

# Simulation of trawl processes using SINN architectures

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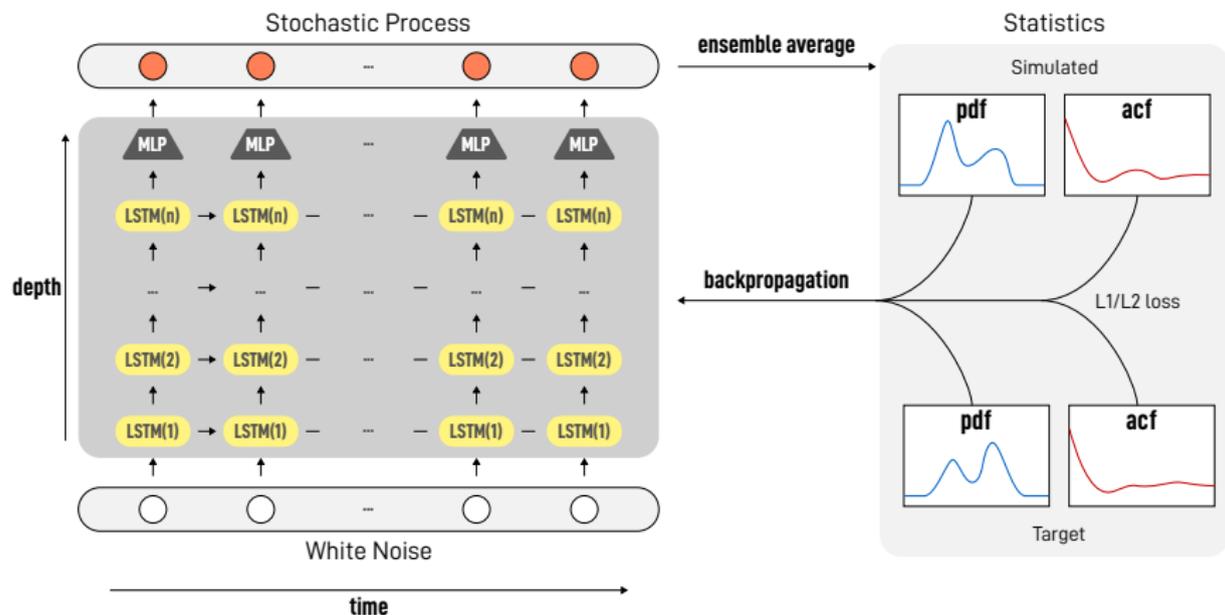
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- 1 Introduction
- 2 Purpose of the works
- 3 Losses based on characteristic functions
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**Ambit processes** are a class of stochastic processes that generalize many known models and are suitable for modeling complex spatio-temporal phenomena.

- This class includes Levy processes, fractional Brownian motion, Lévy-driven Volterra processes etc
- Application areas: turbulence physics, meteorology and climate, financial mathematics
- Known simulation methods require a lot of expensive computations related to inversion of the Fourier integrals

# SINN architectures



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The aim of the work is to investigate the applicability of SINN models for modeling ambit-processes

- The disadvantage of the original approach is that another simulation method is required for training.
- Most ambit-processes are non-stationary, and their distributions do not have closed forms in the form of densities/probability functions; however, their Fourier transforms can be expressed explicitly
- We limit ourselves to a special case — trawl processes, and try to construct a suitable loss function based on characteristic functions

- Informally speaking, trawl process is a random measure of a moving geometric figure in a higher-dimensional space. Trawl processes always stationary and ergodic
- More formally, consider a random measure  $L$  (of particular kind) and a set  $A \subset \mathbb{R} \times (-\infty; 0)$ ; The trawl process  $X_t$  is defined as  $L(A_t)$ , where  $A_t = A + (0, t)$
- Special cases include Ornstein-Uhlenbeck process, fractional Ornstein-Uhlenbeck process and in general any stationary Gaussian process with differentiable autocovariance function that is non-increasing and convex

