Novelty Assessment Report

Paper: Multifidelity Simulation-based Inference for Computationally Expensive Simulators

PDF URL: https://openreview.net/pdf?id=bj0dcKp9t6

Venue: ICLR 2026 Conference Submission

Year: 2026

Report Generated: 2026-01-04

Abstract

Across many domains of science, stochastic models are an essential tool to understand the mechanisms underlying empirically observed data. Models can be of different levels of detail and accuracy, with models of high-fidelity (i.e., high accuracy) to the phenomena under study being often preferable. However, inferring parameters of high-fidelity models via simulation-based inference is challenging, especially when the simulator is computationally expensive. We introduce MF-(TS)NPE, a multifidelity approach to neural posterior estimation that uses transfer learning to leverage inexpensive low-fidelity simulations to efficiently infer parameters of high-fidelity simulators. MF-(TS)NPE applies the multifidelity scheme to both amortized and non-amortized neural posterior estimation. We further improve simulation efficiency by introducing A-MF-TSNPE, a sequential variant that uses an acquisition function targeting the predictive uncertainty of the density estimator to adaptively select high-fidelity parameters. On established benchmark and neuroscience tasks, our approaches require up to two orders of magnitude fewer high-fidelity simulations than current methods, while showing comparable performance. Overall, our approaches open new opportunities to perform efficient Bayesian inference on computationally expensive simulators.

Core Task Landscape

This paper addresses: **Bayesian Inference for Computationally Expensive Simulators Using Multifidelity Models**

A total of **50 papers** were analyzed and organized into a taxonomy with **16 categories**.

Taxonomy Overview

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

- **Multifidelity Bayesian Optimization**
- **Multifidelity Bayesian Inference**
- **Multifidelity Surrogate Modeling**
- **Methodological Foundations and Transfer Learning**

Complete Taxonomy Tree

- Bayesian Inference for Computationally Expensive Simulators Using Multifidelity Models Survey Taxonomy
- Multifidelity Bayesian Optimization
  - General Multifidelity Bayesian Optimization Frameworks (5 papers)
  - [2] Multifidelity Bayesian Optimization: A Review (Bach Do, 2025) View paper
  - [8] Survey of multifidelity methods in uncertainty propagation, inference, and optimization (Peherstorfer, 2018) View paper
  - [21] Best practices for multi-fidelity Bayesian optimization in materials and molecular research (VÃctor Sabanza-Gil, 2025) View paper
  - [25] Practical multi-fidelity Bayesian optimization for hyperparameter tuning (Jian Wu, 2020) View paper
  - [33] Multi-fidelity bayesian optimisation with continuous approximations (Kirthevasan Kandasamy, 2017) View paper
  - Constrained and Multi-Objective Multifidelity Bayesian Optimization (3 papers)
  - [6] A multi-fidelity bayesian optimization approach for constrained multi-objective optimization problems (Quan Lin, 2024) View paper
  - [13] Constrained multi-fidelity surrogate framework using Bayesian optimization with non-intrusive reduced-order basis (Hanane Khatouri, 2020) View paper
  - [45] Multi-Fidelity Multi-Objective Bayesian Optimization: An Output Space Entropy Search Approach (Belakaria, 2020) View paper
  - Application-Specific Multifidelity Bayesian Optimization
  - Aerospace and Fluid Dynamics Applications (2 papers)
    - [1] Bayesian and non-Bayesian multi-fidelity surrogate models for multi-objective aerodynamic optimization under extreme cost imbalance (Schouler, 2025) View paper
    - [12] Multi-fidelity Bayesian neural networks for aerodynamic data fusion with heterogeneous uncertainties (Fangfang Xie, 2025) View paper
  - Other Engineering Applications (6 papers)
    - [9] Optimizing Falsification for Learning-Based Control Systems: A Multi-Fidelity Bayesian Approach (Shahrooei, 2024) View paper
    - [11] Multi-fidelity surrogate-based optimization for electromagnetic simulation acceleration (Yi Wang, 2020) View paper
    - [15] Computationally efficient integrated design and predictive control of flexible energy systems using multiâ□□fidelity simulationâ□□based Bayesian optimization (Farshud Sorourifar, 2023) View paper
    - [18] Falsification of Learning-Based Controllers through Multi-Fidelity Bayesian Optimization (Zahra Shahrooei, 2022) View paper
    - [44] Multi-fidelity Bayesian Data-Driven Design of Energy Absorbing Spinodoid Cellular Structures (Leo Guo, 2025) View paper
    - [46] An efficient multi-fidelity Bayesian optimization approach for analog circuit synthesis (Zhang, 2019) View paper

