Signed Bipartite Graph Neural Networks

University of Chinese Academy of Sciences

Junjie Huang[1,3], Huawei Shen[1,3], Qi Cao[1], Shuchang Tao[1,3], Xueqi Cheng[2]

[1]Data Intelligence System Research Center, Institute of Computing Technology, Chinese Academy of Sciences, Beijing, China
[2]CAS Key Laboratory of Network Data Science and Technology, Institute of Computing Technology, Chinese Academy of Sciences, Beijing, China
[3]University of Chinese Academy of Sciences, Beijing, China
{huangjunjie17s, shenhuawei, caoqi, taoshuchang18z, cxq}@ict.ac.cn

Background

Consider a signed bipartite network, $\mathcal{G} = (\mathcal{U}, \mathcal{V}, \mathcal{E})$, where $\mathcal{U} = \{u_1, u_2, ..., u_{|\mathcal{U}|}\}$ and $\mathcal{V} = \{v_1, v_2, ..., v_{|\mathcal{V}|}\}$ represent two sets of nodes with the number of nodes $|\mathcal{U}|$ and $|\mathcal{V}|$. $\mathcal{E} \subset \mathcal{U} \times \mathcal{V}$ is the edges between $\mathcal{U}$ and $\mathcal{V}$. $\mathcal{E} = \mathcal{E}^+ \bigcup \mathcal{E}^-$ is the set of edges between the two sets of nodes $\mathcal{U}$ and $\mathcal{V}$ where $\mathcal{E}^+ \bigcap \mathcal{E}^- = \varnothing$, $\mathcal{E}^+$ and $\mathcal{E}^-$ represent the sets of positive and negative edges, respectively.

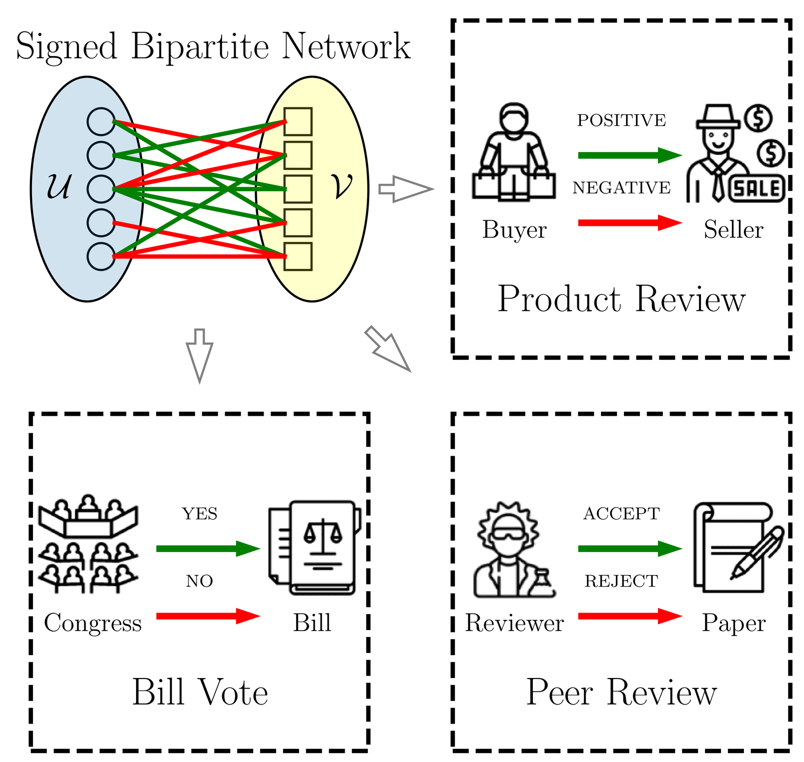

Figure 1. Common application scenarios for signed bipartite networks.

Signed bipartite networks are commonly found in many fields including business, politics, and academics, but have been less studied. Modeling signed bipartite networks is a promising and challenging research field.

Related Work

- **Signed Graph Modeling**: Signed networks are such social networks having both positive and negative links. Balance theory [1] is the fundamental theory in the signed network field.

