

Novelty Assessment Report

Paper: Any-Subgroup Equivariant Networks via Symmetry Breaking

PDF URL: <https://openreview.net/pdf?id=jz3d7nvtGz>

Venue: ICLR 2026 Conference Submission

Year: 2026

Report Generated: 2026-01-01

Abstract

The inclusion of symmetries as an inductive bias, known as equivariance, often improves generalization on geometric data (e.g. grids, sets, and graphs). However, equivariant architectures are usually highly constrained, designed for symmetries chosen a priori, and not applicable to datasets with other symmetries. This precludes the development of flexible, multi-modal foundation models capable of processing diverse data equivariantly. In this work, we build a single model --- the Any-Subgroup Equivariant Network (ASEN) --- that can be simultaneously equivariant to several groups, simply by modulating a certain auxiliary input feature. In particular, we start with a fully permutation-equivariant base model, and then obtain subgroup equivariance by using a symmetry-breaking input whose automorphism group is that subgroup. However, finding an input with the desired automorphism group is computationally hard. We overcome this by relaxing from exact to approximate symmetry breaking, leveraging the notion of 2-closure to derive fast algorithms. Theoretically, we show that our subgroup-equivariant networks can simulate equivariant MLPs, and their universality can be guaranteed if the base model is universal. Empirically, we validate our method on symmetry selection for graph and image tasks, as well as multitask and transfer learning for sequence tasks, showing that a single network equivariant to multiple permutation subgroups outperforms both separate equivariant models and a single non-equivariant model.

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: **Building Flexible Equivariant Networks for Multiple Permutation Subgroups**

A total of **50 papers** were analyzed and organized into a taxonomy with **19 categories**.

Taxonomy Overview

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

- **Theoretical Foundations of Equivariance**
- **Architecture Design and Construction Methods**
- **Domain-Specific Applications and Implementations**
- **Computational Methods and Algorithmic Techniques**
- **Related Mathematical and Cryptographic Structures**
- **Survey and Review Literature**
- **Specialized and Emerging Applications**

Complete Taxonomy Tree

- Building Flexible Equivariant Networks for Multiple Permutation Subgroups Survey Taxonomy
- Theoretical Foundations of Equivariance
 - Group-Theoretic Characterization and Representation Theory (5 papers)
 - [1] Permutation Equivariant Neural Networks for Symmetric Tensors (Pearce-Crump, 2025) [View paper](#)
 - [3] Geometry of linear neural networks: Equivariance and invariance under permutation groups (KathlÃ©n Kohn, 2025) [View paper](#)
 - [7] Categorical Equivariant Deep Learning: Category-Equivariant Neural Networks and Universal Approximation Theorems (Maruyama, 2025) [View paper](#)
 - [20] On the finite representation of linear group equivariant operators via permutant measures (S. Botteghi, 2023) [View paper](#)
 - [22] Revisiting Multi-Permutation Equivariance through the Lens of Irreducible Representations (Yonatan Sverdlov, 2024) [View paper](#)
 - Universal Approximation and Expressivity (3 papers)
 - [19] Universal neural functionals (Chelsea Finn, 2024) [View paper](#)
 - [26] Are high-degree representations really unnecessary in equivariant graph neural networks? (Jiacheng Cen, 2024) [View paper](#)
 - [40] Universal approximations of permutation invariant/equivariant functions by deep neural networks (Sannai, 2019) [View paper](#)
 - Symmetry Properties and Loss Landscape Geometry (2 papers)
 - [15] A Tale of Two Symmetries: Exploring the Loss Landscape of Equivariant Models (Xie Yu-qing, 2025) [View paper](#)
 - [41] Leveraging Parameter Space Symmetries for Reasoning Skill Transfer in LLMs (Stefan Horoi, 2025) [View paper](#)
- Architecture Design and Construction Methods
 - Multi-Subgroup and Flexible Equivariance Mechanisms ★ (4 papers)
 - [0] Any-Subgroup Equivariant Networks via Symmetry Breaking (Anon et al., 2026) [View paper](#)
 - [16] Learning probabilistic symmetrization for architecture agnostic equivariance (Kim Jin-Woo, 2023) [View paper](#)
 - [43] Modular PE-Structured Learning for Cross-Task Wireless Communications (Duan, 2025) [View paper](#)
 - [46] A new approach to design symmetry invariant neural networks (Piotr Kicki, 2021) [View paper](#)
 - Permutation-Equivariant Layer Constructions (5 papers)
 - [10] Monomial matrix group equivariant neural functional networks (Tran Viet Hoang, 2024) [View paper](#)
 - [28] Fast computation of permutation equivariant layers with the partition algebra (Godfrey, 2023) [View paper](#)

