Novelty Assessment Report

Paper: Improved ℓ_{p} Regression via Iteratively Reweighted Least Squares
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Abstract

We introduce fast algorithms for solving ℓ_{p} regression problems using the iteratively reweighted least squares (IRLS) method. Our approach achieves state-of-the-art iteration complexity, outperforming the IRLS algorithm by Adil-Peng-Sachdeva (NeurIPS 2019) and matching the theoretical bounds established by the complex algorithm of Adil-Kyng-Peng-Sachdeva (SODA 2019, J. ACM 2024) via a simpler lightweight iterative scheme. This bridges the existing gap between theoretical and practical algorithms for ℓ_{p} regression. Our algorithms depart from prior approaches, using a primal-dual framework, in which the update rule can be naturally derived from an invariant maintained for the dual objective. Empirically, we show that our algorithms significantly outperform both the IRLS algorithm by Adil-Peng-Sachdeva and MATLAB/CVX implementations.

Core Task Landscape

This paper addresses: **Solving ℓp Regression Problems Using Iteratively Reweighted Least Squares**

A total of **50 papers** were analyzed and organized into a taxonomy with **17 categories**.

Taxonomy Overview

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

- **Core IRLS Theory and Convergence Analysis**
- **Algorithmic Improvements and Variants**
- **Sparse Recovery and Compressed Sensing**
- **Robust Regression and Outlier Handling**
- **Domain-Specific Applications**
- **Extensions and Generalizations**
- **Comparative and Empirical Studies**

Complete Taxonomy Tree

- Solving ℓp Regression Problems Using Iteratively Reweighted Least Squares Survey Taxonomy
- Core IRLS Theory and Convergence Analysis
  - Convergence Guarantees and Rate Analysis ★ (6 papers)
  - [0] Improved ℓ_{p} Regression via Iteratively Reweighted Least Squares (Anon et al., 2026) View paper
  - [1] Iteratively reweighted least squares minimization for sparse recovery (Daubechies, 2010) View paper
  - [11] Improved Convergence for and 1 Regression via Iteratively Reweighted Least Squares (Alina Ene, 2019) View paper
  - [23] Iteratively re-weighted least squares minimization: Proof of faster than linear rate for sparse recovery (I. Daubechies, 2008) View paper
  - [32] Fast, provably convergent IRLS algorithm for p-norm linear regression (Deeksha Adil, 2019) View paper
  - [49] Iteratively Reweighted Least Squares for Basis Pursuit with Global Linear Convergence Rate (Verdun, 2020) View paper
  - Stability and Numerical Analysis (3 papers)
  - [12] Iteratively reweighted least squares: algorithms, convergence analysis, and numerical comparisons (R. Wolke, 1988) View paper
  - [15] Convergence and stability of iteratively re-weighted least squares algorithms (Demba Ba, 2013) View paper
  - [29] On the convergence of IRLS and its variants in outlier-robust estimation (Liangzu Peng, 2023) View paper
- Algorithmic Improvements and Variants
  - Acceleration and Computational Efficiency (4 papers)
  - [3] Improved Regression via Iteratively Reweighted Least Squares (A Ene, 2025) View paper
  - [26] Fast Algorithms for â□□p-Regression (Deeksha Adil, 2024) View paper
  - [37] An analysis of sketched IRLS for accelerated sparse residual regression (Daichi Iwata, 2020) View paper
  - [39] Iterative Refinement for â□□p-norm Regression (Deeksha Adil, 2019) View paper
  - Smoothing and Regularization Techniques (4 papers)
  - [6] Improved Iteratively Reweighted Least Squares for Unconstrained Smoothed Minimization (MJ Lai, 2013) View paper
  - [8] Iteratively Reweighted Least Squares by Diagonal Regularization (Bamrung Tausiesakul, 2023) View paper
  - [14] Global Convergence of Iteratively Reweighted Least Squares for Robust Subspace Recovery (Lerman, 2025) View paper
  - [25] Iterative reweighted linear least squares for exact penalty subproblems on product sets (James V. Burke, 2015) View paper
  - Adaptive and Heuristic Enhancements (3 papers)
  - [13] Iteratively reâ□□weighted and refined least squares algorithm for robust inversion of geophysical data (A. Gholami, 2017) View paper
  - [18] Tail-Iteratively Reweighted Least Squares Technique for Compressed Sensing (Yuan Luo, 2022) View paper

- [30] Robust Least Squares Twin Support Vector Regression With Adaptive FOA and PSO for Short-Term Traffic Flow Prediction (He Yan, 2022) View paper

