Novelty Assessment Report

Paper: On the Wasserstein Geodesic Principal Component Analysis of probability measures
PDF URL: https://openreview.net/pdf?id=OJupg4mDjS
Venue: ICLR 2026 Conference Submission
Year: 2026
Report Generated: 2025-12-27

Abstract

This paper focuses on Geodesic Principal Component Analysis (GPCA) on a collection of probability distributions using the Otto-Wasserstein geometry. The goal is to identify geodesic curves in the space of probability measures that best capture the modes of variation of the underlying dataset. We first address the case of a collection of Gaussian distributions, and show how to lift the computations in the space of invertible linear maps. For the more general setting of absolutely continuous probability measures, we leverage a novel approach to parameterizing geodesics in Wasserstein space with neural networks. Finally, we compare to classical tangent PCA through various examples and provide illustrations on real-world datasets.

Core Task Landscape

This paper addresses: **Geodesic Principal Component Analysis of Probability Measures Using Wasserstein Geometry**

A total of **28 papers** were analyzed and organized into a taxonomy with **17 categories**.

Taxonomy Overview

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

- **Theoretical Foundations and Methodological Development**
- **Computational Methods and Algorithmic Implementations**
- **Domain-Specific Geometries and Extensions**
- **Clustering and Unsupervised Learning**
- **Applications and Domain-Specific Implementations**
- **Related Theoretical Topics and Extensions**

Complete Taxonomy Tree

- Geodesic Principal Component Analysis of Probability Measures Using Wasserstein Geometry Survey Taxonomy
- Theoretical Foundations and Methodological Development
  - Geodesic PCA Theory and Consistency ★ (4 papers)
  - [0] On the Wasserstein Geodesic Principal Component Analysis of probability measures (Anon et al., 2026) View paper
  - [5] Principal geodesic analysis for probability measures under the optimal transport metric (Seguy, 2015) View paper
  - [13] Geodesic PCA in the Wasserstein space by convex PCA (JÃ©rÃ©mie Bigot, 2017) View paper
  - [20] Geodesic PCA in the Wasserstein space (JÃ©rÃ©mie Bigot, 2022) View paper
  - Convex PCA and Constrained Formulations (1 papers)
  - [2] Efficient convex PCA with applications to Wasserstein GPCA and ranked data (Campbell Steven, 2025) View paper
  - Projected and Representation-Based Methods (2 papers)
  - [12] Projected statistical methods for distributional data on the real line with the Wasserstein metric (Pegoraro, 2022) View paper
  - [14] Statistical learning in Wasserstein space (Amir-Hossein Karimi, 2020) View paper
  - Comparative Analysis of PCA Variants (2 papers)
  - [10] Geodesic PCA versus log-PCA of histograms in the Wasserstein space (Elsa Cazelles, 2018) View paper
  - [18] Log-PCA versus Geodesic PCA of histograms in the Wasserstein space (Cazelles, 2017) View paper
- Computational Methods and Algorithmic Implementations
  - Efficient Optimization and B-spline Representations (1 papers)
  - [15] Fast PCA in 1-D Wasserstein Spaces via B-splines Representation and Metric Projection (Pegoraro, 2021) View paper
  - Neural Network Parameterization and General Algorithms (1 papers)
  - [23] An Algorithmic Approach to Compute Principal Geodesics in the Wasserstein Space (Vivien Seguy, 2015) View paper
- Domain-Specific Geometries and Extensions
  - Circular and Manifold-Constrained Measures (1 papers)
  - [4] Wasserstein principal component analysis for circular measures (Mario Beraha, 2024) View paper
  - Distribution-Valued Stochastic Processes (1 papers)
  - [16] Functional Principal Component Analysis for Distribution-Valued Processes (Zhou Hang, 2023) View paper
- Clustering and Unsupervised Learning
  - Wasserstein k-Means Clustering (1 papers)
  - [1] Wasserstein -means for clustering probability distributions (Y Zhuang, 2022) View paper
  - Wasserstein k-Centers Clustering (3 papers)
  - [3] Wasserstein -Centres Clustering for Distributional Data (R Okano, 2024) View paper
  - [8] Wasserstein K-Centres Clustering for Distributional Data (Ryo Okano, 2024) View paper
  - Kernel-Based Clustering Methods (1 papers)

