Novelty Assessment Report

Paper: ActiveCQ: Active Estimation of Causal Quantities

PDF URL: https://openreview.net/pdf?id=CWpQsAubxy

Venue: ICLR 2026 Conference Submission

Year: 2026

Report Generated: 2025-12-30

Abstract

Estimating causal quantities (CQs) typically requires large datasets, which can be expensive to obtain, especially when measuring individual outcomes is costly. This challenge highlights the importance of sample-efficient active learning strategies. To address the narrow focus of prior work on the conditional average treatment effect, we formalize the broader task of Actively estimating Causal Quantities (ActiveCQ) and propose a unified framework for this general problem. Built upon the insight that many CQs are integrals of regression functions, our framework models the regression function with a Gaussian Process. For the distribution component, we explore both a baseline using explicit density estimators and a more integrated method using conditional mean embeddings in a reproducing kernel Hilbert space. This latter approach offers key advantages: it bypasses explicit density estimation, operates within the same function space as the GP, and adaptively refines the distributional model after each update. Our framework enables the principled derivation of acquisition strategies from the CQ's posterior uncertainty; we instantiate this principle with two utility functions based on information gain and total variance reduction. A range of simulated and semi-synthetic experiments demonstrate that our principled framework significantly outperforms relevant baselines, achieving substantial gains in sample efficiency across a variety of CQs.

Core Task Landscape

This paper addresses: **Active Estimation of Causal Quantities Using Sample-Efficient Learning Strategies**

A total of **37 papers** were analyzed and organized into a taxonomy with **13 categories**.

Taxonomy Overview

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

- **Active Learning for Causal Structure Discovery**
- **Active Learning for Treatment Effect Estimation**
- **Active Learning for Optimal Intervention Design**
- **Causal Inference in Reinforcement Learning and Sequential Decision-Making**
- **Foundational Methods and Cross-Domain Applications**

Complete Taxonomy Tree

- Active Estimation of Causal Quantities Using Sample-Efficient Learning Strategies Survey Taxonomy
- Active Learning for Causal Structure Discovery
  - Graph-Based Causal Structure Learning (6 papers)
  - [2] Optimization of Active Learning Strategies for Causal Network Structure (Mengxin Zhang, 2024) View paper
  - [5] Active causal structure learning with advice (Choo, 2023) View paper
  - [9] Active bayesian causal inference (Toth, 2022) View paper
  - [20] Active learning of causal networks with intervention experiments and optimal designs (Yangbo He, 2008) View paper
  - [32] Reconstructing causal biological networks through active learning (Hyunghoon Cho, 2016) View paper
  - [36] Optimal experimental design via Bayesian optimization: active causal structure learning for Gaussian process networks (von KÃ¼gelgen, 2019) View paper
  - Tree-Structured and Probability-Based Causal Models (2 papers)
  - [3] Sample efficient active learning of causal trees (Greenewald Kristjan, 2019) View paper
  - [25] Active learning of causal probability trees (Tue Herlau, 2022) View paper
  - Neural and Deep Learning Approaches for Causal Discovery (3 papers)
  - [16] Policy-Based Bayesian Active Causal Discovery with Deep Reinforcement Learning (Heyang Gao, 2024) View paper
  - [18] Learning neural causal models with active interventions (Scherrer, 2021) View paper
  - [19] Amortized active causal induction with deep reinforcement learning (Annadani, 2024) View paper
  - Domain-Specific Causal Network Learning (2 papers)
  - [11] A Bayesian active learning experimental design for inferring signaling networks (R. Ness, 2018) View paper
  - [12] Active causal learning for decoding chemical complexities with targeted interventions (Zachary Fox, 2024) View paper
- Active Learning for Treatment Effect Estimation
  - Conditional Average Treatment Effect Estimation ★ (4 papers)
  - [0] ActiveCQ: Active Estimation of Causal Quantities (Anon et al., 2026) View paper
  - [1] Causal-EPIG: A prediction-oriented active learning framework for cate estimation (Gao, 2025) View paper
  - [6] Enhancing Treatment Effect Estimation via Active Learning: A Counterfactual Covering Perspective (Wen, 2025) View paper
  - [13] Causal-bald: Deep bayesian active learning of outcomes to infer treatment-effects from observational data (Jesson, 2021) View paper
  - Average Treatment Effect Estimation with Adaptive Design (4 papers)
  - [7] Active adaptive experimental design for treatment effect estimation with covariate choices (Kato Masahiro, 2024) View paper

