Role Model in Human Physical Activity

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ABSTRACT
Physical activity is an area of life in which social influence plays a major role. Observing the activity of a sedentary person may cause the observer to exercise less; observing a persistently active person can serve as a motivating factor. The goal of this research is to determine how to optimally pair individuals in order to facilitate motivational relationships with respect to physical activity. This research performs an observational study of data collected from a mobile health and fitness application, iBurnCalorie, which allows users to follow each other in addition to tracking physical activity. Through this social feature, this study examines the influence of users on each other's activity patterns. Our preliminary results indicate that some users have chosen effective role models without any intervention. If this natural effect can be replicated, such a novel interventional networking feature could have a significant impact within iBurnCalorie and all similar applications.

Author Keywords
Social network; role model; physical activity; social computing

ACM Classification Keywords
H.5.m Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION
Social networks form the backbone of human society. Often in such networks, one person's behavioral change influences others at varying degrees of separation [8, 4]. Society consists of complex networks unceasingly disseminating influence and information [6, 7].

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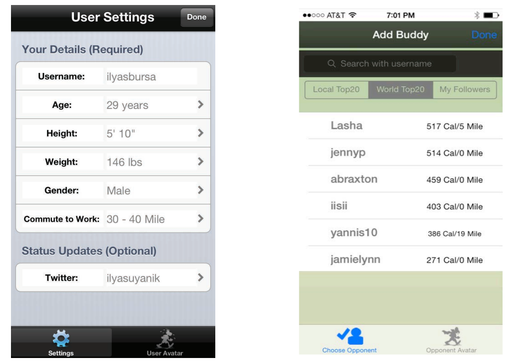
Human social networks are strongly influenced by homophily [5], the tendency to form connections with people similar to oneself. Homophily, in its turn, promotes induction, the spread of characteristics or behavior among people. The prevalence of obesity in the population and within networks of people facilitates its spread. The significance of social networks to the spread of obesity has been the topic of previous research [2]. Christakis and Fowler evaluated 32 years' worth of data, beginning in 1971, collected from the offspring cohort in the Framingham Heart study [3]. Their results showed that social influence is a strong factor in the obesity epidemic. They accordingly suggested that this influence could also be harnessed to spread healthy behaviors in social networks. Christakis and Fowler used some of these tools to perform their study of the Framingham Heart data. However, the data itself was collected through written surveys regularly administered to the participants.

In this century, there is no doubt that the most widely used device is a mobile phone. There are many advantages of using this device to collect data, since people carry mobile phones most of the time. Also, the phones allow capturing of self-reported data in an unobtrusive manner with the help of many built-in sensors. These reasons led us to our use of this ubiquitous device to gather data. Our mobile application (iBurnCalorie) allows users to keep track of their walking, biking, and driving activity, enabling users to reflect on their physical activeness while interacting and motivating each other (Figure 2). The app aims to steer users away from sedentary lifestyles by providing reminders to take a walk three times a day, including lunchtime, and by drawing a map of users daily activity. iBurnCalorie also includes a feature permitting users to track the activity of another user on the home screen. In this way, users can find ”opponents” to compete against or role models to imitate. However, human beings are not always able to judge what best motivates them. Choosing a wrong role model may adversely affect the individual and may also demotivate them, causing them to disengage from the activity. Picking someone as a yardstick plays a very important role in physical activity.

We would like to be able to analyze how the behavior of a user changes as s/he follows other users. Does a particular user's activity increase significantly when that user follows someone who is much more active? Or does their activity drop off due to being unable to keep up with the other user? Users may respond in different ways to various discrepancies between their own regular mode of activity and that of the users they follow. In iBurnCalorie, users can also ”follow” statistical users, which are accounts that are live-updated with the world average, world top, and local average and top user activity. Whether a user's role model is a real person or such a statistical account is another factor of the question of motivation we would like to consider.

In this study, we want to assess the significance of correlation of characteristics, such as gender, Body Mass Index (BMI), and persistency between users who follow each other to see comprehensive picture of dominant and follower interactions. The specific aim of this study is to provide users with optimal matches to other users, pairing them with people from whom they will benefit. The breadth, depth, and scale of our multidimensional data source provide an opportunity to compile footprints of user interactions.



