A Survey and Comparison of Trajectory Classification Methods

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***Abstract*— In trajectory classification tasks, the challenge is to find the subtrajectories or a set of features that better discriminate the class. However, there is a lack of robustness in existing methods, as they do not use the same datasets or do not compare their results with the state of the art. In this paper we survey the state of the art in trajectory classification and compare existing methods using two different classifiers over several datasets with different characteristics, guiding the best scenarios for using each technique.**

***Index Terms*—Trajectory Classification; Classification Survey.**

I. Introduction

Trajectory classification is an important task in mobility data mining that has the objective of predicting the class labels of the moving object based on its trajectories [1]. Examples include predicting the transportation modes of the moving object (e.g. car, taxi, bus, pedestrian, bike), animal categories, the type of a vessel (e.g. cargo, fishing), the person that is the owner of the trajectory, etc.

Fig. 1. Example of GPS trajectory (left) and check-in trajectory (right).

Trajectory data are characterized by sequences of spatial positions recorded along time. An example of trajectory is shown in Figure 1 (left). With the increasing use of social media and sensors spread across the world, trajectory data have become more complex, having not only space and time information, but many other semantic dimensions that give more meaning to the data, such as the name and category of a visited place, the goal of the visit, the weather condition, etc. An example of this type of trajectory is shown in Figure 1 (right).

Trajectory classification methods, in general, do not propose new types of classifiers. Differently from other domains, methods for mobility data classification focus on extracting the best trajectory features for classification problems. These features represent any sort of information that can be inferred from the entire trajectory or a trajectory part, and can be obtained by using different segmentation methods, statistics about the trajectory attributes, and more recently, using machine learning methods for discovering the best features. The extracted features are then used to train well known classifiers, as neural networks (NN), random forests (RF), support vector machines (SVM), etc.

There are two main problems related to trajectory classification methods of the state of the art: first, they do not present a robust experimental evaluation over several datasets in order to understand how the used features do effectively contribute for classification problems; and, second, they do not compare their improvement over state of the art. With these limitations, it is difficult to understand the robustness of the existing methods for different types of trajectory data.

In this paper we survey the state of the art on trajectory classification methods and present an experimental comparison over several datasets with different properties in order to compare their behavior using different classifiers.

The rest of the paper is organized as follows: Section II describes the basic concepts; Section III presents the main works in the literature for trajectory classification; Section IV presents the experimental evaluation and Section V concludes the paper and presents the future works.

II. Basic Concepts

In this section we introduce the main definitions that are used along the paper and that are necessary to understand the trajectory classification problem. The first definition is the concept of raw trajectory, that is a type of mobility data collected with GPS devices.

Definition 1. *Trajectory: A raw trajectory consists on a sequence of* n *points* $T = \langle p_1, p_2, ..., p_n \rangle$*, in which* $p = \{x, y, t\}$*, where* x, y *is the position of the moving object in space and* t *is the timestamp that the point was collected.*

The first problem in raw trajectory classification is that existing classifiers cannot deal with the spatial dimension. The attributes x and y represent the latitude and longitude over the geographic space, and must be considered together in order to compare the spatial position of a moving object with respect to the position of other objects. Therefore, the most common solution to deal with the space and time dimensions is to extract spatio-temporal features and use these features as input

2643-6264/19/$31.00 ©2019 IEEE
DOI 10.1109/BRACIS.2019.00141

for the classifier. A number of numerical features can be extracted from raw trajectories as speed, acceleration, direction, etc. These features can be extracted from the entire trajectory, the so-called *global features*, or from a subtrajectory, the so-called *local features*.

Multiple aspect trajectories [2] can have several aspects associated to each trajectory point. Examples of aspects include the name or category of visited places or Points of Interest (POIs), the goal of the visit, the activity, the weather conditions, etc. All information associated to trajectories that is neither spatial nor temporal, we call semantic information or *aspects*. In the following we define multiple aspect trajectory, according to [3].

