# Novelty Assessment Report

**Paper**: Minimax-Optimal Aggregation for Density Ratio Estimation

**PDF URL**: https://openreview.net/pdf?id=gDxJK8yvZU

**Venue**: ICLR 2026 Conference Submission

**Year**: 2026

**Report Generated**: 2025-12-27

## Abstract

Density ratio estimation (DRE) is fundamental in machine learning and statistics, with applications in domain adaptation and two-sample testing. However, DRE methods are highly sensitive to hyperparameter selection, with suboptimal choices often resulting in poor convergence rates and empirical performance. To address this issue, we propose a novel model aggregation algorithm for DRE that trains multiple models with different hyperparameter settings and aggregates them. Our aggregation provably achieves minimax-optimal error convergence without requiring prior knowledge of the smoothness of the unknown density ratio. Our method surpasses cross-validation-based model selection and model averaging baselines for DRE on standard benchmarks for DRE and large-scale domain adaptation tasks, setting a new state of the art on image and text data.



## Core Task Landscape

This paper addresses: **Density Ratio Estimation with Model Aggregation**

A total of **33 papers** were analyzed and organized into a taxonomy with **19 categories**.

### Taxonomy Overview

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

- **Core Density Ratio Estimation Methods**
- **Model Aggregation and Ensemble Techniques for Density Ratios**
- **Density Estimation with Aggregation**
- **Domain Adaptation and Transfer Learning with Density Ratios**
- **Bayesian Optimization and Sequential Decision Making**
- **Statistical Inference and Hypothesis Testing**
- **Specialized Applications of Density Ratio Estimation**

### Complete Taxonomy Tree

- Density Ratio Estimation with Model Aggregation Survey Taxonomy
- Core Density Ratio Estimation Methods
  - Direct Density Ratio Modeling (3 papers)
  - [17] Density-ratio matching under the bregman divergence: a unified framework of density-ratio estimation (æ□□å±± å°□, 2012) View paper
  - [26] Voice activity detection based on density ratio estimation and system combination (Yuuki Tachioka, 2013) View paper
  - [27] Adaptive Multi-stage Density Ratio Estimation for Learning Latent Space Energy-based Model (Xiao, 2022) View paper
  - Tree-Based and Structured Density Ratio Models (1 papers)
  - [1] Two-sample comparison through additive tree models for density ratios (Awaya, 2025) View paper
  - Kernel-Based Density Ratio Estimation (1 papers)
  - [22] Ensemble kernel mean matching (Yun-Qian Miao, 2015) View paper
- Model Aggregation and Ensemble Techniques for Density Ratios
  - Minimax-Optimal Aggregation ★ (1 papers)
  - [0] Minimax-Optimal Aggregation for Density Ratio Estimation (Anon et al., 2026) View paper
  - Ensemble Learning for Density Ratio Estimation (2 papers)
  - [12] Frequentist Uncertainties on Neural Density Ratios with wifi Ensembles (Thaler, 2025) View paper
  - [21] Improved Density Ratio Estimation for Evaluating Synthetic Data Quality (L Gruber, n.d.) View paper
- Density Estimation with Aggregation
  - Theoretical Aggregation of Density Estimators (4 papers)
  - [14] Aggregation of density estimators and dimension reduction (Alexander Samarov, 2007) View paper
  - [15] Linear and convex aggregation of density estimators (Rigollet, 2022) View paper
  - [16] Optimal exponential bounds for aggregation of density estimators (Bellec, 2022) View paper
  - [23] Data-driven aggregation in non-parametric density estimation on the real line (Miguel, 2020) View paper
  - Empirical Aggregation of Density Estimators (1 papers)
  - [28] Aggregating density estimators: an empirical study (M Bourel, 2012) View paper
  - Kernel Density Estimation Ensembles (1 papers)
  - [25] Ensemble Kernel Density Estimation (Ancell, 2022) View paper
- Domain Adaptation and Transfer Learning with Density Ratios
  - Multistream Classification with Density Ratios (2 papers)
  - [9] Ensemble direct density ratio estimation for multistream classification (Swarup Chandra, 2018) View paper

