Lecture 5
PCTL Model Checking for DTMCs

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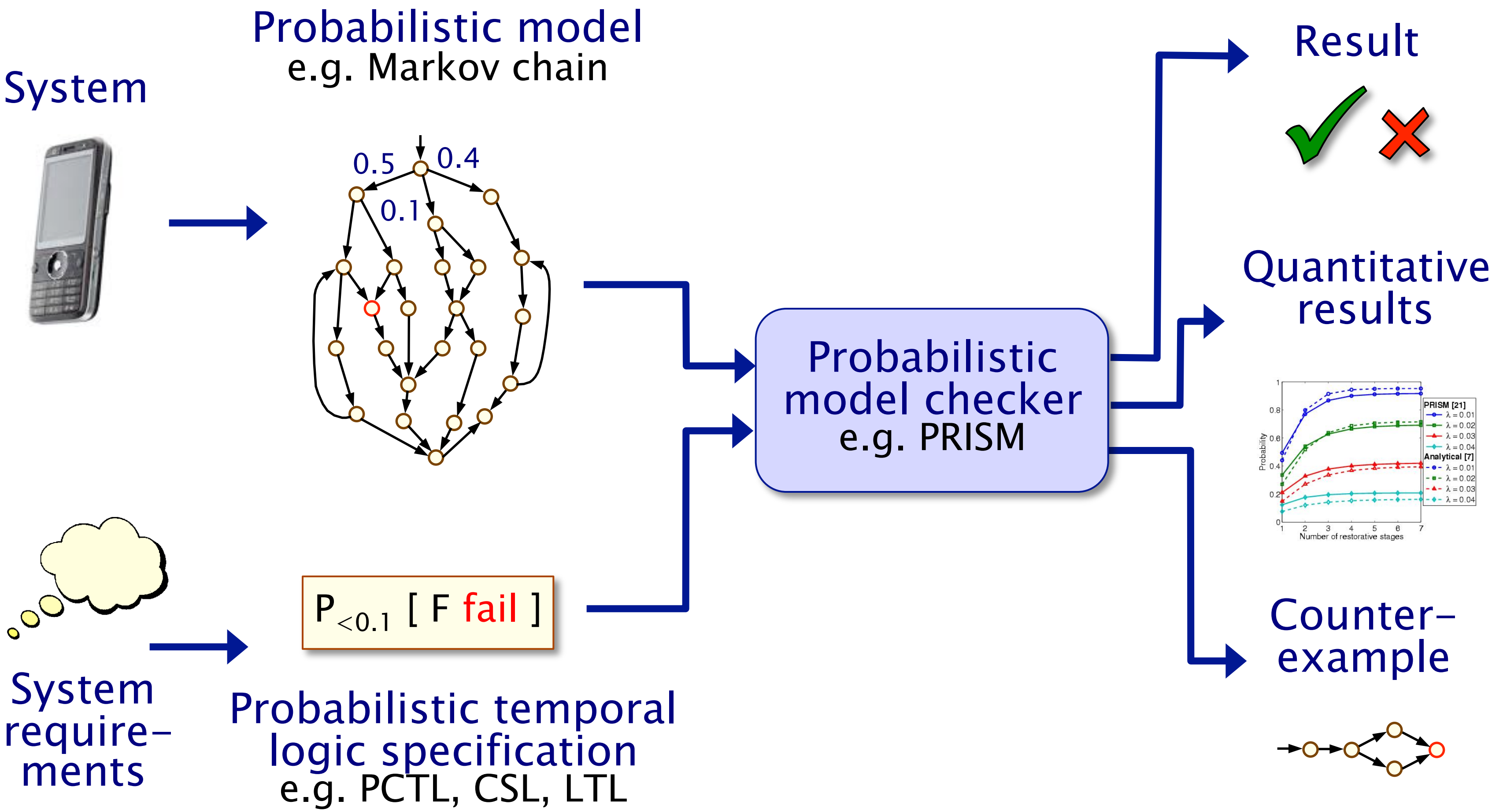
Probabilistic model checking



