Proceedings of the Fifteenth International AAAI Conference on Web and Social Media (ICWSM 2021)

# SIGNLENS : A Tool for Analyzing Polarized Social Relationship Based on Signed Graph Modeling

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### Abstract

SIGNLENS is a tool that helps to analyze polarized social relationships based on signed graph modeling. It could be used by political analysts, historical researchers, and social media community organizations to analyze the social network with negative links (i.e., conflicts or disagreement). SIGNLENS can handle signed temporal graph by doing individual analysis and group analysis. Individual analysis gives a Web dashboard to users to explore the nodes who users focus on. Group analysis provides another perspective of analyzing the whole graph, which mainly analyzes the changes in the unbalance of the signed graph over time. We give two examples to demonstrate how our tool works, which consist of The China Biographical Database and the United States Congress Vote. More details about these two examples can be found in https://github.com/huangjunjie-cs/SIGNLENS.

## Introduction

With the growing popularity of online social media, many interactions between people are recorded on the web. Modeling and understanding these interactions is a useful perspective on a range of social computing studies. In the past decades, a lot of graph analysis tools, for exmaple, Ucinet (Borgatti, Everett, and Freeman 2002), Gephi (Bastian, Heymann, and Jacomy 2009), and NetworkX (Hagberg, Swart, and S Chult 2008) are proposed to do social network analysis, computing, and visualization. However, most of them are designed to handle only networks with positive links. Nowadays, the conflict on the web (Kumar et al. 2018) is everywhere. These interactions include both positive social relationships and negative conflicts. Signed graphs are used to model such networks where edges have positive and negative signs. Signed graph modeling is successfully applied in many different fields of research (e.g., political science and international relations).

In this paper, we propose a new tool for exploring the social relationships between people based on signed graph modeling. Our tool integrates many algorithms that are widely used in signed graph modeling (e.g., community detection, frustration index, and spectral analysis) and provides two different perspectives to analyze signed networks.



## SIGNLENS

### Input Data

SIGNLENS is a web system designed to handle signed temporal graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{X}, S, T)$ as input, where $\mathcal{V} = \{v_i\}_{i=1}^{|\mathcal{V}|}$ is the set of nodes, $\mathcal{E} = \mathcal{E}^+ \bigcup \mathcal{E}^-$ is the edge list containing both positive $(+)$ and negative $(-)$ links, and $\mathcal{X}$ is the features of nodes. The network input format is the edge list $(v_i, v_j, s, t)$, which means that $v_i$ has a sign $s$ event with $v_j$ in time $t$. For a node $v_i$, the feature input format is the JSON format data that contains profile information for $v_i$. The common data can be extracted from historical records (Huang and Luo 2018), political voting networks (Derr et al. 2019), and social networks (Kunegis, Lommatzsch, and Bauckhage 2009).

### System Design

Our analysis system consists of two parts: Individual Analysis and Group Analysis.

**Individual Analysis** For individual analysis, we usually focus on some specific nodes. Our system allows you to input the nodes you want to analyze and a depth $K$, our system starts from these nodes, extract the subgraph with $K$ hops. We usually use NetworkX (Hagberg, Swart, and S Chult 2008) to extract the centrality of nodes you analyze including Degree, Eigenvector, Closeness, and Betweenness. These centrality metrics are computed by ignoring the sign. Since the network is a signed graph, we introduce positive and negative degree centrality for nodes to analyze whether the individual has more negative relationships with other nodes. These centrality metrics help users to find who is "Mr. No".

Besides, our system provides an interaction function to directly view the records sorted by time. It is useful to explore the historical changes of the relationship between nodes. Based on we selected nodes with $K$ hops subgraph, we do group partition using signed community detection algorithms (Traag and Bruggeman 2009).

**Group Analysis** Compared to traditional social networks, sign networks have negative edges which usually indicate enmity or distrust. Structural balance in signed graphs is a structural property that has become a focus in network science. Balance theory was the first attempt to understand the

