Novelty Assessment Report

Paper: Directed Semi-Simplicial Learning with Applications to Brain Activity Decoding

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Abstract

Graph Neural Networks (GNNs) excel at learning from pairwise interactions but often overlook multi-way and hierarchical relationships. Topological Deep Learning (TDL) addresses this limitation by leveraging combinatorial topological spaces, such as simplicial or cell complexes. However, existing TDL models are restricted to undirected settings and fail to capture the higher-order directed patterns prevalent in many complex systems, e.g., brain networks, where such interactions are both abundant and functionally significant. To fill this gap, we introduce Semi-Simplicial Neural Networks (SSNs), a principled class of TDL models that operate on semi-simplicial sets---combinatorial structures that encode directed higher-order motifs and their directional relationships. To enhance scalability, we propose Routing-SSNs, which dynamically select the most informative relations in a learnable manner. We theoretically characterize SSNs by proving they are strictly more expressive than standard graph and TDL models, and they are able to recover several topological descriptors. Building on previous evidence that such descriptors are critical for characterizing brain activity, we then introduce a new principled framework for brain dynamics representation learning centered on SSNs. Empirically, we test SSNs on 4 distinct tasks across 13 datasets, spanning from brain dynamics to node classification, showing competitive performance. Notably, SSNs consistently achieve state-of-the-art performance on brain dynamics classification tasks, outperforming the second-best model by up to 27\%, and message passing GNNs by up to 50\% in accuracy. Our results highlight the potential of topological models for learning from structured brain data, establishing a unique real-world case study for TDL. Code and data are uploaded as supplementary material.

Core Task Landscape

This paper addresses: **Learning from Directed Higher-Order Structures in Brain Networks**

A total of **26 papers** were analyzed and organized into a taxonomy with **15 categories**.

Taxonomy Overview

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

- **Directed Higher-Order Topological Frameworks**
- **Brain Network Analysis and Neuroimaging Applications**
- **Knowledge Graph Completion and Temporal Reasoning**
- **General Graph Neural Network Architectures**
- **Specialized Network Learning Paradigms**

Complete Taxonomy Tree

- Learning from Directed Higher-Order Structures in Brain Networks Survey Taxonomy
- Directed Higher-Order Topological Frameworks
  - Directed Simplicial and Semi-Simplicial Methods ★ (3 papers)
  - [0] Directed Semi-Simplicial Learning with Applications to Brain Activity Decoding (Anon et al., 2026) View paper
  - [13] Higher-Order Topological Directionality and Directed Simplicial Neural Networks (Manuel Lecha, 2025) View paper
  - [18] Towards a Quantitative Theory of Digraph-Based Complexes and its Applications in Brain Network Analysis (Heitor Baldo, 2024) View paper
  - Directed Hypergraph Neural Networks (2 papers)
  - [19] Constructing Effective Hyper-Connectivity Networks through Adaptive Directed Hypergraph Embedded Dictionary Learning: Application to Early Mild Cognitive Impairment Detection. (Lan Yang, 2025) View paper
  - [21] Topological cluster synchronization via Dirac spectral programming on directed hypergraphs (Yupeng Guo, 2025) View paper
  - Topological Spectral and Clustering Methods (2 papers)
  - [17] Tensor Spectral Clustering for Partitioning Higher-order Network Structures (Austin R. Benson, 2015) View paper
  - [22] Enhancing Ensemble Clustering with Adaptive High-Order Topological Weights (Jiaxuan Xu, 2024) View paper
- Brain Network Analysis and Neuroimaging Applications
  - Brain Functional Connectivity and Disorder Classification (3 papers)
  - [1] Spatial Craving Patterns in Marijuana Users: Insights From fMRI Brain Connectivity Analysis With High-Order Graph Attention Neural Networks (Jun-En Ding, 2024) View paper
  - [7] A triple-pooling graph neural network for multi-scale topological learning of brain functional connectivity: Application to ASD diagnosis (Zhiyuan Zhu, 2021) View paper
  - [8] MHNet: Multi-view High-Order Network for Diagnosing Neurodevelopmental Disorders Using Resting-State fMRI (Yueyang Li, 2024) View paper
  - Structural-Functional Connectivity Integration (2 papers)
  - [3] : A Neural Pathway Transformer for Joining the Dots of Human Connectomes (Z Wei, 2024) View paper
  - [24] NeuroPath: A Neural Pathway Transformer for Joining the Dots of Human Connectomes (Wei, 2024) View paper
  - EEG Graph Analysis and Emotion Recognition (1 papers)

