SMILE: Smartphone-based Isolation Analysis for Older Adults

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***Abstract*— We discuss the design and development of a social isolation detection platform for older adults, SMartphone-based Isolation anaLysis for oldEr adults (SMILE), using various types of information gathered from smartphones including contacts, phone logs and social media activity. Our approach uses an analysis of activity/cellphone data to detect changes in patterns of interaction over time. The idea is to trigger interventions (nudge caregivers/family to engage or call) when it is inferred that there are changes in regular patterns/interactions etc. The platform contains data collection, storage, analytics, and alerting components distributed across mobile devices, remote servers, using cloud databases as a conduit. Analysis techniques were developed to fuse information from these multiple data sources and calculate a metric that we designed to quantify the level of interaction experienced by specific individuals over time. Techniques used to improve accuracy and reduce false positives include change detection methods to focus more on significant variations in behavioural patterns, and personalized weights to capture people's preferences for means of interaction. We implemented and evaluated SMILE using a real-world dataset containing call and text logs of multiple individuals.**

***Keywords*— social isolation, smartphones, data analytics, interaction frequency, older adults**

I. Motivation

During the COVID-19 pandemic, two thirds of U.S. adults reported experiencing social isolation and loneliness [AP20,QZ22] - this statistic is even more alarming for older adults. As defined in a recent working group study [L20], social isolation is defined as “an experienced or perceived lack of personal relationships with family, friends, and acquaintances on which people can rely in case of need”. It is a global challenge, as studies from Netherlands [M15], Canada [MN20] and Finland [HK04] indicate. While social isolation has health implications across all age groups [HL88], it tends more harmful for older adult populations [CH01, TT06, BB01] who are more impacted by stressful life events, deterioration of health and disability.

Studies have reported that multiple factors contribute to the health risks associated with social isolation as well as perceived lack of social support [CW90]. Health implications of diminished social relationships or infrequent social contact include higher rates of mortality and morbidity, depression, cognitive decline and infection [BB01,S94,UC96, CD97,BM04, PC05,HK04]. As experts argue, this has become a public health crisis. Designing and implementing interventions to reduce social isolation is especially important for older adults with mobility challenges and cognitive decline. A key issue is that of accurately detecting when an individual is isolated or lonely. Today, medical personnel use introspective techniques via interviews, surveys and forms where individuals self-report their current state of mind. In our work, we address this issue through a technology-based solution that uses mobile devices such as smartphones to collect data about individuals and perform an analysis of this data to extract potential signs of social isolation. Mobile phones are increasingly common and used widely today across different age groups including older adults [AA20], especially among those who live independently and in continuing care facilities. Our conjecture is that such a data-centric approach can provide higher levels of accuracy since it allows the capture and analysis of information about the behaviour of individuals over longer periods of time. The outcome of the analysis can help determine whether additional intervention methods are required. In our approach, we inject interventions in the form of nudges to caregivers/family members - i.e., nudging them to engage or call the older adult when it is inferred that there are changes in regular patterns of interactions etc. While our current implementation utilizes smartphone-based data, the platform can also leverage data from other IoT devices including wearables (smart watches, pendants) and health monitoring devices. This paper is organized as follows. In Section 2, we present the design and implementation of our proposed social isolation detection platform called SMILE and discuss the information workflow through the system. In Section 3 and 4, we explain algorithms used to extract and create social networks from user data and the inference of social isolation from social networks. We present results in Section 5 and conclude with future directions in Section 6.

Related Work:

While use of mobile phone data to detect social isolation has previously been explored (E.g., {MA20]), such work is limited in the scope of features used. . For instance, [MA 20] only considers call logs of an individual and uses decision-tree based on features such as recency of call from friends / family. Often such features (E.g., list of friends versus family) are not available. In our work, we exploit data not just from call logs, but other modalities of communication (E.g., messages). Further, instead of requiring data to be provided, we learn social networks based on communication and infer strength of relationships. In addition, we develop mechanisms to accommodate for special events and holidays that influences the level of interaction across population. There are other studies such as HypAD [B23] that monitors changes in activity of daily living (AD) to infer isolation. Such work is, however, less related to our project which focuses on using technology of daily use such as cell phones. [Q22] surveys a large number of related technologies that have been considered for detecting social isolation in older adults.

