

# Individual mobility profiles: methods and application on vehicle sharing

**Roberto Trasarti, Fabio Pinelli,  
Mirco Nanni and Fosca Giannotti**

KDDLab, ISTI-CNR, Pisa  
IBM Research Lab, Dublin

---

# People are boring...

People follow the same behaviors almost every day... can we extract this information?

In literature there are works saying that the mobility of an user can be theoretically predicted up to 93%

(<http://www.sciencemag.org/content/327/5968/1018.abstract>)

**Let's see what we can do!**

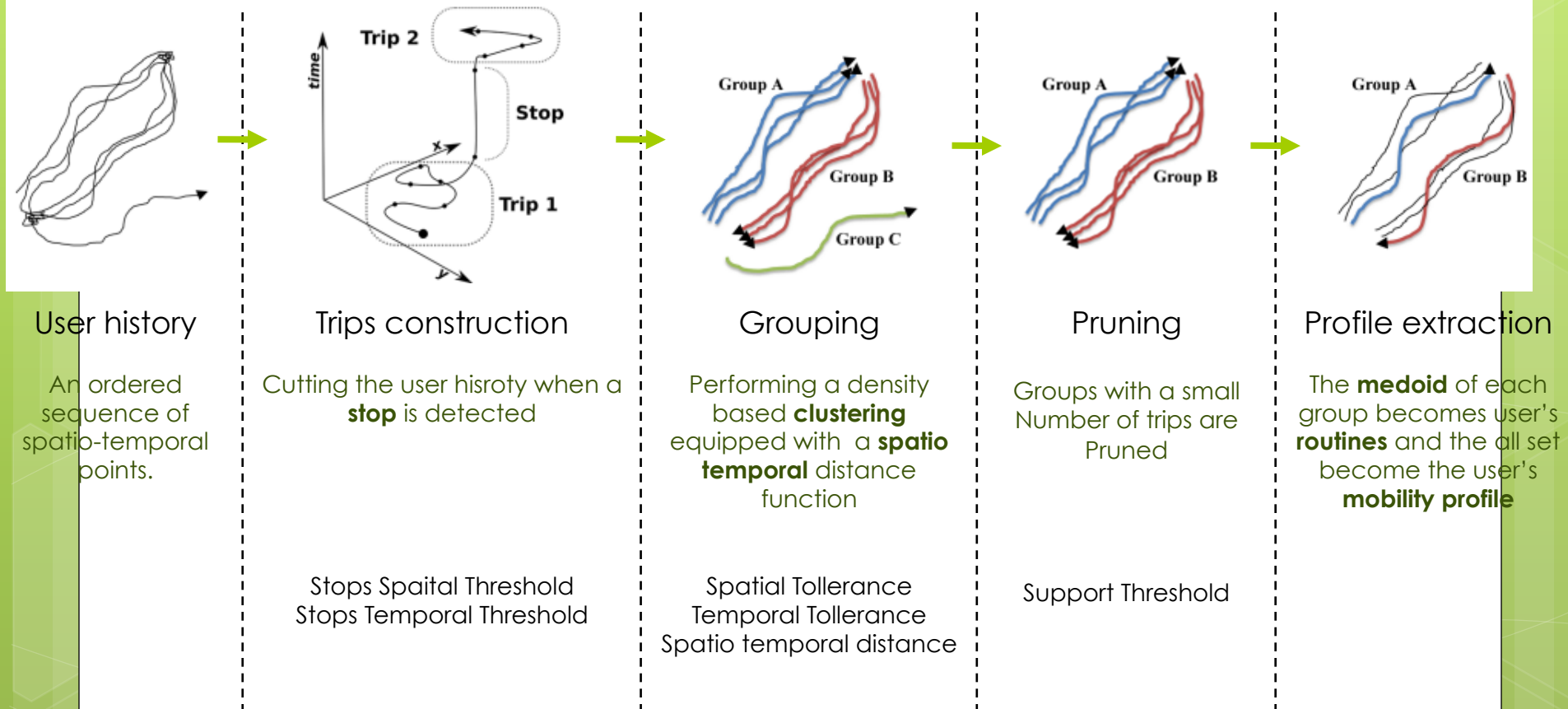
# User's Mobility Profile

Given the user history as an ordered sequence of spatio-temporal points, we want to extract a set of *routes* in order to create the his\her *mobility profile*.