Overview

- PCTL model checking for DTMCs
- Computation of probabilities for PCTL formulae
  - next
  - bounded until
  - (unbounded) until
- Solving large linear equation systems
  - direct vs. iterative methods
  - iterative solution methods

PCTL

- PCTL syntax:
  - ϕ ::= true | a | $\phi \wedge \phi$ | $\neg\phi$ | $P_{\sim p}$ [ψ]   (state formulae)
  - ψ ::= X ϕ | ϕ $U^{\leq k}$ ϕ | ϕ U ϕ (path formulae)
  - where a is an atomic proposition, $p \in [0,1]$ is a probability bound, $\sim \in \{<,>,\leq,\geq\}$, $k \in \mathbb{N}$

ψ is true with probability ~p

"next"

"bounded until"

"until"

- Remaining operators can be derived (false, $\vee$, $\rightarrow$, F, G, …)
  - hence will not be discussed here

PCTL model checking for DTMCs

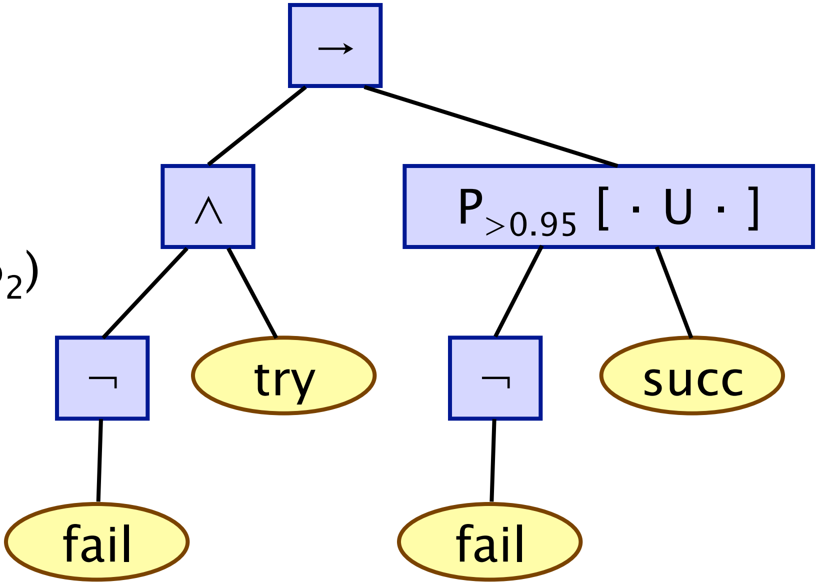
- Algorithm for PCTL model checking [CY88,HJ94,CY95]
  - inputs: DTMC $D=(S,s_{init},P,L)$, PCTL formula ϕ
  - output: $Sat(\phi) = \{ s \in S \mid s \vDash \phi \}$ = set of states satisfying ϕ

- What does it mean for a DTMC D to satisfy a formula ϕ?
  - often, just want to know if $s_{init} \vDash \phi$, i.e. if $s_{init} \in Sat(\phi)$
  - sometimes, want to check that $s \vDash \phi\ \forall\ s \in S$, i.e. $Sat(\phi) = S$

- 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 ϕ
  - example: $\phi = (\neg fail \wedge try) \rightarrow P_{>0.95} [\ \neg fail\ U\ succ\ ]$
- For the non-probabilistic operators:
  - $Sat(true) = S$
  - $Sat(a) = \{ s \in S \mid a \in L(s) \}$
  - $Sat(\neg\phi) = S \setminus Sat(\phi)$
  - $Sat(\phi_1 \wedge \phi_2) = Sat(\phi_1) \cap Sat(\phi_2)$



- For the $P_{\sim p} [\ \psi\ ]$ operator:
  - need to compute the probabilities $Prob(s, \psi)$ for all states $s \in S$
  - $Sat(P_{\sim p} [\ \psi\ ]) = \{ s \in S \mid Prob(s, \psi) \sim p \}$