II. SMILE: System Design and Workflow

In this section, we describe the architecture and design of the SMILE social isolation detection platform. Information required for determining whether an individual is experiencing social isolation can be obtained from a variety of features and sources. Examples of useful features include age of the person, his/her current/prior occupation, calendar events, call logs, location (via GPS, WiFi connectivity information), health statistics (sleep and exercise data), email, messaging apps (through keyword detection), camera data (with image recognition and detection). Secondary information can also be obtained by getting logs of screen time statistics to monitor social media usage, capturing relationship closeness of friends and family based on querying call logs, knowledge of health state (current or prior diagnoses of illness) and time spent in video calls through apps (e,g, Skype, Zoom, Facetime). Much of this information can be obtained from data that resides on the individual's smartphone (either

Fig. SEQ Figure * ARABIC 1: The SMILE System Architecture

directly or through logs and records of activity already gathered by devices).

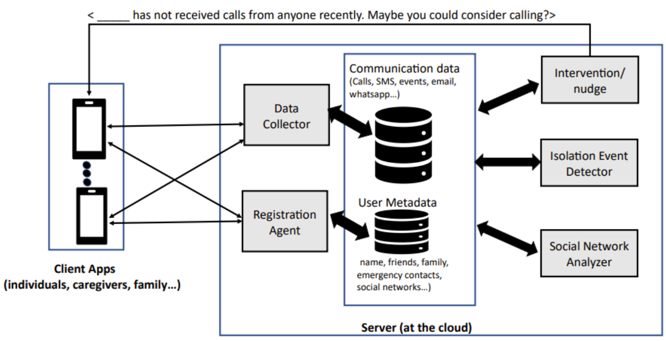


Fig 1 shows the basic components in the end-to-end architecture of SMILE. SMILE is designed to execute as a client-server-cloud application with multiple modules that communicate via specific APIs and interaction protocols. The client side (Android or IoS app) periodically gathers log files and uploads this data into an open-source cloud database (in our prototype implementation, we use ElephantSQL). Data from the cloud is ingested, i.e., pulled into the server side platform and database (we use PostgresDB as the server side DB platform). In this paper, we focus on the server architecture where data (and meta-data) about users is stored, processed, and analyzed. The following modules address distinct functionalities on the server side: (1) ***Registration Agent***: Interfaces for clients (older adults, caregivers, family, providers) to register and provide information; stored in SMILE metadata store.
(2) ***Data Ingestor/Collector:*** Obtains dynamic data for a user (call/text logs) incrementally directly from user (or cloud engine).
(3) ***Data Storage/Representation:*** Implements a designed data model; enables storage of static and live data with support for rapid query processing of critical data
(4) ***Social network Analyzer:*** Uses data in datastores (live,static) to extract/update a annotated social network for each user.
(5) ***Isolation Event Detection:*** Implement techniques to accurately quantify the level of isolation experienced by a user via data fusion/analytics methods.
(6)***Intervention processing:*** Select how interventions/nudges are implemented for an isolation event, based on availability/history of interactions with social contacts.

We next discuss steps and implementation details in the Information flow of SMILE.

Step 1: (Data Representation): This involves the creation of a schema (a system of organization) for the underlying data stored in a relational database at the SMILE server. We use PostgresDB in the SMILE prototype. We store user metadata that is relatively static in multiple tables (e.g., person, friends) – this includes an individual's name/ids, names/ids of friends and family and the corresponding relationship parameters. A relationship strength column is initialized based on type of relationship and is further updated during a social network detection/analysis phase. Information about social interactions (e.g. phone calls etc.) are stored in separate communication tables within the Postgres DB on the SMILE server.

