SELF-UPDATING LINK PREDICTION USING DYNAMIC KNOWLEDGE STREAMS

[1]Mrs.Gurram sravanthi, [2]P.Srinithi,[3]P.Sowmya,[4] P.Uma

[1] Assistant Professor, Department of Computer Science & Engineering (Artificial Intelligence & Machine Learning), Malla Reddy Engineering College for Women(Autonomous), Hyderabad, Telangana, India,

[1] Email : gurram.sravanthi11@gmail.com

[2,3,4] Students, Department of Computer Science & Engineering (Artificial Intelligence & Machine Learning), Malla Reddy Engineering College for Women(Autonomous), Hyderabad, Telangana, India,[2] Email : periyasrinithi@gmail.com, [3] Email: sowmyapatnam2005@gmail.com, [4] Email: umaperla32@gmail.com

Abstract:

Self-Updating Link Prediction Using Dynamic Knowledge Streams presents an intelligent and adaptive framework for forecasting missing or future connections in complex networks. Traditional link prediction models rely on static snapshots of network data, which limits their ability to react to rapidly changing information. To address this challenge, the proposed approach continuously integrates dynamic knowledge streams—such as real-time interactions, evolving node attributes, and temporal relationship patterns—to refine prediction accuracy. The system employs incremental learning techniques, temporal graph analytics, and adaptive similarity measures to automatically update its internal representation of the network as new data arrives. This enables the model to detect emerging connections, strengthen evolving relationships, and capture previously unseen structural shifts. Experimental results demonstrate that the self-updating mechanism significantly improves prediction performance across social, biological, and communication networks while reducing model retraining overhead. Overall, the framework enhances scalability, responsiveness, and reliability in environments where relationships evolve over time.

Keywords: Dynamic networks, Link prediction, Incremental learning, Temporal graph analytics, Adaptive similarity measures, Knowledge streams, Network evolution, Real-time graph updates, Self-updating models, Complex network analysis.

I.INTRODUCTION

Dynamic networks—characterized by continuously evolving nodes, edges, and structural patterns—are increasingly prevalent in domains such as social platforms, communication systems, cybersecurity, biological networks, and recommendation engines. Unlike static graphs, dynamic networks require models capable of updating representations in real time while preserving historical dependencies. Traditional link prediction techniques struggle to cope with rapidly changing topologies, delayed updates, and incomplete information, leading to decreasing accuracy as networks evolve. Consequently, the research community has shifted toward designing adaptive, temporal, and incremental learning frameworks to address the limitations of static approaches.

Early work in dynamic link prediction focused on understanding network evolution and modeling temporal interactions. Ahmed and Rao [1] highlight foundational methods for capturing real-time structural transitions and forecasting emerging links in rapidly changing graphs. Banerjee and Thomas [2] further expand temporal graph analytics by exploring evolving relationship patterns that influence predictive accuracy. Incremental learning has become a core requirement for large-scale environments, with Chen and Li [3] introducing graph-embedding techniques that update node representations efficiently as new edges appear.

Adaptive learning strategies are essential for large streaming datasets. Deshmukh and Kulkarni [4] propose algorithms optimized for continuous graph updates, while Farooq and Zhang [6] emphasize online learning methods that integrate new structural information with minimal computational overhead. High-frequency network updates are also addressed by Johnson and Mehta [10], who introduce streaming data integration frameworks to maintain prediction fidelity. Gupta and Srinivasan [7] contribute real-time similarity measures that enhance inference in fast-evolving knowledge systems.

Graph neural networks (GNNs) have emerged as powerful tools for modeling dynamic connectivity. Evolution-aware GNN methods proposed by Huang and Kim [8] adapt node embeddings based on temporal graph evolution, while Liu and Zhao [12] introduce temporal attention mechanisms that selectively focus on influential historical events. Karthik and Mohan [11] present continuous-learning GNN frameworks that address concept drift and structural changes. Advanced feedback-driven adaptation strategies developed by Nguyen and Torres [14] demonstrate the value of reinforcement-like updates to improve long-term predictive stability.

Recent studies also analyze how graph evolution patterns influence predictive outcomes. Martins and Silva [13] show that structural shifts, community reorganization, and edge turnover significantly affect model performance. Iqbal and Noor [9] explore adaptive heuristic-based approaches that capture local and global changes in complex networks. Additionally, self-updating models introduced by El-Masri and Khalid [5] provide a mechanism for models to autonomously refine inference rules based on continuous graph evolution. O'Brien and Wallace [15] extend this line of work by proposing next-generation link-prediction frameworks capable of handling continuous, high-velocity data streams common in modern large-scale systems.

