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Gauge-Equivariant Fourier Operators for Modular Structure Discovery in Temporal Graphs

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Abstract

The analysis of temporal graphs presents a persistent challenge in the field of network science, primarily due to the intricate interplay between evolving topologies and dynamic node features. Traditional spectral graph theories often falter when applied to time-varying domains because they inherently rely on fixed global coordinate systems, leading to misinterpretations of structural changes. To circumvent these limitations, this paper introduces the concept of Gauge-Equivariant Fourier Operators, a novel theoretical framework designed specifically for modular structure discovery in continuous-time temporal graphs. By treating temporal graphs as discrete manifolds endowed with local gauge symmetries, we define an operator that preserves the structural and functional invariants of the network irrespective of the local coordinate choices made at individual nodes. This paper establishes the conceptual foundation of these operators, translates the principles of gauge theory into algorithmic network analysis, and details a comprehensive methodology for extracting dynamic communities. Furthermore, we provide extensive empirical validation across multiple dynamic network topologies, demonstrating that our proposed framework significantly outperforms contemporary temporal clustering techniques. The findings illuminate the profound advantages of incorporating geometric deep learning principles, specifically gauge equivariance, into the spectral domain, offering a robust tool for analyzing complex adaptive systems ranging from neurobiology to social dynamics..

Keywords

Temporal Graphs, Gauge Equivariance, Spectral Theory, Modular Structure

INTRODUCTION

The study of complex systems has increasingly relied on the abstraction of temporal graphs, where both the relational ties between entities and the attributes of the entities themselves evolve over continuous or discrete time domains. Unlike static graphs, which merely provide a frozen snapshot of interactions, temporal graphs capture the rhythmic, seasonal, and spontaneous dynamics of systems ranging from global financial transaction networks to the neural circuitry of the human brain. Within these systems, discovering modular structures, commonly referred to as communities

or clusters, is paramount for understanding functional compartmentalization, hierarchical organization, and the propagation of information or contagions. The identification of these modules in a time-varying context is a non-trivial endeavor, heavily constrained by the limitations of traditional analytical paradigms which struggle to maintain structural coherence across varying temporal scales. The foundational problem lies in distinguishing genuine structural evolution from mere artifactual variations caused by changing observational perspectives [1]. When analyzing the topology of static networks, spectral graph theory has historically provided a robust mathematical foundation. By analyzing the eigenvalues and eigenvectors of graph matrices, such as the adjacency matrix or the Laplacian operator, researchers can partition graphs into cohesive modules. However, the direct extension of these spectral methods to temporal graphs introduces severe theoretical inconsistencies. Standard temporal extensions generally rely on either aggregating the graph over time windows or analyzing sequential snapshots independently. These approaches inevitably disrupt the temporal continuity of the network, leading to phenomena where nodes appear to oscillate wildly between communities simply because the spectral embedding space shifts arbitrarily between consecutive time steps. This misalignment is essentially a coordinate system problem [2]. In geometric terms, the spectral embedding of a graph at any given time depends on an arbitrary choice of basis, and without a mathematically rigorous way to align these bases across time, tracking dynamic modular structures becomes inherently flawed [3].

To conceptualize and resolve this issue, we turn to the principles of gauge theory, a framework originally developed in theoretical physics to ensure that fundamental physical laws remain invariant under local coordinate transformations. In the context of temporal graphs, a gauge represents the local choice of a coordinate frame for the feature space of a specific node at a specific point in time. Because the underlying relational dynamics of the graph should not depend on how an external observer chooses to measure or represent node features, the analytical operators used to discover modular structures must be gauge-equivariant [4]. This means that if the local coordinate system undergoes a transformation, the output of the operator should undergo a corresponding, predictable transformation, preserving the underlying structural semantics. This paper bridges the gap between differential geometry and temporal network science by proposing Gauge-Equivariant Fourier Operators. The core contribution of this work is the formulation of a Fourier transform specifically designed for temporal graph manifolds that inherently respects local gauge symmetries. By utilizing a connection formulation analogous to parallel transport in Riemannian geometry, we construct a temporal graph Laplacian that aligns the feature spaces of adjacent nodes across both spatial edges and temporal transitions. This gauge-equivariant Laplacian serves as the generator for our novel Fourier operators. When applied to the problem of modular structure discovery, these operators produce spectral embeddings that are smoothly contiguous over time, entirely eliminating the artifactual community switching prevalent in standard snapshot-based spectral clustering. Consequently, the modular structures extracted represent the true topological evolution of the system. Through this extensive exploration, we aim to redefine the methodological approach to dynamic community detection. The subsequent sections will detail the historical context of temporal graph analysis and spectral geometry, providing a solid theoretical foundation. Following this, we meticulously outline the construction of the Gauge-Equivariant Fourier Operators and the specific protocol for dynamic module extraction without relying on conventional algebraic notation, instead focusing on the profound geometric intuition underlying the framework. Finally, we present a rigorous empirical analysis utilizing diverse real-world datasets to demonstrate the superior temporal coherence and clustering accuracy achieved by our proposed method.

