Hawkes-modeled telecommunication patterns reveal relationship dynamics and personality traits

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ABSTRACT
It is not news that our mobile phones contain a wealth of private information about us, and that is why we try to keep them secure. But even the traces of how we communicate can also tell quite a bit about us. In this work, we start from the calling and texting history of 200 students enrolled in the Netsense study, and we link it to the type of relationships that students have with their peers, and even with their personality profiles. First, we show that a Hawkes point process with a power-law decaying kernel can accurately model the calling activity between peers. Second, we show that the fitted parameters of the Hawkes model are predictive of the type of relationship and that the generalization error of the Hawkes process can be leveraged to detect changes in the relation types as they are happening. Last, we build descriptors for the students in the study by jointly modeling the communication series initiated by them. We find that Hawkes-modeled telecommunication patterns can predict the students’ Big5 psychometric traits almost as accurately as the user-filled surveys pertaining to hobbies, activities, well-being, grades obtained, health condition and the number of books they read. These results are significant, as they indicate that information that usually resides outside the control of individuals (such as call and text logs) reveal information about the relationship they have, and even their personality traits.

KEYWORDS
modeling call series, Hawkes processes, predicting relationship types, detect relationship dynamics, infer personality traits

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1 INTRODUCTION
It is a known fact that we give away personal information whenever we act and interact online [42]. This has been repeatedly shown for online social media platforms such as Facebook [26, 53] or Twitter [29], and even knowledge creation sites like Wikipedia [40]. More specifically, people’s personality profiles have been predicted from personal websites [30], blogs [52], Twitter messages [21] or Facebook profiles [26].

Recently, Stachl et al. [45] showed that personality profiles can be estimated using information collected from user’s smartphones (such as communication and social behavior, music consumption, app usage, mobility, overall phone activity, and day- and night-time activity). However, obtaining the above-mentioned data requires access to user’s social media activity, or to the user’s phones, which might provide certain degrees of safety to the user. In this work, we investigate what information can be learned about users using data outside their control, e.g. from the patterns of communication with their peers.

This paper addresses three open questions concerning modeling and learning from call and text data traces. The first question relates to modeling the communication patterns between individuals. It is known that human communication is bursty, and that it exhibits a long-tail distribution of inter-event times [18, 28]. Hawkes point processes have been successfully applied to model other bursty phenomena, such as information diffusion [33] or neuron firing patterns in the human brain [20]. The question is can we model the call patterns between individuals using Hawkes point processes? The second question relates to learning about relationships between individuals using call patterns. Hawkes processes fitted on event series have been shown useful in predicting the final popularity of online items [35], and even differentiating between controversial and authoritative news sources [25]. The question is therefore can we differentiate the relationship type between two individuals, given their call and texting timing series fitted using a Hawkes model? can we detect their dynamics over time? The third question relates to users’ inferring personality traits from their outgoing call timing series. While there exist several prior work learning user personality traits using mobile phone data [15, 34, 45], these usually rely on behavioral information collected via sensor and log data from smartphones, which requires access to the users’ phones. The question is can we use the Hawkes model outputs, fitted on the outbound call series originating from the same user to infer their personality traits?

We address the above open questions using NetSense, a dataset issued from the Netsense study [47] in which calling and texting information was recorded for about 200 students, who also filled in periodic surveys. We answer the first question by fitting the parameters of a Hawkes point process to the series of communication events – phone calls or texts – occurring between each pair of individuals with a minimum threshold of activity (i.e. at least 20 events). Using a temporal holdout setup, we show that the Hawkes process with a power-law decaying kernel function generalizes better to unseen data than the exponential kernel.

