

第一章、马氏链

§1.1 定义与例子

1. 定义

- 离散型分布/随机变量.
- S : 可数集, 取值/位置/状态空间. ①
- $i \in S$: 值/位置/状态. ②
- 分布(列), 色子: $\{p_i, i \in S\}$.
- 随机变量, 粒子: $P(X = i) = p_i, \forall i$. ③
- 马氏链(模型)描述一个在 S 上运动的粒子. ④
- 离散时间: $n = 0, 1, 2, \dots, n \in \mathbb{Z}_+$. ⑤
- 粒子的位置: 一系列取值于 S 的随机变量

X_0, X_1, X_2, \dots , 也记为 $\{X_n\}$.

- 运动机制/概率转移图: 每个位置 i 上放置色子 $\{p_{ij}, j \in S\}$.

- $p_{ij} \geq 0, \forall i, j;$
- $\sum_j p_{ij} = 1, \forall i.$

- 转移(概率)矩阵:

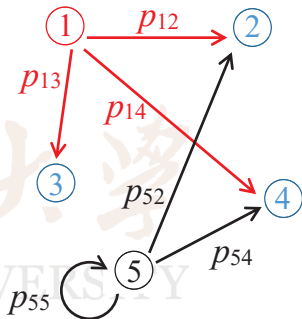
$$\mathbf{P} = (p_{ij})_{i,j \in S} = (p_{ij})_{S \times S} = (p_{ij}).$$

- $\{X_n\}$ 是(时齐)马氏链指:

$$\forall n \geq 0; \forall i, j, i_0, \dots, i_{n-1} \in S,$$

若 $P(A, C) > 0$, 则

$$P(X_{n+1} = j | X_n = i, X_0 = i_0, \dots, X_{n-1} = i_{n-1}) = p_{ij}.$$



- 马氏链 = 发展机制: $\mathbf{P} = (p_{ij})_{S \times S}$.
- 再配上初分布 μ : $\mu_i = P(X_0 = i)$, 得到有限维轨道分布:

$$\begin{aligned}
 & P(X_0 = i_0, X_1 = i_1, \dots, X_n = i_n) \\
 &= P(X_0 = i_0, \dots, X_{n-1} = i_{n-1}) \\
 & \quad \times P(X_n = i_n | X_0 = i_0, \dots, X_{n-2} = i_{n-2}, X_{n-1} = i_{n-1}) \\
 &= P(X_0 = i_0, X_1 = i_1, \dots, X_{n-1} = i_{n-1}) \times p_{i_{n-1}i_n} = \dots \\
 &= \mu_{i_0} p_{i_0i_1} \dots p_{i_{n-2}i_{n-1}} p_{i_{n-1}i_n}.
 \end{aligned}$$

- 或者,

$$P(X_0 = i_0) = \mu_{i_0},$$

$$P(X_0 = i_0, X_1 = i_1) = \mu_{i_0} p_{i_0i_1},$$

$$P(X_0 = i_0, X_1 = i_1, X_2 = i_2) = \mu_{i_0} p_{i_0i_1} p_{i_1i_2}, \quad \dots \dots$$

2. 例子

例1.1.1. 一维随机游动. $S = \mathbb{Z}$.

- 简单随机游动: $p_{i,i+1} = p_{i,i-1} = \frac{1}{2}$.



紧邻随机游动: $p_{i,i+1} = 1 - p_{i,i-1} = p$.

- 轨道图:



- 一维随机游动: ξ_1, ξ_2, \dots i.i.d., $S_n = \xi_1 + \dots + \xi_{n-1} + \xi_n$.



相关模型:

● 吸收壁



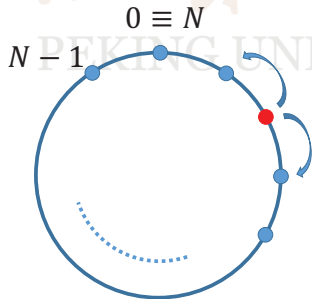
● 反射壁



● 粘滞边界/区间上

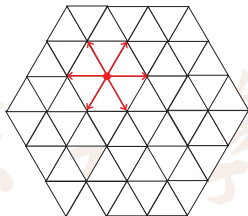
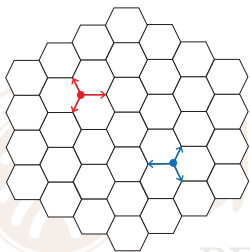


● 离散圆圈上



例1.1.11. 图上的(简单)随机游动.

- 图 $G = (V, E)$.



- 位置空间: $S = V$.

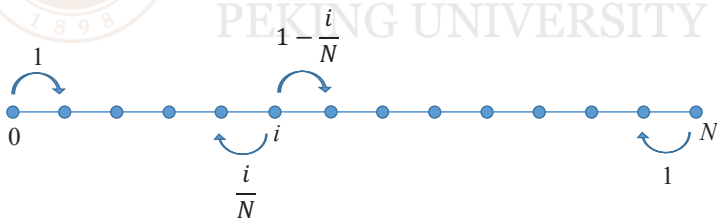
$$p_{i,j} = \begin{cases} \frac{1}{d_i}, & \text{若 } j \sim i, \\ 0, & \text{否则.} \end{cases}$$

例1.1.8. Ehrenfest模型. N 个球, 两个纸箱A, B.

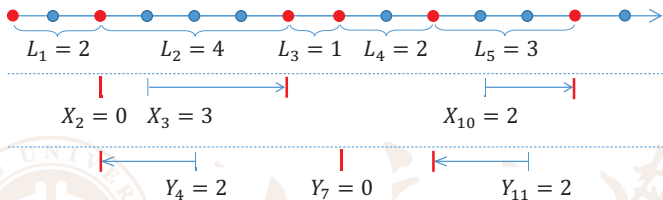
每次独立地随机选一个球, 把它换到另一个纸箱中.

- X_n : n 次操作后纸箱A 的状态, 即, 其中球的个数.
则 $\{X_n\}$ 是马氏链.
- $S = \{0, 1, \dots, N\}$,

$$p_{i,i-1} = \frac{i}{N}, \quad p_{i,i+1} = 1 - \frac{i}{N}.$$



例1.1.9 & 1.1.10. L_1, L_2, \dots i.i.d., 取正整数.



- X_n : 灯泡的余寿(更新过程). $S = \mathbb{Z}_+$.

$$p_{i,i-1} = 1, \quad \forall i \geq 1, \quad p_{0,i} = P(L = i + 1), \quad \forall i \geq 0.$$

- Y_n : 灯泡已经使用的时间(老化过程). $S = \mathbb{Z}_+$.

$$p_{i,i+1} = 1 - p_{i,0}, \quad \forall i \geq 0.$$

3. 性质

- $P(X_{n+1} = j | X_n = i, \vec{Z} = \vec{i}) = p_{ij},$

$$\vec{Z} = (X_0, \dots, X_{n-1}), \quad \vec{i} = (i_0, \dots, i_{n-1}).$$

- 由条件概率的定义 $P_A(B) = \frac{P(AB)}{P(A)}$ 知,

$$P(B|A, C) = \frac{P(A, B, C)}{P(A, C)} = \frac{P_A(B, C)}{P_A(C)} = P_A(B|C).$$

- 翻译马氏链定义: $P_A(X_{n+1} = j | \vec{Z} = \vec{i}) = p_{ij}$. (不依赖于 \vec{i} .)

- 在 P_A 下, X_{n+1}, \vec{Z} 相互独立:

$$P_A(X_{n+1} = j, \vec{Z} = \vec{i}) = p_{ij} \times P_A(\vec{Z} = \vec{i}).$$

对 \vec{i} 求和知 $P_A(X_{n+1} = j) = p_{ij}$, 再代入上式即可.

- 命题1.1.12.(马氏性).

在已知现在(的状态)的条件下, 将来与过去相互独立.

- 现在: 时刻 n , 变量 X_n ; 已知: $X_n = i$.
- 将来: $\vec{Y} = (X_{n+1}, \dots, X_{n+m})$; 过去: $\vec{Z} = (X_0, \dots, X_{n-1})$.
- 已知 $A = \{X_n = i\}$,
将来事件 $B = \{\vec{Y} = (j_1, \dots, j_m) =: \vec{j}\}$;
过去事件 $C = \{\vec{Z} = (i_0, \dots, i_{n-1}) =: \vec{i}\}$.
- 命题1.1.12. $\forall n, m, \forall \vec{i}, \forall \vec{j}$, 都有

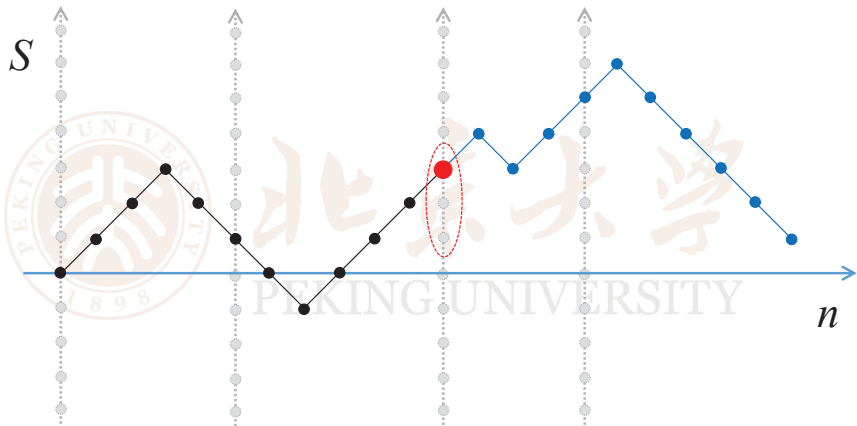
$$P_A(B|C) = p_{ij_1} \cdots p_{j_{m-1}j_m}.$$

命题1.1.12的证明:

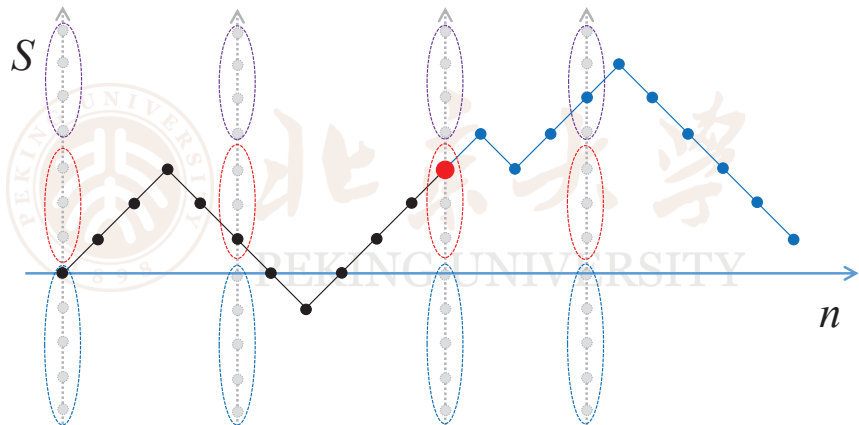
- $A = \{X_n = i\}$, $B = \{\vec{Y} = \vec{j}\}$, $C = \{\vec{Z} = \vec{i}\}$.

$$\begin{aligned} P_A(B|C) &= P(B|A, C) = \frac{P(C, A, B)}{P(A, C)} \\ &= \frac{\mu_{i_0} p_{i_0 i_1} \cdots p_{i_{n-1} i} \times p_{i j_1} \cdots p_{j_{m-1} j_m}}{\mu_{i_0} p_{i_0 i_1} \cdots p_{i_{n-1} i}} \\ &= p_{i j_1} \cdots p_{j_{m-1} j_m}. \end{aligned}$$

- 注1. 上式右边不依赖于 \vec{i} . 因此, 在 P_A 下, \vec{Y} 与 \vec{Z} 相互独立.
- 注2: 特别地, 补充定义 $Y_0 = X_n$,
则在 P_A 与 $P_{A,C}$ 下, $\{Y_m\}$ 是从 i 出发的马氏链.
- 注3. 在 P_A 下, $\forall 1 \leq m_1 < \dots < m_r; 0 \leq n_1 < \dots < n_s < n$,
 $(X_{n+m_1}, \dots, X_{n+m_r})$ 与 $(X_{n_1}, \dots, X_{n_s})$ 相互独立.



习题10.



- n 步转移概率:

$$p_{ij}^{(n)} := P(X_{m+n} = j | X_m = i).$$

- $\forall r \geq 1, \forall 0 < n_1 < \dots < n_r, \forall i_0, i_1, \dots, i_r,$

$$\begin{aligned} & P(X_0 = i_0, X_{n_1} = i_1, \dots, X_{n_r} = i_r) \\ &= P(X_0 = i_0, X_{n_1} = i_1, \dots, X_{n_{r-1}} = i_{r-1}) \\ & \quad \times P(X_{n_r} = i_r | X_0 = i_0, X_{n_1} = i_1, \dots, X_{n_{r-1}} = i_{r-1}) \\ &= P(X_0 = i_0, \dots, X_{n_{r-1}} = i_{r-1}) P(X_{n_r} = i_r | X_{n_{r-1}} = i_{r-1}) \\ &= \mu_{i_0} p_{i_0 i_1}^{(n_1)} p_{i_1 i_2}^{(n_2 - n_1)} \dots p_{i_{r-1} i_r}^{(n_r - n_{r-1})}. \end{aligned}$$

- n 步转移矩阵: $(p_{ij}^{(n)})_{S \times S} =: \mathbf{P}^{(n)}$.

- Chapman-Kolmogorov等式:

$$p_{ij}^{(n+m)} = \sum_k p_{ik}^{(n)} p_{kj}^{(m)}.$$

- 概率角度: 由全概公式,

$$\begin{aligned} & P(X_{n+m} = j | X_0 = i) \\ &= \sum_k P(X_{n+m} = j, X_n = k | X_0 = i) \\ &= \sum_k P(X_n = k | X_0 = i) P(X_{n+m} = j | X_n = k, X_0 = i). \end{aligned}$$

- 矩阵角度: $\mathbf{P}^{(n+m)} = \mathbf{P}^{(n)} \times \mathbf{P}^{(m)}$.

由归纳法知, $\mathbf{P}^{(n)} = \mathbf{P}^n$.

4. 补充.

- 命题1.1.12.(马氏性).

在已知现在(的状态)的条件下, 将来与过去相互独立.

- 思考: 假设 U_0, U_1, U_2, \dots i.i.d., $U_0 \sim U(0, 1)$.

如何用 U_0, U_1, U_2, \dots 构造马氏链?

- 马氏链模型对应的随机试验.
- 样本/轨道:

$$\Omega := \{\omega = (\omega_0, \omega_1, \omega_2, \dots) : \omega_n \in S, \forall n \geq 0\}.$$

- (坐标)过程:

$$X_0(\omega) := \omega_0, \quad X_1(\omega) := \omega_1, \quad X_2(\omega) := \omega_2, \dots$$

- σ -代数:

$$\mathcal{F} := \sigma(\mathcal{G}) = \sigma(\mathcal{C}),$$

$$\mathcal{G} : \{X_n = i\}, \quad \forall n \geq 0, \quad \forall i \in S,$$

$$\mathcal{C} : C_{i_0 i_1 \dots i_n} = \{X_0 = i_0, X_1 = i_1, \dots, X_n = i_n\} \quad (\text{柱集}).$$

- 概率: $\exists! P$ 使得

$$\begin{aligned} & P(X_0 = i_0, X_1 = i_1, \dots, X_n = i_n) \\ & = P(C_{i_0 i_1 \dots i_n}) = \mu_{i_0} p_{i_0 i_1} \cdots p_{i_{n-1} i_n}, \quad \forall n \geq 0, \forall i_0, i_1, \dots, i_n \in S. \end{aligned}$$

- P 也是 $\{X_n\}$ 的“联合分布”，被称为轨道分布。
- 随机过程与轨道分布。

§1.2 不变分布与可逆分布

1. 不变分布

- 初分布 μ & 转移机制 $\mathbf{P} = (p_{ij})$.

$$P_{\mu}(X_0 = i_0, X_1 = i_1, \dots, X_n = i_n) = \mu_{i_0} p_{i_0 i_1} \cdots p_{i_{n-1} i_n}.$$

当 $\mu_i = 1$ 时, P_{μ} 简记为 P_i .