Step2 (Device Data Collection): The SMILE client collects information about end-user activity directly from the device using a mobile frontend. The mobile code is written in React Native, a mobile development framework built on Javascript. React Native was chosen due to its speed of development and because of its ability to be written once and run on both iOS and Android systems. The app was then tested on physical iOS devices along with a Pixel 4a emulator from the Android SDE. On launch, the app opens to a screen of Call Logs that was gathered from the phone using the react-native-call-log package. We parse this data and present it in a logical manner that shows Name, DateTime, Duration, PhoneNumber, RawType, Timestamp, and Outgoing/Incoming status. A subsequent Calendar Screen displays all calendar events of the user using the react-native-calendar-events package. On Android Phones, this will access a user's Google calendar, and on iOS this will access a person's iOS calendar. Finally, a PersonalInfo Screen allows users to input personal data (e.g. home phone number, mobile number) to local storage on the phone using the @react-native-async-storage package. On a button press or on the appearance of new call logs, new data is pushed to our backend SQL database. To ensure privacy, note that data onboard the device is directly uploaded to the SMILE server (i.e. not uploaded/stored to unauthorized intermediate locations).

Step 3: (Data Ingest): Data and logs gathered from user devices in Step 2 are periodically inserted into the PostgresDB database at the SMILE server. The SMILE data ingest protocol is designed to be efficient, available, and reliable. For this, Communication between the client and server in SMILE is achieved through a cache maintained in the cloud. We use ElephantDB [EDB], a cloud key-value datastore to implement this cloud cache. Using a cloud-based cache ensures availability. Clients connect periodically, or when convenient, to the cache to transfer data from their mobile device to the cache. Clients tag data with an "update id" that is sequentially incremented and passed to the cache in the log-update header. The cache maintains the latest "update id" for each client. When a client connects with the cache, the cache informs the client about which updates it has already received, and from which point the client needs to transmit or retransmit (in case of lost updates) its data. The client can delete all records up to the received update-id without the concern of data loss. This implements reliable communication. The cache receives data from multiple clients and pushes update records from these clients into stable storage (disk) periodically. It simultaneously also pushes the client's update-ids to the disk so ensure that if, ElephantDB fails, on recovery, the state of each client (i.e., last update-id) indeed corresponds to the last message stored stably in its storage.

The analysis server of SMILE periodically connects with the cloud cache to fetch data updates from the clients. By combining data updates of all users, we achieve efficiency since we only require fewer communication rounds. This communication between the cache and the SMILE server follows a similar reliable messaging protocol as followed for client/cache communications and is skipped for brevity.

Step 4 (Data Analysis and Visualization): The data analysis module in SMILE executes two distinct analysis functions - social network detection (details in SecIII) and Isolation Event Detection (details in Sec1V). Results of the analysis are visualized using Grafana (SecV) Based on the results, appropriate interventions to potential contacts are triggered based on computing social network strength, their interaction factors and associated calendars.

III. SOCIAL NETWORK DETECTION

In this section, we discuss our approach to extract the underlying social network (SN) from input data (e.g. logs obtained during data collection). The SN generated is a graph-based representation of interactions used to detect isolation. The SN Analyzer module iterates through each entry in the input datasets, i.e. call logs and text logs of multiple users, to extract the social network graph where nodes represent individuals and edges between nodes represent interactions between individuals. First, data from user logs is used to populate a user-table. The user-table is used to generate distinct nodes for each user in an SN graph with associated labels/ids. We next use call information to generate a "call-edge" table where each row represents a connection, i.e., a directed edge in the SN graph. Each entry in the edge table is of the form (source-id, destination-id, #-of-interactions). The number of interactions represents the edge weight and is initialized to 1 when an edge is created; note that the presence of an edge indicates that at least one interaction between two nodes/individuals has occurred. The edge weight is then incremented for every for every additional interaction on that connection. The result is a directed SN graph with weighted edges for all individuals.

We utilize this large SN graph to next extract a personalized network (PN) for everyone. This will aid in ranking the strength of the contacts in the SN of an individual based on number of interactions. The PN of an individual ***i*** is a subgraph of the SN graph that contains only nodes directly connected to node ***i***. The sum of weights on all connections indicates the total number of interactions the person has had (when the graph was constructed).

While a simple version of the PN for an individual can determine if the person has had very little to no interaction, a more detailed analysis is required to accurately determine isolation which we discuss next. PN graphs help in such analysis as will become clear. SN & PN graphs are generated periodically.