- [14] Granger-Causality-Based Multi-Frequency Band EEG Graph Feature Extraction and Fusion for Emotion Recognition (Jing Zhang, 2022) View paper
- Knowledge Graph Completion and Temporal Reasoning
  - Temporal Knowledge Graph Prediction (2 papers)
  - [2] DHyper: A Recurrent Dual Hypergraph Neural Network for Event Prediction in Temporal Knowledge Graphs (Xing Tang, 2024) View paper
  - [5] Enhanced Temporal Knowledge Graph Completion via Learning High-Order Connectivity and Attribute Information (Minwei Wen, 2023) View paper
  - High-Order Connectivity for Knowledge Graph Embedding (2 papers)
  - [10] High-Order Neighbors Aware Representation Learning for Knowledge Graph Completion (Hong Yin, 2024) View paper
  - [11] Enhanced Knowledge Graph Embedding for Multi-Task Recommendation via Integrating Attribute Information and High-Order Connectivity (Yani Wang, 2021) View paper
  - Knowledge Graph-Enhanced Recommendation (1 papers)
  - [16] Interpretable High-order Knowledge Graph Neural Network for Predicting Synthetic Lethality in Human Cancers (Xuexin. Chen, 2025) View paper
- General Graph Neural Network Architectures
  - Topological and Higher-Order GNN Architectures (2 papers)
  - [6] Topological Neural Networks: Mitigating the Bottlenecks of Graph Neural Networks via Higher-Order Interactions (Giusti, 2024) View paper
  - [26] ATPGNN: Reconstruction of Neighborhood in Graph Neural Networks With Attention-Based Topological Patterns (Kehao Wang, 2021) View paper
  - Hypergraph Neural Network Distillation and Efficiency (1 papers)
  - [9] LightHGNN: Distilling hypergraph neural networks into MLPs for 100x faster inference (Y Feng, 2024) View paper
  - Subgraph Pattern and Dynamic Graph Learning (2 papers)
  - [12] Subgraph pattern neural networks for high-order graph evolution prediction (Changping Meng, 2018) View paper
  - [23] TMetaNet: Topological Meta-Learning Framework for Dynamic Link Prediction (Li Hao, 2025) View paper
- Specialized Network Learning Paradigms
  - Federated and Multiplex Heterogeneous Graph Learning (2 papers)
  - [4] Horizontal Federated Heterogeneous Graph Learning: A Multi-Scale Adaptive Solution to Data Distribution Challenges (Jia Wang, 2025) View paper
  - [20] Multiplex Network Embedding Model with Highâ□□Order Node Dependence (Nianwen Ning, 2021) View paper
  - Synchronization in Fractional Higher-Order Networks (1 papers)
  - [15] Synchronization of Short-Memory Fractional Directed Higher-Order Networks (Xiaoqin Wang, 2025) View paper
  - Hierarchical Neural Models with Asymmetric Structures (1 papers)
  - [25] Axon shape as a basis for multinode functional units in a hierarchical neural model (James L. Eilbert, 1988) View paper

Narrative

Core task: learning from directed higher-order structures in brain networks. The field has evolved to address the challenge that traditional graph models often overlook the directional and multi-way interactions inherent in neural connectivity. The taxonomy reflects this evolution through several main branches. Directed Higher-Order Topological Frameworks develop mathematical formalisms—such as simplicial and semi-simplicial complexes—that explicitly encode directional flow and higher-order dependencies, as seen in works like Higher-Order Topological Directionality[13] and Digraph-Based Complexes[18]. Brain Network Analysis and Neuroimaging Applications focus on translating these abstractions into practical tools for understanding neural pathways and cognitive states, exemplified by Neural Pathway Transformer[3] and Spatial Craving Patterns[1]. Meanwhile, Knowledge Graph Completion and Temporal Reasoning, General Graph Neural Network Architectures, and Specialized Network Learning Paradigms address complementary challenges—ranging from temporal dynamics and heterogeneous data integration to scalable message-passing schemes—that arise when modeling complex relational structures beyond the brain.

A particularly active line of work centers on extending classical topological methods to capture directional flows in simplicial structures, where the interplay between algebraic topology and neural computation remains an open question. Directed Semi-Simplicial Learning[0] sits squarely within this cluster, proposing a framework that generalizes semi-simplicial complexes to directed settings. It shares conceptual ground with Higher-Order Topological Directionality[13], which also emphasizes directional higher-order features, and with Digraph-Based Complexes[18], which explores alternative combinatorial constructions for directed graphs. The main trade-off across these approaches involves balancing expressive power—capturing intricate directional motifs—against computational tractability and interpretability in neuroimaging contexts. While some methods prioritize rigorous topological guarantees, others lean toward flexible neural architectures that can adapt to heterogeneous brain data, leaving the optimal synthesis of theory and practice an ongoing area of exploration.

