

Novelty Assessment Report

Paper: Price of Quality: Sufficient Conditions for Sparse Recovery using Mixed-Quality Data

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Abstract

We study sparse recovery when observations come from mixed-quality sources: a small collection of high-quality measurements with small noise variance and a larger collection of lower-quality measurements with higher variance. For this heterogeneous-noise setting, we establish sample-size conditions for information-theoretic and algorithmic recovery. On the information-theoretic side, we show that (n_1, n_2) must satisfy a linear trade-off defining the Price of Quality: the number of low-quality samples needed to replace one high-quality sample. In the agnostic setting, where the decoder is completely agnostic to the quality of the data, it is uniformly bounded, and in particular one high-quality sample is never worth more than two low-quality samples. In the informed setting, where the decoder is informed of per-sample variances, the price of quality can grow arbitrarily large. On the algorithmic side, we analyze the LASSO in the agnostic setting and show that the recovery threshold matches the homogeneous-noise case and only depends on the average noise level, revealing a striking robustness of computational recovery to data heterogeneity. Together, these results give the first conditions for sparse recovery with mixed-quality data and expose a fundamental difference between how the information-theoretic and algorithmic thresholds adapt to changes in data quality.

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: **Sparse Recovery with Heterogeneous Noise Observations**

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

Taxonomy Overview

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

- **Sparse Signal Recovery Methods Under Non-Uniform Noise**
- **Sparse Recovery Under Impulsive and Heavy-Tailed Noise**
- **Quantized and One-Bit Compressive Sensing**
- **Non-Uniform Sampling and Reconstruction**
- **Structured Sparsity and Block Sparse Recovery**
- **Statistical and Bayesian Sparse Recovery Frameworks**
- **Application-Specific Sparse Recovery Methods**
- **Algorithmic Advances and Optimization Methods**

Complete Taxonomy Tree

- Sparse Recovery with Heterogeneous Noise Observations Survey Taxonomy
- Sparse Signal Recovery Methods Under Non-Uniform Noise
 - Direction-of-Arrival Estimation with Non-Uniform Noise (9 papers)
 - [1] Robust Gridless DOA Estimation Using Coprime Array Under Nonuniform Noise (Jing Song, 2025) [View paper](#)
 - [7] Underwater DOA Estimator Based on Variational Bayesian Inference with Non-uniform Noise (Yongfeng Huang, 2024) [View paper](#)
 - [9] One-bit DOA estimation using robust sparse covariance fitting in non-uniform noise (Mingyang Chen, 2022) [View paper](#)
 - [22] Robust direction finding via acoustic vector sensor array with axial deviation under non-uniform noise (Weidong Wang, 2022) [View paper](#)
 - [24] Doa estimation based on sparse reconstruction via acoustic vector sensor array under non-uniform noise (Xiangshui Li, 2022) [View paper](#)
 - [26] Robust DOA estimation in RIS-assisted miso systems (Canping Yu, 2024) [View paper](#)
 - [37] Real-valued sparse DOA estimation for MIMO array system under unknown nonuniform noise (Fang Dong, 2018) [View paper](#)
 - [45] Robust sparse Bayesian learning for off-grid DOA estimation with non-uniform noise (Huafei Wang, 2018) [View paper](#)
 - [50] Sparse representation based direction-of-arrival estimation in nonuniform noise via tail minimisation (cao zeng, 2021) [View paper](#)
 - Theoretical Foundations and Recovery Guarantees ★ (3 papers)
 - [0] Price of Quality: Sufficient Conditions for Sparse Recovery using Mixed-Quality Data (Anon et al., 2026) [View paper](#)
 - [2] Compressed sensing for inverse problems II: applications to deconvolution, source recovery, and MRI (Alessandro Felisi, 2025) [View paper](#)
 - [40] Fast recovery of non-negative sparse signals under heterogeneous noise (Lei Hu, 2017) [View paper](#)
 - Graph Signal Reconstruction Under Heterogeneous Noise (1 papers)
 - [28] Graph signal reconstruction under heterogeneous noise via adaptive uncertainty-aware sampling and soft classification (Alessio Fascista, 2024) [View paper](#)
- Sparse Recovery Under Impulsive and Heavy-Tailed Noise
 - Robust DOA Estimation Under Impulsive Noise (3 papers)
 - [8] Variational Bayesian inference for DOA estimation under impulsive noise and nonuniform noise (Kun Guo, 2023) [View paper](#)
 - [17] Off-grid DOA estimation using sparse Bayesian learning for MIMO radar under impulsive noise (Jitong Ma, 2022) [View paper](#)

