Building Health Persona from Personal Data Streams

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ABSTRACT
Most people already use phones with myriad sensors that continuously generate data streams related to most aspects of their life. By detecting events in basic data streams and correlating and reasoning among them, it is possible to create a chronicle of personal life. We call it Personicle and use this to build individual Health Persona. Such Health Persona may then be used for understanding societal health as well as making decisions in emerging Social Life Networks. In this paper, we present a framework that collects, manages, and correlates personal data from heterogeneous data sources and detects events happening at personal level to build health persona. We use several data streams such as motion tracking, location tracking, activity level, and personal calendar data. We illustrate how two recognition algorithms based on Formal Concept Analysis and Decision Trees can be applied to Life Event detection problem. Also, we demonstrate the applicability of this framework on simulated data from Move app, GPS, Nike fuel band, and Google calendar. We expect to soon have results for several individuals using real data streams from disparate wearable and smart phone sensors.

Categories and Subject Descriptors
H.1.2 [Models And Principles]: User/Machine Systems – human factors, human information processing; H.3.5 [Information Storage And Retrieval]: Online Information Services – Web-based services; H.3.4 [Information Storage And Retrieval]: Systems And Software – User profiles and alert services;

General Terms
Management, Design; Human Factors

Keywords
Health Persona; Wearable Sensors; EventShop; Personal EventShop; Health and Wellness; Life Event; Personicle

1. INTRODUCTION
It’s well known that the amount of money spent on health care in United States is extraordinary. Yet the outcome is not. Chronic Diseases account for up to 96% of Medicare spending and complications from chronic diseases account for 75% of overall US healthcare spending [33]. 20 million Americans have Diabetes. 20 million Americans have Kidney disease [45]. An estimated 80 million Americans have one or more types of heart disease. In 2008, the total cost of cardiovascular diseases (coronary heart disease, hypertensive disease, heart failure and stroke) in the U.S. was estimated at $448.5 billion. [46]. 2 of 3 Americans are overweight; 1 in 5 is Obese [47]. Due to population growth, aging, and other factors; it is projected that demand for physicians will outpace supply by 2025 [48]. Simply educating and training more physicians will not be enough to address these shortages.

One solution for this problem is in pervasive technologies that rely on convergence of ubiquitous sensing, cloud computing, wireless connectivity, social networks, fitness devices, and wearable sensors. With the emergence of wearable sensors big data can be the tiny device one wears to track his movement, calories and sleep for tracking his personal health and fitness. Advances in low power wireless communications, MEMS (Micro Electro-Mechanical Systems) and multi-sensor arrays have resulted in viable body area network applications for clinical patient monitoring, assisted care, at-home chronic disease management and general wellness, at the same time, there has been enormous growth for mobile sensing apps for smart phones and tablets. By 2017, there will be 1.4 billion mobile health and fitness apps being download worldwide [49].

Data collected from wearable sensors and mobile apps is incredibly powerful. Numbers measure, define and shape our existence every single day. However, numbers alone can’t lead or motivate all individuals to pursue a healthier life style. To improve one’s health insights into her habits and life patterns is the first step. All data from mobile phones, wearable sensors, environmental sensors, personal calendar and social networks are available but we still lack computational frameworks to unify and process such heterogeneous streams to provide actionable insights. In this paper we address more detailed aspects of observing and analyzing all data sources to get objective self health information and identify needs to build a powerful platform to accomplish this. The system should be able to help answer questions like: how my activity level is affected by my daily schedule or weather change? Or, in which events or situations I am most stressed out? By tracking multiple metrics, we can correlate them and gain insights. For example, we can determine the effect activity level has on sleep quality, or that mood has on productivity levels. In fact interesting insights can be gained by examining the co-occurrence of temporal patterns in data streams. We call individual health characteristics Health Persona and describe it in more details in the next sections.

EventShop [50, 51] is a generic situation detection framework that focuses on combining heterogeneous real-time data streams into actionable situation. The framework supports data from different sources and continuously ingests spatiotemporal data streams and converts them to E-mage streams. Multiple operators are provided for analysis and characterization of temporal E-mage streams. EventShop is a societal situation recognition engine. Research presented in this paper is to collect, manage, and correlate personal data in Health Persona framework in order to detect personal situations. In other words, we propose Personal EventShop as a wealth of representational and computational
techniques that collect and correlate temporally asynchronous data streams from heterogeneous sources and include them in continuously refining the Health Persona. This platform should have appropriate data ingestion and data unification components and analytical tools to detect structural patterns and relevant data properties. Schematic diagram of personal EventShop is illustrated in figure 1.