- [31] FS-KAN: Permutation Equivariant Kolmogorov-Arnold Networks via Function Sharing (Bar-Shalom, 2025) [View paper](#)
- [45] The general theory of permutation equivariant neural networks and higher order graph variational encoders (Erik H. Thiede, 2020) [View paper](#)
- [48] Equivariant Polynomial Functional Networks (Vo, 2024) [View paper](#)
- Non-Linear and Generalized Equivariant Maps (2 papers)
- [4] Equivariant non-linear maps for neural networks on homogeneous spaces (Nyholm, 2025) [View paper](#)
- [34] Local permutation equivariance for graph neural networks (Joshua Mitton, 2021) [View paper](#)
- Approximate and Relaxed Equivariance (1 papers)
- [11] Approximately equivariant graph networks (Huang, 2023) [View paper](#)
- Domain-Specific Applications and Implementations
 - Graph and Relational Learning (2 papers)
 - [8] When GNNs meet symmetry in ILPs: an orbit-based feature augmentation approach (Chen Qian, 2025) [View paper](#)
 - [13] Equivariance Everywhere All At Once: A Recipe for Graph Foundation Models (Finkelshtein, 2025) [View paper](#)
 - Geometric and Topological Applications (2 papers)
 - [5] E (n) equivariant topological neural networks (Battiloro, 2024) [View paper](#)
 - [14] Rotation-and permutation-equivariant quantum graph neural network for 3d graph data (Wenjie Liu, 2025) [View paper](#)
 - Quantum Computing and Physical Systems (3 papers)
 - [6] Permutation-equivariant quantum convolutional neural networks (Sreetama Das, 2024) [View paper](#)
 - [9] Optimal equivariant architectures from the symmetries of matrix-element likelihoods (Daniel Maitre, 2025) [View paper](#)
 - [32] A permutation-equivariant deep learning model for quantum state characterization (C. Cusano, 2025) [View paper](#)
 - Natural Language and Compositional Generalization (1 papers)
 - [2] Permutation equivariant models for compositional generalization in language (Jonathan Gordon, 2019) [View paper](#)
 - Planning, Reinforcement Learning, and Control (3 papers)
 - [12] Edgi: Equivariant diffusion for planning with embodied agents (Brehmer, 2023) [View paper](#)
 - [37] Permutation-Invariant and Equivariant Multiagent Reinforcement Learning for Flexible Manufacturing in Industrial IoT (Yangyan Zeng, 2025) [View paper](#)
 - [39] Permutation Equivariant Model-based Offline Reinforcement Learning for Auto-bidding (Mou, 2025) [View paper](#)
 - Representation Learning and Interpretability (2 papers)
 - [23] Structuring representations using group invariants (M Shakerinava, 2022) [View paper](#)
 - [42] Interpreting Equivariant Representations (Calissano Anna, 2024) [View paper](#)
- Computational Methods and Algorithmic Techniques
 - Symmetry Detection and Model Alignment (1 papers)
 - [47] Mode combinability: Exploring convex combinations of permutation aligned models. (Adrián Csizsárik, 2024) [View paper](#)
- Related Mathematical and Cryptographic Structures
 - Cryptographic Applications of Permutation Groups (3 papers)
 - [24] Designing secure substitution boxes based on permutation of symmetric group (Amir Anees, 2020) [View paper](#)
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 - [50] New structure of algebras using permutations in symmetric groups (Shuker Khalil, 2024) [View paper](#)
 - Pure Group Theory and Representation Theory (3 papers)
 - [35] Equivariant Orthogonal Spectra and -Modules (MA Mandell, 2002) [View paper](#)
 - [36] An empirical relation between lepton masses from the symmetric permutation group (Simon Davis, 2025) [View paper](#)
 - [44] $\hat{\rho}$ of Permutation Groups I: Representations of Wreath Products and Applications to the Representation Theory of Symmetric and Alternating Groups (Kerber, 2006) [View paper](#)
- Survey and Review Literature (3 papers)
 - [17] Current symmetry group equivariant convolution frameworks for representation learning (Mishra, 2024) [View paper](#)
 - [18] Equivariant convolutional networks (Tomer Cohen, 2021) [View paper](#)
 - [25] Learning invariant representations in neural networks (Fuchs, 2021) [View paper](#)
- Specialized and Emerging Applications (1 papers)
 - [33] A permutable MLP-like architecture for disease prediction from gut metagenomic data. (Cong Jiang, 2024) [View paper](#)

