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► **To cite this version:**

Danyang Sun, Fabien Leurent, Xiaoyan Xie. Uncovering mobility typologies of territorial zones based on Floating Car Data mining. EWGT2020: 23RD EURO WORKING GROUP ON TRANSPORTATION, Sep 2020, Paphos, Cyprus. hal-02955642

**HAL Id: hal-02955642**

**<https://hal.science/hal-02955642>**

Submitted on 13 Feb 2023

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23rd EURO Working Group on Transportation Meeting, EWGT 2020, 16-18 September 2020,  
Paphos, Cyprus

## Uncovering mobility typologies of territorial zones based on Floating Car Data mining

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### Abstract

This paper describes a data exploration study using Floating Car Data to analyze mobility patterns of geographical spaces. The objective is to build a mobility-related typology of territorial zones by investigating related vehicle movements. Mobility features at the level of trips and stay places are recovered from daily vehicle trajectories. Place visiting frequentation is further analyzed at each vehicle level to identify significant places and corresponding activity regularity. Based on these mined patterns, a multi-view cooperative clustering method is developed to feature out the zonal mobility typology in terms of the composition of local stays, temporal flows of trip generation and attraction, and spatial connections in trip distance distribution. The proposed framework was applied to the Great Paris region for an experiment using 14 days data. Consequentially, 5 mobility types of zones were obtained, with each holding a different orientation of mobility usage. Discovered areas were also compared with the common recognition of their social functions, which showed a consistent matching. Overall, this study provides a data-driven approach to study mobility interactions with territorial spaces, by spatial segmentation, characterization, and differentiation.

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Peer-review under responsibility of the scientific committee of the 23rd EURO Working Group on Transportation Meeting.

*Keywords:* Territorial mobility pattern; Space clustering; Mobility typology; Floating Car Data;

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### 1. Introduction

Understanding mobility patterns has been widely acknowledged as a critical role in urban planning, traffic management, and many other place-based applications. Generally, the spatial configuration may induce mobility generation, while reversely, human movement would further re-impact the space development (Wegener and Fürst, 2004). The evolution between them is reciprocal. Therefore, investigating the mobility pattern of territorial spaces will help to reveal such interaction and provide valuable guidance for future development. With the growing

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diffusion of location tracking technologies, digital traces are becoming more and more available nowadays. Among them, Floating Car Data (FCD) has emerged as a new essential data source on roadway traffic for a high spatial and temporal coverage, which thus offers a great potential to investigate mobility patterns of territorial spaces.

In the existing literature, FCD was mainly used to determine traffic states, including speed detection, travel time estimation, and congestion prediction (Altintasi et al., 2017; Fusco et al., 2016; Mori et al., 2015). Mobility perspective analysis using FCD was relatively limited. Among those works, some studies analyzed the city structure by deriving hotspots from taxi pick-ups and drop-offs (Jahnke et al., 2017; Liu et al., 2015). Major hubs such as airports were also analyzed to further investigate its specific mobility role interacted with the city (Ding et al., 2016). Some other studies analyzed mobility origin-destination patterns aiming to extract major spatial movement and their temporal variations (Ciscal-Terry et al., 2016; Lian et al., 2018). Yet the related studies hardly dealt with the detailed mobility pattern on each intra-homogenous geographical space unit, namely territorial zone at a regional level.

In fact, human mobility dynamics are largely correlated with the spatial configuration. Investigating people's mobility activities could contribute to revealing the social functions of territory zones. Yuan et al. (2014) conducted a study to discover urban functional zones based on human trajectories and POIs by developing a topic-modeling-based approach. Another study by Qi et al. (2011) measured social functions of regions according to the temporal variation of get-on/off amounts from taxi GPS data. These studies showed the potential of capturing spatial functions by mining mobility trajectories. However, an issue of them was found as such region functions were mostly interpreted according to limited perspectives of mobility information, which was either by the time of flows or by the origin-destination transitions. A more comprehensive exploration would therefore be prompted by combining different perspectives together. Another persistent issue is the lack of focus on the activity stay following the movement, which leads to the role of space occupation.

Therefore, the objective of this study is to investigate the mobility pattern of territorial zones by mining multiple aspects of information from Floating Car Data. By building a zonal mobility profile in terms of trip departures and arrivals, and related vehicles' activity context as well as their hour and weekday variation, this research aims to cluster mobility patterns of territorial zones so as to build a typology.

