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How social interactions lead to polarized relations?

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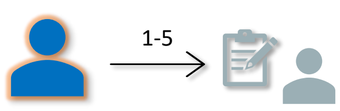
In this research the focus was on how interactions might impact future relations. Such analysis might be helpful in future understanding of social networks creation dynamics, where people can have either positive or negative (polarized) relations. One can make intuitive assumptions that the frequency of interactions between a pair, who will later have a positive relations would be different, than for a to-be-negative pair. The presented work focuses on a example of such analysis for a real dataset.

The table shows how many pairs of users have certain proportions of interactions before trust declaration. Pairs which do not interact before the relation is created are not significant in numbers. Those would not impact conclusions from previous plots.

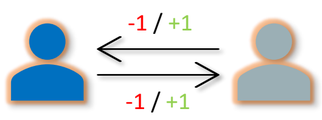
Interactions before trust declaration	Positive trust pairs	Negative trust pairs
No interactions	11%	9%
All interactions	44%	77%
Other	45%	14%

Dataset
In this work Epinions dataset was used. Epinions was an internet portal, where people could write articles.

Other people were able to rate them on the scale 1-5.
There was a possibility to anonymize information about rater if chosen.



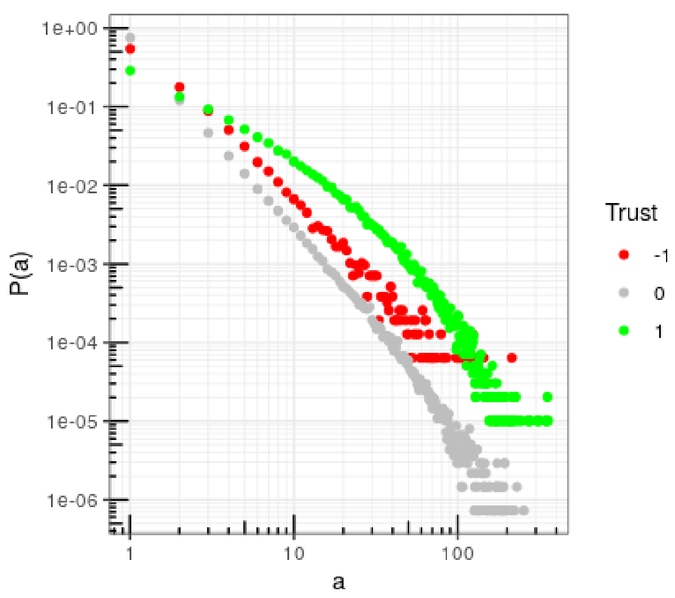
Users were able to declare a trust or distrust to others.
The trust did not have to be symmetrical.
After declaring distrust user would not be recommended articles from the distrusted source.



For the purpose of this research, we treated ratings as interactions and trust declarations as relations. The positive relations is where user A trusts B and negative – if A distrusts B. Trust declaration could not be changed. After cleaning the data there was 91 486 users and 1 491 571 ratings. Not every possible pair of users declared trust – those were considered neutral relations. The date range was from January 2001 to May 2002 and all data points had precise datetime assigned.

The information of the sign of the relations could be helpful in predicting the number of interactions that can occure in this example. To check how much each type of relation impacts interaction occurences, a multilayer hypergeometric model was used.

Multilayer hypergeometric model
In short summary in this model one defines a certain number of agents which can be considered as nodes in the network. The layers consists of one or more attribute layer. In each some agents are connected, which represents a relation according to a certain attribute. Those networks are directed and unweighted. There is also an interaction layer, which is directed and multiedge (each edge will represent the number of interactions).
After preparing the network a set number of edges in interaction layer is created. The probability of creating a interaction between a pair of users depends on the connections or their lack in attribute layers. The propensity value represents how many times the probability of interacting is different depending on each attribute layer. Estimating those values can show the impact of each attribute on creating interactions.



The plot on the left shows the probability distribution of number of all interactions from one user to another. The colors represent relation, which could be declared at any point. We can see that pairs which end up declaring trust rate more often compared to other relation states.

In this work each polarization of the relation made an attribute layer. A connection in a layer of positive relations would mean that this directed pair of users would declare trust at some point. Similarly in the negative relation layer. The total number of interactions in the dataset was taken as the number of edges to simulate.

Trust layers	Propensity	St. Dev.
Positive	3,303	0,003
Negative	1,406	0,008

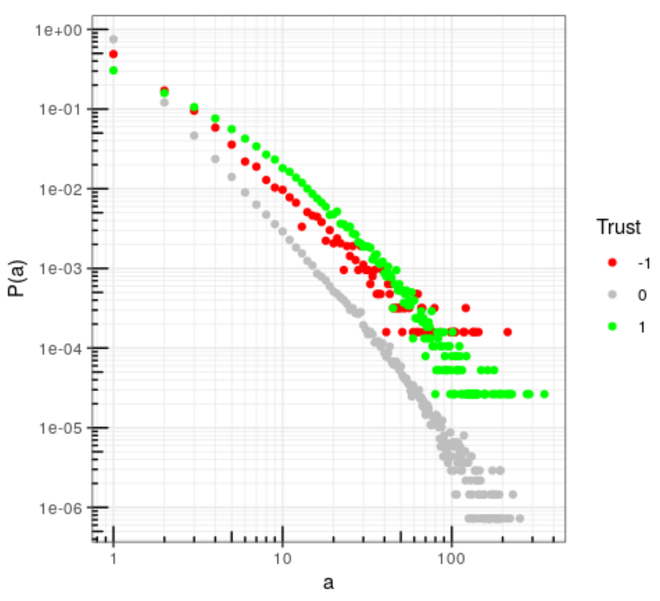
All interactions

Trust layers	Propensity	St. Dev.
Positive	1,844	0,004
Negative	1,207	0,006

Interactions before trust declaration

Tables above show the impact of relations on interactions occuring between pairs of users. Values of propensity greater than 1 mean, that a connection in an attribute layer (here – a relations) increases the probability of interactions. On the right one can say that more interactions are needed for a relation to establish when compared to pairs which never .

The problem with this approach is the existence of recommendation algorithm, which would reduce probability of interactions after declaring distrust.



The plot on the left shows the probability distribution of number of all interactions from one user to another, but only using interactions **BEFORE** the trust was declared. The probability of having higher number of interactions is greater, when a pair ends up declaring trust. In other words more interactions can lead to a relations of any sort.

This work showed that more interactions happen between people, who will openly declare the relations, when compared to those, which will stay neutral. This points to confirmation of assumptions mentioned in the first paragraph. Numbers of interactions needed to create both negative and positive relations are similar.
In future steps the focus will be to confirm findings using different datasets and find methods of estimating relations without direct declaration using multiple types of interactions.

Based on: G. Casiraghi *Multiplex Network Regression: How do relations drive interactions?*

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