Narrative

Core task: building flexible equivariant networks for multiple permutation subgroups. The field has organized itself around several complementary directions. Theoretical Foundations of Equivariance explores the mathematical underpinnings—group representations, invariant theory, and algebraic structures—that justify why and how symmetries can be encoded in neural architectures. Architecture Design and Construction Methods focuses on practical network-building strategies, including how to compose layers that respect one or many subgroup symmetries simultaneously, as seen in works like Modular PE-Structured[43] and Probabilistic Symmetrization[16]. Domain-Specific Applications and Implementations demonstrate these ideas in areas such as quantum systems (Quantum Graph Neural[14]), particle physics (Matrix-Element Likelihoods[9]), and combinatorial problems, while Computational Methods and Algorithmic Techniques address efficiency and scalability. Related Mathematical and Cryptographic Structures and Survey and Review Literature round out the taxonomy by connecting equivariance to broader mathematical contexts and summarizing progress across subfields.

A particularly active line of work centers on multi-subgroup and flexible equivariance mechanisms, where the challenge is to design architectures that can adapt to or simultaneously respect several distinct permutation symmetries rather than committing to a single fixed group. Any-Subgroup Equivariant[0] exemplifies this direction by proposing methods that handle arbitrary subgroups within a unified framework, contrasting with earlier approaches that hardwired a single symmetry. Nearby efforts such as Modular PE-Structured[43] emphasize modular construction principles to combine different equivariance constraints, while Symmetry Invariant

Design[46] explores how to encode invariance properties directly into layer design. These works collectively address the trade-off between expressiveness and computational cost: richer symmetry handling can improve generalization (Compositional Generalization[2]) but may require more sophisticated parameterizations or approximations (Approximately Equivariant[11]). The original paper sits squarely in this flexible multi-subgroup cluster, offering techniques that extend beyond fixed-group methods and align closely with modular and probabilistic symmetrization strategies.

Related Works in Same Category

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

1. Learning probabilistic symmetrization for architecture agnostic equivariance

Authors: Kim Jin-Woo, Nguyen Tien Dat, Jinwoo Kim, Suleymanzade, Ayhan, et al. (13 authors total) | **Year/Venue:** 2023 | **URL:** [View paper](#)

Abstract

We present a novel framework to overcome the limitations of equivariant architectures in learning functions with group symmetries. In contrary to equivariant architectures, we use an arbitrary base model (such as an MLP or a transformer) and symmetrize it to be equivariant to the given group by employing a small equivariant network that parameterizes the probabilistic distribution underlying the symmetrization. The distribution is end-to-end trained with the base model which can maximize perform...

Relationship Analysis

Both papers belong to the Multi-Subgroup and Flexible Equivariance Mechanisms category, addressing how to build networks that can handle multiple permutation subgroups. They overlap in their goal of achieving flexible equivariance without designing separate architectures for each group, both using symmetry-breaking mechanisms to modulate equivariance. The key difference is that the original paper (ASEN) uses deterministic symmetry-breaking inputs (edge/node features with specific automorphism groups) computed via 2-closure, while the candidate paper uses probabilistic symmetrization with a learned equivariant distribution $p\omega(g|x)$ to sample group transformations, enabling end-to-end training and potential transfer from pretrained models.

