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Measuring the Relevance of Trajectory Matching and Profile Matching in the Context of Carpooling Computational Systems

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Abstract: Carpooling consists of sharing individual vehicle space among people with comparable trajectories. Although there are some software initiatives to help carpooling practice, none of them really implements features similarly to searching for people with similar trajectories and profile. In this study, we propose an innovative approach to generate clusters of users that share similar trajectories and profile for carpooling purposes based on Optics, K-means algorithm and ensemble learning. First, we provide a proper definition of fundamental elements of the carpooling context in order to contribute to a standardization of the concerning nomenclatures. Next, we perform four different experiments for the purpose of showing the feasibility of the approach. We also contribute to the construction of a real dataset (donated to UCI), properly depicted, used in two of these experiments. Results with Davies-Boulding index indicate that the generated clusters are feasible to the design of a carpooling recommendation system. Time performance evaluation of the approach has been also performed for both dynamic program analyses via software profiling method and time complexity analysis according to Big O notation.

Keywords: Carpooling, Trajectory Similarity, User Profile Similarity, Clustering

Introduction

Traffic jams are a serious concern in metropolitan areas (He *et al*., 2012). Economic losses, health issues and environmental damages are some of the known consequences (Resende and Sousa, 2009; Currie and Walker, 2010; Levy *et al*., 2010; Hart *et al*., 2009). According to the DENATRAN (Brazilian National Department of Traffic), the number of vehicles has increased more than 100% in the last 10 years (DENATRAN, 2013). An alternative to avoid the congestion is to adopt the policy of restricting traffic for private cars. For example, in Beijing, China, the government has adopted these solutions to solve the problem of the one worst traffic in the world. Although it is a solution, the traffic is still critical in peak hours. (He *et al*., 2014). Since the USA suffered a loss of almost $78 billion in 2007 due to traffic jam issues (Schrank and Lomax, 2007), a lot of measures has been adopted to reduce the problem such as: Improve traffic light synchronization (He *et al*., 2014), building new roads/avenues, encouraging the use of bicycles as daily transportation and improvements in public transportation.

Carpooling (share individual vehicle space among people with similar destinations) is a typical solution used by some nations to avoid the problems generated by the increase traffic condition. However, this solution is strongly related to some cultural aspects (Gowri, 2008; Matos *et al*., 2014). Sharing cars' empty seats may be seen as an optimization method if we consider, for instance, the low occupancy rate per vehicles in traffic (He *et al*., 2014). In 2011, a research conducted by the Michigan University has shown an occupancy rate of 1.5 in the U.S.A. Such occupancy rate is easily decreased to 1.4 if we consider only "home->work" or "work->home" trajectories. In other words, there are plenty of vehicles with just the driver inside (Ghoseiri *et al*., 2011).

There are software initiatives to facilitate the carpooling's practice. Caronas Brasil (Azzam and Bellis, 2008), Zumpy, Poolmyride, BlaBlaCar (Mazzella, 2004), Go! (Matos *et al*., 2014), Carma (O'Sullivan, 2015), Carticipate (Frost, 2015), BeepMe, Lyft (Zimmer and Logan, 2012) and Bynd are some examples. However, to

date, few of them have had commercial success (Ghoseiri *et al*., 2011). Some services provided by that software require that interested users execute a search for people who offer a ride with the same or alike trajectories. In some cases, it's not so simple to find this trajectory. Another problem is the fact that the driver and the passenger are unfamiliar. This kind of information contributes to the increasing of trust among users of the services (Furuhata *et al*., 2013). There are other factors that may discourage carpooling: The presence of a smoker, features of the vehicle itself, some aspects of the driver's profile (Agatz *et al*., 2012) and gender (Levin *et al*., 1977). The ridematching procedure has been proposed to deal with these issues and suggest the carpooling formation instantaneously (Agatz *et al*., 2012). It promises to facilitate the matching process among candidates by correctly attributing users who want to get a ride to users that offers.

Currently, the propagation and the facility of use of smartphone apps, the Global Position System (GPS) and APIs like GoogleMaps allow people to track their own trajectories and share them broadly: GPS-Way-Points, Share-My-Route, Bikely, Facebook (Shang *et al*., 2012). These shared data can be used to the development of a lot of impressive characteristics such as: Mining frequent trajectories (Savage *et al*., 2010), finding similar trajectories (Pelekis *et al*., 2007), mining Points of Interests (POIs) (Telles *et al*., 2012), find out sub-trajectories and so on. He *et al*. (2014) and Lee *et al*. (2007) have tried different approaches of mining trajectory to provide ridematching among users. Surely, most research centers on the improvement of the trajectory mining process, but few propose an effective approach to define the suitable granularity level of GPS-based trajectory and none have properly formalized central elements and features of carpooling context. As a consequence, a range of terms with the same meaning is used in different works and may confuse the reader: Route (He *et al*., 2014) or trajectory (Lee *et al*., 2007), a driver (Furuhata *et al*., 2013), passenger or riders (Agatz *et al*., 2012), etc. Finally, in the context of carpooling, few academic types of research consider both similarity of profile and trajectory (Furuhata *et al*., 2013; Yan and Chen, 2011).

