

Planning as Model Checking

AIPS'02 Tutorial

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Planning as Model Checking – p. 1

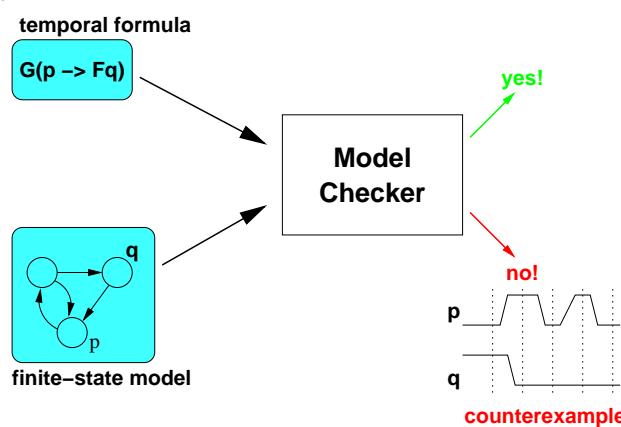
Introduction



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Model Checking

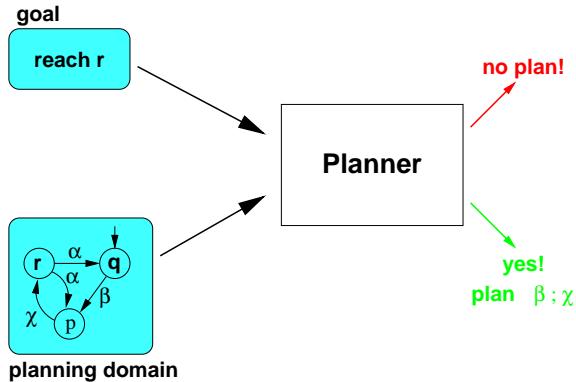
Model Checking: a technique to validate a *formal model* of a system against a *logical specification*.



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Planning as Model Checking

Planning as Model Checking: a technique to *synthesize* a plan from a *formal model of a domain* and a *logical specification of a goal*.



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Planning as Model Checking

Remarkable success of the “Planning as Model Checking” approach:

- ➊ Several papers in the most important planning conferences.
- ➋ Dedicated sessions on Planning as Model Checking.
- ➌ Workshops on this topic (e.g., AIPS’00, IJCAI’01, AIPS’02).
- ➍ Wide range of planning systems exploit Model Checking techniques (BDDPlan, CIRCA, MBP, MIPS, Proplan, Simplan, SPUDD, TalPlan, TLPlan, UMOP...).
- ➎ Practical application of “Planning as Model Checking” on real problems (design of controllers for autonomous systems, power supply recovery systems,...).



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The “Planning as Model Checking” Tutorial

This tutorial...

- ➊ ...is motivated by the strong interest in “Planning as Model Checking”.
- ➋ ...is intended to give an overview of “Planning as Model Checking”.
- ➌ ...is designed to be *hands-on*: during the hands-on session the participants will confront with the “practical” problems of planning.

In particular:

- ➊ we will focus on the approach developed at IRST: use of *Symbolic Model Checking* techniques for planning in non-deterministic domains.
- ➋ the MBP planner will be used in the practical sessions.



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Index of the tutorial

1. Introduction.
2. Overview on Planning.
3. Introduction to Model Checking.
4. Planning as (Symbolic) Model Checking.
5. MBP – The Model Based Planner.
6. Hands on!
7. Conclusions.



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Plan

09.00-10.00	Overview Model Checking An introduction to Planning as Model Checking
10.00-10.30	Coffee Break
10.30-12.30	Planning as Model Checking MBP: system architecture & demo
12.30-14.00	Lunch
14.00-14.30	nuPDDL: extended planning domain definition language
14.30-15.30	Assignments & Hands-On, pt.1
15.30-16.00	Coffee Break
16.00-18.00	Hands-on, Pt.2 & Conclusions



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Acknowledgments



This tutorial is sponsored by PLANET.



Many thanks to the AIPS'02 organizers for the support.



Many thanks to the colleagues at IRST for the helps and the suggestions.



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Overview on Planning

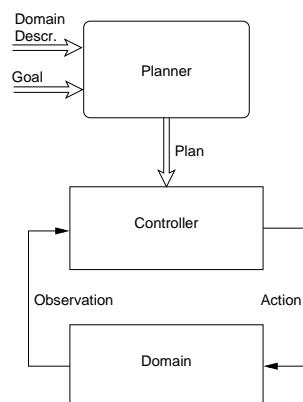
Planning

- “Planning” is the problem of building a suitable *plan* for achieving a given *goal* on a given dynamic domain.
- The plan describes the actions to be executed in the domain in order to achieve the goal.

Different approaches to planning differ for:

- the assumptions on the *domain*.
- the assumptions on the *goals*.
- the assumptions on the *plans*.
- the techniques used in the *planning algorithm*.

The conceptual model



- the *domain* evolves according to performed *actions*.
- the *controller* provides the *actions* according to the *observations* on the domain and to a *plan*.
- the *planner* synthesizes a *plan* from a *domain description* and a *goal*.

Thanks to “Automated Task Planning: Theory and Practice”, M. Ghallab, D. Nau, P. Traverso

Classical planning: assumptions

Classical planning relies on simplifying assumptions:

- ➊ ***finite***: the domain has a finite set of different states.
- ➋ ***implicit time***: actions are instantaneous state transitions.
- ➌ ***deterministic***: the initial state is completely specified; each action, if applicable in a state, brings to a single new state.
- ➍ ***observable***: the state of the system is fully observable to the controller.
- ➎ ***basic goals***: goals are sets of target states; the objective is to build a plan that leads to one of the goal states.
- ➏ ***off-line planning***: the plan is built once and for all, before its execution.
- ➐ ...



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Classical planning

- ➊ A plan is a *sequence of actions* whose execution leads from the initial state of the domain to a goal state.
 - the evolution is completely determined by the executed actions (deterministic domain).
 - no feedback is needed from the domain (observation is not necessary).
- ➋ Main difficulty:
 - in spite of simplifying assumptions, search space is huge for practical domains.



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Non-Determinism

The restriction to *deterministic* domains is unrealistic in many practical cases:

- ➊ There may be uncertainty on the *initial state*.
- ➋ Actions may have *non-nominal outcomes* that are highly critical.
- ➌ Actions may have *no nominal outcome* (e.g., throwing a dice).
- ➍ There may be *exogenous events* or *non-controllable actions*.

In *non-deterministic domains*:

- ➊ More than one initial state is possible.
- ➋ An action executed in a state may lead to many different states.

Main difficulties:

- ➊ Plans cannot simply be sequences of actions.
- ➋ Domain models are more complex.
- ➌ Lifting most classical planning techniques does not work in practice.



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Non-determinism: probabilistic outcomes

It is often possible to associate probabilities to the outcomes of actions:

- ➊ non-nominal outcomes of actions often have a very small probability.
- ➋ when throwing a fair dice, all the outcomes have equal probability.
- ➌ exogenous events occurs with a given probability.

In planning with probabilistic domains (e.g., MDP-based planning):

- ➊ probabilities are associated to the outcomes of actions.
- ➋ goals are represented by utility, or value functions.
- ➌ planning consists in searching for a plan maximizing the utility function.

Main difficulty:

- ➊ *optimality* comes into play.



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Partial observability

In several realistic problems the domain status is only partially visible at run-time to the controller:

- ➊ different states of the domain are *indistinguishable* for the controller.
- ➋ certain information on the domain is available only after some *sensing actions*.

Particular cases:

- ➊ *full observability*.
- ➋ *null observability* (conformant planning).

Main difficulty:

- ➊ for non-deterministic domains, the controller has a partial knowledge of the domain status.



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Extended goals

The assumption that planning goals are sets of final desired states is unrealistic in many cases:

- ➊ *safety conditions* (states to be avoided) may complement the main goal.
- ➋ *reactive systems* (infinite plans that react to changes).
- ➌ *preferences* among plans and *search control rules* can be specified.

Temporally extended goals express conditions on the whole, possibly infinite sequences of states resulting from plan execution.

Main difficulty:

- ➊ the plan should trace past history (different “active” goals depending on past events).



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Explicit time

Several planning domains require to represent:

- duration of actions.
- concurrency of actions in accessing resources.
- temporal constraints on the occurrence of events with respect to an absolute time reference.

An *explicit* representation of time is necessary for dealing effectively with these aspects.

Main difficulties:

- planning algorithms have to deal with time and resources.
- time is continuous → it cannot be modeled directly in finite-state systems.



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Plans

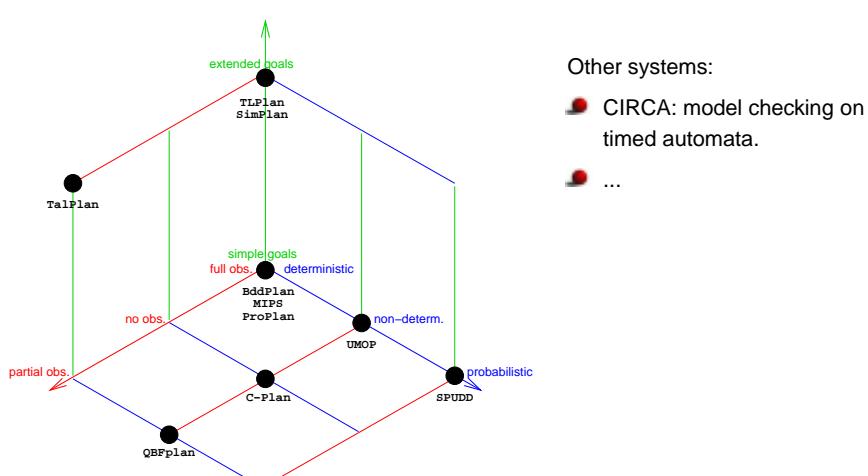
Different kinds of plans are necessary for dealing with different assumptions on domains and goals.

- sequences of actions* are sufficient for *classical planning*.
- conditional plans* are necessary for dealing with *non-deterministic* domains under *partial observability*.
- history-dependent* plans are necessary for *extended goals*.
- explicit time representation* may be necessary in plans.
- ...



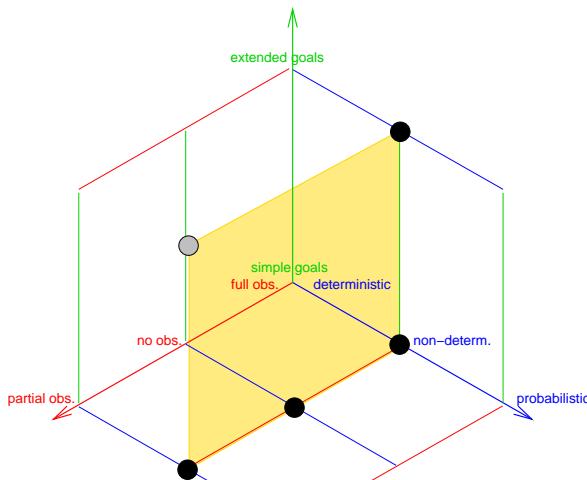
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Planning as Model Checking



Overview on Planning – p. 21

In this tutorial: the MBP system



A planning system...

...must not be limited to plan synthesis.

- ➊ Plan validation: verification that a *plan* satisfies a given *property* (not necessarily a goal...).
- ➋ Plan simulation: interactive simulation of the executions of a *plan* on a given *domain*.
- ➌ Plan synthesis: automatic generation of the plan from a description of the *domain* and from the *goal*.
- ➍ ...

Introduction to Model Checking

Talk Overview

Model Checking is a widely used automatic technique for verifying design and for discovering possible bugs.

In this talk ...

- An introduction to model checking.
- Symbolic representation of FSM based on BDDs.
- An introduction to symbolic model checking algorithms for CTL.



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Model Checking

- Model Checking is a verification technique that solves the problem

$$\mathcal{M} \models \varphi$$

where...

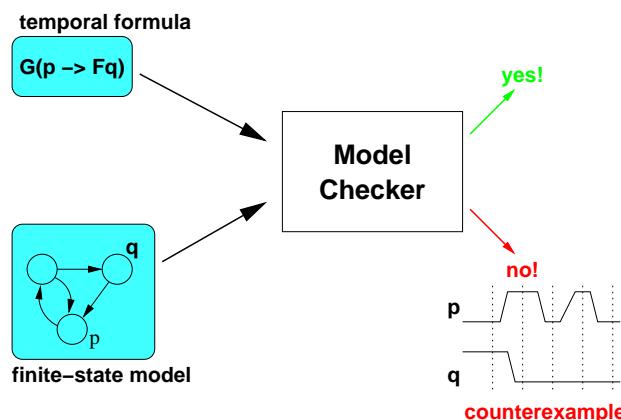
- Model \mathcal{M} is represented as a FSM.
- Property φ is a temporal logic formula.
- Model checking algorithms traverse the model guided by the property.



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Model Checker

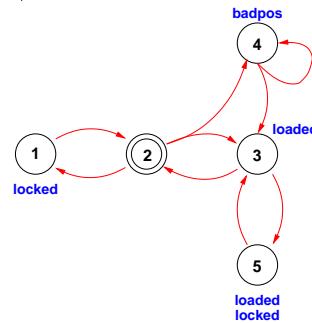
- Software tool for system verification.



Introduction to Model Checking – p. 27

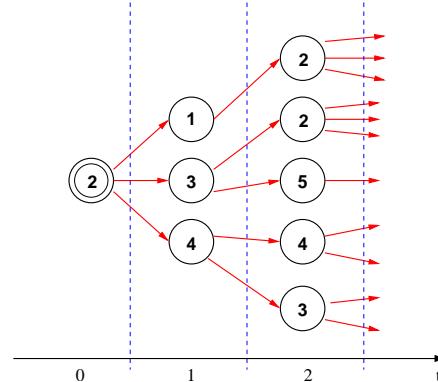
Formal Model: FSM

- A model is defined as a tuple $\mathcal{M} = \langle S, S_0, T, P, L \rangle$, where:
 - S is a finite set of states.
 - S_0 is the initial set of states.
 - P is a finite set of atomic propositions.
 - $T \subseteq S \times S$ is the transition relation.
 - $L : P \rightarrow 2^S$ assigns to each proposition $p \in P$ the set of states where p holds.



