

# 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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1-player SG: separate papers giving stopping criteria for each objective [BCC+14, HM14, BKL+17, ACD+17].

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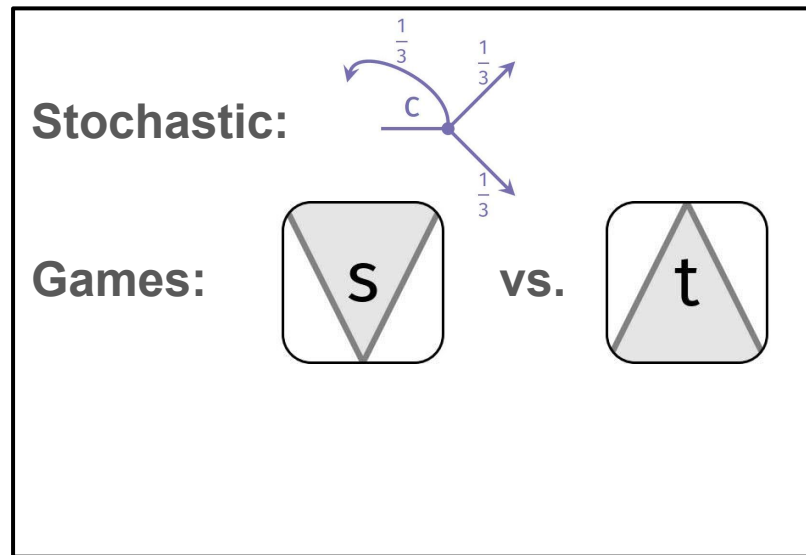
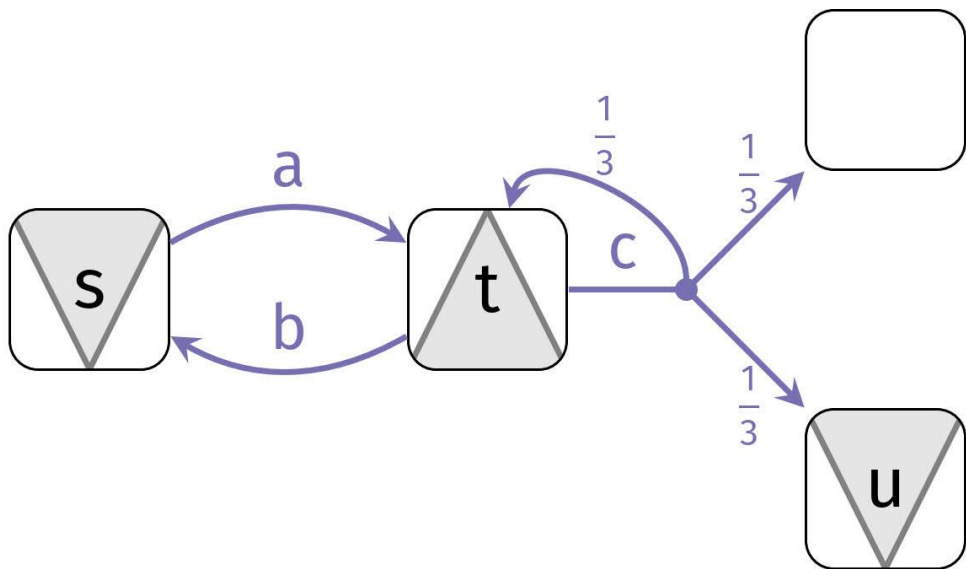
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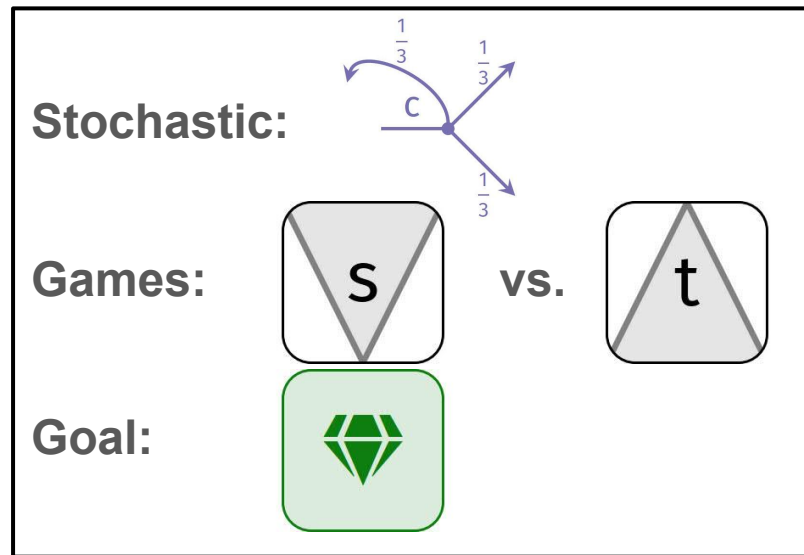
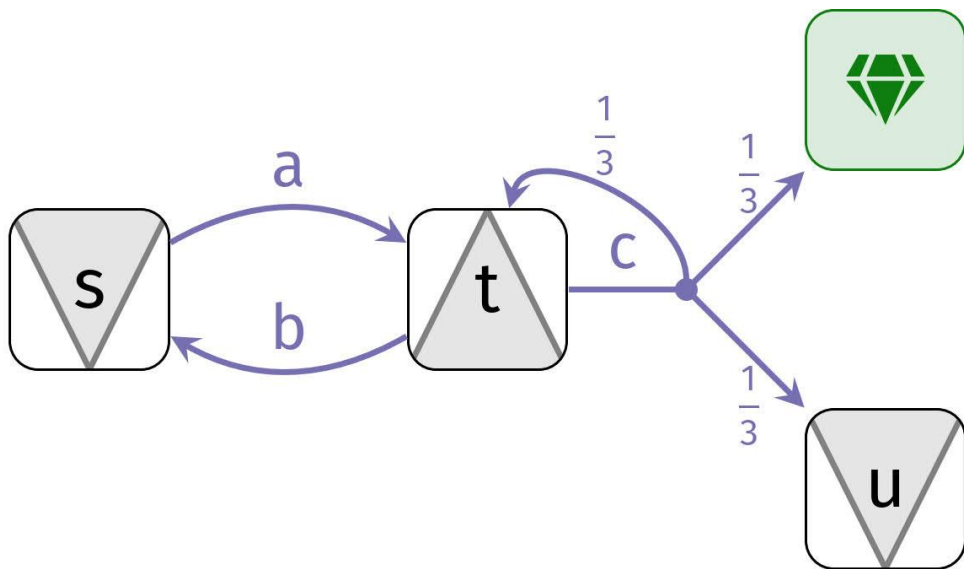
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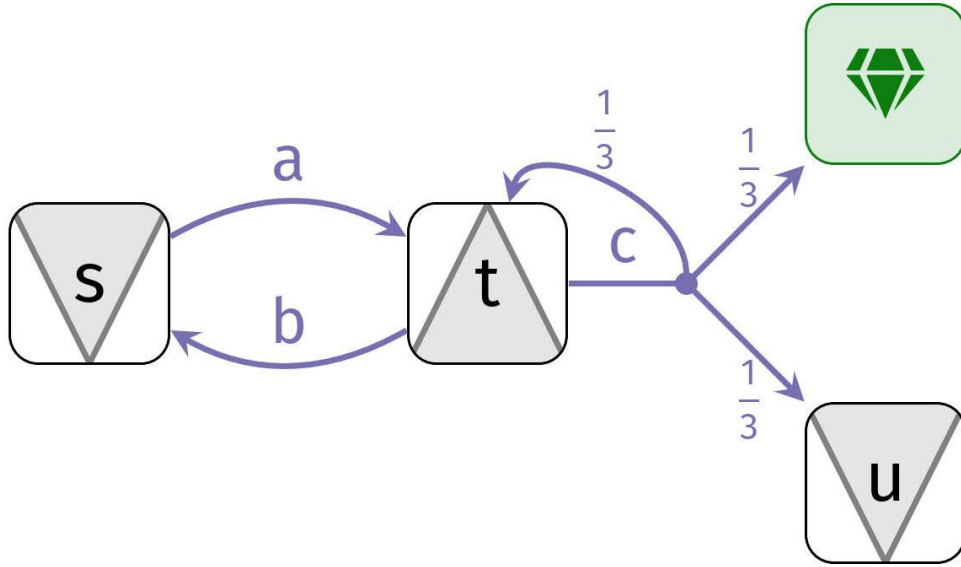
# Stochastic Games