Figure 1. Micro situation detection in Personal EventShop

In this paper, we particularly address the following:

1) Design a framework to define relationship between data from sensors (wearable physiological sensors and logical sensors) and life events/activities.
2) Define methods to map variable dimensional sensor data to four event categories that are related to life events.
3) Create a chronicle of life events called Personical as a higher level of abstraction of person’s life history.

2. HEALTH PERSONA FRAMEWORK

Users are unique; they have different background, health status, behavior, preferences, goals and interests. In order to personalize any communication with user, a model of the user should be prepared and maintained. User modeling and user profiling have been studied extensively in Human Computer Interaction, Expert Systems, Recommendation Systems, Adaptive Learning Systems, etc. We are witnessing an unprecedented revolution in digitizing human species, from gene sequencing to continuous monitoring of vitals. The trend to equip people with low-cost sensors and mobile devices, and collecting the sensed data and experiences exchanged on social media, generates massive amount of data that spans physical, cyber, and social worlds. As this trend moves away from simple static user profiles, the need to capture evolving nature of human's characteristics in more sophisticated models becomes more important. We utilize spatio-temporal-thematic data streams collected from sensors and mobile devices to create the persona that may be used in different contexts. Persona is the mask or appearance a person presents to the world [39]. A persona models relevant aspects of a person involving characteristics, professional, social, health, preferences, and interests. In this paper we focus on Health aspect to create Health Persona. The data streams that we use are related to many sensors now being used by people to collect fitness data, personal events, eating habits, sleep patterns, and every day activities using wearable sensors, mobile phones, calendar, and social networks. A high level schematic view of Health Persona is shown in figure 2.

2.1 Wearable Sensors

The availability of low-cost sensors and mobile devices for monitoring physiological, physical, environmental, and cognitive health—on humans [37, 38] and around humans [31] — are revolutionizing healthcare. Sensors such as Microsoft Kinect and on-board sensors on mobile phones are being increasingly adopted in assisted living environments for monitoring daily activities [26, 29], fall risk assessment and mitigation [44, 40]. Ingestible sensors are being developed that may change diagnosis and understanding of disease progression radically. Food and Drug Administration (FDA) has approved the first ingestible sensor by Proteus Digital Health for monitoring compliance with medication [41]. Qualcomm has a major effort in mobile health called Qualcomm life [42], and similarly, Verizon has a digital healthcare suite since 2011 [43].

We use the notion of logical sensors from [31] to capture context information. We divide wearable physiological sensors in two categories: Vital sign monitoring sensors and Motion detection sensors. Table 1 summarizes sensor types and examples of each category.

Figure 2. High level view of Health Persona framework.

<table>
<thead>
<tr>
<th>Table 1. Different types of sensors.</th>
</tr>
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<tbody>
<tr>
<td><strong>Vital Sign Monitoring Sensors</strong></td>
</tr>
<tr>
<td>Blood Pressure</td>
</tr>
<tr>
<td>Heart rate</td>
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<tr>
<td>Saturation of peripheral oxygen (SpO2)</td>
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<tr>
<td>Body Temperature</td>
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<tr>
<td>Electrocardiography (ECG)</td>
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<tr>
<td>Electroencephalography(EEG)</td>
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<tr>
<td><strong>Motion Detection Sensors</strong></td>
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<tr>
<td>Accelerometers</td>
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</table>

2.2 Events

Data is continuously collected from asynchronous data streams from heterogeneous sources. We use events as unification mechanism and combine these discrete events in one schema.
Health Persona should be viewed as a wealth of representational techniques that model the person’s health and fitness related aspects using analytics on multidimensional signals. The proposed paradigm discovers co-occurrence of temporal patterns in different event categories to define persona.

Note that the term event is sometimes used to refer to a large-scale activity that is unusual relative to normal patterns of behavior, such as a large meeting in a building, a malicious attack on a Web server, or a traffic accident on a freeway. Sometimes people use event in a different manner, by referring to individual measurements or observation called point events (e.g., the recording of a single person walking through a door at a particular time, or the activity level measurement of a single person at a particular time). However, in our work we only pay attention to interval events. We consider event as a real world observable occurrence of some phenomena that unfold over space and time.

