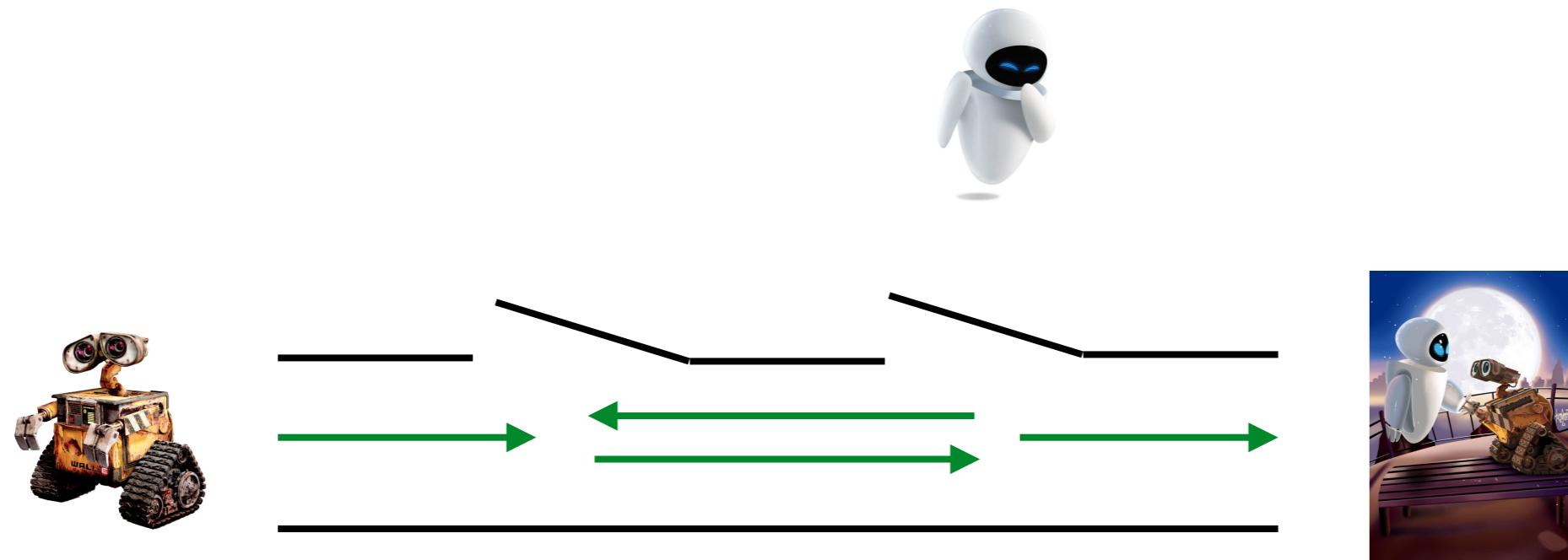


# **Tableaux for Policy Synthesis for MDPs with PCTL\* Constraints**

Peter Baumgartner, Sylvie Thiébaux, Felipe Trevizan

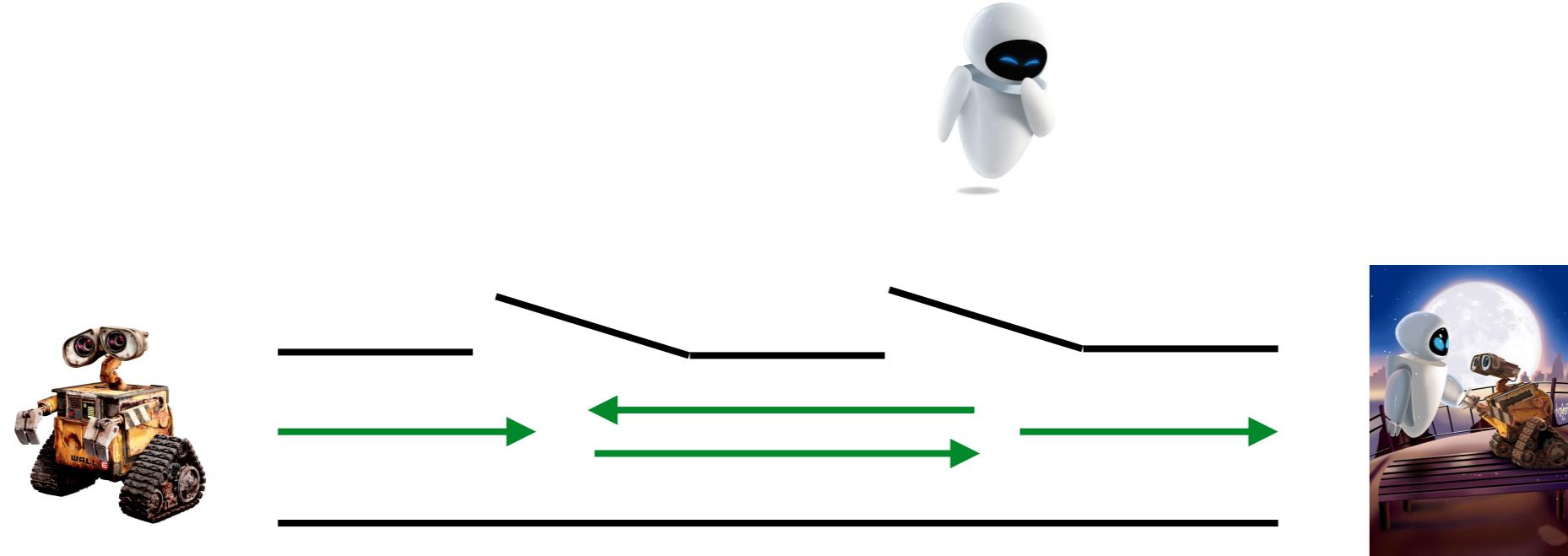
Data61/CSIRO and Research School of Computer Science, ANU  
Australia

# Markov Decision Processes (MDPs)



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

# Markov Decision Processes (MDPs)

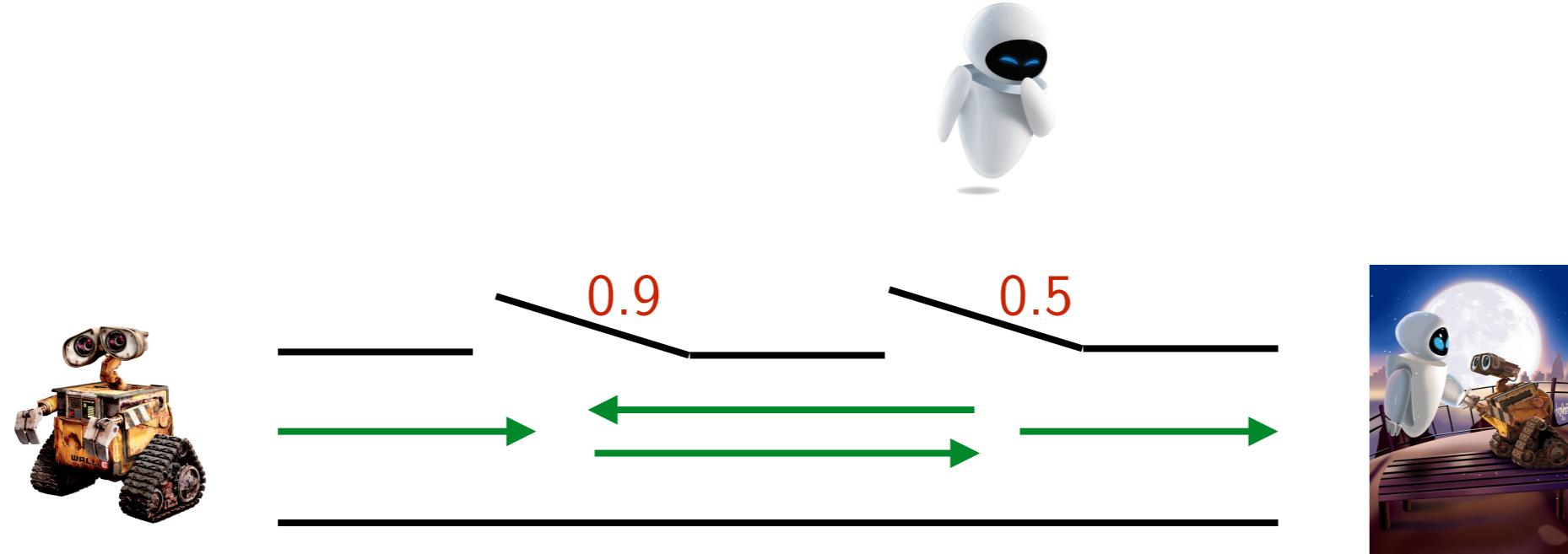


**Nondeterministic action  $\Rightarrow$  stochastic environment response**

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

**Environment:** door possibly jams, location of Eve uncertain (10% - 90%)

# Markov Decision Processes (MDPs)

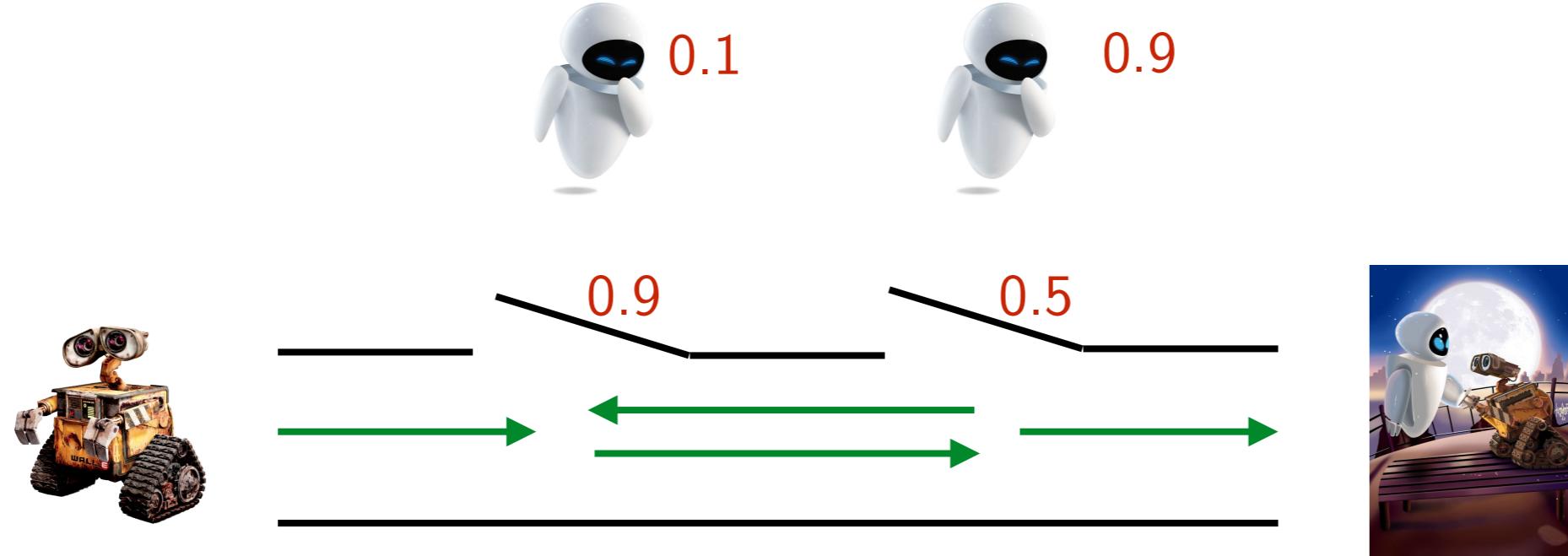


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# Markov Decision Processes (MDPs)

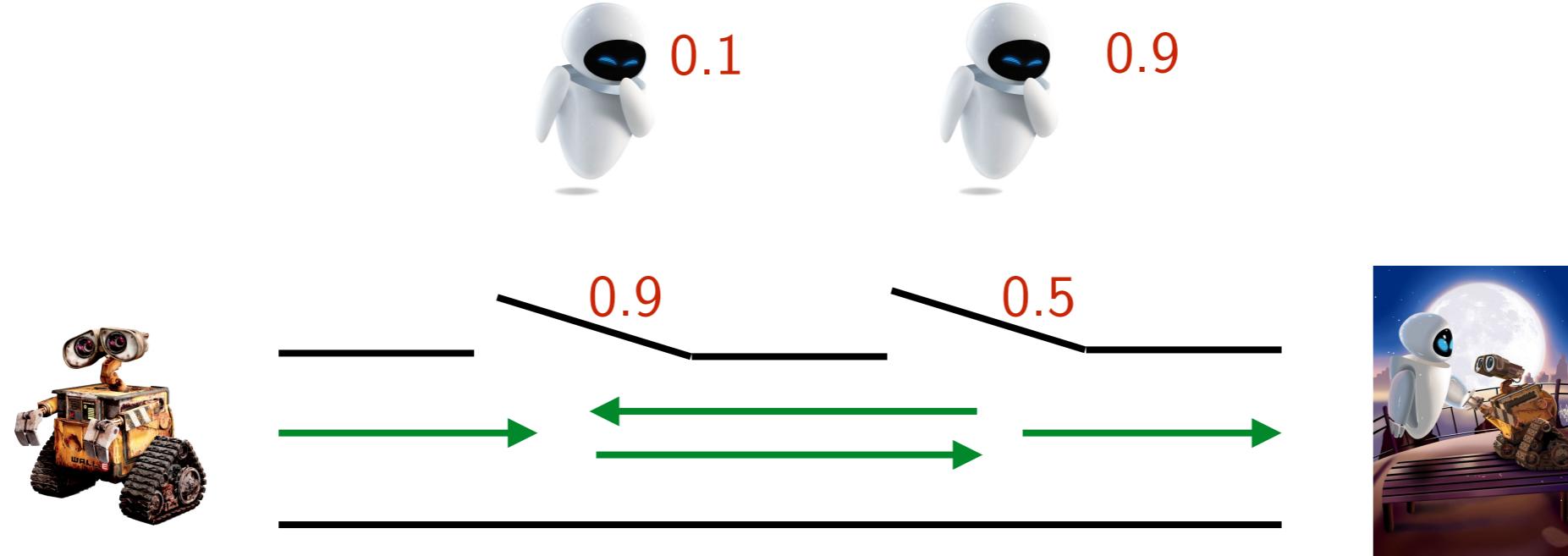


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# Markov Decision Processes (MDPs)



**Nondeterministic action  $\Rightarrow$  stochastic environment response**

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

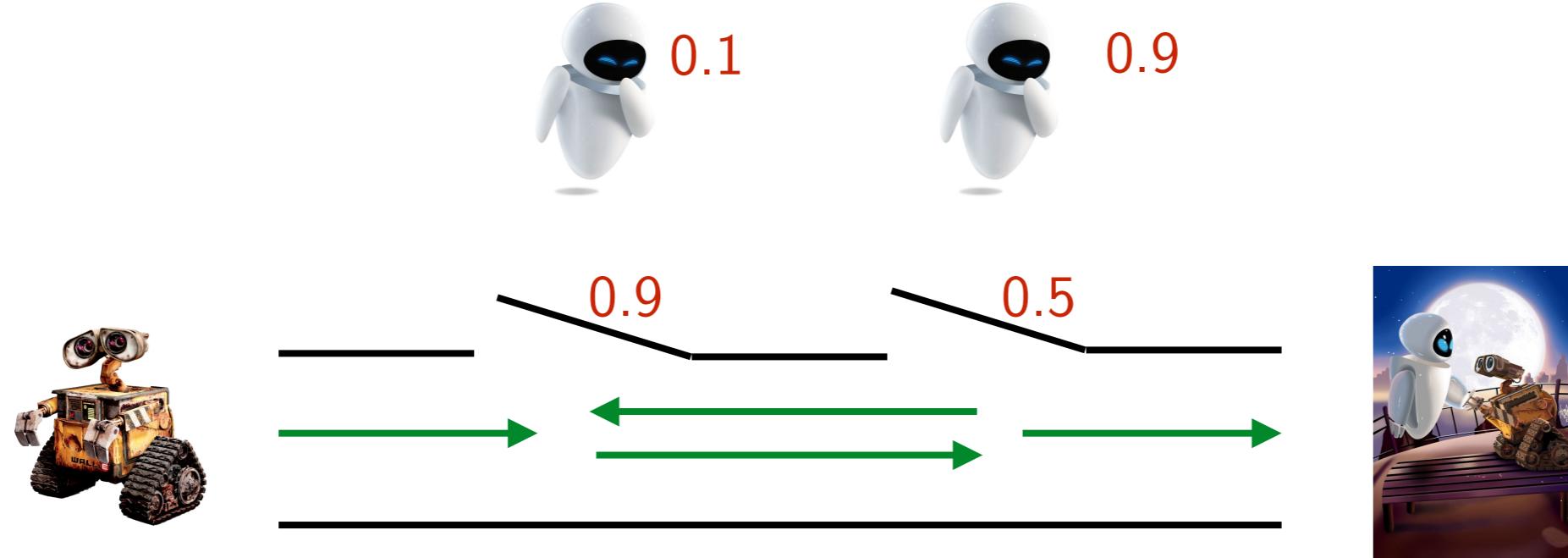
**Environment:** door possibly jams, location of Eve uncertain (10% - 90%)

**Decision making:**

What **action** to take in what **state** to achieve **objective**?

Objective:  $P_{>0.9} \ F \ (Eve \wedge X \ P_{>0.8} \ F \ Done)$

# Markov Decision Processes (MDPs)



**Nondeterministic action  $\Rightarrow$  stochastic environment response**

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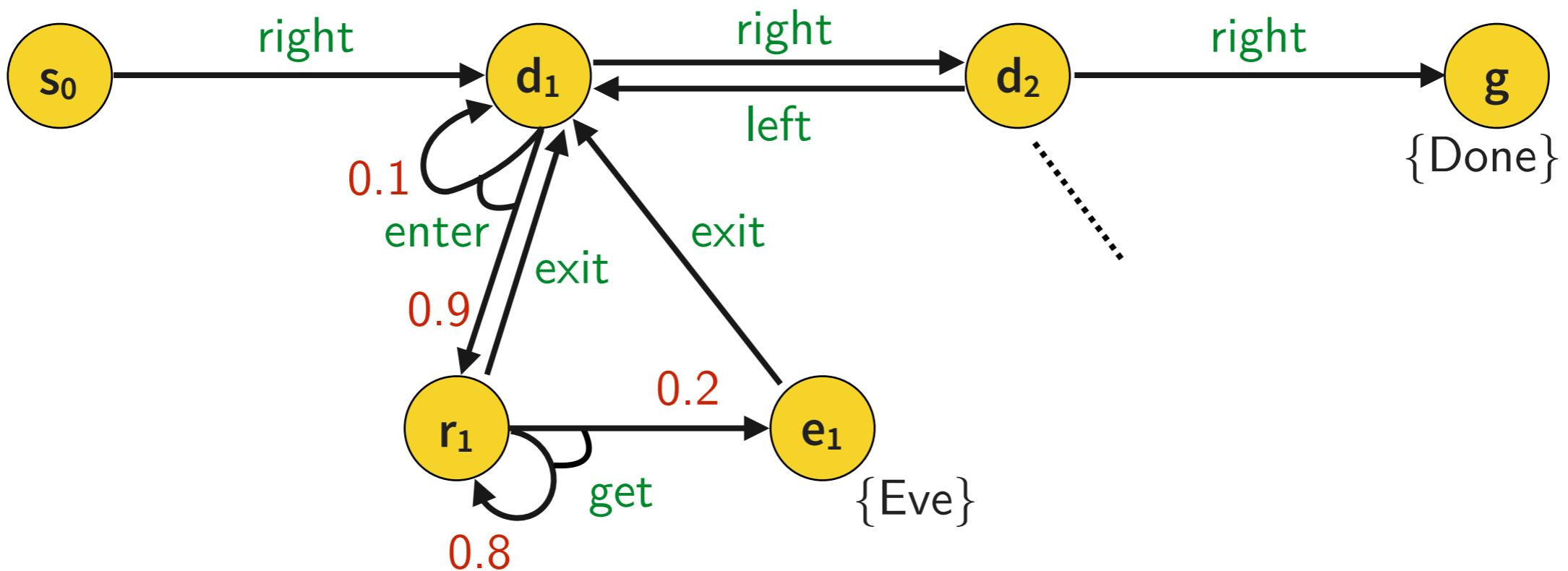
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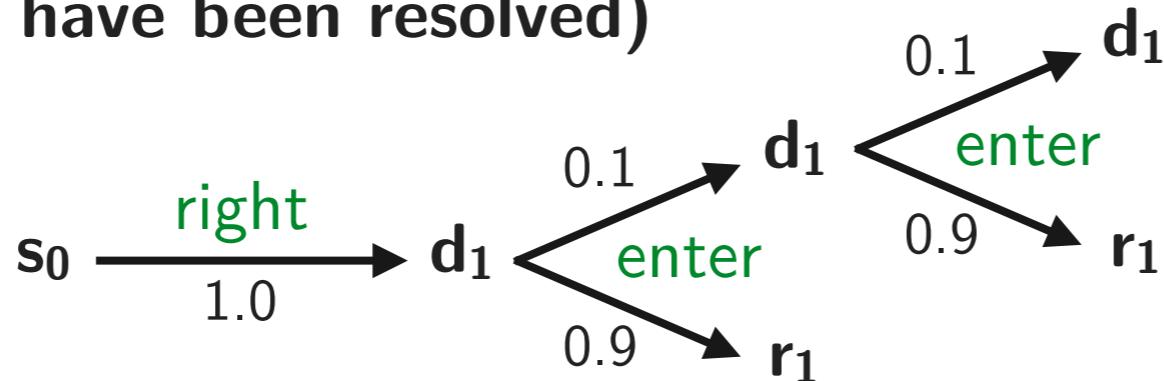
$\rightarrow$  **MDP formalism**

# MDPs, Execution Paths and Probabilities

Nondeterministic action  $\Rightarrow$  stochastic environment response

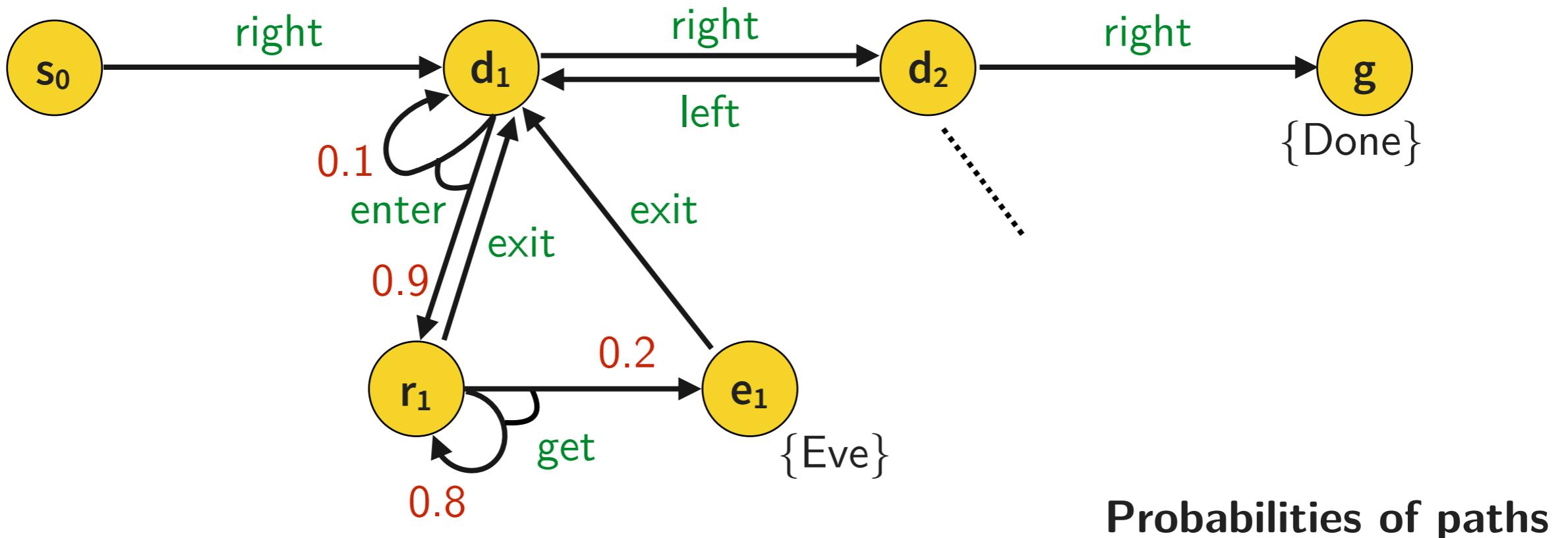


Paths (actions have been resolved)

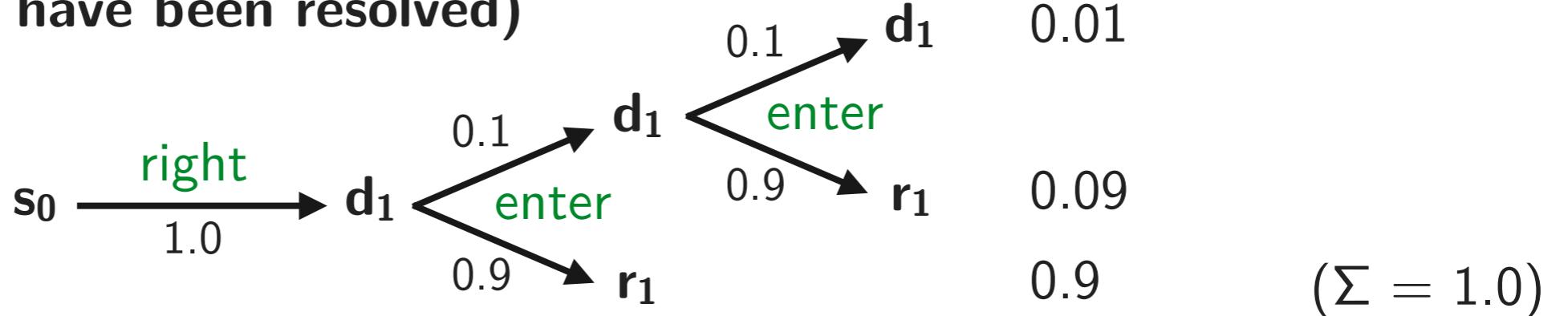


# MDPs, Execution Paths and Probabilities

Nondeterministic action  $\Rightarrow$  stochastic environment response



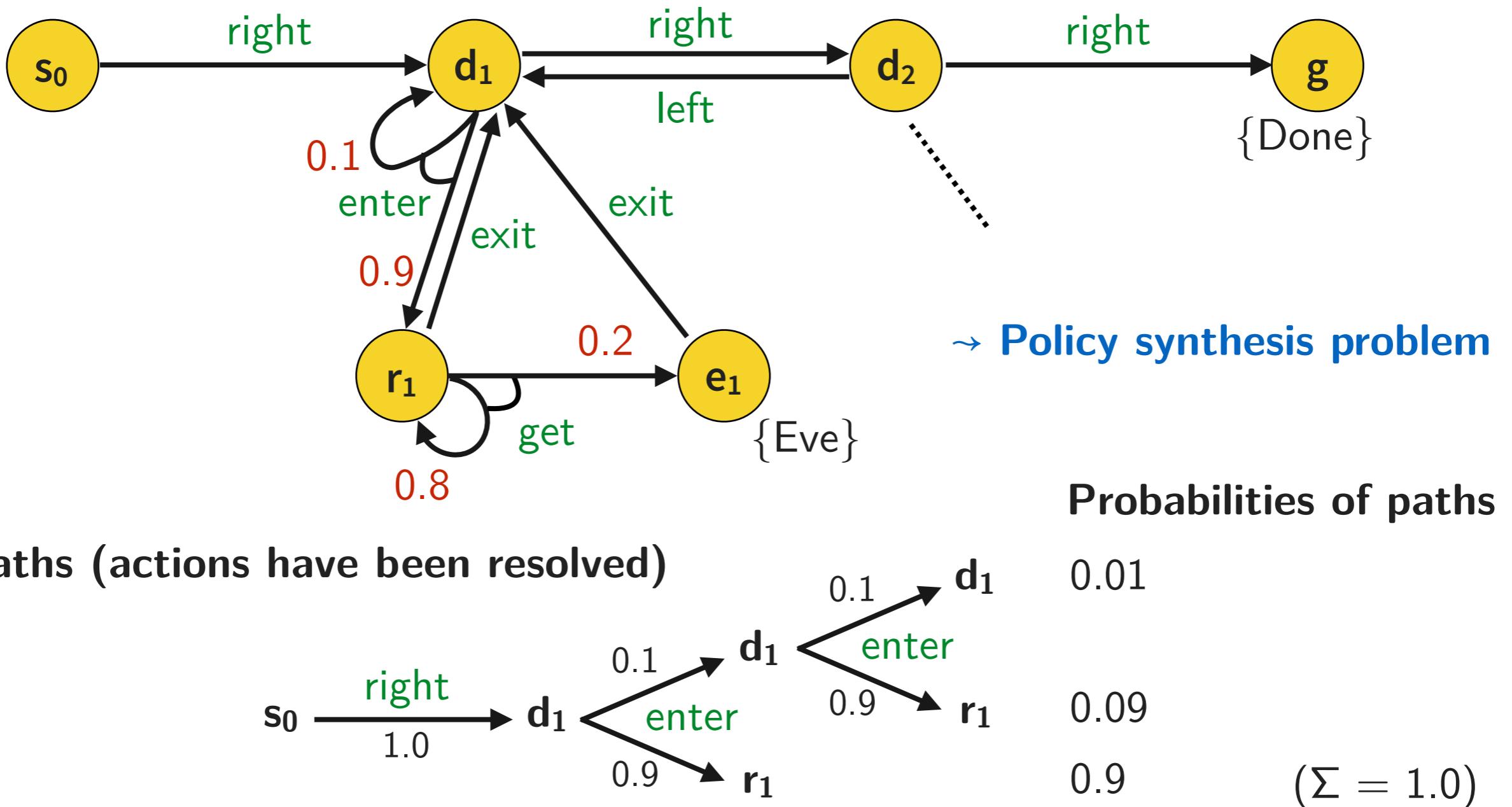
Paths (actions have been resolved)



