Novelty Assessment Report

Paper: Approximate Equivariance via Projection-Based Regularisation
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Abstract

Equivariance is a powerful inductive bias in neural networks, improving generalisation and physical consistency. Recently, however, non-equivariant models have regained attention, due to their better runtime performance and imperfect symmetries that might arise in real-world applications. This has motivated the development of approximately equivariant models that strike a middle ground between respecting symmetries and fitting the data distribution. Existing approaches in this field usually apply sample-based regularisers which depend on data augmentation at training time, incurring a high sample complexity, in particular for continuous groups such as $SO(3)$. This work instead approaches approximate equivariance via a projection-based regulariser which leverages the orthogonal decomposition of linear layers into equivariant and non-equivariant components. In contrast to existing methods, this penalises non-equivariance at an operator level across the full group orbit, rather than point-wise. We present a mathematical framework for computing the non-equivariance penalty exactly and efficiently in both the spatial and spectral domain. In our experiments, our method consistently outperforms prior approximate equivariance approaches in both model performance and efficiency, achieving substantial runtime gains over sample-based regularisers.

Core Task Landscape

This paper addresses: **Approximate Equivariance in Neural Networks via Projection-Based Regularisation**

A total of **14 papers** were analyzed and organized into a taxonomy with **11 categories**.

Taxonomy Overview

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

- **Projection-Based and Operator-Level Equivariance Methods**
- **Regularization-Based Approximate Equivariance**
- **Domain-Specific Equivariant Architectures**
- **Theoretical Foundations and Interpretability**

Complete Taxonomy Tree

- Approximate Equivariance in Neural Networks via Projection-Based Regularisation Survey Taxonomy
- Projection-Based and Operator-Level Equivariance Methods
  - Projection-Based Regularisation for Approximate Equivariance ★ (1 papers)
  - [0] Approximate Equivariance via Projection-Based Regularisation (Anon et al., 2026) View paper
  - Projective Equivariance Theory and Construction (3 papers)
  - [9] In search of projectively equivariant networks (BÃ¶kman, 2023) View paper
  - [11] In Search of Projectively Equivariant Neural Networks (BÃ¶kman, 2022) View paper
  - [14] Projective Equivariant Networks via Second-order Fundamental Differential Invariants (Y Li, n.d.) View paper
  - Hard Constraints and Universal Approximation (1 papers)
  - [6] Hard-constrained neural networks with universal approximation guarantees (Y Min, 2024) View paper
- Regularization-Based Approximate Equivariance
  - Adaptive Regularization for Mixed and Approximate Symmetries (2 papers)
  - [2] A Regularization-Guided Equivariant Approach for Image Restoration (Yulu Bai, 2025) View paper
  - [3] Regularizing towards soft equivariance under mixed symmetries (Kimï¼ Hyunsu, 2023) View paper
  - Equivariant Regularization in Inverse Problems and Imaging (1 papers)
  - [4] Sketched equivariant imaging regularization and deep internal learning for inverse problems (Xu Guixian, 2024) View paper
- Domain-Specific Equivariant Architectures
  - Equivariance in Optimization and Planning (2 papers)
  - [1] Equivariant ensembles and regularization for reinforcement learning in map-based path planning (Mirco Theile, 2024) View paper
  - [5] Learning to generate projections for reducing dimensionality of heterogeneous linear programming problems (T Iwata, 2025) View paper
  - Graph and Geometric Equivariant Networks (1 papers)
  - [8] Learning from Frustration: Torsor CNNs on Graphs (Li Daiyuan, 2025) View paper
  - Spherical and SO(3)-Equivariant Networks (1 papers)
  - [12] On the Benefits of SO(3)-Equivariant Neural Networks for Spherical Image Processing (Martin Simon, 2022) View paper
- Theoretical Foundations and Interpretability
  - Universal Approximation and Equivariance Theory (1 papers)
  - [13] On neural networks with equivariance or invariance property (Pan Zhong, 2021) View paper
  - Latent Representations and Interpretability (1 papers)

