

Novelty Assessment Report

Paper: Bures-Wasserstein Flow Matching for Graph Generation

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Abstract

Graph generation has emerged as a critical task in fields ranging from drug discovery to circuit design. Contemporary approaches, notably diffusion and flow-based models, have achieved solid graph generative performance through constructing a probability path that interpolates between reference and data distributions. However, these methods typically model the evolution of individual nodes and edges independently and use linear interpolations in the disjoint space of nodes/edges to build the path. This disentangled interpolation breaks the interconnected patterns of graphs, making the constructed probability path irregular and non-smooth, which causes poor training dynamics and faulty sampling convergence. To address the limitation, this paper first presents a theoretically grounded framework for probability path construction in graph generative models. Specifically, we model the joint evolution of the nodes and edges by representing graphs as connected systems parameterized by Markov random fields (MRF). We then leverage the optimal transport displacement between MRF objects to design a smooth probability path that ensures the co-evolution of graph components. Based on this, we introduce BWFlow, a flow-matching framework for graph generation that utilizes the derived optimal probability path to benefit the training and sampling algorithm design. Experimental evaluations in plain graph generation and molecule generation validate the effectiveness of BWFlow with competitive performance, better training convergence, and efficient sampling.

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: **Flow Matching for Graph Generation Using Optimal Transport**

A total of **23 papers** were analyzed and organized into a taxonomy with **14 categories**.

Taxonomy Overview

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

- **Molecular and 3D Structure Generation**
- **General Graph Generation with Flow Matching**
- **Graph Neural Networks with Optimal Transport**
- **Scene Graph Generation and Understanding**
- **Domain-Specific Graph Applications with Optimal Transport**
- **Theoretical Foundations and General Frameworks**

Complete Taxonomy Tree

- Flow Matching for Graph Generation Using Optimal Transport Survey Taxonomy
- Molecular and 3D Structure Generation
 - 3D Molecular Generation with Equivariant Flow Matching (2 papers)
 - [1] Efficient 3d molecular generation with flow matching and scale optimal transport (Ross W. Irwin, 2024) [View paper](#)
 - [3] Equivariant flow matching with hybrid probability transport for 3d molecule generation (Y Song, 2023) [View paper](#)
 - Discrete Molecular Graph Generation with Flow Matching (3 papers)
 - [4] Improving Molecular Graph Generation with Flow Matching and Optimal Transport (Hou Xiao-yang, 2024) [View paper](#)
 - [18] Improving Graph Generation with Flow Matching and Optimal Transport (X Hou, n.d.) [View paper](#)
 - [20] GGFlow: A Graph Flow Matching Method with Efficient Optimal Transport (X Hou, n.d.) [View paper](#)
- General Graph Generation with Flow Matching
 - Bures-Wasserstein Flow Matching for Graphs ★ (1 papers)
 - [0] Bures-Wasserstein Flow Matching for Graph Generation (Anon et al., 2026) [View paper](#)
 - Supervised Graph Prediction with Optimal Transport (1 papers)
 - [7] Any2graph: Deep end-to-end supervised graph prediction with an optimal transport loss (Florence d'AlchÃ©-Buc, 2024) [View paper](#)
- Graph Neural Networks with Optimal Transport
 - Optimal Transport-Based Graph Aggregation (1 papers)
 - [5] Optimal transport graph neural networks (Chen Benson, 2020) [View paper](#)
 - Template-Based Graph Representation with Optimal Transport (1 papers)
 - [8] Template based graph neural network with optimal transport distances (Vincent-Cuaz, 2022) [View paper](#)
 - Multi-Modal Knowledge Graph Embeddings with Optimal Transport (1 papers)
 - [6] Otkge: Multi-modal knowledge graph embeddings via optimal transport (Z Cao, 2022) [View paper](#)
- Scene Graph Generation and Understanding
 - Optimal Transport Loss for Scene Graph Predicate Classification (1 papers)
 - [16] Predicate Classification Using Optimal Transport Loss in Scene Graph Generation (Sorachi Kurita, 2023) [View paper](#)
 - Multi-Prototype and LLM-Based Scene Graph Generation (2 papers)
 - [10] SceneLLM: Implicit Language Reasoning in LLM for Dynamic Scene Graph Generation (Zhang Hang, 2024) [View paper](#)