- [15] ABC3: Active Bayesian Causal Inference with Cohn Criteria in Randomized Experiments (Taehun Cha, 2025) View paper
    - [17] ACE: Active learning for causal inference with expensive experiments (Song, 2023) View paper
    - [35] Active Treatment Effect Estimation via Limited Samples (Z Zhang, n.d.) View paper
    - Treatment Effect Estimation with Network Interference (1 papers)
    - [10] Integrating Active Learning in Causal Inference with Interference: A Novel Approach in Online Experiments (Zhu, 2024) View paper
    - Data-Efficient Causal Effect Estimation (3 papers)
    - [21] Progressive Generalization Risk Reduction for Data-Efficient Causal Effect Estimation (Tong Chen, 2025) View paper
    - [22] Causal inference with selectively deconfounded data (Gan, 2021) View paper
    - [24] Active learning for decision-making from imbalanced observational data (Sundin, 2019) View paper
- Active Learning for Optimal Intervention Design (2 papers)
    - [14] Active learning for optimal intervention design in causal models (Jiaqi Zhang, 2023) View paper
    - [26] Goal-Oriented Sequential Bayesian Experimental Design for Causal Learning (Zhang, 2025) View paper
- Causal Inference in Reinforcement Learning and Sequential Decision-Making (2 papers)
    - [8] Can active sampling reduce causal confusion in offline reinforcement learning? (Gupta, 2023) View paper
    - [33] Sample-Efficient Blockage Prediction and Handover Using Causal Reinforcement Learning (Tamizharasan Kanagamani, 2024) View paper
- Foundational Methods and Cross-Domain Applications
    - Bayesian Active Learning Frameworks (5 papers)
    - [23] Deep Reinforcement Learning Data Collection for Bayesian Inference of Hidden Markov Models (Mohammad Alali, 2024) View paper
    - [27] Efficient sampling-based Bayesian Active Learning for synaptic characterization. (C. Gontier, 2023) View paper
    - [31] Efficient Graph-Based Active Learning with Probit Likelihood via Gaussian Approximations (Miller, 2020) View paper
    - [34] Bayesian Sequential Experimental Design for a Partially Linear Model with a Gaussian Process Prior (Horii, 2022) View paper
    - [37] Bayesian Active Learning for Bivariate Causal Discovery (Y Wang, n.d.) View paper
    - Meta-Learning and Transfer Learning for Causal Inference (2 papers)
    - [29] Advanced in Interactive Learning: Alternative Feedback Mechanisms and Adaptive Causal Inference (Neopane, 2025) View paper
    - [30] Actively Learning to Learn Causal Relationships (Chentian Jiang, 2024) View paper
    - Applications in Non-Causal and Specialized Domains (2 papers)
    - [4] Causal-guided active learning for debiasing large language models (Du Li, 2024) View paper
    - [28] Active Uncertainty Representation Learning: Toward More Label Efficiency in Deep Learning (Salman Mohamadi, 2024) View paper

Narrative

Core task: active estimation of causal quantities using sample-efficient learning strategies. The field organizes around several complementary branches that address different facets of causal inference under data scarcity. Active Learning for Causal Structure Discovery focuses on efficiently uncovering graphical relationships among variables, often through strategic intervention selection (e.g., Causal Network Structure[2], Bivariate Causal Discovery[37]). Active Learning for Treatment Effect Estimation targets the precise quantification of intervention impacts, including conditional average treatment effects where methods like Causal Trees[3] and Causal BALD[13] guide sample allocation to regions of high uncertainty. Active Learning for Optimal Intervention Design emphasizes choosing which variables to manipulate and at what levels to maximize information gain or optimize downstream objectives (Optimal Intervention Design[14]). Causal Inference in Reinforcement Learning and Sequential Decision-Making bridges causal reasoning with dynamic environments, while Foundational Methods and Cross-Domain Applications provide theoretical underpinnings and demonstrate utility in domains ranging from biological networks to telecommunications.

