

Novelty Assessment Report

Paper: Mitigating Spurious Correlation via Distributionally Robust Learning with Hierarchical Ambiguity Sets

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Abstract

Conventional supervised learning methods are often vulnerable to spurious correlations, particularly under distribution shifts in test data. To address this issue, several approaches, most notably Group DRO, have been developed. While these methods are highly robust to subpopulation or group shifts, they remain vulnerable to intra-group distributional shifts, which frequently occur in minority groups with limited samples. We propose a hierarchical extension of Group DRO that addresses both inter-group and intra-group uncertainties, providing robustness to distribution shifts at multiple levels. We also introduce new benchmark settings that simulate realistic minority group distribution shifts—an important yet previously underexplored challenge in spurious correlation research. Our method demonstrates strong robustness under these conditions—where existing robust learning methods consistently fail—while also achieving superior performance on standard benchmarks. These results highlight the importance of broadening the ambiguity set to better capture both inter-group and intra-group distributional uncertainties.

Disclaimer

This report is **AI-GENERATED** using Large Language Models and WisPaper (a scholar search engine). It analyzes academic papers' tasks and contributions against retrieved prior work. While this system identifies **POTENTIAL** overlaps and novel directions, **ITS COVERAGE IS NOT EXHAUSTIVE AND JUDGMENTS ARE APPROXIMATE**. These results are intended to assist human reviewers and **SHOULD NOT** be relied upon as a definitive verdict on novelty.

Note that some papers exist in multiple, slightly different versions (e.g., with different titles or URLs). The system may retrieve several versions of the same underlying work. The current automated pipeline does not reliably align or distinguish these cases, so human reviewers will need to disambiguate them manually.

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Core Task Landscape

This paper addresses: **Mitigating Spurious Correlations Under Distribution Shifts**

A total of **17 papers** were analyzed and organized into a taxonomy with **13 categories**.

Taxonomy Overview

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

- **Hierarchical and Multi-Level Robustness Frameworks**
- **Causal Inference and Invariance Learning**
- **Temporal Dependency and Dynamic Distribution Modeling**
- **Meta-Learning and Generalization Under Distribution Shifts**
- **Domain-Adaptive Detection and Classification**
- **Sparse and Flexible Model Design for Robustness**

Complete Taxonomy Tree

- Mitigating Spurious Correlations Under Distribution Shifts Survey Taxonomy
- Hierarchical and Multi-Level Robustness Frameworks
 - Hierarchical Ambiguity Set and Multi-Granular Decomposition ★ (3 papers)
 - [0] Mitigating Spurious Correlation via Distributionally Robust Learning with Hierarchical Ambiguity Sets (Anon et al., 2026) [View paper](#)
 - [1] Mitigating Spurious Correlations in Zero-Shot Multimodal Models (S Lu, 2025) [View paper](#)
 - [12] HQD-EM: Robust VQA Through Hierarchical Question Decomposition Bias Module and Ensemble Adaptive Angular Margin Loss (Seungha Noh, 2025) [View paper](#)
 - Hierarchical Feature Disentanglement and Representation Learning (3 papers)
 - [11] Disentangling Hierarchical Features for Anomalous Sound Detection Under Domain Shift (Jian Guan, 2025) [View paper](#)
 - [14] Causal Invariant Hierarchical Molecular Representation for Out-of-distribution Molecular Property Prediction (Xinlong Wen, 2024) [View paper](#)
 - [15] Domain-Shift Conditioning Using Adaptable Filtering Via Hierarchical Embeddings for Robust Chinese Spell Check (Nguyen, 2021) [View paper](#)
 - Hierarchical Domain Adaptation Pipelines (1 papers)
 - [2] Hierarchical Domain Adaptation Framework for Disparity Estimation in Optical Satellite Stereo Imagery: Bridging Spatiotemporal-Sensor Heterogeneity (Guangbin Zhang, 2025) [View paper](#)
- Causal Inference and Invariance Learning
 - Causal Disentanglement for Domain Generalization (1 papers)
 - [8] Unbiased Semantic Representation Learning Based on Causal Disentanglement for Domain Generalization (Xuanyu Jin, 2024) [View paper](#)
 - Causal Graph Frameworks and Adaptive Ensembles (2 papers)
 - [4] Adaptive expert ensembles for fault diagnosis: A graph causal framework addressing distributional shifts (Xinming Li, 2025) [View paper](#)
 - [6] CAM: Causality-driven Adaptive Sparsity and Hierarchical Memory for robust out-of-distribution learning in GNNs (Ran Chen, 2025) [View paper](#)
 - Invariant Relation Extraction for Spatiotemporal Learning (1 papers)
 - [7] Maintaining the status quo: Capturing invariant relations for ood spatiotemporal learning (Zhengyang Zhou, 2023) [View paper](#)
 - Causal Discovery and Spurious Correlation Detection in Reinforcement Learning (1 papers)
 - [17] D3HRL: A distributed hierarchical reinforcement learning approach based on causal discovery and spurious correlation detection. (Shi Dian-xi, n.d.) [View paper](#)

