Continuous-time Markov Decisions based on Partial Exploration

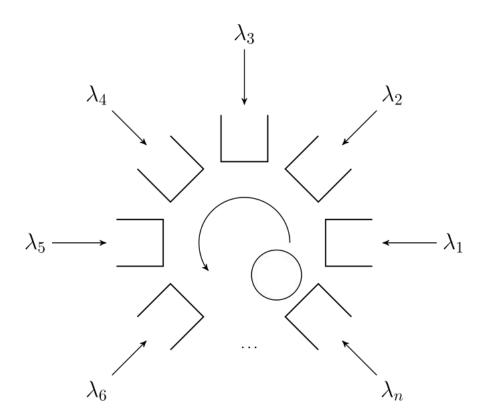
Pranav AshokTechnical University of Munich

Highlights 2018, Berlin

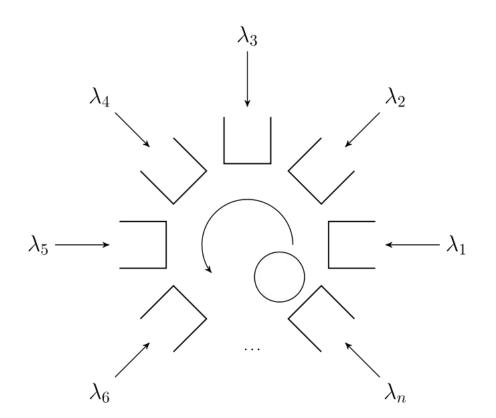
Joint work with Yuliya Butkova¹, Holger Hermanns¹ and Jan Kretinsky²

¹Saarland University, Germany

²Technical University of Munich, Germany

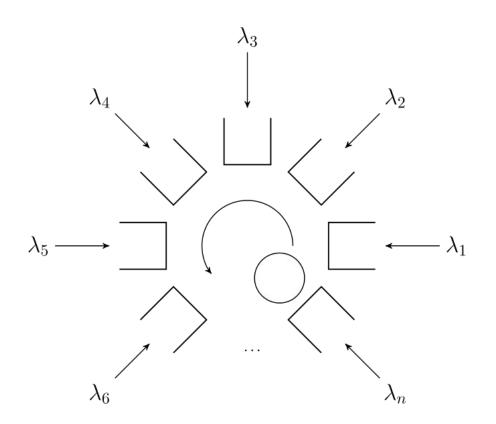


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- you pick a student's mail to process it
- **if** processed: remove from queue
- **else**: put it back into queue



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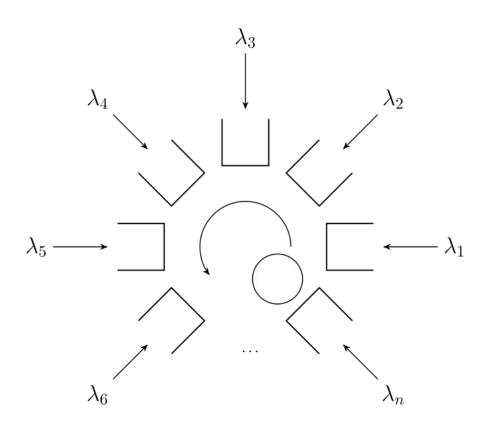
Q1: What is the max. prob. (over all strategies) that all queues are empty at the end of the week?



- n students mail @ λ_1 , λ_2 ,..., λ_n /day
- you pick a student's mail to process it
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Q1: What is the max. prob. (over all strategies) that all queues are empty at the end of the week?

Q2: What is the min. prob. that student *X* quits your group after a semester?



Continuous-time Markov Decision Process (CTMDP)

Time-bounded Reachability

Maximal probability (over all strategies) of reaching some goal state within T time units

$$max_{\sigma} \mathbf{P}_{\sigma}(\Diamond^{\leq T} \mathbf{G})$$

Challenge

Existing reachability algorithms sometimes perform extremely bad in practice even though in **PTIME**

Can we improve them?

