

Stein's method for Gibbs process approximation in the total variation metric

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A short history of Stein's method for point process approximation

Poisson process approximation:

Barbour and Brown (1992); Brown, Weinberg and Xia (2000); Chen and Xia (2004); S and Xia (2008); S (2009).

Compound poisson process approximation:

Barbour and Månsson (2002).

“Polynomial birth-death” point process approximation:

Xia and Zhang (2012).

In all of these articles the locations of (multi-)points are independent.

- Gibbs processes
- A coupling of two spatial birth-death processes
- Generator approach
- Upper bounds in the total variation metric

Gibbs point processes

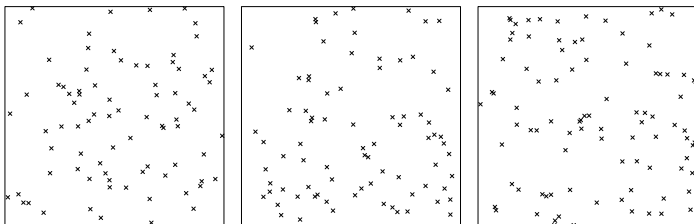
Point process preliminaries

- (\mathcal{X}, d) compact metric space with Borel σ -algebra.
- α diffuse, finite measure on \mathcal{X} .
- $(\mathfrak{N}, \mathcal{N})$ space of finite counting measures on \mathcal{X} with usual σ -algebra.
- $\text{PoP}(\alpha)$ distribution of Poisson process with expectation measure α .
Will be our reference measure for point process distributions, write $P_0 := \text{PoP}(\alpha)$.

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E.g. $\mathcal{X} \subset \mathbb{R}^d$, α Lebesgue measure, P_0 homogeneous Poisson process on \mathcal{X} .



Gibbs processes

A function $u: \mathfrak{N} \rightarrow \mathbb{R}_+$ is called **hereditary** if $u(\xi) = 0$ implies $u(\eta) = 0$ for all point configurations $\xi, \eta \in \mathfrak{N}$ with $\xi \subset \eta$.

A point process Ξ is called a **Gibbs process** if it has a hereditary density $u: \mathcal{F} \rightarrow \mathbb{R}_+$ with respect to the standard Poisson process distribution P_0 .

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A point process Ξ is called a **Gibbs process** if it has a hereditary density $u: \mathcal{F} \rightarrow \mathbb{R}_+$ with respect to the standard Poisson process distribution P_0 .

A Gibbs process is completely described by its **conditional intensity** $\lambda(\cdot | \cdot)$, where

$$\lambda(x | \xi) = \frac{u(\xi + \delta_x)}{u(\xi)} \quad \text{for all } \xi \in \mathfrak{N}, x \in \mathcal{X} \text{ with } \xi(\{x\}) = 0.$$

Intuitively the pressure to have a point at x given we know that the point pattern everywhere else is ξ .

We write $\text{Gibbs}(\lambda)$ for the distribution of this Gibbs process.

Pairwise interaction process (PIP)

A pairwise interaction process (PIP) has density of the form

$$u(\xi) = c \left(\prod_{x \in \xi} \beta(x) \right) \left(\prod_{\{x,y\} \subset \xi} \varphi_2(x,y) \right)$$

for suitable functions $\beta: \mathcal{X} \rightarrow \mathbb{R}_+$ and $\varphi_2: \mathcal{X}^2 \rightarrow \mathbb{R}_+$ (symmetric).

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E.g. Homogeneous Strauss process:

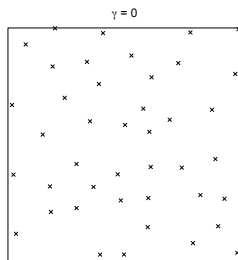
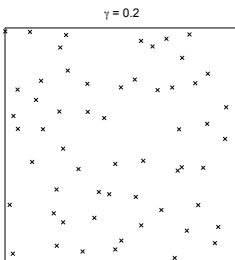
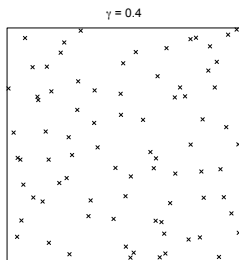
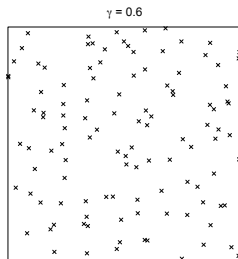
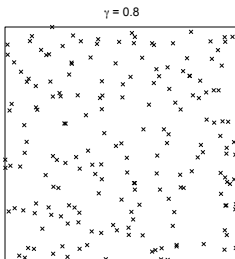
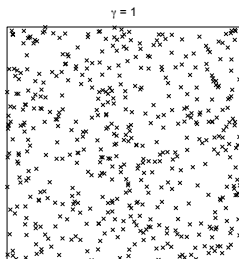
$$\varphi_2(x,y) = \begin{cases} \gamma & \text{if } d(x,y) \leq R, \\ 1 & \text{otherwise,} \end{cases}$$

where $\gamma \in [0, 1]$, $R > 0$; furthermore $\beta > 0$ constant.

In this case

$$u(\xi) = c \beta^{|\xi|} \gamma^{\#\{\{x,y\} \subset \xi: d(x,y) \leq R\}}$$

Simulated Strauss processes



Other parameters are $R = 0.1$ and $\beta = 500$.

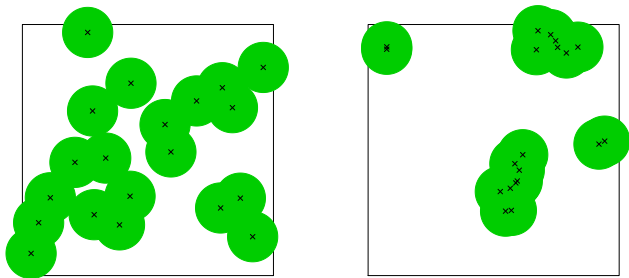
Interactions of arbitrary order: the homogeneous AIP

The homogeneous area-interaction process has density

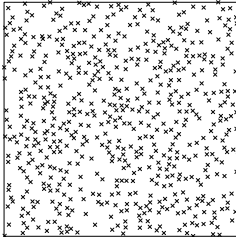
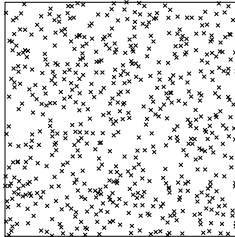
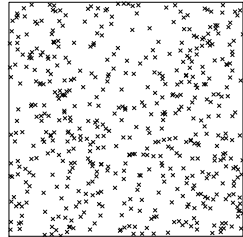
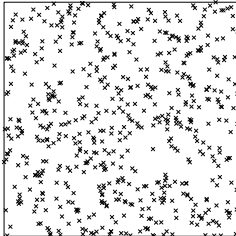
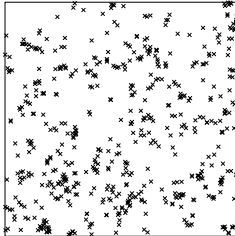
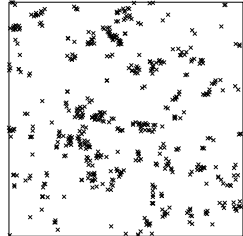
$$u(\xi) := c \beta^{|\xi|} \gamma^{-\alpha(U_R(\xi))},$$

where $\gamma > 0$, $R > 0$, and $\beta > 0$.

$U_R(\xi) = \bigcup_{x \in \xi} B(x, R)$ denotes the green area.



Simulated area-interaction processes

 $\beta = 1500, \eta = 0.001$  $\beta = 1000, \eta = 0.15$  $\beta = 600, \eta = 0.6$  $\beta = 450, \eta = 2$  $\beta = 160, \eta = 15$  $\beta = 48, \eta = 100$ 

$R = 0.02$ and β was adjusted so that expected number of points remains the same.

