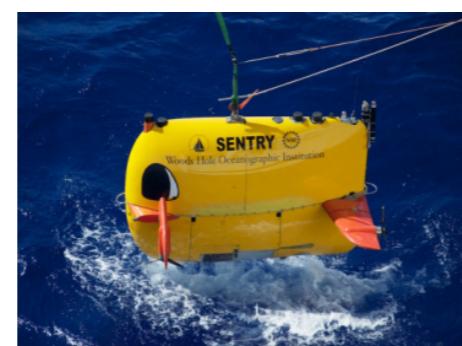


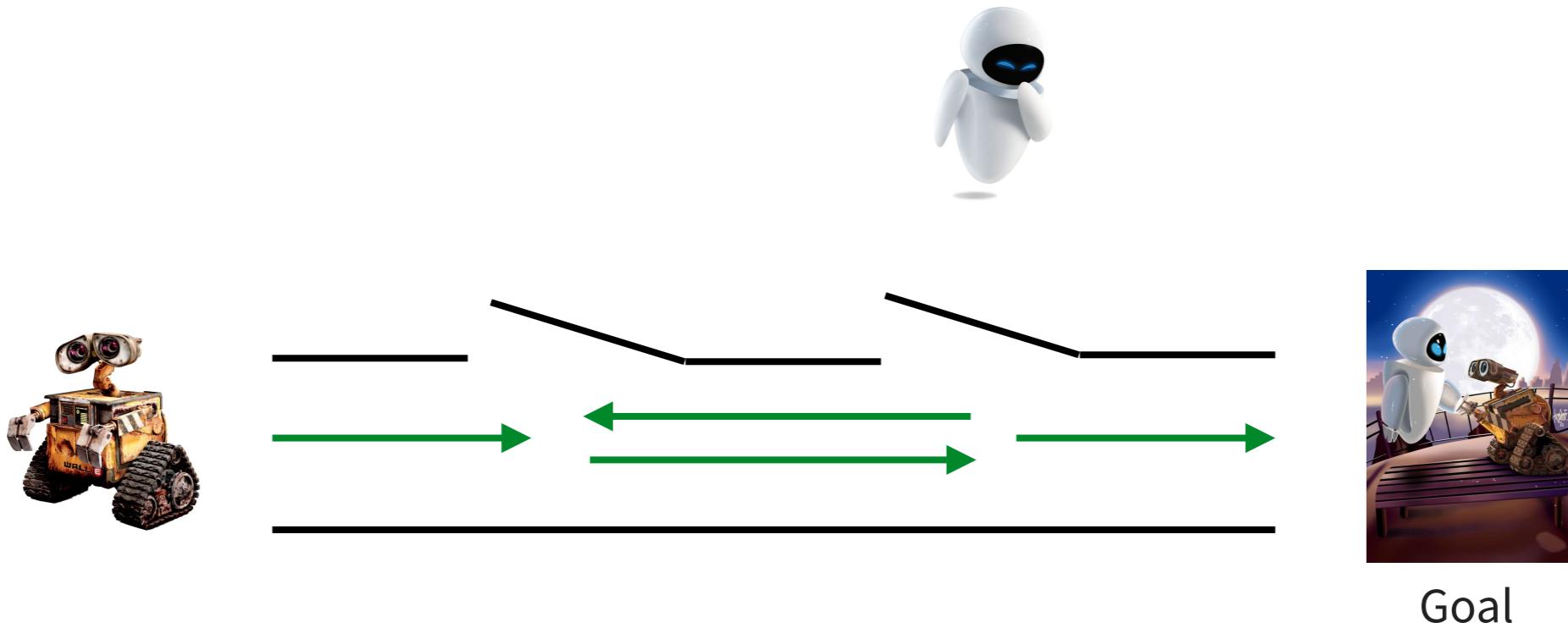
# **Heuristic Search Planning With Multi-Objective Probabilistic LTL Constraints**

Peter Baumgartner, Sylvie Thiébaux, Felipe Trevizan

Data61/CSIRO and Research School of Computer Science, ANU  
Australia

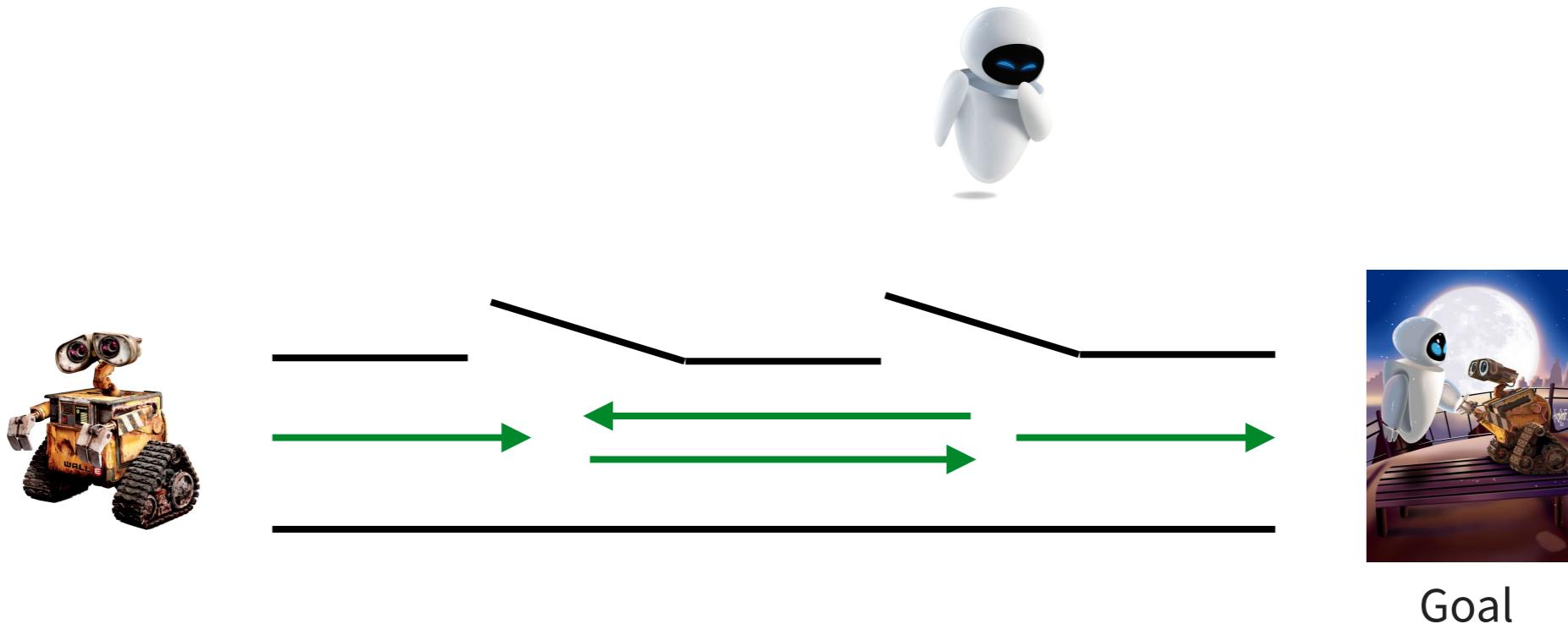


# Planning Under Uncertainty



**Actions:** move left, move right, enter, get Eve, exit

# Planning Under Uncertainty

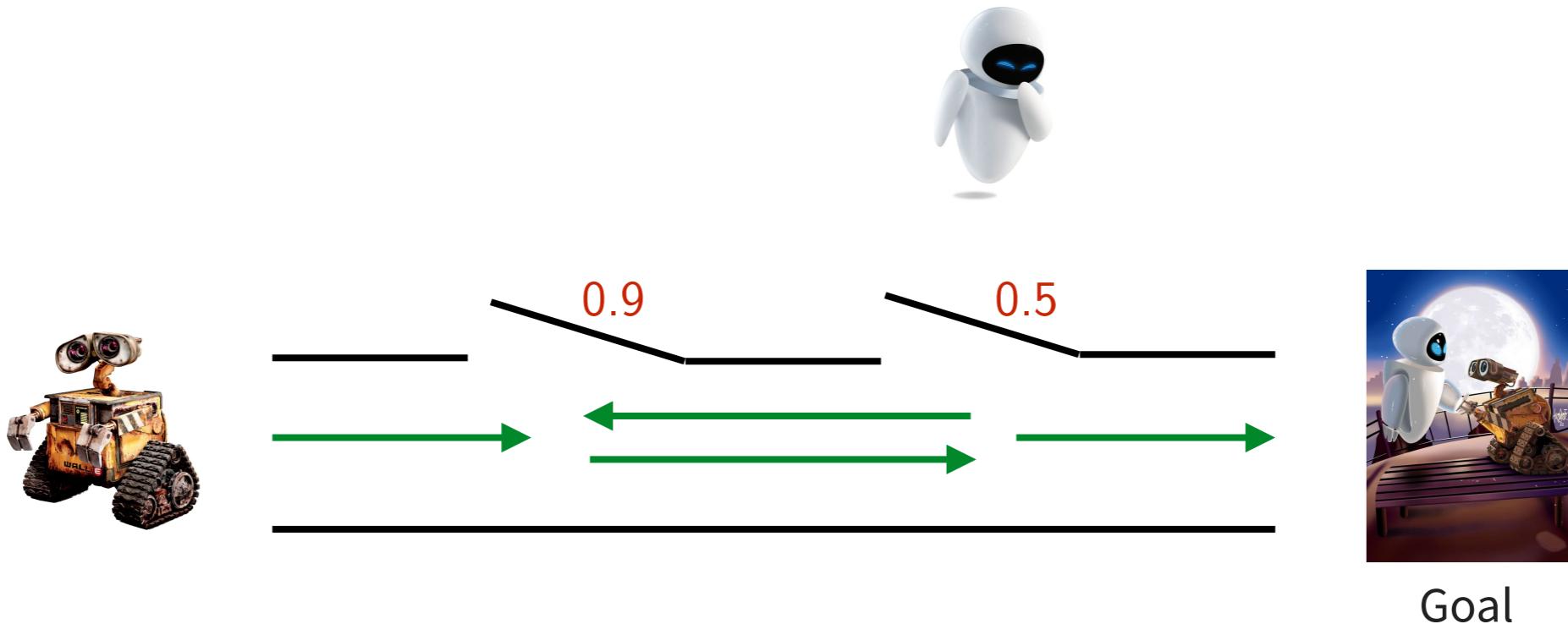


action  $\implies$  stochastic environment response

**Actions:** move left, move right, enter, get Eve, exit

**Environment:** door possibly jams, ...

# Planning Under Uncertainty

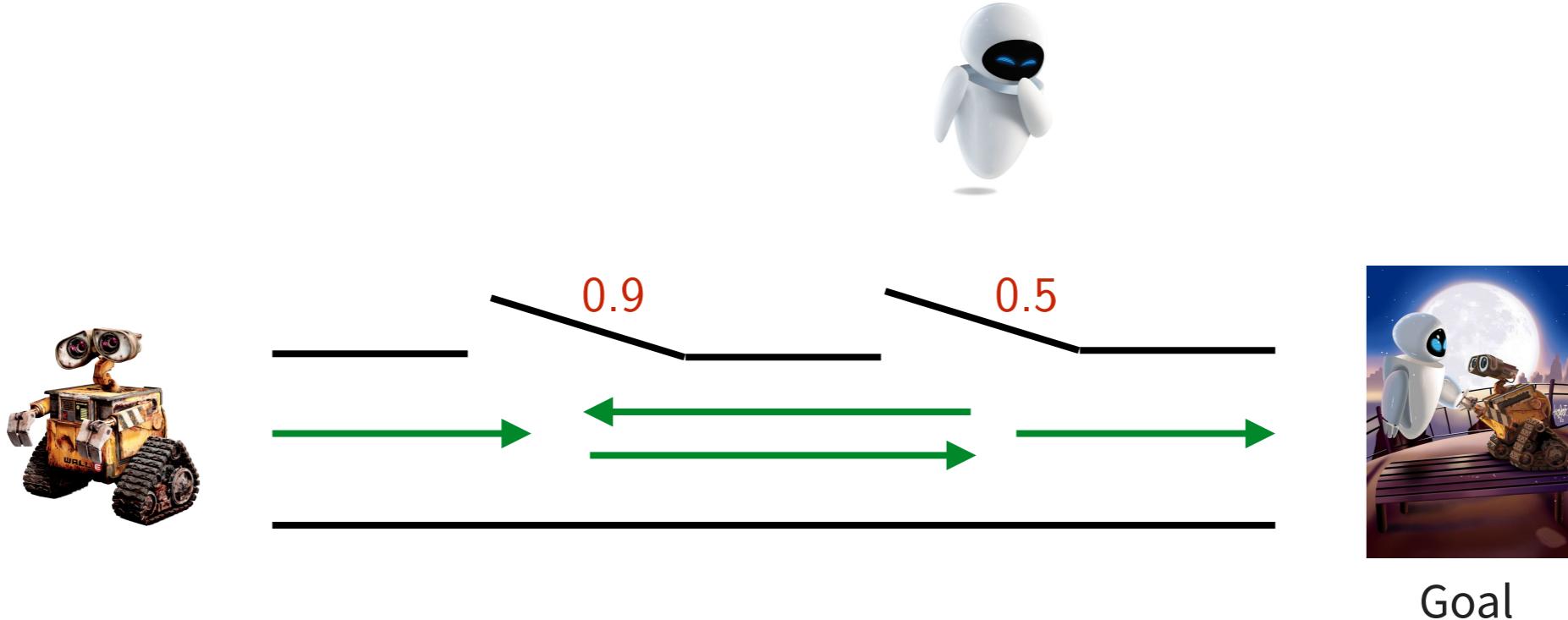


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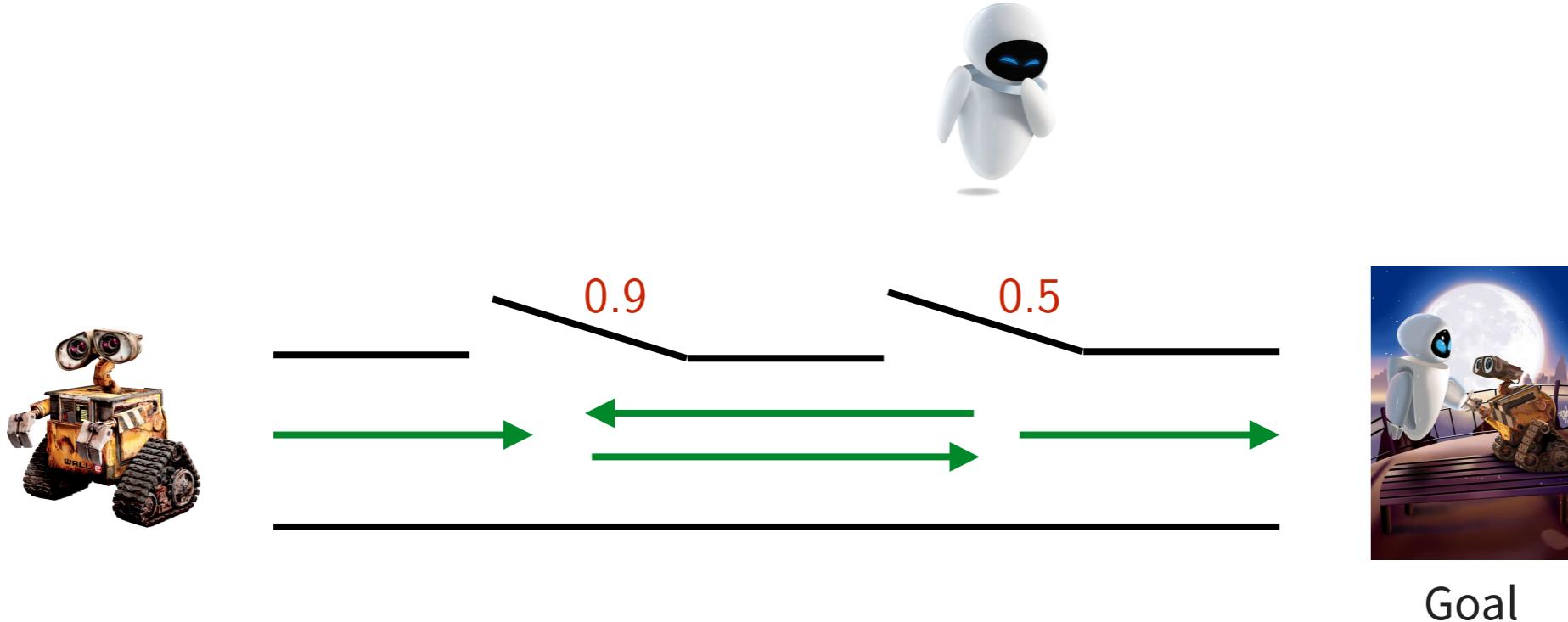
## Stochastic Shortest Path Problem (SSP)

**Problem:** What *action* to take in what *state* to reach the *goal* with *minimal costs*?

**Solution:** *Stochastic policy*: probability distribution on actions

“When at door 1 enter the room 3 out of 10 times,...”

# Planning Under Uncertainty



action  $\implies$  stochastic environment response

**Actions:** move left, move right, enter, get Eve, exit

**Environment:** door possibly jams, ...

**Add constraints for better expressivity (C-SSP)**

- well-known: “fuel < 5”
- here: PLTL

**Stochastic Shortest Path Problem (SSP)**

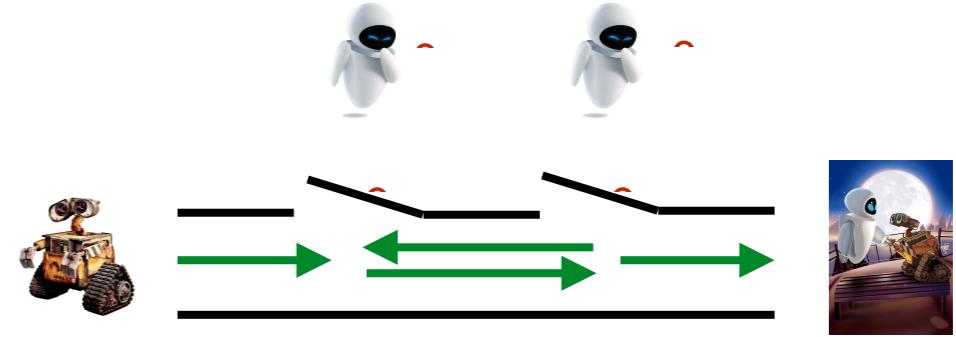
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“When at door 1 enter the room 3 out of 10 times,...”

# Multi-Objective Probabilistic LTL (MO-PLTL)

$$\begin{aligned}\Psi &:= \top \mid A \mid \Psi \wedge \Psi \mid \Psi \vee \Psi \mid \neg \Psi \\ &\mid X \Psi \mid \Psi U \Psi \mid F \Psi \mid G \Psi \quad (\text{LTL}) \\ \phi &:= P_{>z} \Psi \mid P_{\geq z} \Psi \quad (\text{PLTL})\end{aligned}$$



*Eve stays in a room until Eve and Wall-E are together*

$$\text{eve\_in\_a\_room } U \text{ together} \quad (\Psi_1)$$

*Once together, eventually together forever*

$$G (\text{together} \Rightarrow F G \text{ together}) \quad (\Psi_2)$$

*Wall-E never visits room1 twice*

$$G (\text{wall-E\_room1} \Rightarrow (\text{wall-E\_room1} U G \neg \text{wall-E\_room1})) \quad (\Psi_3)$$

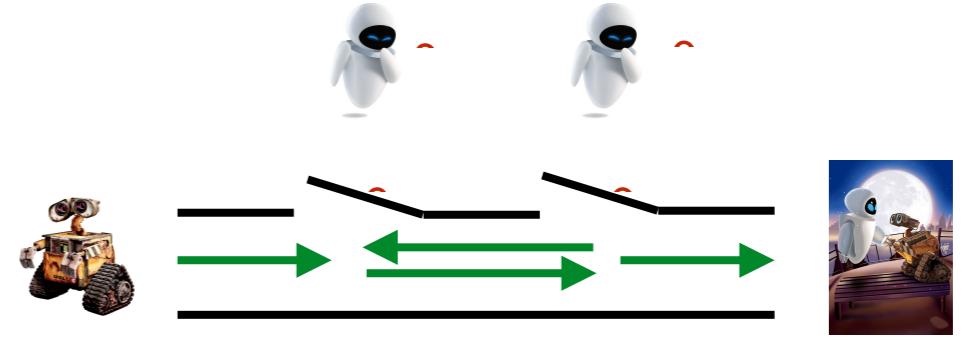
## Additional Multi-Objective PLTL Constraint

$$\phi = P_{\geq 0.8} \Psi_1 \wedge P_{\geq 1.0} \Psi_2 \wedge P_{\geq 0.5} \Psi_3 \quad (\text{MO-PLTL})$$

**Task:** compute a cost-minimal stochastic policy for reaching the goal (with probability 1)  
such that  $\phi$  is satisfied

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 **Not as used in “optimisation”**

## Additional Multi-Objective PLTL Constraint

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# Solving MO-PLTL

## Methods Based on Probabilistic Verification

- State of the art method, implemented in PRISM probabilistic model checker
- Needs infinite runs
  - (1) add self-loop at Goal
  - (2) add Goal constraint :  $\phi = P_1 \psi_1 \wedge \dots \wedge P_k \psi_k \wedge P_{\geq 1} F Goal$
- Compute cross-product automaton

$A = DRA(\psi_1) \times \dots \times DRA(\psi_k) \times DRA(F Goal) \times S$       ( $S$  is given state transition system, MDP).

