Scooter Trajectories Clustering

Machine Learning and Deep Learning

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Introduction

Trajectories clustering is a problem really difficult to be treated but can be useful for several applications:

- Monitoring
- Forecasting
- Viability
- Smart City
- Security

State of art

The current researches can be divided into 5 categories:

- Spatial based clustering: *DBSCAN* algorithm.
- Time depended clustering: *OPTICS* algorithm.
- Partition and group based clustering: *Lee partition & group*.
- Uncertain trajectory clustering: *Fuzzy C-Means* algorithm.
- Semantic trajectory clustering: *Stops and Moves* model.

Dataset weighs: **2GB**.

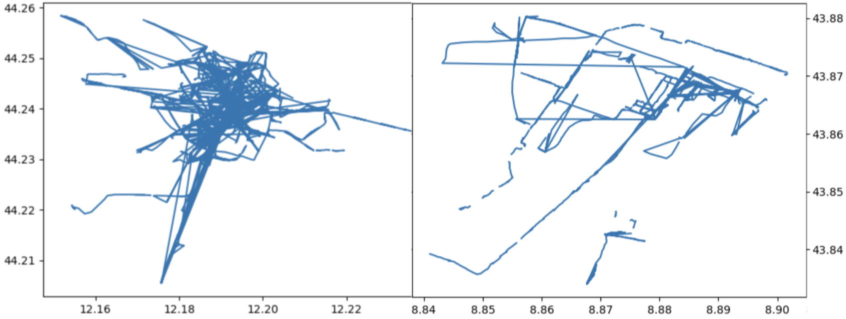
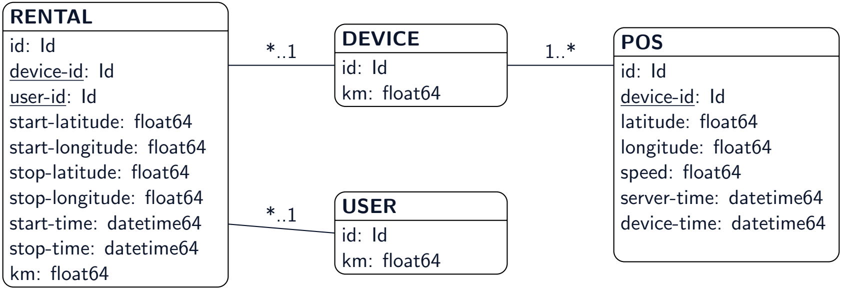


Figure: Rentals showed: 200.

Original dataset diagram

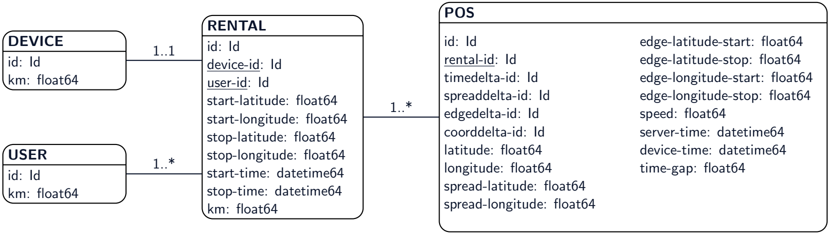
Dataset entities: position, rental, device and user. The dataset has been previously processed in order to delete sensitive informations.



