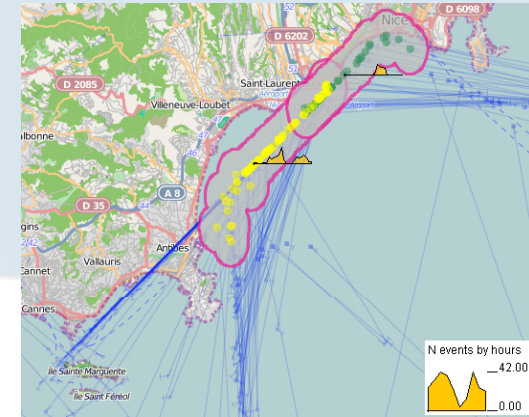
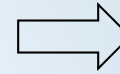
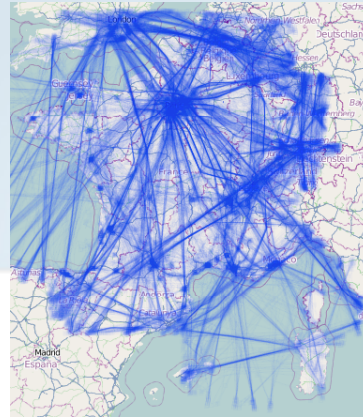


From Movement Tracks through Events to Places: Extracting and Characterizing Significant Places from Mobility Data

Gennady Andrienko, Natalia Andrienko,
Christophe Hurter, Salvatore Rinzivillo, Stefan Wrobel

<http://geoanalytics.net/and>

Why Visual Analytics



- Places are to be identified from data;
 - Unknown size and shape; places may overlap
- Huge amounts of imprecise and incomplete complex data
 - Moving objects trajectories of variable duration with varying sampling rate
- Human intelligence is needed to control and guide the analysis process
 - Scalable computations
 - Intelligent visualizations

General Analytical Procedure

Extract relevant movement events

Find significant places

Aggregate events by significant places

Analyze spatio-temporal aggregates

Find dense spatial clusters of events, taking into account time and attributes

Surround clusters with spatial buffers

Events, trajectories
→ places + time series of attribute values

Trajectories → flows between places

•Flow = vector <place 1, place 2> + time series of attribute values

Examples of movement events (m-events)

- Stop or low-speed driving
- Turn
- High acceleration
- Take-off / landing of an aircraft
- Meeting of two or more moving objects
- Driving late at night
- Stop at a place of interest
- Leaving stadium after a football game
- High heart rate {during jogging}

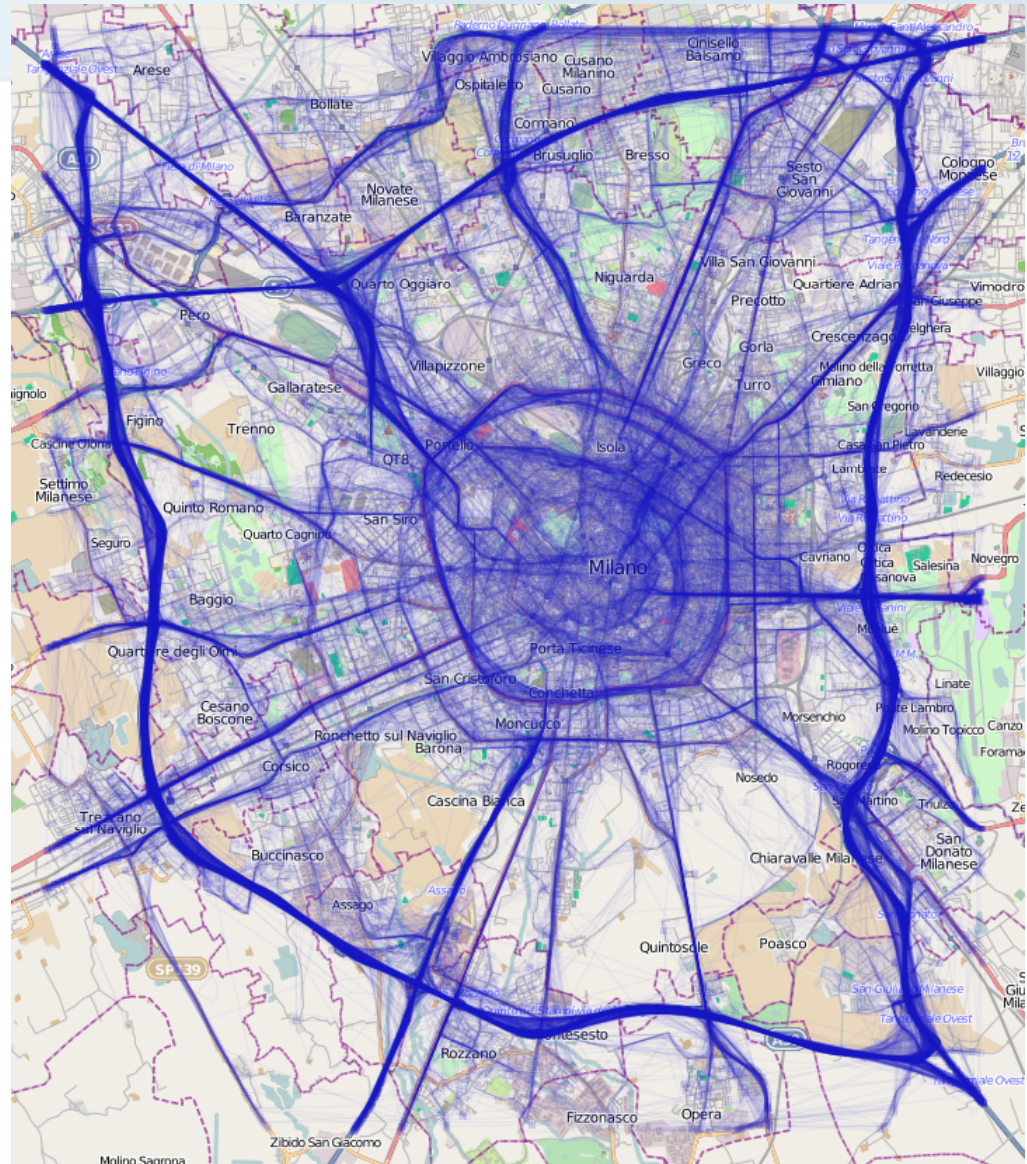
m-events are defined based on attributes

- Instant speed, travelled path in time window / from the beginning of the trip
- Heart rate, body temperature...
- Time of day, day of week of trajectory points
- Relationship to places, spatial objects, and events measured as
 - Spatial distance to n^{th} nearest place/object
 - Temporal distance to n^{th} nearest event
 - Neighborhood (counts of objects or events in given S,T,ST windows)

Example 1: detection and analysis of places of traffic congestions in Milan

- 8,206 GPS-tracks of cars in Milan, Italy; 235,448 points
- Collected during one day: Wednesday, the 4th of April, 2007
- Received from Comune di Milano (Municipality of Milan)

The trajectories are drawn on a map with 5% opacity

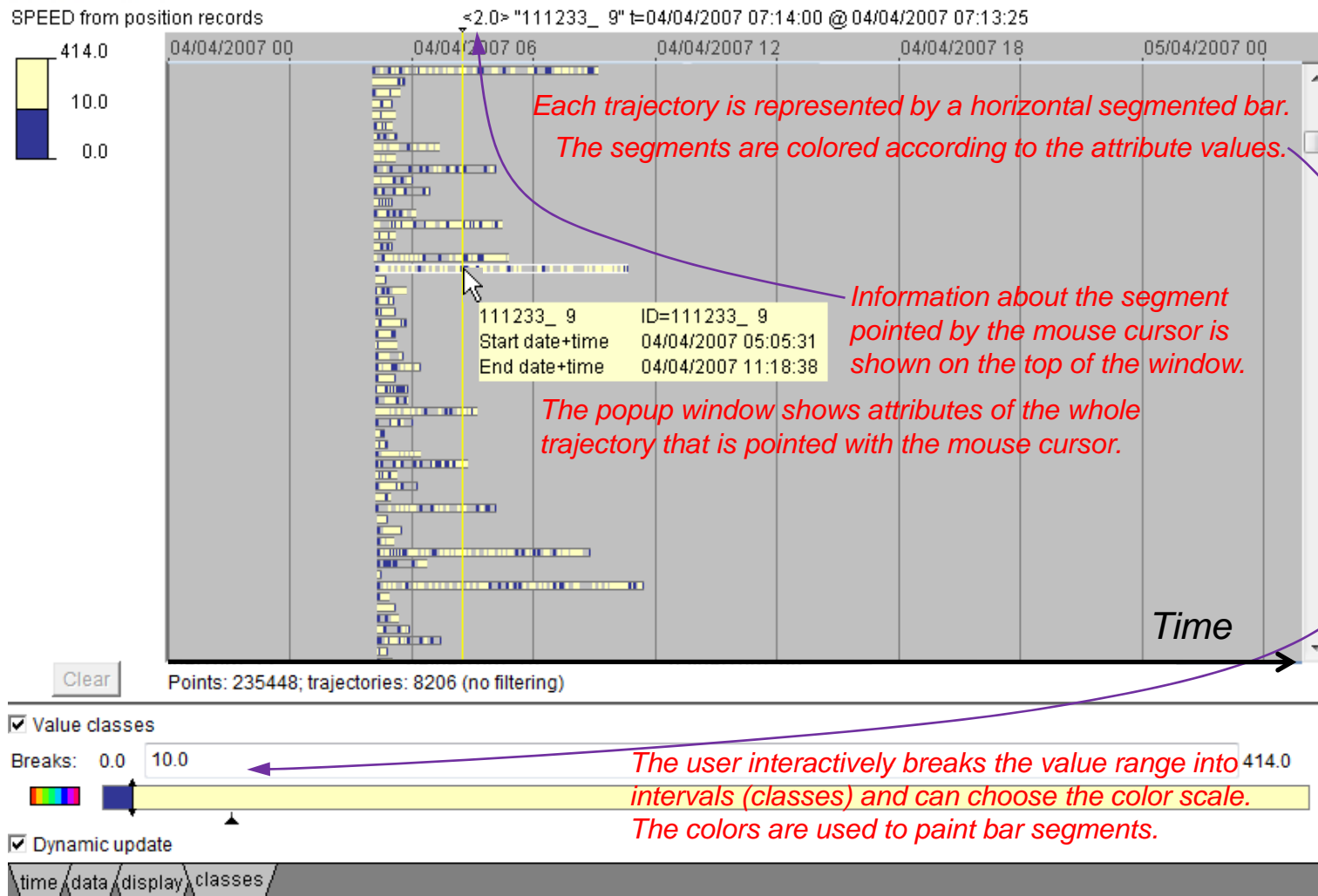


Step 1: extraction of relevant events

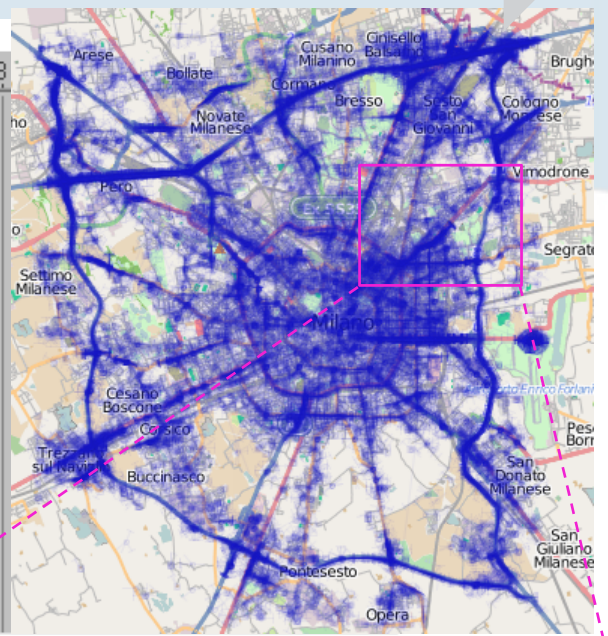
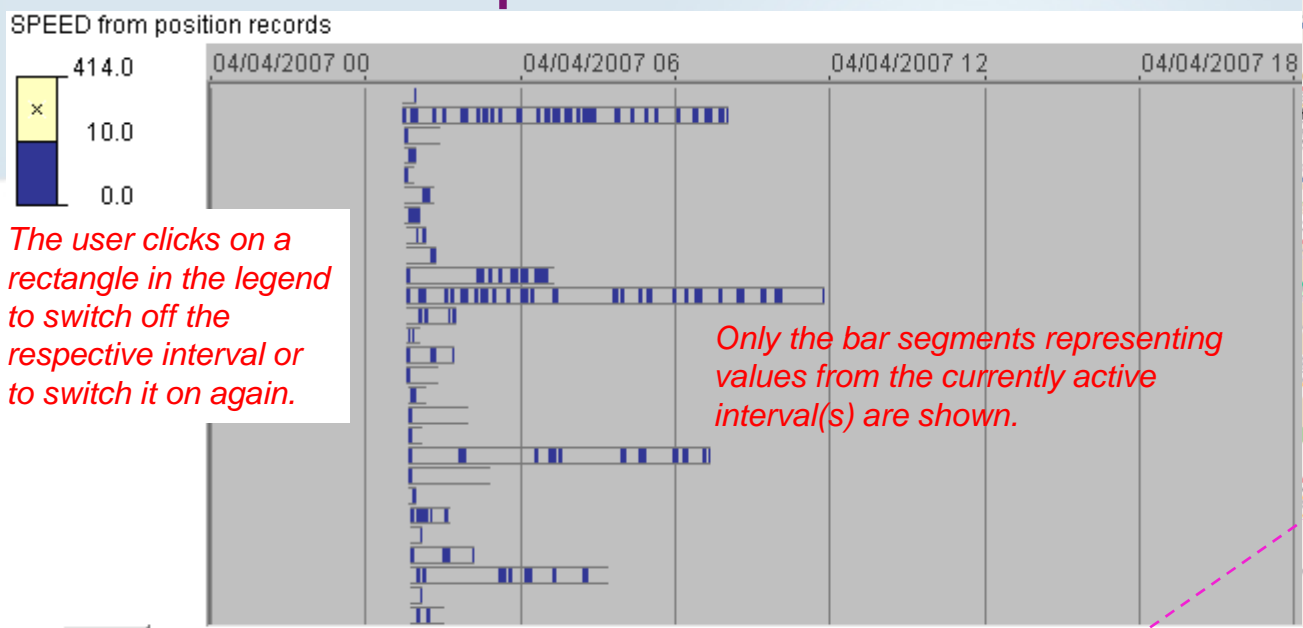


