On Temporal Regularity in Social Interactions: Predicting Mobile Phone Calls

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Abstract—In this paper we predict outgoing mobile phone calls using a machine learning approach. We analyze to which extent the activity of mobile phone users is predictable. The premise is that mobile phone users exhibit temporal regularity in their interactions with majority of their contacts. In the sociological context, most social interactions have fairly reliable temporal regularity. If we quantify the extension of this behavior to interactions on mobile phones we expect that caller-callee interaction is not merely a result of randomness, rather it exhibits a temporal pattern. To this end, we tested our approach on an anonymized mobile phone usage dataset collected specifically for analyzing temporal patterns in mobile phone communication. The data consists of 783 users and more than 12,000 caller-callee pairs. The results show that users’ historic calling patterns can predict future calls with reasonable accuracy.

I. INTRODUCTION AND MOTIVATION

An estimated 261 million Americans own mobile phones. A typical American makes an average of 5 calls in a single day [18]. With a daily average of almost 1.3 billion communication events and an annual total of 2.45 trillion minutes of usage [10] in the US alone, mobile phones represent one of the most commonly used communication medium. Judging from the trend in recent years, the user base of cell phones can be expected to further increase in the future. Hence, a deeper understanding of the temporal structure of the mobile phone communication would allow us to optimize and streamline a technology that has penetrated the very fabric of human life.

Users generally make phone calls in two ways: either by selecting the callee from a contact list, or through the call log [6,7,8]. The former displays contacts in alphabetical order with no consideration of past calling behavior. While most mobile phones offer the capability of selecting certain contacts as favorites, the favorites list is, however, still a static list, requiring active intervention by the user in order to update. Call logs, on the other hand, do take past user behavior into account, displaying called numbers in reverse chronological order. The model of user behavior assumed by call logs is, nonetheless, highly simplistic. It supposes that the likelihood of calling a particular contact c, is $P(c)$, which is a monotonically decreasing function of the time elapsed since last contact. Sociologists have, however, shown that human life is temporally organized and that most social interactions have fairly reliable temporal regularity [24]. This implies that $P(c)$ could be periodic. Such an implication, if correct, would allow for the design of a considerably more efficient calling interface than what is provided by either contact lists, or chronological call logs. From the service providers’ perspective, it would enable them to predict users’ behavior, thereby allowing targeted and personalized product recommendations. This would, in turn, lead to greater customer loyalty [14]. In addition, the ability to predict periods of high usage would lead to better load balancing and, hence, better service quality.

Based on the assumption that one could predict the users’ calling behavior using temporal features, we use a machine learning approach that aims at predicting the future calls made by a user, based on his/her past calling behavior.

Contributions Our contributions are as follows:

1) We focus on predicting outgoing calls by modeling the problem as a multiclass classification problem. Our approach can generate real time predictions for the outgoing calls based on the historical calling patterns.

2) Sociological theories show that most social interactions have fairly reliable temporal regularity. Based on this premise we have identified features that can accurately predict the future calls of a user.

3) There are about 150 Mn. mobile phone users in Pakistan and 31% of them have smartphones. Till date, we did not find any substantial analysis on the data of this huge user base. We test our approach on a large dataset which we specifically collected for analyzing calling behaviour of mobile phone users based in Pakistan.

Paper organization The remainder of the paper is organized as follows: In section II, we briefly summarize the existing work on finding periodic patterns in human social interaction and previous call prediction methodologies. In section III we discuss a smartphone application (app) that was used for collecting data and report the data statistics. This is followed by section IV that overviews our methodology. In section V we present our results. In section VI we discuss our findings and compare our results with previous approaches. This is followed by a conclusion and future work section.
II. RELATED WORK

Call log data can provide insights into the underlying relational dynamics of societies, evolution of relationships over time and, can also help in prediction of social network structures [13]. Data of calling patterns has been used to infer friendships relations and uncover individual and collective human dynamics [13], [9], [15]. Call-volume data has been used to explore whether the distribution of calls in an urban population follow routine patterns or not, and whether the variation of such patterns in different parts of the city can be explained [22]. While studying social network turnover, Aledavood et al. [3], [2] found that individual calling and messaging behavior follows a circadian rhythm. Their study of 24 subjects revealed that the frequency and entropy of communication displays a distinct daily pattern that remains persistent over time.

