Novelty Assessment Report

Paper: ℓ_1 Latent Distance based Continuous-time Graph Representation

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Abstract

Continuous-time graph representation (CTGR) is a widely-used methodology in machine learning, physics, bioinformatics, and social networks. The sequential survival process in a latent space with the squared ℓ_2 distance is an important ultra-low-dimensional embedding for CTGR. However, the squared ℓ_2 distance violates the triangle inequality, which may cause distortion of the relative node positions in the latent space and thus deteriorates in social, contact, and collaboration networks. Reverting to the ℓ_2 distance is infeasible because the corresponding integral computation is intractable. To solve these problems, we propose a theoretically-sound ℓ_1 latent distance based continuous-time graph representation (ℓ_1LD-CTGR). It facilitates a true latent metric space for the sequential survival process. Moreover, the integral of the hazard function is found to be a closed-form piece-wise exponential integral, which well fits the ultra-low-dimensional embedding. To handle the non-differentiable ℓ_1 norm, we successfully find a descent direction of the hazard function to replace the gradient, enabling mainstream learning architectures to learn the parameters. Extensive experiments using both synthetic and real-world data show the competitive performance of ℓ_1LD-CTGR.

Core Task Landscape

This paper addresses: **continuous-time graph representation learning with latent distance metrics**

A total of **28 papers** were analyzed and organized into a taxonomy with **16 categories**.

Taxonomy Overview

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

- **Latent Space Models for Continuous-Time Networks**
- **Discrete-Time Temporal Network Embeddings**
- **Temporal Knowledge Graph Embeddings**
- **Link Prediction and Optimization in Dynamic Networks**
- **Temporal Graph Distance and Similarity Metrics**
- **Domain-Specific Temporal Network Applications**
- **Theoretical Foundations and Cross-Domain Frameworks**

Complete Taxonomy Tree

- continuous-time graph representation learning with latent distance metrics Survey Taxonomy
- Latent Space Models for Continuous-Time Networks
  - Distance-Based Survival Process Models ★ (2 papers)
  - [0] ℓ_1 Latent Distance based Continuous-time Graph Representation (Anon et al., 2026) View paper
  - [1] Continuous-time Graph Representation with Sequential Survival Process (Abdulkadir Ã elikkanat, 2023) View paper
  - Hawkes Process Latent Space Models (1 papers)
  - [21] A Mutually Exciting Latent Space Hawkes Process Model for Continuous-time Networks (Huang Zhi-peng, 2022) View paper
  - Trajectory-Based Latent Dynamics (3 papers)
  - [16] Dynamic social network analysis using latent space models (Purnamrita Sarkar, 2005) View paper
  - [19] Latent space models for dynamic networks (Sewell, 2015) View paper
  - [20] Piecewise-Velocity Model for Learning Continuous-time Dynamic Node Representations (Ã elikkanat, 2022) View paper
- Discrete-Time Temporal Network Embeddings
  - Tensor Factorization for Temporal Networks (2 papers)
  - [2] Dynamic Network Representation Based on Latent Factorization of Tensors (Hao Wu, 2023) View paper
  - [15] MNL: A Highly-Efficient Model for Large-scale Dynamic Weighted Directed Network Representation (Minzhi Chen, 2023) View paper
  - Hyperbolic and Non-Euclidean Temporal Embeddings (1 papers)
  - [4] Discrete-time Temporal Network Embedding via Implicit Hierarchical Learning in Hyperbolic Space (Yang, 2021) View paper
  - Latent Function Distance Models (1 papers)
  - [3] Exploratory analysis of dynamic networks using latent functions (Haosheng Shi, 2025) View paper
  - Temporal Graph Neural Network Architectures (2 papers)
  - [7] Spatial-temporal graph transformer network for skeleton-based temporal action segmentation (Xiaoyan Tian, 2024) View paper
  - [9] Distributed Hierarchical Temporal Graph Learning for Communication-Efficient High-Dimensional Industrial IoT Modeling (Fangyu Li, 2024) View paper
- Temporal Knowledge Graph Embeddings (2 papers)
  - [14] Temporal-Aware bicomplex embeddings with implicit attention for knowledge graph link prediction (Thanh Le, 2025) View paper

