An Analytical Framework for Understanding Urban Functionality from Human Activities

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Abstract

The intertwined relationship between urban functionality and human activity has been widely recognized and quantified with the assistance of big geospatial data. In specific, urban land uses as an important facet of urban structure can be identified from spatiotemporal patterns of aggregate human activities. In this article, we propose a space, time and activity cuboid based analytical framework for clustering urban spaces into different categories of urban functionality based on the variation of activity intensity (T-fiber), mixture (A-fiber) and interaction (I- and O-fiber). The ability of the proposed framework is empirically evaluated by three case studies.

2012 ACM Subject Classification General and reference → General literature

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Category Short Paper

1 Introduction

Human activities and urban functionality are strongly intertwined. As stated in [3], "Land use typically refers to the distribution of activities across space, including the location and density of different activities, where activities are grouped into relatively coarse categories, such as residential, commercial, office, industrial and other activities". It implies that different land use types inherently demonstrate distinct patterns of activity density and intensity [12], which are their most intuitive characteristics and can be both aggregate and temporal.

The interconnection between land use and urban activity, on the one hand, enables the generation, allocation and prediction of urban activities in space and time. For instance,

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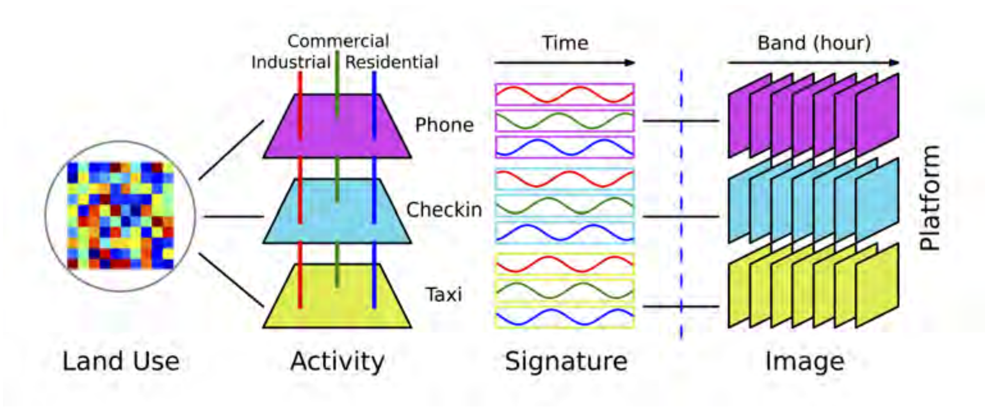

Figure 1 Urban land use inference as a analog to remote sensing.

there exists an abundant body of literature in urban modeling relying on the link between the two [1]. On the other hand, urban activity and its spatiotemporal dynamics can be regarded as good proxies of urban land use distributions. The usage of a specific urban space depends on those who occupy it and when, and what they do. These factors, in turn, constitute of a unique signature of the given urban space or land use zone [10]. Yet, an universal analytical framework for unraveling the relationship between urban land use types and their associated signatures of human activity is still missing.

Earlier research attempts show that utilizing urban activities to identify land use types can be analog to remote sensing for geographical classification [7]. As shown in Figure 1, the signature of changes of activity intensity along time can be taken as spectral characteristics of remote sensing for differentiating geographical objects. Recent advances in land use inferences and urban space segmenting based on urban activities follow this scheme in general. The procedure can be summarized as: (1) building feature vectors of urban spaces (e.g., places and regions) based on the variations of human activities in a predefined temporal granularity (e.g., hours of weekdays and weekends); (2) classifying urban spaces into different land use types (e.g., residential, commercial, leisure) based on the similarity between their feature vectors using mainstream clustering algorithms. Due to this fact, traditional classification approaches used in remote sensing are naturally adapted for the purpose, for instance Principal Component Analysis [10], K-means [8], Supervised Classification [11], and just name a few. However, it is still an open and interesting question that how to build the signature from the spatiotemporal dynamics of human activity to inform stakeholders the characteristic of the underlying urban spaces.