Methodology

Generated dataset diagram

Dataset	Samples	Features
rental	14826	10
pos	817076	18
merge	817076	18
dataset	14826	13
partition city 1	608251	18
partition city 2	202795	18



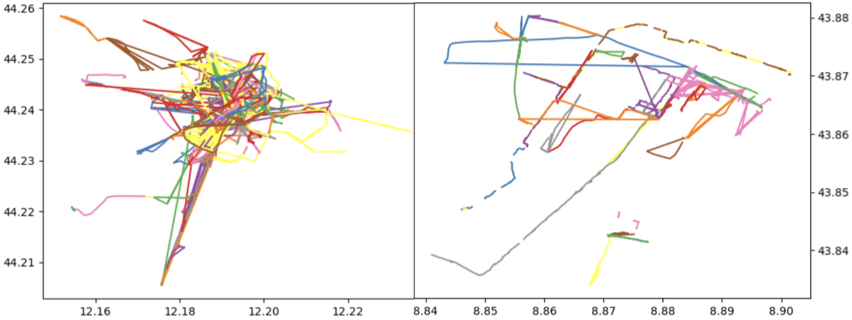


Figure: Rentals showed in the 2 cities: 200 (left), 50 (right).

HEURISTICS: *timedelta* AND *spreaddelta*

The following heuristics methodologies use a `delta` value that is values with the statistic's empirical rule.

- **timedelta heuristic**: a rental trajectory can be divided in a sequence of trajectories if the time gap between a position and previous one exceeds a *timedelta* value.

$$TIMEGAPS = \{p.time - p[-1].time \mid \forall p \in POS\} \quad (1)$$

- **spreaddelta heuristic**: a rental trajectory is similar to another one if they spread a similar amount of area.

$$SPREADS = \{max(t) - min(t) \mid \forall t \in TRAJ\} \quad (2)$$

Heuristics: *edgedelta* and *coorddelta*

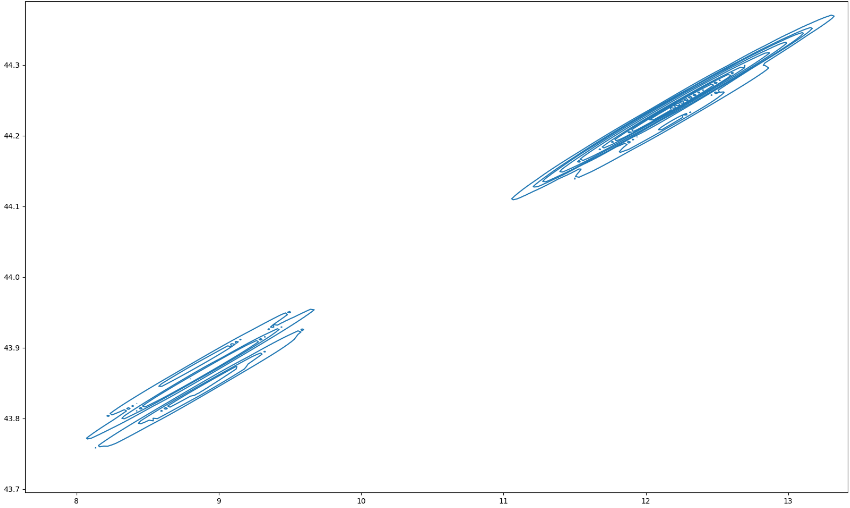
- **edgedelta heuristic**: acts as the *spreaddelta heuristic*, but it considers the edges of a trajectory, or rather the first position and the last position of a trajectory. The main issue is the bimodal distribution of edges.

$$EDGES = \{concat(p[0], p[-1]) \mid \forall t \in TRAJ\} \tag{3}$$

- **coorddelta heuristic**: combination of spread and edge heuristics in order to combine the main advantages.

Position distributions

The positions are concentrated in 2 distant cities:



Feature extraction

Pipeline: integration of heuristic data as features, *Standardization*, *Normalization* and than *Principal Component Analysis (PCA)*.