- Obtain policy for  $\phi$  as a solution of a certain linear program obtained from  $A$

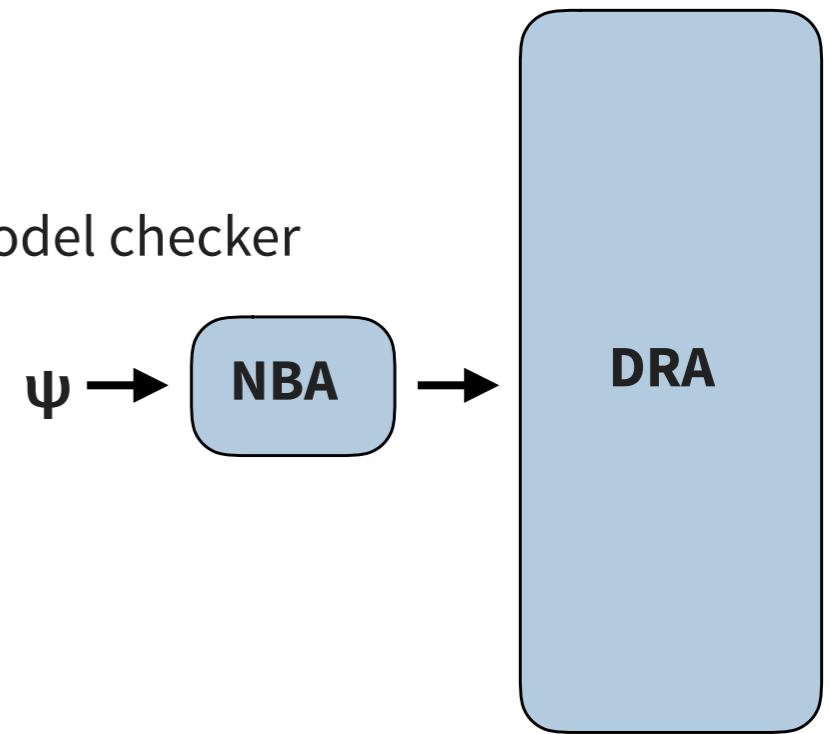
## Complexity

- $|DRA(\psi)|$  is double exponential in  $|\psi|$
- $|S|$  is usually huge for planning problems - cannot afford to generate in full
- Upfront DRA-computation/crossproduct is problematic even for small examples
- The verification/synthesis problem is 2EXPTIME complete
- Complicated algorithms (see also [deGiacomo&Vardi IJCAI2013, IJCAI2015])

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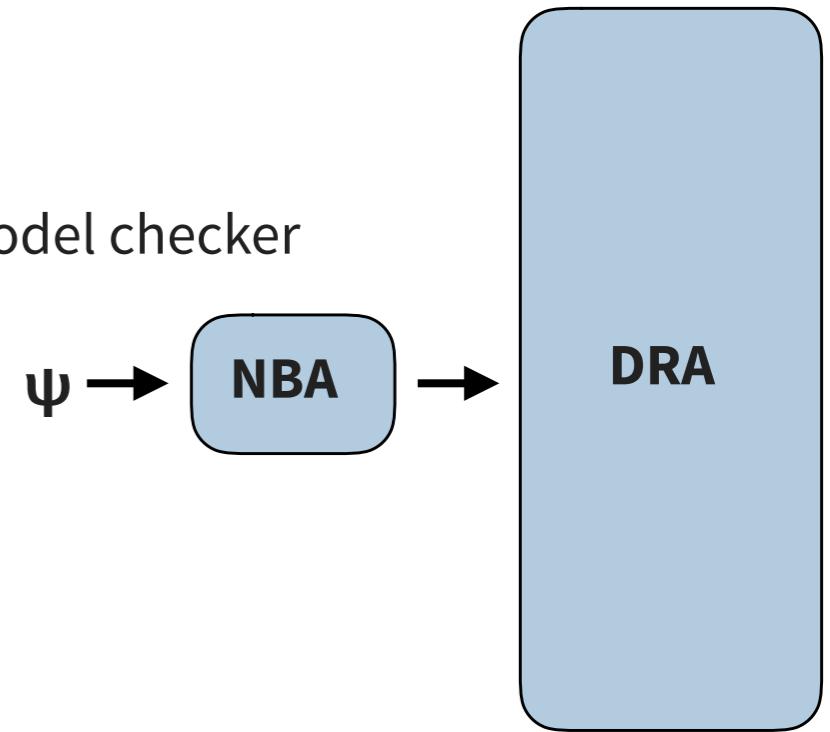
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We have a specific problem - all BSCCs are self-loops at goals - and can do better

# Contributions

	Verification Based	Our Method
<b>General</b>	Yes	No (Requires Goal)
<b>Approach</b>	Automata (DRA)	(1) Formula progression, Tseitin (2) NBA
<b>State Space</b>	Upfront	On-the-fly
<b>Complexity</b>	Double exponential in $\Phi$	Single exponential in $\Phi$ for (1)
<b>Heuristics</b>	No	Yes ( $i^2$ Dual)

Baier&McIlraith ICAPS 2006: non-stochastic planning w/ LTL, heuristics, NFA, by compilation

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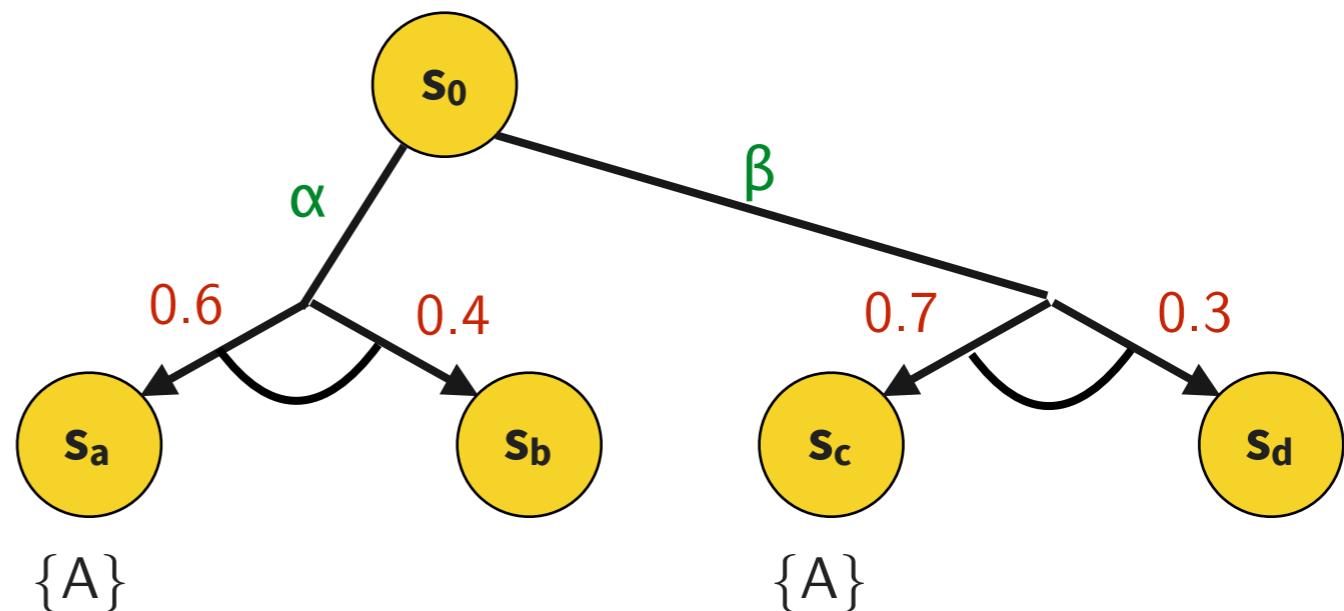
**Rest of this talk:** approach, complexity, heuristics, experiments

## How to Check a Policy $\pi$ for Satisfying a PLTL Formula

Given policy  $\pi =$

$$s_0: [\alpha \rightarrow 0.6, \beta \rightarrow 0.4]$$

It follows  $s_0 \models P_{>0.6} F A$



**Proof**

$$s_0 \models P_{>0.6} F A$$

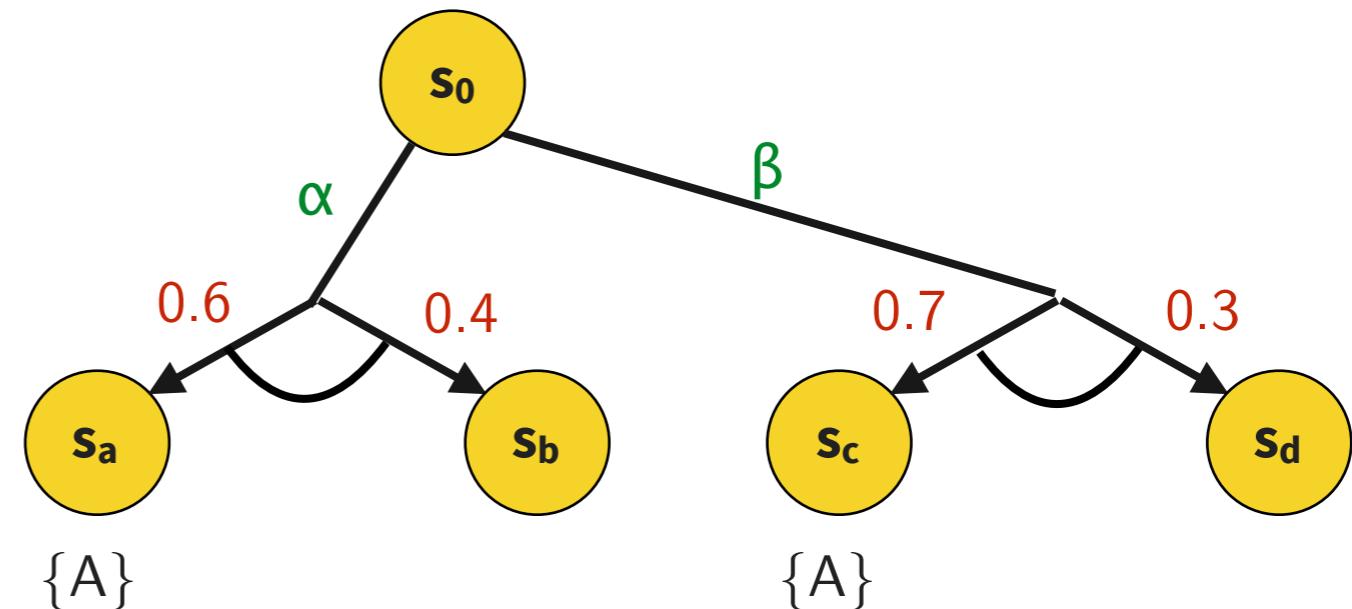
*The probability of all paths from  $s_0$  satisfying  $F A$  is  $> 0.6$*

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iff

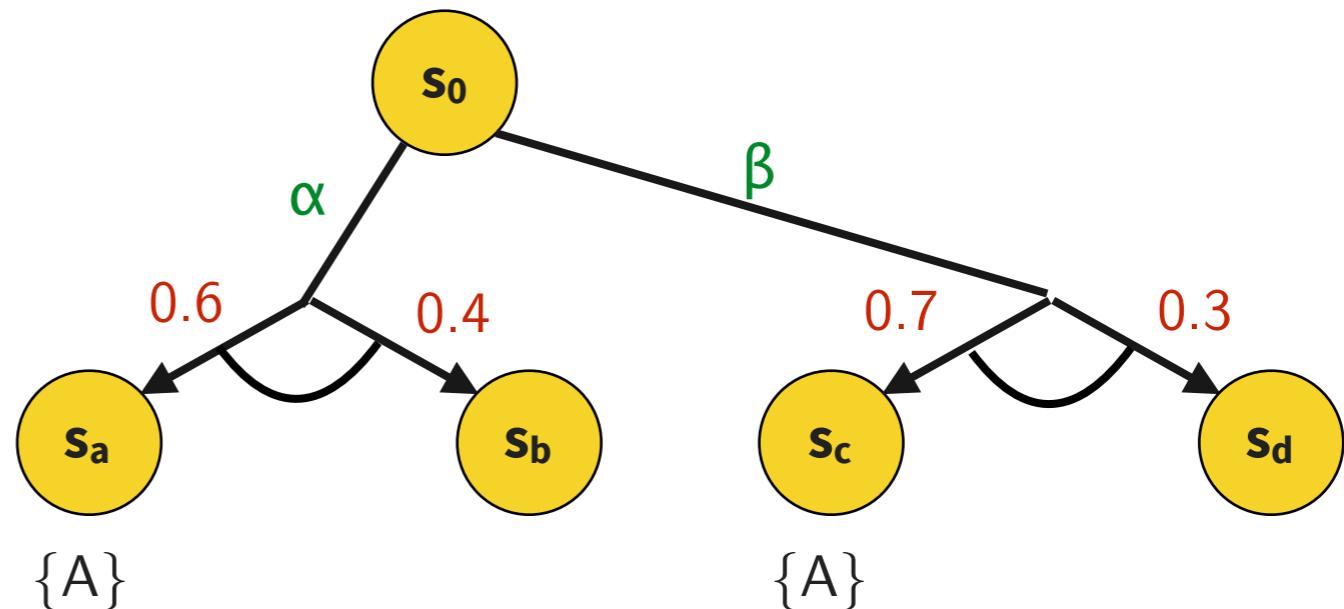
$$\Pr\{p \mid p \text{ is a path from } s_0 \text{ and } p \models F A\} > 0.6$$

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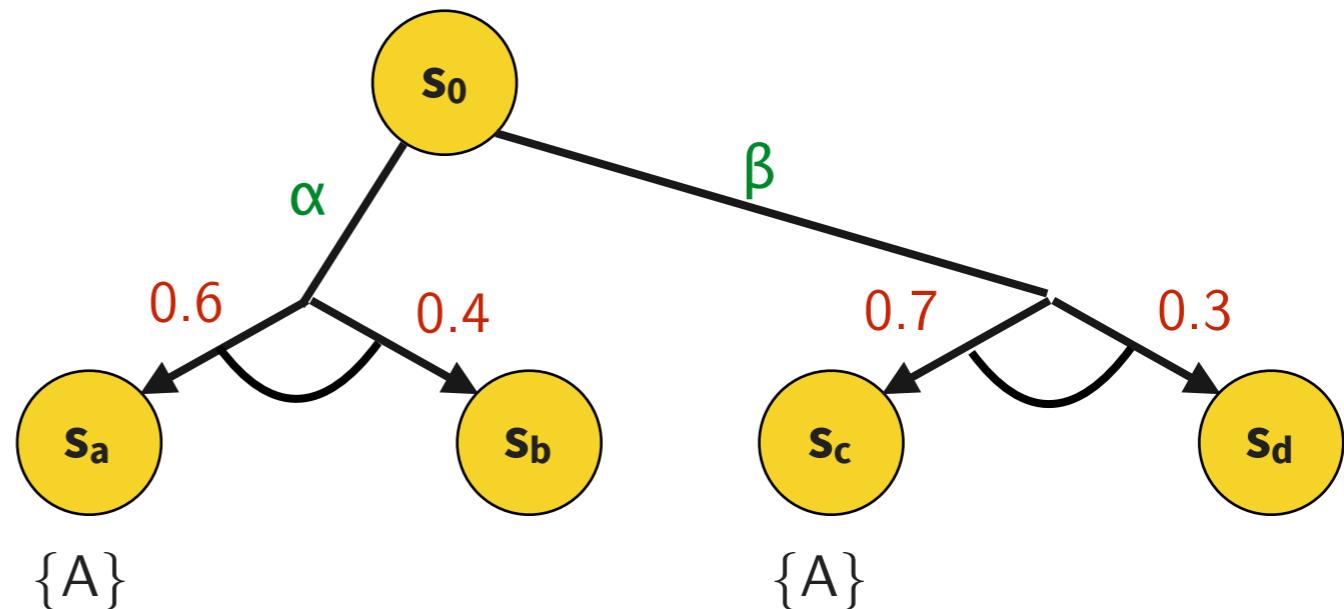
Non-probabilistic LTL  
Ignore finiteness of paths on this slide

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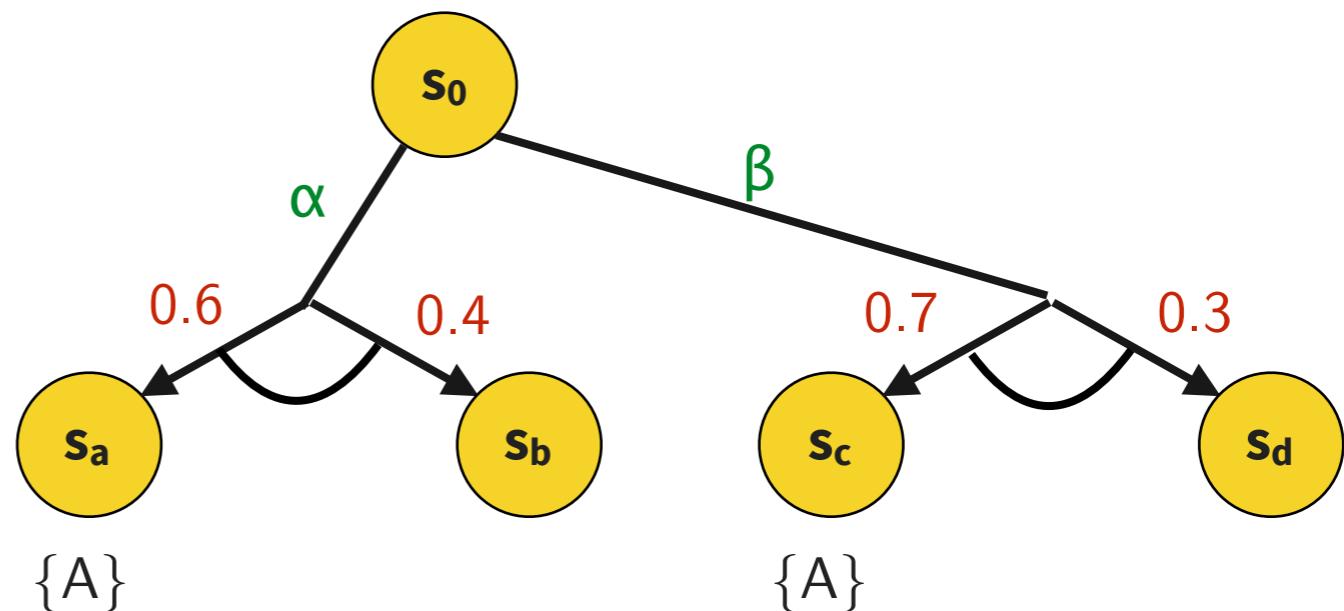
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$$0.6 \cdot 0.6 + 0.4 \cdot 0.7 = 0.64 > 0.6$$

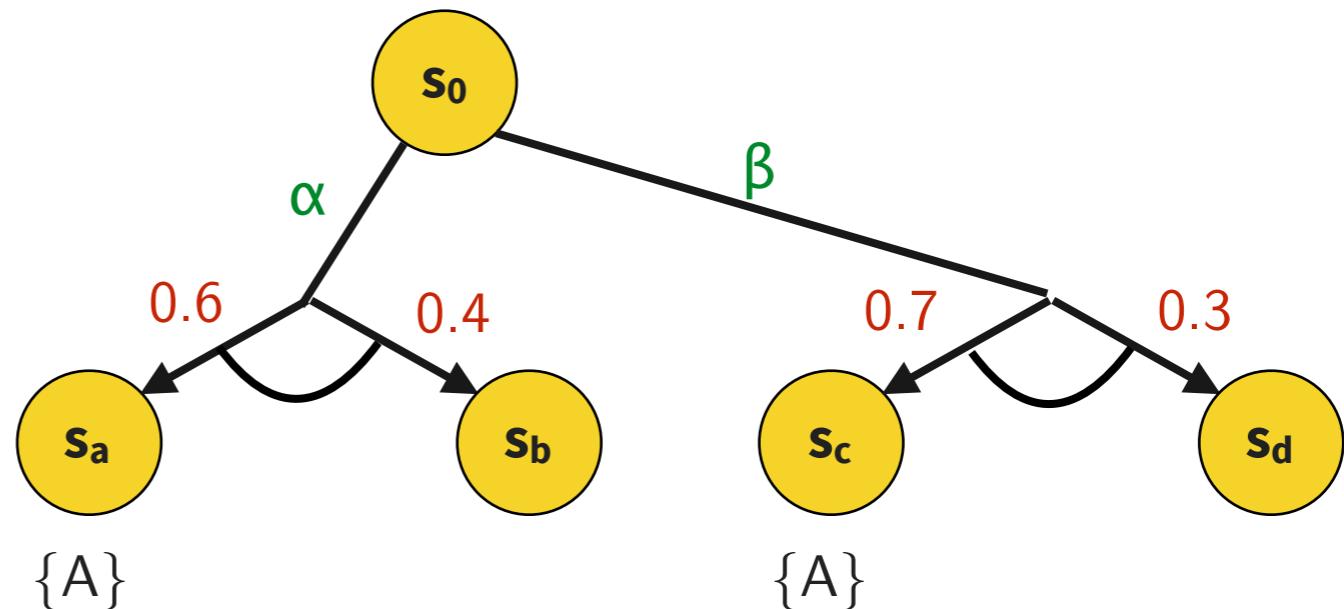
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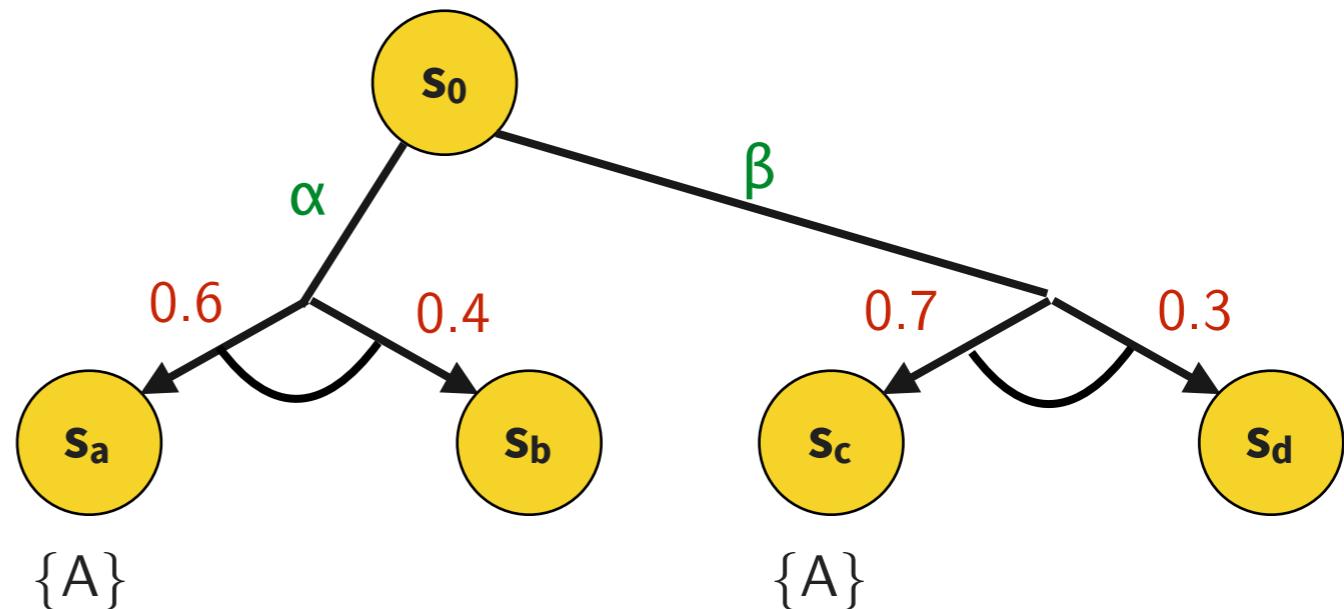
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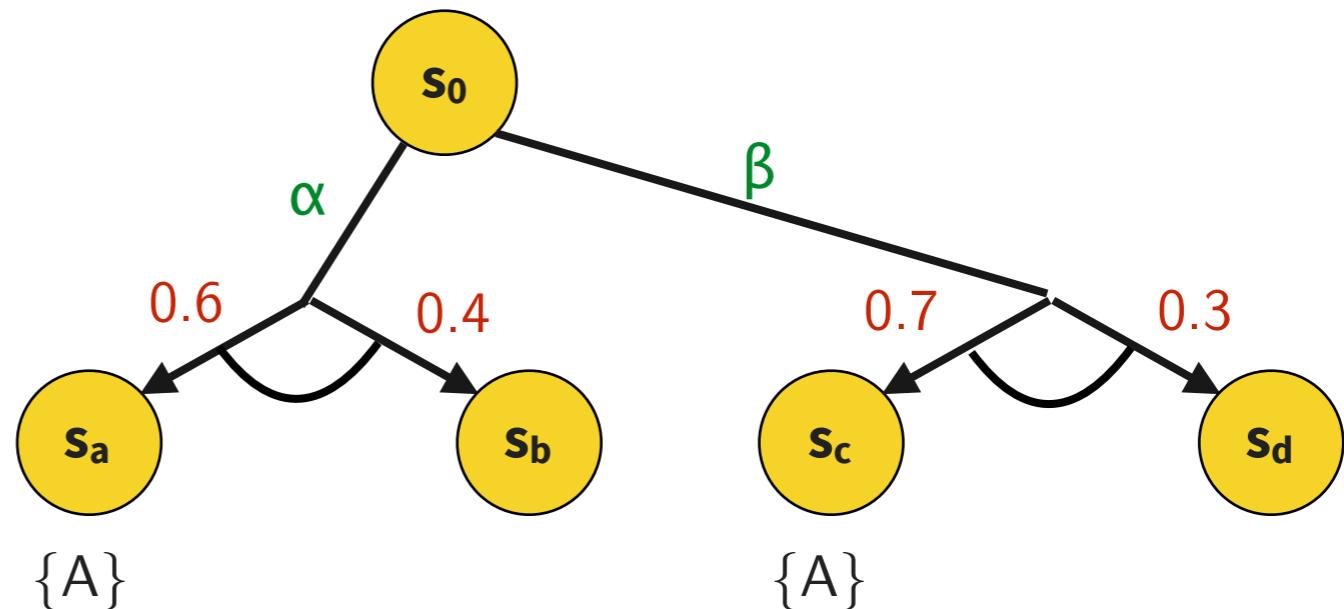
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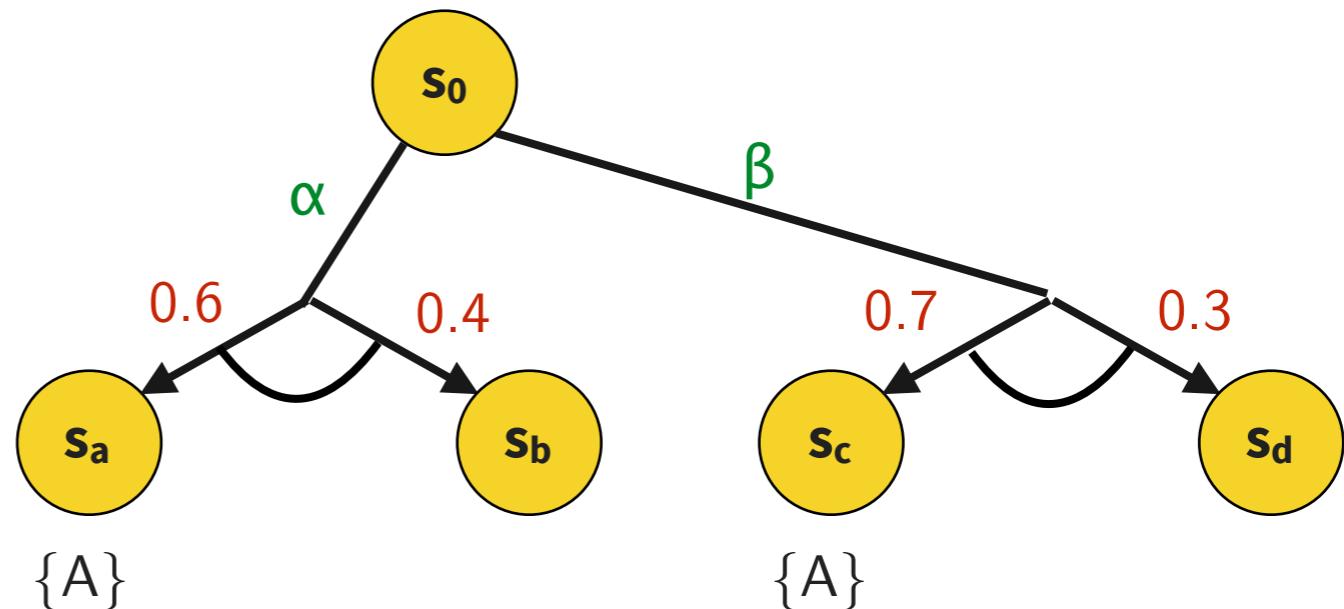
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Find policy  $\pi =$

