SE-SGformer with Temporal Weights: A Small Boost with Big Implications

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***Abstract*—Temporal signed networks - where both positive and negative relationships evolve over time - are central to complex real-world systems such as financial and online trust-based platforms. While recent advances in graph neural networks (GNNs) have dramatically improved link prediction in static or unsigned scenarios, there remains a critical gap in the cross-section of non-static signed networks. To address this, we propose a temporally-weighted enhancement of the Self-Explainable Signed Graph transformer (SE-SGformer), a cutting-edge static signed GNN framework. Our unique approach integrates a network's historical context through LSTM-based sequence modeling and temporal attention, enabling an adaptive aggregation of node embeddings across time while preserving interpretability. We benchmark our model against a comprehensive suite of classical and sign-aware heuristics, including signed two-hop paths, balance theory, status theory, and preferential attachment on both real-world and synthetic signed temporal graphs. Our simulations reveal that our enhancement to the existing SE-SGformer can improve signed link prediction performance, marking a positive step in an otherwise challenging field of research. We intend for this report to establish a foundation for future research on adaptive and interpretable graph learning in dynamic, real-world environments.**

I. Introduction

Real-world networks range from recommendation engines to financial transaction systems. Represented by (G = (V, E)), a graph (G) is a collection of nodes (V) with relationships known as edges (E). They may evolve over time, with edges forming or ceasing to exist. Indeed, most real-world networks fall under this category, being known as temporal graphs. Temporal graph neural networks (TGNNs) are a rising subsection of GNN research, aiming to utilize machine learning in understanding meaningful network representations. Though this field has witnessed promising advancements, it has been limited to unsigned or static graphs, ultimately neglecting the intersection of temporal dynamics on signed networks.

Unlike traditional unsigned graphs that only capture the mere presence of connections, signed networks encode the polarity of relationships – trust versus distrust, cooperation versus competition, or approval versus disapproval. These features offer notable semantic enrichment, making signed networks particularly valuable for areas such as financial networks, where identifying fraudulent connections is crucial for risk management. Thus, the task of signed link prediction aims to infer whether future or missing edges will be positive or negative based on the network's structure. Traditional approaches to signed network analysis have relied on balance theory and structural properties, but recent GNNs breakthroughs like the Self-Explainable Signed Graph transformer (SE-SGformer) have demonstrated superior performance and explainability by leveraging complex node representations that capture multi-hop neighbourhood aggregations.

A crucial limitation in existing signed graph neural network (SGNN) approaches, including the SE-SGformer, relates to their treatment of networks as static entities. In real-world systems, signed networks are typically temporal in nature, evolving over time as relationships and polarities evolve and decay. That said, temporality introduces several complications for signed network analysis. First, the significance of historical information may decay over time, requiring sophisticated weighting mechanisms to accurately balance recent observations against established trends. Second, temporal dynamics must account for balance theory evolution, where triadic structures change over time, impacting overall network stability. Third, the integration of temporal weighting poses a risk to model explainability, particularly in critical applications where understanding the rationale behind predictions is essential.

Our contribution includes a proposal that addresses the above challenges by offering a temporally-weighted enhancement of the SE-SGformer framework. It recognizes the value of recency-bias in historical data, relationship stability over time, and local network dynamics. By adaptively aggregating network information across time steps, our method better captures evolutionary patterns, all while maintaining explainability. We compare our extension's effect on predictive performance to the baseline – and offer a well-rounded evaluation by contrasting the results to comparable heuristic approaches.

II. Related Works

A. Static Signed Graph Neural Networks

Much research focuses on articulating learning representations from static signed networks, neglecting temporal datasets. In the static domain, the SE-SGformer architecture marks a significant advancement in SGNN performance. It introduces a self-explainable transformer architecture that utilizes signed random walk encodings to achieve a superior performance on real-world datasets with a 2.2% prediction accuracy gain and 73.1% enhancement in explainability over comparable state-of-the-art models [1]. Explainability is paramount in real-world prediction-tasks, making the SE-SGformer all the more valuable in its discovery of K-nearest positive and negative neighbours to replace traditional neural network decoders, providing interpretable decision processes for the link sign prediction [1].

Signed Graph Convolutional Networks (SGCNs) pioneered the integration of balance theory into GCN architectures, making possible the aggregation of signed links during message-passing [2]. This architecture has proven particularly effective in learning graphical representations whilst addressing the added complexities of signed links [2]. Further advancing the field, the Signed Graph Diffusion Network (SGDNet) introduced a specialized random walk technique for signed graphs, achieving end-to-end representation learning that outperforms traditional methods in link sign prediction [3]. Both the SGCN and SGDNet architectures offer clarity into GNN-based signed link prediction tasks, leading the field in key performance metrics. That said, a primary limitation is their inability to capture temporal evolutionary patterns of any given network.