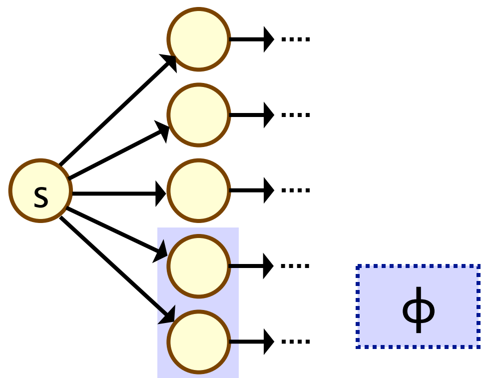
Probability computation

- Three temporal operators to consider:
- Next: $P_{\sim p}[\ X\ \phi\ ]$
- Bounded until: $P_{\sim p}[\ \phi_1\ U^{\leq k}\ \phi_2\ ]$
  - adaptation of bounded reachability for DTMCs
- Until: $P_{\sim p}[\ \phi_1\ U\ \phi_2\ ]$
  - adaptation of reachability for DTMCs
  - graph-based “precomputation” algorithms
  - techniques for solving large linear equation systems

PCTL next for DTMCs

- Computation of probabilities for PCTL next operator
  - $\text{Sat}(P_{\sim p}[\ X\ \phi\ ]) = \{\ s \in S \mid \text{Prob}(s, X\ \phi) \sim p\ \}$
  - need to compute $\text{Prob}(s, X\ \phi)$ for all $s \in S$

- Sum outgoing probabilities for transitions to ϕ-states
  - $\text{Prob}(s, X\ \phi) = \Sigma_{s' \in \text{Sat}(\phi)}\ \mathbf{P}(s,s')$



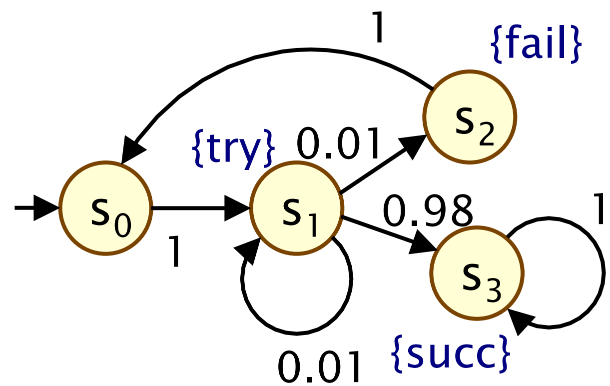
- Compute vector $\underline{\text{Prob}}(X\ \phi)$ of probabilities for all states s
  - $\underline{\text{Prob}}(X\ \phi) = \mathbf{P} \cdot \underline{\phi}$
  - where $\underline{\phi}$ is a 0-1 vector over S with $\underline{\phi}(s) = 1$ iff $s \models \phi$
  - computation requires a single matrix-vector multiplication

PCTL next – Example

- Model check: $P_{\geq 0.9}$ [X (¬try ∨ succ)]
  – Sat (¬try ∨ succ) = (S \ Sat(try)) ∪ Sat(succ)
  = ($\{s_0,s_1,s_2,s_3\}$ \ $\{s_1\}$) ∪ $\{s_3\}$ = $\{s_0,s_2,s_3\}$

