# Adaptive Gamification in Collaborative Location Collecting Systems: a Case of Traveling Behavior Detection

## Ludificación Adaptativa en Sistemas Colaborativos de Recolección Basados en la Ubicación: un Caso de Detección de Comportamiento Espacio-Temporal

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## Abstract

Collaborative location collecting systems (CLCS) is a particular case of collaborative systems where a community of users collaboratively collects data associated with a geo-referenced location. Gamification is a strategy to convene participants to CLCS. However, it cannot be generalized because of the different users' profiles, and so it must be tailored to the users and playing contexts. A strategy for adapting gamification in CLCS is to build game challenges tailored to the player's spatio-temporal behavior. This type of adaptation requires having a user traveling behavior profile. Particularly, this work is focused on the first steps to detect users' behavioral profiles related to spatial-temporal activities in the context of CLCS. Specifically, this article introduces: (1) a strategy to detect patterns of spatial-temporal activities, (2) a model to describe the spatial-temporal behavior of users based on (1), and a strategy to detect users' behavioral patterns based on unsupervised clustering. The approach is evaluated over a Foursquare dataset. The results showed two types of behavioral atoms and two types of users' behavioral patterns.

**Keywords:** Adaptive gamification challenges, Spatial-temporal user profiling, Users behavioural patterns

## Resumen

Los sistemas colaborativos de recolección basados en la ubicación (CLCS, por sus siglas en inglés) son un caso particular de sistemas colaborativos donde una comunidad de usuarios recopila de forma colaborativa datos asociados con una ubicación georreferenciada. La ludificación es una estrategia para convocar participantes a CLCS. Sin embargo, no se puede generalizar debido a los diferentes perfiles de los usuarios, por lo que debe adaptarse a los usuarios y contextos de juego. Una estrategia para adaptar la gamificación en CLCS es crear desafíos de juego adaptados al comportamiento del jugador. Este tipo de adaptación requiere tener un perfil del comportamiento espacio-temporal del usuario y en particular, este trabajo se centra en los primeros pasos para detectar este tipo de perfiles en relación a las actividades espacio-temporales en el contexto de los CLCS. Específicamente, este artículo presenta: (1) una estrategia para detectar patrones de actividades espacio-temporales, (2) un modelo para describir el comportamiento espacio-temporal de los usuarios basado en (1), y una estrategia para detectar patrones de comportamiento de los usuarios, basada en en agrupamiento (*clustering*) no supervisado. El enfoque se evaluó sobre un conjunto de datos de la aplicación Foursquare. Los resultados mostraron dos tipos de átomos de comportamiento y dos tipos de patrones de comportamiento de los usuarios.

**Palabras claves:** Desafío de juego adaptativos, Perfilamiento espacio-temporal de usuarios, Patrones de comportamiento de usuario

## 1 Introduction

Collaborative location collecting systems (CLCS) is a particular case of collaborative systems where a community of users collaboratively collects data associated with a geo-referenced location. The community of users travels around the globe collecting data.There are a vast number of CLCS. For example, the so-called Location Based Social Network, are CLCS where people share with their friends visited places; Foursquare (`https://foursquare.com/`) is a well-known case. Another example is the citizen science collecting systems that allow users to collect location-based data with a scientific goal. For example, iNaturalist (`https://www.inaturalist.org/`) is a biodiversity mapping social system where users spot in a map, using a mobile application, the visualization of any living being. In many of these systems with users worldwide, a large amount of data is already stored[1, 2, 3] .

CLCS should develop strategies to "convene participants, keep them active and committed with the specific project's task, keep them engaged with the project, and make them feel part of it" [4]. The use of game elements in non-game contexts, known as **gamification**, is a widespread approach to increase user engagement [5]. Nevertheless, it is also well known that gamification cannot be generalized because of the users' different motivations, personalities, needs, or values. So it must be tailored to the users, and playing contexts [6]. This research field is known as **adaptive gamification** which is presented as a promising possibility to improve user engagement towards these systems [7].