IV. DETECTING ISOLATION EVENTS

In this section, we describe an algorithm to analyse interactions, and infer the degree of isolation of individuals. For this, we define a term Interaction Factor (***IntrF***), a metric that is periodically calculated using the PNs described earlier. We begin by introducing terminology that will help with evaluation of IntrF for an individual ***i.***

Defn: Social Connection Strength (SCStr): We use the well-established Unidimensional Relationship Closeness Scale(URCS) [GB94, L98, LR95] scale, which is a standard tool in psychological analysis to assess relationship closeness to determine the strength of a contact. URCS has been shown to have high validity and reliability in capturing the strength of social and personal relationships. Using the URCS scale and relationship categories, we assign to each member of an individual's social network, a numeric value, that represents the strength of the relationship to the user. For each URCS relationship category, we assign (*Category, SC_value*) as below:

(SC_CloseFamily, 2) > (SC_CloseFriend, 1.5) > (SC_Family, 1.3) > (SC_Friend,, 1.0) > (SC_Acquaintance, 0.5) > (SC_Random, 0.1)

Social connection strength between user *i* and user *j* is calculated as :

$$SCStr(i,j) = SC\_value(j) * Intr\_freq(i, Category(j))$$

where *Intr_freq* is the interaction frequency, a learned value from historical data representing the average frequency of interactions with individuals in the corresponding SC category. We set the initial value of *Intr_freq* to 1.

Defn: SpecialDay (SD) Coefficient: Interactions are expected to increase during special events and special days (e.g. birthdays, holidays, anniversaries, weekends) and can skew the estimation of isolation. We introduce *SDcoefficient,* a factor from 1 to 5, where 1 associated with an ordinary day and 5 for special days when interactions are expected to be very high.

Defn Interaction Factor(IntrF): is a metric defined for an individual that represents the degree of loneliness/isolation experienced by a person over a period of time. We compute *IntrF* for an individual as a weighted sum of interactions through multiple communication modalities including phone calls, text messages and social media activity. A low *IntrF* value indicates low levels of interaction, i.e. high likelihood of isolation. Studies indicate that a minimum level of interaction is required to maintain adequate levels of mental health. While the absolute value of *IntrF* could be important (e.g., to set a threshold minimum value above which immediate intervention is not required), SMILE focuses on a more personalized measure of change in *IntrF* of individuals. Since individuals have different levels of communication with others, a personalized *IntrF* baseline needs to be evaluated periodically to determine when there is significant change in activity levels. We are interested in determining when *IntrF* drops significantly. We use 4 measured factors to determine a current *IntrF* value for an individual: (i) Call logs - phone call activity based on number of calls, duration and relationship to the contact; (ii) Text messages - number of messages, length of text chain, relationship to contact; (iii) Social media activity - time spent on a social media app and level of interactions on the app and (iv) Calendar events - Meta-data that can provide some insight into social and in-person engagements. For an individual *i,* we calculate the interaction factor as:

$$IntrF(i) = w1*IntrF\_calendar(i) + w2*IntrF\_calls(i) + w3*IntrF\_texts(i) + w4*IntrF\_SM(i)$$

where weights represent preferences of individual's modality preferences. We posit that $w1>w2>w3>w4$, though, in general, a learning-based approach should be used to determine such importance. We next discuss how to calculate the *IntrF* measure for each modality by explaining how we compute *IntrF_calls(i)* using call log information based on call length, SD coefficient, and the strength of social connection, we compute IntrF for calls as :

$$IntrF\_calls(i) = \Sigma j(SCStr(i,j))(Call\_len\_factor)/(SDCoefficient)$$

The call length factor in the equation above converts the length of the call to the level of engagement of a person in the call between 0-2. We use:

(t>=10min, CL=2) > (5<t<10, CL= 1.5) > (1<=t<=5), CL=1) > (t<1 min, CL=0.5)

Other factors such as *IntrF_texts, IntrF_SM*, etc. are similarly computed and not discussed for brevity.