- [25] Infinite Weighted p-Norm Sparse Iterative DOA Estimation via Acoustic Vector Sensor Array under Impulsive Noise (Zhiqiang Liu, 2023) [View paper](#)
- Robust Image and Signal Reconstruction (3 papers)
- [10] Sparse Overdispersed Photon-Limited Signal Recovery with Upper and Lower Bounds (Yu Lu, 2023) [View paper](#)
- [18] Multiply complementary priors for image compressive sensing reconstruction in impulsive noise (Yunyi Li, 2024) [View paper](#)
- [41] Robust Tensor Recovery in Impulsive Noise Based on Correntropy and Hybrid Tensor Sparsity (Le Gao, 2022) [View paper](#)
- Quantized and One-Bit Compressive Sensing (3 papers)
 - [12] Distributed Decoding From Heterogeneous 1-Bit Compressive Measurements (Liping, 2022) [View paper](#)
 - [20] Robust mixed one-bit compressive sensing (Xiaolin Huang, 2019) [View paper](#)
 - [42] Support Recovery in 1-Bit Compressed Sensing with Burst Sparse Noise (Saikiran Bulusu, 2025) [View paper](#)
- Non-Uniform Sampling and Reconstruction
 - Fourier and Spectral Reconstruction from Non-Uniform Samples (5 papers)
 - [4] Non-uniform sparse Fourier transform and its applications (Deyun Wei, 2022) [View paper](#)
 - [6] Streaming Reconstruction from Non-uniform Samples (Romberg, 2022) [View paper](#)
 - [27] Reconstruction technique of non-uniform sampling system based on OMP algorithm (Hanxi Zhao, 2018) [View paper](#)
 - [34] An Efficient Spectrum Reconstruction Algorithm for Non-Uniformly Sampled Signals and Its Application in Terahertz SAR (Guohua Zhang, 2023) [View paper](#)
 - [39] Accurate reconstruction of frequency-sparse signals from non-uniform samples (Kang-Yu Ni, 2012) [View paper](#)
 - Multi-Receiver and Array-Based Reconstruction (2 papers)
 - [11] Data reconstruction based on non-uniformly sampled signal (Xuebo Zhang, 2021) [View paper](#)
 - [48] Sparse reconstruction method of non-uniform sampling and its application in blade tip timing system (Jie Tian, 2020) [View paper](#)
 - NMR Spectroscopy Non-Uniform Sampling (4 papers)
 - [21] Compressed sensing: Reconstruction of non-uniformly sampled multidimensional NMR data (M Bostock, 2017) [View paper](#)
 - [30] Non-uniform sampling: post-Fourier era of NMR data collection and processing (Krzysztof Kazimierczuk, 2015) [View paper](#)
 - [31] Noise reduction in spectroscopic detection with compressed sensing (Junyan Sun, 2025) [View paper](#)
 - [38] Applications of non-uniform sampling and processing (Sven G. Hyberts, 2011) [View paper](#)
- Structured Sparsity and Block Sparse Recovery (3 papers)
 - [5] Noisy Non-negative Tucker Decomposition With Sparse Factors and Missing Data (Xiong-jun Zhang, 2025) [View paper](#)
 - [14] Recovery of block sparse signals from non-uniform finite wavelet frame transform (Sunder Deep, 2025) [View paper](#)
 - [36] Group Projected Subspace Pursuit for Block Sparse Signal Reconstruction: Convergence Analysis and Applications (Roy Y. He, 2024) [View paper](#)
- Statistical and Bayesian Sparse Recovery Frameworks (4 papers)
 - [13] A deep heterogeneous optimization framework for Bayesian compressive sensing (Le Qin, 2021) [View paper](#)
 - [44] Compressive sensing by learning a Gaussian mixture model from measurements (Jianbo Yang, 2014) [View paper](#)
 - [47] Statistical compressed sensing of Gaussian mixture models (Yu, 2011) [View paper](#)
 - [49] Optimal compressed sensing for mixing stochastic processes (Gutman, 2025) [View paper](#)
- Application-Specific Sparse Recovery Methods
 - Imaging and Medical Applications (4 papers)
 - [3] Side-scan sonar image denoising algorithm based on deep learning and compressed sensing (Jingwen Li, 2025) [View paper](#)
 - [29] Combination of iterative reconstruction and CNN-based denoising for non-uniform noise for parallel imaging in MRI (A SUZUKI, 2023) [View paper](#)
 - [35] Effect of MRI acquisition acceleration via compressed sensing and parallel imaging on brain volumetry (Michael Dieckmeyer, 2021) [View paper](#)
 - [46] Sparse Mixture-of-Experts for Non-Uniform Noise Reduction in MRI Images (Campbell, 2025) [View paper](#)
 - Radar and Sonar Signal Processing (1 papers)
 - [32] Reduced dimension STAP based on sparse recovery in heterogeneous clutter environments (Wei Zhang, 2019) [View paper](#)
 - Communication and Distributed Systems (2 papers)
 - [19] Distributed machine learning with sparse heterogeneous data (Richards, 2021) [View paper](#)
 - [23] Investigation of NOMA 5G Systems Under Non-Gaussian Channels (Hasan Abu Hilal, 2024) [View paper](#)
 - Biomedical Signal Processing (1 papers)
 - [43] Robust multichannel EEG compressed sensing in the presence of mixed noise (Chang Li, 2019) [View paper](#)
- Algorithmic Advances and Optimization Methods (3 papers)
 - [15] Controlling the false discovery rate in transformational sparsity: Split knockoffs (Cao Yang, 2024) [View paper](#)
 - [16] Compressive Sensing-Assisted Mixed Integer Optimization for Dynamical System Discovery With Highly Noisy Data (Tony Shi, 2025) [View paper](#)
 - [33] Analysis of regularized LS reconstruction and random matrix ensembles in compressed sensing (2016) [View paper](#)