    - [22] Global-Local Latent on Learning Model for Temporal Knowledge Graphs Based on Graph Neural Networks (Shibin Zhang, 2025) View paper
- Link Prediction and Optimization in Dynamic Networks (2 papers)
    - [18] Scalable temporal latent space inference for link prediction in dynamic social networks (Linhong Zhu, 2016) View paper
    - [28] Scalable Link Prediction in Dynamic Networks via Non-Negative Matrix Factorization (Zhu Linhong, 2014) View paper
- Temporal Graph Distance and Similarity Metrics (1 papers)
    - [10] An embedding-based distance for temporal graphs (Lorenzo Dall'Amico, 2024) View paper
- Domain-Specific Temporal Network Applications
    - Epidemiological and Spatial-Temporal Networks (2 papers)
    - [8] Dynamic network analysis of COVID-19 with a latent pandemic space model (Amanda M. Y. Chu, 2021) View paper
    - [12] A dynamic latent space time series model to assess the spread of mumps in England (Kaur Hardeep, 2024) View paper
    - Neurophysiological and Biological Networks (1 papers)
    - [5] A latent representation of brain networks based on EEG (Falconi, 2024) View paper
    - Recommendation Systems with Temporal Preferences (1 papers)
    - [27] ALSP: Adaptive Long Short-term Preference Modeling with Temporal Graph Neural Networks (Huixuan Chi, 2023) View paper
- Theoretical Foundations and Cross-Domain Frameworks
    - Temporal-Static Equivalence and Theoretical Analysis (3 papers)
    - [17] On the equivalence between temporal and static equivariant graph representations (J Gao, 2022) View paper
    - [23] Machine Learning for Static and Single-Event Dynamic Complex Network Analysis (Nakis, 2025) View paper
    - [26] Latent factor representations of dynamic networks with applications in cyber-security (Francesco Sanna Passino, 2021) View paper
    - Dynamics-Constrained Latent Representations (3 papers)
    - [11] From Latent Dynamics to Meaningful Representations. (Dedi Wang, 2024) View paper
    - [13] Dynamically Meaningful Latent Representations of Dynamical Systems (Imran Nasim, 2024) View paper
    - [25] FRIREN: Beyond Trajectories - A Spectral Lens on Time (Wang Qilin, 2025) View paper
    - Cross-Modal and Multi-View Temporal Learning (2 papers)
    - [6] Globally-Aware Continuous-Time Redistribution Learning for RS Image Change Detection (Xiao-wen Zhang, 2024) View paper
    - [24] Cross-Modal Contrastive Learning for Robust Representation of the Extracellular Matrix in Static and Dynamic Full-Field OCT Images (D. Mandache, 2023) View paper

Narrative

Core task: continuous-time graph representation learning with latent distance metrics. The field addresses how to embed evolving networks into latent spaces where distances capture the likelihood or timing of interactions. The taxonomy reveals several complementary perspectives: Latent Space Models for Continuous-Time Networks focus on probabilistic frameworks that treat node positions as evolving continuously and model edge formation via distance-based survival or point processes; Discrete-Time Temporal Network Embeddings discretize time into snapshots and learn embeddings per interval; Temporal Knowledge Graph Embeddings extend relational reasoning to time-stamped facts; Link Prediction and Optimization branches emphasize algorithmic efficiency and predictive accuracy; Temporal Graph Distance and Similarity Metrics develop measures to compare dynamic graphs; Domain-Specific Applications tailor methods to areas like social networks or epidemiology; and Theoretical Foundations provide cross-domain principles. Representative works such as Latent Functions Networks[3] and Tensor Factorization Networks[2] illustrate how different branches balance expressiveness, scalability, and interpretability.

Within the latent-space modeling branch, a particularly active line explores distance-based survival process models, which treat the hazard of edge formation as a function of latent distances that evolve smoothly over time. L1 Latent Distance[0] sits squarely in this cluster, proposing an L1-norm metric to capture anisotropic node dynamics and improve interpretability compared to Euclidean alternatives. Its closest neighbor, Sequential Survival Process[1], similarly models continuous-time interactions via survival analysis but emphasizes sequential event dependencies. Both contrast with earlier static latent-space approaches like Social Network Latent[16] and more recent hybrid methods such as Hyperbolic Temporal Embedding[4], which leverage non-Euclidean geometries. A central open question across these works is how to balance model complexity—richer distance functions or time-varying embeddings—against computational tractability and the risk of overfitting sparse temporal data.

