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Inductive Representation Learning in Temporal Networks via Mining Neighborhood and Community Influences

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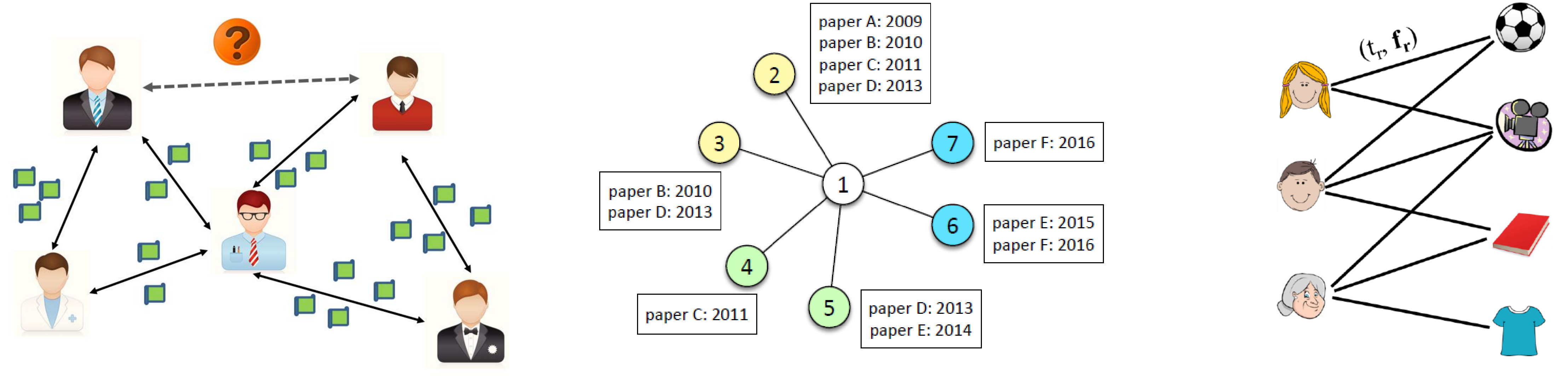
Background

Many real-world datasets are networks, such as social networks of email or social platforms, citation or co-authorship networks of academia, and commerce networks of shopping platforms.



(1) social network[1] (2) co-author network[2] (3) business network[3]

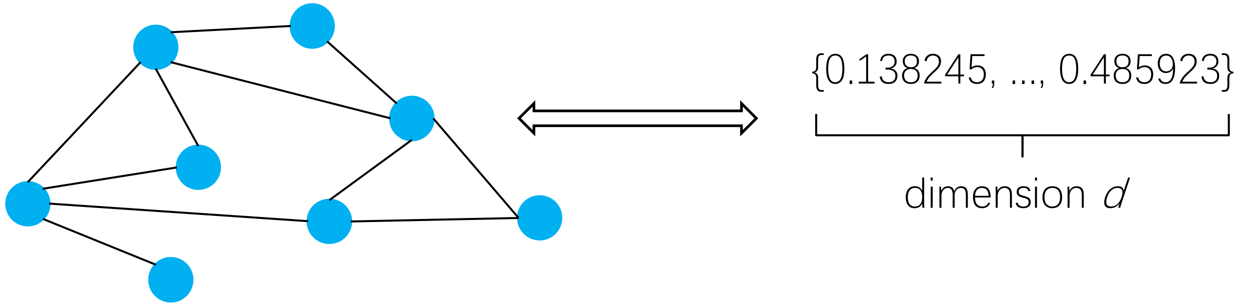
[1] Tu, Cunchao, et al. TransNet: Translation-Based Network Representation Learning for Social Relation Extraction[C]. IJCAI, 2017, pp. 2864–2870.

[2] Zuo, Yuan, et al. Embedding Temporal Network via Neighborhood Formation[C]. Proceedings of the 24th ACM SIGKDD, 2018, pp. 2857–2866.

