Definition Let {X(t), t>0} be a continuous-time stochastic process with discrete state space DC. The process is a Markov chain (Markov process) if for t>0:

$$\mathbb{P}(\mathsf{x}(\mathsf{s}\mathsf{t}\mathsf{t}) = \mathsf{j}| \mathsf{X}(\mathsf{t}) = \mathsf{i}, \mathsf{X}(\mathsf{t}_n) = \mathsf{x}_n, \mathsf{X}(\mathsf{t}_{n-1}) = \mathsf{x}_{n-1}, \ldots, \mathsf{X}(\mathsf{t}_1) = \mathsf{x}_1) = \\ = \mathbb{P}(\mathsf{X}(\mathsf{s}\mathsf{t}\mathsf{t}) = \mathsf{j}| \mathsf{X}(\mathsf{s}) = \mathsf{i}),$$

for all $0 \leq \pm_1 < \pm_2 < \ldots < \pm_n < s < s + t$ and $i, j, \infty, \ldots, \infty \in \mathcal{X}$ s.t. $\mathbb{P}(X(s) = i, X(t_n) = \infty_n, X(t_{n-1}) = \infty_{n-1}, \ldots, X(t_1) = \infty_n) > 0.$

If we also have that probabilities $\mathbb{P}(X(s+t)=j|X(s)=i)$ are independent of S, then such Markov chain is called time-homogeneous (homogeneous, has stationary | homogeneous transition probabilities).

Example Let $(N(t), t \ge 0)$ be a Paisson process (homogeneous) with rate N. This process has independent and stationary increments. Let us grow that $(N(t), t\ge 0)$ is a Markov chain. Take arbitrary $0 \le t_1 \le t_2 \le \ldots \le t_k \le 5 \le t + 5$, states $n_1 \le \ldots \le n_k \le i \le j$ (so that $\mathbb{P}(N(t_1)=n_1, \ldots, N(t_k)=n_k, N(t_k)=i) \ge 0$) and consider $\mathbb{P}(N(t_1)=t_1, \ldots, N(t_k)=n_k, N(t_k)=n_k, N(t_k)=i) =$ $= \frac{\mathbb{P}(N(t_1)=t_1, \ldots, N(t_k)=n_k, \ldots, N(t_k)=n_k, N(t_k)=i)}{\mathbb{P}(N(t_1)=n_1, \ldots, N(t_k)=n_k, N(t_k)=i)} =$ $= \frac{\mathbb{P}(N(t_1)=n_k, N(t_k)-N(t_1)=n_k, \ldots, N(t_k)-N(t_{k-1})=n_{k-1}, N(t_k)-N(t_k)=i-n_k)}{\mathbb{P}(N(t_1)=n_k, N(t_k)-N(t_k)=n_k, N(t_{k-1})=n_k, N(t_k)-N(t_k)=i-n_k)}$

$$= \frac{\mathbb{P}(N(t_1)=n_1) \cdots \mathbb{P}(N(s_0-N(t_k)=i-n_k) \mathbb{P}(N(s_1+t_1)-N(s_0)=j-i))}{\mathbb{P}(N(t_1)=n_1) \cdots \mathbb{P}(N(s_0-N(t_k)=i-n_k))} =$$

=
$$\mathbb{P}(N(s+t) - N(s) = j - i) = \frac{(\lambda + j)^{j-i}}{(j-i)!} e^{-\lambda + j} - does not depend on s.$$

Similarly,

$$\mathbb{P}(N(t+s) = j \mid N(s) = i) = \frac{(\lambda t)^{j-i}}{(j-i)!} e^{-\lambda t}$$
.