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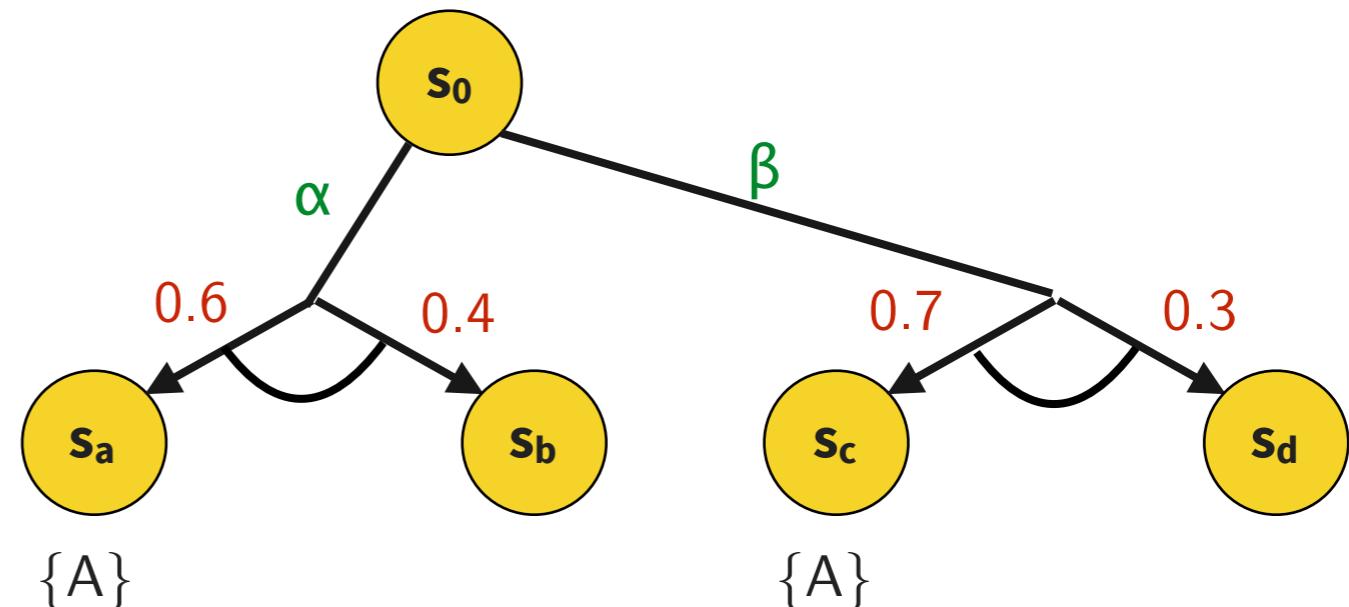
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→ Quantify over action probabilities and compute solution



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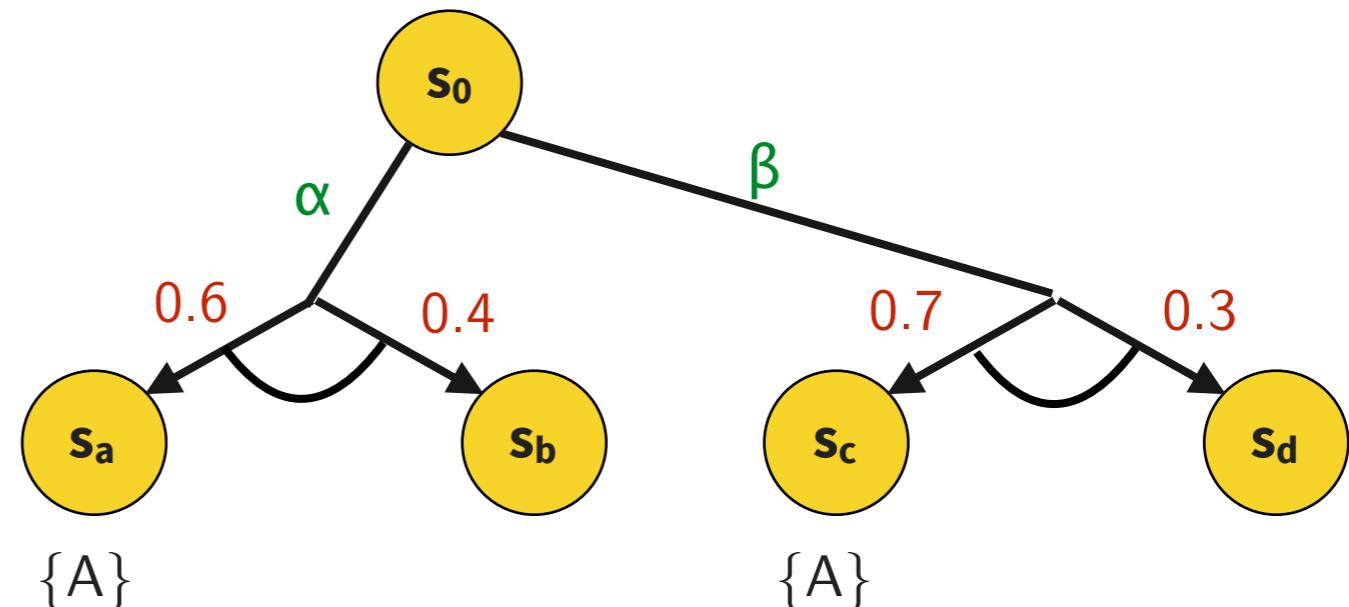
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$\pi(\alpha \mid s_0) 0.6 + \pi(\beta \mid s_0) 0.7$

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Non-probabilistic LTL  
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**Proof**

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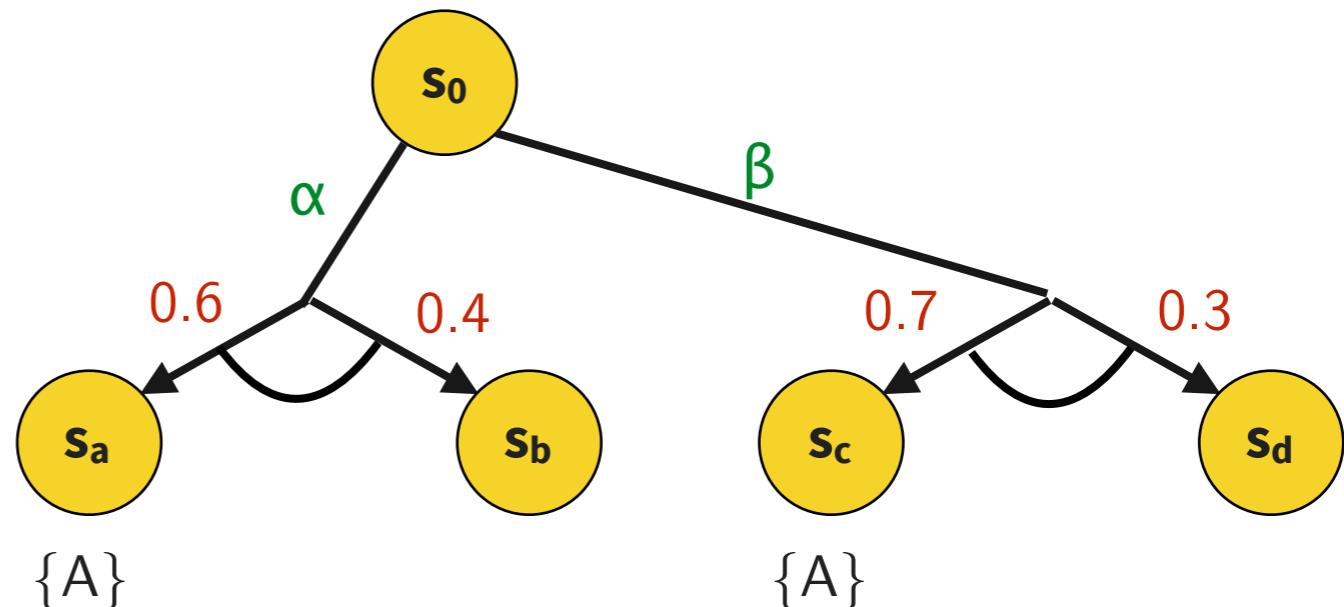
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$$\pi(\alpha \mid s_0) 0.6 + \pi(\beta \mid s_0) 0.7 > 0.6$$

$$\pi(\alpha \mid s_0) + \pi(\beta \mid s_0) = 1$$



Non-probabilistic LTL  
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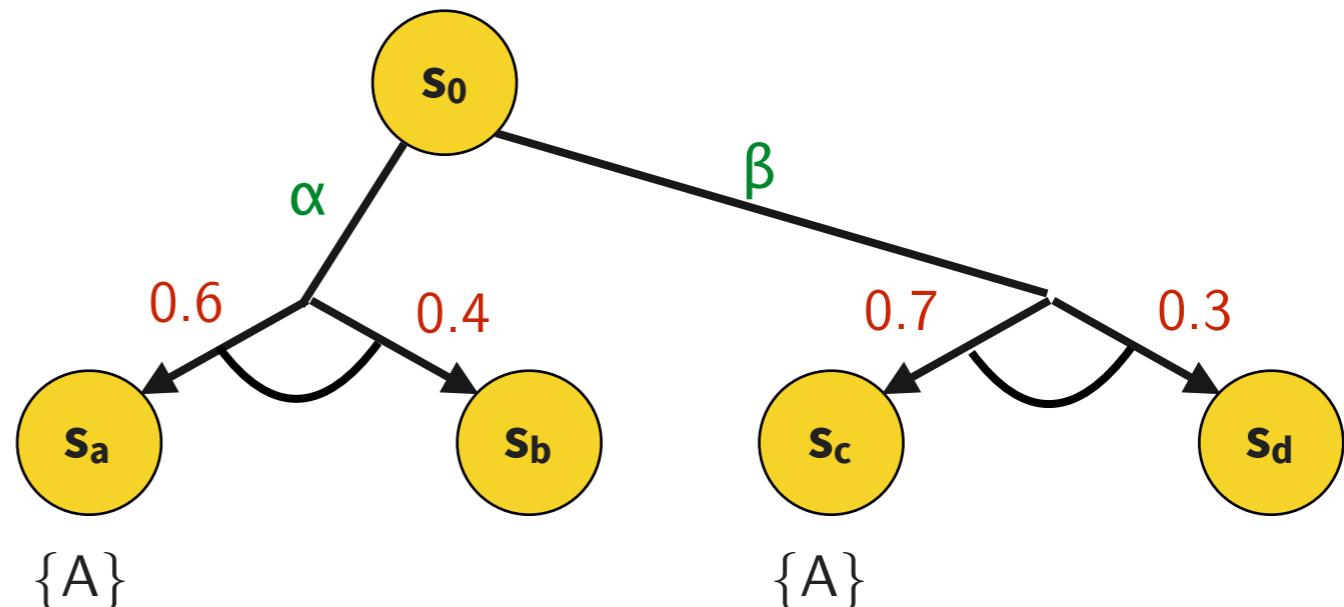
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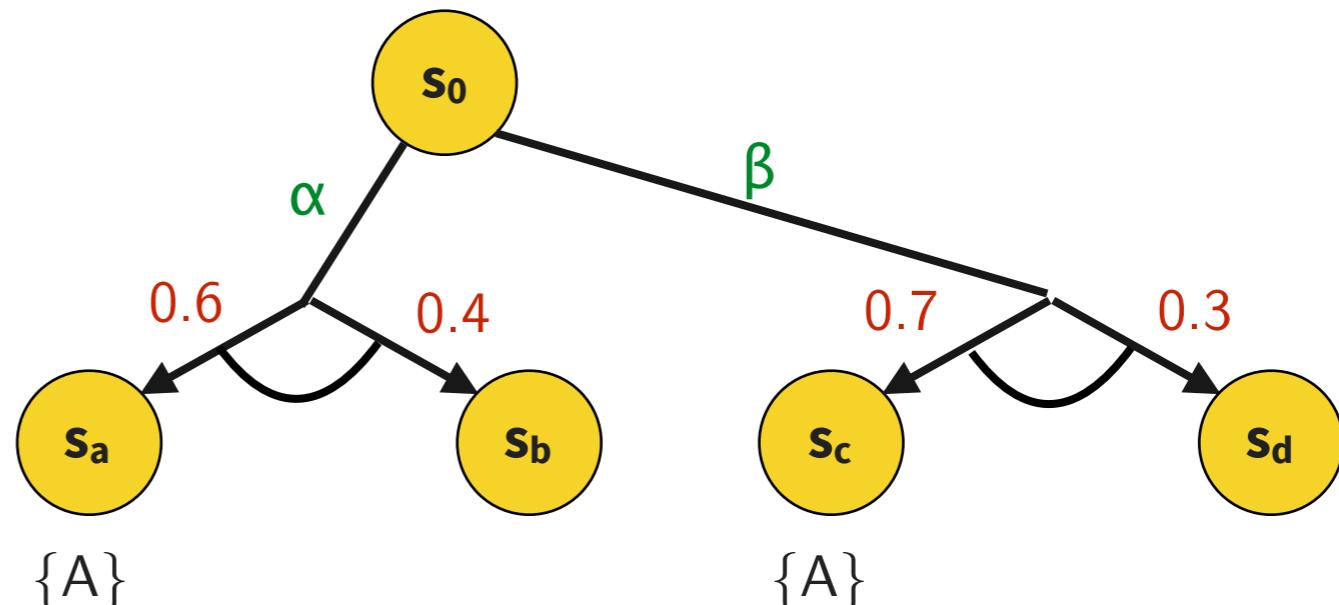
$$\pi(\alpha \mid s_0) 0.6 + \pi(\beta \mid s_0) 0.7$$

$$> 0.6$$

→ Quantify over action probabilities and  
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$$\pi(\alpha \mid s_0) + \pi(\beta \mid s_0) = 1$$

Non-linear program in general - we use dual-space LPs instead



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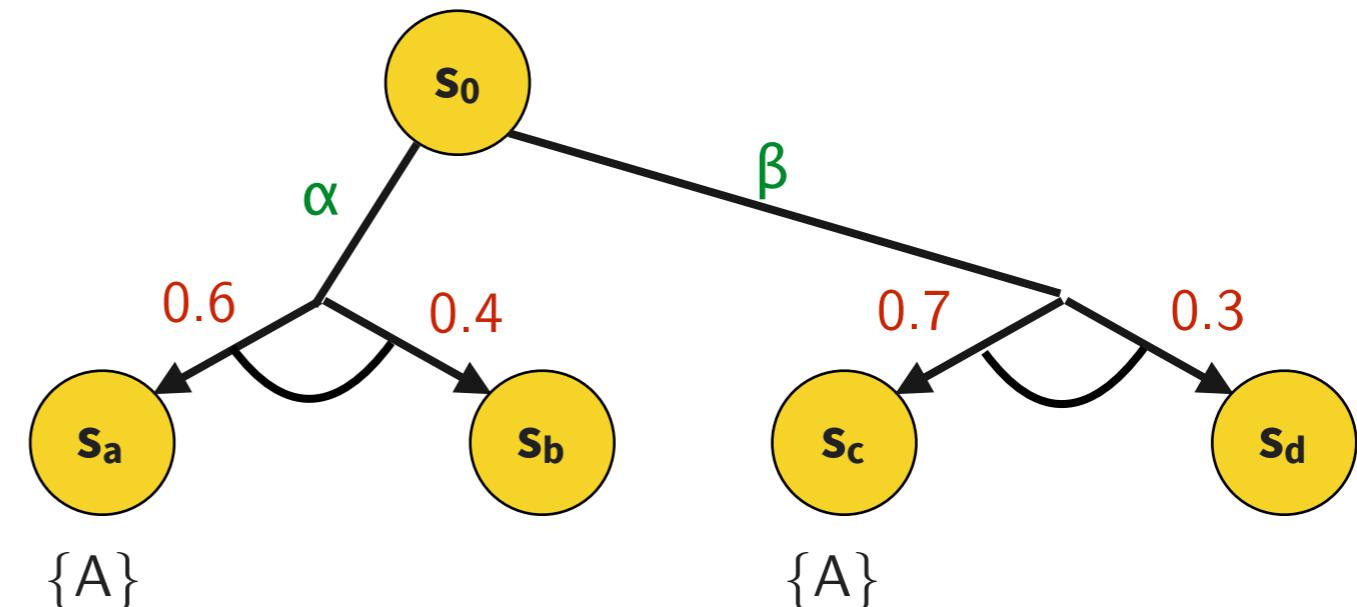
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iff

$$\pi(\alpha \mid s_0) 0.6 + \pi(\beta \mid s_0) 0.7 > 0.6 \rightarrow \text{Quantify over action probabilities and compute solution}$$

$$\pi(\alpha \mid s_0) + \pi(\beta \mid s_0) = 1$$

Non-linear program in general - we use dual-space LPs instead

# How to Synthesize Policy $\pi$ for Satisfying a PLTL Formula

**Find** policy  $\pi =$

$$s_0: [\alpha \rightarrow 0.6 \quad \beta \rightarrow 0.4]$$

**such that**  $s_0 \models P_{>0.6} F A$

**Proof**

$$s_0 \models P_{>0.6} F A$$

The probability of all paths from  $s_0$  satisfying  $F A$  is  $> 0.6$

iff

$$\Pr\{p \mid p \text{ is a path from } s_0 \text{ and } p \models F A\} > 0.6$$

iff

$$\Pr\{s_0s_a, s_0s_c\} > 0.6$$

iff

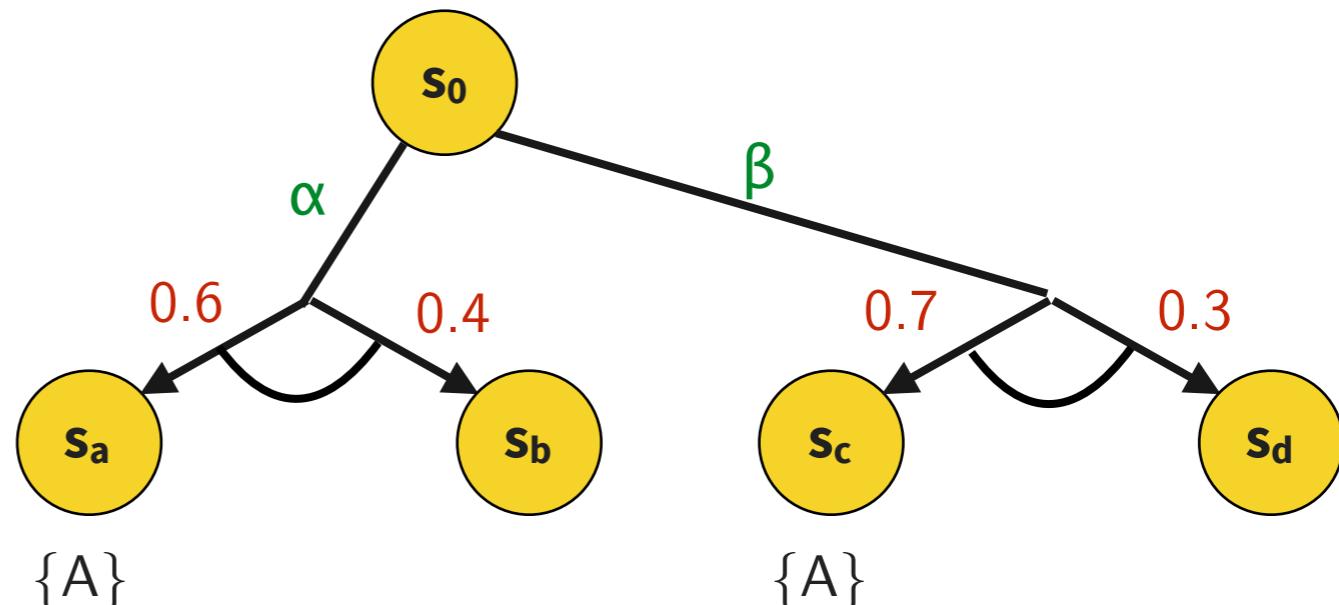
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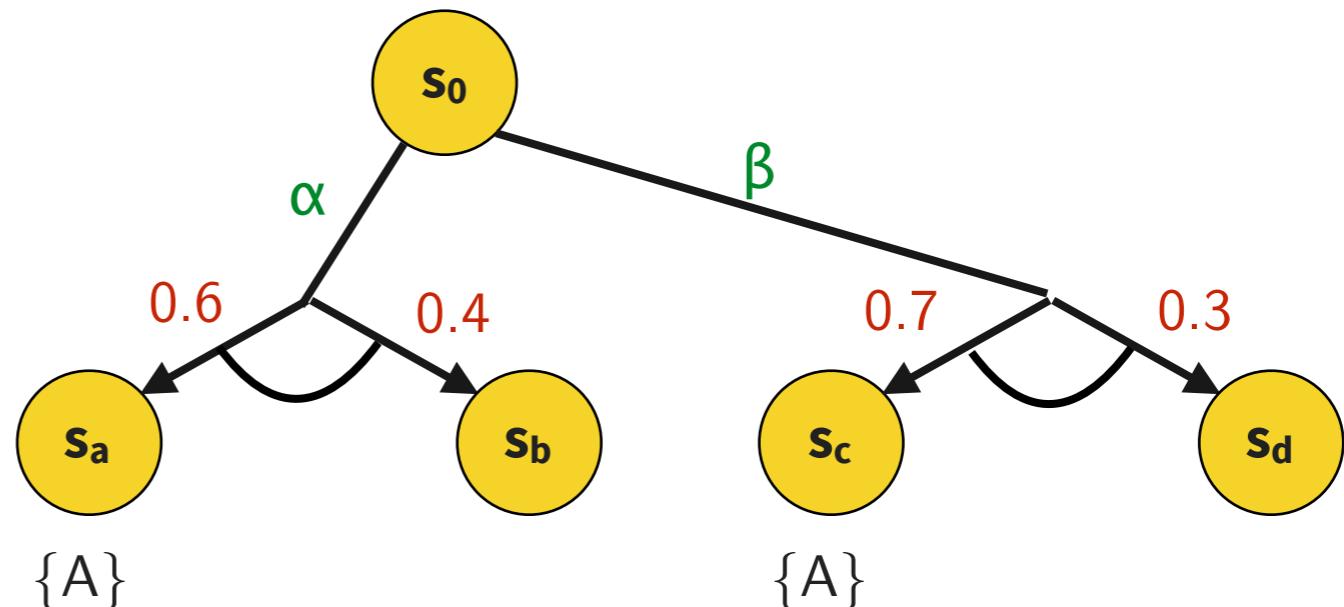
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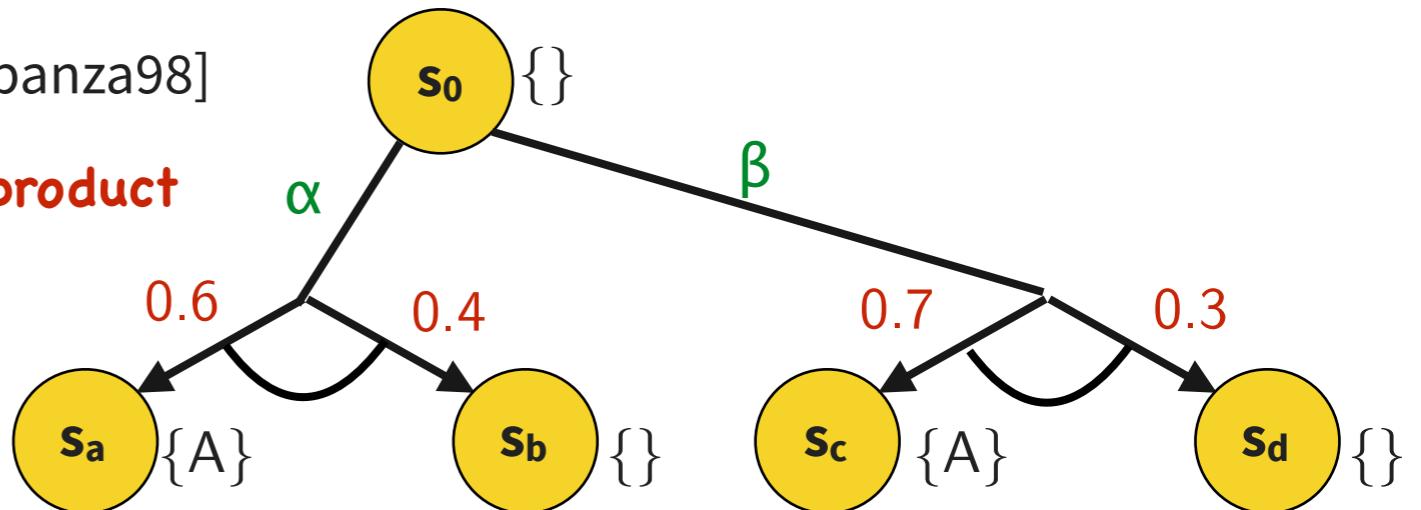
Next