  – <u>Prob</u>(X (¬try ∨ succ)) = **P** · <u>(¬try ∨ succ)</u> = …

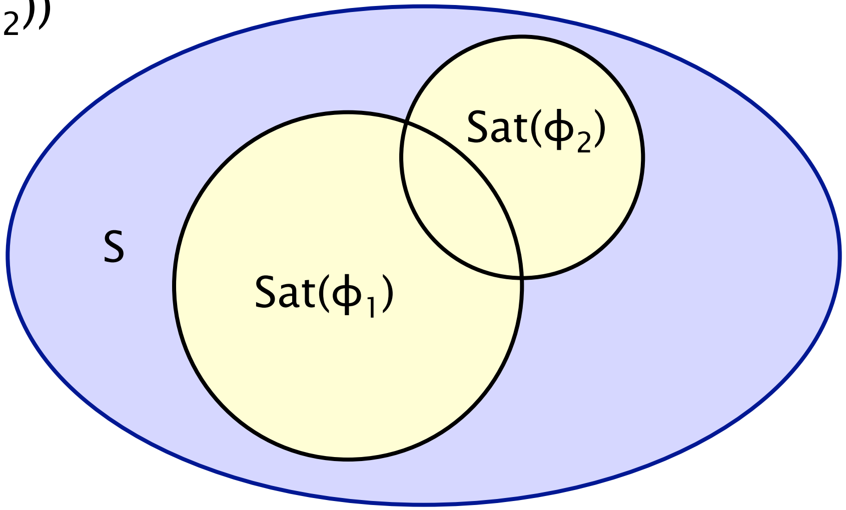
$$= \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0.01 & 0.01 & 0.98 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0.99 \\ 1 \\ 1 \end{bmatrix}$$



- Results:
  – <u>Prob</u>(X (¬try ∨ succ)) = [0, 0.99, 1, 1]
  – Sat($P_{\geq 0.9}$ [X (¬try ∨ succ)]) = $\{s_1, s_2, s_3\}$

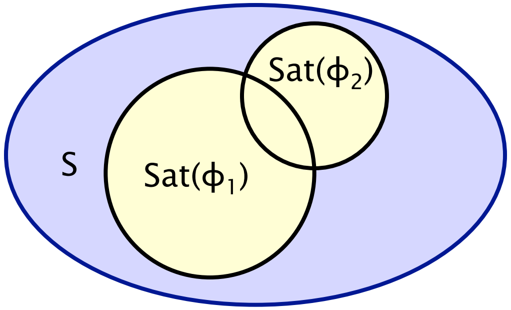
PCTL bounded until for DTMCs

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



PCTL bounded until for DTMCs

- Let:
  - $S^{yes} = Sat(\phi_2)$
  - $S^{no} = S \setminus (Sat(\phi_1) \cup Sat(\phi_2))$
- And let:
  - $S^{?} = S \setminus (S^{yes} \cup S^{no})$



- Compute solution of recursive equations:

$$
Prob(s, \phi_1 U^{\leq k} \phi_2) = \begin{cases} 1 & \text{if } s \in S^{yes} \\ 0 & \text{if } s \in S^{no} \\ 0 & \text{if } s \in S^{?} \text{ and } k = 0 \\ \sum_{s' \in S} P(s,s') \cdot Prob(s', \phi_1 U^{\leq k-1} \phi_2) & \text{if } s \in S^{?} \text{ and } k > 0 \end{cases}
$$

PCTL bounded until for DTMCs

- Simultaneous computation of vector $\underline{\text{Prob}}(\phi_1\ U^{\leq k}\ \phi_2)$
  - i.e. probabilities $\text{Prob}(s, \phi_1\ U^{\leq k}\ \phi_2)$ for all $s \in S$

- Iteratively define in terms of matrices and vectors
  - define matrix **P'** as follows: $\mathbf{P}'(s,s') = \mathbf{P}(s,s')$ if $s \in S^?$, $\mathbf{P}'(s,s') = 1$ if $s \in S^{yes}$ and $s=s'$, $\mathbf{P}'(s,s') = 0$ otherwise
  - $\underline{\text{Prob}}(\phi_1\ U^{\leq 0}\ \phi_2) = \underline{\phi}_2$
  - $\underline{\text{Prob}}(\phi_1\ U^{\leq k}\ \phi_2) = \mathbf{P}' \cdot \underline{\text{Prob}}(\phi_1\ U^{\leq k-1}\ \phi_2)$
  - requires k matrix-vector multiplications

- Note that we could express this in terms of matrix powers
  - $\underline{\text{Prob}}(\phi_1\ U^{\leq k}\ \phi_2) = (\mathbf{P}')^k \cdot \underline{\phi}_2$ and compute $(\mathbf{P}')^k$ in $\log_2 k$ steps
  - but this is actually inefficient: $(\mathbf{P}')^k$ is much less sparse than **P'**