Where:

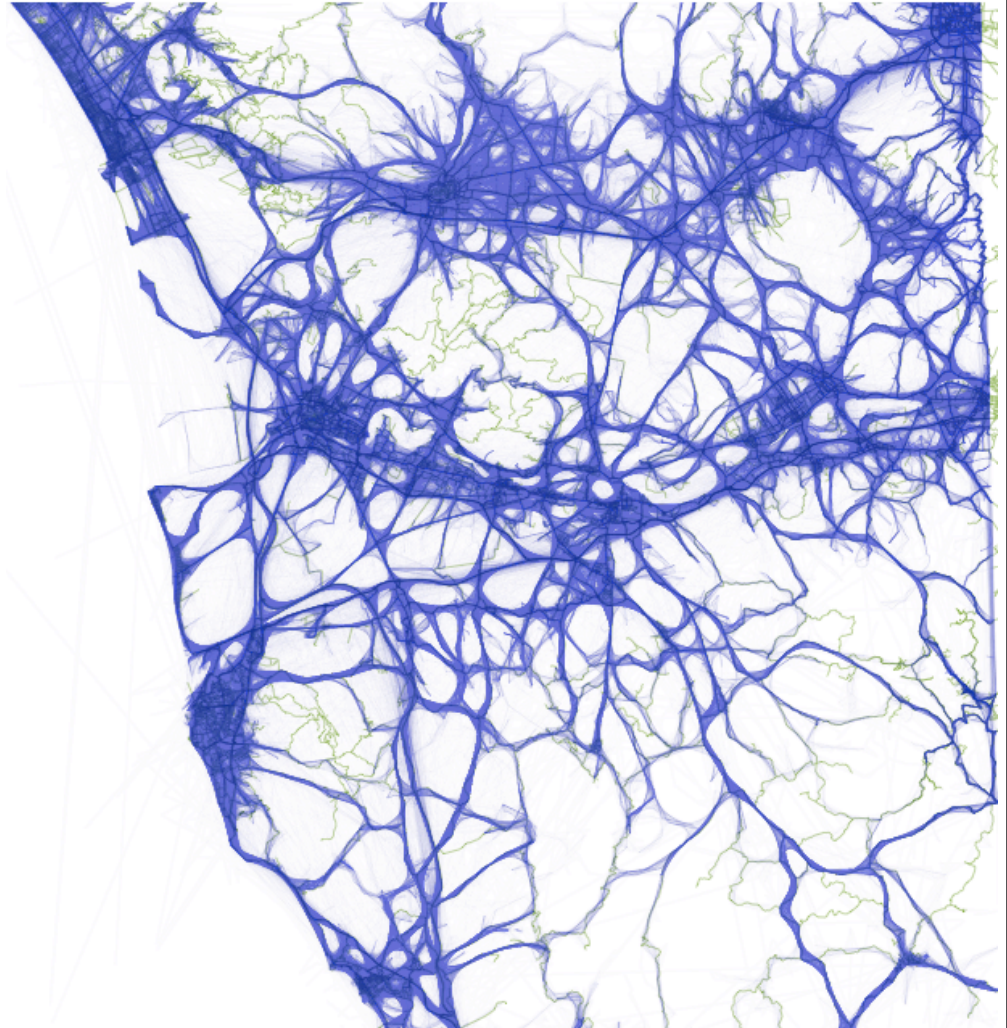
- A *Routine* is a typical local behavior of the user.
- A *Mobility profile* is the set of user's routines

