Novelty Assessment Report

Paper: Transport Clustering: Solving Low-Rank Optimal Transport via Clustering
PDF URL: https://openreview.net/pdf?id=YKTJJCNXF4
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Abstract

Optimal transport (OT) finds a least cost transport plan between two probability distributions using a cost matrix over pairs of points. Constraining the rank of the transport plan yields low-rank OT, which improves statistical stability and interpretability compared to full-rank OT. Further, low-rank OT naturally induces co-clusters between distributions and generalizes K-means clustering. Reversing this direction, we show that solving a clustering problem on a set of correspondences, termed transport clustering, solves low-rank OT. This connection between low-rank OT and transport clustering relies on a transport registration of the cost matrix which registers the cost matrix via the transport map. We show that the reduction of low-rank OT to transport clustering yields polynomial-time, constant-factor approximation algorithms for low-rank OT. Specifically, we show that for the low-rank OT problem this reduction yields a $(1+\gamma)$-approximation algorithm for metrics of negative-type and a $(1+\gamma+\sqrt{2\gamma}\,)$-approximation algorithm for kernel costs where $\gamma \in [0,1]$ denotes the approximation ratio to the optimal full-rank solution. We demonstrate that transport clustering outperforms existing low-rank OT methods on several synthetic benchmarks and large-scale, high-dimensional real datasets.

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.

If you have any questions, please contact: mingzhang23@m.fudan.edu.cn

Core Task Landscape

This paper addresses: **Low-Rank Optimal Transport**

A total of **50 papers** were analyzed and organized into a taxonomy with **26 categories**.

Taxonomy Overview

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

- **Low-Rank Factorization Methods for Entropic OT**
- **Low-Rank Approximations of Cost and Kernel Matrices**
- **Unbalanced and Robust Low-Rank OT**
- **Low-Rank OT for Gromov-Wasserstein and Quadratic Problems**
- **Computational Frameworks and Software for Low-Rank OT**
- **Applications of Low-Rank OT in Machine Learning**
- **Theoretical Foundations and Algorithmic Analysis**
- **Statistical Inference and Estimation with Low-Rank OT**
- **Domain-Specific Applications of Low-Rank OT**
- **Related Low-Rank Methods and Broader Context**

Complete Taxonomy Tree

- Low-Rank Optimal Transport Survey Taxonomy
- Low-Rank Factorization Methods for Entropic OT
  - Low-Rank Coupling Factorization Algorithms (3 papers)
  - [3] Low-rank sinkhorn factorization (Meyer Scetbon, 2021) View paper
  - [16] Low-Rank Optimal Transport through Factor Relaxation with Latent Coupling (Julian Gold, 2024) View paper
  - [47] Approximating Optimal Transport via Low-rank and Sparse Factorization (Weijie Liu, 2021) View paper
  - Hierarchical and Structured Low-Rank OT (3 papers)
  - [8] A hierarchically low-rank optimal transport dissimilarity measure for structured data (Mohammad Motamed, 2022) View paper
  - [20] Low-rank tensor approximations for solving multi-marginal optimal transport problems (Christoph StrÃ¶ssner, 2023) View paper
  - [48] Hierarchical Low-Rank Approximation of Regularized Wasserstein Distance (Motamed, 2020) View paper
  - Schatten-Norm Regularized OT (2 papers)
  - [5] Simplifying Optimal Transport through Schatten- Regularization (Maunu, 2025) View paper
- Low-Rank Approximations of Cost and Kernel Matrices (2 papers)
  - [18] Fast entropic regularized optimal transport using semidiscrete cost approximation (Evgeny Tenetov, 2018) View paper
  - [49] Linear Time Sinkhorn Divergences using Positive Features (Meyer Scetbon, 2020) View paper
- Unbalanced and Robust Low-Rank OT (2 papers)
  - [4] Unbalanced Low-rank Optimal Transport Solvers (Scetbon, 2023) View paper
  - [11] Infrared search and track with unbalanced optimal transport dynamics regularization (Nicholas P. Bertrand, 2020) View paper
- Low-Rank OT for Gromov-Wasserstein and Quadratic Problems (1 papers)
  - [9] Linear-time gromov wasserstein distances using low rank couplings and costs (Scetbon, 2022) View paper
- Computational Frameworks and Software for Low-Rank OT (1 papers)
  - [7] Optimal transport tools (ott): A jax toolbox for all things wasserstein (Cuturi, 2022) View paper
- Applications of Low-Rank OT in Machine Learning
  - Domain Adaptation and Transfer Learning (2 papers)

