Renewal Monte Carlo:

Renewal theory based reinforcement learning

Jayakumar Subramanian and Aditya Mahajan

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December 17-19, 2018

RL has achieved considerable success…

Image credit: MIT Technology review

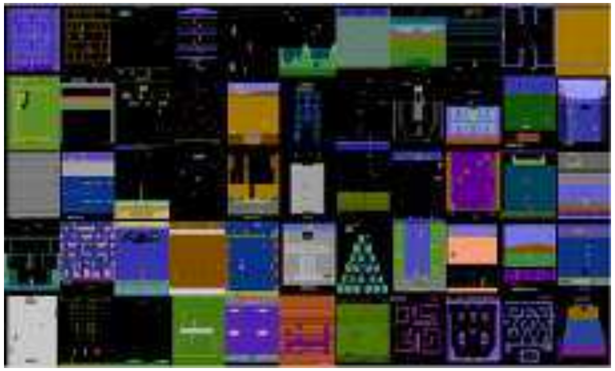

Image credit: Towards Data Science

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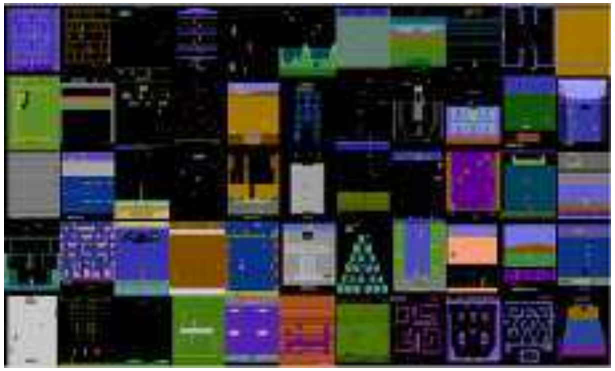

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Salient features

- ⊕ Model-free method
- ⊕ Use policy search

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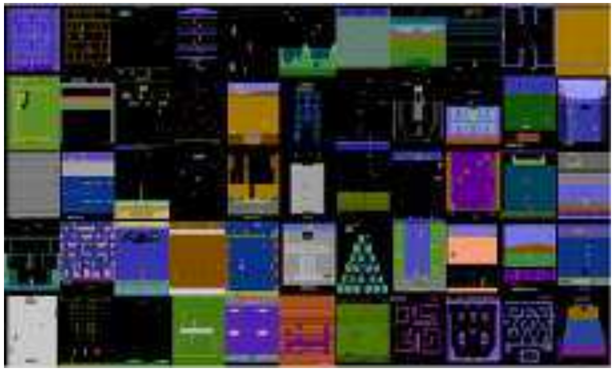

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Limitation

⊖ Learning is slow (takes ~ 10^9 to 10^15 iterations to converge)

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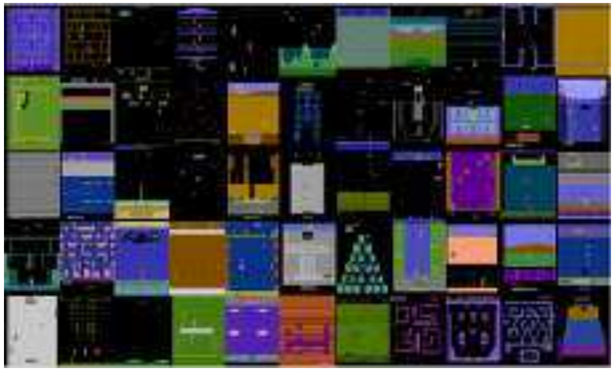

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Limitation

- ⊖ Learning is slow (takes ~ 10^9 to 10^15 iterations to converge)

- ⊕ Can we exploit features of the model to make it learn faster? …
- ⊕ Without sacrificing generality?

An RL problem can be formulated as…

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Agent

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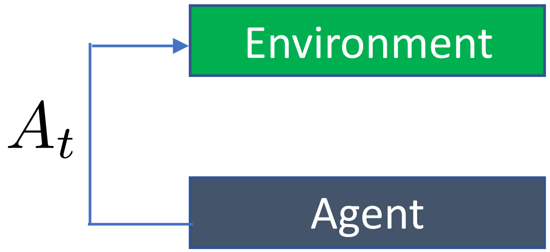

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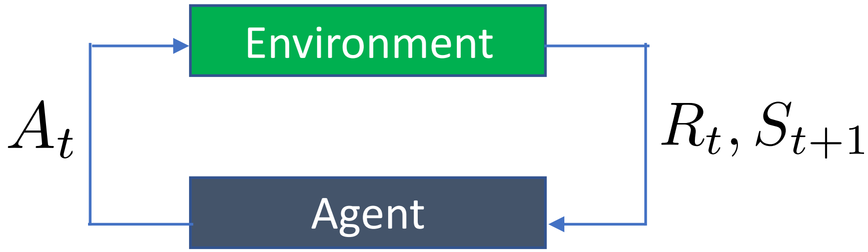

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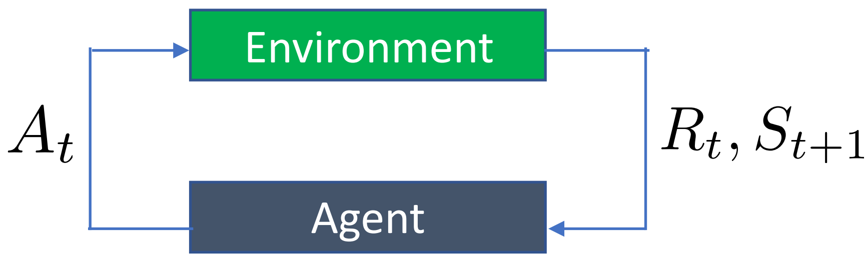

Infinite horizon Markov decision process (MDP) Model	
State space	$S_t \in \mathcal{S}$
Action space	$A_t \in \mathcal{A}$
Transition probability	$\mathbb{P}(S_{t+1} \vert S_t, A_t) = [P(A_t)]_{S_t, S_{t+1}}$
Per-step reward	$R_t = r(S_t, A_t, S_{t+1})$

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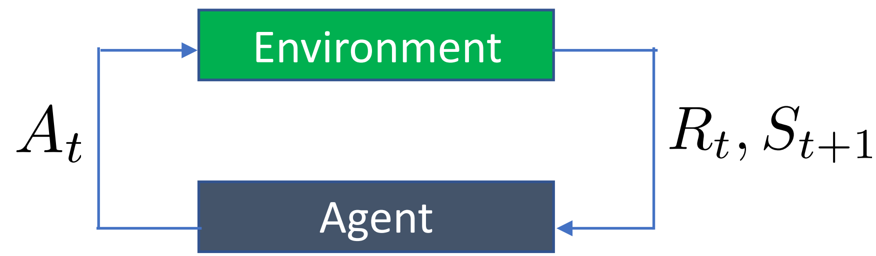

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Unknown in RL

Policy parametrization

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Gibbs (softmax) policy

$$\mu_\theta(a|s) = \frac{\exp(\tau\theta(s,a))}{\sum_{a'} \exp(\tau\theta(s,a))}$$

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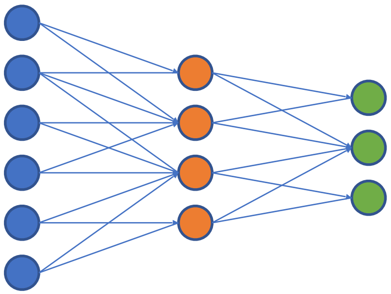
Neural network (NN) policy

$$\mu_\theta(a|s) =$$



θ: weights of NN

Policy gradient

Policy gradient

Performance Gradient Estimate

Policy gradient

Performance Gradient Estimate

$$J_\theta = \mathbb{E}\Big[\sum_{t=0}^{\infty} \gamma^t R_t \,|\, S_0 = s_0, A_t \sim \mu_\theta(S_t)\Big]$$

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How do we estimate this?

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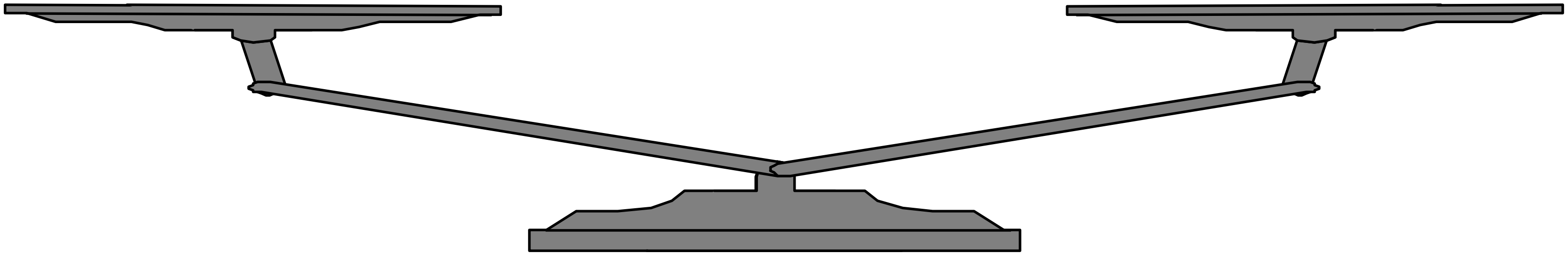
Actor Critic with eligibility traces estimate (SARSA-λ)

$$G_\theta = \sum_{t=0}^{\infty} \left[\nabla_\theta \log(\mu_\theta(A_t | S_t)) \gamma^t Q^\lambda(S_t, A_t) \right]$$

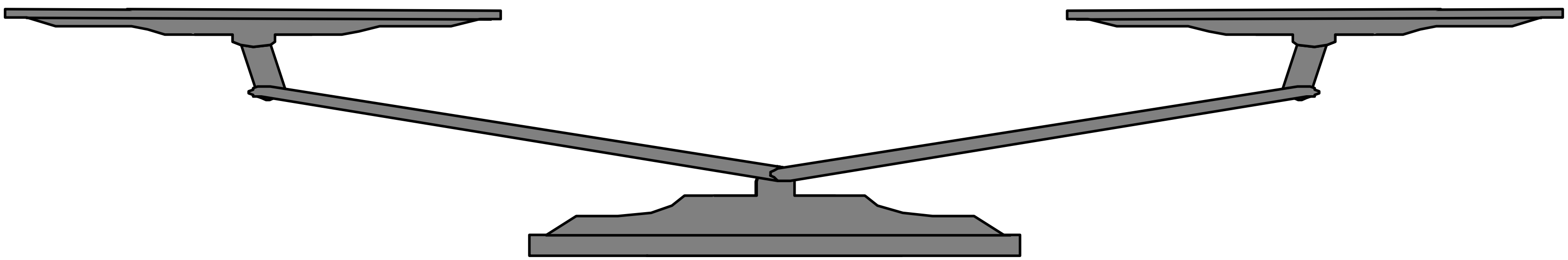
MC vs. TD

MC	TD



MC vs. TD

MC	TD
⊕ Unbiased ⊕ Simple & easy to implement ⊕ Discounted & average reward cases ⊖ High variance ⊖ End-of-episode updates ⊖ Not asymptotically optimal for inf. hor.	



