

# Novelty Assessment Report

**Paper:** Learning Dynamic Causal Graphs Under Parametric Uncertainty via Polynomial Chaos Expansions

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**Venue:** ICLR 2026 Conference Submission

**Year:** 2026

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## Abstract

Existing causal discovery methods are fundamentally limited by the assumption of a static causal graph, a constraint that fails in real-world systems where causal relationships dynamically vary with underlying system parameters. This discrepancy prevents the application of causal discovery in critical domains such as industrial process control, where understanding how causal effects change is essential. We address this gap by proposing a new paradigm that moves beyond static graphs to learn functional causal representations. We introduce a framework that models each causal link not as a static weight but as a function of measurable system parameters. By representing these functions using Polynomial Chaos Expansions (PCE), we develop a tractable method to learn the complete parametric causal structure from observational data. We provide theoretical proofs for the identifiability of these functional models and introduce a novel, provably convergent learning algorithm. On a large-scale chemical reactor dataset, our method learns the dynamic causal structure with a 90.9% F1-score, nearly doubling the performance of state-of-the-art baselines and providing an interpretable model of how causal mechanisms evolve.

### 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: **Learning Dynamic Causal Graphs Under Parametric Uncertainty**

A total of **50 papers** were analyzed and organized into a taxonomy with **18 categories**.

### Taxonomy Overview

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

- **Causal Graph Structure Learning and Identifiability**
- **Bayesian Network Inference and Dynamic Modeling**
- **Temporal Causal Modeling and Reasoning**
- **Time-Varying Parameter Models and Forecasting**
- **Graph Neural Networks for Spatiotemporal Causal Modeling**
- **Application Domains and Specialized Methods**

### Complete Taxonomy Tree

- Learning Dynamic Causal Graphs Under Parametric Uncertainty Survey Taxonomy
- Causal Graph Structure Learning and Identifiability
  - Parametric and Functional Causal Models ★ (2 papers)
  - [0] Learning Dynamic Causal Graphs Under Parametric Uncertainty via Polynomial Chaos Expansions (Anon et al., 2026) [View paper](#)
  - [1] Identifiability of causal graphs under nonadditive conditionally parametric causal models (Bodik, 2023) [View paper](#)
  - Nonparametric Causal Discovery (1 papers)
  - [14] Nonlinear Causal Discovery via Dynamic Latent Variables (Xing Yang, 2025) [View paper](#)
  - Time Series Causal Discovery (1 papers)
  - [48] Bootstrap aggregation and confidence measures to improve time series causal discovery (Debeire, 2023) [View paper](#)
- Bayesian Network Inference and Dynamic Modeling
  - Dynamic Bayesian Networks (3 papers)
  - [8] Learning Dynamic Bayesian Networks from Data: Foundations, First Principles and Numerical Comparisons (Vyacheslav Kungurtsev, 2024) [View paper](#)
  - [19] Temporal state change Bayesian networks for modeling of evolving multivariate state sequences: model, structure discovery and parameter estimation (Artur Mrowca, 2022) [View paper](#)
  - [28] Statistical network inference for time-varying molecular data with dynamic Bayesian networks (Frank Dondelinger, 2018) [View paper](#)
  - Static Network Inference (1 papers)
  - [34] Structural learning with time-varying components: tracking the cross-section of financial time series (Makram Talih, 2005) [View paper](#)
- Temporal Causal Modeling and Reasoning
  - Dynamic Uncertain Causality Graphs
  - Core DUCG Methodology (3 papers)
    - [7] Knowledge representation and reasoning with an extended dynamic uncertain causality graph under the Pythagorean uncertain linguistic environment (Yu-Jie Zhu, 2022) [View paper](#)
    - [31] Stochastic simulation method for reasoning of dynamic uncertain causality graph (DUCG) (Hao Nie, 2020) [View paper](#)
    - [42] Dynamic uncertain causality graph for knowledge representation and reasoning: continuous variable, uncertain evidence, and failure forecast (Qin Zhang, 2015) [View paper](#)

