SMART DIARY-A GUIDE TO MAN'S DAILY PLANNING

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Abstract— In this paper we present Smart phone app that senses and analyses mobile data to understand, predict, and summarize a man's daily activities, such as his daily routine. These activities are used to represent knowledge, which helps in generating digital personal diaries in an automatic manner. Here we make use of different sensors for the purpose of sensing. Smart Diary is able to make predictions based on a wide range of information sources, like phones' sensor readings, locations, along with interaction history with the users, by integrating such information into a sustainable mining model.. This Android app is specifically developed to handle heterogeneous and noisy data, and it is made to be extensible in which people can define their own logic rules which will express predictions like short-term, mid-term, and long-term events and patterns about their daily routine. The app's evaluation results are based on the platform provided by Android.

Index Terms—Mobile computing, sensors, knowledge discovery, inference algorithms

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• INTRODUCTION

Smart diary is a periodical software which is suited for all men and women- It can be anyone's personal organizer, a health tracker, secret diary, an utritional tracker, health monitor, contacts organizer, schedule software, tasks manager- all in one a simple to use and integrated package. There are several editions from which you can choose, so that you can be sure that your diary is tailored to your specific needs. A personal diary is the one which records human's experiences, thoughts, and feelings on occasions in the outside world. Some personal diaries like those by Anne Frank, have become popular and widely read books and the basis of plays and films. Besides their value in terms of being a hobby and a literature source, diaries also serve vital roles for scientists in social science. Some researches use diaries to study the relationship between certain activities (e.g., yoga) and health problems (e.g., heart attack) in certain populations Using a smart diary you can plot your exercise or yoga program against your diary of health notes and see how they interrelate. Add information about changes in your diet and lifestyle and see how these changes have affected your fitness and activity levels. See how your mood is affected by your sleep. Track lethargy against dreams, diet or any part of your daily life that you choose. Smart diary has all the features that you would expect to find in a professionally designed personal information manager. However, recent researches have reported that this research method is insufficient due to the quality of diaries collected from a group of volunteers. For developing smart diary app we use sensors which have the ability to collect data and information from the environment around us The data collected by sensors is usually incomplete, redundant fragmented, or incorrect. Various sensors equipped with smart phones are GPS, Accelerometer, proximity sensor, etc. By using the GPS sensor, we can get current information from the GPS receiver like latitude and longitude coordinates, bearing and speed. An accelerometer is a device which measures proper acceleration. With the rise of Internet, the form of diaries has undergone noteworthy changes. Online journals, micro blogs, Tweets, and Facebook status all contain nonstop Updates on a person's life events. Moreover, the complication of people's lives have increased dramatically due to the tight Intertwining of both "online" and "offline" lives. On the other hand, since more and more activities are attracting our attention, we have less and less time to note down the stories belonging to our unique life. It also provides data from verified sources for social studies. we suggest a an approach which is fully software-based to generate personalized diaries .Due to the widespread use of smart phones in recent years this approach has been adopted. Our main idea in this paper is that, as the user carries the smartphone, this device will be able to perceive the environment through sensors and infer users' behavior. For example, user's life activities like. motion, SMS, phone call, etc. throughout day, from which we can deduce many different types of user-interested actions and record them. The inference results are then summarized into human-readable forms example a diary. We name this application as "Smart Diary", as it is purely based on software, and does not require interference from user. Although the central idea of Smart Diary isquite simple, there are many challenges that we have to face to bring it into reality.Due to the battery limitations on the smartphone, it is usually not acceptable to keep the application active for long periods of time. Therefore, tradeoffs have to be made in terms of the amount of data that the application collects, and the precision that it achieves. Specifically, we summarize the following challenges that our design faces:

• Smart Diary has to report the challenge of user Secrecy as the dairies generated contain unique daily Actions of users, such as their entertainments, important social contacts, and health conditions, it is necessary to ensure that such information is not leaked to other people. This challenge is particularly urgent as recently exposed security loopholes have proven that it is possible for these phones to be hacked through hackers or NFC (near field communication) techniques.

• We need a mechanism to support the personalization of Smart Diary, as each user has their own life styles and experiences. Different users may interpretate the same sensing readings in their own manners, leading to user-specific output in diary contents. The output from Smart Diary should reflect the user's personality, and consist of the most appreciated and interesting experiences, which can be different from user to user. In addition, the system's framework should be adaptive to the changing requirements of the users. we develop a variety of techniques to address the above mentioned challenges, and summarize their major contributions:

•We present a Smart Diary, a fully automatic softwaresystem that allows highly intellectual and human-centricgeneration of diaries based on the sensing readings fromusers' smartphones. The app does not require human input as the whole process is flexible and customizable.