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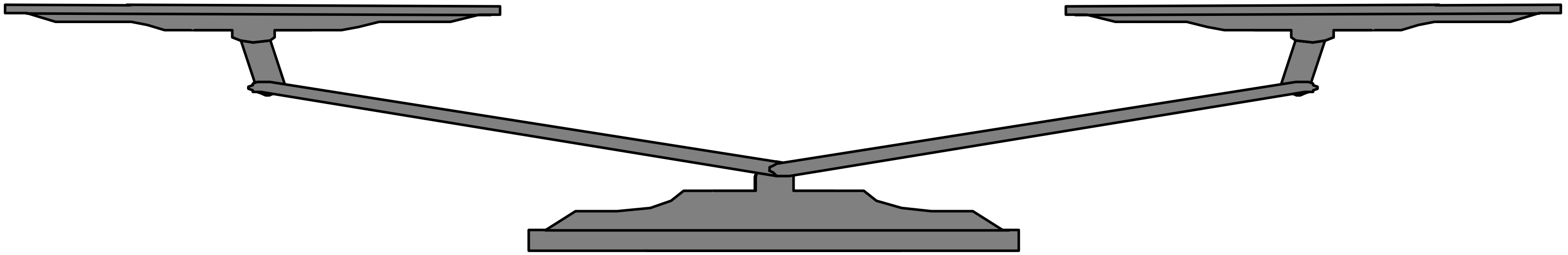

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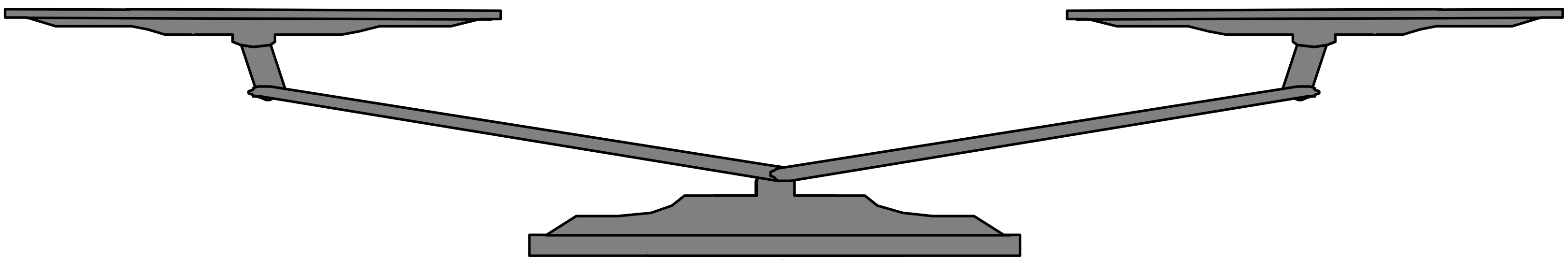
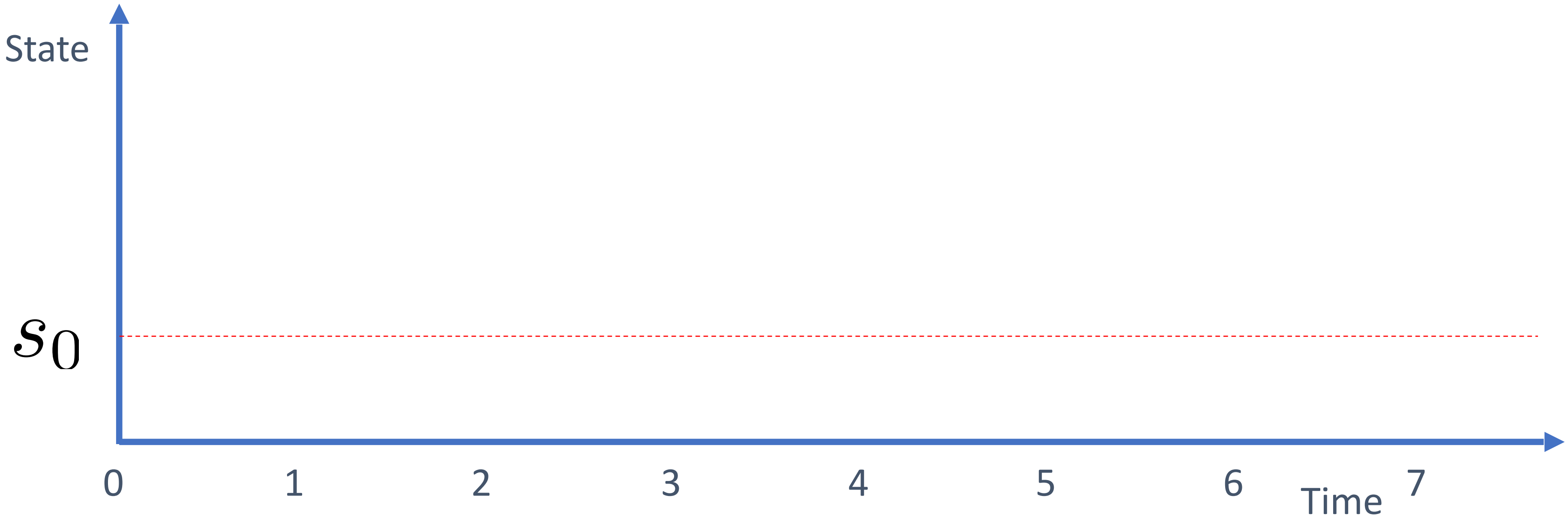


Can we get the best of both worlds?

Renewal Monte Carlo



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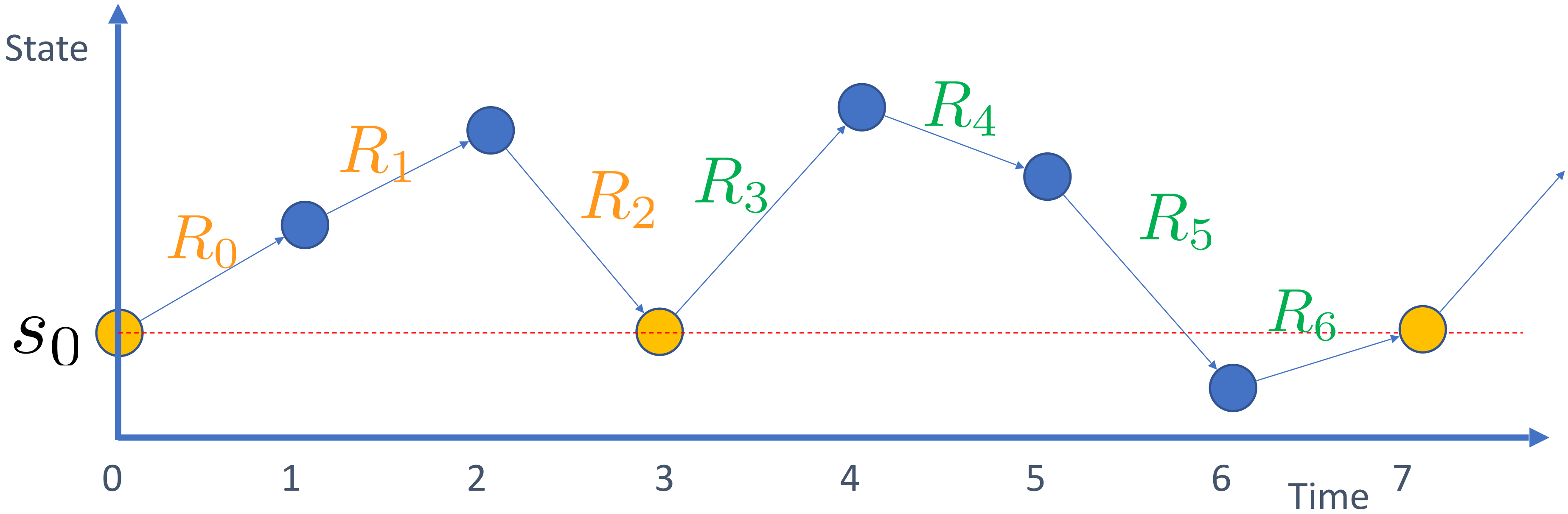

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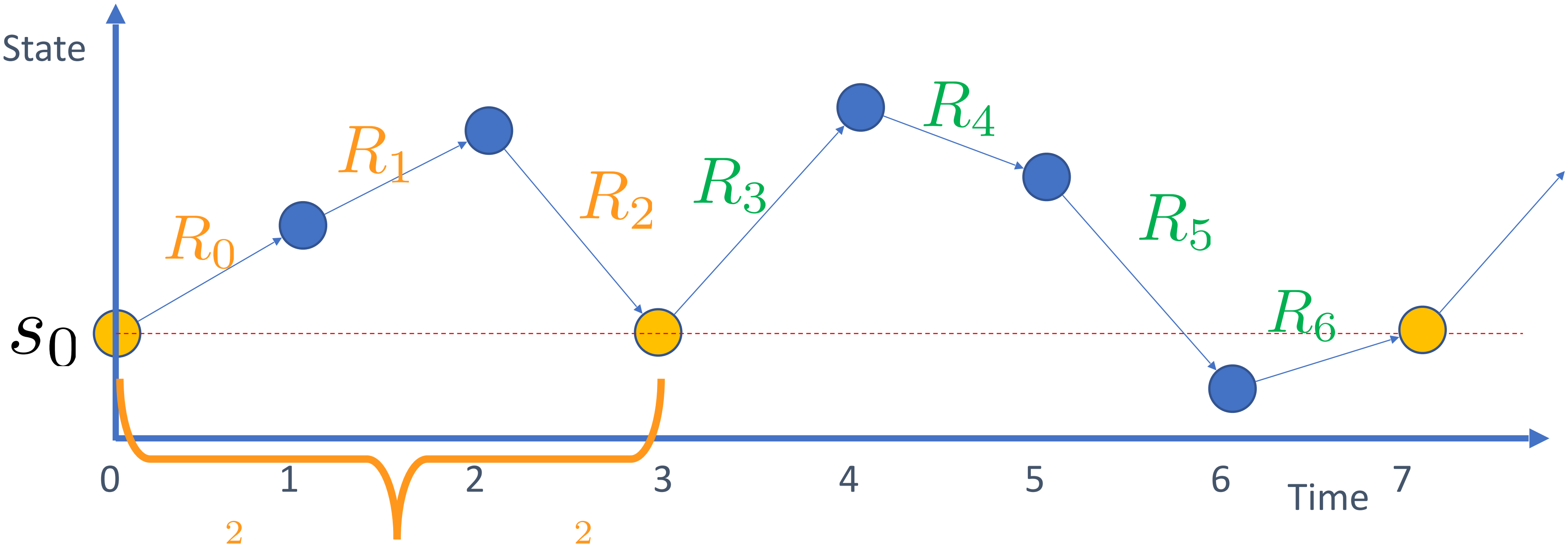
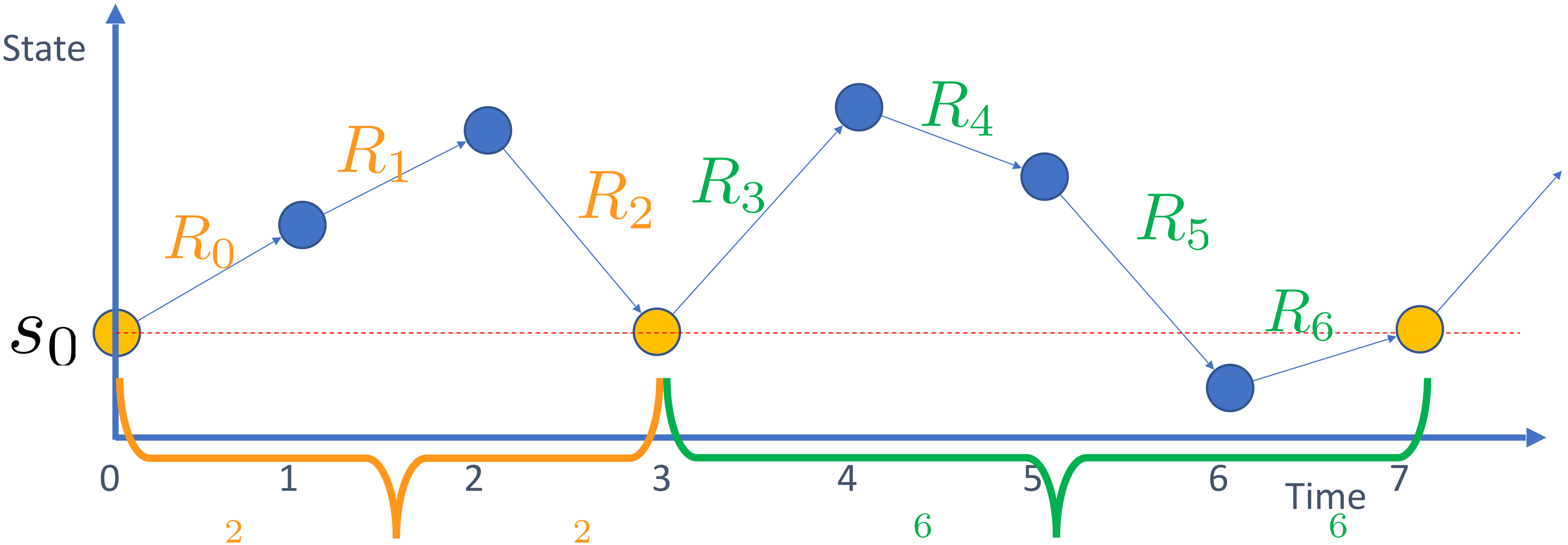


$$\mathsf{R}^{(1)} = \sum_{t=0}^{2} \gamma^t R_t, \mathsf{T}^{(1)} = \sum_{t=0}^{2} \gamma^t$$