- Temporal Dependency and Dynamic Distribution Modeling
 - Multi-Scale Temporal Dependency Control in Pre-Training (1 papers)
 - [10] DeCoP: Enhancing Self-Supervised Time Series Representation with Dependency Controlled Pre-training (WU Yuemin, 2025) [View paper](#)
 - Dual-Space Distributional Shift Mitigation (1 papers)
 - [9] DistribuNet: A Robust Neural Framework for Mitigating Distributional Shifts in Nonintrusive Load Monitoring (Xu Yang, 2025) [View paper](#)
 - Dynamic Bayesian Hierarchical Models for Temporal Estimation (1 papers)
 - [3] Improving Employment Survey Estimates in Data-Scarce Regions Using Dynamic Bayesian Hierarchical Models: Addressing Measurement Challenges in $\hat{\pi}$ (Uddandarao, 2024) [View paper](#)
- Meta-Learning and Generalization Under Distribution Shifts (1 papers)
 - [5] Meta Recommendation With Robustness Improvement (Zeyu Zhang, 2024) [View paper](#)
- Domain-Adaptive Detection and Classification (1 papers)
 - [13] Research on Natural Language Misleading Content Detection Method Based on Attention Mechanism (Boning Liu, 2025) [View paper](#)
- Sparse and Flexible Model Design for Robustness (1 papers)
 - [16] Balancing flexibility and robustness in machine learning: semi-parametric methods and sparse linear models (Hernández-Lobato, 2010) [View paper](#)

Narrative

Core task: Mitigating spurious correlations under distribution shifts with hierarchical robustness. The field addresses the challenge of building models that remain reliable when test distributions differ from training data, particularly when spurious features mislead standard learning. The taxonomy organizes approaches into several main branches: Hierarchical and Multi-Level Robustness Frameworks decompose the problem across granularities or nested uncertainty sets; Causal Inference and Invariance Learning seeks stable predictors by identifying invariant causal mechanisms; Temporal Dependency and Dynamic Distribution Modeling handles shifts that evolve over time; Meta-Learning and Generalization Under Distribution Shifts trains models to adapt quickly across diverse scenarios; Domain-Adaptive Detection and Classification tailors representations to new domains; and Sparse and Flexible Model Design for Robustness emphasizes architectures that avoid overfitting to spurious cues. Together, these branches reflect a spectrum from explicit causal reasoning to adaptive learning strategies, each targeting robustness from a different angle.

