Stochastic Processes

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Definition 1 (Stochastic Process). *Let $\mathcal{T} \subseteq \mathbb{R}$. For any $t \in \mathcal{T}$, let X_t (or $X(t)$) be a random variable with support D. Then $X := \{X_t : t \in \mathcal{T}\}$ is called a* stochastic process *on state-space D and time $\mathcal{T}$. Usually, $\mathcal{T}$ is either $\mathbb{Z}_{\geq 0}$ (discrete-time) or $\mathbb{R}_{\geq 0}$ (continuous-time).*

1 Discrete-Time Markov Chains

Definition 2 (Markov Chain). *Let $X := [X_0, X_1, \ldots]$ be a stochastic process on state-space D and time $\mathbb{Z}_{\geq 0}$. X is called a discrete-time markov chain if $\Pr(X_{t+1} = d \mid X_t, X_{t-1}, \ldots, X_0) = \Pr(X_{t+1} = d \mid X_t)$. If $\Pr(X_{t+1} = v \mid X_t = u) = \Pr(X_1 = v \mid X_0 = u)$ for all t, u, v, then X is called* time-homogeneous.

Definition 3 (Transition function). *Let X be a markov chain on state space D. Define $P^{(k)} : D \times D \mapsto [0, 1]$ as $P^{(k)}(i, j) = \Pr(X_k = j \mid X_0 = i)$. Then $P^{(k)}$ is called the k-step transition function of X. For $k = 1$, we simply write P instead of $P^{(1)}$. For a finite state space, we can represent P as a matrix.*

Lemma 1 (Chapman-Kolmogorov Equation). $P^{(m+n)}(i, j) = \sum_k P^{(m)}(i, k)P^{(n)}(k, j)$.

1.1 Classification of States, Recurrence, Limiting Probabilities

Definition 4. *Let $f_{i,j} := \Pr\left(\bigvee_{t\geq 1}(X_t = j) \;\middle|\; X_0 = i\right)$. Then $f_{i,j}$ is called the* eventual transition probability *from i to j. If $i = j$, then we write $f_{i,i}$ as f_i, and call it the* recurrence probability *of state i.*

Definition 5. *For a state i, let N_i be the random variable that counts the number of times we are in state i, i.e., $N_i := \sum_{t=0}^{\infty} \mathbf{1}(X_t = i)$. Then N_i is called the visit-count of i.*

Definition 6. *A state i of a markov chain is* recurrent *iff (the following are equivalent):*

- *the recurrence probability (f_i) of i is 1.*
- *i is visited infinitely often, i.e., $\Pr(N_i = \infty \mid X_0 = i) = 1$.*
- *i is visited infinitely often in expectation, i.e., $\mathrm{E}(N_i \mid X_0 = i) = \infty$.*

A non-recurrent state is called a transient *state.*

Lemma 2. $\Pr(N_i = k \mid X_0 = i) = f_i^{k-1}(1 - f_i)$.

Lemma 3. $\mathrm{E}(N_i \mid X_0 = i) = 1/(1 - f_i) = \sum_{t=0}^{\infty} P^{(t)}(i, i)$.

Definition 7. *State j is* accessible *from state i if $P^{(t)}(i,j) > 0$ for some t. States i and j* communicate *(denoted as $i \leftrightarrow j$) if i and j are both accessible from each other.*

Lemma 4. *Accessibility is reflexive and transitive. Communication is an equivalence relation. The equivalence classes of communicability are called* state classes*. A markov chain is* irreducible *if it has just one state class.*

Definition 8. *Let T_i be the time when a markov chain moves to state i, i.e., $T_i := \min_{t \geq 1}(X_t = i)$. When conditioned on $X_0 = i$, T_i is called the* recurrence time *of i. State i is called* positive recurrent *if $\mathrm{E}(T_i \mid X_0 = i)$ is finite, otherwise it is* null recurrent*.*

Lemma 5. *Recurrence and positive recurrence are class properties, i.e., they are same for all states in a class.*

Lemma 6. *In a finite-state markov chain, all recurrent states are positive recurrent, and there is at least one recurrent state.*

Definition 9 (Periodicity)**.** *For a state i, its period is defined as $\gcd(\{t : \Pr(T_i = t \mid X_0 = i) > 0\})$. A state is* aperiodic *if its period is 1.*

Lemma 7. *Periodicity is a class property.*

Definition 10 (Ergodicity)**.** *A state is ergodic if it is positive recurrent and aperiodic. A markov chain is ergodic if all its states are ergodic.*