One of the most used game elements in gamified collaborative systems is challenges[4]. A game challenge is a task or problem in which difficulty depends on the user's skills, abilities, motivation, and knowledge [8] and count toward progress and outcomes. However, most of the use of this game element is not tailored to the user.

There is a wide range of types of challenges detailed in the literature [9]. Particularly, those that require endurance faculties or those that require sustaining a temporality and rhythm can be mentioned, which are the ones considered to develop this proposal. To develop challenges of this type in a personalized way, it is necessary to categorize people based on how they interact with the CLCS in terms of distance traveled and time between data collection moments (check-in).

This work is focused on the first steps to detect users' behavioral profiles related to spatial-temporal activities in the context of CLCS. Specifically, this article introduces: (1) a strategy to detect patterns of spatial-temporal activities, (2) a model to describe the spatial-temporal behavior of users based on (1), and finally, a strategy to detect users' behavioral patterns. These patterns will be the input for *endurance* and *rhythm* challenge adaptation in CLCS.

Specifically, this work presents three contributions. (a) A way to characterize the playing activities in terms of the invested time, the traveled distance, and the number of performed actions given a short time frame, for example, a day or a couple of hours; then these activities are categorized into categories called behavior atoms. Then, (b) a description of each user traveling gaming behavior is presented by sequencing the behavior atoms in a long time interval, for example, a year. Finally, (c) categorization of the users detecting similarities in their temporal sequences (b).

An unsupervised clustering strategy is proposed to infer user profiles from analyzing their traveling behavior with a time series strategy. The approach will be evaluated with a Foursquare dataset. The results show the detection of two behavioral atoms and two types of users' behavioral patterns.

This paper is structured as follows: in Section 2 the related work is described, Section 3 gives the motivation of this work in terms of two specific problems. Section 4 details the proposed approach to these problems, Section 5 describes the steps of the approach over a Foursquare dataset, Section 6 presents some discussions around possible improvements to this work, and finally, the conclusions and further work are given in Section 7.

## 2 Related Work

A user profile is a central component of information systems such as adaptive systems, and it has been widely studied. Ponciano et al. [10], and Aristeidou et al. [11] worked in profiling the users' motivations and contribution patterns in citizen science projects, looking at engagement metrics. Several works have been done specifically with Foursquare datasets to estimate the user's behavior. The work in [1] studies the geo-temporal dynamics of user activity to unfold place transitions and identify sequences of activities. Also, mobile users' spatial-temporal activity preference was inferred from the user-generated digital footprints in LBSNs [12]. Long et al. [13] focus on exploring the local geographic topics using the Latent Dirichlet Allocation (LDA) model to discover the local geographic topics from the check-ins datasets.

To estimate sequence similarity and feature representations for sequence classification and clustering is one of the main tasks of exploratory data mining and is used in many fields such as bioinformatics, pattern recognition, image analysis, or machine learning.

None of the mentioned contributions are related to personalizing the gaming experience based on the space-time behavior record, as is introduced in this article.

## 3 Problem Statement

The available literature records the work in the classification of challenges from different aspects. Vahlo et al. [9] perform an exhaustive classification of thirty-eight videogame challenge types into five challenge types: Physical, Analytical, Socioemotional, Insight, and Foresight. Challenges of *endurance* and *rhythm* are considered in this work as the types of challenges most related to the activities of the CLCS since they require a change of geographical position. In the context of the CLCS application, an *endurance challenge* can be related to the number of check-ins or the frequency. For example, to obtain five check-ins in a day or to travel ten kilometers per day for three days. A *rhythm challenge* would be a situation that involves check-in at certain times or repeating a sequence of activities. For example, to check in before noon and after dinner through four days.

This work aims to classify users according to their traveling behavior profile, focusing on distances traveled, invested time, and number of check-ins in a period. The input is a check-in set with information about their geographic position and a timestamp.

For this classification purpose, this work proposes a model of user behavior over time that involves the definition of two strategies. Firstly, a strategy to synthesize the user's interaction with the CLCS in a single value for each time frame based on the traveling aspects. Lastly, a strategy to classify users from the similarity of their time series.