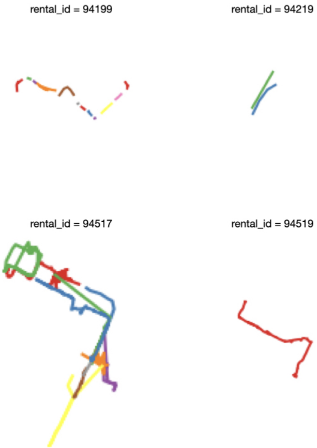
The component extracted by *PCA* can be decided in 3 different ways:

- By a number a priori;
- By the cumulative variance with 80% cover;
- Concatenation of columns produced by *PCA* for different subset of features;

Clustering

- **K-Means**: simple technique with distance based metric, fast and cheap in memory terms. $O(n * k * I)$
- **Mean Shift**: density based, automatically sets the number of clusters, but it needs a bandwidth parameter. $O(n^2)$
- **Gaussian Mixture**: estimation of linear combination of a finite number of Gaussian distributions with unknown parameters and *expectation-maximization (EM)* algorithm. $O(I * n^3)$
- **Full Hierarchy Agglomerative**: hierarchical clustering with bottom up approach and minimization metric on the maximum distance between observations in pairs of clusters. $O(n^3)$
- **Ward Hierarchy Agglomerative**: hierarchical clustering with bottom up approach and minimization metric on the sum of squared differences between all clusters. $O(n^3)$

Results



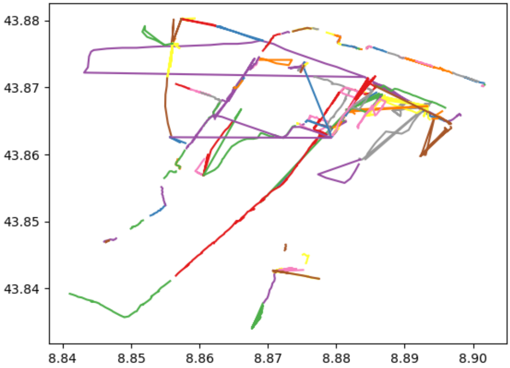


Figure: Rentals showed: 50.

Spreaddelta heuristic results

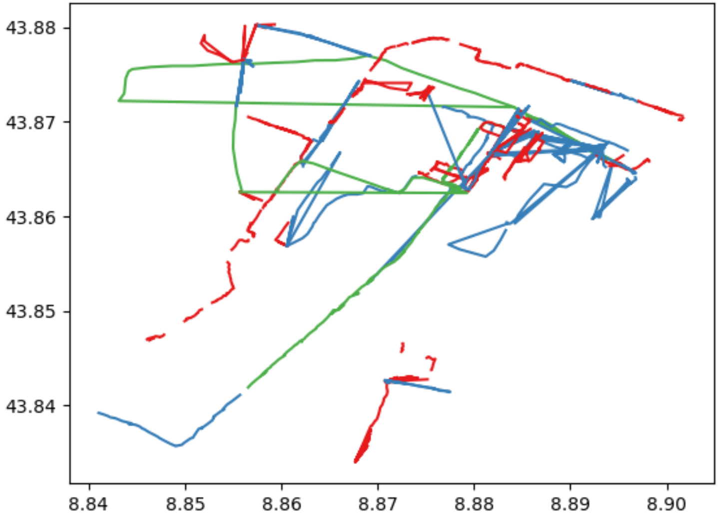


Figure: Rentals showed: 50.

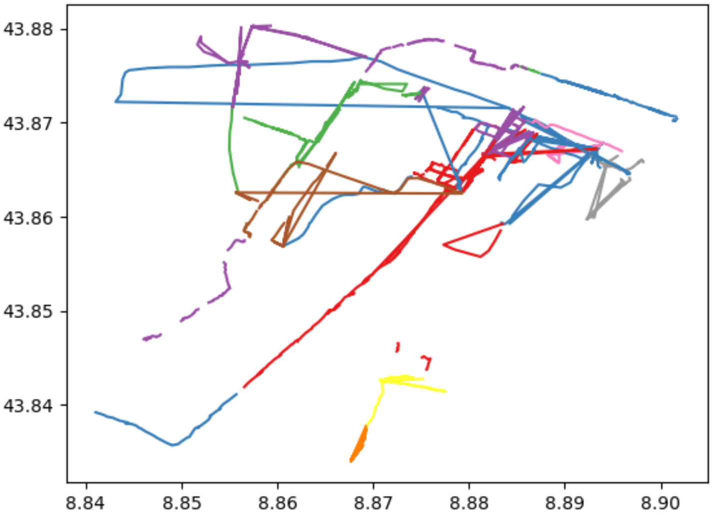


Figure: Rentals showed: 50.

