# AI Planning

## 2. Planning Formalisms

How to Describe Problems, and What is a "Problem" Anyway?

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Winter Term 2018/2019

Thanks to Prof. Jörg Hoffmann for slide sources





## Agenda







## Reminder: Planning = General Problem Solving

(some new problem)

describe problem in planning language $\mapsto$ use off-the-shelf solver

(its solution)

- Any problem that can be formulated as a planning problem.
- Don't write the C++ code, just describe the problem!
- Don't maintain the C++ code, maintain the description!





## What is a Planning Problem?

**Given a planning task:**

- A description of the initial state.
- A description of the goal condition.
- A description of a set of possible actions.

$\rightarrow$ Find a schedule of actions (a plan) that brings us from the initial state to a state in which the goal condition holds.

## Classical Planning

. . . makes **Simplifying Assumptions:**

- Initial situation unique and completely known, environment deterministic, static, discrete, single-agent.
- Actions executed one-by-one, plans are sequences.

This is often not the case in practice! Examples? Handling uncertainty (robot control), temporal/parallel execution (transportation), . . .

**So why do we do this?**

- Clean framework to study planning problems. (Simplicity is a virtue!)
- Most influential ideas were conceived there. → **This course!**
- Successful applications using classical planning. → **Chapter 4**
- We can successfully compile many extended paradigms into classical planning. → **Outlined later in this Chapter**

→ We focus entirely on classical planning in this course.





## Algorithmic Problems in Planning

**Satisficing Planning**

**Input:** A planning task $\Pi$.
**Output:** A plan for $\Pi$, or **unsolvable** if no plan for $\Pi$ exists.

**Optimal Planning**

**Input:** A planning task $\Pi$.
**Output:** An optimal plan for $\Pi$, or **unsolvable** if no plan for $\Pi$ exists.

→ The techniques successful for either one of these are almost disjoint!
→ Satisficing planning is *much* more effective in practice.

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





## Computational Complexity in Planning

**Why?** From this course's point of view, it's simply one technical tool we need.

→ To get a heuristic $h$, we map the planning problem into a simpler (abstract/ relaxed) planning problem, from whose solution we compute $h$. To compute $h$ efficiently, the "simpler" problem must be solvable in polynomial time.

**Definition (PlanEx and PlanOpt).** *PlanEx is the problem of deciding, given a (STRIPS or FDR) planning task $\Pi$, whether or not there exists a plan for $\Pi$. PlanOpt is the problem of deciding, given $\Pi$ and $B \in \mathbb{R}_0^+$, whether or not there exists a plan for $\Pi$ whose cost is at most $B$.*

→ PlanEx ≈ satisficing planning, PlanOpt ≈ optimal planning.

**Theorem (Planning is Hard).** *Each of PlanEx and PlanOpt is* **PSPACE**-*complete.*

**Proof.** See AI'18.





## Our Agenda for This Chapter

2. **Transition Systems:** The basic framework we'll be moving in; forms the basis for both STRIPS and FDR. (= state space, cf. AI'18)
3. **STRIPS Planning:** STRIPS is by far the most wide-spread planning formalism. It is also the simplest possible reasonably expressive planning formalism, and thus a canonical subject to study.
4. **Finite-Domain Representations (FDR):** FDR is only slightly more general than STRIPS, but as we shall see can be quite useful.
5. **STRIPS vs. FDR:** The two formalisms can be compiled into each other. Such compilations are wide-spread in practice, and we will use them at some points during the course.
6. **Extended Planning Frameworks:** To at least give you a brief glimpse beyond classical planning.

## Transition Systems

→ State space of planning task = a transition system.

**Definition (Transition System).** *A transition system is a 6-tuple* $\Theta = (S, L, c, T, I, S^G)$ *where:*

- $S$ *is a finite set of states.*
- $L$ *is a finite set of transition labels.*
- $c : L \mapsto \mathbb{R}_0^+$ *is the cost function.*
- $T \subseteq S \times L \times S$ *is the transition relation.*
- $I \in S$ *is the initial state.*
- $S^G \subseteq S$ *is the set of goal states.*

*The size of* $\Theta$ *is its number of states, size*$(\Theta) := |S|$.
*We say that* $\Theta$ *has the transition* $(s, l, s')$ *if* $(s, l, s') \in T$. *We also write this* $s \xrightarrow{l} s'$, *or* $s \rightarrow s'$ *when not interested in* $l$.
*We say that* $\Theta$ *is deterministic if, for all states* $s$ *and labels* $l$, *there is at most one state* $s'$ *with* $s \xrightarrow{l} s'$.
*We say that* $\Theta$ *has unit costs if, for all* $l \in L$, $c(l) = 1$.