Definition 2. *Multiple Aspect Trajectory: A multiple aspect trajectory is a sequence of* n *points* $T = \langle p_1, p_2, ..., p_n \rangle$*, in which* $p = \{x, y, t, A\}$*, where* x, y *is the position in space at time* t*, and* A *is a set with* r *aspects* $A = \{a_1, a_2, ..., a_r\}$*.*

Basically what distinguishes trajectory classification problems from conventional data is the feature extraction process. As trajectories cannot be directly feed as input for classifiers because of their complex information and the heterogeneity of the dimensions, the great challenge is to find the best features or trajectory segmentation process to find the features and/or subtrajectories that discriminate the class. In the following section we detail how existing works deal with these challenges for classification problems.

III. Literature Review

Trajectory classification literature can be divided in two main categories: classification methods for raw trajectories, that will be detailed in Section III-A, and methods for multiple aspect trajectories, detailed in Section III-B. The methods summarization is presented in Section III-C.

Most existing methods for trajectory classification extract a set of features and transform them into a matrix, where each row is a trajectory and the columns are the features extracted from each trajectory. The main difference of the methods is which features they extract and which dimensions they support.

A. Classification Methods for Raw Trajectories

Methods for raw trajectory classification may consider only the spatial dimension or space and time. One of the first techniques in the literature for trajectory classification was TraClass, proposed by Lee in [1], and that supports only the spatial dimension. TraClass first divides the space in a grid and keeps reducing the size of the grid cells until most trajectories inside a cell belong to the same class. If the trajectories inside a cell are mostly from the same class, then the cell is selected as a feature, and is no longer split in smaller sizes. Otherwise, the process continues for this cell until it reaches the lowest possible size, where the size is defined by a threshold. Then it splits the subtrajectories inside this cell by direction change, and these subtrajectories are then grouped by class. Finally, all grid cells and subtrajectory clusters are then used as trajectory features.

Methods that consider both space and time dimensions extract features from the spatio-temporal points (e.g. speed, acceleration), and they basically differ from each other on the number and type of local and global features they extract. These works can be divided in three main categories: (i) extract local features from subtrajectories or trajectory points; (ii) extract global features from the entire trajectory; and (iii) extract both local and global features from both subtrajectories and the entire trajectory.

There are three main works for trajectory classification that extract *local features*, and they are limited to specific classification problems: [4] and [5] focus on transportation mode classification, and [6] on classifying fish. Bolbol [4] segments the trajectories based on a pre-defined number of subtrajectories. After the segmentation process, a sliding window of fixed size is used, and for the subtrajectories inside the window it extracts features as average acceleration and average speed. Soleymani [6] divides the space in grids of three different sizes (large, medium and small), and calculates the time duration of the subtrajectories inside each grid. In parallel, the temporal split is based on time windows of different sizes, and features as average and standard deviation of speed, acceleration, turning angle and traveled distance are extracted from the subtrajectories inside each time window.

Dabiri in [5] uses Convolutional Neural Networks (CNNs) for classifying transportation mode. It first extracts features from every pair of sequential trajectory points (e.g speed, acceleration, direction change, and stop rate). Then it represents the trajectories as a vector of four dimensions, one for each feature, similar to a time series of four dimensions. This vector is used as the entry of a CNN, which is tested with multiple CNN architectures. As the CNNs need a fixed input size, an m threshold value is chosen, and trajectories with size greater than m are split in subtrajectories of size *m*, while the shorter trajectories receive a padding with zeros to reach the *m* size.

The works that extract *global features* are [7], [8] and [9]. Zheng in [7] focuses on transportation mode classification. It computes the speed and acceleration between two consecutive points of each trajectory, and then extracts global features as length, the maximum speed and acceleration, the average, expectation and variance of the speed, the heading change rate, the stop rate and the velocity change rate. Sharma [8] initially calculates the pairwise consecutive point features of speed, acceleration, turning angle, displacement, direction, distance and time between the points. Trajectories are then represented as the sequence of these features, and they are used as input to a Nearest Neighbour Trajectory Classification (NNTC) to predict the classes based on the label of the nearest trajectory, which is the same principle of a common 1-NN approach.

The ANALYTiC [9] is an Active Learning approach that computes the speed, the direction variation and the traveled distance between the consecutive points, and it calculates the global features of minimun, maximun and average values from the other features. The Active Learning uses the extracted features to gradually train a binary classifier, which can predict if an example is of a certain class or not. The examples with high level of uncertainty are reinforced by re-training the binary classifier with new and similar labeled examples. As the training process is only capable of determining whether the trajectory is of a given label or not, the approach is only suitable for datasets with a few classes.

