

# Lecture-09: Kurtz's theorem: preliminaries

## 1 Preliminaries

**Assumption 1.1.** Consider a density-dependent family of CTMCs  $((X^N : \Omega \rightarrow (\mathcal{Z}^N)_{\perp}^{\mathbb{R}}) : N \in \mathbb{N})$ . For each  $N$ , state  $x \in \mathcal{Z}^N$ , empirical distribution of states  $a(x) \in \mathcal{M}(\mathcal{Z})$ , and  $z, w \in \mathcal{Z}$ , the transition rate  $Q_{z,w}^{X^N} : \mathcal{M}(\mathcal{Z}) \rightarrow \mathbb{R}$  for a single particle  $n$  is Lipschitz continuous in the empirical distribution.

**Proposition 1.2.** *If Assumption 1.1 holds, then the following statements are true.*

1. The maximum transition rate  $\bar{Q} \triangleq \max \{Q_{z,w}^{X^N}(a) : z, w \in \mathcal{Z}, a \in \mathcal{M}(\mathcal{Z})\}$  is finite.
2. The rate change function  $f : \mathcal{M}(\mathcal{Z}) \rightarrow \mathbb{R}^{\mathcal{Z}}$  in McKean-Vlasov ODE is Lipschitz continuous.
3. McKean-Vlasov ODE is well-posed.

*Proof.* From hypothesis, we have  $|Q_{z,w}^{X^N}(b) - Q_{z,w}^{X^N}(a)| \leq M \|b - a\|_{\text{TV}}$  for all  $a, b \in \mathcal{M}_N(\mathcal{Z})$  and some finite  $M \in \mathbb{R}_+$ .

1. Fix  $a, b \in \mathcal{M}_N(\mathcal{Z})$ , then we get

$$|Q_{z,w}^{X^N}(b)| \leq |Q_{z,w}^{X^N}(a)| + |Q_{z,w}^{X^N}(b) - Q_{z,w}^{X^N}(a)| \leq |Q_{z,w}^{X^N}(a)| + M \|b - a\|.$$

The result follows from finiteness of  $\mathcal{Z}$  and of the norm of difference  $\|b - a\|$  for all  $a, b \in \mathcal{M}(\mathcal{Z})$ .

2. We can write the generator matrix for empirical distribution for transitioning states  $b, c \in \mathcal{M}_N(\mathcal{Z})$  such that  $N(c - b) = -e_z + e_w$ , as

$$Q_{b,c}^{A^N} = \sum_{n=1}^N \sum_{z \in \mathcal{Z}} \mathbb{1}_{\{X_n^N = z\}} \sum_{w \neq z} \mathbb{1}_{\{N(c-b) = e_w - e_z\}} Q_{z,w}^{X^N}(b) = \sum_{z \in \mathcal{Z}} N b_z \sum_{w \neq z} \mathbb{1}_{\{N(c-b) = e_w - e_z\}} Q_{z,w}^{X^N}(b).$$

Substituting this expression in the definition of  $f(b) = \sum_{c \in \mathcal{M}_N(\mathcal{Z})} Q_{b,c}^{A^N}(c - b)$ , we obtain

$$f(b) = \sum_{c \in \mathcal{M}_N(\mathcal{Z})} \sum_{z \in \mathcal{Z}} N b_z \sum_{w \neq z} \mathbb{1}_{\{N(c-b) = e_w - e_z\}} Q_{z,w}^{X^N}(b) \frac{1}{N} (e_w - e_z) = \sum_{z \in \mathcal{Z}} b_z \sum_{w \neq z} Q_{z,w}^{X^N}(b) (e_w - e_z).$$

Thus, we can write the difference between rate functions evaluated at two different distributions as

$$f(b) - f(a) = \sum_{z \in \mathcal{Z}} b_z \sum_{w \neq z} Q_{z,w}^{X^N}(b) (e_w - e_z) - \sum_{z \in \mathcal{Z}} a_z \sum_{w \neq z} Q_{z,w}^{X^N}(a) (e_w - e_z).$$

Since  $Q_{z,w}^{X^N}(b) - Q_{z,w}^{X^N}(a) \leq M \|b - a\|_{\text{TV}}$  and  $\bar{Q} = \max_{z,w,a} Q_{z,w}^{X^N}(a)$ , we get

$$\begin{aligned} f(b) - f(a) &\leq M \|b - a\|_{\text{TV}} \sum_{z \in \mathcal{Z}} b_z \sum_{w \neq z} (e_w + e_z) + \sum_{z \in \mathcal{Z}} (b_z - a_z) \sum_{w \neq z} Q_{z,w}^{X^N}(a) (e_w - e_z) \\ &\leq M \|b - a\|_{\text{TV}} \left( \sum_{w \in \mathcal{Z}} e_w + (|\mathcal{Z}| - 1)b \right) + \bar{Q} \sum_{z \in \mathcal{Z}} e_z |b_z - a_z| (|\mathcal{Z}| - 1) + \bar{Q} \sum_{z \in \mathcal{Z}} |b_z - a_z| \sum_{w \in \mathcal{Z}} e_w \\ &\leq (M + \bar{Q}) |\mathcal{Z}| \|b - a\|_{\text{TV}} \sum_{z \in \mathcal{Z}} e_z. \end{aligned}$$