•To maintain the privacy and secrecy, we have to perform all recognition of activity and context inference on the phone siderather than on the centralized server, so that no data needshould be transmitted over the Wi-Fi network. We present energy-efficient algorithms that adaptively classify user's activities based on sensed by sensors , based on which we areable to infer higher level events to achieve this goal.

•In order to fulfill the needs of different users, we present asustainable mining model and extensible event mining model and thelogic language for rule-based event inferences, whereusers can follow their own inference rules for higherlevel event generation. These rules are written in a logicalmanner, which make them easy to write and modify. We also develop a feedback mechanism so that users can also provide optional opinions on the generated diaries, so thatthe system can learn continuously over time to improve itsdiary generating abilities. In the long term, we believe that this system we have developed will not only prove useful for people to recall their life events, but also will be very helpful for social studies where accurate user profiles of their activities are needed. Our evaluation results on Smart Diary illustrate that it has achieved its goals with reasonable performance.

• LITERATURE SURVEY

• *Activity Recognition using Cell Phone Accelerometers:*

In this paper we described how a smart phone can be used to performactivity recognition, simply by keeping it in ones pocket.We further showed that activity recognition can be highly accurate,with most activities being recognized correctly over 90% ofthe time. In addition, these activities can be recognized quickly,since each example is generated from only 10 seconds worth ofdata. We have several interesting applications in mind for activityrecognition and plan to implement some of these applications inthe near future.

- *Semantic Streams: A Framework for Composable Semantic Interpretation of Sensor Data:*

The framework presented in this paper provides a declarative language for describingand composing inference over sensor data. There are several benefitsto this framework. First, declarative programming is easier to understand thanlow-level, distributed programming and allows common people to query highlevel information from sensor networks. Second, the declarative language allows the user to specify desired quality of service trade-offs and have the query interpreter execute on them, rather than writing imperative code that must provide the QoS. Finally, the framework allows multiple users to task and retask the network concurrently, optimizing for reuse of services between applications and automatically resolving resource conflicts. Together, the declarative20 K. Whitehouse, F. Zhao, and J. Liuprogramming model and the constraint-based planning engine in our framework allow non-technical users to leverage previous applications to quickly extractsemantic information from raw sensor data, thus addressing one of the mostsignificant barriers to widespread use of sensor infrastructure today.

- *Activity and LocationRecognition UsingWearable Sensors:*

Here we come to know that what sensor is giving us what input and in what way. Using measured acceleration and angular velocity data gathered throughinexpensive, wearable sensors, this dead-reckoning method can determinea user's location, detect transitions between preselected locations,and recognize and classify sitting, standing, and walking behaviors.

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- *Activity Recognition from User-Annotated Acceleration Data:*

This paper suggests that how the sensors take input in different ways from the user. It also suggests that a mobile computer and small wireless accelerometersplaced on an individual's thigh and dominant wrist may be able to detect some commoneveryday activities in naturalistic settings using fastFFT-based feature computation and a decision tree classifier algorithm.

- *A Framework of Energy Efficient Mobile Sensing for Automatic User State Recognition:*

We used this paper to understand the energy consumption by the different sensors.Rich contextualinformation about users and their environment forhigher layer applications and services is provided by mobile device based sensing. However, the energy consumption by these sensors, coupled with limited battery capacities, makes it infeasible to be continuously running such sensors.

• SYSTEM DESIGN AND OVERVIEW

we first present a high level view of SmartDiary and then elaborate those components in details in thefollowing sections.The framework is shown in Fig. 1, which includes fourlayers: raw data collection, context analysis, event personalization,and diary generation. Through these four layers, SmartDiary captures important events according to users' preferences,and automatically generates diaries to the user.

- *Raw Data Collection:*

Smart phones are equipped with a wide range of sensors, that provide anideal platform for user's data collection. We are particularlyinterested in six representative data sources: motion activities,location data, app usage, calendar events, phone calls or SMSmessages, and web history.

- *Motion Activity:*

We compare the performance of using accelerometer alone versus using accelerometer and gyroscope together to capture motion activities. Based on ourinferences, we observe that it is sufficient to use accelerometerreadings alone to infer users' activities such as driving,walking, sitting, and playing games.

- *Location Data:*

The user's most visited places (such as office,restaurants, etc.) and commuting routes can be easily tracked by precise location readings.We use these locationsto deduce the location context of users' activities.

