

Novelty Assessment Report

Paper: Causal Structure Learning in Hawkes Processes with Complex Latent Confounder Networks

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Abstract

Multivariate Hawkes process provides a powerful framework for modeling temporal dependencies and event-driven interactions in complex systems. While existing methods primarily focus on uncovering causal structures among observed subprocesses, real-world systems are often only partially observed, with latent subprocesses posing significant challenges. In this paper, we show that continuous-time event sequences can be represented by a discrete-time causal model as the time interval shrinks, and we leverage this insight to establish necessary and sufficient conditions for identifying latent subprocesses and the causal influences. Accordingly, we propose a two-phase iterative algorithm that alternates between inferring causal relationships among discovered subprocesses and uncovering new latent subprocesses, guided by path-based conditions that guarantee identifiability. Experiments on both synthetic and real-world datasets show that our method effectively recovers causal structures despite the presence of latent subprocesses.

Disclaimer

This report is **AI-GENERATED** using Large Language Models and WisPaper (a scholar search engine). It analyzes academic papers' tasks and contributions against retrieved prior work. While this system identifies **POTENTIAL** overlaps and novel directions, **ITS COVERAGE IS NOT EXHAUSTIVE AND JUDGMENTS ARE APPROXIMATE**. These results are intended to assist human reviewers and **SHOULD NOT** be relied upon as a definitive verdict on novelty.

Note that some papers exist in multiple, slightly different versions (e.g., with different titles or URLs). The system may retrieve several versions of the same underlying work. The current automated pipeline does not reliably align or distinguish these cases, so human reviewers will need to disambiguate them manually.

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Core Task Landscape

This paper addresses: **Causal Structure Learning in Partially Observed Hawkes Processes**

A total of **11 papers** were analyzed and organized into a taxonomy with **8 categories**.

Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Causal Structure Identification with Latent Confounders**
- **Observable Network Learning and Granger Causality**
- **Causal Inference for Individual Events and Pairs**
- **Domain Applications and Extensions**

Complete Taxonomy Tree

- Causal Structure Learning in Partially Observed Hawkes Processes Survey Taxonomy
- Causal Structure Identification with Latent Confounders
 - Theoretical Foundations for Latent Confounder Identification ★ (2 papers)
 - [0] Causal Structure Learning in Hawkes Processes with Complex Latent Confounder Networks (Anon et al., 2026) [View paper](#)
 - [2] Local Independence Testing for Point Processes (Årjæ, 2023) [View paper](#)
 - Algorithmic Approaches for Deconfounding High-Dimensional Networks (2 papers)
 - [3] Causal discovery in high-dimensional point process networks with hidden nodes (Xu Wang, 2021) [View paper](#)
 - [4] Generative Machine Learning, Granger Causality, and Optimal Intervention in Self-exciting Spatiotemporal Processes (Das, 2025) [View paper](#)
- Observable Network Learning and Granger Causality
 - Data-Efficient Learning from Limited Observations (1 papers)
 - [6] Learning Hawkes processes from a handful of events (Salehi, 2019) [View paper](#)
 - Network Topology Inference from Partial Node Observations (1 papers)
 - [5] Passive Wireless Network Topology Inference Using a Multi-Dimensional Hawkes Process (Q Wang, 2025) [View paper](#)
- Causal Inference for Individual Events and Pairs (1 papers)
 - [7] Causal inference for event pairs in multivariate point processes (Tian Gao, 2021) [View paper](#)
- Domain Applications and Extensions
 - Social and Mass Media Event Analysis (1 papers)
 - [9] Statistical Hypothesis Testing and Modelling of Peoples' Power: A Causal Study of the # BlackLivesMatter Movement via Hawkes Processes on Social and Mass Media (Alfred Lindström, 2023) [View paper](#)
 - Security and Healthcare Applications (2 papers)
 - [1] Missing Data Imputation Based on Causal Inference to Enhance Advanced Persistent Threat Attack Prediction (Xiang Cheng, 2024) [View paper](#)
 - [10] Statistical Inference and Experimental Design for Recurrent Event Data with Applications in Neuroscience (Chen, 2019) [View paper](#)
 - Reinforcement Learning Integration and General Modeling Frameworks (2 papers)
 - [8] Learning by doing: an online causal reinforcement learning framework with causal-aware policy (Ruichu Cai, 2026) [View paper](#)
 - [11] Point process-based modeling and analysis of asynchronous event sequences. (Hongteng Xu, 2017) [View paper](#)

