

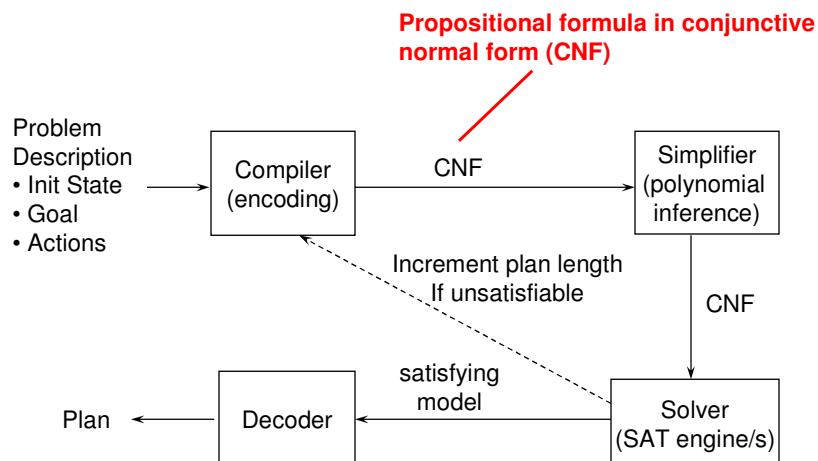
Planning as Satisfiability

- Planning as propositional satisfiability

* Based on slides by Alan Fern, Stuart Russell and Dana Nau

1

Architecture of a SAT-based Planner



2

Propositional Satisfiability

- A formula is **satisfiable** if it is true in some model
 - ▲ e.g. $A \vee B, \quad C$
- A formula is unsatisfiable if it is true in no models
 - ▲ e.g. $A \wedge \neg A$
- Testing satisfiability of CNF formulas is a famous NP-complete problem

3

Propositional Satisfiability

- Many problems (such as planning) can be naturally encoded as instances of satisfiability
- Thus there has been much work on developing powerful satisfiability solvers
 - ▲ these solvers work amazingly well in practice (we will touch on some later)

4

Encoding Planning as Satisfiability: Basic Idea

- Bounded planning problem (P,n) :
 - ▲ P is a planning problem; n is a positive integer
 - ▲ Find a solution for P of length n
- Create a propositional formula that represents:
 - ▲ Initial state
 - ▲ Goal
 - ▲ Action Dynamicsfor n time steps
- We will define the formula for (P,n) such that:
 - 1) **any** model (i.e. satisfying truth assignment) of the formula represent a solution to (P,n)
 - 2) if (P,n) has a solution then the formula is satisfiable

5

Encoding Planning Problems

- We can encode (P,n) so that we consider either layered plans or totally ordered plans
 - ▲ an advantage of considering layered plans is that fewer time steps are necessary (i.e. smaller n translates into smaller formulas)
 - ▲ for simplicity we first consider totally-ordered plans
- Encode (P,n) as a formula Φ such that
 - $\langle a_0, a_1, \dots, a_{n-1} \rangle$ is a solution for (P,n)
 - if and only if
 - Φ can be satisfied in a way that makes the fluents a_0, \dots, a_{n-1} true
- Φ will be conjunction of many other formulas ...

6

Formulas in Φ

- Formula describing the **initial state**: (let E be the set of possible facts in the planning problem)

$$\bigwedge\{e_0 \mid e \in s_0\} \wedge \bigwedge\{\neg e_0 \mid e \in E - s_0\}$$

Describes the complete initial state (both positive and negative fact)

▲ E.g. $\text{on}(A,B,0) \wedge \neg\text{on}(B,A,0)$

- Formula describing the **goal**: (G is set of goal facts)

$$\bigwedge\{e_n \mid e \in G\}$$

says that the goal facts must be true in the final state at timestep n

▲ E.g. $\text{on}(B,A,n)$

- Is this enough?
 - ▲ Of course not. The formulas say nothing about actions.

7

Formulas in Φ

- For every action a and timestep i , formula describing what fluents must be true if a were the i 'th step of the plan:

▲ $a_i \Rightarrow \bigwedge\{e_i \mid e \in \text{Precond}(a)\}$, a 's preconditions must be true

▲ $a_i \Rightarrow \bigwedge\{e_{i+1} \mid e \in \text{ADD}(a)\}$, a 's ADD effects must be true in $i+1$

▲ $a_i \Rightarrow \bigwedge\{\neg e_{i+1} \mid e \in \text{DEL}(a)\}$, a 's DEL effects must be false in $i+1$

- **Complete exclusion axiom**:

▲ For all actions a and b and timesteps i , formulas saying a and b can't occur at the same time

$$\neg a_i \vee \neg b_i$$

▲ this guarantees there can be only one action at a time

- Is this enough?