- *App Usage:*

The usage patterns of apps provide anattractive resource In order to identify a user's behavior, social activitiesand personal interest, the usage patterns of apps provide attractive resource. In our system, we record such activities over time to support dynamic inference of users' interest.

- *Calendar Events:*

As an explicit resource that reflectsusers' schema, the events in a calendar usually give us themost direct insight on the user's life, such as their businessmeetings, friend parties, and travel plans.

- *Phone Calls and SMS Messages:*

These informationsources provide us with the users' "off-line" social groupsand the interaction of the user with his/her friends via phonecalls and SMS messages.

- *Web History:*

History from the smartphone's browserhelps Smart Diary to learn and analyze those topics that the user is interested in, and monitor how the users' personal preferences change with time.

- *Context Analysis*

The context analysis layer takes the processed raw data collected in the lower layer as input, so that it may extract multiple types of events from the users' life. Each event is produced by a mining component, and we develop multiple types of mining components in the system. To better manage the reuse of resources, we propose a novel *sustainable mining model*, which decomposes a mining component's algorithm procedures into separate processing units. These units will continuously shuffle raw data, and provide the relevant ones to all the mining components where events are assembled. Specifically, we classify the events into three classes: entertainmentactivities, social activities, and health conditions.Processing of these events either adopts existing algorithmsor relies on user-specific logic rules.

- *Event Personalization*

However, the events extracted by the context analysis layer are purely objective. From the perspective of the users, however, some events are more meaningful than others. Event personalization, as its name suggests, allows Smart Diary to select those most interesting events for a user based on their preferences. Two major modules are involved in this layer: the ranking module and the filtering module. The ranking module calculates the importance based on our three criteria, then ranks these events. The filtering module only provides those most interesting events as output, which are handed over to the next layer for diary generation.

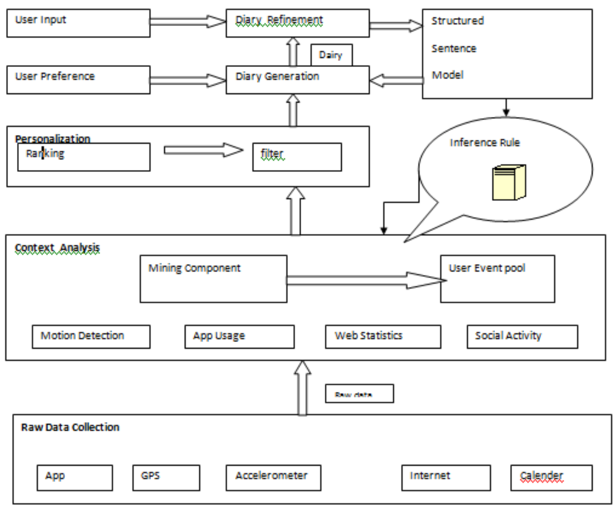

Fig 1.Framework of smart diary

• *Diary Generation*

Given the personalized events, this layer translates the Events into recognizable sentences. To facilitate this process, we develop a model called the narrative structured sentence model. One key feature of this model is that it uses regular expression formats to construct natural language sentence templates. During runtime, real event properties, such as the time of the day and the user's activities, replace these wild cards in the regular expression templates to generate diary outputs. Furthermore, to make language output natural, each type of events has multiple corresponding structured sentence templates for use. After diaries are generated, we also provide an optional stepwhere the user may provide additional feedback regarding thegenerated diaries. For example, the user may want to sharetheir sentence with other users or revise an existing sentence.In practice, this stage is not only useful for improving thequality of the diaries, but also for enhancing the narrativestructured sentence model by adopting better structured sentencesfor each event. Note that the raw data like sensorreadings and locations are not collected, the user's privacy concern has been preserved.

• RAW DATA COLLECTION

A smart phone is equipped with various types of sensors by which we can obtain heterogeneous data ranging from motion activities to location data. Among the various information sources, we choose the following types of sensors: the accelerometer, GPS location service, phone call history, SMS service, and app usage.Table I summarizes the types of raw data we collect to mine the user's behavioural patterns and daily activities. For instance, we use the accelerometer and location data to deduce whether a user is working in his/her office or driving on the highway. In short, we are interested in the "when-where-whowhat" aspect for each event, namely, what the user is doing, who is involved in, where the event happens, and when it happens. The simplest way to retrieve raw data, is to survey the source directly and periodically. For example, to detect the current active app used by the user we can set up a timer. The raw data coming out from the diverse sources may not be exactly periodical (e.g. the accelerometer in Android OS does not sample in equal rate due to restrictions of the Android operating system), the mining component may need different sampling frequency, and the loss of GPS signal may unexpectedly happen. Hence , we propose a layer of *middlebuffer* between the source and the raw data. Sensor source

