Signed Bipartite Graph Neural Networks

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Outline

1. Background
2. Related Work
3. Balance Theory in Signed Bipartite Networks
4. Proposed Methodology
5. Experiments
6. Conclusions and Future Work

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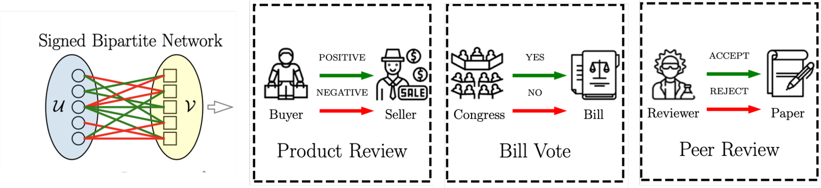
Signed Bipartite Networks

- 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.

It is commonly found in many fields including business, politics, and academics, but has been less studied.



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Signed Graph Modeling

Signed networks are such social networks having both positive and negative links.

Balance theory is the fundamental theory in the signed network field.

- For classical signed networks, signed triangles are the most common way to measure the balance of signed networks.

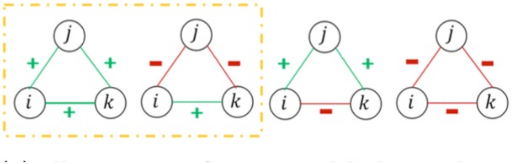

Figure: Illustration of structural balance theory. (Huang et al., ICANN2019)

Graph representation learning

- Matrix factorization-based methods
  - HOPE (Ou et al., 2016, KDD2016)
- Random-walk based algorithms
  - DeepWalk (Perozzi et al., KDD2014), Node2vec (Grover and Leskovec, KDD2016), LINE (Tang et al., WWW2015)
  - BiNE (Gao et al., SIGIR2016)
- Graph neural networks
  - GCN (Kipf and Welling, ICLR2017), GraphSAGE (Hamilton et al., NIPS2017), GAT (Veličković et al., ICLR2018), GIN (Xu et al., ICLR2018)

Signed graph representation learning

- Signed network embeddings
  - SiNE (Wang et al., SIAM2017), SIDE (Kim et al., WWW2018)
- Signed GNNs
  - SGCN (Derr et al., ICDM2018), SDGNN (Huang et al., AAAI2021)

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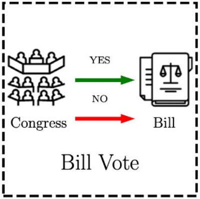
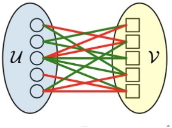
In different scenarios, the negative ratio varies.



	Bonanza	U.S. House	U.S. Senate	Preliminary Review	Final Review
$\|\mathcal{U}\|$	7,919	515	145	182	182
$\|\mathcal{V}\|$	1,973	1,281	1,056	304	304
$\|\mathcal{E}\| = \|\mathcal{E}^+\| + \|\mathcal{E}^-\|$	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

Signed Bipartite Network



Signed Caterpillars, Signed Butterflies and Signed Triangles

Two different perspectives:

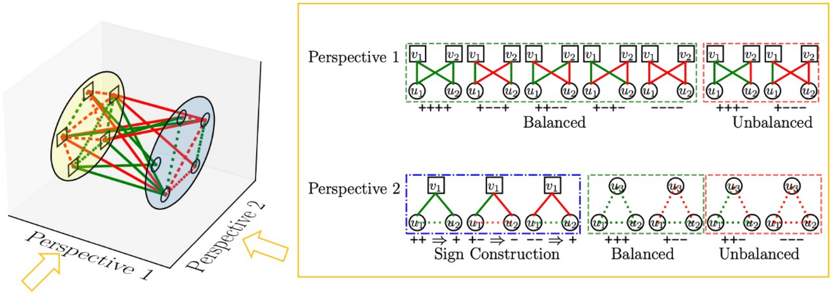


Figure: Perspective 1 offers to analyze the signed butterfly isomorphism. For Perspective 2, we can analyze the signed triangle isomorphism by sign construction.

Findings:

- 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.