- [22] Wasserstein-based Kernel Principal Component Analysis for Clustering Applications (Gjorgiev, 2025) View paper
- Applications and Domain-Specific Implementations
  - Biomedical and Clinical Applications (2 papers)
  - [6] Low dimensional representation of multiâ□□patient flow cytometry datasets using optimal transport for measurable residual disease detection in leukemia (Erell Gachon, 2025) View paper
  - [9] Low dimensional representation of multi-patient flow cytometry datasets using optimal transport for minimal residual disease detection in leukemia (Bigot, 2024) View paper
  - Industrial Process Monitoring (1 papers)
  - [11] Weighted Wasserstein distance-based improved serial principal component analysis for incipient fault detection of complex industrial process (Jiabing Dai, 2021) View paper
  - General Statistical Data Analysis (3 papers)
  - [7] Statistical data analysis in the Wasserstein space (Bigot, 2020) View paper
  - [24] Nonlinear principal components analysis for measures and images (Alfageme, 2013) View paper
  - [28] JAN MACUTEK (MAKAROVA, n.d.) View paper
- Related Theoretical Topics and Extensions
  - Distributionally Robust Optimization (1 papers)
  - [17] Enhancing Distributional Robustness in Principal Component Analysis by Wasserstein Distances (Wang Lei, 2025) View paper
  - Generative Models and GANs (1 papers)
  - [26] Wasserstein GAN Can Perform PCA (Jaewoong Cho, 2022) View paper
  - Broader Statistical Learning Frameworks (3 papers)
  - [21] Statistical learning of random probability measures (Beraha, 2023) View paper
  - [25] Optimization Problems in Model-Free Stochastic Portfolio Theory and Sequential Testing Games (Campbell, 2023) View paper
  - [27] Measure Transport Approaches for Data Visualization and Learning (Vivien Seguy, 2018) View paper

Narrative

Core task: Geodesic principal component analysis of probability measures using Wasserstein geometry. This field extends classical dimensionality reduction to spaces of probability distributions by leveraging the Wasserstein metric and its associated geodesic structure. The taxonomy reveals a rich landscape organized around several complementary themes. Theoretical Foundations and Methodological Development establishes the mathematical underpinnings of geodesic PCA in Wasserstein space, including consistency guarantees and convergence properties. Computational Methods and Algorithmic Implementations addresses the practical challenges of computing geodesics and principal components efficiently, often through discretization or approximation schemes. Domain-Specific Geometries and Extensions explores adaptations to specialized settings such as circular or functional data, while Clustering and Unsupervised Learning applies Wasserstein geometry to grouping and center-finding problems. Applications and Domain-Specific Implementations demonstrate the utility of these methods in areas like flow cytometry and portfolio theory, and Related Theoretical Topics and Extensions connect to broader questions in optimal transport and statistical learning.

A particularly active line of work focuses on the interplay between geodesic and tangent-space approaches to PCA on probability measures. Early foundational studies such as Principal Geodesic Analysis[5] and Geodesic PCA Convex[13] laid the groundwork for understanding how principal geodesics capture variability in non-Euclidean spaces, while later works like Geodesic versus Log-PCA[10] and Geodesic PCA Wasserstein[20] have clarified trade-offs between geodesic methods and log-map-based alternatives. The original paper Wasserstein Geodesic PCA[0] sits squarely within this theoretical core, contributing to the rigorous development of geodesic PCA theory and consistency results. Its emphasis on foundational properties aligns closely with Geodesic PCA Convex[13] and Geodesic PCA Wasserstein[20], yet it also engages with the broader methodological questions that distinguish geodesic from tangent-space projections. Meanwhile, parallel branches explore robust variants, kernel extensions, and clustering formulations, reflecting the field's ongoing effort to balance mathematical elegance with computational feasibility and domain-specific demands.

Related Works in Same Category

The following **3 sibling papers** share the same taxonomy leaf node with the original paper:

1. Principal geodesic analysis for probability measures under the optimal transport metric

Authors: Seguy, Vivien, Vivien Seguy, Cuturi, Marco, et al. (6 authors total) | **Year/Venue**: 2015 | **URL**: View paper

Abstract

Given a family of probability measures in P(X), the space of probability measures on a Hilbert space X, our goal in this paper is to highlight one ore more curves in P(X) that summarize efficiently that family. We propose to study this problem under the optimal transport (Wasserstein) geometry, using curves that are restricted to be geodesic segments under that metric. We show that concepts that play a key role in Euclidean PCA, such as data centering or orthogonality of principal directions, fi...