*“The probability of reaching  $r_1$  after at most two enter steps is 0.99”*

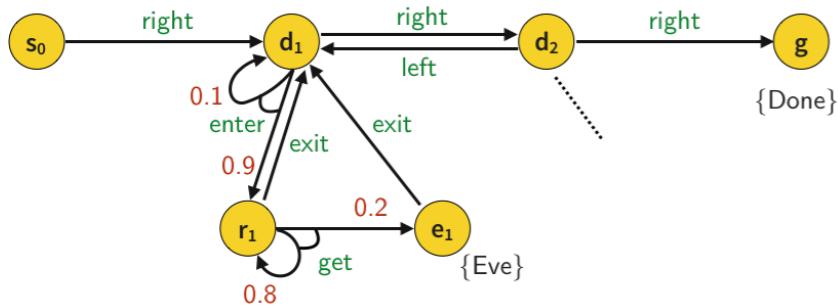
# MDPs, Execution Paths and Probabilities

Nondeterministic action  $\Rightarrow$  stochastic environment response

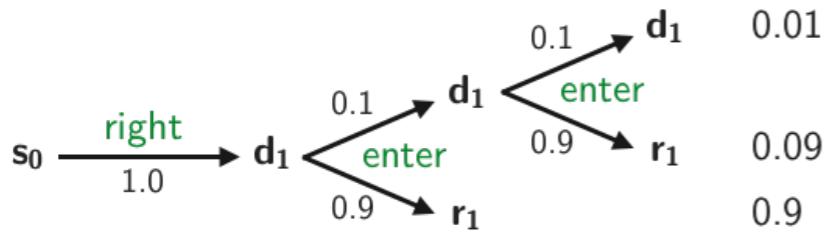


"The probability of reaching  $r_1$  after at most two enter steps is 0.99"

# Policy Synthesis Problem



- **Static:** MDP



$$s_0 \models P_{>0.9} F (Eve \wedge X P_{>0.8} F Done)$$

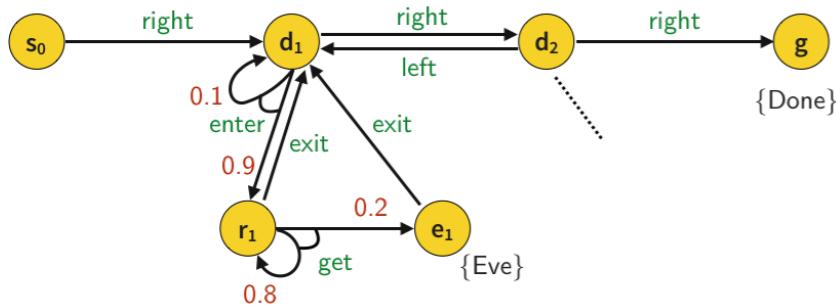
- **Dynamics:** paths and probabilities of paths
- Induced by actions chosen
- **Logic:** specification of target property (see below)
- Constraints on probabilities of these paths

## Policy synthesis problem

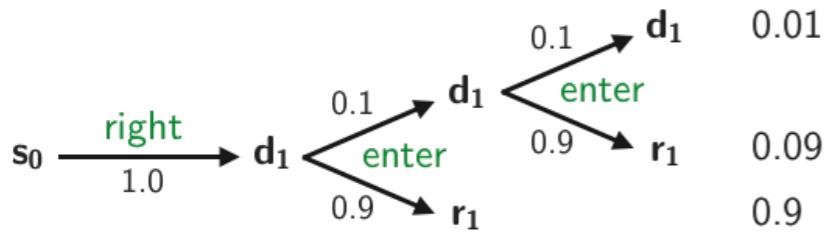
**Policy  $\sigma$ :** what actions to chose in what state

**Synthesis problem:** determine  $\sigma$  such that target property is satisfied

# Policy Synthesis Problem



- **Static:** MDP



- **Dynamics:** paths and probabilities of paths
- Induced by actions chosen
- **Logic:** specification of target property (see below)
- Constraints on probabilities of these paths

## Policy synthesis problem

**Policy  $\sigma$ :** what actions to chose in what state  $\rightarrow$  **Different kinds of policies**

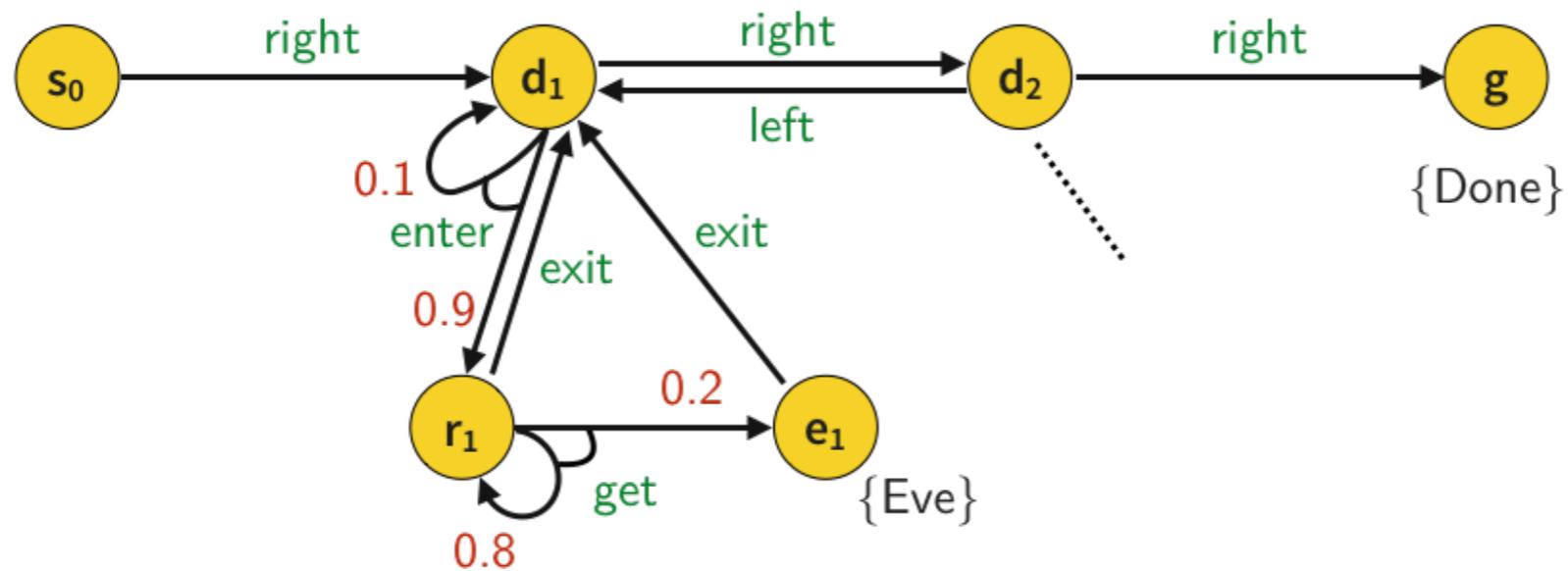
**Synthesis problem:** determine  $\sigma$  such that target property is satisfied

# Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case M: History-independent policy

Attempt 1



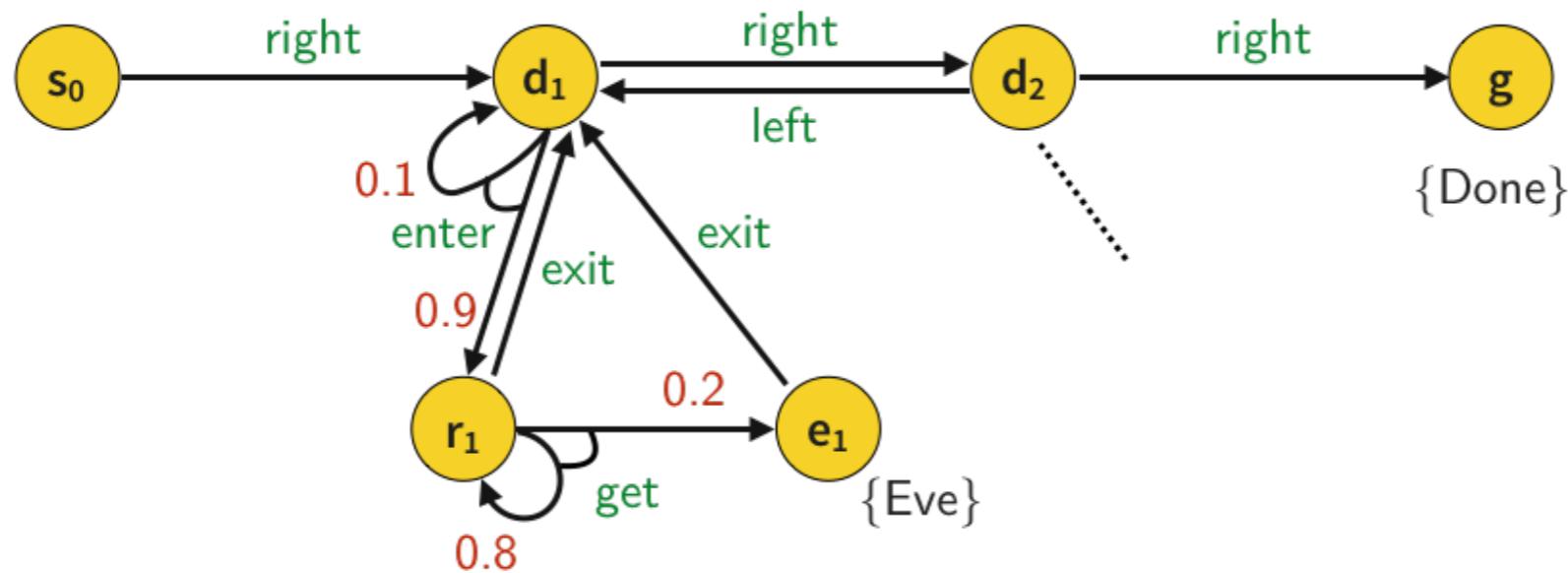
# Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case M: History-independent policy

Attempt 1

$s_0$ : right



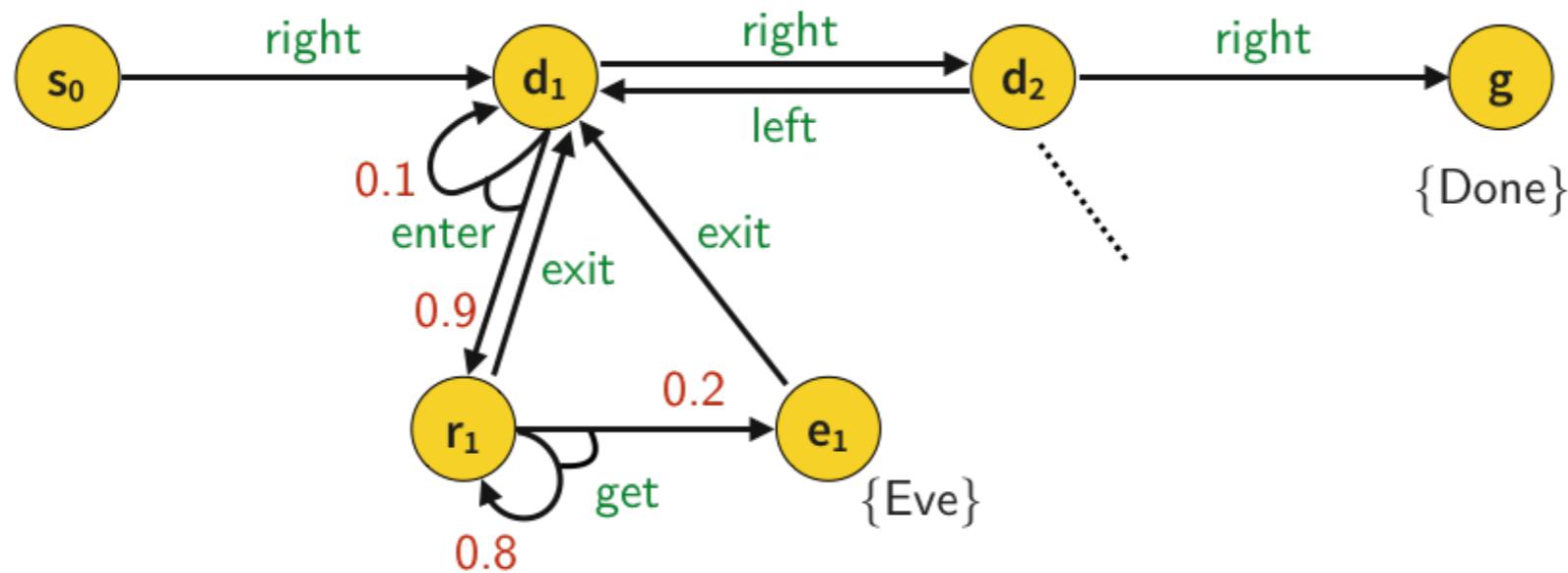
# Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case M: History-independent policy

Attempt 1

$s_0$ : right     $d_1$ : enter



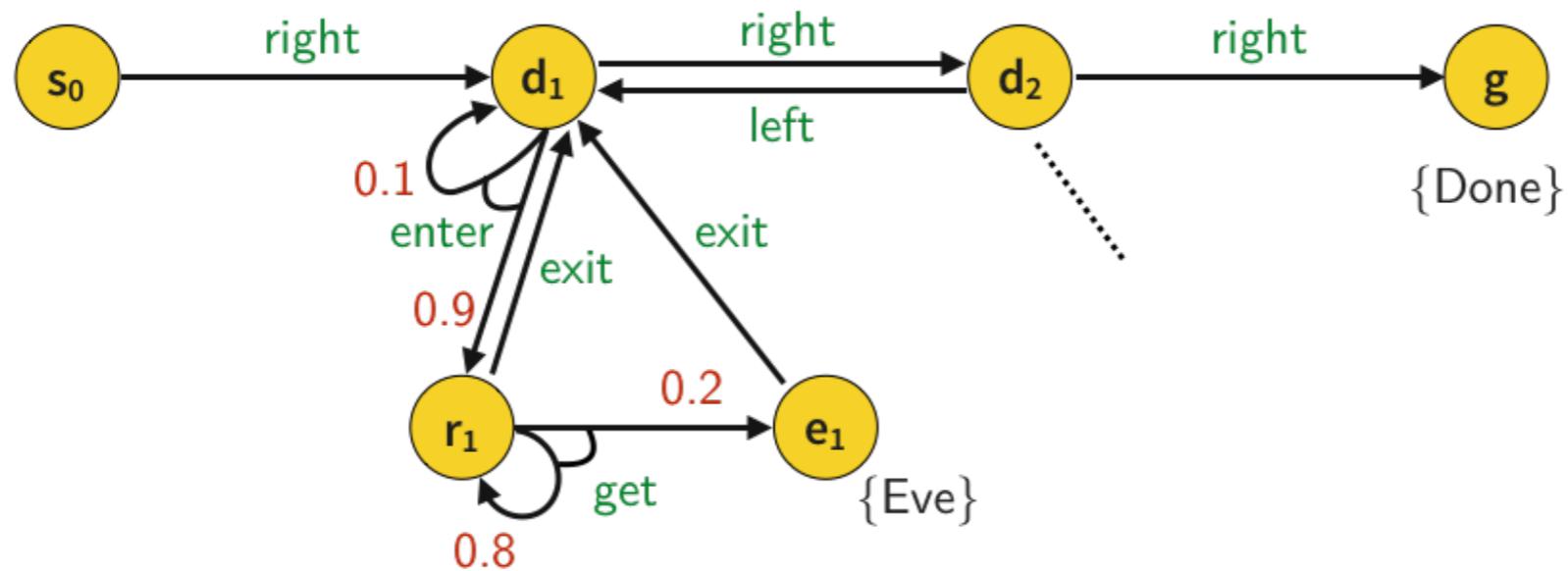
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Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

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Attempt 1

$s_0$ : right     $d_1$ : enter     $r_1$ : get



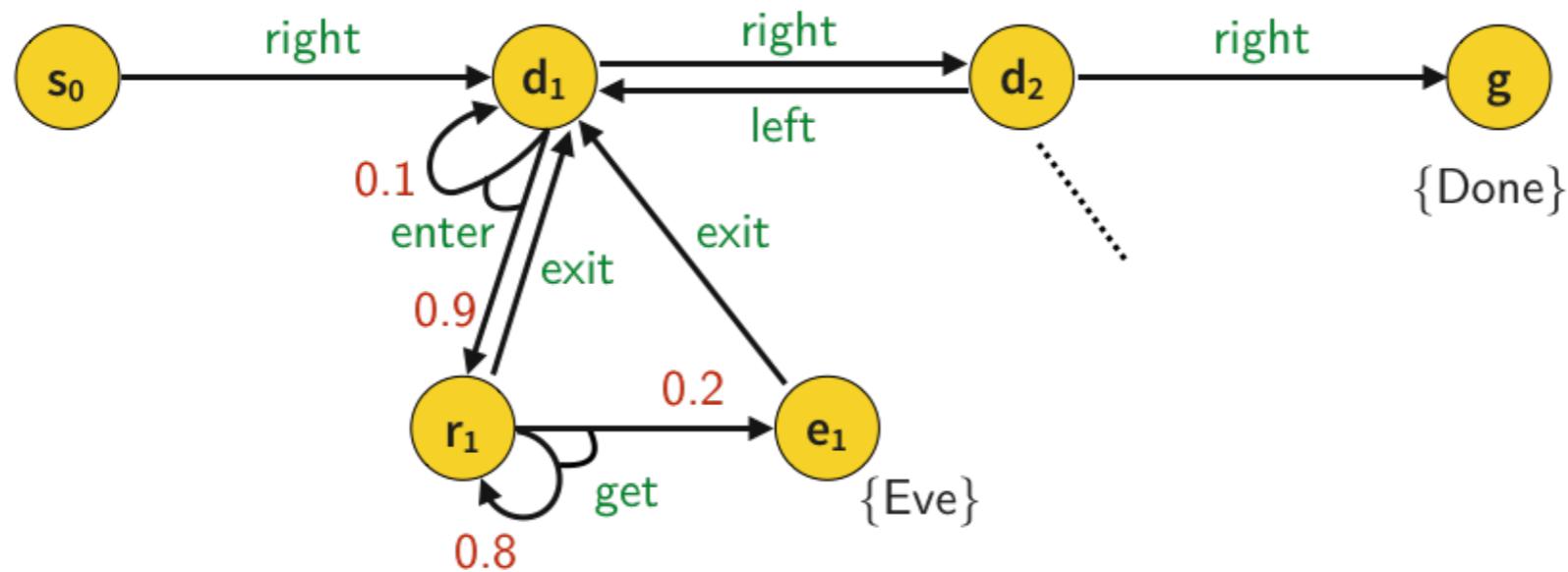
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# Policies - History Dependence and Randomization

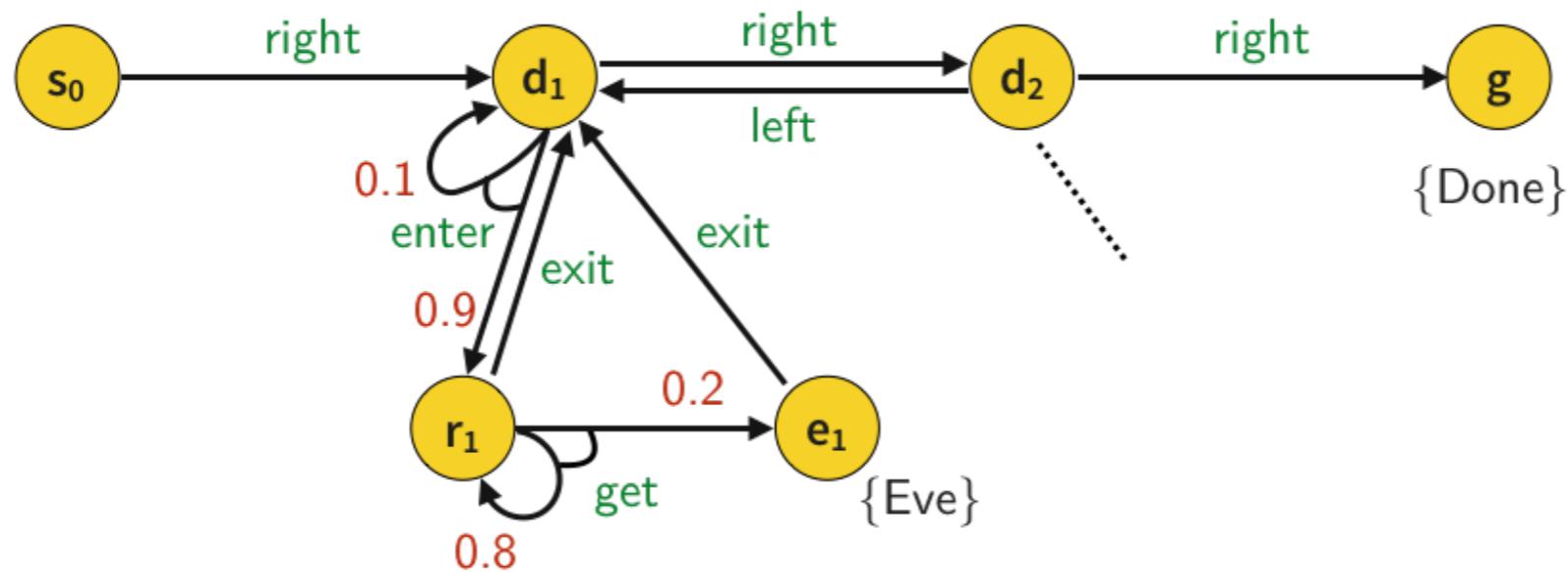
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## Case M: History-independent policy

Attempt 1

$s_0$ : right     $d_1$ : enter     $r_1$ : get     $e_1$ : exit

✓ eventually Eve  
✗ never Done



# Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

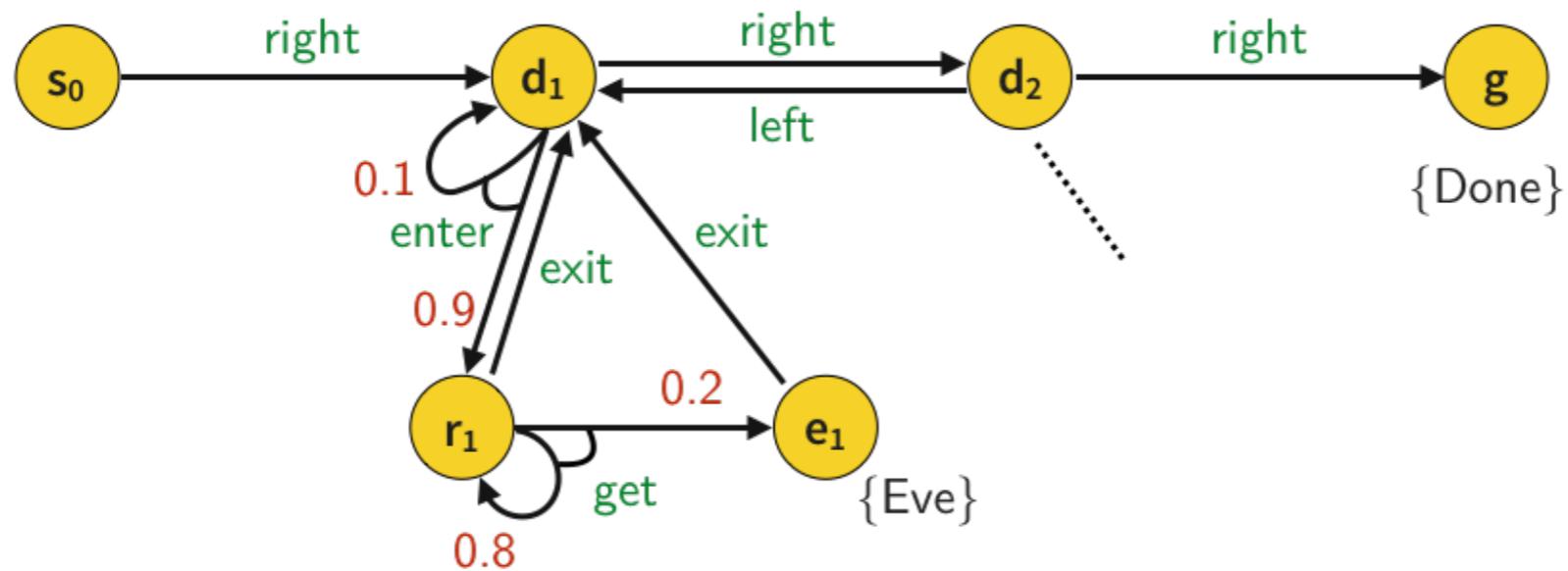
## Case M: History-independent policy

Attempt 1

$s_0$ : right     $d_1$ : enter     $r_1$ : get     $e_1$ : exit

✓ eventually Eve  
✗ never Done

Attempt 2



# Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case M: History-independent policy

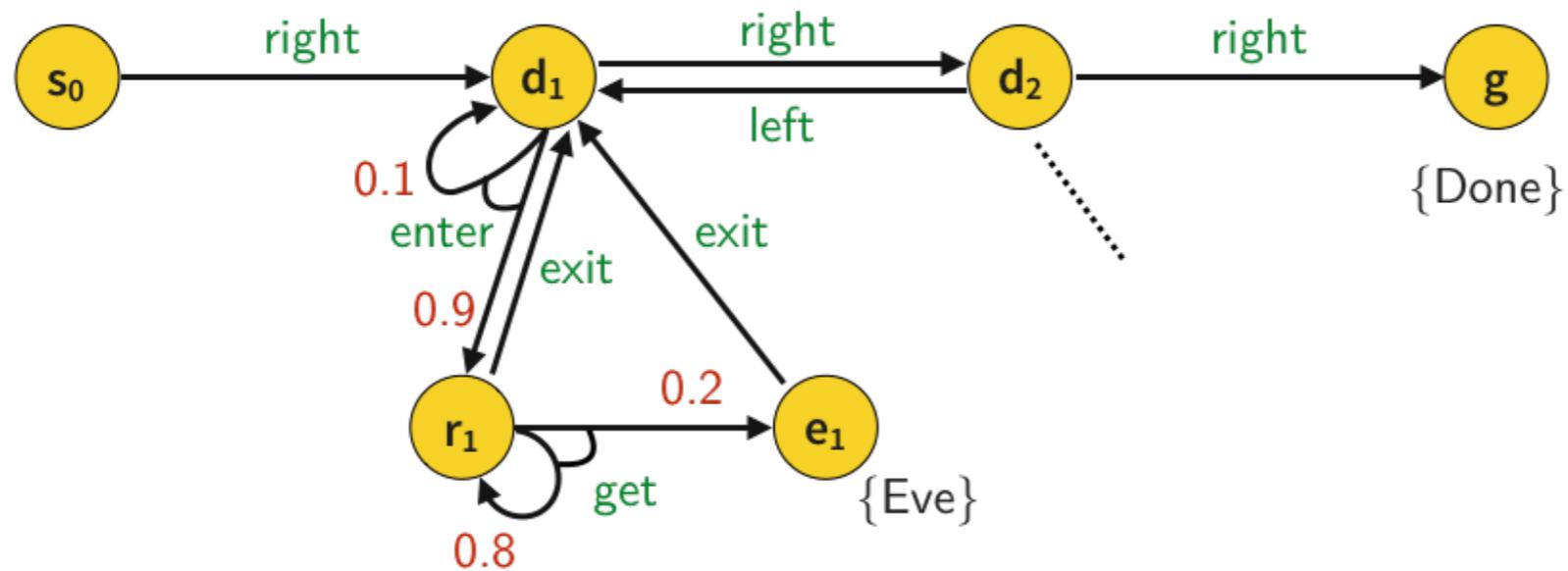
Attempt 1

$s_0$ : right     $d_1$ : enter     $r_1$ : get     $e_1$ : exit

✓ eventually Eve  
✗ never Done

Attempt 2

$s_0$ : right



# Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case M: History-independent policy

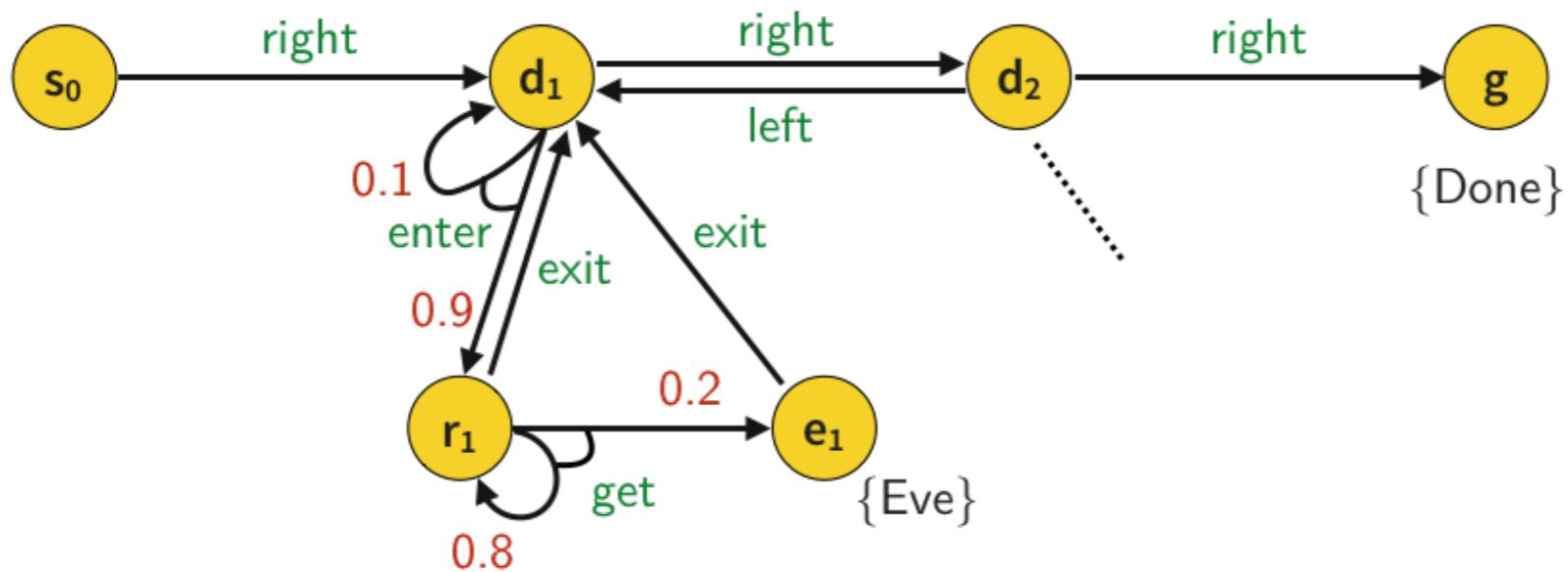
Attempt 1

$s_0$ : right    $d_1$ : enter    $r_1$ : get    $e_1$ : exit

✓ eventually Eve  
✗ never Done

Attempt 2

$s_0$ : right    $d_1$ : right



# Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case M: History-independent policy

