Signed Graph Attention Networks

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Introduction

Recently, **Graph Neural Networks (GNNs)** are proposed as a general and powerful framework to handle tasks on graph data, e.g., node embedding, link prediction and node classification. As a representative of GNNs, **Graph Attention Networks (GATs)** are successfully applied in a variety of tasks on real datasets. However, GAT is designed to networks with only positive links and fails to handle **signed networks** which contain both positive and negative links. In this paper, we propose **Signed Graph Attention Networks (SiGATs),** generalizing GAT to signed networks. SiGAT incorporates **graph motifs** into GAT to capture two well-known theories in signed network research, i.e., **balance theory and status theory**. In SiGAT, motifs offer us the flexible structural pattern to aggregate and propagate messages on the signed network to generate node embeddings.

Related Theory

Signed Network: (Likes or Dislikes)

Social networks can contain both positive(+) and negative(-) links, i.e. signed networks[1]. For example, in the Epinions social network, users can create relationships (links) with other users that are based on opposing semantics of "trust" (positive) and "distrust" (negative).

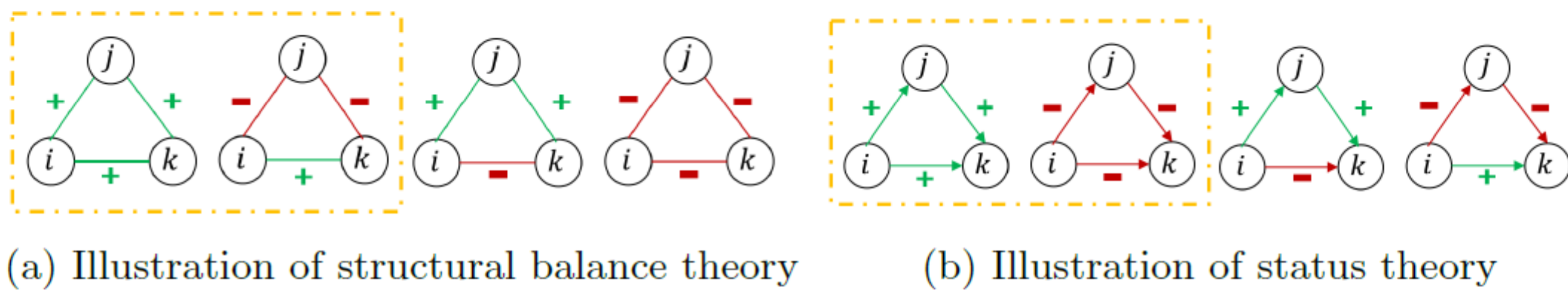(a) Illustration of structural balance theory (b) Illustration of status theory

Fig. 1. The balance theory and status theory

Balance Theory: (The enemy of my enemy is my friend)

Balance theory originated in social psychology in the mid-20th-century [1]. It was initially intended as a model for undirected signed networks. All signed triads with an even number of negative edges are defined as balanced. In other words, for the four triangles in Fig.1(a), the triangles which all three of these users are friends or only one pair of them are friends are defined as balanced i.e., the first two triads are balanced. Balance theory suggests that people in a social network tend to form into a balanced network structure.

Status Theory: (The person respected by me should have higher status than me)