Several call prediction models have been proposed in the literature. Phithakkitnukoon et al. [21] predicted the outgoing and incoming calls on Reality Mining dataset [12] based on most recent calling data. Out of the 94 datasets, they used a small subset of 30 users for performance evaluation. Haddad et al. [14] presented a probabilistic model that uses call frequency to predict incoming and outgoing calls for each individual contact. Their underlying assumption is that the calling behavior of users can indeed be modeled as a periodic phenomenon. They have modeled the users’ recurrent phone call behavior using Poisson process. The authors tested their model on a large sample by making it available as a mobile application. Several recent studies of human behavior indicate that the timing of communication events is characterized by long dormant periods interspersed with bursts of high activity [4], [16], [23]. Barabasi [4] attributes this bursty non-Poisson character of human behavior to a priority-based queuing process. This view is supported by Jo et al. [16] who show that burstiness remains in mobile communication data even after circadian and weekly patterns have been removed, precluding the attribution of periods of inactivity to nights or weekends. They conclude that burstiness results from non-homogeneity in human task execution mechanisms. Another study conducted by Kim et al. [17] on a large dataset from North-American users also suggests that the caller-callee behavior cannot solely be modeled using the Poisson distribution. Kim et al. [17] performed a comprehensive analysis of interaction frequencies by analyzing the communication activity of over one million pairs of mobile phone subscribers from a American cellular service provider. They focus on studying the impact of family relationship on communication patterns. Based on frequency of information exchange, they classified the user-pairs into three classes characterized by the inter-arrival times between calls made between pairs.

III. DATA

We tested our approach on the following two datasets.

A. Reality Mining Dataset

The first data set is from Reality Mining experiment [12], referred to as: ‘Reality Mining dataset’. This dataset contains data from 94 users which were either students, faculty or staff at the Massachusetts Institute of Technology, USA.

B. Smartphone Dataset

We collected the second dataset using a smartphone app referred to as: ‘Smartphone dataset’. Data collection was limited demographically to users of smartphones running the Android OS, and geographically to the country of Pakistan. While industry sources estimate that Android users represent 68% of the total smartphone population in that country, extensive market surveys are lacking and, hence, conclusive judgments about the qualitative nature of the sample cannot be made.

To make its value proposition more attractive, the app presented users with the most economical mobile subscription service for their needs based on past calling behavior. These subscription services - also referred to as “packages” in the local parlance - differ primarily in the calling rates they offer during specific hours of the week. A recommender system for similar telecom products was developed by Zhang et al. [25]. But, where they used fuzzy-set techniques to select the most economical product, our recommendations are based on a simple simulation run with the users’ call history. Including...
this additional functionality in our data-gathering app not only expanded our sample set, but we also expected it to mitigate the volunteer bias natural in such survey data collection methods. Users were notified that their call data would be used for academic research purpose.

**Data Statistics** The process of Smartphone dataset collection lasted from July 28, 2015 till September 24, 2015. The data was collected from April 19, 2015 till September 23, 2015. The data consists of 783 users (egos) with 229,450 communication events. The data for each ego was grouped according to the contact the communication event was initiated to - an alter - thereby, yielding a over 12,000 ego-alter pairs in the smartphone dataset, and over 2000 pairs in the Reality Mining dataset. The probability distribution function (PDF) of number of calls per user are shown in Figure [1] and an hourly and a daily autocorrelation measure was calculated for all these datasets (Smartphone dataset and Reality Mining dataset) for determining whether caller-callee pairs have a regular calling pattern. The communication between mobile phone users was modeled as a time series data analysis problem. In many time series, it is plausible to expect that the $K$ recent data points are likely to have an influence on the future data points. In order to identify whether the ego-alters communication data has a pattern, autocorrelation was used which is a type of correlation statistic specifically for correlating the recent data point to other data points in the series. For each ego-alter pair, an hourly and a daily autocorrelation measure was calculated using the LjungBox test (Q test) where a $p-value < 0.05$ means there is autocorrelation. The LjungBox test, also known as a portmanteau test, is a function of the accumulated sample autocorrelations $r_k, k=1, \ldots, l$ up to any specified time lag $l$ [19] (we checked the autocorrelation up to six lags). If the lag is too small, the Q-test may not detect serial correlation at high-orders. If its too large, the test may have low power since the significant correlation at one lag may be diluted by insignificant correlations at other lags). As the hourly autocorrelation measure may have been biased by lack of activity at night hours, a third autocorrelation for communication events between 7am and 8pm was also calculated. Results obtained on these datasets quantitatively show that a reasonable number of ego-alter pairs exhibit autocorrelation. More than 50% of ego-alter pairs in the Reality Mining dataset exhibit a daily as well as hourly periodic calling behaviour. In the Smartphone dataset, few ego-alter pairs exhibited daily temporal autocorrelation, but it was observed that there was indeed an indication of periodic calling at finer levels (hourly basis). The difference in results obtained from the datasets could be an artifact arising from the shift in communication from mobile phone calls/text messages to smartphone instant messengers in recent years. Reality Mining dataset was collected when other means of smartphone communication such as Whatsapp, Viber, Facetime, etc. did not exist. Another tenable explanation could be the bias in the datasets. Contrary to the Reality Mining dataset that contains data from students or faculty of MIT media lab with fixed university schedule, the smartphone dataset contains data from general population with different demographics.