PCTL bounded until – Example

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

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

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

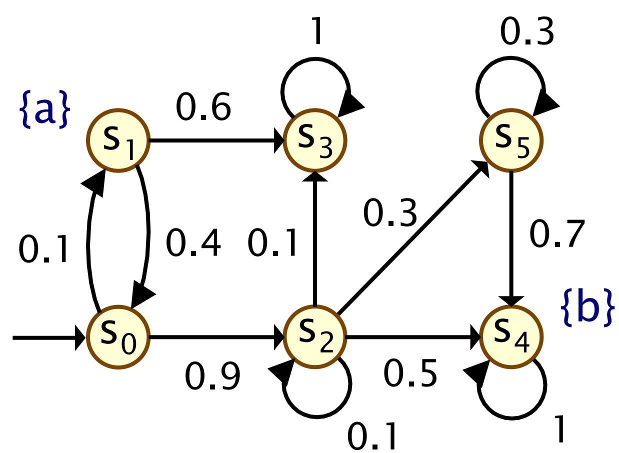
  - Sat($P_{>0.98}$ [$F^{\leq 2}$ succ]) = $\{s_1, s_3\}$

PCTL until for DTMCs

- Computation of probabilities Prob(s, ϕ_1 U ϕ_2) for all s $\in$ S
- First, identify all states where the probability is 1 or 0
  - S^{yes} = Sat($P_{\geq 1}$ [ϕ_1 U ϕ_2])
  - S^{no} = Sat($P_{\leq 0}$ [ϕ_1 U ϕ_2])
- Then solve linear equation system for remaining states

- Running example:

$P_{>0.8}$ [¬a U b]



Precomputation

- We refer to the first phase (identifying sets S^{yes} and S^{no}) as "precomputation"
  - two algorithms: Prob0 (for S^{no}) and Prob1 (for S^{yes})
  - algorithms work on underlying graph (probabilities irrelevant)

- Important for several reasons
  - ensures unique solution to linear equation system
    - only need Prob0 for uniqueness, Prob1 is optional
  - reduces the set of states for which probabilities must be computed numerically
  - gives exact results for the states in S^{yes} and S^{no} (no round-off)
  - for model checking of qualitative properties ($P_{\sim p}[\cdot]$ where p is 0 or 1), no further computation required

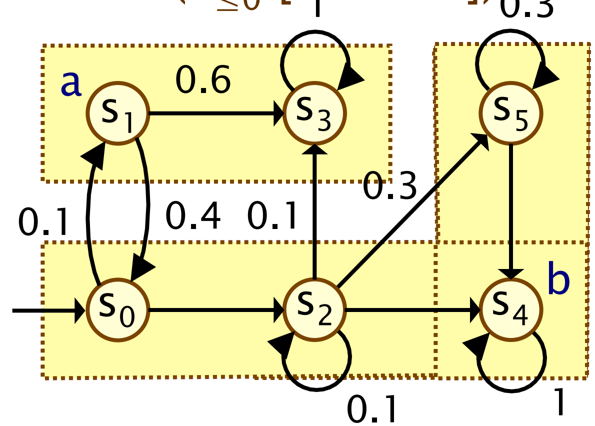
Precomputation – Prob0

- Prob0 algorithm to compute $S^{no} = Sat(P_{\leq 0}[\ \phi_1\ U\ \phi_2\ ])$:
  - first compute $Sat(P_{>0}[\ \phi_1\ U\ \phi_2\ ]) \equiv Sat(E[\ \phi_1\ U\ \phi_2\ ])$
  - i.e. find all states which can, with non-zero probability, reach a ϕ_2-state without leaving ϕ_1-states
  - i.e. find all states from which there is a finite path through ϕ_1-states to a ϕ_2-state: simple graph-based computation
  - subtract the resulting set from S

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

Example:

$P_{>0.8}[\neg a\ U\ b\ ]$



Sat(b)