Status theory[2] is another key social psychological theory for directed signed networks. It is based on directed signed networks. It supposes directed relationship labeled by a positive sign **"+"** or negative sign **"-"** means target node has a higher or lower status than source node. For the triangles in Fig.1(b), the first two triangles satisfy the status ordering and the latter two do not satisfy it.
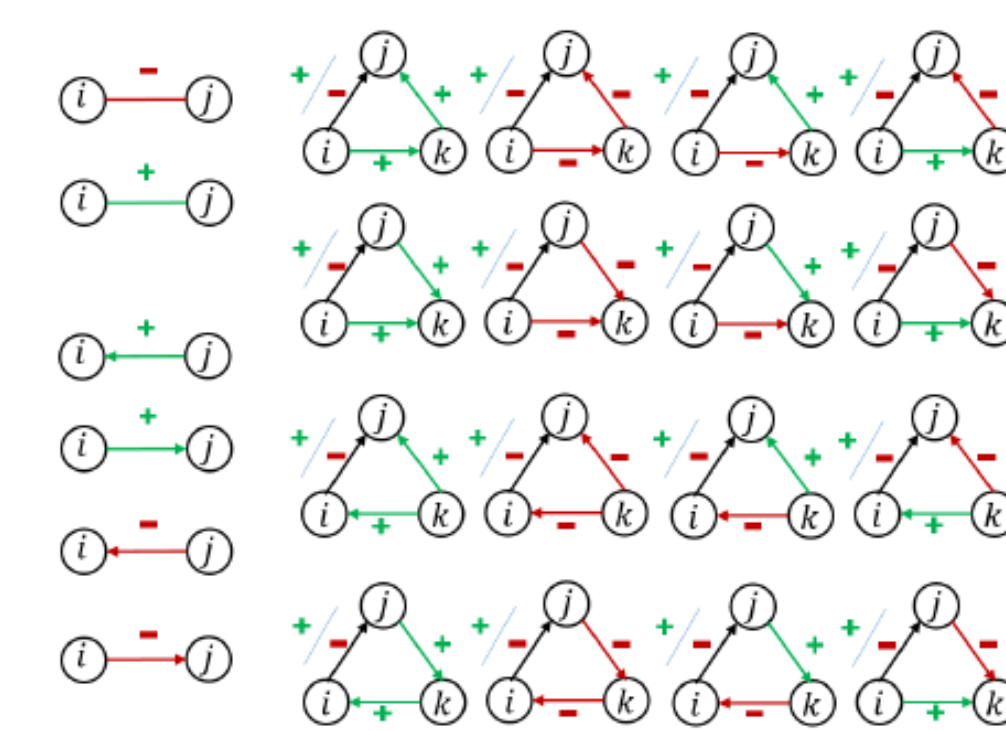
Methods

Fig. 2. 38 different motifs in SiGAT, mean different influences from node j to node i

Since positive neighbors and negative neighbors should have different effects on the target node, they should obviously be treated separately. Furthermore, for directed signed networks, the direction and triads also contain some knowledge, e.g., status theory and balance theory. We extracted 38 different motifs to our model in Fig.3.
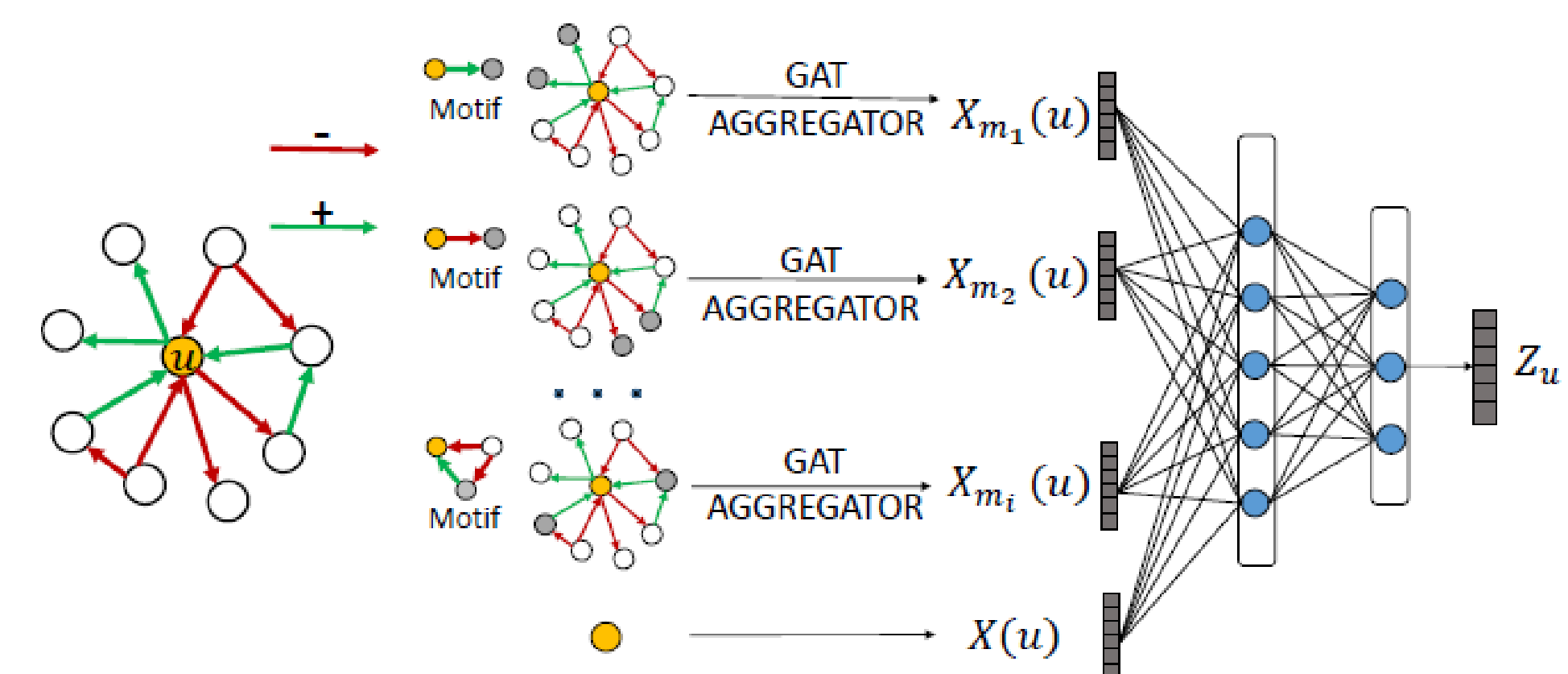