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[Bachus&Kabanza98]

Why? On-the-fly instead of upfront cross-product

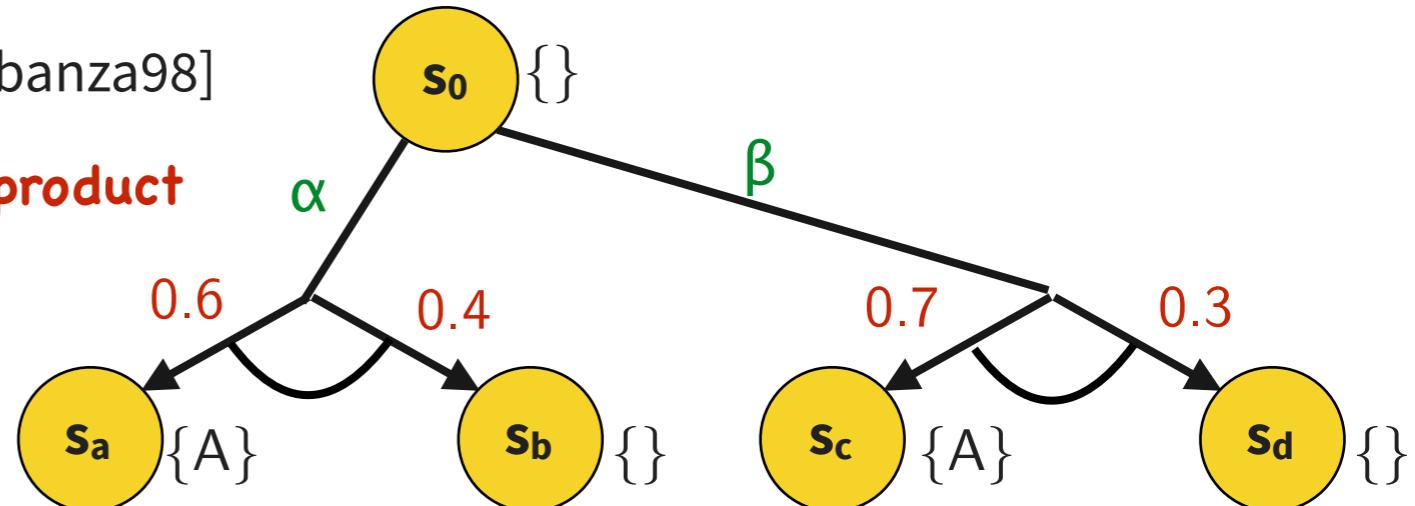


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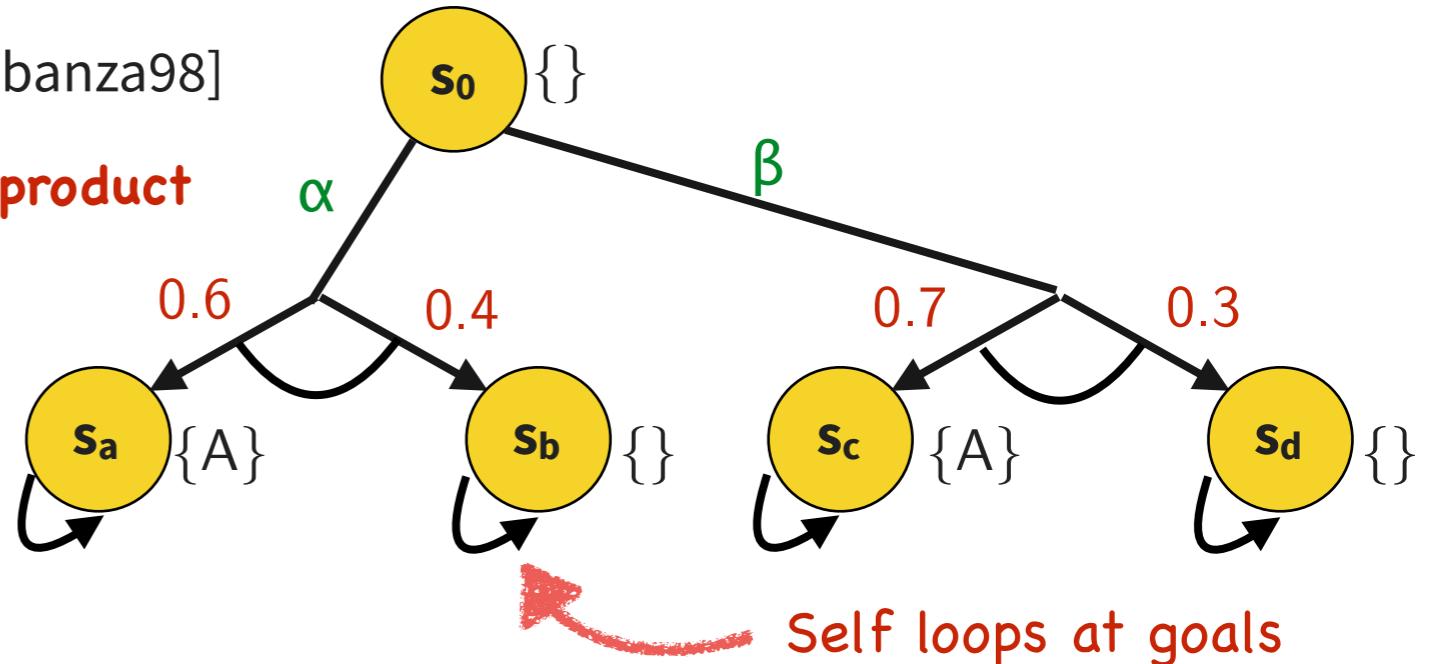


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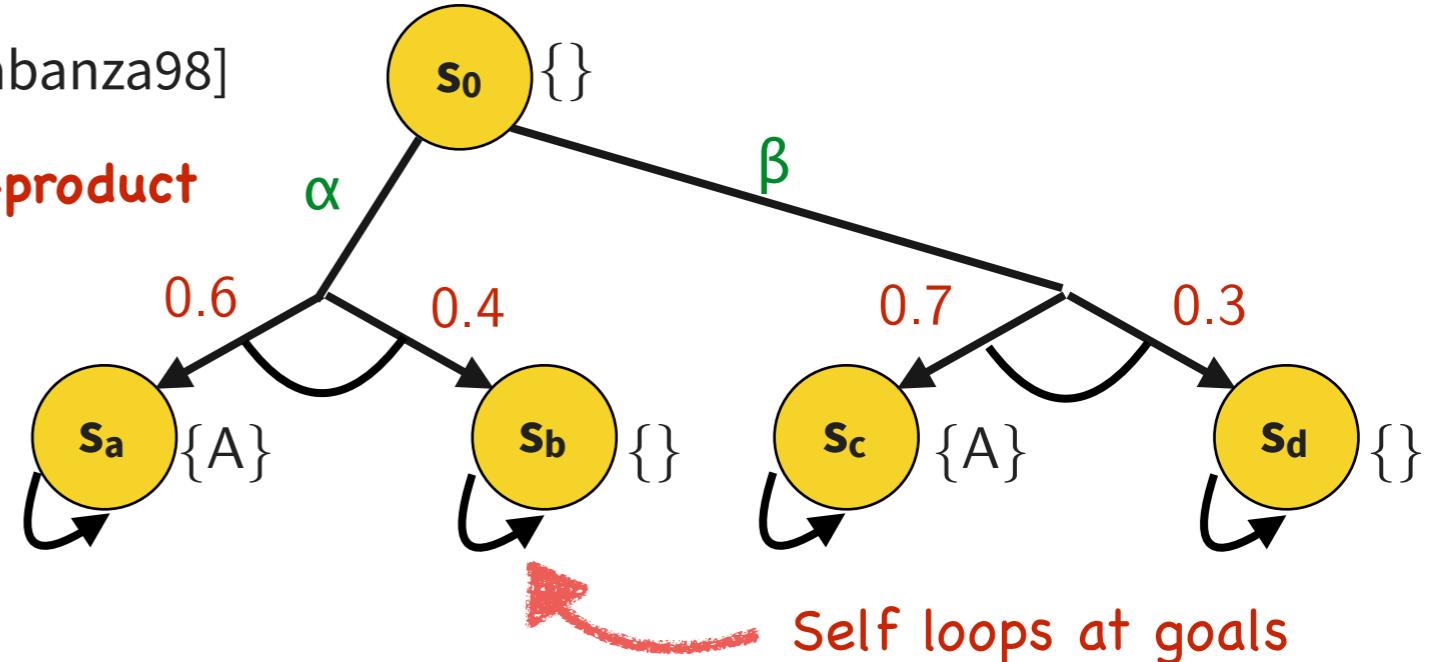
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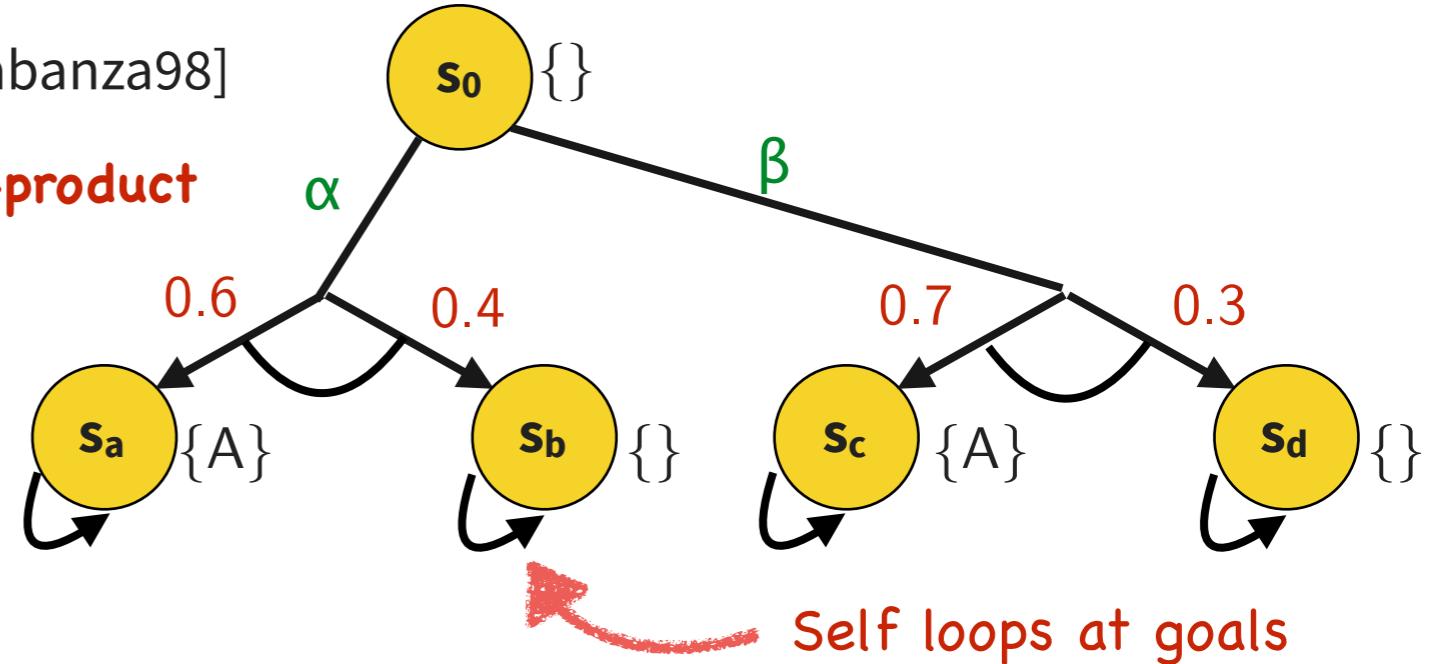
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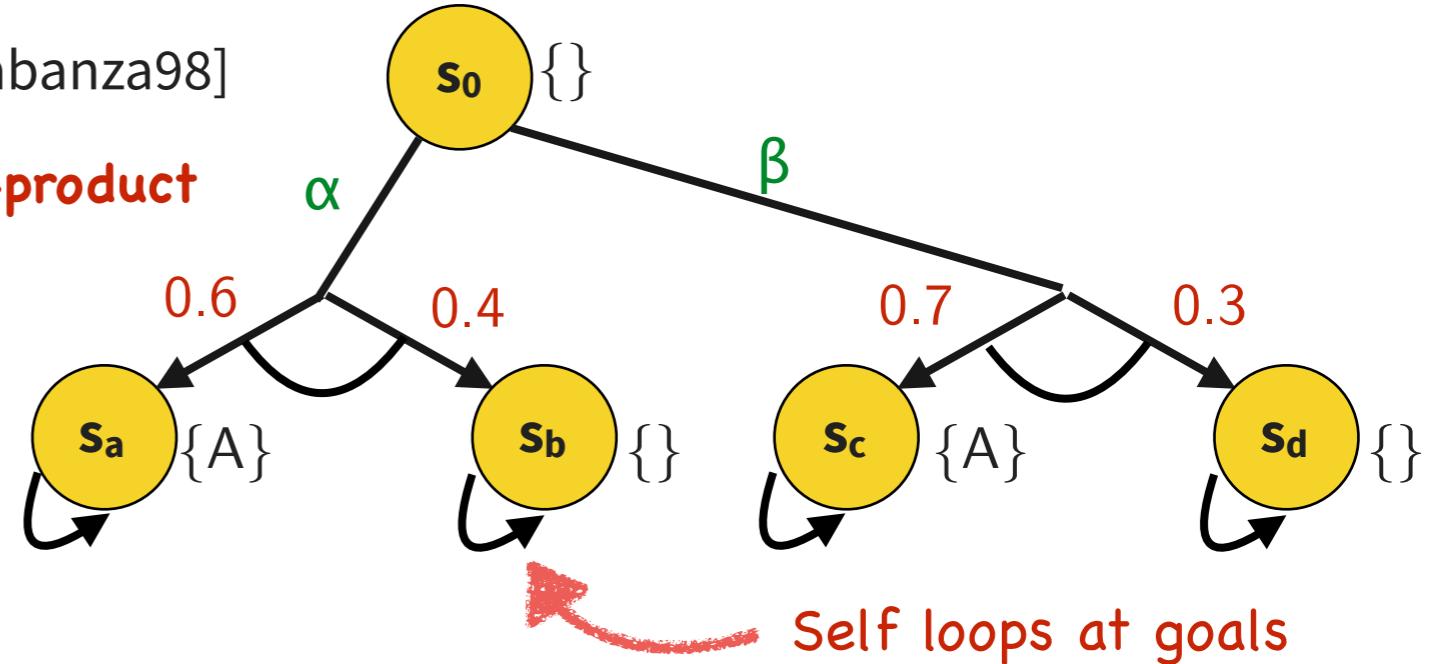
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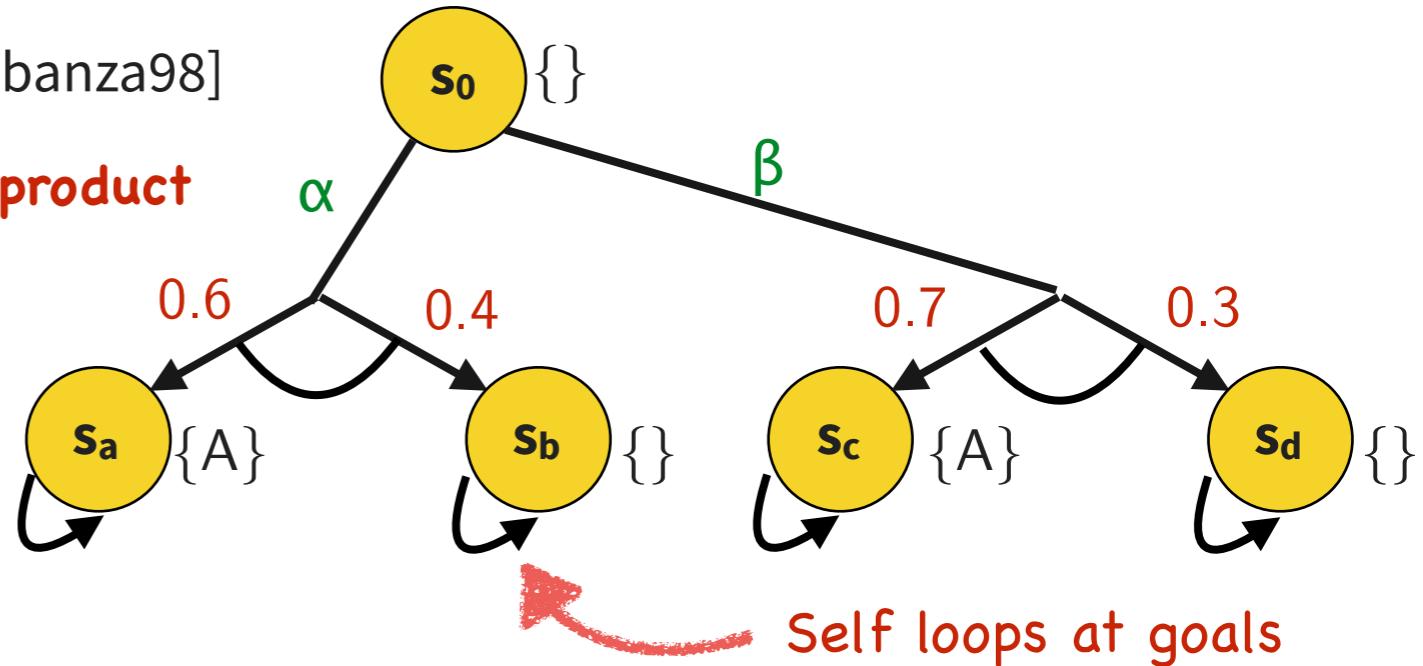
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Progression: expand and simplify a given LTL formula along a path