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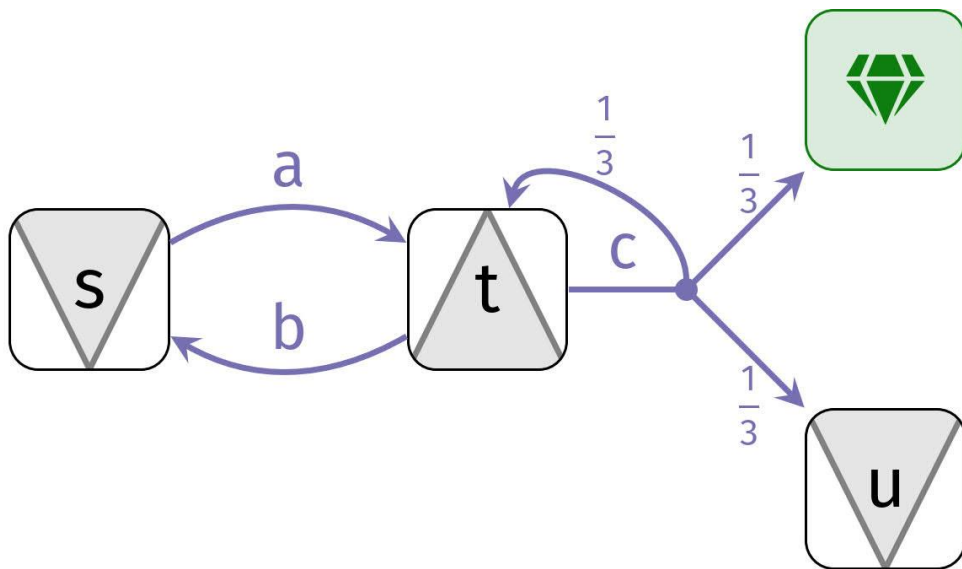


# Stochastic Games and Value Iteration



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

# Stochastic Games and Value Iteration



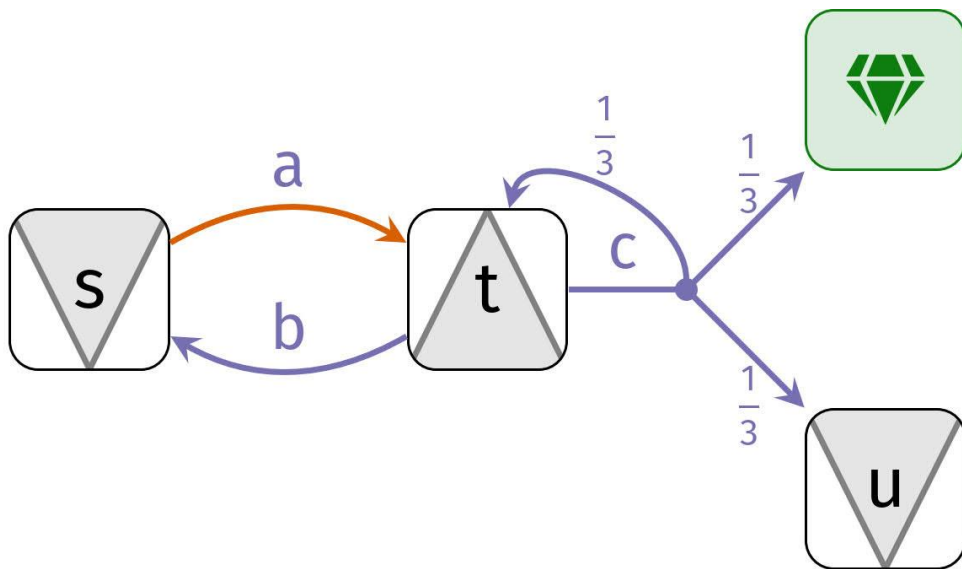
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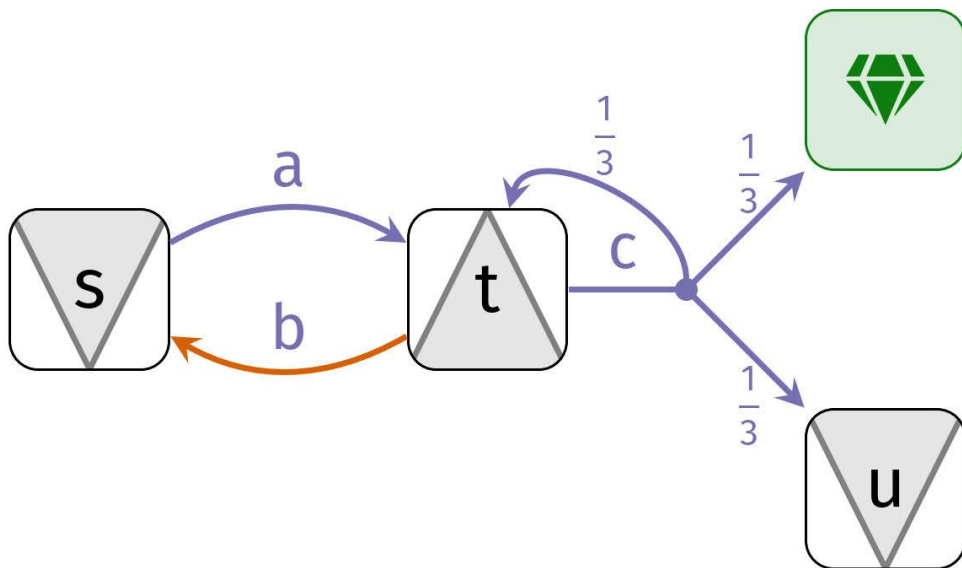


