
Multi-perspective Analysis of Movement Data with Visual Analytics

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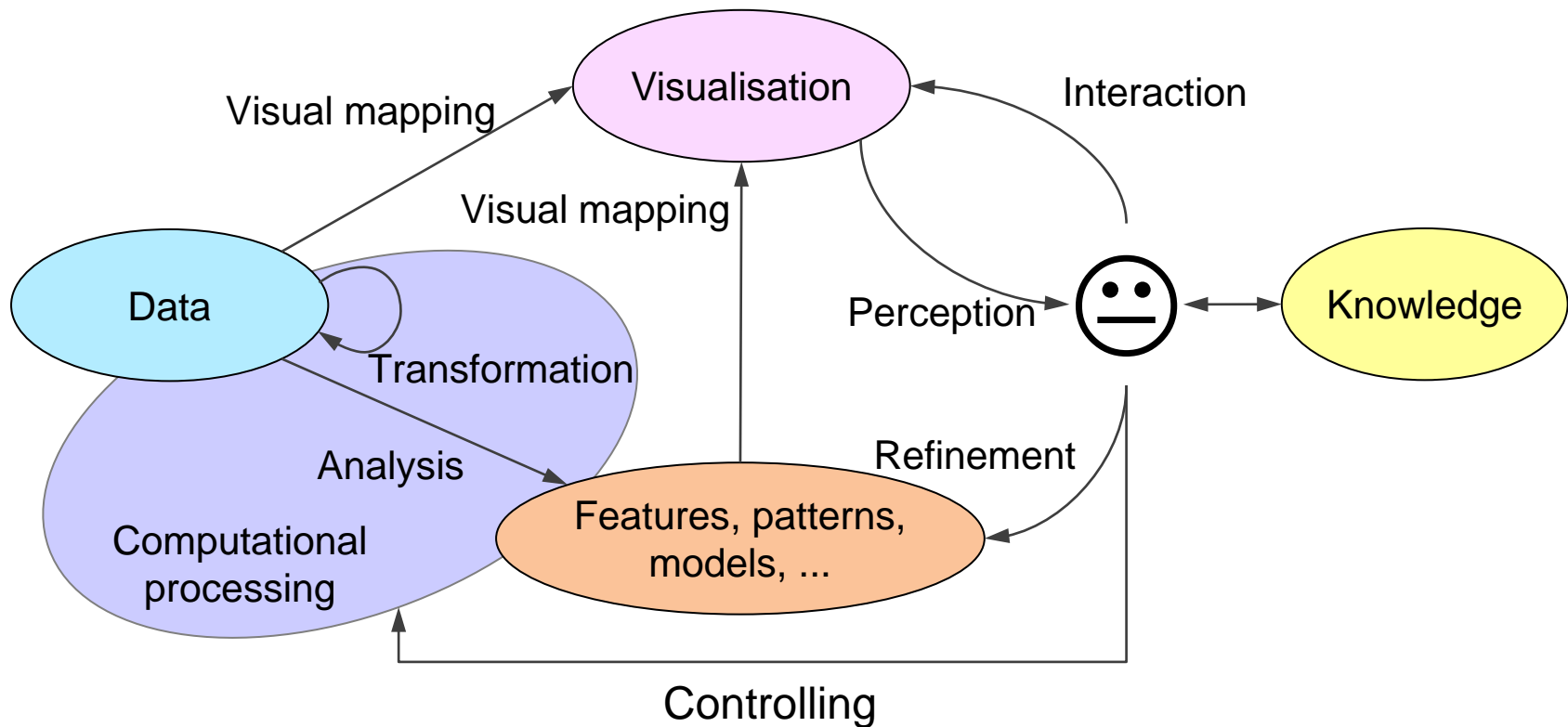


Fraunhofer

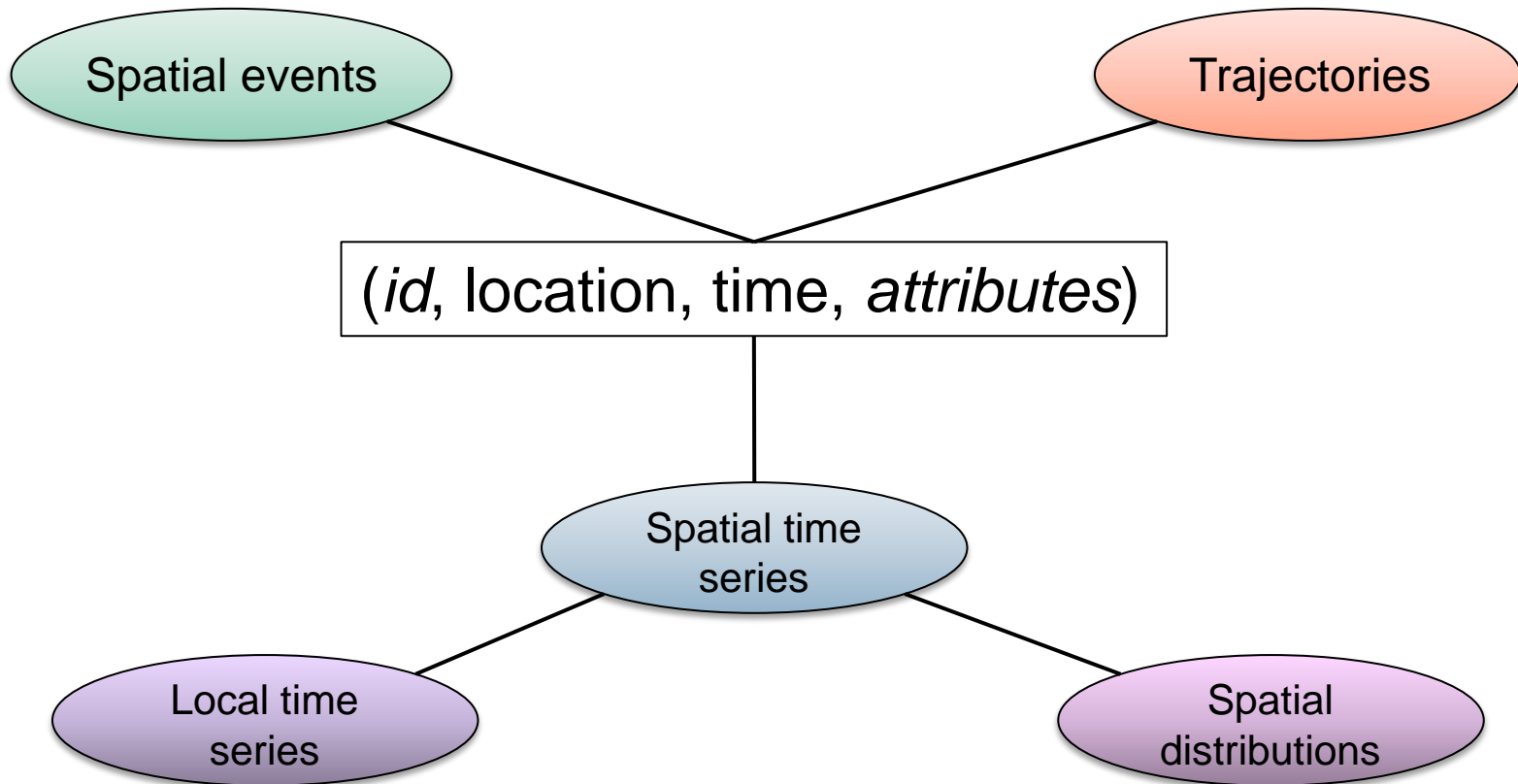
IAIS

Visual Analytics

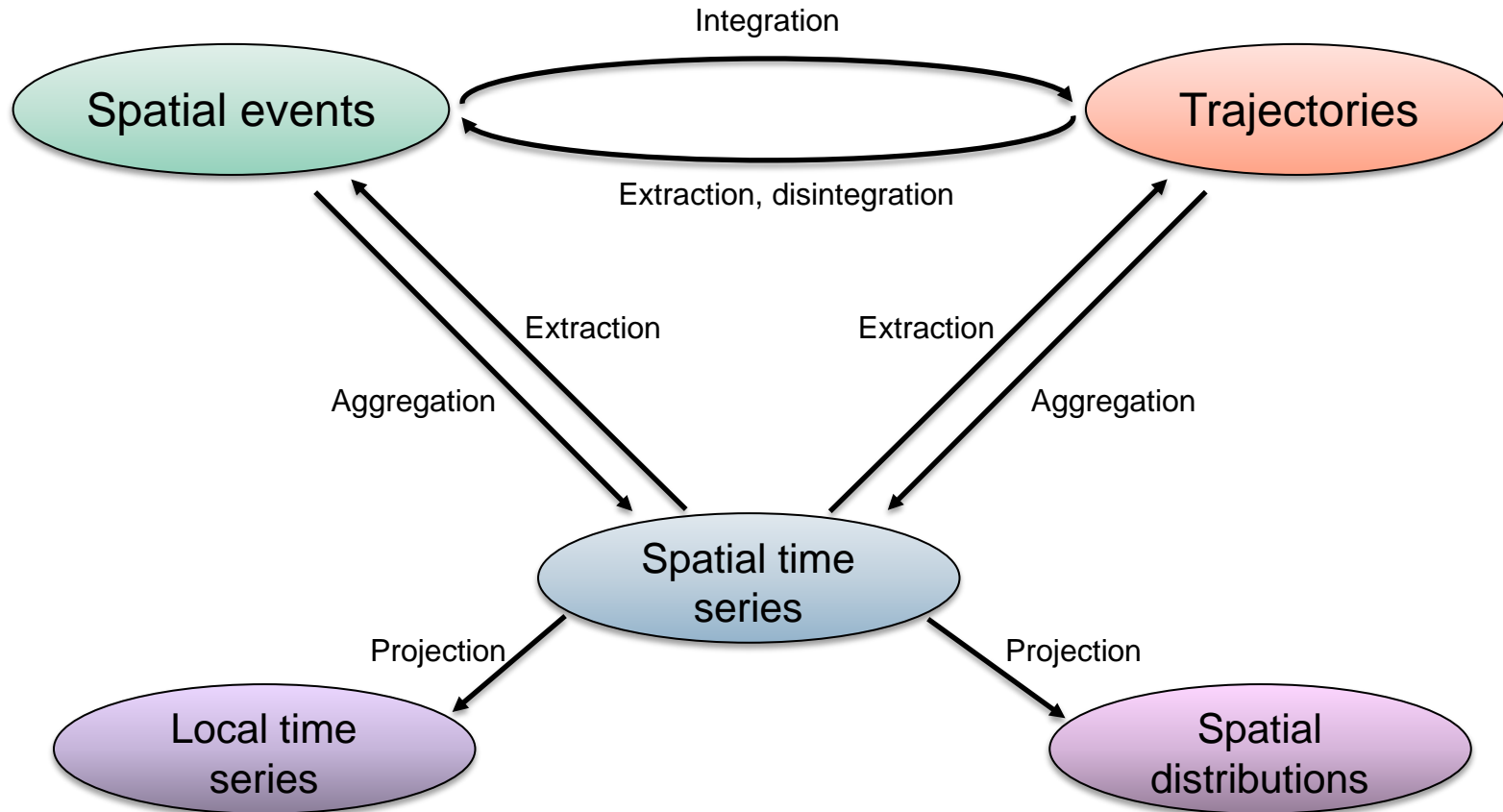
Enabling synergetic work of humans and computers



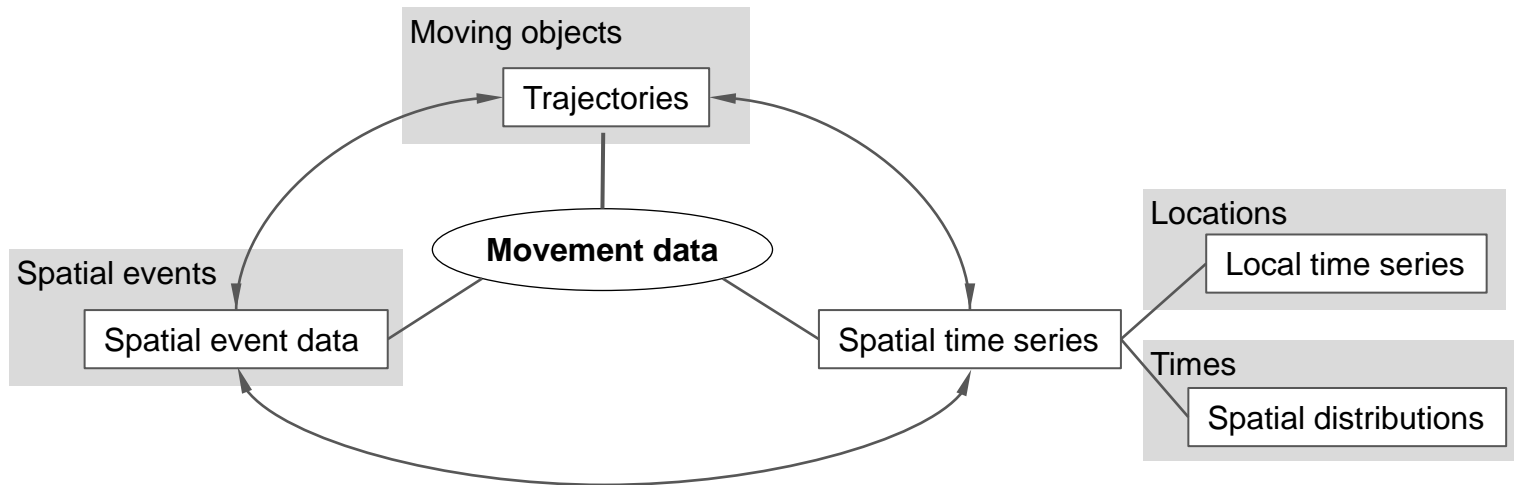
Types of spatio-temporal data



Transformations of spatio-temporal data structures



Transformations enable multi-perspective analysis of movement data



Running example dataset: trajectories of cars in Milan



GPS-tracks of 17,241 cars in Milan, Italy

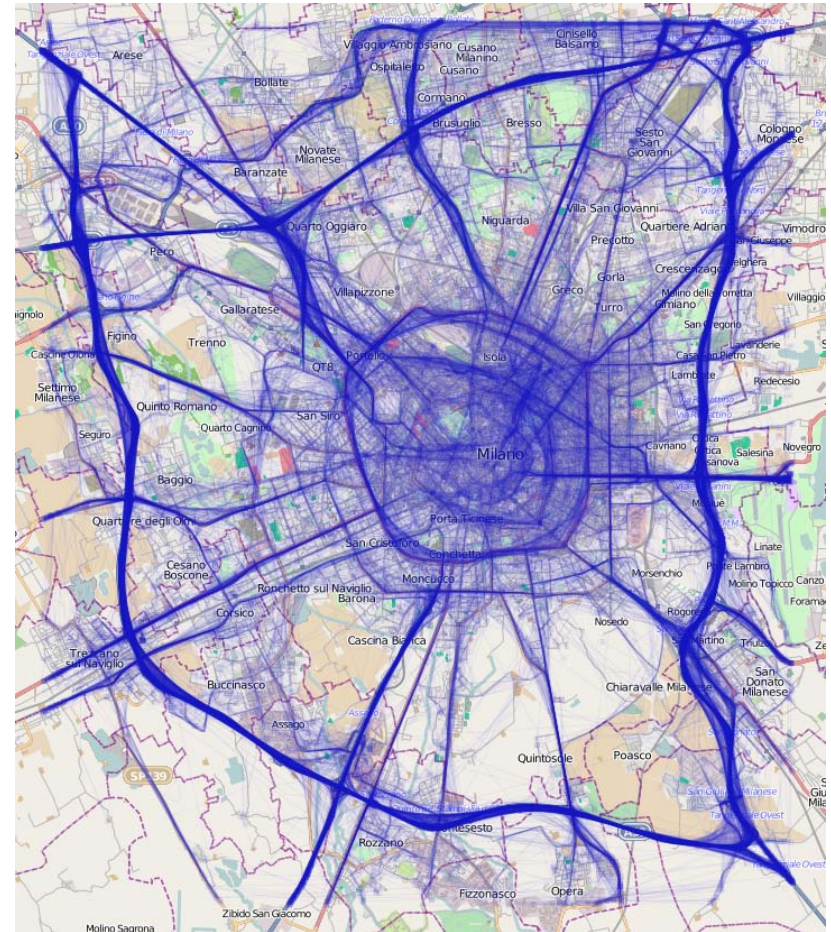
Time period: from Sunday, the 1st of April,
to Saturday, the 7th of April, 2007

Received from Octo Telematics
www.octotelematics.com
special thanks to T.Martino

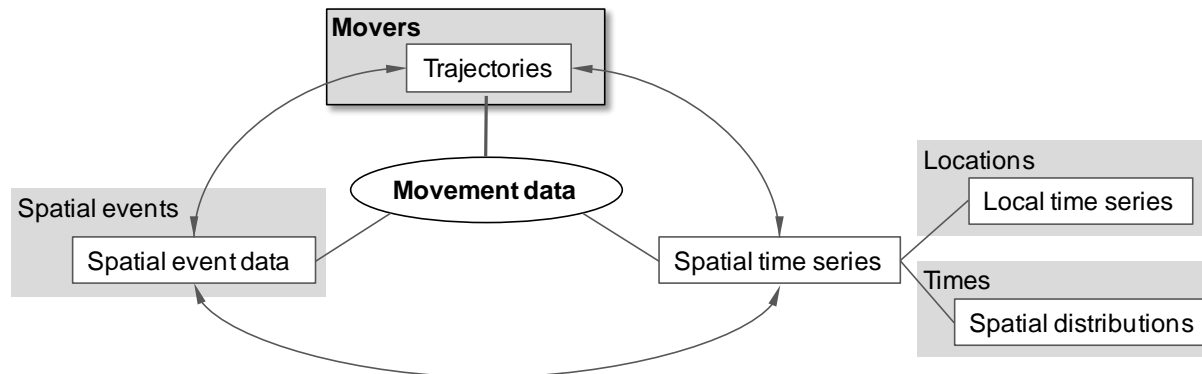
Data structure:

- Anonymized car identifier
- Date and time
- Geographic coordinates
- Speed

The trajectories from one day are drawn on a map with 5% opacity



Perspective 1: Movement data in the form of trajectories



Density-based clustering of trajectories: What distance measure to use?

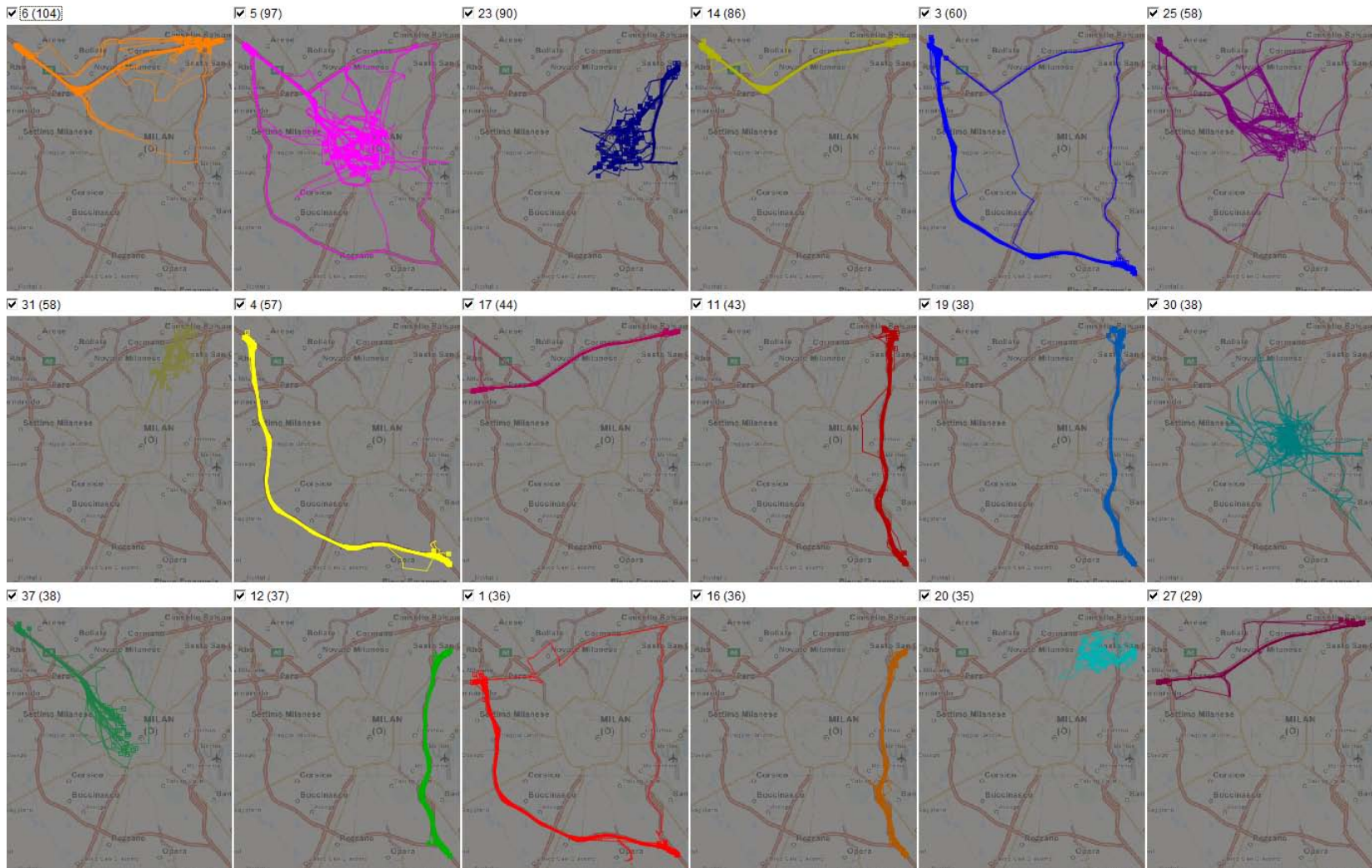
- Trajectories are time series of spatial positions and other movement attributes
- Trajectories are complex objects with heterogeneous properties: positions in space and in time, shape, dynamics of speed, ...
- A single distance measure accounting for all properties would be hard to implement and results would be hard to interpret
- It is more feasible to create a library of simple distance measures (a.k.a. distance functions) addressing different properties. For example,
 - spatial distance between origins and/or between destinations,
 - average spatial distance between corresponding points along the routes,
 - average spatial distance between points reached at the same times, ...
- Different aspects of trajectories are studied using different distance functions.

DB clusters of trajectories (example 1)

Distance function: the average spatial distance between the origins and between the destinations;

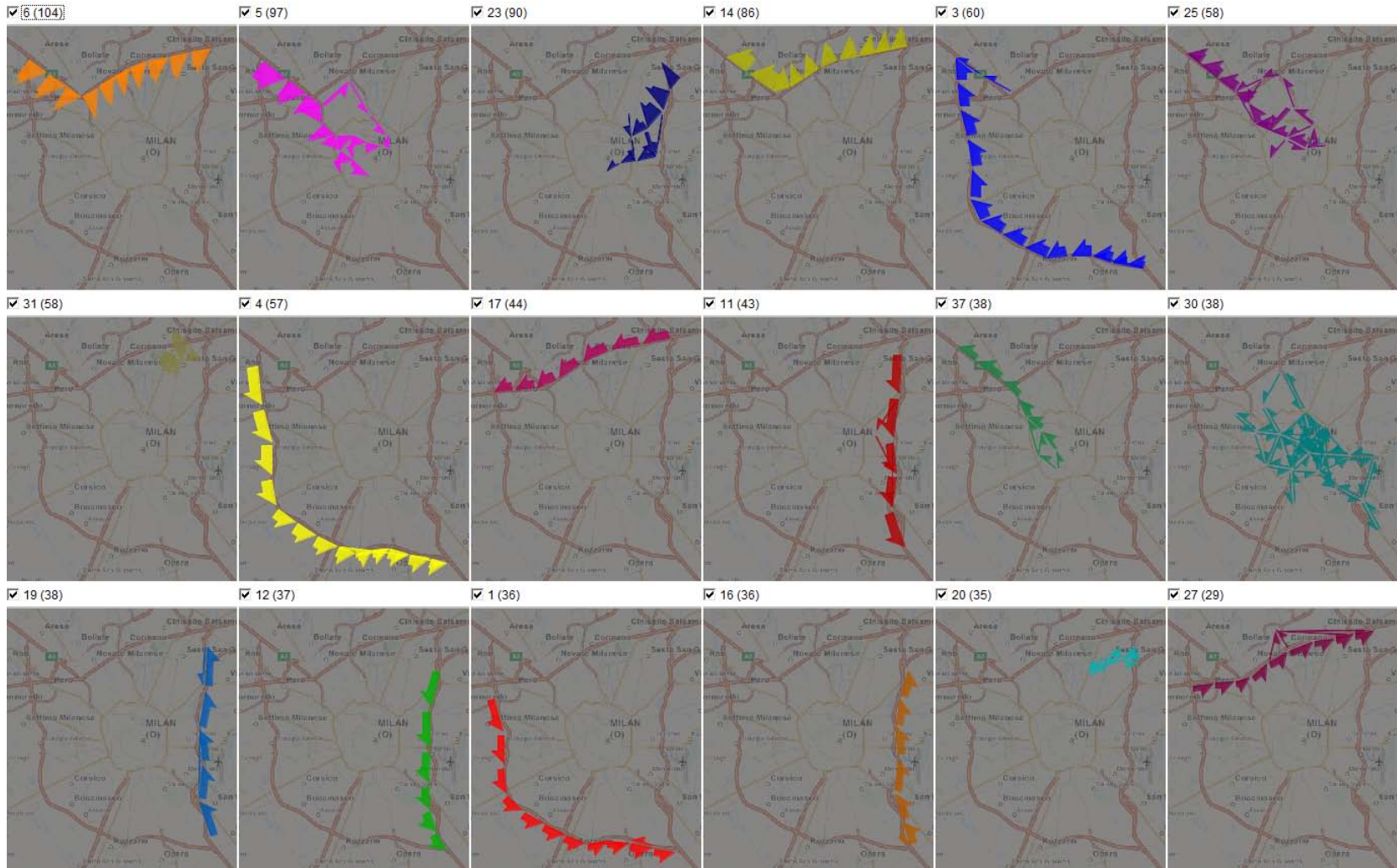
$R=750m, N=5$

Only 18 largest clusters are shown.



Summarised representation of clusters of trajectories

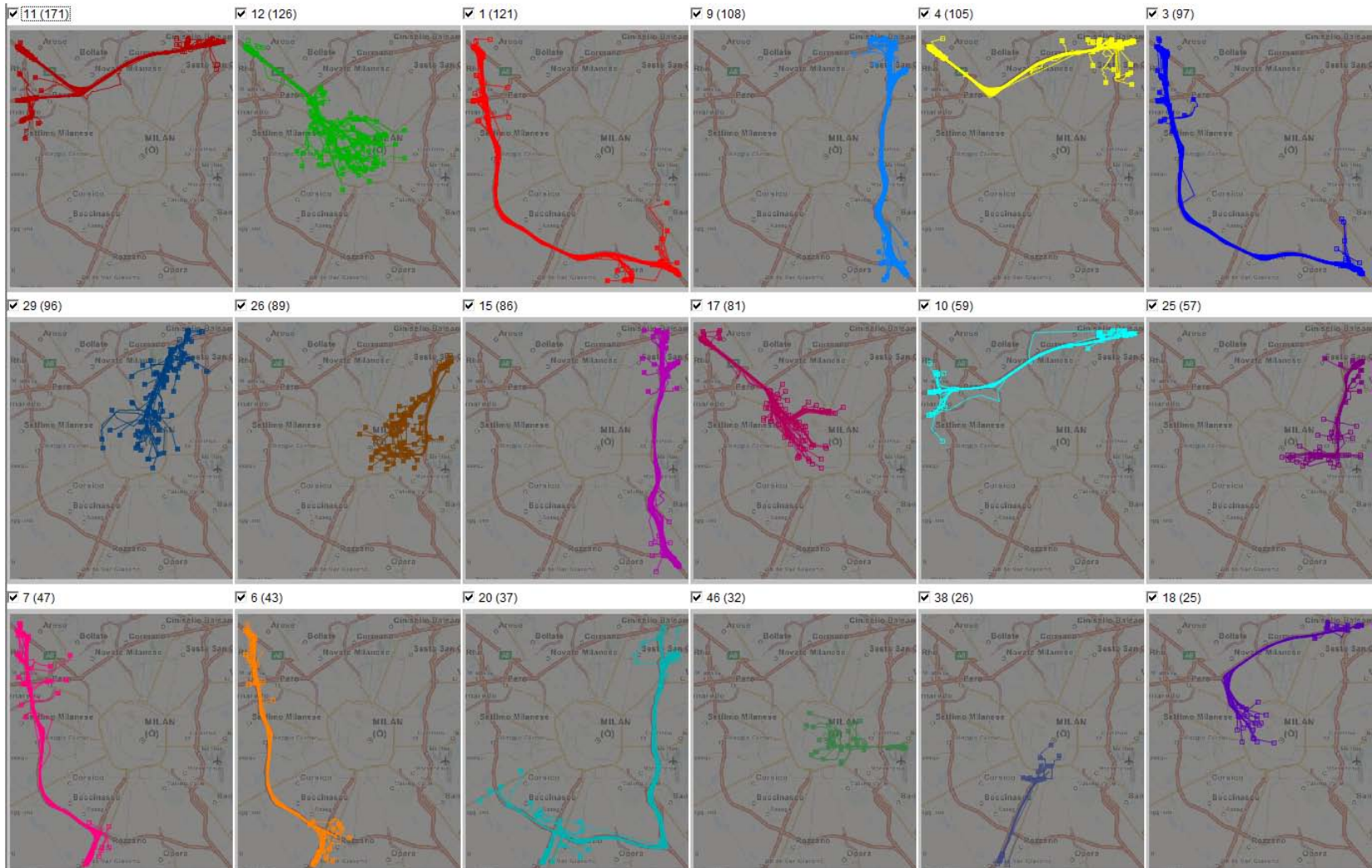
Minor flows are omitted for a clearer view.



DB clusters of trajectories (example 2)

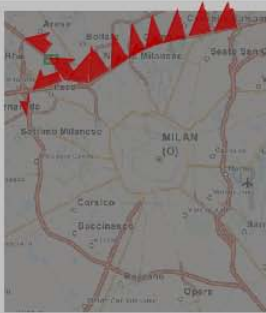
Distance function: "route similarity", i.e., the average spatial distance between the corresponding points along the route; $R=750m$, $N=5$

Only 18 largest clusters are shown.



