# Stopping Criteria for Value Iteration on Stochastic Games with Quantitative Objectives

Jan Kretinsky, Tobias Meggendorfer, Maximilian Weininger





#### Talk in one slide

- Probabilistic systems: Best algorithm (usually) is Value Iteration (VI)
- But: Requires a stopping criterion
   For Stochastic Games (SG) with most infinite-horizon, quantitative objectives there is none!

 This paper: Uniform solution for large class of quantitative objectives (including total reward, mean payoff, ...)

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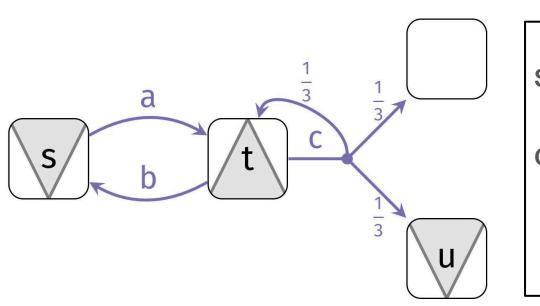
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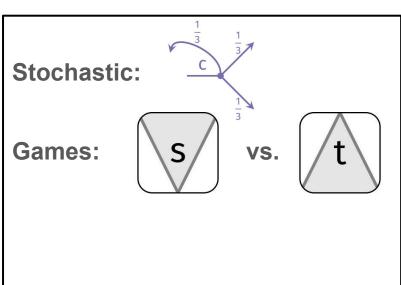
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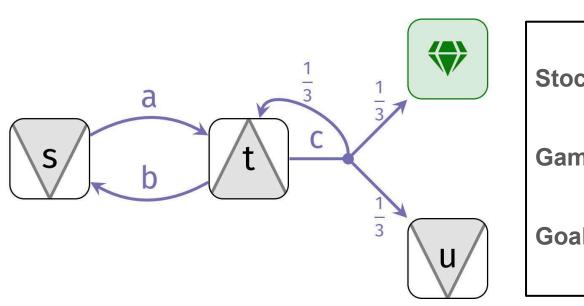
Unifies all previous ones and is more broadly applicable.

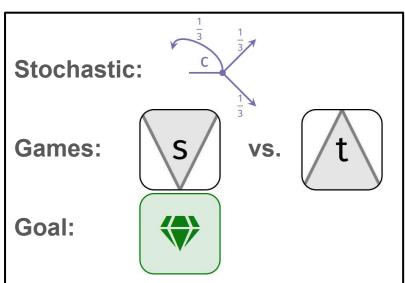
## **Stochastic Games**

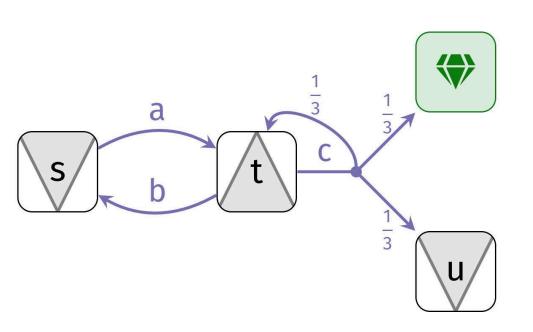




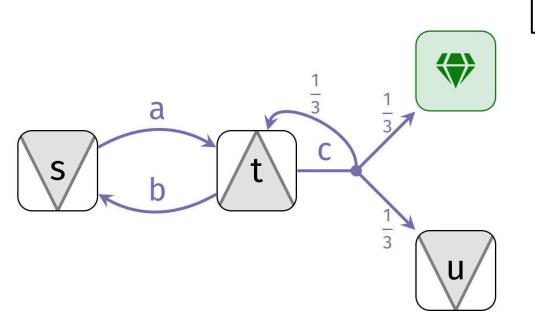
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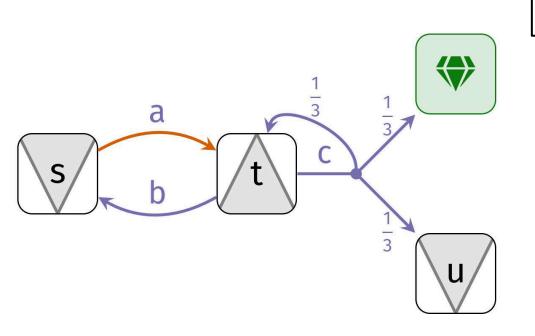


