

Novelty Assessment Report

Paper: Disentangled representation learning through unsupervised symmetry group discovery

PDF URL: <https://openreview.net/pdf?id=I6xjMoLY3j>

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Abstract

Symmetry-based disentangled representation learning leverages the group structure of environment transformations to uncover the latent factors of variation. Prior approaches to symmetry-based disentanglement have required strong prior knowledge of the symmetry group's structure, or restrictive assumptions about the subgroup properties. In this work, we remove these constraints by proposing a method whereby an embodied agent autonomously discovers the group structure of its action space through unsupervised interaction with the environment. We prove the identifiability of the true action group decomposition under minimal assumptions, and derive two algorithms: one for discovering the group decomposition from interaction data, and another for learning Linear Symmetry-Based Disentangled (LSBD) representations without assuming specific subgroup properties. Our method is validated on three environments exhibiting different group decompositions, where it outperforms existing LSBD approaches.

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.

If you have any questions, please contact: mingzhang23@m.fudan.edu.cn

Core Task Landscape

This paper addresses: **Unsupervised Symmetry Group Discovery for Disentangled Representation Learning**

A total of **33 papers** were analyzed and organized into a taxonomy with **18 categories**.

Taxonomy Overview

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

- **Group-Theoretic Foundations and Theoretical Frameworks**
- **Unsupervised Learning Architectures and Algorithms**
- **Equivariance and Invariance Learning**
- **Domain-Specific Applications and Representations**
- **Specialized Representation Properties and Metrics**

Complete Taxonomy Tree

- Unsupervised Symmetry Group Discovery for Disentangled Representation Learning Survey Taxonomy
- Group-Theoretic Foundations and Theoretical Frameworks
 - Formal Definitions and Identifiability Theory ★ (3 papers)
 - [0] Disentangled representation learning through unsupervised symmetry group discovery (Anon et al., 2026) [View paper](#)
 - [7] Quantifying and learning disentangled representations with limited supervision (Loek Tonnaer, 2020) [View paper](#)
 - [28] Desiderata for Representation Learning from Identifiability, Disentanglement, and Group-Structuredness (H Keurti, n.d.) [View paper](#)
 - Group Structure Discovery and Algebra Extraction (3 papers)
 - [13] Theoretical Analysis of HyperCube Objective for Group Representation Learning (D Huh, 2025) [View paper](#)
 - [27] Algebras of actions in an agent's representations of the world (Dean Alexander, 2023) [View paper](#)
 - [29] Learning a Lie Algebra from Unlabeled Data Pairs (Christopher Ick, 2022) [View paper](#)
 - Commutative Lie Groups and Irreducible Representations (2 papers)
 - [10] Learning the irreducible representations of commutative lie groups (Cohen, 2014) [View paper](#)
 - [25] Commutative Lie Group VAE for Disentanglement Learning (Zhu Xinqi, 2021) [View paper](#)
- Unsupervised Learning Architectures and Algorithms
 - Variational Autoencoder Extensions (4 papers)
 - [2] CFASL: Composite Factor-Aligned Symmetry Learning for Disentanglement in Variational AutoEncoder (Jung, 2024) [View paper](#)
 - [3] Towards building a group-based unsupervised representation disentanglement framework (Tao Yang, 2021) [View paper](#)
 - [4] Unsupervised learning of group invariant and equivariant representations (Winter, 2022) [View paper](#)
 - [8] Unsupervised Object Representation Learning using Translation and Rotation Group Equivariant VAE (Nasiri Alireza, 2022) [View paper](#)
 - Self-Supervised and Iterative Learning Methods (2 papers)
 - [1] Self-supervised learning disentangled group representation as feature (Wang Tan, 2021) [View paper](#)
 - [11] Efficient Iterative Amortized Inference for Learning Symmetric and Disentangled Multi-Object Representations (Emami, 2021) [View paper](#)
 - Canonical Orientation and Pose Normalization (2 papers)
 - [12] RECON: Robust symmetry discovery via Explicit Canonical Orientation Normalization (Urbano Alonso, 2025) [View paper](#)
 - [22] Equivariant Representation Learning via Class-Pose Decomposition (Marchetti, 2022) [View paper](#)
 - Subspace Diffusion and Manifold Geometry Methods (2 papers)
 - [15] Unsupervised learning of equivariant structure from sequences (Miyato, 2022) [View paper](#)
 - [18] Disentangling by subspace diffusion (Pfau, 2020) [View paper](#)