- Scientific Discovery Applications (2 papers)
  - [7] A multifidelity Bayesian optimization method for inertial confinement fusion design (J. Wang, 2024) View paper
  - [37] Multifidelity and multiscale Bayesian framework for high-dimensional engineering design and calibration (Soumalya Sarkar, 2019) View paper
- Physics-Aware and Safeguarded Multifidelity Bayesian Optimization (2 papers)
- [17] Physics-aware multifidelity Bayesian optimization: A generalized formulation (Francesco Di Fiore, 2024) View paper
- [20] Safeguarding multi-fidelity Bayesian optimization against large model form errors and heterogeneous noise (Zahra Zanjani Foumani, 2024) View paper

- Multifidelity Bayesian Inference
  - Neural Simulation-Based Inference with Multifidelity ★ (3 papers)
  - [0] Multifidelity Simulation-based Inference for Computationally Expensive Simulators (Anon et al., 2026) View paper
  - [14] Multilevel neural simulation-based inference (Bharti, 2025) View paper
  - [41] Transfer learning for multifidelity simulation-based inference in cosmology (Piras, 2025) View paper
  - Gaussian Process-Based Multifidelity Inference (4 papers)
  - [28] MFNets: Multi-fidelity data-driven networks for Bayesian learning and prediction (A. Gorodetsky, 2020) View paper
  - [35] Model inversion via multi-fidelity Bayesian optimization: a new paradigm for parameter estimation in haemodynamics, and beyond (Paris Perdikaris, 2016) View paper
  - [42] Multifidelity approximate Bayesian computation (Prescott, 2020) View paper
  - [47] Bayesian analysis of hierarchical multifidelity codes (Gratiet, 2013) View paper
  - Multifidelity Inference for Specific Physical Systems (6 papers)
  - [23] Multi-fidelity Bayesian inference of hypersonic flow free-stream conditions and heterogeneous chemistry model parameters (Michele, 2024) View paper
  - [31] Towards efficient uncertainty quantification in complex and large-scale biomechanical problems based on a Bayesian multi-fidelity scheme (J. Biehler, 2015) View paper
  - [38] Multi-fidelity modeling for uncertainty quantification in laser powder bed fusion additive manufacturing (Paromita Nath, 2022) View paper
  - [39] Accelerating Bayesian Inference via Multi-Fidelity Transport Map Coupling (Martins, 2025) View paper
  - [48] Multifidelity Bayesian inference of gravitational wave sources (Saleh, 2024) View paper
  - [50] Multi-fidelity approach to dynamics model calibration (Ghina N. Absi, 2016) View paper
  - Multifidelity MCMC and Delayed Acceptance (1 papers)
  - [49] Multi-Fidelity Delayed Acceptance: hierarchical MCMC sampling for Bayesian inverse problems combining multiple solvers through deep neural networks (Filippo Zacchei, 2025) View paper
  - Multifidelity Importance Sampling and Rare Event Estimation (3 papers)
  - [16] Context-aware surrogate modeling for balancing approximation and sampling costs in multifidelity importance sampling and Bayesian inverse problems (Alsup, 2023) View paper
  - [36] Multi-fidelity Bayesian experimental design to quantify extreme-event statistics (Gong, 2022) View paper
  - [40] Sequential design of experiments to estimate a probability of exceeding a threshold in a multi-fidelity stochastic simulator (Stroh, 2017) View paper
- Multifidelity Surrogate Modeling
  - Neural Network-Based Multifidelity Surrogates (3 papers)
  - [5] A Bayesian neural network approach to multi-fidelity surrogate modeling (Baptiste Kerleguer, 2024) View paper
  - [22] PINN surrogate of Li-ion battery models for parameter inference. Part I: Implementation and multi-fidelity hierarchies for the single-particle model (Malik Hassanaly, 2023) View paper
  - [32] An adaptive surrogate modeling based on deep neural networks for large-scale Bayesian inverse problems (Liang Yan, 2019) View paper
  - Gaussian Process Multifidelity Surrogates (4 papers)
  - [4] Multifidelity surrogate modeling for noisy and stochastic simulators (Giannoukou, 2025) View paper
  - [24] Local transfer learning Gaussian process modeling, with applications to surrogate modeling of expensive computer simulators (Wang Xinming, 2024) View paper
  - [29] Bayesian low-fidelity correction approach to multi-fidelity aerospace design (Christopher C. Fischer, 2017) View paper
  - [30] Bayesian-enhanced low-fidelity correction approach to multifidelity aerospace design (C. Corey Fischer, 2018) View paper
  - Diffusion-Based and Generative Multifidelity Surrogates (2 papers)
  - [3] Diffusion-based surrogate modeling and multi-fidelity calibration (Naichen Shi, 2025) View paper
  - [19] Multi-physics Simulation Guided Generative Diffusion Models with Applications in Fluid and Heat Dynamics (Naichen Shi, 2024) View paper
  - Multifidelity Surrogates for Specific Applications (3 papers)
  - [10] Precision Calibration in Wire-Arc-Directed Energy Deposition Simulations Using a Machine-Learning-Based Multi-Fidelity Model (Fuad Hasan, 2024) View paper
  - [27] Multifidelity strategies for forward and inverse uncertainty quantification of wind energy applications (Gianluca Geraci, 2020) View paper
  - [43] Assessing fire safety using complex numerical models with a Bayesian multi-fidelity approach (RÃ©mi Stroh, 2017) View paper
- Methodological Foundations and Transfer Learning (2 papers)
  - [26] Bayesian, Gradient-Free, and Multi-Fidelity Supervised Dimension Reduction Methods for Surrogate Modeling of Expensive Analyses with High-Dimensional Inputs (Gautier, 2022) View paper
  - [34] Efficient Bayesian multi-fidelity inverse analysis for expensive and non-differentiable physics-based simulations in high stochastic dimensions (Jonas Nitzler, 2025) View paper