# The proposed method



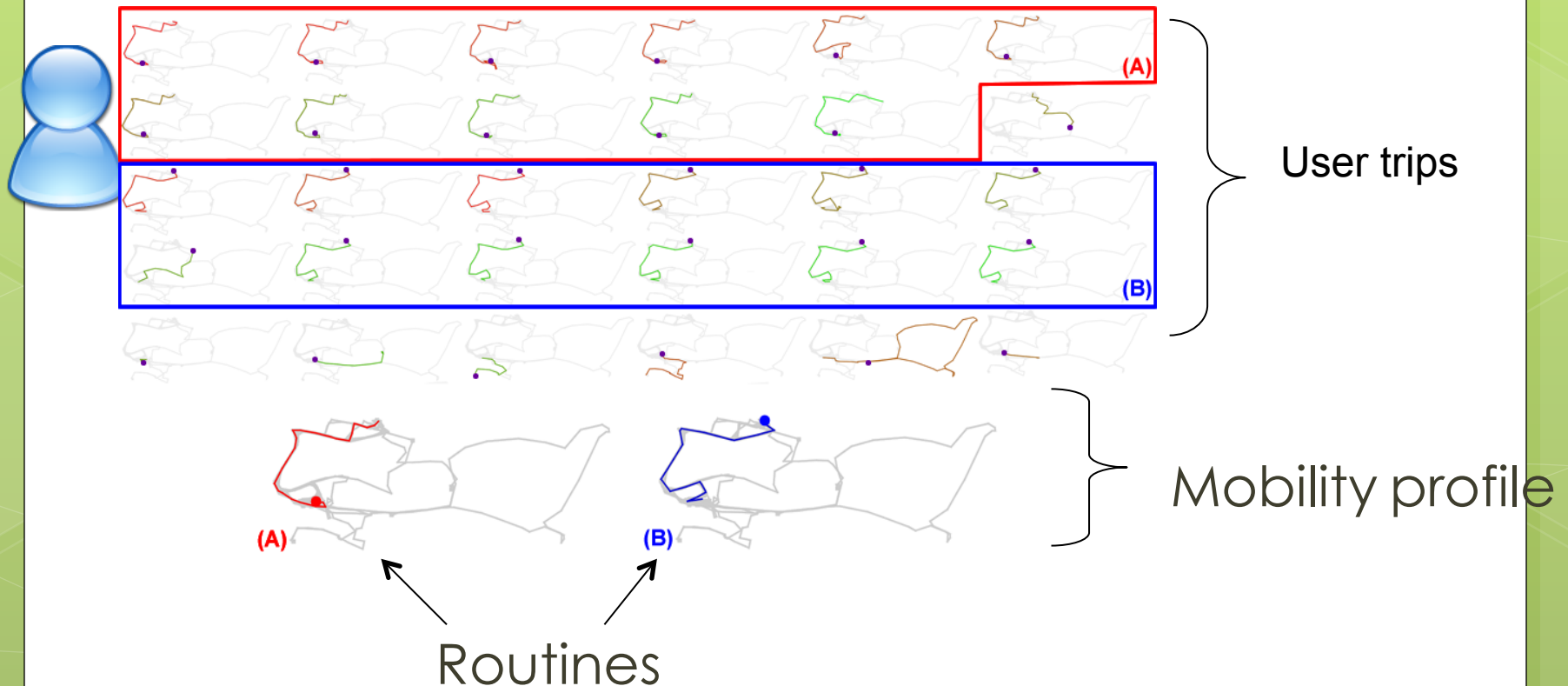
# GPS traces

- 38416 vehicles
- 1,449,258 trips
- 35 days monitoring
- 16,426,768 km covered (410 times equator length)
- 1,926,213,632 seconds of travel time
  - 535,060 hours
  - 22,294 days
  - 61 years



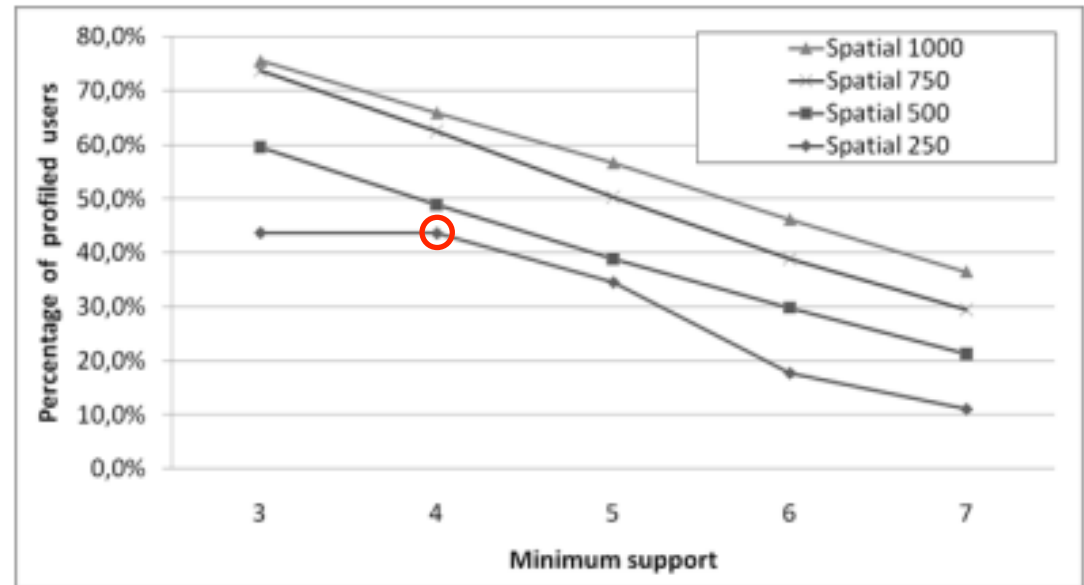
# Extracting travellers profiles

- Analysis focused on the single individual
- Find his/her systematic mobility



# Experiments on real data

Selecting 2017 users in a period of 12 days we generated 46,163 trips and extracted 1,504 routines over 919 mobility profiles (43.6%)