Coorddelta heuristic results

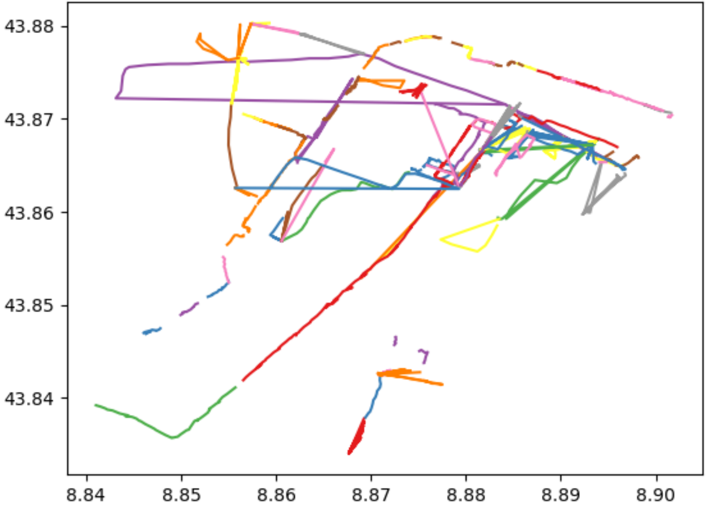
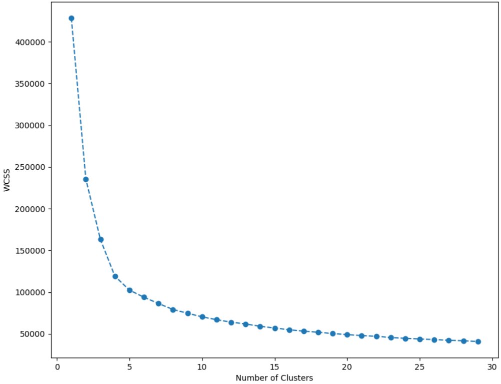


Figure: Rentals showed: 50.

WCSS and Elbow method

Within Cluster Sum of Squares (WCSS) graph for *Elbow method* in range from 1 to 30 with K-Means



Number of clusters estimated: **5**.

Gaussian Mixture clustering

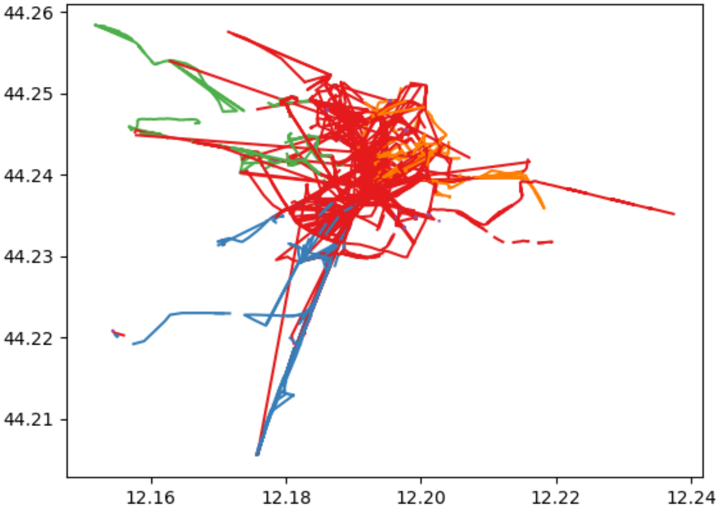


Figure: Silhouette: -0.02. Rentals showed: 200.