Narrative

Core task: Bayesian inference for computationally expensive simulators using multifidelity models. This field addresses the challenge of performing rigorous statistical inference when high-fidelity simulations are prohibitively costly, by strategically combining information from multiple model resolutions or approximations. The taxonomy organizes the landscape into four main branches. Multifidelity Bayesian Optimization focuses on efficiently searching design or parameter spaces by querying cheaper low-fidelity models more frequently while reserving expensive high-fidelity evaluations for promising regions, as exemplified by works like Multifidelity Bayesian Optimization Review[2] and Constrained Multiobjective Multifidelity[6]. Multifidelity Bayesian Inference emphasizes posterior estimation and uncertainty quantification, often employing neural or simulation-based techniques to fuse information across fidelities. Multifidelity

Surrogate Modeling develops emulators that learn discrepancies or correlations between fidelity levels, enabling fast approximations for downstream tasks such as optimization or sensitivity analysis; representative approaches include Diffusion Surrogate Modeling[3] and Bayesian Neural Multifidelity[5]. Finally, Methodological Foundations and Transfer Learning explores theoretical underpinnings and strategies for transferring knowledge across related simulation settings, as seen in Cosmology Transfer Learning[41] and Local Transfer Learning[24].

Across these branches, a central trade-off concerns how aggressively to exploit cheap approximations versus when to invest in costly high-fidelity runs, with many studies exploring adaptive sampling and hierarchical modeling strategies. Within the Multifidelity Bayesian Inference branch, a particularly active line of work leverages neural simulation-based inference to handle complex, implicit likelihoods. Multifidelity Simulation Inference[0] sits squarely in this neural inference cluster, sharing methodological kinship with Multilevel Neural Inference[14], which also targets scalable posterior approximation by combining neural density estimators with hierarchical fidelity structures. Compared to Cosmology Transfer Learning[41], which emphasizes domain adaptation for specific scientific applications, Multifidelity Simulation Inference[0] focuses more broadly on the algorithmic machinery for fusing neural surrogates across fidelities. This positioning highlights an emerging emphasis on flexible, data-driven inference frameworks that can accommodate diverse simulator types without requiring explicit likelihood functions.

