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SDGNN: Learning Node Representation for Signed Directed Networks

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Introduction

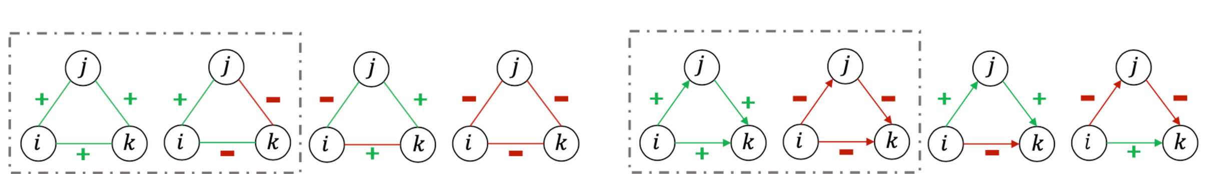
Graph Neural Networks (GNNs) have received widespread attention and lead to state-of-the-art performance in learning node representations. In this paper, we first review two fundamental sociological theories (i.e., **status theory and balance theory**) and conduct empirical studies on real-world datasets to analyze the social mechanism in **signed directed networks**. Guided by related sociological theories, we propose a novel **Signed Directed Graph Neural Networks model** named SDGNN to learn node embeddings for **signed directed networks**. The proposed model simultaneously reconstructs **link signs, link directions, and signed directed triangles**. Experiments demonstrate the proposed model outperforms existing models, including feature-based methods, network embed- ding methods, and several GNN methods.

Background

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).

Sociological Theory: (status theory and balance theory)



(a) Balance theory (b) Status theory

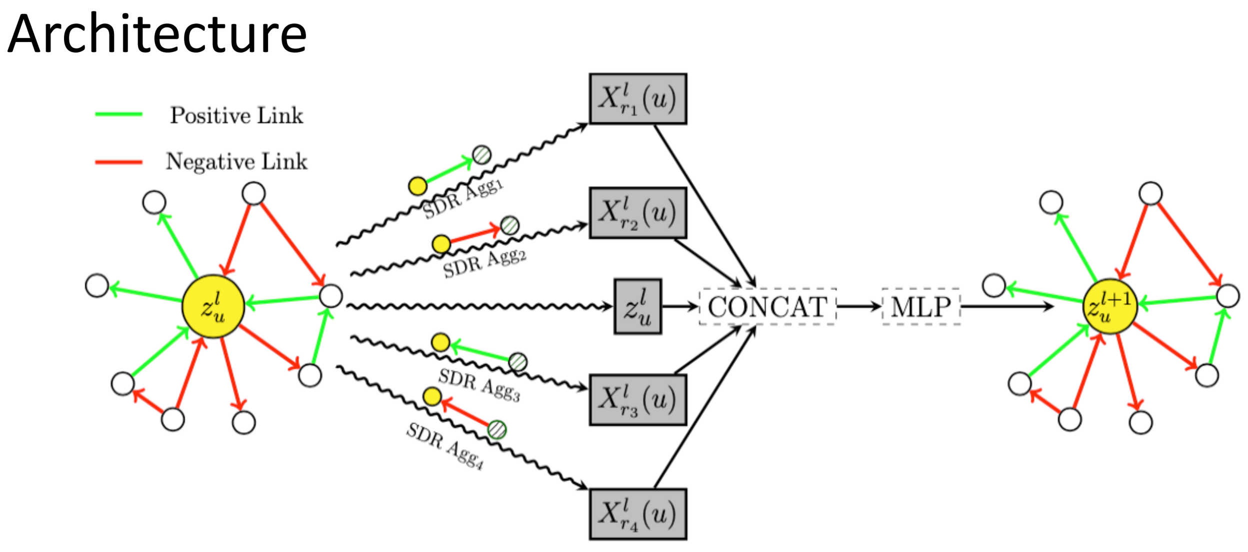
Dataset	Both	Only Balance	Only Status	Neither
Bitcoin-Alpha	0.673	0.208	0.094	0.025
Bitcoin-OTC	0.686	0.208	0.083	0.023
Wikirfa	0.686	0.059	0.189	0.066
Slashdot	0.751	0.167	0.066	0.016
Epinions	0.769	0.156	0.066	0.009

a) Balance Theory: *the friend of my friend is my friend* and *the enemy of my enemy is my friend*.

b) Status Theory: *B is A's friend and B has a higher status than A* .