In this article, we will show readers a proposed space, time and activity cuboid based analytical framework for understanding the functionality of urban spaces based on human mobility data. With the cuboid, different activity signatures are derived for urban land use inference from the perspectives of the variation of activity intensity, mixture and interaction. The proposed framework is applied in three case studies based on three types of activity datasets (i.e., bus ridership, taxicab ridership and metro ridership) in different geographical regions. For each of the three types of activities, we build, normalize and cluster the signatures of each urban zone using different approaches. The results are accessed by the ground truth land use map as an evaluation of the capabilities of each combination of activity, feature, normalization and clustering algorithm.

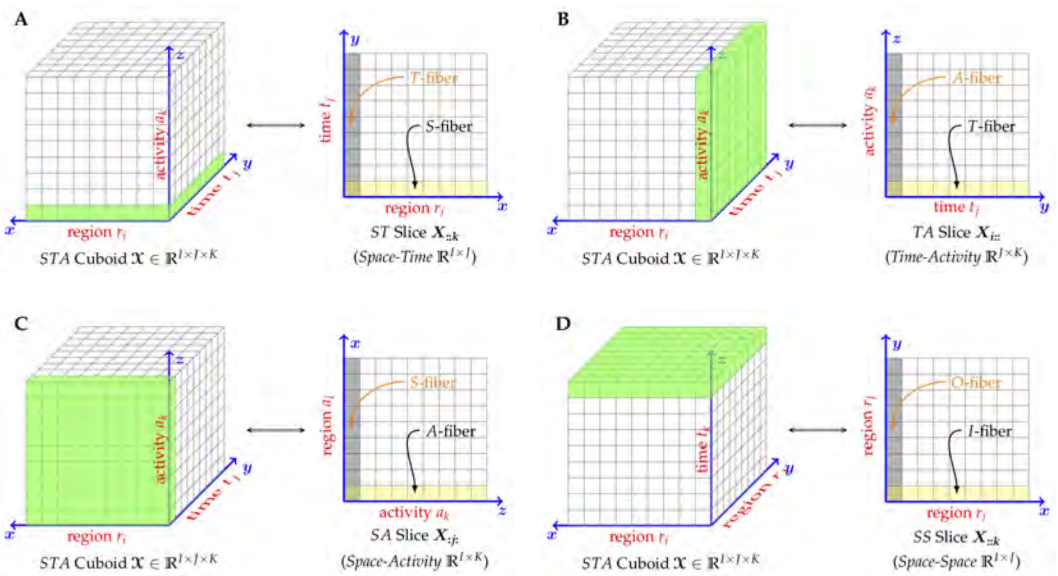

Figure 2 The **STA** cuboid of human **a**ctivity in **s**pace and **t**ime. In A, B and C, the 3-dimension tensor $\mathcal{X}$ consists of I regions, J time slots and K features (or activities). In addition, S-norm, T-norm and A-norm define the normalizations of fibers $\mathbf{x}_{:\,jk}$ (i.e., fixing time and activity), $\mathbf{x}_{i:\,k}$ (i.e., fixing space and activity), $\mathbf{x}_{ij:}$ (i.e., fixing space and time), respectively. Intuitively, S-fiber $\mathbf{x}_{:\,jk}$ quantifies the spatial distribution of a given activity a_k at the given time t_j, T-fiber $\mathbf{x}_{i:\,k}$ the temporal signature of a given activity a_k in the given region r_i, and A-fiber $\mathbf{x}_{ij:}$ the mixture of distinct activities in a give region r_i and at a given time t_j. In principle, S-norm captures the relative intensity of activities in different regions (**volume**), T-norm the fluctuations of activity intensity along time (**shape**), and A-norm the component of activities of a region (**texture**). Additionally, if the interaction between spatial regions can be observed, a new tensor $\mathcal{X}$ consists of I regions ($I = J$) and K time slots is built in D. Under this scenario, SS-norm captures the flow patterns between each pair of regions along time (**network**), and I-fiber $\mathbf{x}_{:\,jk}$, O-fiber $\mathbf{x}_{i:\,k}$ quantify the inflow and outflow of human mobility in the region, respectively.

2 A space, time and activity cuboid based analytical framework

For urban land use inference, we concentrate on three dimensions as *Space*, *Time* and *Activity* (**STA**) and propose a cuboid representation of the three dimensions as shown in Figure 2. In the cuboid, the *Space* dimension denotes the I distinct regions which are usually regular grids across space; the *Time* dimension represents the J different time slots; and the *Activity* dimension contains the K types of activities. Therefore, the proposed **STA** cuboid quantifies the distributions of human activities in space and time.