For events, we use time as the primary independent variable in all our analysis.

As shown in the framework in Figure 2, we define four categories of event: Life Event, Kinetic Events, Food events, and Physiological Events. To construct the event signal from observations we use robust estimation process. The central thesis behind this work is that all data streams are inherently correlated and are related to underlying natural processes. By processing, aggregating, connecting, and visualizing data the underlying process may be discovered. In this paper we focus on detection of Life Events and leave the other three event categories for future work.

3. LIFE EVENTS

Tracking and identifying of daily activities has been investigated in different research areas. A number of researchers have investigated activities of daily living (ADL). Mihailidis et al [7] has successfully used cameras and a bracelet to infer hand washing. The system discussed in [8] used contact switches, temperature switches, and pressure sensors to infer meal preparation. Several sensors like motion sensors, pressure pads, door latch sensors, and toilet flush sensors are used to infer behavior reported in the system described in [9]. The idea of a “life-log” or a personal digital archive is a notion that can be traced back at least 60 years [10]. Since then a variety of modern projects have spawned such as the Rememberance Agent [11], MyLifeBits [12], Memories for Life [13], and What Was I Thinking [14]. In [15] the authors evaluate the user’s context in real time and then use variables like current location, activity, and social interaction to predict moments of interest. Audio and video recordings using a wearable device can then be triggered specifically at those times, resulting in more interest per recording. Some previous examples of this approach are the Familiar and iSensed systems [16, 15] which structure multimedia on the fly; the eyeBlog system [17] which records video each time eye contact is established; and the SenseCam [18] which records images and sound whenever there’s a significant change in the user’s environment or the user’s movement. Life log includes people’s experiences which are collected from various sensors and stored in mass storage device. It is used to support user's memory and satisfy user's needs for personal information. If he wants to inform other people of his experience, he can easily share his experience with them by means of providing his life log.

Sensor functionality continues to improve significantly. Future smartphones will incorporate new sensor types such as biometric, pressure, and environmental sensors. Analysts project the smartphone and tablet industry will soon consume over $2 billion of sensors annually [3]. However, to use this data to gain actionable insights, there are several challenges. Some of these are: (1) the selection of the attributes to be measured, (2) the construction of a portable, unobtrusive, and inexpensive data acquisition system, (3) the design of feature extraction and inference methods, (4) the collection of data under realistic conditions, (5) the flexibility to support new users without the need of re-training the system, and (6) the implementation in mobile devices meeting energy and processing requirements [23].

The recognition of human activities has been approached in two different ways, namely using external sensors and using wearable sensors. In the former, the devices are fixed at predetermined points of interest in the environment. The inference of activities entirely depends on the voluntary interaction of the users with the sensors. In the later, the devices are attached to the user. Intelligent homes [19, 20, 21, 22] are a typical example of external sensing. These systems are able to recognize fairly complex activities (e.g., eating, taking a shower, washing dishes, etc.) because they rely on data from a number of sensors placed in target objects which people are supposed to interact with (e.g., stove, faucet, washing machine, etc.). Nonetheless, nothing can be done if the user is out of the reach of the sensors or they perform activities that do not require interaction with sensors. Additionally, the installation and maintenance of the sensors usually entail high costs.

The above limitations motivate the use of wearable sensors in Life Event Recognition. Most of the measured attributes are related to the user’s movement (e.g., using accelerometers or GPS), environmental variables (e.g., temperature and humidity), or physiological signals (e.g., heart rate or activity level). These data are naturally indexed over the time dimension.

To make use of the heterogeneous data streams for detecting Life Events, we need to design a unified data model to integrate these data streams. The solution is based on the understanding of the fundamental nature of data streams from real-world observation about an individual’s activities. As the world is dynamic and the events in the world are evolving, these events are detected and best captured as a stream of data, where the latest event data gets appended to the stream.