- Relevant events = low speed events (e.g. speed \leq 10 km/h)

Extracting m-events from trajectories: interactive operations



Extracting m-events from trajectories: interactive operations



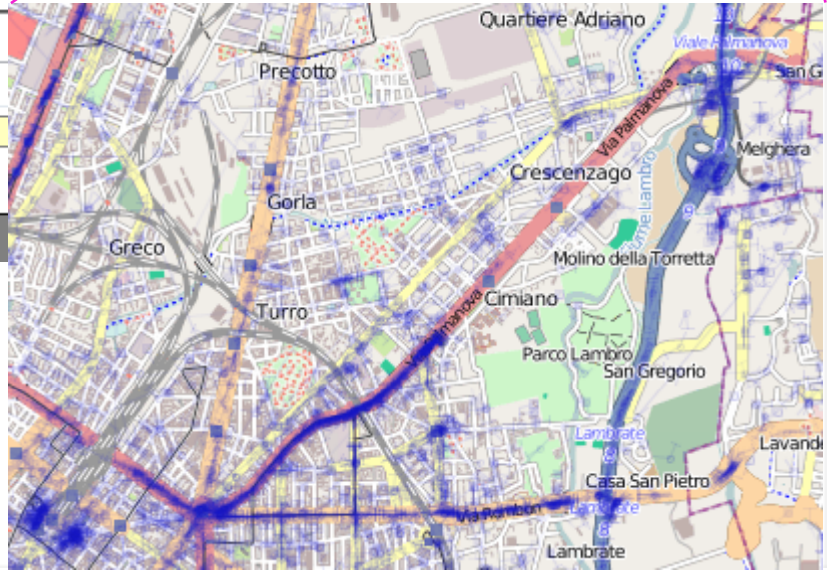
Clear Points: 235448-53543-53543; 100%-22.7%-22.7%. Segments: 8206-31747-31747. Trajectories: 8206-7525-7525; 100%-91.7%-

Value classes

Breaks: 0.0 10.0

Dynamic update

time data display classes

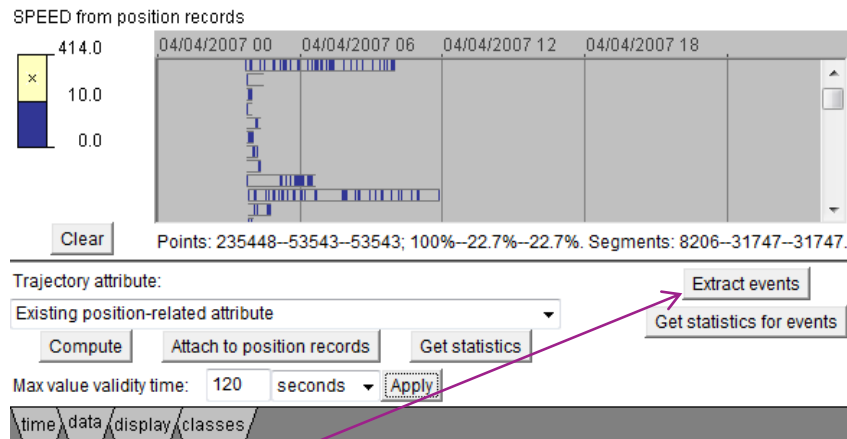


The map shows only the points and segments of the trajectories where the values of the dynamic attribute satisfy the filter.

Here we see the points and segments where the speed was not more than 10 km/h.

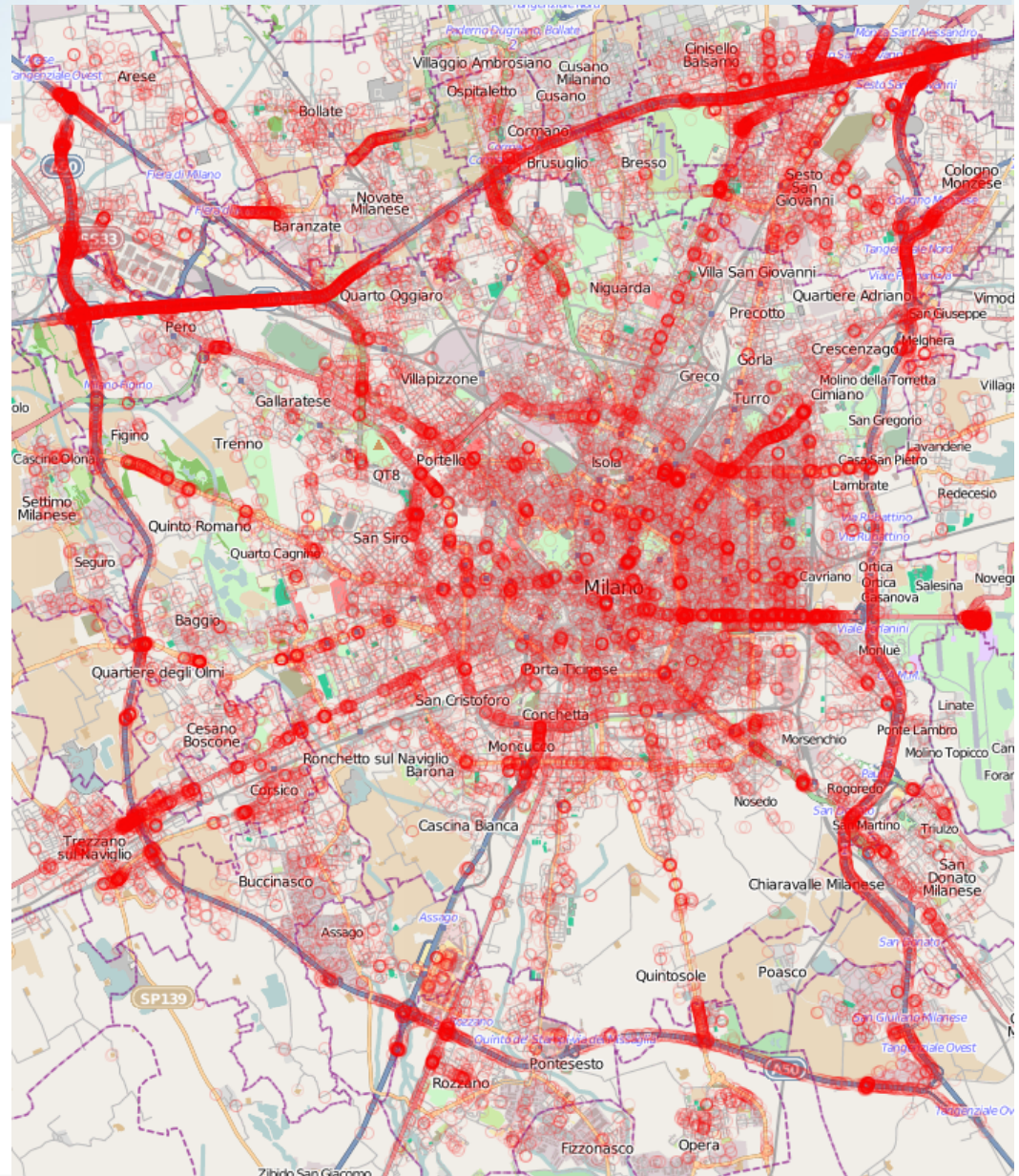


Extraction of relevant movement events



This button in the “data” tab allows the user to extract m-events from the trajectories according to the current segment filter. The extracted events are organized in a new dataset consisting of points and multi-points with time references and attributes.

The map shows the extracted low speed events as an independent map layer. The m-events are represented by red hollow circles.



Step 2: determination of the relevant places



- Relevant places = areas where traffic congestions occurred

To distinguish low speed events caused by probable traffic congestions from occasional low speed events, we first find STD-clusters (Space, Time, Direction) of low speed events:

many events close in space and time and having similar direction \Rightarrow traffic congestion

Clustering

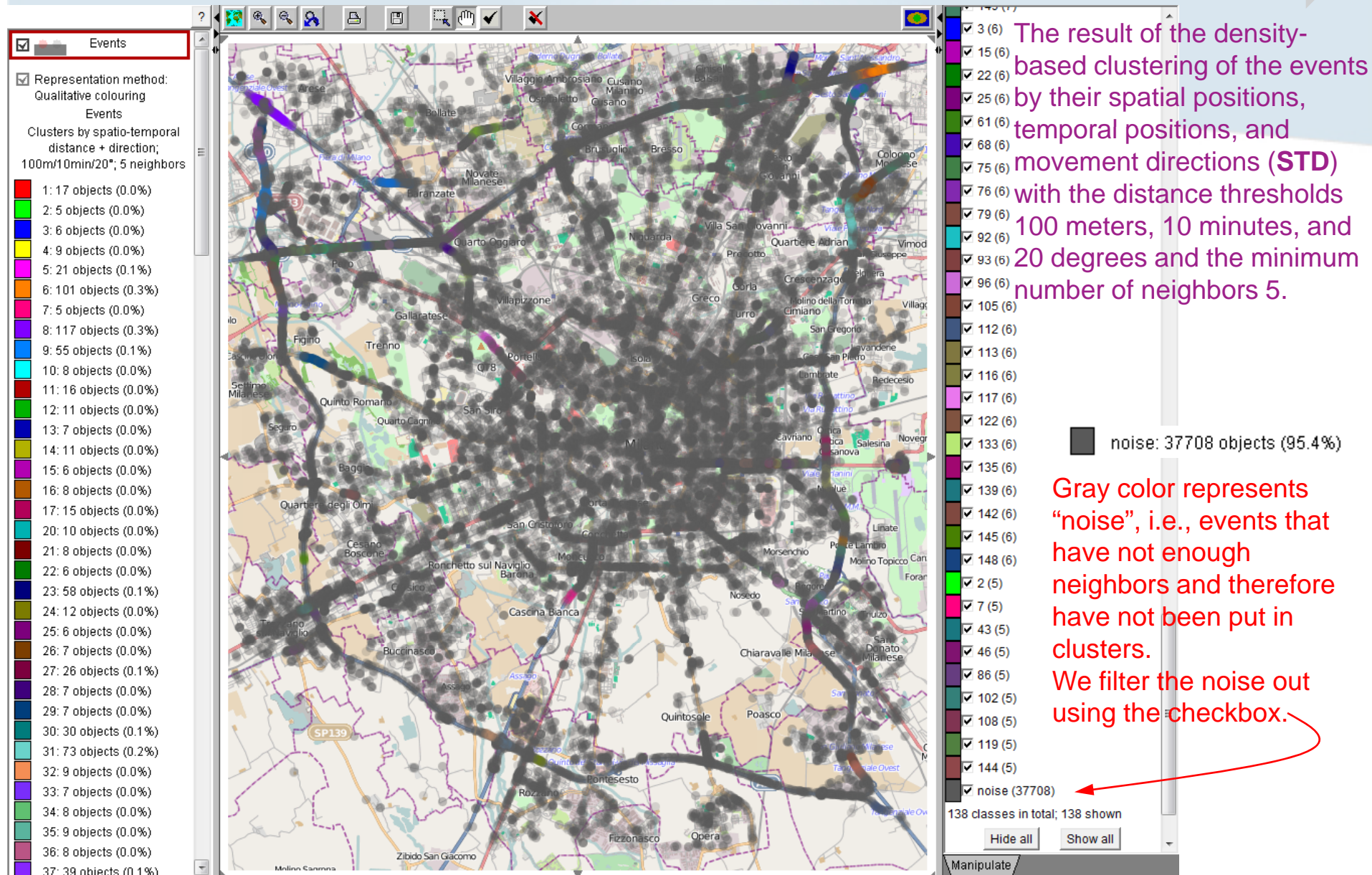
- Density based clustering of points (Optics, DBScan) with appropriate distance function (similarity measure)

$$d_t(t_1, t_2) = \begin{cases} t_2^{start} - t_1^{end} & \text{if } t_1^{end} < t_2^{start} \\ t_1^{start} - t_2^{end} & \text{if } t_1^{start} > t_2^{end} \\ 0 & \text{otherwise} \end{cases} \quad (1) \quad - \textit{time}$$