## Transition Systems, ctd.

**Terminology:** $\Theta = (S, A, c, T, I, S^G)$; $s, s', s_i \in S$

- $s'$ successor of $s$ if $s \rightarrow s'$; $s$ predecessor of $s'$ if $s \rightarrow s'$.
- $s'$ reachable from $s$ if there exists a sequence of transitions:

$$s = s_0 \xrightarrow{l_1} s_1, \ \dots, \ s_{n-1} \xrightarrow{l_n} s_n = s'$$

  - $n = 0$ possible; then $s = s'$.
  - $l_1, \dots, l_n$ is called path from $s$ to $s'$.
  - $s_0, \dots, s_n$ is also called path from $s$ to $s'$.
  - The cost of that path is $\sum_{i=1}^{n} c(l_i)$.
- $s'$ reachable (without reference state) means reachable from $I$.
- Solution for $s$: path from $s$ to some $s' \in S^G$; optimal if cost is minimal among all solutions for $s$.
- $s$ is solvable if it has a solution; else, $s$ is a dead end.
- Solution for $I$ is called solution for $\Theta$; $\Theta$ is solvable if it has a solution.

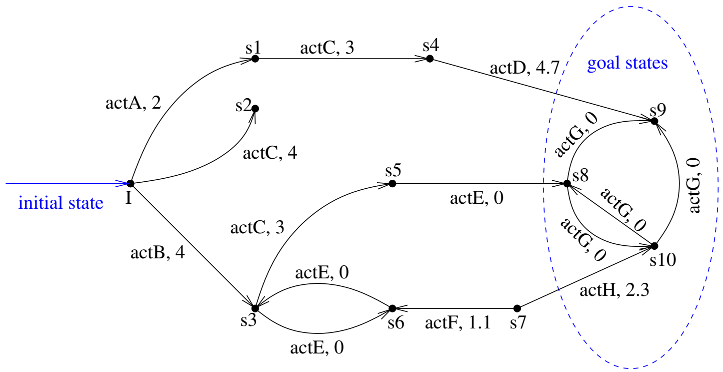
**Note:** We allow non-deterministic $\Theta$ here: In each state $s_i$, a solution may select any one outgoing transition labeled with $l_{i+1}$. We will need this only for abstractions (→ **Chapters 11–13**).





## Transition Systems: Illustration

Directed labeled graphs + mark-up for initial state and goal states:



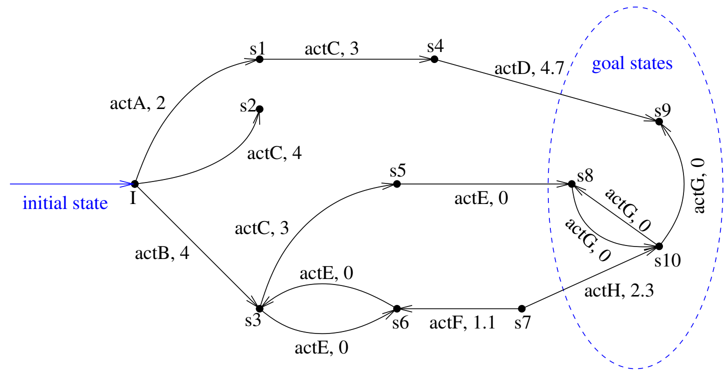

- Are all states in $\Theta$ reachable? No: state at bottom, 2nd from right.
- Are all states in $\Theta$ solvable? No: state near top, 2nd from left.
- Is this $\Theta$ deterministic? No: On two of the goal states, actG labels more than one outgoing transition.





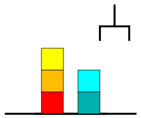
## Transition Systems: Illustration, ctd.

Directed labeled graphs + mark-up for initial state and goal states:




- Is this $\Theta$ deterministic? Yes.
- What are the optimal solutions for $\Theta$? Any path that starts with actB, applies actE $n \in \{0, 2, 4, \dots\}$ times, then applies actC then actE and then no action other than actG.

## Why don't we simply use Dijkstra? Example Blocksworld



- $n$ 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 | blocks | states |
|---|---|---|---|
| 1 | 1 | 10 | 58941091 |
| 2 | 3 | 11 | 824073141 |
| 3 | 13 | 12 | 12470162233 |
| 4 | 73 | 13 | 202976401213 |
| 5 | 501 | 14 | 3535017524403 |
| 6 | 4051 | 15 | 65573803186921 |
| 7 | 37633 | 16 | 1290434218669921 |
| 8 | 394353 | 17 | 26846616451246353 |
| 9 | 4596553 | 18 | 588633468315403843 |

→ We are interested in solving **huge** transition systems, represented in a **compact** way as planning tasks (up next).