3. McKean-Vlasov ODE is well-posed. □

**Lemma 1.3.** Consider a homogeneous Poisson counting process  $\bar{N} : \Omega \rightarrow \mathbb{Z}_+^{\mathbb{R}^+}$  with unit rate adapted to its natural filtration  $\mathcal{F}_\bullet$ , and define  $\bar{N} : \Omega \rightarrow \mathbb{R}^{\mathbb{R}^+}$  as  $\bar{N}_t \triangleq N_t - t$  for all  $t \in \mathbb{R}_+$ . Then  $\bar{N}$  is martingale adapted to  $\mathcal{F}_\bullet$ .

*Proof.* We check the three conditions for  $\bar{N}$  to be a martingale adapted to  $\mathcal{F}_\bullet$ .

1. We observe that  $\mathbb{E} |N_t - t| \leq \mathbb{E} N_t + t < \infty$ .
2. Since  $\sigma(N_t) \subseteq \mathcal{F}_t$ , it follows that  $\sigma(\bar{N}_t) \subseteq \mathcal{F}_t$ .
3. We can write  $N_t - t = N_t - N_s + N_s - t$ . Let  $s < t$ . From the increment independent property of  $N$  and the fact that  $\sigma(N_s) \subseteq \mathcal{F}_s$ , we observe  $\mathbb{E}[N_t - t \mid \mathcal{F}_s] = \mathbb{E}[N_t - N_s] + N_s - t$ . Further, since  $N$  is unit rate Poisson counting process, it follows that  $\mathbb{E}[N_t - N_s] = t - s$ . Therefore, we have  $\mathbb{E}[N_t - t \mid \mathcal{F}_s] = N_s - s$  for all  $s < t$ .

□

**Lemma 1.4.** Consider a homogeneous Poisson counting process  $N : \Omega \rightarrow \mathbb{Z}_+^{\mathbb{R}^+}$  with unit rate adapted to its natural filtration  $\mathcal{F}_\bullet$  and  $\theta > 0$ . We define  $Y, Z : \Omega \rightarrow \mathbb{R}_+^{\mathbb{R}^+}$  as  $Y_t \triangleq e^{\theta(N_t - t)} = 1/Z_t$  for all  $t \in \mathbb{R}_+$ . Then  $Y, Z$  are submartingales adapted to  $\mathcal{F}_\bullet$ .

*Proof.* From Lemma 1.3, we know that centered Poisson counting process  $\bar{N}$  is a martingale adapted to  $\mathcal{F}_\bullet$ . Further, we observe that functions  $x \mapsto e^{\theta x}$  and  $x \mapsto e^{-\theta x}$  are convex for  $\theta > 0$ . In addition, we have

$$\mathbb{E} \left| e^{\theta(N_t - t)} \right| = \mathbb{E} e^{\theta(N_t - t)} = e^{t(e^\theta - 1 - \theta)} < \infty, \quad \mathbb{E} \left| e^{-\theta(N_t - t)} \right| = \mathbb{E} e^{-\theta(N_t - t)} = e^{t(e^{-\theta} - 1 + \theta)} < \infty.$$

It follows that  $Y, Z$  are submartingales adapted to  $\mathcal{F}_\bullet$ .

□

**Lemma 1.5.** Consider a submartingale  $X : \Omega \rightarrow \mathbb{R}^{\mathbb{N}}$  and a stopping time  $\tau : \Omega \rightarrow \mathbb{N}$  adapted to filtration  $\mathcal{F}_\bullet$ . If  $\tau \leq n$  almost surely, then  $\mathbb{E} X_1 \leq \mathbb{E} X_\tau \leq \mathbb{E} X_n$ .