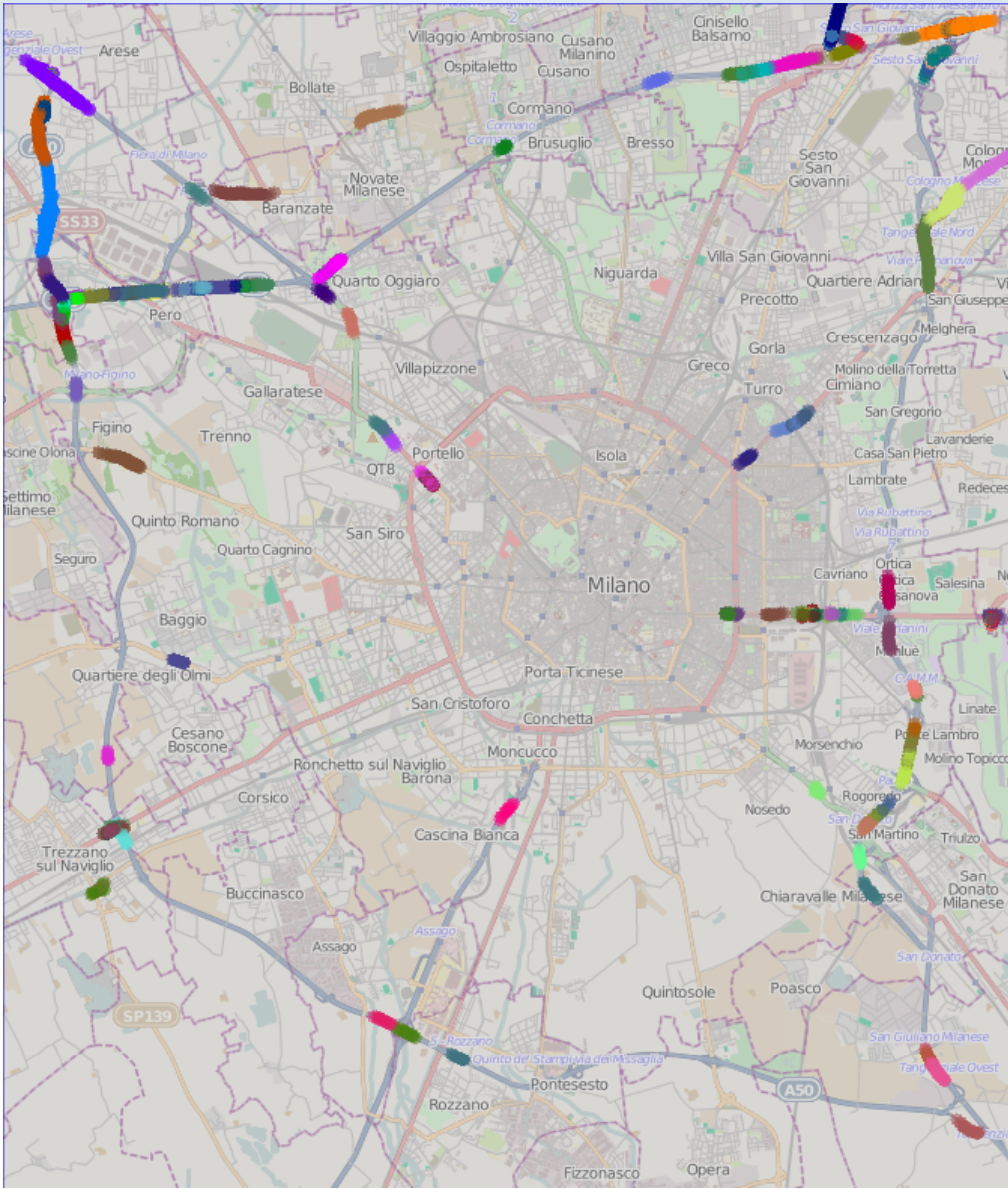
$$d(v_1, v_2, V) = \begin{cases} |v_1 - v_2|, & |v_1 - v_2| < V/2 \\ V - |v_1 - v_2|, & \text{otherwise} \end{cases} \quad (2) \quad - \textit{cyclic attrs}$$

$$d = \begin{cases} \infty, & \text{if } (d_s > D_s) \text{ or } \exists i \mid (d_i > D_i), \quad i = 0..n \\ D_s * \max\left(\frac{d_s}{D_s}, \frac{d_0}{D_0}, \dots, \frac{d_n}{D_n}\right), & \text{if (a)} \\ D_s * \sqrt{\left(\frac{d_s}{D_s}\right)^2 + \sum_{i=0}^n \left(\frac{d_i}{D_i}\right)^2}, & \text{if (b)} \end{cases} \quad (3)$$

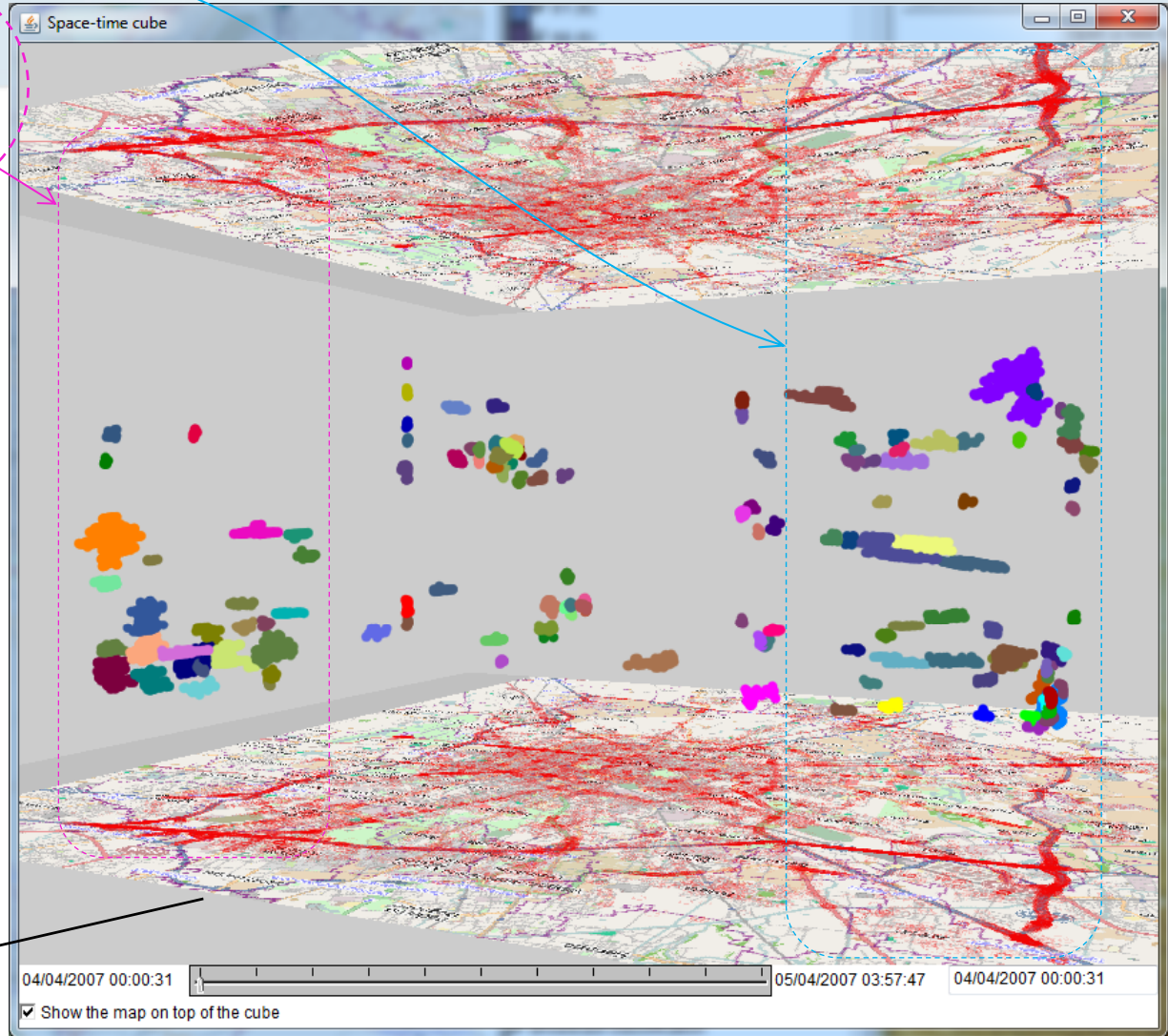
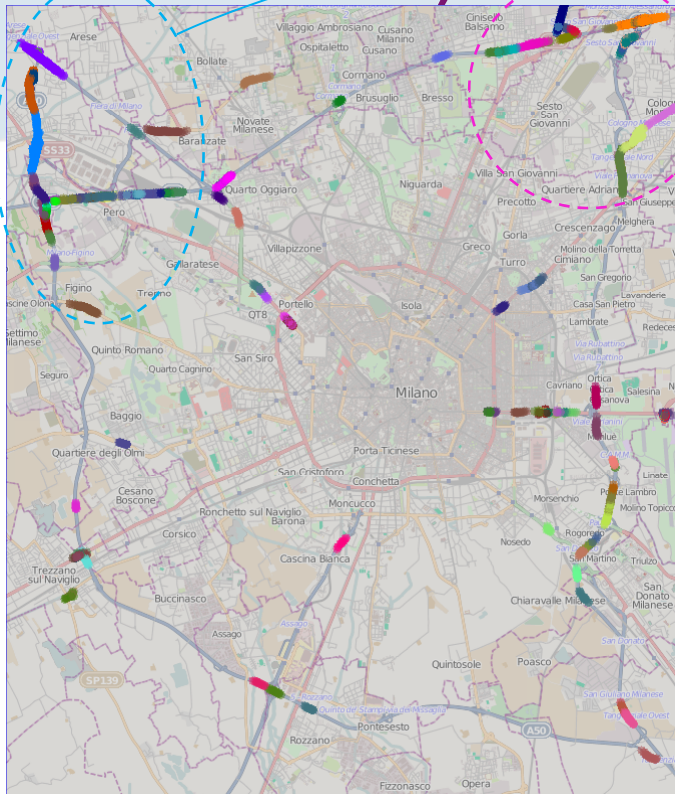
STD-clustering of the m-events



STD-clusters of m-events (noise excluded)



STD-clusters of m-events (noise excluded)

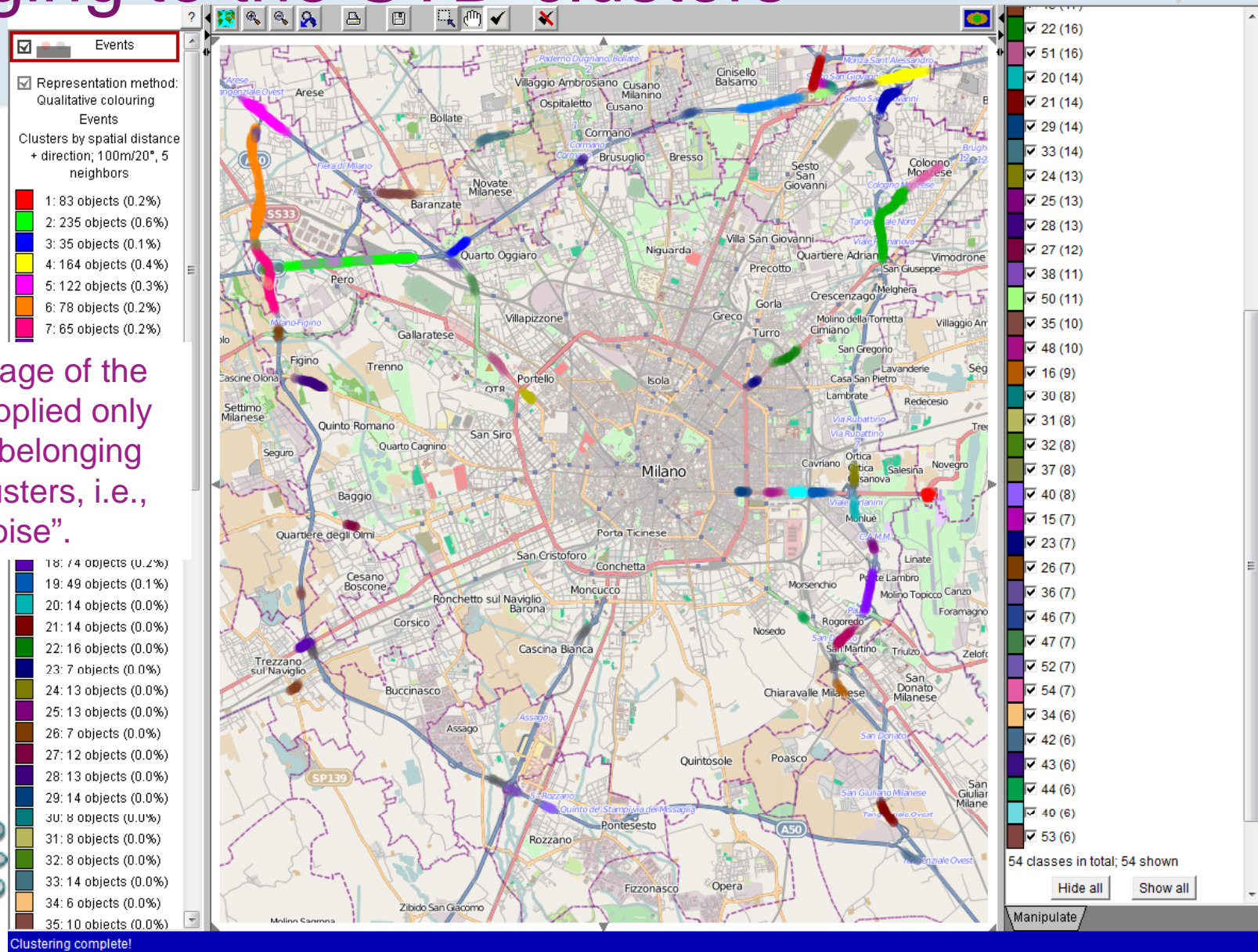


The space-time cube is viewed from the north.