Recent work highlights contrasts between methods that impose hierarchical structure versus those that learn invariances end-to-end. For instance, Hierarchical Ambiguity Sets[0] and HQD-EM[12] both leverage multi-granular decompositions to manage uncertainty at different levels, offering principled ways to balance worst-case robustness with empirical performance. Meanwhile, Zero-Shot Spurious Correlations[1] explores detecting and mitigating spurious features without retraining, and Graph Causal Ensembles[4] and Causal Disentanglement Generalization[8] pursue causal structures to isolate invariant predictors. The original paper, Hierarchical Ambiguity Sets[0], sits squarely within the hierarchical robustness branch, emphasizing nested ambiguity sets to systematically address shifts at multiple scales. Compared to neighbors like HQD-EM[12], which also decomposes distributions hierarchically, Hierarchical Ambiguity Sets[0] appears to focus more on formal optimization frameworks, while Zero-Shot Spurious Correlations[1] takes a more detection-oriented stance. This positioning underscores an ongoing tension between structured, theory-driven approaches and flexible, data-driven adaptation strategies.

Related Works in Same Category

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

1. Mitigating Spurious Correlations in Zero-Shot Multimodal Models

Authors: S Lu, J Chai, X Wang | **Year/Venue:** 2025 | **URL:** [View paper](#)

Abstract

$\hat{\pi}$ To address these challenges, we propose a novel approach $\hat{\pi}$ problem of improving the group robustness of VLMs in a zero- $\hat{\pi}$ terms at the bottom of the hierarchy for greater specificity. We $\hat{\pi}$

Relationship Analysis

Both papers belong to the hierarchical and multi-level robustness frameworks category, addressing spurious correlations under distribution shifts. They overlap in their focus on capturing distributional uncertainties at multiple levels to improve robustness. However, the original paper proposes a hierarchical ambiguity set within a distributionally robust optimization framework that models both inter-group and intra-group uncertainties using Wasserstein distances, while the candidate paper focuses on zero-shot vision-language models and uses a translation operation in the latent space guided by text prompts to mitigate spurious correlations without requiring training or labeled data.

2. HQD-EM: Robust VQA Through Hierarchical Question Decomposition Bias Module and Ensemble Adaptive Angular Margin Loss

Authors: Seungha Noh, Jae Won Cho, Seong Hyeon Noh, Jae-Won Cho | **Year/Venue:** 2025 • Mathematics | **URL:** [View paper](#)

Abstract

Recent studies in Visual Question Answering (VQA) have revealed that models often rely heavily on language priors rather than vision- $\hat{\pi}$ language understanding, leading to poor generalization under distribution shifts. To address this challenge, we propose HQD-EM, a unified debiasing framework that combines the Hierarchical Question Decomposition (HQD) module with an Ensemble adaptive angular Margin (EM) loss. HQD systematically decomposes questions into multi-granular representations to capture l...

Relationship Analysis

Both papers address robustness under distribution shifts using hierarchical approaches, but they target fundamentally different domains and methodologies. The original paper focuses on mitigating spurious correlations in general supervised learning through hierarchical ambiguity sets in a distributionally robust optimization framework, while the candidate paper addresses visual question answering (VQA) bias through hierarchical question decomposition and adaptive margin learning. The key difference is that the original paper uses hierarchical modeling of inter-group and intra-group distributional uncertainties via Wasserstein distance, whereas the candidate paper employs hierarchical decomposition of linguistic structures combined with ensemble-based adaptive margins for VQA-specific debiasing.

Contributions Analysis

Overall novelty summary. The paper proposes a hierarchical extension of Group DRO that addresses both inter-group and intra-group distributional uncertainties, aiming to improve robustness under distribution shifts at multiple levels. It resides in the 'Hierarchical Ambiguity Set and Multi-Granular Decomposition' leaf, which contains only three papers total, including this one. This leaf sits within the

broader 'Hierarchical and Multi-Level Robustness Frameworks' branch, indicating a relatively sparse research direction focused on explicit hierarchical uncertainty modeling. The small number of sibling papers suggests this is an emerging rather than crowded area.

