Defining Status: A novel formulation for signed networks

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***Abstract*—The paper "Signed Networks in Social Media" [1] motivates towards the formulation of status theory in predicting network structures. Implicit notions of status already exist in modern social media, such as the number of followers of an Instagram user or the karma system in Reddit. In light of the findings of the aforementioned paper, this work focuses on a relative definition of status within local triads, using edge signs. This work attempts to supplement the analysis of the paper by using an extended Epinions dataset which contains additional information beyond the signed network. Nodal features such as number of reviews by a particular user or user anonymity, should intuitively play a strong role in determining the user's status within the social media hierarchy and we explore these relationships in this study. By the end of this study, we want to be able to explicitly formulate what parameters play a role in the decision of a user A to rate positively or negatively a user B.**

I. Introduction

Social media has become widely pervasive in recent years and the analysis of social networks offers useful perspectives about interactions between users, as well as understanding global relationships. Often, these networks contain some notion of signed edges, that serve to highlight some particular relationship between the connected nodes. The work by Leskovec et al.[1] analyzes the structure of signed networks in 3 datasets: Epinions, Slashdot and Wikipedia-Elections. The authors highlight deficiencies in the existing theory of structural balance [3] in explaining signed social networks and motivate towards a theory of status for signed networks, that better explains the structural properties of such networks. To directly contrast with balance theory, they present their results through analysis of triadic relationships. However, they do not formalize the notion of status beyond a vague description of social relationships in triads. Moreover, in general, there is no clear way to predict the relationship between two nodes without knowing the edge signs *apriori*.

To address these shortcomings, we aim to crystallize the notion of status in signed networks, in particular on the ratings platform Epinions. We hypothesize that such an approach is feasible for networks in which signed relations are explicitly defined and enough data is available on the activities and relationships of the nodes. More specifically, using relevant nodal features and the existing graph structure, we characterize a model and illustrate its practical efficacy in link prediction, while staying consistent with status theory.

The rest of the report is organized as follows: We specify the choice and salient points of our dataset in section II, followed by the feature selection and modelling assumptions in section III. We describe our model performance and evaluation results in section V-B and wrap up with some final conclusions in section VI.

II. Dataset Wrangling

A. Dataset description

For this extension, we collected 3 Epinions datasets that contain extended information of the user behavior patterns. The datasets are available on trustlet.org.

1) user_ratings: This represents the trust/distrust list of users.
2) mc.txt: This represents the list of total articles written by users. The dataset contains the ID of the item article, the ID the user who wrote the article, and the ID the item that is being reviewed
3) ratings.txt: This represents how much a certain user rates a review article written by an other user. The dataset contains the ID of the article that is being rated, the ID the user who rated the article, the rating, the last modification date of the rating, and whether the rating is anonymized.

We also have the original epinions dataset that was used in the 'Signed Network in Social Media' paper, that contains a list of signed edges.

B. Recreating the papers setting

The starting point of our analysis assumes the applicability of status theory on predicting triadic links on the Epinions dataset as described in [1]. However, we use an extended version of Epinions composed of three sub-datasets, whose node labels differ from the original epinions dataset. Therefore, in order to proceed with our assumptions, we need to first check if these datasets represent the same graph structure. Fortunately, we successfully verify that the graph structure induced by the two datasets are indeed isomorphic to each other. Consequently, we can safely work with the extended Epinions dataset for our analysis. The second processing step is then to filter the edges in the same way as described in the reference. For the analysis, the authors only considered the edges formed by a contextualized link. This means that for the three nodes in a triad, we select the edge that was formed the latest. More concretely, we extract triads as in 4 and we retain the set of AB edges in this configuration.

III. Feature Selection and Engineering

With details about behaviour patterns of individual users on the network provided in the new datasets, we extract potentially relevant features for link prediction based on status theory, for each node. For each feature, we provide an intuitive reason to motivate its relevance, and we supplement this using statistical tests, whenever relevant.