  - [1] Low-Rank Optimal Transport for Robust Domain Adaptation (Bingrong Xu, 2024) View paper
  - [27] Kernel manifold alignment for domain adaptation (Tuia Devis, 2016) View paper
  - Clustering and Unsupervised Learning ★ (3 papers)
  - [0] Transport Clustering: Solving Low-Rank Optimal Transport via Clustering (Anon et al., 2026) View paper
  - [33] Fast unsupervised ground metric learning with tree-Wasserstein distance (K. M. Dusterwald, 2024) View paper
  - [34] Graph Convolutional Optimal Transport for Hyperspectral Image Spectral Clustering (Liu Shujun, 2022) View paper
  - Attention Mechanisms and Neural Architectures (1 papers)
  - [12] LOTFormer: Doubly-Stochastic Linear Attention via Low-Rank Optimal Transport (Shahbazi, 2025) View paper
  - Generative Modeling and Uncertainty Quantification (4 papers)
  - [17] Low-rank Wasserstein polynomial chaos expansions in the framework of optimal transport (Gruhlke, 2022) View paper
  - [19] An Eulerian approach to regularized JKO scheme with low-rank tensor decompositions for Bayesian inversion (Vitalii Aksenov, 2025) View paper
  - [22] Deep Inverse Rosenblatt Transport for Structural Reliability Analysis (Tyagi, 2025) View paper
  - [35] Generative modeling with low-rank Wasserstein polynomial chaos expansions (Gruhlke, 2022) View paper
- Theoretical Foundations and Algorithmic Analysis
  - Approximation Algorithms and Complexity (2 papers)
  - [2] Hierarchical Refinement: Optimal Transport to Infinity and Beyond (Gold, 2025) View paper
  - [42] Polynomial-time algorithms for Multimarginal Optimal Transport problems with structure (Altschuler, 2020) View paper
  - Convergence and Optimization Theory (1 papers)
  - [32] The Sparse-Plus-Low-Rank Quasi-Newton Method for Entropic-Regularized Optimal Transport (C Wang, n.d.) View paper
  - Low-Dimensional Embeddings and Projections (1 papers)
  - [25] Efficient estimates of optimal transport via low-dimensional embeddings (Fulop, 2022) View paper
- Statistical Inference and Estimation with Low-Rank OT
  - Hypothesis Testing and Distributional Comparison (2 papers)
  - [10] Soft and subspace robust multivariate rank tests based on entropy regularized optimal transport (Masud, 2021) View paper
  - [50] Nonparametric Two-Sample Hypothesis Testing for Random Graphs with Negative and Repeated Eigenvalues (Agterberg, 2020) View paper
  - Parameter and Affinity Matrix Estimation (2 papers)
  - [28] Estimating matching affinity matrices under low-rank constraints (Arnaud Dupuy, 2019) View paper
  - [40] Estimating matching affinity matrix under low-rank constraints (Arnaud Dupuy, 2022) View paper
  - Barycenters and Low-Rank Matrix Recovery (2 papers)
  - [38] Applications of the Bures-Wasserstein Distance in Linear Metric Learning (Davis Cooper, 2023) View paper
  - [39] Bures-Wasserstein Barycenters and Low-Rank Matrix Recovery (Maunu, 2022) View paper
- Domain-Specific Applications of Low-Rank OT
  - Signal Processing and Source Separation (1 papers)
  - [26] Determined Blind Source Separation with Sinkhorn Divergence-based Optimal Allocation of the Source Power (Wang Jian-yu, 2025) View paper
  - Imaging and Computer Vision (2 papers)
  - [13] Low-rank optimal transport and application to color transfer (MÃ¼ller, 2022) View paper
  - [31] SceneLLM: Implicit Language Reasoning in LLM for Dynamic Scene Graph Generation (Hang Zhang, 2024) View paper
  - Biological and Spatial Data Analysis (2 papers)
  - [21] Learning Latent Trajectories in Developmental Time Series with Hidden-Markov Optimal Transport (Peter Halmos, 2025) View paper
  - [29] Autoencoder Denoising for Network-Based Spatial Transcriptomics Data with Applications for Cell Signaling Estimation (A Javaid, 2025) View paper
- Related Low-Rank Methods and Broader Context
  - Reduced-Rank Estimation and Filtering (4 papers)
  - [14] Optimal reduced-rank estimation and filtering (Y. Hua, 2001) View paper
  - [23] Optimal and adaptive reduced-rank STAP (J.R. Guerci, 2000) View paper
  - [36] Optimal reduced rank modeling, prediction, monitoring and control using canonical variate analysis (Wallace E. Larimore, 1997) View paper
  - [41] Space-time reduced rank methods and CFAR signal detection algorithms with applications to HPRF radar (Ayoub, 1998) View paper
  - Low-Rank Matrix Factorization and Normalization (1 papers)
  - [6] Supervised Quantile Normalization for Low-rank Matrix Approximation (Cuturi, 2020) View paper
  - Local Low-Rank Denoising Methods (3 papers)
  - [30] Benchmarking local low rank denoising methods for task-based fMRI data analysis (Pierre-Antoine Comby, 2024) View paper
  - [44] Denoising of fMRI Volumes Using Local Low Rank Methods (Pierre-Antoine Comby, 2023) View paper
  - [45] Optimal Superpixel Kernel-Based Kernel Low-Rank and Sparsity Representation for Brain Tumour Segmentation. (Ting Ge, 2022) View paper
  - Low-Rank Preconditioners and Numerical Linear Algebra (1 papers)
  - [43] Low rank preconditioner updates for sequences of linear systems arising from an optimal transport problem (Claudia Cozzolino, 2018) View paper
  - Hardware and Neuromorphic Applications (1 papers)
  - [46] Effect of OTS Selector Reliabilities on NVM Crossbar-based Neuromorphic Training (Adam Gina, 2022) View paper
  - Theses and Comprehensive Surveys (2 papers)
  - [24] Advances in Optimal Transport : Low-Rank Structures and Applications in Machine Learning (Scetbon, 2023) View paper
  - [37] Uncertainty quantification of material imperfections: surrogates, upscaling and inference (Gruhlke, 2023) View paper