Findings in [1] suggest that mobile phone users exhibit periodicity in their calling behavior (at daily or hourly levels). Based on these findings, we set the focus of this paper on predicting the future outgoing calls using time based features.

**IV. METHODOLOGY**

We model the problem as a supervised multi-class classification problem. Multiclass, also known as multinomial classification is the problem of classifying instances into one of the more than two classes. In every ego profile, alters that have been called in the past are the classes. The classifier predicts at a given time and day which number(s) a user is likely to call. Each dataset and further each ego profile is evaluated independently.

**A. User Behavior Model**

Let $U$ be the set of all egos in the dataset. For every $u_i \in U$, let $X_i$ be the set of contacts. Formally, we define the call prediction problem as follows: Given the historical communication events, $\{Y_i(t_0), \ldots, Y_i(t_{n-1})\}$ consisting of outgoing, incoming and missed calls that occurred at time $t_0, \ldots, t_{n-1}$, for a user $u_i \in U$, predict which contact $x_i \in X_i, u_i$ is going to call at time $t_n$.

As a first step, for every ego we find the outgoing calls distribution. There is a general observation that there are fewer contacts who are called more often and a lot many contacts who are called less often. We observed that the outgoing calls are not normally distributed. We then test the null hypothesis that the outgoing calls distribution for each ego is exponential. We use the Kolmogorov-Smirnov test (KS test), which is a nonparametric test of the equality of continuous, one-dimensional probability distributions. It can be used to compare a sample with a reference probability distribution. We found that KS test fails to reject the null hypothesis at the 5% significance level for 80.08% of Reality Mining users and for 87.64% of Smartphone users. Thus, for each ego, we remove the callees who are called less than a certain threshold. For our experiments we selected the mean of the calling frequency as the cut-off threshold (Figure [2] shows a histogram of the mean of calling frequency per user per contact). It is plausible to remove those callees which are very sporadically contacted. Mobile phone users have various kinds of contacts in the contacts list such as friends, acquaintances, family members, workplace contacts, services related contacts, etc [6]. Some of these contacts are frequently called, others are

| Dataset          | $\epsilon(15\text{Min})$ | $\epsilon(1\text{Hr})$ | $\epsilon(10\text{Hr})$ | $\epsilon(24\text{Hr})$ |
|------------------|----------------------------|-------------------------|--------------------------|--------------------------|
| Reality Mining   | 0.40                       | 0.44                    | 0.60                     | 0.70                     |
| Smartphone       | 0.26                       | 0.31                    | 0.33                     | 0.63                     |

1Ego is the focal actor who installed the application. Alterns are his/her contacts.
of most likely numbers to be dialed at any given time (within the next hour) based on the results produced by the classifier.

2) In the second evaluation method, we measure the proportion of calls that are predicted within a certain error threshold (\(\epsilon\)). For a given time, a 'single phone number' is predicted which the user is likely to call. We then measure how well the number is predicted with regards to different time-deviation thresholds.

V. Performance Analysis

Predictions are made for the users who have at least 50 communication events in the dataset. Hence we analyzed 89 users in the Reality Mining Dataset and 604 users in the Smartphone dataset. Further, we want to improve accuracy using fewer dimensions. For the last calls related features, we have used data pertinent to only the last two calls since there is a trade-off between adding dimensions to the feature set and efficiency.

A. Top-\(k\) recommendations

From the users’ perspective, top-\(k\) recommendations should be more accurate as compared to last-\(k\) calls. We generate a list of most likely numbers to be dialed at any given time: the ‘top-\(k\) recommendations’. We compare the accuracy of top-\(k\) recommendations with the accuracy obtained by last-\(k\) calls. We show the performance of our approach for individual users for varying list lengths (5, 10 and 15). In Figure [3] x-axis represents the users (egos) in the dataset. For every user in the datasets, we report the accuracy achieved by top-\(k\) recommendations vs. last-\(k\) calls and top-\(k\) called numbers (most frequently called contacts). The accuracy is reported for each user in Reality Mining dataset: points in blue; and Smartphone dataset: points in red. A higher concentration of points below the identity line indicates that top-\(k\) recommendations has better performance against the respective method. Table [II] reports the average performance of our approach along with performance achieved by baseline methods, whereas, Table [III] reports the proportion of correctly predicted calls for various list lengths.