- [7] Interpreting Equivariant Representations (Calissano Anna, 2024) View paper
- Robustness and Semantic Recovery (1 papers)
- [10] Robustness as Latent Symmetry: A Theoretical Framework for Semantic Recovery in Deep Learning (Deblina Banerjee, 2025) View paper

Narrative

Core task: Approximate equivariance in neural networks via projection-based regularisation. The field of equivariant neural networks has evolved into several complementary directions, each addressing how to encode or approximate symmetries in learned representations. The taxonomy reveals four main branches: projection-based and operator-level methods that explicitly construct equivariant layers or use projection operators to enforce symmetry constraints; regularization-based approaches that soften exact equivariance into a learnable objective; domain-specific architectures tailored to particular symmetry groups or application areas such as imaging and robotics; and theoretical work examining the foundations, interpretability, and robustness guarantees of equivariant models. Works like Projectively Equivariant Networks[9] and Projectively Equivariant Search[11] illustrate how projection operators can be designed to respect group actions, while Soft Equivariant Mixed[3] and Hard Constrained Networks[6] exemplify the spectrum from flexible regularization to strict architectural constraints. Meanwhile, domain-focused studies such as Equivariant Image Restoration[2] and Equivariant Path Planning[1] demonstrate how these principles translate into practical gains in specific settings.

A central tension across these branches concerns the trade-off between exact and approximate equivariance: strict architectural constraints guarantee perfect symmetry but may limit expressiveness or scalability, whereas regularization-based methods offer flexibility at the cost of weaker guarantees. Recent efforts have explored hybrid strategies that combine projection operators with soft penalties, aiming to balance inductive bias and model capacity. The original paper, Approximate Equivariance Projection[0], sits squarely within the projection-based regularization cluster, proposing a framework that uses projection operators to regularize networks toward approximate equivariance rather than enforcing it exactly. This approach contrasts with purely soft methods like Soft Equivariant Mixed[3], which rely on loss-based penalties, and with hard constraint designs such as Hard Constrained Networks[6], which build equivariance directly into layer operations. By framing approximate equivariance as a projection-based regularization problem, the work bridges operator-level techniques and flexible training objectives, offering a middle ground that may prove useful when exact symmetries are unknown or only partially present in data.

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

The original leaf focuses on projection-based regularization methods that decompose network layers into equivariant and non-equivariant components, using orthogonal projections to penalize deviations from exact equivariance. The sibling subtopics represent different approaches to achieving or studying equivariance: one enforces equivariance as hard constraints with theoretical guarantees, while the other develops theoretical frameworks for projective equivariance using modified group representations. All three areas deal with equivariance in neural networks but differ fundamentally in whether they treat equivariance as a soft constraint (original), hard constraint (first sibling), or modified algebraic structure (second sibling).

Similarities: - All three subtopics address equivariance properties in neural network architectures - Projection concepts appear across topics: the original uses orthogonal projections for regularization, while projective equivariance theory uses modified representations - All aim to incorporate symmetry considerations into network design, though through different mechanisms

Differences: - The original leaf uses soft penalties to approximate equivariance, while Hard Constraints enforces exact equivariance as architectural constraints - The original focuses on decomposing existing layers and penalizing non-equivariant components, whereas Projective Equivariance Theory constructs new theoretical frameworks with modified group representations - Hard Constraints emphasizes universal approximation guarantees, while the original leaf focuses on practical regularization techniques without necessarily providing such theoretical guarantees - Projective Equivariance Theory is primarily theoretical (frameworks and construction methods), while the original leaf is more methodological (regularization techniques)

Suggested Search Directions: - Investigate connections between projection-based regularization and projective group representations to understand if decomposition methods relate to modified symmetry structures - Explore whether projection-based regularization can provide approximation guarantees similar to hard constraint methods - Examine hybrid approaches that combine soft projection-based penalties with hard architectural constraints

Sibling Subtopics

- **Hard Constraints and Universal Approximation** (leaves: 1, papers: 1)
- Scope: Methods encoding equivariance as hard constraints with theoretical guarantees on universal approximation properties.
- Exclude: Soft regularization approaches belong in Regularization-Based Approximate Equivariance; projection methods for optimization belong in Equivariance in Optimization and Planning.
- **Projective Equivariance Theory and Construction** (leaves: 1, papers: 3)
- Scope: Theoretical frameworks and construction methods for projectively equivariant networks using modified group representations.
- Exclude: Applications to specific domains or data types belong in Domain-Specific Equivariant Architectures; approximate symmetry handling belongs in Regularization-Based Approximate Equivariance.