## 2. Data description

FCD of 14 days over the Great Paris region was explored, which was obtained by onboard GPS devices from Coyote, a major roadway information service provider in France. The data collected the localization coordinates (longitudes and latitudes) of vehicles with the timestamps periodically, as well as corresponding instantaneous vehicle states such as moving speed and heading direction etc. The dataset was organized as sequences of logs with anonymized vehicles identifiers. The recording was around every 30s to 60s, which was at a low frequency standard but is a common trend for energy saving in the industry. A total of 168,308 unique vehicles were found showing up within the Great Paris region during the time period. However, due to the inefficiency to do the data exploration on the whole large dataset with total logs over 15 million, the dataset was downsized by a pre-selection. As a result, 2,500 random vehicles were selected from the pool of those having frequent usage among the 14 days. Such a frequent usage was defined as showing up on at least 4 distinct days and holding at least one re-visiting location.

A territory can normally be divided into sub-zones for different functions. These zones can be either developed artificially by urban planners or progressively formulated by human's activities. Administrative boundaries and physical characteristics can contribute to the delimitation of zones (Dubrova et al., 2015). In this study, the zones of IRIS (Islands Grouped for Statistical Information) were used as the territorial division units for zonal typology discovery. Such IRIS zones were developed by INSEE (the national statistics bureau of France), which divides the country into units of equal size on the basis of population with respect to geographic and demographic limitations. The Great Paris region consists of 5260 IRIS zones.

## 3. Trip and stay place mining

### 3.1. Trajectory sequencing into trips

Trajectory information by FCD is collected as a sequence of logs (trace points) with no direct semantic representations. The first step of mining was to recover the trajectories for each vehicle and segment them into

meaningful trips. Hereby, we defined a few notions that are: 1) A trip indicates a set of consecutive trace points by which the vehicle makes for a certain purpose of movement; 2) A stay point indicates a location visited at the end of a trip. 3) A temporal stop is made between two trips which indicates the time duration for the activity.

Many efforts in the literature have been made on such trajectory sequencing on GPS traces, however, the majority of them was dealing with personal trips based on mobile phone GPS data (Gong et al., 2015, 2014). Only limited work was found on a vehicle basis (Chen et al., 2017; Lin et al., 2016). Among those studies, the time interval between two succeeding points was most widely used as the decisive feature for identifying trip ends, with other criteria set on distance and interval average speed by some studies. However, thresholds of those criteria varied from one to another subjecting to the data source and local context. In this study, we developed a trip identification algorithm, extending from our previous study (Sun et al., 2020), by adopting two main criteria: the time interval  $t$  and a gap distance ratio  $i$ , which leverages both of the distance and speed information recorded in the data with the formula given as below.

$$i = \frac{\text{observed distance}}{\text{expected distance}} = \frac{\text{distance}(P_a \text{ to } P_b)}{0.5 * (V_a + V_b) * t}$$

where  $\text{distance}(P_a \text{ to } P_b)$  denotes the planar distance between point a and point b of an interval,  $V_a$  and  $V_b$  denote the recorded speeds respectively. The process of the algorithm can be illustrated as in Figure 1. Thresholds were drawn by spotting significant distinctions in the statistical distributions. As a result, a new dataset of detected trips was generated along with describing features including origin-destination locations, time window (departure and arrival time), and trip distance. A total of 63036 trips were identified for the 2500 vehicles during the 14 days.

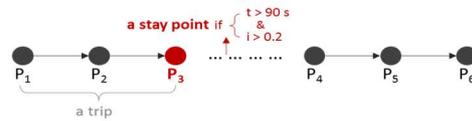


Fig. 1. Trips and stay points detection

### 3.2. Stay points clustering into meaningful places

The stay points at the end of trips can be concatenated to represent the location visiting history for each vehicle. However, due to the fussiness of locations, stay points with slightly different geo-coordinates may correspond to the same place. The second step of mining was therefore conducted to group up those that were spatially adjacent to recover the meaningful places. To address this, density-based clustering methods can be employed by detecting spatial clusters based on the geo-coordinates (Vanhoof et al., 2018; Ye et al., 2009). In this study, the widely used DBSCAN clustering method was adopted. Such a method requires two input parameters which are the distance threshold ( $eps$ ) and the minimum number of points ( $minPts$ ) to form a cluster. In this study, the  $eps$  was set as 150 m and  $minPts$  was set as 3 based on performance comparisons to other setups, results of which were visually inspected and fitted well in our application with an overall demonstration as in Figure 2. The stay points were finally grouped into 8 554 clusters. By detecting these spatial clusters, places with the same representations were bundled and activity frequentation in visiting them could be further investigated.

