Mean-Payoff Optimization in Continuous-Time Markov Chains with Parametric Alarms

Christel Baier, Clemens Dubslaff,
Ľuboš Korenčiak, Antonín Kučera, Vojtěch Řehák

TU Dresden, Germany
Faculty of Informatics, Masaryk University, Brno, Czech Republic

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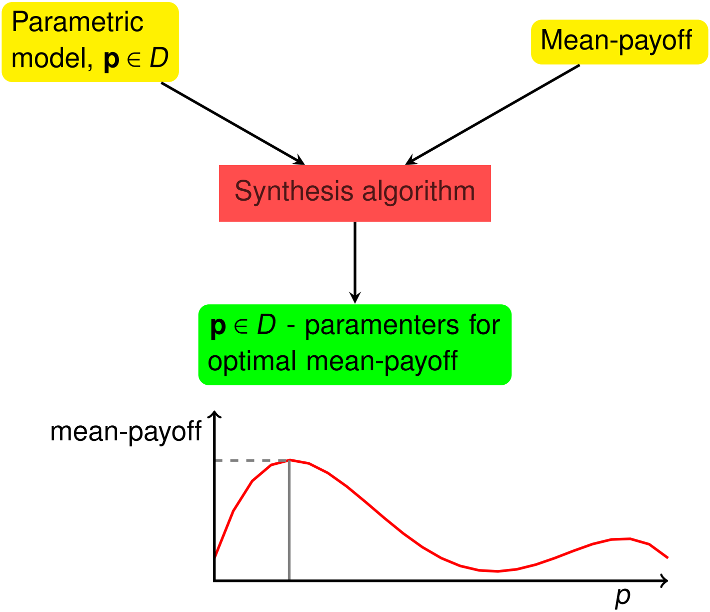
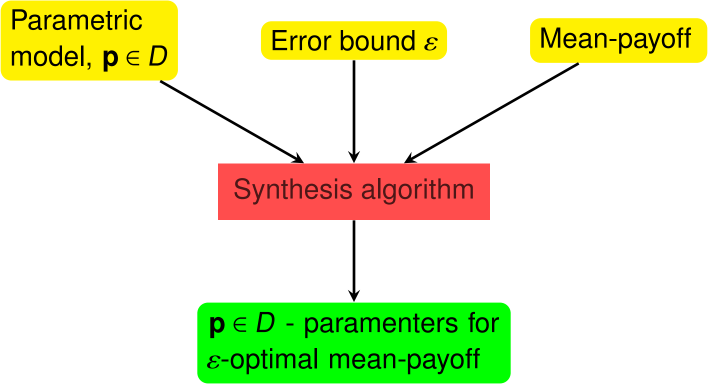
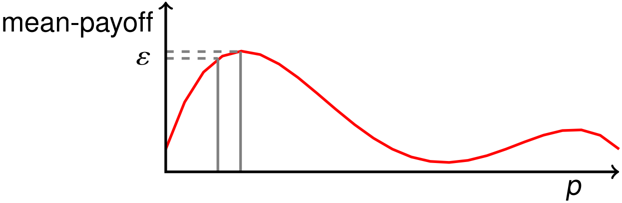
The Aim

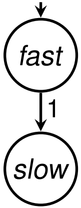

Parametric model, $\mathbf{p} \in D$
Mean-payoff
Synthesis algorithm
$\mathbf{p} \in D$ - paramenters for optimal mean-payoff
mean-payoff
p

The Aim


Parametric model, **p** ∈ *D*
Error bound ε
Mean-payoff
Synthesis algorithm
p ∈ *D* - paramenters for ε-optimal mean-payoff


mean-payoff
ε
p

Continuous-time Markov Chain with Alarms (ACTMC)



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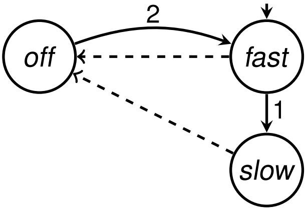

