Novelty Assessment Report

Paper: Distributionally Robust Linear Regression with Block Lewis Weights

PDF URL: https://openreview.net/pdf?id=0r1KU3dlps

Venue: ICLR 2026 Conference Submission

Year: 2026

Report Generated: 2025-12-29

Abstract

We present an algorithm for the empirical group distributionally robust (GDR) least squares problem. Given M groups, a parameter vector in $\mathbb{R}^d$, and stacked design matrices and responses $\mathbf{A}$ and $\bm{b}$, our algorithm obtains a $(1+ \varepsilon)$-multiplicative optimal solution using $\widetilde{O}(\min{\mathsf{rank}(\mathbf{A}),m}^{1/3}\varepsilon^{-2/3})$ linear-system-solves of matrices of the form $\mathbf{A}^{\top}\mathbf{B}\mathbf{A}$ for block-diagonal $\mathbf{B}$. Our technical methods follow from a recent geometric construction, block Lewis weights, that relates the empirical GDR problem to a carefully chosen least squares problem and an application of accelerated proximal methods. Our algorithm improves over known interior point methods for moderate accuracy regimes and matches the state-of-the-art guarantees for the special case of ℓ_{∞} regression. We also give algorithms that smoothly interpolate between minimizing the average least squares loss and the distributionally robust loss.

Core Task Landscape

This paper addresses: **Distributionally Robust Linear Regression with Multiple Groups**

A total of **38 papers** were analyzed and organized into a taxonomy with **18 categories**.

Taxonomy Overview

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

- **Core Group Distributionally Robust Optimization Frameworks**
- **Algorithmic Approaches and Computational Methods**
- **Regularization and Penalty-Based Robust Methods**
- **Theoretical Foundations and Statistical Guarantees**
- **Multi-Source and Transfer Learning Extensions**
- **Application-Specific Robust Learning**
- **Distributed and Federated Robust Learning**
- **Alternative Robust Regression Approaches**
- **Peripheral and Unrelated Methods**

Complete Taxonomy Tree

- Distributionally Robust Linear Regression with Multiple Groups Survey Taxonomy
- Core Group Distributionally Robust Optimization Frameworks
  - Worst-Case Group Risk Minimization (4 papers)
  - [1] Distributionally robust losses for latent covariate mixtures (John Duchi, 2023) View paper
  - [3] Group distributionally robust machine learning under group level distributional uncertainty (Shen Yi, 2025) View paper
  - [11] Learning models with uniform performance via distributionally robust optimization (Duchi, 2021) View paper
  - [25] Focus on the common good: Group distributional robustness follows (Vihari Piratla, 2021) View paper
  - Probabilistic and Soft Group Membership Frameworks (2 papers)
  - [10] Distributionally Robust Optimization with Probabilistic Group (Ghosal, 2023) View paper
  - [15] Per-Group Distributionally Robust Optimization (Per-GDRO) with Learnable Ambiguity Set Sizes via Bilevel Optimization (S Jung, 2025) View paper
  - Wasserstein Distributionally Robust Optimization (3 papers)
  - [14] Distributionally Robust Learning (Ruidi Chen, 2021) View paper
  - [21] Wasserstein Distributionally Robust Optimization with Wasserstein Barycenters (Lau, 2022) View paper
  - [34] Robust Grouped Variable Selection Using Distributionally Robust Optimization (Chen, 2022) View paper
- Algorithmic Approaches and Computational Methods
  - Stochastic and Variance-Reduced Algorithms (3 papers)
  - [4] Efficient algorithms for empirical group distributionally robust optimization and beyond (Cai, 2024) View paper
  - [29] Communication-Efficient Federated Group Distributionally Robust Optimization (Guo, 2024) View paper
  - [33] Near-Optimal Algorithms for Group Distributionally Robust Optimization and Beyond (Soma, 2022) View paper
  - Specialized Optimization Techniques ★ (2 papers)
  - [0] Distributionally Robust Linear Regression with Block Lewis Weights (Anon et al., 2026) View paper
  - [31] Multi-Fractional Gradient Descent: A Novel Approach to Gradient Descent for Robust Linear Regression (Robab Kalantari, 2024) View paper
- Regularization and Penalty-Based Robust Methods
  - Group-Structured Regularization (1 papers)
  - [9] Distributionally robust groupwise regularization estimator (Blanchet, 2017) View paper
  - Square-Root and L1-Based Robust Estimation (3 papers)

