

$$\rightarrow \langle \Phi \rangle = Y \cdot \Lambda(B) \dots \text{Cov } \Phi$$

9. Let  $\Phi$  be a mixed Poisson point process with the driving measure  $Y \cdot \Lambda$ , where  $Y$  is a non-negative random variable and  $\Lambda$  is a locally finite diffuse measure. Determine the covariance  $\text{cov}(\Phi(B_1), \Phi(B_2))$  for  $B_1, B_2 \in \mathcal{B}_0$  and show that it is non-negative.

$$\rightarrow \Phi(B_1 \setminus B_2) + \Phi(B_1 \cap B_2)$$

we know:  $\text{cov}(\Phi(B_1), \Phi(B_2)) = \dots (*)$

$$\hookrightarrow \Phi(B_2 \setminus B_1) + \Phi(B_1 \cap B_2)$$

var  $\Phi(B) = ?$

$$\mathbb{E}[\Phi(B)] = \mathbb{E}[\underbrace{\mathbb{E}[\Phi(B) | Y]}_{P_0(Y \cdot \Lambda(B))}] = \mathbb{E}[Y \Lambda(B)] = \Lambda(B) \cdot \mathbb{E}Y$$

$$\mathbb{E}[\Phi(B)^2] = \mathbb{E}[\mathbb{E}[\Phi(B)^2 | Y]] = \dots$$

$\Rightarrow$  assume:  $\mathbb{E}Y^2 < \infty$

$$\text{var } \Phi(B) = \underbrace{\Lambda(B)^2 \cdot \text{var } Y}_{\text{variance of cond. expectation}} + \underbrace{\Lambda(B) \cdot \mathbb{E}Y}_{\text{expectation of conditional variance}}$$

$$\text{cov}(\Phi(B_1), \Phi(B_2)) = \text{cov}(\Phi(B_1 \setminus B_2), \Phi(B_1 \cap B_2)) + \text{cov}(\Phi(B_1 \cap B_2), \Phi(B_2 \setminus B_1)) + \text{cov}(\Phi(B_1 \setminus B_2), \Phi(B_2 \setminus B_1)) + \text{var } \Phi(B_1 \cap B_2)$$

assume  $A, B \in \mathcal{B}$  disjoint:  $(\mathbb{E}Y)^2 \Lambda(A) \Lambda(B)$

$$\text{cov}(\Phi(A), \Phi(B)) = \mathbb{E}[\Phi(A)\Phi(B)] - (\mathbb{E}\Phi(A))(\mathbb{E}\Phi(B))$$

$$\mathbb{E}[\Phi(A)\Phi(B)] = \mathbb{E}[\mathbb{E}[\Phi(A)\Phi(B) | Y]] = \mathbb{E}[\mathbb{E}[\Phi(A) | Y] \cdot \mathbb{E}[\Phi(B) | Y]] =$$

$$\hookrightarrow \downarrow \text{independent under the condition, } \Phi(A) \sim P_0(Y \cdot \Lambda(A))$$

$$= \mathbb{E}[Y \Lambda(A) \cdot Y \Lambda(B)] = \Lambda(A) \Lambda(B) \mathbb{E}Y^2$$

$$\text{cov}(\Phi(A), \Phi(B)) = \Lambda(A) \Lambda(B) \cdot \text{var } Y + \underbrace{\Lambda(B_1 \setminus B_2) \cdot \Lambda(B_2)}_{\dots}$$

$$\text{cov}(\Phi(B_1), \Phi(B_2)) = \text{var } Y \left[ \underbrace{\Lambda(B_1 \setminus B_2) \cdot \Lambda(B_2 \setminus B_1) + \Lambda(B_1 \setminus B_2) \Lambda(B_1 \cap B_2) + \Lambda(B_2 \setminus B_1) \Lambda(B_1 \cap B_2) + \Lambda(B_1 \cap B_2) \Lambda(B_1 \cap B_2)}_1 \right] + \Lambda(B_1 \cap B_2) \cdot \mathbb{E}Y =$$

$$= \Lambda(B_1 \cap B_2) \Lambda(B_2)$$

$$= \underbrace{\mathbb{1}_{\mathcal{B}_1}}_{\geq 0} \left[ \underbrace{\mathbb{1}_{\mathcal{B}_1}}_{\geq 0} \wedge \underbrace{\mathbb{1}_{\mathcal{B}_2}}_{\geq 0} \right] + \underbrace{\mathbb{E}Y}_{\geq 0} \cdot \underbrace{\mathbb{1}_{\mathcal{B}_1 \cap \mathcal{B}_2}}_{\geq 0} \geq 0$$

makes sense:  $\mathbb{P}(\mathcal{B}_1)$  is high  $\Rightarrow \mathbb{P}(\mathcal{B}_2)$  is likely to be high too because  $Y$  is likely to be high. (even if  $\mathcal{B}_1, \mathcal{B}_2$  disjoint).