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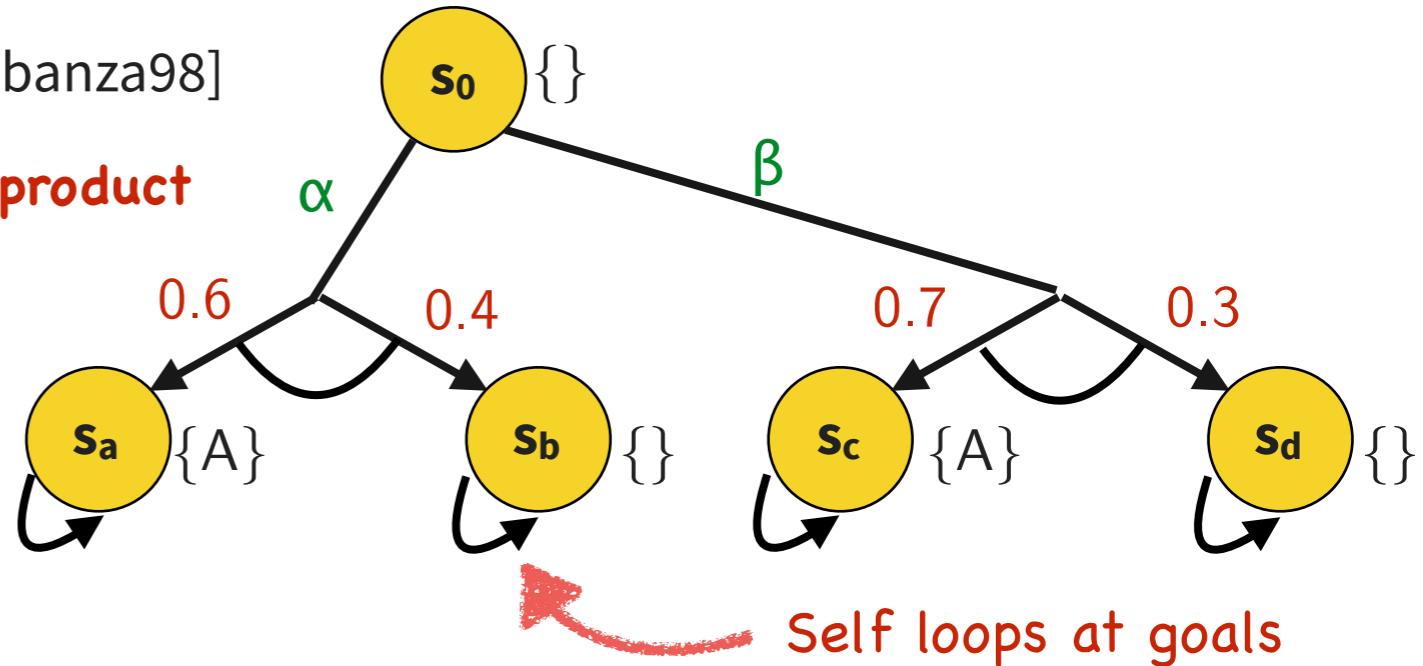
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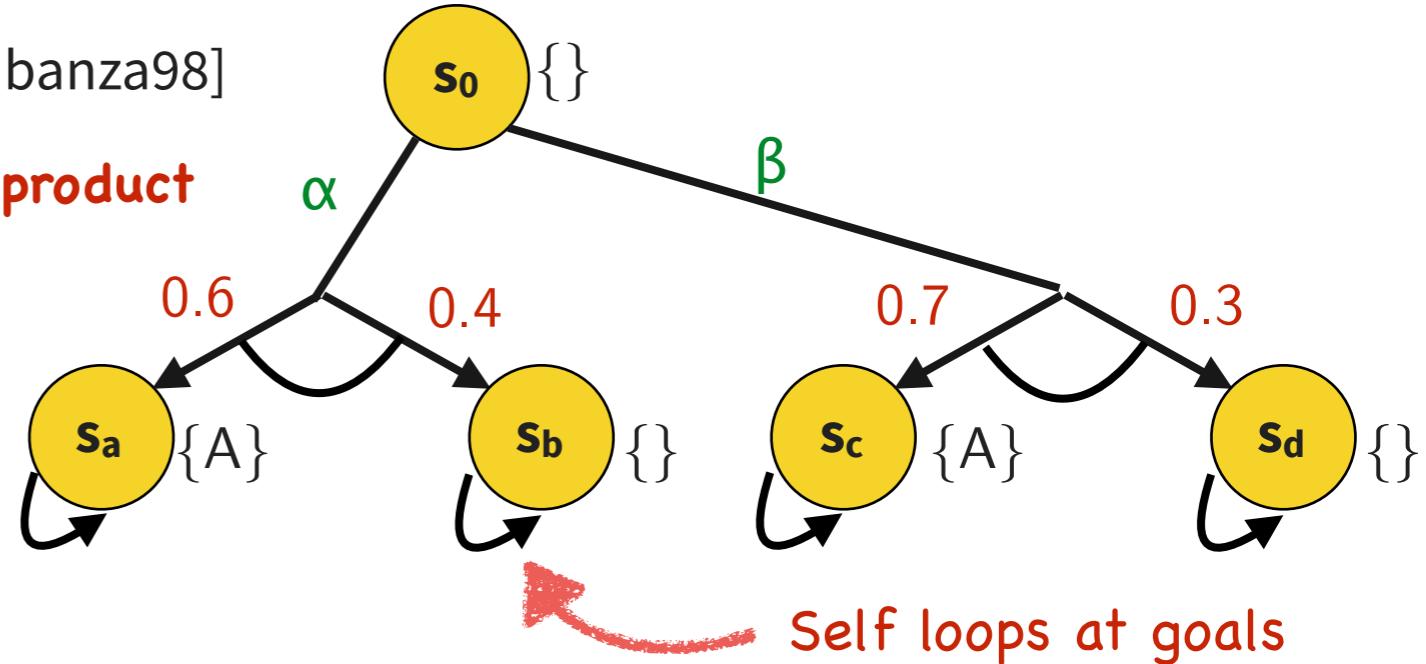
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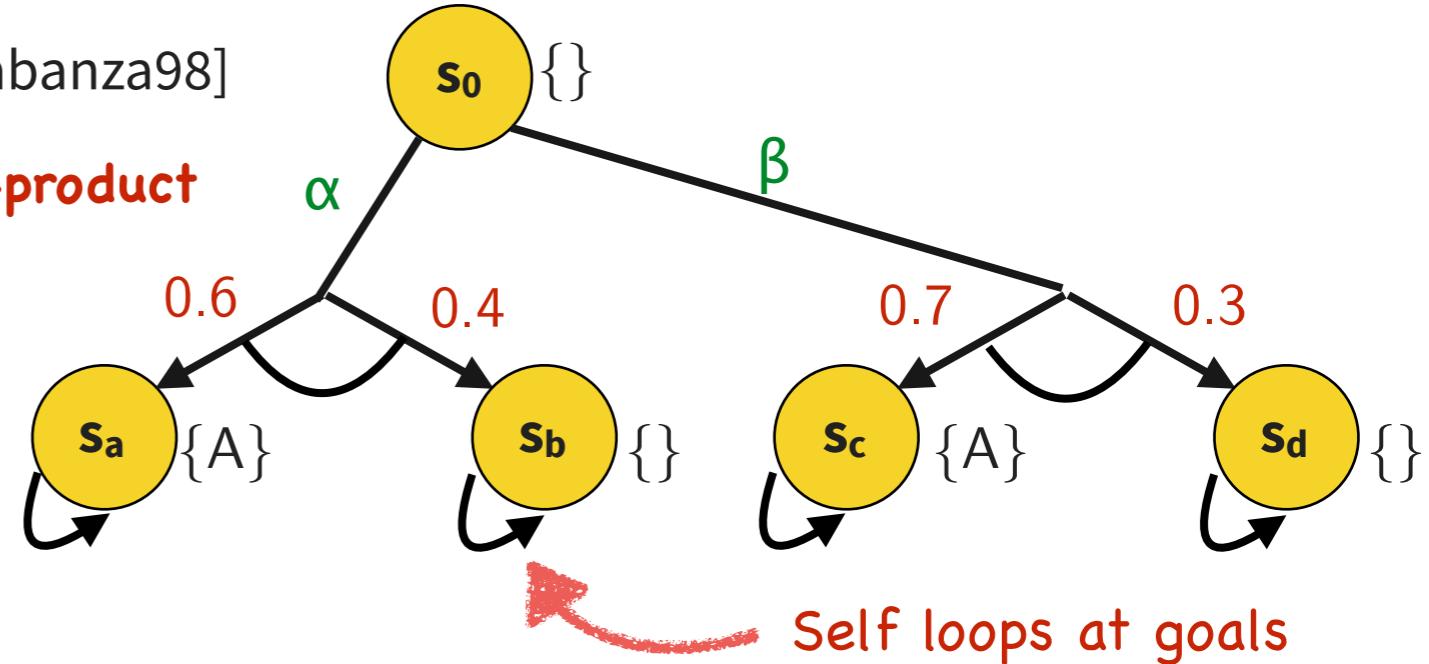
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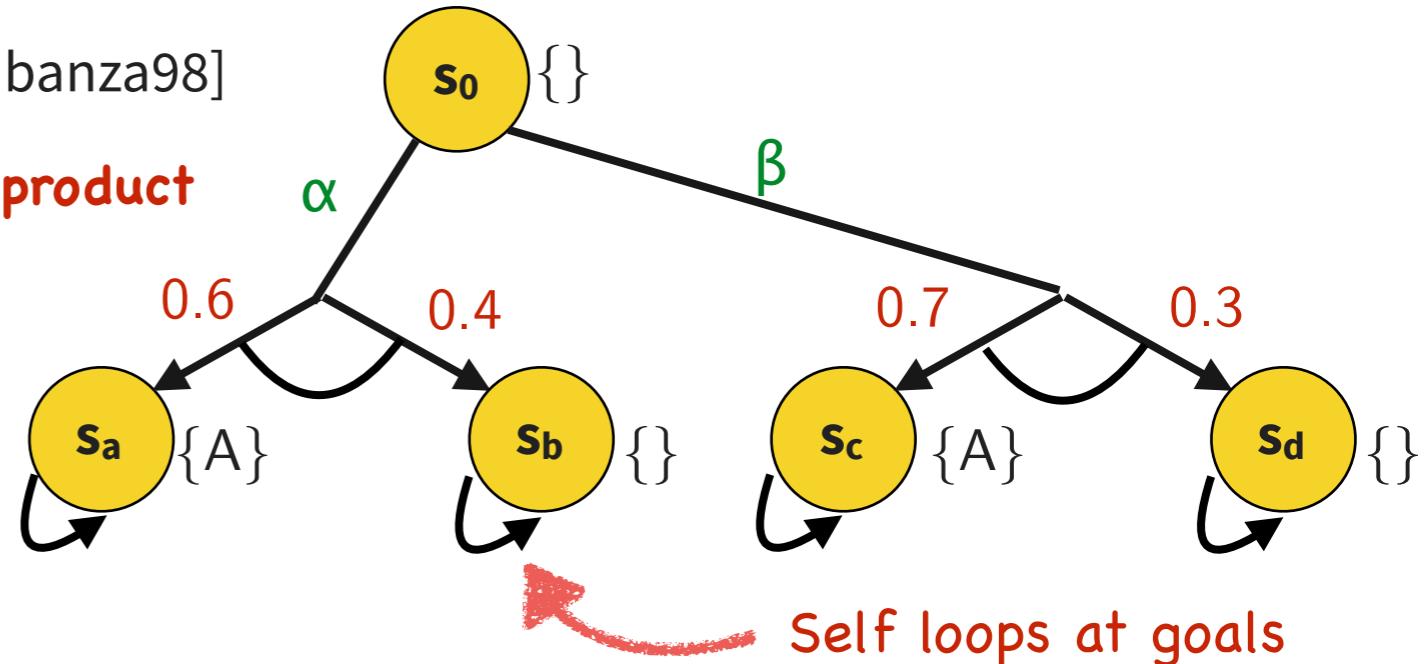
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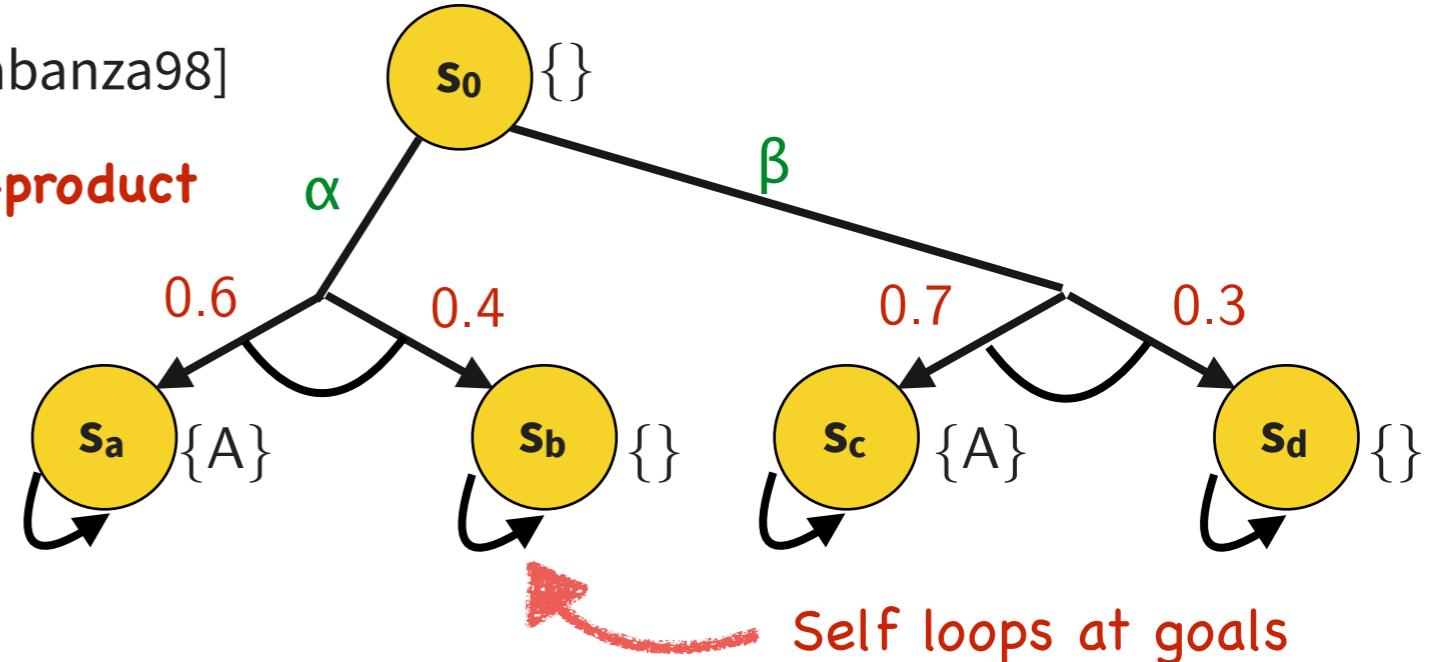
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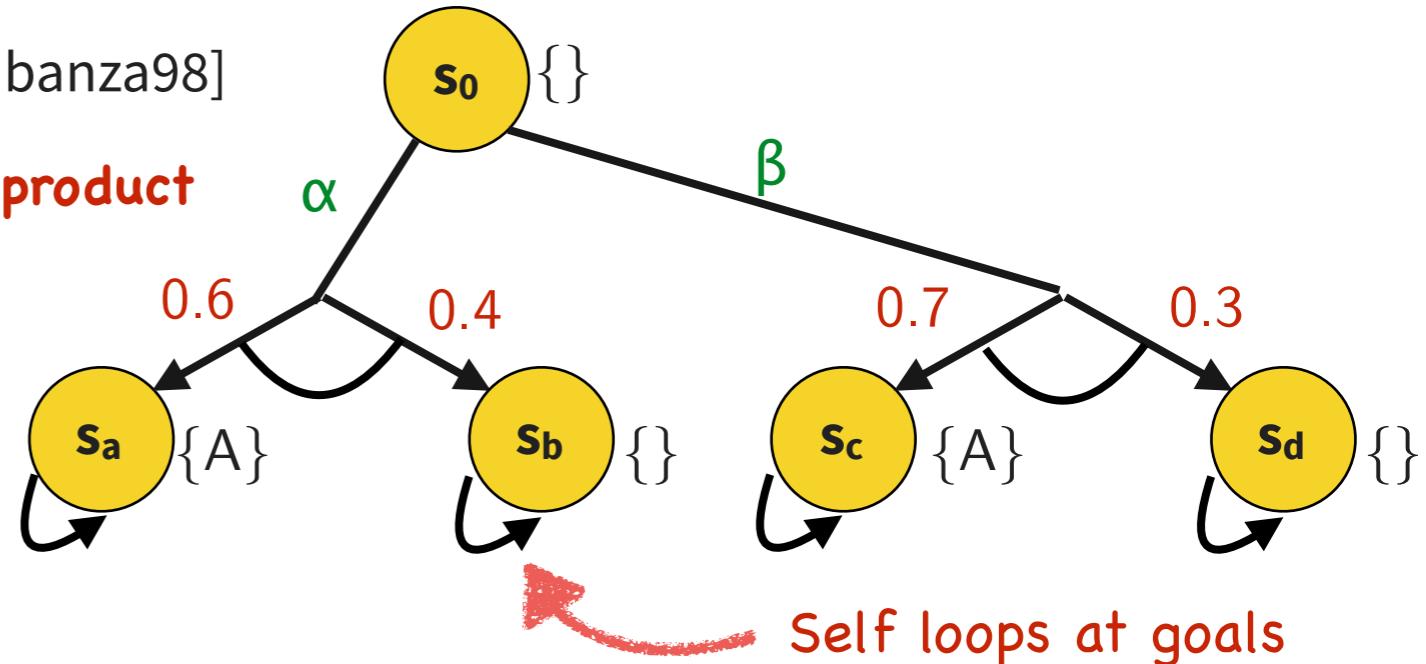
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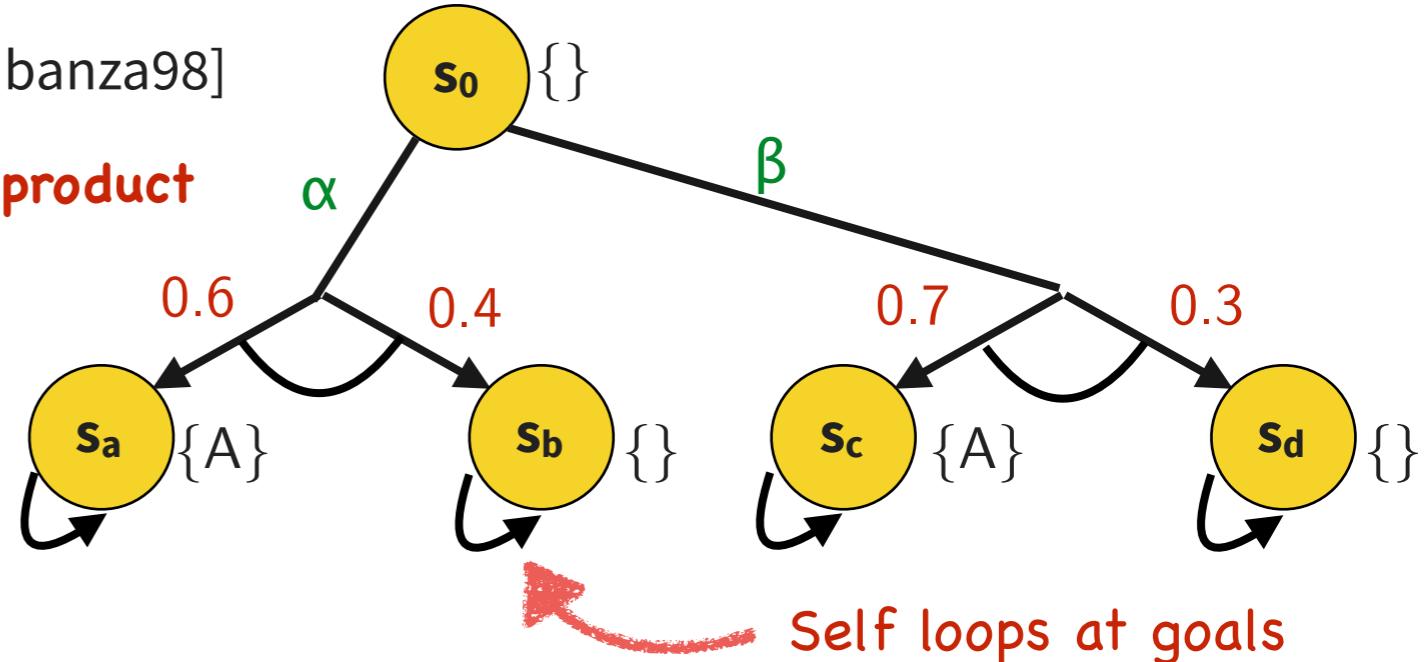
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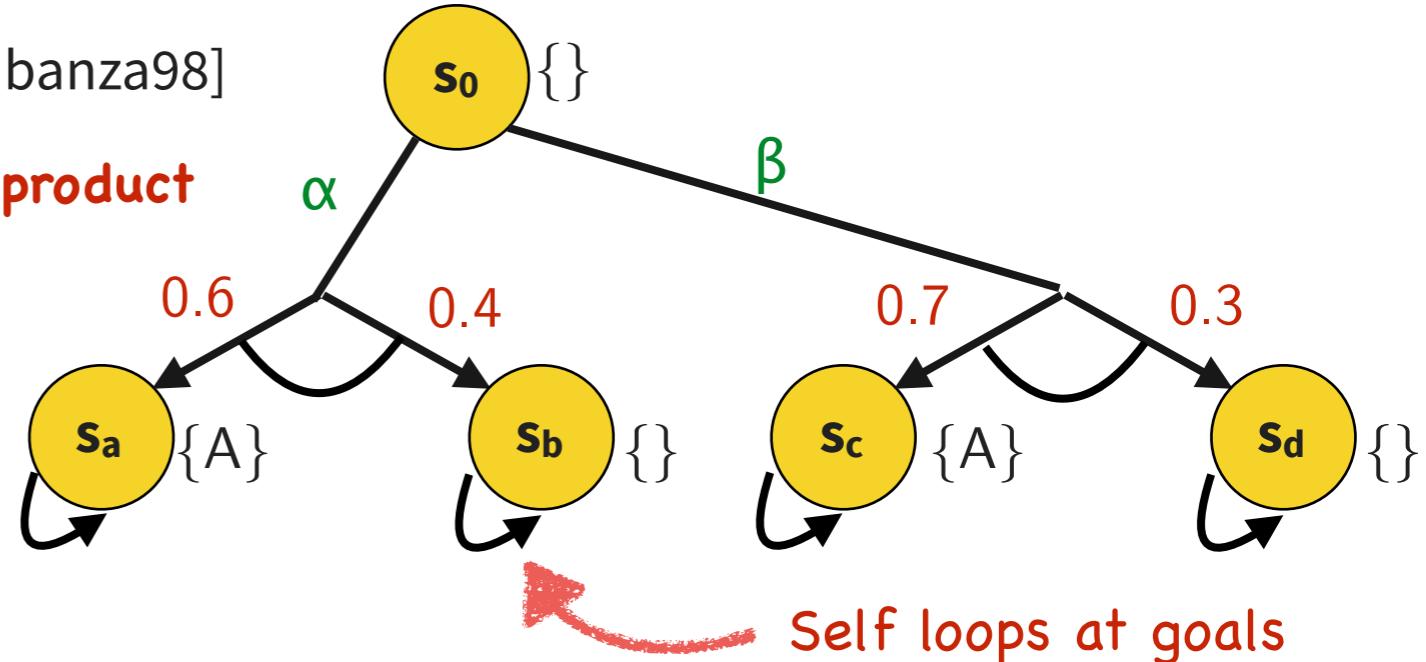
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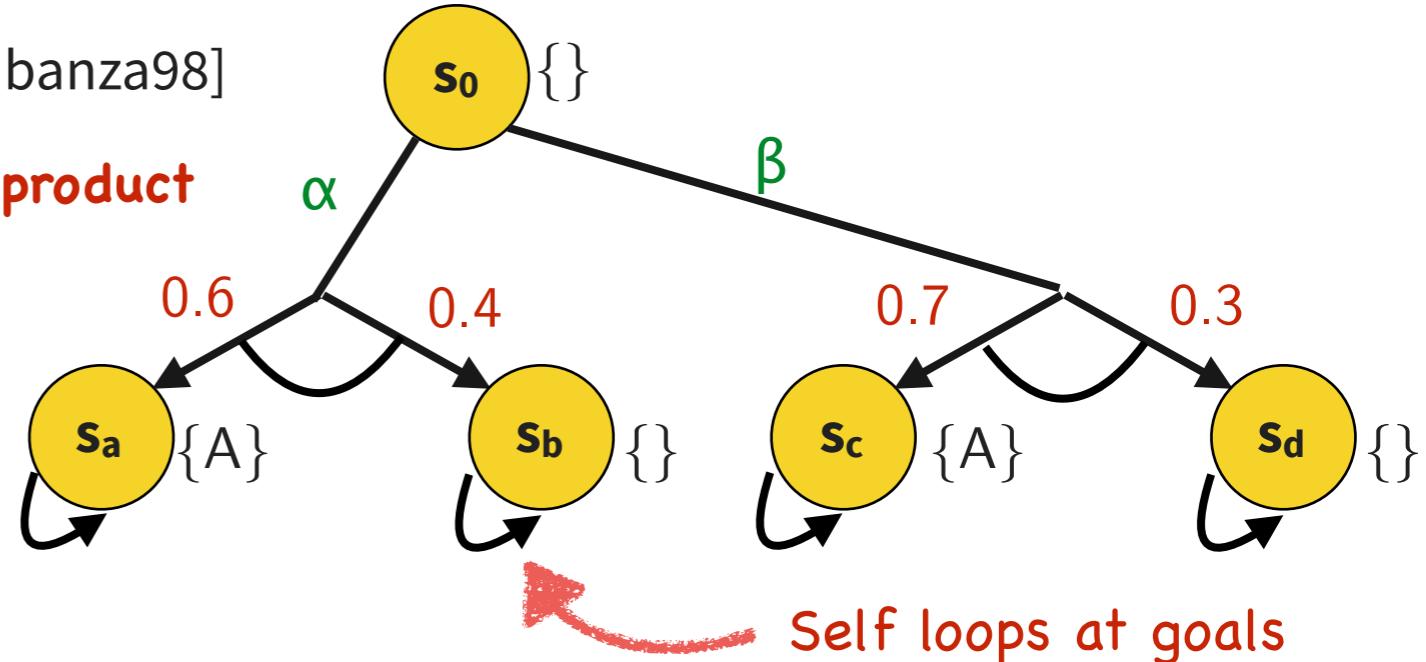
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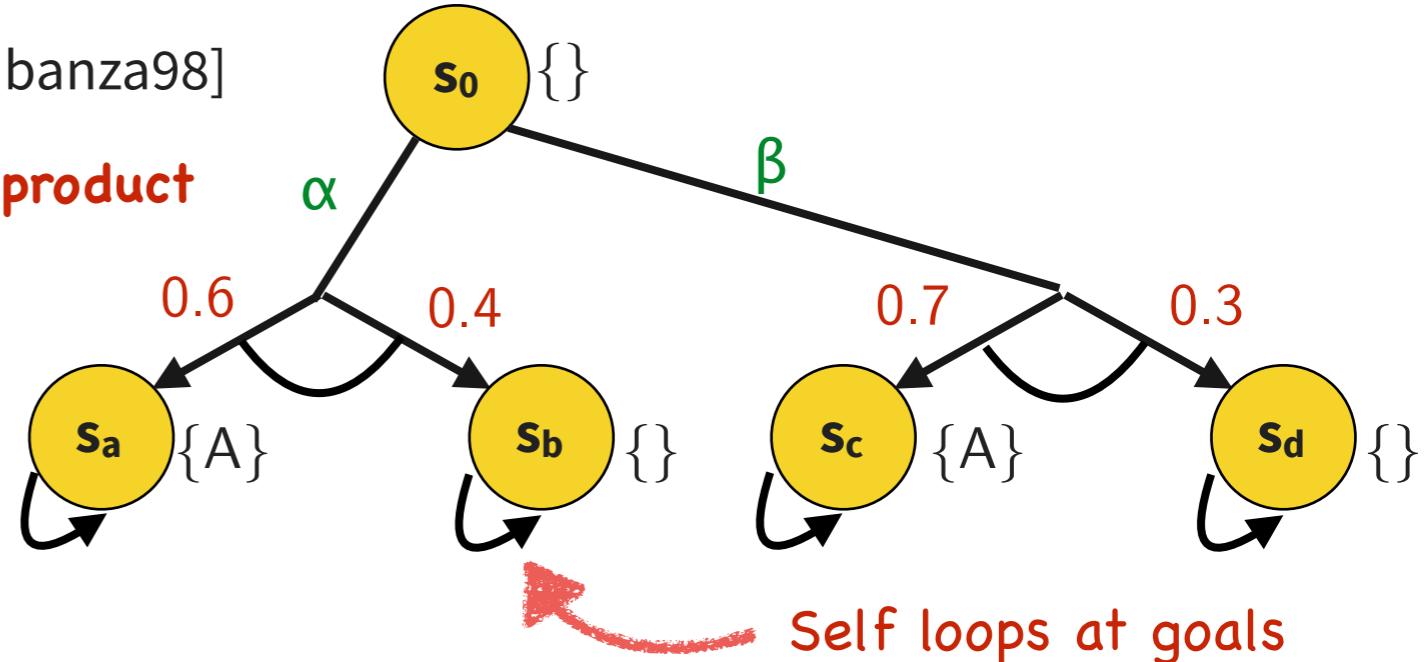
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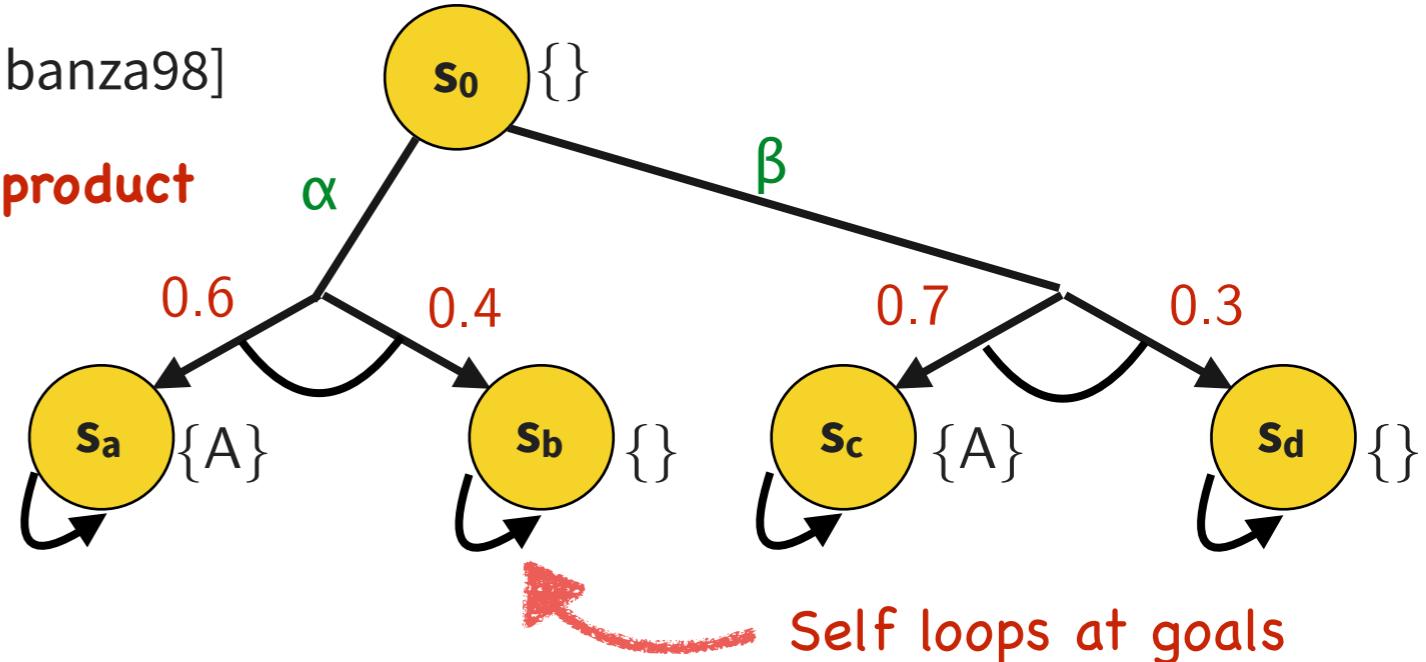
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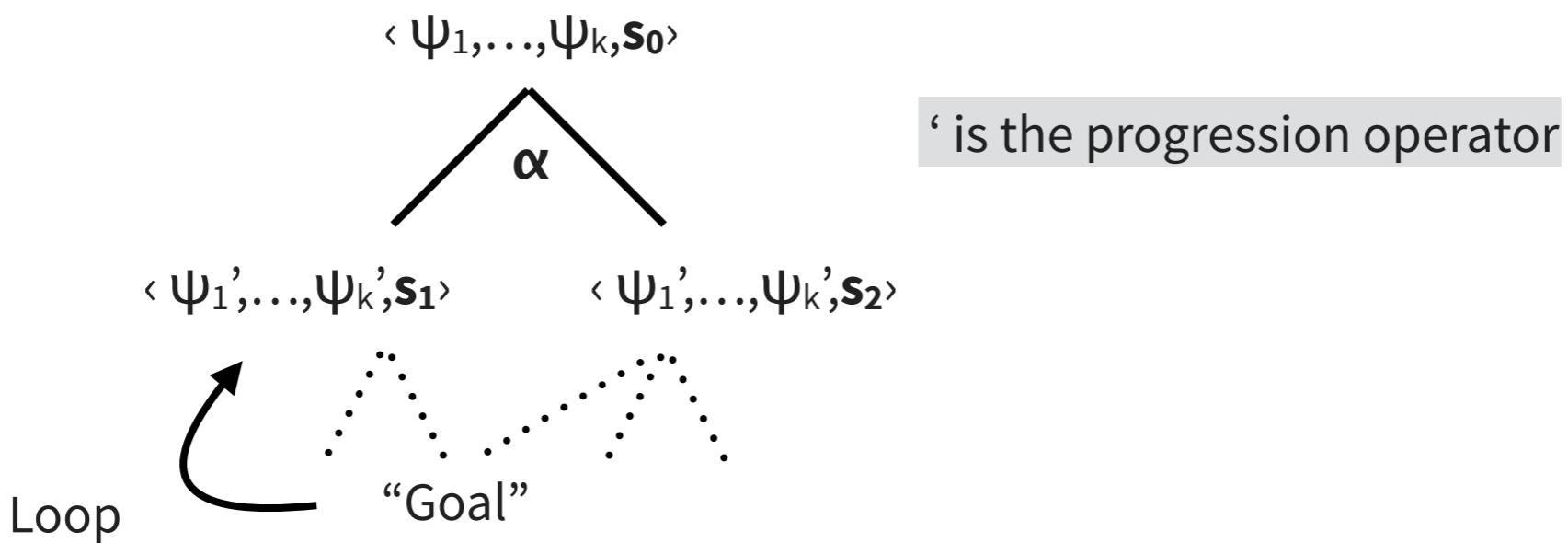
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All transitions “if and only if”