Related Works in Same Category

The following **2 sibling papers** share the same taxonomy leaf node with the original paper:

1. Multilevel neural simulation-based inference

Authors: Bharti, Ayush, Jeffrey, Niall, Briol, et al. (6 authors total) | **Year/Venue**: 2025 • arXiv.org | **URL**: View paper

Abstract

Neural simulation-based inference (SBI) is a popular set of methods for Bayesian inference when models are only available in the form of a simulator. These methods are widely used in the sciences and engineering, where writing down a likelihood can be significantly more challenging than constructing a simulator. However, the performance of neural SBI can suffer when simulators are computationally expensive, thereby limiting the number of simulations that can be performed. In this paper, we propo...

Relationship Analysis

Both papers belong to the Neural Simulation-Based Inference with Multifidelity category, leveraging multiple fidelity levels of simulators to improve Bayesian inference efficiency for expensive models. They overlap in addressing the computational challenge of simulation-based inference by combining low-fidelity and high-fidelity simulations through neural density estimation methods. The key difference is that the original paper (MF-(TS)NPE) uses transfer learning to pre-train on low-fidelity data and fine-tune on high-fidelity data with optional active learning, while the candidate paper applies multilevel Monte Carlo techniques to combine multiple fidelity levels within the inference framework.

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2. Transfer learning for multifidelity simulation-based inference in cosmology

Authors: Piras, Davide, Jeffrey, Niall, Mancini, et al. (10 authors total) | **Year/Venue**: 2025 | **URL**: View paper

Abstract

Simulation-based inference (SBI) enables cosmological parameter estimation when closed-form likelihoods or models are unavailable. However, SBI relies on machine learning for neural compression and density estimation. This requires large training datasets which are prohibitively expensive for high-quality simulations. We overcome this limitation with multifidelity transfer learning, combining less expensive, lower-fidelity simulations with a limited number of high-fidelity simulations. We demo...

Relationship Analysis

Both papers belong to the Neural Simulation-Based Inference with Multifidelity category, employing transfer learning to leverage low-fidelity simulations for efficient Bayesian inference with neural density estimators. They overlap in their core approach of pre-training neural networks on inexpensive simulations before fine-tuning on high-fidelity data to reduce computational costs. The key difference is that the original paper presents a general methodological framework (MF-(TS)NPE with active learning variants) tested across multiple benchmark and neuroscience tasks, while the candidate paper focuses specifically on a cosmological application using dark matter density maps from the CAMELS dataset.

Contributions Analysis

Overall novelty summary. The paper introduces MF-(TS)NPE, a multifidelity approach to neural posterior estimation that uses transfer learning to leverage low-fidelity simulations for efficient parameter inference in high-fidelity simulators. It resides in the 'Neural Simulation-Based Inference with Multifidelity' leaf, which contains only three papers total, indicating a relatively sparse and emerging research direction. This leaf sits within the broader 'Multifidelity Bayesian Inference' branch, which encompasses approximately twelve papers across five distinct methodological clusters, suggesting the neural simulation-based approach represents a minority but growing subfield.

The taxonomy reveals that neighboring leaves pursue alternative inference strategies: 'Gaussian Process-Based Multifidelity Inference' contains four papers using co-kriging and GP surrogates, while 'Multifidelity MCMC and Delayed Acceptance' explores sampling-based methods. The 'Multifidelity Surrogate Modeling' branch (fourteen papers across four leaves) focuses on emulator construction without explicit inference loops, representing a complementary but distinct research direction. The paper's neural density estimation approach diverges from these GP-centric and MCMC-based methods, positioning it at the intersection of modern deep learning and classical multifidelity modeling.

Among thirty candidates examined, the contribution-level analysis reveals mixed novelty signals. The core MF-(TS)NPE framework examined ten candidates with one refutable match, suggesting some prior work addresses multifidelity neural posterior estimation. The sequential acquisition function variant (MF-TSNPE-AF) similarly found one refutable candidate among ten examined. However, the empirical analysis of transfer learning effectiveness in multifidelity simulation-based inference examined ten candidates with zero refutations, indicating this specific investigation may represent a less-explored angle within the limited search scope.

Given the sparse three-paper leaf and the limited thirty-candidate search, the work appears to occupy an emerging niche where neural simulation-based inference meets multifidelity modeling. The presence of refutable candidates for two contributions suggests the core technical ideas have some precedent, though the scale of prior work remains unclear beyond the top-thirty semantic matches examined. The taxonomy structure indicates this neural approach is less established than GP-based or MCMC alternatives in the multifidelity inference landscape.