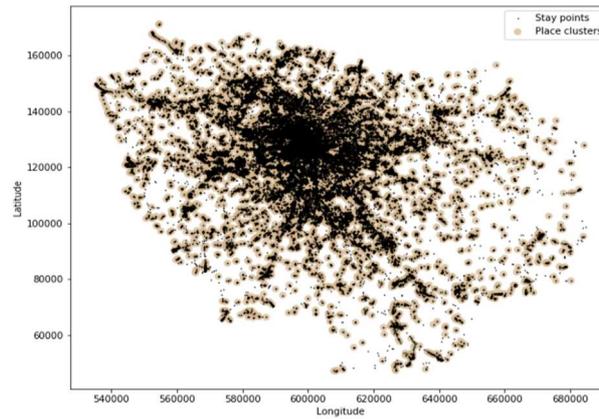


Fig. 2. Stay points vs Place clusters

#### 4. Place frequentation at the individual level

##### 4.1. Place frequentation modeling

Places may hold different roles in people's mobility activities, with some visited more frequently and others less primary. Investigating presence frequentation at different places can help to understand individual mobility regularities and further contribute to analyze the spatial functions. The recovered meaningful places were examined for each vehicle with the aim to identify their significant places such as home place, work place and other regularly visited places. Three major features were considered in such a place frequentation modeling, which were 1) time of the day in visiting the place (Tongsinoot and Muangsin, 2017; Vanhoof et al., 2018); 2) attendance among distinct days in visiting the place (Vanhoof et al., 2018); 3) activity duration at the place. Places were treated separately with different vehicles by bundling place identifiers with vehicle identifiers. This is because one same place may mean differently to different visitors, e.g a place of restaurant may represent the work place for vehicle user 1, while just playing as an entertainment stop for the others.

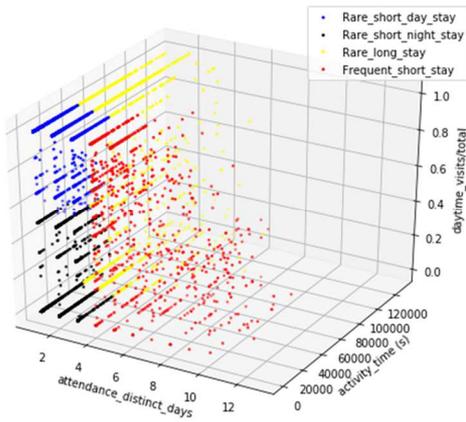
##### 4.2. Significant places identification

A decision rule and clustering combined method was developed to investigate the place frequentation and identify significant places. The approaches were conducted at two levels.

The first level was to identify primary places including home and work places, which are commonly acknowledged in deriving fundamental mobility activities. As the two kinds of places can be characterized with explicit criteria, a series of decision rules were designed for the identification according to the common sense and criteria proposed in previous literature (Ahas et al., 2010; Vanhoof et al., 2018), which are described as below:

- Home place: 1) High probability ( $p > 0.5$ ) as the first/end place visited during a day sequence. 2) High attendance among distinct days ( $> 80\%$ ) when the vehicle is used.
- Work place: 1) More daytime (8h-18h) activities at the places; 2) High attendance during weekdays ( $> 60\%$ ); 3) Long average activity duration ( $> 2$  hours)

As for the other places not detected in primary ones, the second level of identification was to explore their frequentation difference by conducting a K-means clustering analysis. Three features were used for distinguishing, which were 1) Attendance among distinct days; 2) Average activity duration on site and 3) Ratio of visits during daytime. The number of clusters can be determined according to the average silhouette value or the elbow method. As a result, these secondary places were partitioned into 4 clusters, as shown by a scatter plot in Figure 3(a). Each cluster was also characterized with a label as displayed in the figure according to its relatively prominent characteristic. Overall, to sum up the two levels of identification, 6 types of significant places were drawn, the statistics of which were summarized in Figure 3(b).