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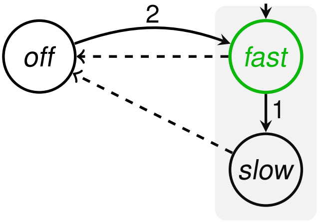
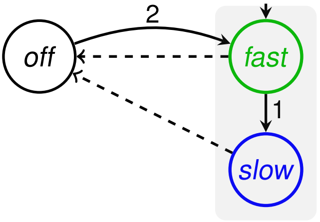


$\omega =$ (o=3.5, s=2),

Continuous-time Markov Chain with Alarms (ACTMC)



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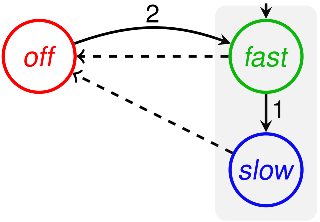
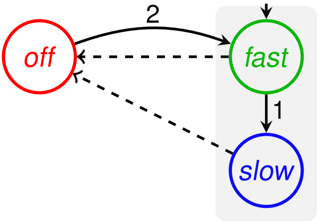
Continuous-time Markov Chain with Alarms (ACTMC)

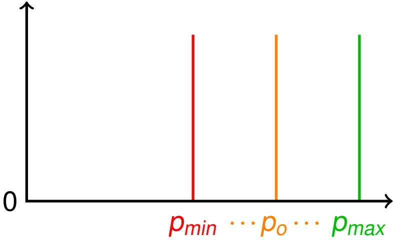


$\omega =$ (o=3.5, s=2), (o=1.5), (f=4), (. . .), . . .

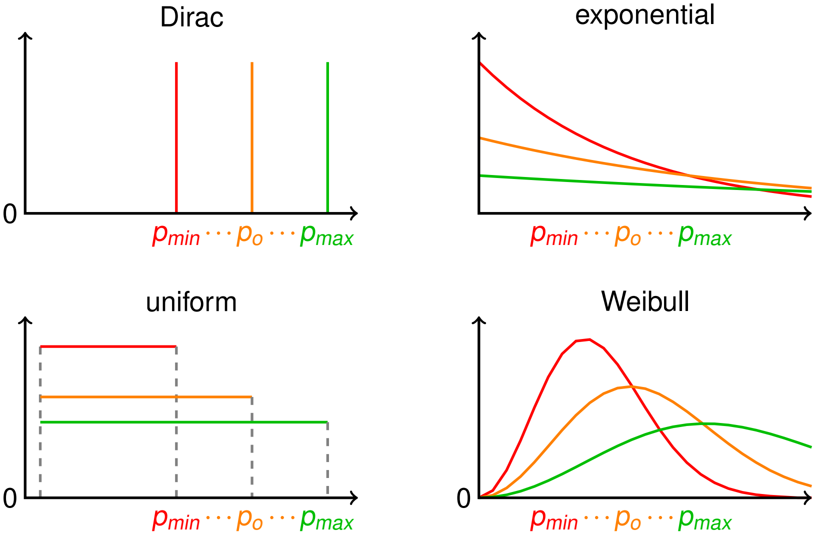
Parametric ACTMC



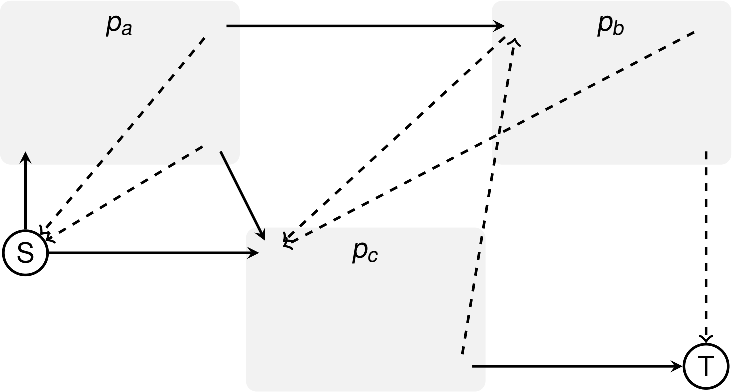
$\omega =$ (o=3.5, s=2), (o=1.5), (f=4), (...), ...



