

Under the continuity condition  $\|Q_t - I\|_{op} \rightarrow 0$ ,  $(Q_t)_{t \geq 0}$  has a bounded generator  $A$ .

In the (countable) discrete setting,  $Q_t$  has matrix  $q_t$ , and we showed that

$$Af(i) = \sum_j a(i,j)f(j), \text{ where } a(i,j) = \frac{d}{dt} q_t(i,j) \Big|_{t=0}.$$

It's the generator, so  $Q_t = e^{tA} = \sum_{n=0}^{\infty} \frac{t^n}{n!} A^n = I + tA + O(t^2)$ .

$$\therefore q_t(i,j) = S_{ij} + t a(i,j) + O(t^2).$$

Now, if  $(X_t)_{t \geq 0}$  is a Markov chain with transition kernels  $(q_t)_{t \geq 0}$ ,

we have  $P(X_t=j | X_0=i) = q_t(i,j) = S_{ij} + t a(i,j) + O(t^2)$ .

The  $a(i,j)$  are the **transition rates** of the process.

I.e. if  $i \neq j$ , then  $P(X_t=j | X_0=i) \cong a(i,j)t$  for small  $t > 0$ .

More precisely  $\frac{d}{dt} P(X_t=j | X_0=i) \Big|_{t=0} = a(i,j)$

For this reason, this is called the **bounded rates** case.

$$\inf_i q_t(i,i) \rightarrow 1 \text{ as } t \rightarrow 0.$$

$$\Rightarrow \sup_i \sum_j |a(i,j)| = \sup_i (|a(i,i)| + \sum_{j \neq i} |a(i,j)|) = 2 \sup_i |G(i,i)|$$

The generator matrix  $a$  completely describes the evolution of the process.  
But how?

$$e^{t \cdot \frac{1}{\lambda} A} = Q_{t/\lambda} - \text{time-rescaled.}$$

First: rescaling  $a$  produces a new generator:  $\frac{1}{\lambda}a$  for some  $\lambda > 0$

$$\text{Let } p = I + \frac{1}{\lambda}a \quad \|p\|_\infty \leq 1 + \frac{1}{\lambda} \|a\|_\infty < \infty.$$

$$\text{If } \lambda > \frac{1}{2} \|a\|_\infty = \sup_i \|a(i, \cdot)\|, \quad p(i, i) = 1 + \frac{1}{\lambda} a(i, i) \geq 0 \quad \left| \frac{a(i, j)}{\lambda} \right| \leq 1.$$

$$\text{and } \sum_j p(i, j) = \sum_j \left( S_{i,j} + \frac{1}{\lambda} a(i, j) \right) = 1 + \frac{1}{\lambda} \cdot 0 = 1 \quad \forall i.$$

Thus,  $p$  is a Markov matrix: it is the 1-step transition operator  
for some discrete time Markov chain  $(Y_n)_{n \in \mathbb{N}}$  on the same state space.

**Theorem:** Let  $(Y_n)_{n \in \mathbb{N}}$  be a Markov chain with 1-step  
transition matrix  $p = I + \frac{1}{\lambda}a$ . Let  $(N_t)_{t \geq 0}$  be a Poisson  
process with intensity  $\lambda \geq \frac{1}{2}\|a\|_\infty$ , independent from  $(Y_n)_{n \in \mathbb{N}}$ .

Then  $X_t = Y_{N_t}$  is a Markov process with generator  
 $A$  whose matrix is  $a$ .

Theorem: Let  $A$  be a bounded generator on  $\mathcal{B}(S)$  (for a discrete countable state space  $S$ ), with matrix  $a$ . Fix some  $\lambda \geq \frac{1}{2} \|A\|_{\infty}$ . Let  $(Y_n)_{n \in \mathbb{N}}$  be a Markov chain with 1-step transition operator  $P = I + \frac{\lambda}{2} A$ . Let  $(N_t)_{t \geq 0}$  be a Poisson process with intensity  $\lambda$ , independent from  $(Y_n)_{n \in \mathbb{N}}$ . Then  $X_t = Y_{N_t}$  is a Markov process with generator  $A = \lambda(P - I)$ .

$$\text{Pf. } e^{tb(A)} = e^{\lambda tb(P-I)} = e^{-\lambda t} e^{\lambda t P} = e^{-\lambda t} \sum_{n=0}^{\infty} \frac{(\lambda t)^n}{n!} P^n = \sum_{n=0}^{\infty} P(N_{t+s} - N_s = n) P^n$$

$$\text{Now } P(N_t = n) = P(N_{t+s} - N_s = n) = e^{-\lambda t} \frac{(\lambda t)^n}{n!}.$$

We can now compute all f.d. distributions of  $(X_t)_{t \geq 0}$ :

