Abstract

Despite the advent of wearable devices and the proliferation of smartphones, there still is no ideal platform that can continuously sense and precisely collect all available contextual information. Mobile sensing data collection approaches should deal with uncertainty and data loss originating from software and hardware restrictions. We have conducted life logging data collection experiments from many users and created a rich dataset (7.5 million records) to represent the real-world deployment issues of mobile sensing systems. We create a novel approach to identify human behavioral motifs while considering the uncertainty of collect data objects. Our work benefits from combinations of sensors available on a device and identifies behavioral patterns with a temporal granularity similar to human time perception. Employing a combination of sensors rather than focusing on only one sensor can handle uncertainty by neglecting sensor data that is not available and focusing instead on available data. Moreover, we demonstrate that using a sliding window significantly improves the scalability of our analysis, which can be used by applications for small devices such as smartphones and wearables.

1 Introduction

The proliferation of smartphones and, more recently, wearable devices such as fitness trackers and smart watches equipped with sensors, has led to a significant expansion of possibilities to study human behavior. Computing and networking capabilities of these devices within their multiple sensors makes them capable enough so we can easily observe and collect useful contextual information (mobile sensing). For instance, mobile health, which benefits from mobile sensing, offers the possibility of a shift from treatment to prevention in medical care systems. Researchers show that 69% of U.S. adults monitor and track their health status and 21% of them use technology for this purpose [8]. Unlike wearable devices, which are still quite new in the market, the smartphone platform has benefited from a significant amount of scientific work ranging from personal air pollution footprint trackers applications [15] to well-being [13]. Both wearable devices and smartphones are very capable of sensing and collecting basic patterns of human behavior and collecting contextual information.

While human behaviors are predictable, at least in aggregate [1], traditional approaches for detecting human behavioral patterns (which are not digital) are often difficult. However, the advent of these ubiquitous devices enables researchers to identify human behavior to an extent that was not previously possible. On one hand, this information collection paradigm should be moved from simple data collection tools to intelligent systems with cognition capabilities [4]. On the other hand, there is still a lack of wide acceptance of mobile sensing applications in real-world settings.

There are several reasons for this mismatch of capability and acceptance. First is the resource limitation and lack of accuracy in the collected contextual data, especially with regard to the battery life [24]. The size of sensors that are dealing with radio frequency, i.e., Bluetooth, WiFi and GPS, affects the quality of their data [22] (smaller devices have less accurate data). The next reason, which has been noted but has not been widely explored, is the proximity of the smartphone to users [5]. Smartwatches and wearables are body-mounted and thus the proximity problem has been resolved in those devices, but they still suffer from a lack of accuracy [12].

The third reason for this problem is operating system restrictions of mobile devices, which removes background services when the CPU is under a heavy load in order to preserve the battery life. As a result, there is no ideal data collection approach that can sense and record individuals information 24/7 with no data loss. The uncertainty of these data objects is a major challenge that limits the applications that can benefit from them.

Existing research [6, 11] on mobile sensing data has of-
ferred tentatively promising results, but does not address the uncertainty that exists in a real-world deployment. These studies employ specific hardware which is known for data quality among users; for example, Reality Mining [6] uses Nokia N6600 and the Lausanne data campaign [11] uses Nokia N95. Since in the real world there are different phone brands and each device has its own restrictions and specifications in terms of software and hardware, we believe these experiments do not consider all aspects of a real-world deployment.

To resolve the data collection uncertainty in mobile sensing data analysis, here we introduce a novel algorithm that benefits from the variety of sensors on the device, and by leveraging previously-collected data it can predict human behavior with a temporal granularity similar to the human perception of time. The algorithm mines users’ activities, which have been collected from different device sensors, and is able to create a profile. The profile can be used for prediction and application-specific purposes. In a more technical sense, this research has the following novel characteristics:

- **Realistic Data:** We argue that the dataset we have created is the most realistic life logging dataset created to date in comparison with other mobile sensing datasets, such as [6] and [11]. Although these studies provide promising results, their data collection is hardware-specific. We claim our approach is very similar to a real-world deployment for the following reasons: (i) Unlike existing research, our experiment did not hand over specific hardware to participants. We relied on users’ Android smartphones, which are different brands with different hardware capabilities and different sensors, and this is a significant challenge for data collection. (ii) We asked volunteers to participate in our experiment. This presents a drawback in that about 2/3 of participants removed themselves from the experiment, but we managed to finish the experiment with an acceptable number of participants: 33.