Computation Trees

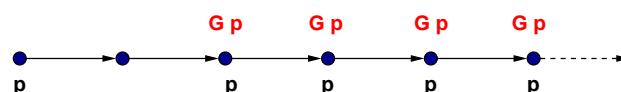
- Computation model is a *tree*:



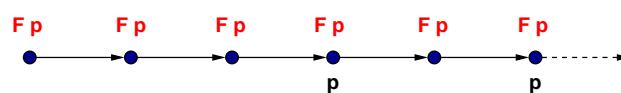
Temporal Logic: LTL

- Express properties of all computation paths.

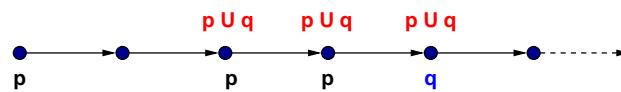
Invariantly p : $\mathbf{G} p$



Finally p : $\mathbf{F} p$



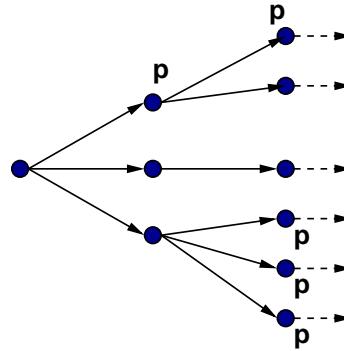
p holds until q holds: $p \mathbf{U} q$



Temporal Logic: CTL

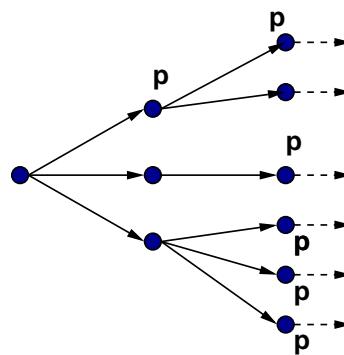
Express properties on computation paths.

- There exists a path where p finally holds: $\text{EF } p$



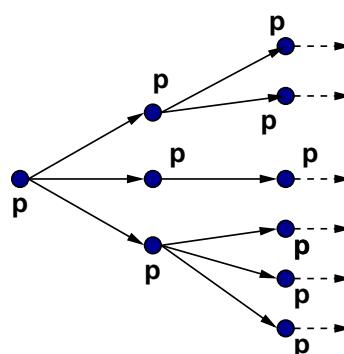
Temporal Logic: CTL (II)

- Property p finally holds for all paths: $\text{AF } p$



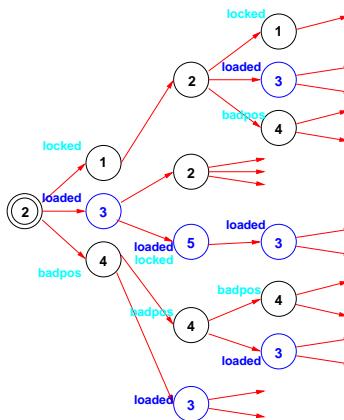
Temporal Logic: CTL (III)

- Invariant p holds along all paths: $\text{AG } p$



CTL Examples: AG EF

- It is always possible to reach a state where *loaded* holds : **AG EF loaded**



Symbolic Model Checking

- Symbolic model checking:

- Face the *state explosion problem* of explicit state model checking.
- Use the formula φ to represent the set of states where φ holds.

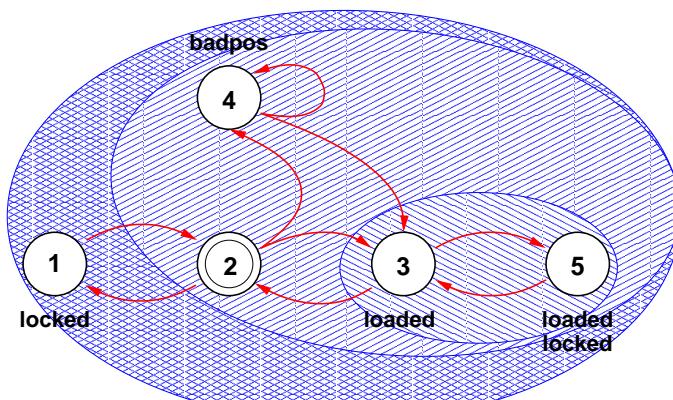
$$\varphi \rightsquigarrow \{s \mid M, s \models \varphi\}$$

- Use of Boolean formulas to represent sets and relations.
- Fix-point characterization of CTL operators.

$\text{EF}p \leftrightarrow p \vee \text{EX}\text{EF}p$	$\text{EF}p = \text{lfp}_Z\{p \cup \text{EX}Z\}$
$\text{E}[p \mathbf{U} q] \leftrightarrow p \vee \text{EX}(\text{E}[p \mathbf{U} q])$	$\text{E}[p \mathbf{U} q] = \text{lfp}_Z\{q \cup (p \cap \text{EX}Z)\}$
$\text{AG}p \leftrightarrow p \wedge \text{AX}\text{AG}p$	$\text{AG}p = \text{gfp}_Z\{p \cap \text{AX}Z\}$
$\text{EG}p \leftrightarrow p \wedge \text{EX}\text{EG}p$	$\text{EG}p = \text{gfp}_Z\{p \cap \text{EX}Z\}$
.....	

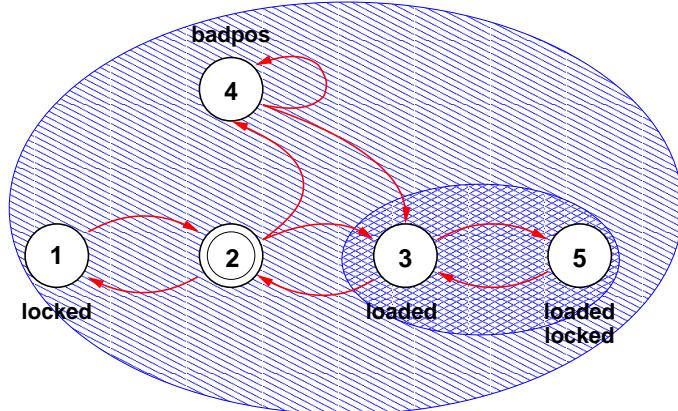
Fix-point characterization of CTL operators

- EF *loaded*



Fix-point characterization of CTL operators (II)

- EG loaded



Symbolic Representation

- A vector \mathbf{x} of Boolean variables where each Boolean variable corresponds to an atomic proposition in P .

$$\mathbf{x} = \{locked, badpos, loaded\}$$

- A state s is represented with a formula $\xi(s)$ on the propositions:

$$\begin{aligned} \textcircled{1} &\rightsquigarrow \textit{locked} \wedge \neg \textit{badpos} \wedge \neg \textit{loaded} \\ \textcircled{3} &\rightsquigarrow \neg \textit{locked} \wedge \neg \textit{badpos} \wedge \textit{loaded} \\ \textcircled{5} &\rightsquigarrow \textit{locked} \wedge \neg \textit{badpos} \wedge \textit{loaded} \end{aligned}$$

- A set of states $Q \subseteq S$ represented symbolically as:

$$\xi(Q) = \bigvee_{s \in Q} \xi(s)$$

Symbolic Representation (II)

- A formula φ represents the set of states where the formula holds:

$$\begin{array}{ll} \textit{loaded} & \rightsquigarrow \{\textcircled{3}, \textcircled{5}\} \\ \neg \textit{badpos} & \rightsquigarrow \{\textcircled{1}, \textcircled{2}, \textcircled{3}, \textcircled{5}\} \\ \textit{loaded} \wedge \textit{locked} & \rightsquigarrow \{\textcircled{5}\} \\ \textit{badpos} \wedge \textit{locked} \wedge \textit{loaded} & \rightsquigarrow \emptyset \\ \textit{loaded} \vee \textit{locked} & \rightsquigarrow \{\textcircled{1}, \textcircled{3}, \textcircled{5}\} \end{array}$$

- Set theoretic operations map to propositional operations:

$$\begin{aligned} \xi(Q_1 \setminus Q_2) &= \xi(Q_1) \wedge \neg \xi(Q_2) & \xi(Q_1 \cup Q_2) &= \xi(Q_1) \vee \xi(Q_2) \\ \xi(Q_1 \cap Q_2) &= \xi(Q_1) \wedge \xi(Q_2) \end{aligned}$$

Symbolic Representation (III)

- A new vector \mathbf{x}' of Boolean variables to encode next state:

$$\mathbf{x}' = \{\text{loaded}', \text{locked}', \text{badpos}'\}$$

- A transition $t = \langle s_s, s_d \rangle$ encoded as

$$\xi(t) = \xi(\langle s_s, s_d \rangle) = \xi(s_s) \wedge \xi'(s_d)$$

$$\begin{aligned} \langle \textcircled{1}, \textcircled{2} \rangle &\rightsquigarrow \left(\begin{array}{l} (\text{locked} \wedge \neg \text{badpos} \wedge \neg \text{loaded}) \\ (\neg \text{locked}' \wedge \neg \text{badpos}' \wedge \neg \text{loaded}') \end{array} \right) \wedge \\ \langle \textcircled{2}, \textcircled{3} \rangle &\rightsquigarrow \left(\begin{array}{l} (\text{locked} \wedge \neg \text{badpos} \wedge \neg \text{loaded}) \\ (\neg \text{locked}' \wedge \neg \text{badpos}' \wedge \text{loaded}') \end{array} \right) \wedge \end{aligned}$$

- Transition relation T represented symbolically as:

$$\xi(T) = \bigvee_{t \in T} \xi(t)$$



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Symbolic Exploration of the Model

- Images work on sets of states:

- The forward image $FImg(S)$ of a set S is

$$FImg(S) = \{s' \mid s \in S \wedge \langle s, s' \rangle \in T\} \rightsquigarrow \exists \mathbf{x}. (S(\mathbf{x}) \wedge T(\mathbf{x}, \mathbf{x}'))$$

- The backward image $BImg(S)$ of a set S is

$$BImg(S) = \{s \mid s' \in S \wedge \langle s, s' \rangle \in T\} \rightsquigarrow \exists \mathbf{x}'. (S(\mathbf{x}') \wedge T(\mathbf{x}, \mathbf{x}'))$$



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Symbolic CTL model checking

- The set of states where a formula φ holds is represented symbolically.

- $M, S_0 \models \varphi$ reduces to $(\neg \varphi \wedge S_0) = \perp$

- Basic CTL operations represented as

$$\mathbf{EX}(\varphi) = \exists \mathbf{x}'. (T(\mathbf{x}, \mathbf{x}') \wedge \varphi(\mathbf{x}'))$$

$$\mathbf{AX}(\varphi) = \forall \mathbf{x}'. (T(\mathbf{x}, \mathbf{x}') \rightarrow \varphi(\mathbf{x}'))$$

- Fix-point computations as propositional transformations.

$$\mathbf{AF} \varphi = \text{fp}_Z \{\varphi \cup \mathbf{AX}Z\}$$

$$\begin{aligned} s_0 &= \perp \\ s_1 &= \varphi \vee \mathbf{AX}s_0 = \varphi \\ s_2 &= \varphi \vee \mathbf{AX}s_1 = \varphi \vee \mathbf{AX}\varphi \\ s_3 &= \varphi \vee \mathbf{AX}s_2 = \varphi \vee \mathbf{AX}(\varphi \vee \mathbf{AX}\varphi) \\ &\dots \\ s_i &= s_{i-1} \end{aligned}$$



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Binary Decision Diagrams

- The problem in symbolic model checking:
 - The need for efficient and practical representation and manipulation of propositional formulae.
- **Binary Decision Diagrams (BDDs).**
 - Canonical form for propositional formulae.
 - Efficiently managed by BDD packages.



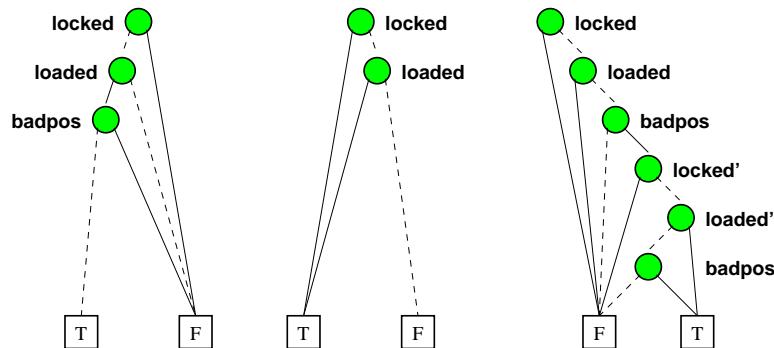
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Binary Decision Diagrams (II)

$\{③\}$

$\{①, ③, ⑤\}$

$\{\langle ④, ④ \rangle, \langle ④, ③ \rangle\}$

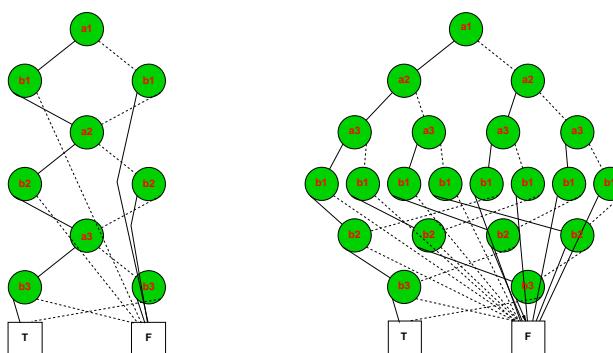


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Binary Decision Diagrams (III)

- BDDs variable ordering is important.

$$(a_1 \leftrightarrow b_1) \wedge (a_2 \leftrightarrow b_2) \wedge (a_3 \leftrightarrow b_3)$$



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Binary Decision Diagrams: Pros and Cons

Pros

- Equality test of two BDDs in constant time.
- Basic propositional operations polynomial on the size of operands.

$$O(\varphi_1 \otimes \varphi_2) = O(|\varphi_1||\varphi_2|)$$

Cons

- Quantification exponential in the variables being quantified.
- BDD size may be exponential in the number of variables.
 - e.g., multiplier.

- They work well in several practical applications.



