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SNAP4 Appliances and Dockers Installations

SNAP4CITY

KM4CITY

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LIVING LAB

Data Analytics vs Smart Applications

11 November 2020, Course

https://www.snap4city.org/577

SCALABLE SMART ANALYTIC APPLICATION BUILDER FOR SENTIENT CITIES

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DINFO DIPARTIMENTO DI INGEGNERIA DELL'INFORMAZIONE

DISIT DISTRIBUTED SYSTEMS AND INTERNET TECHNOLOGIES LAB

SNAP4CITY

Powered by KM4CITY

scalable Smart aNalytic APplication builder for sentient Cities: for Living Lab and co-working with Stakeholders

https://www.Snap4City.org

100% OPEN SOURCE

Data Analytics vs Smart Applications

11 November 2020, Course

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Paolo Nesi, paolo.nesi@unifi.it
https://www.Km4City.org
https://www.disit.org


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DASHBOARDS AND APPS - CONTROL ROOMS - DECISION SUPPORT SYSTEMS - WHAT-IF ANALYSIS
EXPERT SYSTEM
KNOWLEDGE BASE
STORAGE
BIG DATA ANALYTICS
ARTIFICIAL INTELLIGENCE
BUSINESS INTELLIGENCE
MACHINE LEARNING
DATA FLOWS, WORKFLOWS
MICROSERVICES
MANAGEMENT
METHODOLOGIES
COURSES AND COMMUNITY
LIVING LABS
DEVELOPMENT TOOLS
INDUSTRY4.0
ENVIRONMENT
HEALTH
BUILDING
SECURITY
PARKING
AGRICOLTURE
ENERGY
MOBILE
WASTE
TRANSPORT
CONTROL ROOM

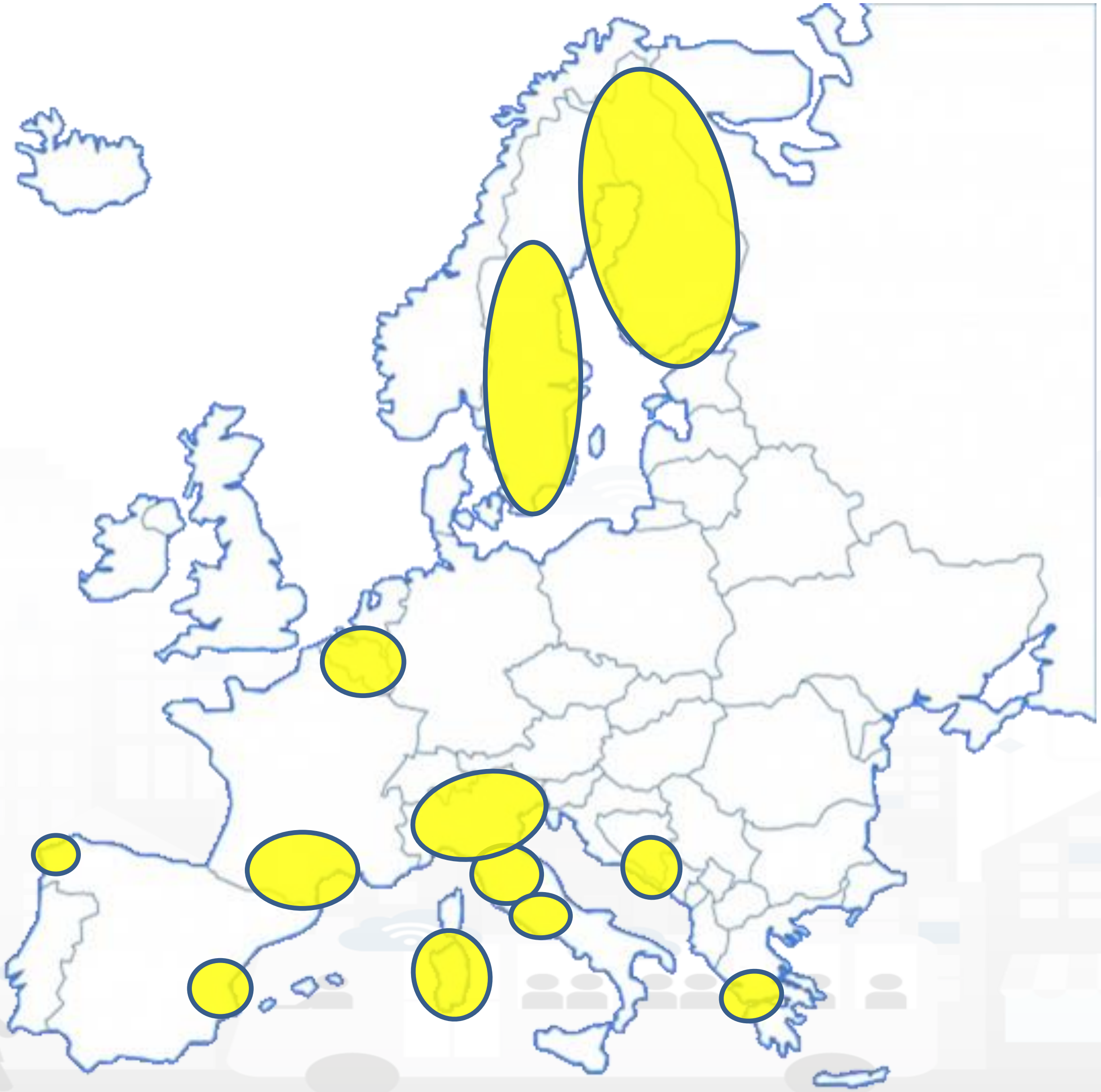
Snap4City/Industry structure

- The **Snap4xxxx** solution is released in Open Source, VM and Docker with fully support of MultiTenant/multiple-Organizations
  - Each Organization may be configured for a separate environment with a set of Maps, Menus, Users, Data, Dashboards, IOT Apps, MicroApplications, Custom Widgets, Models, resources, open data, etc.
- **Https://www.Snap4City.ORG** is the main instance of Snap4xxxx solution managed by DISIT Lab. The main documentation is located and updated on Snap4City.org, GitHUB, dockerHub and Node-Red Library. Snap4City.org is where the last tools are tested and news published.
  - Organizations on Snap4City.org have been created with contracts as for *Platform as a Service*, for testing and for providing *SmartCity as a Service* as well as *Industry 4.0 as a Service*

Coverage 2020

Main Organizations/areas

- Antwerp area (Be)
- Capelon (Sweden: Västerås, Eskilstuna, Karlstad)
- DISIT demo (multiple)
- Dubrovnik, Croatia
- Firenze area (I)
- Garda Lake area (I)
- Helsinki area (Fin)
- Livorno area (I)
- Lonato del Garda (I)
- Modena (I)
- Mostar, Bosnia-Herzegovina
- Pisa area (I)
- Pont du Gard, Occitanie (Fr)
- Roma (I)
- Santiago de Compostela (S)
- Sardegna Region (I)
- SmartBed (multiple)
- Toscana Region (I), SM
- Valencia (S)
- Venezia area (I)
- WestGreece area (Gr)



Snap4City/Industry Community

- Most of Organizations on Snap4City.org also correspond to companies or institutions that have an installation of Snap4City tools on their Premise,
  - such as: Pisa, SmartGarda Lake, Snap4, ALTAIR, etc.
- This double way allows them to:
  - test the news,
  - share experiences with other groups,
  - get visibility,
  - work in the collaborative environment, and
  - be better supported by Snap4City.org and DISIT Lab personnel.
- Each instance of Snap4xxxx solution ***can decide to join the federation*** of SmartCity API to exploit shared data.
  - This allows to exploit regional data for city installations applications (web, mobile, dashboards, etc.) without reloading them for example.

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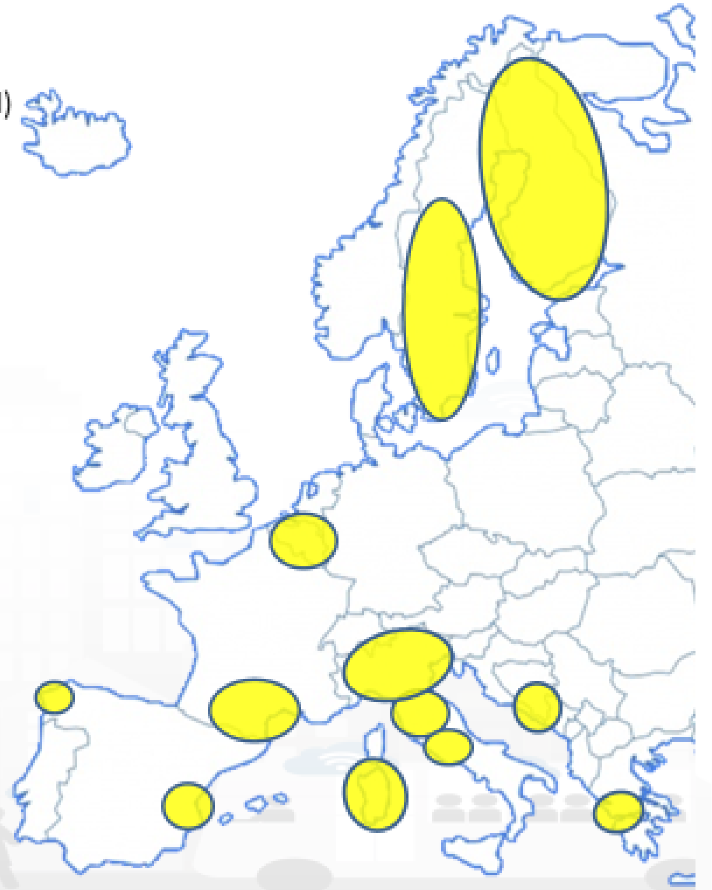
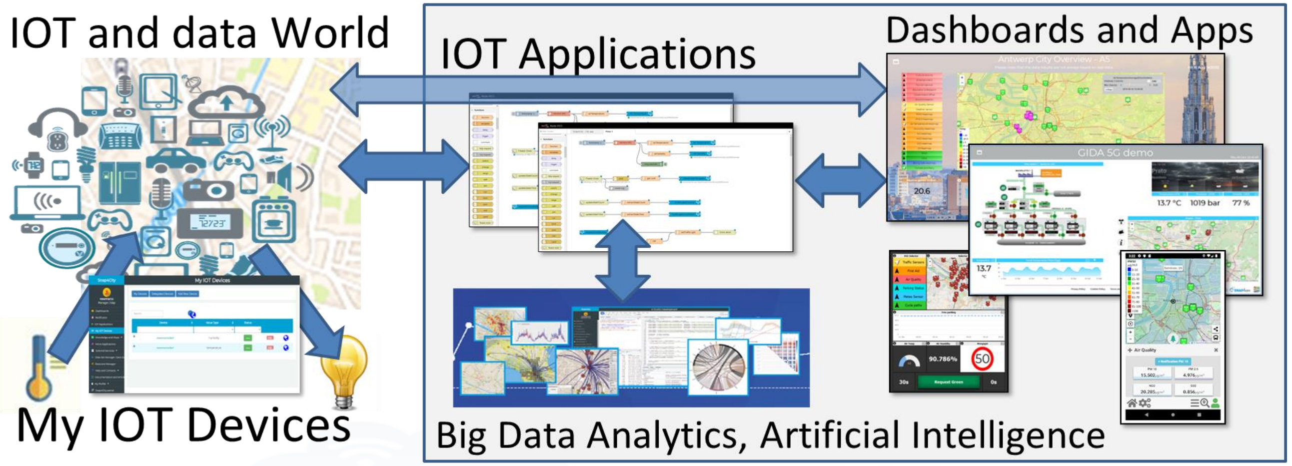


Snap4City (C), October 2020

Free Trial

- Register on WWW.snap4city.org
  - Subscribe on **DISIT Organization**
- **You can:**
  - Access on basic Tools
  - Access to a large volume of Data
  - Create Dashboards
  - Create IOT Applications
  - Connect your IOT Devices
  - Exploit Tutorials and Demonstrations



IF you need to go more in deep you can ask us to pass at the next Role becoming full AreaManager with full rights of development, also for Data Analytics, machine learning, etc.

https://www.snap4city.org/577

On Line Training Material (free of charge)

	1st part (*)	2nd part (*)	3rd part (*)	4th part (*)	5th part (*)	6th part (*)	7th part (*)
what	General	Dashboards	IOT App, IOT Network	Data Analytics	Data Ingestion processes	System and Deploy Install	Smart City API: Web & Mob. App
PDF							
Inter active							
Video1							
Video2							
Video3							
Video4				none		none	none
duration	2:55	3:16	3:41	2:00	2:48	2:35	1:47

General Overview of the full Course

- ***1st part:*** *General Overview*
- ***2nd part:*** *Dashboards Creation and Management*
- ***3rd part:*** *IOT Applications development, IOT Devices, IOT Networks*
- ***4th part:*** *Data Analytics, in R Studio, in Python, how to Exploit and Manage Data Analytics in IOT Applications*
- ***5th part:*** *Data Ingestion, Data Warehouse, Data Gate, IOT Device Data ingestion, IOT App for Data Ingestion, etc.*
- ***6th part:*** *Snap4City Architecture, How To Install and Manage Snap4City*
- ***7th part****: Smart city API (internal and external) Web and Mobile App development tool kit*

A number of the training sections include exercitations

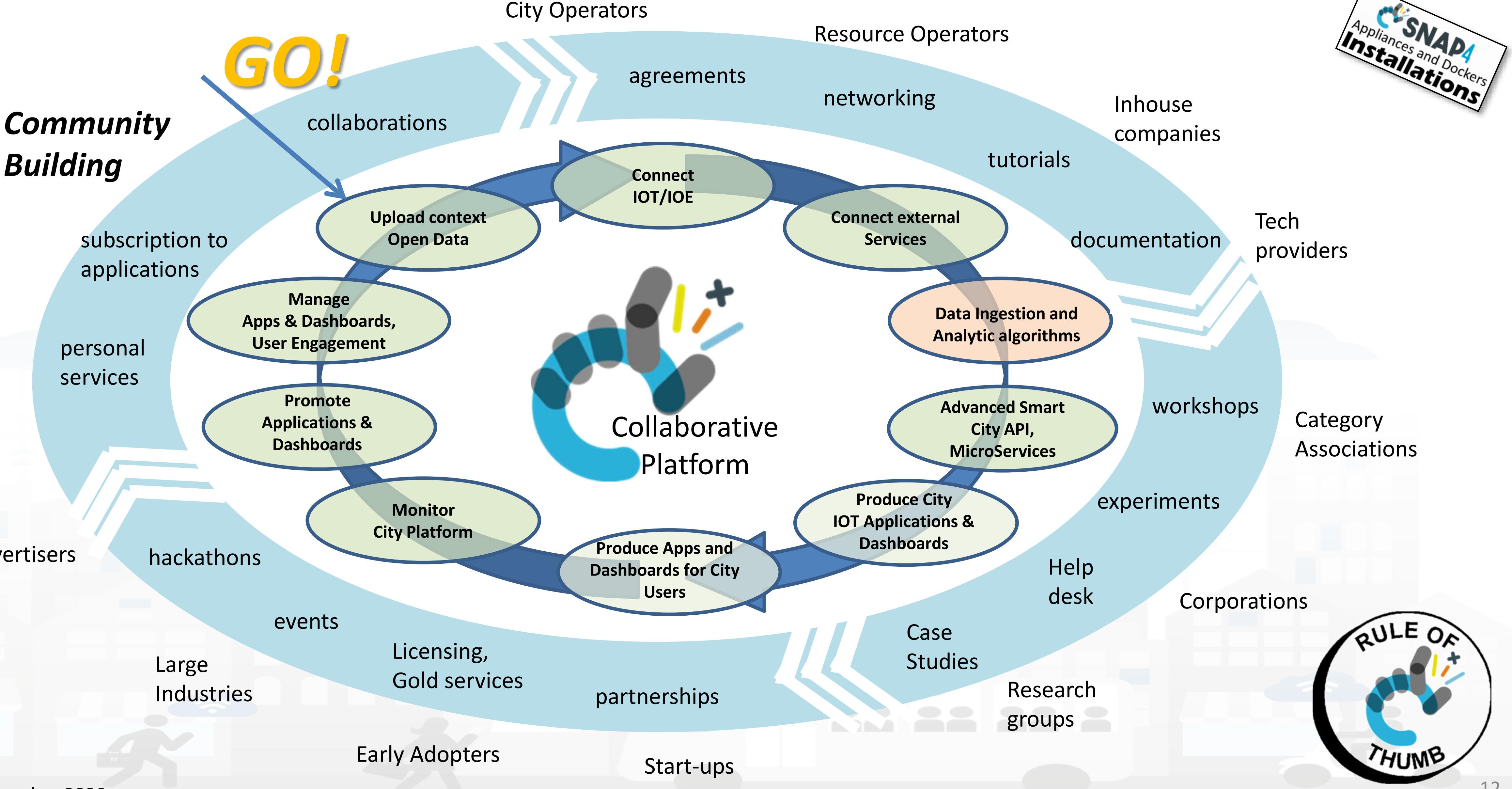
Updated versions on: https://www.snap4city.org/577

See also courses in ITALIANO: https://www.snap4city.org/485

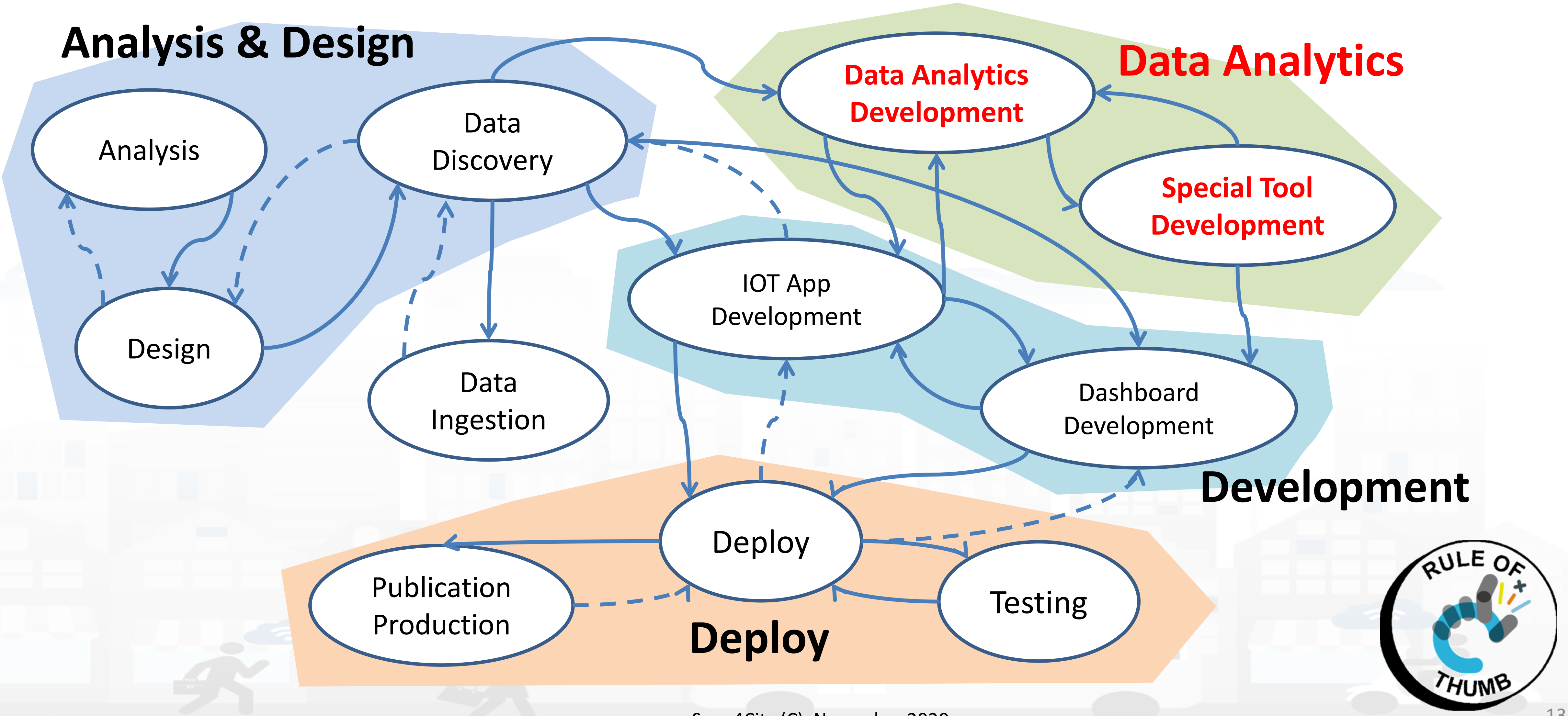
4th part Agenda

- GO **Data Analytics: Examples from Snap4City**
  - GO Smart parking: Predictions
  - Smart Bike Sharing
  - GO User Behavior Analysis, via Wi-Fi, OD, trajectories
  - GO Recognition of Used Transportation means
  - Traffic Flow Predictions,
  - GO Traffic Flow Reconstruction, from Traffic Sensors Data
  - GO Covid-19 vs other data: traffic and environmental
  - GO Quality of Public Transport Service
  - GO Origin Destination Matrices from: Wi-Fi, Mobile Apps, etc.
  - GO Demand of Mobility vs Offer of Transportation
  - GO Modal and Multimodal Routing for Navigation and Travel Planning
  - GO Environmental Data Analysis and Predictions, early Warning
  - GO Prediction of Air Quality Conditions
  - GO Anomaly Detection
  - GO What-IF Analysis
- GO **Data Analytics: Enforcing and Exploiting**
  - Real Time Data Analytics: using R Studio Exploitation in IOT Applications
- GO **Engaging City users Towards a Virtuous behavior**
- GO **Decision Support Systems, Smart DS and Resilience DS**
- GO **Twitter Vigilance: Social Media Analysis: Early Warning, Predictions**

Living Lab Accelerating



Development Life Cycle Smart City Services



Levels of Difficulty

• Easy.		non programmer level
• Moderate.		Some JavaScript rudiment coding
• Good.		JavaScript programming
• Golden.		Programming in R Studio
• Professional.		Exploiting Smart City API
• Excellent.		Developing Full IOT Applications, Dashboard and Mobile Apps

TOP

Data Analytic: Examples from Snap4City

Data vs Smart Services enabling on Snap4City

- **Public Transportation and mobility activated services in some where with Snap4City**
  - **Smart parking** (parking locations and real time parking data) … predictions
  - **Smart Fuel pricing** (fuel station locations and real time prices)
  - **Routing** (detailed GIS information, text indexing of streets, POI, etc.)
    - **Quite routing, perfect shopping, etc. etc**. (more data in needed….)
  - **multimodal routing** (detailed GIS information, Public transport time schedule)
  - **Info traffic** (traffic flow sensors, real time Traffic events, their localization, etc.)
  - **Dense info traffic** (traffic flow sensors and traffic flow reconstruction algorithm)
  - **Car/Bike/Scooter Sharing** (position and availability of Cars/Bikes, Scooters) … predictions
  - **Smart Biking** (cycling paths, environmental data) … predictions on bike racks
  - **E-vehicles** (position, status of recharging stations,. …) … predictions vs booking
  - **Smart river crossing** (position and status of Underpass, Ferry) … prediction
  - **Quality of Public Transport** (actual time of arrival at the bus stops, wrt planned time schedule)
  - **Early Warning vs Resilience** (combination of several data including mobility, events, Social to perform early warning…)

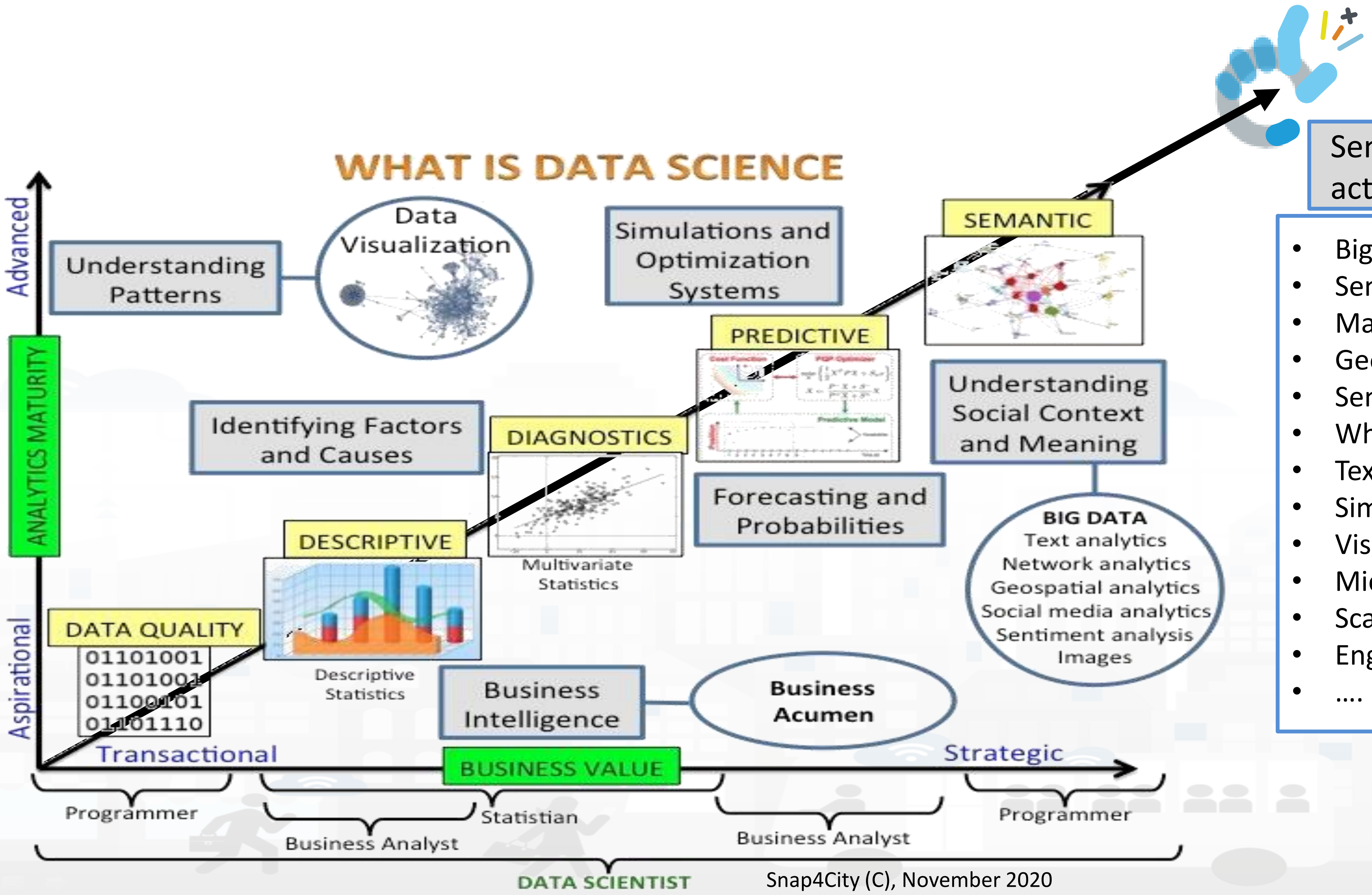
Data vs Smart Services enabling on Snap4City

- Social and Users Behaviour
  - Smart First Aid (Location of First AID, real time status of triage)
  - search for POI and public transport services (POI geolocalized, spatial queries, along paths)
  - Social Media Monitoring and acting (Identif. of dysfunction, quality of service perceived)
  - Information to Tourists (Entertainment Events)
  - Early Warning, prediction of audience (Twitter data, social media)
  - Improvement of services for Tourists (people flow, usage of services)

    (Origin Destination Matrices, trajectories, heatmaps)
    (People Monitoring, via App, Wifi, PAX Counter)
    (Twitter Data, social mea,….)
- Weather and environment, quality of life
  - Weather forecast/condition (Weather forecast)
  - Air quality Pollution (pollution sensors, PM10, PM2.5, NOX, etc.)
  - Pollination (Pollination sensors)
  - Alerting on Air quality for multiple parameters (Prediction of parameters time slots, notification)
  - Information Heatmaps for weather and air quality (air quality sensors, heatmaps, prediction)
  - Air quality indexes, and forecast (…………………..

DATA ANALYTICS

- Resilience
  - Resilience and risk analysis
  - Early warning computation
  - What-if analysis, dynamic routing, origin destination matrices production from a large range of sources
- Mobility and transport
  - Traffic flow reconstruction from sensors and other sources
  - Predictions for: traffic flow, smart parking, smart bike sharing, etc.
  - Analysis of the demand vs offer of mobility according to public transportation and multiple data sources
  - Accidents heatmaps
  - Tracking fleets, people, via devices: OBU, OBD2, mobile apps, etc.
  - Routing and multimodal routing
- Environment and weather
  - NOX, PM10 pollution prediction on the basis of traffic flow, 48 hours
  - Long term prediction of European Commission KPIs on NOX, PM10, etc.
  - Heatmaps production, dense data interpolation
- User and Social
  - People flows prediction and reconstruction, via Wi-Fi, mobile apps, etc.
  - User engagement for sustainable mobility
  - User’s behaviour analysis, origin destination matrices, hot places, time schedule, Recency and frequency, permanence, etc.
  - People flow analysis from PAX Counters
  - Social media analysis on specific channel, specific keywords: see Twitter Vigilance, for NLP and Sentiment Analysis, SA
  - Tweet proneness, retweet-ability of tweets, impact guessing
  - Audience prediction to TV channels and physical events
- Generic
  - Data quality assessment, prediction, anomaly detection
  - Maintenance prediction and costs predictions
  - Estimation of KPI and local indexes for: quality of life, 15 minutes, etc.



Sentient and active processes

- Big Data
- Semantic Computing
- Machine Learning
- Geo Spatial Reasoning
- Sentiment Analysis
- What If Analysis
- Text Analysis
- Simulations
- Visual Analytics
- MicroServices
- Scalability
- Engagement Analysis
- ….

Disappearing Data Analytics

	Antwerp					Helsinki								Where				
	City official	ICT official	Developer	Citizen, tourist, visitor	Business owner	City officials	City officials Domain experts	City officials City developers	Third party developers	Citizen	Citizens with respiratory problems	Tourists	Business owners	Mobile	MIcroApplication	Tool, via Portal (ICT Developers)	Dashboards	Main Data Sources
Discovery near to me	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X			POI, OSM
Discovery along a path	X	X	X	X		X		X	X	X	X	X		X	X			POI, OSM
Discovery in an area, shape	X	X	X	X	X	X	X	X	X	X	X	X	X	X		X		POI, OSM
browsing Public Transport	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X			OSM, GTFS
Full Text search	X	X	X	X	X	X		X	X	X	X	X	X	X		X		POI, OSM
Routing: pedestrian				X	X			X	X	X	X	X	X	X	X			OSM
Routing: pedestrian quite				X	X			X	X	X	X	X	X	X	X			OSM
Routing: private vehicles	X		X	X		X		X	X	X	X	X		X	X			OSM
Routing: Multimodal Public Transport				X					X	X	X	X		X	X	X		OSM, GTFS
heatmaps: weather (Temp, Humidity)	X	X		X	X	X	X		X	X	X	X	X	X			X	Sensors data, OSM
heatmaps: environmental variables, PM10, PM2.5, NO2, EAQI	X	X		X	X	X	X		X	X	X	X	X	X			X	Sensors data, OSM
heatmaps: environmental variables, Noise						X	X		X	X	X	X	X	X			X	Sensors data, OSM
heatmaps: safe on bike (Antwerp)	X	X		X	X									X			X	Spec. Portal
heatmaps: Enfuser prediction, PM10, PM2.5, AQI						X	X		X	X	X	X	X	X			X	Enfuser data
heatmaps piking values any place	X	X			X	X	X	X	X				X				X	Computed Heatmps
heatmaps: GRAL prediction, PM10						X	X		X	X	X	X	X	X			X	OSM, Traffic, Weather
Comparsison: Enfuser, Gral, Real Time						X	X										X	Enfuser, Sensors, GRAL
Sensors Data Time Trends, & drill down	X	X	X		X	X	X	X					X			X	X	Sensors data, OSM
Weather Forecast	X	X		X	X	X	X		X	X	X	X	X	X			X	Forecast Service
Origin Destination Matrices	X	X	X		X	X	X	X	X				X				X	Snap4City Mobile App
Typical trajectories	X	X	X	X	X	X	X	X	X				X			X	X	Snap4City Mobile App
Hot Area in the city	X	X	X	X	X	X	X	X	X	X	X	X	X	X		X	X	Snap4City Mobile App
Hot Places in Smart Zone	X	X	X	X	X									X		X	X	Snap4City PAXcounters
Services Suggestions on mobiles				X						X	X	X		X	X			Snap4City Mobile App
Alerts on critical cases: several variables	X			X	X	X	X			X	X		X	X				Sensors data, OSM
The most used services		X		X	X		X			X	X	X	X				X	Snap4City Mobile App
Twitter Trends Daily	X	X	X		X	X	X	X	X				X			X	X	Twitter Vigilance
The auditing of user and living lab		X				X		X								X		Snap4City Portal
Self assessment	X	X	X	X	X	X	X	X	X	X	X	X	X			X		Snap4City Portal
Trajectories reg from mobile PAX Counters	X	X	X			X	X	X							X		X	PAX Counters
Engagement real time assessment	X	X	X			X	X	X									X	Snap4City Mobile App

From Simple Data Analytic to Complex Tools

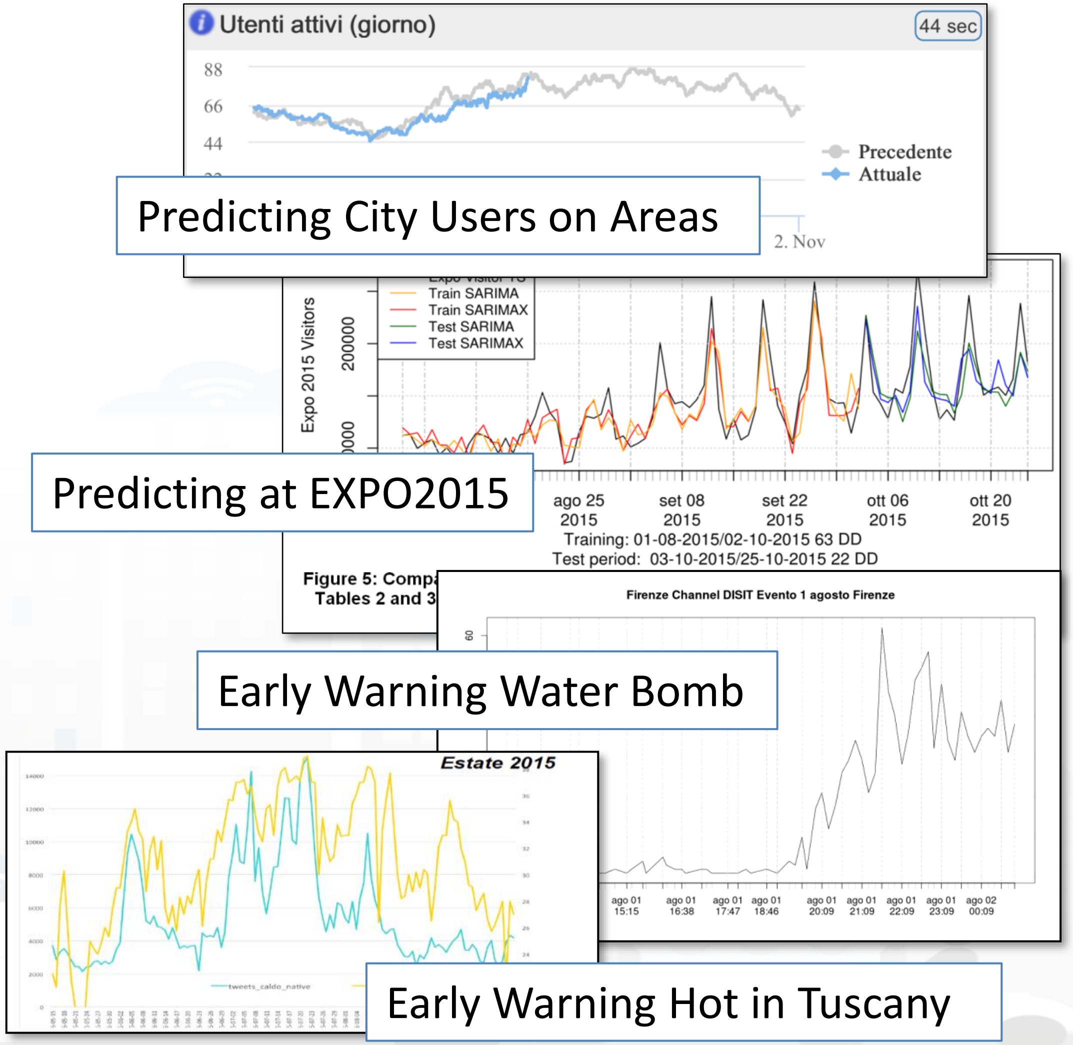
- **Structural:**
  - **Data Ingestion, Quality Control** on data: data mining, anomaly detection, etc.
  - **Typical Time trends**: traffic flow, people flow, sensors data, etc.
  - **Indexing** for fast search and retrieval: Geospatial, textual, temporal, mixt
- **Dynamical:**
  - **Analysis**: heatmap, hot places, distribution, statistical analysis
  - **Predictions** to inform and plan (e.g.: parking, people flow,)
  - **Anomaly detection** for Early Warning, Alerting
- **Special Analytics and Tools** → What-IF Analysis:
  - **Routing** for navigation: modal, multimodal, constrained
  - **Typical Trajectories** of: people flows, vehicles, etc.
  - **Traffic Flow** reconstruction
  - **Origin Destination Matrices:** people and vehicles, …
  - **Simulations**: demand vs offer, etc.

Snap4City and Data Analytic (summary)

- allows to create simple data processing as well as massive computing solutions exploiting statistics, machine learning, operating research, etc. for:
  - predictions, anomaly detection, early warning, OD Matrix construction, simulation, trajectories, typical trends, what-if analysis, smart routing, heatmaps, etc.
- **can be developed** in:
  - R Studio / Tensor Flow, Java, Python, ETL, IOT Applications
  - If HDFS/Hadoop/Hbase/Phoenix is installed: MapReduce, Spark, etc.
- **may be shared** with other colleagues, and organizations via the Resource Manager

Predicting Models for Administrators & City Users

- **Aiming at improving**
  – quality of service, distributing workload
  – early warning
- **Predictions**:
  – Short (15 min, 30 Min), mid Term (1 week), long term (months)
- **Data Analytics**: ML/AI, NLP/SA, Clust., …
  – Traffic Flows → multi-flow reconstruction
  – Parking Status → free slots
  – Environmental Alarms
  – Air Quality parameters and indexes
  – People Flows (Wi-Fi, Twitter)
    → crowd , #number of people



Development in R Studio (self training)

- [R Studio Development]
- [TC7.2 - R Studio for Analytics, exploiting Tensor Flow]
- [TC7.4 - From R Studio process to MicroService for IOT application, data analytics, machine learning]
- [TC7.5 - Developing Data Analytics Processes]
- [US7. Data Analytics and related integration aspects]

TOP

Smart Parking: predictions


autostrada
FIESOLE
SIENA
AREZZO - FORLI'

UNIVERSITÀ DEGLI STUDI FIRENZE

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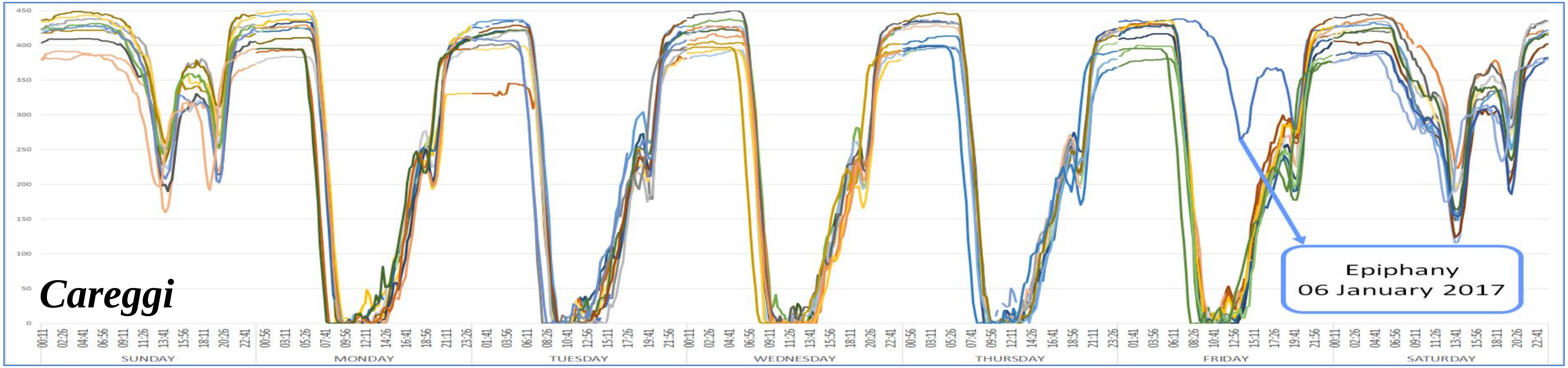
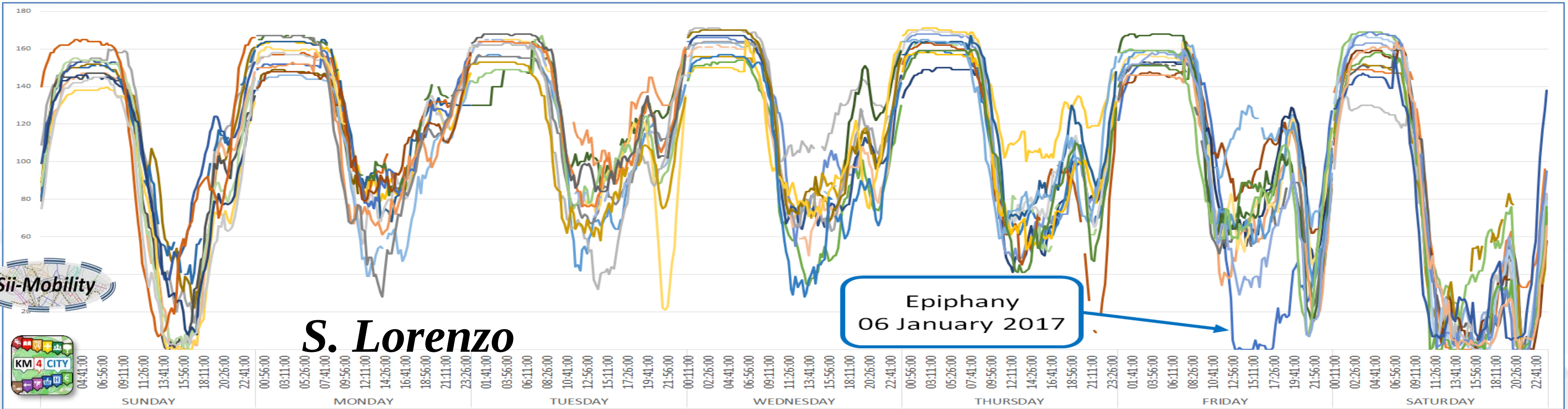
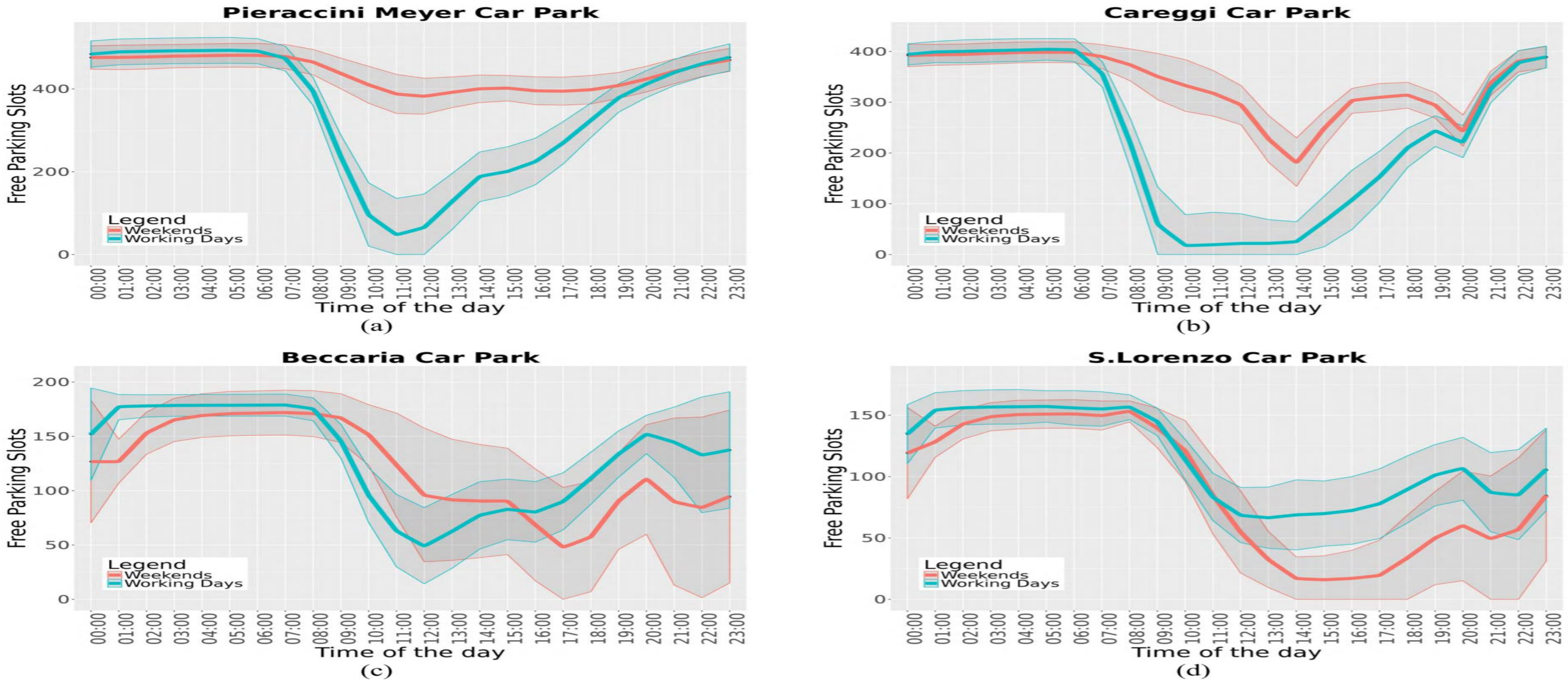
Free Parking space trends





Sii-Mobility

Free Parking space trends

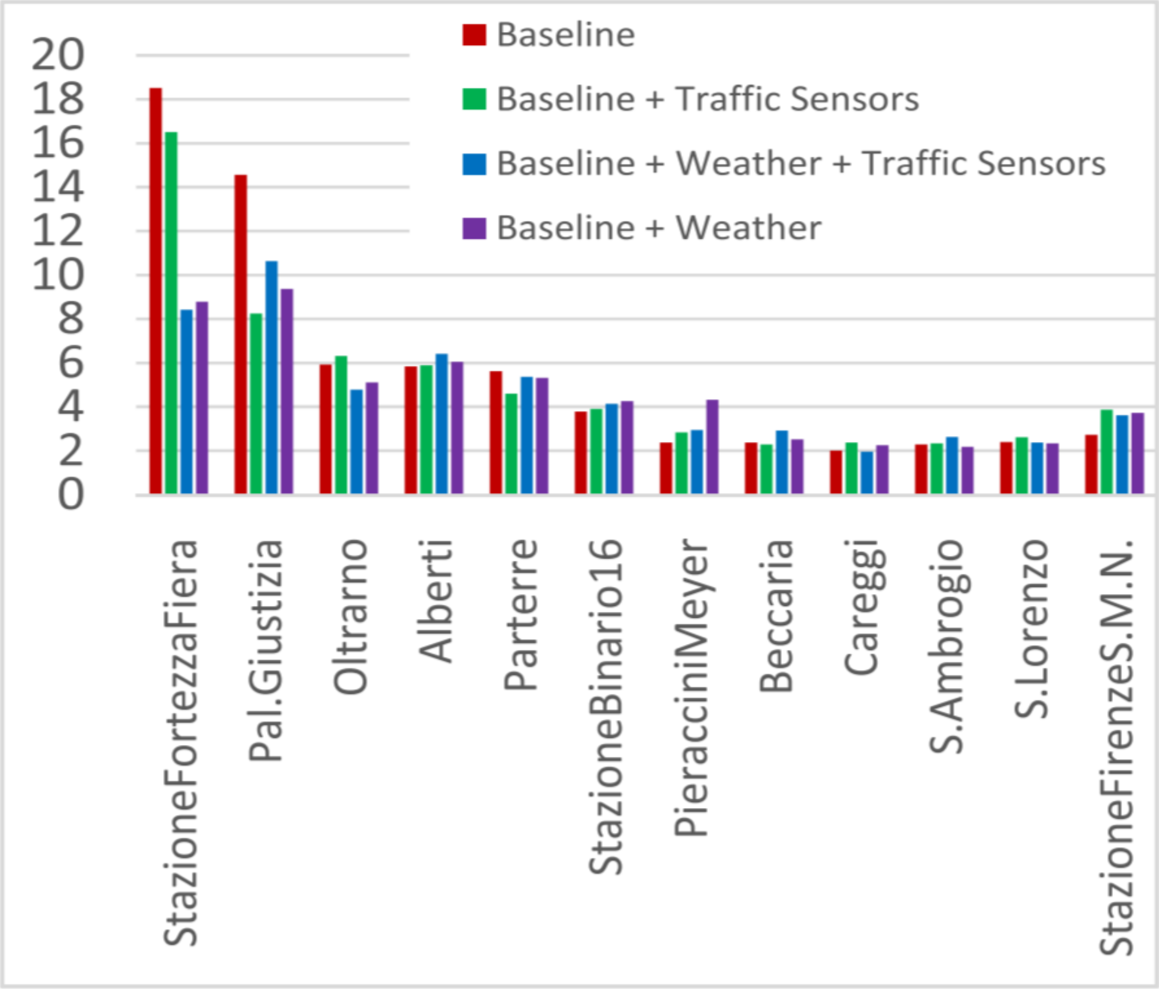


12 parking areas in Florence

Free Parking PREDICTIONS

C. Badii, P. Nesi, I. Paoli, "Predicting available parking slots on critical and regular services exploiting a range of open data", IEEE Access, preprint, 2018, https://ieeexplore.ieee.org/abstract/document/8430514/

Comparison Error	Forecasting Techniques		
	BRANN	SVR	RNN
Careggi car park			
MASE Night	34.85	16.29	20.01
MASE Morning	0.76	1.42	2.82
MASE Afternoon	1.89	4.34	3.66
MASE Evening	1.99	1.51	2.33
MASE	1.87	2.34	3.16
Pieraccini Meyer car park			
MASE Night	6.08	12.83	10.03
MASE Morning	0.86	1.27	4.90
MASE Afternoon	1.87	2.91	6.75
MASE Evening	1.36	1.57	10.23
MASE	1.37	2.06	6.67
S. Lorenzo car park			
MASE Night	10.33	11.81	18.34
MASE Morning	2.13	1.91	3.93
MASE Afternoon	2.70	3.15	2.37
MASE Evening	2.15	3.09	3.82
MASE	2.72	3.21	4.19
Beccaria car park			
MASE Night	9.32	7.80	12.47
MASE Morning	0.95	1.25	4.87
MASE Afternoon	2.49	2.14	2.45
MASE Evening	2.96	4.75	5.91
MASE	2.13	2.67	4.85



ML models

The best selected models for the purpose have been:

- BRNN:
  - Bayesian Regularized Neural Network
- SVR:
  - Support Vector Regression
- ARIMA
  - Autoregressive Integrated Moving Average
- RNN
  - Recurrent neural networks

BRNN: Bayesian Regularized Neural Network

$$y_i = g(x_i) + e_i$$
$$y_i = \sum_{k=1}^{s} w_k g_k \left(b_k + \sum_{j=1}^{p} x_{ij} \beta_j^{[k]} \right) + e_i, \quad i = 1, \ldots, n$$

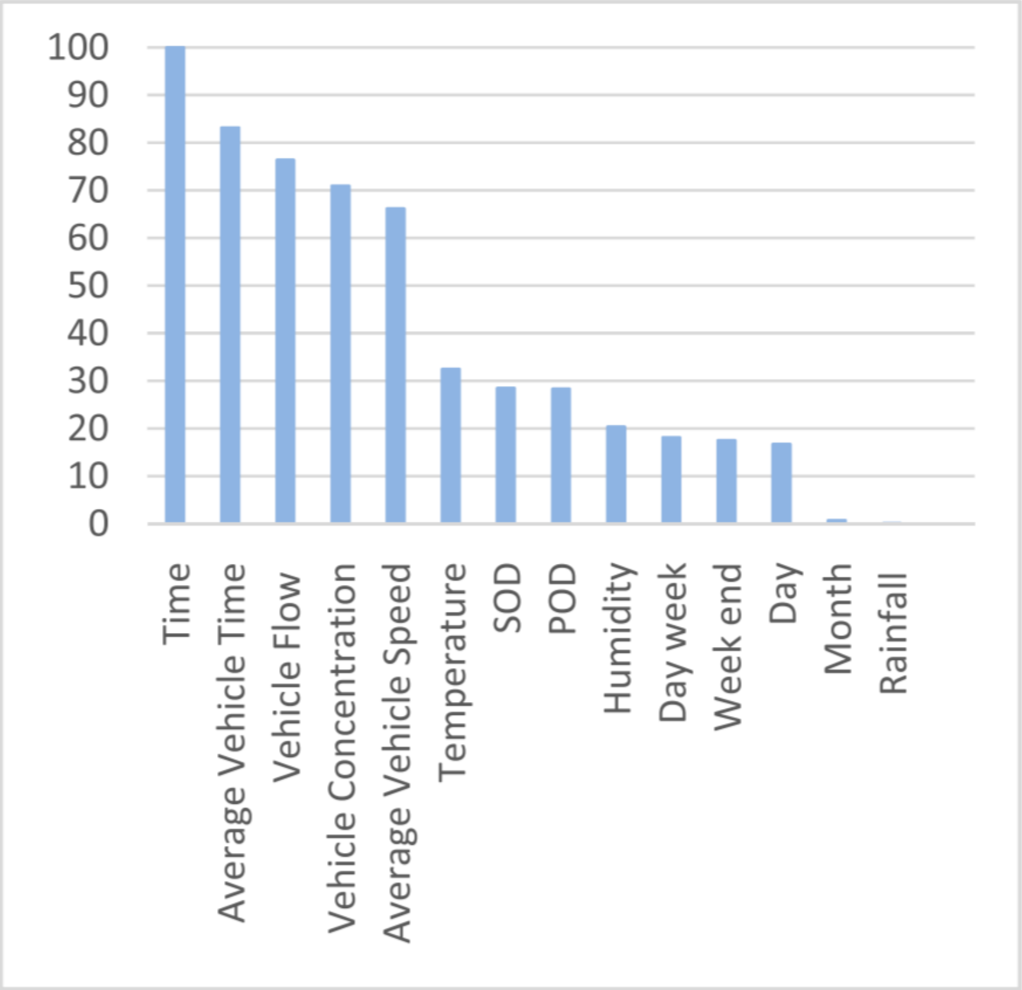
- $e_i \sim N(0, \sigma_e^2)$;
- s is the number of neurons;
- w_k is the weight of the k -th neuron, $k = 1, \ldots, s$;
- b_k is a bias for the k -th neuron, $k = 1, \ldots, s$;
- $\beta_j^{[k]}$ is the weight of the j -th input to the net, $j = 1, \ldots, p$;
- $g_k(\cdot)$ is the activation function: in this case

$$g_k(x) = \frac{e^{2x} - 1}{e^{2x} + 1}$$

The objective function consists of minimizing $F = \alpha E_W + \beta E_D$, where E_W is the sum of squares of network parameters (weight and bias), and E_D is the error (sum of squares), α and β are the objective function parameters.