Significant places	Attendance among distinct days	Ratio of visits during daytime	Duration of activities
Home	9.52	0.50	60624s
Work	6.27	0.85	46533s
Rare short day stay	1.27	0.99	3761s
Rare short night stay	1.33	0.06	4172s
Rare long stay	2.04	0.50	139366s
Frequent short stay	5.41	0.55	17983s

(a) Clustering results on secondary places

(b) Statistics summary

Fig. 3. Identified significant places

## 5. Zonal mobility typology discovery

### 5.1. Usage-based zonal attributes

Mobility usage of a territory zone can be naturally described from different perspectives. By exploiting the information presented in multiple views, a more precise data structure can be disclosed (Mitra and Saha, 2019). The mobility patterns of zones were modeled from three views to form the attributes.

- View 1: Composition of local stays

Significant places identified in section 4 were counted in each type  $j$  for a zone and used as the attribute in reflecting activity frequentation and duration. Place counts were then converted to percentage values  $r$  by zone subtotals and normalized to explore relative difference in composition ratios. Such an attribute was formed as a vector  $\{r_{i1}, \dots, r_{ij}\}$  for the zone  $i$ .

- View 2: Time of flows

Trips leaving from and arriving to the zone were counted by time bins to reflect the temporal mobility pattern. 8 time bins ( $k$ ) were used by considering both of time of day and day of the week, which were pre-defined as: *Morning* (5-10h), *Mid-day*(11h-15h), *Evening*(16-21h), *Night*(22h-4h) for weekdays and weekends respectively. To weigh each dimension equally, each period count was converted to a period flow factor  $p$  by further dividing by the day average trip number of the corresponding zone. The attribute was finally formed as a vector of 16 factors  $\{p_{i1O}, \dots, p_{ikO}, p_{i1D}, \dots, p_{ikD}\}$  for the zone  $i$  for both trip departures  $O$  and arrivals  $D$ .

- View 3: Spatial complementarities

This view looks at the distance ranges of trip generations and attractions. Distance bands by the power of 2 kilometers were used in counting the trips. Counts in different range bands were converted to percentage values  $d$  and normalized. The attribute was formed as a vector  $\{d_{i2O}, \dots, d_{i2^nO}, d_{i2D}, \dots, d_{i2^nD}\}$  for the zone  $i$  for both trip departures  $O$  and arrivals  $D$ .

For each IRIS zone, mobility patterns (feature vectors) of the above views were assembled and used as the input for base clustering. Results of these base clusterings can be further integrated to get a more comprehensive understanding of a zone’s mobility characteristics.

### 5.2. Multi-view cooperative clustering

A multi-view cooperative clustering method was employed to identify the final zone typology by integrating the explorations from different views. Many different terminologies were used to refer to this kind of method in the literature, involving: cooperative clustering, multi-view clustering, clustering ensemble etc. (Topchy et al., 2004;

Cornuéjols et al., 2018; Mitra and Saha, 2019). Overall, a similar aim of such methods is to improve the clustering quality by combining complementary contributions from different base clusterings on different omics of features with each holding its own bias. More hidden patterns are expected to be spotted, which are, otherwise, likely to be diluted if all features are concatenated into a single-view. More so, other benefits include its robustness to data variations, and a wider range of applications on real-world problems of multiple modalities. In our application, the routine approaches conducted are as below:

- 1) Perform the base clusterings (K-means) on different views of mobility patterns respectively.
- 2) Integrate base clustering results to build a co-association matrix (Mitra and Saha, 2019), which depicts the average frequency that a pair of objects is partitioned into the same cluster.
- 3) Build a connection graph of the zones based on the co-association matrix.
- 4) Perform the spectral clustering to final partition the graph and discover zone typology.