## STRIPS Planning: Syntax

**Definition (STRIPS Planning Task).** *A STRIPS planning task is a 5-tuple* $\Pi = (P, A, c, I, G)$ *where:*

- $P$ *is a finite set of facts, also 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* $add_a \cap del_a = \emptyset$.
- $c : A \mapsto \mathbb{R}_0^+$ *is the cost function.*
- $I \subseteq P$ *is the initial state.*
- $G \subseteq P$ *is the goal.*

*We say that* $\Pi$ *has unit costs if, for all* $a \in A$, $c(a) = 1$. *We will often give each action* $a \in A$ *a name (a string), and identify* $a$ *with that name.*

Diff to AI'18: The cost function $c$.

→ What for do we allow $0$-cost actions? Negligible cost (e.g. switch light on, take photo with smartphone), asking questions about only one kind of actions (e.g. Mars rover *take-picture* only).





## STRIPS Encoding of "TSP" in Australia


- Propositions $P$: $\{at(x), visited(x) \mid x \in \{Sydney, Adelaide, Brisbane, Perth, Darwin\}\}$.
- 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 $del_a$: $\{at(x)\}$.
- Cost function $c$:

$$c(drive(x,y)) = \begin{cases} 1 & \{x,y\} = \{Sydney, Brisbane\} \\ 1.5 & \{x,y\} = \{Sydney, Adelaide\} \\ 3.5 & \{x,y\} = \{Adelaide, Perth\} \\ 4 & \{x,y\} = \{Adelaide, Darwin\} \end{cases}$$





## STRIPS Planning: Semantics

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

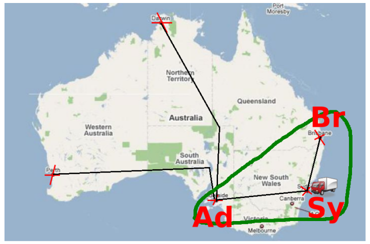
- *The states (also world states)* $S = 2^P$ *are the subsets of* $P$.
- *The labels* $L = A$ *are* $\Pi$*'s actions; the cost function* $c$ *is that of* $\Pi$.
- *The transitions are* $T = \{s \xrightarrow{a} s' \mid a \in A[s], s' = s[\![a]\!]\}$, *where* $A[s] := \{a \in A \mid pre_a \subseteq s\}$ *are the actions applicable in* $s$*; for* $a \in A[s]$, $s[\![a]\!] := (s \cup add_a) \setminus del_a$*; for* $a \notin A[s]$, $s[\![a]\!]$ *is undefined,* $s[\![a]\!] := \bot$.
- *The initial state* $I$ *is identical to that of* $\Pi$.
- *The goal states* $S^G = \{s \in S \mid G \subseteq s\}$ *are those that satisfy* $\Pi$*'s goal.*

*An (optimal) plan for* $s \in S$ *is an (optimal) solution for* $s$ *in* $\Theta_\Pi$. *A solution for* $I$ *is called a plan for* $\Pi$. $\Pi$ *is solvable if a plan for* $\Pi$ *exists.*

*For* $\vec{a} = \langle a_1, \dots, a_n \rangle$, $s[\![\vec{a}]\!] := \begin{cases} s & n = 0 \\ s[\![\langle a_1, \dots, a_{n-1} \rangle]\!][\![a_n]\!] & n > 0 \end{cases}$

→ Is $\Theta_\Pi$ deterministic? Yes: the successor state $s'$ in $s \xrightarrow{a} s'$ is uniquely determined by $s$ and $a$, through $s' = s[\![a]\!]$.