Narrative

Core task: low-rank optimal transport. The field of low-rank optimal transport has grown into a rich landscape organized around several complementary themes. At the highest level, one finds branches dedicated to low-rank factorization methods for entropic OT (e.g., Low-rank Sinkhorn[3]), low-rank approximations of cost and kernel matrices, and unbalanced or robust variants (Unbalanced Solvers[4], Subspace Robust[10]) that handle outliers or mass discrepancies. Parallel branches address quadratic and Gromov-Wasserstein problems

(Linear-time Gromov[9]), computational frameworks and software (OTT JAX[7]), and a diverse set of machine learning applications ranging from clustering and unsupervised learning to domain adaptation (Robust Domain Adaptation[1]) and generative modeling (Generative Modeling[35]). Additional branches cover theoretical foundations, statistical inference, domain-specific uses (e.g., color transfer, infrared tracking), and connections to broader low-rank methods in optimization and matrix factorization.

Within this ecosystem, a particularly active line of work explores regularization strategies that enforce or exploit low-rank structure, including Schatten-norm penalties (Schatten Regularization[5], Schatten-p Regularization[15]) and hierarchical or multiscale refinements (Hierarchical Refinement[2], Hierarchical Wasserstein[48]). Transport Clustering[0] sits naturally in the clustering and unsupervised learning branch, leveraging low-rank transport plans to group data in a computationally efficient manner. Its emphasis on clustering contrasts with nearby works such as Tree-Wasserstein[33] and Graph Convolutional[34], which focus on structured or graph-based representations, and complements methods like Hierarchical Dissimilarity[8] that build hierarchical partitions. Overall, Transport Clustering[0] exemplifies how low-rank constraints can be harnessed to scale unsupervised learning tasks, bridging algorithmic efficiency with interpretable groupings in high-dimensional settings.