- Equivariance and Invariance Learning
 - Equivariant Neural Networks with Statistical Guarantees (1 papers)
 - [9] Equivariant Representation Learning for Symmetry-Aware Inference with Guarantees (Ordoñez-Apreaz, 2025) [View paper](#)
 - Symmetry-Induced Constraints and Attention Mechanisms (3 papers)
 - [5] Symmetry-induced disentanglement on graphs (G Mercatali, 2022) [View paper](#)
 - [23] Developmental Symmetry-Loss: A Free-Energy Perspective on Brain-Inspired Invariance Learning (D'Ágostino, 2025) [View paper](#)
 - [24] Partial Symmetry Enforced Attention Decomposition (PSEAD): A Group-Theoretic Framework for Equivariant Transformers in Biological Systems (Olanrewaju, 2025) [View paper](#)
 - Sequence-Based and Temporal Equivariance (1 papers)
 - [17] Learning Group Structure and Disentangled Representations of Dynamical Environments (Quessard, 2020) [View paper](#)
- Domain-Specific Applications and Representations
 - Graph and Network Representations (1 papers)
 - [16] A Neighbor-Induced Graph Convolution Network for Undirected Weighted Network Representation (Jiufang Chen, 2023) [View paper](#)
 - Physical and Scientific Imaging (1 papers)
 - [14] Physics and chemistry from parsimonious representations: image analysis via invariant variational autoencoders (Mani Valletti, 2023) [View paper](#)
 - 3D Shape Analysis and Chirality (1 papers)
 - [20] Symmetry Understanding of 3D Shapes via Chirality Disentanglement (Wang, 2025) [View paper](#)
 - Robotics and Skill Discovery (1 papers)
 - [6] Divide, Discover, Deploy: Factorized Skill Learning with Symmetry and Style Priors (Mittal, 2025) [View paper](#)
 - Reinforcement Learning and World Models (1 papers)
 - [26] Learning Abstract World Models with a Group-Structured Latent Space (Thomas Delliaux, 2025) [View paper](#)
- Specialized Representation Properties and Metrics
 - Linear Disentanglement and Action Estimation (2 papers)
 - [19] Linear disentangled representations and unsupervised action estimation (Matthew A. Painter, 2020) [View paper](#)
 - [21] On the learning and structure of symmetry based disentangled representations (Painter, 2022)
 - Consistency and Symmetry Representation Alignment (2 papers)
 - [31] Learning Disentanglement in Autoencoders through Euler Encoding (J Cha, n.d.) [View paper](#)
 - [32] Consistent Symmetry Representation over Latent Factors of Variation (HJ Jung, n.d.) [View paper](#)
 - Quantum Information and Density Matrix Approaches (2 papers)
 - [30] Classification of two-particle quantum channels of information transfer (Usenko Constantin V., 2007) [View paper](#)
 - [33] Classification of quantum channels of information transfer (Usenko Constantin V., 2007) [View paper](#)

Narrative

Core task: Unsupervised symmetry group discovery for disentangled representation learning. This field seeks to learn interpretable latent representations by identifying and exploiting the underlying symmetry structures in data without manual supervision. The taxonomy reveals a landscape organized around several complementary perspectives. Group-Theoretic Foundations and Theoretical Frameworks establish the mathematical underpinnings, addressing questions of identifiability and formal definitions that determine when and how symmetries can be provably recovered. Unsupervised Learning Architectures and Algorithms develop practical methods—ranging from variational autoencoders to novel training objectives—that can discover group structure from raw observations. Equivariance and Invariance Learning focuses on building models that respect or exploit known or learned symmetries through architectural constraints. Domain-Specific Applications and Representations explore how these principles apply to concrete settings like robotics, molecular chemistry, or visual scenes, while Specialized Representation Properties and Metrics provide tools to evaluate and characterize the quality of learned disentanglements.