Narrative

Core task: sparse recovery with heterogeneous noise observations. The field addresses the challenge of reconstructing sparse signals when measurements are corrupted by noise that varies in character or intensity across observations. The taxonomy reveals a landscape organized around several complementary perspectives. One major branch focuses on non-uniform noise models, where different measurements may have distinct noise variances or distributions, leading to methods that adaptively weight or reweight observations. Another branch tackles impulsive and heavy-tailed noise, which arises in robust signal processing scenarios where outliers or non-Gaussian disturbances dominate. Quantized and one-bit compressive sensing forms a third pillar, dealing with extreme measurement constraints where observations are coarsely discretized. Additional branches cover non-uniform sampling and reconstruction (e.g., Nonuniform Sparse Fourier[4], Streaming Nonuniform Reconstruction[6]), structured sparsity models that exploit block or group structure (Block Sparse Wavelet[14]), and statistical or Bayesian frameworks that model heterogeneity through hierarchical priors (Deep Heterogeneous Bayesian[13]). Application-specific methods span domains from MRI and NMR (Nonuniform NMR Reconstruction[21], CNN Nonuniform MRI[29]) to direction-of-arrival estimation (Robust Gridless DOA[1], Variational DOA Impulsive[8]) and beyond.

Several active lines of work highlight key trade-offs and open questions. Robust methods for impulsive noise (Complementary Priors Impulsive[18], Robust Tensor Impulsive[41]) often employ variational or heavy-tailed likelihood models, contrasting with classical Gaussian assumptions. Quantized sensing approaches (Onebit DOA Sparse[9], Distributed Onebit Decoding[12]) push the limits of

information extraction from minimal bit budgets, raising questions about optimal quantizer design under heterogeneous conditions. Meanwhile, non-uniform sampling strategies (Nonuniform Data Reconstruction[11]) and application-driven methods (Compressed Sensing Applications[2], Spectroscopic Compressed Sensing[31]) explore domain-specific structure to improve recovery guarantees. The original paper, Price of Quality[0], sits within the theoretical foundations branch of non-uniform noise recovery, examining fundamental limits and recovery guarantees when observation quality varies. Its emphasis on theoretical characterization complements nearby works such as Nonnegative Heterogeneous Recovery[40], which incorporates additional structural constraints, and contrasts with more application-oriented studies like Sonar Denoising Deep[3] that leverage domain-specific architectures. This positioning underscores a broader tension between deriving rigorous performance bounds and designing practical algorithms for diverse noise regimes.

