

Applied Probability

1 Continuous time Markov Chains

1.1 Poisson process

- Poisson process with intensity λ

(i) $N(0) = 0, N(s) \leq N(t)$ for $s < t$

(ii) $\mathbb{P}(N(t+h) = n+m | N(t) = n) = \begin{cases} \lambda h + o(h) & \text{if } m = 1 \\ o(h) & \text{if } m > 1 \\ 1 - \lambda h + o(h) & \text{if } m = 0 \end{cases}$

(iii) $N(t) - N(s)$ independent of $(N(k))_{k \leq s}$

Theorem 1.1. $N(t) \sim Poi(\lambda t)$

Proof. derive differential equation, then generating function □

- $p_j(t) = \mathbb{P}(N(t) = j)$
- Generating function $G(s, t) = \sum p_j(t) s^j$
- Arrival time T_n
- interarrival time U_n

Theorem 1.2.

(i) $U_i \sim Exp(\lambda)$

(ii) U_i independent

Proof. use $N(t)$ Poisson □

Fact. $N(t) \geq j \iff T_j \leq t$

- order statistics

Theorem 1.3. T_1, \dots, T_n conditional on $\{N(t) = n\}$ same as joint distribution of order statistics of n i.i.d. Uniform $[0, t]$

Proof. U to T , then calculate density □

1.2 Birth process

- birth process with birth rates $\lambda_0, \lambda_1, \dots$

(i) $N(0) = 0, N(s) \leq N(t)$ for $s < t$

$$(ii) \mathbb{P}(N(t+h) = n+m | N(t) = n) = \begin{cases} \lambda_n h + o(h) & \text{if } m = 1 \\ o(h) & \text{if } m > 1 \\ 1 - \lambda_n h + o(h) & \text{if } m = 0 \end{cases}$$

(iii) $N(t) - N(s)$ independent of $(N(k))_{k \leq s}$

Example.

(i) *Poisson process*: $\lambda_n = \lambda$

(ii) *Simple birth*: $\lambda_n = n\lambda$

(iii) *Simple birth with immigration*: $\lambda_n = n\lambda + \nu$

$$- T_\infty = \lim T_n = \sum_{i=0}^{\infty} U_i$$

$$- \text{non-explosive / honest} \implies \mathbb{P}(T_\infty = \infty) = 1$$

Theorem 1.4. birth process N , $\lambda_n > 0$, then non-explosive $\iff \sum_n \frac{1}{\lambda_n} = \infty$

Lemma 1.5. $U_n \sim \text{Exp}(\lambda_n)$, independent, then $\mathbb{P}(T_\infty < \infty) = \begin{cases} 0 & \text{if } \sum_n \frac{1}{\lambda_n} = \infty \\ 1 & \text{if } \sum_n \frac{1}{\lambda_n} < \infty \end{cases}$

$$- \text{forward system of equations: } p'_{ij}(t) = \lambda_{j-1} p_{i,j-1}(t) - \lambda_j p_{ij}(t)$$

$$- \text{backward system of equations: } p'_{ij}(t) = \lambda_i p_{i+1,j}(t) - \lambda_i p_{ij}(t)$$

Theorem 1.6.

(i) forward system has unique solution $\{p_{ij}(t)\}$

(ii) $\{p_{ij}(t)\}$ satisfy backward system

Theorem 1.7. $\{p_{ij}(t)\}$ unique solution of forward equations, $\{\pi_{ij}(t)\}$ any solution of backward equations, then $p_{ij}(t) \leq \pi_{ij}(t)$

Fact. $\sum_j p_{ij}(t) = 1 \iff \mathbb{P}(T_\infty > t) = 1$

– weak Markov property

– stopping time

- strong Markov property
- right continuity
- stationary independent increments
 - (i) $N(t) - N(s)$ only depends on $t - s$
 - (ii) $\{N(t_i) - N(s_i)\}$ independent where $s_1 \leq t_1 \leq \dots \leq s_n \leq t_n$