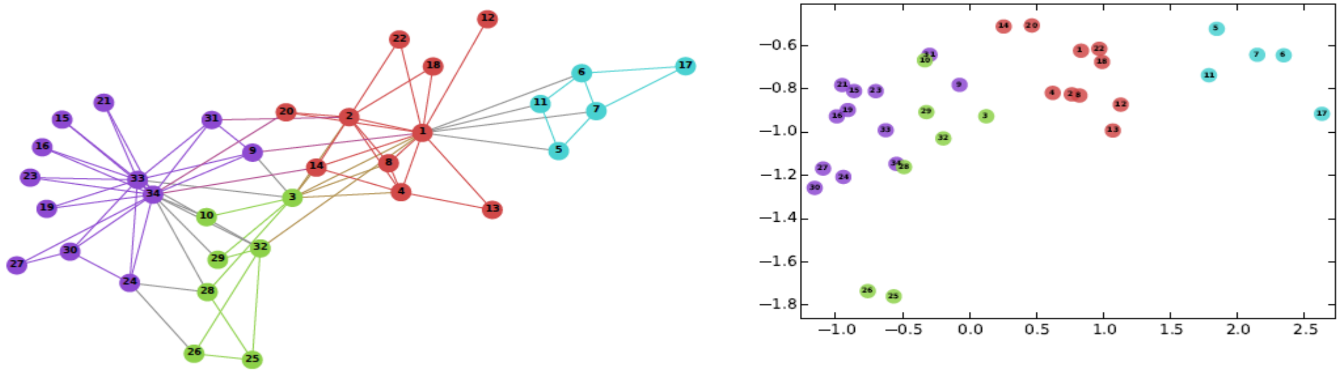
[3] Kumar, Srijan, et al. Predicting Dynamic Embedding Trajectory in Temporal Interaction Networks[C]. Proceedings of the 25th ACM SIGKDD, 2019, pp. 1269–1278.

Network Representation Learning

NRL, also known as graph embedding, aims to represent the large-scale networks by mapping nodes into a low-dimensional space.



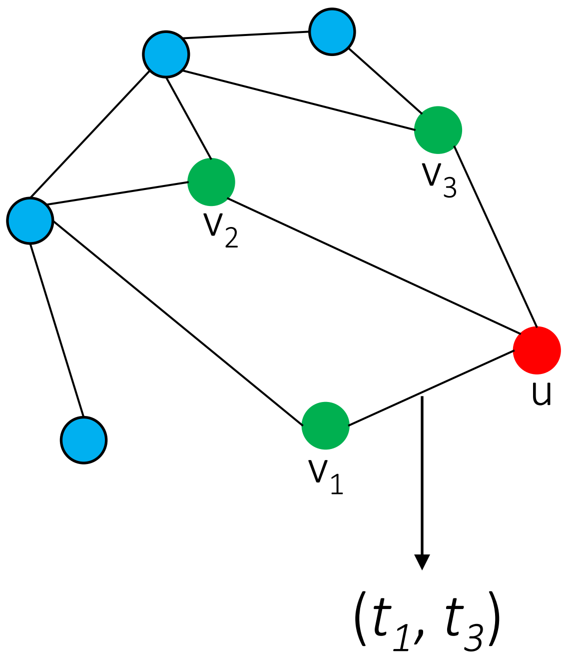
(4) Each node is represented as a vector.



(5) Projection of node embedding[1]

[1] Perozzi, Bryan, et al. DeepWalk: online learning of social representations[C]. ACM Knowledge Discovery and Data Mining abs/1403.6652 (2014): 701-710.