Within treatment effect estimation, a central tension emerges between model-based approaches that leverage parametric assumptions for efficiency and nonparametric methods that prioritize flexibility at the cost of sample complexity. Works like Causal EPIG[1] and Counterfactual Covering[6] exemplify information-theoretic acquisition strategies that balance exploration of covariate space with exploitation of known effect heterogeneity. ActiveCQ[0] situates itself in this landscape by proposing sample-efficient strategies for conditional treatment effects, sharing methodological kinship with Causal BALD[13] in its use of uncertainty quantification but differing in how it prioritizes queries across subpopulations. Compared to tree-based partitioning methods such as Causal Trees[3], ActiveCQ[0] appears to emphasize adaptive querying mechanisms that refine estimates iteratively. Open questions persist around scalability to high-dimensional covariates, robustness to model misspecification, and the trade-off between local precision and global coverage in heterogeneous effect landscapes.

Related Works in Same Category

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

1. Causal-EPIG: A prediction-oriented active learning framework for cate estimation

Authors: Gao, Erdun, Fawkes, Jake, Erdun Gao, et al. (9 authors total) | **Year/Venue**: 2025 | **URL**: View paper

Abstract

Estimating the Conditional Average Treatment Effect (CATE) is often constrained by the high cost of obtaining outcome measurements, making active learning essential. However, conventional active learning strategies suffer from a fundamental objective mismatch. They are designed to reduce uncertainty in model parameters or in observable factual outcomes, failing to directly target the unobservable causal quantities that are the true objects of interest. To address this misalignment, we introduce ...

Relationship Analysis

Both papers belong to the same taxonomy category focusing on active learning strategies for CATE estimation with prediction-oriented or uncertainty-based acquisition functions. They share overlapping areas in using information-theoretic principles (information gain, variance reduction) and Gaussian Process modeling to guide sample-efficient CATE estimation. The key difference is that the original paper (ActiveCQ) provides a unified framework for multiple causal quantities (ATE, ATT, ATEDS, CATE) using conditional mean embeddings, while the candidate paper (Causal-EPIG) focuses exclusively on CATE estimation and introduces the principle of causal objective alignment with two distinct strategies (targeting potential outcomes vs. directly targeting CATE).

---

2. Enhancing Treatment Effect Estimation via Active Learning: A Counterfactual Covering Perspective

Authors: Wen, Hechuan, Chen Tong, Hechuan Wen, Gong, et al. (17 authors total) | **Year/Venue**: 2025 | **URL**: View paper

Abstract

Although numerous complex algorithms for treatment effect estimation have been developed in recent years, their effectiveness remains limited when handling insufficiently labeled training sets due to the high cost of labeling the effect after treatment, e.g., expensive tumor imaging or biopsy procedures needed to evaluate treatment effects. Therefore, it becomes essential to actively incorporate more high-quality labeled data, all while adhering to a constrained labeling budget. To enable data-e...

Relationship Analysis

Both papers belong to the same taxonomy category focusing on active learning strategies for conditional average treatment effect (CATE) estimation with sample-efficient approaches. They share the common goal of strategically selecting data points to improve CATE estimation accuracy under budget constraints, both employing uncertainty-based acquisition functions within a Bayesian framework. The key difference is that the original paper (ActiveCQ) provides a unified framework for multiple causal quantities beyond CATE using Gaussian Processes with conditional mean embeddings, while the candidate paper (FCCM) specifically addresses CATE estimation through a geometric covering perspective with factual and counterfactual covering radius optimization.

---

3. Causal-bald: Deep bayesian active learning of outcomes to infer treatment-effects from observational data

Authors: Jesson, Andrew, Tigas, Panagiotis, A. Jesson, et al. (18 authors total) | **Year/Venue**: 2021 | **URL**: View paper

Abstract

Estimating personalized treatment effects from high-dimensional observational data is essential in situations where experimental designs are infeasible, unethical, or expensive. Existing approaches rely on fitting deep models on outcomes observed for treated and control populations. However, when measuring individual outcomes is costly, as is the case of a tumor biopsy, a sample-efficient strategy for acquiring each result is required. Deep Bayesian active learning provides a framework for effic...

