

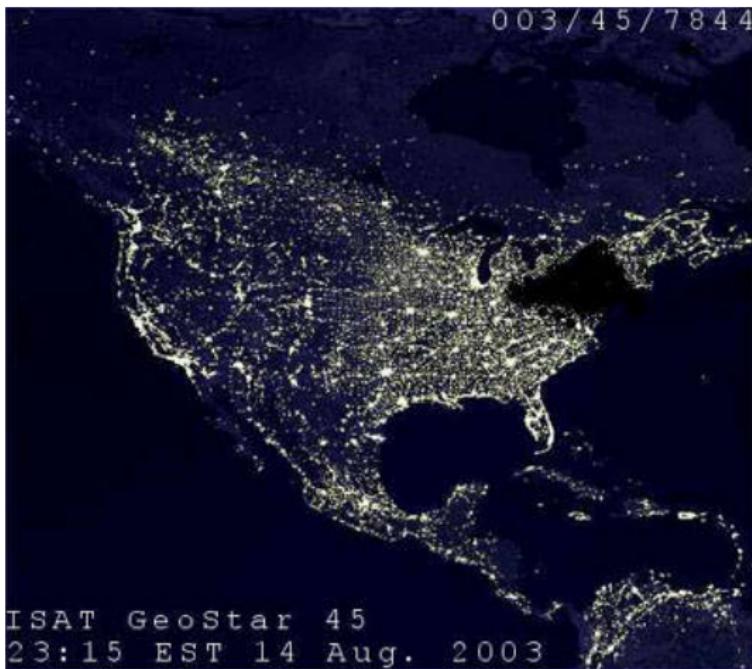
# **Refined Probabilistic Abstraction**

**Björn Wachter**



December 8, 2010

003 / 45 / 7844



ISAT GeoStar 45  
23:15 EST 14 Aug. 2003

- Bug in control software of power network
- ⇒ 50 million people without electricity

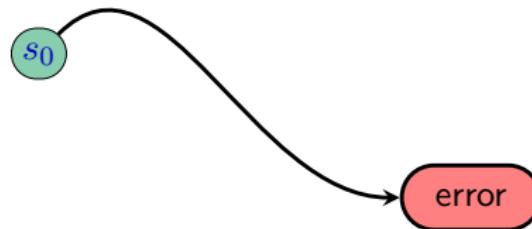
## Model checking:

"does a computing **system** behave as **intended**?"

- mathematical model  $M$  of system
- specification  $\varphi$
- automatic proof or refutation of:

$$M \models \varphi$$

- Example:  $\varphi = \text{no arithmetic overflow}$



e.g., arithmetic overflow

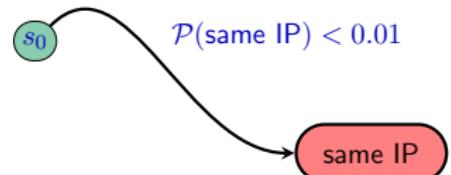
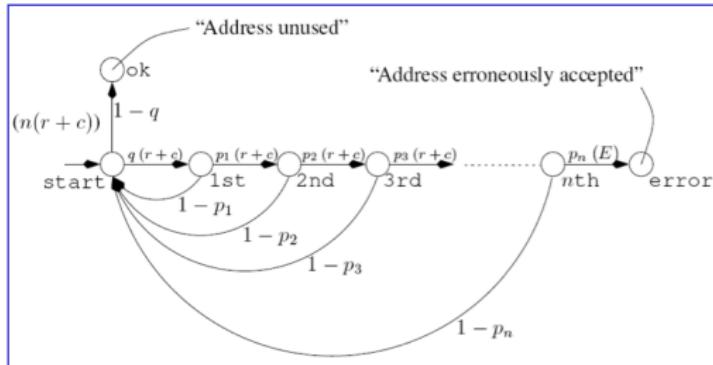
# Probabilities are Important

- computer networks
  - performance:  $P(\text{message loss}) = 2\%$
  - reliability:  $P(\text{node failure}) = 3\%$
- randomized algorithms
  - network protocols
  - sorting algorithms
  - ...

# Probabilistic Model checking

- models: Markov chains
- properties: PCTL

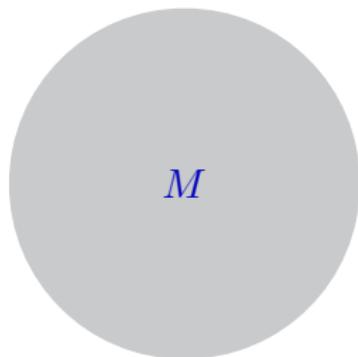
# Probabilistic Model checking



- models: Markov chains
- properties: PCTL
- Zeroconf protocol
- IP for new member picked probabilistically
- bad: two members have the same IP!

# Why Abstraction?

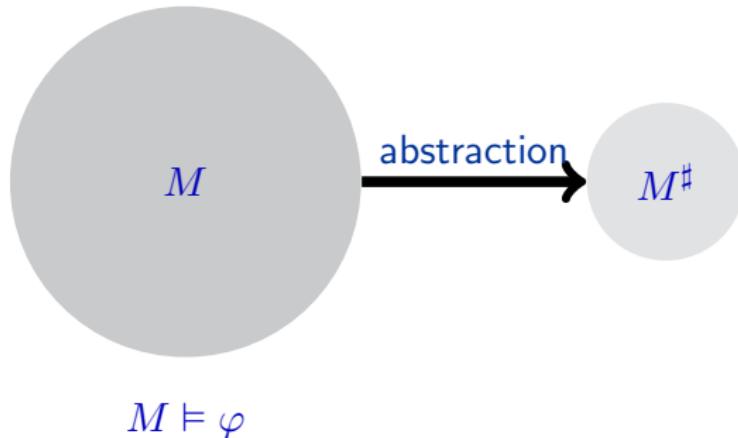
- Limitations of probabilistic model checking
  - based on state-space exploration
  - **state-space explosion** problem



$$M \models \varphi$$

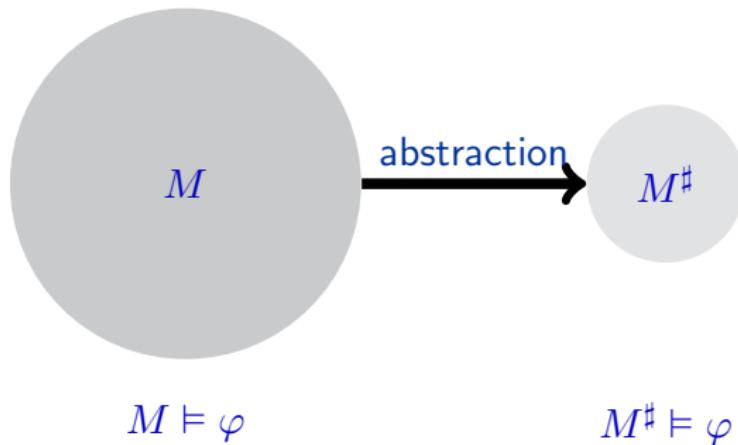
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- Limitations of probabilistic model checking
  - based on state-space exploration
  - **state-space explosion** problem
- Abstraction very successful



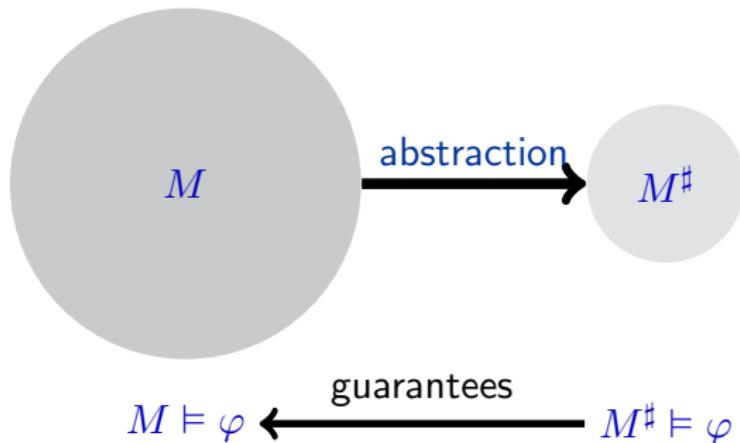
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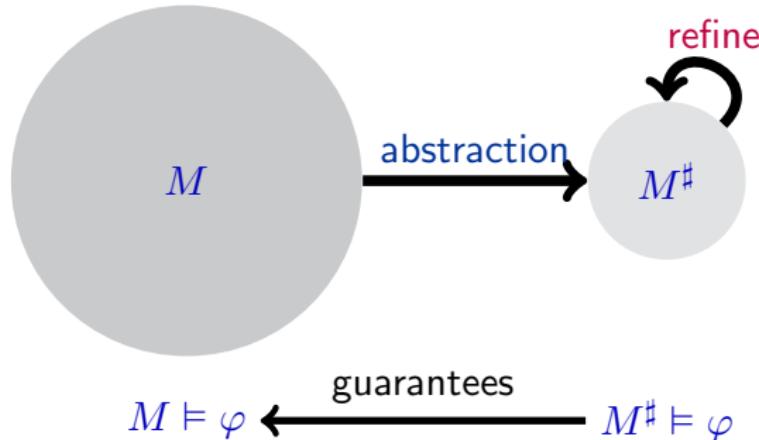
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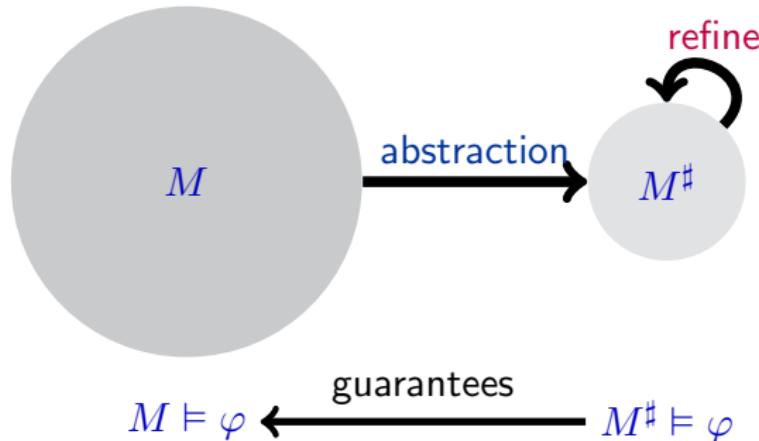
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- Limitations of probabilistic model checking
  - based on state-space exploration
  - **state-space explosion** problem
- Abstraction very successful
  - **Refinement** fits the abstraction to the property



# Contribution

Abstraction refinement for very large probabilistic models

- ... even infinite ones!
- implementation in PASS tool
- successful on various network protocols
  - Wireless LAN
  - IPV4
  - BRP
  - ...

# Background

# Probabilistic Programs

```
// parallel composition of modules
module sender
  i : int; // variable definition
  ...
endmodule

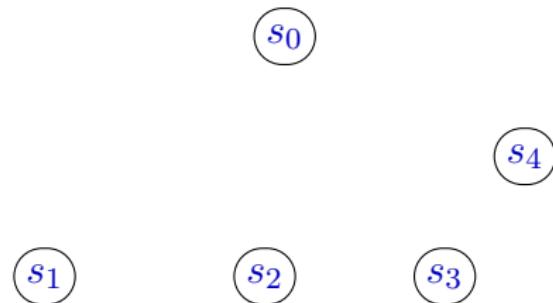
module channelK
  [aF] (k=0) -> 0.98 : (k'=1) // probabilistic
                           + 0.02 : (k'=2); // guarded command
endmodule

init T=false & ... endinit // initial states
```

# Semantics: Markov Decision Process (MDP)

states  $S$

$\cong$  assignments to program variables



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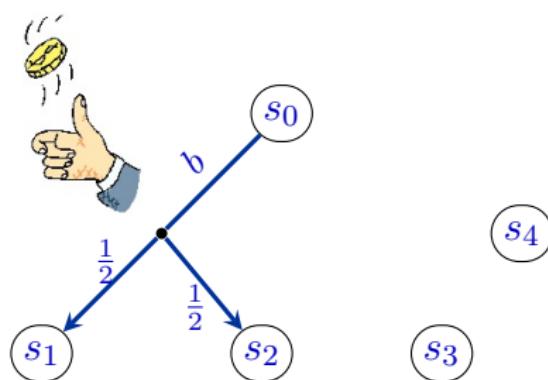
$\cong$

assignments to program variables

probabilistic transitions

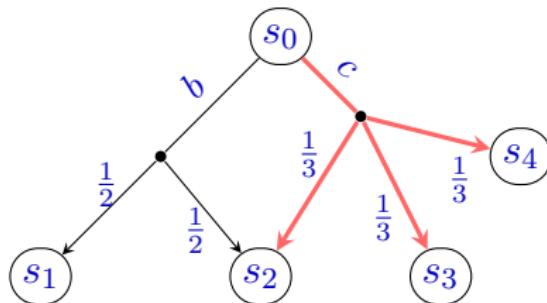
$\dots$

probabilistic choice



## Semantics: Markov Decision Process (MDP)

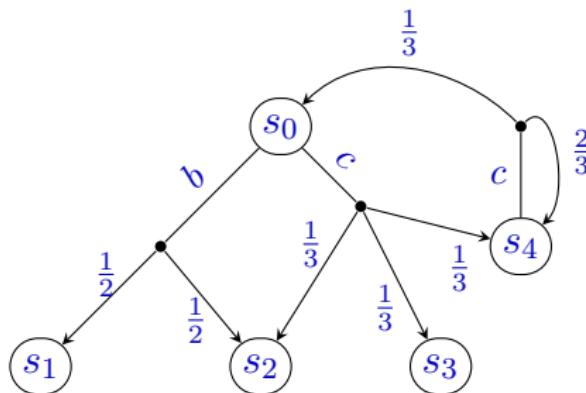
states $S$	$\cong$	assignments to program variables
probabilistic transitions	$\dots$	probabilistic choice
non-deterministic choice	$\dots$	concurrency