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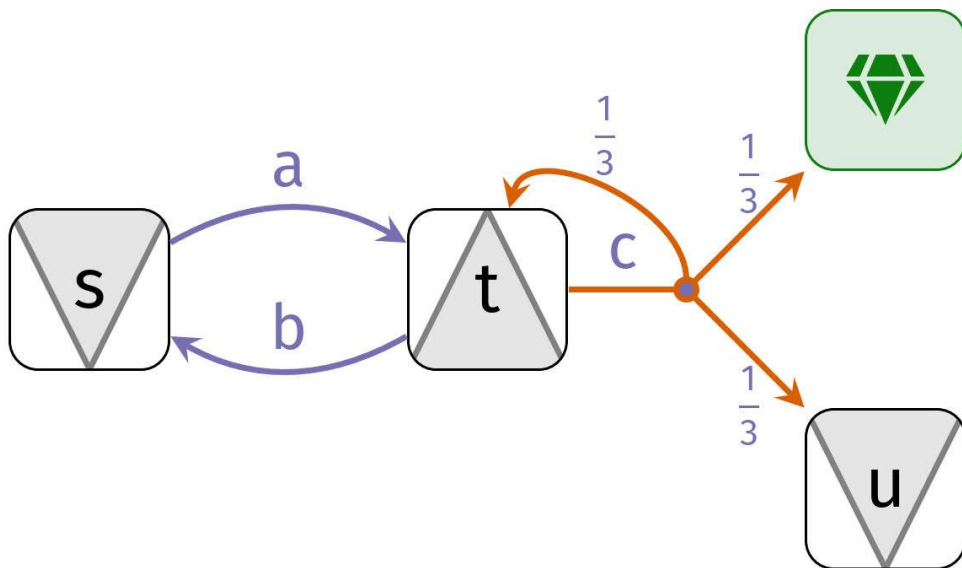


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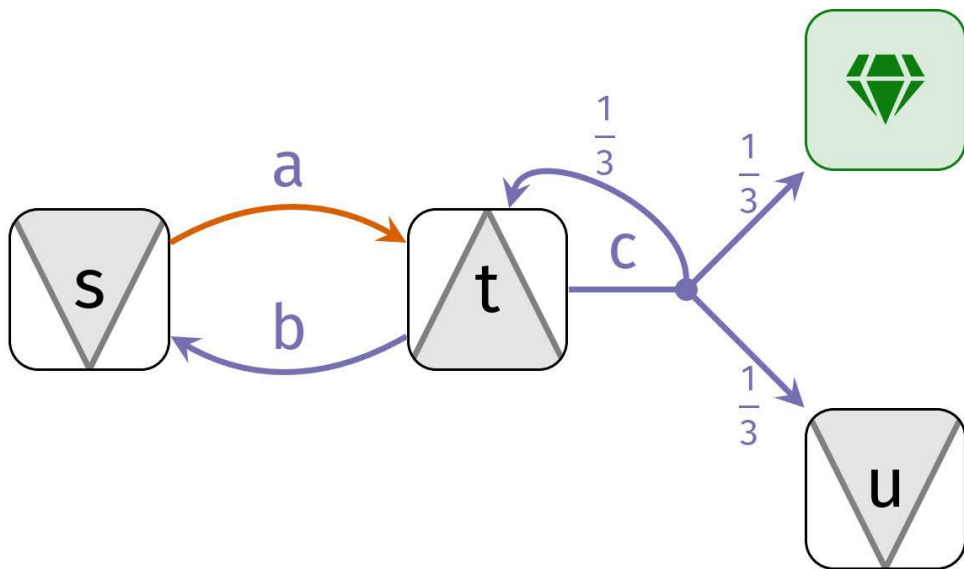


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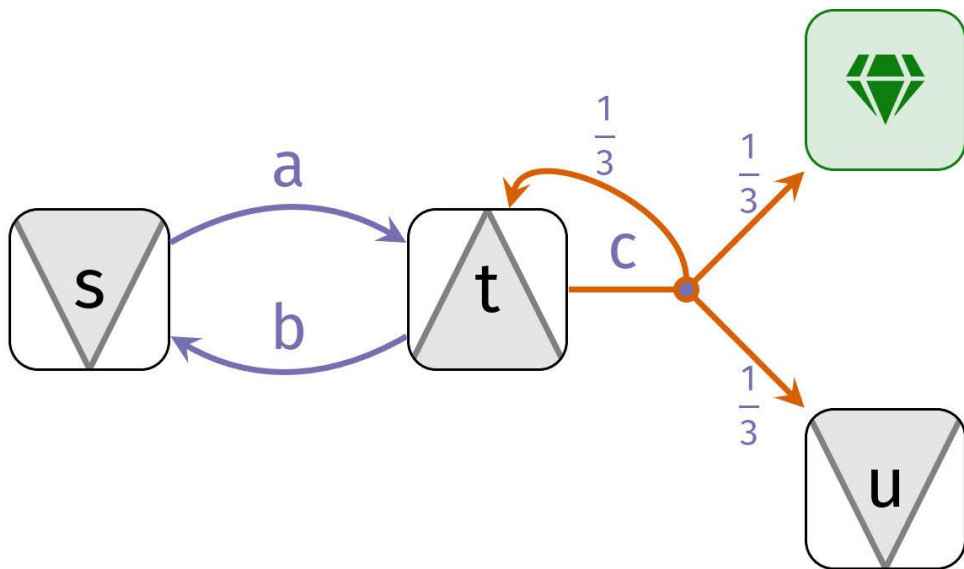


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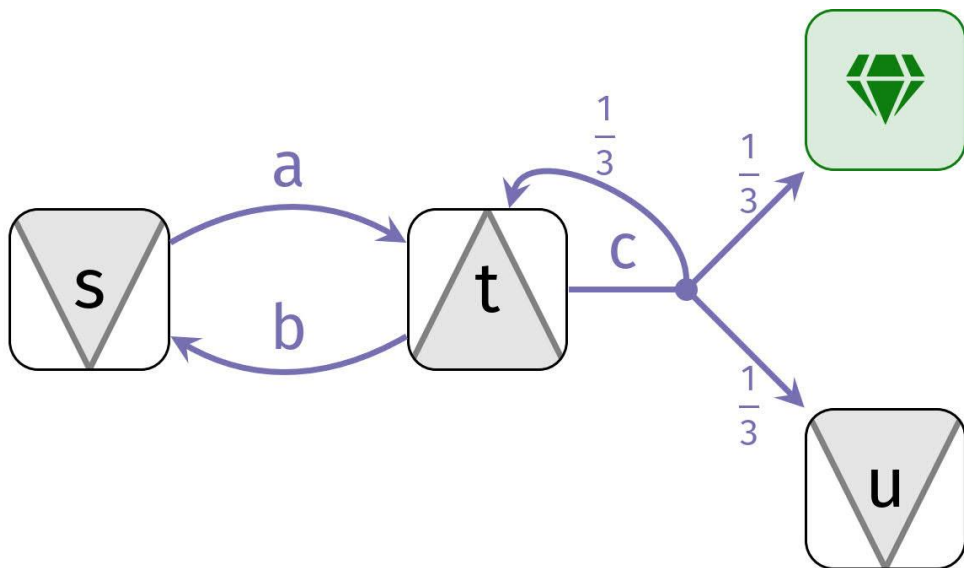


