Novelty Assessment Report

Paper: Distributional Equivalence in Linear Non-Gaussian Latent-Variable Cyclic Causal Models: Characterization and Learning
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Abstract

Causal discovery with latent variables is a fundamental task. Yet most existing methods, if not all, rely on strong structural assumptions, such as enforcing specific indicator patterns for latents or restricting how they can interact with others. We argue that a core obstacle to a general, structural-assumption-free approach is the lack of an equivalence characterization: without knowing what can be identified, one generally cannot design methods for how to identify it. In this work, we aim to close this gap for linear non-Gaussian models. We establish the graphical criterion for when two graphs with arbitrary latent structure and cycles are distributionally equivalent, that is, they induce the same observed distribution set. Key to our approach is a new tool, edge rank constraints, which fills a missing piece in the toolbox for latent-variable causal discovery in even broader settings. We further provide a procedure to traverse the whole equivalence class and develop an algorithm to recover models from data up to such equivalence. To our knowledge, this is the first equivalence characterization with latent variables in any parametric setting without structural assumptions, and hence the first structural-assumption-free discovery method. Code and an interactive demo are available at https://equiv.cc.

Core Task Landscape

This paper addresses: **Causal Discovery with Latent Variables in Linear Non-Gaussian Models**

A total of **50 papers** were analyzed and organized into a taxonomy with **26 categories**.

Taxonomy Overview

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

- **Identifiability Theory and Equivalence Characterization**
- **Algorithm Design and Methodology**
- **Specialized Model Extensions and Settings**
- **Causal Effect Estimation and Inference**
- **Model Validation and Testing**
- **Domain-Specific Applications and Extensions**
- **Methodological Reviews and Surveys**
- **Special Latent Confounder Structures**

Complete Taxonomy Tree

- Causal Discovery with Latent Variables in Linear Non-Gaussian Models Survey Taxonomy
- Identifiability Theory and Equivalence Characterization
  - General Identifiability Conditions ★ (4 papers)
  - [0] Distributional Equivalence in Linear Non-Gaussian Latent-Variable Cyclic Causal Models: Characterization and Learning (Anon et al., 2026) View paper
  - [7] Parameter identification in linear non-Gaussian causal models under general confounding (Tramontano, 2024) View paper
  - [29] Statistical undecidability in linear, non-gaussian causal models in the presence of latent confounders (Konstantin Genin, 2021) View paper
  - [31] Estimation in linear non-Gaussian causal models under general confounding (Hug, 2024) View paper
  - Identifiability Under Restricted Latent Structure (4 papers)
  - [3] Identification of linear non-gaussian latent hierarchical structure (F Xie, 2022) View paper
  - [16] Identification of partially observed linear causal models: Graphical conditions for the non-gaussian and heterogeneous cases (Jeffery Adams, 2021) View paper
  - [26] Identification of partially observed causal models: Graphical conditions for the linear non-gaussian and heterogeneous cases (J Adams, 2021) View paper
  - [39] Rank Constraints of High-Order Cumulants for Learning Linear Non-Gaussian Latent Polytree (Ruichu Cai, 2025) View paper
  - Measurement Error and Proxy Variables (2 papers)
  - [14] Causal discovery in linear latent variable models subject to measurement error (Yang Yu-qin, 2022) View paper
  - [37] Causal Discovery with Linear Non-Gaussian Models under Measurement Error: Structural Identifiability Results. (Zhang, 2018) View paper
- Algorithm Design and Methodology
  - Constraint-Based and Hybrid Methods (3 papers)
  - [13] Causal discovery in linear non-gaussian acyclic model with multiple latent confounders (Wei Chen, 2021) View paper
  - [40] Discovering unconfounded causal relationships using linear non-gaussian models (Doris Entner, 2010) View paper
  - [47] FRITL: A Hybrid Method for Causal Discovery in the Presence of Latent Confounders (Chen Wei, 2021) View paper
  - Score-Based and Continuous Optimization Methods (4 papers)
  - [4] Score-based causal discovery of latent variable causal models (I Ng, 2024) View paper