- Markov chain  $\cong$  deterministic MDP

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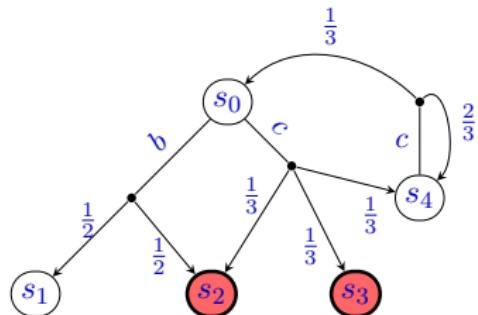
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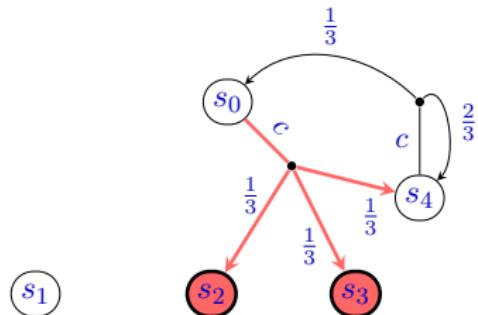
## Properties: Probabilistic Reachability

- probabilities to reach states  $F \subseteq S$
- valuations  $[0, 1]^S \cong S \rightarrow [0, 1]$



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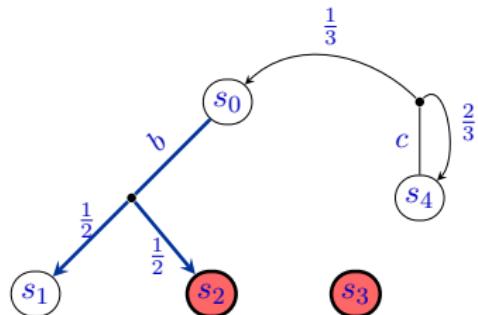
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reachability probability: 1

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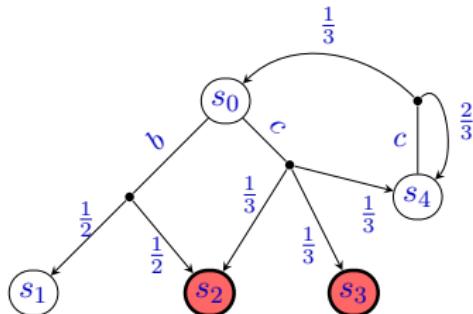
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reachability probability:  $\frac{1}{2}$

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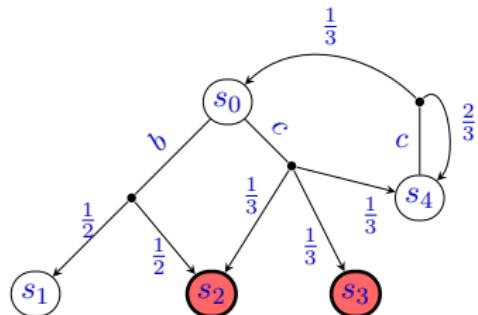
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  - depends on adversary  $\eta$

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- resolves non-determinism
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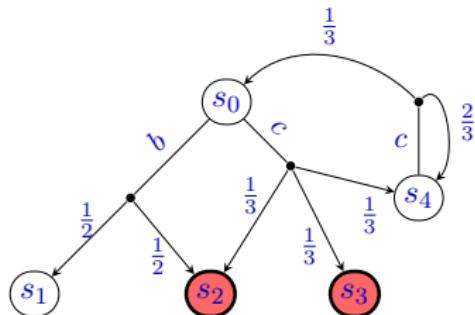
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- minimal/maximal
  - $p^{\min}_F = \inf_\eta p_F^\eta$
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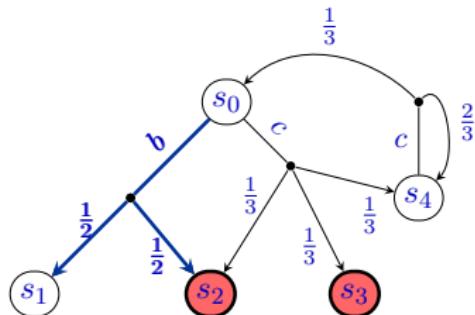
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$$w \mapsto \lambda s. \begin{cases} 1 & ; s \in F \\ 0 & ; s \in F_0 \\ \min_{a \in A(s)} \sum_{(u,t) \in U \times S} R(s, u, t) \cdot w(t) & ; \text{ow.} \end{cases}$$

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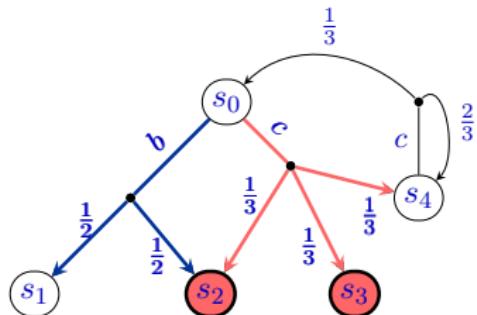
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# Abstraction

# Abstraction for Probabilistic Reachability

- Problem: many states  $S$

reachability probability

1.0	0.5	1.0	1.0
0.2	0.1	1.0	1.0
0.3	0.7	0.4	0.1
0.0	0.8	0.3	0.2

**in general, hard to compute**

# Abstraction for Probabilistic Reachability

- Problem: many states  $S$



- ➊ merge states to blocks  $Q$

reachability probability

$B_1$	$\begin{matrix} 1.0 & 0.5 \\ \circ & \circ \end{matrix}$	$\begin{matrix} 1.0 & 1.0 \\ \circ & \circ \end{matrix}$	$B_2$
$B_3$	$\begin{matrix} 0.2 & 0.1 \\ \circ & \circ \end{matrix}$	$\begin{matrix} 1.0 & 1.0 \\ \circ & \circ \end{matrix}$	
	$\begin{matrix} 0.3 & 0.7 & 0.4 & 0.1 \\ \circ & \circ & \circ & \circ \end{matrix}$		
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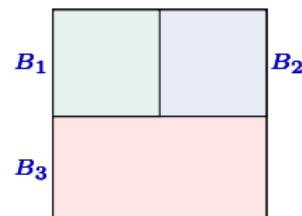


- ➊ merge states to blocks  $Q$

- in example, 16 states but only 3 blocks  $Q = \{B_1, B_2, B_3\}$ .

reachability probability

$B_1$	$\begin{matrix} 1.0 & 0.5 \\ \circ & \circ \\ 0.2 & 0.1 \\ \circ & \circ \end{matrix}$	$\begin{matrix} 1.0 & 1.0 \\ \circ & \circ \\ 1.0 & 1.0 \\ \circ & \circ \end{matrix}$	$B_2$
$B_3$	$\begin{matrix} 0.3 & 0.7 & 0.4 & 0.1 \\ \circ & \circ & \circ & \circ \\ 0.0 & 0.8 & 0.3 & 0.2 \\ \circ & \circ & \circ & \circ \end{matrix}$		



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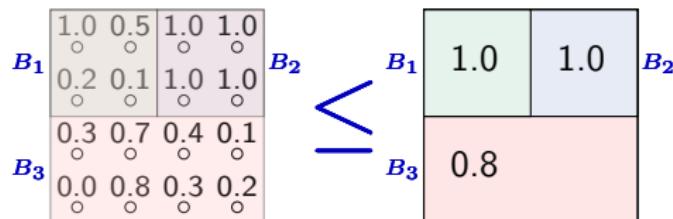


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- ➋ compute abstract valuations  $[0, 1]^Q$

reachability probability



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- ➋ compute abstract valuations  $[0, 1]^Q$

reachability probability

$B_1$	0.1	1.0
$B_2$		
$B_3$	0.0	

$B_2$



$B_3$

1.0	0.5	1.0	1.0
○	○	○	○
0.2	0.1	1.0	1.0
○	○	○	○
0.3	0.7	0.4	0.1
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$B_2$



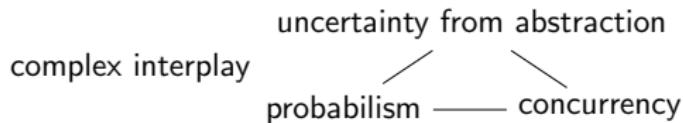
$B_3$

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lower-bound analysis

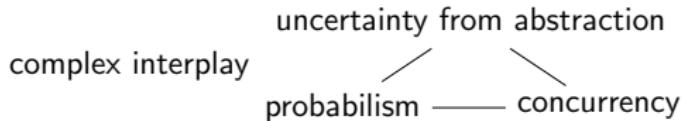
upper-bound analysis

# Challenge of Analysis Design



- Open Question:  
what does an optimal analysis look like?

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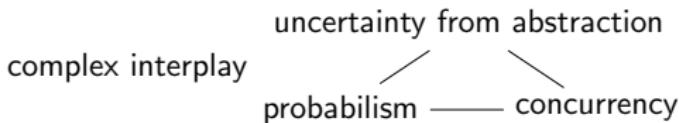


- Open Question:  
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- Our solution:



- Recipe: **Abstract Interpretation** [Cousot77]

# Challenge of Analysis Design



- Open Question:  
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- Recipe: **Abstract Interpretation** [Cousot77]
- Ingredients:
  - abstraction functions

# Abstraction & concretization

## ① abstraction functions:

- mappings

$$[0, 1]^S \mapsto [0, 1]^Q$$

$$[0, 1]^S$$

$$[0, 1]^Q$$

<i>w</i>			
<i>B</i> <sub>1</sub>	1.0 ○ 0.2 ○	0.5 ○ 0.1 ○	1.0 ○ 1.0 ○
<i>B</i> <sub>2</sub>			
<i>B</i> <sub>3</sub>	0.3 ○ 0.0	0.7 ○ 0.8	0.4 ○ 0.3
			0.1 ○ 0.2 ○

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- lower bound:

$$\alpha^l(w) = \lambda B. \inf_{s \in B} w(s)$$

$$[0, 1]^S$$

$$[0, 1]^Q$$

		w					
		1.0	0.5	1.0	1.0		
		○	○	○	○		
B <sub>1</sub>	0.2	0.1		1.0	1.0	B <sub>2</sub>	
	○	○	○	○			
B <sub>3</sub>	0.3	0.7	0.4	0.1		B <sub>2</sub>	
	○	○	○	○			
B <sub>1</sub>	0.0	0.8	0.3	0.2		B <sub>2</sub>	
	○	○	○	○			

B<sub>3</sub>

B<sub>1</sub>

w

B<sub>2</sub>

Q'

B <sub>1</sub>	0.1	1.0	B <sub>2</sub>
B <sub>3</sub>			0.0

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## ① abstraction functions:

- mappings

$$[0, 1]^S \mapsto [0, 1]^Q$$

- lower bound:

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- upper bound:

$$\alpha^u(w) = \lambda B. \sup_{s \in B} w(s)$$

$$[0, 1]^S$$

$$[0, 1]^Q$$

w	B <sub>1</sub>	B <sub>2</sub>	B <sub>3</sub>
1.0 0.5 ○ ○	1.0 1.0 ○ ○		
0.2 0.1 ○ ○	1.0 1.0 ○ ○		
0.3 0.7 ○ ○	0.4 0.1 ○ ○		
0.0 0.8 ○ ○	0.3 0.2 ○ ○		

w	B <sub>1</sub>	B <sub>2</sub>	B <sub>3</sub>
1.0 1.0 ○ ○			
0.8			

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1.0 1.0 ○ ○			
0.8			

w	B <sub>1</sub>	B <sub>2</sub>	B <sub>3</sub>
1.0 1.0 ○ ○			
0.8			

w	B <sub>1</sub>	B <sub>2</sub>	B <sub>3</sub>
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1.0 1.0 ○ ○			
0.8			

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w	B <sub>1</sub>	B <sub>2</sub>	B <sub>3</sub>
1.0 1.0 ○ ○			
0.8			

w	B <sub>1</sub>	B <sub>2</sub>	B <sub>3</sub>
1.0 1.0 ○ ○			
0.8			

w	B <sub>1</sub>	B <sub>2</sub>	B <sub>3</sub>
1.0 1.0 ○ ○			
0.8			

w	B <sub>1</sub>	B <sub>2</sub>	B <sub>3</sub>
1.0 1.0 ○ ○			
0.8			

w	B <sub>1</sub>	B <sub>2</sub>	B <sub>3</sub>
1.0 1.0 ○ ○			
0.8			

w	B <sub>1</sub>	B <sub>2</sub>	B <sub>3</sub>
1.0 1.0 ○ ○			
0.8			

w	B<sub>1</sub>	B<sub>2</sub>	B<sub>3</sub>


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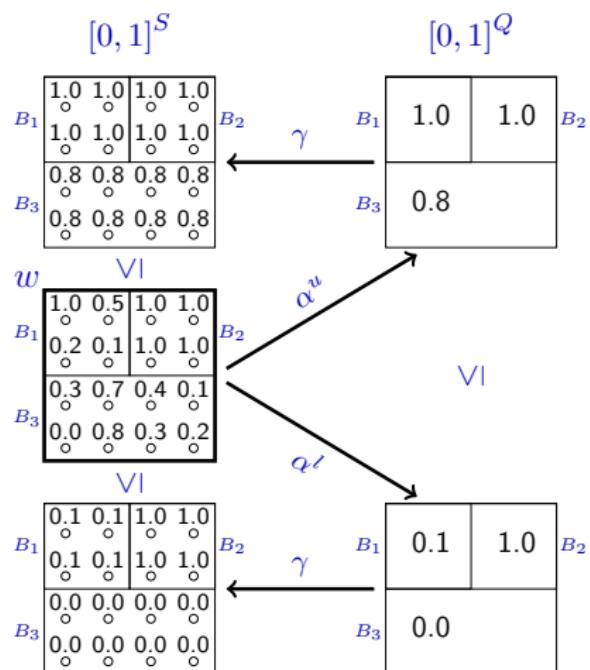
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- upper bound:  $\alpha^u(w) = \lambda B. \sup_{s \in B} w(s)$

## ② concretization function

(or meaning function)

- $[0, 1]^Q \mapsto [0, 1]^S$
- $\gamma(w^\sharp) = \lambda s. w^\sharp([s]).$



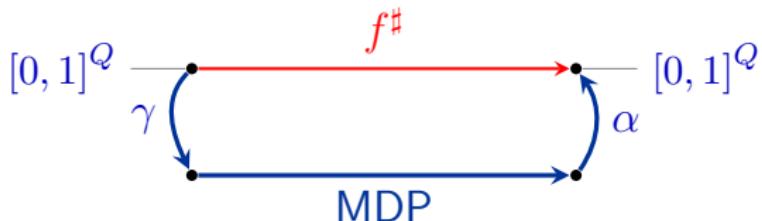
# How do we get an Abstract Analysis?