- **Temporal Granularity:** Human understanding of time is not precise, unlike digital systems. Our daily behaviors occur in time intervals. For instance, a person does not arrive at work every day at exactly the same time, or eat lunch at exactly the same time every day. There is always a time interval for routine behaviors, even if only a small interval, e.g., five minutes for a precise time scheduled such as a meeting. Therefore, there is a need for flexibility in temporal analysis. We implement this important requirement by introducing a simple human-centric temporal granularity method. Our data analysis and algorithms use this temporal granularity instead of the original timestamp.

- **Uncertainty:** Although some behaviors such as mobility are highly predictable [26], due to the lack of sensor accuracy and data loss, there is always uncertainty in sensing and collecting contextual data. As a result, there is a need for methods that are able to cope with uncertainty. The algorithm we propose here is able to handle uncertainty via (i) its support for multiple sensors (heterogeneous information sources), i.e., a combination of sensors are more reliable than focusing on one single sensor; (ii) a user-defined confidence for motif detection (i.e., increasing confidence increases precision but decreases support); and (iii) focusing only on intervals which have similar or repeated data and neglecting the rest.

- **Heterogeneous Data:** A salient advantage of our algorithm is its semantic independence, which does not consider the type of the underlying sensor data. This makes the algorithm capable of running in any settings that deal with uncertainty and have multiple source of information. It can use any information source (sensors) that has data with a timestamp, whether a continuous timestamp or discrete timestamp. This demonstrate the reliability of the algorithm and makes it applicable to different problem domains.

- **Unsupervised:** In the real world it is hard or impractical to obtain a ground truth for supervised learning or to expect users to assist in bootstrapping and training a system with their labels. Recently, researchers tried to tackle this issue by employing a small amount of labeling at the beginning and creating a data dictionary [3 4]. Our approach is completely unsupervised and thus easily applicable to the real-world setting.

The contributions of our work are listed as follows: (i) an algorithm for converting digital timestamp to a temporal representation similar to human temporal cognition; (ii) a model that quantifies human behavior based on sensor data; and (iii) algorithms that will be used to exploit daily-life behavioral motif from raw sensor data and their evaluation from three different perspectives, including when to run the algorithm.

The remainder of this paper is organized as follows. First we start by describing the dataset and its characteristics. Then we formalize the problem. Next, we describe the design and implementation of our algorithm; this is followed by the experimental evaluation. Afterward we explain related work and conclude this paper.

2 Dataset

We relied on participants smartphones and collected a life log dataset from each participant. To create
such a dataset, we used UbiqLog [23], which is open source and has proven to be resource efficient via [20]. Despite the difficulty in doing so, we asked only students who were willing to collect data about their personal lives to participate in our data collection experiment. To preserve participants privacy, UbiqLog is designed in such a way that participants can disable or enable sensors at any time. Due to technical difficulties and privacy issues we ran the experiment twice; this paper uses the dataset for the second experiment. There were 33 participants, whom 22 are female and 11 male, with ages ranging from 19 to 22 (Mean 21.2, SD=1.7). They collected their data for about two months. We asked participants to enable the following sensors: WiFi, Bluetooth, Location, Application Usage, Call, SMS and Activity (which has been extracted from Google Play Services: on foot, on bicycle, in a vehicle, tilting and still). Since at the time of running the experiment, late 2013 and early 2014, Google play services had not been widely adopted among smartphones, few participants provided activity data. Therefore, we ignored this activity sensor and removed it from our analysis. Contact numbers in Call and SMS were stored with pseudonymization and SMS content was completely anonymized.

Figure 1: Three-day visualization of user data.

| Sensor Name            | Num. of Instances | Discarded Instances |
|------------------------|-------------------|--------------------|
| WiFi                   | 5937220           | 84                 |
| Location               | 612442            | 14                 |
| SMS                    | 28124             | 180                |
| Call                   | 96567             | 7                  |
| Application Usage      | 750695            | 16                 |
| Bluetooth Proximity    | 84109             | 22                 |
| All Data Instances     | 7509157           | 323                |

Table 1: Dataset records for each sensor.