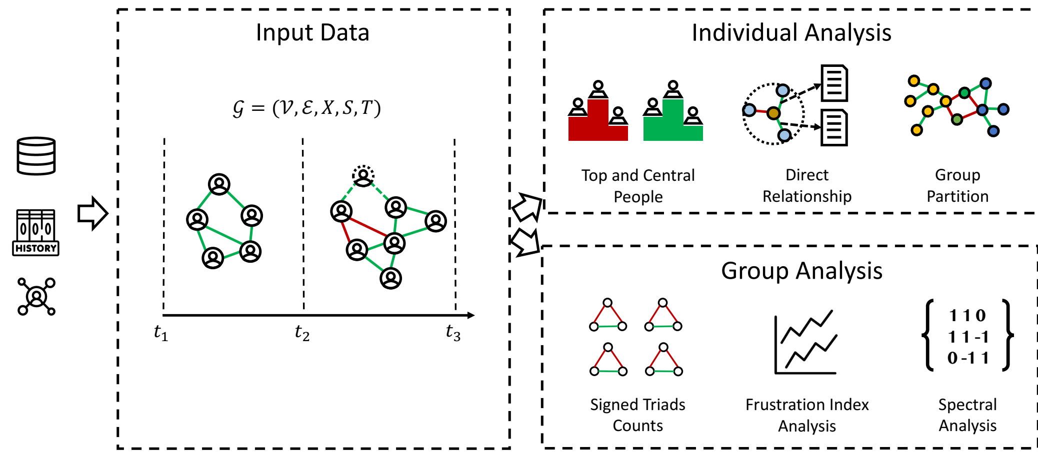


Figure 1: The illustration of the proposed SIGNLENS . SIGNLENS contains individual analysis and group analysis. The individual analysis will visualize the relationships between nodes that users focus on. Group analysis gives the measures of unbalance of a signed graph over time.

sources of tensions and conflicts in groups of people with signed ties (Heider 1944). A lot of measures of balance have been proposed and deployed in the past few decades (Facchetti, Iacono, and Altafini 2011).

Our system measures balance by counting the unbalance triangles (Huang et al. 2021). For a triangle, it has four types of connections (i.e., $+++$, $++-$, $+--$, and $---$). The triangles are balanced when the direct and the indirect relationships have the same sign, unbalanced otherwise. It means that $+++$ and $+--$ are the balanced triangles. Our system counts the number and proportion of balanced triangles in the network as different time intervals $[t_1, t_2]$.

Another way to measure unbalance is the normalized version of the frustration index. The frustration index $\epsilon$ of signed graph $\mathcal{G}$ is defined as the minimum number of edges whose deletion leads to a balanced graph (Aref, Mason, and Wilson 2020). Finding the frustration index is an NP-hard problem, so we use the approximation method from Aref, Mason, and Wilson. Similarly, we compute the frustrate index of $\mathcal{G}_t, t \in [t_1, t_2]$ and analyze the change of $\epsilon$ over time.

The last one for group analysis is spectral analysis. Many graph-theoretic data mining problems can be solved by spectral methods that consider graphs as matrices to compute their eigenvalues. For signed graph, Kunegis et al. define the signed Laplacian matrix as $\hat{L} = \hat{D} - A$, where $A$ is the matrices of signed graph, the signed degree matrix $\hat{D} \in R^{|\mathcal{V}| \times |\mathcal{V}|}$ is the diagonal matrix given by $\hat{D}_{ii} = \sum_j |A_{ij}|$. The smallest Laplacian eigenvalue can be a characteristic value denoting the balance of a signed graph. The higher the eigenvalue, the more unbalanced is the signed graph $\mathcal{G}$. Similarly, we also calculate the value in different time intervals.

## Applications

Based on our system design, we use signed graph modeling to analyze signed social networks. We give two examples from real-world applications to demonstrate how our system works. The first example is the analysis of ancient Chinese Political Figures. The data is collected from The China Biographical Database[1] (CBDB), which is a freely accessible relational database with biographical information about approximately 471,000 individuals as of November 2020, primarily from the 7th through 19th centuries. We follow Huang and Luo (2018) steps to sign the links and do data cleaning.

Another example is the United States Congress vote analysis. The data is collected from GovTrack.us[2], which is a website to track the vote records for the United States Congress. We construct the signed graph through the following rules: If two members of Congress vote the same decision to a bill (i.e., both "Yea" or "Nay"), a positive edge is constructed. If their votes are different, a negative edge is constructed.

It's worth mentioning that our system can also be used to analyze the network of online communities whose signs can be extracted by sentiment analysis tools.

## Conclusions and Future Work

In this paper, we propose a new tool for modeling the signed graph by individual analysis and group analysis. In the future, we will integrate more graph neural networks methods (Derr, Ma, and Tang 2018; Huang et al. 2019) to enhance our system to discover more useful knowledge. We will also try to use our tools to analyze more online social networks that may arise conflicts on the web.


## Acknowledgments

This work is funded by the National Natural Science Foundation of China under grant numbers 91746301 and 61433014. Huawei Shen is also funded by Beijing Academy of Artificial Intelligence (BAAI) and K.C. Wong Education Foundation.


[1] https://projects.iq.harvard.edu/cbdb

[2] https://www.govtrack.us/

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