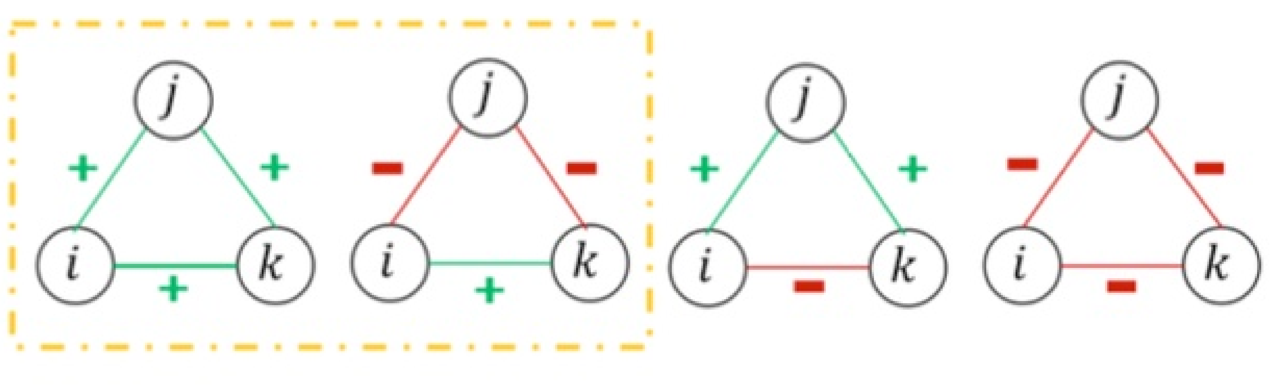

Figure 2. Illustration of structural balance theory. [2]

- **Graph Representation Learning**:
  - Matrix factorization-based methods: HOPE
  - Random-walk based algorithms: Deepwalk, Node2vec, LINE, BiNE
  - Graph neural networks: GCN, GAT, GraphSAGE, GAT, GIN
  - Signed network embeddings: SiNE, SIDE
  - Signed graph neural networks: SGCN, SDGNN

Signed Bipartite Networks

In different scenarios, the negative ratio varies. In the scenario of product reviews, the ratio of negative links is relatively lower (i.e., 0.02). Buyers rarely give bad rates to sellers. In the scenario of bill vote, the proportion of negative links increases comparing to the scenario of product reviews (i.e., 0.460 and 0.447). In many bills, it is more difficult for legislators to reach consensus due to different political standpoints.

Table 1. Statistics on Signed Bipartite Networks.

	Bonanza	U.S. House	U.S. Senate	Preliminary Review	Final Review
$\lvert\mathcal{U}\rvert$	7,919	515	145	182	182
$\lvert\mathcal{V}\rvert$	1,973	1,281	1,056	304	304
$\lvert\mathcal{E}\rvert = \lvert\mathcal{E}^+\rvert + \lvert\mathcal{E}^-\rvert$	36,543	114,378	27,083	1,170	1,170
% Positive Links	0.980	0.540	0.553	0.403	0.397
% Negative Links	0.020	0.460	0.447	0.597	0.603

In the scenario of peer reviews, the ratio of negative links is higher than the ratios of positive links (i.e., 0.603 > 0.397). In the top conferences of computer science, the acceptance rate needs to be controlled (e.g., about 20Surprisingly, after the rebuttal phase, the proportion of negative links has slightly risen (i.e., from 0.597 to 0.603).

