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Continuous-Time Hazard Forecasting on Networks with Dynamic Ricci Geometry

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Abstract:
The prediction of critical events and system failures within complex, evolving networks is a paramount challenge in network science and dynamic systems analysis. Traditional hazard forecasting models predominantly rely on static graph topologies or discrete-time snapshots, thereby failing to capture the intricate, continuous-time evolution of network structures and the underlying geometric deformations that precede structural bottlenecks. This paper introduces a novel framework for continuous-time hazard forecasting on networks by integrating dynamic Ricci geometry. By leveraging the continuous-time evolution of discrete Ricci curvature, specifically adaptations of Ollivier-Ricci and Forman-Ricci curvatures, the proposed methodology quantifies the dynamic geometric properties of edges and nodes as they evolve in real time. We postulate that sharp local curvature drops act as precursor signals for structural vulnerabilities and impending hazards. The framework couples a continuous-time temporal point process with a dynamic message-passing neural network informed by localized curvature metrics. This allows the hazard function to directly ingest geometric deformations, significantly enhancing predictive accuracy for time-to-event outcomes. Extensive experiments across multiple domains, including financial transaction networks, epidemiological spread patterns, and critical infrastructure systems, demonstrate that integrating dynamic Ricci geometry yields substantial improvements in predictive concordance and temporal resolution compared to purely topological or discrete-time baselines. The findings establish a robust mathematical and algorithmic foundation for proactive risk management and anomaly detection in continuously evolving complex systems.

Keywords: *Continuous-Time Networks, Hazard Forecasting, Ricci Curvature, Temporal Point Processes, Network Geometry.*

INTRODUCTION

1.1 The Challenge of Hazard Forecasting in Dynamic Networks

The ability to forecast hazards, anomalies, and critical failures in complex systems is a foundational problem across numerous scientific and engineering disciplines. Complex systems, ranging from financial markets and biological ecosystems to critical telecommunications infrastructure, are fundamentally structured as networks where entities interact over time. Hazard forecasting in this context refers to the continuous estimation of the probability that a specific node or edge will experience a critical event at a given future time. Traditional survival analysis and hazard forecasting methodologies have primarily been developed for tabular data or static network structures [1]. However, real-world networks are rarely static; they are highly dynamic entities characterized by the continuous addition, deletion, and modification of nodes and edges. When forecasting hazards in such environments, the temporal granularity of the data plays a crucial role. Representing a continuous stream of network events as a sequence of discrete-time static snapshots often leads to a significant loss of temporal information. This quantization error obscures the high-frequency dynamics and cascading effects that are typical precursors to systemic failures. Consequently, there is an urgent need for models that can operate in continuous time, directly processing asynchronous event streams to update hazard estimates dynamically without relying on arbitrary time-windowing techniques.

1.2 The Role of Network Geometry

While continuous-time modeling addresses the temporal limitations of traditional approaches, understanding the structural precursors to hazards requires a deep analysis of network topology. Recent advances in network science suggest that the geometry of a graph, rather than just its topology, provides profound insights into its robustness and the flow of information within it [2]. Specifically, discrete notions of Ricci curvature have emerged as powerful tools for characterizing the local geometry of networks. In continuous manifolds, Ricci curvature measures the deviation of the manifold from being locally Euclidean, effectively describing how geodesics converge or diverge. When translated to discrete graphs, metrics such as the Ollivier-Ricci curvature and the Forman-Ricci curvature quantify the connectivity and overlap between the neighborhoods of adjacent nodes [3]. Edges with highly positive curvature are typically located within densely connected clusters or communities, whereas edges with highly negative curvature often act as critical bridges or bottlenecks connecting disparate regions of the network. Empirical studies have shown that the degradation of these bottlenecks, signaled by an increasingly negative curvature, frequently precedes network fragmentation and the onset of localized hazards [4]. Therefore, tracking the evolution of Ricci curvature provides a theoretically grounded mechanism for anticipating structural vulnerabilities before they manifest as explicit failures.