- [32] Differentiable Causal Discovery of Linear Non-Gaussian Acyclic Models Under Unmeasured Confounding (Shohei, 2025) View paper
- [43] Score matching through the roof: linear, nonlinear, and latent variables causal discovery (Montagna Francesco, 2024) View paper
- [50] Gradient-based causal discovery with latent variables (Haotian Ni, 2025) View paper
- ICA-Based and Overcomplete ICA Methods (2 papers)
- [1] Causal discovery of linear non-gaussian causal models with unobserved confounding (Robeva, 2024) View paper
- [25] Disentangling observed causal effects from latent confounders using method of moments (Liu Anqi, 2021) View paper
- Higher-Order Cumulant and Moment-Based Methods (2 papers)
- [21] Third-order moment varieties of linear non-Gaussian graphical models (AmÃ©ndola, 2021) View paper
- [24] Causal Discovery for Linear DAGs with Dependent Latent Variables via Higher-order Cumulants (Cai Ming, 2025) View paper
- Repetitive and Iterative Discovery Procedures (3 papers)
- [17] RCD: Repetitive causal discovery of linear non-Gaussian acyclic models with latent confounders (Takashi Maeda, 2020) View paper
- [30] Repetitive causal discovery of linear non-Gaussian acyclic models in the presence of latent confounders (Takashi Maeda, 2021) View paper
- [33] Causal discovery of linear non-Gaussian acyclic models in the presence of latent confounders (Shohei, 2020) View paper
- Generalized Independent Noise Condition Methods (2 papers)
- [12] Generalized independent noise condition for estimating latent variable causal graphs (Feng Xie, 2020) View paper
- [35] Generalized Independent Noise Condition for Estimating Linear Non-Gaussian Latent Variable Graphs (Feng Xie, 2020) View paper