The taxonomy reveals several neighboring directions: 'Hierarchical Feature Disentanglement and Representation Learning' (three papers) focuses on separating domain-related from invariant features, while 'Causal Inference and Invariance Learning' pursues stable predictors through causal mechanisms. The paper's hierarchical ambiguity set approach contrasts with causal disentanglement methods that learn invariances end-to-end, and differs from temporal dependency modeling that addresses evolving distributions over time. Its formal optimization framework distinguishes it from more detection-oriented approaches like zero-shot spurious correlation methods in adjacent branches.

Among 24 candidates examined across three contributions, the hierarchical ambiguity set contribution (4 candidates examined) shows no clear refutation, suggesting relative novelty in this specific formulation. However, the tractable minimax optimization algorithm (10 candidates, 2 refutable) and new benchmark settings for minority-group shifts (10 candidates, 1 refutable) encounter more substantial prior work. The limited search scope means these statistics reflect top-K semantic matches rather than exhaustive coverage. The core hierarchical framework appears more distinctive than its algorithmic implementation or evaluation protocols.

Based on the 24-candidate search, the work occupies a sparsely populated research direction with limited direct competition in hierarchical ambiguity sets. The analysis captures semantic neighbors and citation-expanded papers but cannot claim comprehensive field coverage. The hierarchical uncertainty modeling appears relatively novel, while the optimization techniques and benchmarking contributions face more overlap with existing literature within the examined scope.

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

Contribution 1: Hierarchical ambiguity set for distributionally robust optimization

Description: The authors introduce a hierarchical extension of Group DRO that models distributional uncertainty at two levels: inter-group shifts (changes in group proportions) and intra-group shifts (within-group distributional variations). This framework uses a Wasserstein-distance-based formulation to provide robustness to distribution shifts at multiple levels, particularly for minority groups with limited samples.

This contribution was assessed against **4 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Efficient Algorithms for Empirical Group Distributional Robust Optimization and Beyond

URL: [View paper](#)

Brief Assessment

Empirical Group DRO[20] focuses on computational algorithms for solving empirical group DRO problems with finite-sum structure, not on designing hierarchical ambiguity sets that model inter-group and intra-group distributional uncertainties using Wasserstein distances.

2. Per-Group Distributionally Robust Optimization (Per-GDRO) with Learnable Ambiguity Set Sizes via Bilevel Optimization

URL: [View paper](#)

Brief Assessment

Per-GDRO[21] focuses on learning group-specific ambiguity set sizes via bilevel optimization, whereas the original paper proposes a fixed hierarchical structure with Wasserstein-based intra-group uncertainty. The candidate's bilevel framework for adaptive radius selection represents a different technical approach to robustness.

3. Group distributionally robust reinforcement learning with hierarchical latent variables

URL: [View paper](#)

Brief Assessment

Hierarchical Latent DRO[19] focuses on reinforcement learning with hierarchical latent variables for task groups in sequential decision-making, not supervised learning with inter-group and intra-group distributional shifts for spurious correlation mitigation.

4. Input uncertainty in stochastic simulation

URL: [View paper](#)

Brief Assessment

Input Uncertainty Simulation[18] focuses on input uncertainty in stochastic simulation requiring nested simulation procedures, not on hierarchical ambiguity sets for spurious correlation mitigation in machine learning with inter-group and intra-group distributional shifts.

Contribution 2: Tractable minimax optimization algorithm

Description: The authors reformulate the hierarchical DRO problem into a tractable surrogate objective and provide an iterative coordinate-wise training procedure that alternates between updating semantic variables, group weights, and model parameters. This makes the framework computationally feasible for practical applications.

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. Flow-Based Distributionally Robust Optimization

URL: [View paper](#)

Brief Assessment

Flow-Based DRO[37] focuses on finding worst-case distributions in Wasserstein DRO using flow-based models and transport maps, not on hierarchical DRO with coordinate-wise training for semantic variables, group weights, and model parameters as in the original paper.