- abstract analysis
  - function  $f^\sharp : [0, 1]^Q \rightarrow [0, 1]^Q$   
⇒ lower/upper bound = fixpoint of  $f^\sharp$
- Best-transformer paradigm [Cousot 2002]



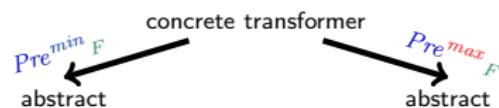
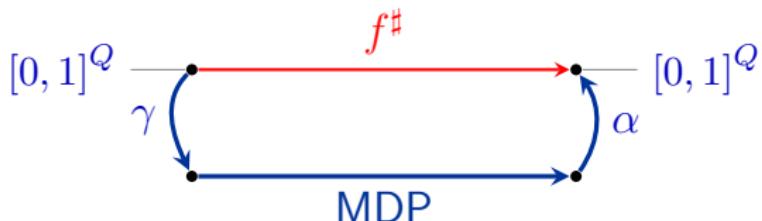
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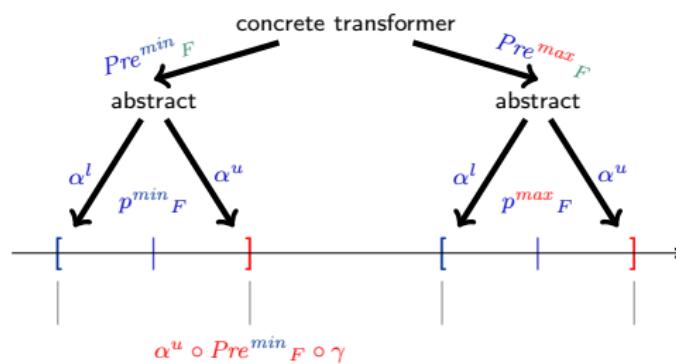
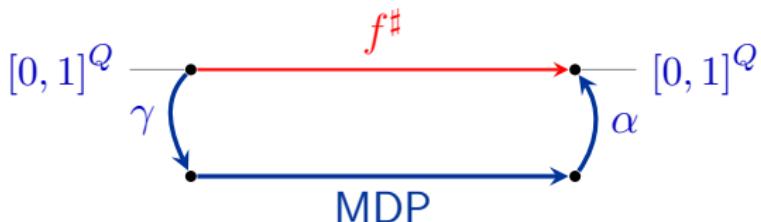
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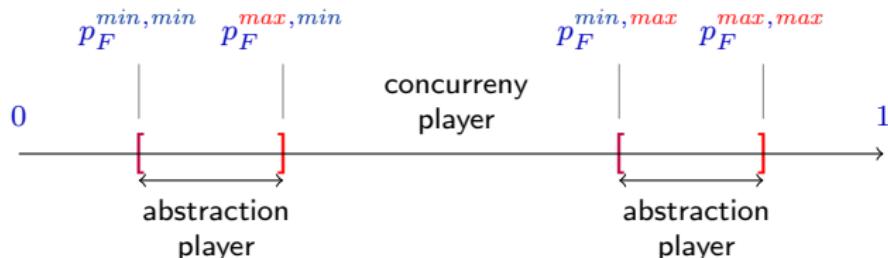


# Abstract Transformers = Stochastic Games

$$(\alpha^u \circ \text{Pre}_F^{\min} \circ \gamma(w^\sharp))(B) = \sup_{s \in B} \text{Pre}_F^{\min}(\gamma(w^\sharp))(s)$$

$$= \sup_{s \in B} \min_{a \in A(s)} \sum_{s' \in S} R(s, a)(s') \cdot (\gamma(w^\sharp))(s')$$

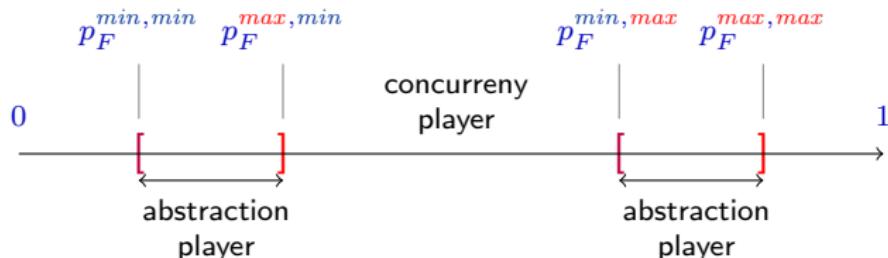
- Markov models
  - Markov chain =  $\frac{1}{2}$  player
  - MDP =  $1\frac{1}{2}$  player
  - stochastic game =  $2\frac{1}{2}$  player
- minimum / maximum over all strategies *for both players*



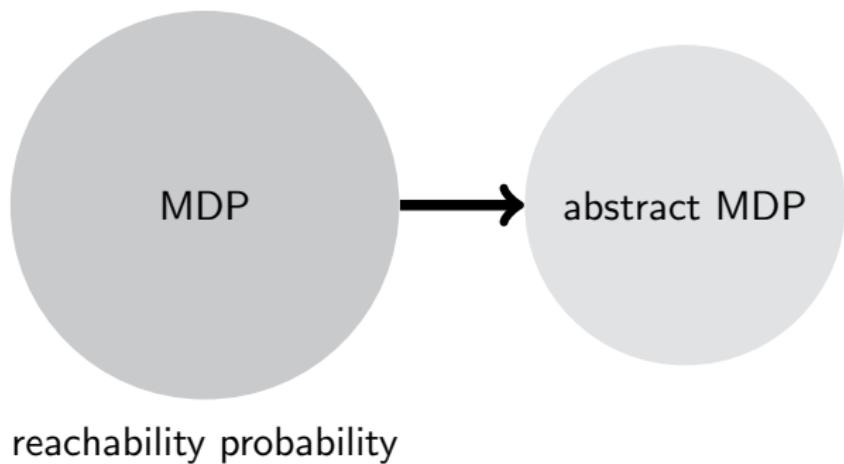
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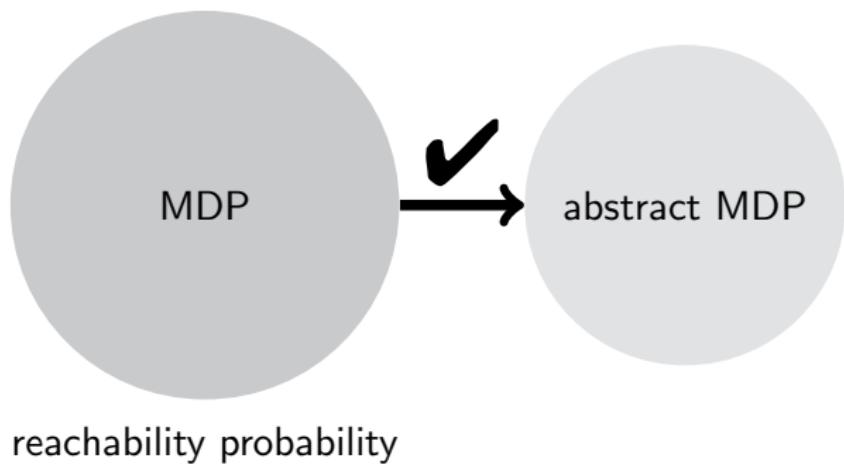
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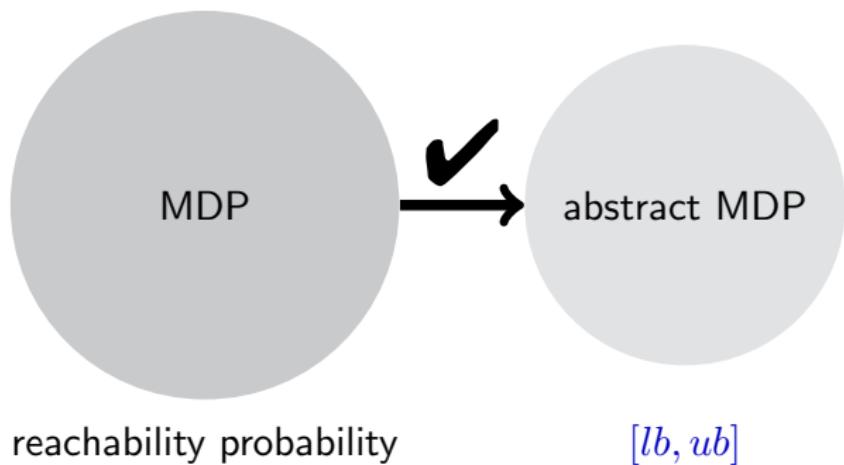
## Wrap-up



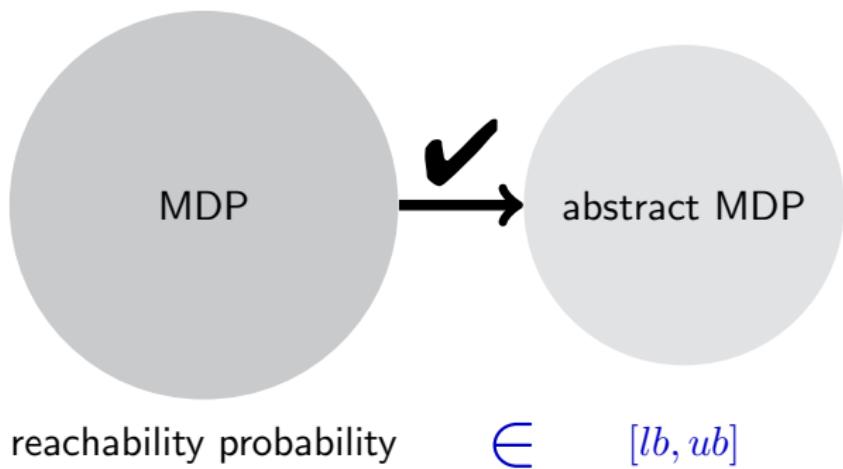
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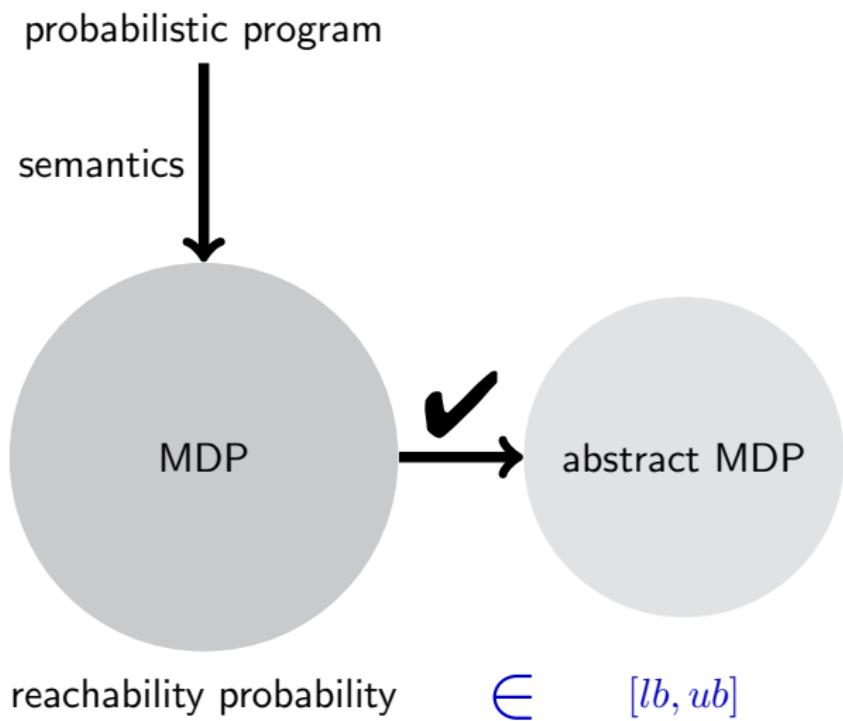
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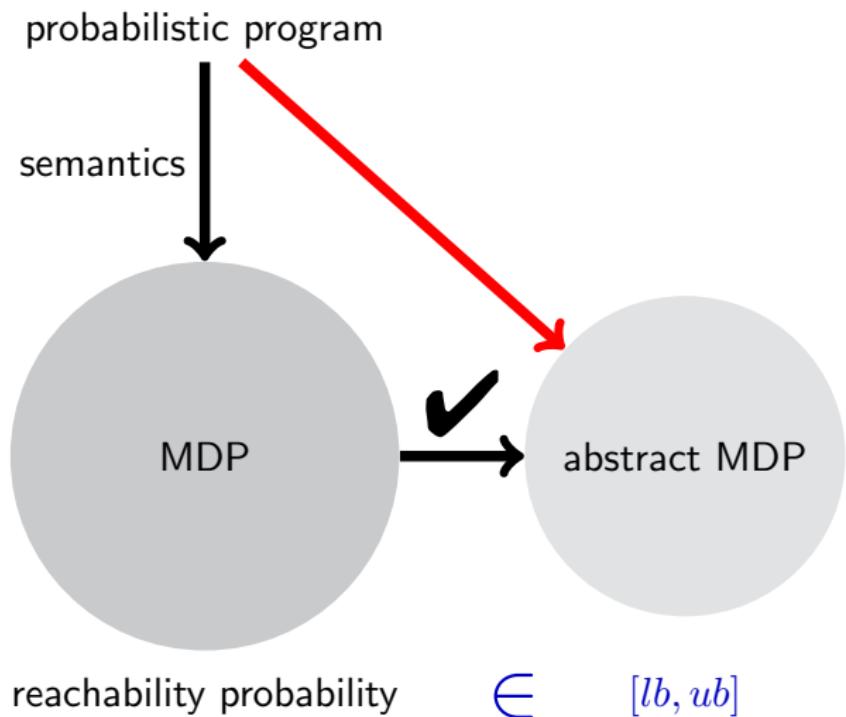


