

Novelty Assessment Report

Paper: WFR-FM: Simulation-Free Dynamic Unbalanced Optimal Transport

PDF URL: <https://openreview.net/pdf?id=1nqu7bK1mm>

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Abstract

The Wasserstein-Fisher-Rao (WFR) metric extends dynamic optimal transport (OT) by coupling displacement with change of mass, providing a principled geometry for modeling unbalanced snapshot dynamics. Existing WFR solvers, however, are often unstable, computationally expensive, and difficult to scale. Here we introduce **WFR Flow Matching (WFR-FM)**, a simulation-free training algorithm that unifies flow matching with dynamic unbalanced OT. Unlike classical flow matching which regresses only a transport vector field, WFR-FM simultaneously regresses a vector field for displacement and a scalar growth rate function for birth-death dynamics, yielding continuous flows under the WFR geometry. Theoretically, we show that minimizing the WFR-FM loss exactly recovers WFR geodesics. Empirically, WFR-FM yields more accurate and robust trajectory inference in single-cell biology, reconstructing consistent dynamics with proliferation and apoptosis, estimating time-varying growth fields, and applying to generative dynamics under imbalanced data. It outperforms state-of-the-art baselines in efficiency, stability, and reconstruction accuracy. Overall, WFR-FM establishes a unified and efficient paradigm for learning dynamical systems from unbalanced snapshots, where not only states but also mass evolve over time.

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: **dynamic unbalanced optimal transport with mass evolution**

A total of **50 papers** were analyzed and organized into a taxonomy with **24 categories**.

Taxonomy Overview

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

- **Theoretical Foundations and Mathematical Formulations**
- **Computational Methods and Algorithms**
- **Applications in Biological and Medical Sciences**
- **Applications in Machine Learning and Computer Vision**
- **Applications in Physical Sciences and Engineering**
- **Metric Learning and Ground Metric Adaptation**

Complete Taxonomy Tree

- dynamic unbalanced optimal transport with mass evolution Survey Taxonomy
- Theoretical Foundations and Mathematical Formulations
 - Dynamic and Static Formulation Equivalence (4 papers)
 - [13] On the equivalence between static and dynamic optimal transport governed by linear control systems (Einav, 2025) [View paper](#)
 - [26] Unbalanced optimal transport: Dynamic and Kantorovich formulations (L^Á@na^Ác Chizat, 2015) [View paper](#)
 - [31] Dynamic models of Wasserstein-1-type unbalanced transport (Bernhard Schmitzer, 2019) [View paper](#)
 - [39] Unbalanced Optimal Transport: Dynamic and Kantorovich Formulation (Lenaic Chizat, 2022) [View paper](#)
 - Duality Theory and Convex Relaxation (2 papers)
 - [10] Nonlinear Dynamical Unbalanced Optimal Transport: Relaxation and Duality (Wu Dongjun, 2025) [View paper](#)
 - [41] A Benamou-Brenier Proximal Splitting Method for Constrained Unbalanced Optimal Transport (Mao Nishino, 2025) [View paper](#)
 - Geometric and Regularity Properties (2 papers)
 - [40] Simple Unbalanced Optimal Transport (Boris Khesin, 2024) [View paper](#)
 - [49] Regularity theory and geometry of unbalanced optimal transport (Thomas Gallou^Át, 2021) [View paper](#)
 - Constrained and Path-Restricted Transport (3 papers)
 - [1] Dynamic Optimal Transport with Optimal Preferential Paths (Carioni, 2025) [View paper](#)
 - [16] An Unbalanced Optimal Transport Problem with a Growth Constraint (Dai, 2024) [View paper](#)
 - [20] Path constrained unbalanced optimal transport (Martin Bauer, 2024) [View paper](#)
 - Second-Order and Kinetic Extensions (1 papers)
 - [8] Kinetic Optimal Transport (OTIKIN) -- Part 1: Second-Order Discrepancies Between Probability Measures (Brigati, 2025) [View paper](#)
 - Non-Conservative and Mass-Scaling Transport (2 papers)
 - [28] Non-conservative optimal transport (Kov^Ái^Áov^Ái, 2025) [View paper](#)
 - [32] Optimal dynamic transport with mass consumption (Hug, 2020) [View paper](#)
- Computational Methods and Algorithms
 - Deep Learning and Neural Network Approaches ★ (5 papers)
 - [0] WFR-FM: Simulation-Free Dynamic Unbalanced Optimal Transport (Anon et al., 2026) [View paper](#)
 - [6] Neural Unbalanced Optimal Transport via Cycle-Consistent Semi-Couplings (L^Á¼beck, 2022) [View paper](#)
 - [11] Learning stochastic dynamics from snapshots through regularized unbalanced optimal transport (Zhang Zhenyi, 2024) [View paper](#)

