



# Quantitative Abstraction Refinement

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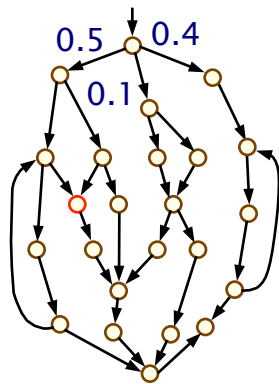
Joint work with:

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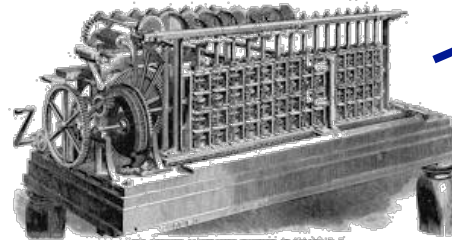
PEPA Club, University of Edinburgh, November 2009

# Probabilistic model checking

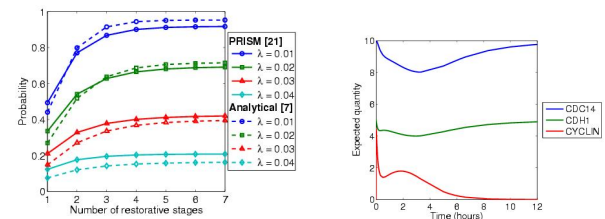
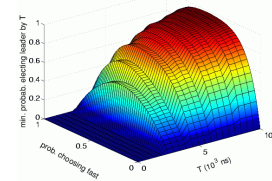
Probabilistic model  
e.g. Markov chain



Probabilistic  
model checker  
e.g. PRISM



Result



$P_{<0.01}$  [ F error ]

Probabilistic temporal  
logic specification  
e.g. PCTL, CSL, LTL

Quantitative results

# Overview

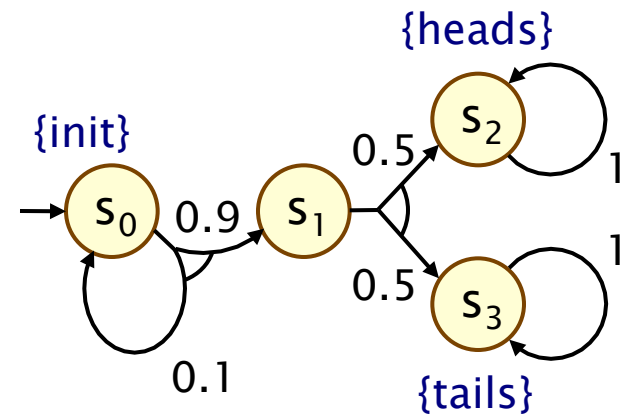
- Probabilistic model checking
  - discrete-time Markov chains (DTMCs)
  - Markov decision processes (MDPs)
  - probabilistic reachability
- Abstraction for probabilistic models
  - abstractions of DTMCs (MDPs)
  - abstractions of MDPs (two-player stochastic games)
- Quantitative abstraction refinement
  - abstraction-refinement loop
  - verification of probabilistic software, real-time systems
- Current/future work & Conclusions

# Probabilistic models

- Discrete-time Markov chains (DTMCs)
  - discrete states, discrete probability distributions
- Markov decision processes (MDPs)
  - discrete states, probability and nondeterminism
  - uses: concurrency, under-specification, abstraction
  - models: randomised distributed algorithms, randomised communication protocols, security protocols, ...
- Continuous-time Markov chains (CTMCs)
  - discrete states, exponentially distributed delays
  - performance modelling, biological reaction systems, ...

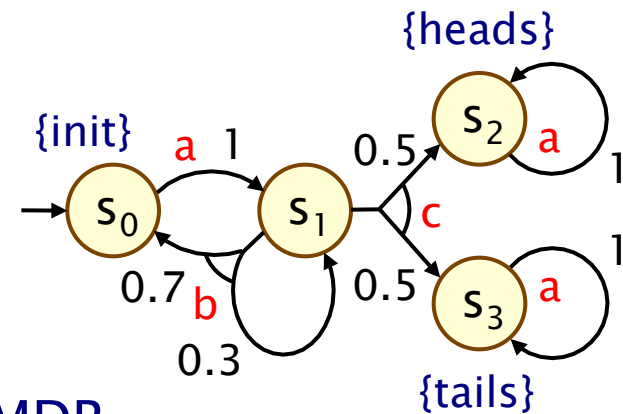
# Discrete-time Markov chains (DTMCs)

- Model **fully probabilistic** behaviour
  - state-transition systems augmented with probabilistic choice
- Transition probability matrix
  - over state space  $S$
  - $P : S \times S \rightarrow [0,1]$
- Paths through a DTMC
  - finite/infinite state sequences
  - **Path(s)** = set of all (infinite) paths from state  $s$
  - define probability space  $\Pr_s$  over **Path(s)**
- Probabilistic reachability (for a set of goal states  $F \subseteq S$ )
  - probability of reaching  $F$  from state  $s$
  - $p_s(F) = \Pr_s \{ s_0 s_1 s_2 s_3 \dots \in \text{Path}(s) \mid s_i \in F \text{ for some } i \}$
  - reduces to solution of a linear equation system



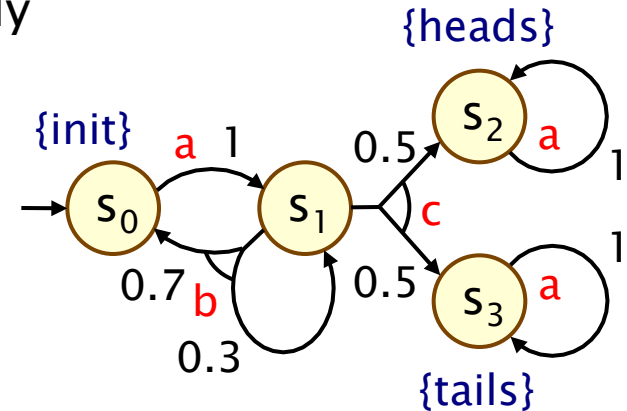
# Markov decision processes (MDPs)

- Model **nondeterministic** as well as **probabilistic** behaviour
  - extension of discrete-time Markov chains
  - nondeterministic choice between probability distributions
- **Transition probability function**
  - **Steps** :  $S \rightarrow 2^{\text{Act} \times \text{Dist}(S)}$
  - maps states to non-empty sets of action-probability distribution pairs
- A (finite or infinite) **path** through an MDP
  - is a sequence of (connected) states
  - represents an execution of the system
  - resolves both the probabilistic and nondeterministic choices



# Strategies of MDPs

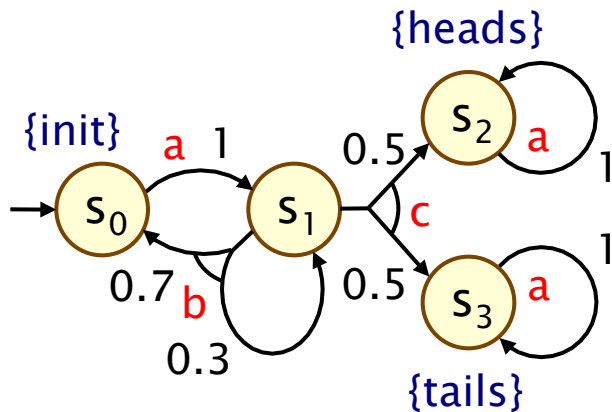
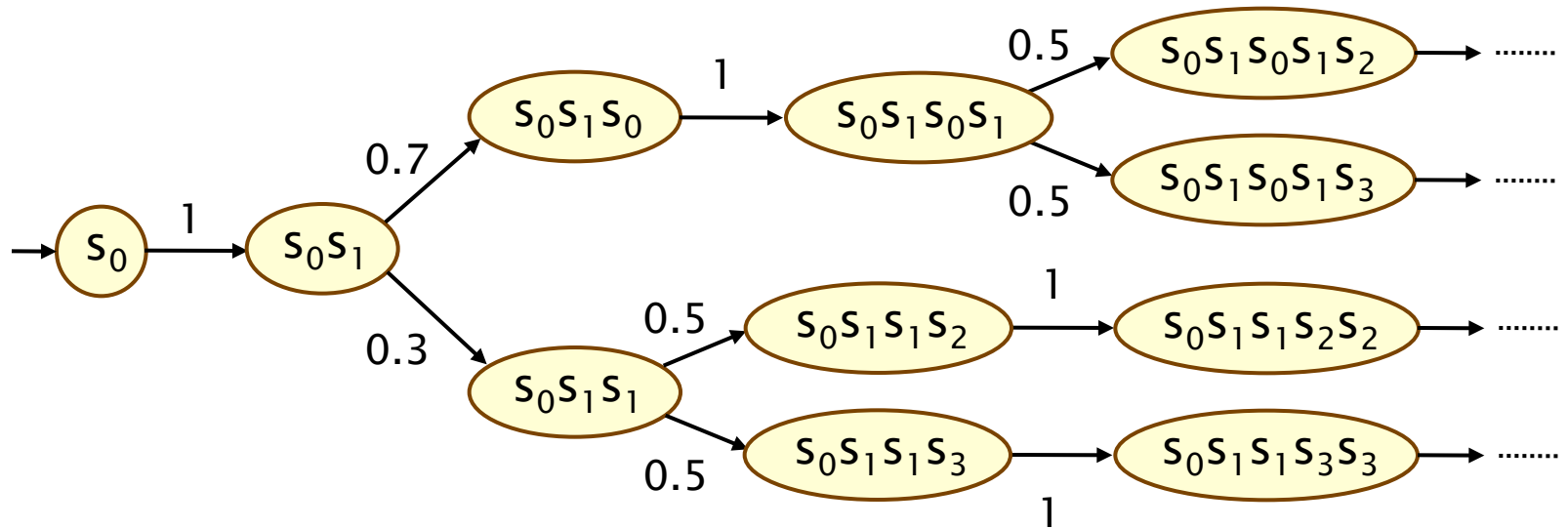
- A **strategy** (aka. “adversary”, “scheduler”, ...) of an MDP
  - is a resolution of nondeterminism only
  - is (formally) a mapping from finite paths to distributions