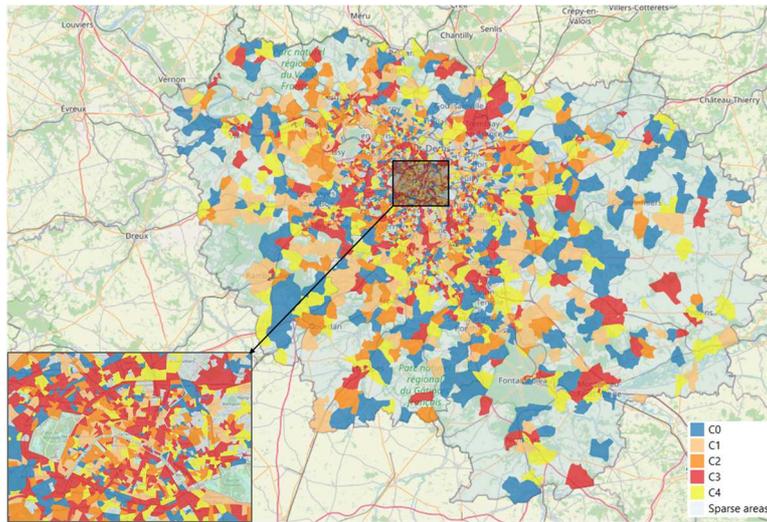
### 5.3. Results and zone types annotation

5 clusters (C0-C4) of zones were drawn from the final clustering analysis. Geographical distributions of them are geo-visualized in Figure 4(a) along with their attributes displayed by heatmaps in Figure 4(b). The color gradient in the heatmap indicates the mean values of corresponding attribute vectors. By comparing the attribute characteristics, the zones were annotated into 5 types, described as below.

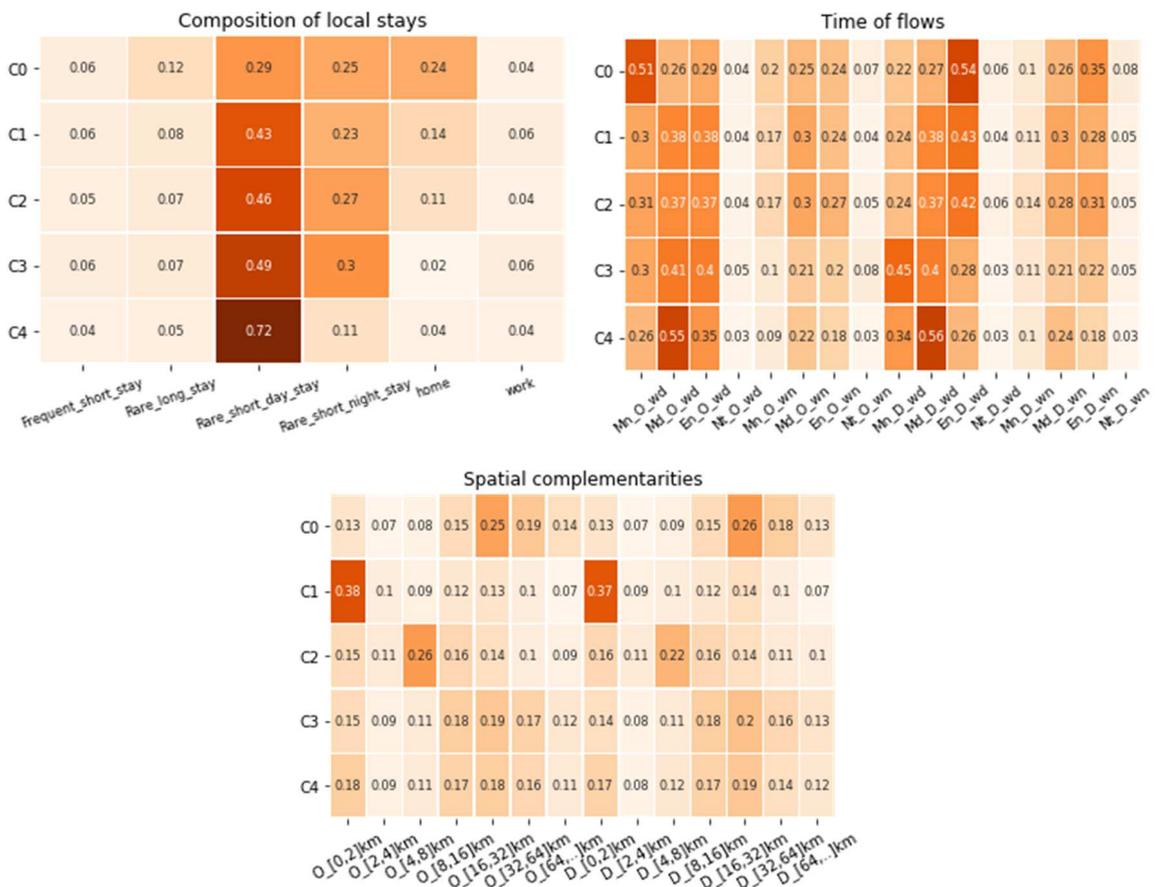
- *C0 Residential oriented areas*: These zones were constituted of higher departure rate in the morning and higher arrival rate in the evening on weekdays, which is a typical temporal pattern of residential areas. A relatively larger portion of home places was also shown in the composition of stays. Spatial travel patterns were mixed with more mid-range and local trips.
- *C1 Commercial-residential mixed areas (locally-accessible-based)*: These zones were composed by more of less-frequently-visited places and home places, which can be interpreted as a mix of residential dwellings and living quarters such as super-markets, cafés, restaurants etc. More activities showed up during mid-day and evening, with no significant flow drops on weekends. The trip distance was more local based.
- *C2 Commercial-residential mixed areas (intermediate-range-accessible-based)*: This cluster had a similar pattern with C1, except the spatial patterns were composed more of longer trips.
- *C3 Business/employment oriented areas*: These zones showed up a significant higher arrivals in the morning and higher departures in the evening on weekdays with the overall volume dropping on weekends. Such a time of flows is consistent with employment areas with vehicles used for commuting. Home places were also found least in this cluster.
- *C4 Day-time mobility-oriented areas*: These zones had a maximum portion of less-frequently day-time visited places. Significant more vehicles usage was also presented during mid-day time period. Such a pattern may correspond to retail shops or commons, town center in the rural areas and campus of educational places, where the visiting time is flexible during the day.