- P_{μ} 与 P_i :

$$P_{\mu}(A) = \sum_i \mu_i P_i(A), \quad P_i(A) = P_{\mu}(A | X_0 = i).$$

- X_1 的分布:

$$P_{\mu}(X_1 = j) = \sum_i P_{\mu}(X_0 = i, X_1 = j) = \sum_i \mu_i p_{ij} = (\mu \mathbf{P})_j.$$

- X_2 的分布: $(\mu \mathbf{P}) \mathbf{P} = \mu \mathbf{P}^2, \dots$ 或, X_n 的分布:

$$P_{\mu}(X_n = j) = \sum_i \mu_i p_{ij}^{(n)} = (\mu \mathbf{P}^n)_j.$$

- 不变分布/测度(定义1.2.1): 若 π 是分布/测度, 且

$$\sum_i \pi_i p_{ij} = \pi_j, \quad \forall j,$$

则称 π 为不变分布/测度.

- $\mathbf{P} : \mu \mapsto \mu\mathbf{P}$. 不变分布= 线性变换 \mathbf{P} 的(左)不动点.
- 特征向量: $\pi\mathbf{P} = \pi$, $\mathbf{P}\mathbf{1} = \mathbf{1}$. (Perron-Frobenius 定理)
- $\mathbf{P} : f \mapsto \mathbf{P}f$,

$$(\mathbf{P}f)(i) = \sum_j p_{ij} f(j) = E_i f(X_1).$$

- 右不动点被称为调和函数.

• $X_0 \sim \pi$ 则 $X_n \sim \pi, \forall n \geq 0$. 不变分布 = 系统位于稳态.

• 若

$$(X_0, X_1, \dots, X_m) \stackrel{d}{=} (X_n, X_{n+m}, \dots, X_{n+m}), \quad \forall n, m \geq 0,$$

则称 $\{X_n\}$ 平稳. 不变分布 = 产生平稳过程.

• 假设 $\{X_n\}$ 平稳, $f: S^\infty \rightarrow S'$. 令 $Y_n = f(X_n, X_{n+1}, \dots)$, 则 $\{Y_n\}$ 平稳.

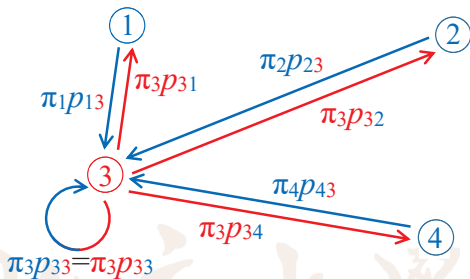
- 概率流: $\forall i,$

$$\sum_j \pi_j p_{ji} = \pi_i,$$

$$\sum_{j \neq i} \pi_j p_{ji}$$

$$= \pi_i \sum_{j \neq i} p_{ij}$$

$$= \pi_i (1 - p_{ii})$$

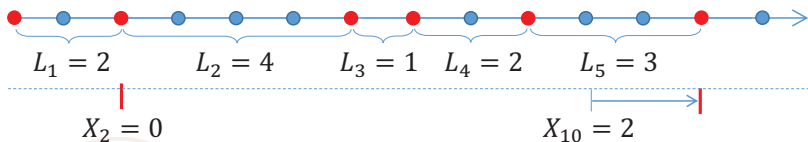


- 不变分布 = 每个状态的总收与总支相抵.
- 不变分布 = 每个状态组的总收与总支相抵.

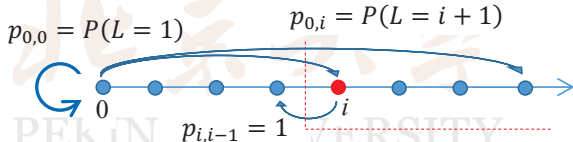
$$\sum_{i \in A} \sum_j \pi_j p_{ji} = \sum_{j \in A} \pi_j = \sum_{i \in A} \sum_j \pi_i p_{ij},$$

$$\sum_{j \notin A, i \in A} \pi_j p_{ji} + \sum_{i, j \in A} \pi_j p_{ji} = \sum_{i \in A, j \notin A} \pi_i p_{ij} + \sum_{i, j \in A} \pi_i p_{ij}.$$

例1.2.4. 更新过程. L_1, L_2, \dots i.i.d., ≥ 1 . 求 $\{Y_n\}$ 的不变分布.

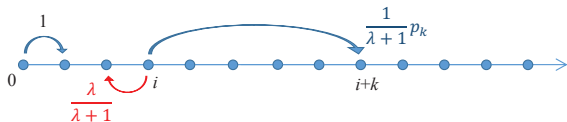


● 概率转移图:

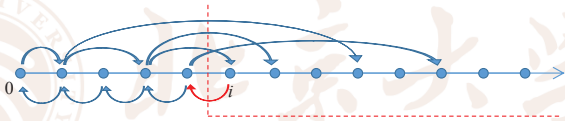


- 取 $A = \{i, i+1, \dots\}$, 则 $\pi_0 P(L > i) = \pi_i$.
- $\sum_i \pi_i = \pi_0(1 + P(L > 1) + P(L > 2) + \dots) = \pi_0 EL$.
- 不变分布存在 iff $EL < \infty$, 此时 $\pi_i = \frac{1}{EL} P(L > i), \forall i$.

例1.2.5. $S = \mathbb{Z}_+$, $1 = \sum_{k=1}^{\infty} p_k < m := \sum_{k=1}^{\infty} k p_k < \lambda$.



- 取 $A_i = \{i, i+1, i+2, \dots\}$.



- 当 $i = 1$ 时: $\pi_1 \frac{\lambda}{\lambda+1} = \pi_0$.
- 当 $i \geq 2$ 时: $\pi_i \frac{\lambda}{\lambda+1} = \sum_{j=1}^{i-1} \pi_j \frac{f_{i-j}}{\lambda+1}$, 其中 $f_r = p_r + p_{r+1} + \dots$
- $\sum_{i=j+1}^{\infty} f_{i-j} = f_1 + f_2 + \dots = m$, 故

$$(1 - \pi_0) \frac{\lambda}{\lambda+1} \times 1 = \pi_0 \times 1 + (1 - \pi_0) \frac{1}{\lambda+1} \times m.$$

2. 可逆分布

- 细致平衡条件:

$$\pi_i p_{ij} = \pi_j p_{ji}, \quad \forall i, j.$$

- 细致平衡 = 每对状态的收支平衡,

- 可逆分布/配称测度(定义1.2.7):

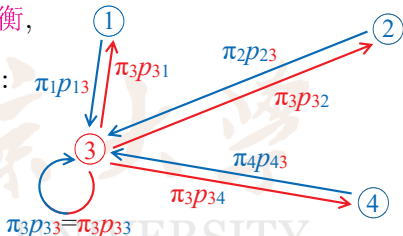
满足细致平衡的分布/测度.

- 若存在可逆分布/配称测度, 则称 \mathbf{P} 为可逆的/可配称的.

- 配称 \Rightarrow 不变. 可逆分布 iff 配称 & 归一.

- 可配称的含义:

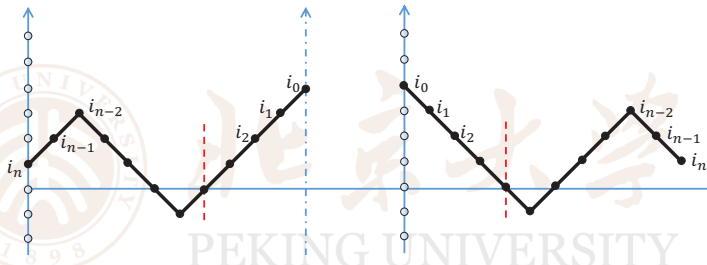
$$q_{ij} = \sqrt{\frac{\pi_i}{\pi_j}} p_{ij}, \quad \mathbf{Q} = \mathbf{Q}^T.$$



- 可逆的含义:

固定 n . $\{X_m : 0 \leq m \leq n\}$ 的(时间倒)逆过程为

$$\{Y_m : 0 \leq m \leq n\}, \quad \text{其中 } Y_m = X_{n-m}.$$



- $\{Y_m : 0 \leq m \leq n\}$ 的(有限维)轨道分布:

$$\begin{aligned} & P(Y_0 = i_0, Y_1 = i_1, \dots, Y_{n-1} = i_{n-1}, Y_n = i_n) \\ &= P(X_0 = i_n, X_1 = i_{n-1}, \dots, X_{n-1} = i_1, X_n = i_0) \\ &= \pi_{i_n} p_{i_n i_{n-1}} p_{i_{n-1} i_{n-2}} \cdots p_{i_1 i_0}. \end{aligned}$$

- 逆过程 $\{Y_m : 0 \leq m \leq n\}$ 的(有限维)轨道分布:

$$P(Y_0 = i_0, Y_1 = i_1, \dots, Y_n = i_n) = \pi_{i_n} p_{i_n i_{n-1}} \cdots p_{i_1 i_0}.$$

- 如果 π 是可逆分布, 即 $\pi_i p_{ij} = \pi_j p_{ji}, \forall i, j$, 那么,

$$\begin{aligned} \pi_{i_n} p_{i_n i_{n-1}} p_{i_{n-1} i_{n-2}} \cdots p_{i_1 i_0} &= \pi_{i_{n-1}} p_{i_{n-1} i_n} p_{i_{n-1} i_{n-2}} \cdots p_{i_1 i_0} \\ &= p_{i_{n-1} i_n} \pi_{i_{n-1}} p_{i_{n-1} i_{n-2}} \cdots p_{i_1 i_0} \\ &= p_{i_{n-1} i_n} p_{i_{n-2} i_{n-1}} \pi_{i_{n-2}} \cdots p_{i_1 i_0} = \cdots \\ &= p_{i_{n-1} i_n} p_{i_{n-2} i_{n-1}} \cdots p_{i_0 i_1} \pi_{i_0} = \pi_{i_0} p_{i_0 i_1} \cdots p_{i_{n-2} i_{n-1}}. \end{aligned}$$

- 如果初分布 π 为可逆分布, 那么 $\{X_n\}$ 与其逆过程同分布. 此时, 称 $\{X_n\}$ 为可逆的.
- 可逆分布 = 产生可逆过程.

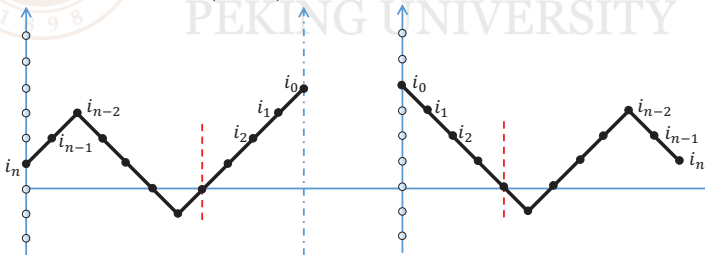
- 如果 π 是不变分布, 那么 $\hat{\mathbf{P}} = (\hat{p}_{ij})_{S \times S}$ 是转移矩阵,

$$\text{其中, } \hat{p}_{ij} := \frac{\pi_j p_{ji}}{\pi_i} \text{ 满足 } \pi_j p_{ji} = \pi_i \hat{p}_{ij}, \forall i, j.$$

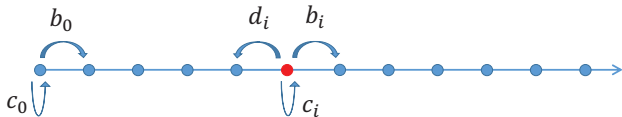
- 如果 π 是不变分布, 那么,

$$\begin{aligned} \pi_{i_n} p_{i_n i_{n-1}} p_{i_{n-1} i_{n-2}} \cdots p_{i_1 i_0} &= \hat{p}_{i_{n-1} i_n} \pi_{i_{n-1}} p_{i_{n-1} i_{n-2}} \cdots p_{i_1 i_0} \\ &= \cdots = \pi_{i_0} \hat{p}_{i_0 i_1} \cdots \hat{p}_{i_{n-2} i_{n-1}}. \end{aligned}$$

- 马氏性: 已知现在(状态)的条件下, 将来与过去独立.



例1.2.10. 生灭链.



- $\pi_0 b_0 = \pi_1 d_1 \Rightarrow \pi_1 = \pi_0 \frac{b_0}{d_1}$.

- $\pi_1 b_1 = \pi_2 d_2 \Rightarrow \pi_2 = \pi_1 \frac{b_1}{d_2} = \pi_0 \frac{b_0 b_1}{d_1 d_2}$.

- $\pi_{i-1} b_{i-1} = \pi_i d_i \Rightarrow \pi_i = \pi_{i-1} \frac{b_{i-1}}{d_i} = \dots = \pi_0 \frac{b_0 \dots b_{i-1}}{d_1 \dots d_i}$.

- 归一化: 令

$$C := 1 + \frac{b_0}{d_1} + \frac{b_0 b_1}{d_1 d_2} + \dots$$

当 $C < \infty$ 时, 取

$$\pi_0 = \frac{1}{C}, \quad \pi_i = \frac{1}{C} \cdot \frac{b_0 \dots b_{i-1}}{d_1 \dots d_i}$$

即得可逆分布. 当 $C = \infty$ 时, 不变分布不存在.

求可逆分布的步骤:

(1) 固定 o .

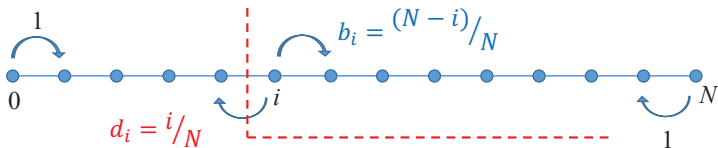
$\forall i \neq o$, 找 $n \geq 1$ 以及 $i_0 := o, i_1, \dots, i_n := i$, 使得 $p_{i_0 i_1} \cdots p_{i_{n-1} i_n} > 0$, 并令

$$\pi_i = \pi_o \frac{p_{i_0 i_1} \cdots p_{i_{n-1} i_n}}{p_{i_1 i_0} \cdots p_{i_n i_{n-1}}}.$$

(2) 验证细致平衡条件: $\pi_i p_{ij} = \pi_j p_{ji}, \forall i, j$.

(3) 将 π 归一化.

例1.1.8, 1.2.10 & 1.2.11 Ehrenfest模型.



- $\pi_i \times \frac{i}{N} = \pi_{i-1} \times \frac{N-(i-1)}{N}$.

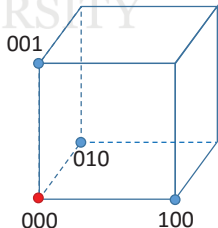
- $\pi_i = \frac{N-i+1}{i} \pi_{i-1} = \dots = \frac{(N-i+1)(N-i+2)\dots(N+1-1)}{i(i-1)\dots 1} \pi_0$.
 $= \frac{N!}{(N-i)!i!} \pi_0 = C_N^i \pi_0$.

- $\pi_0 \sum_{i=0}^N C_N^i = 1 \Rightarrow \pi_0 = \frac{1}{2^N}$.

i.e. $\pi = B(N, \frac{1}{2})$.

- $Y_n \in \{0, 1\}^N = \mathbb{H}_N$. $X_n = f(Y_n)$.

$\mu_k = 2^{-N}, \forall k \in \mathbb{H}_N$.



例1.2.12. 一维紧邻随机游动. $p_{i,i+1} = 1 - p_{i,i-1} = p$.



- 可逆分布不存在. 否则,

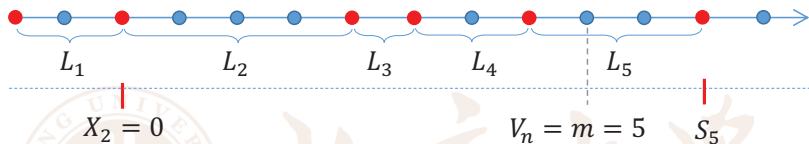
$$\pi_1 = \pi_0 \frac{p}{q}, \dots, \pi_{-1} = \pi_0 \frac{q}{p} = \pi_0 \frac{p^{-1}}{q^{-1}}, \dots, \pi_i = \pi_0 \frac{p^i}{q^i}, \quad \forall i.$$

但, 上述 π 不可以归一化.

- 不变分布不存在. 否则, 取 $A = \{i, i+1, \dots\}$, 则不变方程转变为细致平衡条件.
- $\mu_i = \mu_0, \forall i$ 是不变测度. 但, A 的总收 \neq 总支.
- $p = \frac{1}{2}$ 时, π 就是 μ . 事实上, 不变测度“唯一”.
- $p \neq \frac{1}{2}$ 时, π 不是 μ . 不变测度“不唯一”.

3. 访问频率

定理1.2.13 & 例1.2.14. 更新定理.