B. Temporal Unsigned Graph Neural Networks

Temporal GNNs for unsigned datasets have made substantial performance gains in recent years. The Temporal Graph Attention Network (TGAT) introduced functional time encoding based on Bochner's theorem, facilitating inductive representation learning that effectively manages an evolving network structure through self-attention mechanisms [4]. Although facing scalability challenges, TGAT has demonstrated superior performance in aggregating spatial-temporal neighbourhood features within both transductive and inductive tasks [4].

Temporal Graph Networks (TGNs) address continuous-time dynamic graphs by leveraging memory modules and message-passing engines to capture evolving node representations within the network [5]. By adopting this novel approach, the architecture is much more computationally efficient and scalable than alternatives like TGAT with a 30X speed increase per epoch, demonstrating superior performance can be achieved without suffering memory limitations [5].

C. Temporal Signed Network Modeling

Developers and scientists alike are currently limited by available options for temporal signed link prediction due to a pervasive literature gap in the area. That said, ground has been covered on fundamental theories - particularly in the evolution of the ratio of balanced, signed relationship triads over time [6]. The results of the study exemplify the notion that the dynamics of signed relationships are complex, requiring models that supersede the that of the current simple static or unsigned temporal approaches.

Sign-adapted Temporal Exponential Random Graph Models (TERGMs) also represent a recent advancement in the field. By leveraging a statistical approach to modeling signed network evolution, the common theme of explicitly denoting triadic transformations over time surfaces [7]. The study notes the significant performance upside associated with systems that utilize the network's triangle. Though not leveraging the expressive power of deep learning, the statistical models do provide valuable insights into how balance theory operates in dynamic contexts, and inspires us to investigate a similar approach for our research.

There remains an open opportunity for further exploration and development within this area. Though the literature's advancements and discoveries are encouraging, they still rely on statistical models over GNNs. Our approach within this report begins to narrow the gap by introducing a neural network model that not only encodes signed structure, but also aggregates historical context.

D. Learned and Explicit Time-Decay Mechanisms

Determining how the past should influence the future remains a central challenge in temporal graph learning. The basic exponential decay - as seen in earlier studies - has been superseded by learned attention mechanisms that adaptively weight a network's historical information. Inspiring our approach is the Long Short-Term Memory (LSTM) architecture, especially when combined with attention. This historical context aggregation technique has proven particularly effective at capturing long-term dependencies in sequential and temporal graph data [8], thus proving crucial to our effort to utilize historical embeddings to influence predictions of future states.

We are further inspired by the TGAT and TGN architectures in how we approach GNN time-awareness. With unsigned temporal graph analysis, these approaches utilize time-aware attention and memory modules to automatically learn how much importance to assign to recent versus older events. These architectures' associated studies have presented results indicating their improved ability in dynamic link prediction [4] [5], thus inspiring our own LSTM-plus-attention historical context module that will be explained in the Methodology section.

III. Methodology

A. SE-SGformer Overview

As our enhancement directly integrates with the SE-SGformer source code, it is important to outline and understand its fundamental architecture. It utilizes a trio of specialized encoding mechanisms. Details like node centrality, normalized sign graph adjacency, and random-walking ensure stable and effective message-passing between each node are collected. They are then passed to multi-head self-attention layers within a transformer-style architecture to produce rich node embeddings. Finally, a discriminator head is used to decode the embeddings and predict the polarity of each edge.

B. Temporal Weighting Mechanism

To introduce temporal embeddings, we integrate our Historical Context Extractor PyTorch module with the existing

SE-SGformer framework. Our system stacks historical node embeddings, passing them through a LSTM network. This process ensures we effectively capture sequential temporal dependencies. We additionally utilize a multi-head attention mechanism to allow the model to capture and emphasize the most relevant historical patterns on a per-node basis whilst filtering irrelevant noise. We support this with a multifaceted loss function that penalizes incorrect predictions as well as embeddings that do not respect the underlying signed structure of the network.

C. Architectural Modifications

To seamlessly integrate both systems, we made small modifications to the base SE-SGformer source code. Our combination is carefully managed by a learnable gating mechanism implemented as a small multi-layer perceptron (MLP) which computes a per-node historical context weight. This approach conserves the explainability of the original SE-SGformer - all while introducing temporal awareness.

D. Heuristic Methods

To provide a robust benchmark for our temporally-weighted SE-SGformer enhancement, we utilize heuristic-based link prediction from classical network science. Despite the rise of deep learning models, "simple and highly efficient heuristics often outperform" them [9], raising questions about the computational cost associated with advanced GNN techniques. Thus, by benchmarking our model against a diverse set of heuristics, we ensure a comprehensive, yet fair evaluation that highlights the specific advantages of GNNs over heuristics.