- Sparse Recovery and Compressed Sensing
  - Unconstrained and Constrained Sparse Recovery (3 papers)
  - [17] Iteratively reweighted least squares minimization for sparsely corrupted measurements (Taner Ä°nce, 2011) View paper
  - [34] Speech compressive sensing with â□□1-minimzation and iteratively reweighted least squares-â□□p-minimization: A comparative study (Wafa Derouaz, 2017) View paper
  - [50] Comparison of l1-Minimization and Iteratively Reweighted least Squares-l p-Minimization for Image Reconstruction from Compressive Sensing (Endra Oey, 2010) View paper
  - Structured Sparsity and Block Recovery (3 papers)
  - [2] Iteratively reweighted least squares for block sparse signal recovery with unconstrained minimization (Y Cai, 2025) View paper
  - [4] Iterative re-weighted least squares algorithms for non-negative sparse and group-sparse recovery (Angshul Majumdar, 2022) View paper
  - [7] Iteratively reweighted least squares for block-sparse recovery (S. Li, 2014) View paper
  - Analysis-Based and Transform-Domain Methods (2 papers)
  - [20] Fast iteratively reweighted least squares for lp regularized image deconvolution and reconstruction (Xu Zhou, 2014) View paper
  - [33] Fast iteratively reweighted least squares algorithms for analysis-based sparse reconstruction. (Chen Chen, 2019) View paper
- Robust Regression and Outlier Handling
  - M-Estimation and Resistant Methods (4 papers)
  - [10] Iteratively reweighted least squares for maximum likelihood estimation, and some robust and resistant alternatives (P. J. Green, 1984) View paper
  - [21] On resistant Lp-Norm Estimation by means of iteratively reweighted least Squares (Christian Marx, 2013) View paper
  - [42] Robust regression using iteratively reweighted least-squares (P. Holland, 1977) View paper
  - [43] Normal/independent distributions and their applications in robust regression (Kenneth Lange, 1993) View paper
  - Global Convergence for Robust Problems (2 papers)
  - [31] Nonlinear Lp-norm estimation (Vince A. Sposito, 2017) View paper
  - [44] Globally-convergent Iteratively Reweighted Least Squares for Robust Regression Problems (Mukhoty, 2020) View paper
- Domain-Specific Applications
  - Signal and Image Processing (3 papers)
  - [24] 3D high-resolution Radon transform based on strong sparse LPâ□□1 norm and its applications (Wei Shi, 2024) View paper
  - [45] Prestack imaging of seismic data using Lp iterative reweighted least-squares wavefield extrapolation filters in the frequency-space domain (Wail A. Mousa, 2018) View paper
  - [46] Variational Weighted â□□p-â□□q$\ell _p-\ell _q$ Regularization for Hyperspectral Image Restoration Under Mixed Noise (Hazique Aetesam, 2025) View paper
  - Statistical Estimation and Correlation Analysis (4 papers)
  - [5] An iteratively reweighted least squares algorithm for skew-probit binary regression with Firthâ□□s penalization (Hojin Yang, 2025) View paper
  - [27] Iteratively Reweighted Least Squares Method for Estimating Polyserial and Polychoric Correlation Coefficients (Zhang, 2023) View paper
  - [38] Iteratively Reweighte Least Squares Method for Estimating Polyserial and Polychoric Correlation Coefficients (Zhang, 2022) View paper
  - [47] Iteratively reweighted least squares in crystal structure refinements. (MarcellÎ¿ Merli, 2011) View paper
  - Engineering and System Identification (3 papers)
  - [16] Local basis function method for identification of nonstationary systems (GaÅ□cza, 2024) View paper
  - [19] Power system state estimation using an iteratively reweighted least squares method for sequential L1-regression (Jabr, 2006) View paper
  - [22] Iteratively reweighted least-squares implementation of the WLAV state-estimation method (R. Jabr, 2004) View paper
- Extensions and Generalizations
  - Nonlinear and Kernel Methods (2 papers)
  - [9] Iteratively reweighted least square for kernel expectile regression with random features (Yue Cui, 2023) View paper
  - [40] Robust Supervised and Semisupervised Least Squares Regression Using â□□2,p-Norm Minimization (Jingyu Wang, 2022) View paper
  - Streaming and Large-Scale Algorithms (1 papers)
  - [35] Streaming Algorithms For â□□p Flows and â□□p Regression. (A Chakrabarti, 2025) View paper
  - Alternative Optimization Frameworks (3 papers)
  - [36] Iteratively reweighted optimum linear regression in the presence of generalized Gaussian noise (Fuxi Wen, 2016) View paper
  - [41] Iteratively Reweighted Least Squares (Donald B. Rubin, 2018) View paper
  - [48] Iterative reweighted minimization methods for regularized unconstrained nonlinear programming (Lu, 2014) View paper
- Comparative and Empirical Studies (1 papers)
  - [28] A Comparative Study of Particle Swarm Optimization and Iteratively Reweighted Least Squares in Regression Modelling (Elgiz AskeroÄ□lu, 2025) View paper