$Sat(P_{>0}[\neg a\ U\ b\ ])$

Prob0 algorithm

PROB0($Sat(\phi_1), Sat(\phi_2)$)
1. $R := Sat(\phi_2)$
2. $done :=$ **false**
3. **while** $(done =$ **false**$)$
4. $\quad R' := R \cup \{s \in Sat(\phi_1) \mid \exists s' \in R \,.\, \mathbf{P}(s,s') > 0\}$
5. $\quad$ **if** $(R' = R)$ **then** $done :=$ **true**
6. $\quad R := R'$
7. **endwhile**
8. **return** $S \backslash R$

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

Precomputation – Prob1

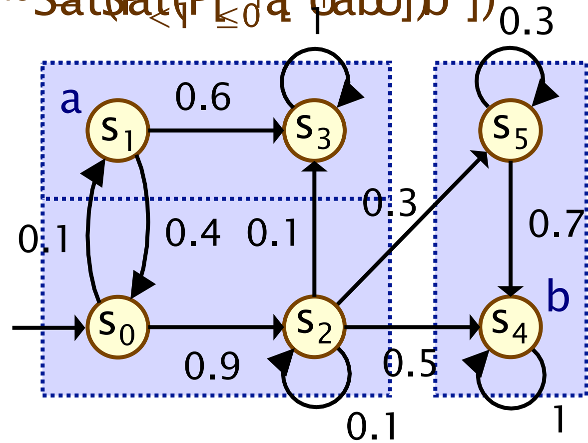
- Prob1 algorithm to compute $S^{yes} = Sat(P_{\geq 1} [\ \phi_1\ U\ \phi_2\ ])$:
  - first compute $Sat(P_{<1} [\ \phi_1\ U\ \phi_2\ ])$, reusing S^{no}
  - this is equivalent to the set of states which have a non-zero probability of reaching S^{no}, passing only through ϕ_1-states
  - again, this is a simple graph-based computation
  - subtract the resulting set from S

Example:

$P_{>0.8}$ [¬a U b]

$S^{no} = Sat(P_{\leq 0}$ [¬a U b])

$Sat(P_{<1}$ [¬a U b])



S^{yes} =

$Sat(P_{\geq 1}$ [¬a U b])

Prob1 algorithm

$\textsc{Prob1}(Sat(\phi_1), Sat(\phi_2), S^{no})$

$R := S^{no}$

$done :=$ **false**

while $(done =$ **false**$)$

    $R' := R \cup \{s \in (Sat(\phi_1) \backslash Sat(\phi_2)) \mid \exists s' \in R \,.\, \mathbf{P}(s,s') > 0\}$

    if $(R' = R)$ **then** $done :=$ **true**

    $R := R'$

endwhile

return $S \backslash R$

Prob 1 explanation

PCTL until – linear equations

- Probabilities Prob(s, ϕ_1 U ϕ_2) can now be obtained as the unique solution of the following set of linear equations
  - essentially the same as for probabilistic reachability

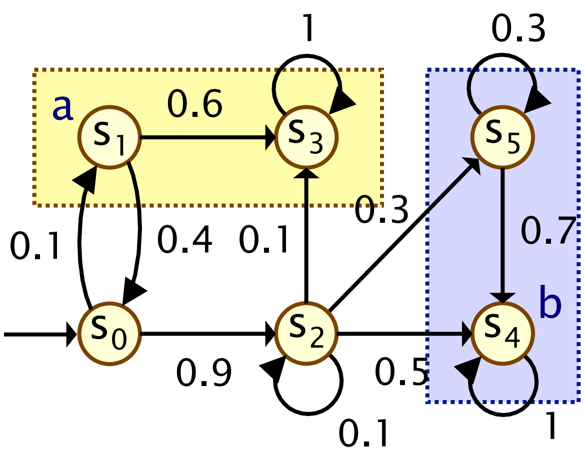
$$\mathrm{Prob}(s, \phi_1 \mathrm{\ U\ } \phi_2) = \begin{cases} 1 & \text{if } s \in S^{yes} \\ 0 & \text{if } s \in S^{no} \\ \sum_{s' \in S} P(s,s') \cdot \mathrm{Prob}(s', \phi_1 \mathrm{\ U\ } \phi_2) & \text{otherwise} \end{cases}$$