1) Majority Class Heuristic: Serving as a trivial baseline, the Majority Class heuristic always predicts the most common edge sign in the network. In most polar networks, the positive sign significantly outweighs that of the negative, thus the output of this heuristic would be a positive link in all scenarios. The heuristic does not not consider any network structure or node attributes, making it a purely frequency-based predictor. Though basic, it establishes a minimal performance threshold, assisting us in contextualizing the performance of more sophisticated methods.

2) Signed Two-Hop Paths Heuristic: We've additionally implemented a signed two-hop paths heuristic. This approach is inspired by the classical Katz index, which counts the number of short paths between nodes - and has been proven effective in both signed and unsigned networks [10]. We adapt the heuristic to account for the sign of the paths it computes. Intuitively, indirect positive connections (e.g., "a friend of a friend") signals a high probability of a positive future relationship - while the vice versa case is true for paths of distrust. The heuristic operates by summing the products of edge signs along all two-step paths between the node pair, thus incorporating both the quantity and polarity of indirect connections.

3) Signed Clustering Coefficient: Signed balance theory heuristics are also founded upon the social psychology principle of "the enemy of my enemy is my friend" and "the friend of my friend is my friend". The use of such triads as a basis for predicting edge signs has been formalized - and have been demonstrated that, on a local scale, patterns of social balance are highly predictive in signed networks [10]. Additionally, empirical evidence has been provided that balanced triangles are overrepresented in real-world signed networks and that the presence of balanced triads can be leveraged for both clustering and sign prediction tasks [11]. For this reason, we've implemented the Signed Clustering Coefficient heuristic for evaluation purposes.

4) Signed Jaccard & Adamic-Adar Heuristics: We've extended the Jaccard Coefficient and Adamic-Adar heuristics, which originally compute neighbourhood overlap measures. These have been shown to be robust predictors in both unsigned and signed settings, particularly when combined with structural balance considerations [12]. Thus, we've implemented a measure to count only positive (or negative) shared neighbours, weighing rarer neighbours more heavily. For signed Jaccard, we divide the number of shared positive neighbors by the total number of unique positive neighbors, while for signed Adamic-Adar, we sum the inverse logarithm of the positive degree of each shared neighbor, emphasizing the predictive value of less-connected nodes

5) Positive Common Neighbors: Established as a robust and interpretable baseline for link prediction, the classical common neighbours (CN) measure is foundational. This approach is closely linked to the concept of triadic closure: if two nodes share many mutual friends, they are more likely to form a connection themselves. Furthermore, the number of shared neighbors is strongly correlated with the likelihood of future link formation [12]. With this in mind, we've adapted the CN heuristic to a "positive CN" variant, counting the number of shared positive neighbors between two nodes.

6) Signed Status Theory: The Signed Status Theory heuristic evaluates the net positive degree (i.e., status) between nodes, extending the sociological theories that links are more likely between nodes of similar or compatible status [11]. Empirically validated, Status Theory showcases that status differences directly tie to the formation and sign of edges. Comprehensive analysis asserts that Status Theory often proves superior to Balance Theory - especially within social networks where directed, signed relationships are commonplace. Operationally, this heuristic assigns higher likelihood to edges between nodes whose net positive (minus negative) degrees are similar, reflecting the tendency for individuals of comparable status to connect.

7) Signed Preferential Attachment: Finally, we've implemented a signed preferential attachment heuristic, extending the classical preferential attachment principle to signed networks. Preferential attachment posits that nodes with higher degree are more likely to attract new links (i.e., "the rich get richer") [13]. For signed networks, we adapt this heuristic by computing the product of the positive degrees of two nodes, capturing the intuition that nodes with many positive relationships are more likely to form additional positive links.

IV. Experimental Setup

A. Datasets

To ensure a well-rounded evaluation of our temporally-weighted enhancement to SE-SGformer, we utilize both real-world and synthetic signed temporal network datasets for our simulations. Our primary assessment involves the Bitcoin OTC trust network [14]. This dataset represents a well-established benchmark in signed temporal network analysis, and demarks trust and distrust ratings among anonymous Bitcoin traders. It consists of 5,881 nodes (traders) and 35,592 directed, timestamped edges (trust ratings). A complication of real-world datasets such as this lies in the heavy class imbalance between positive and negative links; approximately 89% of edges within the Bitcoin network are positive, while the vast minority of relationships represent a negative relationship.

Complementing the real-world dataset, we synthesize a signed temporal Erdős–Rényi graph dataset to validate our approach under controlled conditions. The artificial network consists of 5,000 nodes and 306,563 edges over time, with each potential edge - and its sign - included with a fixed probability, chosen such that the expected number of edges approximates that of a real-world dataset while mirroring the positive edge imbalance seen in the Bitcoin OTC network. This approach enables a systematic investigation of the impact of network structure, sign distribution, and temporal evolution on model performance, bolstering our findings from the real-world dataset.