Relationship Analysis

Both papers belong to the same taxonomy category of active learning for conditional average treatment effect (CATE) estimation, focusing on sample-efficient strategies for causal inference. The candidate paper (Causal-BALD) specifically addresses CATE estimation from observational data using Bayesian active learning with acquisition functions that account for overlap between treated and control groups, employing deep Bayesian methods like Gaussian processes. The original paper (ActiveCQ) presents a broader unified framework for multiple causal quantities beyond CATE (including ATE, ATT, and distribution shift scenarios), using Gaussian processes with conditional mean embeddings and deriving principled acquisition strategies based on information gain and total variance reduction for the general class of causal quantities.

Contributions Analysis

Overall novelty summary. The paper formalizes the ActiveCQ task and proposes a unified framework for actively estimating general causal quantities beyond the conditional average treatment effect. It resides in the 'Conditional Average Treatment Effect Estimation' leaf, which contains four papers total (including this one). This leaf sits within the broader 'Active Learning for Treatment Effect Estimation' branch, indicating a moderately populated research direction. The taxonomy reveals that while CATE estimation has received focused attention, the generalization to arbitrary causal quantities represents a less crowded extension of this established area.

The taxonomy tree shows neighboring leaves addressing average treatment effects with adaptive design, network interference settings, and data-efficient observational methods. The paper's position suggests it bridges CATE-focused work with the broader 'Foundational Methods' branch, particularly Bayesian active learning frameworks that handle sequential experimental design. The scope notes clarify that this work diverges from causal structure discovery (a separate major branch with eleven papers across four leaves) and optimal intervention design, instead concentrating on efficient estimation of predefined causal targets through adaptive sampling.

Among twenty-five candidates examined across three contributions, none were found to clearly refute any component. The first contribution (ActiveCQ formalization) examined nine candidates with zero refutations, suggesting limited prior work on this generalized task framing. The second contribution (Gaussian Process with Conditional Mean Embeddings) also examined nine candidates without refutation, indicating potential novelty in this modeling choice for causal quantities. The third contribution (acquisition strategies from posterior uncertainty) examined seven candidates, again with no clear overlaps. These statistics reflect a focused semantic search rather than exhaustive coverage, so undetected prior work remains possible.

Based on the limited search scope of top-twenty-five semantic matches, the work appears to occupy a relatively sparse position at the intersection of CATE estimation and general causal quantity inference. The absence of refutations across all contributions, combined with the taxonomy's structure showing only three sibling papers in the same leaf, suggests the generalization beyond CATE may be underexplored. However, the search scale leaves open the possibility of relevant work in adjacent communities not captured by this analysis.

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

Contribution 1: Formalization of Active Estimation of Causal Quantities (ActiveCQ) task and unified framework

Description: The authors formalize a new task called ActiveCQ that extends beyond the narrow focus on conditional average treatment effect (CATE) to encompass a broader class of causal quantities. They propose a unified framework that represents diverse causal quantities as integrals of regression functions, enabling systematic treatment of multiple causal estimation problems.

This contribution was assessed against **9 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

---

1. Causal-bald: Deep bayesian active learning of outcomes to infer treatment-effects from observational data

URL: View paper

Brief Assessment

Causal BALD[13] focuses specifically on active learning for conditional average treatment effects (CATE) from observational data, not on a general framework for diverse causal quantities beyond CATE.

---

2. Active learning for optimal intervention design in causal models

URL: View paper

Brief Assessment

Optimal Intervention Design[14] focuses on designing interventions to achieve a desired outcome in causal models, not on active learning for estimating diverse causal quantities like CATE, ATE, ATT, and ATEDS as a unified task.

---

3. ACE: Active learning for causal inference with expensive experiments

URL: View paper

Brief Assessment

ACE[17] focuses on adaptive experimental design where treatments can be assigned or observed sequentially, targeting specific causal estimands (ATE, ATTE, ITE). The original paper addresses active learning from observational data for a broader class of causal quantities with a unified integral representation framework.

