

Activity-Based Mobility Profiling: A Purely Temporal Modeling Approach

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ABSTRACT

Several studies have shown that the spatio-temporal mobility traces of human movements can be used to identify an individual. However, this work presents a novel framework for activity-based mobility profiling of individuals using only the temporal information. The proposed framework is conducive to model individuals' activity patterns in temporal scale, and quantifies the uniqueness measures based on certain temporal features of the activity sequence.

KEYWORDS

Temporal modeling, Mobility trace, Human Activity, User profiling

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1 INTRODUCTION

With the pervasiveness of sensor technologies, wireless network advancements and location-acquisition technologies, various mobility information such as travel-logs, GPS traces, or activity information are readily available for analysis and providing a diverse range of location based services [1], namely, trip-planning [2], traffic-forecasting, or personalized recommendation systems. On the flip-side, mobility data is sensitive to privacy as it collects the whereabouts of individuals in space and time. Nevertheless, sharing only temporal activity patterns, without particular location information, may reduce the privacy concerns. While spatio-temporal characteristics of human mobility is known to provide significant insights about human mobility behaviour [3], the question is whether temporal characteristics alone may also be sufficient to map behavioral patterns. Further, time can be more accurately observed than location, while location information often suffers from uncertainty or imprecision. The major focus of this work is to come up with a temporal mobility-profiling framework that is capable to uniquely identify an individual. The fundamental idea of profiling, or fingerprinting, is to map large volumes of mobility data to a shorter representation capturing the unique temporal characteristics of

individual movements. To the best of our knowledge, no existing work has undertaken the profiling of individuals based on temporal properties only.

To further progress in this research direction, this paper aims to model an individual's activity sequences in different temporal scales. Inherent patterns of activities will be used to profile (mobility profile) this individual, in order to derive their personal contexts and intentions. There are a number of questions to be addressed, namely, i) How does a person use her time at different levels of activity abstraction, and how can these daily activity sequences be modeled in a temporal fingerprint? ii) Are there some associations among the activities that show better consistency scores in different temporal scales, and how does this help to build a personalized recommendation system?

Problem definition: Consider a set of users and daily user activity logs (e.g., travelling, reading a book, being at work) over a time period. The objective is to represent the feature set of the activity patterns such that each user's (u_i) mobility pattern over time can be represented and similarities among users' mobility patterns can be measured by comparing their mobility profiles (MF_i).

Contribution: The contributions can be summarized briefly as: i) Modelling the activity-sequence of people in different temporal scales using Allen's *temporal calculus*; ii) proposing an *activity-time graph* to capture the temporal properties of the activity-sequence in a hierarchical manner; iii) mobility profiling to fingerprint an individual's temporal mobility patterns using a variant of Graph-Edit distance; and iv) measuring the consistency-pattern by analyzing the variability or entropy of the activity-sequence over the studied time. The experimental results indicate that temporal mobility profiling is capable to capture the uniqueness of human mobility, and that the proposed temporal hierarchy provides an insight about the activity pattern of the users. Further, we explore the temporal consistency patterns of activity sequences, which is an important factor while measuring the similarity among users.

The paper is organized as follows: Section 2 reviews the recent progress in this research domain. Section 3 describes the different modules of a temporal profiling architecture. Experimental evaluations of the framework are shown in Section 4. Section 5 concludes the paper with some future directions of the work.

2 RELATED WORKS

Significant research efforts have been made in mobility pattern mining for travel demand and travel modes, and in the semantic analysis of these traces to explore human intent of the movement or activity recognition, including privacy-risk and anonymization techniques.

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Most of mobility pattern mining research works have focused on the analysis of GPS trajectories of moving agents. Yu *et al.* [2] propose a framework to model an individual's location history with a tree-based hierarchical graph and infer location importance and habitual travel sequences. Zhao *et al.* [4] present statistical and unsupervised clustering based methods to understand individual metro passengers' spatio-temporal patterns. There is work on summarizing GPS logs [5], user categorization [6], and finding the similarity among the trajectories of sets of users [7]. These examples are representative for a broad range of literature that consider both spatial and temporal properties of trajectories.

Understanding intent of the human movement to predict the next move and observing activity patterns of individuals are major aspects to build any context-aware intelligent recommendation system. Wun *et al.* [8] model the intra-urban human mobility by combining activity-based analysis and movement analysis from 15 million check-in records constructing a temporal transition probability matrix. Activity sequence prediction using Markov models and regression tree classifiers to predict the expected time until the next activity occurs [9] are some of the significant contributions in the present literature.

In principle, sharing location data poses security threats or privacy issues not only instantly but also because people follow more or less regular schedules in their daily life. Song *et al.* [3] observe 93% potential predictability of human dynamics exploring the mobility patterns of 50,000 mobile phone users for three months. Vice versa there is literature emerging on the obfuscation of location where inaccuracy and imprecision are introduced for the purpose of preserving privacy [10]. Duckham *et al.* [11] propose a spatio-temporal model of location privacy that represents an individual's movements over time with obfuscated location knowledge, as well as a speculation on how refinement of this knowledge might invade the individual's privacy.

Our proposed approach differs from the existing studies in many aspects. Firstly, we do not include location information in our analysis since sharing location information may exhibit privacy intrusion. Further, instead of using *time* as a discrete feature, we model the activity sequences of individuals using several qualitative temporal relations. Previously, temporal correlations between mobility patterns have been analyzed by segmenting time into different time-slices or time-intervals, while we propose a temporal mobility framework, where activity-patterns are represented using several hierarchical levels based on the temporal relations.

