

Lecture 4: Sample paths and simulation

– A simple, useful check / tool using estimation

Concepts checklist

At the end of this lecture, you should be able to:

- Prove the *sample path behaviour* of a CTMC:
 - the state next visited by a CTMC at the time of a state transition is proportional to the rate of visiting that state, and that it is independent of the time of the jump;
 - the time spent in a state before transitioning to another state is exponentially-distributed with rate equal to the sum of the rates of all possible transitions out of that state;
- Produce *realisations* of a CTMC using a computer.

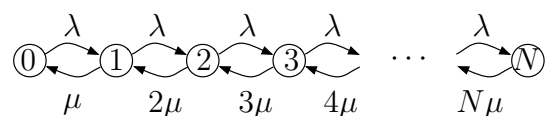
Example 4. N-machine reliability (Repairman problem), or a birth-death process, or an immigration-death process

Let us consider a process $\mathcal{X} = (X(t), t \geq 0)$ which, for example, models the number of N machines currently working, or the number of individuals in a population with a strict population ceiling of size N .

- State space $\mathcal{S} = \{0, 1, 2, \dots, N\}$, where i is the number of machines currently working.

In terms of machines, as for the repairman problem, we have each machine fails at a constant rate, here μ , and the one repairman repairs each machine one at a time at a constant rate, here λ . In a population context, what does λ represent, and what does μ represent?

- State transition diagram



- The transition rates are

$$\begin{aligned}
 & \text{(repairing)} \quad q_{n,n+1} = \lambda \quad \text{for } n = 0, 1, 2, \dots, N-1, \\
 & \text{(breaking down)} \quad q_{n,n-1} = n\mu \quad \text{for } n = 1, \dots, N, \\
 & \quad \quad \quad q_{n,n} = -(n\mu + \lambda) \quad \text{for } n = 0, \dots, N-1, \\
 & \quad \quad \quad q_{N,N} = -N\mu.
 \end{aligned}$$

Thus, the generator Q is

$$Q = \begin{bmatrix} -\lambda & \lambda & \cdots & \cdots & \cdots & \cdots & 0 \\ \mu & -(\mu + \lambda) & \lambda & & & & \vdots \\ 0 & 2\mu & -(2\mu + \lambda) & \lambda & & & \vdots \\ \vdots & & 3\mu & -(3\mu + \lambda) & \lambda & & \vdots \\ \vdots & & & \ddots & \ddots & \ddots & \vdots \\ \vdots & & & & \ddots & \ddots & \lambda \\ 0 & \cdots & \cdots & \cdots & N\mu & & -N\mu \end{bmatrix}.$$

Where does the rate $n\mu$ come from? In the 2-printer example in Lecture 2, we had that the rate of a single failure when both machines are working was twice the rate of a single failure. Extend the calculations there to answer this question! After that, we are back to a process with at most only two events possible in each state; what about a continuous-time Markov chain with an arbitrary number of possible events. What is its behaviour?

Theorem 1. Consider a continuous-time Markov chain \mathcal{X} on state space \mathcal{S} with generator Q . Then, for all $i \in \mathcal{S}$,

$$\Pr(\text{moves to state } j \neq i \mid \text{leaves state } i \text{ at time } t) = \frac{q_{ij}}{-q_{ii}}. \quad (1)$$

Proof. Let T_{ij} , for $i, j \in \mathcal{S}$, denote the time to leave i for j , then $T_{ij} \sim \text{Exp}(q_{ij})$. Define $M = \min_{k \neq i, k \in \mathcal{S}} T_{ik}$. Then,

$$\Pr(\text{moves to state } j \neq i \mid \text{leaves state } i \text{ at time } t)$$

$$\begin{aligned} &= \frac{\Pr(T_{ij} = t \cap \min_{k \neq i, k \neq j, k \in \mathcal{S}} T_{ik} > t)}{\Pr(M \in [t, t + dt))} \\ &= \frac{\Pr(T_{ij} \in [t, t + dt)) \prod_{k \neq i, k \neq j} \Pr(T_{ik} > t)}{\Pr(M \in [t, t + dt))} \quad (\text{independence}) \\ &= \frac{\Pr(T_{ij} \in [t, t + dt)) \Pr(Z > t)}{\Pr(M \in [t, t + dt))} \quad \text{where } Z \sim \exp\left(\sum_{k \neq i, k \neq j, k \in \mathcal{S}} q_{ik}\right) \\ &= \frac{q_{ij}}{q_{ij} + \sum_{k \neq i, k \neq j, k \in \mathcal{S}} q_{ik}} \\ &= \frac{q_{ij}}{\sum_{k \neq i, k \in \mathcal{S}} q_{ik}} \\ &= \frac{q_{ij}}{-q_{ii}}. \end{aligned}$$

□

Theorem 2. Consider a continuous-time Markov chain \mathcal{X} on state space \mathcal{S} with generator Q . Once moving to some state $i \in \mathcal{S}$, the time the system stays in i until it moves out of i is exponentially distributed with rate $-q_{ii}$.