North



SD-clustering of the m-events belonging to the STD-clusters

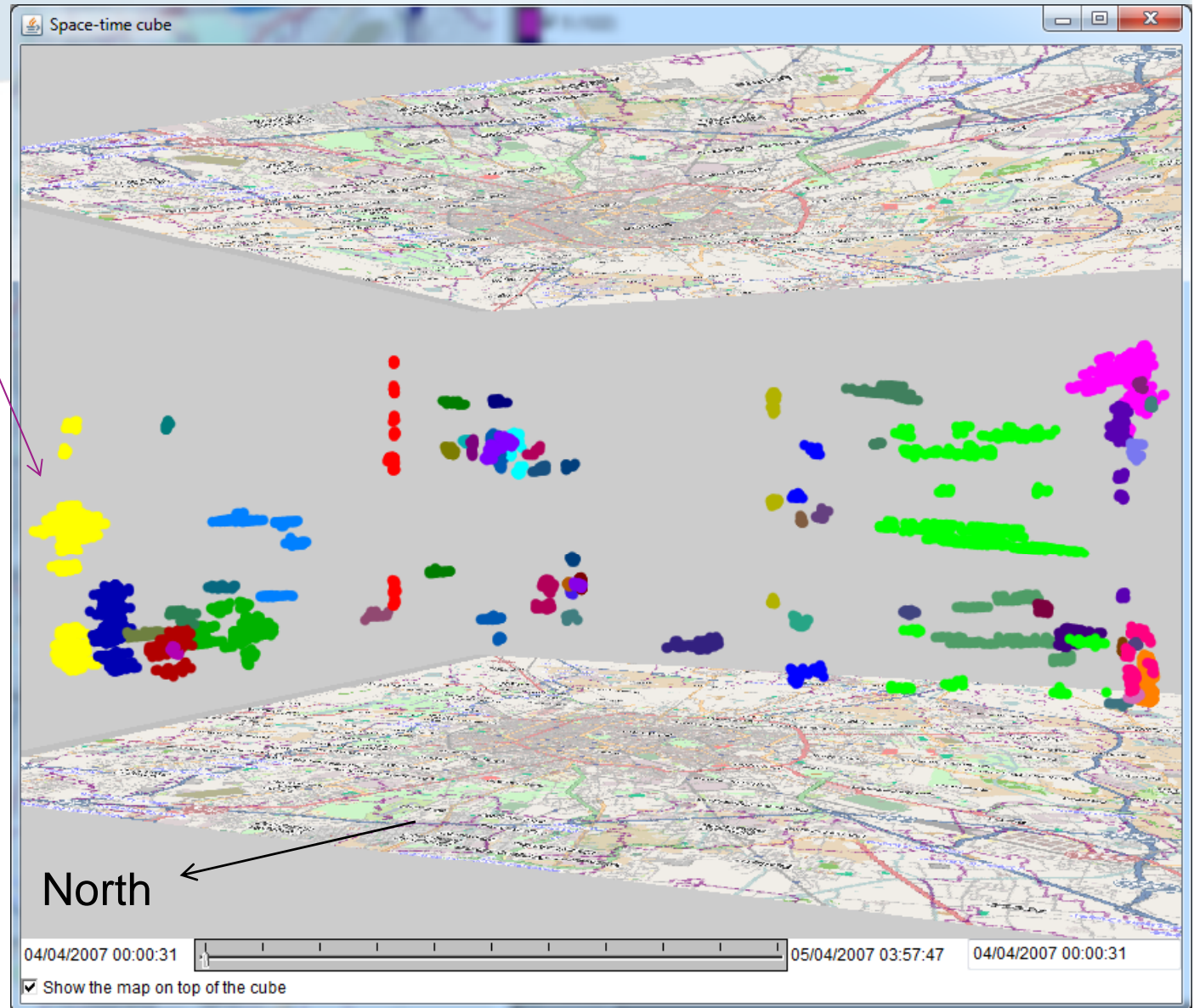


The second stage of the clustering is applied only to the objects belonging to the STD-clusters, i.e., without the “noise”.

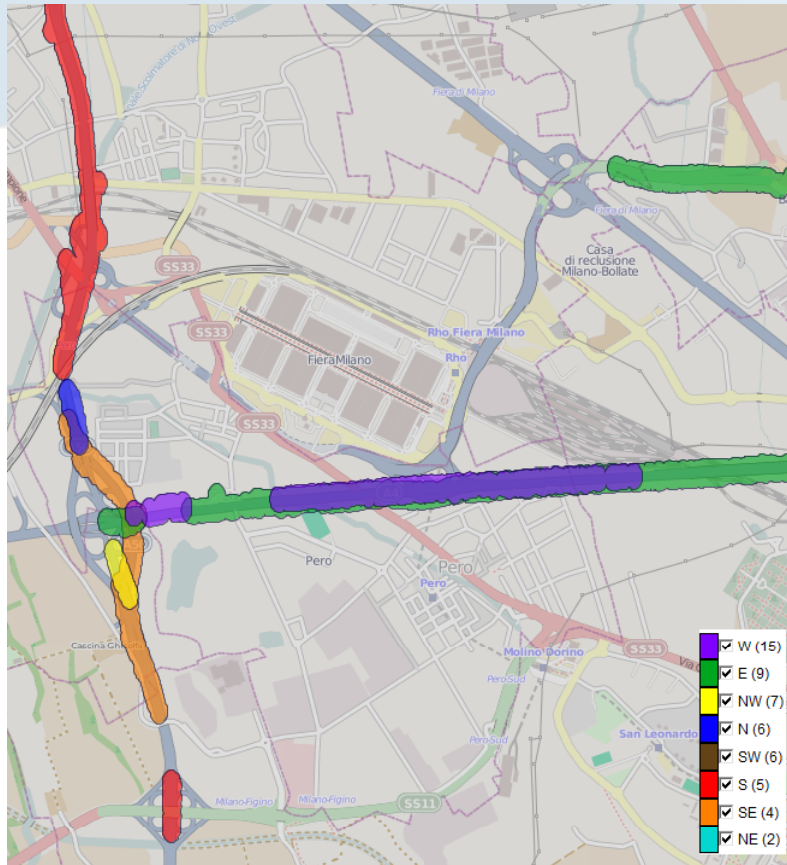


SD-clusters of the m-events

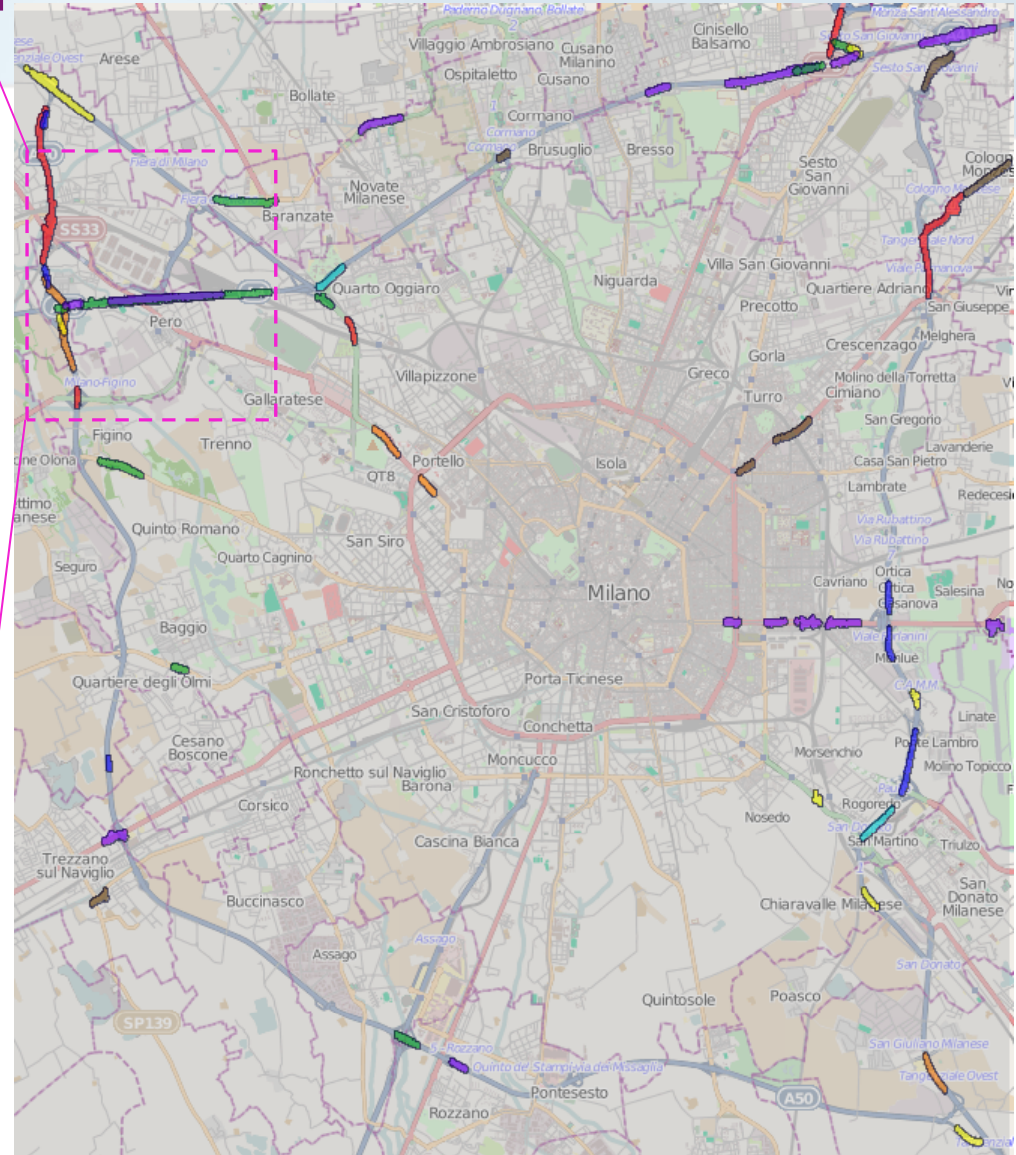
The SD-clustering has united STD-clusters that occurred in different times but overlap in space.



Spatial buffers around the clusters define the relevant places



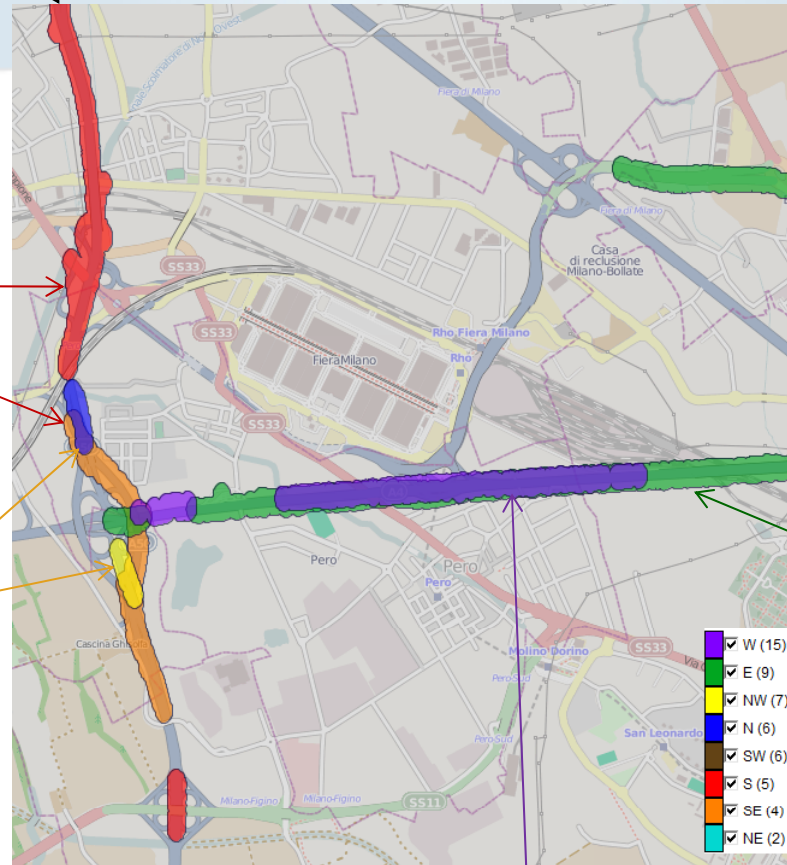
The places are painted according to the prevailing movement directions of the respective events.



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

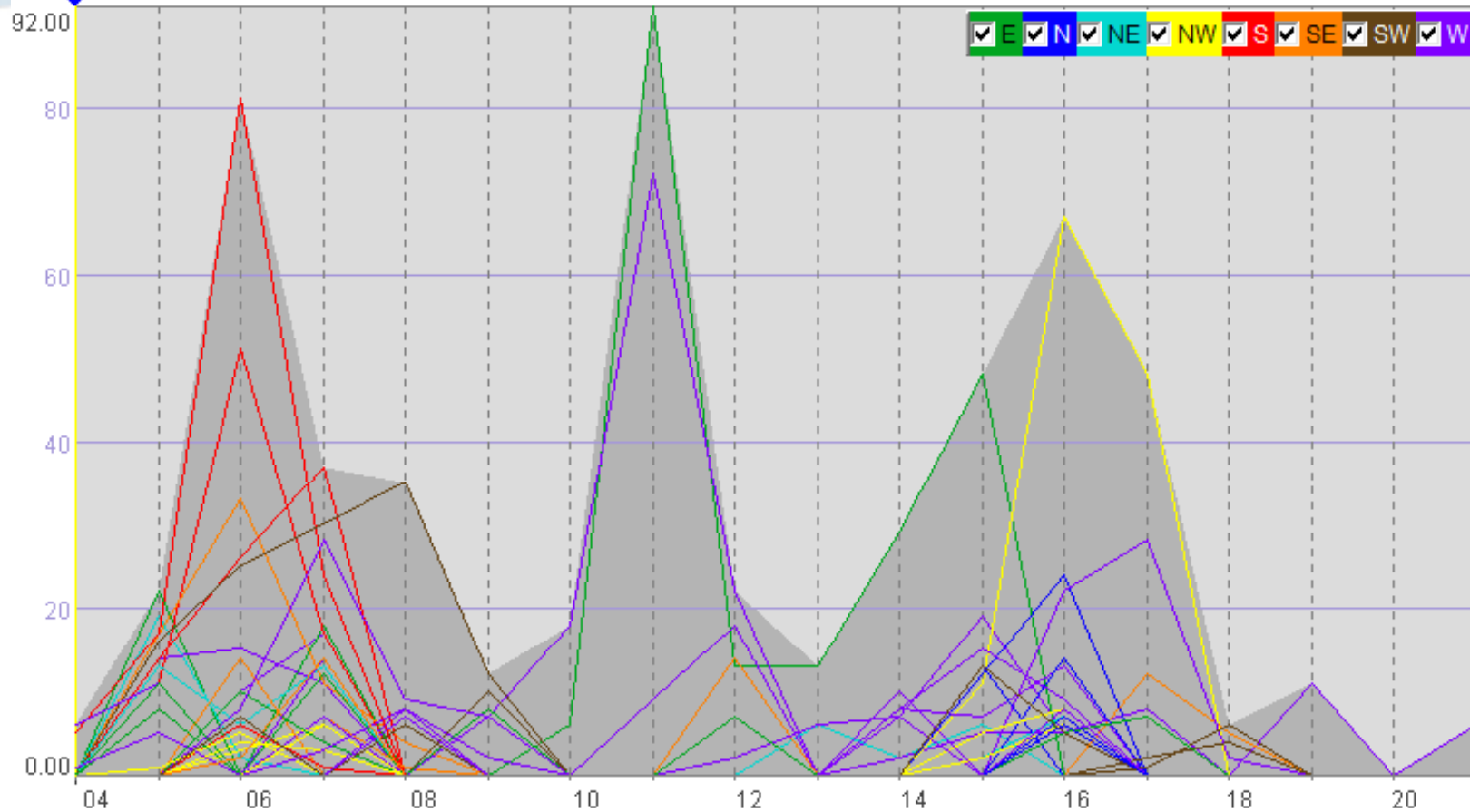
Step 3: spatio-temporal aggregation of the low speed events

- The m-events are aggregated by the areas (spatial buffers) and time intervals, e.g., hourly.
- Each area receives one or more time series of the aggregate attributes, e.g., event counts.