Related Works in Same Category

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

1. Higher-Order Topological Directionality and Directed Simplicial Neural Networks

Authors: Manuel Lecha, Andrea Cavallo, M. Lecha, Francesca Dominici, Elvin Isufi, et al. (6 authors total) | **Year/Venue**: 2025 | **URL**: View paper

Abstract

Topological Deep Learning (TDL) has emerged as a paradigm to process and learn from signals defined on higher-order combinatorial topological spaces, such as simplicial or cell complexes. Although many complex systems have an asymmetric relational structure, most TDL models forcibly symmetrize these relationships. In this paper, we first introduce a novel notion of higher-order directionality and we then design Directed Simplicial Neural Networks (Dir-SNNs) based on it. Dir-SNNs are message-pass...

Relationship Analysis

Both papers belong to the Directed Simplicial and Semi-Simplicial Methods category, developing message-passing neural networks for directed higher-order structures in brain networks. The candidate paper (Dir-SNNs) introduces a notion of higher-order directionality and operates on directed simplicial complexes, while the original paper (SSNs) extends this to the more general semi-simplicial sets with face-map-induced relations and includes a learnable routing mechanism (R-SSNs) for scalability. The key difference is that SSNs operate on a broader class of topological spaces (semi-simplicial sets vs. directed simplicial complexes only) and provide a comprehensive framework specifically designed for brain dynamics classification with dynamical activity complexes (DACs), whereas Dir-SNNs focus on foundational expressivity results and synthetic validation.

2. Towards a Quantitative Theory of Digraph-Based Complexes and its Applications in Brain Network Analysis

Authors: Heitor Baldo | **Year/Venue**: 2024 | **URL**: View paper

Abstract

In this work, we developed new mathematical methods for analyzing network topology and applied these methods to the analysis of brain networks. More specifically, we rigorously developed quantitative methods based on complexes constructed from digraphs (digraph-based complexes), such as path complexes and directed clique complexes (alternatively, we refer to these complexes as"higher-order structures,"or"higher-order topologies,"or"simplicial structures"), and, in the case of directed clique com...

Relationship Analysis

Both papers belong to the Directed Simplicial and Semi-Simplicial Methods category, focusing on learning from directed higher-order structures in brain networks using directed simplicial complexes and related topological frameworks. They overlap in applying directed clique complexes to brain connectivity analysis and leveraging topological invariants to characterize neural activity patterns. However, the original paper introduces Semi-Simplicial Neural Networks (SSNs) as end-to-end learnable architectures with theoretical expressivity guarantees and dynamic routing mechanisms, while the candidate paper develops a quantitative mathematical theory for digraph-based complexes with characterization and similarity measures applied to EEG-based epilepsy biomarker discovery, without proposing neural network architectures.

Contributions Analysis

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

Contribution 1: Semi-Simplicial Neural Networks (SSNs)

Description: The authors propose SSNs, a novel class of Topological Deep Learning architectures that operate on semi-simplicial sets and leverage face-map–induced relations to capture directed higher-order motifs. They prove SSNs are strictly more expressive than message-passing GNNs, Directed GNNs, and Message-Passing Simplicial Neural Networks in the Weisfeiler-Leman hierarchy.

This contribution was assessed against **2 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Higher-Order Topological Directionality and Directed Simplicial Neural Networks

URL: View paper

Prior Art Analysis

Higher-Order Topological Directionality[13] demonstrates prior work on neural networks operating on directed simplicial complexes that leverage directed higher-order structures. The candidate paper introduces directed simplicial neural networks (dir-snns) as message-passing networks on directed simplicial complexes, predating the original paper's SSN proposal. Both works address the same fundamental problem of processing directed higher-order topological structures through neural architectures, with the candidate explicitly stating it is 'the first tdl model using a notion of higher-order directionality.' The candidate also proves expressivity results comparing their model to directed graph neural networks, similar to the original paper's theoretical contributions.

Evidence

Evidence 1 - **Rationale**: Both papers claim to introduce the first TDL models for directed higher-order structures. The candidate explicitly states dir-snns are 'the first tdl model using a notion of higher-order directionality,' which directly challenges the original paper's novelty claim of introducing 'the first tdl models explicitly designed for semi-simplicial sets' that operate on directed higher-order structures. - **Original**: we introduce semi-simplicial neural networks (ssns), the first tdl models explicitly designed for semi-simplicial sets. the rich variety of ways ssns propagate information across simplices is formalized via face-map-induced relations collected in a relational algebra and generalizing common (directe... - **Candidate**: we first introduce a novel notion of higher-order directionality and we then design directed simplicial neural networks (dir-snns) based on it. dir-snns are message-passing networks operating on directed simplicial complexes able to leverage directed and possibly asymmetric interactions among the si...