To facilitate a temporal analysis, we partition the dataset into a number of time bins, where each bin represents a single - or a collection - of unique time steps, each consisting of non-overlapping chronological intervals. If, for example, six time bins exist, the first five constitute historical context, while the final interval is reserved for evaluating model predictions. This approach enables a realistic assessment of both static and dynamic link prediction performance on any given time bin. It also empowers us to conduct a systematic investigation of the impact of network structure, sign distribution, and temporal evolution on model performance, bolstering our findings from the real-world dataset.

B. Baselines

To provide a balanced assessment of our temporally-weighted SE-SGformer enhancement, we compare its performance directly against the original model. The question being analyzed with this baseline comparison is simple: can temporally-weighted embeddings improve the performance of a model that otherwise exclusively operates on the target time step without access to historical information? Beyond this static baseline, we include implementations and tests for several heuristic approaches to signed link prediction as described above. The goal of this comparison is to enable an assessment of the true value of developing GNN systems, especially in light of the immense time, data, and fiscal costs associated with it. The selected baselines facilitate isolation between three unique approaches, allowing us to quantify the benefits of our temporal-weighting mechanism and context aggregation.

C. Evaluation Metrics

We utilize a trio of metrics to assess our enhancement's performance.

Our most comprehensive measure involves the Area Under the Receiver Operating Characteristic Curve (AUC-ROC). This evaluation provides a normalized value of 0 to 1, where 1 represents the model's ability to perfectly discriminate between each class (in our case, negative or positive edges - if an edge exists at all), while 0.5 or lower indicates completely random guessing in the best-case - in other words, a dysfunctional model.

Next, to ensure the model adequately addresses our data's class imbalances, we utilize the F1 score. This metric evaluates our model's ability to correctly identify relevant links whilst avoiding false positives and negatives. It is done by observing the harmonic mean between precision and recall. Precision measures the proportion of correctly predicted signed edges, while recall quantifies the model's ability to correctly identify actual signed edges. The F1 is particularly important in ensuring the model can pick out under-represented patterns.

Finally, we utilize Precision@100, where we assess the top 100 predicted neighbours. It ascertains our model's ability to correctly classify the top-ranked 100 neighbours relative to the ground-truth, allowing the us to understand how well the model can identify the network's most influential relationships.

D. Implementation Details

Our configuration of the SE-SGformer includes a node embedding dimension of 128, two transformer layers, and four attention heads. Our MLP unit consists of a small two-layer neural network, while our LSTM mechanism has a hidden dimension of 64, followed by multi-head attention.

Our training algorithm utilizes a very similar structure to the SE-SGformer's. We instantiate the Adam optimizer with a learning rate of 0.001, and train the model for up to 500-1000 epochs, though our scheduler - a basic cosine annealing function with warm restarts - may cancel the training as it plateaus. Additionally, we employ a comprehensive loss function that combines signed classification loss with embedding regularization. Finally, the training is powered by a single NVIDIA T4 GPU with 16GB VRAM and 64GB system RAM.

V. Results & Analysis

A. Bitcoin OTC Network Results

TABLE I
Performance metrics for Bitcoin OTC Network - Time Step 4.

Method	AUC-ROC	F1 Score	Precision@100
Base SE-SGformer	0.901 ± 0.005	0.940 ± 0.001	0.980 ± 0.006
Enhanced SE-SGformer	0.911 ± 0.004	0.941 ± 0.002	0.994 ± 0.004
Majority Class	0.494	0.891	0.780
Signed 2-Hop Paths	0.734	0.696	0.990
Signed Clustering Coeff.	0.462	0.607	1.000
Signed Jaccard Coeff.	0.729	0.705	1.000
Signed Adamic-Adar	0.730	0.705	0.980
Pos. Common Neighbors	0.730	0.705	0.970
Signed Status Theory	0.470	0.593	1.000
Signed Pref. Attachment	0.805	0.704	0.990

TABLE II
Performance metrics for Bitcoin OTC Network - Time Step 6.

Method	AUC-ROC	F1 Score	Precision@100
Base SE-SGformer	0.931 ± 0.005	0.946 ± 0.003	0.991 ± 0.006
Enhanced SE-SGformer	0.955 ± 0.004	0.962 ± 0.003	0.995 ± 0.003
Majority Class	0.469	0.967	0.960
Signed 2-Hop Paths	0.682	0.664	0.980
Signed Clustering Coeff.	0.714	0.684	1.000
Signed Jaccard Coeff.	0.656	0.672	0.960
Signed Adamic-Adar	0.667	0.672	0.980
Pos. Common Neighbors	0.668	0.672	0.980
Signed Status Theory	0.376	0.638	0.860
Signed Pref. Attachment	0.861	0.682	0.960

When predicting time step four of the Bitcoin dataset, both the baseline and the enhanced model achieved a high precision score. The enhanced model showed an improvement in AUC score of approximately 1 percentage point, corresponding with a relative improvement of 1.11%. The error reduction was approximately 10.10%. The F1 score was nearly the same for both the baseline and the enhanced model, with the enhanced showing slight improvement.