# Suggesting a mobility profile match

User A (as host)



Mobility Profile

Spatio Temporal  
Routing matches



User B (as guest)



Mobility Profile



The user **A** can serve a good percentage of the routines of the use **B** so the match is suggested.

# Car pooling application

The user profiling might be deployed in a car pooling service which provides a pro-active suggestions without the need for the user to explicitly describe (and update) the trips of interest

Matching of two routines:

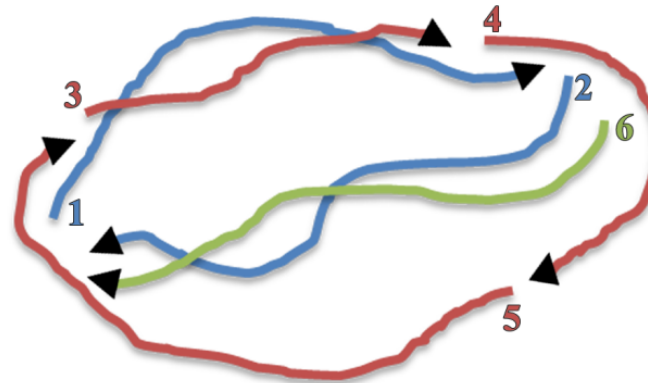
$$T_1 = \langle p_1^1 \dots p_n^1 \rangle \text{ and } T_2 = \langle p_1^2 \dots p_m^2 \rangle$$

$$\begin{aligned} \text{contained}(T_1, T_2, th_{distance}^{walking}, th_{time}^{wasting}) &\equiv \exists i, j \in \mathcal{N} \mid \\ &0 < i \leq j \leq m \wedge \\ &Dist(p_1^1, p_i^2) + Dist(p_n^1, p_j^2) \leq th_{distance}^{walking} \wedge \\ &Dur(p_1^1, p_i^2) + Dur(p_n^1, p_j^2) \leq th_{time}^{wasting} \end{aligned}$$

Mobility profile share-ability:

mobility profiles  $\tilde{T}_1$  and  $\tilde{T}_2$

$$\begin{aligned} \text{profileShare}(\tilde{T}_1, \tilde{T}_2, th_{distance}^{walking}, th_{time}^{wasting}) = \\ \frac{|\{p \in \tilde{T}_1 \mid \exists q \in \tilde{T}_2. \text{Share}(p, q, th_{distance}^{walking}, th_{time}^{wasting})\}|}{|\tilde{T}_1|} \end{aligned}$$

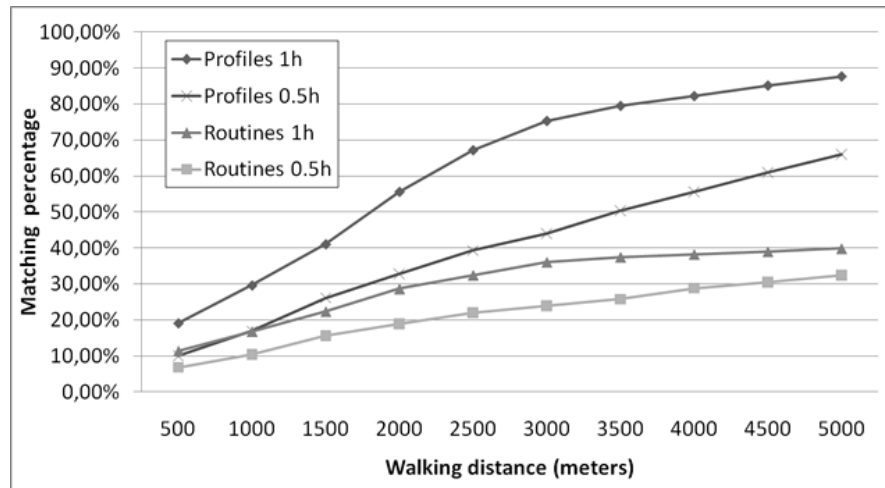


	1	2	3	4	5	6
1	-	-	F	F	F	F
2	-	-	F	F	F	T
3	T	F	-	-	-	F
4	F	F	-	-	-	F
5	F	F	-	-	-	F
6	F	T	F	F	F	-



	1	2	3	4
1	-	0	1/2	
2	1/3	-	0	
3	1	0	-	

# Evaluating the impact of an hypothetical car pooling service



This is an upper bound for a car pooling application.

