Novelty Assessment Report

Paper: Quotient-Space Diffusion Model

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Abstract

Diffusion-based generative models have reformed generative AI, and have enabled new capabilities in the science domain, for example, generating 3D structures of molecules. Due to the intrinsic problem structure of certain tasks, there is often a symmetry in the system, which identifies objects that can be converted by a group action as equivalent, hence the target distribution is essentially defined on the quotient space with respect to the group. In this work, we establish a formal framework for diffusion modeling on a general quotient space, and apply it to molecular structure generation which follows the special Euclidean group SE(3) symmetry. The framework reduces the necessity of learning the component corresponding to the group action, hence simplifies learning difficulty over conventional group-equivariant diffusion models, and the sampler guarantees recovering the target distribution, while heuristic alignment strategies lack proper samplers. The arguments are empirically validated on structure generation for small molecules and proteins, indicating that the principled quotient-space diffusion model provides a new framework that outperforms previous symmetry treatments.

Core Task Landscape

This paper addresses: **Diffusion Modeling on Quotient Spaces with Group Symmetry**

A total of **45 papers** were analyzed and organized into a taxonomy with **18 categories**.

Taxonomy Overview

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

- **Theoretical Foundations and Mathematical Frameworks**
- **Algorithmic Techniques and Computational Methods**
- **Application Domains**
- **Related Mathematical and Physical Contexts**

Complete Taxonomy Tree

- Diffusion Modeling on Quotient Spaces with Group Symmetry Survey Taxonomy
- Theoretical Foundations and Mathematical Frameworks
  - Quotient Space Diffusion Theory ★ (3 papers)
  - [0] Quotient-Space Diffusion Model (Anon et al., 2026) View paper
  - [20] Diffusion Models under Group Transformations (H Lu, 2025) View paper
  - [21] Group Symmetries in Diffusion Models: Formulation, Generalization, and Enforcement (Bharthulwar, 2025) View paper
  - Riemannian Manifold Diffusion (3 papers)
  - [5] Efficient Diffusion Models for Symmetric Manifolds (Mangoubi, 2025) View paper
  - [9] Geometric neural diffusion processes (Mathieu, 2023) View paper
  - [12] Scaling Riemannian diffusion models (Lou, 2023) View paper
  - Discrete and Finite Group Diffusion (2 papers)
  - [4] Symmetricdiffusers: Learning discrete diffusion on finite symmetric groups (Zhang Yongxing, 2024) View paper
  - [17] Operator growth in random quantum circuits with symmetry (Hunter-Jones, 2018) View paper
  - Lie Group and Homogeneous Space Diffusion (3 papers)
  - [28] Reduction and integrability of stochastic dynamical systems (Zung, 2022) View paper
  - [31] Diffusion Maps for Group-Invariant Manifolds (Hoyos, 2023) View paper
  - [44] Path Integral Method with Symmetry (Shogo Tanimura, 2000) View paper
- Algorithmic Techniques and Computational Methods
  - Equivariant Neural Architectures (3 papers)
  - [3] PDE-based group equivariant convolutional neural networks (Smets, 2023) View paper
  - [16] Fast, Expressive SE(n) Equivariant Networks through Weight-Sharing in Position-Orientation Space (Bekkers, 2023) View paper
  - [27] Diffusion Models with Group Equivariance (H Lu, 2024) View paper
  - Symmetric Diffusion Frameworks (2 papers)
  - [6] Geometric trajectory diffusion models (Stefano Ermon, 2024) View paper
  - [10] On Diffusion Process in SE(3)-invariant Space (Zhou, 2024) View paper
  - PDE-Based and Geometric Processing (3 papers)
  - [38] Diffusion, Convection and Erosion on SE(3)/({0} \times SO(2)) and their Application to the Enhancement of Crossing Fibers (Duits, 2011) View paper
  - [39] Controlled anisotropic diffusion (Rougon, 1995) View paper
  - [40] Left-invariant parabolic evolutions on SE(2) and contour enhancement via invertible orientation scores. Part II: Non-linear left-invariant diffusions on invertible orientation scores (R. Duits, 2010) View paper

