Novelty Assessment Report

Paper: Causal Time Series Generation via Diffusion Models
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Abstract

Time series generation (TSG) synthesizes realistic sequences and has achieved remarkable success. Among TSG, conditional models generate sequences given observed covariates, however, such models learn observational correlations without considering unobserved confounding. In this work, we propose a causal perspective on conditional TSG and introduce causal time series generation as a new TSG task family, formalized within Pearl's causal ladder, extending beyond observational generation to include interventional and counterfactual settings. To instantiate these tasks, we develop CaTSG, a unified diffusion-based framework with backdoor-adjusted guidance that causally steers sampling toward desired interventions and individual counterfactuals while preserving observational fidelity. Specifically, our method derives causal score functions via backdoor adjustment and the abduction–action–prediction procedure, thus enabling principled support for all three levels of TSG. Extensive experiments on both synthetic and real-world datasets show that CaTSG achieves superior fidelity and also supporting interventional and counterfactual generation that existing baselines cannot handle. Overall, we propose the causal TSG family and instantiate it with CaTSG, providing an initial proof-of-concept and opening a promising direction toward more reliable simulation under interventions and counterfactual generation.

Core Task Landscape

This paper addresses: **causal time series generation with interventions and counterfactuals**

A total of **50 papers** were analyzed and organized into a taxonomy with **22 categories**.

Taxonomy Overview

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

- **Causal Inference and Counterfactual Reasoning Frameworks**
- **Causal Generative Models for Time Series**
- **Causal Forecasting and Prediction**
- **Synthetic Control and Counterfactual Estimation**
- **Counterfactual Explanation for Time Series**
- **Specialized Applications and Domain-Specific Methods**

Complete Taxonomy Tree

- causal time series generation with interventions and counterfactuals Survey Taxonomy
- Causal Inference and Counterfactual Reasoning Frameworks
  - Vector Autoregressive and Time Series Causal Models (4 papers)
  - [1] On counterfactual interventions in vector autoregressive models (Kurt Butler, 2024) View paper
  - [26] Combining counterfactual outcomes and ARIMA models for policy evaluation (Fiammetta Menchetti, 2023) View paper
  - [46] Counterfactual reasoning with vector autoregressive models (Kurt Butler, 2025) View paper
  - [49] MDM: An R package for causal multivariate time series tasks (Lilia Costa, 2025) View paper
  - Structural Causal Models for Temporal Data (4 papers)
  - [2] Variational counterfactual intervention planning to achieve target outcomes (X Wang, 2025) View paper
  - [14] Counterfactual reasoning in space and time: Integrating graphical causal models in computational movement analysis (Saeed Rahimi, 2023) View paper
  - [45] Causal Regime Detection in Energy Markets With Augmented Time Series Structural Causal Models (Thumm, 2025) View paper
  - [50] A Novel Application of SCMs to Time Series Counterfactual Estimation in the Pharmaceutical Industry (T Garriga, 2024) View paper
  - Neural Causal Discovery from Time Series (3 papers)
  - [19] CAnDOIT: Causal Discovery with Observational and Interventional Data from Time Series (Luca Castri, 2024) View paper
  - [27] Granger causal representation learning for groups of time series (Ruichu Cai, 2024) View paper
  - [47] CUTS: Neural Causal Discovery from Irregular Time-Series Data (Cheng, 2023) View paper
- Causal Generative Models for Time Series
  - Diffusion-Based Causal Generation ★ (1 papers)
  - [0] Causal Time Series Generation via Diffusion Models (Anon et al., 2026) View paper
  - Variational and Flow-Based Causal Generation (4 papers)
  - [18] Causal Recurrent Variational Autoencoder for Medical Time Series Generation (Li Hongming, 2023) View paper
  - [31] Counterfactual Generative Modeling with Variational Causal Inference (Wu, 2024) View paper
  - [37] DoFlow: Causal Generative Flows for Interventional and Counterfactual Time-Series Prediction (Wu Dongze, 2025) View paper
  - [42] Time-Causal VAE: Robust Financial Time Series Generator (Acciaio, 2024) View paper
  - Counterfactual Data Augmentation (3 papers)