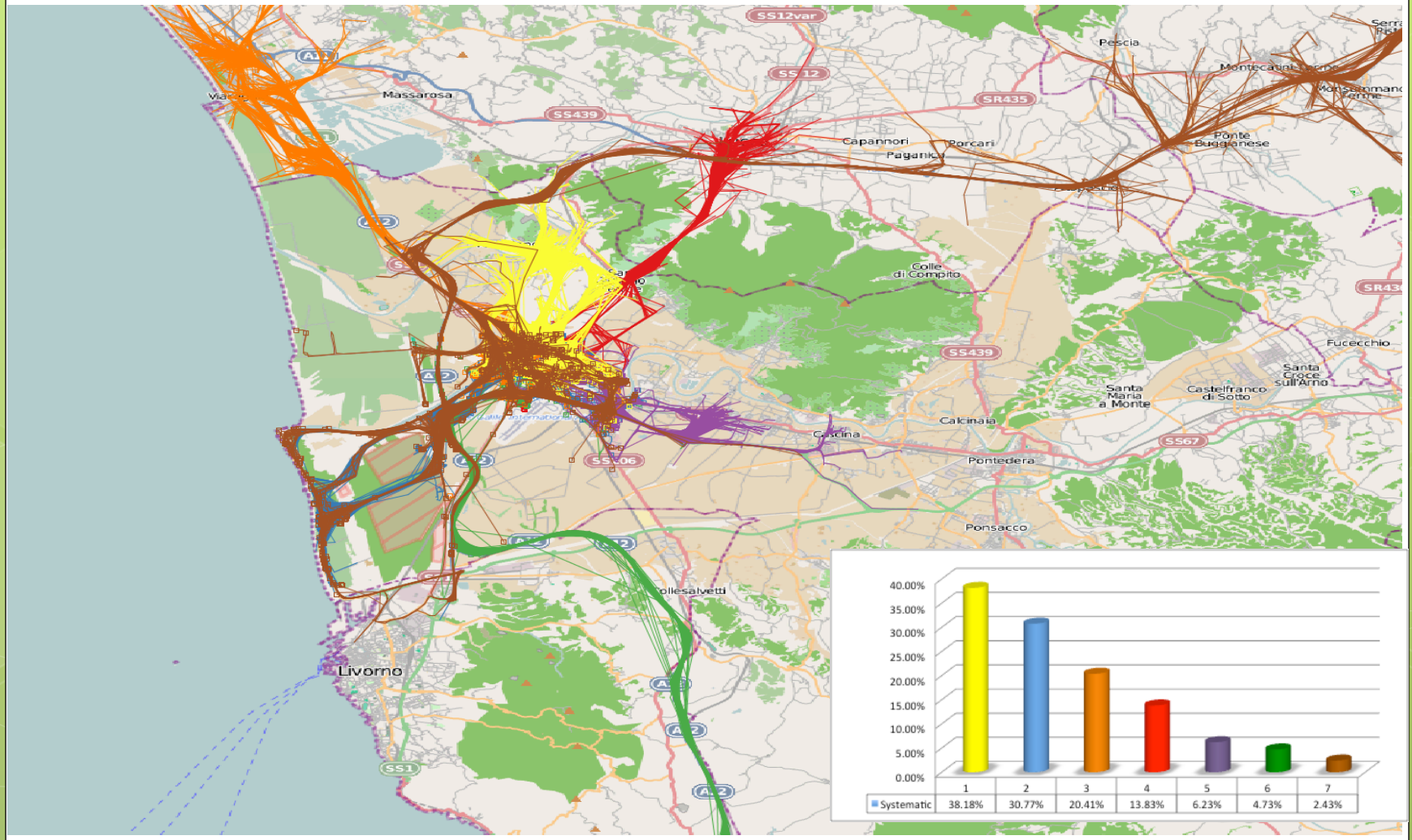
Considering a hypothetical car pooling service built on top of the proposed method, using a walking distance of 2.5 km and a wasting time of 1 hour, we obtain that the 32.4% of participants, receive at least one indication of a possible host for one of their routines.