Iteration	L(s)	L(t)
0	0	0
1		
2		
•••		



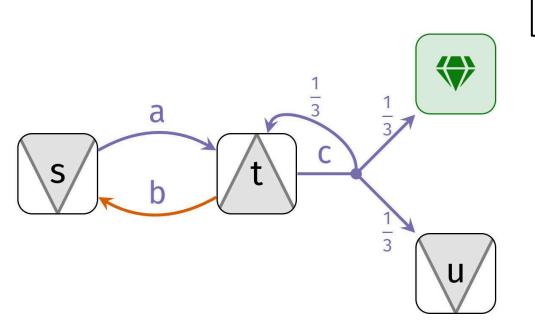
$$x_i(s) = \mathbf{opt}_a \ x_{i-1}(s, a)$$

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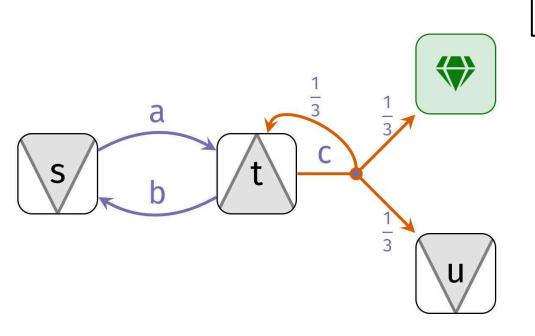
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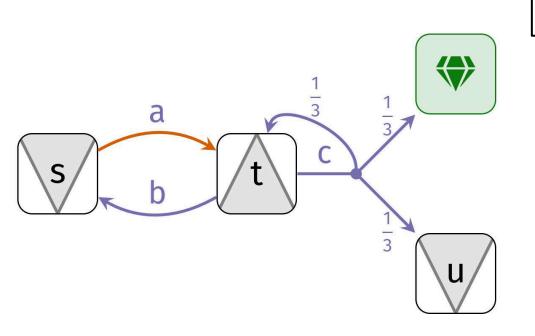
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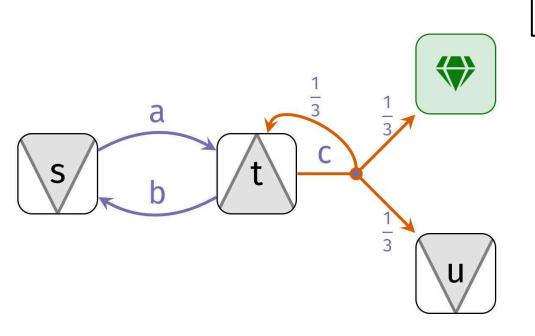
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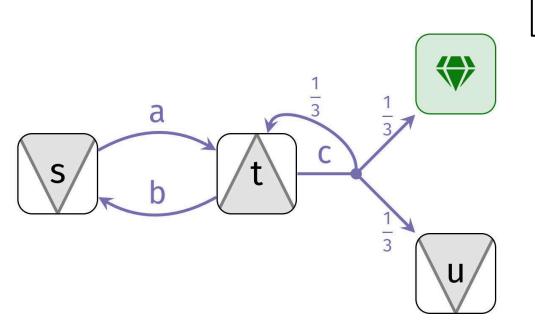
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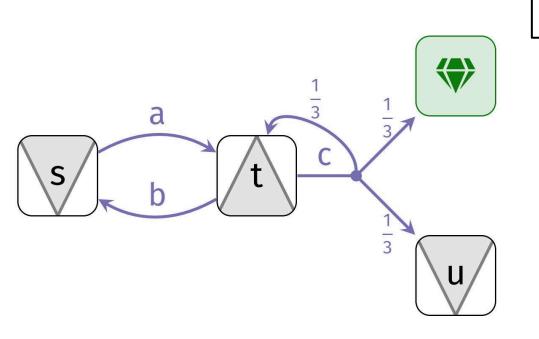
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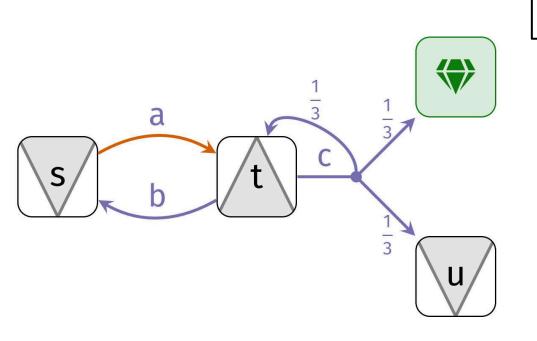