Step 4: exploration of the aggregated data

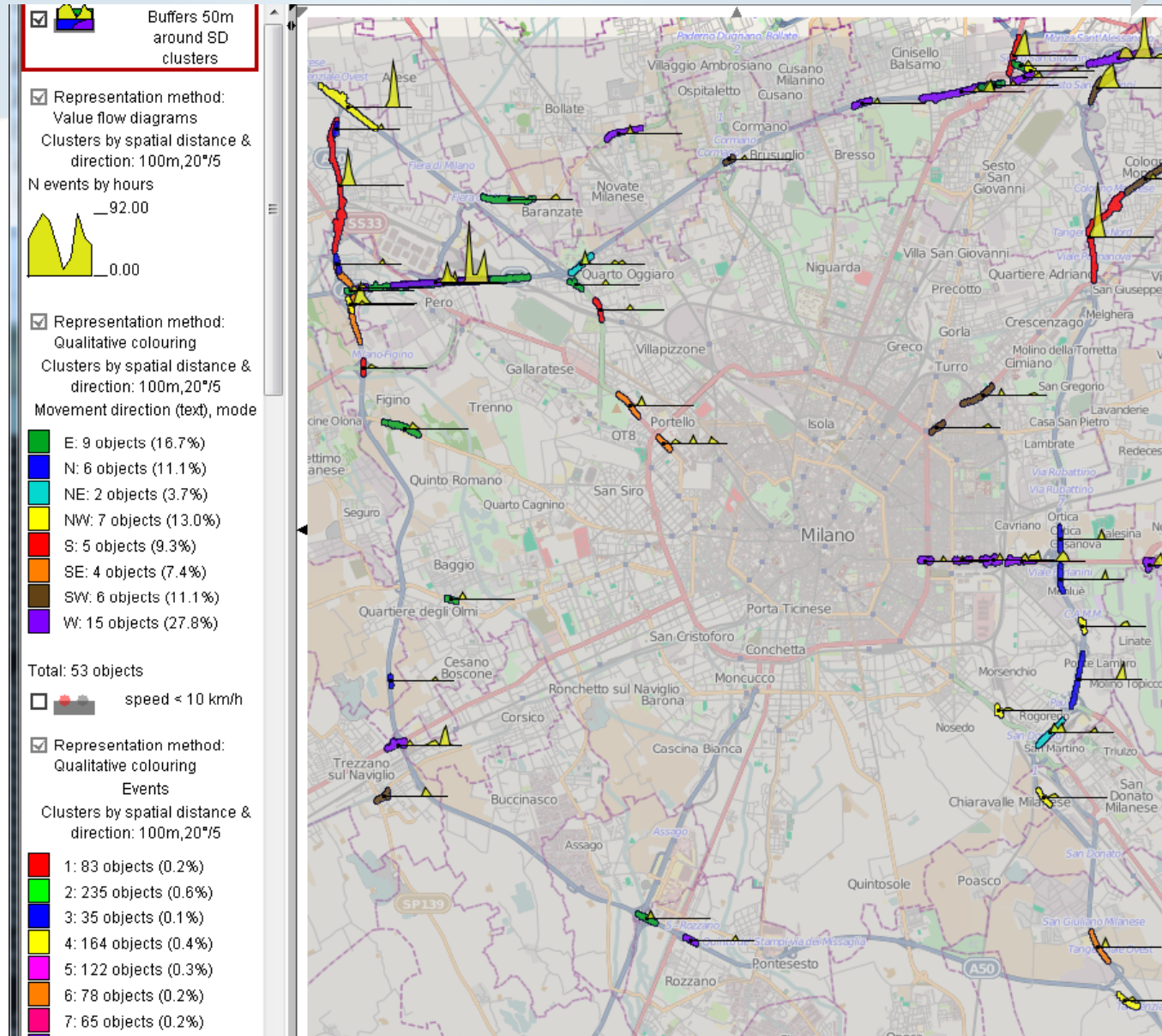
Time graph: counts of the low speed events by the places and hourly intervals

N events by hours

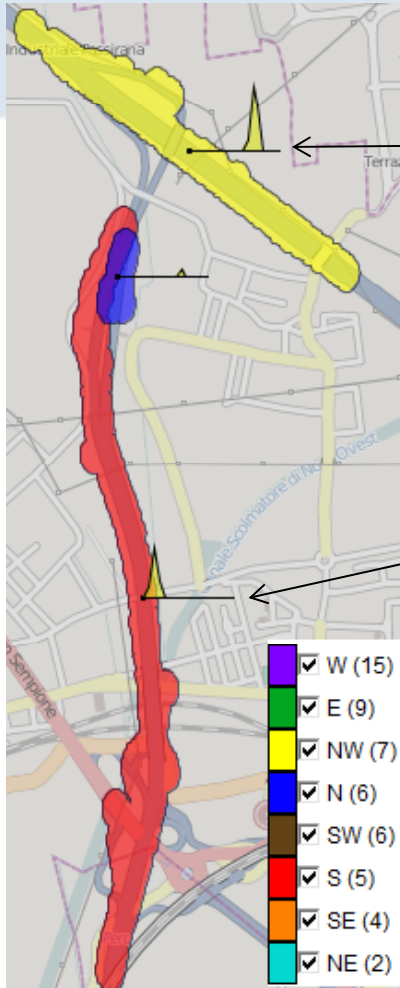


The temporal variation profiles on a map

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



Map fragment (northwest) enlarged



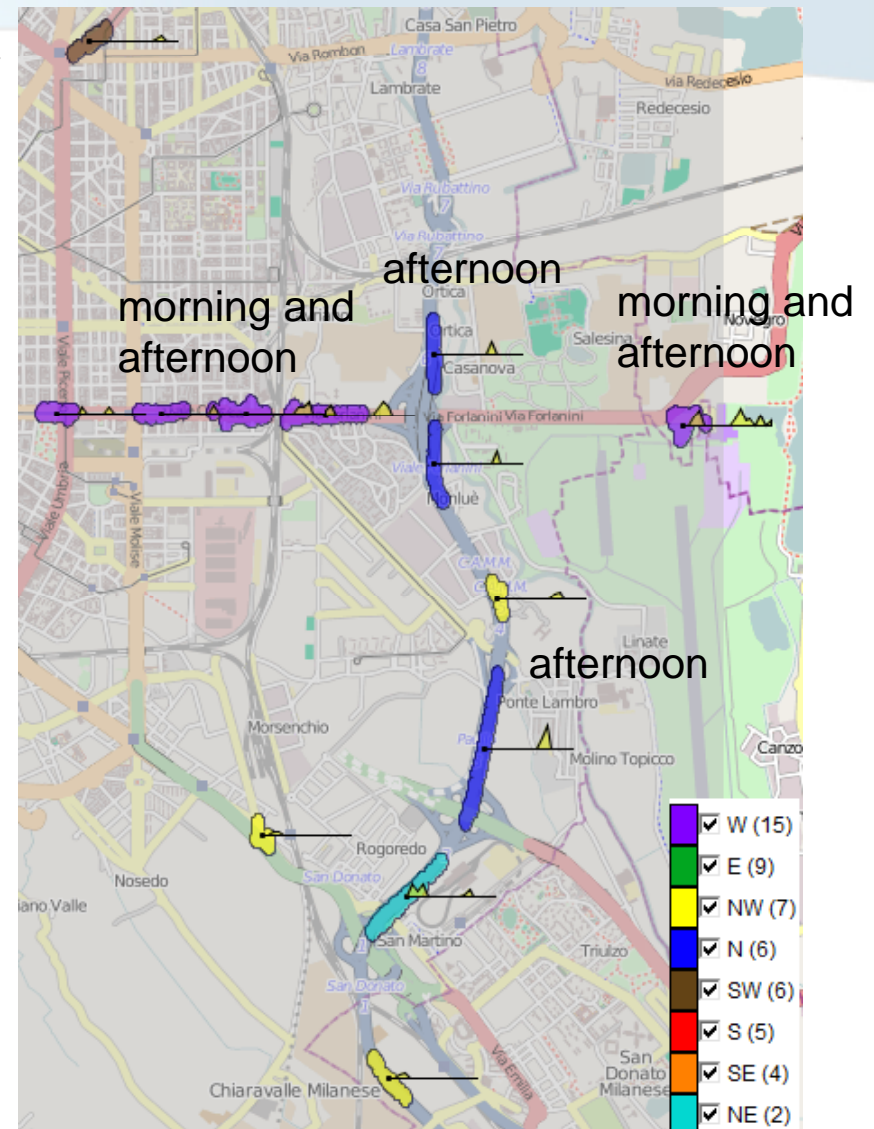
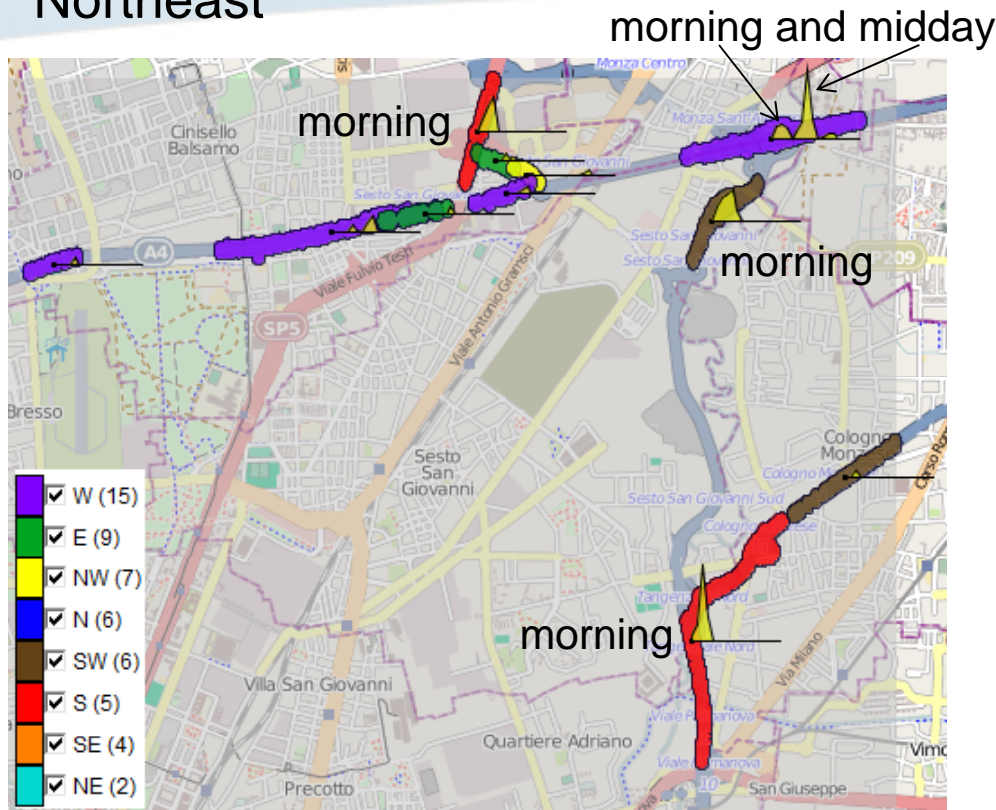
Congested traffic in the afternoon in the direction out of the city (northwest)

Congested traffic in the morning in the direction to the south

Map fragments enlarged

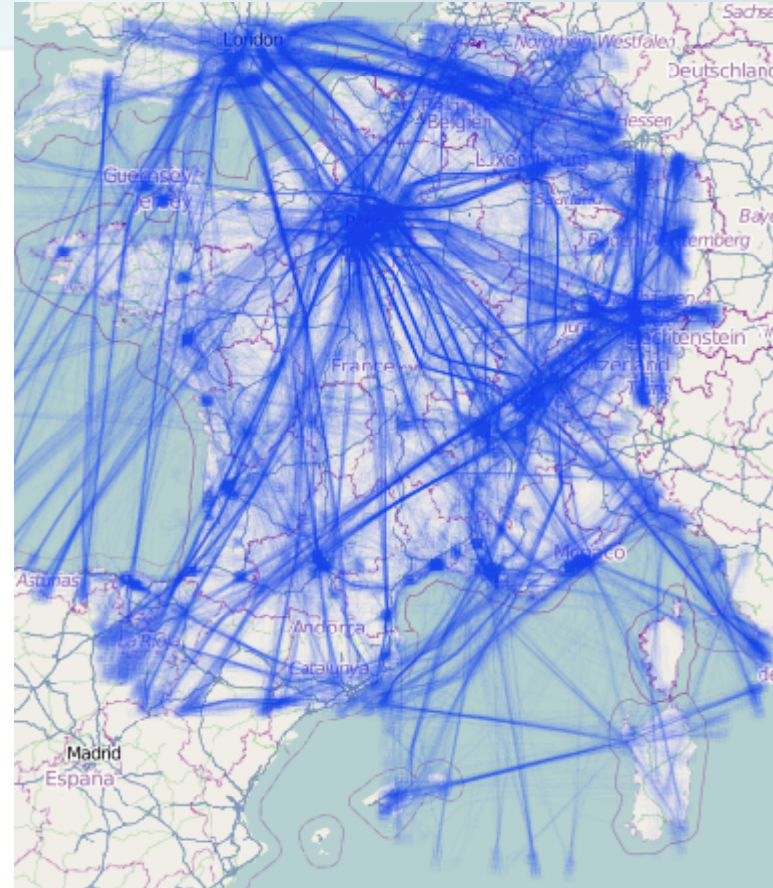
East

Northeast



Example 2: investigation of spatio-temporal patterns of air traffic in France

- 17,851 trajectories; 427,651 records collected by radars
- Friday, the 22nd of February, 2008
- Received from ENAC Toulouse, France



