

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 $X := [X_0, X_1, \dots]$ be a stochastic process on state-space D and time $\mathbb{Z}_{\geq 0}$. X is called a discrete-time markov chain if $\Pr(X_{t+1} = d \mid X_t, X_{t-1}, \dots, X_0) = \Pr(X_{t+1} = d \mid X_t)$. 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 $f_{i,j} := \Pr\left(\bigvee_{t \geq 1} (X_t = j) \mid X_0 = i\right)$. 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., $E(N_i \mid X_0 = i) = \infty$.

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

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 $E(T_i | X_0 = i)$ 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 $\gcd(\{t : \Pr(T_i = t | X_0 = i) > 0\})$. 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 , $\lim_{t \rightarrow \infty} P^{(t)}(j, i) = \pi_i$ 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, $E(T_i | X_0 = i) = 1/\pi_i$.

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 , $N(t) \geq n \iff S_n \leq t$.*

Definition 16 (Stopping time). *Let $X = [X_1, X_2, \dots]$ be a sequence of random variables. The random variable N is called a stopping time for X if for all $n \geq 0$, (the following two definitions are equivalent):*

- $N = n$ is independent of X_{n+1}, X_{n+2}, \dots
- $N \leq n$ is independent of X_{n+1}, X_{n+2}, \dots

Theorem 14 (Wald's identity). *Let $X = [X_1, X_2, \dots]$ be a sequence of random variables where $E(X_i) = \mu$ for all i . Let N be a stopping time for X . Then*

$$E\left(\sum_{i=1}^N X_i\right) = \mu E(N).$$

Proof sketch. For all i , $N \geq i$ is independent of X_i , and $\sum_{i=1}^N X_i = \sum_{i=1}^{\infty} X_i \mathbf{1}(N \geq i)$. □

3 Poisson Process

Definition 17 (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 $N(t_2) - N(t_1) \sim \text{Poisson}(\mu)$, 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 15. *A Poisson process N is homogeneous iff it has stationary increments.*

Theorem 16 (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 $g(u, t) := \text{MGF}_u(N(t)) = \mathbb{E}(e^{uN(t)})$. 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 $\lim_{h \rightarrow 0} (g(u, t+h) - g(u, t))/h$; this gets rid of $o(h)$). Conclude that $N(t) \sim \text{Poisson}(\lambda t)$ since $g(u, t)$ is MGF of $\text{Poisson}(\lambda t)$. \square

Lemma 17. *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 18. *Let N be a counting process. Then N is a homogeneous Poisson process with rate λ iff all interarrival times are independent and distributed $\text{Expo}(\lambda)$.*

Theorem 19 (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 20 (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 $N_i(t) \mid N(t) \sim \text{Binom}(N(t), p_i)$.*

Lemma 21. *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. \square

Theorem 22 (arrival times distributed as order statistics). *Let $X = [X_1, X_2, \dots, X_n]$ be IID uniform variables over $[0, t]$. Let $U = \text{sorted}(X)$. 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 18 (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 23 (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 $(T_i^{(s)} \mid X(s) = i, Y(s)) \sim \text{Expo}(\nu_i)$, 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 24 (Chapman-Kolmogorov DiffEqs). *For a TH CTMC X , let $P_{i,j}(t) := \Pr(X(t) = j \mid X(0) = i)$. Then*

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

Lemma 25. *Let X be a TH CTMC.*

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

Lemma 26 (Limiting probability). *In an irreducible positive-recurrent TH CTMC X , for every state j , $\lim_{t \rightarrow \infty} P_{j,i}(t) = P_i$ 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 27 (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 19. *A CTMC is time-reversible iff the corresponding embedded discrete-time MC is time-reversible.*

4.1 Birth and Death Process

Definition 20. *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 28. *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*

$$\begin{aligned} \mathbb{E}(T_n) &= \frac{1}{\lambda_n} + \frac{\mu_n}{\lambda_n} \mathbb{E}(T_{n-1}) = \frac{1}{\lambda_n} \sum_{i=0}^n \prod_{j=1}^i \frac{\mu_{n-j+1}}{\lambda_{n-j}}. \\ \text{Var}(T_n) &= \frac{1}{\lambda_n(\lambda_n + \mu_n)^2} + \frac{\mu_n}{\lambda_n} \text{Var}(T_{n-1}) + \frac{\mu_n}{\lambda_n + \mu_n} (\mathbb{E}(T_{n-1}) + \mathbb{E}(T_n))^2 \end{aligned}$$