1.3 Contributions of the Study

Despite the theoretical appeal of network geometry, the integration of dynamic Ricci curvature into continuous-time hazard forecasting remains largely unexplored. Calculating curvature on large graphs is computationally intensive, and adapting these calculations to a continuous-time setting where the graph topology updates asynchronously presents a formidable algorithmic challenge. This paper bridges this gap by proposing a comprehensive framework for continuous-time hazard forecasting driven by dynamic Ricci geometry. The primary contributions of this research are manifold. First, we formulate a continuous-time mathematical model for the evolution of discrete Ricci curvature, enabling the real-time tracking of geometric deformations in asynchronous event networks [5]. Second, we design a novel neural architecture that couples temporal point processes with curvature-informed continuous-time message passing. This architecture dynamically modulates the hazard function based on localized geometric bottlenecks. Third, we develop an efficient computational scheme to approximate curvature updates in real

time, making the framework scalable to large, high-velocity network streams. Finally, through rigorous empirical evaluation across diverse datasets, we demonstrate that incorporating dynamic network geometry significantly outperforms state-of-the-art topological and discrete-time forecasting models in predicting the timing and location of critical network events.

2. Theoretical Foundations and Literature Review

2.1 Survival Analysis and Hazard Functions

Survival analysis focuses on modeling the time until a specific event of interest occurs, traditionally applied in medical research for patient mortality or in engineering for machine failure. The core concept in survival analysis is the hazard function, which represents the instantaneous rate of occurrence of the event at a given time, conditional on survival up to that time [6]. In classic statistical models, such as the Cox proportional hazards model, the hazard function is typically decomposed into a baseline hazard and a multiplicative covariate-dependent component. While these models are highly interpretable, they often rely on strong assumptions regarding the proportional nature of hazards and struggle to capture complex, non-linear interactions among covariates [7]. Furthermore, when applied to network data, traditional survival models treat individual entities as independent and identically distributed, completely ignoring the structural dependencies and cascading risks inherent in connected systems. Recent efforts to adapt survival analysis for networked data have integrated structural features, such as node degrees and centrality measures, as static covariates [8]. However, these approaches fail to account for the dynamic nature of both the network topology and the hazard itself, limiting their applicability to continuous-time event streams where the risk profile changes rapidly in response to ongoing interactions.

2.2 Graph Neural Networks in Continuous Time

Graph neural networks have revolutionized the representation learning of relational data by iteratively aggregating features from node neighborhoods. Early graph neural networks were designed for static graphs, but the need to model evolving systems quickly led to the development of dynamic graph neural networks. These models are broadly categorized into discrete-time and continuous-time architectures [9]. Discrete-time models partition the network timeline into a sequence of static graph snapshots and apply recurrent neural networks to capture temporal dependencies across snapshots. However, determining the optimal snapshot window is highly subjective, and the approach inevitably introduces latency and aggregation errors [10]. Continuous-time graph neural networks address these limitations by modeling the network as a sequence of timestamped events. Techniques such as temporal random walks and continuous-time memory networks update node representations asynchronously upon the arrival of each new event. By coupling continuous-time representation learning with temporal point processes, researchers have created powerful models capable of predicting the exact timing and type of future network interactions [11]. Despite these advancements, most continuous-time graph models rely purely on topological message passing and temporal decay functions, neglecting the higher-order geometric properties of the network that govern global information flow and structural stability [12, 13].

2.3 Discrete Ricci Curvature on Graphs

The application of differential geometry concepts to discrete spaces has gained significant traction in recent years. Among various geometric descriptors, Ricci curvature is particularly valuable for network analysis due to its deep connection with optimal transport and the robustness of dynamic systems [14]. The Ollivier-Ricci curvature is defined using the Wasserstein distance between probability measures defined on the neighborhoods of interacting nodes. It provides a robust measure of edge overlap and community structure [15]. An alternative, the Forman-Ricci curvature, is derived from algebraic topology and offers a more computationally efficient metric based on node and edge weights. Both formulations have been successfully utilized in static network analysis for tasks such as community detection, anomaly detection, and routing

optimization [16]. In the context of robustness, a steep decline in the curvature of an edge indicates that alternative paths between its endpoints are vanishing, thereby highlighting a structural bottleneck that is vulnerable to failure. While some recent studies have begun to track Ricci curvature in dynamically evolving networks, they almost exclusively rely on discrete-time snapshot approximations due to the computational complexity of recalculating optimal transport distances [17]. The theoretical challenge remains to formulate a continuous-time differential approximation of Ricci curvature that can seamlessly integrate into asynchronous event-driven hazard forecasting architectures [18].