Cruz *et al*. (2015) propose a clustering approach to trajectories in the context of carpooling. This paper aims to extend the work of (Cruz *et al*., 2015) along three axes: (i) Propose (semi-formal definition of the elements of the carpooling context, towards a standardized nomenclature, (ii) Add users' profiles to the clustering approach and (iii) Provide a proper evaluation of the trajectories' dataset (GO! Track) used to train the clustering model.

In section 2 we provide proper definitions to the elements of carpooling context. In Section 3, we describe our approach to generating user's clusters with similar profiles and trajectories. In Section 4, we present the experiments and discuss the results. We conclude the work in section 5.

Formalization

Definition 1:

Trajectory is a sequence of multi- dimensional points. These points are discrete and finite and they are represented by $Tr = \{p_1, p_2, p_3,...,p_n\}$. Here, p is a 3-dimensional point: Latitude, longitude and time-stamp, $p = \{\text{lat, lng, t}\}$.

Definition 2:

Driver is the user who shares a vehicle with the passenger and has similar trajectory with all passengers. $Tr(d)$ is a trajectory that pertains to the driver. In this study, $Tr(d) \sim U = \{T\ \text{r}(a_1), (a_2), ..., T\ r(a_n)\}$ means that the driver's trajectory and passengers' trajectory are similar. In such case, $\text{dist}(Tr(d), Tr(a_i)) \leq r$, where dist() is some distance function and r is a limit constant.

Definition 3:

A vehicle is defined as any means by which someone may travel: A car, a motorcycle, etc. Here, a vehicle is represented by V, where $V(d)$ is a vehicle that belongs to the driver d.

Definition 4:

Passenger is a user who shares a vehicle with a driver. $Tr(a)$ is a trajectory that belongs to a passenger a. In this study, $Tr(a) \simeq T\ r(d)$ means that the driver's trajectory and passenger´s trajectory are similar.

Definition 5:

Ride is described as a form to share a private vehicle space among people with similar trajectory and interests. A ride is represented by $R = (V(d), d, Tr(d), A)$, where $V(d)$ is driver's vehicle, d is a driver, $Tr(d)$ is a driver's trajectory and A is the set of passengers.

Definition 6:

Origin is defined as the first point $p_1 \in Tr$ of each trajectory.

Definition 7:

Destination is defined as the last point $p_n \in Tr$ of each trajectory.

Method

Our approach extends clustering trajectory proposed by (Cruz *et al*., 2015) with K-means (Macqueen, 1967) algorithm as follows. Given a set of users, $U = \{S_1, S_2, \ldots, S_n\}$, where each S_i is denoted by a tuple set by a user's trajectory Tr_i and user's profile P_i, Optics* generates a set of cluster $A = \{C_1, C_2, ..., C_n\}$, where each

$C_i = \{Tr_1, Tr_2, ..., Tr_n\}$ denotes a set of user's trajectory and it has at least one trajectory from a user called driver d that gives a ride. Next, K-means produces a set of cluster $B = \{X_1, X_2,..., X_n\}$, where each $X_i = \{P_1, P_2, ..., P_n\}$ represents a set of user's profiles. Finally, the set of clusters A and B are combined using an ensemble approach. The result is a set of clusters R of users related profile and trajectory.

Figure 1 describes the entire method. Perceive that the clustering process takes into account proper distances between trajectories and social distance between user's profile. The method is split into five principal steps: (i) Defining the granularity of user's trajectory, (ii) Temporal filter, (iii) Optics clustering, (iv) K-means clustering and (v) Relabel and intersection clusters. Since the first three steps are properly described in (Cruz *et al*., 2015), we present them briefly.

Trajectory's Granularity

Considerer U a set of user's trajectories. Each trajectory contains points that was collected in the short time interval. Because of this, it's necessary to reduce it. RotaFacil (Telles *et al*., 2012; 2013) dramatically reduces the number of trajectory's points by detecting Points of Interest (POIs) (Fig. 2). A new subset U' is thus generated.

Temporal Filter

Figure 2 POIs within a circumference for a given radius.

