
CE7490 Project: Benchmarking Algorithms for Weight Prediction in Weighted Signed Networks

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Abstract

The abstract paragraph should be indented 1/2 inch (3 picas) on both the left- and right-hand margins. Use 10 point type, with a vertical spacing (leading) of 11 points. The word **Abstract** must be centered, bold, and in point size 12. Two line spaces precede the abstract. The abstract must be limited to one paragraph.

1 Introduction

[Context] A number of weighted signed networks (WSN) exist in our world while many of them are incomplete. The values for weights prediction are ...

[Existing Solutions] State-of-the-art fairness and goodness. Baselines: Reciprocal, Triadic balance, Triadic Status, Pagerank

[Our project] To better understand theories and master practical skills, we investigate and implement a common set of algorithms and evaluate their performance on real-world datasets.

The rest of the paper is structured as follows: Section 2 presents related work in this topic. Section 3 describes the overview of our project. Section 4 formulates the problem of weight prediction in weighted signed networks. Section 5 conducted experiments on real-world datasets using different algorithms. Section 6 evaluates the performance of all tested methods. The conclusion is summarized in Section 7.

2 Related Work

Edge Sign Prediction in SSNs ...

Edge Weight Prediction in Social Networks ...

3 Project Overview

In this project, we extensively investigate and experiment methods for edge weight prediction in weighted signed networks. All algorithms are tested and evaluated on published real-world datasets. Moreover, we try our best to improve the performance on some traditional methods. The finished works are summarized as follows:

1. Literature review on OSN and select a topic about predicting weight of edges for weighted signed network.
2. Investigate the state-of-the-art algorithms *fairness-goodness* in [] and studied a common set of baselines for weight prediction.
3. Conducted experiments on each algorithm and reproduce the results mentioned in original paper using real-world dataset.
Experimental 1 - Removing one edge prediction : ...
Experimental 2 - Removing N %-out edge prediction : ...
4. Evaluate results of different methods.

4 Problem formulation

5 Experiments implementation

Fairness and goodness

5.1 Page Rank

We first compute Page Rank (ωPR) value of every vertex(k) in an unsigned graph according to [1]:

$$\omega PR(k) = \frac{1 - \alpha}{|V|} + \alpha \sum_{z \in in(k)} \frac{\omega PR(z) * W(z, k)}{|out(z)|} \quad (1)$$

α is the probability called damping factor meaning a person will continue clicking on links(travelling in graph), and we set α to 0.85. $|V|$ is the number of all nodes. Eventually, $\omega PR(k)$ will converge to the probability that a person will go and stay at node k.

Then we compute edge weight of (u, v) using weighted average of PageRank values:

$$W(u, v) = \frac{\sum_{z \in out(u)} \omega PR(z) * W(u, z) + \sum_{z \in in(v)} \omega PR(z) * W(z, v)}{\sum_{z \in out(u)} \omega PR(z) + \sum_{z \in in(v)} \omega PR(z)} \quad (2)$$

Bias and deserve

Reciprocal

5.2 Signed-Hits

The prediction is computed by using a modified version of HITS for signed network, called Signed-HITS[2]. Signed-HITS will compute the hub and authority scores of every node separately on positive graph(all edges' weights are positive) and negative graph, using the equation:

$$\begin{aligned} h^+(u) &= \sum_{v \in out^+(u)} a^+(v); a^+(u) = \sum_{v \in in^+(u)} h^+(v) \\ h^-(u) &= \sum_{v \in out^-(u)} a^-(v); a^-(u) = \sum_{v \in in^-(u)} h^-(v) \end{aligned} \quad (3)$$

after convergence, we assign the authority score $a(u) = a^+(u) - a^-(u)$ and hub score $h(u) = h^+(u) - h^-(u)$ to each vertex u . Authority scores estimate the node value based on the incoming links, while hub scores estimate the node value based on outgoing links. However, the paper[3] didn't deliver the method to compute edge weight by using the authority score and hub score. Again, we use weighted average to compute the weight prediction:

$$W(u, v) = \frac{h(u) * \sum_{z \in out(u)} W(u, z) + a(v) * \sum_{z \in in(v)} W(z, v)}{h(u) * |V_{z \in out(u)}| + a(v) * |V_{z \in in(v)}|} \quad (4)$$

In this equation, we use $h(u)$ to be the weight of all out-going edges and $a(v)$ to be the weight of all in-coming edges. The reason is that $h(u)$ represents the node value based on out-going edges. So the predicted weight of out-edges from u should be higher if $h(u)$ is high. Likewise, the predicted weight of in-edges into v should be higher if $a(v)$ is high.