Narrative

Core task: solving ℓp regression problems using iteratively reweighted least squares. The field organizes around several complementary directions. Core IRLS Theory and Convergence Analysis investigates the mathematical foundations—establishing convergence guarantees, analyzing iteration complexity, and proving rate bounds for various p-norms. Algorithmic Improvements and Variants explores practical enhancements such as sketching techniques, diagonal regularization, and smoothing strategies to accelerate convergence or handle numerical instabilities. Sparse Recovery and Compressed Sensing applies IRLS methods to recover sparse signals, often leveraging reweighting schemes to approximate ℓ0 or ℓ1 penalties. Robust Regression and Outlier Handling focuses on using ℓp norms (especially p < 2) to downweight outliers and achieve robustness in contaminated data settings. Domain-Specific Applications demonstrates IRLS in geophysical inversion, state estimation, and signal processing tasks, while Extensions and Generalizations broaden the framework to nonlinear models, block-sparse structures, and variational formulations. Comparative and Empirical Studies benchmark IRLS against alternative optimization methods, providing practical guidance on when reweighting strategies excel.

A particularly active line of work centers on tightening convergence rates and reducing per-iteration costs. Improved Lp Regression[0] sits squarely within the convergence analysis branch, offering refined guarantees that complement earlier results such as Improved Convergence IRLS[11] and Fast IRLS Convergent[32]. These studies contrast with algorithmic variants like Sketched IRLS[37] or Improved IRLS Smoothed[6], which prioritize scalability over purely theoretical bounds. Meanwhile, sparse recovery methods (e.g., IRLS Sparse Recovery[1], IRLS Block Sparse[2]) emphasize sparsity-inducing penalties rather than general ℓp fitting, and robust regression approaches (e.g., IRLS Outlier Robust[29]) target heavy-tailed noise models. The original paper's emphasis on convergence rate analysis places it alongside works that rigorously quantify iteration complexity, distinguishing it from more application-driven or heuristic extensions elsewhere in the taxonomy.

Related Works in Same Category

The following **5 sibling papers** share the same taxonomy leaf node with the original paper:

1. Iteratively reweighted least squares minimization for sparse recovery

Authors: Daubechies, Ingrid, DeVore, Ronald, Fornasier, et al. (8 authors total) | **Year/Venue**: 2010 | **URL**: View paper

Abstract

We analyze an Iteratively Re-weighted Least Squares (IRLS) algorithm for promoting l1-minimization in sparse and compressible vector recovery. We prove its convergence and we estimate its local rate. We show how the algorithm can be modified in order to promote lt-minimization for t<1, and how this modification produces superlinear rates of convergence. We analyze an Iteratively Re-weighted Least Squares (IRLS) algorithm for promoting l1-minimization in sparse and compressible vector recovery...

Relationship Analysis

Both papers belong to the Convergence Guarantees and Rate Analysis category, focusing on proving convergence properties and establishing convergence rates for IRLS variants in solving ℓp regression problems. The candidate paper analyzes IRLS for sparse recovery with l1-minimization and lt-minimization (t<1), proving convergence and estimating local rates including superlinear convergence for t<1, while the original paper develops improved IRLS algorithms for general ℓp regression (p≥2) with state-of-the-art iteration complexity O(p²n^((p-2)/(3p-2))log(n/ε)) using a novel primal-dual framework. The key difference is that the candidate focuses on sparse recovery applications with theoretical convergence analysis for small p values, whereas the original paper targets general ℓp regression for larger p values with both theoretical guarantees matching prior best bounds and practical algorithmic improvements.

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2. Improved Convergence for and 1 Regression via Iteratively Reweighted Least Squares

Authors: Alina Ene, Adrian Vladu | **Year/Venue**: 2019 | **URL**: View paper

Abstract

N/A

⚠ Similarity Notice

The candidate paper appears to be a variant or near-duplicate of the original paper based on the highly similar title structure ('Improved … Regression via Iteratively Reweighted Least Squares'). Both papers focus on IRLS methods for ℓp regression with convergence analysis. Manual verification is recommended to confirm whether this is the same work, a preprint/published version pair, or a closely related follow-up study.

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3. Iteratively re-weighted least squares minimization: Proof of faster than linear rate for sparse recovery

Authors: I. Daubechies, R. DeVore, M. Fornasier, Ingrid Daubechies, Sinan GÃ¼ntÃ¼rk, et al. (8 authors total) | **Year/Venue**: 2008 | **URL**: View paper

Abstract

Given an mtimesN matrix Phi, with m<N, the system of equations Phix=y is typically underdetermined and has infinitely many solutions. Various forms of optimization can extract a "best" solution. One of the oldest is to select the one with minimal lscr $_2$ norm. It has been shown that in many applications a better choice is the minimal lscr <sub xmlns:mml="http://www.w3.org/1998/Math/MathML" xmlns:x...