- 假设 $EL < \infty$. 不变分布存在, 且 $\pi_0 = \frac{1}{EL}$.
- $V_n = m$ iff $S_{m-1} \leq n < S_m$, 其中 $S_m = L_1 + \dots + L_m$.
- SLLN: $\frac{S_m}{m} \xrightarrow{\text{a.s.}} EL$
 $\Rightarrow \frac{n}{m} \xrightarrow{\text{a.s.}} EL$
 $\Rightarrow \frac{V_n}{n} \xrightarrow{\text{a.s.}} \frac{1}{EL}$, (更新定理).
- $\{X_n\}$ 访问状态0 的频率 $\xrightarrow{\text{a.s.}} \pi_0$.

4. 访问概率的收敛性

例1.2.5. 两状态马氏链.

$$\mathbf{P}: \begin{array}{c|cc} & 0 & 1 \\ \hline 0 & 1-p & p \\ 1 & q & 1-q \end{array}$$

Diagram illustrating the transition probabilities for the two-state Markov chain:

- State 0: $1-p$ (self-loop), $p_{01} = p$ (transition to 1)
- State 1: $1-q$ (self-loop), $p_{10} = q$ (transition to 0)

- $\pi_0 p = \pi_1 q \Rightarrow \pi_0 = \frac{q}{p+q}, \pi_1 = \frac{p}{p+q}.$

- 特征向量: $\pi \mathbf{P} = \pi, \mathbf{P} \mathbf{1} = \mathbf{1}.$ (Perron-Frobenius 定理)

- $\mu \mapsto \mu \mathbf{P}: X_0 \sim \mu \Rightarrow X_1 \sim \mu P.$

- $f \mapsto \mathbf{P}f: (\mathbf{P}f)(i) = \sum_j p_{ij} f(j) = E_i f(X_1),$
 $(\mathbf{P}^n f)(i) = E_i f(X_n).$

- 不动点: 不变测度、调和函数.

$$\bullet \mathbf{P} = \begin{pmatrix} 1 & p \\ 1 & -q \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & \boxed{1-p-q} \end{pmatrix} \begin{pmatrix} \frac{q}{p+q} & \frac{p}{p+q} \\ \frac{1}{p+q} & -\frac{1}{p+q} \end{pmatrix}$$

$$\bullet \mathbf{P}^n \rightarrow \begin{pmatrix} 1 & \star \\ 1 & \star \end{pmatrix} \cdot \begin{pmatrix} 1 & 0 \\ 0 & \boxed{0} \end{pmatrix} \begin{pmatrix} \pi_0 & \pi_1 \\ * & * \end{pmatrix} = \begin{pmatrix} \pi_0 & \pi_1 \\ \pi_0 & \pi_1 \end{pmatrix}$$

$$\bullet p_{ij}^{(n)} = P_i(X_n = j) \rightarrow \pi_j, \forall i, j.$$

$$\bullet \mu \mathbf{P}^n \rightarrow (\mu_0, \mu_1) \begin{pmatrix} \pi_0 & \pi_1 \\ \pi_0 & \pi_1 \end{pmatrix} = (\pi_0, \pi_1).$$

$$\bullet P(X_n = 0) \rightarrow \pi_0, \quad P(X_n = 1) \rightarrow \pi_1.$$

- 不变分布 π 的存在(唯一)性.
- 正常返(不可约).

● 对任意初始分布 μ , 都有 $\mu\mathbf{P}^n \rightarrow \pi$?

● 强遍历定理.

● 访问 i 的频率 $\rightarrow \pi_i$.

● 遍历定理.



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§1.3 状态的分类

- 定义1.1.3. 可达, $i \rightarrow j$: $P_i(\exists n \geq 0 \text{ 使得 } X_n = j) > 0$.
- 或者 $j = i$,

或者 $\exists n \geq 1, i_0, \dots, i_n$,

($i_0 = i, i_n = j$),

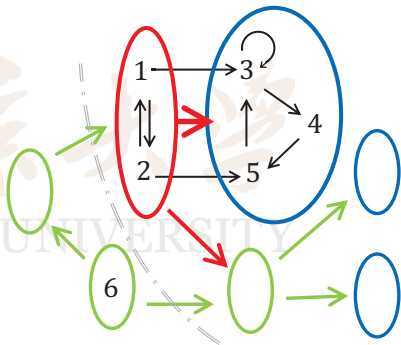
使得 $p_{i_0 i_1} \cdots p_{i_{n-1} i_n} > 0$.

- 存在 $n \geq 0$ 使得 $p_{ij}^{(n)} > 0$.

证明: $P_i(X_n = j)$

$\leq P_i(\exists m \geq 0 \text{ 使得 } X_m = j)$

$\leq \sum_{m=0}^{\infty} P_i(X_m = j)$.



- 定义1.3.3. 互通 $i \leftrightarrow j: i \rightarrow j$ 且 $j \rightarrow i$.

若所有 i, j 都互通, 则称 \mathbf{P} (S , 马氏链) 不可约, 否则称可约.

- 互通类: $[i] = \{j : j \leftrightarrow i\}$.

- 定义1.3.5. 若

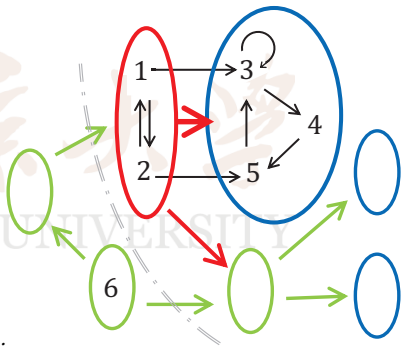
$$p_{ij} = 0, \quad \forall i \in A, \forall j \notin A,$$

则称 A 为闭集/闭的.

闭的互通类称为闭类.

- 命题1.3.6. 若 A 为非空闭集, 则

$$P_i(X_n \in A, \forall n \geq 0) = 1, \quad \forall i.$$



§1.4 强马氏性

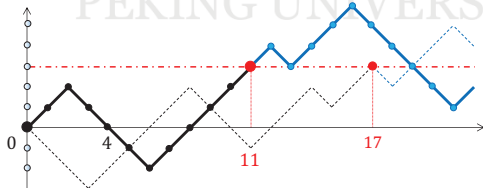
- 样本轨道: $\omega = (X_0(\omega), X_1(\omega), X_2(\omega), \dots) = \vec{X}(\omega)$.
- 首达时 τ_i 与首入时 σ_i :

$$\tau_i(\omega) = \tau_i(\vec{X}) := \inf\{n \geq 0 : X_n = i\}.$$

$$\sigma_i(\omega) = \sigma_i(\vec{X}) := \inf\{n \geq 1 : X_n = i\}.$$

- τ_i, σ_i 是随机变量.

例, $\tau_3(\omega) = 11, \tau_3(\hat{\omega}) = 17; \tau_0(\omega) = 0, \sigma_0(\omega) = 4$.

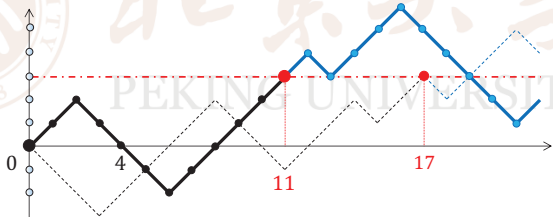


- $i \rightarrow j: P_i(\tau_j < \infty) > 0$.

- 固定 i , 简记 $\tau := \tau_i$. 在 $\{\tau < \infty\}$ 上, 令

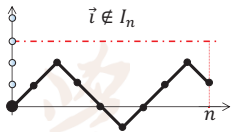
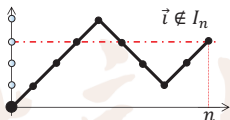
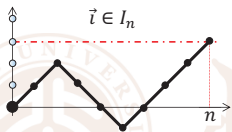
$$\vec{Y} = (Y_0, Y_1, Y_2, \dots) := (X_\tau, X_{\tau+1}, X_{\tau+2}, \dots),$$

$$\vec{Z} := (X_0, \dots, X_\tau).$$



- 固定 n , 记 $\vec{i} := (i_0, i_1, \dots, i_n)$, 令

$$I_n := \left\{ \vec{i} \in S^{n+1} : i_0, \dots, i_{n-1} \neq i \text{ 且 } i_n = i \right\}.$$

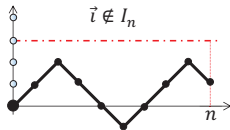
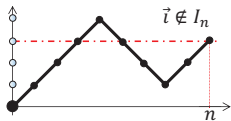
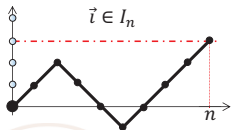


- 记 $\vec{X}^{(n)} := (X_0, \dots, X_n)$.
- 重要结论1:** 若 $\vec{i} \notin I_n$, 则

$$\{\vec{X}^{(n)} = \vec{i}\} \subseteq \{\tau \neq n\}, \quad \{\vec{Z} = \vec{i}\} = \emptyset.$$

- 在 $\{\tau_i < \infty\}$ 上, \vec{Z} 是离散型. 取值于 $\bigcup_{n=0}^{\infty} I_n$.

- (i) 若 $\vec{i} \in I_n$, 则 $\vec{X}^{(n)} = \vec{i}$ 表明 $\tau = n$, 从而 $\vec{Z} = \vec{X}^{(n)} = \vec{i}$.



- (ii) $\vec{Z} = \vec{i}$ 表明 $\tau = n$, 从而 $\vec{X}^{(n)} = \vec{Z} = \vec{i}$.

- **重要结论2:** 若 $\vec{i} \in I_n$, 则

$$\{\vec{Z} = \vec{i}\} = \{\vec{X}^{(n)} = \vec{i}\} \subseteq \{\tau = n\}.$$

- 若 $\vec{i} \in I_n$, 则

$$P(\vec{Z} = \vec{i}) = P(\vec{X}^{(n)} = \vec{i}) = \mu_{i_0} p_{i_0 i_1} \cdots p_{i_{n-1} i_n}.$$

命题 (命题1.4.2)

在 $\{\tau_i < \infty\}$ 发生的条件下,

(1) $\{Y_n\}$ 是从 i 出发的马氏链; (2) $\{Y_n\}$ 与 \vec{Z} 相互独立.

• 记 $\tau_i = \tau$, $\vec{i} := (i_0, \dots, i_n)$; $\vec{j} := (j_0, \dots, j_m)$,

$$B := \{(Y_0, \dots, Y_m) = \vec{j}\} = \{(X_\tau, \dots, X_{\tau+m}) = \vec{j}\},$$

$$C := \{\vec{Z} = \vec{i}\} = \{(X_0, \dots, X_\tau) = \vec{i}\}.$$

• 只需验证:

$\forall n \geq 0, \forall \vec{i} \in I_n$ (由重要结论1); $\forall m \geq 0, \forall \vec{j} \in S^{m+1}$,

$$P_{\{\tau < \infty\}}(BC) = 1_{\{j_0=i\}} p_{j_0 j_1} \cdots p_{j_{m-1} j_m} \times P_{\{\tau < \infty\}}(C).$$

- $B = \{(X_\tau, \dots, X_{\tau+m}) = \vec{j}\}$, $C = \{\vec{Z} = \vec{i}\}$.
- 回顾重要结论2: 若 $\vec{i} \in I_n$, 则

$$\{\vec{Z} = \vec{i}\} = \{\vec{X}^{(n)} = \vec{i}\} \subseteq \{\tau = n\}.$$

- 令 $\hat{B} := \{(X_n, \dots, X_{n+m}) = \vec{j}\}$, $\hat{C} := \{\vec{X}^{(n)} = \vec{i}\}$.
- 由重要结论2知, 因为 $\vec{i} \in I_n$, 所以 $C = \hat{C}$. 从而,

$$BC = B\hat{C} \cap \{\tau = n\} = \hat{B}\hat{C} \cap \{\tau = n\} = \hat{B}\hat{C}.$$

- 于是

$$\begin{aligned} P_{\{\tau < \infty\}}(BC) &= \frac{P(BC)}{P(\tau < \infty)} = \frac{P(\hat{B}\hat{C})}{P(\tau < \infty)} \\ &= \frac{P(\hat{C}) \times 1_{\{j_0=i\}} p_{j_0 j_1} \cdots p_{j_{m-1} j_m}}{P(\tau < \infty)} = ** \times P_{\{\tau < \infty\}}(C). \end{aligned}$$

● **重要结论:**

若 $\vec{i} \in I_n$, 则

$$\{(X_0, \dots, X_n) = \vec{i}\} \subseteq \{\tau = n\}. \quad (1)$$

若 $\vec{i} \notin I_n$, 则

$$\{(X_0, \dots, X_n) = \vec{i}\} \subseteq \{\tau \neq n\}. \quad (2)$$

- 若存在 $I_n \subseteq S^{n+1}$ 使得**重要结论**成立, 则称 τ 为停时.
即, $\forall \vec{i} \in S^{n+1}$, (1) 与(2) 之一成立, 则 τ 为停时. (命题1.4.7)
- τ 为停时 iff $\{\tau \leq n\} \in \sigma(X_0, \dots, X_n) =: \mathcal{F}_n, \forall n$. (定义1.4.6)
- $\tau_i, \tau_D := \inf_{i \in D} \tau_i; \quad \sigma_i, \sigma_D := \inf_{i \in D} \sigma_i$ 都是停时.
- $\varepsilon_i = \sup\{n \geq 0 : X_n = i\}$ 不是停时.

- 在 $\{\tau < \infty\}$ 上, 令

$$\vec{Y} = (Y_0, Y_1, Y_2, \dots) := (X_\tau, X_{\tau+1}, X_{\tau+2}, \dots),$$

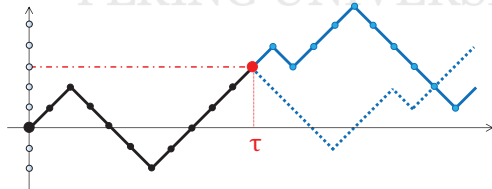
$$\vec{Z} := (X_0, \dots, X_\tau).$$

- 强马氏性(命题1.4.10).

假设 τ 是停时. 那么, 在 $\{\tau < \infty, X_\tau = i\}$ 发生的条件下,

(1) $\{Y_n\}$ 是从 i 出发的马氏链, (2) $\{Y_n\}$ 与 \vec{Z} 相互独立.

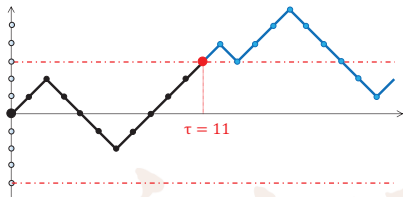
- 拼接轨道:



例. 一维简单随机游动(SRW) $\{S_n\}$.

- 固定 $i, j \geq 1$, 记

$$\tau := \tau_i \wedge \tau_{-j}.$$



- 以后会证明:

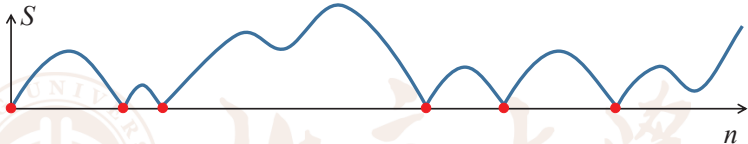
$$P(\tau < \infty) = 1, \quad P(S_\tau = i) = \frac{j}{i+j} =: p.$$

- $\{Y_n := S_{\tau+n}\}$ 也是SRW, 初分布为 $\mu_i = p, \mu_{-j} = 1 - p =: q$.
- 对于轨道集 A ,

$$\begin{aligned} P(\vec{Y} \in A) &= pP(\vec{Y} \in A | S_\tau = i) + qP(\vec{Y} \in A | S_\tau = -j) \\ &= pP_i(A) + qP_{-j}(A). \end{aligned}$$

§1.5 常返性

- 固定 i . 轨道图:



- 令 $V_i = \sum_{n=0}^{\infty} 1_{\{X_n=i\}}$.

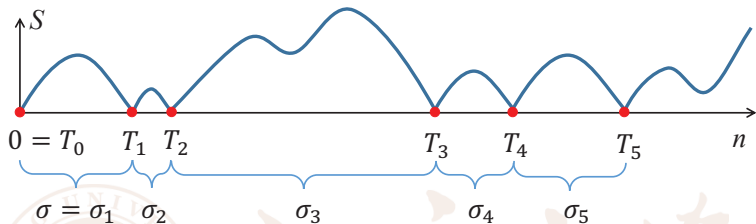
定义 (定义1.5.3)

若 $P_i(V_i = \infty) = 1$, 则称 i 是常返的(recurrent).