Relationship Analysis

Both papers belong to the Geodesic PCA Theory and Consistency category, addressing the fundamental problem of computing principal geodesic components in Wasserstein space. They share the core objective of identifying geodesic curves that capture variability in probability measure datasets, with both proposing optimization-based approaches to minimize projection residuals. The key difference is that the original paper focuses on exact GPCA with theoretical consistency guarantees and leverages Bures-Wasserstein geometry for Gaussians and Otto geometry for general measures, while the candidate paper introduces generalized geodesics (relaxing strict geodesic constraints) and uses entropy-regularized optimal transport for computational tractability, prioritizing scalability over exactness.

---

2. Geodesic PCA in the Wasserstein space by convex PCA

Authors: JÃ©rÃ©mie Bigot, Raul Gouet, Thierry Klein, Alfredo LÃ³pez | **Year/Venue**: 2017 | **URL**: View paper

Abstract

We introduce the method of Geodesic Principal Component Analysis (GPCA) on the space of probability measures on the line, with finite second moment, endowed with the Wasserstein metric. We discuss the advantages of this approach, over a standard functional PCA of probability densities in the Hilbert space of square-integrable functions. We establish the consistency of the method by showing that the empirical GPCA converges to its population counterpart, as the sample size tends to infinity. A ke...

Relationship Analysis

Both papers belong to the Geodesic PCA Theory and Consistency category, focusing on theoretical foundations and consistency properties of geodesic PCA in Wasserstein space. They overlap in addressing the fundamental problem of computing principal components of probability measures using Wasserstein geometry and establishing theoretical guarantees. The key difference is that the original paper develops computational methods for both Gaussian distributions (via Bures-Wasserstein geometry) and general absolutely continuous measures (via neural network parameterization), while the candidate paper focuses specifically on one-dimensional probability measures and establishes consistency through an isometry with a convex subset of square-integrable functions.

3. Geodesic PCA in the Wasserstein space

Authors: JÃ©rÃ©mie Bigot, RaÃºl Gouet, Thierry Klein, Alfredo Quijano-LÃ³pez | **Year/Venue**: 2022 | **URL**: View paper

Abstract

We introduce the method of Geodesic Principal Component Analysis (GPCA) on the space of probability measures on the line, with finite second moment, endowed with the Wasserstein metric. We discuss the advantages of this approach, over a standard functional PCA of probability densities in the Hilbert space of square-integrable functions. We establish the consistency of the method by showing that the empirical GPCA converges to its population counterpart, as the sample size tends to infinity. A ke...

Relationship Analysis

Both papers belong to the Geodesic PCA Theory and Consistency category, focusing on theoretical foundations of geodesic principal component analysis in Wasserstein space. They overlap in addressing the fundamental problem of defining and computing geodesic PCA for probability measures, establishing consistency properties, and leveraging the Riemannian-like structure of the Wasserstein space. The key difference is that the original paper develops a neural network-based approach for general absolutely continuous measures and provides a lifting framework to the space of invertible matrices for Gaussian distributions, while the candidate paper establishes theoretical consistency results and focuses on the isometry between Wasserstein space and a closed convex subset of L2 space, with emphasis on one-dimensional measures.

Contributions Analysis

Overall novelty summary. The paper develops geodesic principal component analysis for probability distributions in Otto-Wasserstein space, addressing both Gaussian collections via Bures-Wasserstein geometry and general absolutely continuous measures through neural network parameterization. It resides in the 'Geodesic PCA Theory and Consistency' leaf alongside three sibling papers, forming a small but foundational cluster within the broader taxonomy of 28 papers across 17 leaf nodes. This leaf sits at the core of 'Theoretical Foundations and Methodological Development', indicating the work occupies a central but not overcrowded research direction focused on establishing rigorous properties of geodesic PCA.

The taxonomy reveals neighboring leaves addressing alternative PCA formulations: 'Convex PCA and Constrained Formulations' explores Hilbert space constraints, 'Projected and Representation-Based Methods' uses tangent space projections, and 'Comparative Analysis of PCA Variants' contrasts geodesic with log-PCA approaches. The paper's position suggests it contributes to the foundational geodesic framework rather than projection-based or convex alternatives. Sibling papers in the same leaf establish consistency and convergence properties, while the broader 'Computational Methods' branch addresses algorithmic efficiency—indicating the paper bridges theoretical development with practical implementation concerns through its neural network approach.

