## Applied Stochastic Processes

## Solution sheet 11

## Solution 11.1

(a) For $B \in \mathcal{B}(\mathbb{R})$,

$$
T \# \mu(B)=\mu\left(T^{-1}(B)\right)=\mu(B \times[0,2])=2 \cdot \operatorname{Leb}_{\mathbb{R}}(B)
$$

Hence, $T \# \mu$ is $\sigma$-finite and $T \# M$ is a Poisson point process on $\mathbb{R}$ with intensity measure $T \# \mu=2 \cdot$ Leb.
(b) For $B \in \mathcal{B}(\mathbb{R})$,

$$
T \# \mu(B)=\mu(B \times \mathbb{R})= \begin{cases}0 & \text { if } \operatorname{Leb}_{\mathbb{R}}(B)=0 \\ \infty & \text { if } \operatorname{Leb}_{\mathbb{R}}(B)>0\end{cases}
$$

Hence, $T \# \mu$ is not $\sigma$-finite and $T \# M$ is a not a Poisson point process on $\mathbb{R}$.
(c) For $B \in \mathcal{B}([0,1])$,

$$
T \# \mu(B)=4 \cdot \operatorname{Leb}_{[0,1]}(B)
$$

Hence, $T \# \mu$ is $\sigma$-finite and $T \# M$ is a Poisson point process on $[0,1]$ with intensity measure $T \# \mu=4 \cdot$ Leb.
(d) We note that $T: \mathbb{R}^{2} \rightarrow \mathbb{R}^{2}$ is a $\mathcal{C}^{1}$-diffeomorphism and $T^{-1}\left(y_{1}, y_{2}\right)=\left(y_{2} / 2, y_{1} / 2\right)$. Therefore, for all $\left(y_{1}, y_{2}\right) \in \mathbb{R}^{2},\left|\operatorname{det}\left(d T^{-1}\left(y_{1}, y_{2}\right)\right)\right|=1 / 4$. Hence, $T \# \mu=1 / 4 \cdot$ Leb is $\sigma$-finite and $T \# M$ is a Poisson point process on $\mathbb{R}$ with intensity measure $T \# \mu=1 / 4 \cdot$ Leb.
(e) By the restriction theorem, the restricted processes $M_{[0,1]^{2}}, M_{[0,2]^{2}}$, and $M_{[2,3]^{2}}$ are Poisson point processes with intensity measure Leb (on the subsets). Again by the restriction theorem, $M_{[0,1]^{2}}$ is independent of $M_{[2,3]^{2}}$ and $M_{[0,2]^{2}}$ is independent of $M_{[2,3]^{2}}$ (note that $M(\{(2,2)\})=0$ a.s. $)$. The restricted processes $M_{[0,1]^{2}}$ and $M_{[0,2]^{2}}$ are not independent. For example, it can be seen by noticing that $M_{[0,2]^{2}}\left([0,2]^{2}\right)=0$ implies $M_{[0,1]^{2}}\left([0,1]^{2}\right)=0$.

## Solution 11.2

(a) We consider the map $T: \mathbb{R}^{d} \rightarrow[0, \infty)$ defined by $T(x)=\|x\|_{2}=\sqrt{x_{1}^{2}+\cdots+x_{d}^{2}}$, which is a continuous function, and so it is measurable. Since $T \# \mu$ is $\sigma$-finite (by considering the sequence $\left.([0, n])_{n \geq 1}\right)$, the mapping theorem implies that $T \# M$ is a Poisson point process on $[0, \infty)$ with intensity measure $T \# \mu$.
Let $s \geq r \geq 0$. Then we have

$$
T \# \mu([r, s])=\mu\left(T^{-1}([r, s])\right)=\mu\left(B_{s} \backslash B_{r}\right)=\lambda \cdot\left(\left|B_{s}\right|-\left|B_{r}\right|\right)=\lambda \cdot \frac{\pi^{d / 2}}{\Gamma(d / 2+1)} \cdot\left(s^{d}-r^{d}\right) .
$$

More generally, $T \# \mu(B)=\lambda \cdot \operatorname{Leb}\left(T^{-1}(B)\right)$ for $B \in \mathcal{B}([0, \infty))$.
(b) Fix a sequence $\left(r_{k}\right)_{k \geq 0}$ with $\left|B_{r_{k}}\right|=k$. Using the restriction property from Section 6.8 , we note that $\left(M\left(B_{r_{k}} \backslash \bar{B}_{r_{k-1}}\right)\right)_{k \geq 1}$ is a sequence of independent, identically distributed random variables with

$$
M\left(B_{r_{1}} \backslash B_{r_{0}}\right) \sim \operatorname{Pois}(\lambda)
$$

Hence, by the strong law of large numbers, we have almost surely

$$
\lim _{r \rightarrow \infty} \frac{M\left(B_{r}\right)}{\left|B_{r}\right|}=\lim _{n \rightarrow \infty} \frac{M\left(B_{r_{n}}\right)}{\left|B_{r_{n}}\right|}=\lim _{n \rightarrow \infty} \frac{\sum_{k=1}^{n} M\left(B_{r_{k}} \backslash B_{r_{k-1}}\right)}{n}=\mathbb{E}\left[M\left(B_{r_{1}} \backslash B_{r_{0}}\right)\right]=\lambda
$$