V. Experiments and Results

user_id	other_id	interaction	timestamp	number	call_timestamp	duration	direction	created_at	updated_at
22		202398	2010-09-15 23:03:31	07574455931	2010-09-15 23:03:19	1	Outgoing	2010-11-11 10:20:58	2010-11-11 10:20:58
6		170882	2010-09-15 21:57:54	07028004429	2010-09-15 21:56:52	0	Outgoing	2010-11-11 10:20:58	2010-11-11 10:20:58
12		376185	2010-09-15 21:46:51	07024591762	2010-09-15 21:29:01	1058	Outgoing	2010-11-11 10:21:05	2010-11-11 10:21:05
25		222273	2010-09-15 21:29:51	07806980885	2010-09-15 21:28:11	80	Outgoing	2010-11-11 10:20:59	2010-11-11 10:20:59
25		222271	2010-09-15 21:26:19	07806980885	2010-09-15 21:23:03	181	Outgoing	2010-11-11 10:20:59	2010-11-11 10:20:59
25		222270	2010-09-15 21:22:57	07806980885	2010-09-15 21:22:14	13	Outgoing	2010-11-11 10:20:59	2010-11-11 10:20:59
25		222269	2010-09-15 21:22:54	07806980885	2010-09-15 21:22:50	0	Incoming	2010-11-11 10:20:59	2010-11-11 10:20:59
12		376181	2010-09-15 21:20:34	07564645771	2010-09-15 21:18:54	92	Incoming	2010-11-11 10:21:05	2010-11-11 10:21:05
25		222265	2010-09-15 21:16:39	07806980885	2010-09-15 21:16:18	0	Missed	2010-11-11 10:20:59	2010-11-11 10:20:59
25		222264	2010-09-15 21:16:07	07806980885	2010-09-15 21:15:40	1	Outgoing	2010-11-11 10:20:59	2010-11-11 10:20:59
25		222263	2010-09-15 21:12:09	07806980885	2010-09-15 21:11:48	0	Missed	2010-11-11 10:20:59	2010-11-11 10:20:59
25		222258	2010-09-15 21:05:10	07806980885	2010-09-15 21:04:42	1	Outgoing	2010-11-11 10:20:59	2010-11-11 10:20:59
25		222258	2010-09-15 21:05:10	07806980885	2010-09-15 21:04:14	0	Missed	2010-11-11 10:21:05	2010-11-11 10:21:05
12		376180	2010-09-15 21:04:23	01317709864	2010-09-15 21:03:36	3	Outgoing	2010-11-11 10:20:59	2010-11-11 10:20:59

Figure 3: The Nodobo-2011 dataset

For our experimental evaluation, we use the Nodobo-2011 dataset available on github [21].

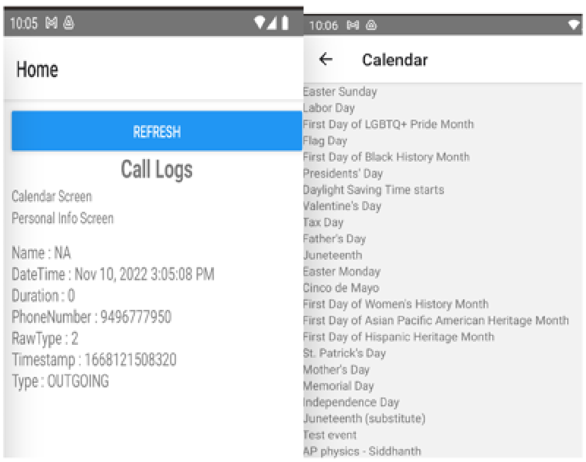


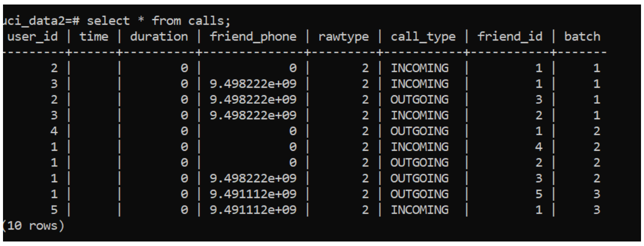
Figure 4: Client-Side Application

The data, gathered from a study of 27 individuals between Sept. 2010-Feb 2011 consists of over 13K call records, 83K messages, and over 500K presence records as well as other related datasets. Sample derived information from the dataset is shown in Figure 3. Screenshots of the client side app indicating input (Fig 4) and sample data from the

Postgres server side DB displaying the processed call logs (Fig 5) are depicted.