# Mobility profiles as starting point....

From this work different direction are explored:

- City accesses analysis
- Profiles as predictive models
- Matching network analysis

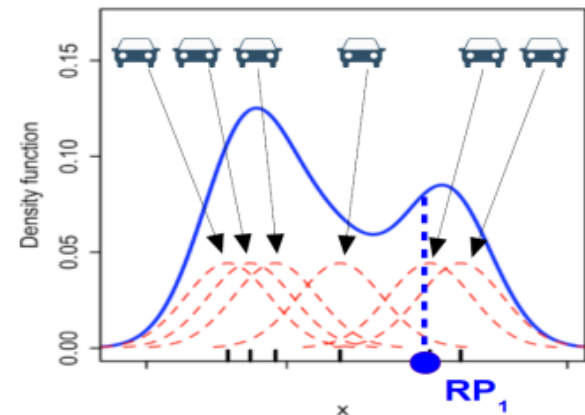
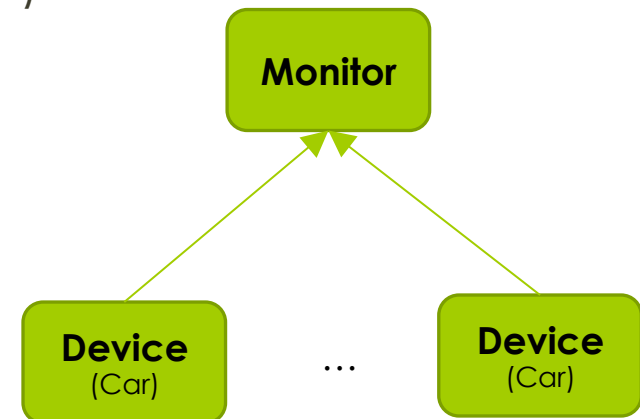
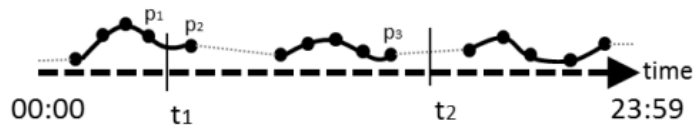
# Using the profiles to classify the incoming flows of a city



# Using Profiles as predictive models

LIFT Project

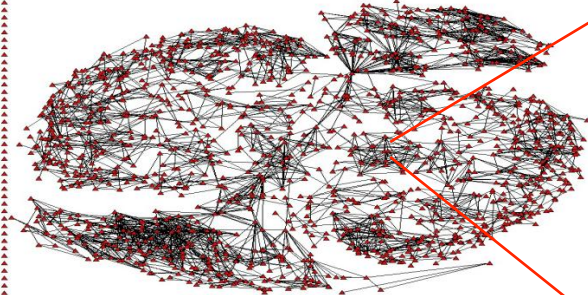
Accepted UrbComp (KDD 2012 Workshop)



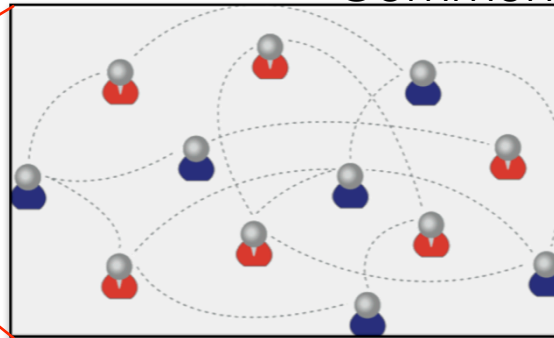
Result: 85% communications saved

# Better understanding of car pooling application and impact

Matching Network



Community



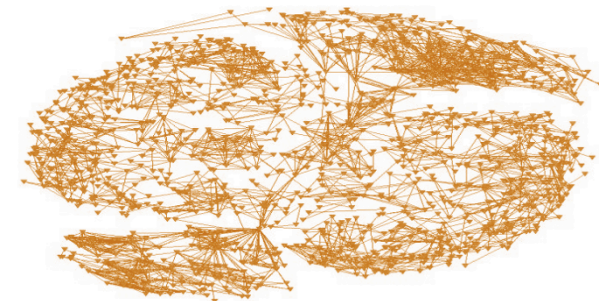
=



Suggestion



=



Actual Network

# Questions?

roberto.trasarti@isti.cnr.it  
<http://kdd.isti.cnr.it/>

KDD Lab – ISTI CNR, Pisa