- Can also be reduced to a system in $|S^?|$ unknowns instead of $|S|$ where $S^? = S \setminus (S^{yes} \cup S^{no})$

PCTL until – linear equations

- Example: $P_{>0.8}$ [¬a U b]
- Let x_i = Prob(s_i, ¬a U b)

S^{no} = Sat($P_{\leq 0}$ [¬a U b])



S^{yes} = Sat($P_{\geq 1}$ [¬a U b])

$x_1 = x_3 = 0$

$x_4 = x_5 = 1$

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

$x_0 = 0.1x_1+0.9x_2 = 0.8$

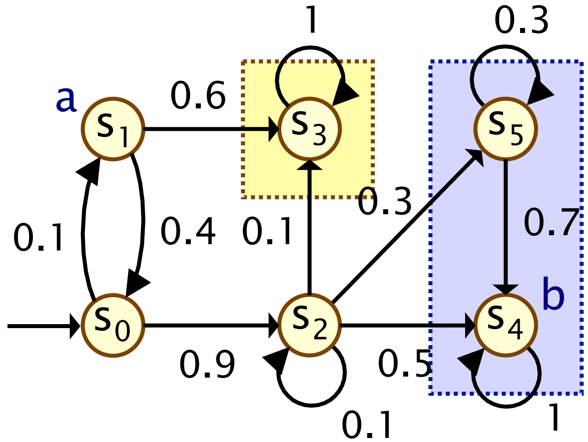
Prob(¬a U b) = $\underline{x}$ = [0.8, 0, 8/9, 0, 1, 1]

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

PCTL Until – Example 2

- Example: $P_{>0.5}$ [G¬b]
- $Prob(s_i, G\neg b)$
  $= 1 - Prob(s_i, \neg(G\neg b))$
  $= 1 - Prob(s_i, F\ b)$
- Let $x_i = Prob(s_i, F\ b)$

$S^{no} = Sat(P_{\leq 0}\ [\ F\ b\ ])$



$S^{yes} =$
$Sat(P_{\geq 1}\ [\ F\ b\ ])$

$x_3 = 0$ and $x_4 = x_5 = 1$

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

$x_1 = 0.6x_3+0.4x_0 = 0.4x_0$

$x_0 = 0.1x_1+0.9x_2 = 5/6$ and $x_1 = 1/3$

$\underline{Prob}(G\neg b) = \underline{1}-\underline{x} = [1/6, 2/3, 1/9, 1, 0, 0\ ]$

$Sat(P_{>0.5}\ [\ G\neg b\ ]) = \{\ s_1, s_3\ \}$

Linear equation systems

- Solution of large (sparse) linear equation systems
  - size of system (number of variables) typically O(|S|)
  - state space S gets very large in practice
- Two main classes of solution methods:
  - direct methods – compute exact solutions in fixed number of steps, e.g. Gaussian elimination, L/U decomposition
  - iterative methods, e.g. Power, Jacobi, Gauss-Seidel, …
  - the latter are preferred in practice due to scalability
- General form: **A**·$\underline{x}$ = $\underline{b}$
  - indexed over integers,
  - i.e. assume S = { 0,1,…,|S|-1 }

$$\sum_{j=0}^{|S|-1} \mathrm{A}(i,j) \cdot \underline{x}(j) \quad = \quad \underline{b}(i)$$

Iterative solution methods

- Start with an initial estimate for the vector $\underline{x}$, say $\underline{x}^{(0)}$
- Compute successive (increasingly accurate) approximations
  - approximation (solution vector) at k^{th} iteration denoted $\underline{x}^{(k)}$
  - computation of $x^{(k)}$ uses values of $x^{(k-1)}$
- Terminate when solution vector has converged sufficiently
- Several possibilities for convergence criteria, e.g.:
  - maximum absolute difference

$$\max_i \left| \underline{x}^{(k)}(i) - \underline{x}^{(k-1)}(i) \right| \quad < \quad \varepsilon$$