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

Contribution 1: MF-(TS)NPE: Multifidelity Neural Posterior Estimation with Transfer Learning

Description: The authors propose a multifidelity simulation-based inference method that pre-trains a neural density estimator on low-fidelity simulations and then fine-tunes it on a smaller set of high-fidelity simulations. This approach applies to both amortized (NPE) and non-amortized (TSNPE) neural posterior estimation, reducing the number of required high-fidelity simulations by up to two orders of magnitude.

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. Local transfer learning Gaussian process modeling, with applications to surrogate modeling of expensive computer simulators

URL: View paper

Brief Assessment

Local Transfer Learning[24] focuses on Gaussian process surrogate modeling for expensive computer simulators, not neural posterior estimation for simulation-based inference. The technical approaches and application domains differ fundamentally.

2. Transfer learning of neural surrogates on multifidelity groundwater simulations

URL: View paper

Brief Assessment

Groundwater Neural Surrogates[52] focuses on transfer learning for neural surrogates in groundwater simulations, not on multifidelity simulation-based inference or neural posterior estimation methods.

3. Multi-fidelity transonic aerodynamic loads estimation using Bayesian neural networks with transfer learning

URL: View paper

Brief Assessment

Transonic Aerodynamic Loads[51] focuses on multi-fidelity surrogate modeling for transonic aerodynamic predictions using Bayesian neural networks, not simulation-based inference for posterior estimation. The candidate addresses a different problem domain (aerodynamic load prediction) with different objectives (surrogate modeling vs. parameter inference).

4. Practical multi-fidelity machine learning: fusion of deterministic and Bayesian models

URL: View paper

Brief Assessment

Fusion Deterministic Bayesian[55] focuses on combining deterministic low-fidelity models (KRR, DNN) with Bayesian high-fidelity models (GPR, BNN) for regression tasks, not simulation-based inference for posterior estimation. The technical domains differ fundamentally.

5. Gar: generalized autoregression for multi-fidelity fusion

URL: View paper

Brief Assessment

Generalized Autoregression Fusion[56] focuses on multi-fidelity fusion for surrogate modeling of high-dimensional PDE outputs using Gaussian processes with tensor factorization, not neural posterior estimation for simulation-based inference. The technical approaches and problem domains are fundamentally different.

6. A probabilistic framework for source localization in anisotropic composite using transfer learning based multi-fidelity physics informed neural network (mfPINN â¦

URL: View paper

Brief Assessment

Source Localization Composite[53] focuses on acoustic emission source localization in composite materials using physics-informed neural networks, not general simulation-based inference for posterior estimation. The application domain and technical approach differ fundamentally from the original paper's contribution.

7. Multilevel neural simulation-based inference

URL: View paper

Brief Assessment

Multilevel Neural Inference[14] uses multilevel Monte Carlo techniques for neural SBI with multiple fidelity levels, whereas the original paper specifically proposes transfer learning (pre-training on low-fidelity, fine-tuning on high-fidelity) for neural posterior estimation. These are distinct technical approaches to the multifidelity problem.

8. A deep neural network, multi-fidelity surrogate model approach for Bayesian model updating in SHM

URL: View paper

Brief Assessment

SHM Deep Surrogate[57] focuses on structural health monitoring applications using deep neural networks for Bayesian model updating, not on general multifidelity simulation-based inference frameworks for neural posterior estimation.

9. Multi-Fidelity Bayesian Neural Network for Uncertainty Quantification in Transonic Aerodynamic Loads

URL: View paper

Brief Assessment

Transonic Uncertainty Quantification[54] focuses on aerodynamic load prediction using Bayesian neural networks for uncertainty quantification in transonic flows, not simulation-based inference for posterior estimation in general scientific simulators.

10. Transfer learning for multifidelity simulation-based inference in cosmology

URL: View paper

Prior Art Analysis

Cosmology Transfer Learning[41] demonstrates that the core methodological approach of using transfer learning for multifidelity simulation-based inference was already applied in cosmology. The candidate paper explicitly describes pre-training on lower-fidelity simulations followed by fine-tuning on high-fidelity simulations to reduce computational costs, which is the same fundamental approach claimed as novel in the original paper. Both papers apply this methodology to neural posterior estimation and report similar orders of magnitude improvements in simulation efficiency.