*Proof.* From the fact that  $X$  is a submartingale and  $\tau$  is a stopping time, both adapted to  $\mathcal{F}_\bullet$ , we get

$$\mathbb{E}[X_n \mathbb{1}_{\{\tau=k\}} \mid \mathcal{F}_k] = \mathbb{1}_{\{\tau=k\}} \mathbb{E}[X_n \mid \mathcal{F}_k] \geq X_\tau \mathbb{1}_{\{\tau=k\}}.$$

Summing over  $k \in [n]$ , then taking expectation on both sides, it follows from the linearity and monotonicity preserving property of expectation that  $\mathbb{E} X_n \sum_{k=1}^n \mathbb{1}_{\{\tau=k\}} \geq \mathbb{E} \sum_{k=1}^n X_\tau \mathbb{1}_{\{\tau=k\}}$ . Since  $\tau \leq n$  almost surely, we have  $X_\tau = \sum_{k=1}^n X_\tau \mathbb{1}_{\{\tau=k\}}$  and  $X_n = X_n \sum_{k=1}^n \mathbb{1}_{\{\tau=k\}}$  almost surely. □

**Lemma 1.6 (Doob).** For a submartingale  $X : \Omega \rightarrow \mathbb{R}_+^{\mathbb{N}}$  adapted to a filtration  $\mathcal{F}_\bullet$ ,  $P \left\{ \max_{i \in [n]} X_i > x \right\} \leq \frac{\mathbb{E} X_n}{x}$  for all  $x > 0$ .

*Proof.* We define a random time  $\tau_x \triangleq \inf \{i \in \mathbb{N} : X_i > x\}$  and  $\tau \triangleq \tau_x \wedge n$ . It follows that  $\tau$  is a stopping time adapted to  $\mathcal{F}_\bullet$  and  $\tau < n$  almost surely. We observe that  $\left\{ \max_{i \in [n]} X_i > x \right\} = \cup_{i \in [n]} \{X_i > x\} = \{X_\tau > x\}$ . From Markov inequality for non-negative random variables, we have  $P \left\{ X_\tau > x \right\} \leq \frac{\mathbb{E} X_\tau}{x}$ . The result follows from Lemma 1.5. □

**Lemma 1.7 (Doob).** For a submartingale  $X : \Omega \rightarrow \mathbb{R}_+^{\mathbb{R}^+}$  adapted to a filtration  $\mathcal{F}_\bullet$ ,  $P \left\{ \sup_{t \in [0, T]} X_t > x \right\} \leq \frac{\mathbb{E} X_T}{x}$  for all  $x > 0$ .

**Corollary 1.8.** For a submartingale  $X : \Omega \rightarrow \mathbb{R}^{\mathbb{R}^+}$  adapted to a filtration  $\mathcal{F}_\bullet$ ,  $P \left\{ \sup_{t \in [0, T]} X_t > x \right\} \leq \frac{\mathbb{E}(X_T \vee 0)}{x}$  for all  $x > 0$ .

*Proof.* The function  $f : \mathbb{R} \rightarrow \mathbb{R}_+$  defined as  $f(x) \triangleq x \vee 0$  is non-negative and convex and hence  $Y : \Omega \rightarrow \mathbb{R}_+^{\mathbb{R}^+}$  defined as  $Y_t \triangleq f(X_t)$  for all  $t \in \mathbb{R}_+$ , is a sub-martingale adapted to  $\mathcal{F}_\bullet$ . The result follows from Lemma 1.7 and the fact that  $\left\{ \sup_{t \in [0, T]} X_t > x \right\} = \left\{ \sup_{t \in [0, T]} Y_t > x \right\}$  for all  $x > 0$ . □

**Definition 1.9.** We define  $h : [-1, \infty) \rightarrow \mathbb{R}_+$  as  $h(t) \triangleq (1+t) \ln(1+t) - t$  for all  $t \geq -1$ .

*Remark 1.* The function  $h$  defined in Definition 1.9 is positive and increasing for  $t > 0$  and  $\lim_{t \rightarrow 0} h(t) = 0$ . Further, we observe that  $h(-t) \geq h(t)$  for  $t \in [0, 1]$ .

**Lemma 1.10.** *Consider a homogeneous Poisson counting process  $N : \Omega \rightarrow \mathbb{Z}_+^{\mathbb{R}_+}$  with unit rate. Then for any  $\epsilon, T > 0$ , we have  $P \left\{ \sup_{t \in [0, T]} |N_t - t| > \epsilon \right\} \leq 2e^{-Th(\frac{\epsilon}{T})}$ .*

*Proof.* From the union bound applied to event  $\left\{ \sup_{t \in [0, T]} |N_t - t| > \epsilon \right\}$ , we obtain

$$P \left\{ \sup_{t \in [0, T]} |N_t - t| > \epsilon \right\} \leq P \left\{ \sup_{t \in [0, T]} e^{\theta(N_t - t)} > e^{\theta\epsilon} \right\} + P \left\{ \sup_{t \in [0, T]} e^{-\theta(N_t - t)} > e^{\theta\epsilon} \right\}.$$