# Multi-Objective Progression in the State Space

X  $A = \text{DRA}(\Psi_1) \times \cdots \times \text{DRA}(\Psi_k) \times \text{DRA}(\mathbf{F} \text{ Goal}) \times S$



## Questions/Issues

- **Q:** Does repeated progression terminate?

**A:** It better does, but some rules even increases formula size:  $\mathbf{F} A \rightarrow A \vee \mathbf{X} \mathbf{F} A$

- **Q:** How to detect a loop  $\langle \Psi, s \rangle \equiv \langle \Psi'', \dots, s \rangle$  ?

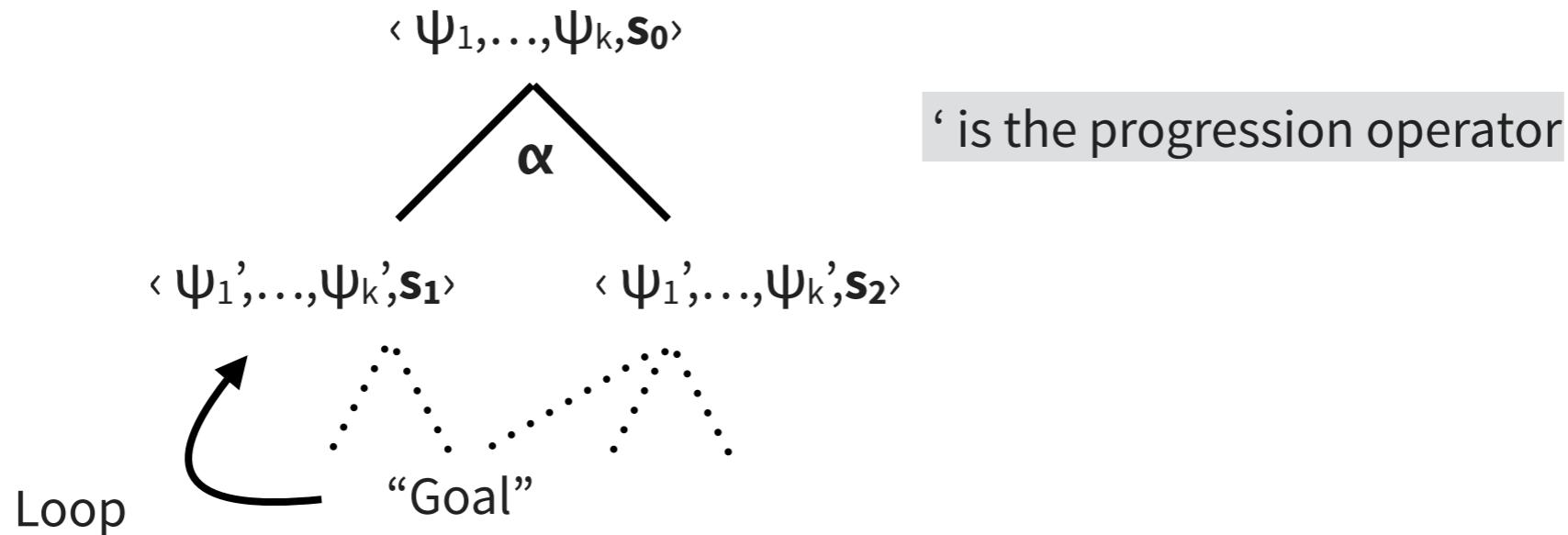
**A:** Check equivalence of LTL formulas. Exponential! X

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 Tseitin-style progression

# Tseitin Transformation for Classical Logic

- Earliest *polynomial* conjunctive normal form (CNF) transformation [Tseitin 1966]
- Improved versions popular with first-order theorem proving [Azmy&Weidenbach 2013]

## How it works

- Introduce *names* for complex subformulas before multiplying-out



$$(A \wedge B) \vee \Psi \rightarrow (A \vee \Psi) \wedge (B \vee \Psi) \quad \text{Duplicates } \Psi$$



$$(A \wedge B) \vee \Psi \rightarrow \Psi_{(A \wedge B)} \vee \Psi \quad \Psi_{(A \wedge B)} \text{ is a name for } (A \wedge B)$$

$$\neg \Psi_{(A \wedge B)} \vee A$$

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Definition of  $\Psi_{(A \wedge B)}$

- Requires polynomially many names, one for each subformula
- Apply once-and-forall to given formula and obtain equi-satisfiable CNF
- That CNF is a conjunction of disjunction of 3-literal clauses

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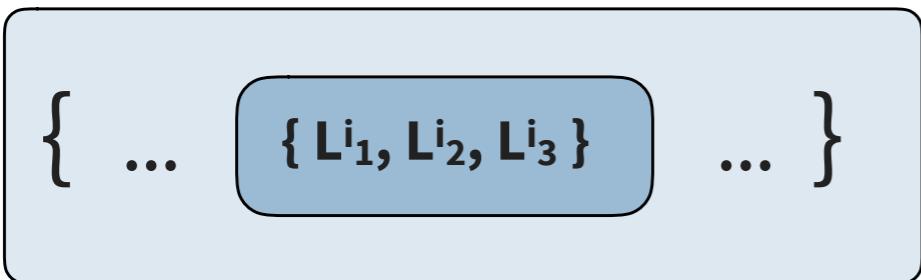
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→ We need to apply Tseitin CNF to every derived formula: **Tseitin-style progression**

# Tseitin-Style Progression

First (?) application to LTL progression

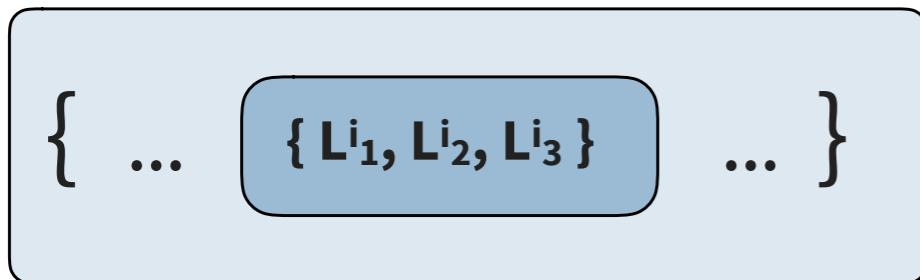
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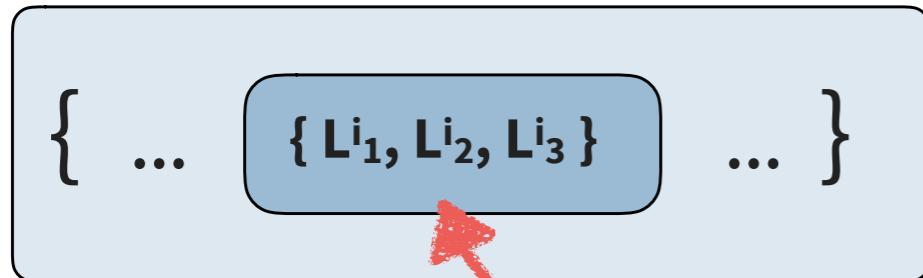
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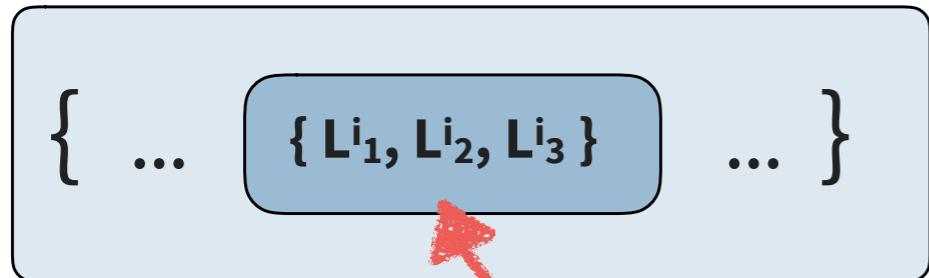
$L^i_k \in \text{sub}(\Psi) \cup \{ \neg\phi, X\phi, X\neg\phi \mid \phi \in \text{sub}(\Psi) \} \cup \text{"Names"} \cup \dots$

where  $\Psi$  = initially given formula

# Tseitin-Style Progression

First (?) application to LTL progression

All LTL formulas are now in 3-CNF



3-CNF:  
^-connected set of 3-literal clauses

## Progression

$L_{i_k} \in \text{sub}(\Psi) \cup \{\neg\phi, X\phi, X\neg\phi \mid \phi \in \text{sub}(\Psi)\} \cup \text{"Names"} \cup \dots$

- Sequence  $s_0 \models \{\{\Psi\}\} \rightarrow s_1 \models \Gamma_1 \rightarrow s_2 \models \Gamma_2 \rightarrow \dots \rightarrow s_i \models \Gamma_i$  where  $\Psi = \text{initially given formula}$
- Initially  $s_0 \models \Gamma_0$  where  $\Gamma_0 = \text{simplified 3-CNF of } \{\{\Psi\}\}$
- Step  $s_i \models \Gamma_i \rightarrow s_{i+1} \models \Gamma_{i+1}$ :
  - (1) Eliminate names from  $\Gamma_i$  and strip  $X$ -operators
  - (2)  $\Gamma_{i+1} = \text{simplified 3-CNF of (1)}$
- Stop if  $s_k \models \Gamma_k = s_i \models \Gamma_i$  for some  $k < i$

Replaces  $\equiv$ -test for LTL-formulas by *polynomial* set equality test!

## Complexity

Literal signature  $|\Sigma| \in O(|\Psi|^2)$

$O(|\Sigma|^3) = O(|\Psi|^6)$  different clauses

$2^{O(|\Psi|^6)}$  different clause sets

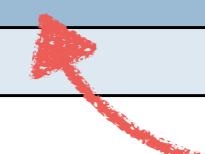
## Theorem

Space and time complexity polynomial in  $|S|$  and *single* exponential  $|\Psi|$

# Tseitin-Style Progression

All LTL formulas are now in CNF

{ ... {  $L_i_1, L_i_2, L_i_3$  } }



## Progression

- Sequence  $s_0 \models \{\{\Psi\}\} \rightarrow s_1 \models \Gamma_1 \rightarrow \dots \rightarrow s_k \models \Gamma_k$
  - Initially  $s_0 \models \Gamma_0$  where  $\Gamma_0 = \{\{\psi\} \mid \psi \in \Psi\}$
  - Step  $s_i \models \Gamma_i \rightarrow s_{i+1} \models \Gamma_{i+1}$ 
    - (1) Eliminate names from  $\Gamma_i$
    - (2)  $\Gamma_{i+1}$  = simplified 3-CNF
  - Stop if  $s_k \models \Gamma_k = s_i \models \Gamma_i$  for some  $i < k$
- Replaces  $\equiv$ -test for LTL-formulas

## Complexity

Literal signature  $|\Sigma| \in O(|\Psi|^3)$   
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## Theorem

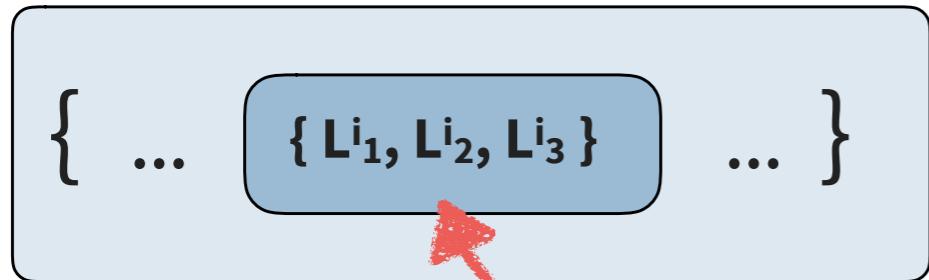
Space and time complexity

$\{\{\}\} \uplus \Gamma \Rightarrow_s \{\{\}\}$ if $\Gamma \neq \emptyset$	(Triv)
$\{\{\top\} \uplus \Psi\} \uplus \Gamma \Rightarrow_s \Gamma$	( $\top$ )
$\{\{\neg\top\} \uplus \Psi\} \uplus \Gamma \Rightarrow_s \{\Psi\} \cup \Gamma$	( $\neg\top$ )
$\{\{(v, d)\} \uplus \Psi\} \uplus \Gamma \Rightarrow_s \Gamma$ if $(v, d) \in AP$ and $s[v] = d$	(Eval1)
$\{\{(v, d)\} \uplus \Psi\} \uplus \Gamma \Rightarrow_s \{\Psi\} \cup \Gamma$ if $(v, d) \in AP$ and $s[v] \neq d$	(Eval2)
$\{\{\neg(v, d)\} \uplus \Psi\} \uplus \Gamma \Rightarrow_s \{\Psi\} \cup \Gamma$ if $(v, d) \in AP$ and $s[v] = d$	(Eval3)
$\{\{\neg(v, d)\} \uplus \Psi\} \uplus \Gamma \Rightarrow_s \Gamma$ if $(v, d) \in AP$ and $s[v] \neq d$	(Eval4)
$\{\{\neg\neg\psi\} \uplus \Psi\} \uplus \Gamma \Rightarrow_s \{\{\psi\} \cup \Psi\} \cup \Gamma$	( $\neg\neg$ )
$\{\{\psi_1 \vee \psi_2\} \uplus \Psi\} \uplus \Gamma \Rightarrow_s \{\{A_{\psi_1 \vee \psi_2}\} \cup \Psi,$ $\{\neg A_{\psi_1 \vee \psi_2}, \psi_1, \psi_2\}\} \cup \Gamma$	( $\vee$ )
$\{\{\neg(\psi_1 \vee \psi_2)\} \uplus \Psi\} \uplus \Gamma \Rightarrow_s \{\{\neg A_{\psi_1 \vee \psi_2}\} \cup \Psi,$ $\{A_{\psi_1 \vee \psi_2}, \overline{\psi_1}\},$ $\{A_{\psi_1 \vee \psi_2}, \overline{\psi_2}\}\} \cup \Gamma$	( $\neg\vee$ )
$\{\{\psi_1 \wedge \psi_2\} \uplus \Psi\} \uplus \Gamma \Rightarrow_s \{\{A_{\psi_1 \wedge \psi_2}\} \cup \Psi,$ $\{\neg A_{\psi_1 \wedge \psi_2}, \psi_1\},$ $\{\neg A_{\psi_1 \wedge \psi_2}, \psi_2\}\} \cup \Gamma$	( $\wedge$ )
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$\{\{\neg(\psi_1 \mathbf{U} \psi_2)\} \uplus \Psi\} \uplus \Gamma \Rightarrow_s \{\{\neg A_{\psi_1 \mathbf{U} \psi_2}\} \cup \Psi,$ $\{A_{\psi_1 \mathbf{U} \psi_2}, \overline{\psi_2}\},$ $\{A_{\psi_1 \mathbf{U} \psi_2}, \neg A_{\psi_1 \wedge \mathbf{X}(\psi_1 \mathbf{U} \psi_2)}\},$ $\{A_{\psi_1 \wedge \mathbf{X}(\psi_1 \mathbf{U} \psi_2)}, \overline{\psi_1}, \mathbf{X}(\neg(\psi_1 \mathbf{U} \psi_2))\}\} \cup \Gamma$	( $\neg\mathbf{U}$ )
$\{\{\neg\mathbf{X}\psi\} \uplus \Psi\} \uplus \Gamma \Rightarrow_s \{\{\mathbf{X}\overline{\psi}\} \cup \Psi\} \cup \Gamma$	( $\neg\mathbf{X}$ )

