



# Probabilistic Model Checking

Marta Kwiatkowska  
Dave Parker

Oxford University Computing Laboratory

ESSLLI'10 Summer School, Copenhagen, August 2010

# Why probability?

- Some systems are inherently probabilistic...
- **Randomisation**, e.g. in distributed coordination algorithms
  - as a symmetry breaker, in gossip routing to reduce flooding
- Examples: real-world protocols featuring randomisation:
  - Randomised back-off schemes
    - CSMA protocol, 802.11 Wireless LAN
  - Random choice of waiting time
    - IEEE1394 Firewire (root contention), Bluetooth (device discovery)
  - Random choice over a set of possible addresses
    - IPv4 Zeroconf dynamic configuration (link-local addressing)
  - Randomised algorithms for anonymity, contract signing, ...

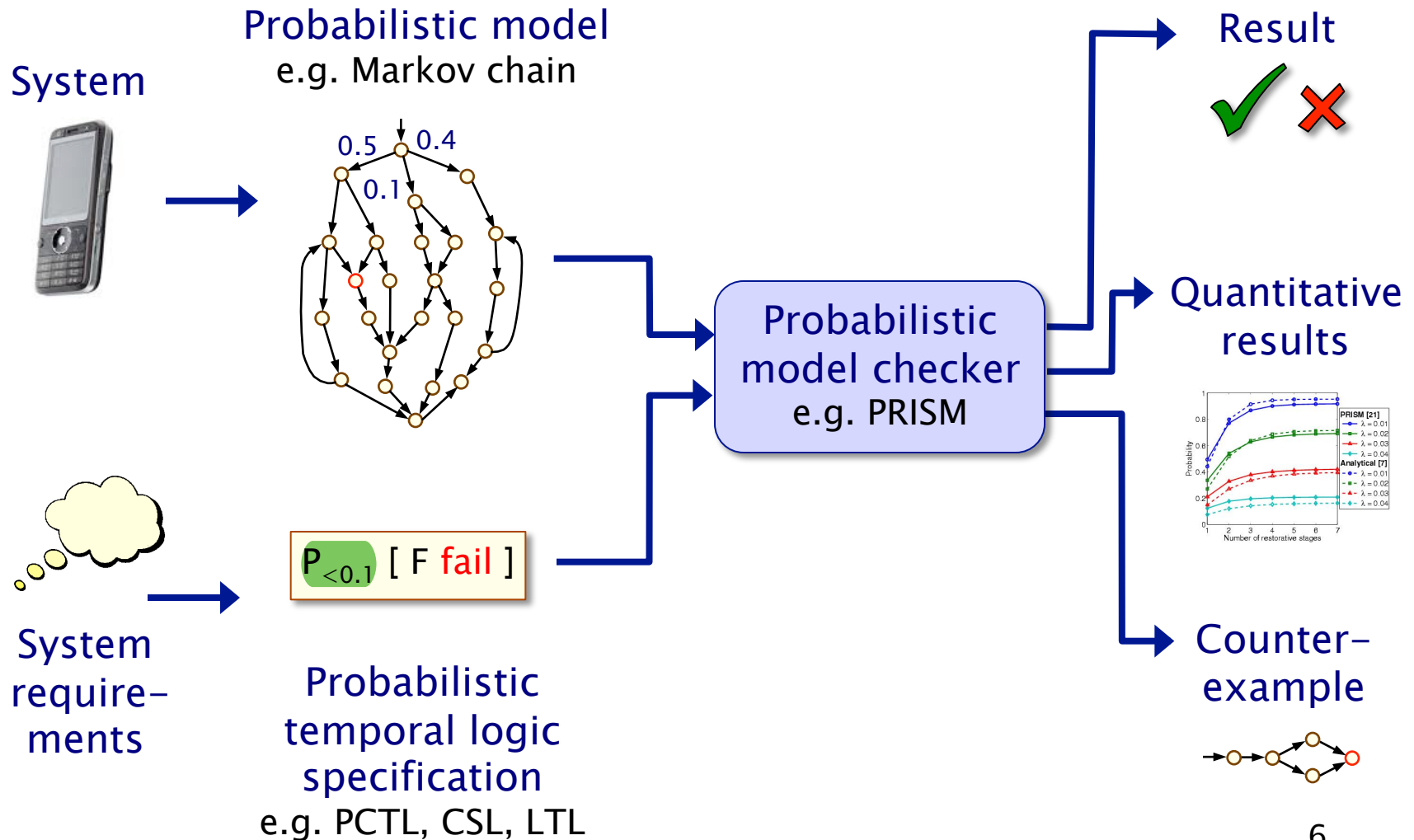
# Why probability?

- Some systems are inherently probabilistic...
- **Randomisation**, e.g. in distributed coordination algorithms
  - as a symmetry breaker, in gossip routing to reduce flooding
- To model **uncertainty** and **performance**
  - to quantify rate of failures, express Quality of Service
- **Examples:**
  - computer networks, embedded systems
  - power management policies
  - nano-scale circuitry: reliability through defect-tolerance

# Verifying probabilistic systems

- We are not just interested in correctness
- We want to be able to quantify:
  - security, privacy, trust, anonymity, fairness
  - safety, reliability, performance, dependability
  - resource usage, e.g. battery life
  - and much more...
- **Quantitative**, as well as qualitative requirements:
  - how reliable is my car's Bluetooth network?
  - how efficient is my phone's power management policy?
  - is my bank's web-service secure?
  - what is the expected long-run percentage of protein X?

# Probabilistic model checking



# Probabilistic models

	Fully probabilistic	Nondeterministic
Discrete time	Discrete-time Markov chains (DTMCs)	Markov decision processes (MDPs) (probabilistic automata)
Continuous time	Continuous-time Markov chains (CTMCs)	CTMDPs/IMCs
		Probabilistic timed automata (PTAs)

we will focus on the red-parts



# Part 1

## Discrete-time Markov chains

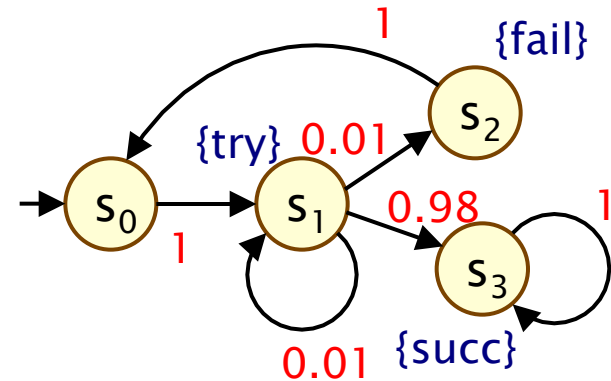
# Overview (Part 1)

- Discrete-time Markov chains (DTMCs)
- PCTL: A temporal logic for DTMCs
- PCTL model checking
- LTL model checking
- Costs and rewards



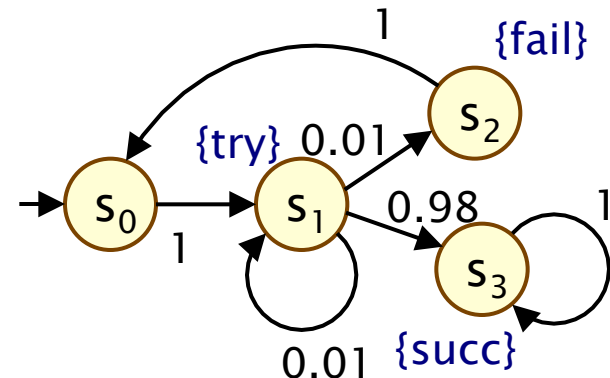
# Discrete-time Markov chains

- Discrete-time Markov chains (DTMCs)
  - state-transition systems augmented with probabilities
- States
  - **discrete set of states** representing possible configurations of the system being modelled
- Transitions
  - transitions between states occur in **discrete time-steps**
- Probabilities
  - probability of making transitions between states is given by **discrete probability distributions**



# Discrete-time Markov chains

- Formally, a DTMC  $D$  is a tuple  $(S, s_{\text{init}}, P, L)$  where:
  - $S$  is a finite set of states (“state space”)
  - $s_{\text{init}} \in S$  is the initial state
  - $P : S \times S \rightarrow [0,1]$  is the **transition probability matrix** where  $\sum_{s' \in S} P(s, s') = 1$  for all  $s \in S$
  - $L : S \rightarrow 2^{\text{AP}}$  is function labelling states with atomic propositions
- Note: no deadlock states
  - i.e. every state has at least one outgoing transition
  - can add self loops to represent final/terminating states

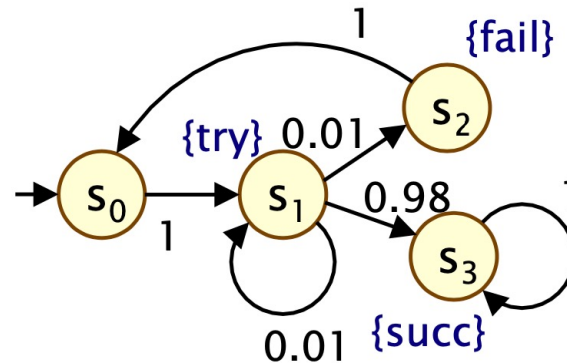


# DTMCs: An alternative definition

- **Alternative definition: a DTMC is:**
  - a family of **random variables**  $\{ X(k) \mid k=0,1,2,\dots \}$
  - $X(k)$  are observations at discrete time-steps
  - i.e.  $X(k)$  is the state of the system at time-step  $k$
- **Memorylessness (Markov property)**
  - $\Pr( X(k)=s_k \mid X(k-1)=s_{k-1}, \dots, X(0)=s_0 )$   
 $= \Pr( X(k)=s_k \mid X(k-1)=s_{k-1} )$
- **We consider homogenous DTMCs**
  - transition probabilities are **independent of time**
  - $P(s_{k-1}, s_k) = \Pr( X(k)=s_k \mid X(k-1)=s_{k-1} )$

# Probability of taking a path or a set of paths

A “DTMC” :

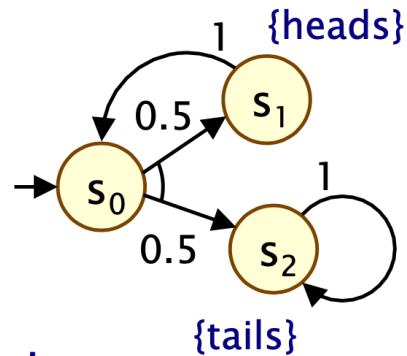


- Consider a path  $\omega$  e.g.  $s_0, s_1, s_2, s_0$ . The probability that the system follows this path when executed with the starting state  $s_0$  is denoted by  $P_{s_0}(\omega)$ . Or simply  $P(\omega)$  if it is clear which  $s_0$  is meant. It is the product of the probability of each transition in  $\omega$ .

Example: for the above  $\omega$ ,  $P(\omega) = 1 * 0.01 * 1 = 0.01$

- For a **set of paths**  $U$  (starting from  $s_0$ ), the probability that the system's execution follows **one of** the paths in  $U$ , denoted by  $P(U)$ , is  $\sum_{\omega \in U} P(\omega)$ .

# Probability of taking a path or a set of paths

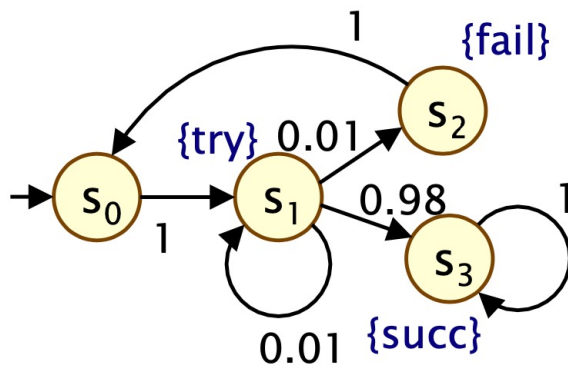


Example: consider  $U$  = the set of paths that ends in  $s_2$ . Note that  $U$  is infinite:  $U = \{ 02, 0102, 010102, \dots \}$ . But we can calculate  $P(U)$ .

$$P(U) = 0.5 + 0.5^2 + 0.5^3 + \dots = \sum_{k \geq 0} 0.5^k$$

$$= 0.5 * \frac{1}{1-0.5} = 1$$

# Probability Matrix Representation



P:

	s0	s1	s2	s3
s0	0	1	0	0
s1	0	0.01	0.01	0.98
s2	1	0	0	0
s3	0	0	0	1

$P_{i,k}$  = the value at the  $i$ -th row and  $k$ -th column. It specifies the probability of taking the transition  $s_i \rightarrow s_k$ , if we are now at  $s_i$ .