For the Poisson counting process  $N$ , consider the submartingales  $Y, Z$  defined in Lemma 1.4 adapted to the natural filtration  $\mathcal{F}_\bullet$  of  $N$ . From Doob's inequality of Lemma 1.7, we observe that

$$P \left\{ \sup_{t \in [0, T]} Y_t > e^{\theta\epsilon} \right\} \leq e^{-\theta\epsilon} \mathbb{E}Y_T, \quad P \left\{ \sup_{t \in [0, T]} Z_t > e^{\theta\epsilon} \right\} \leq e^{-\theta\epsilon} \mathbb{E}Z_T.$$

From the moment generating function for a Poisson counting process with unit rate, we get

$$\mathbb{E}Y_T = \mathbb{E}e^{\theta(N_T - T)} = e^{T(e^\theta - 1 - \theta)}, \quad \mathbb{E}Z_T = \mathbb{E}e^{-\theta(N_T - T)} = e^{T(e^{-\theta} - 1 + \theta)}.$$

We observe that  $e^{-\theta\epsilon} \mathbb{E}Y_T = \exp(-\theta\epsilon + T(e^\theta - 1 - \theta))$  is minimized at  $\theta^* = \ln(\frac{\epsilon}{T} + 1) > 0$ . For this value of  $\theta^*$ , we have

$$e^{-\theta^*\epsilon} \mathbb{E}Y_T(\theta^*) = \exp(-\epsilon \ln(\frac{\epsilon}{T} + 1) + T(\frac{\epsilon}{T} - \ln(\frac{\epsilon}{T} + 1))) = e^{-Th(\frac{\epsilon}{T})}.$$

Similarly,  $e^{-\theta\epsilon} \mathbb{E}Z_T = \exp(-\theta\epsilon + T(e^{-\theta} - 1 + \theta))$  is minimized at  $\theta^{**} = -\ln(1 - \frac{\epsilon}{T}) > 0$ . For this value of  $\theta^{**}$ , we have

$$e^{-\theta^{**}\epsilon} \mathbb{E}Y_T(\theta^{**}) = \exp(\epsilon \ln(1 - \frac{\epsilon}{T}) + T(-\frac{\epsilon}{T} - \ln(1 - \frac{\epsilon}{T}))) = e^{-Th(-\frac{\epsilon}{T})}.$$

Since  $h(-\frac{\epsilon}{T}) \geq h(\frac{\epsilon}{T})$  for  $\epsilon \leq T$ , the result follows.  $\square$

**Definition 1.11.** For a rate function  $\lambda : \mathbb{R}_+ \rightarrow \mathbb{R}_+$ , we can define  $\Lambda : \mathbb{R}_+ \rightarrow \mathbb{R}_+$  as  $\Lambda_t \triangleq \int_0^t \lambda(s) ds$  for all  $t \in \mathbb{R}_+$ . We can define the extension  $\Lambda : \mathcal{B}(\mathbb{R}_+) \rightarrow \mathbb{R}_+$  as  $\Lambda(B) = \int_{s \in B} \lambda(s) ds$  for all Borel sets  $B \in \mathcal{B}(\mathbb{R}_+)$ .

**Lemma 1.12 (Time change).** *Let  $N : \Omega \rightarrow \mathbb{Z}_+^{\mathbb{R}_+}$  be a homogeneous Poisson counting process with unit rate, and  $\Lambda : \mathcal{B}(\mathbb{R}_+) \rightarrow \mathbb{R}_+$  be a measure with rate  $\lambda : \mathbb{R}_+ \rightarrow \mathbb{R}_+$ . The counting process  $M : \Omega \rightarrow \mathbb{Z}_+^{\mathbb{R}_+}$  defined as  $M_t \triangleq N_{\Lambda_t}$  for all  $t \in \mathbb{R}_+$  is non-homogeneous Poisson with instantaneous rate  $\lambda$ .*

*Proof.* We denote the natural filtration for  $N$  and  $M$  as  $\mathcal{F}_\bullet$  and  $\mathcal{G}_\bullet$  respectively. From the independent increment property of  $N$ , we obtain

$$\mathbb{E}[M_t - M_s \mid \mathcal{G}_s] = \mathbb{E}[N_{\Lambda_t} - N_{\Lambda_s} \mid \mathcal{F}_{\Lambda_s}] = \mathbb{E}[N_{\Lambda_t} - N_{\Lambda_s}] = \mathbb{E}[M_t - M_s].$$

It follows that  $M$  has independent increment property. Further with mean number of points in  $(s, t]$  under  $M$  is given by measure  $\Lambda(s, t]$ .  $\square$