Setting 1. $(X(t))$ takes values in countable S

- Markov property ———
 $\mathbb{P}(X(t_n) = j | X(t_{n-1}) = i_{n-1}, \dots, X(t_1) = i_1) = \mathbb{P}(X(t_n) = j | X(t_{n-1}) = i_{n-1})$
- continuous-time Markov chain ——— right-continuous, Markov property
- transition probability $p_{ij}(s, t) = \mathbb{P}(X(t) = j | X(s) = i)$
- homogeneous ——— $p_{ij}(s, t) = p_{ij}(0, t - s)$
- transition semigroup $(P_t)_{ij} = p_{ij}(t)$
- stochastic semigroup
 - (i) $P_0 = I$
 - (ii) P_t stochastic ——— non-negative entries, row sum 1
 - (iii) (Chapman-Kolmogorov) $P_{s+t} = P_s P_t$

Setting 2. $(X(t))$ homogeneous Markov chain

Theorem 1.8. P_t stochastic semigroup

- \mathbb{P}_i ——— probability measure conditional on $X(0) = i$
- \mathbb{E}_i
- t -historical ——— events given by $\{X(s) : s < t\}$
- t -future ——— events given by $\{X(s) : s > t\}$
- stopping time T ——— $\{T \leq t\}$ given by $\{X(s) : s \leq t\}$

Theorem 1.9 (Extended Markov property). H t -historical, F t -future, then $\mathbb{P}(F | X(t) = j, H) = \mathbb{P}(F | X(t) = j)$

Theorem 1.10 (Strong Markov property). T stopping time, conditional on $\{T \leq T_\infty\} \cap \{X(T) = i\}$, then

- (i) $(X_{T+u})_u$ continuous Markov chain start at state i
- (ii) same transition prob
- (iii) independent to $\{X(s) : s < T\}$

Setting 3. $X(0) = i$

– $U_0 = \inf \{t : X(t) \neq i\}$

Fact. right continuous $\Rightarrow U_0 > 0$

Theorem 1.11.

- (i) $U_0 \sim \text{Exp}(g_i)$
- (ii) U_0 stopping time

Proof. Extended Markov and homogeneity to deduce memoryless □

- transition matrix $\mathbf{Y} = (y_{ij})$ — $y_{ij} = \begin{cases} \delta_{ij} & \text{if } g_i = 0 \\ \mathbb{P}_i(X(U_0) = j) & \text{if } g_i > 0 \end{cases}$
- generator $\mathbf{G} = (g_{ij})$ — $g_{ij} = \begin{cases} g_i y_{ij} & \text{if } j \neq i \\ -g_i & \text{if } j = i \end{cases}$

Fact. $\mathbb{P}(X(t+h) = j | X(t) = i) = g_{ij}h + o(h)$

Fact. $g_{ij} = g_i(y_{ij} - \delta_{ij})$

Theorem 1.12. $X(0) = i$, then

- (i) $X(U_0)$ independent of U_0
- (ii) conditional on $X(U_0) = j$, $X^*(s) = X(U_0 + s)$ continuous-time Markov chain, same transition prob, initial state j , independent to the past

- T_m
- holding time $U_m = T_{m+1} - T_m$
- jump chain $Y = \{Y_n\}$
- $T_\infty = \lim T_n$
- minimal process
- explode from state i — $\mathbb{P}_i(T_\infty < \infty) > 0$

Proposition 1.13. X minimal process, then $P_{s+t} = P_s$

Proof. may go to $\{\infty\}$ □

Theorem 1.14. $i \in S$, non-explosive from i if any of the following holds:

- (i) S finite
- (ii) $\sup_j g_j < \infty$
- (iii) i recurrent in jump chain Y

Proof. be dominated by Poisson process which is non-explosive □

- irreducible — $\forall i, j, \exists t > 0, p_{ij}(t) > 0$

Theorem 1.15.