Narrative

Core task: causal structure learning in partially observed Hawkes processes. The field addresses how to recover causal relationships among event sequences when only a subset of processes is observed, a challenge that arises naturally in social networks, neuroscience, and cybersecurity. The taxonomy organizes work into four main branches. The first branch, Causal Structure Identification with Latent Confounders, develops theoretical foundations and identifiability conditions for recovering causal graphs when unobserved processes

confound the observed ones. The second branch, Observable Network Learning and Granger Causality, focuses on methods that infer directed influence networks from fully or partially observed data, often leveraging Granger-style causality tests and optimization-based discovery. The third branch, Causal Inference for Individual Events and Pairs, zooms in on finer-grained questions such as attributing specific events to their causes or learning from very few observed events. The fourth branch, Domain Applications and Extensions, explores how these techniques adapt to specialized settings like social media dynamics, wireless networks, and reinforcement learning.

A central tension runs through the literature: methods that assume full observability (for example, High Dimensional Discovery[3] and Granger Optimal Intervention[4]) can exploit rich statistical structure but may fail when latent confounders are present, while approaches that explicitly model hidden processes must grapple with identifiability and computational complexity. Hawkes Latent Confounders[0] sits squarely in the first branch, providing theoretical guarantees for identifying causal structure even when confounding processes remain unobserved. This contrasts with works like Local Independence Testing[2], which also addresses partial observability but emphasizes testing conditional independence rather than full graph recovery. Meanwhile, domain-driven studies such as BlackLivesMatter Hawkes[9] and Wireless Topology Inference[5] illustrate how these foundational ideas translate into real-world inference tasks, though they often rely on domain-specific assumptions that may not hold universally.

Related Works in Same Category

The following **1 sibling papers** share the same taxonomy leaf node with the original paper:

1. Local Independence Testing for Point Processes

Authors: [Årnlund, Nikolaj Thams, N. Hansen](#) | **Year/Venue:** 2023 | **URL:** [View paper](#)

Abstract

Constraint-based causal structure learning for point processes require empirical tests of local independence. Existing tests require strong model assumptions, e.g., that the true data generating model is a Hawkes process with no latent confounders. Even when restricting attention to Hawkes processes, latent confounders are a major technical difficulty because a marginalized process will generally not be a Hawkes process itself. We introduce an expansion similar to Volterra expansions as a tool t...

Relationship Analysis

Both papers belong to the theoretical foundations category for latent confounder identification in point processes, sharing a focus on establishing identifiability conditions for causal structures. The original paper develops necessary and sufficient conditions for identifying latent subprocesses in Hawkes processes through discrete-time linear causal representations and rank-based tests on cross-covariance matrices, while the candidate paper focuses on local independence testing using higher-order interaction terms and Volterra-like expansions to handle marginalized processes. The key difference is that the original paper provides a comprehensive framework for discovering unknown latent confounders and their causal structure, whereas the candidate paper develops hypothesis tests for local independence given a specified conditioning set, addressing model misspecification through nonparametric intensity approximations rather than structural identification.

Contributions Analysis

Overall novelty summary. The paper contributes a discrete-time causal representation of continuous-time Hawkes processes and establishes identifiability conditions for latent subprocesses via rank constraints. It resides in the 'Theoretical Foundations for Latent Confounder Identification' leaf, which contains only two papers total. This leaf sits within the broader 'Causal Structure Identification with Latent Confounders' branch, indicating a relatively sparse research direction focused on theoretical guarantees rather than algorithmic development or domain applications. The small sibling count suggests this is an emerging area with limited prior theoretical work.

The taxonomy reveals neighboring leaves addressing related but distinct challenges. The 'Algorithmic Approaches for Deconfounding High-Dimensional Networks' leaf focuses on computational methods for learning networks with hidden nodes, while 'Observable Network Learning and Granger Causality' assumes full observability or treats noise as the primary challenge. The paper's theoretical focus on identifiability conditions distinguishes it from these algorithmic and fully-observable settings. The taxonomy's scope notes clarify that this work excludes empirical methods without guarantees and settings where all processes are observed, positioning it at the intersection of causal inference theory and partially observed systems.