TABLE I :THE RAW DATA DETAILS

Type	**Details**
Accelerometer	(timestamp, acc_x, acc_y, acc_z)
Location service	(timestamp, latitude, longnitude, speed)
Phone call/SMS	(timestamp, incoming no, outgoing no, duration)
App usage	(timestamp, app_name, duration)

often updates the readings in the middle buffer's memory, while the independent timers trigger the data collection on their own schedules. The collected data returns themost recently measurement. when data sources are unreliable this middle buffer is especially used: for example, if smartphone loses the GPS signal in an indoor atmosphere, as long as the user does not walk out of the building, theirlocation is still recorded as the last GPS update as they move inthe building because the middle buffer has not been changed.In such a way, we can still use the last updated data when the sensor is not responsive and we can sample the data in different frequency.Initially we used both accelerometer andgyroscope in our study to detect motions. We gathered 7 user's motion sensordata for about 1 month and asked them to label their motionactivity. Then we used the first half of the data to train ourclassifier, and use the rest of the data to test it. We calculatedthe standard deviation features of both accelerometer andgyroscope instead of using the original data values .Based on the experimental study, shown in Table II, weconclude that using the accelerometer alone is enough eventhough using both accelerometer and gyroscope sometimesachieves a slightly higher precision. The gyroscope's sampling rate is much higher than theaccelerometer, leading to much redundant data, which explainswhy there is only a 3% of accuracy increase. On the otherhand, keeping the gyroscope on will drastically increase theenergy overhead. Therefore, we make the trade-off by onlyreading the accelerometer.

- IMPLEMENTATION AND OUTPUT

In the beginning we installed Android studio and sdk for implementing our project. Thereafter we created many activites to build our Android Smart Diary Application. Initially we created Log In Activity. This activity is for a user who is not registered.Such user has to register for using Smart Diary Application. After Log In, the user will be able to see different sections like daily activity, sensors, contacts, browsing history, generate diary and make note. In daily activity, location of the user is tracked by the GPS and the location of user is stored. We have used two sensors namely proximity and accelelometer. All the browsing history which the user searches will be displayed in browsing history section. Browsing history can be different websites like social networking sites which may be facebook, twitter,etc. All this information from different sections is collected together and then in generate diary section, details of the collected information will be displayed. The final diary generation is shown in below figure:

Fig 2:screenshot 1

Fig 3:sceenshot 2

- DIARY GENERATION

- *The Narrative Structured Sentence Model*:

Here we describe the diary generation layer. Essentially, the problem is a variant of natural language processing (NLP) problem (e.g. "speech transcription"), except that here the signal source is not from the speech, rather it is from the events generated by the personalization layer. The traditional ways to handle the NLP problem can be divided into two categories: first is based on statistical methods, and the second is based on language grammar rules and semantics. However, none of the two approaches fit our problem well for the following reasons:

• The statistical NLP solution requires explicit data features to perform the classification tasks. Usually it needs a huge set of data (in GB size) to support the trainingphase for tasks which are complex, so that the output can be efficient. In the Smart Diary case, the source is a series of data which are inherently costly to collect (which requires deploying smart phones to a large population over an extended period of time). Therefore, it is difficult to build a large training data set.

• The second NLP approach is based on analysis of huge
amount of annotated data to achieve precision. However, with the limited memory and battery capacities of smartphones, we find this approach not suitable either. Therefore, we decide to follow an alternative approach where the events are directly translated into language through a novel and lightweight narrative structured sentence model.
The structured sentence model works as follows. It takes the
events generated from the previous layer as input, and chooses a pre-defined sentence template from a candidate list for this particular event. This sentence template comes with a list of sensitive fields that wait to be filled, which are represented by globally distinctive symbols. In other words essential fields of information are sensitive fields whose real values are decided in the diary generation step. As an example, we take a look at the following sentence:
Structured Sentence Template: You and * know each
other so well that you made % calls and spent an average
of % minutes on each call. Generated Sentence by Smart Diary: You and harsh know each other so well that you made 20 calls and spent an average of 55 minutes on each call.