  - Dimensionality Reduction and Embedding (2 papers)
  - [25] On the symmetries of the synchronization problem in Cryo-EM: Multi-Frequency Vector Diffusion Maps on the Projective Plane (G Cesa, 2022) View paper
  - [37] G-invariant diffusion maps (Rosen, 2023) View paper
  - Optimization and Learning Dynamics (2 papers)
  - [19] Leveraging Symmetry to Accelerate Learning of Trajectory Tracking Controllers for Free-Flying Robotic Systems (Jake Welde, 2024) View paper
  - [26] The optimization landscape of Spectral neural network (C Li, 2024) View paper
- Application Domains
  - Molecular and Protein Structure Generation (2 papers)
  - [1] SE(3) diffusion model with application to protein backbone generation (Yim, 2023) View paper
  - [2] Torsional diffusion for molecular conformer generation (Jing, 2022) View paper
  - Crystalline Materials Design (4 papers)
  - [7] Space Group Constrained Crystal Generation (Jiao Rui, 2024) View paper
  - [8] Space Group Equivariant Crystal Diffusion (Chang, 2025) View paper
  - [14] Leveraging generative models with periodicity-aware, invertible and invariant representations for crystalline materials design (Zhilong Wang, 2025) View paper
  - [36] CrysLDM: Latent Diffusion Model for Crystal Material Generation (S Khastagir, n.d.) View paper
  - Geometric and Visual Content Generation (2 papers)
  - [13] Conic Linear Units: Improved Model Fusion and Rotational-Symmetric Generative Model (Changqing Fu, 2024) View paper
  - [24] Generative escher meshes (Noam Aigerman, 2024) View paper
  - Benchmarking and Evaluation (1 papers)
  - [45] MGB: The Material Generation Benchmark (L Yan, n.d.) View paper
- Related Mathematical and Physical Contexts
  - Quantum and Statistical Mechanics (6 papers)
  - [15] Simultaneous Measurements of Noncommuting Observables: Positive Transformations and Instrumental Lie Groups (Christopher S. Jackson, 2023) View paper
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  - [35] Group-invariant solutions of hydrodynamics (Coggeshall, 1995) View paper
  - [41] Cartanâ Weyl Dirac and Laplacian Operators, Brownian Motions: The Quantum Potential and Scalar Curvature, Maxwell's and Dirac-Hestenes Equations, and â¦ (Rapoport, 2005) View paper
  - Signal and Image Processing (3 papers)
  - [29] Differential Invariant Signatures and Flows in Computer Vision: A Symmetry Group Approach (Peter J. Olver, 1994) View paper
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  - Geometric Data Analysis and Optimization (2 papers)
  - [22] A Riemannian quotient structure for correlation matrices with applications to data science (David, 2019) View paper
  - [42] Geometric means of fixed rank positive semi-definite matrices. (S Bonnabel, 2011) View paper
  - Specialized Mathematical Structures (1 papers)
  - [11] Schottky-Invariant P-Adic Diffusion Operators (Bradley, 2024) View paper
  - Medical Imaging Applications (2 papers)
  - [18] Linear rotationally invariant kurtosis measures from double diffusion encoding MRI. (Hunter G. Moss, 2025) View paper
  - [23] Diffusion MRI invariants: from the group of rotations to a complete neuroimaging fingerprint. (Santiago Coelho, 2025) View paper