- [18] A Neural Network Framework for High-Dimensional Dynamic Unbalanced Optimal Transport (Wan Wei, 2024) [View paper](#)
- [25] A scalable deep learning approach for solving high-dimensional dynamic optimal transport (Wan Wei, 2022) [View paper](#)
- Classical Optimization and Proximal Methods (3 papers)
- [2] Fundamental diagram constrained dynamic optimal transport via proximal splitting methods (Dong, 2025) [View paper](#)
- [24] Gradient enhanced ADMM Algorithm for dynamic optimal transport on surfaces (Dong, 2024) [View paper](#)
- [35] A Variational Surface-Evolution Approach to Optimal Transport over Transitioning Compact Supports with Domain Constraints (Anthony Yezzi, 2024) [View paper](#)
- Continuous Normalizing Flows and Dynamical Systems (2 papers)
- [5] TrajectoryNet: A dynamic optimal transport network for modeling cellular dynamics (Tong, 2020) [View paper](#)
- [29] Unbalanced diffusion Schrödinger bridge (Matteo Pariset, 2023) [View paper](#)
- Partial and Regularized Transport Methods (2 papers)
- [14] Flexible and probabilistic topology tracking with partial optimal transport (Mingzhe Li, 2025) [View paper](#)
- [47] Sinkhorn-Flow: Predicting Probability Mass Flow in Dynamical Systems Using Optimal Transport (Bhutani, 2023) [View paper](#)
- Applications in Biological and Medical Sciences
 - Single-Cell Trajectory Inference and Dynamics (4 papers)
 - [7] Reconstructing growth and dynamic trajectories from single-cell transcriptomics data (Yutong Sha, 2024) [View paper](#)
 - [12] Dynamic gene regulatory network inference from single-cell data using optimal transport (François Lamoline, 2025) [View paper](#)
 - [30] Optimal transport reveals dynamic gene regulatory networks via gene velocity estimation. (Wenjun Zhao, 2025) [View paper](#)
 - [42] Time-Varying Network Driver Estimation (TNDE) Quantifies Stage-Specific Regulatory Effects From Single-Cell Snapshots (Jiaxin Li, 2025) [View paper](#)
 - Spatial Transcriptomics and Tissue Dynamics (1 papers)
 - [22] Optimal transport modeling uncovers spatial domain dynamics in spatiotemporal transcriptomics studies (Wenjing Ma, 2025) [View paper](#)
 - Medical Image Reconstruction and Analysis (2 papers)
 - [9] Towards Prospective Medical Image Reconstruction via Knowledge-Informed Dynamic Optimal Transport (Zheng Taoran, 2025) [View paper](#)
 - [34] GlymphVIS: visualizing glymphatic transport pathways using regularized optimal transport (Rena Elkin, 2018) [View paper](#)
 - Population Dynamics and Epidemiological Modeling (1 papers)
 - [36] A measure model for the spread of viral infections with mutations (Xiaoqian Gong, 2022) [View paper](#)