Among 17 candidates examined across three contributions, the Gaussian GPCA algorithm (4 candidates, 0 refutable) and theoretical equivalence result (3 candidates, 0 refutable) appear relatively novel within the limited search scope. The neural network parameterization contribution (10 candidates, 1 refutable) shows more substantial prior work overlap, with one candidate providing overlapping methodology. The statistics suggest the Gaussian-specific methods may represent more distinctive contributions, though the modest search scale (17 total candidates) means these findings reflect top semantic matches rather than exhaustive coverage of the field's approximately 28 documented papers.

Based on the limited literature search covering roughly 60% of the taxonomy's documented papers, the work appears to make incremental but meaningful contributions to geodesic PCA theory. The Gaussian case and theoretical results show less prior overlap, while the neural network approach connects to existing computational frameworks. The taxonomy structure indicates this is a moderately active research area with clear boundaries separating geodesic, convex, and projection-based methods, though the search scope precludes definitive novelty claims.

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

Contribution 1: GPCA algorithm for centered Gaussian distributions using Bures-Wasserstein geometry

Description: The authors develop an exact algorithm for Geodesic Principal Component Analysis on centered Gaussian distributions by lifting computations to the space of invertible linear maps, leveraging the Bures-Wasserstein geometry to avoid linearization approximations.

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

1. Functional data analysis for multivariate distributions through Wasserstein slicing

URL: View paper

Brief Assessment

Wasserstein Slicing FDA[33] focuses on multivariate distributions through Radon slicing and log quantile density transforms, not on geodesic PCA for Gaussian distributions using Bures-Wasserstein geometry.

2. Wasserstein -means for clustering probability distributions

URL: View paper

Brief Assessment

Wasserstein Means Clustering[1] focuses on k-means clustering of probability distributions using Wasserstein distance, not geodesic principal component analysis on Gaussian distributions using Bures-Wasserstein geometry.

3. Generalized Bures-Wasserstein geometry for positive definite matrices

URL: View paper

Brief Assessment

Bures-Wasserstein Geometry[35] focuses on generalizing Bures-Wasserstein geometry for positive definite matrices and deriving geodesics on SPD manifolds. The candidate does not address geodesic principal component analysis or the specific lifting approach to invertible linear maps that characterizes the original paper's contribution.

4. On Barycenter Computation: Semi-Unbalanced Optimal Transport-based Method on Gaussians

URL: View paper

Brief Assessment

Semi-Unbalanced Barycenter[34] focuses on computing robust barycenters among Gaussian measures using semi-unbalanced optimal transport, not on geodesic principal component analysis. The methods address fundamentally different problems despite both operating on the Bures-Wasserstein manifold.

Contribution 2: GPCA algorithm for absolutely continuous probability measures using neural network parameterization

Description: The authors propose an exact GPCA method for general absolutely continuous probability measures by parameterizing geodesics in Wasserstein space with multilayer perceptrons, lifting distributions to the space of maps that pushforward a reference measure following Otto's construction.

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. Wasserstein k-Centers Clustering for Distributional Data: R. Okano, M. Imaizumi

URL: View paper

Brief Assessment

Wasserstein k-Centers R[30] focuses on clustering distributional data using geodesic PCA, not on developing neural network parameterization methods for geodesics in Wasserstein space.

2. Wasserstein principal component analysis for circular measures

URL: View paper

Brief Assessment

Circular Wasserstein PCA[4] focuses on probability measures supported on the unit-circle (S^1) with explicit optimal transport map characterizations, not on general absolutely continuous measures in R^d using neural network parameterization of geodesics as in the original paper.

3. Principal geodesic analysis for probability measures under the optimal transport metric

URL: View paper

Prior Art Analysis

Principal Geodesic Analysis[5] demonstrates that geodesic principal component analysis for probability measures under optimal transport was already proposed and implemented prior to the original paper. The candidate paper presents a complete framework for computing principal geodesics in the Wasserstein space using generalized geodesics parameterized by velocity fields, which directly addresses the same problem of finding geodesic curves that capture modes of variation in probability measure datasets. While the original paper uses neural networks to parameterize geodesics via Otto's construction, the candidate establishes the foundational approach of formulating GPCA as an optimization problem over geodesic curves in the Wasserstein space, which is the core conceptual contribution.