A temporal filter is a way of processing a pipeline in other to find similar trajectories with similar departure and destination times. Surely, it is irrelevant clustering together $Tr(d)$ and $Tr(a)$ if departure and/or destination times of users d and a are very different, even though $Tr(d) \simeq Tr(a)$. Regarding t the time of departure ride and x as a bound that user is prepared to accept requests for a ride, the width of the filter is the interval $[t - x, t + x]$. For instance, a user d can offer a ride with departure time at 6 am and inform a boundary of 30 min earlier or later t to accept a request for a ride in an interval of [5: 30, 6: 30].

Optics Clustering

The clustering trajectory is performed by an adaptation of Optics* algorithm (Ankerst *et al*., 1999). Figure 3 illustrates algorithm's behavior. $Tr(a)$ belongs to a passenger a who wishes to get a ride whereas $Tr(d)$ belongs to the driver. The similarity only takes into account origin and destination points of the passenger´s trajectory.

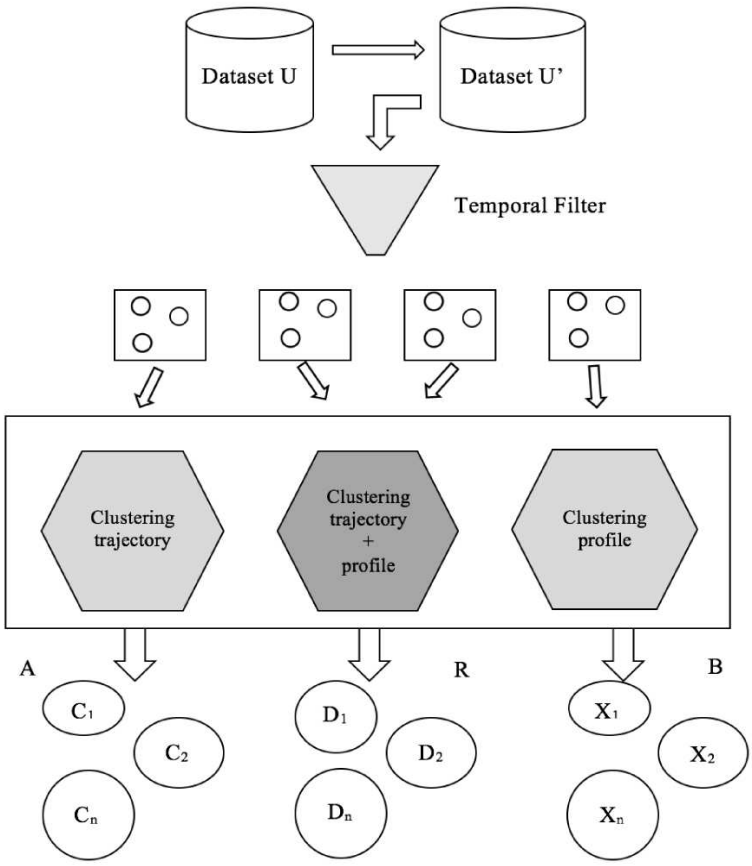


Fig. 1: The method illustrates the step-by-step to reach three types of clusters

Fig. 2: POIs within a circumference for a given radius

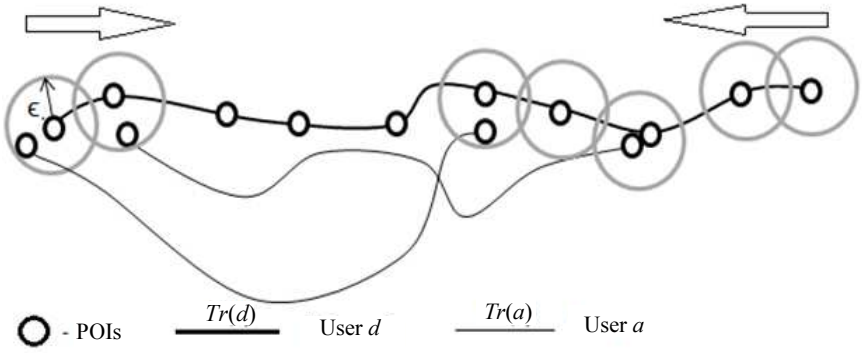


Fig. 3: The approach used to define the similarity between two trajectories

Cosine function has been used to compute the similarity (Theodoridis *et al*., 2010) between two users $sim(P_i, P_j)$:

$$sim(P_i, P_j) = \cos(\theta) = \frac{P_i \cdot P_j}{\|P_i\|, \|P_j\|} \quad (1)$$

Relabel and Intersection

Relabel strategy is a way to arrange clusters granted similar as exhibited in Fig. 4.

The result obtained by Optics* and K-Means are two partitions (A and B) that are processed by Hugarian Algorithm. These algorithms will have relabeled the partitions to verify which clusters have more users in common. Consider, for instance, that cluster C_1 has 4 users with comparable trajectories and cluster X_2 has 10 users with similar profiles. If we are in mind that all combinations between A and B, X_2 and C_1 are clusters that have more users in common.