Free Parking PREDICTIONS

Relevance of Variable



Category	Features	Description of features variable
Baseline features of free slot data	Free parking slots	Real number of available slots recorded every 15 minutes
	Time	Hours and minutes
	Month	Month of the year (1-12)
	Day	Day of the month (1-31)
	Day week	Day of the week (0-6)
	Weekend	0 for working days, 1 else
	Previous observation's difference (POD)	Difference between the number of free spaces at time i and number of free spaces at time (i − 15 minutes) recorded in the previous week
	Subsequent observation's difference (SOD)	Difference between the number of free spaces at time i, and the number of free spaces at time (i + 15 minutes) recorded in the previous week
Weather features	Temperature	City temperature measured one hour earlier than Time (°C)
	Humidity	City humidity measured one hour earlier than Time (%)
	Rainfall	City rainfall measured one hour earlier than Time (mm)
Traffic Sensors features	Average Vehicle Speed	Average speed of vehicles on the road being closest to the parking, over one-hour period (km/h)
	Vehicle Flow	Number of vehicles passing by closest to the parking, over one-hour period
	Average Vehicle Time	Average of distance between vehicles, over one-hour period
	Vehicle Concentration	Number of vehicles per kilometer, over one-hour period

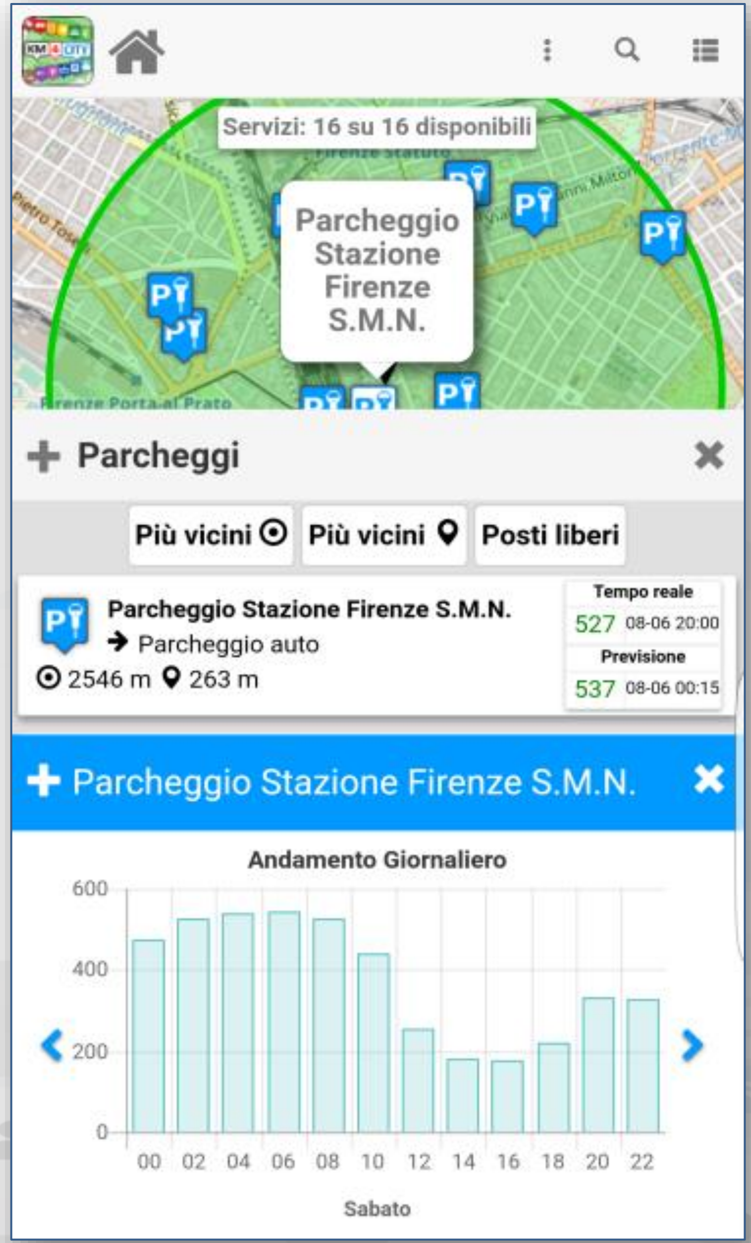
Free Parking PREDICTIONS

Performances

Training	Forecasting Techniques			
	BRANN	**SVR**	**RNN**	**ARIMA**
Average Training processing time (sec)	76.3	9.1	598.7	9.2
Re-Training frequency	Daily	Daily	Daily	Hourly
Training period	3 months	3 months	3 months	3 months
Estimation	**BRANN**	**SVR**	**RNN**	**ARIMA**
Average Estimation time (sec)	0.0031	0.0052	0.034	0.0015
Estimation frequency	Hourly	Hourly	Hourly	Hourly
Estimation predicted period	1 hour	1 hour	1 hour	1 hour

Free Parking Predictions

Careggi car park			
Model features	BRNN model results		
	R-squared	RMSE	MASE
Baseline	0.974	24	1.87
Baseline + Weather	0.975	24	1.75
Baseline + Traffic sensors	0.975	24	2.04
Baseline + Weather + Traffic sensors	0.975	24	1.87



Active on Mobile Apps as:

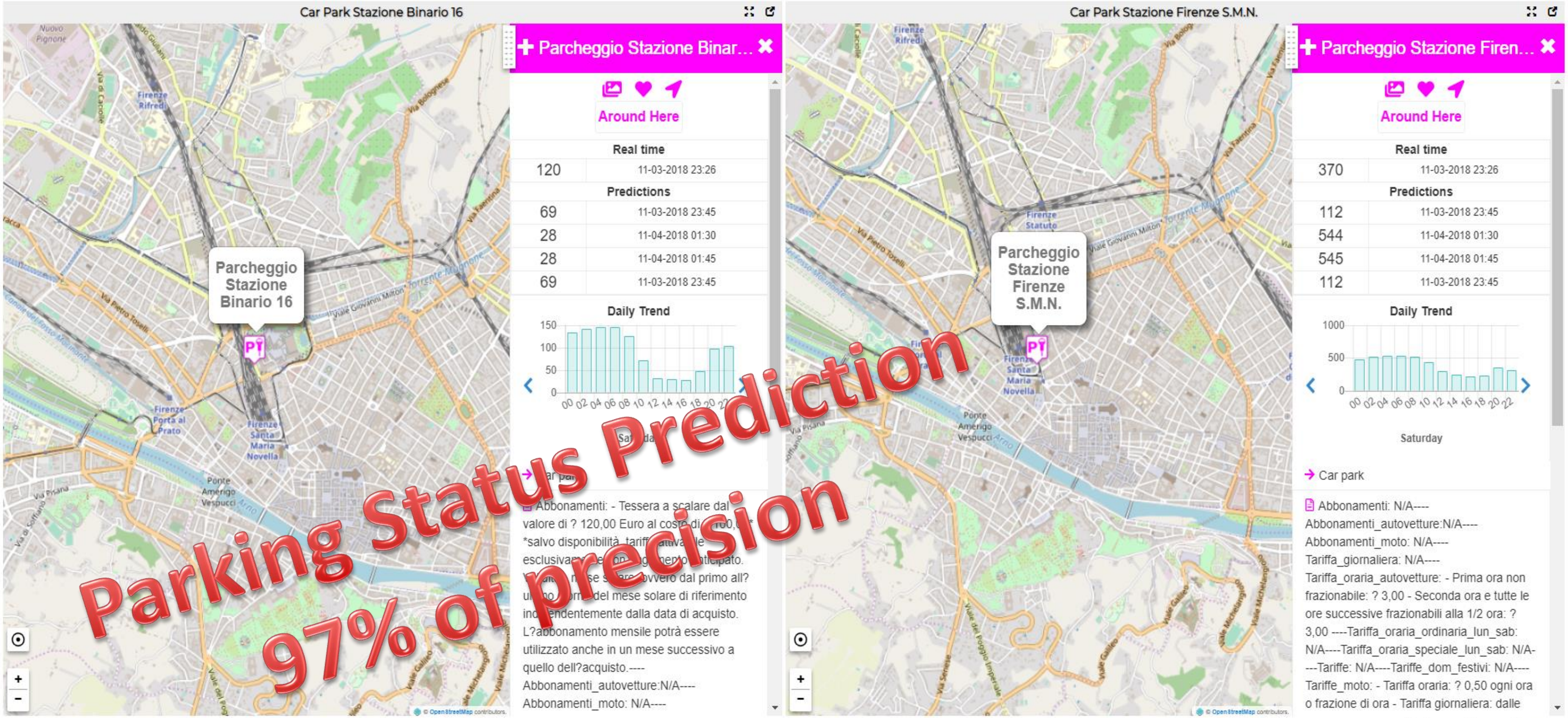
– «Firenze dove cosa»

– «Toscana dove cosa»

Precision: 97,5%

Monitoring Station for Parking

Sat 3 Nov 23:39:55



https://www.disit.org/dashboardSmartCity/view/index.php?iddasboard=MjQ2

Predictions on Parking

- C. Badii, P. Nesi, I. Paoli, "Predicting available parking slots on critical and regular services exploiting a range of open data", IEEE Access, preprint, 2018, https://ieeexplore.ieee.org/abstract/document/8430514/

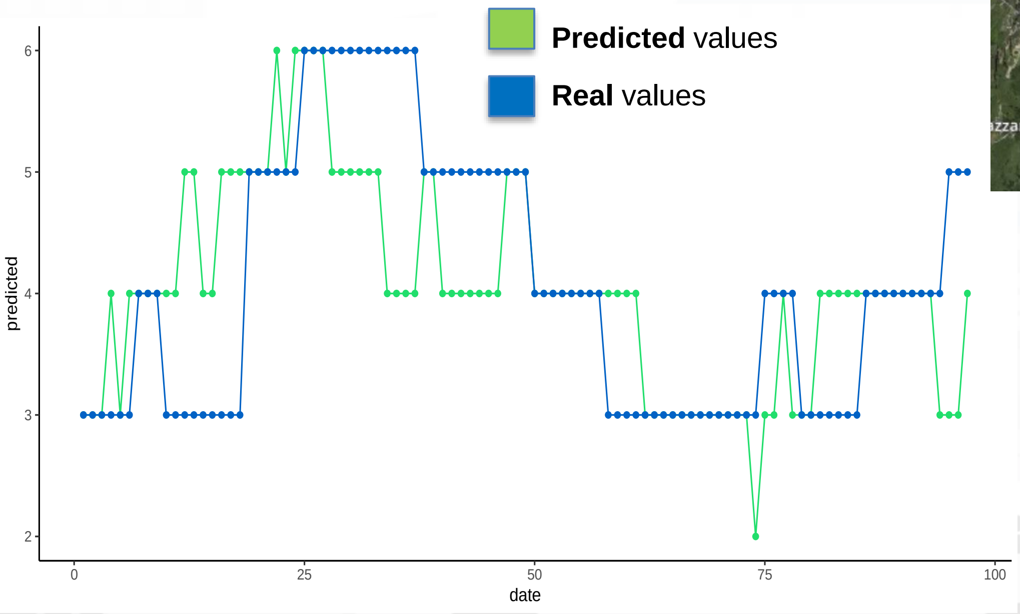
TOP

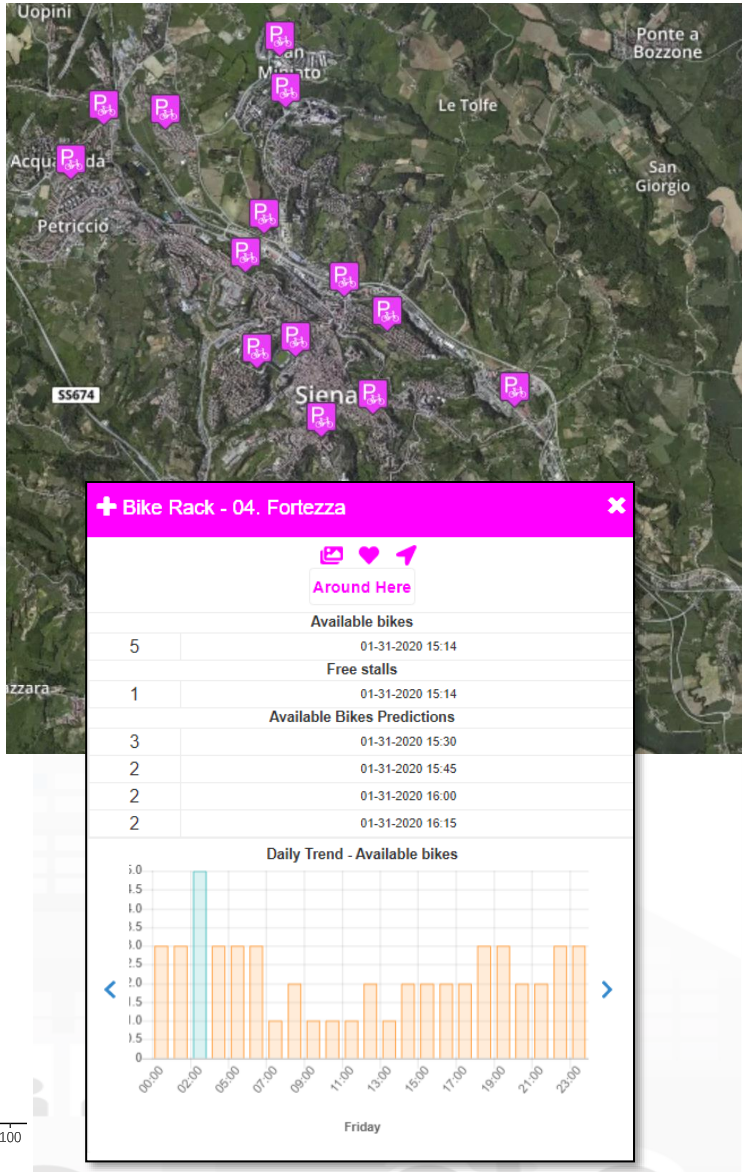
Smart Bike Sharing

Siena Bike Sharing

- For each Bike Rack, Prediction of the number of
  - available bikes in sharing
  - free slots for leaving the bike

- **Machine Learning Model**
  - **Recurrent NN**
  - **MASE 3-4.5**
  - **MAE <0.7-0.8**



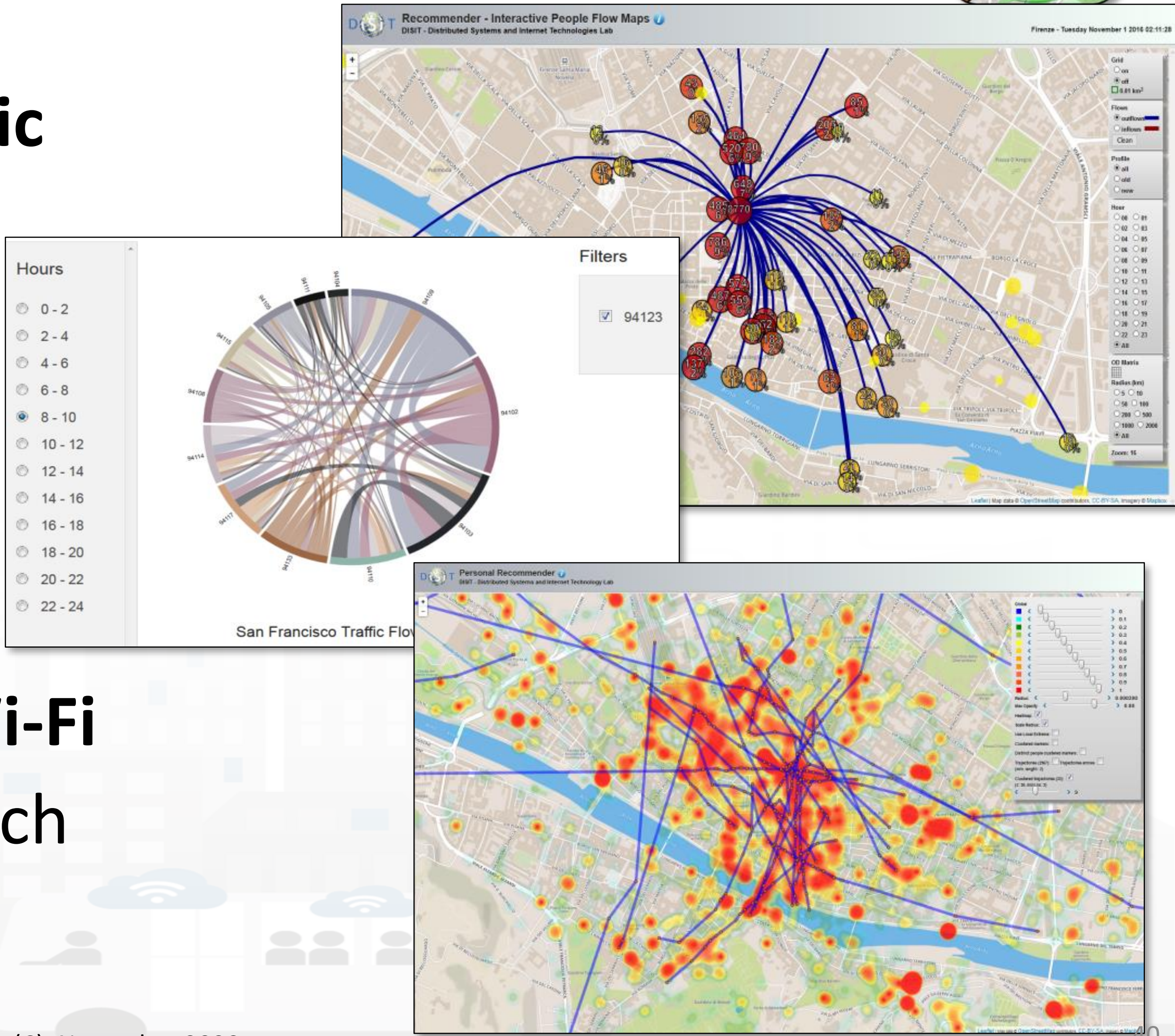


TOP

User Behaviour Analysis via Wi-Fi, OD Matrices

User Behaviour Analysis

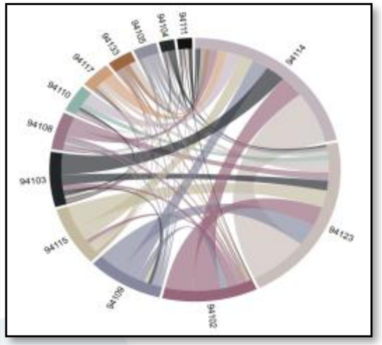
- **Monitoring movements by traffic flow sensors**
  - Spires and virtual spires
- **Monitoring movements from Mobile Cells**
  - Unsuitable for precise tracking and OD production
- **Monitoring movements from Wi-Fi**
- **Monitoring movements** and much more from mobile Apps



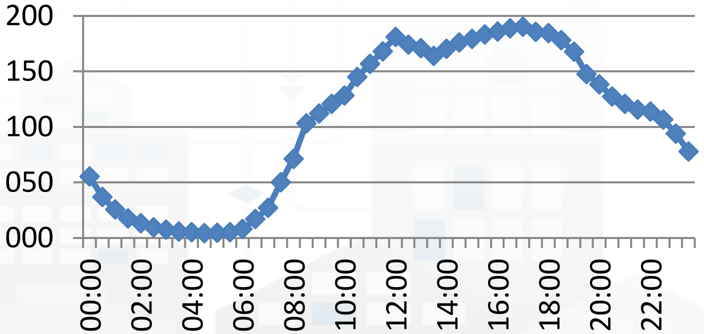

T1 Villa
904
1007
GEST
1016
GEST

Predicting City users movements

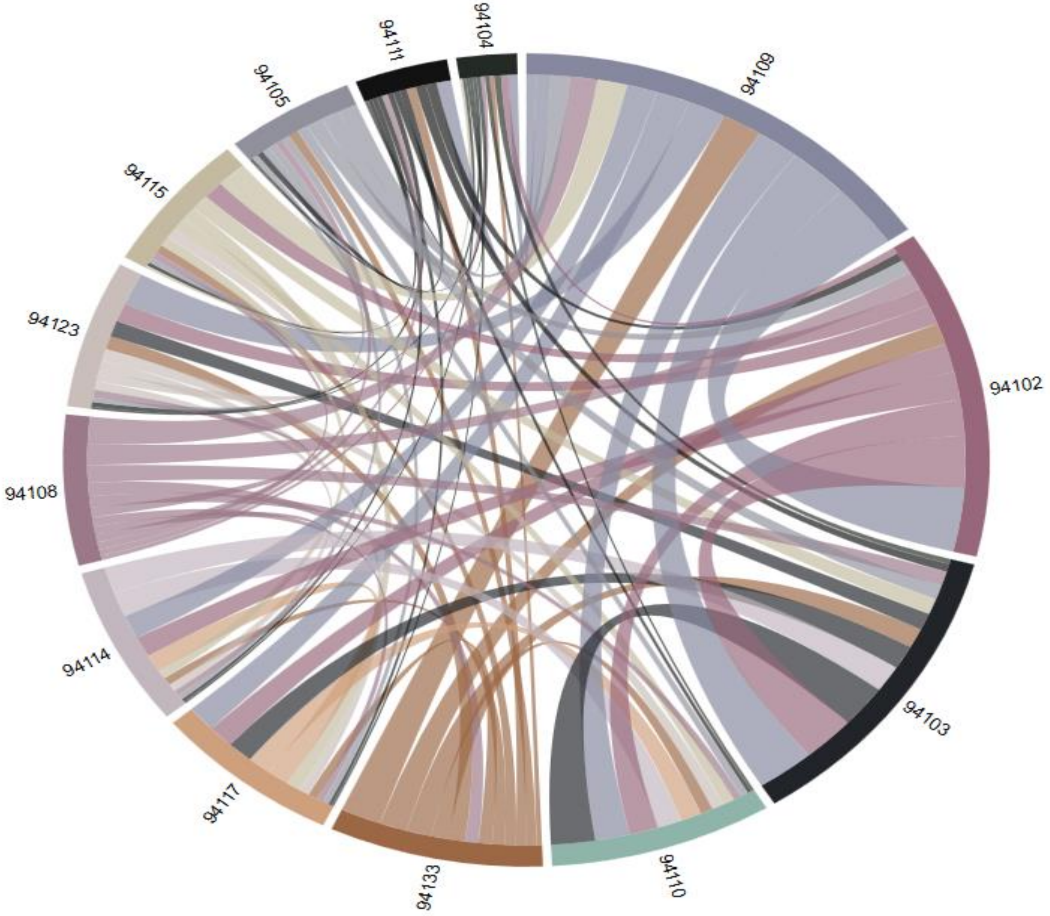
- **Issue:**
  - How they move: vehicles, pedestrian, bike, ferry, metro,
  - Where they go….
- **Impact:**
  - Tuning the services: cleaning, police, control, security
- **Several metrics related to**
  - Knowledge of the city
  - Monitoring traffic and people flow
  - …….

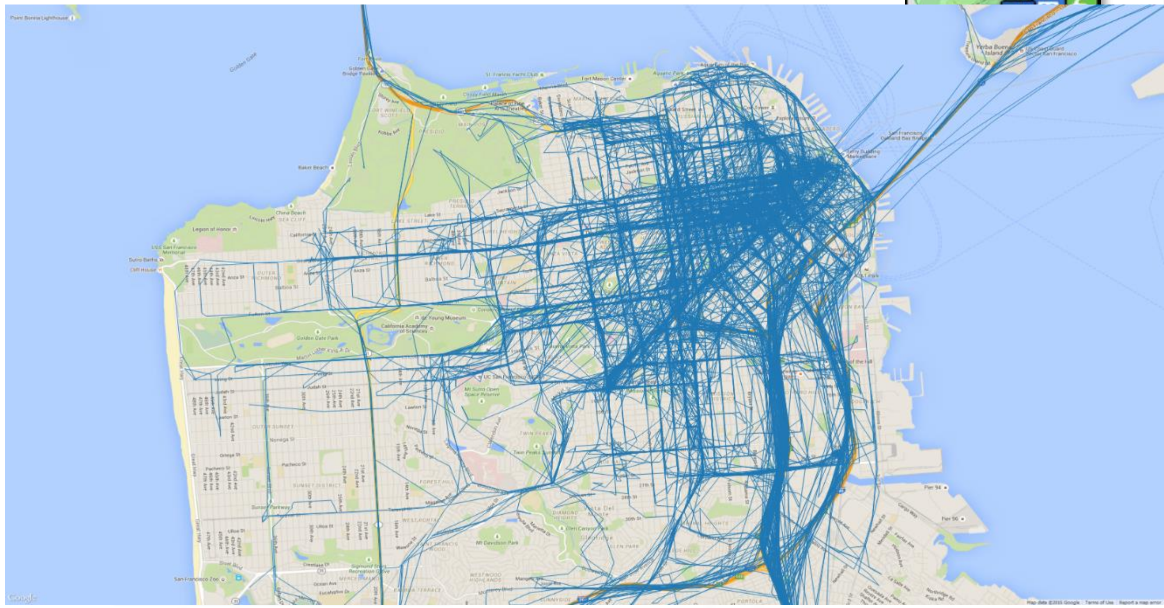


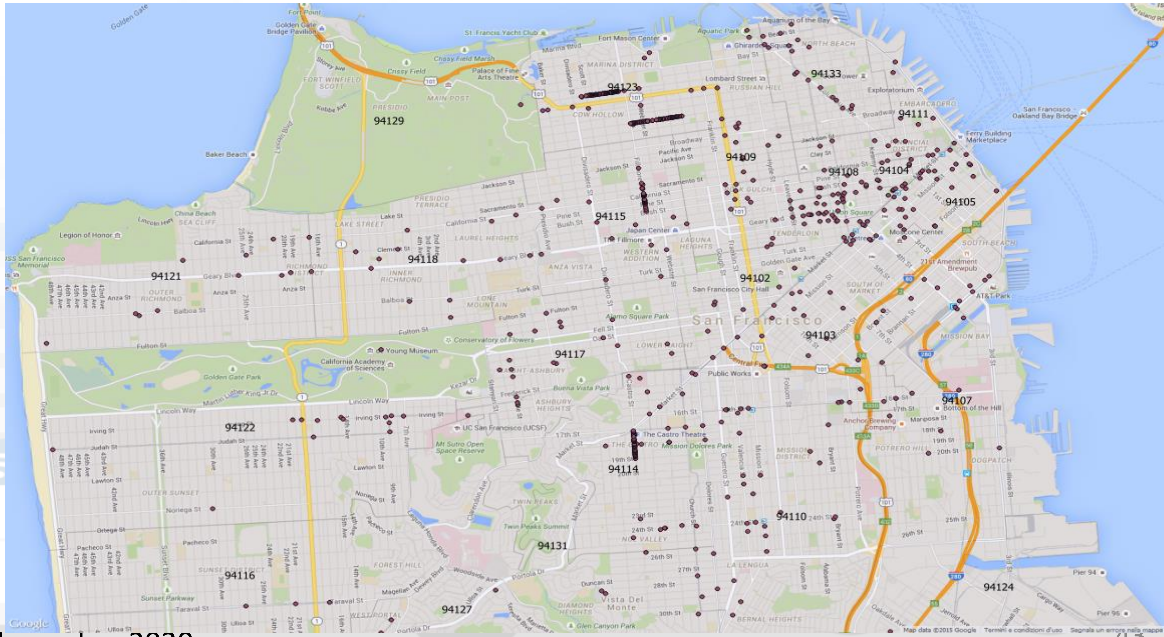
- Daily trends
- OD matrices
- Trajectories
- Prediction models



San Francisco Case

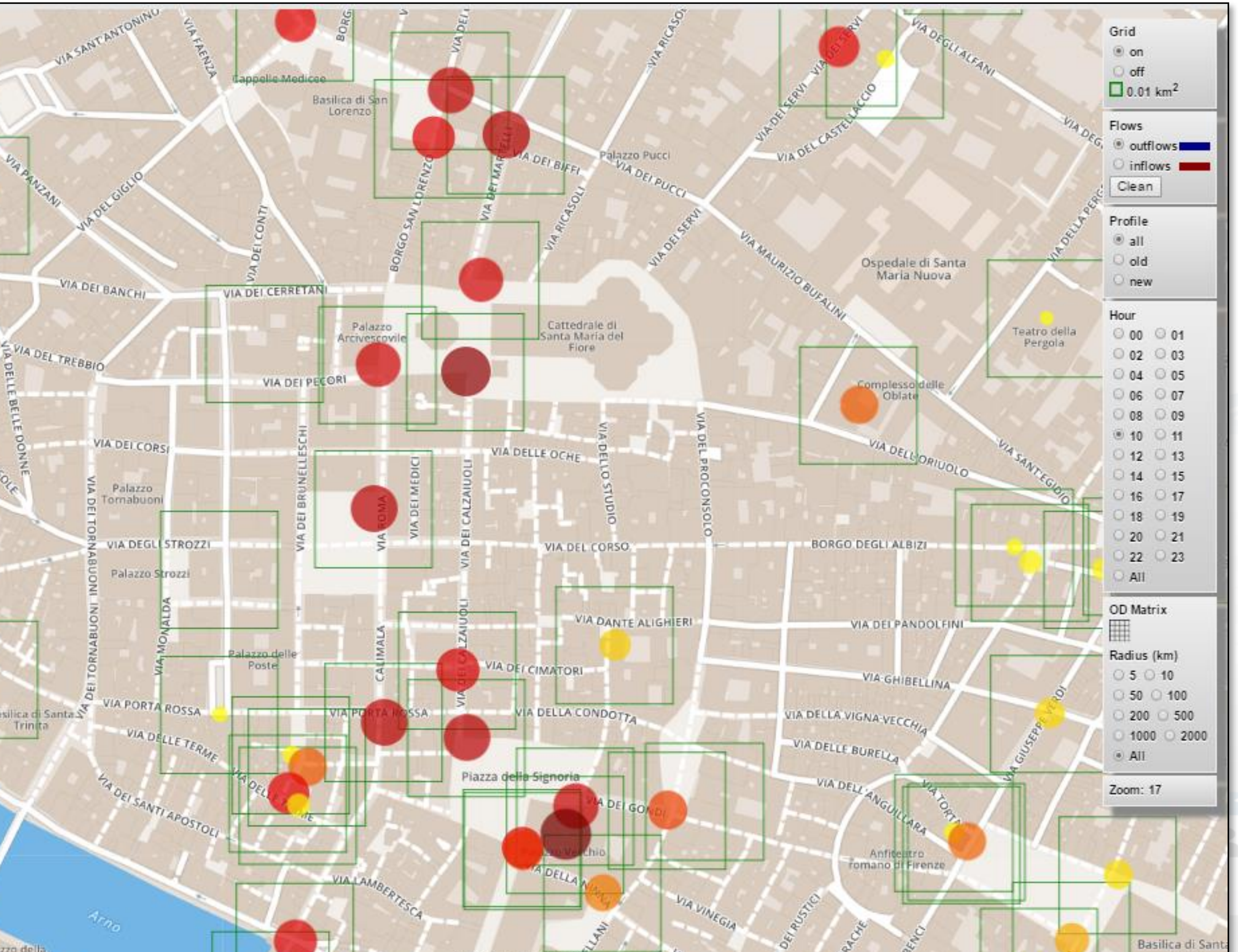






San Francisco OD matrix as a chord diagram among the 13 central ZIP areas of the city (real cab flows)

Firenze Wi-Fi



- AP → heatmap sparsa
- Inflow/outflow
- New/Old users
- per fascia oraria

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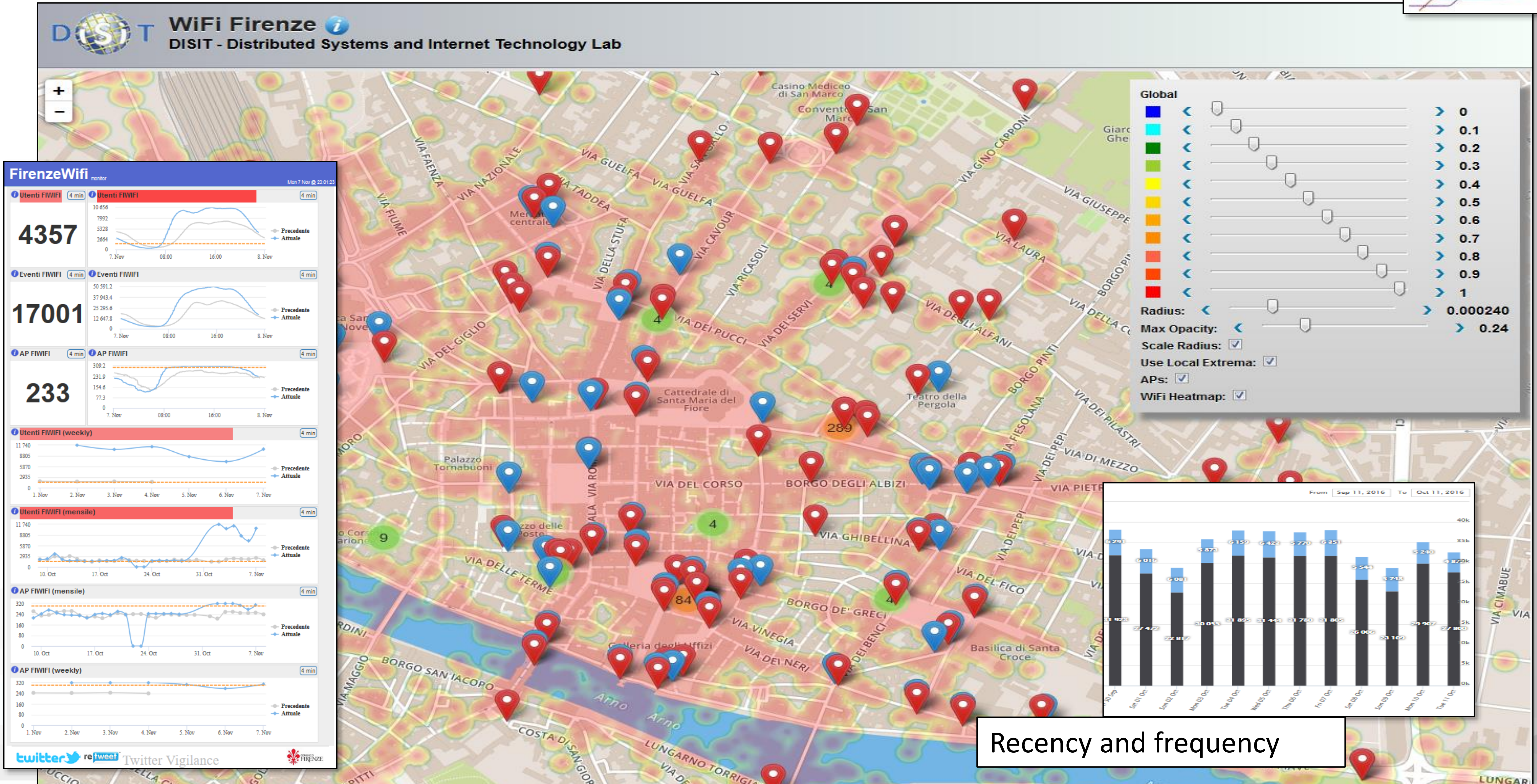
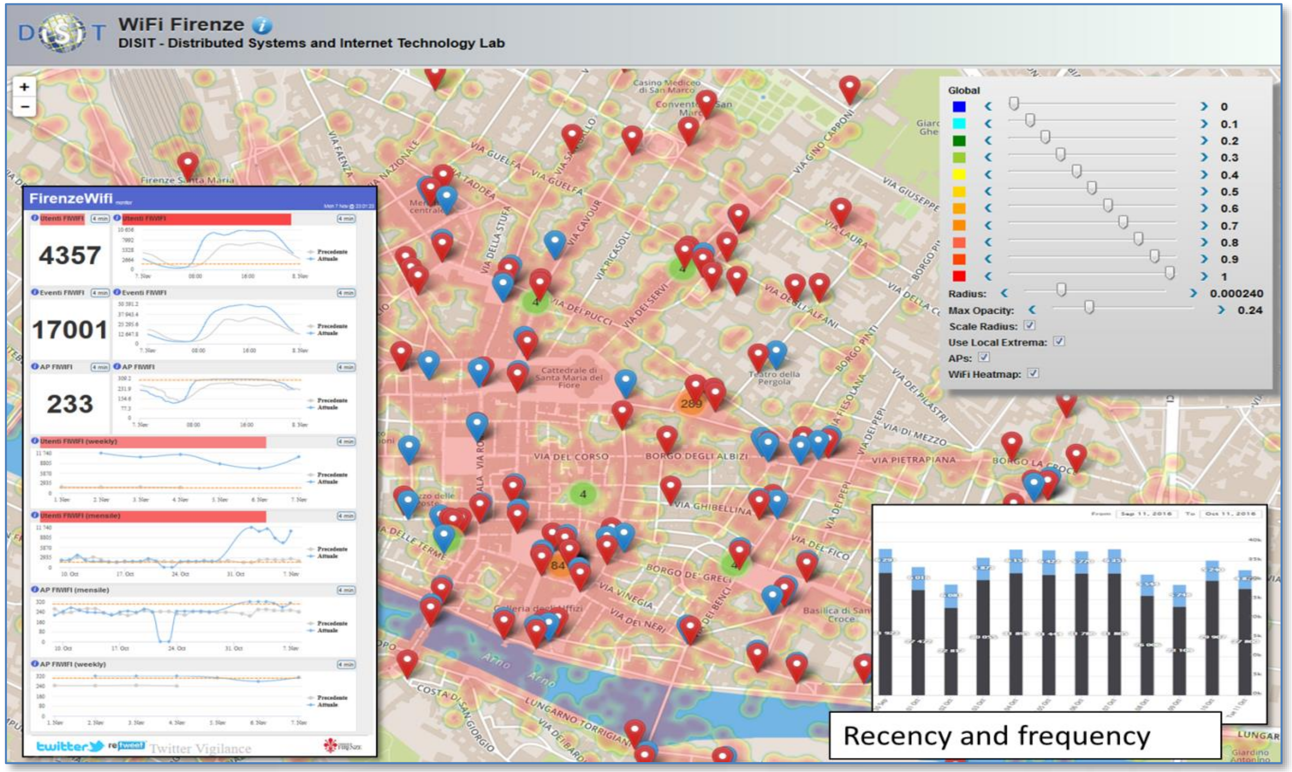
Wi-Fi Monitor Tool

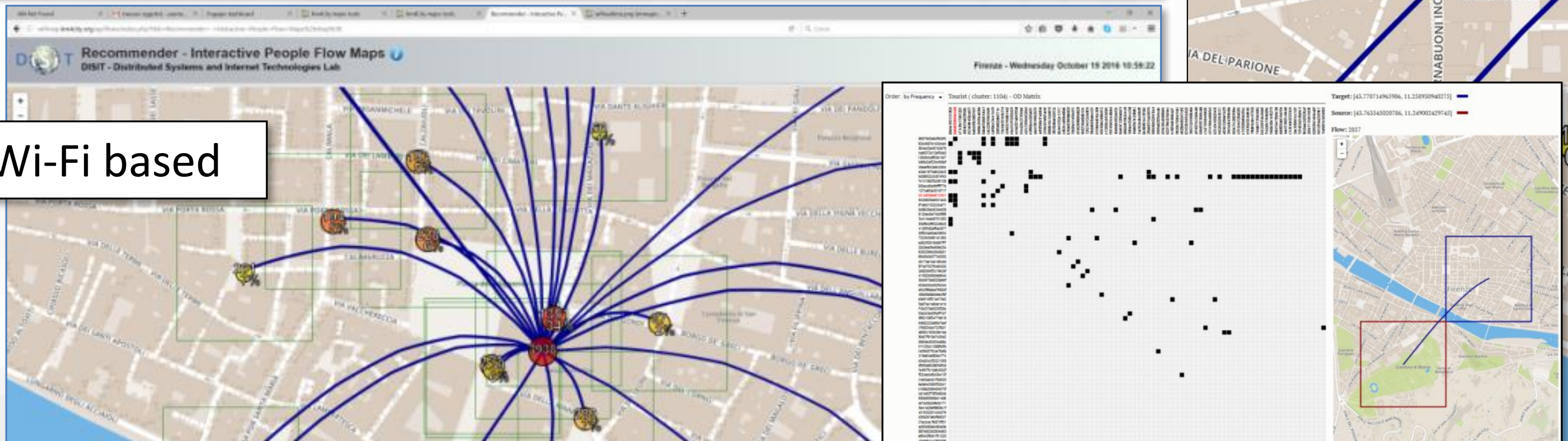


Recency and frequency

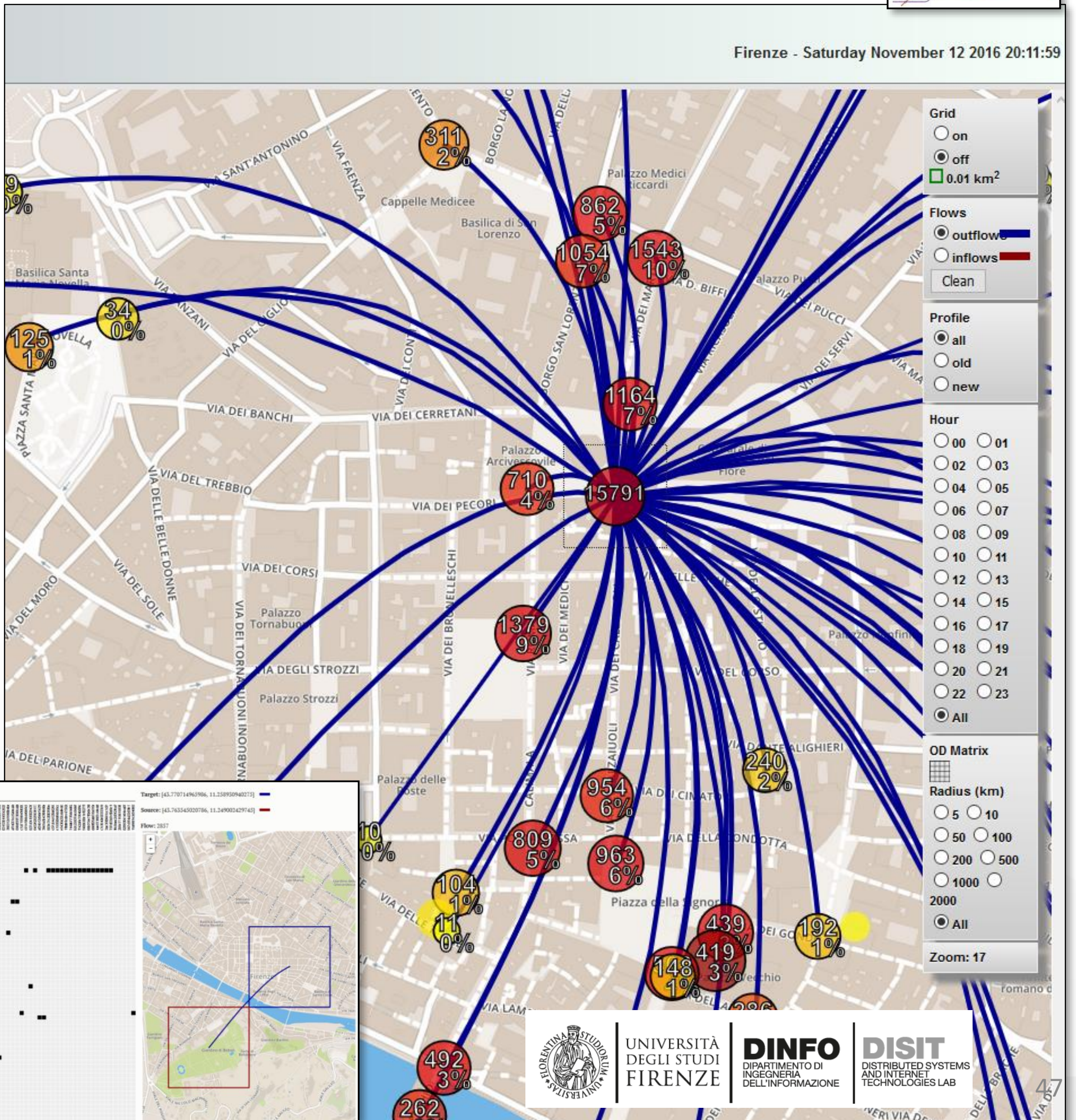
Origin Destination Matrix Estimation



Recency and frequency

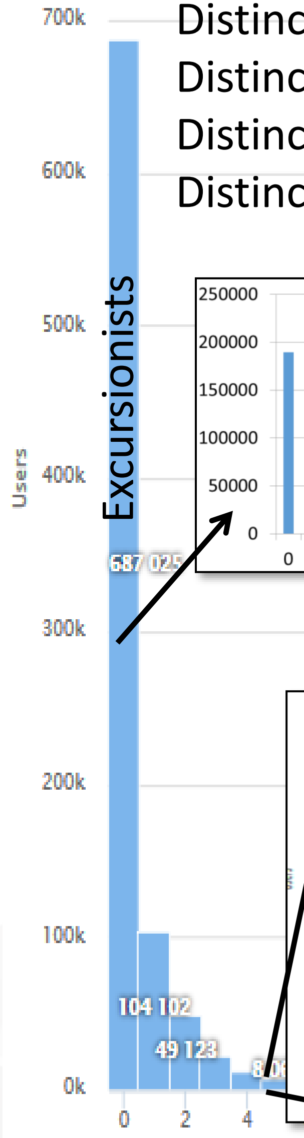


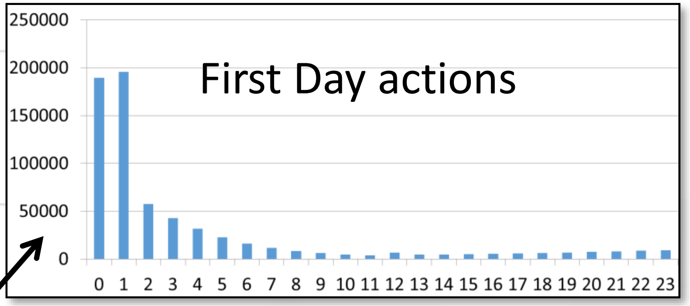
Wi-Fi based

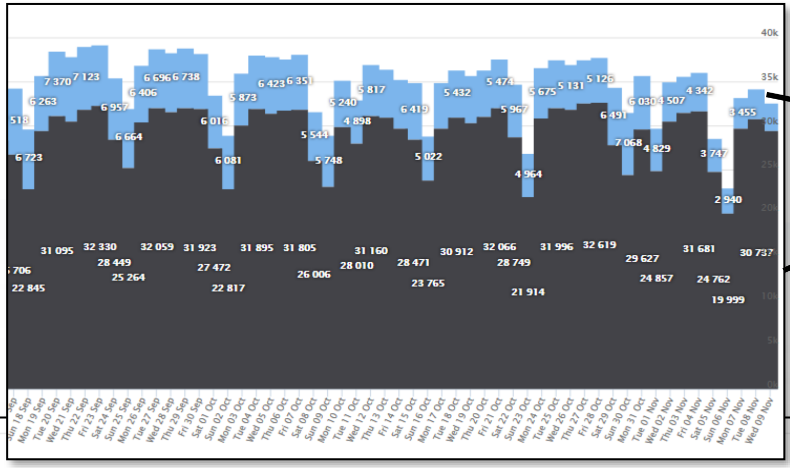


User Behaviour Analysis

Distinct APs: 343
Distinct APs (last 24 hours): 311
Distinct Users (last 180 days): 1102098
Distinct Excursionists (last 180 days, < 24 h): 687025

