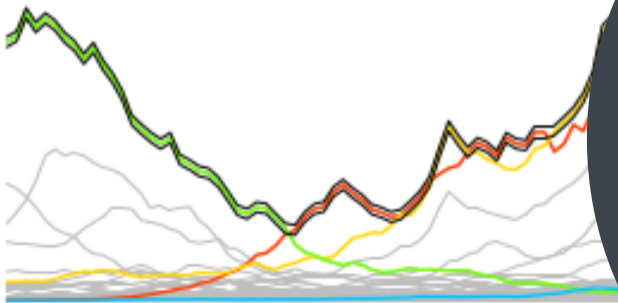


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**Extending
Brown-Resnick
stationarity to the
max-domain of attraction**

EcoSta2025

Outline

- 1 Motivation
- 2 Construction of stationary particle systems
- 3 Max-domain of attraction

Motiva- tion

1

From a stochastic processes point of view

Setting: real-valued (time-homogeneous) Markov process $(X_t)_{t \geq 0}$

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Question: Can we construct stationary objects from σ -finite invariant measures?

From an extreme value theory point of view

Setting: (Z_t) is a max-stable process: for all $n \in \mathbb{N}$ there exist $a_n > 0, b_n \in \mathbb{N}$ such that

$$\max_{i=1, \dots, n} \frac{(Z_t)^{(i)} - b_n}{a_n} =_d (Z_t) \quad \text{where } (Z_t)^{(i)} \text{ are i.i.d. copies of } (Z_t)$$

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- Brown-Resnick process (famous example):
 - $X_t = B_t - t/2$
 - Z_t is stationary even though X_t is not
 - \rightsquigarrow **Question:** When and why is (Z_t) stationary? **Answer:** (Kablichko et. al., 2009)

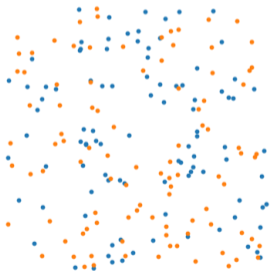
Construction of stationary particle systems

2

Ingredients

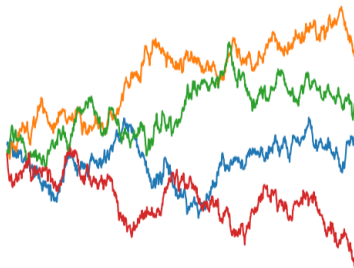
Point Processes

- Markovian particle systems
- stationarity via invariant measure



Stochastic Differential Equations

- SDE driven by Brownian motion
- invariant measures via Fokker-Planck equation



Markovian particle systems and stationarity

Assumptions:

- (X_t) (time-homogeneous) Markov process
- $\{U^{(i)} \mid i \in \mathbb{N}\}$ points of a PPP with σ -finite Borel intensity measure ν

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Takeaway: Invariant process-measure pair $((X_t), \nu)$ gives stationary particle system

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Next: SDE framework for constructing invariant process-measure pair

Invariant measure via SDE theory

Formalism:

$$dX_t = d(X_t) dX_t + dB_t$$

Target:

- drift term d
- invariant measure $\eta = h dx$

↪ Related via stationary **Fokker-Planck equation:**

$$d(x)h(x) = \frac{h'(x)}{2}$$

Under additional regularity conditions—specifying either target—we get an invariant process-measure pair.

Example—from max-stable to max-id process

Question:

Can we allow for a different intensity measure of the PPP initialization?

Idea:

Choose a target invariant measure:

$$\eta(dx) = \frac{1}{\exp(x)} dx$$

Use SDE theory:

- Choose $d(x) = -1/2$

Equation for invariant measure

$$0 = \eta(dx) - \eta'(dx)$$

Resulting SDE:

$$dX_t = -\frac{1}{2} \left(1 \right) dt + dB_t$$

Example—from max-stable to max-id process

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Idea:

Choose a target invariant measure:

$$\eta(dx) = \frac{1}{\exp(x) + 1} dx$$

Use SDE theory:

- Choose $d(x) = \phi_1(x)$

Equation for invariant measure leads to drift equation:

$$\begin{aligned} 0 &= \phi_1(x) \eta(dx) - \eta'(dx) \\ &= \phi_1(x) \frac{1}{\exp(x) + 1} + \frac{\exp(x)}{(\exp(x) + 1)^2} \end{aligned}$$