Narrative

Core task: diffusion modeling on quotient spaces with group symmetry. This field addresses how to design generative diffusion models that respect underlying symmetries by operating on quotient spaces—spaces formed by identifying points related by group actions. The taxonomy reveals four main branches: theoretical foundations that establish the mathematical underpinnings of quotient geometry and group-equivariant diffusion; algorithmic techniques that develop practical computational methods for training and sampling on these structured spaces; application domains spanning molecular design, crystal generation, and other scientific problems where symmetry is intrinsic; and related mathematical contexts that connect to broader topics in differential geometry, Lie theory, and physics. Representative works such as SE3 Protein Backbone[1] and Torsional Diffusion[2] illustrate how specific symmetry groups (e.g., SE(3) for rigid-body transformations) can be incorporated into diffusion architectures, while PDE Group Equivariant[3] and Symmetric Diffusers[4] explore more general equivariance frameworks.

Several active lines of work highlight key trade-offs and open questions. One thread focuses on efficient parameterizations and scalability: Efficient Symmetric Manifolds[5] and Scaling Riemannian Diffusion[12] investigate how to handle high-dimensional or complex manifolds without prohibitive computational cost. Another thread emphasizes discrete symmetries and crystallographic groups, as seen in Space Group Crystal[7] and Space Group Equivariant[8], which are critical for materials science applications. The original paper, Quotient Space Diffusion[0], sits within the theoretical foundations branch alongside Diffusion Group Transformations[20] and Group Symmetries Diffusion[21], providing a rigorous treatment of how diffusion processes can be defined and analyzed on quotient spaces. Compared to these neighbors, Quotient Space Diffusion[0] appears to emphasize the formal mathematical framework, potentially offering new theoretical tools that complement the more algorithm-focused or application-driven studies elsewhere in the taxonomy.

Related Works in Same Category

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

1. Diffusion Models under Group Transformations

Authors: H Lu, S Szabados, Y Yu | **Year/Venue**: 2025 | **URL**: View paper

Abstract

â¦ Additionally, we propose a new framework that considers the geometric structures affecting the â¦ to be group invariant, we explore the sufficient and necessary configurations of diffusion â¦

Relationship Analysis

Both papers belong to the Quotient Space Diffusion Theory category, establishing formal frameworks for diffusion processes on quotient spaces induced by group symmetries. They share overlapping focus on SE(3) and SO(3) symmetries for molecular/point cloud generation, both deriving horizontal lift processes and projection operators to handle group-invariant distributions. The key difference is that the original paper (Quotient-Space Diffusion Model) emphasizes reducing learning difficulty by removing equivalent DOFs through horizontal projections with explicit molecular generation applications, while the candidate paper (Diffusion Models under Group Transformations) provides a more general theoretical characterization of necessary and sufficient conditions for structure preservation across broader linear isometry groups, with applications extending to image generation and style transfer tasks.

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2. Group Symmetries in Diffusion Models: Formulation, Generalization, and Enforcement

Authors: S Bharthulwar | **Year/Venue**: 2025 | **URL**: View paper

Abstract

â¦ structures encoding symmetries in geometry, physics, and â¦ of H divides the order of G, with the quotient |G|/|H| representing â¦ data, employing a group-invariant loss function that connects â¦

Relationship Analysis

Both papers belong to the Quotient Space Diffusion Theory category, establishing formal frameworks for diffusion on quotient spaces induced by group actions. They overlap in addressing how to properly formulate diffusion processes that respect group symmetries (particularly SE(3) and SO(2)) and reduce learning complexity by eliminating redundant equivalent degrees of freedom. However, the original paper focuses on deriving the mathematical framework for quotient-space diffusion with horizontal lifts and applying it to molecular structure generation, while the candidate paper (a bachelor's thesis) investigates whether standard diffusion models can implicitly learn and generalize symmetries from partial data, proposing a per-timestep symmetry loss for enforcement rather than developing the quotient space formalism.

Contributions Analysis

Overall novelty summary. The paper establishes a formal framework for diffusion modeling on general quotient spaces induced by group symmetry, with application to SE(3)-symmetric molecular structure generation. It resides in the 'Quotient Space Diffusion Theory' leaf under 'Theoretical Foundations and Mathematical Frameworks', alongside only two sibling papers. This leaf represents a relatively sparse research direction within the broader taxonomy of 45 papers across 18 leaf nodes, suggesting the work addresses a specialized theoretical niche rather than a crowded application area.