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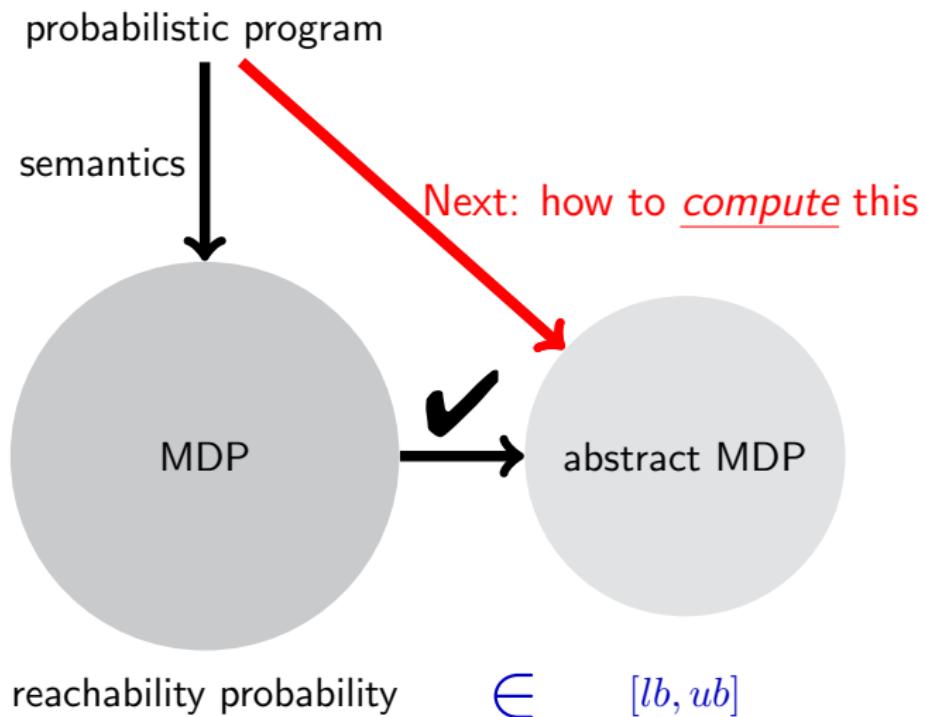
## Wrap-up

- diagram *defines* an abstract semantics (mathematics)



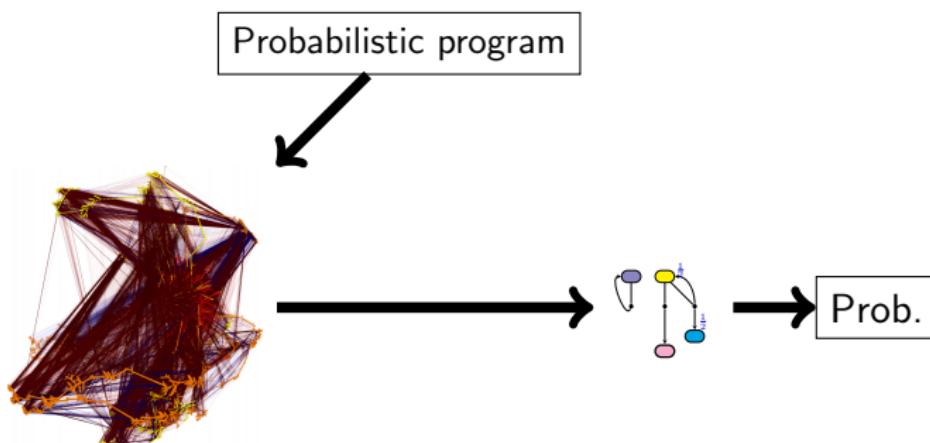
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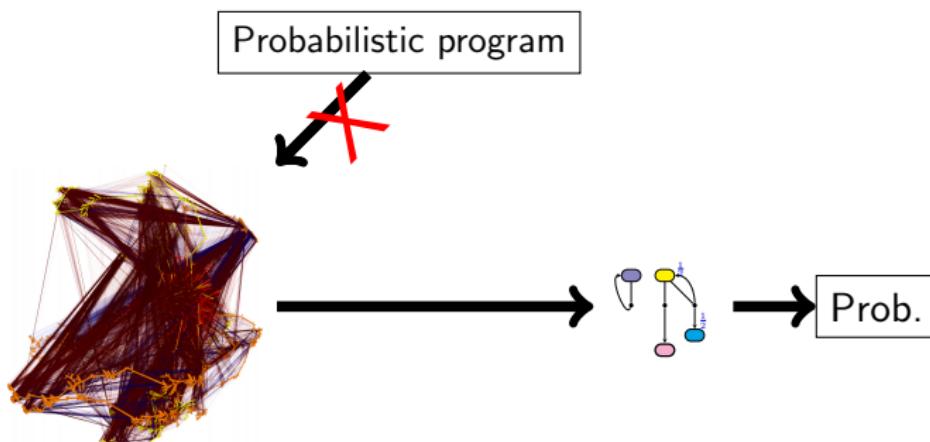
# State of the Art before Thesis

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Magnifying-Lens Abstraction for Markov Decision Processes.. CAV 2007
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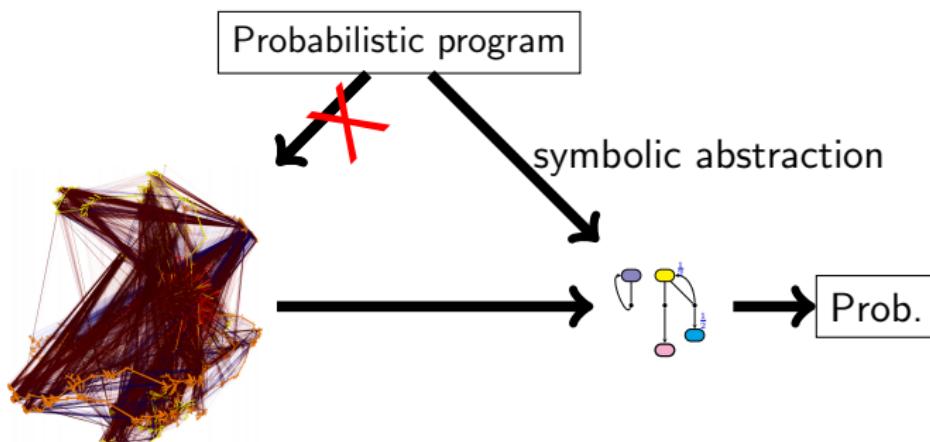


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- ... build full semantics  
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Premiere: 1st symbolic abstraction for probabilistic programs

- abstraction at the language level



# Predicate Abstraction

- Predicates  $\cong$  expressions over program variables
  - e.g.,  $x > 0$ ,  $x < y$

$$\begin{array}{l} x = 0 \\ y = 0 \end{array}$$

$$\begin{array}{l} x = 5 \\ y = 3 \end{array}$$

$$\begin{array}{l} x = 0 \\ y = -1 \end{array}$$

$$\begin{array}{l} x = 5 \\ y = -7 \end{array}$$

$$\begin{array}{l} x = -2 \\ y = 0 \end{array}$$

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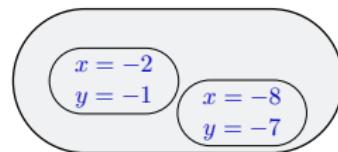
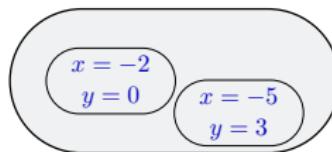
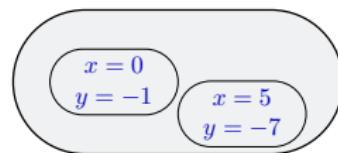
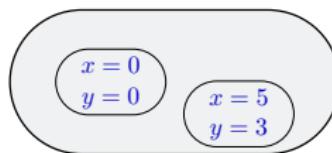
$$\begin{array}{l} x = -8 \\ y = -7 \end{array}$$

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$\xrightarrow{\text{define}}$  partition



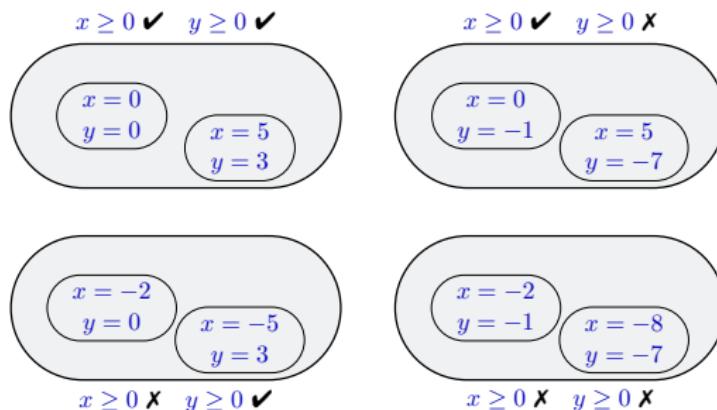
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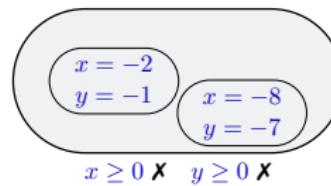
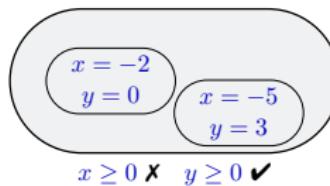
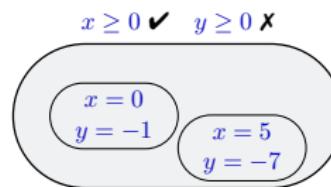
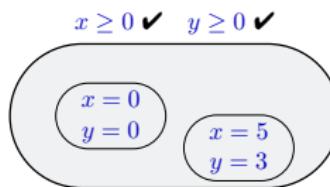
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- stochastic game



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- reduce abstraction to **satisfiability** of logical formulas