The last group of works for raw trajectory classification consider both *local* and *global features*. Dodge in [10] calculates the features of speed, acceleration and direction change between every two consecutive trajectory points, and the trajectories are then represented as sequences of each feature, similar to a unidimensional time series. *Local features* are extracted from subtrajectories with the same characteristics (e.g. same speed, same acceleration, etc.) and global features are statistics of the entire trajectory as the minimum speed, maximum speed, average speed, minimun acceleration, etc. The feature selection method called *Principal Component Analysis* (PCA) is used for selecting the best features.

Xiao in [11] and Etemad in [12] also extract *global* and *local* trajectory features from all pairs of trajectory points, and the main differences are that Xiao [11] adds some new statistics, as the percentiles, interquatile range, skewness, coefficient of variation and kurtosis for transportation mode classification. Etemad [12] calculates new rate values as *global features*, and percentile values as *local features*.

B. Classification Methods for Multiple Aspect Trajectories

Methods developed for multiple aspect trajectories basically differ in the fact that they can deal with semantic dimensions, i.e., non-numerical features, and are split in two types: (i) works that consider only semantics and (ii) works that consider space, time and semantics.

1) Methods based on Semantic Dimensions: There are basically three methods for trajectory classification that consider only the semantic dimension: the work of Lee [13], that uses the semantics of the roads to segment trajectories for classification of vehicles, and the works of Gao [14] and [15] that are limited to the POI identifier to classify the person who is the owner of the trajectory. While Lee uses the semantics of the streets to classify GPS trajectories, the works of Gao [14] and Zhou [15] use word embeddings [16], a technique developed for text classification.

2) Methods based on Space, Time, and Semantic Dimensions: There are a few works for trajectory classification that can deal with all three trajectory dimensions of space, time and semantics. Tragopoulou in [17] and Varlamis in [18] were the first works to consider all three trajectory dimensions for transportation mode classification. Tragopoulou in [17] proposed a smart-phone application which records the user trajectory while enriching the trajectory points with the current speed and the semantic information of the day of the week, the time zone, if it is in a working day and if it is near to a metro station. All features extracted from the spatio-temporal and semantic dimensions are passed as input to tree-based classifiers.Varlamis in [18] extended the work of [17] by adding the semantic information of whether the point is near a touristic place, if in a bus line or if in train rail. It uses an Evolutionary Algorithm to generate new examples for training the classifiers, with the purpose of dealing with datasets with a small number of labeled samples.

A recent method called Movelets [24] has outperformed most works for trajectory classification. It is a general method for classifying any type of trajectory. It extracts all possible subtrajectories of each trajectory and compares the distance of each subtrajectory to all trajectories in the dataset. Each of this subtrajectory is called *movelet candidate*. This process is computationally expensive, but it supports any data dimension (space, time, and semantics), because a different distance function can be used for each dimension. Each movelet candidate is qualified by checking its relevance in the trajectories of the same class, against its relevance in trajectories of different classes. The best movelet candidates are called *movelets*, which are then used as input to traditional classifiers.

In [25] Ferrero extends the method Movelets by not encapsulating the distances of all dimensions into a single *movelet*, but keeping all dimensions either separately or combined, depending on its quality. While in the Movelet method a subtrajectory generated from two trajectory points with three dimensions generates only one *movelet candidate*, the MASTER Movelet may generate eight movelet candidates, because it generates 2^l candidates, where l is the number of dimensions. The main issue of the Movelet and MASTER Movelet techniques is the excessive time consuming when analyzing the movelet candidates in order to generate movelets, which is not feasible for large datasets.

C. Summary of Related Works

In Table I we summarize the related works on trajectory classification considering: (i) the datasets used by each method; (ii) the evaluated classifiers; (iii) the classification purpose; and (iv) to which state of the art method the technique is compared. The first main observation is that most of the works use different datasets for evaluating their methods, and some of them are private datasets, making their experiments difficult to be reproduced and compared. Second, some of the works are developed for generic purposes, i.e., any classification problem, while others are developed for specific problems as transportation mode. The third observation is that the majority of works do not compare their results to state of the art.

