

Cluster Processes

CLP-1

A cluster process N on a space \mathcal{Y} is constructed from a center process N_c on a space \mathcal{X} and a family of component processes $\{N_r(\cdot|x), x \in \mathcal{X}\}$.

We put

$$N(B) := \int N_r(B|x) N_c(dx), \quad B \subset \mathcal{Y}.$$

If $\lambda_c(A) := E[N_c(A)]$ for $A \subset \mathcal{X}$, and $\lambda_r(B|x) := E[N_r(B|x)]$ for $x \in \mathcal{X}$,

If we denote the points of N_c by $\{X_i\}_{i=1}^{\infty}$, $B \subset \mathcal{Y}$, then

$$N(B) = \sum_i N_r(B|X_i).$$

$$\left. \begin{array}{l} E[N(B)] \\ = \int \lambda_r(B|x) \lambda_c(dx) \end{array} \right\}$$

Def. For $g(y) \geq 0$, put

$$\psi_r(g|x) := E \left[e^{-\int g(y) N_r(dy|x)} \right].$$

Prop. If the component processes $\{N_r(\cdot|x)\}$ are mutually independent and independent of the center process N_c , then

$$E \left[e^{-\int g(y) N(dy)} \mid N_c(\cdot) \right] = \exp \left[\int \ln \psi_r(g|x) N_c(dx) \right].$$

Proof. Suppose the points of N_c are $X_i = x_i$. Then

$$\int g(y) N(dy) = \sum_i \int g(y) N_r(dy|x_i), \quad \text{and}$$

$$E \left[e^{-\int g(y) N(dy)} \mid X_i = x_i \text{ all } i \right] = E \left[\prod_i e^{-\int g(y) N_r(dy|x_i)} \right]$$

$$= \prod_i \psi_r(g|x_i) = \exp \left(\sum_i \ln \psi_r(g|x_i) \right)$$

we always assume this - In this case, N is called an independent cluster process

Then CLP-2

$$E\left[e^{-\int g(y) N(dy)} \mid N_c(\cdot) \right] = \exp\left[\sum_i \ln \psi_r(g/x_i) \right]$$

$$= \exp\left[\int \ln \psi_r(g/x) N_c(dx) \right].$$

Corollary If the center process of an independent cluster process is Poisson, with mean measure Λ_c , then

$$\psi(g) := E\left[e^{-\int g(y) N(dy)} \right] = \exp\left[\int \{\psi_r(g/x) - 1\} \Lambda_c(dx) \right].$$

Proof. Write

$$\begin{aligned} \psi(g) &= E\left[e^{-\int g(y) N(dy)} \right] \\ &= E\left[E\left[e^{-\int g(y) N(dy)} \mid N_c(\cdot) \right] \right] \\ &= E\left[e^{s^Y} \right] \Big|_{s=1} \end{aligned}$$

where

$$Y := \int h(x) N_c(dx) \text{ and } h(x) := \ln \psi_r(g/x).$$

Thus,

$$\begin{aligned} \psi(g) &= \exp\left[\int \{e^{sh(x)} - 1\} \Lambda_c(dx) \right] \Big|_{s=1} \\ &= \exp\left[\int \{\psi_r(g/x) - 1\} \Lambda_c(dx) \right]. \end{aligned}$$

If $N_r(\cdot/x)$ is Poisson with mean measure $\Lambda_r(\cdot/x)$, then

$$\psi_r(g/x) = \exp\left[\int \{e^{-g(y)} - 1\} \Lambda_r(dy/x) \right].$$

Now suppose we put $Y = \int h(y) N(dy)$. Then CLP-3
 $M_Y(s) := E[e^{sY}] = \psi(g)$ if $g(y) = -sh(y)$. Thus,
 $M_Y(s) = \psi(sh)$. When N_c is Poisson,

$$M_Y(s) = \psi(sh) = \exp\left[\int \{\psi_r(-sh|x) - 1\} \Lambda_c(dx)\right]$$

If $N_r(\cdot|x)$ is Poisson as well,

$$\psi_r(-sh|x) = \exp\left[\int \{e^{+sh(y)} - 1\} \Lambda_r(dy|x)\right].$$

Then

$$\frac{d}{ds} \psi_r(-sh|x) = \psi_r(-sh|x) \cdot \int h(y) e^{sh(y)} \Lambda_r(dy|x)$$

$$\left. \frac{d}{ds} \psi_r(-sh|x) \right|_{s=0} = \int h(y) \Lambda_r(dy|x).$$

Furthermore,

$$M_Y'(s) = M_Y(s) \cdot \int \frac{d}{ds} \psi_r(-sh|x) \Lambda_c(dx)$$

$$M_Y'(0) = \int \left[\int h(y) \Lambda_r(dy|x) \right] \Lambda_c(dx)$$

Thus,

$$E\left[\int h(y) N(dy)\right] = \int \left[\int h(y) \Lambda_r(dy|x) \right] \Lambda_c(dx).$$