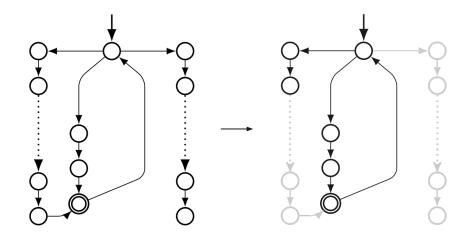
Contributions

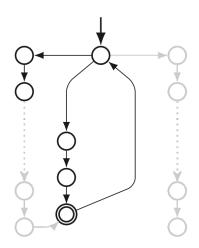
- → Framework for time-bounded reachability (TBR) analysis
- → Use simulations to identify important parts of state-space
- → Instantiate with standard algorithms to show speed up

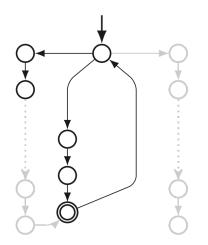
Key Idea

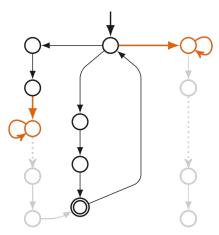
Partial Exploration Suffices

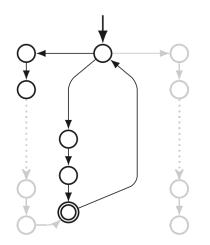
Not necessary to explore all states to get ε -optimal solution

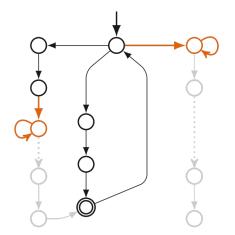


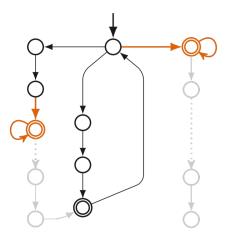


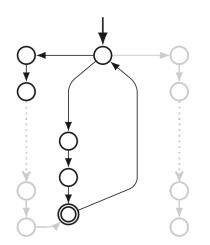


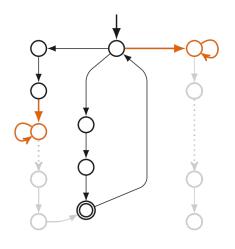


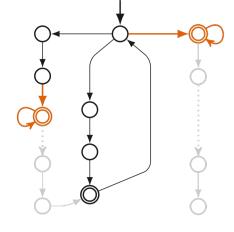








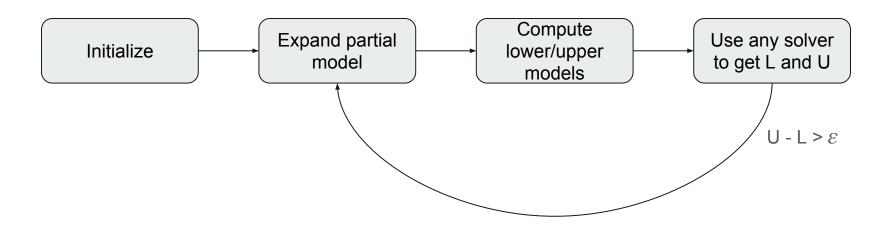




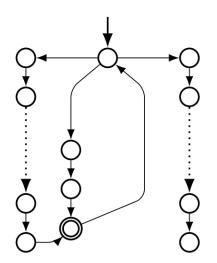
lower-bound model

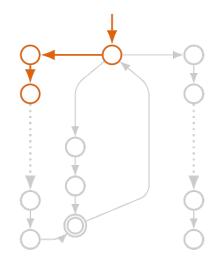
upper-bound model

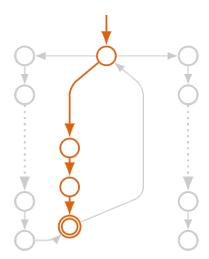
The Framework



Partial model through simulations using $\sigma_{\mbox{\tiny sim}}$







Experiments I Size of partial models

		Explored States		
Benchmark	States	by π_{sim}	%	
gfs-120	1,479k	105	0.01	
ftwc-128	597k	296	0.05	
erlang-10 ⁶ -10	1,000k	559	0.06	
ps-4-24-one	7,562k	23309	0.31	
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Experiments II

Runtimes

Benchmark	States	Unif	Unif Improved	Adap	Adap Improved
erlang-10 ⁶ -10	1,000k	71	1	4	1
gfs-120	1,479k	-TO-	2	-TO-	2
ftwc-128	597k	251	10	114	15
ps-4-24-one	7,562k	507	-TO-	171	105
sjs-2-9	18k	6	99	2	-TO-
ps-4-8-all	119k	1475	-TO-	826	-TO-

 $TO \rightarrow > 1800s (30 min)$

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Conclusion

- → CTMDP TBR analysis **framework** based on partial exploration
- → Partial model through simulations
- → Usable with any TBR solver*
- → Good on models with many unimportant/improbable states

Continuous-time Markov Decision Processes (CTMDP)

- **C** = (S, A, **R**, Goal)
- S: finite set of *states*; A: finite set of non-det choices
- Each choice → multiple *transitions*
- Each transition has a *rate* $\lambda = \mathbf{R}(s, a, s')$
- Time t at which transition fired \leftarrow exp. dist (λ)
- Next state chosen by a race between transitions