  - [11] Rocoda: Counterfactual data augmentation for data-efficient robot learning from demonstrations (Ezra Ameperosa, 2025) View paper
  - [15] Data augmented sequential recommendation based on counterfactual thinking (Xu Chen, 2022) View paper
  - [25] Counterfactual generative models for time-varying treatments (Shenghao Wu, 2024) View paper
  - Constrained and Scenario-Based Generation (2 papers)
  - [30] On the constrained time-series generation problem (Coletta, 2023) View paper
  - [43] Model-based counterfactual synthesizer for interpretation (Yang Fan, 2021) View paper
- Causal Forecasting and Prediction
  - Causal Intervention in Forecasting Models (3 papers)
  - [5] Causal Intervention Is What Large Language Models Need for Spatio-Temporal Forecasting (Shijie Li, 2025) View paper
  - [6] Causal-TSF: A Causal Intervention Approach to Mitigate Confounding Bias in Time Series Forecasting (Qinkang Gong, 2025) View paper
  - [12] Training and Evaluating Causal Forecasting Models for Time-Series (LÃ©cuyer, 2024) View paper
  - Trajectory and Behavioral Prediction with Counterfactuals (4 papers)
  - [3] Counterfactual Forecasting of Human Behavior using Generative AI and Causal Graphs (DP Uddandarao, 2025) View paper
  - [23] Human trajectory prediction via counterfactual analysis (Chen Guangyi, 2021) View paper
  - [34] Causal Intervention and Counterfactual Reasoning for Multimodal Pedestrian Trajectory Prediction (Xinyu Han, 2025) View paper
  - [39] The 'causal revolution' in financial decision making: An AI budget optimization framework based on counterfactual reasoning (Xiaoâ□□Hua Zhou, 2025) View paper
  - Sequential Recommendation with Causal Reasoning (2 papers)
  - [4] Causerec: Counterfactual user sequence synthesis for sequential recommendation (Zhang Shengyu, 2021) View paper
  - [33] Enhancing Temporal Sensitivity of Large Language Model for Recommendation with Counterfactual Tuning (Liu Yutian, 2025) View paper
- Synthetic Control and Counterfactual Estimation
  - Classical Synthetic Control Methods (3 papers)
  - [9] Counterfactual and synthetic control method: Causal inference with instrumented principal component analysis (Cong, 2024) View paper
  - [10] An exact and robust conformal inference method for counterfactual and synthetic controls (Chernozhukov, 2021) View paper
  - [35] A Synthetic Business Cycle Approach to Counterfactual Analysis with Nonstationary Macroeconomic Data (Shi, 2025) View paper
  - Neural and Spatiotemporal Synthetic Control (1 papers)
  - [20] SCouT: synthetic counterfactuals via spatiotemporal transformers for actionable healthcare (Bhishma Dedhia, 2023) View paper
  - Bayesian and State-Space Counterfactual Models (2 papers)
  - [13] Multivariate Bayesian dynamic modeling for causal prediction (Graham Tierney, 2024) View paper
  - [22] Inferring causal impact using Bayesian structural time-series models (RÃ©my, 2015) View paper
  - Interrupted Time Series and Policy Evaluation (2 papers)
  - [36] Can synthetic controls improve causal inference in interrupted time series evaluations of public health interventions? (Michelle Degli Esposti, 2020) View paper
  - [48] Design and analysis of time series experiments (R McCleary, 2017) View paper
  - Event Causality and Adaptive Designs (2 papers)
  - [21] Event causality identification with synthetic control (Wang Haoyu, 2024) View paper
  - [28] Sequential causal inference in a single world of connected units (Bibaut, 2021) View paper
- Counterfactual Explanation for Time Series
  - Multivariate Time Series Counterfactual Explanations (3 papers)
  - [8] Counterfactual explanations for multivariate time-series without training datasets (Xiangyu Sun, 2024) View paper
  - [16] Generating sparse counterfactual explanations for multivariate time series (Jana Lang, 2023) View paper
  - [29] GenFacts-Generative Counterfactual Explanations for Multi-Variate Time Series (Seifi Sarah, 2025) View paper
  - Interactive and Univariate Counterfactual Generation (1 papers)
  - [41] Interactive Counterfactual Generation for Univariate Time Series (Schlegel, 2024) View paper
  - Unified Explanation Frameworks and Benchmarks (1 papers)
  - [44] TimeXAI: Unified Datasets and Concept-Based Counterfactual Explanations for Time Series (K Oublal, 2025) View paper
- Specialized Applications and Domain-Specific Methods
  - Large Language Models for Causal Temporal Reasoning (1 papers)
  - [7] Cretihc: Designing causal reasoning tasks about temporal interventions and hallucinated confoundings (Chun, 2023) View paper
  - Observational Causal Inference from Time Series (1 papers)
  - [32] Data-driven causal analysis of observational time series: A synthesis (AE Yuan, 2020) View paper
  - Time Series Manipulation and Irreversibility (1 papers)
  - [24] Manipulating Time Series Irreversibility Through Continuous Ordinal Patterns (Massimiliano Zanin, 2024) View paper
  - Neuroscience and Behavioral Decision-Making (3 papers)
  - [17] Dynamic prefrontal coupling coordinates adaptive decision-making (Alexander Herman, 2025) View paper
  - [38] Linking confidence biases to reinforcement-learning processes. (palminteri stefano, 2023) View paper
  - [40] Continuous time causal structure induction with prevention and generation. (Tianwei Gong, 2023) View paper