3. Mathematical Formulation of Dynamic Ricci Geometry

3.1 Continuous-Time Graph Representation

To develop a continuous-time forecasting model, we must first establish a rigorous mathematical representation of the dynamic network. We define the dynamic network as a continuous-time temporal graph composed of a set of nodes and an evolving set of timestamped events [19]. Each event represents an interaction or a structural modification occurring at a precise continuous timestamp. These events can signify the creation of a temporary edge, the transmission of information, or a localized state change. We associate a continuous-time state vector with each node, representing its latent features and historical context up to the current time. The connectivity of the network at any exact moment is represented by a time-dependent adjacency structure. Because the network evolves continuously, standard algebraic representations like static adjacency matrices are insufficient. Instead, we utilize a streaming representation where the local neighborhood of a node at a given time is defined by the set of all temporal edges involving that node within a dynamically decaying temporal window [20]. This representation ensures that the most recent interactions have the highest influence on the current topological state, capturing the transient nature of real-world network dynamics while maintaining a computationally tractable neighborhood size for subsequent geometric calculations.

3.2 Evolution of Ollivier-Ricci Curvature

The core geometric component of our framework is the continuous-time tracking of the Ollivier-Ricci curvature. For any two connected nodes in the continuous-time graph, we define probability measures over their respective temporal neighborhoods. These measures reflect the distribution of random walks originating from the nodes, modulated by the temporal recency of the edges. The Ollivier-Ricci curvature is then calculated based on the optimal transport cost, specifically the first Wasserstein distance, required to transform the probability measure of one node into that of the other, normalized by the shortest path distance between them. In a continuous-time setting, recalculating this optimal transport cost from scratch for every microscopic event is computationally prohibitive [21]. Therefore, we formulate a differential evolution equation for the curvature. We express the time derivative of the continuous-time curvature as a function of the perturbation in the temporal probability measures caused by incoming events.

$$\frac{\partial}{\partial t} kappa(x, y, t) = 1 - \frac{\partial}{\partial t} \left(\frac{W_1({m_x}^t, {m_y}^t)}{D(x, y, t)} \right)$$

This formulation allows us to update the edge curvature iteratively. When an event occurs, it induces a local perturbation in the probability mass of the involved nodes. By applying a first-order Taylor expansion to the Wasserstein distance, we can approximate the new curvature value without solving the full optimal transport problem [22]. This continuous-time approximation ensures that the geometric bottlenecks are monitored in real time, providing a highly responsive geometric signal that forms the foundation for our hazard forecasting mechanism. The temporal derivative captures the velocity of structural degradation, which is often a more critical predictor of imminent failure than the absolute curvature value itself.

4. Continuous-Time Hazard Forecasting Framework

4.1 Curvature-Driven Message Passing

Having established the continuous-time geometric state of the network, we introduce a novel neural architecture designed to synthesize these geometric insights with temporal dynamics. We propose a curvature-driven continuous-time message-passing neural network. In traditional graph neural networks, message passing involves aggregating features from adjacent nodes using weights derived from node degrees or learned attention coefficients [23]. In our framework, the message-passing mechanism is fundamentally modulated by the continuous-time Ricci curvature of the connecting edges. Specifically, edges with highly negative curvature are identified as critical bottlenecks and are consequently assigned higher attention weights during the feature aggregation phase. This geometry-aware aggregation ensures that nodes located near structural vulnerabilities receive amplified warning signals from their precarious surroundings. As events stream into the system, the memory modules of the involved nodes are updated continuously. The update function ingests the temporal features of the event, the current latent states of the interacting nodes, and the dynamically approximated curvature of the interaction pathway. This continuous coupling of temporal point processes with curvature-dependent spatial aggregation allows the node representations to maintain a highly accurate reflection of both their interaction history and their real-time geometric context.