Evidence

Evidence 1 - **Rationale**: Both papers describe the same core approach: using multifidelity transfer learning to combine low-fidelity and high-fidelity simulations for efficient parameter inference. - **Original**: we introduce mf- (ts)npe, a multifidelity approach to neural posterior estimation that uses transfer learning to leverage inexpensive low-fidelity simulations to efficiently infer parameters of high-fidelity simulators. - **Candidate**: we overcome this limitation with multifidelity transfer learning, combining less expensive, lower-fidelity simulations with a limited number of high-fidelity simulations.

Evidence 2 - **Rationale**: Both papers demonstrate that pre-training on low-fidelity simulations followed by fine-tuning reduces the number of required high-fidelity simulations, showing the same transfer learning methodology was already applied. - **Original**: mf-npe leverages representations learned from low-fidelity simulations to reduce the number of high-fidelity simulations required to approximate a high-fidelity posterior. to that end, mf-npe adopts a fine-tuning strategy of transfer learning - **Candidate**: pre-training on dark-matter-only n-body simulations reduces the required number of high-fidelity hydrodynamical simulations by a factor between 8 and 15

Evidence 3 - **Rationale**: Both papers report similar benefits: substantial reduction in high-fidelity simulation requirements while maintaining accuracy, demonstrating that the claimed efficiency gains were already achieved by prior work. - **Original**: on established benchmark and neuroscience tasks, our approaches require up to two orders of magnitude fewer high-fidelity simulations than current methods, while showing comparable performance. - **Candidate**: by leveraging cheaper simulations, our approach enables performant and accurate inference on high-fidelity models while substantially reducing computational costs.

Contribution 2: MF-TSNPE-AF: Sequential Variant with Acquisition Function

Description: The authors develop a sequential extension of their multifidelity method that incorporates an acquisition function based on epistemic uncertainty. This active learning strategy adaptively selects which high-fidelity parameters to simulate, further enhancing simulation efficiency for non-amortized posterior estimation.

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

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1. Navigating uncertainties in machine learning for structural dynamics: A comprehensive review of probabilistic and non-probabilistic approaches in forward and inverse â¦

URL: View paper

Brief Assessment

Structural Dynamics Uncertainties[73] focuses on uncertainty quantification in structural dynamics using probabilistic and non-probabilistic machine learning approaches. It does not address sequential posterior estimation with acquisition functions for simulation-based inference, which is the core novelty of the original paper's MF-TSNPE-AF contribution.

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2. Estimation and analysis of slice propagation uncertainty in 3d anatomy segmentation

URL: View paper

Brief Assessment

Slice Propagation Uncertainty[74] focuses on uncertainty quantification in medical image segmentation using slice propagation methods, not on sequential posterior estimation with acquisition functions for simulation-based inference.

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3. Model Already Knows the Best Noise: Bayesian Active Noise Selection via Attention in Video Diffusion Model

URL: View paper

Brief Assessment

Attention Noise Selection[69] focuses on selecting initial noise seeds for video diffusion models using attention-based uncertainty, not on sequential posterior estimation for simulation-based inference. The technical domains and objectives are fundamentally different.

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4. Sequential Bayesian optimal experimental design for structural reliability analysis

URL: View paper

Brief Assessment

Structural Reliability Design[72] focuses on structural reliability analysis with acquisition functions targeting epistemic uncertainty in engineering contexts, not general simulation-based inference for posterior estimation in scientific models.

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5. Bayesian sequential I-optimal designs for split-plot experiments under model uncertainty

URL: View paper

Brief Assessment

Split-plot Optimal Designs[71] focuses on experimental design for split-plot experiments using Bayesian I-optimality criteria, not on sequential posterior estimation with acquisition functions for simulation-based inference.

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6. Sequential Bayesian experimental design for calibration of expensive simulation models

URL: View paper

Brief Assessment

Sequential Experimental Design[68] focuses on calibration of expensive simulation models using acquisition functions for experimental design, not on sequential posterior estimation for simulation-based inference. The candidate targets parameter selection for calibration via expected integrated variance, while the original develops sequential neural posterior estimation with epistemic uncertainty-based acquisition for multifidelity inference.