- [6] Distributionally robust -estimation in multiple linear regression (Z Gong, 2019) View paper
- [7] Distributionally robust $$L_1$$L1-estimation in multiple linear regression (Zhaohua Gong, 2018) View paper
- [27] On Regularized Square-root Regression Problems: Distributionally Robust Interpretation and Fast Computations (Toh, 2022) View paper

- Theoretical Foundations and Statistical Guarantees
  - Generalization and Convergence Analysis (2 papers)
  - [12] Distribution-dependent Generalization Bounds for Tuning Linear Regression Across Tasks (Balcan, 2025) View paper
  - [16] Statistical Analysis of Conditional Group Distributionally Robust Optimization with Cross-Entropy Loss (Guo Zi-jian, 2025) View paper
- Multi-Source and Transfer Learning Extensions
  - Multi-Source Data Integration (2 papers)
  - [8] A robust transfer learning approach for high-dimensional linear regression to support integration of multi-source gene expression data (Lulu Pan, 2025) View paper
  - [13] Robust data integration from multiple external sources for generalized linear models with binary outcomes. (Kyu-Seong Choi, 2024) View paper
  - Domain Generalization and Adaptation (2 papers)
  - [5] Distributionally robust losses against mixture covariate shifts (JC Duchi, 2019) View paper
  - [17] Multi-dimensional domain generalization with low-rank structures (Sai Li, 2023) View paper
- Application-Specific Robust Learning
  - Genomics and Biomedical Applications (3 papers)
  - [22] A Regression-Based Approach to Robust Estimation and Inference for Genetic Covariance (Jianqiao Wang, 2021) View paper
  - [26] AdaReg: data adaptive robust estimation in linear regression with application in GTEx gene expressions (Meng Wang, 2019) View paper
  - [36] EWAS meta analysis results (Anke, 2021) View paper
  - Ranking and Information Retrieval (1 papers)
  - [2] Distributionally Robust Optimization for Unbiased Learning to Rank (Zechun Niu, 2025) View paper
  - Knowledge Distillation and Model Compression (1 papers)
  - [23] Group Distributionally Robust Knowledge Distillation (Xiao Liu, 2023) View paper
  - Fairness and Backward Compatibility (2 papers)
  - [28] Distributionally Robust Group Backwards Compatibility (Bertran, 2022) View paper
  - [35] Long Term Fairness for Minority Groups via Performative Distributionally Robust Optimization (Peet-Pare, 2022) View paper
- Distributed and Federated Robust Learning (1 papers)
  - [37] Robustness of Iteratively Pre-Conditioned Gradient-Descent Method: The Case of Distributed Linear Regression Problem (Kushal Chakrabarti, 2021) View paper
- Alternative Robust Regression Approaches
  - Mixture Model Robust Regression (1 papers)
  - [32] On the robust learning mixtures of linear regressions (Huang Ying, 2023) View paper
  - Heavy-Tailed and Outlier-Robust Methods (1 papers)
  - [30] Environmental effects on survival rates: robust regression, recovery planning and endangered Atlantic salmon (Heather D. Bowlby, 2015) View paper
- Peripheral and Unrelated Methods (5 papers)
  - [18] Role Assignment for Agent Evaluation Under Uncertainty: A Distributionally Robust Approach (Zhihang Yu, 2025) View paper
  - [19] Distributional assumptions in voxel-based morphometry (C. Salmond, 2002) View paper
  - [20] Comparative Analysis of ARIMA, Multiple Linear Regression, and LSTM Models for Stock Price Prediction: Evidence from Starbucks and Luckin Coffee (Zhang, 2025) View paper
  - [24] A Distributionally Robust Linear Receiver Design for Multi-Access Space-Time Block Coded MIMO Systems (Bin Li, 2017) View paper
  - [38] Optimized Targeted Confinements for Future Pandemic Response (S Camelo, n.d.) View paper

Narrative

Core task: Distributionally robust linear regression with multiple groups seeks to learn models that perform well across heterogeneous subpopulations, guarding against worst-case group performance rather than optimizing average loss. The field's structure reflects several complementary perspectives. Core Group Distributionally Robust Optimization Frameworks establish the foundational min-max formulations and uncertainty sets, while Algorithmic Approaches and Computational Methods develop practical solvers—ranging from stochastic gradient techniques to specialized optimization routines that exploit problem structure. Regularization and Penalty-Based Robust Methods incorporate shrinkage or group-specific penalties to stabilize estimates, and Theoretical Foundations provide statistical guarantees on convergence and generalization. Multi-Source and Transfer Learning Extensions address settings where data arrive from distinct domains or tasks, and Distributed and Federated Robust Learning tackle scenarios with decentralized data. Application-Specific Robust Learning branches into domains such as genomics and fairness-aware prediction, while Alternative Robust Regression Approaches explore non-group-based robustness paradigms.