Narrative

Core task: causal time series generation with interventions and counterfactuals. The field organizes itself around several complementary branches. Causal Inference and Counterfactual Reasoning Frameworks provide foundational methods for identifying causal structures and reasoning about what-if scenarios in temporal data, often drawing on structural causal models and potential outcomes frameworks. Causal Generative Models for Time Series focus on learning data-generating processes that respect causal dependencies, employing architectures such as variational autoencoders, diffusion models, and flow-based approaches to produce synthetic sequences under hypothetical interventions. Causal Forecasting and Prediction emphasize forward-looking tasks where causal knowledge improves predictive accuracy or robustness, for instance by incorporating discovered causal graphs or leveraging large language models with temporal reasoning capabilities (e.g., Causal LLM Forecasting[5], Causal-TSF[6]). Synthetic Control and Counterfactual Estimation methods construct comparison units from observed data to estimate treatment effects in quasi-experimental settings, with classical techniques like Bayesian Structural Time Series[22] and newer refinements such as Conformal Synthetic Controls[10]. Counterfactual Explanation for Time Series aims to interpret model decisions by generating minimal perturbations or alternative histories, while Specialized Applications and Domain-Specific Methods tailor these ideas to domains like healthcare, recommendation systems, and autonomous driving.

A particularly active line of work explores how modern generative architectures can be adapted for causal reasoning. Diffusion-based and flow-based models are being extended to handle interventions and counterfactual queries, balancing sample quality with adherence to learned causal structures. Causal Diffusion Generation[0] exemplifies this direction, situating itself within the Diffusion-Based Causal Generation cluster alongside approaches that use variational inference (e.g., Counterfactual Variational Inference[31]) or flow models (DoFlow[37]). Compared to works like Counterfactual VAR Interventions[1] or Counterfactual Behavior Forecasting[3], which often rely on vector autoregressive or trajectory-prediction frameworks, Causal Diffusion Generation[0] emphasizes the flexibility and expressiveness of diffusion processes for capturing complex temporal dependencies under intervention. A central open question across these branches is how to ensure that generated counterfactuals remain both realistic and causally consistent, especially when ground-truth causal graphs are partially known or must be inferred from observational data.

Related Works in Same Category

No sibling papers were found in the same taxonomy leaf. A taxonomy-subtopic-level comparison will be produced instead.

Taxonomy-Level Summary

All subtopics address causal time series generation with interventions and counterfactuals, but differ in their generative architectures and primary objectives. The original Diffusion-Based Causal Generation uses diffusion models with causal guidance, while siblings employ VAEs/flows, constraint-based methods, or focus on data augmentation. The key distinction lies in the generative mechanism (diffusion vs. VAE/flow vs. constraint-driven) and whether the goal is synthesis, augmentation, or scenario testing.