This implies that {N(t), t>03 is a continuous-time Markov chain

Remark In the example above we found

$$P(N(t+s) = j| N(s) = i)$$
for $j \ge i$. Obviously, since $N(t)$, $t \ge 0$, is a
non-decreasing process (by definition, it is a counting
process)

$$P(N(t+s) = j | N(s) = i) = 0,$$
if $i \ge j$. Whence we have that for all $t, s \ge 0$.

$$P(N(t+s) = j | N(s) = i) = \begin{cases} \frac{(N+1)^{j-i}}{(j-i)!}e^{-\lambda t}, & \text{if } j \ge i, \\ 0, & \text{if } j \le i. \end{cases}$$

Consider $f(X_{i+}), t>of$ - homogeneous Markov chain and assume that X_{i+} . $T_{i+} = inff(u>0; X_{i+}) \neq i$

i.e. T_i is the point of time when the process leaves state i. We then set $s_2 \pm 20$ and consider

$$P(\tau_{i} > s+t| \tau_{i} > s) = P(x_{(u)} = i, s \le u \le s+t| x_{(u)} = i, o \le u \le s)$$

$$= P(x_{(u)} = i, s \le u \le s+t| x_{(u)} = i, o \le u \le s)$$

$$= P(x_{(u)} = i, s \le u \le s+t| x_{(s)} = i) \begin{pmatrix} Markov \\ property \end{pmatrix}$$

$$= P(x_{(u)} = i, o \le u \le t| x_{(o)} = i) (homogeneous)$$

$$= P(x_{(u)} = i, o \le u \le t)$$

$$= P(\tau_{i} > t).$$

This implies that T_i is memoryless \Rightarrow [Lecture 14] \Rightarrow \Rightarrow T_i is exponentially distributed.

Assume that X(r) = i and define $T_i := inf\{u>0 : X(r+u) \neq i\},$

i.e T_{i+r} is the moment of time when $(\times(t), t_{i})$ leaves the state i. Then, just as above, $\mathbb{P}(T_{i}>s+t|T_{i}>s) = \mathbb{P}(T_{i}>t) \Rightarrow T_{i}$ is also an exponential r.v.

Definition (alternative definition of a Markov chain)

A continuous-time Markov chain with stationary (homogeneous) transition probabilities and discrete state space \mathcal{X} is a stochastic process such that:

(i) the times spent in different states are independent random variables (because of Markov property);

- (ii) the amount of time spent in state $i \in \mathcal{H}$ is exponentially distributed with some mean \mathcal{N}_i^- (because of Markov property and stationarity);
- (iii) when the process leaves state i, it enters state j with some transition probability $Q_{i,j}$, where $Q_{i,i}=0$, $i \in \mathcal{X}$, $\sum_{j \in \mathcal{X}} Q_{i,j} = s$, $i \in \mathcal{H}$.

(iv) Transitions follow a discrete - time Markov chain.

- Example 6.1 (A shoe Shine Shop) Consider a Markov chain with state space $\mathcal{H} = \{0, 1, 2\}$, where
 - State O: No customer;
 - State 1: Customer sits on chair 1, where their shoes are cleaned and the polish is applied;
 - State 2: Customer sits on chair 2, where the polish is buffed.
 - X(5)=0: in this state, customers arrive in accordance to a Poisson process with rate λ . The time spent in this state is To~ exp(λ). Then the process transits to state 1 with probability $Q_{0,1} = 1$.

- X(t) = 1: The time spent in this state is $T_1 \sim exp(\mu_1)$. Then the process transits to state 2 with probability $Q_{1,2} = s$.
- X(u) = 1: The time spent in this state is $T_2 \sim \exp(\mu_2)$. Then the process transits to state 0 with probability $Q_{2,0} = 1$ and the process repeats the same cycle.

$$Q = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{pmatrix},$$

the built-in discrete time Markov chain is periodic with a period 3. Despite that, the continuous time Markov chain (X(t), t>03 will have a well-defined limiting distribution.