In practice, we usually observe individuals' diverse activities (large K) in fine spatial and temporal granularities (large I and J) with the assistance of the increasing availability of user-centric geospatial data. If fixing activity a_k, we can obtain a ST slice demonstrating the spatial distributions of the given activities along with time (Figure 2A). In the ST slice, each row is a S-fiber of the distribution of the given activity a_k in space at the given time slot t_j. Whereas, each column is a T-fiber of the signature capturing the fluctuations of intensities of activity a_k in region r_i at time t_j. In a similar way, we can obtain a TA slice if fixing the location (region) of interest (Figure 2B). The TA slice delineates the intensities of various types of activities $\{a_1, \cdots, a_K\}$ and their fluctuations along time $\{t_1, \cdots, t_J\}$ within the given region r_i. In the TA slice, each row is a T-fiber while each column is a A-fiber of the component of different types of activities in the given region r_i and time slot t_j. Fixing time t_j, a SA slice demonstrates how the different types of activities distribute across space, and its rows are A-fibers and columns S-fibers. Additionally, if the interaction between regions can be observed, a new tensor $\mathcal{X}$ consists of I regions ($I = J$) and K time slots is built (Figure 2D). Therefore, SS-norm captures the flow patterns between each pair of regions along time. Fixing time t_k, a SS slice demonstrates how the different regions interact with each other in space, and its rows are inflow I-fibers and columns outflow O-fibers.

Based on the fibers (i.e., activity signatures) derived from the space-time-activity tensor, we then relate urban land use and human activity from three distinctive perspective. Considering that the signatures are organized as time series, the clustering approach is adopted to assign urban spaces into different categories of urban functionality based on the similarity of their signatures in terms of the variation of activity intensity (i.e., the T-fiber), the component of activity type (i.e., A-fiber) and the pattern of spatial interaction (i.e., I- and O-fiber). Note that, in addition to the signature, different normalization method and clustering algorithm can result in different classification of urban land use types. To be concise, hereafter we will concentrate on the activity signature and discuss the normalization and clustering method briefly.

3 Applications of the framework for urban functionality inference

3.1 Clustering based on the variation of activity intensity ($\boldsymbol{T}$-fiber)

Using a seven-day taxi trajectory data set collected in Shanghai, we investigate the temporal variations of both pick-ups and drop-offs, and their association with different land use features. For each hour in the seven days, we compute the numbers of pick-ups and drop-offs for each 1 km $\times$ 1 km cell in the study area as the activity signatures. Two T-dimensional vectors, denoted by $\boldsymbol{V^{pickup}}$ and $\boldsymbol{V^{dropoff}}$, can be constructed to represent the temporal variations of trips for each pixel i in the study area as

$$\boldsymbol{V_i^{pickup}} = [V_i^1, V_i^2, \cdots, V_i^T] \tag{1}$$

$$\boldsymbol{V_i^{dropoff}} = [V_i^1, V_i^2, \cdots, V_i^T] \tag{2}$$

Based on the balance between the numbers of drop-offs and pick-ups and its distinctive temporal patterns $\boldsymbol{V_i^{dropoff}} - \boldsymbol{V_i^{pickup}}$ for each pixel i at time t $(= 1, \cdots, T)$, the study area is classified into six traffic 'source-sink' areas using the K-means clustering method. These areas are closely associated with various land use types (commercial, industrial, residential, institutional and recreational) as well as land use intensity. Five sample points are selected from the study area to represent various locations (land uses), and their corresponding $\boldsymbol{V^{pickup}}$ and $\boldsymbol{V^{dropoff}}$ are depicted in Figure 3. Their temporal patterns differed significantly. For example, the average numbers of pick-ups and drop-offs were roughly equal for cells A and B. In either cell C or D, however, the average number of pick-ups was much fewer than the average number of drop-offs. Cell E had far lower numbers of pick-ups and drop-offs than the other four locations. It confirms that the temporal patterns of pick-ups and drops-offs vary a great deal from place to place, and are manifest of the function of the place.

