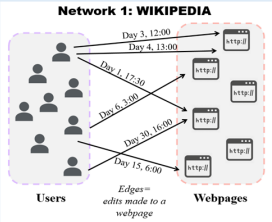
Improving Temporal Graph Network Messaging

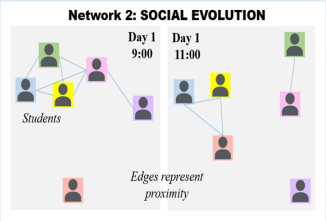
Altering TGN Algorithm to incorporate additional neighbourhood information in networks that change over time

Introduction

Task — *Link Prediction in Temporal Graphs*

- Predict next edge between nodes over time
- Can model processes such as recommendation systems, social networks, protein-protein interactions, etc.



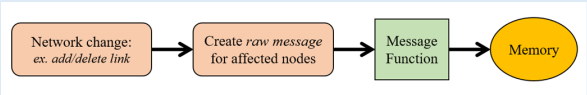


Algorithm - *Temporal Graph Network (TGN)* (Rossi et al. 2020)

- Graph Neural Network algorithm TGN-attn significantly outperforms recent algorithms such as JODIE, TGAT, DyRep for link prediction

How does it work?

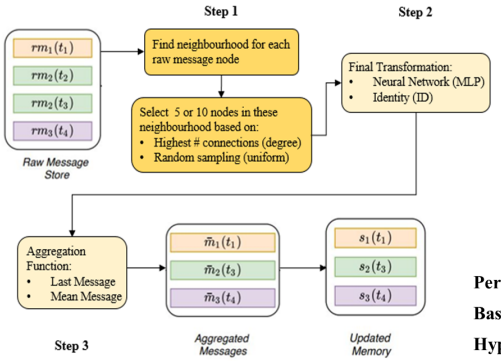
TGN works by storing a *memory for each node* which stores changes that affect it over time.



Question — *Room for improvement?*

- Can we improve link predictions by taking into account neighbourhood changes in the message function of TGN-attn.?

Methodology



Variants Tested:

Variant Name	*# Neighbours*	*Nbhd Sample*	*Msg Transformation*
0-Rec-ID	0	Recent	ID
5-Rec-ID	5	Recent	ID
10-Rec-ID	10	Recent	ID
5-Deg-ID	5	Degree	ID
10-Deg-ID	10	Degree	ID
5-Uni-ID	5	Uniform	ID
10-Uni-ID	10	Uniform	ID
5-Deg-MLP	5	Degree	MLP
10-Deg-MLP	10	Degree	MLP
5-Uni-MLP	5	Uniform	MLP
10-Uni-MLP	10	Uniform	MLP

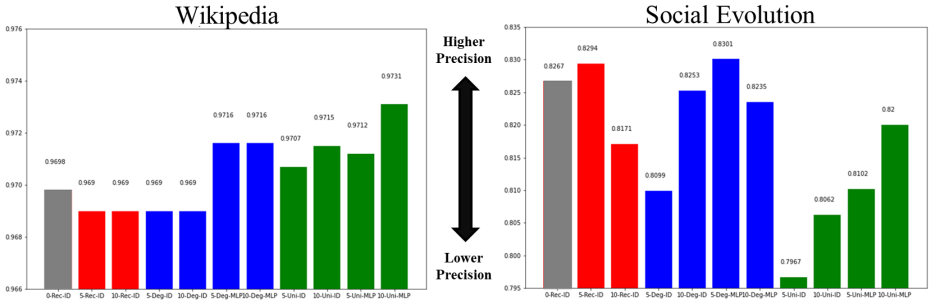
Performance Metric: Average Precision (AP) over 4 runs

Baseline Comparison Variant: 0-Rec-ID

Hyperparameters: Same as in baseline variant

Results

Average Precision — Grouped by Neighbourhood Sample Type



Gray = Baseline, Red = Most Recent, Blue = Highest # Connections (Degree), Green = Random (Uniform)

Best Performing Variants Overall:

- *Wikipedia:* 10-Uni-MLP
- *Social Evolution:* 5-Rec-ID/5-Deg-MLP

Discussion and Conclusions

Very small improvement in Average Precision for addition of neighbourhood information in message function

- Graph attention likely captures enough message sharing, so additional neighbourhood information makes little difference

Neighbourhood Sample: Different neighbourhood samples performed best in both networks, reflecting their very different structure

Neighbourhood Effect: No clear pattern for either 5 or 10

- It is possibly more dependent on the data and the other variant options

Transformation: Neural Network (MLP) was best

Time: Addition of neighbourhood information and MLP transformation make runs take 4-5 times longer, but can still be considered as trade-off

Future Directions

- Use alternate embedding (not graph attention) with neighbourhood additions to message function
- Compare results on more temporal network data with similar structures to Wikipedia and Social Evolution
- Consider 2nd neighbourhood, different number of neighbours

Thank you for your interest in my project! Feel free to reach out if you have further questions.

Contact Info

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