

# Applied Stochastic Processes

## Solution sheet 10

### Solution 10.1

- (a) On  $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$ , we define the measure  $\mu$  by

$$\mu(B) = \begin{cases} +\infty & \text{if } 0 \in B, \\ 0 & \text{otherwise,} \end{cases}$$

for  $B \in \mathcal{B}(\mathbb{R})$ . The measure  $\mu$  is *not*  $\sigma$ -finite since for any family  $(B_i)_{i \geq 1} \subset \mathcal{B}(\mathbb{R})$  with  $\mu(B_i) < \infty$  for all  $i \geq 1$ , it holds that  $0 \notin \bigcup_{i \geq 1} B_i$ .

- (b) By assumption,  $U$  is a random variable taking values in  $[0, 5]$ . Therefore, the random variable

$$\delta_U : \begin{cases} \Omega & \rightarrow \mathcal{M} \\ \omega & \mapsto \delta_{U(\omega)} \end{cases}$$

is well-defined since for all  $u \in [0, 5]$ ,  $\delta_u$  is a  $\sigma$ -finite measure on  $([0, 5], \mathcal{B}([0, 5]))$  taking values in  $\{0, 1\}$ . Hence,  $\delta_U$  is point process on  $([0, 5], \mathcal{B}([0, 5]))$ .

- (c) For all  $u \in [0, 5]$ ,  $2 \cdot \delta_u$  is a  $\sigma$ -finite measure on  $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  taking values in  $\{0, 2\}$ . As in (b), we deduce that  $2 \cdot \delta_U$  is a point process on  $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$ .
- (d)  $\delta_U$  is not a Poisson point process on  $([0, 5], \mathcal{B}([0, 5]))$  since  $\delta_U([0, 1])$  and  $\delta_U([4, 5])$  are not independent.
- (e) By the superposition theorem from Section 6.6, the process  $M_1 + M_2$  is a Poisson point process if the measure  $\mu := \mu_1 + \mu_2$  is  $\sigma$ -finite. It therefore suffices to note that the  $\sigma$ -finiteness of  $\mu$  follows from the  $\sigma$ -finiteness of  $\mu_1$  and  $\mu_2$ . Indeed, let  $(A_i)_{i \geq 1} \subset \mathcal{E}$  and  $(B_i)_{i \geq 1} \subset \mathcal{E}$  be increasing sequences such that  $\bigcup_{i \geq 1} A_i = \bigcup_{i \geq 1} B_i = E$ , and  $\mu_1(A_i) < \infty$  and  $\mu_2(B_i) < \infty$  for all  $i \geq 1$ . Then  $(A_i \cap B_i)_{i \geq 1}$  is an increasing sequence satisfying for all  $i \geq 1$ ,

$$\mu(A_i \cap B_i) = \underbrace{\mu_1(A_i \cap B_i)}_{\leq \mu_1(A_i)} + \underbrace{\mu_2(A_i \cap B_i)}_{\leq \mu_2(B_i)} < \infty,$$

and  $\bigcup_{i \geq 1} (A_i \cap B_i) = E$ .

- (f) By the superposition theorem from Section 6.6, the process  $\sum_{i=1}^{\infty} M_i$  is a Poisson point process if the measure  $\mu := \sum_{i=1}^{\infty} \mu_i$  is  $\sigma$ -finite. Even though the measures  $\mu_i$ ,  $i \geq 1$ , are all  $\sigma$ -finite, this is not necessarily the case. For example, if  $\mu_i := \delta_0$  for all  $i \geq 1$ , then the measure  $\mu$  is not  $\sigma$ -finite as shown in (a).

**Solution 10.2**

- (a) First, we note that the measure  $\mu \otimes \nu$  is  $\sigma$ -finite. Indeed, choose a partition  $(E_i)_{i \geq 1}$  of  $\mathbb{R}$  such that  $E_i$  measurable and  $\mu(E_i) < \infty$  for every  $i$ , and then consider the partition  $(E_i \times \{j\})_{i \geq 1, j \in \{0,1\}}$ , which satisfies

$$\mu \otimes \nu(E_i \times \{j\}) = \mu(E_i) \cdot \underbrace{\nu(\{j\})}_{=1} = \mu(E_i) < \infty.$$

It now follows from the superposition theorem in Section 6.6 that  $M_0 + M_1$  is a Poisson point process on  $\mathbb{R} \times \{0, 1\}$  with intensity  $\mu_0 + \mu_1$  and it suffices to note that  $\mu_0 + \mu_1 = \mu \otimes \nu$ .