(a) (b)

Figure 1: iBurnCalorie: (a) registration and (b) the buddy selection screen.

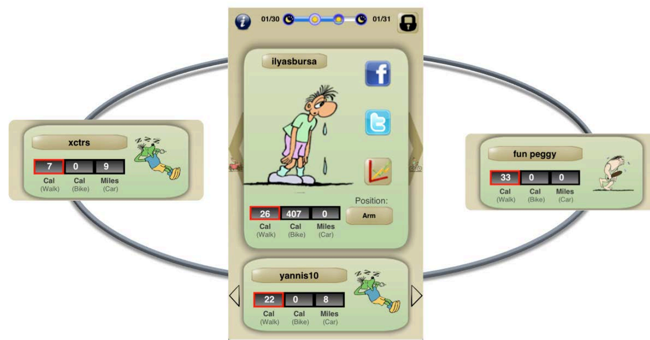


Figure 2: iBurnCalorie app Extension.

METHODOLOGY

Our study combines use of sophisticated data analysis tools with a novel, real-time method of collecting social and physical activity information through a mobile app. We designed our application to motivate users to be active through social networking intervention.

An important distinction here is that our data comes from a much less controlled group than the Framingham Heart cohort. We are tracking individuals who may have never met in person, which reflects a type of relationship common today. Users of social networking websites, such as Facebook and especially Twitter, can be strongly influenced by other users with whom they have no real-life relation. The iBurnCalorie buddy selection protocol is similar to that used by Twitter. If a user wants to follow some other user, s/he can immediately begin by tracking the other user's activity in real time. A notification is sent to the user being followed, so that this user can block the following user(s) if s/he would like to. A user may follow several other users at one time, but the activity of only one will be tracked on the home screen. This is illustrated by Figure 1b. Discussions in this paper of the user an individual is following refer to the user whose activity they choose to view on their home screen at a given time.

At first launch, the user sees a registration screen, where s/he enters her/his preferred username and some profile information needed for the caloric calculation and subsequent data analysis. This information includes the user's gender, age, weight, and height (Figure 1a). After the login and registration process, the user by default follows a virtual or statistical user called ‘World Average’, a statistic computed by the application. At the user's discretion, through the buddy selection process described above, this virtual user can be replaced by other statistics like World Top or World Top 5, or another real user (Figure 1b). The application's main screen shows an avatar representing the user (Figure 2). When the user walks, the avatar walks. When the user does not walk, the avatar ‘sleeps’. The number of walking calories spent thus far in the day is shown below the avatar.

To visualize the social network component of the iBurnCalorie application, we used an open-source software, Gephi [1]. Gephi is a network visualization software that allows the user to generate a graph of connections and examine the underlying data. We used the software to create several graphs of the users appearing in the iBurnCalorie social network, showing which of them have followed each other. Approximately one-and-a-half months (May 7, 2014 to June 23, 2014) of data from iBurnCalorie social network was used.

To create the graphs in Figure 3, we first calculated the BMI of each user participating in the network in order to determine their BMI classification (underweight, normal, overweight, or obese). This choice of classification was influenced by Christakis and Fowler [3] and intended to present a clear picture of connections between various BMI categories, such as obese and non-obese people, within the iBurnCalorie network. The size of each node is proportional to the value of the user's BMI. The nodes are users, with the curves (edges) between them showing other users they follow or who follow them. Edges in these graphs should be read clockwise from the source node to the target node. Certain user and connection attributes have been represented by color, size, and edge