To answer the second question, we use the student surveys to label the relationship with their peers. In each of the six surveys,
the students labeled their communication peers with family, friend, significant other etc. Using the sequence of answers in the surveys, we first split the pairwise relations in the Netsense dataset into six categories: family-relaxing, family-stable, friendship-relaxing, friendship-stable, friendship-strengthening and romantic-relaxing. Next, we characterize each pairwise relationship in our dataset using the fitted parameters and secondary quantities of the Hawkes model. We show that, using Hawkes descriptors, off-the-shelf classifiers can predict the relationship type significantly better than a random baseline (achieving a macro F1-score of 0.19), with the best identified categories being family-stable and friendship-stable. Note that the six classes that we built also embed a temporal dynamic (e.g. a friendship-relaxing relation evolves from friend to acquaintance or other over the time of the study). We implement a temporal holdout setup to test whether the fitted Hawkes models can detect the change points in the relation. We find that for the evolving friendship relations (friendship-relaxing and friendship-strengthening), there is a statistically significant difference between the generalization score of the Hawkes model before and after the change. This shows that Hawkes point process models can be leveraged to detect changes in the relation types between users using telecommunication data, as it is happening.

We answer the third question by applying a novel joint modeling of Hawkes processes [25] to model together the outbound call series of each student participating in the Netsense study. Based on the Hawkes parameters and the activity descriptors, we build a user description vector that we use together with off-the-shelf regressors to predict individual Big5 personality traits [13]. The ground truth for this data is the Big Five Inventory [19], a personality assessment survey filled in by each student. We find that agreeableness appears the most predictable traits (with an RMSE of 0.25), and openness the least predictable (RMSE = 0.55). Importantly, our Hawkes model based descriptors outperform a recent baseline [45], which use a wide range of mobile phone and activity features and report RMSE values around 0.7 (arguably on another dataset). We also predicted the Big5 personality traits using 204 features extracted from the student filled-in surveys, relating to grades, health, happiness, activity, book reading and club membership. Surprisingly, we find the prediction results using such rich data representations are only marginally better than using the Hawkes-based descriptors. This indicates that the outbound call activity modeled using Hawkes processes embeds a surprising amount of personal information.

The main contributions of this paper are as follows:

- We show that a Hawkes point process with a power-law decaying kernel can model the phone call contact series between individuals;
- We use the fitted parameters of a Hawkes model to distinguish between types of relations (such as family, friendship or romantic) and detect their temporal dynamics;
- We show that the call activity (modeled using Hawkes point processes) is as predictive of the user’s Big5 psychometric traits as the user filled-in questionnaire.

The ethics of personality profiling. Personality profiling, and in particular social media-inferred personality traits, are sometimes seen as a Pandora’s box. On the one hand, personality dispositions have been shown to be associated with happiness, physical and psychological health, the quality of relationships with peers, family, and romantic others, as well as community involvement, criminal activity, and political ideology at a social institutional level [37]. Furthermore, it has been also shown that personality traits could be predictive of three critical life outcomes: mortality, divorce, and occupational attainment [41]. Such research show the positive aspects of personality profiling research: one could build systems to prevent and improve mental health issues of individuals, or their relation with the community. On the other hand, it was also showed that persuasive messaging is more effective when tailored for individuals’ psychological characteristics [32], and that the same processes used to infer personality traits from social data can leak sensitive information, such as ethnicity, political and sexual orientation [26]. And while social media privacy settings could (at least theoretically) bring some of the data back under the control of the user, our research shows that personality traits can be inferred from data sources completely outside the control of the user (such as call logs data). This work adds to the understanding of what can be achieved with call logs data, and advocates the creation of policy regulating its usage. The latter is increasingly important, as more and more calls are being made outside the traditional communication network, and onto online messaging platforms such as WhatsApp, which are currently not nationally regulated.

2 PREREQUISITES: HAWKES PROCESSES

In this section, we briefly review the theoretical prerequisites concerning modeling event series using Hawkes point processes.

**Event series and point processes.** An event is a tuple (timestamp, event features), where the timestamp is a continuous position along the non-negative time axis, and the event features are any descriptors related to the event. For example, an event can be the reception of a phone call [38, 48], and the features could be the caller id, length of the call or whether it was answered or not. Or an event could be a tweet [25, 39, 54], and its features would be the user emitting the tweet, the tweet content, contained hashtags, URLs etc. An event series is a sequence of events $t_1, t_2, \ldots$, where $t_i$ are the event timestamps of the of the $i$th event, relative to the first event ($t_0 = 0$). For ease of notation, in this paper we use $t_i$ to denote both the event timestamp, and the event itself. A point process is a random process whose realizations consists of event series, i.e. a model that can explain and generate event series. We denote an event series observed up to time $T$ as $\mathcal{H}(T) = \{t_0, t_1, \ldots \}$.

