

"$drive(x, y)$: $\Rightarrow truck(y)$"; "$load(x)$: $\Rightarrow pack(T)$"; "$unload(x)$: $\Rightarrow pack(x)$".

→ Say we want to use this for generating a heuristic function.

Solving Only-Adds STRIPS Tasks

Our problem:

- Given STRIPS task $\Pi = (P, A, I, G)$.
- Find action sequence $\vec{a}$ leading from I to a state that contains G, when pretending that preconditions and deletes are empty.

Solution 1: (simplest possible approach)

$\vec{a} := \langle\rangle$
while $G \neq \emptyset$ **do**
  select $a \in A$
  $G := G \setminus add_a$
  $\vec{a} := \vec{a} \circ \langle a \rangle$; $A := A \setminus \{a\}$
endwhile
return $h := |\vec{a}|$

$\rightarrow$ Is this h admissible? No. Admissibility is only guaranteed if we find a shortest possible $\vec{a}$; else, $\vec{a}$ might be longer than a plan for Π itself. Selecting an arbitrary action each time, $\vec{a}$ may be longer than needed.

Solving Only-Adds STRIPS Tasks, ctd.

So, what about this?

$\vec{a} := \langle\rangle$
while $G \neq \emptyset$ **do**
  select $a \in A$ s.t. $|add_a|$ is maximal
  $G := G \setminus add_a$
  $\vec{a} := \vec{a} \circ \langle a \rangle$; $A := A \setminus \{a\}$
endwhile
return $h := |\vec{a}|$

$\rightarrow$ h admissible? No, large add_a doesn't help if the intersection with G is small.

And this?

$\vec{a} := \langle\rangle$
while $G \neq \emptyset$ **do**
  select $a \in A$ s.t. $|add_a \cap G|$ is maximal
  $G := G \setminus add_a$
  $\vec{a} := \vec{a} \circ \langle a \rangle$; $A := A \setminus \{a\}$
endwhile
return $h := |\vec{a}|$

$\rightarrow$ h admissible? Still no. Example: $G = \{A, B, C, D, E, F\}$; $add_{a_1} = \{A, B\}$; $add_{a_2} = \{C, D\}$; $add_{a_3} = \{E, F\}$; $add_{a_4} = \{A, C, E\}$.

Solving Only-Adds STRIPS Tasks, ctd.

From [Garey and Johnson (1979)]:

222 NP-COMPLETE PROBLEMS

[SP5] **MINIMUM COVER**

INSTANCE: Collection C of subsets of a finite set S, positive integer $K \leqslant |C|$.
QUESTION: Does C contain a cover for S of size K or less, i.e., a subset $C' \subseteq C$ with $|C'| \leqslant K$ such that every element of S belongs to at least one member of C'?

Reference: [Karp, 1972]. Transformation from X3C.
Comment: Remains NP-complete even if all $c \in C$ have $|c| \leqslant 3$. Solvable in polynomial time by matching techniques if all $c \in C$ have $|c| \leqslant 2$.

So what?

- Given STRIPS task $\Pi = (P, A, I, G)$.
- Find optimal $\vec{a}$ leading from I to a state that contains G, when pretending that preconditions and deletes are empty.

$\rightarrow$ $\vec{a}$ leads to G $\Leftrightarrow$ $\bigcup_{a \in \vec{a}} add_a \supseteq G$ $\Leftrightarrow$ the add lists in $\vec{a}$ cover G. QED.

Questionnaire

Assume: In 3 years from now, you have finished your studies and are working in your first industry job. Your boss Mr. X gives you a problem and says "Solve It!". By which he means, "write a program that solves it efficiently".

Question!

How could knowing about NP-hardness help?

→ Assume further that, after trying in vain for 4 weeks, you got the next meeting with Mr. X. Do you want to say "Um, sorry, but I couldn't find an efficient solution, please don't fire me"?

Or would you rather say "Look, I didn't find an efficient solution. But neither could all the Turing-award winners out there put together, because the problem is **NP**-hard"?