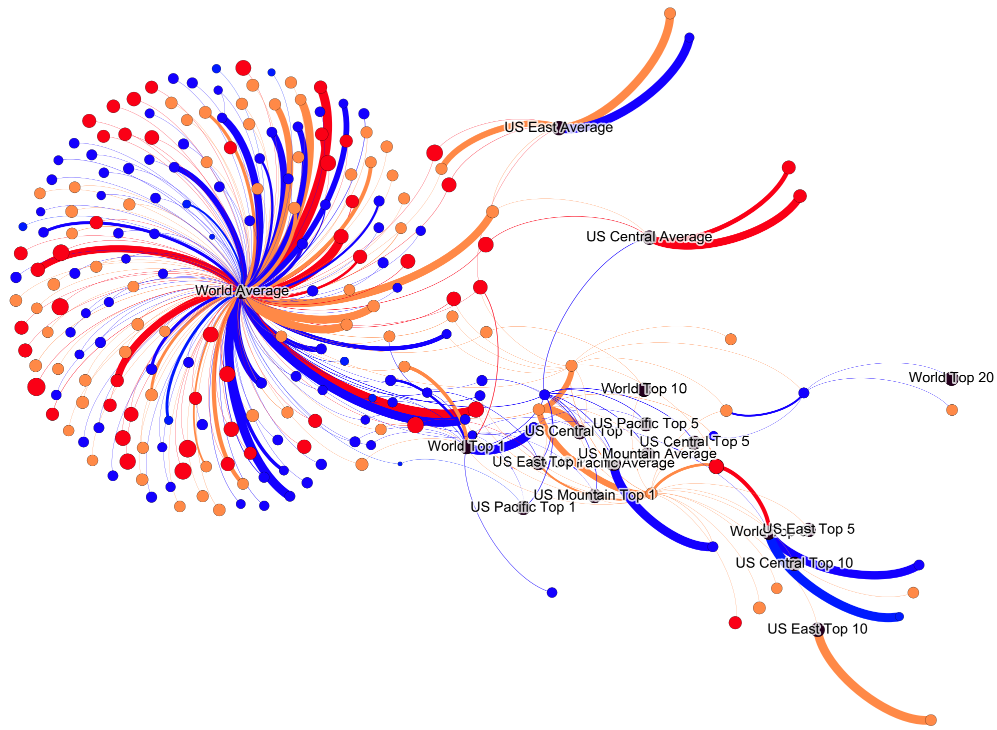


Figure 3: Graph of all users and connections in iBurnCalorie network.

weight. The thickness of each edge corresponds to the length of time the source user has spent following the target. The color of each node corresponds to that users BMI classification. Blue represents underweight or normal, orange overweight, and red obese. Underweight and normal users were grouped together because the app is mainly focused on reaching overweight and obese users, and underweight users made up a small percentage of the total users participating in the network (8 out of 220 users, or 3.64%). The black nodes are the statistical users mentioned in the introduction.

In order to facilitate meaningful data analysis, we categorized the users according to the persistence with which they used the application. For this, we defined a variable called User Persistence (UP). We determined what class of persistency each user belongs to, with low denoting a total of five or less days of use, medium five to ten days, and high ten or more days.

Our data provides us only with information regarding when a user began to follow another user. Therefore, we made an assumption regarding the last connection recorded within our time frame for each user. We calculated these connections as lasting from their recorded starting time until the end of our time frame. For active users, those who regularly use the app and purposefully follow other users (i.e., medium- and high-persistence users), this provided a reasonable depiction of which users they prefer to follow. However, for mostly inactive users (i.e., low-persistence users), especially those who joined the network but followed no users other than the default (the 'World Average' statistic), the resulting graphs appeared to indicate that those users spent many days or weeks tracking other users, although they may only have used the app for a total of a few minutes. Therefore, we replaced the weights of edges with sources at low persistence users with the total time the low persistence users spent using the app.

STUDIES

We performed quantitative analysis of how users are influenced by those whom they follow in order to discover whether users are truly following others as role models, aspiring to be like them. For this analysis, we focused on users from the high persistence category, as these users were most likely to have consistently followed others.

It is important to note that users of the application are always following someone, whether the default (World Average) or whatever user they last chose to follow. Therefore, a user must have switched from, or re-selected, the user they were following previously to our data collection period in order to appear in the records. If there were users who chose a buddy prior to the start of our data collection and simply continued to follow that person throughout the time frame, these users did not appear in the collected data. While this obviously excludes users with no interest in the social network feature, thereby benefitting our analysis, it may also exclude extremely meaningful long-term user connections. We also do not have any information about whom, if anyone, a user was following prior to their first entry in our data.