The Hawkes processes. Hawkes processes [16] are a type of point processes with the self-exciting property, i.e., the occurrence of past events increases the likelihood of future events. This results in the cluster property of the Hawkes property [17], which states that events modeled by Hawkes appear to be grouped in time. This latter property makes Hawkes processes desirable to model human interaction activity, which is known to follow a bursty pattern [4, 22, 55]. The occurrence of events in a Hawkes process is controlled by the event intensity function:

$$\lambda(t \mid \mathcal{H}(T)) = \mu(t) + \sum_{t_i < t} \phi(t - t_i)$$

where $\mu(t)$ is the background intensity function and $\phi : \mathbb{R}^+ \rightarrow \mathbb{R}^+$ is a kernel function capturing the decaying influence from a
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We note that some applications, such as modeling phone call series, all events are considered to be offspring of the initial event, i.e. there is no background event rate \( \mu(t) = 0 \). Two widely adopted parametric forms for the kernel function \( \phi \) include the exponential function \( \phi_{\text{EXP}}(t) = \kappa e^{-\beta t} \) and the power-law function \( \phi_{\text{PL}}(t) = \kappa(t + c)^{-(1 + \theta)} \).

The branching factor \( n^* \) is defined as the expected number of events directly spawned by a single event, i.e., \( n^* = \int_0^\infty \phi(t)dt \). \( n^* \) is an important quantity for the Hawkes process as it defines the regime of the process: when \( n^* > 1 \), the process is in a super-critical regime in which each events generates more than one event. The process is expected to generate an infinite number of events; when \( n^* < 1 \), the process is in a sub-critical regime, it generates a finite number of events and it is expected to die out.

Parameter estimation. We estimate the parameters of Hawkes using the log-likelihood function for point processes [11]:

\[
\mathcal{L}(\Theta \mid \mathcal{H}(T)) = \sum_{t_j \in \mathcal{H}(T)} \log \lambda(t_j \mid \mathcal{H}(T)) - \int_0^T \lambda(\tau \mid \mathcal{H}(T))d\tau \tag{2}
\]

Joint modeling of event series. When analyzing the event series relating to a single entity (say all phone call series generated by the same individual, or all the retweet cascades relating to the same online item), it is desirable to simultaneously account for the multiple event series. Kong et al. [25] proposed to jointly model a group of retweet cascades with a shared Hawkes model by summing the log-likelihood functions of individual cascades. In Section 4.4, we jointly model the phone call sequences initiated by the same user, and we show that the learned models can be linked to users’ psychometric traits.

3 METHODS

In this section we introduce the NetSense dataset (Section 3.1), how we build the relationship labels (Section 3.2), and how we fit Hawkes processes to telecommunication data (Section 3.4).

3.1 The NetSense Dataset

This research is based on the NetSense dataset collected at the University of Notre Dame [47]. The NetSense project lasted for two and half years and gathered metadata regarding phone calls as well as demographic and networking information about students enrolled in the study, during 2011-2013. The dataset consists of two parts: the calling and texting activity, and the student surveys.

The calling and texting activity. The NetSense dataset records all calls and texts made from the phones of the students enrolled in the study, both receiving and incoming. For each phone call, the dataset records the caller id, the receiver id, the timestamp and the duration of the call. For text messages, it records the sender, the receiver and the timestamp. Note that where both the sender (or caller) and the receiver are students enrolled in the program, the call (or text) will be recorded twice: once for the caller, and once for the receiver. Note also that NetSense records calls and texts from people outside the study (such as the family and friends).

The surveys. The dataset also includes detailed data on the students, since each participating student was surveyed every term about their areas of interests, opinions or relationships with others. In total, the students have been surveyed six times. In this paper, we are interested in two aspects of these surveys: how students describe their relationships with others, and how they describe themselves. For the former, participants labeled the relationship with their peers using descriptors such as: friend, family, significant other, co-worker, other, or not to label at all. For the latter, the students provided information about their hobbies, activities, well-being, grades, weight and height, health condition and number of books they read. We use this information in Section 4.4 to build a baseline for predicting personality traits.