- Cubic DUCG Extensions (4 papers)
  - [13] Temporal Constrained Dynamic Uncertain Causality Graph for Root Cause Analysis of Intermittent Faults. (Qiqi Ma, 2025) [View paper](#)
  - [22] The cubic dynamic uncertain causality graph: A methodology for temporal process modeling and diagnostic logic inference (Chunling Dong, 2020) [View paper](#)
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  - [41] Cubic dynamic uncertain causality graph: A new methodology for modeling and reasoning about complex faults with negative feedbacks (Chunling Dong, 2018) [View paper](#)
- DUCG Applications (6 papers)
  - [10] Methodology and real-world applications of dynamic uncertain causality graph for clinical diagnosis with explainability and invariance (Zhang Zhan, 2024) [View paper](#)
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  - [45] Differential disease diagnoses of epistaxis based on dynamic uncertain causality graph. (Xusong Bu, 2023) [View paper](#)
- General Temporal Causal Frameworks (4 papers)
  - [18] Conditional simple temporal networks with uncertainty and decisions (Zavatteri, 2017) [View paper](#)
  - [35] Modeling time-varying uncertain situations using dynamic influence nets (Sajjad Haider, 2008) [View paper](#)
  - [44] Probabilistic temporal networks: A unified framework for reasoning with time and uncertainty (Eugene Santos, 1999) [View paper](#)
  - [49] Modeling dynamic causal interaction with Bayesian networks: temporal noisy gates (SF Galın, 2000) [View paper](#)
- Time-Varying Parameter Models and Forecasting
  - Time-Varying Vector Autoregressions (4 papers)
    - [24] Structural panel bayesian var with multivariate time-varying volatility to jointly deal with structural changes, policy regime shifts, and endogeneity issues (Antonio Pacifico, 2021) [View paper](#)
    - [29] Large Mixed-Frequency Vars with a Parsimonious Time-Varying Parameter Structure (Thomas Gıtzt, 2021) [View paper](#)
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    - [47] General Bayesian time-varying parameter VARs for predicting government bond yields (Manfred M. Fischer, 2021) [View paper](#)
  - Time-Varying Regression Models (2 papers)
    - [17] Manifold-constrained Gaussian process inference for time-varying parameters in dynamic systems (Yan Sun, 2023) [View paper](#)
    - [26] Fast and Flexible Bayesian Inference in Time-varying Parameter Regression Models (Hauzenberger, 2021) [View paper](#)
  - Causal Inference with Time-Varying Effects (5 papers)
    - [12] Time-varying causality between investor sentiment and oil price: Does uncertainty matter? (Mohamed Sahbi Nakhli, 2023) [View paper](#)
    - [15] Inferring causal impact using Bayesian structural time-series models (Rmy, 2015) [View paper](#)
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  - [4] Causal Spherical Hypergraph Networks for Modelling Social Uncertainty (Harit, 2025) [View paper](#)
  - [11] Dynamic causal explanation based diffusion-variational graph neural network for spatiotemporal forecasting (Guojun Liang, 2024) [View paper](#)
  - [20] Diff-MGR: Dynamic causal graph attention and pattern reproduction guided diffusion model for multivariate time series probabilistic forecasting (Tianlong Zhao, 2024) [View paper](#)
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  - [40] CausalGRIT: Causal Graph Reasoning for Traffic Congestion Prediction From Statistical Association to Casual Intervention (S Liu, 2025) [View paper](#)
- Application Domains and Specialized Methods
  - Industrial and Engineering Systems (3 papers)
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    - [3] Causal inference-based dynamic optimization for disassembly line balancing with uncertain component states (Yilin Fang, 2025) [View paper](#)
    - [9] A new framework for water quality forecasting coupling causal inference, time-frequency analysis and uncertainty quantification (Chi Zhang, 2024) [View paper](#)
  - Spatiotemporal Pattern Discovery (2 papers)
    - [5] Visual causal analysis of multivariate time series (Xiaoxi Zhang, 2025) [View paper](#)
    - [6] Discovering Spatio-Temporal Co-Occurrence Patterns of Crimes with Uncertain Occurrence Time (Yuanfang Chen, 2022) [View paper](#)
  - Knowledge Graphs and Embedding (1 papers)
    - [23] Embedding Uncertain Temporal Knowledge Graphs (Tongxin Li, 2023) [View paper](#)
  - Cognitive and Behavioral Sciences (3 papers)
    - [27] Neural processing as causal inference (Timm Lochmann, 2011) [View paper](#)
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    - [37] Integrating Causal Inference with Deep Reinforcement Learning for Autonomous Cyber-Physical System Adaptation (Bhosale, 2025) [View paper](#)

## Narrative

Core task: learning dynamic causal graphs under parametric uncertainty. The field addresses how causal relationships evolve over time when model parameters themselves are uncertain or changing. The taxonomy reveals several complementary perspectives: one branch focuses on Causal Graph Structure Learning and Identifiability, examining foundational questions about when and how causal structures can be uniquely recovered from data, including parametric and functional models such as Nonadditive Causal Identifiability[1]. Another branch emphasizes Bayesian Network Inference and Dynamic Modeling, leveraging probabilistic frameworks like Learning Dynamic Bayesian[8] networks to handle temporal dependencies and uncertainty propagation. Temporal Causal Modeling and Reasoning explores methods for tracking causality across time, as seen in Temporal Causal Inference[2] and works on uncertain temporal graphs[23]. Time-Varying Parameter Models and Forecasting tackle scenarios where parameters drift or shift, exemplified by Bayesian Structural Timeseries[15] and Timevarying Structural VAR[38]. Graph Neural Networks for Spatiotemporal Causal Modeling apply deep learning architectures to capture complex spatial and temporal patterns, while Application Domains and Specialized Methods demonstrate how these techniques solve real-world problems in healthcare, finance, and industrial diagnostics.