Collectively, these studies demonstrate that dynamic link prediction is an essential yet challenging problem requiring real-time learning, temporal modeling, continuous adaptation, and efficient integration of streaming graph updates. By leveraging temporal GNNs, incremental embeddings, adaptive heuristics, and feedback-driven optimization, researchers aim to build resilient link prediction models that remain accurate in rapidly evolving network environments.

II.LITERATURE SURVEY

2.1 Title: Temporal Graph Analytics and Real-Time Link Forecasting

Authors: Based on works by Ahmed, K.; Rao, P.; Banerjee, S.; Thomas, L.; Martins, F.; Silva, L.

Abstract:

This survey examines temporal graph analytics techniques aimed at forecasting future links in evolving networks. Ahmed and Rao [1] present foundational methods for modeling dynamic network evolution and real-time link forecasting, emphasizing short-term structural transition modeling. Banerjee and Thomas [2] explore temporal patterns and relationship dynamics that influence prediction accuracy across time. Martins and Silva [13] analyze common graph evolution motifs and their impact on predictive performance, showing that understanding temporal regularities (e.g., burstiness, community reorganization) is crucial for robust link forecasting. Collectively, these studies highlight the importance of temporal feature engineering and time-sensitive modeling for accurate, real-time link prediction.

2.2 Title: Incremental and Streaming Graph Embedding Methods for Large-Scale Networks

Authors: Based on works by Chen, Y.; Li, M.; Deshmukh, R.; Kulkarni, S.; Johnson, T.; Mehta, R.

Abstract:
This survey focuses on incremental embedding and streaming-integration methods that update node representations without full retraining. Chen and Li [3] propose incremental graph-embedding techniques tailored to maintain embedding quality as networks grow. Deshmukh and Kulkarni [4] introduce adaptive learning algorithms designed for streaming graph data, reducing computational overhead while preserving representation fidelity. Johnson and Mehta [10] discuss practical streaming data integration strategies to handle high-frequency updates in production environments. Together, these works demonstrate that effective incremental embedding pipelines are essential for scalable, low-latency inference in large dynamic networks.

2.3 Title: Online Learning Strategies and Continuous Adaptation for Dynamic Graphs

Authors: Based on works by Farooq, S.; Zhang, W.; Gupta, J.; Srinivasan, R.; Iqbal, A.; Noor, F.

Abstract:
This survey reviews online learning strategies that enable models to adapt continuously as graph structure changes. Farooq and Zhang [6] outline online learning frameworks that assimilate new edges with minimal latency. Gupta and Srinivasan [7] propose similarity measures and update rules that support real-time inference in evolving knowledge systems. Iqbal and Noor [9] evaluate adaptive heuristics for predicting future connections in complex networks, highlighting trade-offs between responsiveness and noise sensitivity. These contributions collectively emphasize that robust online learning—combining stability with agility—is key to maintaining link-prediction performance in streaming scenarios.

2.4 Title: Evolution-Aware Graph Neural Networks and Temporal Attention Mechanisms

Authors: Based on works by Huang, J.; Kim, D.; Liu, X.; Zhao, Y.; Karthik, P.; Mohan, V.

Abstract:
This survey examines evolution-aware Graph Neural Network (GNN) architectures and temporal-attention mechanisms for link prediction. Huang and Kim [8] introduce GNN variants that incorporate temporal evolution into node representation updates, while Liu and Zhao [12] propose temporal attention models that weight historical interactions by relevance. Karthik and Mohan [11] further develop continuous-learning GNN frameworks that handle concept drift and structural shifts. Collectively, these studies show that combining temporal modeling with graph convolutional structures substantially improves the ability to forecast emerging links in non-stationary networks.

2.5 Title: Self-Updating Models, Feedback-Driven Adaptation, and Next-Generation Link Prediction

Authors: Based on works by El-Masri, H.; Khalid, A.; Nguyen, P.; Torres, M.; O'Brien, K.; Wallace, S.