For example the circle red value above is  $P_{1,2}$ , specifying the probability of taking the transition from  $s_1$  to  $s_2$  (check the picture), which is 0.01.

# Basic Operations on Probability Matrix

- Multiplying  $P$  with itself:  $P^n$
- Multiplying a vector with  $P$ :  $u \times P$
- Multiplying  $P$  with a vector:  $P \times v$

# P<sup>n</sup>

- $P^0 = I$  (identity matrix)  
 $P^{n+1} = P \times P^n$
- $P^n_{i,k}$  is the probability of ending up in state  $s_k$  in  $n$ -steps, given we start in the state  $s_i$ .
- For example, with the previous  $P$ , let's look at  $P^2$ :

0	1	0	0		0	1	0	0		?	?	0.01	?
0	0.01	0.01	0.98		0	0.01	0.01	0.98		?	?	?	?
1	0	0	0		1	0	0	0		?	?	?	?
0	0	0	1		0	0	0	1		?	?	?	?

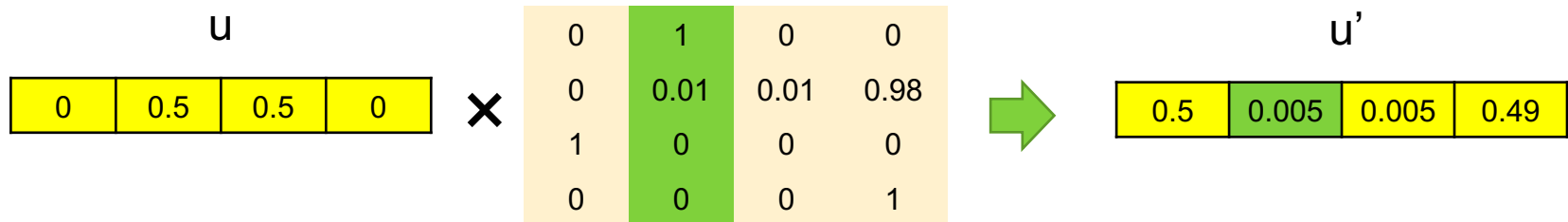
$$P^2_{0,2} = (P \times P)_{0,2}$$

$$= P_{0,0} * P_{0,2} + P_{0,1} * P_{1,2} + P_{0,2} * P_{2,2} + P_{0,3} * P_{3,2}$$



# Probability distribution of the next state, given the current distribution

- The probability of currently being in various states (“*probability distribution*” of the current state) can be given by a vector of size  $K$ , if  $K$  is the number of possible states. E.g. if  $u = [0, 0.5, 0.5, 0]$  is the probability distribution of the current state, it says e.g. that there is 0.5 probability that currently we are in the state  $s_1$ , but 0 probability that we are in the state  $s_0$ .
- The product  $u \times P$  (we often simply write it as  $uP$ ) gives a new vector  $u'$  of size  $K$ , that gives us the probability distribution of the next state.



e.g.  $u'_1 = u \cdot \text{the green column (dot product)}$

$$= u_0 * P_{0,1} + u_1 * P_{1,1} + u_2 * P_{2,1} + u_3 * P_{3,1}$$


# Probability vector

- Sometimes we also want to know what the probability to end up in state, say,  $s_1$  or  $s_2$  as the **next** state, if we start in the state  $s_1$ .
- We can represent “end up in either  $s_1$  or  $s_2$ ” with a vector  $v = [0, 1, 1, 0]$ .
- Let  $v^t$  is the *transpose* of  $v$ . The product  $P \times v^t$  gives a  $w$  such that  $w$  is a (transposed) vector, where  $w_i$  is the probability to end up in one of the states specified in  $v$ , if we start in  $s_i$ .

0	1	0	0
0	0.01	0.01	0.98
1	0	0	0
0	0	0	1

 $\times$ 

0
1
1
0



1
0.02
0
0

$v^t$   $w$

e.g.  $w_1$  = the green row  $\cdot v^t$  (dot product)  
 $= P_{1,0} * v_0 + P_{1,1} * v_1 + P_{1,2} * v_2 + P_{1,3} * v_3$

# Probability vector

- Prob( $\varphi$ ) (notice the underscore) is a probability vector e.g.  $w =$

1
0.02
0
0

such that the  $i$ -th element tells us what the probability that the system would behave as  $\varphi$  if executed in state  $s_i$ .

- Example: the above  $w$  (blue) happens to be equal to Prob( $\mathbf{X}(\text{try } v \text{ fail})$ ).
- This notation Prob will be used later when we discuss model checking of probabilistic-CTL.

# Overview (Part 1)

- Discrete-time Markov chains (DTMCs)
- PCTL: A temporal logic for DTMCs
- PCTL model checking
- LTL model checking
- Costs and rewards

# PCTL

- Temporal logic for describing properties of DTMCs
  - PCTL = Probabilistic Computation Tree Logic [HJ94]
  - essentially the same as the logic pCTL of [ASB+95]
- Extension of (non-probabilistic) temporal logic CTL
  - key addition is **probabilistic operator P**
  - quantitative extension of CTL's A and E operators
- Example
  - $\text{send} \rightarrow P_{\geq 0.95} [\text{true } U^{\leq 10} \text{ deliver}]$
  - “if a message is sent, then the probability of it being delivered within 10 steps is at least 0.95”

# PCTL syntax

- PCTL syntax:

–  $\phi ::= \text{true} \mid a \mid \phi \wedge \phi \mid \neg\phi \mid P_{\sim p} [\psi]$  (state formulas)

–  $\psi ::= X\phi \mid \phi U^{\leq k} \phi \mid \phi U \phi$  (path formulas)

“next”

“bounded  
until”

“until”

$\psi$  is true with  
probability  $\sim p$

– where  $a$  is an atomic proposition, used to identify states of interest,  $p \in [0,1]$  is a probability,  $\sim \in \{<, >, \leq, \geq\}$ ,  $k \in \mathbb{N}$

- A PCTL formula is always a state formula

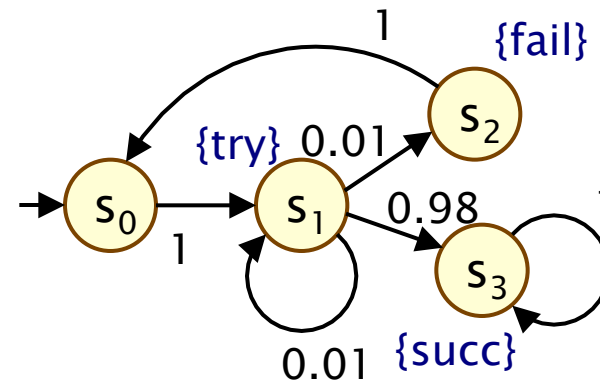
– path formulas only occur inside the  $P$  operator

# PCTL semantics for DTMCs

- PCTL formulas interpreted over states of a DTMC
  - $s \models \phi$  denotes  $\phi$  is “true in state  $s$ ” or “satisfied in state  $s$ ”
- Semantics of (non-probabilistic) state formulas:
  - for a state  $s$  of the DTMC  $(S, s_{\text{init}}, P, L)$ :
  - $s \models a \iff a \in L(s)$
  - $s \models \phi_1 \wedge \phi_2 \iff s \models \phi_1 \text{ and } s \models \phi_2$
  - $s \models \neg\phi \iff s \models \phi \text{ is false}$

- Examples

- $s_3 \models \text{succ}$
- $s_1 \models \text{try} \wedge \neg \text{fail}$



# PCTL semantics for DTMCs

- Semantics of path formulas:

- for a path  $\omega = s_0 s_1 s_2 \dots$  in the DTMC:

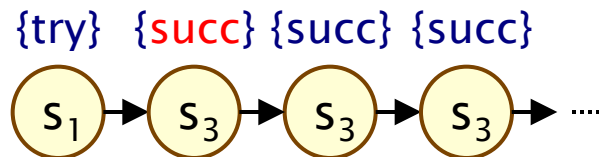
- $\omega \models X \phi \iff s_1 \models \phi$

- $\omega \models \phi_1 U^{\leq k} \phi_2 \iff \exists i \leq k$  such that  $s_i \models \phi_2$  and  $\forall j < i, s_j \models \phi_1$

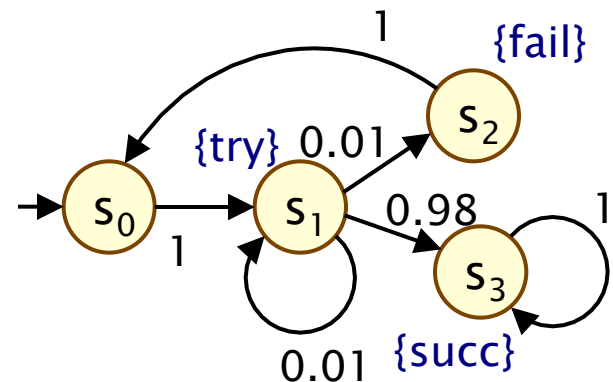
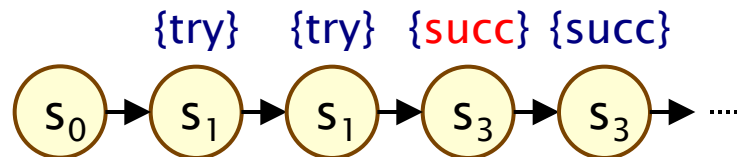
- $\omega \models \phi_1 U \phi_2 \iff \exists k \geq 0$  such that  $\omega \models \phi_1 U^{\leq k} \phi_2$

- Some examples of satisfying paths:

- $X \text{ succ}$



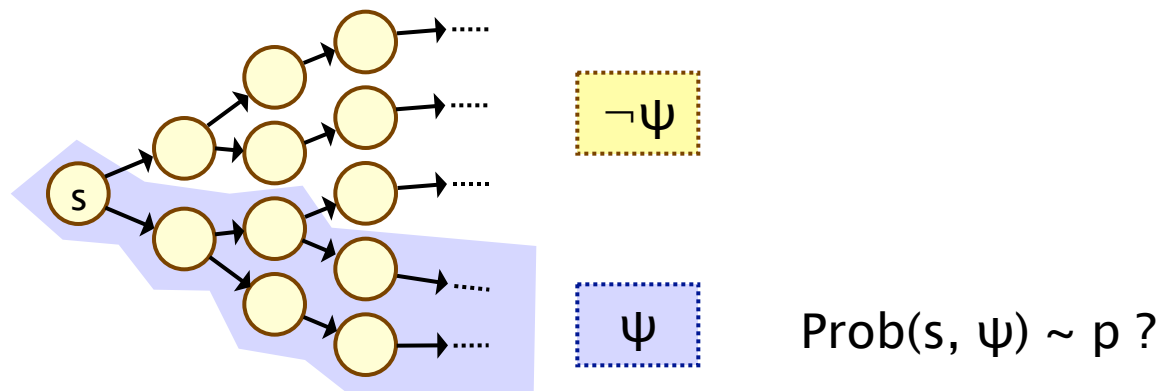
- $\neg \text{fail} U \text{ succ}$





# PCTL semantics for DTMCs

- Semantics of the probabilistic operator  $P$ 
  - informal definition:  $s \models P_{\sim p} [\psi]$  means that “the probability, from state  $s$ , that  $\psi$  is true for an outgoing path satisfies  $\sim p$ ”
  - example:  $s \models P_{<0.25} [X \text{ fail}] \Leftrightarrow$  “the probability of atomic proposition fail being true in the next state of outgoing paths from  $s$  is less than 0.25”
  - formally:  $s \models P_{\sim p} [\psi] \Leftrightarrow \text{Prob}(s, \psi) \sim p$
  - where:  $\text{Prob}(s, \psi) = \Pr_s \{ \omega \in \text{Path}(s) \mid \omega \models \psi \}$
  - (sets of paths satisfying  $\psi$  are always measurable [Var85])



