Time-frequency analysis of locally stationary Hawkes processes

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Introduction

- Diverse application fields of Hawkes processes (Hawkes, 1971) = self-exciting point processes: seismology (Ogata, 1988), genomics (Reynaud-Bouret and Schbath, 2010), neuroscience (Reynaud-Bouret et al., 2013), finance: microstructure dynamics (Bacry et al., 2012), order arrival rate modelling and high-frequency data (Bowsher, 2007), , ...
- Stationary linear Hawkes process N:
 - its conditional intensity:

Approximation results

$$\lambda(t) = \lambda_c + \int_{-\infty}^{t^-} p(t-s) \ N(\mathrm{d}s) = \lambda_c + \sum_{T_i < t} p(t-T_i)$$

▶ alternatively: description by clusters of point processes: immigrants (follow a Poisson process and define the centers of clusters) and offsprings.

Aim of this work: Model and capture time-varying dynamics, i.e. define a model of point process that can be locally interpreted as a stationary Hawkes process (such as for "classical" time series by R. Dahlhaus).

Estimation theory

Introduction - cont'd

Existing approaches of time-varying dynamics for Hawkes processes

Essentially only $\lambda_c=\lambda_c(t)$ (e.g. Chen and Hall, 2013) and no "locally stationary" approach via rescaling in time (taking u=t/T)

Some notation for this talk

- \bullet We look at (time-continuous) processes with values in \mathbb{R}^ℓ (but for today mostly $\ell=1)$
- A point process is identified with a random measure with discrete support: $N = \sum_k \delta_{T_k}$, where δ_t is the Dirac measure at point t and $\{T_k\}$ is the corresponding (countable) random set of points.
- For a test function g, $N(g) = \sum_{k} g(T_k)$.
- (Some) Functional norms:
 - ▶ L^q -norms $|\cdot|_q$ for $q \in [1, \infty]$, and
 - \triangleright β -norm: $|h|_{(\beta)} := |h \times |\cdot|^{\beta}|_{1} = \int |h(s)||s|^{\beta} ds$, for a given $\beta > 0$.

Estimation theory

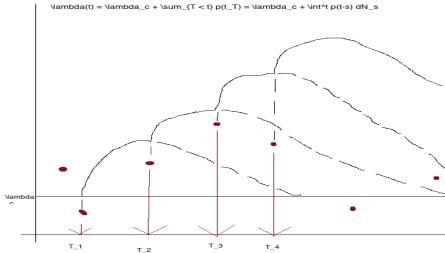
Hawkes processes as cluster processes

- Cluster processes = point processes constructed via conditioning on the realization of a so-called *center process*, usually a PPP in the seguel (Daley and Vere-Jones, 2003).
- Starting point: N_c a PPP with intensity measure μ_c and density λ_c that represents the *immigrants* which appear spontaneously.
- At each center point t of N_c , a (independent branching) PPP $N(\cdot|t)$ with finite intensity $\mu(\cdot|t)$, generating the *offsprings* at t.
- Cluster process N = all the immigrants + all the offspring of each immigrant.
- Standard Hawkes processes are made stationary by assuming that N_c is a homogeneous PPP on the whole space \mathbb{R}^ℓ and $t\mapsto \mu(\cdot|t)$ is shift invariant: $\mu(\cdot|t) = \mu \circ S^t$, where μ is fixed (i.e. $\mu = \mu(\cdot|0)$).