A. Feature Design

The list of features we extracted from the dataset is as follows:

- *#reviews* - The total number of ratings on articles posted by a specific user allows us to measure the activeness of that user on the network and should be relevant to his status.
- *#articles* - By similar reasoning, the total number of articles published by a specific user should be relevant to his status.
- *mean_rating* - The mean value of all ratings issued by a specific user allows us to characterize the behaviour, for instance in terms of strictness or generosity in ratings, and may be useful for predicting his status.
- *sensationalism* - Through this feature, we try to capture the degree to which a user's issued rating deviates, on average, from the mean rating of the item calculated on the entire dataset. More specifically, the sensationalism of user i denoted by $s_i = \frac{1}{\mathcal{Z}_\rangle}\sum_j^{r_{ij}\neq\phi}|o_j - r_{ij}|$, where o_j denotes the mean rating of item j, r_{ij} denotes the rating issued by user i to object j and $\mathcal{Z}$ indicates the number of ratings issued by user i. The notion we want to capture is how often the user posts sensational reviews which tend to differ from the majority opinion.
- *anonymity* - This feature describes the extent to which a user prefers anonymity while rating an object. For each rating, the anonymity is a binary value $\in 0, 1$ and therefore, we average it over the set of that specific user's rating. In social media, behavioural pattern often change when you can anonymize yourself and therefore, it is significant for understanding status.

Since we are using the nodal features to determine their role in edge sign, we need to consider what information node 1 has when they are rating node 2. Here, the anonymity feature for the end node of each edge plays an important role. Particularly, $node_1$ can attribute some specific behaviour to $node_2$ only if $node_2$ does not remain anonymous while exercising that behaviour. Therefore, what is observable for $node_1$ when assigning status to $node_2$ by forming an edge, are the features when $node_2$ was not anonymous. This then affects three of $node_2$'s features in particular; #reviews, mean_rating and sensationalism. And after taking this into account, we drop the anonymity feature for $node_2$, and retain a total of nine features. Note that this also introduces some inherent dependency on the edge direction for our prediction model.

B. Descriptive Analysis

Firstly, we observe that the histogram of both *#reviews* and *#articles* and *sensationalism* over the dataset roughly follow a power law decay. In addition, the range for the feature values is quite high and naive normalization of the data would lead to the feature being driven to 0 for the majority of nodes. Therefore, we first apply a log transform ($\mathcal{F} : x \rightarrow log(x + 1)$) and then normalize the data to make it more tractable for learning.

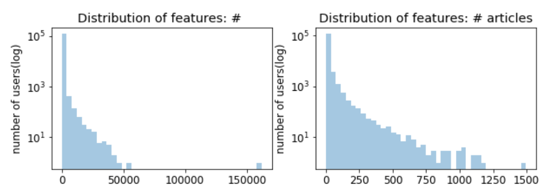

Figure 1: Distribution of features: *#reviews* & *#articles* on log scale.

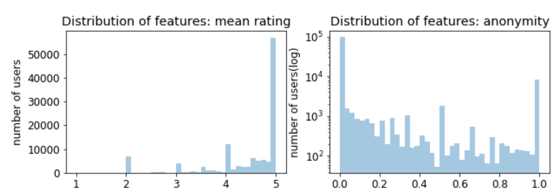

Figure 2: Distribution of features: *rating* & *anonymity*.(anonymity on log scale)

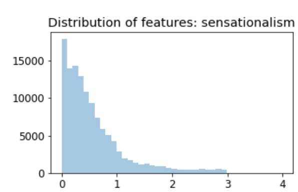

Figure 3: Distribution of features: *sensationalism*

In mean rating and sensationalism, the distribution is skewed towards a certain direction. Mean ratings of users are concentrated on higher scores. This fits our general intuition that people tends to rate generally high scores when they are rating the work of others (here, their articles). Sensationalism of users are concentrated on lower values, which corresponds to general intuition that people tends to follow what majority does.

Finally, anonymities of users are concentrated on both ends, 0 and 1, while the density on lower anonymity is higher than that on higher anonymity. We can draw an insight from here, that it is more common for Epinion users to rate others' reviews non-anonymously.

C. Statistical Testing on Features

Before using the features to train a model, we perform statistical testings for all the features to verify our null hypothesis that the mean value of features are same in both edge signs. For accepting/rejecting the null hypothesis, we select the Welch's corrected unpaired t-test to compare the means of the two groups. We select this test since we have two unpaired populations, but with different variances, whose means we want to compare. For the features #reviews, #articles, and anonymity, we perform a log transform before running the t-test. In all features, we have p-values less than 0.001, so we proceed to regression analysis and model training while keeping all nine features.

IV. Experiment Methodology

Using the features defined in the previous section, our aim is to learn a link prediction model for the edges in the graph. For this purpose, we use a logistic regression model. However, we notice that there is an inherent skew in data, with a large majority of edges being positively signed. To account for this, we introduce class weights to reweigh the loss function and correct for this bias to improve learning.