The taxonomy reveals that neighboring leaves include 'Riemannian Manifold Diffusion' (3 papers on general geometric diffusion), 'Discrete and Finite Group Diffusion' (2 papers on discrete structures), and 'Lie Group and Homogeneous Space Diffusion' (3 papers on continuous group structures). The paper's focus on quotient space formalism distinguishes it from these adjacent directions: while Riemannian methods address general manifolds without explicit quotient structure, and Lie group approaches handle homogeneous spaces, this work specifically targets the quotient geometry arising from group actions, bridging theoretical rigor with practical symmetry reduction.

Among 30 candidates examined, the contribution-level analysis shows mixed novelty signals. The formal framework for general quotient spaces (10 candidates examined, 0 refutable) appears relatively novel within this limited search scope. The SE(3) training and sampling algorithms (10 candidates examined, 1 refutable) show some overlap with prior work, suggesting incremental refinement of existing symmetry-handling techniques. The theoretical characterization of horizontal lift diffusion (10 candidates examined, 0 refutable) appears less contested, though the limited search scope means substantial prior work may exist beyond the top-30 semantic matches.

Based on the limited literature search, the work appears to contribute primarily through theoretical formalization rather than entirely new algorithmic primitives. The sparse population of the 'Quotient Space Diffusion Theory' leaf and the modest refutation rate suggest the framework offers a distinct perspective, though the analysis cannot rule out relevant prior work outside the examined candidates. The positioning between pure theory and applied molecular generation indicates potential bridging value, but definitive novelty assessment would require broader literature coverage.

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

Contribution 1: Formal framework for diffusion modeling on general quotient spaces

Description: The authors develop a principled mathematical framework that enables diffusion-based generative models to operate on quotient spaces defined by group symmetries. This framework formally derives the diffusion process on the quotient space and constructs a corresponding horizontal lift process in the original space that removes unnecessary movements within equivalent classes.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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1. Symmetry-aware generative modeling through learned canonicalization

URL: View paper

Brief Assessment

Learned Canonicalization[63] focuses on learning orbit representative maps through canonicalization networks for generative modeling, rather than developing a formal mathematical framework for diffusion processes on quotient spaces with horizontal lift constructions.

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2. SymmCD: Symmetry-Preserving crystal generation with diffusion models

URL: View paper

Brief Assessment

SymmCD[59] focuses on crystallographic symmetry groups (space groups) for crystal generation, not general quotient spaces. The candidate develops methods specific to crystal structures with SE(3) symmetry, while the original paper presents a general mathematical framework applicable to arbitrary quotient spaces defined by group symmetries.

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3. Conic Linear Units: Improved Model Fusion and Rotational-Symmetric Generative Model

URL: View paper

Brief Assessment

Conic Linear Units[13] focuses on activation functions and model fusion in neural networks, not on diffusion-based generative models or quotient space frameworks for diffusion processes.

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4. Crystal structure prediction by joint equivariant diffusion

URL: View paper

Brief Assessment

Joint Equivariant Crystal[57] focuses on crystal structure prediction with SE(3) symmetry using fractional coordinates, not on developing a general mathematical framework for diffusion on arbitrary quotient spaces with group symmetries.

5. Trivialized momentum facilitates diffusion generative modeling on lie groups

URL: View paper

Brief Assessment

Trivialized Momentum Lie[60] focuses on diffusion models specifically on Lie groups using trivialization techniques, not on general quotient spaces with arbitrary group symmetries. The candidate's approach leverages group structure to create a trivialized momentum variable in a fixed Lie algebra, which is fundamentally different from the original paper's quotient space framework that handles general group actions on manifolds.