The same clusters represented in a summarised form

✓ 11 (171)



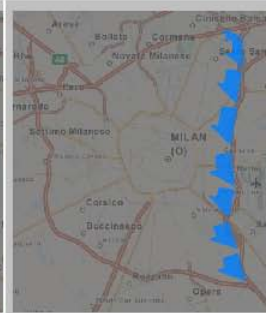
✓ 12 (126)



✓ 1 (121)



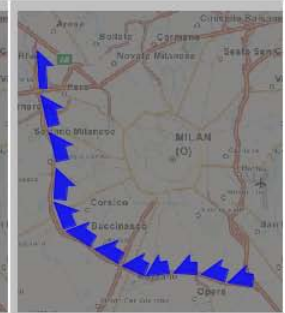
✓ 9 (108)



✓ 4 (105)



✓ 3 (97)



✓ 29 (96)



✓ 26 (89)



✓ 15 (86)



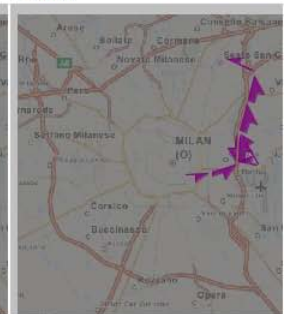
✓ 17 (81)



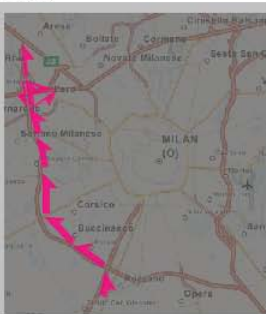
✓ 10 (59)



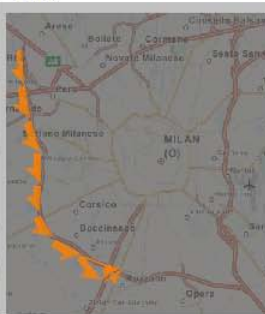
✓ 25 (57)



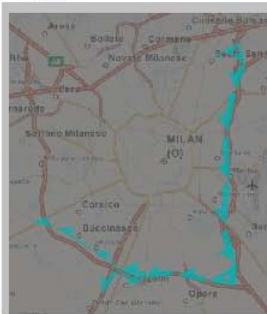
✓ 7 (47)



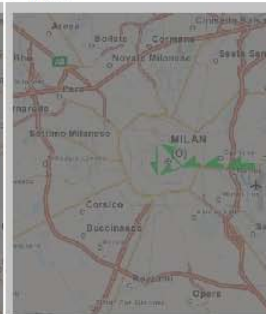
✓ 6 (43)



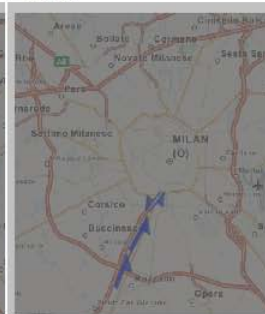
✓ 20 (37)



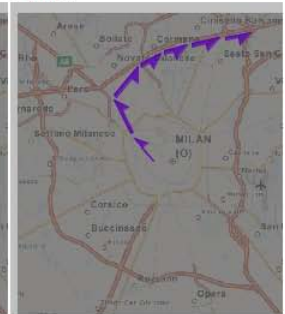
✓ 46 (32)



✓ 38 (26)



✓ 18 (25)



Interactive progressive clustering

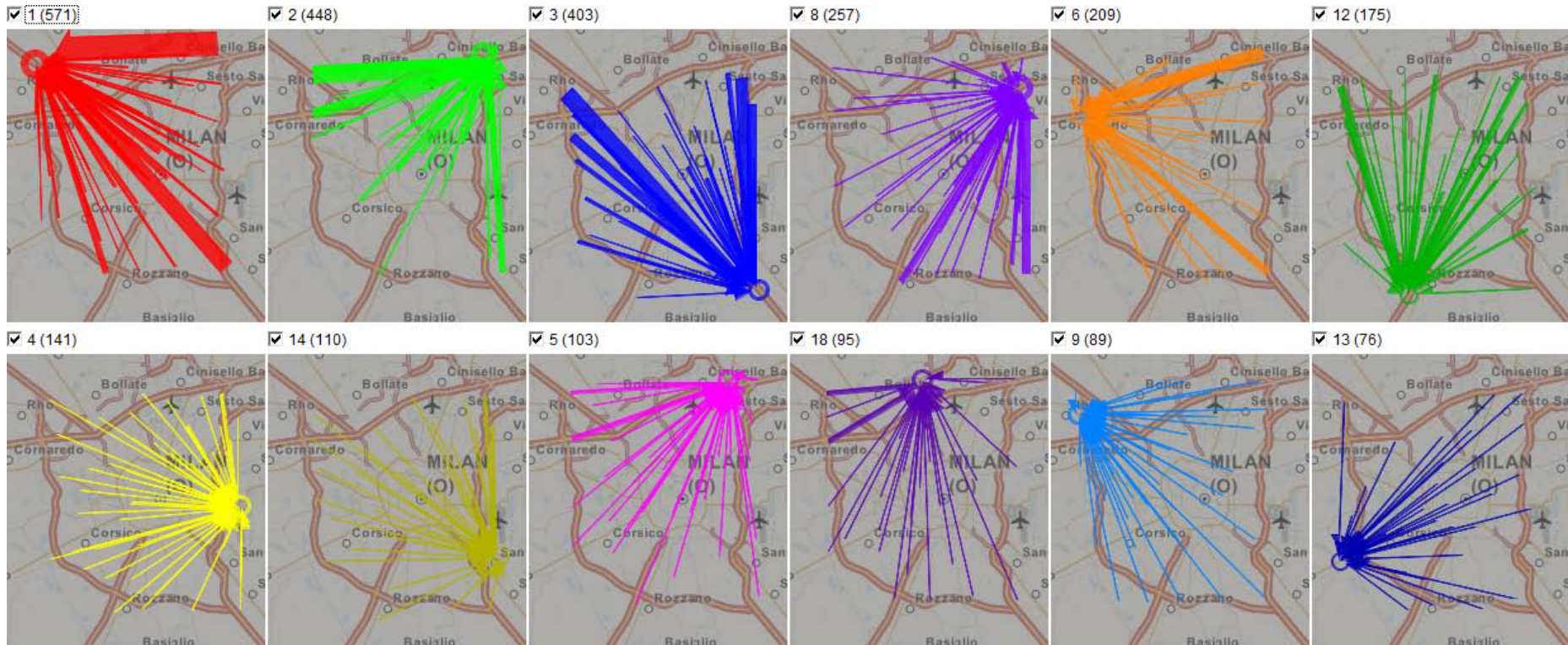
Applying different distance measures at different steps

Data: trajectories of cars in Milan

Step 1: clustering according to the spatial proximity of the end points

Distance function: "common ends"

Question: what are the most frequent destinations of car trips?



Interactive progressive clustering

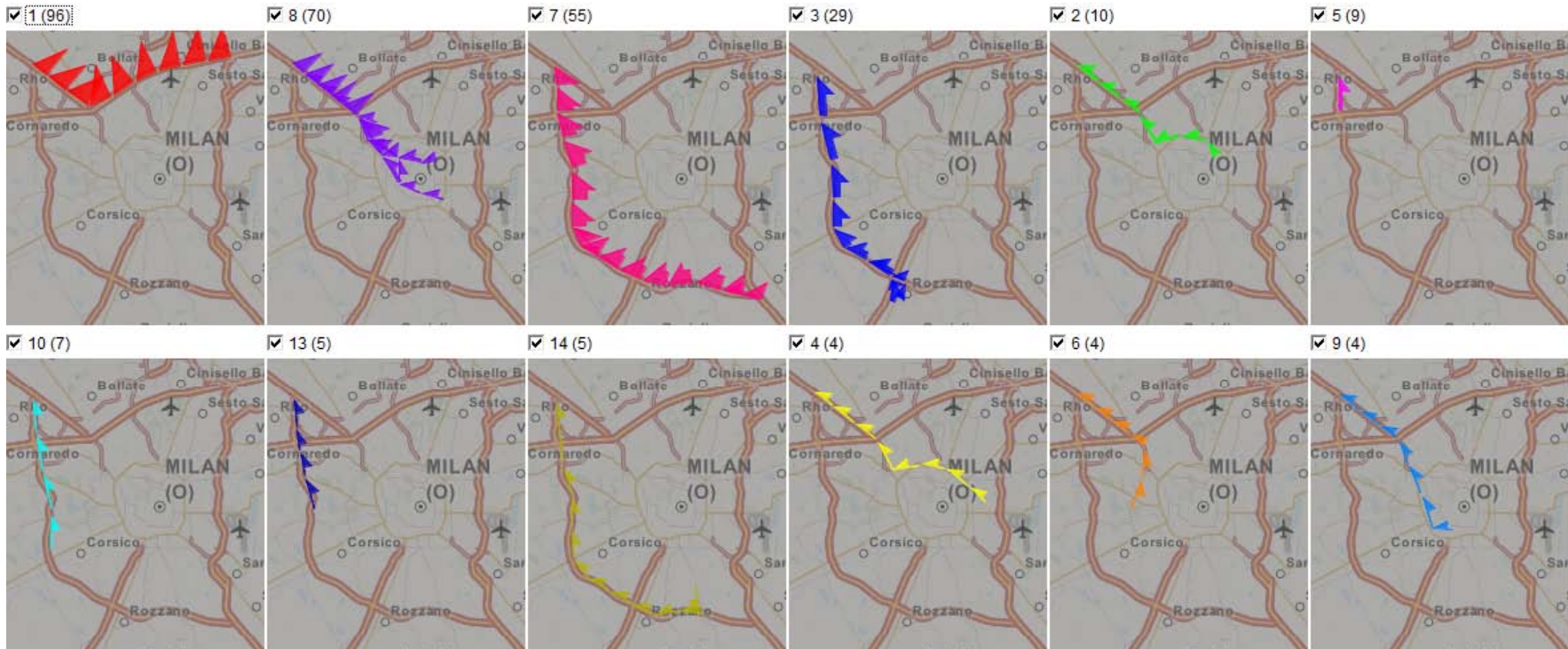
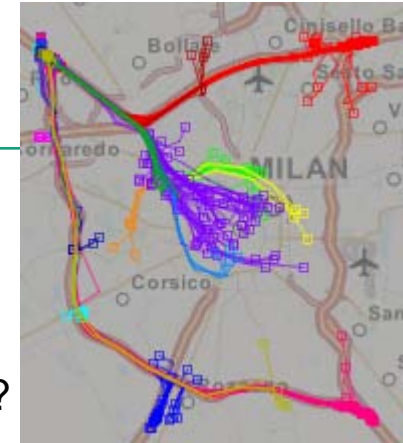
Applying different distance measures (2)

Data: one (or more) selected cluster(s) from the previous step

Step 2: clustering according to the similarity of the routes (shapes)

Distance function: "route similarity"

Question: what routes are usually taken to get to the selected destination?



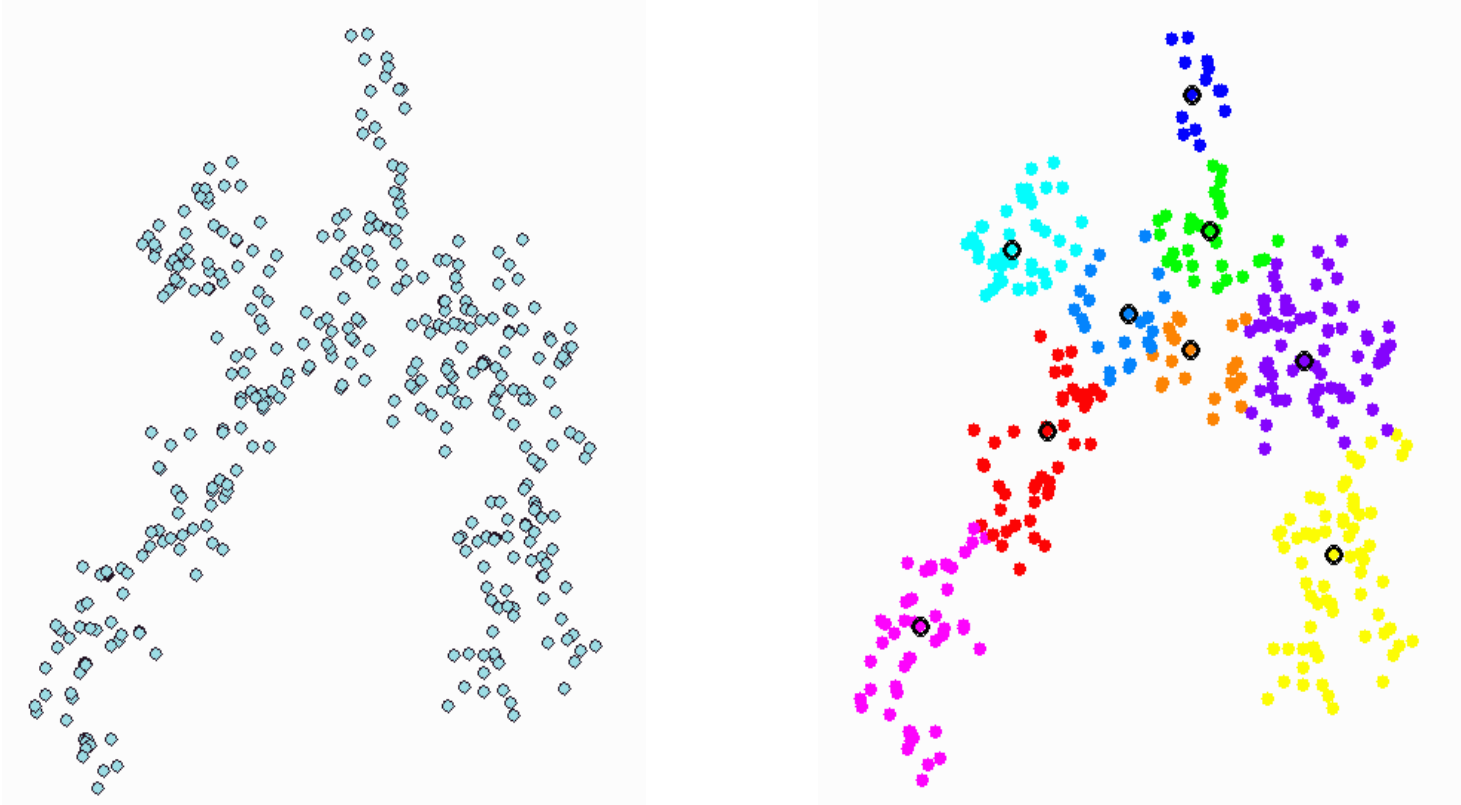
Clustering of very large sets of trajectories

- Problem: clustering of complex objects (such as trajectories) involving non-trivial distance functions (such as “route similarity”) can only be done in RAM, i.e. for a relatively small dataset
- Our approach:
 1. Take a subset (sample) of the objects suitable for processing in RAM.
 2. Discover clusters in the subset.
 3. Load the remaining objects into RAM by portions.
Classify each object = identify to which of the discovered clusters the object belongs.
Store the result of the classification in the database.
 4. Take the objects that remained unclassified and apply steps 1 to 3 to them.
Repeat the procedure until no meaningful new clusters can be discovered.
- Question: how to identify the cluster where an object belongs?

Classifier, the main idea

- From each cluster C_i select one or more representative objects (prototypes) and respective distance thresholds:
 $\{ (pt_1, d_1), \dots, (pt_n, d_n) \}$ such that $\forall o \in C_i \exists k, 1 \leq k \leq n: \text{distance}(o, pt_k) < d_k$
 - The set of all cluster prototypes with the respective distance thresholds defines the classifier
- A new object o' may be ascribed to the cluster if the same condition holds for it.
 \Rightarrow For each object from a large database:
 - measure the distances to all prototypes;
 - take the closest prototype among those with the distances below the thresholds and ascribe the object to the respective cluster;
 - if no such prototypes found, label the object as unclassified.
- To select prototypes:
 - Divide the cluster into “round” subclusters
 - Take the medoid of each subcluster as one of the prototypes
 - Take the maximum of the distances from the subcluster medoid to the subcluster members as the distance threshold for this prototype

Dividing a cluster into round sub-clusters: an illustration using points



This can be done by a variant of the K-medoids clustering algorithm where the desired maximum radius of a subcluster is a parameter.

Division of a cluster of trajectories into “round” subclusters

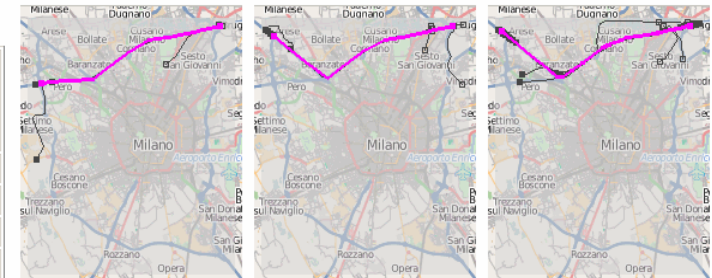
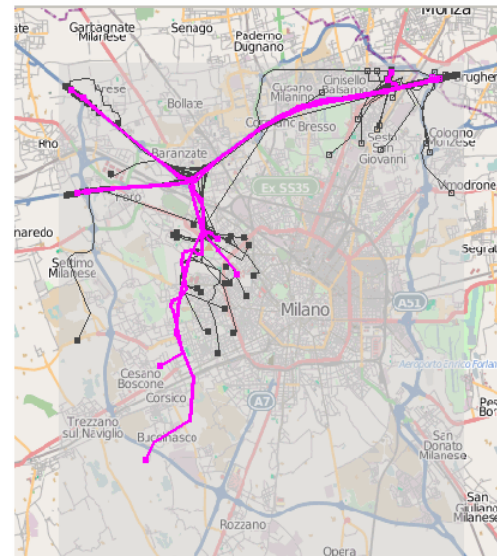
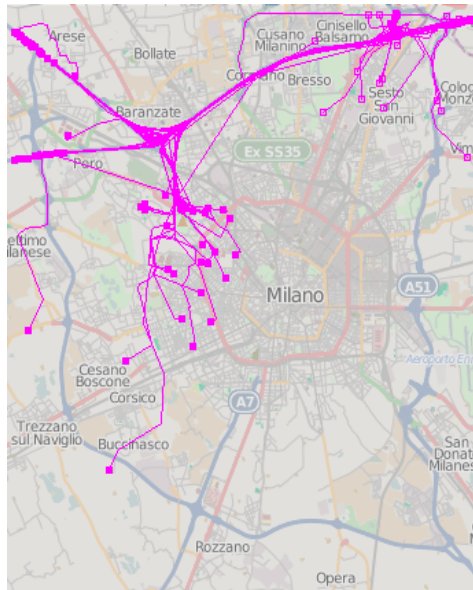
25.09.2009 11:05:24 - Cluster 7

prototype ID	Distance threshold	Original subcluster size	N neighbours found in the test	Mean distance to the original neighbours	Mean distance to the found neighbours
89133	438.2	4	0	240.5	0
96013	200.0	8	0	96.9	0
6548	526.5	29	0	161.1	0
43285	200.0	1	0	0.0	0
34239	414.3	19	0	186.7	0
32809	368.2	15	0	121.2	0
141138	485.0	10	0	271.3	0
109120	200.0	1	0	0.0	0

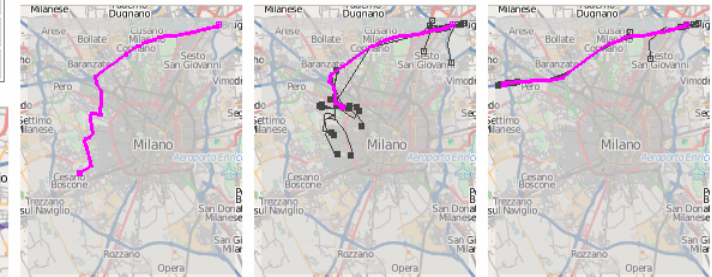
Maximum subcluster radius ✕

To select appropriate cluster prototypes, the density-based clusters will be divided into "round" subclusters.

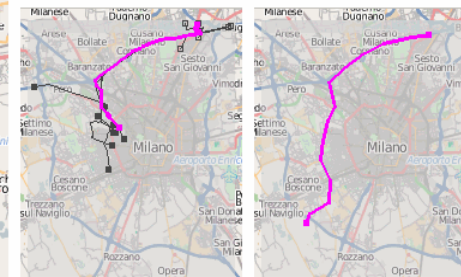
Maximum radius of a subcluster?



89133 96013 6548



43285 34239 32809

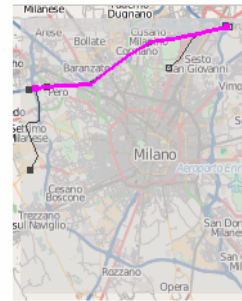


141138 109120

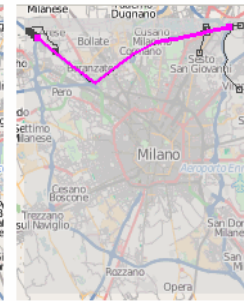
To obtain meaningful results, the analyst may needs to review and, possibly, edit the classifier

25.09.2009 11:05:24 - Cluster 7

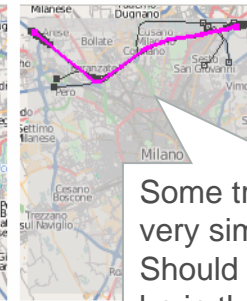
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89133

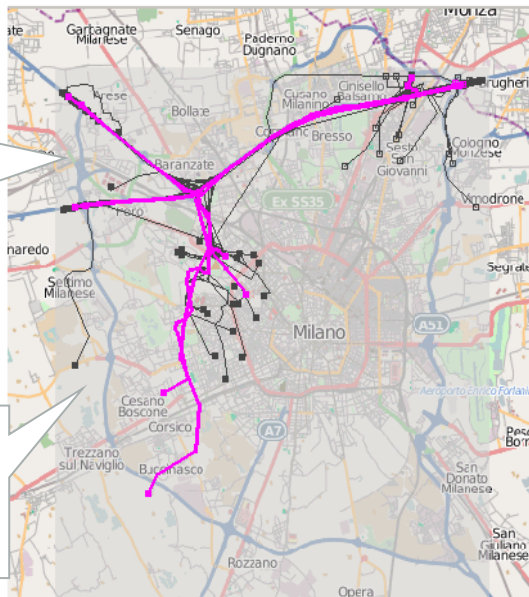


96013



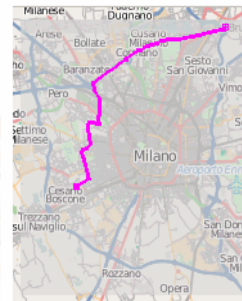
6548

Some trajectories are not very similar to the others. Should such trajectories be in the cluster?

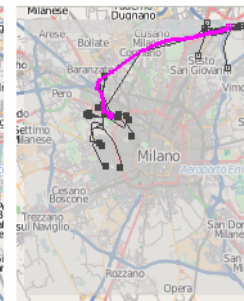


Should I keep the three branches in one cluster?

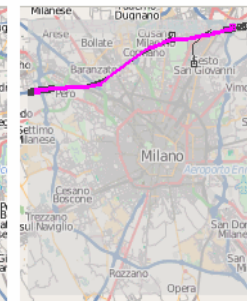
Or should I divide the cluster into two or three clusters?



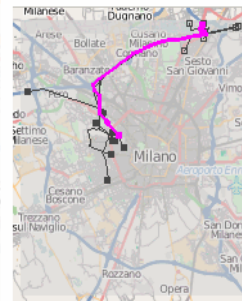
43285



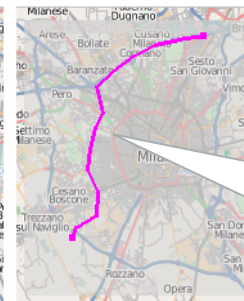
34239



32809



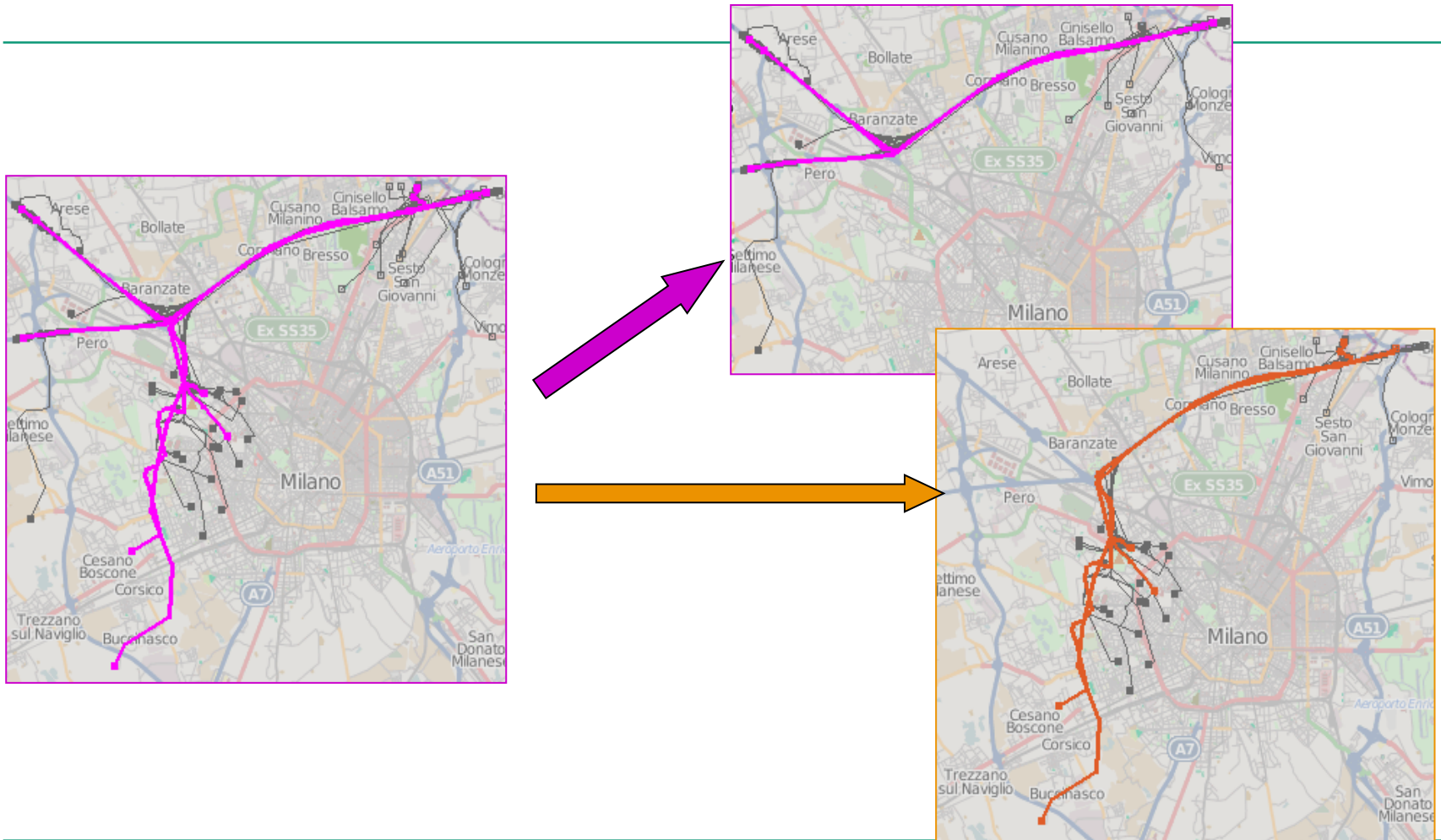
141138



109120

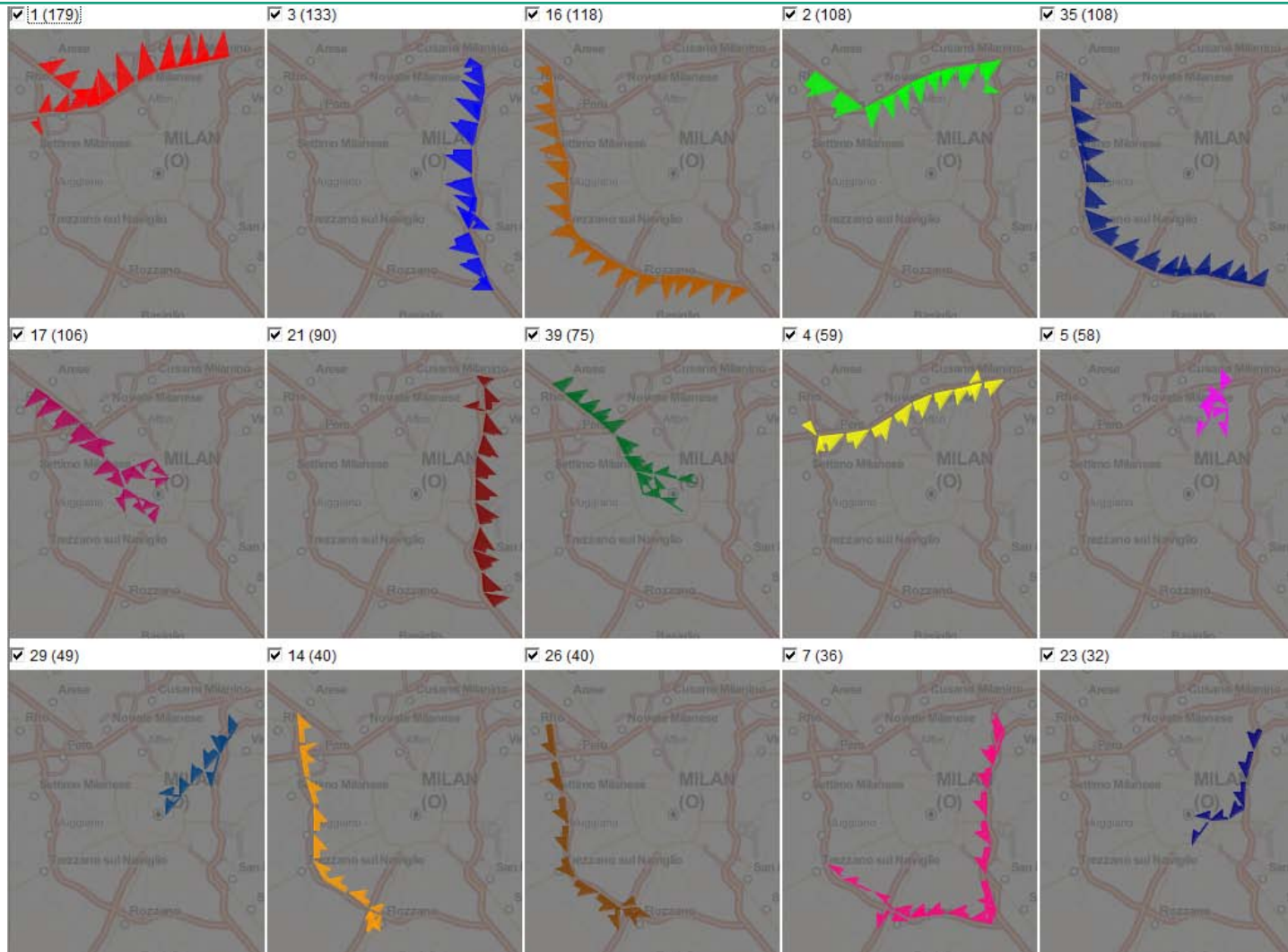
Is it good to have this prototype? This is not a core trajectory of the cluster.

Example of interactive editing



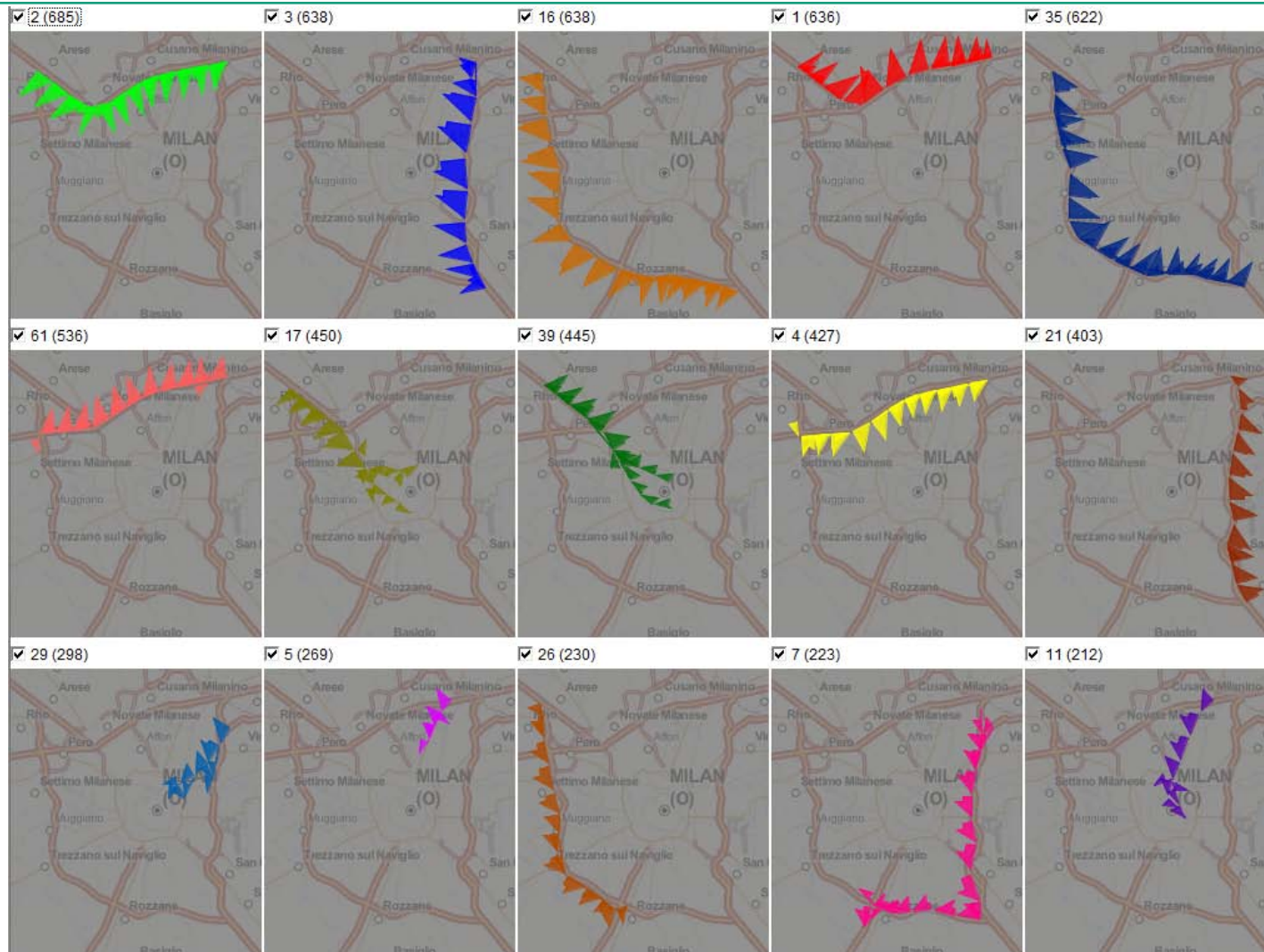
What are the most frequent routes on Wednesday?

Result of clustering of single-day trajectories by route similarity



How frequent are these routes during the whole week?

Result of building a classifier and applying it to the whole set of trajectories



Further analysis of the trajectories

- The analysis is continued by loading a subset of the unclassified trajectories (“noise”) to RAM, applying clustering to it, building a new classifier, and applying the classifier to the whole set of unclassified trajectories.
- Empirical experience:
 - With each new iteration step, the number and the sizes of discovered clusters substantially decrease in comparison to the previous step.
 - After 4-5 steps of the procedure, only very small clusters can be discovered.
 - The analyst’s effort needed for editing of the classifier also decreases.
 - The editing effort is high for big clusters with high internal variation, which mostly appear in the first step; the following clusters are smaller and “cleaner”.
- Unfortunately, no formal criterion for terminating the procedure.