Let us continue with second derivatives. Then

$$M_Y''(s) = M_Y(s) \left(\int \frac{d}{ds} \psi_r(-sh|x) \Lambda_c(dx) \right)^2 \\ + M_Y(s) \cdot \int \frac{d^2}{ds^2} \psi_r(-sh|x) \Lambda_c(dx).$$

We also need

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$$\begin{aligned} \frac{d^2}{ds^2} \psi_r(-sh/x) &= \psi_r(-sh/x) \cdot \left(\int h(y) e^{sh(y)} \Lambda_r(dy|x) \right)^2 \\ &\quad + \psi_r(-sh/x) \int h(y)^2 e^{sh(y)} \Lambda_r(dy|x). \end{aligned}$$

Then

$$\begin{aligned} M_Y''(0) &= \left(\int \left[\int h(y) \Lambda_r(dy|x) \right] \Lambda_c(dx) \right)^2 \\ &\quad + \int \left[\left(\int h(y) \Lambda_r(dy|x) \right)^2 + \int h(y)^2 \Lambda_r(dy|x) \right] \Lambda_c(dx). \end{aligned}$$

Thus,

$$\begin{aligned} E \left[\left(\int h(y) N(dy) \right)^2 \right] &= \left(E \left[\int h(y) N(dy) \right] \right)^2 \\ &\quad + \int \left[\int h(y) \Lambda_r(dy|x) \right]^2 \Lambda_c(dx) \\ &\quad + \int \left[\int h(y)^2 \Lambda_r(dy|x) \right] \Lambda_c(dx), \end{aligned}$$

and so

$$\begin{aligned} \text{var} \left(\int h(y) N(dy) \right) &= \int \left[\int h(y) \Lambda_r(dy|x) \right]^2 \Lambda_c(dx) \\ &\quad + \int \left[\int h(y)^2 \Lambda_r(dy|x) \right] \Lambda_c(dx). \end{aligned}$$

We also need $E \left[\left\{ \int p(y) N(dy) \right\} \left\{ \int q(y) N(dy) \right\} \right]$.

Let $g(y) = -s_1 p(y) - s_2 q(y)$ so that if

$$P := \int p(y) N(dy) \quad \text{and} \quad Q := \int q(y) N(dy),$$

then

$$\begin{aligned} M(s_1, s_2) &:= E[e^{s_1 P + s_2 Q}] \\ &= E[e^{-\int g(y) N(dy)}] \end{aligned}$$

and

$$E[PQ] = \frac{\partial^2}{\partial s_2 \partial s_1} M(s_1, s_2) \Big|_{s_1 = s_2 = 0}.$$

Now,

$$M(s_1, s_2) = \exp\left[\int \{\psi_r(g|x) - 1\} \lambda_c(dx)\right],$$

where now

$$\psi_r(g|x) = \exp\left[\int \{e^{s_1 p(y) + s_2 q(y)} - 1\} \lambda_r(dy|x)\right].$$

So,

$$\frac{\partial}{\partial s_1} \psi_r(g|x) = \psi_r(g|x) \cdot \int p(y) e^{s_1 p(y) + s_2 q(y)} \lambda_r(dy|x),$$

and

$$\frac{\partial}{\partial s_1} M(s_1, s_2) = M(s_1, s_2) \int \frac{\partial}{\partial s_1} \psi_r(g|x) \lambda_c(dx).$$

Next,

$$\begin{aligned} \frac{\partial^2}{\partial s_2 \partial s_1} \psi_r(g|x) &= \psi_r(g|x) \left[p(y) e^{s_1 p(y) + s_2 q(y)} \lambda_r(dy|x) \right. \\ &\quad \left. + \int q(y) e^{s_1 p(y) + s_2 q(y)} \lambda_r(dy|x) \right. \\ &\quad \left. + \psi_r(g|x) \cdot \int p(y) q(y) e^{s_1 p(y) + s_2 q(y)} \lambda_r(dy|x) \right] \end{aligned}$$

and so

$$\frac{\partial^2}{\partial s_2 \partial s_1} M(s_1, s_2) = M(s_1, s_2) \int \frac{\partial}{\partial s_1} \psi_r(g/x) \Lambda_c(dx) \int \frac{\partial}{\partial s_2} \psi_r(g/x) \Lambda_c(dx) \\ + M(s_1, s_2) \int \frac{\partial^2}{\partial s_2 \partial s_1} \psi_r(g/x) \Lambda_c(dx).$$