The trajectories are drawn on a map with 1% opacity

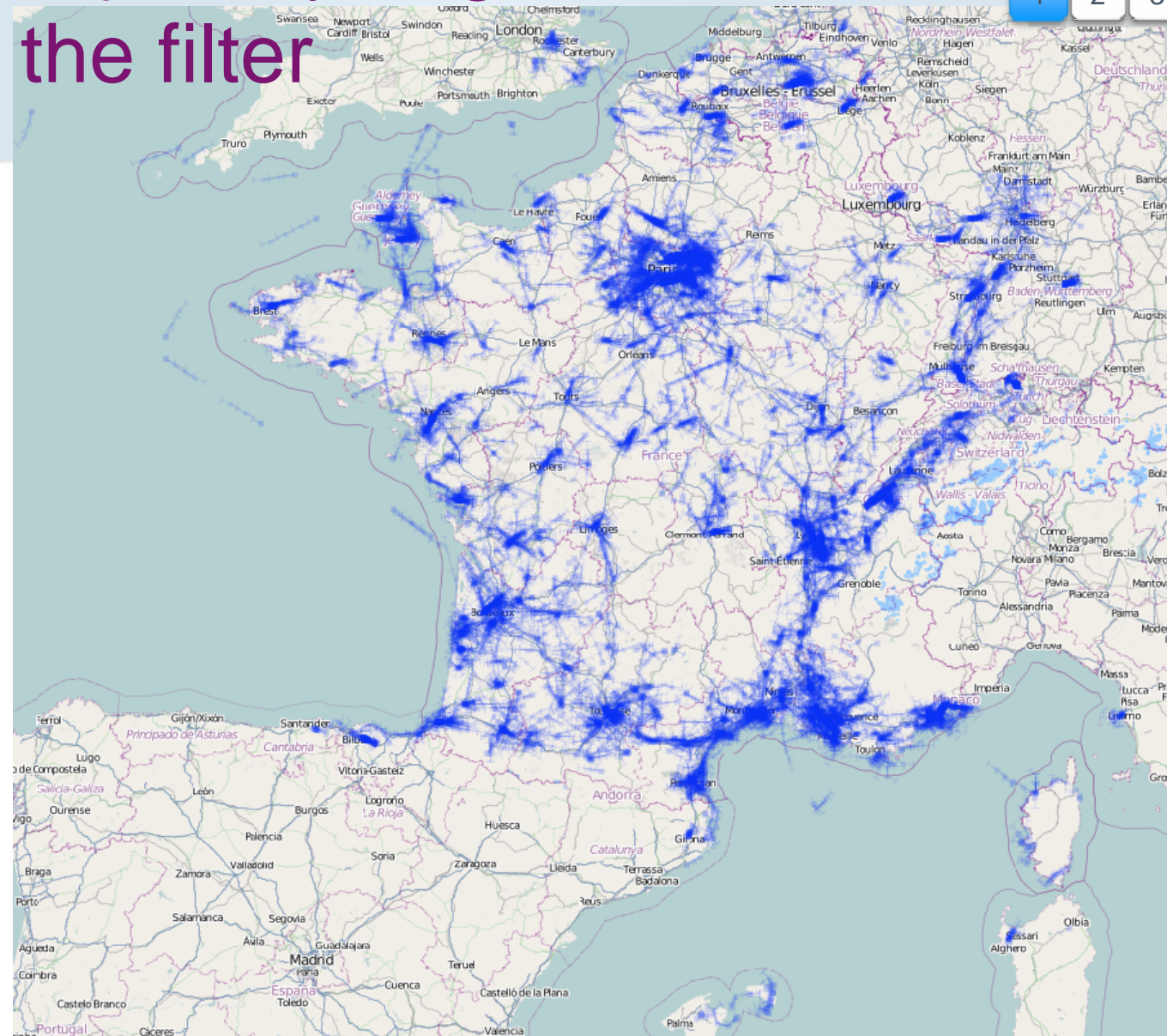
Step 1a: extraction of relevant events



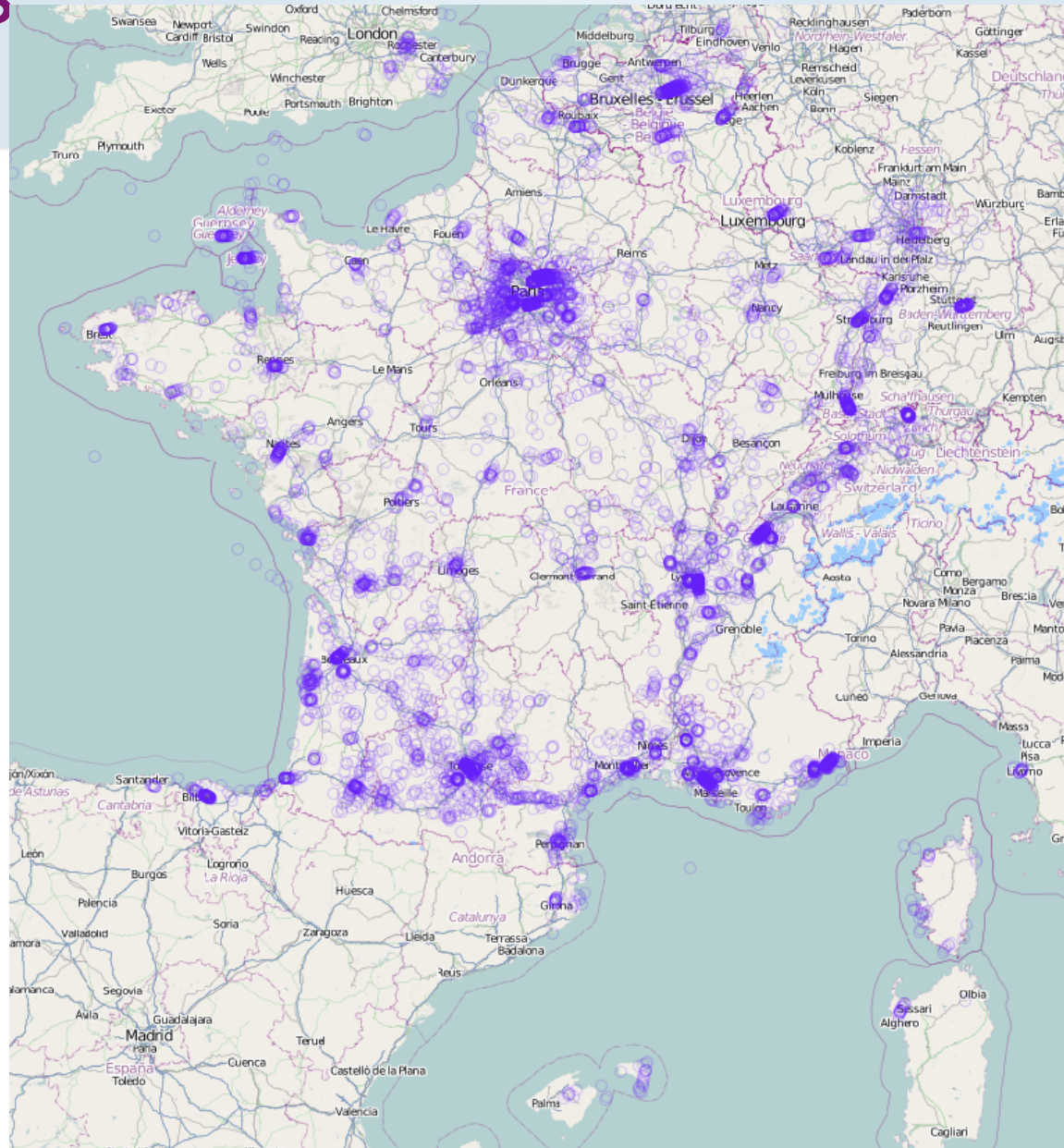
- Relevant events = landings
 - Altitude ≤ 1 km in the last 5 minutes of a trajectory
 - In case of multiple points, take the last one

**** complex condition involving an attribute and a temporal relation*

Map with trajectory segments satisfying the filter



Extracted events of probable landings

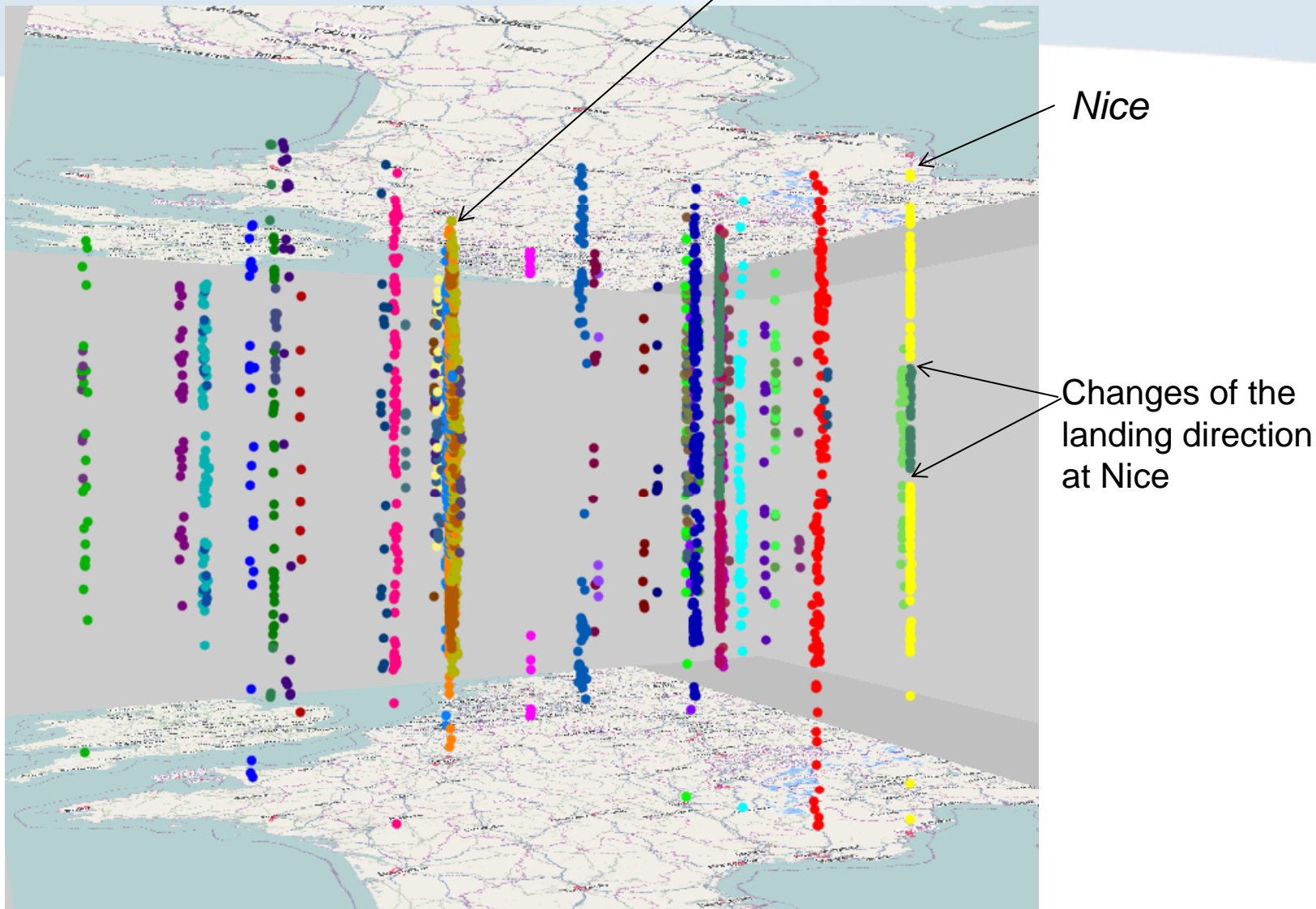


Step 2a: determination of the relevant places



- Relevant places = areas where the landings occur
 - Determined by means of SD-clustering using thresholds 1 km and 30 degrees; minimum number of neighbors 5