Figure 5 illustrates relabeling process. The columns and rows represent the partitions and the users respectively. The permutation is used to align the most alike clusters. Users that belong to alike clusters will make part of the final clusters. This work uses trajectory partition as a reference partition which is used as the support to align other partitions. As Fig. 4 and 5 show, the voting approach is not used fully because, in our context, there is no need to vote to generate final clusters with just two partitions.

The consensus functions (represented by τ on Fig. 4) considers the intersection between clusters:

$$\tau(C_i, X_j) = C_i \cap X_j \quad (2)$$

because the partition D is resulted from two others partitions: A and B. These final partition is composed by clusters with users that have similar trajectory and profile.

Experiments

We have conducted four experiments to prove the feasibility of the ridematching with trajectory and profile. The first two experiments were based on (Cruz *et al*., 2015). The difference is that we will use a larger real dataset and show the result produced using Optics*. Third experiment shows the results of Optics and K-means using the clusters of user's profile. Finally, the fourth experiment presents results that were obtained from clusters with users that have both trajectory and profile similarity.

Datasets

Three different datasets have been used. The first consists of trajectories of users driving cars or taking buses collected by the Go!Track app. The second consists of trajectories that were roduced by Rota Facil artificially. It was produced 500 trajectories. The third dataset consists of 500 registers of profile attribute also artificially produced.

GO!Track Dataset

The Table 1 presents the first dataset. A total of 445 trajectories from 65 different mobile devices were collected between September 2014 and March 2016 in the city of Aracaju/SE. Each trajectory is a set of points obtained at an interval of 0.5 sec (for car) and 10 sec (for bus). The values of these parameters were defined empirically.

Table 2 and 3 show the fields of the dataset. First table stores the collected trajectories and the second one, latitude and longitude mainly.

Figure 6 a trajectory instance and corresponding data.

The present version of the dataset includes an important set of streets and avenues of Aracaju city. We have plotted all the dataset points on Aracaju city map (Fig. 7).

In addition, Table 4 lists the top-20 most visited traffic roads by GO! Track users, according to the **number of trajectories** (#T) that actually used it. This was accomplished by the Google Geocode API. The column **number of points** (#P) shows the number of points presented in that traffic road, regardless of the trajectory. We highlight the known principal city traffic roads according to traffic density during peak hours.

Many useful applications use date-time data to predict traffic states or traveling time. Coming graphs provide relations between geographic points and the time. The graph of Fig. 8 presents the similarity between the trajectories and date-time.

The x-axis represents the 163 trajectories and the y-axis the time bands. Each line in the graph represents a trajectory: The higher the line, more time has been spent in the trajectory regardless of the traveled distance. Points represent the city in a diverse range of times, allowing to observe situations where the traffic is probably increased (peak time).

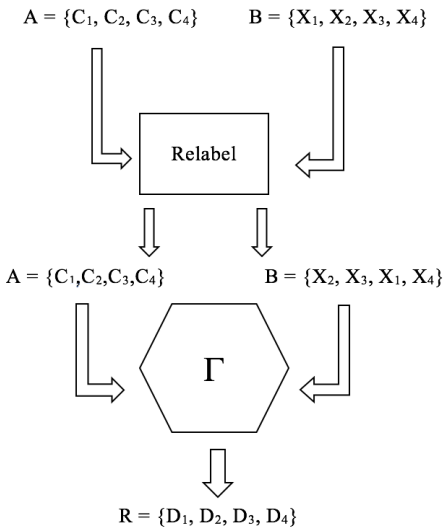


Fig. 4: The approach used to relabel and realign clusters

	A	B
S_1	1	A
S_2	1	A
S_3	2	C
S_4	3	D
S_5	2	C
S_6	3	D

	A	B	FC
S_1	1	1	D_1
S_2	1	1	D_1
S_3	2	2	D_2
S_4	3	3	D_3
S_5	2	2	D_2
S_6	3	3	D_3

Fig. 5: Basic relabel and assembly final clusters

Table 1: GO!Track dataset

Measures	Values
Num. of trajectories	445.00
Num. of different devices	65.00
Mean of points by trajectory	111.08
Num. of car trajectories	328.00
Num. of bus trajectories	117.00
Num. of points collected by cars	44715.00
Num. of points collected by buses	3918.00
Distinct Address visited	358.00