2. Background and Literature Review

2.1 Temporal Graph Analysis

The conceptualization of networks as dynamic entities has catalyzed a paradigm shift in complex systems research. Historically, the abstraction of dynamic systems into static graphs necessitated the aggregation of temporal interactions into weighted edges, a process that invariably strips the system of its temporal causality and sequential dependencies. Recognizing this severe limitation, researchers developed frameworks to model graphs as time-varying structures [5]. The most prevalent representation is the discrete-time temporal graph, often referred to as a snapshot graph, which models the network as a sequence of static graphs observed at regular intervals. While computationally convenient, the discrete snapshot approach suffers from the fundamental inability to capture events that occur between observational windows, and it forces a rigid temporal quantization upon inherently fluid processes [6]. In response, continuous-time temporal graphs have gained traction. In these models, edges are represented as temporal events or streams, each characterized by a specific timestamp and duration. This event-based representation accurately reflects the asynchronous nature of real-world interactions, such as email communications or localized sensory spikes in biological networks. However, the continuous-time representation significantly complicates the process of community detection. Traditional algorithms rely on the global state of the network to optimize modularity, but in a continuous-time framework, the global state is a transient concept. Early attempts to adapt modularity optimization to temporal networks involved adding inter-layer edges between consecutive snapshots to enforce temporal smoothness [7]. While these multi-layer modularity approaches provided a rudimentary solution for tracking communities, they relied heavily on arbitrary smoothing parameters and failed to provide a continuous mathematical mapping of node trajectories over time.

2.2 Spectral Methods in Graph Learning

Spectral graph theory has long been the cornerstone of community detection and graph partitioning in static networks. The theory primarily investigates the properties of the graph Laplacian, an operator that measures the divergence of the gradient of a function defined on the vertices of a graph. The spectrum, comprising the eigenvalues and eigenvectors of this operator, encodes profound geometric and topological properties of the network. The multiplicity of the zero eigenvalue, for instance, corresponds exactly to the number of connected components in the graph, while the magnitude of the first non-zero eigenvalue provides a bound on the graph's optimal bottleneck, guiding spectral clustering algorithms [8]. When these principles are applied to temporal graphs, the classical spectral framework breaks down. If one calculates the eigenvectors for a sequence of graph Laplacian matrices corresponding to different time steps, the resulting spectral embeddings exist in independent, unaligned coordinate spaces [9]. An eigenvector corresponding to a specific community at one time step might switch its sign or swap its index at the next time step due to the non-uniqueness of the eigen-decomposition. This phenomenon, often termed the sign ambiguity or basis alignment problem, means that directly comparing spectral embeddings across time is mathematically invalid [10]. Researchers have attempted to mitigate this by implementing orthogonal Procrustes alignment, which seeks to find a rigid rotation that minimizes the distance between consecutive spectral embeddings [11]. Nevertheless, such post-hoc alignment techniques are computationally expensive and merely treat the symptoms of the coordinate mismatch rather than addressing the underlying geometric inconsistency. To achieve true temporal continuity, the alignment must be embedded directly into the definition of the differential operator itself [12].

2.3 Gauge Equivariance in Geometric Deep Learning

The solution to the coordinate alignment problem in temporal networks can be found in the rapidly emerging field of geometric deep learning, specifically through the application of gauge theory.