Where to read more

G.Andrienko, N.Andrienko, S.Rinzivillo, M.Nanni, D.Pedreschi, F.Giannotti

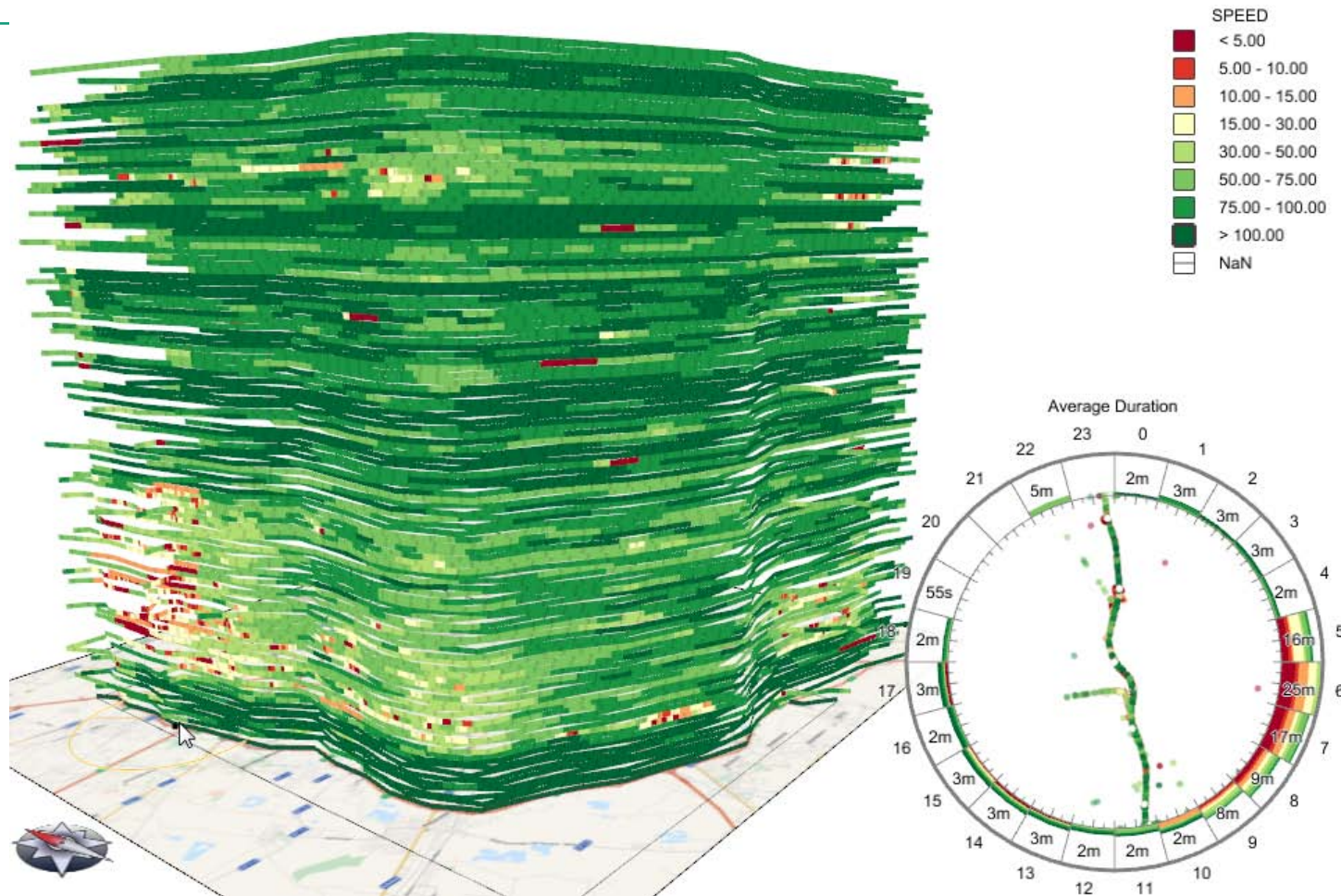
Interactive Visual Clustering of Large Collections of Trajectories

IEEE Visual Analytics Science and Technology (VAST 2009)

Proceedings, IEEE Computer Society Press, 2009, pp.3-10

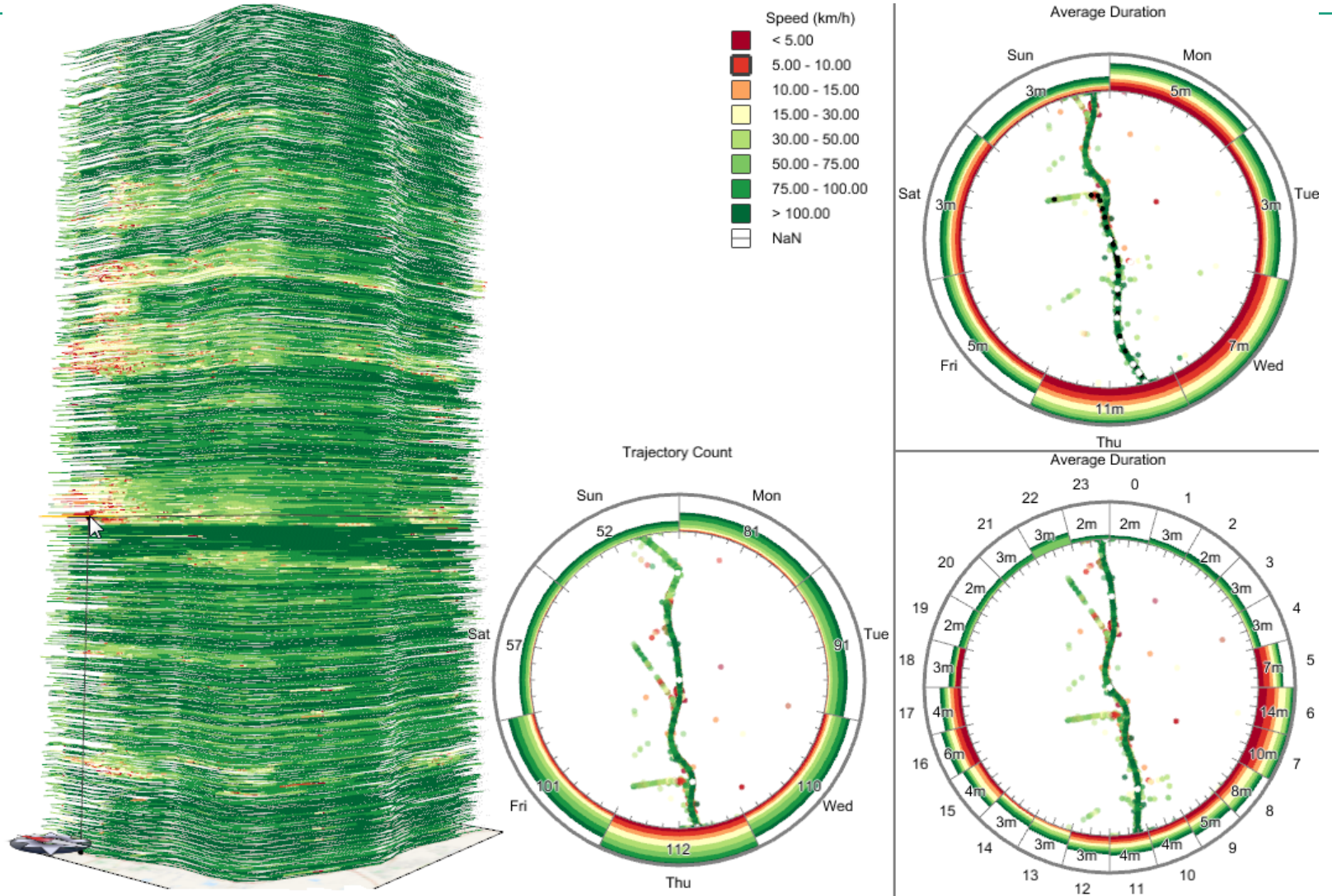
Analysis of movement attributes

Investigate speed variation along a selected route: single day

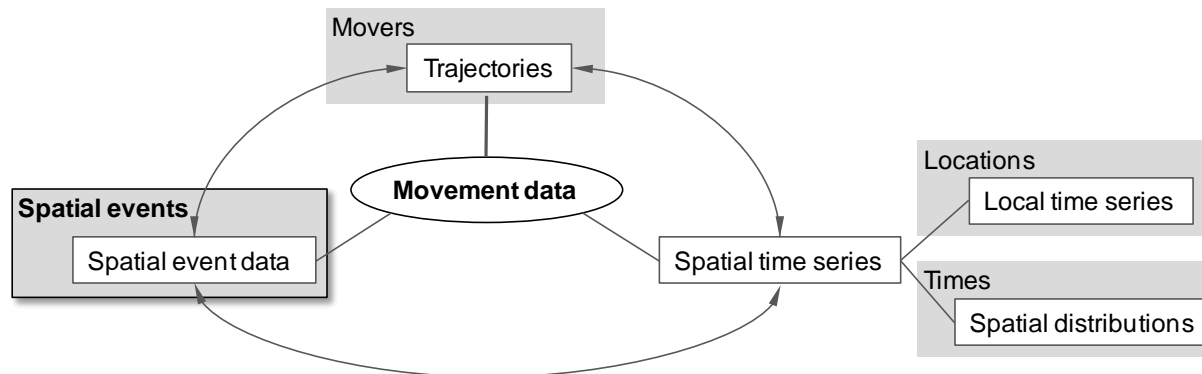


Analysis of movement attributes

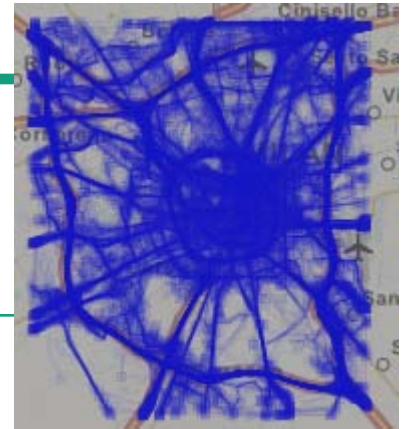
Investigate speed variation along a selected route: whole week



Perspective 2: Movement data in the form of spatial events

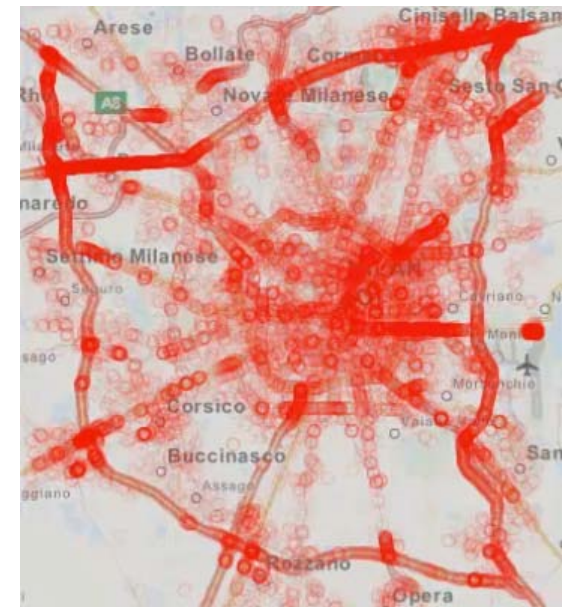
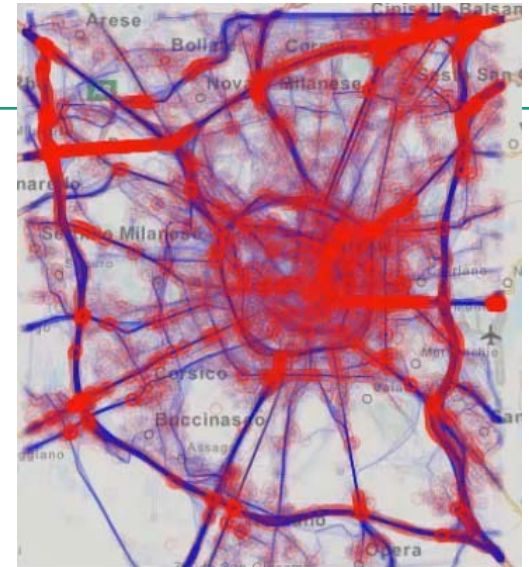
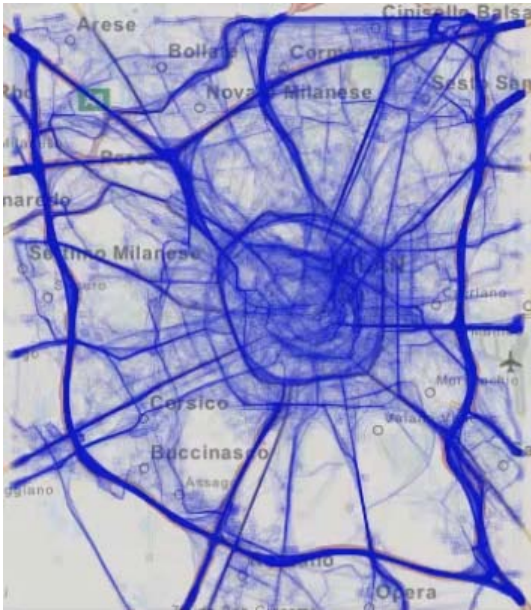


Example of analysis focusing on movement events

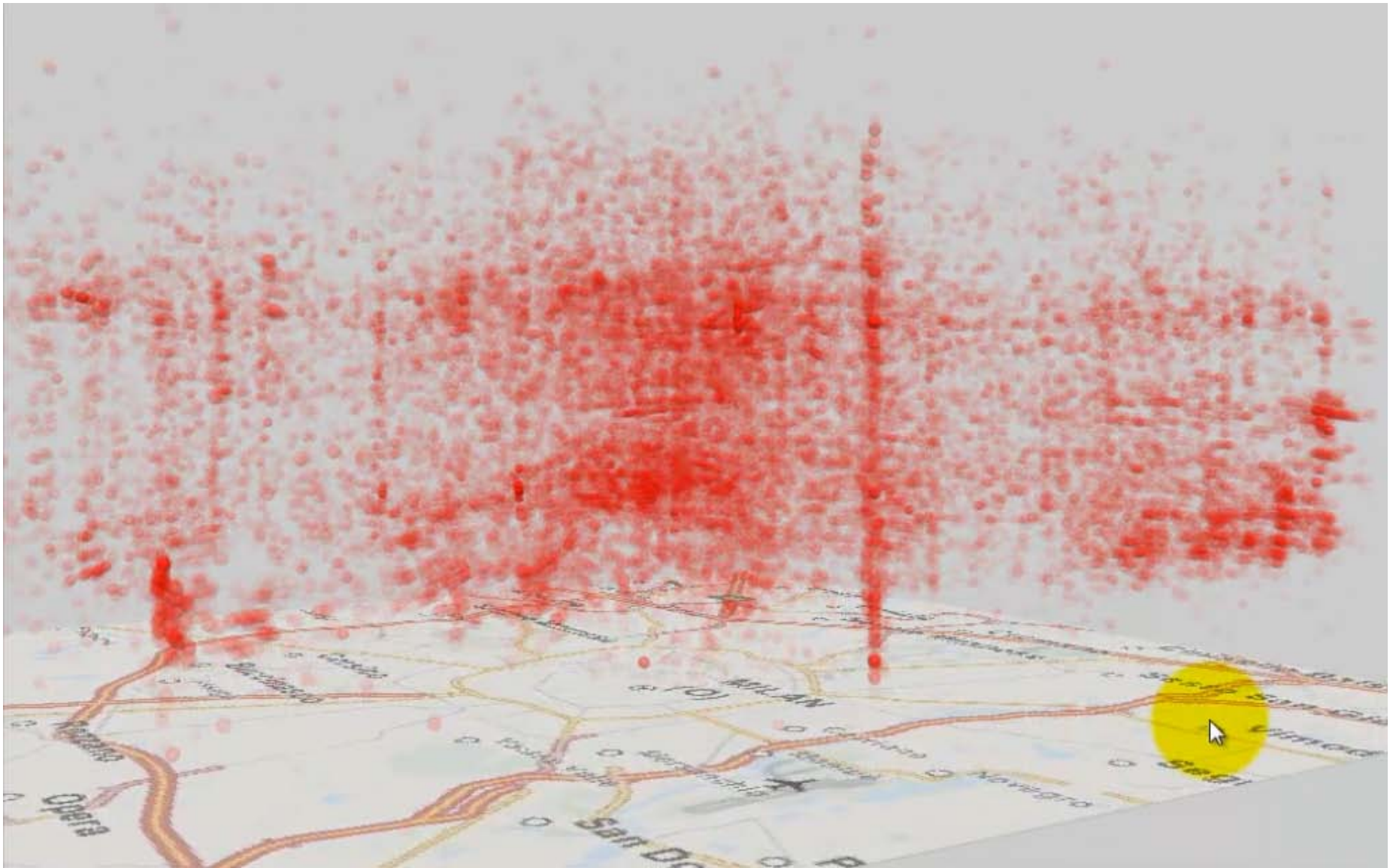


- Data: trajectories of cars in Milan
- Task: find places of traffic congestions and determine their characteristics (times of the congestions, durations, numbers of cars involved, ...)
- Traffic congestion \approx dense spatio-temporal cluster of low speed movement events
 - Movement direction must be taken into account
- Places of interest: areas where at least one traffic congestion occurred \approx areas containing the clusters
- Characteristics of places: time series of event counts, vehicle counts, ...
- Data transformations:
Trajectories \rightarrow Events \rightarrow Places \rightarrow Spatial time series

Step 1: extract low speed events from the trajectories



Low speed := speed \leq 10 km/h



Vertical dimension ← time

Step 2: density-based clustering of events

by spatio-temporal positions and directions

Distance function:

$$d = \begin{cases} \infty, & \text{if } (d_s > D_s) \text{ or } \exists i \mid (d_i > D_i), \quad i = 0..n \\ D_s * \max\left(\frac{d_s}{D_s}, \frac{d_0}{D_0}, \dots, \frac{d_n}{D_n}\right), & \text{if (a) - neighbourhood defined as a cube} \\ D_s * \sqrt{\left(\frac{d_s}{D_s}\right)^2 + \sum_{i=0}^n \left(\frac{d_i}{D_i}\right)^2}, & \text{if (b) - neighbourhood defined as a sphere} \end{cases}$$

D_s – spatial distance threshold; D_0, D_1, \dots, D_N - distance thresholds for other attributes

$d_s, d_0, d_1, \dots, d_N$ – distances; d_s – distance in space

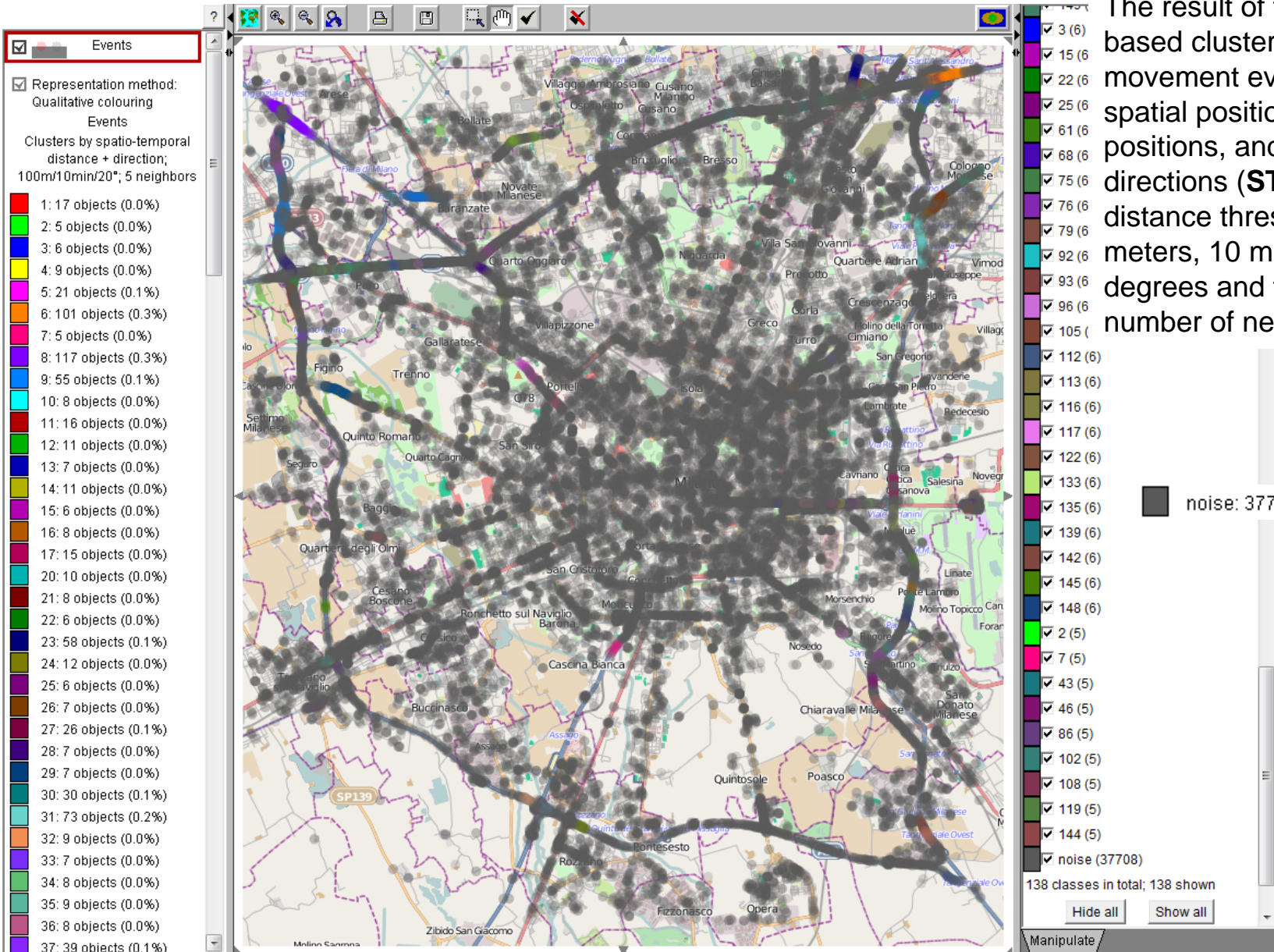
Distance in time (t_1, t_2 are intervals):

$$d_t(t_1, t_2) = \begin{cases} t_2^{start} - t_1^{end} & \text{if } t_1^{end} < t_2^{start} \\ t_1^{start} - t_2^{end} & \text{if } t_1^{start} > t_2^{end} \\ 0 & \text{otherwise} \end{cases}$$

Distance for a cyclic attribute (V is the cycle length):

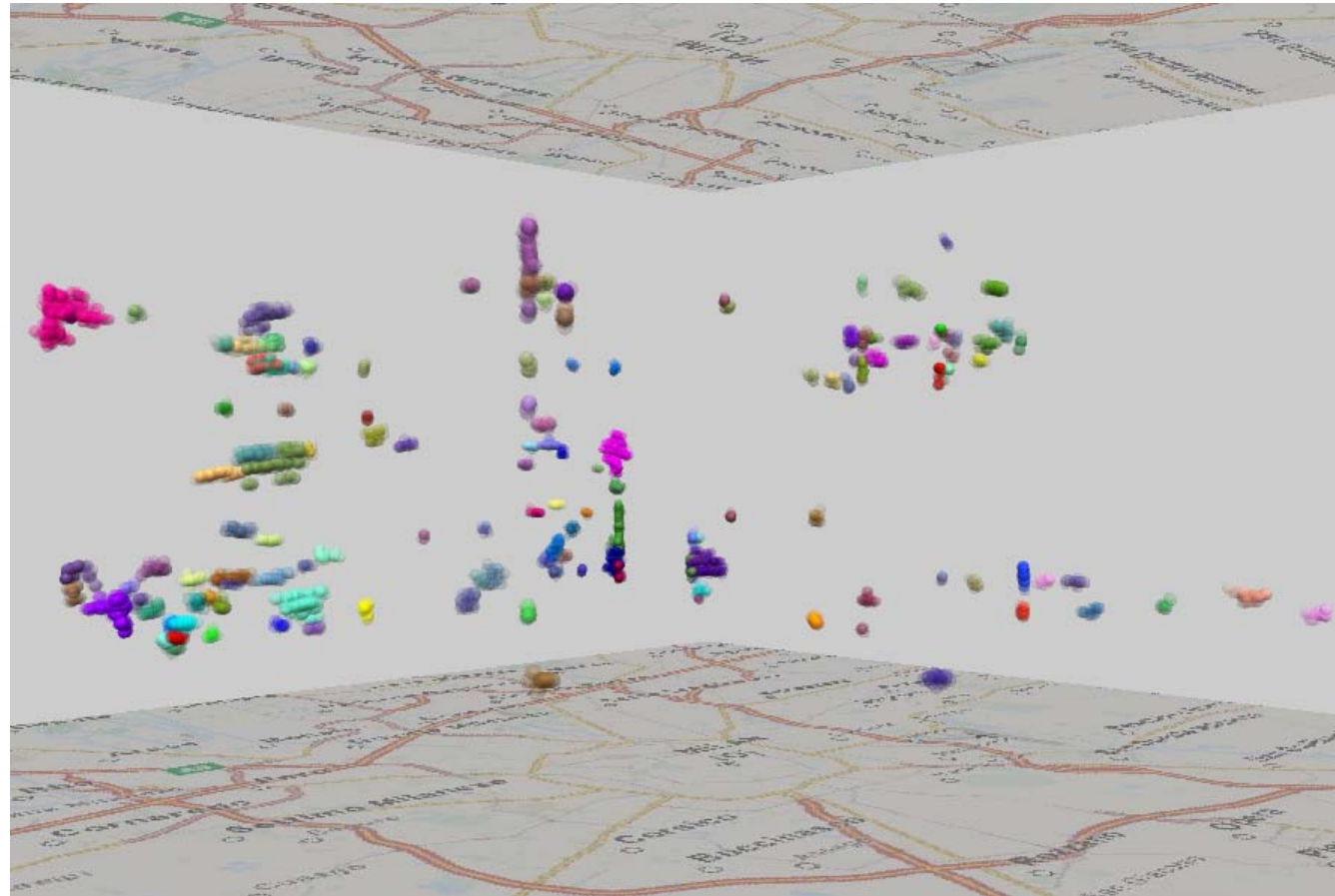
$$d(v_1, v_2, V) = \begin{cases} |v_1 - v_2|, & |v_1 - v_2| < V/2 \\ V - |v_1 - v_2|, & \text{otherwise} \end{cases}$$

E.g., direction: $V = 360^\circ$; $d(5^\circ, 355^\circ, 360^\circ) = 10^\circ$



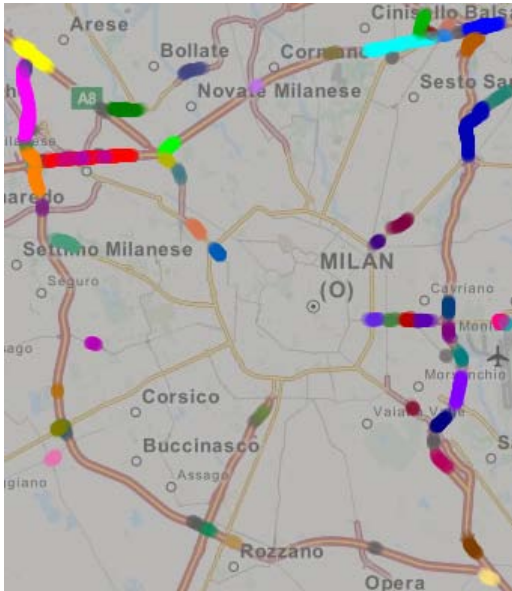
The result of the density-based clustering of the slow movement events by their spatial positions, temporal positions, and movement directions (**STD**) with the distance thresholds 100 meters, 10 minutes, and 20 degrees and the minimum number of neighbors 5.

The STD-clusters, noise hidden

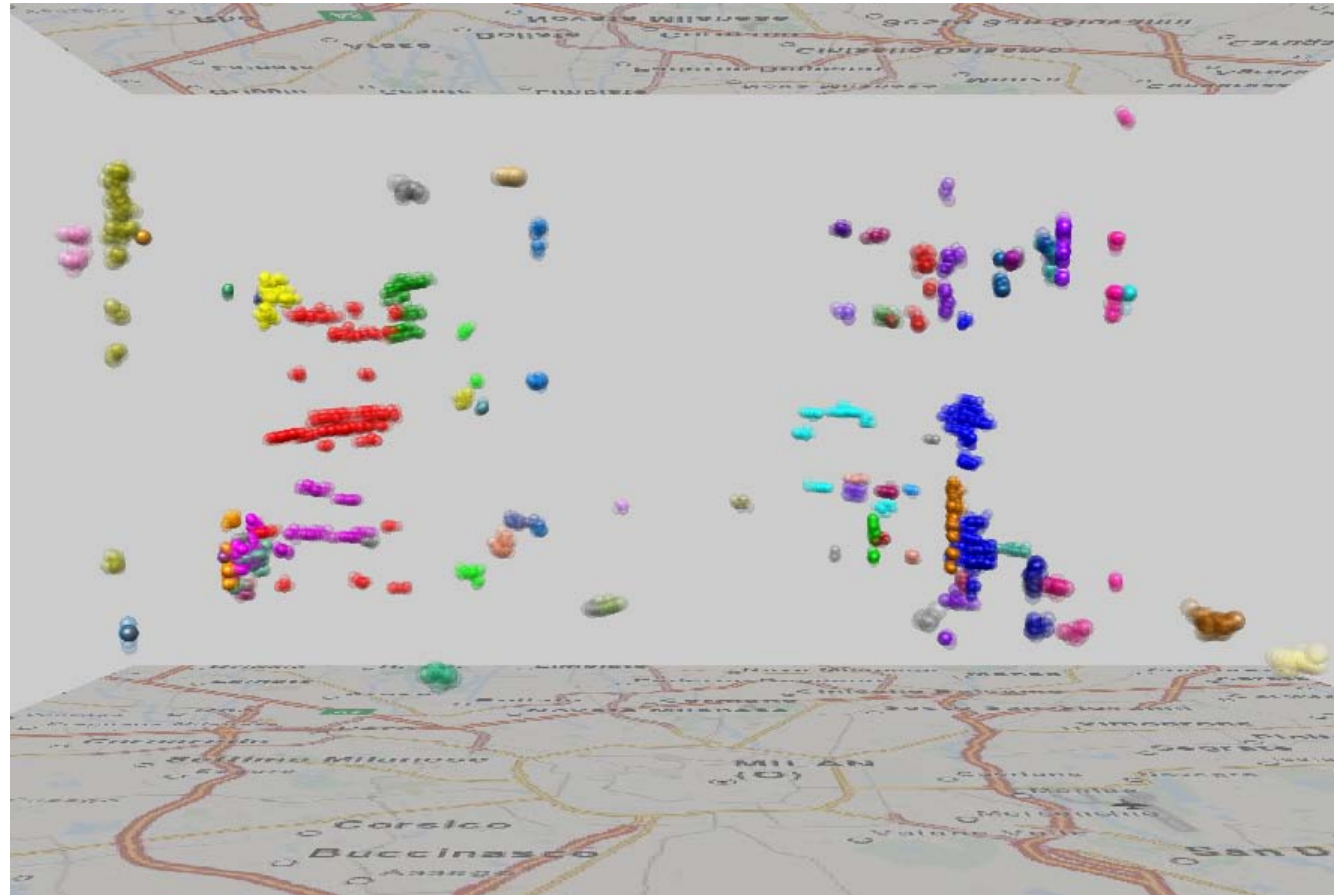


Step 3: unite STD-clusters in SD-clusters

Cluster the events from the STD-clusters by the spatial positions and directions



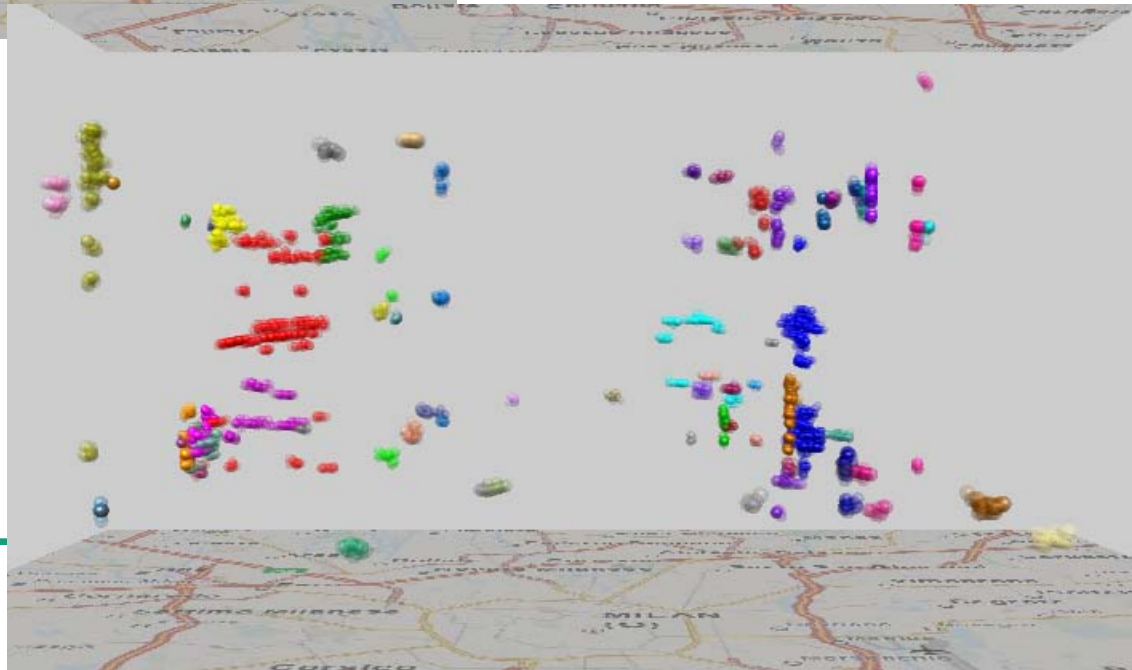
The result of the density-based clustering with the spatial distance threshold of 100 m and direction distance threshold of 20°