	Bonanza	U.S. House	U.S. Senate	Preliminary Review	Final Review
Signed Butterfly Isomorphism ++++ (%, %E)	(0.986, 0.922)	(0.244, 0.085)	(0.262, 0.094)	(0.109, 0.026)	(0.115↑, 0.025)
Signed Butterfly Isomorphism +−−+ (%, %E)	(0.000, 0.001)	(0.109, 0.123)	(0.108, 0.122)	(0.109, 0.116)	(0.072↓, 0.115)
Signed Butterfly Isomorphism ++−− (%, %E)	(0.001, 0.001)	(0.111, 0.123)	(0.110, 0.122)	(0.101, 0.116)	(0.057↓, 0.115)
Signed Butterfly Isomorphism +−+− (%, %E)	(0.000, 0.001)	(0.186, 0.123)	(0.184, 0.122)	(0.156, 0.116)	(0.215↑, 0.115)
Signed Butterfly Isomorphism −−−− (%, %E)	(0.000, 0.000)	(0.147, 0.045)	(0.133, 0.040)	(0.249, 0.127)	(0.315↑, 0.133)
Balanced Signed Butterfly Summary (%, %E)	(**0.988**, 0.924)	(**0.798**, 0.500)	(**0.798**, 0.500)	(**0.724**, 0.501)	(**0.774↑**, 0.501)
Signed Butterfly Isomorphism +++− (%, %E)	(0.012, 0.076)	(0.118, 0.289)	(0.122, 0.302)	(0.070, 0.156)	(0.075↑, 0.151)
Signed Butterfly Isomorphism +−−− (%, %E)	(0.000, 0.000)	(0.085, 0.211)	(0.081, 0.197)	(0.206, 0.343)	(0.151↓, 0.349)
Unbalanced Signed Butterfly Summary (%, %E)	(**0.012**, 0.076)	(**0.202**, 0.500)	(**0.202**, 0.500)	(**0.276**, 0.499)	(**0.226↓**, 0.499)
Signed Triangles Isomorphism +++ in $\mathcal{U}$ (%, %E)	(0.978, 0.949)	(0.338, 0.217)	(0.360, 0.248)	(0.327, 0.213)	(0.446↑, 0.310)
Signed Triangles Isomorphism +−− in $\mathcal{U}$ (%, %E)	(0.011, 0.001)	(0.476, 0.287)	(0.436, 0.261)	(0.451, 0.290)	(0.346↓, 0.212)
Balanced Signed Triangles Summary in $\mathcal{U}$ (%, %E)	(**0.989**, 0.950)	(**0.815**, 0.504)	(**0.796**, 0.508)	(**0.778**, 0.504)	(**0.792↑**, 0.522)
Signed Triangle Isomorphism ++− in $\mathcal{U}$ (%, %E)	(0.011, 0.050)	(0.176, 0.432)	(0.189, 0.440)	(0.194, 0.431)	(0.195↑, 0.444)
Signed Triangle Isomorphism −−− in $\mathcal{U}$ (%, %E)	(0.000, 0.000)	(0.009, 0.063)	(0.015, 0.051)	(0.027, 0.065)	(0.012↓, 0.034)
Unbalanced Signed Triangles Summary in $\mathcal{U}$(%, %E)	(**0.011**, 0.050)	(**0.185**, 0.496)	(**0.204**, 0.492)	(**0.222**, 0.496)	(**0.208↓**, 0.478)

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Message/Aggregation/Update Function

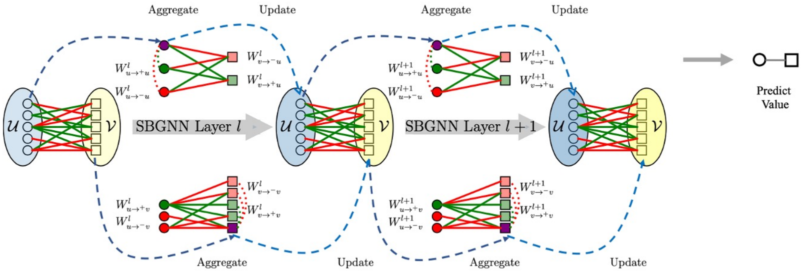

Figure: Illustration of SBGNN. SBGNN Layer includes Aggeregate and Update functions. The aggregated message comes from the Set_1 and Set_2 with positive and negative links. After getting the embedding of the node u_i and v_i, it can be used to predict the link sign relationship.