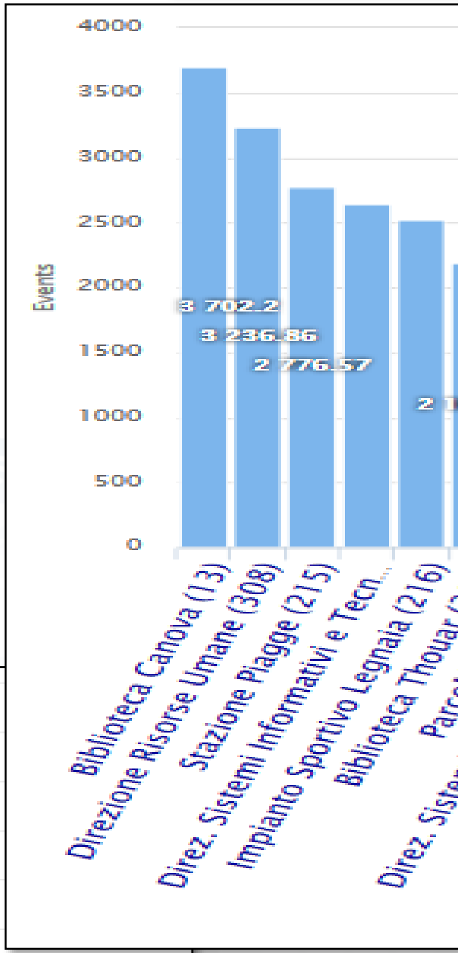


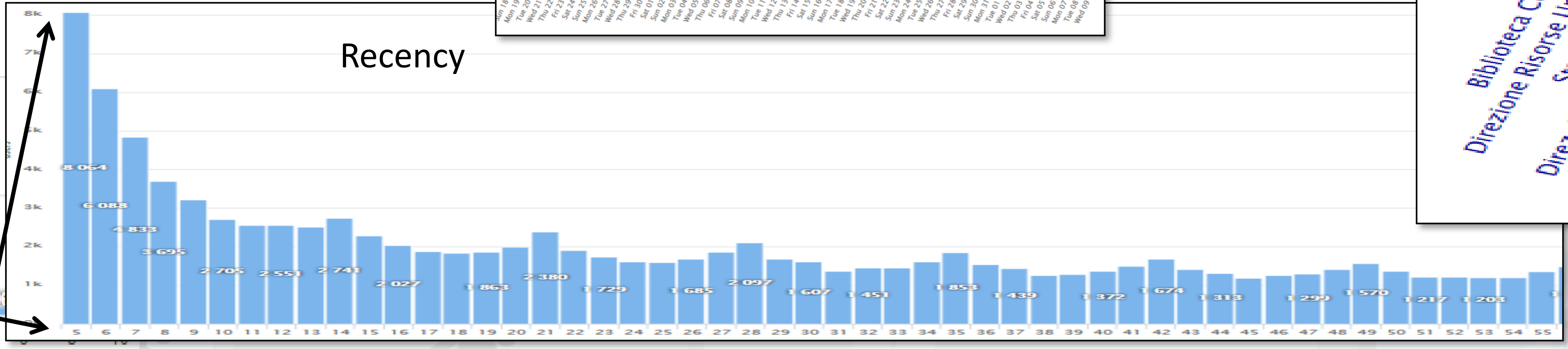




New City Users
VS
Returning

Where

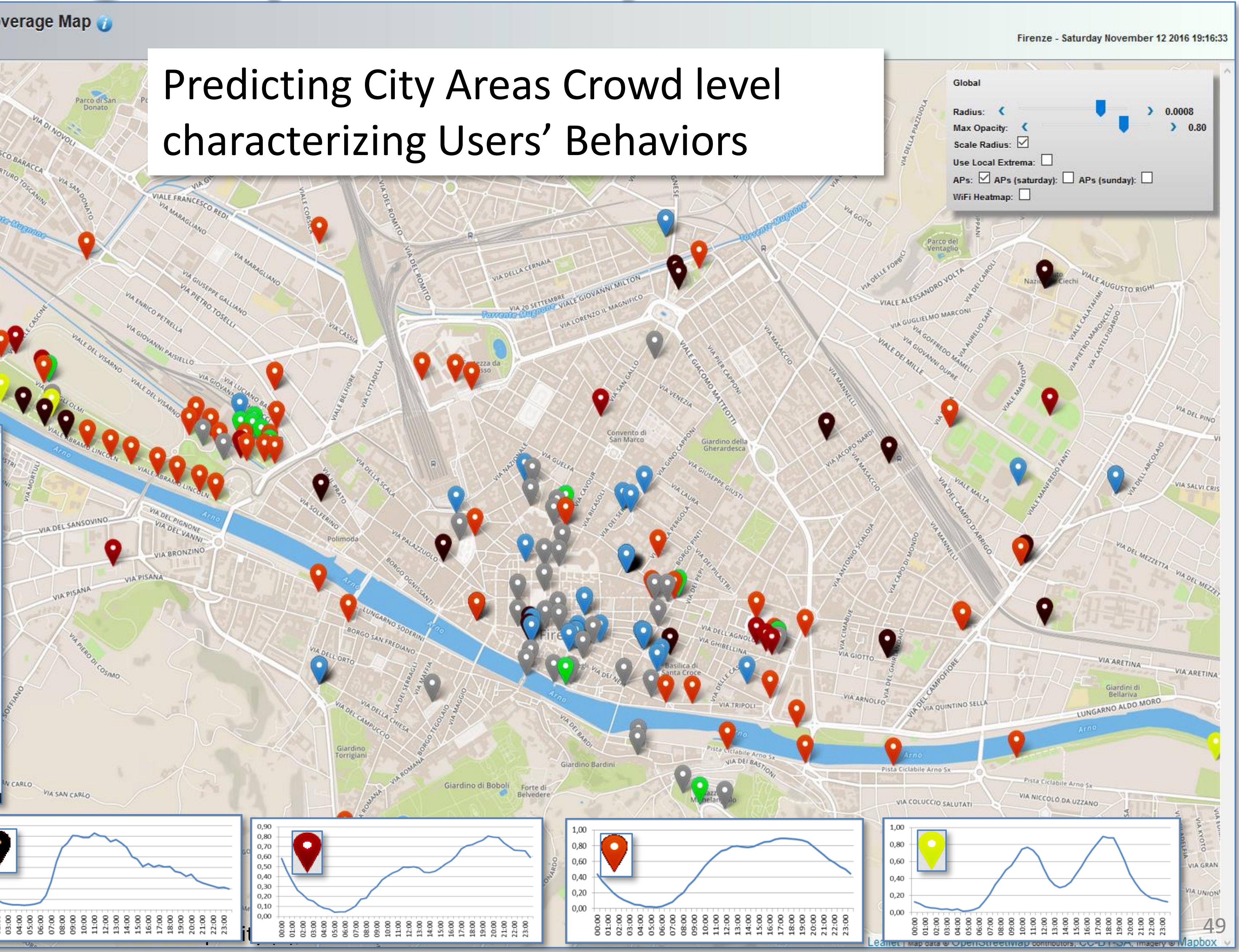


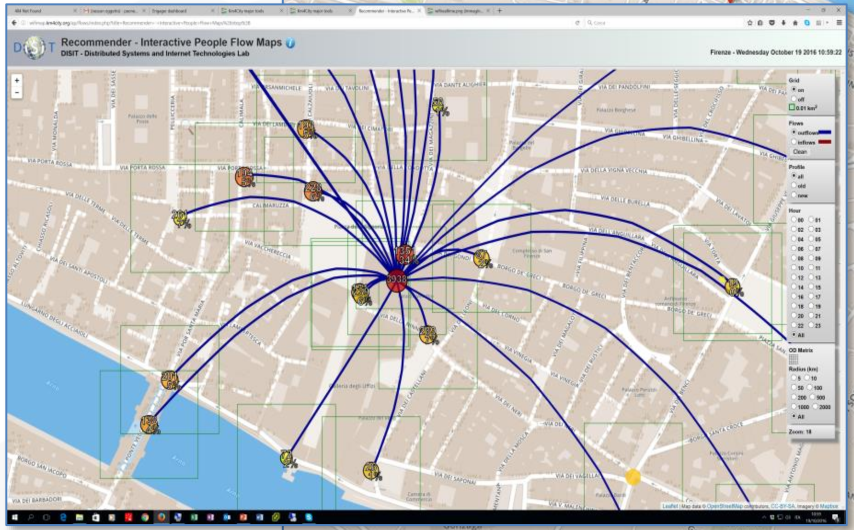


Characterizing City Areas by User Behavior

Wi-Fi based

Predicting City Areas Crowd level characterizing Users' Behaviors





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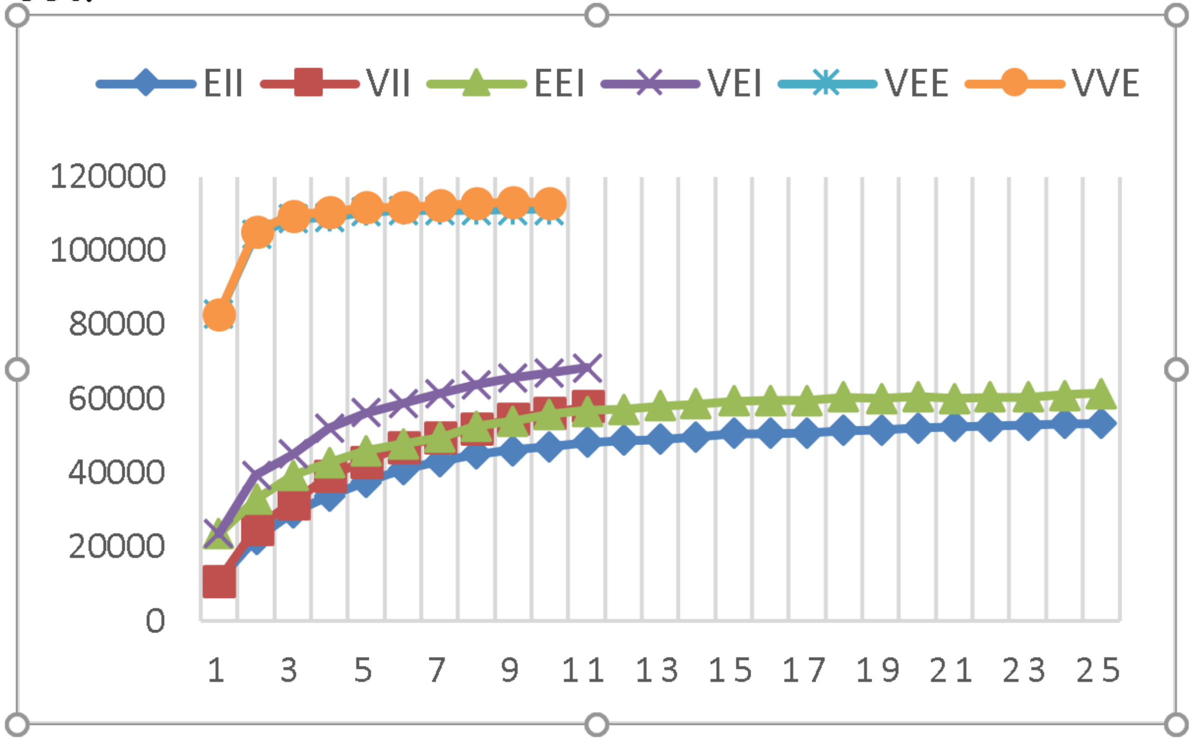
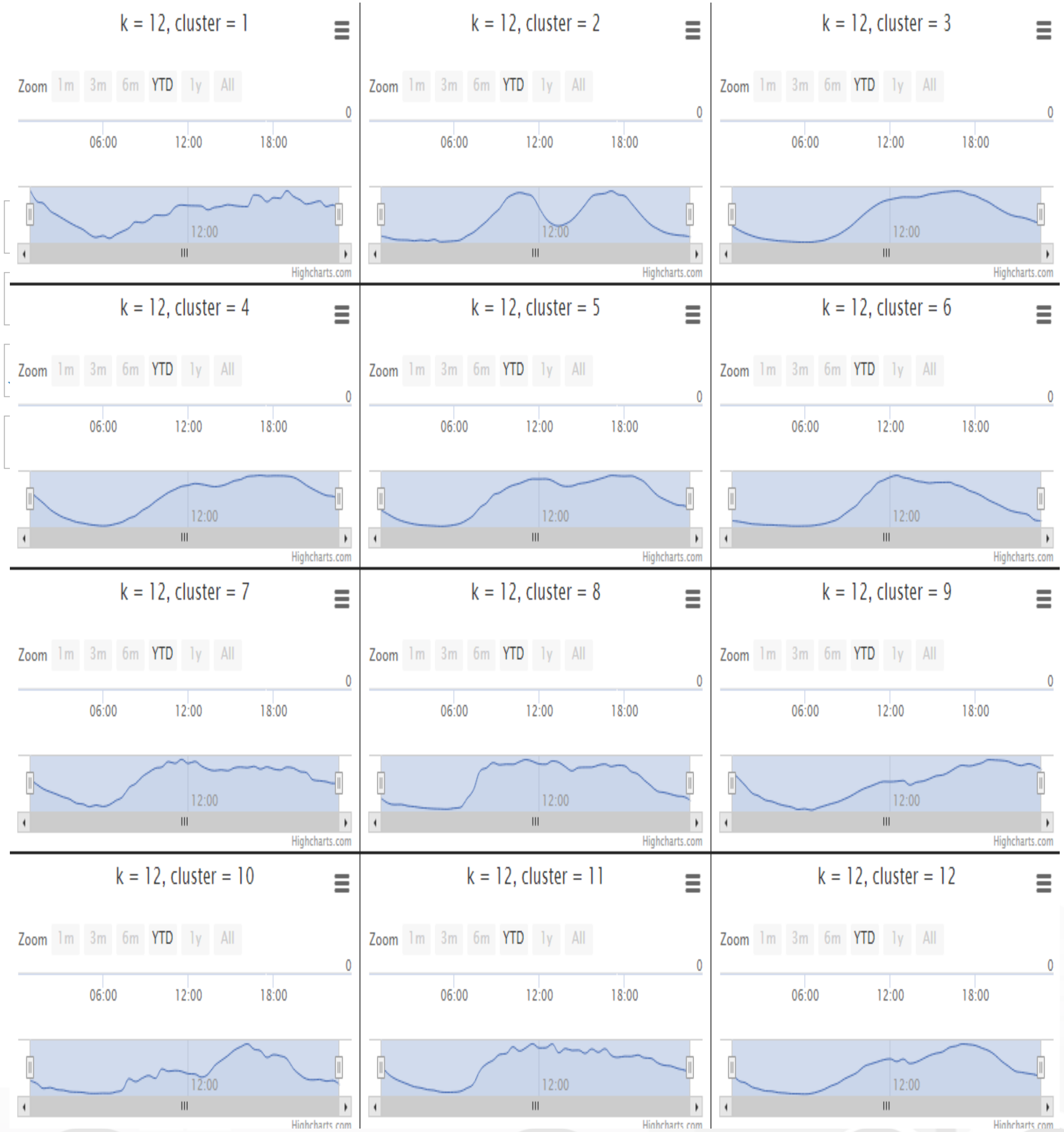
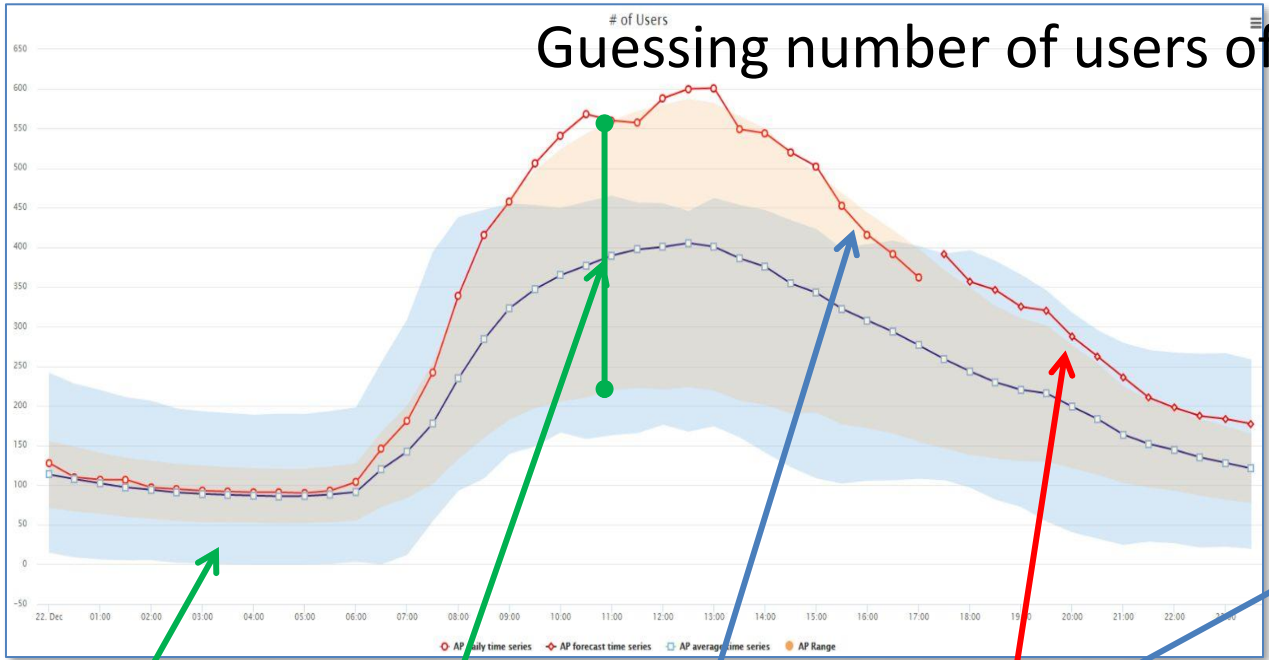


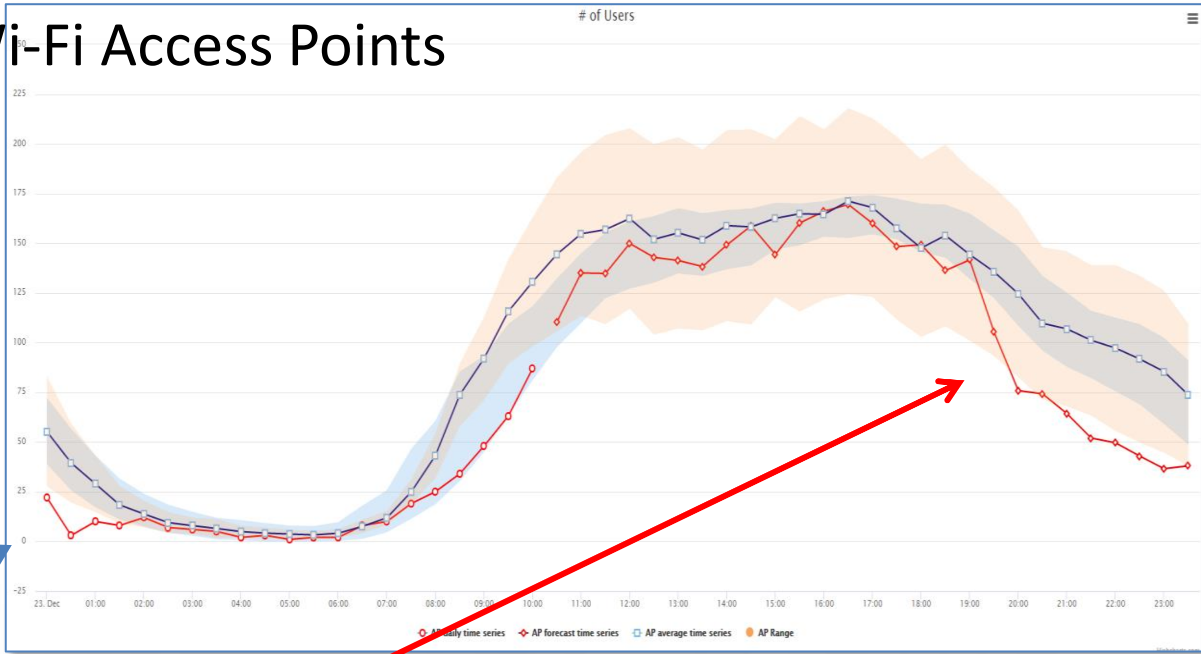
Figure 14 – Average BIC for mixture models vs K number of cluster, higher values are better, the curves are truncated at the best value for K they found.



Prediction and Identification of Anomalies

Guessing number of users of Wi-Fi Access Points





Cluster confidence

AP average and confidence

Actual AP trend for today

AP prediction for the next time slot in the day on the basis of past weeks

Predictive precision of the 95%

User Behaviour Analysis

- P. Bellini, D. Cenni, P. Nesi, I. Paoli, "Wi-Fi Based City Users' Behaviour Analysis for Smart City", Journal of Visual Language and Computing, Elsevier, 2017. http://www.sciencedirect.com/science/article/pii/S1045926X17300083

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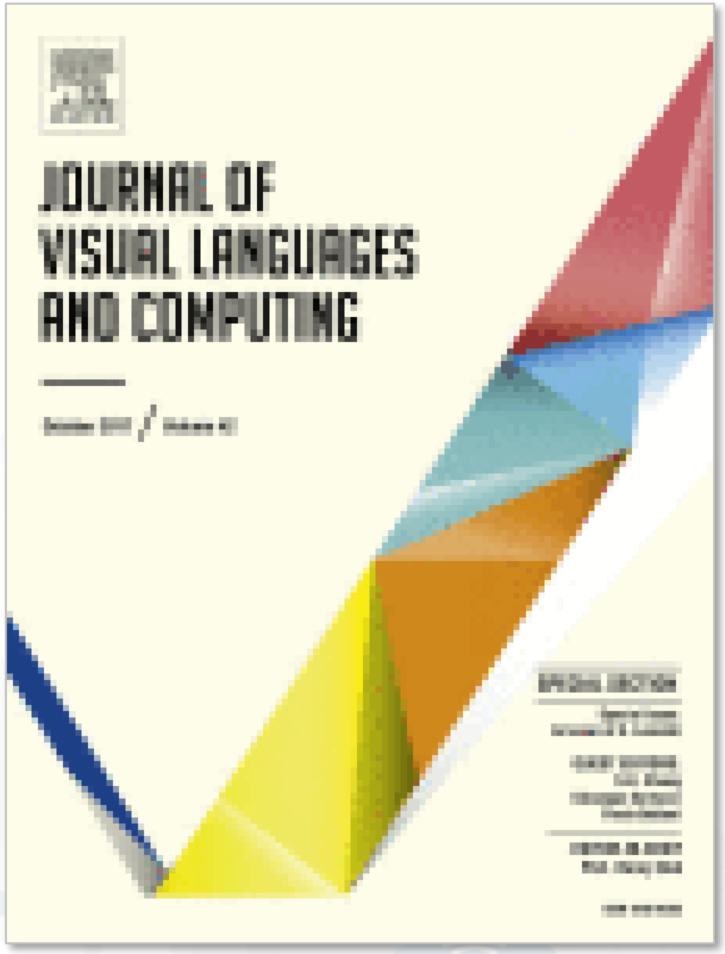
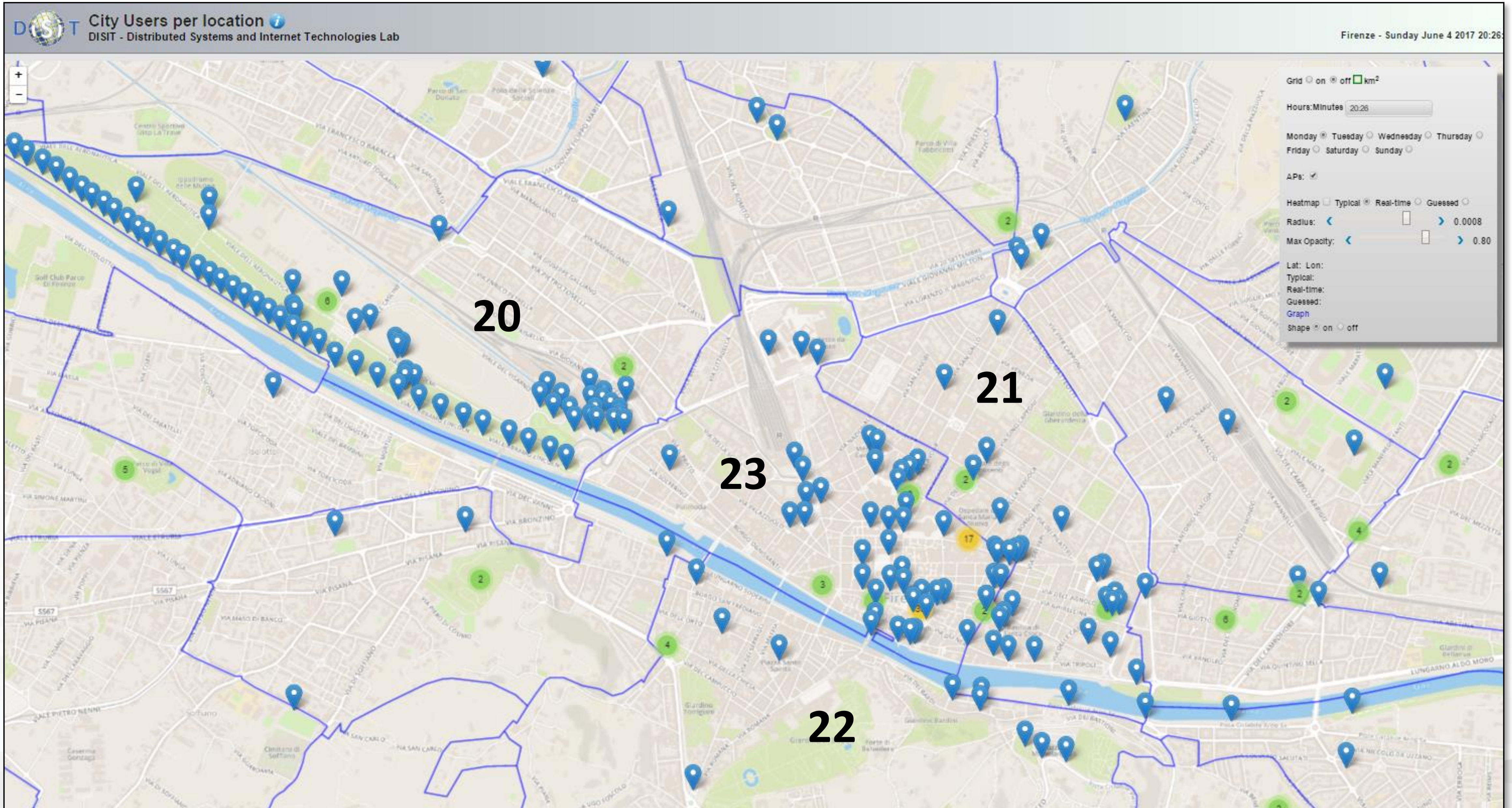


Firenze Wi-Fi vs ACE



TOP

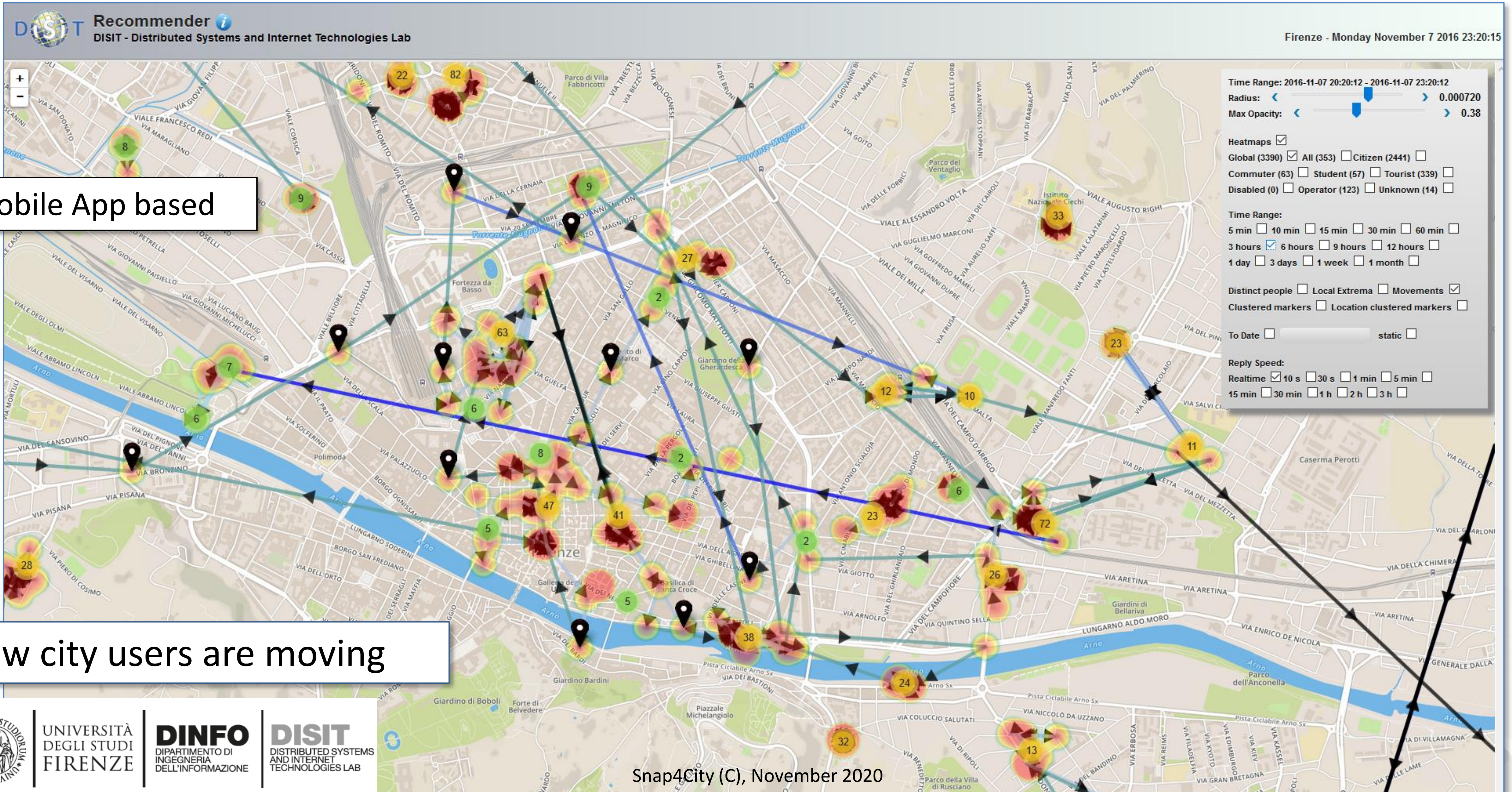
User Behaviour Analysis via Trajectories

Anonymous User Behavior Analysis

Case Study E

Sii-Mobility

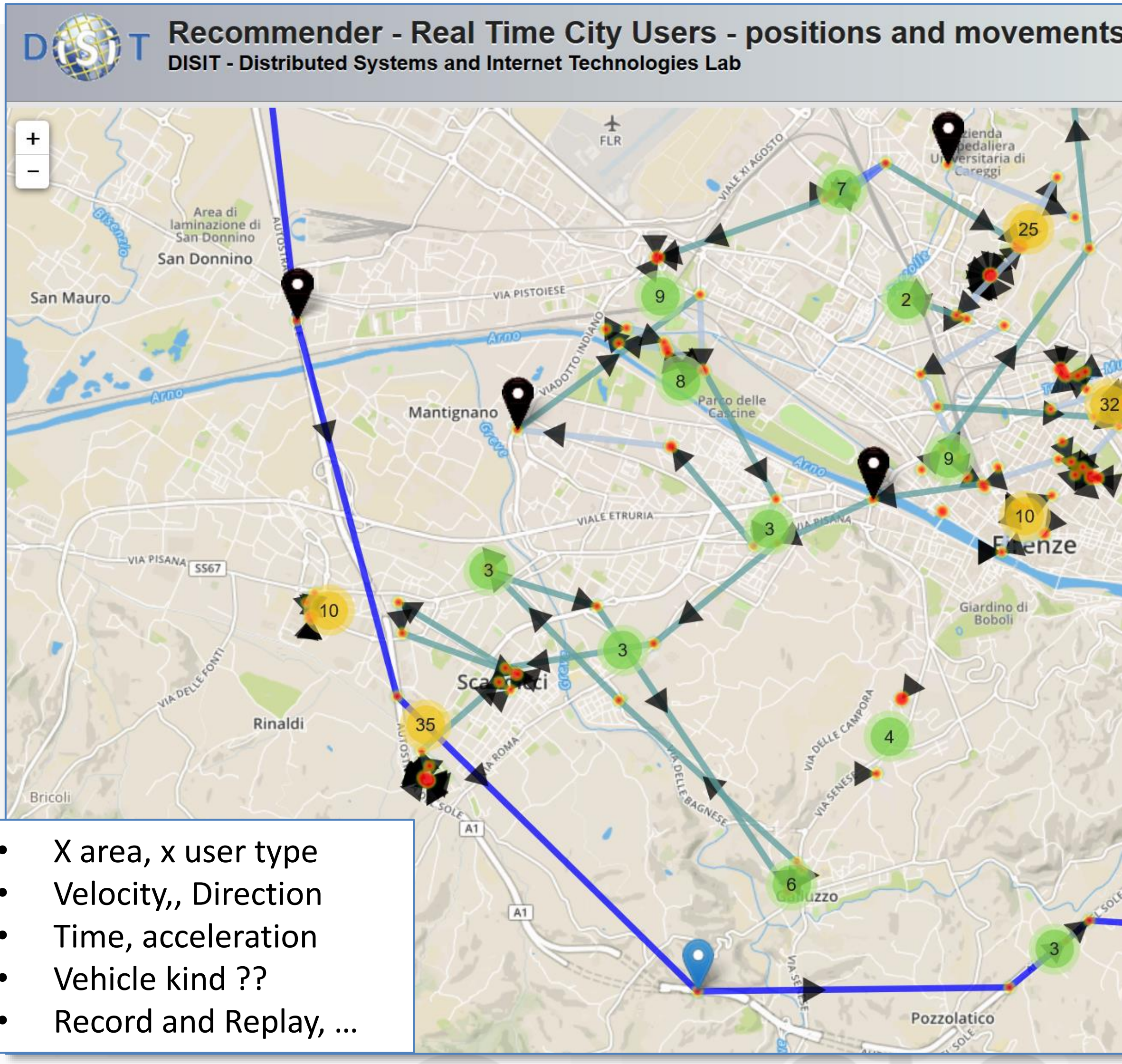
Mobile App based



How city users are moving

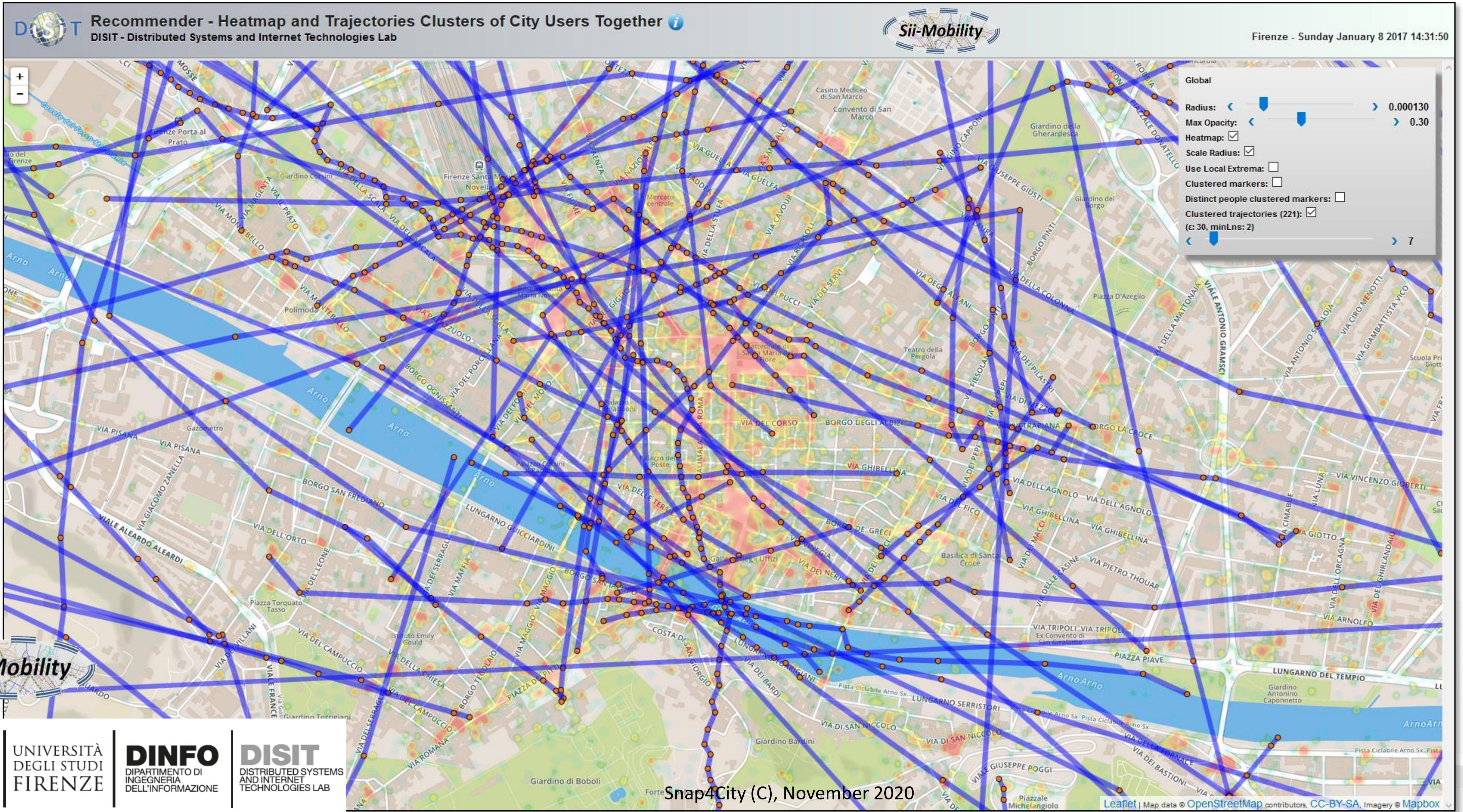
Problems of Trajectories from Apps

- **From mobile app:**
  - Resolving GPS location: GPS, cells, wifi-network, ..mixt
  - Noisy, different kind of devices, ..
  - Smart algorithm on devices for location acquisition
  - Anonymized data, terms of use on mobile
- **Issues and Filtering**
  - Gps Accuracy, kind of measure (GPS, mixt)
  - Jump in time, space, velocity
  - General noise (diff. devices)
  - Knowledge of precision map
- **Clustering**: time, space, user kind, etc.

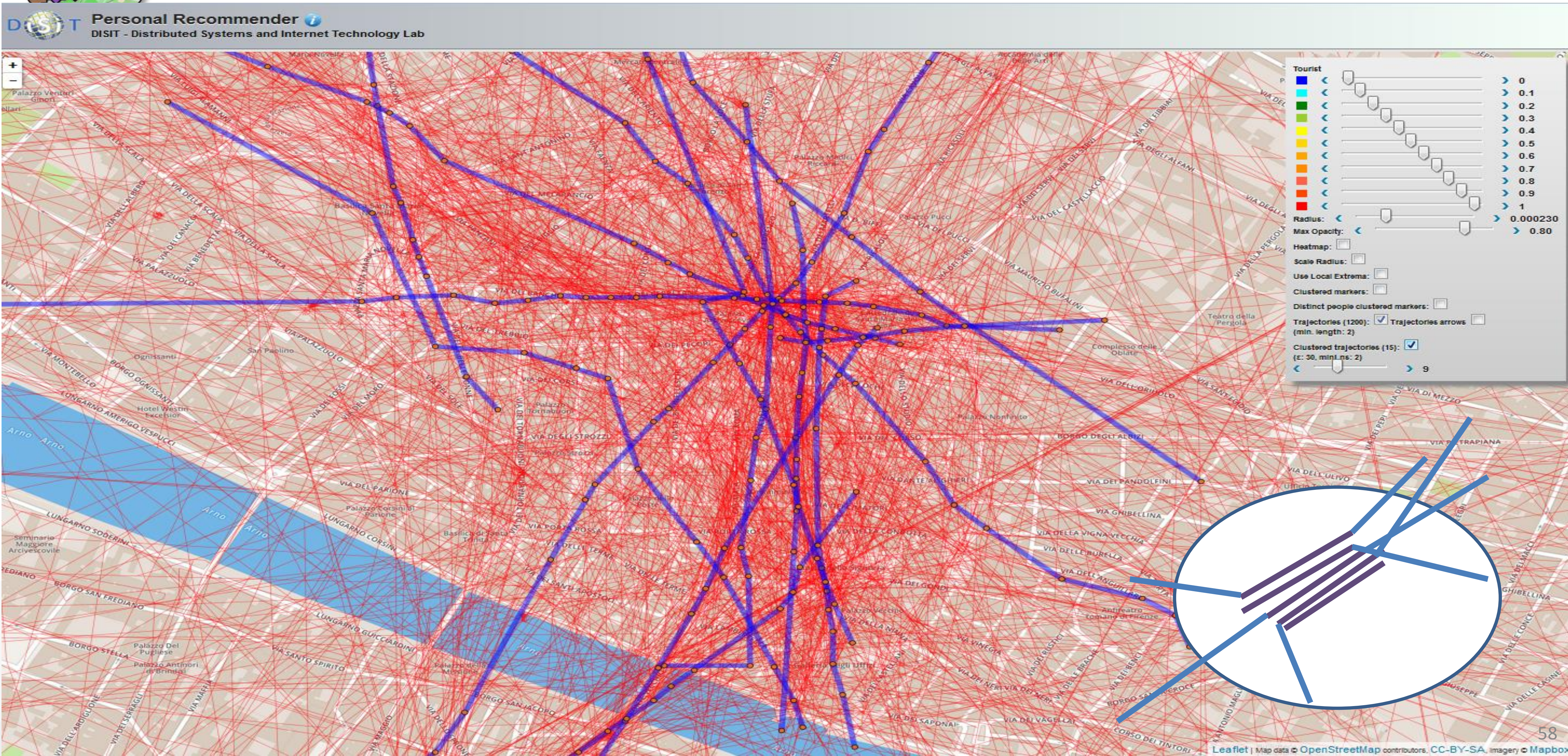


- X area, x user type
- Velocity,, Direction
- Time, acceleration
- Vehicle kind ??
- Record and Replay, …

Heat Map from Mobile: users as sensors



Cluster di Trajectories



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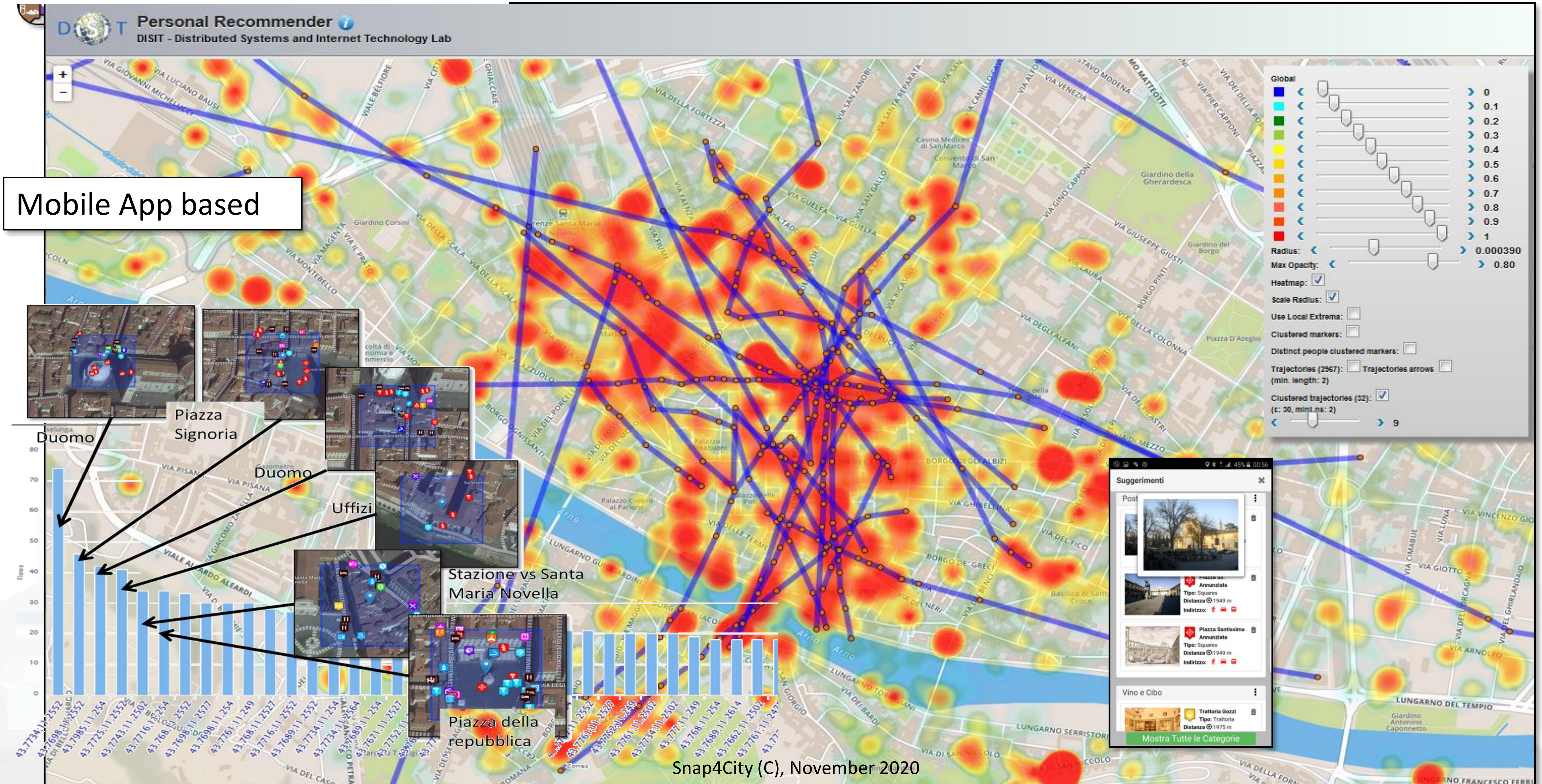
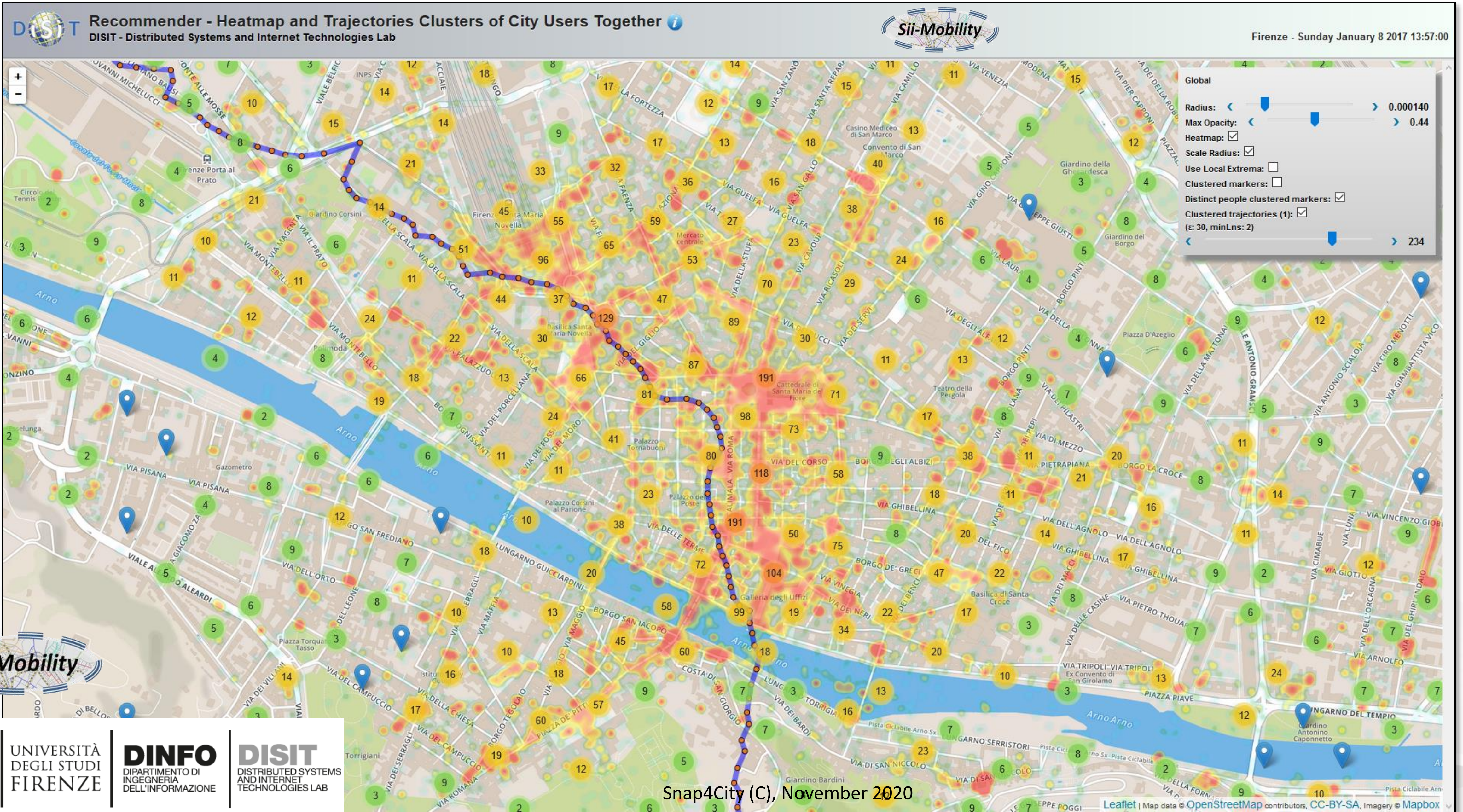
User Behavior Analyzer

Sii-Mobility



Heat Map from Mobile: users as sensors



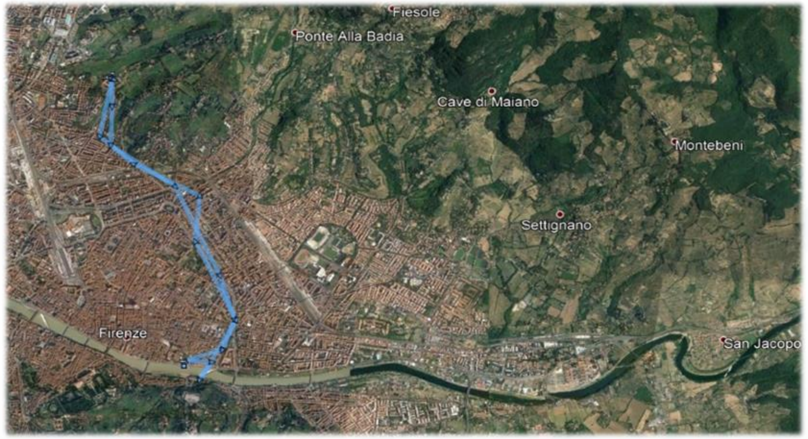
TOP

Recognition of City Users' Transportation means

Automated Classification of Users' Transportation Modality in Real Conditions

Variables taken into account:

- ***Day/Time Baseline and GPS***:
- ***Accelerometer***
- ***Proximity***
- ***Temporal window***



Dataset:

- 30K observations
- 25 variables
- 38 different users
- 30 different kinds of devices
- 4 classes (Stationary, Walking, Private Transport, Public Transport)

Four combinations of the different categories of data:

1. Baseline features and distance feature
2. Baseline, distance feature and accelerometer features
3. Baseline, distance feature and temporal window features
4. Baseline, distance, accelerometer, temporal features together

Note that, *each user have used the mean of transport of his/her own preference*. When the mode of transport is changed, the user was asked to notify the change to the App for creating the learning set and for validation.

