

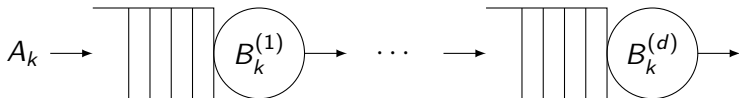
Splitting for a non-Markovian tandem queue

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Introduction



- d queues in tandem
- A_k - inter-arrival time of customer $k + 1$
- $B_k^{(j)}$ - service time of customer k in queue j
- Interested in the probability that the total number of customers reaches N before the system is empty again = p_N
- For large N , this is a rare event when the system is stable.

Introduction - Splitting

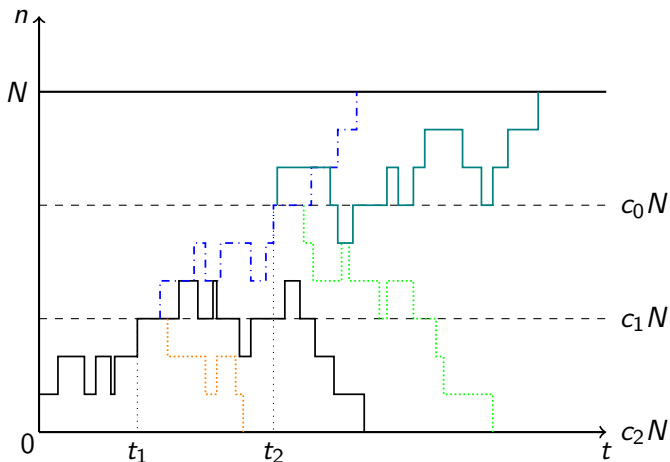


Figure: An example of splitting: a possible realization of particles and splitting thresholds. In this example, $\hat{\rho}_N = \frac{2}{9}$.

Introduction

- We want the estimator of p_N to be *asymptotically efficient*.
- This means that the relative error grows less than exponentially fast in N *and* that the computational effort grows less than exponentially fast in N .

Introduction

For the same model, importance sampling has been shown to be asymptotically efficient under some conditions.

For splitting, similar conditions turn out *not* to be necessary.

State space

Let $\mathbf{Z}_j = (Z_{1,j}, \dots, Z_{d,j}, \bar{Z}_{0,j}, \dots, \bar{Z}_{d,j})$ be the state after j transitions.

- $Z_{i,j}$ is the number of customers at queue i
- $\bar{Z}_{0,j}$ is the residual inter-arrival time
- $\bar{Z}_{i,j}$ is the residual service time at queue i

We start with a busy cycle, i.e. $\mathbf{Z}_0 = (1, 0, \dots, 0, 0, \dots, 0)$

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 $\mathbf{Z}_0 = (1, 0, 0)$, $\mathbf{Z}_{j+1} = \mathbf{Z}_j + \mathbb{V}_Z(\mathbf{Z}_j)$.

$$\mathbb{V}_Z(\mathbf{z}) = \begin{cases} \{(1, -\bar{z}_0 + a, -\bar{z}_0) : a \geq 0\} & \text{if } \bar{z}_0 < \bar{z}_1 \\ \{(-1, -\bar{z}_1, -\bar{z}_1 + \mathbb{1}\{z_1 > 1\}b_1) : b_1 \geq 0\} & \text{if } \bar{z}_0 \geq \bar{z}_1 \\ \{(0, a, b_1) : a, b_1 \geq 0\} & \text{if } \mathbf{z} = \mathbf{Z}_0, \end{cases}$$

where a, b_1 are any realization of the random variables A and $B^{(1)}$ respectively.

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This means that depending on the state it is known which type of transition to take and almost each of them has infinitely many possibilities.

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Let $\mathbf{X}_j = \frac{\mathbf{Z}_j}{N}$ be the *scaled* state of the system.

$$\mathbf{X}_{j+1} = \mathbf{X}_j + \frac{1}{N} \mathbb{V}_X(\mathbf{X}_j),$$

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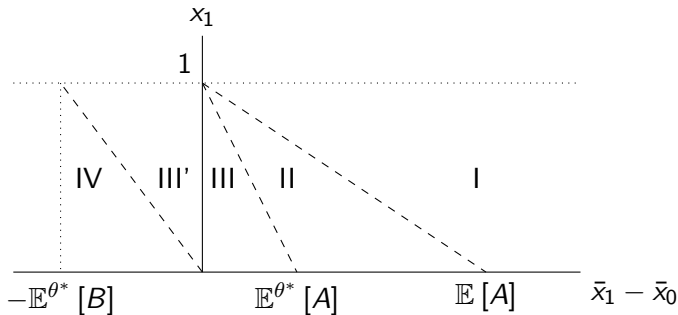
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- The use of the (negative) decay rate $-\gamma(\mathbf{x})$, starting at some general point \mathbf{x} .
- Then $U(\mathbf{x}) = \min\{\gamma(\mathbf{0}), \gamma(\mathbf{0}) - \gamma(\mathbf{x})\} = \gamma(\mathbf{0}) - \gamma(\mathbf{x})$.