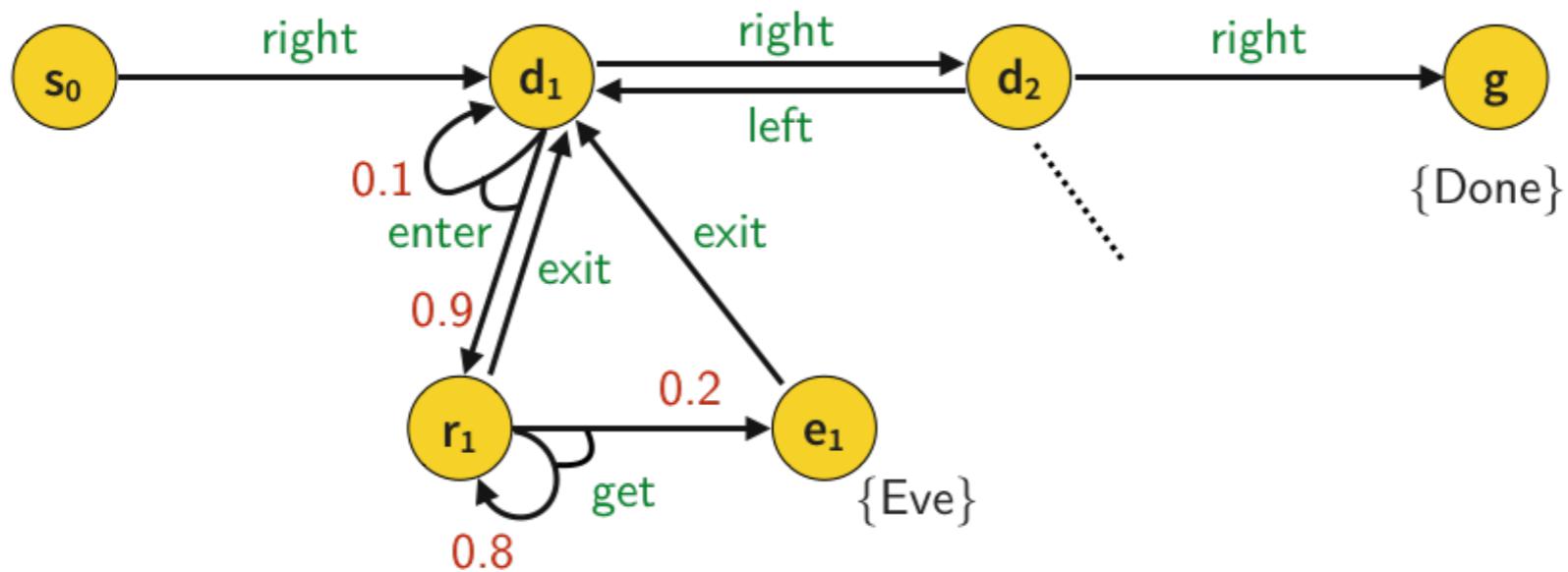
Attempt 1

$s_0$ : right    $d_1$ : enter    $r_1$ : get    $e_1$ : exit

✓ eventually Eve  
✗ never Done

Attempt 2

$s_0$ : right    $d_1$ : right    $d_2$ : right



# Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case M: History-independent policy

Attempt 1

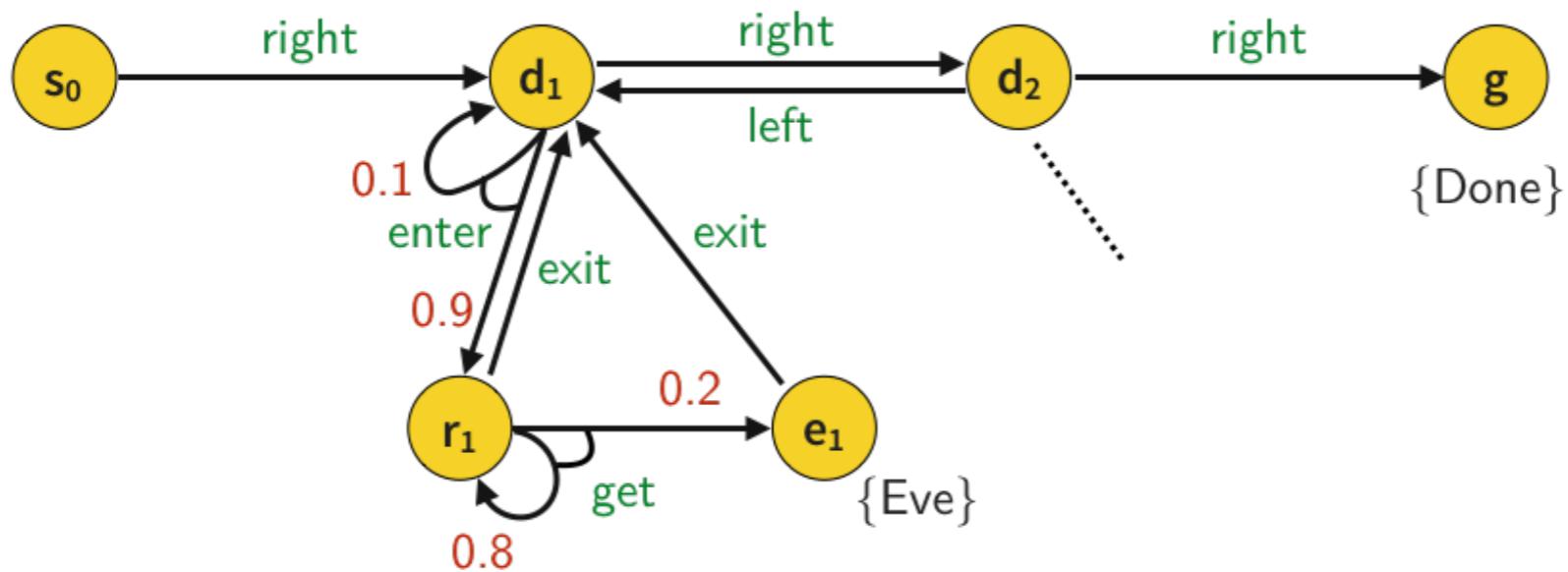
$s_0$ : right    $d_1$ : enter    $r_1$ : get    $e_1$ : exit

✓ eventually Eve  
✗ never Done

Attempt 2

$s_0$ : right    $d_1$ : right    $d_2$ : right

✓ eventually Done  
✗ never Eve



# Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case M: History-independent policy

Attempt 1

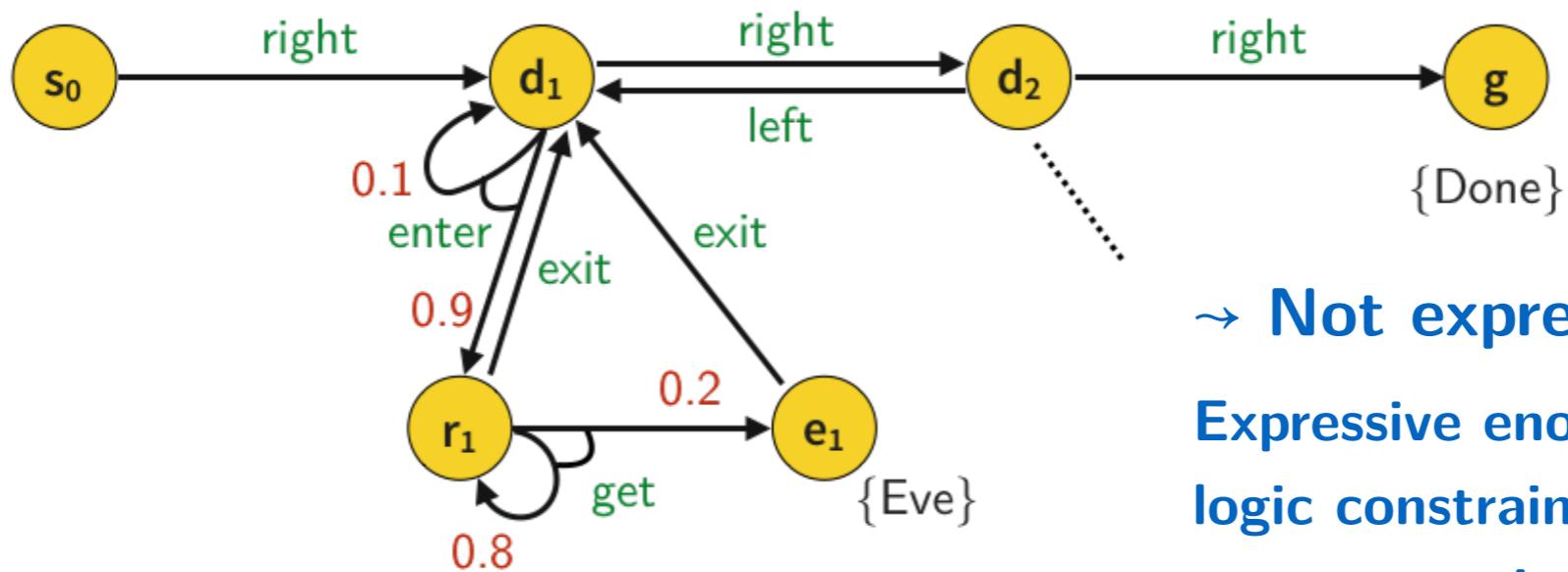
$s_0$ : right    $d_1$ : enter    $r_1$ : get    $e_1$ : exit

✓ eventually Eve  
✗ never Done

Attempt 2

$s_0$ : right    $d_1$ : right    $d_2$ : right

✓ eventually Done  
✗ never Eve

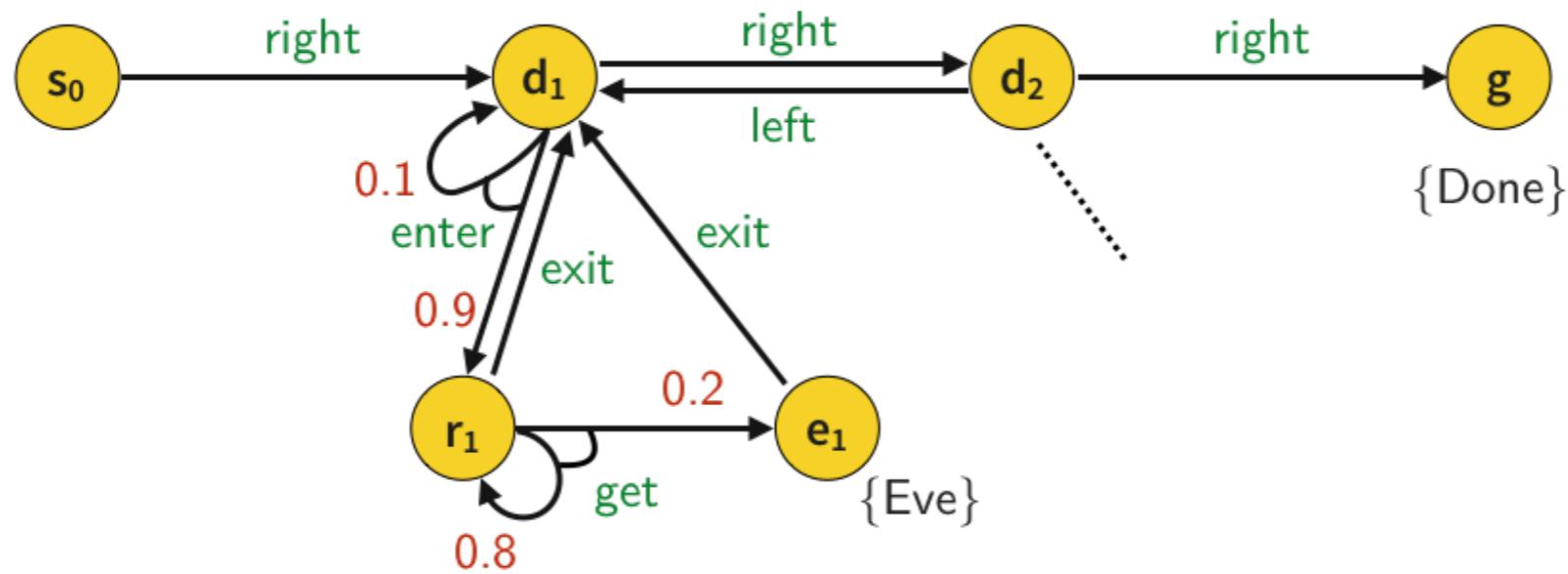


→ Not expressive enough  
Expressive enough without  
logic constraints, e.g.  
cost constraints only

# Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case H: History-dependent policy

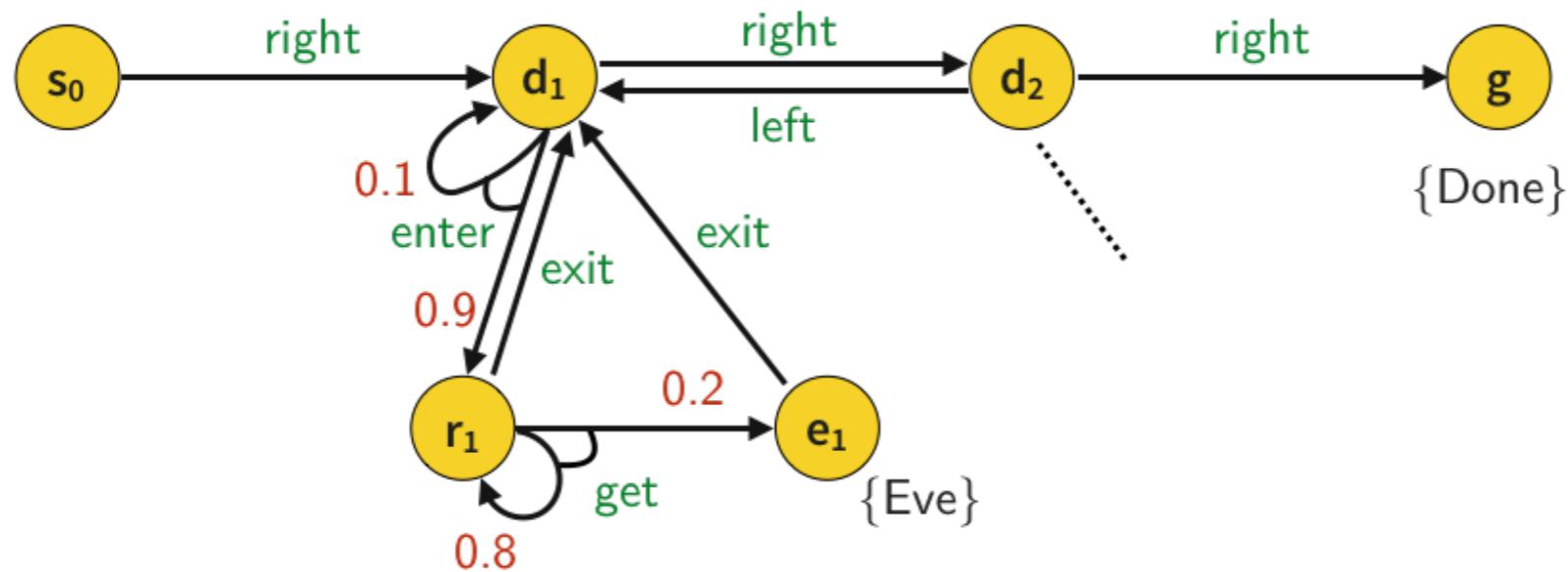


# Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case H: History-dependent policy

$s_0$ : right

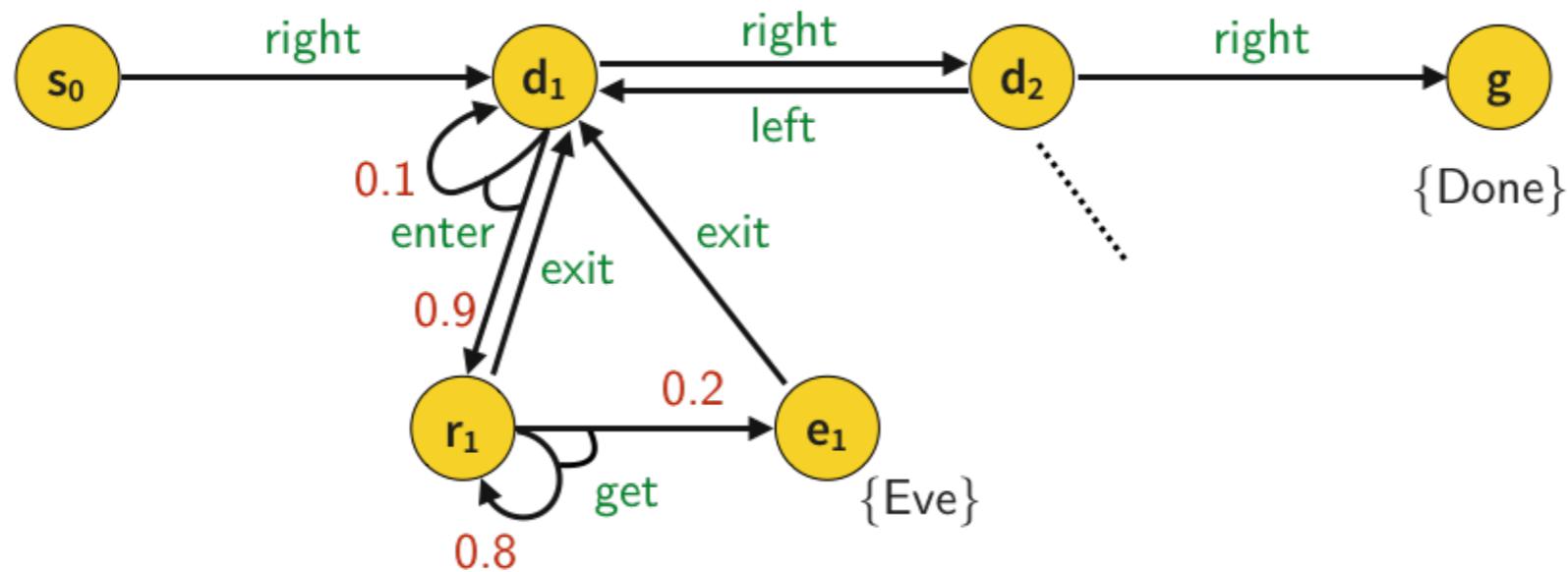


# Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case H: History-dependent policy

$s_0$ : right     $s_0$   $d_1 \dots d_1 \dots d_1$ : enter

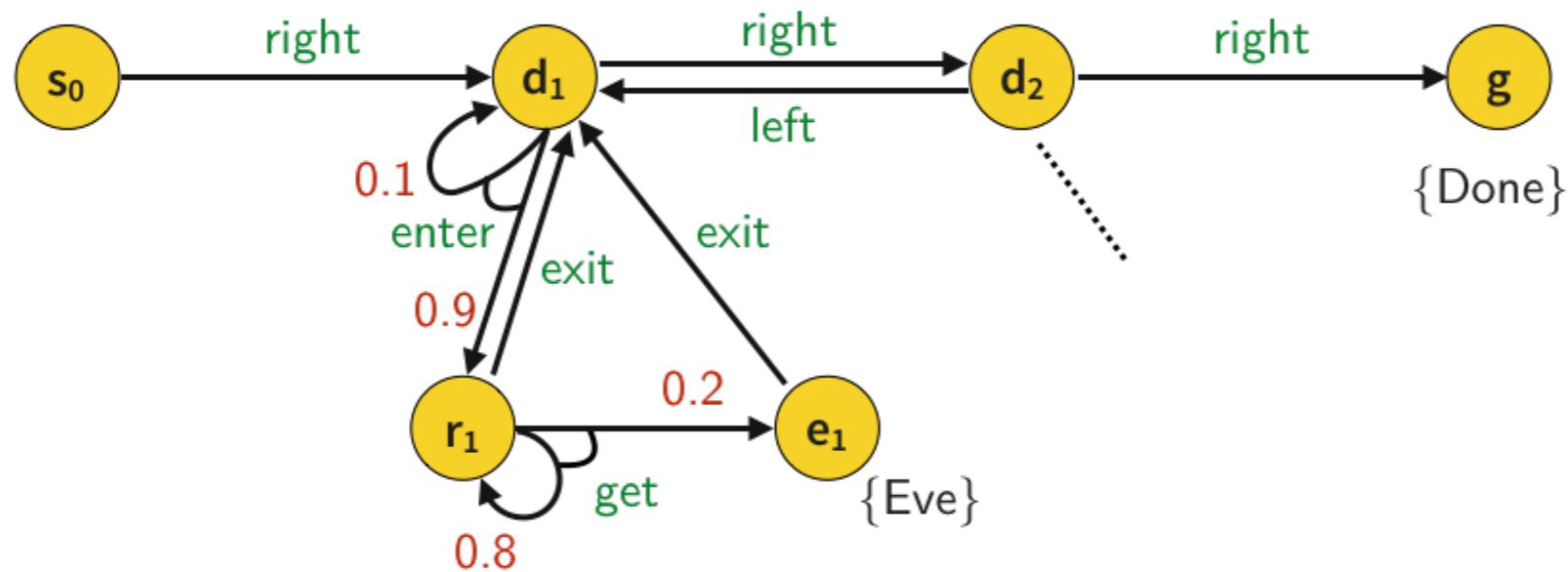


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$s_0$ : right     $s_0$   $d_1 \dots d_1 \dots d_1$ : enter     $s_0 \dots r_1$ : get

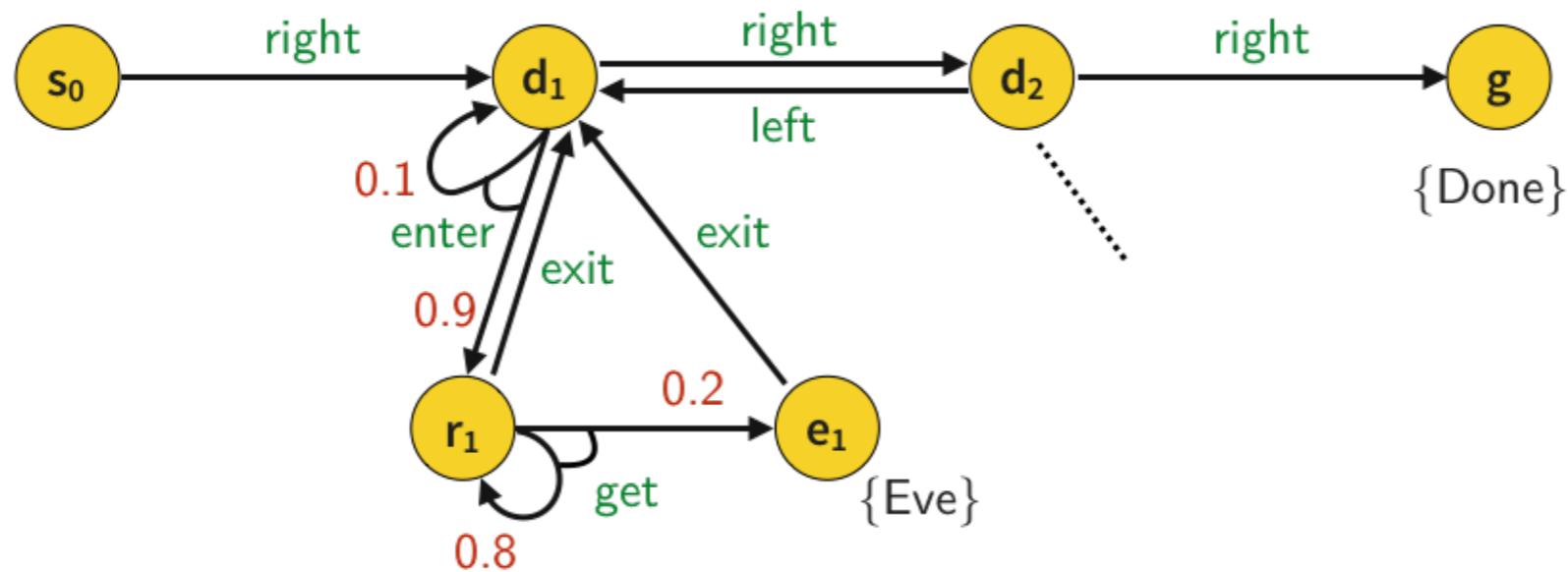


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Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case H: History-dependent policy

$s_0$ : right     $s_0 \ d_1 \dots d_1 \dots d_1$ : enter     $s_0 \dots r_1$ : get     $s_0 \dots e_1$ : exit

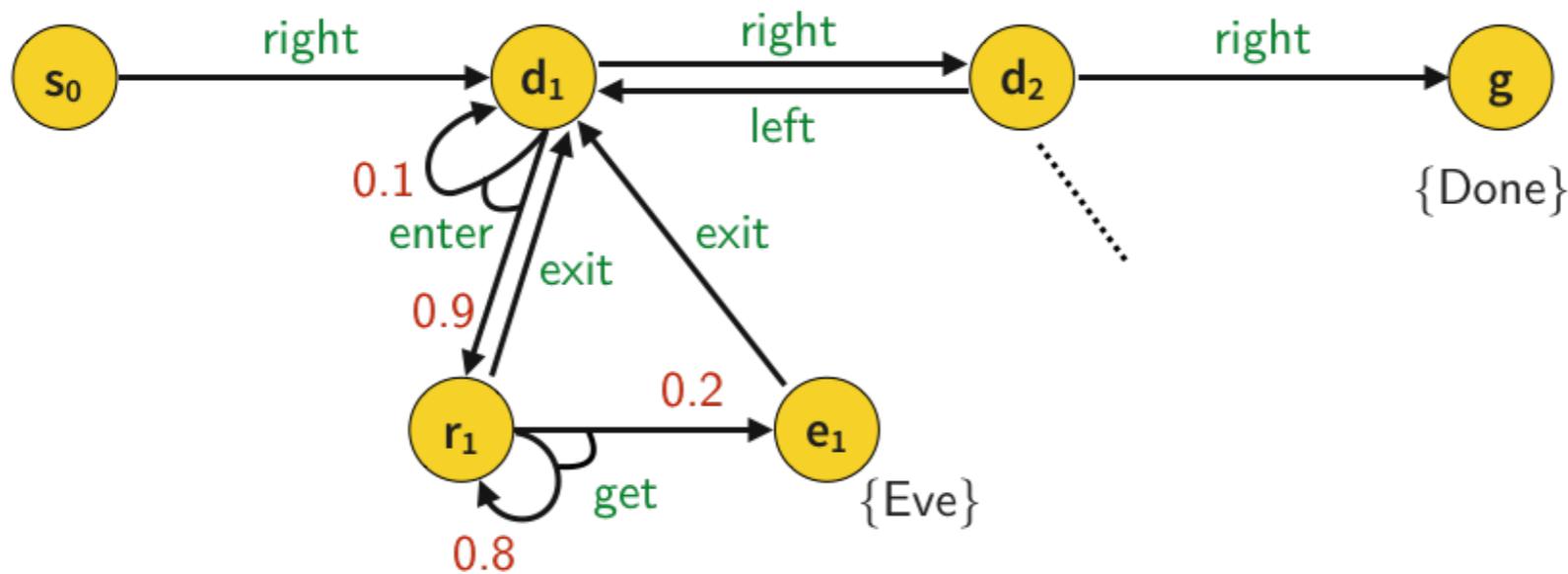


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Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

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$s_0$ : right     $s_0 \ d_1 \dots d_1 \dots d_1$ : enter     $s_0 \dots r_1$ : get     $s_0 \dots e_1$ : exit  
 $s_0 \ d_1 \dots e_1 \dots d_1$ : right

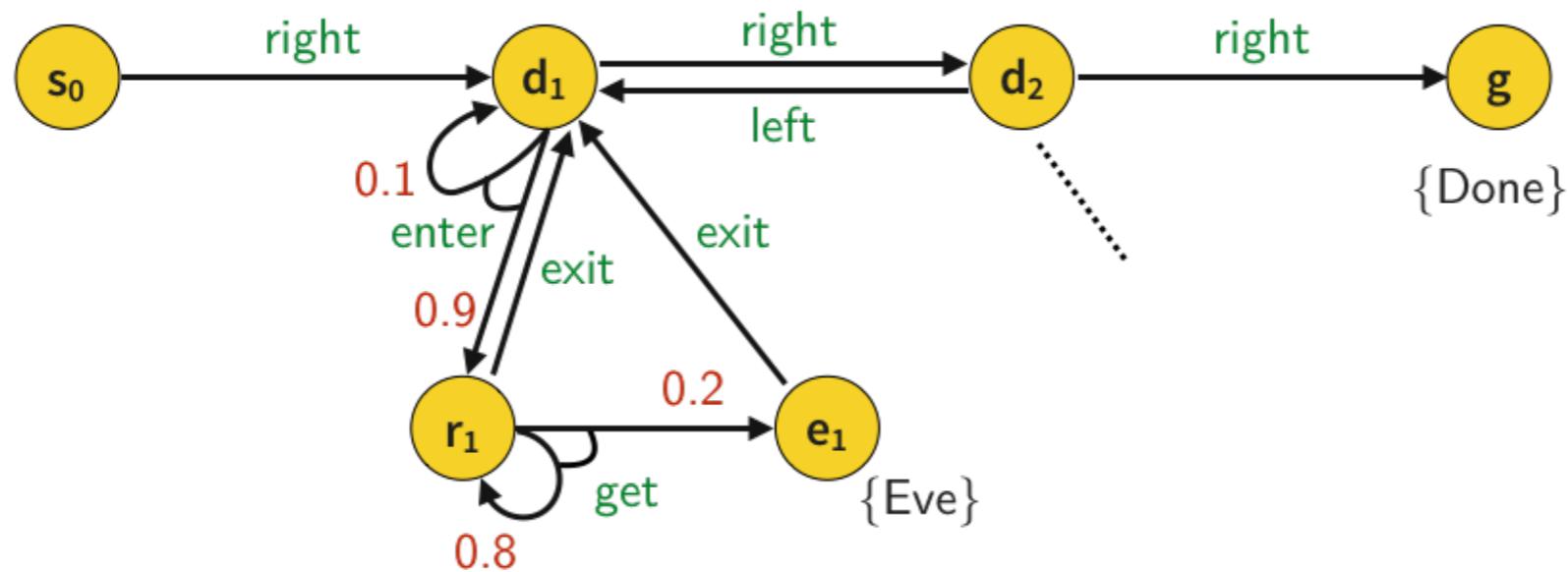


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Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case H: History-dependent policy