Among 21 candidates examined across three contributions, the discrete-time representation shows the most substantial prior work: 10 candidates examined with 2 appearing to provide overlapping results. The identifiability conditions contribution examined only 1 candidate with no clear refutation, while the two-phase algorithm examined 10 candidates with none refuting its novelty. This pattern suggests the discrete-time representation may build on established connections between continuous and discrete models, whereas the identifiability conditions and algorithmic contributions appear less anticipated by the limited search. The analysis explicitly covers top-K semantic matches plus citation expansion, not an exhaustive literature review.

Given the sparse taxonomy leaf and limited search scope, the work appears to address a theoretically underexplored problem. The identifiability conditions and algorithm contributions show minimal overlap among examined candidates, though the discrete-time representation connects to existing frameworks. The analysis reflects what 21 semantically similar papers reveal, leaving open whether broader searches across causal inference or point process literature would uncover additional related work. The theoretical focus and sparse leaf placement suggest meaningful novelty within the examined scope.

This paper presents **3 main contributions**, each analyzed against relevant prior work:

Contribution 1: Discrete-time linear causal representation of Hawkes processes

Description: The authors establish that multivariate Hawkes processes admit a linear autoregressive representation in discrete time as the bin width approaches zero. This theoretical result enables the use of second-order statistics to infer causal structure from discretized event counts.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Stability of discrete-time Hawkes process with inhibition: towards a general condition

URL: [View paper](#)

Brief Assessment

Hawkes Inhibition Stability[25] focuses on discrete-time Poisson autoregressive processes with inhibitory dynamics (allowing negative parameters), not on establishing linear causal representations for structure learning from continuous-time Hawkes processes.

2. Forecasting High Frequency Order Flow Imbalance using Hawkes Processes

URL: [View paper](#)

Brief Assessment

Order Flow Forecasting[24] focuses on forecasting order flow imbalance in high-frequency trading using Hawkes processes, not on establishing discrete-time linear autoregressive representations for causal structure learning.

3. A Markov switching discrete-time Hawkes process: application to the monitoring of bats behavior

URL: [View paper](#)

Brief Assessment

Markov Switching Hawkes[29] focuses on a discrete-time Hawkes process with Markov-switching immigration rates for behavioral modeling, not on establishing a general linear autoregressive representation for causal structure learning from discretized event counts.

4. Nonlinear Poisson autoregression and nonlinear Hawkes processes

URL: [View paper](#)

Brief Assessment

Nonlinear Hawkes Processes[23] focuses on nonlinear Poisson autoregression and nonlinear extensions of Hawkes processes, whereas the original paper establishes a linear autoregressive representation for multivariate Hawkes processes in discrete time. The candidate's emphasis on nonlinearity represents a fundamentally different modeling approach that does not challenge the novelty of the linear representation framework.

5. An estimation procedure for the Hawkes process

URL: [View paper](#)

Prior Art Analysis

Hawkes Estimation Procedure[26] demonstrates that multivariate Hawkes processes can be represented as discrete-time linear autoregressive models (specifically INAR(p) models) as the bin width approaches zero. This establishes the same fundamental discrete-time linear representation that the original paper claims as novel. The candidate paper proves weak convergence of INAR-based point processes to Hawkes processes (Theorem 2.4) and shows that INAR(p) sequences admit a linear autoregressive representation with white-noise errors (Proposition 3.1, Corollary 3.2), enabling the use of second-order statistics for inference—the exact contribution claimed by the original paper.

Evidence

Evidence 1 - **Rationale:** This theorem establishes the convergence of discrete-time INAR processes to continuous-time Hawkes processes as bin width decreases, which is the foundational result for the discrete-time linear representation claimed in the original paper. - **Original:** we show that, as the time interval shrinks, the multivariate Hawkes process admits a discrete-time linear causal representation, leveraging second-order (cross-covariance) statistics of this representation, we show that the causal graph is virtually identifiable. - **Candidate:** theorem 2.4. let n be a univariate Hawkes process with baseline intensity $\eta > 0$ and piecewise-continuous excitement function $h : \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}_{\geq 0}$ such that $\sum_{k=1}^{\infty} h(k\Delta) \Delta < 1$ for all $\Delta \in (0,1)$. furthermore, let $(x(\Delta)_n)$ be a univariate INAR(∞) sequence with immigration parameter $\alpha(\Delta) = \Delta\eta$ and reproduction coefficient...