▲ The formulas say nothing about what happens to facts if they are not effected by an action

▲ This is known as the **frame problem**

8

Frame Axioms

- *Frame axioms*:
 - ▲ Formulas describing what *doesn't* change between steps i and $i+1$
- Several ways to write these (your book shows another way)
 - ▲ Here I show an alternative that typically works best in practice
- **explanatory frame axioms**
 - ▲ One axiom for every possible fact e at every timestep i
 - ▲ Says that if e changes truth value between s_i and s_{i+1} , then the action at step i must be responsible:

$$\neg e_i \wedge e_{i+1} \Rightarrow \bigvee \{a_i / e \text{ in ADD}(a)\}$$

If e became true then some action must have added it

$$e_i \wedge \neg e_{i+1} \Rightarrow \bigvee \{a_i / e \text{ in DEL}(a)\}$$

If e became false then some action must have deleted it

9

Example

- Planning domain:
 - ▲ one robot $r1$
 - ▲ two adjacent locations $l1, l2$
 - ▲ one operator (move the robot)
- Encode (P, n) where $n = 1$
 - ▲ Initial state: $\{at(r1, l1)\}$
Encoding: $at(r1, l1, 0) \wedge \neg at(r1, l2, 0)$
 - ▲ Goal: $\{at(r1, l2)\}$
Encoding: $at(r1, l2, 1)$
 - ▲ Action Schema: see next slide

10

Example (continued)

- Schema: $\text{move}(r, l, l')$
PRE: $\text{at}(r, l)$
ADD: $\text{at}(r, l')$
DEL: $\text{at}(r, l)$

Encoding: (for actions $\text{move}(r_1, l_1, l_2)$ and $\text{move}(r_1, l_2, l_1)$ at time step 0)

$\text{move}(r_1, l_1, l_2, 0) \Rightarrow \text{at}(r_1, l_1, 0)$
 $\text{move}(r_1, l_1, l_2, 0) \Rightarrow \text{at}(r_1, l_2, 1)$
 $\text{move}(r_1, l_1, l_2, 0) \Rightarrow \neg \text{at}(r_1, l_1, 1)$

$\text{move}(r_1, l_2, l_1, 0) \Rightarrow \text{at}(r_1, l_2, 0)$
 $\text{move}(r_1, l_2, l_1, 0) \Rightarrow \text{at}(r_1, l_1, 1)$
 $\text{move}(r_1, l_2, l_1, 0) \Rightarrow \neg \text{at}(r_1, l_2, 1)$

11

Example (continued)

- Schema: $\text{move}(r, l, l')$
PRE: $\text{at}(r, l)$
ADD: $\text{at}(r, l')$
DEL: $\text{at}(r, l)$

- Complete-exclusion axiom:
 $\neg \text{move}(r_1, l_1, l_2, 0) \vee \neg \text{move}(r_1, l_2, l_1, 0)$

- Explanatory frame axioms:
 $\neg \text{at}(r_1, l_1, 0) \wedge \text{at}(r_1, l_1, 1) \Rightarrow \text{move}(r_1, l_2, l_1, 0)$
 $\neg \text{at}(r_1, l_2, 0) \wedge \text{at}(r_1, l_2, 1) \Rightarrow \text{move}(r_1, l_1, l_2, 0)$
 $\text{at}(r_1, l_1, 0) \wedge \neg \text{at}(r_1, l_1, 1) \Rightarrow \text{move}(r_1, l_1, l_2, 0)$
 $\text{at}(r_1, l_2, 0) \wedge \neg \text{at}(r_1, l_2, 1) \Rightarrow \text{move}(r_1, l_2, l_1, 0)$