Table 2: Collected trajectories

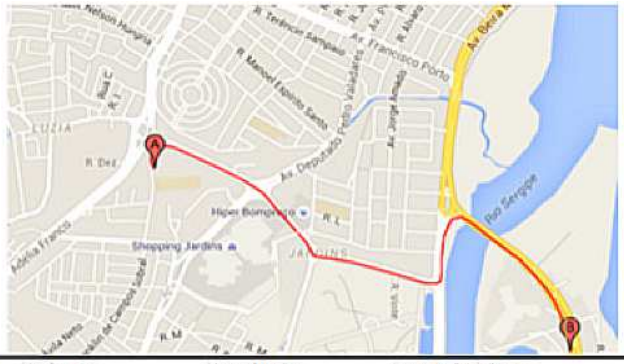
Field	Description
id	A unique key to identify each tra jectory.
id_android	An identifier for each device that was used to collect trajectories.
Time	the duration of the pathway in minutes.
Distance	The distance of the trajectory in a kilometer.
Speed	Average speed during all pathway.
Rating	The user evaluation of the traffic.
Line	Information about the bus that does the pathway (available just in bus case).
car_or_bus	indicates if the trajectory was collected by a car or a bus.
rating_weather	indicates the conditions of the weather available just in bus case).
rating_bus	indicates the quality of the travel (available just in bus case).

Table 3: Geographic points

Field	Description
Id	A unique key to identify each point
Latitude	Latitude from where the point is
Longitude	Longitude from where the point is
Track_id	The trajectory to which the point belongs
Time	Date-time the point was collected

Table 4: Most visited traffic roads in Aracaju according to GO!Track users

Order	Address	#T	#P
1	R. Boa Viagem	48	527
2	Av. Pres. Tancredo	38	1068
3	Av. Beira Mar	34	1216
4	Av. Ivo do Prado	23	581
5	Av. Mário J. M. Vieira	22	571
6	Av. Simeão Sobral	21	141
7	Av. Des. Maynard	21	950
8	BR-235	19	56
9	Av. Confiança	18	137
10	SE-100	18	280
11	Av. Eng. Gentil Tavares	14	253
12	Av. Adélia Franco	14	271
13	Av. Filadelfo Dória	14	34
14	Av. Dr. José S. R. Filho	14	184
15	R. de Muribeca	14	117
16	Av. Barão de Maruim	13	196
17	Av. Antônio Cabral	13	123
18	Av. Coelho e Campos	13	69
19	Av. Farmacêutica C. R	13	158
20	Av. João Ribeiro	13	265



id	latitude	longitude	track_id	time
1	-10.9393413858164	-37.0627421097422	1	2014-09-13 10:24:32
2	-10.939341385769	-37.0627421097809	1	2014-09-13 10:24:37
3	-10.9393239478718	-37.0627645137212	1	2014-09-13 10:24:42
4	-10.9392105616561	-37.0628430455445	1	2014-09-13 10:24:47
5	-10.9389389789911	-37.0628785984113	1	2014-09-13 10:24:53
6	-10.9385435911514	-37.0628386631358	1	2014-09-13 10:24:59
7	-10.9383460576505	-37.0625875627021	1	2014-09-13 10:25:04
8	-10.9384484455051	-37.0619998251528	1	2014-09-13 10:25:10
9	-10.9386660746204	-37.0614969339645	1	2014-09-13 10:25:15
10	-10.9389862284613	-37.0608192197261	1	2014-09-13 10:25:21
11	-10.9393429131892	-37.0600866959415	1	2014-09-13 10:25:27
12	-10.9396414360875	-37.0595030996298	1	2014-09-13 10:25:32
13	-10.9398579141531	-37.0591213205945	1	2014-09-13 10:25:38
14	-10.9400772902018	-37.0587290032396	1	2014-09-13 10:25:43