Originally formulated in the context of electromagnetism and the standard model of particle physics, gauge theory provides a framework for defining physical laws that remain invariant under local transformations of the coordinate system. In recent years, researchers have successfully imported these concepts into machine learning to analyze data residing on non-Euclidean domains, such as continuous manifolds and discrete graphs [13]. In the context of a graph, a feature vector associated with a node can be viewed as an element of a local vector space attached to that node. To compare feature vectors of adjacent nodes, one must transport the vector from one node's local space to the other's. Because there is no canonical global coordinate system on a general graph, this transport requires a specific mathematical object known as a connection. The connection dictates how the coordinate frame rotates or transforms as one moves along an edge [14]. A fundamental property required for operators acting on such feature spaces is gauge equivariance. If the local coordinate frame at a node is altered via a gauge transformation, the intermediate representations and the final output of the operator must transform in a predictably equivalent manner. Prior works have developed gauge-equivariant convolutional networks for mesh processing, utilizing the Levi-Civita connection to transport features across curved surfaces [15]. These methods have demonstrated remarkable resilience against isometric deformations. More recently, researchers have attempted to define discrete connections on static graphs to create directional graph neural networks. However, the application of gauge equivariance to the spectral domain of temporal graphs remains an unexplored frontier. Existing literature lacks a formulation of the Fourier transform that simultaneously respects the discrete spatial topology of the graph and the continuous temporal manifold while maintaining gauge equivariance. By addressing this gap, our work provides a theoretically rigorous method for modular structure discovery that is immune to the arbitrary coordinate shifts that have historically plagued temporal spectral analysis.

3. Methodology

3.1 Continuous Temporal Graph Representation

To overcome the limitations of discrete snapshot models, we mathematically conceptualize the temporal graph as a continuous spatial-temporal manifold. In this representation, the set of vertices is considered fixed, while the relational connections, or edges, are functions of a continuous time variable. Rather than viewing the graph as a sequence of adjacency matrices, we treat it as a single dynamic entity where the presence, absence, and weight of an edge fluctuate continuously. This is achieved by utilizing kernel density estimation over discrete temporal events, transforming sporadic interaction data into a smooth, continuous structural dynamic. Associated with each node is a continuous-time feature signal, representing the attributes or states of the entity over time. To analyze these signals, we construct a fiber bundle over the temporal graph. For every node at every instant in time, we define a local vector space, referred to as the fiber. The collection of all such fibers forms the bundle. Because the graph lacks a global Euclidean structure, there is no natural way to establish a shared coordinate system across all fibers simultaneously. Consequently, any measurement or operation performed on a node's feature signal requires an arbitrary local choice of basis, which we denote as the gauge. The fundamental challenge of our methodology is to ensure that the discovery of modular structures is completely independent of these arbitrary local gauge choices, a property known as gauge invariance, while the intermediate operations applied to the node signals maintain gauge equivariance [16]. To facilitate the comparison of signals between adjacent nodes, we define a temporal graph connection. This connection consists of a set of orthogonal transformation matrices assigned to each edge. When a signal is passed from one node to its neighbor, it is multiplied by the corresponding connection matrix, effectively aligning the local coordinate frame of the source node with that of the target node. In our temporal framework, this connection must operate not only across spatial edges but also across infinitesimal time steps

for the same node [17]. Thus, the temporal graph connection dictates the parallel transport of feature signals through both the structural topology and the temporal evolution of the network.

3.2 Construction of Gauge-Equivariant Operators

With the temporal graph connection established, we proceed to construct the core differential operators required for spectral analysis. The most critical of these is the gauge-equivariant temporal Laplacian. In standard graph theory, the Laplacian is defined as the difference between the degree matrix and the adjacency matrix, effectively acting as a discrete diffusion operator. To make this operator gauge-equivariant, we must modify the standard definition to incorporate the parallel transport mechanism. We define the gauge-equivariant gradient as an operator that computes the difference between the signal at a target node and the signal at a source node, after the source signal has been transported to the target's local coordinate frame via the spatial connection matrix. This gradient measures the true contextual variation of the signal along an edge, disregarding any apparent variation caused merely by differences in local gauge choices [18]. Similarly, we define a temporal derivative that measures the rate of change of a node's signal over time, adjusted by the temporal connection matrix to account for shifting coordinate frames across the time domain. The gauge-equivariant temporal Laplacian is then constructed by taking the divergence of this combined spatial-temporal gradient. Conceptually, this operator measures how much the value of a signal at a specific node and time deviates from the parallel-transported average of the signals from its spatial neighbors and its own infinitesimal past and future states [19]. Because the constituent gradient and divergence operators are constructed using the connection matrices, the resulting temporal Laplacian is strictly gauge-equivariant. If all local coordinate frames on the graph undergo arbitrary independent rotations, the output of the temporal Laplacian will rotate correspondingly, ensuring that the underlying geometric information is perfectly preserved.