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Planning as Symbolic Model Checking



Planning as Symbolic Model Checking – p. 47

Introduction

The “*Planning as Model Checking*” approach defines a general framework for dealing with:

- non-deterministic domains...
- extended goals...
- partial observability...
- ...and their combination

In “*Planning as Symbolic Model Checking*” BDD-based symbolic techniques are used for:

- a compact representation of domains and plans
- an efficient search in the domain in the planning algorithm



Planning as Symbolic Model Checking – p. 48

Talk Overview

In this talk:

1. General framework
2. Reachability goals
3. Extended goals
4. Partial observability
5. Conclusions



Planning as Symbolic Model Checking – p. 49

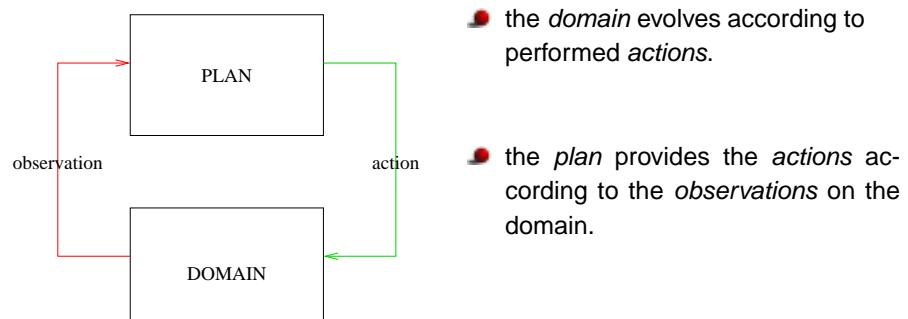
Planning as Symbolic Model Checking

General framework



Planning as Symbolic Model Checking: General framework – p. 50

The general framework

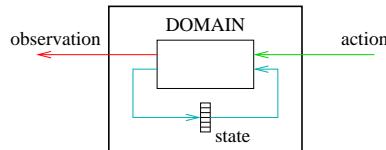


Planning as Symbolic Model Checking: General framework – p. 51

The model of the domain

A domain D is a finite-state machine:

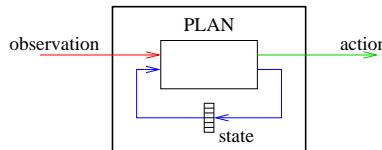
- D's input is an *action*.
- D's output is an *observation*.
- D's state represents the *domain state*.
- D's output and next state are non-deterministic.



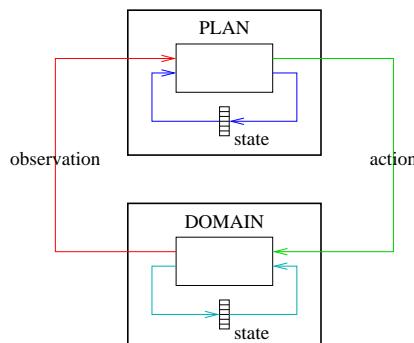
Model of the plan

A plan P is a finite-state machine:

- P's input is an *observation*.
- P's output is an *action*.
- P's state represents the *plan state*.
- P's output and next state are deterministic.



Plan execution

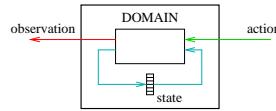


- The execution of a plan on a domain is the “synchronous execution” of the two machines.
- The state of the execution juxtaposes the state of the domain and that of the plan.
- Plan validation → model checking on execution structures.

Planning Domain: Formal Definitions

- A *planning domain* is defined as a tuple $\mathcal{D} = \langle S, S_0, A, T, P, L, O, X \rangle$:

- S is a finite set of states.
- S_0 is the initial set of states.
- A is a finite set of actions.
- $T \subseteq S \times A \times S$ is the transition relation.
- P is a finite set of atomic propositions.
- $L : P \mapsto 2^S$ assigns to each $p \in P$ the set of states where p holds.
- O is a finite set of possible observations.
- $X \subseteq S \times O$ is the observation relation.



Planning as Symbolic Model Checking: General framework – p. 55

Planning Domains Symbolic Representation

- States represented as in symbolic model checking: $\xi(s)$.
- A vector α of Boolean variables, each corresponding to an action in A :

$$\alpha = \{GoWest, GoEast, GoNorth, GoSouth\}$$

- An action represented by assigning *True* to the corresponding Boolean variable:

$$\xi(\text{GoWest}) \rightsquigarrow GoWest \quad \xi(\text{GoSouth}) \rightsquigarrow GoSouth$$

- Alternatively, compact logarithmic encoding of actions.
- A transition $t = \langle s_s, a, s_d \rangle$ encoded as

$$\xi(t) = \xi(\langle s_s, a, s_d \rangle) = \xi(s_s) \wedge \xi(a) \wedge \xi'(s_d)$$



Planning as Symbolic Model Checking: General framework – p. 56

Planning Domains Symbolic Representation (II)

- Observations encoded with a vector o of Boolean variables.

$$o = \{O_{WallN}, O_{WallS}, O_{WallE}, O_{WallO}\}$$

- An observation represented by assigning *True* to the corresponding Boolean variable.

$$\xi(O_{WallW}) \rightsquigarrow O_{WallW} \quad \xi(O_{WallS}) \rightsquigarrow O_{WallS}$$



Planning as Symbolic Model Checking: General framework – p. 57

Symbolic Exploration of the Domains

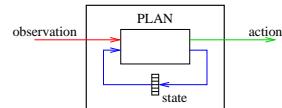
- Images work on set of states:
 - Forward: set of states reachable from a set of states S
 $FImg(S) = \{s' \mid s \in S \wedge \langle s, a, s' \rangle \in T\} \rightsquigarrow \exists \mathbf{x}. \alpha. (S(\mathbf{x}) \wedge T(\mathbf{x}, \alpha, \mathbf{x}'))$
 - Backward: set of states from which a set of states S is reachable
 $BImg(S) = \{s \mid s' \in S \wedge \langle s, a, s' \rangle \in T\} \rightsquigarrow \exists \mathbf{x}' . \alpha. (S(\mathbf{x}') \wedge T(x, \alpha, \mathbf{x}'))$



Planning as Symbolic Model Checking: General framework – p. 58

Plans: Formal Model

- A *plan* Π for a planning domain \mathcal{D} is a tuple $\Pi = \langle \Sigma, \sigma_0, \Psi, \Upsilon \rangle$ where:
 - Σ is a finite set of *plan states*.
 - σ_0 is the *initial* plan state.
 - $\Psi : \Sigma \times O \rightarrow A$ associates to a pair $\langle \sigma, o \rangle$ an action α to execute.
 - $\Upsilon : \Sigma \times O \rightarrow \Sigma$ associates to a pair $\langle \sigma, o \rangle$ a new plan state σ' .
- A configuration for a domain \mathcal{D} and a plan Π is a pair $\langle s, \sigma \rangle \in S \times \Sigma$.
- Plan execution is represented with configuration transitions:



Planning as Symbolic Model Checking: General framework – p. 59

Planning as Symbolic Model Checking

Reachability Goals



Planning as Symbolic Model Checking: Reachability Goals – p. 60

Motivations

Reachability goals:

- First and “basic” planning problem:
 - find a plan to achieve a desired final situation.
- When tackled within classical planning:
 - solutions are sequences of actions.
 - solutions are guaranteed to achieve the goal.

Adding non-determinism:

- Plans as sequences of actions are bound to failure.
 - Initial situation might be uncertain.
 - Actions can have non-deterministic effects.
- Plans of different strength, e.g. weak, strong.
- Plans of different structure: sense current state and execute an action.

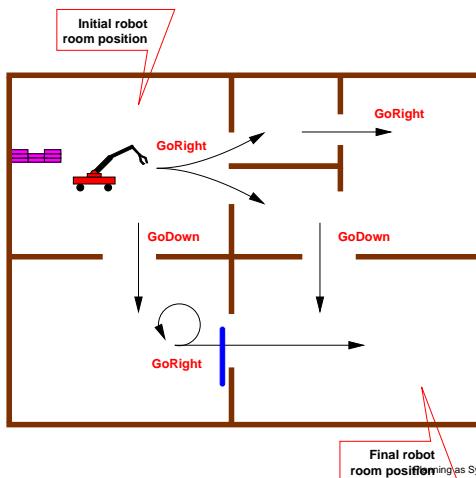


Planning as Symbolic Model Checking: Reachability Goals – p. 61

Example

The problem ...

- ... find a plan from a (set of) initial state(s) to a goal set of states.



Aim

Objectives:

- Allow for planning under *full observability* in *non-deterministic* domains.
- Synthesis of plans of different *strength*.
- Deal in practice with *large size* domains.

Problems:

- How can we handle non-deterministic actions?
- Which kind of plans must be generated?
- Which planning algorithms?
- How can planning algorithms handle large domains?



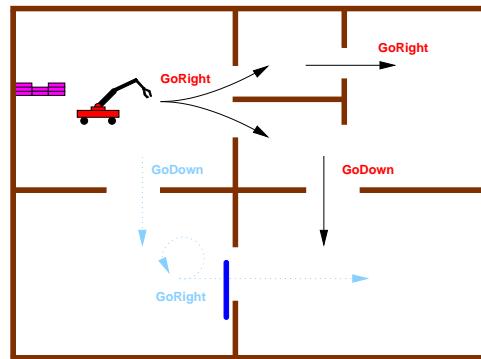
Planning as Symbolic Model Checking: Reachability Goals – p. 63

The PMC approach for Reachability goals

- Solution plans encode conditional behavior based on domain state.
- Planning algorithms exploit ...
 - symbolic representation of the domain.
 - symbolic representation of solution plans.
- Experimental results show that algorithms work in practice.

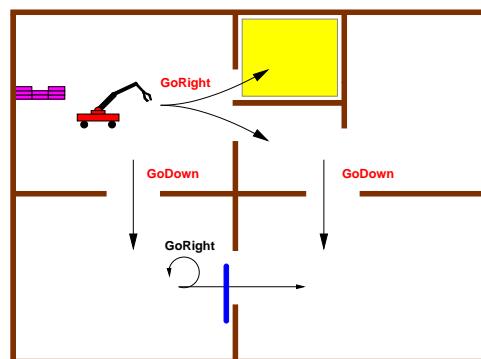
Example

- Strong Solutions: plans that are guaranteed to reach the goal.
 - All executions traces are acyclic and reach the goal.



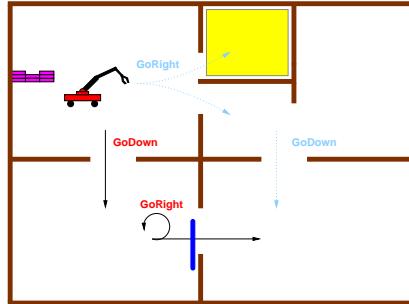
Example

- Weak Solutions: plans that may achieve the goal.
 - At least one execution trace reaches the goal.



Example

- Strong Cyclic Solutions: trial and error strategies.
- The goal is reachable from all states of the execution traces.
- Solutions are guaranteed to reach the goal under the assumption of "fair" execution.



State-Action Tables

- Solutions are **memory-less** plans that map states to actions to execute.
- Such solutions can be represented as "**state-action tables**" (SA).

State	Action
R1	GoUp
R2	GoRight
R3	GoDown
R4	GoRight

- State-action tables map in a general plan...
 - ... without plan states.
 - ... switching on the current state.

Symbolic Representation of SA Tables

- A state-action pair $p = \langle s, a \rangle$ is represented symbolically as:

$$\xi(p) = \xi(s) \wedge \xi(a)$$

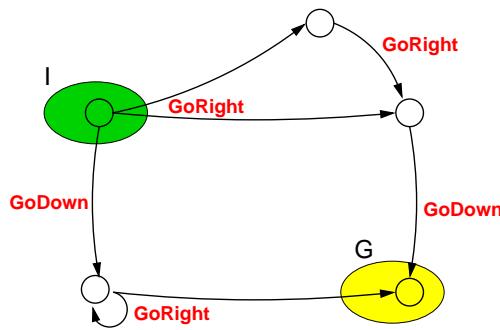
- A state-action table π is encoded as symbolically as:

$$\xi(\pi) = \bigvee_{p \in \pi} \xi(p)$$

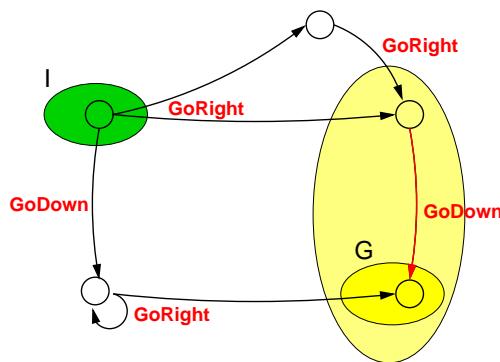
- Set operations on state-action tables performed as:

$$\begin{aligned}\xi(\pi_1 \setminus \pi_2) &= \xi(\pi_1) \wedge \neg\xi(\pi_2) & \xi(\pi_1 \cup \pi_2) &= \xi(\pi_1) \vee \xi(\pi_2) \\ \xi(\pi_1 \cap \pi_2) &= \xi(\pi_1) \wedge \xi(\pi_2)\end{aligned}$$