Conditional intensities

For the Strauss($\beta, \gamma; R$)-Process

$$\lambda(x | \xi) = \beta \gamma^{\#\{y \in \xi \setminus \{x\} : d(y, x) \leq R\}}$$

For the AIP($\beta, \gamma; R$)

$$\lambda(x | \xi) = \beta \gamma^{-\alpha(\mathbb{B}(x, R) \setminus U_R(\xi \setminus \{x\}))}$$

The conditional intensity is (usually) explicit, without the “unknown” factor c .

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Furthermore the **Georgii–Nguyen–Zessin equation** holds

$$\mathbb{E} \left(\int_{\mathcal{X}} h(x, \Xi - \delta_x) \Xi(dx) \right) = \int_{\mathcal{X}} \mathbb{E}(h(x, \Xi) \lambda(x | \Xi)) \alpha(dx)$$

for every measurable $h: \mathcal{X} \times \mathfrak{N} \rightarrow \mathbb{R}_+$.

Stability condition

Let H always be a Gibbs process with conditional intensity λ that satisfies the following “stability condition”:

$$(S) \quad \sup_{\xi \in \mathfrak{N}} \int_{\mathcal{X}} \lambda(x | \xi) \alpha(dx) < \infty.$$

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Is satisfied if H is *locally stable*, i.e. if

$$\lambda(x | \xi) \leq \psi^*(x),$$

where $\psi^*: \mathcal{X} \rightarrow \mathbb{R}_+$ is an integrable function.

Satisfied e.g. if H is an AIP or an inhibitory PIP (i.e. $\varphi_2 \leq 1$).

A coupling of two spatial birth-death processes

Spatial birth-death processes

Suppose that we have birth rates and death rates

$$b(\cdot | \cdot): \mathcal{X} \times \mathfrak{N} \rightarrow \mathbb{R}_+ \quad \text{with } \bar{b}(\xi) := \int_{\mathcal{X}} b(x | \xi) \alpha(dx) < \infty;$$

$$d(\cdot | \cdot): \mathcal{X} \times \mathfrak{N} \rightarrow \mathbb{R}_+ \quad \text{with } \bar{d}(\xi) := \sum_{x \in \xi} d(x | \xi) < \infty.$$

Let $\bar{a}(\xi) = \bar{b}(\xi) + \bar{d}(\xi)$.

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Let $\bar{a}(\xi) = \bar{b}(\xi) + \bar{d}(\xi)$.

A $\text{SBD}^{(\xi_0)}(b, d)$ -process is a pure-jump Markov process on \mathfrak{N} that starts in $\xi_0 \in \mathfrak{N}$ and holds each state ξ for an $\text{Exp}(\bar{a}(\xi))$ -distributed time, after which

- with probability $\bar{b}(\xi)/\bar{a}(\xi)$ a point is added, positioned according to the density $b(\cdot | \xi)/\bar{b}(\xi)$, or
- with probability $d(x | \xi)/\bar{a}(\xi)$ the point at x is deleted.

SBD($\lambda, 1$)-process

In what follows always $b = \lambda$, $d \equiv 1$ (“unit per-capita death rate”).

Let $Z = (Z(t))_{t \geq 0} \sim \text{SBD}(\lambda, 1)$. Under Condition (S)

- Z is non-explosive;

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- Z is non-explosive;
- Z has $\text{Gibbs}(\lambda)$ as its unique stationary distribution.
- Z has the infinitesimal generator

$$\mathcal{A}h(\xi) = \int_{\mathcal{X}} [h(\xi + \delta_x) - h(\xi)] \lambda(x | \xi) \alpha(dx) + \int_{\mathcal{X}} [h(\xi - \delta_x) - h(\xi)] \xi(dx)$$

for certain functions $h: \mathfrak{N} \rightarrow \mathbb{R}$.

A coupling of $\text{SBD}(\lambda, 1)$ -processes

Goal: For $\xi, \eta \in \mathfrak{N}$ find a coupling (Z_1, Z_2) with $Z_1 \sim \text{SBD}^{(\xi)}(\lambda, 1)$, $Z_2 \sim \text{SBD}^{(\eta)}(\lambda, 1)$ so that Z_1 and Z_2 coincide “as soon as possible”.