- Specialized Model Extensions and Settings
  - Streaming and Online Learning (1 papers)
  - [9] LiNGAM-SF: Causal Structural Learning Method With Linear Non-Gaussian Acyclic Models for Streaming Features (Chenglin Zhang, 2025) View paper
  - Multi-Dataset and Multi-Domain Learning (2 papers)
  - [11] Causal Discovery with Hidden Variables Based on Non-Gaussianity and Nonlinearity (Takashi Nicholas Maeda, 2024) View paper
  - [22] Causal discovery from multiple data sets with non-identical variable sets (Biwei Huang, 2020) View paper
  - Mixed Graph and Multidirected Edge Models (2 papers)
  - [8] Causal discovery with unobserved confounding and non-gaussian data (Y. Samuel Wang, 2023) View paper
  - [27] Learning linear non-Gaussian graphical models with multidirected edges (Yi-Heng Liu, 2020) View paper
  - Nonlinear and Dynamic Extensions (1 papers)
  - [2] Nonlinear Causal Discovery via Dynamic Latent Variables (Xing Yang, 2025) View paper
  - ODE and Continuous-Time Models (1 papers)
  - [6] Identifiability analysis of linear ODE systems with hidden confounders (Xi Geng, 2024) View paper
- Causal Effect Estimation and Inference
  - Causal Effect Identification and Estimation (3 papers)
  - [10] Learning linear non-Gaussian causal models in the presence of latent variables (Salehkaleybar, 2020) View paper
  - [18] Estimation of causal effects using linear non-Gaussian causal models with hidden variables (Patrik O. Hoyer, 2008) View paper
  - [48] Identifiability of causal effects with non-Gaussianity and auxiliary covariates (SHUAI KANG, 2023) View paper
  - Instrumental Variable Methods (2 papers)
  - [19] Testability of Instrumental Variables in Linear Non-Gaussian Acyclic Causal Models (Feng Xie, 2022) View paper
  - [23] Testing the validity of instrumental variables in justâidentified linear nonâGaussian models (Wolfgang Wiedermann, 2025) View paper
  - Sample-Specific and Root Cause Analysis (1 papers)
  - [42] Sample-Specific Root Causal Inference with Latent Variables (Strobl, 2022) View paper
- Model Validation and Testing
  - Goodness-of-Fit Tests (1 papers)
  - [15] Goodness-of-fit tests for linear non-Gaussian structural equation models (Schkoda, 2023) View paper
  - Bivariate Causal Direction Testing (2 papers)
  - [5] Distinguishing cause from effect in psychological research: An independenceâbased approach under linear nonâGaussian models (Dexin Shi, 2025) View paper
  - [49] Latent causation: An algorithm for pairs of correlated latent variables in linear non-Gaussian structural equation modeling (Bontempi, 2020) View paper
- Domain-Specific Applications and Extensions
  - Biomedical and Temporal Pathway Analysis (1 papers)
  - [28] Identifying temporal pathways using biomarkers in the presence of latent non-Gaussian components. (Shanghong Xie, 2024) View paper
  - Manufacturing and Industrial Applications (1 papers)
  - [41] Toward Discovering Causal Relations from Manufacturing Data: Heteroscedasticity and Variable Groups (Kikuchi, 2024) View paper
  - Incomplete Time-Series Data (1 papers)
  - [34] A Survey on Causal Discovery with Incomplete Time-Series Data (X Chen, 2023) View paper
- Methodological Reviews and Surveys
  - LiNGAM Framework Reviews (2 papers)
  - [38] LiNGAM: Non-Gaussian methods for estimating causal structures (Shimizu, 2014) View paper
  - [45] Statistical causal discovery: LiNGAM approach (Shimizu, 2022) View paper
  - Theses and Comprehensive Treatments (2 papers)
  - [36] Causal structure learning and effect identification in linear non-Gaussian models and beyond (Doris Entner, 2013) View paper
  - [44] Linear Structural Equation Models with Non-Gaussian Errors: Estimation and Discovery (Y. Samuel Wang, 2018) View paper
- Special Latent Confounder Structures
  - Gaussian Latent Confounders (1 papers)

- ◦ [46] Causality in linear nongaussian acyclic models in the presence of latent gaussian confounders (Zhitang Chen, 2013) View paper
- ◦ Independence Testing Under Measurement Error (1 papers)
- ◦ [20] Independence Testing-Based Approach to Causal Discovery under Measurement Error and Linear Non-Gaussian Models (Dai, 2022) View paper

Narrative

Core task: Causal discovery with latent variables in linear non-Gaussian models. The field is organized around several complementary branches. Identifiability Theory and Equivalence Characterization establishes the theoretical foundations, clarifying when and under what conditions latent-variable structures can be uniquely recovered from observed data—works such as Parameter Identification Confounding[7] and Statistical Undecidability Latent[29] explore these boundaries. Algorithm Design and Methodology develops practical procedures, including constraint-based and score-based approaches like Score-based Latent Discovery[4] and Gradient-based Latent Discovery[50], while Specialized Model Extensions and Settings address nonlinear dynamics (Nonlinear Dynamic Latent[2]), measurement error (Measurement Error Discovery[14]), and hierarchical structures (Linear NonGaussian Hierarchical[3]). Additional branches cover Causal Effect Estimation and Inference, Model Validation and Testing (e.g., Goodness-of-fit LiNGAM[15]), Domain-Specific Applications, and Methodological Reviews. Special Latent Confounder Structures examine particular patterns such as instrumental variables and repetitive confounding.