Lemma 8. *In an irreducible ergodic markov chain, for every state j, $\lim_{t\to\infty} P^{(t)}(j,i) = \pi_i$ for a unique real number π_i. π_i is called the* limiting probability *of state i. Furthermore, π_i is the unique solution to this system of equations: $\pi_i = \sum_j \pi_j P(j,i)$ for all i ($\pi = P^T \pi$ in matrix form) and $\sum_i \pi_i = 1$.*

Lemma 9. *In an irreducible ergodic markov chain, $\mathrm{E}(T_i \mid X_0 = i) = 1/\pi_i$.*

Corollary 9.1. *A state i is null recurrent iff $\pi_i = 0$.*

Theorem 10. *If the transition function of markov chain X is doubly-stochastic (i.e., each row and each column sums to 1), then the limiting probability of each state is $1/n$, where n is the number of states.*

1.2 Time-Reversibility

Definition 11. *For an irreducible ergodic markov chain X with limiting probabilities π. Let Y be a markov chain whose transition function is $Q(i,j) = P(j,i)(\pi_j/\pi_i)$. Then Y is called the* time-reversed *markov chain of X. X is called* time-reversible *if $Q = P$.*

Theorem 11. *Let X be a time-reversible markov chain with limiting probabilities π. Then π is the unique solution to this system of equations: $x_j P(j,i) = x_i P(i,j)$ for all states i and j, and $\sum_i x_i = 1$.*

Theorem 12. *If the transition function of markov chain X is symmetric, then X is time-reversible.*

2 Counting Process

Definition 12 (Counting Process). *Let N be a stochastic process on state space $\mathbb{Z}_{\geq 0}$ and time $\mathbb{R}_{\geq 0}$. Then N is called a counting process if $N(0) = 0$ and $N(t)$ is monotone in t, i.e., $t_1 < t_2 \implies N(t_1) \leq N(t_2)$.*

Definition 13 (Independent increments). *A counting process N has* independent increments *iff for any two disjoint intervals $(u_1, v_1]$ and $(u_2, v_2]$ in $\mathbb{R}_{\geq 0}$, the random variables $N(v_1) - N(u_1)$ and $N(v_2) - N(u_2)$ are independent.*

Definition 14 (Stationary increments). *A counting process N has* stationary increments *iff for any $u \leq v$, the random variables $N(v) - N(u)$ and $N(v - u)$ have the same distribution.*

Definition 15 (Arrival and interarrival times). *For a counting process N, for $i \in \mathbb{Z}_{\geq 0}$, define the i^{th} arrival time $S_i := \min_{t \geq 0}(N(t) = i)$. For $i \in \mathbb{Z}_{\geq 1}$, define the i^{th} interarrival time $T_i := S_i - S_{i-1}$.*

Lemma 13. *For a counting process N with arrival times S, $N(t) \geq n \iff S_n \leq t$.*

3 Poisson Process

Definition 16 (Poisson process). *A counting process N is a Poisson process with rate function $\lambda : \mathbb{R}_{\geq 0} \mapsto \mathbb{R}_{\geq 0}$ if N has independent increments and $N(t_2) - N(t_1) \sim \mathrm{Poisson}(\mu)$, where $\mu := \int_{t_1}^{t_2} \lambda(t)dt$. N is called* homogeneous *if $\lambda(t) = \lambda(0)$ for all t, otherwise it is called* inhomogeneous. *For a homogeneous process, we denote $\lambda(0)$ by λ.*

Lemma 14. *A Poisson process N is homogeneous iff it has stationary increments.*

Theorem 15 (Alternative definition of Poisson process). *A counting process N is a Poisson process with continuous rate function λ iff N has independent and stationary increments and $\Pr(N(t+h) - N(t) = 1) = \lambda(t)h + o(h)$ and $\Pr(N(t+h) - N(t) \geq 2) = o(h)$.*

Proof sketch for homogeneous. Let $g(u, t) := \mathrm{MGF}_u(N(t)) = \mathrm{E}(e^{uN(t)})$. Show $g(u, t) = 1 + \lambda t(e^u - 1) + o(t)$ straightforwardly. Use calculus to show that $g(u, t) = \exp(e^{\lambda t}(e^u - 1))$ (find derivative w.r.t t by computing $\lim_{h \to 0}(g(u, t+h) - g(u, t))/h$; this gets rid of $o(h)$). Conclude that $N(t) \sim \mathrm{Poisson}(\lambda t)$ since $g(u, t)$ is MGF of $\mathrm{Poisson}(\lambda t)$. □

Lemma 16. *For a homogeneous Poisson process N,*

$$\Pr(N(s) = a \mid N(s + t) = a + b) = \binom{a+b}{a} \left(\frac{s}{s+t}\right)^a \left(\frac{t}{s+t}\right)^b.$$

Theorem 17. *Let N be a counting process. Then N is a homogeneous Poisson process with rate λ iff all interarrival times are independent and distributed* $\mathrm{Expo}(\lambda)$.