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Construction: For $\zeta_1, \zeta_2 \in \mathfrak{N}$ let

$$\begin{aligned} \lambda_{\max}(x \mid \zeta_1, \zeta_2) &= \max(\lambda(x \mid \zeta_1), \lambda(x \mid \zeta_2)) & \bar{\lambda}_{\max}(\zeta_1, \zeta_2) &= \int_{\mathcal{X}} \lambda_{\max}(x \mid \zeta_1, \zeta_2) \alpha(dx) \\ \lambda_{\min}(x \mid \zeta_1, \zeta_2) &= \min(\lambda(x \mid \zeta_1), \lambda(x \mid \zeta_2)) & \bar{\lambda}_{\min}(\zeta_1, \zeta_2) &= \int_{\mathcal{X}} \lambda_{\min}(x \mid \zeta_1, \zeta_2) \alpha(dx), \\ \text{and furthermore } \bar{a}(\zeta_1, \zeta_2) &= \bar{\lambda}_{\max}(\zeta_1, \zeta_2) + |\zeta_1 \cup \zeta_2|. \end{aligned}$$

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and furthermore $\bar{a}(\zeta_1, \zeta_2) = \bar{\lambda}_{\max}(\zeta_1, \zeta_2) + |\zeta_1 \cup \zeta_2|$.

Let (Z_1, Z_2) be the pure-jump Markov process on $\mathfrak{N} \times \mathfrak{N}$ that starts in (ξ, η) and holds each state (ζ_1, ζ_2) for an $\text{Exp}(\bar{a}(\zeta_1, \zeta_2))$ -distributed time, after which

- with probability $\bar{\lambda}_{\max}(\zeta_1, \zeta_2) / \bar{a}(\zeta_1, \zeta_2)$ a birth occurs at $X \sim \lambda_{\max}(\cdot | \zeta_1, \zeta_2) / \bar{\lambda}_{\max}(\zeta_1, \zeta_2)$. Given X , a point at X is added to the process Z_i with probability $\lambda(X | \zeta_i) / \lambda_{\max}(X | \zeta_1, \zeta_2)$.
- with probability $1 / \bar{a}(\zeta_1, \zeta_2)$ a death occurs at $X \in \zeta_1 \cup \zeta_2$. Given X , a point at X is deleted from the process Z_i if it has such a point.

A coupling of $\text{SBD}(\lambda, 1)$ -processes

How can we control how quickly the two processes meet?

A coupling of SBD($\lambda, 1$)-processes

How can we control how quickly the two processes meet?

Consider the jump chain $(Z_1(T_j), Z_2(T_j))_{j \in \mathbb{N}}$. At each step j there are three possibilities:

- (1) Z_1 and Z_2 both have the same birth or death event.
- (2) Only one process has a birth (“bad birth”). We have

$$\mathbb{P}(\text{“bad birth”} \mid Z_1(T_{j-1}), Z_2(T_{j-1})) = \frac{\bar{\lambda}_{\max}(Z_1(T_{j-1}), Z_2(T_{j-1})) - \bar{\lambda}_{\min}(Z_1(T_{j-1}), Z_2(T_{j-1}))}{\bar{\lambda}_{\max}(Z_1(T_{j-1}), Z_2(T_{j-1})) + |Z_1(T_{j-1}) \cup Z_2(T_{j-1})|}.$$

- (3) One of the non-common points of $Z_1(T_{j-1})$ and $Z_2(T_{j-1})$ dies (“good death”). Then

$$\mathbb{P}(\text{“good death”} \mid Z_1(T_{j-1}), Z_2(T_{j-1})) = \frac{\|Z_1(T_{j-1}) - Z_2(T_{j-1})\|}{\bar{\lambda}_{\max}(Z_1(T_{j-1}), Z_2(T_{j-1})) + |Z_1(T_{j-1}) \cup Z_2(T_{j-1})|}.$$

Probability for becoming closer

Suppose that in the total variation norm $\|\zeta_1 - \zeta_2\| = n$, i.e. ζ_1 and ζ_2 differ in n points.

Let A_n be the event that good death occurs before bad birth, i.e. the next time something interesting happens the two BDPs come closer together.