Balance theory in Signed Bipartite Networks

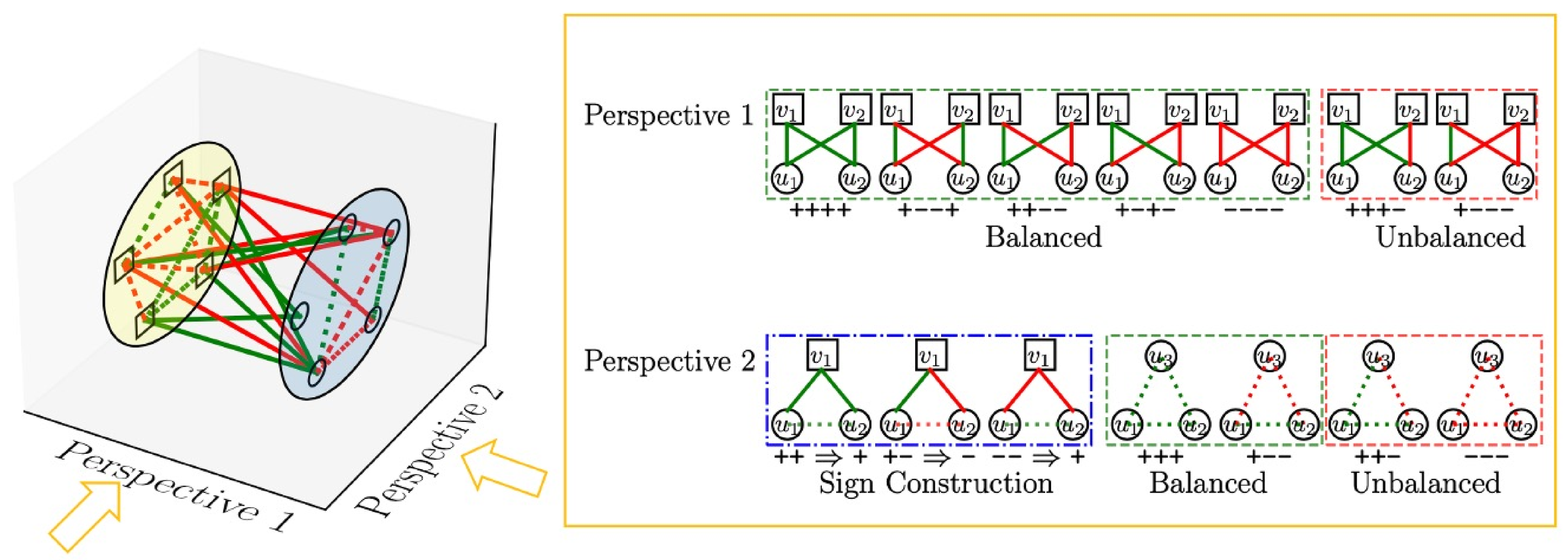

Figure 3. Perspective 1 offers to analyze the signed butterfly isomorphism.
For Perspective 2, we can analyze the signed triangle isomorphism by sign construction.

In this section, we give two perspectives to analyze balance theory in signed bipartite networks. We analyze the balance theory in different datasets from different perspectives. We calculate the percentage each isomorphism class takes up of the total signed isomorphism count with the the expectation of signed isomorphism when randomly reassigning the positive and negative signs to the signed bipartite network. We find that:

- Large majority of signed butterflies/signed triangles in signed bipartite networks are more balanced than expectation.
- In the scenario of peer reviews, after rebuttal phase, the balance of signed bipartite networks increased.

Proposed Methodology

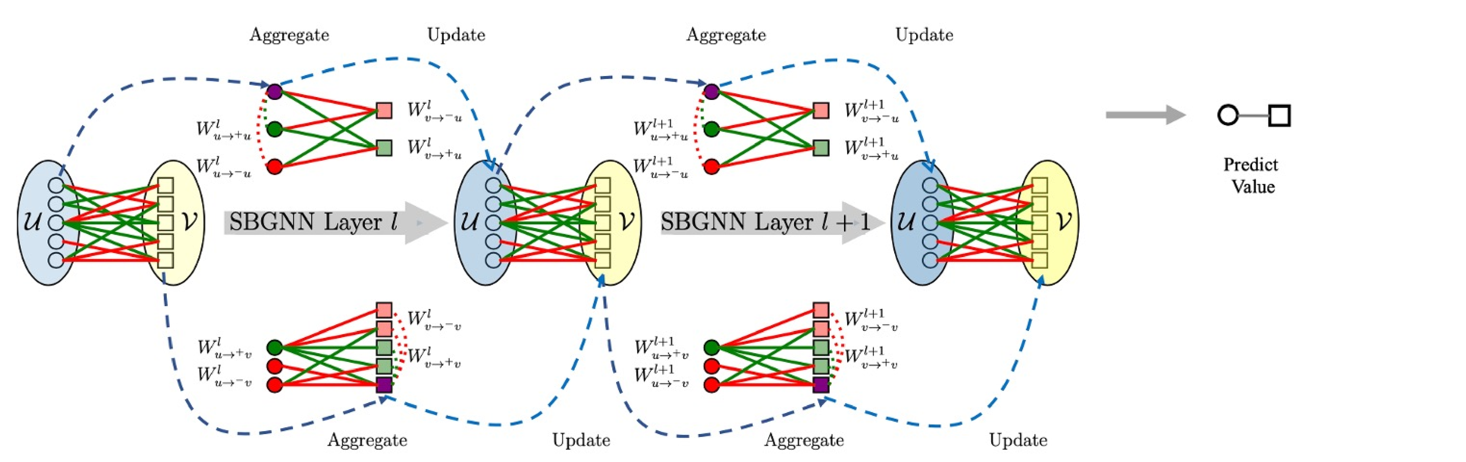

Figure 4. Illustration of SBGNN. SBGNN Layer includes Aggeregate and Update functions. The aggregated message comes from the Set_1 and Set_2 with positive and negative links. After getting the embedding of the node u_i and v_i, it can be used to predict the link sign relationship.