Solving gives:

$$\phi_1(x) = 1 - \frac{1}{\exp(x) + 1}$$

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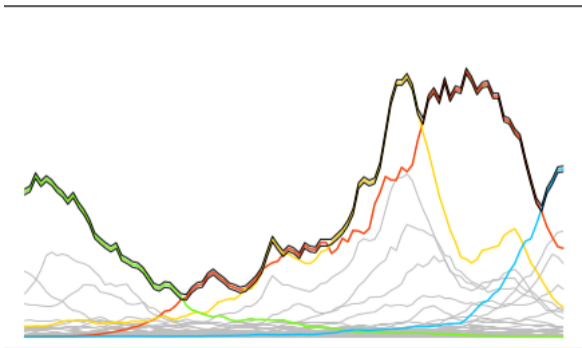
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Example—continued

The particle system

$$\left\{ X_t^{(i)} \left(V^{(i)} \right) \mid i \in \mathbb{N} \right\} \quad \text{is stationary and so is} \quad \max_{i \in \mathbb{N}} X_t^{(i)} \left(V^{(i)} \right)$$

Note: This is only max-id in general, not max-stable.



Max- domain of attrac- tion

3

Max domain of attraction

For marginal distribution:

A distribution function F is in the max-domain of attraction of an extreme value distribution G (for example $G = \Lambda$ the Gumbel distribution)—in short $F \in \text{MDA}(G)$ —if there exist $a_n > 0, b_n \in \mathbb{R}$ such that

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For processes: A process (Y_t) is in the max-domain of attraction of a process (Z_t) if there exist $a_n > 0, b_n \in \mathbb{R}$ such that

$$\max_{i=1, \dots, n} \frac{(Y_t)^{(i)} - b_n}{a_n} \rightarrow_d (Z_t),$$

for example in finite dimensional distributions or in the space of cadlag functions.

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- There exists $a_n > 0, b_n \in \mathbb{R}$ such that $(X_t - b_n)/a_n \rightarrow B_t - t/2$ in distribution
- $\max_{i \in \mathbb{N}} X_t^{(i)}(V^{(i)})$ is in the MDA of $\max_{i \in \mathbb{N}} (U^{(i)} + B_t^{(i)} - t/2)$

Revisit Example—SDE perspective

Original SDE:

$$dX_t = -\frac{1}{2} \left(1 - \frac{1}{\exp(X_t) + 1} \right) dt + dB_t$$

Scaled SDE: Write $X_t^n = X_t - \log(n) \rightsquigarrow a_n = 1$ and $b_n = \log(n)$

$$dX_t^n = -\frac{1}{2} \left(1 - \frac{1}{\exp(X_t^n + \log(n)) + 1} \right) dt + dB_t$$

Limit SDE: Take $n \rightarrow \infty$ to get

$$dX_t^\infty = -\frac{1}{2} dt + dB_t$$

\rightsquigarrow spectral process in the limit: $X_t^\infty = B_t - t/2$ Brownian motion with drift

Revisit Example—Invariant measure perspective

Original:

$$-\log(F(x)) = \eta([x, \infty)) = \int_x^\infty \frac{1}{\exp(s) + 1} ds$$

Scaled:

$$-\log(F^n(x - \log(n))) = n\eta([x - \log(n), \infty)) = \int_x^\infty \frac{1}{\exp(s) + 1/n} ds$$

Limit:

$$-\log(\Lambda(x)) = \int_x^\infty \exp(-s) ds = \exp(-x)$$

↪ marginal distribution in the limit: Gumbel distribution $\Lambda(x) = \exp(-\exp(-x))$

Takeaway: Our example is in the MDA of the "classical" Brown-Resnick process

Summary

Motivation:

Understand and extend structure of classical Brown-Resnick process

Construction:

Find invariant process-measure pairs

- stationarity by Markovian particle system started in invariant measure
- find invariant process-measure pair via SDE theory

Max-domain of attraction:

Constructed max-id processes are in the MDA of the classical Brown-Resnick process

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Thank you!

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