The Big5 psychometric questionnaire. With each survey, students provided answers on forty four questions from the Big Five Inventory [19]. Students answered the questions on whether they would describe themselves as talkative, curious about many different things, tending to be quiet, among others. Their answers can map each student as a point in the big five personality traits space [13], where each of five traits (openness, conscientiousness, extraversion, agreeableness, neuroticism) is represented as a numeric value between one and five.

3.2 Relationships

The relations of the students with their peers evolve over time, and the dynamics are captured over the course of the six surveys that students fill in. We discriminate between three kinds of temporal dynamics for relationships: stable, strengthening and relaxing. When a student labels a relationship identically across all surveys, we denote it to be a stable relation. When the relationship reported by student transition between categories, we annotated it with the type and direction of the development, following the rules listed in Table 1. We discard the relationship classes with less than 10 instances, in order to have enough instances in each class for building classifiers in Section 4.2. Relations whose labeling fluctuates considerably over the course of the surveys (e.g. friend to significant other to family to other) are excluded from the analysis in the rest of this paper.

3.3 Dataset profiling

The NetSense dataset covers 175 students that filled the surveys, and whose mobile phone communication is available. There are a total of 7,575,864 phone interactions with others recorded by the applications installed on the mobile phones of the students. In Fig. 1 we present the exploratory analysis of the communication dataset. Fig. 1a shows the density of the number of communication events per student – visibly, the majority of students emitted between 5,000 and 15,000 communication events during the 2.5 years of the study. Fig. 1b shows the density of communication events with respect to the time of day when they were initiated. The vast majority of communication starts around noon and continues up to 11 PM. Fig. 1c plots the empirical cumulative distribution of the inter-event times – it is observed that these inter-event times are long-tailed distributed, a result already known in literature [18]. Lastly, Fig. 1d presents the number of communication peers for each of the students participating in the survey, separately for incoming and outgoing communication events, limited for the peers with which at least 20 interactions in order to remove occasional phone calls. Visibly, the two density plots overlap, and most students have less than 130 peers, which is compatible with Dunbar’s
Table 1: The rules for categorizing relationships – limited to the ones used in the study due to small number of instances of other classes –, and the number of obtained instances for each label.

| Previous relation | New relation | Label               | Count |
|-------------------|--------------|---------------------|-------|
| friend            | sibling      | family-relaxing     | 115   |
| friend            | parent       | family-relaxing     | 359   |
| parent            | sibling      | family-relaxing     | 546   |
| friend            | coworker     | friendship-relaxing | 41    |
| friend            | acquaintance | friendship-strengthening | 13    |
| other             | friend       | friendship-stable   | 662   |
| coworker          | friend       |                     |       |
| acquaintance      | friend       |                     |       |
| significant other | other        | romantic-relaxing   |       |

number and the theory on cognitive limits of our brain [12]. Out of 3,159,669 total outgoing communication events, 2,012,816 have been the interactions with the peers the students described in the surveys with the type of the relationship. That gives 1,736 relationships to investigate in this study - the number of instances for each category is shown in Table 1. In the next section, we fit a Hawkes model to each of these communication relationships.

3.4 Analyzing call patterns using Hawkes

We first propose the call series between two individuals as a point process, and to fit it using Hawkes point process model. We show how a general purpose point process R library (evently [24]) can be leveraged to produce user-level descriptions based solely on the fitted model parameters of the outbound call series.

Map calls to point processes. In this work, we use both phone calls and texts (both denoted hereafter as calls) as events (in the sense of point process events, as defined in Section 2). An event in the Netsense dataset is a tuple (timestamp, sender, receiver). We build event series by grouping together events with the same sender and the same receiver. Each timestamp $t_i$ is the time difference (in hours) between the recorded timestamp of calls and the timestamp of the first call. As a result, $t_0 = 0$. We retain only the series where the sender is a student enrolled in the study (i.e. we only study outbound call series of the students enrolled in Netsense). We impose the latter condition so that we can match call series with the surveys sent by the sender student. When both the sender and the receiver are students in the study, the outgoing series for the sender is identical to the incoming series for the receiver. We further filter our call series which have less that 20, or more than 3000 recorded calls or texts. The former is required so that we have enough data to fit the Hawkes processes (described next), and the latter to avoid the computational explosion (given that fitting Hawkes is quadratic with respect to the number of events). This results in 10,964 outbound call series associated with 175 sender users, totaling more than two millions call events.