A central tension across these branches concerns the trade-off between identifiability guarantees and model flexibility: stronger non-Gaussian assumptions enable finer-grained recovery of latent structures, yet relaxing these assumptions often leads to partial identification or equivalence classes. Within Identifiability Theory, Distributional Equivalence Cyclic[0] investigates general conditions for distinguishing models under latent confounding, situating itself alongside Parameter Identification Confounding[7], which focuses on parameter-level uniqueness, and General Confounding Estimation[31], which addresses broader estimation frameworks. While Parameter Identification Confounding[7] emphasizes sufficient conditions for parameter recovery and General Confounding Estimation[31] targets practical inference strategies, Distributional Equivalence Cyclic[0] contributes by characterizing when different causal graphs yield indistinguishable distributions—a foundational question that informs both algorithmic design and the interpretation of empirical results. This line of work underscores ongoing challenges in balancing theoretical rigor with computational tractability when latent variables are present.

Related Works in Same Category

The following **3 sibling papers** share the same taxonomy leaf node with the original paper:

1. Parameter identification in linear non-Gaussian causal models under general confounding

Authors: Tramontano, Daniele, Drton, Mathias, Etesami, et al. (6 authors total) | **Year/Venue**: 2024 | **URL**: View paper

Abstract

Linear non-Gaussian causal models postulate that each random variable is a linear function of parent variables and non-Gaussian exogenous error terms. We study identification of the linear coefficients when such models contain latent variables. Our focus is on the commonly studied acyclic setting, where each model corresponds to a directed acyclic graph (DAG). For this case, prior literature has demonstrated that connections to overcomplete independent component analysis yield effective criteria...

Relationship Analysis

Both papers belong to the General Identifiability Conditions category, establishing identifiability criteria for linear non-Gaussian causal models with latent variables without restrictive structural assumptions. They overlap in addressing parameter identifiability in latent variable settings using linear non-Gaussian assumptions and developing graphical criteria for identifiability. However, the original paper focuses on distributional equivalence characterization in cyclic models with arbitrary latent structure, while the candidate paper specifically addresses parameter identification under general (including non-linear) confounding in acyclic DAG settings, providing polynomial-time algorithmic implementations for deciding generic identifiability of direct causal effects.

2. Statistical undecidability in linear, non-gaussian causal models in the presence of latent confounders

Authors: Konstantin Genin | **Year/Venue**: 2021 | **URL**: View paper

Abstract

â¦ , and all faithful acyclic linear non-Gaussian models over some â¦ knew exactly how many latent variables were necessary to â¦ In recent years, the field of causal discovery has produced â¦

Relationship Analysis

Both papers belong to the General Identifiability Conditions category, establishing identifiability criteria for causal structures in linear non-Gaussian models with latent variables. The original paper focuses on distributional equivalence characterization in cyclic models with arbitrary latent structure, introducing edge rank constraints and providing a complete equivalence class traversal procedure. The candidate paper addresses statistical decidability of causal orientation in acyclic models with latent confounders, proving that while causal ancestry is identifiable in the limit under faithfulness, it is not statistically decidable (cannot bound error probabilities at finite samples), contrasting with the original paper's structural equivalence characterization approach.

3. Estimation in linear non-Gaussian causal models under general confounding

Authors: Melanie Hug | **Year/Venue**: 2024 • mediaTUM â the media and publications repository of the Technical University Munich (Technical University Munich) | **URL**: View paper

Abstract

In many areas of science, understanding dependencies in data and identifying cause-and-effect relationships is essential. Linear causal models are a powerful approach for this. In these models, random variables are expressed as linear functions of parent variables and error terms. In most cases, normally distributed error terms are considered. In this paper, however, we consider models whose error terms are not normally distributed and which are distorted by the influence of general confounding ...

Relationship Analysis

Both papers belong to the General Identifiability Conditions category, establishing identifiability criteria for linear non-Gaussian causal models without restricting latent variable interactions or graph topology. The original paper focuses on distributional equivalence characterization in cyclic models with arbitrary latent structure, introducing edge rank constraints as a novel tool for equivalence class traversal. The candidate paper addresses identifiability and estimation under general confounding using ADMGs (acyclic-directed mixed graphs), implementing a practical optimization-based estimation method with Python, thus focusing on the acyclic case with a more applied estimation perspective rather than the original's theoretical equivalence characterization in cyclic settings.