(This particular **NP** sales pitch is not my invention. This is how Garey and Johnsson start their book [Garey and Johnson (1979)].)

Reminder: Algorithmic Problems in Planning

Satisficing Planning

Input: A planning task Π.
Output: A plan for Π, or "unsolvable" if no plan for Π exists.

Optimal Planning

Input: A planning task Π.
Output: An *optimal* plan for Π, or "unsolvable" if no plan for Π exists.

Decision Problems in (STRIPS) Planning

Definition (PlanEx). *By PlanEx, we denote the problem of deciding, given a STRIPS planning task Π, whether or not there exists a plan for Π.*

$\rightarrow$ Corresponds to satisficing planning.

Definition (PlanLen). *By PlanLen, we denote the problem of deciding, given a STRIPS planning task Π and an integer B, whether or not there exists a plan for Π of length at most B.*

$\rightarrow$ Corresponds to optimal planning.

Definition (PolyPlanLen). *By PolyPlanLen, we denote the problem of deciding, given a STRIPS planning task Π and an integer B bounded by a polynomial in the size of Π, whether or not there exists a plan for Π of length at most B.*

$\rightarrow$ Corresponds to optimal planning with "small" plans. Example of a planning domain with exponentially long plans? Towers of Hanoi.

Complexity of PlanEx [Bylander (1994)]

Lemma. PlanEx is **PSPACE**-hard.

→ "*At least* as hard as any other problem contained in **PSPACE**."

Proof Sketch. Given a Turing machine with space bounded by polynomial $p(|w|)$, we can in polynomial time (in the size of the machine) generate an equivalent STRIPS planning task. Say the possible symbols in tape cells are $x_1, \dots, x_m$ and the internal states are $s_1, \dots, s_n$, accepting state s_{acc}.

- The contents of the tape cells: $in(1, x_1), \dots, in(p(|w|), x_1), \dots, in(1, x_m), \dots, in(p(|w|), x_m)$.
- The position of the R/W head: $at(1), \dots, at(p(|w|))$.
- The internal state of the machine: $state(s_1), \dots, state(s_n)$.
- Transitions rules ↦ STRIPS actions; accepting state ↦ STRIPS goal $\{state(s_{acc})\}$; initial state obvious.
- This reduction to STRIPS runs in polynomial-time because we need only polynomially many facts.

Complexity of PlanEx, ctd. [Bylander (1994)]

Lemma. *PlanEx is a member of* **PSPACE**.

→ "*At most* as hard as any other problem contained in **PSPACE**."

Proof. Because **PSPACE** = **NPSPACE**, it suffices to show that PlanEx is a member of **NPSPACE**:

1. $s := I$; $l := 0$;
2. Guess an applicable action a, compute the outcome state s', set $l := l + 1$;
3. If s' contains the goal then succeed;
4. If $l \geq 2^{|P|}$ then fail else goto 2;

→ Remembering the actual action *sequence* would take exponential space in case of exponentially long plans (cf. slide 39). But, to decide PlanEx, we only need to remember its length.

Theorem (Complexity of PlanEx). *PlanEx is* **PSPACE**-*complete.* (Immediate from previous two lemmas)

Complexity of PlanLen [Bylander (1994)]

PlanLen isn't any easier than PlanEx:

Corollary. *PlanLen is* **PSPACE***-complete.*

Proof. Membership: Same as before but failing at $l \geq B$. Hardness? Setting $B := 2^{|P|}$, PlanLen answers PlanEx: If a plan exists, then there exists a plan that traverses each possible state at most once.

PolyPlanLen is easier than PlanEx:

Theorem. *PolyPlanLen is* **NP***-complete.*

Proof. Membership? Guess B actions and check whether they form a plan. This runs in polynomial time because B is polynomially bounded. Hardness: E.g., by reduction from SAT.

→ Bounding plan length does not help in the general case as we can set the bound to a trivial (exponential) upper bound on plan length. If we restrict plan length to be "short" (polynomial), planning becomes easier.