A particularly active line of work centers on parametric and functional causal models, where researchers grapple with identifiability under nonstandard assumptions and evolving structures. Dynamic Causal Graphs[0] sits squarely within this branch, addressing the challenge of inferring causal graphs when both structure and parameters change over time. Its emphasis on parametric uncertainty distinguishes it from nearby efforts like Nonadditive Causal Identifiability[1], which focuses on static identifiability conditions under nonadditive noise, and Temporal Causal Inference[2], which prioritizes temporal reasoning without explicit parametric drift modeling. Meanwhile, Bayesian approaches such as Variational Bayesian Causal[32] and Dynamic Bayesian Networks[28] offer complementary probabilistic machinery for uncertainty quantification, though they often assume fixed or slowly varying structures. Open questions remain about scalability, the trade-off between model flexibility and identifiability guarantees, and how to integrate domain knowledge when parameters exhibit abrupt regime changes.

## Related Works in Same Category

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

### 1. Identifiability of causal graphs under nonadditive conditionally parametric causal models

**Authors:** Bodik, Juraj, Juraj Bodik, Chavez-Demoulin ValÃ©rie, ValÃ©rie Chavezâ€œDemoulin, et al. (6 authors total) | **Year/Venue:** 2023 | **URL:** [View paper](#)

#### Abstract

Existing approaches to causal discovery often rely on restrictive modeling assumptions that limit their applicability in real-world settings, particularly when data are heavy-tailed or contain a mixture of discrete and continuous variables. Identifiability of causal graphs has been established under several structural models, including linear non-Gaussian models, post-nonlinear models, and location-scale models. However, these frameworks may not capture the diversity of distributions observed in...

#### Relationship Analysis

Both papers belong to the parametric and functional causal models category, modeling causal relationships as functions of system parameters or under specific parametric assumptions. The original paper focuses on learning dynamic causal graphs where edge weights are explicit functions of measurable operating parameters (e.g., temperature, catalyst activity) using Polynomial Chaos Expansions, targeting industrial process control with time-varying mechanisms. The candidate paper addresses identifiability of causal graphs under conditionally parametric causal models where conditional distributions belong to known parametric families (Gaussian, Poisson, Gamma), focusing on theoretical identifiability conditions and handling mixtures of discrete and continuous variables rather than dynamic parameter-dependent edge functions.

## Contributions Analysis

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**Overall novelty summary.** The paper proposes a framework for learning functional causal representations where each causal link is modeled as a function of measurable system parameters, using Polynomial Chaos Expansions for tractability. It resides in the 'Parametric and Functional Causal Models' leaf, which contains only two papers total. This is a notably sparse research direction within the broader taxonomy of fifty papers, suggesting the specific combination of functional causal modeling with parametric uncertainty remains relatively unexplored compared to neighboring areas like Dynamic Bayesian Networks or Time-Varying Parameter Models.

The taxonomy reveals several related but distinct research directions. The sibling leaf 'Nonparametric Causal Discovery' focuses on latent variables and distribution-free approaches without explicit functional forms. Nearby branches include 'Dynamic Bayesian Networks' with probabilistic temporal dependencies and 'Time-Varying Parameter Models' addressing parameter drift in forecasting contexts. The paper's approach diverges by explicitly modeling causal links as parameter-dependent functions rather than treating parameters as latent states or time-indexed coefficients, positioning it at the intersection of structural causal discovery and parametric modeling.

Among twenty candidates examined across three contributions, no clearly refuting prior work was identified. The functional causal representation framework examined three candidates with zero refutations, the PCT-CD algorithm examined seven candidates with zero refutations, and the theoretical convergence guarantees examined ten candidates with zero refutations. This suggests that within the limited search scope, the specific combination of functional causal modeling, PCE-based representations, and identifiability proofs for parameter-dependent structures appears relatively novel, though the search scale precludes definitive claims about the broader literature.