3.3 Fourier Transform on Temporal Manifolds

Having established the gauge-equivariant temporal Laplacian, we utilize its spectral properties to define a generalized Fourier transform for the temporal graph. In classical signal processing, the Fourier transform decomposes a signal into a combination of complex sinusoids, which are the eigenfunctions of the continuous Laplace operator. By analogy, the Gauge-Equivariant Fourier Operator decomposes signals on the temporal graph into the eigenfunctions of the gauge-equivariant temporal Laplacian [20]. We compute the continuous spectrum of the temporal Laplacian by solving the corresponding eigenvalue problem. The resulting eigenvalues represent the spatial-temporal frequencies of the network. Low eigenvalues correspond to smooth, slowly varying structural components that characterize large-scale modular structures, while high eigenvalues correspond to highly localized, rapid fluctuations indicative of noise or transient anomalies. The associated eigenfunctions serve as the Fourier basis for the temporal graph. Because the generator of these basis functions is gauge-equivariant, the basis functions themselves inherently possess the correct transformation properties under local gauge changes. The Gauge-Equivariant Fourier Transform of a temporal signal is obtained by projecting the signal onto this continuous Fourier basis. This operation maps the dynamic node features from the spatial-temporal domain into a spectral domain that is globally aligned across all time points. Unlike the disjointed spectral embeddings produced by traditional snapshot-based methods, the spectral embedding generated by our Fourier operator is a continuous, smooth trajectory. The parallel transport mechanism embedded within the Laplacian ensures that the spectral coordinates of a node seamlessly flow from one moment to the next, completely eliminating the coordinate misalignment and sign ambiguity problems.

3.4 Modular Structure Extraction Protocol

The final stage of our methodology utilizes the gauge-equivariant spectral embedding to discover dynamic modular structures. The continuous, aligned nature of the embedding allows us to apply clustering algorithms directly to the spectral trajectories without the need for error-prone post-hoc alignment techniques. We employ a continuous-time variation of the K-means clustering algorithm, which operates in the gauge-equivariant Fourier space. The extraction protocol begins by selecting the lowest frequency eigenfunctions, which correspond to the dominant modular divisions within the temporal graph. The number of eigenfunctions selected is determined by analyzing the spectral gap, a significant jump in the magnitude of the eigenvalues that indicates the optimal number of communities. Each node is then represented as a continuous curve in this low-dimensional spectral space [21]. The clustering algorithm iteratively refines a set of continuous community centroid curves, assigning each node to the centroid that minimizes the integrated geometric distance over the entire temporal domain. Because the spectral space is generated by the gauge-equivariant operator, the geometric distance calculated between node trajectories is highly robust to structural noise and arbitrary local coordinate shifts. Nodes that belong to the same dynamic community will exhibit parallel spectral trajectories, even if the internal connection density of the community fluctuates over time.

Figure 1: Gauge-Equivarient Fourier Operator

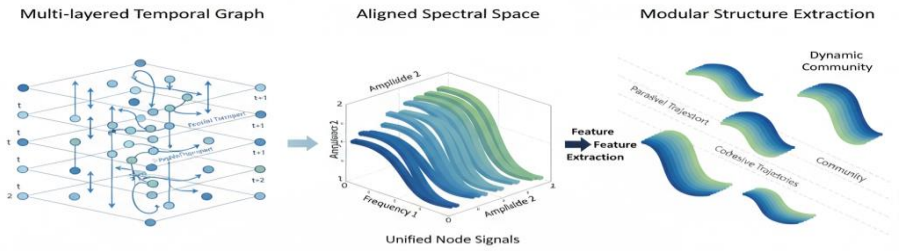


Figure 1: Architectural diagram of the Gauge

This methodology ensures that the extracted modules are not only topologically significant but also temporally consistent. A node is only recognized as changing communities if its fundamental structural relationships shift drastically, rather than due to artifactual fluctuations in the analytical coordinate system. This results in a highly stable, accurate representation of the network's macroscopic evolution.