4. Integrating Active Learning in Causal Inference with Interference: A Novel Approach in Online Experiments

URL: View paper

Brief Assessment

Active Learning Interference[10] focuses on network-based interference in online experiments with active learning for treatment assignment optimization, not on estimating diverse causal quantities beyond CATE in observational settings without interference.

5. Active causal learning for decoding chemical complexities with targeted interventions

URL: View paper

Brief Assessment

Chemical Complexities[12] focuses on active learning for molecular design in chemical spaces using graph-based methods, not on formalizing a general framework for estimating diverse causal quantities like CATE, ATE, ATT, and ATEDS in observational settings.

6. Two optimal strategies for active learning of causal models from interventional data

URL: View paper

Brief Assessment

Two Optimal Strategies[57] focuses on active learning for causal model discovery from interventional data, not on active estimation of diverse causal quantities from observational data with costly outcome measurements.

7. Active learning of causal networks with intervention experiments and optimal designs

URL: View paper

Brief Assessment

Intervention Experiments[20] focuses on active learning for discovering causal DAG structures through intervention experiments, not on estimating diverse causal quantities like CATE, ATE, ATT, or ATEDS from observational data with strategic outcome acquisition.

8. Active invariant causal prediction: Experiment selection through stability

URL: View paper

Brief Assessment

Invariant Causal Prediction[56] focuses on active experiment selection for identifying direct causes of a response variable through stability testing across environments, not on active learning for estimating diverse causal quantities beyond CATE as a unified framework.

9. Active bayesian causal inference

URL: View paper

Brief Assessment

Bayesian Causal Inference[9] focuses on integrated causal discovery and reasoning for specific causal queries, while the original paper formalizes a broader task (ActiveCQ) for actively estimating diverse causal quantities beyond CATE using a unified integral representation framework.

Contribution 2: Gaussian Process modeling with Conditional Mean Embeddings for causal quantity estimation

Description: The framework models the regression function using a Gaussian Process and represents the target distribution component via conditional mean embeddings (CMEs) in a reproducing kernel Hilbert space. This approach bypasses explicit density estimation, operates within the same function space as the GP, and adaptively refines the distributional model after each update.

This contribution was assessed against **9 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Gaussian Processes for Observational Dose-Response Inference

URL: View paper

Brief Assessment

Dose Response Inference[40] focuses on dose-response function estimation in observational settings using Gaussian processes with propensity score integration, not on the broader framework of active causal quantity estimation with conditional mean embeddings for distribution representation as proposed in the original paper.

2. ACE: Active learning for causal inference with expensive experiments

URL: View paper

Brief Assessment

ACE[17] uses Gaussian Process regression to model conditional mean functions separately for treatment and control groups, but does not employ conditional mean embeddings in reproducing kernel Hilbert spaces for representing target distributions as described in the original paper.

3. Noise Contrastive Meta-Learning for Conditional Density Estimation using Kernel Mean Embeddings

URL: View paper

Brief Assessment

Noise Contrastive Meta[44] focuses on meta-learning conditional densities for general regression tasks, not causal quantity estimation. The original paper's contribution is specifically about active learning for causal inference using GP with CME, which is a distinct application domain and methodological context.

4. Bayesian deconditional kernel mean embeddings

URL: View paper

Brief Assessment

Deconditional Kernel Embeddings[39] focuses on recovering latent functions from conditional means using deconditional mean embeddings, not on estimating causal quantities. The paper addresses a different inference problem (deconditional mean problem) rather than causal effect estimation.

5. Recent Developments at the Interface Between Kernel Embeddings and Gaussian Processes

URL: View paper

Brief Assessment

Kernel Embeddings Interface[45] focuses on causal data fusion and downscaling problems using conditional mean embeddings with GPs, but does not address the active learning framework for causal quantity estimation that is central to the original paper's contribution.

---

6. Active learning of conditional mean embeddings via bayesian optimisation

URL: View paper

Brief Assessment

Conditional Mean Embeddings[38] focuses on Bayesian optimization for maximizing conditional expectations in sequential control settings, not on causal quantity estimation or active learning for causal inference as in the original paper.