Mean Shift clustering

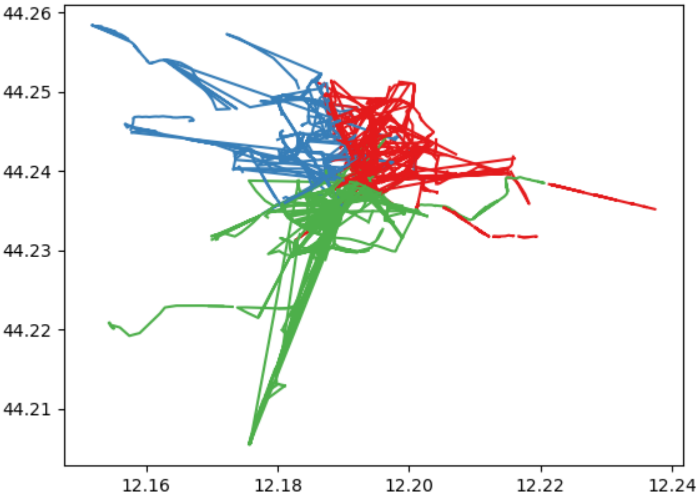


Figure: Silhouette: 0.40. Rentals showed: 200.

Full Hierarchical Agglomerative

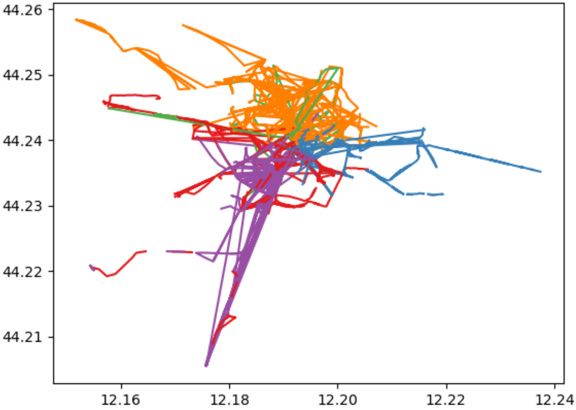


Figure: Silhouette: 0.16. Rentals showed: 200.

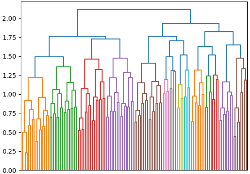


Figure: Dendrogram up to level 5 of merge

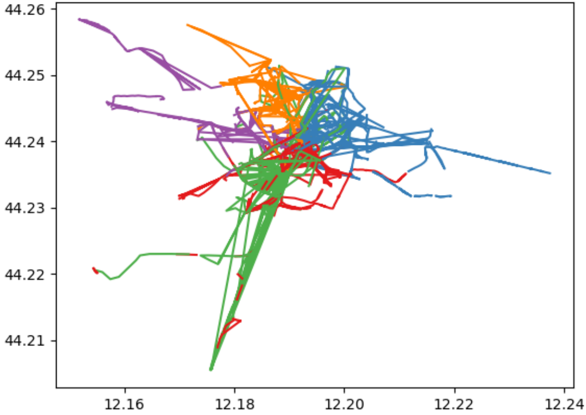


Figure: Silhouette: 0.28. Rentals showed: 200.