Evidence

Evidence 1 - **Rationale**: Both papers address the same fundamental problem: computing principal geodesic analysis for probability measures in Wasserstein space. The candidate establishes this approach before the original paper. - **Original**: for the more general setting of absolutely continuous probability measures, we leverage a novel approach to parameterizing geodesics in wasserstein space with neural networks. - **Candidate**: we propose to study this problem under the optimal transport (wasserstein) geometry, using curves that are restricted to be geodesic segments under that metric.

Evidence 2 - **Rationale**: Both papers explicitly state the identical goal of finding geodesic curves that capture variation in probability measure datasets, demonstrating that the candidate proposed this objective first. - **Original**: the goal is to identify geodesic curves in the space of probability measures that best capture the modes of variation of the underlying dataset. - **Candidate**: given a family of probability measures in p(x), the space of probability measures on a hilbert space x, our goal in this paper is to highlight one ore more curves in p(x) that summarize efficiently that family.

Evidence 3 - **Rationale**: Both papers formulate GPCA as minimizing distances from data measures to points on a geodesic curve, showing the candidate established this optimization framework prior to the original work. - **Original**: following this approach, the first geodesic component of a set of probability measures ν1, . . . , νn in the wasserstein space solves inf t7→μ(t) geodesic nx i=1 inf ti w2 2 (μ(ti), νi). - **Candidate**: the goal of principal geodesic analysis is to define geodesic curves in p(x) that go through the mean ¯μand which pass close enough to all target measures μi.

Evidence 4 - **Rationale**: Both papers use Otto's geometric framework for the Wasserstein space, with the candidate already employing tangent spaces and velocity fields to parameterize geodesics, which is the conceptual foundation the original paper builds upon. - **Original**: in the general case of a.c. probability distributions, we lift the probability distributions to the space of (non necessarily optimal) maps that pushforward a given reference measure, as described by otto (2001). - **Candidate**: let μ : i ⊂r →p(x) be a curve in p(x). for a given time t, the tangent space of p(x) at μt is a subset of l2(μt,x), the space of square-integrable velocity fields supported on supp (μt).

Evidence 5 - **Rationale**: While the original paper uses MLPs specifically, the candidate already proposed parameterizing geodesics via velocity fields and optimizing them to minimize distances, establishing the core algorithmic approach. - **Original**: we parametrize geodesic components using multilayer perceptrons (mlps), trained to minimize the cost in equation 1. - **Candidate**: to parameterize a wasserstein principal component (pc) using two velocity fields defined on the support of the wasserstein mean of all measures, and formulate the wpg problem as that of optimizing these velocity fields so that the average distance of all measures to that pc is minimal.

4. A generalized Bayesian approach to distribution-on-distribution regression

URL: View paper

Brief Assessment

Bayesian Distribution Regression[31] focuses on distribution-on-distribution regression using Bayesian inference and optimal transport maps, not on geodesic principal component analysis or neural network parameterization of geodesics in Wasserstein space.

5. Wasserstein -means for clustering probability distributions

URL: View paper

Brief Assessment

Wasserstein Means Clustering[1] addresses clustering via k-means formulations and SDP relaxation, not geodesic PCA with neural network parameterization of geodesics in Wasserstein space.

6. Statistical data analysis in the Wasserstein space

URL: View paper

Brief Assessment

Wasserstein Data Analysis[7] focuses on statistical inference and geodesic PCA for probability measures but does not propose neural network parameterization of geodesics. The candidate discusses GPCA conceptually and algorithmically for $d=1$ and $d\geq 2$ cases, but the implementation approach differs fundamentally from the original paper's MLP-based Otto geodesic parameterization.

7. Manifold learning in Wasserstein space

URL: View paper

Brief Assessment

Manifold Wasserstein Learning[29] focuses on constructing submanifolds in Wasserstein space and recovering tangent spaces via spectral analysis, not on geodesic PCA with neural network parameterization of geodesics.

8. Wasserstein-based Kernel Principal Component Analysis for Clustering Applications

URL: View paper

Brief Assessment

Wasserstein Kernel PCA[22] focuses on kernel-based clustering methods using Wasserstein distances with kernel PCA for feature mapping, not on geodesic principal component analysis or neural network parameterization of geodesics in Wasserstein space.

9. Log-PCA versus Geodesic PCA of histograms in the Wasserstein space

URL: View paper

Brief Assessment

Log-PCA Geodesic Histograms[18] focuses on comparing log-PCA and geodesic PCA methods for histograms using forward-backward algorithms, not on neural network parameterization of geodesics via Otto's construction for general absolutely continuous measures.