3.2 Clustering based on the component of activity type ($\boldsymbol{A}$-fiber)

Leveraging a comprehensive data collection of bus, metro and taxi ridership from Shenzhen, China, we furture unveil the spatio-temporal interplay between the mixed use of transport modes and the underlying urban land use. For each spatial analysis unit (SAU), we build

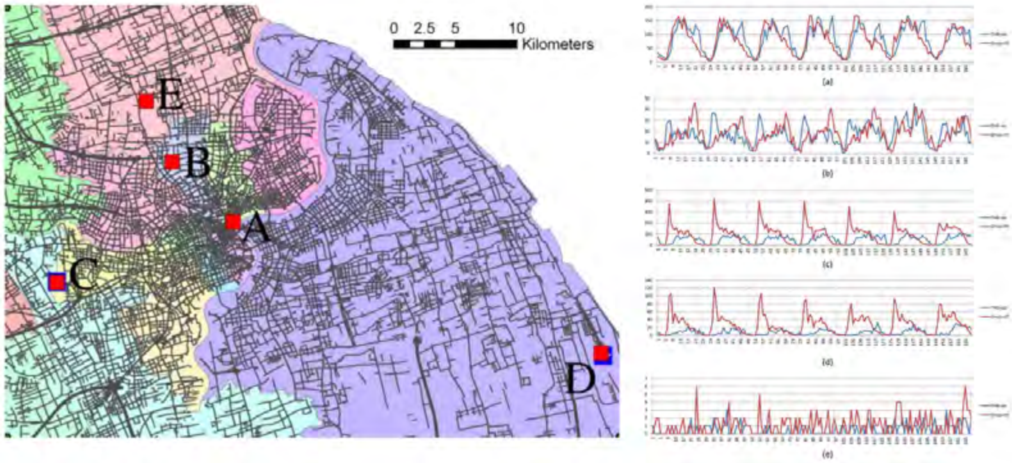

Figure 3 Temporal variations of pick-ups and drop-offs of 5 sample points in Shanghai, China (A: downtown; B: residential; C: Hongqiao Airport; D: Pudong Airport; E: suburban) [8].

a volume signature capturing the temporal fluctuations of ridership of mass transit modes during a day. Taking 15-minutes as the temporal granularity, the signature $\boldsymbol{V_i}$ of a SAU i is denoted as a $1 \times T$ vector quantifying the ridership of bus, metro or cab within the nth time slot. Targeting to compare three distinct mass transit modes, we therefore obtain the signatures of volume $\{ \boldsymbol{V_i^{bus}}, \boldsymbol{V_i^{metro}}, \boldsymbol{V_i^{cab}} \}$ for bus, metro and cab ridership within each SAU i, as well as the signatures of ratio $\{ \boldsymbol{R_i^{bus}}, \boldsymbol{R_i^{metro}}, \boldsymbol{R_i^{cab}} \}$ of ridership of different mass transit modes over time:

$$\boldsymbol{R_i^{bus}} = \boldsymbol{V_i^{bus}} / (\boldsymbol{V_i^{bus}} + \boldsymbol{V_i^{metro}} + \boldsymbol{V_i^{cab}}) \tag{3}$$
$$\boldsymbol{R_i^{metro}} = \boldsymbol{V_i^{metro}} / (\boldsymbol{V_i^{bus}} + \boldsymbol{V_i^{metro}} + \boldsymbol{V_i^{cab}}) \tag{4}$$
$$\boldsymbol{R_i^{cab}} = \boldsymbol{V_i^{cab}} / (\boldsymbol{V_i^{bus}} + \boldsymbol{V_i^{metro}} + \boldsymbol{V_i^{cab}}) \tag{5}$$

where $\cdot / \cdot$ represents the itemwise division between two input vectors.