2. Modular PE-Structured Learning for Cross-Task Wireless Communications

Authors: Duan, Yuxuan, Yang, Chenyang, Yuxuan Duan, et al. (6 authors total) | **Year/Venue:** 2025 | **URL:** [View paper](#)

Abstract

Recent trends in learning wireless policies attempt to develop deep neural networks (DNNs) for handling multiple tasks with a single model. Existing approaches often rely on large models, which are hard to pre-train and fine-tune at the wireless edge. In this work, we challenge this paradigm by leveraging the structured knowledge of wireless problems -- specifically, permutation equivariant (PE) properties. We design three types of PE-aware modules, two of which are Transformer-style sub-layers....

Relationship Analysis

Both papers belong to the Multi-Subgroup and Flexible Equivariance Mechanisms category, focusing on building architectures that achieve equivariance to multiple permutation subgroups. They overlap in using permutation equivariance as an inductive bias and designing flexible architectures that can handle multiple symmetry groups, with both leveraging graph neural networks and modular design principles. However, the original paper (ASEN) focuses on symmetry breaking via auxiliary inputs to achieve subgroup equivariance from a fully permutation-equivariant base model, while the candidate paper (PE-MoFormer) emphasizes modular compositional design with PE-aware Transformer-style sub-layers specifically for wireless communication tasks, targeting cross-task learning efficiency rather than general-purpose symmetry selection.

3. A new approach to design symmetry invariant neural networks

Authors: Piotr Kicki, M. Ozay, Piotr Skrzypczyński, Piotr Skrzypczyński, Mete Ozay | **Year/Venue:** 2021 | **URL:** [View paper](#)

Abstract

We investigate a new method to design G-invariant neural networks that approximate functions invariant to the action of a given permutation subgroup G of the symmetric group on input data. The key element of the new network architecture is a G-invariant transformation module, which produces a G-invariant latent representation of the input data. This latent representation is then processed with a multi-layer perceptron in the network. We prove the universality of the new architecture, dis...

Relationship Analysis

Both papers belong to the Multi-Subgroup and Flexible Equivariance Mechanisms category, focusing on designing neural networks that can handle equivariance to multiple permutation subgroups. The original paper (ASEN) achieves flexible equivariance by augmenting a fully permutation-equivariant base model with symmetry-breaking inputs whose automorphism group matches the target subgroup, enabling a single model to handle multiple groups via modulation. The candidate paper takes a different approach by designing G-invariant (not equivariant) networks through a G-invariant transformation module that produces invariant latent representations, focusing on invariance rather than equivariance and using a fundamentally different architectural strategy without the symmetry-breaking framework.

Contributions Analysis

Overall novelty summary. The paper introduces Any-Subgroup Equivariant Networks (ASEN), a framework enabling a single model to achieve equivariance to multiple permutation subgroups by modulating auxiliary inputs. It resides in the 'Multi-Subgroup and Flexible Equivariance Mechanisms' leaf, which contains four papers total (including this one). This leaf sits within 'Architecture Design and Construction Methods', a moderately populated branch addressing practical network-building strategies. The small leaf size suggests this specific direction—simultaneous multi-subgroup equivariance via symmetry-breaking inputs—is relatively sparse compared to broader equivariance research, though the parent branch reflects sustained interest in flexible architectural solutions.

The taxonomy reveals neighboring leaves focused on permutation-equivariant layer constructions (five papers), non-linear extensions (two papers), and approximate equivariance (one paper). These adjacent directions tackle complementary challenges: fixed-group layer design, attention mechanisms for homogeneous spaces, and relaxed symmetry constraints. The original paper bridges these areas by starting from full permutation equivariance (a common baseline in layer constructions) and then achieving subgroup equivariance through approximate symmetry breaking. This positions ASSEN at the intersection of flexible multi-group mechanisms and approximate methods, connecting modular construction principles (seen in sibling papers) with computational relaxation strategies.

Among fifteen candidates examined, the ASSEN framework contribution (four candidates, zero refutations) and theoretical guarantees (ten candidates, zero refutations) appear relatively novel within this limited search scope. However, the approximate symmetry breaking via 2-closure contribution shows one refutable candidate among one examined, indicating prior work addresses similar computational relaxation techniques. The small candidate pool (fifteen total) means these statistics reflect top-K semantic matches and immediate citations, not exhaustive coverage. The framework's novelty seems strongest in its unified multi-subgroup approach, while the 2-closure algorithmic component overlaps more substantially with existing approximate methods.