Related Works in Same Category

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

1. Compressed sensing for inverse problems II: applications to deconvolution, source recovery, and MRI

Authors: Alessandro Felisi, S. Ivan Trapasso, Giovanni S. Alberti, Matteo Santacesaria | **Year/Venue:** 2025 | **URL:** [View paper](#)

Abstract

â€¦ examine a fundamental problem in compressed sensing: the â€¦ guarantees within the compressed sensing framework [48, 19â€¦]. Second, we handle the non-uniform noise case (3) â€¦

Relationship Analysis

Both papers address sparse recovery problems but from fundamentally different perspectives. The original paper studies sparse recovery with heterogeneous noise observations (mixed-quality data with different noise variances), establishing information-theoretic and algorithmic thresholds for support recovery and introducing the "Price of Quality" concept. The candidate paper focuses on compressed sensing for ill-posed inverse problems (deconvolution, source recovery, MRI), developing sample complexity theory based on quasi-diagonalization and coherence bounds in infinite-dimensional settings. While both involve sparse signal recovery, the original paper's core contribution is characterizing the trade-off between high- and low-quality measurements, whereas the candidate paper extends abstract compressed sensing frameworks to specific inverse problems with measurement constraints.

2. Fast recovery of non-negative sparse signals under heterogeneous noise

Authors: Lei Hu, Zemin Wu, Lei Zhang, Chang Tian | **Year/Venue:** 2017 • International Conference on Wireless Communications and Signal Processing | **URL:** [View paper](#)

Abstract

N/A

Relationship Analysis

Both papers belong to the sparse recovery domain and address heterogeneous noise settings, focusing on recovery conditions and sample complexity under non-uniform noise distributions. Both papers study sparse signal recovery with heterogeneous (non-uniform) noise observations and analyze recovery conditions. They share the core problem of understanding how different noise levels across observations affect recovery guarantees. The original paper focuses on mixed-quality data with two distinct noise levels (high-quality vs low-quality), establishing information-theoretic and LASSO algorithmic thresholds while introducing the 'Price of Quality' concept. The candidate paper specifically targets non-negative sparse signals and emphasizes fast recovery algorithms, suggesting a focus on computational efficiency and the non-negativity constraint rather than the agnostic/informed decoder framework of the original paper.

Contributions Analysis

Overall novelty summary. The paper establishes information-theoretic and algorithmic conditions for sparse recovery when measurements come from mixed-quality sources with heterogeneous noise variances. It resides in the 'Theoretical Foundations and Recovery Guarantees' leaf, which contains only three papers total, indicating a relatively sparse research direction focused on fundamental limits rather than application-specific methods. This leaf sits within the broader 'Sparse Signal Recovery Methods Under Non-Uniform Noise' branch, distinguishing itself from sibling categories addressing direction-of-arrival estimation or graph signal reconstruction by emphasizing rigorous recovery thresholds and sample-complexity trade-offs.

The taxonomy reveals that most neighboring work addresses either application-driven scenarios (DOA estimation with nine papers, imaging with four papers) or alternative noise models (impulsive noise with six papers, quantized sensing with three papers). The paper's theoretical focus contrasts with these domain-tailored approaches. Nearby branches explore non-uniform sampling patterns and structured sparsity, but the scope notes clarify these exclude the heterogeneous-noise variance setting central to this work. The taxonomy structure suggests that foundational theory for mixed-quality data remains less developed than methods for uniform noise or specific application contexts.

Among thirty candidates examined across three contributions, none were identified as clearly refuting the paper's claims. For the sufficient conditions contribution, ten candidates were reviewed with zero refutable matches; the Price of Quality concept similarly showed ten examined and zero refutable; the LASSO extension likewise found no overlapping prior work among ten candidates. This absence of refutation within the limited search scope suggests the specific framing—quantifying sample-size trade-offs between high- and low-quality measurements and analyzing LASSO robustness to data heterogeneity—may represent a novel angle within sparse recovery theory.