Dynamics of Hawkes processes

$$\lambda(t) = \lambda_c + \int_{-\infty}^{t^-} p(t-s) \ N(\mathrm{d}s) = \lambda_c + \sum_{T_i < t} p(t-T_i)$$

Introduction



Estimation theory

Our work on non- and locally stationary Hawkes processes

Roadmap of our approach on approximation (SPA 2015):

- First, we show existence of non-stationary Hawkes processes
- Then, we define *locally stationary* Hawkes processes using a series of regularity conditions on immigrant intensity $\lambda_c(t/T)$ and fertility function $p(\cdot; t/T)$
- The key tool for existence of an approximating stationary process: local approximation of the log Laplace functional
- This allows for approximation of the first and second order moment structure of the non-stationary by the (locally) stationary Hawkes process
- In particular: existence of a local (i.e. time-varying) Bartlett spectrum (time-frequency analysis)

Approximation results

Estimation theory

Existence of non-stationary Hawkes process

Give up shift invariance of $t\mapsto \mu_c(t)$ and $t\mapsto \mu(\cdot|t)$, i.e. their densities $\lambda_c(t)$ (immigrant intensity) and $\rho(\cdot;t)$ (fertility function) depend on t.

We can define a non stationary Hawkes process via these t-v densities if

$$\zeta_1 := \sup_{t \in \mathbb{R}} \mu\left(\mathbb{R}^\ell ig| t
ight) = \sup_{t \in \mathbb{R}^\ell} \int p(s;t) \, \mathrm{d} s < 1 \quad ext{and} \quad \left|\lambda_c
ight|_\infty < \infty \; .$$

Theorem 1: The component process $N(\cdot|t)$ has finite moment measure $\mathbb{E}[N(\mathbb{R}^{\ell}|t)] \leqslant \frac{1}{1-\zeta_1}$ and its density is uniformly bounded by $\frac{|\lambda_c|_{\infty}}{1-\zeta_1}$.

Proof via the cluster construction: each component $N(\cdot|t)$ can be constructed as the superposition of point processes defined iteratively.

Non-stationary Hawkes processes (under the density assumption) with λ_c and $p(\cdot; \cdot)$ still quite general: can still evolve quite arbitrarily in the space.

Estimation theory

Locally stationary Hawkes processes

• Aim: Define a locally stationary approximation - similarly to autoregressive processes. In the following, to simplify notation, consider univariate case only, i.e. $\ell = 1$ w.l.o.g.

Definition of a locally stationary Hawkes process

A locally stationary Hawkes process with local immigrant intensity $\lambda_c^{< Ls>}$ and local fertility function $p^{\langle LS \rangle}(\cdot; \cdot)$ is

- a collection $(N_T)_{T>0}$ of non-stationary Hawkes processes with
- immigrant intensity $\lambda_{cT}(t) = \lambda_c^{\langle LS \rangle}(t/T)$ and
- fertility function $p_T(\cdot;t) = p^{\langle LS \rangle}(\cdot;t/T)$.

Approximation results

For a given real location t, the scaled location t/T is typically called an absolute location in [0; 1] and denoted by u.

Analogy with locally stationary AR-processes

Note the similarities/differences with an AR(p)-process (p = 1 w.l.o.g.):

Dahlhaus (SPA 1996) shows that ($t=1,\ldots,T$, $T\geqslant 1$)

$$X_{t,T} = a(t/T) X_{t-1,T} + \varepsilon_t , \quad \varepsilon_t \sim (0,1) ,$$

has a representation

Introduction

$$X_{t,T} = \int_{-\pi}^{\pi} A_{t,T}^{o}(\omega) \exp(i\omega t) d\xi(\omega)$$

with the existence of an $A(u,\omega) = (1-a(u)\exp(-i\omega))^{-1}$ such that $\sup_{t,\omega} |A^o_{t,T}(\omega) - A(t/T,\omega)| = O(T^{-1})$.

Here,
$$A_{t,T}^o(\omega) = \sum_{\ell \geqslant 0} (-1)^\ell \prod_{j=0}^{\ell-1} a(\frac{t-j}{T}) \exp(-i\omega\ell)$$
.

Unfortunately, this is not possible for the more elaborated recursive dynamics of a Hawkes process.

Under assumption (LS-1):

Approximation results

$$\zeta_1^{<\mathtt{LS}>} := \sup_{u \in [0,1]} \int p^{<\mathtt{LS}>} \big(t; u\big) \, \mathrm{d}t < 1 \quad \text{and} \quad \big|\lambda_c^{<\mathtt{LS}>}\big|_\infty < \infty \;,$$

for all T > 0, the non-stationary Hawkes process N_T admits a uniformly bounded intensity function.