# More PCTL...

- Usual temporal logic equivalences:

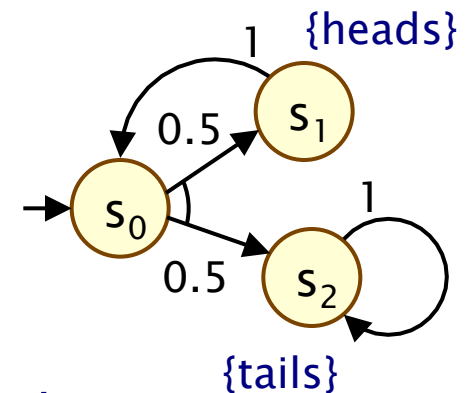
- $\text{false} \equiv \neg \text{true}$  (false)
- $\phi_1 \vee \phi_2 \equiv \neg(\neg\phi_1 \wedge \neg\phi_2)$  (disjunction)
- $\phi_1 \rightarrow \phi_2 \equiv \neg\phi_1 \vee \phi_2$  (implication)
- $F \phi \equiv \Diamond \phi \equiv \text{true} \cup \phi$  (eventually, “future”)
- $G \phi \equiv \Box \phi \equiv \neg(F \neg\phi)$  (always, “globally”)
- bounded variants:  $F^{\leq k} \phi$ ,  $G^{\leq k} \phi$

- Negation and probabilities

- e.g.  $\neg P_{>p} [\phi_1 \cup \phi_2] \equiv P_{\leq p} [\phi_1 \cup \phi_2]$
- e.g.  $P_{>p} [G \phi] \equiv P_{<1-p} [F \neg\phi]$

# Qualitative vs. quantitative properties

- P operator of PCTL can be seen as a **quantitative** analogue of the CTL operators A (for all) and E (there exists)
- A PCTL property  $P_{\sim p} [\psi]$  is...
  - **qualitative** when p is either 0 or 1
  - **quantitative** when p is in the range (0,1)
- $P_{>0} [F \phi]$  is identical to  $EF \phi$ 
  - there exists a finite path to a  $\phi$ -state
- $P_{\geq 1} [F \phi]$  is (similar to but) weaker than  $AF \phi$ 
  - e.g. **AF “tails”** (CTL)  $\neq$   **$P_{\geq 1} [F \text{“tails”}]$**  (PCTL)

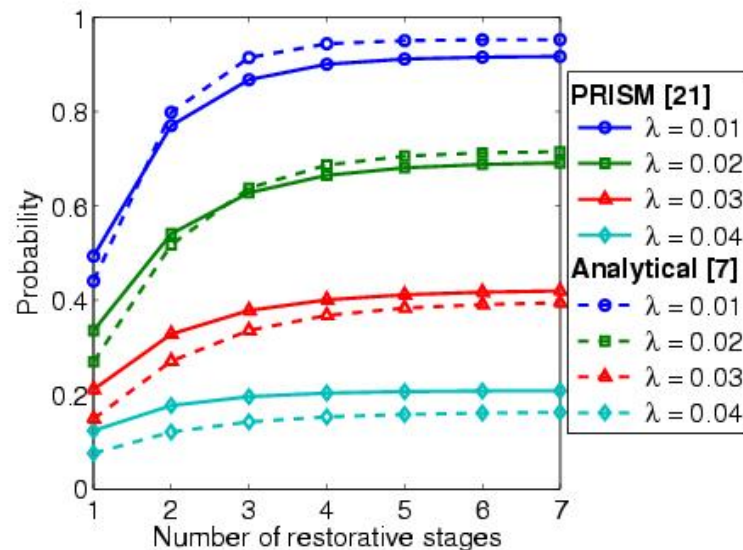


# Quantitative properties

- Consider a PCTL formula  $P_{\sim p} [\psi]$ 
  - if the probability is **unknown**, how to choose the bound  $p$ ?
- When the outermost operator of a PTCL formula is  $P$ 
  - we allow the form  $P_{=?} [\psi]$
  - “**what is the probability that path formula  $\psi$  is true?**”
- Model checking is no harder: compute the values anyway
- Useful to spot patterns, trends

- **Example**

- $P_{=?} [F \text{ err}/\text{total} > 0.1]$
- “what is the probability that 10% of the NAND gate outputs are erroneous?”



# Some real PCTL examples

- **NAND multiplexing system**

- $P_{=?} [ F \text{ err/total} > 0.1 ]$
- “what is the probability that 10% of the NAND gate outputs are erroneous?”

reliability

- **Bluetooth wireless communication protocol**

- $P_{=?} [ F^{\leq t} \text{ reply\_count} = k ]$
- “what is the probability that the sender has received k acknowledgements within t clock-ticks?”

performance

- **Security: EGL contract signing protocol**

- $P_{=?} [ F (\text{pairs\_a} = 0 \ \& \ \text{pairs\_b} > 0) ]$
- “what is the probability that the party B gains an unfair advantage during the execution of the protocol?”

fairness

# Overview (Part 1)

- Discrete-time Markov chains (DTMCs)
- PCTL: A temporal logic for DTMCs
- **PCTL model checking**
- LTL model checking
- Costs and rewards

# PCTL model checking for DTMCs

- Algorithm for PCTL model checking [CY88,HJ94,CY95]
  - inputs: DTMC  $D=(S,s_{init},P,L)$ , PCTL formula  $\phi$
  - output:  $Sat(\phi) = \{ s \in S \mid s \models \phi \}$  = set of states satisfying  $\phi$
- What does it mean for a DTMC  $D$  to satisfy a formula  $\phi$ ?
  - sometimes, want to check that  $s \models \phi \ \forall s \in S$ , i.e.  $Sat(\phi) = S$
  - sometimes, just want to know if  $s_{init} \models \phi$ , i.e. if  $s_{init} \in Sat(\phi)$
- Sometimes, focus on quantitative results
  - e.g. compute result of  $P=?$  [ F error ]
  - e.g. compute result of  $P=?$  [  $F^{\leq k}$  error ] for  $0 \leq k \leq 100$

# PCTL model checking for DTMCs

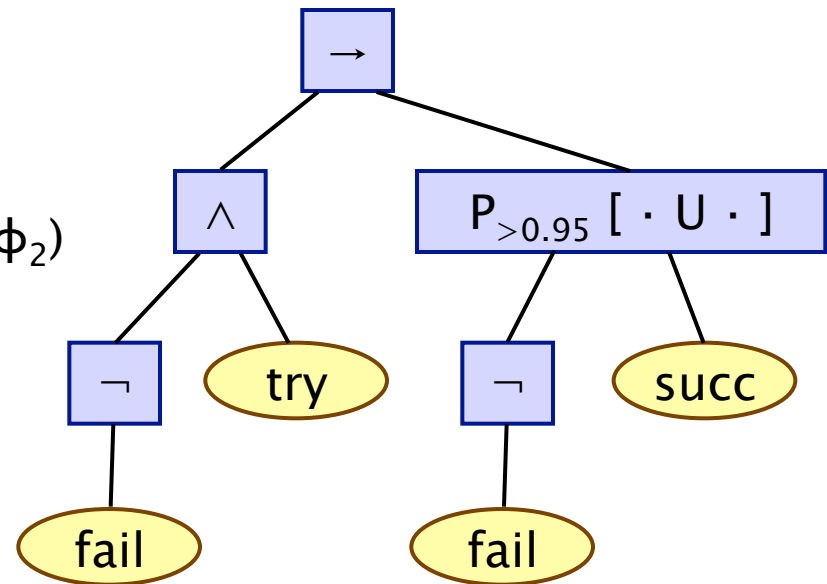
- Basic algorithm proceeds by induction on parse tree of  $\phi$ 
  - example:  $\phi = (\neg \text{fail} \wedge \text{try}) \rightarrow P_{>0.95} [\neg \text{fail} \text{ U succ}]$

- For the non-probabilistic operators:

- $\text{Sat}(\text{true}) = S$
- $\text{Sat}(a) = \{ s \in S \mid a \in L(s) \}$
- $\text{Sat}(\neg \phi) = S \setminus \text{Sat}(\phi)$
- $\text{Sat}(\phi_1 \wedge \phi_2) = \text{Sat}(\phi_1) \cap \text{Sat}(\phi_2)$

- For the  $P_{\sim p} [\psi]$  operator

- need to compute the probabilities  $\text{Prob}(s, \psi)$  for all states  $s \in S$
- focus here on “until” case:  $\psi = \phi_1 \text{ U } \phi_2$





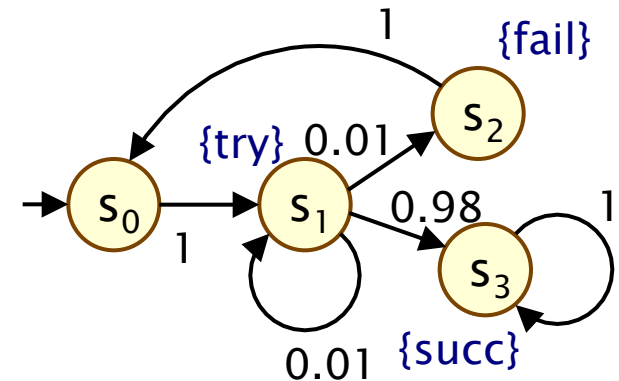
# PCTL next – Example

- Model check:  $P_{\geq 0.9} [ X (\neg \text{try} \vee \text{succ}) ]$

$$\begin{aligned} - \text{Sat} (\neg \text{try} \vee \text{succ}) &= (S \setminus \text{Sat}(\text{try})) \cup \text{Sat}(\text{succ}) \\ &= (\{s_0, s_1, s_2, s_3\} \setminus \{s_1\}) \cup \{s_3\} = \{s_0, s_2, s_3\} \end{aligned}$$

$$- \text{Prob}(X (\neg \text{try} \vee \text{succ})) = \mathbf{P} \cdot \underline{(\neg \text{try} \vee \text{succ})} = \dots$$

$$= \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0.01 & 0.01 & 0.98 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0.99 \\ 1 \\ 1 \end{bmatrix}$$



- Results:

$$- \text{Prob}(X (\neg \text{try} \vee \text{succ})) = [0, 0.99, 1, 1]$$

$$- \text{Sat}(P_{\geq 0.9} [ X (\neg \text{try} \vee \text{succ}) ]) = \{s_1, s_2, s_3\}$$

# PCTL until for DTMCs

- Computation of probabilities  $\text{Prob}(s, \phi_1 \cup \phi_2)$  for all  $s \in S$
- First, identify all states where the **probability** is **1** or **0**
  - $S^{\text{yes}} = \text{Sat}(P_{\geq 1} [\phi_1 \cup \phi_2])$
  - $S^{\text{no}} = \text{Sat}(P_{\leq 0} [\phi_1 \cup \phi_2])$
- Then solve linear equation system for remaining states
- We refer to the first phase as “**precomputation**”
  - two algorithms: Prob0 (for  $S^{\text{no}}$ ) and Prob1 (for  $S^{\text{yes}}$ )
  - algorithms work on underlying graph (probabilities irrelevant)
- Important for several reasons
  - reduces the set of states for which probabilities must be computed numerically (which is more expensive)
  - gives **exact results** for the states in  $S^{\text{yes}}$  and  $S^{\text{no}}$  (no round-off)
  - for  $P_{\sim p}[\cdot]$  where  $p$  is 0 or 1, no further computation required