### 3.1 Definitions

Before going into details about the approach, it is necessary to present some definitions that will give a conceptual context.

A *check-ins dataset* is a dataset that includes the log of users' check-ins. It is defined by user id, latitude, longitude, and timestamp.

In this work, the *time frame* is the interval applied to group the user's activities and aggregate them from the temporal and spatial point of view. Time frame size could be variable, for example, in terms of days or weeks. Therefore, the check-ins dataset is divided into fixed-size time frames. The time frames are calculated from the interval covered by the dataset's samples and a frame size parameter. Time frames are used to define the size of the behavioral atom described below.

The activities aggregation are computed by the $checkInCounts$, $investedTime$, and $traveledDistance$ functions as are defined below.

**Definition** userDataFrame(user_id,timeFrame): List of checkins dataset entries by user_id in the given timeframe,ordered by timestamp.

**Definition** checkInCounts(user, timeFrame): the number of entries in userDataFrame(user,timeFrame)

**Definition** investedTime(user, timeFrame): difference between the first and last check-in timestamp in userDataFrame(user,timeFrame)

**Definition** traveledDistance (user, timeFrame): Sum of all distances between two consecutive check-ins in userDataFrame(user,timeFrame)

A **behavioral atom** is a categorical value that describes the user's interaction with the CLCS within a time frame from the mentioned activity aggregation.

A **user travel behavior (UTB)** is a sequence of behavioral atoms organized as a time series in chronological order to describe the user's behavior during the check-in dataset period.

Figure 1 shows an example of a check-in dataset and the transformation into a UTB set.

Lastly, given the users' time series, it is possible to define a similarity criterion between them based on the value patterns (or variation in the values) that make up the sequence. The second problem to be addressed was classifying users based on this idea of similarity, and with this objective, different machine learning techniques were applied. The following are the definition of the problems.

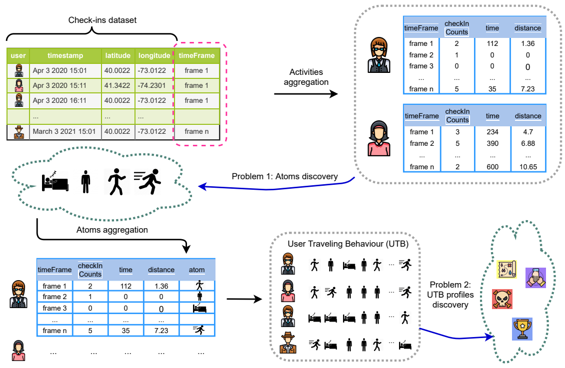



Figure 1: Data transformation into UTBs. The atoms alphabet in this example is made up with 4 elements: L (low), M (moderate), A (average), H (high)

**Problem 1:** Detect the atoms alphabet that better describes spatial-temporal activities patterns in the check-in dataset. The atoms alphabet will be the elements that shape the UTBs.

**Problem 2:** Detect users behavioural profiles by means of theirs UTBs.

## 4 Approach

For the analysis of the first problem, a KMeans-based clustering of the aggregated activities is performed. Clustering is an unsupervised machine learning technique to identify groups of samples based on their similarity. This technique allows the discovery of features from sample data, and in particular to this first problem, the similarity among aggregated activity records. Precisely, three aggregated values are calculated: the number of check-ins of the time frame, the time that elapses between the first and the last check-in of that time segment, and the distance traveled, based on the geographical distance between consecutive registered positions.

Regarding the second problem analysis, two studies are carried out using time series k-means, considering the full and half sampled period. This makes it possible to study whether the characterization of the users depends to a greater extent on the length of the UTB series. To measure the similarity between user time series, and given that each user's activity may not occur on the same time frames, at least two ways of normalizing the observations can be considered: an absolute and a relative approach. In the former case, the temporary frames are fixed depending on the total period of the dataset (or period of analysis), and when a user has no activity in a time frame, it is filled in with zeros (or values that do not deviate the clustering). In the latter case, only the activity records sequence is taken into account, causing the zero filled values to be at the end of the user records. The drawbacks of the absolute approach are that users are compared in a synchronized way, apparently losing the possibility that two users with the same behavior pattern will result in the same cluster: a similar number of check-ins and distance traveled, but at different time frames. On the other hand, with the relative approach, the overall calendar is ignored.