Contributions Analysis

Overall novelty summary. The paper establishes a graphical criterion for distributional equivalence in linear non-Gaussian models with arbitrary latent structure and cycles, introduces edge rank constraints as a new analytical tool, and proposes the glvLiNG algorithm for structural-assumption-free causal discovery. It resides in the 'General Identifiability Conditions' leaf alongside three sibling papers that also address identifiability without restricting latent variable interactions. This leaf sits within the broader 'Identifiability Theory and Equivalence Characterization' branch, which contains three leaves totaling nine papers, indicating a moderately populated but not overcrowded research direction focused on theoretical foundations.

The taxonomy reveals that neighboring leaves address 'Identifiability Under Restricted Latent Structure' (four papers assuming hierarchical or polytree arrangements) and 'Measurement Error and Proxy Variables' (two papers on noisy observations). The paper's structural-assumption-free approach contrasts with these restricted settings, positioning it closer to the general identifiability frontier. Adjacent branches include 'Algorithm Design and Methodology' (eighteen papers across six leaves) and 'Specialized Model Extensions' (five papers), suggesting that while algorithmic development is well-explored, foundational equivalence characterization in unrestricted settings remains less densely studied. The taxonomy's scope and exclude notes confirm that this work targets theoretical conditions rather than algorithm-centric contributions.

Among twenty-two candidates examined via limited semantic search, none clearly refute any of the three contributions. The graphical equivalence criterion examined five candidates with zero refutations, edge rank constraints examined seven with zero refutations, and the glvLiNG algorithm examined ten with zero refutations. This suggests that within the search scope, no prior work provides overlapping results for these specific contributions. However, the limited scale—twenty-two candidates rather than an exhaustive survey—means that relevant prior work outside the top semantic matches or citation network may exist. The absence of refutations across all contributions indicates either genuine novelty or gaps in the search coverage.

Based on the limited literature search, the work appears to occupy a relatively sparse area within general identifiability theory, with no immediate prior work overlapping its core contributions among the candidates examined. The taxonomy context shows that while the broader field is active, structural-assumption-free equivalence characterization remains underexplored compared to algorithm design or restricted-structure settings. The analysis covers top semantic matches and citation expansion but does not claim exhaustive coverage, leaving open the possibility of relevant work beyond the examined scope.

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

Contribution 1: Graphical criterion for distributional equivalence in linear non-Gaussian latent-variable cyclic models

Description: The authors provide the first equivalence characterization for linear non-Gaussian models that allows arbitrary latent variables and cycles without structural assumptions. This characterization determines when two causal graphs induce the same observed distribution set.

This contribution was assessed against **5 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. Near-Optimal Experiment Design in Linear non-Gaussian Cyclic Models

URL: View paper

Brief Assessment

Experiment Design Cyclic[60] focuses on experiment design for causal structure learning in cyclic models, not on characterizing distributional equivalence with latent variables. The candidate addresses a different problem domain.

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2. Causal Discovery for Linear Non-Gaussian Models with Disjoint Cycles

URL: View paper

Brief Assessment

Disjoint Cycles Discovery[59] focuses on cycle-disjoint graphs without latent variables, whereas the original contribution addresses arbitrary latent variables and cycles without structural assumptions.

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3. Causal discovery of linear non-gaussian causal models with unobserved confounding

URL: View paper

Brief Assessment

Linear NonGaussian Confounding[1] focuses on acyclic models with latent confounding, not cyclic models. The paper explicitly states 'we consider linear non-gaussian structural equation models that involve latent confounding' with acyclic graphs, whereas the original contribution addresses arbitrary cycles.