10. Geodesic PCA in the Wasserstein space by convex PCA

URL: View paper

Brief Assessment

Geodesic PCA Convex[13] focuses on one-dimensional probability measures using an isometry to a convex subset of L^2 functions, not neural network parameterization of geodesics in higher dimensions as proposed in the original paper.

Contribution 3: Theoretical result on equivalence of GPCA for univariate Gaussians

Description: The authors establish a theoretical result showing that for one-dimensional Gaussian distributions, performing GPCA in the full space of absolutely continuous distributions produces identical results to restricting GPCA to the Gaussian submanifold.

This contribution was assessed against **3 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Functional data analysis for multivariate distributions through Wasserstein slicing

URL: View paper

Brief Assessment

Wasserstein Slicing FDA[33] does not address GPCA equivalence results for univariate Gaussians in Wasserstein space versus Gaussian submanifolds.

2. On Manifold Dimension Estimation

URL: View paper

Brief Assessment

Manifold Dimension Estimation[32] focuses on intrinsic dimension estimation methods and mentions PCA only in the linear case context. It does not address GPCA in Wasserstein space or the equivalence result for univariate Gaussians claimed by the original paper.

3. Manifold learning in Wasserstein space

URL: View paper

Brief Assessment

Manifold Wasserstein Learning[29] does not address GPCA on Gaussian distributions or equivalence results between full space and Gaussian submanifold GPCA.

Appendix: Text Similarity Detection

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

References

- [0] On the Wasserstein Geodesic Principal Component Analysis of probability measures View paper
- [1] Wasserstein -means for clustering probability distributions View paper
- [2] Efficient convex PCA with applications to Wasserstein GPCA and ranked data View paper
- [3] Wasserstein -Centres Clustering for Distributional Data View paper
- [4] Wasserstein principal component analysis for circular measures View paper
- [5] Principal geodesic analysis for probability measures under the optimal transport metric View paper
- [6] Low dimensional representation of multiâ□□patient flow cytometry datasets using optimal transport for measurable residual disease detection in leukemia View paper
- [7] Statistical data analysis in the Wasserstein space View paper
- [8] Wasserstein K-Centres Clustering for Distributional Data View paper
- [9] Low dimensional representation of multi-patient flow cytometry datasets using optimal transport for minimal residual disease detection in leukemia View paper
- [10] Geodesic PCA versus log-PCA of histograms in the Wasserstein space View paper
- [11] Weighted Wasserstein distance-based improved serial principal component analysis for incipient fault detection of complex industrial process View paper
- [12] Projected statistical methods for distributional data on the real line with the Wasserstein metric View paper
- [13] Geodesic PCA in the Wasserstein space by convex PCA View paper
- [14] Statistical learning in Wasserstein space View paper
- [15] Fast PCA in 1-D Wasserstein Spaces via B-splines Representation and Metric Projection View paper

- [16] Functional Principal Component Analysis for Distribution-Valued Processes View paper
- [17] Enhancing Distributional Robustness in Principal Component Analysis by Wasserstein Distances View paper
- [18] Log-PCA versus Geodesic PCA of histograms in the Wasserstein space View paper
- [19] Wasserstein K-Centers Clustering for Distributional Data View paper
- [20] Geodesic PCA in the Wasserstein space View paper
- [21] Statistical learning of random probability measures View paper
- [22] Wasserstein-based Kernel Principal Component Analysis for Clustering Applications View paper
- [23] An Algorithmic Approach to Compute Principal Geodesics in the Wasserstein Space View paper
- [24] Nonlinear principal components analysis for measures and images View paper
- [25] Optimization Problems in Model-Free Stochastic Portfolio Theory and Sequential Testing Games View paper
- [26] Wasserstein GAN Can Perform PCA View paper
- [27] Measure Transport Approaches for Data Visualization and Learning View paper
- [28] JAN MACUTEK View paper
- [29] Manifold learning in Wasserstein space View paper
- [30] Wasserstein k-Centers Clustering for Distributional Data: R. Okano, M. Imaizumi View paper
- [31] A generalized Bayesian approach to distribution-on-distribution regression View paper
- [32] On Manifold Dimension Estimation View paper
- [33] Functional data analysis for multivariate distributions through Wasserstein slicing View paper
- [34] On Barycenter Computation: Semi-Unbalanced Optimal Transport-based Method on Gaussians View paper
- [35] Generalized Bures-Wasserstein geometry for positive definite matrices View paper