Recent work has intensified around efficient algorithms that scale to many groups and high dimensions, balancing computational cost with strong worst-group guarantees. For instance, Efficient Group DRO[4] and Near-Optimal Group DRO[33] push the frontier of sample complexity and runtime, while methods like Probabilistic Group DRO[10] and Group Level Uncertainty[3] incorporate uncertainty quantification over group memberships. Block Lewis Weights[0] sits within the Specialized Optimization Techniques cluster, proposing a novel leverage-score-based sampling scheme to accelerate robust regression solvers. This approach contrasts with gradient-based methods such as Multi-Fractional Gradient[31], which also targets computational efficiency but through fractional-order updates. By exploiting block structure in the design matrix, Block Lewis Weights[0] offers a distinct algorithmic angle that complements existing stochastic and bilevel optimization strategies, addressing the persistent challenge of scaling robust group-aware regression to large, structured datasets.

Related Works in Same Category

The following **1 sibling papers** share the same taxonomy leaf node with the original paper:

1. Multi-Fractional Gradient Descent: A Novel Approach to Gradient Descent for Robust Linear Regression

Authors: Robab Kalantari, Khashayar Rahimi, Saman Naderi Mezajin | **Year/Venue**: 2024 | **URL**: View paper

Abstract

Authors: This work introduces a novel gradient descent method by generalizing the fractional gradient descent (FGD) such that instead of the same fractional order for all variables, we assign different fractional orders to each variable depending on its characteristics and its relation to other variables. We name this method Multi-Fractional Gradient Descent (MFGD) and by using it in linear regression for minimizing loss function (residual sum of square) and apply it on four financial time serie...

Relationship Analysis

Both papers belong to the Specialized Optimization Techniques category, focusing on novel optimization methods for robust regression. They overlap in addressing robust linear regression through specialized gradient-based approaches that go beyond standard first-order methods. However, the original paper develops block Lewis weights with accelerated proximal methods for group distributionally robust regression with provable iteration complexity guarantees, while the candidate paper proposes Multi-Fractional Gradient Descent using fractional calculus with variable fractional orders per feature, primarily demonstrating empirical robustness to multicollinearity on financial time series without theoretical convergence analysis.

Contributions Analysis

Overall novelty summary. The paper contributes an algorithm for empirical group distributionally robust least squares that achieves approximate optimality using a number of linear-system solves dependent on rank or group count and accuracy. It resides in the 'Specialized Optimization Techniques' leaf under 'Algorithmic Approaches and Computational Methods', which contains only two papers total. This leaf represents a relatively sparse research direction focused on novel optimization methods beyond standard stochastic gradient approaches, suggesting the paper enters a less crowded algorithmic niche within the broader group-DRO landscape.

The taxonomy reveals that most algorithmic work clusters in 'Stochastic and Variance-Reduced Algorithms' (three papers), while the paper's leaf emphasizes structural exploitation through block Lewis weights and proximal methods. Neighboring branches include 'Core Group Distributionally Robust Optimization Frameworks' with multiple formulation-focused papers and 'Regularization and Penalty-Based Robust Methods' addressing robustness through penalties. The scope note for the paper's leaf explicitly excludes standard stochastic gradient methods, positioning this work as an alternative computational pathway that leverages geometric constructions rather than variance reduction or sampling strategies.

Among seventeen candidates examined, the contribution-level analysis shows mixed novelty signals. The core algorithm for group-DRO least squares examined six candidates with none providing clear refutation, suggesting this specific solver design may be relatively fresh. The block Lewis weights construction examined only one candidate without refutation, indicating limited prior work in this geometric direction. However, the interpolation algorithm between average and robust objectives examined ten candidates and found one refutable match, implying this aspect has more substantial overlap with existing methods for balancing robustness and average performance.