Several active lines of work reveal key trade-offs between theoretical guarantees and practical flexibility. Some approaches, such as Disentangled Group Representation[1] and Group-Based Disentanglement Framework[3], emphasize explicit group-theoretic structures and provable identifiability conditions, often requiring strong assumptions about data generation. Others, like CFASL[2] and Symmetry-Induced Disentanglement Graphs[5], pursue more flexible discovery mechanisms that can handle complex or partially observable symmetries. Symmetry Group Discovery[0] sits within the theoretical foundations branch, closely aligned with works like Limited Supervision Disentanglement[7] and Identifiability Disentanglement Desiderata[28], which rigorously examine when unsupervised methods can uniquely recover ground-truth factors. Compared to neighboring efforts, Symmetry Group Discovery[0] places particular emphasis on formal identifiability theory, contrasting with more algorithm-focused contributions that prioritize empirical performance over theoretical completeness. This positioning reflects an ongoing tension in the field between establishing rigorous guarantees and developing broadly applicable learning systems.

Related Works in Same Category

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

1. Quantifying and learning disentangled representations with limited supervision

Authors: Loek Tonnaer, Luis A. Páez-Rey, Vlado Menkovski, Mike Holenderski, Jacobus W. Portegies | **Year/Venue:** 2020 | **URL:** [View paper](#)

Abstract

Learning low-dimensional representations that disentangle the underlying factors of variation in data has been posited as an important step towards interpretable machine learning with good generalization. To address the fact that there is no consensus on what disentanglement entails, Higgins et al. (2018) propose a formal definition for Linear Symmetry-Based Disentanglement, or LSB, arguing that underlying real-world transformations give exploitable structure to data. Although several works foc...

Relationship Analysis

Both papers belong to the Formal Definitions and Identifiability Theory category, focusing on proving identifiability conditions for disentangled representations under group actions. They overlap in addressing Linear Symmetry-Based Disentanglement (LSB) frameworks and establishing theoretical guarantees for when disentangled representations can be recovered from data. The original paper proves identifiability of symmetry group decomposition from transitions and derives algorithms for unsupervised group discovery, while the candidate paper focuses on quantifying LSB through a metric and learning representations with limited supervision on transformations, assuming the group structure is already known.

2. Desiderata for Representation Learning from Identifiability, Disentanglement, and Group-Structuredness

Authors: H Keurti, P Reizinger, B Schäflkopf, W Brendel | URL: [View paper](#)

Abstract

in the unsupervised learning of disentangled representations. The structure of the latent space and the symmetry group is. Ie, disentangled representations are non-unique since the

Relationship Analysis

Both papers belong to the Formal Definitions and Identifiability Theory category, addressing theoretical foundations for disentangled representations under group actions. The candidate paper provides a theoretical analysis of the shortcomings and relationships between identifiability, disentanglement, and group-structured representations, proposing equivalence classes for group-structured representations. In contrast, the original paper focuses on proving identifiability of symmetry group decomposition from transition data and derives practical algorithms for unsupervised discovery of group structure and learning LSBSD representations without prior knowledge of subgroup properties.

Contributions Analysis

Overall novelty summary. The paper contributes an identifiability proof for symmetry group decomposition, an algorithm for discovering this decomposition from interaction data, and a novel LSBSD representation learning method that removes restrictive subgroup assumptions. It resides in the 'Formal Definitions and Identifiability Theory' leaf alongside two sibling papers (9488b7d948f6955491a468d8eade44d1, 60c806e98df2456a2fd937bb45f95453), forming a small cluster of three papers within the broader 'Group-Theoretic Foundations and Theoretical Frameworks' branch. This leaf represents a relatively sparse research direction focused on theoretical guarantees rather than algorithmic implementation, suggesting the work addresses foundational questions in a less crowded theoretical niche.

The taxonomy tree reveals neighboring leaves addressing 'Group Structure Discovery and Algebra Extraction' (three papers) and 'Commutative Lie Groups and Irreducible Representations' (two papers), both within the same parent branch. These adjacent directions focus on discovering group structure from data and handling specific commutative group cases, respectively. The paper's emphasis on autonomous discovery without prior group knowledge connects it to the structure discovery leaf, while its identifiability proofs align with the formal definitions focus of its own leaf. The broader taxonomy shows substantial activity in 'Unsupervised Learning Architectures and Algorithms' (ten papers across four leaves), indicating that while theoretical foundations remain sparse, practical implementation methods dominate the field's attention.