3 TEMPORAL MOBILITY PROFILING FRAMEWORK

This paper proposes a conceptual framework to describe an individual's activity sequences purely by time, and in different temporal scales. The activity sequences will be used to profile the individual, in order to derive their personal context and intentions.

Figure 1 depicts the overview of the proposed framework. From the activity log of the persons (the users of a particular service), the activity sequence is mapped to an *activity-time graph* (ATG), using qualitative temporal relations followed by the extraction of signature activity patterns of the individual persons. A temporal pattern mining module analyzes temporal consistency of activities

Table 1: Sequence of activities performed by a user

ActivityType (a_i)	StartTime (t_i^s)	FinishTime (t_i^f)
Travelling on a bus	9.30	10.50
Reading a newspaper	9.45	10.20
Listening to music	10.10	10.20
Talking with other passengers	10.30	10.40
Watching sports scores	10.30	10.40
Walking	10.52	11.00

and obtains a user temporal mobility profile. The mobility profiles can be used for the identification of users, for similarity measurements of user profiles, and for analysis on the temporal consistency pattern of the activities. Typically, similar profiles among users may help in clustering or categorization of users based on their activity patterns whereas identification accuracy depicts the uniqueness measures of the mobility profiles. And analyzing consistency patterns of activities in different temporal scales is helpful in intelligent recommendation system.

3.1 Preliminaries

Here, we define some preliminary concepts that are subsequently used in this paper.

- **Activity Node** An activity node (A) is defined as an ordered pair (a_i, T_i) , where a_i denotes the activity name performed by the individual and T_i represents the time interval of the activity, consisting of a start time t_i^s and finish time t_i^f . Table 1 shows some activity names and temporal values of the activities. Each row of Table 1 constitutes an *activity node*. The basis for modelling activities has been provided by activity theory [12]. Activity theory is conceptualized by a hierarchical structure where an activity can be broken down into actions and subsequently actions into sub-actions and so on. In this work, activity nodes are modeled in a hierarchical representation based on the time interval T_i .
- **Activity Sequence** As shown in Figure 2, a pair of activity nodes are connected following their temporal relations, based on the start and finish time of the activities.

$$ASeq = \bigcup_{\forall (a_i, a_j) \in \{A\}} a_i \xrightarrow{TR} a_j \quad (1)$$

TR denotes the qualitative temporal relations between any two activities as represented in Table 2. As time is monotonically increasing, temporal logic postulates statements such as "an activity performed in interval T_1 is *before* interval T_2 if $t_1^f < t_2^s$ ". Such reasoning about time is established on the notion of (singly-connected) time intervals and binary qualitative relations among them, as for example defined in Allen's temporal calculus [13]. Each time interval has non-zero duration, i.e. $\forall i : t_i^s < t_i^f$, for activity i .

- **Disjoint and Concurrent Activity Set** The disjoint activity set is defined in the temporal scale:

$$D = \{a_i | t_{i+1}^s \geq t_i^f, \forall i\} \quad (2)$$

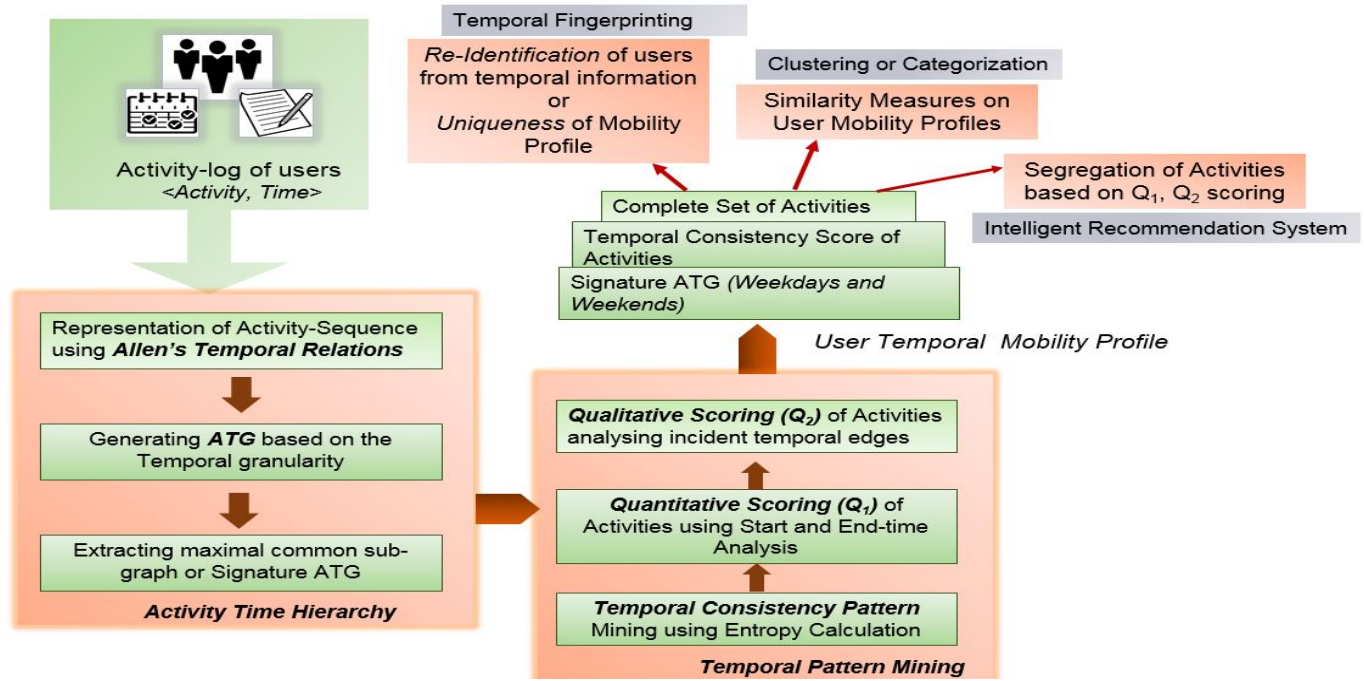


Figure 1: Workflow of Temporal Mobility Profiling framework

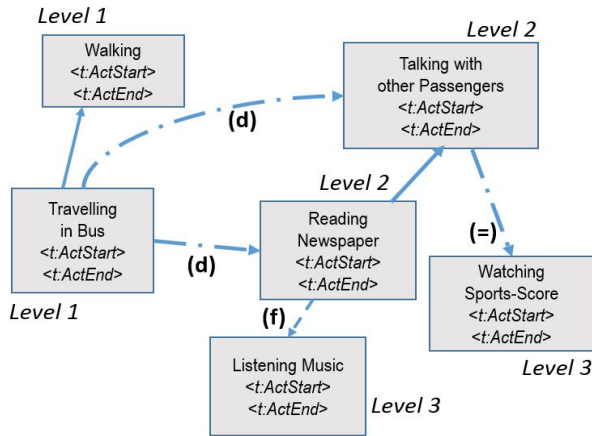


Figure 2: Mapping of Activity sequences to Activity Time Graph

The concurrent activity set consists the activities that are embedded in other activities in the temporal scale.

$$C = \{a_i | (t_j^s \leq t_r^s \leq t_j^f) \text{ and } (t_r^s \leq t_j^f \leq t_r^f), \\ i \in [0, \dots, j, r, \dots, n]\} \quad (3)$$

In the example of Table 1, *travelling on a bus* and *walking* are disjoint activities while the other activities are all embedded within *travelling on a bus*.

- **Activity Time Graph (ATG)** An ATG is the collection of all activities performed by the individual in a day. The ATG

Table 2: Temporal relationships between two activities following Allen's temporal calculus

Temporal relationship	Network representation	Time-interval property
a_1 before (b) a_2	$a_1-(b)-> a_2$	$t_1^f < t_2^s$
a_1 after a_2	$a_1 <-(b)-a_2$	$t_2^f < t_1^s$
a_2 during (d) a_1	$a_1-(d)-> a_2$	$(t_1^s < t_2^s) \wedge (t_2^f < t_1^f)$
a_1 during a_2	$a_1 <-(d)-a_2$	$(t_2^s < t_1^s) \wedge (t_1^f < t_2^f)$
a_1 starts (s) a_2	$a_1-(s)-> a_2$	$t_1^s = t_2^s \wedge t_1^f < t_2^f$
a_2 starts a_1	$a_1 <-(s)-a_2$	$t_1^s = t_2^s \wedge t_2^f < t_1^f$
a_1 finishes (f) a_2	$a_1 <-(f)-a_2$	$t_1^f = t_2^f \wedge t_2^s < t_1^s$
a_2 finishes a_1	$a_1-(f)-> a_2$	$t_1^f = t_2^f \wedge t_1^s < t_2^s$
a_1 meets (m) a_2	$a_1-(m)-> a_2$	$t_1^f = t_2^s$
a_2 meets a_1	$a_1 <-(m)-a_2$	$t_2^f = t_1^s$
a_1 equals (e) a_2	$a_1-(=)-a_2$	$t_2^f = t_1^f \wedge t_2^s = t_1^s$
a_1 overlaps (o) a_2	$a_1-(o)-> a_2$	$t_2^s < t_1^f < t_2^f$
a_2 overlaps a_1	$a_1 <-(o)-a_2$	$t_1^s < t_2^f < t_1^f$

levels are introduced following time hierarchy of activities and partitioning the disjoint and concurrent set of activities. Thus, the $ATG = (A, E)$, representing activities of users in nodes A and the temporal relationships between activities in edges E , also provides a function $h : A \rightarrow \mathbb{N}$ assigning a level number $l \geq 1$ to each node $a_i \in A$, and a function $f : E \rightarrow TR$ assigning this temporal relationship for each edge $e_i \in E$.

Of the activities in Table 1 [also depicted in Figure 2], *travelling on a bus* and *walking* are Level 1 activities (l_1), and

reading a newspaper, talking with other passengers and watching sports scores – the activities embedded in or concurrent with the l_1 activity *travelling on a bus* – are Level 2 activities (l_2). Again, *listening music* is embedded in an l_2 activity, say, *reading a newspaper*, therefore is a l_3 activity.

3.2 Activity-Time Hierarchy

An activity sequence (including overlapping of activities) is a series of activities to achieve some desired goals. The sequence is represented by nodes (activities) and edges (temporal relations between the connected activities). Table 2 depicts the complete set of temporal relations. Here, all possible temporal relations of two activities (a_1, a_2) are represented using the temporal interval properties of start (t_1^s, t_2^s) and finish time (t_1^f, t_2^f).

Since Allen's temporal calculus is jointly exhaustive and pairwise disjoint, and since by the definition above any activity is singly-connected between a start and end, any sequence of two activities has exactly one of these qualitative temporal relationships. Hence, a temporal profiling model based on Allen's temporal calculus is complete and unambiguous.