Based on top-twenty semantic matches and the sparse taxonomy leaf, the work appears to occupy a distinct niche combining causal discovery with parametric functional modeling. The analysis covers closely related methods in causal structure learning and temporal modeling but does not exhaustively survey all parametric uncertainty literature or industrial process control applications, which may contain relevant domain-specific approaches not captured in this search.

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

### Contribution 1: Functional causal representation framework with identifiability guarantees

**Description:** The authors formalize an industrial structural causal model where edge weights are explicit functions of operating conditions rather than static values. They prove identifiability of these parametric mechanisms under mild assumptions, establishing that the DAG and parameter-dependent functions can be uniquely recovered from observational data.

This contribution was assessed against **3 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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### 1. Causal Discovery in Linear Structural Causal Models with Deterministic Relations

**URL:** [View paper](#)

#### Brief Assessment

Deterministic Causal Models[60] focuses on linear structural causal models with deterministic relations and latent confounders, not on parametric edge functions that vary with operating conditions. The original paper models edge weights as explicit functions of

measurable system parameters using polynomial chaos expansions, whereas the candidate addresses identifiability under deterministic dependencies among observed variables.

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## 2. SCM-VAE: Learning Identifiable Causal Representations via Structural Knowledge

URL: [View paper](#)

### Brief Assessment

SCM-VAE[59] focuses on learning causal representations in latent variable models using structural causal models with additive noise, not on industrial parametric edge functions that vary with operating conditions as explicit functions of measurable system parameters.

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## 3. Counterfactual (Non-)identifiability of Learned Structural Causal Models

URL: [View paper](#)

### Brief Assessment

Counterfactual Nonidentifiability[58] focuses on counterfactual identifiability of learned structural causal models with deep generative models, not on learning parametric edge functions that vary with operating conditions as in the original paper's industrial process control framework.

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## Contribution 2: PCT-CD algorithm for parametric causal discovery

**Description:** The authors develop an end-to-end algorithm that uses Polynomial Chaos Expansions to represent causal functions, introduces a novel conditional independence test tailored to parametric uncertainty, and employs natural gradient optimization for score-based refinement. The method learns complete parametric causal structures from observational data.

This contribution was assessed against **7 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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## 1. Robust Model-Free Identification of the Causal Networks Underlying Complex Nonlinear Systems

URL: [View paper](#)

### Brief Assessment

Robust Causal Networks[55] uses polynomial functions for model-free Granger causality analysis in time-series networks, whereas the original paper develops polynomial chaos expansions to represent parameter-dependent causal functions in structural equation models with explicit parametric uncertainty quantification.

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## 2. Bayesian active causal discovery with multi-fidelity experiments

URL: [View paper](#)

### Brief Assessment

Bayesian Active Discovery[52] focuses on multi-fidelity experimental design for causal discovery, not on polynomial chaos expansions for representing parameter-dependent causal functions. The candidate addresses oracle selection across fidelities, whereas the original models causal edge weights as explicit functions of operating parameters using PCE.

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## 3. Learning Causal Structures from Mixed Dynamics via Polynomial Chaos Expansion

URL: [View paper](#)

### Brief Assessment

Polynomial Chaos Expansion[56] focuses on mixed linear-nonlinear causal discovery from observational data, not on parametric uncertainty where edge weights vary as functions of operating parameters. The candidate uses PCE for residual analysis to detect nonlinearity, while the original uses PCE to represent parameter-dependent causal coefficients.

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## 4. Model Construction of the Basic Theories of Probability Theory in the Quantification of Uncertainty

URL: [View paper](#)

### Brief Assessment

Probability Theory Quantification[54] focuses on general probability theory frameworks for uncertainty quantification in various domains (autonomous driving, medical diagnosis), not on causal discovery algorithms using polynomial chaos expansions and conditional independence tests for learning dynamic causal graphs.

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## 5. Plenary Session 1. Chair: Peter Z. Qian (University of Wisconsin) From Big Data to Big Statistics John Sall (SAS Institute Inc.) When you scale up the analysis â

URL: [View paper](#)

### Brief Assessment

Big Data Statistics[57] appears to be a plenary session abstract discussing general statistical concepts for big data. The minimal context provided mentions polynomial chaos and independence concepts but does not present a complete causal discovery algorithm or methodology that would challenge the novelty of PCT-CD's integrated framework combining PCE representation, conditional independence testing, and score-based optimization for parametric causal structures.

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## 6. Dimension reduction of polynomial regression models for the estimation of Granger causality in high-dimensional time series

URL: [View paper](#)

### Brief Assessment

Granger Causality Reduction[53] focuses on dimension reduction for Granger causality estimation in time series using polynomial VAR models, not on learning complete parametric causal structures from observational data with polynomial chaos expansions and conditional independence tests as in the original paper.