Similarities: - All methods generate time series that respect causal relationships and support interventional or counterfactual reasoning - Each approach aims to produce synthetic data that maintains structural causal properties from the original distribution - All subtopics exclude methods that ignore causal structure or focus purely on observational generation without intervention capabilities

Differences: - Diffusion-Based uses iterative denoising with causal guidance; Variational/Flow-Based uses explicit latent variable models with causal encodings; Constrained uses numerical constraints or scenarios - Counterfactual Data Augmentation specifically targets training data enhancement, while Diffusion-Based and Variational/Flow-Based focus on general synthesis capabilities - Constrained Generation emphasizes stress testing and specific scenario simulation rather than learning general causal mechanisms - Diffusion-Based methods typically don't require explicit causal graph encoding in the architecture, while VAE/flow approaches often encode causal structure directly in the latent space

Suggested Search Directions: - Hybrid approaches combining diffusion models with VAE or flow-based causal encodings - Methods that integrate constraint satisfaction into diffusion-based causal generation - Comparative studies on sample quality and causal fidelity across different generative architectures

Sibling Subtopics

- **Constrained and Scenario-Based Generation** (leaves: 1, papers: 2)
- Scope: Approaches generating time series under numerical constraints or specific counterfactual scenarios for stress testing and simulation.
- Exclude: Excludes unconstrained generation methods; those belong under other generative categories.
- **Counterfactual Data Augmentation** (leaves: 1, papers: 3)
- Scope: Methods generating synthetic counterfactual samples to augment training data while preserving causal relationships.
- Exclude: Excludes methods focused on explanation rather than augmentation; those belong under counterfactual explanation.
- **Variational and Flow-Based Causal Generation** (leaves: 1, papers: 4)
- Scope: Approaches using VAEs or normalizing flows with explicit causal structure encoding for counterfactual and interventional generation.
- Exclude: Excludes diffusion-based methods; those belong under diffusion-based generation.

Contributions Analysis

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

Contribution 1: Causal time series generation task family

Description: The authors formalize causal time series generation as an extension of conditional TSG along Pearl's causal ladder, introducing two new tasks beyond association: interventional TSG (Int-TSG) and counterfactual TSG (CF-TSG). This framework enables generation under interventions and counterfactual queries rather than purely observational correlations.

This contribution was assessed against **6 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. A method for decomposing multivariate time series into a causal hierarchy within specific frequency bands.

URL: View paper

Brief Assessment

Causal Hierarchy Decomposition[53] focuses on decomposing multivariate time series into causal hierarchies within frequency bands, which is a fundamentally different problem from generating time series under Pearl's causal ladder framework (association, intervention, counterfactual).

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2. Towards Explainable Time Series

URL: View paper

Brief Assessment

Explainable Time Series[55] focuses on post-hoc local explanations for time series classification/regression models, not on causal generation tasks along Pearl's ladder. The candidate addresses interpretability of existing models rather than generating time series under interventions or counterfactuals.

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3. Causal Inference: history, perspectives, adventures, and unification (an interview with Judea Pearl)

URL: View paper

Brief Assessment

Pearl Interview[52] discusses causal inference concepts and temporal interventions in general terms, but does not address time series generation tasks or propose a framework for generating synthetic time series under causal interventions or counterfactuals.

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4. Transferable time-series forecasting under causal conditional shift

URL: View paper

Brief Assessment

Transferable Causal Forecasting[51] focuses on domain adaptation for time-series forecasting under causal conditional shift, not on extending conditional time series generation along Pearl's causal ladder to include interventional and counterfactual generation tasks.

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5. The Do-Calculus Revisited

URL: View paper

Brief Assessment

Do-Calculus Revisited[56] focuses on the do-calculus framework for causal inference, identification, and transportability problems, but does not address time series generation tasks or propose generative models for temporal data.

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6. Estimating causal effects from time series

URL: View paper

Brief Assessment

Causal Effects Estimation[54] focuses on estimating causal effects from time series data using Pearl's do-operator, not on generating time series under interventions or counterfactuals. The candidate addresses causal inference/estimation, while the original proposes a generative modeling framework.