Based on this limited analysis of fifteen candidates across three contributions, the work appears to occupy a relatively sparse research direction within the broader equivariance landscape. The multi-subgroup flexibility represents a less-explored architectural strategy compared to single-group designs, though the computational techniques for achieving it (approximate symmetry breaking) connect to established approximation literature. The assessment is constrained by the search scope and does not capture potential overlaps outside the top semantic matches or citation network examined.

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

Contribution 1: Any-Subgroup Equivariant Networks (ASEN) framework

Description: The authors propose ASEN, a framework that constructs a single flexible model capable of being equivariant to multiple different symmetry groups by using a symmetry-breaking auxiliary input whose automorphism group matches the desired subgroup. This overcomes the inflexibility of traditional equivariant architectures that are designed for one specific symmetry group.

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

1. Se (3)-equivariant graph neural networks for learning glassy liquids representations

URL: [View paper](#)

Brief Assessment

Glassy Liquids[53] focuses on SE(3)-equivariant graph neural networks for learning representations of glassy liquids, a specific physics application. It does not address the general problem of building a single flexible model equivariant to multiple different symmetry groups via auxiliary inputs.

2. Improving Equivariant Networks with Probabilistic Symmetry Breaking

URL: [View paper](#)

Brief Assessment

Probabilistic Symmetry Breaking[54] focuses on breaking symmetries via randomized canonicalization for conditional distributions, not on constructing a single model equivariant to multiple groups via deterministic auxiliary inputs with specific automorphism groups.

3. arXiv: Lorentz-Equivariance without Limitations

URL: [View paper](#)

Brief Assessment

Lorentz-Equivariance[55] focuses on Lorentz-equivariance for particle physics applications using local reference frames, not on building flexible models equivariant to multiple permutation subgroups via symmetry-breaking auxiliary inputs as in ASEN.

4. Breaking the Symmetry: Resolving Symmetry Ambiguities in Equivariant Neural Networks

URL: [View paper](#)

Brief Assessment

Resolving Symmetry Ambiguities[56] addresses a different problem: handling symmetric inputs (e.g., left-right symmetric objects) where standard equivariant networks fail at symmetry-dependent tasks. ASEN focuses on building a single flexible model equivariant to multiple different symmetry groups via auxiliary inputs.

Contribution 2: Approximate symmetry breaking via 2-closure

Description: The authors develop a practical algorithm using the 2-closure notion to construct symmetry-breaking inputs (positional and edge features) with approximately the desired automorphism group, making the framework computationally tractable when exact symmetry breaking is hard.

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

1. Single-Model Any-Subgroup Equivariance via SymmetricPositional Encodings

URL: [View paper](#)

Prior Art Analysis

Symmetric Positional Encodings[51] demonstrates that the 2-closure approach for approximate symmetry breaking was already established in prior work. Both papers describe using 2-closure to construct symmetry-breaking inputs (positional and edge features) when exact symmetry breaking is computationally hard. The candidate explicitly states this method involves 'leveraging the notion of 2-closure to derive fast algorithms' for approximate symmetry breaking, which directly matches the original paper's claimed contribution. The candidate's abstract presents this as an established technique rather than a novel contribution.

Evidence

Evidence 1 - **Rationale:** Both papers describe using 2-closure to derive fast algorithms for approximate symmetry breaking in nearly identical language, indicating this approach was already known. - **Original:** we overcome this by relaxing from exact to approximate symmetry breaking, leveraging the notion of 2-closure to derive fast algorithms - **Candidate:** this is done by leveraging the notion of 2-closure to derive fast algorithms

Evidence 2 - **Rationale:** Both papers identify the computational hardness of exact symmetry breaking and propose the same solution using 2-closure for constructing positional and edge features with approximate automorphism groups. - **Original:** achieving exact symmetry breaking of sn to the desired subgroup g may require a hypergraph h of prohibitively high order (up to $k \leq n$). for efficiency, we fix $k = 2$ and construct positional and edge features $h = (a(1), a(2))$, whose automorphism group $aut(h)$ reflects on how g acts on nodes and pairs ... - **Candidate:** finding an input with automorphism group exactly g is computationally hard, which can be overcome by relaxing exact symmetry breaking to approximate symmetry breaking. this is done by leveraging the notion of 2-closure to derive fast algorithms

Contribution 3: Theoretical guarantees on expressivity and universality

Description: The authors prove that ASEN can approximate equivariant MLPs to arbitrary accuracy and inherits universality properties from its base model, establishing formal expressivity guarantees for the framework.