- E.g. strategy that picks **b** then **c** in  $s_1$ 
  - $\sigma(s_0s_1) = (b, \mu_b)$ ,  $\sigma(s_0s_1s_1) = (c, \mu_c)$ ,  
 $\sigma(s_0s_1s_0s_1) = (c, \mu_c)$
- A strategy results in a fully probabilistic model
  - i.e. an (infinite-state) DTMC over finite paths
  - on which we can define a probability space over infinite paths
- Strategy  $\sigma$  is **simple** (memoryless) iff  $\sigma(s_1 \dots s_n) = \sigma(s_n)$ 
  - in this case, resulting model reduces to finite Markov chain

# Example strategy

- Fragment of DTMC for strategy which picks **b** then **c** in  $s_1$



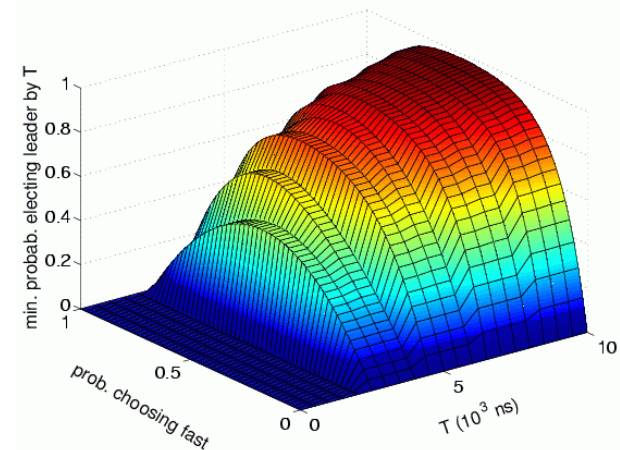
# Probabilistic reachability for MDPs

- A strategy  $\sigma$  induces, for each state  $s$  in the MDP:
  - a set of infinite paths  $\text{Path}^\sigma(s)$
  - a probability space  $\text{Pr}_s^\sigma$  over  $\text{Path}^\sigma(s)$
- Probabilistic reachability (for a set of goal states  $F \subseteq S$ )
  - probability of reaching  $F$  from state  $s$  under strategy  $\sigma$
  - $p_s^\sigma(F) = \text{Pr}_s^\sigma \{ s_0 s_1 s_2 s_3 \dots \in \text{Path}^\sigma(s) \mid s_i \in F \text{ for some } i \}$
- Minimum/maximum probabilities over all strategies
  - $p_s^{\min}(F) = \inf_\sigma p_s^\sigma(F)$
  - $p_s^{\max}(F) = \sup_\sigma p_s^\sigma(F)$
  - simple strategies suffice
- Used to reason about best/worst-case behaviour
  - e.g. “maximum probability of an error occurring”



# Probabilistic model checking for MDPs

- Also: Bounded reachability properties
  - e.g. “min. probability of algorithm termination within T steps”
- Also: Cost- and reward-based properties
  - augment states/transitions of MDP with real-valued costs
  - define properties as random variables over  $\text{Path}^\sigma(s)$
  - e.g. “max. expected power consumption for the duration of the protocol”
- Probabilistic temporal logics
  - e.g. PCTL extends CTL
- We focus on quantitative analysis
  - i.e. just compute  $p_s^{\min}(F)$  and  $p_s^{\max}(F)$
  - useful to spot patterns/trends



# Probabilistic model checking for MDPs

- Probabilistic reachability is efficiently computable
  - **linear optimisation problem** (polynomial complexity)
  - or **value iteration** (dynamic programming) – simple iterative numerical method; more efficient in practice
  - **best/worst** case simple strategy can also be generated
- Mature tool support exists, e.g. PRISM
  - efficient (e.g. symbolic) implementations
  - successful application to wide range of application domains
- But major challenges remain, e.g.
  - state-space explosion
  - automating model extraction

# Overview

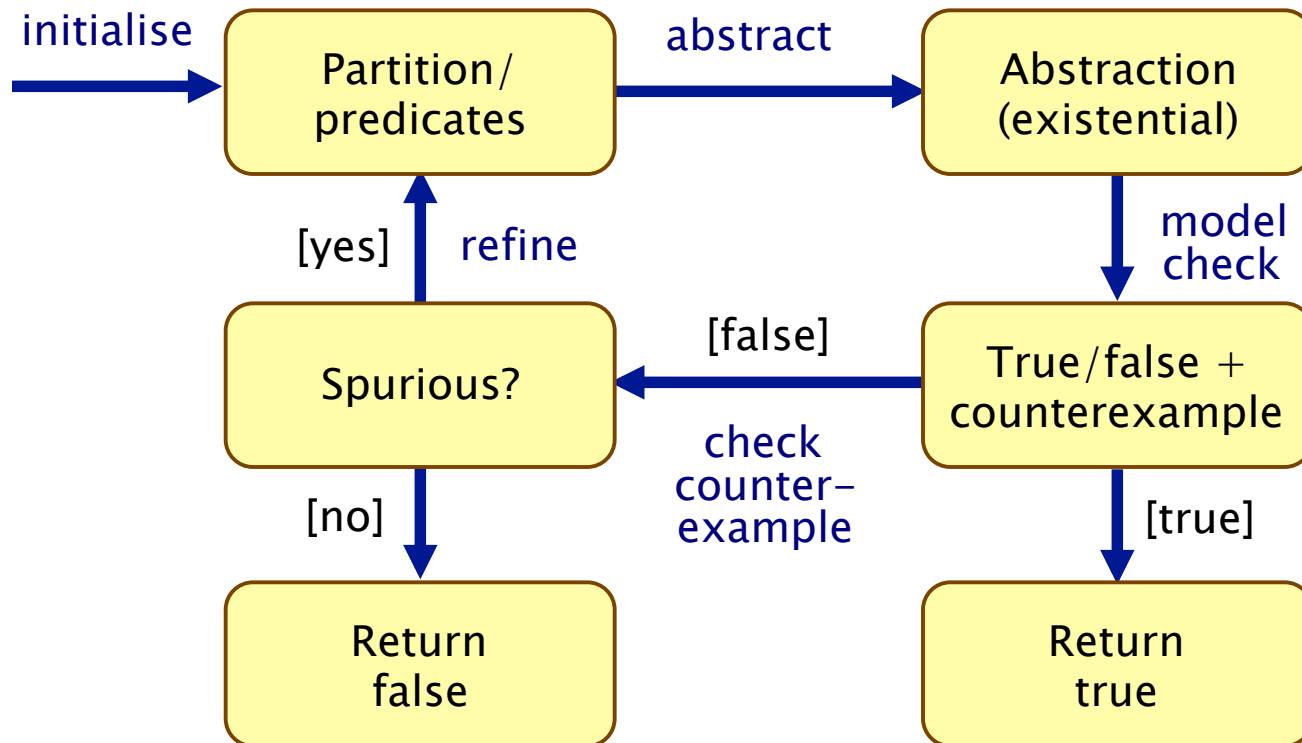
- Probabilistic model checking
  - discrete-time Markov chains (DTMCs)
  - Markov decision processes (MDPs)
  - probabilistic reachability
- **Abstraction for probabilistic models**
  - abstractions of DTMCs (MDPs)
  - abstractions of MDPs (two-player stochastic games)
- Quantitative abstraction refinement
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# Abstraction

- Very successful in (non-probabilistic) model checking
  - essential for verification of large/infinite-state systems
- Construct abstract model **A** of concrete model **M**
  - details not relevant to some property of interest removed
  - e.g. partition of state space based on a set of predicates
- Non-probabilistic case: existential abstraction
  - conservative: existence of path in **M** implies existence in **A**
  - hence can model check **A** to verify safety properties of **M**
- Abstraction refinement
  - automate process of constructing abstraction
  - start with simple coarse abstraction, then iteratively refine