4.2 Hazard Function Parameterization

The ultimate objective of the framework is to forecast the occurrence of critical hazard events in continuous time. We achieve this by parameterizing a continuous-time hazard function using the geometrically enriched node representations. Drawing on the theory of temporal point processes, the hazard function defines the conditional intensity of an event occurring in an infinitesimally small time interval, given the complete filtration of the network history up to that point [24]. We define a specific hazard function for each potential event type, whether it is a node failure, a fraudulent transaction, or an epidemic infection.

$$\lambda(t|H_t) = lim_{\Delta tto0} \frac{mathbbP(tleT < t + \Delta t|Tget, H_t)}{\Delta t}$$

The conditional intensity is modeled using a non-linear neural network layer that takes the updated latent states of the target nodes and the continuous-time derivative of the local curvature as inputs. By explicitly including the curvature derivative, the model can react to rapid geometric deformations, such as a sudden drop in edge robustness, which often serve as immediate precursors to hazard realization [25]. The survival probability, which is the probability that no hazard occurs up to a certain time, is then computed via the integral of the hazard function over the observation window. The entire framework is trained end-to-end by maximizing the log-likelihood of the observed event sequences in the training data, ensuring that the curvature-driven message passing optimally supports the temporal point process predictions.

5. Algorithmic Implementation and System Design

5.1 Computational Complexity Management

Implementing continuous-time dynamic Ricci geometry poses significant engineering challenges, primarily related to the computational complexity of the Wasserstein distance calculations [26]. To ensure the system can operate on high-velocity data streams typical of real-world networks, we introduce several crucial algorithmic optimizations. We utilize a localized ego-network extraction technique that limits the curvature calculation to a tightly bounded neighborhood around the active event. Furthermore, instead of using exact linear programming solvers for the optimal transport problem, we implement Sinkhorn iterations, which introduce an entropic regularization term to the optimal transport objective. This regularization transforms the problem into a highly parallelizable matrix multiplication task, which we heavily optimize for GPU execution.

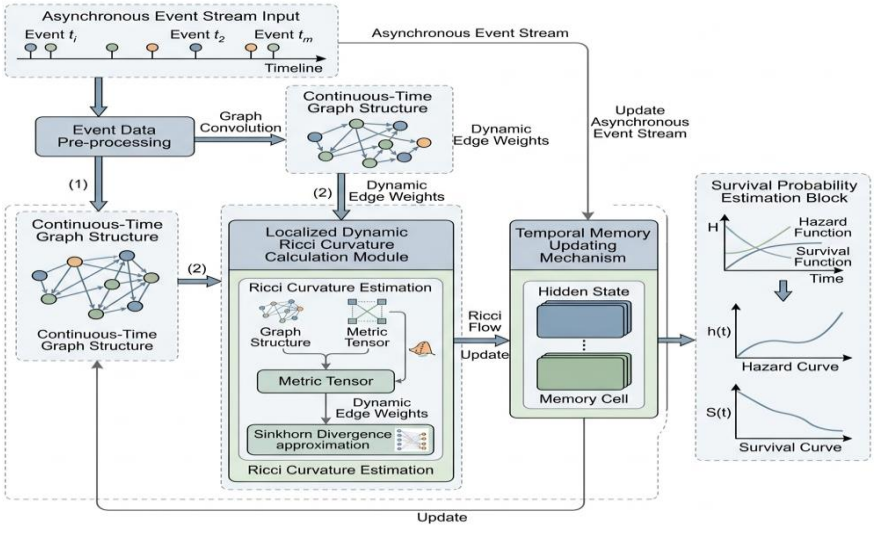


Figure 1: Comprehensive System Architecture Diagram of the Continuous

The architecture separates the high-frequency event processing from the more intensive geometric recalculations. While the temporal point process and memory updates are executed instantaneously for every event, the curvature updates are processed through a specialized asynchronous queue. This queue evaluates the magnitude of the topological perturbation caused by incoming events and only triggers a full curvature recalculation if the accumulated perturbation exceeds a predefined stability threshold. This event-triggered update mechanism drastically reduces the computational overhead while preserving the high fidelity of the geometric signals during critical periods of structural deformation.