Among thirty candidates examined through semantic search, none were found to clearly refute any of the three contributions. The identifiability proof examined ten candidates with zero refutable matches, the discovery algorithm examined ten with zero refutable matches, and the LSBSD method examined ten with zero refutable matches. This suggests that within the limited search scope, the combination of autonomous group discovery, formal identifiability guarantees, and assumption-free LSBSD learning appears relatively novel. However, the analysis explicitly covers only top-K semantic matches and does not represent an exhaustive literature review, leaving open the possibility of relevant prior work outside this search radius.

Based on the limited search scope of thirty semantically similar papers, the work appears to occupy a distinctive position combining theoretical rigor with practical discovery algorithms. The sparse population of its taxonomy leaf (three papers total) and the absence of refuting candidates among examined works suggest meaningful novelty, though this assessment is constrained by the non-exhaustive search methodology. The paper's removal of strong prior assumptions distinguishes it from sibling works in formal identifiability theory, which typically require more restrictive conditions.

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

Contribution 1: Identifiability proof for symmetry group decomposition

Description: The authors establish theoretical guarantees that the true decomposition of the symmetry group into subgroups can be uniquely recovered from transition data, given minimal assumptions about the environment and action 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. The International Tables Symmetry Database

URL: [View paper](#)

Brief Assessment

The International Tables Symmetry Database[47] is a crystallographic database for space-group and point-group symmetry information, not a machine learning framework for discovering symmetry groups from transition data in reinforcement learning environments.

2. Operator algebras and quantum statistical mechanics: Volume 1: C-and W-Algebras. Symmetry Groups. Decomposition of States

URL: [View paper](#)

Brief Assessment

The candidate paper (Operator Algebras Quantum[48]) focuses on C-algebras and W-algebras in quantum statistical mechanics, not on symmetry group decomposition from transition data in reinforcement learning contexts.

3. Phase diagram of extensive-rank symmetric matrix denoising beyond rotational invariance

URL: [View paper](#)

Brief Assessment

Extensive-Rank Matrix Denoising[44] addresses Bayesian matrix denoising with factorized structures and rotational invariance properties, focusing on mean-field techniques and phase transitions. This is fundamentally different from proving identifiability of symmetry group decomposition from transition data in reinforcement learning environments.

4. Excited state symmetry assignment through polarized two-photon absorption studies of fluids

URL: [View paper](#)

Brief Assessment

Polarized Two-Photon Absorption[53] focuses on molecular symmetry assignment through two-photon spectroscopy in fluids, not on identifiability of symmetry group decomposition from transition data in reinforcement learning contexts.

5. Homomorphism Autoencoder-Learning Group Structured Representations from Interactions

URL: [View paper](#)

Brief Assessment

Homomorphism Autoencoder[49] focuses on learning group representations through homomorphism properties using 2-step transitions, but does not address the identifiability of symmetry group decomposition from transition data, which is the core theoretical contribution of the original paper.

6. Structuring representations using group invariants

URL: [View paper](#)

Brief Assessment

Group Invariants Structuring[46] focuses on using group invariants to regularize representations toward simple linear actions, not on proving identifiability of symmetry group decomposition from transition data. The paper does not address the theoretical guarantees for recovering group decomposition structure.

7. Self-supervised latent symmetry discovery via class-pose decomposition

URL: [View paper](#)

Brief Assessment

Latent Symmetry Discovery[45] focuses on identifying conjugate group representations from uniform motion sequences, not on decomposing symmetry groups into subgroups from transition data as in the original paper.

8. Abrupt symmetry-preserving transition from the chimera state.

URL: [View paper](#)

Brief Assessment

The candidate paper (Chimera State Transition[51]) focuses on abrupt symmetry-preserving transitions in chimera states, which is a completely different domain from symmetry group decomposition in representation learning. No relevant content was found in the provided context.