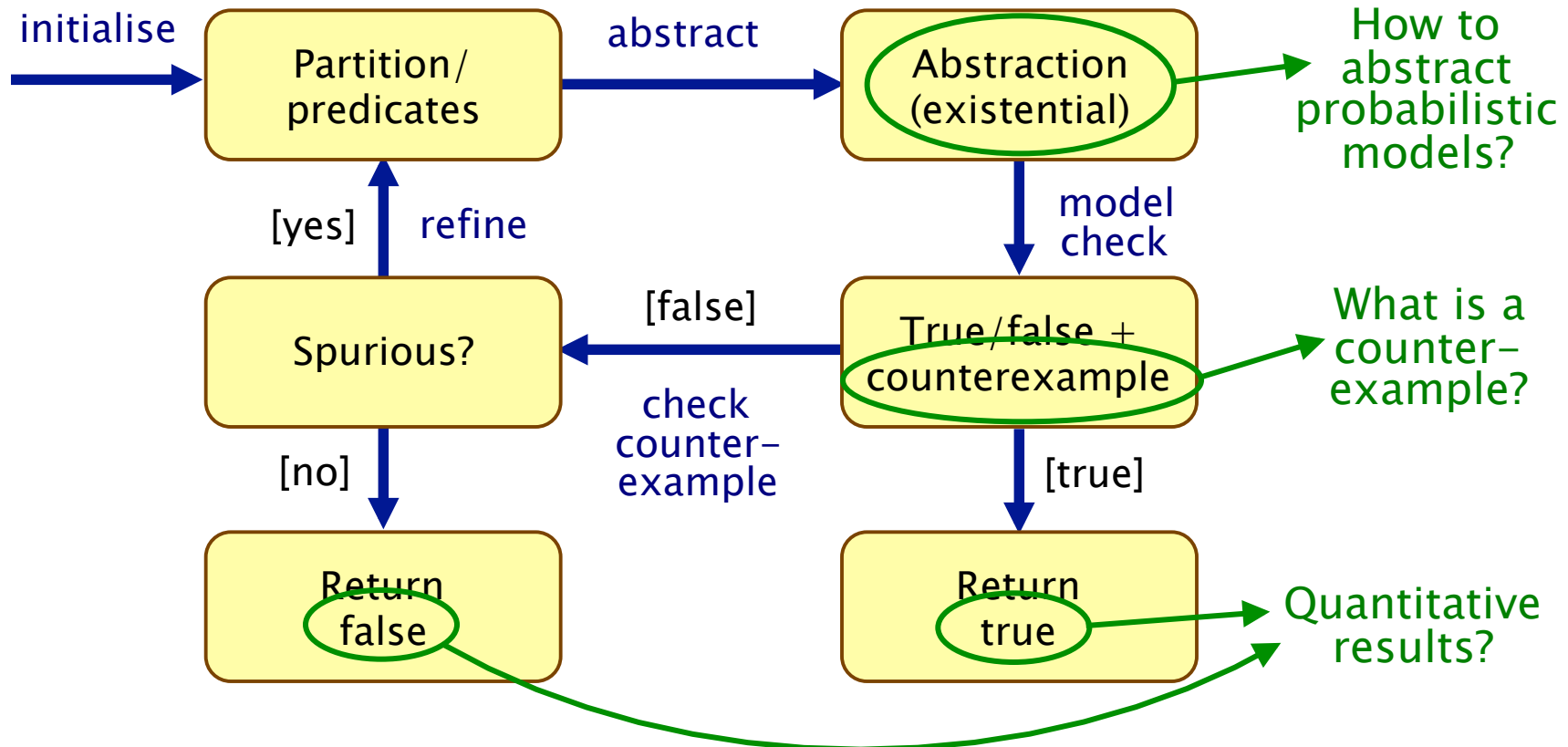
# Abstraction + CEGAR

- Counterexample-guided abstraction refinement
  - (non-probabilistic) model checking of reachability properties



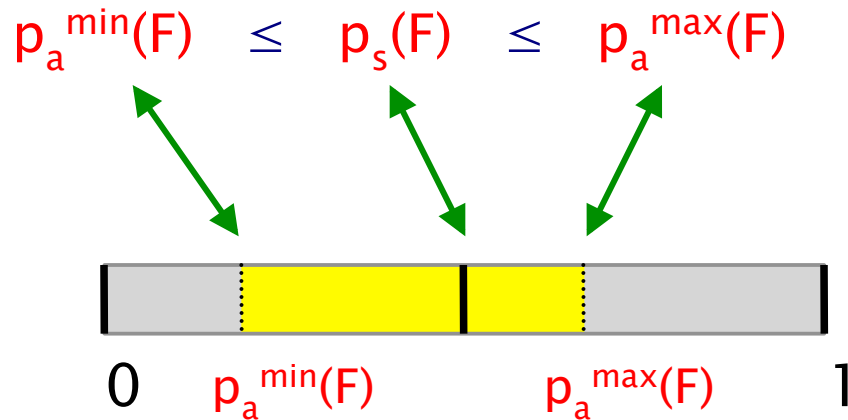
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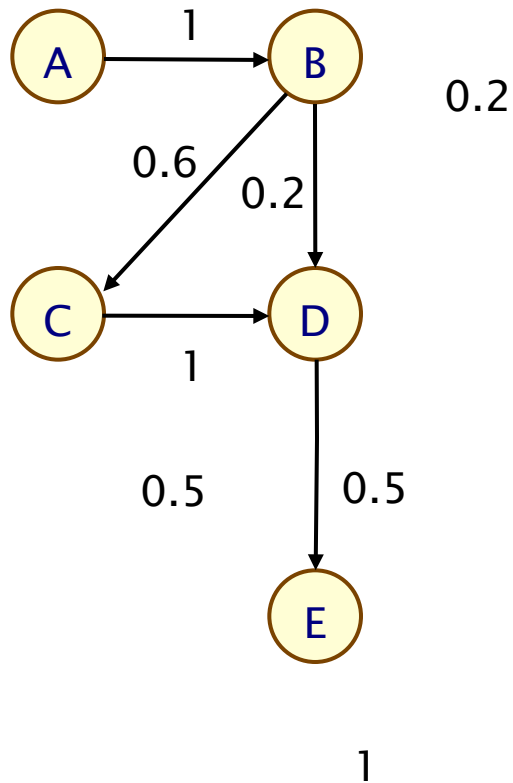
# Abstraction of DTMCs

- We use MDPs as abstractions of DTMCs
  - based on a partition  $A$  of the (concrete) state space  $S$
  - i.e. each element  $a \in A$  is an abstract state
- Analysis of MDP yields lower/upper bounds:
  - for target  $F \in A$ ,  $s \in S$  and  $a \in A$  with  $s \in a$



# DTMC $\rightarrow$ MDP

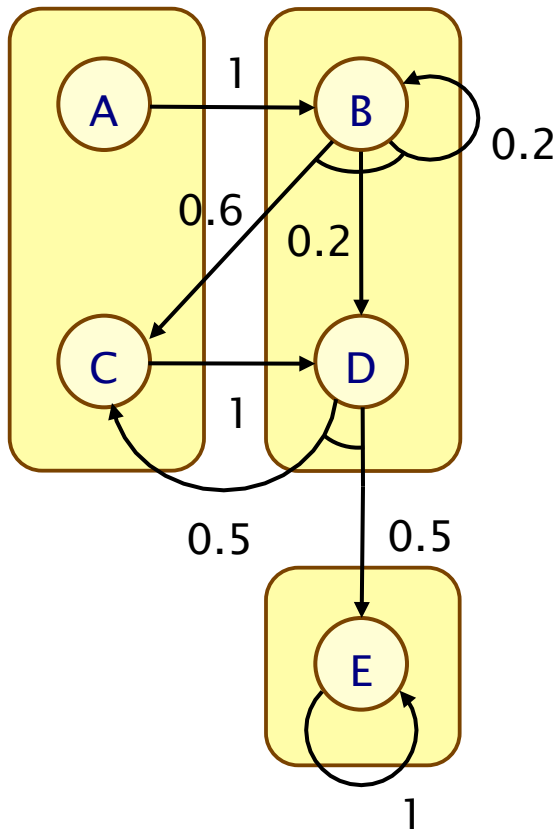
- Partition of (concrete) state space gives abstract states



Concrete model (DTMC)

# DTMC $\rightarrow$ MDP

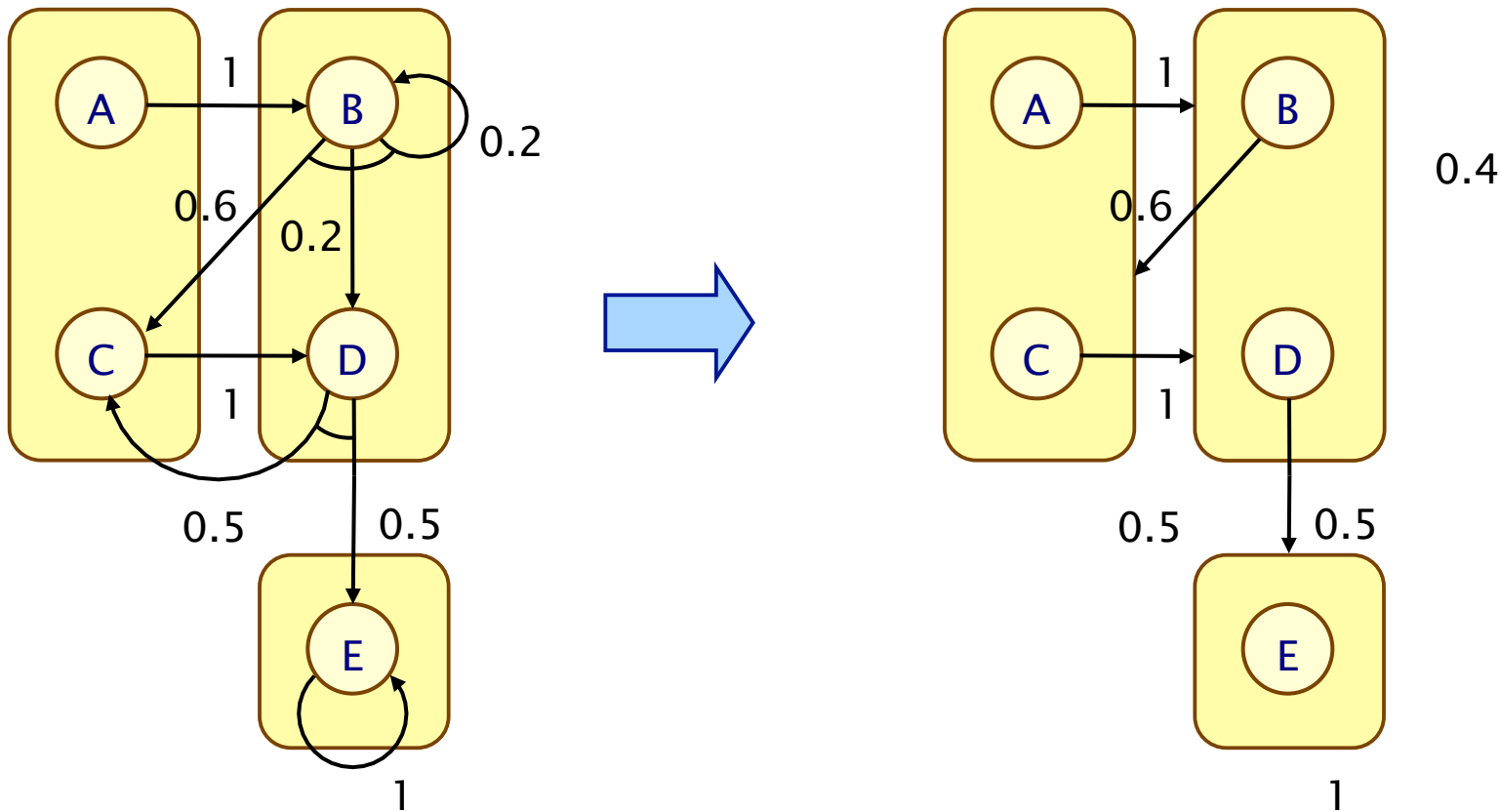
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Concrete model (DTMC)