- Under (LS-1), moreover, for each $u \in \mathbb{R}^{\ell}$, the function $t \mapsto p^{<\mathbf{LS}>}(t; u)$ satisfies the required condition for the fertility function of a stationary Hawkes process.
- Notation: $N(\cdot; u) = a$ "stationary" Hawkes process with immigrant intensity $\lambda_c^{<\mathbf{LS}>}(u)$ and fertility function $t\mapsto p^{<\mathbf{LS}>}(t;u)$.
- More regularity assumptions:
 - ▶ (LS-2): smoothness conditions on $\lambda_c^{< LS>}(u)$
 - ▶ (LS-3): smoothness conditions on $p^{<LS>}(t, u)$ w.r.t. its second argument u
 - ▶ (LS-4): some uniform decay condition on $p^{< LS>}(\cdot, \cdot)$ w.r.t. its first argument

Local approximation of the log Laplace functional

The process $N_T \circ S^{-Tu}$, i.e. N_T shifted at the *real location Tu*, follows approximately the distribution of a stationary Hawkes process $N(\cdot; u)$.

Proof: via Convergence of the log-Laplace function of N_T (i.e. log of $\mathcal{L}_T(g) = \mathbb{E}\left[\exp N_T(g)\right]$):

Theorem 2

Under Ass. (LS-1:4), for $\beta \in (0;1]$ and an appropriate test-function g

- the log-Laplace transform $\log \mathcal{L}_T(S^{-Tu}g)$ of $N_T \circ S^{-Tu}$, converges to the log-Laplace $\log \mathcal{L}(g;u)$ of $N(\cdot;u)$,
- with rate $T^{-\beta}$ and with explicit bounds for the constants depending only on the ("functional") β and ℓ_1 —norms of the test function g.

Corollary 3

As application, for any $u \in [0, 1]$, as $T \to \infty$, the point process $N_T \circ S^{-Tu}$ converges in distribution to $N(\cdot; u)$.

Local approximation of the cumulants

Apply Theorem 2 to $\mathcal{L}_T(S^{-Tu}g): z \mapsto \mathbb{E} \left[\exp N_T(g(\cdot - Tu, z)) \right].$

Key result for treatment of "all" moments (used in estimation theory) via

$$\operatorname{Cum}(N(g_1),\ldots,N(g_m))=\partial^{1_m}|_{z=0_m}\log \mathcal{L}(z_1g_1+\cdots+z_mg_m),$$

Theorem 4

Let $\beta \in (0,1]$. Assume (LS-1:4).

Let for any $m \ge 1$, g_1, \ldots, g_m be real valued bounded integrable.

Then for any T and any $u \in [0,1]$, we have

$$\begin{split} &\left| \operatorname{Cum} \left(N_T(S^{-Tu} g_1), \dots, N_T(S^{-Tu} g_m) \right) - \operatorname{Cum} \left(N(g_1; u), \dots, N(g_m; u) \right) \right| \\ & \leq \frac{2^{m-1} C_1 T^{-\beta}}{\left(-\log \zeta_1^{<\mathbf{LS}>} \right)^{m-1}} \left\{ \sum_{j=1,\dots,m} \left(\left| g_j \right|_{(\beta)} + C_2 \left| g_j \right|_1 \right) \right\} \left\{ \sum_{j=1,\dots,m} \left(\left| g_j \right|_{\infty} + C_3 \left| g_j \right|_1 \right) \right\}^{m-1}. \end{split}$$

First Application: Convergence of local mean density

Theorem 4 with m=1 implies:

- For any T, N_T admits a uniformly bounded density function $m_{1T}(t)$.
- The intensity measure of the (approximating) stationary Hawkes process admits a time-constant mean density:

$$m_1^{<\mathtt{LS}>}(u) = \frac{\lambda_c^{<\mathtt{LS}>}(u)}{1 - \int p^{<\mathtt{LS}>}(\cdot; u)}$$

- \rightarrow local mean density at absolute location u.
- Convergence of $m_{1T}(t)$ to $m_1^{<\mathbf{L}\mathbf{s}>}(\cdot;u)$ with rate $T^{-\beta}$ in a local neighbourhood of Tu (and explicit bounds on the constants depending only on the β and ℓ_1 —norms of the test function g).