After getting embeddings $z_{u_i} \in \mathbb{R}^{d_u}$ and $z_{v_j} \in \mathbb{R}^{d_v}$ of the node u_i and v_j, we can use product operation/MLP methods to get the prediction value for $u_i \rightarrow v_j$.

Experiments

We do Link Sign Prediction on four datasets and compare our SBGNNs with lots of baselines.

Table 2. The results of Link Sign Prediction on four datasets.

		Random Embedding	Unsigned Network Embedding			Signed/Bipartite Network Embedding			Signed Butterfly Based Methods			Signed Bipartite Graph Neural Networks	
Dataset	Metric	Random	Deepwalk	Node2vec	LINE	SiNE	BiNE	SBiNE	SCsc	MFwBT	SBRW	SBGNN-MEAN	SBGNN-GAT
Bonanza	AUC	0.5222	0.6176	0.6185	0.6124	0.6088	0.6026	0.5525	**0.6524**	0.5769	0.5315	0.5841	0.5769
	Binary-F1	0.7282	0.7843	0.7530	0.6974	0.9557	0.7426	0.8514	0.6439	0.8927	**0.9823**	0.9488*	0.9616*
	Macro-F1	0.3868	0.4258	0.4087	0.3790	**0.5422**	0.4016	0.4538	0.3543	0.4813	0.5353	0.5311*	0.5404*
	Micro-F1	0.5770	0.6497	0.6093	0.5424	0.9157	0.5960	0.7436	0.4843	0.8076	**0.9652**	0.9044*	0.9269*
Review	AUC	0.5489	0.6324	0.6472	0.6236	0.5741	#N/A	0.5329	0.5522	0.4727	0.5837	0.6584*	**0.6747***
	Binary-F1	0.4996	0.5932	0.6141	0.5974	0.5247	#N/A	0.4232	0.3361	0.4346	0.5423	0.6128*	**0.6366***
	Macro-F1	0.5426	0.6268	0.6400	0.6120	0.5688	#N/A	0.5262	0.4823	0.4696	0.5767	0.6556*	**0.6629***
	Micro-F1	0.5487	0.6325	0.6444	0.6137	0.5744	#N/A	0.5521	0.5812	0.4752	0.5812	0.6632*	**0.6667***
U.S. House	AUC	0.5245	0.6223	0.6168	0.5892	0.6006	0.6103	0.8328	0.8274	0.8097	0.8224	0.8474*	**0.8481***
	Binary-F1	0.5431	0.6401	0.6323	0.6304	0.6118	0.6068	0.8434	0.8375	0.8234	0.8335	0.8549*	**0.8560***
	Macro-F1	0.5238	0.6215	0.6158	0.5883	0.5991	0.6097	0.8323	0.8267	0.8096	0.8219	0.8463*	**0.8471***
	Micro-F1	0.5246	0.6224	0.6166	0.5892	0.5996	0.6108	0.8330	0.8274	0.8106	0.8226	0.8468*	**0.8476***
U.S. Senate	AUC	0.5251	0.6334	0.6260	0.5743	0.5875	0.6071	0.7998	0.8163	0.7857	0.8142	0.8209*	**0.8246***
	Binary-F1	0.5502	0.6603	0.6526	0.6159	0.5923	0.5968	0.8175	0.8294	0.8043	0.8291	0.8277	**0.8320**
	Macro-F1	0.5239	0.6325	0.6251	0.5722	0.5842	0.6037	0.7992	0.8148	0.7850	0.8131	0.8177*	**0.8215***
	Micro-F1	0.5254	0.6347	0.6271	0.5732	0.5848	0.6042	0.8009	0.8160	0.7867	0.8145	0.8183*	**0.8221***

- Modeling the balance theory in the signed bipartite network is key for Link Sign Prediction .
- Our SBGNN models outperform other baseline models.

Conclusion

- We discuss two different perspectives to model the signed bipartite networks.
- Combining two perspectives, we introduce a new layer-by-layer SBGNN model.

References

[1] Fritz Heider. Attitudes and cognitive organization. *The Journal of psychology*, 21(1):107–112, 1946.
[2] Junjie Huang, Huawei Shen, Liang Hou, and Xueqi Cheng. Signed graph attention networks. In *ICANN*, 2019.