3.2.1 Generating time-based hierarchical structure of activity-nodes. The activities performed by an individual can be modeled in a hierarchical structure, based on the granularity of the temporal scale. In order to generate a meaningful hierarchical activity structure, additional constraints are imposed on the activity selection. Activities are often associated with points of interest (POI) (say, *BeingAtHome* or *BeingAtUniversity*), and spatial separation clearly constructs a disjoint subset of activities. Also the change of location (e.g., *travelling*) is an activity disjoint with POI-bound activities. From the next level, nodes are concurrent activities in the time-scale with upper level activities. Therefore people are involved either in some POI-bound activities or travelling, and thus these activities comprise of Level 1. From the next level an activity selection algorithm, *Greedy-Iterative-Activity Selector*, is deployed to find out the concurrent activities of Level 1 and disjoint activities in each of the levels. The optimal solution of the problem returns a maximum number of such disjoint activities. Due to the limitation of multi-tasking capabilities of individuals the number of concurrent activities becomes less with increasing depth of concurrent levels. Moreover, this work proposes an iterative matching between two ATGs based on the levels. Therefore, greater number of activities in upper levels gives the provision of discovering larger sequences of matches.

After determining the levels of the activities following the above procedure and time-hierarchy rule, *activity-splitting* may be required for overlapping activities. It might happen that an activity at a lower level (say Level 2) overlaps time-wise with the last activity of a higher level (say Level 1), which violates the strict time hierarchy rule; then the Level 2 activity is divided in two activity-instances and the non-overlapping part moves to the upper level. For example, for an activity log such as: [Travelling, <9.30-10.50>]; [Listening to music, <10.40-11.00>], the time hierarchy of activities will be of the form: [Travelling, <9.30-10.50>, Level 1]; [Listening to music, <10.40-10.50>, Level 2]; [Listening to music, <10.50-11.00>, Level 1]. Splitting is required as the activity hierarchy not only represents activities in several time scales but also provides an insight

how people performs concurrent activities. The splitting leads to a proper tree structure and thus an unambiguous representation of an activity-time hierarchy.

In Level 1, $A(1) = (\text{ActivityName}, \text{startTime}, \text{finishTime})$ information is captured, and f assigns edge information based on the temporal values of each node. From the next level, all nodes are represented by $A(l) = (l, p, T)$, where l is the level or height of the activity-node, T is the list of concurrent temporal relations among the activities of same level and p is the parent activity where $A(l)$ is embedded. The concept of a hierarchical representation is useful for comparing ATGs. It allows to analyze the activity types at macro-levels of the input ATG, and utilizes the knowledge of different levels in different applications.

3.2.2 Extracting individual signature activity patterns. To come up with the mobility profile of an individual the most followed activity sequences need to be extracted. The *signature ATG* captures regular activity sequences over a studied period. It leads to the classical problem of maximal-common sub-graphs from a pair of ATGs, as the daily activity sequence of an individual is represented as ATG. For this purpose, the *graph edit distance* measurement of all ATGs of the individual is used since Bunke [14] formally proved that under a given cost function the graph edit distance and the maximum common subgraph are equivalent problems. Generally, the graph edit distance between two graphs (G_1, G_2) is defined as:

$$ged_{\lambda_{min}}(G_1, G_2) = \min_{\lambda \in \gamma(G_1, G_2)} \sum_{e_i \in \lambda} c(e_i) \quad (4)$$

$c(e_i)$ denotes the cost of edit operations. In this paper, $\gamma(G_1, G_2)$ includes graph-edit operations on edges (edge insertion, edge remove, edge substitution, or modification of temporal attributes) and on nodes (modifications of temporal information). The edit distance is computed by finding the sequence of graph-edit operations which minimizes the cost of the path traversing from source graph to target graph. The features of the maximal common sub-graph are used as the signature features between source and target graph.

While defining sub-graphs of ATGs, also the levels are considered, along with the edge and node sets.

Let $ATG_1 = (A_1, E_1, l_1, f_1)$ and $ATG_2 = (A_2, E_2, l_2, f_2)$ be two ATGs, then ATG_2 is a subgraph of ATG_1 , and is represented by $ATG_2 \subseteq ATG_1$, if

- $A_2 \subseteq A_1$
- $|l_2| \leq |l_1|$
- $f_1(a_i, a_j) = f_2(a_i, a_j); \forall (a_i, a_j) \in A_2 \times A_2$

Let $ATG_1 = (A_1, E_1, l_1, f_1)$ and $ATG_2 = (A_2, E_2, l_2, f_2)$ be two ATGs, then a graph isomorphism is defined by edge-preserving vertex bijection mapping $I_G : A_1 \rightarrow A_2$ in all levels,

- $a_1 = I_G(a_2); \forall a_1 \in A_1$
- $f_1(a_i, a_j) = f_2(I_G(a_i, a_j)); \forall (a_i, a_j) \in A_1 \times A_1$

ATG_3 is the common subgraph of ATG_1 and ATG_2 if there is a graph isomorphism between ATG_3 to ATG_1 , and between ATG_3 to ATG_2 . Again, ATG_3 is the maximal common subgraph if there is no other common subgraph of ATG_1 and ATG_2 that has more edges than ATG_3 .

