

Persistence exponent for GSPs

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Joint work with N.D. Feldheim and O.N. Feldheim

- 1 What is the question?
- 2 An overview of our results
- 3 Outline of the proof
 - Smooth densities
 - UB for general densities
 - LB for general densities
 - Important tools
- 4 Conclusion

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- Comment: Slepian's Lemma applies for non stationary Gaussian processes.

Slepian+non-negative covariance

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$$\begin{aligned} & \mathbb{P}\left(\inf_{t \in [0, T+S]} X(t) > 0\right) \\ & \geq \mathbb{P}\left(\inf_{t \in [0, T]} X(t) > 0\right) \mathbb{P}\left(\inf_{t \in [T, T+S]} X(t) > 0\right) [\rho(\cdot) \geq 0] \end{aligned}$$

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- By sub-additivity, $\theta_\rho := -\lim_{T \rightarrow \infty} \frac{1}{T} \log p(T)$ exists in $[0, \infty]$.

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- Taking log and dividing by T gives

$$\frac{1}{T} \log \mathbb{P}\left(\inf_{t \in [0, T]} X(t) > 0\right) \geq k \log \mathbb{P}\left(\inf_{t \in [0, 1/k]} X(t) > 0\right).$$

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- But this is a contradiction, as $\mathbb{P}(X(0) > 0) \neq 0$.

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- Finally, in [Aurzada-M. 2020](#) it was shown that

$$\theta_\rho = 0 \quad \Leftrightarrow \quad \int_0^\infty \rho(t)dt = \infty.$$

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- Then ρ_k is not integrable for any k , and so $\theta_{\rho_k} = 0$.
- On the other hand $\lim_{k \rightarrow \infty} \rho_k = \rho^{(int)}$ which is integrable, and so $\theta_{\rho^{(int)}} > 0$.

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- $\rho_k(\cdot)$ converges to $\rho_\infty(\cdot)$ pointwise;
- $\limsup_{t \rightarrow \infty} \sup_{k \geq 1} \frac{\rho_k(t)}{|t|^\alpha} < \infty$ for some $\alpha > 1$; (uniform decay of correlations)

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- (c) $\limsup_{t \rightarrow 0} \sup_{k \geq 1} |\log t|^\beta (1 - \rho_k(t)) < \infty$ for some $\beta > 1$. (tightness)

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- Thus $\log \mathbb{P}(\sqrt{Z_1^2 + Z_2^2} < 0) = -\infty$. Consequently, $\theta_\rho = \infty$.

- A more interesting example is the sinc process, which has correlation

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- The existence of exponent for the sinc process remained open.

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- Moreover, given any finite symmetric measure μ , its Fourier ρ is a continuous correlation function.
- As an example, for the sinc process, μ is $\frac{1}{2}$ times Lebesgue measure on $[-1, 1]$.

Parametrizing via spectral measure

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Then there exists finite positive constants $C_1 < C_2$ such that

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- In fact, the existence of exponent was not known in any non-trivial example (including the sinc process).
- Can we study continuity properties of such exponents, in terms of $\rho(\cdot)$ or μ ?
- Can we compare persistence exponents by comparing spectral measures?

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- Let $p_T(\mu) := \mathbb{P}(\inf_{t \in [0, T]} X_\mu(t) > 0)$.

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(A2) *The limit*

$$\mu'(0) := \lim_{\varepsilon \downarrow 0} \frac{\mu[-\varepsilon, \varepsilon]}{2\varepsilon}$$

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- If $\mu'(0) > 0$ then $\theta(\mu) < \infty$.
- Conversely, if $\mu([0, t]) \sim t^\alpha$ for $\alpha < 1$ near 0, then $\theta(\mu) = \infty$ (Feldheim-Feldheim-Nitzan 2017).