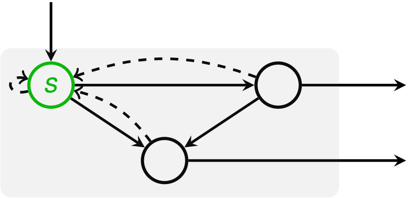
Parametric distributions



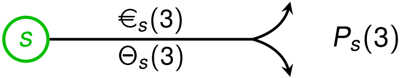
Restrictions - disjoint regions



Explicit Algorithm



ACTMC and ε; $\mathbf{p} = ?$



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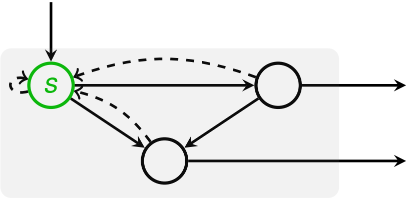
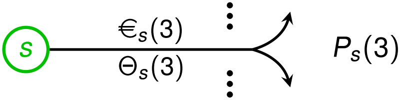


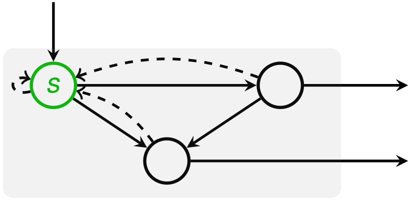


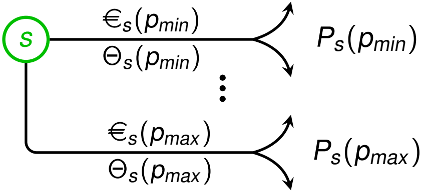
ACTMC and ε; **p** $=$?

↓

uncountable action space MDP

Explicit Algorithm





ACTMC and ε; $\mathbf{p} = ?$

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uncountable action space MDP

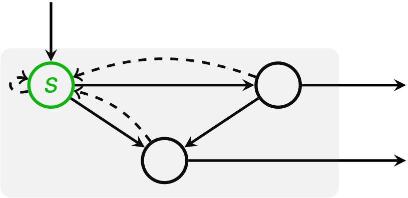
↓

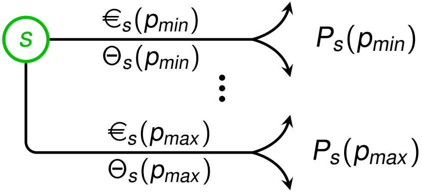
finite MDP

↓

ε-optimal $\mathbf{p}$

Explicit Algorithm





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For $\varepsilon = 0.1$ we get at least 10^{20} actions.

Symbolic Algorithm

Our contribution is based on two ideas:

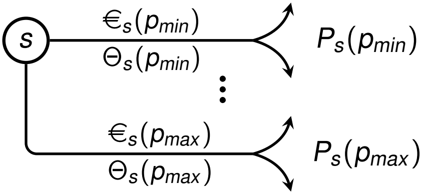
- policy iteration
- symbolic representation of actions

Symbolic Algorithm

policy iteration

$$\arg\max_{p \in D} \; F_s(p)$$

$$F_s(p) \; = \; \ldots \text{€}_s(p) \ldots \Theta_s(p) \ldots P_s(p) \ldots$$



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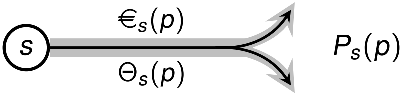

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MDP with symbolic actions

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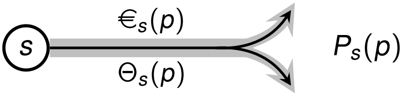

Message:

Sometimes it is better to use continuous approach than finite discretization.

ACTMC and ε; $\mathbf{p} = ?$

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uncountable action space MDP

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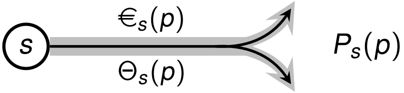

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MDP with symbolic actions

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Thank you for your attention!