Automated Classification of Users' Transportation Modality in Real Conditions

Note that:

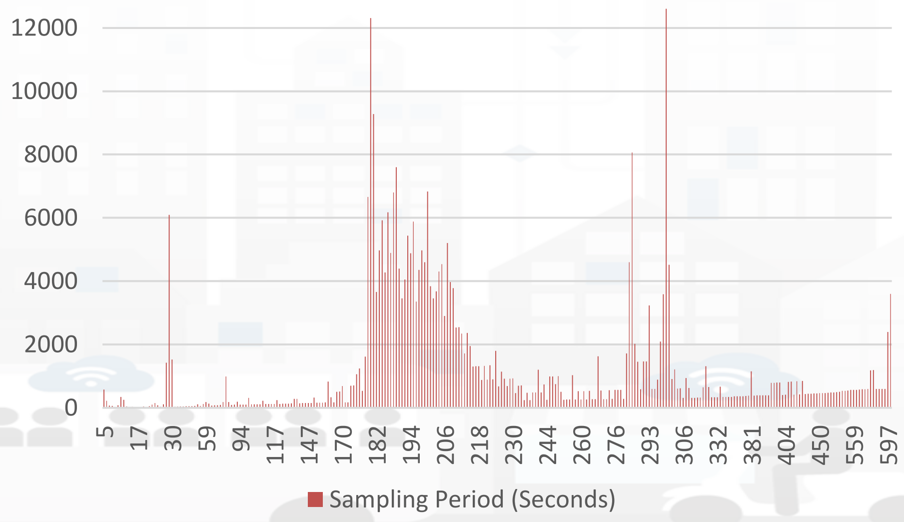
- ***Large discontinuities samples of data*** (from sensors and sporadic communications to the central computation modules)
- Relevant ***differences due to the different kind of mobile phone features in terms of sensors and precision***.

In the state of the art experiments the devices have been asked to keep the application running in foreground to get more precise GPS data, the device in a proper position/orientation during the usage and to use specific devices.

In the proposed solution *no restrictions on the modality of mobile device usage have been imposed.*

- **Most of the data was collected in the background** because the phones were kept in pocket or bag.
- **There is a non-conformity in the Sampling Period frequency distribution** of the collected data.

In details, the frequency average is equal to 180 seconds and the variance is equal to 13240 seconds.



Automated Classification of Users' Transportation Modality in Real Conditions

One-Step machine learning approach:

- *Random Forest* (**RF**)
- *Extremely Randomized Trees* (**Extra-Trees**)
- *Extreme Gradient Boosting procedure* (***XGBoost***)

Classifier Models	Accuracy	Precision	Recall	F_1 score
Extreme Gradient Boosting	0.947	0.773	0.828	0.800
Random Forest	0.942	0.774	0.869	0.819
Extra-Trees	0.953	0.827	0.869	**0.847**

Extra Trees Model	Stay	Walk	Private Transport	Public Transport
Sensitivity	0.978	0.731	0.869	0.917
Specificity	0.901	0.988	0.987	0.996
Pos Pred Value	0.977	0.770	0.827	0.936
Neg Pred Value	0.904	0.985	0.990	0.994
Balanced Accuracy	0.940	0.859	0.928	0.956

Super Learner Binary Classification Models Combination	Accuracy	Precision	Recall	F_1 score
	0.960	0.865	0.857	**0.861**

Super Learner Model	Stay	Walk	Private Transport	Public Transport
Sensitivity	0.990	0.662	0.857	0.927
Specificity	0.892	0.993	0.990	0.996
Pos Pred Value	0.975	0.831	0.865	0.953
Neg Pred Value	0.955	0.982	0.989	0.994
Balanced Accuracy	0.941	0.828	0.924	0.961

- **Super Learner approach:** identification of the multi-class problem into binary classification sub-problems to estimate the risk on future data and select the optimal learner based on the One-Step machine learning approach candidates.
  - Four binary classification models have been constructed:
    1. *stationary vs walking, private transport, public transport*
    2. *walking vs stationary, private transport, public transport*
    3. *private transport vs stationary, walking, public transport*
    4. *public transport vs stationary, walking, private transport*

❖ In **Super Learner**, Binary Classification Models results have been combined **on the highest probability estimation**.

Automated Classification of Users' Transportation Modality in Real Conditions

Two-Steps Hierarchical approach:

combination of the **Extra-Tree** multi-class classification and the **Super learner** algorithm.

- **First Step**: Extra-Tree multi-class classifier *to select* the *two transportation means with higher probability* - 4 different training models.

A **threshold** has been used to decide which class can be considered directly correct at the first step: *if the probability of the class is higher respect the considered threshold* (0.90), *the transportation modality is regarded correct* without proceeding to the second step.

- **Second Step:** Super learner approach to *discriminate between the two transportation means selected in the first step* - 24 different training models

(6 transportation modality pairs combinations per 4 categories combinations)

Two-Steps Hierarchical Approach		Predicted			
		Stay	Walk	Private Transport	Public Transport
Actual	Stay	**0.98**	0.30	0.09	0.03
	Walk	0.01	**0.60**	0.02	0.01
	Private Transport	0.01	0.07	**0.87**	0.07
	Public Transport	0.00	0.03	0.01	**0.89**

Accuracy = **0.940**
Precision= 0.786
Recall = 0.869

TOP

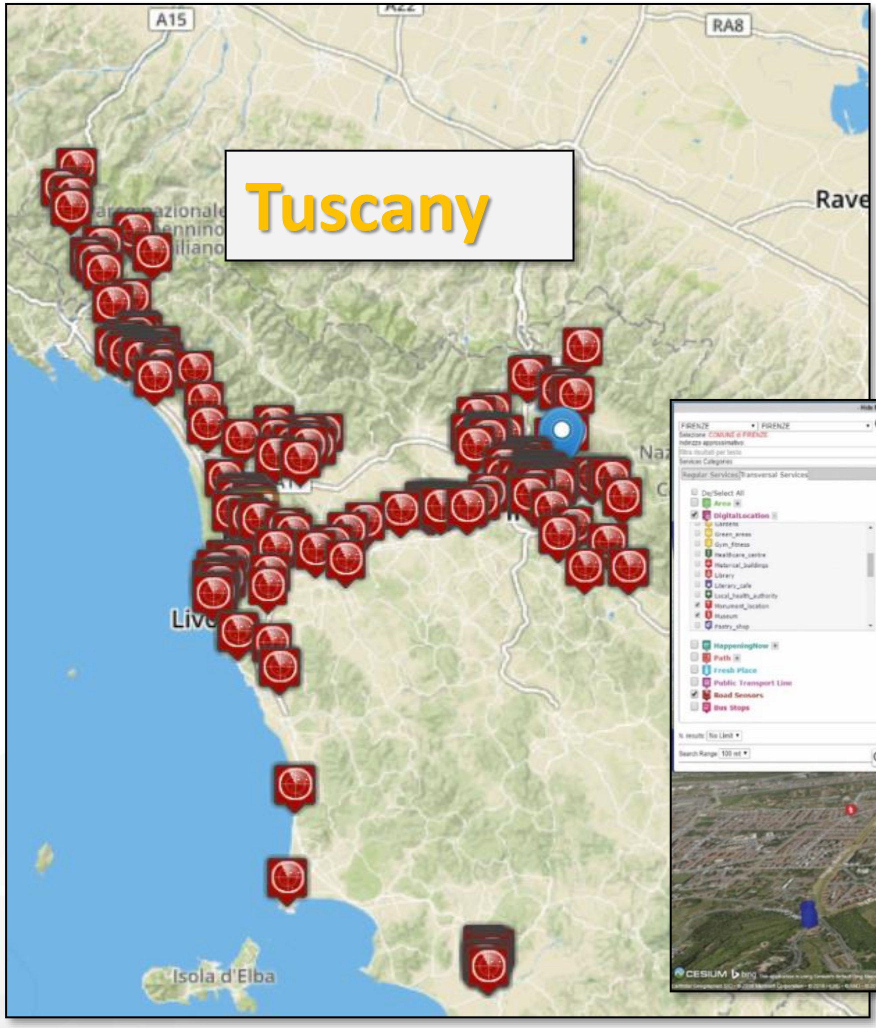
Traffic Flow Prediction

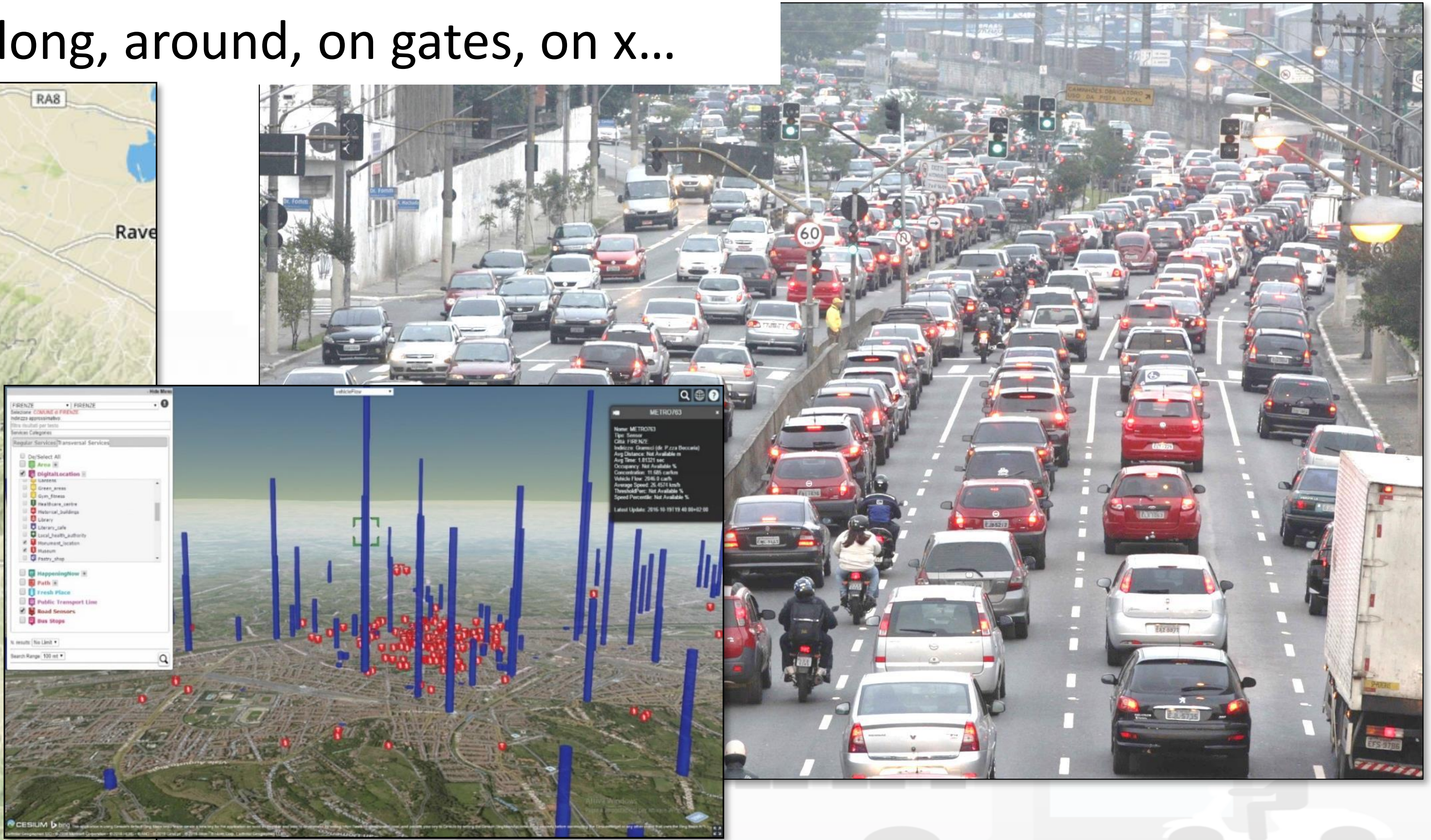

60

Traffic Flow Tools

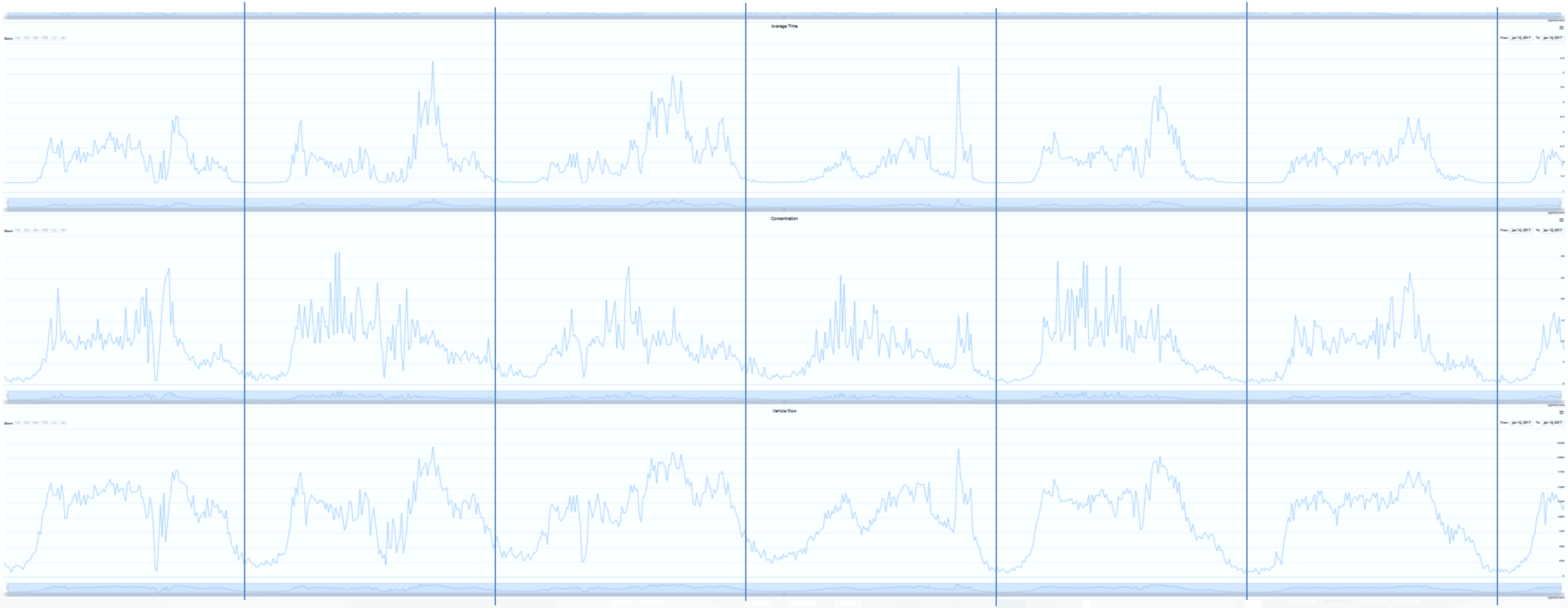
Spire and Virtual Spires (cameras), Bluetooth, ...

Specifically located: along, around, on gates, on x...

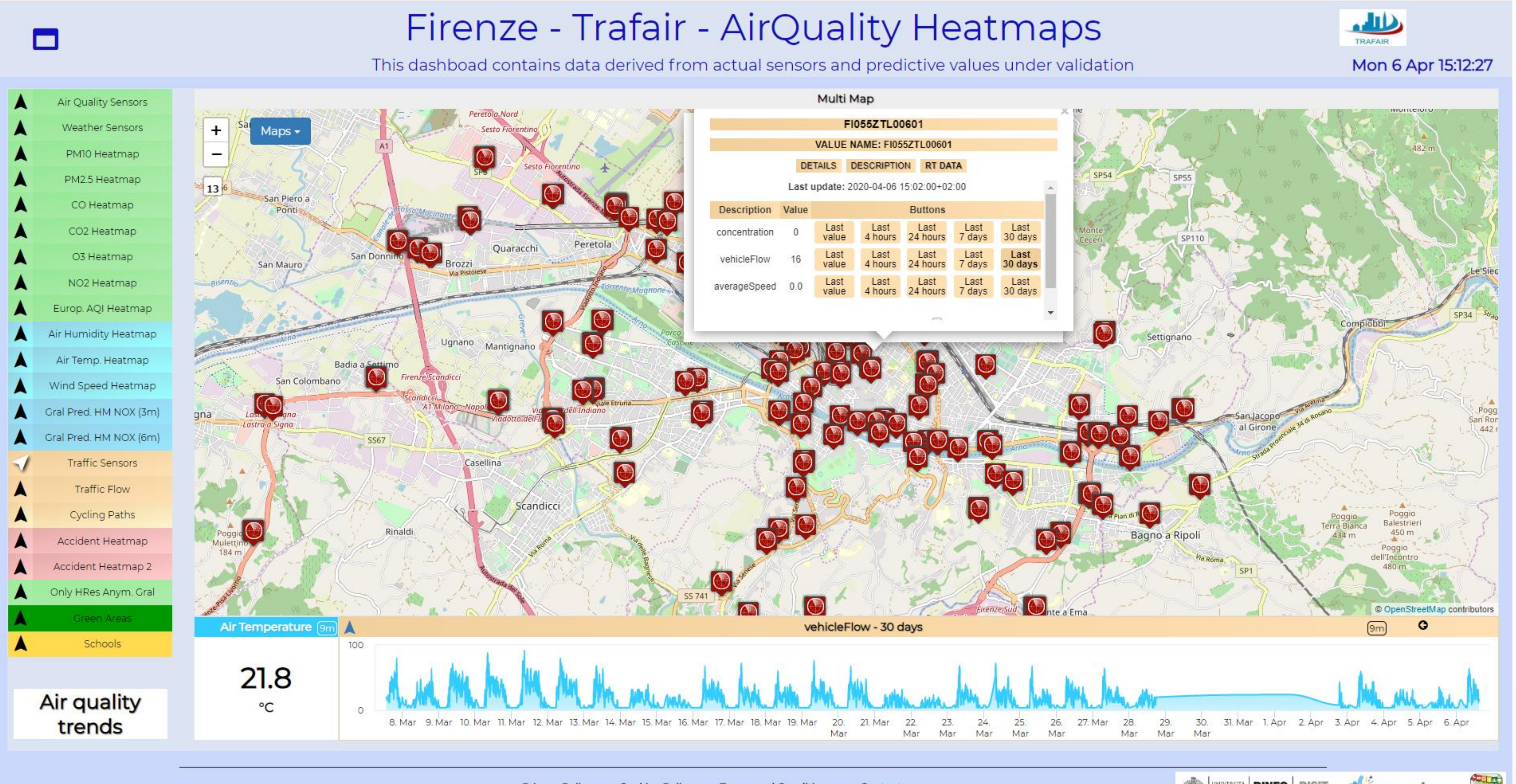




Traffic Flow data



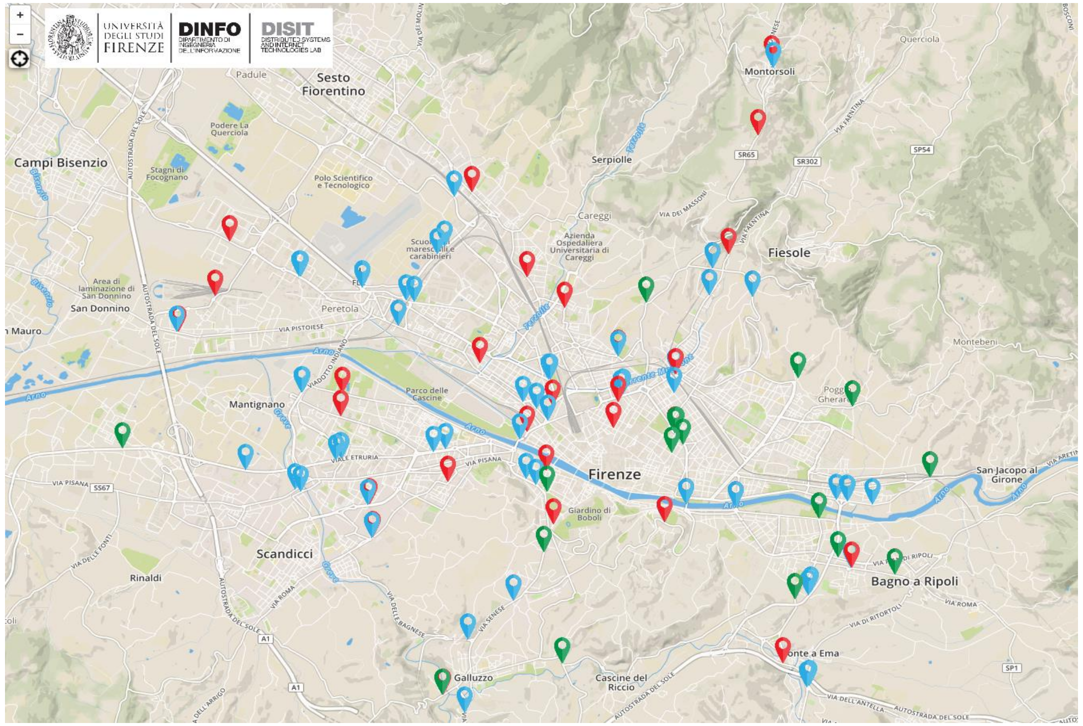
- Day by day traffic flow data from 3 sensors



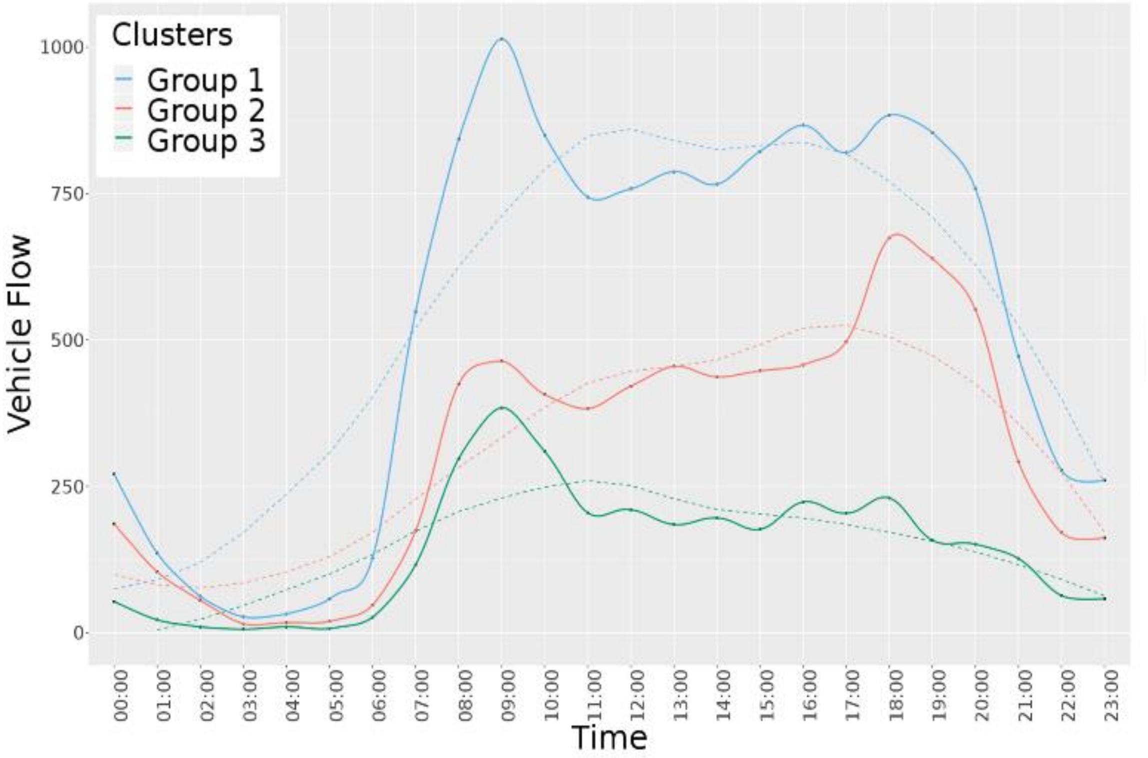
https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTUzMg==

Traffic Data Analysis

Map of the traffic sensors location per cluster in Florence municipality

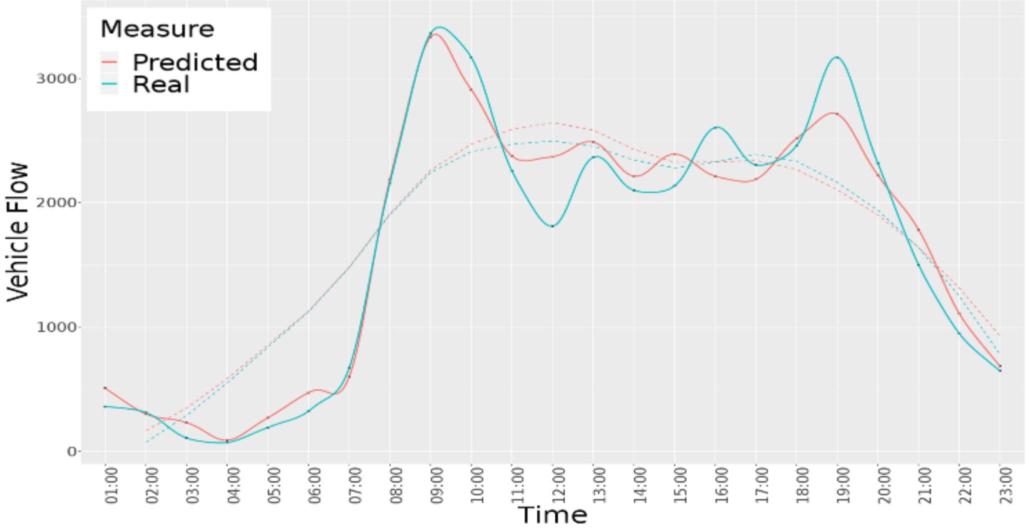


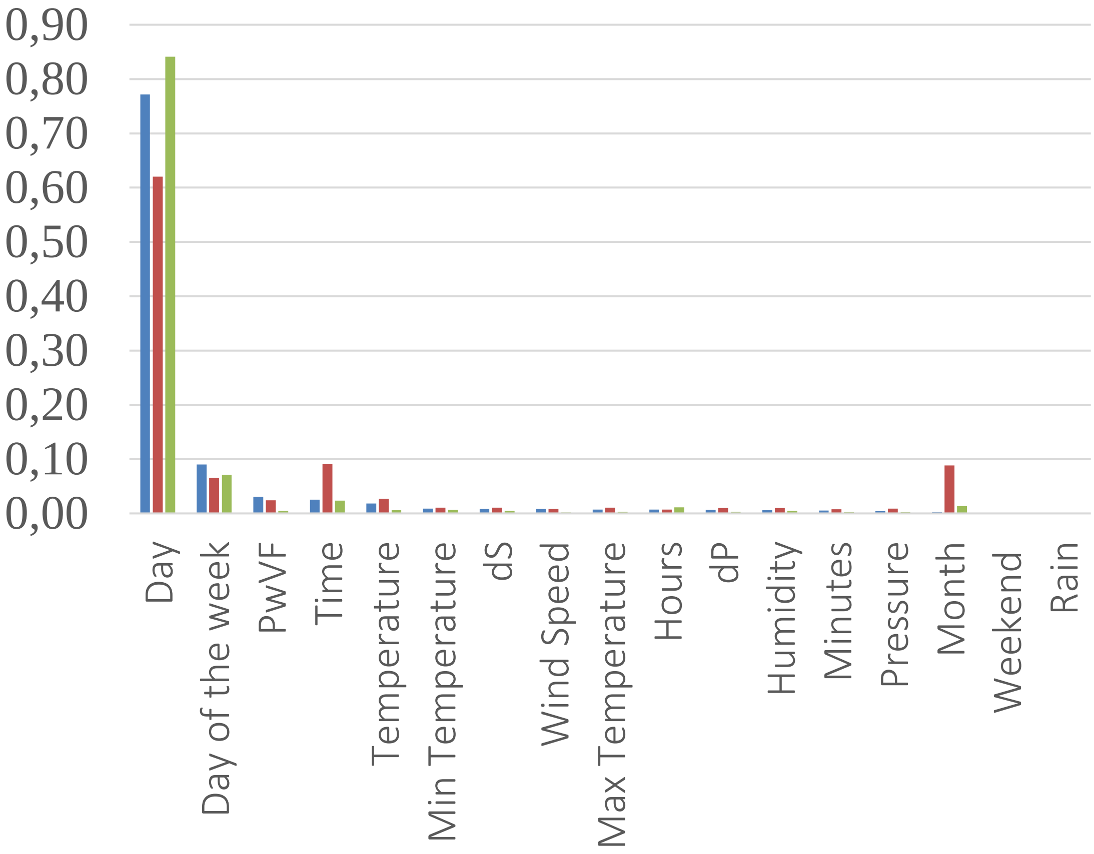
Hourly median vehicle flow trends per cluster



Traffic Data Analysis

XGBoost Model Results	R^2	RMSE	MASE
Sensors of Group 1	0.95	215	0.89
Sensors of Group 2	0.91	178	0.82
Sensors of Group 3	0.86	127	0.92





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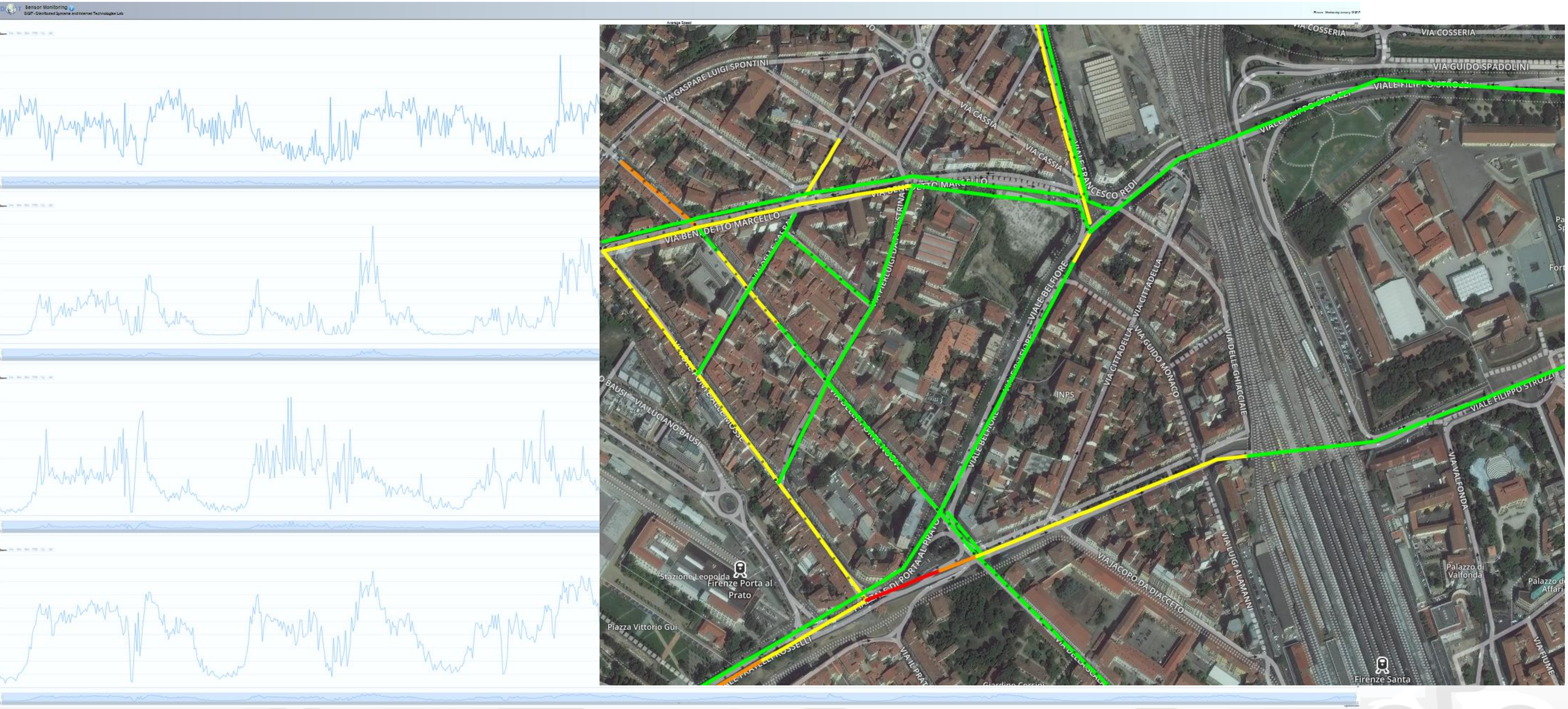
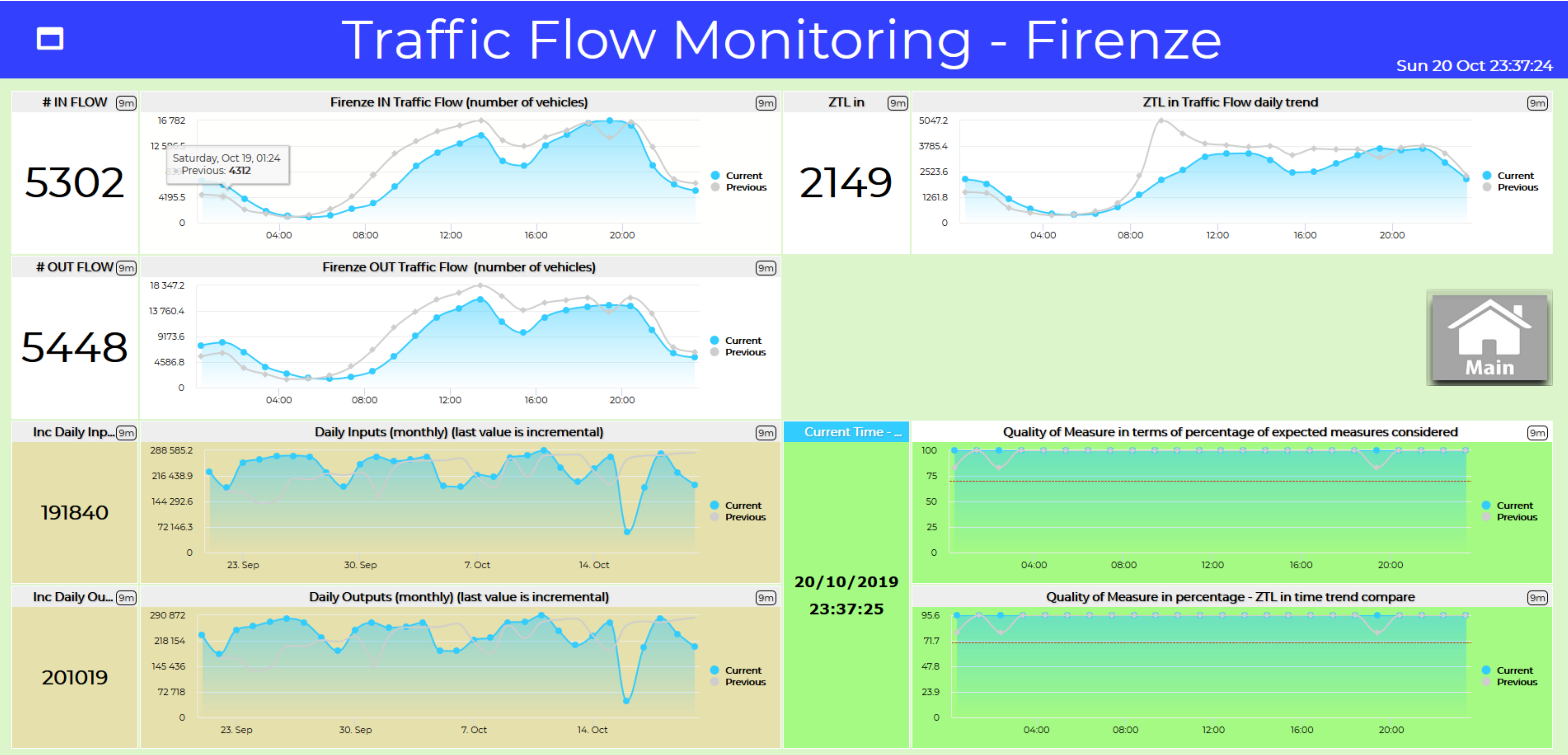
Traffic Flow Reconstruction from Traffic Sensors Data

Traffic Flow data





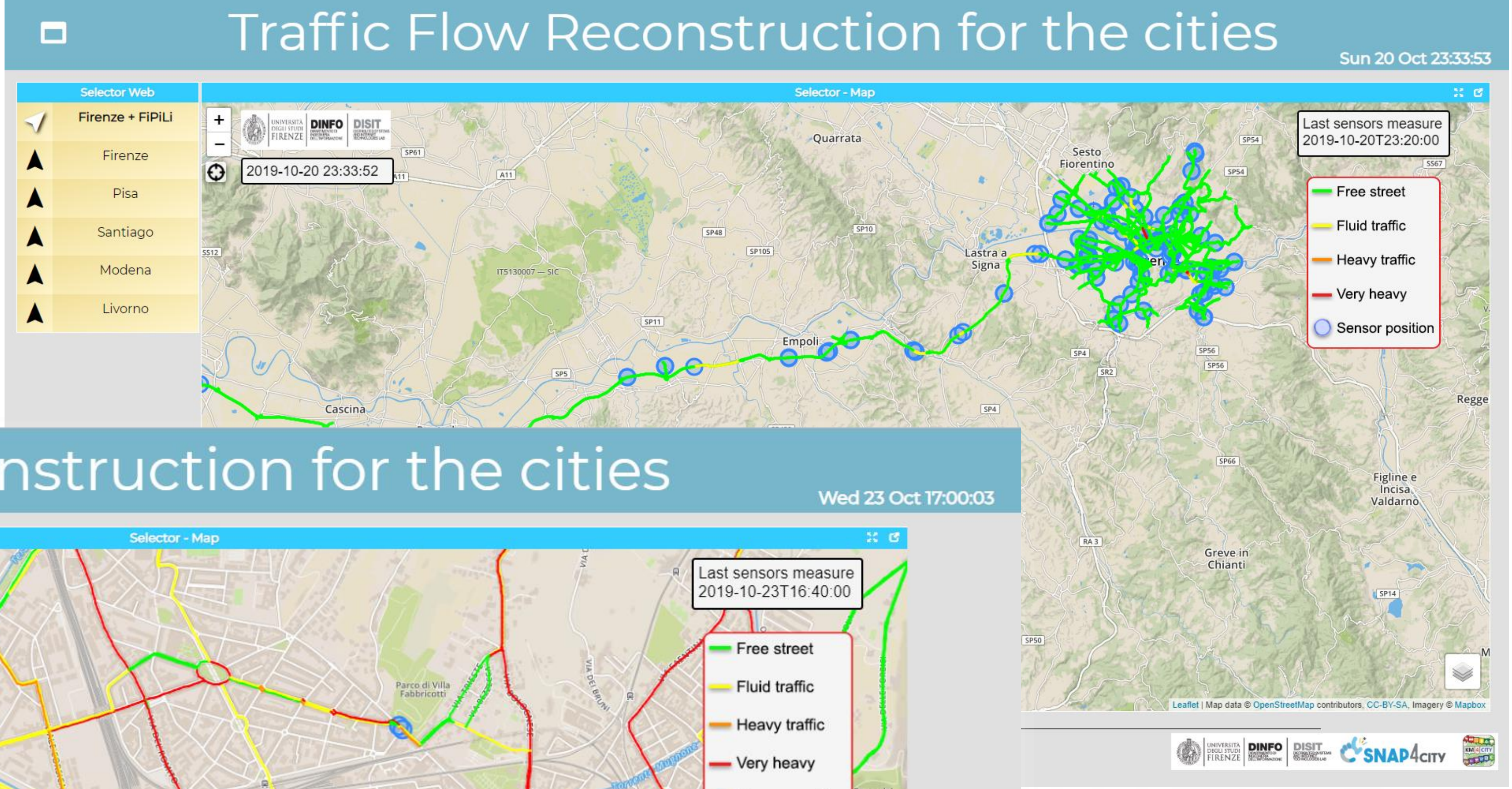
https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTc2MQ==

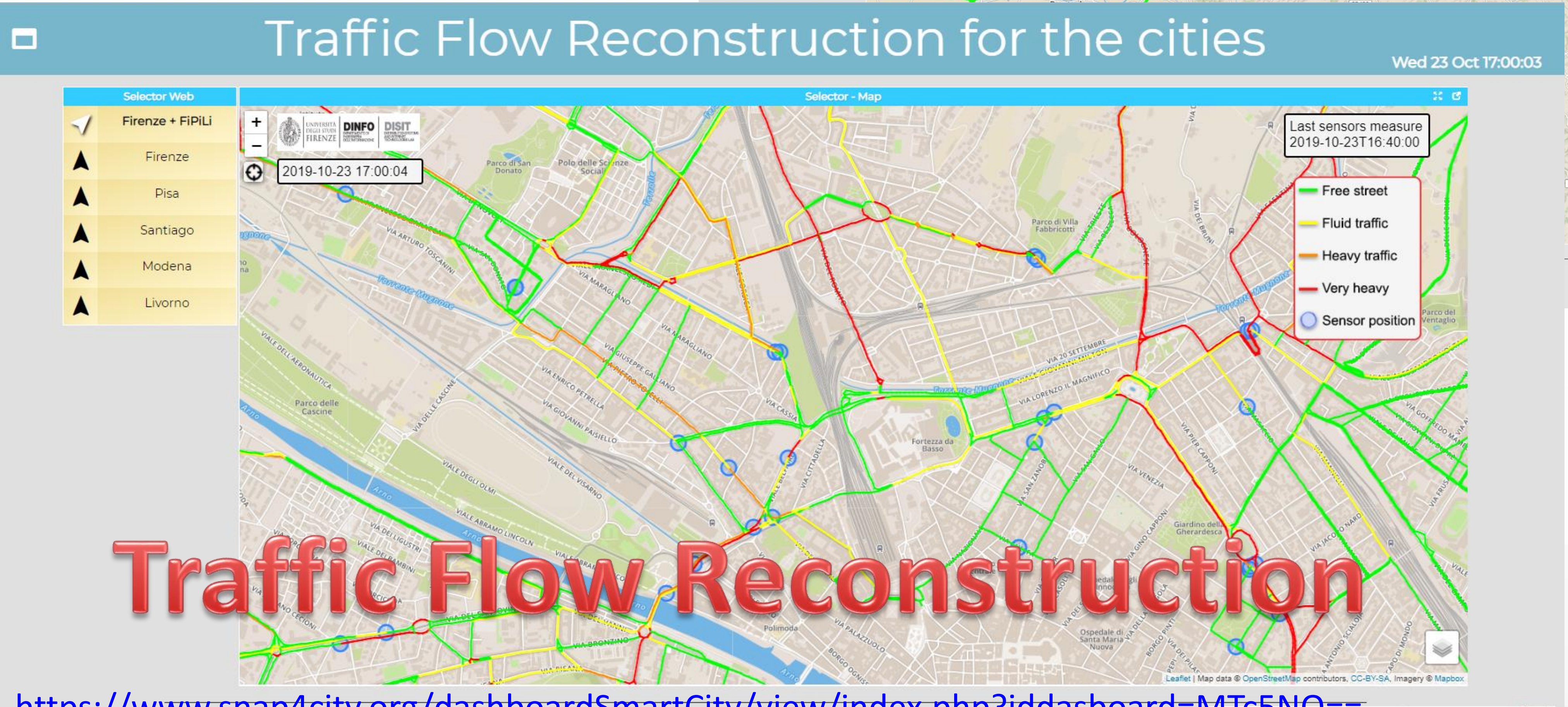
On sunday

Traffic Flow Reconstruction

Firenze
FiPiLi
Pisa
Modena

real time





Traffic Flow Reconstruction

https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTc5NQ==

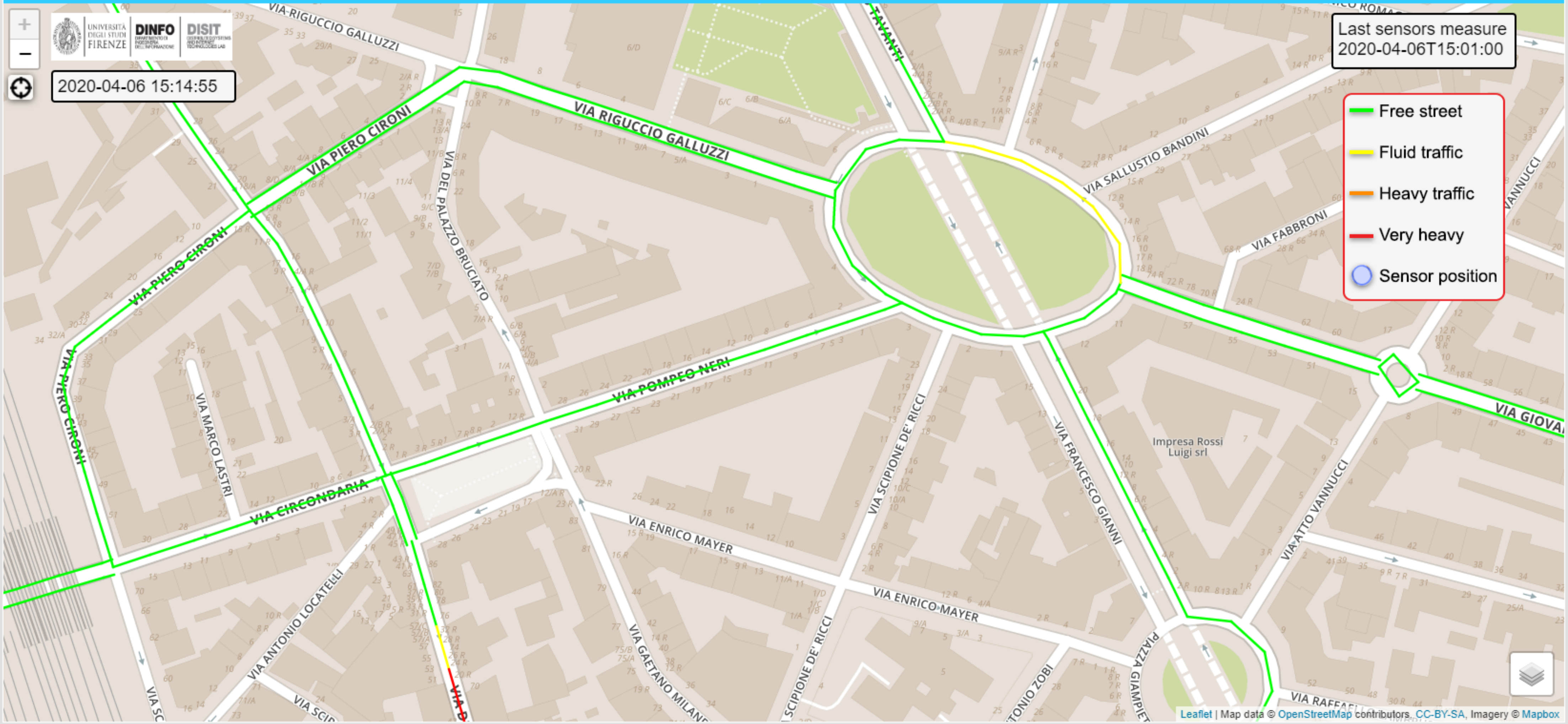
Traffic Flow Reconstruction for the cities

Mon 6 Apr 15:14:55

Selector Web

- **Firenze + FiPiLi**
- Firenze
- Pisa
- Santiago
- Modena
- Livorno

Selector - Map



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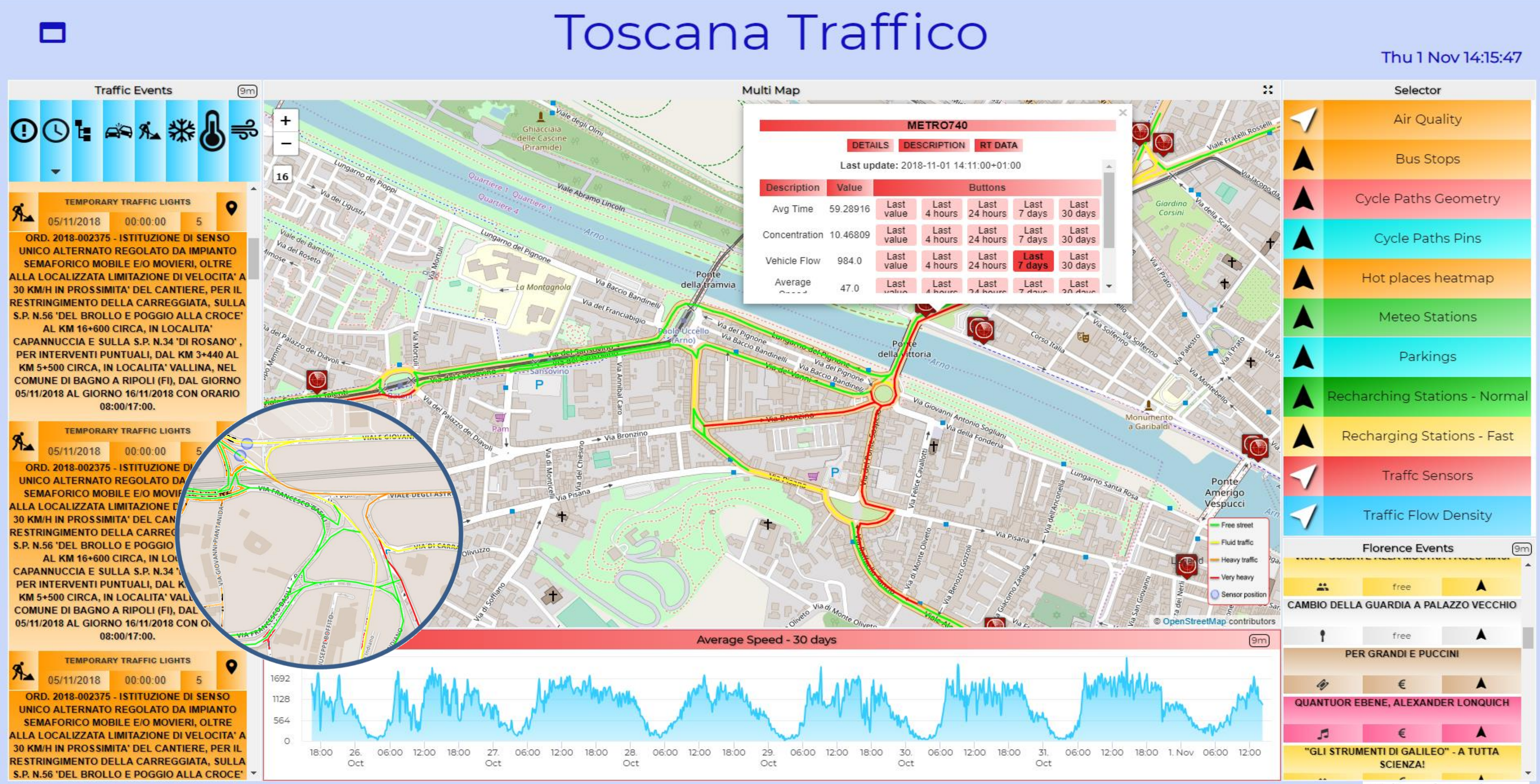
https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTc5NQ==



https://main.snap4city.org/view/index.php?iddasboard=MTE5MQ==

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Traffic Flow reconstruction, real time