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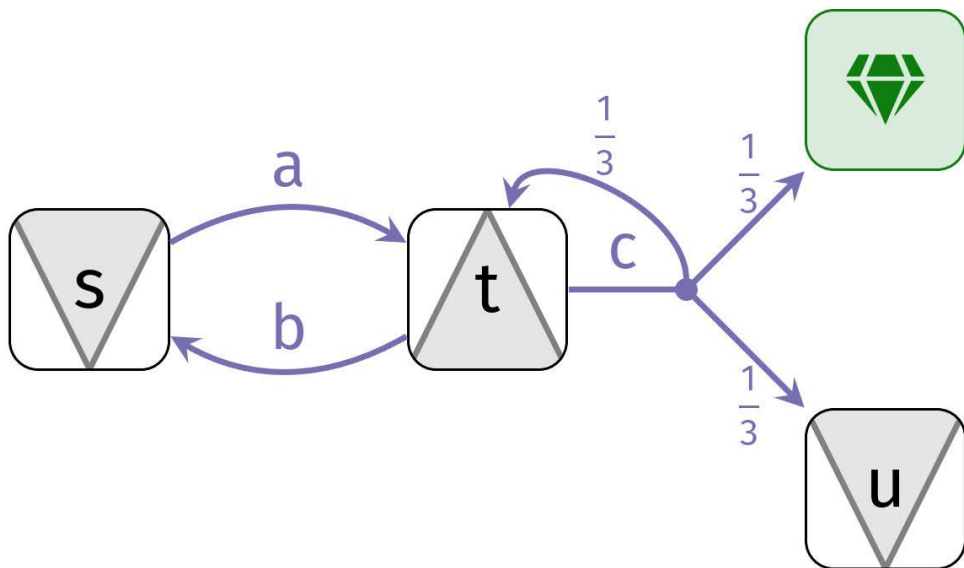


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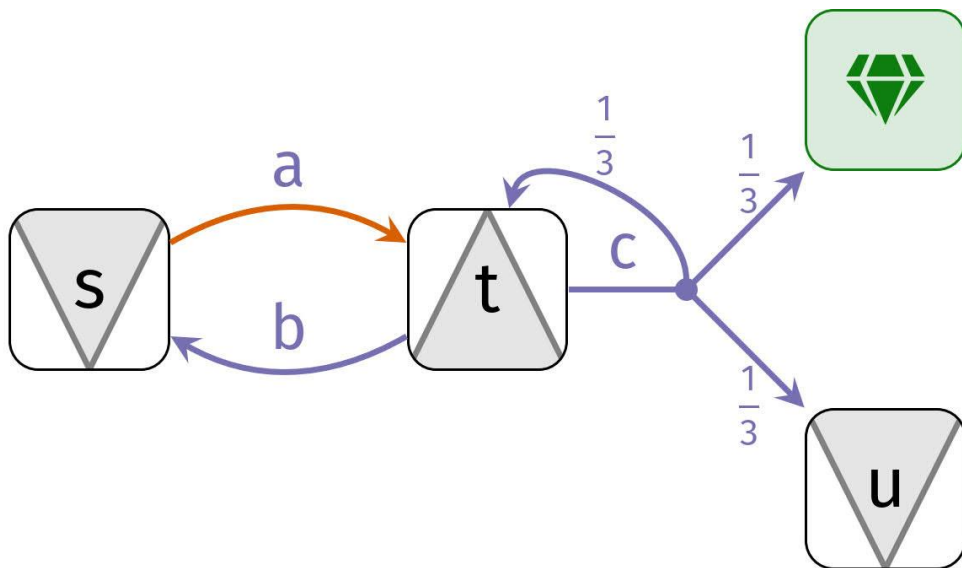


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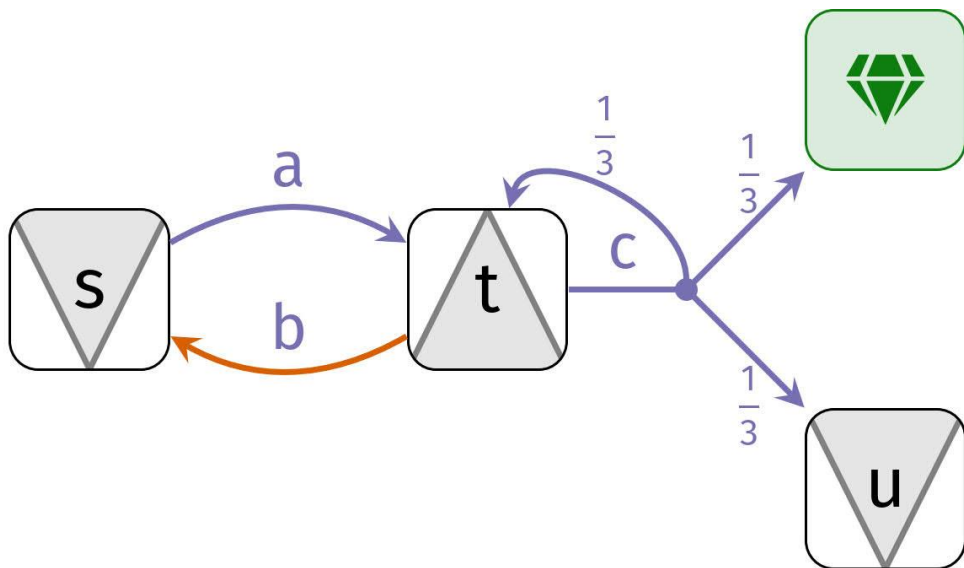
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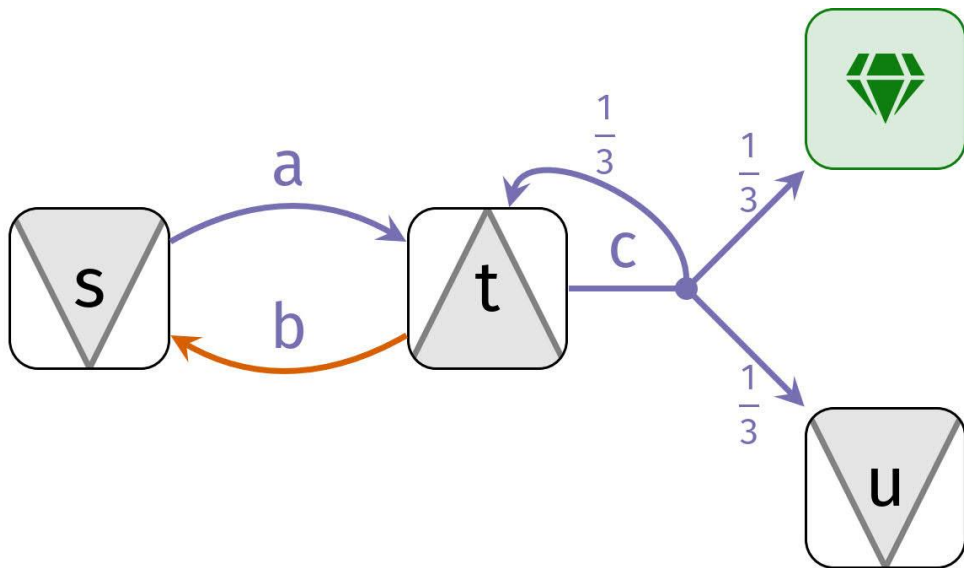