Evidence 2 - **Rationale**: Both papers provide theoretical expressivity results for their respective architectures operating on directed higher-order structures, comparing against directed graph neural networks. This demonstrates that similar theoretical characterizations of expressivity for directed topological neural networks existed prior to the original paper. - **Original**: we prove that ssns are strictly more expressive than message-passing gnns (gilmer et al., 2017), directed gnns (dirgnns) (rossi et al., 2024), and message-passing simplicial neural networks (mpsnns) (bodnar et al., 2021b) in the wl hierarchy - **Candidate**: we theoretically and empirically prove that dir-snns are more expressive than their directed graph counterpart in distinguishing non-isomorphic directed graphs.

2. Simplicial Methods in Graph Machine Learning

URL: View paper

Brief Assessment

Simplicial Methods[27] focuses on algorithms for identifying simplices in graphs and message propagation methods, not on proposing a novel neural network architecture operating on semi-simplicial sets with face-map-induced relations and proven WL-expressivity guarantees.

Contribution 2: Topology-grounded framework for brain dynamics representation learning

Description: The authors introduce Dynamical Activity Complexes (DACs), which are directed simplicial complexes with time-evolving binary features encoding neuronal co-activation. They formally prove that SSNs operating on DACs can recover a broader class of topological invariants known to characterize brain network activity, which existing graph and TDL models cannot.

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. Principled simplicial neural networks for trajectory prediction

URL: View paper

Brief Assessment

Principled Simplicial Neural[43] focuses on trajectory prediction over simplicial complexes with emphasis on permutation and orientation equivariance properties. It does not address brain dynamics, neuronal co-activation patterns, or the specific topological invariants (Dynamical Activity Complexes) that characterize brain network activity as claimed in the original contribution.

2. Multiscale Simplicial Complex Entropy Analysis of Heartbeat Dynamics

URL: View paper

Brief Assessment

Multiscale Simplicial Entropy[38] focuses on cardiac interbeat time series analysis using simplicial complex approximate entropy, not brain dynamics or neuronal co-activation patterns. The domains and applications are fundamentally different.

3. Simplicial and topological descriptions of human brain dynamics

URL: View paper

Brief Assessment

Simplicial Topological Brain[47] focuses on topological data analysis methods for distinguishing brain states from fMRI data, not on learning representations via neural networks operating on directed simplicial complexes encoding neuronal co-activation patterns.

4. Directed simplicial complexes in brain real-world networks

URL: View paper

Brief Assessment

Directed Simplicial Brain[40] focuses on structural brain network topology using directed simplicial complexes, but does not address dynamical representation learning or time-evolving neuronal co-activation patterns as formalized in the original paper's DAC framework.

5. Simplicial complexes: higher-order spectral dimension and dynamics

URL: View paper

Brief Assessment

Simplicial Spectral Dimension[41] focuses on spectral properties of higher-order Laplacians and diffusion dynamics on simplicial complexes in general network models. It does not address representation learning, neural network architectures, or brain activity decoding tasks that are central to the original paper's contribution.

6. Neurospectrum: A Geometric and Topological Deep Learning Framework for Uncovering Spatiotemporal Signatures in Neural Activity

URL: View paper

Brief Assessment

Neurospectrum[44] focuses on encoding neural activity as latent trajectories using graph wavelets and manifold-regularized autoencoders with topological descriptors like persistent homology. The original paper introduces Dynamical Activity Complexes (DACs) as directed simplicial complexes with binary time-evolving features for neuronal co-activation, which is a fundamentally different topological representation approach.

7. Geometric and topological inference for deep representations of complex networks

URL: View paper

Brief Assessment

Geometric Topological Inference[45] focuses on topological data analysis methods for general complex networks and does not propose directed simplicial complexes or dynamical activity complexes (DACs) for brain dynamics. The candidate addresses different topological structures and application domains.

8. From Density to Void: Why Brain Networks Fail to Reveal Complex Higher-Order Structures

URL: View paper

Brief Assessment

Density to Void[46] focuses on analyzing why conventional persistent homology methods fail to reveal higher-order structures in resting-state fMRI brain networks, rather than proposing a learning framework for brain dynamics using directed simplicial complexes with time-evolving features.