Mathematical model

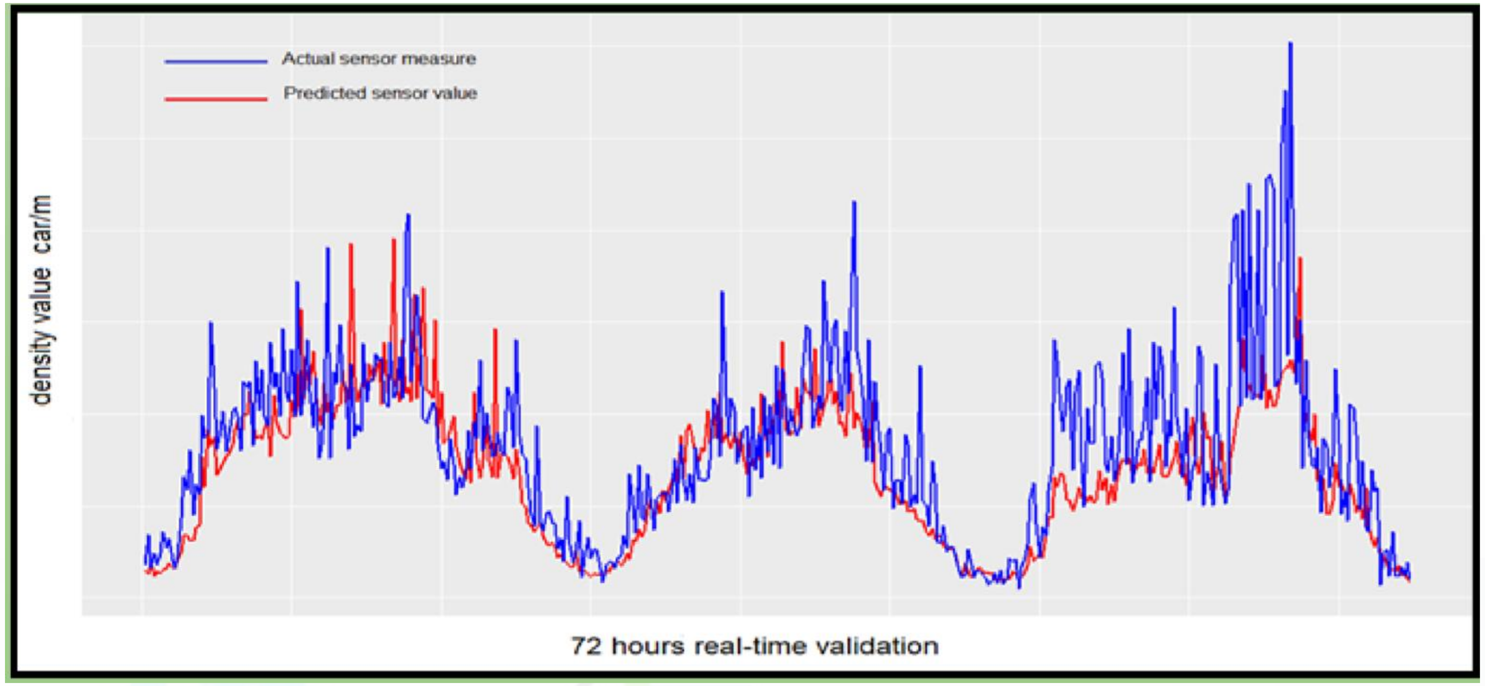
The vehicular traffic flow is propagated in the city graph according to a fluid dynamics model which is based on the conservation law of the vehicles. In a single road, it is described by the following partial differential equation:

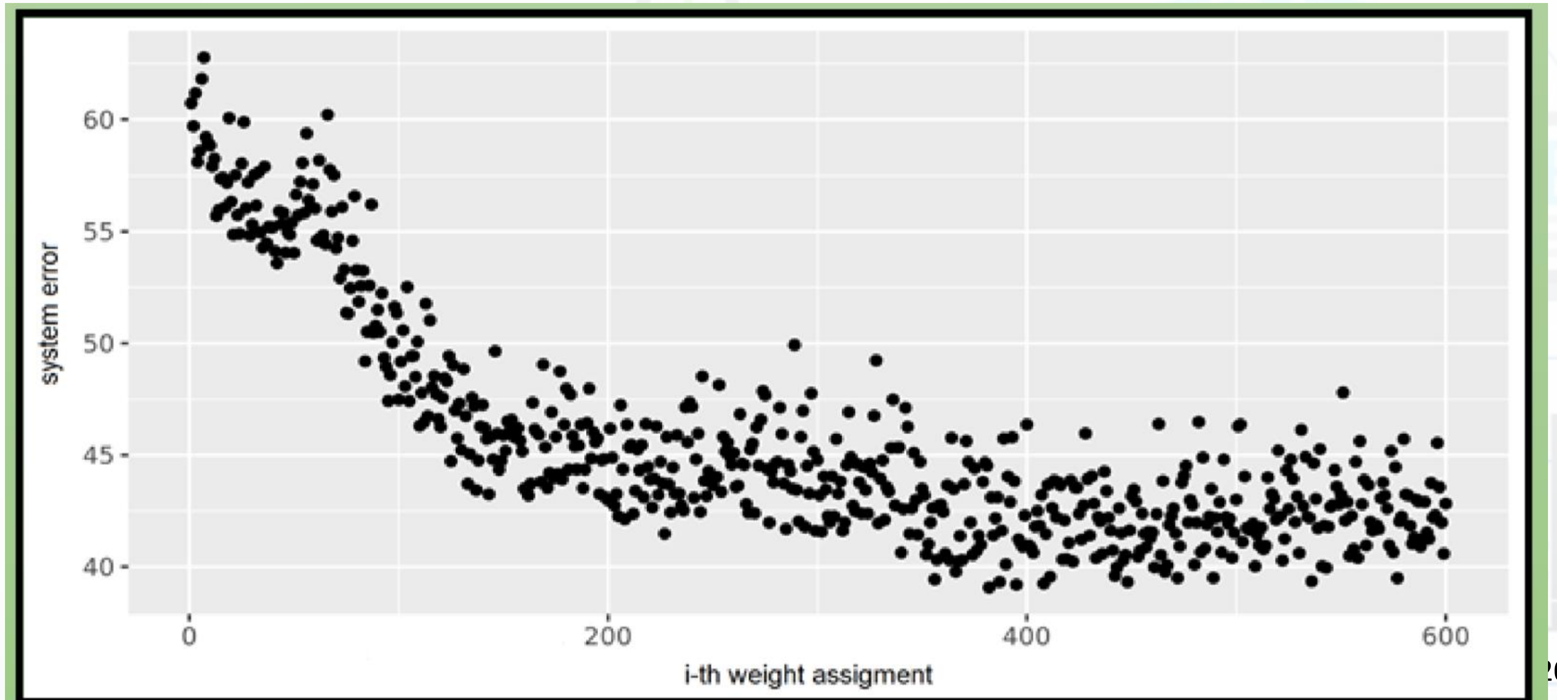
$$\frac{\partial \rho(t,x)}{\partial t} + \frac{\partial f\big(\rho(t,x)\big)}{\partial x} = 0$$

where $\rho(t,x)$ denotes the vehicular density and the function $f(\rho(t,x))$ is the vehicular flux which is defined as the product $\rho(t,x)v(t,x)$, being $v(t,x)$ the local speed of the vehicles.

A discretization scheme in terms of *finite differences* is considered to obtain a numerical solution of the above equation. The traffic flow is then distributed through the junctions in the city.

Convergence of learning phase





Traffic Flow reconstruction, real time

ScienceDirect

ELSEVIER

- Stefano Bilotta,
  Paolo Nesi,
- **Traffic flow reconstruction by solving indeterminacy on traffic distribution at junctions,** Future Generation Computer Systems, Volume 114, 2021, Pages 649-660, ISSN 0167-739X, https://doi.org/10.1016/j.future.2020.08.017.

https://www.sciencedirect.com/science/article/pii/S0167739X20308359

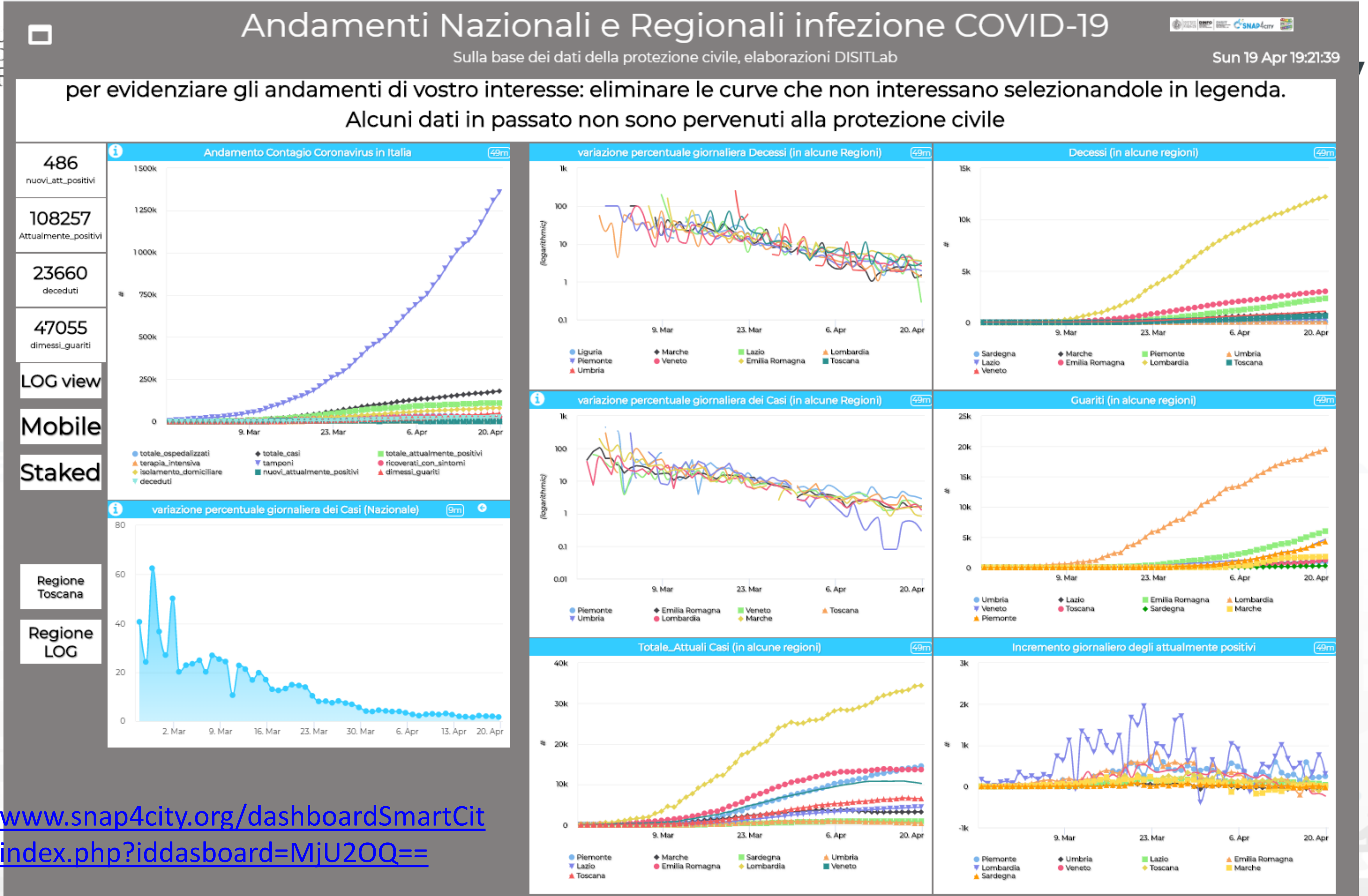
10.2	6.125
CiteScore	Impact Factor

Traffic Flow Reconstruction (self training)

- P. Bellini, S. Bilotta, P. Nesi, M. Paolucci, M. Soderi, "Traffic Flow Reconstruction from Scattered Data", IEEE SMARTCOMP, IEEE international conference on smart computing, 18-20 June, Taormina, Sicily, Italy. 2018
- P. Bellini, S. Bilotta, P. Nesi, M. Paolucci, M. Soderi, "Real-Time Traffic Estimation of Unmonitored Roads", IEEE-DataCom'2018, Athens, 2018

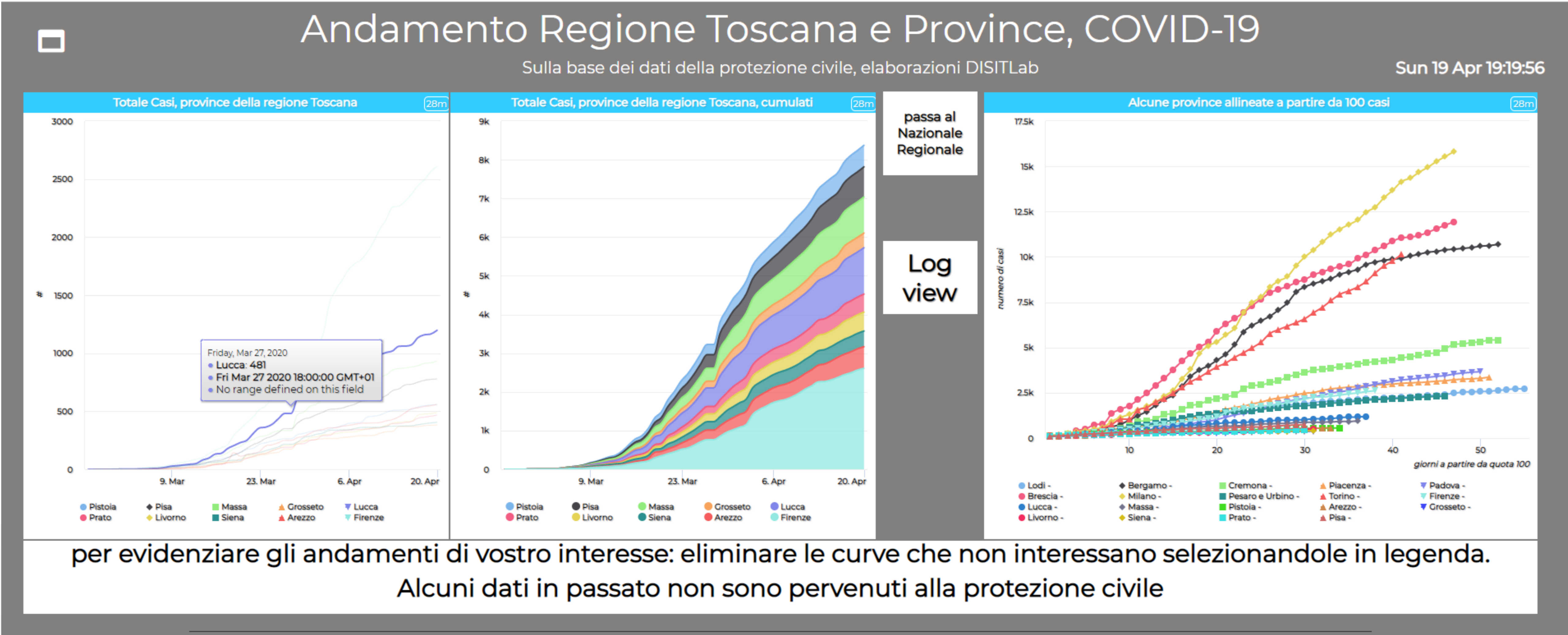
TOP

COVID-19 vs other data: traffic and environment

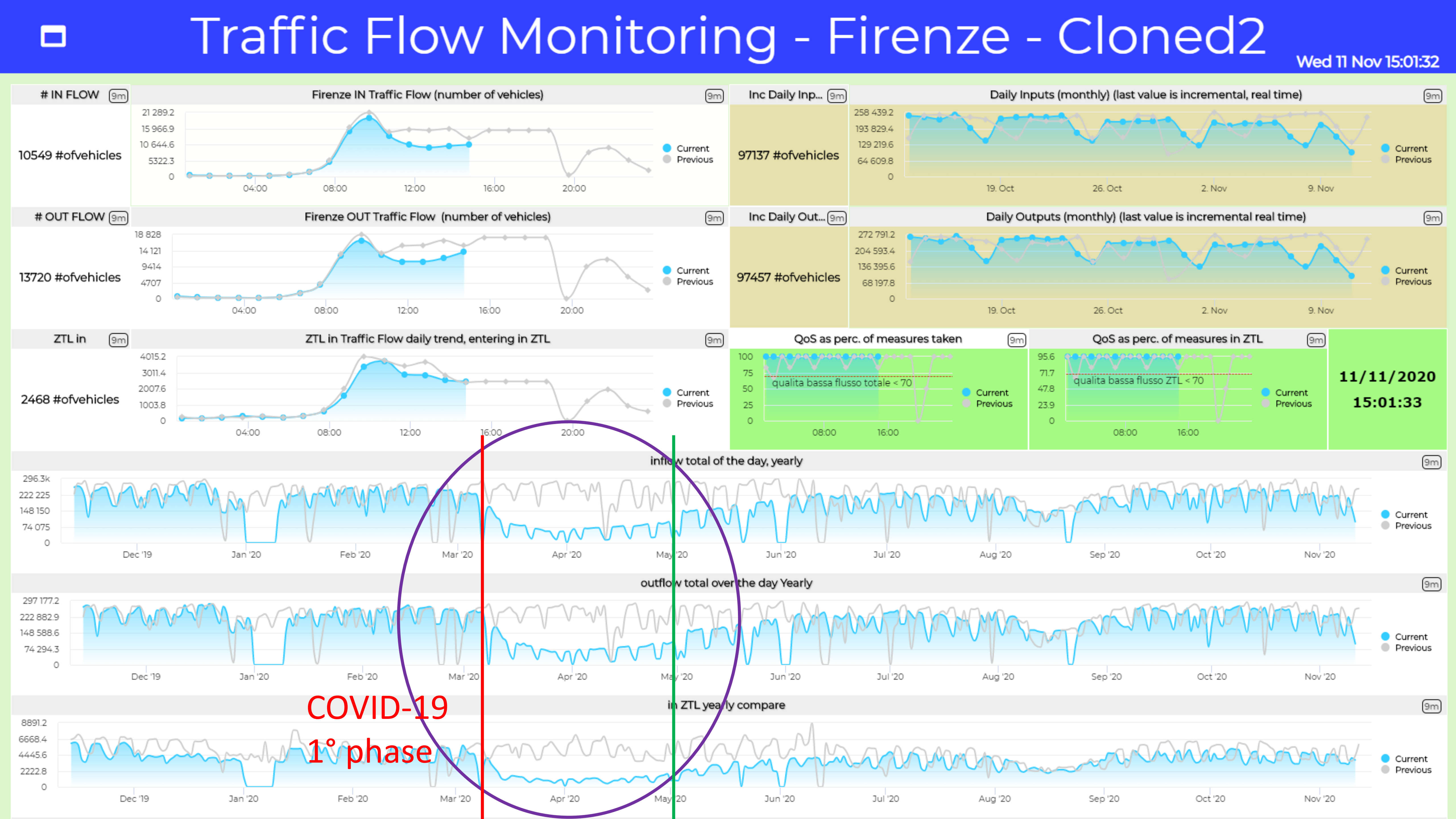


https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MjU2OQ==

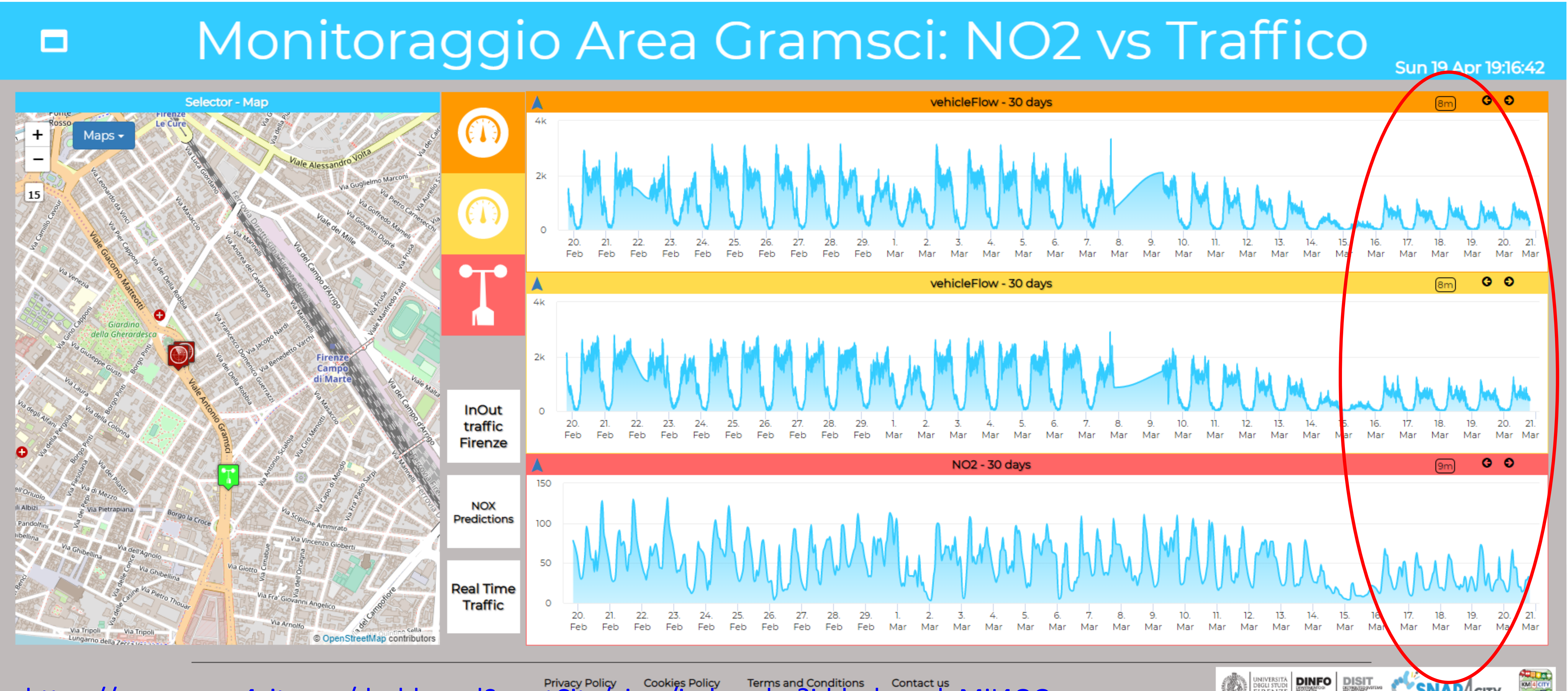
Main IT Provinces vs Tuscany Provinces: COVID-19



https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MjU3NQ==


Traffic Flow Monitoring - Firenze - Cloned2
Wed 11 Nov 15:01:32
IN FLOW
10549 #ofvehicles
Firenze IN Traffic Flow (number of vehicles)
Inc Daily Inp...
97137 #ofvehicles
Daily Inputs (monthly) (last value is incremental, real time)
OUT FLOW
13720 #ofvehicles
Firenze OUT Traffic Flow (number of vehicles)
Inc Daily Out...
97457 #ofvehicles
Daily Outputs (monthly) (last value is incremental real time)
ZTL in
2468 #ofvehicles
ZTL in Traffic Flow daily trend, entering in ZTL
QoS as perc. of measures taken
qualita bassa flusso totale < 70
QoS as perc. of measures in ZTL
qualita bassa flusso ZTL < 70
11/11/2020
15:01:33
inflow total of the day, yearly
outflow total over the day Yearly
in ZTL yearly compare
Current
Previous
COVID-19
1° phase

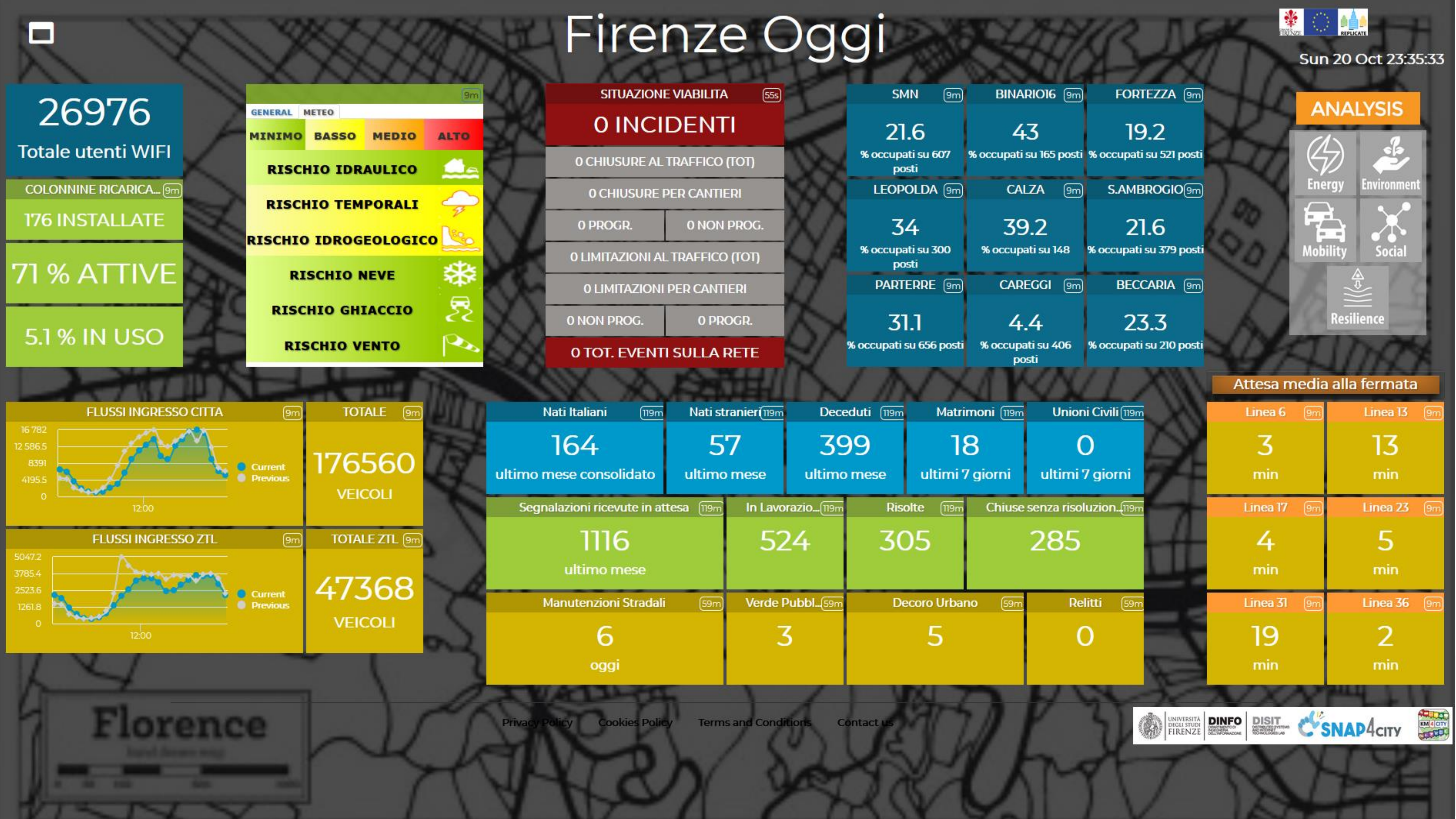
NOX reduction for COVID



https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MjI4OQ==

TOP

Quality of Public Transport


Firenze Oggi
Sun 20 Oct 23:35:33
26976
Totale utenti WIFI
COLONNINE RICARICA...
176 INSTALLATE
71 % ATTIVE
5.1 % IN USO
GENERAL
METEO
MINIMO
BASSO
MEDIO
ALTO
RISCHIO IDRAULICO
RISCHIO TEMPORALI
RISCHIO IDROGEOLOGICO
RISCHIO NEVE
RISCHIO GHIACCIO
RISCHIO VENTO
SITUAZIONE VIABILITA
0 INCIDENTI
0 CHIUSURE AL TRAFFICO (TOT)
0 CHIUSURE PER CANTIERI
0 PROGR.
0 NON PROG.
0 LIMITAZIONI AL TRAFFICO (TOT)
0 LIMITAZIONI PER CANTIERI
0 NON PROG.
0 PROGR.
0 TOT. EVENTI SULLA RETE
SMN
21.6
% occupati su 607 posti
BINARIO16
43
% occupati su 165 posti
FORTEZZA
19.2
% occupati su 521 posti
LEOPOLDA
34
% occupati su 300 posti
CALZA
39.2
% occupati su 148
S.AMBROGIO
21.6
% occupati su 379 posti
PARTERRE
31.1
% occupati su 656 posti
CAREGGI
4.4
% occupati su 406 posti
BECCARIA
23.3
% occupati su 210 posti
ANALYSIS
Energy
Environment
Mobility
Social
Resilience
FLUSSI INGRESSO CITTA
16 782
12 586.5
8391
4195.5
0
12:00
Current
Previous
TOTALE
176560
VEICOLI
FLUSSI INGRESSO ZTL
5047.2
3785.4
2523.6
1261.8
0
12:00
Current
Previous
TOTALE ZTL
47368
VEICOLI
Nati Italiani
164
ultimo mese consolidato
Nati stranieri
57
ultimo mese
Deceduti
399
ultimo mese
Matrimoni
18
ultimi 7 giorni
Unioni Civili
0
ultimi 7 giorni
Segnalazioni ricevute in attesa
1116
ultimo mese
In Lavorazio...
524
Risolte
305
Chiuse senza risoluzion...
285
Manutenzioni Stradali
6
oggi
Verde Pubbl...
3
Decoro Urbano
5
Relitti
0
Attesa media alla fermata
Linea 6
3
min
Linea 13
13
min
Linea 17
4
min
Linea 23
5
min
Linea 31
19
min
Linea 36
2
min
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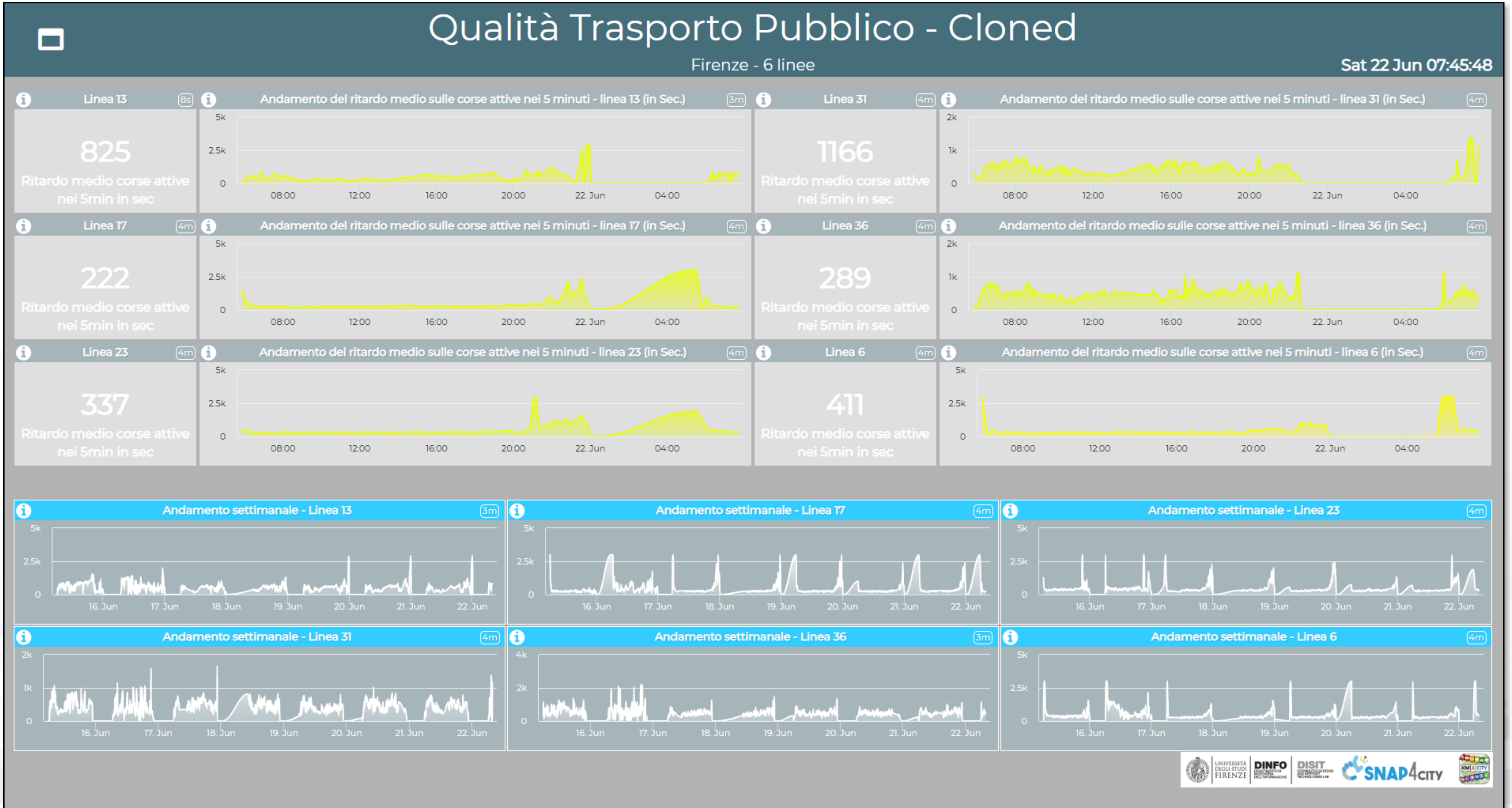
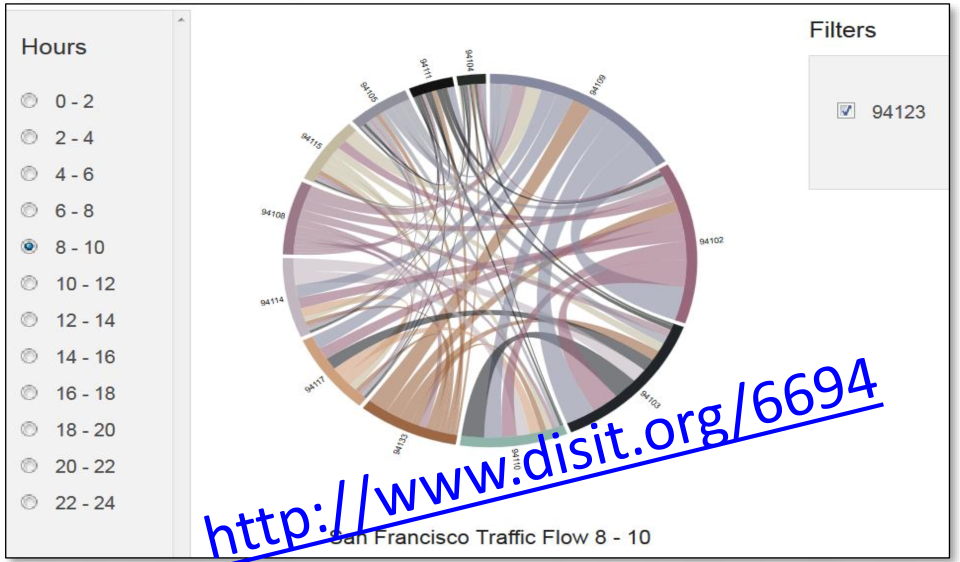


TOP

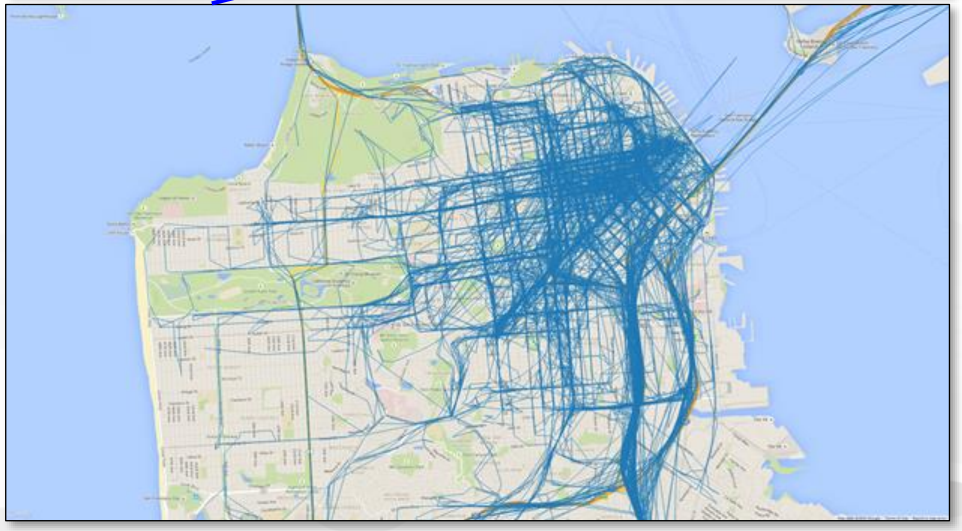
Origin Destination Matrices

Traffic and People Flow Assessment

- **Origin Destination Matrix**
  - Specific Sensors, vehicle Kits, mobile App, Wi-Fi Access Points, etc.
  - Data from Taxi in San Francisco
- **Assess people and traffic flows to**
  - improve services
  - predict critical conditions on Crit. Infra.
  - take real time decisions and sending messages in push to population
  - Increase city resilience
  - optimize traffic flow
  - take decision of routing

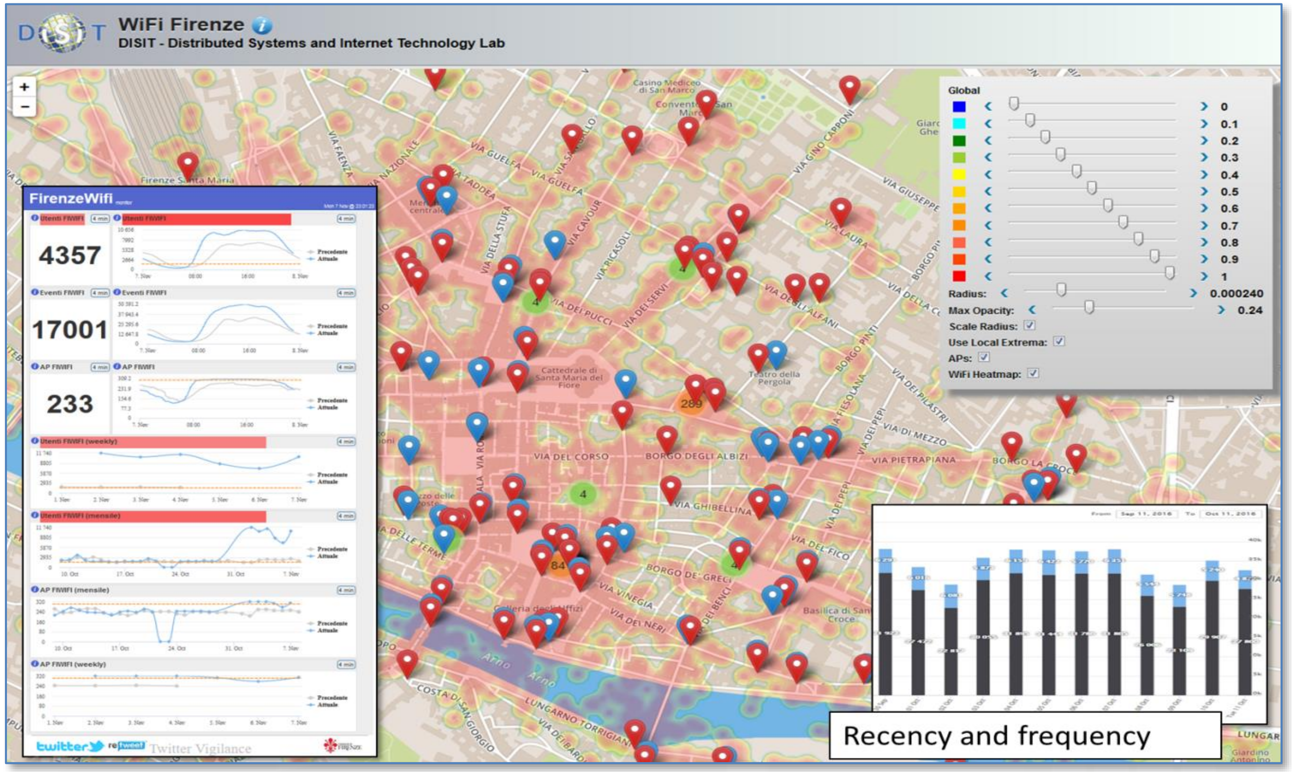


http://www.disit.org/6694

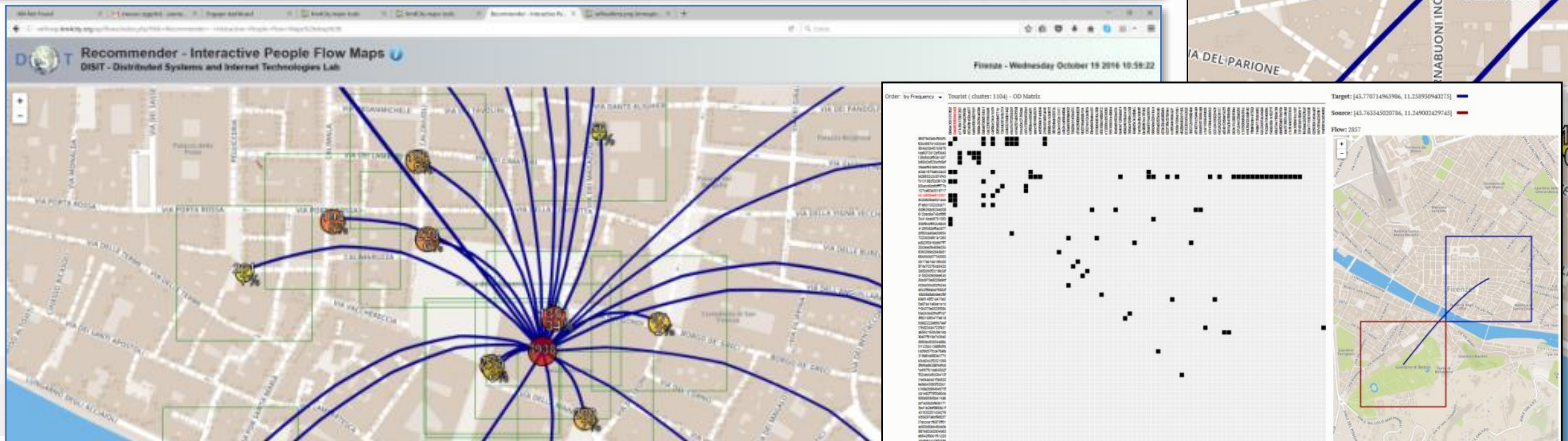


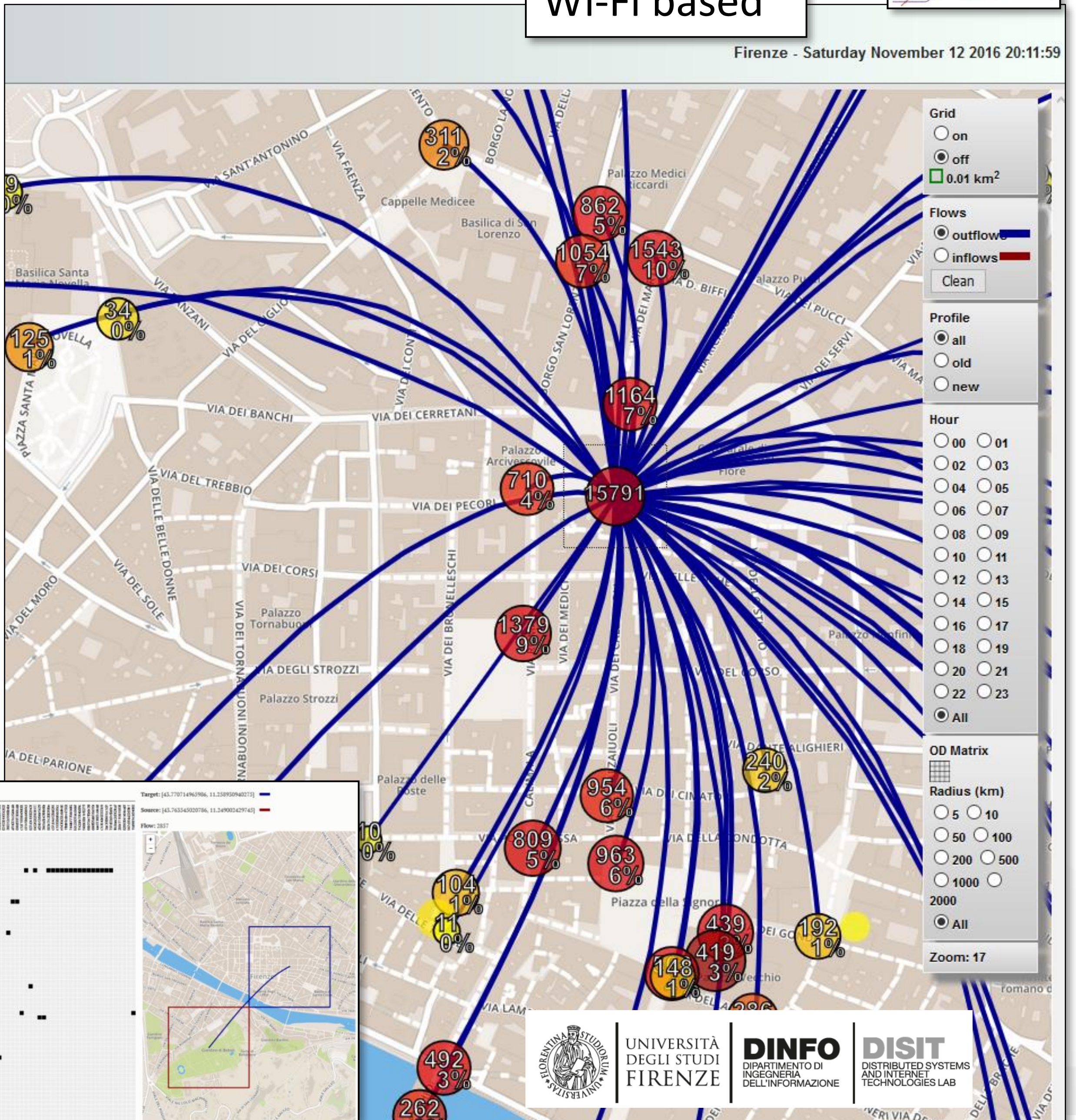
Origin Destination Matrix Estimation

Wi-Fi based



Recency and frequency





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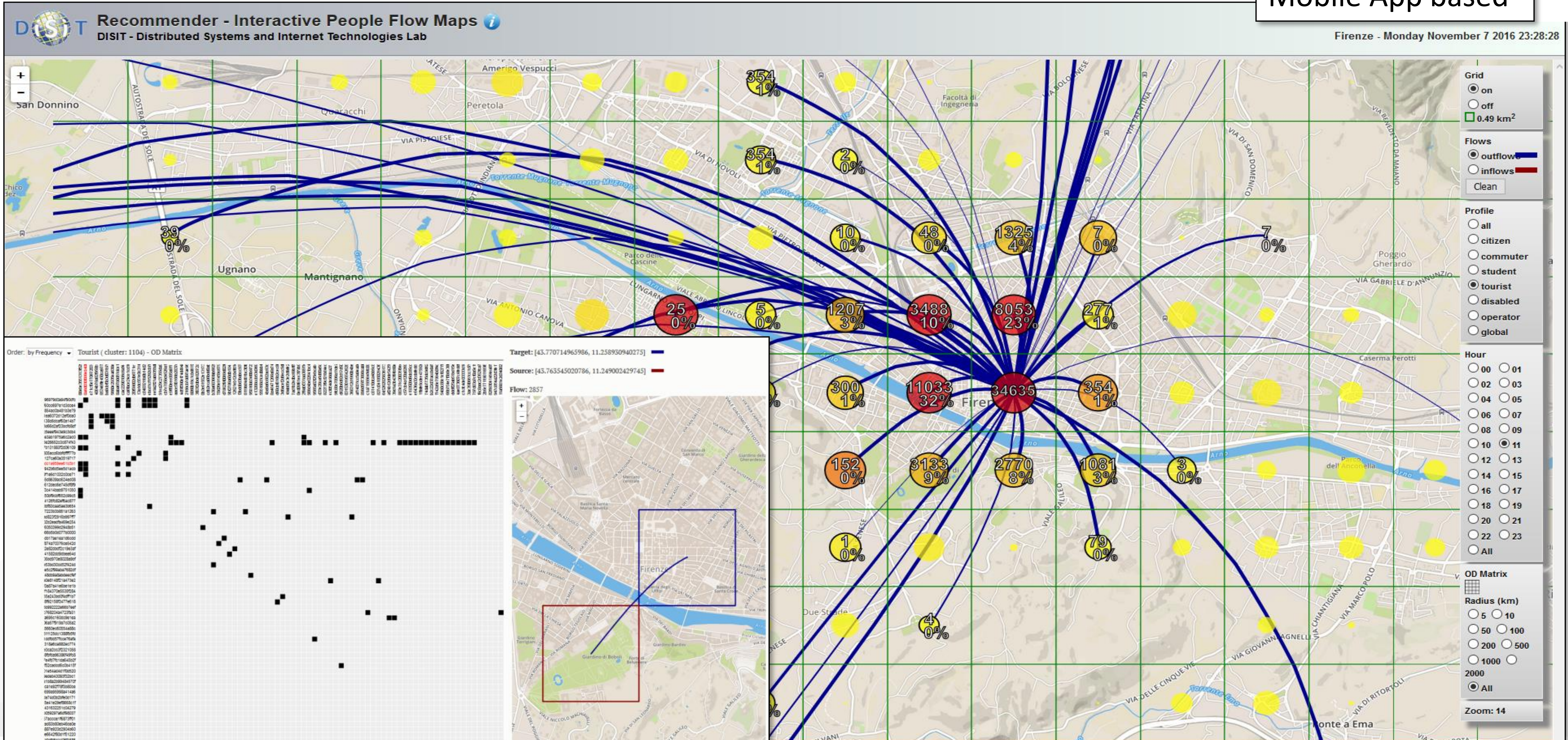
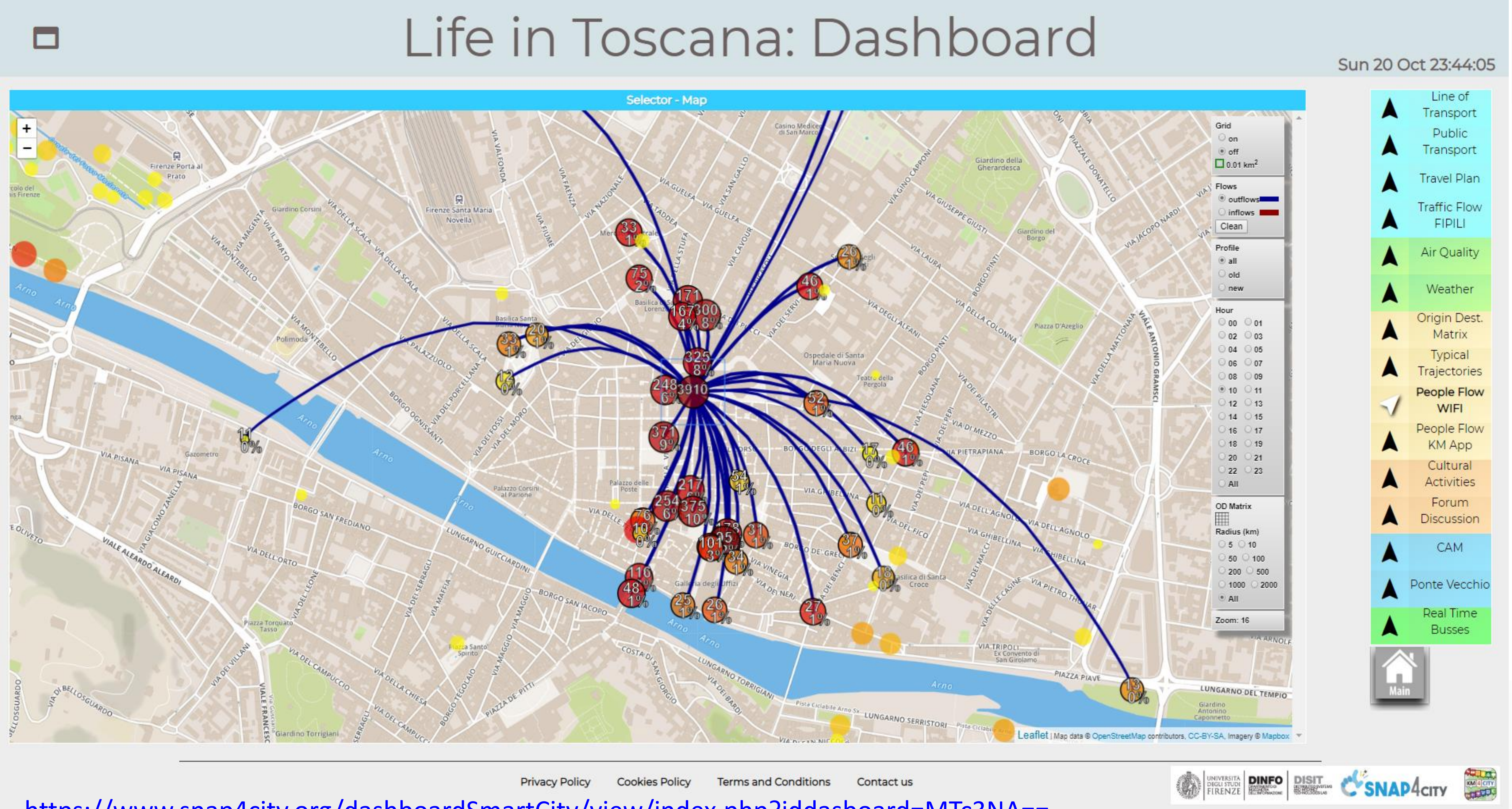
Scalable multiresolution OD matrix