# DTMC $\rightarrow$ MDP

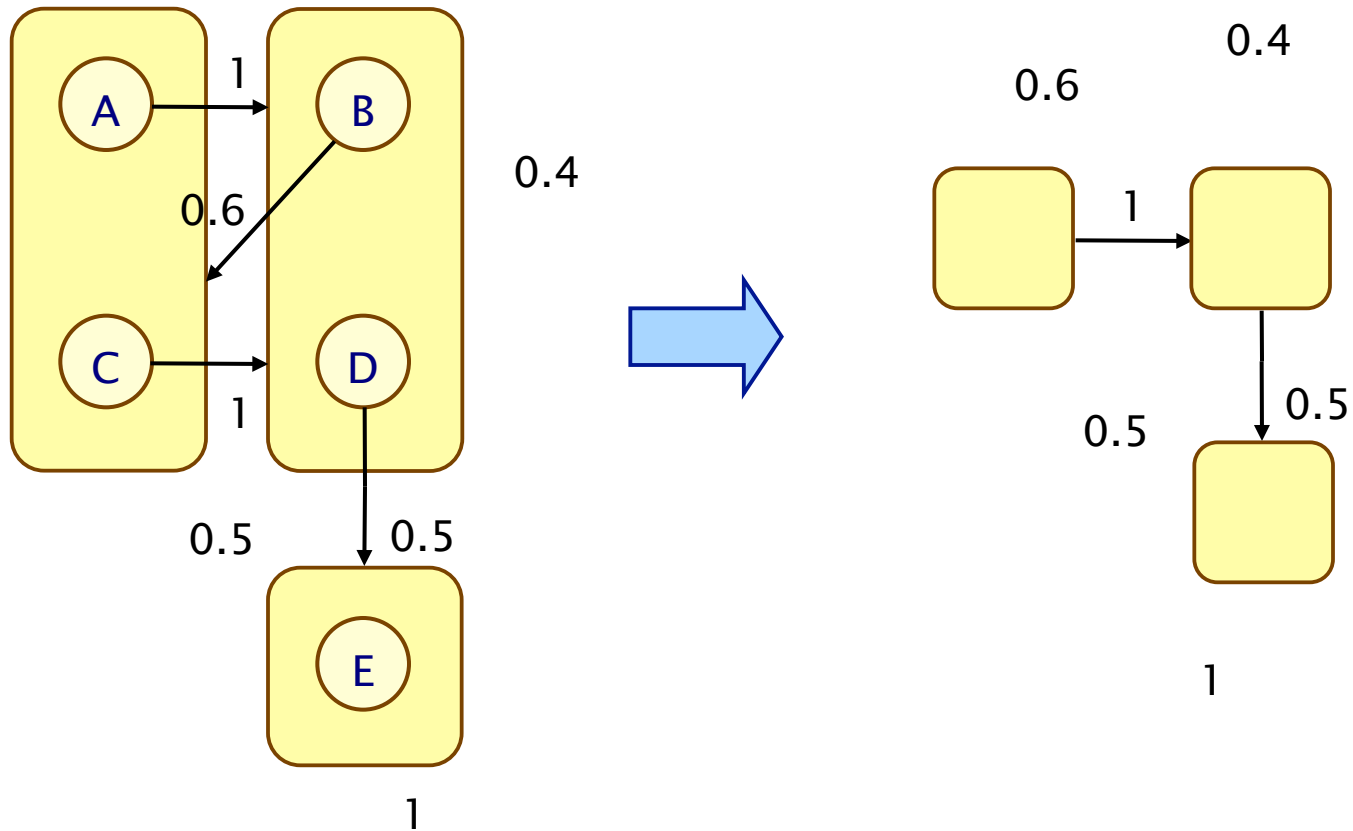
- Distributions are lifted to the abstract state space



Concrete model (DTMC)

# DTMC $\rightarrow$ MDP

- Choices in abstract states become choices in MDP



Concrete model (DTMC)

Abstraction (MDP)

# Abstraction of MDPs

- Abstraction increases degree of nondeterminism
  - i.e. minimum probabilities are lower and maximums higher



- what form does the abstraction of an MDP take?

- Our approach: two-player stochastic games [QEST'06]
- Key idea: **separate two forms of nondeterminism**
  - (a) from abstraction and (b) from original MDP
  - then generate separate lower/upper bounds for min/max

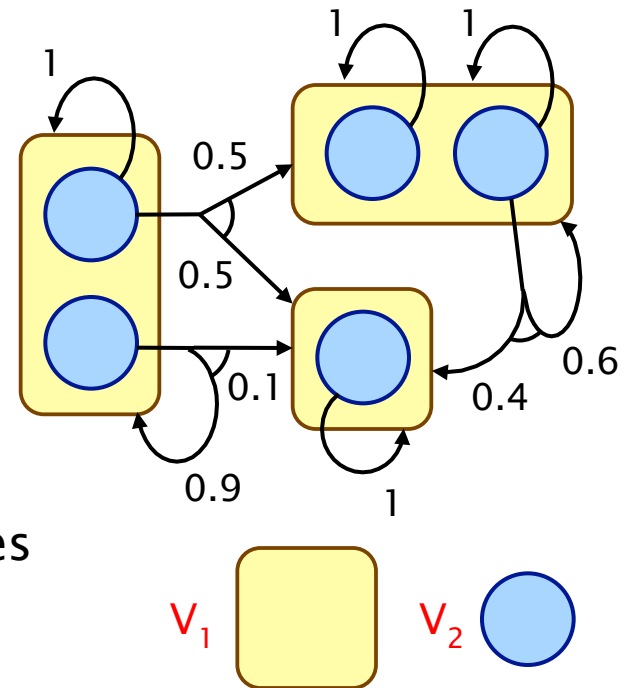


# Two-player stochastic games

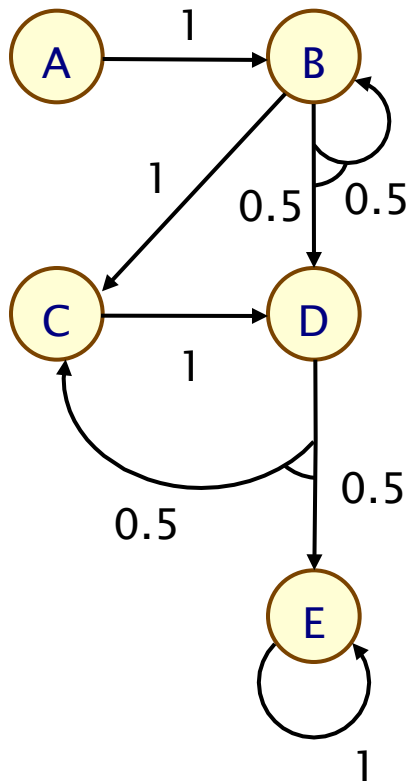
- Subclass of simple stochastic games [Shapley], [Condon]
  - two nondeterministic players and probabilistic choice
  - vertices  $V$  of game partitioned into  $V_1$  and  $V_2$  (player 1 / 2 vertices)
  - player 1 has choices between  $V_2$  vertices
  - player 2 has choices between distributions over  $V_1$  vertices
- A resolution of the nondeterminism in the game
  - corresponds to a pair of strategies for players 1 and 2:  $(\sigma_1, \sigma_2)$
  - $p_v^{\sigma_1, \sigma_2}(F)$  = probability of reaching  $F$  from  $v$  under  $(\sigma_1, \sigma_2)$
- Optimal reachability probabilities for player 1 and player 2
  - informally: the maximum probability of reaching  $F$  a player can guarantee, no matter what the other player does
  - formally:  $\sup_{\sigma_1} \inf_{\sigma_2} p_v^{\sigma_1, \sigma_2}(F)$  and  $\sup_{\sigma_2} \inf_{\sigma_1} p_v^{\sigma_1, \sigma_2}(F)$
  - computable (and simple strategies) with value iteration

# Games as abstractions of MDPs

- Abstraction of an MDP is a two-player stochastic game
  - based on a partition  $A$  of the concrete state space
- where:
  - player 1 controls the nondeterminism of the abstraction
  - player 2 controls the nondeterminism of the MDP
- Player 1 vertices: abstract states
  - elements of partition  $A$
- Player 2 vertices: choices of MDP **lifted** to abstract states
  - sets of distributions over  $A$
  - or equivalently, sets of concrete states with the same abstract choices