Renewal Monte Carlo



$$\mathsf{R}^{(1)} = \sum_{t=0}^{2} \gamma^t R_t, \mathsf{T}^{(1)} = \sum_{t=0}^{2} \gamma^t \qquad \mathsf{R}^{(2)} = \sum_{t=3}^{6} \gamma^{t-3} R_t, \mathsf{T}^{(2)} = \sum_{t=3}^{6} \gamma^{t-3}$$

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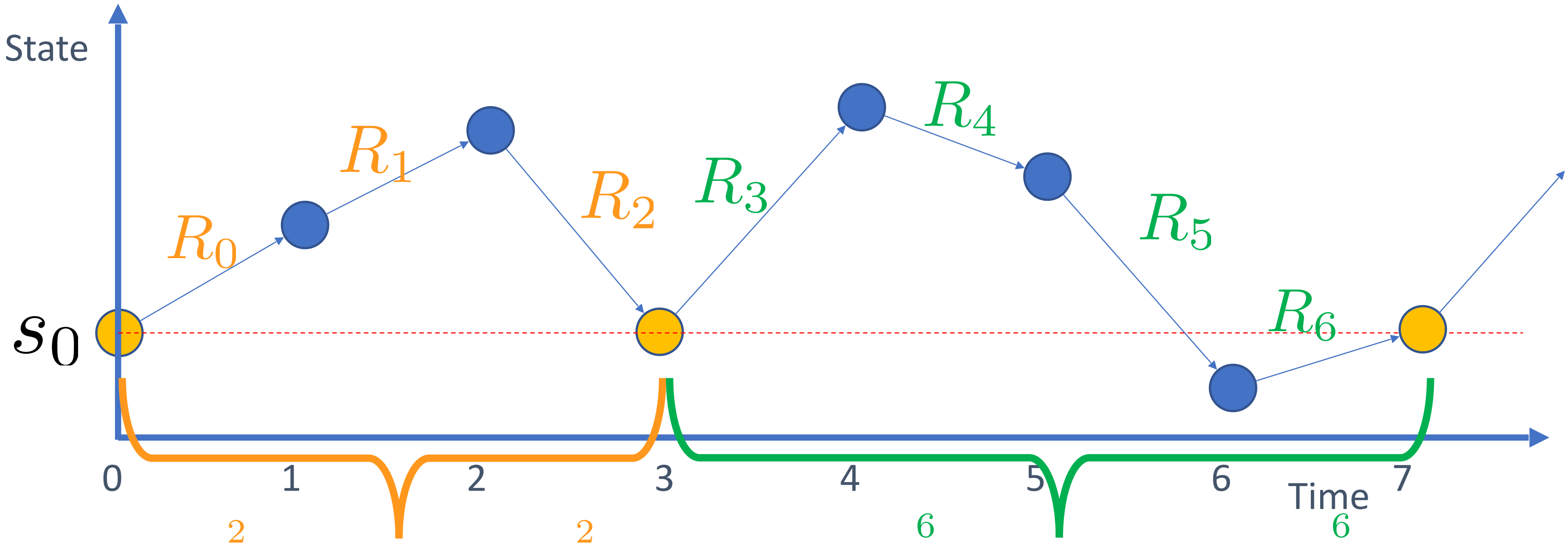

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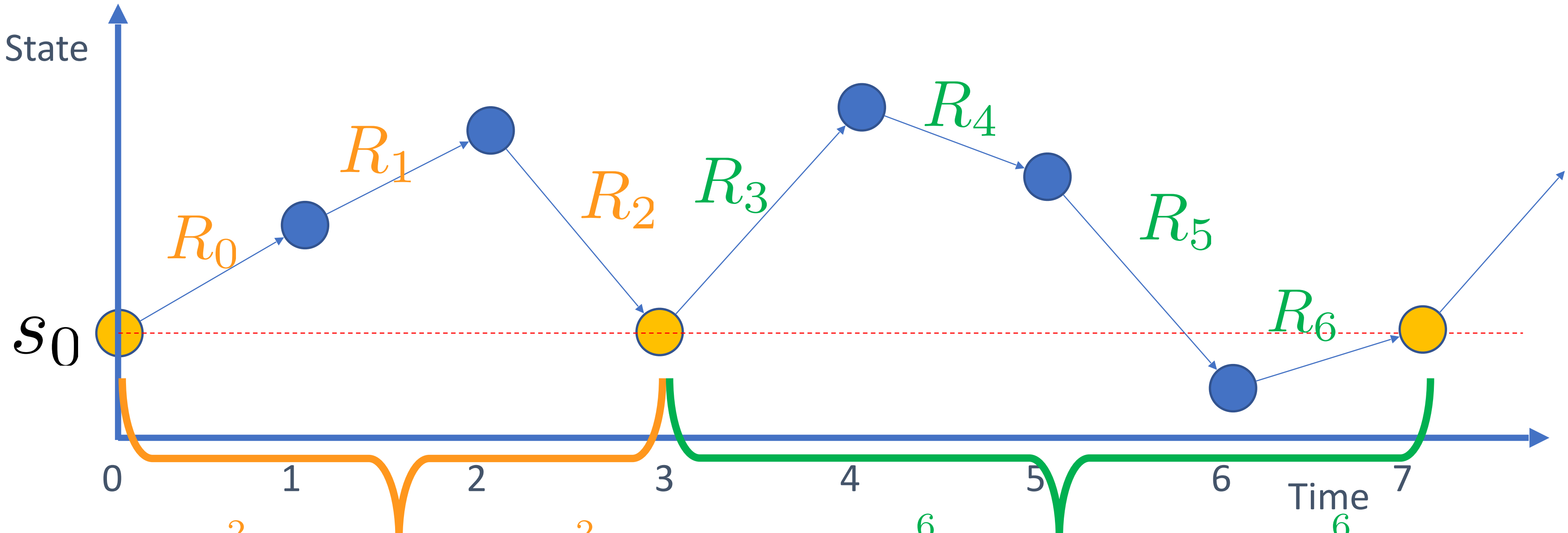

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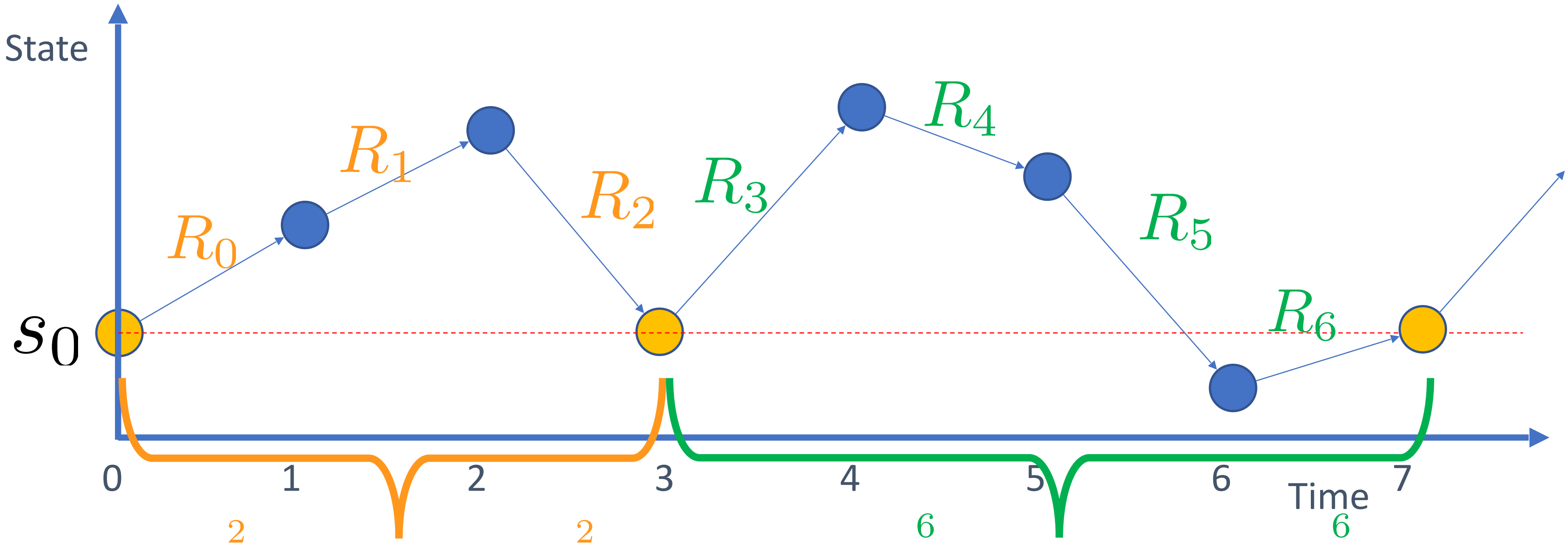

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RMC based policy gradient

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Performance Gradient Estimate

$$J_\theta = \frac{\mathsf{R}_\theta}{(1-\gamma)\mathsf{T}_\theta}$$

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$$J_\theta = \frac{\mathsf{R}_\theta}{(1-\gamma)\mathsf{T}_\theta} \quad ; \quad \nabla_\theta J_\theta = \frac{H_\theta}{(1-\gamma){\mathsf{T}_\theta}^2}$$

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$\widehat{\mathsf{R}}_\theta, \widehat{\mathsf{T}}_\theta$ estimated using MC / TD ; $\nabla_\theta \widehat{\mathsf{R}}_\theta, \nabla_\theta \widehat{\mathsf{T}}_\theta$ using RL policy gradient