Mobile App based



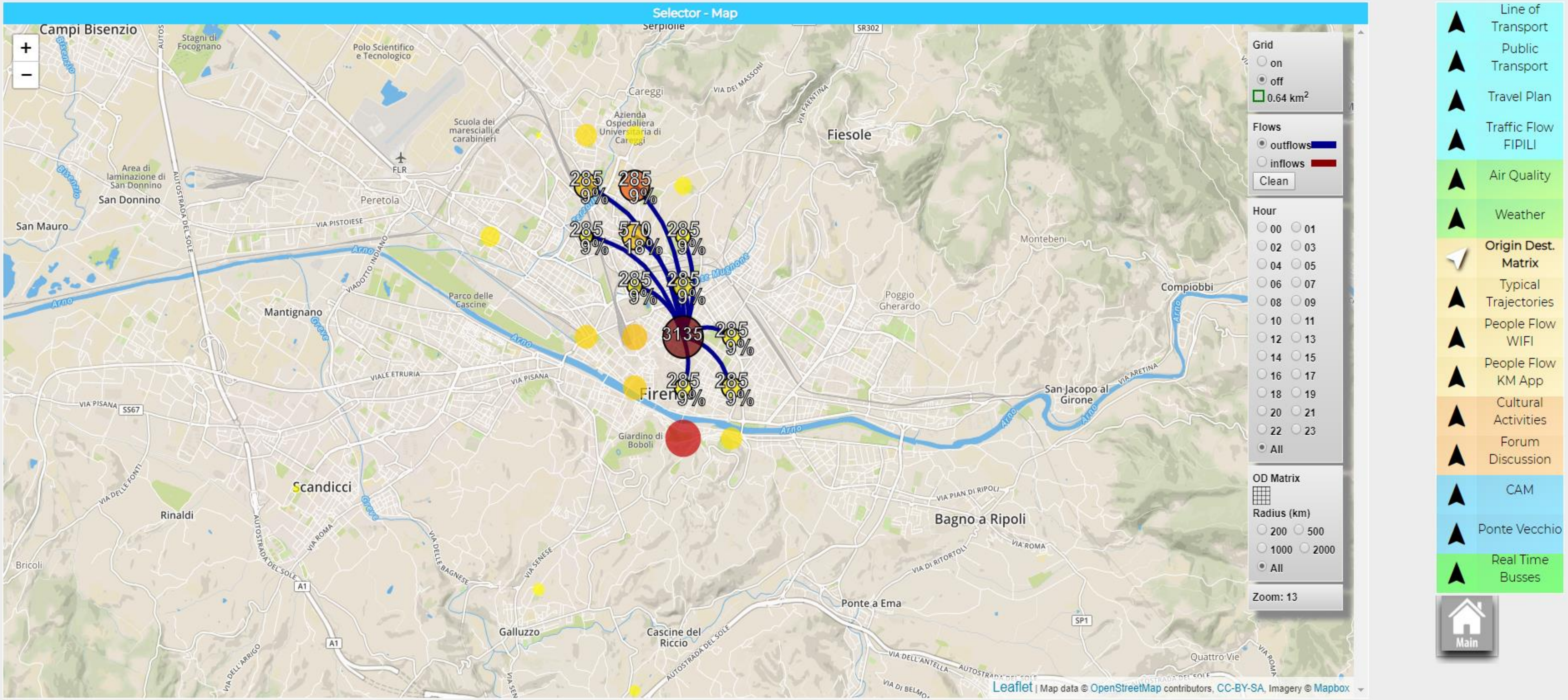
Life in Toscana: Dashboard



https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTc3NA==

Life in Toscana: Dashboard

Sun 20 Oct 23:40:25



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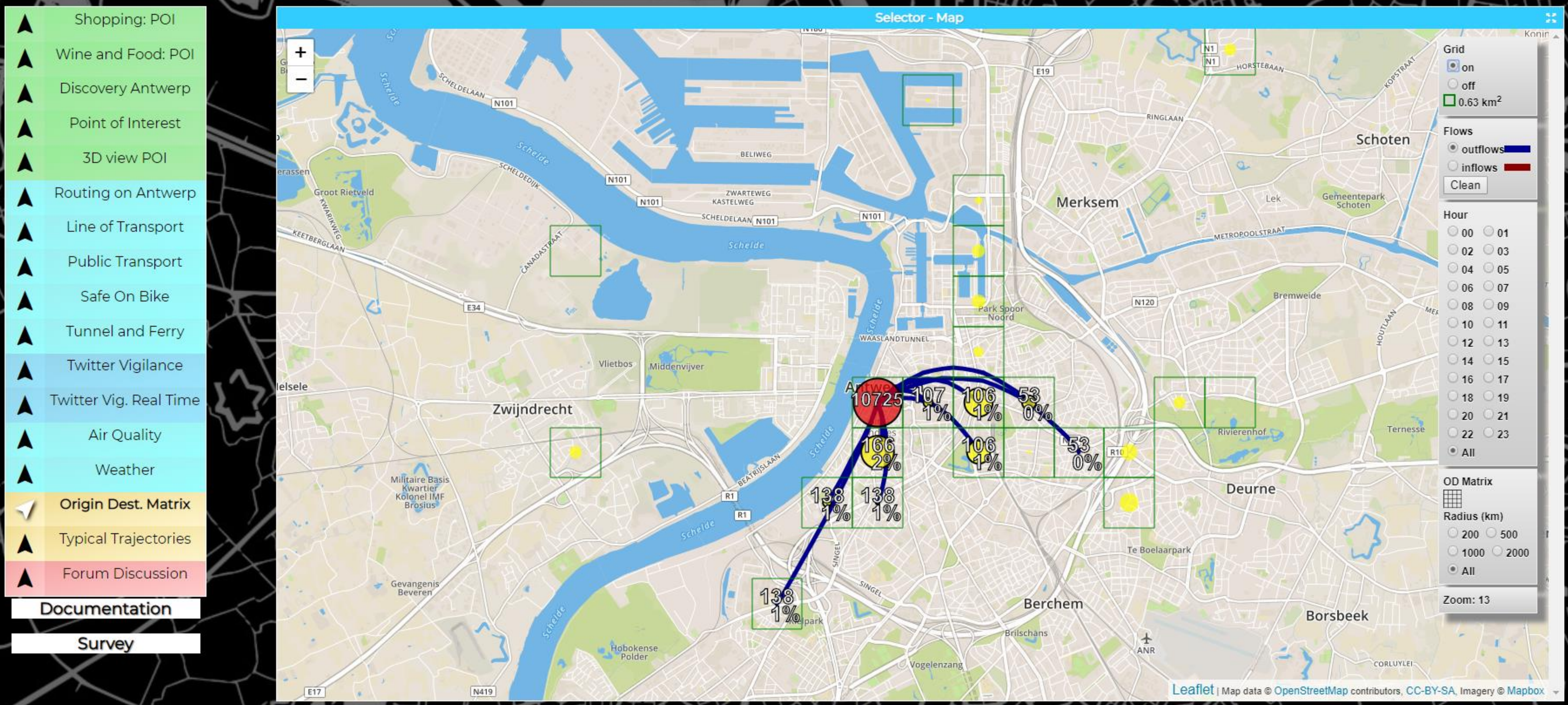
https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTc3NA==

The Life of Antwerp

Please note that the data results are not always based on real data.

Sun 20 Oct 23:42:07



https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTcwNg==

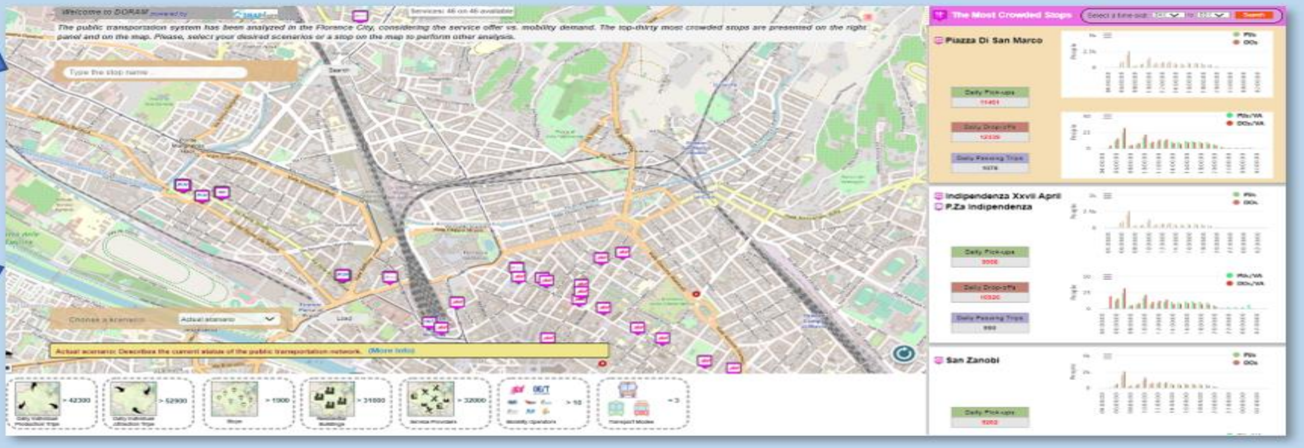
TOP

Demand of Mobility vs Offer of Transportation

DORAM - Demand OffeR Analyzer for Mobility

Citizen Mobility demand and habits, real time traffic

Service offer (GTFS)



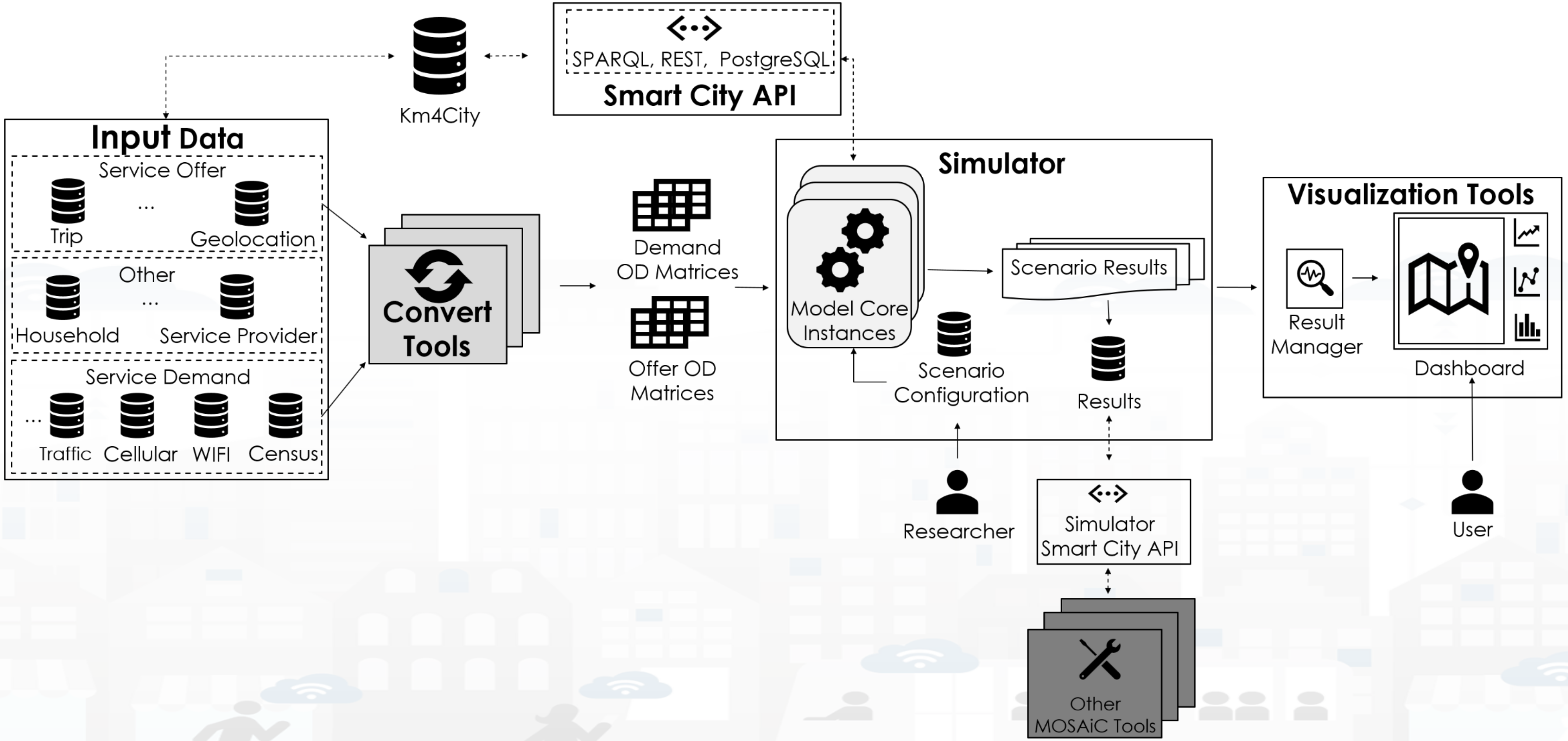
City Mobility Operator(s)

analysis of the offer vs demand (DORAM)

GTFS variation to improve the efficiency of the service

Planned Bus/Tram/Train/ etc. stops/trips and timetables (GTFS)

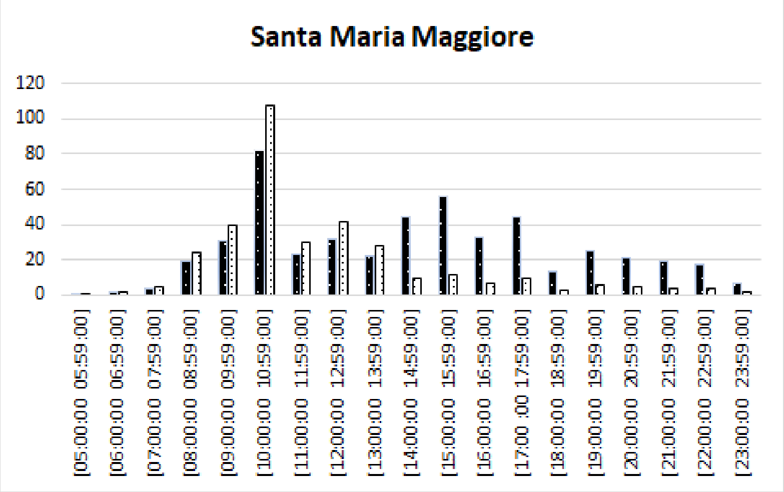
Demand vs Offer of Mobility Analysis

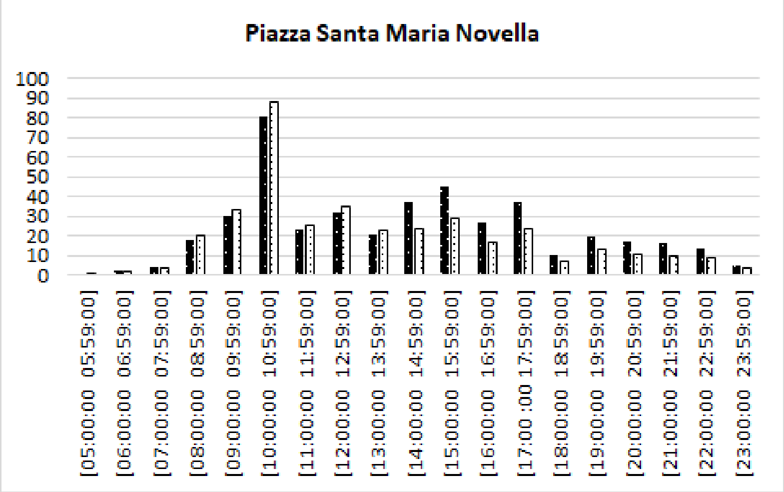


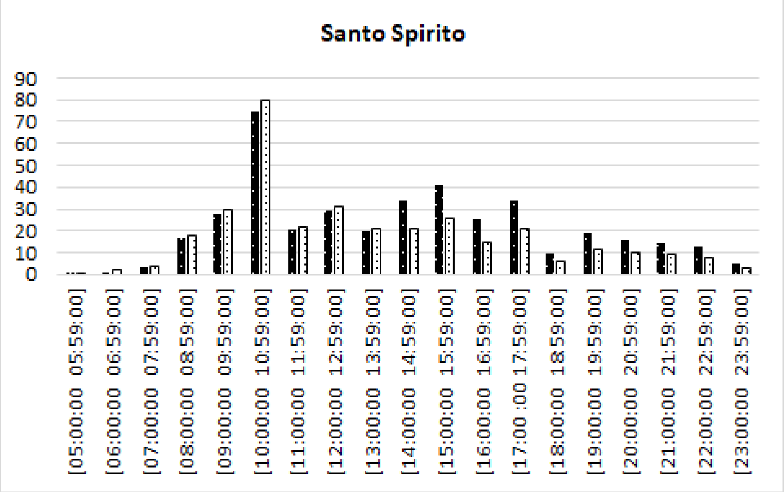
What can produce the Analysis tool

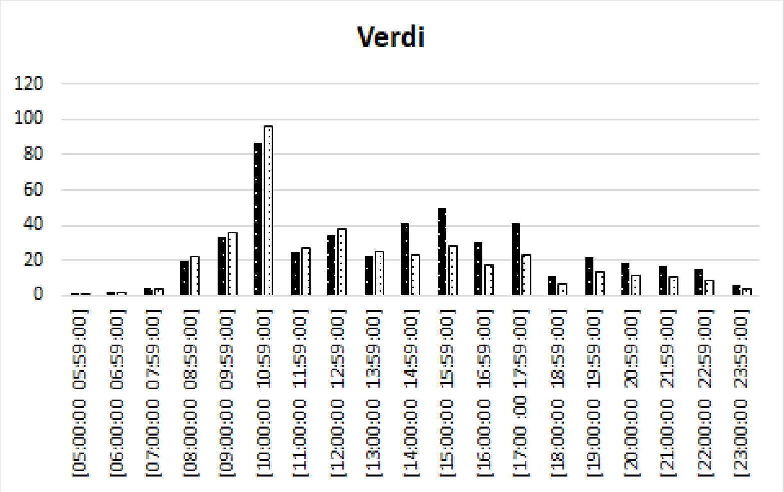
- Identification of critical Bus Stops over time
- Identification of critical courses of bus lines, over day and week
- Effects of changing the position of Bus Stops, courses and line schedules, bus size, etc.
- Effects of changing the contextual conditions:
  - The opening of shopping centers, cinemas, schools, etc..
  - Seize of the buses

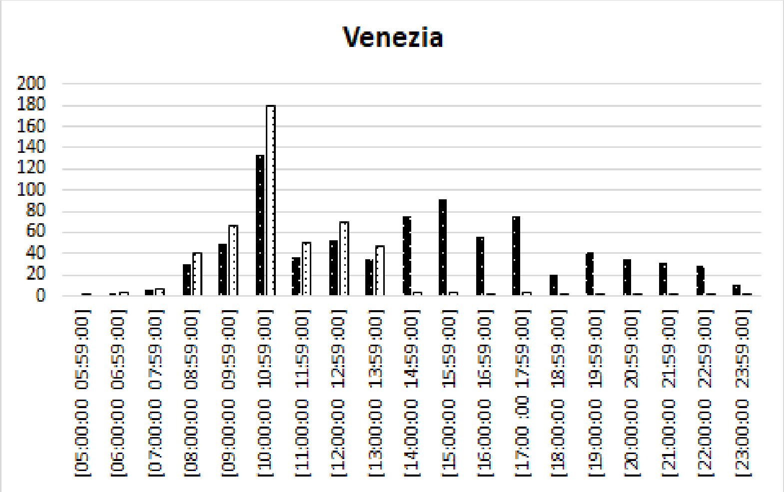
Pick-ups (black bars) and drop-offs (white bars) for the six selected stops

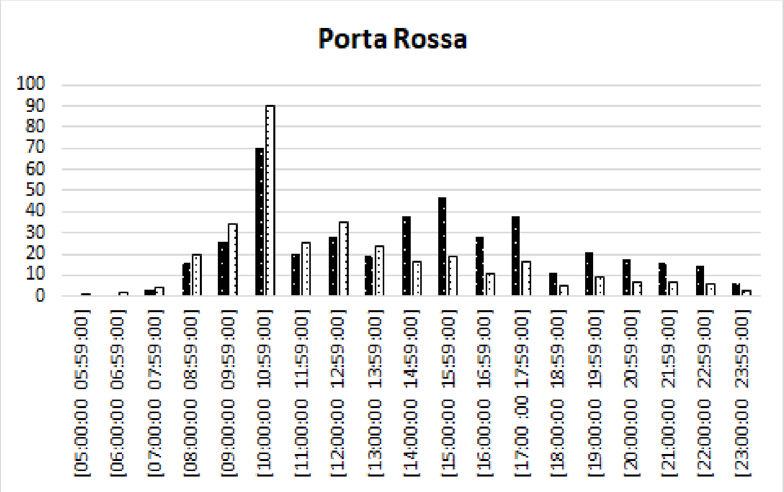


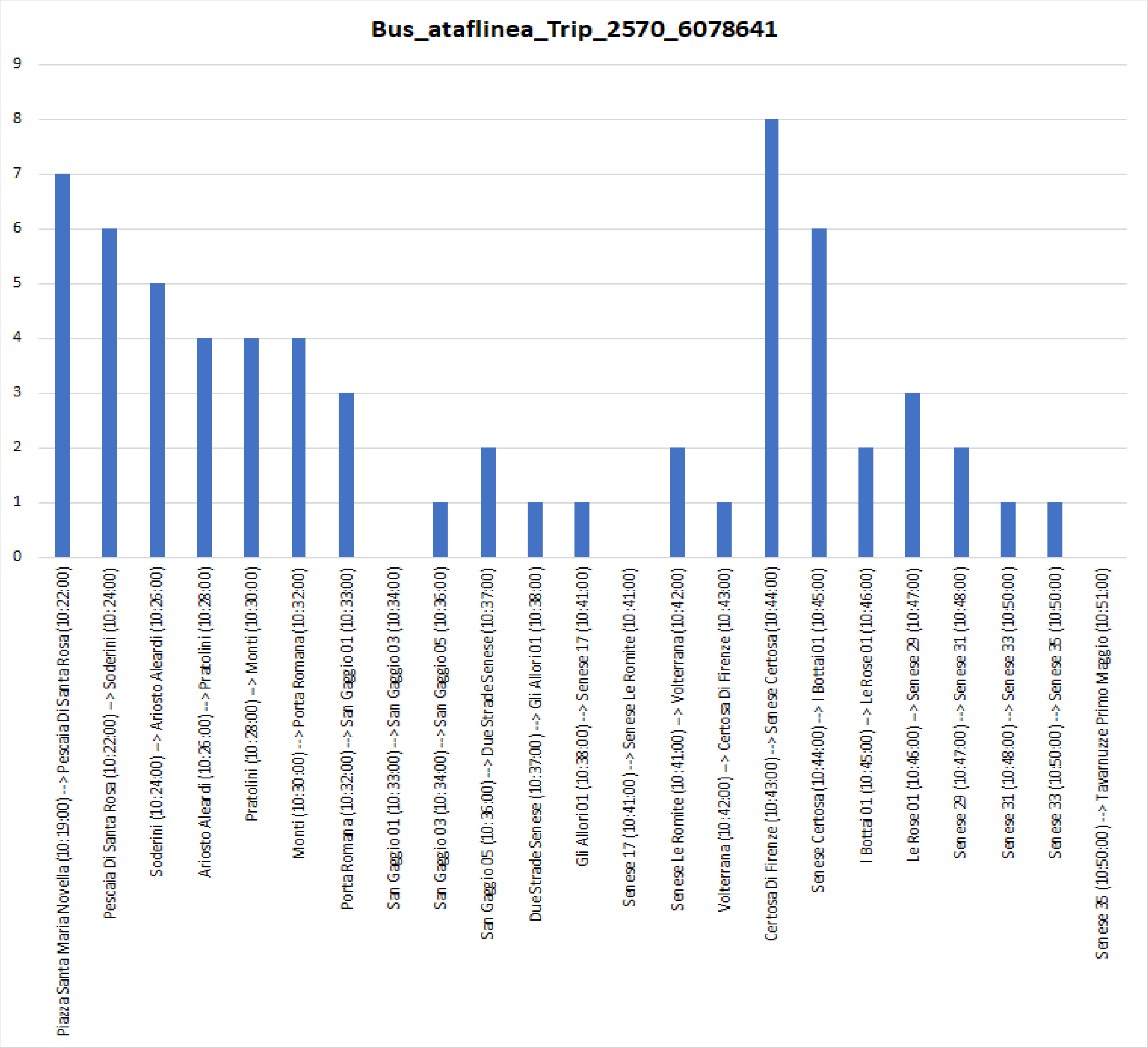


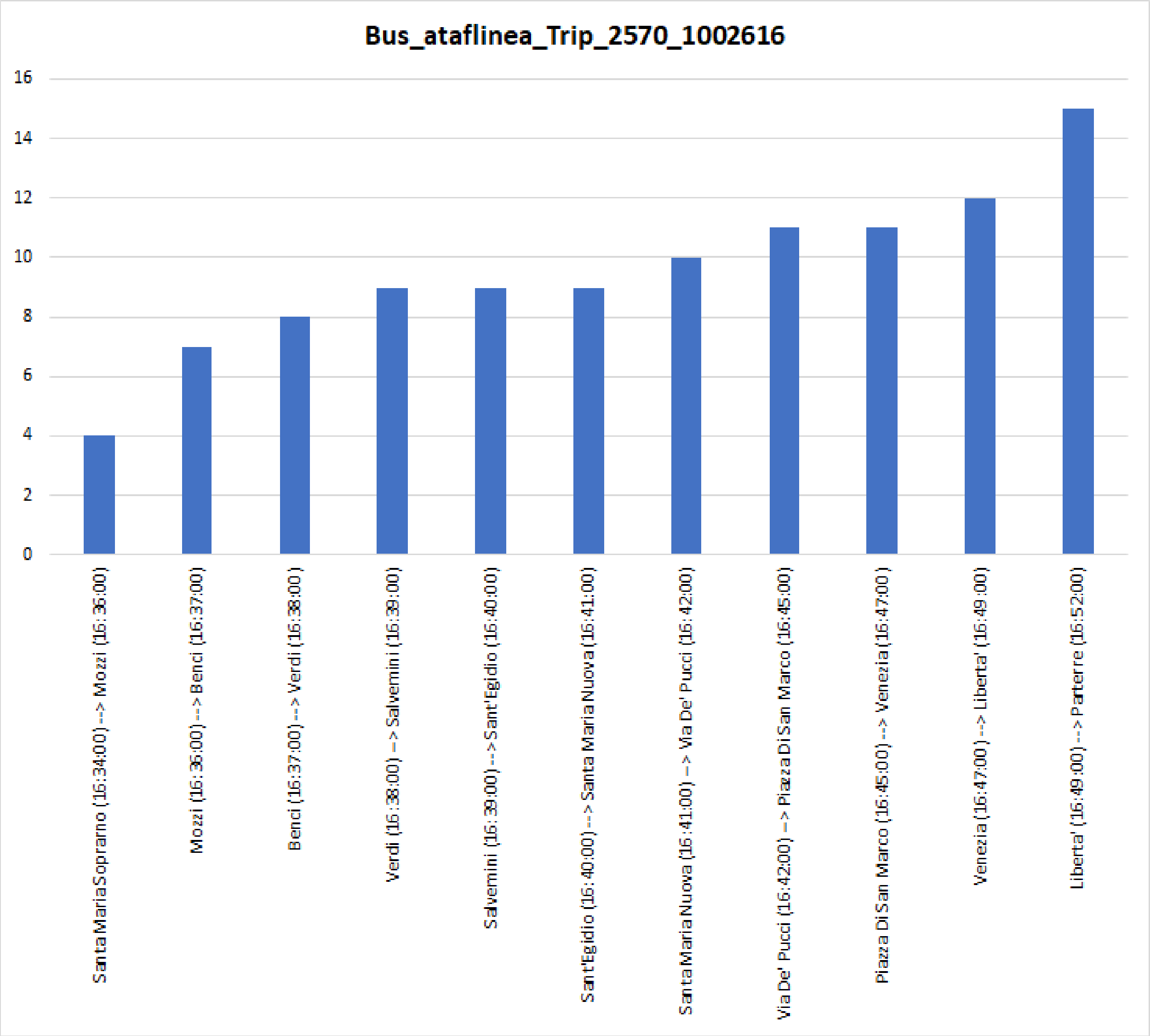




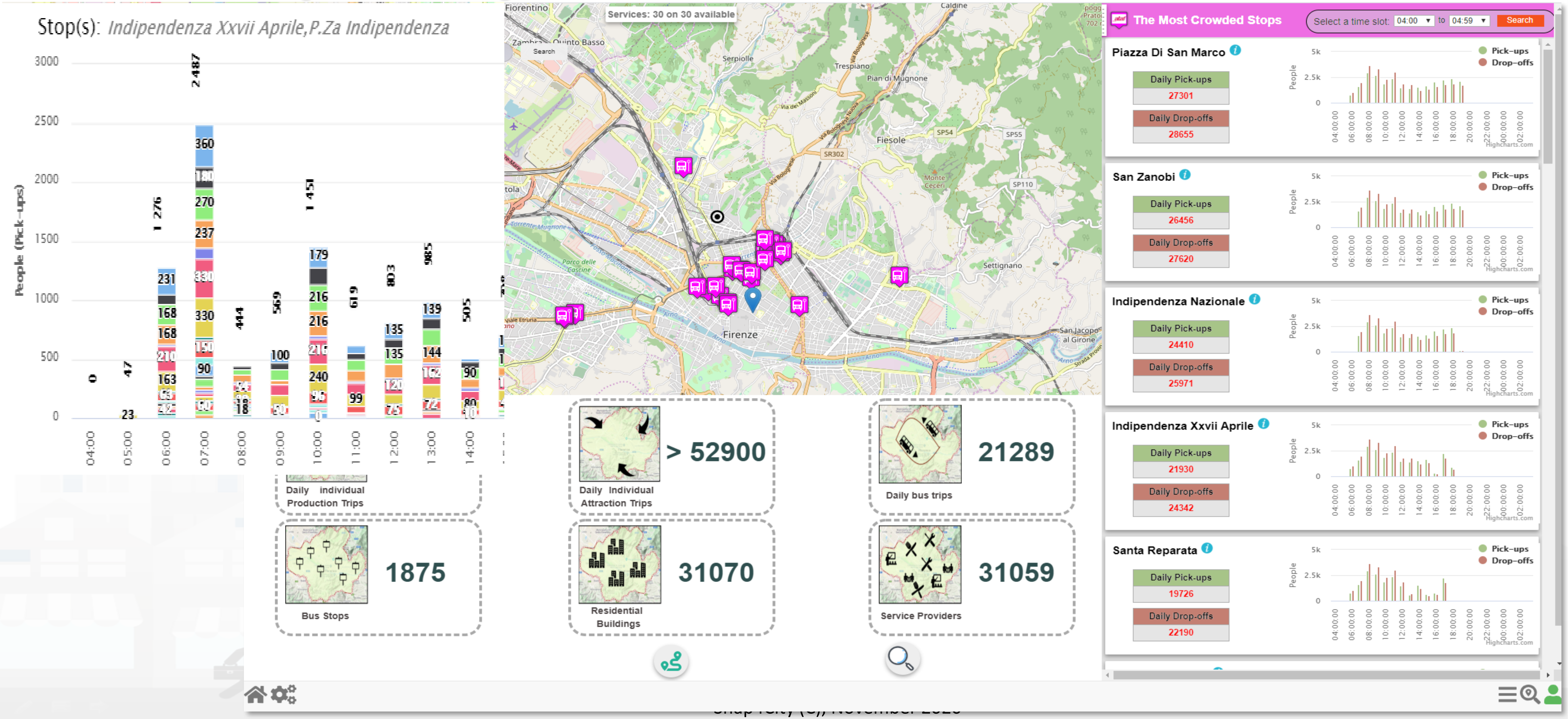





Bus_ataflinea_Trip_2570_6078641
0
1
2
3
4
5
6
7
8
9
Piazza Santa Maria Novella (10:19:00) --> Pescaia Di Santa Rosa (10:22:00)
Pescaia Di Santa Rosa (10:22:00) --> Soderini (10:24:00)
Soderini (10:24:00) --> Ariosto Aleardi (10:26:00)
Ariosto Aleardi (10:26:00) --> Pratolini (10:28:00)
Pratolini (10:28:00) --> Monti (10:30:00)
Monti (10:30:00) --> Porta Romana (10:32:00)
Porta Romana (10:32:00) --> San Gaggio 01 (10:33:00)
San Gaggio 01 (10:33:00) --> San Gaggio 03 (10:34:00)
San Gaggio 03 (10:34:00) --> San Gaggio 05 (10:36:00)
San Gaggio 05 (10:36:00) --> Due Strade Senese (10:37:00)
Due Strade Senese (10:37:00) --> Gli Allori 01 (10:38:00)
Gli Allori 01 (10:38:00) --> Senese 17 (10:41:00)
Senese 17 (10:41:00) --> Senese Le Romite (10:41:00)
Senese Le Romite (10:41:00) --> Volterrana (10:42:00)
Volterrana (10:42:00) --> Certosa Di Firenze (10:43:00)
Certosa Di Firenze (10:43:00) --> Senese Certosa (10:44:00)
Senese Certosa (10:44:00) --> I Bottai 01 (10:45:00)
I Bottai 01 (10:45:00) --> Le Rose 01 (10:46:00)
Le Rose 01 (10:46:00) --> Senese 29 (10:47:00)
Senese 29 (10:47:00) --> Senese 31 (10:48:00)
Senese 31 (10:48:00) --> Senese 33 (10:50:00)
Senese 33 (10:50:00) --> Senese 35 (10:50:00)
Senese 35 (10:50:00) --> Tavarnuzze Primo Maggio (10:51:00)

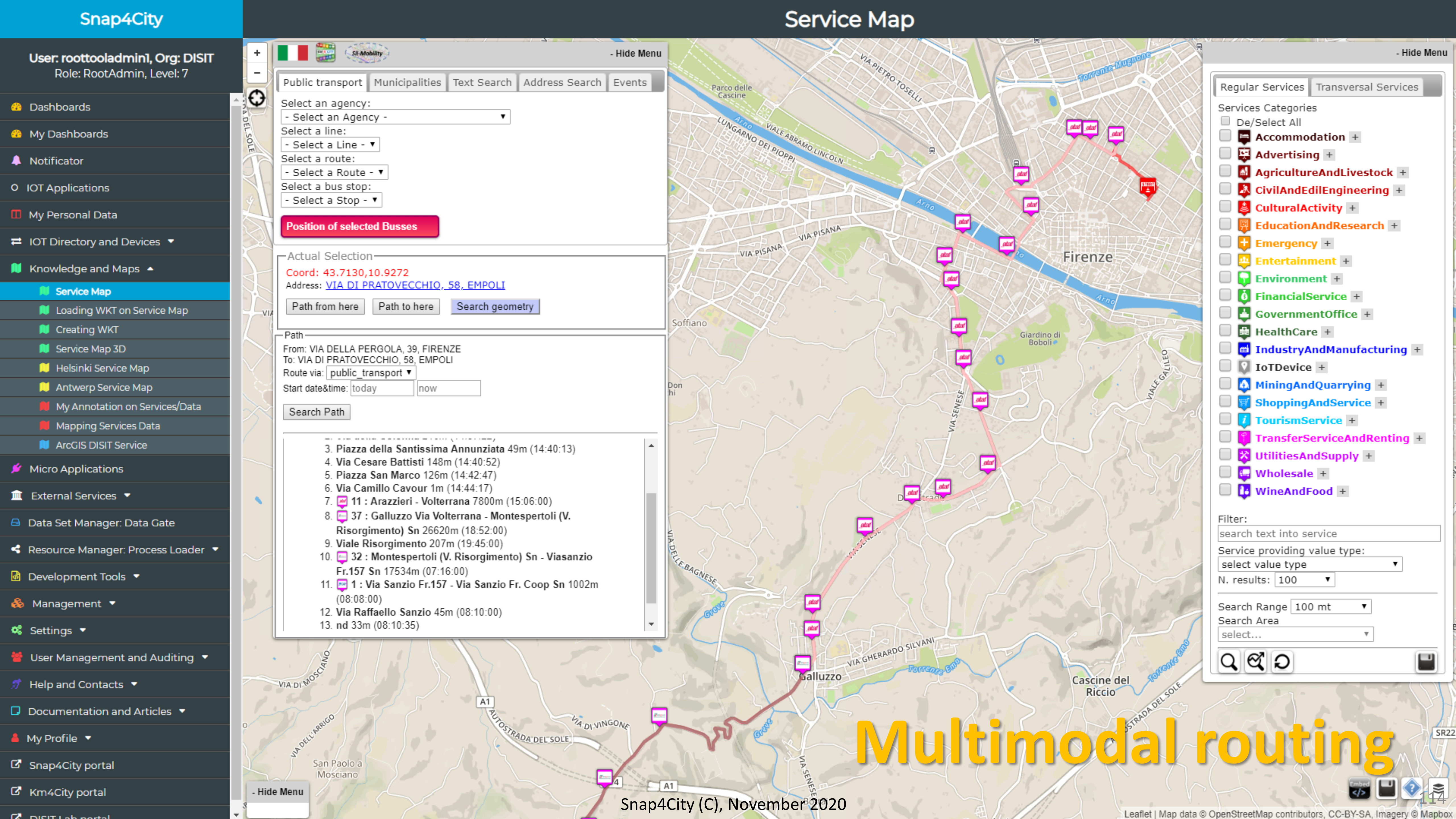

Bus_ataflinea_Trip_2570_1002616
0
2
4
6
8
10
12
14
16
Santa Maria Soprarno (16:34:00) --> Mozzi (16:36:00)
Mozzi (16:36:00) --> Benci (16:37:00)
Benci (16:37:00) --> Verdi (16:38:00)
Verdi (16:38:00) --> Salvemini (16:39:00)
Salvemini (16:39:00) --> Sant'Egidio (16:40:00)
Sant'Egidio (16:40:00) --> Santa Maria Nuova (16:41:00)
Santa Maria Nuova (16:41:00) --> Via De' Pucci (16:42:00)
Via De' Pucci (16:42:00) --> Piazza Di San Marco (16:45:00)
Piazza Di San Marco (16:45:00) --> Venezia (16:47:00)
Venezia (16:47:00) --> Liberta' (16:49:00)
Liberta' (16:49:00) --> Parterre (16:52:00)

Bus Stop Analysis: identification of criticalities



TOP

Modal & Multimodal Routing for Navigation and Travel Planning



Multimodal routing

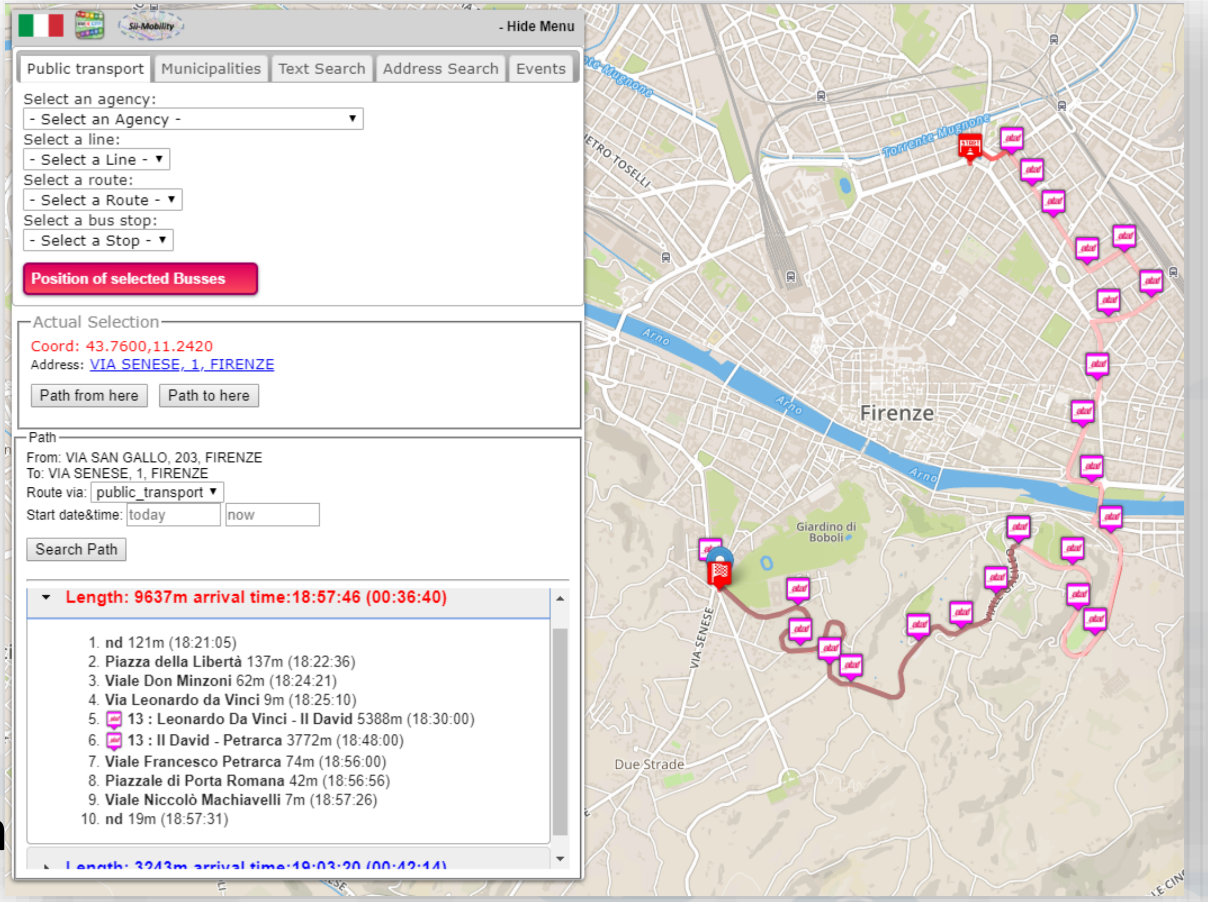
Routing and Multimodal Routing

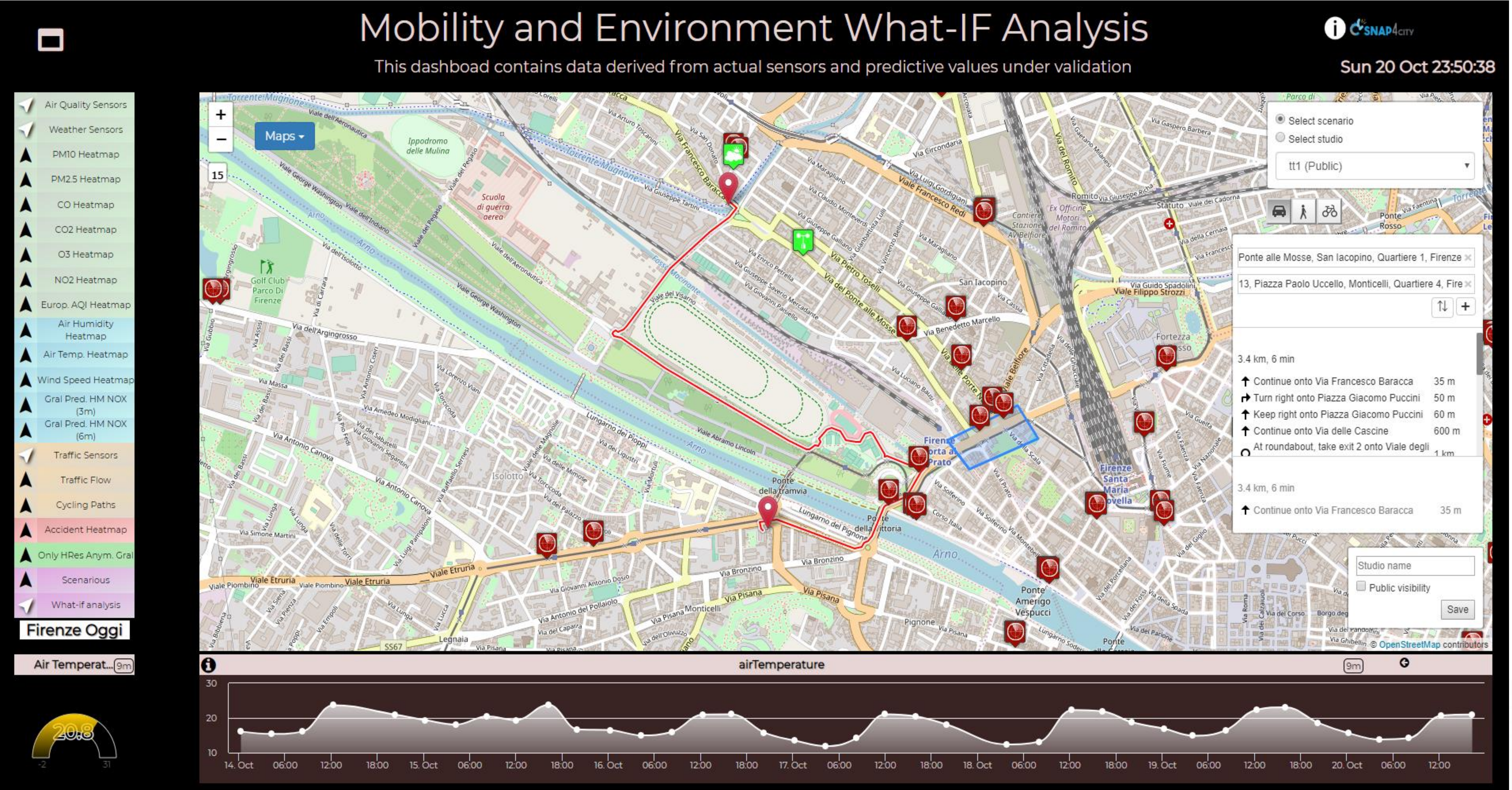
Modes:

- Pedonal, Vehicles
- Public Multimodal
- Multi Point for Delivering
- Constrained: quite, blocked, etc.