We are living in a spatio-temporal world. Meaning, all of our life events except dreams happen in a specific location and at a specific time. Based on the current available technologies, it is not always possible to sense the location, because location sensors such as GPS do not function in every environment. For instance, a GPS cannot function in indoor environments. There are other approaches such as A-GPS (Assisted GPS) to solve this problem, but they are not always able to sense location, and they are imprecise. On the other hand, most operating systems have date-time, which is accessible as long as the target device has not been turned off. This means most devices with computing capabilities can provide time-stamps. Therefore, we use time as the primary field for any event entry, and all information objects will be stored with the time-stamp. It leads us to believe that a timeline structure is naturally suitable representation for various temporal data. We can further divide timeline into time units. Examples of time units are: days, hours, minutes, etc. The size of a unit is defined as the number of minutes in the unit. Some useful unit sizes can be defined in the system: DAY_UNIT_SIZE, HOUR_UNIT_SIZE, FIFTEEN_MINUTE_UNIT_SIZE and FIVE_MINUTE_UNIT_SIZE.
Life Event recognition problem is temporal partitioning of time \( P : < P_0, P_1, \ldots, P_n, \ldots > \) using heterogeneous data streams such that each \( P_i \) is allocated to one of the activities/events. We assume temporal partitions to be non-overlapping and only one activity can happen in each partition. Since the duration of each event is unknown, finding transition points between partitions become a hard task. To overcome this problem we use the timeline structure mentioned before and divide it to fixed length units. Hence, given the input streaming data Life Event will be detected for each time unit.

We define the life event recognition problem as follows:

**Life Event Recognition:** Given a set \( S = \{ S_1, S_2, \ldots, S_m \} \) of equally sized time units such that each unit \( S_i \) contains a set \( I \) of \( k \) input signals, \( I_i = \{ I_{i1}, I_{i2}, \ldots, I_{ik} \} \) each signal is from one measured attribute (motion, activity level, scheduled events, etc) and \( L = \{ l_1, l_2, \ldots, l_f \} \) is a set of labels representing life activity/event names (e.g. meeting, commuting,...) that comes from an activity ontology. The problem is to map each time unit given the set of input signals to an activity name. Function \( f \) shows this mapping \( f : I_i \rightarrow L \) such that \( f(I_i) \) be the abstraction of the life event at time unit \( S_i \).

Furthermore, one or several sources of information can contribute to one measured attribute \( I_{wi} \), \( i=1,2,\ldots,k \). In other words each \( I_{wi} \) has a set of registered sources \( C_i=[c_{i1}, c_{i2}, \ldots, c_{in}] \) where the output combination of them determines the value of input signal \( I_{wi} \).

\[
I_{wi} = I_{wi1} \cup I_{wi2} \cup \ldots \cup I_{wim}.
\]

Where \( \Phi \) is a logical or mathematical operation.

From life logging literature [24] we derived a list of 30 target activities and created activity ontology (Figure3) using Protégé [6]. These activities were chosen base on their time dominance, generality, and their high frequency.

In this paper we use motion tracking and location tracking from mobile phone GPS and Moves application [25], scheduled events from the person’s Google calendar, and activity level data stream from accelerometer sensor in Nike Fuel band and FitBit devices. Moves is an app on iOS that geo-locates user movements throughout the day. It analyzes core motion data to identify if the person is walking, running, cycling or taking another form of transportation. System knows geo-location of user’s home and work place. Also GPS data is collected every 5 minutes from user’s smart phone. Using latitude and longitude coordinates and reverse geo-coding, system can determine if the person is in a shopping place, mall, coffee shop or restaurant. Also, time as logical sensor is used to distinguish if the eating event is breakfast (before 11am), lunch (11am-3pm), or dinner (after 3pm). With respect to the sources of information we use in the current version of our work, we focus on the following activities: Walking, Running, Cycling, Driving, Meeting, Exercise, Eating, Shopping, and Working.

Figure 4 shows the schematic approach of creating Life Events from four data streams. Personal History is as an enrichment element for our model. Through time system detects more Life Events. Hence the history data can be used as an insight about person’s life style. What time does he usually eat? How does he usually commute to work? Whether he works out regularly or not? This kind of information can be collected as Personal History and be used in detecting future Life Events more accurately.