Fig. 3. For a signed network, the target u is the orange node. Red/Green links mean positive/negative links, the arrows indicate the directions. We define different motifs and obtain the corresponding neighborhoods in them. Under a motif definition, the gray color nodes are the neighborhoods, we use GAT to describe the influences from these neighborhoods. After aggregating the information from different motifs, we use these $\mathbf{X}_{m_i}(u)$ and $\mathbf{X}(u)$ to get the representation $\mathbf{Z}_u$.

Results and Conclusion

Table 1. Statistics of Three Datasets

Dataset	# nodes	# pos links	# neg links	% pos ratio
Bitcoin-Alpha	3,783	22,650	1,536	93.65
Slashdot	82,140	425,072	124,130	77.40
Epinions	131,828	717,667	123,705	85.30

Table 2. The results of Signed Link Prediction on three datasets

Dataset	Metric	Random	Unsigned Network Embedding			Signed Network Embedding			Feature Engineering	Graph Neural Network		
		Random	Deepwalk	Node2vec	LINE	SiNE	SIDE	SIGNet	FExtra	SGCN	SiGAT$_{+/-}$	SiGAT
Bitcoin-Alpha	Accuracy	0.9365	0.9365	0.9274	0.9350	0.9424	0.9369	0.9443	0.9477	0.9351	0.9427	**0.9480**
	F1	0.9672	0.9672	0.9623	0.9662	0.9699	0.9673	0.9706	0.9725	0.9658	0.9700	**0.9727**
	Macro-F1	0.4836	0.4836	0.5004	0.5431	0.6683	0.5432	0.7099	0.7069	0.6689	0.6570	**0.7138**
	AUC	0.6395	0.6435	0.7666	0.7878	0.8788	0.7832	**0.8972**	0.8887	0.8530	0.8699	0.8942
Slashdot	Accuracy	0.7740	0.7740	0.7664	0.7638	0.8269	0.7776	0.8391	0.8457	0.8200	0.8331	**0.8482**
	F1	0.8726	0.8726	0.8590	0.8655	0.8921	0.8984	**0.9061**	0.9042	0.8860	0.8959	0.9047
	Macro-F1	0.4363	0.4363	0.5887	0.4463	0.7277	0.5469	0.7559	0.7371	0.7294	0.7380	**0.7660**
	AUC	0.5415	0.5467	0.7622	0.5343	0.8423	0.7627	0.8749	0.8859	0.8440	0.8639	**0.8864**
Epinions	Accuracy	0.8530	0.8518	0.8600	0.8262	0.9131	0.9186	0.9116	0.9206	0.9092	0.9124	**0.9293**
	F1	0.9207	0.9198	0.9212	0.9040	0.9502	0.9533	0.9491	0.9551	0.9472	0.9498	**0.9593**
	Macro-F1	0.4603	0.4714	0.6476	0.4897	0.8054	0.8184	0.8065	0.8075	0.8102	0.8020	**0.8449**
	AUC	0.5569	0.6232	0.8033	0.5540	0.8882	0.8893	0.9091	**0.9421**	0.8818	0.9079	0.9333

We evaluate the proposed SiGAT method by applying it to the signed link prediction tasks. (To predict unobserved signs of existing edges in the test dataset given train dataset.

Experimental results on three datasets demonstrate that SiGAT outperforms feature-based methods, network embedding methods and GNN-based methods like SGCN.

References:

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