Based on the top-thirty semantic matches and taxonomy positioning, the work appears to address an underexplored theoretical gap. The sparse population of its taxonomy leaf and the lack of refutable prior work within the examined candidates indicate potential novelty, though the limited search scope means exhaustive coverage of all relevant literature cannot be claimed. The analysis covers foundational recovery guarantees but does not extend to application-specific validation or algorithmic implementations beyond LASSO.

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

Contribution 1: Sufficient conditions for sparse recovery with mixed-quality data

Description: The authors derive sufficient conditions on sample sizes (n_1 , n_2) for recovering sparse signals when observations come from two sources with different noise variances. They analyze both information-theoretic recovery (via maximum likelihood) and algorithmic recovery (via LASSO) in agnostic and informed settings.

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. Robust and efficient sparse learning over networks: a decentralized surrogate composite quantile regression approach

URL: [View paper](#)

Brief Assessment

Decentralized Quantile Regression[71] addresses distributed optimization with heterogeneous noise across network nodes, not sparse signal recovery with mixed-quality measurements or sample-size conditions for LASSO/MLE recovery.

2. Low-frequency sound source localization algorithm for small aperture AVSA under non-uniform noise scenarios

URL: [View paper](#)

Brief Assessment

Lowfrequency AVSA Localization[78] focuses on acoustic source localization using sparse Bayesian learning for array signal processing under non-uniform noise, not on deriving sample-size conditions for sparse signal recovery with heterogeneous noise variances in statistical estimation contexts.

3. Recovery conditions of sparse signals using orthogonal least squares-type algorithms

URL: [View paper](#)

Brief Assessment

Orthogonal Least Squares[77] focuses on greedy iterative algorithms (OLS, MOLS, BOLS) for sparse signal reconstruction using mutual incoherence property conditions, not on sample-size requirements for heterogeneous noise settings with mixed-quality data sources.

4. High-dimensional variable selection with heterogeneous signals: A precise asymptotic perspective

URL: [View paper](#)

Brief Assessment

Heterogeneous Signals Selection[72] focuses on variable selection with heterogeneous signal strengths (weak, rare signals with different magnitudes) rather than heterogeneous noise variances. The paper studies sample-size conditions for identifying sparse signals when signal magnitudes vary, not when measurement noise varies across observations.

5. Sparse signal detection in heteroscedastic Gaussian sequence models: Sharp minimax rates

URL: [View paper](#)

Brief Assessment

Sparse Heteroscedastic Detection[73] focuses on signal detection (hypothesis testing) in heteroscedastic Gaussian sequence models, not on sparse recovery or reconstruction. The candidate studies testing whether a signal exists, while the original paper addresses conditions for recovering the signal's support using methods like MLE and LASSO.

6. Distributed Decoding From Heterogeneous 1-Bit Compressive Measurements

URL: [View paper](#)

Brief Assessment

Distributed Onebit Decoding[12] addresses distributed 1-bit compressive sensing with heterogeneous noise across nodes, while the original paper studies centralized sparse recovery with two distinct noise variance levels in a mixed-quality data framework. The technical settings and recovery guarantees differ fundamentally.

7. Direction-of-Arrival Estimation Based on Variational Bayesian Inference Under Model Errors.

URL: [View paper](#)

Brief Assessment

Variational Model Errors[74] addresses direction-of-arrival estimation under non-uniform noise and gain/phase errors in sensor arrays, not sparse signal recovery with heterogeneous measurement quality. The technical problems and methodologies are fundamentally different.

8. Gridless sparse recovery STAP algorithm with array amplitude-phase errors for non-uniform linear array

URL: [View paper](#)

Brief Assessment

Gridless STAP Errors[76] addresses radar signal processing with array calibration errors in non-uniform linear arrays, not sparse signal recovery with heterogeneous noise variances or mixed-quality data sources.

9. Off-grid DOA estimation using sparse Bayesian learning for MIMO radar under impulsive noise

URL: [View paper](#)

Brief Assessment

Offgrid MIMO DOA[17] focuses on direction-of-arrival estimation for MIMO radar under impulsive noise using sparse Bayesian learning, not on deriving sample-size conditions for sparse signal recovery with heterogeneous noise variances in statistical inference settings.

10. Off-grid DOA estimation using improved root sparse Bayesian learning for non-uniform linear arrays

URL: [View paper](#)

Brief Assessment

Offgrid Root Bayesian[75] addresses direction-of-arrival estimation using sparse Bayesian learning with dictionary mismatch problems, not sample-size conditions for heterogeneous-noise sparse recovery in regression settings.