SD-clusters of the landing events in a space-time cube

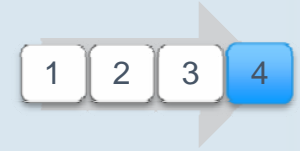


Step 3a: spatio-temporal aggregation of the landing events

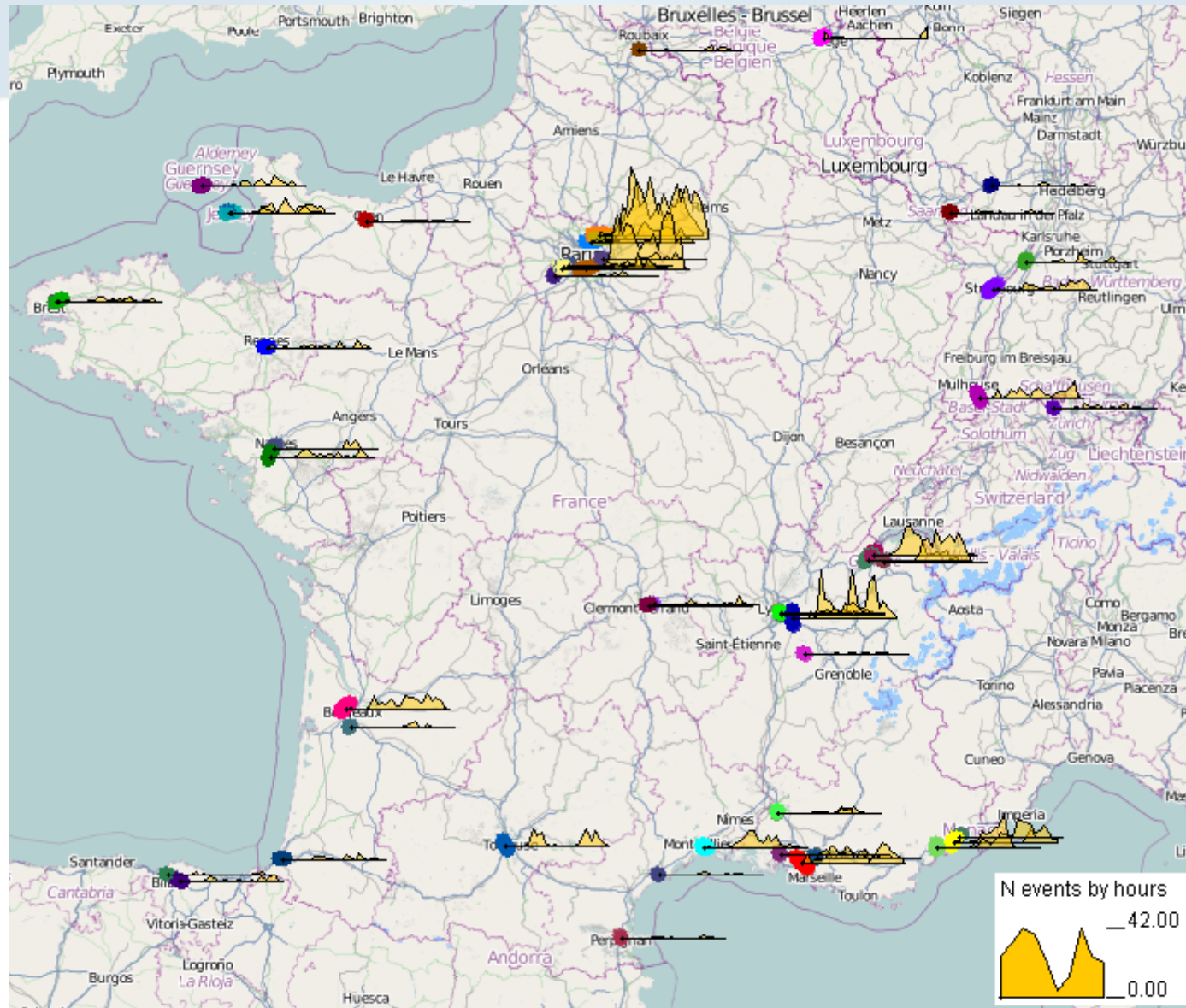


- The m-events are aggregated by the areas (spatial buffers around the SD-clusters) and hourly time intervals.
- Each area receives one or more time series of the aggregate attributes, e.g., event counts.

Step 4a: exploration of the aggregated event data

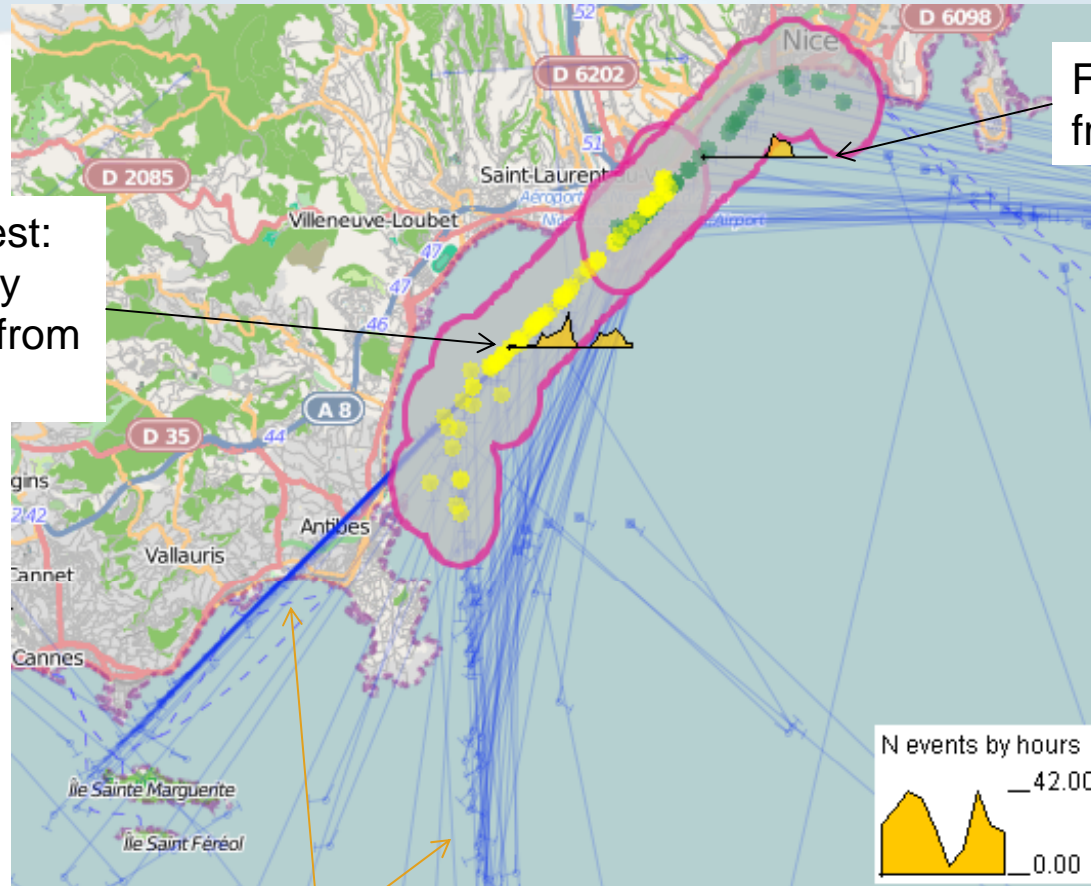


The dynamics of the landings by the places



Temporal profiles for the two landing directions at Nice

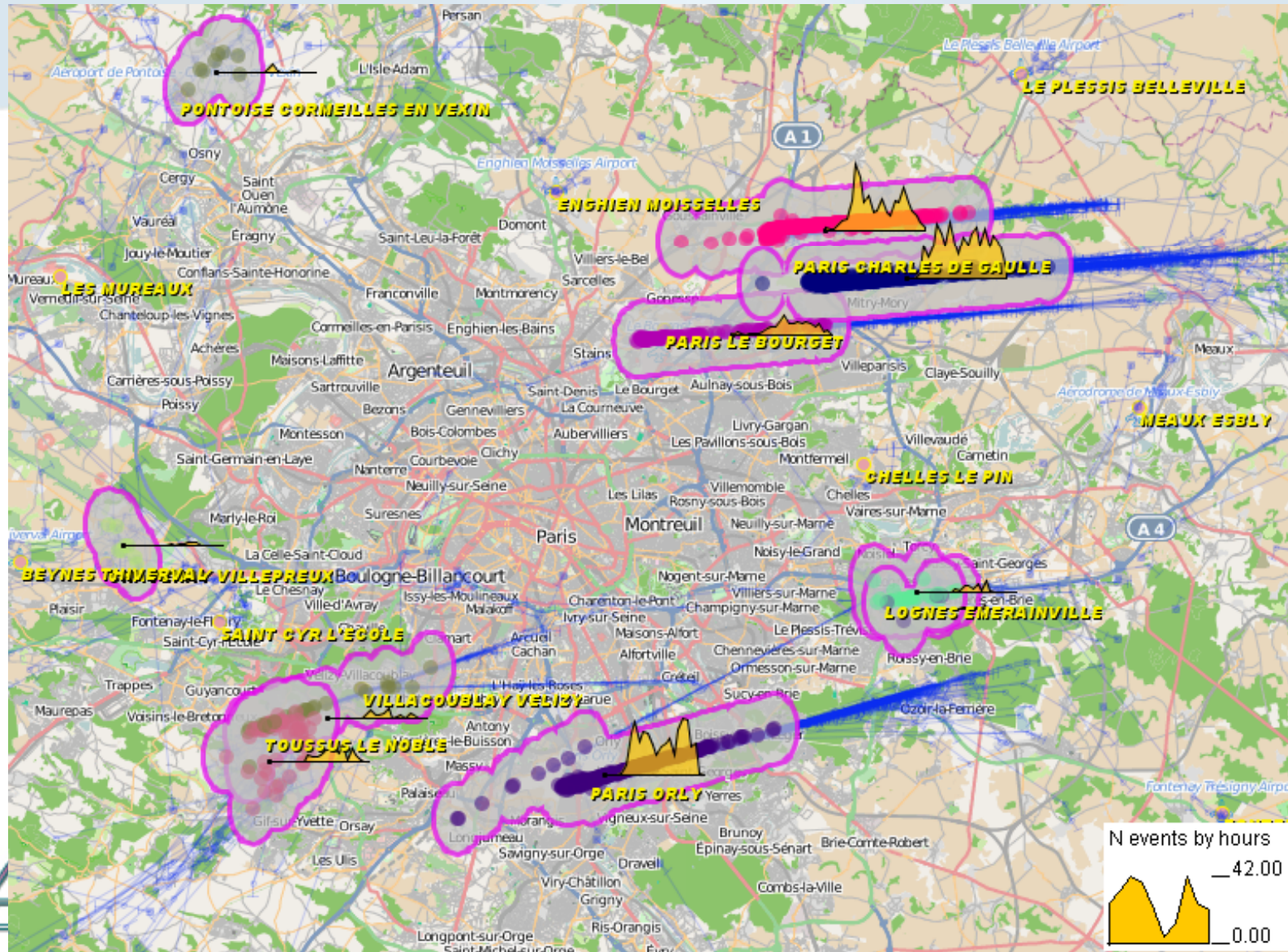
From the southwest:
morning till midday
and then starting from
17 o'clock



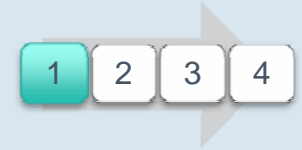
From the northeast:
from 13 till 16 o'clock

Lines represent last 10 minutes
of the trajectories

Temporal profiles of the landings in Paris



Step 1b: extraction of relevant events



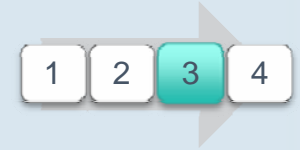
- Relevant events = landings (extracted previously) + takeoffs *
 - * Altitude \leq 1km in the first 5 minutes of a trajectory
 - In case of multiple points, take the first one

Step 2b: determination of the relevant places



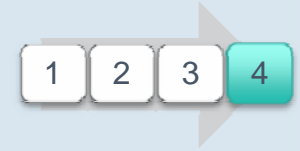
- Relevant places = airport areas = areas (spatial buffers) around spatial clusters of takeoff and landing events
 - Stage 1: SD-clustering of the takeoff events using thresholds 1 km and 30 degrees; minimum number of neighbors 5
 - exclude the noise
 - Stage 2: S-clustering of the takeoff and landing events taken together (noise excluded)

Step 3b: spatio-temporal aggregation of the trajectories



- Select the trajectories having both takeoff and landing events.
- For each pair of places <place 1, place 2>, find all trajectories that start in place 1 and end in place 2.
- Compute statistics (e.g. counts) by time intervals (e.g. hourly) and whole time
- Result: vector <place 1, place 2> + time series of aggregate attributes + totals (for the whole time)

Step 4b: exploration of the aggregated movement data



Major flows between airports

The arrows represent aggregate moves (flows) between areas.