Based on the limited search scope of seventeen semantically similar papers, the work appears to introduce a distinct algorithmic approach in a sparsely populated taxonomy leaf, though the interpolation component shows clearer precedent. The analysis does not cover the full literature on leverage-score sampling or proximal methods outside the group-DRO context, so the geometric construction's novelty may extend beyond what these top-K matches reveal.

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

Contribution 1: Algorithm for empirical group distributionally robust least squares

Description: The authors introduce an algorithm that solves the group distributionally robust regression problem with iteration complexity that depends on the minimum of the matrix rank and the number of groups, improving over standard interior point methods in moderate accuracy regimes and matching state-of-the-art for l_∞ regression.

This contribution was assessed against **6 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

---

1. Near-Optimal Algorithms for Group Distributionally Robust Optimization and Beyond

URL: View paper

Brief Assessment

Near-Optimal Group DRO[33] focuses on stochastic algorithms for general DRO problems including group DRO with convergence rate analysis, while the original paper presents a deterministic algorithm specifically for least squares regression with iteration complexity depending on matrix rank or number of groups.

---

2. On Regularized System Identification from a Martingale Distributional Robustness Perspective

URL: View paper

Brief Assessment

Martingale System Identification[41] focuses on system identification with martingale constraints in Wasserstein ambiguity sets, not on general group distributionally robust regression with iteration complexity improvements.

---

3. Group Distributionally Robust Optimization with Flexible Sample Queries

URL: View paper

Brief Assessment

Flexible Sample Queries[40] focuses on GDRO with flexible sample queries per iteration (varying between 1 and m samples), while the original paper addresses a different problem: solving group distributionally robust least squares regression with iteration complexity dependent on matrix rank or number of groups. The candidate's contribution is about sample query flexibility in online optimization, not about iteration complexity improvements for least squares problems.

---

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

URL: View paper

Brief Assessment

Group Level Uncertainty[3] focuses on group distributionally robust machine learning with Wasserstein-based DRO for distributional uncertainty within groups, not on developing algorithms for least squares regression with iteration complexity guarantees.

---

5. Revisiting Group Robustness: Class-specific Scaling is All You Need

URL: View paper

Brief Assessment

Class-Specific Scaling[42] focuses on post-processing techniques for group robustness in classification tasks, not on algorithms for solving group distributionally robust regression problems with specific iteration complexity guarantees.

---

6. Stochastic approximation approaches to group distributionally robust optimization

URL: View paper

Brief Assessment

Stochastic Group DRO[39] focuses on stochastic approximation methods for group DRO with general convex losses, not specifically on least squares regression with iteration complexity dependent on matrix rank. The candidate addresses a different algorithmic approach (stochastic gradient methods) rather than the geometric construction and block Lewis weights used in the original paper.

Contribution 2: Block Lewis weights for distributionally robust optimization

Description: The authors employ block Lewis weights, a geometric construction, to relate the distributionally robust problem to a structured least squares problem. This enables the design of their algorithm with improved iteration complexity by choosing an appropriate geometry for proximal subproblems.

This contribution was assessed against **1 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

---

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

URL: View paper

Brief Assessment

Per-GDRO Bilevel[15] focuses on per-group distributionally robust optimization with learnable ambiguity set sizes via bilevel optimization, addressing inter-group and intra-group distributional shifts. It does not employ block Lewis weights or relate the distributionally robust problem to structured least squares problems as described in the original contribution.

Contribution 3: Algorithm for interpolating between average and robust objectives

Description: The authors provide an algorithm (Algorithm 5, Theorem 2) that optimizes a family of objectives parameterized by p that interpolate between the utilitarian (average loss) and egalitarian (robust) approaches, allowing smooth trade-offs between utility and robustness.

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. Model Predictive Task Sampling for Efficient and Robust Adaptation

URL: View paper

Brief Assessment

Task Sampling Adaptation[45] focuses on task sampling strategies for foundation model adaptation and robotic policy learning, not on algorithms that interpolate between utilitarian and egalitarian loss objectives in regression problems.

---

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

URL: View paper

Brief Assessment

Efficient Empirical DRO[51] focuses on empirical group distributionally robust optimization using a two-level finite-sum minimax formulation with variance reduction techniques. It does not address interpolation between utilitarian and egalitarian objectives via parameterized families (p-norms), which is the core novelty of the original paper's Algorithm 5.

---

3. Distributionally robust optimization and robust statistics

URL: View paper

Brief Assessment

DRO Robust Statistics[44] focuses on distributionally robust optimization formulations for statistical estimation, not on algorithms for group distributionally robust regression with interpolating objectives as in the original paper.