Fit Hawkes processes. For each obtained call series, we fit the parameters of a Hawkes model, using the exponential and the power-law kernel functions ($\phi_{\text{EXP}}(t)$ and $\phi_{\text{PL}}(t)$, respectively, defined in Section 2). We fit the Hawkes process using the software package evently [24], a R package for modeling events series using Hawkes processes and their variants. Internally, evently leverages IPOPT [51] – the current state of the art in constrained, non-linear optimization – to maximize the log-likelihood function in Eq. (2).

By design, it supports a wide array of kernel functions, and it provides an integrated set of functionalities to enable one to conduct event series-level or aggregated-level analyses. For each event series, evently outputs the fitted parameters $\kappa$, $\theta$ and $c$ for $\phi_{\text{PL}}(t)$, and its branching factor $\pi^*$. Build user representation. We construct user descriptions starting from all the outbound call series initiated by a given user.

4 EXPERIMENTAL RESULTS AND FINDINGS

4.1 Fitting Hawkes to call data

The first step in our research was to determine which kernel better models the pattern of calls between two people. We tested two commonly used kernels: the exponential and the power-law function.

The communication history of each pair of users was divided by time into two sets: the training set containing 80% of the data and the test set containing 20% of the data. The training set was used to fit the Hawkes process; furthermore, the negative log-likelihood for the training period was calculated using Eq. (2). Then, using the obtained parameters of the fitted Hawkes process, we computed the total negative log-likelihood for the entire period of communication between two people. Finally, we calculated the holdout negative log-likelihood by subtracting the training negative log-likelihood from the total negative log-likelihood. To be able to compare the two kernels, we divided the obtained negative holdout log-likelihood by the number of events in the test period.

The aggregate results for all pairs of users are presented in Fig. 2. It is visible that the power-law kernel is better at generalizing call history and has less variance than the exponential function. For this reason, in the further stages of our research, we focused solely on using the power-law kernel.

4.2 Identifying relationship types

Here, we ask whether the relationships described by fitted Hawkes processes are identifiable one from another. We fit the telecommunication activity along each of the 1,736 relationships (see Section 3.3) using Hawkes processes (as described in Section 3.4). We describe each relationship using the Hawkes process parameters $\kappa$, $\theta$ and $c$.\n
and its branching factor $n^*$. Finally, we train four off-the-shelf classification algorithms: k-nearest neighbours [1], decision trees [50], XGBoost [7] and support vector machines [9]. We tune hyperparameters using a 5-fold nested cross-validation and the random search algorithm with 50 combinations. Moreover, we used the SMOTE algorithm to balance the size of the classes.

We present our results in Fig. 3a. All the evaluated models obtained a similar f1-score with the macro average around 0.19. However, if we look at the results for individual classes, the decision tree is characterized by the lowest variance. Our models coped relatively well with stable relationships, while some dynamic relationships, such as strengthening or relaxing, were difficult to predict. Furthermore, Fig. 3c, shows a confusion matrix for the decision tree model that contains the relative percentage of each class’s predictions. It is visible that relationships such as family or romantic are often confused with a friendship relationship, especially a stable one.

Afterwards, we focused on the most representative stable relationships: friendship-stable and family-stable. The former one was represented by 662 cases whilst the latter one had 359 instances, i.e. so many relationships have been described by surveyed students as either friendship or family and these descriptions did not change over the course of all surveys. The experimental results for the classification of stable relationships are shown in Fig. 3b. We compared the predictions with the true relationship type using the f1-score with the macro average. All classifiers obtained similar f1-score around 60%; however, if we look at the results for each class, we can see that the family-stable relationship achieved lower results than friendship-stable. The explanation of this phenomenon may be that family members are often treated like friends, which can affect the communication pattern. This dual nature of the relationship may, in some cases, result in similar parameters of the Hawkes process, so a trained model will have difficulty distinguishing friends from family. Nevertheless, obtained results show that the Hawkes process parameters used as features for machine learning algorithms are able to discriminant the these two types of stable relationships.