- Applications in Machine Learning and Computer Vision
 - Clustering and Classification with Imbalanced Data (2 papers)
 - [3] PROTOCOL: Partial Optimal Transport-enhanced Contrastive Learning for Imbalanced Multi-view Clustering (Lei Yiming, 2025) [View paper](#)
 - [17] P2OT: Progressive Partial Optimal Transport for Deep Imbalanced Clustering (Zhang Chuyu, 2024) [View paper](#)
 - Generative Modeling and Image Interpolation (1 papers)
 - [15] Improving Autoencoder Image Interpolation via Dynamic Optimal Transport (Feng Xue, 2024) [View paper](#)
 - Temporal Domain Adaptation and Distribution Shift (2 papers)
 - [19] Temporal domain generalization via learning instance-level evolving patterns (Lingzhi Wang, 2024) [View paper](#)
 - [21] Averaging Spatio-temporal Signals using Optimal Transport and Soft Alignments (Janati, 2022) [View paper](#)
 - Causal Inference and Counterfactual Estimation (1 papers)
 - [44] Counterfactual Identifiability via Dynamic Optimal Transport (Ribeiro, 2025) [View paper](#)
 - Motion Segmentation and Video Analysis (1 papers)
 - [50] Temporal Wasserstein non-negative matrix factorization for non-rigid motion segmentation and spatiotemporal deconvolution (Varol, 2022) [View paper](#)
- Applications in Physical Sciences and Engineering
 - Fluid Dynamics and Mixing Problems (1 papers)
 - [4] Incompressible Optimal Transport and Applications in Fluid Mixing (Emerick, 2025) [View paper](#)
 - Control Systems and Trajectory Optimization (3 papers)
 - [23] Optimal mass transport and kernel density estimation for state-dependent networked dynamic systems (Mathias Hudoba de Bady, 2018) [View paper](#)
 - [43] Optimal Mass Transport over the Euler Equation (Charlie Yan, 2023) [View paper](#)
 - [45] Solution of the Probabilistic Lambert's Problem: Optimal Transport Approach (Nodozi, 2024) [View paper](#)
 - Network Design and Infrastructure Optimization (3 papers)
 - [37] Branching structures emerging from a continuous optimal transport model (Enrico Facca, 2021) [View paper](#)
 - [38] Designing Networks with Adaptation Rules and Optimal Transport (Lonardi, 2024) [View paper](#)
 - [48] Dynamic Optimal Transport on Networks (Martin Burger, 2023) [View paper](#)
 - Particle Tracking and Stochastic Systems (1 papers)
 - [27] Unbalanced Optimal Transport For Stochastic Particle Tracking (Kairui Hao, 2024) [View paper](#)
- Metric Learning and Ground Metric Adaptation (2 papers)
 - [33] Ground metric learning on graphs (Matthieu Heitz, 2021) [View paper](#)
 - [46] SYNCHRONIZED OPTIMAL TRANSPORT FOR JOINT MODELING OF DYNAMICS ACROSS MULTIPLE SPACES. (Zixuan Cang, 2025) [View paper](#)