$s_0$ : right     $s_0 \ d_1 \dots d_1 \dots d_1$ : enter     $s_0 \dots r_1$ : get     $s_0 \dots e_1$ : exit  
 $s_0 \ d_1 \dots e_1 \dots d_1$ : right     $s_0 \dots d_2$ : right

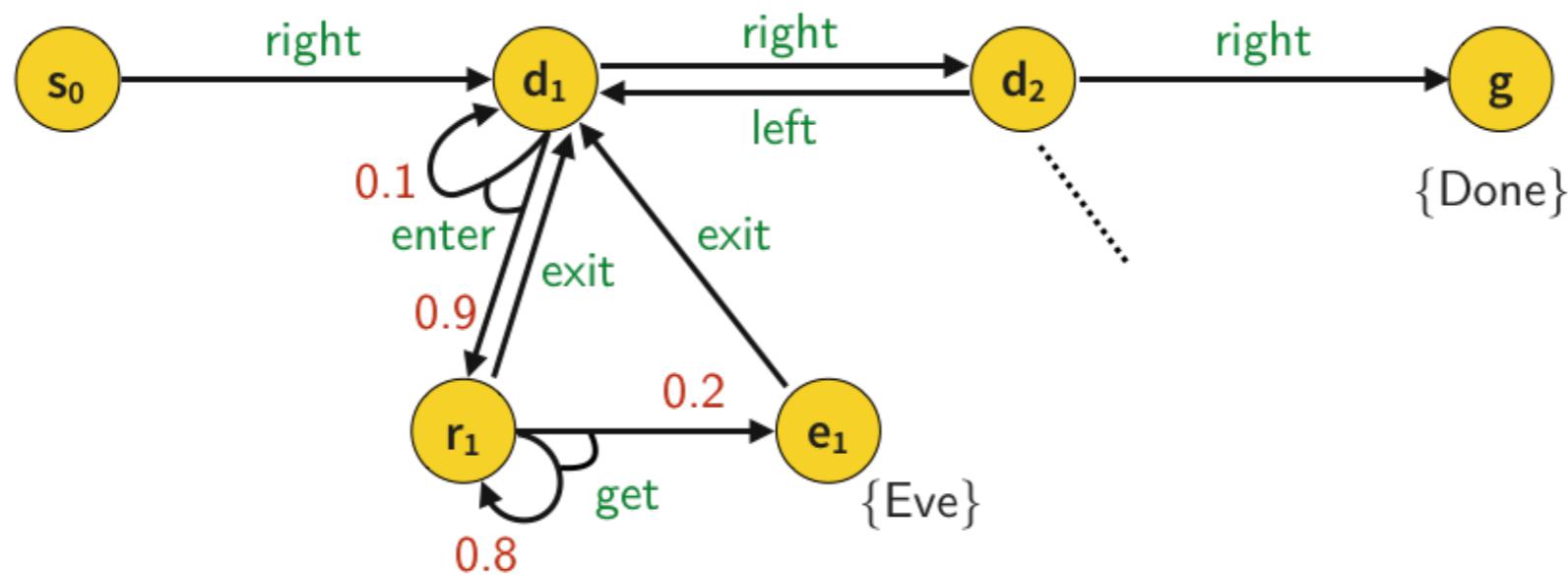


# Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case H: History-dependent policy

$s_0: \text{right}$     $s_0 \ d_1 \dots \ d_1 \dots \ d_1: \text{enter}$     $s_0 \dots \ r_1: \text{get}$     $s_0 \dots \ e_1: \text{exit}$  ✓ eventually Eve  
 $s_0 \ d_1 \dots \ e_1 \dots \ d_1: \text{right}$     $s_0 \dots \ d_2: \text{right}$    ✓ eventually Done



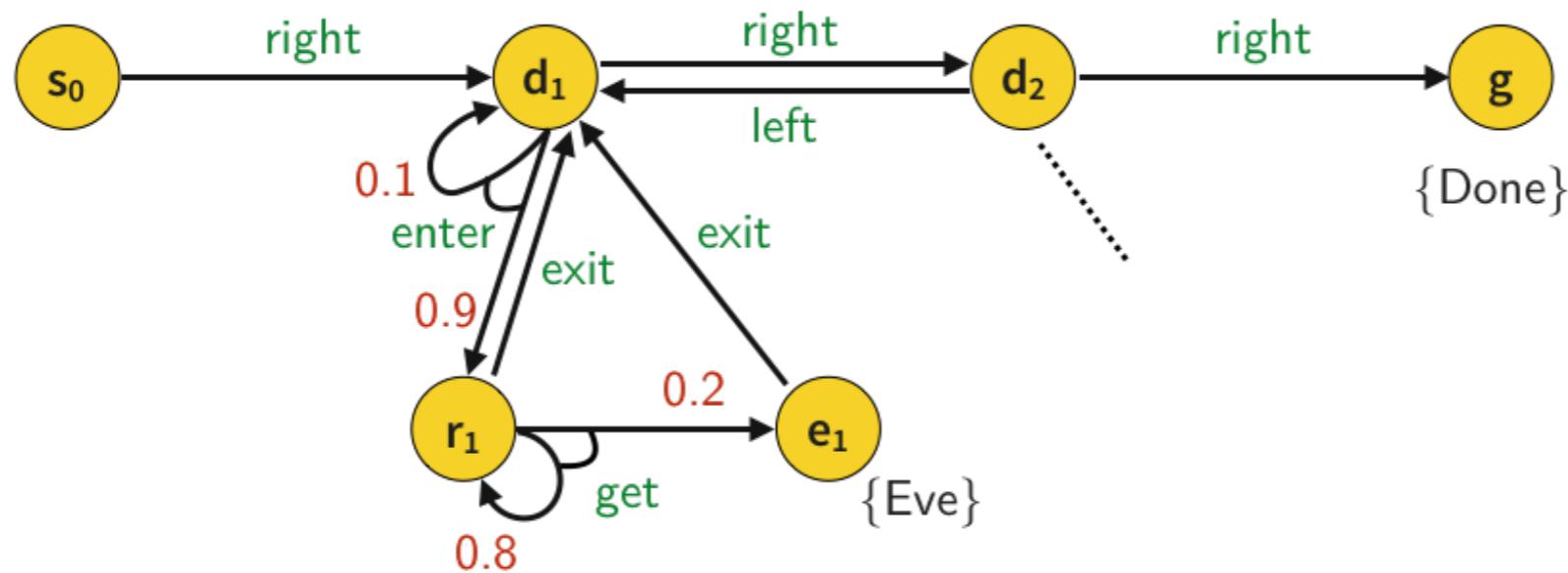
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Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case H: History-dependent policy

$s_0: \text{right}$     $s_0 \ d_1 \dots \ d_1 \dots \ d_1: \text{enter}$     $s_0 \dots \ r_1: \text{get}$     $s_0 \dots \ e_1: \text{exit}$  ✓ eventually Eve  
 $s_0 \ d_1 \dots \ e_1 \dots \ d_1: \text{right}$     $s_0 \dots \ d_2: \text{right}$    ✓ eventually Done

**X** unbounded history length - highly undecidable

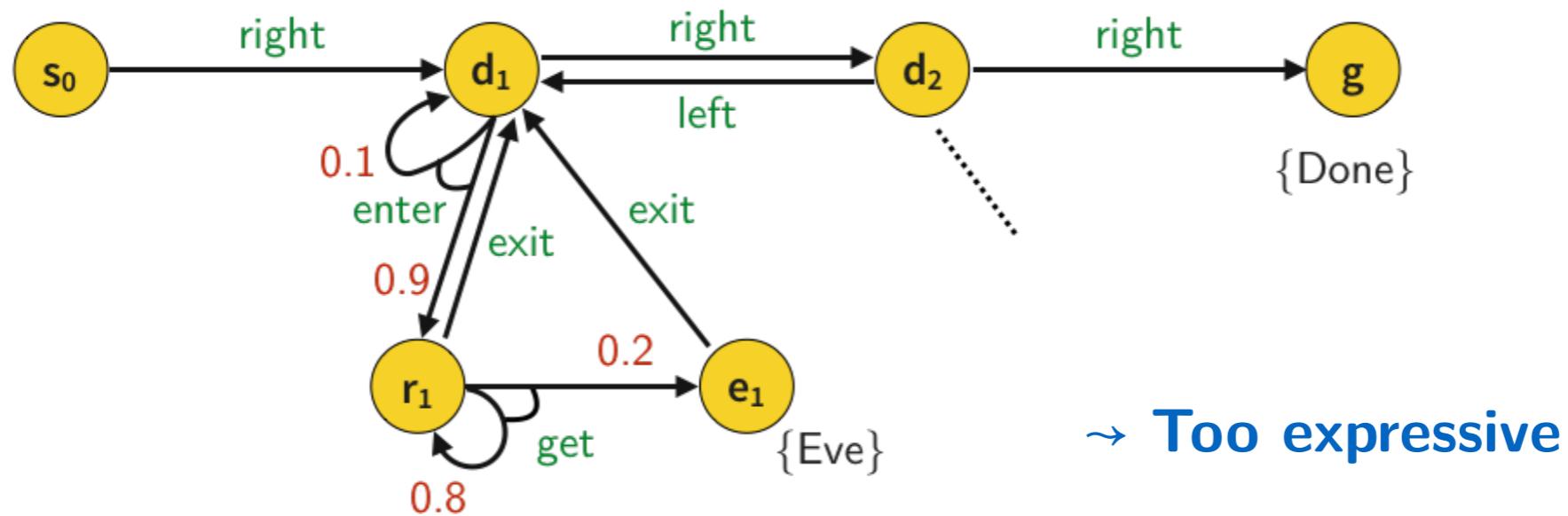


## Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case H: History-dependent policy

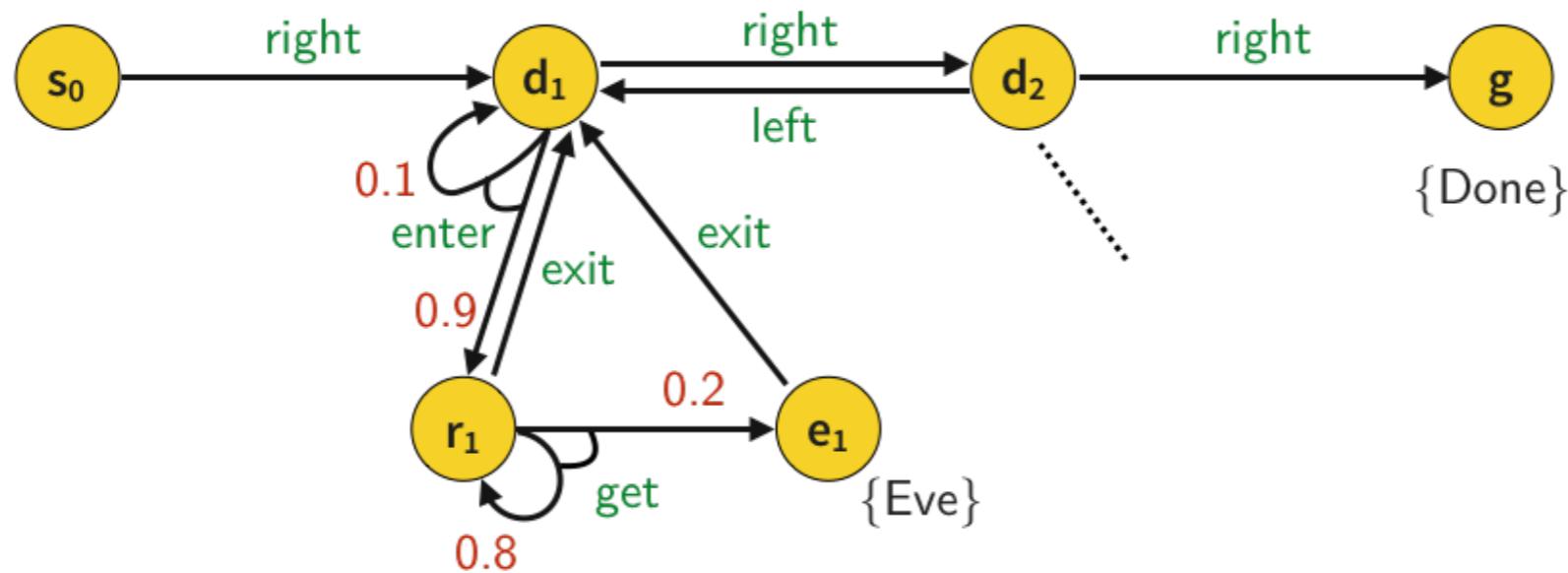
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# Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

**Case F: Finite history-dependent policy**

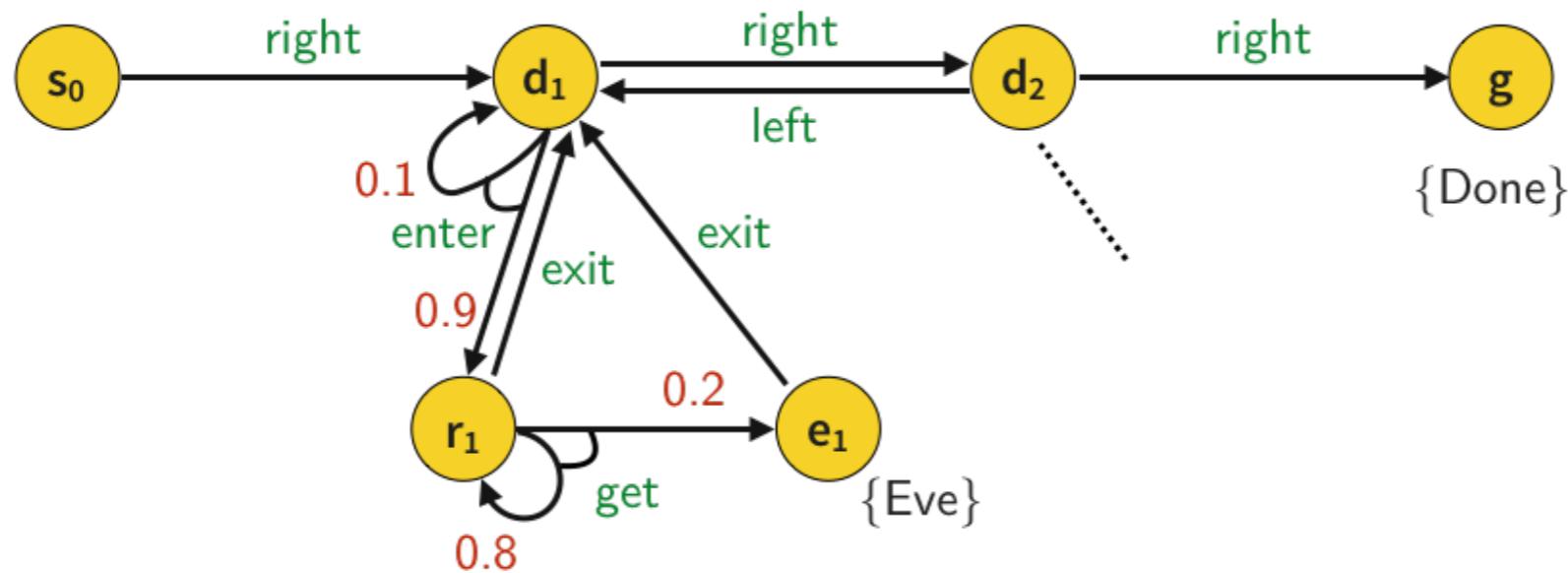


# Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case F: Finite history-dependent policy

$s_0$ : right

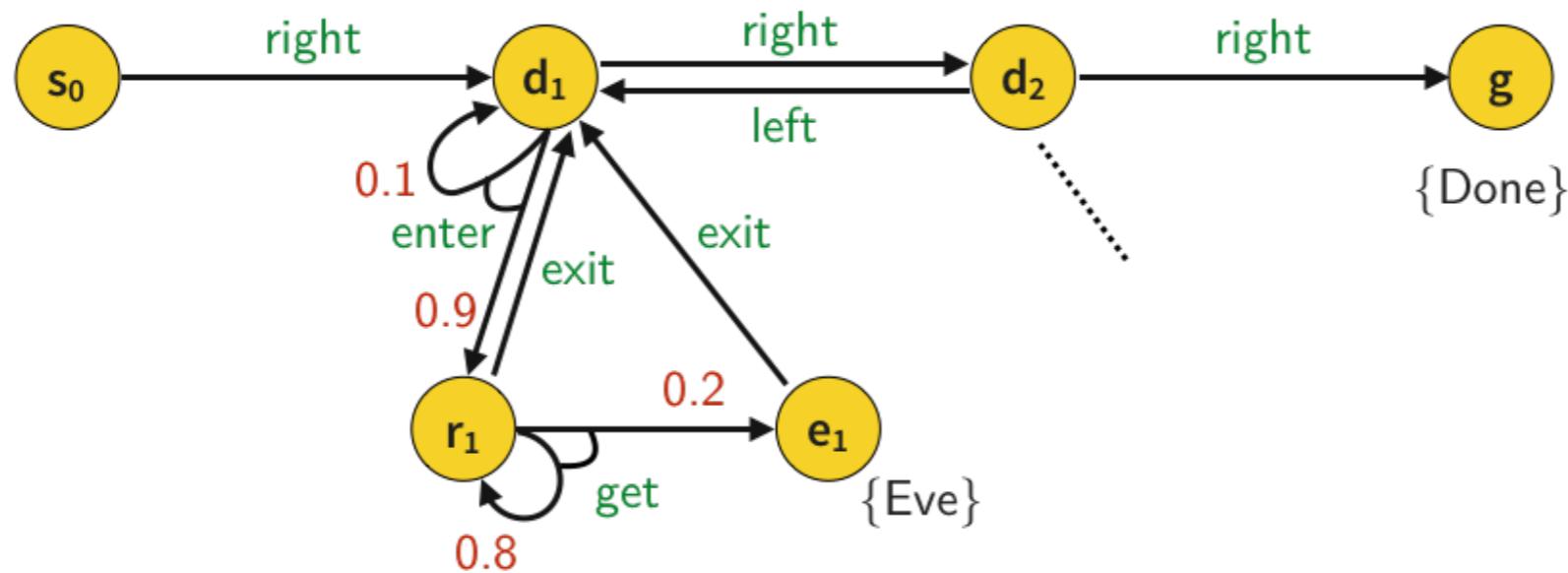


# Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case F: Finite history-dependent policy

$s_0$ : right     $s_0 d_1$ : enter



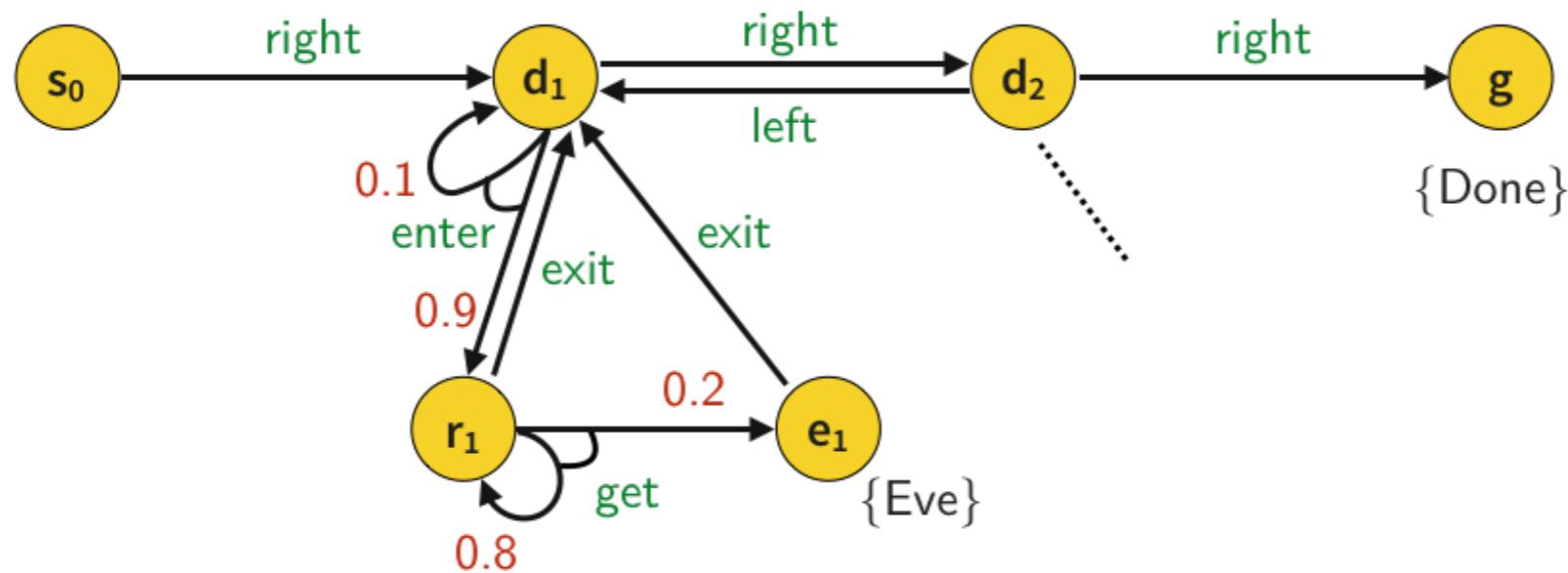
# Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case F: Finite history-dependent policy

$s_0$ : right     $s_0 d_1$ : enter

$d_1 d_1$ : enter

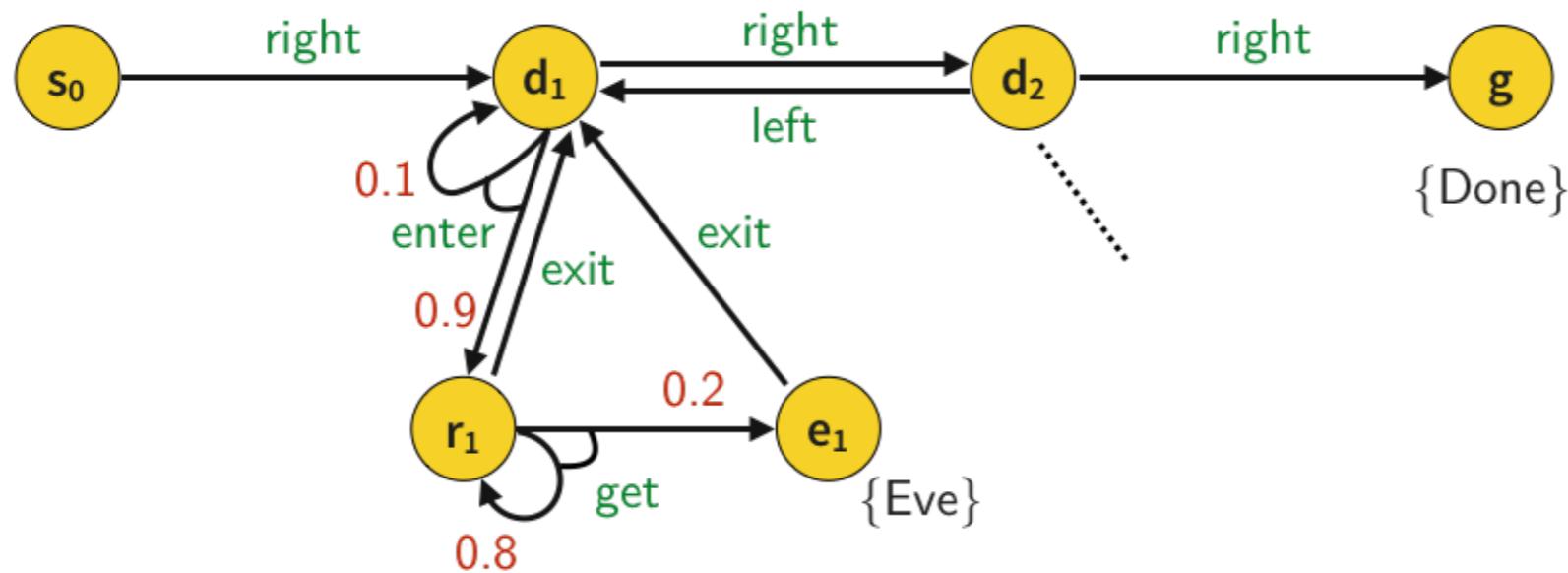


# Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case F: Finite history-dependent policy

$s_0$ : right     $s_0d_1$ : enter     $d_1r_1$ : get  
 $d_1d_1$ : enter

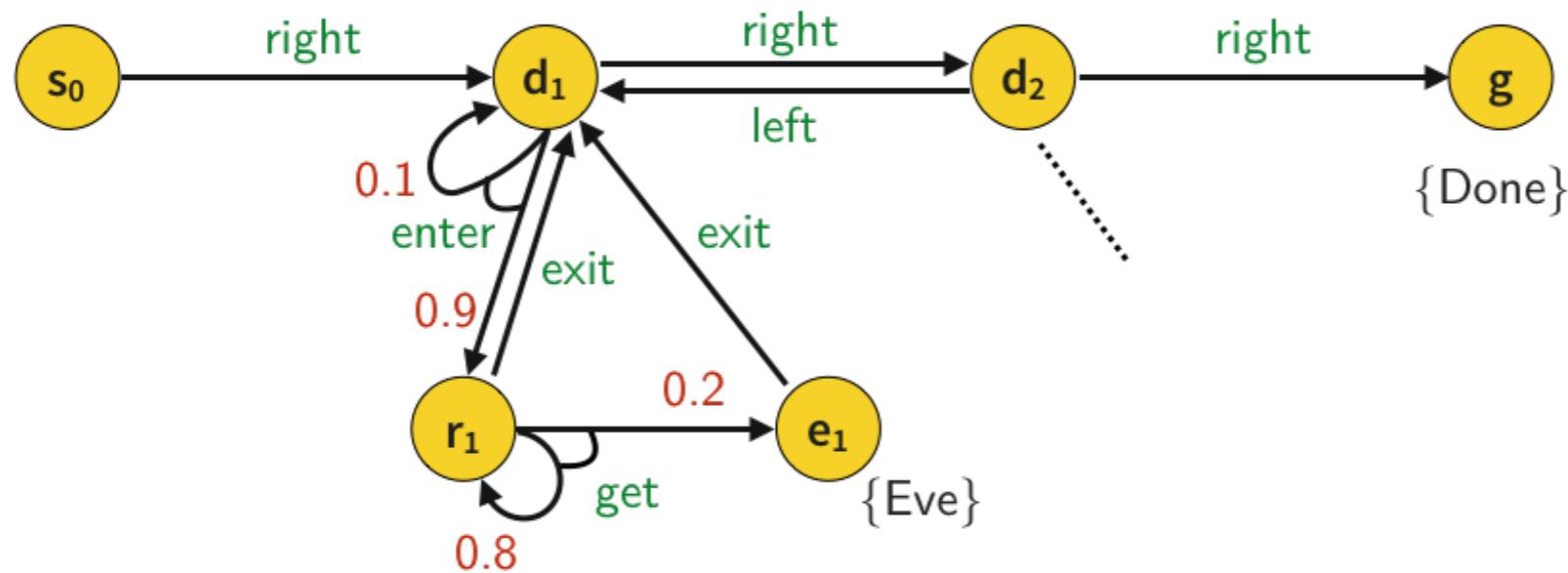


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Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case F: Finite history-dependent policy

$s_0$ : right     $s_0d_1$ : enter     $d_1r_1$ : get  
 $d_1d_1$ : enter     $r_1r_1$ : get

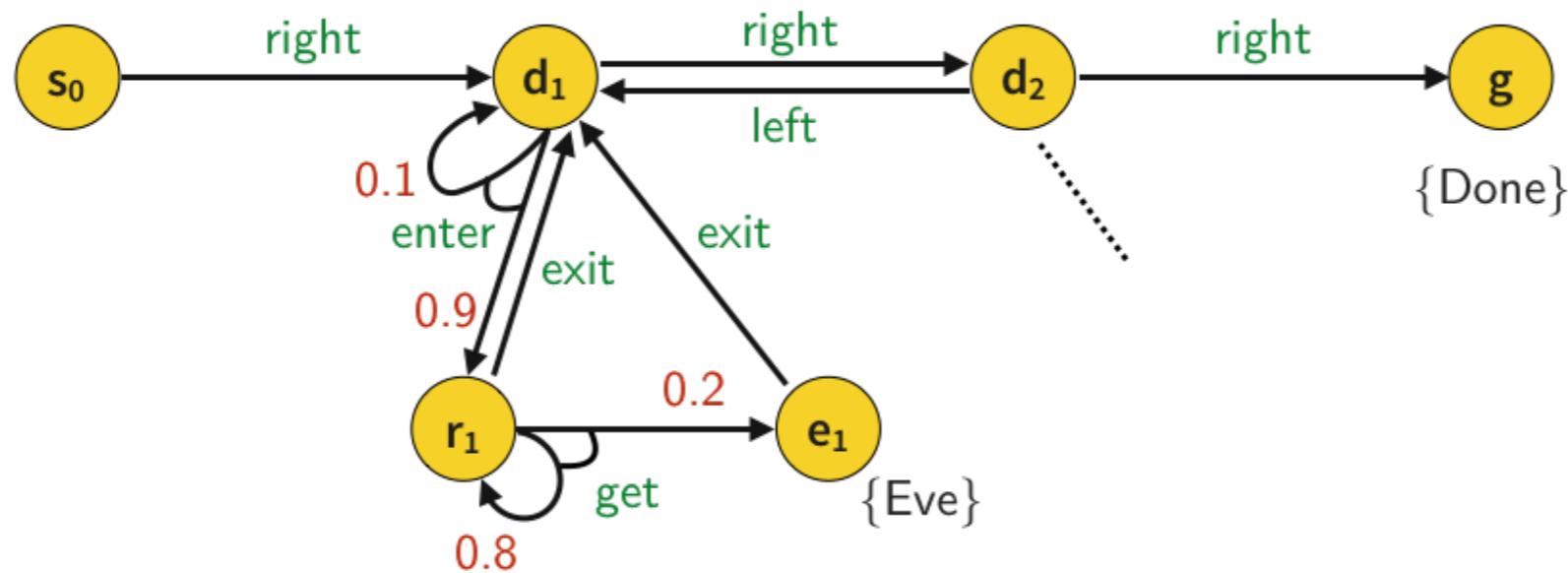


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Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

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$s_0$ : right     $s_0d_1$ : enter     $d_1r_1$ : get     $r_1e_1$ : exit  
 $d_1d_1$ : enter     $r_1r_1$ : get