---

7. Kernel Synthetic Control: A Proxy Variable Viewpoint

URL: View paper

Brief Assessment

Kernel Synthetic Control[43] focuses on synthetic control methods for causal inference using proxy variables, not on active learning for causal quantity estimation. The candidate's use of conditional mean embeddings and Gaussian processes serves a different methodological purpose within a proxy variable framework rather than the original's active learning context for sample-efficient causal estimation.

---

8. Sequential Decision Making on Unmatched Data using Bayesian Kernel Embeddings

URL: View paper

Brief Assessment

Unmatched Data[41] addresses sequential decision-making in multi-armed bandit settings, not causal quantity estimation. The paper uses conditional mean embeddings for modeling reward distributions in a reinforcement learning context, which is fundamentally different from the original paper's focus on active learning for causal inference with distribution adjustment.

---

9. Kernel Embeddings and Gaussian Processes: Applications in Causal Data Fusion and Statistical Downscaling

URL: View paper

Brief Assessment

Causal Data Fusion[42] focuses on causal data fusion and statistical downscaling using kernel embeddings and Gaussian processes, not on active learning for causal quantity estimation. The candidate addresses different problems: fusing unmatched observational datasets and downscaling spatial data, rather than strategically selecting samples to efficiently estimate causal quantities.

Contribution 3: Principled derivation of acquisition strategies from posterior uncertainty

Description: The authors derive acquisition strategies systematically from the posterior uncertainty of the causal quantity of interest. They instantiate this principle with two utility functions: information gain and total variance reduction, which are expressed in closed-form and automatically tailored to the specific causal quantity being estimated.

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.

---

1. Interventions, where and how? experimental design for causal models at scale

URL: View paper

Brief Assessment

Interventions at Scale[49] focuses on experimental design for causal discovery (selecting intervention targets and values), not on active estimation of causal quantities like CATE or ATE from observational data with selective outcome acquisition.

---

2. Inferring causal impact using Bayesian structural time-series models

URL: View paper

Brief Assessment

Structural Time Series[54] focuses on causal impact estimation using Bayesian state-space models for time-series interventions, not on active learning acquisition strategies derived from posterior uncertainty for causal quantity estimation.

---

3. A Bayesian multivariate factor analysis model for causal inference using time-series observational data on mixed outcomes

URL: View paper

Brief Assessment

Multivariate Factor Analysis[52] focuses on Bayesian causal inference for time-series observational data with mixed outcomes, not on active learning acquisition strategies derived from posterior uncertainty for causal quantity estimation.

---

4. Semiparametric posterior corrections

URL: View paper

Brief Assessment

Semiparametric Posterior Corrections[47] focuses on correcting posterior distributions for semiparametric inference of causal functionals, not on deriving acquisition strategies for active learning from posterior uncertainty.

---

5. A theory of statistical inference for matching methods in causal research

URL: View paper

Brief Assessment

Matching Methods Theory[50] focuses on statistical inference for matching methods in causal research using stratified random sampling, not on deriving acquisition strategies from posterior uncertainty for active learning in causal quantity estimation.

---

6. Machine learning for causal inference

URL: View paper

Brief Assessment

The candidate paper appears to be a coversheet template for ERIC submissions, not a research paper on machine learning or causal inference. It contains no technical content related to acquisition strategies, posterior uncertainty, or causal quantity estimation.

7. Bayesian causal inference for discrete data

URL: View paper

Brief Assessment

Discrete Data[51] focuses on Bayesian causal inference methods for discrete data using saturated models, not on active learning acquisition strategies derived from posterior uncertainty for causal quantity estimation.