## STRIPS Encoding of Simplified "TSP"



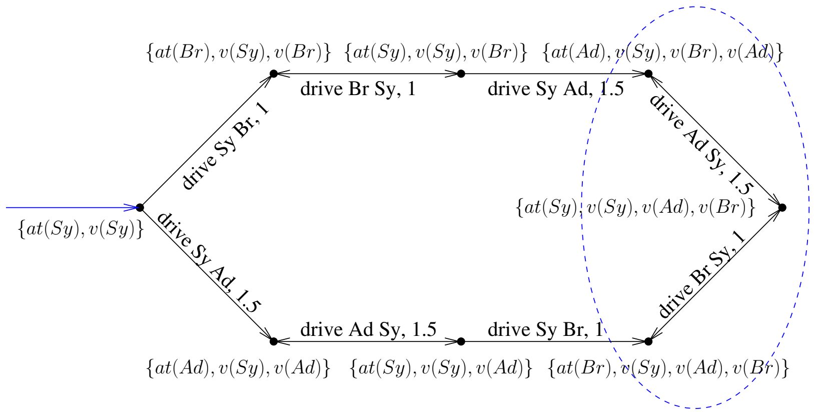

- Propositions $P$: $\{at(x), visited(x) \mid x \in \{Sydney, Adelaide, Brisbane\}\}$.
- Initial state $I$: $\{at(Sydney), visited(Sydney)\}$.
- Goal $G$: $\{visited(x) \mid x \in \{Sydney, Adelaide, Brisbane\}\}$. (Note: no "$at(Sydney)$".)
- Actions $a \in A$: $drive(x, y)$ where $x, y$ have a road.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

$$c(drive(x,y)) = \begin{cases} 1 & \{x,y\} = \{Sydney, Brisbane\} \\ 1.5 & \{x,y\} = \{Sydney, Adelaide\} \end{cases}$$





## STRIPS Encoding of Simplified "TSP": State Space



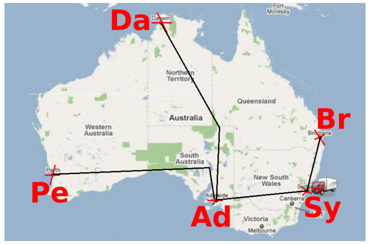

→ Exactly one optimal plan: drive Sy Br, drive Br Sy, drive Sy Ad.

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





## Questionnaire




- Propositions $P$: $\{at(x), visited(x) \mid x \in \{Sydney, Adelaide, Brisbane, Perth, Darwin\}\}$.
- Initial state $I$: $\{at(Sydney), visited(Sydney)\}$.

How many states are there in the "TSP in Australia" task?

→: $2^{10} = 1024$. But only a small portion of them are reachable (less than $5 \cdot 2^4 = 80$)!





## FDR Planning: Syntax

**Definition (FDR Planning Task).** *A finite-domain representation planning task, short FDR planning task, is a 5-tuple $\Pi = (V, A, c, I, G)$ where:*

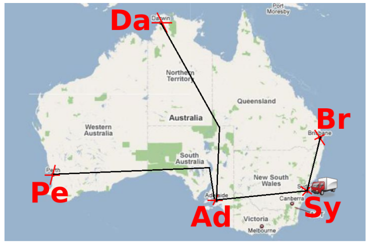
- *$V$ is a finite set of state variables, each $v \in V$ with a finite domain $D_v$. We refer to (partial) functions on $V$, mapping each $v \in V$ into a member of $D_v$, as (partial) variable assignments.*
- *$A$ is a finite set of actions; each $a \in A$ is a pair $(pre_a, eff_a)$ of partial variable assignments referred to as the action's precondition and effects.*
- *$c : A \mapsto \mathbb{R}_0^+$ is the cost function.*
- *$I$ is a complete variable assignment called the initial state.*
- *$G$ is a partial variable assignment called the goal.*

*We say that $\Pi$ has unit costs if, for all $a \in A$, $c(a) = 1$.*

→ In FDR, a (partial) variable assignment represents a state in $I$, a condition in $pre_a$ and $G$, and an effect instruction in $eff_a$.

**Notation:** Pairs $(v, d)$ are facts, also written $v = d$. We identify partial variable assignments $p$ with fact sets. We write $V[p] := \{v \in V \mid p(v) \text{ is defined}\}$.

## FDR Encoding of "TSP"




- Variables $V$: $at : \{Sydney, Adelaide, Brisbane, Perth, Darwin\}$; $visited(x) : \{T, F\}$ for $x \in \{Sydney, Adelaide, Brisbane, Perth, Darwin\}$.
- Initial state $I$: $at = Sydney, visited(Sydney) = T, visited(x) = F$ for $x \neq Sydney$.
- Goal $G$: $at = Sydney, visited(x) = T$ for all $x$.
- Actions $a \in A$: $drive(x, y)$ where $x, y$ have a road.
  Precondition $pre_a$: $at = x$.
  Effect $eff_a$: $at = y, visited(y) = T$.
- Cost function $c$:

$$c(drive(x,y)) = \begin{cases} 1 & \{x,y\} = \{Sydney, Brisbane\} \\ 1.5 & \{x,y\} = \{Sydney, Adelaide\} \\ 3.5 & \{x,y\} = \{Adelaide, Perth\} \\ 4 & \{x,y\} = \{Adelaide, Darwin\} \end{cases}$$