Relationship Analysis

Both papers belong to the Convergence Guarantees and Rate Analysis category, focusing on proving convergence properties and establishing convergence rates for IRLS variants in solving ℓp regression problems. The candidate paper establishes exponential convergence rates (linear and faster-than-linear) for IRLS methods targeting $\ell 1$ and $\ell \tau$ minimization with τ<1, primarily in the sparse recovery context under restricted isometry property conditions. In contrast, the original paper develops improved IRLS algorithms for general ℓp regression (p≥2) with state-of-the-art iteration complexity bounds of O(p²n^((p-2)/(3p-2))log(n/ε)), using a novel primal-dual framework rather than traditional weight update schemes, and provides both theoretical guarantees and practical implementations.

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4. Fast, provably convergent IRLS algorithm for p-norm linear regression

Authors: Deeksha Adil, Richard Peng, Sushant Sachdeva | **Year/Venue**: 2019 | **URL**: View paper

Abstract

Linear regression in ℓ_p-norm is a canonical optimization problem that arises in several applications, including sparse recovery, semi-supervised learning, and signal processing. Generic convex optimization algorithms for solving ℓ_p-regression are slow in practice. Iteratively Reweighted Least Squares (IRLS) is an easy to implement family of algorithms for solving these problems that has been studied for over 50 years. However, these algorithms often diverge for p > 3, and since the w...

Relationship Analysis

Both papers belong to the Convergence Guarantees and Rate Analysis category, focusing on proving convergence properties for IRLS variants in ℓp regression. They overlap in addressing convergence rates for IRLS methods with p ≥ 2, both achieving iteration complexity bounds with polynomial dependence on problem dimensions. The key difference is that the original paper introduces a primal-dual framework with a novel update scheme maintaining specific invariants, while the candidate paper (p-IRLS by Adil-Peng-Sachdeva) uses a residual problem formulation with iterative refinement and achieves O(p³·⁵m^((p-2)/(2(p-1))) log(m/ε)) iterations compared to the original's O(p²n^((p-2)/(3p-2)) log(n/ε)) bound.

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5. Iteratively Reweighted Least Squares for Basis Pursuit with Global Linear Convergence Rate

Authors: Verdun, Claudio Mayrink | **Year/Venue**: 2020 | **URL**: View paper

Abstract

The recovery of sparse data is at the core of many applications in machine learning and signal processing. While such problems can be tackled using ℓ_1-regularization as in the LASSO estimator and in the Basis Pursuit approach, specialized algorithms are typically

required to solve the corresponding high-dimensional non-smooth optimization for large instances. Iteratively Reweighted Least Squares (IRLS) is a widely used algorithm for this purpose due its excellent numerical performance. How...

Relationship Analysis

Both papers belong to the Convergence Guarantees and Rate Analysis category, focusing on proving convergence properties for IRLS variants in solving ℓp regression problems. While the original paper develops IRLS algorithms for general ℓp regression ($p \in (1,\infty)$) with state-of-the-art iteration complexity $O(p^2 n^{((p-2)/(3p-2))} \log(n/\epsilon))$, the candidate paper specifically addresses the Basis Pursuit ($\ell 1$-regularized) sparse recovery problem and proves global linear convergence rate for an IRLS variant under null space property assumptions, representing a more specialized application with different convergence guarantees.

Contributions Analysis

Overall novelty summary. The paper contributes fast IRLS algorithms for ℓp regression with state-of-the-art iteration complexity, matching theoretical bounds from prior complex methods via a simpler primal-dual framework. It resides in the 'Convergence Guarantees and Rate Analysis' leaf, which contains six papers total—a moderately populated node within the broader 'Core IRLS Theory and Convergence Analysis' branch. This leaf focuses specifically on proving convergence properties and establishing iteration complexity bounds, distinguishing it from algorithmic acceleration techniques or application-specific adaptations found in sibling branches.

The taxonomy reveals neighboring directions including 'Stability and Numerical Analysis' (three papers on robustness under noise) and 'Acceleration and Computational Efficiency' (four papers on matrix-free methods and reweighting strategies). The paper's primal-dual framework bridges theoretical convergence analysis with practical algorithmic design, connecting to acceleration work while maintaining rigorous complexity guarantees. Sibling papers in the same leaf (five others) similarly establish convergence rates, but the taxonomy's scope notes clarify that algorithmic modifications without convergence proofs belong elsewhere, suggesting this work's dual contribution spans multiple conceptual boundaries.

Among thirty candidates examined across three contributions, none yielded clear refutations. The first contribution (fast IRLS with state-of-the-art complexity) examined ten candidates with zero refutable matches; the primal-dual framework and high-precision refinement contributions showed identical patterns. This limited search scope—top-K semantic matches plus citation expansion—suggests the specific combination of primal-dual invariants and iteration complexity bounds may represent a less-explored intersection. However, the analysis explicitly does not claim exhaustive coverage, and the moderately populated taxonomy leaf indicates active prior work on convergence rate analysis exists.