The edit distance $ged(ATG_1, ATG_2)$ of two ATGs is computed as:

$$ged(ATG_1, ATG_2) = \min \{C_T(g) \mid g \text{ is an ecgm from } ATG_1 \text{ to } ATG_2\} \quad (5)$$

Here, *ecgm* is an error-correcting graph matching function that transforms ATG_1 to ATG_2 following graph-edit operations. A variation of Bunke's cost function [14] is applied for computing the edit-distance in each level of the ATGs.

$$\begin{aligned}
 C_{ns}(x) &= \begin{cases} 0 & \text{if } a_i == a_j \text{ and } T_i == T_j \\ 1 - \frac{|T_i \cap T_j|}{|T_i \cup T_j|} & \text{if } a_i == a_j \text{ and } T_i \neq T_j \\ \infty & \text{if } a_i \neq a_j \end{cases} \\
 C_{nd}(x) &= 1 \\
 C_{ni}(x) &= 1 \\
 C_{es}(x) &= \begin{cases} 0 & \text{if } f_1(x, y) = f_2(g(x), g(y)) \\ \infty & \text{otherwise} \end{cases} \\
 C_{ed}(x) &= 1 \\
 C_{ei}(x) &= 1
 \end{aligned} \tag{6}$$

C_{ns} , C_{ni} , C_{nd} , C_{es} , C_{ed} , and C_{ei} denote *node-substitution*, *node-insertion*, *node-deletion*, *edge-substitution*, *edge-deletion* and *edge-insertion*. For node-substitution, when both the activity name and the time interval match, the cost is zero. When only the activity name matches but the time intervals show a concurrent relation, the cost function is changed based on the time modification required to match both the nodes. Bunke [14] proposed obtaining *ecgm* by summing up all costs of edit operations imposed by the mapping:

$$\begin{aligned}
 c(f) &= \sum_{x \in A'_1} c_{ns}(x) + \sum_{x \in A_1 - A'_1} c_{nd}(x) + \sum_{x \in A_2 - A'_2} c_{ni}(x) \\
 &+ \sum_{e \in E'_1} c_{es}(e) + \sum_{e \in E_1 - E'_1} c_{ed}(e) + \sum_{e \in E_2 - E'_2} c_{ei}(e)
 \end{aligned} \tag{7}$$

$ATG'_1(A'_1, E'_1)$ and $ATG'_2(A'_2, E'_2)$ are sub-graphs of ATG_1 and ATG_2 , respectively.

Generally, the distance between two graphs G_1 and G_2 is measured as:

$$d(G_1, G_2) = 1 - \frac{|mcs(G_1, G_2)|}{\max(|G_1|, |G_2|)} \tag{8}$$

Here, *mcs* refers to the maximal common sub-graph of G_1 and G_2 . Typically, $|G|$ is represented by the number of nodes or number of edges. In the present paper, however, nodes at different levels carry significant importance, hence additionally the levels and edges are used in the computations. $|ATG| = \sum_{l=1}^m l \times |e(l)|$, where $|e(l)|$ is the number of temporal edges in level l . The edit-distance computation is applied in an iterative way: First, the distance between the Level 1 elements of the ATGs is computed, following by the lower levels. Reasonably, while measuring distances among Level 2 nodes (embedded within Level 1 nodes), the distance values of Level 1 nodes need to be considered. Hence, the total cost C_T is given as:

$$C_T = c_1(g) + \sum_{i=2}^m c_{i-1}(g) \times c_i(g) \tag{9}$$

c_i denotes the cost at Level i .

An iterative computation (based on the levels of ATG) of graph-edit distance is proposed because the levels of the ATGs not only represent activities in different temporal scales but inherently present semantic information. For example, *listening to music* during *eating breakfast at home* is different from *listening to music* while *traveling*. The objective is not only extracting the maximal sub-graph but providing more weight to different levels of the ATGs in the computation.

The method of extracting signature activity patterns from the ATGs is deployed by partitioning the weekdays and weekend ATGs. For both sets of ATGs pair-wise edit-distance is measured. The common disjoint sub-sequences of activities (node-substitution) are extracted, followed by analyzing the temporal similarity relations in the embedded sub-graphs for each nodes.

3.3 Temporal Pattern Mining

In this section, *temporal patterns* of activities are analyzed, which involves analyzing temporal consistency patterns of activities, and quantitative and qualitative scoring of activities.

3.3.1 Temporal consistency patterns of activities. Temporal consistency patterns are observed from the variability of activity performance on the time scale where time is measured based on time intervals T_i and duration of the activity.

The variability of a random variable is generally measured by *entropy*, which is, in information theory, the average of the information content in a message. Shannon's entropy (H) [15] is defined as:

$$H = - \sum_{j=1}^n p_j \log_2 p_j \tag{10}$$

where $\sum_{j=1}^n p_j = 1$, and p_1, p_2, \dots, p_n are the empirical probability distributions. There are two obvious questions while measuring the overall variability of an activity-time pair: a) V_i : What is the variability measure of each activity performed by an individual in the studied period? b) V_T : How (in terms of variability of activities) an individual uses her time? To analyze the variability of an activity (say a_i), we study the *startTime* and *finishTime* of all occurrences of a_i in the activity log. Our goal is to partition the activity instances into several temporal classes where *startTime* and *finishTime* of all members (or activity instances of a_i) of one class remain within a threshold value (t_{thresh}). Therefore variability of the activities is calculated on the temporal scale, i.e., how consistently an individual performs the activity, or starts and finishes the activity within a time threshold. For measuring the *startTime* and *finishTime* variability, the frequency of the activities starting or finishing at the same time is calculated.

- (1) Observe the activity-sequences for the complete studied-time and extract the total number of instances each activity occurs. Say, activity a_i occurs N times in the study period.
- (2) Extract the unique timestamps, m (for *startTime* and *finishTime*) for the activity and split up the data into m classes.
- (3) Count the frequency (f_j) for each such classes j .
- (4) Finally, estimate the entropy following Equation 11.