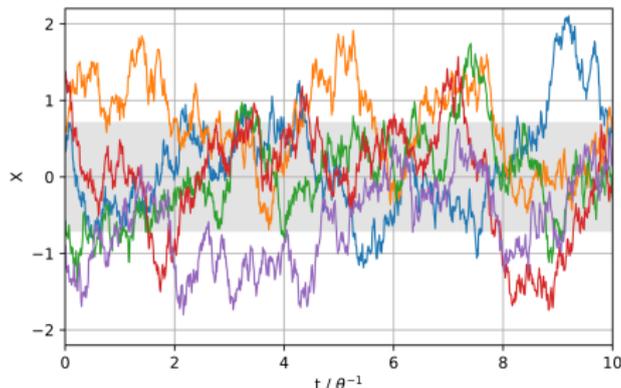
## Special case: OU-process

Ornstein–Uhlenbeck process is defined to be the stationary solution of the SDE

$$dX_t = \lambda(\mu - X_t)dt + \sigma dW_t$$

It can be represented as trawl process with  $L$  being standard on  $\mathbb{R}^2$  white noise  $L(dx, dt) = W(dx, dt)$  and trawl set given by

$$A = \left\{ (x, t) \mid 0 \leq x \leq \frac{\sigma^2}{2} \cdot \exp(\lambda t), t < 0 \right\}$$



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# Naive variant of CF-based loss

Consider now the problem of the learning parameters  $\theta$  of a SINN model to simulate the distribution  $\mathbf{X}_t$  of the process  $X_t$  at times  $\mathbf{t} = (t_1, \dots, t_d)$ ;  
Define

- $\varphi_{X_t}(\mathbf{u}, \mathbf{t})$  — analytical / MC-estimated CF of the  $\mathbf{X}_t$
- $\varphi_{\text{sin}n(\theta)}(\mathbf{u}, \mathbf{t})$  — MC-estimate of the CF of the distribution originated by SINN model

Suggested loss approximates  $\int_{\mathbb{R}^d} |\varphi_{X_t}(\mathbf{u}, \mathbf{t}) - \varphi_{\text{sin}n(\theta)}(\mathbf{u}, \mathbf{t})| d\mathbf{u}$ :

$$\begin{aligned} \mathcal{L}_{\text{cf}}(\theta, \mathbf{t}) &= \int_{[-T; T]^d} |\varphi_{X_t}(\vec{u}) - \varphi_{\text{sin}n(\theta)}(\vec{u})| d\mathbf{u} \approx \\ &\approx \frac{2^d T^d}{N} \sum_{i=1}^N |\varphi_{X_t}(\vec{u}_i) - \varphi_{\text{sin}n(\theta)}(\vec{u}_i)|, \quad \vec{u}_i \stackrel{\text{i.i.d}}{\sim} U([-T; T]^d) \end{aligned}$$

# General schema for CF-based loss

Consider set of multi-indexes  $\mathcal{T} \subset [d] = \{1, \dots, d\}$ ; General loss is given by:

$$\mathcal{L}(\theta) = \sum_{\mathbf{i} \in \mathcal{T}} \alpha_{\mathbf{i}} \cdot \mathcal{L}_{\text{cf}}(\theta, \mathbf{t}_{\mathbf{i}})$$

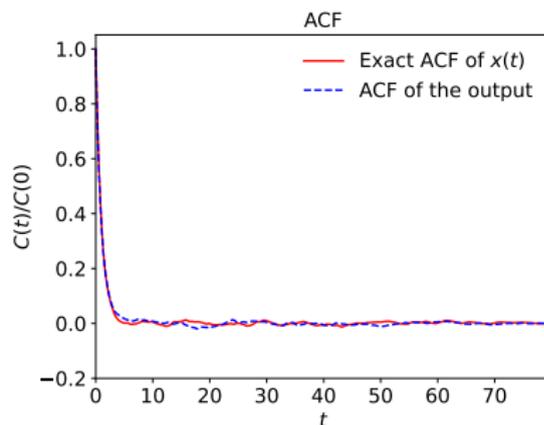
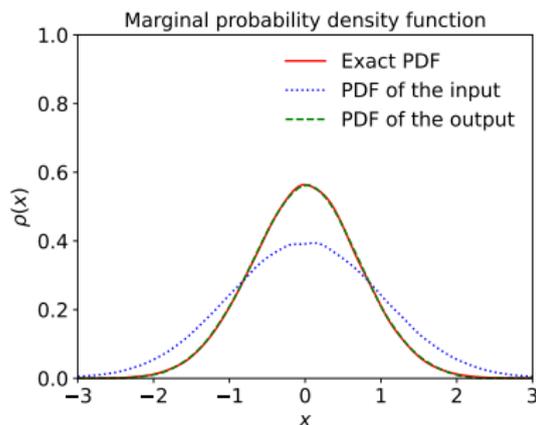
Notable special cases:

- $\mathcal{T} = \{(1, \dots, d)\}$  — joint-distribution
- $\mathcal{T} = \{(1), \dots, (d)\}$  — all marginal distributions
- $\mathcal{T} = \{(1, 2), (1, 3), \dots, (d-1, d)\}$  — all possible pairwise distributions