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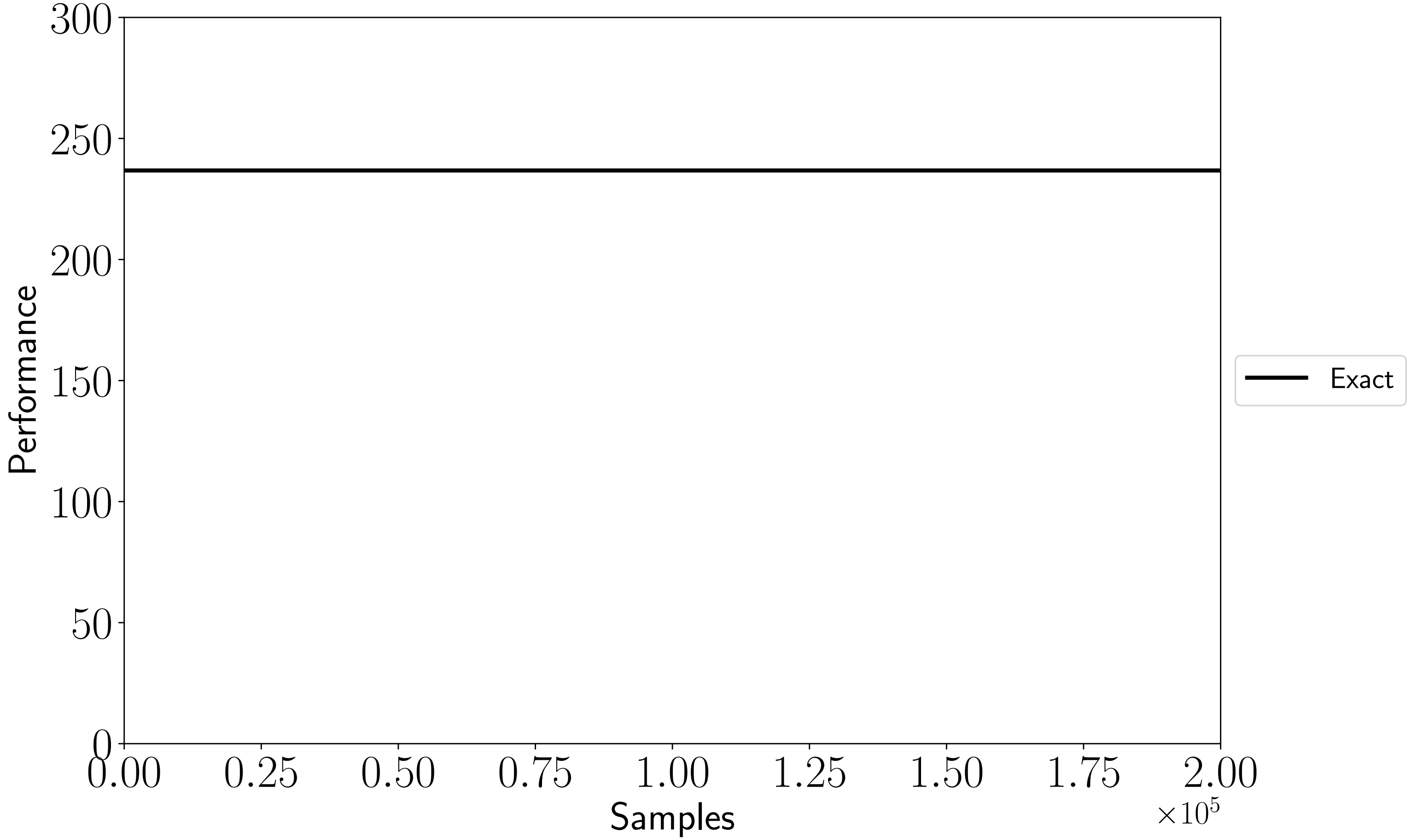
Iteration for θ_k converges a.s. to a value where $\nabla_\theta J_\theta = 0$

E.g. – Randomly generated MDP



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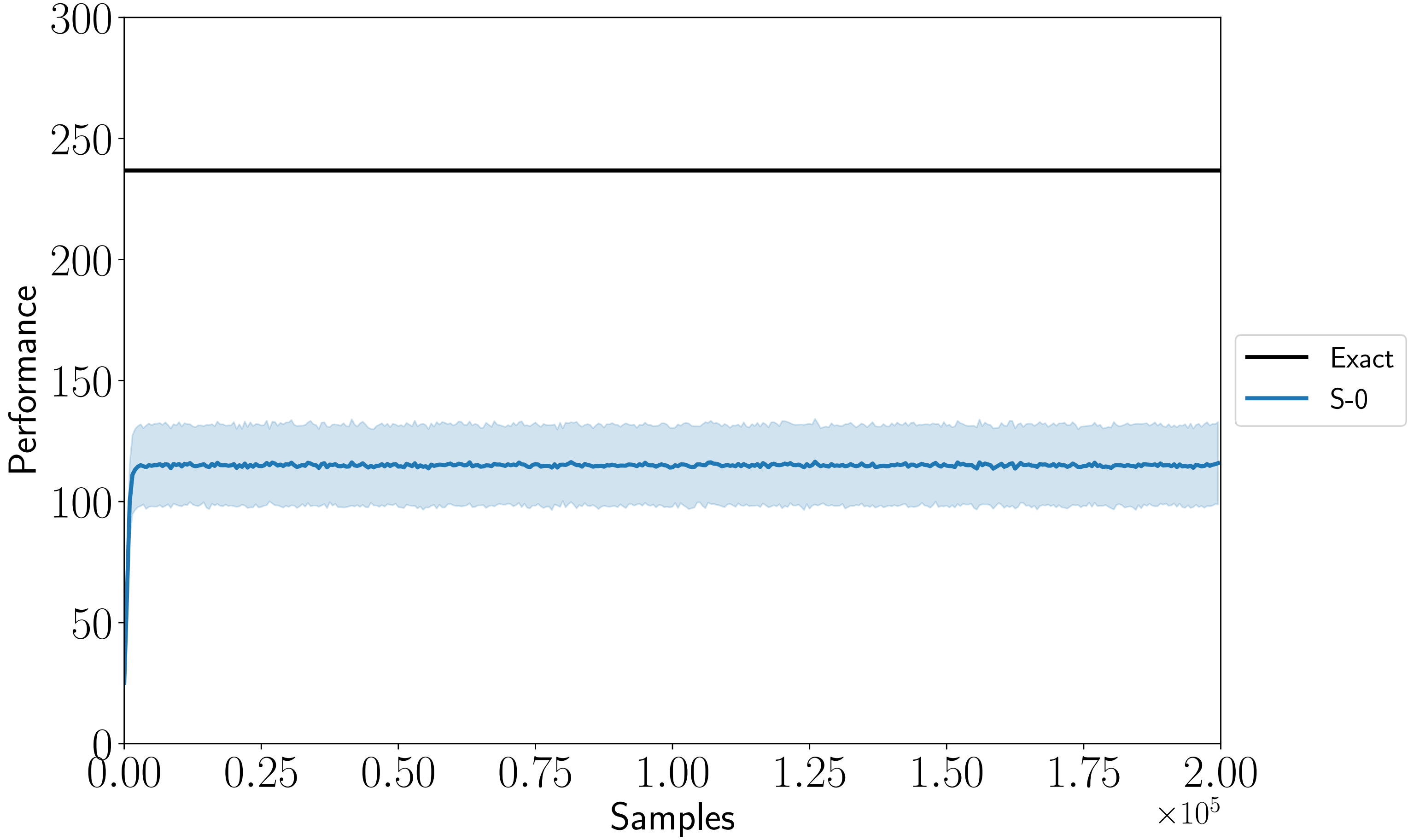

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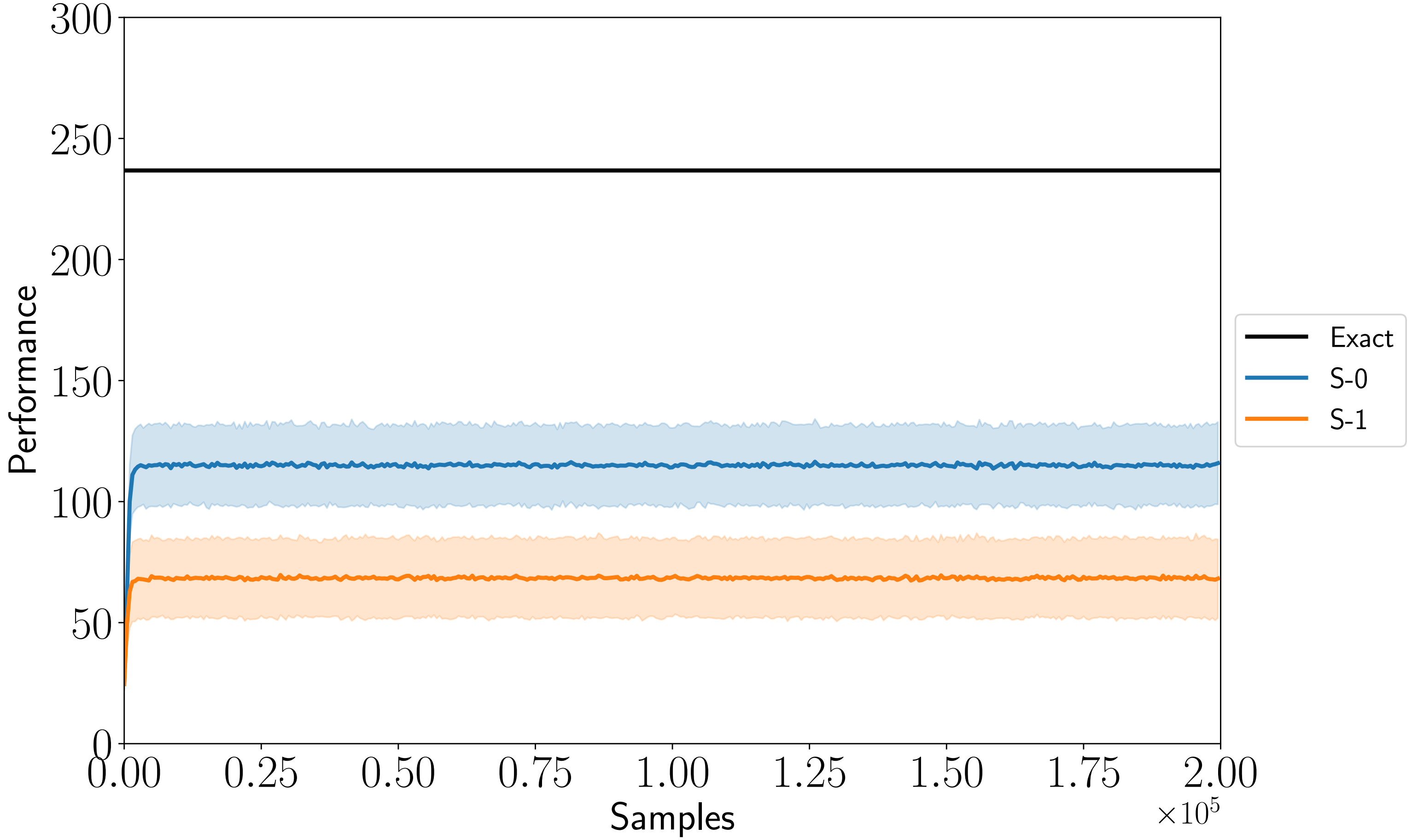

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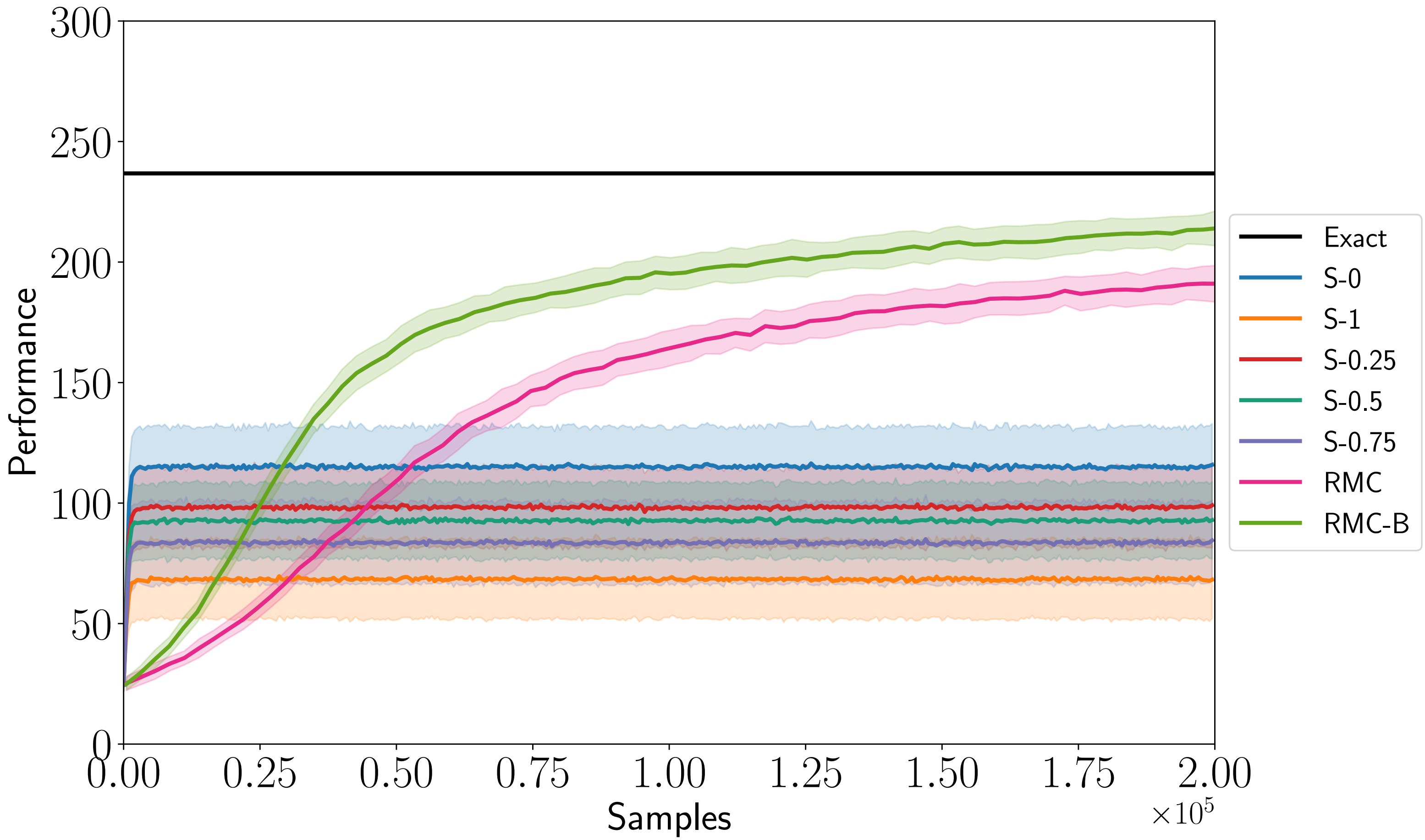

Related work

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- Renewal theory for RL: [Marbach & Tsitsiklis 2001, 2003]
  - Average reward criterion
  - Relative value function for average reward

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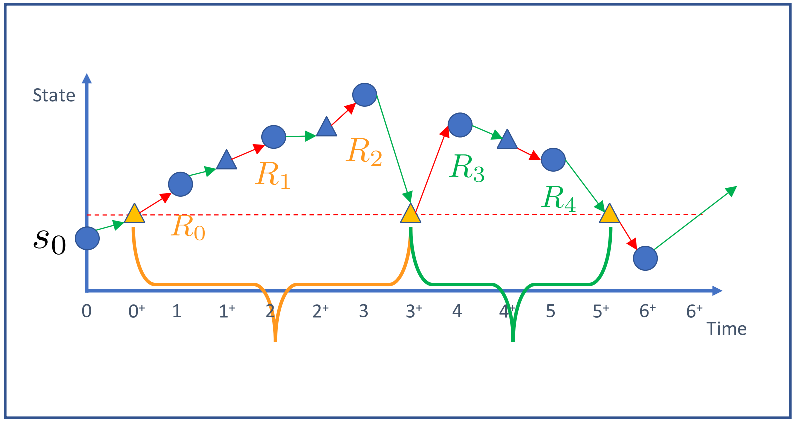

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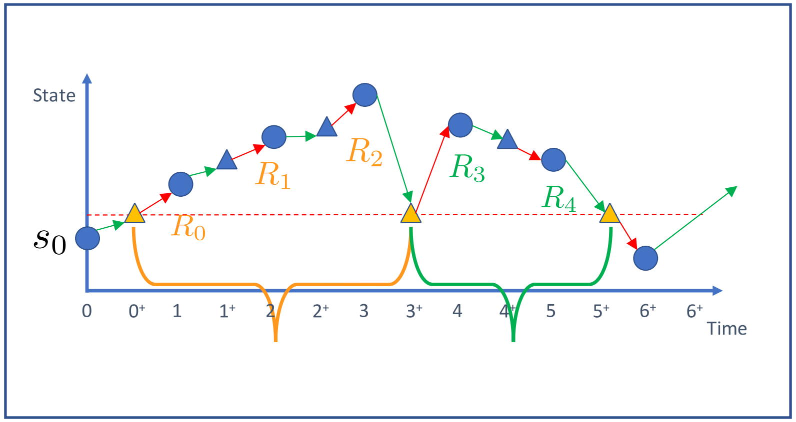
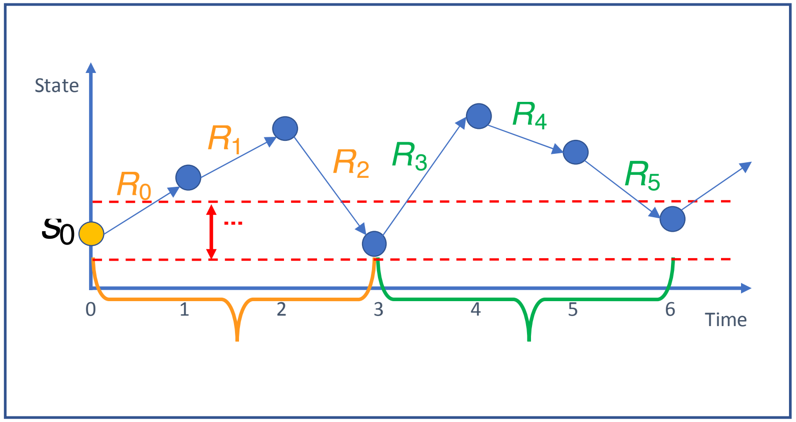
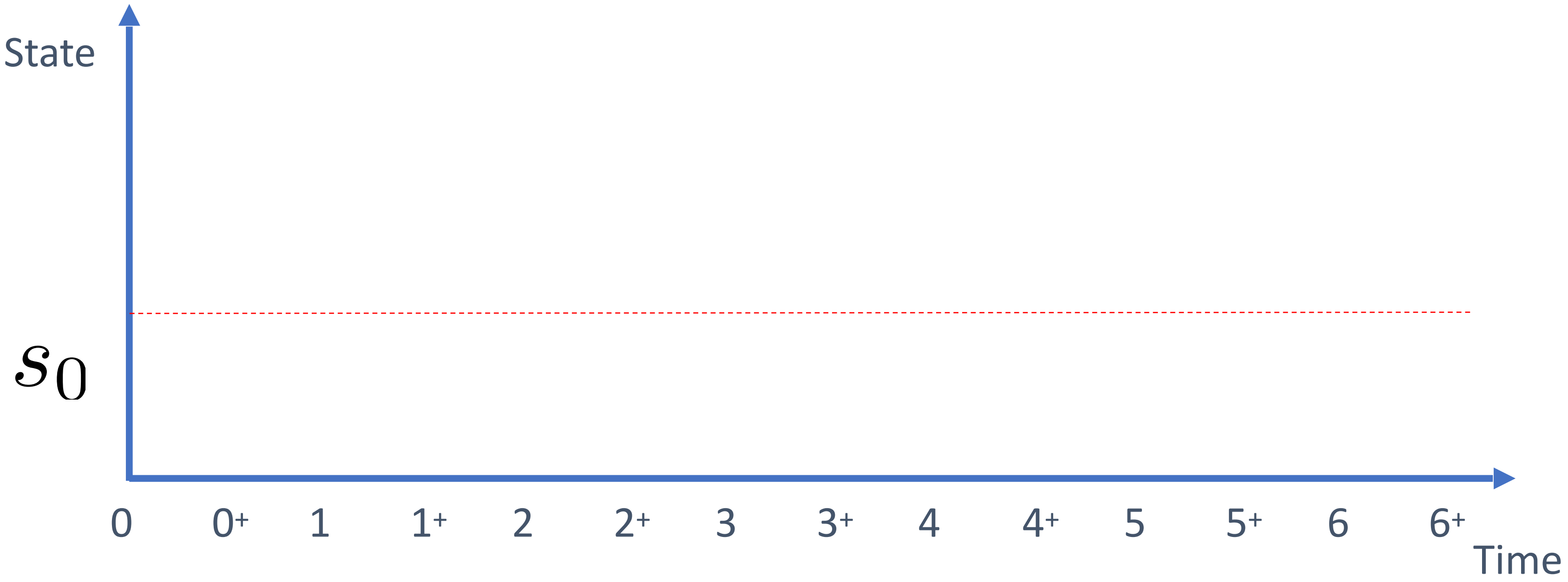