若 $P_i(V_i = \infty) = 0$, 则称 i 是非常返的(transient).

- 0-1律、等价性、判别法.

1. 回访时间



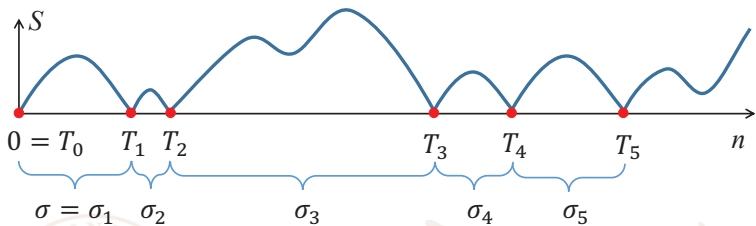
- 固定 i . 令 $T_0 := 0, \forall r \geq 1$,
若 $T_{r-1} < \infty$, 则

$$T_r := \inf\{n \geq T_{r-1} + 1 : X_n = i\}, \quad \sigma_r := T_r - T_{r-1};$$

若 $T_{r-1} = \infty$, 则 $T_r := \infty, \sigma_r := \infty$.

- 常返 $\Leftrightarrow P_i(T_r < \infty, \forall r) = 1$.

关键量: $\sigma = \sigma_1 := \inf\{n \geq 1 : X_n = i\}$.

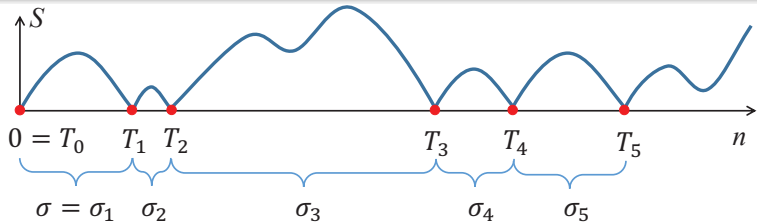


- 固定 n , 记 $\vec{i} := (i_0, i_1, \dots, i_n)$, 令

$$J_n := \{ \vec{i} \in S^{n+1} : i_0 = i_n = i, \text{ 且 } i_r \neq i, r = 1, \dots, n-1 \}.$$

- 在 $\{\sigma < \infty\}$ 上, \vec{Z} 是离散型, 取值于 $\bigcup_{n=1}^{\infty} J_n$.
- $P(\vec{Z} = \vec{i}) = p_{i_0 i_1} \cdots p_{i_{n-1} i_n}, \forall \vec{i} \in J_n$.

$$P(\vec{Z} \in J_n) = P_i(\sigma = n), \quad P(\vec{Z} \in J) = P_i(\sigma < \infty).$$



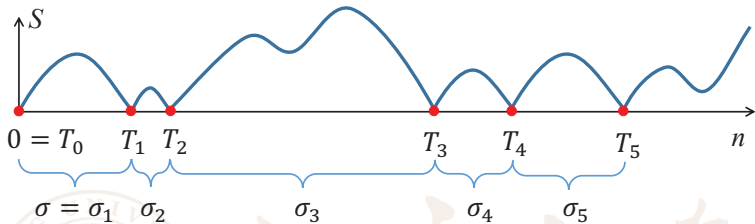
- 命题1.5.1. $\forall r \geq 1; m_1, \dots, m_r \geq 1,$

$$P_i(\sigma_1 = m_1, \sigma_2 = m_2, \dots, \sigma_r = m_r) = \prod_{s=1}^r P_i(\sigma = m_s).$$

- 证: 令 $n_s = \sum_{t=1}^s m_t$; $\vec{X}_s = (X_{n_{s-1}}, \dots, X_{n_s})$. 则

$$\begin{aligned} \text{LHS} &= \sum_{\vec{i}_1 \in J_{m_1}, \dots, \vec{i}_r \in J_{m_r}} P_i(\vec{X}_1 = \vec{i}_1, \dots, \vec{X}_r = \vec{i}_r) \\ &= \prod_{s=1}^r \sum_{\vec{i}_s \in J_{m_s}} P_i(\vec{X}_s = \vec{i}_s) = \text{RHS}. \end{aligned}$$

2. 回访次数



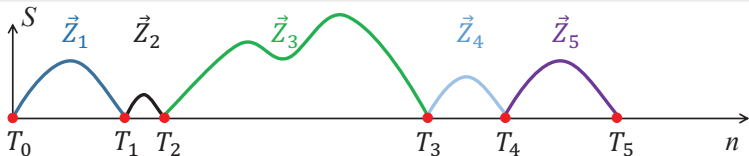
- 记 $\rho_i = P_i(\sigma < \infty) = \sum_{m=1}^{\infty} P_i(\sigma = m)$.
- $P_i(V_i \geq r + 1) = P_i(T_r < \infty) = \rho_i^r$ (推论1.5.2).

$$P_i(T_r < \infty) = P_i(\sigma_1 < \infty, \dots, \sigma_r < \infty) = \rho_i^r.$$

- 0-1律**:

若 $\rho_i = 1$, 则 $P_i(V_i = \infty) = 1$ (常返), $E_i V_i = \infty$.

若 $\rho_i < 1$, 则 $P_i(V_i < \infty) = 1$ (非常返), $E_i V_i < \infty$.



- 假设 i 常返, $X_0 = i$. 令

$$\vec{Z}_r = (X_{T_r-1}, \dots, X_{T_r}).$$

- 命题1.5.4. $\vec{Z}_1, \vec{Z}_2, \dots$ 独立同分布, 且 \vec{Z}_r 的分布列如下:

$$P(\vec{Z} = \vec{i}) = p_{i_0 i_1} \cdots p_{i_{n-1} i_n}, \quad \forall n \geq 1, \vec{i} = (i_0, \dots, i_n) \in J_n.$$

- 证: $\forall r \geq 2, \forall \vec{i}_1, \dots, \vec{i}_r \in \bigcup_{n=1}^{\infty} J_n,$

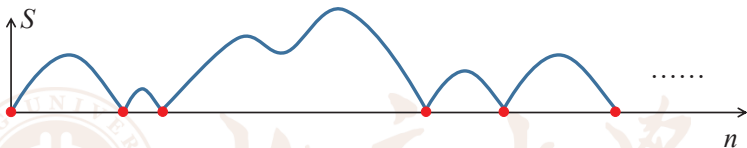
考虑 $\{\vec{Z}_1 = \vec{i}_1, \vec{Z}_2 = \vec{i}_2, \dots, \vec{Z}_r = \vec{i}_r\}$. 由强马氏性,

$$P(B|C) = P(B|A, C) = P_i(\vec{Z}_1 = \vec{i}_2, \dots, \vec{Z}_{r-1} = \vec{i}_r).$$

其中, $A = \{\sigma = |\vec{i}_1|, X_\sigma = i\}$.

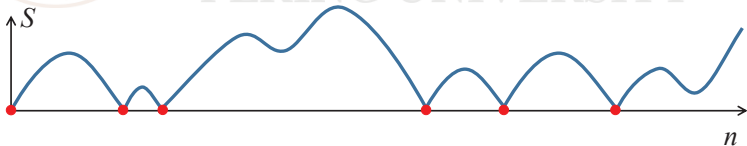
i 常返的等价条件:

- i 常返 $\Leftrightarrow \rho_{ii} = 1 \Leftrightarrow E_i V_i = \infty$.



由 i.i.d. 游弋 (excursion) 拼接.

- i 非常返 $\Leftrightarrow \rho_{ii} < 1 \Leftrightarrow E_i V_i < \infty$.

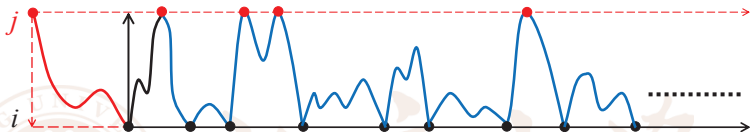


- 判别法: (1) 定义、(2) 吸收概率、(3) 格林函数.

3. 常返是互通类的性质

命题1.5.5. 设 i 常返且 $i \rightarrow j$. 则,

- 设 $X_0 = i$, 则 $\vec{Z}_1, \vec{Z}_2, \dots$ i.i.d..



- $P_i(\sigma_j < \infty) = P_i(V_j = \infty) = 1$:

$$P_i(\exists r \text{ 使得 } j \in \vec{Z}_r) = P_i(\sigma_j < \infty) > 0 \Rightarrow P_i(j \in \vec{Z}_1) > 0.$$

- $P_j(V_i = \infty) = 1$: 进一步, 再由强马氏性,

$$P_j(V_i = \infty) = P_i(V_i = \infty, \sigma_j < \infty) = P_i(V_i = \infty) = 1$$

- $P_j(V_j = \infty) = 1$, 等价性:

$$P_j(V_j = \infty) = P_j(\sigma_i < \infty, V_j = \infty) = P_j(V_j = \infty) = 1.$$

4. 吸收概率与首步分析法

- 吸收态: $p_{ii} = 1$ (定义1.5.6).
- 吸收概率: 给定 $o \in S$, 令

$$x_i = P_i(\tau_o < \infty), \quad \forall i \in S.$$

- 一般地, 给定 $D \subseteq S$, 令

$$x_i = P_i(\tau_D < \infty), \quad \forall i \in S.$$

- $x_i, i \in S$ 是下列方程组的最小非负解,

$$\begin{cases} x_i = \sum_{j \in S} p_{ij} x_j, & \forall i \notin D, \\ x_i = 1, & \forall i \in D. \end{cases}$$

- 命题1.5.7. 若 $\tilde{x}_i, i \in S$ 也是方程组的非负解, 则 $\tilde{x}_i \geq x_i, \forall i$.

$$\begin{aligned}
 \tilde{x}_i &= \sum_{j \in D} p_{ij} \tilde{x}_j + \sum_{j \notin D} p_{ij} \tilde{x}_j \quad (i \notin D) \\
 &= P_i(\tau_D = 1) + \sum_{j \notin D} p_{ij} \left(\sum_{k \in D} p_{jk} \tilde{x}_k + \sum_{k \notin D} p_{jk} \tilde{x}_k \right) \\
 &= P_i(\tau_D = 1) + \frac{P_i(\tau_D = 2)}{1} + \sum_{i_1, i_2 \notin D} p_{ii_1} p_{i_1 i_2} \tilde{x}_{i_2} \\
 &= \dots \geq P_i(\tau_D \leq r) \rightarrow x_i.
 \end{aligned}$$

- $\rho_o = P_o(\sigma_o < \infty) = \sum_{i \in S} p_{oi} P_i(\tau_o < \infty)$.
- 判别法**: 假设不可约. 令 $x_i = P_i(\tau_o < \infty), i \in S$.

常返 iff $x_i = 1, \forall i \in S$.

5. 格林函数

- $V_i = \sum_{n=0}^{\infty} 1_{\{X_n=i\}}$.

- 格林函数:

$$G_{ij} := E_i V_j = E_i \sum_{n=0}^{\infty} 1_{\{X_n=j\}} = \sum_{n=0}^{\infty} p_{ij}^{(n)}.$$

- 常返 iff $G_{ii} = \infty$.

例1.5.11. \mathbb{Z}^d 上的简单随机游动.

• $d = 1. p_{00}^{(2n+1)} = 0,$

$$p_{00}^{(2n)} = C_{2n}^n \frac{1}{2^{2n}} = \frac{(2n)!}{n!n!} \cdot \frac{1}{2^{2n}} \approx \frac{\left(\frac{2n}{e}\right)^{2n} \sqrt{2\pi 2n}}{\left(\frac{n}{e}\right)^{2n} 2\pi n} \cdot \frac{1}{2^{2n}} = \frac{1}{\sqrt{\pi n}}.$$

$$G_{ii} = \sum_{n=0}^{\infty} p_{00}^{(2n)} = \infty. \text{ 常返.}$$

• $d = 2.$

$$\begin{aligned} p_{00}^{(2n)} &= \sum_{n_1+n_2=n} \frac{(2n)!}{(n_1!)^2(n_2!)^2} \frac{1}{4^{2n}} \\ &= C_{2n}^n \frac{1}{2^{2n}} \sum_{m=0}^n C_n^m C_n^{n-m} \frac{1}{2^{2n}} = \left(C_{2n}^n \frac{1}{2^{2n}}\right)^2 \approx \frac{1}{\pi n}. \end{aligned}$$

$$G_{ii} = \sum_{n=0}^{\infty} p_{00}^{(2n)} = \infty. \text{ 常返.}$$

例1.5.11. \mathbb{Z}^d 上的简单随机游动(续).

- $d \geq 3$. $p_{00}^{(2n)} = \sum_{n_1+\dots+n_d=n} \frac{(2n)!}{(n_1!)^2 \dots (n_d!)^2} \times \frac{1}{(2d)^{2n}}$.

- $P(\xi_1 = 2n_1, \dots, \xi_d = 2n_d) = \frac{(2n)!}{(2n_1)! \dots (2n_d)!} \frac{1}{d^{2n}}$.

$$P(B_i) = C_{2n_i}^{n_i} \frac{1}{2^{2n_i}}, \quad i = 1, \dots, d.$$

- $p_{00}^{(2n)} = \sum_{n_1+\dots+n_d=n} P(A)P(B_1) \dots P(B_d)$.

- SLLN $\Rightarrow n_1, \dots, n_d \approx \frac{n}{d}$. 具体地,

$$\vec{n} \in I: |n_i - \frac{n}{d}| \leq \varepsilon n, \quad i = 1, \dots, d; \quad J = \mathbb{Z}_+^d \setminus I.$$

- 若 $\vec{n} \in I$, 则

$$P(B_i) \approx \frac{1}{\sqrt{\pi n_i}} \approx \frac{1}{\sqrt{\pi n/d}}.$$

- $\sum_J P(A) \times \mathbf{1} \leq d \cdot P(|\xi_1 - \frac{n}{d}| > \varepsilon n) \leq e^{-\bar{C}n}$.

- $p_{00}^{(2n)} \leq \sum_I \hat{C}^d / \sqrt{n}^d + \sum_J P(A) \leq Cn^{-d/2}$, $n \gg 1$. 非常返.

例. 区域 D 中的格林函数. 固定 $D \subseteq S$, 令 $\tau = \tau_{D^c}$,

$$G_{ij}^{(D)} = E_i \sum_{n=0}^{\tau-1} 1_{\{X_n=j\}}, \quad i, j \in D.$$

- 固定 j . $x_i = G_{ij}^{(D)}$, $i \in D$ 是下列方程组的最小非负解,

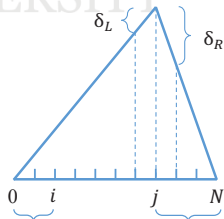
$$\begin{cases} x_i = \sum_k p_{ik} x_k, & \forall i \in D, i \neq j, \\ x_j = 1 + \sum_k p_{jk} x_k, \\ x_i = 0, & \forall i \notin D. \end{cases}$$

- 特例. 一维简单随机游动. $D = (0, N)$.

$$\delta_L = \frac{1}{j} x_j; \quad \delta_R = \frac{1}{N-j} x_j.$$

$$0 = -1 + \delta_L/2 + \delta_R/2.$$

- $G_{ij}^{(N)} = G_{ji}^{(N)} = \frac{2}{N} (i \wedge j)(N - i \vee j)$.



例. 区域 D 中的格林函数(续). $i, j \in D$.

- $G_{ij}^{(D)} = E_i \sum_{n=0}^{\tau-1} 1_{\{X_n=j\}} \neq \sum_{n=0}^{\tau-1} P_i(X_n = j)$.

- $G_{ij}^{(D)} = E_i \sum_{n=0}^{\infty} 1_{\{X_n=j, \tau > n\}} = \sum_{n=0}^{\infty} P_i(X_n = j, \tau > n)$.

- 令 $I_n := \{\vec{i} = (i_0, \dots, i_n) \in S^{n+1} : i_0, \dots, i_n \in D\}$.

$$** = \sum_{\vec{i} \in I_n : i_0=i, i_n=j} p_{i_0 i_1} p_{i_1 i_2} \cdots p_{i_{n-1} i_n}.$$

- $\mathbf{G}^{(D)} = \sum_{n=0}^{\infty} \hat{\mathbf{P}}^n = (\mathbf{I} - \hat{\mathbf{P}})^{-1}$. 其中 $\hat{\mathbf{P}} = \mathbf{P}|_{D \times D}$.

- 若有配称测度 π , 则 $\pi_i G_{ij}^{(D)} = \pi_j G_{ji}^{(D)}$.