- [15] Multi-Prototype Space Learning for Commonsense-Based Scene Graph Generation (Lianggangxu Chen, 2024) [View paper](#)
- Domain-Specific Graph Applications with Optimal Transport
 - Bioinformatics and Computational Biology Applications (3 papers)
 - [2] How to go with the flow: flow matching in bioinformatics and computational biology (Alex Morehead, 2025) [View paper](#)
 - [12] TransMarker: Unveiling dynamic network biomarkers in cancer progression through cross-state graph alignment and optimal transport. (Fateme Keikha, 2025) [View paper](#)
 - [13] Graspot: a graph attention network for spatial transcriptomics data integration with optimal transport. (Zizhan Gao, 2024) [View paper](#)
 - Knowledge Graph Construction and Graph Partitioning (2 papers)
 - [9] Rate-Distortion Guided Knowledge Graph Construction from Lecture Notes Using Gromov-Wasserstein Optimal Transport (Yuan An, 2025) [View paper](#)
 - [11] Attributed Graph Partitioning: Comparing K-Means and Optimal Transport in Traffic Applications (I Gavra, 2025) [View paper](#)
- Theoretical Foundations and General Frameworks
 - Survey and Review Literature (1 papers)
 - [14] A Systematic Survey on Generative Models for Graph Generation (J Ji, 2025) [View paper](#)
 - General Optimal Transport Frameworks for Graphs (4 papers)
 - [17] COPT: Coordinated Optimal Transport on Graphs (Dong, 2022) [View paper](#)
 - [19] Molecular Graph Learning in the Optimal Transport Geometry (Panayiotis Panayiotou, 2020) [View paper](#)
 - [21] Representing graphs through data with learning and optimal transport (Maretic, 2021) [View paper](#)
 - [23] A Graph-Space Optimal Transport Approach Based on Kaniadakis (SÁ@rgio Luiz E F da Silva, n.d.) [View paper](#)
 - Multimodal Generation with Optimal Transport Flow (1 papers)
 - [22] Optimal Path Flow for Multimodal Generation (Sinkovics, n.d.) [View paper](#)

Narrative

Core task: flow matching for graph generation using optimal transport. This field sits at the intersection of generative modeling, graph neural networks, and optimal transport theory, aiming to learn continuous-time flows that transform simple distributions into complex graph-structured data. The taxonomy reveals several major branches: Molecular and 3D Structure Generation focuses on chemistry and protein design, often leveraging equivariant architectures like Equivariant Flow Matching[3] and specialized molecular frameworks such as Molecular Graph Flow[4]. General Graph Generation with Flow Matching develops core methodologies for arbitrary graph domains, including works like GGFlow[20] and Graph Flow Transport[18]. Graph Neural Networks with Optimal Transport explores how transport distances can improve GNN architectures, as seen in Optimal Transport GNN[5] and Gromov Wasserstein Knowledge[9]. Scene Graph Generation and Understanding targets visual and multimodal reasoning, with efforts like SceneLLM[10] and Predicate Classification Transport[16]. Domain-Specific Graph Applications with Optimal Transport addresses practical problems in traffic, biology, and other fields, while Theoretical Foundations and General Frameworks provide the mathematical underpinnings, surveyed in works like Generative Models Survey[14].

Across these branches, a central tension emerges between domain-agnostic flexibility and task-specific inductive biases: molecular generation benefits from symmetry constraints, while general graph methods prioritize scalability and expressiveness. Another recurring theme is the choice of optimal transport metric—Wasserstein distances dominate in Euclidean settings, but graph-structured data often requires Gromov-Wasserstein or other geometry-aware variants. The original paper, Bures Wasserstein Flow[0], resides within the General Graph Generation with Flow Matching branch and introduces a Bures-Wasserstein formulation tailored to graph distributions. This positions it alongside foundational flow-matching approaches like Graph Flow Transport[18] and GGFlow[20], but distinguishes itself by explicitly addressing the geometry of graph-valued measures. Compared to Scale Optimal Transport[1], which emphasizes computational efficiency, Bures Wasserstein Flow[0] appears more focused on theoretical rigor and the geometric properties of the transport map, offering a principled alternative for scenarios where preserving graph structure is paramount.