Estimation theory

- Locally stationary time series provide a nonparametric statistical framework for time-frequency analysis of time series (Dahlhaus, 2009).
- Such ideas can now be applied to locally stationary Hawkes processes.
- Stationary case
 - ▶ The Bartlett spectrum Γ of a second order point process N on \mathbb{R} is defined as the (unique) nonnegative measure on \mathbb{R} s.t., for any bounded and compactly supported function f on \mathbb{R} ,

$$\operatorname{Var}(N(f)) = \Gamma(|\hat{f}|^2) = \int \left|\hat{f}(\omega)\right|^2 \, \gamma(\omega) \, d\omega \,,$$

where $\hat{f}(\omega) = \int f(t) e^{-it\omega} dt$.

 For Hawkes processes, the density of the Bartlett spectrum is given by

$$\gamma(\omega) = \frac{\lambda_c}{2\pi(1-\int p)} |1-\hat{p}(\omega)|^{-2}$$
.

Numerical experiments

Under (LS-1), applying this result to the stationary Hawkes process $N(\cdot; u)$, we have, for any bounded and compactly supported function f,

$$\operatorname{Var}\big(\mathit{N}(\mathit{f};\mathit{u})\big) = \Gamma^{<\mathsf{LS}>}\left(|\hat{\mathit{f}}|^2;\mathit{u}\right) = \int \left|\hat{\mathit{f}}(\omega)\right|^2 \, \gamma^{<\mathsf{LS}>}(\omega;\mathit{u}) \, \mathrm{d}\omega \; ,$$

where

•
$$\gamma^{\langle LS \rangle}(\omega; u) = \frac{m_1^{\langle LS \rangle}(u)}{2\pi} \left| 1 - \hat{p}^{\langle LS \rangle}(\omega; u) \right|^{-2}$$
, with

•
$$\hat{p}^{<\mathsf{LS}>}(\omega;u) = \int p^{<\mathsf{LS}>}(t;u) e^{-\mathrm{i}t\omega} dt.$$

- $\Gamma^{< LS>}(\cdot; u)$ and $\gamma^{< LS>}(\omega; u)$ are called the *local Bartlett spectrum* and the *local spectral density*, respectively, at absolute location u.
- Corollary 6: Under (LS-1:4), for $\beta \in (0,1]$ and bounded functions f supported inside [-b,b], for some b>0:

Convergence of $\operatorname{Var}\left(N_T(S^{-Tu}f)\right)$ to $\Gamma^{<\mathtt{LS}>}(|\hat{f}|^2;u)$ with rate of order $T^{-\beta}$ (and again, explicit bounds on constants ..)

- f a test function and m a moment function (such as m(x) = x, $m(x) = x^2$, ...).
- b_1 a given time bandwidth and u_0 a fixed time in [0; 1] (namely, $u_0 = t_0/T$ with $t_0 \in [0; T]$).
- We build an estimator of $\mathbb{E}[m(N(f; u_0))]$ based on the empirical observations of N_T and defined by

$$\widehat{E}[m \circ N_T(S^{-Tu_0}f); W_{b_1}] := \frac{1}{T} \int m \circ N_T(f(\cdot - t - Tu_0)) W_{b_1}(t/T) dt,$$

for some fixed kernel function W.

• In practice, f should be compactly supported, so that this integral can be computed from a finite set of observations in [0, T].