3 Definitions and Problem Statement
We live in a spatio-temporal world and all of our behaviors occur in a specific location and time. Therefore, a digital system for quantifying human behavior should sense both time and location. Since location sensors such as GPS are not reliable (especially indoor) and it is not possible to collect their data 24/7, we can only use time to link different information together. Human behavior is composed of many daily activities that are distinctive and recurring. These types of activities have been called motifs (or life routines [6]) and our goal is to create a user profile that summarizes the behavioral motifs of a person.

We define entity as a unit of human activity. It is a tuple of three $e =< T, S, D >$. Each entity contains a timestamp, $T$, sensor name, $S$, and sensor data, $D$. The first task is to find entities that are occurring in the same time interval on different days, based on a given activity threshold $\theta$. Therefore, we define the concept of Group, $g$ as a set of entities that repeat during a specific number of days, in a specific time interval, i.e., $g = \{e_1, e_2, ..., e_m\}$, $e \in g$. We can simply compare entities together without creating groups, but to avoid
computational complexity we introduce the concept of groups. If we compare entities for all days together, this creates a huge burden on performance $O(2^n)$, so to avoid this, we use the sliding window approach. The sliding window reduces the number of comparisons to the size of the window, $m$, and results in windows that can be compared to each other. Therefore, the complexity is $O((n/m)^2+n/m(m^2))$, and as $m$ is small, the resulting complexity is $O(n/m^2)$. Since the resulting sets are only similar groups and not all entities for a day, the comparison will be reduced significantly.

The minimum threshold for counting similar entities in a specific time interval between days and builds a group. For instance, if $\theta$ is set to three, at least three entities should be repeated in a fixed time interval among a specific number of days. Assuming $T$ (time) is constant among different days, the following equation (3.1) defines the notation of a group:

$$g = \{ \forall e : (e_i(T) = e_{i+1}(T)) \land \sum e > \theta \}$$

$B$ denotes behavior and is characterized by a set of repeated similar groups $g$ with the same entity among a specific number of days. Each $B$ has at least one group. Therefore, $B = \{g_1, g_2, ..., g_n\}$ and $g \subseteq B$.

After behavior ($B$) have been created for given dates, the window moves to another set of days and creates another $B$. The second task is to find similar groups that are repeated on all days, with a minimum threshold. In other words, the second step is to find behavioral groups (motifs) that repeat themselves between days. To calculate the similarities between two days we define a threshold, $\lambda$, and name it motif confidence threshold. Equation (3.2) presents a user profile, which is based on intersections between $k$ number of behavior objects.

$$\text{profile} = \bigcap_{i=0}^{k} B_i \land \sum (B_i \cap B_{i+1}) \geq \lambda$$

At the end we have a single (or multiple if we do the same for weekends or other settings) temporal profile for each user. The profile is composed of users’ behavioral groups (motifs) and each identified behavior has a confidence. The confidence presents the probability of the target behavior occurring.

### 4.1 Data Transformation

As has been stated before, the data was collected from heterogeneous sources and each sensor provided more than one data element. The following shows a snippet of raw data.

```
{ "Application": { 
  "ProcessName":"com.example.test" ,
  "time":"Oct 15 , 2013 6:21:40 AM" }
}
```

These examples show different elements for each record. Therefore, for each sensor we choose a unique identifier, i.e., BSSID for WiFi and Bluetooth, the pseudonymized number for SMS and Call, process name for Application and steady or moving for location. Delving deep into location identification is beyond the scope of this paper, but to estimate if the current state is steady or moving, we simply compare the given longitude and latitude to the previous three recorded ones and if the distance is more than 800 meters, we annotate it either with moving or steady. This is applicable to location data where their provider is network cell ID, if it is Google Location API; since there is a “speed” parameter inside each record the status can be recognized easily. Moreover, GPS records are precise enough to indicate whether the user is steady or moving. Afterward, we created a CSV file for each user. This file includes the sensor name, timestamp and sensor value, which is a presentation of a three-tuple entity.

### 4.2 Temporal Granularity

According to [19], we do not perceive time in and of itself, but rather, we perceive changes or events in time. To be able to model human behavior, a precise machine timestamp should be transferred to a format similar to the way human perceive time. In a more technical sense, humans perceive events in relation to both location and time [21].