$\Rightarrow$  implemented by **SMT solver**

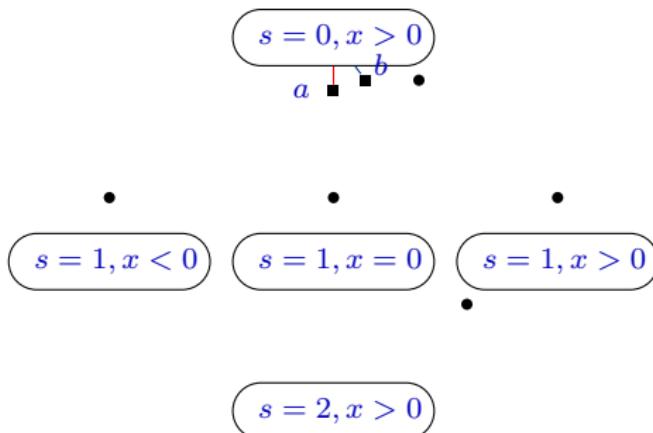
- SMT = Satisfiability Modulo Theories

## Example

- Consider program

```
module main
    s : [0..2];      // control flow
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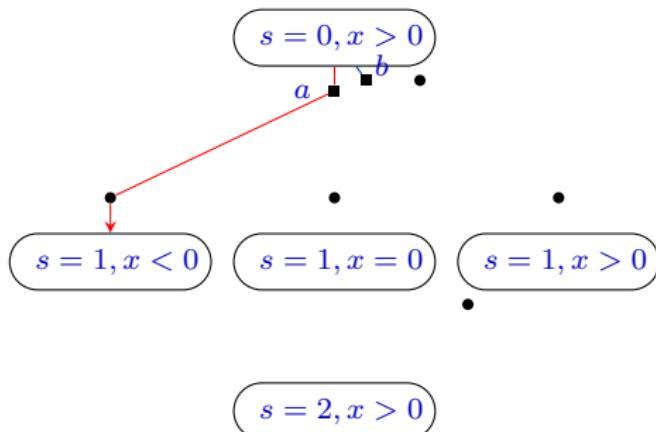


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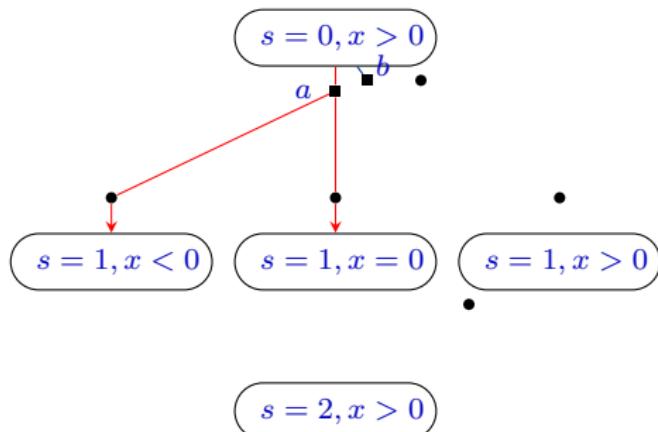


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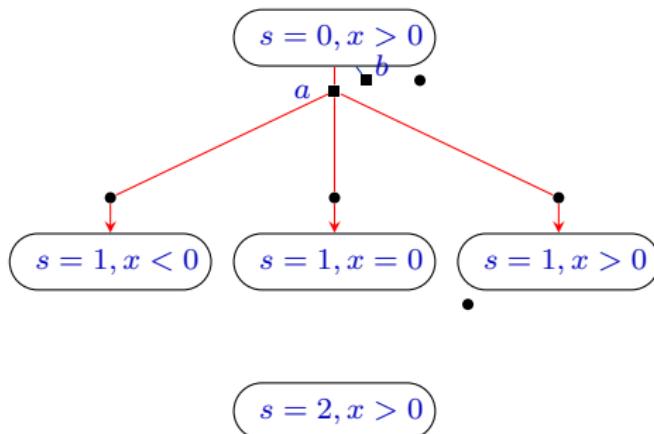


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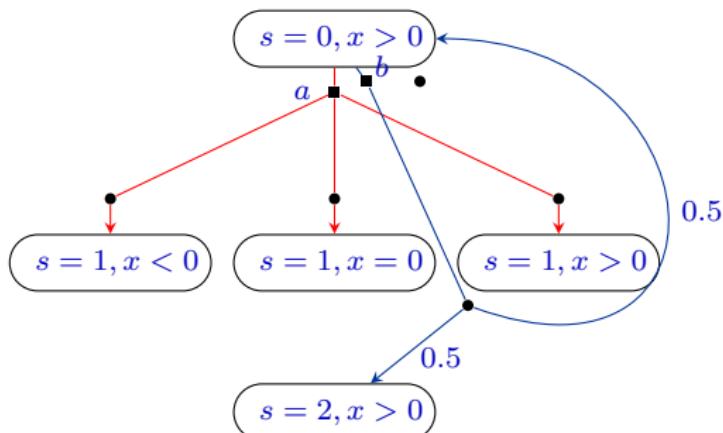


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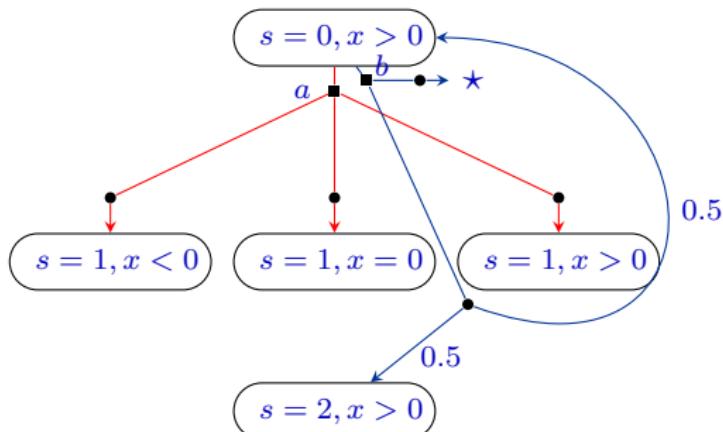


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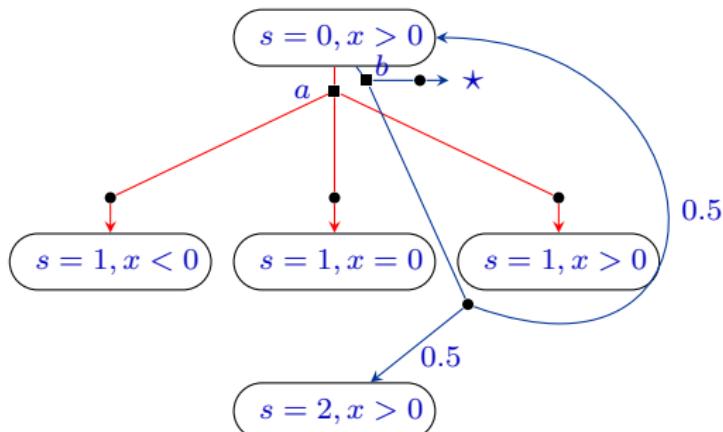


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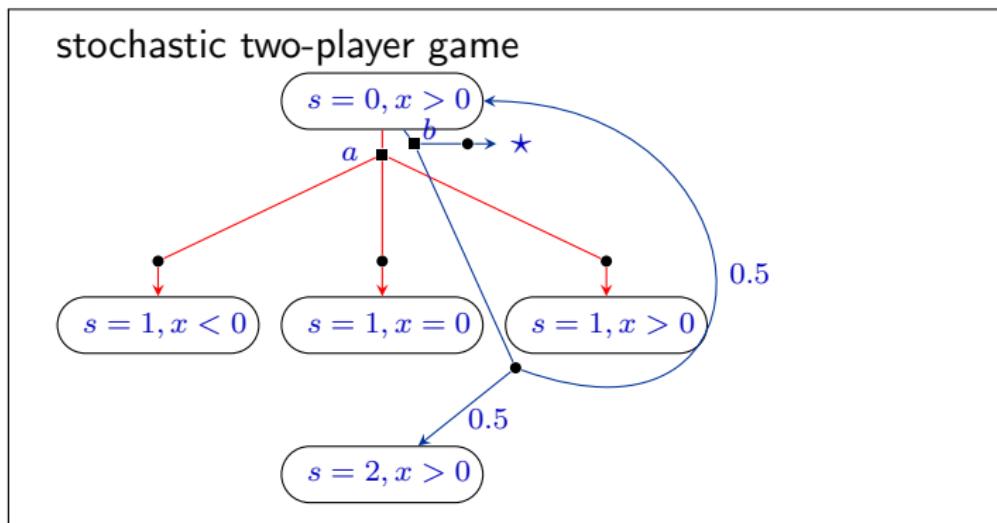


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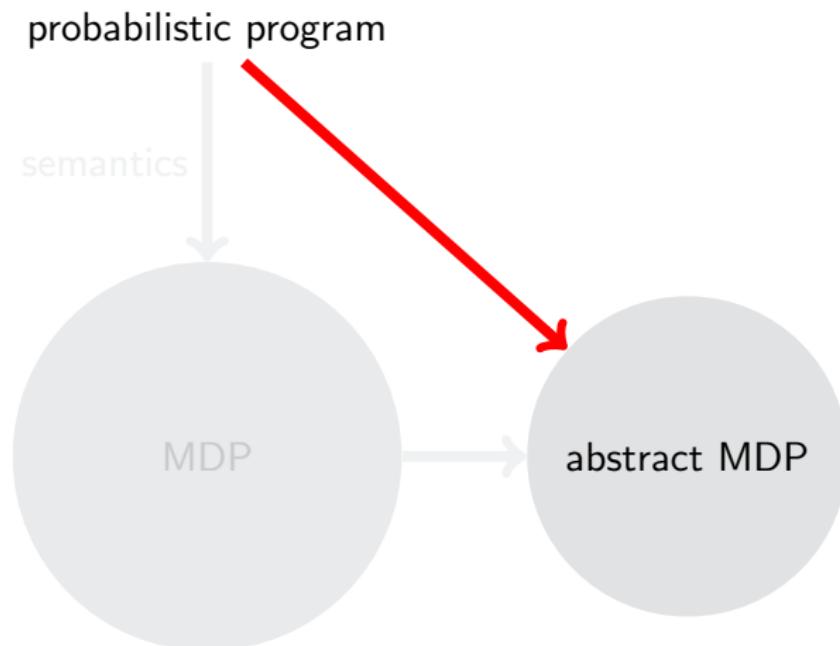
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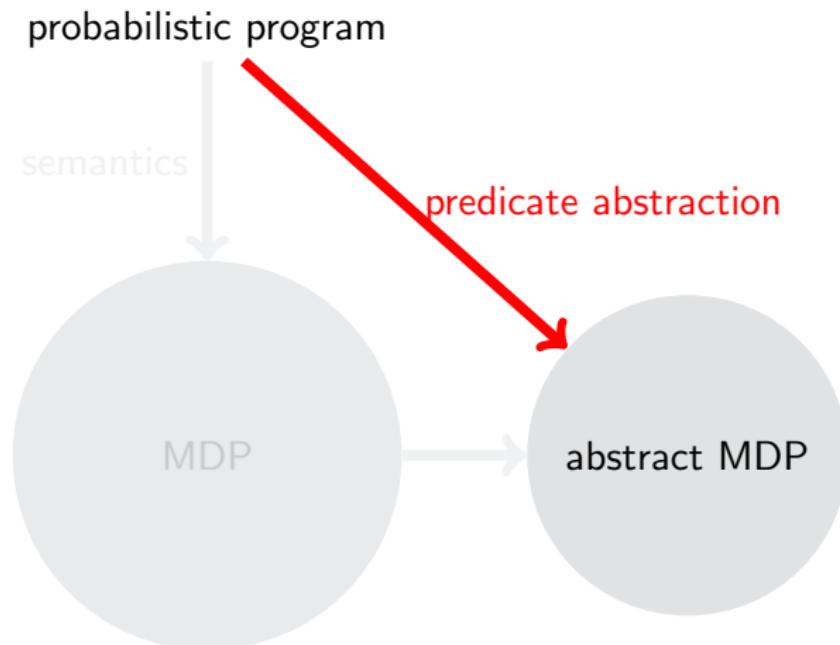
## Wrap-up

- fully **automatic** and **symbolic** abstraction
  - for given **predicate** set



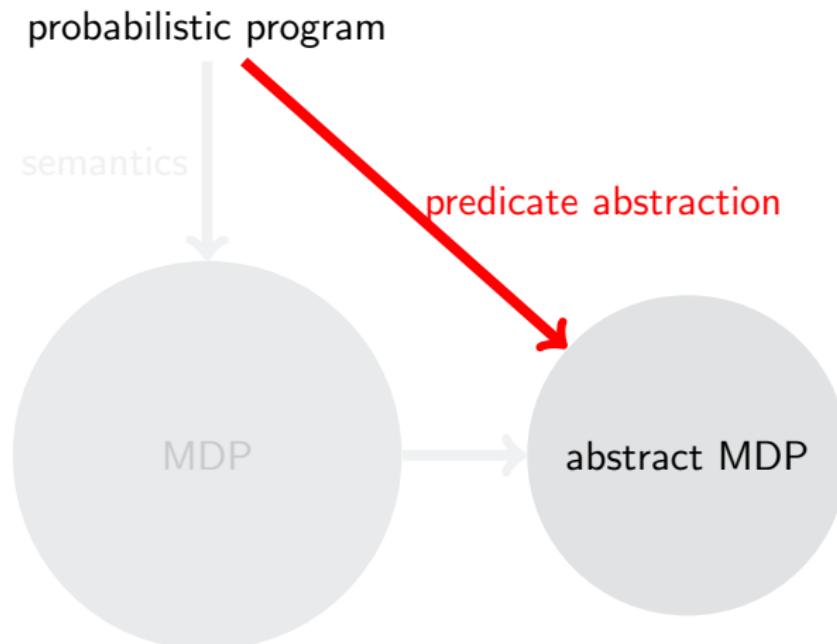
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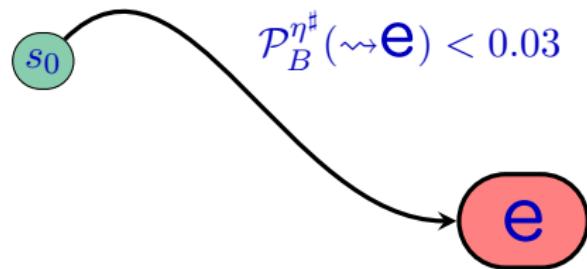


## Wrap-up

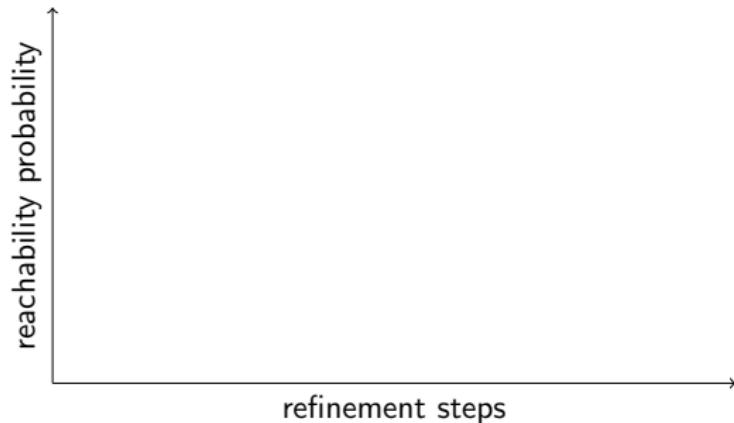
- fully **automatic** and **symbolic** abstraction
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- ... but where do predicates come from?



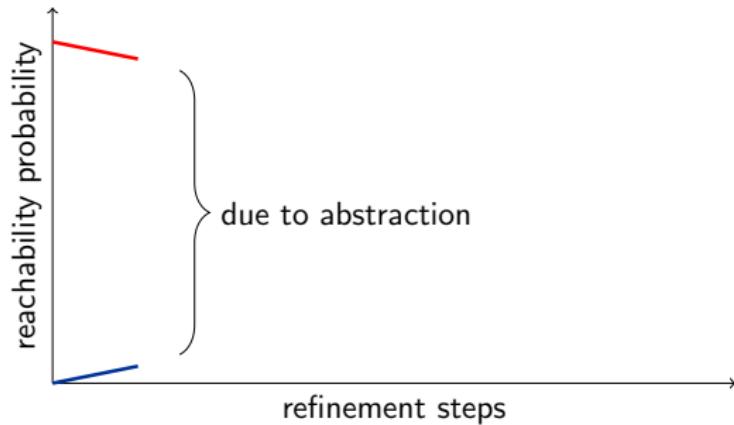
## Reachability Properties



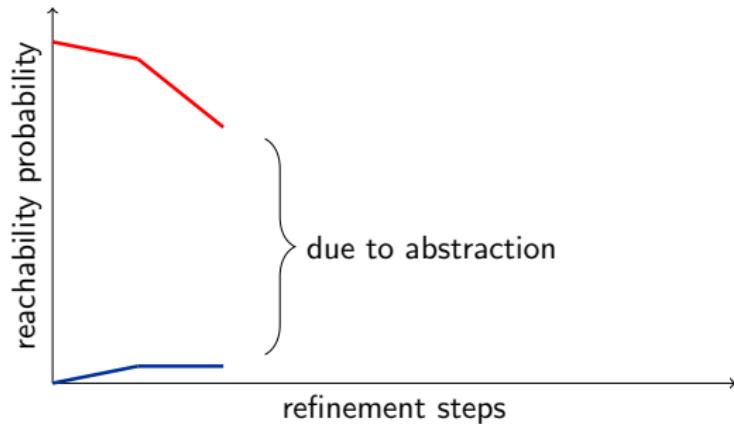
# Abstraction Refinement



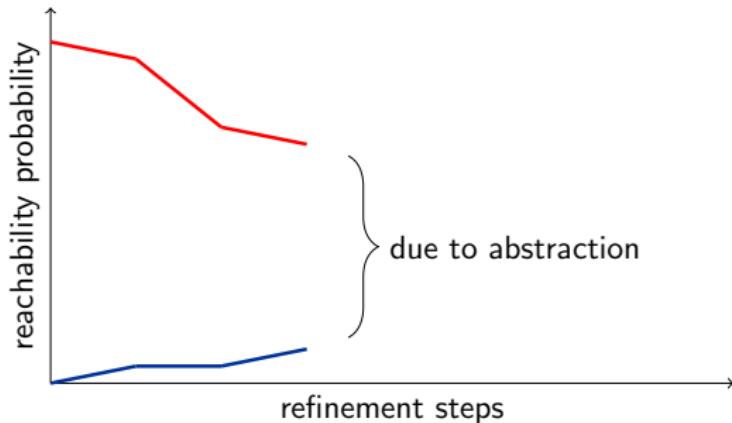
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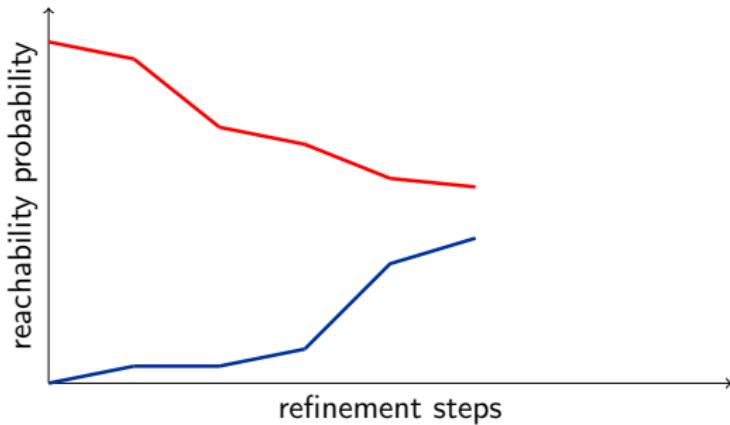
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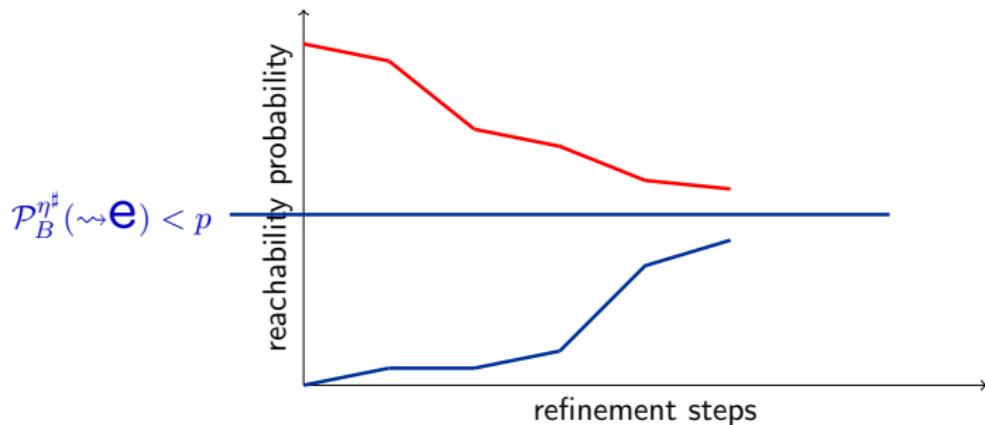
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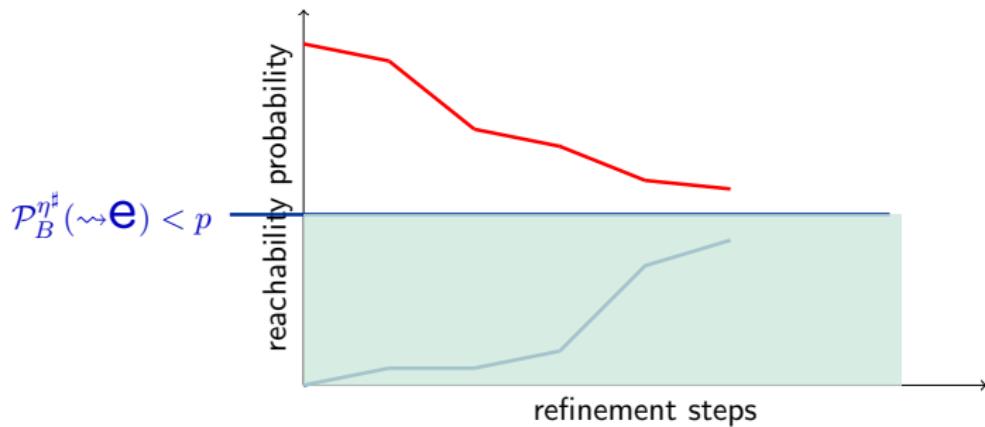
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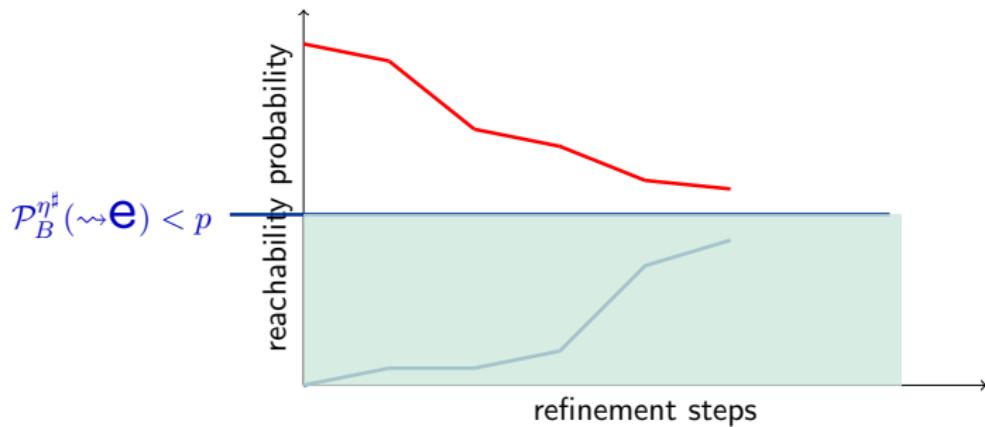
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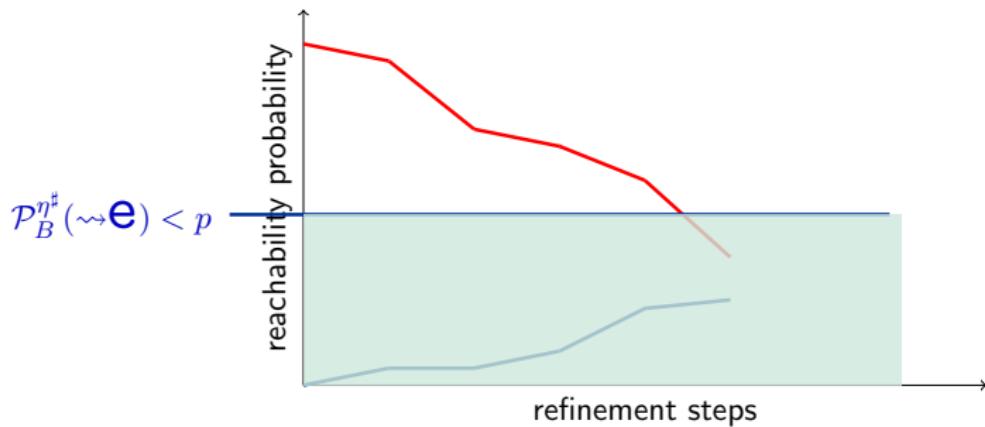
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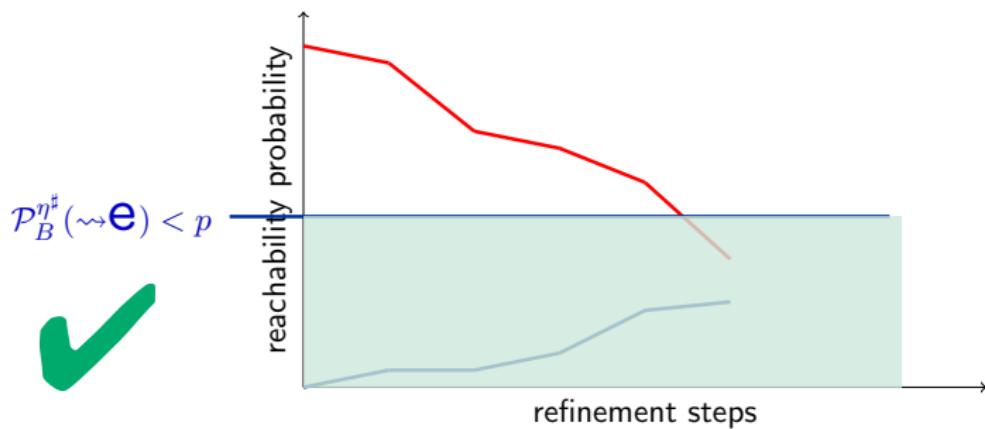
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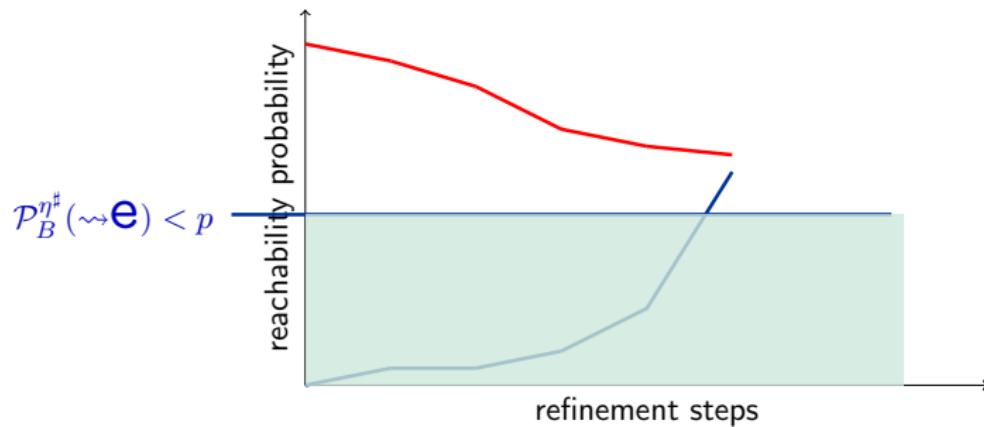
## Property shown



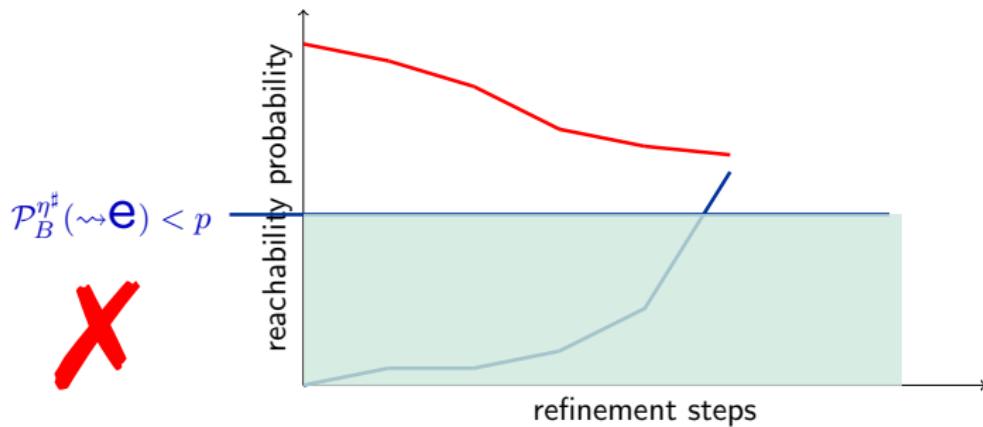
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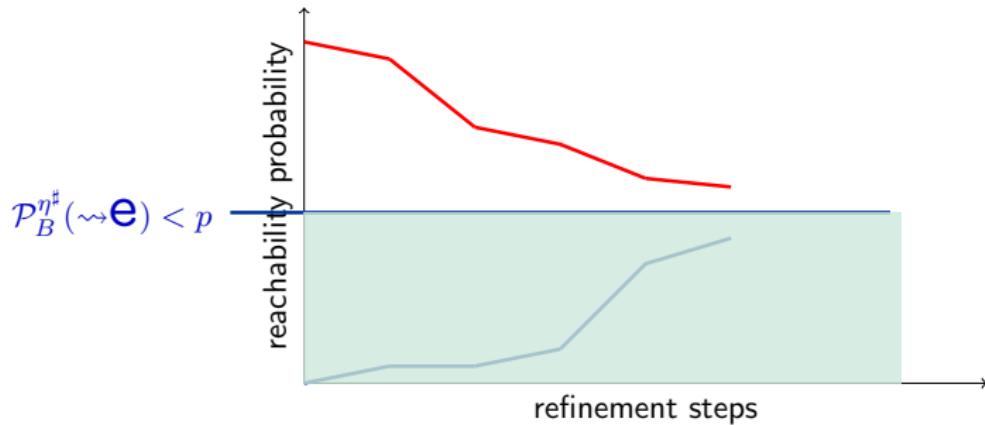
## Property refuted



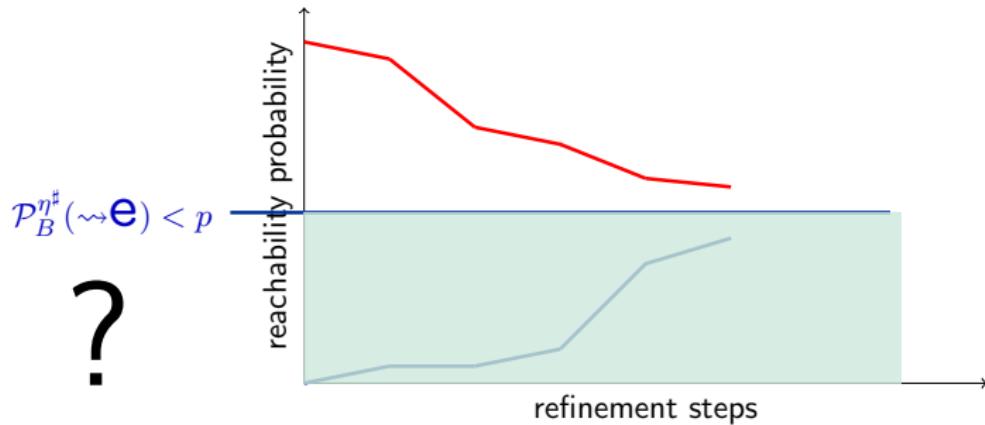
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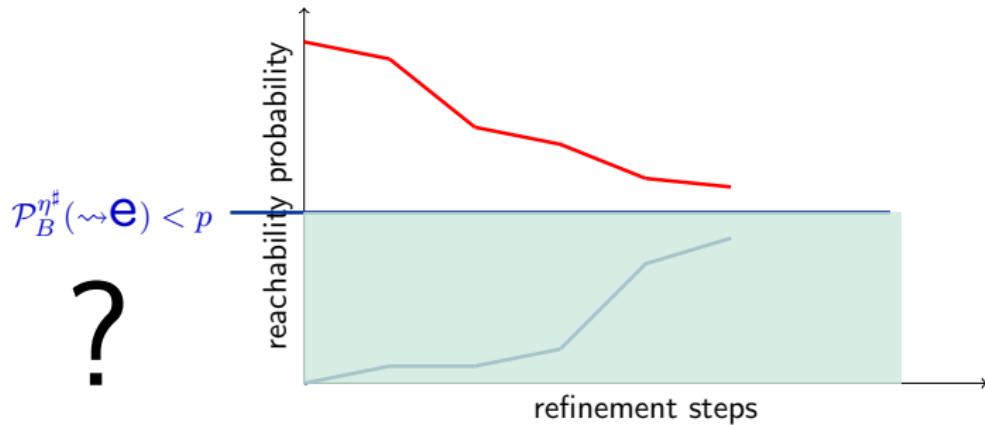
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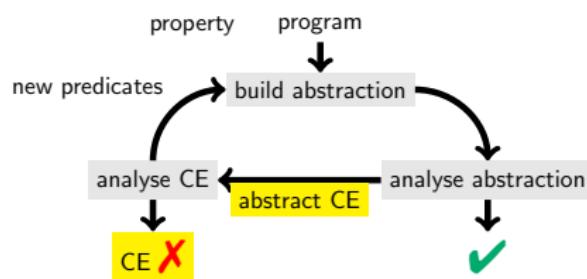


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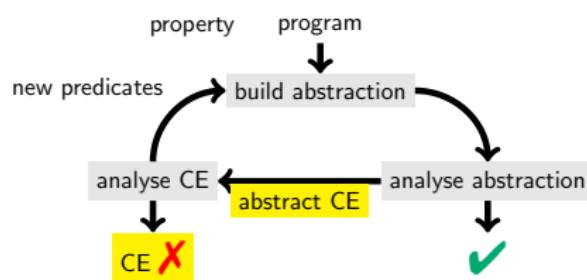