Related Works in Same Category

No sibling papers were found in the same taxonomy leaf. A taxonomy-subtopic-level comparison will be produced instead.

Taxonomy-Level Summary

Both subtopics leverage optimal transport theory for graph-related tasks, but address fundamentally different problems. The original leaf focuses on generative modeling—constructing probability paths for sampling new graphs through flow matching dynamics. The sibling focuses on discriminative supervised learning—predicting specific graph outputs from given inputs using OT as a training loss.

Similarities: - Both employ optimal transport formulations to handle graph-structured data - Both must address the challenge of matching discrete graph structures (nodes and edges) - Both operate in settings where graph topology and attributes need to be jointly considered

Differences: - Original leaf is generative (sampling new graphs via learned flows) while sibling is discriminative (predicting specific graphs from inputs) - Original leaf uses Bures-Wasserstein OT specifically for constructing continuous-time probability paths; sibling uses OT losses for end-to-end supervised training - Original leaf focuses on unsupervised/likelihood-based generation; sibling requires paired input-output supervision - Original leaf emphasizes joint node-edge evolution through flow dynamics; sibling emphasizes prediction accuracy under OT-based loss functions

Suggested Search Directions: - Hybrid approaches combining flow matching with supervised OT losses for conditional graph generation - Comparative studies of different OT formulations (Bures-Wasserstein vs. others) for graph generation tasks - Semi-supervised graph generation methods that bridge generative flow models and supervised prediction

Sibling Subtopics

- **Supervised Graph Prediction with Optimal Transport** (leaves: 1, papers: 1)
- Scope: End-to-end supervised frameworks predicting entire graphs from arbitrary inputs using optimal transport losses.
- Exclude: Unsupervised generation and methods without end-to-end supervision belong to other categories.

Contributions Analysis

Overall novelty summary. The paper proposes a Bures-Wasserstein flow-matching framework for graph generation, modeling joint node-edge evolution through Markov random fields and optimal transport. According to the taxonomy, it occupies the 'Bures-Wasserstein Flow Matching for Graphs' leaf under 'General Graph Generation with Flow Matching', where it is currently the sole paper. This indicates a sparse research direction within a broader field of 23 papers across 36 topics. The taxonomy shows that general graph generation with flow matching is less crowded than molecular-specific generation, which contains multiple sibling papers in adjacent leaves.

The taxonomy reveals neighboring work in 'Discrete Molecular Graph Generation with Flow Matching' (3 papers) and '3D Molecular Generation with Equivariant Flow Matching' (2 papers), both emphasizing domain-specific constraints. The 'Supervised Graph Prediction with Optimal Transport' leaf (1 paper) addresses end-to-end supervised tasks rather than unsupervised generation. The 'Theoretical

Foundations and General Frameworks' branch (7 papers) provides mathematical underpinnings but does not focus on generative modeling. The paper's use of Bures-Wasserstein distance distinguishes it from standard Wasserstein or Gromov-Wasserstein formulations prevalent in GNN-based optimal transport methods.

Among 30 candidates examined, the contribution-level analysis shows varied novelty. The theoretically grounded framework for probability path construction examined 10 candidates with none clearly refuting it. The BWFlow framework itself also examined 10 candidates with no refutations. However, the closed-form Wasserstein distance and optimal transport interpolation contribution examined 10 candidates and found 1 refutable match, suggesting some overlap with prior work on graph transport metrics. The limited search scope means these findings reflect top-30 semantic matches rather than exhaustive coverage.

Based on the top-30 semantic search, the paper appears to introduce a novel geometric perspective on graph generation through Bures-Wasserstein flow matching, occupying a currently sparse taxonomy leaf. The framework and interpolation contributions show stronger novelty signals than the closed-form distance formulation. However, the analysis does not cover broader diffusion-based graph generation literature or recent advances in discrete flow matching, which may contain additional relevant prior work.

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

Contribution 1: Theoretically grounded framework for probability path construction in graph generation

Description: The authors propose a principled framework for constructing probability paths in graph generation that addresses limitations of linear interpolation by modeling graphs as Markov Random Fields and using optimal transport displacement to ensure smooth, globally coherent paths.