The approach is detailed below through a case study using the Foursquare dataset for New York between April 2012 and February 2013.

# 5 Evaluation

The following steps are carried out to address both problems: First, a pre-processing of the dataset is carried out to eliminate null data, standardize the data, and analyze the correlation between the variables.

The evaluation is done for four frame sizes: one week, three weeks, five weeks and seven weeks. All of the activities a user performed in the same time frame were grouped and aggregated. In each case, the elbow curve is analyzed to decide the number of clusters. Next, the clustering algorithm is run over the dataset with the number of cluster parameters defined before. Then, how the clusters are formed and distributed are plotted and analyzed. Finally, the categories are determined.

All the analysis was developed in Kaggle environment[1], using Python language with Pandas and sklearn as main libraries.

## 5.1 The Foursquare dataset

In Foursquare, users visit and comment about the places of interest, and share them with their friends.

The foursquare dataset has information about users' check-ins, particularly the venue id, venue category, geographic location, and timestamp. This work uses the Foursquare dataset from New York with 227,428 records between April 2012 and February 2013[12] which includes all the activities that each user has done with the system. Each record includes check-in timestamp, GPS coordinates as a latitude/longitude pair, user id, venue id, venue category id, venue category name, and time zone offset. This work focus only on user id, GPS coordinates, and timestamp. Time zone offset was ignored because all of them had the same value.

The dataset describes the activity information of 1,083 users through 318 days. It is important to note that there are periods in which the dataset does not have check-ins. The largest occur between August 21, 2012, and September 12, 2012, and between September 19, 2012, and October 10, 2012. Although it would be nice to have these data, we consider that they will not alter the analysis. In time series figures, they can be seen as blank spaces.

## 5.2 Activities aggregation

The aggregation step computed for each user and time frame the aggregated values defined in Section 3.1. The result was a pandas dataframe with user id, checkIncounts, investedTime, traveledDistance, and frameId on each row. The statistical characterization of these variables is described in Table 1.

The data reflects a high standard deviation in most of the variables. This revealed that users had different characteristics in their behaviors instead of monotony. Indeed, it is coherent and validates the purpose of this article.

As we can notice, these data frames does not include rows representing the absence of activities in a time frame. For example, if a user did not perform a check-in on a given time frame, it does not appear.

## 5.3 Problem #1 analysis

As a pre-processing stage, two steps were developed. Firstly the normalization of the samples with the described absolute approach in such a way as to record the activity of all users in all time intervals, filling in with zero values when there was no user activity. The results of this process are shown in the first rows of Table 2.

Lastly, a common practice is to standardize the aggregated values to the range between 0 and 1 to avoid a bias in the distance calculation carried out in clustering.

A K-means clustering was executed in order to detect behavioral atoms. The main objective of this clustering strategy is to synthesize the user activity within the time frame in a single value and thus be able to shape historical activity as a time series. A critical step for any unsupervised clustering algorithm is to determine the optimal number of clusters into which the data can be clustered. The *elbow method* [14] is one of the most popular methods for determining this optimal value of *k*. The values of k are iterated from 1 to 10 and calculate the inertia (the sum of squared distances of samples to their closest cluster center) or silhouette score for each value of k in the given dataset, to finally choose the smaller inertia or the largest silhouette score. The algorithm is described in Algorithm 1.

For this objetive, the *KElbowVisualizer* method from *yellowbrick* python library, with silhouette metric was used, and can be seen in row 3 of Table 2. Therefore, the KMeans clustering was executed with $k = 2$, for every scenario (one week, three weeks, five weeks and seven weeks time frames), and the euclidean distance was applied in every case.

Figures in row 4 of Table 2 explain the distribution of the atom clusters, where the x-axis details each

[1] `https://www.kaggle.com`

| | | One week | Three weeks | Five weeks | Seven weeks |
|---|---|---|---|---|---|
| check-in | mean | 7.52 | 17.8 | 26.9 | 36.3 |
| | sd | 9.75 | 2.9 | 37.5 | 49.9 |
| | min | 1 | 1 | 1 | 1 |
| | max | 140 | 374 | 584 | 852 |
| | 75% | 9 | 21 | 33 | 43 |
| time | mean | 4650 min (3.2 days) | 18129 min (12.5 days) | 32600 min (22.6 days) | 48200 min (33.4 days) |
| | sd | 3400 min | 9858 min | 17373 min | 20900 min |
| | min | 0 min | 0 min | 0 min | 0 min |
| | max | 10100 min (≈1 week) | 30200 min (≈3 weeks) | 50300 min (≈5 weeks) | 70500 min (≈7 weeks) |
| | 75% | 7825 min | 27300 min | 47600 min | 65000 min |
| dist | mean | 25.4 km | 667.4 km | 105 km | 144 km |
| | sd | 39 km | 94.9 km | 149 km | 196 km |
| | min | 0 km | 0 km | 0 | 0 |
| | max | 467 km | 1300 km | 1830 km | 2890 km |
| | 75% | 11.9 km | 8.4 km | 129 km | 175 km |

Table 1: Aggregated spatial-temporal variables

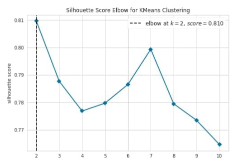
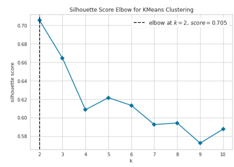
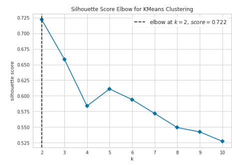
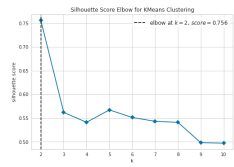
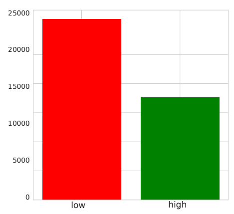
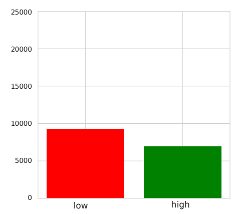
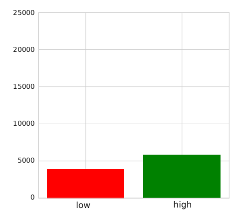
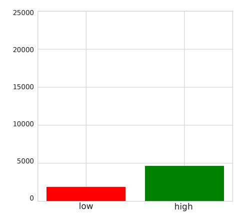
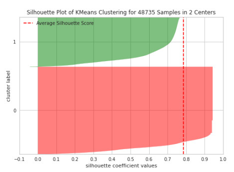
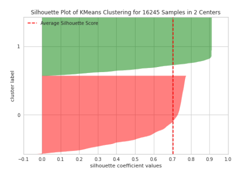
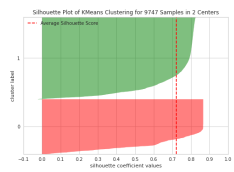
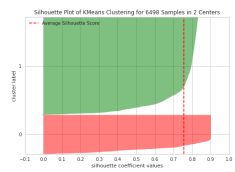
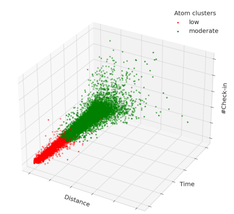
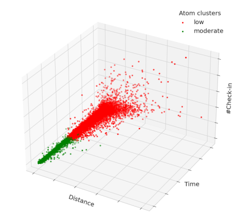
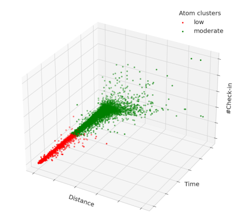
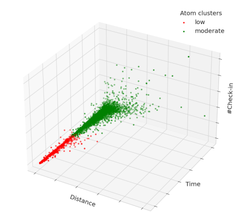
| | One week | Three weeks | Five weeks | Seven weeks |
|---|---|---|---|---|
| (1) Total time frames | 48735 | 16245 | 9747 | 6498 |
| (2) No activity time frames | 18995 | 3929 | 1788 | 995 |
| (3) Cluster estimation |  |  |  |  |
| (4) Clusters distribution |  |  |  |  |
| $C_0$ (low) size | 31078 | 9300 | 3908 | 1857 |
| $C_1$ (moderate) size | 17657 | 6945 | 5839 | 4641 |
| (5) Silhouette score |  |  |  |  |
| (6) 3D plots of atoms |  |  |  |  |

Table 2: comparison between scenarios

**Algorithm 1** Elbow method for optimal cluster number

*score* = []
**for** i in range(1,11) **do**
  kmeans = KMeans(*n_clusters* = *i*, init='k-means++', random_state=0)
  kmeans.fit(data)
  score.append(kmeans.inertia_)
**end for**

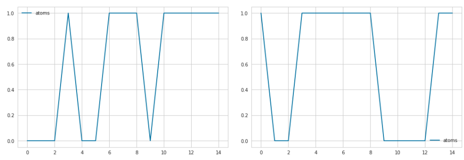


Figure 2: 3 weeks UTB series from 2 users

cluster, and the y axis the cluster's element count. On the one hand, with a one-week and three-weeks time frame, the low cluster (red color) is the largest one, and the reason can be found in the injection of zero-activity entries by the normalization process and the activity records of a single check-in. Notice that with bigger time frames the zero-activity entries decrease significantly.

Then, the instance's silhouette coefficient was plotted, including a red line indicating the average Silhouette score, as can be seen in row 5 of the Table 2. Notice that in all cases, the clusters are well balanced and with a good average silhouette score, and only in a one-week time frame there is one cluster that does not reach the average silhouette score.

Furthermore, observing in addition the histogram that illustrates the clusters' sizes (see Table 2 (4)) and the aforementioned silhouette coefficient, it can be seen that both three-weeks and five-weeks time frames present the best distribution of the clusters in terms of quantity of elements and purity index, so they may be eligible for the analysis of problem 2. For this reason, the analysis of problem #2 is supported by this three-weeks atoms and the five-weeks atoms remain for a future analysis.

## 5.4 Problem #2 analysis

Having computed the behavioral atoms for each aggregated three weeks time frame using two categories (low, high), the UTB sequences were constructed for each user. Figure 2 shows an example of two users' UTB series for a three weeks time frame: The *y axis* details the atoms type, and the *x axis* the time 15 time frames. Each point represents a type of atom the user performed in the time frame. As was introduced in Section 4, two studies were developed, with the full sampled period and with half sampled period. So, the full-length UTB series for each user has 15 atoms and the half-period UTB series has 7 atoms.

As the UTBs are time series, they can be classified using time series k-means clustering. A time series is a sequence of observations of a continuous variable, and a sequence is analogous to a discrete or categorical variable. For this reason, they are considered a particular type of time series. One of the most popular approaches in time series classification is the use of the nearest neighbor (NN) classifier in conjunction with a distance function[15].

On the other hand, to address the problem of synchronization of the absolute approach described in section 4, dynamic time warping (DTW) was chosen as a function of distance, instead of euclidean distance, which was applied in the approach of Problem 1 (Section 5.3). In time series analysis, DTW is one of the algorithms for measuring similarity between two temporal sequences, which may vary in speed. It has been shown that dynamic time warping (DTW) distance with an NN classifier worked effectively [16].

As was done to analyze Problem 1, the elbow method was developed to determine the optimal number of clusters for the classification of UTBs. The result is shown in Figure 3 (A), and it can be seen that the optimal number of clusters for the full period, as well as for the half of the period, is 2.

The clusters' distribution is plotted in Figure 3 (B) and their Dynamic Time Warping Barycenter Averaging (DBA) are plotted in Table 3 (D). DBA is a method to extract the shape of the cluster instead of averaging each series in the cluster, applying the Dynamic Time Warping distance. Nevertheless, notice that the average line is made up of values that do not represent the atoms' categorical values: the UTB series have a two values alphabet and despite this the average line is made up of many intermediate values.

To study the results of each scenario, both graphs are considered in a complementary way. Also, the clusters' purity index is measured by the silhouette score that is shown in Table 3(E), indicating that the average silhouette score is higher for the half period (0.25) than for the full period (0.18). Nevertheless, in both cases, the clusters are acceptably balanced since the plot shape shows that most of the items reach or exceed the average score.

On the one hand, considering the full period, it can be seen that the majority cluster (C0) is described by a timeline where activity fluctuates during the first half and then declines in the second half of the period, while users in cluster C1 apparently behaves in a complementary way.

Similarly, considering the half-sized period, both cluster average lines had also complementary shapes with a high activity intensity at the beggining or at the end of the period.

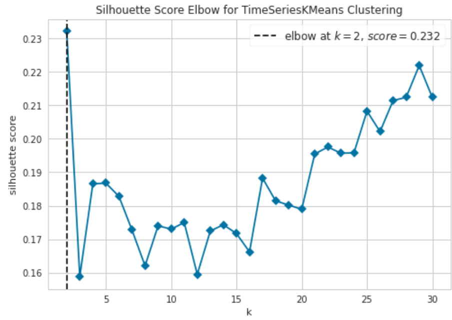
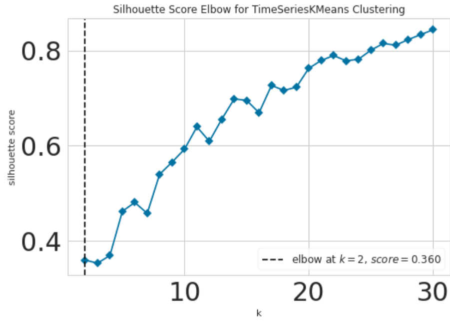
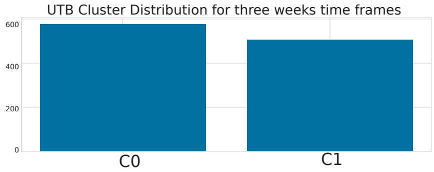
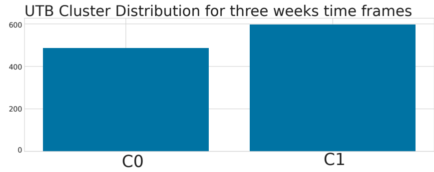
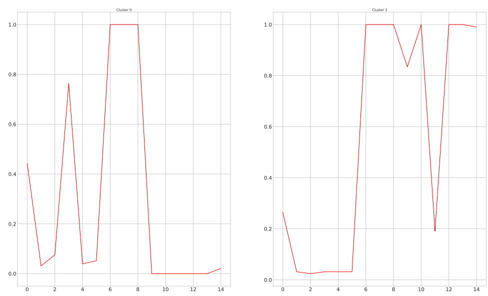
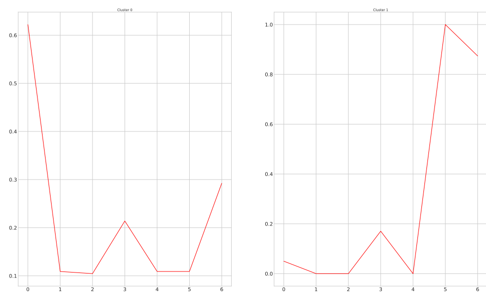
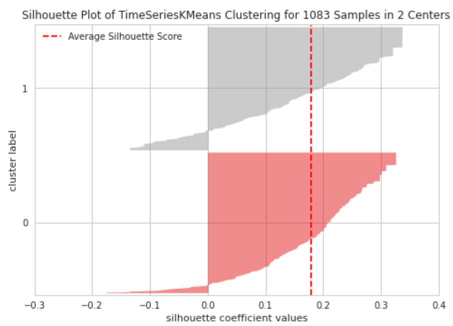
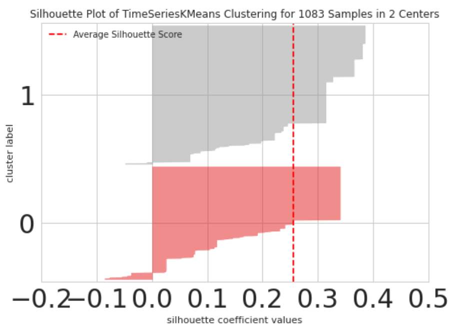
| Full Period | Half Period |
|---|---|
| **(A) Cluster number estimation** | |
|  |  |
| **(B) Cluster distribution** | |
|  |  |
| **(C) Cluster sizes** | |
| (752, 331) | (48,597) |
| **(D) DBA plots** | |
|  |  |
| **(E) Silhouette score** | |
|  |  |

Table 3: Problem #2 Analysis

## 6 Discussion

The way the UTBs clusters' average is computed assigns a numerical representation to each behavioral atom. Consequently, when the DBA has high values, it identifies clusters with a considerable amount of atoms of type H and A. Nevertheless, this line does not plot categorical values because it represents the average among the numerical values given to the categories, i.e., L=0, H=1. Thus, it is necessary to carry out an analysis where the clusters' central lines can be plotted in such a way that they truly represent the complete series. For example, taking the value that occurs the most in each timeframe, considering the large number of zero values, does not bias this centroid and make it fall. Building a more real centroid would allow a more refined grain analysis of each cluster's users' behavioral atoms.

On the other hand, based on what is observed in Table 3 (B), it can be thought that some clusters are more cohesive and therefore more focused on the recommendation of challenges. As we have described in Section 3, traveled distance and invested time can be an input for endurance game challenges. In this work, the behavioral atoms describe activity levels, and the height of the DBA line in Table 3(D) shows part of this information.

The user activity level can be a reference to provide challenges that can motivate them to improve. On the one hand, these challenges should exceed the user's current level and allow users to overcome the challenges. Otherwise, the challenge will be unattainable and will therefore generate disappointment or boredom in the users.

A high DBA line can be related to a high level of user endurance in a period. The analysis could help tailor endurance challenges with a high-intensity level to users that could reach those challenges.

Knowing the spatial-temporal activity profiles of users allows recommending challenges in two aspects. On the one hand, those challenges that motivate users to increase their activity and on the other hand, take advantage of the beginning of an upward activity trend.

When the user is in a period of low activity, challenges that motivate the increase in activity should be recommended. On the other hand, when the user is in a period of high activity, challenges that promote the maintenance of a high level of activity should be recommended.

From the point of view of the objectives pursued by the CLCS, when detecting that a user initiates an upward curve in their DBA, the system must recommend challenges that take advantage of that productive moment of the user without altering the activity trend.

Regarding the rhythm game challenges, it is possible to consider the similarity of sequences and the repetition of sub-sequences among users. In the analysis carried out, grouping the clusters using DTW takes into account grouping people with similar sequences of atoms. However, the analysis of recurrent sub-sequences is a pending task to be addressed in the future.

## 7 Conclusions and further work

In this work, a user classification mechanism was presented in terms of their movement behavior. A possible future work is to reconsider the temporal aspect taking the frequency of check-ins instead of the time elapsed between the first and the last check-in.

It may also be of interest for user profiling to calculate the frequency of check-ins for each user in a venue category (such as hotel, cinema, mall) and then measure the similarity between users who have the same frequencies. Finally, determining the shortest representative length of a UTB is proposed as future work.

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## Competing interests

The authors have declared that no competing interests exist.

## Authors' contribution

MDA and DT conceived the idea, analyzed the results and revised the manuscript; MDA wrote the python scripts and conducted the experiments; All authors read and approved the final manuscript."

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