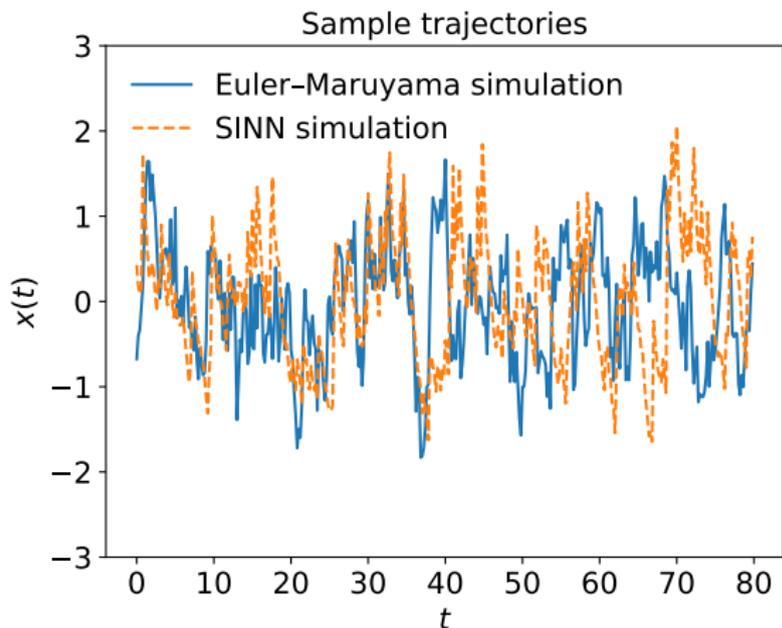
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# Simulation-based approach for OU-process

- SINN depth: 1, time grid size: 400, discretization step: 0.1
- Scheme: full loss with CF empirically estimated from Euler–Maruyama simulations
- T4 x 2 GPU, learning time  $\approx$  15 min

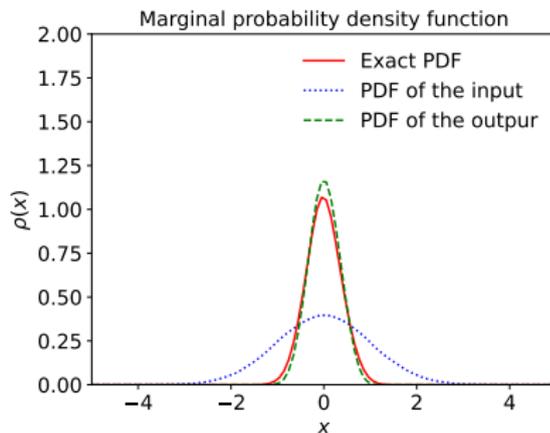
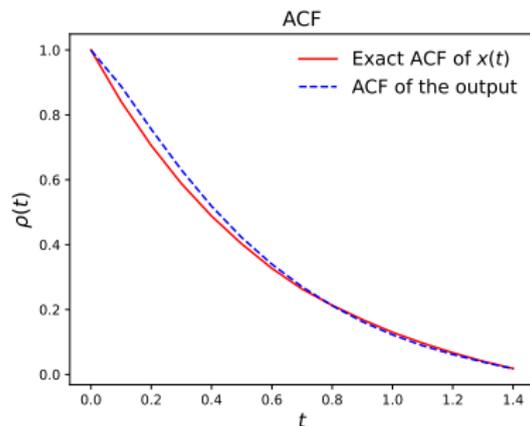


# Simulation-based approach for OU-process



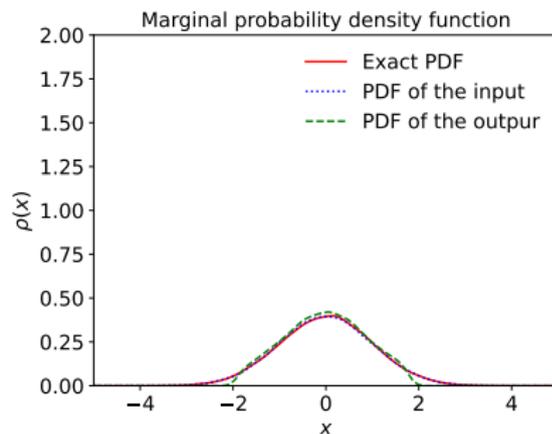
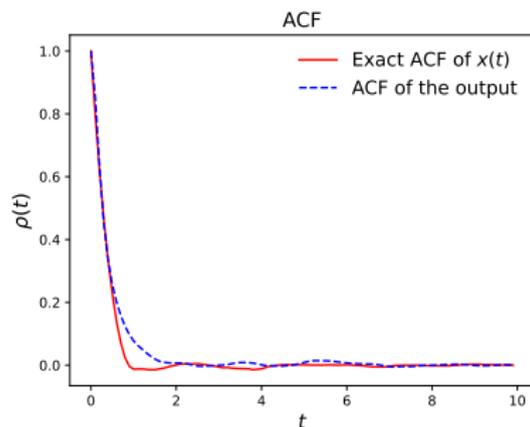
# Simulation-free approach for OU-process with CF-based loss