Due to the location sensor data loss problem we cannot always record daily information with location, but all existing digital mobile and wearable devices can record the sensed information objects with a timestamp. In order to simulate human perception we have studied the literature in temporal data analysis [14]. This concept has been identified as the temporal granularity [2]. Temporal granularity is application-specific and therefore there is no generic solution that can be applied to all problems. Here we attempt to make a temporal granularity for the daily behavior. For instance, assume a user makes a telephone call to his mother in the evening. It is unlikely that he will call her every day exactly at 5:00; he could call one day at 5:21 and
another day at 4:53. As a result, we define temporal granularities based on common daily time scheduling, and we provide an algorithm that can convert times based on the given precision. The algorithm we propose for temporal granularity is flexible enough to work with different timeframes, but in our experimental evaluation we define four timeframes: Five minutes (for time-sensitive tasks such as attending a meeting), a quarter of an hour, half an hour and an hour.

Algorithm 1: Temporal granularity calculation

Data: $D_{in}$, Precision

Result: $D_{out}$

1. //iterate through entities of a date
2. for (i=0; i < $D_{in}.e(length)$) do
3.   // read hour and minutes of current entity
4.   $TmpCeil ← ceil(e_i(T), precision)$;
5.   $TmpFloor ← floor(e_i(T), precision)$;
6.   $T_{abs} ← distance(TmpCeil, TmpFloor)$;
7.   $e_i(T) ← T_{abs}$;
8.   $D_{out}.add(e_i(T))$
9. return $D_{out}$

It is notable that this temporal similarity transformation can handle uncertainty by focusing on similar data in a perceptible time interval (i.e. a quarter of an hour, half an hour, etc.).

4.3 Motif Identification and Profiling

After the data has been transformed and its timestamp has been converted, then we can start applying the similarity detection algorithm to build groups of similar activities. First, we introduce group creation algorithms from similar entities and then we describe the method that builds users profiles by extracting behavioral motifs from groups. Figure 2 visualizes the algorithm we propose for group creation.

The window size is set to be three; one day as a weekend will be neglected and $\theta$ is equal to two. By comparing two days, D1,W1, with D2,W2, two groups, G1 and G2, have been extracted. For the sake of brevity we did not visualize a comparison between more than two days. Algorithm 2 first iterates through days, and reads entities for each day. Then it compares the current entities to the next days entities using the compare method and keeps the similar ones in a temporary group, grpTmp. If a previous similarity group exists, grpPrev, then it updates that group via the getSimilar method. This process repeats for given learning days and all similar groups in the given window size. The result will be returned in the array grpAll. In summary, each window returns a set of groups. Collected groups for each window constitute a behavior object, B. Since behaviors are just combinations of groups, we can add them all together to have one set that includes group objects. The last step is to summarize the collected groups. This process includes calculating an intersection between groups and if the appearance of a group is more than the $\lambda$ threshold, then this group will be added to the users profile. As has been previously noted, groups are the unit for predicting and quantifying human behavioral dynamics. Existing works [16, 27] provide association rule mining on pure contextual information. Since this work aims to identify human behavior, instead of the unique contextual information approach we propose temporal group-based contextual information. We still cannot map these information objects onto real-life events, but our work offers another approach for a more intuitive understanding of human behavior and life events, especially with the temporal granularity we are using. Moreover, our approach does not rely on a unique sensor; therefore, data is extracted

Algorithm 2: Group creation from similar entities

Data: $D_{in}$, ws, $\theta$

Result: All Detected Groups in a Window

1. grpAll, grpPrev ← $\emptyset$
2. entArr, entArrNext ← $\emptyset$
3. while ($D_{in}.hasNext() < ws$) do
4.   //reading entities of current day
5.   entArr ← $D_{in}.next.e$;
6.   //reading entities of next day
7.   entArrNext ← $D_{in}.next.e$;
8.   //compare and create groups
9.   grpPrevious ← compare(entArr, entArrNext, $\theta$);
10. if (grpPrevious.containsData()) then
11.     grpAll.add(grpPrevious);
12.     grpAll.add(grpPrev);
13. else
14.     grpAll.add(grpPrev);
15. return grpAll
Figure 2: Semantic visualization of group creation based on similarities between entities. Figure (a) presents a sliding window with a size of three. Figure (b) presents similar entities that have been detected between two days; window size and $\theta$ both are equal to two.

from multiple sensors so if a single sensor fails, its impact is insignificant. This helps mitigate the problem of uncertainty that originated from the sensor data.