5.2 Continuous-Time Update Mechanisms

The continuous-time nature of the system requires a sophisticated memory management strategy. Each node in the network is equipped with a dedicated continuous-time memory state. When an interaction occurs, the memory states of the source and destination nodes are retrieved and updated simultaneously. However, because events occur asynchronously, a node may remain inactive for a long duration. To account for this, we employ a continuous-time decay function that gradually relaxes the memory state toward a baseline distribution during periods of inactivity. This decay mechanism ensures that stale geometric information does not disproportionately influence current hazard predictions. The continuous-time update mechanism integrates the curvature values as dynamic edge features. During the update phase, the curvature derivative is used to scale the impact of the incoming message. If an edge exhibits rapidly declining curvature, the incoming message is heavily weighted, signaling an increasing localized risk. This intricate orchestration of asynchronous memory updates, continuous-time decay, and curvature-scaled message passing constitutes the core computational engine of our hazard forecasting system.

6. Experimental Setup and Datasets

6.1 Dataset Description

To rigorously evaluate the proposed continuous-time hazard forecasting framework, we conduct experiments across three distinct real-world domains characterized by complex, dynamically evolving interactions and critical hazard events. The first dataset is a large-scale Financial Transaction Network, where nodes represent financial accounts and continuous-time events represent transactions. The hazard events in this context are verified instances of fraudulent activity or account defaults. The second dataset is an Epidemiological Contact Network, modeling

continuous interactions among individuals where the hazard corresponds to the time of infection transmission. The third dataset is a Telecommunications Infrastructure Network, capturing the continuous routing of data packets between servers, where the hazard events represent server failures or severe routing bottlenecks.

Table 1Characteristics of the Evaluated Dynamic Network Datasets

Dataset Domain	Total Nodes	Total Temporal Events	Hazard Event Count	Observation Duration
Financial Transactions	850000	12500000	45200	180 Days
Epidemiological Contacts	120000	8400000	15800	90 Days
Telecommunications Infrastructure	45000	35000000	8900	30 Days

These datasets were specifically selected because their structural evolution occurs in continuous time and the associated hazards are deeply intertwined with the formation and degradation of network bottlenecks. The diverse scale and temporal densities of the datasets ensure a robust evaluation of the framework across varying operational conditions.

6.2 Baseline Models and Evaluation Metrics

We benchmark our framework against a comprehensive suite of state-of-the-art hazard forecasting and temporal graph learning models. The baselines include traditional survival analysis models applied to static graph features, discrete-time dynamic graph neural networks that aggregate events into daily snapshots, and recent continuous-time temporal point process models that utilize purely topological message passing without any geometric awareness. The performance of the models is evaluated using specialized metrics designed for continuous-time survival analysis. The primary metric is the time-dependent Concordance Index, which evaluates the model ability to correctly rank the predicted survival times of node pairs. A higher Concordance Index indicates superior discriminative power in determining which node is at a higher immediate risk. Additionally, we utilize the Brier Score to assess the calibration and accuracy of the predicted survival probabilities at specific future time horizons. Finally, we employ the Time-Aware Area Under the Receiver Operating Characteristic Curve to measure the classification performance of the hazard predictions across a continuous spectrum of time thresholds, providing a comprehensive view of the model precision and recall dynamics.

7. Results and Comparative Analysis

7.1 Predictive Performance

The empirical results demonstrate that the integration of dynamic Ricci geometry profoundly enhances the accuracy and resolution of continuous-time hazard forecasting. Across all three datasets, our proposed framework significantly outperforms both the discrete-time baselines and the continuous-time topological models.