- $G_{ii} = \sum_{n=0}^{\infty} p_{ii}^{(n)}$.

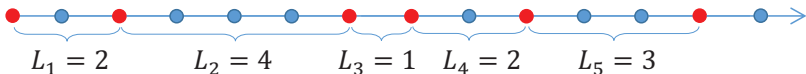
$$P_i(X_n = i) = \sum_{m=1}^n P_i(\sigma_i = m) P_i(X_{n-m} = i), \quad n \geq 1.$$

- 令 $G_{ii}(s) = \sum_{n=0}^{\infty} p_{ii}^{(n)} s^n$. 那么,

$$\begin{aligned} G_{ii}(s) - 1 &= \sum_{n=1}^{\infty} \sum_{m=1}^n P_i(\sigma_i = m) s^m p_{ii}^{(n-m)} s^{n-m} \\ &= \sum_{m=1}^{\infty} P_i(\sigma_i = m) s^m \sum_{\ell=0}^{\infty} p_{ii}^{(\ell)} s^{\ell} = F_{ii}(s) G_{ii}(s). \end{aligned}$$

- 例1.1.9. $p_m = P(L = m)$, $a_n = P_0(Y_n = 0)$. 更新方程:

$$a_n = \sum_{m=1}^n p_m a_{n-m}.$$



§1.6 可配称马氏链的常返性

- 可配称马氏链 \Leftrightarrow 加权图(上的随机游动) \Leftrightarrow 电网络:

$$G = (V, E): V = S, i \stackrel{e}{\sim} j \Leftrightarrow p_{ij} > 0.$$

电阻、权:

$$r_{ij} = r_{ji} = \frac{1}{w_{ij}} = \frac{1}{\pi_i p_{ij}}, \quad i \sim j.$$

- 取定 $o \in S$. 吸收概率法: $x_i = P_i(\tau_o < \infty)$ 满足:

$$x_o = 1; \quad x_i = \sum_{j \in S} p_{ij} x_j, \quad \forall i \neq o.$$

$$\sum_j \pi_i p_{ij} (x_j - x_i) = 0.$$

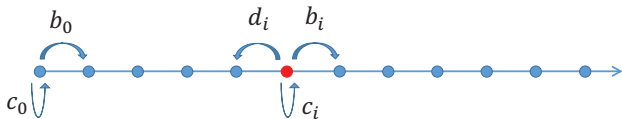
- 在 o 接电势为1 的电源: 电势 V_i 满足:

$$V_o = 1; \quad \sum_{j \in S} \frac{1}{r_{ij}} (V_j - V_i) = 0, \quad \forall i \neq o.$$

- 命题1.6.2. 常返 $\Leftrightarrow R = R(0, \infty) = \infty$.

$$R = I^2 R = \inf \{ \sum_e f_e^2 r_e : f \text{ 是从 } o \text{ 出发的单位流} \}.$$

例1.6.5. 生灭链.



- 可配称. 并且

$$\frac{r_{i,i+1}}{r_{i,i-1}} = \frac{w_{i,i-1}}{w_{i,i+1}} = \frac{d_i}{b_i}$$

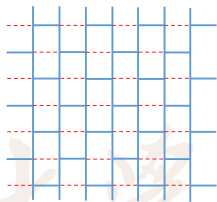
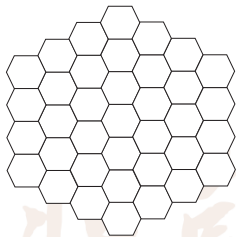
$$\Rightarrow r_{i,i+1} = \frac{d_i}{b_i} r_{i-1,i} = \cdots = \frac{d_i}{b_i} \cdots \frac{d_1}{b_1} r_{0,1}.$$

- 串联. 因此, 常返 iff $\sum_i \frac{d_1}{b_1} \cdots \frac{d_i}{b_i} = \infty$.

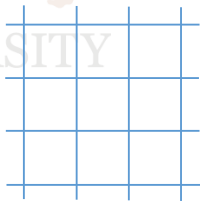
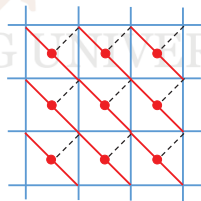
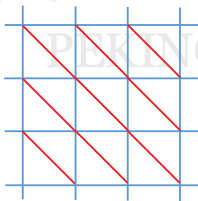
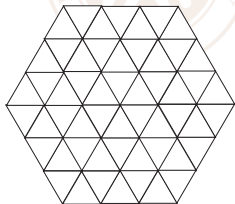
推论1.6.4. $G_1 \subseteq G_2$. 若 G_2 常返, 则 G_1 常返.

例: 已知 \mathbb{Z}^2 常返.

● 蜂窝图常返



● 三角图常返



例1.6.9. \mathbb{Z}^d 非常返.

- $d = 3$ 时, 找单位流 f , 使得 $\sum_e f_e^2 r_e < \infty$. 则非常返.
- Polya 坛子: (X_n, Y_n, Z_n) , $X_0 = Y_0 = Z_0 = 1$. 例如:

$$\vec{i} = (i, j, k), \vec{j} = (i + 1, j, k), \quad p_{\vec{i}, \vec{j}} = \frac{i}{i + j + k}$$

- $(X_n, Y_n, Z_n) \sim U(S_n)$,

$$S_n = \{\vec{i} = (i, j, k) : i, j, k \geq 1 \text{ 且 } i + j + k = 3 + n\}.$$

- 概率转移流: $f_{\vec{i}, \vec{j}} = \pi_{\vec{i}} \cdot p_{\vec{i}, \vec{j}}$.

- $\sum_e f_e^2 r_e < \infty$:

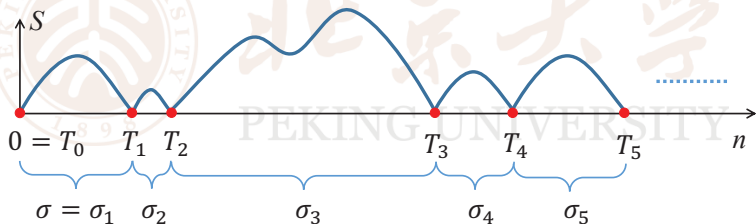
$$\sum_{\vec{i} \in S_n} \frac{1}{|S_n|^2} \cdot \frac{i^2 + j^2 + k^2}{(i + j + k)^2} \leq \frac{1}{|S_n|} = O\left(\frac{1}{n^2}\right).$$

§1.7 遍历定理与正常返

1. 频率的极限

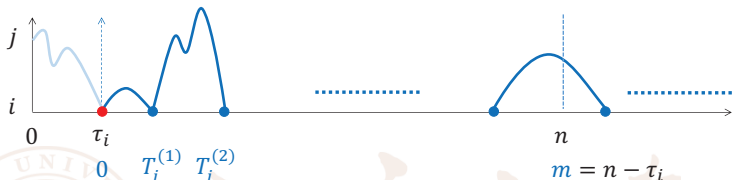
定理 (定理1.7.1)

假设 \mathbf{P} 不可约. 则 $P\left(\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{m=0}^{n-1} 1_{\{X_m=i\}} = \frac{1}{E_i \sigma_i}\right) = 1.$



- 假设非常返. 那么, 左右都为0.
- 假设常返. 假设 $X_0 = i$, 用更新定理即可.

- 假设 $X_0 = j$: $P_j(\tau_i < \infty) = 1$.



- $\omega = (\tilde{\omega}, \hat{\omega})$. $n = m + \tau_i(\tilde{\omega})$, $V_i(n, \omega) = V_i(m, \hat{\omega})$.

- $n \rightarrow \infty$ iff $m \rightarrow \infty$:

$$\frac{1}{n} V_i(n, \omega) = \frac{m}{n} \times \frac{1}{m} V_i(m, \hat{\omega}) \rightarrow \frac{1}{E_i \sigma_i}.$$

- 假设 $X_0 \sim \mu$:

$$P \left(\lim_{n \rightarrow \infty} \frac{1}{n} V_i(n) = \frac{1}{E_i \sigma_i} \right) = \sum_j \mu_j P_j(A) = 1.$$

命题 (命题1.7.2, 频率 \rightarrow 概率)

假设 \mathbf{P} 不可约, π 为不变分布. 则

$$\pi_i = \frac{1}{E_i \sigma_i} > 0, \quad \forall i \in S.$$

- $\pi_i > 0$: $\pi_i = \sum_j \pi_j p_{ji}^{(n)} \geq \pi_o p_{oi}^{(n)} > 0.$

- 由遍历定理,

$$P_\pi \left(\lim_{n \rightarrow \infty} \frac{1}{n} V_i(n) = \frac{1}{E_i \sigma_i} \right) = 1.$$

- 再由有界收敛定理,

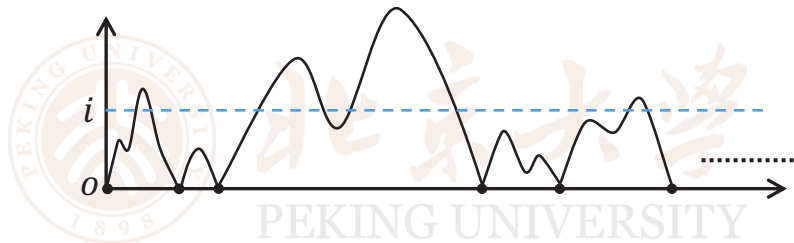
$$\lim_{n \rightarrow \infty} E_\pi \frac{1}{n} V_i(n) = \frac{1}{E_i \sigma_i}.$$

- π 是不变分布:

$$E_\pi \frac{1}{n} V_i(n) = E_\pi \frac{1}{n} \sum_{m=0}^{n-1} 1_{\{X_m=i\}} = \frac{1}{n} \sum_{m=0}^{n-1} P_\pi(X_m = i) = \pi_i.$$

2. 正常返与不变分布

- 再看频率: 固定 o . 记 $\sigma = \sigma_o$.



$$i \text{ 出现的频率} \approx \frac{V_i^{(1)} + \dots + V_i^{(r)}}{\sigma_1 + \dots + \sigma_r} \approx \frac{E_o V_i^{(1)}}{E_o \sigma} \propto E_o V_i^{(1)}.$$

命题 (命题1.7.4 & 1.7.20)

假设不可约、常返. 固定 o , 令 $\mu_i = \underbrace{E_o \sum_{n=0}^{\sigma_o-1} 1_{\{X_n=i\}}}$. 那么, μ 是唯一^(c)满足 $\mu_o = 1$ 的不变^(a)测度^(b).

证明, (a) 不变性, 即, 验证 $\sum_j \mu_j p_{ji} = \mu_i$. (记 $\sigma = \sigma_o$.)

$$\bullet \mu_j = E_o \sum_{n=0}^{\infty} 1_{\{n < \sigma, X_n=j\}} = \underbrace{\sum_{n=0}^{\infty} P_o(n < \sigma, X_n = j)}.$$

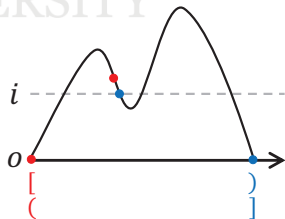
$$\bullet \text{于是, } \sum_j \mu_j p_{ji} = \sum_j \sum_{n=0}^{\infty} P_o(n < \sigma, X_n = j) \\ \times P(X_{n+1} = i | X_n = j, n < \sigma)$$

$$\bullet = \sum_{n=0}^{\infty} \sum_j P_o(n < \sigma, X_n = j, X_{n+1} = i)$$

$$= \underbrace{\sum_{n=0}^{\infty} P_o(n < \sigma, X_{n+1} = i)}.$$

$$\bullet = \underbrace{E_o \sum_{n=0}^{\sigma-1} 1_{\{X_{n+1}=i\}}} = E_o \sum_{n=1}^{\sigma} 1_{\{X_n=i\}}$$

$$\bullet \stackrel{(*)}{=} E_o \sum_{n=0}^{\sigma-1} 1_{\{X_n=i\}} = \mu_i.$$



证明(续), (b) 略. (c) 唯一性: 假设 $\lambda \mathbf{P} = \lambda$ 且 $\lambda_o = 1$.

- 方法二、令 $\hat{p}_{ij} = \frac{\mu_j p_{ji}}{\mu_i}$. 则 $\hat{p}_{ij}^{(n)} = \frac{\mu_j p_{ji}^{(n)}}{\mu_i}$.

- $\hat{p}_{ii}^{(n)} = p_{ii}^{(n)}$, 所以 $\{\hat{X}_n\}$ 也常返.

- 令 $f(i) = \frac{\lambda_i}{\mu_i}, \forall i$. 则

$$(\hat{\mathbf{P}}f)(i) = \sum_j \hat{p}_{ij} f(j) = \sum_j \frac{\mu_j p_{ji}}{\mu_i} \cdot \frac{\lambda_j}{\mu_j} = \sum_j \frac{\lambda_j p_{ji}}{\mu_i} = f(i).$$

- $M_n = f(\hat{X}_n), n \geq 0$ 是鞅:

$$\begin{aligned} E(M_{n+1} | \hat{X}_n = i, \hat{X}_0 = i_0, \dots, \hat{X}_{n-1} = i_{n-1}) \\ = \sum_j \hat{p}_{ij} f(j) = (\hat{\mathbf{P}}f)(i) = f(i) = M_n. \end{aligned}$$

- 定理: 非负鞅 a.s. 收敛. 因此, $f(\hat{X}_n)$ a.s. 收敛.

- $\{\hat{X}_n\}$ 常返 $\Rightarrow f \equiv f(o) = 1$.

定义 (定义1.7.3)

若 $E_i \sigma_i < \infty$, 则称 i 是正常返的.

若 $P_i(\sigma_i < \infty) = 1$ 但 $E_i \sigma_i = \infty$, 则称 i 是零常返的.

定理 (定理1.7.5)

假设不可约. 则下面几条等价: (1) 所有状态正常返, (2) 存在正常返态, (3) 存在不变分布. 此时, $\pi_i = \frac{1}{E_i \sigma_i}, \forall i \in S$.

- 推论1.7.7. 假设 S 有限、不可约. 那么, 不变分布存在.

$$1 = \sum_i \frac{1}{n} \sum_{m=0}^{n-1} 1_{\{X_m=i\}} \rightarrow \sum_i \frac{1}{E_i \sigma_i}.$$

- 推论1.7.21. \exists 不能归一化的不变测度, 则不变分布不存在.
- 频率:

$$i \text{ 出现的频率} \approx \frac{V_i^{(1)} + \dots + V_i^{(r)}}{\sigma_1 + \dots + \sigma_r} \approx \frac{E_o V_i^{(1)}}{E_o \sigma} = \frac{1}{E_i \sigma_i} = \pi_i.$$

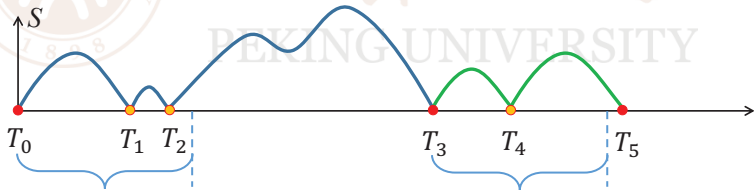
例1.7.17. 设不可约、正常返. 令 $\sigma := \inf\{n \geq m : X_n = i\}$. 证明:

$$E_i \sum_{n=0}^{\sigma-1} 1_{\{X_n=j\}} = \pi_j E_i \sigma.$$

- 方法一、仿照命题1.7.5., 证明 $\tilde{\mu}_i, i \in S$ 是不变测度.

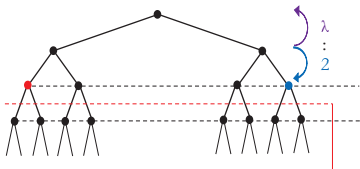
$$\tilde{\mu}_i = c\pi_i \Rightarrow c = \sum_i \tilde{\mu}_i = E_i \sigma.$$

- 方法二、令 $S_0 = 0, S_r = \inf\{n \geq m + S_{r-1} : X_n = i\}$, 则



$$\text{频率} = \frac{\tilde{V}_j^{(1)} + \cdots + \tilde{V}_j^{(r)}}{\sigma_1 + \cdots + \sigma_r} \rightarrow \frac{\star\star}{E_i \sigma}.$$

例1.7.15. \mathcal{T}^d 上 λ -biased 随机游动:



- 对称性 $\Rightarrow \pi_i = c_{|i|}$.