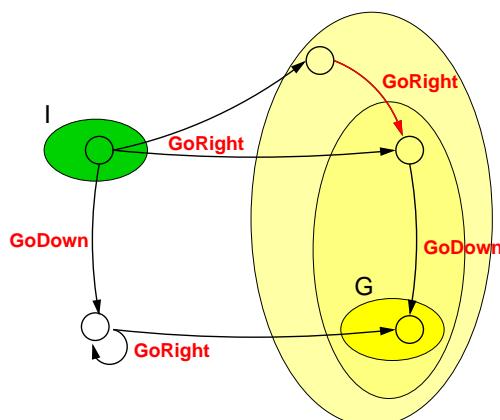
STRONGPLAN: Algorithm intuition



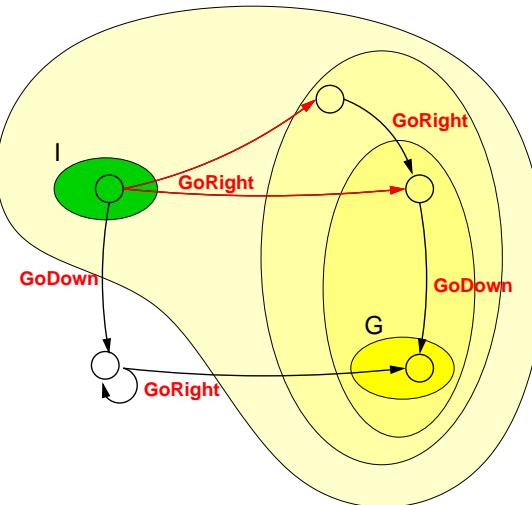
STRONGPLAN: Algorithm intuition



STRONGPLAN: Algorithm intuition

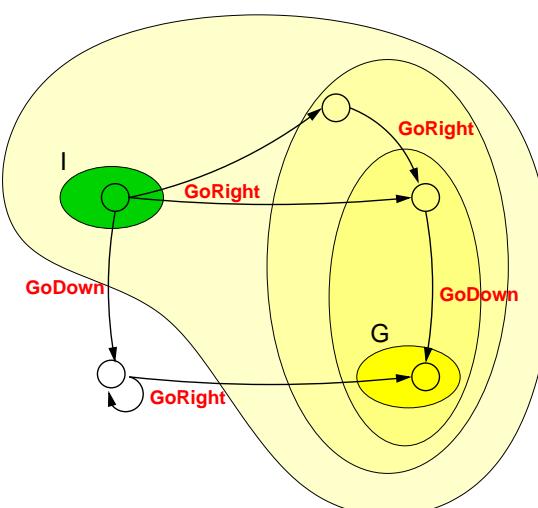


STRONGPLAN: Algorithm intuition



Planning as Symbolic Model Checking: Reachability Goals – p. 70

STRONGPLAN: Algorithm intuition



Planning as Symbolic Model Checking: Reachability Goals – p. 70

STRONGPLAN: Algorithm

```
function STRONGPLAN (I, G);
  OSA := FAIL; SA := ∅;
  while (OSA ≠ SA) do
    PIMG := SPIMG(G ∪ STOF(SA));
    NSA := PRUNESTATES(PIMG, G ∪ STOF(SA));
    OSA := SA;
    SA := SA ∪ NSA;
  done;
  if (I ⊆ (G ∪ STOF(SA))) then
    return SA;
  else
    return FAIL;
end;

function AF (I, G);
  OS := FAIL; S := ∅;
  while (OLDS ≠ S) do
    PIMG := AX(G ∪ S);
    OS := S;
    S := S ∪ PIMG;
  done;
  if (I ⊆ (G ∪ S)) then
    return OK;
  else
    return FAIL;
end;
```



Planning as Symbolic Model Checking: Reachability Goals – p. 71

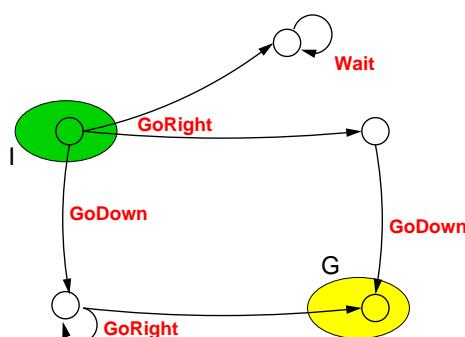
STRONGPLAN: properties

- ➊ The algorithm terminates.
- ➋ The algorithm is correct and complete.
 - Whenever a strong solution exists it finds a state-action table that is a strong solution.
 - Whenever a strong solution does not exist FAIL is returned.
- ➌ The algorithm computes “optimal” solutions.
 - Optimality defined on the length of the plan execution traces.

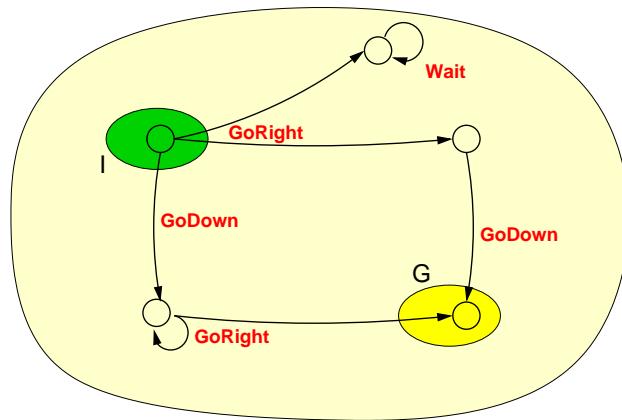
WEAKPLAN: algorithm intuitions

- ➊ WEAKPLAN is similar to the STRONGPLAN algorithm.
 - It performs a *weak pre-image* as basic step.
 - weak pre-image of a set S computes those state-action pairs whose execution *may* lead to a state $s \in S$.
- ➋ WEAKPLAN similar to the SMC algorithm to compute EF.

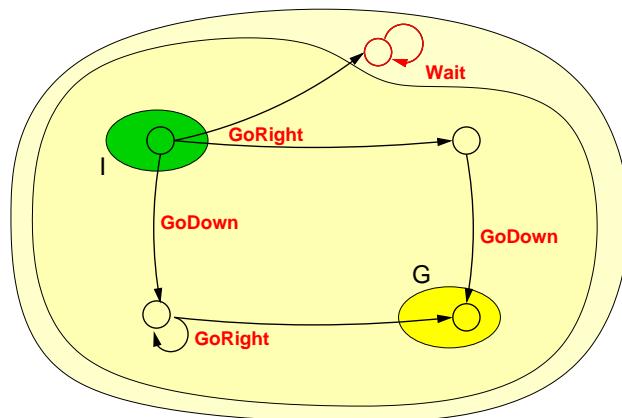
STRONGCYCLICPLAN: algorithm intuition



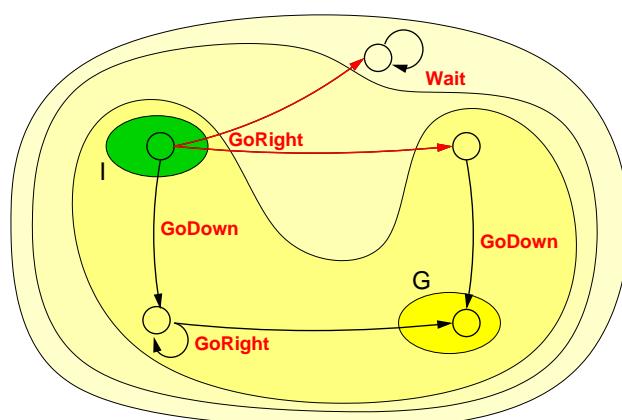
STRONGCYCLICPLAN: algorithm intuition



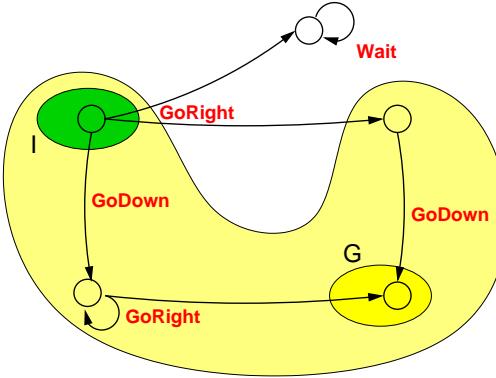
STRONGCYCLICPLAN: algorithm intuition



STRONGCYCLICPLAN: algorithm intuition



STRONGCYCLICPLAN: algorithm intuition



STRONGCYCLICPLAN: algorithm

```
function STRONGCYCLICPLAN ( $I, G$ );
    OSA :=  $\emptyset$ ;
    SA := UNIVSA;
    while (OSA  $\neq$  SA) do
        OSA := SA;
        SA := PRUNEUNCONNECTED(PRUNEOUTGOING(SA, $G$ ), $G$ );
    done;
    if ( $I \subseteq (G \cup \text{STOF}(SA))$ ) then
        return REMOVENONPROGRESS(SA, $G$ );
    else
        return FAIL;
    end;
```

STRONGCYCLICPLAN vs AG EF

Similarities:

- Similar meaning (i.e., from all reached states it is possible to achieve the goal).
- Plan validation performed by verifying $\mathbf{AG} \mathbf{EF}_p$ on the synchronous product of domain and plan.

Differences:

- The computation of $\mathbf{AG} \mathbf{EF}$ is performed with two *nested distinct* fix point calculations.
- STRONGCYCLICPLAN *interleaves* the steps of the two fix point calculations.

STRONGCYCLICPLAN: properties

- ➊ The algorithm terminates.
- ➋ The algorithm is correct and complete.
 - ➌ Whenever a strong cyclic solution exists it finds a state-action table that is a strong cyclic solution.
 - ➍ Whenever a strong cyclic solution does not exist FAIL is returned.



Planning as Symbolic Model Checking: Reachability Goals – p. 77

Planning as Symbolic Model Checking

Extended Goals



Planning as Symbolic Model Checking: Extended Goals – p. 78

Motivations

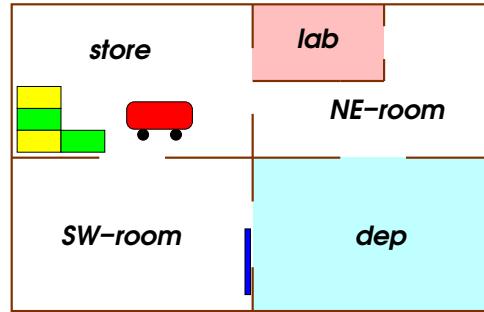
The main motivations for introducing extended goals are:

- ➊ *safe planning*:
 - ➌ safety conditions (“avoid dangerous states”) complement the main goal.
- ➋ *planning for reactive systems*:
 - ➌ infinite plan that reacts to events in the environment (mail delivery, elevator system, ...).
- ➌ *non-determinism*:
 - ➌ need to express (reachability/maintainability) goals of different strength.



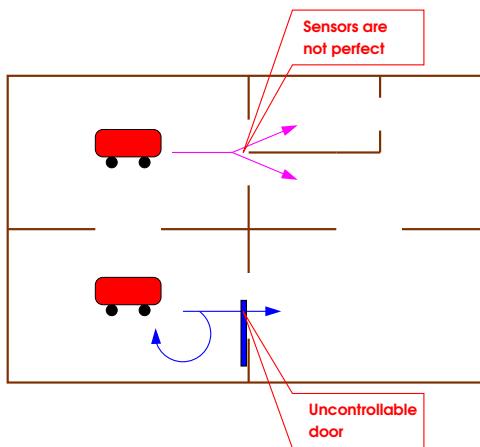
Planning as Symbolic Model Checking: Extended Goals – p. 79

Example

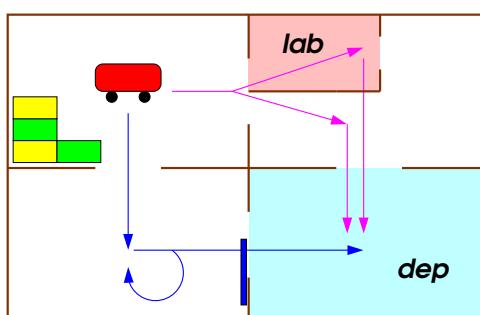


Example (II)

- Non-determinism: actions may lead to many different states.



Example (III)



Goal “Reach *dep* and avoid *lab*”

- “**Do reach *dep* and do avoid *lab***” is *unsatisfiable*.
- “**Do reach *dep* and try avoid *lab***” is *satisfiable* by route →.
- “**Try reach *dep* and do avoid *lab***” is *satisfiable* by route →.

Aim

Objectives:

- ➊ Planning for *extended goals*...
- ➋ ... in *non-deterministic domains*.
- ➌ Dealing *in practice* with *complex goals* and domains of *large size*.

Problems:

- ➊ How can we express extended goals?
- ➋ Which kind of plans must be generated?
- ➌ Planning algorithms?
- ➍ How can planning algorithms deal with large domains?



Planning as Symbolic Model Checking: Extended Goals – p. 83

The PMC approach for Extended Goals

- ➊ **Extended goals** are formulae in a **branching-time temporal logics** (e.g., CTL):
 - they express temporal conditions that take into account non-determinism.
- ➋ **Plans** can encode **conditional, iterative, and history-dependent behaviors**:
 - all these features are necessary for extended goals.
- ➌ **Planning algorithms** use BDD-based **symbolic model checking** techniques:
 - designed to deal with large state spaces.



Planning as Symbolic Model Checking: Extended Goals – p. 84

Goal language: CTL

We propose CTL as the language for expressing extended goals.

The “Reach dep and avoid lab” example:

- ➊ **Do reach dep and do avoid lab** → AF dep \wedge AG \neg lab
- ➋ **Do reach dep and try avoid lab** → AF dep \wedge EG \neg lab
- ➌ **Try reach dep and do avoid lab** → EF dep \wedge AG \neg lab

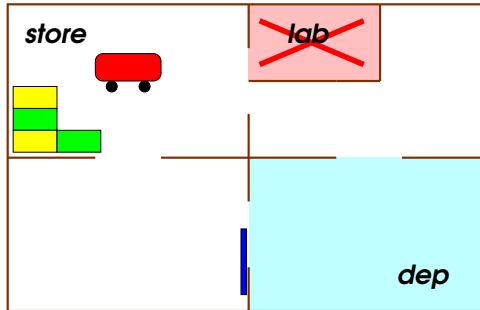
“Reachability” goals:

- ➊ “weak” planning → EF
- ➋ “strong” planning → AF
- ➌ “strong cyclic” planning → AG EF



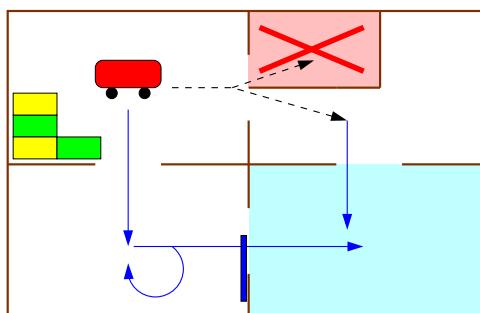
Planning as Symbolic Model Checking: Extended Goals – p. 85

Plan generation



- The **lab** is a dangerous room — it harms the robot.
- The goal is “Continuously, try reach **dep** and do reach **store**”.
- CTL goal: AG (EF **dep** \wedge AF **store**).

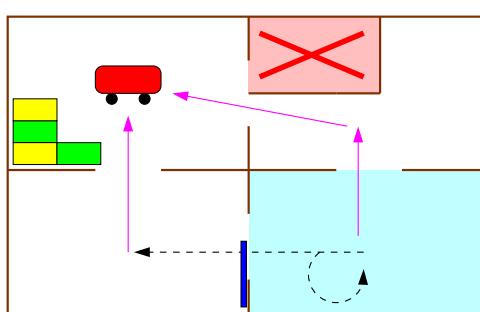
Plan generation (II)



Goal “Continuously, try reach **dep** and do reach **store**”:

- Satisfying “try reach **dep**” (EF **dep**)...