  - [13] Multistream classification with relative density ratio estimation (Bo Dong, 2019) View paper
  - Domain Shift and Distribution Correction (3 papers)
  - [3] Optimal aggregation of prediction intervals under unsupervised domain shift (Jianqing Fan, 2024) View paper
  - [29] Evaluating Parameter Choice Methods for Unsupervised Domain Adaptation of Sentiment Classification/Author Andrea Katharina Huber, BSc (Huber, 2023) View paper
  - [31] Ensemble Learning for Domain Adaptation by Importance Weighted Least Squares (MC Dinu, n.d.) View paper
- Bayesian Optimization and Sequential Decision Making (3 papers)
  - [4] MBORE: multi-objective bayesian optimisation by density-ratio estimation (Rahat, 2022) View paper
  - [6] Batch Bayesian optimisation via density-ratio estimation with guarantees (Oliveira, 2022) View paper
  - [10] Model-based offline policy optimization with distribution correcting regularization (Jian Shen, 2021) View paper
- Statistical Inference and Hypothesis Testing
  - Likelihood Ratio Combination for Diagnostics (3 papers)
  - [18] Likelihood ratio combination of multiple biomarkers viaÂ smoothing spline estimated densities (Zhiyuan Du, 2024) View paper
  - [24] Using a monotonic density ratio model to find the asymptotically optimal combination of multiple diagnostic tests (Li Pengfei, 2016) View paper
  - [33] Using a monotonic density ratio model to find the asymptotically optimal combination of multiple diagnostic tests: Supplementary document (B Chen, n.d.) View paper
  - Score Likelihood Ratios and Forensic Applications (1 papers)
  - [7] Ensemble learning for score likelihood ratios under the common source problem (Federico Veneri, 2023) View paper
- Specialized Applications of Density Ratio Estimation
  - Speech and Audio Processing (1 papers)
  - [5] Combining multiple end-to-end speech recognition models based on density ratio approach (Keigo Hojo, 2023) View paper
  - Ecological and Species Distribution Modeling (1 papers)
  - [2] Flexible Methods for Species Distribution Modeling with Small Samples (Brian S. Maitner, 2025) View paper
  - Causal Inference with Density Ratios (1 papers)
  - [11] A Density Ratio Super Learner (Wu Wencheng, 2024) View paper
  - Visualization and Feature Exploration (1 papers)
  - [30] eFESTA: Ensemble Feature Exploration with Surface Density Estimates. (Wenbin He, n.d.) View paper
  - Federated Learning with Density Ratios (1 papers)
  - [20] Knowledge-driven federated learning: A systematic literature review on approaches, challenges, and prospects: X. Lin et al. (X Lin, 2025) View paper
  - Miscellaneous Specialized Applications (3 papers)
  - [8] Effective-aggregation Graph Convolutional Network for Imbalanced Classification (Kefan Wang, 2022) View paper
  - [19] Scoping review of methodology for aiding generalisability and transportability of clinical prediction models (Kritchavat Ploddi, 2024) View paper
  - [32] Application of Bagged Copula-GP: Confirming Neural Dependency on Pupil Dilation (Walden, n.d.) View paper

### Narrative

Core task: density ratio estimation with model aggregation. The field encompasses a diverse set of methodological branches that address how to estimate ratios of probability densities and how to combine multiple models or estimators to improve performance. At the highest level, the taxonomy distinguishes core density ratio estimation methods—which develop direct techniques for computing ratios without separately estimating each density—from model aggregation and ensemble techniques that focus on combining predictions from multiple base learners. Additional branches cover density estimation with aggregation (where ensembles are applied to density estimation itself), domain adaptation and transfer learning (which leverage density ratios to handle distribution shift), Bayesian optimization and sequential decision making (where density ratios guide exploration), statistical inference and hypothesis testing (using ratios for two-sample tests or covariate shift correction), and specialized applications ranging from speech recognition to species distribution modeling. Representative works such as Ensemble Direct Density[9] and Density Ratio SuperLearner[11] illustrate how aggregation strategies can be tailored to density ratio problems, while methods like MBORE[4] show the utility of ratios in active learning settings.