Domain-Specific PlanEx vs. PlanLen ...

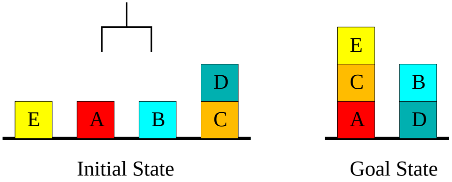
... is more interesting than the general case.

- *In general*, both have the same complexity.
- *Within particular applications*, bounded length plan existence is often harder than plan existence.

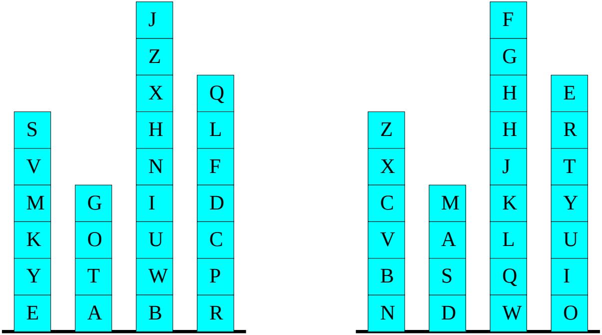
- This happens in many IPC benchmark domains: PlanLen is **NP**-complete while PlanEx is in **P**.
- For example: Blocksworld and Logistics.

$\rightarrow$ PlanEx $\approx$ satisficing planning, PlanLen $\approx$ optimal planning. In practice, optimal planning is (almost) never "easy".

The Blocksworld is Hard?



The Blocksworld is Hard!

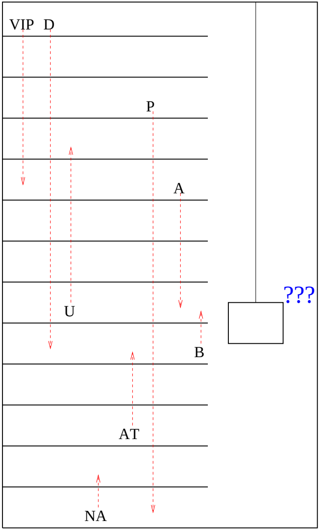


Initial State

Goal State

Miconic-ADL: PlanEx is Hard

- VIP: Served first.
- D: Lift may only go *down* when inside; similar for U.
- NA: Never-alone; AT: Attendant.
- A, B: Never together in the same elevator (!)
- P: Normal passenger :-)



Summary

- General problem solving attempts to develop solvers that perform well across a large class of problems.
- Planning, as considered here, is a form of general problem solving dedicated to the class of classical search problems. (Actually, we also address inaccessible, stochastic, dynamic, continuous, and multi-agent settings.)
- Heuristic search planning has dominated the International Planning Competition (IPC). We focus on it here.
- STRIPS is the simplest possible, while reasonably expressive, language for our purposes. It uses Boolean variables (facts), and defines actions in terms of precondition, add list, and delete list.
- PDDL is the de-facto standard language for describing planning problems.
- Plan existence (bounded or not) is **PSPACE**-complete to decide for STRIPS. If we bound plans polynomially, we get down to **NP**-completeness.

Reading

- *Chapters 10: Classical Planning and 11: Planning and Acting in the Real World* [Russell and Norvig (2010)].

  Content: Although the book is named "A Modern Approach", the planning section was written long before the IPC was even dreamt of, before PDDL was conceived, and several years before heuristic search hit the scene. As such, what we have right now is the attempt of two outsiders trying in vain to catch up with the dramatic changes in planning since 1995.

  Chapter 10 is Ok as a background read. Some issues are, imho, misrepresented, and it's far from being an up-to-date account. But it's Ok to get some additional intuitions in words different from my own.

  Chapter 11 is annoyingly named (I've seen lots of classical planning in the "real world"), but is useful in our context here because I don't cover any of it. If you're interested in extended/alternative planning paradigms, do read it.

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