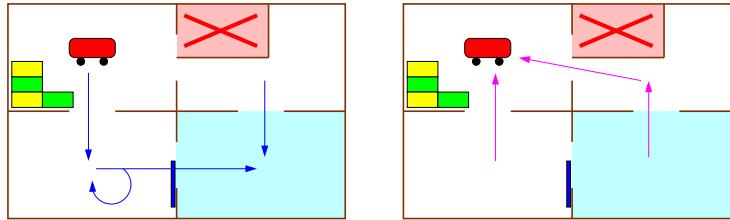
Plan generation (III)



Goal “Continuously, try reach **dep** and do reach **store**”:

- Satisfying “do reach **store**” (AF **store**)...

Plan generation (IV)

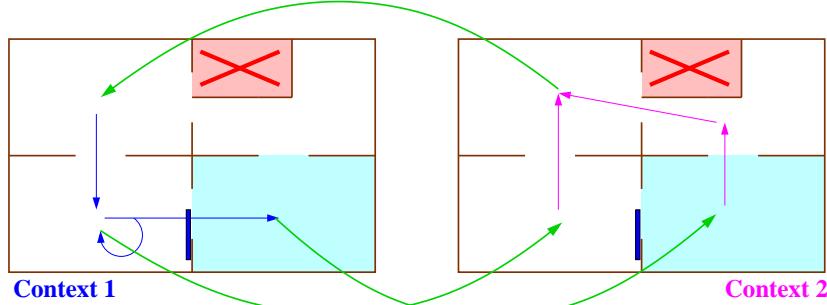


?

Plan generation (V)

More execution contexts needed for the different intentions of the executor:

- Context 1: “try reach dep”.
- Context 2: “do reach store”.



Plans

- A plan for a domain \mathcal{D} is defined by:
 - a set C of (execution) contexts, and an initial context $c_0 \in C$,
 - the action function $act: \mathcal{S} \times C \rightharpoonup \mathcal{A}$,
 - the context function $ctxt: \mathcal{S} \times C \times \mathcal{S} \rightharpoonup C$.

state	context	action	next state	next context
SW-room	context 1	go-east	SW-room	context 2
SW-room	context 1	go-east	dep	context 2
SW-room	context 2	go-north	store	context 1
...

- ... that is, a plan is a FSM (as prescribed by the “general framework”).

Plan validation

Plan execution:

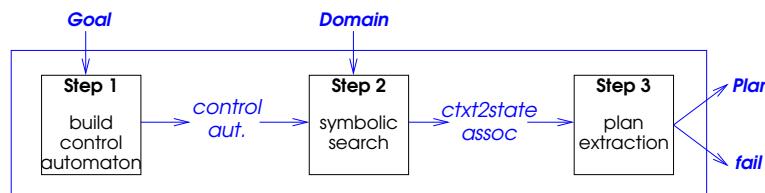
- is defined as the *synchronous execution* of the domain and of the plan.
- the *states* of the execution structure are pairs (s, c) , where s is a state of the domain and c is a context of the plan.
- a *transition* $(s, c) \xrightarrow{a} (s', c')$ exists iff:
 - $a = act(s, c)$,
 - $s \xrightarrow{a} s'$,
 - $c' = ctxt(s, c, s')$.

Plan validation:

- plan π satisfies goal g in state s_0 iff CTL formula g holds in the initial state (s_0, c_0) of the execution structure.
- plan validation is reduced to a model checking problem!



The symbolic algorithm



1. Build the control automaton for the given goal:

- it represents the possible progresses of the intentions of the executor.

2. Search in the state space, guided by the control automaton:

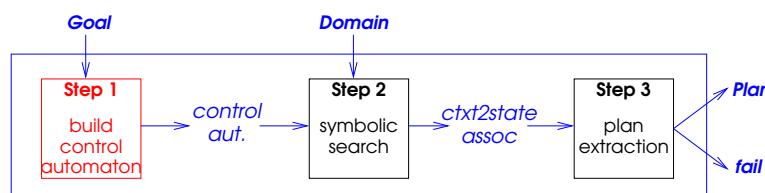
- finds the sets of states for which a context is satisfiable.

3. Extract the plan for the given goal (if it exists):

- the information on the states associated to the contexts is exploited.



The symbolic algorithm Step 1: build the control automaton



- The control states are the contexts of the plan that is being built.
- The transitions represent the possible evolutions (progresses) of the contexts when actions are executed.



The symbolic algorithm

Step 1: build the control automaton (II)



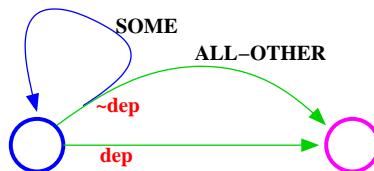
Two contexts are needed for goal AG (EF dep \wedge AF store):

- ➊ one corresponding to intention EF dep.
- ➋ one corresponding to intention AF store.



The symbolic algorithm

Step 1: build the control automaton (III)



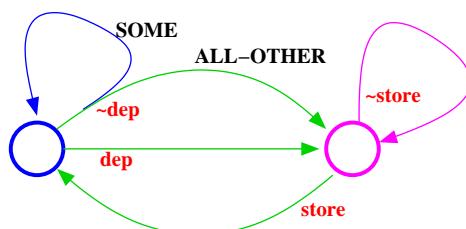
In order to satisfy context EF dep, find an action such that:

- ➊ if dep holds, then:
 - ➋ context AF store is satisfiable for ALL the outcomes.
- ➋ if dep does not hold then:
 - ➋ context EF dep is satisfiable for SOME of the outcomes.
 - ➋ context AF store is satisfiable for ALL the other outcomes.



The symbolic algorithm

Step 1: build the control automaton (IV)

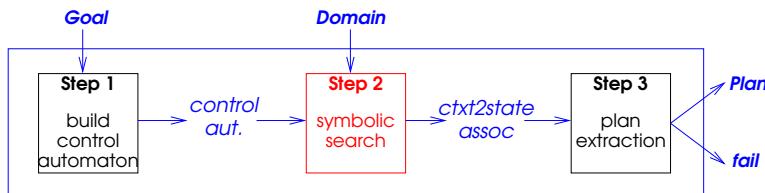


In order to satisfy context AF store, find an action such that:

- ➊ if store holds, then:
 - Ⓑ context EF dep is satisfiable for ALL the outcomes.
- ➋ if store does not hold then:
 - Ⓑ context AF store is satisfiable for ALL the outcomes.



The symbolic algorithm Step 2: symbolic search



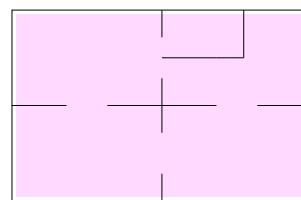
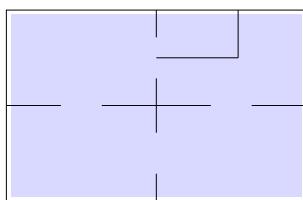
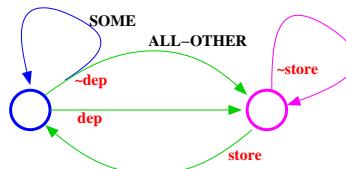
- The states associated to the contexts are obtained via a **fix-point computation**:
 - least fix-point for reach-like goals.
 - greatest fix-point for maintain-like goals.
- There are **mutual dependencies** among the contexts:
 - iterative refinements, until a stable association is obtained.
- **BDD-based symbolic exploration techniques** are exploited



Planning as Symbolic Model Checking: Extended Goals – p. 98

The symbolic algorithm Step 2: symbolic search (II)

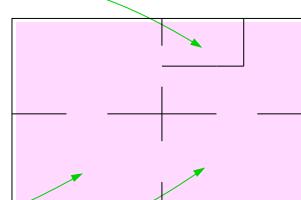
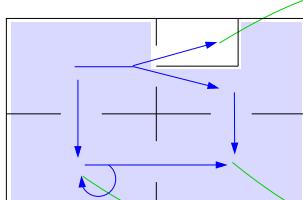
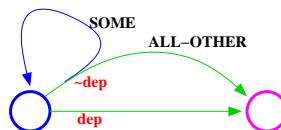
- Initially:



Planning as Symbolic Model Checking: Extended Goals – p. 99

The symbolic algorithm Step 2: symbolic search (III)

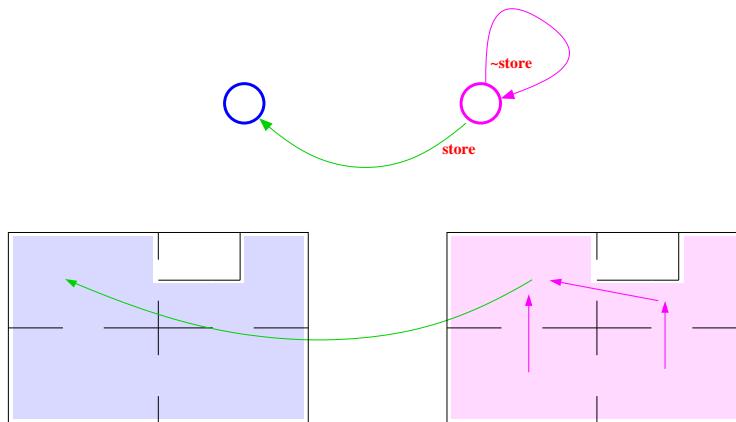
- Refine context **EF dep**:



Planning as Symbolic Model Checking: Extended Goals – p. 100

The symbolic algorithm Step 2: symbolic search (IV)

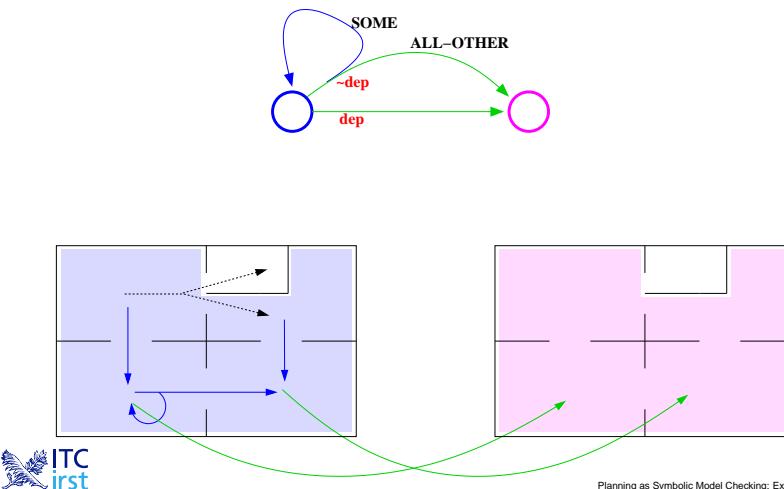
- Refine context AF store:



Planning as Symbolic Model Checking: Extended Goals – p. 101

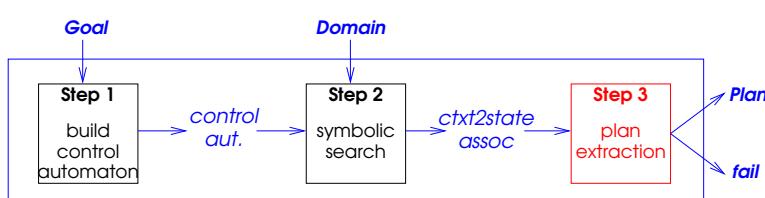
The symbolic algorithm Step 2: symbolic search (V)

- Refine context EF dep:



Planning as Symbolic Model Checking: Extended Goals – p. 102

The symbolic algorithm Step 3: plan extraction



- All the information necessary to extract the plan has been already computed in the search phase.

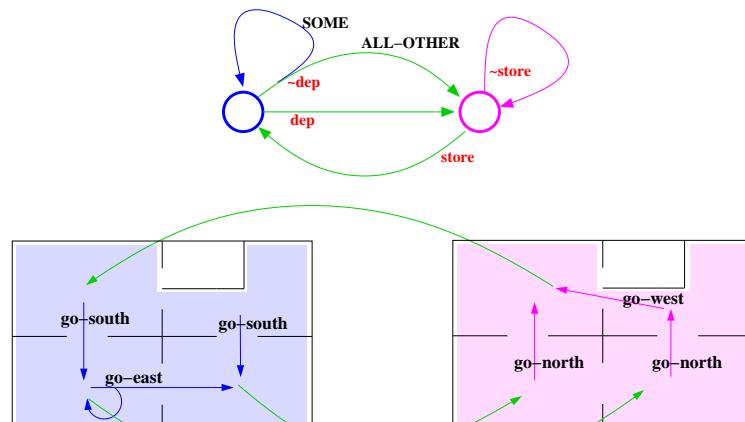


Planning as Symbolic Model Checking: Extended Goals – p. 103

The symbolic algorithm

Step 3: plan extraction (II)

- Find suitable actions:



Properties of the algorithm

- The algorithm terminates.
- The algorithm is correct and complete:
 - Whenever plans exist, the algorithm finds one.
 - Whenever there is no plan, the algorithm returns FAIL.
- The critical step for performance is “plan search”.

Future work

- Improving the *quality of plans*:
 - rewarding functions, as in MDP-based planning.
- Using extended goals as search *control rules*:
 - control automata define a search strategy.
- Defining a *better language* for goals:
 - see next slides...

Limits of CTL goals

- ➊ CTL goals do not capture *intentionality*:
 - “**Try reach** p ” is modeled as “**EF** p ”...
 - ... but “**EF** p ” means “ p is reached for some non-deterministic outcomes”.

- ➋ One has to deal with *failure* of goals:
 - consider goal “**Try maintain** p **Fail Do Reach** q ”...
 - ... goal “**EG** $p \vee AF q$ ” has a different meaning...
 - ... also goal “**AG** ($\neg p \rightarrow AF q$)” does not work...
 - ... in fact, there is no way for representing the goal in CTL!



Planning as Symbolic Model Checking: Extended Goals – p. 107

The EAGLE goal language

We are defining EAGLE, a new *Extended Goal Language* that:

- ➊ captures the *intentional aspects* of goals.
- ➋ can deal with *failure recovery*.