Methods

Model Architecture



GNN Aggregator

Mean Aggregator

$$X^l_{r_i}(u) = \sigma(\mathbf{W}^l_{r_i} \cdot \mathrm{MEAN}(\{z^l_u\} \cup \{z^l_v, \forall v \in \mathcal{N}_{r_i}(u)\}))$$
$$z^{l+1}_u = \mathrm{MLP}(\mathrm{CONCAT}(X^l(u), X^l_{r_1}(u), ..., X^l_{r_i}(u)))$$

Attention Aggregator

$$\alpha^{r_i}_{uv} = \frac{\exp\left(\mathrm{LeakyReLU}\left(\vec{\mathbf{a}}^\top_{r_i}[\mathbf{W}^l_{r_i} z^l_u \| \mathbf{W}^l_{r_i} z^l_v]\right)\right)}{\sum_{k\in\mathcal{N}_{r_i}(u)} \exp\left(\mathrm{LeakyReLU}\left(\vec{\mathbf{a}}^\top_{r_i}[\mathbf{W}^l_{r_i} z^l_u \| \mathbf{W}^l_{r_i} z^l_k]\right)\right)}$$

$$X^l_{r_i}(u) = \sum_{v\in\mathcal{N}_{r_i}(u)} \alpha^{r_i}_{uv} \mathbf{W}_{r_i} z^l_v,$$
$$z^{l+1}_u = \mathrm{MLP}(\mathrm{CONCAT}(X^l(u), X^l_{r_1}(u), ..., X^l_{r_i}(u)))$$

Loss Function

Sign

$$\mathcal{L}_{sign}(u,v) = -y_{u,v} \log\left(\sigma(z_u^\top z_v)\right) - (1-y_{u,v}) \log\left(1-\sigma(z_u^\top z_v)\right)$$
$$\mathcal{L}_{sign} = \sum_{e_{u,v}\in\mathcal{E}} \mathcal{L}_{sign}(u,v)$$

Direction

$$\mathcal{L}_{direction}(u\to v) = (q_{uv} - (s(z_u) - s(z_v)))^2$$
$$q_{uv} = \begin{cases} \max(s(z_u)-s(z_v),\ \gamma) & u\to v: - \\ \min(s(z_u)-s(z_v), \gamma) & u\to v: + \end{cases}$$
$$\mathcal{L}_{direction} = \sum_{e_{u,v}\in\mathcal{E}} \mathcal{L}_{direction}(u\to v)$$

Triads

$$\mathcal{L}_{\triangle_{i,j,k}} = \mathcal{L}_{ij} + \mathcal{L}_{ik} + \mathcal{L}_{kj},$$
$$\mathcal{L}_{ij} = -y_{i,j}\log P(+|e_{ij}) - (1-y_{i,j})\log(1-P(+|e_{ij}))$$
$$= -y_{i,j}\log\left(\sigma(z_i^\top z_j)\right) - (1-y_{i,j})\log(1-\sigma(z_i^\top z_j))$$

Experiments

Datasets

Statistics of five datasets.

Dataset	# nodes	# pos links	# neg links	% pos ratio
Bitcoin-Alpha	3,783	22,650	1,536	93.65
Bitcoin-OTC	5,881	32,029	3,563	89.99
Wikirfa	11,259	138,813	39,283	77.94
Slashdot	82,140	425,072	124,130	77.40
Epinions	131,828	717, 667	123,705	85.30

Results

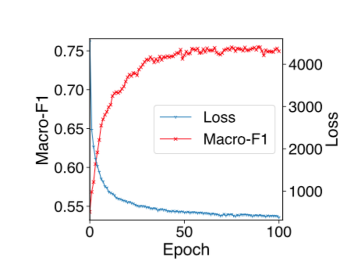
The results of link sign prediction on five datasets.

