ETMCC v2.0

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Outline

O Goals Data structures and Algorithms ETMCC v2.0 vs. v1.0 • Conclusions **O** PRCTL **Extensions**

Goals

Develop a unified tool for **PCTL**, **CSL**, **PRCTL** and **CSRL** \bullet Improve and extend ETMCC v1.0 Use efficient data structures Use improved algorithms for **CSL** ● Steady state detection Faster until operators **• Faster BSCCs search** \bullet etc. ;

Data structures and Algorithms

 \bullet Data structures:

- Sparse Matrix special representation
- Fast Matrix Vector multiplication
- **C** Linear memory allocation
- **•** Predecessor sets
- Algorithms:
	- \bullet Direct search only for required BSCCs
	- Bounded until (CSL)
	- Unbounded until (CSL)
	- Collapse $\varphi \& \neg \phi \land \neg \varphi$ states
	- Bisimulation minimization
	- \bullet On the fly steady state detection

Data Structure

• Make states absorbing \bullet Compute Uniformized DTMC from CTMC

Fast M*v and v*M multiplication

C Linear memory representation,

- Multiply only certain valid elements,
- **Rely on the matrix row elements ordering,**

 \bullet Multiply v^{*}M by row; 1_{row}

0.0 0.3 0.7

0.25 0.0 0.75

 $0.5\quad 0.5\quad 0.0$

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Re-sorting the matrix

Speed up matrix vector multiplication in iterative methods for steady state operator (BSCC) and making states absorbing.

Searching for BSCCs, *S* $\Big($ *F* $_{\triangleleft p}(F)$

Based on the Tarjan's algorithm for searching MSCCs: **C** Search for BSCC, not MSCC **• Find BSCCs for Set(F) states** *If* $x ∈ Set(F) ∧ ∃ path from x to MSC [−] > stop$ The complexity remains $O(N+M)$

Steady state detection

$$
\sum_{k=0}^\infty e^{-qt}\,\frac{\big(q\cdot t\big)^{\!k}}{k!}\,\overrightarrow{P_0}\cdot P^k
$$

● Steady state

$$
\exists k : \forall j > 0 \overrightarrow{p_0} \cdot P^k \approx \overrightarrow{p_0} \cdot P^{k+j}
$$

O Detect steady state

• Check sequence convergence

$$
\left| \overrightarrow{p_0} \cdot P^{i \cdot m} - \overrightarrow{p_0} \cdot P^{(i-1) \cdot m} \right| \longrightarrow 0
$$

Check final convergence $0 \t \vert -8$ $_0\cdot P^{s+1}$ $\left| \overrightarrow{p_{0}}\cdot P^{s+1}-\overrightarrow{p_{0}}\cdot P^{s}\right| \leq\frac{\mathcal{E}}{\epsilon}$

Unbounded until

Unbounded Until

U₀ = no path through Φ -states exists to a Ψ -state

 $U_2 = S \setminus (U_0 \cup U_1)$ U_1 = Prob. Measure to reach Ψ -state through Φ -states is 1

Then $Prob(s, \Phi \cup \Psi)$ is:

$$
\underline{x}_{s} = \begin{cases} 0: s \in U_{0} \\ 1: s \in U_{1} \\ \sum_{s' \in U_{2}} P(s, s') \cdot \underline{x}_{s'} + \sum_{s' \in U_{1}} P(s, s') : s \in U_{2} \end{cases}
$$

Bounded until (CSL)

Bounded Until can be computed as: **•** The solution:

$$
\operatorname{Prob}^{\mathrm{M}}(\phi \mathbf{U}^{\leq t} \; \varphi) = \sum_{s''} \pi^{\mathrm{M}[\neg \phi \lor \varphi]}(s, s'', t)
$$

$$
\pi^{\mathrm{M}[\neg \phi \lor \varphi]}(s, s'', t) = \mathrm{Prob}^{\mathrm{M}[\neg \phi \lor \varphi]}(s, \Diamond^{[t, t]}at_{s''})
$$

Using uniformisation:

$$
\operatorname{Prob}\left(\phi\ U_{\triangleright\triangleleft p}^{\leq t}\ \varphi\right)\right)=e^{q\cdot t\cdot(P-I)}\cdot\vec{i}_{\varphi}=\sum_{k=0}^{\infty}e^{-qt}\frac{\left(q\cdot t\right)^{k}}{k!}P^{k}\cdot\vec{i}_{\varphi}
$$

Interval Until: Modification of Prob $^{\textrm{\tiny{M}}} \left(\phi \ \textrm{U}^{\leq \textrm{t}} \ \ \varphi \right)$ $\mathsf{ob}^\mathsf{M}\big(\phi\ \ \mathsf{U}^{\leq\mathsf{t}}\ \ \varphi$

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PRCTL logic

Syntax:

 $\Phi ::= \mathit{tt} \, | \, a \in AP \, | \, \Phi \wedge \Phi \, | \, \neg \Phi \, | \, L_{\mathit{\triangleleft} p} \big(\Phi\big) | \, P_{\mathit{\triangleleft} p} \big(\Phi U_{J}^{N} \Phi \big)$) $\text{E}_J^n\big(\Phi\big)|\,\text{E}_{_J}\big(\Phi\big)|\,C_J^n\big(\Phi\big)|\,Y_J^n\big(\Phi\big)$ $\int_J(\Phi)\vert\, C^n_J$ $\int_J^n(\Phi) |E_{_J}(\Phi)| C_J^n(\Phi) |Y_{_J}(\Phi)|$ *N* $\phi:=\operatorname{tr}\left| \right. a\in \operatorname{AP}\left| \right. \Phi \wedge \Phi\left| \left. \neg\Phi \right. \right| L_{\triangleleft p}(\Phi)\right| P_{\triangleleft p}(\Phi U_{J}^{N}\Phi))$

• Semantics:

 $L_{\mathfrak{q}_p}(\Phi)$ - Long-run probability meets probability bound

 $P_{\text{ap}}(\Phi U_J^N \Phi)$ - Path-probability operator for until formula

- $E_J^n(\Phi)$ Expected reward rate at n-th transition for phi-states meets reward bound
- $E_J(\Phi)$ Long-run expected reward rate for phistates meets reward bound
- $C_{J}^{n}(\Phi)$ Instantaneous reward rate in phi-states meets the reward bound
- $Y_J^n(\Phi)$ Expected accumulated reward until the n-th transition meets the reward bound

PRCTL model checking

All formulas have been implemented

Slight modifications: Until formula (Path Graph)

● Better access to the rate matrix

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Matrix vector multiplication: *NNE* ∈[4374,623554]

The Cluster Computing example $S_{<0.05}$ (!*minimum*)

Twente, 2005

The Cluster Computing example, space usage

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Krylov Subspaces

$$
\pi^{M[\neg \phi \lor \varphi]}(s, s'', t) = \text{Prob}^{\text{M}[\neg \phi \lor \varphi]}(s, \Diamond^{[t, t]}at_{s''})
$$

Solution of the linear differential equation $w(t) = e^{t \cdot M[\neg \phi \lor \varphi]} \cdot \vec{v}$ Typical approach – Uniformisation Makes elements positive For $\lambda t > 500$ Krylov-based algorithms work better [R. Sidje]. Compute $e^{i\pi i \left(\psi + \psi\right)} \cdot v$ at once • Map w(t) onto a much smaller subspace $e^{t\cdot M\left[-\phi\vee\varphi\right]}\cdot\vec{\nu}$

The Prob $(\phi \, U_{\triangleright\triangleleft p}^{\leq t}\, \varphi)$ estimate) $U_{\triangleright\lhd p}^{\leq t}$ $\mathop{\rm Prob}\nolimits(\phi \, U_{\triangleright \triangleleft}^{\leq t}$

Idea 1: In DTMC consider only some paths to φ . Get $Min^{\kappa} \leq P^{\kappa} \cdot i$ estimate. $Min_{\varphi}^{\kappa} \leq P^{\kappa} \cdot i_{\varphi}$ $k\leq P^k$.

In DTMC compute $Min_{\neg \phi \land \neg \phi}^{\wedge}$, then $Max_{\infty}^{\kappa} = 1 - Min_{\infty}^{\kappa}$. **Idea 2:** In DTMC compute $Min_{\neg \phi \land \neg \phi}^k$ $Max_{\varphi}^k = 1 - Min_{-}^k$ $=$ 1 $-$ M M $_{\neg \phi \land \neg \phi}$ 1

Idea 3: The estimates for CTMC are now obtainedwith the formula:

$$
\operatorname{Prob}\nolimits\!\big(\!\not{\!{\partial}}\,U^{\leq t}_{\triangleright\lhd p}\,\varphi\big)\!=\!\sum\limits_{k=L_{\varepsilon}}^{U_{\varepsilon}}\!e^{-qt}\,\frac{\big(q\cdot t\big)^{\!k}}{k!}\,P^k\cdot\stackrel{\rightharpoonup}{i_{\varphi}}
$$

Example for the Prob $(\phi U_{\rightarrow\gamma\rho}^{\le t} \varphi)$ estimate) $U_{\triangleright\lhd p}^{\leq t}$ $\mathop{\rm Prob}\nolimits(\!\phi \, U_{\triangleright \triangleleft}^{\leq t}$

 $k=5$: P_{min}^{5} = (1/9, 2/9, 0, 13/18, 5/18, 5/9, 1)
 P^{5} = (55/324, 181/486, 0, 43/54, 5/12, 47/54, 1)

Conclusions

● Support PCTL, CSL, PRCTL logics

• The implementation is faster

O Ongoing work: **Incorporate CSRL logic** Collapse $\neg \phi \lor \varphi$ states Involve bisimulation minimization \bullet Further v^{*}M, M^{*}v improvement

Any further wishes?

Link to BDD implementation? **O** Graphic User Interface? \bullet etc.