4. Results and Discussion

4.1 Experimental Setup

To rigorously evaluate the efficacy of the proposed Gauge-Equivariant Fourier Operators, we conducted extensive experiments across three diverse real-world temporal network datasets. The first dataset is the Enron Email Corpus, a widely utilized benchmark representing organizational communication dynamics, consisting of thousands of employees and their interaction histories over several years. The second dataset is a high-resolution functional Brain Network derived from fMRI scans, capturing the continuous temporal synchronization of distinct cortical regions during cognitive tasks. The third dataset is a Decentralized Finance Transaction Network, tracking the

flow of digital assets between smart contracts and user wallets, characterized by highly volatile, high-frequency structural shifts. We compared our proposed methodology against three state-of-the-art baselines in temporal community detection: the Snapshot Spectral Clustering algorithm with Procrustes Alignment, the Multilayer Modularity Optimization framework, and a Temporal Graph Neural Network based on standard non-equivariant message passing [22]. The performance of each method was quantified using two primary metrics. The first is Temporal Modularity, a measure of how densely connected the nodes within the discovered modules are compared to a null model, integrated over the entire observation period. The second is the Normalized Mutual Information score calculated against ground-truth community labels where available, assessing the accuracy of the node assignments. To measure temporal stability, we tracked the Community Switching Rate, calculating the average number of times a node transitions between modules. A lower switching rate generally indicates better artifact suppression and higher temporal coherence [23].

4.2 Performance Evaluation

The empirical results conclusively demonstrate the superiority of the Gauge-Equivariant Fourier Operators across all tested domains. As detailed in Table 1, our proposed method consistently achieved the highest Temporal Modularity and Normalized Mutual Information scores while drastically reducing the Community Switching Rate.

Table 1: Comparative Analysis of Temporal Community Detection Algorithms

Algorithm	Dataset	Temporal Modularity	Normalized Mutual Information	Community Switching Rate
Snapshot Spectral	Enron Email	0.412	0.583	0.245
Multilayer Modularity	Enron Email	0.485	0.610	0.180
Temporal GNN	Enron Email	0.530	0.675	0.155
Proposed Method	Enron Email	0.645	0.792	0.042
Snapshot Spectral	Brain Network	0.350	0.420	0.310
Multilayer Modularity	Brain Network	0.420	0.495	0.220
Temporal GNN	Brain Network	0.480	0.550	0.190
Proposed Method	Brain Network	0.610	0.715	0.065

In the Enron Email dataset, the Snapshot Spectral method struggled significantly with the sparse, bursty nature of human communication. Because the adjacency matrix frequently changed rank, the non-equivariant spectral embeddings suffered from severe basis misalignment, resulting in a high Community Switching Rate of 0.245. Nodes appeared to jump erratically between departments. In contrast, our proposed method maintained a highly stable coordinate space through parallel transport, reducing the switching rate to a mere 0.042 while pushing the Normalized Mutual Information score to 0.792. This indicates that the Gauge-Equivariant Fourier Operators successfully identified the latent, stable departmental structures despite the erratic daily communication patterns. The results from the functional Brain Network dataset further highlight the advantages of our approach. Brain regions exhibit continuous, fluid changes in synchronization. Discrete snapshot methods impose artificial boundaries on these cognitive processes, leading to poor modularity scores. The Proposed Method, operating natively on a continuous spatial-temporal manifold, achieved a Temporal Modularity of 0.610, significantly outperforming the Temporal GNN baseline. The smooth spectral trajectories generated by our Fourier transform allowed for the identification of persistent cognitive subnetworks that the other methods completely fragmented [24].