- SINN depth: 2, time grid size: 15, discretization step: 0.1
- Scheme: pairwise + marginal loss
- T4 x 2 GPU, learning time  $\approx$  15 min



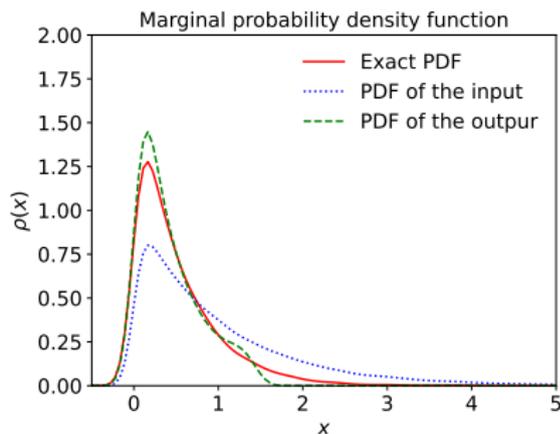
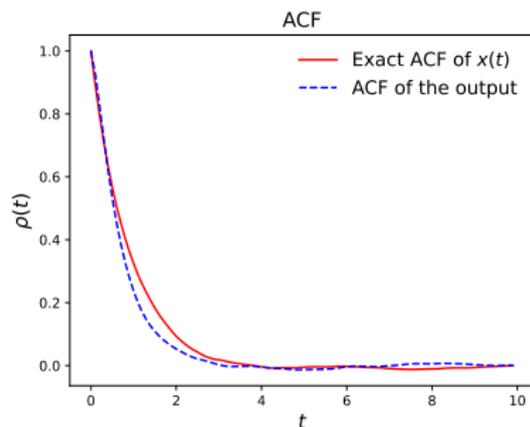
# CF-based loss for short-memory trawl process

- SINN depth: 2, time grid size: 100, discretization step: 0.1
- Scheme: rolling window + marginal loss + selected pairs
- T4 x 2 GPU, learning time  $\approx$  25 min