The (negative) decay rate

$$\begin{aligned} -\gamma(\mathbf{x}) &= \lim_{N \rightarrow \infty} \frac{1}{N} \log \mathbb{P}(K_N(\mathbf{x}_N) < K_0(\mathbf{x}_N)) \\ &= \begin{cases} 0 & \text{if } \bar{x}_1 - \bar{x}_0 \geq (1 - x_1)\mathbb{E}[A], \\ (1 - x_1)\Lambda_A(-\theta) + (\bar{x}_1 - \bar{x}_0)\theta & \text{if } \bar{x}_1 - \bar{x}_0 = (1 - x_1)\mathbb{E}^\theta[A] \text{ for some } \theta \in (0, \theta^*), \\ (1 - x_1)\Lambda_A(-\theta^*) + (\bar{x}_1 - \bar{x}_0)\theta^* & \text{if } -x_1\mathbb{E}^{\theta^*}[B] \leq \bar{x}_1 - \bar{x}_0 \leq (1 - x_1)\mathbb{E}^{\theta^*}[A], \\ \Lambda_A(-\theta^*) + x_1\Lambda_B(\theta) + (\bar{x}_1 - \bar{x}_0)\theta & \text{if } \bar{x}_1 - \bar{x}_0 = -x_1\mathbb{E}^\theta[B] \text{ for some } \theta > \theta^*, \end{cases} \end{aligned}$$

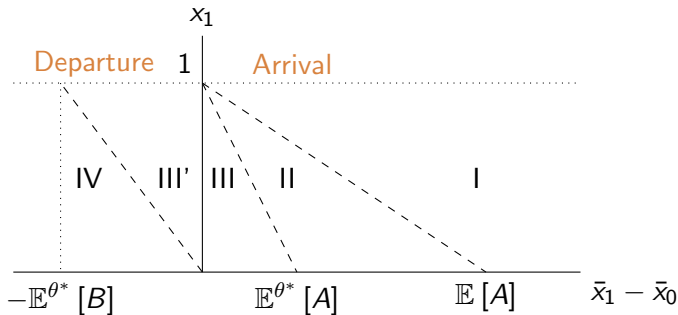
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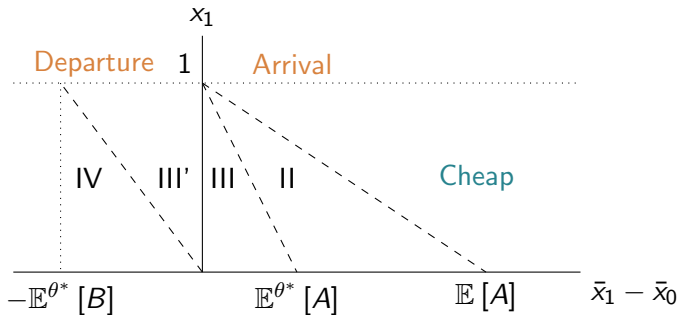
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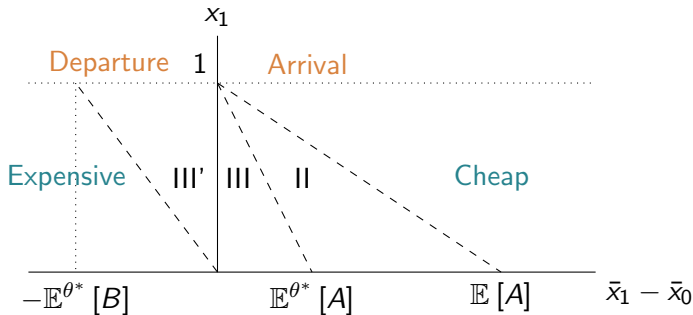
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The (negative) decay rate - sketch of the proof

Sketch of the proof for the upper bound:

$$\mathbb{P}(K_N(\mathbf{x}_N) < K_0(\mathbf{x}_N)) = \mathbb{E}^{\theta, \tilde{\theta}} \left[L^{\theta, \tilde{\theta}} \mid K_N(\mathbf{x}_N) < K_0(\mathbf{x}_N) \right] \mathbb{P}^{\theta, \tilde{\theta}}(K_N(\mathbf{x}_N) < K_0(\mathbf{x}_N))$$

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Sketch of the proof for the lower bound:

- Similar proof as Sadowsky 1991 when $\bar{x}_0 = \bar{x}_1$.
- Lower bound probability by the product of the probability to end up in a state where $\bar{x}_0 = \bar{x}_1$ and the probability to reach the overflow level starting from this new state.

Proof of asymptotic efficiency

Need to show:

$$\limsup_{N \rightarrow \infty} \frac{1}{N} \log \left(w(N) R^{-2J_N} \mathbb{E} [T^2] \right) \leq -2\gamma(\mathbf{0}),$$

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- Use $W(\mathbf{x}) = \min_{j=1, \dots, d} (-(x_1 + \dots + x_j)\gamma(\mathbf{0}) + (\bar{x}_0 - \bar{x}_j)\theta^* + \gamma(\mathbf{0}))$.

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- Proofs for asymptotic efficiency are extendable to d -nodes.

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Thank you for your attention!

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