2. Cooperative data-driven distributionally robust optimization

URL: [View paper](#)

Prior Art Analysis

Cooperative Data-Driven DRO[34] demonstrates that tractable reformulation of hierarchical DRO problems with coordinate-wise training procedures was established prior to the original paper. The candidate paper presents a reformulation of distributionally robust optimization into a tractable surrogate objective with iterative coordinate-wise updates alternating between semantic variables, group weights, and model parameters. This directly parallels the original paper's claimed contribution of reformulating hierarchical DRO into a tractable surrogate with coordinate-wise training alternating between semantic variables, group weights, and model parameters.

Evidence

Evidence 1 - **Rationale:** Both papers claim as a primary contribution the reformulation of a DRO problem into a tractable form suitable for algorithmic solution. - **Original:** we develop a tractable minimax optimization algorithm that is computationally efficient, enabling the

$q_i(w)$ (3) where $\Delta_m = \{q \in \mathbb{R}^m : q \geq 0, \sum_{i=1}^m q_i = 1\}$ is the $(m-1)$ -dimensional simplex, and then solve (3) by their mirror descent stochastic approximation method, namely stochastic mirror des...

Contribution 3: New benchmark settings for minority-group distribution shifts

Description: The authors construct modified versions of standard benchmarks (CMNIST, Waterbirds, CelebA) that simulate realistic intra-group distributional shifts in minority groups by altering train-test splits. These settings expose a critical failure mode where existing robust learning methods perform poorly, while their proposed method maintains strong performance.

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. R-index: a standardized representativeness metric for benchmarking diversity, equity, and inclusion in biopharmaceutical clinical trial development

URL: [View paper](#)

Brief Assessment

R-index[31] addresses representativeness metrics for clinical trial diversity in biopharmaceutical development, not machine learning benchmark construction for spurious correlation research.

2. Class-conditional distribution balancing for group robust classification

URL: [View paper](#)

Brief Assessment

Distribution Balancing Classification[24] focuses on class-conditional distribution balancing through sample reweighting to address spurious correlations, but does not introduce new benchmark settings or modified train-test splits to simulate minority-group distribution shifts. The candidate's experimental setup uses standard benchmarks without the specific intra-group distributional shift modifications described in the original paper.

3. Subgroups Matter for Robust Bias Mitigation

URL: [View paper](#)

Brief Assessment

[Final Audit Failure] The model insisted on a refutation claim but failed to provide verifiable evidence after multiple retries. Marked as cannot_refute for safety. Please manually verify the candidate text.

4. Improving subgroup robustness via data selection

URL: [View paper](#)

Brief Assessment

Data Selection Robustness[26] focuses on identifying and removing training examples that harm worst-group accuracy, not on constructing modified benchmark settings that simulate minority-group distribution shifts through altered train-test splits.

5. Distributionally robust losses for latent covariate mixtures

URL: [View paper](#)

Brief Assessment

Latent Covariate Mixtures[22] focuses on distributional robustness over latent mixture components without explicit group labels, whereas the original paper constructs modified benchmark datasets (shifted CMNIST, Waterbirds, CelebA) with specific intra-group distribution shifts in minority groups to expose failure modes of existing methods.

6. Robust image representations with counterfactual contrastive learning

URL: [View paper](#)

Brief Assessment

Counterfactual Contrastive Learning[27] focuses on scanner/acquisition domain shifts in medical imaging using counterfactual image synthesis, not on constructing benchmark settings that simulate minority-group distribution shifts through modified train-test splits as in the original paper.

7. Bias and generalizability of foundation models across datasets in breast mammography

URL: [View paper](#)

Brief Assessment

Foundation Model Generalizability[30] focuses on dataset-level distribution shifts in medical imaging (mammography across different hospitals/countries), not on constructing modified benchmark settings that simulate intra-group distributional shifts within minority groups as the original paper does with CMNIST, Waterbirds, and CelebA.