IV. Experimental Evaluation

We implemented seven methods for trajectory classification from the literature, which are in bold in Table I, based on some characteristics: (i) the number of details given in the paper in order to allow reproducability, (ii) if they were evaluated over publicly available datasets, and (iii) deal with raw trajectories or semantic trajectories. In summary, we compare the following works: Dodge by [10], Zheng by [7], Xiao by [11], Movelets by [24], Bi-TULER by [14], TULVAE by [15] and MASTER Movelets by [25]. In the following we

TABLE I
DATASETS AND CLASSIFIERS USED BY EACH STATE OF THE ART METHOD.

Technique	**Datasets**	**Evaluated Classifier**	**Classification Purpose**	**Compares to**
Lee (2008) [1]	**Animals**, Vessels, **Hurricanes** and Synthetic Dataset	**SVM**	General	None
Zheng (2008) [7]	**Geolife**	DT	Transportation Mode	None
Dodge (2009) [10]	Open Street Map and Eye-Track	**SVM**	General	None
Sharma (2010) [8]	Milan Metropolitan	KNN	Road Vehicles	None
Lee (2011) [13]	Taxis from San Francisco and Synthetic Dataset	**SVM**	Road Vehicles	None
Santos (2011) [19]	**Animals**, Vessels and **Hurricanes**	**SVM, MLP**, Bayes	General	[1]
Patel (2012) [20]	**Geolife, Animals, Hurricanes** and School Buses	**SVM, DT**, Bayes	General	None
Bolbol (2012) [4]	Private Dataset	**SVM**	Transportation Mode	None
Soleymani (2014) [6]	Private Dataset	**SVM**	Medicated Fish	None
Tragoupoulou (2014) [17]	Private Dataset	RF, DT	Transportation Mode	None
Varlamis (2015) [18]	Private Dataset	RF, DT, KNN, **SVM**, **MLP**	Transportation Mode	None
Xiao (2017) [11]	**Geolife**	KNN, DT, **SVM**, RF	Transportation Mode	[7], [10]
Junior (2017) [9]	**Animals**, Vessels and **GeoLife**	DT, Bayes, KNN, RF, Logistic Regression	General	None
Gao (2017) [14]	**Brightkite, Gowalla**	**SVM**, **MLP**, LDA	Users	None
Dabiri (2018) [5]	**Geolife**	CNN	Transportation Mode	[7], [21], [22]
Etemad (2018) [12]	**Geolife**	DT, RF, **MLP**, Bayes, Quadratic Discriminant Analysis	Transportation Mode	[7], [21], [11], [23], [5]
Ferrero (2018) [24]	**Animals**, Athens Vehicles, **Hurricanes** and **Geolife**	Bayes, DT, **SVM**	General	[1], [10], [7], [11]
Zhou (2018) [15]	**Foursquare, Gowalla, Brightkite**	LDA, DT, RF, **MLP**	Users	[14]
Ferrero (2019) [25]	**Gowalla**	**MLP**, RF	General	[14]

describe the datasets in Section IV-A, the experimental setup in Section IV-B and the classification results in Section IV-C.

A. Datasets

For the experimental evaluation, we used six publicly available and commonly used datasets, among which three of them are raw trajectories, and three are multiple aspect trajectories.

GeoLife [1]**:** Dataset from the GeoLife project [7] with daily trajectories of 182 users. The classes in this dataset are transportation mode (bike, bus, car, subway, train, taxi, walk). As the dataset is dense, after removing duplicated records we split trajectories with time gaps, we selected the transportation mode trajectories with more than 100 points and we selected 20% of the total trajectories from each transportation mode, resulting in a dataset with $1,763$ trajectories.

Animals[2]**:** Raw trajectories of three different animal species: elk, deer and cattle. It has a total of 253 trajectories, and $287,136$ trajectory points. We used the entire dataset, as it has a low number of trajectories but that are long in size.

Hurricanes[3]**:** The hurricanes are labeled in six classes where the class is the strength of the hurricane (0 to 5). It consists of 996 trajectories, and we used the entire dataset, as the trajectories are not dense in number of points.