5 Experimental Evaluation

To evaluate our work we analyzed the dataset which has been described previously. Since our behavioral pattern mining approach should be lightweight enough to be used in wearable and mobile devices, we start by evaluating the performance of our “motif identification and profiling” algorithms. Then we present a statistical overview of behavioral motif detection based on changing threshold and precision values, and analyze their effects on the output. Our subsequent analysis provide an estimate of users’ behavioral changes over time, which enables the identification of the best time to run the proposed algorithms. To the best of our knowledge, no other research that benefits from all available informational resources for behavior prediction exists; therefore, it is important to understand the approximate time for executing such algorithms.

5.1 Execution Time Performance One of the novel contributions of this work is the adoption of a sliding window to improve the execution time performance of behavioral motif detection algorithms. Execution time performance is critical, because our algorithms must be capable of being integrated into small devices which have restricted computational resources compared to desktop computers. Therefore, this evaluation demonstrates the scalability of our algorithms on small devices.

We have analyzed the execution time performance of our algorithms with different window sizes for 60 days. Figure 3 summarizes these performance changes. The legend on the bottom shows the window size; we have tested for window sizes 2, 3, 4 and 5. In particular, this figure demonstrates that increasing the window size significantly improves the performance.

It is notable that numbers depicted in figure 3 belong to all 33 users and an application that uses this approach will use data only for one user. Therefore, these numbers will be reduced significantly. However, they have been measured on a MacBook with 2.4 GHz CPU and 8 GB RAM. If the algorithm is ported to a wearable or mobile device that has limited resources, these numbers will increase based on the devices capabilities. Nevertheless, for this analysis the slope is important (a
smaller slope means better performance), and increasing the window size decreases the slope significantly.

5.2 Thresholds Effects

“Activity threshold,” “behavioral motif confidence” and “temporal precision” are three configurable variables. We test our motif identification and profiling algorithms with four different types of temporal precision of 5 minutes, a quarter of an hour, half an hour and an hour. Table 2 shows the average number of detected behavioral motifs from different activity thresholds ($\theta$) and the behavioral motif confidence ($\lambda$). There are no best combinations of these variables because their values are application-dependent. However, these results show that increasing both $\lambda$ and $\theta$ to more than three reduces the chance of detecting any behavioral group in this dataset.

| $\theta$ | $\lambda$ | 5' | s.d. | 15' | s.d. | 30' | s.d. | 60' | s.d. |
|---------|----------|----|------|----|------|----|------|----|------|
| 2       | 2        | 21.25 | 44.51 | 6.78 | 14.37 | 2.97 | 6.54 | 1.63 | 3.45 |
| 3       | 2        | 10.31 | 22.25 | 4.16 | 9.27  | 1.69 | 4.29 | 0.91 | 2.32 |
| 2       | 2        | 2.81  | 7.74  | 1.69 | 4.48  | 0.69 | 2.19 | 0.44 | 1.37 |
| 2       | 3        | 6.06  | 16.84 | 2.13 | 6.61  | 1.03 | 2.71 | 0.63 | 1.52 |
| 3       | 3        | 2.43  | 10.31 | 1.22 | 4.42  | 0.47 | 1.68 | 0.28 | 0.99 |
| 2       | 4        | 0.06  | 0.24  | 0.09 | 0.30  | 0.09 | 0.39 | 0.06 | 0.25 |
| 3       | 4        | 0.03  | 0.18  | 0.06 | 0.25  | 0.06 | 0.35 | 0.03 | 0.18 |
| 4       | 4        | 0     | 0     | 0.03 | 0.17  | 0   | 0   | 0   | 0   |

Table 2: Average behavioral motif detection based on different activity thresholds, behavioral motif confidences and temporal precision.

5.3 Validity of Identified Behaviors

As has been stated previously, data mining is a resource-intensive task, and mobile and wearable devices suffer from resource weaknesses in comparison to desktop computers, thus data mining algorithms should not run continuously on such devices. Therefore, it is important to know when to run such algorithms, or how often it is necessary to run such algorithms and detect new behavioral motifs. In other words, we need to identify how long a system can stay silent and ensure that identified behavioral motifs are valid.