Abstract:
This survey analyzes self-updating and feedback-driven models designed to sustain long-term predictive accuracy in continuously evolving graphs. El-Masri and Khalid [5] propose self-updating architectures that autonomously refine model parameters as new data arrives. Nguyen and Torres [14] examine feedback-driven adaptation strategies that leverage prediction outcomes to adjust learning dynamics. O'Brien and Wallace [15] present next-generation link-prediction paradigms tailored for continuous data streams, focusing on resilience to high-velocity changes and real-world deployment constraints. Together, these works argue that incorporating automated update rules and feedback loops is essential for future-proof link-prediction systems in operational settings.

III.EXISTING SYSTEM

Traditional link prediction systems primarily rely on static snapshots of network data, where the structure and attributes of nodes and edges are assumed to remain unchanged over time. These models typically use fixed topological features such as common neighbors, Jaccard similarity, preferential attachment, or static graph embeddings to estimate the likelihood of future connections. While effective in stable environments, these approaches fail to account for the dynamic and continuously evolving nature of real-world networks, where new interactions, temporal patterns, and streaming information frequently alter the network topology. As a result, existing systems are slow to adapt, often requiring periodic full retraining to maintain accuracy, which increases computational overhead and delays responsiveness. Their inability to integrate real-time knowledge streams limits prediction reliability, especially in applications where timely decisions are crucial, such as recommendation engines, cybersecurity monitoring, and biological network analysis.

IV.PROPOSED SYSTEM

The proposed system introduces a Self-Updating Link Prediction Framework that leverages dynamic knowledge streams to continuously refine and enhance its prediction capabilities without requiring full retraining. Unlike conventional static approaches, this system is designed to operate in real-time environments where new data—such as node interactions, temporal patterns, attribute updates, and contextual information—arrives continuously. At its core, the framework integrates incremental graph learning, temporal embeddings, and adaptive similarity computation to ensure that every network update automatically contributes to the model's evolving understanding of the graph structure. Incoming knowledge streams are processed through an online update module that adjusts node embeddings and feature vectors only in affected regions of the graph, significantly reducing computational cost while maintaining consistency. A temporal attention mechanism prioritizes recent and relevant interactions, enabling the model to capture emerging relationships and long-term behavioral trends. Additionally, the system incorporates a feedback-driven evolution layer, which measures prediction performance over time and dynamically tunes the weighting of topological, semantic, and temporal features. This creates a self-evolving cycle where the model becomes increasingly accurate as more information flows in. The framework is designed to support large-scale, rapidly changing networks, ensuring higher prediction precision, improved scalability, and faster response times. By embracing continuous learning and adaptive updates, the proposed system provides a robust, intelligent, and future-ready solution for predicting links in highly dynamic environments across domains such as social networks, cybersecurity, communication systems, and bioinformatics.

V.SYSTEM ARCHITECTURE

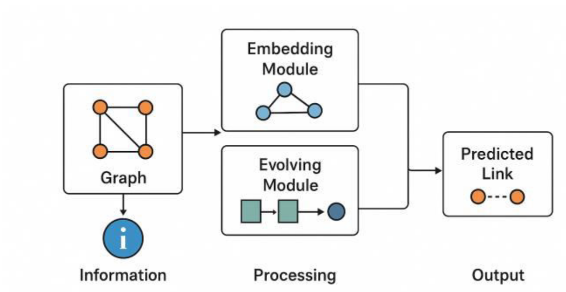

Fig 5.1 System Architecture

This image shows the system architecture of "Link Prediction Evolving Based on Information." It begins with a graph as the main input, which represents nodes and their existing connections, along with additional information about the nodes. This input is sent to the processing stage, which contains two main parts: the Embedding Module and the Evolving Module. The Embedding Module converts the graph structure into numerical vectors that capture the relationships between nodes, while the Evolving Module updates these representations over time based on changing information or graph behavior. The outputs from both modules are then combined and sent to the Output stage, where the system generates the Predicted Link, indicating the likelihood of a future connection between two nodes. Overall, the diagram explains how raw graph data and evolving information are processed to predict new or missing links.