6. Navigating the design space of equivariant diffusion-based generative models for de novo 3d molecule generation

URL: View paper

Brief Assessment

Equivariant Molecule Design[58] focuses on molecular generation using E(3)-equivariant diffusion models with specific architectural choices (graph attention networks), not on developing a general mathematical framework for diffusion on quotient spaces with arbitrary group symmetries.

7. Equivariant score-based generative models provably learn distributions with symmetries efficiently

URL: View paper

Brief Assessment

Equivariant Score Based[62] focuses on score-based generative models with group symmetries in Euclidean/Riemannian settings, not on constructing diffusion processes on quotient spaces with horizontal lift mechanisms as in the original paper.

8. Equivariant diffusion for molecule generation in 3d

URL: View paper

Brief Assessment

Equivariant Molecule Generation[61] focuses on E(3) equivariant diffusion for molecular generation, not on developing a general mathematical framework for quotient spaces. The candidate does not present formal theorems about diffusion processes on arbitrary quotient spaces defined by group symmetries.

9. Rao-blackwell gradient estimators for equivariant denoising diffusion

URL: View paper

Brief Assessment

Rao Blackwell Equivariant[56] focuses on variance reduction in gradient estimation for equivariant diffusion models through Rao-Blackwellization, not on constructing diffusion processes on quotient spaces with horizontal lift formulations.

10. Edgi: Equivariant diffusion for planning with embodied agents

URL: View paper

Brief Assessment

EDGI[64] focuses on equivariant diffusion for embodied agent planning with SE(3)×Z×Sn symmetries, not on developing a general mathematical framework for diffusion on quotient spaces with arbitrary group symmetries.

Contribution 2: Quotient-space diffusion training and sampling algorithms for SE(3) symmetry

Description: The authors instantiate their general framework for the specific case of molecular structure generation under SE(3) symmetry. They derive explicit training objectives using horizontal projection operators and sampling algorithms (both ODE and SDE) that guarantee recovering the target distribution while reducing learning difficulty by removing redundant spatial transformations.

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. Manipulating 3D Molecules in a Fixed-Dimensional SE (3)-Equivariant Latent Space

URL: View paper

Brief Assessment

Fixed SE3 Latent[72] focuses on learning a fixed-dimensional SE(3)-equivariant latent space for molecular VAEs, not on quotient-space diffusion processes or horizontal projection operators for training/sampling.

2. Accurate transition state generation with an object-aware equivariant elementary reaction diffusion model

URL: View paper

Brief Assessment

Transition State Generation[68] focuses on molecular reaction systems with object-aware SE(3) equivariance for multiple distinct molecules (reactant, TS, product), not the quotient-space framework for general SE(3) symmetry reduction proposed in the original paper.

3. Equivariant 3D-conditional diffusion model for molecular linker design

URL: View paper

Brief Assessment

Equivariant Linker Design[67] focuses on molecular linker design using E(3)-equivariant diffusion, not on quotient-space formulations or horizontal projection operators for SE(3) symmetry reduction.

4. A group symmetric stochastic differential equation model for molecule multi-modal pretraining

URL: View paper

Brief Assessment

Group Symmetric Pretraining[70] focuses on SE(3)-equivariant diffusion for molecule generation from 2D topology to 3D conformation in a pretraining context, not on quotient-space diffusion frameworks for general molecular structure generation with horizontal projection operators and guaranteed target distribution recovery.

5. A dual diffusion model enables 3D molecule generation and lead optimization based on target pockets

URL: View paper

Brief Assessment

Dual Diffusion Pockets[69] focuses on conditional molecule generation for drug discovery using protein pocket information, not on developing general SE(3) equivariant diffusion frameworks with quotient-space formulations.

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6. SE(3) diffusion model with application to protein backbone generation

URL: View paper

Brief Assessment

SE3 Protein Backbone[1] focuses on diffusion models directly on SE(3)^n for protein frames without the quotient-space formulation. The candidate does not demonstrate prior work on quotient-space diffusion theory or horizontal projection operators for SE(3) symmetry.