To understand this, we analyze behavioral group detection algorithms with five minutes precision and the following settings: $\theta = 2$, with the window size equal to three days. $\lambda$ is not used here, because we have changed the code to identify new behavioral groups in each window and if a group is repeated in upcoming windows it will be neglected. In other words, once a group has been detected we count it only if it is a newly detected group; otherwise, we do not count it. This approach helps us to identify whether there is a pattern that can be used to estimate newly detected groups during this time. Figure 4 shows three sample users with three different types of observed behaviors. These behaviors are common across users and we show only three of them in this figure for the sake of readability. All three users show a fluctuation in their behavioral group detection. These fluctuations represent behavioral motif changes during this time. We did not calculate the exact number of this fluctuation because it is different among users. For instance, user U2 has about two window fluctuations in the first ten windows (about 30 days and per week one day as a weekend has been neglected). This means such an algorithm requires being executed every seven days on his/her device. Another finding worth men-

![Image of Figure 4](image-url)

Figure 4: Number of newly-identified groups in each window during the time of the experiment.
6 Related Works

A major contribution of this research is a generic mobile data mining system. We claim it is generic because of its multi-sensor support and application independence. A secondary contribution is our modeling of the temporal aspect of human behavior. Therefore, we study two categories of related works: mobile data mining efforts that focus on device data collection but not data collection from external parties such as cell ID, and temporal granularity analysis in human behavior.

6.1 Mobile Data Mining Research that relies on collecting data from users’ mobile devices is mostly application-specific and focuses on predicting one element of data (single sensor). For instance, a category of research explores activity recognition from accelerometer data. Recent approaches have tried to employ a data dictionary and use semi-supervised learning to learn human activities. This makes the data mining process light as well as scalable for implementation on mobile devices. However, there still is no perfect solution for activity recognition even in commercial wearables, and researchers must also deal with the uncertainty problem of activity recognition techniques. Another category of mobile data mining approaches focuses on location mining, which mainly uses the reality mining dataset. Semantically, location is the most valuable information in digital human behavior identification, and therefore these studies map location onto human behavior. We believe human behavior is not just based on changes in location, and studies should include activities that are happening in the location too. Therefore, our interpretation of human behavior is different from those interpretations. Since our research can use all existing sensors on the device, it can be extended to any type of human behavior analysis application. In other words, we benefit from a combination of sparse information sources and not just one information source.

There are two works relevant to our research: MobileMiner and ACE. Both studies are very similar and consider the co-occurrence patterns in human behavior via mobile phones through association rule mining. Their approach is realistic in terms of deployment, but since they use association rule mining, they are restricted to co-occurrences of more than one data object. In contrast, we identify behavior motifs and not just co-occurrences. Likewise, since we aim for human behavior detection we benefit from the temporality of behavior, and thus there is no need to have at least two data objects available for prediction (one is enough if the application uses $\theta = 1$).

6.2 Temporal Granularity for Human Behavior

As has been stated previously, our work tries to digitally map timestamps for human activities onto human temporal perception. The term temporal granularity has been introduced by [2], and is different from temporal abstraction. It is notable that temporal abstraction is the process of converting high-dimensional timestamp data to low-level qualitative descriptions of time and has been introduced by [25]. Temporal granularity specifies the temporal qualification of a set of data, similar to its use in the temporal qualification of statements in natural languages.

We review temporal granularity models that are being used for human behavior analysis. There is a limited number of works that consider how to apply temporal granularity to human behavioral data. One of the earlier works, [17], proposes a method to analyze human activities in the office via a probabilistic representation for inferring temporal granularity. Our goal is not to infer temporal granularity, but we benefit from this concept to mine patterns of human behavior. The work most similar to ours is [30], which focuses on mining users daily location patterns via trajectory mining and defines the temporal granularity as a day. [18] is another approach for identifying daily behavior and tries to profile the daily location changes of users. They converted a day into eight 3-hour segments and analyze each segment.

7 Conclusion

In this paper, we have proposed a scalable approach for daily behavioral pattern mining from multiple information sources. This work benefits from a realistic dataset and users who use different smartphone brands. We use a novel temporal granularity transformation algorithm that makes changes on timestamps to mirror the human perception of time. Our behavioral motif detection approach is generic and not dependent on a single source of information; therefore, we reduce the risk of uncertainty by relying on a combination of sensors to identify behavioral motifs and patterns. We investigate the efficiency of our work by evaluating it from three different perspectives: the execution time performance, the effect of threshold changes on motif detection, and the validity of the identified behavior from a temporal perspective. This approach is scalable enough to be used in several types of applications such as mobile health, context-aware recommendations and other quantified-self applications. Our future work will use the same algorithm and enrich it by introducing a spatial dimension for behavioral pattern detection.
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