# Tseitin-Style Progression

First (?) application to LTL progression

All LTL formulas are now in 3-CNF



3-CNF:  
^-connected set of 3-literal clauses

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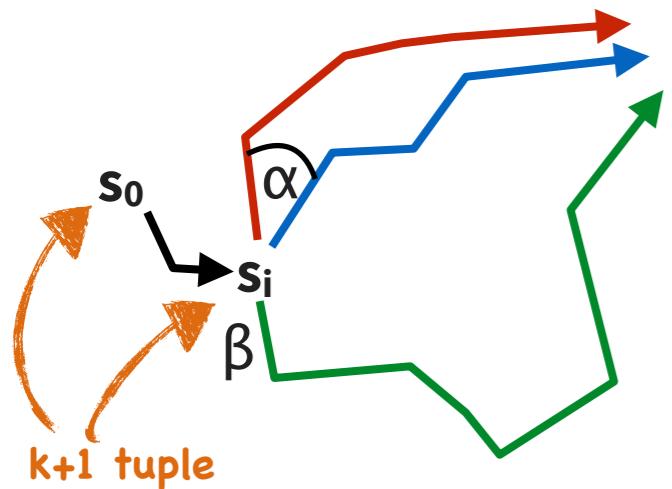
$2^{O(|\Psi|^6)}$  different clause sets

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Space and time complexity polynomial in  $|S|$  and *single* exponential  $|\Psi|$

# Policy Synthesis by Translation to Linear Program

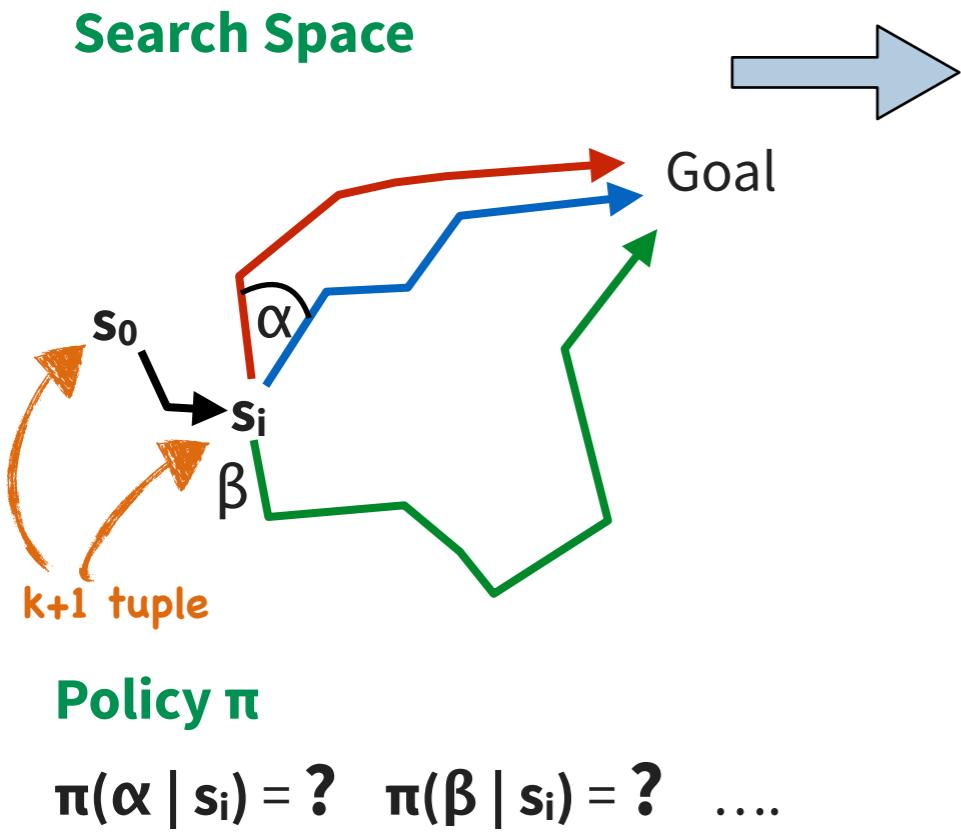
## Search Space



## Policy $\pi$

$$\pi(\alpha | s_i) = ? \quad \pi(\beta | s_i) = ? \quad \dots$$

# Policy Synthesis by Translation to Linear Program



**Linear program computes expected values**

**Expected number of times  $\alpha$  is executed in  $s_i$**

$$x(s_i, \alpha) = \sum_{S_i} \pi(\alpha | s_i) \times \Pr(\text{---} | s_i)$$

**Expected policy costs**

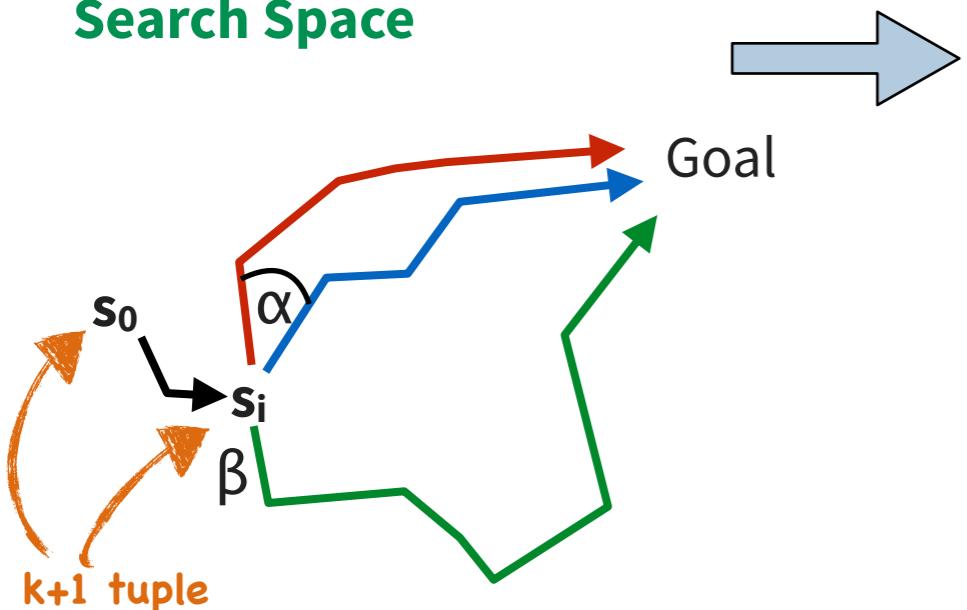
$$\begin{aligned} & \text{Cost}(\text{--- red}) \times \Pr(\text{--- red}) + \\ & \text{Cost}(\text{--- blue}) \times \Pr(\text{--- blue}) + \\ & \text{Cost}(\text{--- green}) \times \Pr(\text{--- green}) \\ &= \dots + x(s_i, \alpha) \times C(\alpha) \\ & \quad + x(s_i, \beta) \times C(\beta) + \dots \end{aligned}$$

**Primary:** e.g. time

**Secondary:** e.g. fuel < 50

# Policy Synthesis by Translation to Linear Program

Search Space



Policy  $\pi$

$$\pi(\alpha | s_i) = ? \quad \pi(\beta | s_i) = ? \quad \dots$$

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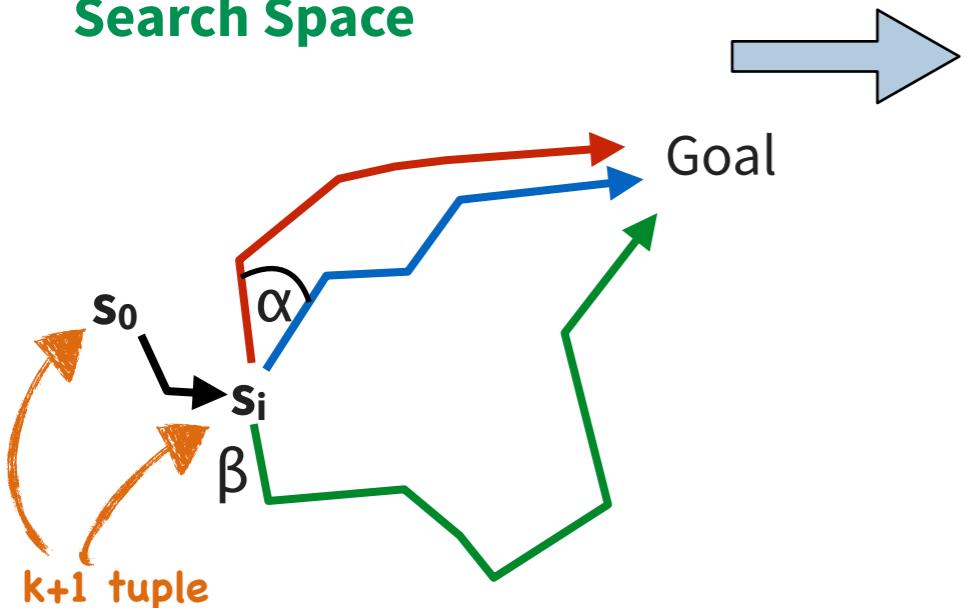
Linear Program Solver

Optimal solution of linear program, i.e., values for  $x(s_i, \alpha)$  s.th.

- primary cost is *minimized*, and
- secondary cost constraints are *satisfied* in expectation

# Policy Synthesis by Translation to Linear Program

## Search Space



## Policy $\pi$

$$\begin{aligned}\pi(\alpha | s_i) &= ? \quad \pi(\beta | s_i) = ? \quad \dots \\ \pi(\alpha | s_i) &= x(s_i, \alpha) / (x(s_i, \alpha) + x(s_i, \beta))\end{aligned}$$

Linear program computes expected values

Expected number of times  $\alpha$  is executed in  $s_i$

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Expected policy costs

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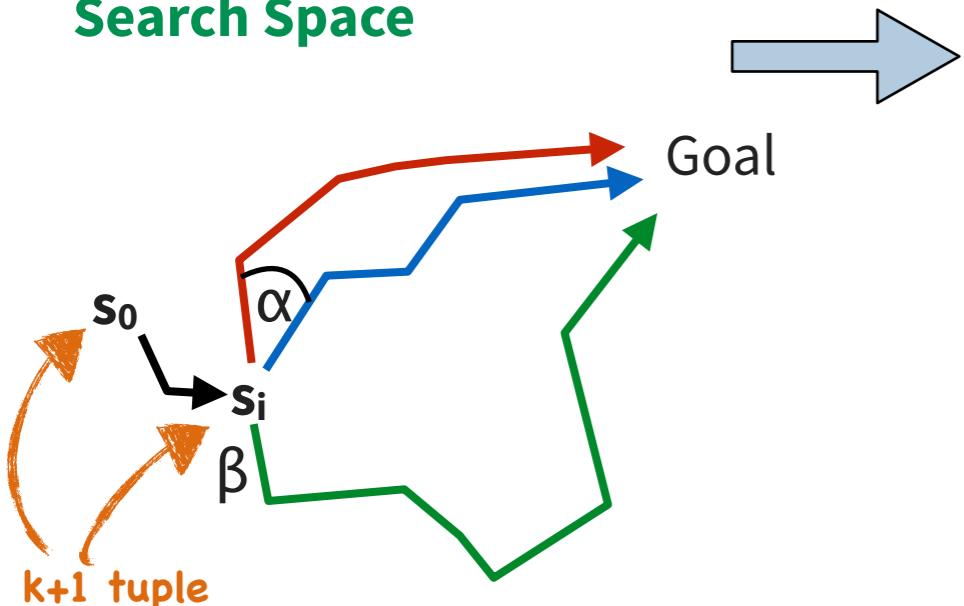
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Search Space



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$$\text{Cost}(\text{--- red }) \times \Pr(\text{--- red }) +$$

$$\text{Cost}(\text{--- blue }) \times \Pr(\text{--- blue }) +$$

$$\text{Cost}(\text{--- green }) \times \Pr(\text{--- green })$$

Primary: e.g. time

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Policy  $\pi$

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$$= \dots + x(s_i, \alpha) \times C(\alpha)$$

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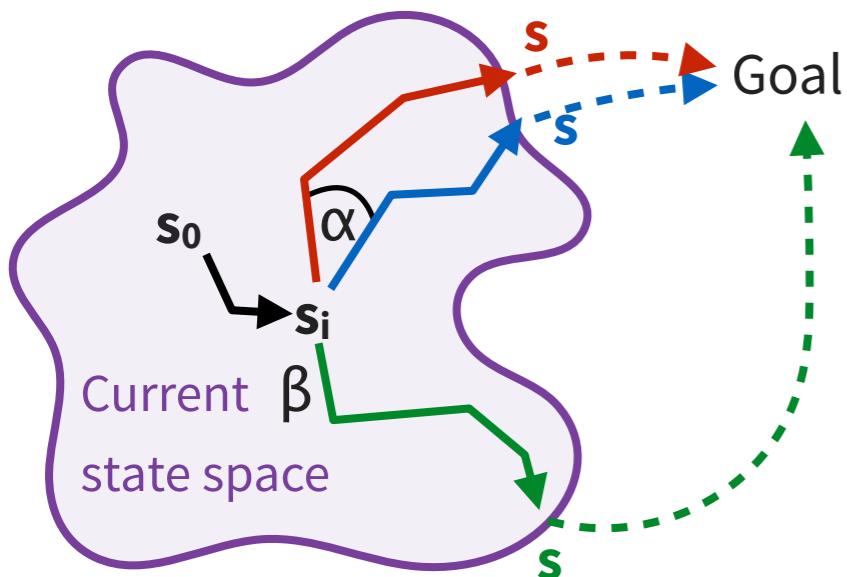
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Amenable to heuristics

## Heuristics Search: i-dual and i<sup>2</sup>-dual

- First heuristic search algorithms for constrained SSPs [Trevizan, Thiebaux, Haslum, Williams, Santana]  
i.e. primary expected cost (“time”) and secondary expected cost constraints (“fuel < 5”)
- Sound, complete and optimal for admissible heuristics H (H must underestimate expected costs)

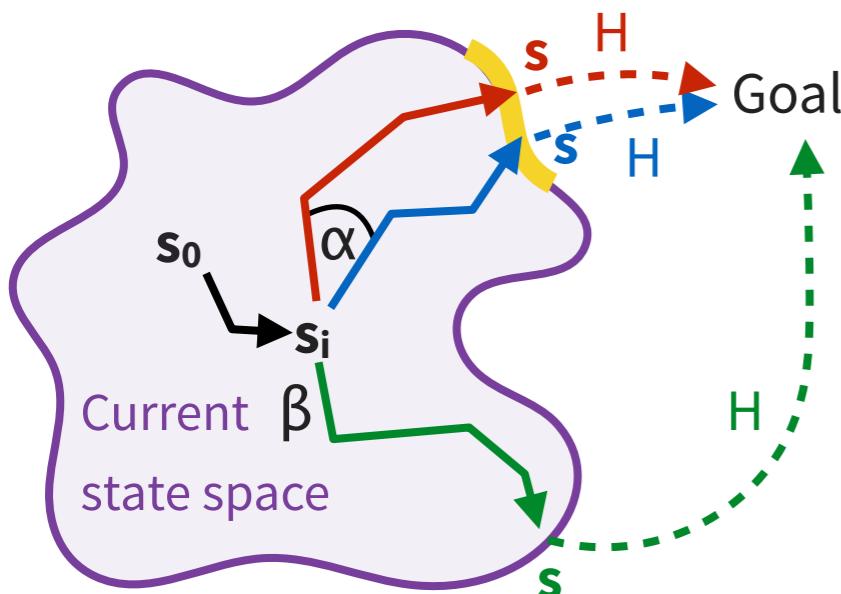
Exploring the state space ...



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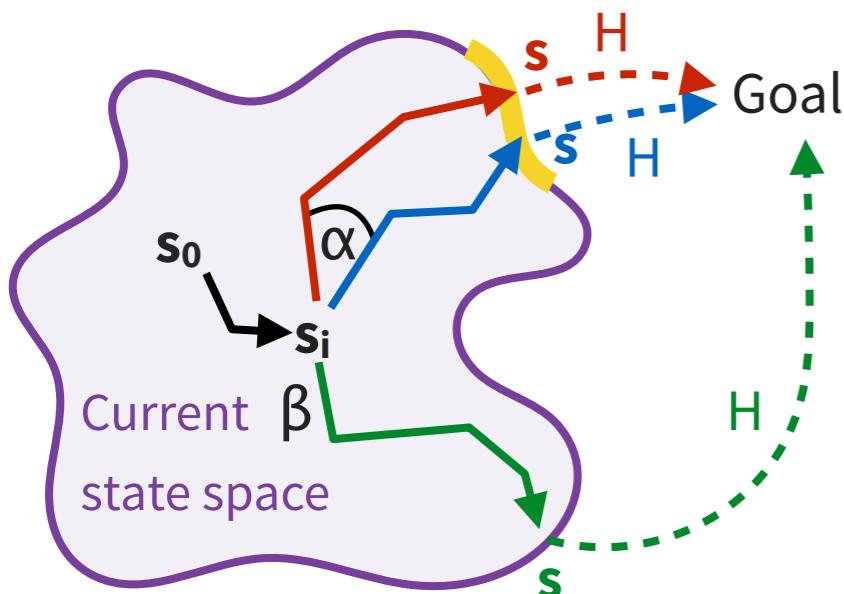
... with A\*-like heuristic estimation function H

- (1) Compute best policy  $\pi^*$  for current state space  
by translation into LP with **fringe as artificial goals**  
**with costs H**  
 $\pi^*$  minimizes  $f = g + H$
- (2) Expand all **fringe states reachable under  $\pi^*$**
- (3) If all reachable fringe states are original goals  
then stop else repeat

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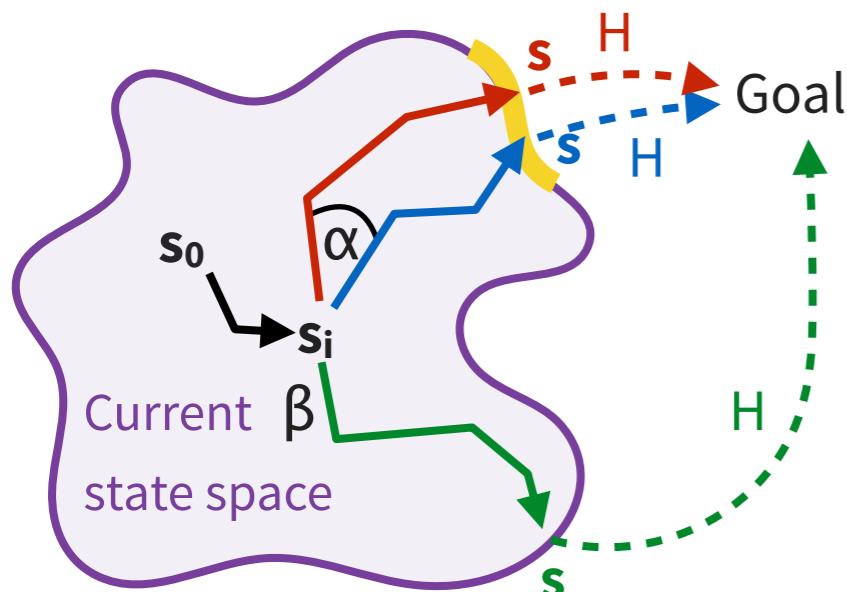
Search space

- Over policies, not paths;  $g(s)$  may change in each step
- Policies may become constrained  
E.g.  $\text{Pr}(\text{---}) < 0.1$  if  $H_{\text{fuel}}(s) = 50$   
as otherwise fuel < 5 not achievable

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Exploring the state space ...



→ For PLTL constraints

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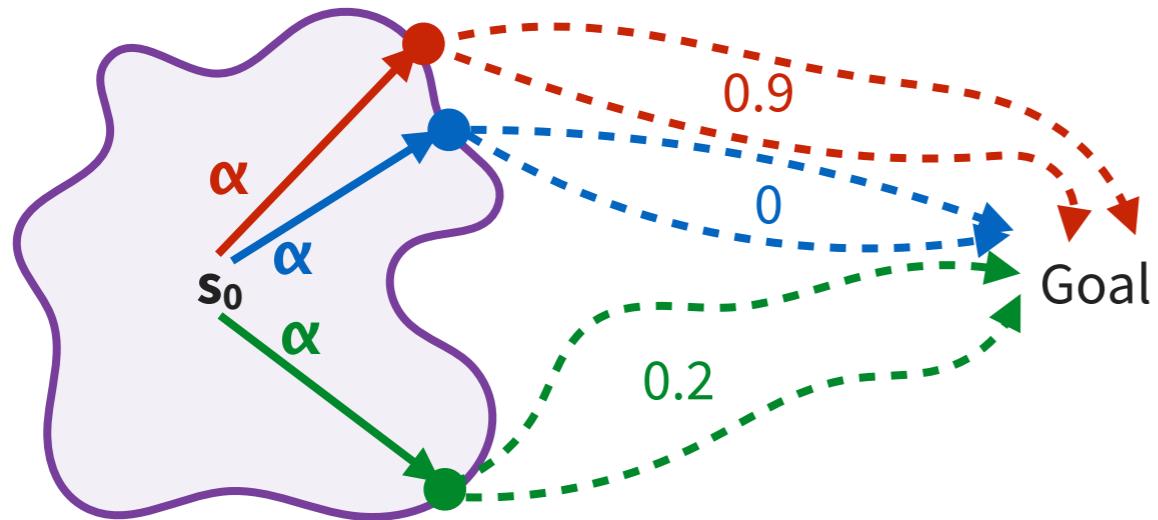
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# Heuristic Search for PLTL - PLTL-dual

A universal heuristic for search space pruning

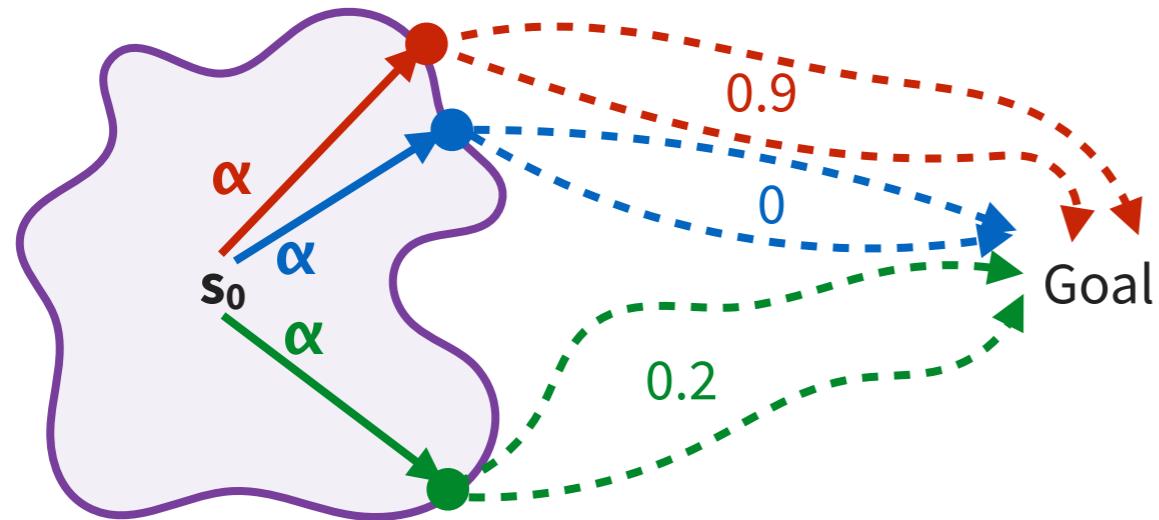
Find policy  $\pi$  s.th.  $s_0, \pi \models P_{\geq 0.9} \Psi$



