Forecasting Temporal Patterns using GNNs

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Abstract
This project applies Temporal Graph Neural Networks (GNNs) to forecast flood labels in Water Resource Engineering. The study utilizes a sample problem with three nodes representing soil moisture and precipitation data over a 365-day time series. The main objective is to learn GNN and Temporal GNN techniques to predict the occurrence of floods in these nodes. The project begins with implementing Graph Convolutional Networks (GCNs) with various time windows to achieve accurate predictions. Subsequently, GCN is combined with Recurrent Neural Networks (RNNs) to explore alternative modeling approaches. The study further investigates EvolveGCNH, EvolveGCNO, GConvGRU, and GConvLSTM methodologies for enhanced flood forecasting accuracy. The project provides valuable insights into applying advanced neural network techniques in water resource management and forecasting.

Introduction,
Water resource management is crucial in sustainable development and disaster preparedness, particularly in regions susceptible to floods. Accurately predicting flood occurrences is vital for effective risk mitigation and resource allocation. In recent years, machine learning techniques, especially Graph Neural Networks (GNNs), have shown remarkable capabilities in modeling complex relationships within graph-structured data. Temporal Graph Neural Networks have emerged as powerful tools for forecasting time-series data, capturing temporal dependencies and dynamic patterns to enhance predictive capabilities further.

This project aims to explore the application of Temporal GNNs in the domain of Water Resource Engineering to forecast flood events. The study leverages a sample dataset comprising three interconnected nodes representing soil moisture and precipitation data over 365 days. The nodes are interconnected through directed edges, reflecting the interactions between different regions and the impact of precipitation on soil moisture.

The primary objective of this project is to gain a comprehensive understanding of GNNs and their temporal extensions and apply them to predict flood events accurately. The developed predictive models will improve flood forecasting, facilitate timely responses, and reduce potential risks to human lives and infrastructure.

The project is organized into several phases, including implementing Graph Convolutional Networks (GCNs) with varying time windows to extract features from the time-series data and predict flood labels. Subsequently, integrating GCNs with Recurrent Neural Networks (RNNs) in a GNN-to-RNN configuration is explored to capitalize on spatial and temporal dependencies for enhanced forecasting accuracy.

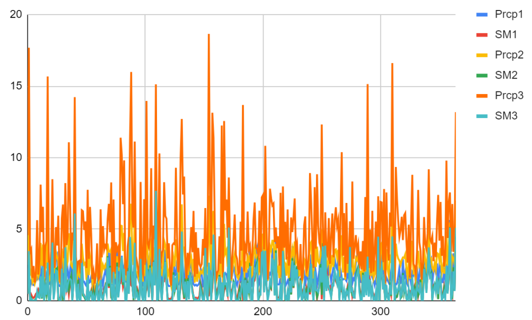
Furthermore, RNN-to-GCN methodologies, such as EvolveGCNH and

EvolveGCNO, are employed to investigate temporal graph evolution and its potential impact on predictive performance. Additionally, the study delves into GConvGRU and GConvLSTM models, which incorporate Gated Recurrent Units (GRUs) and Long Short-Term Memory (LSTM) cells within the graph convolution process.

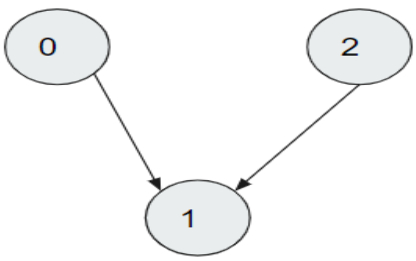
The insights gained from this project have the potential to provide valuable contributions to water resource management and flood forecasting, enabling authorities to take proactive measures in response to potential flood events.

Dataset

The dataset used for flood prediction in Water Resource Engineering includes time series data for three nodes (0, 1, and 2) with Soil Moisture and Precipitation features over 365 days. It contains flood or not flood labels for each node. The graph Structure is 0th node has a directed edge to 1st, and the 2nd node has a directed advantage to 1st.