## Solution 11.3

(a) To see that the restricted measures are diffuse, it suffices to note that for every $i \in \mathbb{N}$,

$$
\mu_{i}(\{x\}) \leq \mu(\{x\})=0, \quad \forall x \in E_{i}
$$

and so $\mu_{i}$ is diffuse.
The fact that $M_{E_{1}}, M_{E_{2}}, \ldots$ are independent Poisson point processes with respective intensities $\mu_{E_{1}}, \mu_{E_{2}}, \ldots$ follows directly from the restriction property in Section 6.8.
(b) Fix any $i \in \mathbb{N}$. Since $\mu\left(E_{i}\right)<\infty$, we can use Proposition 6.10 to the explicitly construct a Poisson point process with intensity measure $\mu_{E_{i}}$ as

$$
\widetilde{M}_{E_{i}}=\sum_{j=1}^{Z} \delta_{X_{j}}
$$

where $Z \sim \operatorname{Pois}\left(\mu\left(E_{i}\right)\right)$ and $X_{j} \sim \frac{\mu_{E_{i}}(\cdot)}{\mu_{E_{i}}}, j \geq 1$, are independent. Since being simple is a property of the law and $P_{\widetilde{M}_{E_{i}}}=P_{M_{E_{i}}}$ by Proposition 6.14, it suffices to prove that $\widetilde{M}_{E_{i}}$ is almost surely simple. To this end, we compute

$$
\mathbb{P}\left[\widetilde{M}_{E_{i}} \text { is not simple }\right] \leq \mathbb{P}\left[\exists j \neq k: X_{j}=X_{k}\right] \leq \sum_{j \neq k} \mathbb{P}\left[X_{j}=X_{k}\right]=0
$$

where we used in the last equality that

$$
\mathbb{P}\left[X_{j}=X_{k}\right]=\int_{E_{i}} \underbrace{\mathbb{P}\left[X_{j}=x\right]}_{=0} \frac{\mu_{E_{i}}(d x)}{\mu\left(E_{i}\right)}
$$

by the independence of $X_{j}$ and $X_{k}$. This concludes that $\widetilde{M}_{E_{i}}$ and thereby $M_{E_{i}}$ is almost surely simple.
(c) Since $\mathbb{P}\left[M_{E_{i}}\right.$ is simple $]=1$ by part (b), we deduce that

$$
\mathbb{P}[M \text { is simple }]=\mathbb{P}\left[\bigcap_{i=1}^{\infty}\left\{M_{E_{i}} \text { is simple }\right\}\right]=1
$$

## Solution 11.4

(a) Since the Lebesgue measure on $\mathbb{R} \times[0, \infty)$ is diffuse and $\sigma$-finite, $M$ is almost surely simple.
(b) For $x \in \mathbb{Z} \subset \mathbb{R}, \mu(\{x\})=1$ and so $M(\{x\}) \sim \operatorname{Pois}(1)$, which takes values in $\{2,3, \ldots\}$ with positive probability. Hence, the process is not almost surely simple.

## Solution 11.5

To show $(i) \Longleftrightarrow(i i)$, we note that by definition,

$$
P_{M}=P_{M^{\prime}} \Longleftrightarrow \forall A \in \mathcal{B}(\mathcal{M}), P_{M}(A)=P_{M^{\prime}}(A) \Longleftrightarrow \forall A \in \mathcal{B}(\mathcal{M}), \mathbb{P}[M \in A]=\mathbb{P}\left[M^{\prime} \in A\right]
$$

The implications $(i i) \Longrightarrow(i i i) \Longrightarrow(i v)$ are clear by inclusion.
To show $(i i i) \Longrightarrow(i i)$, we use Dynkin's lemma. The family
$\mathcal{B}:=\left\{\left\{\eta: \eta\left(B_{1}\right)=n_{1}, \ldots, \eta\left(B_{k}\right)=n_{k}\right\}: k \geq 1 ; B_{1}, \ldots, B_{k} \in \mathcal{E}\right.$ disjoint $\left.; n_{1}, \ldots, n_{k} \in \mathbb{M}\right\} \subset \mathcal{B}(\mathcal{M})$
is a $\pi$-system and $\sigma(\mathcal{B})=\mathcal{B}(\mathcal{M})$ by definition. The family

$$
\mathcal{D}:=\left\{A \in \mathcal{B}(\mathcal{M}): \mathbb{P}[M \in A]=\mathbb{P}\left[M^{\prime} \in A\right]\right\}
$$

is a Dynkin-system and it contains $\mathcal{B}$ by assumption. Hence, we conclude using Dynkin's lemma that $\mathcal{D}=\mathcal{B}(\mathcal{M})$ and so (ii) holds.

To show $(i v) \Longrightarrow(i i i)$, we consider $B_{1}, \ldots, B_{k}$ and $n_{1}, \ldots, n_{k}$ for some $k \geq 1$ and define the disjoint sets

$$
C_{1}=B_{1}, C_{2}=B_{2} \backslash B_{1}, \ldots, C_{k}=B_{k} \backslash \bigcup_{i=1}^{k-1} B_{i}
$$

(iii) then follows from (iv) by summing over all possible ways how the points could be distributed over the disjoint sets $C_{1}, \ldots, C_{k}$ under the constraints $M\left(B_{1}\right)=n_{1}, \ldots, M\left(B_{k}\right)=n_{k}$.