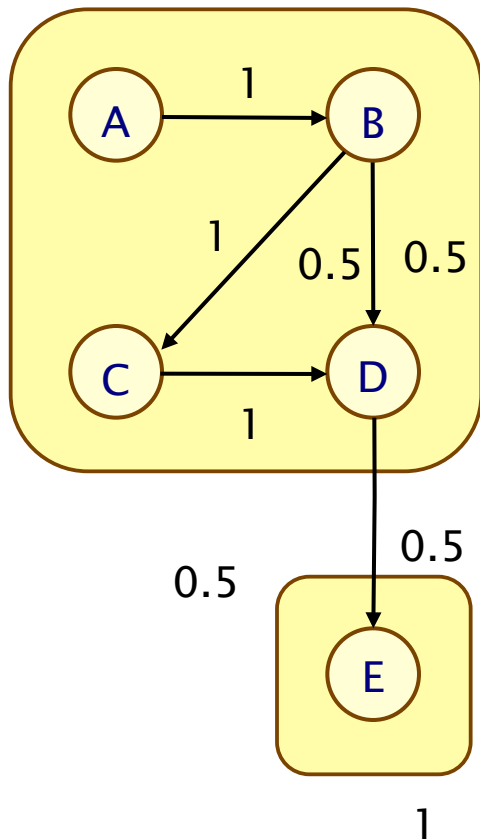


# MDP $\rightarrow$ Game



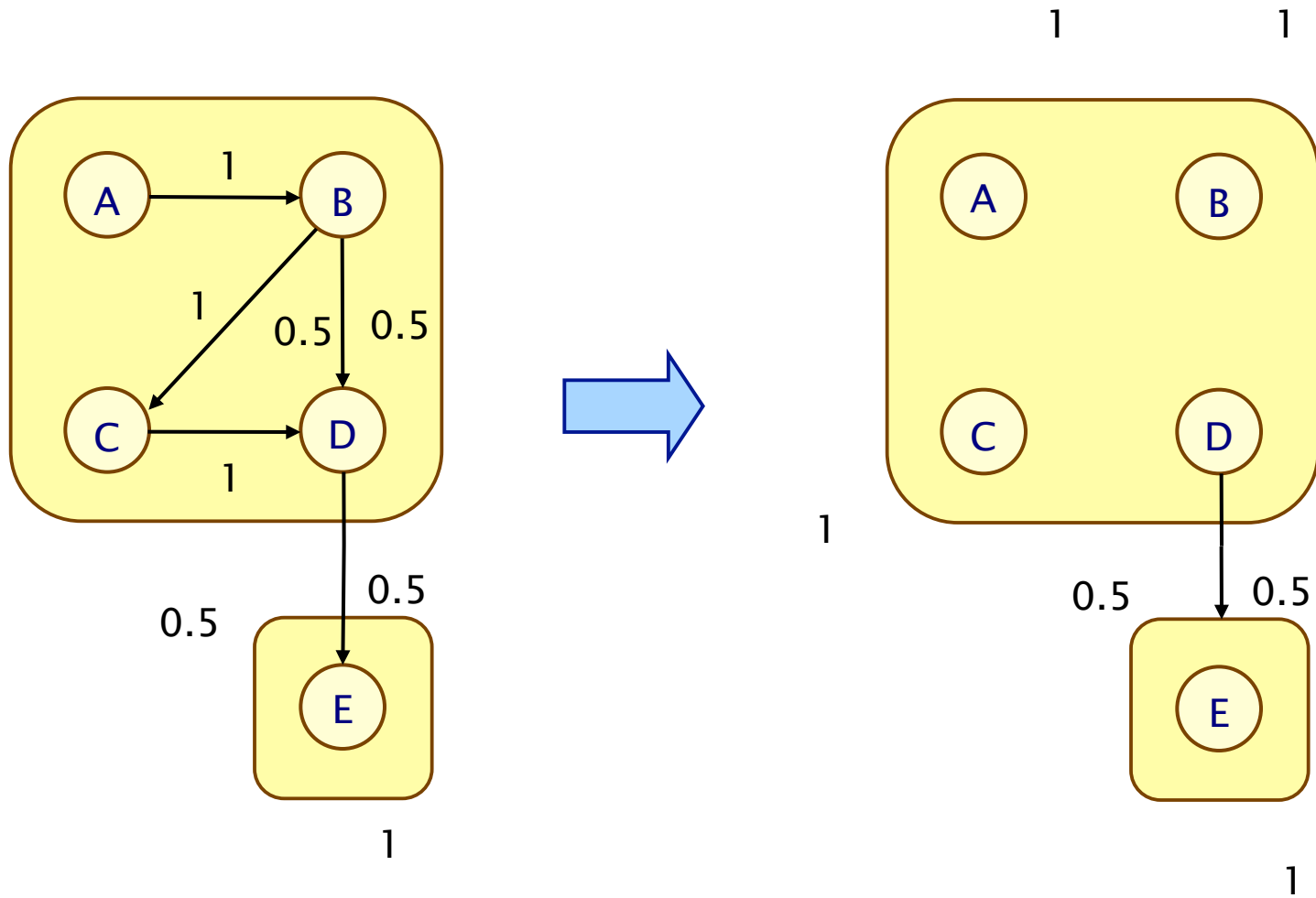
# MDP $\rightarrow$ Game

- Player 1 vertices are partition elements (abstract states)



