

# **Measures everywhere**

## **Variation analysis for Poisson processes**

Sergei Zuyev

*University of Strathclyde, Glasgow, U.K.*

## Finite Poisson processes

Poisson process models an array of points scattered randomly and independently with a density proportional to  $\mu(dx)$  in a given region  $X$ .

More exactly:

**Definition:**  $\Pi$  is a Poisson process in  $[X, \mathcal{B}]$  with the intensity measure  $\mu$ :  $\mu(X) < \infty$  if for any disjoint  $B_1, \dots, B_n \in \mathcal{B}$ , the number of points of  $\Pi$  in these sets are independent Poisson random variables  $\Pi(B_1), \dots, \Pi(B_n)$  with parameters  $\mu(B_1), \dots, \mu(B_n)$ .

The definition implies:

- If  $\mu$  is *diffuse*, i. e.  $\mu(\{x\}) = 0$  for any singleton  $\{x\}$ , then with probability 1 no realisation of  $\Pi$  contains multiple points.
- $\mathbf{E} \Pi(B) = \mu(B)$ , that is why  $\mu(dx)$  is also called the mean measure.

□ We treat each realisation  $\{x_1, \dots, x_{\Pi(X)}\}$  of the process  $\Pi$  as a *(random) counting measure* and write  $\Pi = \sum_i \delta_{x_i}$ , so that  $\Pi(B)$  equals the number of points in  $B$  and

$$\int f(x) \Pi(dx) = \sum_{x_i \in \Pi} f(x_i).$$

## Palm distribution

Given an event  $\Xi$ , for every  $B \in \mathcal{B}$  one can define *Campbell measure*  $\mathcal{C}(\Xi, B) = \mathbf{E}_\mu \mathbb{I}_\Xi(\Pi)\Pi(B)$ . This is a measure on  $\mathcal{B}$  and  $\mathcal{C}(\Xi, \cdot) \ll \mu(\cdot)$ , therefore there exists a Radon-Nikodym derivative

$$\frac{d\mathcal{C}(\Xi, \cdot)}{d\mu}(x) = \mathbf{P}_\mu^x(\Xi)$$

which can be chosen to be a *probability* distribution on events  $\Xi$ .  $\mathbf{P}_\mu^x$  is called the *Palm distribution* of  $\Pi$  and has a meaning of the conditional distribution of  $\Pi$  'given there is a point of the process in  $x$ '.

Another interpretation is that of the distribution of a configuration seen from a typical point of the process.

## Campbell formula

From definition

$$\mathbf{E} \int_B \mathbb{1}_{\Xi}(\Pi) \Pi(dx) = \int_B \mathcal{C}(\Xi, dx) = \int_B \mathbf{P}_{\mu}^x(\Xi) \mu(dx)$$

and thus by the standard monotone class argument

$$\mathbf{E}_{\mu} \int f(x, \Pi) \Pi(dx) = \int \mathbf{E}_{\mu}^x f(x, \Pi) \mu(dx) \quad (1)$$

which is known as *Refined Campbell formula* – continuous analog of the full probability formula. In particular, we have *Campbell formula*:

$$\mathbf{E}_{\mu} \sum_{x_i \in \Pi} f(x_i) = \mathbf{E}_{\mu} \int f(x) \Pi(dx) = \int f(x) \mu(dx).$$

## Slivnyak's theorem and Mecke's characterisation

As the points in Poisson process are independent, we should have that the distribution of  $\Pi - \delta_x$  under  $\mathbf{P}_\mu^x$  should be just  $\mathbf{P}_\mu$ . This is known as Slivnyak's theorem and equivalent to the following form of Campbell formula (1): for any process  $f(x, \Pi)$ , one has

$$\mathbf{E}_\mu \int f(x, \Pi) \Pi(dx) = \mathbf{E}_\mu \int f(x, \Pi + \delta_x) \mu(dx). \quad (2)$$

Mecke established that (2), in fact, *characterises* a Poisson process.