- $d^n c_n \times \frac{\lambda}{\lambda+d} = d^{n-1} c_{n-1} \times \frac{d}{\lambda+d}$,

$$c_n = \frac{1}{\lambda} c_{n-1} = \cdots = \frac{1}{\lambda^n} c_0.$$

- 第 n 层的总权重:

$$\sum |i| = n \pi_i = \left(\frac{d}{\lambda}\right)^n c_0.$$

- 正常返 $\Leftrightarrow \lambda > d$.

- 零常返 $\Leftrightarrow \lambda = d$, 非常返 $\Leftrightarrow \lambda < d$.

3. 遍历定理(假设不可约、正常返).

- 频率 \rightarrow 概率:

$$\frac{1}{n} \sum_{m=0}^{n-1} 1_{\{X_m=i\}} \xrightarrow{\text{a.s.}} \pi_i = \frac{1}{E_i \sigma_i} = \frac{E_o V_i^{(1)}}{E_o \sigma_o}.$$

- 再由有界收敛定理:

$$\frac{1}{n} \sum_{m=0}^{n-1} P(X_m = i) \rightarrow \pi_i.$$

- 引理1.7.8: 如果 $\nu^{(n)}, n \geq 1$ 都是分布列, $\nu_i^{(n)} \rightarrow \pi_i, \forall i$. 那么,

$$\sum_i |\nu_i^{(n)} - \pi_i| \rightarrow 0.$$

- 命题1.7.9.

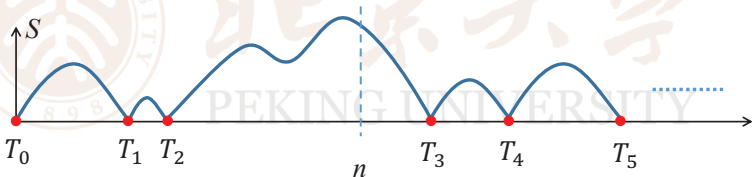
$$\sum_{i \in S} \left| \frac{1}{n} \sum_{m=0}^{n-1} p_{ji}^{(m)} - \pi_i \right| \rightarrow 0, \quad \sum_{i \in S} \left| \frac{V_i(n)}{n} - \pi_i \right| \xrightarrow{\text{a.s.}} 0.$$

定理 (遍历定理, 定理1.7.11)

假设不可约、正常返. 若 $\sum_i \pi_i |f(i)| < \infty$, 则

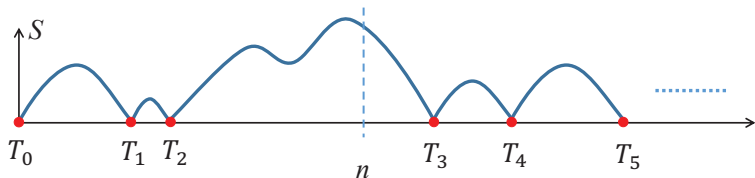
$$\frac{1}{n} \sum_{m=0}^{n-1} f(X_m) \xrightarrow{a.s.} \sum_i \pi_i f(i).$$

- 不妨设 $X_0 = o$. 固定 o . $\xi_r = \sum_{n=T_{r-1}}^{T_r-1} f(X_n)$, $r \geq 1$ i.i.d..



- $T_r < n \leq T_{r+1}$:

$$** = \xi_1 + \cdots + \xi_r + \sum_{m=T_r}^{n-1} f(X_m).$$



- $\xi = \sum_i f(i)V_i^{(1)}, \quad \eta = \sum_i |f(i)|V_i^{(1)}.$

$$|\xi| \leq \eta, \quad \max_{0 \leq m \leq \sigma-1} \left| \sum_{n=0}^m f(X_n) \right| \leq \eta.$$

- 期望存在:

$$E\eta = \sum_i |f(i)| \underbrace{E_o V_i^{(1)}} = \sum_i |f(i)| \underbrace{\pi_i E_o \sigma} < \infty,$$

- $\frac{1}{n}(\xi_1 + \cdots + \xi_r + \eta_r) \xrightarrow{\text{a.s.}} \sum_i f(i)\pi_i:$

$$\frac{\xi_1 + \cdots + \xi_r}{r} \xrightarrow{\text{a.s.}} E\xi = \sum_i f(i)\pi_i E_o \sigma, \quad \frac{\eta_r}{r} \xrightarrow{\text{a.s.}} 0, \quad \frac{r}{n} \rightarrow \frac{1}{E_o \sigma}.$$

补充: 遍历.

- 保测变换: $\theta : (\Omega, \mathcal{F}, P) \leftrightarrow, P(\theta^{-1}(D)) = P(D)$.
 - 例: 平稳马氏链, $\theta : \omega = (\omega_0, \omega_1, \omega_2, \dots) \mapsto (\omega_1, \omega_2, \dots)$.
 $\{(X_1, X_2, \dots) \in D\} \stackrel{\text{w.p.}}{=} \{(X_0, X_1, \dots) \in D\} = D$.
- 遍历: 若 $D \in \mathcal{F}$ 满足 $D \subseteq \theta^{-1}D$, 则 $P(D) = 0$ 或 1 .
 - 例: $\vec{X} \in D \Rightarrow \theta \vec{X} = (X_1, X_2, \dots) \in D$.
 - 反例: $S = S_1 \cup S_2, \mu = \frac{1}{2}\pi + \frac{1}{2}\nu, D = \{X_n \in S_1, \forall n\}$.
 - 遍历 \Rightarrow 若 $P(D) > 0$, 则 $P(\bigcup_{n=0}^{\infty} \theta^{(-n)}D) = 1$.
- 遍历定理: 遍历, $\xi : (\Omega, \mathcal{F}) \rightarrow (\mathbb{R}, \mathcal{B}), E|\xi| < \infty$. 则
$$\frac{1}{n} \sum_{m=0}^{n-1} \xi(\theta^{(m)}(\omega)) \xrightarrow{\text{a.s.}} E\xi.$$
 - 例: 不可约、正常返. 令 $\xi(\omega) = f(X_0)$, 则 $\star\star = f(X_m)$.

例1.7.16. 假设 \mathbf{P} 不可约、正常返. 则

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{m=0}^{n-1} 1_{\{X_m=i, X_{m+1}=j\}} \xrightarrow{\text{a.s.}} \pi_i p_{ij}.$$

- 方法一、 $\{Y_n = (X_n, X_{n+1})\}$ 是马氏链,
转移概率: $p_{(i,j)(j,k)} = p_{jk}$, 不变分布: $\mu_{(i,j)} = \pi_i p_{ij}$. 故,

$$\frac{1}{n} \sum_{m=0}^{n-1} 1_{\{X_m=i, X_{m+1}=j\}} = \frac{1}{n} \sum_{m=0}^{n-1} 1_{\{Y_m=(i,j)\}} \xrightarrow{\text{a.s.}} \mu_{(i,j)} = \pi_i p_{ij}.$$

- 方法二: 假设 n 之前完成 r 次游弋,

$$\frac{r}{n} \times \frac{1}{r} \sum_{s=0}^{r-1} 1_{\{X_{T_s+1}=j\}} \xrightarrow{\text{a.s.}} \pi_i p_{ij}.$$

§1.8 强遍历定理

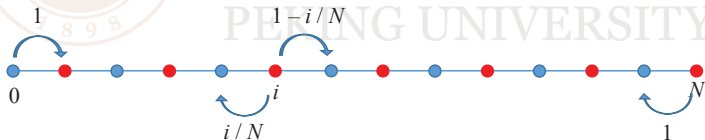
假设: 不可约、正常返.

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{m=0}^{n-1} P(X_m = i) = \pi_i.$$

- $P(X_n = i) \approx \pi_i, \forall i? (n \gg 1)$
- 反例: 例1.6.1. Ehrenfest模型. $S = \{0, 1, \dots, N\}$.

$$\pi_i = C_N^i 2^{-N}, \forall i.$$

$$\text{取 } X_0 = 0. P(X_{2n} = 1) = 0, \forall n.$$



- 希望: $p_{ij}^{(n)} > 0, \forall n \gg 1.$

• 定义1.8.3: 若 $\exists n_i$ 使得 $p_{ii}^{(n)} > 0, \forall n \geq n_i$, 则称 i 为**非周期的**.

• 等价性: 如果 $i \leftrightarrow j$ 且 i 非周期, 则 j 也非周期.

• 证: 存在 r, s 使得 $p_{ij}^{(r)}, p_{ji}^{(s)} > 0$, 于是

$$p_{jj}^{(r+s+n)} \geq p_{ji}^{(s)} p_{ii}^{(n)} p_{ij}^{(r)} > 0, \quad \forall n \geq n_i.$$

• 推论1.8.4. 若不可约、非周期, 则 $\forall i, j, \exists n_{ij}$ 使得

$$p_{ij}^{(n)} > 0, \quad \forall n \geq n_{ij}.$$

• 假设不可约. 若存在 i 使得 $p_{ii} > 0$, 则非周期.

定理 (定理1.8.5. 强遍历定理)

假设不可约、**正常返**、**非周期**, 不变分布为 π . 那么, $\forall \mu$,

$$\lim_{n \rightarrow \infty} \sum_i |P_\mu(X_n = i) - \pi_i| = 0.$$

- 证明方法: 耦合(coupling).
- $\{Z_n = (W_n, Y_n)\}$: 状态空间、转移概率、初分布:

$$\tilde{S} = S \times S, \quad r_{(i,j)(k,\ell)} = p_{ik}p_{j\ell}.$$

- Step 1 ~ 3. $\{Z_n\}$ **不可约**、非周期、**(正)常返**:

$$r_{(i,j)(k,\ell)}^{(n)} = p_{ik}^{(n)} p_{j\ell}^{(n)} > 0, \quad \forall n \geq n_{ik} \vee n_{j\ell};$$

$$\tilde{\pi} = \pi \times \pi, \quad \text{i.e. } \tilde{\pi}_{i,j} = \pi_i \pi_j, \quad \forall (i,j) \in \tilde{S}.$$

- Step 4. $P(\tau < \infty) = 1$:

$$\tau = \inf\{n \geq 0 : W_n = Y_n\} = \tau_D.$$

- Step 5. $P(W_n = j, \tau \leq n) = P(Y_n = j, \tau \leq n)$:
 $\forall 0 \leq m \leq n, i \in S$:

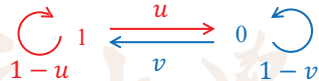
$$\begin{aligned}
 & P(W_n = j, \tau = m, Z_m = (i, i)) \\
 &= P(*, *)P_{(i,i)}(W_n = j) = P(*, *)P_{(i,i)}(Y_n = j) \\
 &= P(Y_n = j, \tau = m, Z_m = (i, i)).
 \end{aligned}$$

- Step 6. $P_i(X_n = j) - \pi_j = P_{\mu \times \pi}(W_n = j) - P_{\mu \times \pi}(Y_n = j)$:

$$\begin{aligned}
 |\star| &= |P(W_n = j, \tau > n) - P(Y_n = j, \tau > n)| \\
 &\leq 2P(\tau > n) \rightarrow 0.
 \end{aligned}$$

例1.8.6. Wright-Fisher模型. N 个人, 表态: “1” 或 “0” 每人每天独立任选一人并随机跟随或改变. $X_n =$ 第 n 天表态1的人数.

求: $EX_n = \sum_{j=0}^N jP(X_n = j)$ 在 $n \rightarrow \infty$ 时的极限.

- 若 $X_n = i$, 则 $X_{n+1} \sim B(N, \rho_i)$, 

其中, $\rho_i = (1 - u)\frac{i}{N} + v\frac{N-i}{N}$.

- 不可约、正常返、非周期, $EX_n \rightarrow \sum_{j=0}^N j\underline{\pi}_j$.

- $$A = \sum_j j \sum_i \pi_i p_{ij} = \sum_i \pi_i \sum_j \underbrace{j p_{ij}} = \sum_i \pi_i \underbrace{N \rho_i}$$

$$= \sum_i \pi_i [(1 - u)i + v(N - i)] = (1 - u - v)A + vN.$$

- $A = \frac{v}{u+v}N.$

- $u = v = \frac{1}{2}$. $\rho_i = \frac{1}{2}$. X_1, X_2, \dots i.i.d., $\pi = B(N, 1/2)$.

命题 (命题1.8.9)

若不可约、零常返、非周期, 则 $p_{ij}^{(n)} \rightarrow 0, \forall i, j$.

- Claim 1. $\forall \varepsilon > 0, \exists M$ 使得 $\forall n$, 在

$$p_{ij}^{(n)}, p_{ij}^{(n+1)}, \dots, p_{ij}^{(n+M)}$$

中存在某个 $p_{ij}^{(n+m)}$ 使得 $p_{ij}^{(n+m)} < \varepsilon$.

- Claim 2. 当 $n \gg 1$ 时, $|p_{ij}^{(n)} - p_{ij}^{(n+m)}| < \varepsilon, \forall 1 \leq m \leq M$.
- Claims $\Rightarrow p_{ij}^{(n)} < 2\varepsilon, n \gg 1$.

证明Claim 1. $\exists M$ 使得 $\min\{p_{ij}^{(n)}, p_{ij}^{(n+1)}, \dots, p_{ij}^{(n+M)}\} < \varepsilon, \forall n$.

- $E_i \sigma_i = P_i(\sigma_i \geq 1) + P_i(\sigma_i \geq 2) + \dots = \sum_{\ell=0}^{\infty} P_i(\sigma_i > \ell) = \infty$.

取 M 使得 $\sum_{\ell=0}^M P_i(\sigma_i > \ell) > \frac{1}{\varepsilon}$.

- $\{X_{n+M} = j\}$: $p_{ij}^{(n+M)} P_j(\sigma_j > 0)$
- $\{X_{n+M-1} = j, X_{n+M} \neq j\}$: $p_{ij}^{(n+M-1)} P_j(\sigma_j > 1)$
- $\{X_{n+M-2} = j, X_{n+M-1}, X_{n+M} \neq j\}$: $p_{ij}^{(n+M-2)} P_j(\sigma_j > 2)$
- \dots
- $\{X_n = j, X_{n+1}, \dots, X_{n+M} \neq j\}$: $p_{ij}^{(n)} P_j(\sigma_j > M)$
- $\{X_n, \dots, X_{n+M} \neq j\}$
- 反证法: 若 $* \geq \varepsilon$, 则 $\sum \text{RHS} \geq \varepsilon \times * > 1$, 矛盾!

证明, Claim 2. 当 $n \gg 1$ 时, $|p_{ij}^{(n)} - p_{ij}^{(n+m)}| < \varepsilon, \forall 1 \leq m \leq M$.

- $\{Z_n = (W_n, Y_n)\}$ 不可约.

情形I. $\{Z_n\}$ 非常返. 则

$$p_{ij}^{(n)} p_{ij}^{(n)} = \tilde{p}_{(i,i)(j,j)}^{(n)} \rightarrow 0.$$

- 情形II. $\{Z_n\}$ 常返. 取 $\mu_j = 1_{\{j \neq i\}}, j \in S$;

$$|*| = |P_{\mu \times \mu \mathbf{P}^m}(W_n = j) - P_{\mu \times \mu \mathbf{P}^m}(Y_n = j)|$$

$$\leq 2P_{\mu \times \mu \mathbf{P}^m}(\tau > n) \rightarrow 0.$$

总结: 假设不可约、非周期.

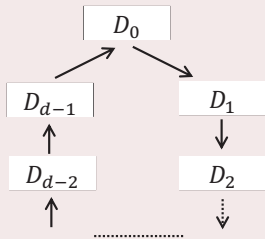
- 正常返: $p_{ij}^{(n)} \rightarrow \pi_j$.
- 零常返或非常返: $p_{ij}^{(n)} \rightarrow 0$.
- $P_\mu(X_n = j) \rightarrow \star$.

$$\sum_{i \in D} \mu_i p_{ij}^{(n)} + \sum_{i \notin D} \mu_i p_{ij}^{(n)} \approx \sum_{i \in D} \mu_i \star + \varepsilon \approx \sum_i \mu_i \star + 2\varepsilon.$$

定理 (定理1.8.2)

假设不可约. 那么, 存在唯一的正整数 d 以及 S 的一个分割 D_0, D_1, \dots, D_{d-1} (对任何 n 补充定义 $D_{nd+r} := D_r$), 使得:

- $\forall r \geq 0, i \in D_r, s \geq 0,$
$$\sum_{j \in D_{r+s}} p_{ij}^{(s)} = 1;$$
- $\forall r \geq 0, i, j \in D_r, \exists N \geq 0$ 使得
$$p_{ij}^{(nd)} > 0, \forall n \geq N.$$



- 定理中的 d 被称为“周期”. 非周期指 $d = 1$.
- $d > 1$ 时: $\hat{\mathbf{P}} = \mathbf{P}^d$ 在每个 D_r 上不可约、非周期.