### 3.1 Life Event Recognition Methods

According to Chen and Nugent, activity recognition algorithms can be broadly divided into two major strands [26]. The first
strand uses machine learning techniques based on probabilistic and statistical reasoning. The second strand of algorithms is based on logical modeling and reasoning. The majority of the current techniques use the first approach, whose major strength is capability of handling noisy, uncertain and incomplete sensor data. Also in general machine learning techniques can be divided into supervised and unsupervised learning methods. There exists a wide range of algorithms and models for supervised learning. Commonly used methods in the context of activity recognition include Naïve Bayes classifiers [27, 28], C4.5 decision trees [27, 29], and nearest neighbor methods [30]. Hidden Markov Models (HMMs) are well-suited for capturing temporal patterns in the data, but can be difficult to train due to an abundance of parameters [30, 34]. Nam et al [35] create an activity recognition that classifies the individual activity signals and then apply a rule-based information combination method on the results of classification. Patterson et al [36] use unsupervised learning schemes based on graphical models. Their focus is on inferring transportation modes (such as bus, car, walking) and destination goals of the user. Huynh et al [30] use the concept of multiple Eigenspaces for unsupervised learning of activities such as walking or juggling.

Mittal et al [31] has an interesting approach using concept lattice for situation recognition of an elderly person living alone in a sensor rich environment and possible situations of person are described in terms of coexisting contexts. Formally, concepts are a pair of a set of objects (extent) sharing a set of attributes (intent). The concept lattice organizes the whole set of formal concepts as partial ordered sets. For Situation Recognition, it is assumed that a set of current context of entity is given and target situation needs to be identified. The proposed approach is to traverse the concept lattice from top element and move downwards till intent of the concept associated with the node, matches the set of given context. Once such concept is found the extent of this concept is the recognized situation. We utilize concept lattice and decision tree as recognition techniques, as discussed below.

3.1.1 Life Event Recognition Using Concept Lattice
Various sensors such as motion tracking, location tracking, activity level and, scheduled calendar events can be utilized to detect a subset of activities in activity ontology. The symbolic names of input signals and situation descriptions in terms of those input signals are shown in Table 2.

For example if input signals are (Location: Home V Work) AND (Activity level: Sedentary V Low) AND (Calendar: Meeting) AND (Duration: > 15min) THEN the Life Event is “MEETING”. It’s important to note that if only the calendar entry is marked as meeting event, it doesn’t imply that person is in meeting. But other signals such as activity level play an important role here since probably person in a meeting doesn’t have considerable motion and activity level is low. Of course it might be a case that person has a meeting while she is having lunch in a restaurant or while she is walking outdoor. But in the current version we assume that activities are non-overlapping and only one activity can happen at each time segment. The lattice from table 2 is constructed using ConExp [32] software and result is shown in figure 5. Each concept is a pair of extent (situation) and intent (input signal). From cross table all possible formal concepts can be extracted and organized as a lattice. This lattice is maintained in memory and later can be navigated to extract situations.

3.1.2 Life Event Recognition Using Decision Trees
A decision tree is a rooted tree with internal nodes corresponding to attributes and leaf nodes corresponding to class labels. Internal nodes have a child node for each attribute value. The learning element generates a tree recursively by selecting the attribute that best splits the examples into their proper classes, creating child nodes for each value of the selected attribute, and distributing the examples to these child nodes based on the values of the selected attribute. The algorithm then removes the selected attribute from further consideration and repeats for each child node until producing nodes containing examples of the same class. It is also possible to further process trees into decision rules. Most implementations use a measure based on the information gain, called the gain ratio, for attribute selection [4]. Decision tree can be constructed by hand but they are typically learned. For learning decision trees we need a training set containing input signals and labeled activity for each time segment then algorithms such as C4.5 can be used to construct the tree from examples. The general form of a hand constructed decision tree for this problem is illustrated in Figure 6. Once the relationship is extracted, then one or more decision rules can be derived that describe the relationships between input signals and activities.

4. PERSONICLE
One of the first notions to be fixed in a temporal context is the time domain, that is, the set of primitive temporal entities used to define and interpret time-related concepts [1]. In our context given a set \( S = \{S_1, S_2, \ldots, S_n\} \) of equally sized time units, the time domain is the pair (\( S \leq \)), and \( S \leq \) is the order on \( S \). Intuitively time unit \( S_1 \) is before \( S_2 \) so \( S_1 \leq S_2 \).
We know that person’s life in real life is a combination of different activities. For example, by relying only on GPS data, we might conclude that person was walking behind the desk or attending meetings the whole time at work. However, having a boost in activity level reveals that person was exercising for a period of time. Because the gym location is inside the work building, GPS data was misleading.