Numerical experiments

Estimation theory

- Localisation (smoothing) in frequency by a real valued kernel K, compactly supported, with Fourier transform \hat{K} such that $\int |\hat{K}(\omega)|^2 d\omega = 1.$
- b_2 a given frequency bandwidth and ω_0 a fixed frequency.
- We wish to estimate the quantity

Approximation results

$$\gamma_{b_2}(\omega_0; u_0) := \int \frac{1}{b_2} |\hat{K}((\omega - \omega_0)/b_2)|^2 \Gamma^{\langle \mathsf{Ls} \rangle}(\mathrm{d}\omega; u_0),$$

which in turn is an approximation of the local spectral density $\gamma^{\langle Ls \rangle}(\omega_0; u_0)$ of $\Gamma^{\langle Ls \rangle}(\cdot; u_0)$ at ω_0 .

- $f = K_{b_2.\omega_0}$ is the kernel having Fourier transform $\omega \mapsto b_2^{-1/2} \hat{K}((\omega - \omega_0)/b_2).$
- Consequently, we get that $K_{b_2,\omega_0}(t) = b_2^{1/2} e^{i\omega_0 t} K(b_2 t)$.
- Finally, take $m(x) = x^2$ and m(x) = x to define: $\widehat{\gamma}_{b_2,b_1}(\omega_0; u_0) =$

$$= \widehat{E} \left(|N_{T}(S^{-Tu_{\mathbf{0}}}K_{b_{\mathbf{2}},\omega_{\mathbf{0}}})|^{2}; W_{b_{\mathbf{1}}} \right) - \left| \widehat{E} \left(N_{T}(S^{-Tu_{\mathbf{0}}}K_{b_{\mathbf{2}},\omega_{\mathbf{0}}}); W_{b_{\mathbf{1}}} \right) \right|^{2}.$$

Numerical experiments

Specific class of Gamma-shaped local fertility functions $p^{<\text{Ls}>}(\cdot;u)$ and time-constant immigrant intensity $\lambda_c^{<\text{Ls}>}(u)=1/2$.

• Example 1 [Exponential without delay]:

$$p^{<\mathbf{L}\mathbf{s}>}(s;u) = \zeta(u) \; \frac{\theta(u)\mathrm{e}^{-\theta(u)s}}{\Gamma(1)} \mathbb{1}_{s>0} \; , \quad \zeta(u), \; \theta(u) \; \text{of cosine form.}$$

• Example 2 [Gamma with varying delay $\delta(u)$ and constant $\zeta(u)$]:

$$p^{<\mathbf{LS}>}(s;u) = \frac{1}{2}(s - \delta(u)) \frac{\mathrm{e}^{-(s - \delta(u))}}{\Gamma(2)} \mathbb{1}_{s > \delta(u)}$$
 with $\delta(u) = (6 - 10u) \times \mathbb{1}_{[0:1/2]}(u) + (10u - 4) \times \mathbb{1}_{(1/2:1]}(u)$

with $\delta(u) = (6 - 10u) \times \mathbb{1}_{[0;1/2]}(u) + (10u - 4) \times \mathbb{1}_{(1/2;1]}(u)$ inducing a periodic phenomenon in the self-excitation.

Here, $\zeta(u)$, $\theta(u)$ and $\delta(u)$ are Lipschitz $\beta=1$, and one gets explicit formulas for the local mean density

$$m_1^{\langle LS \rangle}(u) = m_1^{\langle LS \rangle}(\zeta(u)) = \frac{\lambda_c}{1 - \zeta(u)}.$$

and local Bartlett spectrum $\Gamma^{< \text{LS}>}(\mathrm{d}\omega;u) = \Gamma^{< \text{LS}>}(\mathrm{d}\omega;\delta(u),\zeta(u),\theta(u)).$

Simulation of locally stationary Hawkes processes

Use time-varying conditional intensity

$$\lambda_T(t) := \lambda_c^{<\mathtt{LS}>}(t/T) + \sum_{T_i < t} p^{<\mathtt{LS}>}(t-T_i;t/T) \; ,$$

where $(T_i)_{i\in\mathbb{Z}}$ denote the points of N_T .