Brightkite : Multiple aspect trajectories from users of the Brightkite social media [26], with the semantic and the spatio-temporal reference of the check-in place. Trajectories are split in weeks, and we used a total of 300 random users for analysis, with a filter of a minimum of 10 points per trajectory. The check-in points were enriched with the semantic information of the weekday and the resultant dataset has a total of $7,911$ trajectories and $130,494$ trajectory points.

Gowalla : Multiple aspect trajectories from users around the world on the Gowalla social media [26], it has the same configuration as the Brightkite dataset, but with a total of $5,329$ trajectories, and $98,158$ check-ins.

Foursquare: Dataset from the Foursquare social media with multiple aspect trajectories from users in New York, USA [27]. Trajectories are split in weeks and we select 193 users with at least 10 check-ins in each trajectory, totalling $3,079$ trajectories. The points are enriched with semantic information of weekday, POI category, weather condition, and with the numerical information of the price and rating of the POIs.

B. Experimental Setup

To evaluate the results, we used the Accuracy (ACC) and F-Score, as they are commonly used for evaluating classification tasks. All datasets are split in a proportion of 70% for training and 30% for testing, and always respecting the class balancing. After the extraction of the features, the Multilayer-Perceptron (MLP) and the Support Vector Machine (SVM) are evaluated. The MLP was implemented in Python language, using the the "keras" package, with fully-connected hidden layer of 100 units, Dropout Layer with dropout rate of 0.5, learning rate of 10^{-3} and softmax activation function in the Output Layer. Adam Optimization is used to avoid the categorical cross entropy loss, with 200 of batch size, and a total of 200 epochs per training. The SVM was also implemented in Pyhton using the "sklearn" package, with linear kernel and default structure. Other structure details are default.

To extract the local features of [10], the sinuosity threshold is given by the average between the minimum and maximum sinuosity value. To extract the Zheng features that require

[1]https://www.microsoft.com/en-us/download/details.aspx?id=52367
[2]http://www.fs.fed.us/pnw/starkey/data/tables/
[3]http://weather.unisys.com/hurricane/atlantic/

thresholds, we evaluated each feature individually for finding the best set of thresholds for each dataset, using DT (Decision Tree) as suggested in [7]. The structure for Bi-TULER and TULVAE is the same proposed in [14] and [15], respectively, by using 250 as fixed size of POI embeddings, 300 units for the RNN required for Bi-TULER, 512 units for the autoencoder RNN with latent variable z of 100 units which are required for TULVAE. In the Movelets the distance measure is euclidean, and we use the space dimension only, which was indicated as the best dimension in [24]. For the MASTER Movelets, the distance measures are: the euclidean for space, the difference for the numerical dimensions and simple equality (if is equal or not) for the semantic dimensions.

C. Results and Discussion

The classification results are shown in Tables II and III, for MLP and SVM, respectively. The values in bold represent the highest scores reached for each dataset, while the underlined values represent the second highest scores. In these tables we separate the methods developed for raw trajectories and those that can be applied to multiple aspect trajectories.

The Movelets method is very time consuming and did not converge for the Geolife dataset. The methods Bi-Tuler and TULVAE are evaluated only with the MLP classifier because they are suitable for neural networks only.

From the methods specifically developed for raw trajectories, Xiao achieved the best results when compared to Dodge and Zheng for the datasets of Geolife and Animals. The methods developed for raw trajectories were not accurate for multiple aspect trajectories in the Brightkite, Gowalla, and Foursquare datasets, because the features extracted from the spatio-temporal dimensions as speed, acceleration, direction change and others are not discriminant for trajectories extracted from social media data, that are characterized by sparse points with more semantics. On the other hand, we notice that the method MOVELETS, that by considering only the spatio-temporal dimension, i.e. the geographic location of the moving object, reached the second best results in five datasets, either for raw or multiple aspect trajectories with the SVM classifer (Table III).

Bi-Tuler and TULVAE are suitable for comparison only for multiple aspect trajectories because they consider the single dimension of POI identifier. Their best accuracy (see table II) is in the Brightkite dataset where they achieved the second best score compared to other methods, but in general, they lose for both Movelets and MASTER Movelets in all three multiple aspect trajectory datasets (Brightkite, Gowalla and Foursquare). This shows that embedding only the POI identifier is not enough for multiple aspect trajectory classification.