Status theory

Triadic balance

5.3 Triadic Status

Imaging there are two nodes named A and B , and they are unlinked. What we want to do is to predict the weight of the edge from A to B . Suppose that there is another node X , and (A, B, X) compose a triangle once A and B are linked. Overall, there are four different triangle-links, as the edge between X and A can go in either direction and similarly for the edge between X and B , if the sign of weight is not considered.

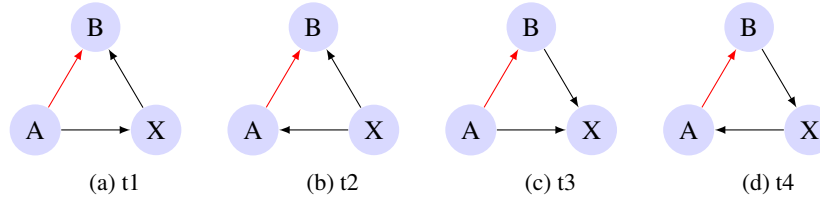


Figure 1: Triadic Status

And we predict the weight of the edge (A, B) using three rules:

1. In Graph t1, the predicted weight of the transitive edge is the sum of the two non-transitive edge weights.
2. In Graph t2 and t3, the predicted weight of a non-transitive edge is the difference of the transitive and the other non-transitive edge weights.
3. In Graph t4, since it is a cyclic triad, the weight of the missing edge is the negative of the sum of other two edge weights.

In the end, we take the average of predicted weights over all triadic-links that these two nodes are a part of.

5.4 Linear Regression

In this experiment, we use a linear regression model to predict the weight of edge. Our features are generated from some algorithms mentioned above. First, the test edge e_t whose weight is to be predicted is removed from the network. Second, we remove the second edge e_s and predict the weight of e_s from the rest of the edges. And the predicted value of e_s will be the feature and the true value of e_s will be the ground truth. The second step is done multiple times to generate enough samples for training. After training, we use this model to predict the value of the removed edge e_t .

6 Performance Evaluation

7 Conclusion

References

- [1] Sergey Brin and Lawrence Page. The anatomy of a large-scale hypertextual web search engine. *Computer networks and ISDN systems*, 30(1-7):107–117, 1998.
- [2] Moshen Shahriari and Mahdi Jalili. Ranking nodes in signed social networks. *Social network analysis and mining*, 4(1):172, 2014.