9. Stability of synchronization in simplicial complexes

URL: View paper

Brief Assessment

Stability Simplicial Synchronization[42] focuses on synchronization stability in simplicial complexes with coupled dynamical systems, not on representation learning for brain dynamics or topological invariant recovery.

10. Higher-order connection Laplacians for directed simplicial complexes

URL: View paper

Brief Assessment

Higher-Order Connection Laplacians[39] focuses on connection laplacians for directed simplicial complexes and higher-order diffusion dynamics, not on representation learning for brain dynamics or neuronal co-activation patterns.

Contribution 3: Routing-SSNs for scalable relation selection

Description: The authors introduce Routing-SSNs (R-SSNs), which employ a learnable gating mechanism to dynamically select the top-k most relevant relations from predefined relation classes. This addresses scalability and efficiency by reducing parameter count and inference time while maintaining competitive performance.

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. Communication Efficient Federated Learning via Channel-wise Dynamic Pruning

URL: View paper

Brief Assessment

Channel-Wise Dynamic Pruning[32] focuses on model compression for federated learning through channel-wise parameter pruning, not on dynamic relation selection mechanisms in neural network architectures for topological or graph-structured data.

2. A new lightweight deep learning model optimized with pruning and dynamic quantization to detect freezing gait on wearable devices.

URL: View paper

Brief Assessment

The candidate paper (Lightweight Pruning Quantization[37]) focuses on lightweight deep learning models for freezing gait detection on wearable devices using pruning and quantization techniques. This is entirely unrelated to neural network architectures for relation selection or topological deep learning, operating in a completely different domain (medical wearable applications vs. graph/topological neural networks).

3. Drtr: Distance-aware graph representation learning

URL: View paper

Brief Assessment

Distance-Aware Graph[35] focuses on graph representation learning through distance-aware message passing and topology refinement, not on dynamic relation selection mechanisms for topological deep learning architectures.

4. Hybrid Dynamic Pruning: A Pathway to Efficient Transformer Inference

URL: View paper

Brief Assessment

Hybrid Dynamic Pruning[36] focuses on pruning attention mechanisms in transformers for edge deployment, not on dynamic relation selection in graph neural networks or topological deep learning frameworks.

5. Edge-side fine-grained sparse CNN accelerator with efficient dynamic pruning scheme

URL: View paper

Brief Assessment

Edge-Side Sparse CNN[28] focuses on hardware-level CNN compression and acceleration for edge devices through pruning schemes, not on learnable gating mechanisms for dynamic relation selection in neural network architectures.

6. Large Language Models Tool Retrieval and Context Compression via Dynamic Graph-Based Relation Modeling

URL: View paper

Brief Assessment

Dynamic Graph Relation[30] addresses tool retrieval in LLMs using graph neural networks for semantic tool selection, not scalable neural network architectures with dynamic relation selection for topological deep learning on semi-simplicial sets.

7. Rethinking Graph Neural Architecture Search from Message-passing

URL: View paper

Brief Assessment

Rethinking Graph Architecture[33] focuses on neural architecture search for graph neural networks with message-passing mechanisms, not on dynamic relation selection in topological deep learning frameworks. The candidate addresses a fundamentally different problem domain (graph NAS) than the original paper's semi-simplicial neural networks.

8. Reinforced neighborhood selection guided multi-relational graph neural networks

URL: View paper

Brief Assessment

Reinforced Neighborhood Selection[29] focuses on multi-relational graph neural networks with reinforcement learning for neighbor selection in heterogeneous graphs, not on topological deep learning with dynamic relation selection from predefined simplicial relation classes as in R-SSNs.

9. Communication-Efficient and Private Federated Learning with Adaptive Sparsity-Based Pruning on Edge Computing

URL: View paper

Brief Assessment

Sparsity-Based Pruning[31] focuses on federated learning with adaptive pruning for communication efficiency and privacy, not on scalable neural networks with dynamic relation selection mechanisms for topological deep learning.

10. Dynamic Relation Graph Learning for Time-Aware Service Recommendation

URL: View paper

Brief Assessment

Dynamic Relation Graph[34] addresses scalability in service recommendation through coarse-to-fine recalling strategies for graph structure learning, not neural network relation selection mechanisms. The technical domains and approaches differ fundamentally.

Appendix: Text Similarity Detection

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

References

- [0] Directed Semi-Simplicial Learning with Applications to Brain Activity Decoding View paper
- [1] Spatial Craving Patterns in Marijuana Users: Insights From fMRI Brain Connectivity Analysis With High-Order Graph Attention Neural Networks View paper
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