Given the limited thirty-candidate search, the work appears to occupy a distinctive position combining theoretical iteration complexity with practical algorithmic simplicity. The absence of refutable candidates across all contributions, within this bounded scope, suggests the primal-dual approach may offer a novel angle on a well-studied problem. The taxonomy structure shows this is neither a sparse frontier nor an overcrowded space, with the convergence analysis leaf representing established but not saturated research territory.

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

Contribution 1: Fast IRLS algorithm with state-of-the-art iteration complexity for lp regression

Description: The authors develop an IRLS-based algorithm for lp regression that achieves $O(p^2 n^{((p-2)/(3p-2))} \log(n/\epsilon))$ iteration complexity, matching the best known theoretical bounds while using a simpler iterative framework than prior complex algorithms. This bridges the gap between theoretical and practical algorithms for lp regression.

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. Prestack imaging of seismic data using Lp iterative reweighted least-squares wavefield extrapolation filters in the frequency-space domain

URL: View paper

Brief Assessment

Prestack Lp Imaging[45] applies IRLS to seismic wavefield extrapolation filter design, not to general lp regression optimization. The candidate focuses on geophysical imaging applications rather than algorithmic complexity theory for regression problems.

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2. Iterative reweighted minimization for generalized norm/quasi-norm difference regularized unconstrained nonlinear programming

URL: View paper

Brief Assessment

Reweighted Norm Difference[55] focuses on Lp-q difference regularization for sparse recovery and nonlinear programming, not standard Lp regression. The candidate addresses unconstrained minimization with difference of norms metrics, while the original paper solves constrained Lp regression (min ||x||p subject to Ax=b) using a primal-dual IRLS framework.

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3. Convergence and stability of iteratively re-weighted least squares algorithms

URL: View paper

Brief Assessment

IRLS Convergence Stability[15] focuses on sparse signal recovery using IRLS with ℓ_β norms ($0 < \beta \leq 1$) and convergence to stationary points, not on ℓ_p regression ($p \geq 2$) with $O(p^2 n^{((p-2)/(3p-2))} \log(n/\epsilon))$ iteration complexity bounds.

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4. Improved Regression via Iteratively Reweighted Least Squares

URL: View paper

Brief Assessment

Improved Regression IRLS[3] addresses the same ℓp regression problem and also uses IRLS methods, but the extremely limited candidate text provided (only fragments with ellipses) makes it impossible to determine whether it predates the original work or achieves similar complexity bounds. Without access to publication dates, algorithmic details, or complexity analysis from the candidate, no refutation can be established.

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5. A Fine Line: Total Least-Squares Line Fitting as QCQP Optimization

URL: View paper

Brief Assessment

Total Least Squares[53] focuses on line-fitting problems using IRLS for outlier rejection with Geman-McClure cost functions, not general ℓp regression with theoretical iteration complexity bounds. The candidate addresses a different problem domain (geometric fitting) rather than the general ℓp regression framework discussed in the original paper.

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6. Baseline correction for Raman spectra using a spectral estimation-based asymmetrically reweighted penalized least squares method.

URL: View paper

Brief Assessment

Baseline Correction Raman[51] focuses on baseline correction for Raman spectroscopy using asymmetrically reweighted penalized least squares for signal processing, not on lp regression algorithms or iteration complexity theory for optimization problems.

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7. A cooperative magnetic inversion method with lp-norm regularization

URL: View paper

Brief Assessment

Cooperative Magnetic Inversion[54] applies IRLS methods to geophysical magnetic inversion problems with lp-norm regularization, not to the lp regression problem studied in the original paper. The candidate focuses on recovering magnetization models from magnetic data rather than solving general lp regression with theoretical iteration complexity guarantees.

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8. Global Convergence of Iteratively Reweighted Least Squares for Robust Subspace Recovery

URL: View paper

Brief Assessment

IRLS Subspace Recovery[14] focuses on robust subspace estimation with global convergence guarantees under deterministic conditions, not on lp regression problems. The candidate addresses a fundamentally different optimization problem (subspace recovery) compared to the original paper's lp regression framework.

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9. Robust and flexible mixed-norm inversion

URL: View paper

Brief Assessment

Mixed Norm Inversion[56] focuses on geophysical inversion using IRLS for mixed-norm regularization in 3D imaging, not on theoretical iteration complexity bounds for lp regression problems.

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10. Convergence analysis of iteratively reweighted

â□□1algorithms for computing the proximal operator of â□□pâ□□norm

URL: View paper

Brief Assessment

IRLS Proximal Operator[52] focuses on computing the proximal operator of ℓp-norm, which is a different problem from ℓp regression. The candidate's full text context is too limited to assess overlap with the original paper's IRLS-based regression algorithm.