Lemma

The probability of the event A_n is bounded from below as

$$\mathbb{P}(A_n) \geq \left(1 + \frac{1}{n} \sup_{\|\xi' - \eta'\| = n} \int_{\mathcal{X}} |\lambda(x | \xi') - \lambda(x | \eta')| \alpha(dx)\right)^{-1},$$

which is > 0 by the stability condition (S).

Coupling time

Theorem

For all configurations ξ, η the coupling time $\tau_{\xi, \eta} := \inf\{t \geq 0: Z_1^{(\xi)}(t) = Z_2^{(\eta)}(t)\}$ has finite expectation. In particular if ξ and η differ in only one point, we have

$$\mathbb{E}\tau_{\xi, \eta} \leq \frac{e^c - 1}{c} + \int_0^c \frac{e^s - 1}{s} ds,$$

where $c = \sup_{\xi', \eta' \in \mathfrak{N}} \int_{\mathcal{X}} |\lambda(x | \xi') - \lambda(x | \eta')| \alpha(dx)$, which is finite by the stability condition (S).

Idea of the proof

- Denote by $X(t) = (\|Z_1^{(\xi)}(t) - Z_2^{(\eta)}(t)\|)_{t \geq 0}$ the process counting the non-common points of $Z_1^{(\xi)}$ and $Z_2^{(\eta)}$. Let $p_n = (1 + c/n)^{-1} \leq \mathbb{P}(A_n)$.

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- Construct a (non-spatial) birth-death process $(Y(t))_{t \geq 0}$ with birth rate $(1 - p_n)n$ and death rate $p_n n$ such that

$$\tau_{\xi, \eta} = \tau^{(X, 0)} \leq_{st} \tau^{(Y, 0)},$$

where $\tau^{(X, 0)}, \tau^{(Y, 0)}$ are the hitting times in 0.

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where $\tau^{(X,0)}, \tau^{(Y,0)}$ are the hitting times in 0.

- Compute $\mathbb{E}_{\tau^{(Y,0)}}$ by standard techniques for pure-jump Markov processes, i.e. as smallest solution of a certain recurrence relation.

Construction of $(Y(t))_{t \geq 0}$

- 1 Set $Y'(0) = X(0)$.
- 2 If $Y'(t) = X(t) = n$ for some t , let the next jump of $Y'(t)$ occur at the same time T_j as the next jump of $X(t)$. The jump for $Y'(t)$ goes to $n - 1$ with probability $p_n = (1 + c/n)^{-1} \leq \mathbb{P}(A_n)$ and to $n + 1$ with probability $1 - p_n$, coupled with $X(t)$ in such a way that $Y'(T_j) \geq X(T_j)$.
- 3 If $Y'(t) > X(t)$, let $Y'(t)$ behave like an independent birth-death process with birth rate $(1 - p_n)n$ and death rate $p_n n$ until $Y'(t)$ and $X(t)$ meet again.
- 4 $(Y'(t))$ has the right up-/down-probabilities, and its holding times in n can be stochastically dominated by $\text{Exp}(n)$ -random variables. $\rightsquigarrow (Y(t))$.

A refined bound

Theorem

If ξ and η differ in only one point, we have for any $n^ \in \mathbb{N} \cup \{\infty\}$*

$$\mathbb{E}\tau_{\xi,\eta} \leq (n^*-1)! \left(\frac{\varepsilon}{c}\right)^{n^*-1} \left(\frac{1}{c} \sum_{i=n^*}^{\infty} \frac{c^i}{i!} + \int_0^c \frac{1}{s} \sum_{i=n^*}^{\infty} \frac{s^i}{i!} ds \right) + \frac{1+\varepsilon}{\varepsilon} \sum_{i=1}^{n^*-1} \frac{\varepsilon^i}{i} =: c_1(\lambda),$$

where

$$\varepsilon = \sup_{\|\xi-\eta\|=1} \int_{\mathcal{X}} |\lambda(x \mid \xi) - \lambda(x \mid \eta)| \alpha(dx) \quad \text{and}$$

$$c = c(n^*) = \sup_{\|\xi-\eta\| \geq n^*} \int_{\mathcal{X}} |\lambda(x \mid \xi) - \lambda(x \mid \eta)| \alpha(dx).$$