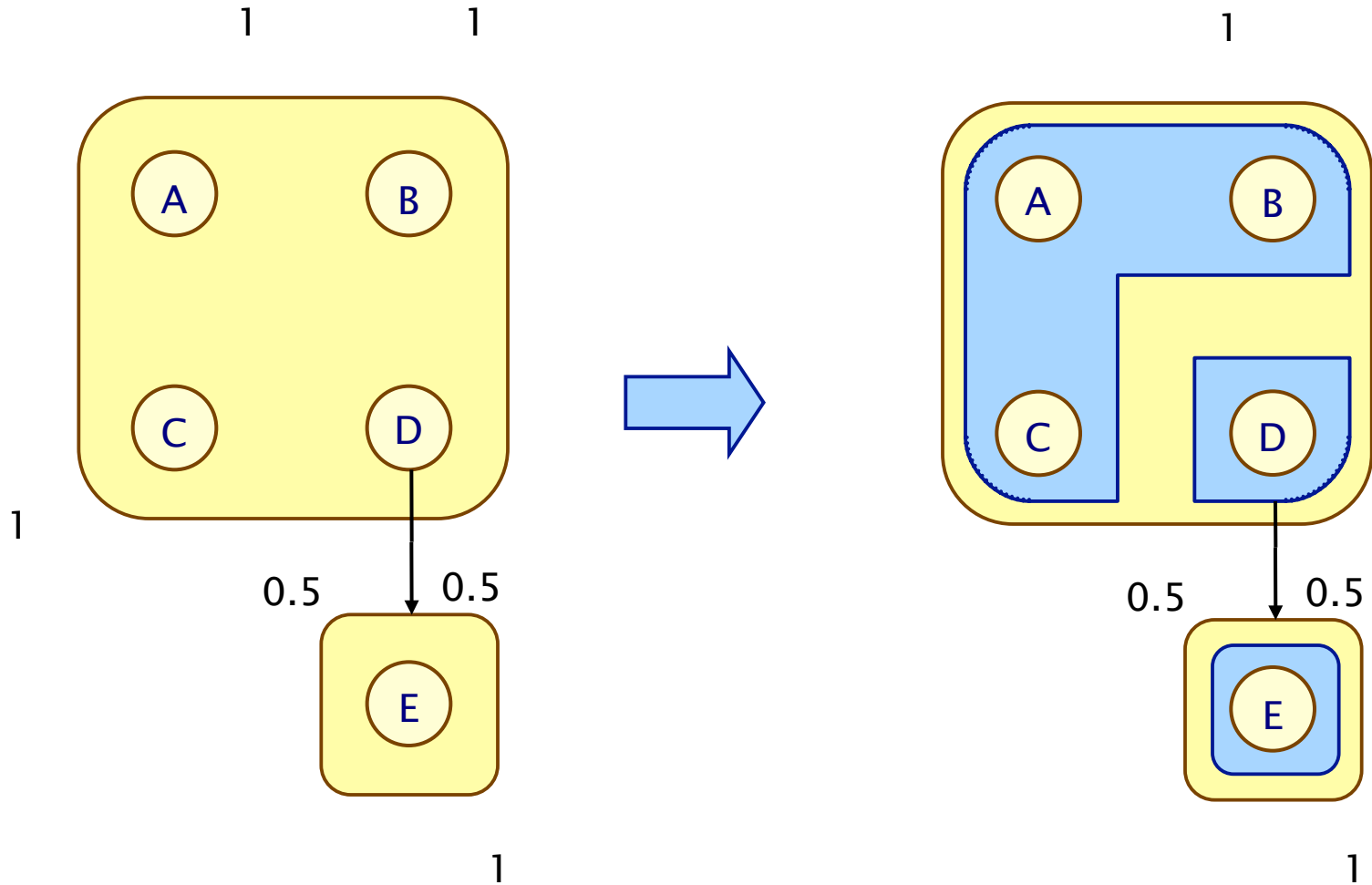
# MDP $\rightarrow$ Game

- (Sets of) distributions are lifted to the abstract state space



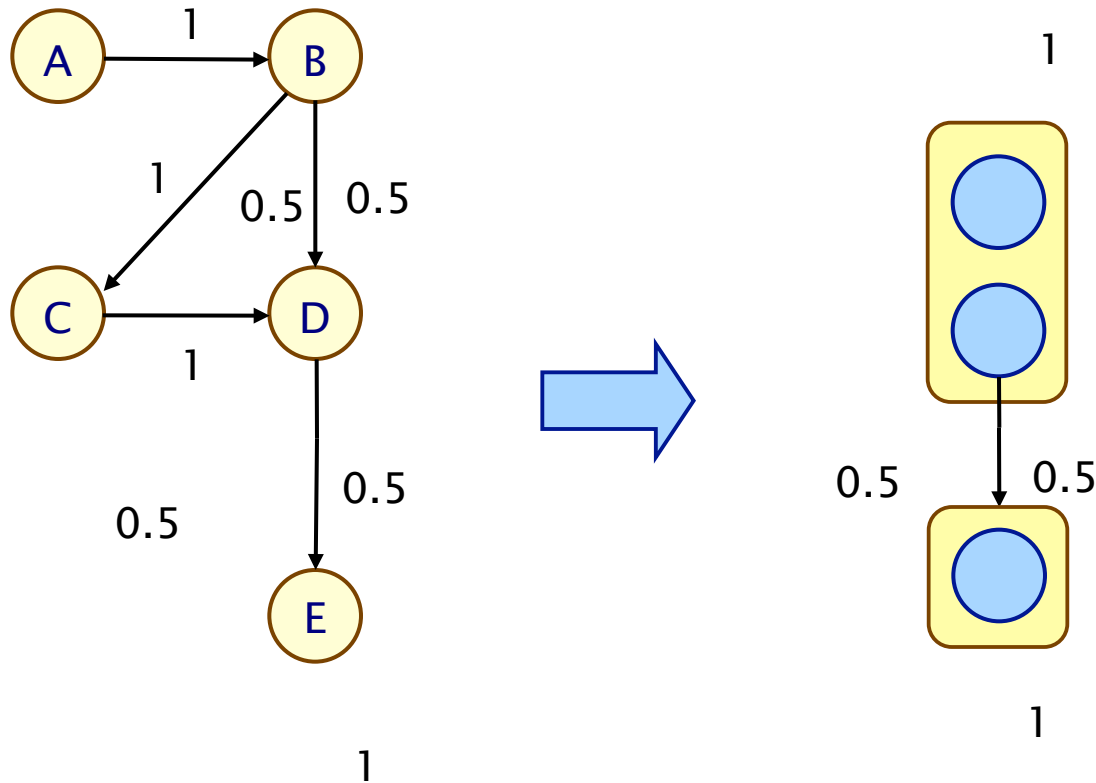
# MDP $\rightarrow$ Game

- States with same (sets of) choices form player 2 vertices



# MDP $\rightarrow$ Game

- Complete transformation:



Concrete model (MDP)

Abstraction (game)

# Analysis of the abstraction

- Analysis of game yields lower/upper bounds:
  - for target  $F \in A$ ,  $s \in S$  and  $a \in A$  with  $s \in a$

$$\inf_{\sigma_1, \sigma_2} p_v^{\sigma_1, \sigma_2}(F) \leq p_s^{\min}(F) \leq \sup_{\sigma_1} \inf_{\sigma_2} p_v^{\sigma_1, \sigma_2}(F)$$

$$\sup_{\sigma_2} \inf_{\sigma_1} p_v^{\sigma_1, \sigma_2}(F) \leq p_s^{\max}(F) \leq \sup_{\sigma_1, \sigma_2} p_v^{\sigma_1, \sigma_2}(F)$$

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min/max reachability probabilities for original MDP



# Analysis of the abstraction

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  - for target  $F \in A$ ,  $s \in S$  and  $a \in A$  with  $s \in a$

$$\begin{array}{ccccc}
 \inf_{\sigma_1, \sigma_2} p_a^{\sigma_1, \sigma_2}(F) & \leq & p_s^{\min}(F) & \leq & \sup_{\sigma_1} \inf_{\sigma_2} p_a^{\sigma_1, \sigma_2}(F) \\
 \sup_{\sigma_2} \inf_{\sigma_1} p_a^{\sigma_1, \sigma_2}(F) & \leq & p_s^{\max}(F) & \leq & \sup_{\sigma_1, \sigma_2} p_a^{\sigma_1, \sigma_2}(F)
 \end{array}$$

optimal probabilities for player 1, player 2 in game



# Analysis of the abstraction

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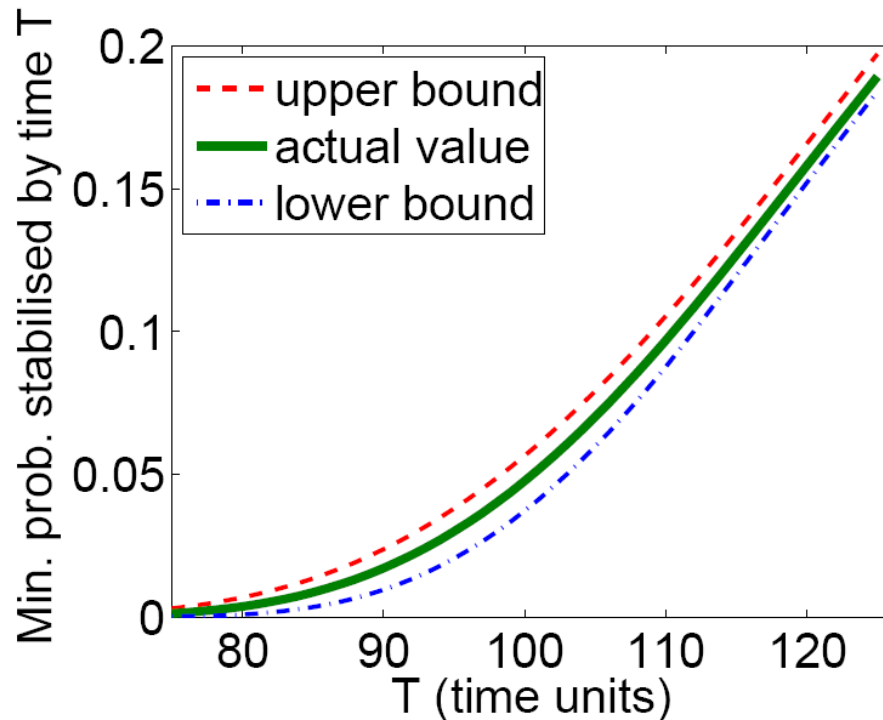
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min/max reachability probabilities, treating game as MDP  
(i.e. assuming that players 1 and 2 cooperate)



# Abstraction: Results

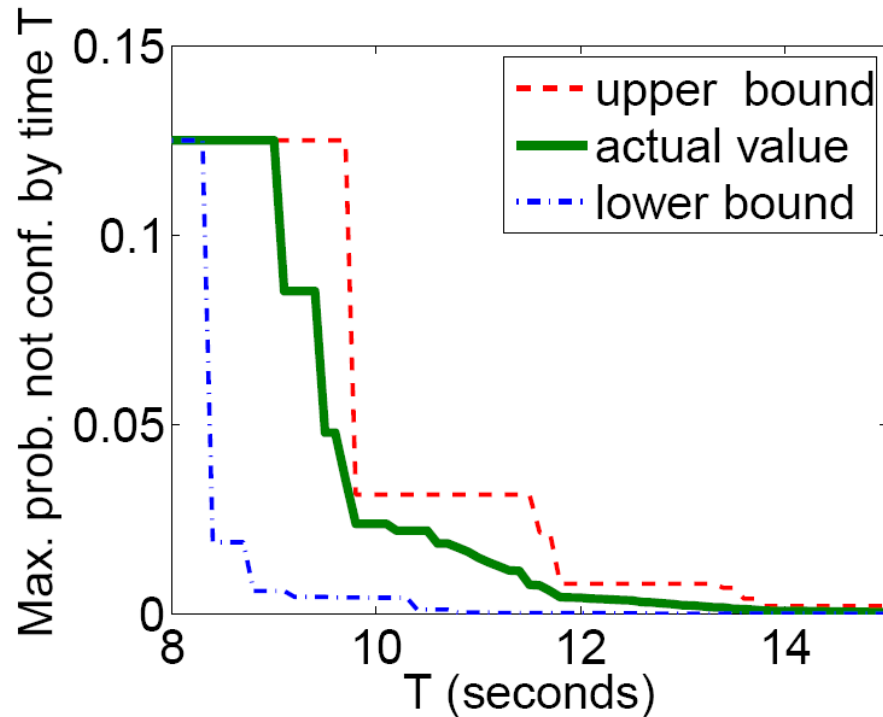
- Israeli & Jalfon's Self Stabilisation [IJ90]
  - protocol for obtaining a stable state in a token ring
  - minimum probability of reaching a stable state by time  $T$



concrete states: 1,048,575  
abstract states: 627

# Abstraction: Results

- IPv4 Zeroconf [CAG02]
  - protocol for obtaining an IP address for a new host
  - maximum probability the new host not configured by T

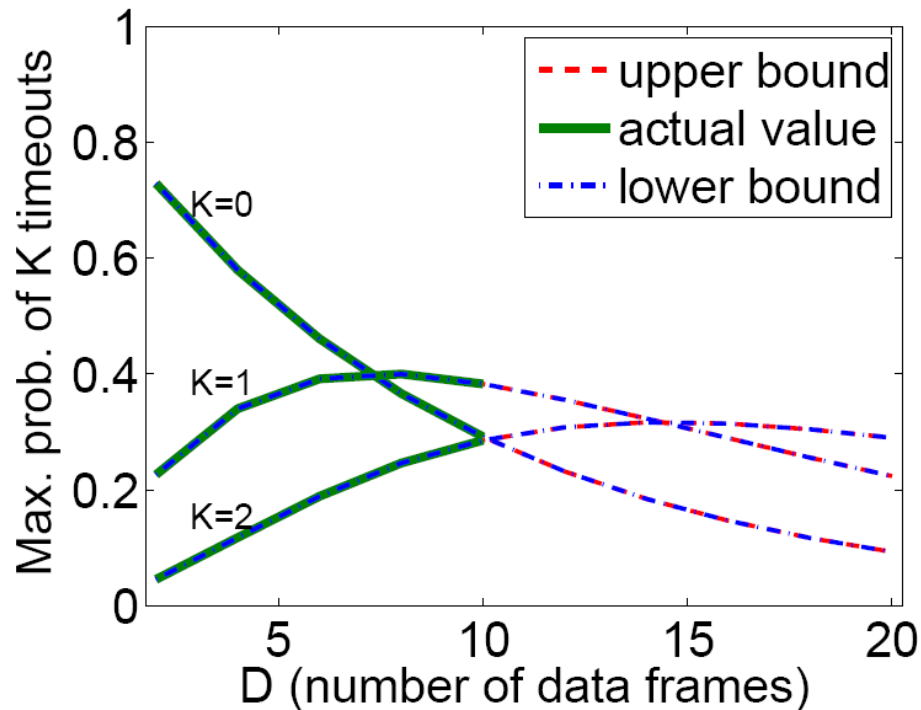


concrete states: 838,905  
abstract states: 881

# Abstraction: Results

- Sliding Window Protocol

- protocol for sending data over an insecure medium
- maximum probability of K timeouts