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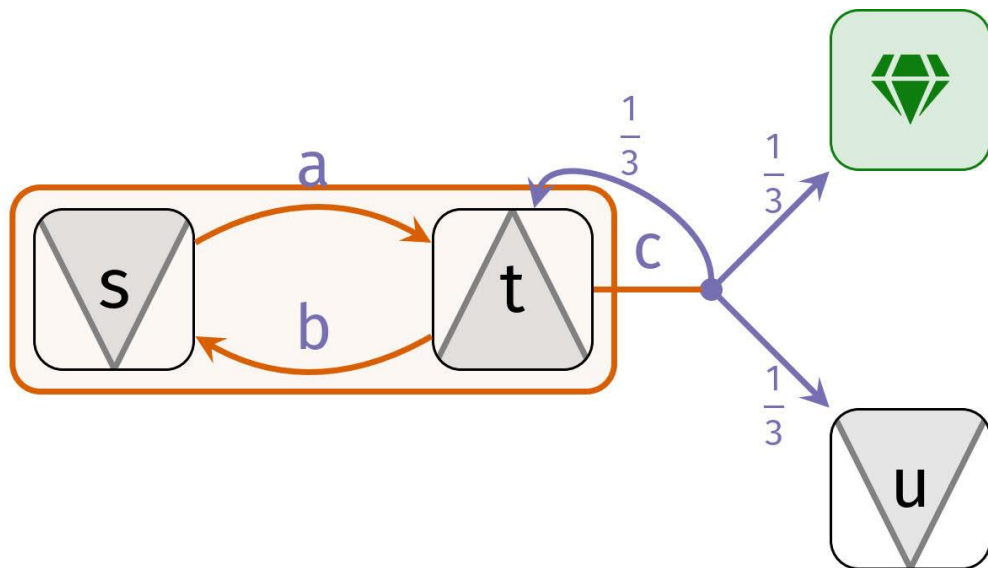


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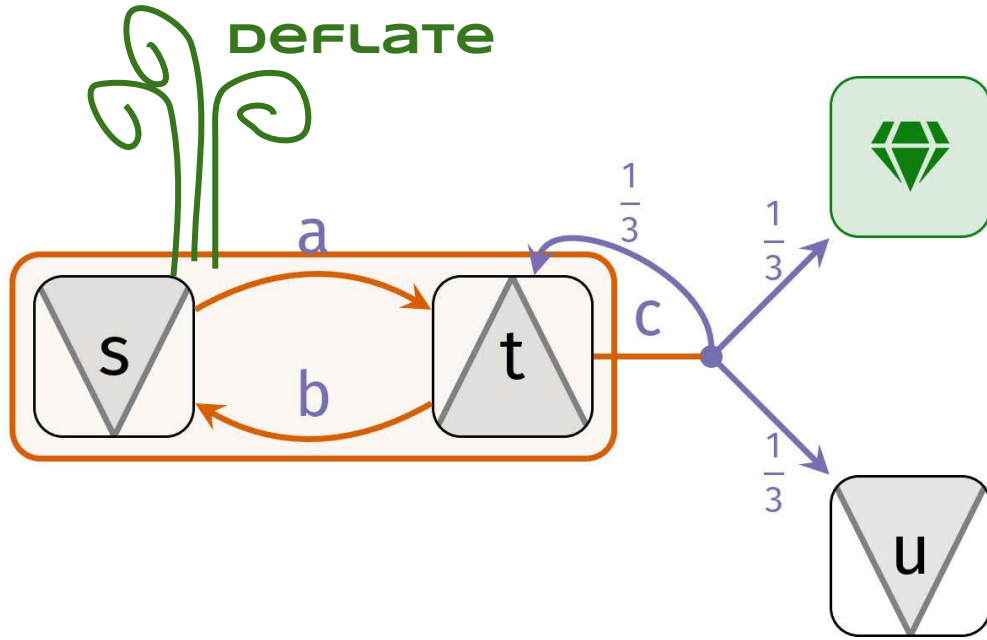


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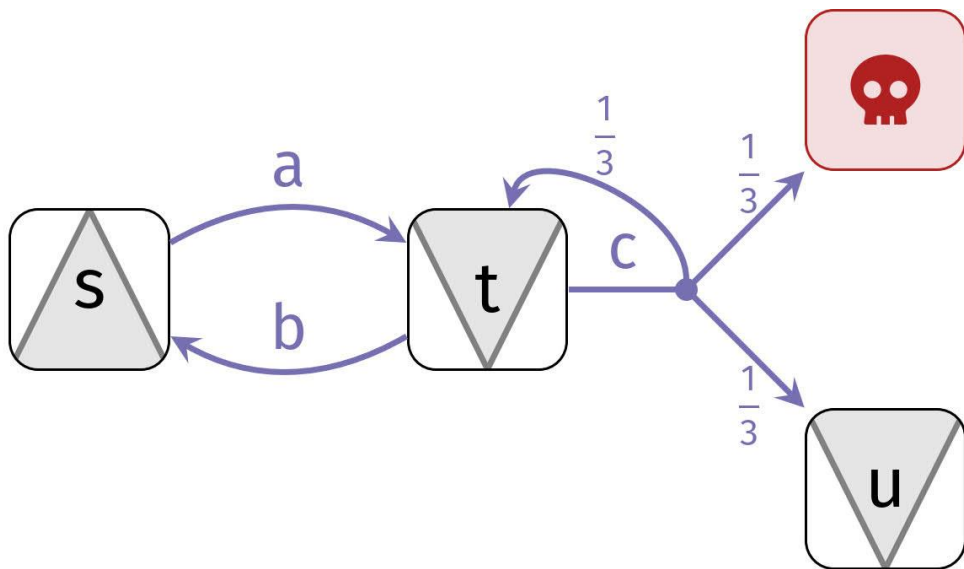