Applying a novel spectral clustering on the proposed signatures of the ratio of ridership, we obtain 5 clusters of SAUs that demonstrate distinct patterns of bus, metro and cab ridership dynamics as shown in Figure 4. In Cluster 1, metro rails play the most important role within these SAUs. During morning and evening commuting periods, metro ridership increase significantly. In comparison, the ratios of bus ridership and cab ridership are relatively low. Besides, the temporal fluctuations of bus ridership and cab ridership are also distinct. In Cluster 2, bus ridership and metro ridership are at a comparative level, which is significant higher than cab ridership. It indicates passengers have easy access to bus and metro at the same time. However, during morning and evening commuting periods, bus and metro ridership show no significant increase to that of working time periods. In Cluster 3, metro ridership demonstrate substantial increase during the morning and the evening commuting periods. On the contrary, bus ridership show no peaks during the commuting periods and its ratio is very low. In Cluster 4, bus ridership and metro ridership are very similar to that of Cluster 2. However, within these SAUs, increase of ridership during the morning commuting period are high while that during the evening commuting period is low. In Cluster 5, bus and metro compete for the dominant mass transit mode during different time regimes. During the morning commuting period, metro rails are the dominant mass transit mode. Whereas, during the evening commuting period, buses become the dominant mass transit

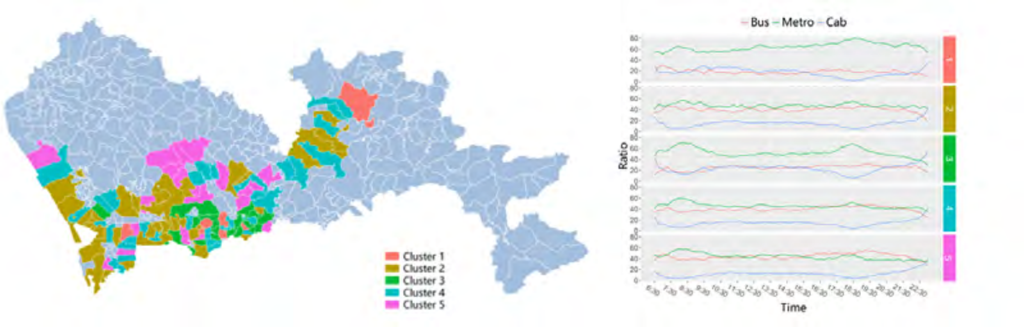

Figure 4 Temporal variations of ridership patterns of mass transit modes associated with different clusters of SAUs in Shenzhen, China (Cluster 1: business and commercial; Cluster 2: rich residential; Cluster 3: mixed-use; Cluster 4: middle-income residential; Cluster 5: recreational) [13].

mode. Over the entire day, cab ridership is always relatively low. This phenomena reveals the transmission of passengers' preference of different mass transit modes over time. In general, different categorized urban spaces are associated with different accessibility levels (such as high-, medium-, and low-ranked) and different urban functionalities (such as residential, commercial, leisure-dominant, and home-work balanced). The results indicate that the demographic and socioeconomic attributes of the underlying urban environments can be revealed by the ridership dynamics of different mass transit modes.

3.3 Clustering based on the pattern of spatial interaction ($\boldsymbol{I}$- and $\boldsymbol{O}$-fiber)

Based on the observation that spatial interaction patterns between places of two specific land uses are similar, we derive a new type of place signature to infer urban land uses from a perspective of connections. The method is validated with a case study using taxi trip data from Shanghai. Assuming that intra-city spatial interactions between N different places represented by travel flows can be extracted from the massive data sets, in each hour of a day, an $N \times N$ origin-destination (OD) matrix M^t ($t \in [1, 2, \cdots, T]$) of population movements can be constructed, denoting the population moving from place i to j at time slot t as $m^t_{i,j}$ ($i, j \in [1, 2, \cdots, N]$). Using $m^{t,k}_{i,j}$ and $m^{t,k}_{j,i}$ to denote the outflows from place i to j and inflows from j to i at time slot t, while the assumed land use type of j is K, we build the grouped interaction signature $\boldsymbol{V^{group}}$ for place i as

$$\boldsymbol{V_i^{group}} = \begin{pmatrix} m^{1,1}_{i,\cdot} & \cdots & m^{T,1}_{i,\cdot} & m^{1,1}_{\cdot,i} & \cdots & m^{T,1}_{\cdot,i} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ m^{1,K}_{i,\cdot} & \cdots & m^{T,K}_{i,\cdot} & m^{1,K}_{\cdot,i} & \cdots & m^{T,K}_{\cdot,i} \end{pmatrix} \tag{6}$$

which represents the flow patterns of a place with a trade-off between aggregated patterns and individual spatial interactions.