9. Nature of Symmetry Breaking at the Excitonic Insulator Transition: Ta₂NiSe₅.

URL: [View paper](#)

Brief Assessment

Excitonic Insulator Transition[50] focuses on symmetry breaking in excitonic phase transitions in solid-state materials (specifically Ta₂NiSe₅), not on identifiability of symmetry group decomposition from transition data in reinforcement learning contexts.

10. Learning finite symmetry groups of dynamical systems via equivariance detection

URL: [View paper](#)

Brief Assessment

Equivariance Detection Learning[52] focuses on discovering finite symmetry groups in dynamical systems through equivariance detection, not on proving identifiability of symmetry group decomposition from transition data in reinforcement learning environments.

Contribution 2: Algorithm for discovering symmetry group decomposition

Description: The authors develop a practical clustering algorithm that autonomously discovers how the symmetry group decomposes into subgroups by analyzing action representations learned from environment interactions, without requiring prior knowledge of the group structure.

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. ci-fGBD: Cluster-Integrated Fast Generalized Bruhat Decomposition for Multimodal Data Clustering in Alzheimer's Disease.

URL: [View paper](#)

Brief Assessment

ci-fGBD[61] focuses on multimodal data clustering in Alzheimer's Disease using Bruhat decomposition, which is a completely different domain and methodology from discovering symmetry group decomposition through reinforcement learning interactions.

2. Group Crosscoders for Mechanistic Analysis of Symmetry

URL: [View paper](#)

Brief Assessment

Group Crosscoders[54] focuses on discovering symmetrical features in neural network representations through dictionary learning, not on discovering symmetry group decomposition from environment interactions as in the original paper.

3. Non-negative matrix factorization revisited: Uniqueness and algorithm for symmetric decomposition

URL: [View paper](#)

Brief Assessment

Symmetric NMF Uniqueness[58] focuses on matrix factorization uniqueness conditions and algorithms for symmetric decomposition, not on discovering symmetry group decompositions from environment interactions in reinforcement learning contexts.

4. A group-theoretic approach to computational abstraction: Symmetry-driven hierarchical clustering

URL: [View paper](#)

Brief Assessment

Symmetry-Driven Hierarchical Clustering[55] focuses on computational abstraction via group-theoretic clustering of data spaces, not on discovering symmetry group decompositions from learned action representations in reinforcement learning environments.

5. Clustering group-sparse mode decomposition and its application in rolling bearing fault diagnosis

URL: [View paper](#)

Brief Assessment

Group-Sparse Mode Decomposition[60] focuses on signal decomposition for bearing fault diagnosis using clustering to group intrinsic mode functions, not on discovering symmetry group decompositions in reinforcement learning environments through action representations.

6. SYMMOL: a program to find the maximum symmetry group in an atom cluster, given a prefixed tolerance

URL: [View paper](#)

Brief Assessment

SYMMOL[63] addresses molecular symmetry detection in crystallography, not autonomous discovery of symmetry group decomposition through clustering of learned action representations in reinforcement learning environments. The candidate focuses on finding maximum symmetry groups in atom clusters given coordinates and tolerance, while the original develops algorithms for discovering group structure from environment interactions without prior knowledge.

7. The impact of graph symmetry on clustering

URL: [View paper](#)

Brief Assessment

Graph Symmetry Clustering[62] focuses on analyzing the impact of graph automorphism groups on modularity-based clustering partitions in network analysis, not on discovering symmetry group decompositions through action representations in reinforcement learning environments.

8. Non-negative matrix factorization for semi-supervised data clustering

URL: [View paper](#)

Brief Assessment

Semi-Supervised NMF Clustering[59] focuses on semi-supervised data clustering using non-negative matrix factorization with pairwise constraints, not on discovering symmetry group decompositions in reinforcement learning environments.

9. A factorization approach to grouping

URL: [View paper](#)

Brief Assessment

Factorization Grouping Approach[57] addresses visual grouping through affinity matrix factorization for scene segmentation, not symmetry group decomposition in action spaces for disentangled representation learning.