Besides, there were zones without enough observations of trips (<15) for the total of departures and arrivals), so that they were excluded from the clustering analysis and grouped into a separate type, which was annotated as *Observation sparse areas*.

Validation of such explorations is a common problem in published research of mobility trace exploration due to the absence of ground truth for the evaluation. Within this restriction, the results of our zone annotations were inspected by geo-visualizing their locations and comparing the annotation to the common recognitions of their social functions. For example, La defense, Val de Fontenay and Charles De Gaulle airports surrounding areas are commonly known as employment areas consisting of business centers or company facilities, which matches with our identification with these areas clustered into C3. More so, the Paris center are highly urbanized areas, especially for the zones of 1e, 2e, 8e 9e arrondissements, most areas of which were detected as commercial or mixed areas. It also has to be noted that many zones were found with mixed place functions which is partially consistent to the fact that land uses are rarely monotonous within an urban area. However, future exploration may be done to with further segmented zone units of the territory.



(a) Geo-locations of discovered zone clusters



\*Where *O* indicates departure trips; *D* indicates arrival trips; *Mn* indicates morning; *Md* indicates mid-day, *En* indicates evening, *Nt* indicates, night, *wd* indicates weekday, and *wn* indicate weekend.

(b) Patterns of zonal attribute vectors

Fig. 4. Discovered mobility types of zones and their usage attributes

## 6. Conclusions and discussions

This research proposed a methodological approach to discover mobility typology of territorial space by mining FCD. An application study was dealt with the Great Paris region. Mobility features at the level of trips and stays were firstly recovered from vehicle trajectories. Meaningful places were then detected based on stay points. Place frequentation at different places was modeled at each individual level to identify their anchorage places and other regular presences. Upon those, 3 views of zonal attributes were assembled for each zone to describe the pertaining vehicle usage, including the composition of local stays by frequentation, time of trip flows and spatial complementarities in trip distance distribution. Consequentially, 5 mobility types of zones were obtained through the analysis. The discovered areas were visualized on the map and showed a consistent matching with the common recognition of their social functions.

The explorative approach by multi-view cooperative clustering enabled to explore more patterns from different perspectives and combine them to get a more comprehensive discovery. Practically, this research provides a big data driven instance to analyze mobility interaction with geographical spaces, the knowledge of which may provide useful insights in understanding their heterogeneity and similarity and thus benefit many place-based applications. Our current results were restricted to the vehicle mobility level due to the essence of data used. However, the proposed framework can be scaled with data of other modes of transport, which may contribute to a more complete picture of the zone mobility typology in the future.

## Acknowledgements

The research was supported by Chair Eco-design Vinci at Ecole des Ponts ParisTech. The authors would like to thank Geolytics project, with partners IT4PME and Coyote, for the data and assistances, and Chair ENPC-IdFM in facilitating this research.

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