In particular, if $\varepsilon < 1$, we may choose $n^ = \infty$, so that*

$$\mathbb{E}\tau_{\xi,\eta} \leq \frac{1+\varepsilon}{\varepsilon} \log \left(\frac{1}{1-\varepsilon} \right) \leq \frac{1+\varepsilon}{1-\varepsilon}.$$

Some Examples

- **Poisson:** $\lambda(x | \xi) = \lambda(x)$, hence

$$\varepsilon = 0.$$

- **Inhibitory PIP:** $\lambda(x | \xi) = \beta(x) \prod_{y \in \xi \setminus \{x\}} \varphi_2(x, y)$, hence

$$\varepsilon \leq \sup_{y \in \mathcal{X}} \int_{\mathcal{X}} \beta(x) (1 - \varphi_2(x, y)) \alpha(dx).$$

- **Homogeneous Strauss:** $\lambda(x | \xi) = \beta \prod_{y \in \xi \setminus \{x\}} \gamma^{1_{\{d_0(x, y) \leq R\}}}$, hence

$$\varepsilon \leq \beta(1 - \gamma) \sup_{y \in \mathcal{X}} \alpha(B_R(y)).$$

The generator approach

Our goal:

Find upper bound for the total variation distance

$$d_{TV}(\text{Gibbs}(\nu), \text{Gibbs}(\lambda)) = \sup_{f \in \mathcal{F}} |\mathbb{E}f(\Xi) - \mathbb{E}f(H)|,$$

where λ satisfies the stability condition (S), $\mathcal{F} = \mathcal{F}_{TV} = \{1_C; C \in \mathcal{N}\}$ and $\Xi \sim \text{Gibbs}(\nu)$, $H \sim \text{Gibbs}(\lambda)$.

Generator approach (Barbour, 1988)

For every $f \in \mathcal{F}$ find $h = h_f: \mathfrak{N} \rightarrow \mathbb{R}$ such that

$$f(\xi) - \mathbb{E}f(H) = \mathcal{A}h(\xi) \quad \text{for all } \xi \in \mathfrak{N}, \quad (\text{Stein equation})$$

where \mathcal{A} is the generator of a Markov process with stationary distribution $\text{Gibbs}(\lambda)$ (generator approach).

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Natural choice: the $\text{SBD}^{(\xi)}(\lambda, 1)$ -process $Z^{(\xi)} := (Z_t^{(\xi)})_{t \geq 0}$ from earlier.

Solution of the Stein equation

It can be shown for bounded f that the function $h = h_f : \mathfrak{N} \rightarrow \mathbb{R}$,

$$h(\xi) := - \int_0^\infty [\mathbb{E}f(Z_t^{(\xi)}) - \mathbb{E}f(H)] \, dt,$$

is well-defined and solves the Stein equation $f(\xi) - \mathbb{E}f(H) = \mathcal{A}h(\xi)$.

Bounding the first differences

By our result on expected coupling times (coupling $(Z_t^{(\xi+\delta_x)})$ and $(Z_t^{(\xi)})$ accordingly) we have for every $\xi \in \mathfrak{N}$ and every $x \in \mathcal{X}$

$$\begin{aligned}
 & |h_f(\xi + \delta_x) - h_f(\xi)| \\
 &= \left| \int_0^\infty [\mathbb{E}(f(Z_t^{(\xi+\delta_x)})) - \mathbb{E}f(H)] dt - \int_0^\infty [\mathbb{E}(f(Z_t^{(\xi)})) - \mathbb{E}f(H)] dt \right| \\
 &= \left| \mathbb{E} \int_0^\infty [f(Z_t^{(\xi+\delta_x)}) - f(Z_t^{(\xi)})] \mathbf{1}_{\{\tau_{\xi+\delta_x, \xi} > t\}} dt \right| \\
 &\leq \sup_{\xi', \eta' \in \mathfrak{N}} |f(\xi') - f(\eta')| \int_0^\infty \mathbb{P}(\tau_{\xi+\delta_x, \xi} > t) dt \\
 &\leq \mathbb{E} \tau_{\xi+\delta_x, \xi} \\
 &\leq c_1(\lambda).
 \end{aligned}$$