## FDR Planning: Semantics

**Definition (FDR State Space).** *Let $\Pi = (V, A, c, I, G)$ be an FDR planning task. The state space of $\Pi$ is the labeled transition system $\Theta_\Pi = (S, L, c, T, I, S^G)$ where:*

- *The states (also world states) $S$ are the complete variable assignments.*
- *The labels $L = A$ are $\Pi$'s actions; the cost function $c$ is that of $\Pi$.*
- *The transitions are $T = \{s \xrightarrow{a} s' \mid a \in A[s], s' = s[\![a]\!]\}$, where $A[s] := \{a \in A \mid pre_a \subseteq s\}$ are the actions applicable in $s$; for $a \notin A[s]$, $s[\![a]\!] := \bot$; for $a \in A[s]$, $s[\![a]\!](v) := \begin{cases} eff_a(v) & v \in V[eff_a] \\ s(v) & v \notin V[eff_a] \end{cases}$*
- *The initial state $I$ is identical to that of $\Pi$.*
- *The goal states $S^G = \{s \in S \mid G \subseteq s\}$ are those that satisfy $\Pi$'s goal.*

→ In $s[\![a]\!]$, instead of "adding/deleting" facts, we overwrite the previous variable values by $eff_a$.

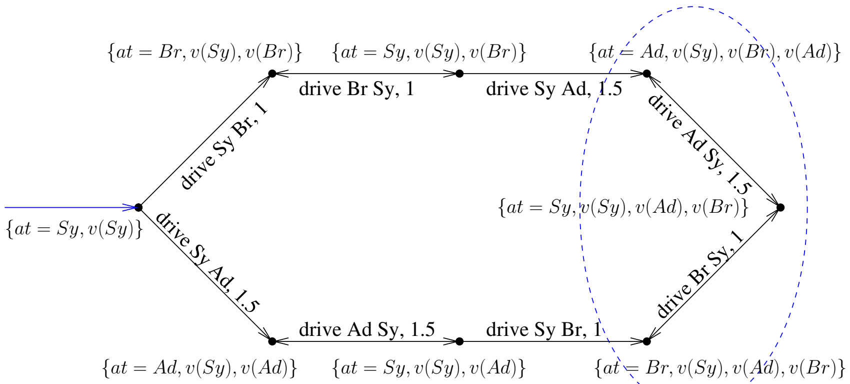
→ Plan, optimal plan, $s[\![\vec{a}]\!]$ for action sequence $\vec{a}$: as before (slide 19).





## FDR Encoding of Simplified "TSP": State Space

(using "$v(x)$" as shorthand for $visited(x) = T$)




→ This is only the reachable part of the state space: E.g., $\Theta_\Pi$ also includes the state $\{at = Sy, v(Br)\}$. (But neither $\{v(Sy)\}$ nor $\{at = Sy, at = Br\}$, compare slide 21.)





## Questionnaire

**Question!**

**How many STRIPS state variables are needed to encode the problem of finding a path in a graph with $n$ vertices?**

(A): $1$ (B): $n$
(C): $\lceil \log_2 n \rceil$ (D): $2 * \lceil \log_2 n \rceil$

→ (D): We need to encode our current position in the graph. This can be done with $n$ propositions of the form "$at(p)$", but it can be done more compactly by: numbering the positions $ID(p)$; representing $ID(p)$ in the binary system using $\lceil \log_2 n \rceil$ bits $bit_i$; and representing each $bit_i$ with two STRIPS facts $True(bit_i)$ and $False(bit_i)$.

**Question!**

**How many FDR state variables are needed for this?**

(A): $1$ (B): $n$
(C): $\lceil \log_2 n \rceil$ (D): $2 * \lceil \log_2 n \rceil$

→ (A): We need $1$ variable with $n$ values, encoding our current position in the graph.

## STRIPS vs. FDR in Practice

**How do people use FDR?**

- Our surface language is PDDL, which corresponds to STRIPS.
- Most implemented planning tools are based on Fast Downward (FD) [Helmert (2009)], which reads PDDL input, then internally uses a "clever" STRIPS-2-FDR translation (see next).
- That translation involves a **PSPACE**-complete sub-problem.

**Why???** Practical Efficiency!

- Regression: FDR avoids myriads of unreachable states. → **Chapter 6**
- Causal Graphs: Capture variable dependencies; have a much clearer structure for clever FDR (e.g., acyclic vs. cyclic). → **Chapter 5**
- Complexity Analysis: Better with clearer causal graph. → **Chapter 5**
- Construction of Heuristic Functions: Better with multiple-valued variables and clearer causal graph. → **Chapters 10 and 12**
- Modeling: Anyway, FDR is more natural! (It's just one truck, after all.)