Syntax:

- ➊ basic goals: **DoReach** p , **DoMaint** p , **TryReach** p , **TryMaint** p .
- ➋ conjunction: g **And** g' .
- ➌ failure: g **Fail** g' .
- ➍ control operators: g **Then** g' , **Repeat** g .

Algorithm:

- ➊ new algorithm for “control automaton construction”.
- ➋ “symbolic search” and “plan extraction” can be reused.



Planning as Symbolic Model Checking: Extended Goals – p. 108

Planning as Symbolic Model Checking

Partial Observability

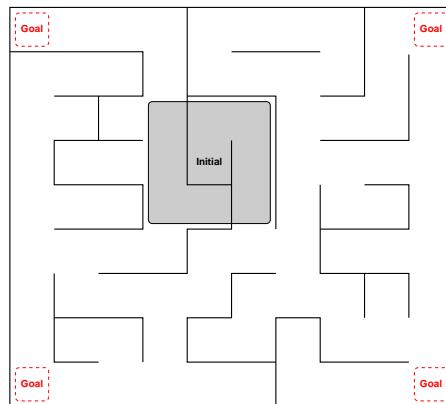


Planning as Symbolic Model Checking: Partial Observability – p. 109

Motivations

- ➊ Realistic:
 - Environment is seldomly fully observable.
 - Some form of sensing is often available.
- ➋ General: full observability, conformance are special cases.
- ➌ Related to relevant problems:
 - Diagnosis.
 - Homing/distinguishing problem.
 - Game theory.

Example: a robot-world with sensing



Aim

Objectives:

- ➊ Allow for planning under *partial observability*...
- ➋ in *non-deterministic domains*.
- ➌ Deal in practice with domains of *large size*.

Problems:

- ➊ How can we express partial observability?
- ➋ Which kind of plans must be generated?
- ➌ Planning algorithms?
- ➍ How can planning algorithms deal with large domains?

The PMC approach for PO

- Partial observability expressed by formulae that encode observation relation.
 - Plans encode conditional behavior based on sensing.
 - Planning algorithms exploit symbolic representation of observations (as well as actions and states).
 - Experimental results show that algorithms work in practice.



Planning as Symbolic Model Checking: Partial Observability – p. 113

Goals

- Due to nondeterminism and partial observability, the controller has a partial knowledge of the state.
 - We consider *strong reachability* goals:
 - At the end of plan execution, the executor *knows* that the goal has been reached...
 - ...in spite of possibly not knowing exactly the state.



Planning as Symbolic Model Checking: Partial Observability – p. 114

Plans

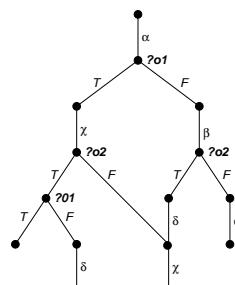
Structure of plans:

- In general: conditional over observations
 - Conformant case: sequences
 - Full observability case: conditional over states

Expressed as general ESM:

- Plan state: “plan program counter”.
 - Branching conditions on:
 - “plan program counter”.

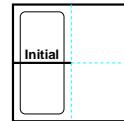
Validated by model checking



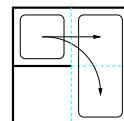
Planning as Symbolic Model Checking: Partial Observability

Plan search: Belief States

- Due to nondeterminism and partial observability, status known to controller can be uncertain:
 - ...because the initial situation is uncertain...



- ... or because actions may have unpredictable results.



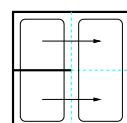
Thus, planning proceeds over sets of states: *belief states (BS)*



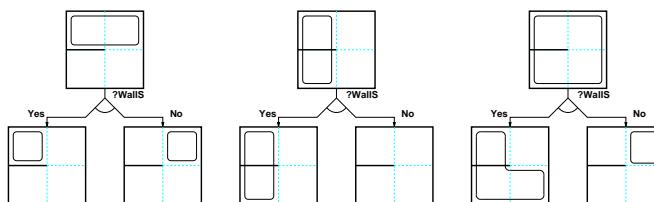
Planning as Symbolic Model Checking: Partial Observability – p. 116

Plan Search: base steps

- An action transforms a BS into a BS

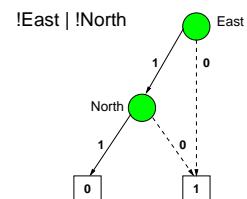
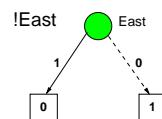
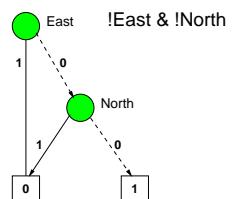
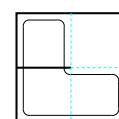
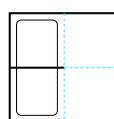
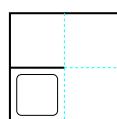


- Observing *may* split a BS



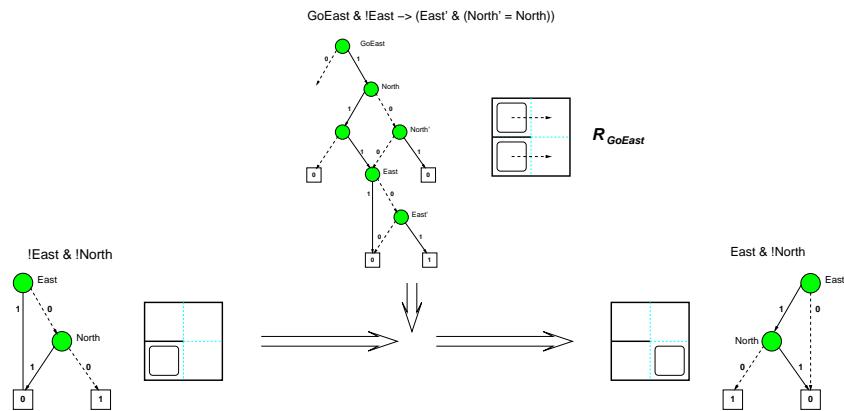
Planning as Symbolic Model Checking: Partial Observability – p. 117

BDD representation of BS

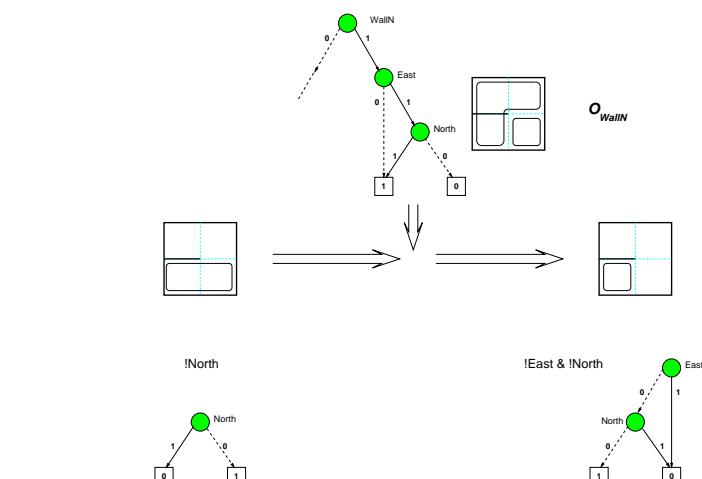


Planning as Symbolic Model Checking: Partial Observability – p. 118

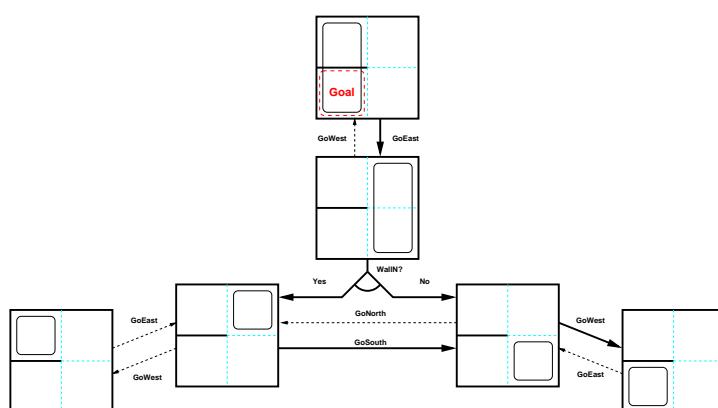
BDD transformation of BS: acting



BDD transformation of BS: observing



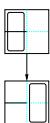
Search space



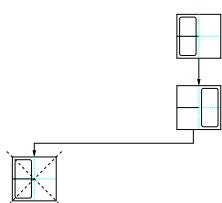
Search algorithm: a DFS search



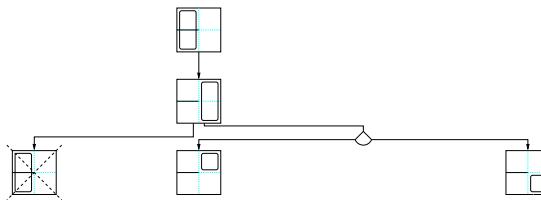
Search algorithm: a DFS search



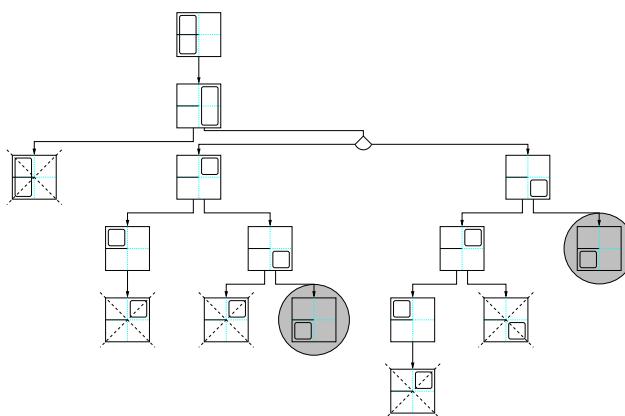
Search algorithm: a DFS search



Search algorithm: a DFS search



Search algorithm: a DFS search



Heuristic search

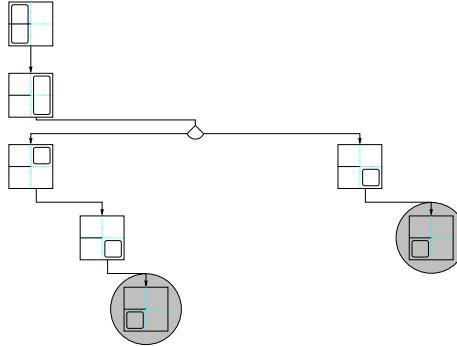
Motivations:

- ➊ DFS may produce dumb plans.
- ➋ DFS may be not efficient.
- ➌ Even simple user-provided heuristics may help a lot.
- ➍ Heuristics may be extracted from domain/problem.

Example:

- ➊ Favouring observations.
- ➋ Avoiding “stepping back”.

Search algorithm: a Heuristic search



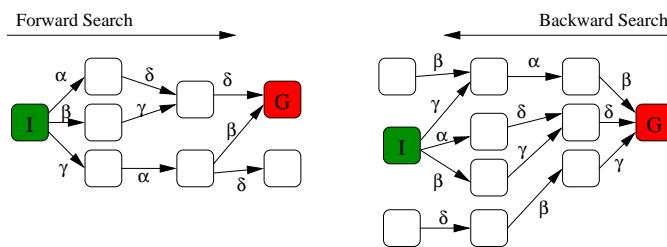
Conformant algorithms

Motivations:

- ➊ Relevant applications (e.g. reset sequences).
- ➋ Ad-hoc highly efficient planning algorithms.
- ➌ Dedicated heuristics and fwd/bwd algorithms, e.g.:
 - breadth-first search in belief space
 - knowledge-driven search
 - ...

Conformant algorithms (II)

- ➊ Search space only features “or” branching.
- ➋ BFS search in belief space is feasible...
- ➌ ...but it's not the only way.



Properties of algorithms

- ➊ The algorithms terminate.
- ➋ The algorithms are correct and complete:
 - ➌ Whenever a strong solution exists they find a plan which is a strong solution.
 - ➍ Whenever a strong solution does not exist they return FAIL.



Planning as Symbolic Model Checking: Partial Observability – p. 131

Future work

- ➊ Heuristics in Belief Space.
- ➋ Strategies.
- ➌ Interleaving planning and execution.
- ➍ Diagnosis; homing/distinguishing.
- ➎ Realistic case studies.



Planning as Symbolic Model Checking: Partial Observability – p. 132

Planning as Symbolic Model Checking

Conclusions



Planning as Symbolic Model Checking: Conclusions – p. 133

Combining Extended Goals and Partial Observability

Realistic domains (robot navigation, embedded controllers) combine *partial observability* and *extended goals*.

Challenging problem:

- knowledge goals: introducing “knows” in the goal language.
- plan synthesis requires combining plan contexts and belief states.
- no trivial combination of existing PO and EG algorithms.

Work done so far:

- a language for expressing temporally-extended knowledge goals:
 - example: $\text{AG } p \wedge \text{AF } K q$
- a framework for the validation of plans:
 - a monitor is used for epistemic tracing to trace the belief state.



Planning as Symbolic Model Checking: Conclusions – p. 134

Planning in “adversarial” environment

So far we have assumed a “fair” environment:

- all the action outcomes have some chance to occur.

In several applications:

- the non-determinism is due to uncontrollable, adversarial agents:
 - we cannot assume that they will execute actions in a fair way.
 - they can apply a strategy to prevent goal achievement.
- the non-determinism is due to lack of information:
 - some action outcomes may never happen in the “real” domain.

State of the art:

- some forms of *adversarial* planning as model checking addressed by R. Jensen, M. Veloso et al.
- partial observability and extended goals are still open.

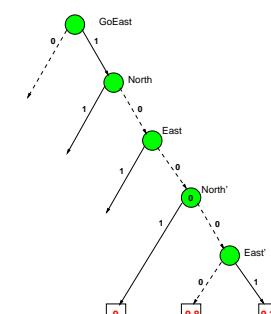
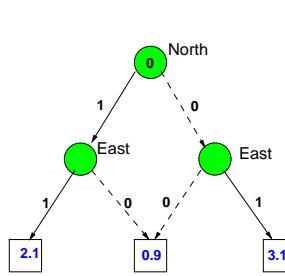


Planning as Symbolic Model Checking: Conclusions – p. 135

Planning with probabilities

ADDs (Algebraic Decision Diagrams) can be used for representing:

- expected rewards:
- probabilities of outcomes:



In SPUDD, ADDs are exploited for efficient value iteration in MDP planning.