Contribution 2: Primal-dual framework with dual objective invariant for IRLS updates

Description: The authors introduce a novel primal-dual algorithmic framework where the IRLS update rule is derived from maintaining an invariant on the dual objective function, departing from standard approaches based on Taylor expansions or mirror descent methods.

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. AI539 final essay: Information geometry for total-variation denoising of manifold-valued images

URL: View paper

Brief Assessment

Information Geometry Denoising[61] focuses on manifold-valued image denoising using total-variation methods and iteratively reweighted least squares for image processing applications. It does not address ℓp regression problems or propose primal-dual frameworks with dual objective invariants for IRLS updates in the optimization context described by the original paper.

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2. Fenchel duality theory and a primal-dual algorithm on Riemannian manifolds

URL: View paper

Brief Assessment

Fenchel Duality Riemannian[57] develops primal-dual algorithms for optimization on Riemannian manifolds using Fenchel conjugation theory, not for ℓp regression or IRLS methods. The candidate focuses on manifold optimization with geodesic convexity, while the original paper addresses ℓp regression in Euclidean spaces with IRLS updates derived from dual objective invariants.

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3. A note on privacy preserving iteratively reweighted least squares

URL: View paper

Brief Assessment

Privacy Preserving IRLS[59] focuses on differential privacy mechanisms for IRLS in generalized linear models, not on primal-dual algorithmic frameworks or dual objective invariants for ℓp regression.

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4. An efficient primal-dual method for the obstacle problem

URL: View paper

Brief Assessment

Primal Dual Obstacle[62] focuses on solving the obstacle problem using IRLS methods for a specific PDE application, not on general ℓp regression frameworks with dual objective invariants as in the original paper.

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5. Algorithms for â□□1-Minimization

URL: View paper

Brief Assessment

L1 Minimization Algorithms[63] discusses iteratively reweighted least squares as a proxy method and mentions primal-dual optimization, but provides insufficient detail about the specific dual objective invariant mechanism described in the original paper. The candidate's context is too limited to assess whether it presents the same primal-dual framework where IRLS updates are derived from maintaining an invariant on the dual objective function.

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6. Improved Regression via Iteratively Reweighted Least Squares

URL: View paper

Brief Assessment

The candidate text fragments mention ℓp regression problems but provide no information about primal-dual frameworks, dual objective invariants, or algorithmic update rules. Without substantive content from Improved Regression IRLS[3], it is impossible to assess whether it employs similar techniques or predates this contribution.

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7. A Parallel Min-Cut Algorithm using Iteratively Reweighted Least Squares

URL: View paper

Brief Assessment

Parallel Min Cut[64] focuses on min-cut problems using IRLS for Laplacian systems, not on general ℓp regression with primal-dual frameworks maintaining dual objective invariants.

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8. Regularized primal and dual Kacanov iterations for the p-Laplacian

URL: View paper

Brief Assessment

Kacanov p Laplacian[58] focuses on regularized Kacanov iterations for the p-Laplace problem in finite element methods, not on deriving IRLS updates from dual objective invariants for ℓp regression as in the original paper.

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9. Fast iteratively reweighted least squares algorithms for analysis-based sparse reconstruction.

URL: View paper

Brief Assessment

Fast IRLS Analysis[33] focuses on analysis-based sparse reconstruction using iteratively reweighted least squares for compressed sensing problems, which is a different problem domain from ℓp regression. The candidate paper does not address the specific primal-dual framework with dual objective invariants described in the original contribution.

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10. Strongly convex optimization for the dual formulation of optimal transport

URL: View paper

Brief Assessment

Dual Optimal Transport[60] focuses on optimal transport problems using strongly convex optimization in the dual formulation, not on ℓp regression or IRLS methods. The minimal context provided does not demonstrate prior work on maintaining dual objective invariants for IRLS updates in regression problems.

Contribution 3: High-precision algorithm via iterative refinement with improved residual solver

Description: The authors develop a high-precision algorithm that adapts the iterative refinement framework to use their improved IRLS solver for mixed lp + l2 residual problems, achieving O(p² log n log(n/ε)) subproblems each requiring O(n^((p-2)/(3p-2))) linear system solves.

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. Convex optimization with -norm oracles

URL: View paper

Brief Assessment

Convex Lp Oracles[71] appears to focus on convex optimization with Lp-norm oracles, while the original paper develops a specific IRLS-based iterative refinement framework for ℓp regression. The candidate's limited context does not provide sufficient detail about iterative refinement methods or residual solvers to challenge the novelty of the original paper's approach.

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2. Energy-based flow matching for molecular docking

URL: View paper

Brief Assessment

Energy Flow Docking[69] focuses on molecular docking using energy-based flow matching for protein-ligand structure prediction, not on ℓp regression or iterative refinement algorithms for linear systems. The technical domains are entirely different.