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

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

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 29 (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 26 and add adjacent equations. \square

5 Renewal Theory

Definition 21. *Let $[X_1, X_2, \dots]$ be a sequence of IID non-negative randvars, called interarrival times, such that $\Pr(X_1 = 0) < 1$ and $\Pr(X_1 = \infty) = 0$. Let $S_n := \sum_{i=1}^n X_i$ (called arrival times). Let $N(t) := \max_n (S_n \leq t)$. Then N is called a renewal process (note that it is a counting process).*

We let F and f denote the CDF and PDF/PMF of X_1 , respectively. We let $F^{(n)}$ and $f^{(n)}$ denote the CDF and PDF/PMF of S_n , respectively.

Let R_i be the reward obtained at time X_i for all $i \geq 1$, where all R_i are independent. Let $R(t) := \sum_{i=1}^{N(t)} R_i$. Then R is called a renewal reward process.

Lemma 30. *For all $t \geq 0$, $\Pr(N(t) = \infty) = 0$. $\Pr(\lim_{t \rightarrow \infty} N(t) = \infty) = 1$.*

Proof. Let $\mu := E(X_1)$. $\mu > 0$ since $\Pr(X_n = 0) < 1$.

$$\Pr\left(\lim_{t \rightarrow \infty} \frac{S_n}{n} = \mu\right) = 1. \quad (\text{strong law of large numbers})$$

$$N(t) = \infty \iff (\forall n, S_n \leq t) \implies \lim_{t \rightarrow \infty} \frac{S_n}{n} = 0.$$

$\Pr(N(\infty) = \infty) = 1$ since $\Pr(X_1 = \infty) = 0$. \square

Definition 22. *For a renewal process N , let $m_N(t) := E(N(t))$. Then m_N is called the mean-value function of N . (If N is clear from context, we will write m instead of m_N .)*

Lemma 31. $m(t) = \sum_{n=1}^{\infty} \Pr(S_n \leq t) = \sum_{n=1}^{\infty} F^{(n)}(t)$.

Theorem 32. m uniquely characterizes F .

Lemma 33. $m(t)$ is finite for all t .

Theorem 34 (Renewal equation). *When interarrival times are continuous randvars,*

$$m(t) = F(t) + \int_0^t m(t-x)f(x)dx.$$

Proof sketch. Let $N'(t) := \max_n (\sum_{i=2}^{n+1} X_i \leq t)$. Then N and N' are identically distributed and

$$N(t) = \begin{cases} 1 + N'(t - X_1) & \text{if } X_1 \leq t \\ 0 & \text{if } X_1 > t \end{cases}.$$

Finally, $m(t) = E(E(N(t) \mid X_1))$. □

Theorem 35 (Limit theorems). *For a renewal process N with $\mu := E(X_1)$,*

$$\Pr \left(\lim_{t \rightarrow \infty} \frac{N(t)}{t} = \frac{1}{\mu} \right) = 1. \qquad \lim_{t \rightarrow \infty} \frac{m(t)}{t} = \frac{1}{\mu}.$$

Theorem 36 (Limit theorems for rewards). *For a renewal process N with rewards $\{R_i : i \in \mathbb{Z}_{\geq 1}\}$, let $\alpha := E(R_1)$ and $\mu := E(X_1)$. Then*

$$\Pr \left(\lim_{t \rightarrow \infty} \frac{R(t)}{t} = \frac{\alpha}{\mu} \right) = 1. \qquad \lim_{t \rightarrow \infty} \frac{E(R(t))}{t} = \frac{\alpha}{\mu}.$$

Theorem 37 (Central limit theorem for renewals). *For a renewal process N with $\mu := E(X_1)$ and $\sigma^2 := \text{Var}(X_1)$, the random variable*

$$\lim_{t \rightarrow \infty} \frac{N(t) - t/\mu}{\sqrt{t\sigma^2/\mu^3}}$$

tends to the standard normal distribution.

Lemma 38 (Stopping time). *Let $X = [X_1, X_2, \dots]$ be the sequence of interarrival times for renewal process N . Then $N(t) + 1$ is a stopping time for X .*

Proof sketch. $N(t) + 1 \leq n \iff S_n > t$. □