ER Structure Natural Language ElementsER Structure Natural Language Elements
Entity Users,Nouns
Relationship Transitive Verbs
Attribute for Entity Adjectives, Intransitive Verbs
Attribute for Relationship Adverbs

This example will help us understand how this process works, suppose we want to represent a simple user activity: the user watcheda film last Monday evening. Such a description is straightforward in natural language, and can also be represented easily with the ER model as shown in
we consider that there are two entities, the user, and the film, both of which are nouns.The transitive verb "watch" is mapping to a relationship inthis ER model. The attribute, "last Monday evening", comes from the adverb on the description of the user activity. So generally, in our application domain, the generationprocess for the ER models is as follows. First, the entity is a noun, such as the user. When the user performs an action, this action will either be translated into a relationship or an attribute. Example, if the action is transitive, such as "the user calls a friend of his", this will be translated into a relationship;on the other side, if the action is intransitive, such as "the user goes jogging", it will be translated into attributes. A challenge when we apply the ER model is the original model was basically developed to describe static relations in databases. In the target domain of our's, however, the generated model is greatly affected by time, i.e., it should be evolving over time. The solution is to add a time dimension, so that the
ER model generated will change over the timeline. Therefore,we assume the ER model we use is a time-enhanced.Specifically, whenever we derive higher level user actions from the mining process, we also generate the corresponding ER model representations in XML formats. Such formats are not intended to be directly read by users, but provide a machine interpretable method.

A.Sentence Generating Process

In Smart diary the diary generation does not have to be done daily instead a user interface is provided to control the whole procedure.A time span selection of events is provided so that user can keep record of most interesting events within a day, month or year. The personalization layer chooses those events which are most related to the user's personal life based on the score ranking. When an event has multiple structured sentence templates to choose from, a *random selection* is done to pick one in equal chance. This selection approach is shown in algorithm 2. As we do not have prior knowledge of user's preference of language.

- *User Refinement*

We also provide an optional user refinement layer after thediary is generated so that the user may add personal

Diary Generation Process

Input: The personalized event sequence: events
Output: A Full diary of sequence of events:diary
1:Initial diary <-Ø
2:for all e in event seq events do
3: fetched structured sentences s by e.id
4: if s.size> 1 then
5: select sentence by random s.
Else
Sentence <- s.front.
Fill e. fields into sentene symbols.
Append sentence to diary
Return diary

Flavors to their diaries by providing additional feedbacks. Smart Diary integrates user inputs in the following manner. Once the diary is generated, a user may modify a sentence, which may lead to a new structured sentence template to be stored in the dictionary; or he may change some sensitive information directly, which, however, does not generate new structured templates. If a user prefers a certain sentence, then he can vote on this structured sentence template so as to increase the probability that this sentence will be selected in the future.

- SYSTEM PERFORMANCE

The performance evaluation consists of following three parts:

- *Experiment Setup*

The prototype of this Smart Diary app implements 12 events' mining components (MCs) and 12 structured sentence templates in the deployed application. Among these events, 6 belong to the entertainment activity category, 3 belong to the social activity category, and 3 belong to the health condition category. The above experiment consists of two parts:

- The performance of our motion recognition

Component is evaluated

- We evaluate the end-to-end diary generation.

- *Diary Quality*

Here the user is required to log in his major events that happened during the day, so that he can obtain ground truth for his evaluation purpose. Smart Diary generates the diaries sentence by sentence for each of the users events. Using the BLEU precision score and the METEOR score we evaluate the output of smart diary app. The results are shown in by category. The METEOR score implies that the entertainment category obtains the lowest score while the BLEU implies it is the highest. This is quite normal because the two objective score systems have different focuses, and the small-scale deployment only have 12 structured sentences whose performances may vary a lot based on different criteria. In overall, all three categories in total have an average score at 0.5, which, according to the suggested use of BLEU and METEOR scores, reflects acceptable performance for the target experiment.

- *Application Performance*

Battery level

The energy consumption here is critically important because it is a Smartphone application. To evaluate the energy efficiency of Smart Diary, the battery level curve indicates that the battery life stays more than 11 hours before dropping down to 30%, which is reasonably good given that many people have the habit of recharging during the night in their daily lives. The dynamic energy consumption of the smartphone when Smart Diary is deployed is around 250 mW. Comparing to the average usage range of [200,1100] mW [9], it is reasonable to say that Smart Diary is lightweight and energy efficient Hence , it is safe to conclude that the Smart Diary app performance is competitive to other widely used Apps in Android.

• CONCLUSION

In this we have discussed the motivation, plan, implementation and estimation of Smart Diary, an integrated sensing framework that integrates mobile data analysis, human activity inference, and natural language processing on the smart phone platform. Our preliminary evaluation results on the working prototype are thrilling. We have demonstrated that the system works as desired in that it may infer people's daily life devotedly and generate dairies automatically and flexibly according to user's preferences. In the future, we hope that this app can further expand the types of MCs by adding more inference rules, develop more possible ways to display man's daily activities, and make the sensing framework to be publicly available

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