GNNs Message Passing Scheme

$$m_{j\to i}^{(l)}(i,j) = \mathrm{MSG}^{(l)}\left(h_i^{(l)}, h_j^{(l)}, h_{e_{ji}}^{(l)}\right), j \in \mathcal{N}(j),$$

$$m_{j\to i}^{(l)}(i) = \mathrm{AGG}^{(l)}\left(\left\{m_{j\to i}^{(l)}(i,j) \mid j \in \mathcal{N}(i)\right\}\right),$$

$$h_i^{(l+1)} = \mathrm{UPT}^{(l)}\left(h_i^{(l)}, m_{j\to i}^{(l)}(i)\right),$$

Loss Function

- 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 following methods to get the prediction value for $u_i \to v_j$.
  - product operation:

    $$y_{pred} = \mathrm{sigmoid}(z_{u_i}^\top \cdot z_{v_j}),$$

    where $\cdot^\top$ is the transpose function and $\mathrm{sigmoid}$ is the sigmoid function $f(x) = \frac{1}{1+e^{-x}}$.
  - $\textsc{Mlp}$:

    $$y_{pred} = \mathrm{sigmoid}\big(\textsc{Mlp}(z_{u_i} \parallel z_{v_i})\big)$$

    where $\textsc{Mlp}$ is a two layer neural networks, $\parallel$ is the concatenation operation.
- After getting the prediction values, we use binary cross entropy as the loss function:

$$\mathcal{L} = -w\left[y \cdot \log y_{pred} + (1-y) \cdot \log(1-y_{pred})\right]$$

where w is the rescaling weight for the unblanced negative ratios; y is the ground truth with mapping $\{-1, 1\}$ to $\{0, 1\}$.

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Experimental Settings

- Datasets
  - Bonanza, Review, U.S. House, U.S. Senate
- Tasks: LINK SIGN PREDICTION (binary classification problem)
- Train/Val/Test: 85/5/10 (5 times train/val/test splits)
- Baselines:
  - Random Embeddings
  - Unsigned Network Embeddings: DeepWalk, Node2vec, LINE
  - Signed/Bipartite Network Embedding: SiNE, BiNE, SBiNE
  - Signed Butterfly Based Methods: SCsc, MFwBT, SBRW
  - Signed Bipartite Graph Neural Networks: SBGNN-MEAN, SBGNN-GAT
- Evaluation Metrics
  - AUC, Binary-F1, Macro-F1, and Micro-F1

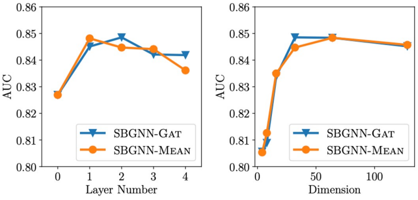
Experiment results

Table: 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.

Parameter Analysis and Ablation Study



(a) #Layer l **(b) Dimension d**

Figure: Parameter analysis on the number of SBGNN Layer l and imension d for SBGNN on the U.S. House dataset.

Table: Ablation study results for SBGNN model on the U.S. House dataset.

Method	AUC	Binary-F1	Macro-F1	Micro-F1
SBGNN-GAT	0.8485	0.8586	0.8477	0.8485
SBGNN-GAT (w/o Set_1)	0.8406	0.8521	0.8400	0.8409
SBGNN-GAT (w/o Set_2)	0.8440	0.8567	0.8438	0.8448
SBGNN-GAT (with LR)	0.6281	0.6195	0.6227	0.6227
SBGNN-GAT (with MLP)	0.8365	0.8480	0.8358	0.8367
SBGNN-MEAN	0.8447	0.8519	0.8429	0.8434
SBGNN-MEAN (w/o Set_1)	0.8419	0.8496	0.8402	0.8408
SBGNN-MEAN (w/o Set_2)	0.8296	0.8410	0.8288	0.8297
SBGNN-MEAN (with LR)	0.6285	0.6387	0.6263	0.6267
SBGNN-MEAN (with MLP)	0.8443	0.8531	0.8430	0.8436

- d=32 and l=2 can have a better result.
- MLP is much better than simple LR but not better than product operation.

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Conclusions

- We discuss two different perspectives to model the signed bipartite networks.
- We further use these two perspectives to model peer review and find that after rebuttal, the balance of reviewers' opinions improved.
- Under the definition of a new perspective, we propose a new graph neural network model SBGNN to learn the node representation of signed bipartite graphs .
- Our SBGNN model achieve the state-of-the art performance in several datasets.

Future work

- We will explore signed bipartite networks with node features.
- We will try to introduce signed bipartite graph neural networks into recommender system.

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