Contributions Analysis

Overall novelty summary. The paper proposes a projection-based regularization framework for approximate equivariance, decomposing linear layers into equivariant and non-equivariant components and penalizing the latter. Within the taxonomy, it occupies a singleton leaf under 'Projection-Based and Operator-Level Equivariance Methods,' with no sibling papers in the same category. This placement suggests the specific combination of projection operators and approximate equivariance regularization is relatively unexplored in the examined literature, though the broader parent branch contains related work on projective equivariance theory and hard constraints.

The taxonomy reveals neighboring leaves focused on projective equivariance theory (three papers on modified group representations) and hard constraint methods (one paper on universal approximation guarantees). A parallel branch, 'Regularization-Based Approximate Equivariance,' contains adaptive regularization and imaging-specific techniques that handle approximate symmetries through soft penalties and data augmentation. The paper's approach sits at the intersection: it uses projection operators (aligning with the operator-level branch) but applies them as soft regularizers (echoing the regularization branch), distinguishing it from both purely theoretical projective constructions and purely sample-based augmentation methods.

Among 28 candidates examined, the projection-based regularization framework (Contribution 1) shows one refutable candidate out of 10 examined, indicating some prior overlap in the limited search scope. The Fourier-domain computation method (Contribution 2) and operator-level penalty over full group orbits (Contribution 3) each examined 10 and 8 candidates respectively, with no refutable matches found. This suggests that while the high-level idea of projection-based approximate equivariance has some precedent, the specific computational techniques and orbit-level formulation appear less directly anticipated in the top-30 semantic matches and their citations.

Based on the limited search scope of 28 candidates, the work appears to occupy a relatively sparse position combining projection operators with approximate equivariance regularization. The singleton taxonomy leaf and low refutation rates for computational contributions suggest novelty in execution, though the single refutable match for the core framework indicates the conceptual territory is not entirely uncharted. A broader literature search beyond top-K semantic similarity might reveal additional related work in optimization-based equivariance or spectral methods for symmetry enforcement.

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

Contribution 1: Projection-based regularisation framework for approximate equivariance

Description: The authors introduce a novel framework that promotes equivariance in neural networks by penalising the non-equivariant component of model weights at the operator level, rather than through sample-based methods. This approach leverages the orthogonal decomposition of linear layers into equivariant and non-equivariant components.

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. Equivariant Test-Time Training with Operator Sketching for Imaging Inverse Problems

URL: View paper

Brief Assessment

Equivariant Test Time[17] focuses on test-time training for imaging inverse problems using sketched equivariant regularization, not on operator-level projection methods for promoting equivariance in general neural networks.

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2. Hard-constrained neural networks with universal approximation guarantees

URL: View paper

Brief Assessment

Hard Constrained Networks[6] focuses on enforcing hard constraints (e.g., safety, feasibility) on neural network outputs through projection layers, not on promoting equivariance through regularization. The candidate addresses a fundamentally different problem domain—constraint satisfaction rather than symmetry preservation.

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3. Equivariant ensembles and regularization for reinforcement learning in map-based path planning

URL: View paper

Brief Assessment

Equivariant Path Planning[1] focuses on equivariant ensembles and regularization for RL in path planning tasks, not on projection-based operator-level regularization methods for general neural networks.

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4. Equivariant neural operators for gradient-consistent topology optimization

URL: View paper

Brief Assessment

Equivariant Topology Optimization[16] enforces equivariance as an architectural constraint in neural operators for PDE solving, not through projection-based regularization of weights. The candidate focuses on guaranteeing exact equivariance in network design rather than penalizing non-equivariant components via operator-level projections.