D=8  
concrete states: 189,952  
abstract states: 742

D=10  
concrete states: 987,136  
abstract states: 964

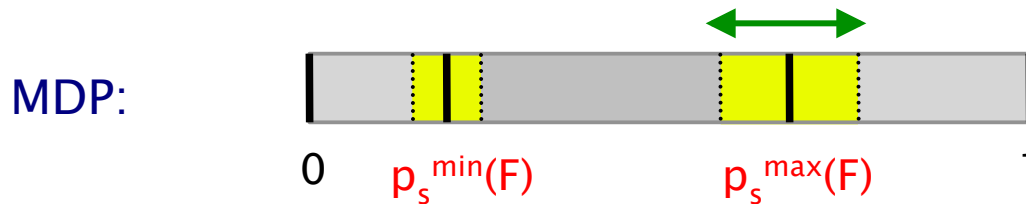
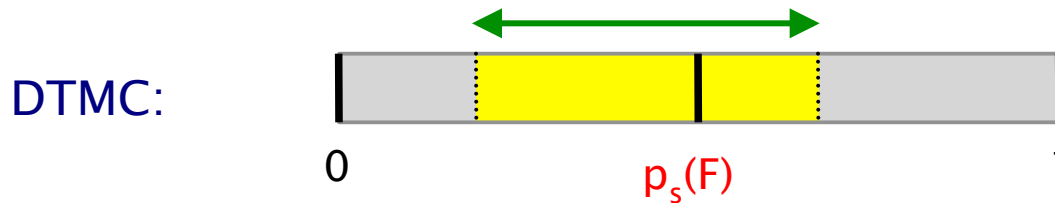
D=20  
concrete states: ??  
abstract states: 2,074

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  - abstraction-refinement loop
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# Abstraction refinement

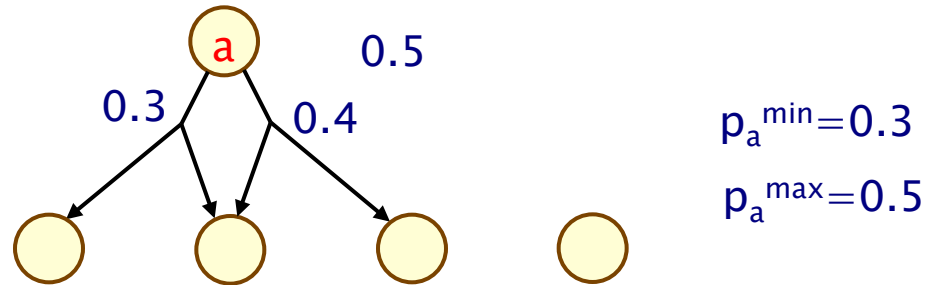
- Consider (max) difference between lower/upper bounds
  - gives a **quantitative measure** of the abstraction's **precision**



- If the difference (“error”) is too great, **refine** the abstraction
  - a finer partition yields a more precise abstraction
  - model checking results (bounds/strategies) guide refinement

# Abstraction refinement

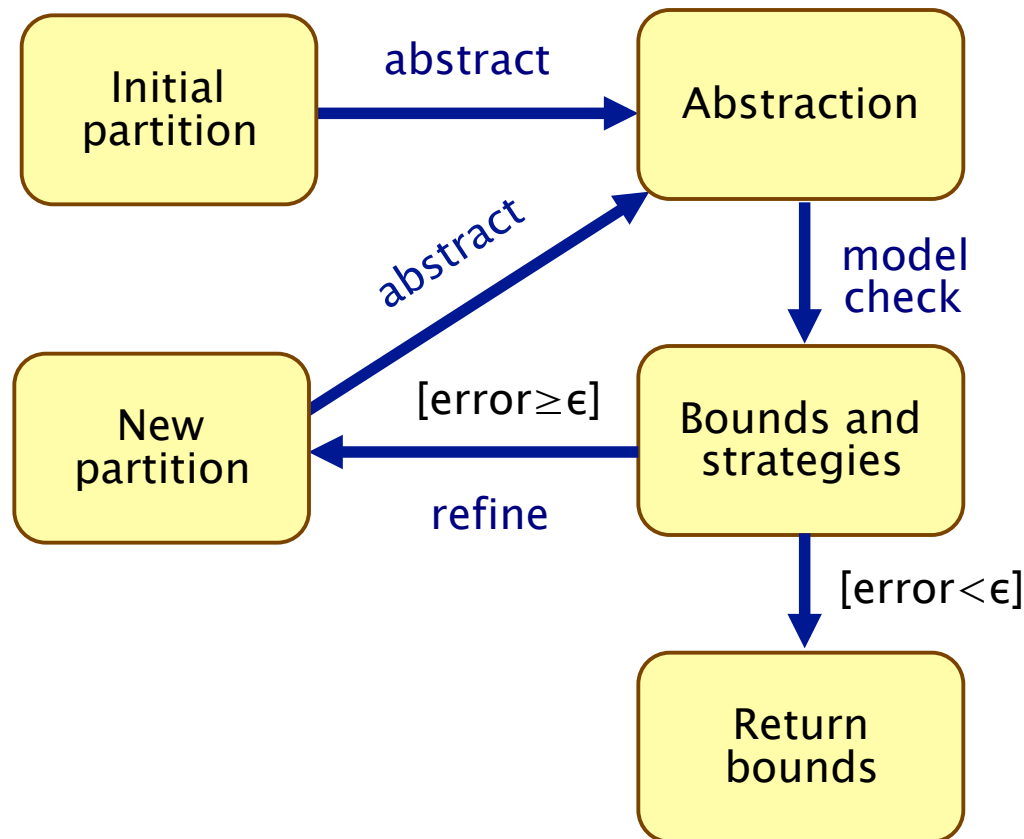
- Probabilistic reachability yields **simple** strategies
- Consider abstract state **a** with “error” 0.2:



- Abstract state **a** represents a **set** of concrete states
  - each choice in **a** corresponds to a **subset** of these
- Refine (split) **a** accordingly:
  - “strategy-based” refinement or “value-based” refinement

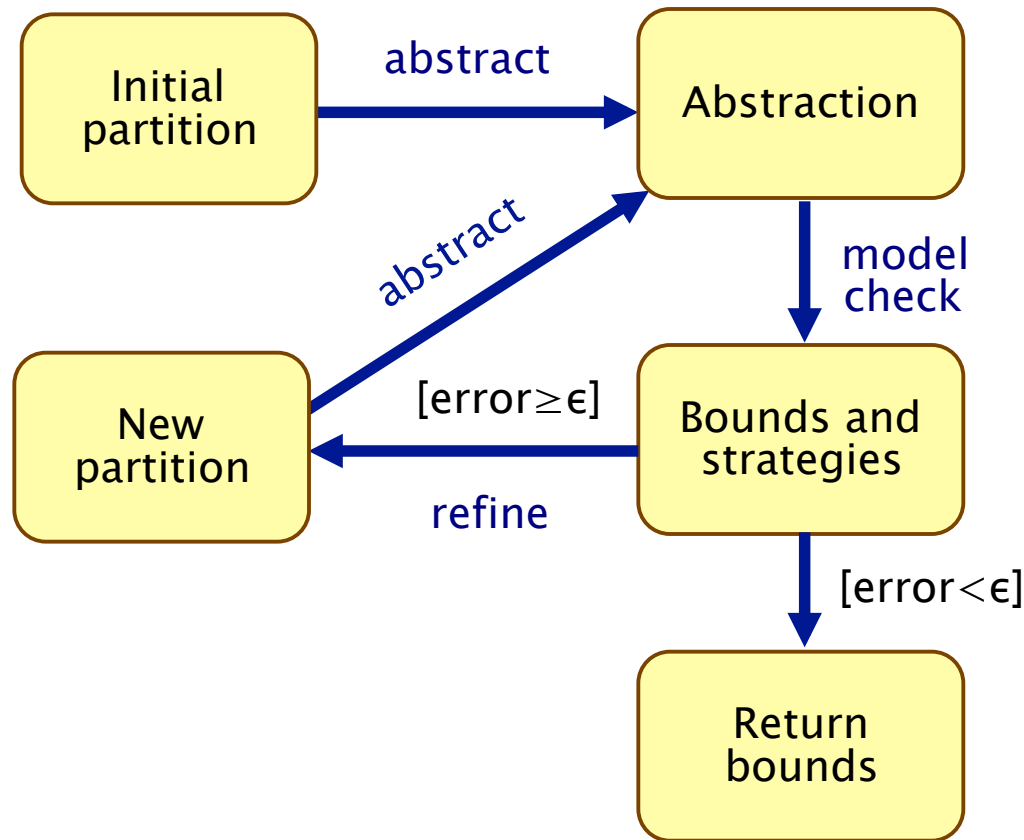
# Abstraction-refinement loop

- Quantitative abstraction-refinement loop for MDPs



# Abstraction–refinement loop

- **Quantitative** abstraction–refinement loop for MDPs



- Refinements yield strictly finer partition

- Guaranteed to converge for finite models

- Guaranteed to converge for infinite models with finite bisimulation

# Abstraction–refinement loop

- Implementations of **quantitative abstraction refinement...**
- 1. Explicit–state prototype implementation
  - confirms viability of game–based abstraction/refinement
- 2. Compositional abstraction of PRISM models [QAPL'08]
  - efficient construction of (manually specified) abstractions
- 3. Verification of probabilistic software [VMCAI'09]
  - (predicate) abstraction/refinement of infinite–state MDPs
- 4. Verification of probabilistic timed automata [FORMATS'09]
  - (DBM–based) abstraction/refinement of infinite–state MDPs