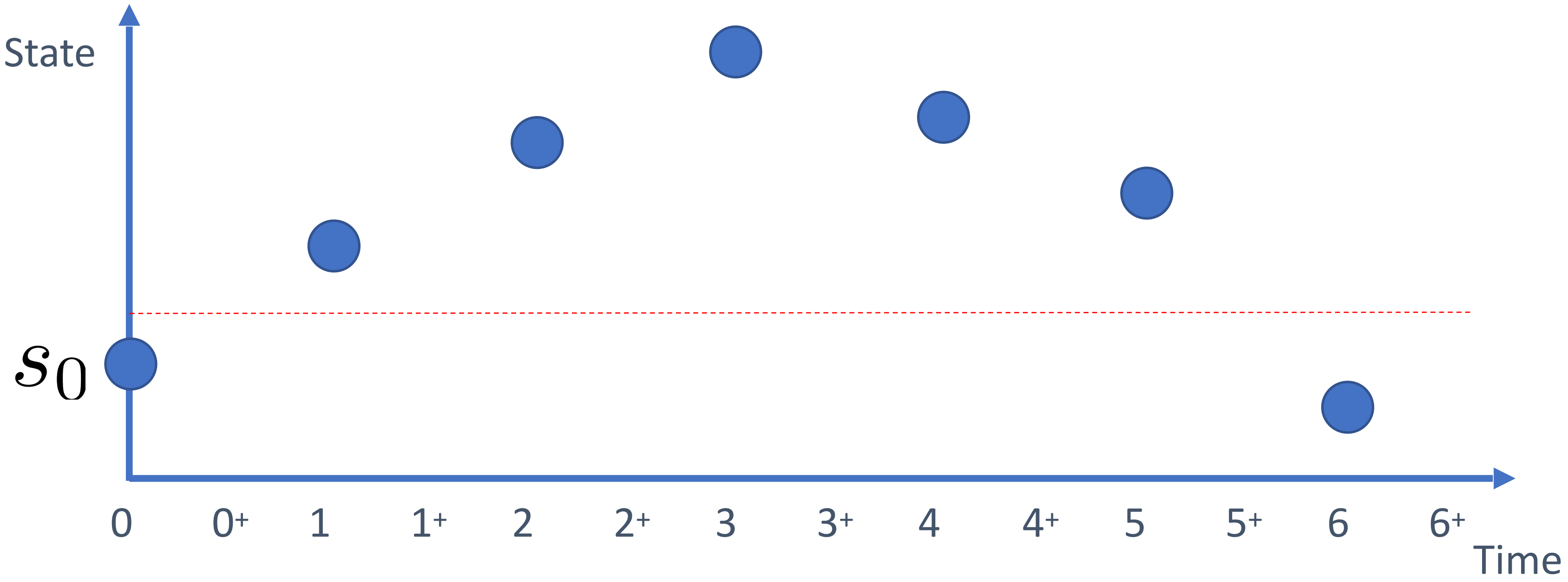
Approximate renewal model



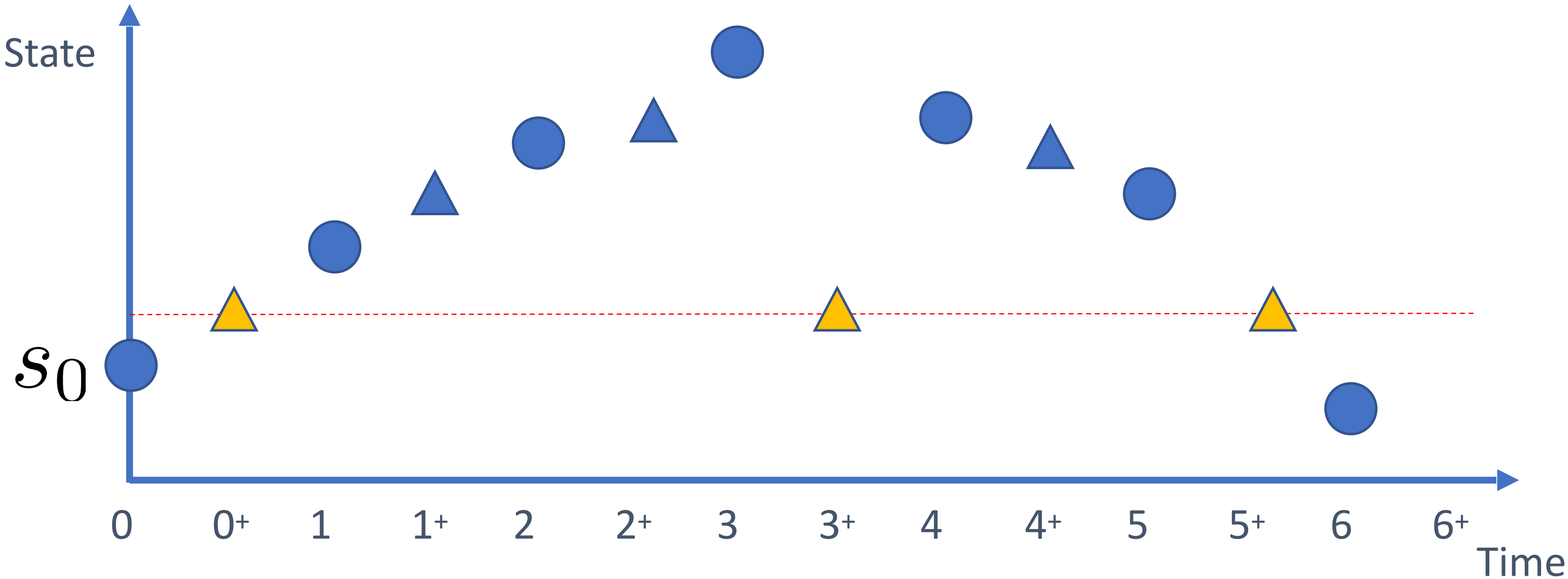
Post-decision state model



Post-decision state model



Post-decision state model



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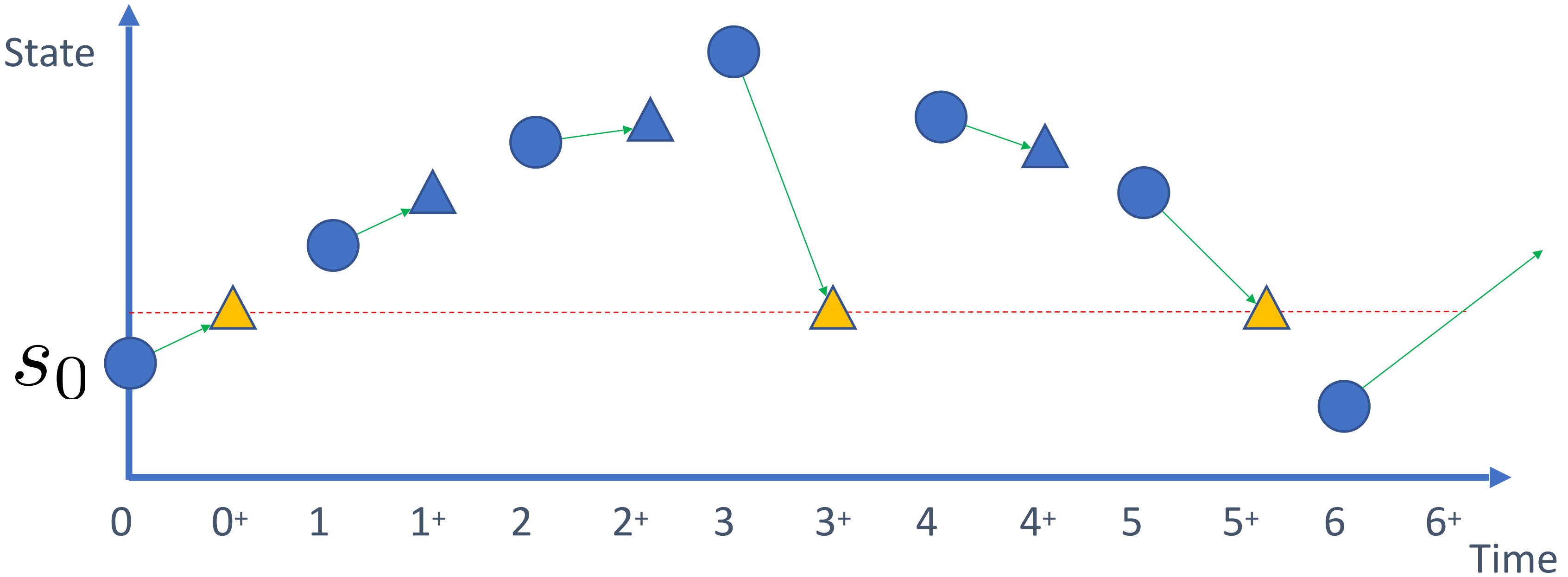

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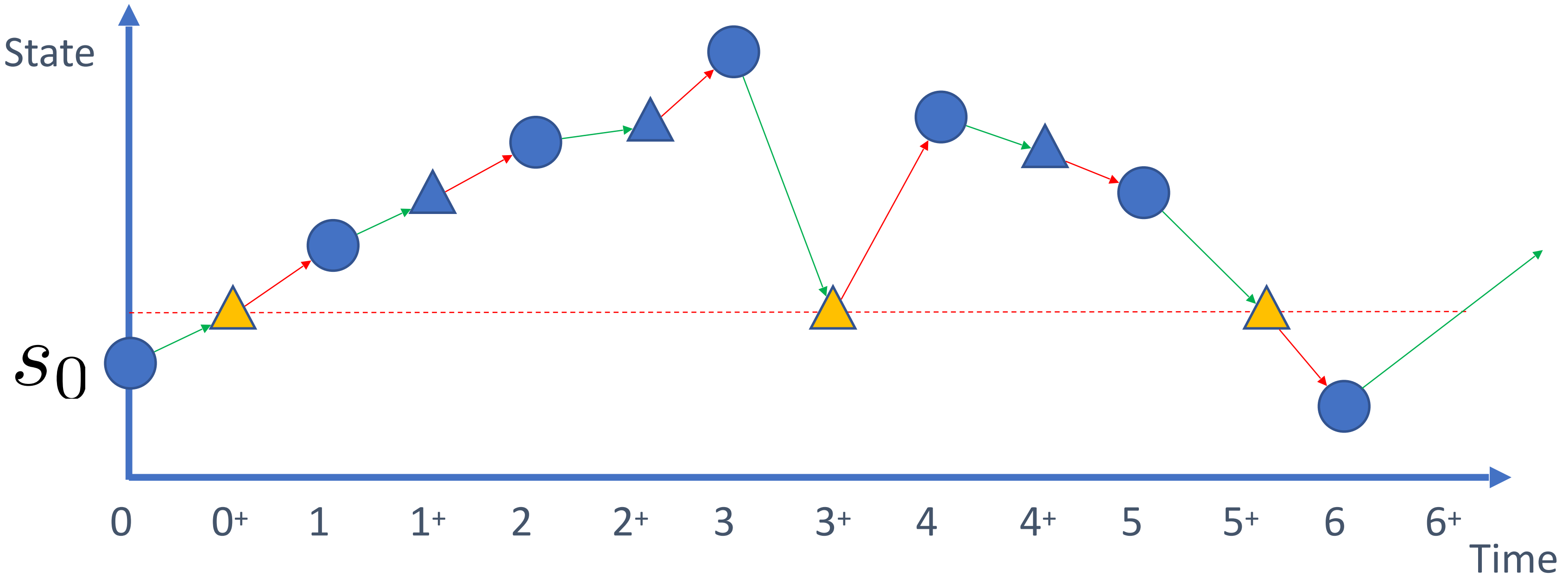

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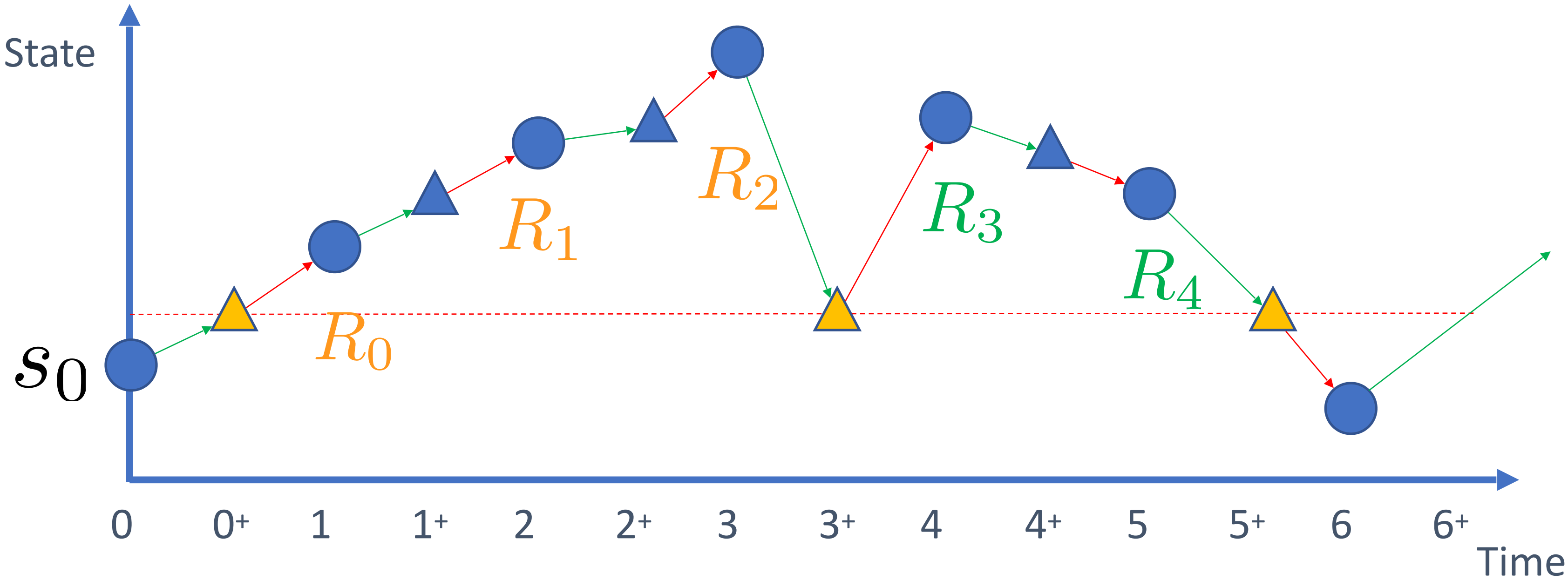