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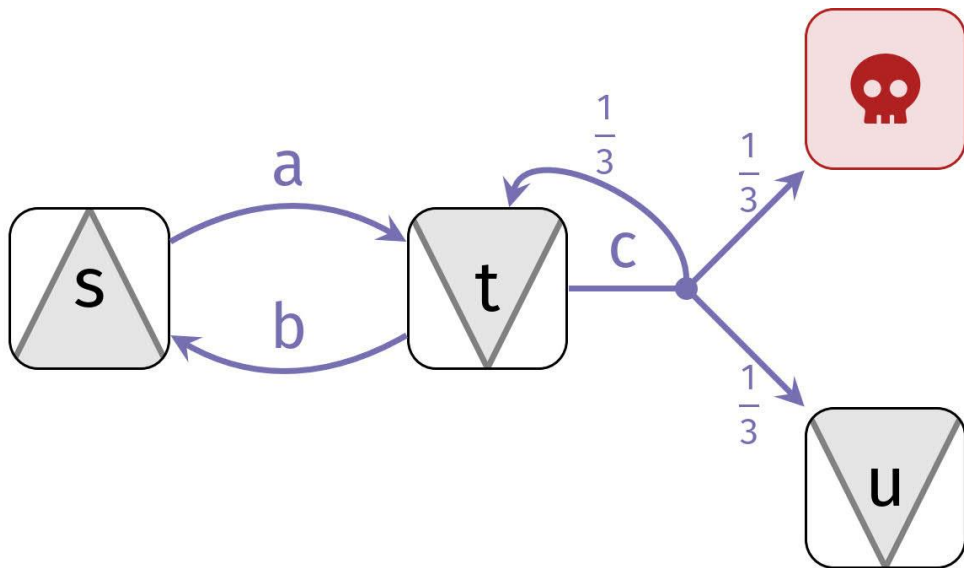
$$x_i(s) = \mathbf{opt}_a x_{i-1}(s, a)$$

Iteration	L(s)	L(t)		U(s)	U(t)
0	0	0		1	1
1	0	1/3		1	<b>2/3</b>
2	1/3	4/9		<b>2/3</b>	<b>5/9</b>
...	...	...		...	...

# Stochastic Games and Value Iteration



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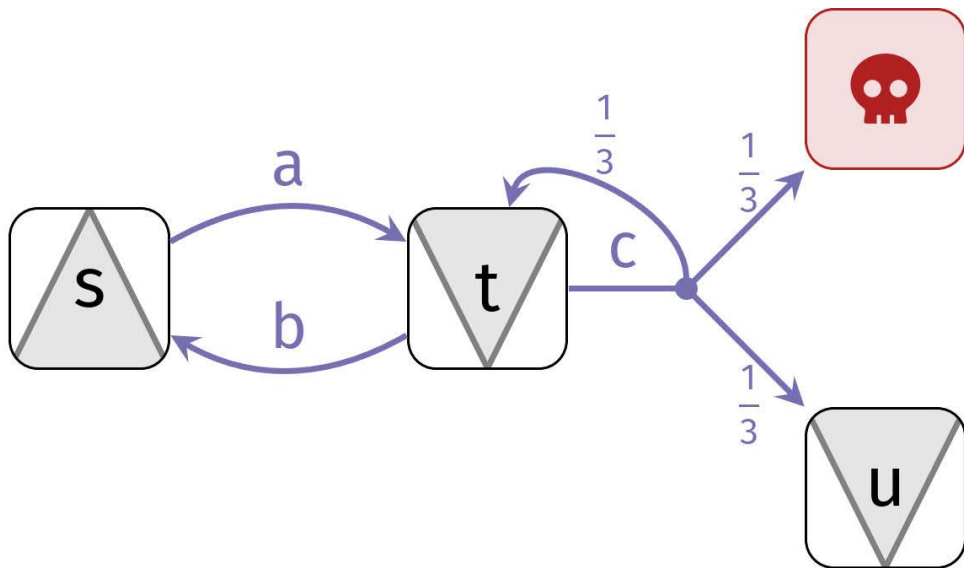


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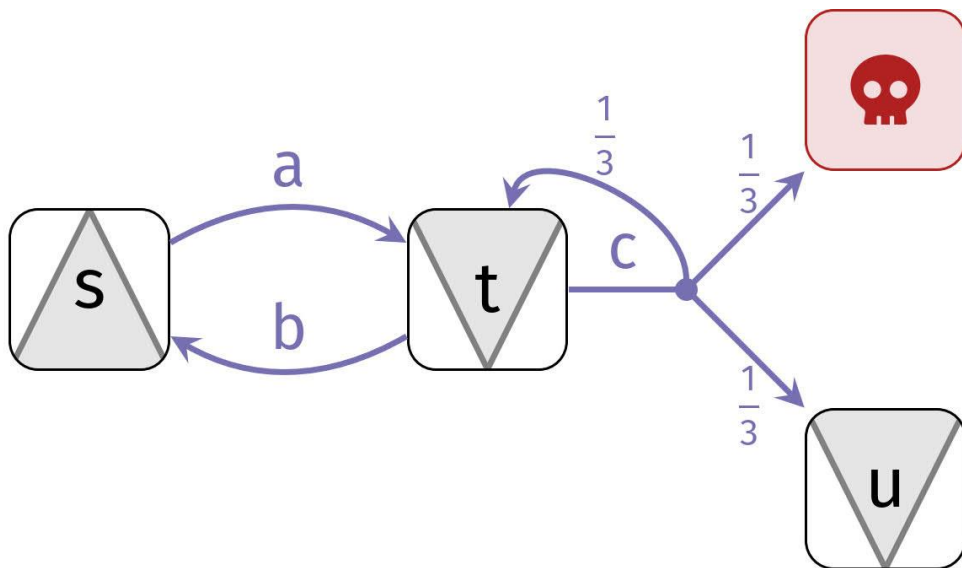