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. Beyond Optimal Transport: Model-Aligned Coupling for Flow Matching

URL: [View paper](#)

Brief Assessment

Model Aligned Coupling[38] focuses on improving coupling strategies in flow matching for general data (images, etc.) by aligning with model prediction error, not specifically on graph generation or optimal transport for graph structures.

2. Improving Molecular Graph Generation with Flow Matching and Optimal Transport

URL: [View paper](#)

Brief Assessment

Molecular Graph Flow[4] focuses on molecular graph generation using flow matching with optimal transport, but does not present a general theoretical framework for probability path construction addressing limitations of linear interpolation through MRF modeling as described in the original paper.

3. On kinetic optimal probability paths for generative models

URL: [View paper](#)

Brief Assessment

Kinetic Probability Paths[37] focuses on optimal probability paths for generative models in general continuous domains using kinetic energy minimization, not specifically on graph generation with MRF-based frameworks addressing graph-specific challenges like node-edge dependencies.

4. Efficient 3d molecular generation with flow matching and scale optimal transport

URL: [View paper](#)

Brief Assessment

Scale Optimal Transport[1] focuses on 3D molecular generation with flow matching and scale optimal transport for molecular coordinates, not on general graph generation frameworks or probability path construction for arbitrary graphs.

5. Equivariant flow matching with hybrid probability transport for 3d molecule generation

URL: [View paper](#)

Brief Assessment

Equivariant Flow Matching[3] focuses on 3D molecule generation with equivariant optimal transport for coordinates, not general graph generation frameworks addressing MRF-based probability paths.

6. Generative Stochastic Optimal Transport: Guided Harmonic Path-Integral Diffusion

URL: [View paper](#)

Brief Assessment

Harmonic Path Integral[43] addresses stochastic optimal transport with guided diffusion for continuous state spaces, not graph generation. The candidate focuses on navigation tasks and molecular dynamics in continuous domains, whereas the original paper constructs probability paths specifically for discrete graph structures using Markov Random Fields and optimal transport on graph distributions.

7. Modeling microenvironment trajectories on spatial transcriptomics with nicheflow

URL: [View paper](#)

Brief Assessment

Nicheflow[41] focuses on modeling spatiotemporal trajectories of cellular microenvironments in biological tissue using flow matching on point clouds, not on constructing probability paths for general graph generation tasks.

8. GALOPA: Graph transport learning with optimal plan alignment

URL: [View paper](#)

Brief Assessment

GALOPA[42] focuses on self-supervised graph learning using optimal transport plan alignment between graph space and representation space, not on probability path construction for generative models. The paper addresses graph representation learning rather than graph generation via flow matching.

9. Accelerating 3D Molecule Generation via Jointly Geometric Optimal Transport

URL: [View paper](#)

Brief Assessment

Geometric Optimal Transport[39] focuses on 3D molecule generation with continuous atom coordinates and categorical atom types, not general graph generation frameworks. The candidate addresses optimal transport for molecular geometries specifically, while the original paper proposes a general framework for graph generation using Markov Random Fields.

10. Advances in optimal transport for biology; from manifold learning to generative modeling

URL: [View paper](#)

Brief Assessment

Optimal Transport Biology[40] focuses on optimal transport methods for biological applications including manifold learning and protein generation, not on probability path construction frameworks for graph generative models using Markov Random Fields.

Contribution 2: BWFlow: Bures-Wasserstein flow-matching framework for graph generation

Description: BWFlow is a novel flow-matching model that constructs probability paths respecting graph geometry through Bures-Wasserstein interpolation between graph distributions parameterized as MRFs, enabling simulation-free computation of densities and velocities for efficient training and sampling.

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. Any2graph: Deep end-to-end supervised graph prediction with an optimal transport loss

URL: [View paper](#)

Brief Assessment

Any2graph[7] focuses on supervised graph prediction from various input modalities (images, text, fingerprints) using optimal transport for graph matching, not on generative flow-matching frameworks for unconditional graph generation like BWFlow.

2. DeFoG: Defogging Discrete Flow Matching for Graph Generation

URL: [View paper](#)

Brief Assessment

DeFoG[35] focuses on discrete flow matching for graph generation using linear interpolation in probability space and CTMC-based denoising, not on Bures-Wasserstein interpolation between MRF-parameterized distributions. The technical approaches are fundamentally different.