Within the model aggregation branch, a particularly active line of research investigates minimax-optimal aggregation strategies that provide theoretical guarantees on the combined estimator's performance. Minimax Density Ratio[0] sits squarely in this subfield, emphasizing rigorous risk bounds and optimal weighting schemes when aggregating density ratio estimators. This contrasts with more heuristic ensemble approaches seen in works like Ensemble Kernel Matching[22] or Bagged Copula GP[32], which prioritize empirical flexibility over worst-case optimality. A central trade-off across these aggregation methods is between computational tractability and the strength of theoretical guarantees: some techniques achieve near-oracle performance under mild assumptions, while others sacrifice formal optimality for broader applicability or ease of implementation. The original paper's focus on minimax optimality places it among a small cluster of theoretically driven aggregation studies, distinguishing it from the many empirical ensemble methods and from branches that apply density ratios to downstream tasks without emphasizing aggregation theory.

## 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

Both subtopics address aggregation/combination of multiple models for density ratio estimation, but differ fundamentally in their theoretical foundations. Minimax-Optimal Aggregation focuses on methods with rigorous theoretical guarantees achieving optimal convergence rates, while Ensemble Learning for Density Ratio Estimation encompasses broader ensemble techniques like bagging and model combination that may lack formal optimality proofs.

**Similarities:** - Both involve combining multiple models or estimators rather than relying on a single model - Both aim to improve density ratio estimation performance through aggregation - Both fall under the broader umbrella of model aggregation approaches for density ratio estimation

**Differences:** - Minimax-Optimal Aggregation requires theoretical guarantees and proven minimax-optimal convergence rates, while Ensemble Learning may use heuristic or empirical approaches - Minimax-Optimal Aggregation emphasizes optimality theory, whereas Ensemble Learning focuses on practical ensemble techniques like bagging - Heuristic aggregation methods without optimality guarantees are explicitly excluded from Minimax-Optimal but would fit within Ensemble Learning

**Suggested Search Directions:** - Investigate whether ensemble methods like boosting for density ratios have minimax-optimal variants - Explore the boundary between empirically successful ensemble methods and those with theoretical optimality guarantees - Search for papers bridging practical ensemble techniques with minimax-optimal theory in density ratio contexts

## Sibling Subtopics

- **Ensemble Learning for Density Ratio Estimation** (leaves: 1, papers: 2)
- Scope: Methods using ensemble techniques like bagging or model combination for density ratio estimation.
- Exclude: Single-model methods and application-specific ensembles belong elsewhere.

# Contributions Analysis

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

## Contribution 1: Novel model aggregation algorithm for density ratio estimation

**Description**: The authors introduce a new aggregation method that combines multiple density ratio estimators trained with different hyperparameters. The method optimizes aggregation weights by minimizing an upper bound on the Bregman divergence, yielding an analytic solution that is computationally efficient.

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. Existence of Direct Density Ratio Estimators

**URL**: View paper

**Brief Assessment**

Direct Density Existence[39] focuses on existence conditions for KLIEP estimators in density ratio estimation, not on aggregating multiple models with different hyperparameters. The paper addresses when density ratio estimators exist mathematically rather than proposing aggregation methods.

### 2. Density ratio estimation in machine learning

**URL**: View paper

**Brief Assessment**

Density Ratio Machine[37] focuses on general density ratio estimation in machine learning contexts, not specifically on aggregating multiple models with different hyperparameters as the original paper proposes.

### 3. Application of Bagged Copula-GP: Confirming Neural Dependency on Pupil Dilation

**URL**: View paper

**Brief Assessment**

Bagged Copula GP[32] focuses on copula-based mutual information estimation for neuroscience applications, not density ratio estimation. The aggregation method uses Bayesian model averaging for copula models, which is a different statistical framework than the Bregman divergence-based aggregation for density ratio estimators proposed in the original paper.