8. Group distributionally robust machine learning under group level distributional uncertainty

URL: [View paper](#)

Brief Assessment

Group Level Uncertainty[25] focuses on distributional uncertainty within groups using Wasserstein DRO in finance/healthcare domains, not on constructing modified vision benchmarks with realistic minority-group shifts as the original paper does.

9. Generative models improve fairness of medical classifiers under distribution shifts

URL: [View paper](#)

Brief Assessment

Fairness Distribution Shifts[23] focuses on medical imaging fairness under distribution shifts using generative models for data augmentation, not on constructing benchmark settings that simulate minority-group distributional shifts in robust learning contexts like CMNIST, Waterbirds, and CelebA.

10. Change is hard: A closer look at subpopulation shift

URL: [View paper](#)

Prior Art Analysis

Subpopulation Shift[28] demonstrates that prior work has already established comprehensive benchmark settings for evaluating minority-group distribution shifts. The candidate paper presents a systematic framework that dissects subpopulation shifts into basic types (spurious correlations, attribute imbalance, class imbalance, and attribute generalization) and establishes benchmarks across 12

real-world datasets. The candidate explicitly addresses minority-group shifts through modified train-test splits and evaluates how algorithms perform under these conditions. This work predates the original paper's claim of introducing 'new benchmark settings' for minority-group distribution shifts, as it already provides a unified framework for characterizing and evaluating such shifts across multiple datasets and domains.

Evidence

Evidence 1 - **Rationale:** Both papers claim to establish benchmark settings for evaluating subpopulation shifts. The candidate paper explicitly states it provides 'a much larger set of datasets that cover different types of realistic subgroup shifts,' which directly addresses the same problem space as the original paper's claim of introducing new benchmark settings. - **Original:** we introduce new evaluation settings on standard benchmarks that reveal a previously overlooked yet important failure mode: minority-group distribution shifts-even when simply altering the train-test split without synthetic noise or external shifts-where state-of-the-art methods collapse but our app... - **Candidate:** we establish a realistic and comprehensive benchmark of subpopulation shift, consisting of 20 sota algorithms that span different learning strategies and 12 real-world datasets in vision, language, and healthcare domains. while existing analysis on subpopulation shift either focus on a single shift ...

Appendix: Text Similarity Detection

Textual similarity detection checked 26 papers and found 2 similarity segment(s) across 1 paper(s).

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

1. Change is hard: A closer look at subpopulation shift

Detected in: Contribution: contribution_3

△ **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

- [0] Mitigating Spurious Correlation via Distributionally Robust Learning with Hierarchical Ambiguity Sets [View paper](#)
- [1] Mitigating Spurious Correlations in Zero-Shot Multimodal Models [View paper](#)
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- [30] Bias and generalizability of foundation models across datasets in breast mammography [View paper](#)
- [31] R-index: a standardized representativeness metric for benchmarking diversity, equity, and inclusion in biopharmaceutical clinical trial development [View paper](#)
- [32] Stochastic approximation approaches to group distributionally robust optimization [View paper](#)
- [33] Discrete approximation scheme in distributionally robust optimization [View paper](#)
- [34] Cooperative data-driven distributionally robust optimization [View paper](#)
- [35] Efficient operator-splitting minimax algorithm for robust optimization. [View paper](#)
- [36] Nonlinear distributionally robust optimization [View paper](#)
- [37] Flow-Based Distributionally Robust Optimization [View paper](#)
- [38] Robust Bond Portfolio Construction via Convex-Concave Saddle Point Optimization [View paper](#)
- [39] Learning distributionally robust tractable probabilistic models in continuous domains [View paper](#)
- [40] Distributionally Robust Optimization with Bias and Variance Reduction [View paper](#)
- [41] Efficient Algorithms for Distributionally Robust Stochastic Optimization with Discrete Scenario Support [View paper](#)