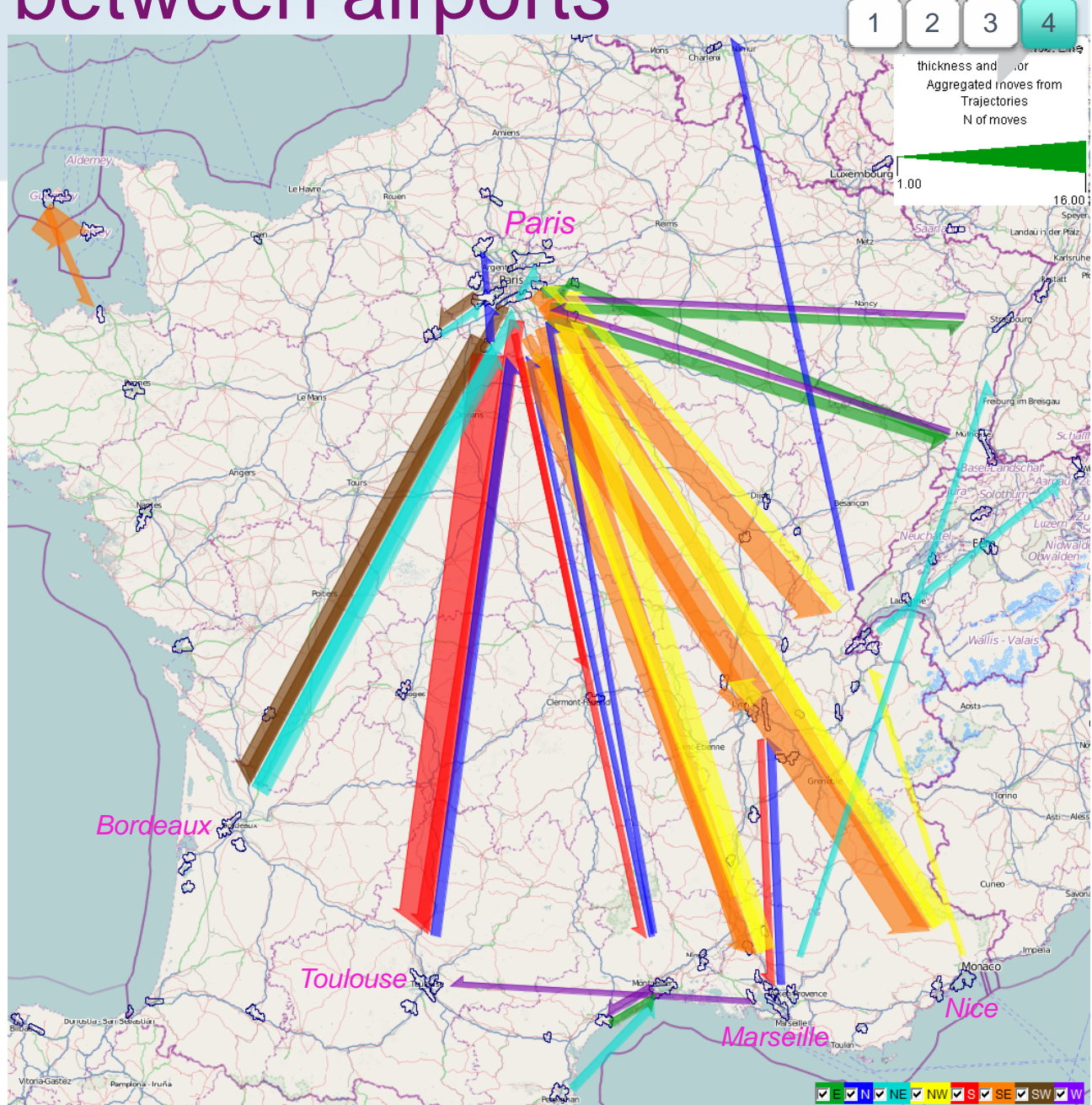
The thickness is proportional to the total number of flights.

The colors represent the directions.

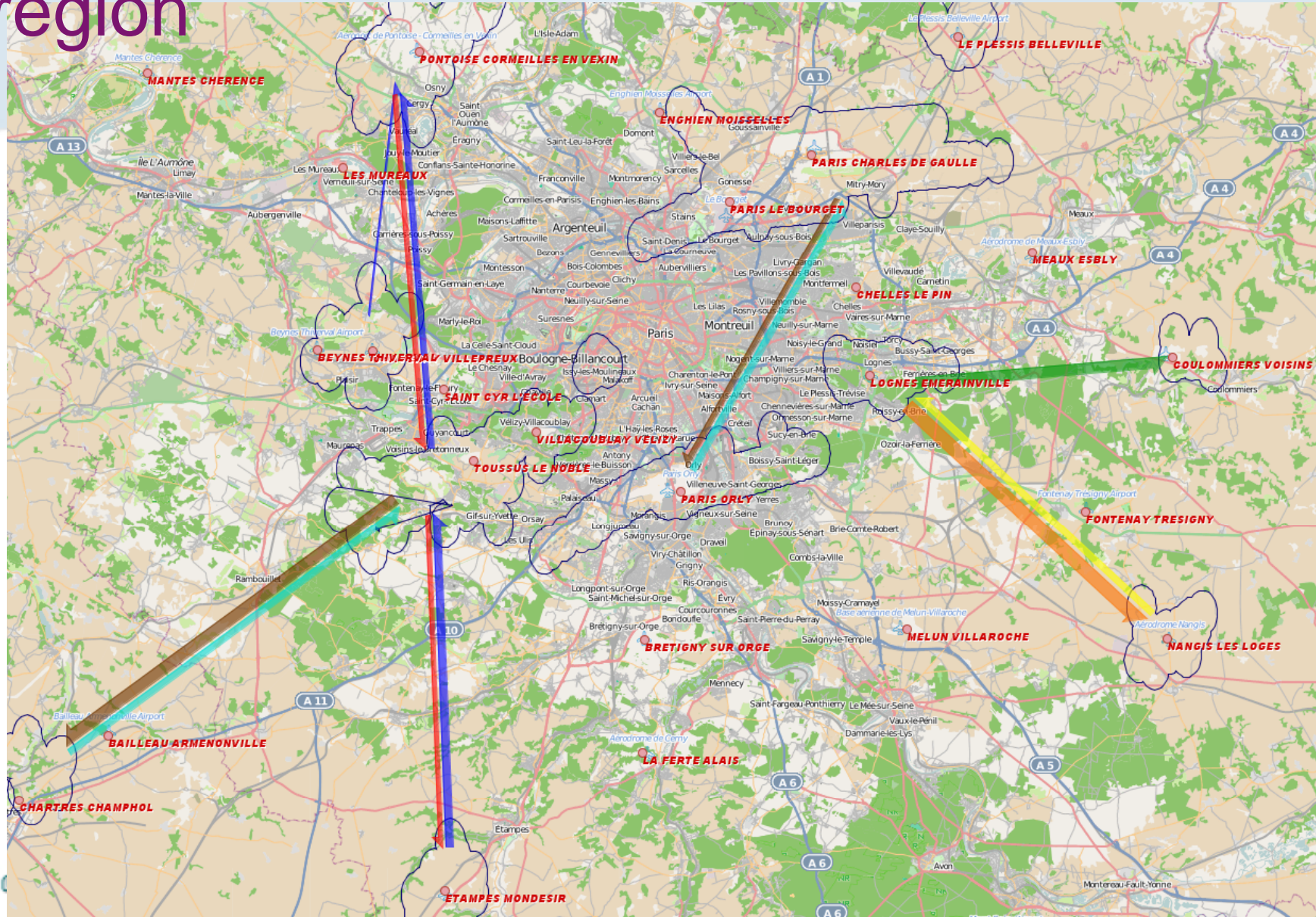
Minor flows (less than 5 flights) have been hidden.

A radial structure of the air traffic is visible (Paris ↔ periphery).

Different airports in Paris may be used for flights to/from the same city (e.g., Bordeaux, Toulouse, Marseille, Nice)

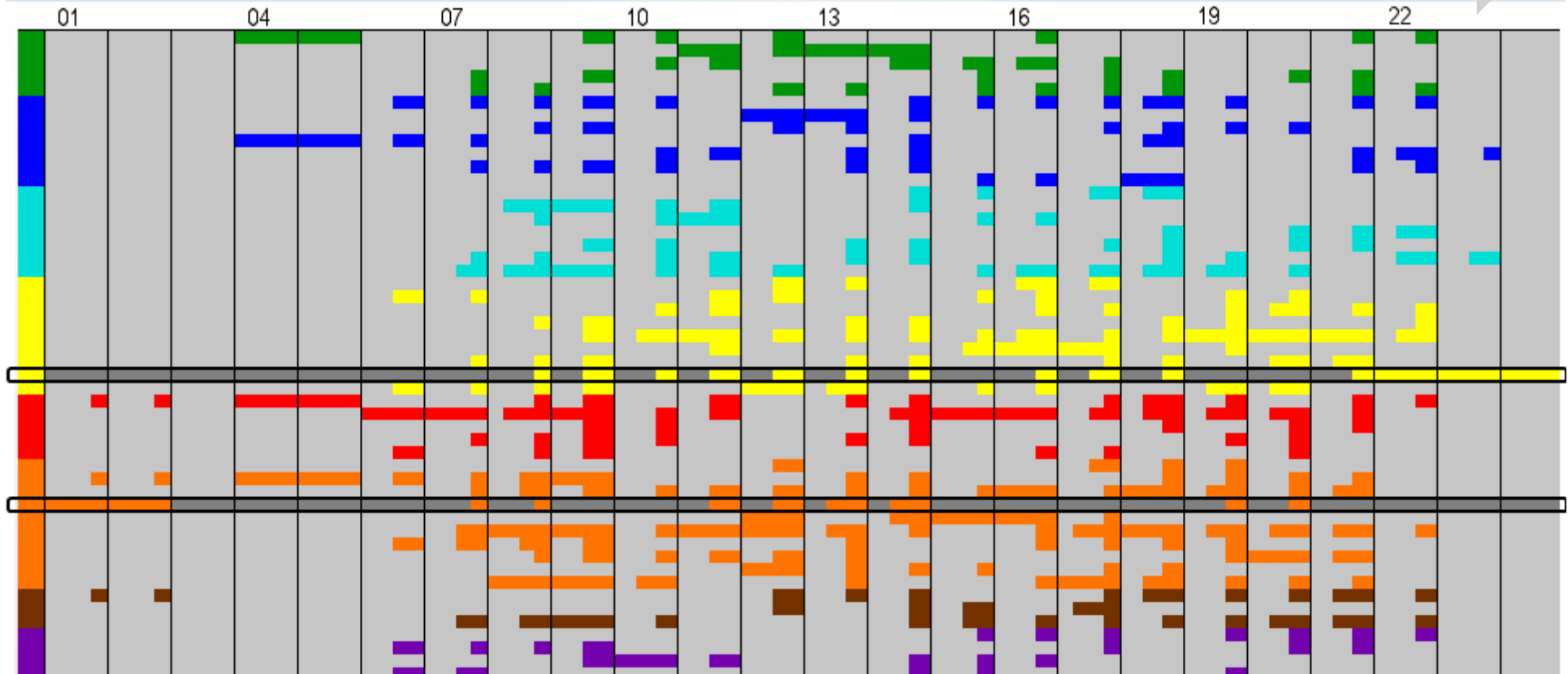


Short-distance flows in the Paris region



Counts of the flights by hourly intervals

1 2 3 4

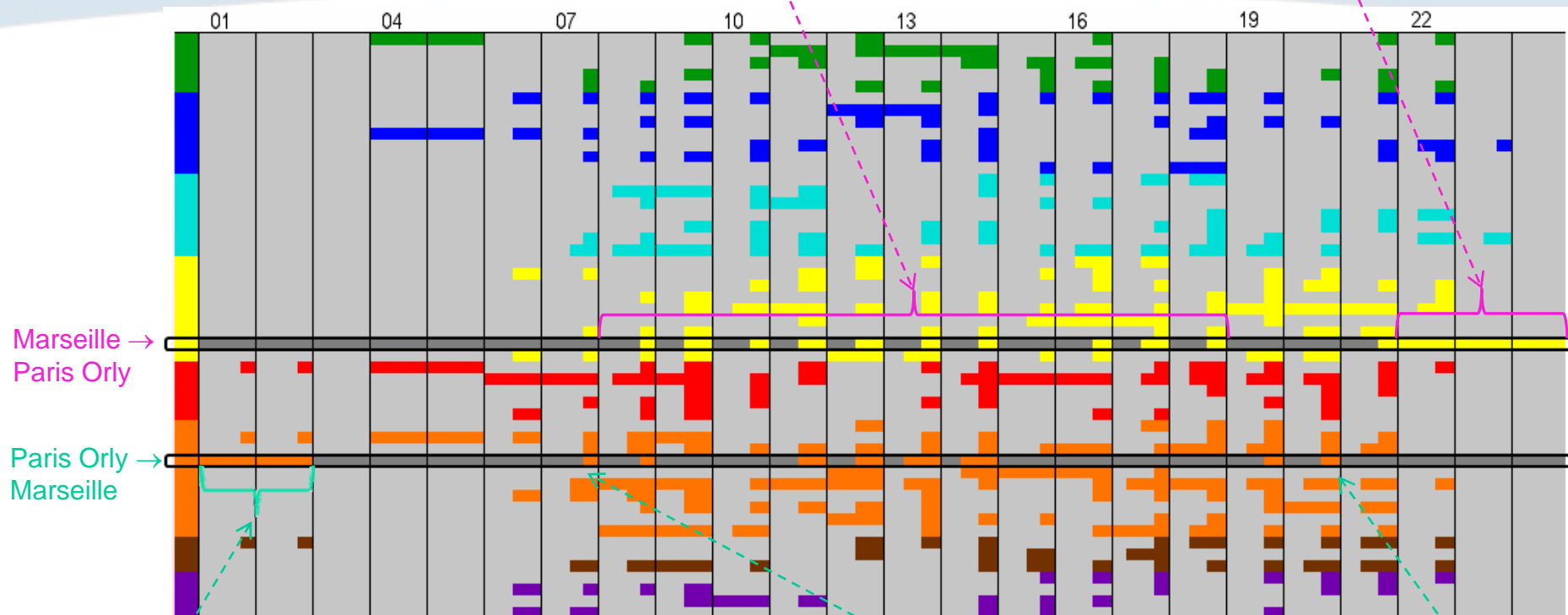


The rows correspond to the aggregate flows, i.e., pairs of places. The columns correspond to the time intervals used for the aggregation. The flow counts are represented by proportional lengths of the colored segments. The colors represent the flight directions. The rows corresponding to the connections Marseille → Paris Orly (yellow) and Paris Orly → Marseille (orange) are highlighted.

Connections Marseille ↔ Paris Orly

One or two flights every hour between 08h and 18h except 15h

Three flights every hour from 22h to 24h



Marseille → Paris Orly

Paris Orly → Marseille

Three flights per hour at 01h and 02h

One flight per hour in intervals 07h, 08h, from 11h to 14h, 19h, 20h



Conclusions: generic and scalable analytical procedure

1. Extract relevant movement events from trajectories
2. Find and delineate significant places
 - a) Find dense spatial clusters (S-clusters) of the events
 - Possibly, also by time (T), direction (D) and/or other attributes*
 - Possibly, 2-stage clustering: $ST \rightarrow S$, $STD \rightarrow SD$, $SD \rightarrow S$, etc.
** appropriate similarity measures*
 - b) Surround the clusters by spatial buffers or convex hulls
3. Aggregate the events and/or trajectories by the significant places and time intervals
4. Analyze the spatio-temporal aggregates

All steps could be scaled up by database processing



<http://geoanalytics.net/and>