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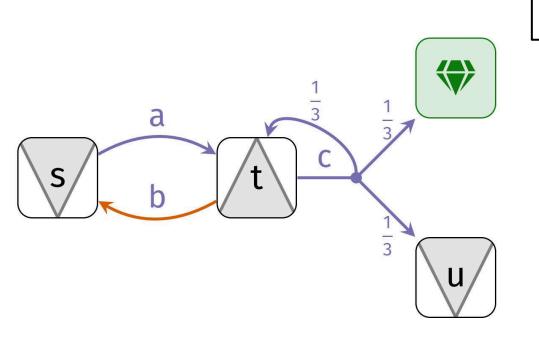
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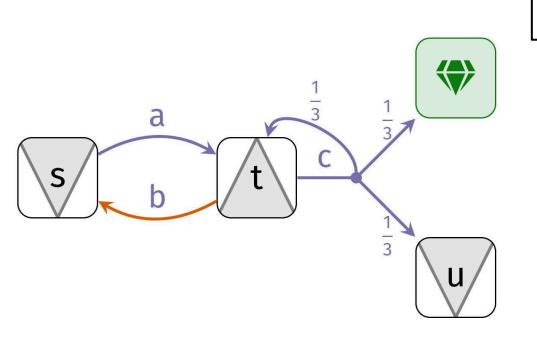
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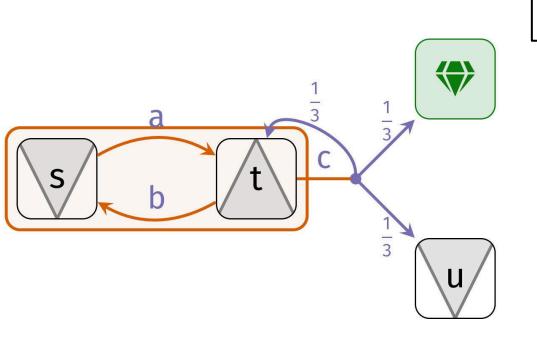
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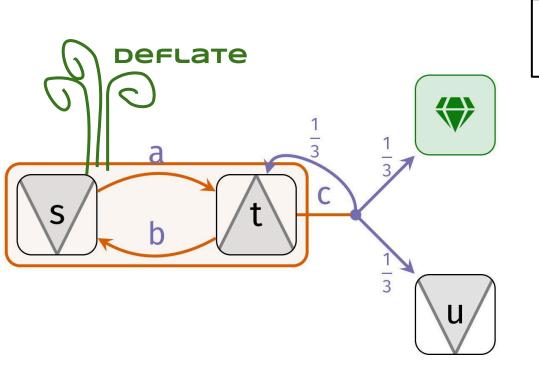
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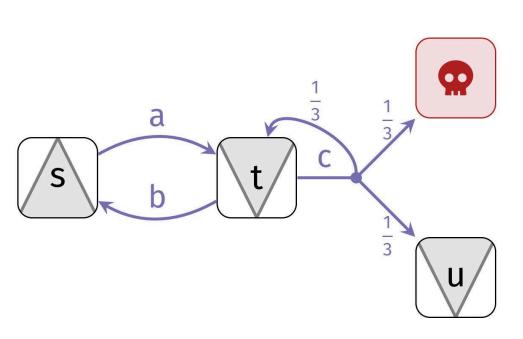
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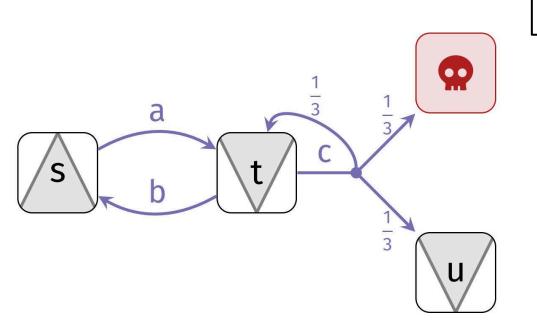
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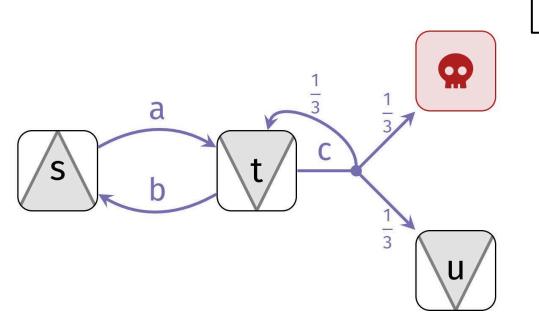