# CEGAR: Counterexample-Guided Abstraction Refinement

- refinement technique in software model checking
  - SLAM project at Microsoft [Ball/Rajamani 2002,...]
  - Blast
  - ...



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What **is** an abstract CE?

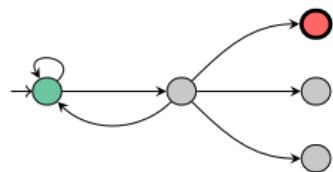
- pioneering work in probabilistic verification

# Counterexamples

**Safety: Error State Unreachable**

**Probabilistic Reachability**

Transition System

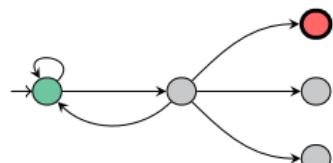


# Counterexamples

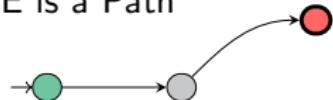
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## Probabilistic Reachability

Transition System



CE is a Path

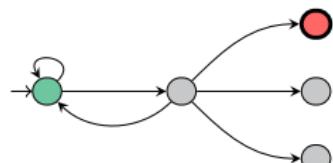


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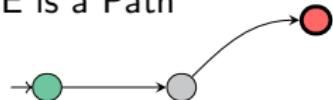
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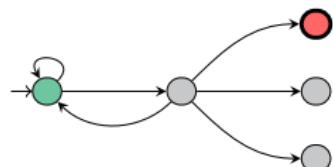


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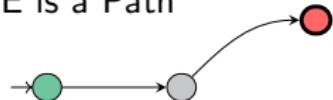
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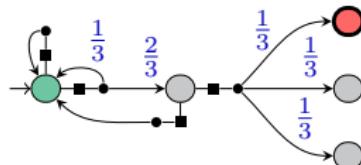


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Stochastic Game



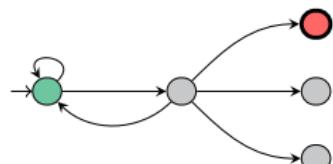
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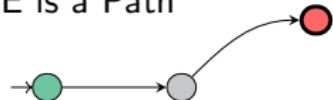
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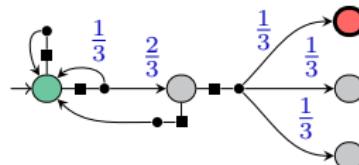
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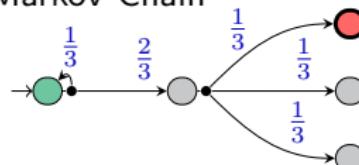
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Markov Chain

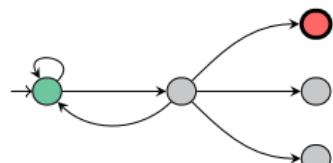


“probability to reach error state =  $\frac{1}{3}$ ”

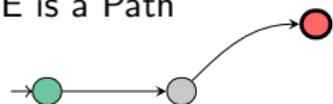
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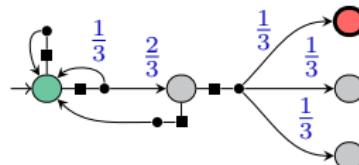
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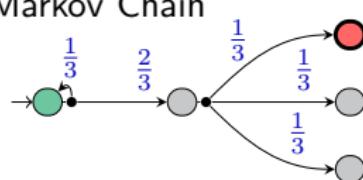
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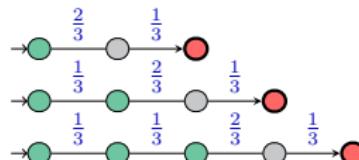
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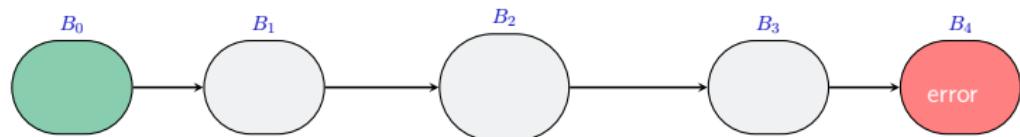
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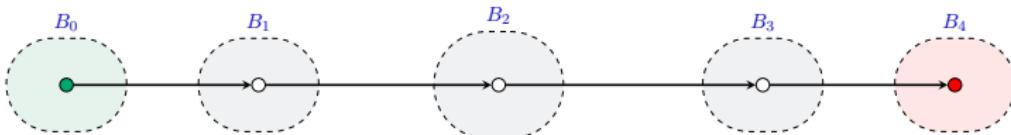
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- check if the abstract counterexample is realisable ...



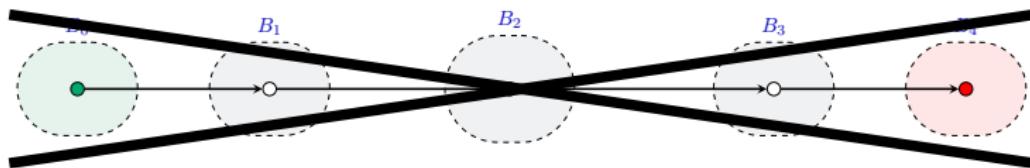
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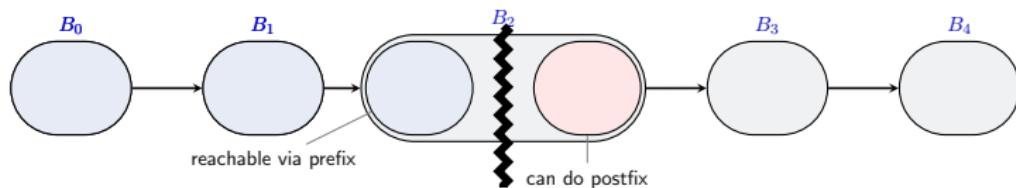


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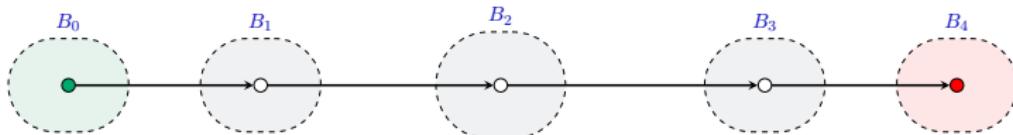


- ... or spurious
  - abstraction too coarse, i.e., needs **refinement**

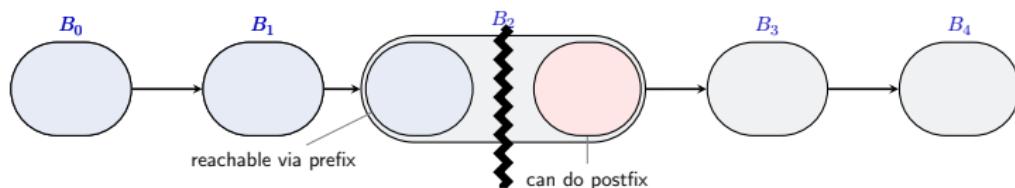


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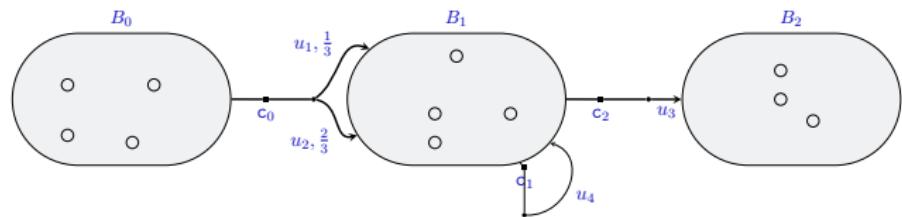


- Implementation with SMT solver:
  - convert path to formula
  - path realisable  $\iff$  formula satisfiable