Fig. 6: A trajectory instance and corresponding data

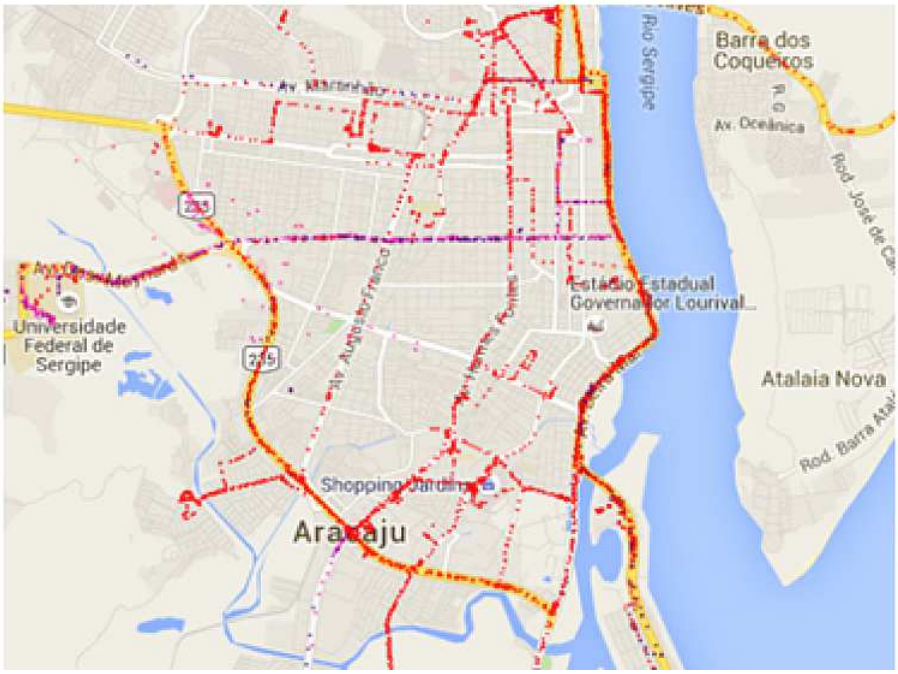


Fig. 7: Streets and avenues of Aracaju city in the GO! Track dataset

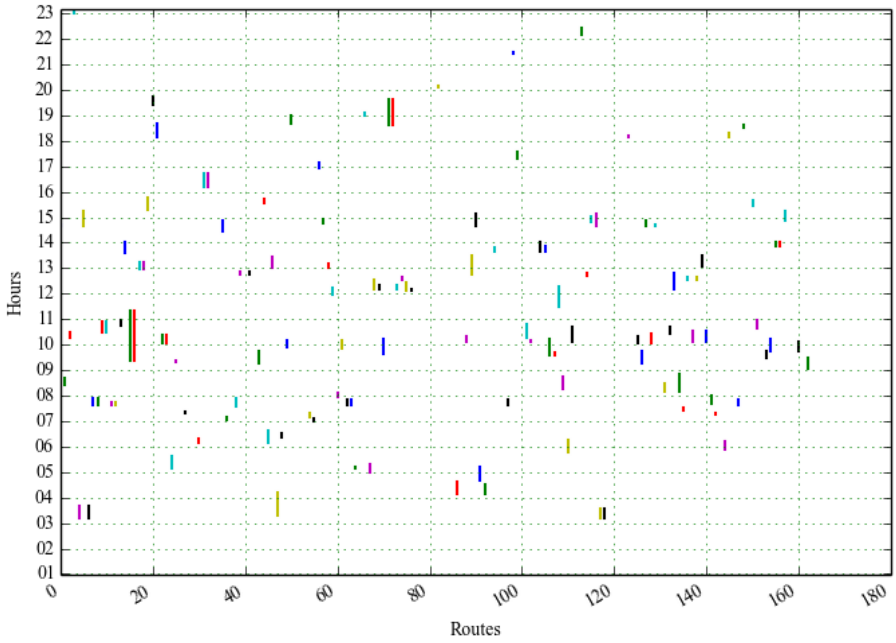


Fig. 8: The relationship between trajectories and the date-time

Similarly, the graph of Fig. 9 shows the relation between each of the top-20 most visited traffic roads (street and avenues) and the specific instant it was visited. We have considered a daily time interval, in particular, at peak hours.

The experiments were realized using the follow parameters adjustment. For experiments one and two the value of the parameter ε was set to 100, 150, 200 and 300 m. The MinPts was set to 2 and 3. We have assumed that 100 to 300 m are moderate distance limits for a user who wants a ride to move towards the destination point of an offering ride. The values 50, 150, 200 and 250 were set to parameter ε which is used in cluster extraction algorithm.