# PCTL until – Linear equations

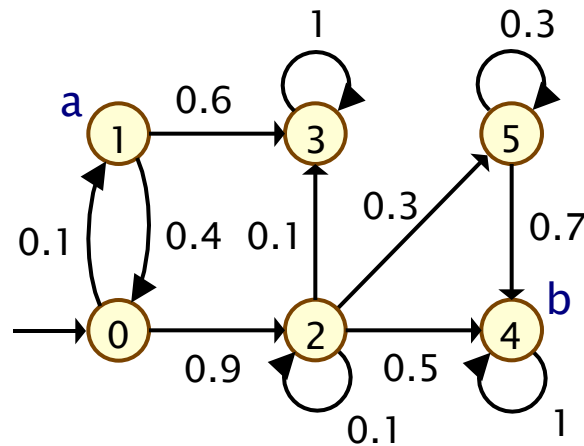
- Probabilities  $\text{Prob}(s, \phi_1 \cup \phi_2)$  can now be obtained as the unique solution of the following set of **linear equations**:

$$\text{Prob}(s, \phi_1 \cup \phi_2) = \begin{cases} 1 & \text{if } s \in S^{\text{yes}} \\ 0 & \text{if } s \in S^{\text{no}} \\ \sum_{s' \in S} P(s, s') \cdot \text{Prob}(s', \phi_1 \cup \phi_2) & \text{otherwise} \end{cases}$$

- can be reduced to a system in  $|S^?|$  unknowns instead of  $|S|$  where  $S^? = S \setminus (S^{\text{yes}} \cup S^{\text{no}})$
- This can be solved with (a variety of) standard techniques
  - direct methods, e.g. Gaussian elimination
  - iterative methods, e.g. Jacobi, Gauss–Seidel, ... (preferred in practice due to scalability)

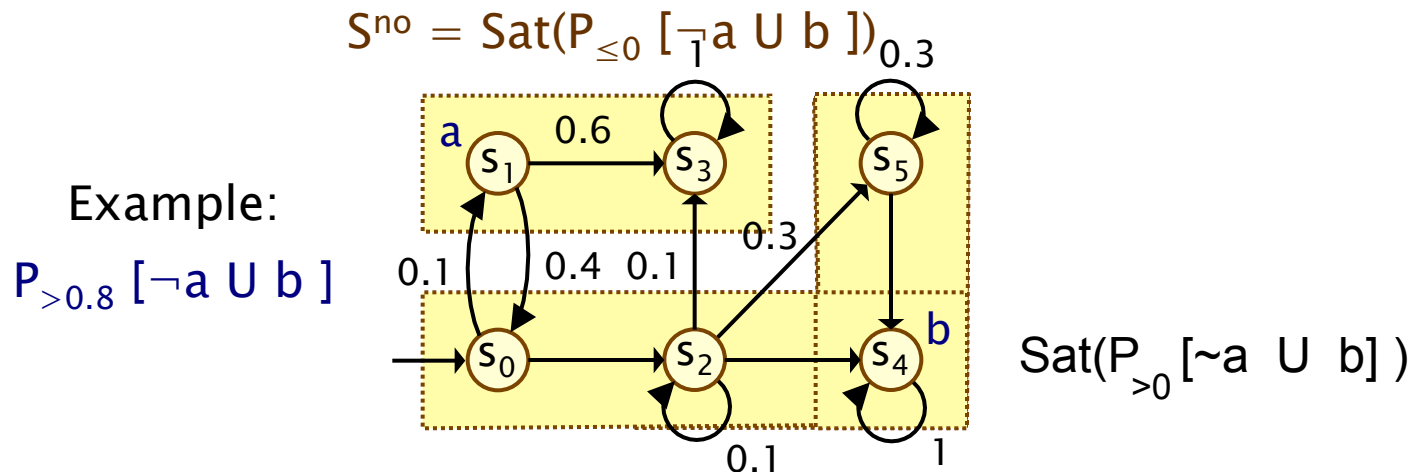
# PCTL until – Example

- Example:  $P_{>0.8} [\neg a \text{ U } b]$



# Precomputation – Prob0

- Prob0 algorithm to compute  $S^{\text{no}} = \text{Sat}(P_{\leq 0} [\phi_1 \cup \phi_2])$ :
  - first compute  $\text{Sat}(P_{>0} [\phi_1 \cup \phi_2]) \equiv \text{Sat}(E[\phi_1 \cup \phi_2])$
  - i.e. find all states which can, **with non-zero probability, reach a  $\phi_2$ -state without leaving  $\phi_1$ -states**
  - i.e. find all states from which there is a finite path through  $\phi_1$ -states to a  $\phi_2$ -state: simple **graph-based computation**
  - subtract the resulting set from  $S$



# Prob0 algorithm

---

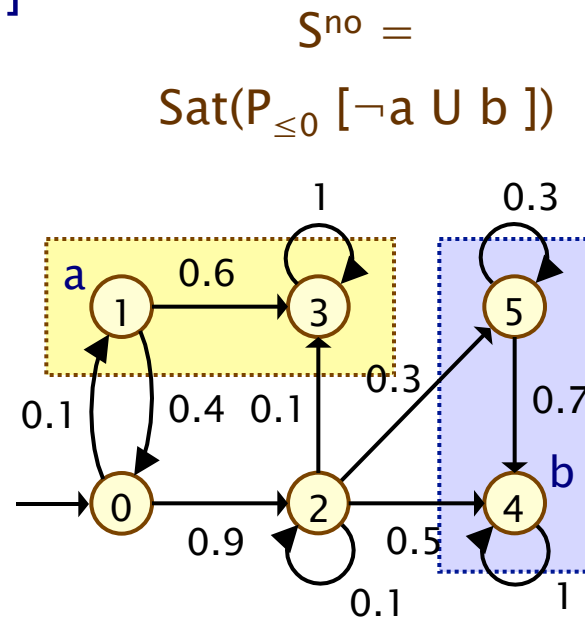
$\text{PROB0}(\text{Sat}(\phi_1), \text{Sat}(\phi_2))$

```
1.   $R := \text{Sat}(\phi_2)$ 
2.   $done := \text{false}$ 
3.  while ( $done = \text{false}$ )
4.       $R' := R \cup \{s \in \text{Sat}(\phi_1) \mid \exists s' \in R. \mathbf{P}(s, s') > 0\}$ 
5.      if ( $R' = R$ ) then  $done := \text{true}$ 
6.       $R := R'$ 
7.  endwhile
8.  return  $S \setminus R$ 
```

- **Note:** can be formulated as a least fixed point computation
  - also well suited to computation with binary decision diagrams

# PCTL until – Example

- Example:  $P_{>0.8} [\neg a \text{ U } b]$

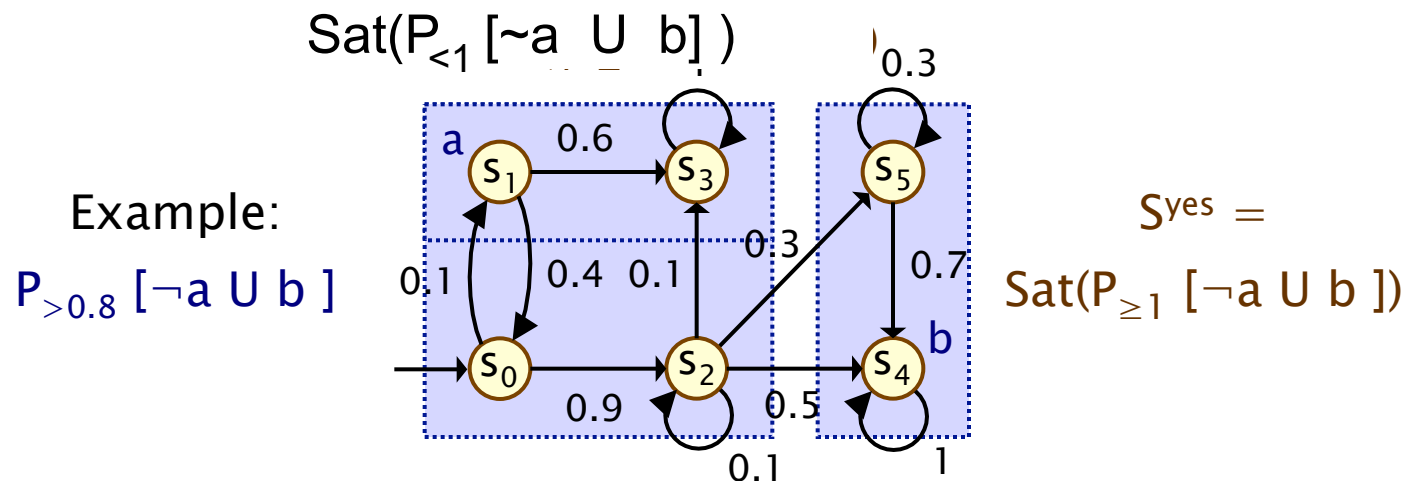


$$S^{\text{no}} = \text{Sat}(P_{\leq 0} [\neg a \text{ U } b])$$

$$S^{\text{yes}} = \text{Sat}(P_{\geq 1} [\neg a \text{ U } b])$$

# Precomputation – Prob1

- Prob1 algorithm to compute  $S^{\text{yes}} = \text{Sat}(P_{\geq 1} [\phi_1 \cup \phi_2])$ :
  - first compute  $\text{Sat}(P_{<1} [\phi_1 \cup \phi_2])$ , reusing  $S^{\text{no}}$
  - this is equivalent to the set of states which have a **non-zero probability of reaching  $S^{\text{no}}$ , passing only through  $\phi_1$ -states**
  - again, this is a simple **graph-based computation**
  - subtract the resulting set from  $S$





# Prob1 algorithm

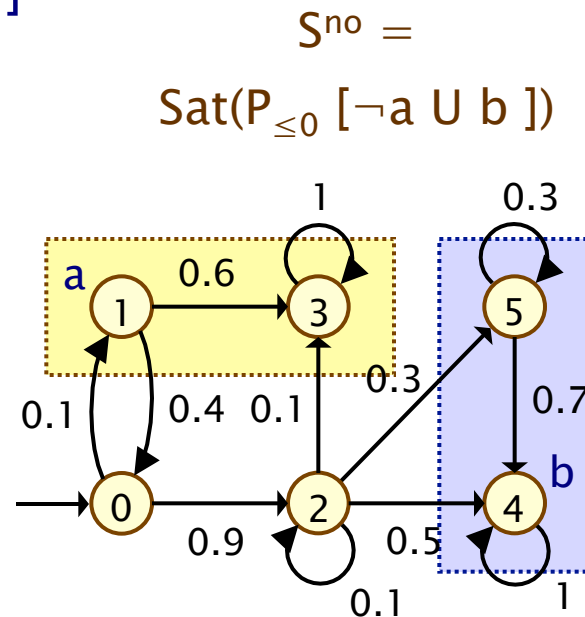
---

$\text{PROB1}(\text{Sat}(\phi_1), \text{Sat}(\phi_2), S^{no})$

1.  $R := S^{no}$
2.  $done := \text{false}$
3. **while** ( $done = \text{false}$ )
4.      $R' := R \cup \{s \in (\text{Sat}(\phi_1) \setminus \text{Sat}(\phi_2)) \mid \exists s' \in R. \mathbf{P}(s, s') > 0\}$
5.     **if** ( $R' = R$ ) **then**  $done := \text{true}$
6.      $R := R'$
7. **endwhile**
8. **return**  $S \setminus R$