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5. Regularizing towards soft equivariance under mixed symmetries

URL: View paper

Prior Art Analysis

Soft Equivariance Mixed[3] demonstrates prior work on projection-based regularization for equivariance. Both papers use orthogonal projection onto equivariant subspaces to penalize non-equivariant components of model weights. The candidate paper presents a projection-based equivariance regularizer (PER) that measures distance from weights to the equivariant subspace using the formula r^per_k(w,b) = λ_k/2 ||vec(w) - Q_kQ_k^T vec(w)||^2, which is conceptually identical to the original paper's approach of penalizing ||t - p(t)|| where p(t) is the projection operator. Both methods leverage the orthogonal decomposition of linear layers into equivariant and non-equivariant components at the operator level, rather than using sample-based methods.

Evidence

Evidence 1 - **Rationale**: Both papers use projection onto the equivariant subspace to measure and penalize non-equivariance. The candidate's PER formula directly implements the projection-based approach described in the original paper's abstract. - **Original**: this work instead approaches approximate equivariance via a projection-based regulariser which leverages the orthogonal decomposition of linear layers into equivariant and non-equivariant components. in contrast to existing methods, this penalises non-equivariance at an operator level across the ful... - **Candidate**: our projection-based equivariance regularizer (per) for a group gk is defined by rper k (w, b) = λk 2 ‖vec(w) - qkq⊺ kvec(w)‖2 + λk 2 ‖b - rkr⊺ kb‖2, (5) where w and b are parameters of the l-th layer of the network, and λk is a regularization coefficient for the group gk. modulo the reshaping into...

Evidence 2 - **Rationale**: Both papers describe penalizing non-equivariance at the operator level by moving parameters toward the equivariant subspace through regularization. - **Original**: making use of the orthogonal decompostion of functions into equivariant and non-equivariant components, we are able to penalise non-equivariance on an operator level over the whole group orbit. - **Candidate**: this regularizer can be a part of a learning objective during training, so that the training moves the parametersw and b towards the space of thegk-equivariant linear maps orgkinvariant vectors. an advantage of this regularizer-based approach for enforcing symmetries is that we can easily combine mu...

Evidence 3 - **Rationale**: Both papers use the orthogonal decomposition into equivariant and non-equivariant components as the theoretical foundation for their projection-based regularization approach. - **Original**: lemma 2.1 (elesedy & zaidi (2021), lemma 1) . let h ⊂ {(v, π) → (v ′, π′)} be a function space that is closed under p (i.e. p(t) ∈ hwhenever t ∈ h). define s = {t ∈ h: t is g-equivariant}, a = ker p = {t ∈ h: p(t) = 0}. (2) then p is an orthogonal projection with range s and kernel a, and hence h = ... - **Candidate**: write qk and rk for the matrices from the equations in (2); the columns of qk form an orthonormal basis of gk-equivariant linear maps from rnl to rnl+1 after being reshaped into nl+1 x nl matrices, and the columns of rk form an orthonormal basis of nl+1-dimensional gk-invariant vectors in rnl+1 . ou...

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6. Sketched equivariant imaging regularization and deep internal learning for inverse problems

URL: View paper

Brief Assessment

Sketched Equivariant Imaging[4] focuses on accelerating equivariant imaging regularization for inverse problems using operator sketching techniques, not on promoting equivariance in general neural networks through operator-level penalties on weight decomposition.

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7. A Regularization-Guided Equivariant Approach for Image Restoration

URL: View paper

Brief Assessment

Equivariant Image Restoration[2] focuses on image restoration tasks using rotation-equivariant regularization for CNNs, not on general operator-level penalties across arbitrary groups. The original paper addresses broader group theory with orthogonal decomposition of linear operators, while the candidate applies equivariance concepts specifically to convolutional networks for low-level vision tasks.

8. Implicit bias of linear equivariant networks

URL: View paper

Brief Assessment

Linear Equivariant Bias[18] focuses on implicit bias of linear equivariant networks during training (gradient descent convergence to low-rank Fourier solutions), not on explicit regularization methods for promoting equivariance through operator-level penalties as proposed in the original paper.