\mathbf{P} 正(零、非)常返 iff $\hat{\mathbf{P}}$ 正(零、非)常返.

总结: 假设不可约.

- 正常返、非周期:

$$p_{ij}^{(n)} \rightarrow \pi_j.$$

- 正常返、周期:

$$p_{ij}^{(nd+s)} \rightarrow d\pi_j$$

$$p_{ij}^{(m)} \rightarrow 0, \quad m \neq nd + s, \quad i \in D_r, \quad j \in D_{r+s}.$$

- 零常返:

$$p_{ij}^{(n)} \rightarrow 0, \quad \text{但} \quad \sum_n p_{ij}^{(n)} = \infty.$$

- 非常返:

$$p_{ij}^{(n)} \rightarrow 0, \quad \text{且} \quad \sum_n p_{ij}^{(n)} < \infty.$$

§1.1 习题5. 投球成功的概率取决于前两次的投球成绩.

求成功概率、成功(频)率的渐近值.

- 成功概率: $p_n = P(\xi_n = 1)$
 $= P(X_n = 10) + P(X_n = 11).$

- 强遍历: $\lim_n p_n = \pi_{10} + \pi_{11}.$

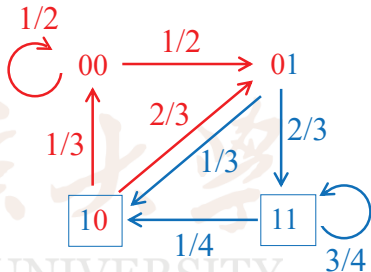
- $\frac{1}{2}\pi_{00} = \frac{1}{3}\pi_{10},$

- $\frac{2}{3}\pi_{01} = \frac{1}{4}\pi_{11},$

- $\pi_{10} = \pi_{01}.$

解得 $\pi = (\frac{1}{8}, \frac{3}{16}, \frac{3}{16}, \frac{1}{2}).$

- 遍历定理: 成功频率 = $\frac{1}{n} \sum_{m=0}^{n-1} 1_{\{\xi_m=1\}}$
 $= \frac{1}{n} \sum_{m=0}^{n-1} (1_{\{X_n=10\}} + 1_{\{X_n=01\}}) \rightarrow \pi_{10} + \pi_{11}.$



马氏链蒙特卡洛算法(Markov chain Monte Carlo, MCMC).

- 目标: 模拟 $X \sim \pi$.
- 思想: 构造以 π 为不变分布的马氏链转移矩阵 \mathbf{P} .
- 输入初值 i_0 , 迭代产生 i_1, \dots, i_n .
- 输出 $X = i_n$ (强遍历定理).
- 处理 $d \neq 1$: 考虑 $\hat{\mathbf{P}} = \varepsilon \mathbf{I} + (1 - \varepsilon) \mathbf{P}$.
 $\pi \mathbf{I} = \pi \Rightarrow \pi$ 为 $\hat{\mathbf{P}}$ 的不变分布.

例:(Lawler书§7.3) 令 $\mathbb{M} = \{\mathbf{M} = (m_{ij})_{N \times N} : m_{ij} = 0 \text{ 或 } 1\}$,

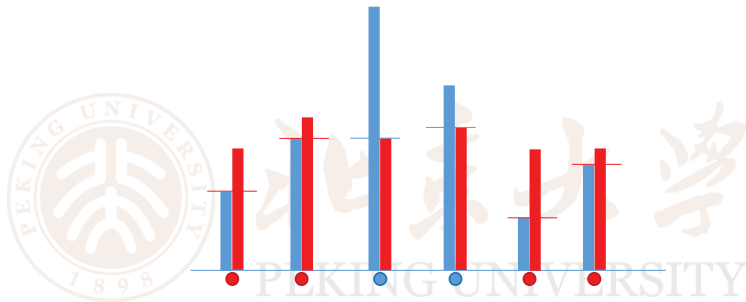
$$\mathcal{M} = \{\mathbf{M} \in \mathbb{M} : \text{若 } m_{ij} = 1 \text{ 则 } m_{i\pm 1, j} = m_{i, j\pm 1} = 0\}.$$

模拟服从 \mathcal{M} 上的均匀分布的“随机变量”.

- $|\mathbb{M}| = 2^{N^2}$, $|\mathcal{M}| \approx \beta^{N^2}$.
- 输入: $\mathbf{M} = \mathbf{0}$.
- 迭代: 任取 (i, j) , 改变 m_{ij} 得到 $\hat{\mathbf{M}}$.
若 $\hat{\mathbf{M}} \in \mathcal{M}$ 则用 $\hat{\mathbf{M}}$ 代替 \mathbf{M} .
- 迭代 n 次后输出: \mathbf{M} .
- $\mathbf{M} \sim \hat{\mathbf{M}}$: 仅一个元素不同. 此时, $p_{\mathbf{M}\hat{\mathbf{M}}} = \frac{1}{N^2}$.
 $p_{\mathbf{M}\mathbf{M}} = 1 - \frac{1}{N^2} \times \mathbf{M}$ 的邻居数.

§1.9 收敛速度

- 全变差距离: $d_{TV}(\mu, \nu) = \|\mu - \nu\| := \frac{1}{2} \sum_i |\mu_i - \nu_i|$.



- $= \mu(A) - \nu(A) = \nu(A) - \mu(A) = \sup_{A \subseteq S} |\mu(A) - \nu(A)|$.
- $= \inf_{X \sim \mu, Y \sim \nu} P(X \neq Y) = \inf_{**} E1_{\{X \neq Y\}}$.
- $d_\varphi(\mu, \nu) := \inf_{**} E\varphi(X, Y) = \sup_{|f(x) - f(y)| \leq \varphi(x, y)} (E_\mu f - E_\nu f)$.

- $\|\mu\mathbf{P} - \nu\mathbf{P}\| \leq \|\mu - \nu\|.$

$$\begin{aligned} \text{LHS} &= \frac{1}{2} \sum_j |\sum_i \mu_i p_{ij} - \sum_i \nu_i p_{ij}| \\ &= \frac{1}{2} \sum_j \sum_i |\mu_i - \nu_i| p_{ij} = \text{RHS}. \end{aligned}$$

- 找 $X_0 \sim \mu, Y_0 \sim \nu$ 使得 $\text{RHS} = P(X_0 \neq Y_0)$. 取

$$r_{(i,i)(k,k)} = p_{ik}; \quad r_{(i,j)(k,\ell)} = p_{ik}p_{j\ell}, \quad \forall i \neq j.$$

则 $\text{LHS} \leq P(X_1 \neq Y_1) \leq P(X_0 \neq Y_0)$.

- $\|\mu\mathbf{P}^n - \pi\| \leq Ce^{-\beta n}, \forall n \geq 0.$

- 例: $\mathbf{P} = \mathbf{P}^T, \& \dots, \mu = \pi \oplus \pi^\perp,$

$$\mu\mathbf{P}^n = \pi \oplus \lambda^n \pi^\perp, \quad |\lambda| < 1.$$

§1.10 一维简单随机游动(SRW)

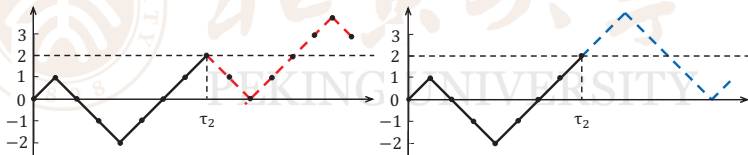
1. 首达时.

$$S_n = \xi_1 + \cdots + \xi_n, \quad P(\xi = 1) = P(\xi = -1) = \frac{1}{2}.$$

命题 (命题1.10.1, 反射原理)

$$P_0(\tau_i < n, S_n = i + j) = P_0(\tau_i < n, S_n = i - j).$$

- 前 n 步轨道: $\{\tau_i < n, S_n = i + j\} \leftrightarrow \{\tau_i < n, S_n = i - j\}$.



- $\{X_n\}$ 仍然是SRW.

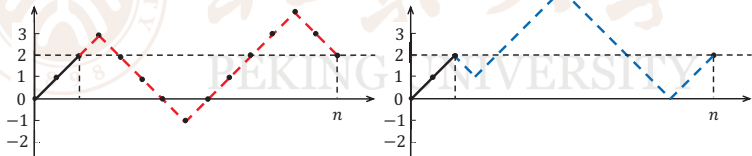
$$X_n = \begin{cases} S_n, & \text{若 } n \leq \tau_i; \\ 2i - S_n, & \text{若 } n > \tau_i \end{cases}$$

命题 (命题1.11.1)

$$P_0(\tau_i = n) = \frac{i}{n}P_0(S_n = i), \forall i \geq 1.$$

- $\tau_i = n$ 当且仅当 $S_n = i$, $S_1, \dots, S_{n-1} \neq i$.
- $\{S_n = i\} - \{\tau_i = n\} = \{\tau_i < n, S_n = i\}$.

$$P(A) = 2P(S_{n-1} = i + 1, S_n = i).$$

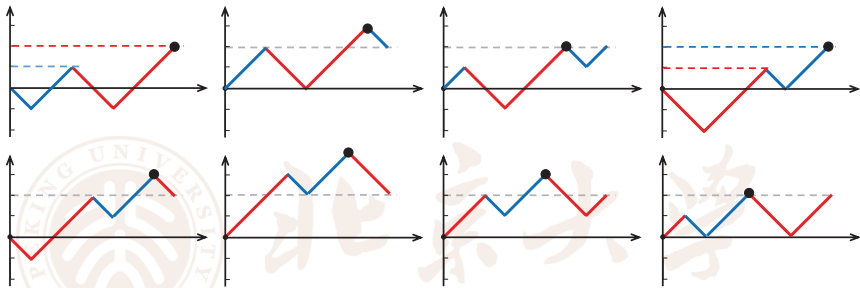


- $P(\tau_i = n) = P(S_n = i) - P(S_{n-1} = i + 1),$

$$** = C_{n-1}^{(n+i)/2} \frac{1}{2^{n-1}} = \frac{n-i}{n} P(S_n = i).$$

Ballot定理: 假设 $\xi \leq 1$, 那么 $P(\tau_i = n) = \frac{i}{n}P(S_n = i), \forall i \geq 1$.

• n 步轨道: $\omega, \theta\omega, \theta^2\omega, \theta^3\omega; \theta^4\omega, \theta^5\omega, \theta^6\omega, \theta^7\omega$.



•
$$\frac{P(\tau_i = n)}{P(S_n = i)} = \frac{nP(\tau_i = n)}{n(p_1 + \dots + p_N)} = \frac{ip_1 + \dots + ip_N}{n(p_1 + \dots + p_N)} = \frac{i}{n}$$

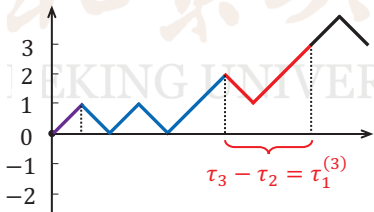
$p_1 :$	ω_1	$\theta\omega_1$	$\theta^2\omega_1$	$\theta^3\omega_1$	$\theta^4\omega_1$	$\theta^5\omega_1$	$\theta^6\omega_1$	$\theta^7\omega_1$
$p_2 :$	ω_2	$\theta\omega_2$	$\theta^2\omega_2$	$\theta^3\omega_2$	$\theta^4\omega_2$	$\theta^5\omega_2$	$\theta^6\omega_2$	$\theta^7\omega_2$
\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots
$p_N :$	ω_N	$\theta\omega_N$	$\theta^2\omega_N$	$\theta^3\omega_N$	$\theta^4\omega_N$	$\theta^5\omega_N$	$\theta^6\omega_N$	$\theta^7\omega_N$

- 推论1.10.3. $P(\tau_1 > 2n - 1) = P(S_{2n} = 0)$

$$P(\tau_1 \leq 2n) = P(S_{2n} \geq 2) + P(S_{2n} \leq 0) = P(|S_{2n}| \geq 2).$$

- 推论1.10.3. $P_0(\tau_1 < \infty) = 1, E_0\tau_1 = \infty.$ (零常返).

- 命题1.10.6. $\tau_i = \tau_1^{(1)} + \dots + \tau_1^{(i)}.$



命题 (命题1.10.7. 反正弦律)

$$\lim_{n \rightarrow \infty} P_0(S_r \neq 0, \forall \delta n < r \leq n) = \frac{2}{\pi} \arcsin \sqrt{\delta}.$$

- 令 $m = [\delta n]$. 则 $\star = \sum_i P(S_m = i) P_i(\tau_0 > n - m)$.
- $1 - \star = \sum_i P(S_m = i) P_0(\tau_i \leq n - m)$.
- 取与 $\{S_n\}$ 独立的SRW $\{T_n\}$:

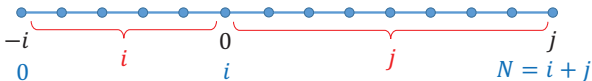
$$P_0(\tau_i \leq n - m) = P(T_{n-m} = i) + P(|T_{n-m}| > |i|).$$

- $1 - \star \approx \sum_i P(S_m = i) P(|T_{n-m}| > |i|) = P(|T_{n-m}| > |S_m|)$.
- $\star = P(|T_{n-m}| \leq |S_m|) \rightarrow \frac{2}{\pi} \arcsin \sqrt{\delta}$:

$$P\left(\sqrt{n-m} \cdot \left|\frac{T_{n-m}}{\sqrt{n-m}}\right| \leq \sqrt{m} \cdot \left|\frac{S_m}{\sqrt{m}}\right|\right) \approx P\left(\left|\frac{W}{Z}\right| \leq \frac{\sqrt{\delta}}{\sqrt{1-\delta}}\right).$$

3. Wald等式.

- $\tau := \tau_{-i} \wedge \tau_j.$



- $P_0(S_\tau = j) = P_i(\tau_N < \tau_0) = \frac{i}{i+j}.$

- $E_0 S_\tau = 0:$

$$E_0 S_\tau = j \cdot P_0(S_\tau = j) + (-i) \cdot P_0(S_\tau = -i) = 0.$$

- $E_0 \tau = ES_\tau^2:$

$$ES_\tau^2 = j^2 \cdot \frac{i}{i+j} + i^2 \cdot \frac{j}{i+j} = i \cdot j,$$

$$E_0 \tau = E_i(\tau_0 \wedge \tau_N) = \sum_{j=1}^N E_i V_j = i \cdot j.$$

- 要点:** $ES_n = 0$, $ES_n^2 = n$, $E_0 \tau^k < \infty$ (引理1.10.9).

$$S_n = \xi_1 + \cdots + \xi_n.$$

定理 (Wald 等式, 定理1.10.10)

假设 τ 是 $\{S_n\}$ 停时, $E|\xi|, E\tau < \infty$, 那么 $ES_\tau = E\xi \cdot E\tau$.

- $S_\tau = \sum_{n=1}^{\tau} \xi_n = \sum_{n=1}^{\infty} \xi_n 1_{\{\tau \geq n\}}$.
- $\{\tau \leq n-1\} \in \sigma(S_1, \dots, S_{n-1}) = \sigma(\xi_1, \dots, \xi_{n-1})$.
- $|S_\tau| \leq \sum_{n=1}^{\infty} |\xi_n| 1_{\{\tau \geq n\}}$,

$$E|S_\tau| = \sum_{n=1}^{\infty} E|\xi_n| P_0(\tau \geq n) = E_0\tau \cdot E|\xi| < \infty.$$

- 因此,

$$ES_\tau = \sum_{n=1}^{\infty} E(\xi_n 1_{\{\tau \geq n\}}) = E\xi \cdot E\tau.$$

定理 (Wald 第二等式, 定理1.10.10)

假设 τ 是 $\{S_n\}$ 停时, $E\tau < \infty$, $E\xi = 0$, $E\xi^2 < \infty$, 存在 M 使得 $|S_n| \leq M, \forall n \leq \tau$. 那么, $ES_\tau^2 = E\tau \cdot E\xi^2$.