## Expectation

Given a functional  $F = F(\Pi)$ , by the full probability formula

$$\begin{aligned}\mathbf{E}_\mu F &= \sum_{n=0}^{\infty} \frac{(\mu(X))^n}{n!} e^{-\mu(X)} \int_{X^n} F\left(\sum_{i=1}^n \delta_{x_i}\right) \frac{\mu(dx_1)}{\mu(X)} \cdots \frac{\mu(dx_n)}{\mu(X)} \\ &= e^{-\mu(X)} \sum_{n=0}^{\infty} \frac{1}{n!} \int_{X^n} F\left(\sum_{i=1}^n \delta_{x_i}\right) \mu(dx_1) \cdots \mu(dx_n)^a. \quad (3)\end{aligned}$$

□ We view  $\mathbf{E}_\mu F$  as a function  $\psi(\mu)$  of the intensity measure.

---

<sup>a</sup>By definition we have  $F(\emptyset)$  for  $n = 0$  in the sum above.

## Variation analysis

Substituting  $\mu \leftarrow (\mu + \eta)$  into (3) and assuming, for simplicity, that  $F$  is bounded we get

$$\begin{aligned}
 \mathbf{E}_{\mu+\eta} F &= e^{-\mu(X)} (1 - \eta(X) + o(\|\eta\|)) \times \\
 &\left[ F(\emptyset) + \sum_{n=1} \frac{1}{n!} \int_{X^n} F\left(\sum_{i=1}^n \delta_{x_i}\right) (\mu + \eta)(dx_1) \dots (\mu + \eta)(dx_n) \right] \\
 &= \mathbf{E}_{\mu} F + e^{-\mu(X)} \sum_{n=1} \frac{n}{n!} \int_{X^n} F\left(\sum_{i=1}^n \delta_{x_i}\right) \mu(dx_1) \dots \mu(dx_{n-1}) \eta(dx_n) \\
 &\quad - \eta(X) e^{-\mu(X)} \sum_{n=0} \frac{1}{n!} \int_{X^n} F\left(\sum_{i=1}^n \delta_{x_i}\right) \mu(dx_1) \dots \mu(dx_n) + o(\|\eta\|)
 \end{aligned}$$

Thus

$$\begin{aligned}
& \mathbf{E}_{\mu+\eta} F - \mathbf{E}_{\mu} F \\
&= e^{-\mu(X)} \sum_{n=0}^{\infty} \frac{1}{n!} \int_{X^{n+1}} F\left(\sum_{i=1}^n \delta_{x_i} + \delta_x\right) \mu(dx_1) \dots \mu(dx_n) \eta(dx) \\
&- e^{-\mu(X)} \sum_{n=0}^{\infty} \frac{1}{n!} \int_{X^{n+1}} F\left(\sum_{i=1}^n \delta_{x_i}\right) \mu(dx_1) \dots \mu(dx_n) \eta(dx) + o(\|\eta\|) \\
&= \mathbf{E}_{\mu} \int_X [F(\Pi + \delta_x) - F(\Pi)] \eta(dx) + o(\|\eta\|)
\end{aligned}$$

We see that  $\mathbf{E}_{\mu} F$  is differentiable and possesses a gradient function

$$\bar{\Delta}_{\mu}(x) = \mathbf{E}_{\mu}[F(\Pi + \delta_x) - F(\Pi)]$$

which we call the expected first difference.

## Analyticity of the expectation

**Theorem 1.** Assume that there exist a constant  $b > 0$  such that  $|F(\sum_{i=1}^n \delta_{x_i})| \leq b^n$  for all  $n \geq 0$  and  $(x_1, \dots, x_n) \in X^n$ . Then  $\psi(\mu) = \mathbf{E}_\mu F(\Pi)$  is analytic on  $\mathbb{M}_+$  and

$$\mathbf{E}_{\mu+\eta} F = \sum_{n=0}^{\infty} \frac{1}{n!} \int_{X^n} \overline{\Delta}_\mu^n(x_1, \dots, x_n) \eta^n(dx_1 \dots dx_n), \quad (4)$$

where

$$\begin{aligned} \overline{\Delta}_\mu^n(x_1, \dots, x_n) &= \mathbf{E}_\mu \Delta_\mu^n(x_1, \dots, x_n; \Pi) \\ &= \mathbf{E}_\mu \left[ \sum_{m=0}^n (-1)^{n-m} \binom{n}{m} F\left(\Pi + \sum_{j=1}^m \delta_{x_j}\right) \right]. \end{aligned} \quad (5)$$