10. Quasifibrations of graphs to find symmetries and reconstruct biological networks

URL: [View paper](#)

Brief Assessment

Quasifibrations Symmetries[56] focuses on graph fibrations to identify symmetries in biological networks through clustering nodes with similar connectivity patterns, not on discovering symmetry group decomposition in reinforcement learning environments through action representations.

Contribution 3: Novel LSBDD representation learning method without structural assumptions

Description: The authors propose GMA-VAE, a new approach for learning Linear Symmetry-Based Disentangled representations that does not require prior knowledge about subgroup properties or structure, accompanied by theoretical disentanglement guarantees.

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. F-3DGS: Factorized Coordinates and Representations for 3D Gaussian Splatting

URL: [View paper](#)

Brief Assessment

F-3DGS[36] addresses 3D scene representation and storage optimization for Gaussian splatting, not disentangled representation learning or group decomposition. The candidate focuses on factorization techniques for reducing storage costs in 3D rendering, which is an entirely different domain from learning symmetry-based disentangled representations without structural assumptions.

2. Local Geometry Determines Global Landscape in Low-rank Factorization for Synchronization

URL: [View paper](#)

Brief Assessment

The candidate paper addresses orthogonal group synchronization and low-rank factorization for semidefinite programming, which is fundamentally different from learning disentangled representations through symmetry group discovery. The technical domains do not overlap.

3. Nonnegative Matrix Functional Factorization for Hyperspectral Unmixing With Nonuniform Spectral Sampling

URL: [View paper](#)

Brief Assessment

Nonnegative Matrix Functional[42] addresses hyperspectral unmixing using implicit neural representations for endmember learning, which is fundamentally different from the ORIGINAL paper's focus on learning disentangled representations through symmetry group discovery in reinforcement learning environments.

4. Towards a definition of disentangled representations

URL: [View paper](#)

Brief Assessment

Disentangled Representations Definition[41] focuses on defining disentangled representations through symmetry transformations and group theory, without providing algorithmic methods for learning such representations. The original paper proposes GMA-VAE, a specific algorithm for learning LSBDD representations without structural assumptions.

5. Ref-GS: Directional Factorization for 2D Gaussian Splatting

URL: [View paper](#)

Brief Assessment

Ref-GS[37] focuses on directional light factorization and geometry recovery in 3D rendering using Gaussian splatting, not on learning disentangled representations from group decomposition or symmetry-based methods.

6. Higher order tensor factorizations for block encoding vibrational and vibronic Hamiltonians

URL: [View paper](#)

Brief Assessment

Tensor Factorizations Hamiltonians[34] focuses on quantum computing methods for vibrational/vibronic Hamiltonians using tensor decompositions (CP and Tucker), not on learning disentangled representations from group decomposition in machine learning contexts.

7. Identifying Interpretable Latent Factors with Sparse Component Analysis

URL: [View paper](#)

Brief Assessment

Sparse Component Analysis[38] focuses on identifying sparse, orthogonal latent factors from neural activity data in an unsupervised manner, without leveraging group structure or symmetries. The original paper's GMA-VAE specifically exploits symmetry group decomposition for disentanglement, which is a fundamentally different approach.

8. Group-based learning of disentangled representations with generalizability for novel contents

URL: [View paper](#)

Brief Assessment

Group-Based Novel Contents[35] focuses on learning disentangled representations from grouped data (e.g., multiple images of the same face with different poses) without requiring explicit labels, but does not address symmetry-based disentanglement or group decomposition discovery from action spaces as in the original paper.

9. Factorized diffusion autoencoder for unsupervised disentangled representation learning

URL: [View paper](#)

Brief Assessment

Factorized Diffusion Autoencoder[43] focuses on visual interpretability through content-mask factorization for disentanglement, not on learning representations from group decomposition or symmetry-based approaches without structural assumptions.

10. FactoFormer: Factorized Hyperspectral Transformers With Self-Supervised Pretraining

URL: [View paper](#)

Brief Assessment

FactoFormer[39] focuses on factorized transformers for hyperspectral image classification with self-supervised pretraining, not on learning disentangled representations from group decomposition or symmetry-based approaches.

Appendix: Text Similarity Detection

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

References

- [0] Disentangled representation learning through unsupervised symmetry group discovery [View paper](#)
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