Using the dataset we created a SN graph where nodes correspond to people and the edges, interactions. A subgraph of the larger SN graph is shown in Figure 6. Each node is annotated with the id assigned to the individual. The directed edges, when hovered over, display the number of interactions initiated by the source node and received by the target node. We executed both our SN detection and our isolation detection code on the graph to validate our algorithms. From the generated SN graph, we can extract individual personal networks - Figure 7 illustrates such a PN graph for a specific user (i.e. user 13). Using the information encoded in the PN graph, we calculated the interaction factor of user 13 as 0.9123 which indicates a high level of interaction. A deeper look into user 13's PN reveals that the high interaction factor was primarily due to frequent lengthy calls with one user, possibly a close friend or relative. Based on the algorithm, we also identified 4 individuals who could possibly be isolated (user ids 2,12,18,20, two of these can be seen in Figure 6) and may require intervention.

Note: Since our experimental dataset is anonymized and lacks information specific to the user, we lack access to the real SDcoefficient for a user and use a value of 1 in our experiments.



```
uci_data2=# select * from calls;
 user_id | time | duration | friend_phone | rawtype | call_type | friend_id | batch
---------+------+----------+--------------+---------+-----------+-----------+-------
       2 |      |        0 |            0 |       2 | INCOMING  |         1 |     1
       3 |      |        0 | 9.498222e+09 |       2 | INCOMING  |         1 |     1
       2 |      |        0 | 9.498222e+09 |       2 | OUTGOING  |         3 |     1
       3 |      |        0 | 9.498222e+09 |       2 | INCOMING  |         2 |     1
       4 |      |        0 |            0 |       2 | OUTGOING  |         1 |     2
       1 |      |        0 |            0 |       2 | INCOMING  |         4 |     2
       1 |      |        0 |            0 |       2 | OUTGOING  |         2 |     2
       1 |      |        0 | 9.498222e+09 |       2 | OUTGOING  |         3 |     2
       1 |      |        0 | 9.491112e+09 |       2 | OUTGOING  |         5 |     3
       5 |      |        0 | 9.491112e+09 |       2 | INCOMING  |         1 |     3
(10 rows)
```

Figure 5: Server side PostgresDB call data

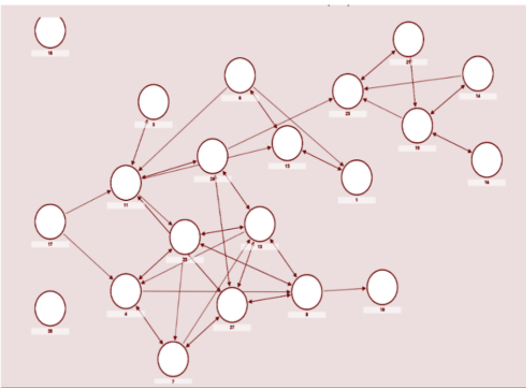


Figure 6: A subgraph of the generated Social Network

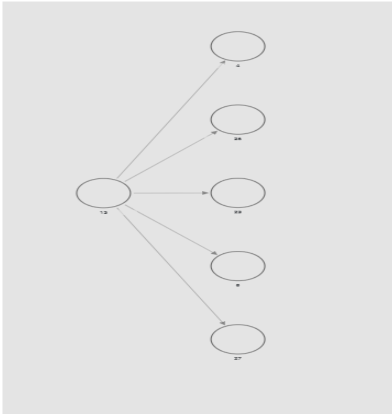


Figure 7: A PN(Personal network) Graph for 1 user

Information from the isolation detection phase is used to select specific contacts to trigger interventions. While our experiments validate the implementation of our code, the effectiveness of the approach to detecting social network, interaction factor and isolation requires a carefully designed user study. We are in consultation with faculty at UC Irvine Senior Health to help conduct such a study in the future.

VI. CONCLUSIONS AND FUTURE WORK

We explored the challenge of using smartphone data to help detect isolation amongst older adults with the aim to use their social networks to nudge interventions. Many references in the literature point to the importance of such an approach to reduce isolation and its negative impacts. Our current prototype is an initial step in developing a deployable system that can help the elderly. Towards such a goal, we need to explore several challenges: a) validation of algorithms through user study, b) improvement of algorithms to incorporate clinically relevant knowledge about isolation, c) addressing privacy and security challenges in the system design & implementation.

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