- $S_{\tau \wedge N} = \sum_{n=1}^N \xi_n 1_{\{\tau \geq n\}} = \sum_{n=1}^{\tau \wedge N} \xi_n \xrightarrow{\text{a.s.}} S_\tau$.
- $S_{\tau \wedge N}^2 = \sum_{n=1}^N \xi_n^2 1_{\{\tau \geq n\}} + 2 \sum_{1 \leq n < m \leq N} \xi_n \xi_m 1_{\{\tau \geq m\}} \xrightarrow{\text{a.s.}} S_\tau^2$.
- $ES_{\tau \wedge N}^2 = E_0(\tau \wedge N) \cdot E\xi^2$.
- 因为**, 所以 $E_0 S_{\tau \wedge N}^2 \rightarrow ES_\tau^2$.
- 又有 $E_0(\tau \wedge N) \rightarrow E_0\tau$.

补充知识:

- $\{S_n\}$ 是鞅: $E(S_{n+1}|\mathcal{F}_n) = S_n$.
- $\{S_n^2\}$ 是下鞅:

$$E(S_{n+1}^2|\mathcal{F}_n) = E(S_n^2 + 2\xi_{n+1}S_n + \xi_{n+1}^2|\mathcal{F}_n) = S_n^2 + 1 \geq S_n^2.$$

- $\{S_n^2 - n\}$ 是鞅.
- 选样定理: $\{M_n\}$ 是鞅, τ 是停时.

若 $E|M_\tau| < \infty$ 且 $E|M_n|1_{\{\tau > n\}} \rightarrow 0$, 则 $EM_\tau = EM_0$.

- $\{S_n\}$: $|S_\tau| \leq N$, $E|S_n|1_{\{\tau > n\}} \leq NP(\tau > n) \rightarrow 0$.
- $\{S_n^2 - n\}$: $|S_\tau^2 - \tau| \leq N^2 + \tau$,
 $E|S_n^2 - n|1_{\{\tau > n\}} \leq E(N^2 + \tau)1_{\{\tau > n\}} \rightarrow 0$.

- 增量: $a_{n+1} := E(S_{n+1}^2 | \mathcal{F}_n) - S_n^2 = E\xi^2 \in \mathcal{F}_n$
- 下鞅 $\{S_n^2\}$ 的Doob 分解:

$$S_n^2 = M_n + A_n,$$

其中, $A_m = a_1 + \dots + a_m = m$, $M_n = S_n^2 - A_n$, $\{M_n\}$ 是鞅.

• $\{M_n = S_n^4 - 6nS_n^2 + 3n^2 + 2n\}$ 是鞅.

• $\tau = \tau_i \wedge \tau_{-i}$, $E\tau^2 < \infty$.

• $E|M_\tau| < \infty$:

$$|M_\tau| \leq i^4 + 5\tau i^2 + 3\tau^2 + 2\tau.$$

• $E|M_n|1_{\{\tau > n\}} \rightarrow 0$:

$$E|M_n|1_{\{\tau > n\}} \leq E(i^4 + 5\tau i^2 + 3\tau^2 + 2\tau)1_{\{\tau > n\}} \rightarrow 0.$$

• $EM_\tau = EM_0 = 0$:

$$i^4 - 6E\tau \cdot i^2 + 3E\tau^2 + 2E\tau = 0$$

• 因此, $E\tau^2 = \frac{1}{3}(5i^4 - 2i^2)$, $\text{Var}(\tau) = \frac{2}{3}i^2(i^2 - 1)$.

§1.11 分支过程(Branching process)

- $\{\xi_{ni} : n \geq 0; i \geq 1\}$ i.i.d.

子代分布: $P(\xi = k) = p_k, k \in \mathbb{Z}_+$. (假设 $p_1 \neq 1$)

- $X_0 = 1, X_1 = \xi_{01}, X_{n+1} = \xi_{n1} + \dots + \xi_{nX_n}$.

$X_n = 0 \Rightarrow X_{n+1} = 0$.

- 分支树 \mathbb{T} (GW 树, Galton-Watson tree):

$\xi = \xi_{01} = 4;$

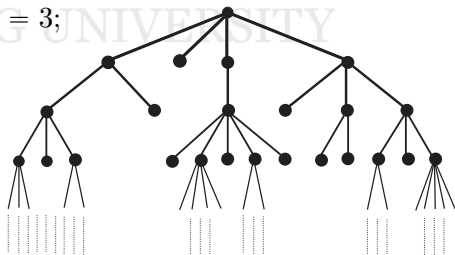
$\xi_{11} = 2, \xi_{12} = 0, \xi_{13} = 1, \xi_{14} = 3;$

$\xi_{21} = 3, \xi_{22} = 0, \xi_{23} = 5,$

$\xi_{24} = 0, \xi_{25} = 2, \xi_{26} = 3;$

$\xi_{31} = 3, \xi_{35} = 4, \xi_{3,13} = 5,$

$\xi_{3i} = 2, i = 3, 7, 11, \dots$



- 迭代结构I: $X_{n+1} = \xi_{n1} + \cdots + \xi_n X_n$.

$$E(X_{n+1} | \mathcal{F}_n) = E(\star\star | \mathcal{F}_n) = mX_n, \quad m = E\xi.$$

- $\{M_n = \frac{X_n}{m^n}\}$ 是鞅.
- $EX_n = m^n$. 若 $m < 1$, 则

$$P(X_n \geq 1) \leq EX_n \rightarrow 0.$$

- 灭绝时间: $\tau_0 = \inf\{n \geq 0 : X_n = 0\}$.

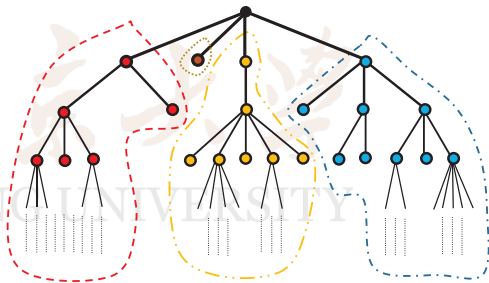
灭绝概率: $\rho = P_1(\tau_0 < \infty)$.

- 命题1.11.2. 若 $m < 1$, 则

$$P(\tau_0 > n) \rightarrow 0 \quad \Rightarrow \quad \rho = 1.$$

- 迭代结构II: $X_{n+1} = X_n^{(1)} + \dots + X_n^{(\xi)}$.

- $$\begin{aligned} \mathbb{T} &= \mathbb{T}_1 \vee \dots \vee \mathbb{T}_\xi. \\ \rho &= P(|\mathbb{T}| < \infty) \\ &= P(|\mathbb{T}_1|, \dots, |\mathbb{T}_\xi| < \infty). \\ &= \sum_k p_k \rho^k. \end{aligned}$$



• ξ 的母函数: $f(s) = f_\xi(s) = Es^\xi = \sum_k p_k s^k$.

• $0 \leq s \leq 1 \Rightarrow 0 \leq f(s) \leq 1$.

• $p_0 = f(0)$, $m = \sum_k k p_k = f'(1)$.

• $f''(s) \geq 0$.

• X_n 的母函数:

$$\begin{aligned} f_{X_{n+1}}(s) &= Es^{X_{n+1}} = \sum_{k=0}^{\infty} P(X_n = k) E(s^{\xi_1 + \dots + \xi_k} | X_n = k) \\ &= \sum_{k=0}^{\infty} P(X_n = k) f(s)^k = f_{X_n}(f(s)). \end{aligned}$$

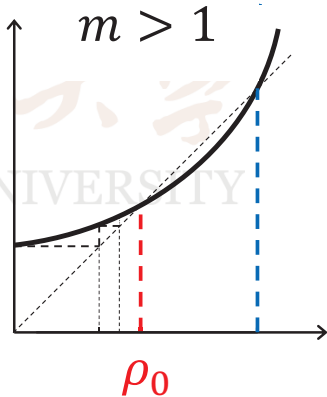
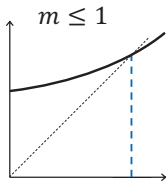
$$f_{X_n}(s) = f^{(n)}(s).$$

• $P(X_n = 0) = f^{(n)}(0)$.

命题1.11.3. $\rho = P_1(\tau_0 < \infty)$
 是方程 $s = f(s)$ 的最小非负解.

$$\rho < 1 \Leftrightarrow m > 1.$$

- $\rho = \lim_n P(\tau_0 \leq n)$
- $P(X_n = 0) = f_{X_n}(0)$
 $= f^{(n)}(0)$
 $\leq P(X_{n+1} = 0).$
- $f(\rho) = f(\lim_n f^{(n)}(0))$
 $= \lim_n f(f^{(n)}(0))$
 $= \lim_n f^{(n+1)}(0) = \rho.$
- $f^{(n)}(0) \leq f^{(n)}(\rho_0) \Rightarrow \rho \leq \rho_0.$



相变(定义1.11.5): $m = \sum_k kp_k$, $\rho = P_1(\tau_0 < \infty)$.

- 次(下)临界 $m < 1$: $\rho = 1$.

- $P_1(\lim_{n \rightarrow \infty} X_n = 0) = 1$.

- 临界 $m = 1$: $\rho = 1$.

- $P_1(\lim_{n \rightarrow \infty} X_n = 0) = 1$.

- 超(上)临界: $m > 1$: $\rho < 1$.

- $\rho = P_1(\lim_{n \rightarrow \infty} X_n = 0) < 1$.

- $1 - \rho = P_1(\lim_{n \rightarrow \infty} X_n = \infty) > 0$.

补充知识2: $m > 1, X_n \rightarrow \infty$ 的速度.

- 非负鞅 $M_n = \frac{X_n}{m^n} \xrightarrow{\text{a.s.}} W \geq 0$, 且 $EW < 1$.
- $P(W \in \mathbb{T}_0 \cup \mathbb{T}_+) = 1$, $\mathbb{T} = \mathbb{T}_0 \cup \mathbb{T}_+ \cup \mathbb{T}_\infty \cup \mathbb{T}_\#$,

$$\mathcal{T}_0 = \{T : W(T) := \lim_n \frac{T_n}{m^n} = 0\}.$$

$$\frac{X_{n+1}}{m^{n+1}} = \frac{1}{m} \left(\frac{X_n^{(1)}}{m^n} + \dots + \frac{X_n^{(\xi)}}{m^n} \right).$$

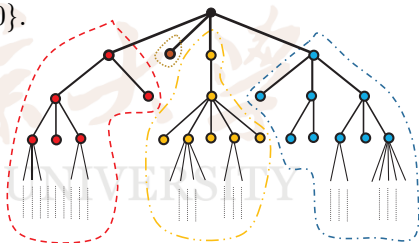
$$W = \frac{1}{m} (W_1 + \dots + W_\xi).$$

$$W = 0 \text{ iff } W_i = 0, \forall i.$$

$$P(W = 0) = p_0 + \sum_{k=1}^{\infty} p_k P(W = 0)^k$$

因此, $P(\mathcal{T}_0) = 1$ 或 ρ .

- $P(\mathcal{T}_+) = 1 - \rho$ 或 0. 在 $\{|\mathbb{T}| = \infty\}$ 上, W 恒正 或 $\equiv 0$.



带王位的分支过程: $(\hat{\mathbb{T}}, \Phi)$ spine.



- $\hat{p}_k = \frac{k p_k}{m}, k \geq 1.$

- $\hat{P}([\hat{\mathbb{T}}]_3 = [T]_3, [\Phi]_3 = [\phi]_3)$

$$= \hat{p}_4 \cdot \frac{1}{4} \times p_2 p_0 p_1 \hat{p}_3 \cdot \frac{1}{3} \times p_3 p_0 p_5 p_0 p_0 \hat{p}_3 \cdot \frac{1}{3}$$

- $\hat{P}([\hat{\mathbb{T}}]_3 = [T]_3, [\Phi]_3 = [\phi]_3) = \frac{1}{m^3} P([\mathbb{T}]_3 = [T]_3)$

- $\hat{P}([\hat{\mathbb{T}}]_3 = [T]_3) = T_3 \times \frac{1}{m^3} P([\mathbb{T}]_3 = [T]_3).$

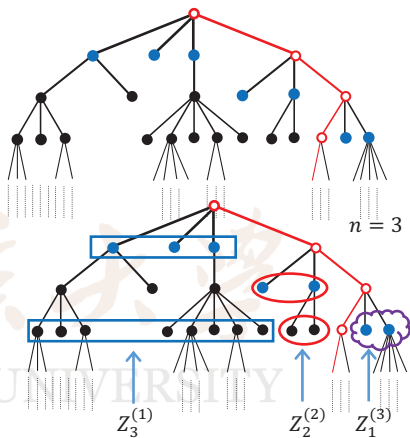
- $\hat{P}([\hat{\mathbb{T}}]_n = [T]_n) = P([\mathbb{T}]_n = [T]_n) \times \frac{T_n}{m^n}.$

- $d\hat{P}(T) = dP(T) \times W.$ “因此” ,

$$P(\mathcal{T}_+) > 0 \text{ iff } \hat{P}(\mathcal{T}_+) > 0; \quad \hat{P}(\mathcal{T}_0) = 0.$$

$\hat{P}(\cdot)$ 是带移民的分支过程:

- $P(Y = k) = \hat{p}_{k+1}$.
- $Z_{n+1} = \xi_{n1} + \dots + \xi_{nZ_n} + Y_{n+1}$.
- $\{Z_n/m^n\}$ 是 $E(\cdot|\mathcal{Y})$ 下鞅.
- $Z_n = Z_n^{(1)} + Z_{n-1}^{(2)} + \dots + Z_1^{(n)}$.



- $E(Z_n|\mathcal{Y}) = m^{n-1}Y_1 + \dots + mY_{n-1} + Y_n$.
- $E(\frac{Z_n}{m^n}|\vec{Y} = \vec{y}) = \frac{y_1}{m} + \dots + \frac{y_n}{m^n}$.
- $E \ln^+ Y < \infty$ ($\sum_{k \geq 2} k p_k \ln k < \infty$):
 $\sum_{k=1}^{\infty} \frac{Y_k}{m^k} \stackrel{\text{a.s.}}{<} \infty \Rightarrow W = \lim_n \frac{Z_n}{m^n}$ 存在且有限. $\hat{P}(\mathbb{T}_+) = 1$.
- $E \ln^+ Y = \infty \Rightarrow \limsup_n \frac{Z_n}{m^n} = \infty$, a.s.. $\hat{P}(\mathbb{T}_+) = 0$.

补充知识3. 分支随机游动(BRW)

• η_{ni} , i.i.d., e.g. $P(\eta = \pm 1) = \frac{1}{2}$.

• $S_u = \eta_{u_0} + \dots + \eta_{u_n}$, $u \in \mathbb{T}_n$.

• $M_n = \max_{u \in \mathbb{T}_n} S_u$. 迭代结构:

$$M_{n+1} = \max_{1 \leq i \leq \xi} (\eta_i + M_n^{(i)}).$$

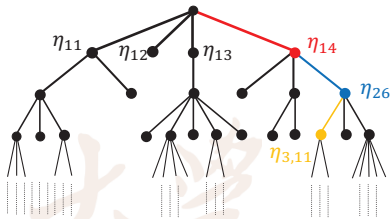
• $V_1 = e^{\eta_1} + \dots + e^{\eta_\xi}$, $\mu = \mathbb{E}V_1$.

• 令 $V_n = \sum_{u \in \mathbb{T}_n} e^{S(u)}$,
则 $\{\frac{V_n}{\mu^n}\}$ 是鞅. $\mathbb{E}V_n = \mu^n$.

• $\mathbb{E}V_n = m^n \hat{\mathbb{E}}e^{S(\phi_n)}$.

• $M_n/n \xrightarrow{\text{a.s.}} x^* > 0$. 例: $\xi \equiv d$, x^* 的上估计: $\forall a > 0$,

$$P\left(\frac{M_n}{n} > y\right) \leq d^n \cdot P(S_n > ny) \leq (d \cdot Ee^{a(\eta-y)})^n.$$



$\xi \equiv d$.

• $ES_{w_1} S_{w_2} = |w| = n$:

$$S_{w_1} = \eta_1 + \cdots + \eta_w + \sum_i \hat{\eta}_i,$$

$$S_{w_2} = \star + \sum_j \tilde{\eta}_j.$$

- 考虑前 N 层树上的
随机游动的格林函数

$$G_{w,v} := E_w \sum_{n=0}^{\tau_o-1} 1_{\{X_n=v\}}.$$

$$G_{w_1,w_2} = G_{w,w_2} = G_{w_2,w} = G_{w,w} = a_n.$$

• $a_n = (d+1)n$.

$$a_n = 1 + \frac{d}{d+1} a_n + \frac{1}{d+1} a_{n-1} \Rightarrow a_n = a_{n-1} + (d+1).$$