Narrative

Core task: dynamic unbalanced optimal transport with mass evolution. This field extends classical optimal transport to settings where mass can be created or destroyed over time, capturing phenomena such as cell proliferation, population dynamics, and evolving distributions. The taxonomy reveals a rich structure organized around six main branches. Theoretical Foundations and Mathematical Formulations establish the rigorous underpinnings, including variational formulations and regularity results. Computational Methods and Algorithms develop numerical schemes ranging from proximal splitting approaches to deep learning techniques that scale to high dimensions. Applications branches span Biological and Medical Sciences (tracking cell lineages, modeling tissue growth), Machine Learning and Computer Vision (domain adaptation, generative modeling), and Physical Sciences and Engineering (fluid dynamics, network evolution). A sixth branch, Metric Learning and Ground Metric Adaptation, addresses the challenge of learning problem-specific distance structures. Representative works like TrajectoryNet[5] and Neural Unbalanced OT[6] illustrate how neural parameterizations enable flexible modeling of complex evolutionary processes.

Several active research directions reveal key trade-offs and open questions. One line focuses on scalability and expressiveness: methods like High-Dimensional Dynamic Unbalanced OT[18] and Scalable Deep Learning OT[25] push toward handling realistic data dimensions, while works such as Stochastic Dynamics Snapshots[11] address inference from sparse temporal observations. Another contrasting theme involves balancing physical constraints with computational tractability, as seen in Fundamental Diagram Constrained OT[2] and Incompressible OT Fluid Mixing[4]. WFR-FM[0] sits within the Deep Learning and Neural Network Approaches cluster, emphasizing neural parameterizations for dynamic unbalanced transport. Compared to Neural Unbalanced OT[6], which introduced foundational neural architectures for this setting, and PROTOCOL[3], which integrates domain-specific constraints, WFR-FM[0] appears to focus on flow-matching techniques that balance flexibility with computational efficiency, contributing to the ongoing effort to make these models both expressive and practical for real-world evolutionary data.

Related Works in Same Category

The following **4 sibling papers** share the same taxonomy leaf node with the original paper:

1. Neural Unbalanced Optimal Transport via Cycle-Consistent Semi-Couplings

Authors: LÅ¼beck, Frederike, Frederike LÅ¼beck, Bunne, Charlotte, et al. (21 authors total) | **Year/Venue:** 2022 • arXiv.org | **URL:** [View paper](#)

Abstract

Comparing unpaired samples of a distribution or population taken at different points in time is a fundamental task in many application domains where measuring populations is destructive and cannot be done repeatedly on the same sample, such as in single-cell biology. Optimal transport (OT) can solve this challenge by learning an optimal coupling of samples across distributions from unpaired data. However, the usual formulation of OT assumes conservation of mass, which is violated in unbalanced s...

Relationship Analysis

Both papers belong to the Deep Learning and Neural Network Approaches category for solving dynamic unbalanced optimal transport problems. They overlap in addressing mass evolution during transport using neural network parameterizations, but differ fundamentally in their formulations: the original paper (WFR-FM) uses flow matching with the Wasserstein-Fisher-Rao metric to jointly regress velocity fields and growth rates in a simulation-free manner, while the candidate paper (NUBOT) employs a semi-coupling formulation with cycle-consistent training of input convex neural networks to learn transport maps and reweighting functions. The original paper focuses on trajectory inference from snapshots with explicit WFR geodesics, whereas the candidate paper emphasizes learning mappings between unbalanced distributions via dual potentials and rescaling functions.

2. Learning stochastic dynamics from snapshots through regularized unbalanced optimal transport

Authors: Zhang Zhenyi, Li Tiejun, Zhenyi Zhang, Zhou, Peijie, et al. (7 authors total) | **Year/Venue:** 2024 | **URL:** [View paper](#)

Abstract

Reconstructing dynamics using samples from sparsely time-resolved snapshots is an important problem in both natural sciences and machine learning. Here, we introduce a new deep learning approach for solving regularized unbalanced optimal transport (RUOT) and inferring continuous unbalanced stochastic dynamics from observed snapshots. Based on the RUOT form, our method models these dynamics without requiring prior knowledge of growth and death processes or additional information, allowing them to...

Relationship Analysis

Both papers belong to the Deep Learning and Neural Network Approaches category for solving dynamic unbalanced optimal transport problems. They share the goal of learning continuous dynamics from snapshots with mass evolution, both employing neural network-based methods to handle unbalanced distributions. The key difference is that WFR-FM uses a simulation-free flow matching framework that jointly regresses velocity fields and growth rates to recover WFR geodesics, while the candidate paper (DeepRUOT) formulates the problem through regularized unbalanced optimal transport with Fisher information regularization and learns stochastic dynamics via neural SDEs/ODEs with a two-stage training approach incorporating energy, reconstruction, and Fokker-Planck constraint losses.

3. A Neural Network Framework for High-Dimensional Dynamic Unbalanced Optimal Transport

Authors: Wan Wei, Wei Wan, Zhang Yue-jin, Jiangong Pan, Bao, et al. (10 authors total) | **Year/Venue:** 2024 | **URL:** [View paper](#)

Abstract

In this paper, we introduce a neural network-based method to address the high-dimensional dynamic unbalanced optimal transport (UOT) problem. Dynamic UOT focuses on the optimal transportation between two densities with unequal total mass, however, it introduces additional complexities compared to the traditional dynamic optimal transport (OT) problem. To efficiently solve the dynamic UOT problem in high-dimensional space, we first relax the original problem by using the generalized Kullback-Leib...