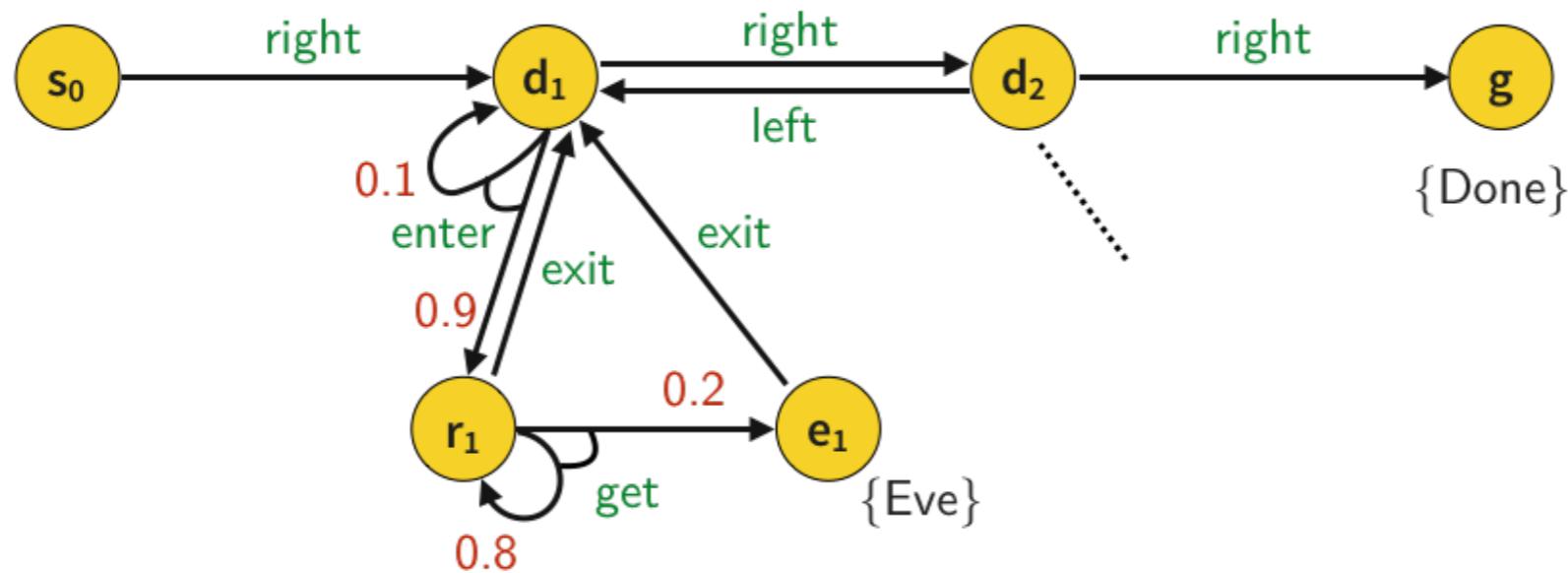


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Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

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$s_0$ : right     $s_0d_1$ : enter     $d_1r_1$ : get     $r_1e_1$ : exit     $e_1d_1$ : right  
 $d_1d_1$ : enter     $r_1r_1$ : get

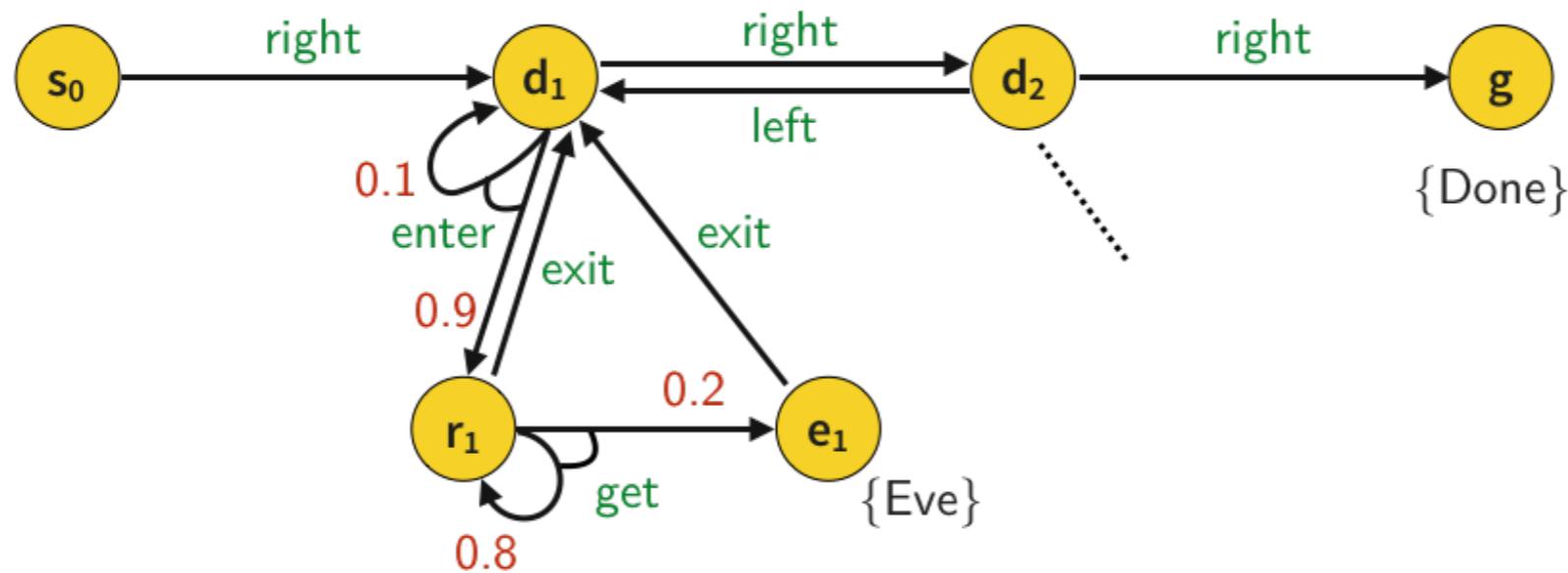


# Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case F: Finite history-dependent policy

$s_0: \text{right}$	$s_0d_1: \text{enter}$	$d_1r_1: \text{get}$	$r_1e_1: \text{exit}$	$e_1d_1: \text{right}$	✓ eventually Eve
$d_1d_1: \text{enter}$		$r_1r_1: \text{get}$			✓ eventually Done



# Policies - History Dependence and Randomization

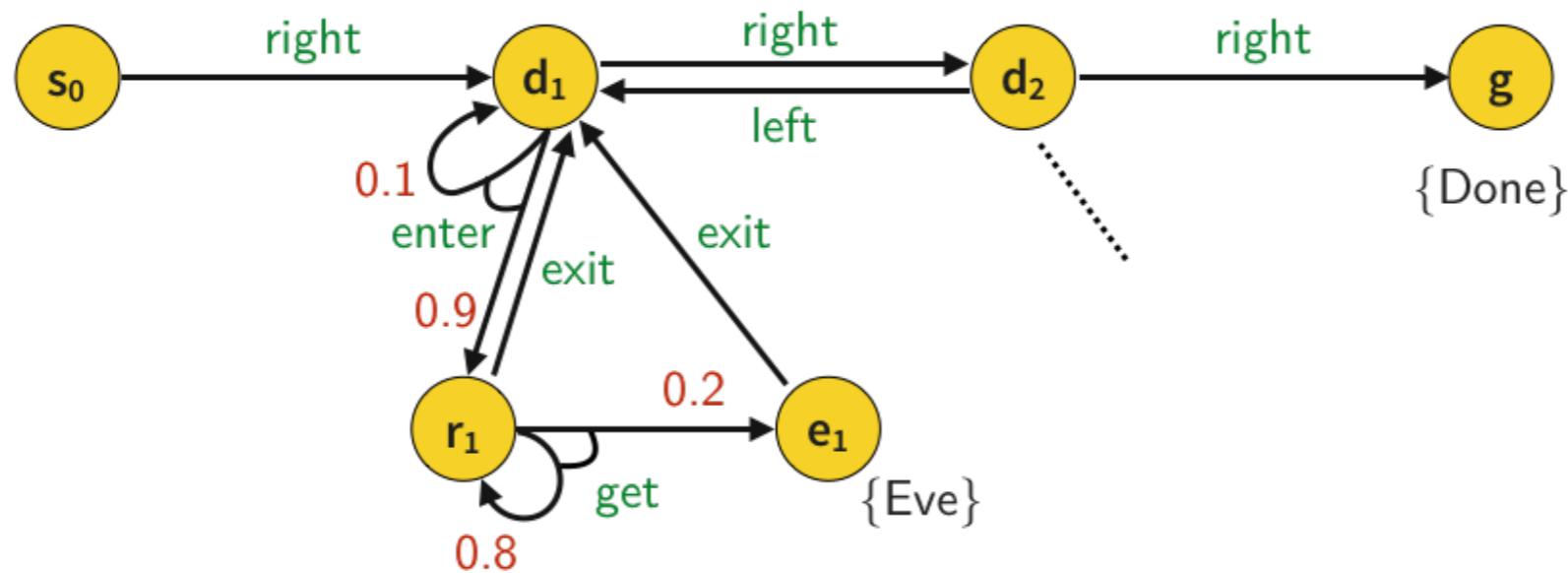
Target property:  $s_0 \models P_{>0} F (Eve \wedge F \text{ Done})$

## Case F: Finite history-dependent policy

$s_0: \text{right}$	$s_0 d_1: \text{enter}$	$d_1 r_1: \text{get}$	$r_1 e_1: \text{exit}$	$e_1 d_1: \text{right}$	✓ eventually Eve
	$d_1 d_1: \text{enter}$	$r_1 r_1: \text{get}$			✓ eventually Done

## Our approach

A priori finitely bounded history length - decidable (our main result)



# Policies - History Dependence and Randomization

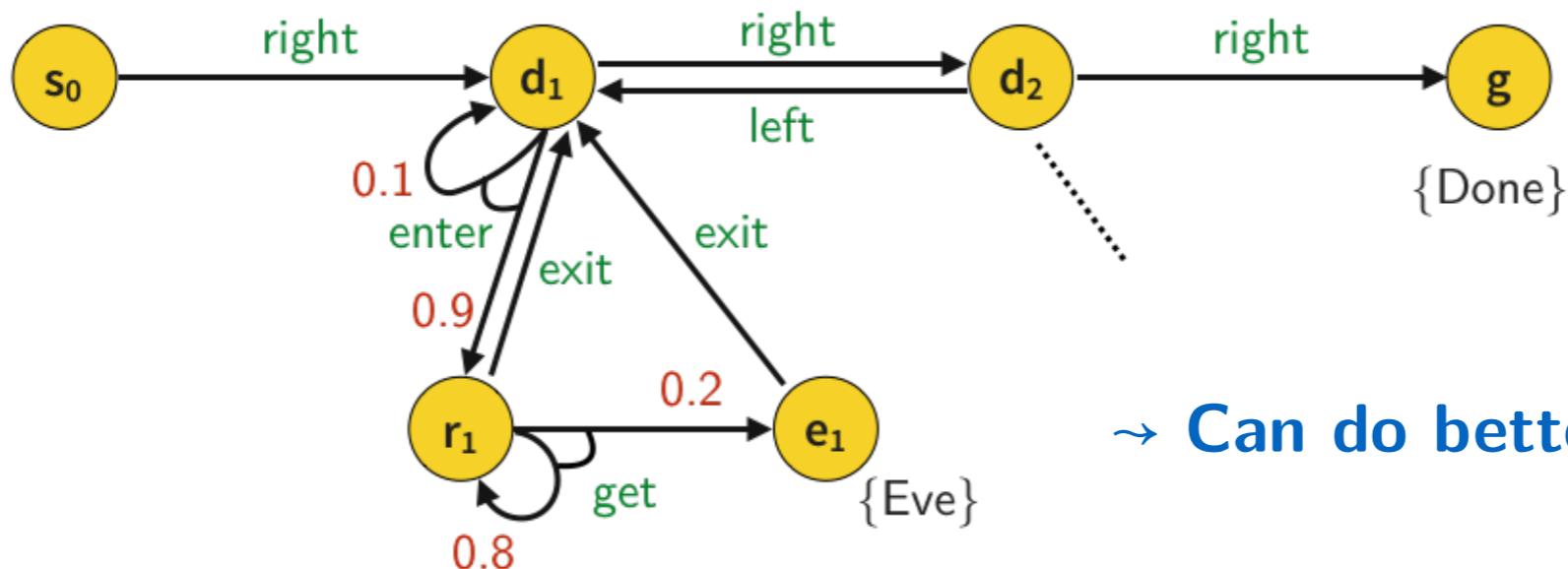
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$s_0: \text{right}$	$s_0d_1: \text{enter}$	$d_1r_1: \text{get}$	$r_1e_1: \text{exit}$	$e_1d_1: \text{right}$	✓ eventually Eve
$d_1d_1: \text{enter}$		$r_1r_1: \text{get}$			✓ eventually Done

## Our approach

A priori finitely bounded history length - decidable (our main result)

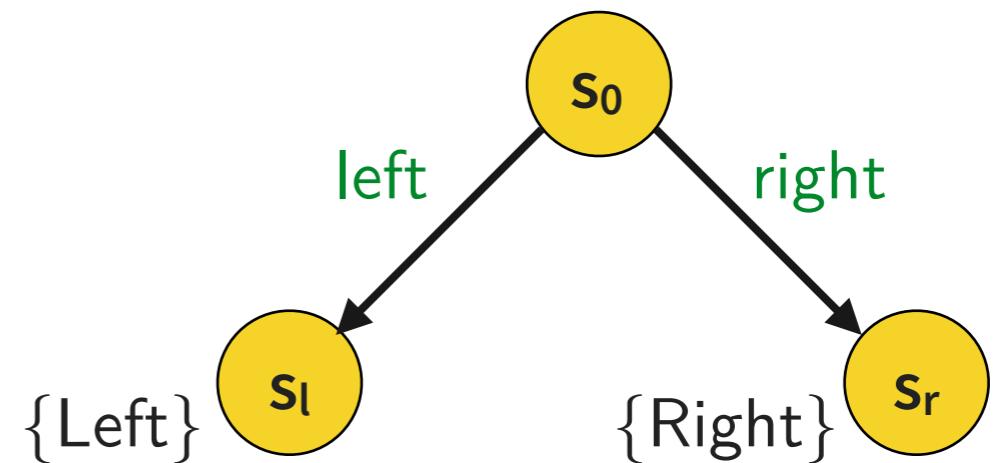


→ Can do better (more expressive)

# Policies - History Dependence and Randomization

Target property:  $\mathbf{P}_{>0} \mathbf{F} \text{ Left} \wedge \mathbf{P}_{>0} \mathbf{F} \text{ Right}$

**Case D: Deterministic policy**



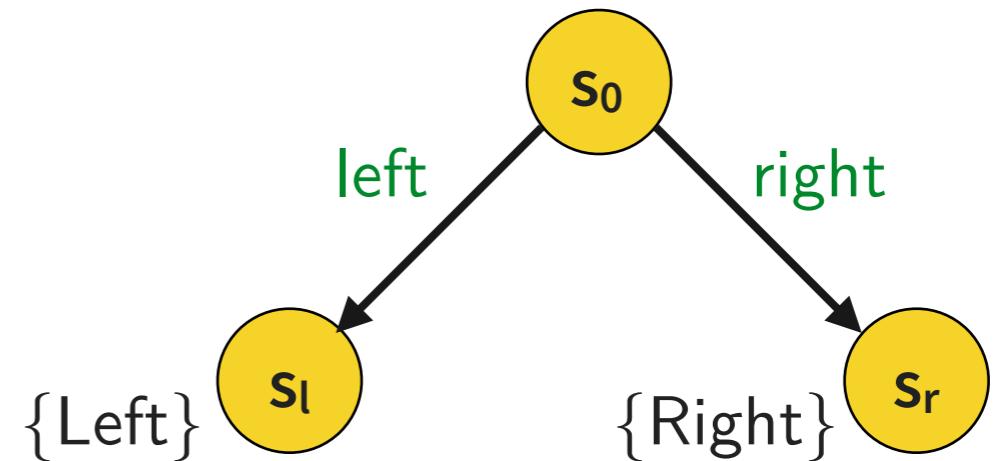
# Policies - History Dependence and Randomization

Target property:  $\mathbf{P}_{>0} \mathbf{F} \text{ Left} \wedge \mathbf{P}_{>0} \mathbf{F} \text{ Right}$

## Case D: Deterministic policy

Attempt 1

- |              |  |
|--------------|--|
| $s_0$ : left | <span style="color: green;">✓</span> $\mathbf{P}_{>0} \mathbf{F} \text{ Left}$ |
|              | <span style="color: red;">✗</span> $\mathbf{P}_{>0} \mathbf{F} \text{ Right}$  |



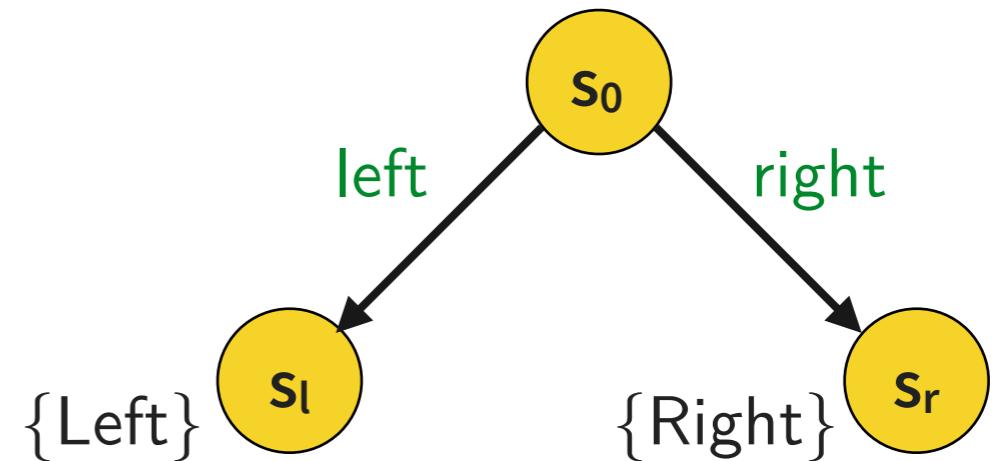
# Policies - History Dependence and Randomization

Target property:  $P_{>0} F \text{ Left} \wedge P_{>0} F \text{ Right}$

## Case D: Deterministic policy

Attempt 1

$s_0: \text{left}$       ✓  $P_{>0} F \text{ Left}$   
                        ✗  $P_{>0} F \text{ Right}$



Attempt 2

$s_0: \text{right}$       ✗  $P_{>0} F \text{ Left}$   
                        ✓  $P_{>0} F \text{ Right}$

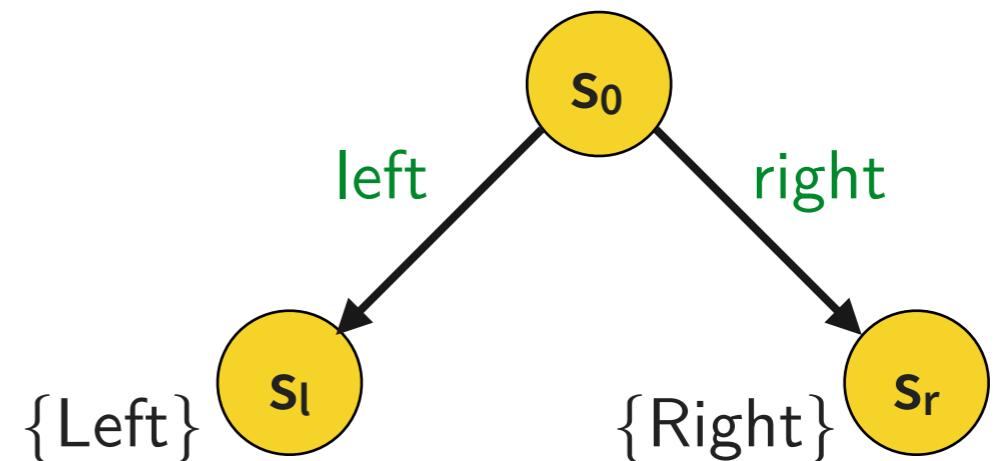
# Policies - History Dependence and Randomization

Target property:  $P_{>0} F \text{ Left} \wedge P_{>0} F \text{ Right}$

## Case D: Deterministic policy

Attempt 1

$s_0: \text{left}$     ✓  $P_{>0} F \text{ Left}$   
                ✗  $P_{>0} F \text{ Right}$



Attempt 2

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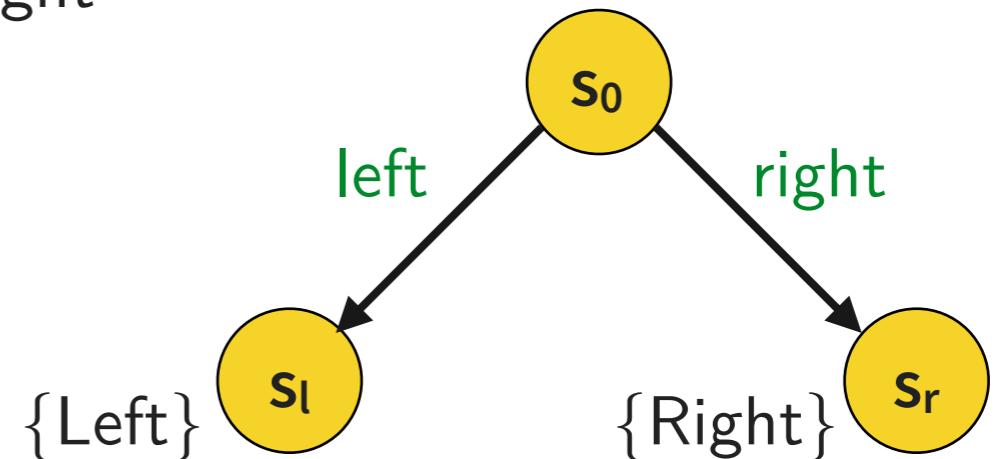
→ Fix: randomized policies

# Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F \text{ Left} \wedge P_{>0} F \text{ Right}$

## Case R: Randomized policy

$\sigma$  is a **probability distribution** over actions  
for each state (history/state)



*"In 6 out of 10 experiments chose left"*

$s_0$ : [left  $\rightarrow$  0.6, right  $\rightarrow$  0.4]

✓  $P_{>0} F \text{ Left}$

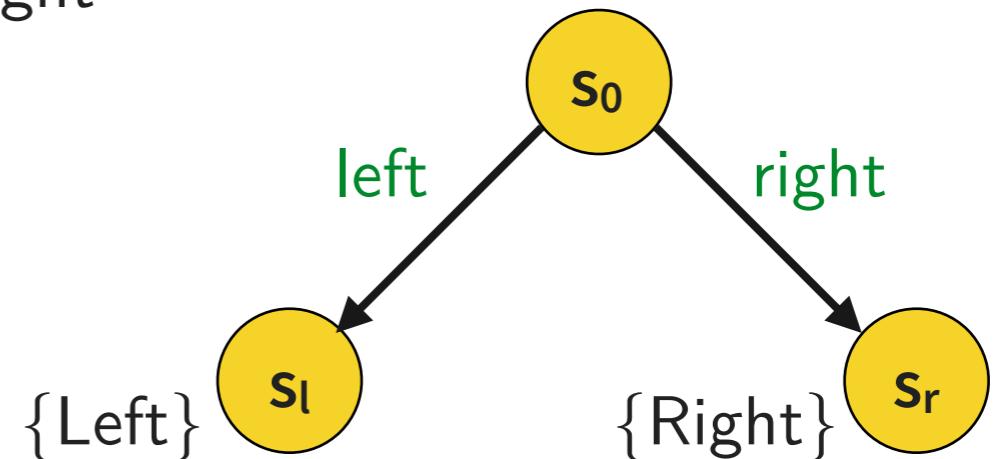
✓  $P_{>0} F \text{ Right}$

# Policies - History Dependence and Randomization

Target property:  $s_0 \models P_{>0} F \text{ Left} \wedge P_{>0} F \text{ Right}$

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$s_0$ : [left  $\rightarrow$  0.6, right  $\rightarrow$  0.4]

✓  $P_{>0} F \text{ Left}$

✓  $P_{>0} F \text{ Right}$

→ Identified target policies: FR

Look at policy synthesis in more detail

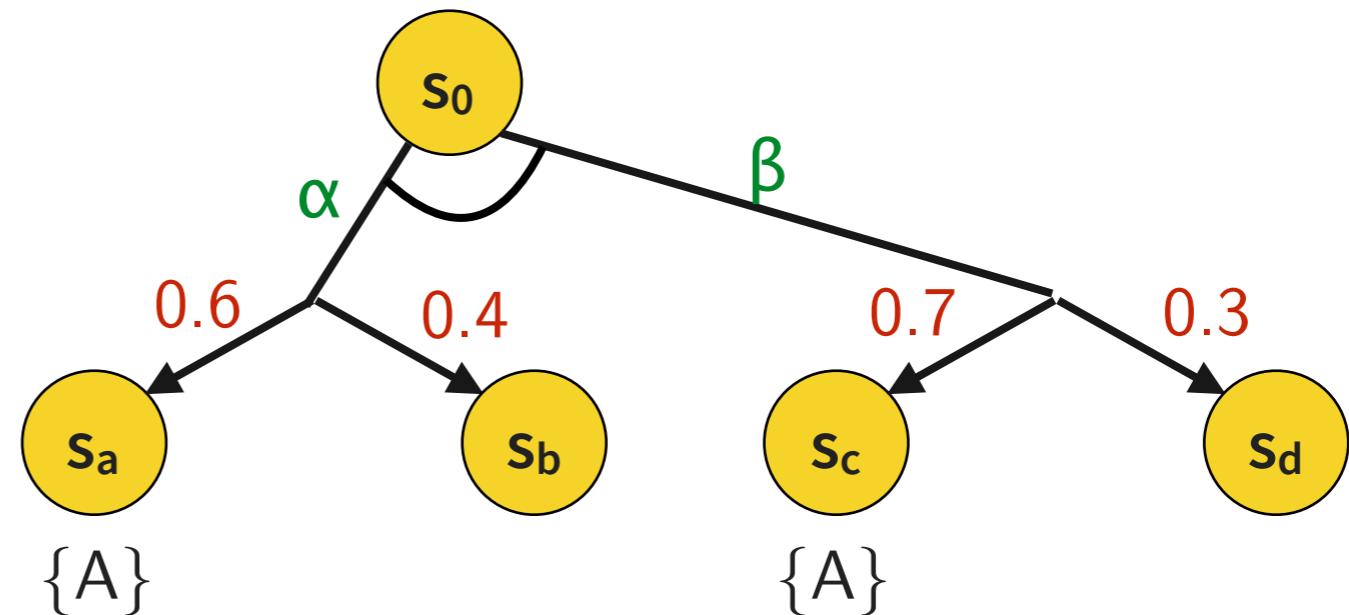
## Probabilities of Paths Again: Randomized case

Policy  $\sigma$

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

Evaluation

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



The probability of all paths from  $s_0$  satisfying  $\mathbf{F} A$  is  $> 0.6$

## Probabilities of Paths Again: Randomized case

Policy  $\sigma$

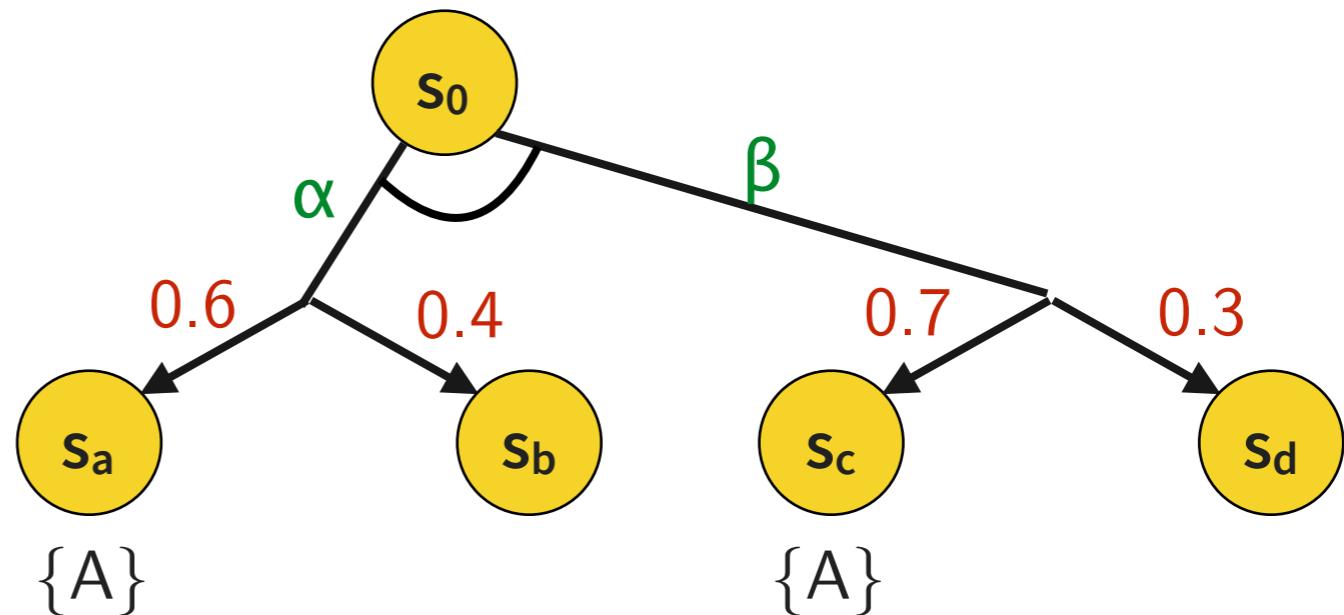
$s_0$ : [ $\alpha \rightarrow 0.6$ ,  $\beta \rightarrow 0.4$ ]

