

# **Compilation of Planning to SAT**

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# Motivation

➤ **Propositional SAT: Given a Boolean formula**

- e.g.,  $(P \vee Q) \wedge (\neg Q \vee R \vee S) \wedge (\neg R \vee \neg P)$ ,

does there exist a model?

- i.e., an assignment of truth values to the propositions that makes the formula true?

➤ **Lots of research on algorithms for solving it**

- This was the very first problem shown to be NP-complete

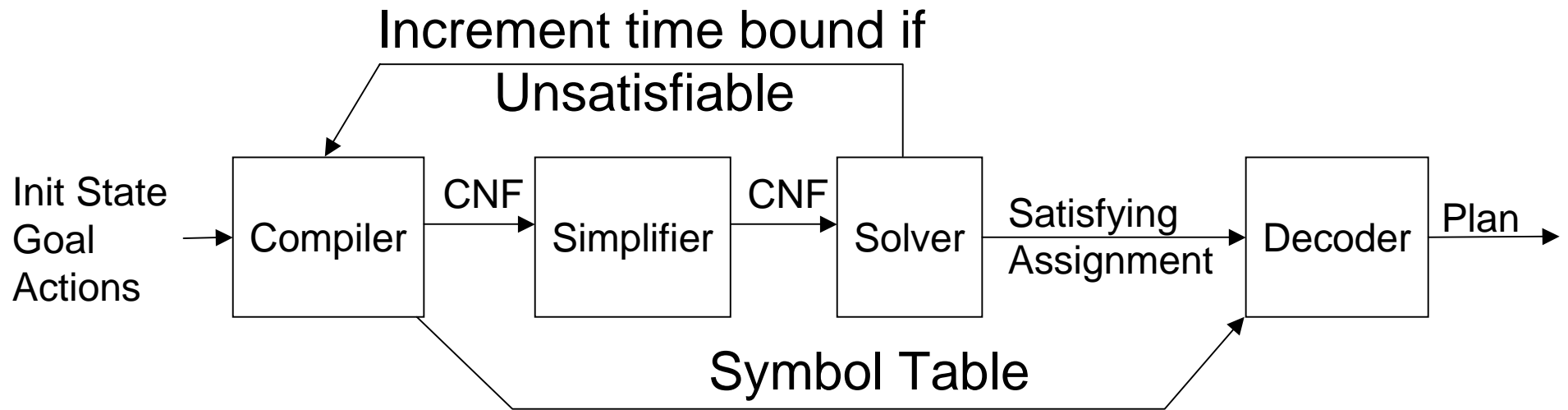
➤ **IDEA:**

- Translate classical planning problems into satisfiability problems, and solving them using highly optimized SATsolvers

# Outline

- **Architecture of SAT-based planning**
- **SAT-based planning approach**
- **Encoding planning problems as SAT problems**
- **Making encodings more efficient**
- **Extracting a plan**
- **Satisfiability algorithms**
  - Systematic SAT Solvers: Davis-Putnam-Logemann-Loveland
  - Stochastic SAT Solvers: GSAT
- **Discussion**

# Architecture of SAT-based planning system



# Architecture of SAT-based planning system Cont.

- **Compiler**
  - take a planning problem as input, guess a plan length, and generate a propositional logic formula, which if satisfied, implies the existence of a solution plan
- **Symbol table**
  - record the correspondence between propositional variables and the planning instance
- **Simplifier**
  - use fast techniques such as unit clause propagation and pure literal elimination to shrink the CNF formula
- **Solver**
  - use systematic or stochastic methods to find a satisfying assignment. If the formula is unsatisfiable, then the compiler generates a new encoding reflecting a longer plan length
- **Decoder**
  - translate the result of solver into a solution plan.

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# Planning Problem Definition

## ➤ Define what a planning problem is

- **Initial State**

Describes the facts that hold and do not hold in initial state

- **Goal State**

Describes the facts that must hold in goal state

- **Transition function**  $\gamma: S \times A \rightarrow S$

- S: Sets of states

- A: Set of actions

- $\gamma$  is encoded in terms of actions' **preconditions** and **effects**, and **exclusion axioms**

## ➤ **Bounded planning problem $(P, n)$ :**

- $P$  is a planning problem;  $n$  is a positive integer

- Find a solution for  $P$  of length  $\leq n$

- $\langle a_0, a_1, \dots, a_{n-1} \rangle$  is a solution for  $(P, n)$ ,

- Plan length not known in advance  $\Rightarrow$  the approach needs to repeat for different tentative lengths