The prediction of time step six showed greater improvement than time step four; the temporal enhanced model achieved a substantial improvement of 2.4 percentage points over the baseline with a corresponding relative improvement of 2.58%. The enhanced model also had a strong error reduction of 36.36% and a lower standard error. F1 Score was improved by 1.6 percentage points with a corresponding relative improvement of 1.69%. The error reduction was 29.63%, and we also saw a similar standard error. The precision of both models remained similar, with a slight improvement from the enhanced model.

Across all evaluations, both machine learning models performed far better than heuristics. Heuristics tend to score very highly in one or two categories, with precision being one, as heuristics are very effective at prioritizing the most likely edges.

B. Erdős–Rényi Network Results

TABLE III
Performance metrics for Erdős–Rényi Network - Time Step 4.

Method	AUC-ROC	F1 Score	Precision@100
Base SE-SGformer	0.641 ± 0.010	0.569 ± 0.078	0.870 ± 0.036
Enhanced SE-SGformer	0.662 ± 0.002	0.715 ± 0.002	0.887 ± 0.020
Majority Class	0.490	0.917	0.850
Signed 2-Hop Paths	0.500	0.098	0.920
Signed Clustering Coeff.	0.521	0.633	1.000
Signed Jaccard Coeff.	0.499	0.097	0.810
Signed Adamic-Adar	0.499	0.097	0.890
Pos. Common Neighbors	0.499	0.097	0.920
Signed Status Theory	0.506	0.571	1.000
Signed Pref. Attachment	0.599	0.648	0.950

TABLE IV
PERFORMANCE METRICS FOR ERDŐS–RÉNYI NETWORK - TIME STEP 6.

Method	AUC-ROC	F1 Score	Precision@100
Base SE-SGformer	0.639 ± 0.007	0.656 ± 0.049	0.894 ± 0.014
Enhanced SE-SGformer	0.655 ± 0.004	0.718 ± 0.003	0.904 ± 0.024
Majority Class	0.465	0.967	0.890
Signed 2-Hop Paths	0.501	0.148	0.990
Signed Clustering Coeff.	0.529	0.520	1.000
Signed Jaccard Coeff.	0.500	0.148	0.880
Signed Adamic-Adar	0.501	0.148	0.850
Pos. Common Neighbors	0.501	0.148	0.990
Signed Status Theory	0.504	0.589	1.000
Signed Pref. Attachment	0.594	0.652	0.960

When predicting time step six, the AUC improvement was similar to time step four at about 2.6 percentage points, with a relative improvement of 4.08% and an error reduction of 7.08%. The F1 scores increased by 1.3 percentage points, or 1.85% relatively, with an error reduction of 4.45%. The standard deviation for F1 scores was also lower. Precision for both models was high, with the enhanced version outperforming the base model.

When predicting time step four of the Erdős–Rényi synthetic dataset, the enhanced model performed better at about 2.1 percentage points or approximately a 3.28% relative improvement for AUC scores with a lower standard error. The AUC error reduction was 5.85%. There was a 14.6 percentage point increase in F1 score, resulting in a 25.66% relative improvement and an error reduction of 33.87%. The enhanced version performed slightly better on precision, but was outperformed by Positive Common Neighbours, Signed 2-Hop Paths, Signed Clustering Coefficient, Signed Status Theory, and Signed Preferential Attachment.

Heuristics tend to score highly in precision or well enough in other categories, but never in all three. The machine learning models appear to be consistent across all metrics.

It is important to note the lower scoring across both models. This can be due to the limitations of synthetic data in capturing real-world temporal dynamics.

VI. DISCUSSION & LIMITATIONS

A. Interpretation of Findings

The temporally enhanced model shows consistent, strong improvements over the original SE-SG model. While some of the increases are mostly present on the later time step testing, that is to be expected when dealing with historical data. The quality of historical data - and how indicative the history is of current interactions - is heavily determinant of whether a model such as this can perform well. Additionally, how well synthetic data is created is also a determining factor, so any future testing should prioritize real-world datasets. Across multiple evaluations, the enhanced model is more consistent, has lower standard error, more error reduction, and improved AUC, F1, and precision scores.

Heuristics still provide valuable uses in some calculations. Signed preferential attachment performed strongly on all datasets across all the metrics and is far quicker to compute than machine learning models. Additionally, heuristics offer high precision for most likely edges, often beating out machine learning models.