B. Prediction deviation

From the service providers’ perspective, accurate prediction of calls would enable them to predict users’ behavior and predict periods of high usage which in turn would lead to better load balancing and, hence, better service quality. Table [II] reports the prediction accuracy for given deviation thresholds. These results show that a reasonable proportion of the phone calls are predictable using the proposed method. For the Reality Mining dataset 44% of the outgoing calls were predicted below one hour error threshold. For the Smartphone dataset 31% of the outgoing calls were predicted below one hour error threshold.
VI. DISCUSSION

Mobile phones represent one of the most commonly used communication medium. The portable nature of the medium means very little can be assumed about the situation in which the phone is used; a typical user makes calls in all kinds of contexts. These two factors, frequency and versatility of use, necessitate an extremely efficient call-making interface design. As a first step we analyzed using a machine learning approach and using few dimensions whether it is possible to predict the calling behavior of mobile phone users (given the time based features). We have identified the day of the week and time as two important features which help in accurately predicting the next outgoing call. This is supported by the fact that human interaction behavior follows a circadian rhythm. We have also analyzed the situations where it is more probable that the user calls a number from one of the last called numbers.

Evaluation methods similar to ours have been used in previous studies. With a few exceptions, most previous studies used different datasets for analyzing calling behavior, therefore, a direct comparison is not equitable. Phithakkitnukoon et al. [21] predicted the outgoing and incoming calls on Reality Mining dataset. Out of the 94 users, they selected only 30 users for experiments. The identities of those users is not disclosed in the paper, therefore, a direct comparison with their results is not possible. For completion, we have reported the performance of our method on 89 out of 94 users. The
remaining 5 users had less than 50 communication events. For outgoing call prediction, they also generated a list of most likely numbers to be dialed at any given time. For the 30 random users in their experiments they achieved an accuracy of 41% if the predicted list is only allowed one entry. If the predicted list has five entries their model correctly predicted the dialed number 70% of the time. On the Reality Mining dataset we achieve an accuracy of 44% when the top-k list has one entry. Our results show more than 78% accuracy on the Reality Mining dataset when the predicted list is allowed 5 entries. Figure 3 and Table II shows that our approach also performs better than the last-k calls on both the datasets.

Barzaq et al. [5] modeled the historic call patterns of users and achieved a 35% accuracy for call prediction. Haddad et al. [14], reports the prediction accuracy for certain time-deviation thresholds on a dataset consisting of more than seven thousand users. Their model predicted about 17% of the outgoing calls with an error below one hour. The results for our approach, reported in Table I, show 44% and 31% accuracy for Reality Mining and Smartphone datasets respectively. Haddad et al. assumes that the call arrival patterns have a Poisson distribution. An initial analysis in [17] on another large dataset suggest that the call arrival process is not Poisson for all callee-caller pairs[11]. It can be argued that the particular pattern Haddad et al. mentioned in the paper was an artifact of their dataset.

In the previous models such as the ones proposed in [14] and [21], a baseline comparison was missing. The motivation behind our study was to come up with a method that could better predict the next call. Hence, from the user’s point of view we found it imperative to check the performance of the last-k calls as well. It is a reasonable expectation that a call prediction approach should perform better than the current approach used for smartphone call logs i.e., displaying the recent calls in chronological order. Table II shows that our approach performs better than the last-k calls and most frequently called numbers list.

### VII. Conclusions and Future Work

We proposed a machine learning approach which uses temporal as well as last-calls features to predict the future outgoing calls. We tested our approach on two datasets from two countries and found that majority of outgoing phone calls can be predicted based on the temporal calling patterns. Our approach outperformed the two baseline approaches i.e. predicting next call based on last-k calls and predicting next call using the most frequently called numbers’ list. We found it very intriguing as it opens many exciting research questions. One of them is to see whether these results can be replicated if we take a large representative sample that can be generalized to all mobile phone users. In order to deeply understand the phone call behaviour, we are in the process of collecting a large call logs dataset along with other relevant information such as demographic, geographical, and socio-economic data. Another future research possibility could be an attempt to redesign the calling interface for mobile phones which could improve the user experience significantly. Such an interface, theoretically, would know the most likely people one is going to call at a given time and day. In future we would like to study how users respond to an improved call log interface. A usability study in this regard is underway.

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