# SAT-based Planning Approach

## ➤ Do iterative deepening:

- for  $n = 0, 1, 2, \dots$ ,
  - encode  $(P, n)$  as a satisfiability problem  $\Phi$
  - if  $\Phi$  is satisfiable, then
    - From the set of truth values that satisfies  $\Phi$ , a solution plan can be constructed, so return it and exit



# Fluents

- If  $\pi = \langle a_0, a_1, \dots, a_{n-1} \rangle$  is a solution for  $(P, n)$ , then it generates the following states:

$$s_0, \quad s_1 = \gamma(s_0, a_0), \quad s_2 = \gamma(s_1, a_1), \quad \dots, \quad s_n = \gamma(s_{n-1}, a_{n-1})$$

- **Fluents: propositions that describe what's true in each  $s_i$**
- $\text{at}(r1, \text{loc1}, i)$  is a fluent that's true iff  $\text{at}(r1, \text{loc1})$  is in  $s_i$
  - We'll use  $l_i$  to denote the fluent for literal  $l$  in state  $s_i$ 
    - e.g., if  $l = \text{at}(r1, \text{loc1})$   
then  $l_i = \text{at}(r1, \text{loc1}, i)$
  - $a_i$  is a fluent saying that  $a$  is the  $i$ 'th step of  $\pi$ 
    - e.g., if  $a = \text{move}(r1, \text{loc2}, \text{loc1})$   
then  $a_i = \text{move}(r1, \text{loc2}, \text{loc1}, i)$

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## What is in $\Phi$ ?

- **Formula describing the *initial state*:**

$$\bigwedge \{l_0 \mid l \in s_0\} \wedge \bigwedge \{\neg l_0 \mid l \in L - s_0\}$$

- **Formula describing the *goal state*:**

$$\bigwedge \{l_n \mid l \in g^+\} \wedge \bigwedge \{\neg l_n \mid l \in g^-\}$$

- **Formulas describing the *preconditions and effects of actions*:**

For every action  $a$  in  $A$ , formulas describing what changes  $a$  would make if it were the  $i$ 'th step of the plan:

- $a_i \Rightarrow \bigwedge \{p_i \mid p \in \text{Precond}(a)\} \wedge \bigwedge \{e_{i+1} \mid e \in \text{Effects}(a)\}$

- **Formulas describing *Complete exclusion*:**

- For all actions  $a$  and  $b$ , formulas saying they cannot occur at the same time

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

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

- **Formulas providing a solution to the *Frame Problem***

# Example

## ➤ Planning domain:

- one robot  $r1$
- two adjacent locations  $l1, l2$
- one action (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:  $at(r1,l2,1) \wedge \neg at(r1,l1,1)$

## Example (continued)

- **Action:** **move(r,l1,l2)**  
precond:  $\text{at}(r,l1)$   
effects:  $\text{at}(r,l2), \neg\text{at}(r,l1)$

### Encoding:

$\text{move}(r1,l1,l2,0) \Rightarrow \text{at}(r1,l1,0) \wedge \text{at}(r1,l2,1) \wedge \neg\text{at}(r1,l1,1)$   
 $\text{move}(r1,l2,l1,0) \Rightarrow \text{at}(r1,l2,0) \wedge \text{at}(r1,l1,1) \wedge \neg\text{at}(r1,l2,1)$

- **Complete-exclusion axiom:**  
 $\neg\text{move}(r1,l1,l2,0) \vee \neg\text{move}(r1,l2,l1,0)$
- **Explanatory frame axioms:**  
 $\neg\text{at}(r1,l1,0) \wedge \text{at}(r1,l1,1) \Rightarrow \text{move}(r1,l2,l1,0)$   
 $\neg\text{at}(r1,l2,0) \wedge \text{at}(r1,l2,1) \Rightarrow \text{move}(r1,l1,l2,0)$   
 $\text{at}(r1,l1,0) \wedge \neg\text{at}(r1,l1,1) \Rightarrow \text{move}(r1,l1,l2,0)$   
 $\text{at}(r1,l2,0) \wedge \neg\text{at}(r1,l2,1) \Rightarrow \text{move}(r1,l2,l1,0)$

**What are these “Explanatory Frame Axioms” and the  
“Complete Exclusion Axioms”?**

# The Frame Problem

The Frame Problem:

Describing what *does not* change between steps  $i$  and  $i+1$

Two Common Solutions:

1. Classical Frame Axioms
2. Explanatory frame axioms

# 1. Classical Frame Axioms

- **Classical frame axioms** (McCarthy & Hayes 1969)
  - State which fluents are unaffected by a given action
  - For each action  $a$ , for each fluent not in  $\text{effects}(a)$ , and for each step  $i$ , we have:  $f_i \wedge a_i \Rightarrow f_{i+1}$
  - Problem: if no action occurs at step  $i$  nothing can be inferred about propositions at level  $i+1$
  - Sol: at-least-one axiom: at least one action occurs
  - If more than one action occurs at a step, either one can be selected.



## 2. Explanatory frame axioms

### ➤ Explanatory frame axioms (Haas 1987)

- Enumerate the set of actions that could have occurred in order to account for a state change.
- Says that if  $f$  changes between  $s_i$  and  $s_{i+1}$ , then the action at step  $i$  must be responsible:

$$(\neg f_i \wedge f_{i+1} \Rightarrow \mathbf{V}\{a_i \mid f \in \text{effects}^+(a)\}) \wedge (f_i \wedge \neg f_{i+1} \Rightarrow \mathbf{V}\{a_i \mid l \in \text{effects}^-(a)\})$$

- Example:

$$\neg \text{at}(r1, l1, 0) \wedge \text{at}(r1, l1, 1) \Rightarrow \text{move}(r1, l2, l1, 0)$$

$$\neg \text{at}(r1, l2, 0) \wedge \text{at}(r1, l2, 1) \Rightarrow \text{move}(r1, l1, l2, 0)$$

$$\text{at}(r1, l1, 0) \wedge \neg \text{at}(r1, l1, 1) \Rightarrow \text{move}(r1, l1, l2, 0)$$

$$\text{at}(r1, l2, 0) \wedge \neg \text{at}(r1, l2, 1) \Rightarrow \text{move}(r1, l2, l1, 0)$$

# Explanatory frame axioms (cont)

## ➤ **Allows parallelism**

- Two actions can be executed in parallel if
  - Their preconditions are satisfied at time  $t$
  - Their effects do not conflict
- Gives shorter plans – smaller encoding

## ➤ **Uncontrolled parallelism is problematic**

- Can create valid plans without valid solution
  - Action  $\alpha$  has precondition  $X$  and effect  $Y$
  - Action  $\beta$  has precondition  $\neg Y$  and effect  $\neg X$