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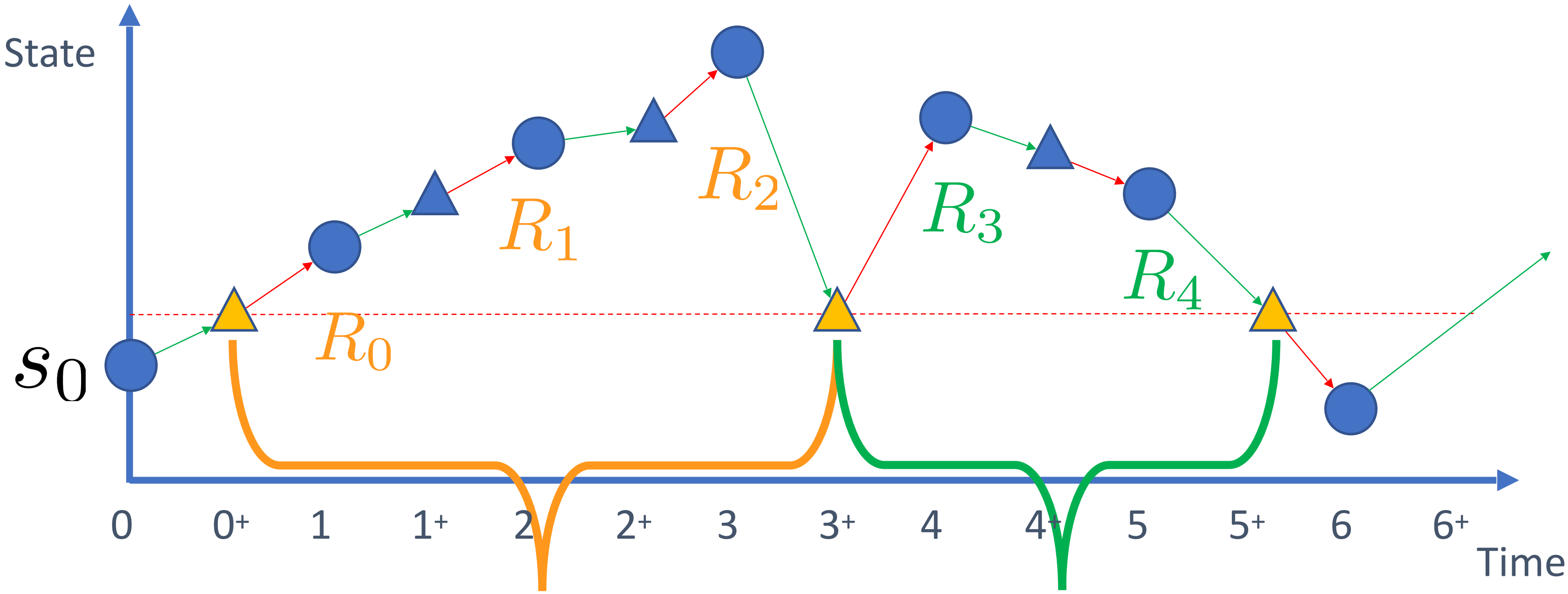
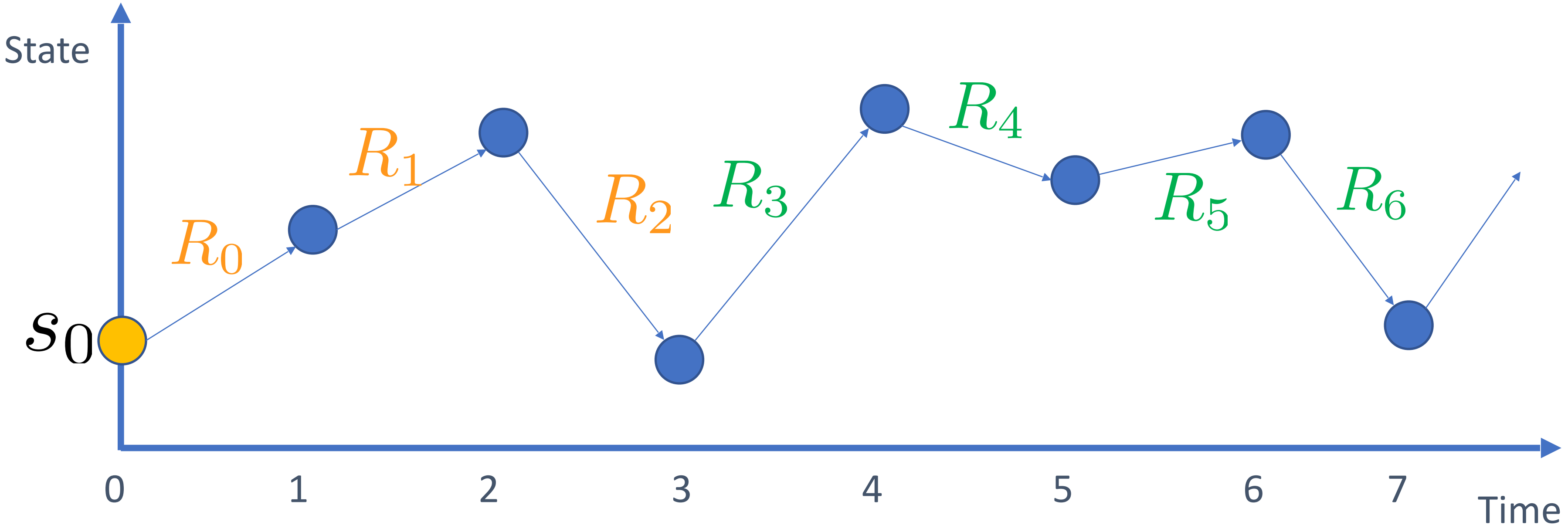
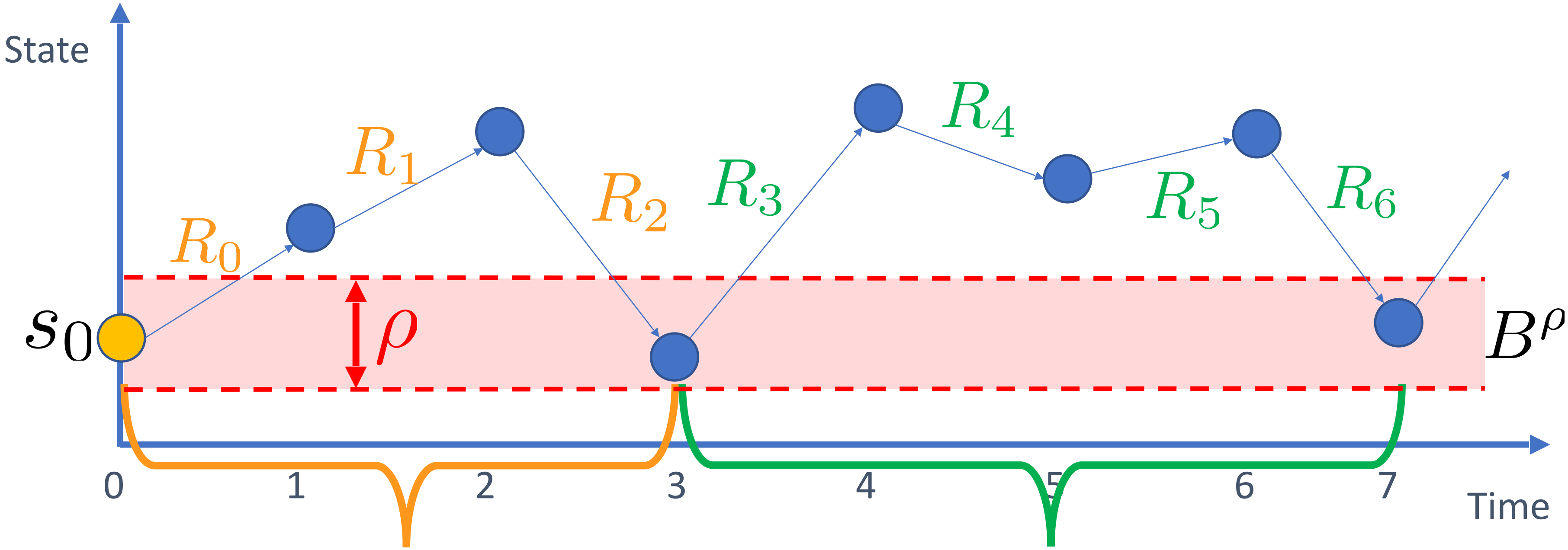


Renewals defined in terms of post-decision states

Approximate RMC



Approximate RMC



$\mathsf{R}^{\rho,(1)} = \sum_{t=0}^{2} \gamma^t R_t, \mathsf{T}^{\rho,(1)} = \sum_{t=0}^{2} \gamma^t$ $\mathsf{R}^{\rho,(2)} = \sum_{t=3}^{6} \gamma^{t-3} R_t, \mathsf{T}^{\rho,(2)} = \sum_{t=3}^{6} \gamma^{t-3}$

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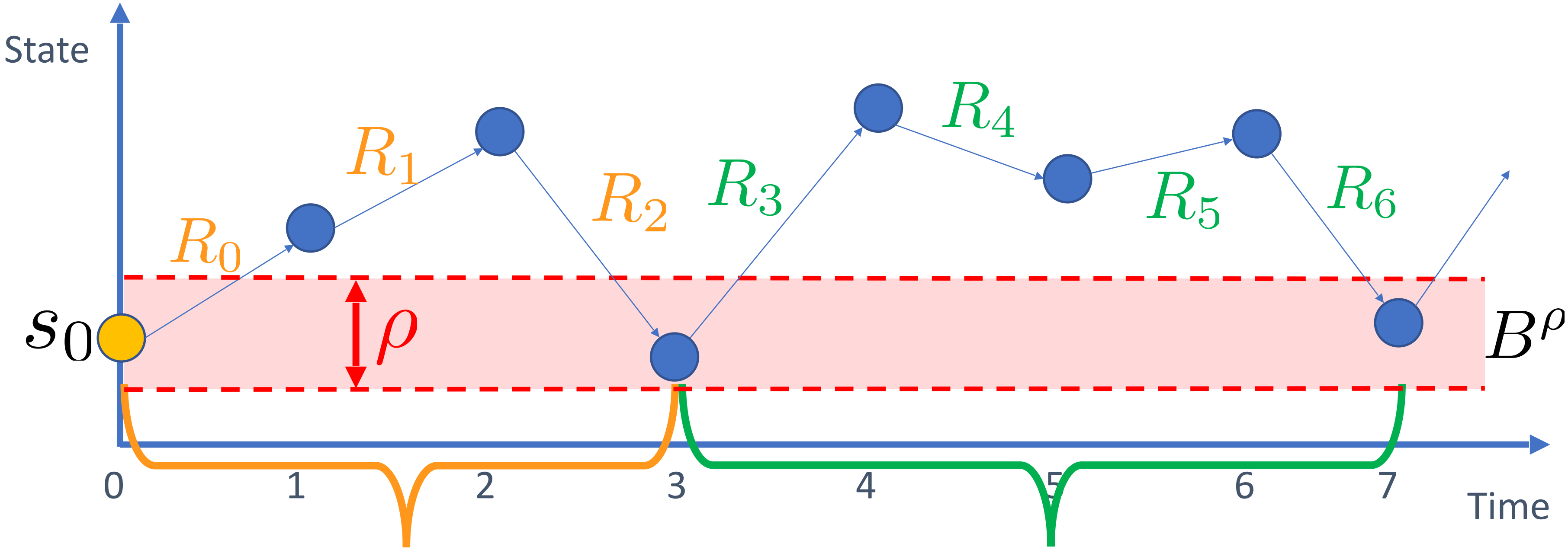

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$\mathsf{R}^{(1)}$, $\mathsf{R}^{(2)}$... are i.i.d and $\mathsf{T}^{(1)}$, $\mathsf{T}^{(2)}$... are i.i.d

$\mathsf{R}^{\rho}_{\theta} = \mathbb{E}[\mathsf{R}^{\rho,(n)}]$ and $\mathsf{T}^{\rho}_{\theta} = \mathbb{E}[\mathsf{T}^{\rho,(n)}]$ ▶ estimated by $\hat{R}^\rho, \hat{T}^\rho$

Error bound

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V_θ is Locally Lipschitz in B^ρ