5. CONCLUSION

Wearable sensors integrate themselves into people’s life in pleasant little ways. Functionality of these sensors continues to improve significantly. All data from mobile phones, wearable sensors, environmental sensors, personal calendar and social networks are available but computational frameworks to unify and process such heterogeneous stream to provide actionable insights are needed. For each individual, information contained in personal data streams is correlated. Each source of information adds one dimension to personal data and we are warehousing time series of multidimensional feature vectors. The central thesis behind this work is that all data streams are inherently correlated and are related to underlying natural processes. By processing, aggregating, connecting, and visualizing data the underlying process may be discovered. We propose a framework to map data streams from disparate sensors to four pre-defined event categories.

This paper is a continuation and refinement of our earlier preliminary work [2] on Health Persona framework and focuses on Life Events definition and detection problem. We illustrate how two recognition algorithms based on Formal Concept Analysis and Decision Trees can be applied to detect Life Events for each time unit. Also Personicle concept is introduced as an abstraction of one’s life history in which Life Events play an important role.

In future work we will continue analyzing the above mentioned event categories to extract time correlations and temporal patterns among them. Hereupon actionable insights hidden in personal data may be revealed.

6. ACKNOWLEDGMENTS

We would like to thank Parul Seth for proposing the term “Personicle”.

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Table 2. Life Event description in terms of input signal streams

<table>
<thead>
<tr>
<th>Input Signals</th>
<th>Location</th>
<th>Motion</th>
<th>Activity Level</th>
<th>Calendar</th>
<th>Time</th>
<th>Duration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Life Events</td>
<td>Home</td>
<td>Work</td>
<td>Restaurant</td>
<td>Mall</td>
<td>Unknown</td>
<td>Walking</td>
</tr>
<tr>
<td>Meeting</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Walking</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Running</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cycling</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Working</td>
<td>X</td>
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<tr>
<td>Eating</td>
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<tr>
<td>Breakfast</td>
<td>X</td>
<td></td>
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<td></td>
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<tr>
<td>Lunch</td>
<td>X</td>
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<tr>
<td>Dinner</td>
<td>X</td>
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<tr>
<td>Shopping</td>
<td>X</td>
<td>X</td>
<td></td>
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<td></td>
<td></td>
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<tr>
<td>Driving</td>
<td>X</td>
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</table>

As mentioned in Life Event Recognition definition $f(I_i)$ is the abstraction of the life event at time $S_i$. Given a set $F=\{f(I_1), f(I_2), ..., f(I_n)\}$ of abstracted life events, $G$ is a grouping operator that combines a few subsequent Life Events that have the same event label. In other words $G(f(I_i), f(I_j))$ is valid if:

- $f(I_i) \leq f(I_j)$ and there does NOT exist a $f(I_k)$ such that $f(I_i) \leq f(I_k) \leq f(I_j)$
- $f(I_k)$ and $f(I_j)$ have the same activity label from activity ontology

For example if considering each time unit to be 15 minutes and $f(I_1) =$“meeting”, $f(I_2) =$“meeting”, and $f(I_3) =$“meeting” then by grouping these three subsequent time units together we will have a meeting event which spans over 45 minutes interval.

The collection of Life Events after applying grouping operation is called Personicle. A Personal Chronicle of life events. A chronicle means “a record or register of historical events in chronological order”. Since we detect and store the abstracted life events of person through time, we call it Personicle.

In this paper we use location tracking from mobile phone GPS and Move application [25], scheduled events from person’s Google calendar, and activity level data stream from accelerometer sensor in Nike Fuel band and FitBit devices. Using these data streams and utilizing a decision tree or concept lattice, it’s conceivable to recognize Life Events and label them with the activity ontology. Figure 7 shows a Personicle creation for one day time interval using simulated data. We know that calendar represents scheduled events, not those actually happened in real life. So while calendar shows that person is in a “meeting with development group”, from GPS location and activity level it is apparent that person was walking. Hence “meeting” Life Event is not exactly aligned with meeting interval from calendar. This indicated that looking at only one source of information might be misleading. For example by relying only on GPS data, we might conclude that person was working behind the desk or attending meetings the whole time at work. However having a boost in activity level reveals that person was exercising for a period of time. Because the gym location is inside the work building, GPS data was misleading.
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