# PCTL until – Example

- Example:  $P_{>0.8} [\neg a \text{ U } b]$



$S^{\text{yes}} =$   
 $\text{Sat}(P_{\geq 1} [\neg a \text{ U } b])$

# PCTL until – Example

- Example:  $P_{>0.8} [\neg a \text{ U } b]$

- Let  $x_s = \text{Prob}(s, \neg a \text{ U } b)$

- Solve:

$$x_4 = x_5 = 1$$

$$x_1 = x_3 = 0$$

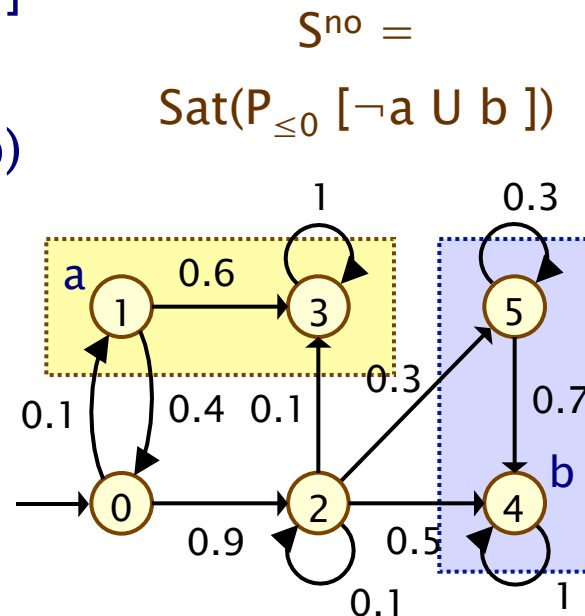
$$x_0 = 0.1x_1 + 0.9x_2 = 0.8$$

$$x_2 = 0.1x_2 + 0.1x_3 + 0.3x_5 + 0.5x_4 = 8/9$$

$$\text{Prob}(\neg a \text{ U } b) = \underline{x} = [0.8, 0, 8/9, 0, 1, 1]$$

note: this Prob-with-underscore is called “probability-vector”

$$\text{Sat}(P_{>0.8} [\neg a \text{ U } b]) = \{s_2, s_4, s_5\}$$



$S^{\text{yes}} =$

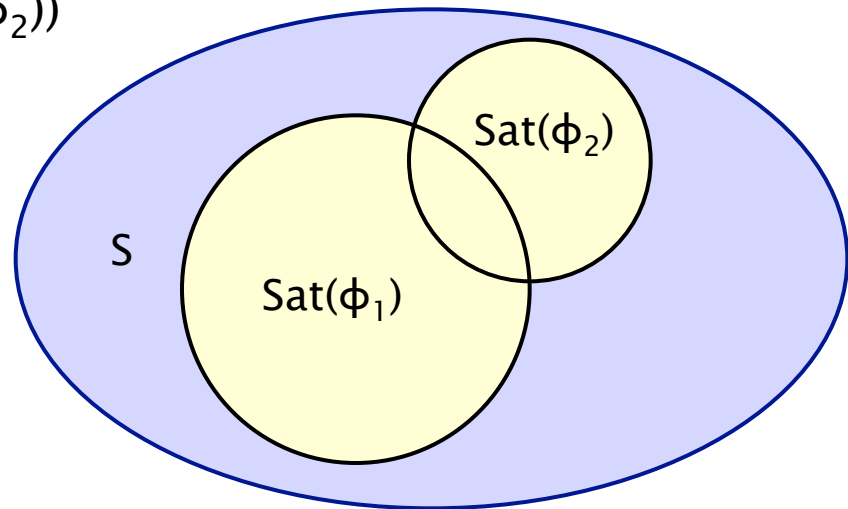
$\text{Sat}(P_{\geq 1} [\neg a \text{ U } b])$

# PCTL bounded until for DTMCs

- Computation of probabilities for PCTL  $U^{\leq k}$  operator
  - $\text{Sat}(P_{\sim p}[\phi_1 U^{\leq k} \phi_2]) = \{s \in S \mid \text{Prob}(s, \phi_1 U^{\leq k} \phi_2) \sim p\}$
  - need to compute  $\text{Prob}(s, \phi_1 U^{\leq k} \phi_2)$  for all  $s \in S$
- First identify (some) states where probability is trivially 1 / 0
  - $S^{\text{yes}} = \text{Sat}(\phi_2)$
  - $S^{\text{no}} = S \setminus (\text{Sat}(\phi_1) \cup \text{Sat}(\phi_2))$

then calculate

$$S^? = S \setminus (S^{\text{yes}} \cup S^{\text{no}})$$



# PCTL bounded until for DTMCs

---

- Simultaneous computation of vector  $\underline{\text{Prob}}(\phi_1 \text{ U}^{\leq k} \phi_2)$ 
  - i.e. probabilities  $\text{Prob}(s, \phi_1 \text{ U}^{\leq k} \phi_2)$  for all  $s \in S$
- Iteratively define in terms of matrices and vectors
  - define matrix  $\mathbf{P}'$  as follows:  $\mathbf{P}'(s, s') = \mathbf{P}(s, s')$  if  $s \in S^?$ ,  $\mathbf{P}'(s, s') = 1$  if  $s \in S^{\text{yes}}$  and  $s = s'$ ,  $\mathbf{P}'(s, s') = 0$  otherwise
  - $\underline{\text{Prob}}(\phi_1 \text{ U}^{\leq 0} \phi_2) = \underline{\phi}_2$
  - $\underline{\text{Prob}}(\phi_1 \text{ U}^{\leq k} \phi_2) = \mathbf{P}' \cdot \underline{\text{Prob}}(\phi_1 \text{ U}^{\leq k-1} \phi_2)$
  - requires **k matrix-vector multiplications**
- Note that we could express this in terms of matrix powers
  - $\underline{\text{Prob}}(\phi_1 \text{ U}^{\leq k} \phi_2) = (\mathbf{P}')^k \cdot \underline{\phi}_2$  and compute  $(\mathbf{P}')^k$  in  $\log_2 k$  steps
  - but this is actually inefficient:  $(\mathbf{P}')^k$  is much less sparse than  $\mathbf{P}'$

# PCTL bounded until – Example

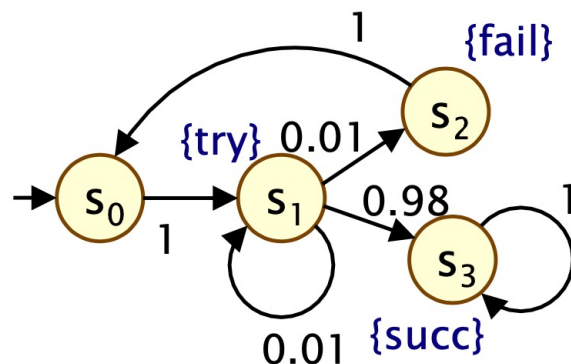
- Model check:  $P_{>0.98} [ F^{\leq 2} \text{ succ} ] \equiv P_{>0.98} [ \text{true } U^{\leq 2} \text{ succ} ]$ 
  - $\text{Sat}(\text{true}) = S = \{s_0, s_1, s_2, s_3\}$ ,  $\text{Sat}(\text{succ}) = \{s_3\}$
  - $S^{\text{yes}} = \{s_3\}$ ,  $S^{\text{no}} = \emptyset$ ,  $S^? = \{s_0, s_1, s_2\}$ ,  $P' = P$
  - $\text{Prob}(\text{true } U^{\leq 0} \text{ succ}) = \underline{\text{succ}} = [0, 0, 0, 1]$

$$\text{Prob}(\text{true } U^{\leq 1} \text{ succ}) = P' \cdot \text{Prob}(\text{true } U^{\leq 0} \text{ succ}) = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0.01 & 0.01 & 0.98 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0.98 \\ 0 \\ 1 \end{bmatrix}$$

$$\text{Prob}(\text{true } U^{\leq 2} \text{ succ}) = P' \cdot \text{Prob}(\text{true } U^{\leq 1} \text{ succ}) = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0.01 & 0.01 & 0.98 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} 0 \\ 0.98 \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 0.98 \\ 0.9898 \\ 0 \\ 1 \end{bmatrix}$$

- $\text{Sat}(P_{>0.98} [ F^{\leq 2} \text{ succ} ]) = \{s_1, s_3\}$

# The construction of $P'$ for bounded Until

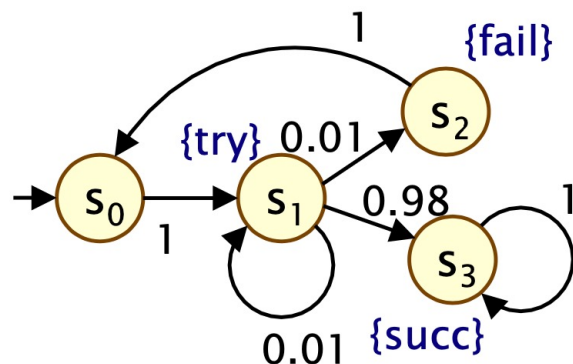


0	1	0	0
0	0.01	0.01	0.98
1	0	0	0
0	0	0	1

The probability matrix  $P$  of the DTMC on the left.

- Consider as an example to check whether the DTMC satisfies  $P_{>0.99}[\text{try} \vee \neg\text{fail} \ U^{\leq 2} \text{succ}]$ .
  - Calculate first the probability vector **Prob** $[\text{try} \vee \neg\text{fail} \ U^{\leq 2} \text{succ}]$ .
  - From there you can calculate the set **Sat** $(P_{>0.99}[\text{try} \vee \neg\text{fail} \ U^{\leq 2} \text{succ}])$ .
  - If the initial state  $s_0$  is in the blue Sat-set then the property  $P_{>0.99}[\text{try} \vee \neg\text{fail} \ U^{\leq 2} \text{succ}]$  holds on the DTMC.**

# The construction of $P'$ for bounded Until



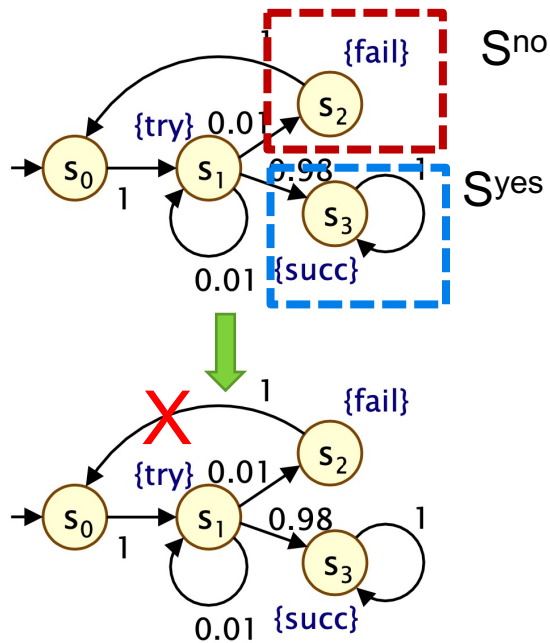
0	1	0	0
0	0.01	0.01	0.98
1	0	0	0
0	0	0	1

The probability matrix  $P$  of the DTMC on the left.

- To calculate the probability vector  $\text{Prob}[\text{try} \vee \neg\text{fail} \ U^{\leq 2} \text{succ}]$ , we would like to use the matrix  $P$  above, however it will also "contain" transitions that cause you to break the green-property. So the idea is to use a "modified" matrix  $P'$ .
- We pre-calculate first the  $S^{\text{yes}} = \text{Sat}(\text{succ}) = \{s3\}$ . On all states in  $S^{\text{yes}}$ , you have the green property immediately (in 0 step).
- We pre-calculate  $S^{\text{no}}$ , we take  $S^{\text{no}} = \text{Sat}(\neg(\text{try} \vee \neg\text{fail}) \wedge \neg \text{succ}) = \{s2\}$ . Executions starting from  $S^{\text{no}}$  won't satisfy your green-property above,



# The construction of $P'$ for bounded Until



$P :$

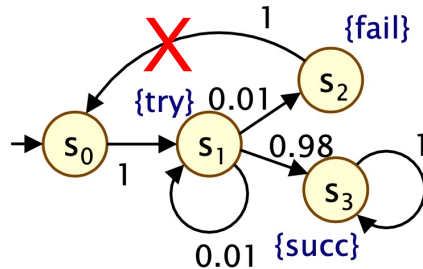
0	1	0	0
0	0.01	0.01	0.98
1	0	0	0
0	0	0	1

$P' :$

0	1	0	0
0	0.01	0.01	0.98
0	0	0	0
0	0	0	1

1. We remove outgoing arrows from the states in  $S^{\text{no}}$  and  $S^{\text{yes}}$ .
2. We keep all arrows that go out from states which are **not** in  $S^{\text{no}}$  nor  $S^{\text{yes}}$ .
3. We add a self-loop  $s \rightarrow s$  with probability 1 for any state  $s$  in  $S^{\text{yes}}$ .