Figure 1: The exploratory analysis of the communication data for students participating in the Netsense study at the University of Notre Dame. (a) density plot for the number of communication events for the students, (b) the distribution of phone activity through the course of the day, (c) the cumulative distribution function of the inter-event times in hours, (d) the number of incoming and outgoing communication peers for the students in Netsense, where there are at least twenty communication events with the peer during the analyzed period.

Figure 2: Generalization performance in a temporal holdout setup, for the exponential and the power-law Hawkes kernel (lower is better).

4.3 Detecting temporal change points

The classification of dynamic types of relations turned out to be a difficult task, so we attempted to predict whether the change itself would occur. Using the history of outbound callings between a pair of users, we tried to predict whether it is possible to predict the change itself without specifying the type of relationship. Based on the Hawkes process, we have proposed a novel method for temporal change detection in a dynamic relationship.

The general idea of our method is presented in Fig. 4. The top axis represents the time during which the student communicated with another specific user. The $S_1$ points symbolize specific points in time when a given student completed the questionnaire defining his relationship with other people. Let us suppose that in surveys $S_1$ and $S_2$ the student described the same type of relationship connecting him with a specific user, e.g., significant other. After completing the second $S_2$ questionnaire, the relationship changed, and the student, when completing the $S_3$ questionnaire, described the relationship as a friendship. The periods that contain data before and after the change are marked below the timeline.

Our method requires fitting the Hawkes process for periods before and after the change and then computing a holdout negative
log-likelihood per event for each period in the same way described in Section 4.1. A significant difference between the obtained values will indicate a change in the relationship between the pair of users. In Fig. 4, we fit the first Hawkes process with events up to tipping point $S_1$ and calculate the holdout negative log-likelihood per event before the change (the period between $S_1$ and $S_2$). Similarly, we do the fitting of the second Hawkes process using the data up to $S_2$ for training and compute the holdout negative log-likelihood per event after the change (the period between $S_2$ and $S_3$).

The limitation of the presented method is the need to define three points in time. In our study, we can detect a change in a relationship at the earliest between the completion of the second and third questionnaires. A potential solution to this problem is the setting of artificial tipping points. We applied this approach to a romantic-relaxing relationship and removed the limit of three thousand events to get a few more samples of this class. We established an artificial tipping point by dividing the training set before the change in half against the time.

We tested our method on 428 relations, which can be divided into four types of dynamic relations. We used the Wilcoxon signed rank test to determine the statistical significance between the negative log-likelihood before and after the change, and the results are presented in Table 2. At the confidence level of 95%, the proposed method detected a change in the friendship-relaxing relationship (P-value = 5.7264e-5). For the remaining types of relationships, no statistically significant difference was obtained, which may be due to the small number of these relationships.

### 4.4 Inferring psychometric traits

The next stage of our research was to find out how much information about personality traits can be retrieved from telephone communication patterns. For this purpose, we generated 115 users’ embeddings based on Hawkes modeling of their activity. The user representation generated in this way was used as input data for machine learning algorithms. For each personality trait from the Big Five, we built regression models using a setup similar to the

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**Table 2: Evaluation of the proposed method of detecting temporal change points in relationships using the Wilcoxon signed rank test (confidence level = 0.95).**

| Type                | P-value  | Number of instances |
|---------------------|----------|---------------------|
| family-relaxing     | 0.5320   | 61                  |
| friendship-relaxing | 5.7264e-05 | 352              |
| friendship-strengthening | 0.4375   | 6                  |
| romantic-relaxing   | 0.9102   | 9                   |
as the best predictor due to its small RMSE and low variance and compared it with other Big Five prediction methods (Fig. 5b).

Our decision tree model based on the Hawkes process and outbound calls, obtained a lower RMSE than the model obtained by Stachl et al. [45], which used behavioral information collected with smartphones. We took this model as the most recent baseline in predicting Big Five personality traits in the literature. As the second baseline, we used a model based on surveys completed by students. We transform the additional questions relating to hobbies, activities, well-being, grades obtained, health condition and number of books they read (defined in Section 3.1) into a 145-length user feature vector, and then we apply the decision tree regressor to predict the Big5 traits values. The model based on survey questions obtained slightly better results than Hawkes, but not many, which may lead to interesting conclusions that the communication patterns contain a lot of hidden information about our personality. Based on the history of calls, we can predict the characteristics of a given person without the need to prepare questionnaires and survey many people, which may raise privacy concerns, mainly because it is difficult to hide information about our pattern of communication.