### 4. Lipschitz density-ratios, structured data, and data-driven tuning

**URL**: View paper

**Brief Assessment**

Lipschitz Density Ratios[38] focuses on density ratio estimation with Lipschitz smoothness conditions and data-driven bandwidth selection, not on aggregating multiple models with different hyperparameters as in the original paper's contribution.

### 5. Training Data Soft Selection via Joint Density Ratio Estimation

**URL**: View paper

**Brief Assessment**

Training Data Selection[36] focuses on joint density ratio estimation for training data selection under distributional shifts, not on aggregating multiple density ratio estimators with different hyperparameters as in the original paper's contribution.

### 6. Ensemble Learning for Domain Adaptation by Importance Weighted Least Squares

**URL**: View paper

**Brief Assessment**

Importance Weighted Least[31] focuses on ensemble learning for domain adaptation using importance weighted least squares, not on aggregating multiple density ratio estimators with different hyperparameters for density ratio estimation itself. The candidate addresses a different problem domain (domain adaptation) rather than the core density ratio estimation aggregation problem.

### 7. Improved Density Ratio Estimation for Evaluating Synthetic Data Quality

**URL**: View paper

**Prior Art Analysis**

Synthetic Data Quality[21] demonstrates that a model aggregation algorithm for density ratio estimation with multiple hyperparameters was previously proposed. The candidate paper presents a nearly identical approach: training multiple models with different hyperparameter configurations, computing aggregation weights via an analytic solution using empirical gram matrices and inner product vectors, and combining outputs through linear aggregation. The mathematical formulation, optimization strategy (minimizing an upper bound on Bregman divergence), and algorithmic structure are substantially similar, indicating prior work exists on this contribution.

**Evidence**

Evidence 1 - **Rationale**: Both papers claim novelty for the same core contribution: a model aggregation algorithm for DRE that trains multiple models with different hyperparameters and achieves optimal convergence without prior smoothness knowledge. The near-identical phrasing suggests this is the same work or that prior work exists. - **Original**: we propose a novel model aggregation algorithm for dre that trains multiple models with different hyperparameter settings and aggregates them. our aggregation provably achieves minimax-optimal error convergence without requiring prior knowledge of the smoothness of the unknown density ratio. - **Candidate**: we propose a novel model aggregation algorithm for dre that trains multiple models with diverse hyperparameter configurations and combines their outputs. our approach achieves fast convergence without requiring prior knowledge of the unknown density ratio smoothness and is minimax optimal for the sq...

Evidence 2 - **Rationale**: The mathematical formulation for computing aggregation weights is identical in both papers, including the optimization objective and the claim of an analytic solution. This demonstrates that the same aggregation method was previously described. - **Original**: our aggregation strategy is to choose the aggregation weights α1, . . . , αk that minimize this upper bound min α1,...,αk∈r kx k=1 αkfk - fh (6) which has three immediate advantages: (a) an analytic solution, (b) computational improvement compared to n-fold cv (see fig. 2, left) and (c) minimax-opti... - **Candidate**: our approach is to choose the aggregation weights α1, . . . , αk that minimize this upper bound min α1,...,αk∈r kx k=1 αkfk - fh 2 (4) which has two advantages: (a) an analytic solution by functional least-squares and (b) fast provable convergence rate for estimators.

### 8. Density-based weighting for imbalanced regression

**URL**: View paper

**Brief Assessment**

Density Weighting Imbalanced[35] focuses on imbalanced regression through density-based sample weighting, not on aggregating multiple density ratio estimators with different hyperparameters for domain adaptation or two-sample testing.

### 9. Knowledge-driven federated learning: A systematic literature review on approaches, challenges, and prospects: X. Lin et al.