6.3. Birth and Death processes

A Birth and Death Process f(X(t), t>0) has state space $\mathcal{X} = \{0, 1, 2, ...\}$. Assume that X(t) = n > 0. Then the next transition is determined as follows:

- Sample random variables V~ exp(ln), W~ exp(nn)
 independent of each other with respective outcomes
 v and w;
- if V < W, then the process transits to state
 n+1 at time t+v, i.e. X(t+v) = n+1 (this is
 colled a birth);
- if W<V, then the process transits to state n-1 at time t+w, i.e. X(t+w)=n-1(this is called a death).

When X(t) = 0, only births are possible, so in this case we assume that $W = \infty$, which corresponds to the rate ruo being 2000 and $A_{0,1} = 1$.

The transition (either a birth or a death) happens at time $U = \min(V, W) \sim \exp(\lambda_n + \mu_n)$. Moreover the transition probabilities for the built-in discrete-time Markov chain

$$P_{n,n+1} = \mathbb{P}(V < W) = \frac{\lambda_n}{\lambda_n + \mathcal{Y}_n}, \quad P_{n,n-1} = \mathbb{P}(W < V) = \frac{\mathcal{Y}_n}{\lambda_n + \mathcal{Y}_n}.$$

Example 6.2 (Pure birth process) Assume that {XLt}, t>o} is a birth and death process with

$$Ju_n = 0, \quad n \ge 0.$$
$$\lambda_n = \lambda, \quad n \ge 0.$$

Since the death rate is zero, this is a pure birth process with constant birth rate λ . This implies that the time between transitions is exponentially distributed with rate $\lambda > 0 \implies \{X(t), t \ge 0\}$ is a Paisson process with rate λ .

Example 6.4 Assume that {x(t), t >0} is a birth and death process with

$$y_n = y_n, \quad for all \quad n \ge 1.$$

$$\lambda_n = \lambda n + \Theta, \quad for all \quad n \ge 1.$$

That can be interpreted as follows: we have some population of size X(t) at moment t; each member dies with rate m; produces off spring with rate 2 and there is also migration with rate 0.

We assume that
$$X(o) = i$$
 and introduce
 $M(t) = \mathbb{E}[X(t)].$

We want to find M(t) by solving a differential equation. Observe that $M(t+h)=\mathbb{E}[X(t+h)] = \mathbb{E}[\mathbb{E}[X(t+h)] \times (t+h)]$

Since the time between transitions is exponentially distributed, the probability of more then one transition in an interval of langth h is o(h). Hence we have: $IP(x(t+h) = x(t)+1| x(t)) = [x(t)x+0] \cdot h + o(h)$ IP(x(t+h) = x(t)-1| x(t)) = x(t)Mh + o(h)P(x(t+h) = x(t)-1| x(t)) = x(t)Mh + o(h)

From this, it follows that

$$E[X(t+R) | X(t)] = (X(t) + 1) (X(t) + 0) \cdot R + (X(t) - 1) X(t) \mu R + (X(t) + 0(R)) = X(t) + 0R - X(t) \mu R + X(t) + 0(R) + (X(t) + 0R - (X(t) + 0R + 0(R)),$$

i.e.

$$M(t+k) - M(t) = (\lambda - m)M(t)k + \Theta k + O(k)$$

$$M'(t) = (\lambda - m)M(t) + \Theta.$$

This is a standard linear ODE that can be easily solved: if $\lambda \pm M$, then $M(\pm) = -\frac{\partial}{\lambda - Ju} + Ce^{(\lambda - Ju)\pm}$, where C is some constant. In order to compute it, we note that $M(o) = i \implies C = i \pm \frac{\partial}{\lambda - Ju}$, i.e.

$$M(t) = -\frac{\theta}{\lambda_{-m}} + (i + \frac{\theta}{\lambda_{-m}}) e^{(\lambda_{-m})t} = \frac{\theta}{\lambda_{-m}} (e^{(\lambda_{-m})t}) + i e^{(\lambda_{-m})t}.$$

If $\lambda = \mu$, the differential equation becomes

$$M'(t) = 0 \implies M(t) = 0t + i$$