  - generate splitting predicate, e.g., by interpolation

# Analysis of Probabilistic CE

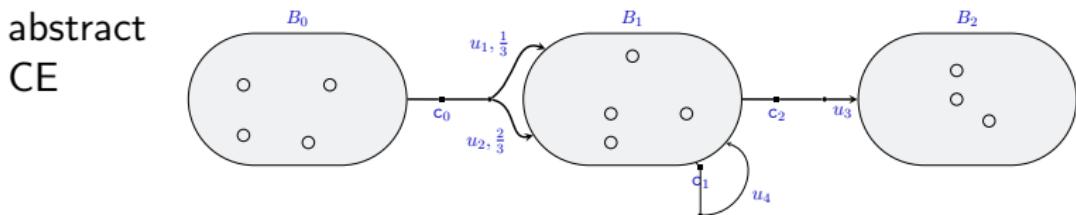
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  - replay decisions of abstract counterexample

abstract  
CE



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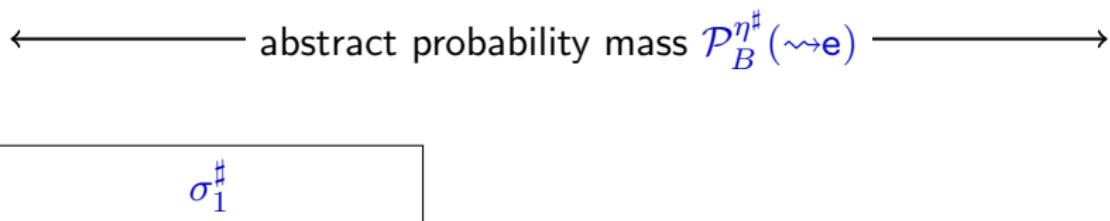
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- Challenge: CE correspond to many paths
  - Markov chain: cyclic & has probabilistic branching
- Goal 1: Leverage conventional counterexample analysis
  - path analysis based on SMT and interpolation
- Goal 2: avoid exploring too many paths

# Probabilistic CEGAR

- enumerate paths of CE Markov chain
- visit paths with highest probability first [Han&Katoen 2007]
  - path  $\sigma_1^\sharp$ 
    - if spurious generate predicate (interpolation)



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- realisable probability mass  $> p$ ?

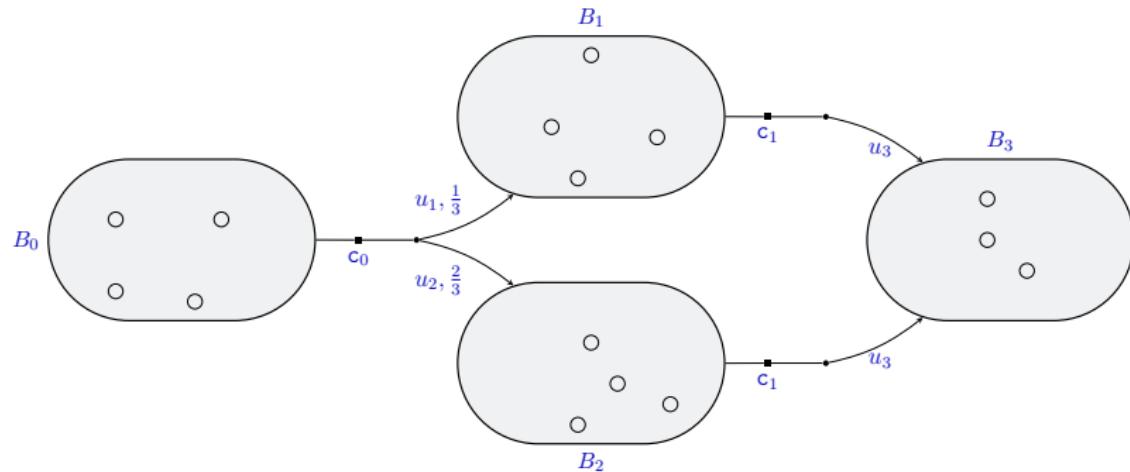
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←  $\mathcal{P}_B^{\eta^\sharp}(\text{realisable paths}) > p?$  →

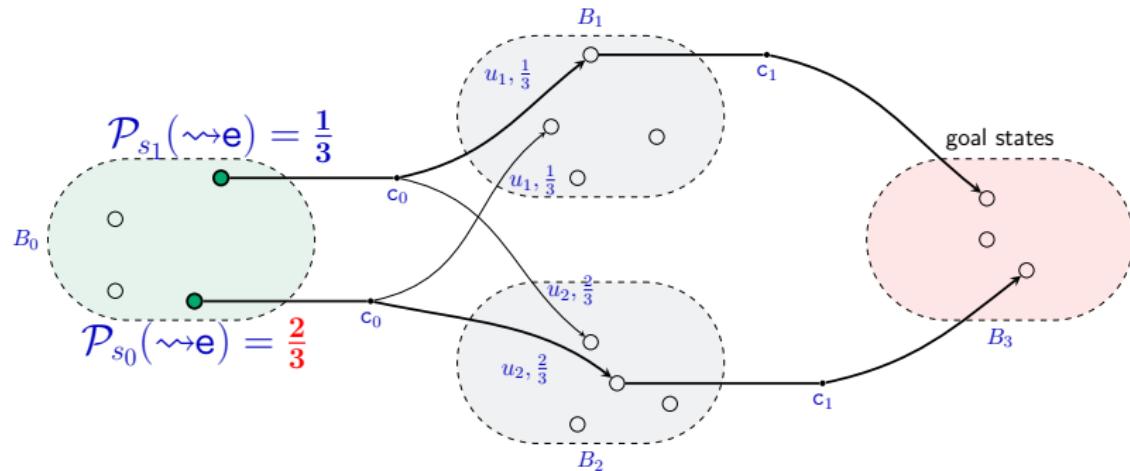
# Computing realisable probability is harder than it seems

**realisable probability**  $\neq \sum\{\mathcal{P}(\sigma^\sharp) \mid \text{realizable path}\} = 1$



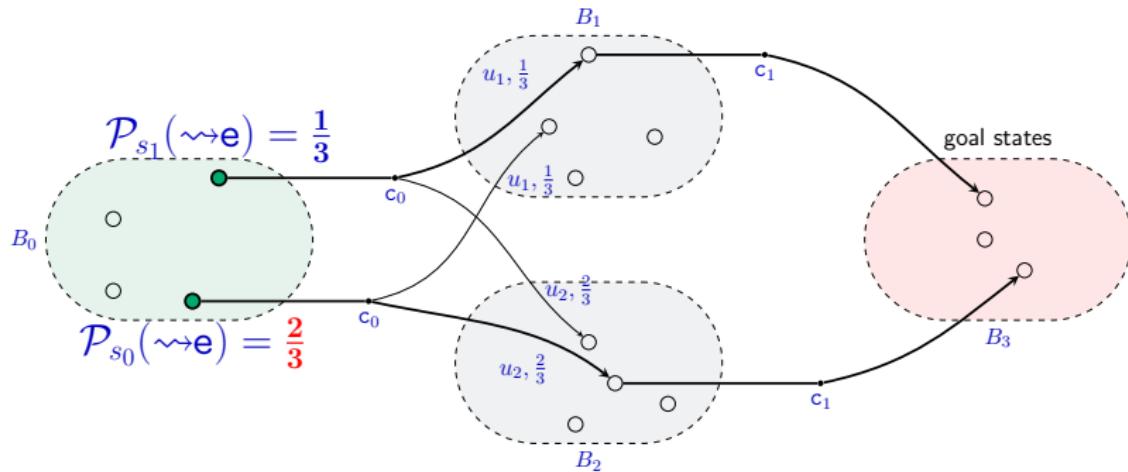
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## Theorem (Realisable probability)

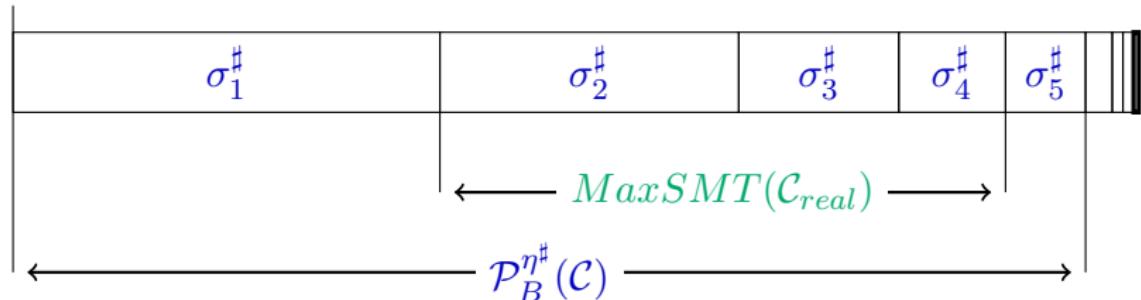
Realisable probability as optimisation problem:

$$\text{MaxSmt}(\exp_1, \dots, \exp_n) = \max \left\{ \sum_{i=1}^n [\![\exp_i]\!]_s \cdot p_i \mid s \in [\![I \wedge F(B)]\!] \right\}$$

where  $\exp_i$  characterizes path  $\sigma_i$

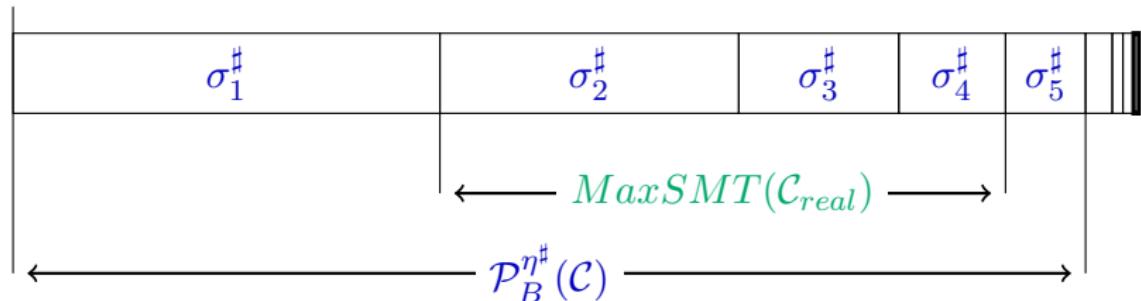
# Probabilistic CEGAR

- analyse paths in Markov chain with decreasing probability
  - spurious paths give predicates
  - realizable paths can improve lower bound
    - MaxSMT



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- **Semi**-decision procedure for probabilistic CE analysis
  - always terminates returning either
    - ✗ CE realizable
    - ✓ CE spurious and predicate
    - ? don't know and predicate
  - **incomplete** to ensure termination
    - limit on number of spurious paths

## Justification for Incompleteness: Undecidability

- A CE analysis problem consists of
  - probabilistic program  $M$
  - threshold  $p$
  - abstraction  $G$  of  $M$
  - CE  $(B, \eta^\sharp)$  in  $G$ , i.e.,  $\mathcal{P}_B^{\eta^\sharp}(\text{~}\rightsquigarrow\text{e}) > p$
- **decide** if the CE is real
  - there is a corresponding concrete CE  $(s, \eta)$  with  $\mathcal{P}_s^\eta(\text{~}\rightsquigarrow\text{e}) > p$

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⇒ conventional counterexample analysis decidable

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### Theorem (Undecidability of Counterexample Analysis)