It is important to note that the number of epochs trained, model parameter tuning, and the number of time bins created from a dataset are also very important in determining the temporally enhanced results. Tuning the parameters is key to getting enhanced results, and default values are not always strong enough to give a proper enhancement.

The overall results across multiple evaluations show that machine learning models are better across all metrics over heuristic methods, and the temporally enhanced model is a great improvement upon the existing SE-SG model. These findings demonstrate that incorporating historical context and leveraging historical patterns through our enhanced model represents a meaningful improvement on signed graph link prediction.

B. Future Work

This report lays the groundwork for several intriguing research directions. The improvements that can be explored for this model are its computational efficiency, investing in techniques that can mitigate the existing overhead. As it currently stands, we rely on storing historical embeddings across a fixed window of previous time steps, which can become unsustainable with increasing memory usage. The second area for improvement is to refine the temporally-weighted extension of our model itself. While our current historical context extractor yields promising results, further work in advancing the architecture presents an opportunity to push the boundaries of performance of the SE-SG model - as well as other models in the field. Currently, the model is laid out for discrete time bins, so an advancement in continuous time adaptation is one of our recommendations as it would enable more precise modeling of complex systems. An additional architectural improvement includes reducing the need for parameter tuning to increase the usability of our enhancement.

One of the biggest opportunities arising from our findings and new approach is the development of new theories for forecasting tasks. As it stands, forecasting tasks for signed link prediction are incredibly complex, and throughout our research, we employed numerous approaches to attempt such a task by utilizing current theoretical approaches - without success. How we approach temporal data in complex graph datasets in this report offers an opportunity to develop new theories beyond the current approaches.

VII. Conclusion

While prior research has made significant strides in modeling static signed graphs and temporal unsigned graphs, the intersection of temporal dynamics and signed relationships remains largely untapped. Our report begins to fill this critical gap by proposing a temporally-weighted enhancement of the cutting-edge SE-SGformer. We introduce an adaptive historical aggregation mechanism by utilizing per-node LSTM-based sequence modeling and temporal attention. This approach seeks to conserve the explainability and performance benefits of existing work while pushing forward with temporal dynamics so often required by real-world applications.

By utilizing the real-world Bitcoin OTC dataset in combination with a synthetic Erdős–Rényi dataset, we offer a well-rounded testing ground for our model. Our evaluation suite and comparison benchmarks encompass a broad range of highly relevant metrics and non-machine learning-based approaches. Observed results indicate that incorporating temporally-weighted historical context yields improvements in signed link prediction performance, though with the caveat that varying performance occurs with limited historical context windows.

Our work represents a step toward filling a notable gap in the literature - and establishes several promising directions for future research. Namely, the incorporation of alternative temporal weighting schemes, the extension of our framework to continuous-time or irregularly sampled networks, and advancements in fundamental model architecture to address computational limitations all stand as opportunities to continue addressing the gap in this area. That said, by advancing the cutting-edge SE-SGformer framework, we envision that our efforts lay the groundwork for more robust, adaptive, and explainable graph learning systems going into the future.

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Appendix A
Appendix: Visualizations

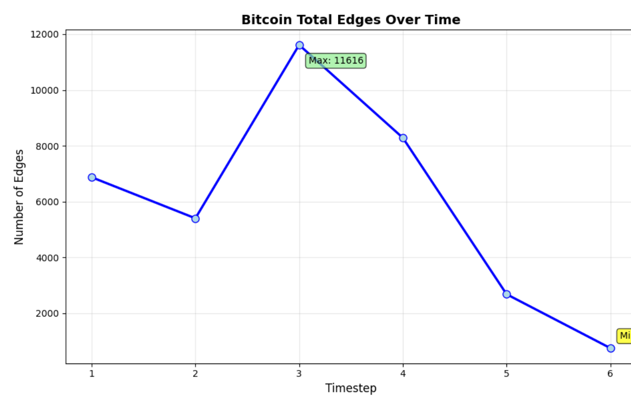

Fig. 1. Visualization of Bitcoin OTC edges over time.

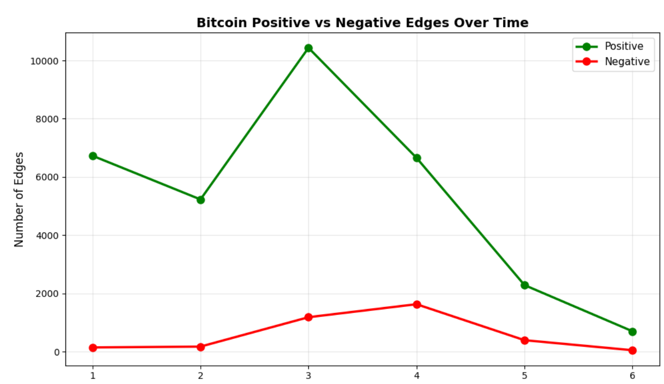

Fig. 2. Visualization of Bitcoin OTC signs over time.