Using Shannon's entropy H , we can define the *variability* (V_i) for each activity (a_i) as:

$$V_i = - \sum_{j=1}^m \left(\frac{f_j}{N} \right) \log_2 \left(\frac{f_j}{N} \right) \tag{11}$$

Say, a user performed activity a_i N times over the studied period, and the activity is done on m unique time intervals or classes. The empirical probability distribution (p_j) is how likely the activity takes place in the same time intervals of other instances of the activity. Larger values of V_i indicate more variability, thus less

consistency and smaller values indicate more consistent pattern of the particular activity in the temporal scale.

To calculate the variability of the activities in different time ranges of a day (V_T), the day is partitioned into two-hour time slices. For each time slice the activities at each level are extracted for a calculation of the probability of the occurrence of these activities in the time slice.

3.3.2 Quantitative and qualitative similarity measures on the temporal scale. The quantitative score (Q_1) and qualitative score (Q_2) of an activity are consistency values between 0 and 1 which represent whether the activity is being performed in a regular time-interval (Q_1) or it follows a consistent sequence (Q_2). For quantitative measures, start time and finish times of the activity-nodes are incorporated, while temporal relations are compared and analyzed in the qualitative analysis.

Algorithm 1: Computation of the quantitative temporal score Q_1 of the activities of an individual.

Input: Collection of ATGs of an individual: $[ATG_1(V_1, E_1), \dots, ATG_n(V_n, E_n)]$
Output: Set of unique activity names; $\langle Q_1 \rangle$ for each activity name
1 **Initialization:** $TClass \leftarrow$ empty priority queue of temporal classes of activities; $TQ_1 \leftarrow$ empty list of temporal scores (Q_1);
2 $A \leftarrow \text{ExtractAct(ATG)}$; \triangleright Extract unique activity-names from ATGs
while $|A|$ is not empty **do**
3 $TClass.insert(A[i]); S \leftarrow 0$; \triangleright Create a new temporal class
4 **for** j in range $(0, |ATG|)$ **do**
5 $t_{start}, t_{finish} \leftarrow ATG_j(A[i]); \triangleright$ Extract temporal-interval
 $t_{thresh} \leftarrow \frac{t_{finish} - t_{start}}{10}$; \triangleright Estimate Threshold value
6 $T_{start}, T_{finish} \leftarrow [t_{start} - t_{thresh}, t_{start} + t_{thresh}], [t_{finish} - t_{thresh}, t_{finish} + t_{thresh}]$;
7 **if** T_{start}, T_{finish} in $TClass.Key$ **then**
8 \quad Increment frequency value of $TClass.Key$;
9 \quad Update Priority value of $TClass.Key$;
10 **else**
11 $\quad \triangleright$ Time-interval does not match with the existing classes
12 \quad Create new $TClass.Key$;
13 \quad Set frequency value as 1 of $TClass.Key$;
14 **end**
15 $S \leftarrow S + 1$;
16 **end**
17 $TQ_1[i] = -\sum_{k=1}^{|TClass|} \frac{TClass[k].value}{S} \log_2 \frac{TClass[k].value}{S}$;
18 $TClass.remove()$;
19 $\text{Print } \langle A[i], 1 - TQ_1[i] \rangle$; \triangleright Activity-name, Quantitative Score
20 **end**

For comparisons of start and finish times, a threshold value $t_{thresh} = (finishTime - startTime)/D$ has been considered. In our experiment we have selected $D = 10$ empirically, i.e. 1/10 of the duration of the activity. Two nodes are *quantitatively* similar when the start time and finish time of the nodes are within t_{thresh} time difference. In the iterative approach through the levels of the hierarchy, first the similar activity nodes of Level 1 are extracted, then the embedded activity nodes within the common nodes are extracted, and this continues till the last level of the ATGs has been considered. Algorithm 1 describes the procedure of computing Q_1

or quantitative score of each activity-name. For brevity, start and finish time of the activities are denoted by t_{start} and t_{finish} and the time range of each temporal class or partition is defined by T_{start} and T_{finish} . The max-priority queue of the temporal classes is initialized such that priority is maintained by the cardinality of the temporal classes. After extracting the unique activity names the number of the temporal classes for the activity names are estimated. Then the quantitative score is measured by calculating (1-variability) of the activity based on the temporal interval.

In the qualitative scoring, temporal attributes (TR) of all incident edges of an activity node are analyzed. Here, the *incident* edge captures the temporal information: how one activity is embedded within another (different level) and the sequence it follows (predecessor and successor nodes in the same level). A procedure similar to Algorithm 1 is followed except the temporal classes are generated by comparing the temporal information of the edges for each activity node.

It is well known that peoples' activity sequences are to a large degree habitual; these habits can follow some qualitative and some quantitative measures. For example, a person could take always medicine after having breakfast (qualitative), but not necessarily at a fix time (quantitative). In this regard, a sequence of activities (taking medicine after having breakfast) shows better qualitative scores than quantitative measurements. In another example, *travelling to university* and *attending class* occurs at fix times, as these are scheduled activities.

3.4 Mobility profiling and dissimilarity of temporal activity information

A mobility profile $MF = (A[], C[], ATG[])$ consists of three components: An exhaustive set (A) of activity names a_i along with the frequencies f_i of these activity names performed by the individual over the whole studied time (i.e., pairs of (a_i, f_i)), a list C of temporal consistency scores of these activity names, and a list of ATGs storing the ATGs of an individual user, analyzed typically separately for weekdays and weekends.