Then

$$E[PQ] = \int \left[\int p(y) \Lambda_r(dy|x) \right] \Lambda_c(dx) \cdot \int \left[\int q(y) \Lambda_r(dy|x) \right] \Lambda_c(dx) \\ + \int \left[\int p(y) \Lambda_r(dy|x) \cdot \int q(y) \Lambda_r(dy|x) \right] \Lambda_c(dx) \\ + \int \left[\int p(y) q(y) \Lambda_r(dy|x) \right] \Lambda_c(dx).$$

Notation Define the linear functional $\bar{\Lambda}_c$ on functions $v(x)$ by

$$\bar{\Lambda}_c v := \int v(x) \Lambda_c(dx).$$

Define the linear transformation $\bar{\Lambda}_r$ that takes functions $p(y)$ and returns functions of x by

$$(\bar{\Lambda}_r p)(x) := \int p(y) \Lambda_r(dy|x).$$

Then

$$E[P] := E\left[\int p(y) \Lambda_r(dy)\right] = \bar{\Lambda}_c(\bar{\Lambda}_r p).$$

$$\text{var}(P) = \bar{\Lambda}_c\left(\left(\bar{\Lambda}_r p\right)^2\right) + \bar{\Lambda}_c\left(\bar{\Lambda}_r(p^2)\right).$$

$$E[PQ] = \bar{\lambda}_c(\bar{\lambda}_r P) \cdot \bar{\lambda}_c(\bar{\lambda}_r Q) \\ + \bar{\lambda}_c((\bar{\lambda}_r P) \cdot (\bar{\lambda}_r Q)) \\ + \bar{\lambda}_c(\bar{\lambda}_r(P \cdot Q)).$$

$$\text{cov}(P, Q) = \bar{\lambda}_c((\bar{\lambda}_r P) \cdot (\bar{\lambda}_r Q)) + \bar{\lambda}_c(\bar{\lambda}_r(P \cdot Q)).$$

$$\psi(\theta) = \exp\left[\bar{\lambda}_c(\exp\{\bar{\lambda}_r(e^\theta - 1)\} - 1)\right].$$

For the center process N_c , if

$$V := \int v(x) N_c(dx) \text{ and } W := \int w(x) N_c(dx),$$

then

$$E[V] = \int v(x) \lambda_c(dx) = \bar{\lambda}_c v,$$

$$E[V^2] = \int v(x)^2 \lambda_c(dx) + \left(\int v(x) \lambda_c(dx)\right)^2 \\ = \bar{\lambda}_c(v^2) + (\bar{\lambda}_c v)^2,$$

$$E[VW] = \int v(x)w(x) \lambda_c(dx) + \int v(x) \lambda_c(dx) \int w(x) \lambda_c(dx) \\ = \bar{\lambda}_c(v \cdot w) + (\bar{\lambda}_c v) \cdot (\bar{\lambda}_c w),$$

$$\text{cov}(V, W) = \int v(x)w(x) \lambda_c(dx) = \bar{\lambda}_c(v \cdot w),$$

$$E[e^V] = \exp[\bar{\lambda}_c(e^v - 1)].$$

The last quantity we compute is

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$$\begin{aligned} E[VP] &= E[E[VP | N_c(\cdot)]] \\ &= E[V E[P | N_c(\cdot)]] \end{aligned}$$

Next, if $X_1 = x_1, X_2 = x_2, \dots$, then

$$\begin{aligned} E[P | X_1 = x_1, \dots] &= E\left[\sum_i \int p(y) N_r(dy | x_i)\right] \\ &= \sum_i E\left[\int p(y) N_r(dy | x_i)\right] \\ &= \sum_i \int p(y) \Lambda_r(dy | x_i) \\ &= \sum_i (\bar{\Lambda}_r p)(x_i). \end{aligned}$$

So,

$$\begin{aligned} E[VP] &= E\left[V \cdot \sum_i (\bar{\Lambda}_r p)(x_i)\right] \\ &= E\left[V \cdot \int (\bar{\Lambda}_r p)(x) N_c(dx)\right] \\ &= E\left[\int v(x) N_c(dx) \cdot \int (\bar{\Lambda}_r p)(x) N_c(dx)\right] \\ &= \bar{\Lambda}_c(v \circ \bar{\Lambda}_r p) + \bar{\Lambda}_c v \cdot \bar{\Lambda}_c(\bar{\Lambda}_r p). \end{aligned}$$

One can also show that

$$E[e^{s(V+P)}] = \exp\left[\bar{\Lambda}_c\left(\exp(sV + \bar{\Lambda}_r\{e^{sP} - 1\}) - 1\right)\right].$$