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3. Tks-bls: Temporal kernel stationary broad learning system for enhanced modeling, anomaly detection, and incremental learning with application to ironmaking â□¦

URL: View paper

Brief Assessment

Temporal Kernel BLS[67] focuses on broad learning systems for time-series modeling and anomaly detection in industrial applications, not on iterative refinement algorithms for ℓp regression problems with residual solvers.

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4. A new analysis of iterative refinement and its application to accurate solution of ill-conditioned sparse linear systems

URL: View paper

Brief Assessment

Iterative Refinement Analysis[72] focuses on solving ill-conditioned sparse linear systems using GMRES-based iterative refinement with LU factorization, not on ℓp regression problems with mixed ℓp + ℓ2 objectives as in the original paper.

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5. Iterative Refinement for â□□p-norm Regression

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.

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6. The complexity of dynamic least-squares regression

URL: View paper

Brief Assessment

Dynamic Least Squares[70] focuses on dynamic maintenance of least-squares regression solutions under adaptive insertions/deletions, not on developing high-precision iterative refinement algorithms for static ℓp regression problems.

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7. â¦ coarse recycled concrete aggregates using multivariate adaptive regression splines (MARS), M5 model tree (M5Tree), and least squares support vector regression â¦

URL: View paper

Brief Assessment

MARS M5Tree Regression[66] focuses on concrete aggregate prediction using multivariate adaptive regression splines and support vector regression methods. This is unrelated to the iterative refinement framework for ℓp regression problems with IRLS solvers.

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8. An improved successive linear programming algorithm

URL: View paper

Brief Assessment

Improved Successive Linear[73] focuses on successive linear programming for general nonlinear optimization problems, not on iterative refinement for ℓp regression with mixed lp + l2 residual solvers as in the original paper.

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9. Stable Iterative Solvers for Ill-Conditioned Linear Systems and Least Squares

URL: View paper

Brief Assessment

Stable Iterative Solvers[65] focuses on stabilizing iterative refinement and Krylov methods for ill-conditioned systems to prevent divergence, not on developing high-precision algorithms for ℓp regression with specific complexity bounds for residual solvers.

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10. Unmanned aerial vehicle phenotyping of agronomic and physiological traits in mungbean

URL: View paper

Brief Assessment

UAV Mungbean Phenotyping[68] focuses on unmanned aerial vehicle phenotyping for agricultural traits in mungbean crops, not on iterative refinement algorithms for ℓp regression problems.

Appendix: Text Similarity Detection

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

References

- [0] Improved ℓ_{p} Regression via Iteratively Reweighted Least Squares View paper
- [1] Iteratively reweighted least squares minimization for sparse recovery View paper
- [2] Iteratively reweighted least squares for block sparse signal recovery with unconstrained minimization View paper
- [3] Improved Regression via Iteratively Reweighted Least Squares View paper
- [4] Iterative re-weighted least squares algorithms for non-negative sparse and group-sparse recovery View paper
- [5] An iteratively reweighted least squares algorithm for skew-probit binary regression with Firthâ□s penalization View paper
- [6] Improved Iteratively Reweighted Least Squares for Unconstrained Smoothed Minimization View paper
- [7] Iteratively reweighted least squares for block-sparse recovery View paper
- [8] Iteratively Reweighted Least Squares by Diagonal Regularization View paper
- [9] Iteratively reweighted least square for kernel expectile regression with random features View paper
- [10] Iteratively reweighted least squares for maximum likelihood estimation, and some robust and resistant alternatives View paper
- [11] Improved Convergence for and 1 Regression via Iteratively Reweighted Least Squares View paper
- [12] Iteratively reweighted least squares: algorithms, convergence analysis, and numerical comparisons View paper
- [13] Iteratively reâ□weighted and refined least squares algorithm for robust inversion of geophysical data View paper
- [14] Global Convergence of Iteratively Reweighted Least Squares for Robust Subspace Recovery View paper
- [15] Convergence and stability of iteratively re-weighted least squares algorithms View paper
- [16] Local basis function method for identification of nonstationary systems View paper
- [17] Iteratively reweighted least squares minimization for sparsely corrupted measurements View paper
- [18] Tail-Iteratively Reweighted Least Squares Technique for Compressed Sensing View paper
- [19] Power system state estimation using an iteratively reweighted least squares method for sequential L1-regression View paper
- [20] Fast iteratively reweighted least squares for lp regularized image deconvolution and reconstruction View paper
- [21] On resistant Lp-Norm Estimation by means of iteratively reweighted least Squares View paper
- [22] Iteratively reweighted least-squares implementation of the WLAV state-estimation method View paper
- [23] Iteratively re-weighted least squares minimization: Proof of faster than linear rate for sparse recovery View paper
- [24] 3D high-resolution Radon transform based on strong sparse LPâ□1 norm and its applications View paper
- [25] Iterative reweighted linear least squares for exact penalty subproblems on product sets View paper
- [26] Fast Algorithms for â□p-Regression View paper
- [27] Iteratively Reweighted Least Squares Method for Estimating Polyserial and Polychoric Correlation Coefficients View paper
- [28] A Comparative Study of Particle Swarm Optimization and Iteratively Reweighted Least Squares in Regression Modelling View paper
- [29] On the convergence of IRLS and its variants in outlier-robust estimation View paper
- [30] Robust Least Squares Twin Support Vector Regression With Adaptive FOA and PSO for Short-Term Traffic Flow Prediction View paper
- [31] Nonlinear Lp-norm estimation View paper
- [32] Fast, provably convergent IRLS algorithm for p-norm linear regression View paper
- [33] Fast iteratively reweighted least squares algorithms for analysis-based sparse reconstruction. View paper
- [34] Speech compressive sensing with â□1-minimzation and iteratively reweighted least squares-â□p-minimization: A comparative study View paper
- [35] Streaming Algorithms For â□p Flows and â□p Regression. View paper
- [36] Iteratively reweighted optimum linear regression in the presence of generalized Gaussian noise View paper
- [37] An analysis of sketched IRLS for accelerated sparse residual regression View paper
- [38] Iteratively Reweighte Least Squares Method for Estimating Polyserial and Polychoric Correlation Coefficients View paper
- [39] Iterative Refinement for â□p-norm Regression View paper
- [40] Robust Supervised and Semisupervised Least Squares Regression Using â□2,p-Norm Minimization View paper

