Social Network Generation and Role Determination Based on Smartphone Data

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Abstract—We deal with the problem of automatically generating social networks by analyzing and assessing smartphone usage and interaction data. We start by assigning weights to the different types of interactions such as messaging, email, phone calls, chat and physical proximity. Next, we propose a ranking algorithm which recognizes the pattern of interaction taking into account the changes in the collected data over time. Both algorithms are based on recent findings from social network research.

I. INTRODUCTION

Over a billion people frequently use social network web sites. The success of these web sites and related applications lies in the convenient connection of the user to a digital social network of friends and acquaintances. As a result of this process, the user creates a digital version of his or her real-life social network. However, the creation and maintenance of the virtual social network requires a large number of interactions, as it is the user’s task to establish or remove the connections to friends and sites of interests.

While these explicit interactions give the user the impression of full control over the virtual social network, they are time-consuming. Moreover users are confronted with the need to organize the internal structure of their personal virtual social network. Some social sites such as Facebook offer a partial support for this process for family members and spouses. Other social networks try to offer a full support by enabling the creation of social circles as desired (Google+). In either case, the user assigns the friends and acquaintances to an individual structure.

In our ongoing work, we deal with the problem of automatically generating the user’s social network by using different sources of interaction data such as physical proximity, messaging, phone calls and video chats. The main challenge of this work is to make inferences from a limited interaction history. We approach this problem by first evaluating the interactions according to their types. Then these values are used to rank friends of users and to find the friendship levels in the social network of each user.

II. SOCIAL NETWORK GENERATION

Smartphones allow us to trace multiple types of interactions between a user and the members of its social network. For instance, text messages, calls and email conversations are stored as history on the device or in the cloud. Moreover, smartphones are equipped with many sensors, which sense, evaluate and record even more information about the user, the environment and contacts. For instance the proximity of two users is detected by acoustic sensors or the location information is collected by GPS receivers.

Usage of all available smartphone data enables us to infer a social network. However, one of the critical problems is that the generation of the network cannot be measured in terms of accuracy or other measures that would allow us to state that the collected data sufficiently describes the corresponding social network. The answers of the questions related to network dynamics such as when a node is a node and when a link really exists are visible influences on our model.

The proximity and mobility data collection part of the approach is based on our the algorithms developed on our previous work [1]. We assume basic interaction information of the format [UserA, UserB, timeStamp, interactionType]. Instead of plainly reading and transforming the interaction data, these structural artifacts are used as structural framework. Additional to the information derived from the interaction data, this framework gives information on how the nodes are located in the network and links have been created.

A. Interaction evaluation

The interaction data derived from mobile devices and sensors need to be evaluated in terms of their importance. Intuitively, an email to a person appears to be more distant than calling the same person and a phone call is shown to be less effective for personal relationships than meeting with the other party in person[2]. In order to take into account these differences, we suggest assigning specific weights to different types of interactions. Weight assignment results in the ability to change the weight according to experience or context and to include additional interaction types as needed. The interaction values are defined in our approach as follows:

\[ i_{A,B} = \alpha \cdot F(T) + \beta \cdot V(T) + \gamma \cdot nP(T) + \delta \cdot E(S) \]

where \( P(T), V(T) \) and \( F(T) \) denote the number of times respectively a phone call, a video conference and a face-to-face interaction occurred for a particular amount of time, \( T \).
$E(S)$ denotes the number of e-mails or text messages with size $S$.

Each interaction type has a different constant $(\alpha, \beta, \gamma, \delta)$, which reflects the variety in effects of different interaction types on personal relations. Formulation of this equation and finding the exact values of constants is one of the next steps of our work. Due to the nature of social sciences, these values may change depending on various factors such as the social group under investigation. Our approach provides the means to utilize results of works in social sciences such as the study of Okdie et al. [3] on comparison of face-to-face communication versus online communication.

**B. Ranking and Role Determination**

The interactions between friends correlate in number with the strength of friendship [2]. Therefore, after determining the friends of a person and evaluating the interactions, our system also ranks the friends to find different levels of friendship in the social network of users.

We say that the friend with a larger interaction value has a win against the friend with lower interaction value for that time period. Therefore, the sports ranking methods, in which teams win/lose against each other, can be utilized to rank friends. However, a simple sports ranking method, which uses win percentage would not satisfy the particularities of our application. Colley [4] and Massey [5] are two of the most important sports ranking methods, which take the history and current ranking into consideration. Chartier et al. [6] made a sensitivity analysis of these methods and concluded that the Colley and Massey methods are insensitive to small changes, which is desirable for social network ranking. For instance when a person spends most of the time in a week with a new friend, this new friend wouldn’t suddenly become one of the closest friends of that person. Colley’s method is based only on results from the field whereas Massey method utilizes actual game scores and homefield advantage, which have no correspondence in social networks. Therefore, we had chosen the Colley method as the basis for our ranking.

The Colley method of sports ranking can be defined by a linear system [4], $C\vec{r} = \vec{b}$, where $\vec{r}_{n \times 1}$ is a column-vector of all the rating $r_i$, $\vec{b}_{n \times 1}$ is the right-hand-side vector defined as follows:

$$\vec{b}_i = 1 + (w_i - l_i)/2$$

$C_{n \times n}$ is called the Colley coefficient matrix and defined as follows:

$$C_{ij} = \begin{cases} 2 + t_{ij} & \text{if } i = j \\ -n_{ij} & \text{if } i \neq j \end{cases}$$

The scalar $n_{ij}$ is the number of times friends i and j are compared to each other, $t_{ij}$ is the total number of comparisons for friend i, $w_i$ is the number of wins and $l_i$ is the number of losses for i. It can be proved that the Colley system $C\vec{r} = \vec{b}$ always has a unique solution since $C_{n \times n}$ is invertible. Then the rank is defined as follows [6]:

$$r_i = \frac{1 + n_{w_{i,j}}}{2 + n_{total,i}}$$

In contrast to traditional methods, the initial rating of any friend with no changes is equal to $\frac{1}{2}$, which is the median value between 0 and 1. Depending on the comparisons, a win increases and loss decreases the value of $r$. This approach results in a system less sensitive to changes.

Dunbar et al. [2] showed that the social network and the number of friends of a person have a common pattern. The types of social groups formed according to ties in our social networks have clear boundaries between each other [7]. Social networks are hierarchically organized in discretely sized groups, which are also referred as circles. The inner most circle includes up to five people and the sizes of circles increase by a factor of three. The discrete groups formed in our approach as friends are ranked and the circle of a friend is decided according to this organization as given in Fig. [1].

**III. CONCLUSION**

The approach outlined in this paper aims to infer the social networks of individuals by assessing their smartphone data. We propose a data collection method, an interaction evaluation function and a ranking method in accordance with the research findings in social networks. Our future work includes testing our approach by using real-life smartphone data.

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