## First Fréchet derivatives

In particular,

$$\overline{\Delta}_\mu(x) = \mathbf{E}_\mu[F(\Pi + \delta_x) - F(\Pi)] \quad \text{gradient function}$$

$$\overline{\Delta}_\mu^2(x_1, x_2) = \mathbf{E}_\mu[F(\Pi + \delta_{x_1} + \delta_{x_2}) - 2F(\Pi + \delta_{x_1}) + F(\Pi)]$$

etc.

□ We call  $\overline{\Delta}_\mu^n(x_1, \dots, x_n)$  the *expected  $n$ th order difference*.

## Perturbation analysis

Consider the case a homogeneous Poisson process with intensity  $\lambda$  in a compact  $X \subset \mathbb{R}^d$  so that the intensity measure is  $\lambda \ell$  ( $\ell$  is the Lebesgue measure). Slightly abusing notation, write simply  $\mathbf{E}_\lambda$  instead of  $\mathbf{E}_{\lambda \ell}$ . Then

$$\begin{aligned} \frac{d}{d\lambda} \mathbf{E}_\lambda F &= \lim_{t \downarrow 0} \frac{1}{t} \left[ E_{\lambda+t} F - \mathbf{E}_\lambda F \right] \\ &= \lim_{t \downarrow 0} \frac{1}{t} \left[ D \mathbf{E}_\lambda F[t\ell] + o(t) \right] = \int_X \mathbf{E}_\lambda [F(\Pi + \delta_x) - F(\Pi)] dx \end{aligned}$$

## Russo's formula for Poisson processes

Let  $F(\Pi) = \mathbb{1}_{\Xi}(\Pi)$  for some event  $\Xi$  and let

$\Upsilon(\Pi) = \{x \in X : \mathbb{1}_{\Xi}(\Pi + \delta_x) \neq \mathbb{1}_{\Xi}(\Pi)\}$ . Then

$$\begin{aligned} \frac{d}{d\lambda} \mathbf{P}_{\lambda}(\Xi) &= \int_X \mathbf{E}_{\lambda}[\mathbb{1}_{\Xi}(\Pi + \delta_x) - \mathbb{1}_{\Xi}(\Pi)] dx \\ &= \mathbf{E}_{\lambda} \int_X [\mathbb{1}_{\Xi}(\Pi + \delta_x) - \mathbb{1}_{\Xi}(\Pi)] \mathbb{1}_{\Upsilon(\Pi)}(x) dx \\ &= \mathbf{E}_{\lambda} \int_X \mathbb{1}_{\Xi}(\Pi + \delta_x) \mathbb{1}_{\Upsilon(\Pi)}(x) dx - \mathbf{E}_{\lambda} \int_X \mathbb{1}_{\Xi}(\Pi) \mathbb{1}_{\Upsilon(\Pi)}(x) dx \end{aligned}$$

By Slivnyak's theorem (2)

$$\begin{aligned}
 \mathbf{E}_\lambda \int_X \mathbb{1}_\Xi(\Pi + \delta_x) \mathbb{1}_{\Upsilon(\Pi)}(x) dx \\
 &= \frac{1}{\lambda} \mathbf{E}_\lambda \int_X \mathbb{1}_\Xi(\Pi) \mathbb{1}_{\Upsilon(\Pi - \delta_x)}(x) \Pi(dx) \\
 &= \frac{1}{\lambda} \mathbf{E}_\lambda \mathbb{1}_\Xi(\Pi) N_\Xi(\Pi),
 \end{aligned}$$

where  $N_\Xi(\Pi) = \text{card}\{x_i \in \Pi : \mathbb{1}_\Xi(\Pi) \neq \mathbb{1}_\Xi(\Pi - \delta_{x_i})\}$  is the number of *pivotal* points for event  $\Xi$  in configuration  $\Pi$ , i. e. the points which removal would break the occurrence of  $\Xi$ .