Figure 3 shows our overall social network graph, that of all the users in the iBurnCalorie network. In the large cluster in the top left of the graph are those users who are following the World Average statistical user and no one else. As mentioned, the World Average is the default for all users participating in the network. The users in this cluster have made no effort to make connections with other users. In the bottom right region of the graph, the network is less uniform. These users have reached out to others in the network, following other people, as well as seeking out the various other statistical users available. There are several thick edges visible in this portion of the graph, showing users who have consistently followed each other.

Among those users for whom some social network activity was recorded during our time frame, we isolated the users classified as high persistence users based on one year of walking activity data collection ($n = 23$). We then pared down the list by taking into account considerations such as whether they were actually active (and therefore able to affect other users) during our time frame, as well as other variables that affected the meaningfulness of our analysis. The subjects who remained after filtering this list ($n = 9$) were those who continued to be active to some extent for at least 10 days and for whom activity was recorded sufficiently early within our data collection period, thereby ensuring non-trivial data. We considered the limited nature of this subject pool not ideal, but sufficient for our preliminary investigation in order to pave the way for future, broader development.

To perform our analysis, we searched our data for all the entries corresponding to each of our subjects. From this information about whom they followed and when, we calculated how much time the subjects spent following each user within each day. This allowed us to determine the user who was dominant in each day for each subject, that is, the user the subject followed for most of the day. These were the "buddies" whom we deemed the role models for the users in the subsequent analysis.

Among the 238 nodes in the network, 220 are real (human) users and 18 are virtual or statistical users. Of the 220 real users, 152 (69.1%) are female and 66 (30%) are male. Two (0.9%) chose not to disclose their gender.

Ninety-five (43.2%) of the users have a BMI classified as normal. Seventy-three (33.2%) are classified as overweight, and 52 (23.6%) as obese. As noted above, eight (3.64%) are classified as underweight and were grouped together with normal users. Finally, 141 (64.1%) of 220 users belong to the low persistency class, nine (4.1%) to the medium class, and 23 (10.5%) to the high class. We do not have persistency information for 47 (21.4%) of the users.

We calculated the Pearson correlation coefficients between the activity signals of follower-role model user pairs along with the corresponding p-values. We also calculated the weight of each connection, that is the significance of each connection to the user, based on the number of days the user spent following a particular user, as compared to the total

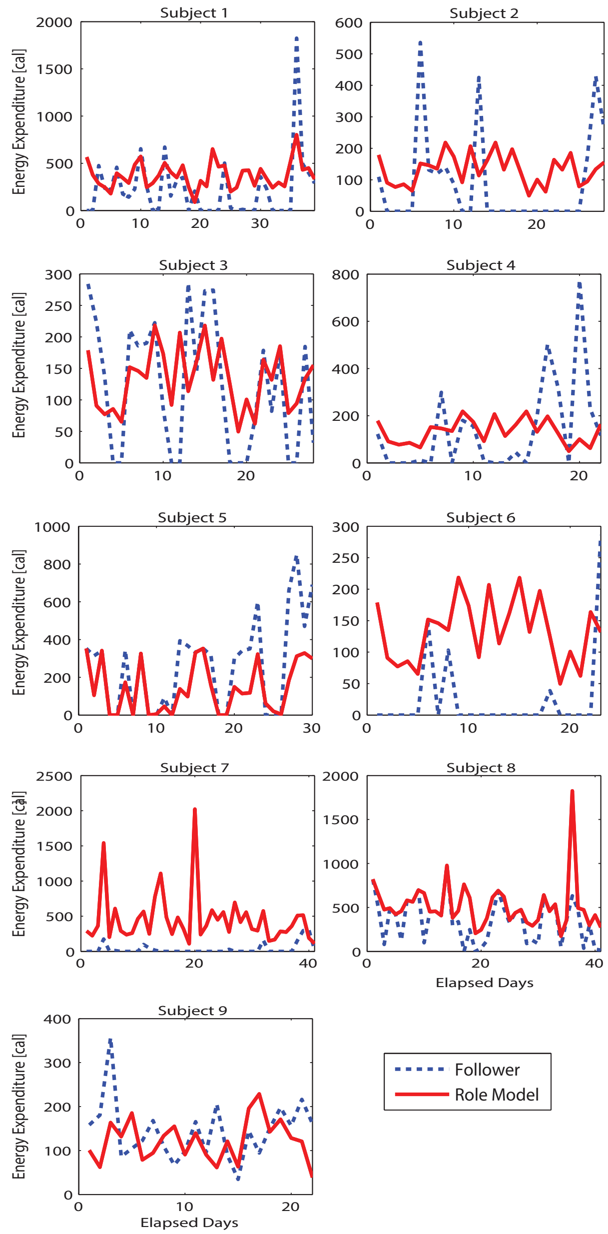


Figure 4: Activity signals of follower-role model user pairs.

number of days they spent following any user, as compared to the total number of days they spent following any user.