- (b) We will show that the process  $\widetilde{M}$  is *not* a Poisson point process on  $\mathbb{R} \times \{0, 1\}$ .

As in part (a), let  $(E_i)_{i \geq 1}$  be a partition of  $\mathbb{R}$  such that  $E_i$  measurable and  $\mu(E_i) < \infty$  for every  $i$ . Without loss of generality, assume that  $\mu(E_i) > 0$  for every  $i$ . We compute

$$\begin{aligned} & \mathbb{P}[\widetilde{M}(E_1 \times \{0\}) = 1, \widetilde{M}(E_1 \times \{1\}) = 1, \widetilde{M}(E_2 \times \{0\}) = 1, \widetilde{M}(E_2 \times \{1\}) = 0] \\ &= \mathbb{P}[M(E_1) \cdot M'(\{0\}) = 1, M(E_1) \cdot M'(\{1\}) = 1, M(E_2) \cdot M'(\{0\}) = 1, M(E_2) \cdot M'(\{1\}) = 0] \\ &= 0, \end{aligned}$$

since the first three events require  $M(E_1) = M(E_2) = 1$  and  $M'(\{0\}) = M'(\{1\}) = 1$  but the fourth event requires  $M(E_2) = 0$  or  $M'(\{1\}) = 0$ .

However, note that the sets  $E_1 \times \{0\}$ ,  $E_1 \times \{1\}$ ,  $E_2 \times \{0\}$  and  $E_2 \times \{1\}$  are disjoint, and so if  $\widetilde{M}$  would be a Poisson point process, independence would imply

$$\begin{aligned} & \mathbb{P}[\widetilde{M}(E_1 \times \{0\}) = 1, \widetilde{M}(E_1 \times \{1\}) = 1, \widetilde{M}(E_2 \times \{0\}) = 1, \widetilde{M}(E_2 \times \{1\}) = 0] \\ &= \mathbb{P}[\widetilde{M}(E_1 \times \{0\}) = 1] \cdot \mathbb{P}[\widetilde{M}(E_1 \times \{1\}) = 1] \cdot \mathbb{P}[\widetilde{M}(E_2 \times \{0\}) = 1] \cdot \mathbb{P}[\widetilde{M}(E_2 \times \{1\}) = 0] \\ &= \mathbb{P}[M(E_1) = M'(\{0\}) = 1] \cdot \mathbb{P}[M(E_1) = M'(\{1\}) = 1] \\ &\quad \cdot \mathbb{P}[M(E_2) = M'(\{0\}) = 1] \cdot \mathbb{P}[M(E_2) \cdot M'(\{1\}) = 0] \\ &> 0 \end{aligned}$$

since  $\mu(E_1), \mu(E_2) \in (0, \infty)$  and  $\nu(\{0\}) = \nu(\{1\}) = 1 \in (0, \infty)$ . Hence,  $\widetilde{M}$  cannot be a Poisson point process.

**Solution 10.3**

- (a) Let  $n \geq 0$ . Using the independence of  $X_1, \dots, X_k$  in the first equality and their Poisson distribution in the second equality, we obtain