$$\mathbf{E}_\lambda \int_X \mathbb{1}_\Xi(\Pi) \mathbb{1}_{\Upsilon(\Pi)}(x) dx = \mathbf{E}_\lambda \mathbb{1}_\Xi(\Pi) V_\Xi(\Pi),$$

where  $V_\Xi(\Pi) = \text{vol}\{x \in X : \mathbb{1}_\Xi(\Pi + \delta_x) \neq \mathbb{1}_\Xi(\Pi)\}$  is the volume of the pivotal locations, where adding a point would break the occurrence of  $\Xi$ .

Finally,

$$\frac{d}{d\lambda} \mathbf{P}_\lambda(\Xi) = \mathbf{E}_\lambda \mathbb{1}_\Xi(\Pi) [\lambda^{-1} N_\Xi(\Pi) - V_\Xi(\Pi)] \quad (6)$$

$$\frac{d}{d\lambda} \log \mathbf{P}_\lambda(\Xi) = \mathbf{E}_\lambda [\lambda^{-1} N_\Xi - V_\Xi \mid \Xi] \quad (7)$$

$$\mathbf{P}_{\lambda_2}(\Xi) = \mathbf{P}_{\lambda_1}(\Xi) \exp \left\{ \int_{\lambda_1}^{\lambda_2} \mathbf{E}_\lambda [\lambda^{-1} N_\Xi - V_\Xi \mid \Xi] d\lambda \right\}. \quad (8)$$

## Toy example

Consider a set  $B$  of volume  $V$  and let  $\Xi = \{\Pi(B) = k\}$ . Surely,

$$\mathbf{P}_\lambda(\Xi) = \frac{(\lambda V)^k}{k!} \exp\{-\lambda V\}.$$

Thus

$$\frac{d}{d\lambda} \log \mathbf{P}_\lambda(\Xi) = \frac{k}{\lambda} - V. \quad (9)$$

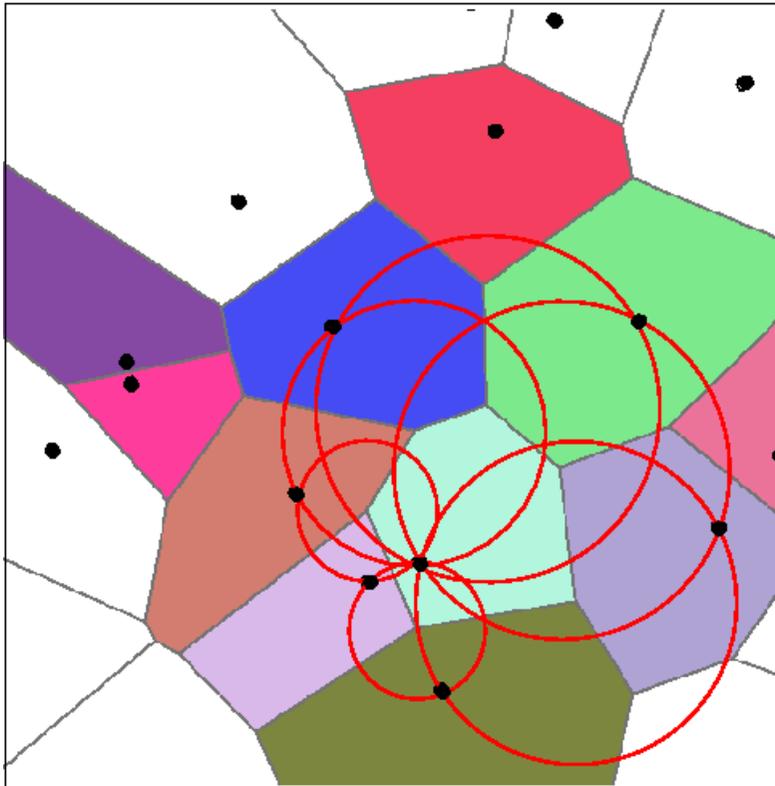
On the other hand, when  $\Xi$  occurs, there are  $k$  points in  $B$  and removing any of them would break occurrence of  $\Xi$ . Thus on  $\Xi$ ,

$N_\Xi = \mathbf{E}_\lambda[N_\Xi \mid \Xi] = k$ . Similarly, no additional point could be added

anywhere in  $B$  without breaking the occurrence of  $\Xi$ . So on  $\Xi$ ,

$V_\Xi = \mathbf{E}_\lambda[V_\Xi \mid \Xi] = V$  and (7) is seen to be equivalent to (9).