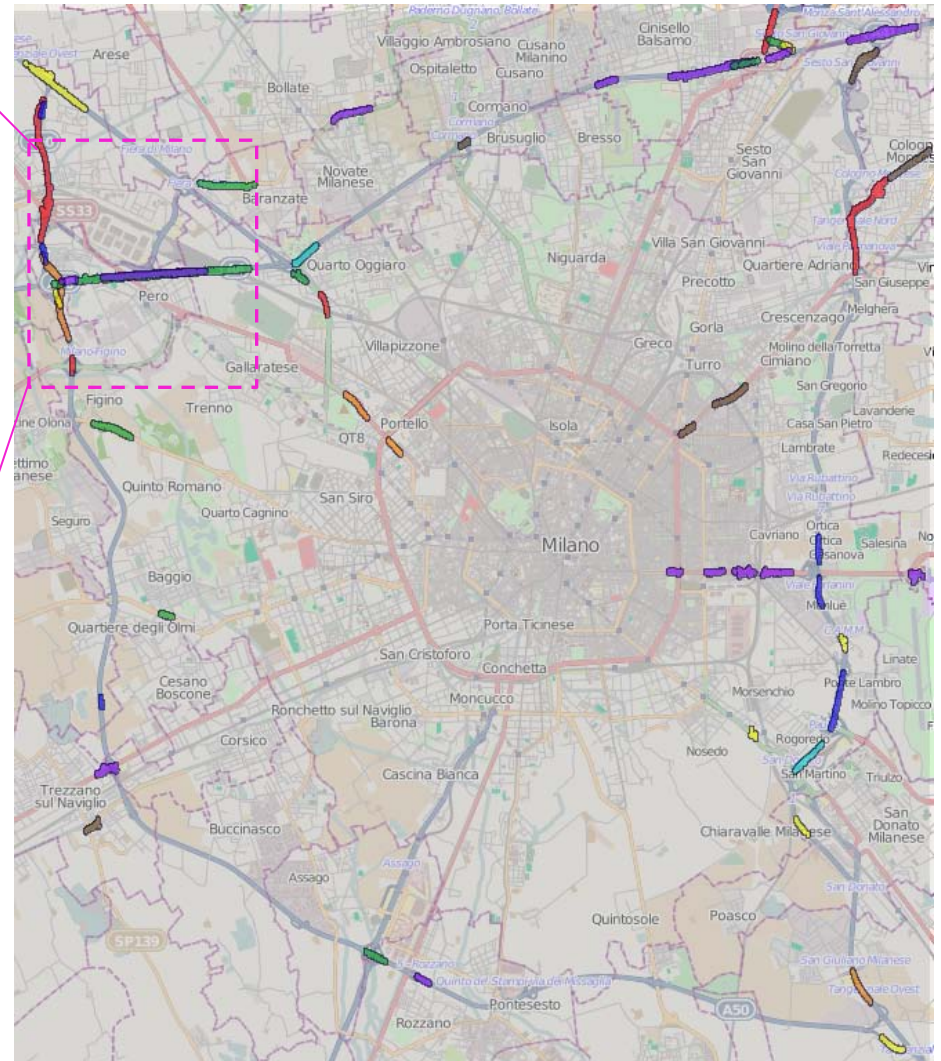
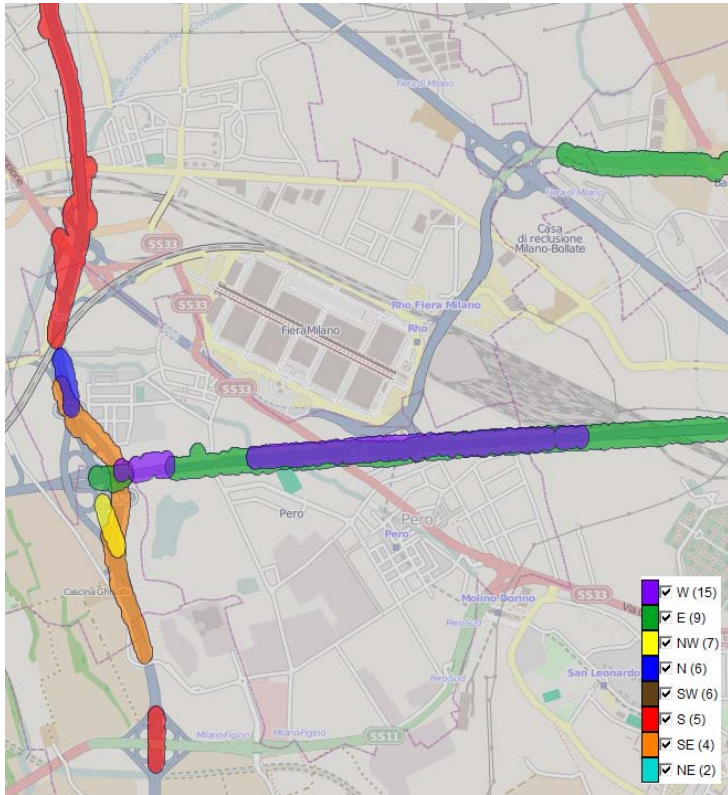
Events that occurred in same or close places but in different times were formerly in different clusters, but now they are in the same clusters.

One SD-cluster includes one or several STD-clusters.



Step 4: outline the places of interest

Build spatial buffers around the SD-clusters of events



The places are painted according to the prevailing movement directions of the respective events.

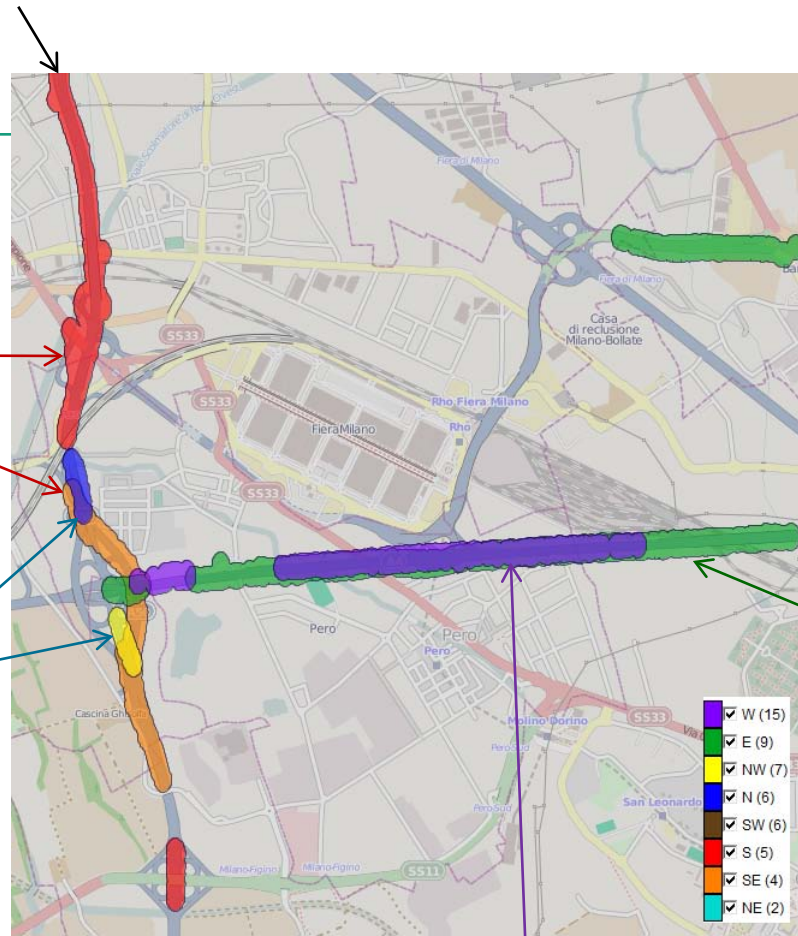
Belt road north-south on the east of the city (A50)

Extended areas of congested traffic directed to the south and southeast

Smaller areas of obstructed movement directed to the north and northwest

Belt road west-east on the north of the city (A4)

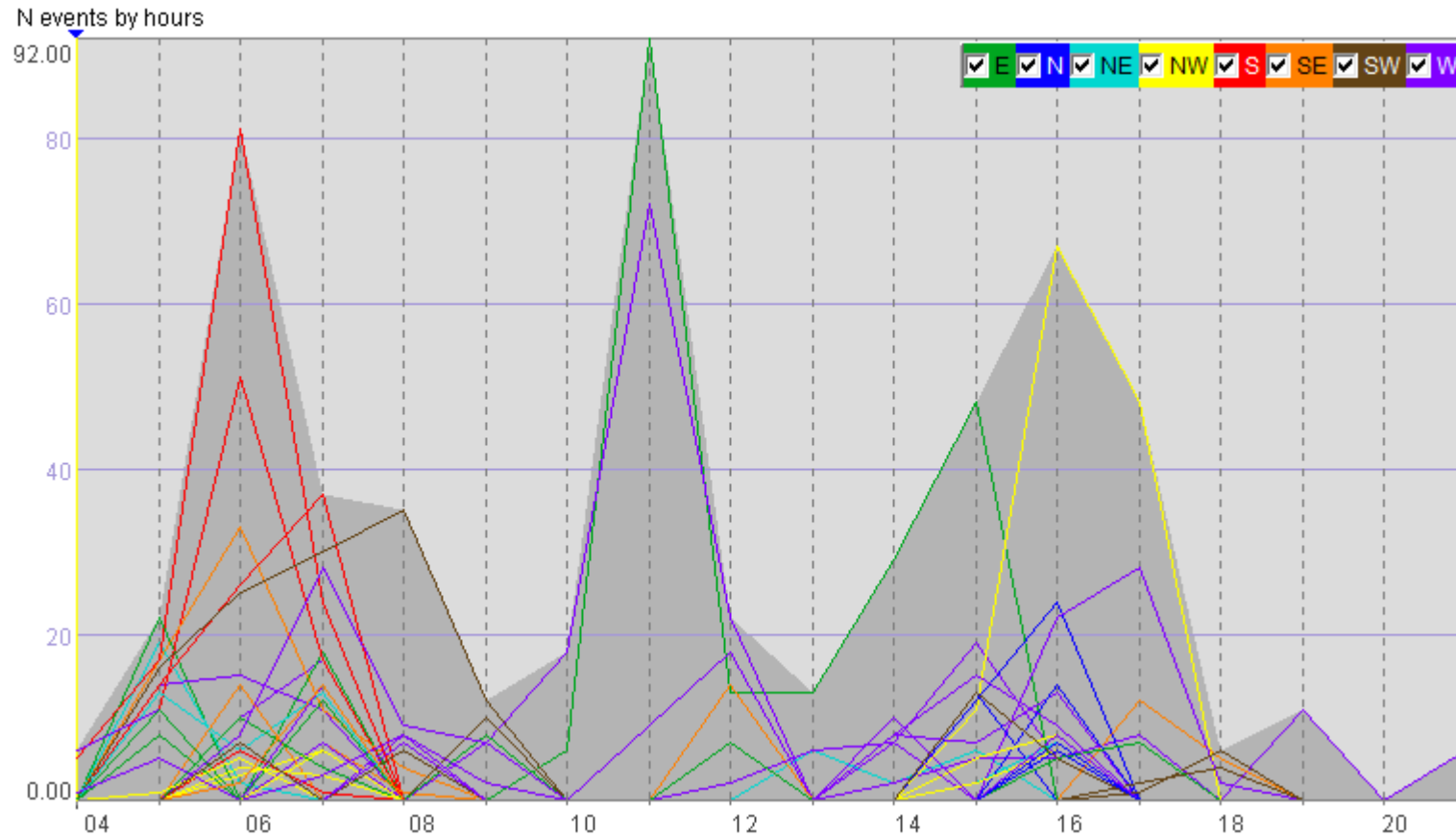
Very long area of congested traffic directed to the east



Long area of congested movements directed to the west

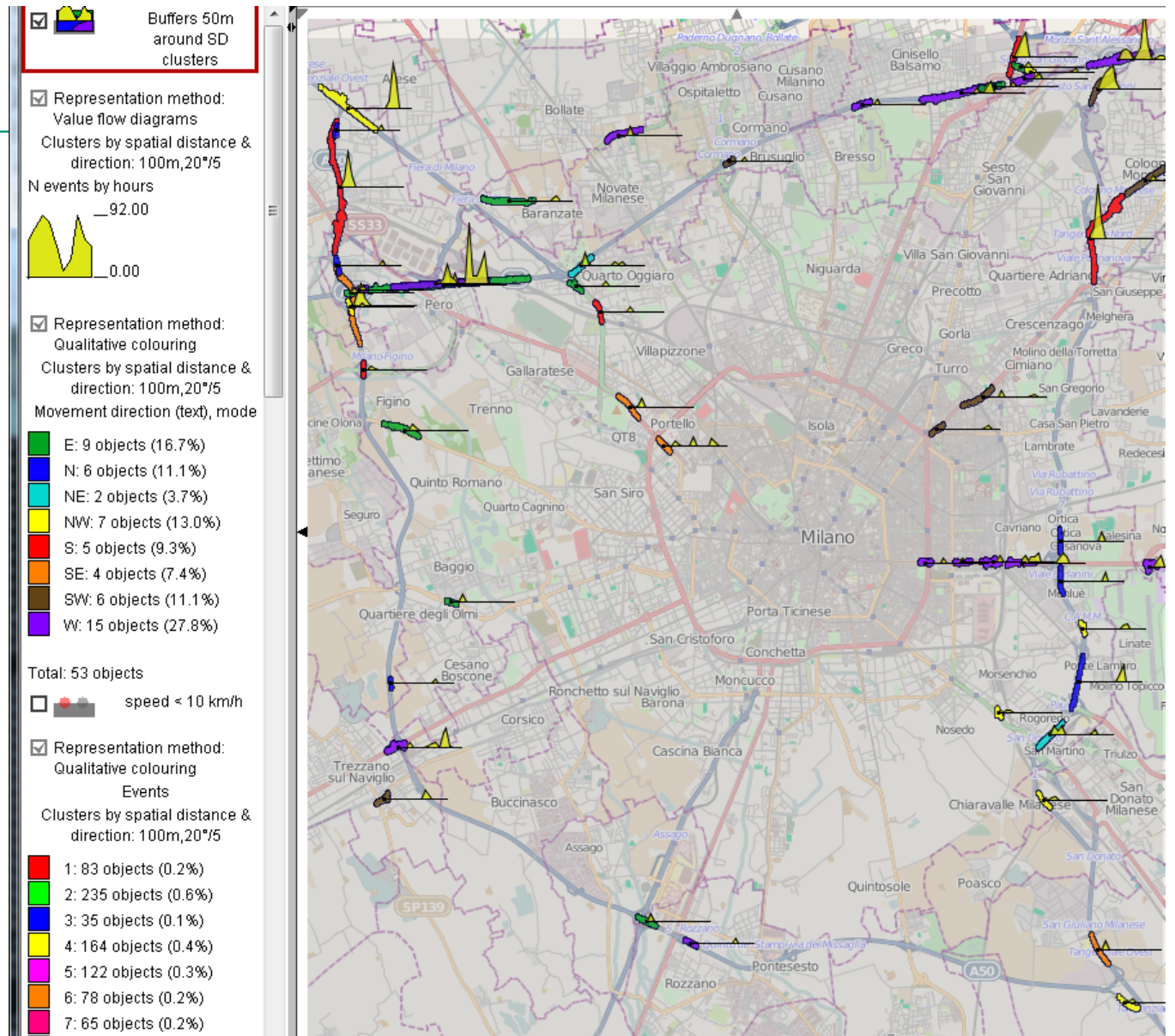
Step 5: aggregate data by the places

and by suitable time intervals, e.g., hourly

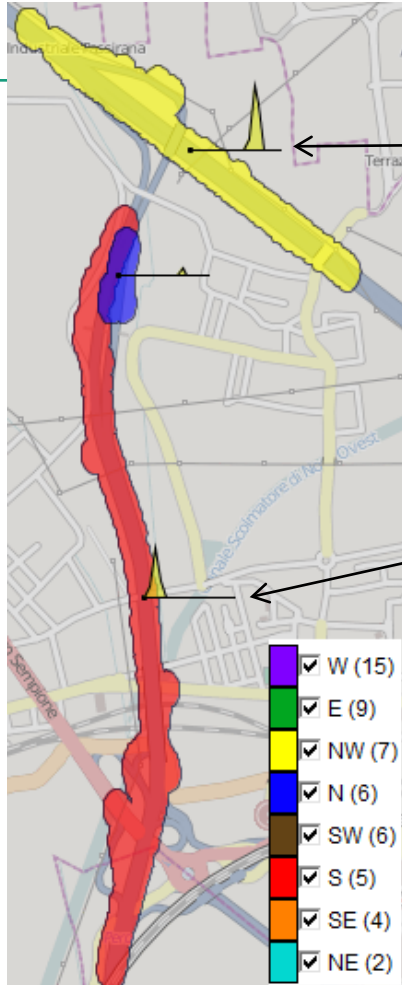


Place-referenced time series of the counts of slow movement events

The temporal diagrams show the variation of the attribute value (vertical dimension) over time (horizontal dimension).



Map fragment (northwest) enlarged

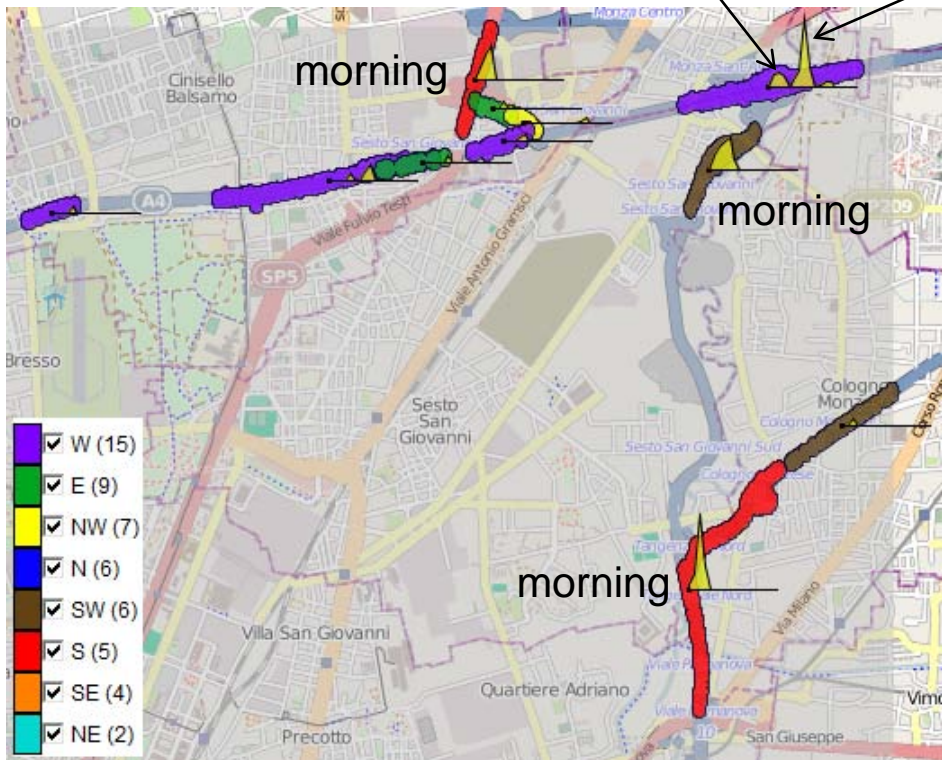


Congested traffic in the afternoon in the direction out of the city (northwest)

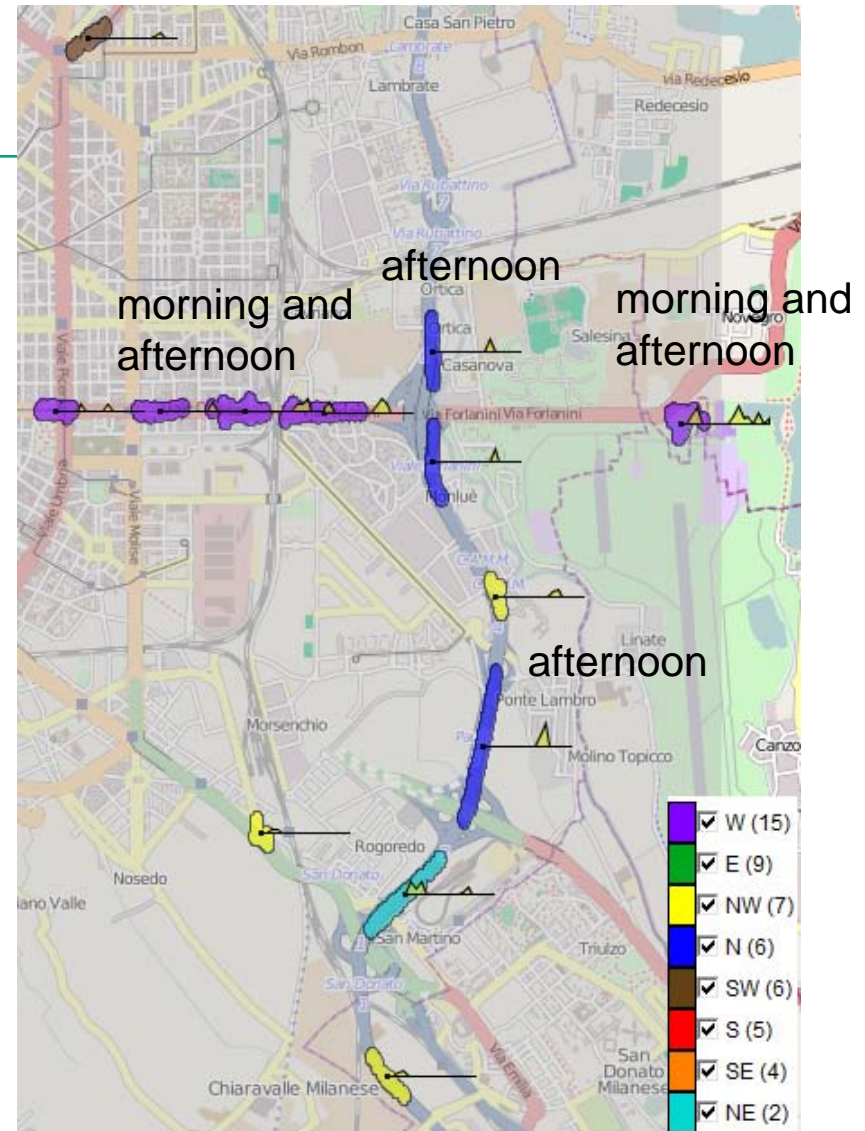
Congested traffic in the morning in the direction to the south

Other map fragments enlarged

Northeast



East



Where to read more

- IEEE VAST 2011 paper (**best paper** award)

G.Andrienko, N.Andrienko, C.Hurter, S.Rinzivillo, S.Wrobel

From Movement Tracks through Events to Places:

Extracting and Characterizing Significant Places from Mobility Data

IEEE Visual Analytics Science and Technology (VAST 2011),

Proceedings, IEEE Computer Society Press, 183-192

- Extended version, covering also scalable clustering of events

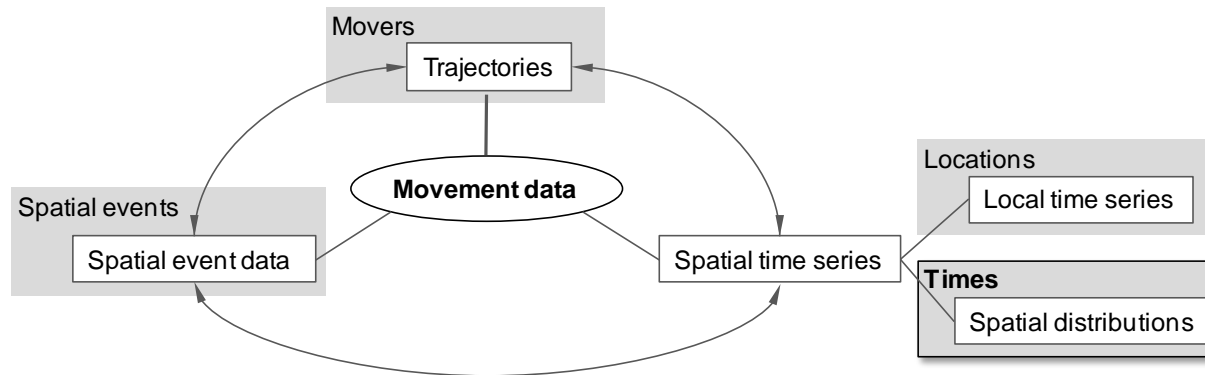
G.Andrienko, N.Andrienko, C.Hurter, S.Rinzivillo, S.Wrobel

**Scalable Analysis of Movement Data for Extracting and Exploring
Significant Places**

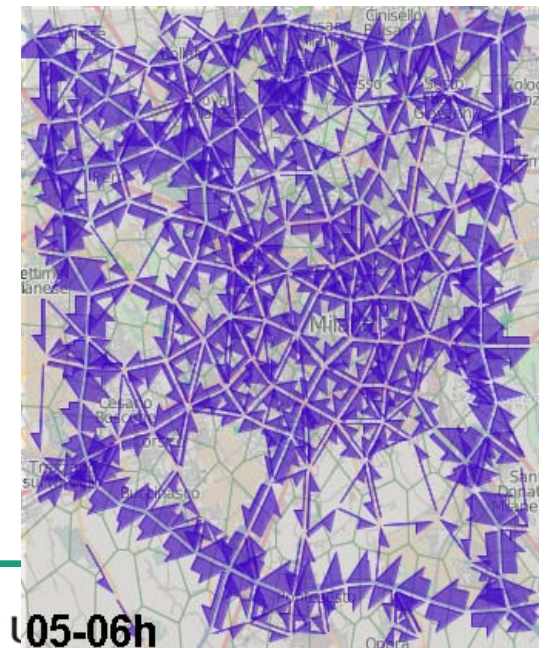
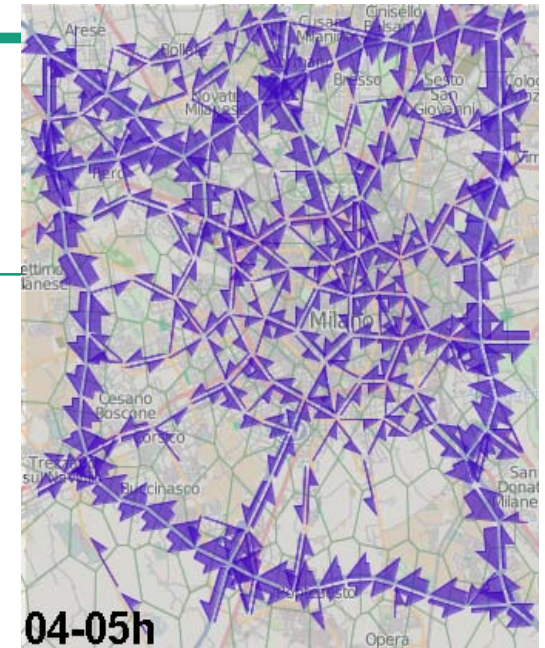
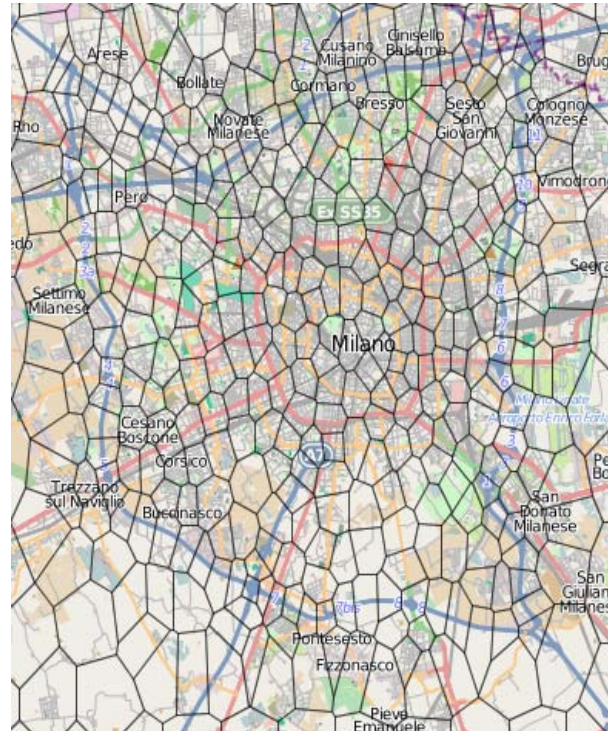
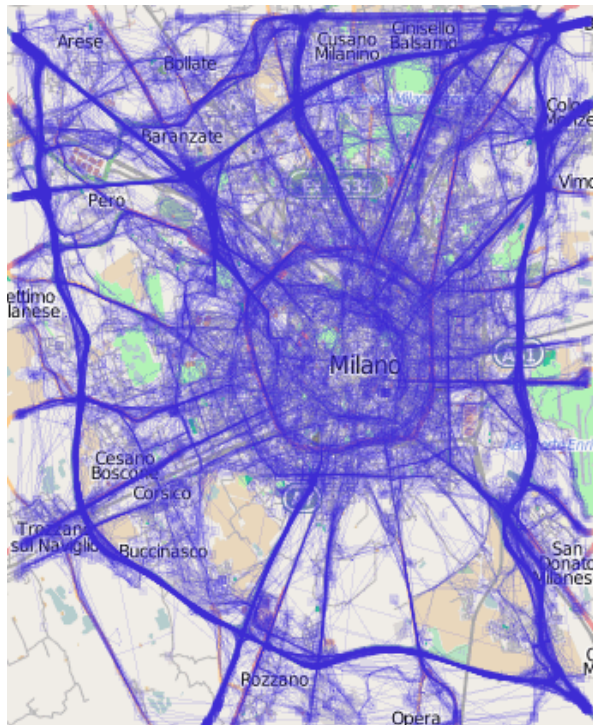
IEEE Transactions on Visualization and Computer Graphics,