Contribution 2: Price of Quality: quantifying the trade-off between high-quality and low-quality samples

Description: The authors introduce and quantify the Price of Quality, which measures how many low-quality samples are needed to replace one high-quality sample. They show this price is uniformly bounded (at most two) in the agnostic setting but can grow arbitrarily large in the informed setting.

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. Neural image compression using masked sparse visual representation

URL: [View paper](#)

Brief Assessment

Masked Sparse Compression[53] focuses on neural image compression using masked sparse visual representations and codebook learning. It does not address sparse recovery with mixed-quality data or quantify trade-offs between high-quality and low-quality samples in the statistical sense described by the original paper.

2. Improved sparse signal recovery via adaptive correlated noise model

URL: [View paper](#)

Brief Assessment

Adaptive Correlated Noise[59] focuses on sparse signal recovery using adaptive correlated noise models and denoisers for inverse problems like compressive imaging and tomography. It does not address the trade-off between high-quality and low-quality samples or quantify a 'Price of Quality' metric as defined in the original paper.

3. Variational Pose Prediction with Dynamic Sample Selection from Sparse Tracking Signals

URL: [View paper](#)

Brief Assessment

Variational Pose Prediction[56] addresses pose reconstruction from sparse VR tracking signals using sample quality monitoring, not the theoretical trade-off between high-quality and low-quality samples in sparse recovery problems.

4. Finger vein recognition via sparse reconstruction error constrained low-rank representation

URL: [View paper](#)

Brief Assessment

Finger Vein Sparse[60] addresses finger vein recognition using sparse reconstruction and low-rank representation for image quality variations, not the theoretical trade-off between high-quality and low-quality samples in sparse recovery problems.

5. Data-iterative optimization score model for stable ultra-sparse-view CT reconstruction

URL: [View paper](#)

Brief Assessment

Data Iterative Score[58] focuses on CT image reconstruction using score-based diffusion models with data consistency constraints, not on analyzing trade-offs between sample quality in sparse recovery or learning contexts.

6. Image and Video Compression Using Generative Sparse Representation with Fidelity Controls

URL: [View paper](#)

Brief Assessment

Generative Sparse Compression[55] focuses on image/video compression using sparse visual representations with fidelity controls, not on quantifying trade-offs between high-quality and low-quality samples in sparse recovery contexts.

7. High-resolution iterative reconstruction at extremely low sampling rate for Fourier single-pixel imaging via diffusion model

URL: [View paper](#)

Brief Assessment

Diffusion Singlepixel Imaging[57] addresses trade-offs between imaging efficiency and quality in Fourier single-pixel imaging, not the statistical trade-off between high-quality and low-quality samples in sparse recovery problems.

8. Spectral-cascaded diffusion model for remote sensing image spectral super-resolution

URL: [View paper](#)

Brief Assessment

Spectral Cascaded Diffusion[52] focuses on spectral super-resolution for remote sensing images using diffusion models. This is a completely different domain (image processing) with different technical objectives than the original paper's work on sparse recovery with mixed-quality data.

9. DECT sparse reconstruction based on hybrid spectrum data generative diffusion model

URL: [View paper](#)

Brief Assessment

DECT Diffusion Reconstruction[51] focuses on medical imaging reconstruction using diffusion models for dual-energy CT, not on sparse recovery or sample quality trade-offs in statistical learning.

10. Synchrotron radiation sparse-view CT artifact correction through deep learning neural networks

URL: [View paper](#)

Brief Assessment

Synchrotron Artifact Correction[54] addresses CT imaging artifact correction through deep learning methods for sparse-view reconstruction. This is fundamentally different from the original paper's theoretical analysis of sparse recovery with mixed-quality data in statistical learning, which quantifies sample quality trade-offs through information-theoretic bounds.

Contribution 3: Extension of LASSO recovery conditions to heterogeneous-noise setting

Description: The authors prove that the LASSO recovery threshold in the heterogeneous-noise agnostic setting matches the homogeneous-noise case and depends only on the average noise level. This reveals that high-quality and low-quality data contribute equally to reaching the algorithmic threshold, showing robustness of computational recovery to data heterogeneity.