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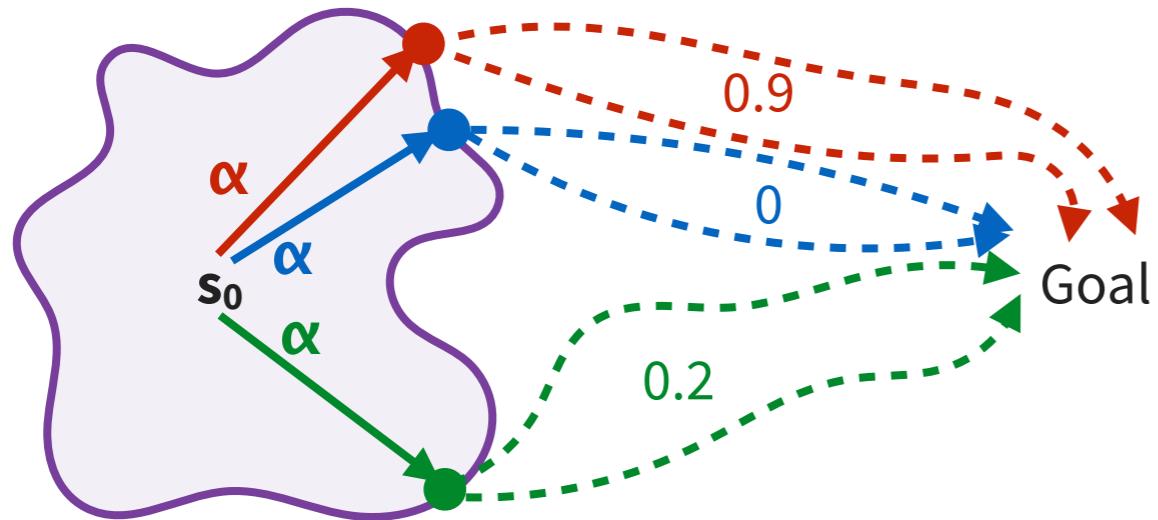
Optimal (final) policy  $\pi^*$

$$\pi^*(\alpha, s_0) = 1 \quad \pi^*(\alpha, s_0) = 0 \quad \pi^*(\alpha, s_0) = 0$$

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Max among all  $\pi^*$   $\leq$  Heuristic value

$$\Pr \{ \text{Red} \dots | \Psi \} = 0.9 \leq H(\text{Red}) = 1$$

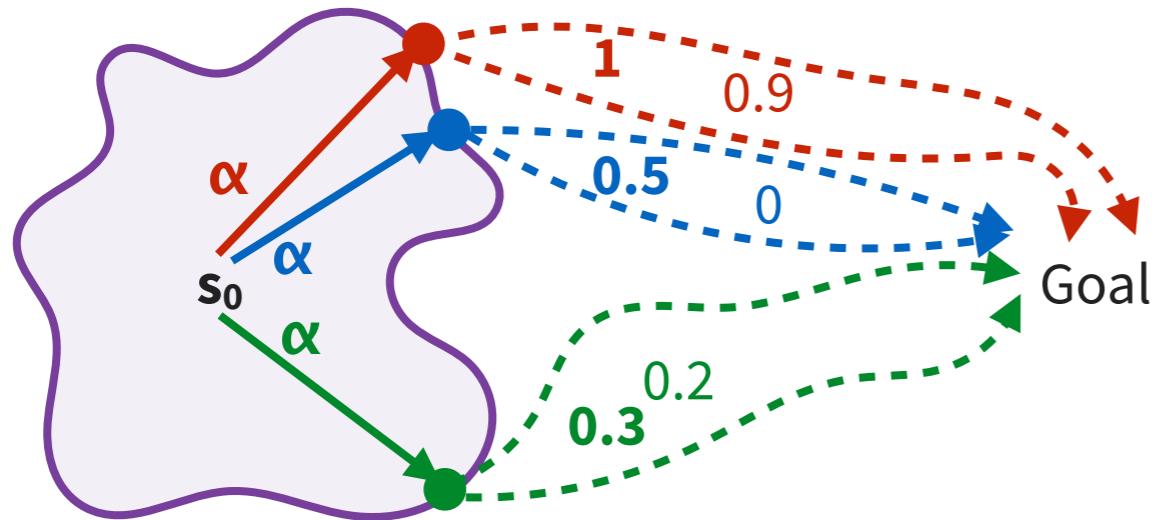
$$\Pr \{ \text{Blue} \dots | \Psi \} = 0 \leq H(\text{Blue}) = 0.5$$

$$\Pr \{ \text{Green} \dots | \Psi \} = 0.2 \leq H(\text{Green}) = 0.3$$

# Heuristic Search for PLTL - PLTL-dual

## A universal heuristic for search space pruning

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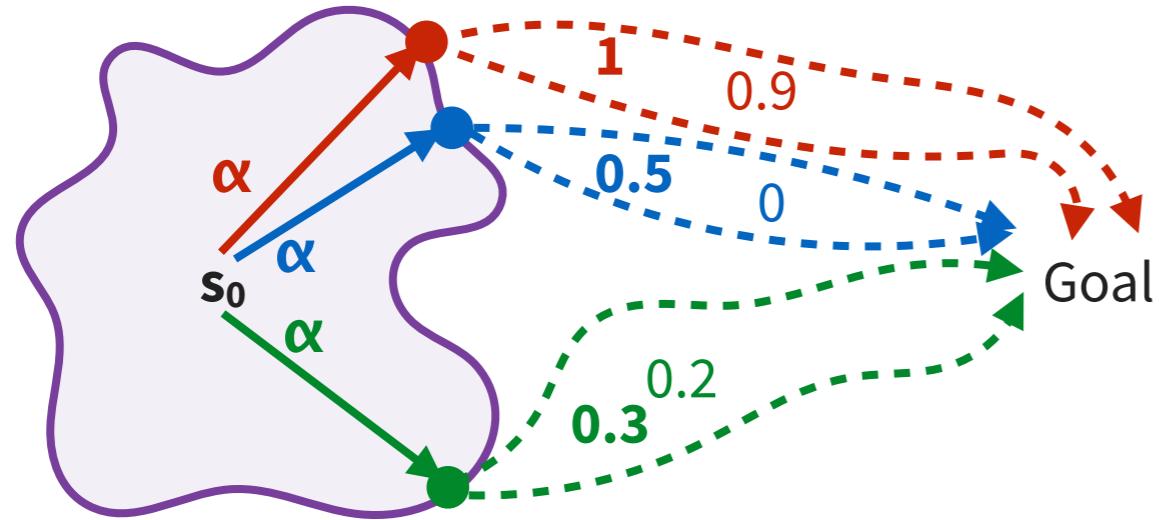
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### Entailed feasibility policy constraint

$$\pi(\alpha, s_0) \leq 0.2$$

Otherwise, e.g. with  $\pi(\alpha, s_0) = 0.21$

$$0.21 \cdot 0.5 + \pi(\alpha, s_0) \cdot 1 \geq 0.9$$

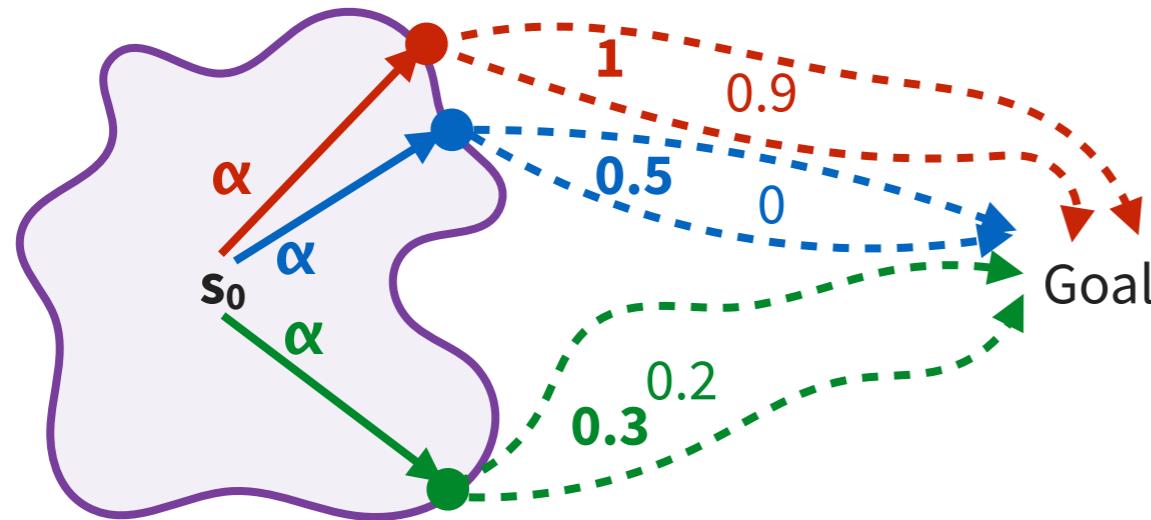
$$\Rightarrow \pi(\alpha, s_0) \geq 0.795$$

But  $0.21 + 0.795 = 1.005 > 1$

# Heuristic Search for PLTL - PLTL-dual

## A universal heuristic for search space pruning

Find policy  $\pi$  s.th.  $s_0, \pi \models P_{\geq 0.9} \Psi$



### How to compute $H(\bullet)$ with NBAs

1.  $\Psi' := \Psi \wedge \text{"finite extension semantics"}$
2. Compute NBA  $\mathbf{B}$  for  $\Psi'$
3. Trace  $\mathbf{B}$  to find  $\bullet$ -states (overapproximation)
4. Trace  $\mathbf{B}$  from  $\bullet$ -states as initial states to Goal
  - using relaxed actions from  $\mathbf{S}$  consistent with trace
  - as a SSP  $\mathbf{T}$
5. Solve  $\mathbf{T}$  putting 1 unit of flow into  $\bullet$ -states
6. Get  $H(\bullet)$  from flow into Goal

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**Max among all  $\pi^*$**   $\leq$  **Heuristic value**

$$\Pr \{ \bullet \text{---} | \Psi \} = 0.9 \leq H(\bullet) = 1$$

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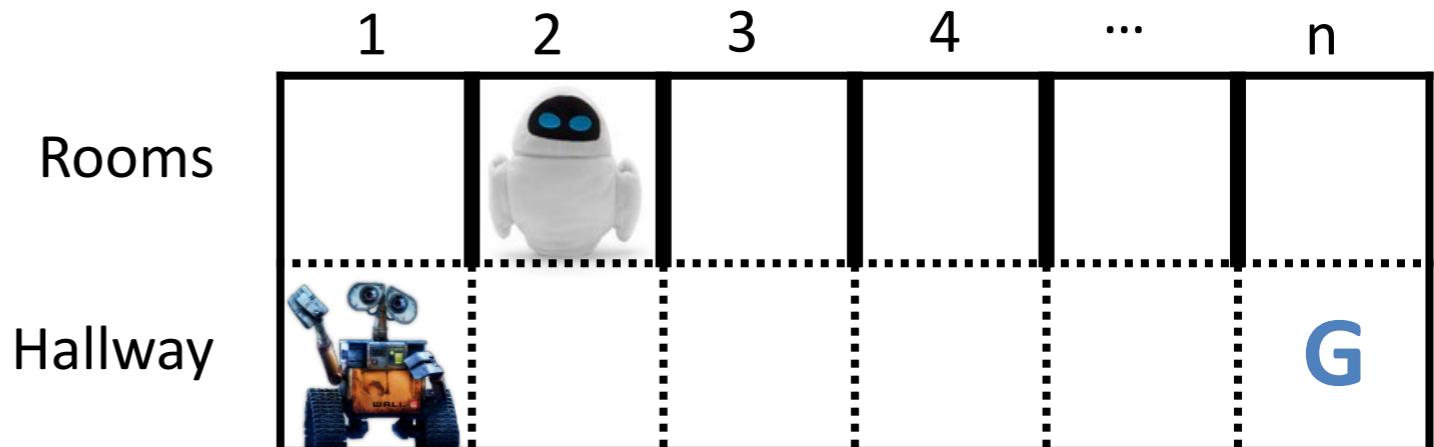
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But  $0.21 + 0.795 = 1.005 > 1$

## Experiment: Wall-e and Eve

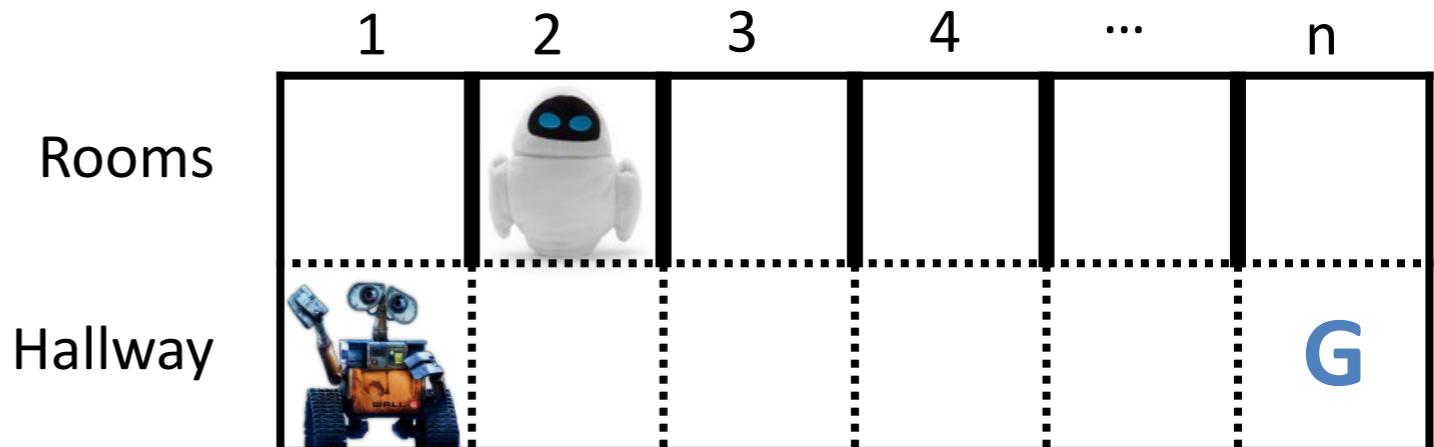


- **Goal:** Wall-e at G

- **Constraints:**

1. Wall-e and Eve must eventually be together ( $P \geq 0.5$ )
2. Eve must be in a room until they are together ( $P \geq 0.8$ )
3. Once together, they eventually stay together ( $P = 1$ )
4. Eve must visit the rooms 1, 2, and 3 ( $P = 1$ )
5. Wall-e never visits a room twice ( $P \geq 0.8$ )

## Experiment: Wall-e and Eve

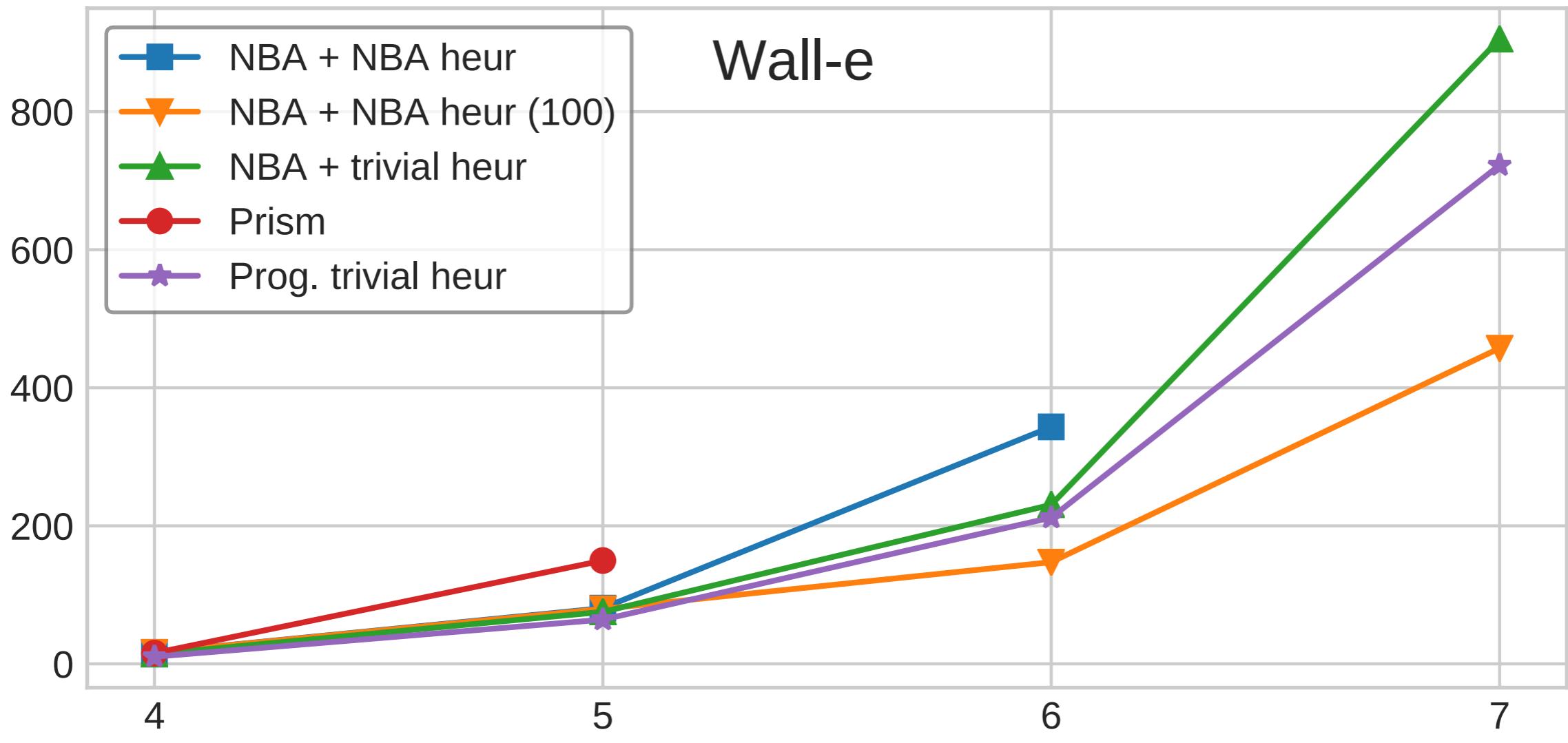


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3. Once together, they eventually stay together ( $P = 1$ )
4. Eve must visit the rooms 1, 2, and 3 ( $P = 1$ )
5. Wall-e never visits a room twice ( $P \geq 0.8$ )

## Experiments - Wall-E



NBA heur: full heuristics, may yield “many” states

NBA heur (100): use trivial heuristics if  $> 100$  states in NBA

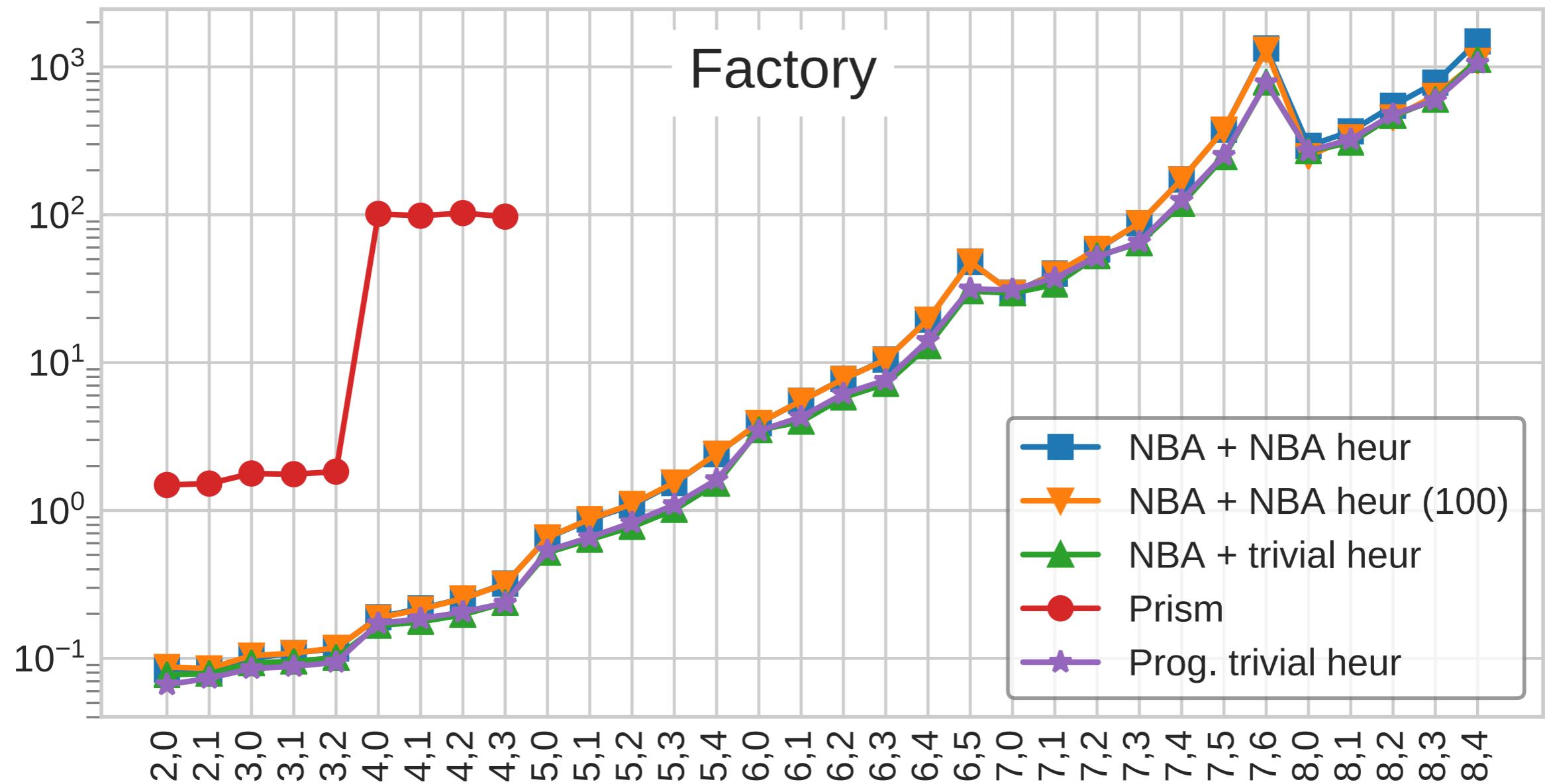
Good also for progression: violated LTL constraints detected early by simplification

*Wall-E never visits room1 twice*

$$\mathbf{G} (\text{wall-E\_room1} \Rightarrow (\text{wall-E\_room1} \mathbf{U} \mathbf{G} \neg \text{wall-E\_room1}))$$

$$(\Psi_3)$$

## Experiments - Factory



# Conclusion

## Summary

- Policy synthesis algorithm for multi-objective PLTL constraints  $\Psi = \mathbf{P}_1 \Psi_1 \wedge \dots \wedge \mathbf{P}_k \Psi_k$   
Resulting history-independent (Markovian) policy over cross-product state space converts to finite-memory policy in the standard way
- Tseitin-style progression  
Better worst-case complexity: single-exponential (vs double-exponential) in  $|\Psi|$
- NBA-based A<sup>\*</sup>-like heuristics
- “Promising experiments”

## Future Work

- Implement progression in full
- Heuristics based on progression (vs NBA)
- Multi-objective PLTL verification (on infinite runs) based on progression
- Quantification over finite domains. Non-prob: [Baier&McIlraith 2006]
- Beyond PLTL, e.g.  $\mathbf{P}_{>0.8} \mathbf{G} (\mathbf{A} \rightarrow \mathbf{P}_{>0.4} \mathbf{F} \mathbf{B})$