For  $0 = t_0 < t_1 < \dots < t_k < \infty$ , and  $i_0, i_1, \dots, i_k \in S$ ,

$$P(X_{t_0} = i_0, X_{t_1} = i_1, \dots, X_{t_k} = i_k)$$

$$= \sum_{0 \leq n_1 \leq \dots \leq n_k} P^{i_0}(Y_{n_1} = i_1, \dots, Y_{n_k} = i_k) \cdot P(N_{t_1} = n_1, \dots, N_{t_k} = n_k)$$

use Markov prop.

to express in terms of  $P$

write in terms  
of invermk.

$$\begin{aligned} \mathbb{P}(N_{t_1}=n_1, \dots, N_{t_k}=n_k) &= \mathbb{P}(N_{t_1}=n_1, \dots, N_{t_{k-1}}=n_{k-1}, N_{t_k}-N_{t_{k-1}}=n_k-n_{k-1}) \\ &= \mathbb{P}(N_{t_1}=n_1, \dots, N_{t_{k-1}}=n_{k-1}) \mathbb{P}(N_{t_k}-N_{t_{k-1}}=n_k-n_{k-1}) \end{aligned}$$

$$\mathbb{P}^{i_0}(Y_{n_1}=i_1, \dots, Y_{n_k}=i_k) = \underbrace{\mathbb{P}(Y_0=i_0)}_{\mathbb{P}^{i_0}(Y_{n_1}=i_1, \dots, Y_{n_{k-1}}=i_{k-1})} q_{0,n_1}^{Y}(i_0, i_1) q_{n_1,n_2}^{Y}(i_1, i_2) \cdots q_{n_{k-2},n_{k-1}}^{Y}(i_{k-2}, i_{k-1}) q_{n_{k-1},n_k}^{Y}(i_{k-1}, i_k)$$

Thus  $\mathbb{P}(X_{t_0}=i_0, X_{t_1}=i_1, \dots, X_{t_k}=i_k)$

$$\begin{aligned} &= \sum_{0 \leq n_1 \leq \dots \leq n_k} \mathbb{P}^{i_0}(Y_{n_1}=i_1, \dots, Y_{n_k}=i_k) \cdot \mathbb{P}(N_{t_1}=n_1, \dots, N_{t_k}=n_k) \\ &= \sum_{0 \leq n_1 \leq \dots \leq n_{k-1}} \mathbb{P}^{i_0}(Y_{n_1}=i_1, \dots, Y_{n_{k-1}}=i_{k-1}) \cdot \mathbb{P}(N_{t_1}=n_1, \dots, N_{t_{k-1}}=n_{k-1}) \end{aligned}$$

$$\cdot \sum_{m=0}^{\infty} \mathbb{P}(N_{t_k}-N_{t_{k-1}}=m) P^m(i_{k-1}, i_k)$$

$$e^{(t_k-t_{k-1})A} (i_{k-1}, i_k) -$$

$$\text{By induction, } = \prod_{l=1}^k e^{(t_l-t_{l-1})A} (i_{l-1}, i_l)$$

$$q_{t_{l-1}, t_l}(i_{l-1}, v_l) \quad //$$

Note: we showed explicitly that the f.d. distributions of  $X_t = Y_{N_t}$  match those of a Markov process with transition Semigroup  $e^{tA}$ .

Thus  $(X_t)_{t \geq 0}$  is a Markov process wrt  $(\mathcal{F}_t^X)_{t \geq 0}$ .

If we want to be a little more explicit about the filtration, we could state the result as follows.

Theorem: Let  $(\Omega, \mathcal{F}, \{\mathcal{F}_n\}_{n \in \mathbb{N}}, P)$  be a filtered probability space, and let  $(Y_n)_{n \in \mathbb{N}}$  be an adapted time-homogeneous Markov chain (countable state space) with 1-step transition operator  $P$ . Let  $(N_t)_{t \geq 0}$  be a Poisson process with intens.  $\lambda$  independent from  $\mathcal{F}_0 = \sigma(\bigcup_{n \in \mathbb{N}} \mathcal{F}_n)$ . Define a new filtration  $\mathcal{G}_t \subseteq \mathcal{F}$  by

$$B \in \mathcal{G}_t \text{ iff } \forall n \in \mathbb{N} \quad B \cap \{N_t = n\} \in \sigma(\mathcal{F}_t^N \cup \mathcal{F}_n)$$

Then  $(Y_t)_{t \geq 0}$  is a filtration,  $X_t = Y_{N_t}$  is adapted to it, and  $X_t$  is a time homogeneous Markov process (rel. to  $\mathcal{G}_t$ ) with transition operators  $Q_t = e^{\lambda t(P - I)}$ .

[Driver, Thm 22.34]