9. A unified framework to enforce, discover, and promote symmetry in machine learning

URL: View paper

Brief Assessment

Unified Symmetry Framework[19] focuses on enforcing, discovering, and promoting exact symmetries through linear constraints and nuclear norm penalties, whereas the original paper specifically addresses approximate equivariance via projection-based regularization that penalizes non-equivariant components at the operator level across full group orbits rather than point-wise.

10. Rotation equivariant proximal operator for deep unfolding methods in image restoration

URL: View paper

Brief Assessment

Rotation Equivariant Proximal[15] focuses on rotation equivariance in proximal operators for image restoration tasks, not on general projection-based regularization frameworks for neural networks. The candidate addresses equivariance through filter parametrization and theoretical error analysis in deep unfolding methods, which is a different technical approach from operator-level projection penalties.

Contribution 2: Efficient closed-form projection computation in Fourier domain

Description: The authors develop a mathematical framework for computing the equivariance projection exactly and efficiently in the spectral domain. This enables practical application to continuous groups by exploiting the block-diagonal structure of equivariant operators in Fourier space.

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. Unified fourier-based kernel and nonlinearity design for equivariant networks on homogeneous spaces

URL: View paper

Brief Assessment

Unified Fourier Equivariant[28] focuses on kernel and nonlinearity design for equivariant networks on homogeneous spaces using Fourier sparsity patterns, not on computing equivariance projections for general continuous groups as in the original paper's regularization framework.

2. Histogram Transporter: Learning Rotation-Equivariant Orientation Histograms for High-Precision Robotic Kitting

URL: View paper

Brief Assessment

Histogram Transporter Rotation[24] focuses on learning rotation-equivariant orientation histograms for robotic manipulation tasks, not on computing equivariance projections in Fourier domain for continuous symmetry groups as a general mathematical framework.

3. GEFTNN-BA: A Gauge-Equivariant Fourier Transformer Neural Network with Bayesian Attention for Trustworthy Temporal Dynamics

URL: View paper

Brief Assessment

GEFTNN Bayesian Attention[23] focuses on gauge-equivariant Fourier transformers for temporal dynamics with Bayesian uncertainty quantification. The candidate does not discuss projection operators onto equivariant subspaces or computing equivariance projections in Fourier space for continuous symmetry groups.

4. Group equivariant fourier neural operators for partial differential equations

URL: View paper

Brief Assessment

Group Equivariant Fourier[25] focuses on designing equivariant Fourier layers for PDEs by leveraging symmetries of the Fourier transform for group convolutions, not on computing equivariance projections for regularization purposes as in the original paper.

5. Coordinate transform fourier neural operators for symmetries in physical modelings

URL: View paper

Brief Assessment

Coordinate Transform Fourier[27] focuses on applying coordinate transforms to achieve equivariance in neural operators for different domain shapes (spheres, cylinders, etc.), not on computing equivariance projections in Fourier space for continuous groups. The candidate's Fourier operations serve coordinate transformation purposes rather than projection-based regularization.

6. The principles behind equivariant neural networks for physics and chemistry

URL: View paper

Brief Assessment

Equivariant Physics Principles[22] focuses on deriving the general form of operations in equivariant neural networks using Fourier space representation theory, not on computing equivariance projections or projection-based regularization methods.

7. GELNO-FD: gauge-equivariant Fourier liquid neural operators for interpretable Markovian Bayesian dynamics

URL: View paper

Brief Assessment

GELNO Fourier Dynamics[21] focuses on gauge-equivariant Fourier liquid neural operators for Bayesian dynamics forecasting, not on computing equivariance projections for continuous symmetry groups in general neural architectures.

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8. On the Fourier analysis in the SO (3) space: EquiLoPO Network

URL: View paper

Brief Assessment

EquiLoPO SO3 Fourier[26] focuses on group convolutions using Wigner matrices as Fourier basis for SO(3) equivariance in volumetric data, not on computing equivariance projections for general continuous groups as in the original paper's framework.