---

4. A Stochastic Algorithm for Sinkhorn Distance-Regularized Distributionally Robust Optimization

URL: View paper

Brief Assessment

Sinkhorn Distance DRO[43] focuses on distributionally robust optimization using Sinkhorn distance with nested stochastic programming. The original paper addresses group distributionally robust regression with interpolation between utilitarian and egalitarian objectives via ℓp norms, which is a different technical approach and problem formulation.

---

5. Stochastic gradient methods for distributionally robust optimization with f-divergences

URL: View paper

Brief Assessment

F-Divergence Methods[47] focuses on stochastic gradient methods for distributionally robust optimization using f-divergences, not on algorithms that interpolate between utilitarian and egalitarian objectives with parameterized families.

---

6. Tilted empirical risk minimization

URL: View paper

Prior Art Analysis

Tilted Risk Minimization[46] demonstrates that a family of objectives parameterized by t can interpolate between utilitarian (average loss) and egalitarian (robust) approaches. The paper explicitly states that for t=0, the objective recovers the average loss, while as $t \to \infty$, it recovers the max-loss objective. This provides a smooth trade-off between utility and robustness through a single hyperparameter, which directly addresses the same problem space as the original paper's Algorithm 5 and Theorem 2.

Evidence

Evidence 1 - **Rationale**: Both papers explicitly describe smooth interpolation between average and robust (max-loss) objectives, demonstrating that this concept was already established in the candidate paper. - **Original**: our algorithm improves over known interior point methods for moderate accuracy regimes and matches the state-ofthe-art guarantees for the special case of $\ell\infty$ regression. we also give algorithms that smoothly interpolate between minimizing the average least squares loss and the distributionally robust... - **Candidate**: for positive values of t, term enables a smooth tradeoff between the average-loss and max-loss (as we demonstrate in figure 10, appendix i). hence, term can selectively improve the worst-performing losses by paying a penalty on average performance, thus promoting a notion of uniformity or fairness

Evidence 2 - **Rationale**: The candidate paper demonstrates the same interpolation concept between different optimization objectives through a continuous parameter, showing prior work on this contribution. - **Original**: varying p from 2 to ∞ and minimizing gives solutions that interpolate between utilitarian and egalitarian approaches, allowing for a smooth trade-off between utility and robustness. - **Candidate**: as tñ´8,term finds a line of best while ignoring outliers. however, this solution may not be preferred if we have reason to believe that these 'outliers' should not be ignored. astñ`8,term recovers the min-max solution, which aims to minimize the worst loss

7. Reliable machine learning via distributional robustness

URL: View paper

Brief Assessment

Reliable Machine Learning[49] focuses on distributional robustness for statistical inference and learning, not on algorithms for group distributionally robust regression. The candidate discusses variance regularization and empirical likelihood methods for stochastic optimization, which are conceptually different from the interpolating algorithm (Algorithm 5, Theorem 2) in the original paper that handles group-wise losses with varying p values.

8. Sensitivity analysis under the F-sensitivity models: a distributional robustness perspective

URL: View paper

Brief Assessment

F-Sensitivity Models[52] focuses on sensitivity analysis in causal inference using distributional robustness for bounding counterfactual means, not on algorithms for interpolating between utilitarian and egalitarian objectives in regression problems.

9. Learning against distributional uncertainty: On the trade-off between robustness and specificity

URL: View paper

Brief Assessment

Robustness Specificity Tradeoff[50] focuses on Bayesian distributionally robust optimization with a different mathematical framework (Bayesian priors, Dirichlet processes) rather than the proximal methods and block Lewis weights used in the original paper's Algorithm 5.

10. Statistical analysis of Wasserstein distributionally robust estimators

URL: View paper

Brief Assessment

Wasserstein Estimators Analysis[48] focuses on statistical properties of Wasserstein distributionally robust estimators for risk minimization, not on algorithms that interpolate between utilitarian and egalitarian objectives in group distributionally robust regression.