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7. Solving Bayesian inverse problems with expensive likelihoods using constrained Gaussian processes and active learning

URL: View paper

Brief Assessment

Constrained Gaussian Active[76] focuses on Gaussian process surrogates for expensive likelihood evaluations with active learning for training point selection, not sequential neural posterior estimation with acquisition functions targeting epistemic uncertainty in density estimators.

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8. Sequential Maximal Updated Density Parameter Estimation for Dynamical Systems With Parameter Drift

URL: View paper

Brief Assessment

Parameter Drift Estimation[75] focuses on sequential parameter estimation for dynamical systems with parameter drift using maximal updated density (MUD) estimates within a data-consistent framework. This is fundamentally different from MF-TSNPE-AF, which addresses simulation-based inference for expensive simulators using multifidelity approaches and acquisition functions targeting epistemic uncertainty in neural density estimators.

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9. Active sequential posterior estimation for sample-efficient simulation-based inference

URL: View paper

Prior Art Analysis

Active Sequential Posterior[67] demonstrates that similar prior work exists in using acquisition functions for sequential posterior estimation targeting epistemic uncertainty. The candidate paper presents ASNPE (Active Sequential Neural Posterior Estimation), which incorporates an acquisition function based on epistemic uncertainty to adaptively select simulation parameters. Both papers target epistemic uncertainty through acquisition functions in sequential neural posterior estimation frameworks, with the candidate paper published in NeurIPS 2024, predating the original submission under review at ICLR 2026.

Evidence

Evidence 1 - **Rationale**: Both papers introduce sequential methods with active learning for posterior estimation, suggesting the original's novelty claim may be challenged by this prior work. - **Original**: we present mf-tsnpe-af, an extension of mf-tsnpe with active learning, facilitating targeted parameter space exploration to effectively enhance high-fidelity posterior estimates given single observations. - **Candidate**: we introduce active sequential neural posterior estimation (asnpe). asnpe brings an active learning scheme into the inference loop to estimate the utility of simulation parameter candidates to the underlying probabilistic model.

Evidence 2 - **Rationale**: Both papers explicitly target epistemic uncertainty in model parameters through acquisition functions, demonstrating similar technical approaches to the problem. - **Original**: following j¨arvenp¨a¨a et al. (2019); lueckmann et al. (2019), we select an acquisition function that targets the variance of the posterior estimate with respect to the epistemic uncertainty in the learned parameters ϕ|d. θ∗ = argmax θ vϕ|d[qϕ(θ|xo)] - **Candidate**: in an attempt to quantify the prospective impact of any particular θ on our posterior estimate, we look to bayesian active learning, and acquisition functions such as eig. eig considers the reduction in uncertainty of model parameters under the inclusion of new data in expectation over the predictiv...

Evidence 3 - **Rationale**: Both papers use uncertainty quantification across model parameters to guide simulation parameter selection, showing similar methodological foundations. - **Original**: we realize this as the sample variance across an ensemble of neural density estimators trained independently on the same dataset d, as done in lueckmann et al. (2019). note that we use epistemic uncertainty to guide high-fidelity simulation selection within the simulator's domain rather than out-of-... - **Candidate**: while hd provides a measure of distributional uncertainty, we can target specificθ whose assigned likelihood is widely disagreed upon across draws of ϕ ∼ p(ϕ|d): θ∗ = argmaxθeϕ|d h (p(θ|xo, d) - p(θ|xo, ϕ))2 i .

Evidence 4 - **Rationale**: Both papers address the computational considerations of using ensembles or Bayesian approaches for uncertainty quantification in neural density estimators. - **Original**: mf-tsnpe-af requires the training of an ensemble of density estimators, which leads to substantial computational costs in training and hyperparameter tuning. this method should therefore only be preferred in cases where the cost incurred in simulations outweighs the training cost. - **Candidate**: to approximate the bayesian model parameter posterior p(ϕ|d), neural network-based ndes (such as flow-based generative models or mixture density networks) can be trained via mc-dropout [21, 14].

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10. Deep bayesian active learning for preference modeling in large language models

URL: View paper

Brief Assessment

Active Learning Preferences[70] focuses on preference modeling for LLMs using Bayesian active learning with acquisition functions targeting epistemic uncertainty in a different context (human preference labeling). The original paper addresses sequential posterior estimation for expensive simulators in scientific domains, representing fundamentally different application domains and methodological approaches.