Test it on our:

- Mobile Apps
- MicroApplication
- Dashboard
- ServiceMap service on Tuscany in Snap4City





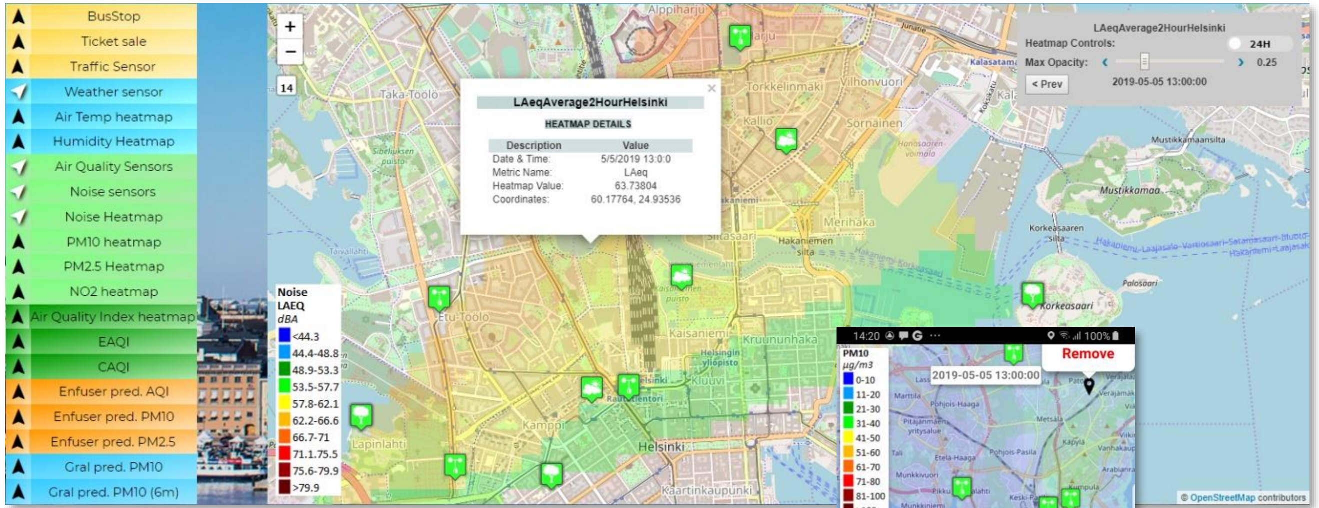
https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MjE5MA==

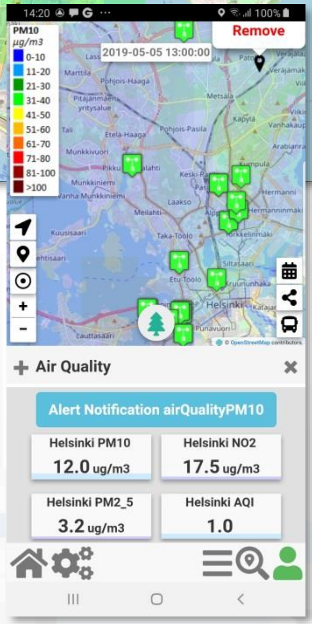
TOP

Environmental Data: Predictions, Early Warning

Data Analytics: Heatmaps

- Over the Gaussian Heatmaps
- Calibrated heatmaps on the basis of Interpolated data for:
  - From 200x200 to 4x4 mt
  - PM10, PM2.5, SO2, NO2, Noise, NO, O3, Enfuser, GRAL,….
  - Any programmed Color map
  - Animations over H24
  - Picking values in any place, values on their position.
  - On Web and Mobile App





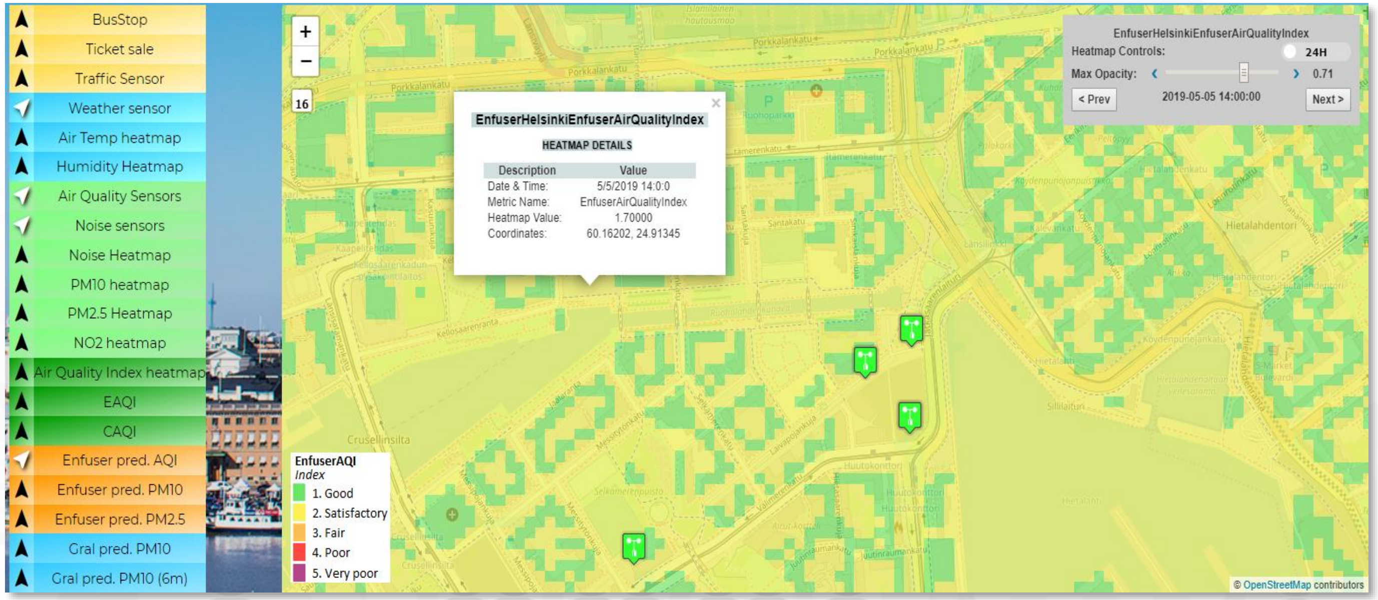
TRAFAIR

Environmental ENFUSER Predictive Measures

ENvironmental information **FU**sion **SER**vice:

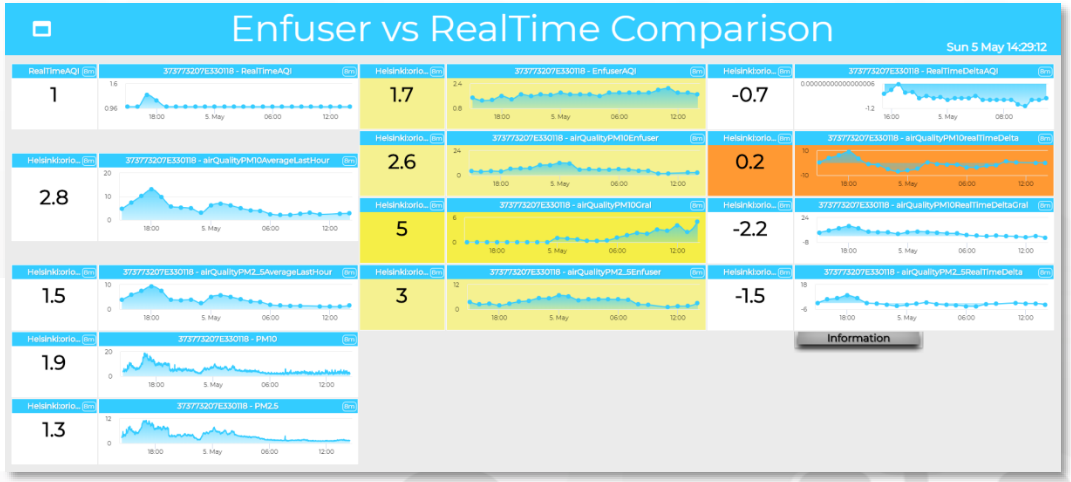
Air quality model that combines *dispersion modelling techniques*, *information fusion algorithms* and *statistical approaches*. The operational modelling system provides both real-time and forecasted, high resolution information on the urban air quality.

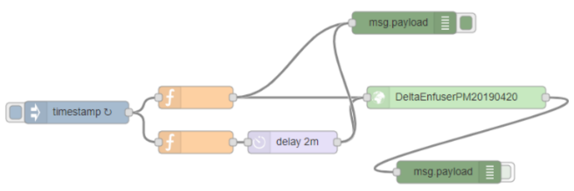
- Data gathering, data processing for Piking
- API for accessing data of Heatmaps in real time



Data Analytics: Enfuser predictions

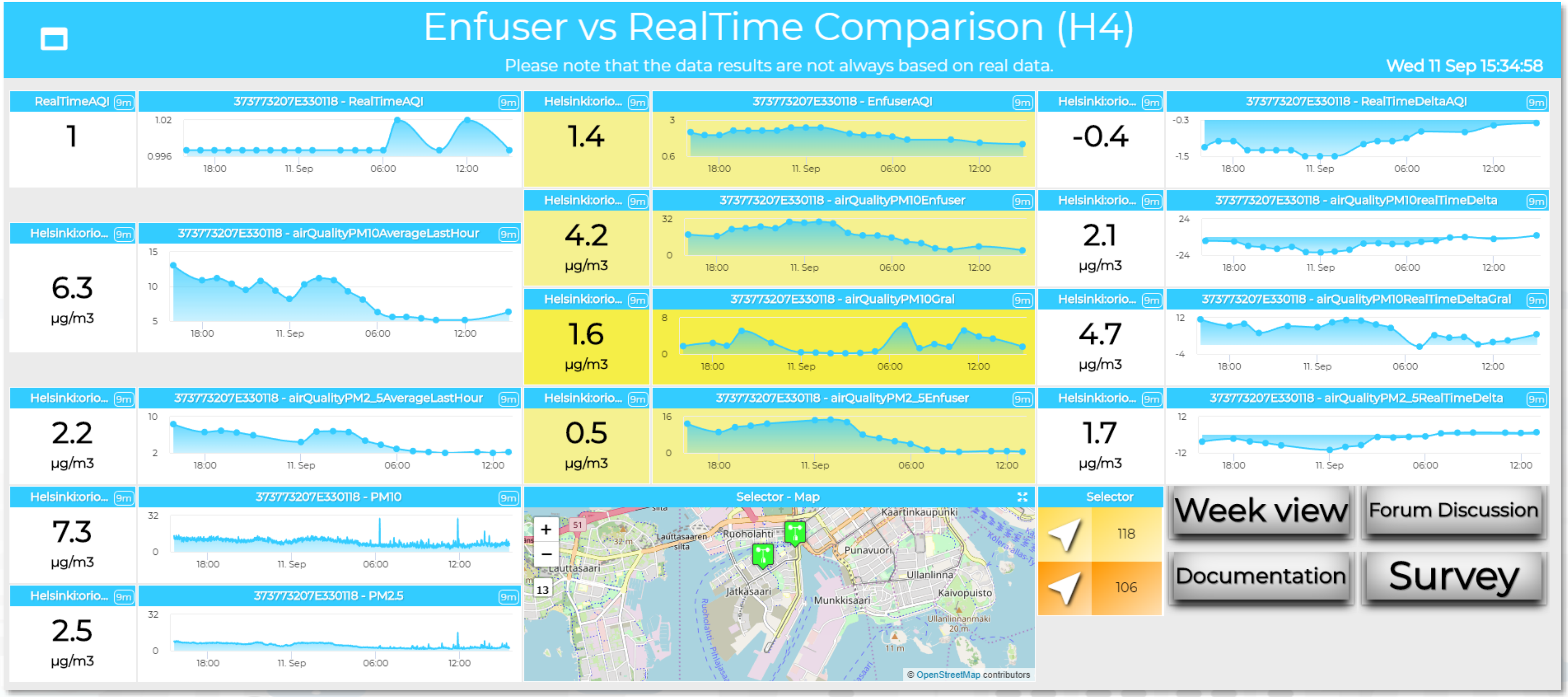
- **Enfuser predictions: AQI, PM10, PM2.5**
  - Data gathering, data processing for Piking
  - Delta Estimation Predictions vs Actual: on 12 points/sensors via R-Studio and IOT App
  - API for accessing data of Heatmaps in real time





Comparative Dashboard

- *Delta Estimation Predictions vs Actual* on 12 points/sensors via R-Studio and IOT App



https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTczMg==

Data Analytics: AQI estimations

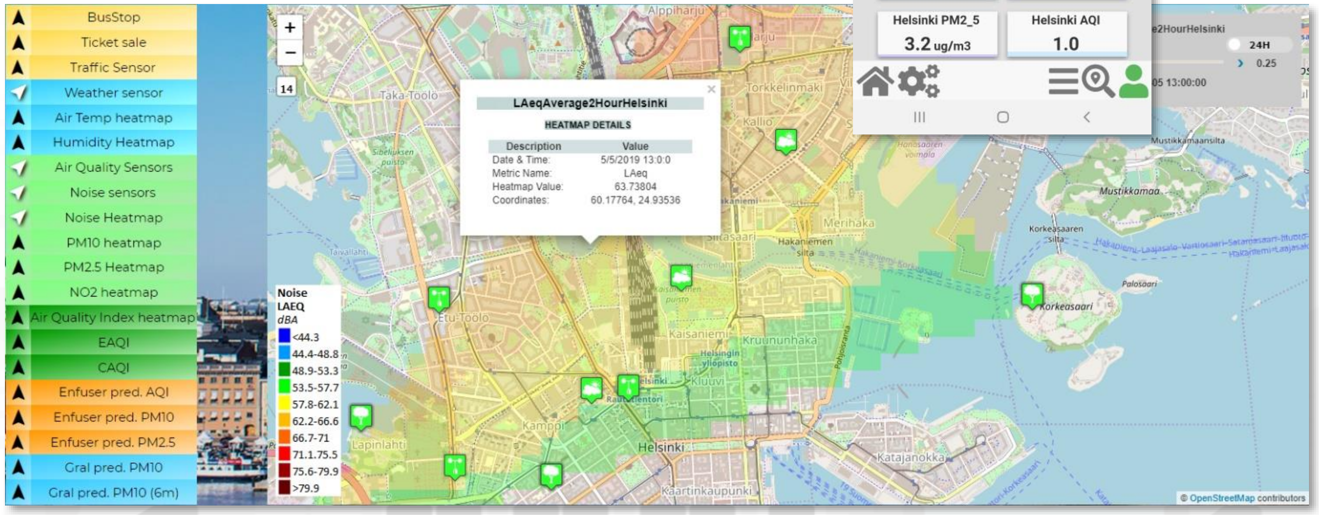
- **Legenda of Environmental data:**
  - https://www.snap4city.org/435

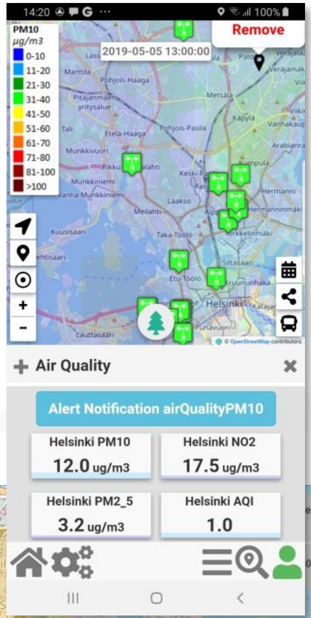
- **AQI estimation via Rstudio and IOT App:**
  - **EAQI, European Air Quality Index**
  - **Enfuser AQI for Delta,**
  - **CAQI**
  - **Their corresponding Heatmaps**

Environmental Heatmaps

Calibrated heatmaps based on **Interpolated data**:

- **Real time** measures (PM_{10}, $PM_{2,5}$, NO_2, SO_2, Noise, NO, O_3, AQI,..)
- **Predictive** measures (ENFUSER, GRAL)
- From **200x200** to **4x4** m
- Hourly concentration
- Any programmed Color map
- Animations over H24
- Picking values in any place
- On Web and Mobile App

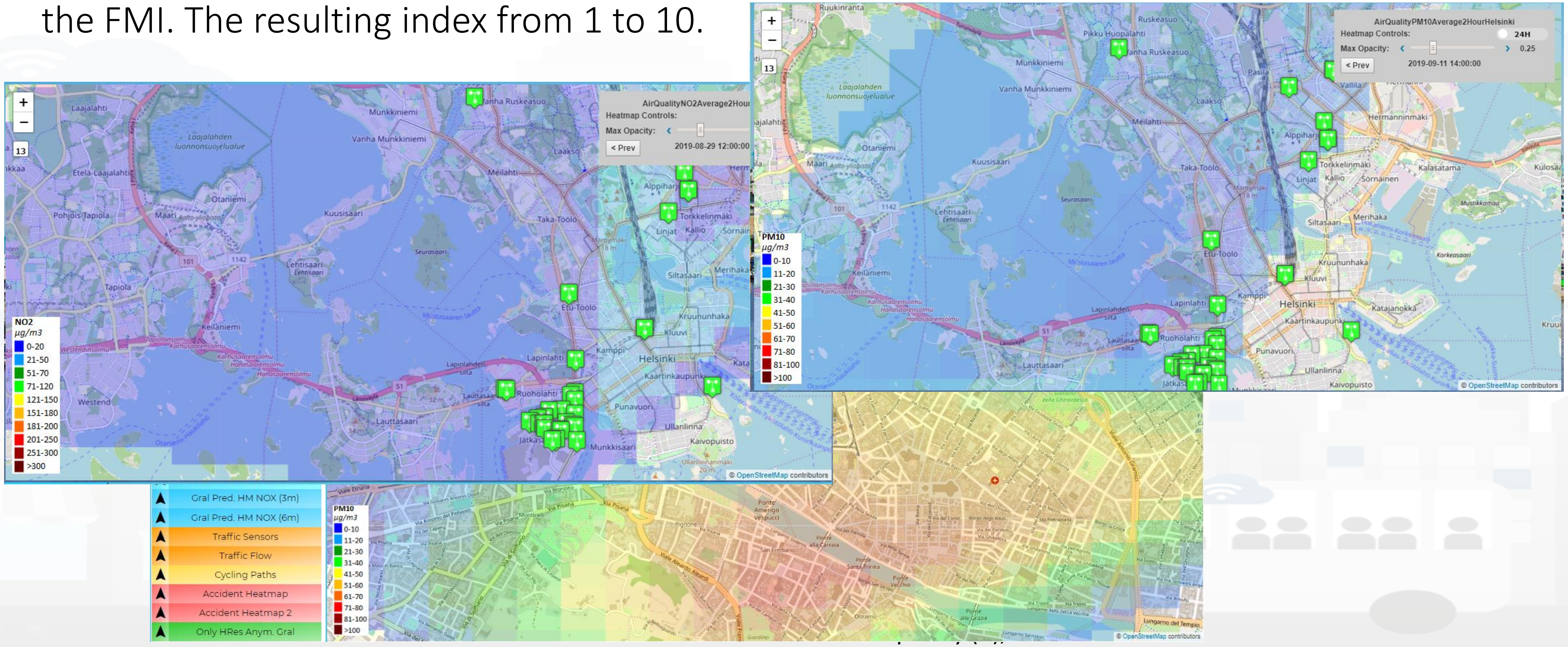


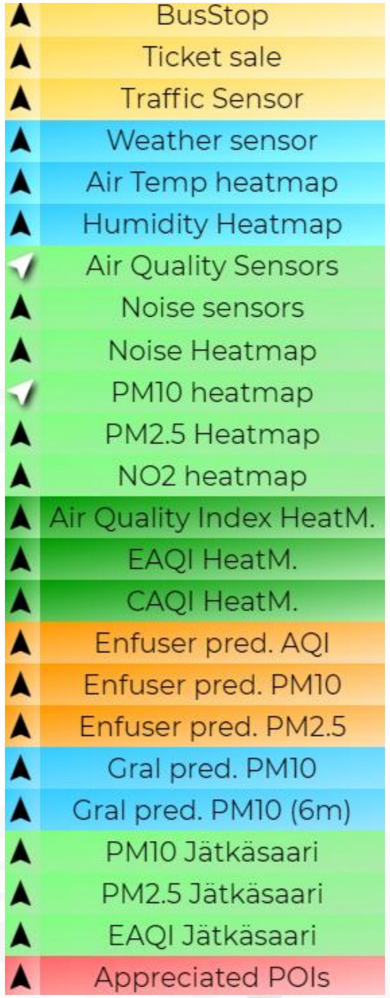


https://www.snap4city.org/snap4cityWebAppHelsinki/

Environmental Real Time Measures

- **Noise:** real time noise levels (measured in dBA).
- **PM$_{10}$:** real time pollutant levels in air in terms of PM$_{10}$ (measured in µg/m$_3$) particles.
- **PM$_{2,5}$:** real time pollutant levels in air in terms of PM$_{2.5}$ (measured in µg/m$_3$) particles
- **NO$_2$:** real time pollutant levels in air in terms of nitrogen dioxide (measured in µg/m$_3$).
- **Air Quality Index (AQI):** real time air quality index of the Helsinki area, provided by the FMI. The resulting index from 1 to 10.





AQI Indexes estimation via R studio and IOT App

European Air Quality Index **EAQI**

http://airindex.eea.europa.eu/

Pollutant	Index level (based on pollutant concentrations in µg/m3)				
	Good	Fair	Moderate	Poor	Very poor
Particles less than 2.5 µm ($PM_{2.5}$)	0-10	10-20	20-25	25-50	50-800
Particles less than 10 µm (PM_{10})	0-20	20-35	35-50	50-100	100-1200
Nitrogen dioxide (NO_2)	0-40	40-100	100-200	200-400	400-1000
Ozone (O_3)	0-80	80-120	120-180	180-240	240-600
Sulphur dioxide (SO_2)	0-100	100-200	200-350	350-500	500-1250

Measurements of up to five key pollutants supported by modelled data determine the index level that describes *the current air quality situation at each monitoring station*.

The index corresponds to **the poorest level for any of five pollutants according to the following scheme.**

Common Air Quality Index **CAQI**

http://www.airqualitynow.eu

Qualitative name	Index or sub-index	Pollutant (hourly) density in µg/m^3			
		NO_2	PM_{10}	O_3	$PM_{2.5}$(optional)
Very low	0–25	0–50	0–25	0–60	0–15
Low	25–50	50–100	25–50	60–120	15–30
Medium	50–75	100–200	50–90	120–180	30–55
High	75–100	200–400	90–180	180–240	55–110
Very high	>100	>400	>180	>240	>110

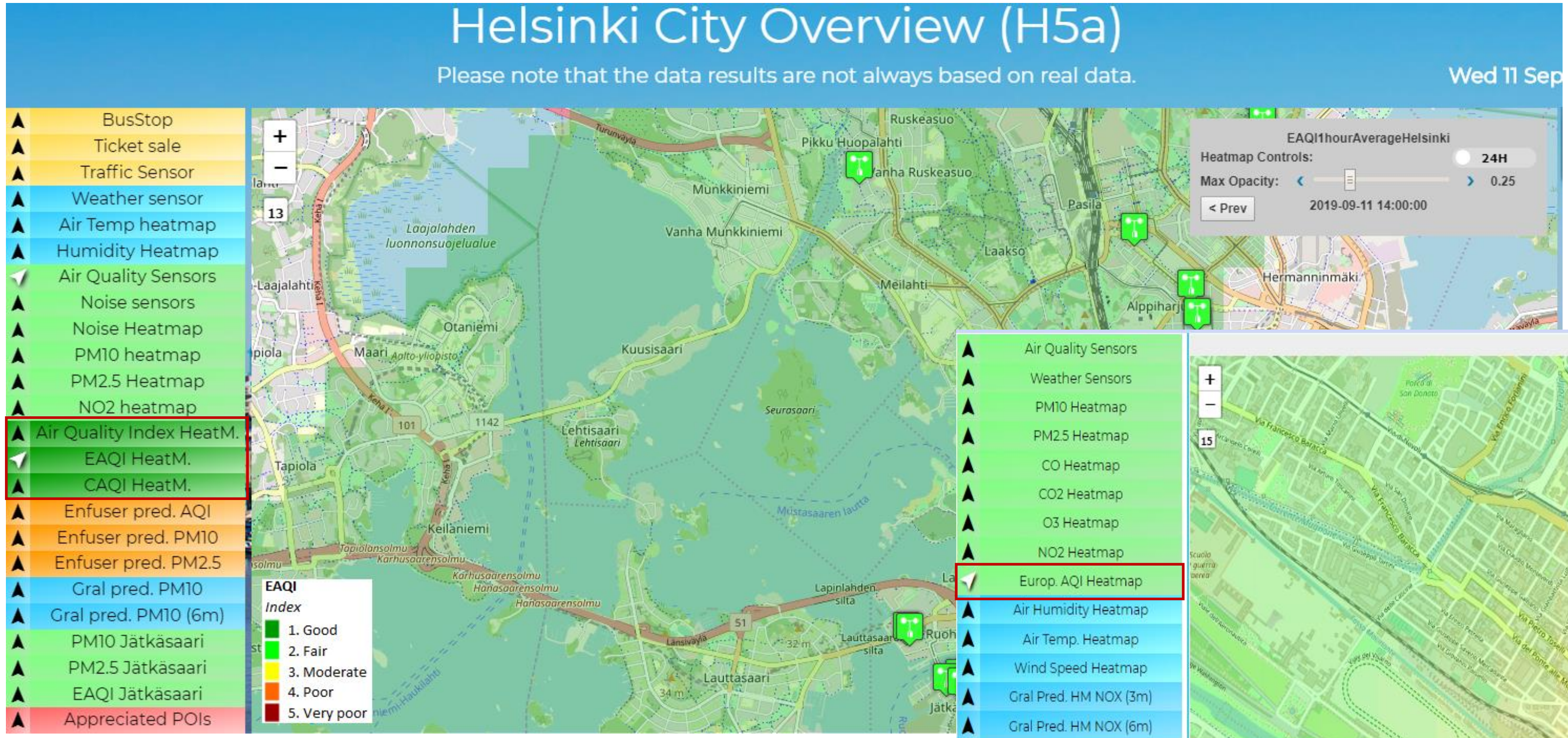
The index is defined away from roads (a "background" index). **CAQI** is computed on the basis of **NO_2, $PM_{2,5}$, PM_{10}** and **O_3**.

Legend of Environmental data:

https://www.snap4city.org/435

AQI Indexes estimation Heatmaps

Hourly pollutant concentration



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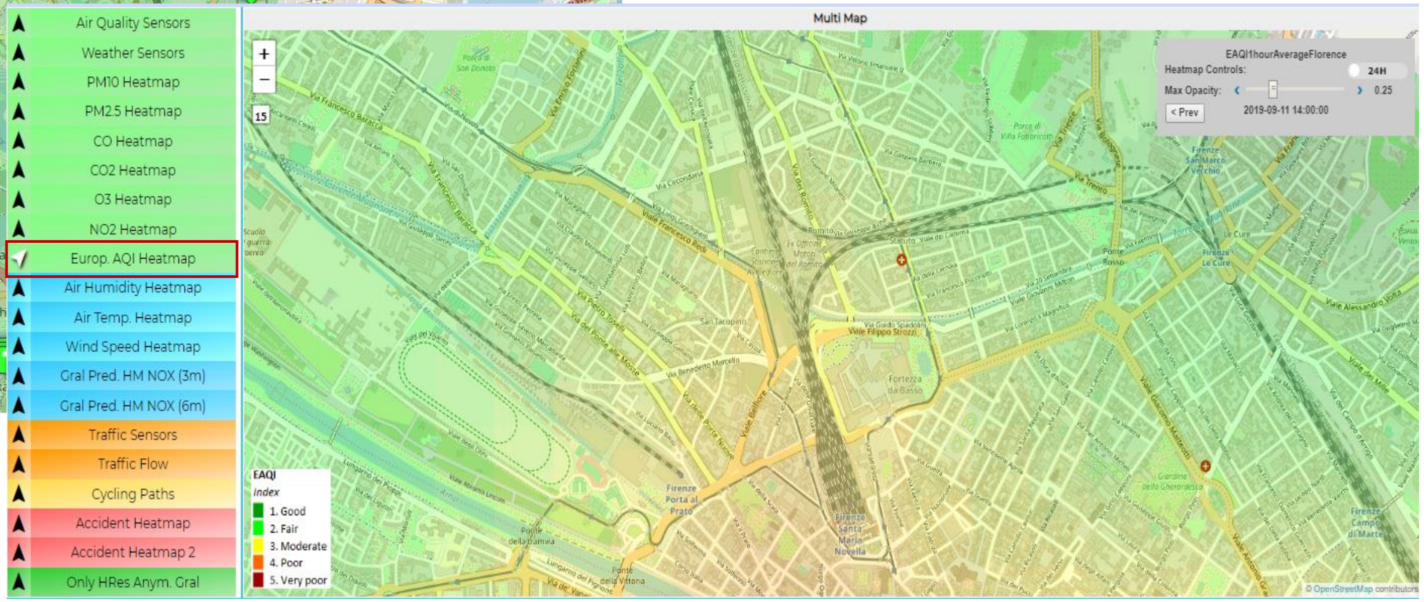
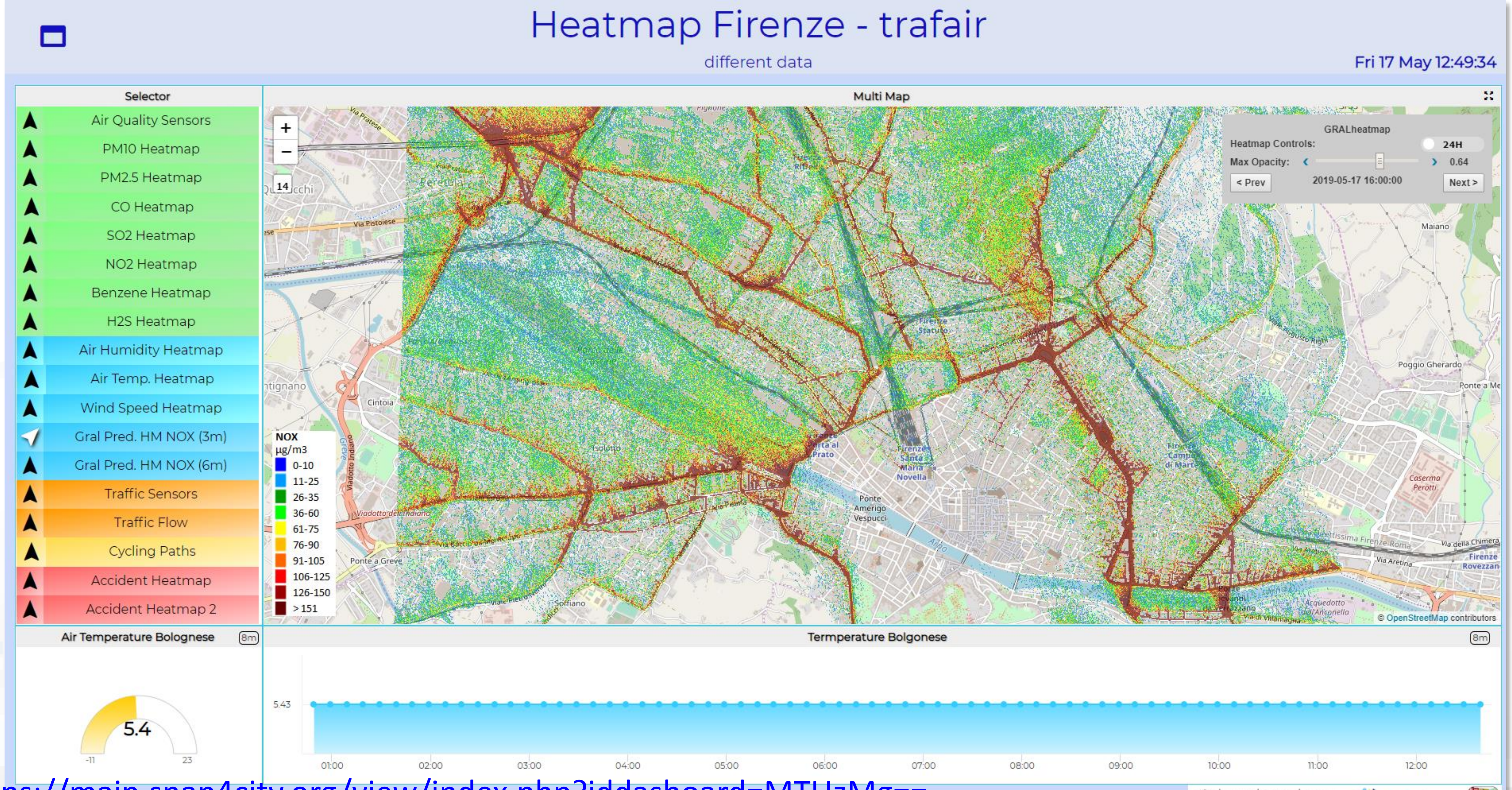


https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTUzMg==

Environmental Data Predictions: GRAL

- **GRAL predictions: PM10, NOX, ….**
  - **Comparison wrt real time values in actual value of Sensors**
  - Graz Lagrangian Model.
- GRAL model takes into account:
  - pollution sources (for example the vehicles, their distribution on the streets, the about of pollution they produce according to their distribution over time and space, etc.),
  - structure of the city (streets and shape 3D of the buildings),
  - weather forecast (wind intensity and direction), etc.
- GRAL can be applied on NOX, PM10, PM2.5, … or any other particles

TRAFAIR



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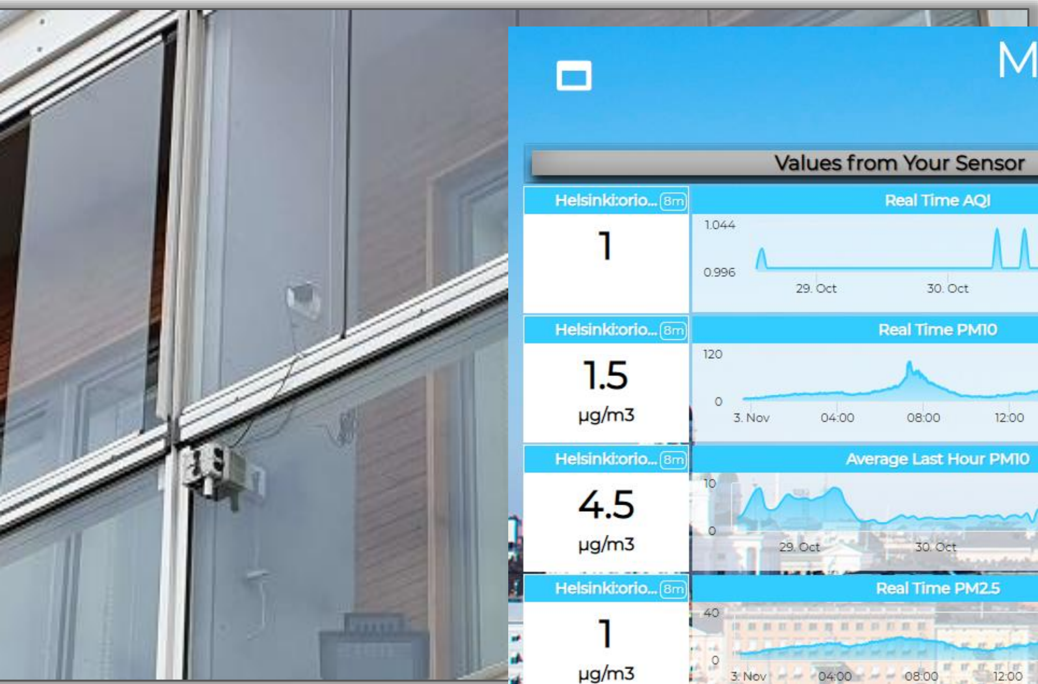
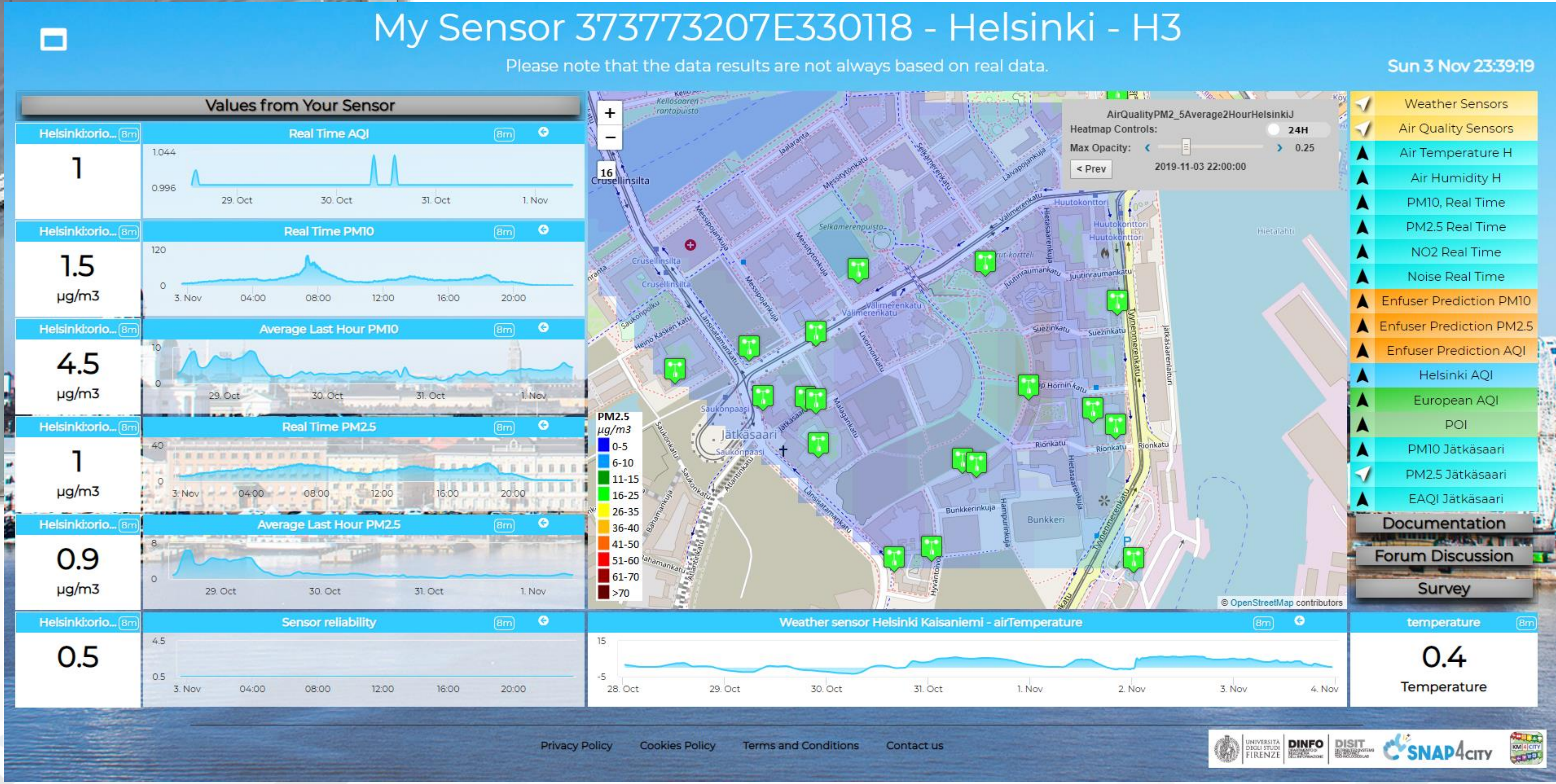
Environmental Devices hosted by Citizens





Environmental Data Network and Automated Analysis and Representation

Goal:

- **Real time aggregation, integration, assessment of data** independently on the number of sensors, on their position.
- **Real time analysis and representation** of environmental data automatically in dedicated Dashboards on Snap4City platform.

The **target** has been to:

- Provide ***informative view of the city users*** regarding Environmental data via some mobile App.
- Provide detailed information about the Environmental data to *city officials for decision making*, as ***comparison between predictions and real time*** in specific point of the city.

Data have been collected from:

- IOT Brokers included ***IOT Devices hosted by city users***.
- Data Providers.

Environmental Data Network and Automated Analysis and Representation

Bivariate interpolation onto a grid for irregularly spaced input data.

- Resolution from **200x200** to **4x4** m
- **Hourly** concentration
- Any programmed Color map
- **Animations** over H24
- Picking values in any place, values on their position
- On Web and Mobile App

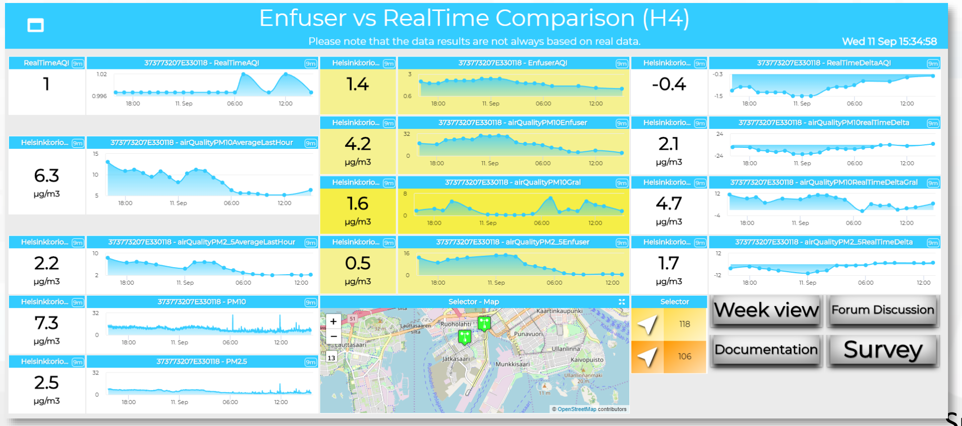
Environmental Real Time Measures:

- **Noise:** real time noise levels (measured in dBA).
- **PM_{10}:** real time pollutant levels in air in terms of PM_{10} (measured in µg/m_3) particles.
- **$PM_{2,5}$:** real time pollutant levels in air in terms of $PM_{2.5}$ (measured in µg/m_3) particles.
- **NO_2:** real time pollutant levels in air in terms of nitrogen dioxide (measured in µg/m_3).
- **Air Quality Index (AQI):** real time air quality index of the area, provided by the FMI. The resulting index from 1 to 10.
- **European Air Quality Index** (**EAQI**): measurements of up to five key pollutants supported by modelled data determine the index level that describes the current air quality situation at each monitoring station.
- **Common Air Quality Index** (**CAQI**): is defined away from roads (a "background" index). CAQI is computed on the basis of NO_2, $PM_{2,5}$, PM_{10} and O_3.

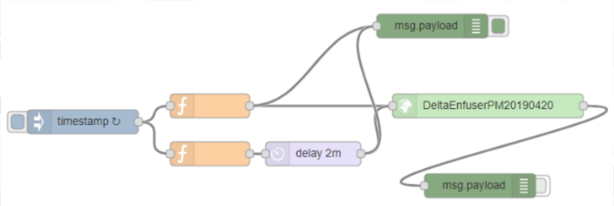
Environmental Data Network and Automated Analysis and Representation

Environmental Predictive Measures:

- **Enfuser pred. AQI:** heatmap of Air Quality Index hourly Enfuser predictions, every 12 mt. the Heatmap Controls widget you can see the forecast.
- **Enfuser pred. PM_{10} :** heatmap of PM_{10} particles hourly Enfuser predictions every 12mt in $\mu g/m^3$.
- **Enfuser pred. $PM_{2,5}$** heatmap of $PM_{2,5}$ particles hourly Enfuser predictions every 12mt in $\mu g/m^3$.
- **Gral pred. PM_{10} (h 3m):** heatmap of PM_{10} particles hourly predictions in µg/m3 measured 3 meters on the ground and computed using Gral model every 4mt.
- **Gral pred. PM_{10} (h 6m)**: heatmap of PM_{10} particles hourly predictions in $\mu g/m^3$ measured 6 meters on the ground and computed using Gral model every 4mt.



- Data gathering, data processing for Piking
- **API** for accessing data of Heatmaps in real time
- ***Delta Estimation Predictions vs Actual***: on 12 points/sensors via R-Studio and IOT App



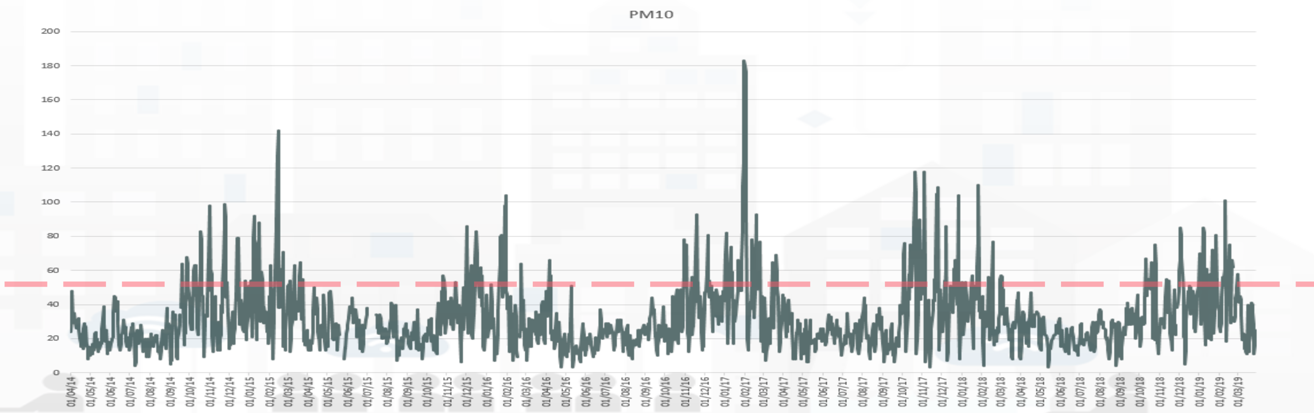
TOP

Prediction of Air Quality

Predicting Air Quality

- European Air Quality Directive
- Predicting critical days
  - PM10 with an accuracy of more than 90% and precision of 85%;
  - PM2.5 with an accuracy of 90% and precision greater than the 95%.
- Simulating Long terms values
  - For long terms predictions

		Air Quality Directive		WHO guidelines	
Pollutant	Averaging period	Objective and legal nature and concentration	Comments	Concentration	Comments
$PM_{2.5}$	One day			25 µg/m³ (*)	99th percentile (3 days/year)
$PM_{2.5}$	Calendar year	Target value, 25 µg/m³	The target value has become a limit value since 1 January 2015	10 µg/m³	
PM_{10}	One day	Limit value, 50 µg/m³	Not to be exceeded on more than 35 days per year.	50 µg/m³ (*)	99th percentile (3 days/year)
PM_{10}	Calendar year	Limit value, 40 µg/m³ (*)		20 µg/m³	
O_3	Maximum daily 8-hour mean	Target value, 120 µg/m³	Not to be exceeded on more than 25 days per year, averaged over three years	100 µg/m³	
NO_2	One hour	Limit value, 200 µg/m³ (*)	Not to be exceeded more than 18 times a calendar year	200 µg/m³ (*)	
NO_2	Calendar year	Limit value, 40 µg/m³		40 µg/m³	

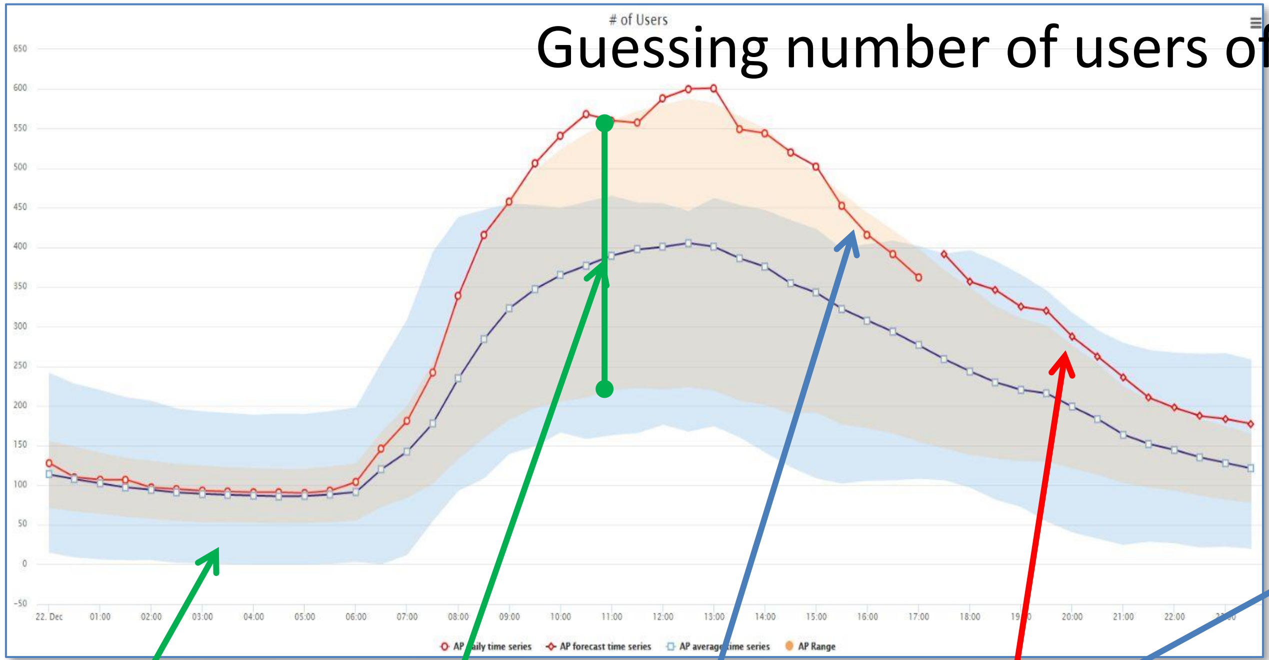


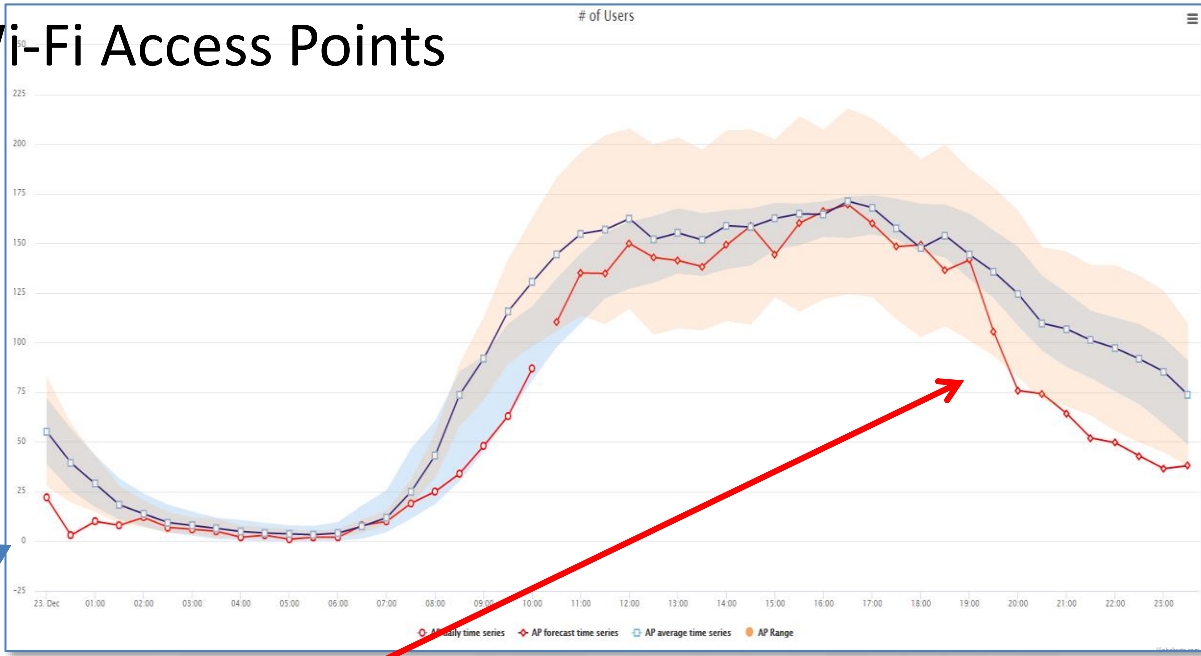
TOP

Anomaly Detection

Prediction and Identification of Anomalies

Guessing number of users of Wi-Fi Access Points





Cluster confidence

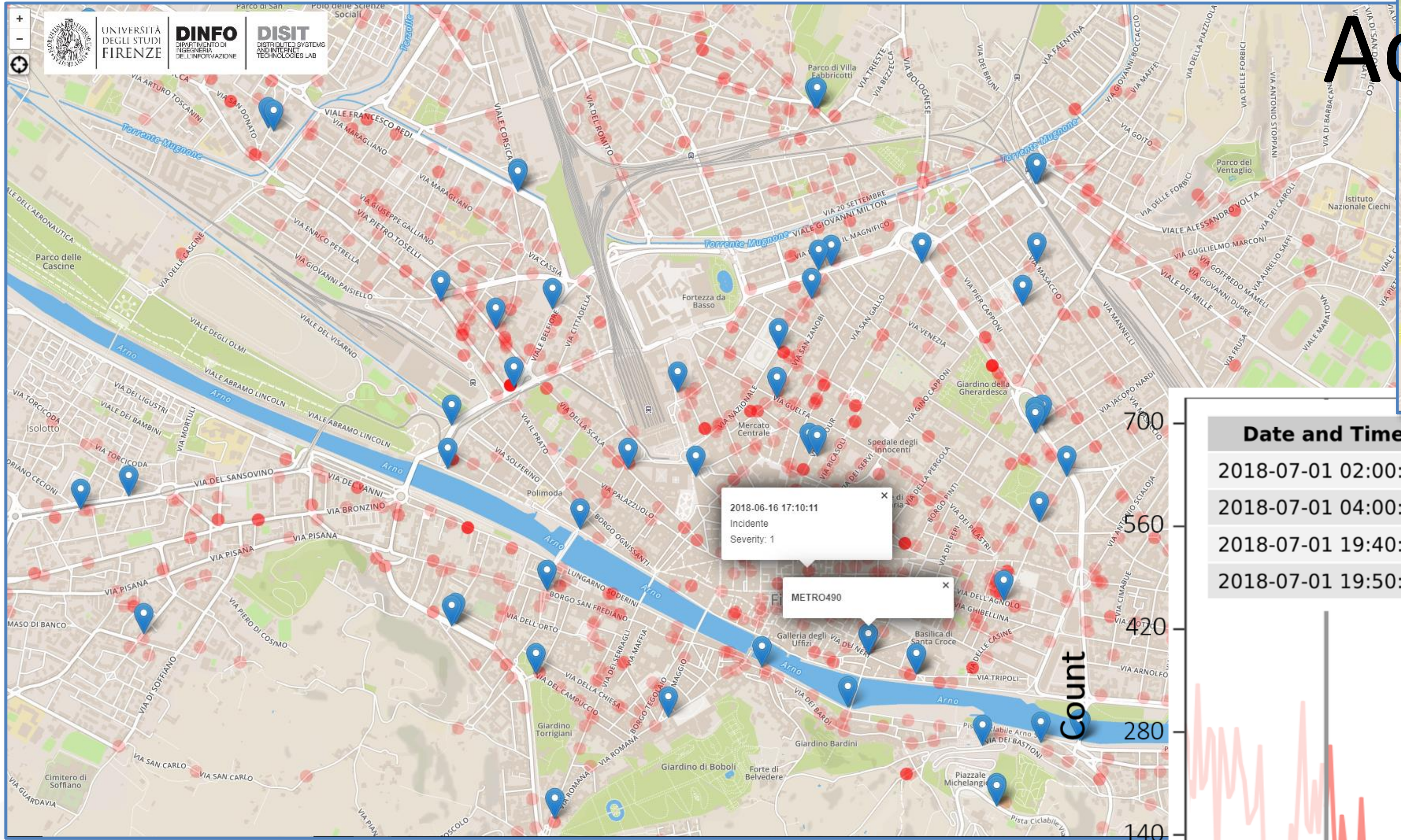
AP average and confidence

Actual AP trend for today

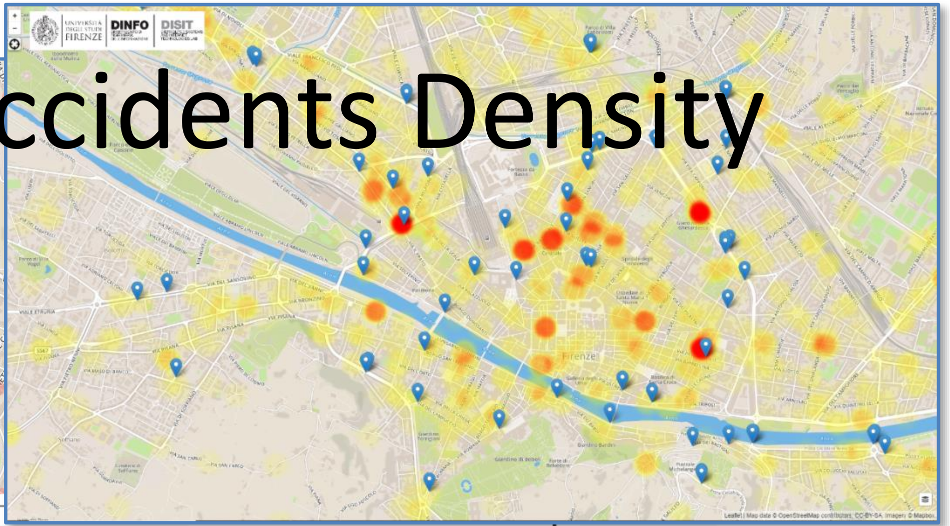
AP prediction for the next time slot in the day on the basis of past weeks