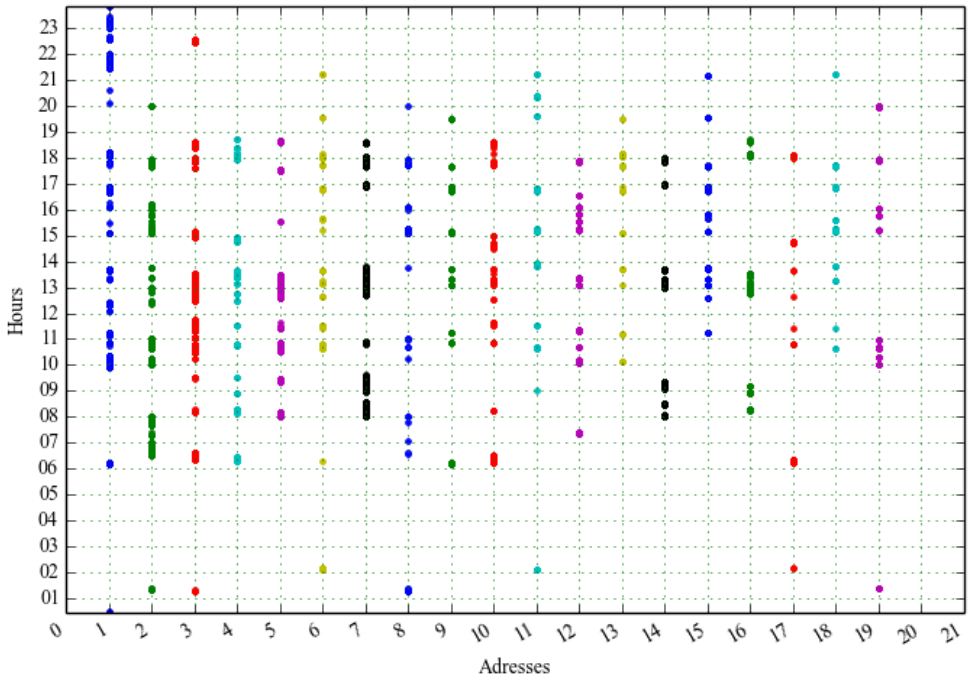


Fig. 9: The relationship between traffic roads and the date-time

In the case of experiments three and four, it was adjustment five attributes: (i) Gender (binary), (ii) *reputation* (discrete), (iii) *age* (discrete) [*child* = 0, *teenager* = 1, *juvenile* = 2, *adult* = 3, *elderly* = 4], (iv) *smoking* (binary), (v) *music* (discrete) [*poprock* = 0, *heavymetal* = 1, *classic* = 2, *jazz* = 3, *reggae* = 4]. All the attributes have been normalized in order to provide variance 1 and mean 0.

Evaluation Metrics

Davies-Boundin Index (DBI) the clustering task. Equation 3 (Theodoridis *et al*., 2010) was used to evaluate defines the DB value:

$$DBI = \frac{1}{n}\sum_{1}^{n} \max_{i \neq j}\left(\frac{\sigma_i + \sigma_j}{d(c_i, c_j)}\right) \quad (3)$$

where, n is the number of clusters, c_i and c_j is the centroid of each cluster. The α_i and α_j are the similarity measures for clusters c_i and c_j.

The values generated by Equation 3 reflect how similar the elements of the same cluster are, as well as the dissimilarity among different clusters. Smaller DBI values are better.

Experimentation Results

Table 5 shows the results of the first experiment. The radius used in granularity definition step was 25 m. The best result occurs when ε was 150 and MinPts were smaller than 3.

Table 6 shows a little contrast compared with Table 5. For example, the best results occur when MinPts was bigger than 2. The radius used in the granularity definition step was 30 m.

Table 7 shows the results of the second experiment. The DBI values among three algorithms are similar. ε directly influences clusters' size according to experimentation. One ε that is "big" enough will produce good results. Unlikely, small ε will generate a plenty of objects with a reachability-distance value equal to undefined. Here, as well as in the work (Cruz *et al*., 2015) neither method was used to deduce the ideal ε.

The results of the third experiment are shown in Table 8. The experiment presents a comparison of clustering methods in regard to the user's profile. First, we show the results for Optics and next for K-means. We can verify that K-means has better results when the number of clusters grows up.

As a consequence of such results, K-means has been used to generate profile clusters in the fourth experiment.

Table 9 shows the results of ensemble learning approach to provide clusters of users with similar trajectories and profiles. The results have been achieved by the matching of trajectory clusters generated by Optics* and profile clusters got with K-means.

Table 9 shows the Number of Final Clusters (NFC), Davies-Boulding Index related to the Trajectory (DBIT) and Davies-Boulding Index related to Profile (DBIP). It shows the results of the Optics* and K-means considering the Number of Clusters (NC) once the ensemble learning approach by DBI metrics is done. DBI metrics is better when a number of clusters are larger (NC≥40).

Table 5: Results for the dataset with real trajectories and radius = 25

ε	MinPts	ε'	NC	DBI
100	2	50	29	0.9203
100	3	50	7	0.9202
150	2	100	46	0.6074
150	3	100	16	1.1775
200	2	150	57	0.6179
200	3	150	24	1.4444
300	2	250	61	0.6597
300	3	250	25	0.7490

Table 6: Results for the dataset with real trajectories and radius = 30

ε	MinPts	ε'	NC	DBI
100	2	50	27	1.261
100	3	50	8	0.614
150	2	100	35	1.234
150	3	100	13	0.683
200	2	150	49	1.141
200	3	150	17	0.997
300	2	250	51	1.119
300	3	250	26	1.385

Table 7: Results of 2nd experiment: Artificially generated dataset

ε	MinPts	ε'	NC	DBI
100	2	50	39	0.7868
200	2	150	54	0.8860
200	3	150	34	0.7235
250	2	150	62	0.8968
250	3	150	36	1.0164
300	2	100	48	0.7946