*Counterexample analysis for probabilistic programs is undecidable*

#### Proof.

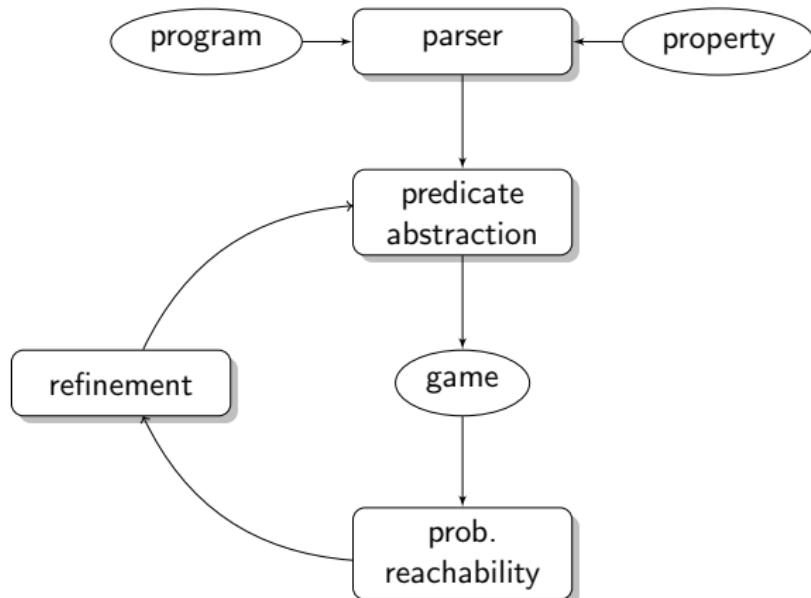
Halting problem for counter machines can be reduced to CE analysis



## Backward Refinement (VMCAI 2010)

- Refinement if no threshold is available
- Target uncertainty from abstraction (leverage game strategies)

# The PASS tool



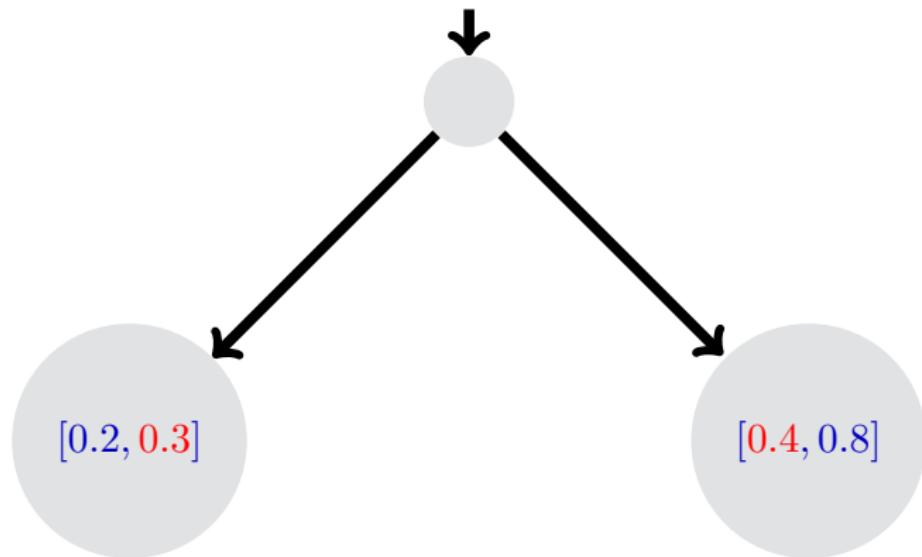
# Case Study: BRP

- Probability to reach:  
“receiver does not receive any chunk and sender tried to send a chunk”
- Can be analyzed for an infinite parameter range with PASS
  - for any file size  $\geq 16$ , probability is  $1.6E - 7$
- PASS provides proof for arbitrary file size
- BRP is just one case study:

Case study (parameters)	Property	Conventional			Abstraction					
		states	trans	time	states	trans	refs	preds	paths	time
WLAN (BOFF T)	5 315	5,195K	11,377K	93	34K	36K	9	120	604	72
	6 315	12,616K	28,137K	302	34K	42K	9	116	604	88
	6 315	12,616K	28,137K	2024	771K	113K	9	182	582	306
	6 9500	—	—	TO	771K	113K	9	182	582	311
CSMA/CD (BOFF)	3	p1	41K	52K	10	1K	2K	8	58	28
	4	p1	124K	161K	56	6K	9K	14	100	56
	3	p2	41K	52K	10	0.5K	0.9K	12	41	28
	4	p2	124K	161K	21	0.5K	1.5K	12	41	11
BRP (N MAX)	16 3	p1	2K	3K	5.4	2K	3K	9	46	41
	32 5	p1	5K	7K	12	5K	7K	9	64	111
	64 5	p1	10K	14K	26	10K	14K	8	95	585
	>16 3	p4	∞	—	—	0.5K	0.9K	7	26	17
	>16 4	p4	∞	—	—	0.6K	1K	7	27	17
	>16 5	p4	∞	—	—	0.7K	1K	8	28	18
SW	goodput	∞	—	—	5K	11K	3	40	7	87
	timeout	∞	—	—	27K	44K	3	49	6	89

## Why abstraction works.

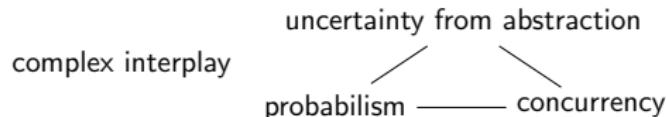
- absolute values do matter but only, e.g., differences between variables
- cannot contribute to optimum



# Contributions

a novel analysis method for probabilistic programs:

- **symbolic abstraction** to tackle large state spaces
  - **Première**: predicate abstraction in probabilistic verification
    - prior work in qualitative software verification
  - **Challenge**



- **refinement** to achieve full automation
  - **Première**: Probabilistic CEGAR
    - prior work: CEGAR in qualitative software verification
  - **Challenge**
    - counterexamples are Markov chains
- implemented in **PASS** tool

## Limitations

- Abstraction is not a panacea / silver bullet
  - can be less efficient for certain finite-state models
- Probabilistic CEGAR:
  - lower thresholds for minimal reachability?
- No support for state-dependent probabilities:

[]  $m=1 \ \& \ x>0 \rightarrow \frac{1}{x} : (x' = x - 1) + \frac{x-1}{x} : (m' = 3)$  ;

## Avenues for Future Work

- Beyond probabilistic reachability for MDPs
  - rewards and expectations
  - Exponential distributions
  - Support for full PCTL
- Richer input language
  - Modest

# Thesis Statement

Abstraction enables automatic verification of probabilistic programs with large and, for the first time, infinite state spaces.