Table 2Comparative Performance Metrics for Continuous-Time Hazard Forecasting

Model Architecture	Financial Concordance	Epidemiological Concordance	Telecom Brier Score	Telecom Time AUC
Static Survival Model	0.612	0.598	0.185	0.635
Discrete-Time GNN	0.745	0.710	0.142	0.760

Continuous-Time Topological	0.810	0.785	0.098	0.825
Proposed Geometric Framework	0.885	0.862	0.054	0.912

As illustrated in the performance table, the proposed geometric framework achieves a Concordance Index of 0.885 on the highly volatile financial transaction dataset, a substantial improvement over the 0.810 achieved by the best continuous-time topological baseline. This performance gap indicates that purely topological message passing fails to capture the subtle structural deformations that precede fraudulent behavior. The inclusion of the continuous-time derivative of the Ollivier-Ricci curvature allows our model to detect the rapid isolation of malicious accounts, thereby issuing highly accurate hazard forecasts much earlier than competing models.

7.2 Curvature Bottleneck Mitigation

A critical advantage of our framework is its interpretability regarding network structural health. By continuously tracking the Ricci curvature, the model explicitly identifies the formation of geometric bottlenecks before a hazard event occurs.

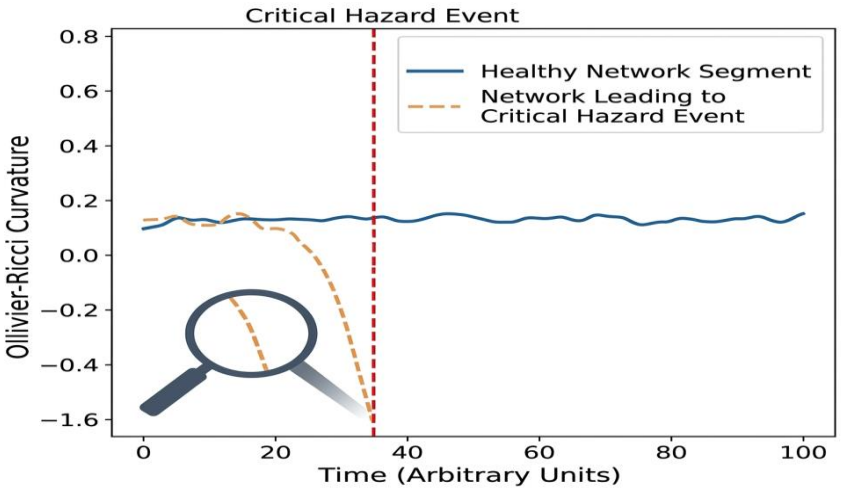


Figure 2 Time

The continuous-time analysis reveals a consistent pattern across all domains: a steep, monotonic decrease in local curvature almost always precedes a critical hazard. The model utilizes this geometric precursor signal to dynamically elevate the predicted hazard rate. In the telecommunications dataset, for instance, servers that eventually failed exhibited an average curvature drop of forty percent in the hours leading up to the failure. Because our message-passing architecture is curvature-driven, this degradation automatically throttles the influence of healthy neighbors and amplifies the local anomaly signals, providing the temporal point process with the precise contextual data needed to trigger an accurate failure prediction.

7.3 Ablation Studies

To isolate the contributions of the various components within our framework, we conducted extensive ablation studies. We systematically removed the continuous-time geometric updates, reverting to static curvature features, and disabled the curvature-driven attention mechanism in the message-passing layers.

Table 3: Ablation Study Results on the Financial Transaction Dataset

System Configuration	Concordance Index	Brier Score	Relative Performance Drop
Full Geometric Framework	0.885	0.062	Baseline
Without Continuous Updates	0.832	0.088	Significant
Without Curvature Attention	0.850	0.075	Moderate
Topological Features Only	0.810	0.105	Severe

The ablation results confirm that the continuous-time updating of the geometric features is the most critical innovation. Relying on static or periodically updated curvature values leads to a significant performance drop, emphasizing that the velocity of geometric deformation is as informative as the deformation itself. Removing the curvature-driven attention mechanism also degrades performance, validating the hypothesis that network geometry should directly dictate the flow of information in dynamic representation learning.