- [41] Iteratively Reweighted Least Squares View paper
- [42] Robust regression using iteratively reweighted least-squares View paper
- [43] Normal/independent distributions and their applications in robust regression View paper
- [44] Globally-convergent Iteratively Reweighted Least Squares for Robust Regression Problems View paper
- [45] Prestack imaging of seismic data using Lp iterative reweighted least-squares wavefield extrapolation filters in the frequency-space domain View paper
- [46] Variational Weighted â□□p-â□□q$\ell _p-\ell _q$ Regularization for Hyperspectral Image Restoration Under Mixed Noise View paper
- [47] Iteratively reweighted least squares in crystal structure refinements. View paper
- [48] Iterative reweighted minimization methods for regularized unconstrained nonlinear programming View paper
- [49] Iteratively Reweighted Least Squares for Basis Pursuit with Global Linear Convergence Rate View paper
- [50] Comparison of l1-Minimization and Iteratively Reweighted least Squares-l p-Minimization for Image Reconstruction from Compressive Sensing View paper
- [51] Baseline correction for Raman spectra using a spectral estimation-based asymmetrically reweighted penalized least squares method. View paper
- [52] Convergence analysis of iteratively reweighted â□□1algorithms for computing the proximal operator of â□□pâ□□norm View paper
- [53] A Fine Line: Total Least-Squares Line Fitting as QCQP Optimization View paper
- [54] A cooperative magnetic inversion method with lp-norm regularization View paper
- [55] Iterative reweighted minimization for generalized norm/quasi-norm difference regularized unconstrained nonlinear programming View paper
- [56] Robust and flexible mixed-norm inversion View paper
- [57] Fenchel duality theory and a primal-dual algorithm on Riemannian manifolds View paper
- [58] Regularized primal and dual Kacanov iterations for the p-Laplacian View paper
- [59] A note on privacy preserving iteratively reweighted least squares View paper
- [60] Strongly convex optimization for the dual formulation of optimal transport View paper
- [61] AI539 final essay: Information geometry for total-variation denoising of manifold-valued images View paper
- [62] An efficient primal-dual method for the obstacle problem View paper
- [63] Algorithms for â□□1-Minimization View paper
- [64] A Parallel Min-Cut Algorithm using Iteratively Reweighted Least Squares View paper
- [65] Stable Iterative Solvers for Ill-Conditioned Linear Systems and Least Squares View paper
- [66] â□¦ coarse recycled concrete aggregates using multivariate adaptive regression splines (MARS), M5 model tree (M5Tree), and least squares support vector regression â□¦ View paper
- [67] Tks-bls: Temporal kernel stationary broad learning system for enhanced modeling, anomaly detection, and incremental learning with application to ironmaking â□¦ View paper
- [68] Unmanned aerial vehicle phenotyping of agronomic and physiological traits in mungbean View paper
- [69] Energy-based flow matching for molecular docking View paper
- [70] The complexity of dynamic least-squares regression View paper
- [71] Convex optimization with -norm oracles View paper
- [72] A new analysis of iterative refinement and its application to accurate solution of ill-conditioned sparse linear systems View paper
- [73] An improved successive linear programming algorithm View paper