The Human Perception of Social Relationships

Luca Maria Aiello[1], Sebastian Deri[2], Jérémie Rappaz[3], Daniele Quercia[1]

[1]Nokia Bell Labs, [2]Cornell University, [3]EPFL

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Social relationships are among the most important things in our life. They determine and relate to who we marry, where we work, and what we make. They take center stage in our digital lives too. Social-networking sites are made of relationships, and the act of maintaining them results into bridging and bonding forms of social capital and, ultimately, into well-being. Researchers have tried to capture the nuances of relationships by measuring them in terms of tie strength. Yet not all ties of the same strength are created equal. Many social factors are too intertwined to consider tie strength a complete or even a distinctive characterization of a relationship. In this study, we set out to study how people perceive the richness of their relationships with the goal of enhancing current tools for social network analysis.

We reviewed the relevant literature in sociology and social psychology and obtained eight tentative dimensions along which relationships could be classified. Independently, we asked 100 crowd-sourcing users to describe their relationships with words and obtained 1,352 terms, 220 of which were unique. We then asked another set of 100 crowd-sourcing users to validate each of these 220 terms through a structured survey. As a result of the crowdsourcing, each word has been characterized by a 100-dimensional rating vector that allowed us to compute the relatedness of words and extract cohesive groups of terms. The groups we found overlap to a large extent with the eight dimensions we found in the social pyschology literature and add two new dimensions. The final list consists of these 10 dimensions: *similarity [5], social support [4], trust [8], romance [2], identity [7], respect [3], knowledge [4], power [1], fun [6], and conflict*. Each dimension is associated to a set of terms.

To show how this nuanced classification can be used to enchance network science applications, we run a study using a dataset of textual conversations between linked individuals in an online social network. For each social tie, we matched the terms that reflect each of the 10 dimensions, with the words occurring in the conversation. We label each edge with the dimension having the highest number of matching words. We selected 100k connected pairs (positives) and 100k disconnected ones at 2 hops away (negatives) to run a link prediction experiment in two scenarios. In the first, we predict the presence of a link from A to B based on their common neighbors count CN. In the latter, we use a feature vector whose entries count the number of common neighbors who are connected to A with a link of a given type (e.g., "support"). In a supervised learning setting with 10-fold cross validation, the latter scenario brings an improvement of 9% in AUC compared to pure CN. Decomposing the tie strength (number of common friends) into its components improves our ability to predict the network structure. The improvement is significant; in link recommendation a +1% in AUC, on a large scale, leads to a large increase in the number of links created.

In addition, when analyzing the sub-graph induced by links of a given type, we find that network properties vary as one would expect from social psychology theories. For example, the network of knowledge exchange tends to be assortative whereas the network of respect is

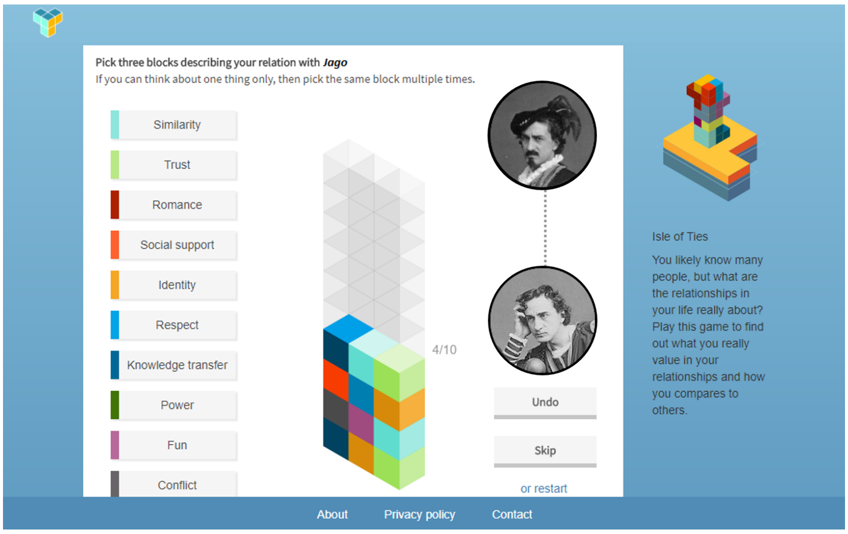

Figure 1: Anonymized screenshot of our platform. Users are asked to label the relationships with their Twitter friends using the ten dimensions we have identified in this study.

disassortative (people who have high "reputation" are given status mostly by less-respected members of the same community).

Last, to test whether the relationship labeling task could be made practical and fun, we have developed an online platform (Figure 1). Users login to play the game through Twitter, their timeline data is accessed and they are sequentially presented with 10 of their actual friends. For each friend, they rate the extent to which that relationship is described by our 10 blocks. The user interface is "gamified" so that the experience is fun and rewarding. This platform allows us to collect categorized data on people's social connections that can be used to train new supervised algorithms that automatically and accurately classify relationships into their 10 fundamental types.

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