## Voronoi flower



By similar method one may derive that the conditional distribution of the volume of a typical Voronoi flower (the one at the origin under  $\mathbf{P}^0$ ) given the corresponding Voronoi cell has  $n$  sides is  $\text{Gamma}(n, \lambda)$ .

## Set indexed filtration

Consider a continuous time process  $\xi_t$ ,  $t \geq 0$  and filtration

$\mathcal{F}_{[0,t]} = \sigma\{\xi_s, 0 \leq s \leq t\}$ .  $\tau$  is a stopping time if  $\{\tau \leq t\} \in \mathcal{F}_{[0,t]} \forall t$   
or equivalently, random set  $[0, \tau]$  is such that  $\{[0, \tau] \subseteq [0, t]\} \in \mathcal{F}_{[0,t]} \forall t$ .

Consider now a homogeneous Poisson process  $\Pi$  in  $\mathbb{R}^d$  and let

$\mathcal{F}_B = \sigma\{\Pi(A), A \subseteq B\}$  be the natural filtration. We have

- monotonicity:  $\mathcal{F}_{K_1} \subseteq \mathcal{F}_{K_2}$  for any two compact  $K_1 \subseteq K_2$ ;
- continuity from above:  $\mathcal{F}_K = \bigcap_{n=1}^{\infty} \mathcal{F}_{K_n}$  if  $K_n \downarrow K$ .

## Stopping sets

**Definition:** A random compact set  $\Delta$  is called a *stopping set* (more precisely,  $\{\mathcal{F}_K\}$ -stopping set) if the event  $\{\Delta \subseteq K\}$  is  $\mathcal{F}_K$  measurable for all compact  $K$ .

Let  $\mathcal{F} = \bigvee_{K \in \mathbb{K}} \mathcal{F}_K$ , where  $\mathbb{K}$  is the collections of compact sets. The *stopping  $\sigma$ -algebra* is the following collection:

$$\mathcal{F}_\Delta = \{A \in \mathcal{F} : A \cap \{\Delta \subseteq K\} \in \mathcal{F}_K \forall K \in \mathbb{K}\}.$$

## Set-indexed martingales

**Definition.** A set indexed random process  $X_K$ ,  $K \in \mathbb{K}$  is called a *martingale* (more precisely, a  $(\mathbf{P}, \{\mathcal{F}_K\})$ -martingale) if for all  $K_1, K_2 \in \mathbb{K}$  such that  $K_1 \subseteq K_2$  one has

$$\mathbf{E}[X_{K_2} \mid \mathcal{F}_{K_1}] = X_{K_1} \quad \mathbf{P} - a. s.$$

**Theorem 2.** Let  $\Delta_1, \Delta_2$  be two a. s. compact stopping sets such that  $\Delta_1 \subseteq \Delta_2$  almost surely. Let  $X_K$  be a uniformly integrable martingale (we omit details here!). Then

$$\mathbf{E} [X_{\Delta_2} \mid \mathcal{F}_{\Delta_1}] = X_{\Delta_1} \quad a. s. \tag{10}$$

provided  $\mathbf{E} |X_{\Delta_2}| < \infty$ .

