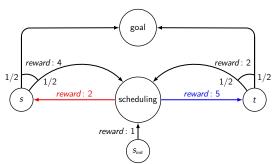
### The variance-penalized stochastic shortest path problem

Jakob Piribauer<sup>1</sup>, Ocan Sankur<sup>2</sup>, and Christel Baier<sup>1</sup>

<sup>1</sup> TU Dresden <sup>2</sup> Univ Rennes, Inria, CNRS, IRISA

> October 2022 Reachability Problems



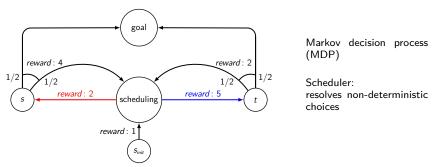
What is the maximal possible reward in expectation?

goal reward : 4 1/2 s t reward : 2 scheduling reward : 5 t scheduling reward : 5 t

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Markov decision process (MDP)

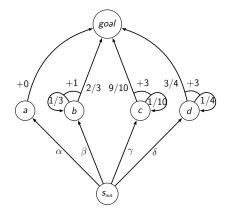
Scheduler: resolves non-deterministic choices

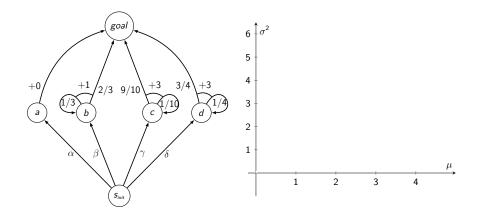


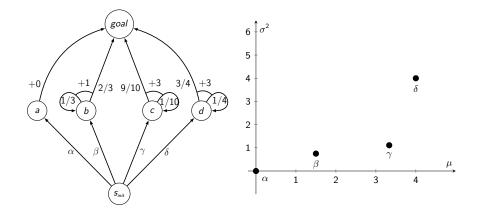
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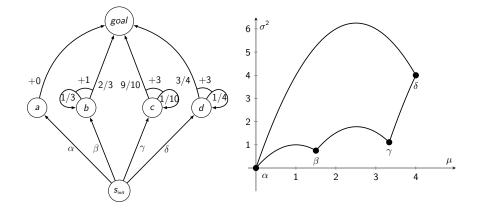
#### Classical problem:

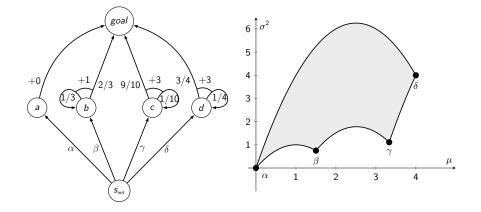
Compute  $\mathbb{E}^{\text{max}}_{\mathcal{M}}(\text{acc. reward}) \stackrel{\text{def}}{=} \sup_{\mathfrak{S}} \mathbb{E}^{\mathfrak{S}}_{\mathcal{M}}(\text{acc. reward})$ where  $\mathfrak{S}$  ranges over schedulers reaching goal almost surely.

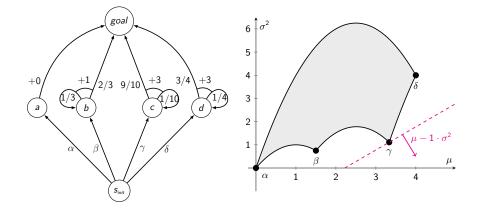












Variance-penalized expectation (VPE):  $\mu - \lambda \cdot \sigma^2$ 

 Established objective in MDPs (finite horizon<sup>1</sup>, discounted expected rewards<sup>2</sup>)

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 Weighted factor method a common approach in multi-objective optimization to obtain a subset of the Pareto-optimal points.<sup>3</sup>

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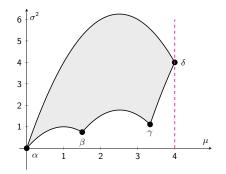
 Weighted factor method a common approach in multi-objective optimization to obtain a subset of the Pareto-optimal points.<sup>3</sup>

• As a stepping stone towards further problems.

<sup>1</sup>See, e.g., Collins (1997)
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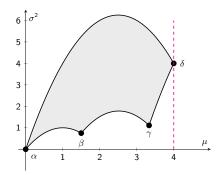
### Theorem

In an MDP with arbitrary (integer) weights, a memoryless, deterministic, and variance-minimal scheduler among all expectation-optimal schedulers can be computed in polynomial time.

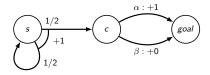


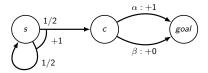
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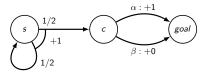
If expected weight is known (and independent of the history) from each state, minimal variance can be computed via a linear program.





X: accumulated weight

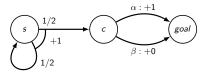
 $\mathsf{Maximize} \ \mathbb{E}^{\mathfrak{S}}(X) - \lambda \mathbb{V}^{\mathfrak{S}}(X) = \mathbb{E}^{\mathfrak{S}}(X) - \lambda \big( \mathbb{E}^{\mathfrak{S}}(X^2) - (\mathbb{E}^{\mathfrak{S}}(X))^2 \big).$ 



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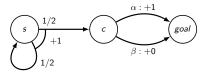
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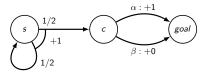


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 $VPE(\mathfrak{A}) - VPE(\mathfrak{B}) = p(1 + \lambda(2\mathbb{E}^{\mathfrak{B}}(X) + p) - \lambda(2k+1)).$ 

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### Lemma

Given an MDP  $\mathcal{M}$  with non-negative weights and a rational penalty factor  $\lambda$ , we can compute a bound K in polynomial time such that any VPE-optimal scheduler has to **minimize** the expected accumulated weight as soon as a weight of at least K has been accumulated.

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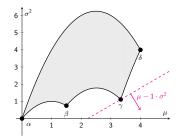
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Computable in polynomial time.

#### Theorem

In an MDP with non-negative weights, the maximal VPE (for a given penalty factor  $\lambda$ ) can be computed in exponential space.

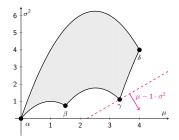
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### Theorem

The threshold problem whether the maximal VPE is greater or equal to a rational  $\vartheta$  is in NEXPTIME and EXPTIME-hard.

# Outlook

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- Investigation of further risk and deviation measures

## References

- Collins. "Finite-horizon variance penalised Markov decision processes." Operations-Research-Spektrum 19.1 (1997): 35-39.
- Filar, Kallenberg, Lee. "Variance-penalized Markov decision processes." Mathematics of Operations Research 14.1 (1989): 147-161.
- White. "Multi-objective infinite-horizon discounted Markov decision processes." Journal of mathematical analysis and applications 89.2 (1982): 639-647.
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