Evidence 2 - **Rationale:** This proposition shows that INAR(p) sequences can be represented as standard linear autoregressive models with white noise, enabling the use of second-order statistics for parameter estimation—the same approach claimed as novel in the original paper. - **Original:** by showing that multivariate Hawkes processes can be represented by a linear causal model over discretized variables, we derive necessary and sufficient conditions for identifying latent subprocesses and inferring causal influences. - **Candidate:** proposition 3.1. let (x_n) be a d -dimensional INAR(p) sequence as in definition 2.3 with immigration-parameter vector $\alpha_0 \in \mathbb{R}_{\geq 0}^d$ and reproduction coefficient matrices $A_k \in \mathbb{R}^{d \times d}$, $k = 1, 2, \dots, p$, such that (10) holds. then $u_n := x_n - \alpha_0 - \sum_{k=1}^p A_k x_{n-k}$, $n \in \mathbb{Z}$, defines a (dependent) white-noise sequence, i.e....

Evidence 3 - **Rationale:** This corollary explicitly shows the linear autoregressive representation of the discretized Hawkes process, which is the exact discrete-time linear causal representation claimed in the original paper. - **Original:** we first show that, as the time interval shrinks, the multivariate Hawkes process admits a discrete-time linear causal representation. - **Candidate:** corollary 3.2. let (x_n) be the multivariate INAR(p) sequence and (u_n) the white-noise sequence from proposition 3.1. then (x_n) solves the system of stochastic difference equations $x_n = \alpha_0 + \sum_{k=1}^p A_k x_{n-k} + u_n$, $n \in \mathbb{Z}$.

Evidence 4 - **Rationale:** This equation demonstrates the linear autoregressive structure of discretized Hawkes processes, showing that bin counts are linear combinations of lagged counts plus noise—the same representation described in the original paper's Theorem 4.1. - **Original:** theorem 4.1 shows that each current-bin count $n(n)$ is (referred to as variable hereafter) is a linear combination of lagged counts $\{n(n-k)_j\}_{k \in \{1, \dots, n\}, j \in \{1, \dots, l\}}$ plus noise. - **Candidate:** we want to argue that for small $\Delta > 0$ and large $p \in \mathbb{N}$, we have that $e^{-\sum_{k=1}^p \sigma_k (x(\Delta)_n - 1, \dots, x(\Delta)_n - 2, \dots)} \approx \Delta \eta + \sum_{k=1}^p \Delta h(\Delta k) x(\Delta)_n - k$, $n \in \mathbb{Z}$.

6. Factorization and discrete-time representation of multivariate CARMA processes

URL: [View paper](#)

Brief Assessment

CARMA Discrete Time[27] focuses on multivariate CARMA processes (continuous-time ARMA models driven by Lévy processes) and their discrete-time VARMA representations, not Hawkes processes. The candidate establishes discrete-time representations for CARMA models, while the original paper addresses event-driven Hawkes processes with self-exciting intensity functions—fundamentally different stochastic processes.

7. (Almost) complete characterization of stability of a discrete-time Hawkes process with inhibition and memory of length two

URL: [View paper](#)

Brief Assessment

Hawkes Stability Characterization[28] focuses on discrete-time Poisson autoregressive processes with inhibition (negative parameters) and stability analysis, not on establishing linear autoregressive representations for causal structure learning from continuous-time Hawkes processes.

8. Modeling and Estimation of Multivariate Discrete and Continuous Time Stationary Processes

URL: [View paper](#)

Brief Assessment

Multivariate Stationary Processes[31] focuses on general stationary processes with autoregressive characterizations, not specifically on Hawkes processes or their discrete-time linear causal representations for event sequences.

9. Functional approximation of the marked Hawkes risk process

URL: [View paper](#)

Brief Assessment

Marked Hawkes Approximation[22] focuses on discrete-time approximation of marked Hawkes risk processes for trajectory convergence in Sobolev and Skorokhod spaces, not on establishing linear autoregressive representations for causal structure inference.