## Likelihood ratio

An important example of a uniformly integrable martingale is provided by a *likelihood ratio*. Namely, let  $\mathbf{Q}$  and  $\mathbf{P}$  be two probability measures on  $\mathcal{F}$  such that  $\mathbf{Q} \ll_{loc} \mathbf{P}$ , i. e. for any  $K \in \mathbb{K}$  the restriction  $\mathbf{Q}^K$  of  $\mathbf{Q}$  onto  $\mathcal{F}_K$  is absolutely continuous with respect to the restriction  $\mathbf{P}^K$  of  $\mathbf{P}$  onto the same  $\sigma$ -algebra. Denote the likelihood ratio by

$$L_K = \frac{d\mathbf{Q}^K}{d\mathbf{P}^K},$$

For Poisson processes we have that

$$L_K = \frac{d\mathbf{P}_{\lambda}^K}{d\mathbf{P}_{\rho}^K}(\Pi) = \left(\frac{\lambda}{\rho}\right)^{\Pi(K)} e^{-(\lambda-\rho)\ell(K)}, \quad \forall K \in \mathbb{K}. \quad (11)$$

## Gamma-type result

**Theorem 3.** *Let  $\Delta$  be an a. s. compact stopping set with respect to the natural filtration of a homogeneous Poisson process  $\Pi$  with density  $\lambda$  in  $\mathbb{R}^d$ . Assume that*

$$\mathbf{P}_\lambda\{\Pi(\Delta) = n\} > 0 \text{ and does not depend on } \lambda. \quad (12)$$

*Then  $\ell(\Delta)$  given  $\Pi(\Delta) = n$  has  $\text{Gamma}(n, \lambda)$  distribution.*

**Remark.** Condition (12) is satisfied if  $\Delta(\Pi)$  is equivariant under scaling:  $\Delta(t\Pi) = t\Delta(\Pi)$  for all  $\Pi$  and  $t > 0$ .

## Examples

- The minimal closed ball centred in the origin and containing exactly  $n$  Poisson process points is a stopping set and its volume conforms to  $\text{Gamma}(n, \lambda)$  distribution (this is trivial).
- A typical Voronoi flower is a stopping set and its volume given that the corresponding Voronoi cell has  $n$  sides, is  $\text{Gamma}(n, \lambda)$ -distributed.

## Proof of the Gamma-type result

Kurtz-Doob theorem 2 implies

$$\mathbf{E}_\lambda F = \mathbf{E}_\rho \left( \frac{\lambda}{\rho} \right)^{\Pi(\Delta)} e^{-(\lambda-\rho)\ell(\Delta)} F \quad (13)$$

for any  $\mathcal{F}_\Delta$ -measurable  $F$ . By (13) for any  $z$  we can write

$$\begin{aligned} \mathbf{E}_\lambda [e^{z\ell(\Delta)} \mid \Pi(\Delta) = n] &= \frac{\mathbf{E}_\lambda [e^{z\ell(\Delta)} \mathbb{I}\{\Pi(\Delta) = n\}]}{\mathbf{P}_\lambda\{\Pi(\Delta) = n\}} \\ &= \frac{\mathbf{E}_\rho [e^{z\ell(\Delta)} \mathbb{I}\{\Pi(\Delta) = n\} \lambda^n \rho^{-n} e^{-(\lambda-\rho)\ell(\Delta)}]}{\mathbf{P}_\rho\{\Pi(\Delta) = n\}}. \end{aligned}$$

Choosing now  $\rho = \lambda - z$  we see that the last expression simplifies to  $(1 - z/\lambda)^{-n}$  which is the Laplace transform for  $\text{Gamma}(n, \lambda)$ .

## References

- D. J. Daley and D. Vere-Jones. An Introduction to the Theory of Point Processes. NY, Springer (1988)
- J. Mecke. Stationäre zufällige Masse auf localcompakten Abelischen Gruppen. *Z. Wahrsch. verw. Gebiete*, **9**, 36–58 (1967)
- S. Zuyev. Russo's Formula for the Poisson Point Processes and its Applications. *Discrete Math. and Applications*, **3**, 355-366 (1993)
- I. Molchanov and S. Zuyev. Variational analysis of functionals of a Poisson process. *Math. Oper. Research*, **25**, 485–508 (2000)
- S. Zuyev. Stopping sets: Gamma-type results and hitting properties. *Adv. Appl. Prob.*, **31**, 63–73 (1999)

□ <http://www.stams.strath.ac.uk/~sergei>