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$$|V_\theta(s) - V_\theta(s')| \leq L_\theta d_S(s, s')$$

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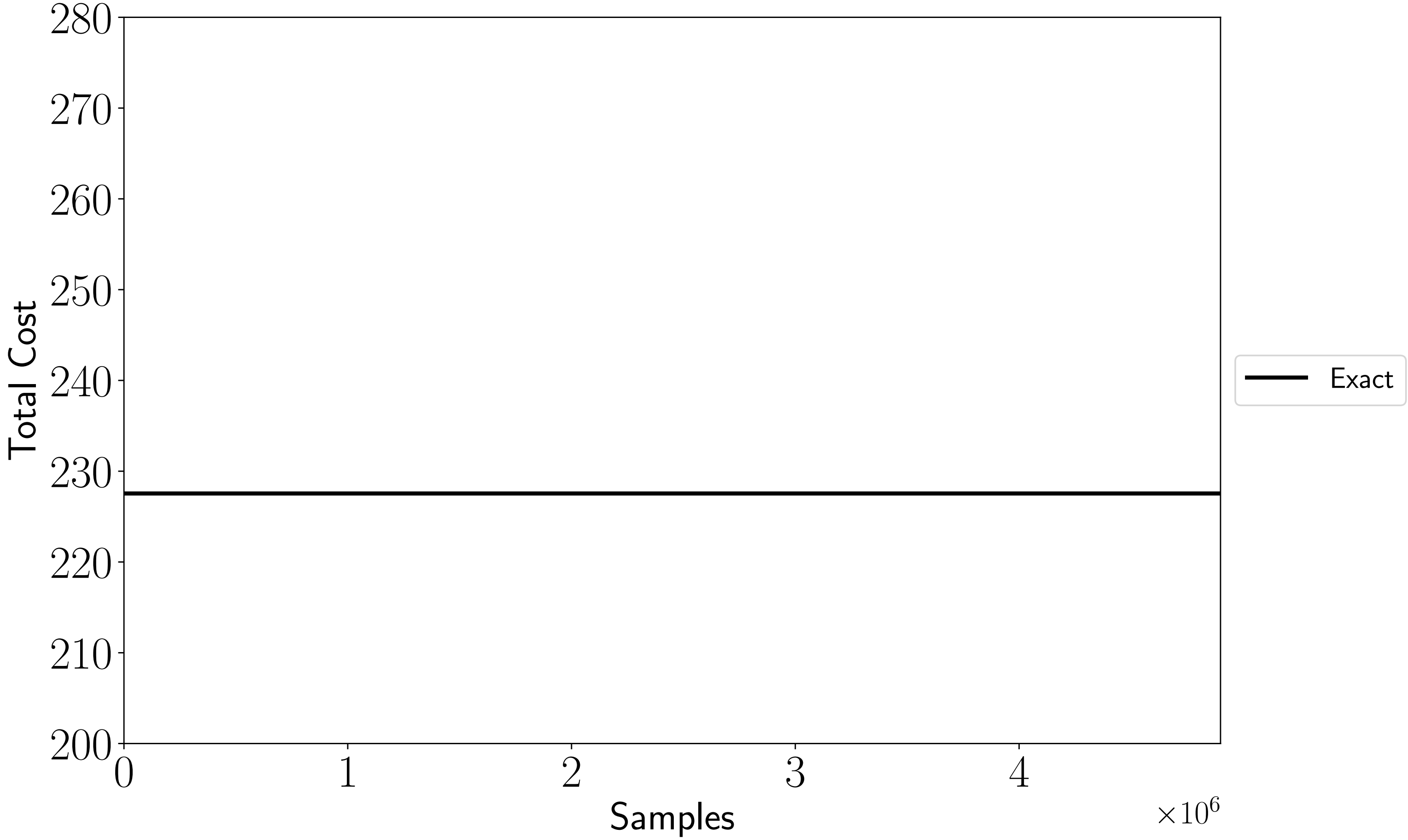
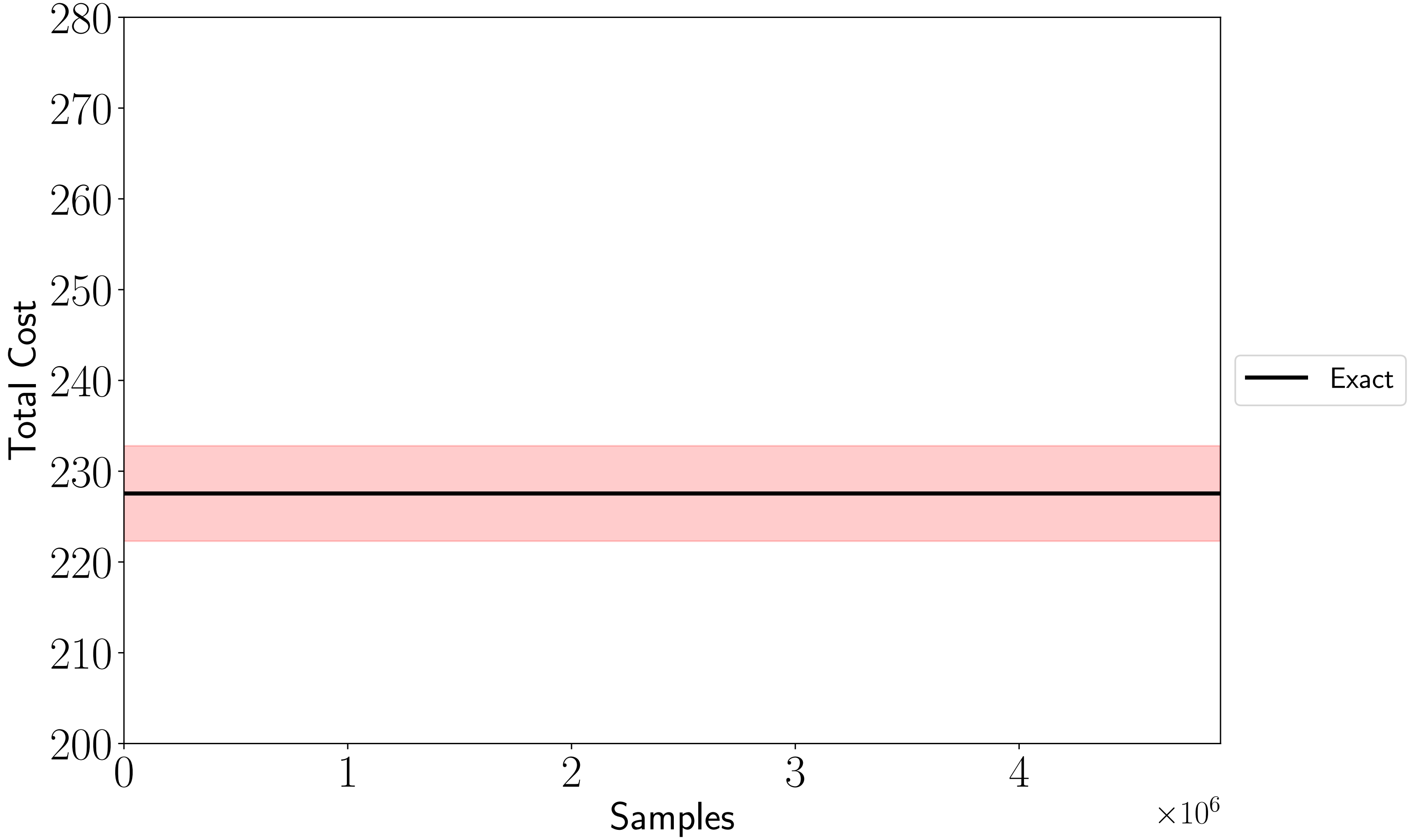
$$J_\theta - J_\theta^\rho \leq \cdots \leq \frac{\gamma}{(1-\gamma)} L_\theta \rho$$

Approximation error bounded by radius of approximation

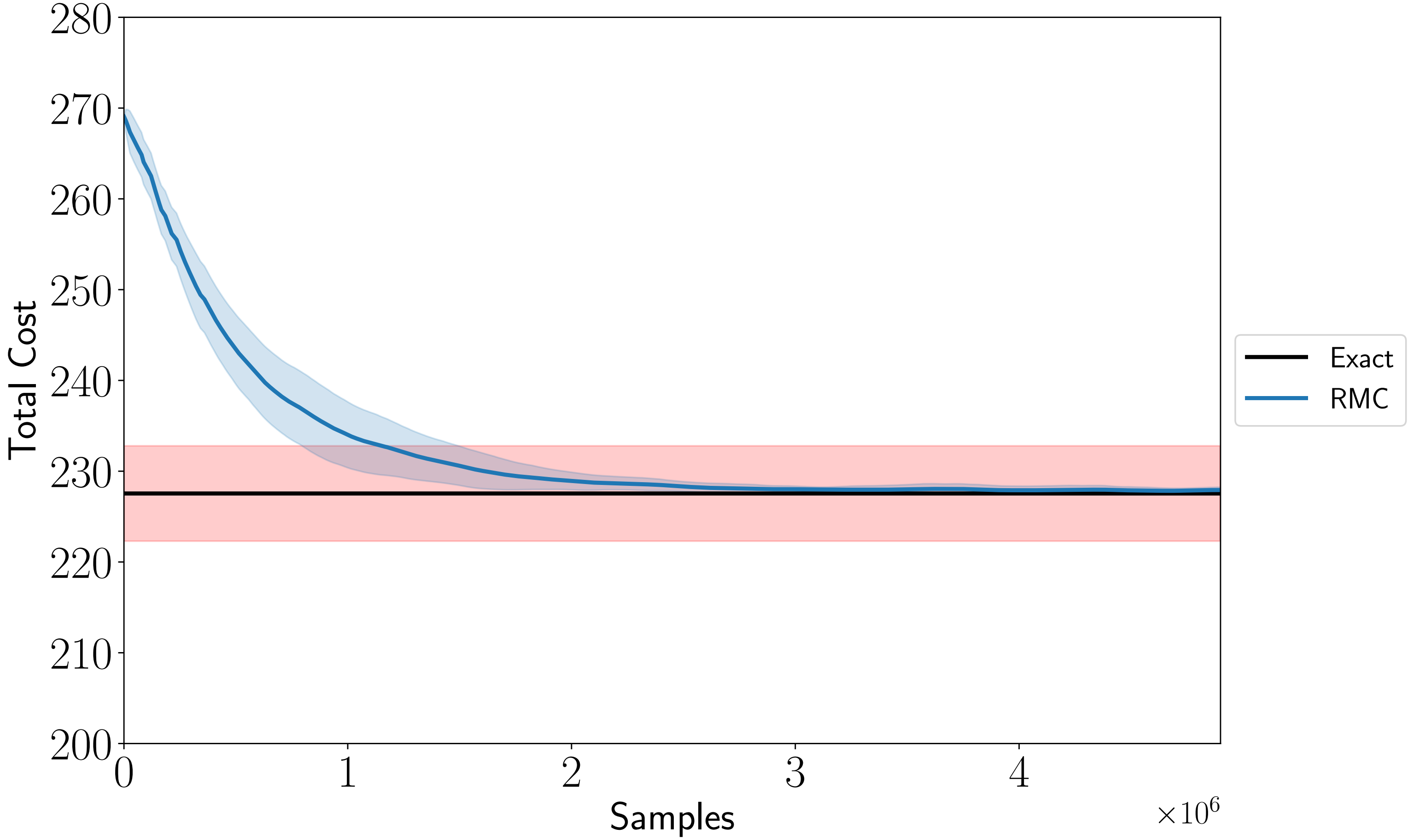
E.g. Inventory management



E.g. Inventory management



E.g. Inventory management



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  - structure of optimal policy is known
  - reset actions are present
- Not so useful in arbitrary high dimensional problems
- In high dimensional problems:
  - RMC can be used as a sub-component of main scheme
  - in the presence of hierarchies, can be used in a level with short renewals

Thank you