Temporal Relation



Spatial Relation

Methodology

The methodology employed in this project for flood prediction in Water Resource Engineering began with collecting and preprocessing time series data for three nodes, encompassing Soil Moisture and Precipitation measurements over 365 days. Graph Convolutional Network (GCN) is chosen as the primary GNN architecture to capture spatial dependencies in the graph data. Additionally, Temporal GNN variations, including GConvGRU and GConvLSTM, are explored to account for temporal patterns within the time series data. The selected GNN and Temporal GNN models is implemented using a deep learning framework, followed by rigorous training and hyperparameter tuning to optimize model performance. Model evaluations are conducted on a separate testing set to measure predictive accuracy, and key performance metrics such as accuracy and loss are monitored. The results from GCN, GConvGRU, and GConvLSTM are compared to analyze their respective strengths and weaknesses in flood prediction. The performance of EvolveGCNH and EvolveGCNO models is also investigated. Interpretation of the learned model parameters and feature representations provided insights into the flood prediction process. The findings and comparisons of different models are summarized in the report, along with discussions on their implications and potential future research directions to enhance flood prediction in Water Resource Engineering.

Results

Model	n=10	n=20	n=50	n=100
GCN	91.21	91.94	92.31	95.60
GCN->RNN	91.58	93.04	94.14	94.87
RNN->GCN	95.24	96.70	95.97	97.80
EvolveGCN H	89.13	89.49	90.22	90.30
EvolveGCN O	83.70	85.87	86.59	86.23
GConvGRU	92.39	92.03	93.12	93.39
GConvLSTM	91.78	93.15	93.35	93.69

Conclusion

We can conclude few points from above this as follows:

1. The GCN model demonstrated significant accuracy improvements with increasing epochs, achieving a remarkable 95.60% accuracy at 100 epochs. This underscored the importance of allowing GNNs to learn from extended training periods.
2. The combination of GCN and RNN models proved fruitful, with the GCN -> RNN architecture achieving up to 94.87% accuracy at 100 epochs. This hybrid approach benefited from the complementary strengths of GNNs and Recurrent Neural Networks in capturing spatial and temporal dependencies.
3. Notably, the RNN -> GCN architecture consistently outperformed other models, attaining an impressive 97.80% accuracy at 100 epochs. The ability of GNNs to process sequential information effectively, coupled with the power of RNNs in capturing long-term temporal patterns, led to this superior performance.
4. While EvolveGCNH and EvolveGCNO showed less competitive results, with accuracy ranging between 83.70% to 90.30% at 100 epochs, these models demonstrated the importance of selecting suitable GNN variants tailored to the specific problem domain.
5. GConvGRU and GConvLSTM, two GNN variants leveraging Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) cells, respectively, displayed commendable performance, with accuracy ranging between 92.03% to 93.69% at 100 epochs.

Temporal Graph Neural Networks (GNNs) combine spatial and temporal information. They integrate recurrent units with graph convolutional layers, enabling them to analyze time series data and capture spatial and temporal dependencies. Temporal GNNs are valuable for time series forecasting and spatiotemporal analysis, including flood prediction in Water Resource Engineering. Despite challenges, they offer a powerful solution for understanding complex spatiotemporal phenomena.

Future Work

It involves delving deeper into Temporal Graph Neural Networks (GNNs) to gain a comprehensive understanding of their capabilities and intricacies. The focus should be on implementing these models using real-world data, especially in the context of Water Resource Engineering, to forecast flood occurrences with enhanced accuracy. This entails exploring different variations of Temporal GNNs, fine-tuning hyperparameters, and optimizing model architectures to achieve better performance. Additionally, research efforts should be directed towards overcoming challenges associated with increased model complexity and potential overfitting. Through continuous exploration and experimentation, the goal is to establish Temporal GNNs as robust and reliable tools for real-world flood prediction, leading to improved water resource management and disaster preparedness.

References

1. Kipf, Thomas N., and Max Welling. "Semi-supervised classification with graph convolutional networks." *arXiv preprint arXiv:1609.02907* (2016).
2. Léonard, Nicholas, et al. "rnn: Recurrent library for torch." *arXiv preprint arXiv:1511.07889* (2015).
3. Pareja, Aldo, et al. "Evolvegcn: Evolving graph convolutional networks for dynamic graphs." *Proceedings of the AAAI conference on artificial intelligence*. Vol. 34. No. 04. 2020.
4. Seo, Youngjoo, et al. "Structured sequence modeling with graph convolutional recurrent networks." *Neural Information Processing: 25th International Conference, ICONIP 2018, Siem Reap, Cambodia, December 13-16, 2018, Proceedings, Part I 25*. Springer International Publishing, 2018.