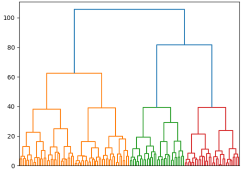


Figure: Dendrogram up to level 5 of merge

K-Means clustering

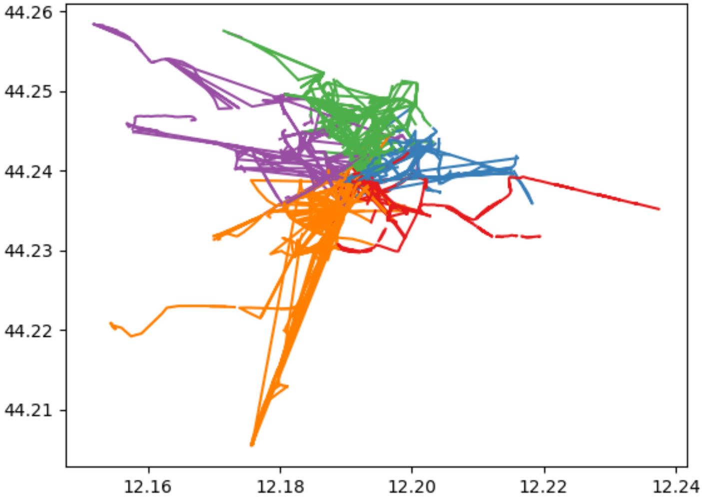


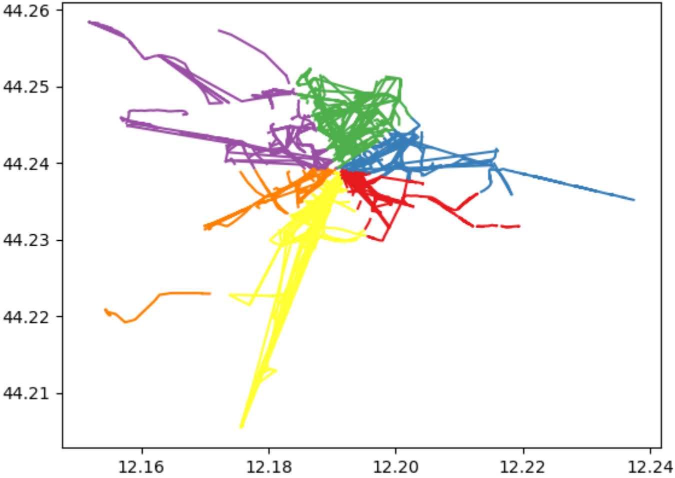
Figure: Silhouette: 0.352. Rentals showed: 200.

Conclusion

Final considerations

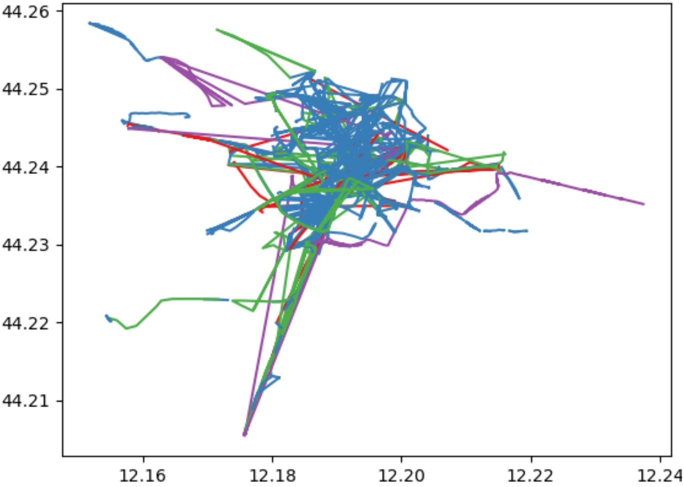
- *K-Means* best result in terms of plot representation and *Silhouette score*;
- Custom *PCA* implementation results similar to traditional *PCA* approach based on the 80% of cumulative variance;
- Time useful for partition and group, but not for bottom-up clustering techniques;
- Clustering with *PCA* shows better results in variance terms;
- Clustering with heuristic features maintains the rental information;
- Clustering has always to be performed on a specific region of interest in order to optimize the results;
- *Silhouette score* is not a validation methodology so reliable, because it depends a lot on the data you are dealing with;

K-Means without *PCA* with only latitude and longitude features.



K-Means bad result

K-Means with 5 clusters performed on all positions showed on one city.



K-Means 3D