Contribution 2: CaTSG unified diffusion framework with backdoor-adjusted guidance

Description: The authors introduce CaTSG, a diffusion-based generative framework that derives causal score functions via backdoor adjustment and the abduction–action–prediction procedure. The framework uses backdoor-adjusted guidance and a learnable latent environment bank to support observational, interventional, and counterfactual generation within a single unified model.

This contribution was assessed against **8 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 variational inference for deconfounded multi-behavior recommendation

URL: View paper

Brief Assessment

Causal Multi-behavior Recommendation[68] focuses on multi-behavior recommendation systems with user-item interactions, not time series generation. The backdoor adjustment is applied to recommendation tasks, not conditional time series generation with interventional/counterfactual objectives.

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2. Ufid: A unified framework for input-level backdoor detection on diffusion models

URL: View paper

Brief Assessment

Unified Backdoor Detection[70] focuses on detecting backdoor attacks in diffusion models through input-level analysis, not on causal generation frameworks with backdoor adjustment for time series generation.

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3. Towards Precise Embodied Dialogue Localization via Causality Guided Diffusion

URL: View paper

Brief Assessment

Causality Dialogue Localization[73] focuses on embodied dialogue localization using backdoor and front-door adjustments for spatial coordinate prediction, not general time series generation with interventional/counterfactual objectives.

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4. Attacks and defenses for generative diffusion models: A comprehensive survey

URL: View paper

Brief Assessment

Diffusion Attacks Survey[67] focuses on security threats to diffusion models, including backdoor attacks that inject malicious triggers. The candidate discusses backdoor attacks as adversarial manipulations, not as a causal inference mechanism for time series generation.

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5. Causal composition diffusion model for closed-loop traffic generation

URL: View paper

Brief Assessment

Causal Traffic Generation[69] focuses on autonomous driving simulation with causal composition for traffic scenarios, not general time series generation with backdoor adjustment for causal inference across observational, interventional, and counterfactual settings.

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6. Graph Representation Learning via Causal Diffusion for Out-of-Distribution Recommendation

URL: View paper

Prior Art Analysis

Causal Diffusion Recommendation[57] demonstrates prior work that combines backdoor adjustment with diffusion models for causal generation. The candidate paper explicitly states it uses 'backdoor adjustment and variational inference' to guide a diffusion process, and provides theoretical derivations for learning invariant representations through this approach. Both papers employ backdoor adjustment within diffusion frameworks to handle confounding, though applied to different domains (recommendation vs. time series generation).

Evidence

Evidence 1 - **Rationale**: Both papers propose diffusion-based frameworks that use backdoor adjustment to handle confounding. The candidate explicitly combines backdoor adjustment with diffusion for causal inference, demonstrating this approach existed prior to the original paper's submission. - **Original**: we develop catsg, a unified diffusion-based framework with backdoor-adjusted guidance that causally steers sampling toward desired interventions and individual counterfactuals while preserving observational fidelity - **Candidate**: we propose a novel approach, graph representation learning via causal diffusion (causaldiffrec) for ood recommendation. this method enhances the model's generalization on ood data by eliminating environmental confounding factors and learning invariant graph representations. specifically, we use back...

Evidence 2 - **Rationale**: Both papers derive theoretical frameworks for using backdoor adjustment within diffusion models. The candidate provides theoretical derivations for learning invariant representations through backdoor-adjusted diffusion, showing this methodological combination was established in prior work. - **Original**: our method derives causal score functions via backdoor adjustment and the abduction-action-prediction procedure, thus enabling principled support for all three levels of tsg - **Candidate**: this inferred distribution is then used as prior knowledge to guide the representation learning in the reverse phase of the diffusion process to learn the invariant representation. in addition,we provide a theoretical derivation that proves optimizing the objective function of causaldiffrec can enco...

7. UFID: A Unified Framework for Black-box Input-level Backdoor Detection on Diffusion Models

URL: View paper

Brief Assessment

UFID[58] addresses backdoor attacks on diffusion models for security purposes, not causal generation. The term 'backdoor' refers to adversarial vulnerabilities, not the causal backdoor adjustment used in CaTSG.