# Explanatory frame axioms (cont)

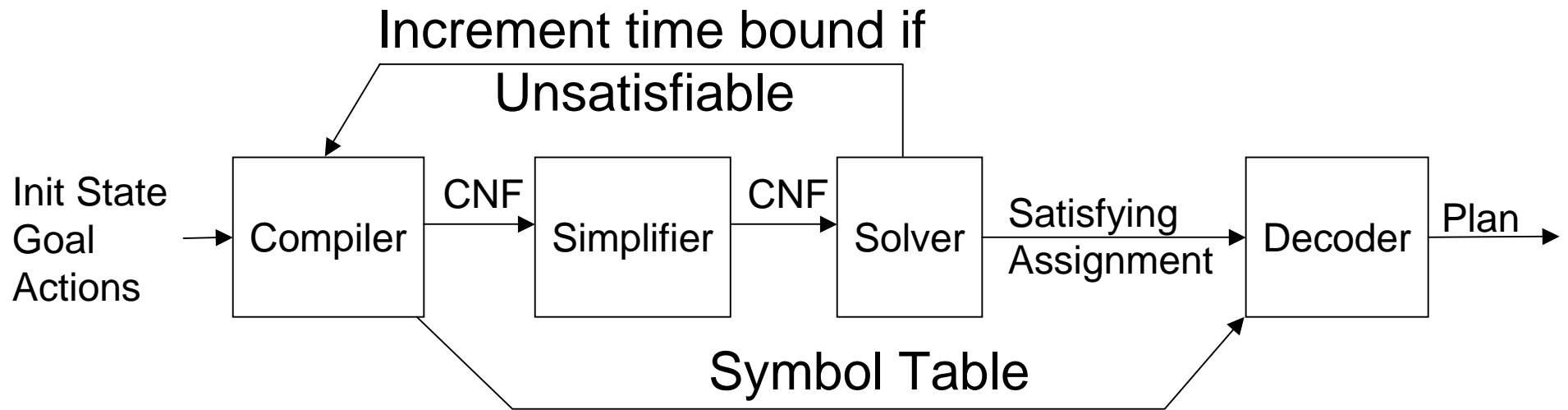
## Need Exclusion Axioms

- **Complete** exclusion axioms – *totally ordered plan*
  - Only one action occurs at a time
$$\neg \alpha_t \vee \neg \beta_t$$
- **Conflict** exclusion axioms – *partially ordered plan*
  - Two actions conflict if one's precondition is inconsistent with the other's effect
  - Conflict exclusion should be used whenever possible

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# Architecture of SAT-based planning system



# Space of Encodings

- **Want a compiler to quickly produce a small SAT encoding**
  - Number of variables
  - Number of clauses
  - Total number of literals summed over all clauses
- **Two factors determine these sizes:**
  - Encoding
    - Choice of **Action Representation**
      - Regular, simple split, overloaded split, or bitwise
      - Tradeoff between the number of variables and the number of clauses in the formula
    - Choice of **Frame Axioms**: classical or explanatory
  - Optimizations being used

# Action Encoding

## ➤ Regular

- Each ground action is represented by a different logical variable

## ➤ Simple Operator Splitting

- Replace each n-ary action proposition with n unary propositions
- Advantage: instances of each action share the same variable
  - $\text{move2}(l1,i)$  is used to represent  $\text{move}(r1,l1,l2,i)$ , can be reused to represent  $\text{move}(r2,l1,l2,i)$  – represent cases where starting location is the same

## ➤ Overloaded Operator Splitting

- Allowing different actions to share the same variable

## ➤ Bitwise

- Propositional variables are represented using bits

# Action Encoding

[Ernst et al, IJCAI 1997]

Representation	One Propositional Variable per	Example
<b>Regular</b>	fully-instantiated action $n F  + n O  D ^{A_0}$	move(r1,l1,l2,i)
<b>Simply-split</b>	fully-instantiated action's argument $n F  + n O  D A_0$	move1(r1,i) $\wedge$ move1(l1,i) $\wedge$ move1(l2,i)
<b>Overloaded-split</b>	fully-instantiated argument $n F  + n( O + D A_0)$	Act(move, i) $\wedge$ Act1(r1, i) $\wedge$ Act2(l1, i) $\wedge$ Act3(l2, i)
<b>Bitwise</b>	Binary encodings of actions $n F  + n[\log_2  O  D ^{A_0}]$	Bit1

more  
vars



more  
clauses

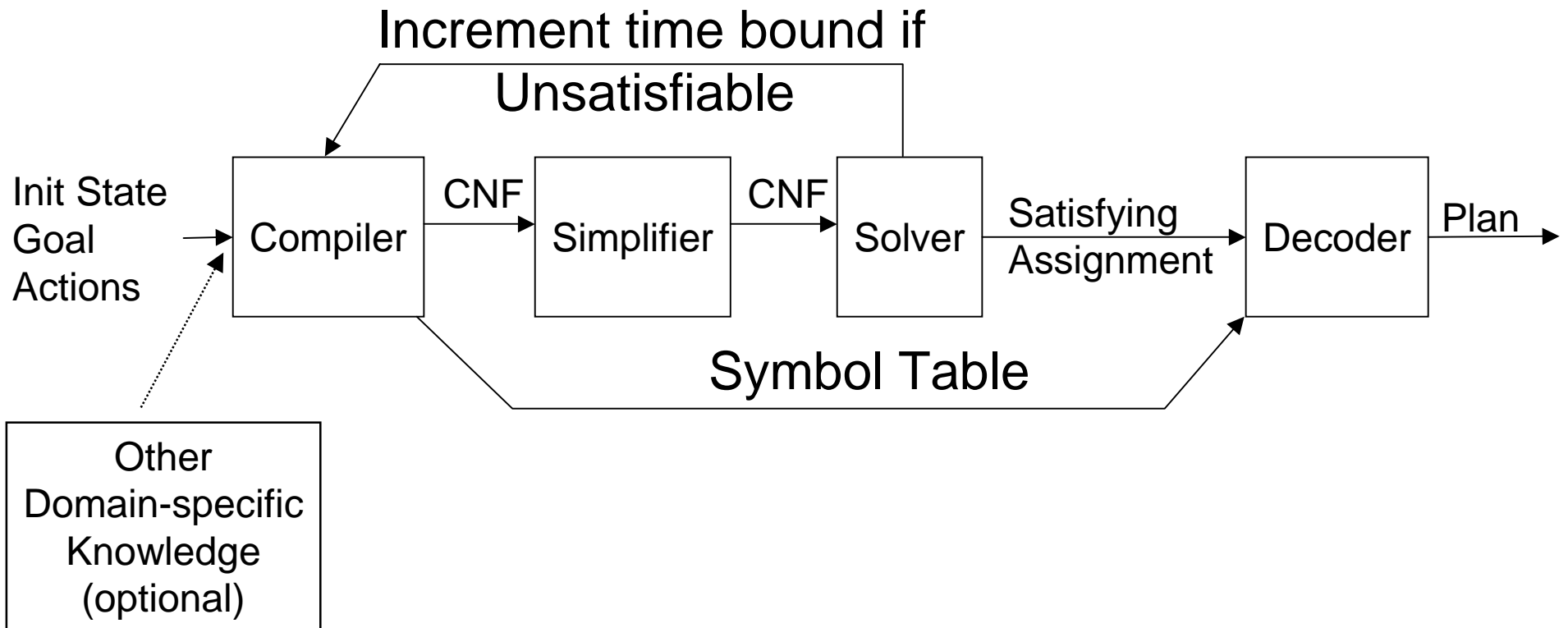
N – number of steps; |F| - number of fluents;  
|O| - number of operators;  $A_0$  – maximum arity of predicates



## Comparisons of Different Encodings

- **Regular explanatory and simple splitting explanatory encodings are the smallest**
  - Explanatory frame axioms are smaller
    - State only what changes, not what does not change
  - Regular explanatory encodings allow for parallel actions
    - Shorter plans
    - Conflict exclusion axioms are a subset of complete exclusion axioms.

# Architecture of SAT-based planning system



# Optimizations

- Optimize the CNF formula produced by a compiler
  1. **Compile-time optimization**
    - Shrink the size of CNF formula that SAT-compiler generates
  2. Adding **domain-specific information** (e.g., control knowledge)
    - Precondition  $\models$  action conflicts, effects  $\models$  derived effects
    - State invariant:
      - A truck is at only one location
    - Optimality: disallowing unnecessary subplans
      - Do not return a package to its original location
    - Simplifying assumptions: not logically entailed
      - Once trucks are loaded they should immediately move

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# Extracting a Plan

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

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# SAT Algorithms

- **How to find an assignment of truth values that satisfies  $\Phi$ ?**
  - Use a satisfiability algorithm
- **Systematic Search**
  - E.g., **DP** (Davis Putnam Logemann Loveland) backtrack search + unit propagation
- **Local Search**
  - E.g., GSAT (Selman), **Walksat** (Selman, Kautz & Cohen) greedy local search + noise to escape minima

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# Discussion

➤ **Recall the overall approach:**

- for  $n = 0, 1, 2, \dots$ ,
  - encode  $(P, n)$  as a satisfiability problem  $\Phi$
  - if  $\Phi$  is satisfiable, then
    - From the set of truth values that satisfies  $\Phi$ , extract a solution plan and return it

➤ **By itself, not very practical (takes too much memory and time)**

➤ **But it can be combined with other techniques**

- e.g., planning graphs
- Blackbox: combines planning-graph expansion and satisfiability checking

# Conclusion

## ➤ **What SATPLAN shows**

- General SAT solvers can compete with state of the art specialized planning systems, in fact today's SAT-based planners are among the fastest!!!

## ➤ **Why SATPLAN works**

- More flexible than forward or backward chaining
- Randomized algorithms less likely to get trapped on bad paths

# Acknowledgement

- **I have reused slides from the following two sources:**
  - Open-Loop Planning as Satisfiability by Henry Kautz  
<http://www.cs.washington.edu/homes/kautz/talks/tutorial99/openloop.ppt>
  - Aussagenlogische Erfüllbarkeitstechniken SATPlan by Ulrich Scholz  
[http://www.intellektik.informatik.tu-darmstadt.de/~scholz/Vorlesung/07\\_Satplan\\_2005\\_12\\_08.pdf](http://www.intellektik.informatik.tu-darmstadt.de/~scholz/Vorlesung/07_Satplan_2005_12_08.pdf)