For verifying the generalizability of the model, we use cross validation to obtain mean F1 scores for the model. We retain the model with the highest F1 score, we report the performance in terms of more extensive metrics on the test set. Finally, we evaluate the performance of the model in predicting the edges for the different types of triads, and compare it to the findings of status theory.

V. Results

A. Model Performance

The simple logistic regression model does quite well in predicting +ve edges in a graph. However, the sticking point here is that it does not seem to do well for -ve edges, with relatively lower precision, recall and f1 scores, despite the weighted loss function. We attribute this partly to the limitations of the learning model. However, it perhaps also points towards the difficulty in making lower status predictions using just the nodal features.

Edge Sign	Precision	Recall	F1 score
$-ve$	0.665	0.546	0.600
$+ve$	0.965	0.979	0.972

Table I: Performance metrics

B. Model Interpretation

Feature	Coefficient Value
avg_ratings1	1.369
avg_ratings2	-0.119
nbr_reviews1	-0.979
nbr_reviews2	0.48
nbr_articles1	-0.245
nbr_articles2	-0.073
sensationalism1	1.316
sensationalism2	-0.71
anonymity_freq1	-0.101

Table II: Model Coefficients for features

The most important features, with the highest coefficient absolute values are *avg_rating1*, *sensationalism1*, *nbr_reviews1* and *sensationalism2*. These features relate to how a user rates others' reviews and how often a user writes reviews. It provides an interesting insight into the explainability of our model. The highest positive coefficient for *avg_rating1* indicates that a person who tends to dish out higher ratings, often rates other people highly. Similarly, the negative coefficient for *nbr_reviews1* indicates that a person who is generally more active on the social network, tends to disregard others as those of lower status.

Another interesting observation is that for almost all the features, it's the features of the user who give the rating that are more important rather than the features of the one who receive them.

VI. Conclusion

This study allowed us to understand and define what comes into place in the rating mechanism present in the dataset Epinions. As our work reproduces the settings of Leskovec et al.'s [1] paper, we can draw the line between the rating mechanism, the users features and the notion of status. An interesting question to further extend this analysis is if the model behaves as well for all the different triad types. In the original paper, the authors underlined the fact that the triad types were each more or less consistent with status, it would be interesting to see if these findings are reflected in our model.

REFERENCES

[1] Jure Leskovec, Daniel Huttenlocher, and Jon Kleinberg, 2010 - ”Signed networks in social media”, In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI ’10), Association for Computing Machinery, New York, NY, USA, 1361–1370.

[2] F. Heider. Attitudes and cognitive organization. Journal of Psychology, 21:107–112, 1946.

[3] cite sklearn, jupyter, statsmodels etc.

APPENDIX

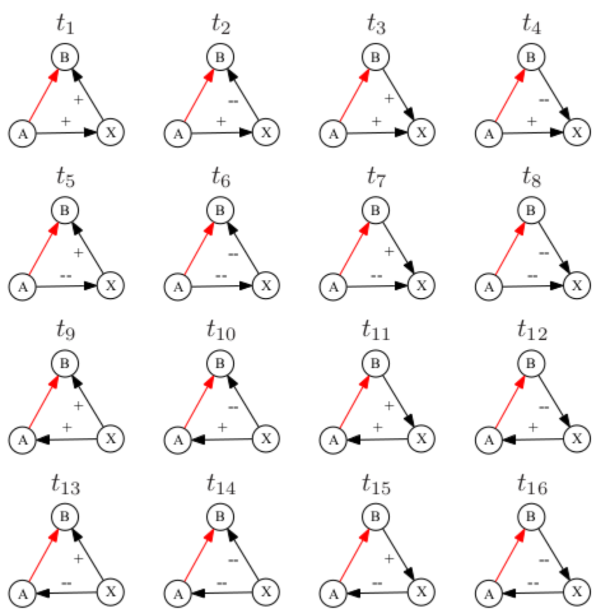

Figure 4: the 16 different triad types. The edge AB in red represents the most recent edge of the triad. [1]

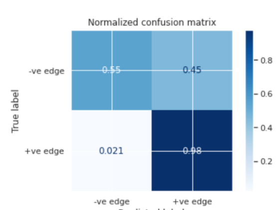

Figure 5: Confusion Matrix