**URL**: View paper

**Brief Assessment**

Knowledge Driven Federated[20] focuses on federated learning contexts with client-side density ratio estimation for outlier detection and server-side model aggregation. This differs from the original paper's focus on aggregating multiple density ratio estimators with different hyperparameters to achieve minimax-optimal convergence rates in centralized settings.

### 10. Rethinking density ratio estimation based hyper-parameter optimization

**URL**: View paper

**Brief Assessment**

Rethinking Hyperparameter Optimization[34] focuses on converting hyperparameter optimization into density-ratio estimation problems, not on aggregating multiple density ratio estimators with different hyperparameters as proposed in the original paper.

## Contribution 2: Minimax-optimal convergence rates without prior smoothness knowledge

**Description**: The authors prove that their aggregation approach achieves minimax-optimal error convergence rates for a broad class of DRE methods optimized in reproducing kernel Hilbert spaces, without needing to know the smoothness of the true density ratio in advance.

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.

### 1. Estimating divergence functionals and the likelihood ratio by convex risk minimization

**URL**: View paper

**Brief Assessment**

Convex Risk Minimization[46] addresses minimax-optimal rates for density ratio estimation but requires explicit smoothness assumptions ($\alpha > d/2$) and does not provide an aggregation framework that automatically adapts to unknown smoothness as claimed in the original paper.

### 2. Minimax rates for conditional density estimation via empirical entropy

**URL**: View paper

**Brief Assessment**

Minimax Conditional Density[48] addresses conditional density estimation under KL risk using empirical Hellinger entropy. The ORIGINAL paper focuses on density ratio estimation in RKHS with Bregman divergences and aggregation methods. These are fundamentally different problem settings with distinct technical approaches.

### 3. Online anomaly detection with minimax optimal density estimation in nonstationary environments

**URL**: View paper

**Brief Assessment**

Online Anomaly Detection[47] focuses on anomaly detection in time series with nonstationary exponential-family distributions, not general density ratio estimation across arbitrary distributions without smoothness assumptions as in the original paper.

### 4. Adaptive learning of density ratios in RKHS

**URL**: View paper

**Prior Art Analysis**

Adaptive RKHS Learning[49] demonstrates prior work achieving minimax-optimal convergence rates for density ratio estimation without requiring prior knowledge of smoothness parameters. The paper presents a Lepskii-type balancing principle that adaptively achieves minimax-optimal rates without knowing the regularity index r in advance. This directly challenges the novelty claim that the ORIGINAL paper is the first to achieve such rates without smoothness knowledge, as Adaptive RKHS Learning[49] explicitly states achieving minimax-optimal rates adaptively and provides a parameter choice method that does not require access to the regularity index.

**Evidence**

Evidence 1 - **Rationale**: Both papers claim to achieve minimax-optimal rates without prior knowledge of smoothness/regularity. The candidate explicitly states their method does not need access to the regularity index r, directly paralleling the original's claim about not requiring smoothness knowledge. - **Original**: our aggregation provably achieves minimax-optimal error convergence without requiring prior knowledge of the smoothness of the unknown density ratio - **Candidate**: our third result (eq. (30)) is a new method for choosing the regularization parameter λ that does not need access to the regularity index r but nevertheless achieves the same rate as in eq. (4) (see theorem 2)

Evidence 2 - **Rationale**: The candidate acknowledges prior work on adaptive methods in related domains, suggesting the landscape of adaptive parameter selection without prior smoothness knowledge was already being explored before the original paper's submission. - **Original**: our method surpasses cross-validation-based model selection and model averaging baselines for dre on standard benchmarks for dre and large-scale domain adaptation tasks - **Candidate**: even if similar adaptivity results hold for cross-validation in supervised learning (caponnetto and yao, 2010) and the aggregation method in covariate shift domain adaptation (gizewski et al., 2022), their extension to density ratio estimation is not straight forward and an open future problem

### 5. Estimating Unbounded Density Ratios: Applications in Error Control under Covariate Shift

**URL**: View paper

**Brief Assessment**

Unbounded Density Ratios[44] focuses on density ratio estimation with unbounded domains and ranges, not on aggregation methods for density ratio estimation in reproducing kernel Hilbert spaces as claimed in the original paper.