Variability measures serve as a major step for uniqueness measures among the individuals. Particularly, three features of mobility profiles can be considered: p_1 , the set of unique activities and their frequency performed by the users, p_2 , the temporal consistency scores among the common set of activities between any pair of users, and p_3 , the graph-edit distance between a pair of ATGs. Similarity is related to the commonality of two entities or two feature values. For measuring the similarity among a set of activity nodes, the common activity names between two mobility profiles are extracted along with the frequency of the activities performed. For example, assume the two mobility profiles of two users (u_i, u_j): $MF_i(A_i, C_i, ATG_i)$ and $MF_j(A_j, C_j, ATG_j)$, where $|A_i| = N_i$ and $|A_j| = N_j$. After a linear scan, the common activity names between A_i and A_j can be extracted, $|A_i \cap A_j| = m$. The relative number of occurrences of the activity a_p is denoted by f_p .

The dissimilarity value based on p_1 feature between A_i and A_j is:

$$D_{p_1}(A_i, A_j) = 1 - \frac{2 \times \sum_{r=1}^m \min(f_r \in A_i, f_r \in A_j)}{\sum_{p=1}^{N_i} f_p + \sum_{q=1}^{N_j} f_q} \quad (12)$$

Using Equation 12, the dissimilarity values between any pair of activity names is calculated based on their occurrences in the studied time. The value of D_{p_1} lies in the interval $[0,1]$.

Next, the dissimilarity value among the consistency scores (or, 1-variability) (duration and start time) of the common activity names are measured. For each of the consistency scores, the dissimilarity value is:

$$D_{p_2}(C_i, C_j) = \frac{\sum_{r=1}^m |C_{r,i} - C_{r,j}|}{\sum_{r=1}^m (C_{r,i} + C_{r,j})} \quad (13)$$

where $C_{r,i}$ is the consistency score of activity-name a_r of mobility profile MF_i . To calculate the dissimilarity among ATGs of MF_i and MF_j , the edit distance among the ATGs is computed as described previously.

Dissimilarity among n users can be represented as a $n \times n$ dissimilarity matrix, where each value (i, j) represents distinctness of users i and j with regard to their temporal activity patterns. Hence, normalized (between 0 and 1) dissimilarity values of p_1 , p_2 , and p_3 need to be aggregated. The aggregated dissimilarity value is a weighted average of the dissimilarity values of each feature variable.

$$D_{ij} = \frac{\sum_{k=1}^3 w_{ijk} \times d_{ijk}}{\sum_{k=1}^3 w_{ijk}} \quad (14)$$

where w_{ijk} is the weight of each feature variable, k represents the feature variables, and d_{ijk} is the dissimilarity value between mobility profile i, j for the feature variable k . Also, similarity values can be calculated as $(1 - D_{ij})$.

4 EXPERIMENTAL OBSERVATIONS

In order to illustrate and evaluate the temporal profiling, we conducted a survey to collect daily activity data of individuals. Participants (from two universities in two different countries) logged their daily activity in different time-scales in a web-based survey form. In this activity survey, 30 activities were specified and the survey had been designed to allow to log also concurrent activities in temporal scales.

Table 3 shows the summaries of the data collected from eight participants over two, three or four weeks. In the table, an ATG is listed as $G(A, E, l)$, where A is the number of activity nodes, E is the set of temporal relations, and l denotes the levels of the ATG of the particular mobility profile. The users' regular activity patterns are represented by Weekday-ATGs and Weekend-ATGs, which are shown in Table 3 by G_1 and G_2 . However, some of the users (u_1, u_2, u_6) have three ATG descriptions, which follows from the fact that maximal sub-graphs are not unique. In our experiment, we observe two maximal sub-graphs (from weekday-ATGs) for these users in the similarity matching procedure, and include both the ATGs in their mobility profile. By all means, users may have two (or more) ATGs in their mobility profile, if they follow two regular activity-patterns over the weekdays or weekends.

The uniqueness measure is defined as $\xi = \frac{N - \sum \delta_o}{N-1}$, where N is the number of total participants (there are eight participants in our experiment), δ_o defines the number of user temporal profile match with the input activity sequences. Using a random sampling approach, any activity sequences (test data) from each individual's (u_i) mobility profiles are selected, and similarity among all other user's temporal mobility profiles are measured based on different

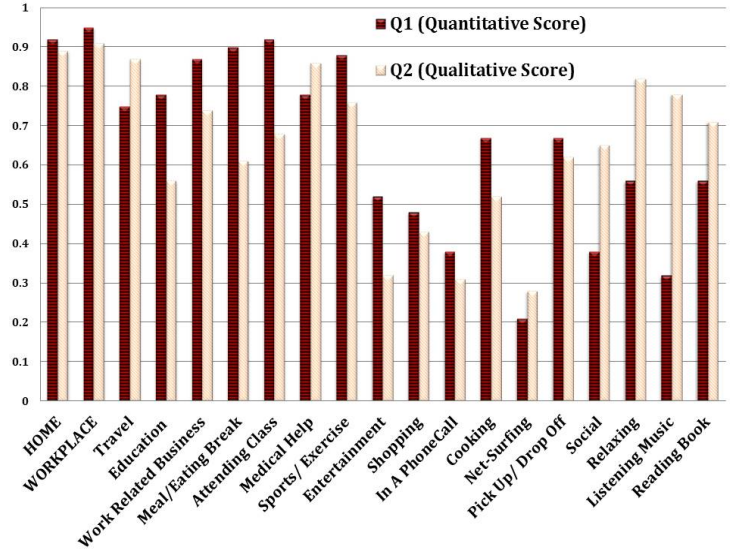


Figure 3: Temporal quantitative and qualitative scores of activities

temporal scales (l_1, l_2, l_3) of ATGs. δ_o is the number of user profiles having similarity scores with the input sequence greater than 0.80.