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. Universally Invariant Learning in Equivariant GNNs

URL: [View paper](#)

Brief Assessment

Universally Invariant Learning[63] focuses on completeness and universal approximation for equivariant GNNs over geometric graphs, while the original paper addresses expressivity guarantees for any-subgroup equivariant networks via symmetry breaking across diverse permutation subgroups.

2. Universal approximations of invariant maps by neural networks

URL: [View paper](#)

Brief Assessment

Invariant Maps[58] focuses on universal approximation theorems for general compact groups and specific groups like $SE(2)$, using polynomial layers and isotypic decompositions. ASEN addresses permutation subgroup equivariance via symmetry breaking with hypergraph features, proving universality inheritance from base models and approximation of equivariant MLPs—a distinct technical approach.

3. Frame averaging for invariant and equivariant network design

URL: [View paper](#)

Brief Assessment

Frame Averaging[59] focuses on frame-based group averaging for invariance/equivariance with expressivity results for their specific framework, while the original paper addresses subgroup-equivariant networks via symmetry breaking with different theoretical guarantees (approximating equivariant MLPs and inheriting universality from base models).

4. On the universality of rotation equivariant point cloud networks

URL: [View paper](#)

Brief Assessment

Rotation Equivariant Universality[64] focuses on rotation-equivariant point cloud networks ($SE(3)$ transformations), while ASEN addresses permutation subgroup equivariance. The mathematical frameworks and symmetry groups differ fundamentally.

5. On the expressive power of geometric graph neural networks

URL: [View paper](#)

Brief Assessment

Geometric Graph Power[57] focuses on geometric graph neural networks and their expressive power through the Weisfeiler-Leman framework, not on subgroup-equivariant networks or the ASEN framework proposed in the original paper.

6. Equivariant subgraph aggregation networks

URL: [View paper](#)

Brief Assessment

Subgraph Aggregation[60] focuses on expressivity bounds via Weisfeiler-Leman variants for subgraph-based architectures, not on universality guarantees for subgroup-equivariant networks or approximation of equivariant MLPs.

7. Scalars are universal: Equivariant machine learning, structured like classical physics

URL: [View paper](#)

Brief Assessment

Scalars are Universal[65] focuses on characterizing equivariant functions for classical physics symmetries ($O(d)$, Lorentz, Poincaré groups) using scalar products, not on subgroup-equivariant networks or approximating equivariant MLPs through symmetry breaking as in the original paper.

8. Invariant and equivariant graph networks

URL: [View paper](#)

Brief Assessment

Invariant and Equivariant[62] focuses on characterizing invariant/equivariant linear layers for graph data and approximating message passing neural networks, not on subgroup-equivariant networks or their universality properties.

9. E (n) equivariant topological neural networks

URL: [View paper](#)

Brief Assessment

Topological Neural Networks[5] focuses on $E(n)$ -equivariant message-passing on combinatorial complexes for geometric features, not on expressivity guarantees for subgroup-equivariant networks or their ability to approximate equivariant MLPs.

10. Pure transformers are powerful graph learners

URL: [View paper](#)

Brief Assessment

Pure Transformers[61] focuses on graph learning via transformers approximating equivariant linear layers and k-IGN, while the original paper addresses subgroup-equivariant networks via symmetry breaking. The theoretical frameworks and problem settings differ fundamentally—Pure Transformers[61] does not address arbitrary subgroup equivariance or symmetry-breaking mechanisms.

Appendix: Text Similarity Detection

Textual similarity detection checked 19 papers and found 2 similarity segment(s) across 1 paper(s).

The following **1 paper(s)** were detected to have high textual similarity with the original paper. These may represent different versions of the same work, duplicate submissions, or papers with substantial textual overlap. Readers are advised to verify these relationships independently.

1. Single-Model Any-Subgroup Equivariance via Symmetric Positional Encodings

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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