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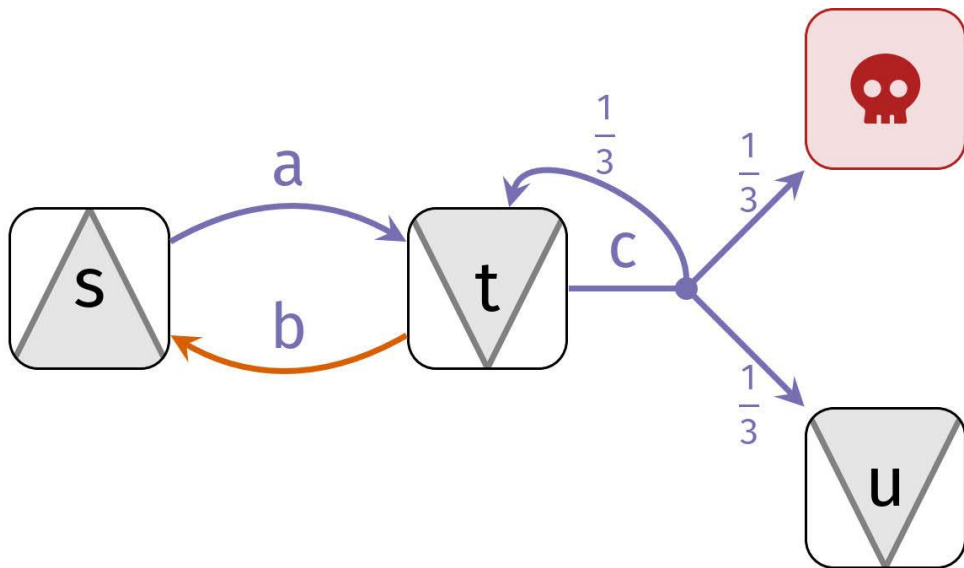
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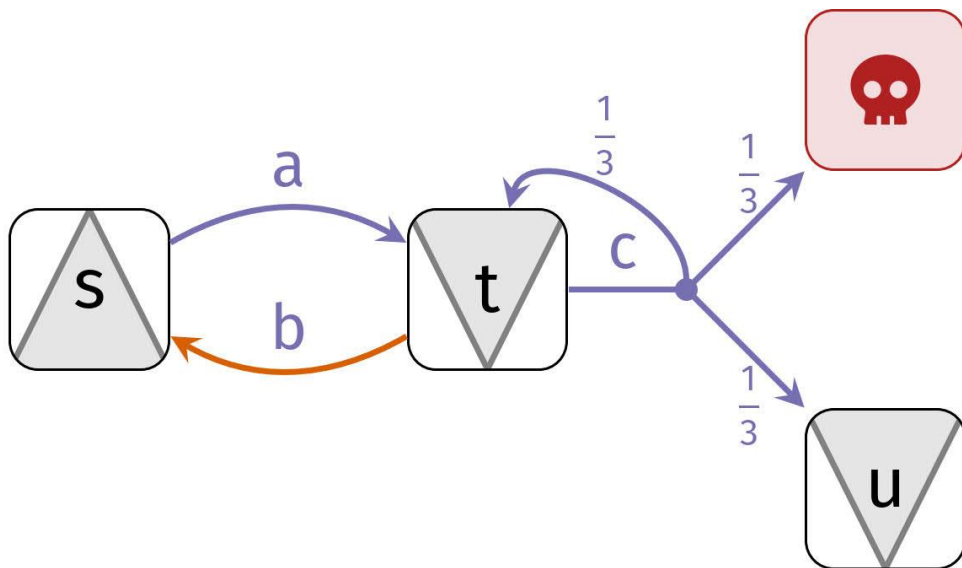


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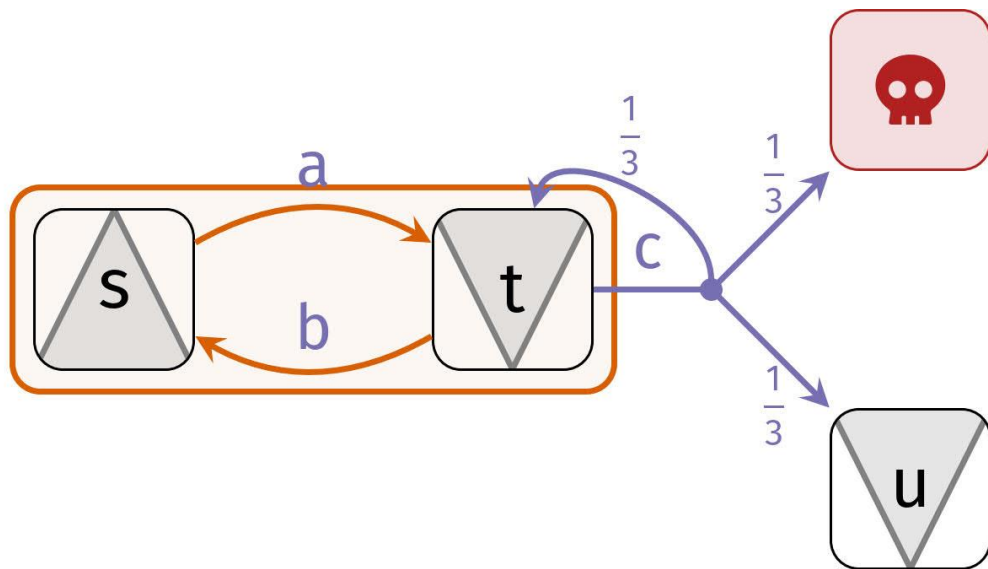


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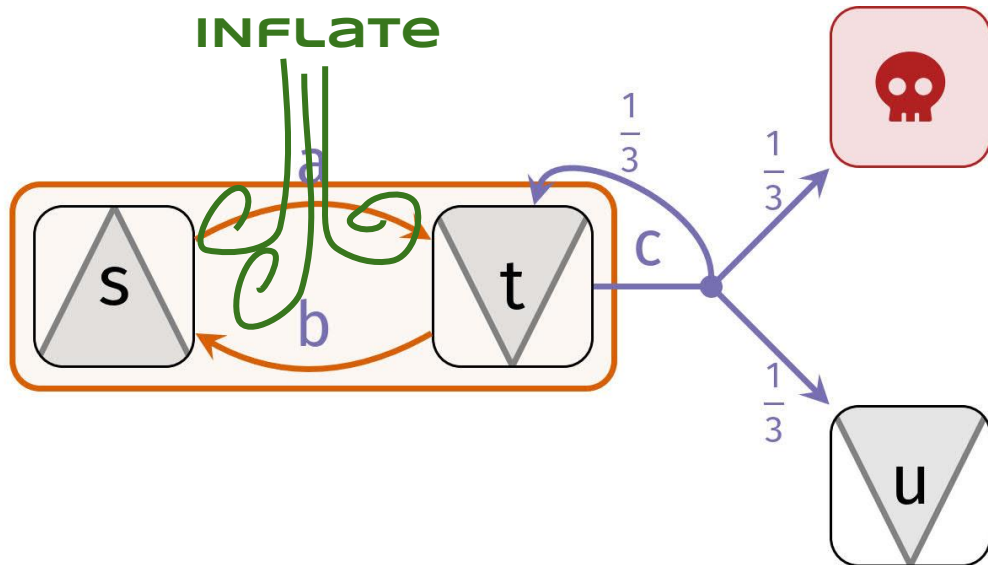


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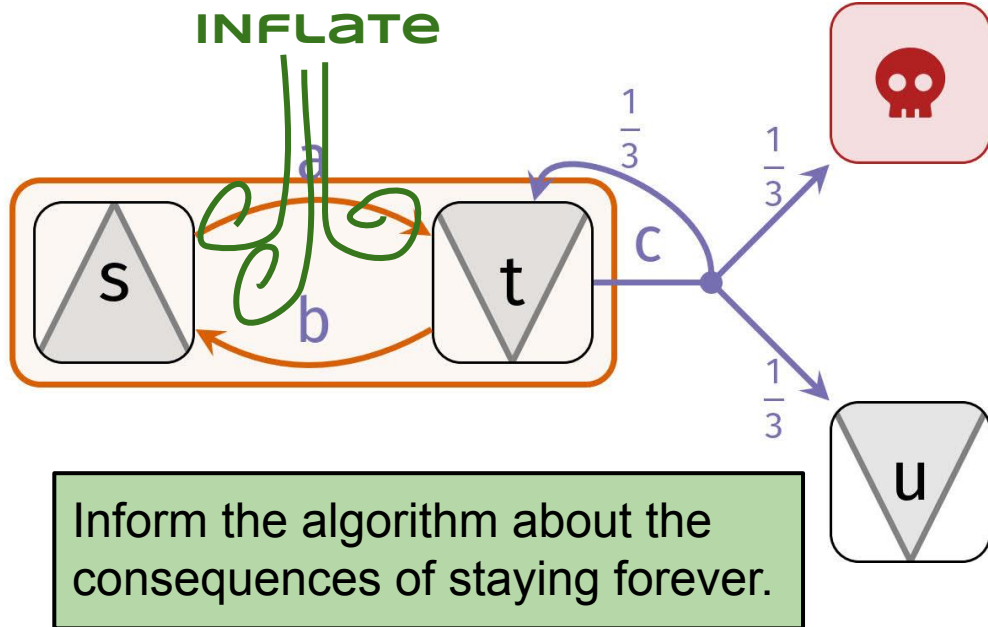