Table 4 shows the ξ value for 8 samples. $l_1 + l_2$ provides better uniqueness scores than individual levels l_1 or l_2 . The table shows also that *temporal embedded information* is more distinctive than *temporal resolution information*. To be more precise, if each level of the ATGs is analyzed separately, the average duration of l_1 activities is greater than for l_2 , which is greater than for l_3 . Consequently, exploring only activity sequences in individual levels provides analysis in different scales of temporal resolution, and disregards all concurrent activity patterns. Another observation reveals that uniqueness scores differ for Q_1 and Q_2 measurements. For this purpose, the activities are partitioned in two sets where elements of one set show better quantitative consistency whereas the other set is more consistent on qualitative analysis. The similarity matching procedure incorporating the segregation of activities based on Q_1 and Q_2 computation yields better uniqueness scores (last column ATG in Table 4) in this experiment.

These experimental findings are significant in many ways. Firstly, they demonstrate the capacity of the theoretical framework presented above to characterize and compare the activity sequences of individuals just based on their temporal patterns in a meaningful manner. Although the number of participants of the experiment is less [8 participants], it is sufficient for experimentation as the work investigates individual's activity pattern. Further, detailed activity-logs [each participant's activity log of at least 14 days and comprising average 18-20 activities/day] of the participants are collected. This dataset allows illustrating the framework and indicates that temporal profiles are individualized. It has also been shown that these signature patterns are not necessarily unique, and that more than one ATG may be required to capture an individual's regular activity patterns. This was expected for weekdays and weekends, but had also occurred within weeks, for example for individuals

Table 3: Temporal activity statistics and ATGs of the eight participants

userId	No. of days	No. of activities	Avg no. of activities/day	Avg duration (hr) of activities/day			ATG descriptions
				Level 1	Level 2	Level 3	
u_1	28	26	24	22	14.5	5.6	$G_1(16, E_1, 3), G_2(13, E_2, 3), G_3(18, E_3, 3)$
u_2	21	21	18	20	15	4.5	$G_1(16, E_1, 3), G_2(20, E_2, 3), G_3(17, E_1, 3)$
u_3	28	18	14	22.5	16	6	$G_1(11, E_1, 3), G_2(14, E_2, 3)$
u_4	21	14	12	20	15.5	3.2	$G_1(12, E_1, 2), G_2(15, E_2, 2)$
u_5	14	18	15	21.5	16	7.6	$G_1(13, E_1, 3), G_2(17, E_2, 3)$
u_6	18	15	14	21	14.6	7.2	$G_1(14, E_1, 3), G_2(10, E_2, 3), G_3(11, E_1, 3)$
u_7	14	16	14	18	12	6.5	$G_1(14, E_1, 3), G_2(12, E_2, 3)$
u_8	21	25	16	22	15	8	$G_1(15, E_1, 3), G_2(14, E_2, 3)$

Table 4: The ξ score on 8 samples of user temporal activity sequences on weekdays

-	$l_1(Q_1)$	$l_1(Q_2)$	$l_2(Q_1)$	$l_2(Q_2)$	$l_3(Q_1)$	$l_3(Q_2)$	$l_1 + l_2(Q_1)$	$l_1 + l_2(Q_2)$	$l_2 + l_3(Q_1)$	$l_2 + l_3(Q_2)$	$ATG(Q_1)$	$ATG(Q_2)$	ATG
1	0.285	0.142	0.428	0.428	0.142	0.428	0.428	0.571	0.285	0.428	0.428	0.571	0.714
2	0.428	0.285	0.428	0.571	0.285	0.285	0.571	0.714	0.285	0.285	0.571	0.857	0.857
3	0.142	0.142	0.285	0.428	0.285	0.428	0.428	0.571	0.285	0.142	0.428	0.571	0.714
4	0.285	0.142	0.428	0.571	0.285	0.285	0.714	0.857	0.285	0.428	0.714	0.857	0.857
5	0.571	0.428	0.714	0.714	0.428	0.428	0.857	0.857	0.428	0.571	0.857	0.857	1.0
6	0.428	0.285	0.571	0.571	0.428	0.428	0.714	0.857	0.428	0.428	0.857	0.857	0.857
7	0.285	0.285	0.428	0.571	0.428	0.285	0.714	0.714	0.428	0.571	0.714	0.714	0.857
8	0.285	0.142	0.428	0.428	0.285	0.285	0.714	0.857	0.428	0.285	0.714	0.857	0.857

with an employment on some days of the week. Therefore, any personalized recommendation system must consider all ATGs to provide meaningful efficacy. Moreover, Figure 3 shows temporal quantitative and qualitative scores of activities and differences of these scores for each activity clearly shows the need of segregation of the activities for an intelligent recommendation system. Users can also be categorized based on their temporal activity patterns, and analyzing consistent time slots for performed activities may provide better classification accuracy. Finally, it turns out that the embedded temporal analysis is more informative than the temporal resolution analysis. Therefore there exists a strong reason to hierarchically represent activity sequences based on the temporal relations among them.

5 CONCLUSION

In this paper, a conceptual framework has been presented to model mobility states and activity patterns at an individual level using purely temporal information, and generating mobility profiles in an optimal way. Such a framework is the core of any context-aware application provision that leverages the temporal information to assist in various personalized activities. In future this can be extended to predict the next activity states and user categorization using their current (or past) activity state(s) and temporal information through a stochastic or machine learning-based approach. The final goal of this research direction, however, is building a personalized recommendation system that will be capable to learn activity patterns over time and provide alerts based on activity contexts. It has been shown that the proposed hierarchical representation of activities will be beneficiary and informative for such a context-aware recommendation system.

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