Proof. Note that:

- The time the system stays in i until it moves out of i , is the same as the time until the system moves to some state $j \neq i$.

- The latter time is $\min_{j \neq i, j \in \mathcal{S}} T_{ij} \sim \text{Exp} \left(\sum_{j \neq i, j \in \mathcal{S}} q_{ij} \right)$.

- This implies that $\min_{j \neq i, j \in \mathcal{S}} T_{ij} \sim \text{Exp}(-q_{ii})$, which completes the proof. \square

We have discussed earlier that the transition function is a powerful tool that we'd like to evaluate, but our specification of models, and the *sample-path behaviour* has been in terms of rates of events/transitions. Before starting to explore the relationship between these in more detail, we should revisit the algorithm mentioned in Lecture 1 in light of the two theorems we just proved.

Simulating a continuous-time Markov chain

Pseudo-code for simulation of a CTMC:

1. INPUTS: initial state, $\text{state} \in \mathcal{S}$; total time to run simulation for, T ; and set $t = 0$, $ts = 0$, and $ss = \text{state}$.
2. Calculate the rate of each possible transition from the current state, $q_{\text{state},j}$.
3. Calculate the sum of these rates, q_{state} .
4. While $t < T$ and $q_{\text{state}} > 0$:
 5. Generate an exponential random variable with rate q_{state} , te , and update time $t = t + te$ and store $ts = [ts; t]$.
 6. Choose the state next visited, j , with probability $q_{\text{state},j}/q_{\text{state}}$, and update the current state, $\text{state} = j$ and store $ss = [ss; \text{state}]$.
7. End while

Let's consider Example 1, the problematic printers in maths. I am interested in the probability of both printers not working in 6 months time, given both are currently working. How can I evaluate this probability?

First, I could evaluate from the transition function presented in Lecture 1. The probability both machines are not working in t time units starting with both machines working is

$$(1 + \exp(-t/6) - 2 \exp(-t/12))/25.$$

Hence, the desired probability is $(1 + \exp(-180/6) - 2 \exp(-180/12))/25 \approx 0.04$.

However, I could also estimate this probability by simulation. Figure 4 below shows the estimate of this probability based upon increasing numbers of simulations.

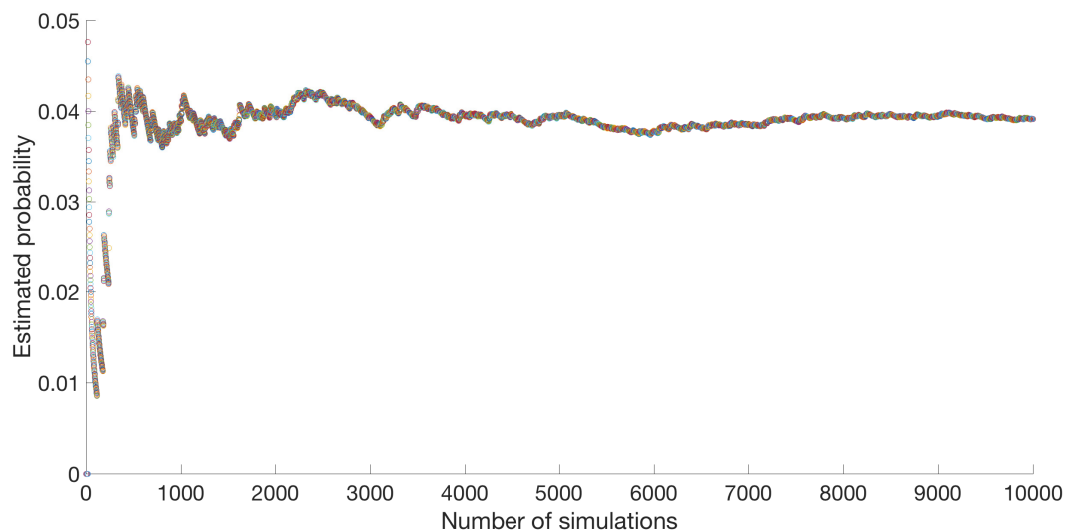


Figure 4: Estimate of the probability of both printers not working after 180 days, given both initially working, versus the number of simulations used.

Do you think 10,000 simulations is sufficient to estimate the probability? How would you assess this?

In the exact expression for the probability, what happens as $t \rightarrow \infty$? What value does this converge to? What is the interpretation of this phenomenon?