$$\begin{aligned} \mathbb{P}[X_1 + \dots + X_k = n] &= \sum_{\substack{i_1, \dots, i_k \geq 0 \\ \text{s.t. } i_1 + \dots + i_k = n}} \mathbb{P}[X_1 = i_1] \cdots \mathbb{P}[X_k = i_k] \\ &= e^{-(\lambda_1 + \dots + \lambda_k)} \sum_{\substack{i_1, \dots, i_k \geq 0 \\ \text{s.t. } i_1 + \dots + i_k = n}} \frac{\lambda_1^{i_1}}{i_1!} \cdots \frac{\lambda_k^{i_k}}{i_k!} \\ &= e^{-(\lambda_1 + \dots + \lambda_k)} \frac{1}{n!} \sum_{\substack{i_1, \dots, i_k \geq 0 \\ \text{s.t. } i_1 + \dots + i_k = n}} \binom{n}{i_1, \dots, i_k} \lambda_1^{i_1} \cdots \lambda_k^{i_k} \\ &= e^{-(\lambda_1 + \dots + \lambda_k)} \frac{(\lambda_1 + \dots + \lambda_k)^n}{n!}, \end{aligned}$$

which shows that  $X_1 + \dots + X_k \sim \text{Pois}(\lambda_1 + \dots + \lambda_k)$ .

- (b) For  $k \geq 1$ , define the partial sums  $\bar{X}_k := \sum_{i=1}^k X_i$ . We first note that  $(\bar{X}_k)_{k \geq 1}$  is almost surely a monotone sequence and thus converges almost surely. Hence,  $\bar{X}_\infty := \sum_{i=1}^\infty X_i$  is a well-defined random variable taking values in  $\mathbb{N} \cup \{+\infty\}$ , and we are left with determining its distribution.

*Case 1:*  $\lambda = \sum_{i=1}^\infty \lambda_i = \infty$ . In this case, a union bound implies that

$$\mathbb{P}[\bar{X}_\infty < \infty] = \mathbb{P}[\exists I \geq 1, \forall i > I : X_i = 0] \leq \sum_{I \geq 1} \mathbb{P}[\forall i > I : X_i = 0] = \sum_{I \geq 1} \exp\left(-\underbrace{\sum_{i>I} \lambda_i}_{=\infty}\right) = 0.$$

Hence,  $\bar{X}_\infty = \infty$  almost surely.

*Case 2:*  $\lambda = \sum_{i=1}^\infty \lambda_i < \infty$ . From part (a), we know that  $\bar{X}_k$  is Poisson-distributed with parameter  $\sum_{i=1}^k \lambda_i$ . Hence, for all  $n \geq 0$ ,

$$\mathbb{P}[\bar{X}_k = n] = \exp\left(-\sum_{i=1}^k \lambda_i\right) \cdot \frac{(\sum_{i=1}^k \lambda_i)^n}{n!} \longrightarrow \exp(-\lambda) \cdot \frac{\lambda^n}{n!} \quad \text{as } k \rightarrow \infty,$$

and so,  $\bar{X}_\infty$  is  $\text{Pois}(\lambda)$ -distributed.

**Solution 10.4** Let us first consider  $u(x) = \mathbf{1}_B(x)$  for some  $B \in \mathcal{E} = \mathcal{B}(\mathbb{R})$ .

- (a) As  $u(x) = \mathbf{1}_B(x)$ , we have  $\int u(x)M(dx) = M(B)$  which is a well-defined random variable according to the definition of a point process (Definition 6.1)
- (b) Moreover, we then have  $\mathbb{E}[\int u(x)M(dx)] = \mathbb{E}[M(B)] = \mu(B) = \int u(x)\mu(dx)$ .

By linearity we can extend both results to simple functions. Since the limit of measurable functions is measurable and using monotone convergence theorem, we can also extend both results to arbitrary  $u : E \rightarrow \mathbb{R}_0^+$ . Now let us consider  $u : E \rightarrow \mathbb{R}$ . We can write  $u = u_+ - u_-$  with  $u_+, u_- : E \rightarrow \mathbb{R}_0^+$ , and this implies that  $\int u(x)M(dx)$  is a well-defined random variable. Assume that  $\int |u(x)|\mu(dx) < \infty$ . Then we also have that

$$\begin{aligned} \mathbb{E}\left[\int u(x)M(dx)\right] &= \mathbb{E}\left[\int u_+(x)M(dx)\right] - \mathbb{E}\left[\int u_-(x)M(dx)\right] \\ &= \int u_+(x)\mu(dx) - \int u_-(x)\mu(dx) = \int u(x)\mu(dx), \end{aligned}$$

which concludes the proof.