In summary, we may observe in all results that the method MASTER Movelet is the best for multiple aspect trajectories, outperforming all state of the art works over the datasets of Brightkite, Gowalla, and Foursquare, because it is the only method that is able to find the best subtrajectories and dimension combination that discriminate the class.

V. Conclusion

In this paper we presented a survey on methods for trajectory classification describing their differences in terms of types of data they support, the dimensions they can deal, the features they extract, which classifiers they use, the evaluated datasets, as well as the classification problem they support (e.g. transportation mode classification, animal classification, etc). We compared seven trajectory classification techniques under two classifiers to understand their behavior in six different datasets. Future works include running the Movelets in a more powerful machine for the Geolife dataset, and proposing an optimization for the Movelets method, based on some heuristics for limiting the movelet search space.

Acknowledgments

This work was financed by the Brazilian agencies Coordenação de Aperfeiçoamento de Pessoal de Nivel Superior - CAPES, Finance code 001, and Conselho Nacional de Desenvolvimento Científico e Tecnológico - CNPq.

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TABLE II
RESULTS OF USING THE MLP CLASSIFIER.

Trajectory Classification - MLP		Raw Trajectory Techniques			Multiple-Aspect Trajectory Techniques			
Datasets		Zheng [2008]	Dodge [2009]	Xiao [2017]	Bi-TULER [2017]	TULVAE [2018]	Movelets [2018]	MASTER Movelets [2019]
Geolife	ACC	70.11	71.05	**75.56**	*	*	**	**
	F-Score	53.93	68.76	**73.83**	*	*	**	**
Animals	ACC	79.48	85.89	**93.58**	*	*	92.31	91.03
	F-Score	78.08	85.71	**93.58**	*	*	92.31	91.03
Hurricanes	ACC	60.85	58.22	58.22	*	*	**62.82**	56.57
	F-Score	61.35	60.26	60.55	*	*	**62.12**	56.37
Brightkite	ACC	05.13	01.73	07.08	90.64	88.41	71.45	**95.09**
	F-Score	00.11	00.11	00.66	87.92	83.63	57.48	**95.01**
Gowalla	ACC	02.37	02.95	06.08	66.15	67.94	83.22	**91.72**
	F-Score	00.12	00.68	01.02	63.26	64.91	82.57	**92.22**
Foursquare	ACC	07.30	07.21	15.87	48.20	54.33	73.71	**97.27**
	F-Score	02.64	03.16	08.80	40.56	46.54	66.25	**96.53**

*The technique does not support this evaluation. **The technique required excessive computational power.

TABLE III
RESULTS FOR THE SVM CLASSIFIER.

Trajectory Classification - SVM		Raw Trajectory Techniques			Multiple-Aspect Trajectory Techniques			
Datasets		Zheng [2008]	Dodge [2009]	Xiao [2017]	Bi-TULER [2017]	TULVAE [2018]	Movelets [2018]	MASTER Movelets [2019]
Geolife	ACC	70.48	71.61	**72.36**	*	*	***	***
	F-Score	60.48	61.39	**62.48**	*	*	***	***
Animals	ACC	79.48	75.64	91.02	*	*	**92.30**	89.74
	F-Score	75.21	74.47	88.73	*	*	**90.82**	85.94
Hurricanes	ACC	56.90	46.71	51.97	*	*	**59.86**	55.92
	F-Score	29.97	26.78	31.87	*	*	**34.86**	20.53
Brightkite	ACC	0.0**	0.0**	0.0**	*	*	87.44	**95.63**
	F-Score	0.0**	0.0**	0.0**	*	*	84.85	**94.94**
Gowalla	ACC	0.0**	0.0**	0.0**	*	*	81.82	**93.51**
	F-Score	0.0**	0.0**	0.0**	*	*	80.64	**93.20**
Foursquare	ACC	0.0**	0.0**	0.0**	*	*	79.06	**95.72**
	F-Score	0.0**	0.0**	0.0**	*	*	76.76	**95.68**

*The technique does not support this evaluation. **The classifier did not converge to a model. ***The technique required excessive computational power.

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