Evaluation

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

iff

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



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

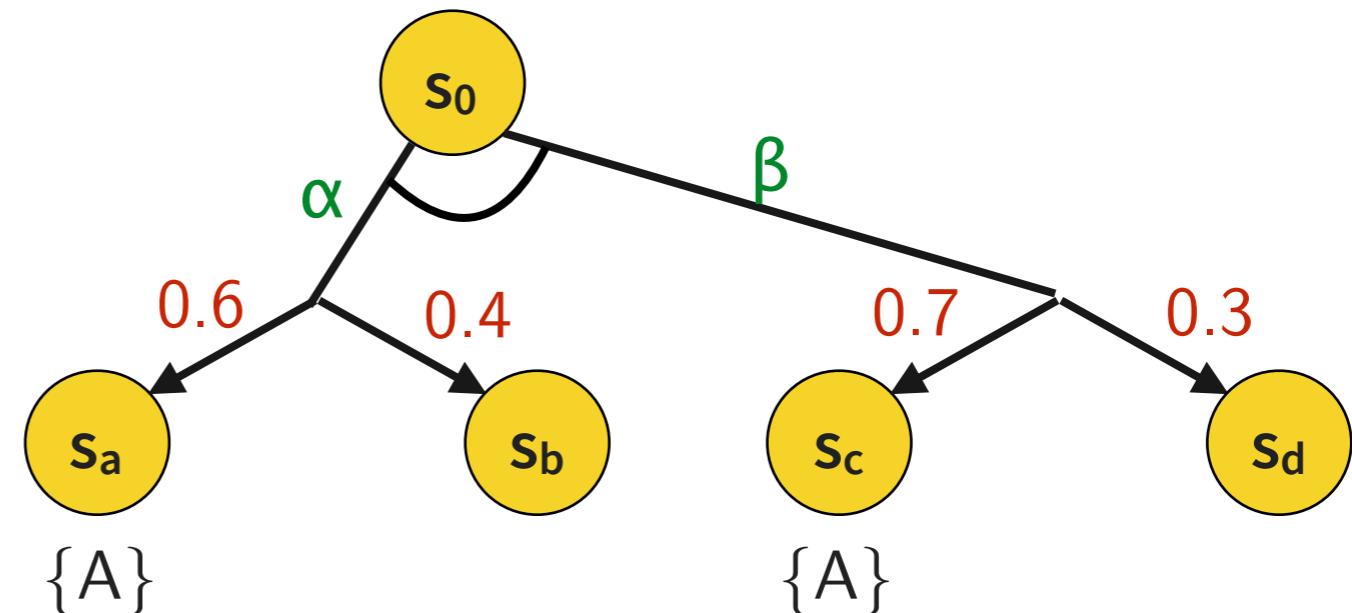
## Probabilities of Paths Again: Randomized case

Policy  $\sigma$

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

Evaluation

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



The probability of all paths from  $s_0$  satisfying  $\mathbf{F} A$  is  $> 0.6$

iff

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Non-probabilistic CTL/LTL/CTL\*  
 $\sigma$ -path: non-0 probability actions

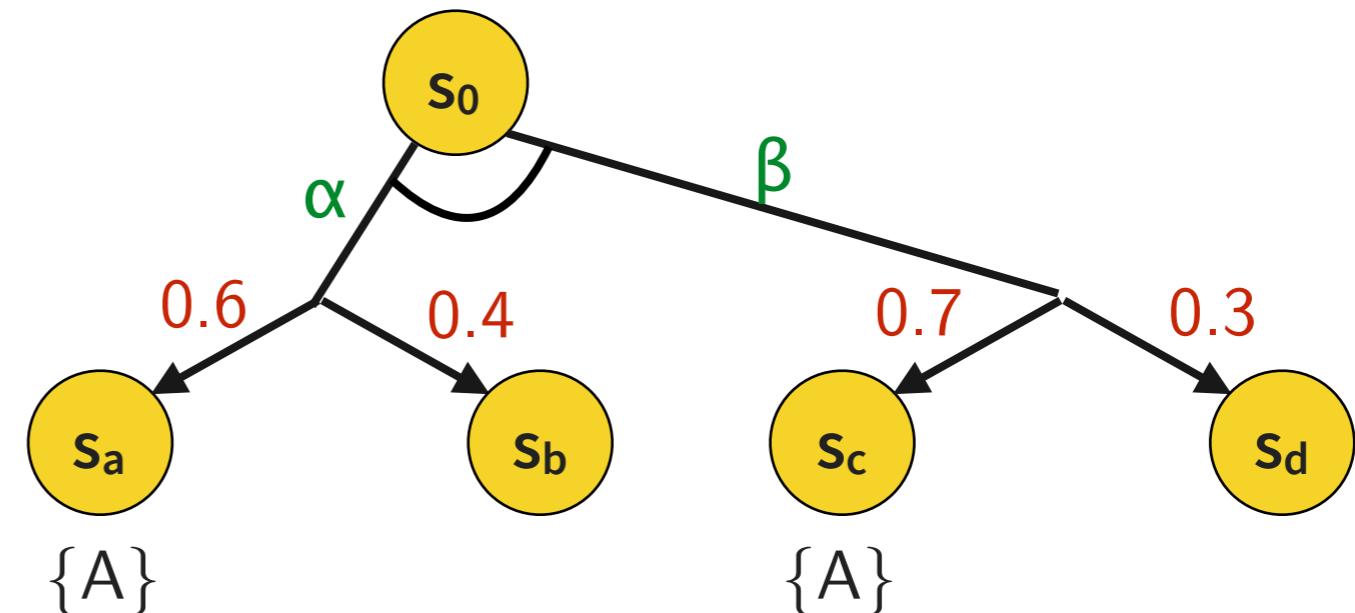
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iff

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

Non-probabilistic CTL/LTL/CTL\*  
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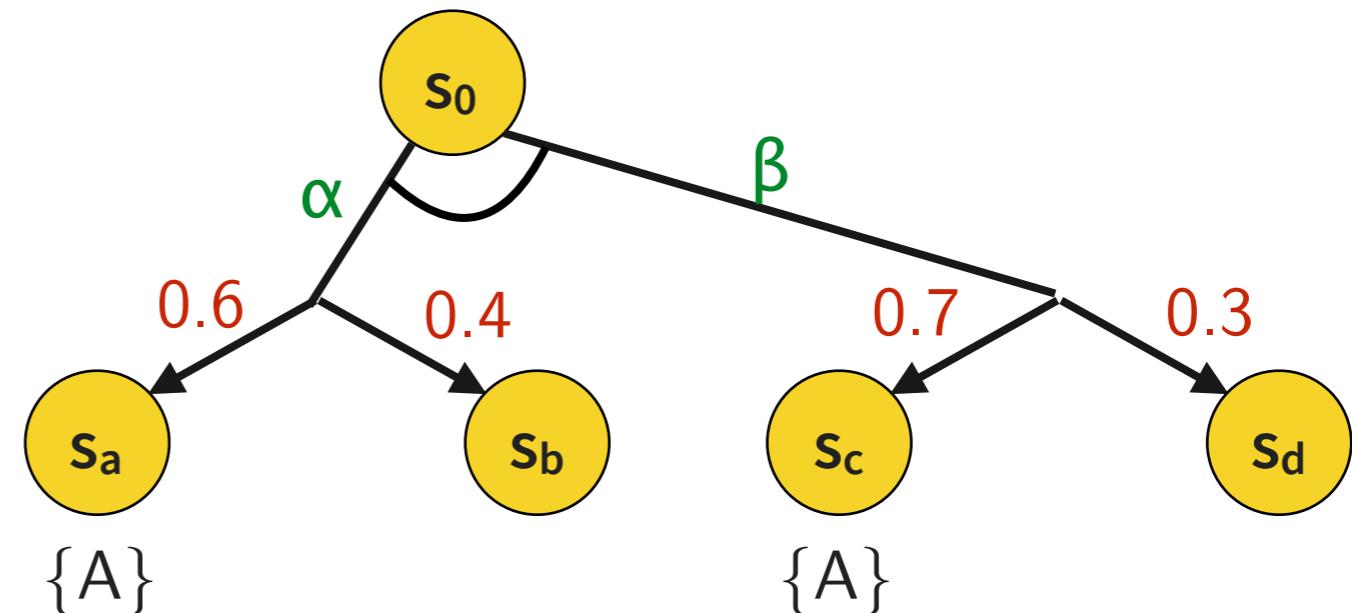
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Evaluation

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



The probability of all paths from  $s_0$  satisfying  $\mathbf{F} A$  is  $> 0.6$

iff

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iff

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

iff

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

Non-probabilistic CTL/LTL/CTL\*  
 $\sigma$ -path: non-0 probability actions

## Probabilities of Paths Again: Randomized case

Policy  $\sigma$

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Evaluation

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

The probability of all paths from  $s_0$  satisfying  $\mathbf{F} A$  is  $> 0.6$

iff

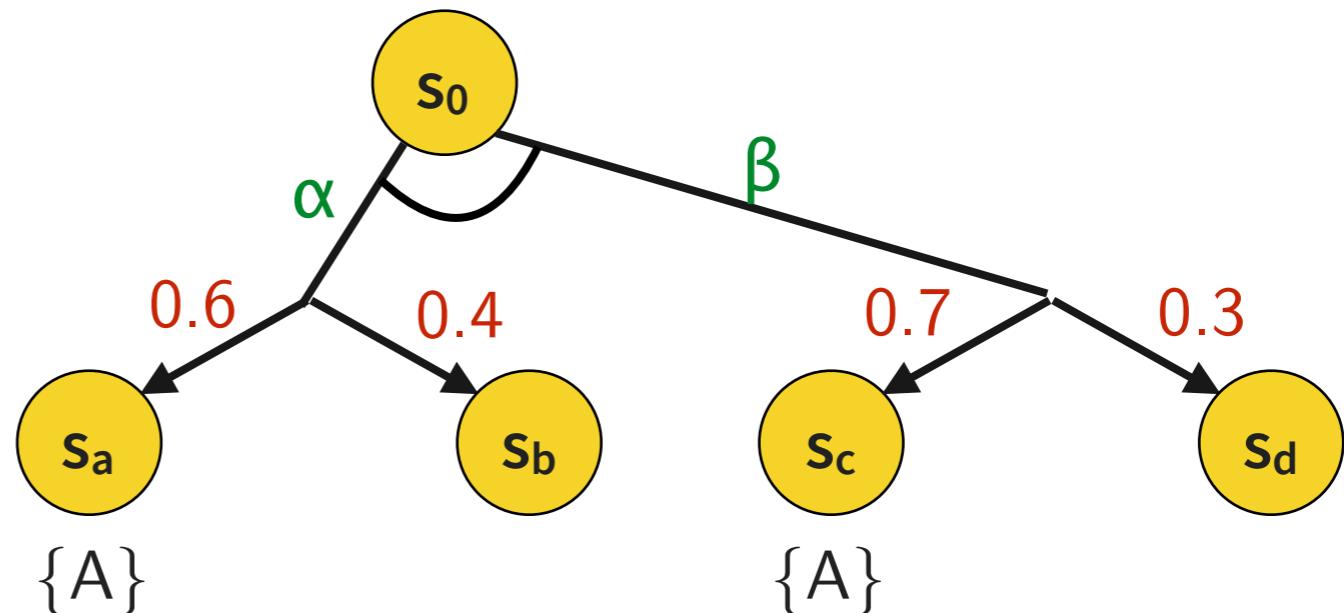
$\Pr\{p \mid p \text{ is a } \sigma\text{-path from } s_0 \text{ and } p \models \mathbf{F} A\} > 0.6$

iff

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

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



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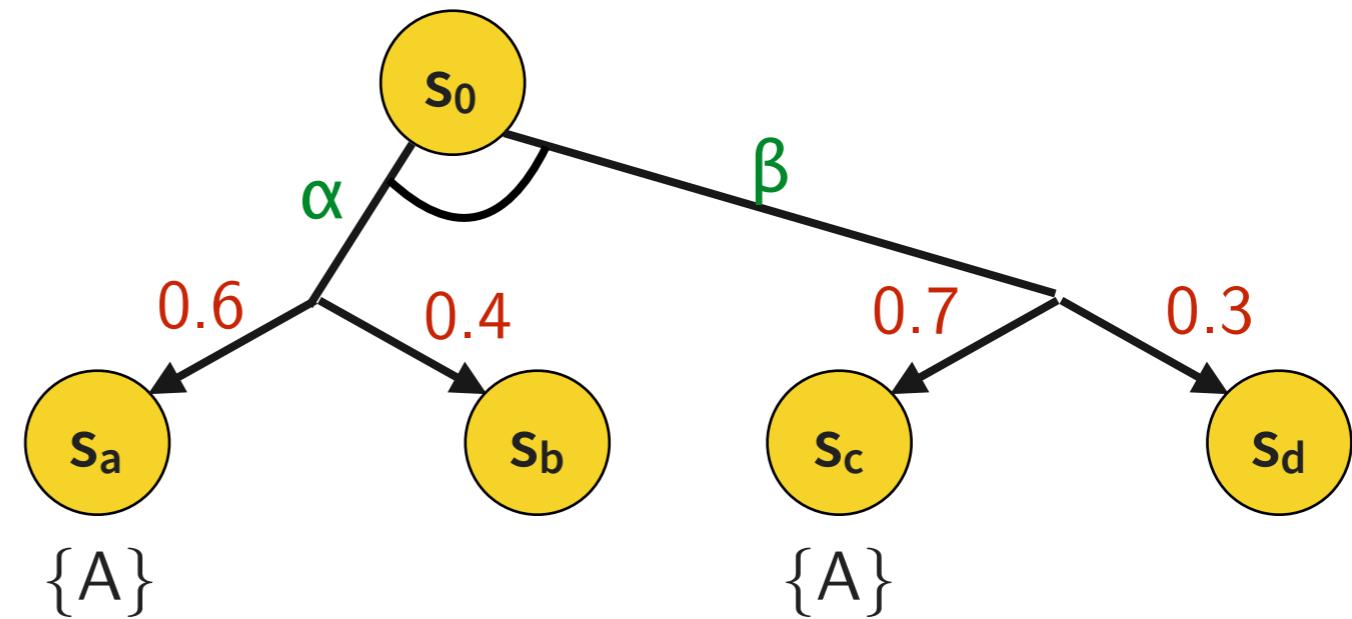
→ Synthesis: quantify over action probabilities

# Policy Synthesis

Policy  $\sigma$  ?

Synthesis

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



*The probability of all paths from  $s_0$  satisfying  $\mathbf{F} A$  is  $> 0.6$*

# Policy Synthesis

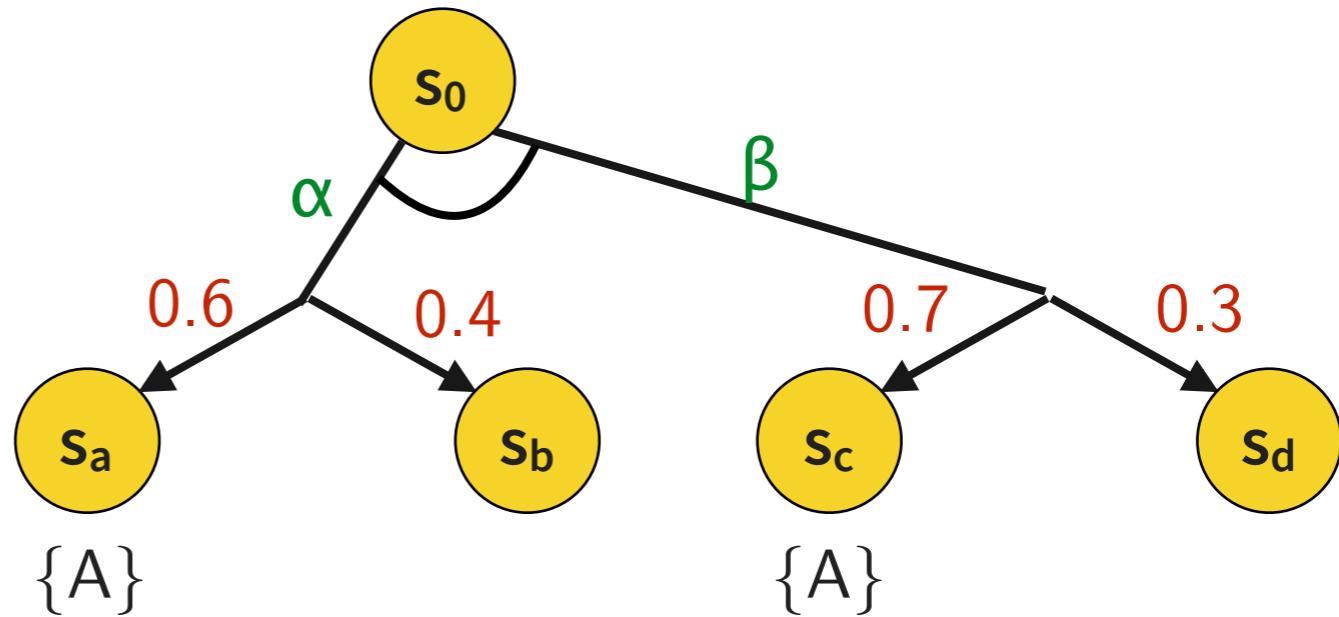
Policy  $\sigma$  ?

Synthesis

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

iff

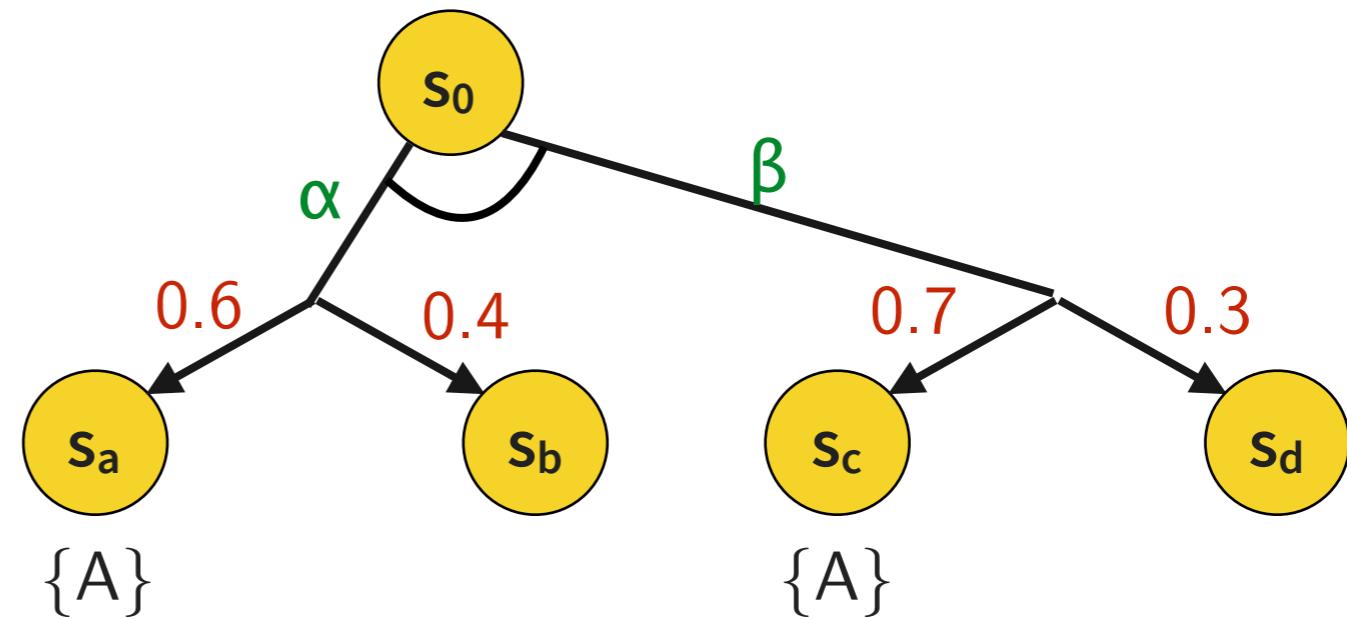
$$\Pr\{p \mid p \text{ is a } \sigma\text{-path from } s_0 \text{ and } p \models \mathbf{F} A\} > 0.6$$



The probability of all paths from  $s_0$  satisfying  $\mathbf{F} A$  is  $> 0.6$

# Policy Synthesis

Policy  $\sigma$  ?



Synthesis

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

The probability of all paths from  $s_0$  satisfying  $\mathbf{F} A$  is  $> 0.6$

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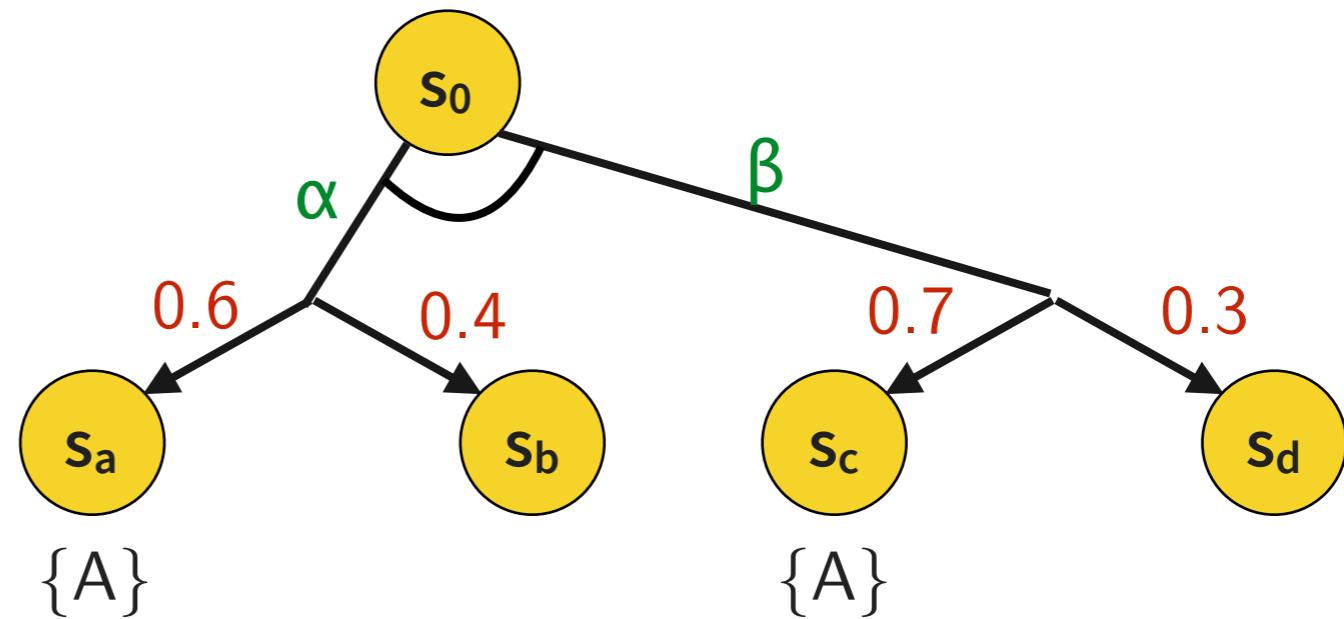
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Policy  $\sigma$  ?



Synthesis

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

The probability of all paths from  $s_0$  satisfying  $\mathbf{F} A$  is  $> 0.6$

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

iff

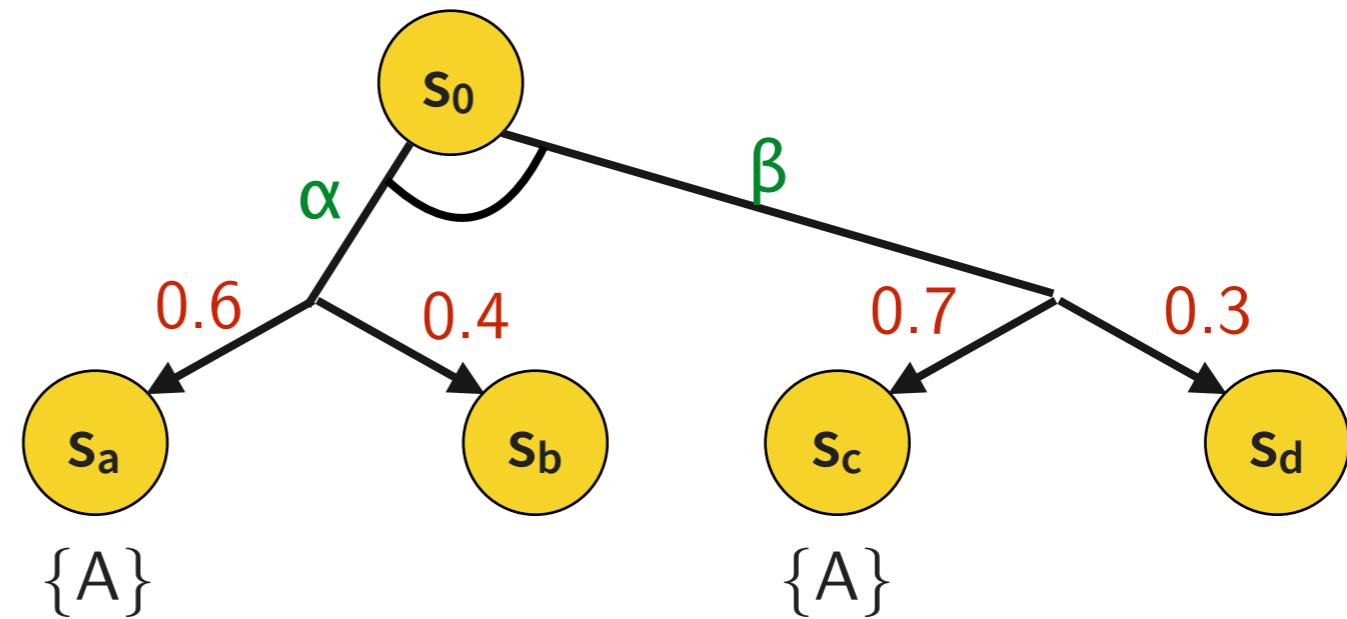
$$\Pr\{s_0s_a, s_0s_c\} > 0.6$$

iff

$$x(s_0, \alpha) \cdot 0.6 + x(s_0, \beta) \cdot 0.7 > 0.6 \text{ and}$$

# Policy Synthesis

Policy  $\sigma$  ?



Synthesis

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

The probability of all paths from  $s_0$  satisfying  $\mathbf{F} A$  is  $> 0.6$

iff

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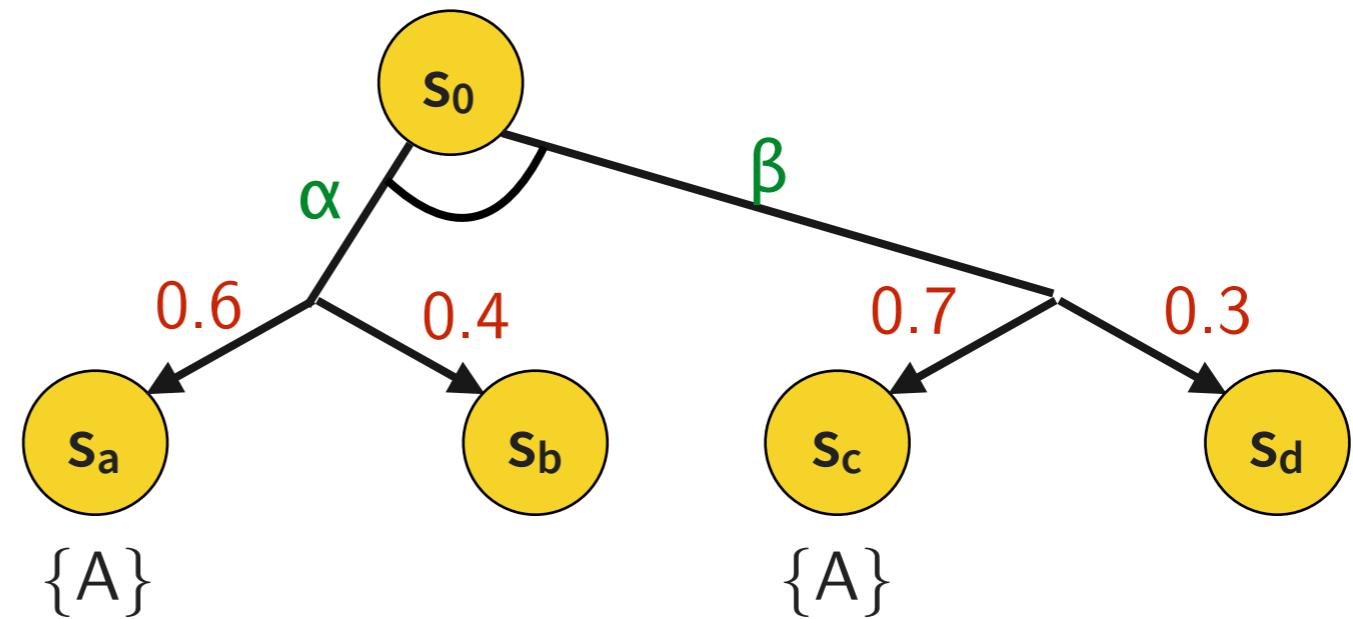
iff

$$x(s_0, \alpha) \cdot 0.6 + x(s_0, \beta) \cdot 0.7 > 0.6 \text{ and}$$

$$x(s_0, \alpha) + x(s_0, \beta) = 1 \text{ and } x(s_0, \alpha) > 0 \text{ and } x(s_0, \beta) > 0$$

# Policy Synthesis

Policy  $\sigma$  ?