Related Works in Same Category

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

1. Fast unsupervised ground metric learning with tree-Wasserstein distance

Authors: K. M. Dusterwald, Yamada Makoto, Samo Hromadka, Makoto Yamada | **Year/Venue**: 2024 | **URL**: View paper

Abstract

The performance of unsupervised methods such as clustering depends on the choice of distance metric between features, or ground metric. Commonly, ground metrics are decided with heuristics or learned via supervised algorithms. However, since many interesting datasets are unlabelled, unsupervised ground metric learning approaches have been introduced. One promising option employs Wasserstein singular vectors (WSVs), which emerge when computing optimal transport distances between features and samp...

Relationship Analysis

Both papers belong to the Clustering and Unsupervised Learning category within low-rank optimal transport applications, sharing a focus on using OT-based methods for unsupervised tasks. The original paper (Transport Clustering) solves low-rank OT by reducing it to a generalized K-means problem via transport registration, providing constant-factor approximation guarantees for co-clustering two datasets. The candidate paper (Fast Unsupervised Ground Metric Learning) instead learns ground metrics in an unsupervised manner using tree-Wasserstein distances and Wasserstein singular vectors, focusing on computational efficiency for feature distance learning rather than directly solving the low-rank OT problem.

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2. Graph Convolutional Optimal Transport for Hyperspectral Image Spectral Clustering

Authors: Liu Shujun, Huajun Wang, Shujun Liu | **Year/Venue**: 2022 | **URL**: View paper

Abstract

Suffering from rich spectral and spatial informa- tion, the hyperspectral images (HSIs) that embed low-dimensional nonlinear manifolds lead to a challenging clustering task. In this article, we propose a promising clustering method for HSIs, termed as graph convolutional optimal transport (GCOT). For capturing the intrinsic geometric structure of data, we develop optimal transport (OT) on their graph embeddings. The OT problem learns discrete transport coupling to form a natural affinity matrix ...

Relationship Analysis

Both papers belong to the same taxonomy category of applying low-rank optimal transport to clustering and unsupervised learning problems. While the original paper (Transport Clustering) focuses on solving low-rank OT through a reduction to generalized K-means clustering with theoretical approximation guarantees, the candidate paper (GCOT) applies optimal transport theory to hyperspectral image clustering by constructing graph embeddings and using OT-derived affinity matrices for spectral clustering. The key difference is that the original paper develops a general algorithmic framework for low-rank OT via clustering, whereas the candidate paper applies OT within a graph convolutional framework specifically for hyperspectral image analysis.

Contributions Analysis

Overall novelty summary. The paper establishes a reduction from low-rank optimal transport to a clustering problem on correspondences, termed transport clustering, via a novel transport registration of the cost matrix. This work resides in the 'Clustering and Unsupervised Learning' leaf of the taxonomy, which contains only three papers total including the original. This is a relatively sparse research direction within the broader low-rank OT landscape, suggesting the specific connection between low-rank OT and clustering via transport registration represents a less-explored angle compared to more crowded areas like low-rank factorization algorithms or domain adaptation applications.

The taxonomy reveals that neighboring leaves focus on domain adaptation and transfer learning, attention mechanisms for neural architectures, and generative modeling with uncertainty quantification. The paper's clustering focus diverges from these supervised or neural-architecture-oriented directions, instead connecting to theoretical branches on approximation algorithms and complexity. The scope notes indicate clear boundaries: this work addresses unsupervised clustering rather than supervised domain adaptation, and emphasizes algorithmic guarantees rather than neural integration. The broader 'Applications of Low-Rank OT in Machine Learning' branch shows substantial activity across multiple application domains, but the clustering-specific angle remains comparatively underexplored.

Among the three contributions analyzed, the literature search examined twenty candidate papers total. The core reduction to transport clustering (Contribution 1) was not directly examined against prior work in the available data. For the polynomial-time approximation algorithms (Contribution 2) and the transport clustering algorithm itself (Contribution 3), ten candidates each were examined with zero refutable pairs identified in either case. This suggests that among the limited set of semantically similar papers retrieved, none provided clear overlapping prior work on these specific algorithmic contributions. The search scope of twenty papers represents a focused but not exhaustive examination of the literature.