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7. 3d equivariant diffusion for target-aware molecule generation and affinity prediction

URL: View paper

Brief Assessment

Target Aware Molecule[65] focuses on target-aware drug design using SE(3)-equivariant diffusion for protein-ligand binding, not on general quotient-space diffusion frameworks or horizontal projection operators for molecular structure generation.

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8. Geodiff: A geometric diffusion model for molecular conformation generation

URL: View paper

Prior Art Analysis

GeoDiff[71] demonstrates prior work on SE(3) equivariant diffusion for molecular structure generation. The candidate paper explicitly addresses the same core challenge: building diffusion models that respect SE(3) symmetry (rotation and translation invariance) for molecular conformations. GeoDiff[71] proposes equivariant Markov kernels and training objectives that handle SE(3) transformations, including alignment strategies to ensure roto-translational invariance during training. The original paper's claim to be first in deriving 'explicit training objectives using horizontal projection operators' is challenged by GeoDiff[71]'s prior work on equivariant training with alignment approaches that also project or align predictions to handle equivalent transformations.

Evidence

Evidence 1 - **Rationale**: GeoDiff[71] proposes an alignment approach that projects predictions to handle SE(3) transformations, similar to the original paper's horizontal projection concept. This demonstrates prior work on training objectives that remove redundant rotational/translational components. - **Original**: we leverage the mathematical construction of horizontal lift to induce a diffusion process back in the original space that embeds the quotient-space diffusion process. the resulting process effectively amounts to projecting the update vector in the original diffusion process onto the subspace that d... - **Candidate**: alignment approach. considering the fact that ϵcan be calculated by ct-√¯αtc0 √1-¯αt , we can first rotate and translate c0 to ˆc0 by aligning w.r.t ct, and then compute ˆϵ as ct-√¯αtˆc0 √1-¯αt . since the aligned conformation ˆc0 is equivariant with ct, the processed ˆϵwill also enjoy the equivarian...

Evidence 2 - **Rationale**: GeoDiff[71] explicitly addresses reducing learning difficulty by modifying the training objective to respect SE(3) equivariance, demonstrating prior work on simplifying learning by handling group actions in molecular diffusion. - **Original**: the framework reduces the necessity of learning the component corresponding to the group action, hence simplifies learning difficulty over conventional groupequivariant diffusion models - **Candidate**: as ϵθ is designed to be equivariant, it is natural to require its supervision signal ϵto be equivariant with ct. note that once this is achieved, the elbo will also become invariant. however, the ϵin the forward diffusion process is not imposed with such equivariance, violating the above properties....

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9. Frame-based Equivariant Diffusion Models for 3D Molecular Generation

URL: View paper

Brief Assessment

Frame Based Equivariant[73] focuses on frame-based canonicalization methods for molecular generation, not quotient-space diffusion theory. The candidate uses local/global frames for E(3)-equivariance rather than horizontal projection operators and quotient manifold theory.

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10. Structure-based drug design with equivariant diffusion models

URL: View paper

Brief Assessment

Structure Based Drug[66] focuses on SE(3)-equivariant diffusion for structure-based drug design using conditional generation on protein pockets, not on quotient-space formulations or horizontal projection operators for general SE(3) symmetry handling.

Contribution 3: Theoretical characterization of horizontal lift diffusion process

Description: The authors establish theoretical results (Theorems 1 and 2) that explicitly characterize how a diffusion process on the quotient space can be lifted to a horizontal process in the original space. This lifted process only has horizontal movements (no movement within equivalent classes) and is proven to recover the correct target distribution with shorter trajectory length.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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1. Geometric Diffusion in Riemannian & Finsler Manifolds

URL: View paper

Brief Assessment

Geometric Diffusion Manifolds[46] focuses on diffusion in Riemannian and Finsler manifolds with different geometric structures, not specifically on quotient space diffusion with group symmetries and horizontal lift processes that recover target distributions on quotient spaces.