Synthesis

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

*The probability of all paths from  $s_0$  satisfying  $\mathbf{F} A$  is  $> 0.6$*

iff

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

iff

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

iff

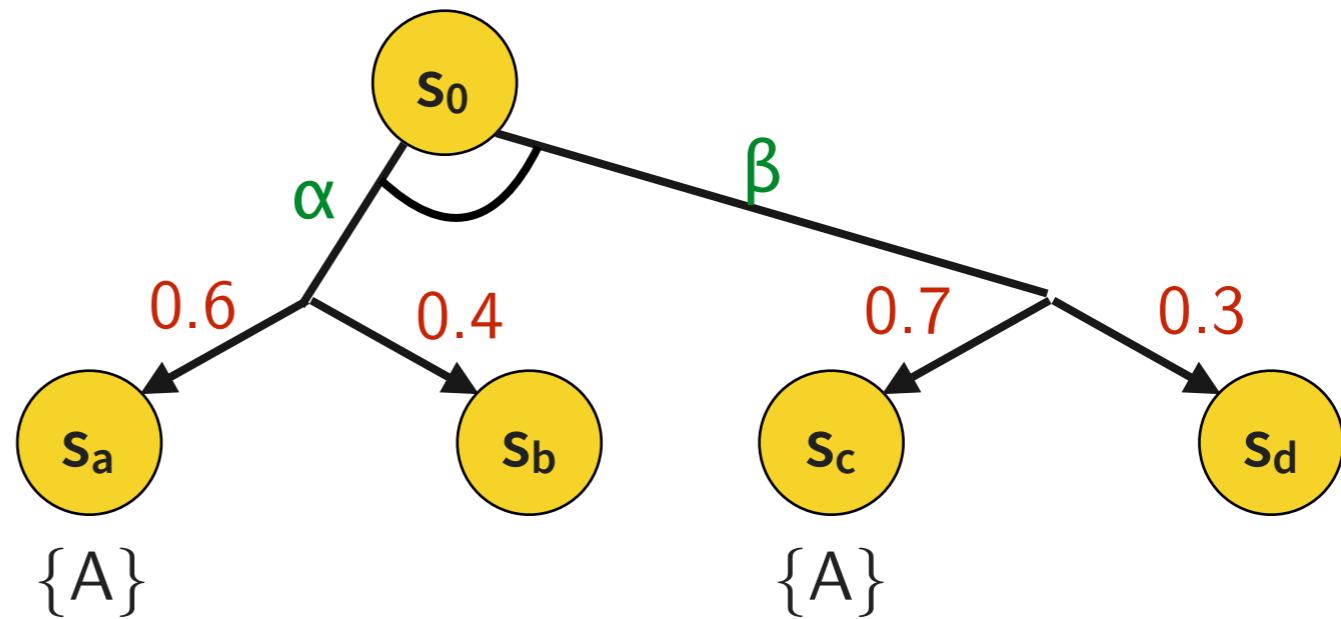
$$x(s_0, \alpha) \cdot 0.6 + x(s_0, \beta) \cdot 0.7 > 0.6 \text{ and}$$

Prescribed actions, define  $\sigma$ -paths

$$x(s_0, \alpha) + x(s_0, \beta) = 1 \text{ and } x(s_0, \alpha) > 0 \text{ and } x(s_0, \beta) > 0$$

# Policy Synthesis

Policy  $\sigma$  ?



Synthesis

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

*The probability of all paths from  $s_0$  satisfying  $\mathbf{F} A$  is  $> 0.6$*

iff

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

iff

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

→ Tableau calculus deriving a set of (in)equations whose solutions, if any, provide a policy

iff

$$x(s_0, \alpha) \cdot 0.6 + x(s_0, \beta) \cdot 0.7 > 0.6 \text{ and}$$

Prescribed actions, define  $\sigma$ -paths

$$x(s_0, \alpha) + x(s_0, \beta) = 1 \text{ and } x(s_0, \alpha) > 0 \text{ and } x(s_0, \beta) > 0$$



# Tableau Calculus

Previous slides: basic notions, intuition, trivial examples

Now: the general case, tableau calculus

## Issues

- Fix a class of **target policies**: FR-policies (done)
- Fix a **logic** for target specifications: PCTL\*
- **Tableau calculus**: complications
  - “Loop check” to prune infinite paths (aka “runs”)
  - Special treatment of bottom strongly connected component (BSCCs)
- **Soundness and completeness proof** (see paper)

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  - **Soundness and completeness proof** (see paper)
- **PCTL\*, Tableau calculus**

## PCTL\*

PCTL\* is like CTL\*, but E path quantifier replaced by P

$$\phi := A \mid \phi \wedge \phi \mid \neg\phi \mid P_{\sim z} \psi \quad \text{State formula}$$

$$\psi := \phi \mid \psi \wedge \psi \mid \neg\psi \mid X \psi \mid \psi U \psi \quad \text{Path formula}$$

where  $\sim \in \{ <, \leq, >, \geq \}$  and  $z \in [0..1]$

Sub-languages “probabilistic LTL” and “PCTL” obtained analogously

$$P_{\geq 0.8} G ((T > 30^\circ) \rightarrow P_{\geq 0.5} F G (T < 24^\circ))$$

*With probability at least 0.8, whenever the temperature exceeds 30°  
it will eventually stay below 24° with probability at least 0.5*

## Semantics

Parametric in policy  $\sigma$

Like CTL\* but patched for P path quantifier

$$s \models P_{\sim z} \psi \text{ iff } \Pr\{r \mid r \text{ is a } \sigma\text{-run from } s \text{ and } r \models \psi\} \sim z$$

# Sequent Data Structure

The tableau inference rules manipulate sequents of the following form

$$\Gamma \vdash \langle m, s \rangle : \Psi$$

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Current policy state  $\langle history, current\ state \rangle$ , e.g.  $\langle \epsilon, s_0 \rangle$

$$\Psi = \{ \Psi_1, \dots, \Psi_n \}$$

A set of formulas, e.g.  $\{ P_{>0.9} F (Eve \wedge X P_{>0.8} F Done) \}$

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Stands for  $\{ r \mid r \text{ is a run from } \langle m, s \rangle \text{ and } r \models \Lambda \Psi \}$

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The tableau inference rules manipulate sequents of the following form

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Current policy state *⟨history, current state⟩*, e.g.  $\langle \epsilon, s_0 \rangle$

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A set of formulas, e.g.  $\{ P_{>0.9} F (\text{Eve} \wedge X P_{>0.8} F \text{ Done}) \}$

$$\langle m, s \rangle : \Psi$$

Stands for  $\{ r \mid r \text{ is a run from } \langle m, s \rangle \text{ and } r \models \Lambda \Psi \}$

$$\Gamma$$

“Program”: set of (non-linear) constraints on  $\langle m, s \rangle : \Psi$ , e.g.

$x_{\langle m, s \rangle} \Psi > 0.5$       *The probability of  $\langle m, s \rangle : \Psi$  is > 0.5*

# Sequent Data Structure

The tableau inference rules manipulate sequents of the following form

$$\Gamma \vdash \langle m, s \rangle : \Psi$$

$$\langle m, s \rangle$$

Current policy state *(history, current state)*, e.g.  $\langle \epsilon, s_0 \rangle$

$$\Psi = \{ \Psi_1, \dots, \Psi_n \}$$

A set of formulas, e.g.  $\{ P_{>0.9} F (\text{Eve} \wedge X P_{>0.8} F \text{ Done}) \}$

$$\langle m, s \rangle : \Psi$$

Stands for  $\{ r \mid r \text{ is a run from } \langle m, s \rangle \text{ and } r \models \Lambda \Psi \}$

$\Gamma \rightarrow$  Tableau: derive definitions  $x_{\langle m, s \rangle} \Psi \doteq \dots ?$

“Program”: set of (non-linear) constraints on  $\langle m, s \rangle : \Psi$ , e.g.

$x_{\langle m, s \rangle} \Psi > 0.5$       *The probability of  $\langle m, s \rangle : \Psi$  is > 0.5*

# Tableau Derivations

## Initialization

Given state formula  $\phi$ , e.g.  $P_{>0.9} F (Eve \wedge X P_{>0.8} F Done)$

Initial tableau with root node  $x_{\langle \epsilon, s_0 \rangle} \{\phi\} \doteq 1 \vdash \langle \epsilon, s_0 \rangle : \{\phi\}$

Obligation to derive a satisfiable  $\Gamma$  that specifies  $\sigma$  and value for  $x_{\langle \epsilon, s_0 \rangle} \{\phi\}$

## Inference rules invariant

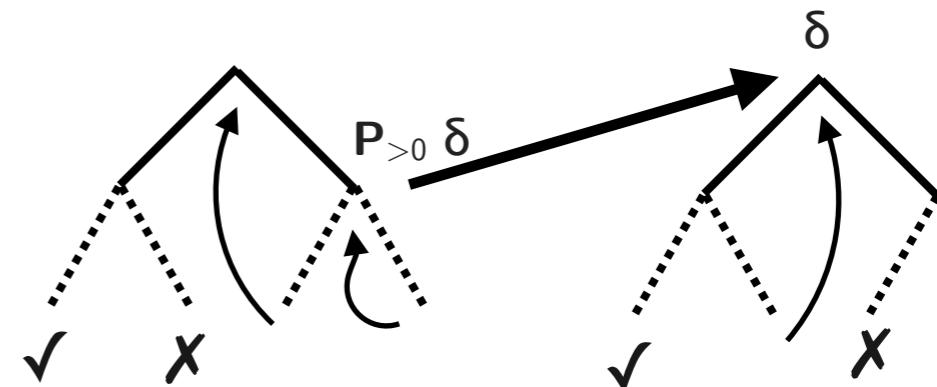
$$\frac{\Gamma \vdash \langle m, s \rangle : \Psi}{\Gamma, x_{\langle m, s \rangle} \Psi \doteq \dots \vdash \Psi'}$$

$\langle m, s \rangle : \Psi$  is eliminated by

adding to  $\Gamma$  an equation  $x_{\langle m, s \rangle} \Psi \doteq \dots$

for the probability of  $\langle m, s \rangle : \Psi$

## Derivation structure



Sub-derivations by nested  $P$ -formulas

Final  $\Gamma$  accumulated from sub-derivations

Solution of final  $\Gamma$  provides policy  $\sigma$

# Some Inference Rules

## Rules for classical formulas

$$\checkmark \quad \frac{\Gamma \vdash \langle m, s \rangle : \emptyset}{\Gamma, x_{\langle m, s \rangle}^{\emptyset} \doteq 1 \vdash \checkmark}$$

$$x \quad \frac{\Gamma \vdash \langle m, s \rangle : \{\psi\} \uplus \Psi}{\Gamma, x_{\langle m, s \rangle}^{\{\psi\} \uplus \Psi} \doteq 0 \vdash x} \quad \begin{cases} \text{if } \psi \text{ is clas-} \\ \text{sical and} \\ L(s) \not\models \psi \end{cases}$$

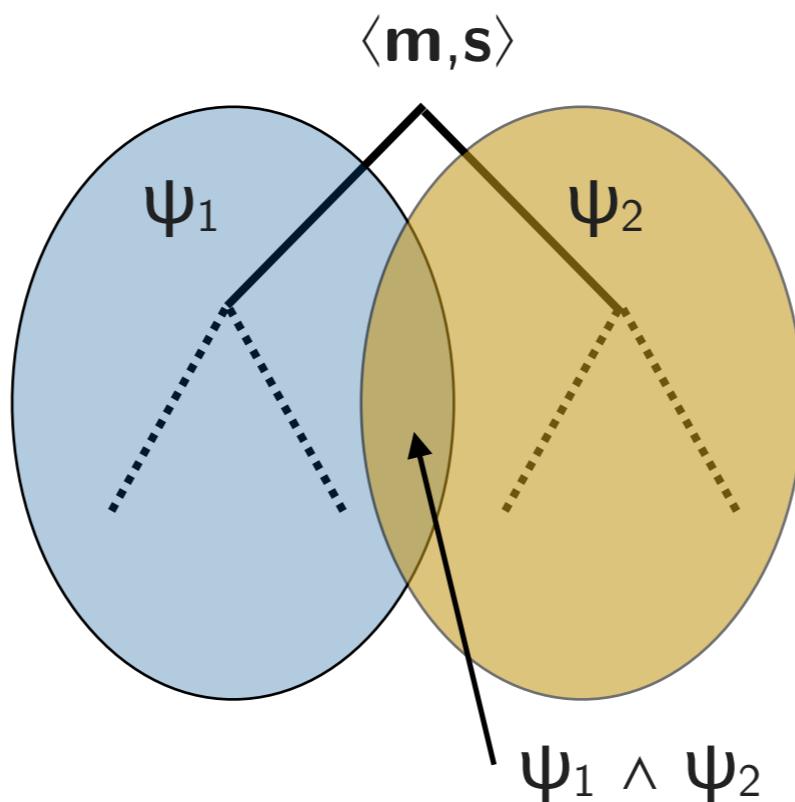
$$\top \quad \frac{\Gamma \vdash \langle m, s \rangle : \{\psi\} \uplus \Psi}{\Gamma, \gamma_{\text{one}} \vdash \langle m, s \rangle : \Psi} \quad \begin{cases} \text{if } \psi \text{ is clas-} \\ \text{sical and} \\ L(s) \models \psi \end{cases}$$

# Some Inference Rules

## Rules for conjunctions (1)

$$\wedge \quad \frac{\Gamma \vdash \langle m, s \rangle : \{\psi_1 \wedge \psi_2\} \uplus \Psi}{\Gamma, \gamma_{\text{one}} \vdash \langle m, s \rangle : \{\psi_1, \psi_2\} \cup \Psi}$$

$\langle m, s \rangle : \psi_1 \wedge \psi_2$  is intersection of  $\langle m, s \rangle : \psi_1$  and  $\langle m, s \rangle : \psi_2$



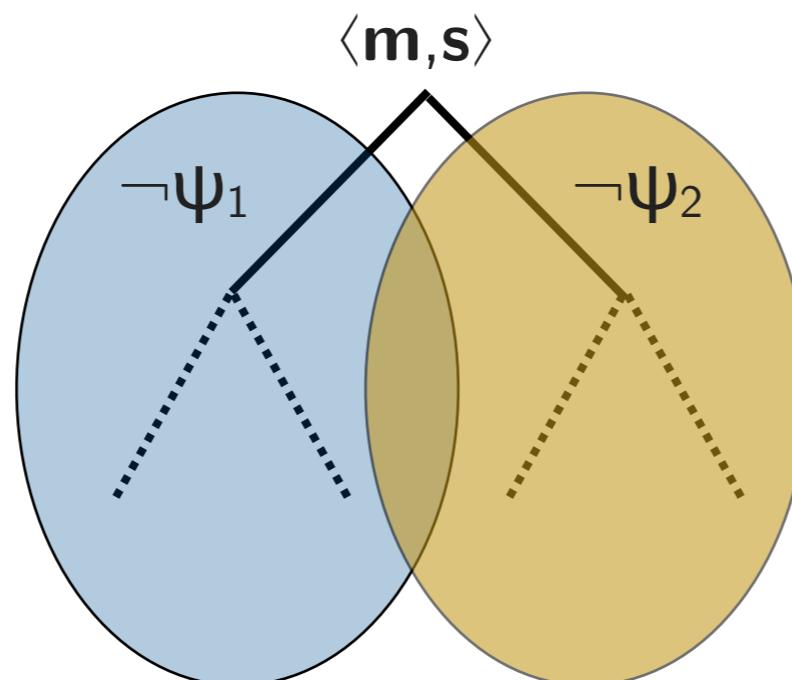
# Some Inference Rules

## Rules for conjunctions (2) (disjunctions, really)

$$\neg\wedge \frac{\Gamma \vdash \langle m, s \rangle : \{\neg(\psi_1 \wedge \psi_2)\} \uplus \Psi}{\Gamma \vdash \langle m, s \rangle : \{\neg\psi_1\} \cup \Psi \quad \cup \quad \Gamma, \gamma \vdash \langle m, s \rangle : \{\psi_1, \neg\psi_2\} \cup \Psi}$$

$$\text{where } \gamma = x_{\langle m, s \rangle}^{\{\neg(\psi_1 \wedge \psi_2)\} \uplus \Psi} \doteq x_{\langle m, s \rangle}^{\{\neg\psi_1\} \cup \Psi} + x_{\langle m, s \rangle}^{\{\psi_1, \neg\psi_2\} \cup \Psi}$$

Branching on disjoint union  $\neg(\psi_1 \wedge \psi_2) \equiv \neg\psi_1 \vee \neg\psi_2 \equiv \neg\psi_1 \vee (\psi_1 \wedge \neg\psi_2)$



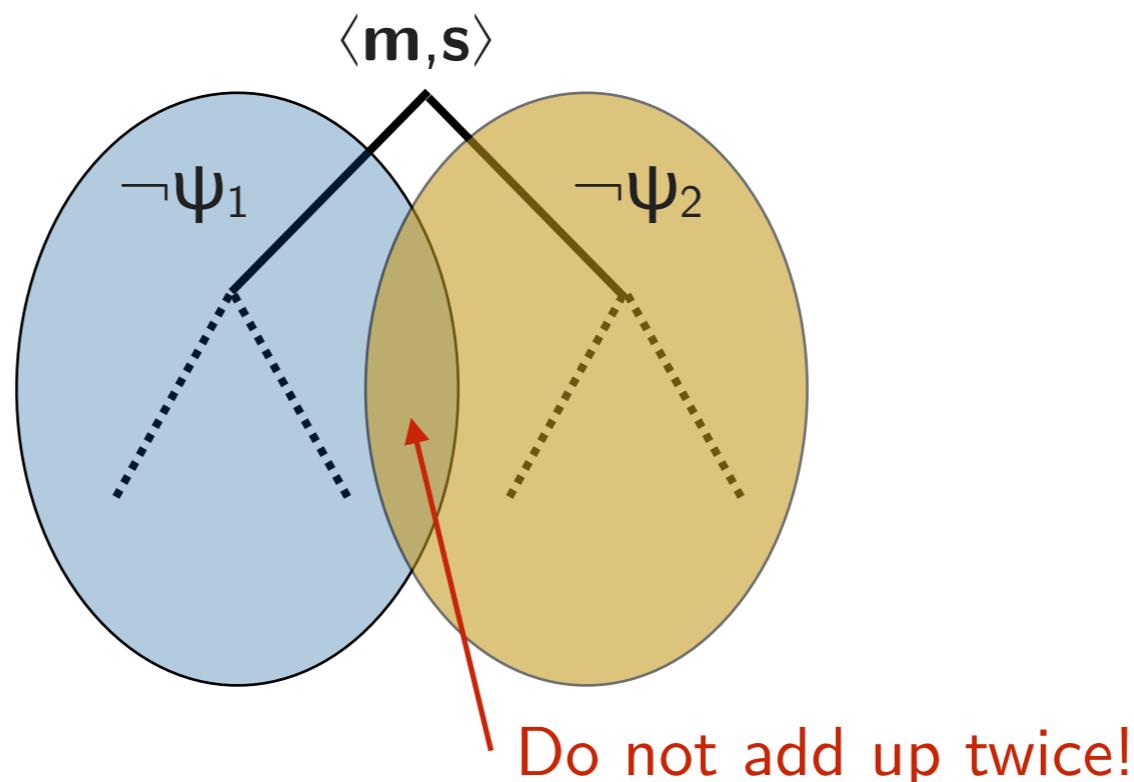
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# Some Inference Rules

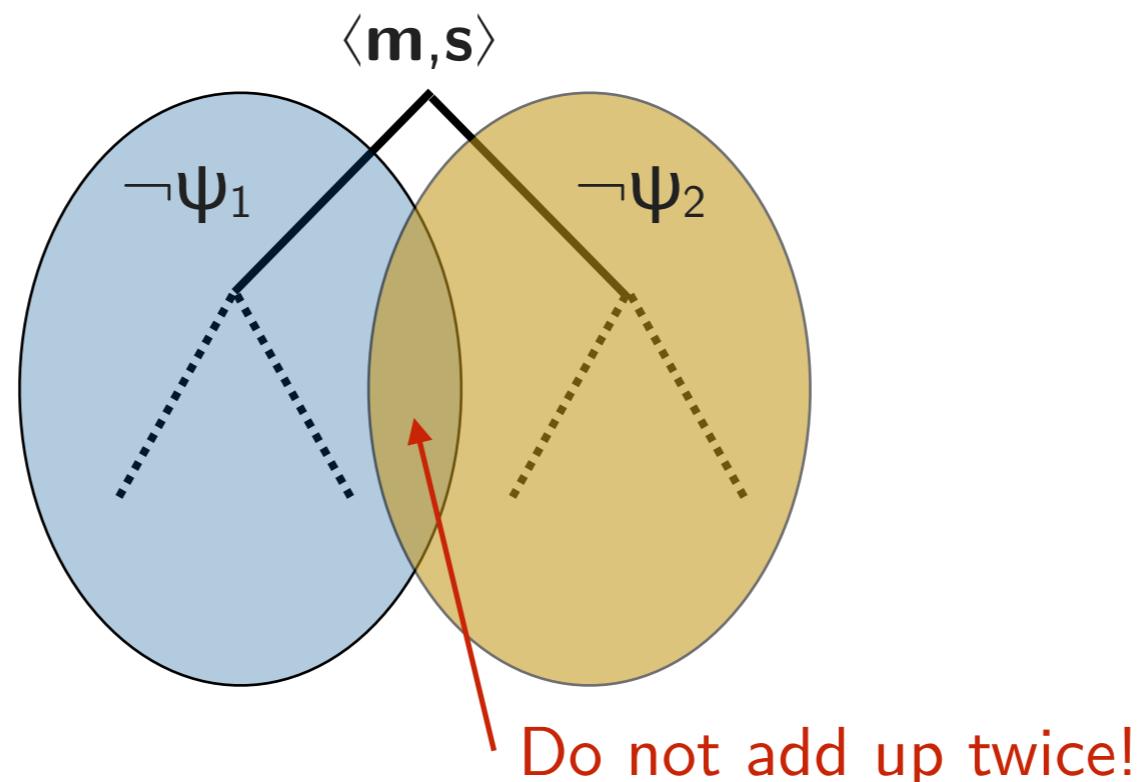
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where  $\gamma = x_{\langle m, s \rangle}^{\{\neg(\psi_1 \wedge \psi_2)\} \uplus \Psi} \doteq x_{\langle m, s \rangle}^{\{\neg\psi_1\} \cup \Psi} + x_{\langle m, s \rangle}^{\{\psi_1, \neg\psi_2\} \cup \Psi}$

**Need both branches**

Branching on disjoint union  $\neg(\psi_1 \wedge \psi_2) \equiv \neg\psi_1 \vee \neg\psi_2 \equiv \neg\psi_1 \vee (\psi_1 \wedge \neg\psi_2)$



# Some Inference Rules

## Rules for P-formulas

Similar to classical state formula, but ...

$$\mathbf{P} \frac{\Gamma \vdash \langle m, s \rangle : \{ P_{\sim z} \Psi \} \uplus \Psi}{\text{"}\langle m, s \rangle \models P_{\sim z} \Psi\text{"} \quad \text{OR} \quad \text{"}\langle m, s \rangle \not\models P_{\sim z} \Psi\text{"}}$$

Cannot know at this stage if  $\langle m, s \rangle \models P_{\sim z} \Psi$  holds or not - may depend on final  $\Gamma$

Hence guess by branching out and invoke tableau with respective constraint

$$x_{\langle m, s \rangle} \sim z \quad \text{or} \quad x_{\langle m, s \rangle} \not\sim z$$

In any case simplify premise with decision made to make progress

# Some Inference Rules

## Rules for U-formulas

Basically: unfold using equivalences

$$\psi_1 \mathbf{U} \psi_2 \equiv \psi_2 \vee (\psi_1 \wedge \mathbf{X}(\psi_1 \mathbf{U} \psi_2))$$

$$\neg(\psi_1 \mathbf{U} \psi_2) \equiv \neg\psi_2 \wedge (\neg\psi_1 \vee \mathbf{X}\neg(\psi_1 \mathbf{U} \psi_2))$$

Disjoint union again

$$\mathbf{U} \frac{\Gamma \vdash \langle m, s \rangle : \{\psi_1 \mathbf{U} \psi_2\} \uplus \Psi}{\Gamma \vdash \langle m, s \rangle : \{\psi_2\} \cup \Psi \quad \cup \quad \Gamma, \gamma \vdash \langle m, s \rangle : \{\psi_1, \neg\psi_2, \mathbf{X}(\psi_1 \mathbf{U} \psi_2)\} \cup \Psi}$$

$$\text{where } \gamma = x_{\langle m, s \rangle}^{\{\psi_1 \mathbf{U} \psi_2\} \uplus \Psi} \doteq x_{\langle m, s \rangle}^{\{\psi_2\} \cup \Psi} + x_{\langle m, s \rangle}^{\{\psi_1, \neg\psi_2, \mathbf{X}(\psi_1 \mathbf{U} \psi_2)\} \cup \Psi}$$

$$\neg\mathbf{U} \frac{\Gamma \vdash \langle m, s \rangle : \{\neg(\psi_1 \mathbf{U} \psi_2)\} \uplus \Psi}{\Gamma \vdash \langle m, s \rangle : \{\neg\psi_1, \neg\psi_2\} \cup \Psi \quad \cup \quad \Gamma, \gamma \vdash \langle m, s \rangle : \{\psi_1, \neg\psi_2, \mathbf{X}\neg(\psi_1 \mathbf{U} \psi_2)\} \cup \Psi}$$

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→ At this stage premise  $\Psi$  is {  $\mathbf{X} \Psi_1, \dots, \mathbf{X} \Psi_n$  }

# Some Inference Rules

$\mathbf{X} \{ \Psi_1, \dots, \Psi_n \}$  shorthand for poised  $\{ \mathbf{X} \Psi_1, \dots, \mathbf{X} \Psi_n \}$

## Rules for X-formulas

Advance to the next state by expansion

$$\mathbf{X} \frac{\Gamma \vdash \langle \mathbf{m}, \mathbf{s} \rangle : \mathbf{X} \Psi}{\text{"}\langle \Delta(\mathbf{m}, \mathbf{s}), \mathbf{s}_1 \rangle \models \Psi\text{"} \cup \text{"}\langle \Delta(\mathbf{m}, \mathbf{s}), \mathbf{s}_n \rangle \models \Psi\text{"}}$$

where

$\mathbf{s}_1 \dots \mathbf{s}_n$  are all “prescribed” successor states of  $\mathbf{s}$ , i.e,  
successor states reachable with non-0 probability

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Requires guessing rule for action probabilities

“ $x_{\langle m, s \rangle} \alpha > 0$ ” OR “ $x_{\langle m, s \rangle} \alpha \doteq 0$ ”

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→ The X-rule is not applied in case of a “loop”

# Loop Check

Adapted from LTL satisfiability tableau by Mark Reynolds

Recurring eventualities  $\mathbf{G} (\mathbf{F} \mathbf{A} \wedge \mathbf{F} \mathbf{B} \wedge \mathbf{F} \mathbf{C})$

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$\langle \mathbf{m}, \mathbf{s} \rangle : \mathbf{X} \mathbf{F} \mathbf{A}, \mathbf{X} \mathbf{F} \mathbf{B}, \mathbf{X} \mathbf{F} \mathbf{C}, \dots$

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=: \mathbf{X} \psi



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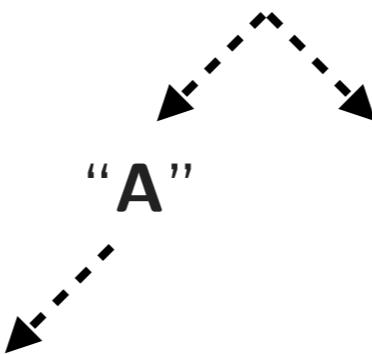


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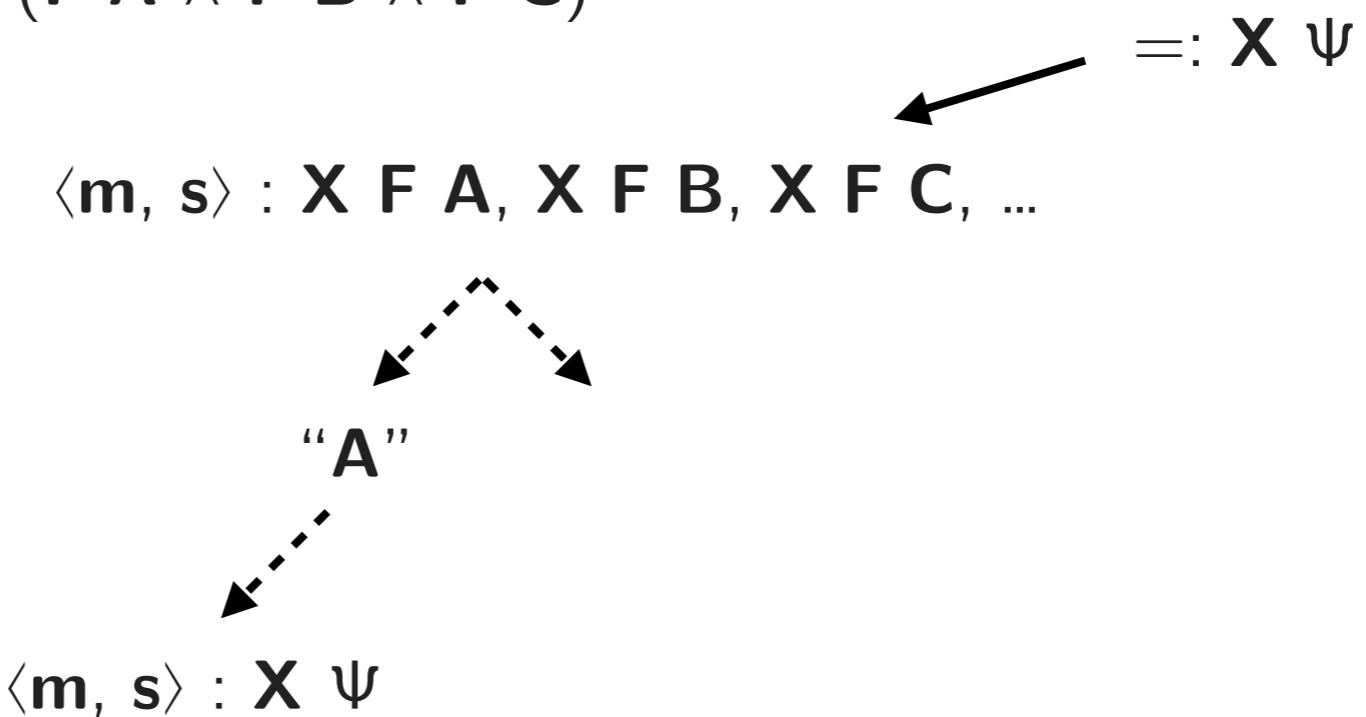
$\langle m, s \rangle : \mathbf{X} \mathbf{F} \mathbf{A}, \mathbf{X} \mathbf{F} \mathbf{B}, \mathbf{X} \mathbf{F} \mathbf{C}, \dots$