# Using $P'$ for bounded Until



$P'$ :

0	1	0	0
0	0.01	0.01	0.98
0	0	0	0
0	0	0	1

- We now use  $P'$  to iteratively calculate  $\text{Prob}[\text{try } \vee \neg\text{fail } \mathbf{U}^{\leq 2} \text{succ}]$

- From  $S^{\text{yes}}$  you know that  $\text{Prob}[\text{try } \vee \neg\text{fail } \mathbf{U}^{\leq 0} \text{succ}] =$

0
0
0
1

- $\text{Prob}[\text{try } \vee \neg\text{fail } \mathbf{U}^{\leq 1} \text{succ}] = P' \times$

0
0
0
1

 $=$ 

0
0.98
0
1

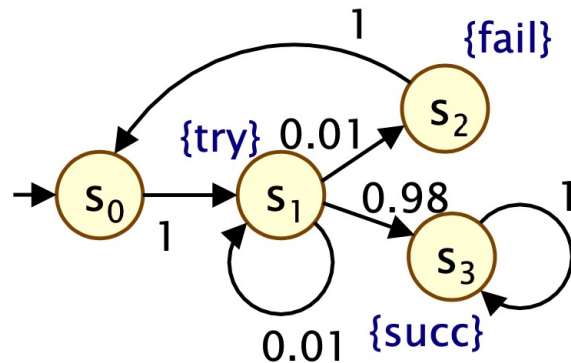
- $\text{Prob}[\text{try } \vee \neg\text{fail } \mathbf{U}^{\leq 2} \text{succ}] = P' \times$

0
0.98
0
1

 $=$ 

0.98
0.9898
0
1

# So, does the property hold?



- We have calculated  $\text{Prob}[\text{try} \vee \neg\text{fail} \text{ } \mathbf{U}^{\leq 2} \text{ succ}] = [0.98, 0.9898, 0, 1]$
- So, the set  $\text{Sat}(P_{>0.99}[\text{try} \vee \neg\text{fail} \text{ } \mathbf{U}^{\leq 2} \text{ succ}]) = \{s_3\}$
- So we conclude that the DTMC does **not** satisfy the claimed property  $P_{>0.99}[\text{try} \vee \neg\text{fail} \text{ } \mathbf{U}^{\leq 2} \text{ succ}]$ .

# PCTL model checking – Summary

- Computation of set  $\text{Sat}(\Phi)$  for DTMC  $D$  and PCTL formula  $\Phi$ 
  - recursive descent of parse tree
  - combination of graph algorithms, numerical computation
- Probabilistic operator  $P$ :
  - $X \Phi$  : one matrix–vector multiplication,  $O(|S|^2)$
  - $\Phi_1 \cup^{\leq k} \Phi_2$  :  $k$  matrix–vector multiplications,  $O(k|S|^2)$
  - $\Phi_1 \cup \Phi_2$  : linear equation system, at most  $|S|$  variables,  $O(|S|^3)$
- Complexity:
  - linear in  $|\Phi|$  and polynomial in  $|S|$

# Overview (Part 1)

- Discrete-time Markov chains (DTMCs)
- PCTL: A temporal logic for DTMCs
- PCTL model checking
- LTL model checking
- Costs and rewards

# Limitations of PCTL

- PCTL, although useful in practice, has limited expressivity
  - essentially: probability of reaching states in  $X$ , passing only through states in  $Y$  (and within  $k$  time-steps)
- More expressive logics can be used, for example:
  - LTL [Pnu77] – (non-probabilistic) linear-time temporal logic
  - PCTL\* [ASB+95,BdA95] – which subsumes both PCTL and LTL
  - both allow path operators to be combined
  - (in PCTL,  $P_{\sim p} [\dots]$  always contains a single temporal operator)
- Another direction: extend DTMCs with costs and rewards...

# LTL – Linear temporal logic

- LTL syntax (path formulae only)

- $\psi ::= \text{true} \mid a \mid \psi \wedge \psi \mid \neg\psi \mid X\psi \mid \psi \cup \psi$
- where  $a \in AP$  is an atomic proposition
- usual equivalences hold:  $F\phi \equiv \text{true} \cup \phi$ ,  $G\phi \equiv \neg(F\neg\phi)$

- LTL semantics (for a path  $\omega$ )

- $\omega \models \text{true}$  always
- $\omega \models a \iff a \in L(\omega(0))$
- $\omega \models \psi_1 \wedge \psi_2 \iff \omega \models \psi_1 \text{ and } \omega \models \psi_2$
- $\omega \models \neg\psi \iff \omega \not\models \psi$
- $\omega \models X\psi \iff \omega[1\dots] \models \psi$
- $\omega \models \psi_1 \cup \psi_2 \iff \exists k \geq 0 \text{ s.t. } \omega[k\dots] \models \psi_2 \wedge \forall i < k \omega[i\dots] \models \psi_1$

where  $\omega(i)$  is  $i^{\text{th}}$  state of  $\omega$ , and  $\omega[i\dots]$  is suffix starting at  $\omega(i)$

# LTL examples

- $(F \text{ tmp\_fail}_1) \wedge (F \text{ tmp\_fail}_2)$ 
  - “both servers suffer temporary failures at some point”
- $GF \text{ ready}$ 
  - “the server always eventually returns to a ready-state”
- $FG \text{ error}$ 
  - “an irrecoverable error occurs”
- $G (\text{req} \rightarrow X \text{ ack})$ 
  - “requests are always immediately acknowledged”



# LTL for DTMCs

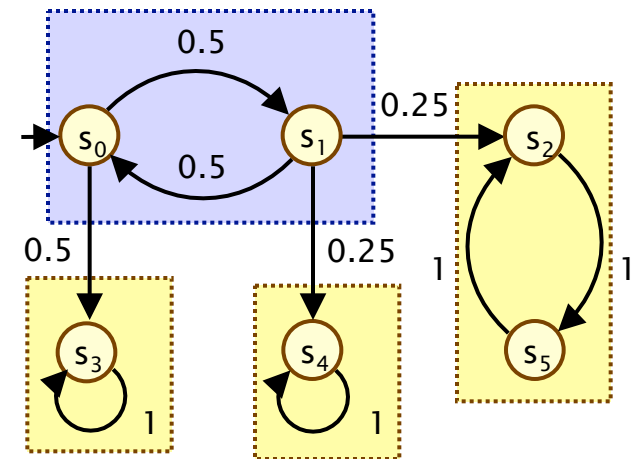
- Same idea as PCTL: probabilities of sets of path formulae
  - for a state  $s$  of a DTMC and an LTL formula  $\psi$ :
  - $\text{Prob}(s, \psi) = \Pr_s \{ \omega \in \text{Path}(s) \mid \omega \models \psi \}$
  - all such path sets are measurable [Var85]
- A (probabilistic) LTL specification often comprises an LTL (path) formula and a probability bound
  - e.g.  $P_{\geq 1} [GF \text{ ready}]$  – “with probability 1, the server always eventually returns to a ready-state”
  - e.g.  $P_{<0.01} [FG \text{ error}]$  – “with probability at most 0.01, an irrecoverable error occurs”
- PCTL\* subsumes both LTL and PCTL
  - e.g.  $P_{>0.5} [GF \text{ crit}_1] \wedge P_{>0.5} [GF \text{ crit}_2]$

# Fundamental property of DTMCs

- Strongly connected component (SCC)
  - maximally strongly connected set of states
- Bottom strongly connected component (BSCC)
  - SCC  $T$  from which no state outside  $T$  is reachable from  $T$

- Fundamental property of DTMCs:

- “with probability 1, a BSCC will be reached and all of its states visited infinitely often”



- Formally:

- $\Pr_s \{ \omega \in \text{Path}(s) \mid \exists i \geq 0, \exists \text{ BSCC } T \text{ such that}$   
 $\forall j \geq i \ \omega(j) \in T \text{ and}$   
 $\forall s' \in T \ \omega(k) = s' \text{ for infinitely many } k \} = 1$

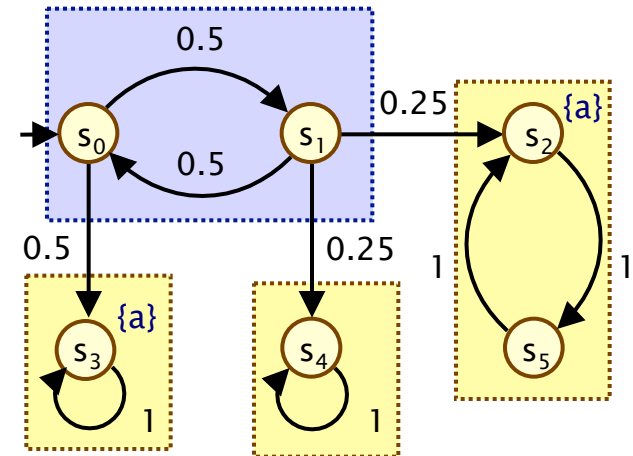
# LTL model checking for DTMCs

- LTL model checking for DTMCs relies on:
  - computing probability of reaching a set of “accepting” BSCCs
  - e.g. for two simple LTL formulae: **GF a** (“always eventually a”), **FG a** (“eventually always a”) we have:

- $\text{Prob}(s, \text{GF } a) = \text{Prob}(s, F T_{\text{GF}a})$ 
  - where  $T_{\text{GF}a}$  = union of all BSCCs containing some state satisfying a

- $\text{Prob}(s, \text{FG } a) = \text{Prob}(s, F T_{\text{FG}a})$ 
  - where  $T_{\text{FG}a}$  = union of all BSCCs containing only a-states

- To extend this idea to arbitrary LTL formula, we use  $\omega$ -automata...



Example:

$$\begin{aligned} \text{Prob}(s_0, \text{GF } a) &= \text{Prob}(s_0, F T_{\text{GF}a}) \\ &= \text{Prob}(s_0, F \{s_3, s_2, s_5\}) \\ &= 2/3 + 1/6 = 5/6 \end{aligned}$$

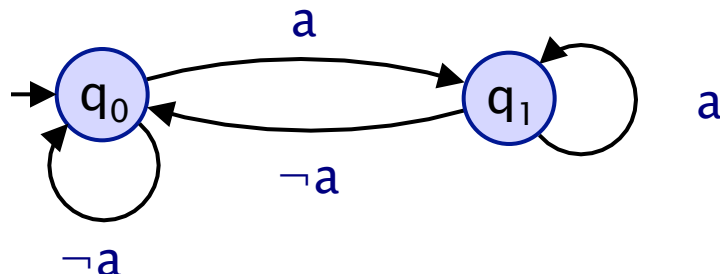
# Deterministic Rabin automata

- $\omega$ -automata represent sets of **infinite** words
  - e.g. Buchi automata, Rabin automata, ...
  - for probabilistic model checking, need **deterministic** automata
  - so we use deterministic Rabin automata (DRAs)
- A deterministic Rabin automaton is a tuple  $(Q, \Sigma, \delta, q_0, \text{Acc})$ :
  - $Q$  is a finite set of states,  $q_0 \in Q$  is an initial state
  - $\Sigma$  is an alphabet,  $\delta : Q \times \Sigma \rightarrow Q$  is a transition function
  - $\text{Acc} = \{ (L_i, K_i) \}_{i=1..k} \subseteq 2^Q \times 2^Q$  is an acceptance condition
- A run of a word on a DRA is accepting iff:
  - for some pair  $(L_i, K_i)$ , the states in  $L_i$  are visited finitely often and (some of) the states in  $K_i$  are visited infinitely often
  - or in LTL: 
$$\bigvee_{1 \leq i \leq k} (\text{FG } \neg L_i \wedge \text{GF } K_i)$$

# LTL & DRAs

- Example: DRA for **FG a**

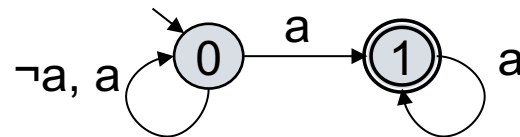
- acceptance condition is  $\text{Acc} = \{ (\{q_0\}, \{q_1\}) \}$



- Can convert any LTL formula  $\psi$  on atomic propositions AP
  - into an equivalent DRA  $A_\psi$  over alphabet  $2^{\text{AP}}$
  - i.e.  $\omega \models \psi \Leftrightarrow \text{trace}(\omega) \in L(A_\psi)$  for any path  $\omega$
  - can potentially incur a double exponential blow-up (but, in practice, this does not occur and  $\psi$  is small anyway)
- LTL model checking for DTMCs – the basic idea
  - construct product of DTMC  $D$  and DRA  $A_\psi$
  - compute  $\text{Prob}^D(s, \psi)$  on product DTMC  $D \otimes A$

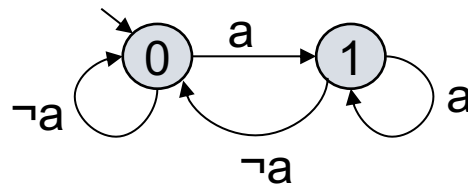
# Buchi vs Rabin

- Consider the LTL property  $\Diamond \Box a$ . This can be described by this Buchi automaton, with  $\{1\}$  as the accepting state:



Notice that this Buchi is **non-deterministic**. As such, we can use it for model checking on a probabilistic model such as DTMC.