Theorem 18 (Decomposition theorem 1). *Let K be a finite set, and let $\{N_i : i \in K\}$ be independent Poisson processes, where N_i has rate function λ_i. Let $N := \sum_{i \in K} N_i$. Then N is a Poisson process with rate function $\sum_{i \in K} \lambda_i$.*

Theorem 19 (Decomposition theorem 2)**.** *Let N be a Poisson process with rate function λ. Let K be a finite set (called set of labels). Suppose the j^{th} event receives label $L_j \in K$, where $\Pr(L_j = i) = p_i(S_j)$ for some function $p_i : \mathbb{R}_{\geq 0} \mapsto \mathbb{R}_{\geq 0}$, and $\{N, L_1, L_2, \dots\}$ are independent. For $i \in K$, let $N_i(t)$ be the number of events having label i, i.e, $N_i(t) = \sum_{j=1}^{N(t)} \mathbf{1}(L_j = i)$. Then N_i is a Poisson process with rate function $p_i\lambda$. Furthermore, all N_i are independent and if all p_i are constant, then $N_i(t) \mid N(t) \sim \operatorname{Binom}(N(t), p_i)$.*

Lemma 20. *Let $N^{(1)}$ and $N^{(2)}$ be independent homogeneous Poisson processes with rates λ_1 and λ_2. Then*

$$\Pr(S_n^{(1)} < S_m^{(2)}) = \sum_{i=n}^{n+m-1} \binom{n+m-1}{i} \frac{\lambda_1^i \lambda_2^{n+m-1-i}}{(\lambda_1 + \lambda_2)^{n+m-1}}.$$

Proof sketch. Model as a continuous markov chain with state space (n_1, n_2), where n_i is the number of events of $N^{(i)}$ that have occurred. □

Theorem 21 (arrival times distributed as order statistics)**.** *Let $X = [X_1, X_2, \dots, X_n]$ be IID uniform variables over $[0, t]$. Let $U = \operatorname{sorted}(X)$. Let $S = [S_1, S_2, \dots, S_n]$. Then conditioned on $N(t) = n$, the distribution of S and U are identical.*

4 Continuous-Time Markov Chain

Definition 17 (CTMC)**.** *Let $X := \{X(t) : t \in \mathbb{R}_{\geq 0}\}$ be a stochastic process on discrete state-space D. X is called a continuous-time markov chain (CTMC) if $\Pr(X(t+s) = d \mid \{X(u) : 0 \leq u \leq s\}) = \Pr(X(t+s) = d \mid X(s))$ for all $s, t \in \mathbb{R}_{\geq 0}$. If $\Pr(X(t+s) = v \mid X(s) = u) = \Pr(X(t) = v \mid X(0) = u)$ for all u, v, s, t, then X is called* time-homogeneous *(TH) or* stationary.

Theorem 22 (Equiv defn of TH CTMC)**.** *Let $X := \{X(t) : t \in \mathbb{R}_{\geq 0}\}$ be a stochastic process on discrete state-space D. Let $Y(t) := \{X(u) : 0 \leq u < t\}$. Let $T_i^{(s)} := \min_{t \geq 0}(X(t+s) \neq i)$. Let $P_{i,j}^{(s)} := \Pr(X(s + T_i^{(s)}) = j \mid X(s) = i, Y(s))$. X is TH CTMC iff $(T_i^{(s)} \mid X(s) = i, Y(s)) \sim \operatorname{Expo}(\nu_i)$, where ν_i is a constant that doesn't depend on s or $Y(s)$, and $\Pr_{i,j}^{(s)}$ is a constant that doesn't depend on s or $Y(s)$.*

Since $T_i^{(s)}$ and $P_{i,j}^{(s)}$ don't depend on s, we simply write T_i and $P_{i,j}$. T_i is called the transition time *out of state i, ν_i is called the* transition rate *out of state i, and $P_{i,j}$ is the* probability of transitioning *from state i to state j.*

Let $q_{i,j} := \nu_i P_{i,j}$. Then $\nu_i = \sum_j q_{i,j}$.