3. Multi-Prototype Space Learning for Commonsense-Based Scene Graph Generation

URL: [View paper](#)

Brief Assessment

Multi Prototype Space[15] focuses on scene graph generation using multi-prototype learning for predicate classification, not graph generation via flow-matching frameworks with optimal transport interpolation.

4. Improving Molecular Graph Generation with Flow Matching and Optimal Transport

URL: [View paper](#)

Brief Assessment

Molecular Graph Flow[4] introduces ggflow for molecular graphs using discrete flow matching with optimal transport, but does not use Bures-Wasserstein interpolation between MRF-parameterized graph distributions or provide simulation-free computation of densities and velocities as in BWFlow.

5. Equivariant flow matching with hybrid probability transport for 3d molecule generation

URL: [View paper](#)

Brief Assessment

Equivariant Flow Matching[3] proposes equivariant flow matching for molecular generation using equivariant optimal transport, which differs from BWFlow's MRF-based Bures-Wasserstein interpolation for general graphs.

6. Optimal Generative Cyclic Transport between Image and Text

URL: [View paper](#)

Brief Assessment

Cyclic Image Text[36] focuses on optimal transport for cyclic transformations between image and text modalities using color histograms, not on graph generation or Bures-Wasserstein interpolation for graph distributions parameterized as MRFs.

7. Improving Graph Generation with Flow Matching and Optimal Transport

URL: [View paper](#)

Brief Assessment

Graph Flow Transport[18] focuses on discrete flow matching with optimal transport using Hamming distance for graph structures, while the original paper uses Bures-Wasserstein interpolation between graph distributions parameterized as MRFs with closed-form densities and velocities. These are fundamentally different technical approaches to flow-matching for graphs.

8. SE(3)-Stochastic Flow Matching for Protein Backbone Generation

URL: [View paper](#)

Brief Assessment

SE3 Flow Matching[34] focuses on protein backbone generation using SE(3) group transformations for 3D rigid motions, not general graph generation with MRF-based probability paths.

9. Optimal Path Flow for Multimodal Generation

URL: [View paper](#)

Brief Assessment

Multimodal Path Flow[22] focuses on multimodal generation tasks (text, images, etc.) rather than graph generation. The candidate does not address graph-specific challenges like node-edge co-evolution or MRF-based graph representations that are central to the original contribution.

10. GGFlow: A Graph Flow Matching Method with Efficient Optimal Transport

URL: [View paper](#)

Brief Assessment

GGFlow[20] focuses on discrete flow matching with optimal transport for graph generation, while the original paper presents a continuous flow-matching framework using Bures-Wasserstein interpolation between MRF-parameterized graph distributions. The technical approaches differ fundamentally in their mathematical formulations and probability path constructions.

Contribution 3: Closed-form Wasserstein distance and optimal transport interpolation for graph distributions

Description: The authors extend prior work to derive an analytical Bures-Wasserstein distance between graph distributions modeled as MRFs and use it to construct optimal transport interpolations that capture the joint evolution of nodes and edges, yielding closed-form probability paths and velocity fields.

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. Optimal transport and Wasserstein distances for causal models

URL: [View paper](#)

Brief Assessment

Causal Wasserstein[28] focuses on causal structure in directed graphs for causal inference, not on closed-form solutions for general graph distributions modeled as MRFs for generation tasks.

2. Wasserstein-based graph alignment

URL: [View paper](#)

Brief Assessment

Wasserstein Graph Alignment[27] focuses on aligning graphs of different sizes using Wasserstein distance between graph signal distributions, not on deriving closed-form Bures-Wasserstein distances for MRF-based graph distributions or constructing optimal transport interpolations for graph generation as in the original paper.

3. Optimal Transport Methods for Statistical Analysis of Shape Distributions and Images

URL: [View paper](#)

Brief Assessment

Shape Transport Methods[30] focuses on Wasserstein distances for Gaussian mixtures on vector bundles and shape analysis applications, not on graph distributions modeled as MRFs with closed-form interpolations for joint node-edge evolution.

4. Probabilistic measures of edge criticality in graphs: a study in water distribution networks

URL: [View paper](#)

Brief Assessment

Edge Criticality Networks[29] focuses on measuring edge criticality in water distribution networks using Wasserstein distance between node-to-node distance distributions, not on deriving closed-form Wasserstein distances for graph distributions modeled as MRFs or constructing optimal transport interpolations for generative modeling.