### 6. Overcoming Saturation in Density Ratio Estimation by Iterated Regularization

**URL**: View paper

**Brief Assessment**

Iterated Regularization Saturation[45] focuses on resolving error saturation in kernel methods for density ratio estimation through iterated regularization. While both papers address convergence rates in density ratio estimation, the candidate does not demonstrate that similar minimax-optimal aggregation methods without smoothness assumptions existed prior to the original work.

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### 7. Improved Density Ratio Estimation for Evaluating Synthetic Data Quality

**URL**: View paper

**Prior Art Analysis**

Synthetic Data Quality[21] presents the same theoretical result regarding minimax-optimal convergence rates for density ratio estimation without requiring prior knowledge of smoothness. Both papers prove that their aggregation approach achieves the rate (m+n)^(-2rα+α)/(2rα+α+1) with high probability, and both claim this is the first such result for parameter choice in DRE. The theoretical framework, including the use of source and capacity conditions, self-concordance assumptions, and the proof strategy, are identical.

**Evidence**

Evidence 1 - **Rationale**: The main theoretical result is identical in both papers, including the convergence rate formula, probability bounds, and conditions. This demonstrates that the theoretical contribution regarding minimax-optimal rates was previously established. - **Original**: theorem 1. let assumptions 1-4 and technical assumptions from appendix a be satisfied. consider k >1, δ >0, {λk}k k=1 as defined in appendix a and associated bfλk as in equation 11. then we have that for bβ of algorithm 1 applied with βk := g( bfλk ): bf β, bβ - bf (β, g(fh)) ≤ c(m + n)- 2rα+α 2rα... - **Candidate**: theorem 1. let assumptions 1-4 and technical assumptions from appendix a be satisfied. consider k >1, δ >0, {λk}k k=1 as defined in appendix a and associated bfλk as in equation 10. then we have that for bβ of algorithm 1 applied with βk := g( bfλk ): bf β, bβ - bf (β, g(fh)) ≤ c(m + n)- 2rα+α 2rα...

Evidence 2 - **Rationale**: Both papers explicitly claim to be the first to provide minimax-optimal convergence rates for parameter choice in DRE, using nearly identical language. This indicates the same theoretical novelty claim was made previously. - **Original**: remark 1. to the best of our knowledge, theorem 1 provides the first provably minimax-optimal convergence rates for a parameter choice procedure in dre. zellinger et al. (2023) provide similar rates but they rely on a heuristically fixed constant for their implementations of the balancing principle. - **Candidate**: remark 1. to the best of our knowledge theorem 1 provides the first provable principled way of achieving minimax optimal convergence rates for a parameter choice procedure in dre, a full proof can be found in appendix a.

Evidence 3 - **Rationale**: Both papers connect the aggregation weight optimization to achieving minimax-optimal rates, demonstrating that the theoretical property was previously linked to this specific algorithmic approach. - **Original**: our approach is to choose the aggregation weights α1, . . . , αk that minimize this upper bound min α1,...,αk∈r kx k=1 αkfk - fh (6) which has three immediate advantages: (a) an analytic solution, (b) computational improvement compared to n-fold cv (see fig. 2, left) and (c) minimax-optimal rates (s... - **Candidate**: our approach is to choose the aggregation weights α1, . . . , αk that minimize this upper bound min α1,...,αk∈r kx k=1 αkfk - fh 2 (4) which has two advantages: (a) an analytic solution by functional least-squares and (b) fast provable convergence rate for estimators.

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### 8. Optimal Estimation under a Semiparametric Density Ratio Model

**URL**: View paper

**Brief Assessment**

Semiparametric Density Ratio[50] focuses on achieving parametric efficiency bounds in density ratio estimation under specific asymptotic regimes (when one sample size dominates), not on minimax-optimal rates without smoothness assumptions across general DRE methods in RKHS.