2013, 19(7), 1078-1094

Perspective 3: Movement data in the form of spatial situations

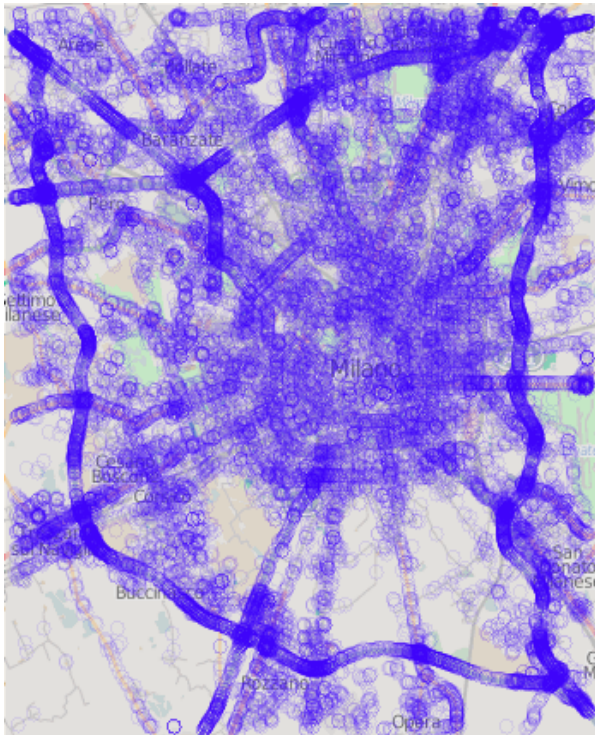


Spatio-temporal aggregation of trajectories

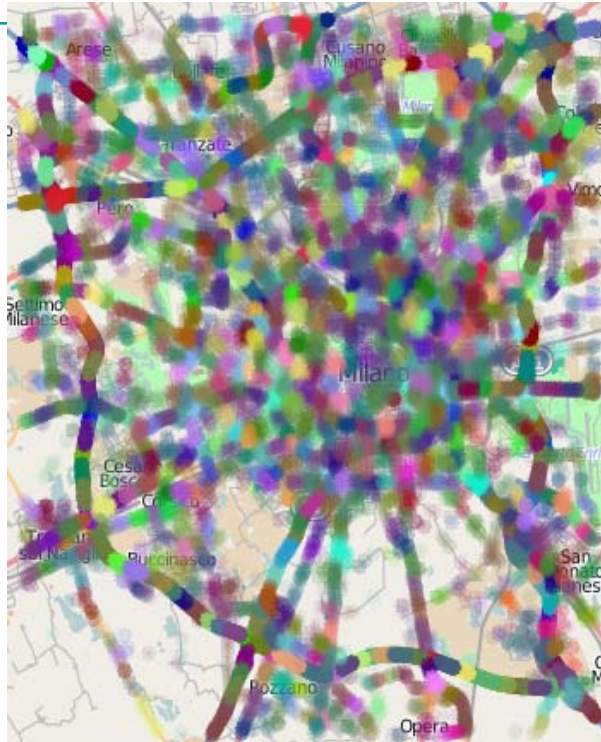


Division of the territory

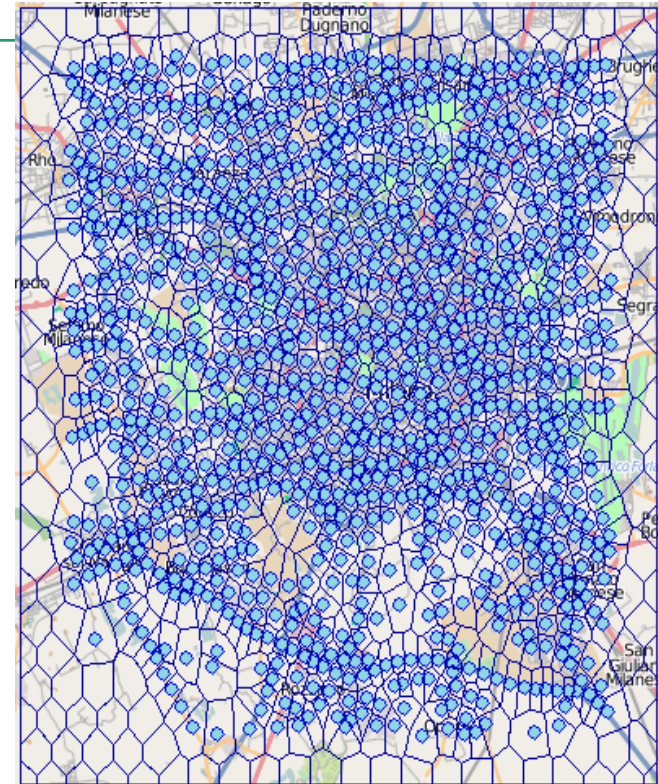
Characteristic points from the trajectories



Spatial clusters of characteristic points



Cluster centres → seeds for Voronoi tessellation



Details:

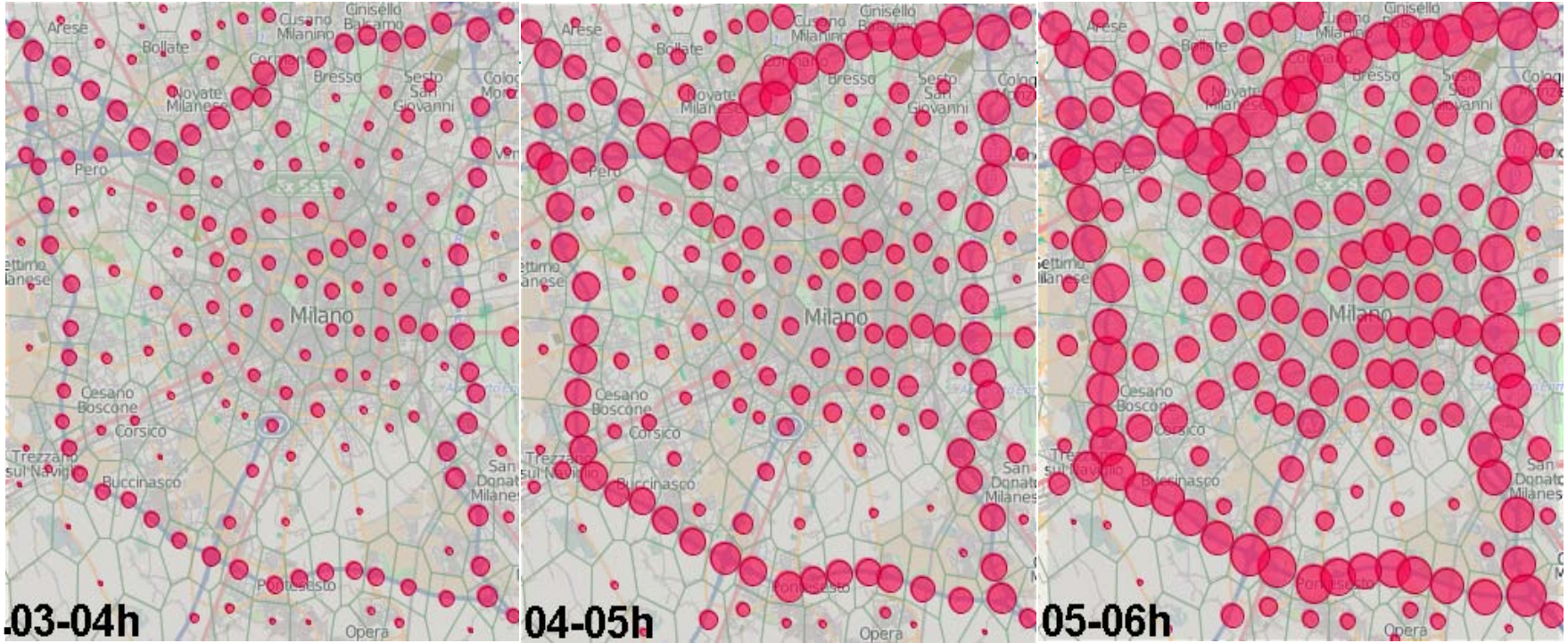
Natalia Andrienko, Gennady Andrienko

Spatial Generalization and Aggregation of Massive Movement Data

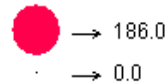
IEEE Transactions on Visualization and Computer Graphics (TVCG), 2011, v.17 (2), pp.205-219

<http://doi.ieeecomputersociety.org/10.1109/TVCG.2010.44>

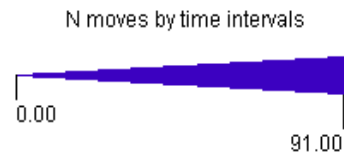
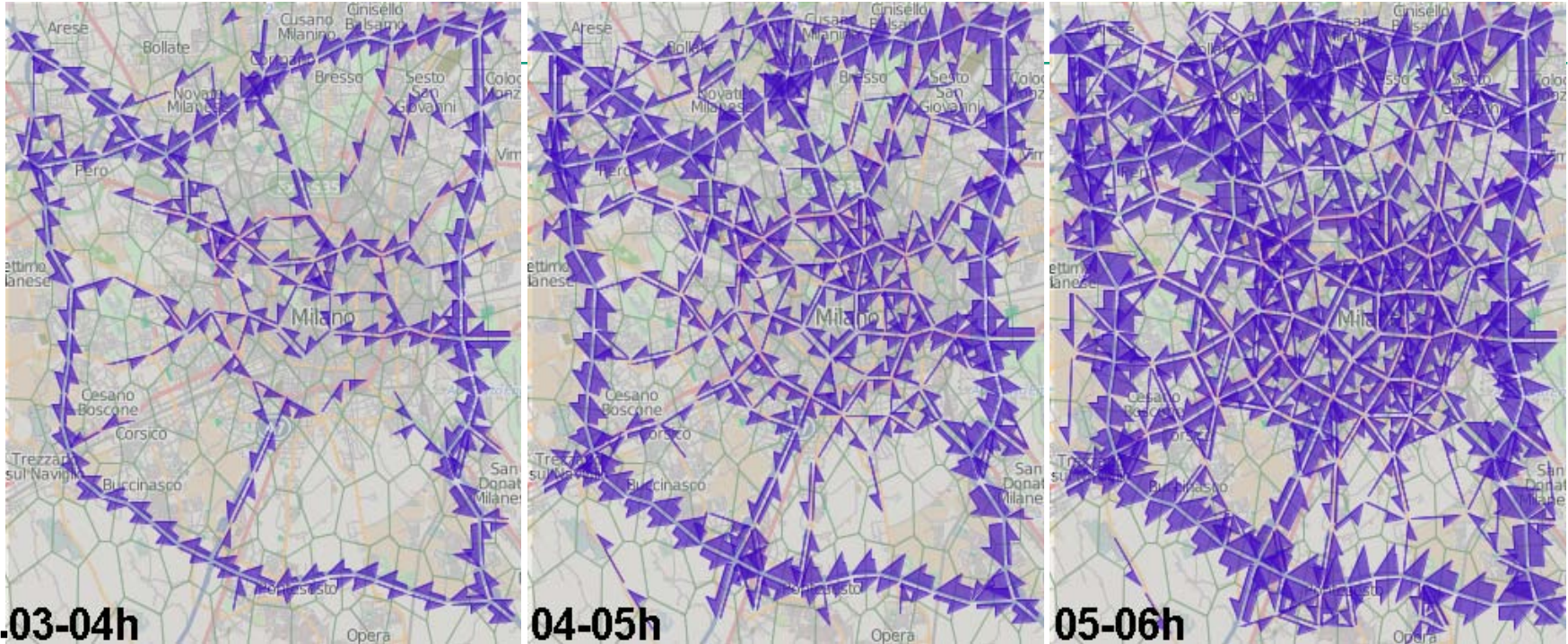
Spatial situations: presence



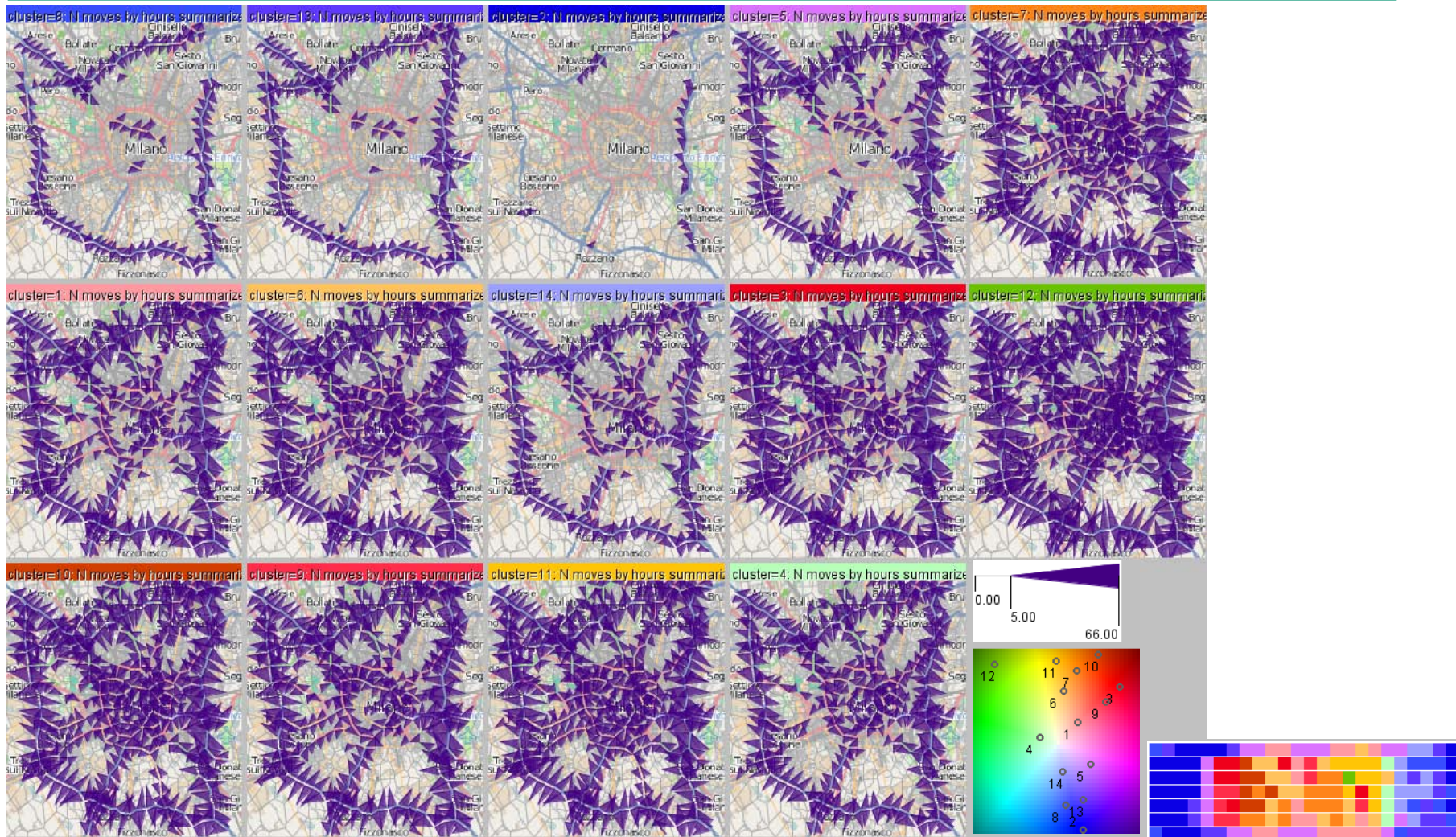
Circle area is proportional to value:



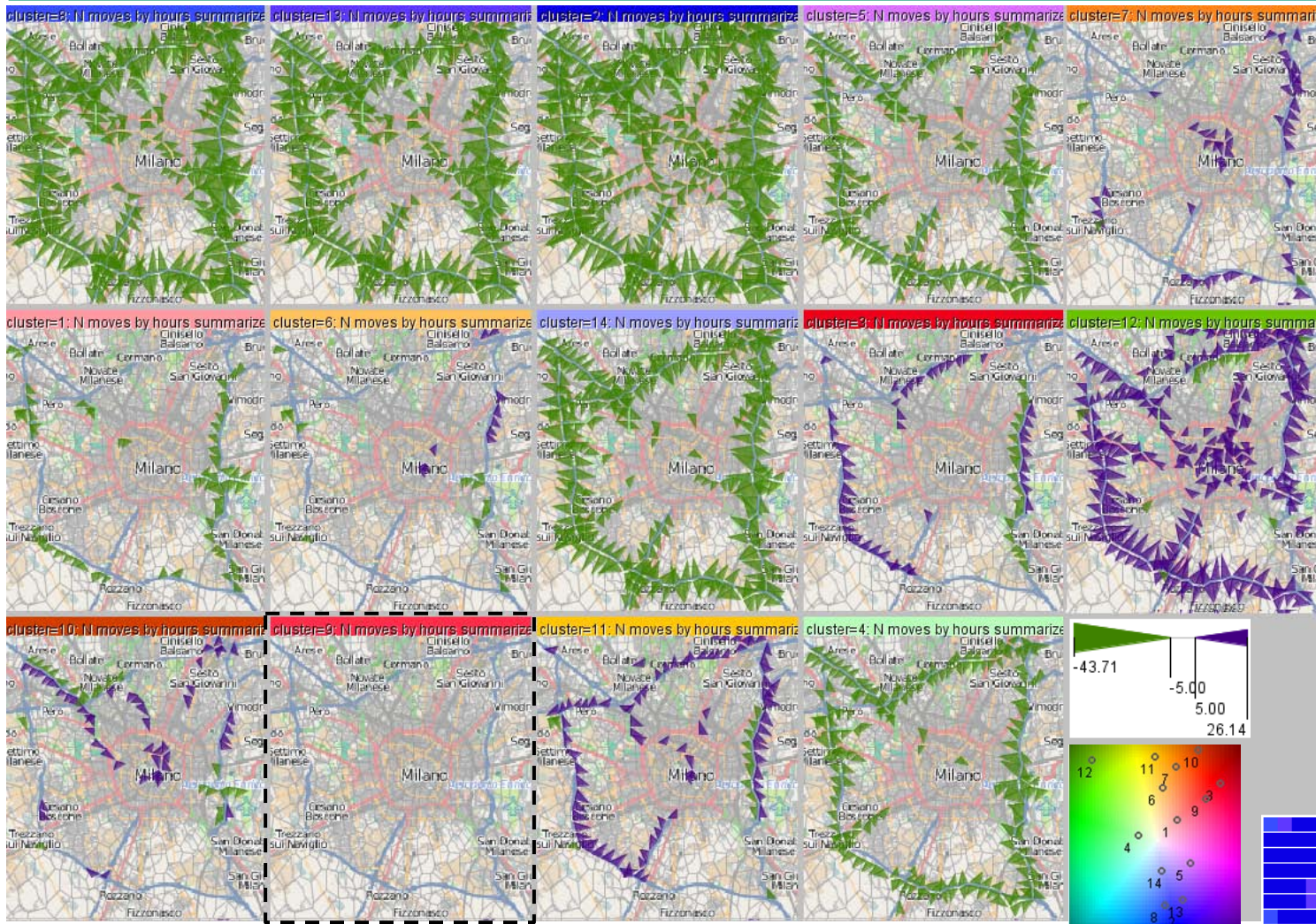
Spatial situations: flows



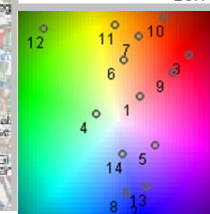
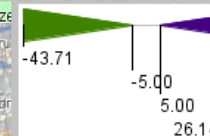
Clustering of spatial (flow) situations by similarity



Comparison of clusters of spatial situations



Values for cluster 9 have been subtracted from values for all other clusters



Where to read more

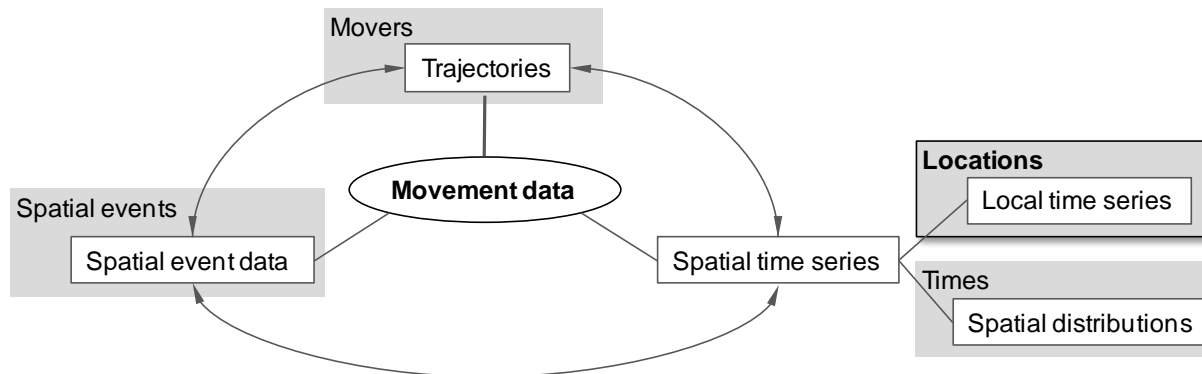
N.Andrienko, G.Andrienko, H.Stange, T.Liebig, D.Hecker

Visual Analytics for Understanding Spatial Situations from
Episodic Movement Data

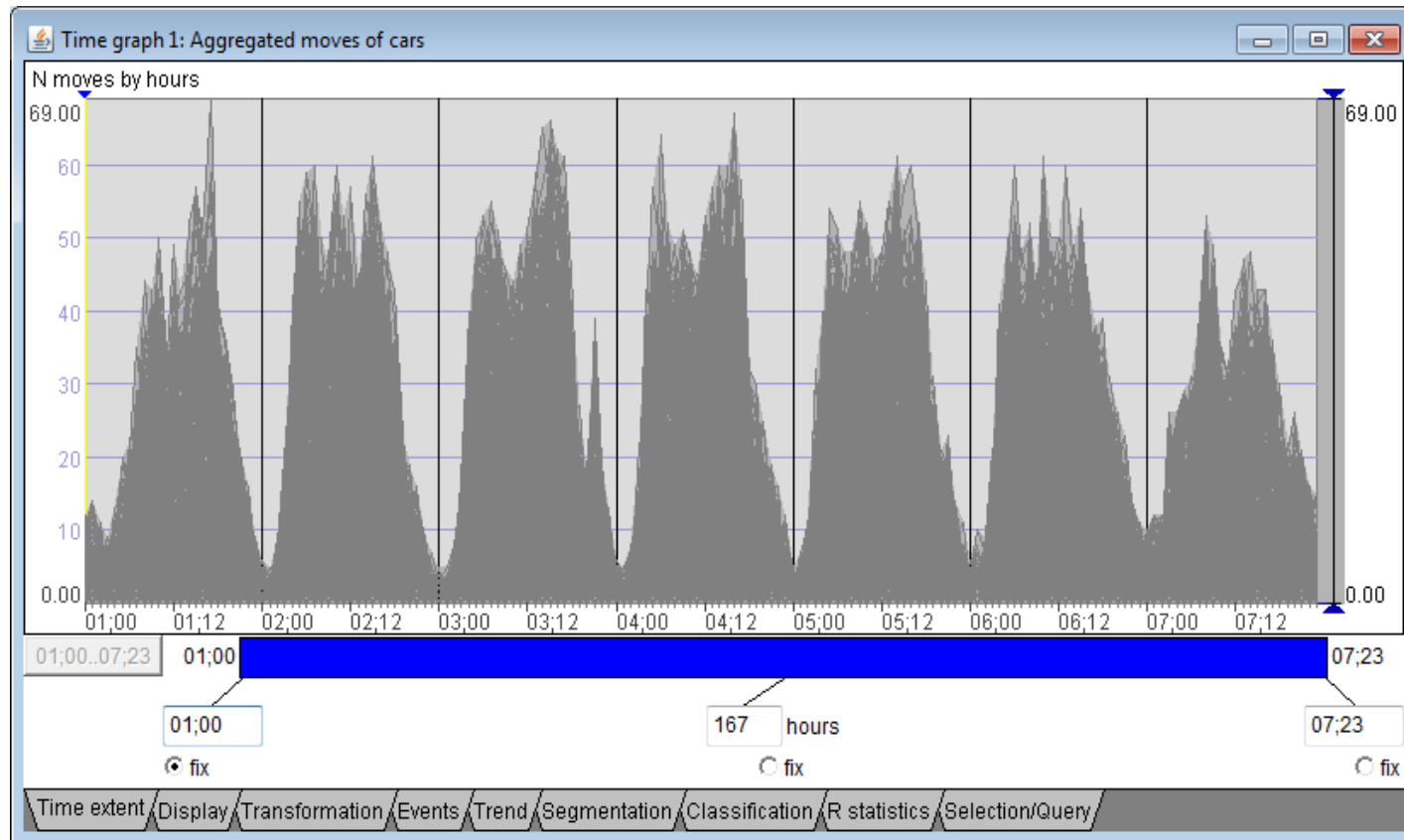
Künstliche Intelligenz, 2012, v.26 (3), pp.241-251

<http://dx.doi.org/10.1007/s13218-012-0177-4>

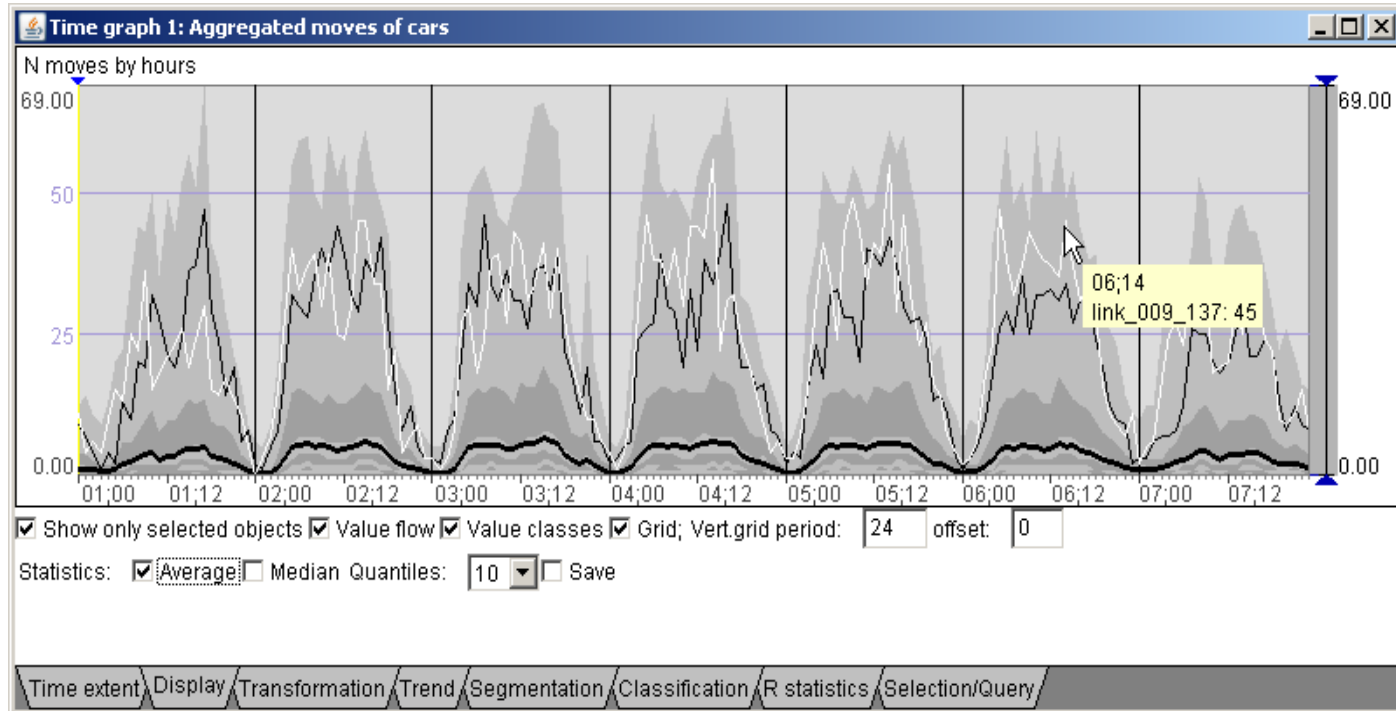
Perspective 4: Movement data in the form of local time series



An alternative view of spatial time series: a set of local time series



An alternative view of spatial time series : a set of local time series



We wish to represent the essential characteristics of the ST-variation explicitly by a formal model or a set of models.

Methods for spatio-temporal modelling (e.g. STARIMA)

- Account for spatial and temporal dependencies
- Require prior specification of multiple weight matrices expressing impacts among locations for different temporal lags
 - may be difficult (the impacts are not easy to quantify)
- Build a single global model of the entire spatio-temporal variation
 - It does not necessarily perform better than a set of local temporal models
- Assume spatial smoothness of the modelled phenomenon, i.e., closer places are more similar than more distant ones
 - May be not very suitable for spatially abrupt phenomena

Existing techniques for time series modelling

- + Widely available in numerous statistical packages and libraries → can be applied to spatially referenced time series
- The modelling methods are designed to deal with singular time series → hard to use for a large number of time series
- Separate consideration of each time series ignores the phenomenon of spatial dependence (relatedness and similarities among spatial locations or objects)
- Separate consideration of each time series does not allow data abstraction and generalisation over space

Combination of spatial and temporal modelling

- Approach 1:
 1. Model the temporal variation independently for each location
 2. Model the spatial variation of the parameters of the temporal models, e.g., as a random field
 - Assumes that the character of the temporal variation is the same everywhere and only the parameters differ
- Approach 2:
 - Model the spatial variation independently for each time step, e.g., as a random field
 - Model the temporal variation of the parameters of the spatial models at each location
- Both approaches assume spatial smoothness of the phenomenon

Our approach

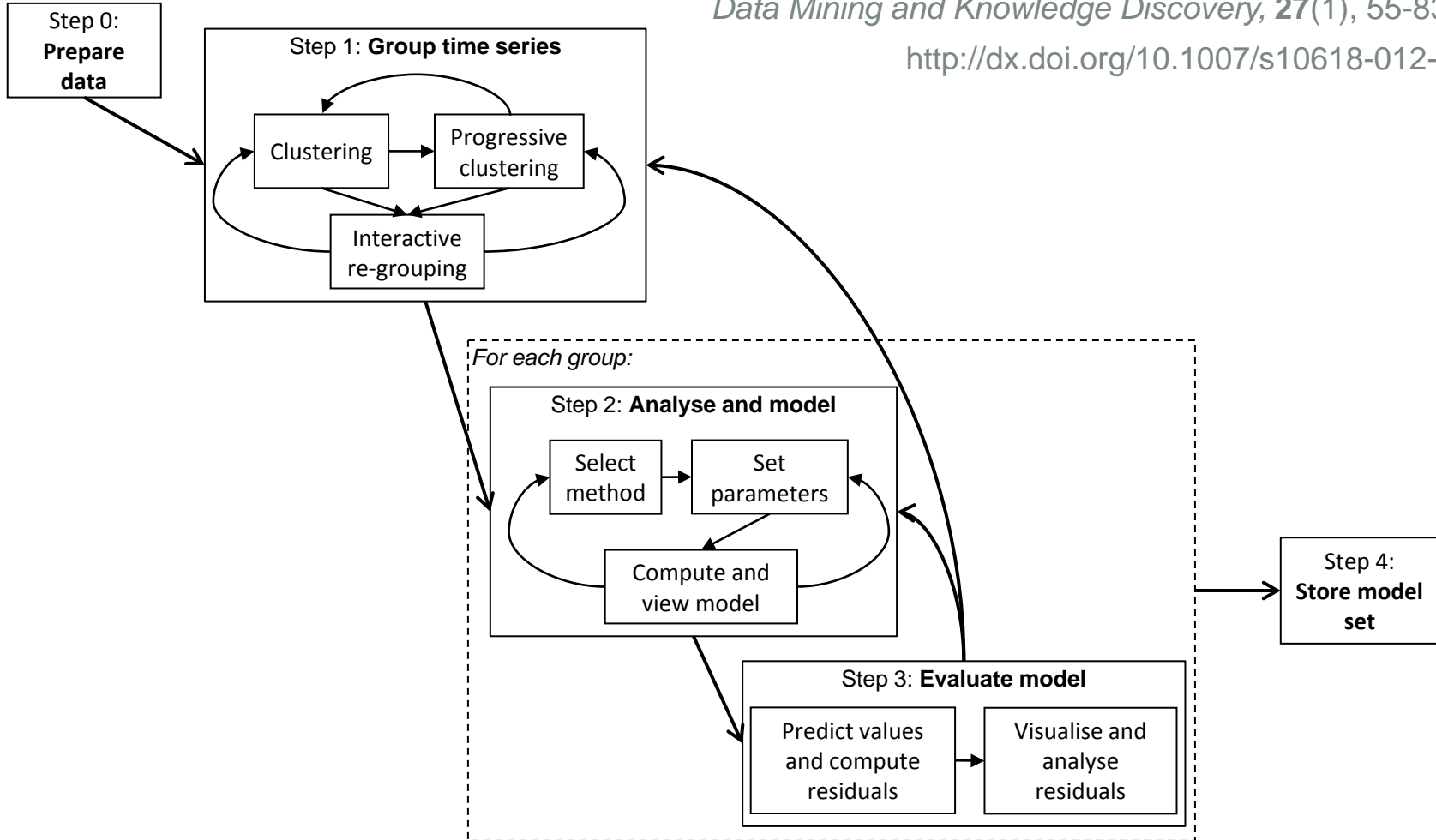
Details:

Natalia Andrienko, Gennady Andrienko

**A Visual Analytics Framework for
Spatio-temporal Analysis and Modelling**

Data Mining and Knowledge Discovery, 27(1), 55-83, 2013

<http://dx.doi.org/10.1007/s10618-012-0285-7>



Step 1: Clustering of local TS

- Here: k-means (Weka) but may be another partition-based method
- Tried different k from 5 to 15
- Immediate visual response facilitates choosing the most suitable k

Aggregated moves of cars

Representation method:
Qualitative colouring
Aggregated moves of cars
Clusters by k-means (7)

- 1: 220 objects (10.2%)
- 2: 126 objects (5.8%)
- 3: 84 objects (3.9%)
- 4: 129 objects (6.0%)
- 5: 80 objects (3.7%)
- 6: 397 objects (18.4%)
- 7: 1119 objects (51.9%)