Relationship Analysis

Both papers belong to the Deep Learning and Neural Network Approaches category for solving dynamic unbalanced optimal transport problems. They overlap in using neural networks to learn velocity fields and handle mass evolution in high-dimensional settings. However, the original paper (WFR-FM) introduces a simulation-free flow matching framework that jointly regresses velocity and growth rate fields based on the Wasserstein-Fisher-Rao metric, while the candidate paper uses Lagrangian discretization with Monte Carlo approximation and GKL divergence relaxation to solve the dynamic UOT problem through neural ODEs.

4. A scalable deep learning approach for solving high-dimensional dynamic optimal transport

Authors: Wan Wei, Wei Wan, Zhang Yue-jin, Yuejin Zhang, Bao, et al. (11 authors total) | **Year/Venue:** 2022 • SIAM Journal on Scientific Computing | **URL:** [View paper](#)

Abstract

The dynamic formulation of optimal transport has attracted growing interests in scientific computing and machine learning, and its computation requires to solve a PDE-constrained optimization problem. The classical Eulerian discretization based approaches suffer from the curse of dimensionality, which arises from the approximation of high-dimensional velocity field. In this work, we propose a deep learning based method to solve the dynamic optimal transport in high dimensional space. Our method ...

Relationship Analysis

Both papers belong to the Deep Learning and Neural Network Approaches category for solving dynamic unbalanced optimal transport problems. They share the goal of using neural networks to learn continuous dynamics from snapshot data, with both addressing high-dimensional transport and employing simulation-free or efficient training strategies. However, the original paper (WFR-FM) focuses specifically on the Wasserstein-Fisher-Rao metric with explicit joint modeling of velocity fields and growth rates for unbalanced transport, while the candidate paper primarily addresses balanced dynamic OT using Lagrangian discretization and Monte Carlo integration, with crowd motion as an extension rather than core unbalanced transport with mass evolution.

Contributions Analysis

Overall novelty summary. The paper introduces WFR Flow Matching, a simulation-free training algorithm that simultaneously learns displacement vector fields and scalar growth rate functions for dynamic unbalanced optimal transport. It resides in the Deep Learning and Neural Network Approaches leaf, which contains five papers total including the original work. This leaf sits within the broader Computational Methods and Algorithms branch, indicating a moderately populated research direction focused on neural solutions to high-dimensional transport problems. The taxonomy shows this is an active but not overcrowded area, with sibling works exploring related neural architectures for unbalanced transport.

The taxonomy reveals neighboring research directions that contextualize this work. The Classical Optimization and Proximal Methods leaf (three papers) offers alternative non-neural approaches, while Continuous Normalizing Flows and Dynamical Systems (two papers) explores related ODE-based trajectory modeling. Upstream, the Theoretical Foundations branch establishes mathematical properties that computational methods must respect, including Dynamic and Static Formulation Equivalence (four papers) and Geometric and Regularity Properties (two papers). The Applications in Biological and Medical Sciences branch, particularly Single-Cell Trajectory Inference (four papers), represents a key downstream consumer of these computational methods, suggesting the work bridges algorithmic innovation with practical biological modeling needs.

Among the three contributions analyzed, the literature search examined twenty-one candidates total. The simulation-free training algorithm contribution examined one candidate with no refutations found. The theoretical guarantee that WFR-FM recovers WFR geodesics examined ten candidates, none appearing to refute this claim. The unified paradigm for learning from unbalanced snapshots examined ten candidates, with one identified as potentially refutable. This suggests the algorithmic and theoretical aspects appear relatively novel within the limited search scope, while the unifying framework claim encounters some prior work overlap among the candidates examined.

Based on this limited analysis of top-K semantic matches, the work appears to occupy a meaningful position within an active research area. The algorithmic and theoretical contributions show limited overlap with examined candidates, while the broader framing as a unified paradigm encounters some prior work. The search scope of twenty-one candidates provides useful signals but cannot guarantee exhaustive coverage of all relevant literature, particularly work published in parallel or in adjacent communities not captured by semantic search.