- We can however represent the property with a **deterministic** Rabin automaton, with the pair  $(\{0\}, \{1\})$  as its accepting condition.



# Product DTMC for a DRA

- The product DTMC  $D \otimes A$  for:

- for DTMC  $D = (S, s_{init}, P, L)$  and
- and (total) DRA  $A = (Q, \Sigma, \delta, q_0, \{ (L_i, K_i) \}_{i=1..k})$
- is the DTMC  $(S \times Q, (s_{init}, q_{init}), P', L')$  where:

$$q_{init} = \delta(q_0, L(s_{init}))$$

$$P'((s_1, q_1), (s_2, q_2)) = \begin{cases} P(s_1, s_2) & \text{if } q_2 = \delta(q_1, L(s_2)) \\ 0 & \text{otherwise} \end{cases}$$

$$l_i \in L'(s, q) \text{ if } q \in L_i \text{ and } k_i \in L'(s, q) \text{ if } q \in K_i$$

- Note:

- $D \otimes A$  can be seen as unfolding of  $D$  where  $q$  for each state  $(s, q)$  records state of automata  $A$  for path fragment so far
- since  $A$  is deterministic,  $D \otimes A$  is a DTMC
- each path in  $D$  has a corresponding (unique) path in  $D \otimes A$
- the probabilities of paths in  $D$  are preserved in  $D \otimes A$

# Product DTMC for a DRA

- For DTMC **D** and DRA **A**

$$\text{Prob}^D(s, A) = \text{Prob}^{D \otimes A}((s, q_s), \bigvee_{1 \leq i \leq k} (\text{FG } \neg l_i \wedge \text{GF } k_i))$$

– where  $q_s = \delta(q_0, L(s))$

- Hence:

$$\text{Prob}^D(s, A) = \text{Prob}^{D \otimes A}((s, q_s), F T_{\text{Acc}})$$

- where  $T_{\text{Acc}}$  is the union of all **accepting BSCCs** in  $D \otimes A$
- an **accepting BSCC**  $T$  of  $D \otimes A$  is such that, for some  $1 \leq i \leq k$ , no states in  $T$  satisfy  $l_i$  and some state in  $T$  satisfies  $k_i$

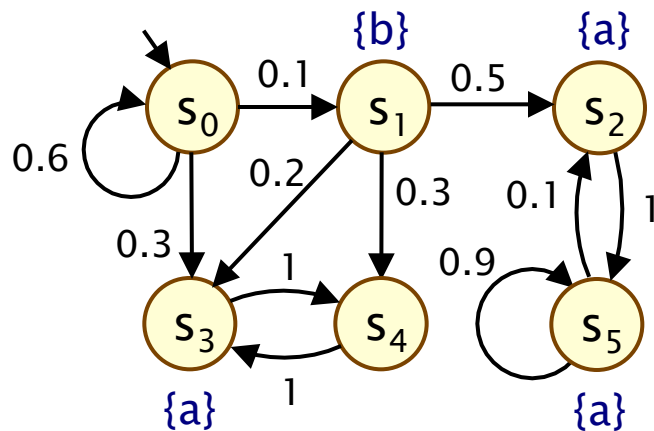
- Reduces to computing BSCCs and reachability probabilities
  - so overall complexity for LTL is doubly exponential in  $|\psi|$ , polynomial in  $|M|$ ; but can be reduced to singly exponential



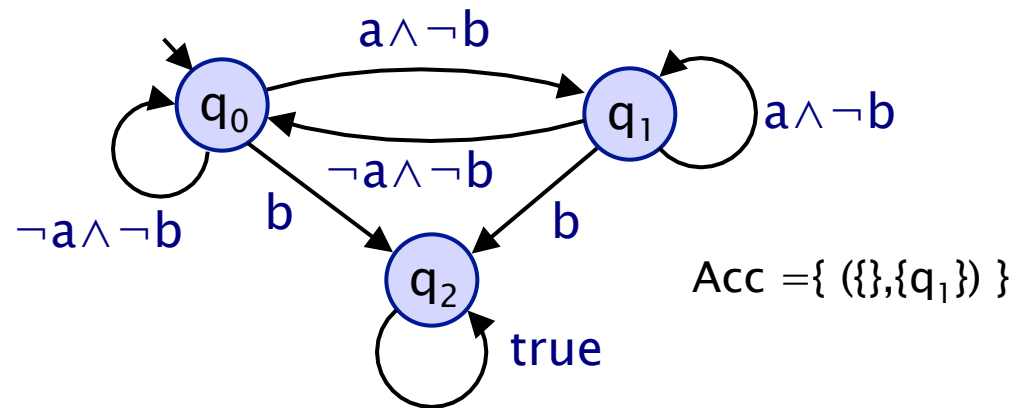
# Example: LTL for DTMCs

- Compute  $\text{Prob}(s_0, G\neg b \wedge GF a)$  for DTMC **D**:

DTMC **D**

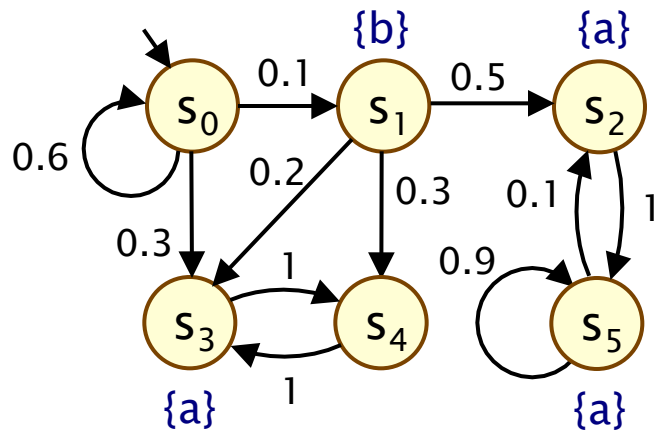


DRA  $A_\psi$  for  $\psi = G\neg b \wedge GF a$

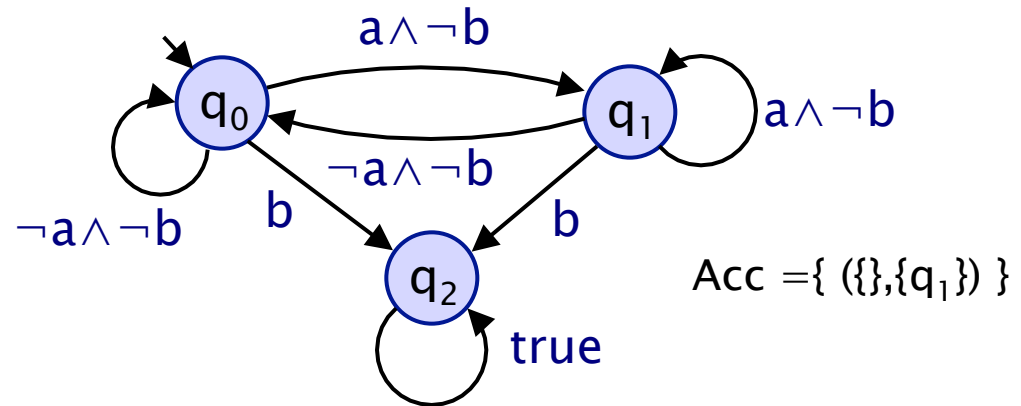


# Example: LTL for DTMCs

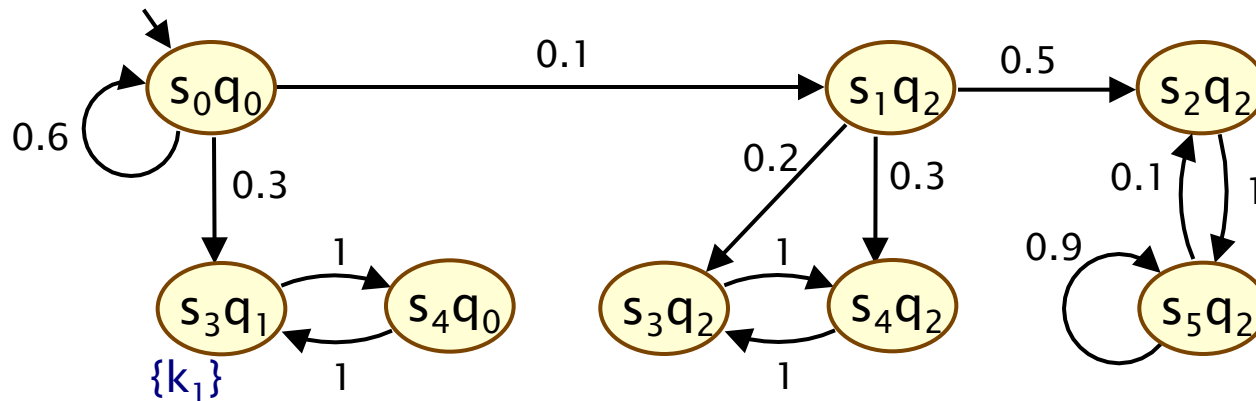
DTMC **D**



DRA  $A_\psi$  for  $\psi = \mathbf{G}\neg b \wedge \mathbf{GF} a$

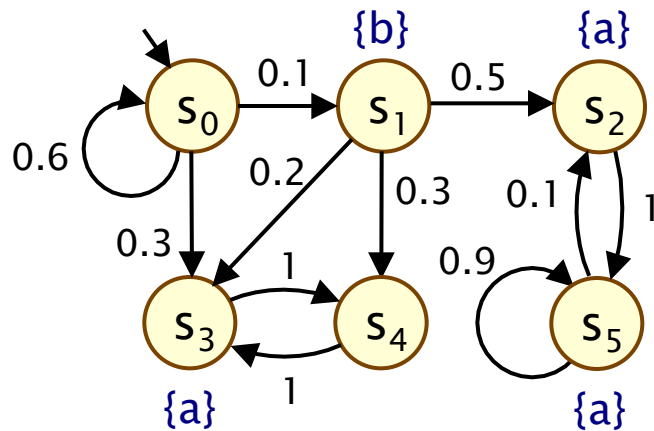


Product DTMC  $\mathbf{D} \otimes A_\psi$

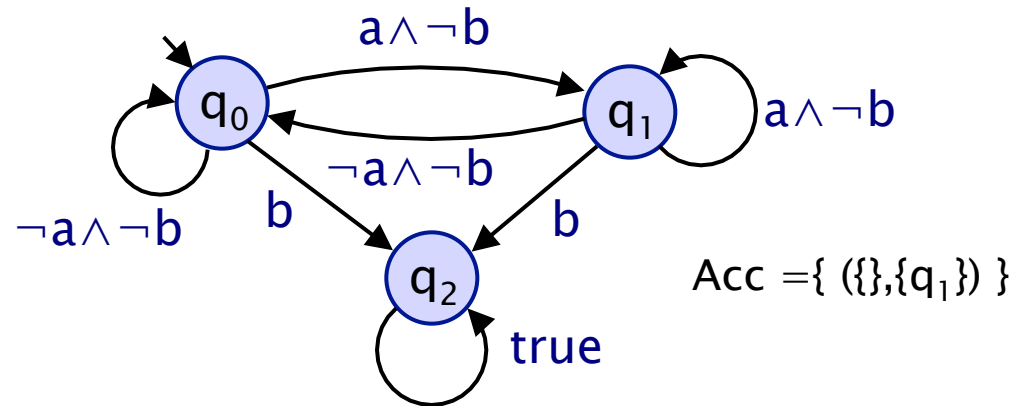


# Example: LTL for DTMCs

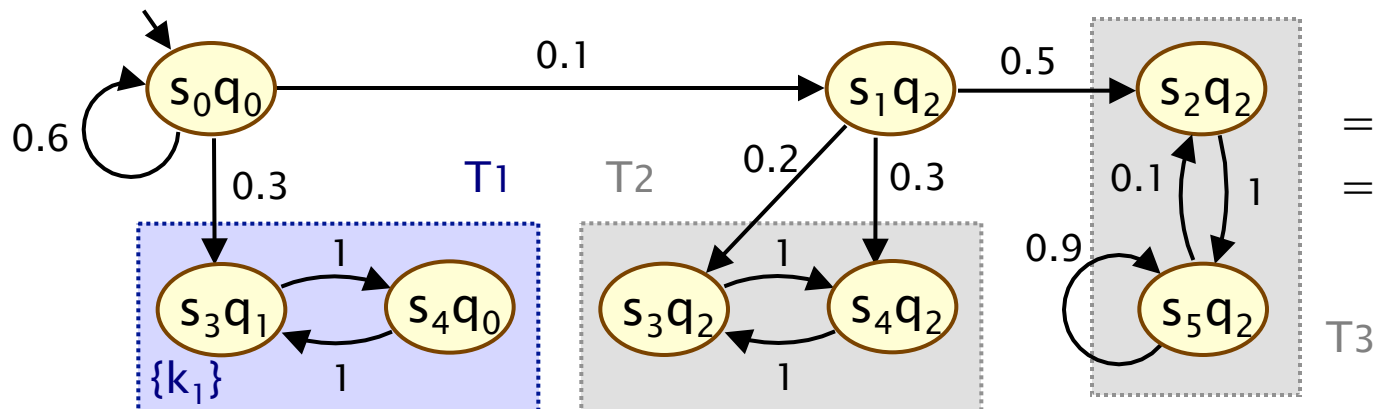
DTMC **D**



DRA  $A_\psi$  for  $\psi = G\neg b \wedge GF a$



Product DTMC **D**  $\otimes$   $A_\psi$



$$\begin{aligned} \text{Prob}^D(s, \psi) &= \text{Prob}^{D \otimes A_\psi}(F T_1) \\ &= 3/4. \end{aligned}$$

# Overview (Part 1)

- Discrete-time Markov chains (DTMCs)
- PCTL: A temporal logic for DTMCs
- PCTL model checking
- LTL model checking
- Costs and rewards

# Costs and rewards

- We augment DTMCs with rewards (or, conversely, costs)
  - real-valued quantities assigned to states and/or transitions
  - these can have a wide range of possible interpretations
- Some examples:
  - elapsed time, power consumption, size of message queue, number of messages successfully delivered, net profit, ...
- Costs? or rewards?
  - mathematically, no distinction between rewards and costs
  - when interpreted, we assume that it is desirable to minimise costs and to maximise rewards
  - we will consistently use the terminology “rewards” regardless

# Reward-based properties

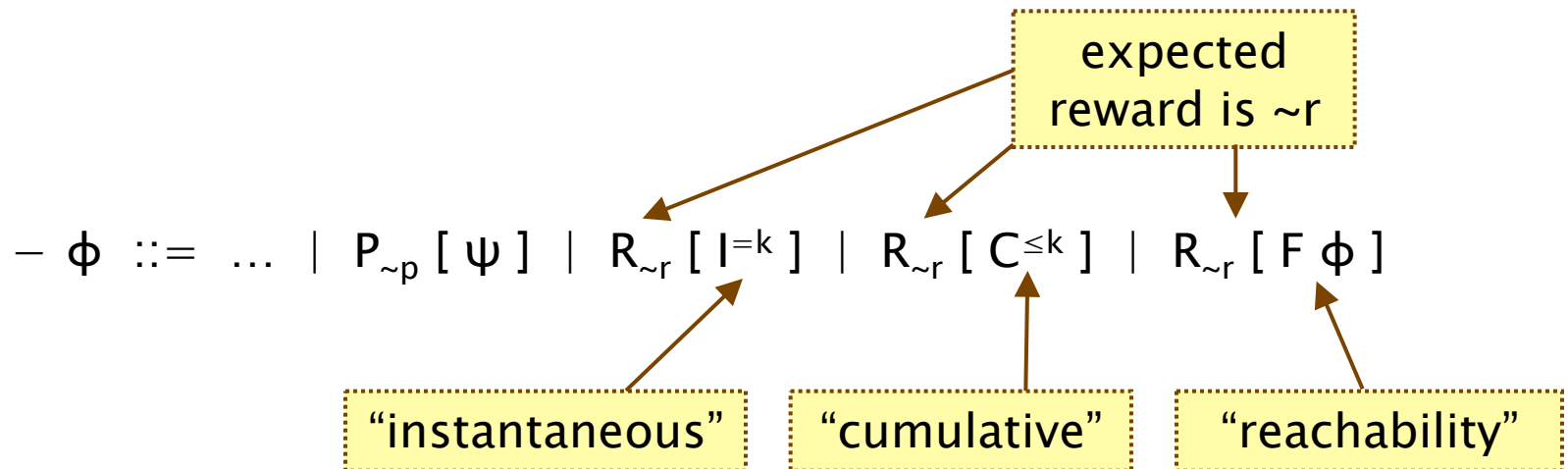
- Properties of DTMCs augmented with rewards
  - allow a wide range of quantitative measures of the system
  - basic notion: expected value of rewards
  - formal property specifications will be in an extension of PCTL
- More precisely, we use two distinct classes of property...
- **Instantaneous** properties
  - the expected value of the reward at some time point
- **Cumulative** properties
  - the expected cumulated reward over some period

# DTMC reward structures

- For a DTMC  $(S, s_{\text{init}}, \mathbf{P}, L)$ , a reward structure is a pair  $(\underline{r}, \underline{t})$ 
  - $\underline{r} : S \rightarrow \mathbb{R}_{\geq 0}$  is the **state reward function** (vector)
  - $\underline{t} : S \times S \rightarrow \mathbb{R}_{\geq 0}$  is the **transition reward function** (matrix)
- Example (for use with instantaneous properties)
  - “size of message queue”:  $\underline{r}$  maps each state to the number of jobs in the queue in that state,  $\underline{t}$  is not used
- Examples (for use with cumulative properties)
  - “**time-steps**”:  $\underline{r}$  returns 1 for all states and  $\underline{t}$  is zero (equivalently,  $\underline{r}$  is zero and  $\underline{t}$  returns 1 for all transitions)
  - “**number of messages lost**”:  $\underline{r}$  is zero and  $\underline{t}$  maps transitions corresponding to a message loss to 1
  - “**power consumption**”:  $\underline{r}$  is defined as the per-time-step energy consumption in each state and  $\underline{t}$  as the energy cost of each transition

# PCTL and rewards

- Extend PCTL to incorporate reward-based properties
  - add an R operator, which is similar to the existing P operator



– where  $r \in \mathbb{R}_{\geq 0}$ ,  $\sim \in \{<, >, \leq, \geq\}$ ,  $k \in \mathbb{N}$

- $R_{\sim r}[\cdot]$  means “the **expected value** of  $\cdot$  satisfies  $\sim r$ ”



# Types of reward formulas

- **Instantaneous:**  $R_{\sim r} [ I^k ]$ 
  - “the expected value of the state reward at time-step  $k$  is  $\sim r$ ”
  - e.g. “the expected queue size after exactly 90 seconds”
- **Cumulative:**  $R_{\sim r} [ C^{\leq k} ]$ 
  - “the expected reward cumulated up to time-step  $k$  is  $\sim r$ ”
  - e.g. “the expected power consumption over one hour”
- **Reachability:**  $R_{\sim r} [ F \phi ]$ 
  - “the expected reward cumulated before reaching a state satisfying  $\phi$  is  $\sim r$ ”
  - e.g. “the expected time for the algorithm to terminate”

# Reward formula semantics

- Formal semantics of the three reward operators
  - based on random variables over (infinite) paths
- Recall:
  - $s \models P_{\sim p} [\psi] \Leftrightarrow \Pr_s \{ \omega \in \text{Path}(s) \mid \omega \models \psi \} \sim p$
- For a state  $s$  in the DTMC:
  - $s \models R_{\sim r} [I^k] \Leftrightarrow \text{Exp}(s, X_{I^k}) \sim r$
  - $s \models R_{\sim r} [C^{\leq k}] \Leftrightarrow \text{Exp}(s, X_{C^{\leq k}}) \sim r$
  - $s \models R_{\sim r} [F \Phi] \Leftrightarrow \text{Exp}(s, X_{F\Phi}) \sim r$

where:  $\text{Exp}(s, X)$  denotes the **expectation** of the **random variable**  $X : \text{Path}(s) \rightarrow \mathbb{R}_{\geq 0}$  with respect to the **probability measure**  $\Pr_s$

# Reward formula semantics

- Definition of random variables:
  - for an infinite path  $\omega = s_0 s_1 s_2 \dots$

$$X_{I=k}(\omega) = \underline{\rho}(s_k)$$

$$X_{C \leq k}(\omega) = \begin{cases} 0 & \text{if } k = 0 \\ \sum_{i=0}^{k-1} \underline{\rho}(s_i) + \iota(s_i, s_{i+1}) & \text{otherwise} \end{cases}$$

$$X_{F\phi}(\omega) = \begin{cases} 0 & \text{if } s_0 \in \text{Sat}(\phi) \\ \infty & \text{if } s_i \notin \text{Sat}(\phi) \text{ for all } i \geq 0 \\ \sum_{i=0}^{k_\phi-1} \underline{\rho}(s_i) + \iota(s_i, s_{i+1}) & \text{otherwise} \end{cases}$$

- where  $k_\phi = \min\{j \mid s_j \models \phi\}$

# Model checking reward properties

- Instantaneous:  $R_{\sim r} [ I^k ]$
- Cumulative:  $R_{\sim r} [ C^{\leq t} ]$ 
  - variant of the method for computing bounded until probabilities
  - solution of **recursive equations**
- Reachability:  $R_{\sim r} [ F \phi ]$ 
  - similar to computing until probabilities
  - precomputation phase (identify infinite reward states)
  - then reduces to solving a **system of linear equation**
- For more details, see e.g. [\[KNP07a\]](#)

# Summary

- Probabilistic model checking
  - automated quantitative verification of stochastic systems
  - to model randomisation, failures, ...
- Discrete-time Markov chains (DTMCs)
  - state transition systems + discrete probabilistic choice
  - probability space over paths through a DTMC
- Property specifications
  - probabilistic extensions of temporal logic, e.g. PCTL, LTL
  - also: expected value of costs/rewards
- Model checking algorithms
  - combination of graph-based algorithms, numerical computation, automata constructions
- Tomorrow: Markov decision processes (MDPs)