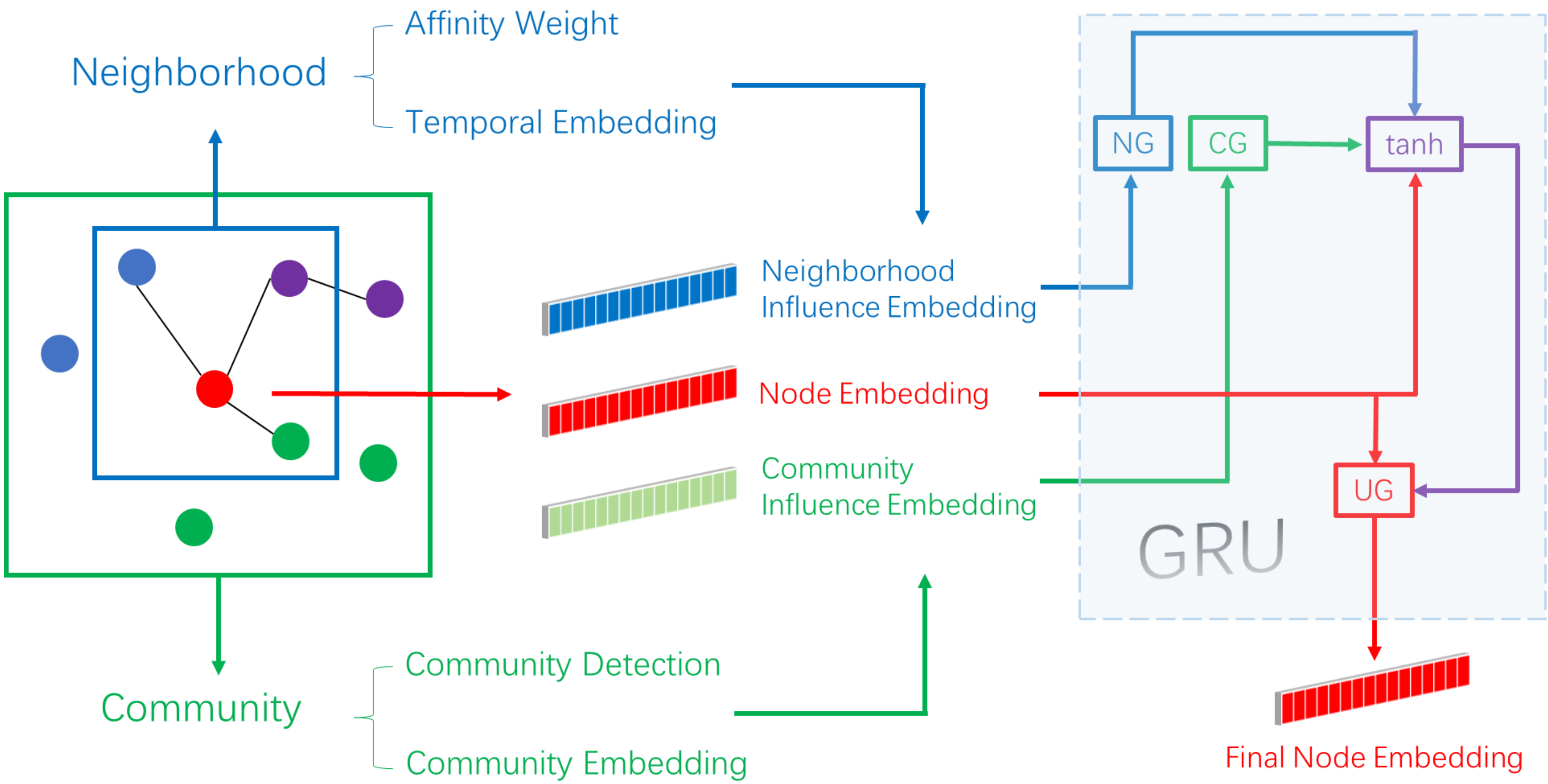
Temporal Network and Inductive Learning



Input: A temporal network can be defined as a graph $G = (V, E, T)$, where V and E denote the set of nodes and edges respectively, and T denotes the set of interactions. Given an edge $e(u, v)$ between node u and v, there is at least one interaction matching $e(u, v)$, i.e., $T(u, v) = \{(u, v, t_1), \cdots, (u, v, t_n)\}$.

Output: Inductive learning aims to learn node embeddings for any node at any time.