Use Ogata's modified thinning algorithm (Ogata, 1981) to simulate the non-stationary Hawkes process N_T on the interval [0, T].

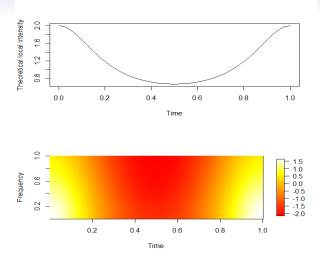


Figure 1: Theoretical local mean density (top) and Bartlett spectrum (bottom) for Example 1.

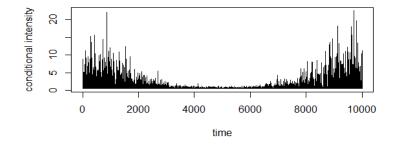


Figure 2 : Conditional intensity function of a simulated Hawkes process following Example 1, with T=10000.

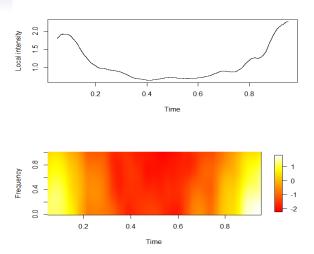


Figure 3: Estimation of the local mean density (top) and of the local Bartlett spectrum (bottom) for Example 1.

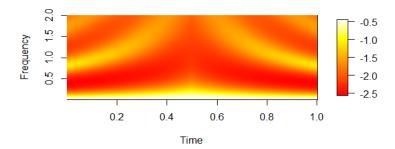


Figure 4: Theoretical local Bartlett spectrum for Example 2 (local mean density being constant over time).

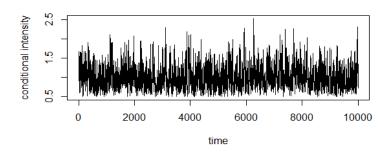


Figure 5 : Conditional intensity function of a simulated Hawkes process following Example 2, with T=10000.

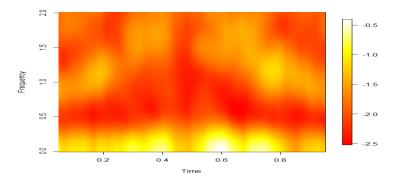


Figure 6: Estimation of the local Bartlett spectrum for Example 2.

Numerical experiments

Some asymptotic estimation theory (work in progress)

Estimation of the local mean intensity

A straightforward estimator of

$$m_1^{<\mathtt{LS}>}(u_0) = rac{\lambda_c^{<\mathtt{LS}>}(u_0)}{1 - \int p^{<\mathtt{LS}>}(\cdot; u_0)}$$
 .

is

$$\widehat{m_1}(u_0) \; := \; N_T(S^{-Tu_0} \, W_{b_1\, T}) \; = \; \int \, W_{b_1\, T}(s-Tu_0) \, \, N_T(ds) \; ,$$

with time-kernel $W_{b_1T}(\cdot) = \frac{1}{b_1T}W(\frac{\cdot}{b_1T}).$

Under suitable conditions (of Theorem 4, integrability of W), with $\beta \in (0,1]$, we have

- Bias: $O\left(b_1^{\beta} + T^{-\beta}\right)$
- Variance: $O((Tb_1)^{-1} + b_1^{\beta} + T^{-\beta})$

This gives an MSE-rate of convergence of order $T^{-\frac{\beta}{\beta+1}}$.