8. DDCI: Unsupervised Domain Adaptation for Remote Sensing Images Based on Diffusion Causal Distillation

URL: View paper

Brief Assessment

DDCI[72] focuses on unsupervised domain adaptation for remote sensing images, not time series generation. The candidate's use of diffusion models and backdoor adjustment appears in a completely different context (domain adaptation) rather than causal time series generation with interventional/counterfactual objectives.

Contribution 3: Causal score functions for diffusion-based TSG

Description: The authors derive interventional and counterfactual score functions by applying backdoor adjustment and the abduction–action–prediction procedure within the diffusion framework. These causal score functions replace standard conditional scores and enable principled generation across all three causal levels without requiring ground-truth interventional labels.

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. CABIN: Debiasing Vision-Language Models Using Backdoor Adjustments

URL: View paper

Brief Assessment

CABIN[65] focuses on debiasing vision-language models using backdoor adjustments in a completely different domain (computer vision), not on deriving causal score functions for diffusion-based time series generation. The technical contexts are fundamentally distinct.

2. Fine-grained Prompt Screening: Defending Against Backdoor Attack on Text-to-Image Diffusion Models

URL: View paper

Brief Assessment

Prompt Screening Defense[61] focuses on backdoor attack detection in text-to-image diffusion models through cross-attention analysis, not on causal score functions or time series generation frameworks.

3. Counterfactual Image Editing with Disentangled Causal Latent Space

URL: View paper

Brief Assessment

Counterfactual Image Editing[59] focuses on image editing using backdoor adjustment in a latent space framework, not on deriving causal score functions for diffusion-based time series generation. The candidate addresses counterfactual image generation, while the original contribution specifically targets time series generation with interventional and counterfactual score functions.

4. Robust Sentiment Classification Based on the Backdoor Adjustment

URL: View paper

Brief Assessment

Backdoor Sentiment Classification[64] applies backdoor adjustment to sentiment classification in NLP, not to diffusion models for time series generation. The technical domains and methodologies are fundamentally different.

5. Diffusion Model in Causal Inference with Unmeasured Confounders

URL: View paper

Prior Art Analysis

Diffusion Unmeasured Confounders[66] demonstrates prior work on deriving causal score functions using backdoor adjustment in diffusion models. The candidate paper explicitly proposes a 'backdoor criterion based DCM (BDCM)' that applies the backdoor criterion to extend diffusion models for causal inference with unmeasured confounders. Both papers derive score functions by applying backdoor adjustment within diffusion frameworks to handle confounding, though the candidate focuses on causal inference rather than time series generation specifically.

Evidence

Evidence 1 - **Rationale**: Both papers work within Pearl's causal framework using DAGs and incorporate diffusion models to answer causal questions, showing the candidate established this integration prior to the original paper. - **Original**: we derive causal score functions via backdoor adjustment and abduction-action-prediction, and instantiatecatsg to embed these principles into diffusion sampling. - **Candidate**: in pearl's framework of using a directed acyclic graph (dag) to capture the causal intervention, a diffusion-based causal model (dcm) was proposed incorporating the diffusion model to answer the causal questions more accurately

6. Graph Representation Learning via Causal Diffusion for Out-of-Distribution Recommendation

URL: View paper

Prior Art Analysis

Causal Diffusion Recommendation[57] demonstrates prior application of backdoor adjustment to derive causal guidance within diffusion models. The candidate uses backdoor adjustment to eliminate environmental confounders and guide the diffusion process, showing that deriving causal functions via backdoor adjustment in diffusion frameworks existed before the original work. While the original focuses on score functions for time series and the candidate on graph representations, both employ the same core principle of using backdoor adjustment to derive causal guidance mechanisms within diffusion models.

Evidence

Evidence 1 - **Rationale**: Both papers derive causal guidance mechanisms using backdoor adjustment within diffusion frameworks. The candidate demonstrates using backdoor adjustment to guide diffusion sampling, showing this approach existed prior to the original paper's claim of novelty. - **Original**: we derive causal score functions via backdoor adjustment and abduction-action-prediction, and instantiatecatsg to embed these principles into diffusion sampling - **Candidate**: specifically, we use backdoor adjustment and variational inference to infer the real environmental distribution, thereby eliminating the impact of environmental confounders. this inferred distribution is then used as prior knowledge to guide the representation learning in the reverse phase of the di...