Theorem 23 (Chapman-Kolmogorov DiffEqs)**.** *For a TH CTMC X, let $P_{i,j}(t) := \Pr(X(t) = j \mid X(0) = i)$. Then*

- *Backward DiffEqs:* $\displaystyle \frac{dP_{i,j}(t)}{dt} = \sum_{k \neq i} q_{i,k} P_{k,j}(t) - \nu_i P_{i,j}(t).$
- *Forward DiffEqs:* $\displaystyle \frac{dP_{i,j}(t)}{dt} = \sum_{k \neq j} P_{i,k}(t) q_{k,j} - P_{i,j}(t) \nu_j.$

Lemma 24. *Let X be a TH CTMC.*

$$\lim_{h\to 0}\frac{1-P_{i,i}(h)}{h}=\nu_i \quad \forall i \qquad\qquad \lim_{h\to 0}\frac{P_{i,j}(h)}{h}=q_{i,j} \quad \forall i\neq j$$

Lemma 25 (Limiting probability)**.** *In an irreducible positive-recurrent TH CTMC X, for every state j, $\lim_{t\to\infty} P_{j,i}(t) = P_i$ for a unique real number P_i. P_i is called the* limiting probability *of state i. Furthermore, P_i is the unique solution to CK forward equations and $\sum_i P_i = 1$.*

Lemma 26 (Limiting probability of embedded chain)**.** *Let X be an irreducible positive-recurrent TH CTMC. Let Y be the sequence of states visited by X. Then Y is a discrete MC. Let P and π be the limiting probabilities of X and Y, respectively. Then $P_i = (\pi_i/\nu_i)/(\sum_j \pi_j/\nu_j)$ and $\pi_i = P_i\nu_i/(\sum_j P_j\nu_j)$.*

Definition 18. *A CTMC is time-reversible iff the corresponding embedded discrete-time MC is time-reversible.*

4.1 Birth and Death Process

Definition 19. *A birth-and-death (B&D) process is a TH CTMC X on state space $\mathbb{Z}_{\geq 0}$ where $q_{i,j}=0$ if $j\notin\{i-1,i+1\}$. Let $\lambda_i := q_{i,i+1}$ for $i\geq 0$, $\mu_i := q_{i,i-1}$ for $i \geq 1$, $\mu_0 := 0$.*

$X(t)$ is called the population *at time t, λ_i is called the* birth rate *at population i, and μ_i is called the* death rate *at population i.*

Lemma 27. *Let X be a B&D process where $X(0)=n$. Let T_n be the time to reach state $n+1$, i.e., $T_n := \min_{t\geq 0}(X(t)=n+1)$. Then*

$$\mathrm{E}(T_n) = \frac{1}{\lambda_n}+\frac{\mu_n}{\lambda_n}\mathrm{E}(T_{n-1}) = \frac{1}{\lambda_n}\sum_{i=0}^{n}\prod_{j=1}^{i}\frac{\mu_{n-j+1}}{\lambda_{n-j}}.$$

$$\mathrm{Var}(T_n) = \frac{1}{\lambda_n(\lambda_n+\mu_n)^2}+\frac{\mu_n}{\lambda_n}\mathrm{Var}(T_{i-1})+\frac{\mu_n}{\lambda_n+\mu_n}(\mathrm{E}(T_{n-1})+\mathrm{E}(T_n))^2$$

Proof sketch. Let $I_i = \mathbf{1}$(next transition goes to state $i+1$). Let X_i be the transition time out of state i. Then $I_i \sim \mathrm{Bernouilli}(\lambda_i/(\mu_i+\lambda_i))$, $X_i \sim \mathrm{Expo}(\lambda_i+\mu_i)$, and

$$\begin{aligned}\mathrm{E}(T_i \mid I_i) &= \mathrm{E}(X_i) + (1-I_i)(\mathrm{E}(T_{i-1})+\mathrm{E}(T_i))),\\ \mathrm{Var}(T_i \mid I_i) &= \mathrm{Var}(X_i) + (1-I_i)(\mathrm{Var}(T_{i-1})+\mathrm{Var}(T_i)).\end{aligned}$$

□

CKBE for B&D:

$$\frac{dP_{i,j}(t)}{dt} = \mu_i P_{i-1,j}(t) + \lambda_i P_{i+1,j}(t) - (\lambda_i+\mu_i)P_{i,j}(t).$$

CKFE for B&D:

$$\frac{dP_{i,j}(t)}{dt} = \mu_{j+1} P_{i,j+1}(t) + \lambda_{j-1} P_{i,j-1}(t) - (\lambda_j+\mu_j)P_{i,j}(t).$$

Theorem 28 (Limiting Probabilities)**.** *Let X be an irreducible B&D process on state space $D\subseteq \mathbb{Z}_{\geq 0}$ where $0\in D$. For $n\in D$, let $\alpha_n := \prod_{i=1}^{n}\frac{\lambda_{i-1}}{\mu_i}$. If $\sum_{i\in D}\alpha_i$ is finite, then $P_i = \alpha_i P_0$, and $P_0 = 1/\sum_{i\in D}\alpha_i$.*

Proof sketch. Use Lemma 25 and add adjacent equations. □