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- It follows from the above theorem that $\theta(\mu)$ exists in $(0, \infty)$, i.e. the sinc process does have an exponent.
- Suppose μ is a spectral measure which satisfies our conditions. Then the truncated measure $\mu_{[-L, L]}$ satisfies our conditions.
- More generally, let $h(\cdot)$ be a bounded non-negative function which is continuous near 0, with $h(0) \neq 0$.

- Then the measure ν defined by $\frac{d\nu}{d\mu} = h$ satisfies our conditions.

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- If μ and ν satisfies our conditions, and one of the measures have a bounded continuous density, then so does the convolution $\mu * \nu$.
- If the correlation function $\rho(\cdot)$ is absolutely integrable, and $1 - \rho(t)$ satisfies very mild decay conditions for $t \approx 0$, then our conditions hold.

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- This basically says that the spectral measure is nice near ∞ .
- We also need (A2), which demands that μ is nice near 0 ($\mu'(0)$ exists and is positive).
- To show the necessity of this, we show the existence of positive reals $A < B$ such that with

$$\mu(dx) = (A + B \cos(1/x))1_{\{|x| < 1\}}dx,$$

the exponent $\theta(\mu)$ does not exist.

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- This example demonstrates the special role of the origin, as a discontinuity away from the origin does not impact existence of exponent.
- We conjecture that the exponent $\theta(\mu)$ does not exist in this example for any A, B (as opposed to some A, B).

Second main result: Impact of singular measures

- Suppose μ is a measure which satisfies our regularity conditions (nice near 0 and ∞), and ν is a measure which is nice near ∞ .

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Theorem (Feldheim-Feldheim-M. 2021+)

$\theta(\mu + \nu) \geq \theta(\mu)$, with equality iff ν is purely singular.

Comments on this theorem

- In particular, if ν is a singular measure whose support does not contain 0, then $\theta(\mu + \nu) = \theta(\mu)$.

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- Here $Z \sim N(0, 1)$, and the sign \oplus denotes point-wise sum of independent processes.
- In this case, we have

$$\mathbb{P}\left(\inf_{t \in [0, T]} \{X_\mu(t) \oplus \sigma Z\} > 0\right) \geq \mathbb{P}\left(\sup_{t \in [0, T]} |X_\mu(t)| < K\right) \mathbb{P}(\sigma Z > K).$$

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- In the above two displays we also use stationarity.
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- This will be sketched in the second part of the talk.

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Continuity in levels

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- One of our central estimates is a change of level lemma for general GSPs, which applies under the much weaker assumptions (A1) and (A2).
- In particular, this change of level lemma applies to “any” non-negative correlation function.

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- In this case, for $T \geq 2\pi$,

$$\begin{aligned}\mathbb{P}\left(\inf_{t \in [0, T]} \{Z_1 \cos(t) \oplus Z_2 \sin(t)\} > \delta\right) &= 0 \text{ if } \delta \geq 0, \\ &= c > 0 \text{ if } \delta < 0.\end{aligned}$$

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- Consequently,

$$\begin{aligned}-\lim_{T \rightarrow \infty} \frac{1}{T} \log \mathbb{P}\left(\inf_{t \in [0, T]} \{Z_1 \cos(t) \oplus Z_2 \sin(t)\} > \delta\right) &= \infty \text{ if } \delta \geq 0, \\ &= 0 \text{ if } \delta < 0.\end{aligned}$$

Why are singular measures special?

- Study of persistence relates very closely to study of small ball probabilities, of the form

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$$\psi(\mu, \ell) := - \lim_{T \rightarrow \infty} \frac{1}{T} \mathbb{P}\left(\sup_{t \in [0, T]} |X_\mu(t)| < \ell\right).$$

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$\psi(\mu, \ell) = 0$ iff μ is singular.

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- Since $\mathbb{P}(\sqrt{Z_1^2 \oplus Z_2^2} < \ell) > 0$, we have $\psi(\mu, \ell) = 0$.