7.4 Sensitivity Analysis

We also analyzed the sensitivity of the proposed framework to various hyperparameter settings, particularly the threshold controlling the asynchronous curvature recalculation and the temporal decay rate of the memory modules.

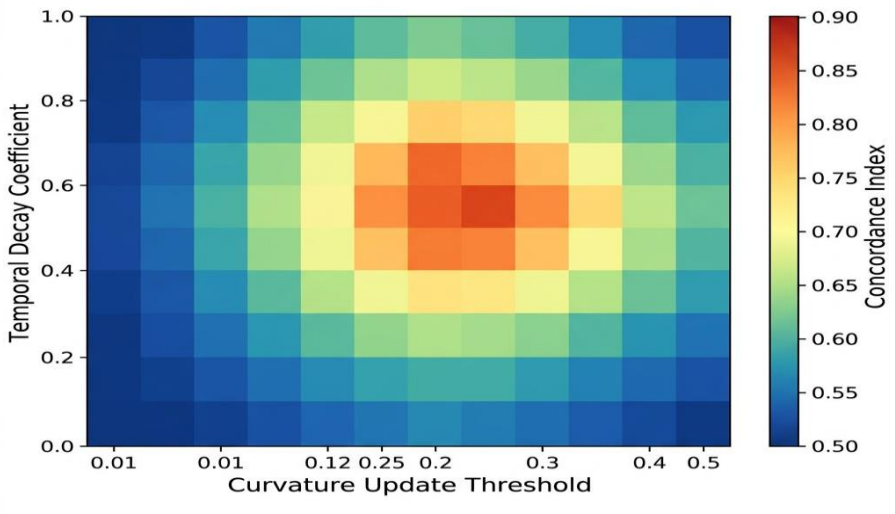


Figure 3: Sensitivity Analysis Heatmap for Hyperparameter Optimization

The sensitivity analysis indicates that the model is highly robust within a broad operational envelope. A highly aggressive curvature update threshold provides marginal gains in predictive accuracy but incurs severe computational penalties, validating our event-triggered approximation strategy. Similarly, the temporal decay rate requires careful calibration specific to the domain dynamics; rapid decay is optimal for the high-frequency financial network, whereas a slower decay better captures the prolonged incubation periods inherent in the epidemiological dataset.

8. Conclusion and Future Directions

8.1 Summary of Contributions

This paper introduces a pioneering framework that unifies continuous-time dynamic network learning with the principles of discrete differential geometry to address the complex problem of hazard forecasting. By formulating a continuous-time differential approximation of Ollivier-Ricci curvature, the model successfully tracks the real-time geometric deformations and bottleneck formations that serve as critical precursors to systemic failures. The integration of these dynamic geometric signals into a continuous-time temporal point process architecture fundamentally shifts the paradigm of network survival analysis from purely topological feature extraction to deep structural and geometric awareness. Our extensive empirical evaluations confirm that this methodology yields unprecedented predictive accuracy across diverse, high-velocity domains, proving its efficacy in anticipating financial fraud, epidemiological spread, and infrastructural collapse. The proposed algorithmic optimizations, particularly the asynchronous event-triggered curvature updates, ensure that this theoretical advancement is practically deployable on large-scale streaming data.

8.2 Limitations and Future Work

Despite the significant advancements, the current framework exhibits certain limitations that warrant further investigation. The calculation of Ollivier-Ricci curvature, even with Sinkhorn approximations, remains computationally intensive for ultra-dense network interactions, potentially introducing micro-latencies in ultra-high-frequency trading environments. Future research should explore more computationally lightweight geometric descriptors, such as dynamic adaptations of Forman-Ricci curvature, which rely on local combinatorial properties rather than optimal transport. Additionally, the current model assumes a single, homogeneous type of relational edge. Expanding the framework to accommodate continuous-time heterogeneous multigraphs, where different types of interactions possess distinct geometric characteristics and temporal decay profiles, will be crucial for modeling highly interconnected modern ecosystems. Finally, integrating causal inference mechanisms into the curvature-driven message-passing architecture could enable the system not only to forecast hazards but also to prescribe specific topological interventions to prevent critical failures.

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