Total: 2155 objects

Places

Total: 451 objects

Google Maps hybrid map

Total: 0 objects

Google Maps terrain map

Total: 0 objects

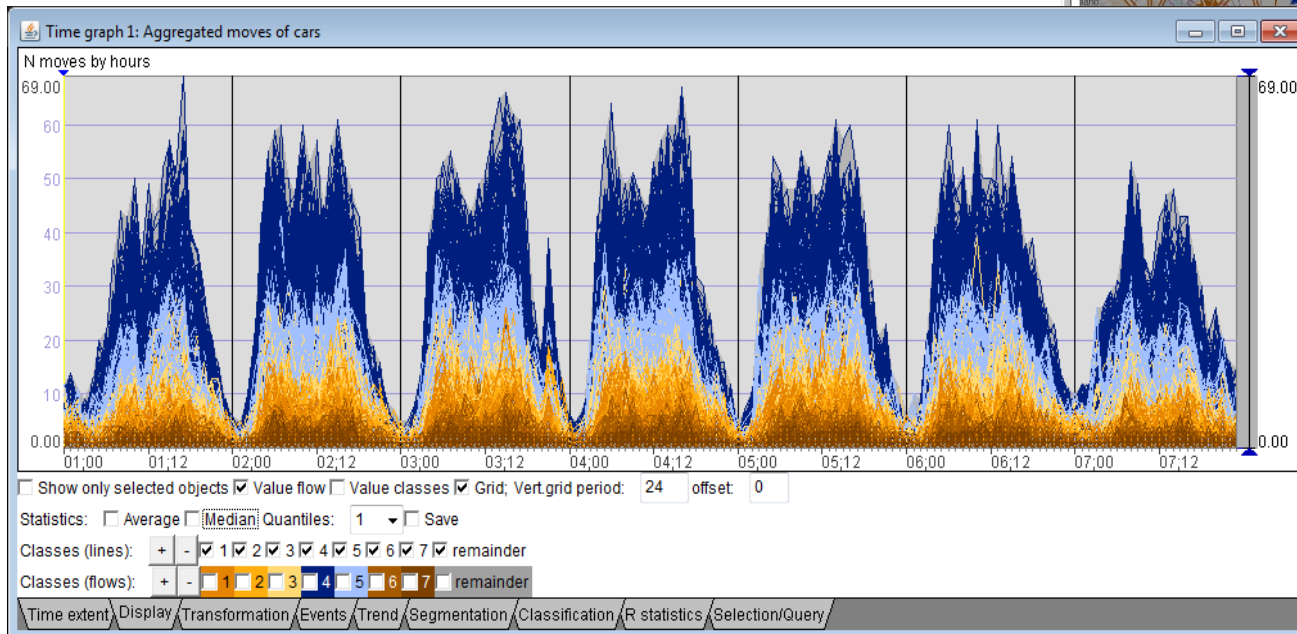
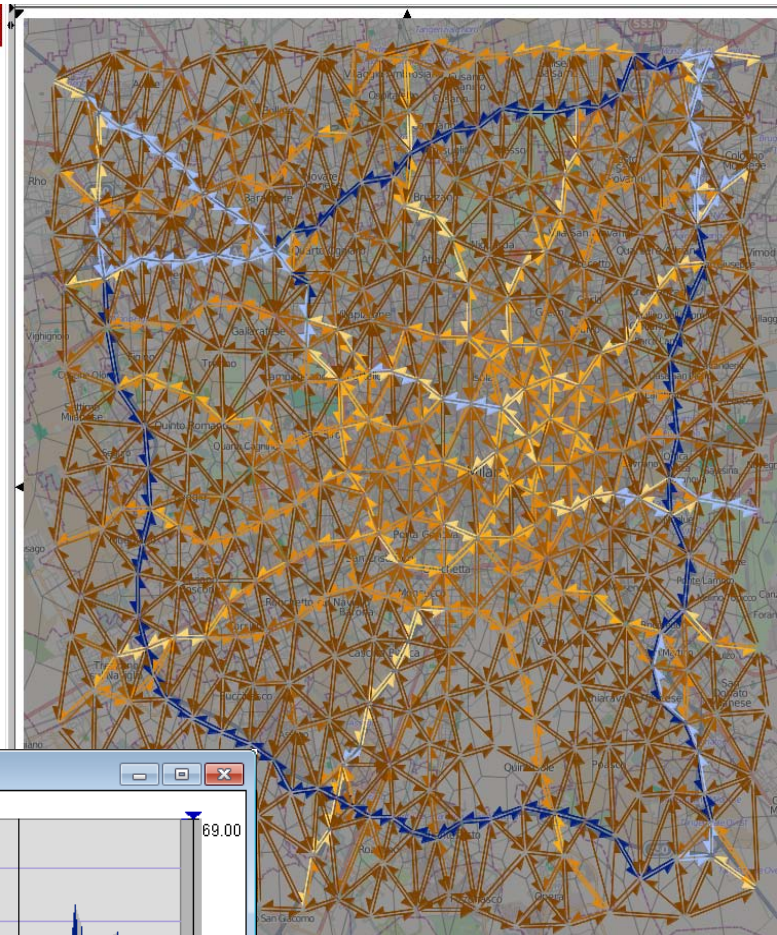
Open Street Maps

Total: 0 objects

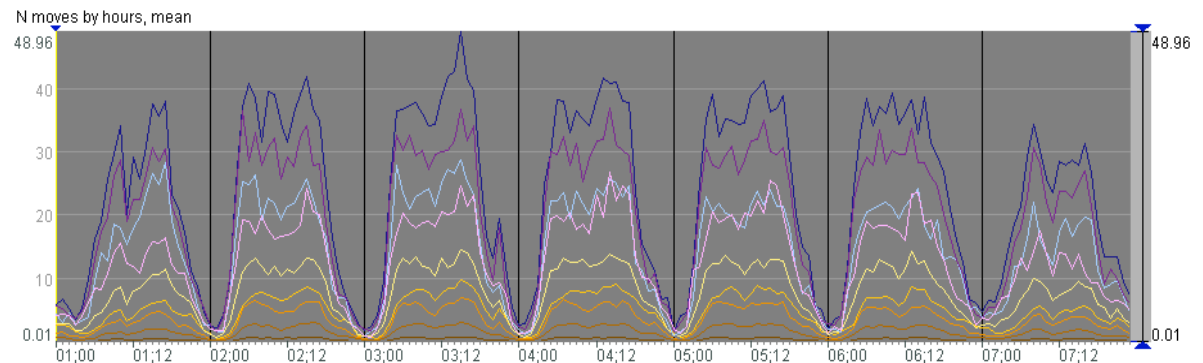
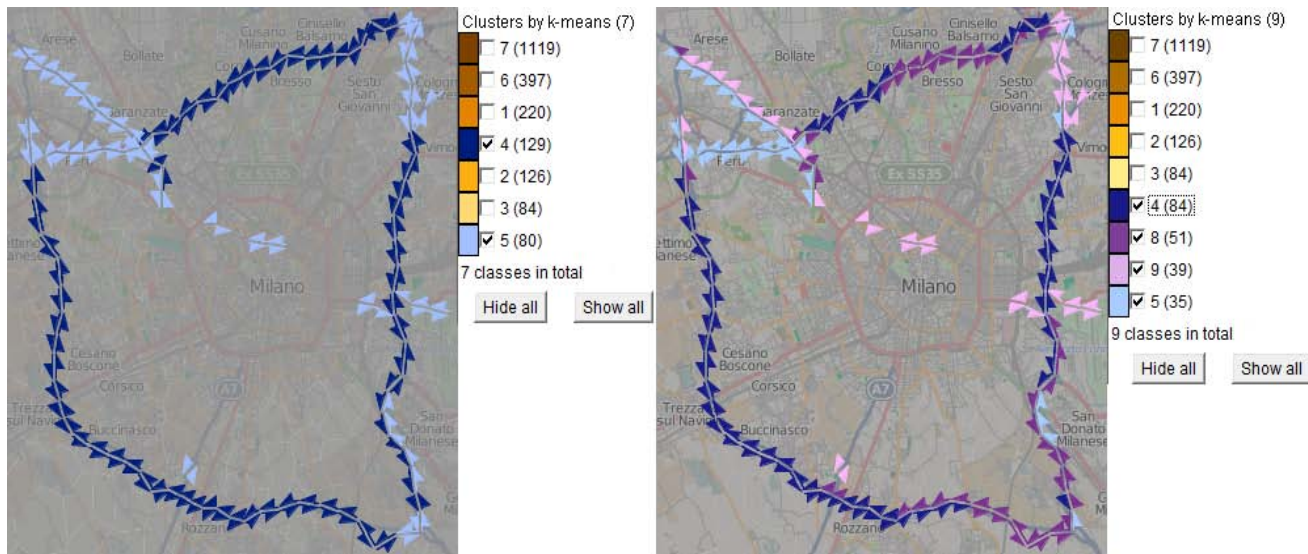
Territory: Milan, Italy

Background

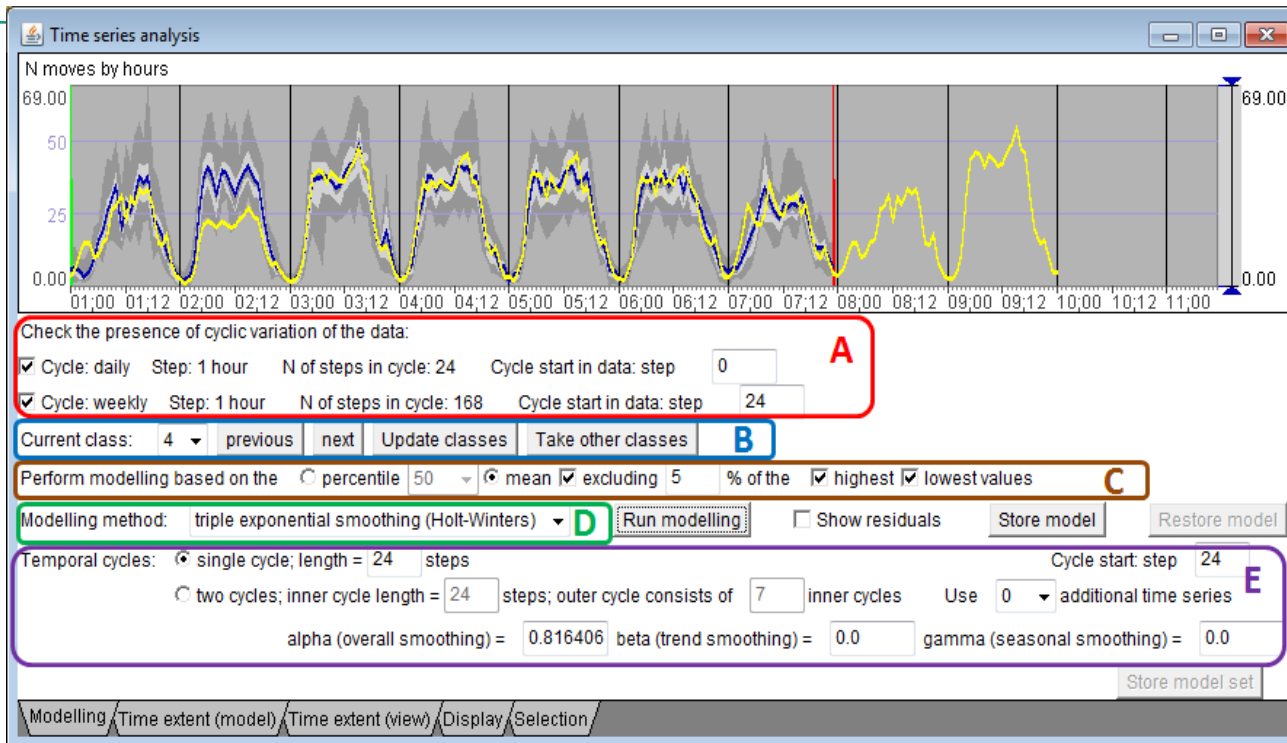
0.01 m



Step 1: Re-grouping by progressive clustering

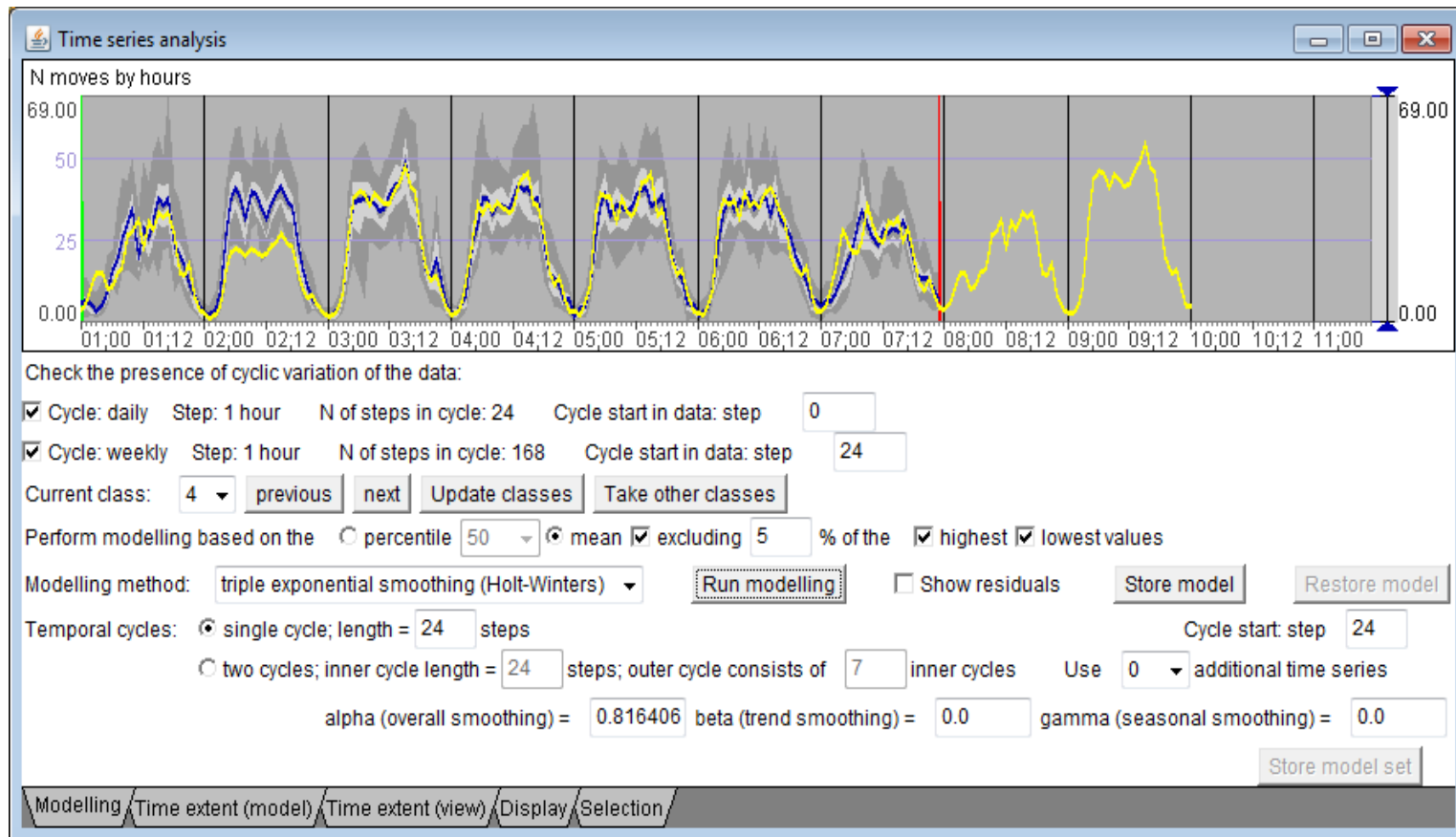


Step 2: Analysis and modelling

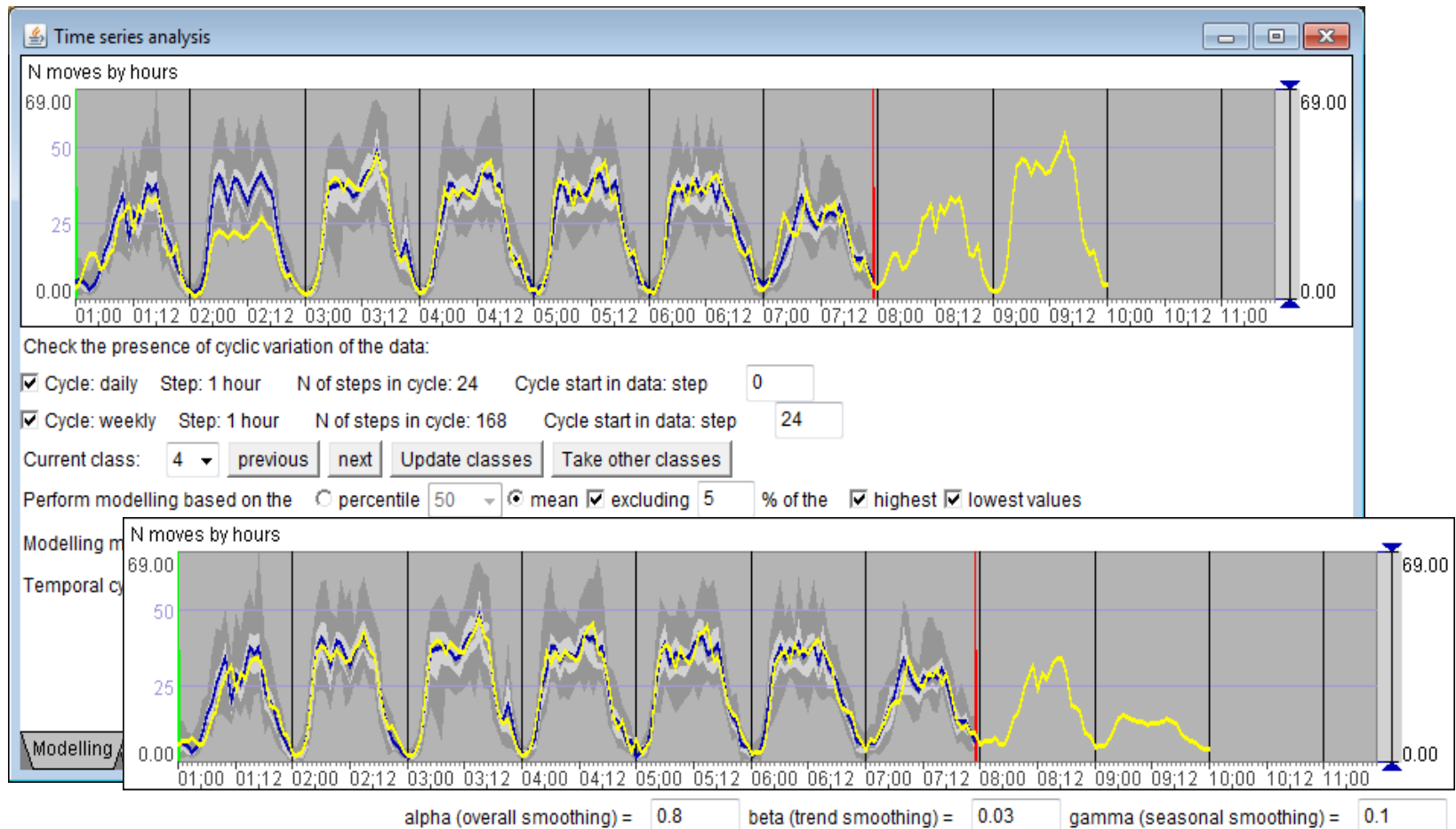


- A) Check automatically detected time cycles in the data.
- B) Select the current class (cluster) for the analysis and modelling.
- C) Build the representative TS.
- D) Select the modelling method.
- E) View and modify model parameters (this section changes depending on the selected modelling method).

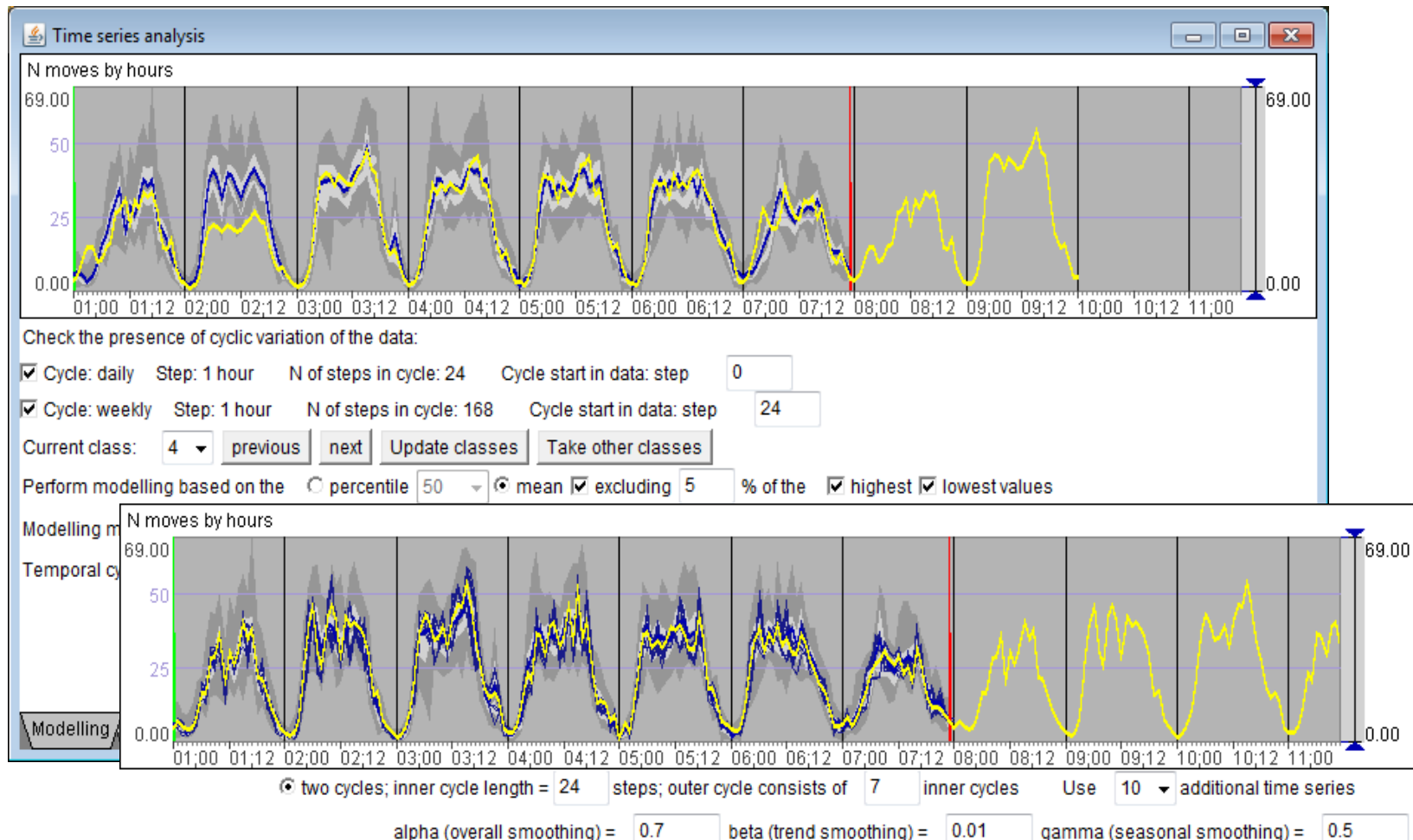
Step 2: Analysis and modelling



Step 2: Analysis and modelling



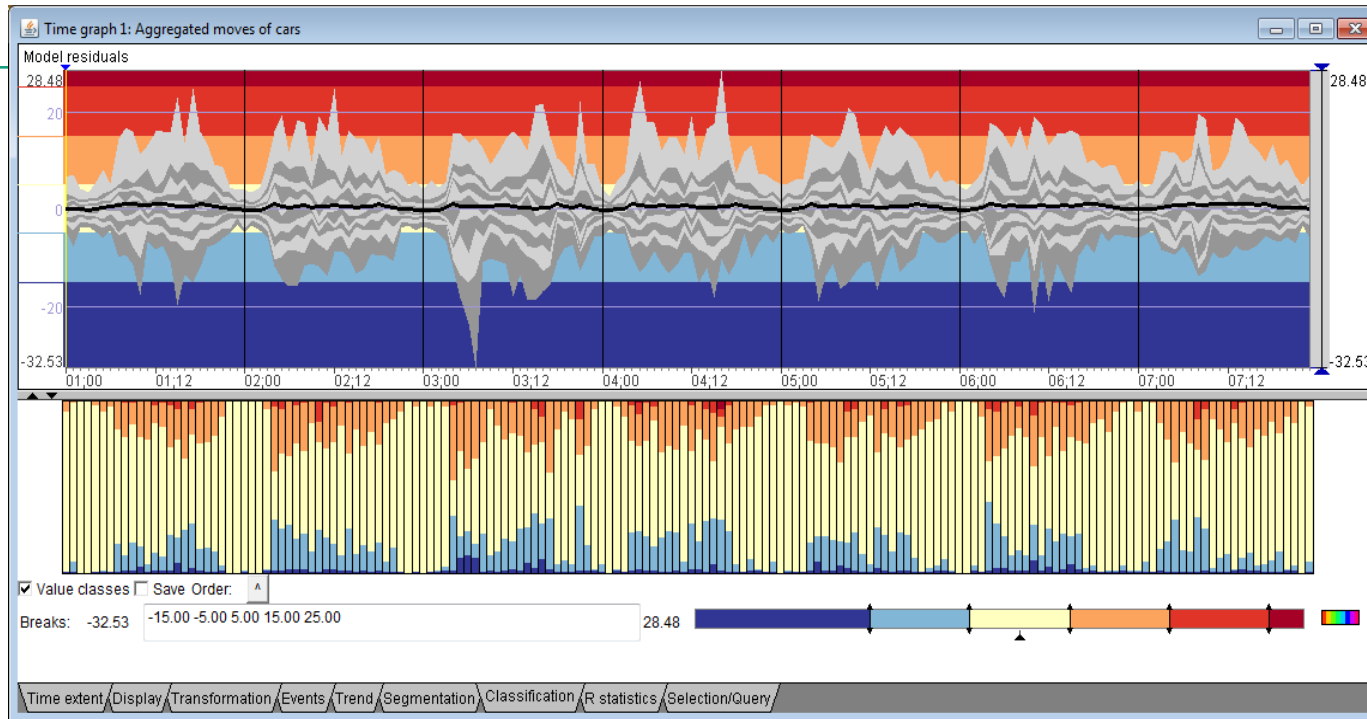
Step 2: Analysis and modelling



Step 3: Model evaluation (analysis of residuals)

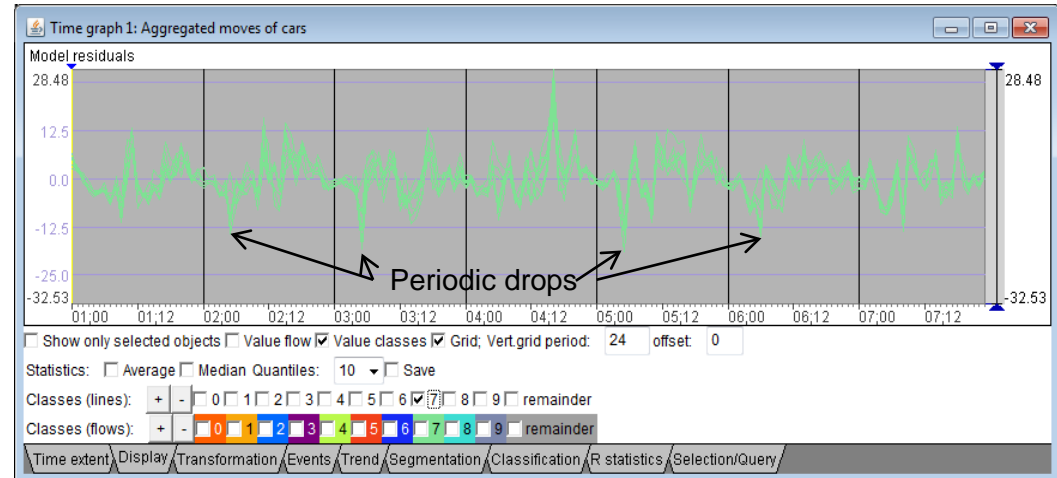
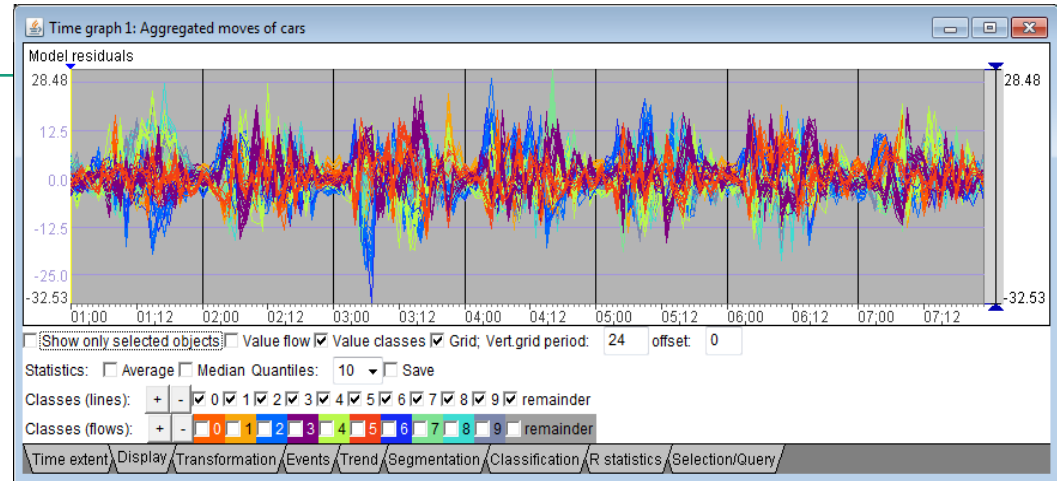
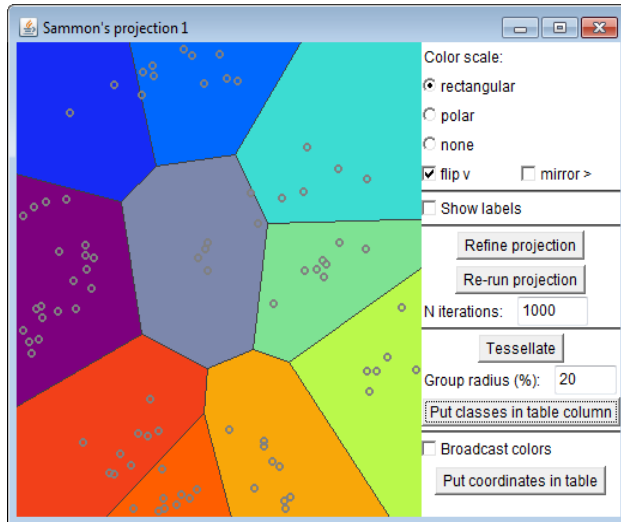
- The goal is not to minimise the residuals
 - The model should not reproduce all fluctuations and outliers present in the data
 - This should be an abstraction capturing the characteristic features of the temporal variation
 - High values of the residuals do not mean low model quality
- The goal is to have the residuals randomly distributed in space and time (no detectable patterns)
 - This means that the model correctly captures the characteristic, non-random features of the temporal variation

Analysis of residuals (example)



- No systematic bias: approximately equal numbers of positive and negative errors in each time step
- No periodic increases and decreases at the level of the whole group
- However, we are not sure about individual objects

More detailed analysis by subgroups



It may be reasonable to consider this subgroup separately -> back to re-grouping

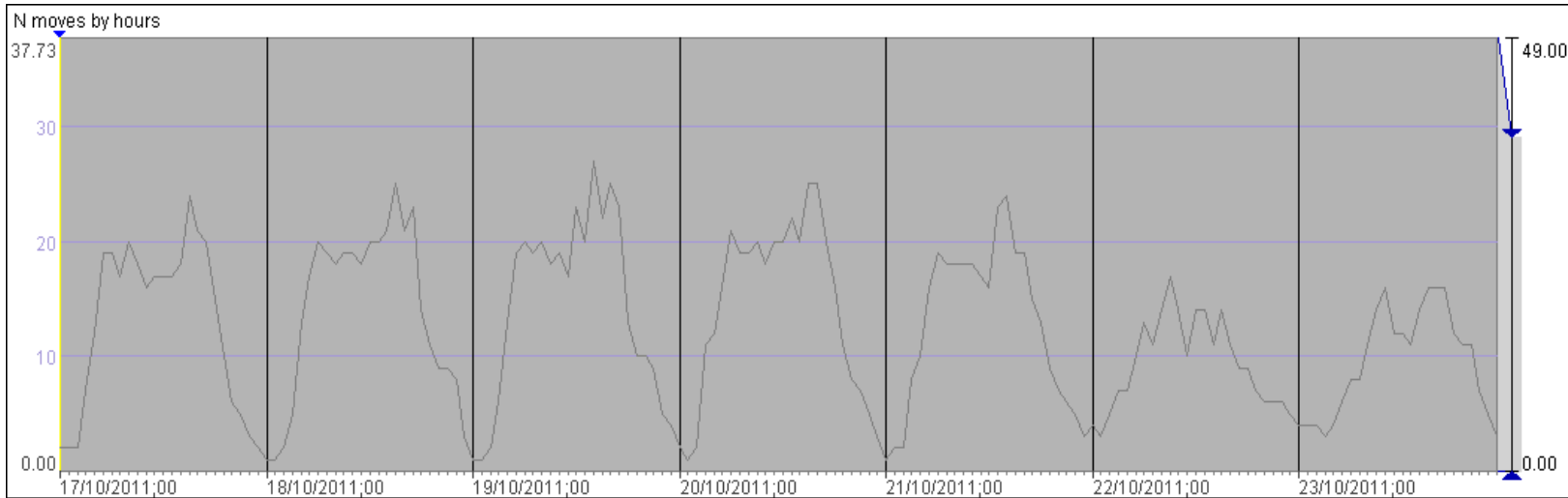
Use of a model for prediction

- We obtain a common model for a group (cluster) of time series
 - Predicts the same values for all objects/places of the group
 - The statistical properties of the distribution of the predicted values in each place differ from the distribution of the original values
- Adjustment of the prediction for individual objects/places:
 - Compute and store the basic statistics (quartiles) of the original values for each object/place i : $Q1_i, M_i, Q3_i$
 - Compute the statistics of the model-predicted values for the same time steps as the original values: $Q1, M, Q3$ (common for the cluster)
 - Shift (*level adjustment*): $S = M_i - M$
 - Scale factors (*amplitude adjustment*): $F_{low} = \frac{M_i - Q1_i}{M - Q1}$ $F_{high} = \frac{Q3_i - M_i}{Q3 - M}$
 - Let v^t be the model-predicted value for an arbitrary time step t and v_i^t the individually adjusted value for the place/object i

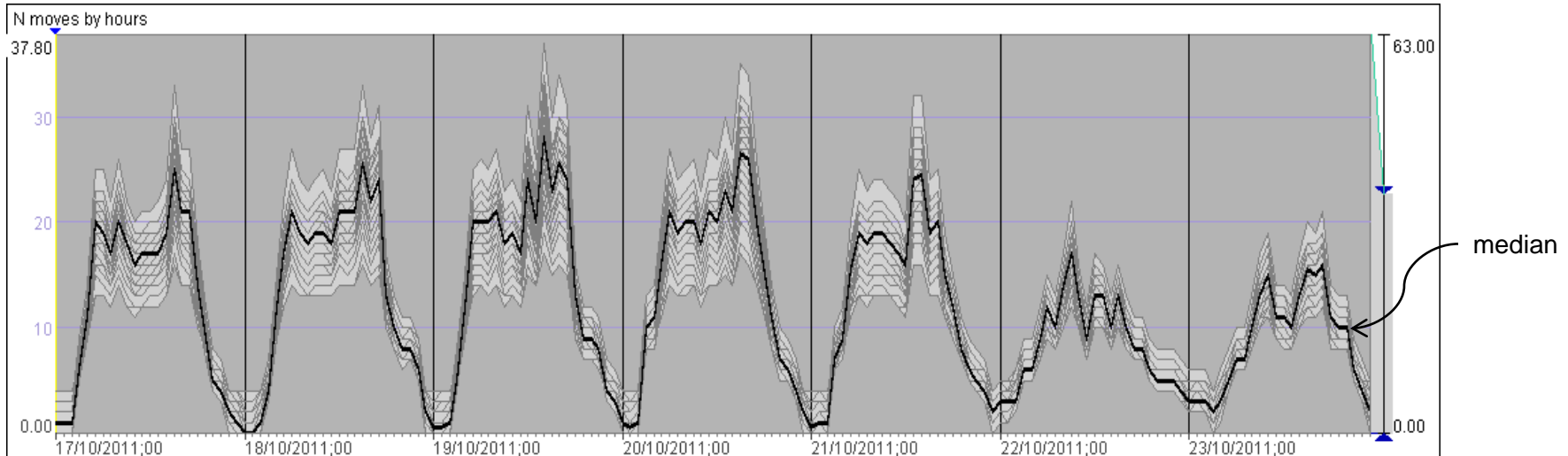
$$v_i^t = \begin{cases} M + F_{low} \cdot (v^t - M) + S, & \text{if } v^t < M \\ M + F_{high} \cdot (v^t - M) + S, & \text{otherwise} \end{cases}$$

Use of a model for prediction: example

Common prediction for a cluster:



Set of individually adjusted predictions for this cluster:



Prediction based on the models

Time interval for prediction?