Table 8: Results of 3rd experiment: artificially generated dataset

ε	MinPts	ε'	NC	DBI
0.5	4	0.1	4	1.5949
0.5	3	0.1	54	2.7418
0.5	2	0.1	34	3.3514
			k	
0	0	0.0	4	2.1671
0	0	0.0	15	2.5023
0	0	0.0	103	1.4670

Table 9: Results with an artificially generated dataset

NC	NFC	DBIT	DBIP
68	10	0.6089	1.1867
44	11	0.5095	0.9953
66	11	0.6619	1.5094
68	8	0.3772	3.3514

Table 10: Profiling method analysis

Function	Number of call	Total time	Cumulative time
Math.cos	13317696	1.846	1.8460
Distance	1902528	16.182	22.2970
Neighbors	408	150.000	24.2230
Mean	40	0.040	0.0053

These results are probably due to the artificial dataset which doesn't have many user's trajectories with the similarity less than 200 m or user's profile aren't so similar according to values used in this study.

Complexity Analysis

We have provided some time analysis for our approach. Firstly, we used the software profiling method which is a form of dynamic program analysis. Next, we calculated the time complexity estimation according to big *O* notation.

The cProfile library enables software profiling analysis. The profiling was used with the purpose to determine which part of the method should be optimized. The analysis covers a set of features such as: A number of function calls *NumofCall*, the total time spent by functions or operations, the cumulative time spent by the functions *C Time*, etc. In addition, we could verify the overall time spent in each method. Table 10 shows the four most expensive functions. Results of Table 10 were obtained with the following setup: ε = 100, MinPts = 2, ε' = 150, k = 54.

Table 10 shows that function math.cos has been called a lot of times, but the time spent by the function is less than 10% of neighbors' function. The neighbor's function is used by Optics algorithm and has fundamental importance. The neighbor's function is a bottleneck of Optics algorithm because it consults the whole trajectories' set when it is called. According to (Ankerst *et al*., 1999), an index structure like tree-based spatial index can be used and consequently decrease the overall runtime.

The first complexity analysis of the method was done. According to (Ankerst *et al*., 1999), the Optics* algorithm has an overall runtime of $O(n^2 . \lg n)$ considering a spatial index and similarity algorithm. Additionally, K-means algorithm has an overall runtime of $O(n^{dk+1} . \lg n)$ where d is the dimension and k the number of clusters. The ensemble approach used has an overall runtime of $O(K^3)$ considering that Hungarian is been employed. The runtime of ensemble approach can be considered constant because K is a number of the partition that is fixed in 2. Thus, the global runtime is $O(n^2 . \lg n + n^{dk+1} . \lg n)$.

Conclusion

Encouraging carpooling is an important effort towards the reduction of in-transit vehicles. Although there are some concerned research initiative and even some related software, they do not appropriately treat carpooling context specificities. In this study, we have proposed an extension to the method developed by (Cruz *et al*., 2015) in order to deal with some of these specificities: Find out groups of users that have similar profile and trajectory and consequently determine potential carpooling possibilities. Furthermore, clustering users' trajectory and clustering users profile are results that can be considered separately in regard to the final interest of who desire to use the proposed approach as carpooling applications.

Density-based algorithm Optics was chosen due to some features like a minimal number of input parameters, ability to build non-spherical clusters and sturdiness to noise. These features are important to take into account in a task of finding similarity among trajectories. The well-known K-means was chosen because shows better results compared to Optics in a context of users' profile.

Clustering results and corresponding Davies-Bouldin Index values obtained from a dataset of actual trajectories collected pervasively have shown the feasibility of the proposal. According to experimentation, POIs with different radius seem to not influence the quality of our approach. Initial runtime analysis indicates the elevated complexity. However, if we consider that the problem of finding out similarity among trajectories of users is a special case of the so-called pickup and delivery problem, which is NP-Complete (Agatz *et al*., 2012), the analysis result proves its feasibility.

We are currently working on experiments that consider weighted profile´s attributes, so the users can define their weighted preferences. We are also currently embedding this similarity approach into a carpooling recommendation service so it could be integrated into some open-source carpooling software, such as the GO!Caronas (Matos *et al*., 2014; Macedo *et al*., 2014). Finally, we intend to compare our ride and profile matching approaches with the approach of (Carvalho and Macedo, 2013), which uses coalition structure to provide proper group's formation.

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Author's Contributions

Michael Cruz: Conceptualization, Design, Execution and Analysis drafting

Hendrik Macedo: Conceptualization, Analysis drafting and Critical revision

Adolfo Guimarães: Analysis drafting, Execution and Critical revision

Ethics

There is no ethical issues with this article.

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