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## Contribution 3: Theory-grounded aggregation method addressing hyperparameter choice

**Description**: The authors develop a principled aggregation framework that addresses the sensitivity of density ratio estimators to hyperparameter selection, providing both theoretical guarantees and practical improvements over cross-validation-based model selection.

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. Frequentist uncertainties on neural density ratios with ensembles

**URL**: View paper

**Brief Assessment**

The candidate paper (Frequentist Uncertainties Ensembles[40]) focuses on ensemble methods for uncertainty quantification in neural density ratio estimation, not on aggregation methods for addressing hyperparameter selection sensitivity in density ratio estimation frameworks.

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### 2. Density ratio estimation in machine learning

**URL**: View paper

**Brief Assessment**

While Density Ratio Machine[37] mentions hyperparameter selection in density estimation, the limited context does not demonstrate a principled aggregation framework with theoretical guarantees for addressing hyperparameter sensitivity as claimed in the original work.

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### 3. MBORE: multi-objective bayesian optimisation by density-ratio estimation

**URL**: View paper

**Brief Assessment**

MBORE[4] focuses on multi-objective Bayesian optimization using density-ratio estimation for scalarization, not on aggregation methods for hyperparameter selection in density ratio estimation itself.

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### 4. A New Classifier for Imbalanced Data Based on a Generalized Density Ratio Model

**URL**: View paper

**Brief Assessment**

Generalized Density Classifier[42] focuses on imbalanced data classification using density ratio models with cross-validation for tuning, not on aggregation methods with theoretical guarantees for hyperparameter selection in density ratio estimation.

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### 5. A density ratio framework for evaluating the utility of synthetic data

**URL**: View paper

**Brief Assessment**

Density Ratio Framework[41] focuses on evaluating synthetic data utility through density ratio estimation, not on aggregation methods for hyperparameter selection in density ratio estimation itself.

### 6. Flexible Methods for Species Distribution Modeling with Small Samples

**URL**: View paper

**Brief Assessment**

Flexible Species Distribution[2] focuses on species distribution modeling with small samples using density-ratio methods, but does not address hyperparameter aggregation frameworks or provide theoretical convergence guarantees for density ratio estimation.

### 7. Batch Bayesian optimisation via density-ratio estimation with guarantees

**URL**: View paper

**Brief Assessment**

Batch Bayesian Optimisation[6] focuses on batch optimization via density-ratio estimation for Bayesian optimization, not on aggregation methods for hyperparameter selection in density ratio estimation as addressed in the original paper.

### 8. Frequentist Uncertainties on Neural Density Ratios with wifi Ensembles

**URL**: View paper

**Brief Assessment**

Frequentist Uncertainties wifi[12] focuses on obtaining frequentist uncertainties for neural density ratio estimation in high-energy physics, not on hyperparameter selection or aggregation methods for density ratio estimators. The paper introduces wifi ensembles for uncertainty quantification rather than addressing hyperparameter sensitivity issues.

### 9. Evaluating Hyperparameter Selection Techniques for the Ratio-Coupled Loss Function

**URL**: View paper

**Brief Assessment**

The candidate paper (Ratio Coupled Loss[43]) focuses on hyperparameter selection techniques for a specific loss function in density ratio estimation, not on developing a general aggregation framework with theoretical guarantees for combining multiple models trained with different hyperparameters.

### 10. Rethinking density ratio estimation based hyper-parameter optimization

**URL**: View paper

**Brief Assessment**

Rethinking Hyperparameter Optimization[34] addresses hyperparameter optimization through density-ratio estimation conversion, which is a different approach from the original paper's aggregation framework that combines multiple models trained with different hyperparameters.

## Appendix: Text Similarity Detection

Textual similarity detection checked 25 papers and found 6 similarity segment(s) across 2 paper(s).

The following **2 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. Improved Density Ratio Estimation for Evaluating Synthetic Data Quality

**Detected in**: Contribution: contribution_1, 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.

### 2. Overcoming Saturation in Density Ratio Estimation by Iterated Regularization

**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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