# Probabilistic software

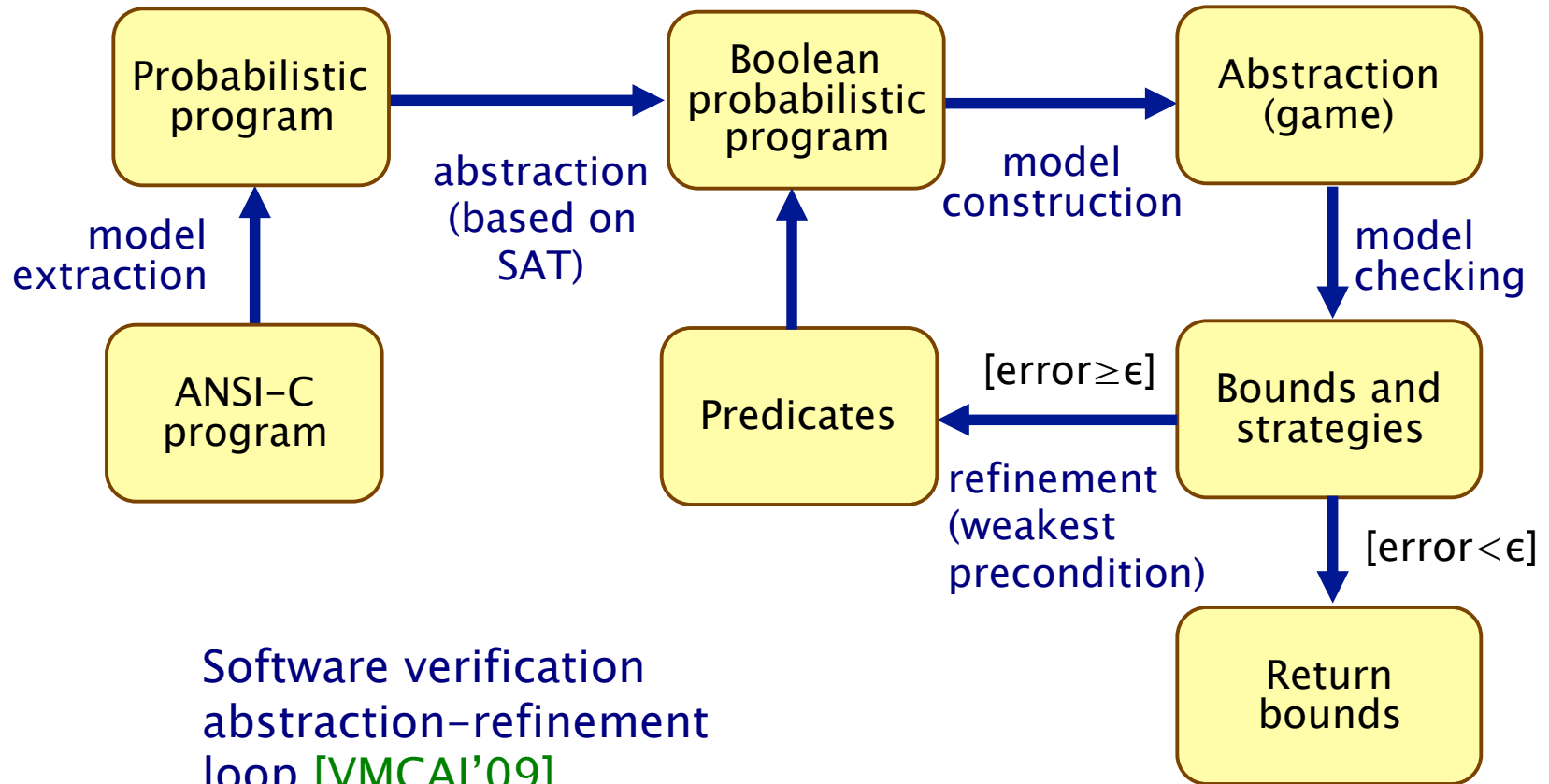
- Consider sequential ANSI C programs
  - support functions, pointers, arrays, but not dynamic memory allocation, unbounded recursion, floating point operations
  - **probabilistic** functions (for failures, randomisation)
  - **nondeterministic** functions (e.g. to abstract system calls)
  - infinite-state MDP semantics
- Quantitative properties based on probabilistic reachability
  - e.g. maximum probability of unsuccessful data transmission
  - e.g. minimum expected number of packets sent
- Prototype tool **qprover**
  - components from PRISM (model checking of stochastic games)
  - components from SATABS (predicate abstraction, SAT solvers)
  - analysed Linux network utilities (ping, tftp) – approx 1KLOC

# Example – sample target program

```
bool fail = false;
int c = 0;
int main ()
{
    // nondeterministic
    c = num_to_send ();
    while (! fail && c > 0)
    {
        // probabilistic
        fail = send_msg ();
        c --;
    }
}
```

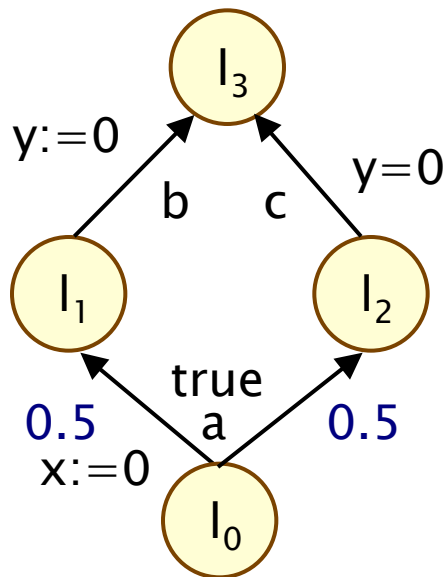
$\Phi$ : “what is the minimum/maximum probability of the program terminating with `fail` being true?”

# Abstraction-refinement loop



# Verification of PTAs

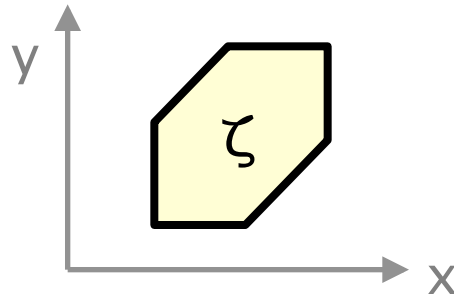
- Verification of probabilistic timed automata (PTAs)
  - discrete states, discrete probabilistic choice, nondeterminism and **real-valued clocks**
  - infinite-state MDP semantics
- Timed automata + probabilities
  - PRISM modelling language + clocks



```
module M
  s : [0..3];
  x : clock;
  [a] s=0 & x<10 → (s'=1);
  [b] s=1 → 0.5:(s'=2) + 0.5:(s'=3)&(x'=0);
endmodule
```

# Verification of PTAs

- Finite-state (game) abstractions using zones
  - efficiently represented as difference bound matrices (DBMs)



- Initial abstraction from forwards reachability
  - subsequent refinements through zone splitting
- Properties:
  - guaranteed to converge in finite time for any  $\epsilon \geq 0$
  - i.e. exact verification of PTAs
- Outperforms existing PTA verification techniques
  - on several large case studies

# Overview

- Probabilistic model checking
  - discrete-time Markov chains (DTMCs)
  - Markov decision processes (MDPs)
  - probabilistic reachability
- Abstraction for probabilistic models
  - abstractions of DTMCs (MDPs)
  - abstractions of MDPs (two-player stochastic games)
- Quantitative abstraction refinement
  - abstraction-refinement loop
  - verification of probabilistic software, real-time systems
- **Current/future work & Conclusions**

# Nondeterministic abstractions

- We can consider a general class of “nondeterministic” abstractions for probabilistic models

Concrete model:		Abstraction:
DTMC	→	MDP
MDP	→	TPSG
CTMC	→	CTMDP
CTMDP	→	CTTPSG

- CTMDP = continuous-time Markov decision process
- CTTPSG = continuous-time two-player stochastic game

# Abstraction for CTMCs

- A useful subset of CTMC properties are untimed
  - unbounded probabilistic reachability
  - steady-state (long-run) probabilities
  - so can abstract embedded DTMC as an MDP
- More interesting: time-bounded (transient properties)
  - can abstract CTMCs as CTMDPs, yielding lower/upper bounds
  - [Smith], [Katoen et al.], ...
  - moreover, abstractions are uniform CTMDPs
- But: How to refine?
  - time-bounded reachability does not yield simple strategies
- How to build abstraction? What high-level model?

# Conclusions

- **Abstraction approach for probabilistic models**
  - DTMCs abstracted as MDPs
  - MDPs abstracted as two-player stochastic games
  - abstraction yields lower/upper bounds on probabilities
- **Quantitative abstraction refinement**
  - bounds give quantitative measure of utility of abstraction
  - bounds/strategies can be used to guide refinement
  - quantitative abstraction-refinement loop (for error  $< \epsilon$ )
  - fully automatic generation of abstraction
  - works in practice: probabilistic software & timed automata
- **Current & future work**
  - CTMCs, timed properties
  - probabilistic/stochastic hybrid systems
  - improved refinement heuristics, imprecise abstractions