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Simple Signed Graph Convolutional Network (SS-GCN) is able to capture the true meaning of negative links in signed graphs, allowing information to be propagated appropriately through the model's layers

Simple Signed Graph Convolutional Network for node classification in signed graphs

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BACKGROUND

Graph Convolutional Networks (GCNs)[1] have achieved a superior performance in node classification tasks; however, they are designed for unsigned graphs only, i.e. graphs containing only positive links.

OBJECTIVE

To introduce a method that builds on the existing GCN approach, but is able to integrate additional information from negative links.

METHODS

We propose Simple Signed Graph Convolutional Network (SS-GCN) by modifying the way in which the model propagates node information via the following two steps (**Table 1**):

(1) Utilizing signed Laplacian[2] to overcome the technical barrier encountered when applying GCN to signed graphs

(2) Adding an additional term (**highlighted in yellow in Table 1**) to the neighborhood information aggregation step. This is the key component allowing the model to capture the actual meaning of negative links

RESULTS

We compare SS-GCN with four variants of GCN and other two baselines on signed real-world networks (**Table 2**) and synthetic networks in node classification tasks.

- SS-GCN outperforms all baselines and achieves high performance consistently showing that it can capture the different properties of negative and positive links in different settings (**Table 3**)
- SS-GCN is able to perform well even when feature values of different classes overlap as long as there is enough information from positive and negative links (**Figure 1**)

Given a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ where $\mathcal{V}$ is the set of vertices, and $\mathcal{E}$ is the set of edges. $v_i \in \mathcal{V}$ denotes a node, and $e_{ij} \in \mathcal{E}$ denotes an edge linking v_i and v_j.

Table 1. The message passing update in GCN and SS-GCN

GCN	SS-GCN
$H_i^{(l+1)} = \sigma(\sum_j \frac{\tilde{A}_{ij}}{\sqrt{\tilde{D}_{ii}\tilde{D}_{jj}}} H_j^{(l)} W^{(l)})$	$H_i^{(l+1)} = \sigma(\sum_j \frac{\lvert\tilde{A}_{ij}\rvert}{\sqrt{\tilde{D}'_{ii}\tilde{D}'_{jj}}} (sign(\tilde{A}_{ij}) H_j^{(l)} + \boxed{\frac{1}{2}(1 - sign(\tilde{A}_{ij}))H_i^{(l)})W^{(l)})}$

Where $H_i^{(l+1)}$ is the hidden representation vector of node v_i of the $(l+1)$-th layer, $H_j^{(l)}$ is the hidden representation vector of node v_j of the l-th layer, $\tilde{A}$ is the adjacency matrix with self-loops, diagonal degree matrices $\tilde{D}_{ii} = \sum_j \tilde{A}_{ii}$ and $\tilde{D}'_{ii} = \sum_j |\tilde{A}_{ii}|$, $W^{(l)}$ is the trainable weight matrix, $\sigma(\cdot)$ is a non-linear activation function.

Table 2. Real-world networks statistics

Datasets	Nodes	Edges	Label 0	Label 1	Positive links	Negative links
Bitcoin-OTC	5881	21492	5159 (87%)	722 (13%)	18339 (85%)	3135 (15%)
Epinions	19737	438108	15335 (78%)	4402 (22%)	369428 (84%)	68680 (16%)

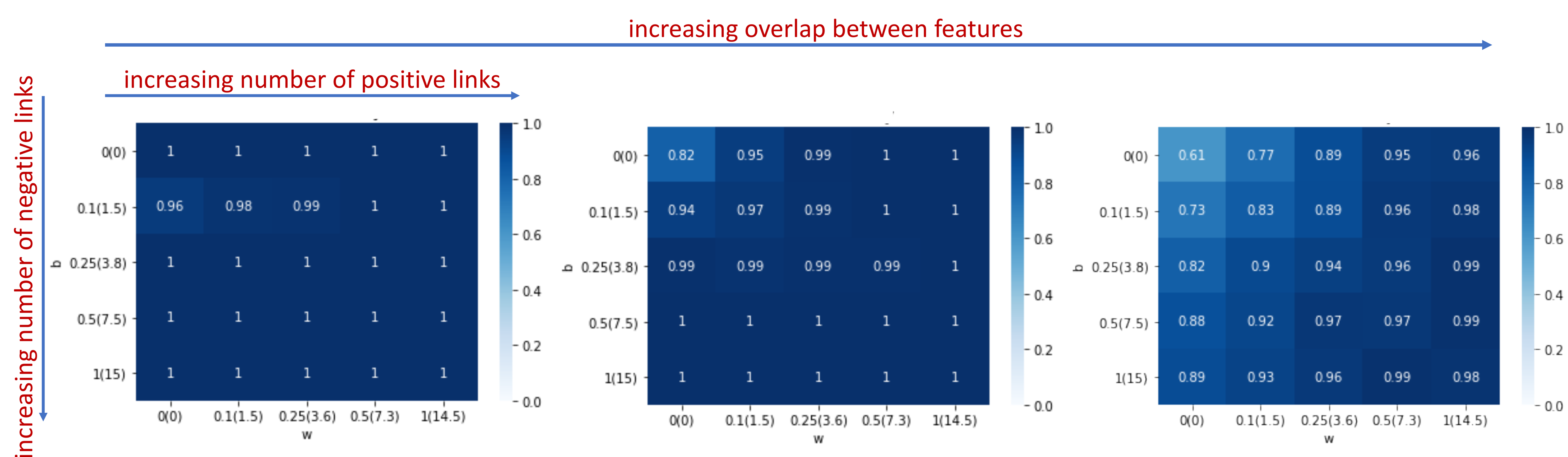
Table 3. Experiments on real-world networks: Summary of results regarding classification binary-F1 and micro-F1 score (in percentage). The best performing model for each metric is printed bold

	Methods	Binary-F1		Micro-F1	
		Bitcoin-OTC	Epinions	Bitcoin-OTC	Epinions
GCN variants	Pos-GCN	26.25 ± 1.28	40.48 ± 0.74	70.69 ± 1.81	60.69 ± 1.26
	Rem-GCN	24.38 ± 6.04	51.26 ± 5.79	50.24 ± 15.14	69.75 ± 0.84
	Nor-GCN	20.48 ± 2.72	50.81 ± 0.95	54.34 ± 6.50	68.76 ± 1.48
	Lap-GCN	20.48 ± 2.72	0.02 ± 0.05	44.40 ± 13.54	80.73 ± 0.10
	MLP	15.36 ± 1.07	27.99 ± 2.67	43.36 ± 3.16	65.36 ± 1.82
	Logistic	17.78 ± 0.99	37.18 ± 0.35	50.15 ± 1.80	60.35 ± 0.51
	SS-CGN	**77.6 ± 1.1**	**82.80 ± 2.51**	**96.25 ± 0.17**	**94.33 ± 0.69**

Pos-GCN[3]: treats negative edges as positive edges
Rem-GCN[4]: removes all negative edges
Nor-GCN[5]: normalizes edge weights in [0, 1]
Lap-GCN[6]: only utilizes signed Laplacian
MLP: Multi-Layer Perceptron
Logistic: Logistic Regression

Figure 1. Experiments on synthetic networks: SS-GCN's accuracy as a function of the number of edges and the amount of overlap between features

Synthetic networks produced by Stochastic Block model include 60 nodes belonging to two equal communities. The edges connecting nodes belonging to the same class are positive, while those linking nodes belonging to different classes are negative.



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