Appendix: Text Similarity Detection

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

References

- [0] ActiveCQ: Active Estimation of Causal Quantities View paper
- [1] Causal-EPIG: A prediction-oriented active learning framework for cate estimation View paper
- [2] Optimization of Active Learning Strategies for Causal Network Structure View paper
- [3] Sample efficient active learning of causal trees View paper
- [4] Causal-guided active learning for debiasing large language models View paper
- [5] Active causal structure learning with advice View paper
- [6] Enhancing Treatment Effect Estimation via Active Learning: A Counterfactual Covering Perspective View paper
- [7] Active adaptive experimental design for treatment effect estimation with covariate choices View paper
- [8] Can active sampling reduce causal confusion in offline reinforcement learning? View paper
- [9] Active bayesian causal inference View paper
- [10] Integrating Active Learning in Causal Inference with Interference: A Novel Approach in Online Experiments View paper
- [11] A Bayesian active learning experimental design for inferring signaling networks View paper
- [12] Active causal learning for decoding chemical complexities with targeted interventions View paper
- [13] Causal-bald: Deep bayesian active learning of outcomes to infer treatment-effects from observational data View paper
- [14] Active learning for optimal intervention design in causal models View paper
- [15] ABC3: Active Bayesian Causal Inference with Cohn Criteria in Randomized Experiments View paper
- [16] Policy-Based Bayesian Active Causal Discovery with Deep Reinforcement Learning View paper
- [17] ACE: Active learning for causal inference with expensive experiments View paper
- [18] Learning neural causal models with active interventions View paper
- [19] Amortized active causal induction with deep reinforcement learning View paper
- [20] Active learning of causal networks with intervention experiments and optimal designs View paper
- [21] Progressive Generalization Risk Reduction for Data-Efficient Causal Effect Estimation View paper
- [22] Causal inference with selectively deconfounded data View paper
- [23] Deep Reinforcement Learning Data Collection for Bayesian Inference of Hidden Markov Models View paper
- [24] Active learning for decision-making from imbalanced observational data View paper
- [25] Active learning of causal probability trees View paper
- [26] Goal-Oriented Sequential Bayesian Experimental Design for Causal Learning View paper
- [27] Efficient sampling-based Bayesian Active Learning for synaptic characterization. View paper
- [28] Active Uncertainty Representation Learning: Toward More Label Efficiency in Deep Learning View paper
- [29] Advanced in Interactive Learning: Alternative Feedback Mechanisms and Adaptive Causal Inference View paper
- [30] Actively Learning to Learn Causal Relationships View paper
- [31] Efficient Graph-Based Active Learning with Probit Likelihood via Gaussian Approximations View paper
- [32] Reconstructing causal biological networks through active learning View paper
- [33] Sample-Efficient Blockage Prediction and Handover Using Causal Reinforcement Learning View paper
- [34] Bayesian Sequential Experimental Design for a Partially Linear Model with a Gaussian Process Prior View paper
- [35] Active Treatment Effect Estimation via Limited Samples View paper
- [36] Optimal experimental design via Bayesian optimization: active causal structure learning for Gaussian process networks View paper
- [37] Bayesian Active Learning for Bivariate Causal Discovery View paper
- [38] Active learning of conditional mean embeddings via bayesian optimisation View paper
- [39] Bayesian deconditional kernel mean embeddings View paper
- [40] Gaussian Processes for Observational Dose-Response Inference View paper
- [41] Sequential Decision Making on Unmatched Data using Bayesian Kernel Embeddings View paper
- [42] Kernel Embeddings and Gaussian Processes: Applications in Causal Data Fusion and Statistical Downscaling View paper
- [43] Kernel Synthetic Control: A Proxy Variable Viewpoint View paper
- [44] Noise Contrastive Meta-Learning for Conditional Density Estimation using Kernel Mean Embeddings View paper
- [45] Recent Developments at the Interface Between Kernel Embeddings and Gaussian Processes View paper
- [46] Prediction, Causation, and Regulation in Machine Learning View paper
- [47] Semiparametric posterior corrections View paper
- [48] Bayesdag: Gradient-based posterior inference for causal discovery View paper
- [49] Interventions, where and how? experimental design for causal models at scale View paper
- [50] A theory of statistical inference for matching methods in causal research View paper
- [51] Bayesian causal inference for discrete data View paper
- [52] A Bayesian multivariate factor analysis model for causal inference using time-series observational data on mixed outcomes View paper
- [53] Machine learning for causal inference View paper
- [54] Inferring causal impact using Bayesian structural time-series models View paper
- [55] Causal entropy optimization View paper
- [56] Active invariant causal prediction: Experiment selection through stability View paper
- [57] Two optimal strategies for active learning of causal models from interventional data View paper