Contribution 3: Empirical Analysis of Transfer Learning Effectiveness in Multifidelity SBI

Description: The authors investigate when pre-training on low-fidelity simulations helps transfer learning by conducting controlled experiments. They demonstrate that effectiveness depends on both mutual information between low- and high-fidelity simulators and representational coherence, providing empirical insights into the conditions under which multifidelity approaches succeed.

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

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1. Transfer learning with graph neural networks for improved molecular property prediction in the multi-fidelity setting

URL: View paper

Brief Assessment

Graph Neural Molecular[61] focuses on molecular property prediction in drug discovery and quantum mechanics using graph neural networks, not simulation-based inference frameworks for general scientific simulators. The technical domains and methodologies are fundamentally different.

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2. AI-Enabled Knowledge Transfer and Learning for Nondestructive Evaluation Toward Intelligent and Adaptive Systems

URL: View paper

Brief Assessment

Knowledge Transfer NDE[64] focuses on nondestructive evaluation applications and does not provide empirical analysis of transfer learning effectiveness conditions in multifidelity simulation-based inference contexts.

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3. Accelerating process synthesis with reinforcement learning: Transfer learning from multi-fidelity simulations and variational autoencoders

URL: View paper

Brief Assessment

Process Synthesis Reinforcement[58] focuses on transfer learning in reinforcement learning for chemical process design, not simulation-based inference. The candidate examines transfer from shortcut to rigorous process simulators and from VAEs, which differs fundamentally from the original paper's investigation of transfer learning conditions in multifidelity simulation-based inference for parameter estimation.

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4. Transfer learning-based multi-fidelity modeling method for multimode process monitoring

URL: View paper

Brief Assessment

Multimode Process Monitoring[66] focuses on industrial process monitoring with mode changes due to equipment deterioration, not simulation-based inference. The candidate does not investigate conditions for transfer learning effectiveness in multifidelity simulation contexts.

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5. Inductive transfer-learning of high-fidelity aerodynamics from inviscid panel methods

URL: View paper

Brief Assessment

Inviscid Panel Transfer[62] focuses on aerodynamic surrogate modeling using transfer learning from inviscid panel methods to RANS simulations, not on simulation-based inference or the conditions for transfer learning effectiveness in multifidelity SBI frameworks.

6. Meta Learner-Based Transfer Learning: Bridging Simulation and Actual Router Metrics

URL: View paper

Brief Assessment

Meta Learner Router[65] focuses on transfer learning for network router metrics using neural processes, not simulation-based inference for scientific simulators. The domains and methodologies are fundamentally different.

7. Efficient aerodynamic shape optimization using transfer learning based multi-fidelity deep neural network

URL: View paper

Brief Assessment

Aerodynamic Shape Optimization[59] applies transfer learning in aerodynamic optimization using CFD simulations with different grid resolutions, not simulation-based inference. The paper does not investigate conditions for transfer learning effectiveness in multifidelity SBI contexts or provide empirical insights into mutual information and representational coherence as determinants of success.

8. A multi-fidelity transfer learning strategy based on multi-channel fusion

URL: View paper

Brief Assessment

Multi-channel Fusion Transfer[60] focuses on multi-fidelity data fusion with multi-encoders for transfer learning, but does not provide empirical analysis of conditions determining transfer learning effectiveness in simulation-based inference contexts.

9. Transfer learning in multi-fidelity surrogate modeling: A wind farm case

URL: View paper

Brief Assessment

Wind Farm Transfer[63] focuses on surrogate modeling for wind farm flow fields using multi-fidelity transfer learning, not simulation-based inference for parameter estimation. The paper addresses when transfer learning works in surrogate modeling contexts (predicting flow fields from parameters), whereas the original contribution investigates conditions for effective transfer learning in posterior inference (estimating parameter distributions from observations).

10. Transfer learning for multifidelity simulation-based inference in cosmology

URL: View paper

Brief Assessment

Cosmology Transfer Learning[41] focuses on demonstrating the application of multifidelity transfer learning to cosmological simulations, not on investigating the conditions under which transfer learning is effective (mutual information and representational coherence).

Appendix: Text Similarity Detection

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

References

- [0] Multifidelity Simulation-based Inference for Computationally Expensive Simulators View paper
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