Related Works in Same Category

The following **1 sibling papers** share the same taxonomy leaf node with the original paper:

1. Continuous-time Graph Representation with Sequential Survival Process

Authors: Abdulkadir Ã□elikkanat, Nikolaos Nakis, Morten MÃ¸rup | **Year/Venue**: 2023 • AAAI Conference on Artificial Intelligence | **URL**: View paper

Abstract

Over the past two decades, there has been a tremendous increase in the growth of representation learning methods for graphs, with numerous applications across various fields, including bioinformatics, chemistry, and the social sciences. However, current dynamic network approaches focus on discrete-time networks or treat links in continuous-time networks as instantaneous events. Therefore, these approaches have limitations in capturing the persistence or absence of links that continuously emerge ...

Relationship Analysis

Both papers belong to the Distance-Based Survival Process Models category, using survival processes with latent distance metrics for continuous-time edge modeling. They share the core framework of modeling edge persistence and absence through sequential survival processes in latent space. The key difference is that the original paper proposes using $\ell 1$ distance instead of squared $\ell 2$ distance to address triangle inequality violations and latent space distortion, while the candidate paper (GRASSP) establishes the foundational framework using squared $\ell 2$ distance with Gaussian integral computation.

Contributions Analysis

Overall novelty summary. The paper proposes an ℓ_1 latent distance model for continuous-time graph representation, addressing triangle inequality violations in prior squared-ℓ_2 approaches. It resides in the 'Distance-Based Survival Process Models' leaf, which contains only two papers total (including this one). This leaf sits within 'Latent Space Models for Continuous-Time Networks', a branch with three sub-topics and six papers overall. The sparse population suggests this is a relatively focused research direction rather than a crowded area, though the broader latent-space modeling branch has moderate activity across multiple geometric and process-based approaches.

The taxonomy reveals neighboring work in 'Hawkes Process Latent Space Models' (one paper) and 'Trajectory-Based Latent Dynamics' (three papers), both exploring continuous-time embeddings but through different mechanisms—mutually exciting processes versus velocity-driven trajectories. The sibling paper in the same leaf (Sequential Survival Process) shares the survival-process foundation but does not explicitly address metric properties or ℓ_1 distances. Adjacent branches like 'Hyperbolic and Non-Euclidean Temporal Embeddings' explore alternative geometries for discrete-time snapshots, highlighting a broader field interest in moving beyond standard Euclidean metrics, though in different temporal modeling regimes.

Among 22 candidates examined, the ℓ_1 latent distance framework (Contribution A) showed no clear refutations across two candidates, suggesting limited direct prior work on ℓ_1-based survival models. The closed-form integral derivation (Contribution B) examined ten candidates with no refutations, indicating novelty in the mathematical treatment. However, the descent direction optimization method (Contribution C) found one refutable candidate among ten examined, pointing to existing subgradient or proximal techniques for non-differentiable norms. The limited search scope (22 papers, not exhaustive) means these findings reflect top semantic matches rather than comprehensive coverage.

Based on the top-22 semantic matches and taxonomy structure, the work appears to occupy a relatively sparse niche within continuous-time latent-space modeling. The ℓ_1 metric choice and closed-form integral derivation show novelty signals, though the optimization approach has partial overlap with known non-smooth methods. The analysis does not cover broader optimization literature or domain-specific survival modeling outside the examined candidates, so conclusions remain provisional pending deeper review.

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

Contribution 1: l1 latent distance based continuous-time graph representation (l1LD-CTGR)

Description: The authors introduce l1LD-CTGR, a new method that uses l1 distance instead of squared l2 distance in the sequential survival process for continuous-time graph representation. This approach establishes a valid metric space that satisfies the triangle inequality, addressing distortion issues in the latent space that affect social, contact, and collaboration networks.

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.

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1. Traffic Forecasting in Bogota, Colombia, with Attention Temporal Graph Convolutional Networks (A3T-GCN)

URL: View paper

Brief Assessment

A3T-GCN Traffic[40] focuses on traffic forecasting using attention mechanisms and graph convolutional networks for spatial-temporal traffic data, not on latent distance metrics or continuous-time graph representation with survival processes.

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2. Attentive graph structure learning embedded in deep spatial-temporal graph neural network for traffic forecasting

URL: View paper

Brief Assessment

Attentive Graph Learning[39] focuses on traffic forecasting using spatial-temporal graph neural networks with L1 regularization for model training, not on continuous-time graph representation with L1 distance metrics in latent spaces for sequential survival processes.

Contribution 2: Closed-form piece-wise exponential integral for l1 distance hazard function

Description: The authors derive a tractable closed-form solution for computing the integral of the hazard function when using l1 distance. This piece-wise exponential integral differs from the Gaussian integral used in squared l2 distance methods and enables efficient computation in ultra-low-dimensional embeddings.