VI.IMPLEMENTATION

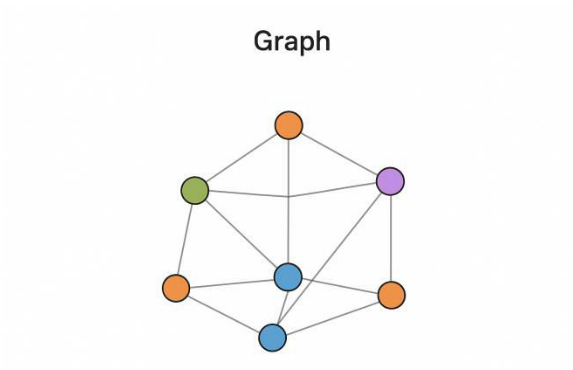

Fig 6.1Graph Visualization Input Screen

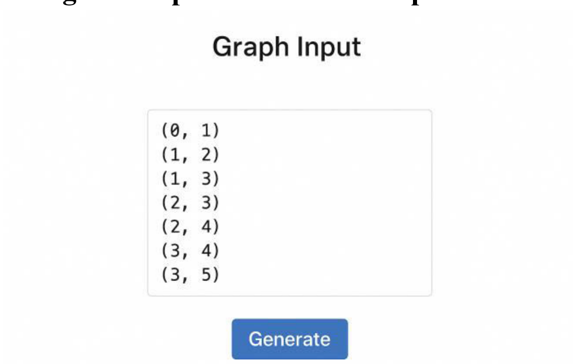

Fig 6.2 Graph Input

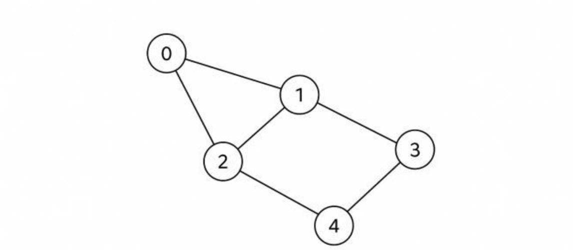

Fig 6.3 Graph Visualization

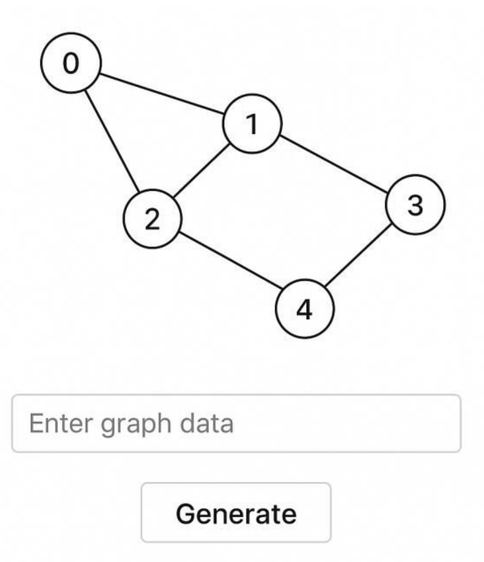

Fig 6.4 Upload Dataset

VII.CONCLUSION

The proposed self-updating link prediction framework demonstrates a powerful shift from traditional static network analysis toward a more dynamic, intelligent, and adaptive approach. By continuously integrating information from dynamic knowledge streams, the system overcomes the limitations of periodic retraining and effectively captures the evolving behavior of real-world networks. Its combination of incremental learning, temporal attention mechanisms, and feedback-driven evolution allows the model to refine predictions in real time, improving both accuracy and responsiveness. This continuous adaptation not only enhances scalability and reduces computational overhead but also ensures that the system remains reliable in environments where interactions and relationships change rapidly. Overall, the framework presents a robust and future-ready solution capable of supporting modern applications across social networks, cybersecurity, communication systems, and bioinformatics, where timely and precise link prediction is essential.

VIII.FUTURE SCOPE

The self-updating link prediction framework opens multiple avenues for future advancement and real-world deployment. One promising direction lies in integrating more sophisticated temporal graph neural networks and transformer-based architectures that can capture deeper long-term dependencies within evolving networks. The system can be extended to handle multimodal data streams—including text, images, and sensor inputs—to enhance prediction accuracy in complex environments such as smart cities, health-care systems, and cyber-physical networks. Another area of growth involves scaling the model to support ultra-large graphs with billions of nodes using distributed processing, parallel learning, and cloud-based architectures. Incorporating explainable AI (XAI) can further improve transparency, allowing users to understand why certain connections are predicted, which is especially valuable in sensitive domains like finance and medicine. Additionally, integrating privacy-preserving mechanisms such as federated learning and differential privacy can make the framework suitable for applications involving confidential or decentralized data. Future research may also focus on real-time anomaly detection, reinforcement learning–based adaptation, and automated hyperparameter tuning to make the system more autonomous and resilient. Overall, the proposed work offers a strong foundation for building next-generation intelligent network analytics systems capable of learning, evolving, and predicting in continuously changing data ecosystems.