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4. Discovering Cyclic Causal Models by Independent Components Analysis

URL: View paper

Brief Assessment

Independent Components Cyclic[61] focuses on discovering cyclic causal models without latent variables, whereas the original paper addresses the more complex setting with arbitrary latent variables and cycles. The candidate does not provide a graphical criterion for distributional equivalence in latent-variable models.

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5. Local Causal Discovery with Linear non-Gaussian Cyclic Models

URL: View paper

Brief Assessment

Local Causal Cyclic[62] focuses on local causal discovery from a target variable's Markov blanket in cyclic models, not on characterizing global distributional equivalence classes with arbitrary latent variables.

Contribution 2: Edge rank constraints as a new tool for latent-variable causal discovery

Description: The authors introduce edge rank constraints, a local edge-level constraint that complements path ranks. This tool enables easier manipulation of rank-based conditions and has potential applications across broader causal discovery settings beyond the specific linear non-Gaussian framework.

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. Latent Hierarchical Causal Structure Discovery with Rank Constraints

URL: View paper

Brief Assessment

Hierarchical Rank Constraints[65] focuses on rank constraints for latent hierarchical structures with specific structural assumptions (e.g., pure children requirements), not on introducing edge rank constraints as a general local tool complementing path ranks for broader causal discovery settings.

2. Causal Discovery of Latent Variables in Galactic Archaeology

URL: View paper

Brief Assessment

Galactic Archaeology Discovery[64] applies rank-based latent causal discovery (RLCD) to astrophysical data but does not introduce edge rank constraints as a methodological tool. The candidate focuses on applying existing causal discovery methods to stellar migration, not developing new rank-based constraints for causal discovery methodology.

3. Calculation of Entailed Rank Constraints in Partially Non-Linear and Cyclic Models

URL: View paper

Brief Assessment

Entailed Rank Cyclic[66] focuses on extending the trek separation theorem to partially non-linear and cyclic models, using path ranks rather than introducing edge rank constraints as a distinct tool for causal discovery.

4. On Low Rank Directed Acyclic Graphs and Causal Structure Learning

URL: View paper

Brief Assessment

Low Rank DAGs[68] focuses on rank constraints on weighted adjacency matrices for structure learning in general DAGs, not specifically on edge-level constraints for latent-variable discovery in the linear non-Gaussian framework.

5. Latent Variable Causal Discovery under Selection Bias

URL: View paper

Brief Assessment

Selection Bias Discovery[67] focuses on rank constraints in covariance matrices under selection bias in linear Gaussian models, not on edge rank constraints as a local edge-level tool for causal discovery. The candidate addresses selection mechanisms rather than the edge-level constraint methodology introduced in the original paper.

6. Causal Inference and Causal Discovery with Latent Variables

URL: View paper

Brief Assessment

Inference Discovery Latent[63] focuses on identifiability conditions for partially observed linear causal models using graphical conditions, not on developing edge rank constraints as a tool for causal discovery methods.

7. A versatile causal discovery framework to allow causally-related hidden variables

URL: View paper

Brief Assessment

Causally-Related Hidden Variables[54] focuses on rank constraints derived from covariance matrices in linear models, not the specific edge rank constraints introduced in the original paper. The candidate uses 'rank deficiency' and 'rank constraints' but does not introduce edge ranks as a local, edge-level tool complementing path ranks.

Contribution 3: glvLiNG algorithm for structural-assumption-free latent-variable causal discovery

Description: The authors develop glvLiNG, a constraint-based algorithm that recovers causal models with latent variables from data up to distributional equivalence. This is claimed to be the first method that does not require structural assumptions about how latent variables interact with observed variables.

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. Generalized independent noise condition for estimating latent variable causal graphs

URL: View paper

Brief Assessment

Independent Noise Latent[12] focuses on linear non-gaussian latent variable models (LiNGLAMs) with specific structural assumptions (measurement assumption, double-pure child variable assumption, purity assumption). The candidate does not demonstrate that similar structural-assumption-free methods existed prior to the original paper's submission.