**Why does anybody use STRIPS?** It's a legacy system.

→ We should be modeling in FDR. For historical reasons, we aren't.





## STRIPS vs. FDR Conversions

**Conversions:**

(I) FDR-2-STRIPS: For each variable $v$ with domain $\{d_1, \dots, d_k\}$, make $k$ STRIPS facts "$v = d_1$", ..., "$v = d_k$".

(II) STRIPS-2-FDR: Naïve vs. clever variants, see slides 34 – 37.

**What role does all this play here?**

- Both STRIPS and FDR are used in practice, cf. slide 30. The **programming exercises** are in FD, hence FDR.
- Some techniques in the remainder of the course are easier to introduce in STRIPS, some are easier in FDR, so we will keep both around.
- Specific relevance of (I): If the course introduces a technique $A$ in STRIPS, then $A$ in FDR (and hence your FD code!) is equivalent to "convert-FDR-2-STRIPS-then-do-$A$".
- Specific relevance of (II): So you get an understanding of how FD processes the PDDL/STRIPS input to FDR.





## FDR-2-STRIPS: Details

**Definition (FDR-2-STRIPS).** *Let $\Pi = (V, A, c, I, G)$ be an FDR planning task. The STRIPS conversion of $\Pi$ is the STRIPS task $\Pi^{\mathsf{STR}} = (P_V, A^{\mathsf{STR}}, c, I, G)$ where:*

- $P_V = \{v = d \mid v \in V, d \in D_v\}$ *is the set of (STRIPS) facts.*
- $A^{\mathsf{STR}} = \{a^{\mathsf{STR}} \mid a \in A\}$ *where* $pre_{a^{\mathsf{STR}}} = pre_a$, $add_{a^{\mathsf{STR}}} = eff_a$, *and*
  $$del_{a^{\mathsf{STR}}} = \bigcup_{(v=d) \in eff_a} \begin{cases} \{v = pre_a(v)\} & \text{if } pre_a(v) \text{ is defined} \\ \{v = d' \mid d' \in D_v \setminus \{d\}\} & \text{otherwise} \end{cases}$$
- *The cost function $c$ is defined by $c(a^{\mathsf{STR}}) := c(a)$ for all $a^{\mathsf{STR}} \in A^{\mathsf{STR}}$.*
- *$I$ and $G$ are identical to those of $\Pi$.*

→ The adds establish the new variable values of $eff_a$; the deletes make sure to erase the previous values of those variables.

→ Take-home message: FDR variable/value pairs ≈ STRIPS facts!

**Proposition.** *Let $\Pi = (V, A, c, I, G)$ be an FDR planning task, and let $\Pi^{\mathsf{STR}}$ be its STRIPS conversion. Then $\Theta_\Pi$ is isomorphic to the sub-system of $\Theta_{\Pi^{\mathsf{STR}}}$ induced by those $s \subseteq P_V$ where, for each $v \in V$, $s$ contains exactly one fact of the form $v = d$. All other states in $\Theta_{\Pi^{\mathsf{STR}}}$ are unreachable.*





## FDR-2-STRIPS: Simplified "TSP"


- FDR $V$: $at : \{Sydney, Adelaide, Brisbane\}$; $visited(x) : \{T, F\}$ for $x \in \{Sydney, Adelaide, Brisbane\}$.
- STRIPS $P$: $at(x), visited(x, T), visited(x, F)$ for $x \in \{Sydney, Adelaide, Brisbane\}$.
- FDR $dr(x, y)$: $pre = \{at = x\}$, $eff = \{at = y, v(y) = T\}$.
- STRIPS $dr(x, y)$: $pre = \{at(x)\}$, $add = \{at(y), v(y, T)\}$, $del = \{at(x), v(y, F)\}$.

## STRIPS-2-FDR: Naïve Translation

**Definition (STRIPS-2-FDR).** *Let* $\Pi = (P, A, c, I, G)$ *be a STRIPS planning task. The FDR conversion of* $\Pi$ *is the FDR task* $\Pi^{\mathsf{FDR}} = (V_P, A^{\mathsf{FDR}}, c, I^{\mathsf{FDR}}, G^{\mathsf{FDR}})$ *where:*

- $V_P = \{v_p \mid p \in P\}$ *is the set of variables, all Boolean.*
- $A^{\mathsf{FDR}} = \{a^{\mathsf{FDR}} \mid a \in A\}$ *where* $pre_{a^{\mathsf{FDR}}} = \{v_p = T \mid p \in pre_a\}$ *and* $eff_{a^{\mathsf{FDR}}} = \{v_p = T \mid p \in add_a\} \cup \{v_p = F \mid p \in del_a\}$.
- *The cost function* $c$ *is defined by* $c(a^{\mathsf{FDR}}) := c(a)$ *for all* $a^{\mathsf{FDR}} \in A^{\mathsf{STR}}$.
- $I = \{v_p = T \mid p \in I\}$*; and* $G = \{v_p = T \mid p \in G\}$.