10. Graphical modeling for multivariate Hawkes processes with nonparametric link functions

URL: [View paper](#)

Prior Art Analysis

Nonparametric Hawkes Modeling[30] demonstrates that multivariate Hawkes processes can be represented as discrete-time linear autoregressive models as the bin width approaches zero. The candidate paper explicitly establishes this correspondence through Theorem 4.1 and related results, showing that discretized event counts admit a linear autoregressive representation. This work predates the original paper (2016 vs. 2026) and provides the theoretical foundation for using second-order statistics to infer structure from discretized Hawkes processes, which is the core theoretical contribution claimed as novel in the original paper.

Evidence

Evidence 1 - **Rationale:** Both papers describe discretizing Hawkes processes to enable analysis using time series methods and second-order statistics. - **Original:** we first show that, as the time interval shrinks, the multivariate Hawkes process admits a discrete-time linear causal representation. leveraging second-order (cross-covariance) statistics of this representation, we show that the - **Candidate:** our approach for nonparametric estimation of the link function ϕ is via discretization and consequently using methods from time series analysis. again, as in section 2 we observe a multivariate point process $n = (n(t))_{t \in \mathbb{C}/\Delta}$ with component processes n_i , $1 \leq i \leq d$. the conditional intensity function ...

Evidence 2 - **Rationale:** Both establish that discretized Hawkes processes can be represented as linear autoregressive models with coefficients related to the excitation functions. - **Original:** theorem 4.1 (Hawkes process as a linear autoregressive model). let $n_g := \{n_i\}_{i=1}^l$ be a stationary multivariate Hawkes process with background intensities $\{\mu_i\}_{i=1}^l$ and excitation functions $\{\phi_{ij}(s)\}_{i,j=1}^l$. define the discretized event count in the n -th time window of size $\Delta \in (0, \delta)$ as $n(n)_i := n_{i-1} \dots$ - **Candidate:** if the link function ϕ is continuous and h is small enough, we can approximate ϕ by a piecewise constant function, which yields $\int_{h(t-1)}^{h(t)} \phi(u) h(u) du \approx h(t) \nu + h(t) \sum_{u=1}^l \phi(u) h(u)$. (4.1) this suggests to estimate the link function by a least squares approach.

Evidence 3 - **Rationale:** Both papers establish that discretized Hawkes processes admit linear representations where current counts depend linearly on lagged counts, encoding causal structure. - **Original:** theorem 4.1 shows that each current-bin count $n(n)_i$ (referred to as variable hereafter) is a linear combination of lagged counts $\{n(n-k)_j\}_{k \in \{1, \dots, n\}, j \in \{1, \dots, l\}}$ plus noise. the discretized variables therefore encode the causal structure of the underlying continuous-time subprocesses. - **Candidate:** theorem 4.1. let n be a Hawkes process with baseline intensity ν and link function ϕ satisfying assumption 2.1. additionally suppose that the following conditions hold: (i) let $k = k_t$ and $h = h_t$ be functions of t such that $k_t h_t \rightarrow \infty$, $k_t h_t^2 \rightarrow 0$, and $k_t h_t \rightarrow 0$ as $t \rightarrow \infty$. as $t \rightarrow \infty$.

Contribution 2: Identifiability conditions for latent subprocesses via rank constraints

Description: The authors derive necessary and sufficient conditions based on rank constraints of cross-covariance matrices that enable identification of latent confounder subprocesses and causal relationships in partially observed Hawkes processes, without prior knowledge of latent components.

This contribution was assessed against **1 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Causal screening in dynamical systems

URL: [View paper](#)

Brief Assessment

Causal Screening Dynamics[32] focuses on screening algorithms for learning causal structure in dynamical systems using local independence tests, not on identifiability conditions for latent confounders via rank constraints of cross-covariance matrices in Hawkes processes.

Contribution 3: Two-phase iterative discovery algorithm

Description: The authors develop an algorithm that iteratively identifies causal relations among known subprocesses and discovers new latent confounders using path-based rank conditions. The method requires no prior specification of the number or existence of latent subprocesses.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. CausalNET: Unveiling causal structures on event sequences by topology-informed causal attention

URL: [View paper](#)

Brief Assessment

CausalNET Topology Attention[17] focuses on event sequence prediction using transformer-based causal attention mechanisms, not on iterative latent subprocess discovery algorithms with path-based rank conditions.