Planning as Symbolic Model Checking: Conclusions – p. 136

Wrap-up

Planning via Model Checking:

- ❶ A single, *founded framework* for a variety of planning problems.
- ❷ Several specialized algorithms available for plan synthesis.
- ❸ Works in practice.
- ❹ Plan validation “for free”: Model Checking of plan against domain.



Planning as Symbolic Model Checking: Conclusions – p. 137

MBP — The Model Based Planner



MBP — The Model Based Planner – p. 138

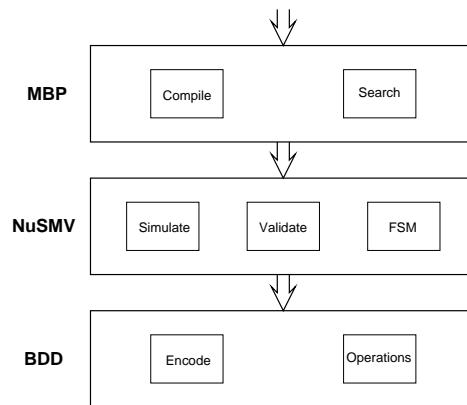
Overview of presentation

- ❶ MBP overview: functions and architecture
- ❷ Domain definition language
- ❸ Problem definition language
- ❹ Plan language
- ❺ MBP in action



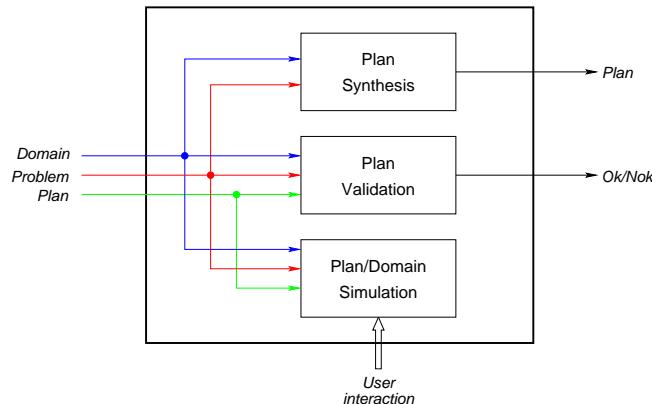
MBP — The Model Based Planner – p. 139

MBP: architecture



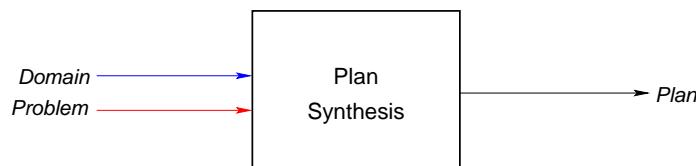
MBP — The Model Based Planner – p. 140

MBP: main functions



MBP — The Model Based Planner – p. 141

MBP: plan synthesis

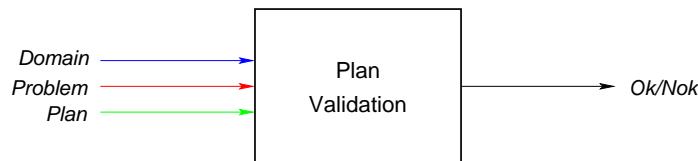


- ➊ Input: A domain and a problem.
- ➋ Output: a plan (or assessment of nonexistence).
- ➌ Plan saved or directly used for validation/simulation.



MBP — The Model Based Planner – p. 142

MBP: plan validation

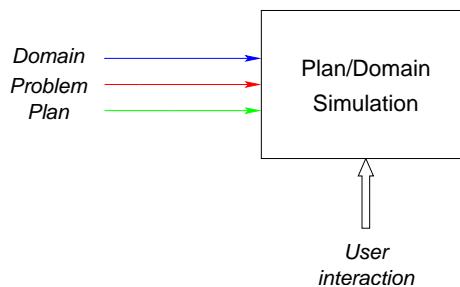


- Input: a domain, a problem, and a plan.
- Output: yes/no.



MBP — The Model Based Planner – p. 143

MBP: plan/domain simulation



- Input: a domain, a problem, and a plan.
- Interactive: the user selects action outcomes.
- May terminate with plan success or failure.



MBP — The Model Based Planner – p. 144

MBP demo



MBP — The Model Based Planner – p. 145

MBP: languages

Domain/problem languages

- AR: an action description language.
- SMV: a hardware description language.
- NuPDDL: extension of PDDL.
 - NuPDDL Plan language
 - captures general framework...
 - ... expressive enough for every special cases ...
 - ... in particular “classical” sequential plans.



MBP — The Model Based Planner – p. 146

Standard PDDL features

- Designed for classical planning:
 - Deterministic
 - Full observability
 - Reachability goals
- Based on closed world assumption
- Implicit inertiality
- Parametrized actions
- Typing (enums) allowed
- Layered structure (STRIPS is layer 0)



MBP — The Model Based Planner – p. 147

A simple PDDL example

```
(define (domain simple_robot)
  (:predicates
    (at_robot_sw) (at_robot_nw)
    (at_robot_se) (at_robot_ne))

  (:action move_robot_sw_se
    :parameters ()
    :precondition (at_robot_sw)
    :effect      (and (not (at_robot_sw)) (at_robot_se)))

    ;.....
    ;.....
  )

  (define (problem robot_pb)
    (:domain simple_robot)
    (:init  (at_robot_nw))
    (:goal   (at_robot_sw)))
```



MBP — The Model Based Planner – p. 148

PDDL: types and parametricity

```
(define (domain simple_robot)
  (:types robot)
  (:predicates
    (at_robot_sw ?r - robot) (at_robot_nw ?r - robot)
    (at_robot_se ?r - robot) (at_robot_ne ?r - robot))

  (:action move_robot_sw_se
    :parameters (?r - robot)
    :precondition (at_robot_sw ?r)
    :effect      (and (not (at_robot_sw ?r)) (at_robot_se ?r)))

    ;....
    ;....
  )

  (define (problem robot_pb)
    (:domain simple_robot)
    (:objects robot_1 robot_2 - robot)
    (:init   (at_robot_nw robot_1) (at_robot_nw robot_2))
    (:goal   (and (at_robot_sw robot_1) (at_robot_sw robot_2))))
```



MBP — The Model Based Planner – p. 149

PDDL: conditional effects

```
(define (domain simple_robot)
  (:predicates
    (at_robot_sw) (at_robot_nw)
    (at_robot_se) (at_robot_ne))
  (:action move_robot_east
    :parameters ()
    :precondition (or (at_robot_sw) (at_robot_nw))
    :effect       (and
      (when (at_robot_sw)
        (and (not (at_robot_sw)) (at_robot_se)))
      (when (at_robot_nw)
        (and (not (at_robot_nw)) (at_robot_ne)))))

    ;....
    ;....
  )

  (define (problem robot_pb)
    (:domain simple_robot)
    (:init   (at_robot_nw))
    (:goal   (at_robot_sw)))
```



MBP — The Model Based Planner – p. 150

PDDL: quantifiers

```
(define (domain simple_robot)
  (:types package)
  (:predicates
    (at_robot_sw) (at_robot_nw)
    (at_robot_se) (at_robot_ne)
    (at_sw ?p - package) (at_nw ?p - package)
    (at_se ?p - package) (at_ne ?p - package))

  (:action move_robot_sw_se
    :parameters ()
    :precondition (at_robot_sw)
    :effect       (and
      (not (at_robot_sw))
      (forall (?p - package) (not (at_sw ?p)))
      (at_robot_se)
      (forall (?p - package) (at_se ?p)))))

    ;....
    ;....
  )
```



MBP — The Model Based Planner – p. 151

PDDL2.1: functions

```
(define (domain simple_robot)
  (:types x_coord y_coord)
  (:constants east west - x_coord
             north south - y_coord)
  (:functions
    (robot_x)
    (robot_y) )

  (:action move_robot_east
    :parameters ()
    :precondition (= (robot_x) 0)
    :effect      (assign (robot_x) 1))
  ;...
  ;...
)

(define (problem robot_pb)
  (:domain simple_robot)
  (:init  (= (robot_y) 1) (= (robot_x) 0))
  (:goal  (and (= (robot_y) 0) (= (robot_x) 0))))
```



MBP — The Model Based Planner – p. 152

NuPDDL

- ➊ Backward compatibility:
 - Retains closed world assumption, inertiality, parametricity.
 - Includes most of PDDL up ADL layer.
 - Includes PDDL2.1 “functions” extension.
- ➋ No layered structure.
- ➋ Typing enforced.
- ➋ Allows nested quantifications and conditionals.
- ➋ Extension: Nondeterminism (initial, action effects).
- ➋ Extension: Partial observability.
- ➋ Extension: Goal classes.



MBP — The Model Based Planner – p. 153

Extension n. 1: uncertainty in initial

- ➊ “oneof” selects one of several *initial situations*.
- ➋ “oneof” is local to the cited elements.
- ➌ “unknown” shortcut: “oneof on every possible value”.

```
(define (domain d) ... (:predicates (P1) (P2) (P3) (P4) (P5) (P6)) ...)
(define (problem p)
  ...
  (:init (and (P1) (oneof (and (P2) (P3)) (P4)) (unknown (P5))))
  ...)
```

P1	P2	P3	P4	P5	P6
T	T	T	F	T	F
T	F	F	T	T	F
T	T	T	F	F	F
T	F	F	T	F	F



MBP — The Model Based Planner – p. 154

Uncertainty in initial (II)

```
(define (problem robot_pb)
  (:domain simple_robot)
  (:init
    (oneof
      (and (= (robot_x) west) (= (robot_y) north))
      (and (= (robot_x) east) (= (robot_y) south))))
  (:goal
    (and (= (robot_y) south)
         (= (robot_x) west)))))

(define (problem robot_pb)
  (:domain simple_robot)
  (:init  (and
            (= (robot_x) west)
            (unknown (robot_y))))
  (:goal
    (and (= (robot_y) south)
         (= (robot_x) west))))
```



MBP — The Model Based Planner – p. 155

Extension n. 2: nondeterministic effects

- “oneof” selects one of several *transitions*.
- “oneof” is local to the cited elements.
- “unknown” is shortcut as usual.

```
(define (domain d) ... (:predicates (P1) (P2) (P3) (P4) (P5) (P6)) ...)
```

```
(define (problem p)
  ...
  (:effect (and (P1) (oneof (and (P2) (P3)) (P4)) (unknown (P5))))
  ....)
```

P1'	P2'	P3'	P4'	P5'	P6'
T	T	T	P4	T	P6
T	P2	P3	T	T	P6
T	T	T	P4	F	P6
T	P2	P3	T	F	P6



MBP — The Model Based Planner – p. 156

Nondeterministic effects (II)

```
(define (domain simple_robot)
  (:types x_coord y_coord)
  (:constants east west - x_coord
             north south - y_coord)
  (:functions
    (robot_x) - x_coord
    (robot_y) - y_coord)
  (:action move_robot_east
    :parameters ()
    :precondition (= (robot_x) west)
    :effect      (and
                  (assign (robot_x) east)
                  (unknown (robot_y))))
  ;.....
  ;.....
  ))
```



MBP — The Model Based Planner – p. 157

Nondeterministic effects (III)

```
(define (domain simple_robot)
  (:types x_coord y_coord)
  (:constants east west - x_coord
             north south - y_coord)
  (:functions
    (robot_x) - x_coord
    (robot_y) - y_coord)
  (:action move_robot_east
    :parameters ()
    :precondition (= (robot_x) west)
    :effect      (oneof
                  (and
                    (assign (robot_x) east)
                    (assign (robot_y) south))
                  (and
                    (assign (robot_x) west)
                    (assign (robot_y) north)))))

;.....
;.....
)
```



MBP — The Model Based Planner – p. 158

Nondeterministic effects (IV)

```
(define (domain simple_robot)
  (:types x_coord y_coord)
  (:constants east west - x_coord
             north south - y_coord)
  (:functions
    (robot_x) - x_coord
    (robot_y) - y_coord)
  (:action move_robot_east
    :parameters ()
    :precondition (= (robot_x) west)
    :effect      (and
                  (assign (robot_x) east)
                  (when (= (robot_y) north)
                        (unknown (robot_y)))))

;.....
;.....
)
```



MBP — The Model Based Planner – p. 159

Nondeterministic effects (V)

```
(define (domain simple_robot)
  (:types x_coord y_coord package)
  (:constants east west - x_coord
             north south - y_coord)
  (:predicates
    (broken ?p - package))
  (:functions
    (robot_x) - x_coord
    (robot_y) - y_coord)
  (:action move_robot_east
    :parameters ()
    :precondition (= (robot_x) west)
    :effect      (and
                  (assign (robot_x) east)
                  (when (= (robot_y) north)
                        (and
                          (forall (?p - package)
                            (when (not (broken ?p))
                                  (unknown (broken ?p))))
                          (unknown (robot_y)))))

;.....
;.....
)
```



MBP — The Model Based Planner – p. 160

Extension n. 3: Partial Observability

- Introduce boolean observations
- Observations are parametric
- Noisy sensing allowed



MBP — The Model Based Planner – p. 161

Partial observability (II)

```
(define (domain simple_robot)
  (:types x_coord y_coord)
  (:constants east west - x_coord
             north south - y_coord)
  (:functions
    (robot_x) - x_coord
    (robot_y) - y_coord)

;.....
;.....
(:observation wall_north - boolean
  :parameters ()
  (imply (= wall_north 0)
         (not (or (= (robot_y) north) (= (robot_x) west))))
  (imply (= wall_north 1)
         (or (= (robot_y) north) (= (robot_x) west))))
;.....
;.....
)
```



MBP — The Model Based Planner – p. 162

NuPDDL numbers

- NuPddl allows for finite numeric ranges.
- NuPddl does not allow for unrange numbers.

```
(define (domain simple_robot)
  (:functions
    (robot_x) - (range 0 1)
    (robot_y) - (range 0 1))

  (:action move_robot_east
    :parameters ()
    :precondition (< (robot_x) 1)
    :effect      (assign (robot_x) (+ (robot_x) 1)))

;.....
)

(define (problem robot_pb)
  (:domain simple_robot)
  (:init  (and (= (robot_y) 1) (= (robot_x) 0)))
  (:goal  (and (= (robot_y) 0) (= (robot_x) 0))))
```



MBP — The Model Based Planner – p. 163

NuPDDL numbers (II)

- Ranges can be instantiated within problem
- Limits of ranges can be accessed via `inf`, `sup`

```
(define (domain simple_robot)
  (:types range_x range_y)
  (:functions
    (robot_x) - range_x
    (robot_y) - range_y)
  (:action move_robot_east
    :parameters ()
    :precondition (< (robot_x) (sup range_x))
    :effect      (assign (robot_x) (+ (robot_x) 1)))
  )

(define (problem robot_pb)
  (:domain simple_robot)
  (:typedef
    range_x - (range 0 4)
    range_y - (range 0 5))
  (:init  (and (= (robot_y) 3) (= (robot_x) 2)))
  (:goal  (and (= (robot_y) 0) (= (robot_x) 0))))
```



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Extension n. 4: goal classes

- Weak reachability under full observability.
(:weakgoal (at_robot_sw))
- Strong reachability under full observability.
(:stronggoal (at_robot_sw))
- Strong cyclic reachability under full observability.
(:strongcyclicgoal (at_robot_sw))
- Strong reachability under partial observability.
(:postronggoal (at_robot_sw))
- Strong reachability under null observability.
(:conformantgoal (at_robot_sw))
- Extended goals under full observability.
(:ctlgoal (au (not (at_robot_sw)) (at_robot_ne)))



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NuPDDL: CTL goals

Do Reach p (“strong goal”):	(af p)
Try Reach p (“weak goal”):	(ef p)
Keep Trying Reach p (“strong cyclic goal”):	(aw (ef p) p)
Continuously Try Reach p:	(ag (ef p))
Do Maintain p:	(ag p)
Try Maintain p:	(eg p)
Do Maintain p Until q:	(au p q)
In All Next States p:	(ax p)
In Some Next States p:	(ex p)
And:	(and g ₁ g ₂ g ₃ ...)
Or:	(or g ₁ g ₂ g ₃ ...)
Implies:	(imply p g)



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NuPDDL: plan language

Overview:

- Consistently with theory, allows defining an automata.
- Simple plan structures easily captured.
- Syntax style taken from domain definition part of NuPDDL.
- User-friendly imperative-style constructs supported.



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NuPDDL: plan language (II)

- A plan *may* feature a set of typed :planvars.
- Plan vars are :initialized (otherwise they assume a default).
- Basic plan steps:
 - (done) signals ending of plan.
 - (fail) signals plan failure.
 - (evolve (assign (next(v1) val1)) ... (action (act)))
 - ..or simply: (action (act))
- Steps can be sequenced.
 - Branch constructs:
 - (if (cond) plan1 plan2)
 - (switch (case (cond1) plan1) ... (else plan_else))
 - Imperative-style constructs: label and goto
 - Iterations: while and repeat



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NuPDDL: plan language (III)

```
(define (plan silly_plan)
  (:domain robot_navigation)
  (:problem navigation_problem)
  (:planvars visited_lab - boolean
            visited_SW_room_no - (range 0 10))
  (:init
    (= (visited_SW_room_no) 0)
    (= (visited_lab) 0)
  )
  (:body
    (sequence
      (while (< (visited_lab) 10)
        (sequence
          (evolve (assign
                    (next (visited_SW_room_no))
                    (+ (visited_SW_room_no) 1))
                    (action (move_robot_down)))
                    (action (move_robot_up))))
          (action (move_robot_right))
        (label i_am_in_lab (if (= (robot_position) lab)
          (sequence
            (evolve
              (assign (next(visited_lab)) 1)
              (action (move_robot_down)))
              (action (move_robot_down)))
              (action (move_robot_down)))
            (action (move_robot_down))))
          (switch
            (case (= (robot_position) dep) (done))
            (case (= (robot_position) lab) (goto i_am_in_lab))
            (case (= (robot_position) store) (fail))
            (else (fail)))))))
    
```



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NuPDDL: further work...

- NuPDDL designed for backward compatibility
- shall take into account axioms
- shall take into account explicit time
- future work on standardizing:
 - Allow for nesting functions?
 - Allow for probabilities?
 -
- **Feedback welcome.**
- NuPDDL: a candidate for possible ND planning competition?



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Hands On!



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Practical session on computer

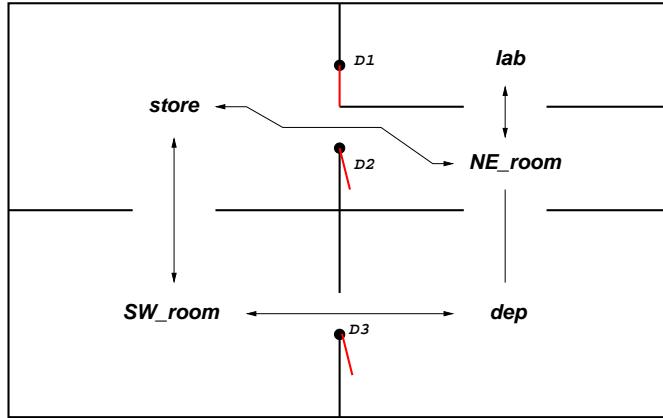
The participants will:

- confront with a set of assignments...
 - design of a planning domain.
 - definition of goals.
 - plan synthesis.
 - plan validation and simulation.
- ...using MBP.



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Starting example: robot navigation



A nuPDDL domain model: `robot.npddl`

```
(define (domain robot_navigation)
  (:types room)
  (:constants store lab NE_room SW_room dep - room)
  (:functions (robot_position) - room)

  (:action move_robot_up
    :precondition (or (= (robot_position) SW_room )
                      (= (robot_position) dep )
                      (= (robot_position) NE_room ))
    :effect (and
              (when (= (robot_position) SW_room ) (assign (robot_position) store ))
              (when (= (robot_position) dep ) (assign (robot_position) NE_room ))
              (when (= (robot_position) NE_room ) (assign (robot_position) lab ))))

  (:action move_robot_down
    :precondition (or (= (robot_position) store )
                      (= (robot_position) lab )
                      (= (robot_position) NE_room ))
    :effect (and
              (when (= (robot_position) store ) (assign (robot_position) SW_room ))
              (when (= (robot_position) lab ) (assign (robot_position) NE_room ))
              (when (= (robot_position) NE_room ) (assign (robot_position) dep ))))

  (:action move_robot_right
    :precondition (or (= (robot_position) SW_room )
                      (= (robot_position) store ))
    :effect (and
              (when (= (robot_position) SW_room ) (assign (robot_position) dep))
              (when (= (robot_position) store ) (assign (robot_position) NE_room ))))

  (:action move_robot_left
    :precondition (or (= (robot_position) dep )
                      (= (robot_position) NE_room ))
    :effect (and
              (when (= (robot_position) dep ) (assign (robot_position) SW_room ))
              (when (= (robot_position) NE_room ) (assign (robot_position) store ))))
```

Questions

1. Synthesize (and save) a strong plan for reaching `dep` from `store`.
2. Synthesize (and save) a conformant plan for the same problem.

Now suppose D3 is closed (initially and forever):

- ➊ Update the domain.
- ➋ Check whether the plans generated before are still valid.
- ➌ Synthesize:
 - A strong plan for reaching `dep` from `store`.
 - A conformant plan for the same problem.

A nondeterministic domain

Now suppose that:

1. (initially and forever) every door is open.
2. going east from *store* may lead to either *lab* or *NE_room*.

Then:

- ➊ Update the domain. (*Tip: modeling doors is not necessary...*)
- ➋ Synthesize a strong plan to reach *lab* from *store*.
- ➌ Synthesize a conformant plan for the same problem.
- ➍ Is the strong plan valid assuming no observability?



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A nondeterministic domain (II)

Now:

- ➊ D3 is uncontrollable, D1 and D2 are open.
- ➋ The robot “bounces” on D3 if closed.

Then:

- ➊ Update the domain. (*Tip: one can model D3 through the way it affects movements...*)
- ➋ Synthesize a strong plan to go from *store* to *dep*.
- ➌ Synthesize a conformant plan for the same problem.



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Extended goals

With D3 uncontrollable, D1 and D2 open, suppose *lab* is a dangerous room.

1. Is there a strong plan from *store* to *dep*, admitting passage into *lab*?
2. Is there a strong plan that leads from *store* to *dep* avoiding *lab*?
3. Is there a weak plan for the same problem?
4. Is there a strong cyclic plan for the same problem?



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Problems with Partial Observability

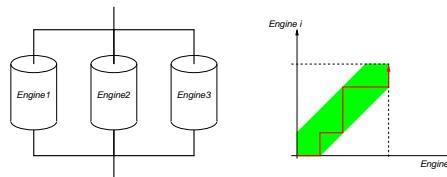
Now suppose that:

- Exactly one of the doors is open.
- The robot cannot try traversing a locked door.
- The robot can sense whether it can move in one direction or not.
- Is there a strong plan from store to dep? A weak plan?
- Is there a conformant plan? A strong plan using observations?
- Suppose the robot can smell whether it's in the lab. Is there a strong plan using observations?



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Advanced assignments: extended goals (I)



- Three engines, each providing from 0 to 4 levels of power.
- Engines start from being off.
- Problem: reach maximum power while keeping balancing (see figure).

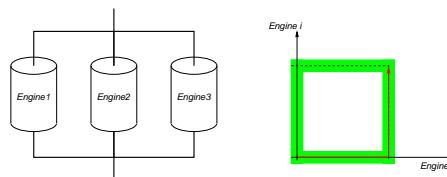
Tasks:

- Model the domain.
- Synthesize a strong plan for the problem (if there is one).
- Simulate the plan.
- Write a smarter plan, validate and simulate it.



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Advanced assignments: extended goals (II)



- Now problem is: reach maximum power following saturation policy.
- Saturation: at most one engine is “half way through” (see figure).

Tasks:

- Model the domain.
- Synthesize a strong plan for the problem.
- Write a smarter plan and validate it.



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Advanced assignments: extended goals (III)

Possible advanced goals:

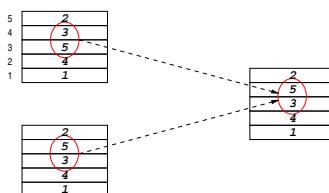
- ➊ Changing request level:
 - the sum of the power provided by the engines should reach a given *request level*;
 - the request level may increase or decrease.
- ➋ Alarm:
 - whenever an alarm is raised, all the engines should be turned off;
 - the alarm ends once all the engines are off.
- ➌ Switching policy:
 - a request of switch from saturation to balancing or vice-versa can be raised at run-time.



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Advanced assignments: conformant (I)

(Sort 3 4)



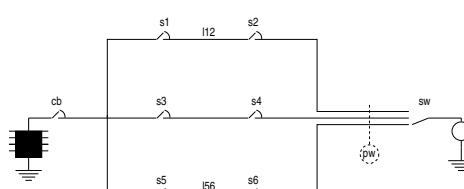
- ➊ A stack of 5 numbers, each ranging from 1 to 5.
- ➋ An atomic pairwise (*sort x y*) operation.
- ➌ Any configuration possible at start.
- ➍ The stack must be sorted at the end.

Tasks: Model the domain and find a conformant plan for the problem.



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Advanced assignments: PO (I)



- ➊ An electric circuit. Possible actions: open/close *cb*, *s1*, ..., *s6*.
- ➋ One of *l12* or *l56* has a shortcircuit.
- ➌ When *cb* feeds a shortcircuit it automatically reopens.
- ➍ Switch *s3* is unreliable: it may not obey.
- ➎ Sensor *pw* tells whether power gets to 3-position switch *sw*.
- ➏ Goal: turn on light. Initially *cb*, *s1*, ..., *s6* are open, *sw* is at position 1.
- ➐ Task: model the domain, solve the problem.,
- ➑ Task: design a smarter plan, validate and simulate it.



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Conclusions

Concluding remarks

- ➊ Planning: a difficult, real problem.
 - Realistic instances are **huge**.
 - Realistic solutions must deal with a number of issues (nondeterminism, partial observability, complex goals,...).
- ➋ Symbolic Model Checking: an advanced validation technique...
 - Clear theoretical framework.
 - A huge amount of existing work on systems and techniques.
- ➌ Planning via Symbolic Model Checking:
 - Smart reuse of Model Checking results...
 - Inherits clear theoretical framework...
 - Nice practical results as well!
- ➍ MBP: a complex planner based on Symbolic Model Checking.

Related work: Reachability

- ➊ Several approaches deal with “classical” reachability:
 - GraphPlan-based: (GRAPHPLAN,IPP,STAN,...)
Build a “planning graph” representing effects and mutual dependencies of actions.
 - Enumerative heuristic-based (FF,GRT,HSP[2],...)
 - Symbolic approaches (BDDPLAN,MIPS,PROPPLAN,SATPLAN,...)
Exploit symbolic representation of problem state to avoid enumeration.
 - Causal planners (UCPOP,...).
 - Hybrid (ALTALT,BLACKBox,STAN,...).
- ➋ Some works deal with nondeterminism and cyclic plans:
 - Logical-based approach (C-PLAN,QBFPLAN,UMOP,...)
Logical encoding of non-determinism.
 - Stochastic (BURIDAN,GPT,SPUDD,...)
Exploit Markov Decision Processes techniques.

Related works: Extended goals

- ➊ Temporal logics have been used:
 - to express extended goals (SIMPLAN,...).
 - to express search control strategies (TLPLAN, TALPLAN,...).
 - to express pre-conditions of actions (in action description languages).
- Most of these approaches are based on LTL.
- ➋ Planning with CTL goals is related to CTL synthesis
[De Giacomo, Kupferman, Vardi]:
 - synthesis of a control automaton,
 - combination with the domain model.
- ➌ Strong relations also with “synthesis of controllers”...



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Related work: Partial Observability

- ➊ Other approaches to same problem:
 - Extensions to GRAPHPLAN (CGP, SGP,...)
 - Stochastic (C-BURIDAN, GPT, ...)
 - Symbolic approaches (QBFPLAN, C-PLAN, ...)
- ➋ Related problem: reactive planning.
 - Offline planning may be overkill.
 - Replanning necessary in several real-world applications (e.g. robotics).
 - Several systems available (e.g. work on Deep Space missions).
- ➌ Related problem: diagnosis.
 - Diagnosis as “planning to remove executor’s uncertainty”.
 - Model-based diagnosis an established field.
 - Several model-based diagnosers available.



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