Principle of proof, using Theorem 4 with $g = W_{b_1T}$

• Bias (Thm 4 with m=1):

$$\mathbb{E}\widehat{m_1}(u_0) - m_1(u_0) \lesssim T^{-eta} \left(\left| W_{b_1T} \right|_1 + \left| W_{b_1T} \right|_{(eta)} \right)$$

 $\lesssim T^{-eta} \left(1 + (b_1T)^{eta} \right) \lesssim b_1^{eta} + T^{-eta} \ .$

• Variance (Thm 4 with m=2 and $g_1=g_2=g$):

$$\begin{split} \mathsf{Var}(\widehat{m_1}(u_0)) &\lesssim \mathsf{Var}((N(W_{b_1T,u_0})) \ + \\ &+ \ T^{-\beta}(|W_{b_1T}|_1 + |W_{b_1T}|_{(\beta)}) \times (|W_{b_1T}|_\infty + |W_{b_1T}|_1) \ \lesssim \\ &\lesssim (Tb_1)^{-1} + \ T^{-\beta} \ \left(1 + (b_1T)^{\beta}\right) \times \left((b_1T)^{-1} + 1\right) \lesssim \ (Tb_1)^{-1} + b_1^{\beta} + T^{-\beta}. \end{split}$$

Asymptotic estimation theory for local Bartlett spectrum

Employed technique:

Control of the expectation and the variance of

$$\widehat{E}[N_T(f);w] := \frac{1}{T} \int N_T(f(\cdot - t))w(t/T) dt$$

estimator of first moment of "stationary" Hawkes process $N(f; u_0)$.

Control of the expectation and the variance of

$$\widehat{E}[N_T^2(f);w] := \frac{1}{T} \int N_T^2(f(\cdot - t))w(t/T) dt$$

estimator of the second moment of $N(f; u_0)$.

Here again with the time-kernel $w = W_{b_1,u_0}$ and now with a "test-function" $f = K_{b_2,\omega_0}$, i.e. the kernel in frequency direction.

Again use Theorem 4, similarly to the proof of consistency of the local mean density estimator (but MUCH more involved).

Possibility of a CLT (future work)....

Bias of the estimator $\widehat{\gamma}_{b_0,b_1}(\omega_0;u_0)$

Numerical experiments

Recall: Estimation of $\gamma_{b_2}(\omega_0; u_0)$ via

$$\widehat{\gamma}_{b_{2},b_{1}}(\omega_{0};u_{0}) = \widehat{E}\left(|N_{T}(S^{-Tu_{0}}K_{b_{2},\omega_{0}})|^{2};W_{b_{1}}\right) - \left|\widehat{E}\left(N_{T}(S^{-Tu_{0}}K_{b_{2},\omega_{0}});W_{b_{1}}\right)\right|^{2}.$$

Under suitable conditions (of Theorem 4, integrability of K and W), with $\beta \in (0,1]$, and for a Bartlett spectrum sufficiently regular in frequency, we have for the Bias a rate of order

$$\frac{1}{Tb_1b_2} + b_2^{-1}\left((Tb_2)^{-\beta} + b_1^{\beta}\right) + b_2^2$$

(The behaviour of the *Variance* has still to be worked out.)

Convergence of the bias under conditions for the two bandwidths:

$$Tb_1b_2 o\infty$$
, $Tb_2^{1+rac{1}{eta}} o\infty$ and $rac{b_1^eta}{b_2} o0$,

plus a traditional bias-condition $b_2 \to 0$ for the convergence of $\gamma_{b_2}(\omega_0; u_0)$ to the "point" spectral density $\gamma^{< LS>}(\cdot; u_0)$ in ω_0 (for a given u_0).

Conclusion

- Self-exciting point processes ("Hawkes" processes) show a far more evolved dynamics over time than, e.g., autoregressive processes.
 Consequently, locally stationary approximations are more difficult to derive.
- Unfortunately, unlike "classical" time series (under usual conditions) no spectral representation exists that would render the approach more "direct".
- The key to success: approximation theory for local Laplace transforms and its derivatives (control of cumulants):
- Existence of (local) mean density (no "explosive" behaviour) and local Bartlett spectrum via control of convergence of first and second moment structure
- Work in progress: Asymptotic estimation theory (control of convergence of first and second empirical moments);
 real data analysis