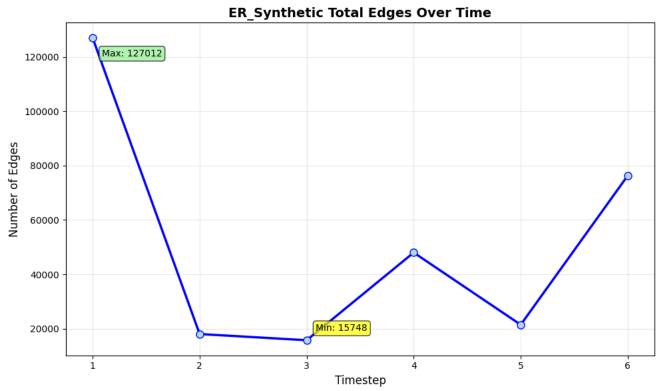

Fig. 3. Visualization of ER edges over time.

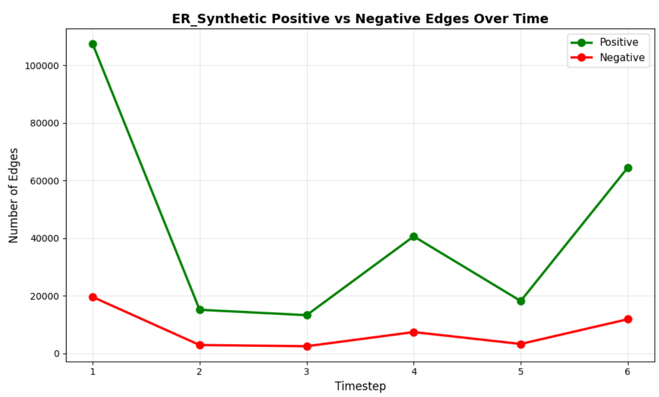

Fig. 4. Visualization of ER signs over time.

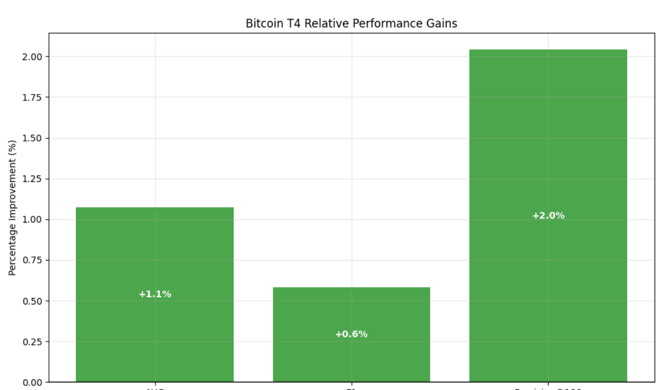

Fig. 5. Performance improvement at $t = 4$ on Bitcoin OTC dataset.

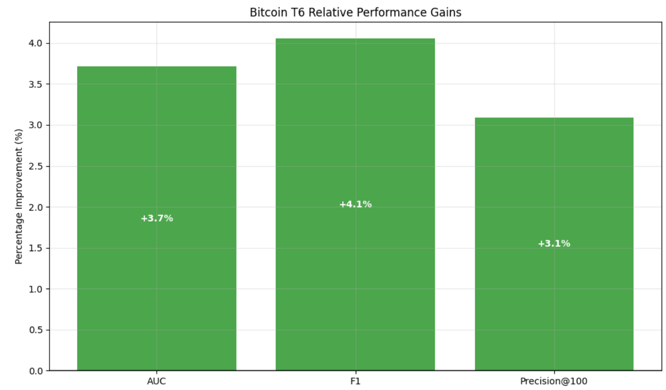

Fig. 6. Performance improvement at $t = 6$ on Bitcoin OTC dataset.

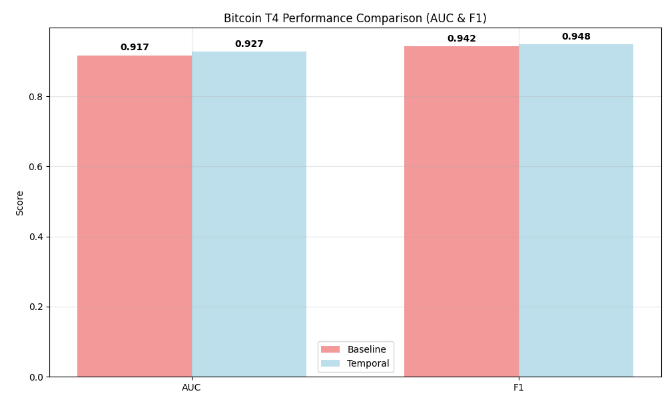

Fig. 7. AUC and F1 scores at $t = 4$ on Bitcoin OTC dataset.