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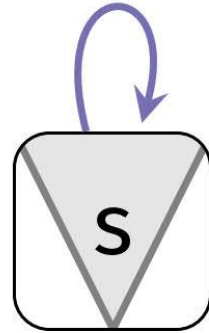
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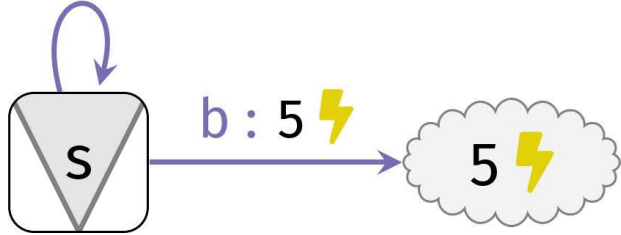
# Deflating and Inflating for Mean Payoff

a : 10 ⚡



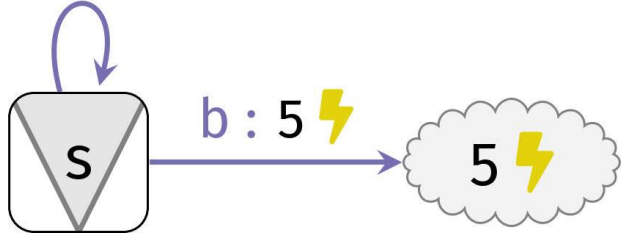
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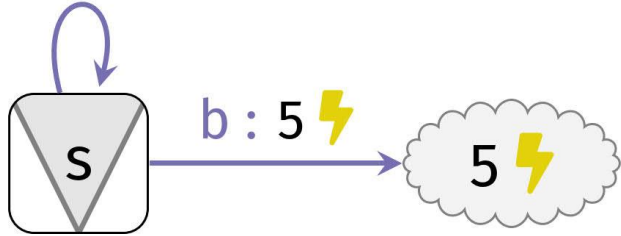
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Inflate from 0 to **exit** value 5

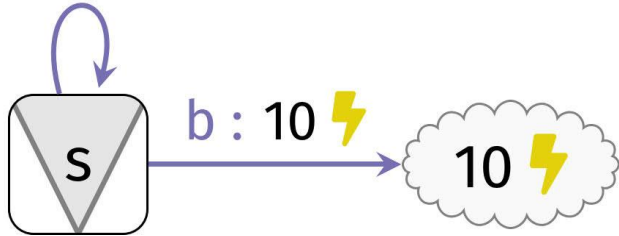
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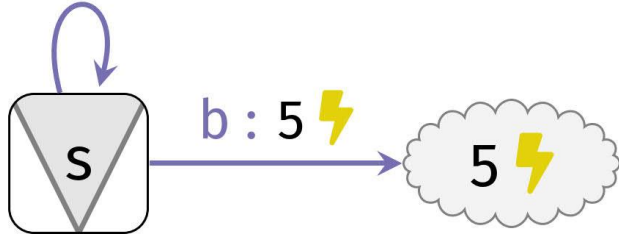
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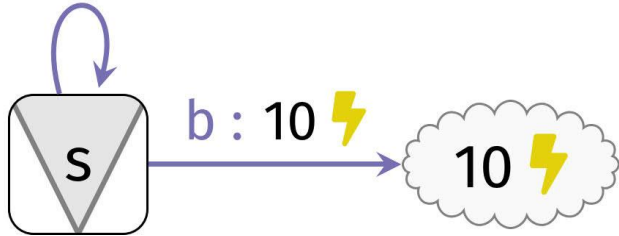
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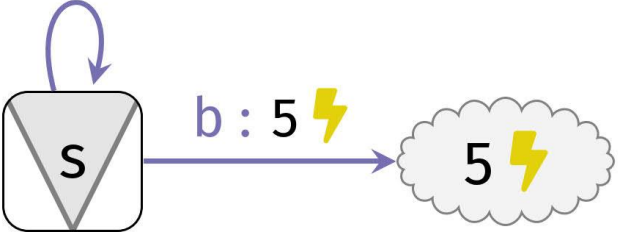
a : 5 ⚡



Inflate from 0 to **stay** value 5

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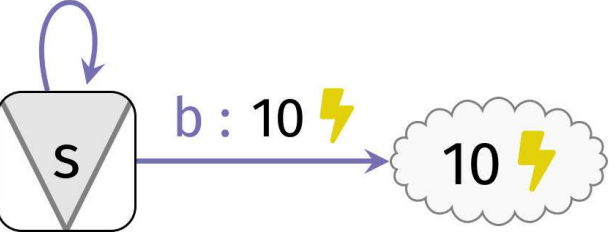
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Inflate from 0 to **exit** value 5

And dually for Maximizer states

a : 5 ⚡



Inflate from 0 to **stay** value 5



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**SOUND**

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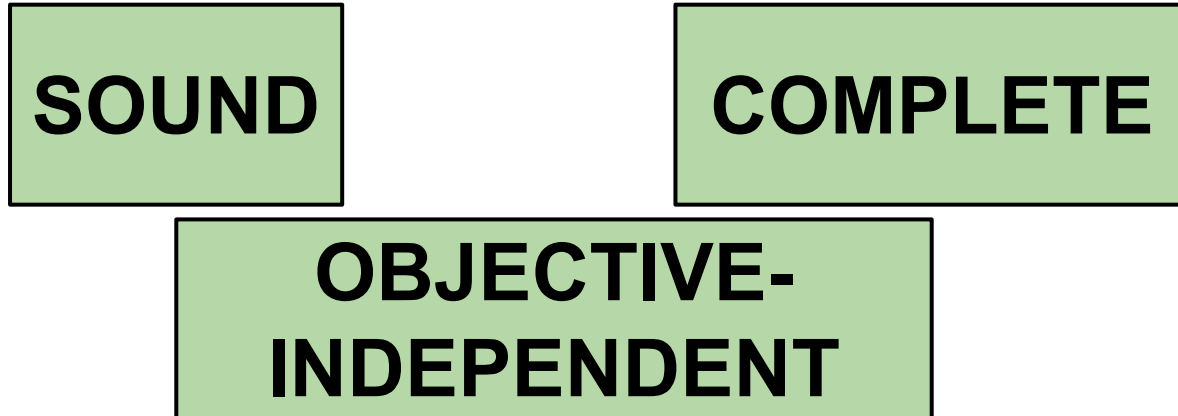
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**COMPLETE**

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# 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**