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.

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1. Estimation in the High Dimensional Additive Hazard Model with l0 Type of Penalty

URL: View paper

Brief Assessment

L0 Additive Hazard[43] focuses on high-dimensional additive hazard models with l0-type penalties for variable selection, not on deriving closed-form integrals for l1 distance-based hazard functions in continuous-time graph representations.

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2. Logistic Regression and Cox Hazard Modeling with Sparse High Dimensional Data via Elastic Net Regularization and Graph-Guided Aggregation

URL: View paper

Brief Assessment

Elastic Net Cox[50] focuses on elastic net regularization for Cox hazard models with sparse high-dimensional data, not on deriving closed-form integrals for l1 distance-based hazard functions in continuous-time graph representations. The candidate's exponential baseline hazard assumption is fundamentally different from the original paper's l1 latent distance formulation.

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3. A novel feature selection method for ultra high dimensional survival data

URL: View paper

Brief Assessment

Ultra High Dimensional[42] focuses on feature selection methods for survival data using Freund's baseline hazard function in multi-component systems (kidneys), not on deriving closed-form integrals for l1 distance hazard functions in continuous-time graph representation.

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4. A provable two-stage algorithm for penalized hazards regression

URL: View paper

Brief Assessment

Penalized Hazards Regression[47] focuses on Cox's proportional hazards model with folded-concave penalties (SCAD/MCP), not on closed-form integrals for l1 distance hazard functions in continuous-time graph representation.

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5. Bayesian survival analysis with flexible penalization using beta process prior for baseline hazard

URL: View paper

Brief Assessment

Beta Process Survival[41] focuses on Bayesian survival analysis with beta process priors for baseline hazard and l1 regularization for variable selection, not on deriving closed-form integrals for l1 distance-based hazard functions in latent space embeddings.

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6. Risk factor identification in heterogeneous disease progression with L1-regularized multi-state models

URL: View paper

Brief Assessment

L1 Multi-State Models[49] focuses on multi-state survival models for disease progression with L1-regularization for variable selection, not on deriving closed-form integrals for hazard functions with l1 distance in graph representation learning. The contexts are fundamentally different.

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7. L1 Penalized Estimation in the Cox Proportional Hazards Model

URL: View paper

Brief Assessment

L1 Cox Model[45] focuses on L1 penalization for parameter estimation in Cox models, not on deriving closed-form integrals for hazard functions with l1 distance metrics in latent space embeddings.

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8. Factor-augmented regularized model for hazard regression

URL: View paper

Brief Assessment

Factor Augmented Hazard[44] focuses on factor-augmented Cox proportional hazards models for handling correlated covariates in survival analysis, not on deriving closed-form integrals for l1 distance-based hazard functions in continuous-time graph representation.

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9. Integration of gene interaction information into a reweighted Lasso-Cox model for accurate survival prediction

URL: View paper

Brief Assessment

Reweighted Lasso Cox[46] focuses on Cox proportional hazard models for gene expression survival prediction using network-based gene weighting, not on deriving closed-form integrals for l1 distance hazard functions in continuous-time graph representations.

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10. Regularization for Cox's proportional hazards model with NP-dimensionality

URL: View paper

Brief Assessment

NP Dimensional Cox[48] focuses on regularization methods (lasso, SCAD) for Cox's proportional hazards model with high-dimensional covariates, not on deriving closed-form integrals for l1 distance-based hazard functions in continuous-time graph representations.

Contribution 3: Descent direction method for non-differentiable l1 norm optimization

Description: The authors develop a method to handle the non-differentiability of the l1 norm by identifying a descent direction that replaces the gradient in optimization. This enables the use of standard learning frameworks like PyTorch for parameter learning despite the non-smooth objective function.

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.

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1. GD doesn't make the cut: Three ways that non-differentiability affects neural network training

URL: View paper

Brief Assessment

Non Differentiability Training[30] focuses on how non-differentiability affects neural network training dynamics (convergence, lasso penalties, edge of stability), not on developing descent direction methods for l1 norm optimization in continuous-time graph representation.

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2. L1- and F-norm joint edge preservation optimization algorithm for complex image sparse SAR reconstruction imaging model

URL: View paper

Brief Assessment

L1 F-norm Preservation[31] uses gradient descent for l1-norm optimization in SAR imaging, not for handling non-differentiability in continuous-time graph representation with hazard functions and survival processes.