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## 7. Testing Causal Models with Hidden Variables in Polynomial Delay via Conditional Independencies

URL: [View paper](#)

### Brief Assessment

Polynomial Delay Testing[51] focuses on testing causal models with hidden variables using conditional independence tests and d-separation criteria, not on learning parametric causal structures using polynomial chaos expansions. The candidate addresses model testing via graph-theoretic properties, while the original develops an end-to-end learning algorithm for parameter-varying causal functions.

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### Contribution 3: Theoretical convergence and sample complexity guarantees

**Description:** The authors establish finite-sample guarantees for graph recovery, proving consistency of coefficient estimators and deriving explicit sample complexity bounds. They also prove linear convergence of the natural gradient descent procedure used in the optimization phase.

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.

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#### 1. Structural agnostic modeling: Adversarial learning of causal graphs

URL: [View paper](#)

##### Brief Assessment

[Final Audit Failure] The model insisted on a refutation claim but failed to provide verifiable evidence after multiple retries. Marked as cannot\_refute for safety. Please manually verify the candidate text.

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#### 2. Sample complexity of distinguishing cause from effect

URL: [View paper](#)

##### Brief Assessment

Cause Effect Complexity[66] addresses sample complexity for distinguishing causal direction in two-variable systems, not for learning dynamic causal graphs with parameter-dependent edge weights as in the original paper.

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#### 3. Sample-efficient learning of concepts with theoretical guarantees: from data to concepts without interventions

URL: [View paper](#)

##### Brief Assessment

Data Efficient Concepts[61] focuses on learning concept-to-representation alignments in concept bottleneck models using causal representation learning, not on causal graph structure learning with parametric uncertainty as in the original paper.

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#### 4. Progressive generalization risk reduction for data-efficient causal effect estimation

URL: [View paper](#)

##### Brief Assessment

Progressive Generalization Risk[65] focuses on active learning for causal effect estimation with generalization risk bounds, not on causal structure learning or graph recovery with sample complexity guarantees as in the original paper.

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#### 5. Sample Complexity of Interventional Causal Representation Learning

URL: [View paper](#)

##### Brief Assessment

Interventional Representation Learning[63] focuses on causal representation learning with latent variables and interventions, establishing sample complexity for recovering latent causal structures. The original paper addresses parametric uncertainty in dynamic causal graphs with polynomial chaos expansions for observable variables, a fundamentally different problem setting.

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#### 6. Combining T-learning and DR-learning: A framework for oracle-efficient estimation of causal contrasts

URL: [View paper](#)

##### Brief Assessment

T DR Learning[64] focuses on oracle-efficient estimation of causal contrasts (CATE, CRR) through efficient plug-in learning, not on causal structure learning or graph recovery which is the focus of the original paper's sample complexity bounds.

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#### 7. Sample Complexity Bounds for Score-Matching: Causal Discovery and Generative Modeling

URL: [View paper](#)

##### Brief Assessment

[Final Audit Failure] The model insisted on a refutation claim but failed to provide verifiable evidence after multiple retries. Marked as cannot\_refute for safety. Please manually verify the candidate text.

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#### 8. Sample Complexity of Nonparametric Closeness Testing for Continuous Distributions and Its Application to Causal Discovery with Hidden Confounding

URL: [View paper](#)

##### Brief Assessment

Nonparametric Closeness Testing[69] focuses on sample complexity for closeness testing of continuous distributions and causal discovery with hidden confounding, not on convergence guarantees for coefficient estimators in parametric causal graph learning with polynomial chaos expansions.

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#### 9. Automatic Debiased Machine Learning of Causal and Structural Effects

URL: [View paper](#)

##### Brief Assessment

The candidate paper focuses on debiased machine learning for causal and structural effects with different theoretical objectives. While both papers provide convergence guarantees, the candidate addresses bias correction in high-dimensional regression settings rather than dynamic causal graph recovery under parametric uncertainty.

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#### 10. Federated learning of generalized linear causal networks

URL: [View paper](#)

##### Brief Assessment

Federated Causal Networks[62] focuses on federated learning of causal graphs with finite-sample oracle guarantees in distributed settings, not on polynomial chaos expansions for parameter-varying causal mechanisms. The theoretical guarantees address different problems.

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### Appendix: Text Similarity Detection

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

## References

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- [66] Sample complexity of distinguishing cause from effect [View paper](#)
- [67] Automatic Debiased Machine Learning of Causal and Structural Effects [View paper](#)
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