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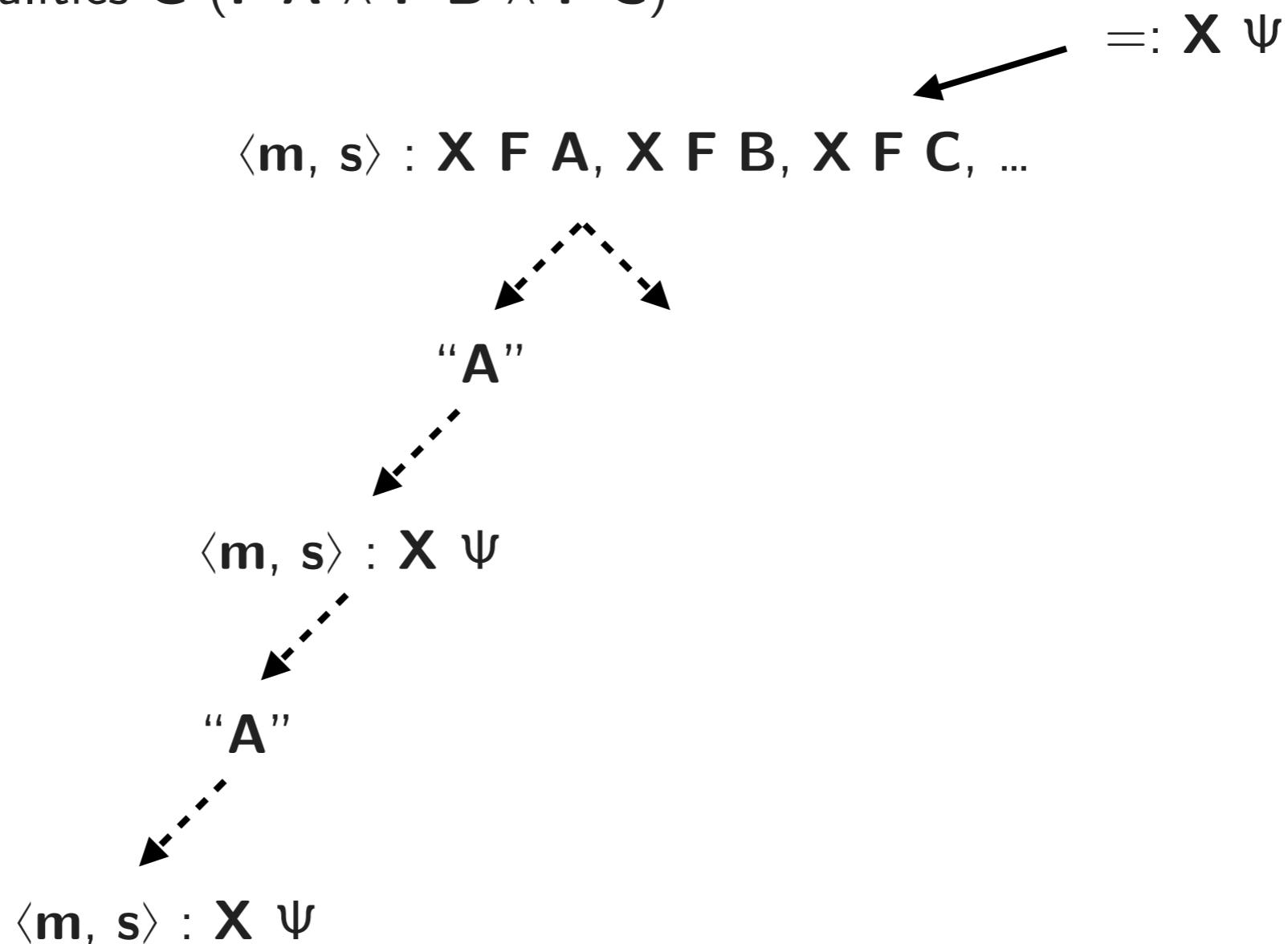
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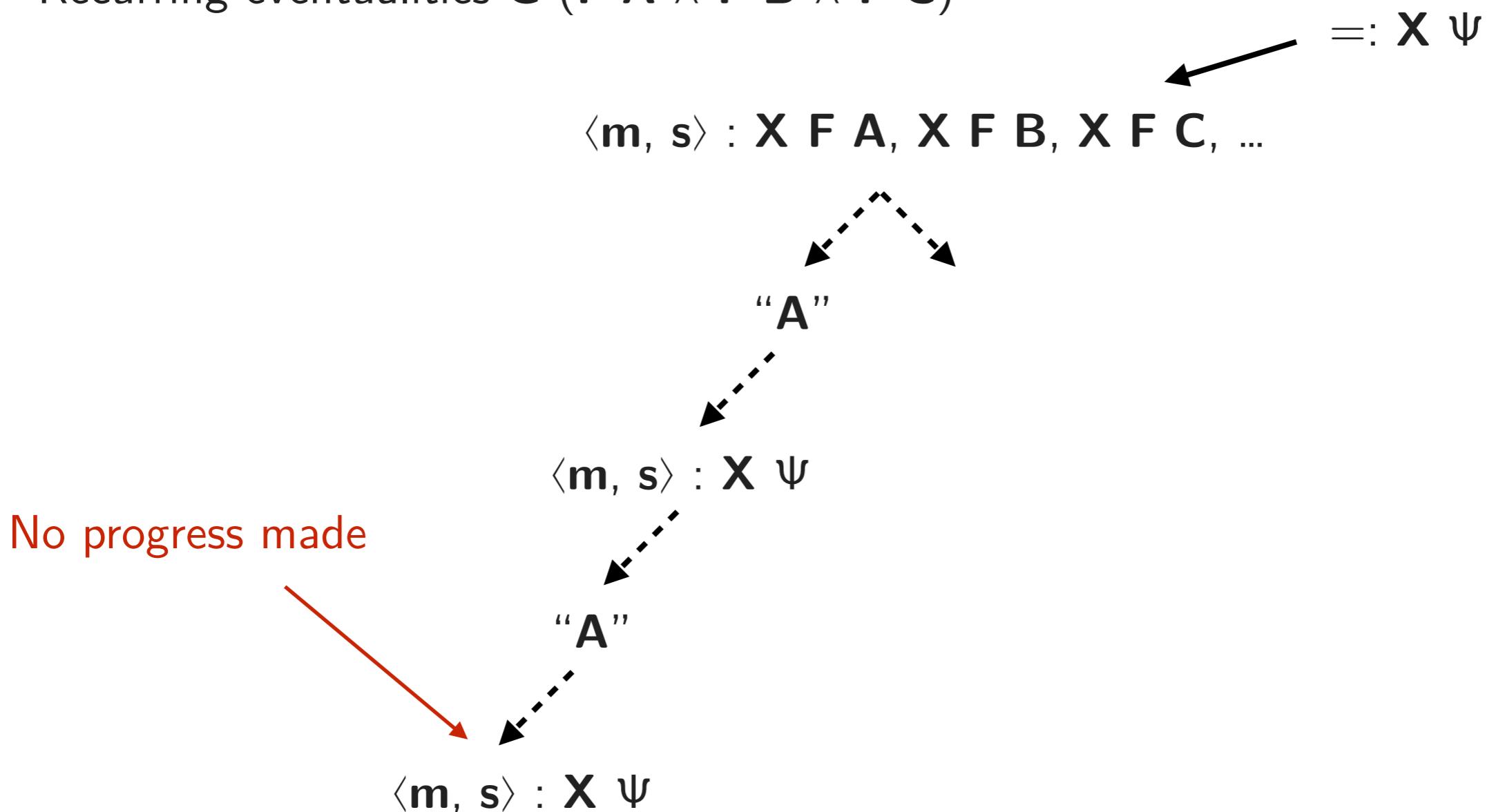
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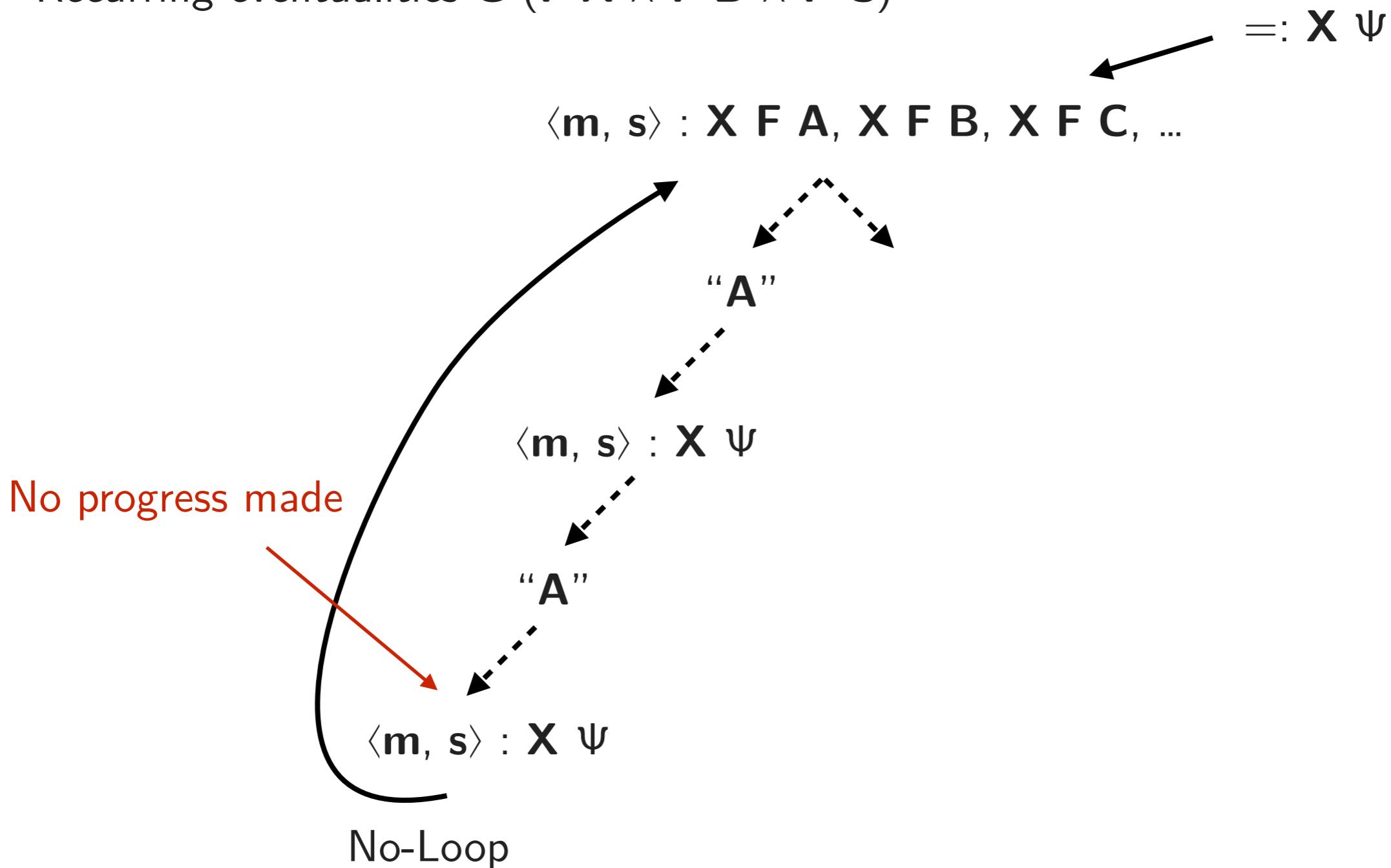
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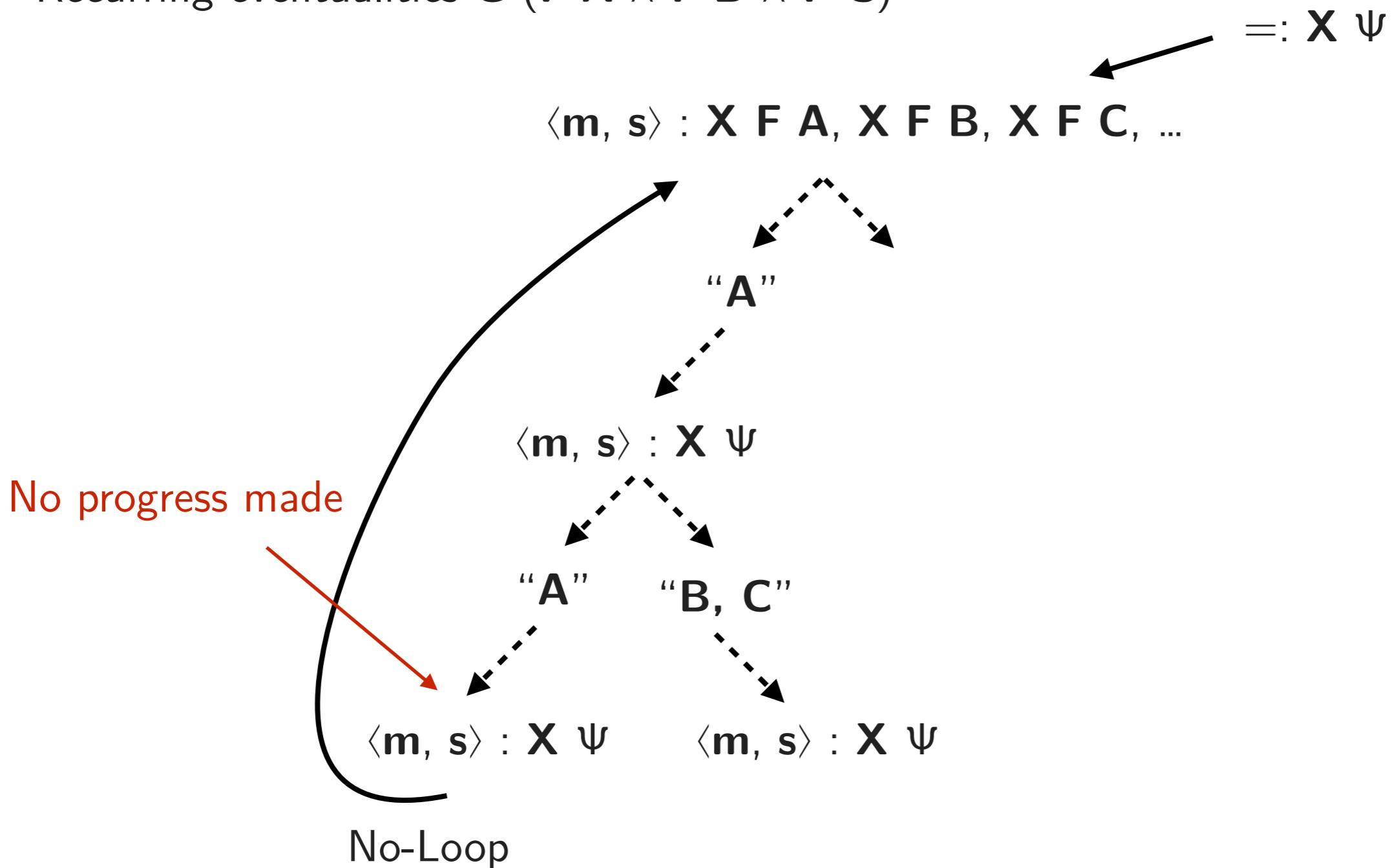
Recurring eventualities  $\mathbf{G} (\mathbf{F} \mathbf{A} \wedge \mathbf{F} \mathbf{B} \wedge \mathbf{F} \mathbf{C})$



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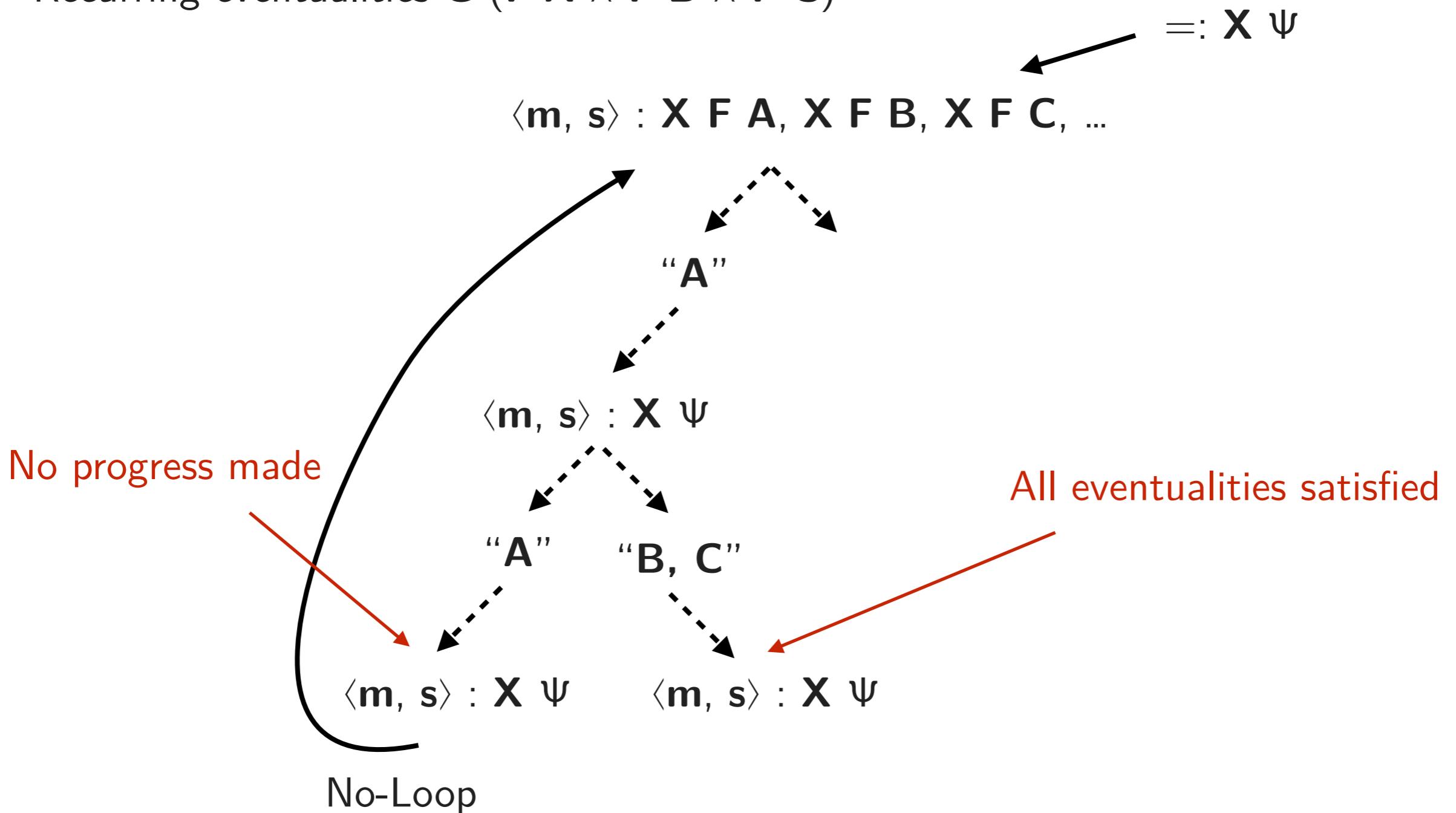
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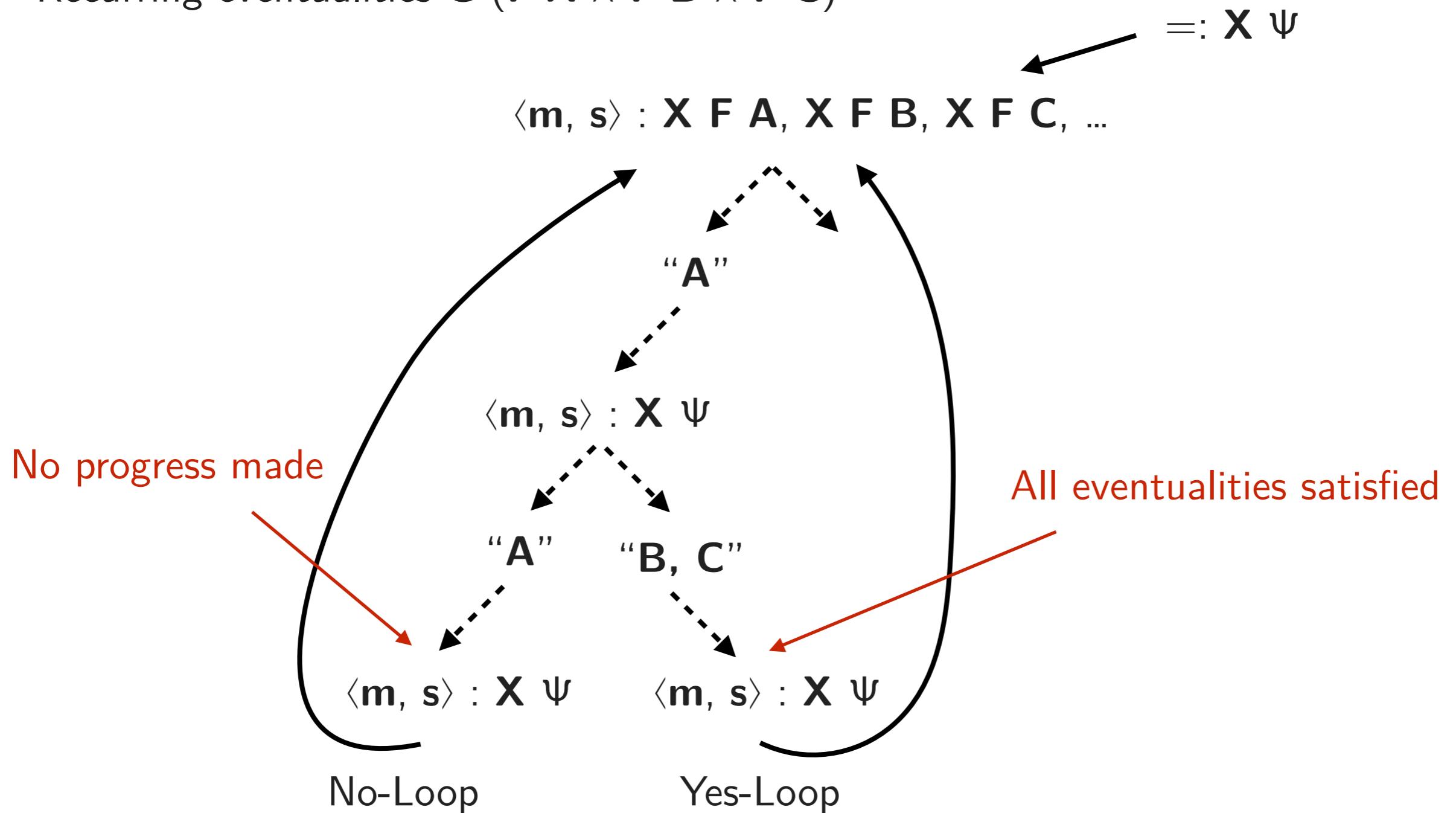
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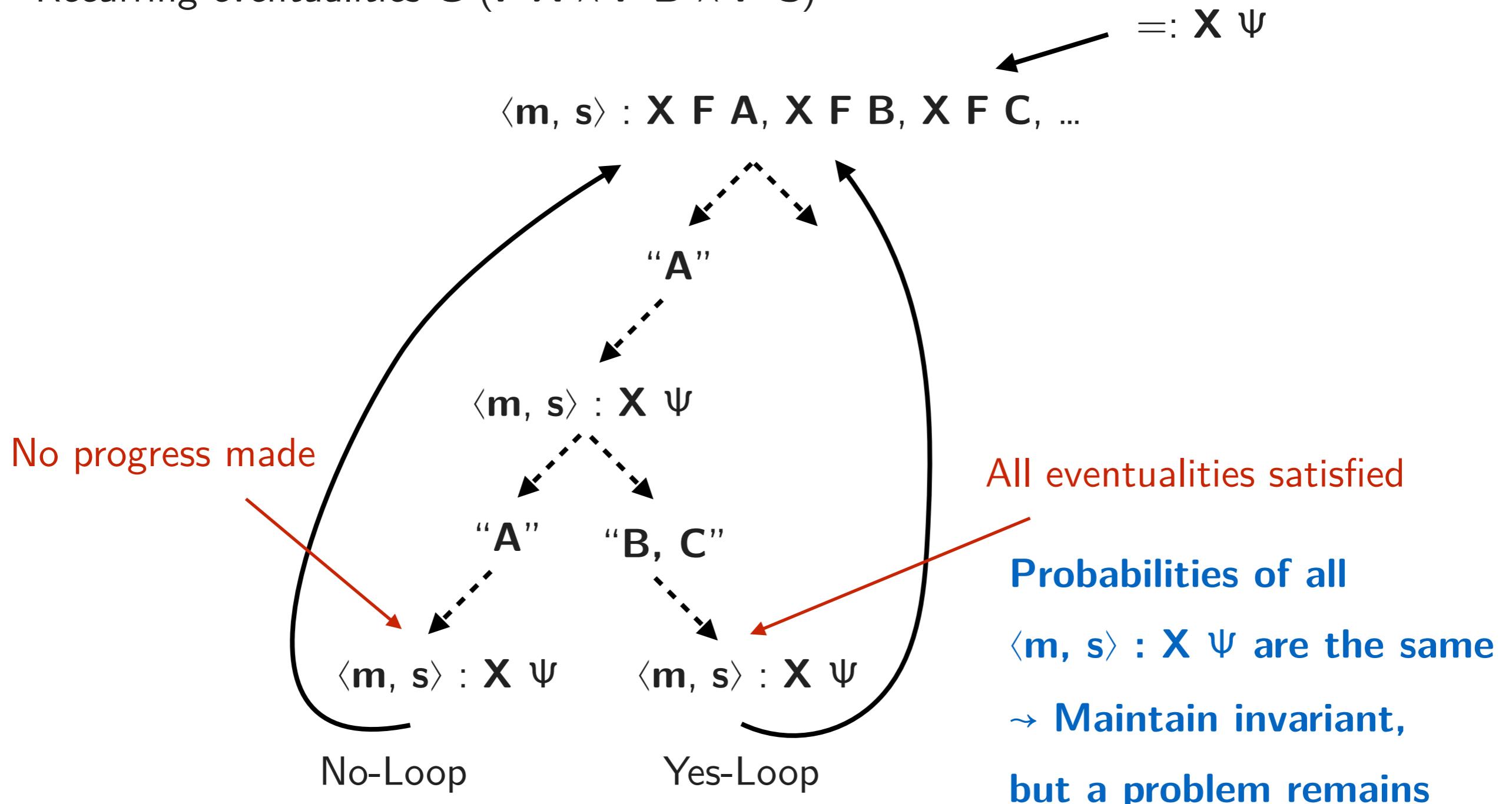
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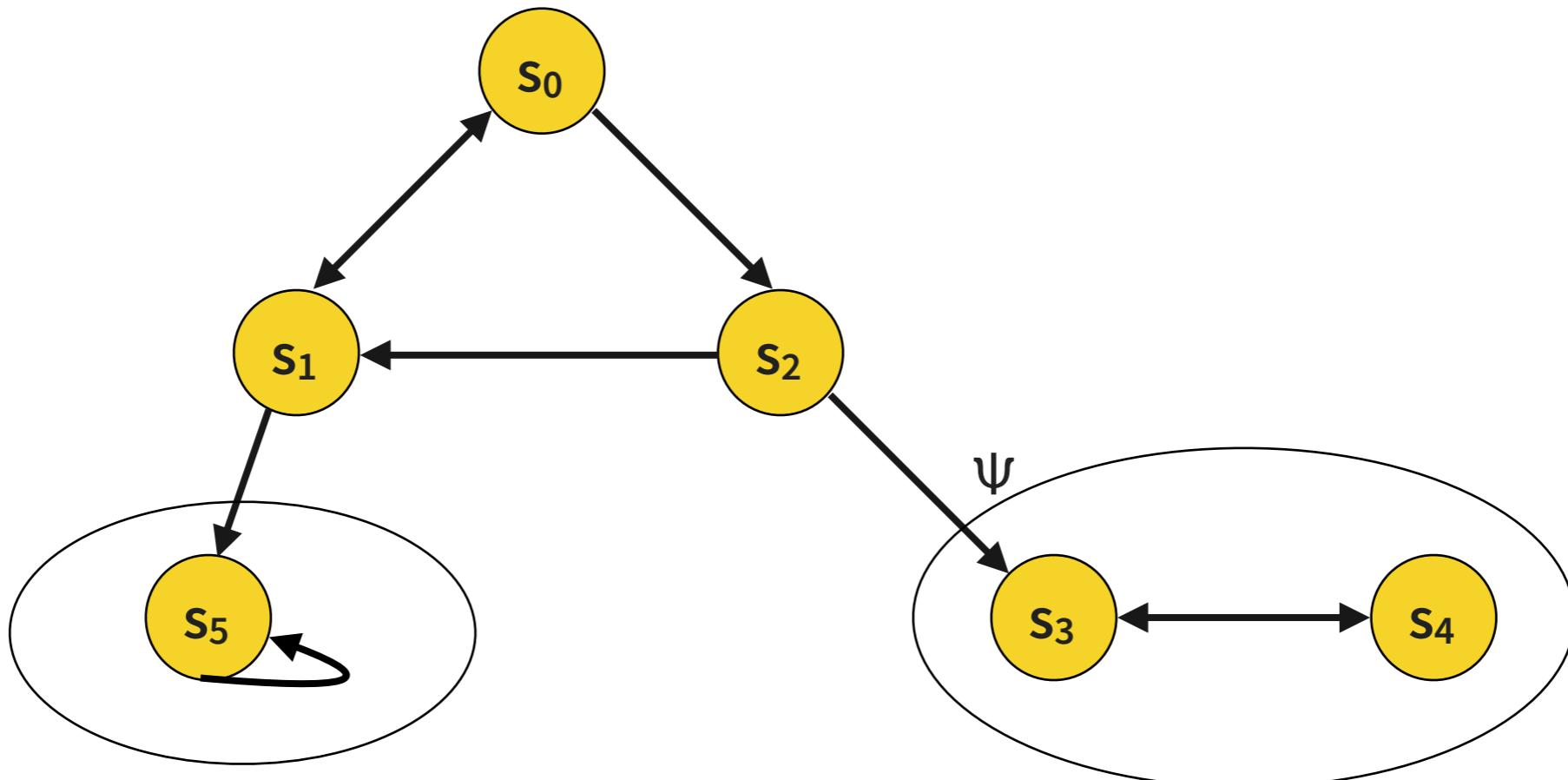
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# Bottom Strongly Connected Components (BSCCs)

BSCC

a reachable sub-graph that is impossible to leave



**Problem:** if tableau contains BSCC for problematic  $\Psi$

then  $\Gamma$  underspecifies probability: " $x_{s3}^\Psi \doteq x_{s3}^\Psi$ "

**Solution:** if have Yes-Loop then add  $x_{s3}^\Psi \doteq 1$  to  $\Gamma$  else add  $x_{s3}^\Psi \doteq 0$  to  $\Gamma$

# Conclusion

- Presented a tableau calculus for policy synthesis
  - Many details left out
- Very expressive target specification language: PCTL\*
- Had to restrict to policies with finite-memory fixed a priori to get decidability
- Novelty: no other algorithm for policy synthesis under stated conditions
- Novelty: explores **reachable** states “only”
  - Traditional synthesis algorithms are based on automata