  - maximum relative difference

$$\max_i \left(\frac{\left| \underline{x}^{(k)}(i) - \underline{x}^{(k-1)}(i) \right|}{\left| \underline{x}^{(k)}(i) \right|} \right) \quad < \quad \varepsilon$$

Jacobi method

- Based on fact that:

$$\sum_{j=0}^{|S|-1} \mathbf{A}(i,j) \cdot \underline{x}(j) \;=\; \underline{b}(i)$$

For probabilistic model checking, **A**(i,i) is always non-zero

- can be rearranged as:

$$\underline{x}(i) \;=\; \left(\underline{b}(i) - \sum_{j \neq i} \mathbf{A}(i,j) \cdot \underline{x}(j) \right) / \mathbf{A}(i,i)$$

- yielding this update scheme:

$$\underline{x}^{(k)}(i) \;:=\; \left(\underline{b}(i) - \sum_{j \neq i} \mathbf{A}(i,j) \cdot \underline{x}^{(k-1)}(j) \right) / \mathbf{A}(i,i)$$

Gauss-Seidel

- The update scheme for Jacobi:

$$\underline{x}^{(k)}(i) \quad := \quad \left(\underline{b}(i) - \sum_{j \neq i} \mathbf{A}(i,j) \cdot \underline{x}^{(k-1)}(j) \right) / \mathbf{A}(i,i)$$

- can be improved by using the most up-to-date values of $\underline{x}^{(j)}$ that are available
- This is the Gauss-Seidel method:

$$\underline{x}^{(k)}(i) \quad := \quad \left(\underline{b}(i) - \sum_{j<i} \mathbf{A}(i,j) \cdot \underline{x}^{(k)}(j) - \sum_{j>i} \mathbf{A}(i,j) \cdot \underline{x}^{(k-1)}(j) \right) / \mathbf{A}(i,i)$$

Over-relaxation

- Over-relaxation:
  - compute new values with existing schemes (e.g. Jacobi)
  - but use weighted average with previous vector

- Example: Jacobi + over-relaxation

$$\underline{x}^{(k)}(i) \;:=\; (1-\omega)\cdot \underline{x}^{(k-1)}(i) + \omega \cdot \left(\underline{b}(i) - \sum_{j \neq i} \mathbf{A}(i,j)\cdot \underline{x}^{(k-1)}(j) \right) / \mathbf{A}(i,i)$$

- where $\omega \in (0,2)$ is a parameter to the algorithm

Comparison

- Gauss-Seidel typically outperforms Jacobi
  - i.e. faster convergence
  - also: only need to store a single solution vector
- Both Gauss-Seidel and Jacobi usually outperform the Power method (see least fixed point method from Lecture 2)
- However Power method has guaranteed convergence
  - Jacobi and Gauss-Seidel do not
- Over-relaxation methods may converge faster
  - for well chosen values of ω
  - need to rely on heuristics for this selection

Model checking complexity

- Model checking of DTMC (S,s_{init},**P**,L) against PCTL formula Φ complexity is linear in |Φ| and polynomial in |S|

- Size |Φ| of Φ is defined as number of logical connectives and temporal operators plus sizes of temporal operators
  - model checking is performed for each operator

- Worst-case operator is $P_{\sim p}$ [Φ_1 U Φ_2]
  - main task: solution of linear equation system of size |S|
  - can be solved with Gaussian elimination: cubic in |S|
  - and also precomputation algorithms (max |S| steps)
- Strictly speaking, $U^{\leq k}$ could be worse than U for large k
  - but in practice k is usually small

Summing up…

- Model checking a PCTL formula ϕ on a DTMC
  - i.e. determine set Sat(ϕ)
  - recursive: bottom-up traversal of parse tree of ϕ

- Atomic propositions and logical connectives: trivial

- Key part: computing probabilities for $P_{\sim p}$ […] formulae
  - $X\ \Phi$: one matrix-vector multiplications
  - $\Phi_1\ U^{\leq k}\ \Phi_2$: k matrix-vector multiplications
  - $\Phi_1\ U\ \Phi_2$: graph-based precomputation algorithms + solution of linear equation system in at most |S| variables

- Iterative methods for solving large linear equation systems