		Random	Unsigned Network Embedding			Signed Network Embedding			Feature Engineering	Graph Neural Network		
Dataset	Metric	Random	Deepwalk	Node2vec	LINE	SiNE	SIGNet	BESIDE	FeExtra	SGCN	SiGAT	SDGNN
Bitcoin-Alpha	Micro-F1	0.9367	0.9367	0.9355	0.9352	0.9458	0.9422	0.9489	0.9486	0.9256	0.9456	**0.9491**
	Binary-F1	0.9673	0.9673	0.9663	0.9664	0.9716	0.9696	**0.9732**	0.9730	0.9607	0.9714	0.9729
	Macro-F1	0.4837	0.4848	0.6004	0.5220	0.6869	0.6965	0.7300	0.7167	0.6367	0.7026	**0.7390**
	AUC	0.6146	0.6409	0.7576	0.7114	0.8728	0.8908	0.8981	0.8882	0.8469	0.8872	**0.8988**
Bitcoin-OTC	Micro-F1	0.9000	0.8937	0.9089	0.8911	0.9095	0.9229	0.9320	**0.9361**	0.9078	0.9268	0.9357
	Binary-F1	0.9473	0.9434	0.9507	0.9413	0.9510	0.9581	0.9628	**0.9653**	0.9491	0.9602	0.9647
	Macro-F1	0.4737	0.5281	0.6793	0.5968	0.6805	0.7386	0.7843	0.7826	0.7306	0.7533	**0.8017**
	AUC	0.6145	0.6596	0.7643	0.7248	0.8571	0.8935	**0.9152**	0.9121	0.8755	0.9055	0.9124
Wikirfa	Micro-F1	0.7797	0.7837	0.7814	0.7977	0.8338	0.8384	0.8589	0.8346	0.8489	0.8457	**0.8627**
	Binary-F1	0.8762	0.8779	0.8719	0.8827	0.8972	0.9001	0.9117	0.8987	0.9069	0.9042	**0.9142**
	Macro-F1	0.4381	0.4666	0.5626	0.5738	0.7319	0.7384	0.7803	0.7235	0.7527	0.7535	**0.7849**
	AUC	0.5423	0.5876	0.6930	0.6772	0.8602	0.8682	**0.8981**	0.8604	0.8563	0.8829	0.8898
Slashdot	Micro-F1	0.7742	0.7738	0.7526	0.7489	0.8265	0.8389	0.8590	0.8472	0.8296	0.8494	**0.8616**
	Binary-F1	0.8728	0.8724	0.8528	0.8525	0.8918	0.8983	0.9105	0.9070	0.8926	0.9055	**0.9128**
	Macro-F1	0.4364	0.4384	0.5390	0.5052	0.7273	0.7554	**0.7892**	0.7399	0.7403	0.7671	**0.7892**
	AUC	0.5370	0.5408	0.6709	0.6145	0.8409	0.8752	**0.9017**	0.8880	0.8534	0.8874	0.8977
Epinions	Micro-F1	0.8525	0.8214	0.8563	0.8535	0.9173	0.9113	0.9336	0.9226	0.9112	0.9293	**0.9355**
	Binary-F1	0.9204	0.9005	0.9170	0.9175	0.9525	0.9489	0.9615	0.9561	0.9486	0.9593	**0.9628**
	Macro-F1	0.4602	0.5131	0.6862	0.6305	0.8160	0.8060	0.8601	0.8130	0.8105	0.8454	**0.8610**
	AUC	0.5589	0.6702	0.8081	0.6835	0.8872	0.9095	0.9351	**0.9444**	0.8745	0.9333	0.9411

Ablation Study && Parameter Analysis

Ablation study on different aggregators.

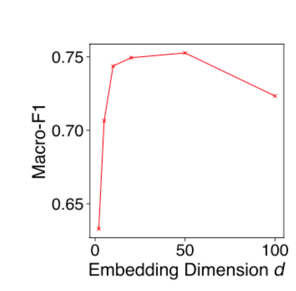
Metric	2-Layer-GAT-AGG	1-Layer-GAT-AGG	2-Layer-MEAN-AGG	1-Layer-MEAN-AGG
Micro-F1	0.9446	0.9442	0.9415	0.9399
Binary-F1	0.9706	0.9703	0.9689	0.9679
Macro-F1	0.7510	0.7516	0.7417	0.7411
AUC	0.9154	0.9095	0.9041	0.9000



(a) Epoch

Ablation study on loss functions.

Metric	$\mathcal{L}_{sign}$	$\mathcal{L}_{sign}+\mathcal{L}_{direction}$	$\mathcal{L}_{sign}+\mathcal{L}_{triangle}$	$\mathcal{L}_{sign}+\mathcal{L}_{direction}+\mathcal{L}_{triangle}$
Micro-F1	0.9386	0.9438	0.9415	0.9475
Binary-F1	0.9677	0.9702	0.9690	0.9721
Macro-F1	0.6738	0.7414	0.7210	0.7585
AUC	0.8883	0.9082	0.9030	0.9109



(b) d

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[1] Huang, Junjie, et al. "Signed graph attention networks." ICANN, 2019.
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[3] Leskovec, Jure, Daniel Huttenlocher, and Jon Kleinberg. "Predicting positive and negative links in online social networks." WWW, 2010.

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