Check model information:

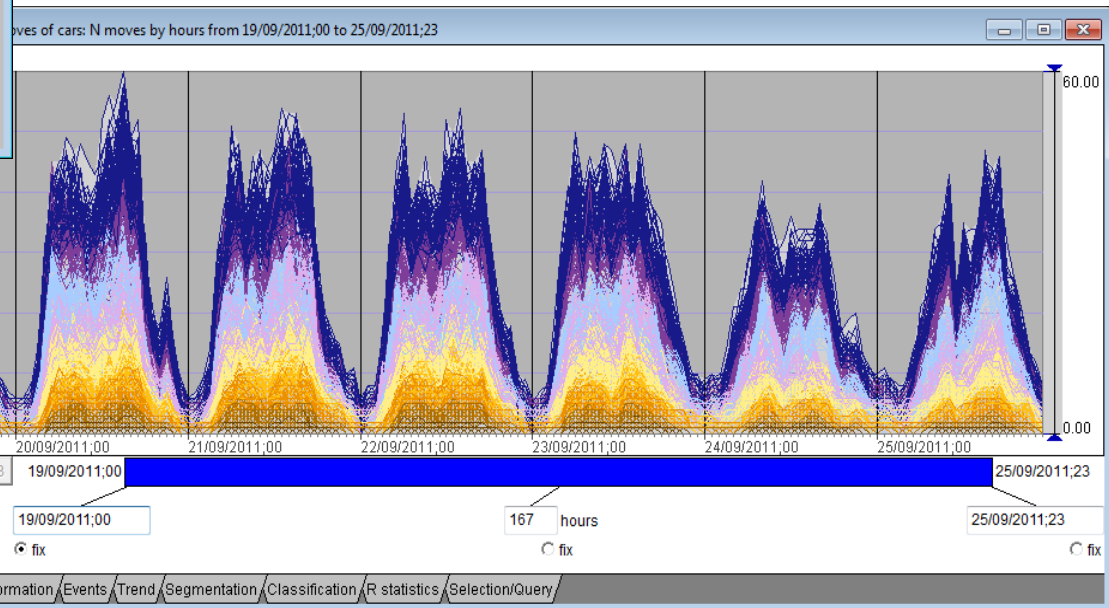
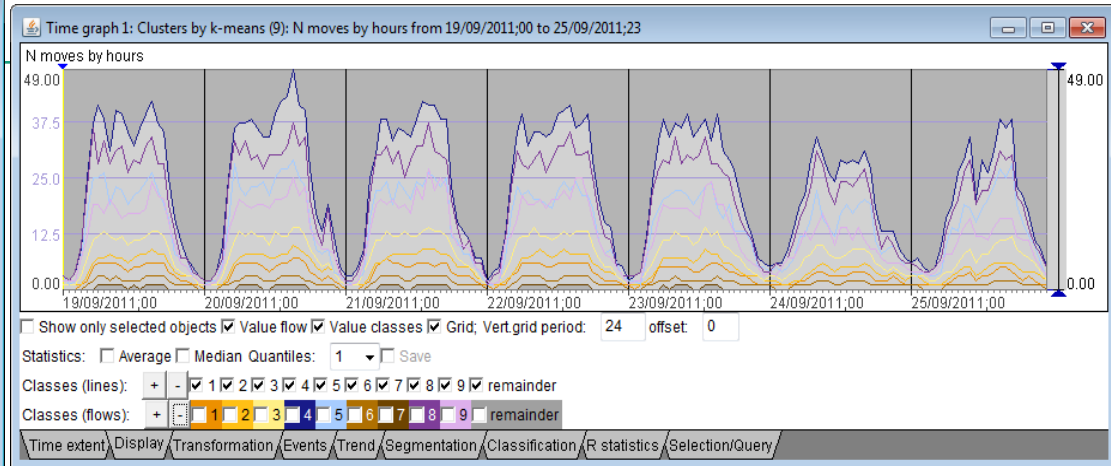
Model name: Variation of N moves by hours: daily and weekly
Modelled attribute: N moves by hours
Objects described by the attribute: Aggregated moves of cars
Object classes: Clusters by k-means (9)
Start time: 01:00H
End time: 07:23H
Number of steps: 168

Time cycle(s):
daily: step length 1 hours; number of steps 24
weekly: step length 1 hours; number of steps 168

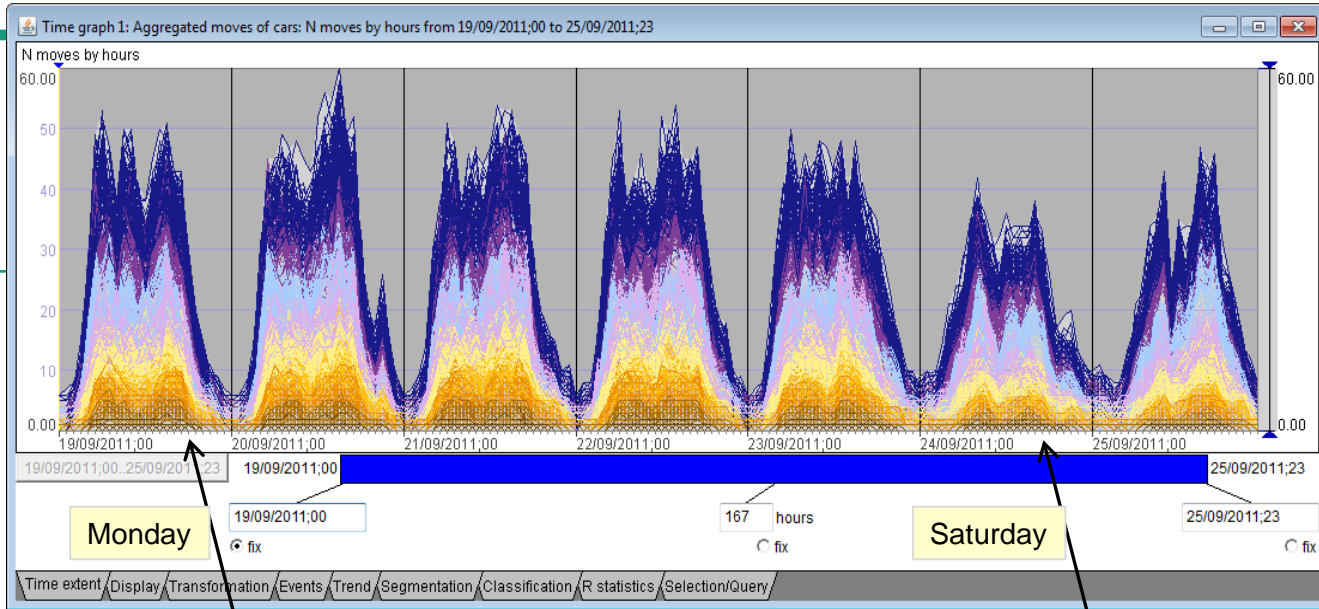
Annotation:
Periodic daily and weekly variation

Specify the time interval for the prediction:
from 19/09/2011,00 to 25/09/2011,23
Date/time template: dd/mm/yyyy;hh (edit if needed)
 Introduce Gaussian noise

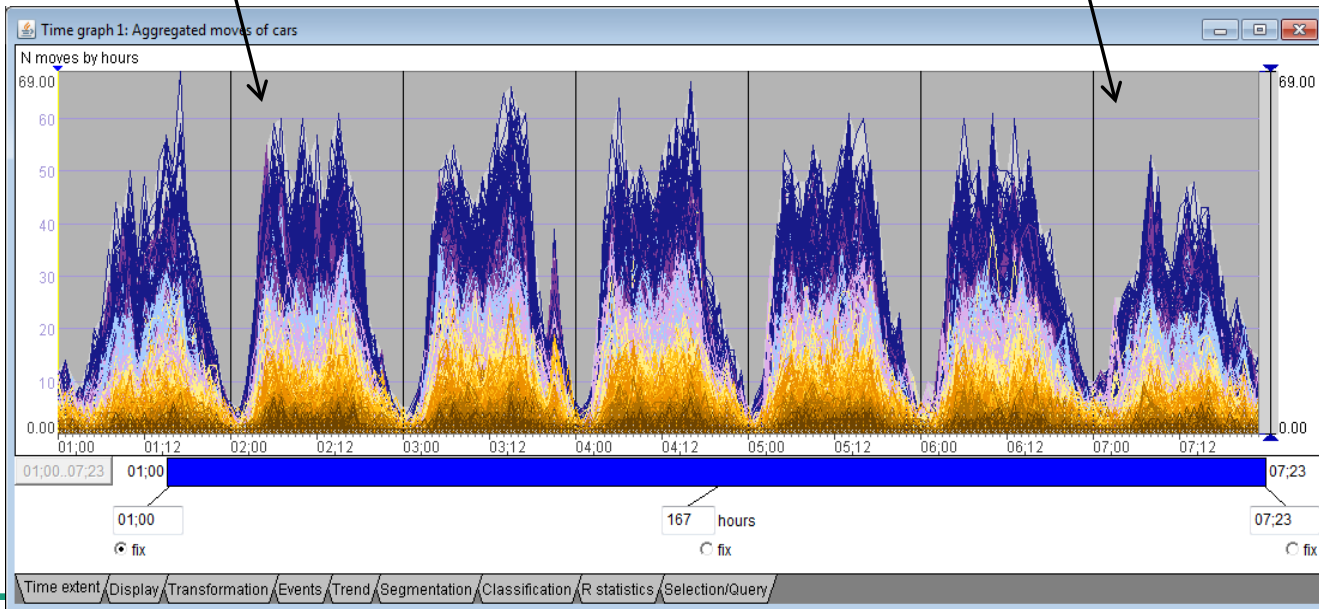
OK Cancel



Predicted:



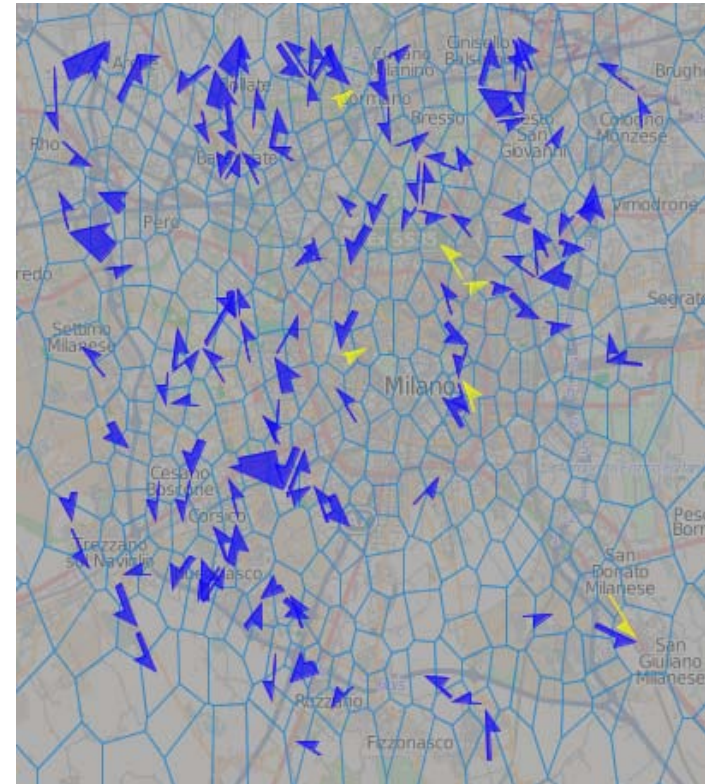
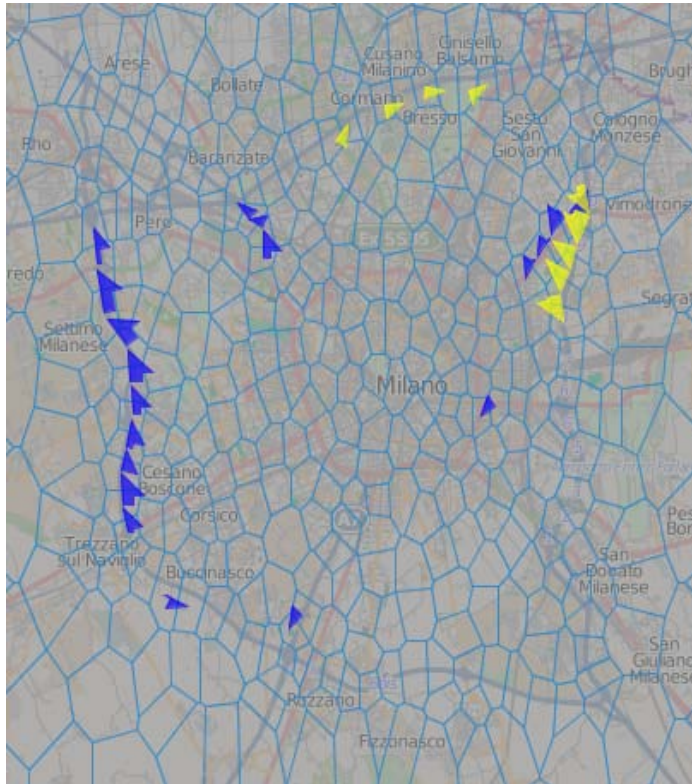
Original:



Comparison of actual values with predicted (e.g., in monitoring)

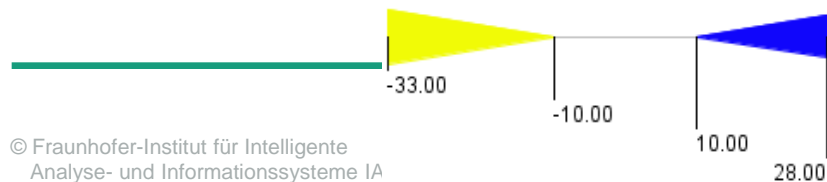
Absolute differences

Normalized differences

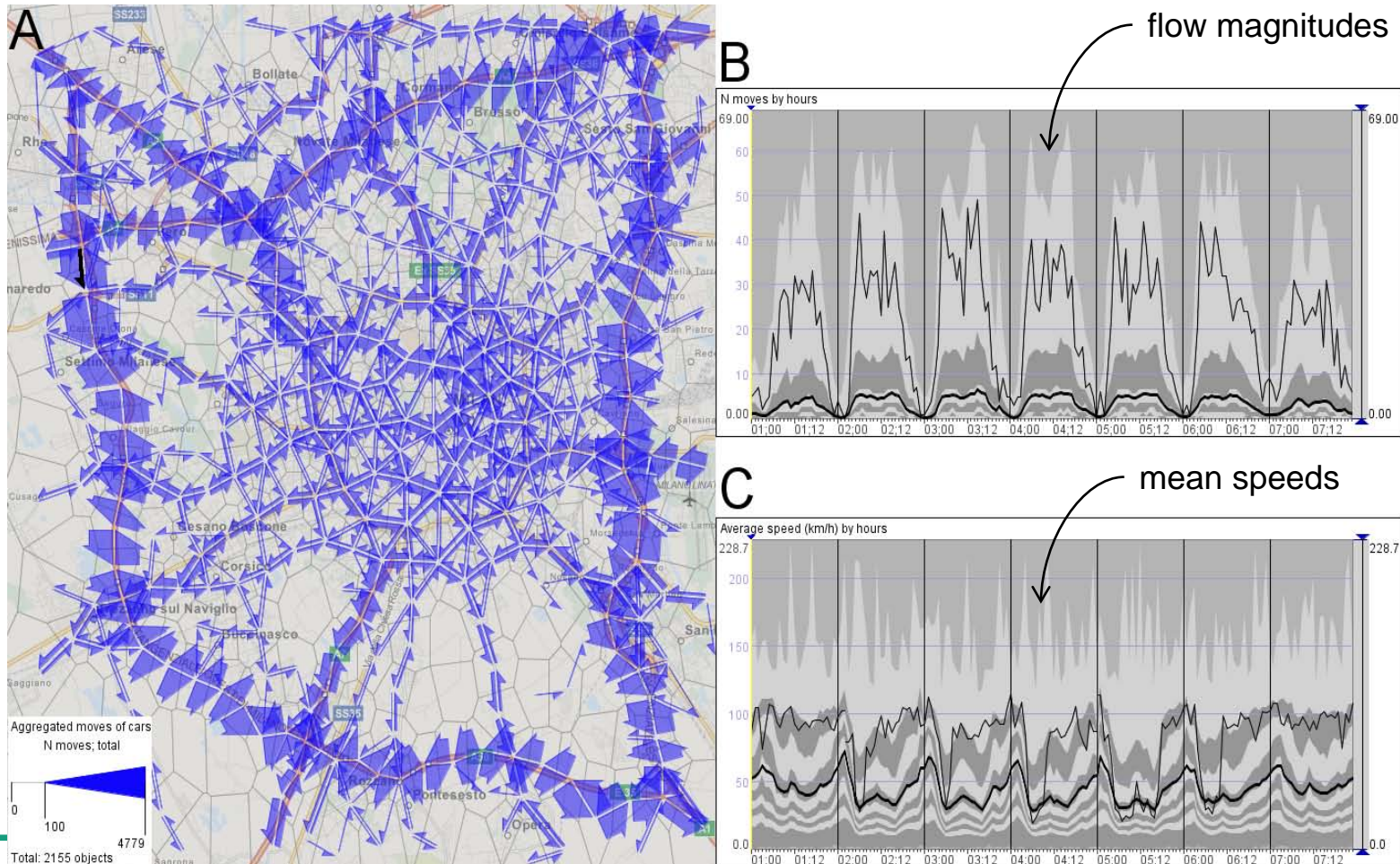


Actual N moves by hours - predicted

Actual N moves by hours - predicted divided by variance of predicted

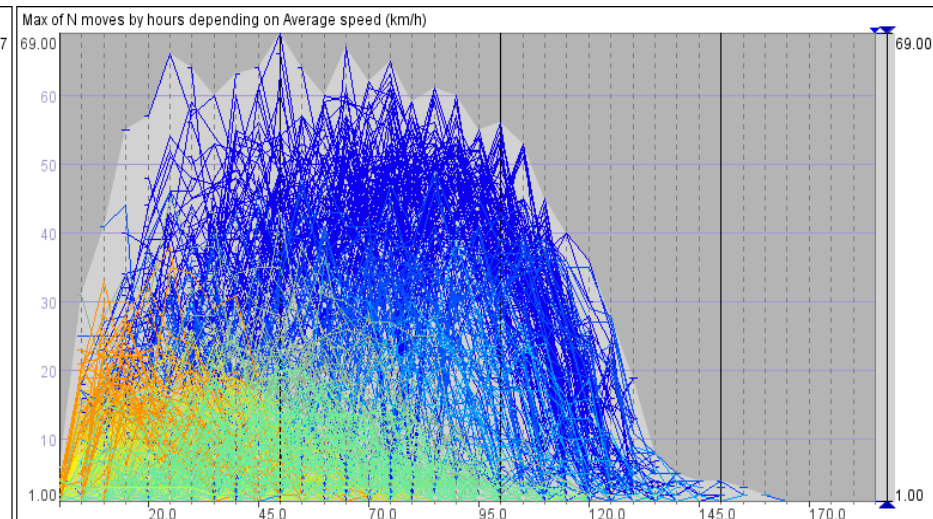
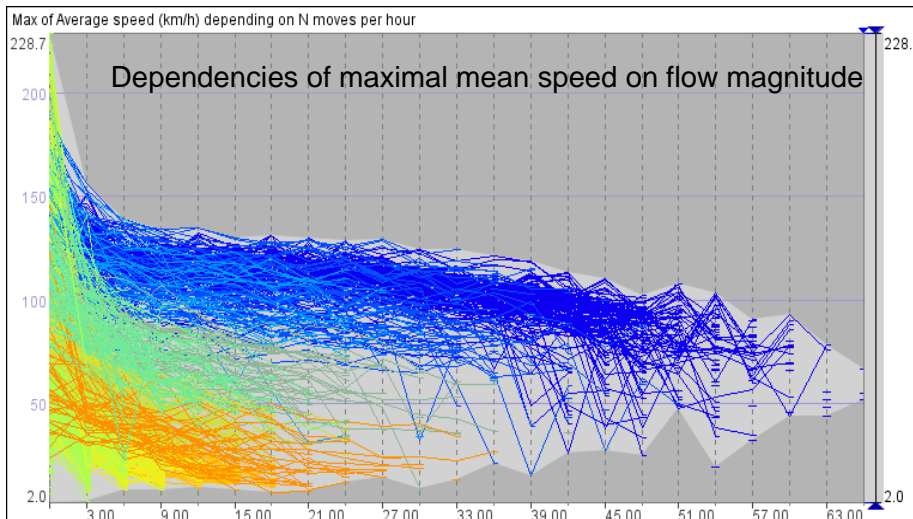
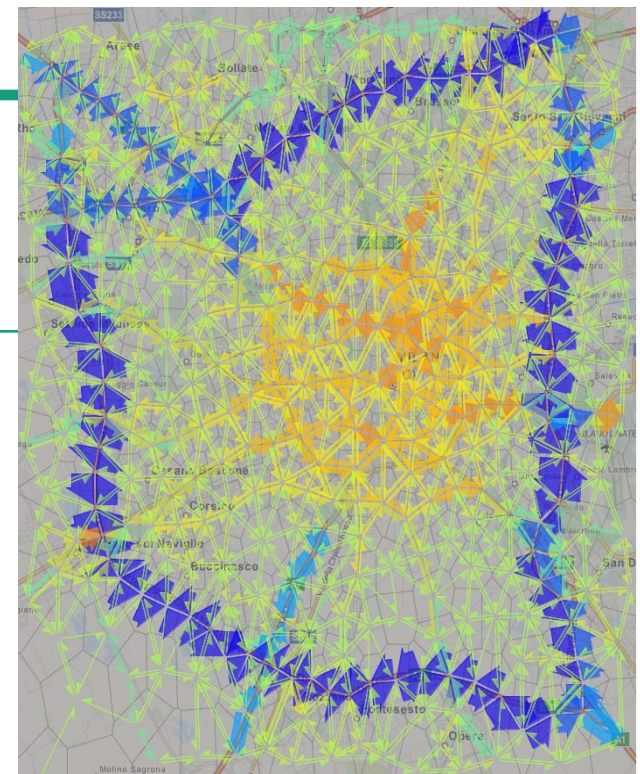


Analysis and modelling of relationships between two time-variant attributes



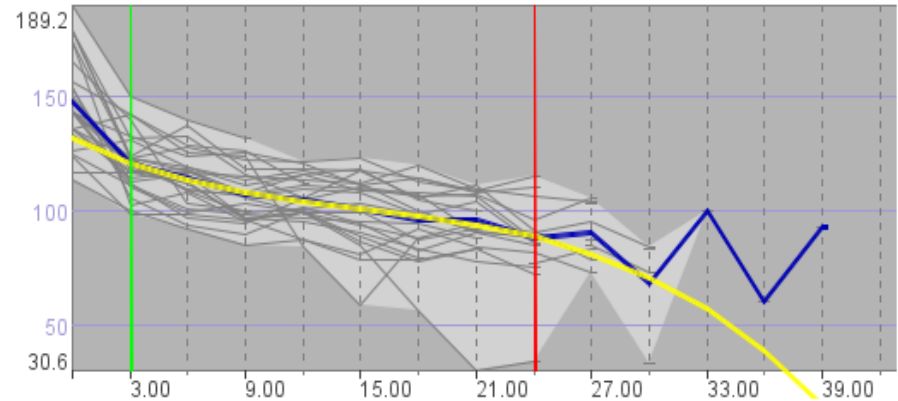
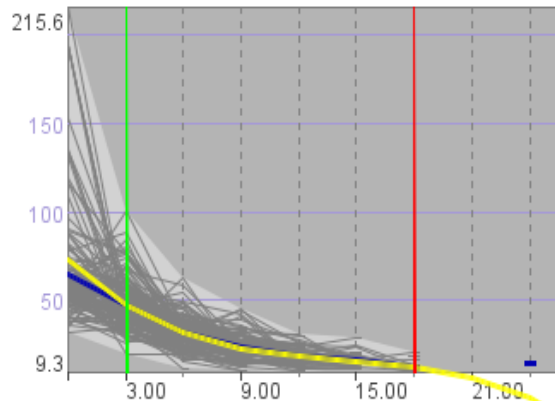
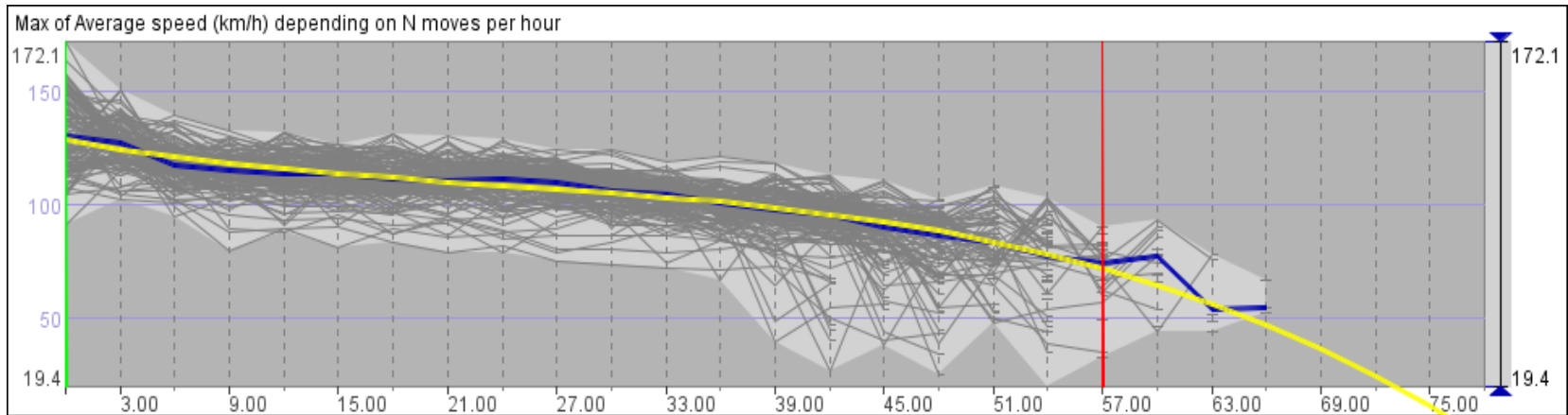
Data transformation and clustering

- Dependency of attribute $A(t)$ on attribute $B(t)$:
 - Divide the value range of B into intervals
 - For each interval, collect all values of A that co-occur with the values of B from this interval
 - Compute statistics of the values of A : minimum, maximum, median, mean, percentiles ...
 - For each of these, there is a series $B \rightarrow A$, or $A(B)$

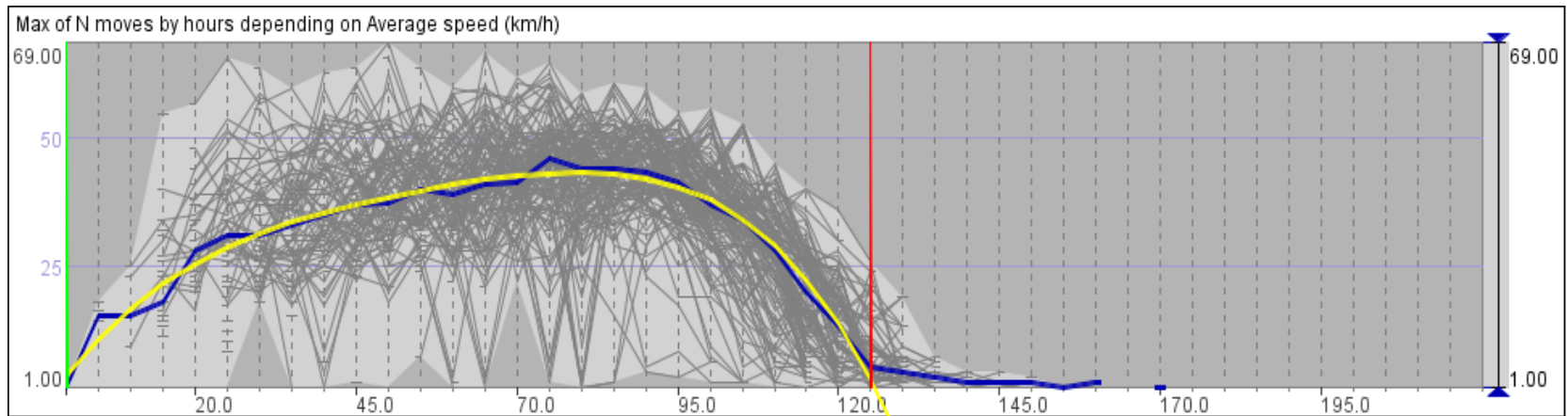


Dependencies of maximal flow magnitude on mean speed

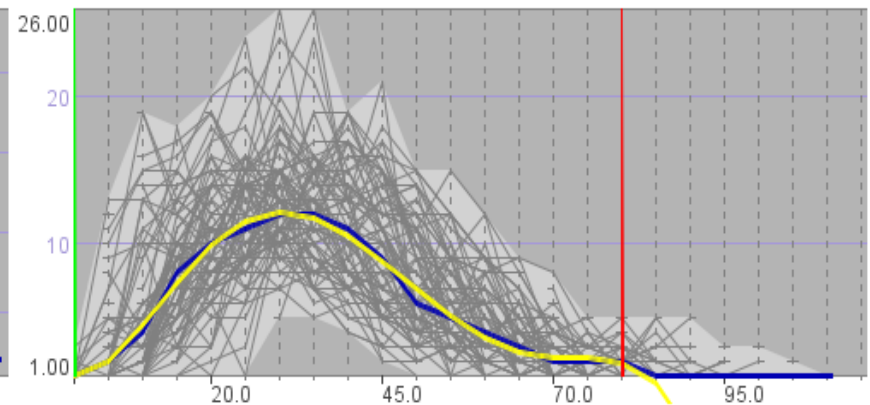
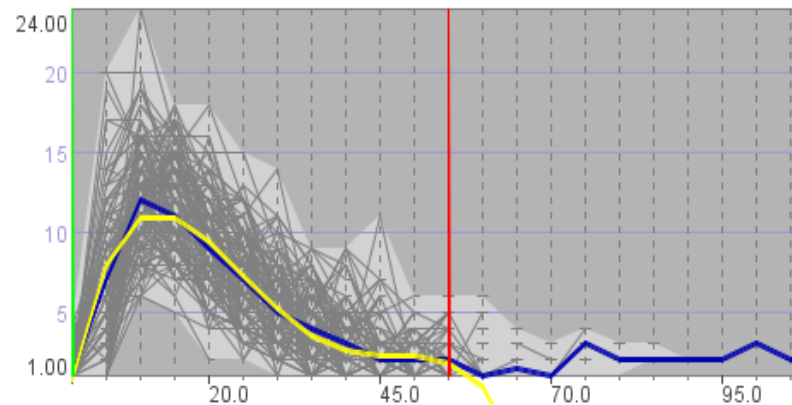
Dependency modelling: flow \rightarrow maximal mean speed