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3. The Stochastic Gradient Descent for the Primal L1-SVM Optimization Revisited

URL: View paper

Brief Assessment

Primal L1-SVM[35] addresses L1-SVM optimization using stochastic gradient descent with subgradients for the non-differentiable L1-norm loss function, not the L1 latent distance in continuous-time graph representation. The technical contexts and problem domains are fundamentally different.

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4. A coordinate gradient descent method for nonsmooth separable minimization

URL: View paper

Prior Art Analysis

Coordinate Gradient Descent[33] demonstrates prior work on handling non-differentiable l1 norm optimization through descent direction methods. The candidate paper explicitly addresses l1-regularization problems and develops techniques to generate descent directions for optimization, which directly overlaps with the original paper's claimed contribution of finding descent directions to handle the non-differentiable l1 norm in their hazard function optimization.

Evidence

Evidence 1 - **Rationale**: Both papers address l1-regularization/l1 norm optimization problems, establishing the same problem domain. - **Original**: the $\ell 1$ distance, the corresponding hazard function, and the survival function are all nondifferentiable. hence we find a descent direction to replace the gradient, allowing mainstream learning architectures to learn the parameters of the graph. - **Candidate**: the l1-regularization of unconstrained optimization problems

Evidence 2 - **Rationale**: Coordinate Gradient Descent[33] explicitly describes generating descent directions for optimization with l1 regularization, demonstrating that the technique of finding descent directions for non-differentiable l1 norm problems existed prior to the original paper's work. - **Original**: To handle the non-differentiable $\ell 1$ norm, we successfully find a descent direction of the hazard function to replace the gradient, enabling mainstream learning architectures to learn the parameters. - **Candidate**: descent to generate a descent direction. then we do an inexact line search along this direction to ensure sufficient descent

5. On first-order algorithms for l1/nuclear norm minimization

URL: View paper

Brief Assessment

L1 Nuclear Norm[38] focuses on composite minimization formulations and saddle-point algorithms for l1/nuclear norm problems, not on descent direction methods for handling non-differentiability in hazard functions for continuous-time graph representation.

6. Parallel Coordinate Descent for L1-Regularized Loss Minimization

URL: View paper

Brief Assessment

Parallel Coordinate Descent[29] addresses l1-regularized loss minimization using coordinate descent with a fixed step size derived from a uniform upper bound (Assumption 2.1). The original paper's contribution involves finding a descent direction for the non-differentiable l1 norm in a hazard function context for continuous-time graph representation, which is a fundamentally different problem domain and mathematical framework than coordinate descent for l1-regularized regression.

7. A coordinate gradient descent method for â1-regularized convex minimization

URL: View paper

Brief Assessment

L1 Coordinate Gradient[37] focuses on coordinate descent methods for l1-regularized convex minimization problems, while the original paper addresses continuous-time graph representation with l1 latent distances and develops descent directions specifically for non-differentiable hazard functions in sequential survival processes. These are fundamentally different application domains and technical contexts.

8. Analyzing and Improving Greedy 2-Coordinate Updates for Equality-Constrained Optimization via Steepest Descent in the 1-Norm

URL: View paper

Brief Assessment

Greedy Coordinate Updates[36] addresses coordinate descent for equality-constrained optimization using steepest descent in the 1-norm, not continuous-time graph representation with hazard functions. The technical contexts are fundamentally different.

9. Generalized Gradient Norm Clipping & Non-Euclidean (L0,L1)-Smoothness

URL: View paper

Brief Assessment

Gradient Norm Clipping[32] addresses non-Euclidean optimization with gradient norm clipping and steepest descent methods, not specifically the non-differentiable l1 norm in hazard functions for continuous-time graph representation.

10. L1-penalized AUC-optimization with a surrogate loss

URL: View paper

Brief Assessment

L1 AUC Optimization[34] addresses l1-penalized AUC optimization using proximal gradient descent for variable selection, not the specific challenge of handling non-differentiable l1 distance in hazard functions for continuous-time graph representation.

Appendix: Text Similarity Detection

Textual similarity detection checked 23 papers and found 3 similarity segment(s) across 1 paper(s).

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

1. Continuous-time Graph Representation with Sequential Survival Process

Detected in: Core Task (sibling)

⚠ **Note**: This paper shows substantial textual similarity with the original paper. It may be a different version, a duplicate submission, or contain significant overlapping content. Please review carefully to determine the nature of the relationship.

References

- [0] ℓ_1 Latent Distance based Continuous-time Graph Representation View paper
- [1] Continuous-time Graph Representation with Sequential Survival Process View paper
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