→ All variables here have two possible values only, so this does not benefit at all from the added expressivity of FDR. Hence the designation "naïve".

**Proposition.** *Let* $\Pi = (P, A, c, I, G)$ *be a STRIPS planning task, and let* $\Pi^{\mathsf{FDR}}$ *be its STRIPS conversion. Then* $\Theta_\Pi$ *is isomorphic to* $\Theta_{\Pi^{\mathsf{STR}}}$.





## STRIPS-2-FDR, Naïve: Simplified "TSP"


- STRIPS $P$: $at(x), visited(x)$ for $x \in \{Sydney, Adelaide, Brisbane\}$.
- FDR $V$: $at(x), visited(x) : \{T, F\}$ for $x \in \{Sydney, Adelaide, Brisbane\}$.
- STRIPS $dr(x, y)$: $pre = \{at(x)\}$, $add = \{at(y), v(y)\}$, $del = \{at(x)\}$
- FDR $dr(x, y)$: $pre = \{at(x) = T\}$, $eff = \{at(y) = T, v(y) = T, at(x) = F\}$.





## STRIPS-2-FDR: Clever Translation

**How to be clever?**

- Find sets $\{p_1, \dots, p_k\}$ of STRIPS facts so that every reachable state $s$ makes exactly one $p_i$ true.

  → Deciding whether this holds, for a given $\{p_1, \dots, p_k\}$, is **PSPACE**-complete (cf. slide 30). But one can design fast algorithms finding *some* such sets [Helmert (2009)].
- For each set $\{p_1, \dots, p_k\}$ found, make *one* FDR variable $v$ with domain $\{d_1, \dots, d_k\}$.
- This is implemented in the pre-processor of Fast Downward.





## STRIPS-2-FDR Naïve vs. Clever: Simplified "TSP"


- STRIPS $P$: $at(x), visited(x)$ for $x \in \{Sydney, Adelaide, Brisbane\}$.
- Naïve $V$: $at(x), visited(x) : \{T, F\}$ for $x \in \{Sydney, Adelaide, Brisbane\}$.
- Clever $V$: $at : \{Sydney, Adelaide, Brisbane\}$; $visited(x) : \{T, F\}$ for $x \in \{Sydney, Adelaide, Brisbane\}$.

→ The naïve version is merely STRIPS in disguise. The clever version is more natural, and is explicit about the "truck position".

## Action Description Language (ADL)

**Framework Definition:** [Pednault (1989); Hoffmann and Nebel (2001)].

**Problem:** Like STRIPS but with PL1 formulas in $pre_a$ and $G$, and with conditional effects that execute only if their individual effect condition holds.

**Plan:** Sequence of actions. (Yes, this is still "classical planning".)

**Example:** If your action $a$ opens the doors of an elevator, then each passenger gets out iff their individual condition ("Is this my destination floor?") holds. If you want to satisfy complex constraints ("Group A should never meet group B in the elevator") then $pre_a$ gets nasty. (See the PDDL file here.)

**Compilation:** PL1 formulas: Ground them (the universe is finite) and transform to DNF [Gazen and Knoblock (1997); Koehler and Hoffmann (2000)].

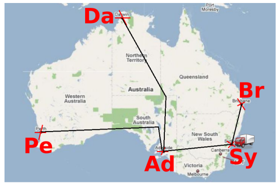
Conditional effects: Either enumerate all combinations of effects, or introduce artificial facts/actions enforcing an "effect evaluation phase" [Nebel (2000)].

**State of the art:** Get rid of PL1 formulas but keep the conditional effects [Hoffmann and Nebel (2001)].





## Numeric and Temporal Planning




**Numeric Planning:** [Fox and Long (2003)]
$pre_a : fuelSupply \geq distance(x,y) * fuelConsumption$
$eff_a : fuelSupply := fuelSupply - distance(x,y) * fuelConsumption$

**Compilation:** Nothing known.

**Temporal Planning:** [Fox and Long (2003)]
$duration_a : distance(x,y)/speed$
$eff_a$ : at Start $\neg at(x)$, at End $at(y)$.