Dependency modelling: mean speed → maximal flow

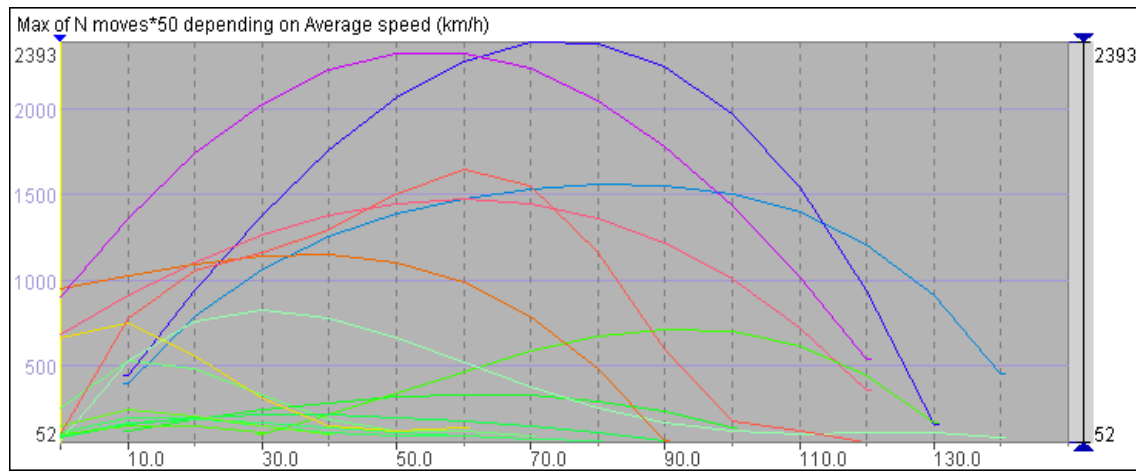
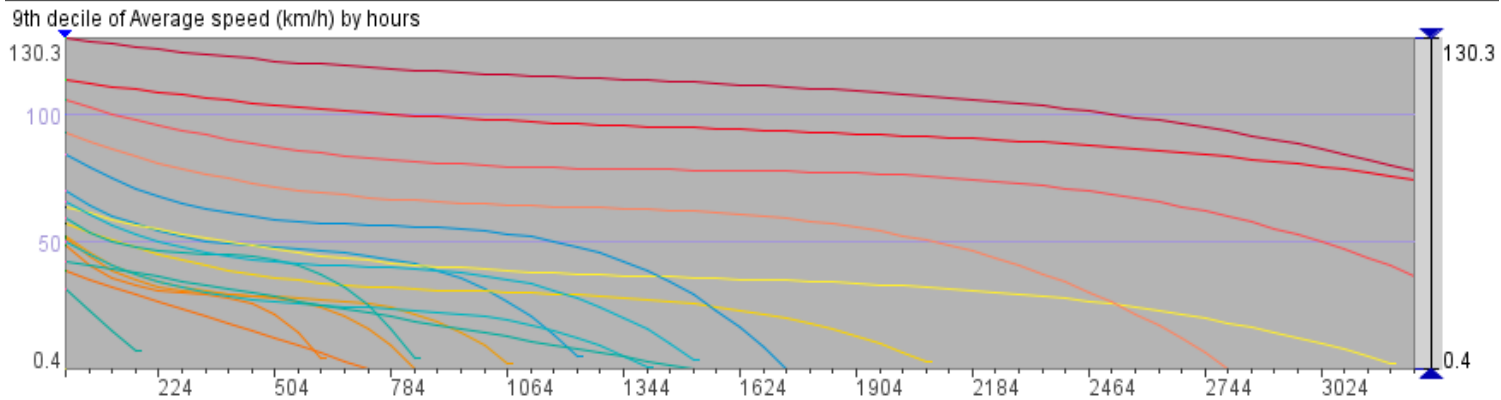


Modelling method: polynomial regression polynomial order = 5



polynomial order = 6

Graphical representation of the models built



Use of the models:

simulation of extraordinary traffic from given places



Set prediction models

The simulation requires the following prediction models:

1. (Place_1, Place_2, Time) -> N of cars
A set of time series models predicting the regular number of moves (flow) from one place to another by time intervals.
Variation of N moves by hours *50: daily and weekly

2. (Place_1, Place_2, N of cars) -> Possible speed
2) A set of dependency models predicting the maximal average speed of moving from one place to another depending on the place link load, i.e., number of cars that try to move.
Variation of Max of Average speed (km/h) depending on N moves

3. (Place_1, Place_2, Possible speed) -> N of cars
A set of dependency models predicting the maximal number of cars (flow) that will be able to move from one place to another within a given time interval depending on the maximal average speed with which the cars can move.
Variation of Max of N moves*50 depending on Average speed (km/h)

Scale factor for the model-predicted values:

Transition times?

Select the attribute defining the transition times.

- Start ID
- End ID
- N of moves
- Length
- Average move duration (minutes); total**
- Average speed (km/h); total
- Average path length; km
- Average path length ratio to link length
- N trajectories; total *50
- N moves; total *50

Use the weights of the links defined by the attribute:

- Length
- Average move duration (minutes); total
- Average speed (km/h); total
- Average path length; km
- Average path length ratio to link length
- N trajectories; total *50
- N moves; total *50
- Average N moves by hours *50**
- Median of N moves by hours *50
- Max N moves by hours *50

Distribute moving objects

Step 2 of the simulation:

Distribute moving objects among the destinations and routes

A given number of moving objects will be distributed among the possible destinations, i.e., places from the layer Places. The places need to have weights defined by some numeric attribute.

Select the attribute defining the weights:

- N visits
- N starts
- N ends
- N visitors total
- N visits total
- N ends after 18:00**

The number of moving objects in the selected place(s) of origin:

In place 171:	<input type="text" value="3000"/>
In place 134:	<input type="text" value="4000"/>
In place 224:	<input type="text" value="3000"/>

The given number of objects will be distributed among the 3 selected places of origin.

Check the link loads

Re-route traffic?

Please check if the expected link loads are reasonable. If not, it may be desirable to re-route a part of the traffic to other links, if possible.

This is modelled by modifying the link weights.

If you decide to do so, modify the weights or choose another attribute defining the weights and press "Re-compute routes".

Otherwise, press "Continue with current routes".

Re-compute routes **Continue with current routes** **Stop the process**

The bottlenecks can be revealed even before the simulation

Qualitative colouring

Possible paths from 171, 134, 224 (12/06/2012 16:19:31): general data

Origin

- 134: 624 objects (35.7%)
- 171: 615 objects (35.2%)
- 224: 510 objects (29.2%)

Total: 1749 objects

Marks of the places of the origin of the simulated extra traffic

Total: 3 objects

Flows of cars

Representation method: Line thickness

Flows of cars

Expected link load

0 3574

Total: 2155 objects

Places

Total: 451 objects

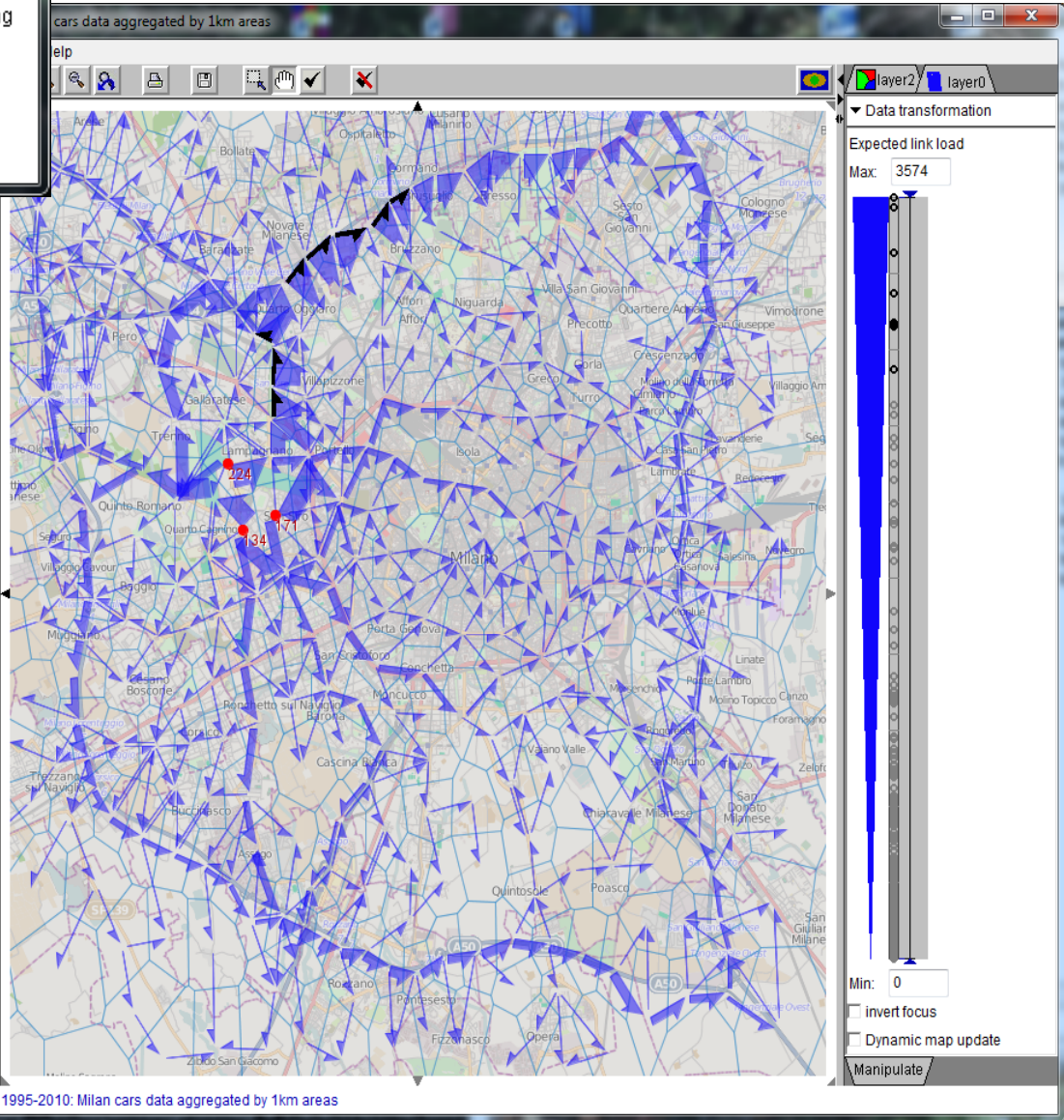
Open Street Map

Total: 0 objects

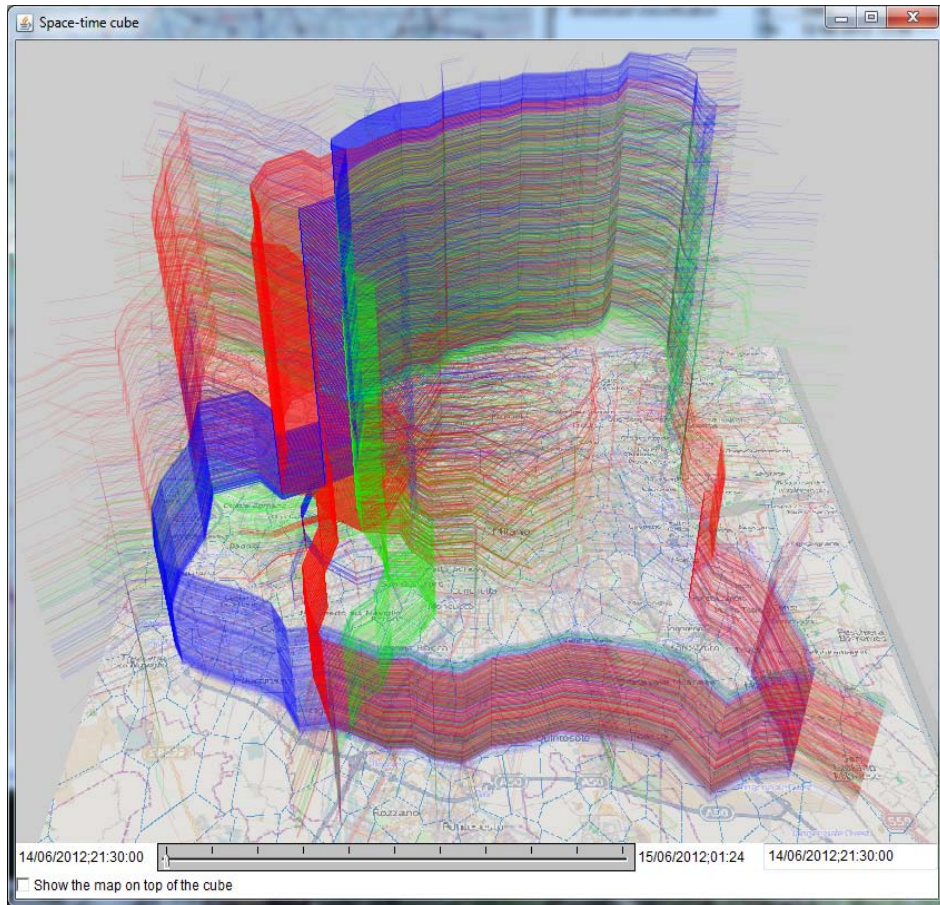
Territory: Milan, Italy

Background

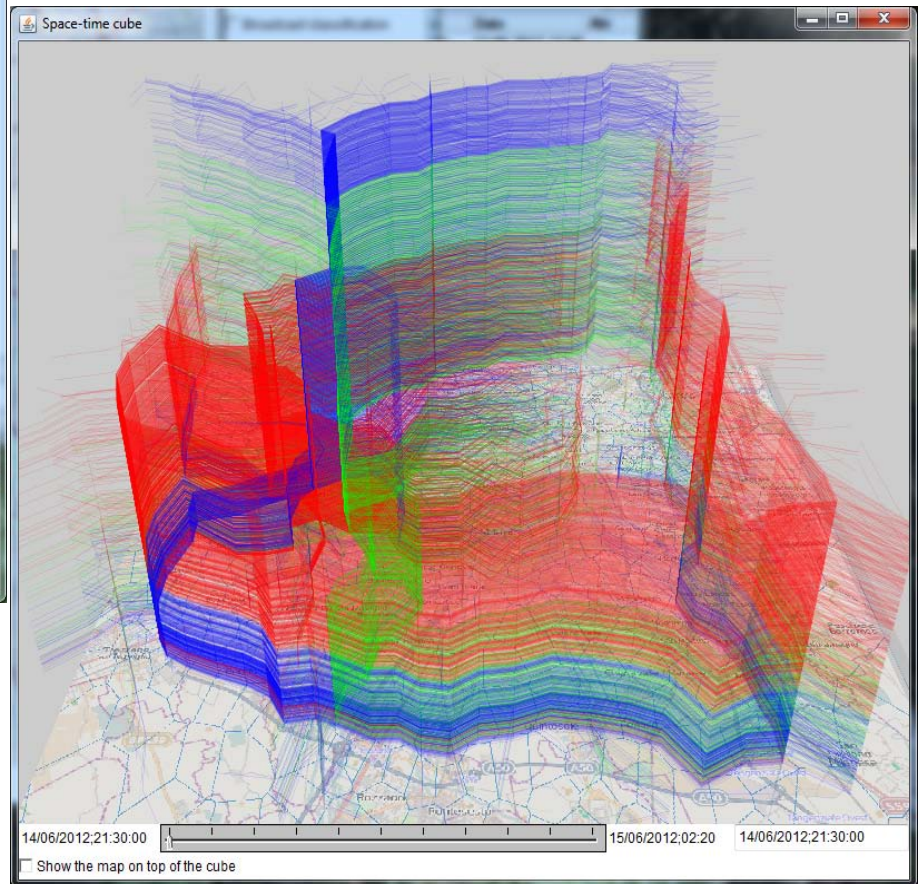
1.015 km



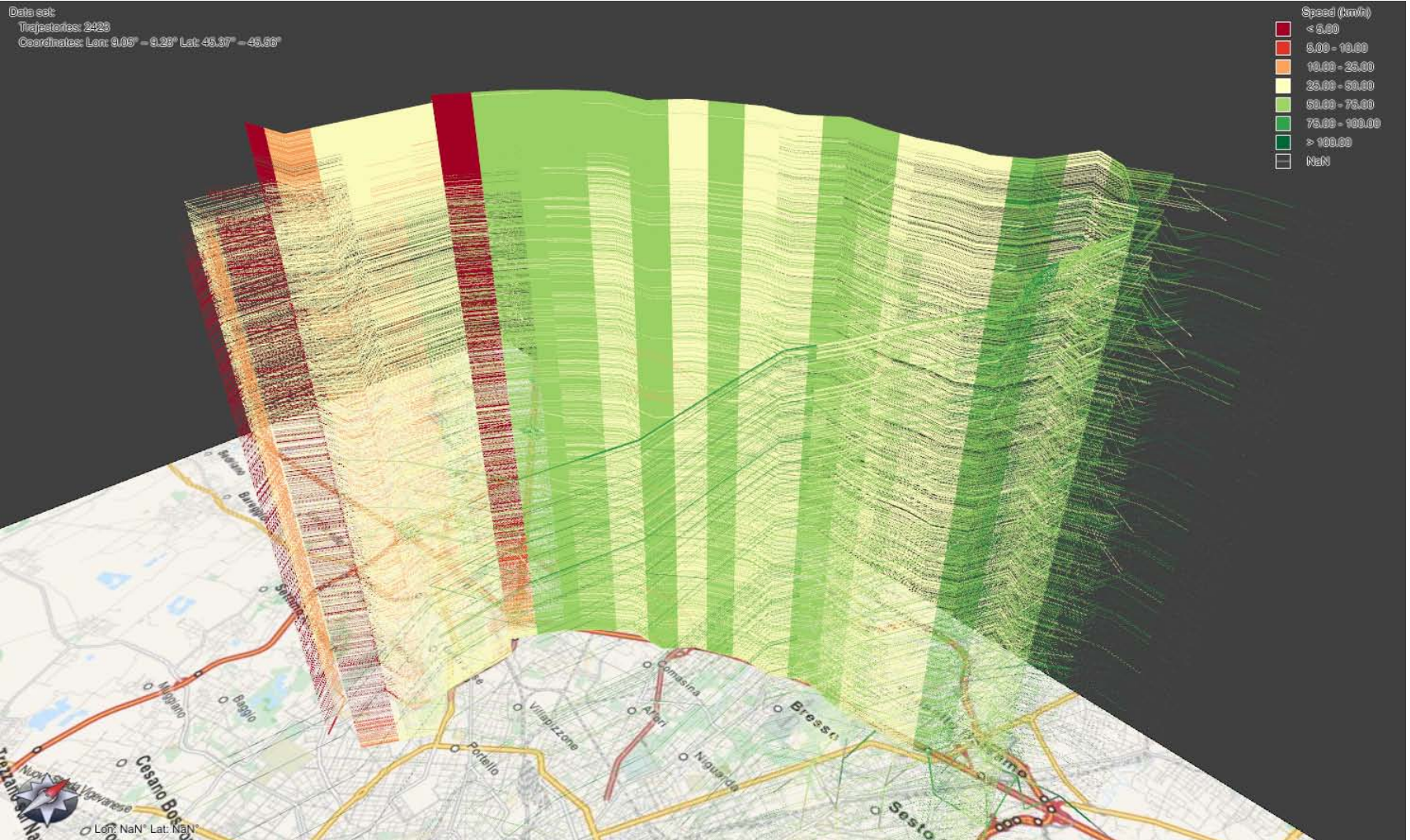
Simulated trajectories



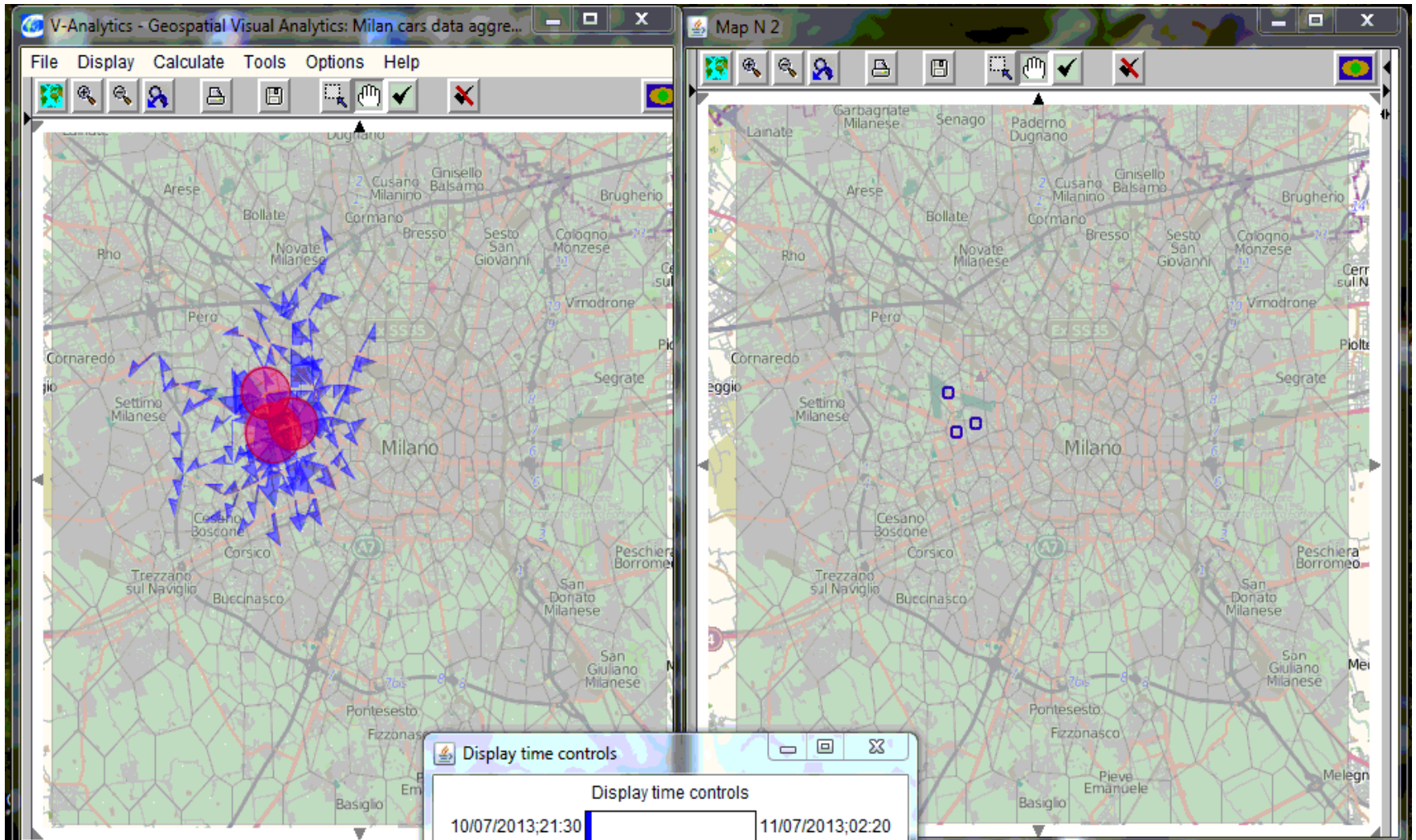
Some traffic re-routed to the south:



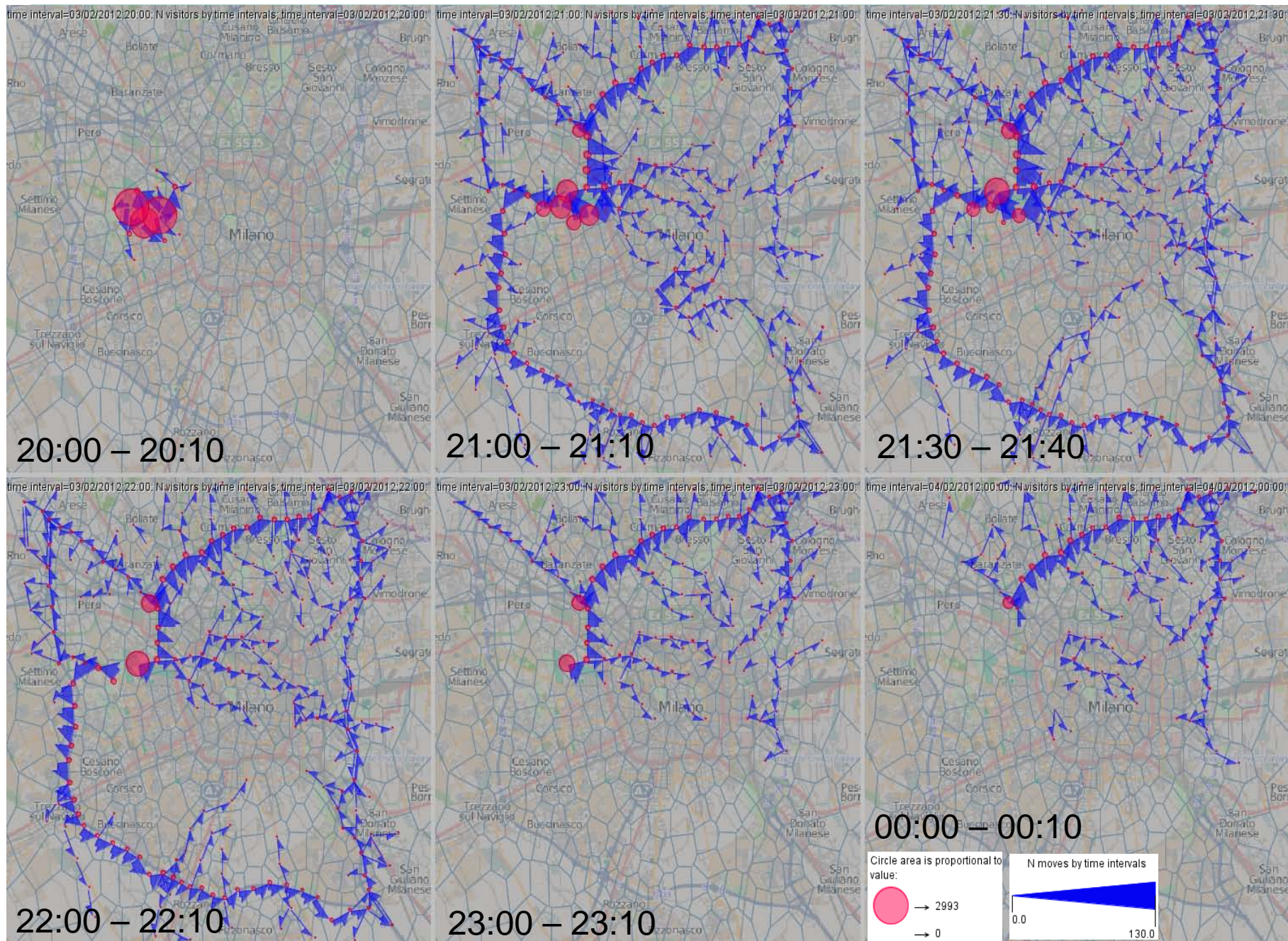
The speeds on the northern motorway



Animation of simulation results

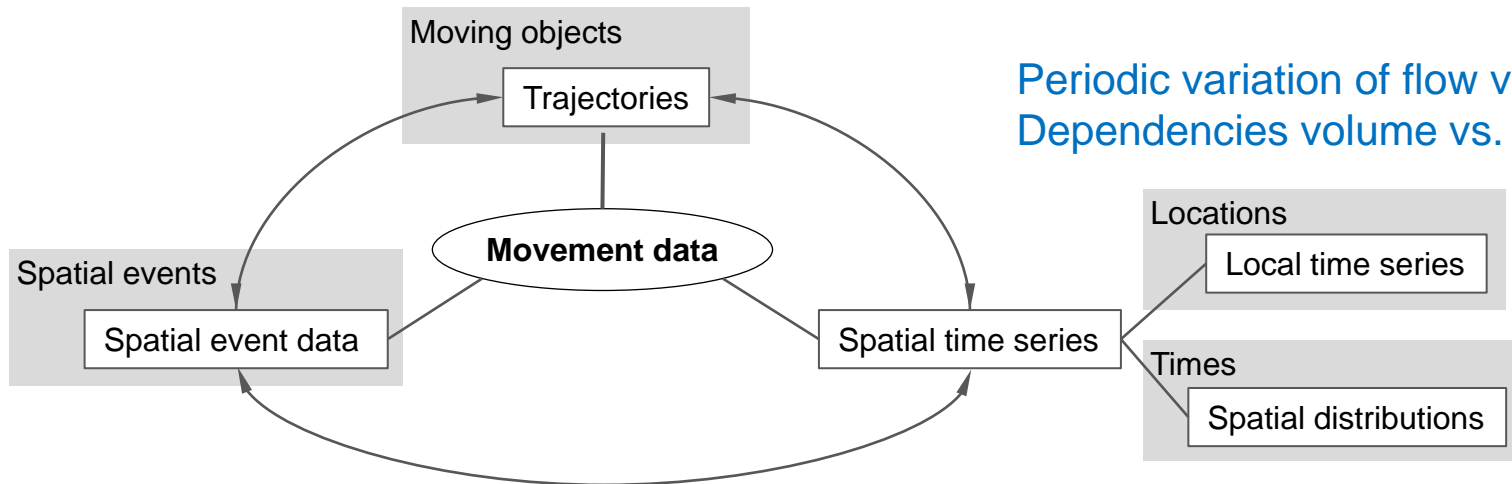


Presence and flows for selected time intervals



Multi-perspective analysis of movement

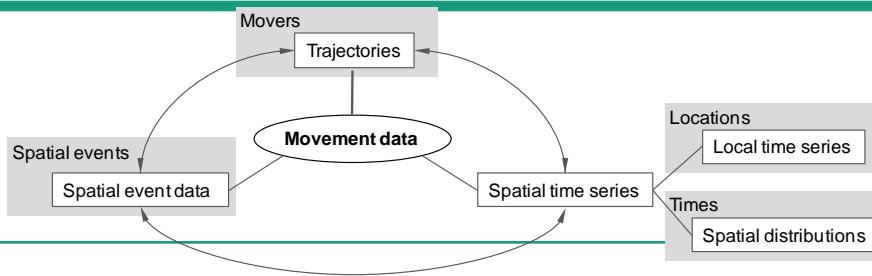
Trip destinations, routes...



Periodic variation of flow volumes;
Dependencies volume vs. speed

Low speed events → traffic jams

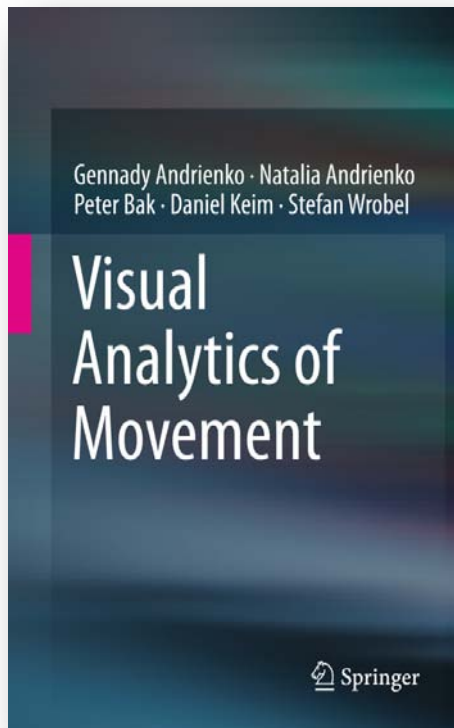
Periodic (daily and weekly)
variation of spatial situations



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397 p. 200 illus., 178 in colour



Ch.1. Introduction

Ch.2. Conceptual framework

Ch.3. Transformations of movement data

Ch.4. Visual analytics infrastructure

Ch.5. Visual analytics focusing on movers

Ch.6. Visual analytics focusing on spatial events

Ch.7. Visual analytics focusing on space

Ch.8. Visual analytics focusing on time

Ch.9. Discussion and outlook