12

Complete Formula for $(P,1)$

```
[ at(r1,l1,0) ∧ ¬at(r1,l2,0) ] ∧  
at(r1,l2,1) ∧  
[ move(r1,l1,l2,0) ⇒ at(r1,l1,0) ] ∧  
[ move(r1,l1,l2,0) ⇒ at(r1,l2,1) ] ∧  
[ move(r1,l1,l2,0) ⇒ ¬at(r1,l1,1) ] ∧  
[ move(r1,l2,l1,0) ⇒ at(r1,l2,0) ] ∧  
[ move(r1,l2,l1,0) ⇒ at(r1,l1,1) ] ∧  
[ move(r1,l2,l1,0) ⇒ ¬at(r1,l2,1) ] ∧  
[ ¬move(r1,l1,l2,0) ∨ ¬move(r1,l2,l1,0) ] ∧  
[ ¬at(r1,l1,0) ∧ at(r1,l1,1) ⇒ move(r1,l2,l1,0) ] ∧  
[ ¬at(r1,l2,0) ∧ at(r1,l2,1) ⇒ move(r1,l1,l2,0) ] ∧  
[ at(r1,l1,0) ∧ ¬at(r1,l1,1) ⇒ move(r1,l1,l2,0) ] ∧  
[ at(r1,l2,0) ∧ ¬at(r1,l2,1) ⇒ move(r1,l2,l1,0) ]
```

Convert to CNF and give to SAT solver.

13

Extracting a Plan

- Suppose we find an assignment of truth values that satisfies Φ .
 - ▲ This means P has a solution of length n
- For $i=0, \dots, n-1$, there will be exactly one action a_i such that $a_i = \text{true}$
 - ▲ This is the i 'th action of the plan.
- Example (from the previous slides):
 - ▲ Φ can be satisfied with $\text{move}(r1,l1,l2,0) = \text{true}$
 - ▲ Thus $\langle \text{move}(r1,l1,l2,0) \rangle$ is a solution for $(P,0)$
 - It's the only solution - no other way to satisfy Φ

14

Supporting Layered Plans

- *Complete exclusion axiom:*
 - ▲ For **all** actions a and b and time steps i include the formula $\neg a_i \vee \neg b_i$
 - ▲ this guaranteed that there could be only one action at a time
- *Partial exclusion axiom:*
 - ▲ For any pair of incompatible actions (recall from Graphplan) a and b and each time step i include the formula $\neg a_i \vee \neg b_i$
 - ▲ This encoding will allowed for more than one action to be taken at a time step resulting in layered plans
 - ▲ This is advantageous because fewer time steps are required (i.e. shorter formulas)

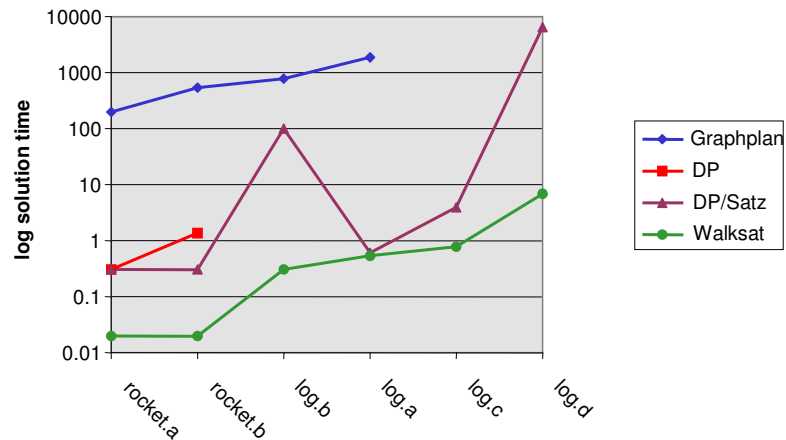
15

Planning Benchmark Test Set

- Extension of Graphplan test set
- **blocks world** - up to 18 blocks, 10^{19} states
- **logistics** - complex, highly-parallel transportation domain.
 - Logistics.d:
 - ▲ 2,165 possible actions per time slot
 - ▲ 10^{16} legal configurations (2^{2000} states)
 - ▲ optimal solution contains 74 distinct actions over 14 time slots
- *Problems of this size never previously handled by general-purpose planning systems*

16

Scaling Up Logistics Planning



17

What SATPLAN Shows

- General propositional reasoning can compete with state of the art specialized planning systems
 - ▲ New, highly tuned variations of DP surprising powerful
 - ▲ Radically new stochastic approaches to SAT can provide very low exponential scaling
- Why does it work?
 - ▲ More flexible than forward or backward chaining
 - ▲ Randomized algorithms less likely to get trapped along bad paths

18

Discussion

- How well does this work?
 - ▲ Created an initial splash but by itself, not very practical without help in choosing good encoding
- However combining SatPlan with planning graphs can overcome this problem