**Compilation:** Ignore durations during search, schedule plan as a post-process [Edelkamp (2003)]. Competitive with state of the art!





## Soft Goals and Trajectory Constraints


**Soft Goals:** [Gerevini *et al.* (2009)]
"I don't absolutely have to visit Darwin, but if I do, I get a certain amount $R$ of reward."

**Compilation:** Artificial actions that allow to forgo each weak goal, at cost $R$; minimize cost [Keyder and Geffner (2009)]. State of the art!

**Trajectory Constraints:** [Gerevini *et al.* (2009)]
"I must visit Perth before I visit Darwin."

**Compilation:** Artificial preconditions/effects, e.g. $visited(Perth)$ into precondition of driving to Darwin [Edelkamp (2006)]. State of the art!





## Conformant Planning

**Framework Definition:** [Smith and Weld (1998); Bonet and Givan (2006)].

**Problem:** There are many possible initial states (represented as a formula), and each action may have several possible effects. We have no observability during plan execution.

**Plan:** Sequence of actions that achieves the goal regardless which initial state and action effects occur.

**Example:** You're in a dark cave but don't know where exactly. The plan is to walk to the right until you reach a wall and can locate yourself (thanks to noticing that the action "walk to the right" does not work anymore). Then navigate to your goal by counting your steps.

**Compilation:** Artificial "what-if" facts, like "If I was at A initially, then I am now at B" [Palacios and Geffner (2009)]. State of the art!

## Contingent Planning

**Framework Definition:** e.g., [Hoffmann and Brafman (2005)].

**Problem:** There are many possible initial states (represented as a formula), and each action may have several possible effects. We have partial observability during plan execution.

**Plan:** Tree of actions that achieves the goal in each of its leaves. ("Plan ahead for all possible contingencies, i.e., situation aspects not known at planning time.")

**Example:** Solving the Wumpus world: You walk some steps, then use sensing (for breeze and stench), and continue depending on the outcome.

**Compilation:** Sample initial states, classical planning with artificial facts encoding knowledge yields a plan tree for those; in case a problem is detected during execution, re-plan with the new state of knowledge [Shani and Brafman (2011)]. Competitive with state of the art!





## Probabilistic Planning

**Framework Definition:** e.g., [Younes *et al.* (2005)].

**Problem:** Each action specifies a probability distribution over its possible effects. We have full observability during plan execution. (Markov Decision Process (MDP) framework.)

**Plan:** Policy that maps states to actions in a way that maximizes the expected reward.

**Example:** Controlling a robot: If navigation comes with an imprecision (which it usually does), then the outcome of a "move" operation is uncertain.

**Compilation:** Make classical problem that acts as if you could *choose* the outcomes; find a plan, and execute; if the plan fails, then re-plan from the current state [Yoon *et al.* (2007)]. State of the art for problems where "reactive behavior" is suitable (things may go wrong, but if they do, they can be easily repaired).





## Summary

- Transition systems are a kind of directed graph (typically huge) that encode how the state of the world can change.
- Planning tasks are compact representations for transition systems, based on state variables; they are the input for planning systems.
- In satisficing planning, we must find a solution to planning tasks (or show that no solution exists). In optimal planning, we must additionally guarantee that generated solutions are the cheapest possible.
- Classical planning makes strong simplifying assumptions, but is very successful in practice and can be used by compilation to tackle more expressive planning problems.
- In STRIPS, state variables are Boolean; in FDR, they may have arbitrary finite domains. The two formalisms can be compiled into each other. FDR is preferrable, but current planning technology is based on STRIPS for historical reasons.

  → PDDL, see **Next Chapter**.





## Remarks

**Regarding the name "FDR":**

- FDR is not consistently named in the literature.
- It is often referred to as $SAS^+$ because that's what some complexity guys called it, in the first papers considering a formalism equivalent to our FDR [e.g., Bäckström and Nebel (1995)].
- [Helmert (2006)] called it multi-valued planning tasks (MPT) which can still be seen in some papers.
- [Helmert (2009)] finally called it FDR.

## Reading

- *Concise Finite-Domain Representations for PDDL Planning Tasks* [Helmert (2009)].

  Available at:

  http://www.informatik.uni-freiburg.de/~ki/papers/helmert-aij2009.pdf

  Content: Describes in detail the "clever" STRIPS-2-FDR conversion implemented in Fast Downward. The sets $\{p_1, \dots, p_k\}$ of STRIPS facts, of which exactly one is true in every reachable state, are found by automatic invariance analysis. Is in wide-spread use, and a basic familiarity with it is relevant for anybody working in planning.





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