Based on the limited search scope of twenty semantically matched candidates, the work appears to occupy a relatively novel position connecting low-rank OT theory to clustering algorithms. The sparse population of the taxonomy leaf and absence of refutable prior work among examined candidates suggest the transport registration approach and resulting approximation guarantees represent fresh contributions. However, this assessment is constrained by the top-K semantic search methodology and does not constitute an exhaustive literature review across all possible related work in optimization, clustering theory, or approximation algorithms.

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

Contribution 1: Reduction of low-rank optimal transport to transport clustering via transport registration

Description: The authors introduce transport clustering, which reduces the low-rank optimal transport problem from a co-clustering problem to a generalized K-means clustering problem. This reduction is achieved through transport registration of the cost matrix, where the cost matrix is registered using the optimal full-rank transport plan.

This contribution was assessed against **0 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

Contribution 2: Polynomial-time constant-factor approximation algorithms for low-rank optimal transport

Description: The authors prove that their transport clustering approach provides polynomial-time approximation algorithms with constant-factor guarantees for low-rank optimal transport. For negative-type metrics, they achieve a $(1 + \gamma)$-approximation, and for kernel costs, they achieve a $(1 + \gamma + \sqrt{2\gamma})$-approximation, where γ represents the ratio between optimal rank K and full-rank OT costs.

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. Robust low-rank training via approximate orthonormal constraints

URL: View paper

Brief Assessment

Approximate Orthonormal[55] focuses on robust low-rank training for neural networks via orthonormal constraints to improve adversarial robustness, not on optimal transport problems or approximation algorithms for transport plans between probability distributions.

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2. Linear-time gromov wasserstein distances using low rank couplings and costs

URL: View paper

Brief Assessment

Linear-time Gromov[9] focuses on Gromov-Wasserstein distances with low-rank couplings, not on general low-rank optimal transport approximation algorithms with constant-factor guarantees for negative-type metrics and kernel costs.

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3. Hierarchical Refinement: Optimal Transport to Infinity and Beyond

URL: View paper

Brief Assessment

Hierarchical Refinement[2] focuses on computing full-rank Monge maps through hierarchical low-rank decomposition, not on approximation algorithms for low-rank optimal transport itself. The paper uses low-rank OT as a subroutine but does not claim to provide polynomial-time constant-factor approximation guarantees for the low-rank OT problem.

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4. Doubly stochastic adaptive neighbors clustering via the marcus mapping

URL: View paper

Brief Assessment

Adaptive Neighbors[54] focuses on doubly stochastic clustering via Marcus mapping for similarity graphs, not on low-rank optimal transport approximation algorithms. The candidate addresses a different problem domain (clustering) with different theoretical guarantees.

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5. Unbalanced Low-rank Optimal Transport Solvers

URL: View paper

Brief Assessment

Unbalanced Solvers[4] focuses on unbalanced optimal transport with KL divergence penalties, not on approximation algorithms for low-rank OT. The paper does not address polynomial-time constant-factor approximation guarantees for low-rank transport problems.

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6. Large-scale graph sinkhorn distance approximation for resource-constrained devices

URL: View paper

Brief Assessment

Graph Sinkhorn[52] focuses on accelerating Sinkhorn distance computation through low-rank matrix approximation for graph analysis, not on providing approximation algorithms for low-rank optimal transport problems with theoretical guarantees.

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7. Low-rank optimal transport: Approximation, statistics and debiasing

URL: View paper

Brief Assessment

Approximation Statistics[53] focuses on statistical properties and approximation error bounds for low-rank OT, not on polynomial-time constant-factor approximation algorithms for solving the problem via clustering approaches.

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8. Low-Rank Optimal Transport through Factor Relaxation with Latent Coupling

URL: View paper

Brief Assessment

Factor Relaxation[16] was not provided with full text context, preventing comparison of approximation algorithms and theoretical guarantees for low-rank optimal transport.

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9. Optimal transport for domain adaptation

URL: View paper

Brief Assessment

Domain Adaptation[51] focuses on domain adaptation using optimal transport for aligning source and target distributions, not on approximation algorithms for low-rank optimal transport problems.

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10. Low-Rank Optimal Transport for Robust Domain Adaptation

URL: View paper

Brief Assessment

Robust Domain Adaptation[1] applies low-rank optimal transport to domain adaptation problems but does not provide polynomial-time constant-factor approximation algorithms or theoretical guarantees for the low-rank OT problem itself.