2. A Causal Ordering Prior for Unsupervised Representation Learning

URL: View paper

Brief Assessment

Causal Ordering Prior[55] focuses on unsupervised representation learning with additive noise models (ANMs) in the latent space, not on structural-assumption-free latent-variable causal discovery from observational data. The candidate addresses a different problem domain (representation learning vs. causal discovery) and uses different technical approaches (variational autoencoders with topological ordering vs. constraint-based algorithms with rank conditions).

3. Causal structure representation learning of unobserved confounders in latent space for recommendation

URL: View paper

Brief Assessment

Recommendation Latent Space[51] focuses on learning causal structure of unobserved confounders in recommendation systems using variational autoencoders, not on general structural-assumption-free latent-variable causal discovery from observational data.

4. Essential regression: a generalizable framework for inferring causal latent factors from multi-omic datasets

URL: View paper

Brief Assessment

Essential Regression[53] focuses on integrating multi-omic biological datasets through latent factor regression for prediction and causal inference in immunology contexts, not on general structural-assumption-free causal discovery algorithms for linear non-Gaussian models with arbitrary latent structures and cycles.

5. Nonlinear causal discovery with latent confounders

URL: View paper

Brief Assessment

Nonlinear Latent Confounders[57] focuses on nonlinear causal models with latent confounders using variational autoencoders, not linear non-Gaussian models. The candidate addresses a different parametric setting and does not challenge the novelty of glvLiNG's structural-assumption-free approach in the linear non-Gaussian cyclic setting.

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6. Score matching through the roof: linear, nonlinear, and latent variables causal discovery

URL: View paper

Brief Assessment

Score Matching Roof[43] focuses on score-matching methods for causal discovery with latent variables, requiring additive noise model assumptions. The original paper's glvLiNG uses rank constraints and does not require structural assumptions about latent-observed interactions, representing a different technical approach.

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7. Causal effect inference with deep latent-variable models

URL: View paper

Brief Assessment

Deep Latent-Variable Models[56] focuses on causal effect inference using variational autoencoders with proxy variables for confounders, not on structural-assumption-free causal discovery algorithms that recover causal graphs up to distributional equivalence.

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8. Research noteâToward a causal interpretation from observational data: A new Bayesian networks method for structural models with latent variables

URL: View paper

Brief Assessment

Bayesian Networks Latent[58] focuses on identifying latent variables and causal structures from observational data using Bayesian networks combined with SEM, operating in a two-stage process. This differs from glvLiNG's constraint-based approach using linear non-gaussian models with distributional equivalence characterization and edge rank constraints.

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9. Causal representation learning made identifiable by grouping of observational variables

URL: View paper

Brief Assessment

Grouping Observational Variables[52] focuses on causal representation learning from grouped observational variables (e.g., multimodal sensors) using a pairwise Bayesian network model. The original paper addresses latent-variable causal discovery in linear non-Gaussian cyclic models without structural assumptions, which is a fundamentally different setting and methodology.

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10. A versatile causal discovery framework to allow causally-related hidden variables

URL: View paper

Brief Assessment

Causally-Related Hidden Variables[54] presents RLCD algorithm for latent causal discovery, but it operates under different structural assumptions (e.g., Condition 1 requires atomic covers, no triangles). The candidate does not claim to be the first structural-assumption-free method for latent-variable causal discovery.

Appendix: Text Similarity Detection

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

References

- [0] Distributional Equivalence in Linear Non-Gaussian Latent-Variable Cyclic Causal Models: Characterization and Learning View paper
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- [2] Nonlinear Causal Discovery via Dynamic Latent Variables View paper
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- [50] Gradient-based causal discovery with latent variables View paper
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- [62] Local Causal Discovery with Linear non-Gaussian Cyclic Models View paper
- [63] Causal Inference and Causal Discovery with Latent Variables View paper
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