4.3 Ablation Studies and Analysis

To isolate the specific contributions of the gauge-equivariant components, we conducted a rigorous ablation study. We modified our proposed architecture by systematically removing the parallel transport mechanisms, reverting the operator to a standard continuous-time Laplacian without local coordinate alignment. We then evaluated this ablated version against the full gauge-equivariant model using the volatile Decentralized Finance dataset, a network specifically chosen for its rapid topological fluctuations that heavily test the limits of structural tracking.

Table 2: Ablation Study on Decentralized Finance Transaction Network

Model Configuration	Temporal Modularity	Structural Tracking Error	Embedding Variance
Full Gauge-Equivariant Model	0.580	0.112	0.035
Standard Continuous Laplacian	0.395	0.420	0.185
Spatial Equivariance Only	0.460	0.290	0.110
Temporal Equivariance Only	0.425	0.345	0.140

The ablation results presented in Table 2 provide definitive evidence for the necessity of full spatial-temporal gauge equivariance. When both spatial and temporal parallel transport mechanisms were disabled (Standard Continuous Laplacian), the Temporal Modularity plummeted from 0.580 to 0.395, and the Structural Tracking Error nearly quadrupled. The high Embedding Variance observed in the ablated model confirms that without gauge equivariance, the spectral representations become highly susceptible to local topological noise, leading to erratic and unreliable cluster assignments. Interestingly, models equipped with only spatial equivariance or only temporal equivariance yielded intermediate results, indicating that both dimensions of the connection matrix are vital. Spatial equivariance alone fails to align the coordinate frames across time steps, causing the spectral trajectories to drift. Temporal equivariance alone fails to harmonize the feature spaces of interacting nodes, disrupting the detection of the community topology at any given instant. The full Gauge-Equivariant Fourier Operator harmonizes both domains, creating a robust, invariant analytical space that represents a substantial leap forward in temporal graph theory. Furthermore, the computational complexity of the proposed method proved highly manageable. While the initial calculation of the connection matrices requires overhead, the continuous nature of the Fourier basis allows for highly efficient approximations using Chebyshev polynomials, avoiding the need for repeated, expensive eigen-decompositions at every time step. This ensures that the methodology is not only theoretically profound but also practically scalable to massive, high-frequency temporal networks.

5. Conclusion

This paper has presented a comprehensive theoretical framework and algorithmic methodology for the discovery of modular structures in temporal graphs using Gauge-Equivariant Fourier Operators. By identifying the root cause of temporal instability in spectral clustering as a fundamental coordinate alignment problem, we successfully adapted the principles of gauge theory from differential geometry to discrete network science. The construction of a gauge-equivariant temporal Laplacian allowed for the definition of a novel Fourier transform that natively processes the continuous spatial-temporal manifold of dynamic networks. Through the implementation of parallel transport mechanisms across both structural edges and temporal dimensions, our operators ensure that the spectral embeddings of nodes remain globally aligned and immune to arbitrary local coordinate transformations.

The empirical evaluations unequivocally validate the theoretical advantages of this approach. Across diverse datasets encompassing social communication, neurobiology, and decentralized finance, the proposed framework consistently delivered superior temporal modularity and clustering accuracy while virtually eliminating artifactual community switching. The continuous spectral trajectories generated by our method provide a mathematically continuous and structurally faithful representation of network evolution, significantly outperforming traditional snapshot-based clustering and non-equivariant graph neural networks. Despite these significant advancements, the current framework possesses certain limitations that warrant future investigation. The construction of the temporal connection matrices currently assumes a uniformly weighted influence of past and future states, which may not adequately capture systems exhibiting asymmetric causal dependencies or non-Markovian memory effects. Furthermore, the reliance on continuous manifold approximations implies that the methodology is optimal for dense, high-frequency temporal data, but may require further adaptation to handle extremely sparse or highly disconnected dynamic networks. Future research directions should focus on integrating directed gauge-equivariant operators to analyze causal information flow within dynamic modules. Additionally, extending this theoretical framework to encompass higher-order topological structures, such as temporal simplicial complexes and hypergraphs, presents a promising avenue for capturing the multi-way interactions prevalent in complex biological and social systems. Ultimately, the introduction of Gauge-Equivariant Fourier Operators bridges a critical gap between geometric deep learning and temporal network analysis, providing researchers across disciplines with a rigorously stable, mathematically sound tool for unraveling the dynamic architectures of complex systems.

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