Contribution 3: Transport Clustering algorithm with theoretical guarantees and practical effectiveness

Description: The authors develop Transport Clustering as a practical algorithm that inherits algorithmic stability and approximation guarantees from modern K-means solvers. The method demonstrates superior performance compared to existing low-rank OT methods on both synthetic benchmarks and large-scale real datasets.

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. Robust Corrupted Data Recovery and Clustering via Generalized Transformed Tensor Low-Rank Representation

URL: View paper

Brief Assessment

Transformed Tensor[62] focuses on tensor data recovery and clustering using transformed tensor SVD for corrupted tensor measurements, not on low-rank optimal transport or K-means clustering algorithms with approximation guarantees.

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2. Linear-time gromov wasserstein distances using low rank couplings and costs

URL: View paper

Brief Assessment

Linear-time Gromov[9] proposes a mirror descent scheme for Gromov-Wasserstein problems, not a clustering-based algorithm for low-rank optimal transport with inherited K-means guarantees.

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3. Statistically Optimal K-means Clustering via Nonnegative Low-rank Semidefinite Programming

URL: View paper

Brief Assessment

Nonnegative Semidefinite[57] focuses on k-means clustering via semidefinite programming relaxations with nonnegative low-rank factorization, not on low-rank optimal transport problems or transport clustering between distributions.

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4. Hierarchical optimal transport for multimodal distribution alignment

URL: View paper

Brief Assessment

Multimodal Alignment[61] focuses on hierarchical optimal transport for aligning multimodal distributions using clustered structure, not on low-rank optimal transport via clustering algorithms with approximation guarantees for the transport plan itself.

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5. Approximating Optimal Transport via Low-rank and Sparse Factorization

URL: View paper

Brief Assessment

Sparse Factorization[47] focuses on decomposing transport plans into low-rank plus sparse matrices for computational efficiency, while the original paper develops Transport Clustering as a reduction from low-rank OT to generalized k-means with specific approximation guarantees. These are distinct algorithmic approaches to low-rank optimal transport.

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6. Optimal clustering by Lloydâs algorithm for low-rank mixture model

URL: View paper

Brief Assessment

Lloyd Mixture[56] focuses on clustering matrix-valued observations using Lloyd's algorithm with low-rank assumptions, not on solving low-rank optimal transport problems between probability distributions as in the original paper.

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7. Clustering-based Low Rank Approximation Method

URL: View paper

Brief Assessment

Clustering-based Approximation[60] focuses on low-rank matrix approximation for general matrix-structured data using clustering techniques, not on optimal transport problems or transport plan clustering. The candidate addresses dimensionality reduction via GLRAM and k-means clustering, while the original paper develops Transport Clustering specifically for solving low-rank optimal transport with approximation guarantees for transport plans between probability distributions.

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8. Robust Spectral Clustering via Low-Rank Sample Representation

URL: View paper

Brief Assessment

Spectral Clustering[59] focuses on low-rank representation for traditional clustering with noisy data in high-dimensional space, not on low-rank optimal transport problems or K-means generalizations with approximation guarantees.

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9. Low-Rank Optimal Transport through Factor Relaxation with Latent Coupling

URL: View paper

Brief Assessment

Factor Relaxation[16] lacks full text context, making it impossible to assess whether it presents a clustering-based approach to low-rank OT with similar algorithmic guarantees.

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10. Optimal Clustering by Lloyd Algorithm for Low-Rank Mixture Model

URL: View paper

Brief Assessment

Lloyd Algorithm[58] focuses on clustering matrix-valued observations under a low-rank mixture model, not on low-rank optimal transport problems. The candidate addresses a fundamentally different problem domain (clustering with low-rank structure) rather than optimal transport between distributions.

Appendix: Text Similarity Detection

Textual similarity detection checked 20 papers and found 2 similarity segment(s) across 1 paper(s).

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

1. Hierarchical Refinement: Optimal Transport to Infinity and Beyond

Detected in: Contribution: contribution_2

⚠ **Note**: This paper shows substantial textual similarity with the original paper. It may be a different version, a duplicate submission, or contain significant overlapping content. Please review carefully to determine the nature of the relationship.

References

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