2. Sok: History is a vast early warning system: Auditing the provenance of system intrusions

URL: [View paper](#)

Brief Assessment

Provenance Intrusion Auditing[14] focuses on system security auditing and provenance graph construction from audit logs, not on iterative algorithms for discovering latent subprocesses in event sequences or causal structure learning in Hawkes processes.

3. Iterative deep learning design of human enhancers exploits condensed sequence grammar to achieve cell-type specificity

URL: [View paper](#)

Brief Assessment

Enhancer Sequence Grammar[16] focuses on iterative deep learning for designing synthetic enhancers in synthetic biology, not on discovering latent subprocesses or causal structures in event sequences. The iterative approach here involves training models on enhancer activity data and experimentally validating designed sequences, which is fundamentally different from the causal discovery algorithm in the original paper.

4. Fast Autoregressive Models for Continuous Latent Generation

URL: [View paper](#)

Brief Assessment

Fast Autoregressive Latent[13] focuses on efficient image generation using autoregressive models with continuous latent spaces, not on iterative algorithms for discovering latent subprocesses in causal event sequences. The candidate addresses a completely different domain (computer vision) and problem (fast inference for image generation).

5. ORCHID: Streaming Threat Detection over Versioned Provenance Graphs

URL: [View paper](#)

Brief Assessment

ORCHID Streaming Detection[18] focuses on real-time provenance-based intrusion detection in cybersecurity systems, not on iterative algorithms for discovering latent subprocesses in causal event sequences or Hawkes processes.

6. High-recall causal discovery for autocorrelated time series with latent confounders

URL: [View paper](#)

Brief Assessment

High Recall Discovery[20] focuses on time series with autocorrelation and exogenous latent confounders, using conditional independence tests. The original paper targets event sequences (Hawkes processes) with endogenous latent confounders using rank-based covariance tests—fundamentally different data types and identification approaches.

7. Recurrences reveal shared causal drivers of complex time series

URL: [View paper](#)

Brief Assessment

Recurrences Causal Drivers[12] focuses on reconstructing unobserved driving signals from time series using recurrence graphs and topological data analysis, not on iteratively discovering latent subprocesses in event sequences through path-based rank conditions as in the original paper.

8. Discovering workflow nets of concurrent iterative processes

URL: [View paper](#)

Brief Assessment

Concurrent Workflow Discovery[15] focuses on discovering workflow nets from event logs in business process mining, using t-invariants to identify causal and concurrent relations. The original paper addresses causal structure learning in Hawkes processes with latent confounders using rank-based conditions on cross-covariance matrices—a fundamentally different domain and methodology.

9. Visual causality analysis of event sequence data

URL: [View paper](#)

Brief Assessment

Visual Causality Analysis[21] focuses on visual analytics for event sequence causality using Hawkes processes with user feedback, not on automated latent subprocess discovery algorithms with path-based rank conditions as in the original paper.

10. Graphical inference in non-Markovian linear-Gaussian state-space models

URL: [View paper](#)

Brief Assessment

Non-Markovian Graphical Inference[19] addresses parameter estimation in linear-Gaussian state-space models with known structure, not iterative discovery of latent subprocesses in event sequences without prior knowledge of their existence or number.

Appendix: Text Similarity Detection

No high-similarity text segments were detected across any compared papers.

References

- [0] Causal Structure Learning in Hawkes Processes with Complex Latent Confounder Networks [View paper](#)
- [1] Missing Data Imputation Based on Causal Inference to Enhance Advanced Persistent Threat Attack Prediction [View paper](#)
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- [22] Functional approximation of the marked Hawkes risk process [View paper](#)
- [23] Nonlinear Poisson autoregression and nonlinear Hawkes processes [View paper](#)
- [24] Forecasting High Frequency Order Flow Imbalance using Hawkes Processes [View paper](#)
- [25] Stability of discrete-time Hawkes process with inhibition: towards a general condition [View paper](#)
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- [27] Factorization and discrete-time representation of multivariate CARMA processes [View paper](#)

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