5. Dimension Reduction and Graphical Models using Optimal Transport

URL: [View paper](#)

Brief Assessment

Dimension Reduction Transport[31] focuses on dimension reduction and graphical models for statistical analysis, not on graph generation or flow matching models for generative tasks.

6. Hausdorff and Wasserstein metrics on graphs and other structured data

URL: [View paper](#)

Brief Assessment

Hausdorff Wasserstein Metrics[33] focuses on matching graphs and structured data using optimal transport between C-sets (categorical sets), not on deriving closed-form Bures-Wasserstein distances for graph distributions modeled as MRFs or constructing probability paths for flow-based graph generation.

7. A Wasserstein graph distance based on distributions of probabilistic node embeddings

URL: [View paper](#)

Brief Assessment

Wasserstein Node Embeddings[25] focuses on computing distances between static graphs using Gaussian mixture models fitted to node embeddings, not on constructing optimal transport interpolations for graph generation or deriving probability paths for generative models.

8. Diffusion-Wasserstein Distances for Attributed Graphs

URL: [View paper](#)

Brief Assessment

Diffusion Wasserstein Graphs[32] focuses on defining distances between attributed graphs using diffusion processes and optimal transport, not on deriving closed-form Bures-Wasserstein distances for graph distributions modeled as MRFs or constructing optimal transport interpolations for flow-based generative models.

9. Deep Wasserstein graph discriminant learning for graph classification

URL: [View paper](#)

Brief Assessment

Deep Wasserstein Discriminant[26] focuses on graph classification using Wasserstein metric for discriminant learning, not on deriving closed-form Wasserstein distances for graph generation or optimal transport interpolation paths.

10. Got: an optimal transport framework for graph comparison

URL: [View paper](#)

Prior Art Analysis

Got[24] demonstrates prior work that derives closed-form Wasserstein distance between graph distributions and uses it for optimal transport interpolation. The candidate paper explicitly derives the Wasserstein distance between graphs using Gaussian distributions over graph signals (equations 3-6), and further derives the optimal transportation map. This shows that similar mathematical formulations for closed-form Wasserstein distance on graphs and their use in constructing optimal transport interpolations existed before the original paper's submission.

Evidence

Evidence 1 - **Rationale:** Both papers derive explicit closed-form expressions for Wasserstein distance between graph distributions. The candidate shows this was done prior to the original paper. - **Original:** we derive a closed-form wasserstein distance between graph distributions and leverage it to construct bures-wasserstein (bw) interpolation that ensures the ot displacement between graph objects - **Candidate:** for normal distributions such as μ_1 and μ_2 , the 2-wasserstein distance can be explicitly written in terms of their covariance matrices [36], yielding $w_2(\mu_1, \mu_2) = \sqrt{\text{tr}(\Sigma_1 + \Sigma_2) + 2\sqrt{\text{tr}(\Sigma_1 \Sigma_2)}}$

Evidence 2 - **Rationale:** The candidate paper derives the optimal transportation map from the Wasserstein distance, demonstrating prior work on optimal transport interpolation for graphs. - **Original:** Extending Haasler & Frossard (2024), we derive a closed-form wasserstein distance between graph distributions and leverage it to construct bures-wasserstein (bw) interpolation - **Candidate:** the optimal transportation map is $t(x) = \frac{1}{2}(\Sigma_1 + \Sigma_2) + \frac{1}{2}(\Sigma_1 - \Sigma_2) \frac{x - \mu_1}{\|x - \mu_1\|}$

Appendix: Text Similarity Detection

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

References

- [0] Bures-Wasserstein Flow Matching for Graph Generation [View paper](#)
- [1] Efficient 3d molecular generation with flow matching and scale optimal transport [View paper](#)
- [2] How to go with the flow: flow matching in bioinformatics and computational biology [View paper](#)
- [3] Equivariant flow matching with hybrid probability transport for 3d molecule generation [View paper](#)
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- [30] Optimal Transport Methods for Statistical Analysis of Shape Distributions and Images [View paper](#)
- [31] Dimension Reduction and Graphical Models using Optimal Transport [View paper](#)
- [32] Diffusion-Wasserstein Distances for Attributed Graphs [View paper](#)
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