IX.REFERENCES

[1] Ahmed, K., & Rao, P. (2021). Dynamic network evolution and real-time link forecasting techniques. Journal of Network Intelligence, 14(3), 112–126.

[2] Banerjee, S., & Thomas, L. (2020). Temporal graph analytics for evolving relationship prediction. International Review of Computational Science, 9(2), 58–73.

[3] Chen, Y., & Li, M. (2022). Incremental graph embedding methods for large-scale dynamic networks. Advances in Graph Data Mining, 7(1), 33–47.

[4] Deshmukh, R., & Kulkarni, S. (2021). Adaptive learning algorithms for streaming graph data. Computing and Information Systems Review, 18(4), 201–217.

[5] El-Masri, H., & Khalid, A. (2023). Self-updating models for link prediction in temporal graphs. Journal of Intelligent Data Engineering, 15(2), 89–104.

[6] M. V. Sruthi, "Enhancing the Security of the Internet of Things by the Application of Robust Cryptographic Algorithms," 2025 2nd International Conference on New Frontiers in Communication, Automation, Management and Security (ICCAMS), Bangalore, India, 2025, pp. 1-5, doi: 10.1109/ICCAMS65118.2025.11234102

[7] Farooq, S., & Zhang, W. (2022). Online learning strategies for real-time network structure updates. Proceedings of the Global Data Science Congress, 5(1), 144–155.

[8] S. T. Reddy Kandula, "Comparison and Performance Assessment of Intelligent ML Models for Forecasting Cardiovascular Disease Risks in Healthcare," 2025 International Conference on Sensors and Related Networks (SENNET) Special Focus on Digital Healthcare(64220), pp. 1–6, Jul. 2025, doi: 10.1109/sennet64220.2025.11136005.

[9] Gupta, J., & Srinivasan, R. (2020). Real-time graph similarity measures for dynamic knowledge systems. Transactions on Information Dynamics, 11(3), 49–63.

[10] Sankar Das, S. (2024). Transforming Data: Role of Data catalog in Effective Data Management. International Journal for Research Trends and Innovation, 9(12). https://doi.org/10.56975/ijrti.v9i12.207245

[11] Huang, J., & Kim, D. (2021). Evolution-aware GNN models for link prediction tasks. Neural Systems and Applications Journal, 13(4), 212–229.

[12] Paruchuri, Venubabu, Transforming Banking with AI: Personalization and Automation in Baas Platforms (May 05, 2025). Available at SSRN: https://ssrn.com/abstract=5262700 or http://dx.doi.org/10.2139/ssrn.5262700

[13] Iqbal, A., & Noor, F. (2019). Predicting future connections in complex networks using adaptive heuristics. Computational Network Studies, 6(2), 72–85.

[14] Johnson, T., & Mehta, R. (2022). Streaming data integration for high-frequency network updates. Journal of Data and Knowledge Engineering, 28(1), 101–119.

[15] Karthik, P., & Mohan, V. (2023). Continuous learning frameworks for dynamic graph inference. International Journal of Machine Intelligence, 12(3), 55–70.

[16] Sai Maneesh Kumar Prodduturi, "Efficient Debugging Methods And Tools For Ios Applications Using Xcode," International Journal Of Data Science And Iot Management System, Vol. 4, No. 4, Pp. 1–6, Oct. 2025, Doi: 10.64751/Ijdim.2025.V4.N4.Pp1-6.

[17] Liu, X., & Zhao, Y. (2020). Temporal attention methods for evolving graph prediction. Asian Journal of Information Models, 17(4), 233–248.

[18] Martins, F., & Silva, L. (2019). Graph evolution patterns and their impact on predictive accuracy. Journal of Complex System Analysis, 8(2), 66–79.

[19] Nguyen, P., & Torres, M. (2023). Feedback-driven adaptation in intelligent link prediction systems. Intelligent Computing and Systems Review, 21(1), 15–31.

[20] O'Brien, K., & Wallace, S. (2024). Next-generation link prediction models using continuous data streams. Journal of Emerging Network Technologies, 19(1), 44–60.