Appendix: Text Similarity Detection

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

References

- [0] Distributionally Robust Linear Regression with Block Lewis Weights View paper
- [1] Distributionally robust losses for latent covariate mixtures View paper
- [2] Distributionally Robust Optimization for Unbiased Learning to Rank View paper
- [3] Group distributionally robust machine learning under group level distributional uncertainty View paper
- [4] Efficient algorithms for empirical group distributionally robust optimization and beyond View paper
- [5] Distributionally robust losses against mixture covariate shifts View paper
- [6] Distributionally robust -estimation in multiple linear regression View paper
- [7] Distributionally robust $$L_1$$L1-estimation in multiple linear regression View paper
- [8] A robust transfer learning approach for high-dimensional linear regression to support integration of multi-source gene expression data View paper
- [9] Distributionally robust groupwise regularization estimator View paper
- [10] Distributionally Robust Optimization with Probabilistic Group View paper
- [11] Learning models with uniform performance via distributionally robust optimization View paper
- [12] Distribution-dependent Generalization Bounds for Tuning Linear Regression Across Tasks View paper
- [13] Robust data integration from multiple external sources for generalized linear models with binary outcomes. View paper
- [14] Distributionally Robust Learning View paper
- [15] Per-Group Distributionally Robust Optimization (Per-GDRO) with Learnable Ambiguity Set Sizes via Bilevel Optimization View paper
- [16] Statistical Analysis of Conditional Group Distributionally Robust Optimization with Cross-Entropy Loss View paper
- [17] Multi-dimensional domain generalization with low-rank structures View paper
- [18] Role Assignment for Agent Evaluation Under Uncertainty: A Distributionally Robust Approach View paper
- [19] Distributional assumptions in voxel-based morphometry View paper
- [20] Comparative Analysis of ARIMA, Multiple Linear Regression, and LSTM Models for Stock Price Prediction: Evidence from Starbucks and Luckin Coffee View paper
- [21] Wasserstein Distributionally Robust Optimization with Wasserstein Barycenters View paper
- [22] A Regression-Based Approach to Robust Estimation and Inference for Genetic Covariance View paper
- [23] Group Distributionally Robust Knowledge Distillation View paper
- [24] A Distributionally Robust Linear Receiver Design for Multi-Access Space-Time Block Coded MIMO Systems View paper
- [25] Focus on the common good: Group distributional robustness follows View paper
- [26] AdaReg: data adaptive robust estimation in linear regression with application in GTEx gene expressions View paper
- [27] On Regularized Square-root Regression Problems: Distributionally Robust Interpretation and Fast Computations View paper
- [28] Distributionally Robust Group Backwards Compatibility View paper
- [29] Communication-Efficient Federated Group Distributionally Robust Optimization View paper
- [30] Environmental effects on survival rates: robust regression, recovery planning and endangered Atlantic salmon View paper
- [31] Multi-Fractional Gradient Descent: A Novel Approach to Gradient Descent for Robust Linear Regression View paper
- [32] On the robust learning mixtures of linear regressions View paper
- [33] Near-Optimal Algorithms for Group Distributionally Robust Optimization and Beyond View paper
- [34] Robust Grouped Variable Selection Using Distributionally Robust Optimization View paper

- [35] Long Term Fairness for Minority Groups via Performative Distributionally Robust Optimization View paper
- [36] EWAS meta analysis results View paper
- [37] Robustness of Iteratively Pre-Conditioned Gradient-Descent Method: The Case of Distributed Linear Regression Problem View paper
- [38] Optimized Targeted Confinements for Future Pandemic Response View paper
- [39] Stochastic approximation approaches to group distributionally robust optimization View paper
- [40] Group Distributionally Robust Optimization with Flexible Sample Queries View paper
- [41] On Regularized System Identification from a Martingale Distributional Robustness Perspective View paper
- [42] Revisiting Group Robustness: Class-specific Scaling is All You Need View paper
- [43] A Stochastic Algorithm for Sinkhorn Distance-Regularized Distributionally Robust Optimization View paper
- [44] Distributionally robust optimization and robust statistics View paper
- [45] Model Predictive Task Sampling for Efficient and Robust Adaptation View paper
- [46] Tilted empirical risk minimization View paper
- [47] Stochastic gradient methods for distributionally robust optimization with f-divergences View paper
- [48] Statistical analysis of Wasserstein distributionally robust estimators View paper
- [49] Reliable machine learning via distributional robustness View paper
- [50] Learning against distributional uncertainty: On the trade-off between robustness and specificity View paper
- [51] Efficient Algorithms for Empirical Group Distributional Robust Optimization and Beyond View paper
- [52] Sensitivity analysis under the F-sensitivity models: a distributional robustness perspective View paper