(Same argument as in Barbour and Brown, 1992)

Bounding the Stein equation

If now Ξ is a Gibbs(ν) process (does not need to satisfy stability), we obtain by the Georgii–Nguyen–Zessin equation

$$\begin{aligned}
 & |\mathbb{E}f(\Xi) - \mathbb{E}f(H)| \\
 &= |\mathbb{E}\mathcal{A}h_f(\Xi)| \\
 &= \left| \mathbb{E} \int_{\mathcal{X}} [h_f(\Xi + \delta_x) - h_f(\Xi)] \lambda(x | \Xi) \alpha(dx) + \mathbb{E} \int_{\mathcal{X}} [h_f(\Xi - \delta_x) - h_f(\Xi)] \Xi(dx) \right| \\
 &= \left| \mathbb{E} \int_{\mathcal{X}} [h_f(\Xi + \delta_x) - h_f(\Xi)] (\lambda(x | \Xi) - \nu(x | \Xi)) \alpha(dx) \right| \\
 &\leq \sup_{\xi \in \mathfrak{N}, x \in \mathcal{X}} |h_f(\xi + \delta_x) - h_f(\xi)| \int_{\mathcal{X}} \mathbb{E} |\nu(x | \Xi) - \lambda(x | \Xi)| \alpha(dx) \\
 &\leq c_1(\lambda) \int_{\mathcal{X}} \mathbb{E} |\nu(x | \Xi) - \lambda(x | \Xi)| \alpha(dx).
 \end{aligned}$$

Upper bounds in the total variation metric

Theorem (S and Stucki, 2014)

For any two Gibbs point processes

Ξ with conditional intensity $\nu(\cdot | \cdot)$,

*H with conditional intensity $\lambda(\cdot | \cdot)$ satisfying the stability condition (S),
we have*

$$d_{TV}(\mathcal{L}(\Xi), \mathcal{L}(H)) \leq c_1(\lambda) \int_{\mathcal{X}} \mathbb{E} |\nu(x | \Xi) - \lambda(x | \Xi)| \alpha(dx),$$

where the general formula for $c_1(\lambda)$ was given earlier. E.g. if

$$\varepsilon = \sup_{\xi \in \mathfrak{N}, y \in \mathcal{X}} \int_{\mathcal{X}} |\lambda(x | \xi + \delta_y) - \lambda(x | \xi)| \alpha(dx) < 1,$$

we have

$$c_1(\lambda) = \frac{1 + \varepsilon}{\varepsilon} \log \left(\frac{1}{1 - \varepsilon} \right) \leq \frac{1 + \varepsilon}{1 - \varepsilon}.$$

Two consequences

- Suppose that $\mathcal{X} \subset \mathbb{R}^D$, and $\Xi \sim \text{PIP}(\beta, \varphi_1)$ and $H \sim \text{PIP}(\beta, \varphi_2)$ are stationary and inhibitory, i.e. β is constant and $\varphi_i(x, y) = \varphi_i(x - y) \leq 1$ for all $x, y \in \mathcal{X}$. Then

$$d_{TV}(\mathcal{L}(\Xi), \mathcal{L}(H)) \leq c_1(\lambda) \beta \mathbb{E}|\Xi| \int_{\mathbb{R}^D} |\varphi_1(x) - \varphi_2(x)| dx.$$

- Suppose that $\mathcal{X} \subset \mathbb{R}^D$, and $\Xi \sim \text{AIP}(\beta \gamma^{\alpha_D (R/2)^D}, \gamma; R/2)$ and $H \sim \text{Strauss}(\beta, 0; R)$, where α_D is the volume of the unit ball in \mathbb{R}^D . Then

$$d_{TV}(\mathcal{L}(\Xi), \mathcal{L}(H)) \leq c_1(\lambda) 2D \alpha_D R^{D-1} \beta \mathbb{E}|\Xi| (\log \gamma^{-\alpha_D})^{-1/D}.$$

Rate for the convergence result in Baddeley and Van Lieshout (1995).