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

Contribution 1: WFR-FM: simulation-free training algorithm for dynamic unbalanced optimal transport

Description: WFR-FM is a novel framework that extends flow matching to unbalanced distributions by jointly regressing a transport vector field and a scalar growth rate function. Unlike classical flow matching which only regresses velocity fields, WFR-FM simultaneously learns displacement and birth-death dynamics, yielding continuous flows under the Wasserstein-Fisher-Rao geometry without requiring costly ODE integration during training.

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

1. Taming Flow Matching with Unbalanced Optimal Transport into Fast Pansharpening

URL: [View paper](#)

Brief Assessment

Flow Matching Pansharpening[60] focuses on pansharpening (image fusion) tasks using unbalanced optimal transport for one-step generation, not on general dynamic unbalanced optimal transport for trajectory inference or single-cell dynamics as in the original paper.

Contribution 2: Theoretical guarantee that WFR-FM recovers WFR geodesics

Description: The authors establish theoretical guarantees demonstrating that minimizing the WFR-FM loss function exactly recovers dynamic unbalanced optimal transport under the WFR metric. This means the constructed cell population trajectories follow WFR geodesics, providing a principled OT-based formulation for unbalanced flow matching.

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. Efficient trajectory inference in wasserstein space using consecutive averaging

URL: [View paper](#)

Brief Assessment

Consecutive Averaging Trajectories[51] focuses on subdivision schemes and consecutive averaging in Wasserstein space for trajectory inference, not on theoretical guarantees for recovering Wasserstein-Fisher-Rao geodesics in unbalanced optimal transport.

2. From unbalanced optimal transport to the Camassa-Holm equation

URL: [View paper](#)

Brief Assessment

Camassa-Holm Unbalanced OT[59] focuses on the mathematical relationship between unbalanced optimal transport and the Camassa-Holm equation on Riemannian manifolds, not on flow matching methods or simulation-free training algorithms for recovering geodesics.

3. On the convergence of discrete dynamic unbalanced transport models

URL: [View paper](#)

Brief Assessment

Discrete Dynamic Unbalanced Convergence[57] focuses on convergence properties of discrete transport problems for matrix-valued measures, not on flow matching methods or geodesic recovery guarantees for neural network-based approaches.

4. Regularity theory and geometry of unbalanced optimal transport

URL: [View paper](#)

Brief Assessment

Unbalanced OT Regularity[49] focuses on regularity theory and geometric properties of unbalanced optimal transport, including polar factorization and Monge-Ampère equations. It does not address simulation-free training algorithms or flow matching methods for recovering WFR geodesics.

5. Unbalanced Optimal Transport: Geometry and Kantorovich Formulation

URL: [View paper](#)

Brief Assessment

Unbalanced OT Geometry[58] establishes the mathematical foundations and equivalence between dynamic and static formulations of the WFR metric, but does not address the specific problem of recovering WFR geodesics through flow matching training algorithms.

6. Sequential Monte Carlo approximations of Wasserstein--Fisher--Rao gradient flows

URL: [View paper](#)

Brief Assessment

Sequential Monte Carlo WFR[55] focuses on approximating WFR gradient flows for sampling problems using importance sampling and SMC methods, not on flow matching for unbalanced optimal transport in trajectory inference contexts.

7. Weight metamorphosis of varifolds and the LDDMM-Fisher-Rao metric

URL: [View paper](#)

Brief Assessment

Weight Metamorphosis Varifolds[56] focuses on varifold metamorphosis with LDDMM-Fisher-Rao metrics for geometric shapes, not on flow matching or simulation-free training for unbalanced optimal transport between probability distributions.

8. Gradient flow sampler-based distributionally robust optimization

URL: [View paper](#)

Brief Assessment

Gradient Flow Sampler[52] focuses on distributionally robust optimization using gradient flows for sampling from worst-case distributions, not on recovering Wasserstein-Fisher-Rao geodesics in unbalanced optimal transport for trajectory inference.

9. On a general matrix-valued unbalanced optimal transport problem

URL: [View paper](#)

Brief Assessment

Matrix-valued Unbalanced OT[54] focuses on matrix-valued measures and a general weighted Wasserstein-Bures distance framework, not on flow matching methods or simulation-free training algorithms for recovering WFR geodesics in single-cell dynamics.

10. Wasserstein Gradient Flows: Theory

URL: [View paper](#)

Brief Assessment

Wasserstein Gradient Flows[53] appears to be a theoretical paper on Wasserstein gradient flow theory. The provided context fragments mention 'constant-speed geodesics' and 'wfr metric' but lack sufficient detail to assess whether this work establishes prior theoretical guarantees for recovering WFR geodesics in the context of flow matching or unbalanced optimal transport formulations similar to the original paper's contribution.

Contribution 3: Unified paradigm for learning dynamical systems from unbalanced snapshots

Description: WFR-FM provides a unified framework that handles both state evolution and mass changes in dynamical systems. The method is particularly suitable for single-cell transcriptomics with multiple time points, enabling efficient and robust trajectory inference that accounts for proliferation and apoptosis while outperforming existing baselines in efficiency, stability, and reconstruction accuracy.

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. Joint Velocity-Growth Flow Matching for Single-Cell Dynamics Modeling

URL: [View paper](#)

Prior Art Analysis

Velocity-Growth Flow Matching[64] demonstrates that a unified framework for handling both state evolution and mass changes in dynamical systems from unbalanced snapshots was proposed prior to WFR-FM. The candidate paper presents joint velocity-growth flow matching (VGFM) that simultaneously learns state transition and mass growth from single-cell snapshots with proliferation and apoptosis, addressing the same core problem of learning dynamics from unbalanced data. Both papers explicitly model displacement/velocity fields and growth rate functions jointly, apply their methods to single-cell transcriptomics with multiple time points, and claim to provide unified frameworks for unbalanced dynamics.

Evidence

Evidence 1 - **Rationale:** Both papers claim their methods are particularly suitable for single-cell transcriptomics with multiple time points and demonstrate superior performance over existing baselines, indicating overlapping scope and claims. - **Original:** we apply wfr-fm to handle multiple time points, making it particularly suitable for single-cell transcriptomics. empirically, this yields more efficient and robust trajectory inference compared to existing neural differential equation-based and ot-based baselines. - **Candidate:** extensive experimental results on both synthetic and real datasets demonstrate that vgfmm can capture the underlying biological dynamics accounting for mass and state variations over time, outperforming existing approaches for single-cell dynamics modeling.

Evidence 2 - **Rationale:** Both papers identify the same biological motivation for unbalanced dynamics: cell proliferation and apoptosis in single-cell systems, showing they address identical problem settings. - **Original:** single-cell dynamics are not mass-conserving: cells can proliferate and undergo apoptosis, resulting in unbalanced distributions across time - **Candidate:** in biological systems, cells can proliferate and die. such behaviors can be captured by a time-dependent weight $w_t(x_t)$ associated with the state transition, whose evolution is controlled by a growth function, simulating cell proliferation or death processes

2. Orbital dynamics in galactic potentials under mass transfer

URL: [View paper](#)

Brief Assessment

Orbital Mass Transfer[61] focuses on galactic dynamics with parameter drift in astronomical systems, not on learning dynamical systems from biological snapshots with mass evolution. The candidate addresses orbital mechanics in time-dependent galactic potentials, which is fundamentally different from the original paper's framework for single-cell transcriptomics with proliferation and apoptosis.

3. Pore-scale study of coupled heat and mass transfer during primary freeze-drying using an irregular pore network model

URL: [View paper](#)

Brief Assessment

Pore-scale Freeze-Drying[65] focuses on pore network modeling for freeze-drying processes in porous materials, not on learning dynamical systems from unbalanced snapshots or trajectory inference from time-series data.

4. Geodetic and model data reveal different spatio-temporal patterns of transient mass changes over Greenland from 2007 to 2017

URL: [View paper](#)

Brief Assessment

Geodetic and model data reveal different spatio-temporal patterns of transient mass[68] focuses on geodetic measurements and mass changes over Greenland, not on learning dynamical systems from unbalanced snapshots or single-cell transcriptomics.

5. Unbalanced Diffusion Schrödinger Bridge

URL: [View paper](#)

Brief Assessment

Unbalanced Diffusion Bridge[66] focuses on diffusion-based Schrödinger bridges for unbalanced optimal transport with birth-death mechanisms, not on flow matching frameworks for trajectory inference in single-cell transcriptomics.

6. Learning stochastic dynamics from snapshots through regularized unbalanced optimal transport

URL: [View paper](#)

Brief Assessment

Stochastic Dynamics Snapshots[11] focuses on regularized unbalanced optimal transport (RUOT) with stochastic dynamics from snapshots, while WFR-FM addresses Wasserstein-Fisher-Rao flow matching for unbalanced distributions. The candidate uses different mathematical formulations (RUOT with Fisher regularization) compared to WFR-FM's simulation-free flow matching approach.

7. Improving the Spatial Resolution of GRACE-Derived Ice Sheet Mass Change in Antarctica

URL: [View paper](#)

Brief Assessment

GRACE Ice Sheet[62] focuses on spatial downscaling of ice mass measurements using geospatial regression techniques, not on learning dynamical systems from unbalanced snapshots with mass evolution.

8. Revealing Cortical Spreading Pathway of Neuropathological Events by Neural Optimal Mass Transport

URL: [View paper](#)

Brief Assessment

Cortical Spreading Pathway[63] focuses on modeling pathology propagation in neurodegenerative diseases using optimal mass transport on brain cortex geometry, not on general dynamical systems with mass evolution from unbalanced snapshots across diverse applications.

9. Adaptive Mascon Modeling for Small Body Gravity Field Reconstruction

URL: [View paper](#)

Brief Assessment

Adaptive Mascon Modeling[67] focuses on gravity field reconstruction for asteroid exploration using mascon-based approaches, not on learning dynamical systems from unbalanced population snapshots with mass evolution over time.

10. Temporal downscaling of glaciological mass balance using seasonal observations

URL: [View paper](#)

Brief Assessment

Temporal Downscaling Glaciological[69] focuses on temporal downscaling of glaciological mass balance measurements using sine functions, not on learning dynamical systems from unbalanced snapshots or single-cell transcriptomics with mass evolution.

Appendix: Text Similarity Detection

Textual similarity detection checked 24 papers and found 1 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. Unbalanced Optimal Transport: Geometry and Kantorovich Formulation

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

- [0] WFR-FM: Simulation-Free Dynamic Unbalanced Optimal Transport [View paper](#)
- [1] Dynamic Optimal Transport with Optimal Preferential Paths [View paper](#)
- [2] Fundamental diagram constrained dynamic optimal transport via proximal splitting methods [View paper](#)
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- [4] Incompressible Optimal Transport and Applications in Fluid Mixing [View paper](#)
- [5] Trajectorynet: A dynamic optimal transport network for modeling cellular dynamics [View paper](#)
- [6] Neural Unbalanced Optimal Transport via Cycle-Consistent Semi-Couplings [View paper](#)
- [7] Reconstructing growth and dynamic trajectories from single-cell transcriptomics data [View paper](#)
- [8] Kinetic Optimal Transport (OTIKIN) -- Part 1: Second-Order Discrepancies Between Probability Measures [View paper](#)
- [9] Towards Prospective Medical Image Reconstruction via Knowledge-Informed Dynamic Optimal Transport [View paper](#)
- [10] Nonlinear Dynamical Unbalanced Optimal Transport: Relaxation and Duality [View paper](#)
- [11] Learning stochastic dynamics from snapshots through regularized unbalanced optimal transport [View paper](#)
- [12] Dynamic gene regulatory network inference from single-cell data using optimal transport [View paper](#)
- [13] On the equivalence between static and dynamic optimal transport governed by linear control systems [View paper](#)
- [14] Flexible and probabilistic topology tracking with partial optimal transport [View paper](#)
- [15] Improving Autoencoder Image Interpolation via Dynamic Optimal Transport [View paper](#)
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