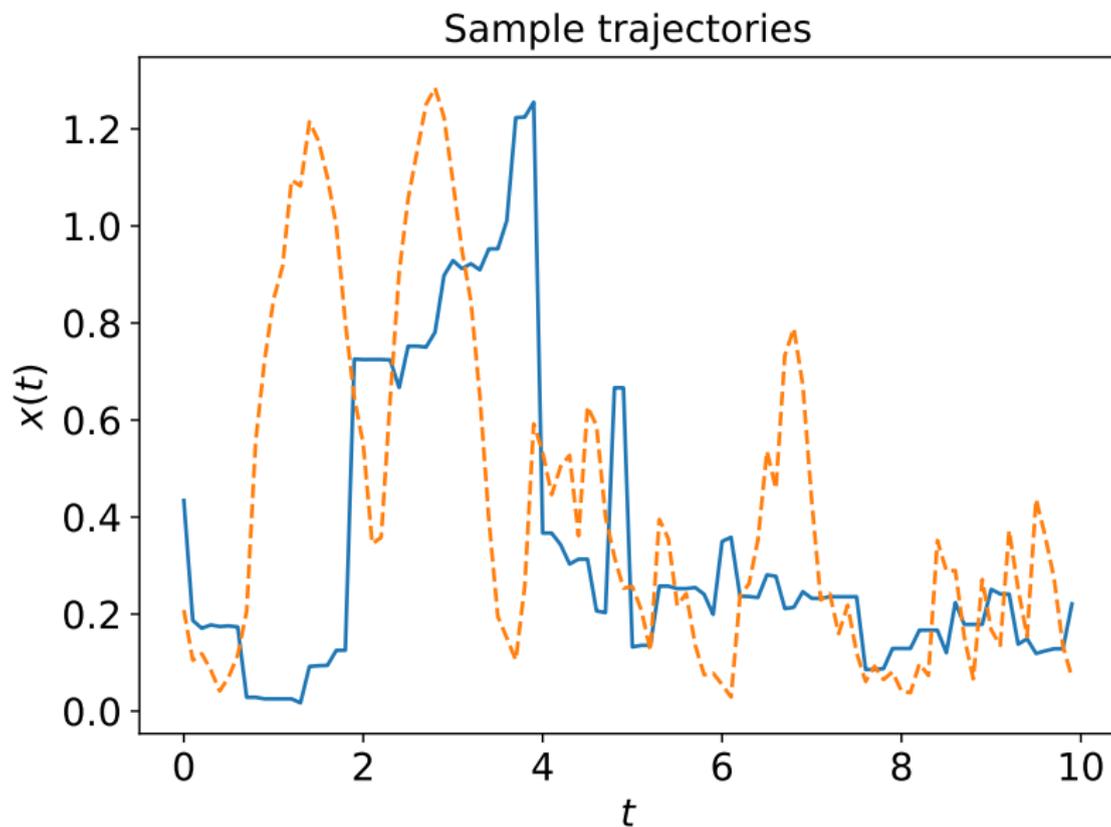


# CF-based loss for gamma trawl process

- SINN depth: 2, time grid size: 100, discretization step: 0.1; exponential distribution as input
- Scheme: rolling window + marginal loss + selected pairs
- T4 x 2 GPU, learning time  $\approx$  25 min



# CF-based loss for gamma trawl process: trajectories



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- Suggested simulation-free approach based on characteristic functions allows for simulation for trawl process; However heuristics for choosing of index schema for loss function should be developed
- It seems that current architecture does not suit for simulation of processes with short memory — SINN cannot learn zero autocorrelation
- Further research includes generalization of this approach to another classes of the ambit processes (BSS/LSS process, VMLV-process, weighted trawl process)

Ambit-field is a random field of the form

$$Y_t(\mathbf{x}) = \int_{A_t(\mathbf{x})} h(\mathbf{x}, t; \mathbf{y}; s) \sigma_s(\mathbf{y}) L(d\mathbf{y}; ds)$$

and ambit process is a process of the form  $Y_t(\gamma(t))$  where  $\gamma(t)$  is some curve in  $\mathbb{R}^d$ ; In the formula above

- $L(d\mathbf{y}, ds)$  – random measure defined on space-time  $\mathbb{R}^d \times \mathbb{R}$
- $\sigma_s(\mathbf{y})$  – stochastic volatility/intermittency field
- $h(\mathbf{x}, t; \mathbf{y}; s)$  – deterministic function (kernel)
- $A_t(\mathbf{x})$  – ambit set of the point  $(\mathbf{x}, t)$  in the space-time, i.e. set of all points which can influence on the value of  $Y_t(\mathbf{x})$

Trawl process defined as ambit process of particular kind:

$$X_t = \int_{\mathbb{R} \times (-\infty: t)} \mathbb{1}_A(\mathbf{y}, t - s) L(d\mathbf{y}, ds)$$

where

- $L$  is stationary Levy basis on  $\mathbb{R}^1 \times \mathbb{R}$  (meaning that distribution of  $L(A)$  is translation invariant)
- $A \subset \mathbb{R} \times (-\infty; 0)$  is some set called *trawl set*

Informally speaking, trawl process is a random measure of a moving geometric figure in a higher-dimensional space

# Characteristic functions

Consider some process  $X_t$  and vector of time moments  $\mathbf{t} = (t_1, \dots, t_d)$ ;  
For the distribution of the  $\mathbf{X}_{\mathbf{t}} = (X_{t_1}, \dots, X_{t_d})$  it's **characteristic functions** defined as

$$\varphi_{X_{\mathbf{t}}}(\mathbf{u}, \mathbf{t}) = \mathbb{E} \left[ e^{i\langle \mathbf{X}_{\mathbf{t}}, \mathbf{u} \rangle} \right]$$

- Characteristic function uniquely determines distribution
- Every stochastic process is uniquely characterized by it's finite-dimensional distributions

# Rainfall exceedance according to Met Office MIDAS

Model:  $\Lambda_t$  is gamma-trawl process with seed  $L' \sim \Gamma(\alpha, \beta)$  and autocorrelation function  $\rho(h) = \exp(-rh)$ . The model is defined as zero-inflated mixture of exponential distributions:

$$X_j \sim \begin{cases} 0 & \text{with probability } 1 - \exp(-\kappa\Lambda_j) \\ \text{Exp}(\kappa\Lambda_j) & \text{with probability } \exp(-\kappa\Lambda_j) \end{cases}$$

Data:

