Discovering Heterogeneous Subsequences for Trajectory Classification

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1. Introduction

Trajectory classification is an important issue in mobility data mining, since it is used for several discovering transportation modes, animal categories, hurricane strengths

There are different works in the literature about semantic trajectory classification, mainly focusing on the next place prediction, such as the place category or the geographic location \cite{1}. However these works are limited to only consider three dimension, as space, time, and semantics. Ferrero in \cite{2} introduced the concept of Multiple Aspect Trajectory Analysis, that consists of analyzing trajectory data by integrating other movement aspects to further enrich trajectory data, such as more information about the visited places, the transportation modes, the weather conditions, and the social interactions.

The proposal in \cite{2} is that time has come to integrate all relevant information about movement in trajectories and explore trajectory analysis over several layers of information. An example of this new kind of trajectory is shown in Figure 1. In this figure, an individual starts his/her trajectory at home, then he/she goes to work by car, and after work, he/she goes to eating

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at a restaurant. Note that during his/her movement the weather condition changes two times, from rainy to cloudy and then to sunny, and part of the trajectory is carried out on foot and part by car. In addition, the individual uses different social networks (e.g. Twitter, Facebook, and Foursquare) to post how he/she is feeling.

Hate the rain : ( t1
I'm so tired! t72
Celebrating!

Figure 1: An example of Multiple Aspect Trajectory.

Multiple aspect trajectory analysis and mining is the research topic of a current European Research Project H2020-MSCA-RISE-2017 called MASTER (Multiple ASpect TrajectoriEs Representation and analysis).

This new representation of multiple aspect trajectories has the challenge of dealing with multiple and heterogeneous dimensions. Because this is a recent and new kind of data, there are no works in the literature to analyze and to extract new knowledge about user’s behavior, which can help to improve location services, privacy measures, safety strategies, and others.

An emerging classification task in trajectory data is to learn discriminant parts of trajectories, called subtrajectories, that characterize the behavior of an individual or a group of individuals. We claim that discovering discriminant subtrajectories from this new kind of data is very important to several supervised tasks, such as building classification models to predict who is the user of a trajectory based on its movement and extracting the movement profile to describe the most important movements that characterize itself. These tasks can play an essential role in privacy protection applications.

In previous work, Ferrero in [3] proposed a novel approach for learning discriminant subtrajectories, called MOVELETS. The method was inspired on time series shapelets [6]. MOVELETS is a parameter-free method and supports multiple dimensions. However, all dimensions need to be considered together, what significantly reduces the efficiency of the learning process, because it is more difficult to find trajectory patterns as the number of dimensions increases. In addition, by analyzing each dimension individually limits the mining task, because the interaction among dimensions is a key issue in
multiple aspect trajectory data analysis. For instance, Figure 2 shows four trajectories $T_1$ to $T_4$ of two class users $L_1$ and $L_2$, that visit cafés, hotels, museums, shops, with different prices. These trajectories are sequences of Foursquare check-ins represented by dimensions $Time$, $Venue$ and venue’s $Price$. Suppose that we want to find a subtrajectory of three check-ins that discriminate the user $L_1$ from the user $L_2$. Figure 2 highlights (thick line around check-ins) a discriminant subtrajectory in trajectories $T_1$ and $T_2$ of class $L_1$ that not happens in trajectories $T_3$ and $T_4$ of class $L_2$.

![Figure 2: The problem of finding relevant subtrajectories in multidimensional trajectories.](image)

Note in Figure 2 that by considering all dimensions together there are no subtrajectories of three sequential check-ins in common between $T_1$ and $T_2$, because $T_1$ goes in a café of price $\$ while $T_2$ goes in café of price $$$.

By analyzing each dimension individually, the dimension $Time$ is not discriminative, because $T_1$ has check-ins at the same time of $T_3$, at 7am, 8am, 9am, and 10am. Also the dimension $Venue$ is not discriminative, because $T_1$ and $T_4$ have both check-ins in Home, Café, Mall, and Home. The problem is that by analyzing all dimensions together or all dimensions individually is not possible to find a discriminant subtrajectory of three sequential check-ins. So, MOVELETS is not useful for this task.

To find the discriminant subtrajectory highlighted in Figure 2 it is necessary to explore dimension combination as well as the sequence of check-ins. There are no methods in the literature to solve the problem of finding relevant subtrajectories in trajectory data represented by multiple dimensions.

In this work, we propose a new method for discovering relevant subtrajectories in multidimensional and heterogeneous sequences, focusing on movement trajectories. Our method explores and finds the dimension combination to achieve the highest discriminative power. The main contributions of our work are summarized as follows:

1. A new method, called MASTERMOVELETS, for discovering relevant subtrajectories that considers multiple and heterogeneous dimensions. The method is parameter-free and domain independent.
2. A new method for multidimensional alignment based on ranking, called \textsc{MasterAlignment}. The method discovers the part of a trajectory that is most similar to a subtrajectory considering multiple dimensions together.

3. A new method to measure the subtrajectory relevance over multiple and heterogeneous dimensions, called \textsc{MasterRelevance}.

The remaining of this paper is structured as follows: Section 2 describes the proposed method, Section 3 shows the experiments, and Section 4 conclusions and future work.

2. Discovering Relevant Multiple Aspect Subtrajectories

In this section we detail our proposal for finding relevant subtrajectories in trajectories represented by multiple and heterogeneous dimensions. Section 2.1 introduces basic definitions, Section 2.2 describes the method for discovering multidimensional \textit{movelets}, Section 2.3 presents a new method for multidimensional subtrajectory alignment, and Section 2.4 presents a new method for measuring the quality of multidimensional subtrajectories.

2.1. Basic Definitions

A multidimensional trajectory $T$ is a sequence of elements $\langle e_1, e_2, \ldots, e_m \rangle$, where each element has a set of $l$ dimensions $D = \{d_1, d_2, \ldots, d_l\}$. Our goal is to find parts of multidimensional trajectories with high discriminative power among classes. A part of a trajectory is called \textit{subtrajectory}. So given a trajectory $T$ of length $m$, a \textit{subtrajectory} $s = \langle e_a, \ldots, e_b \rangle$ is a contiguous subsequence of $T$ starting at point $e_a$ and ending at point $e_b$, where $1 \leq a < m$ and $a \leq b \leq m$. The subtrajectory $s$ can be represented by all dimensions $D$ or a subset of dimensions $D' \subseteq D$. The length of the subtrajectory is defined as $w = |s|$. In addition, we also define the set of all \textit{subtrajectories} of length $w$ in $T$ as $S^w_T$, and the set of all \textit{subtrajectories} of all lengths in $T$ as $S^*_T$.

In order to find discriminant parts of a trajectory we need to define the distance between two subtrajectories. This distance may consider the dimensions of the problem, since a point may have multiple and heterogeneous dimensions, we formally define the concept of \textit{distance between elements}.

\textbf{Definition 1. Distance vector between two multidimensional elements.} Given two elements $e_i$ and $e_j$ represented by $D$ dimensions, the distance between two multidimensional elements $\text{dist}(e_i, e_j)$ returns a \textit{distance}
vector $V = (v_1, v_2, ..., v_d)$, where each $v_k = dist(e_i, e_j)$ is the distance between two elements at dimension $k$, that respects the property of symmetry $dist(e_i, e_j) = dist(e_j, e_i)$.

The idea behind Definition 1 is to allow of using a distance function for each dimension and storing them into a distance vector to help computing the distance between two subtrajectories of equal length, which is given in Definition 2.

**Definition 2. Distance vector between two subtrajectories of equal length.** Given two subtrajectories $s$ and $r$ both of length $w$ and dimensions $D$, $dist_s(s, r)$ computes the pairwise distance between their sequential elements $(V_1, V_2, ..., V_w)$ in a distance vector $V = (v_1, v_2, ..., v_d)$, where each $v_k$ is the distance value between $s$ and $r$ at dimension $k$, which is obtained by a function over the $w$ distances between the two subtrajectories at dimension $k$. Each distance $v_k$ respects the property of symmetry $dist_s(s_k, r_k) = dist_s(r_k, s_k)$.

To evaluate whether a subtrajectory $s$ is into a trajectory $T$, we need to find the most similar subtrajectory of $T$ to the subtrajectory $s$. The most similar subtrajectory of $T$ to $s$ is called best alignment, and is a subtrajectory $r$ with the minimum distance. This comparison is given in Definition 3.

**Definition 3. Distance vector between trajectory and subtrajectory.** Given a trajectory $T$ and a subtrajectory $s$ of length $w = |s|$, the distance between them is the best alignment of $s$ into $T$, which is defined by $W^T_s = min(dist_s(s, r) \mid r \in S^w_T)$, where $S^w_T$ is the set of all subtrajectories of length $w$ into $T$, and $min()$ returns the smallest distance vector that is the best alignment between $s$ and all subtrajectories in $S^w_T$.

The number of all possible subtrajectories of any length in a trajectory problem with $n$ trajectories of length at most $m$, and dimensions $d$, is $O(n \times m^2 \times 2^d)$. By representing trajectories using all subtrajectories as features, the induction of classification models is impracticable, because of the relation between instances and attributes. So, the selection of only the most relevant subtrajectories is necessary. Before defining a relevant subtrajectory we define a subtrajectory candidate in Definition 4.
Definition 4. Subtrajectory Candidate. A subtrajectory candidate is a tuple \((T, \text{start}, \text{end}, C, W, L)\), where \(T\) is the trajectory that originates the candidate; \(\text{start}\) and \(\text{end}\) are the positions that the candidate begins and ends, respectively; \(C\) contains the candidate dimensions; \(W\) is a set of pairs \((W_i, \text{class}_i)\), where \(W_i\) is the distance vector of the best alignment into a trajectory \(T_i\) and \(\text{class}_i\) is the class label of \(T_i\); \(L\) is a pair \((sp, score)\), where \(sp\) contains the split points for each dimension and \(score\) is the relevance score.

Evaluating the relevance of each subtrajectory is fundamental to explore movelets. In classification problems this relevance is given by the capability to differentiate trajectories of one class (target class) from trajectories of other classes. In other words it is expected that a relevant subtrajectory appears into trajectories of the target class and does not appear into trajectories of other classes. To measure the relevance we use the set \(W\) to find a set of distance split points \(sp\) in order to split the set of distances into two subsets: the left side with the nearest distances, from 0 to \(sp\); and the right side with the longest distances, from \(sp\) to \(\infty\). The former contains only distances to trajectories of the target class and the latter the other distances. The greater the number of distances in the left side the greater the relevance of the subtrajectory candidate. Based on the concept of relevance we define a movelet as in given in Definition 5.

Definition 5. Movelet. Given a trajectory \(T\) and a subtrajectory candidate \(s \in T\), the subtrajectory \(s\) is a movelet if for each subtrajectory \(r \in T\) that overlaps \(s\) in at least one element, \(s.L.score > r.L.score\).

In other words, a subtrajectory is considered as a movelet if there is no other candidate overlapping it with more relevance on any dimension combination. The movelet discovery consists of exploring all subtrajectory candidates from a trajectory training set and selecting only the subtrajectories with highest relevance, which are called movelets.

2.2. MASTERMOVELETS: Multidimensional Movelets Discovering Algorithm

In this section we present the algorithm for discovering multidimensional movelets, called MASTERMOVELETS (Multiple ASpect TrajEctoRY Movelets). This method consist of an extension of the algorithm to extract classical MOVELETS with support to multiple and heterogeneous dimensions.
This method is detailed in Algorithm 1 that has as the unique input the trajectory training set $T$, without any parameter. The output is the set of movelets.

Algorithm 1 finds for each trajectory in the training set $T$ the most relevant subtrajectories considering multiple dimensions (lines 2 to 37). For each $T \in T$ it computes all distances between all trajectory elements in $T$ and all elements in $T$, and stores them into the 4-dimensional array $A_0$ of distances. Each value $A_0[i, j, d, k]$ the distance between the element of $T$ at position $j$ and the element of $T_i \in T$ at position $k$, considering dimension $d$. The distance array is precomputed in order to perform this computation only once (line 4). Next, it explores all subtrajectory lengths, one by one (lines 5 to 33). For a length $w$ it computes the array of distances $A_w$, using the distance values computed for subtrajectories of length $(w - 1)$ and for the elements, represented by $A_{w-1}$ and $A_0$, respectively (line 6). $A_w$ contains all the distance sums at subtrajectory length $w$. Next, for each subtrajectory in $T$ of size $w$ starting at the $j$th position, it discovers the best dimension combination for the subtrajectory based on $A_w$, and adds it into the candidates set (lines 7-31). In this loop the algorithm first computes for each subtrajectory in $T$ starting at position $j$ the distance ranking $R$ among all starting positions in the $i$th trajectory, at dimension $k$ (lines 8 to 13). Then, for each dimension combination $C$ of all dimension combination $C^d$ it computes the best alignment between the subtrajectory in $T$ starting at position $j$ to each trajectory $T_i$, using a specific method for multidimensional alignment, called MASTERALIGNMENT, storing the distance vector into $W$ (lines 16 to 20). After that, the algorithm evaluates the set of distances in $W$ using a specific function for measuring the relevance and discovering the split points, called MASTERRELEVANCE, and preserves the relevance and the distances of the best dimension combination (lines 21 to 27). Then, it defines the subtrajectory candidate as the subtrajectory with the most relevant dimension combination and stores it into the set candidates (lines 29 and 30). Next, it stores the subtrajectory candidates of any length into trajectoryCandidates (line 32). Following the external loop, it sorts the trajectory candidates by their relevance and removes those self similar (lines 34 to 35). Two candidates are self similar if they are overlapping on at least one point and the algorithm preserves the highest relevance candidate. Finally, it adds the remaining candidates to the movelets set.

Two key points to perform movelets discovery in trajectories represented by multiple and heterogeneous dimensions are: finding the best alignment
Algorithm 1: MasterMovelets

Input: \( T \) // trajectory training set
Output: movelets // set of relevant subtrajectories

1. \( \text{movelets} \leftarrow \emptyset \);
2. for each trajectory \( T \) in \( T \) do
   3. \( \text{candidates} \leftarrow \emptyset \);
   4. \( A_0 \leftarrow \text{ComputeElementDistances}(T, T) \);
   5. for subtrajectory length \( w \) from 1 to \( T.\text{length} \) do
      6. \( A_w \leftarrow \text{CSD}(A_{w-1}, A_0, w) \);
      7. for position \( j \) from 1 to \( (T.\text{length} - w + 1) \) do
         8. \( R \leftarrow \emptyset \);
         9. for trajectory \( i \) from 1 to \( |T| \) do
            10. for dimension \( d \) from 1 to \( |D| \) do
                11. \( R[i, d, ..] \leftarrow \text{Rank}(A_w[i, j, d, ..]) \);
            end
         end
      12. bestScore \leftarrow 0 ;
      13. for each dimension combination \( C \) in \( C_d^* \) do
         14. \( \text{relevance} \leftarrow \text{assess MasterRelevance}(\text{W}, T.\text{class}) \);
         15. if relevance.score > bestScore then
            16. \( \text{bestL} \leftarrow \text{relevance} \);
            17. \( \text{bestW} \leftarrow \text{W} \);
            18. \( \text{bestC} \leftarrow C \);
            19. bestScore \leftarrow relevance.score ;
         end
      20. \( s \leftarrow \text{SubtrajectoryCandidate}(T, j, (j + w - 1), \text{bestC}, \text{bestW}, \text{bestL}) \);
      21. \( \text{candidates} \leftarrow \text{candidates} \cup s \);
   end
3. \( \text{trajectoryCandidates} \leftarrow \text{trajectoryCandidates} \cup \text{candidates} \);
4. \( \text{SortByQuality(trajectoryCandidates)} \);
5. \( \text{RemoveSelfSimilar(trajectoryCandidates)} \);
6. \( \text{movelets} \leftarrow \text{movelets} \cup \text{trajectoryCandidates} \);
7. end
8. return movelets
of the subtrajectory into a trajectory, performed by the method MASTER-ALIGNMENT and measuring the relevance of subtrajectories, performed by the method MASTERRELEVANCE. These key points substantially change the way to discover classical movelets and are detailed in the next sections.

2.3. Multidimensional Alignment of a Subtrajectory into a Trajectory

The best alignment between a subtrajectory and a trajectory consist of finding the most similar part of the trajectory to the subtrajectory. The function $\text{min}()$ in Definition 3 performs the best alignment and returns the distance. In the case of one-dimensional alignment ($|D| = 1$) the function returns only the minimum distance value, but in the case of $|D| > 1$ all distance values of the $D$ dimensions must be considered, in the form of a distance vector. An ingenuous solution consists of transforming each distance vector in a unique value by normalizing and weighting the dimensions, but this brings two major drawbacks. The first is that the normalization requires to previously know some information about the distance distribution, such as the mean, standard deviation, or maximum and minimum values, which is totally domain dependent. The second is that the predefinition of dimension weights for all classes exclude the possibility of capturing the particular relevant dimensions for each class.

To exemplify, Figure 3a shows an example of a subtrajectory $s$ and Figure 3b a trajectory $T$. In the trajectory of Figure 3b the object: “at 7am, stays at an hotel of price $$$; then walks to the park at 07:15am; has breakfast at 8am at a Café of price $; arrives at work 8:30am, and after an hour goes to a Shop to buy a gift to his/her boss. They use to drink coffee in a Café of price $$ for talking business. Finally, the object returns to work at 11:30am.”. The subtrajectory we want to align is: “Users that visit a Café of price $$$ around 10:30am and after go to work around 11:00am”.

![Figure 3: Example of a subtrajectory $s$ and a trajectory $T$.](image-url)

Based on Figure 3, we consider the following insights about alignments:
1. For the dimension Time, the best alignment of the subtrajectory of Figure 3a into the trajectory of Figure 3b happens between the check-ins 5 and 6. But note that the venues are different (Café ≠ Shop and Work ≠ Café).

2. For the dimension Venue, there are two best alignments: the first between the check-ins 3 and 4 and the other between the 6 and 7.

3. On the Price dimension, the best alignment happens between the check-ins 1 and 2, where the venues are also different.

Considering the previous insights, the question we want to answer is which of these alignments is the best and how to combine the alignments whether the distances are heterogeneous (time in minutes, venue in number of equal venues and price in units)? In order to answer this question, avoiding the dimension normalization and weighting, we propose a new ranking-based approach. In our approach the best alignment is represented by the check-ins 6 and 7, as highlighted in Figure 4.

![Figure 4: Best subtrajectory alignment highlighted into the trajectory.](image)

In this work we introduce the method MasterAlignment (MUltiple Apect SubTrajEctoRy Alignment), that consists in ranking the distances of each dimension individually and getting the position of the minimum average rank to determine the position of the best alignment. Let us consider \( V_1, \ldots, V_6 \) as the distance vectors of the possible alignments, where \( V_i \) corresponds to the alignment between \( s \) and the subtrajectory \( r_i \) in \( T \) starting at the \( i \)th-position. Table 1a presents the distance values of these vectors, where the value at row Time and column 1 is the distance between \( s \) and \( r_i \) on dimension Time. This value is 435 because of the sum of difference between time values in minutes, i.e. \((10:30-7:00) = 210 \) and \((11:00-7:15) = 225 \).

Table 1b shows the distance ranking for each dimension individually, where the value at row Time and column \( i \) is the ranking of the distance
value at starting position \(i\) on dimension \(Time\) (among the other alignments at the same dimension). The best ranking at dimension \(Time\) is 1.0 and corresponds to the 5th starting position, because and dimension \(Time\) it has the lowest distance value for dimension \(Time\), zero minutes. The second best ranking is 2.0 and corresponds to the 6th starting position, because it is the second lowest distance, 60 minutes. Note that it allows fractional ranks in case of tie, such as 1.5 at starting positions 3 and 6 at dimension \(Venue\). After that, it calculates the average rank at each starting position and chooses the lowest average rank as the best overall ranking. In this case, at the starting position 6 it reaches 1.8 (in bold). Finally, it defines the distance vector of the alignment starting at position 6, which is \(W_6 = (60, 0, 2)\).

2.4. Relevance Measuring for Multidimensional Subtrajectory Candidates

The relevance of a subtrajectory is related to the number of trajectories of the same class that performs similar movement. To define which similar the movement needs to be we need to analyze the distances of the best alignments between a subtrajectory and all trajectories, denoting by \(W\). The most common approach consist of putting the distance in an orderline and finding a split point to separate the distances into two groups: the nearest and the farthest. Let us consider trajectories \(T_1, T_2, \ldots T_8\) of classes \(L_1, L_2\), represented by a dimension, \(Time\), and a subtrajectory \(s\) extracted from \(T_1\). The trajectories \(T_1\) to \(T_4\) are of class \(L_1\) and the trajectories \(T_5\) to \(T_8\) are of class \(L_2\), and \(s\) has \(L_1\) as the target class, as well as \(T_1\). Figure 5 shows an example of an orderline.

To find the split point and measure the relevance in a one dimensional orderline (as in Figure 5) have been proposed several techniques, such as the maximum information gain [6], the Kruskal-Wallis and Mood’s Median [5], and the Left Side Pure (LSP) [3]. The LSP returns a split point between \(T_1\) and \(T_5\) in order to keep the left side of the orderline pure.
Finding the split points for multidimensional subtrajectories is a more complex task, due to the best alignment consist of a set of distances, as proposed in Section 2.3. Let us consider trajectories $T_1, T_2, \ldots T_8$ represented by dimensions $\text{Time}$ and $\text{Venue}$, and the subtrajectory $s$ extracted from $T_1$. Figure 6 shows the representation of the distance vectors by an orderline for each dimension. Note that the trajectory $T_1$ is the first distance value on each dimension because $s$ comes from $T_1$.

One way to analyze both the orderlines is by transforming each distance vector in a unique value by normalizing and weighting its dimensions, and finding the best split point using the proposed techniques for one-dimensional orderlines [6, 5, 3]. However, this is not a good solution when leading with heterogeneous distances, because of the difficult to define these weights. Another way is to analyze each dimension independently and then find a split point for each dimension. But this approach does not consider the interaction between dimensions, which is very important to find movelets, and tends to return lower values of split points. For instance, in Figure 6 both the $\text{Time}$ and $\text{Venue}$ orderlines have distance values of $L_2$ on the right of $T_1$ distance, which corresponds to trajectories $T_5$ and $T_6$, respectively. By analyzing each orderline independently is difficult to find good split points, because it results in a set of split points that only separates $T_1$ on the left side, which means that the subtrajectory candidate has very low relevance.

Instead of analyzing each orderline separately, we propose a method to
analyze all dimensions together. Note in Figure 6 the distance vector for $T_7$ may be a good estimator of the split points for $s$, because all the points of class $L_1$ have smaller values. Our method leads with the problem of distances on multiple and heterogeneous dimensions and finds the split points that maximizes the relevance of the subtrajectory. The method, called MasterRelevance (MUltiple Aspect SubTrajectoERy Relevance), consist in three steps and it is exemplified by Figure 7 using two dimensions $Time$ and $Venue$.

Figure 7: Example of finding split points in a multidimensional orderline.

In Figure 7(a) each point in the scatter plot represents the distance vector of a best alignment considering two dimensions, $Time$ and $Venue$, which allows to visualize the interaction between dimensions. The first step consists in selecting only the points of the opposite class $L_2$ and then pruning the points with greater values than some other in both dimensions $Time$ and $Venue$. In Figure 7(b) the point of $T_8$ is pruned because it has greater distance values than $T_7$ for both dimensions. In the second step, it evaluates the unpruned points according the capability to cover points of the target class $L_1$ in all dimensions. Figure 7(c) demonstrates that by using the points values of $T_5$ or $T_6$ as the split points they only cover $T_1$ of class $L_1$, but by using the point values of $T_7$ they cover $T_1, T_2, T_3, and T_4$. In the final step it chooses the split points that cover most points of the target class and it calculates the relevance score. As shown in Figure 7(d), the best split points are the values of the point $T_7$ and the score is 1. To calculate the score we use F-measure that is the harmonic average of the precision and the recall. In this context, the precision is the proportion of point covered by the split points that belongs to the target class of all covered, and the recall is the proportion of point covered by the split points that belongs to the target.
class of all point of target class.

### 3. Preliminary Experiments

#### 3.1. Dataset

The Gowalla dataset is a location-based social networking, where users shared their locations by checking-in [1]. Each check-in contains the anonymized user id, the timestamp, the location (latitude and longitude), and the check-in ID, without any other information about checking-in [1]. This dataset was used in a previous recent work [4] to classify users based on users’ check-in id. From the original dataset containing more than 6mil of check-ins, collected between 2009 and 2010, we cleaned the dataset and segmented the users trajectories into weekly trajectories. We selected check-ins with frequency at least 15, weekly trajectories with at least 10 check-ins and users with at least 10 trajectories, resulting in 33,816 weekly trajectories of 1,952 users. Each check-in is represented by the dimensions: space, time, weekday, and check-in ID. Table 2 shows details about each dimension, such as data type, values range, and the distance measure used to compare two dimension values.

| Dimension      | Type       | Range or examples | Distance measure   |
|----------------|------------|-------------------|--------------------|
| Space          | Composite  | (lat lon) 40.82651 -73.95039 | Euclidean Distance |
| Time           | Temporal   | [00:00,23:59]     | Difference in minutes |
| Weekday        | Ordinal    | {Mon, Tue, ..., Sun} | Weekday Distance |
| Check-in ID    | Nominal    | Any nominal value | Binary Distance |

#### 3.2. Experimental Configuration

We compared MASTERMOVELETS with the classifier Bi-TULER proposed in [4] and classifiers based on four trajectory distance measures: LCSS, EDR, MSM, and DTW. The code of all methods used in this work and the datasets are publicity available in the author’s website.