5 RELATED WORK

We structure the discussion of related works into four sections. First, we discuss previous work that used Hawkes processes to model contacts and interactions. Second, we review theoretical and empirical research on the emergence of contact networks and their properties. Third, we explore work that infer personality traits from online data sources, and finally we glance over other work that use mobile phone data.

**Modeling interactions in contact networks using point processes.** Hawkes processes have been widely used to model social interactions in a number of applications, mainly because they can account for bursts of activity localized in time. Zipkin et al. [55] study electronic communications in a dataset of emails pertaining to the US military, where they observe that activity along the edges of the communication network is bursty. They apply a Hawkes model for the email exchange along edges, and they concentrate on studying parameter estimation in the presence of missing data. Moore and Davenport [35] learn the topology of a wireless network from limited passive observations of network activity. They use a multi-variate Hawkes process, and they show it capable of detecting changes to the existing topology, and extracting higher-level summaries of information flow in the network. Choudhari et al. [8] models simultaneously events and the structure of a social network using a Hidden Markov Hawkes Process that incorporates topical Markov Chains within Hawkes processes to jointly model topical interactions along with the user-user and user-topic patterns. Hawkes processes have also been used to model face-to-face interactions in offices [31] as well as retweet cascades. For the latter task Kobayashi and Lambiotte [23] propose a Time-Dependent Hawkes process to account for the circadian nature of the users and the aging of information when modeling retweet cascades, whereas Mishra et al. [33] leverages a Hawkes process with a power-law relaxation kernel, and leverage it jointly with user and timing features to predict the popularity of retweet cascades.

To the best of our knowledge, this is the first work that applies Hawkes modeling to telecom data and uses its outputs to make predictions about the relation and the personality traits of users.

**Theoretical and empirical research on the emergence of contact networks and their properties.** The connection between bursty behavior and power-law distributions of activity in social networks has been known for more than a decade. Bursts in human and natural activities are highly clustered in time or space, suggesting that these activities are influenced by previous events within the social or natural system [22]. Barabási [4] proposed a decision-based queuing process in which individuals execute tasks based on some perceived priority. The emergence of power-law in social systems has been theoretically studied for movie ratings [22], and the viewcount series of Youtube videos [10]. Further connections have been shown between the arrival of events in contact networks and the structure of the network [48].

A number of empirical studies were set up to infer the link between contact events and the structure of the inferred network. Lee et al. [27] build a study in which they give a group of students mobile phones, and they survey them five times a year. They find that consistent deviations from expected behavior, are crucial for identifying well-established underlying social relationships. Raeder et al. [38] use the same NetSense dataset as our work to predict edge decay in social contact networks, i.e. whether an edge that was active in one time period continues to be so in a future time period. Radio Frequency Identification devices that assess mutual proximity were used by Cattuto et al. [6] to study offline contact networks. The study found an interesting super-linear behavior, which indicates the possibility of defining super-connectors both in the number and intensity of connections.

Our own study relies on contact events along the edges of a social graph, but we do not use these to study the network, but rather what information these uncover concerning the users themselves.