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2. A Global Coordinate-Free Approach to Invariant Contraction on Homogeneous Manifolds

URL: View paper

Brief Assessment

Invariant Contraction Homogeneous[55] focuses on contraction analysis using horizontal lifts for control systems on homogeneous manifolds, not diffusion processes or generative modeling. The mathematical constructs (horizontal lifts, Levi-Civita connections) are shared geometric tools, but applied to fundamentally different problems.

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3. On the geometry of diffusion operators and stochastic flows

URL: View paper

Brief Assessment

Geometry Diffusion Operators[53] focuses on general stochastic flows and differential forms on manifolds, not specifically on quotient space diffusion or horizontal lift processes for symmetry-invariant distributions.

4. Inference on Riemannian Manifolds: Regression and Stochastic Differential Equations

URL: View paper

Brief Assessment

Riemannian Regression SDE[50] focuses on statistical inference methods (regression and OU processes) on Riemannian manifolds, particularly for covariance matrices. It does not address the specific problem of lifting diffusion processes from quotient spaces to horizontal processes in the original space for generative modeling applications.

5. Hamiltonian Lie algebroids over Poisson manifolds

URL: View paper

Brief Assessment

Hamiltonian Lie Algebroids[47] focuses on Hamiltonian Lie algebroids over Poisson manifolds using vector bundle connections, not on diffusion processes or quotient-space sampling for generative models.

6. Geometric aspects of diffusions on manifolds

URL: View paper

Brief Assessment

Geometric Diffusion Aspects[54] discusses horizontal lifting of smooth curves on manifolds but does not address diffusion processes on quotient spaces with group symmetries or provide the specific theoretical framework (Theorems 1 and 2) for lifting diffusion processes that recover target distributions with reduced trajectory length.

7. Introduction to Riemannian manifolds

URL: View paper

Brief Assessment

Introduction Riemannian Manifolds[51] is a textbook on Riemannian geometry fundamentals. It does not address diffusion processes, horizontal lifts in the context of quotient spaces for generative modeling, or the specific theoretical results (Theorems 1 and 2) about lifting diffusion processes to recover target distributions with shorter trajectories.

8. Hydrodynamic limit of the symmetric exclusion process on complete Riemannian manifolds and principal bundles

URL: View paper

Brief Assessment

Hydrodynamic Exclusion Process[52] focuses on symmetric exclusion processes on Riemannian manifolds and principal bundles, obtaining horizontal diffusions as hydrodynamic limits of particle systems. The original paper addresses diffusion-based generative models with horizontal lift processes for quotient spaces in machine learning applications, which is a fundamentally different domain and problem setting.

9. Horizontal flows and manifold stochastics in geometric deep learning

URL: View paper

Brief Assessment

Horizontal Flows Stochastics[49] focuses on horizontal flows in frame bundles for geometric deep learning applications (convolution operators on manifolds), not on characterizing horizontal lift processes for quotient-space diffusion models in generative modeling.

10. Liouville theorems for symmetric diffusion operators on complete Riemannian manifolds

URL: View paper

Brief Assessment

Liouville Symmetric Diffusion[48] studies Liouville theorems for symmetric diffusion operators on complete Riemannian manifolds, focusing on analytical properties rather than constructing diffusion models for generative tasks or establishing correspondence between quotient space processes and horizontal lifts.

Appendix: Text Similarity Detection

Textual similarity detection checked 32 papers and found 4 similarity segment(s) across 2 paper(s).

The following **2 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. Equivariant diffusion for molecule generation in 3d

Detected in: Contribution: contribution_1

⚠ **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.

2. Geodiff: A geometric diffusion model for molecular conformation generation

Detected in: Contribution: contribution_2

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

References

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