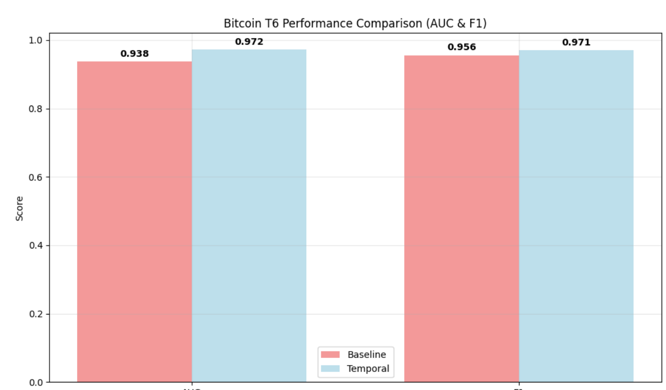

Fig. 8. AUC and F1 scores at $t = 6$ on Bitcoin OTC dataset.

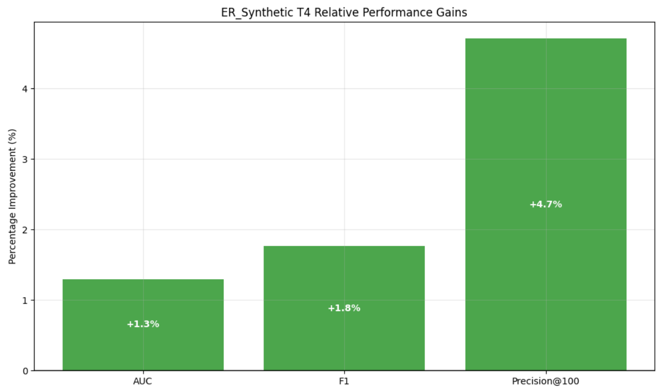

Fig. 9. Performance improvement at $t = 4$ on ER dataset.

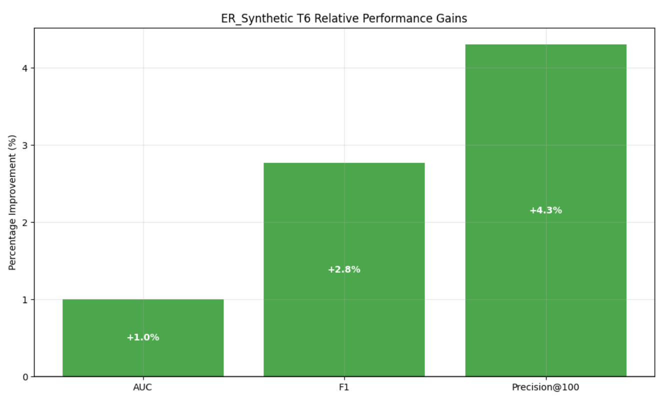

Fig. 10. Performance improvement at $t = 6$ on ER dataset.

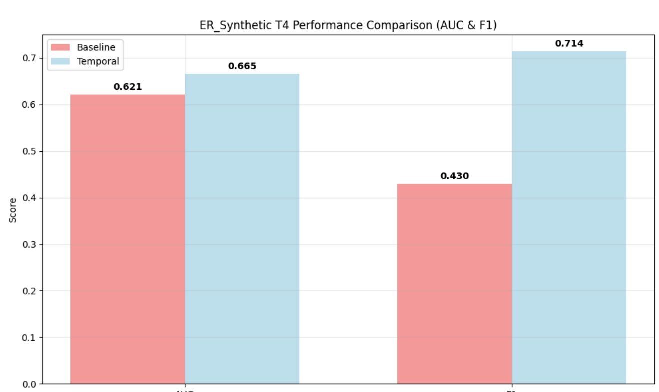

Fig. 11. AUC and F1 scores at $t = 4$ on ER dataset.

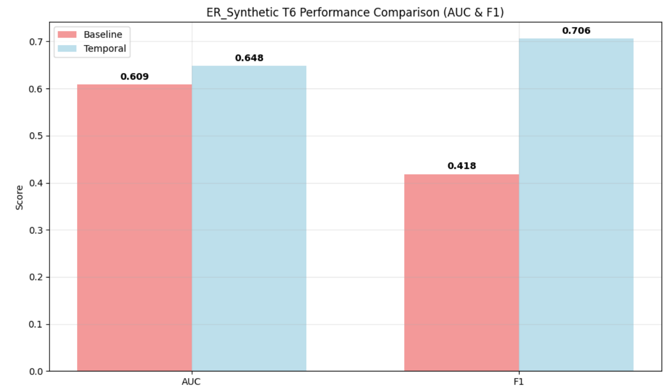

Fig. 12. AUC and F1 scores at $t = 6$ on ER dataset.