- (i) (Levy dichotomy) X irreducible, then $\forall t > 0, p_{ij}(t) > 0$
- (ii) X irreducible $\iff Y$ irreducible

Proof. look at jump chain, $g_{i_0} \cdots g_{i_n} > 0, p_{i_k, i_{k+1}}(t) > 0$ □

Fact. birth process not irreducible

- recurrent — $\mathbb{P}(\{t : X(t) = i\} \text{ unbounded}) = 1$
- transient — $\mathbb{P}(\{t : X(t) = i\} \text{ unbounded}) = 0$
- $R_i = \inf \{t > U_0 : X(t) = i\}$
- mean return time $m_i = \mathbb{E}(R_i)$
- positive recurrent / non-null recurrent — $m_i < \infty$

Theorem 1.16. continuous-time chain X , jump chain Y

- (i) $g_i = 0$, then i recurrent for X
- (ii) $g_i > 0$, then i recurrent for $X \iff$ recurrent for Y
- (iii) i recurrent $\iff \int p_{ii}(t)dt = \infty$
- (iv) i transient $\iff \int p_{ii}(t)dt < \infty$
- (v) X irreducible, then every state recurrent or every state transient

Proof. main point is no explosion. Interchange summation, then old result. \square

- **Forward equation:** $\mathbf{P}'_t = \mathbf{P}_t \mathbf{G}$ with boundary condition $\mathbf{P}_0 = 1$
- **Backward equation:** $\mathbf{P}'_t = \mathbf{G} \mathbf{P}_t$ with boundary condition $\mathbf{P}_0 = 1$

Fact. If states S finite, then $\mathbf{P}_t = e^{t\mathbf{G}}$

- minimal solution — $p_{ij}(t) \leq \pi_{ij}(t)$
- sub-stochastic — $\sum_j p_{ij}(t) < 1$

Theorem 1.17. S countable, X minimal Markov chain with generator \mathbf{G} , then

- (i) \mathbf{P}_t minimal non-negative solution of backward equation $\mathbf{P}'_t = \mathbf{G} \mathbf{P}_t$ with boundary condition $\mathbf{P}_0 = 1$
- (ii) \mathbf{P}_t minimal non-negative solution of forward equation $\mathbf{P}'_t = \mathbf{P}_t \mathbf{G}$

Proof. Solution: condition on $T_1 > t$ or $T_1 \leq t$.

Minimal: reverse argument and induction. \square

Fact. any solution to both equations sub-stochastic

Fact. non-explosive $\Rightarrow \mathbf{P}_t$ unique solution to both equations

- measure
- stationary measure — $\pi = \pi \mathbf{P}_t$
- stationary distribution
- unique measure — unique up to scalar multiplication
- first return time R_i
- $m_i = \mathbb{E}_i(R_i)$

Theorem 1.18. X irreducible, $|S| \geq 2$

- (i) some state k positive recurrent, then
 - (a) \exists unique stationary distribution π
 - (b) unique distribution st $\pi \mathbf{G} = 0$
 - (c) all states positive recurrent
- (ii) X non-explosive, $\exists \pi$ st $\pi \mathbf{G} = 0$, then
 - (a) all states positive recurrent
 - (b) π stationary
 - (c) $\pi_k = \frac{1}{m_k g_k}$

- $\nu_i = x_i g_i$
- $\mu(k) = (\mu_j(k))_j \longrightarrow \mu_j(k) = \mathbb{E}_k \left(\int_0^{R_k} \mathbb{1}_{\{X(s) = j\}} ds \right)$

Lemma 1.19. *X irreducible, $|S| \geq 2$*

- (i) *measure x , then $x\mathbf{G} = 0 \iff \nu\mathbf{Y} = \nu$*
- (ii) *X recurrent, $x\mathbf{G} = 0$ unique measure*
- (iii) *x measure, $x\mathbf{G} = 0$, then $x_j > 0$*
- (iv) *X recurrent, $k \in S$, then $\mu(k)\mathbf{G} = 0$ and stationary*