Inspired by the expectation-maximization (EM) algorithm, we use an iterative algorithm combined with the K-means clustering method to link the clustered parcels to their corresponding land uses. Figure 5 illustrates the classification result based on the grouped interaction signature of parcels. By interpreting the mean temporal signature curves and referring to Google Map information, we assign the roughly corresponding land uses to each parcel cluster. Type 1 have inflow peaks in the morning, afternoon and early evening, representing residents coming for work, business and eating/shopping/entertaining, respectively.

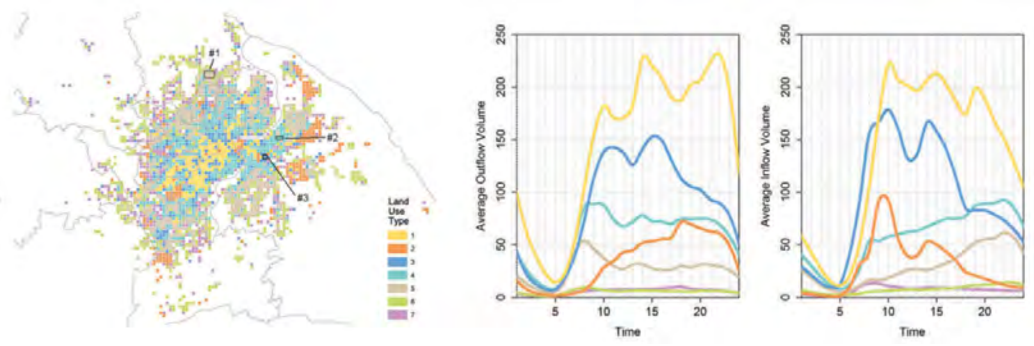

Figure 5 Temporal variations of spatial interaction patterns between different categories of land uses in Shanghai, China [6].

Whereas, the two outflow peaks in the afternoon and night represent people's travels for business and going home, respectively. Therefore, these parcels are urban commercial and business area. Type 2 covers business and industrial area. Type 3 covers civic facilities, such as railway stations, hospitals and museums, and their inflow and outflow peaks are in the daytime. For Type 4, 5 and 6, the normalized mean temporal signatures of them all show that people leave these regions in the morning and return to these areas in the evening, which is consistent with the way people use residential areas. According to their spatial distributions, we name them urban residential area, outskirt urban residential area and suburban residential area, respectively. Type 7 are considered to be other land use area with few taxi trips. These results confirm that urban functionality can be better understood by analyzing the interaction patterns between different land uses.

4 Conclusion and Discussion

In this article, we proposed a space, time and activity cuboid based analytical framework for understanding the functionality of urban spaces. The core contribution is how to organize the human activity data into the cuboid for building meaningful and informative activity signatures. Applied in three case studies with the derived signatures of the variation of activity intensity, the component of activity type and the pattern of spatial interaction, the ability of the proposed analytical framework is confirmed. Note that directly following the remote sensing paradigm surely shows promising potentials for understanding and analyzing urban spaces. However, there are also several pitfalls should be aware of by researchers and practitioners as listed below.

- **Activity**: Different activities have substantially distinct spatiotemporal characteristics. Particularly, the big data revolution has been producing plentiful geo-data associated with individuals and their activities in space-time. Much more urban phenomenon are accessible and identifiable by this new and rich data source. For instance, spatial distributions of mobile phone and taxicab usages are observed to be quite different in many cities [4]. It is of critical importance to choose what kind of activity to analyze.
- **Feature selection**: Even for a single type of activity, the feature or feature combination selected also can result in inconsistent results. For instance, the combination of features related to taxi pick-up/set down dynamics significantly influence the recognition accuracy of urban land uses in a Chinese city [9]. Therefore, the feature should be carefully selected based on the research context.

- **Normalization**: Unlike the spectral curve of remote sensing, which is typically consistent for the same type of geographical objects and invariable with object size, the signatures of same land use types can be very different in magnitude order, in that socioeconomic activities change superlinearly with urban area size [2]. To cope with this issue, normalization is thus usually conducted before clustering the signatures.
- **Clustering**: In the context of using urban activity for land use classification, many classical clustering algorithms can be used because the signatures of urban zones can be simply regarded as time series. A comprehensive survey of time series clustering algorithms can be found in the literature [5]. The main challenge lies in the way to measure the similarity between the activity signatures.

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