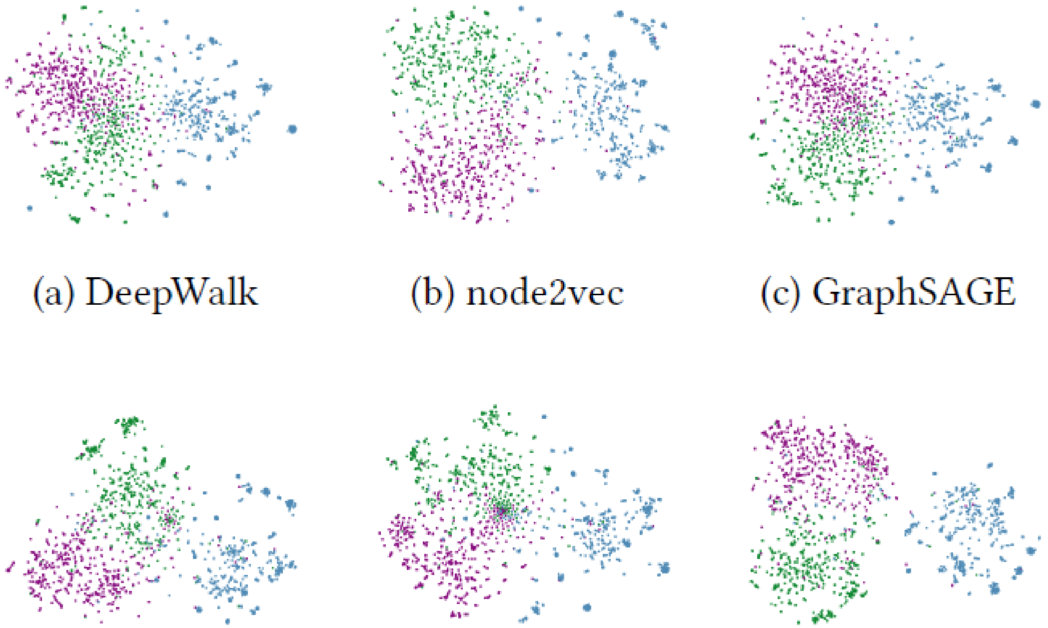
MNCI (Mining Neighborhood and Community Influences)



Experiments

Table 1: Node classification of all methods on all datasets

Metric	method	DBLP	BITotc	BITalpha	ML1M	AMms	Yelp
Accuracy	DeepWalk	0.6140	0.5907	0.7294	0.6029	0.5780	0.5067
	node2vec	0.6249	0.5958	0.7495	**0.6196**	0.5772	0.5135
	GraphSAGE	0.6331	0.6003	0.7389	0.6124	0.5763	0.5184
	HTNE	0.6347	0.5999	0.7635	0.5890	0.5767	0.5273
	DyREP	0.6259	0.6100	0.7430	0.6023	0.5755	0.5209
	MNCI	**0.6395**	**0.6256**	**0.7842**	0.6137	**0.5874**	**0.5334**
Weighted-F1	DeepWalk	0.6107	0.5120	0.6761	0.5863	0.4252	0.3981
	node2vec	0.6210	0.5123	0.6832	0.5836	0.4248	0.4184
	GraphSAGE	0.6239	0.5105	0.6750	0.5766	0.4216	0.4065
	HTNE	0.6307	0.5109	0.6806	0.5415	0.4255	0.4180
	DyREP	0.6203	0.5114	0.6843	0.5729	0.4248	0.4093
	MNCI	**0.6412**	**0.5172**	**0.6859**	**0.6026**	**0.4268**	**0.4293**



(a) DeepWalk (b) node2vec (c) GraphSAGE

(d) HTNE (e) DyREP (f) MNCI

Figure 1: Network visualization

Contributions

- We propose a novel **inductive** representation learning method MNCI to learn node embeddings in **temporal networks**.

- We use the positional encoding technology to **initialize node embedding**, which can speed up the convergence speed in training.

- We mine the **neighborhood and community influences** and modify the GRU framework to aggregate them.

Thanks!

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