Evidence 2 - **Rationale**: Both papers construct structural causal models and use causal inference principles (backdoor adjustment) to derive guidance mechanisms for diffusion models, demonstrating the prior existence of this methodological approach. - **Original**: we adopt a causal view that makes the mechanisms linking conditions and outcomes explicit. pearl's causal ladder (pearl, 2009) offers a precise vocabulary for this extension - **Candidate**: in this study, we construct a structural causal model (scm) to analyze interaction data, revealing that environmental confounders (e.g., the covid-19 pandemic) lead to unstable correlations in gnn-based models

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7. Defending Against Backdoor Attacks through Causality-Augmented Diffusion Models for Dataset Purification

URL: View paper

Brief Assessment

Causality Diffusion Purification[60] applies causal reasoning to backdoor defense in image classification, not time series generation. The candidate uses causal graphs to eliminate backdoor triggers during diffusion-based purification, while the original derives interventional and counterfactual score functions for generating time series under causal queries.

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8. UFID: A Unified Framework for Black-box Input-level Backdoor Detection on Diffusion Models

URL: View paper

Brief Assessment

UFID[58] focuses on detecting backdoor attacks in diffusion models through causal analysis of spurious paths, not on deriving causal score functions for time series generation tasks.

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9. High Dimensional Causal Inference with Variational Backdoor Adjustment

URL: View paper

Brief Assessment

Variational Backdoor Adjustment[63] focuses on high-dimensional causal inference using variational methods for static variables, not on deriving causal score functions within diffusion models for time series generation.

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10. Partially Functional Dynamic Backdoor Diffusion-based Causal Model

URL: View paper

Prior Art Analysis

Functional Backdoor Diffusion[62] demonstrates that causal score functions using backdoor adjustment in diffusion models were proposed prior to the original paper. The candidate explicitly derives interventional and counterfactual score functions by applying backdoor adjustment within a diffusion framework, which directly overlaps with the original paper's claimed novelty. Both papers derive score functions that replace standard conditional scores to enable principled generation across causal levels without requiring ground-truth interventional labels.

Evidence

Evidence 1 - **Rationale**: Both papers describe integrating backdoor adjustment into diffusion sampling to handle unmeasured confounders and support causal generation tasks. - **Original**: we derive causal score functions via backdoor adjustment and abduction-action-prediction, and instantiatecatsg to embed these principles into diffusion sampling. Through backdoor-adjusted guidance and a learnable latent environment bank,catsg supports observational, interventional, and counterfactua... - **Candidate**: First, it integrates valid backdoor adjustments into the diffusion sampling mechanism to mitigate bias from unmeasured confounders. Second, it explicitly models the intricate spatio-temporal dynamics of unmeasured confounders through region-specific structural equations and conditional autoregressiv...

Evidence 2 - **Rationale**: The candidate describes an encoder-decoder architecture that uses backdoor adjustment sets (xbk) to handle unmeasured confounders, implementing the same causal principles claimed in the original paper. - **Original**: specifically, our method derives causal score functions via backdoor adjustment and the abduction-action-prediction procedure, thus enabling principled support for all three levels of tsg. - **Candidate**: The pfd-bdcm's data-generating process is formalized as: {xk : xijk = fij(xbk, uk)}k∈[k]. The encoder g maps (xk, xbk) to a latent variable zk := g(xk, xbk), which captures information of the unmeasured confounders uk. The decoder h reconstructs xk as ˆxk = h(zk, xbk).

Appendix: Text Similarity Detection

Textual similarity detection checked 24 papers and found 1 similarity segment(s) across 1 paper(s).

The following **1 paper(s)** were detected to have high textual similarity with the original paper. These may represent different versions of the same work, duplicate submissions, or papers with substantial textual overlap. Readers are advised to verify these relationships independently.

1. Causal variational inference for deconfounded multi-behavior recommendation

Detected in: Contribution: contribution_2

⚠ **Note**: This paper shows substantial textual similarity with the original paper. It may be a different version, a duplicate submission, or contain significant overlapping content. Please review carefully to determine the nature of the relationship.

References

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