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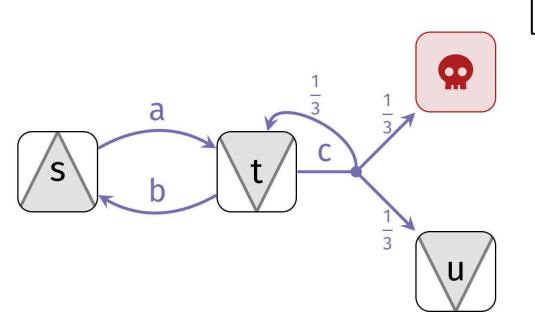
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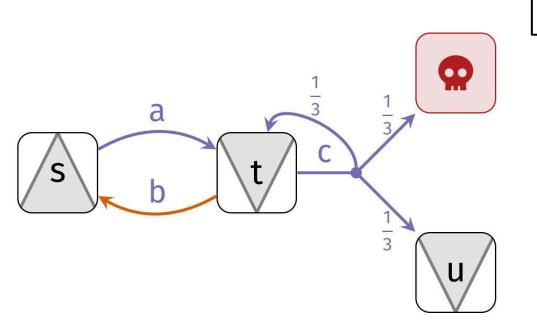
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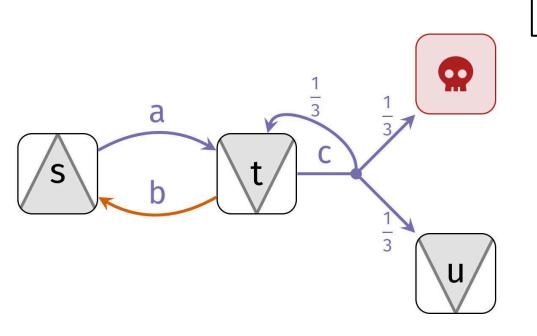
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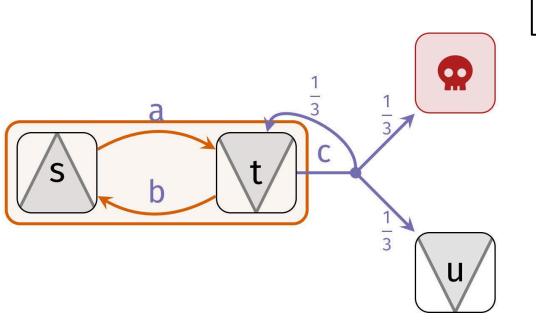
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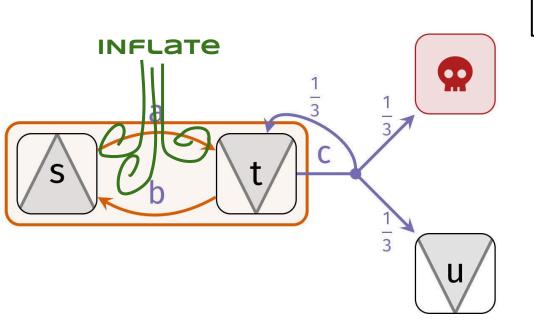
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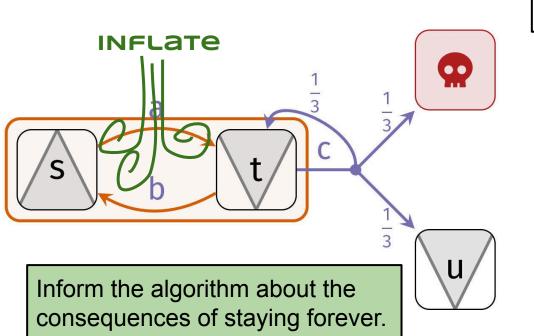
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#### Reachability:

stay=0

#### Safety:

stay=1

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max(stay,exit) = exit

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min(stay,exit) = exit

#### Reachability:

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max(stay,exit) = exit

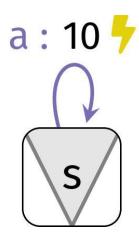
min(stay,exit) = 0

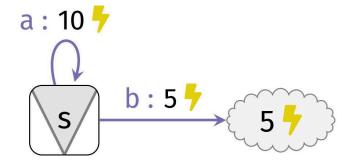
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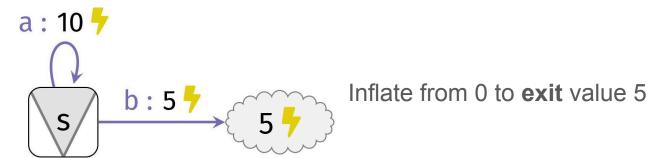
stay=1

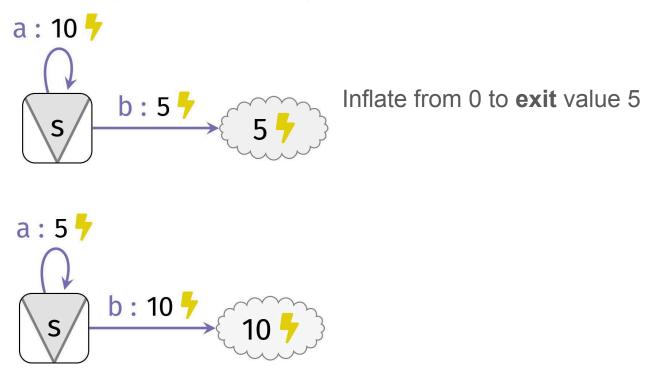
max(stay,exit) = 1

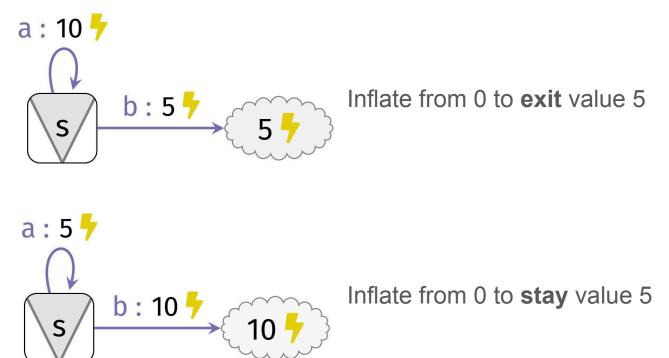
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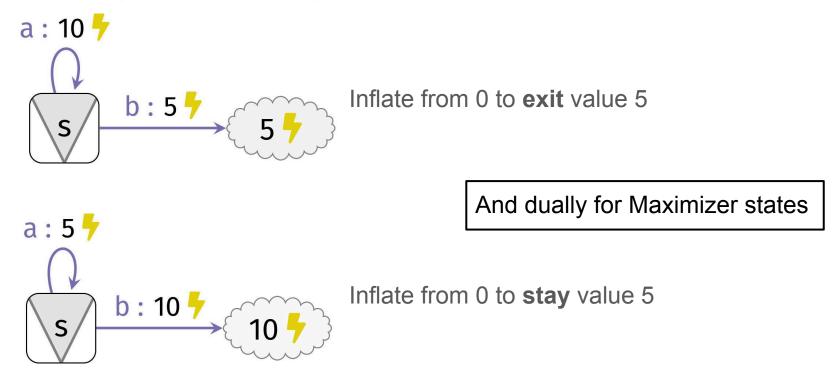












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OBJECTIVE-INDEPENDENT

#### Conclusion

- Given: Stochastic Games with quantitative objectives
   (including reachability, safety, mean payoff, expected total reward, ...),
- Goal: Solving them quickly and with precision-guarantees
- Approach: Value Iteration with our new stopping criterion

Idea: Inform the algorithm about the consequences of staying forever:

Should I stay or should I go now?

Unifies previous work [BCC+14, HM14, BKL+17, ACD+17, KKKW18, PTHH20] in an elegant, objective-independent way