For distance measures we define three values of threshold for each non-nominal dimension, keeping all dimensions with the same weights, and we use the mean and standard deviation of classification accuracy in order to

[1]https://snap.stanford.edu/data/loc-gowalla.html
compare them with our method. For evaluating \textsc{MasterMovelets} we used Neural Networks (NN) and Random Forests (RF). The former is a Multilayer Perceptron with a hidden layer by 100 units and to train it we used the same parameters used in [4], a dropout rate 0.5 and an Adam optimizer with the following learning rates $10^{-4}$ (epochs): $9.5(80)$, $7.5(50)$, $5.5(50)$, $2.5(30)$, and $1.5(20)$. The latter consist of an ensemble of 100 decision trees. We evaluate methods on a stratified holdout evaluation separating 70% for training and 30% percent to test. For \textsc{MasterMovelets} we only used the training set for movelets discovering. For BiTULER we used the entire dataset to build the word embeddings, as suggested in [4].

3.3. Results and Discussion

Table 3 shows the experimental results in terms of classification accuracy ($\text{acc}$) and accuracy on top 5 ($\text{acc top5}$) on the test set. The best result for each dataset and measure are highlighted in bold and the second are underlined.

| Dataset | Measure | DTW | LCSS | EDR | MSM | BiTULER | \textsc{Master Movelets} |
|---------|---------|-----|------|-----|-----|---------|--------------------------|
| Gowalla | $\text{acc}$ | 73.7(0.8) | 87.0(2.5) | 80.9(3.9) | 89.8(1.1) | 34.7 | \textbf{95.2} | \underline{92.6} |
|         | $\text{acc top5}$ | 86.7(0.8) | 91.0(2.5) | 83.9(3.9) | 93.6(1.1) | 56.0 | \textbf{98.2} | \underline{97.8} |

The results show that the use of \textsc{MasterMovelets} to build NN and RF models outperforms the state of the art methods on both datasets. BiTULER presents the worst classification results in both datasets. These classification problems involve multiple dimensions and BiTULER is limited to only consider one, the checkin ID information. DTW uses all dimensions, but it presents the worst results among the distance measures, because it is difficult to weight the distances of all multiple and heterogeneous dimensions. The distance measures LCSS and EDR also do not present good classification accuracy, since the chance of have matching decreases as the number of dimensions increases. The MSM present better results than the LCSS and EDR, because it allows partial matching among dimensions, so it is less affected than those. Both of models built from \textsc{MasterMovelets} present the best results, however the Neural Network model better capture the relation between the movelets and the class. Our NN model only has a hidden...
layer with 100 units, which is much simpler than the Bidirectional LSTM Recurrent Neural Network with 300 units in the hidden layer, proposed in [4]. In general, Neural Networks models lead better with high dimensional spaces than symbolic models, in detriment of its interpretability. RF also achieve better results than the state-of-the-art methods. This model consists of ensembles of decision trees, that allow to extract relevant classification rules.

4. Conclusions

In this paper we proposed a new method for extracting relevant sub-trajectories for multiple aspect trajectory classification, called MASTER-MOVELETS. The method consists of an extension of a previous work to extract relevant subtrajectories from raw trajectories. Our method finds the most relevant subtrajectories leading with the problem of exploring dimension combinations. MASTERMOVELETS is parameter-free and domain independent, which is very important since parameters values are difficult to estimate in many problems and directly affect the data mining results.

We evaluate our method on a dataset of check-ins to classify user’s trajectories and compare it with several methods in the literature for trajectory classification. Initial results demonstrate that MasterMovelets is very promising. This is the first work in the literature for classifying trajectories represented by multiple and heterogeneous dimensions, recently introduced as Multiple Aspects Trajectories.

Future works include a more robust experimental evaluation and improvement of the complexity analysis of movelets discovery, that is the main drawback of our method.

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