To quantitatively analyze the influence on users of the users they follow, we focused on users from the high persistence category. We calculated the Pearson correlation coefficients between the activity signals of source-target user pairs and the corresponding p-values. We also calculated the weight of each connection, that is, the significance of each connection to the user, based on the number of days the user spent following a particular user as compared to the total number of days they spent following any user. Almost all the users we considered followed only one other user consistently during our data collection period, so these connections were given

Table 1: Correlation coefficients, p-values, and weights corresponding to high persistence user connections.

	World Top 5	World Average	Pacific Average	Subject 10	Central Top
Subject 1	0.543, 3.52e-04, 1				
Subject 2		0.119, 0.545, 1			
Subject 3		0.476, 0.010, 1			
Subject 4		0.095, 0.674, 1			
Subject 5			0.789, 2.25e-07, 1		
Subject 6		0.024, 0.912, 1			
Subject 7				0.468, 0.173, 1	
Subject 8		NaN, NaN, 0.024			0.547, 8.26e-04, 0.976
Subject 9		0.042, 0.854, 1			

weight 1. Table 1 presents the calculated coefficients, p-values, and weights for all connections. The rows of the table represent 'following' users, while the columns represent the 'role models' being followed. Each populated cell provides data for the connection between the follower, indicated by the row, and the role model, indicated by the column.

Of the $n = 9$ subjects in the quantitative phase of our analysis, four were classified by BMI as normal, one as overweight, and four as obese. Six of them were female and three were male. Seven of the subjects lived in America. Of these, three each lived in the Central and Eastern time zones and one in the Pacific time zone. The other two subjects lived in Europe and Asia. Finally, one of the subjects was an adolescent (less than 18 years old), three were young adults (18 to 34 years old), three were in early middle age (34 to 45 years old), and two were in late middle age or older (above 45 years old).

Figure 4 visually compares the activity signals of follower-role model user pairs. The signals were plotted from the starting to the ending times of each connection, as recorded in our data. The role model represented by the red line in each figure is the user being followed by each source user or subject, as shown in Table 1.

Table 1 presents the calculated coefficients, p-values, and weights for all connections. Almost all the subjects we considered followed only one other user consistently during our data collection period, so these connections were given weight 1. Subject 8 is the only exception. However, this subject spent only one day following a user other than their dominant role model, rendering correlation meaningless due to the resolution of our data.

Four entries appear in Table 1 which indicate that the corresponding connection has both good correlation values and statistical significance. These entries correspond to Subjects 1, 3, 5, and 8. Subject 5 and Subject 8, who followed the location-specific statistics Pacific Average and Central Top, both live in the time zones local to these statistics.

CONCLUSIONS AND DISCUSSION

Our results support the existence of an entrainment effect among a small number of iBurnCalorie users during the time frame of our data collection. Having established this, we can carry out more intensive study. The aim will now be to reveal what factors play a role in inducing the effect. If, by continuing in such a vein, we are able to determine what makes one user ideally suited to motivate another, we will be able to suggest optimal role models for the majority of the iBurnCalorie user base. Low-persistence users - those who, without external motivation, have no real drive to use the app - will particularly benefit from this kind of intervention. Although we recognize that users are also influenced by factors outside of our application, the aim of our study was to observe their behavior in this sphere and improve iBurnCalorie as an interventional health and fitness application.

Directions for future research should target a longer observation period for deeper analysis, because the number of high persistence users available for analysis plays a critical role in creating a model for future interventions. Attention should also be given to low persistence users. This demographic of users warrants profiling in order to understand why they are, on the whole, not engaging with other users; additionally, low persistence user activity should be tracked once motivational suggestions are implemented, since these are the users we hope to reach with such interventions.

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