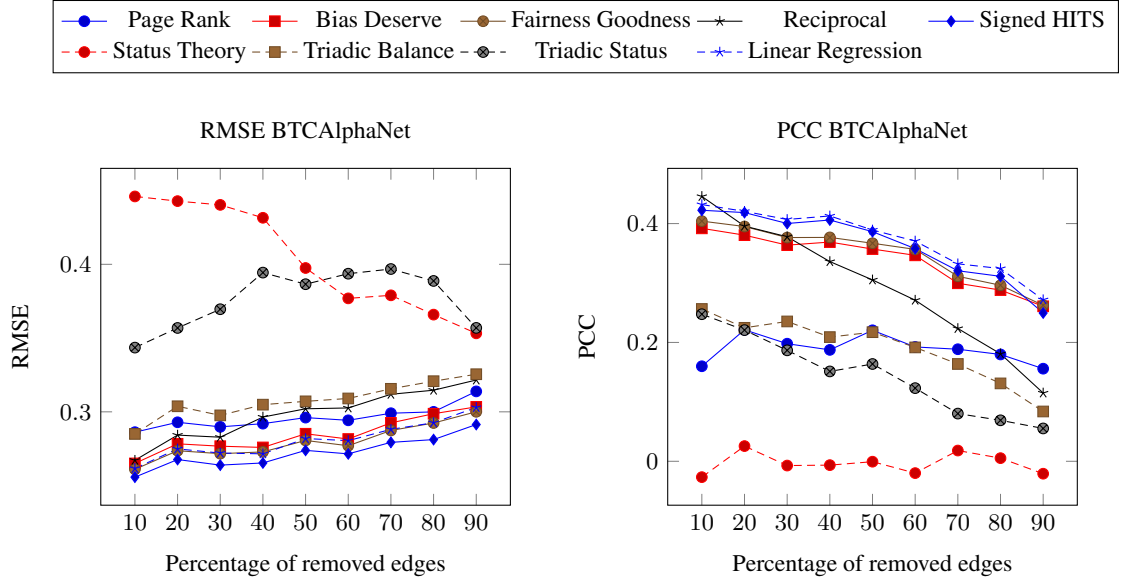


Figure 2: BTCAlphaNet

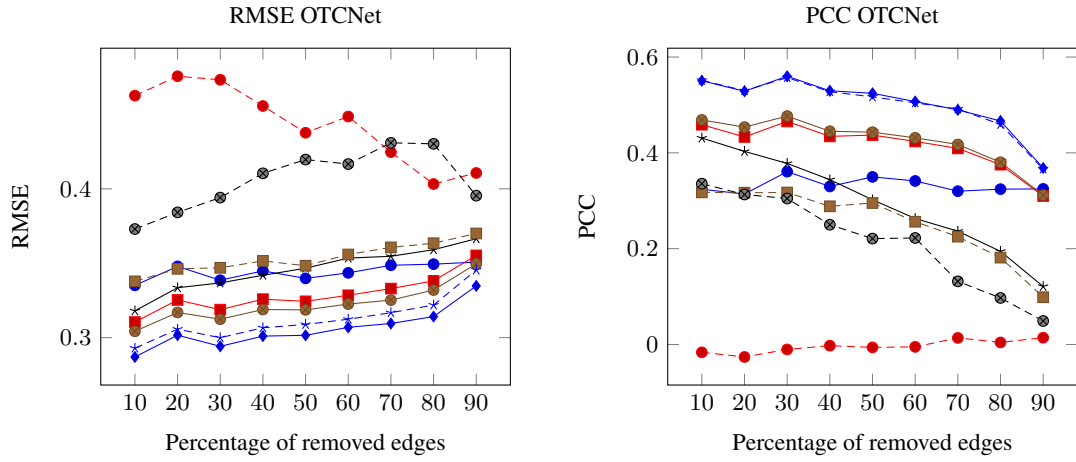


Figure 3: OTCNet

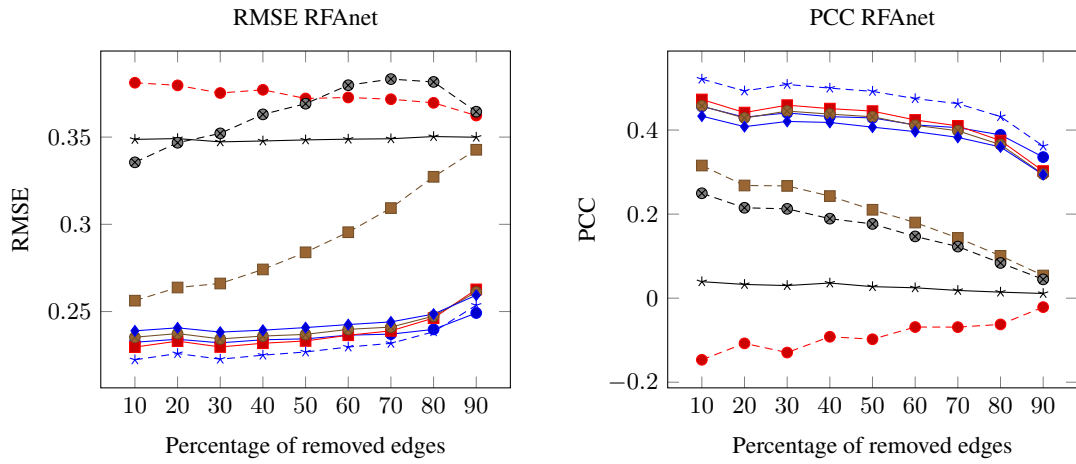


Figure 4: RFAnet

- [3] Srijan Kumar, Francesca Spezzano, VS Subrahmanian, and Christos Faloutsos. Edge weight prediction in weighted signed networks. In *2016 IEEE 16th International Conference on Data Mining (ICDM)*, pages 221–230. IEEE, 2016.