**Predicting personal traits from social interactions.** A fertile area of the field of computational psychology deals with inferring psychometric traits from a range of sources made available by our new interconnected society. For examples, Settanni et al. [42] show that digital traces from social media can be studied to assess and predict theoretically distant psychosocial characteristics with remarkable accuracy. They also show that when additional user demographics is leveraged as additional types of digital traces, the accuracy of predictions improves. Some of these work also use social-media inferred personality traits to influence opinions and behavior, or to infer private traits. For example, Matz et al. [32] performed three field experiments that reached over 3.5 million individuals with psychologically tailored advertising, and found that matching the content of persuasive appeals to individuals’ psychological characteristics rendered the messaging significantly more effective. Kosinski et al. [26] used a public source of social media data (i.e. Facebook likes) to predict the Big5 personality traits of users, alongside with a range of highly sensitive personal attributes, including sexual orientation, ethnicity, religious and political views, personality traits,intelligence, happiness, use of addictive substances, parental separation, age, and gender. A follow-up study performed by Youyou et al. [53] even showed that personality traits prediction based on Facebook likes are more accurate the user’s friends’ estimations based on surveys.
The prior work most relevant to the current study relates to learning personality traits from behavioral information collected via smartphones. Such work usually collect data from the onboard sensors and other phone logs embedded in the smartphone devices [15]. The work closest to ours is by Stachl et al. [45], who predict Big Five personality dimensions using six different classes of behavioral information collected via sensor and log data from smartphones: 1) communication and social behavior, 2) music consumption, 3) app usage, 4) mobility, 5) overall phone activity, and 6) day- and night-time activity. They find that the accuracy of these predictions is similar to that from social media platforms. On the contrary, other studies like [34] claim that smartphone usage is not as predictive of Big5 personality traits as previously reported, and claim that higher predictabilities in the literature are likely due to overfitting on small datasets.

Our work differs from the above-mentioned in two major aspects. First, we use the parameters of the Hawkes models fitted on the call series to make predict user traits. As far as we are aware, no other work has used fitted Hawkes point processes to distill the call interactions between users and predict Big5 traits. Second, the above work requires access to the user’s phone, as most features need to be recorded on the device. Our work shows that the personality traits can be accurately predicted solely on the call and text logs, which can be obtained outside the user device. We also show that the prediction accuracy using our Hawkes descriptors is comparable to that obtained from user-filled surveys.

Other applications. There are a large number of work that use mobile phone data to learn and predict other quantities. While these are only marginally related to our work, we present some of them for completeness reasons. For example, González et al. [14] used the GPS location of the mobile phones to analyze mobility patterns for a six-month period, and found that despite the diversity of their travel history, humans follow simple reproducible patterns. Óskarsdóttir et al. [36] use social media traits to predict customer churn (i.e. whether customers will leave the mobile network for one of the competitors). The same problem is addressed by Backsell et al. [3], who also use network operator information (such as last reload date, number of calls in the last 60 days, card swapped in 30 days) in addition to simple feature relating to the network of callers. Furthermore, Steele et al. [46] and Smith-Clarke et al. [43] use aggregate data from mobile operators to model the spatial distribution of poverty in a population, while Soto et al. [44] use aggregated cell phone records to identify the socioeconomic levels of a population. Finally Bach et al. [2] use mobile usage data to predict voting outcomes. The survey by Calabrese et al. [5] inventories a series of features constructed for analyzing telecom data, but unlike our work, they do not fit Hawkes point process.

6 CONCLUSION AND FUTURE WORK

The goal of this work was to investigate whether the Hawkes processes trained on telecommunication metadata are predictive of human sociological traits and aspects. We employ the extensive NETSense dataset originating from University of Notre Dame, which contains mobile phone communication metadata as well as detailed information on surveyed students. We used the communication data to fit the Hawkes process individually for each pair (participating student, peer), and we use its fitted parameters as descriptors. In a series of experiments, we show that the Hawkes processes are capable of distinguishing between types of relationships, predicting their temporal dynamics and inferring user Big5 psychometric traits. This work shows that Hawkes processes can become a good abstraction of detailed communication events that carries additional human sociological information, and that they could serve as basis for future investigation in this direction.

The ethics of using telecom traces to infer private traits. These capabilities also raise some important questions regarding our privacy. As it was shown in this work, but also some others [26, 43, 44], inferring psychological traits or other sociological aspects can pose a significant risks for individuals and it only should be made understanding the impact on the society. As authors of [49] convince, the number of risks for studying human mobility based on telecom data is high and should always be considered as a double-edged sword. Similar conclusions can be applied to our work.

Limitations and future work. For a given pair of individuals (sender, receiver), this work only accounts for outgoing calls (i.e. from sender to receiver). Future work would be fitting both outgoing and incoming call series as a bivariate Hawkes process, allowing
to model the intertwining of both patterns as a basis of discussion: initiating and receiving phone calls.

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