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- Since $\mathbb{P}(\sqrt{Z_1^2 \oplus Z_2^2} < \ell) > 0$, we have $\psi(\mu, \ell) = 0$.
- The general proof proceeds via approximating a singular X_μ as a combination of $o(T)$ many Gaussians.

Third main result: Continuity

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$\theta(\mu_k) \rightarrow \theta(\mu_\infty)$, if the following hold:

- (a) $\{\mu_k\}_{k \geq 1}$ are uniformly nice near ∞ , i.e. for some $\beta > 1$ we have $\sup_{k \geq 1} \int_{[1, \infty)} (\log x)^\beta \mu_k(dx) < \infty$.

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Theorem (Feldheim-Feldheim-M '2020)

$\theta(\mu_k) \rightarrow \theta(\mu_\infty)$, if the following hold:

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Comments on the theorem

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- In particular, no convergence is necessary for singular component of the measure sequence (away from the origin), as they do not impact persistence.
- This result generalizes the continuity of exponent result for non-negative correlations obtained in [Dembo-M. 2012](#).

- 1 What is the question?
- 2 An overview of our results
- 3 Outline of the proof
 - Smooth densities
 - UB for general densities
 - LB for general densities
 - Important tools
- 4 Conclusion

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- Since $\|f''\|_\infty < \infty$, this gives the bound $|\rho(t)| \leq \frac{C}{t^2}$ for all $t \geq 1$.

Breaking into smaller intervals

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- We split the proof into upper and lower bounds, the proofs of which are very different.

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- Consequently,

$$\mathbb{P}\left(\inf_{t \in [0, T]} X_\nu(t) > 0\right) \geq \mathbb{P}\left(\inf_{t \in [0, T]} X_\mu(t) > \delta\right) \mathbb{P}\left(\sup_{t \in [0, T]} |X_\sigma(t)| < \delta\right)$$

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- Using the assumption gives $\sigma'(0) = \nu'(0) - \mu'(0) \approx 0$.

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- It thus suffices to show that

$$p_T(\mu) = p_T(\mu + h^2\sigma) \stackrel{T}{\geq} p_T(\mu + \sigma) = p_T(\nu).$$

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- Note that if $\mu = 0$, the claim reduces to $p_T(h^2\sigma) \stackrel{T}{\geq} p_T(\sigma)$, which is conceptually easier.

- Indeed, in this case we need to show that

$$\mathbb{P}\left(\inf_{t \in [0, T]} \int X_\sigma(t-s)H(s)ds > 0\right) \stackrel{T}{\geq} \mathbb{P}\left(\inf_{t \in [0, T]} X_\sigma(t) > 0\right).$$

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- Then

$$\inf_{t \in [-L, T+L]} X_\sigma(t) \geq 0 \Rightarrow \inf_{t \in [0, T]} \int X_\sigma(t-s)H(s)ds \geq 0.$$

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- Using stationarity+compact support of H , the LHS is lower bounded by

$$\log \mathbb{P}\left(\inf_{t \in [-L, T+L]} \{X_\mu(t) + v(t)\} > 0\right).$$

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- This completes the sketch of the lower bound.

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- Thus

$$\theta(\nu_{[-L,L]}) = \theta(\mu) = \theta(\mu + h^2\sigma) \leq \theta(\mu + \sigma) = \theta(\nu).$$

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- Combining, we have $\theta(\mu) = \theta(\mu + \sigma)$.
- We also show that equality does not hold if σ is not singular.

- 1 What is the question?
- 2 An overview of our results
- 3 Outline of the proof
 - Smooth densities
 - UB for general densities
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 - Important tools
- 4 Conclusion

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- Can we handle non-stationary Gaussians? One advantage of correlation function is that it makes sense even for non-stationary Gaussian processes.
- Can we say how does the GSP look like conditioned on persistence?

A graphic with the text "The End" in a white, cursive font with a drop shadow. The text is centered on a dark red background with a bright orange-yellow circular glow behind it.

The End