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. Heavy Lasso: sparse penalized regression under heavy-tailed noise via data-augmented soft-thresholding

URL: [View paper](#)

Brief Assessment

Heavy Lasso Regression[62] addresses robust regression under heavy-tailed noise using a Student's t-distribution inspired loss function, not heterogeneous noise with mixed-quality data sources having different variance levels as in the original paper.

2. Effective regions and kernels in continuous sparse regularisation, with application to sketched mixtures

URL: [View paper](#)

Brief Assessment

Effective Regions Kernels[68] focuses on continuous sparse regularization (Beurling-LASSO) for measure recovery with translation-invariant kernels, not discrete LASSO recovery under heterogeneous noise conditions.

3. Robust sparse Bayesian learning for sparse signal recovery under unknown noise distributions

URL: [View paper](#)

Brief Assessment

Unknown Noise Bayesian[66] focuses on Bayesian learning methods for sparse signal recovery under unknown noise distributions, not LASSO recovery conditions or heterogeneous noise settings with mixed-quality data sources.

4. Non-asymptotic uncertainty quantification in high-dimensional learning

URL: [View paper](#)

Brief Assessment

Nonasymptotic Uncertainty Quantification[69] focuses on uncertainty quantification and confidence intervals for debiased LASSO estimators in finite-sample regimes, not on recovery conditions or thresholds for LASSO under heterogeneous noise. The paper addresses a different problem: constructing valid confidence intervals when the remainder term does not vanish asymptotically.

5. Asymptotic analysis of map estimation via the replica method and compressed sensing

URL: [View paper](#)

Brief Assessment

Asymptotic MAP Replica[70] analyzes LASSO using the replica method from statistical physics for large random measurement matrices with Gaussian noise, focusing on asymptotic decoupling into scalar estimators. The original paper studies finite-sample recovery conditions under heterogeneous noise with different variance levels for high-quality and low-quality data, which is a distinct problem setting.

6. Signal-to-noise ratio aware minimax analysis of sparse linear regression

URL: [View paper](#)

Brief Assessment

SNR Minimax Analysis[63] focuses on signal-to-noise ratio variations in sparse linear regression minimax theory, not on heterogeneous noise settings where different observations have different noise variances. The candidate addresses SNR regimes in a homogeneous framework, while the original contribution concerns mixed-quality data with observation-level variance heterogeneity.

7. Complex-Valued Signal Recovery Using a Generalized Bayesian LASSO

URL: [View paper](#)

Brief Assessment

Generalized Bayesian LASSO[67] focuses on complex-valued signal recovery using Bayesian methods, not on heterogeneous-noise conditions for LASSO recovery thresholds in mixed-quality data settings.

8. Distributed Scatterer Interferometry for Fast Decorrelation Scenarios Based on Sparsity Regularization

URL: [View paper](#)

Brief Assessment

Distributed Scatterer Sparsity[64] applies LASSO (graphical LASSO) to interferometric coherence matrix estimation in remote sensing, not to sparse signal recovery under heterogeneous noise. The technical contexts are entirely different—one addresses covariance matrix estimation with sparsity constraints, while the original addresses signal support recovery with mixed-quality measurements.

9. Sparse stable outlier-robust signal recovery under Gaussian noise

URL: [View paper](#)

Brief Assessment

Sparse Outlier Recovery[65] focuses on outlier-robust signal recovery under Gaussian noise, not on heterogeneous-noise settings with mixed-quality data sources. The candidate's context mentions testing LASSO methods but does not address heterogeneous noise conditions or recovery thresholds dependent on average noise levels.

10. Numerical characterization of support recovery in sparse regression with correlated design

URL: [View paper](#)

Brief Assessment

Correlated Design Recovery[61] focuses on numerical characterization of LASSO performance under correlated design matrices, not on theoretical recovery conditions under heterogeneous noise. The candidate examines feature selection with correlated predictors, while the original contribution establishes theoretical thresholds for heterogeneous-noise settings.

Appendix: Text Similarity Detection

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

References

- [0] Price of Quality: Sufficient Conditions for Sparse Recovery using Mixed-Quality Data [View paper](#)
- [1] Robust Gridless DOA Estimation Using Coprime Array Under Nonuniform Noise [View paper](#)
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