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9. General nonlinearities in so (2)-equivariant cnns

URL: View paper

Brief Assessment

SO2 Equivariant Nonlinearities[29] focuses on applying nonlinearities to Fourier representations in SO(2)-equivariant CNNs, not on computing equivariance projections for general continuous groups. The candidate develops FFT-based algorithms for handling nonlinear transformations while maintaining band-limitation, which is a different technical problem than projection-based regularization across group orbits.

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10. Fourier analysis of equivariant quantum cohomology

URL: View paper

Brief Assessment

Fourier Equivariant Cohomology[20] focuses on quantum cohomology and symplectic geometry, not neural network equivariance projections. The mathematical domains are fundamentally different.

Contribution 3: Operator-level equivariance penalty over full group orbit

Description: The method penalises non-equivariance across the entire group orbit at the operator level, in contrast to existing point-wise sample-based approaches. This provides a more comprehensive measure of equivariance violation without requiring data augmentation or sampling at training time.

This contribution was assessed against **8 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. Transformation Robustness in Computer Vision: Invariant & Equivariant Neural Networks

URL: View paper

Brief Assessment

Transformation Robustness Vision[37] is a doctoral thesis overview focusing on designing inherently invariant/equivariant architectures through group theory principles. It does not discuss operator-level projection-based regularization or penalties over group orbits versus sample-based approaches.

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2. Equivariance in the Era of Large Pretrained Models

URL: View paper

Brief Assessment

Equivariance Pretrained Models[35] focuses on canonicalization approaches for adapting large pretrained models to achieve equivariance, rather than operator-level projection-based regularization over group orbits. The candidate does not address penalizing non-equivariance at the operator level across full group orbits as a regularization method.

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3. Data Augmentation and Regularization for Learning Group Equivariance

URL: View paper

Brief Assessment

Augmentation Group Equivariance[34] focuses on achieving equivariance through data augmentation combined with regularization, not on operator-level penalties over group orbits. The candidate's approach is fundamentally sample-based rather than operator-based.

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4. Multi-Group Equivariant Augmentation for Reinforcement Learning in Robot Manipulation

URL: View paper

Brief Assessment

Multi Group Equivariant[33] focuses on data augmentation for robot manipulation using non-isometric group transformations across timesteps, not on operator-level equivariance penalties or projection-based regularization methods.

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5. Training or architecture? how to incorporate invariance in neural networks

URL: View paper

Brief Assessment

Training Architecture Invariance[36] focuses on orbit mappings that select specific elements from group orbits to achieve invariance, rather than penalizing non-equivariance across the full orbit at the operator level as in the original paper.

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6. A simple strategy to provable invariance via orbit mapping

URL: View paper

Brief Assessment

Orbit Mapping Invariance[32] focuses on selecting canonical elements from group orbits via orbit mappings (e.g., gradient-based alignment for rotations, PCA for 3D point clouds) to achieve provable invariance. The original paper penalizes non-equivariance at the operator level across the full group orbit using projection-based regularization in Fourier space. These are fundamentally different technical approaches to achieving equivariance/invariance.

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7. Rao-blackwell gradient estimators for equivariant denoising diffusion

URL: View paper

Brief Assessment

Rao Blackwell Equivariant[30] focuses on variance reduction in diffusion model training through Rao-Blackwellization of gradient estimators, not on operator-level equivariance penalties. The candidate addresses training stability via orbit-weighted targets in diffusion models, while the original paper proposes projection-based regularization that penalizes non-equivariance at the operator level across group orbits without data augmentation.

8. Revisiting Data Augmentation for Rotational Invariance in Convolutional Neural Networks

URL: View paper

Brief Assessment

Rotational Invariance Augmentation[38] focuses on data augmentation for rotational invariance in CNNs, not operator-level projection-based regularization over group orbits. The candidate investigates training with augmented data versus specialized architectures, while the original paper proposes penalizing non-equivariance at the operator level through projection operators in Fourier space.

Appendix: Text Similarity Detection

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

References

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