Predictive precision of the 95%

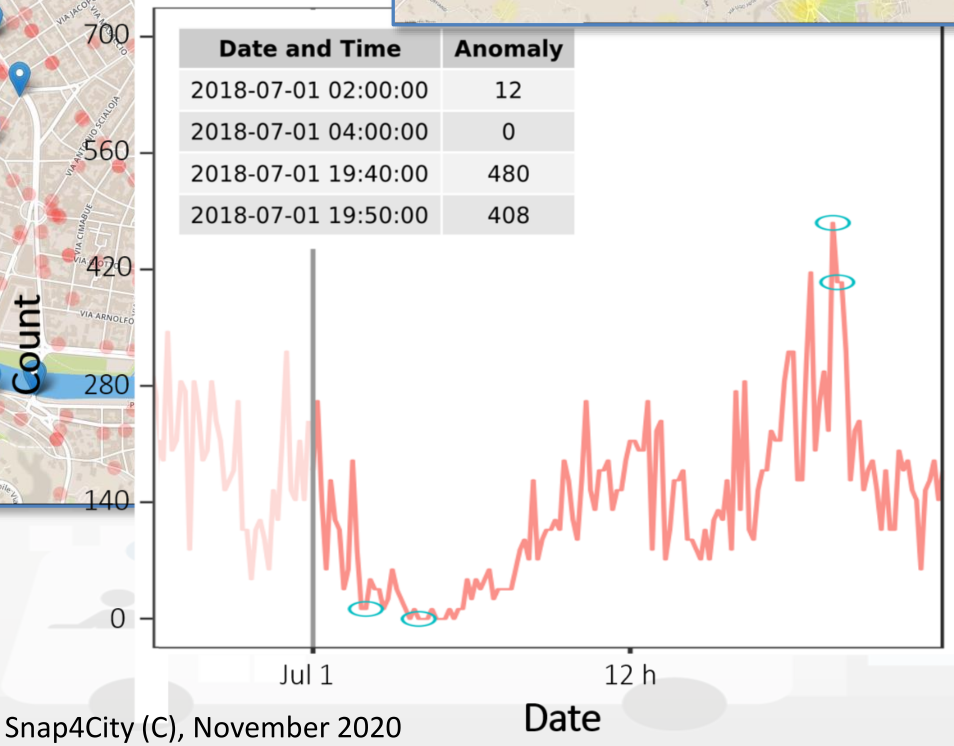
Anomaly Detection



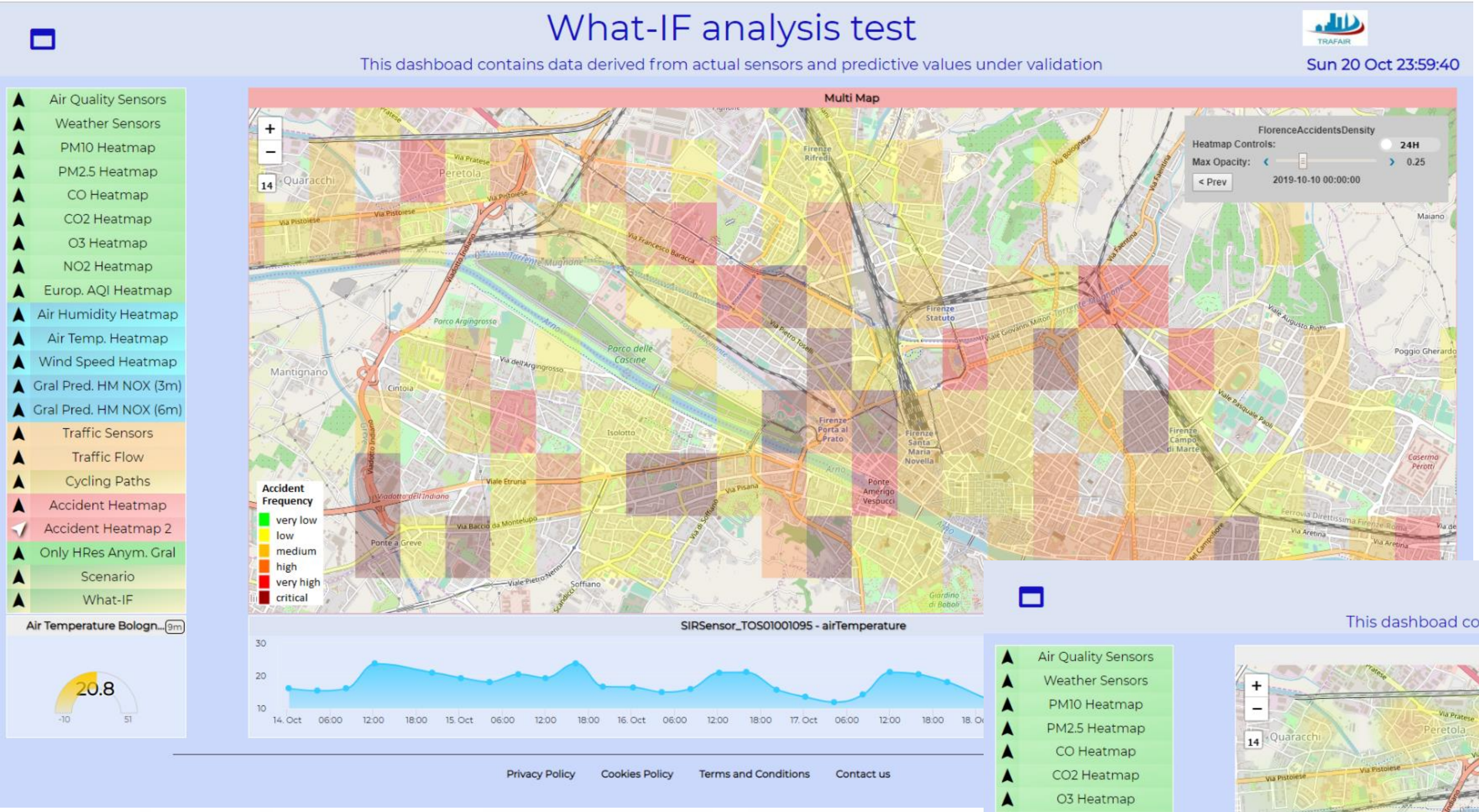
Accidents vs Traffic

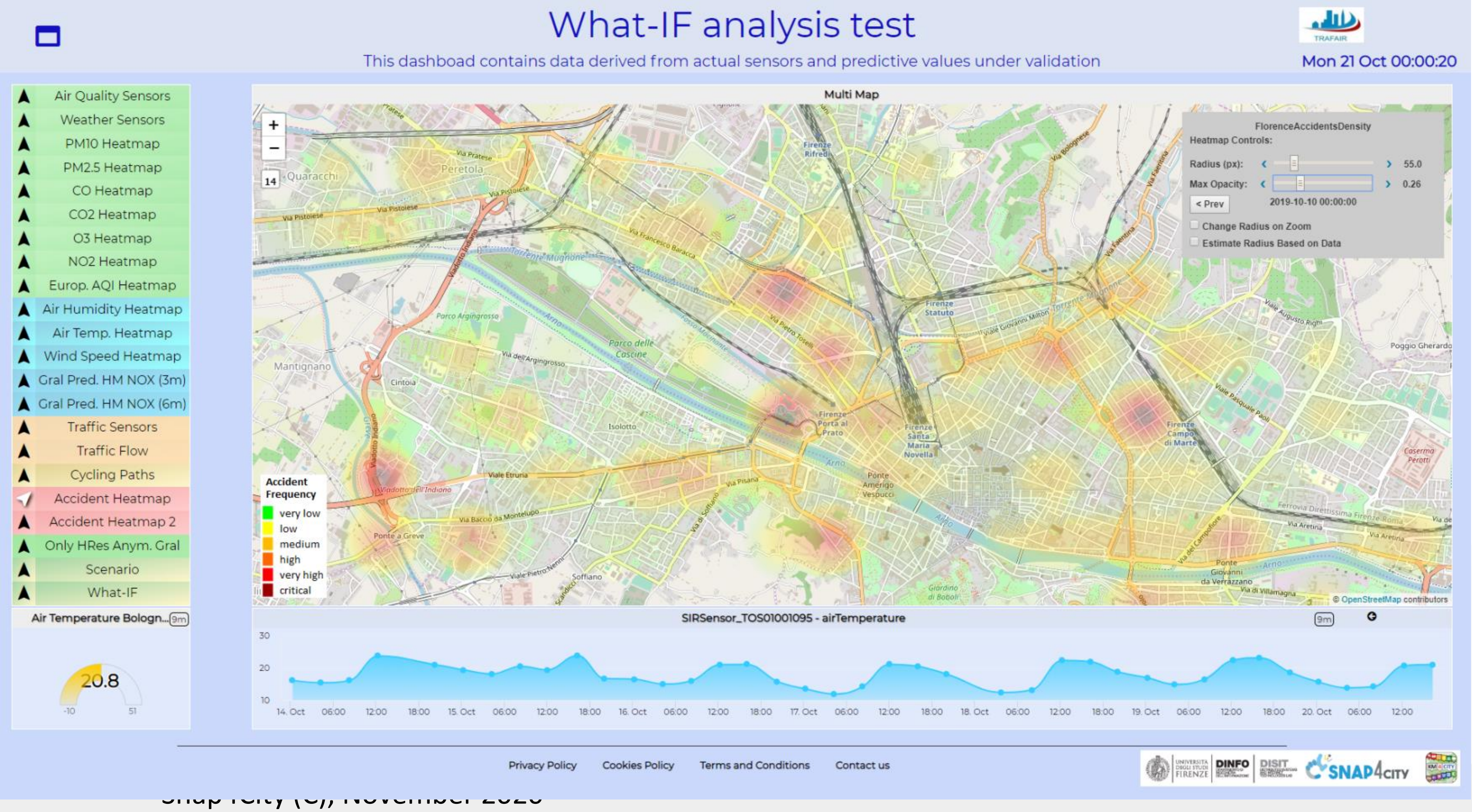


Accidents Density



Date and Time	Anomaly
2018-07-01 02:00:00	12
2018-07-01 04:00:00	0
2018-07-01 19:40:00	480
2018-07-01 19:50:00	408





https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MjE4Nw==

TOP

WHAT-IF Analysis

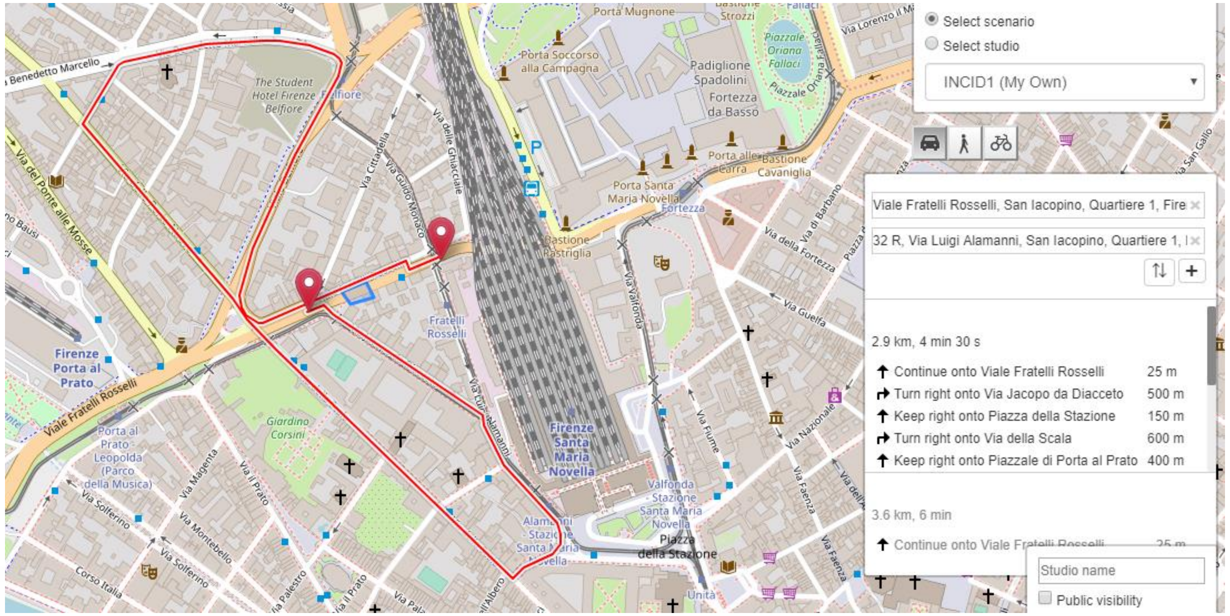
What-If Analysis

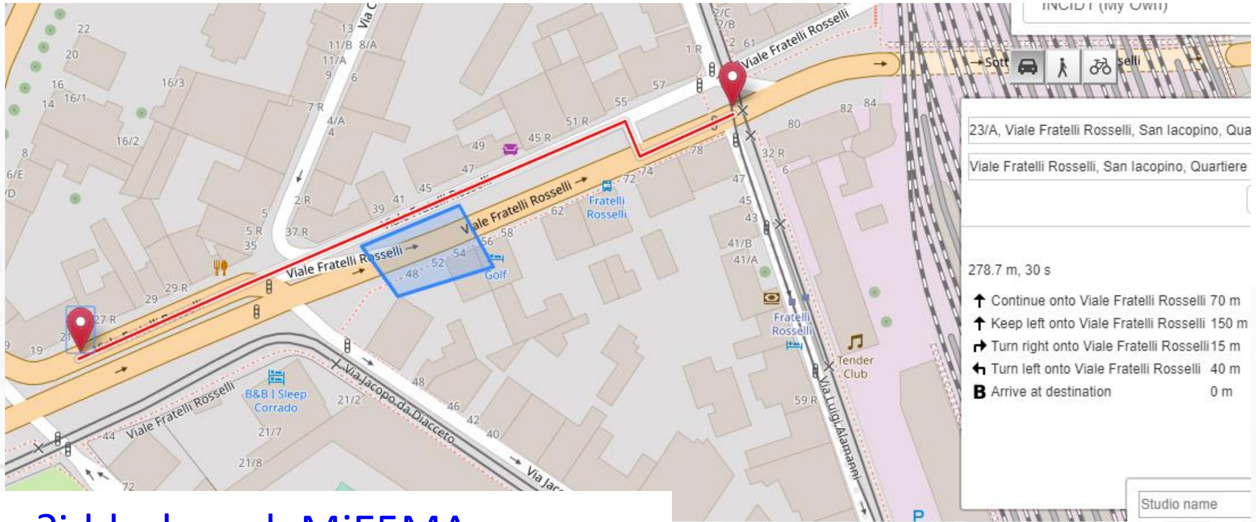
Accidents and elements blocking Points and Shapes taken into account for:

- Routing
- Traffic Flow reconstruction
- Evacuation paths
- Rescue team paths

Assessment on the basis of changes:

- Mobility demand assessment
- Mobility Offer assessment



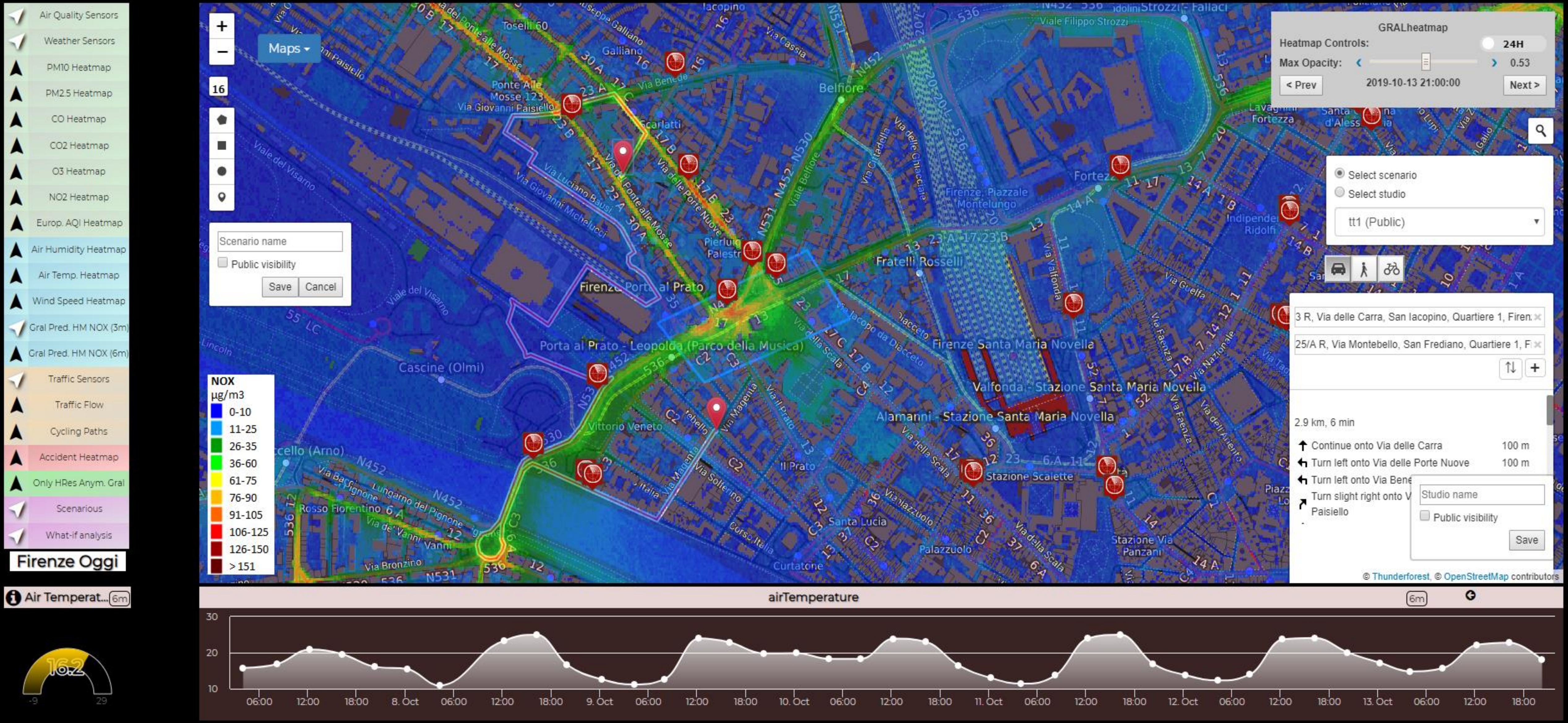


https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MjE5MA==

Mobility and Environment What-IF Analysis

This dashboad contains data derived from actual sensors and predictive values under validation

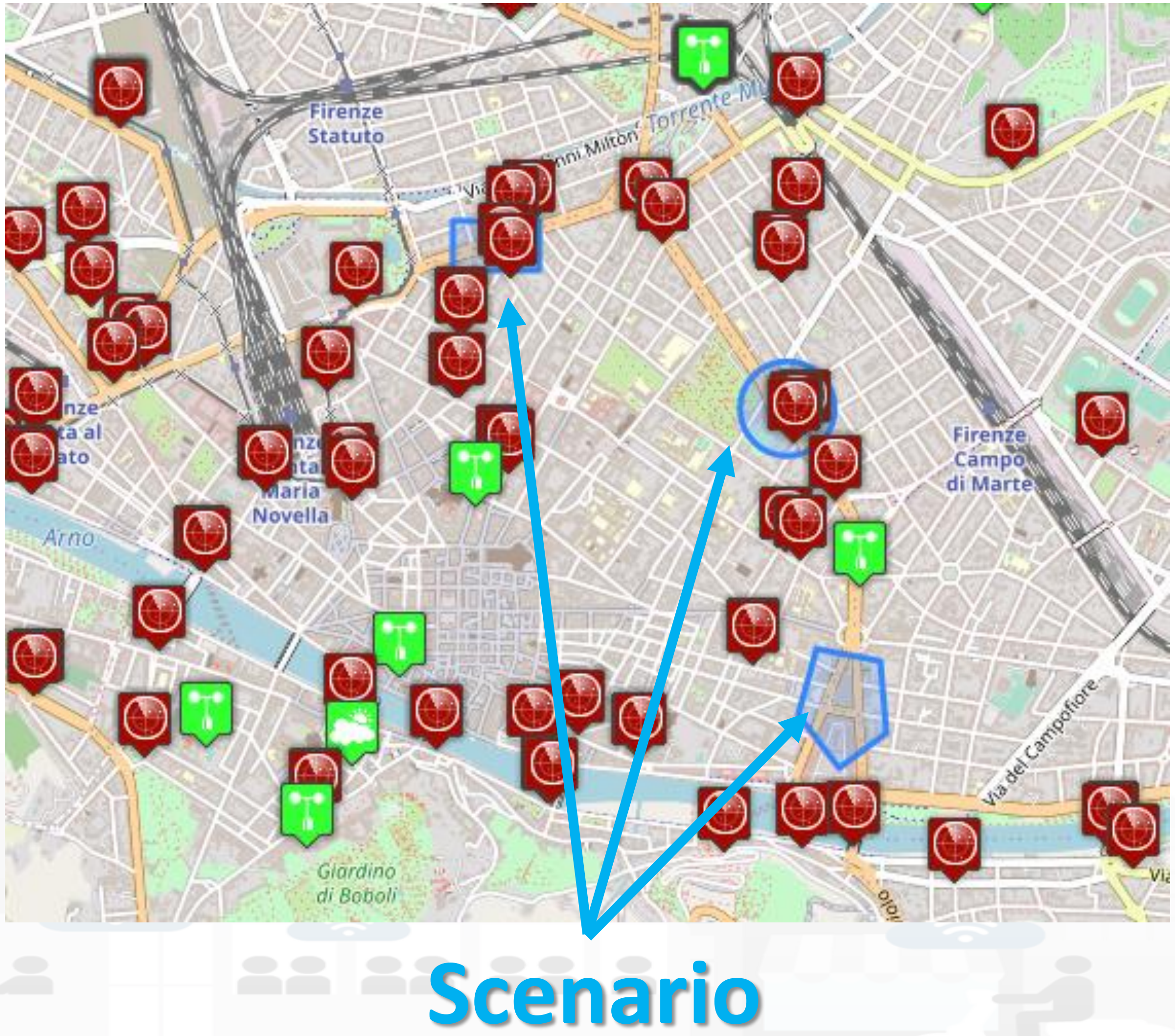
Mon 14 Oct 00:48:17



https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MjE5MA==

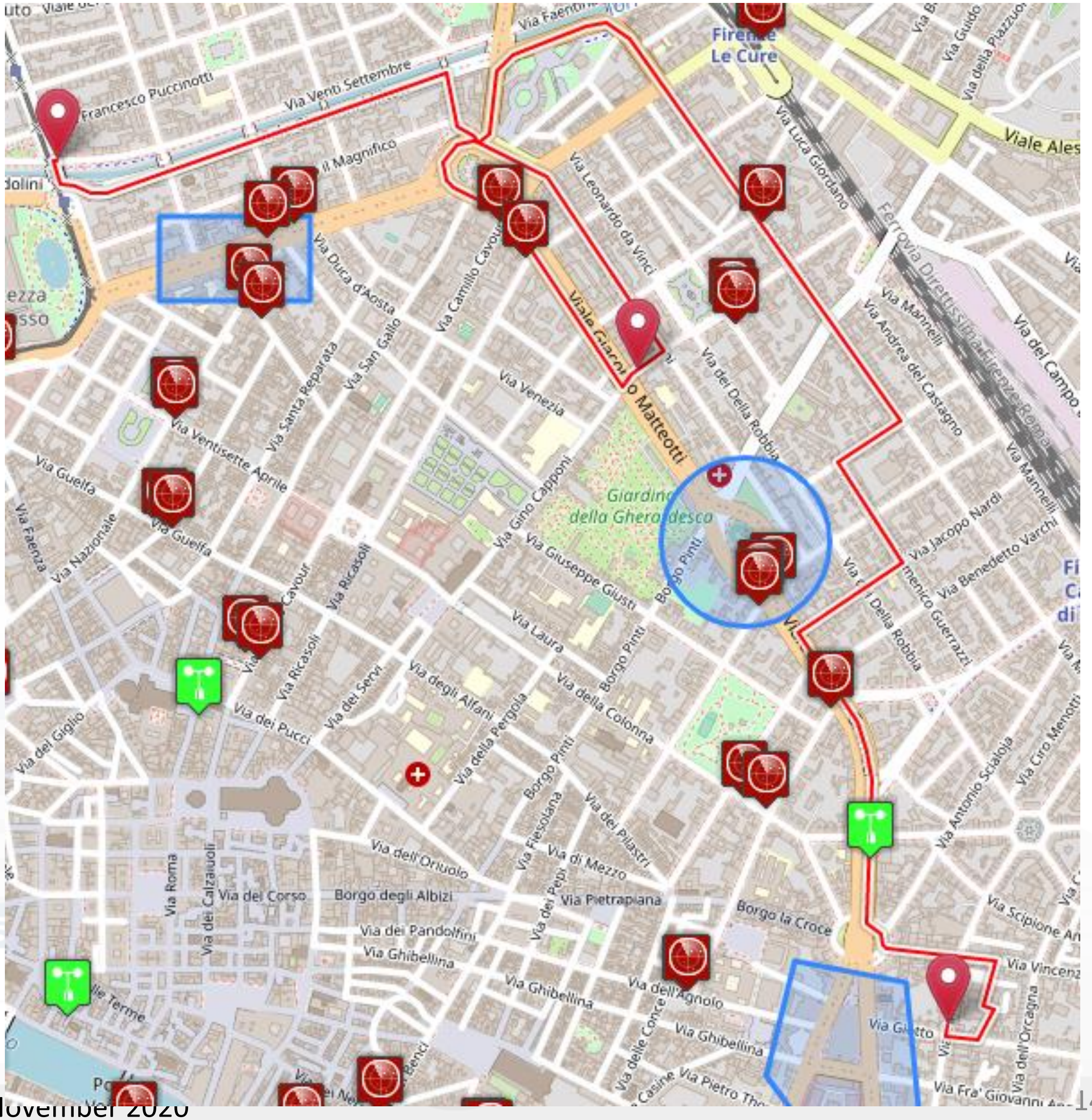
What-If Analysis Concepts

- What is going to happen at Services if certain conditions/cases are going to occur
- Formalize: Conditions/cases, Services
- Scenarios of Cases+Services Vs Solutions are Studios
- You can define, save, load:
  - Scenarios and Studios

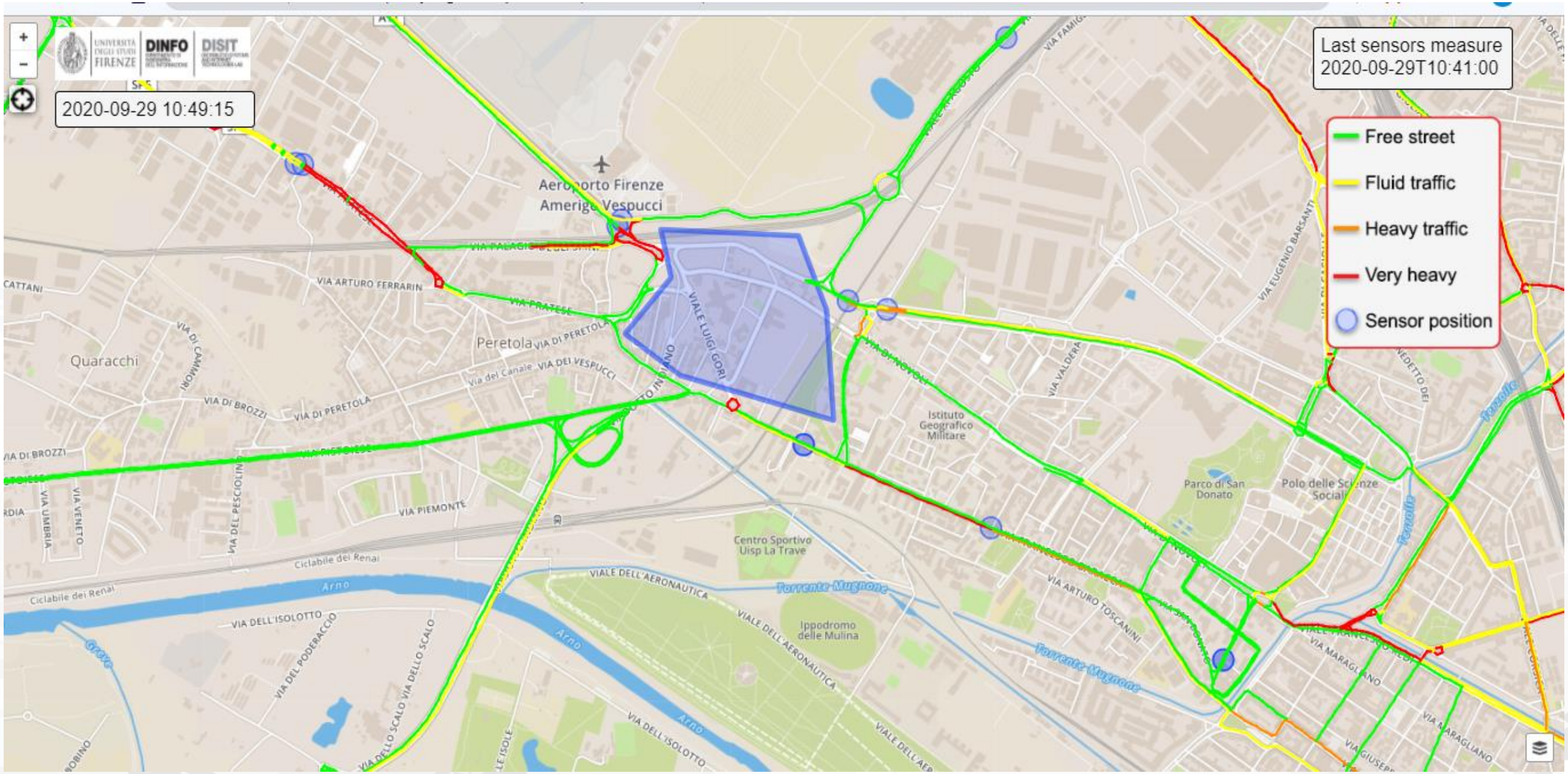


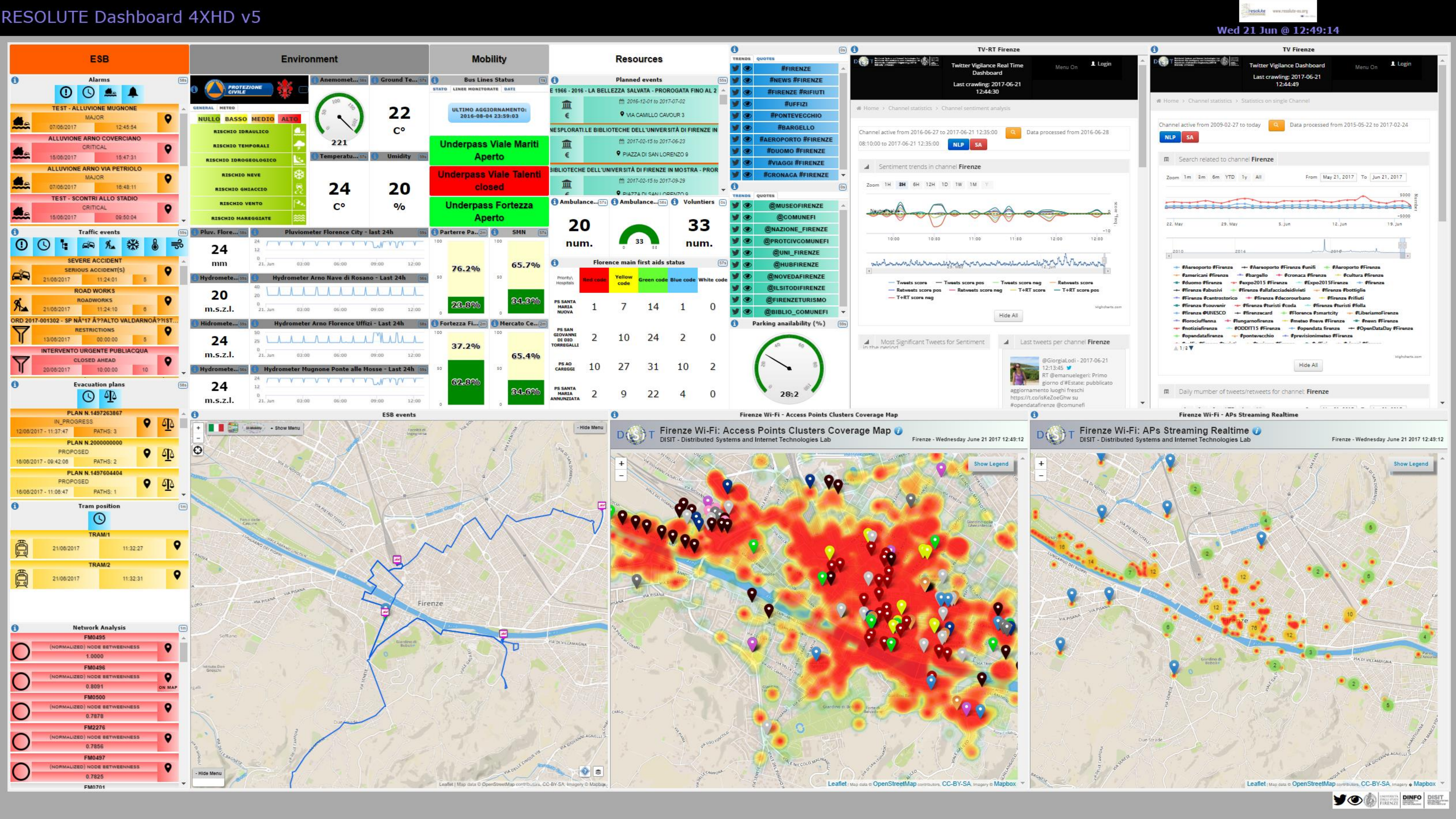
Impact on Routing

- Scenario with multiple shapes
- Conditional Routing
  - avoiding areas or
  - reducing traffic in those areas
  - Multiple stop points

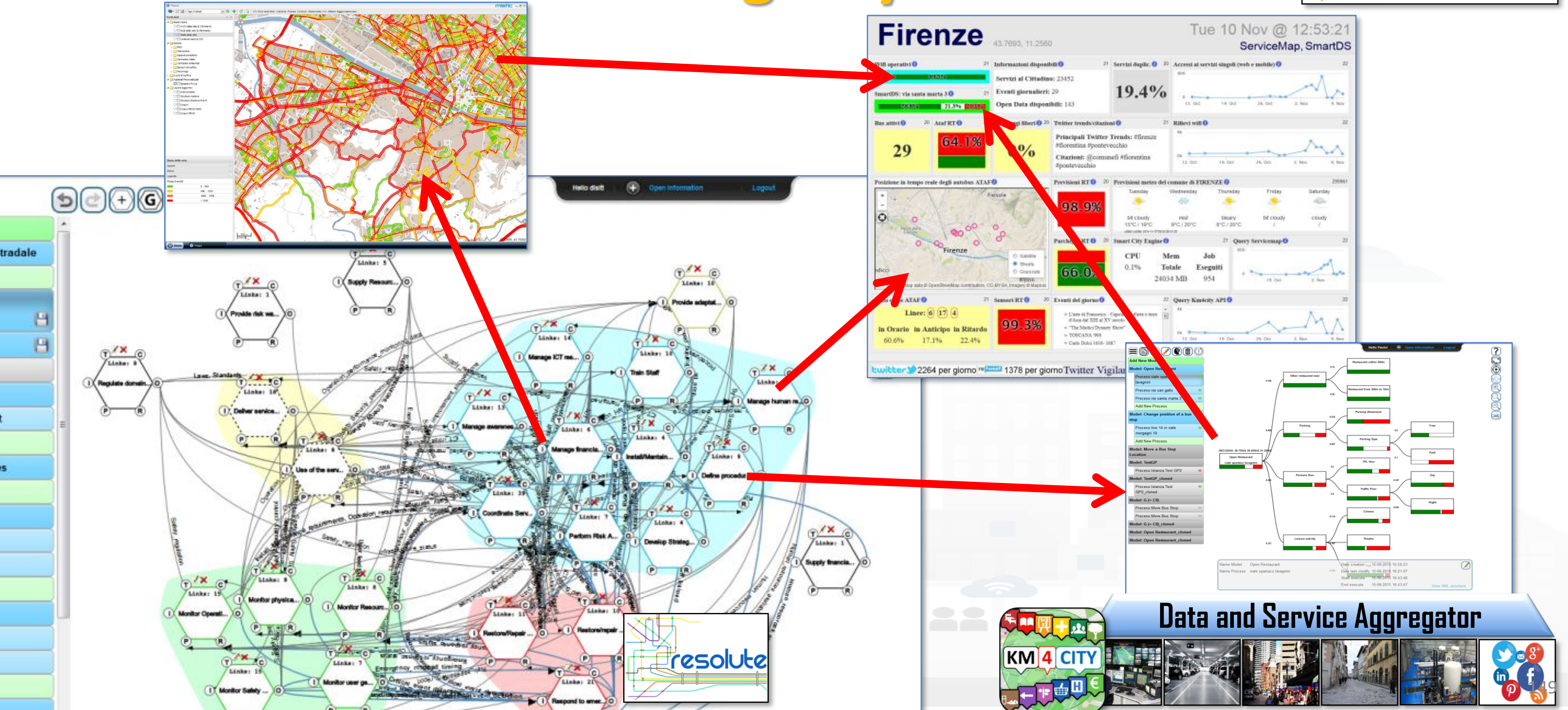


Computation of Traffic Flow Evolution



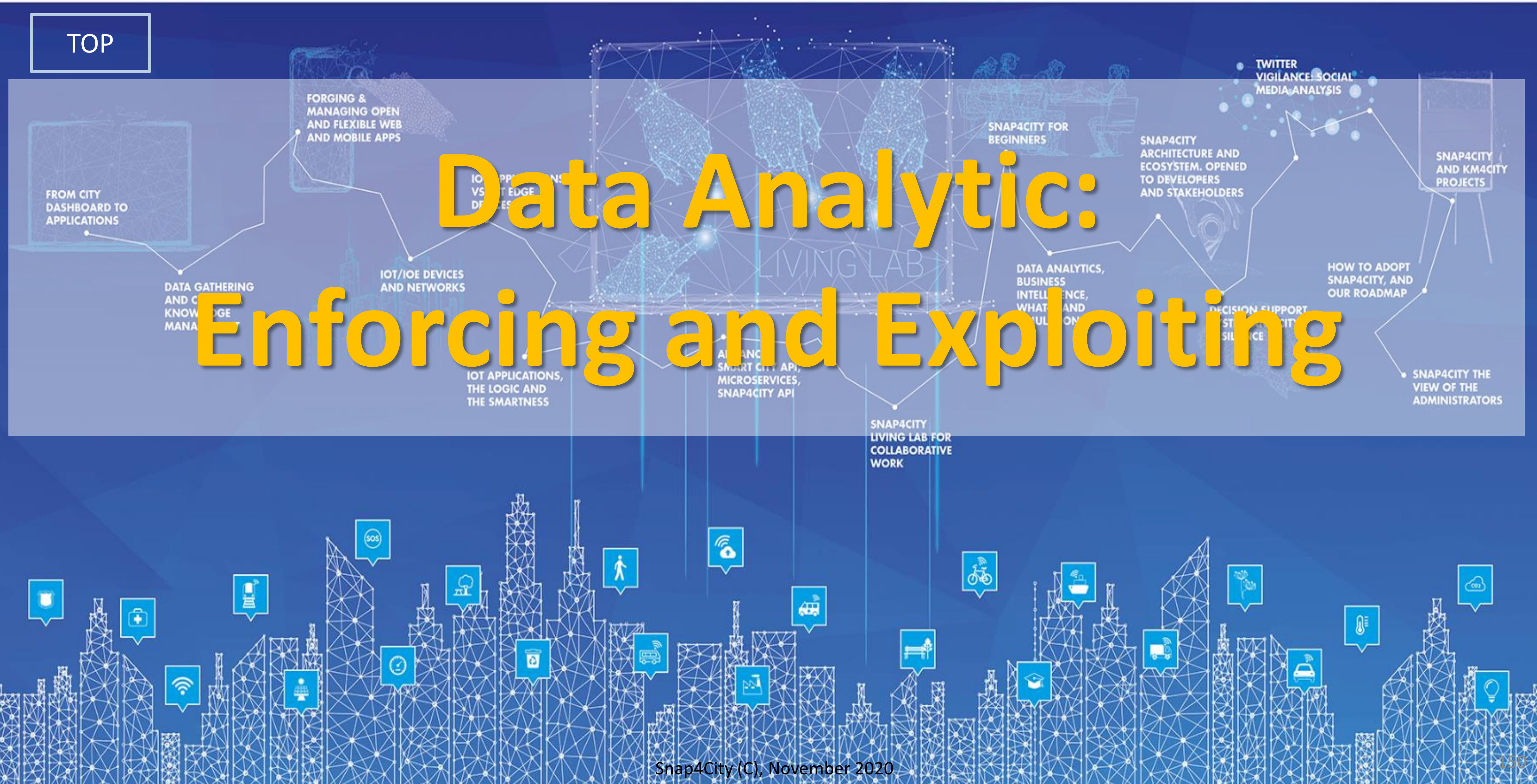

RESOLUTE Dashboard 4XHD v5
Wed 21 Jun @ 12:49:14
ESB
Environment
Mobility
Resources
Alarms
TEST - ALLUVIONE MUGNONE
ALLUVIONE ARNO COVERCIANO
ALLUVIONE ARNO VIA PETRIOLO
TEST - SCONTRI ALLO STADIO
Traffic events
SEVERE ACCIDENT
ROAD WORKS
INTERVENTO URGENTE PUBLIACQUA
Evacuation plans
PLAN N.1497263867
PLAN N.2000000000
PLAN N.1497604404
Tram position
TRAM/1
TRAM/2
Network Analysis
FM0495
FM0496
FM0500
FM2276
FM0497
Bus Lines Status
Underpass Viale Mariti Aperto
Underpass Viale Talenti closed
Underpass Fortezza Aperto
Planned events
Florence main first aids status
Parking availability (%)
TV-RT Firenze
TV Firenze
ESB events
Firenze Wi-Fi - Access Points Clusters Coverage Map
Firenze Wi-Fi: Access Points Clusters Coverage Map
Firenze Wi-Fi - APs Streaming Realtime
Firenze Wi-Fi: APs Streaming Realtime
DISIT - Distributed Systems and Internet Technologies Lab
Firenze - Wednesday June 21 2017 12:49:12
Firenze

Dashboarding City Resilience

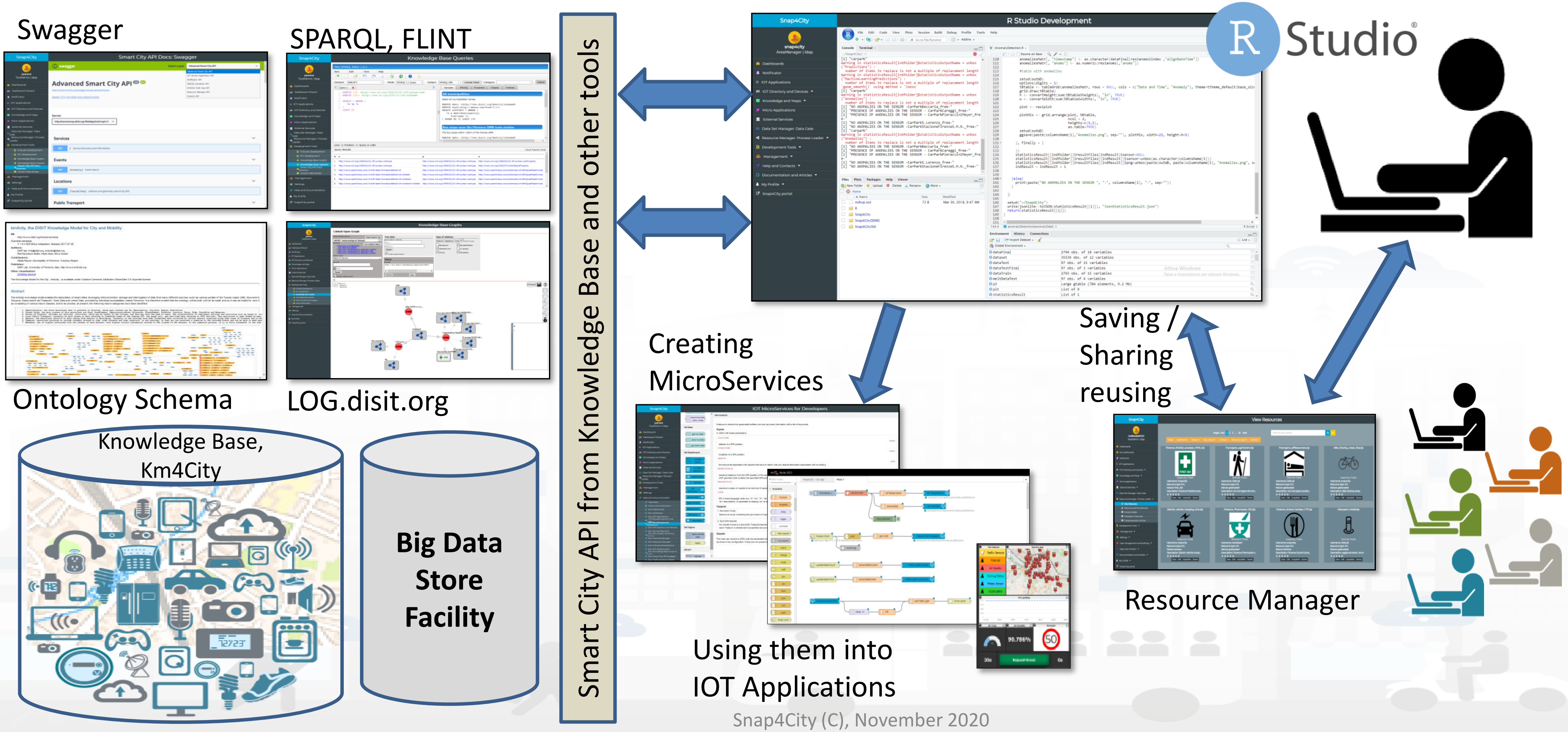


TOP

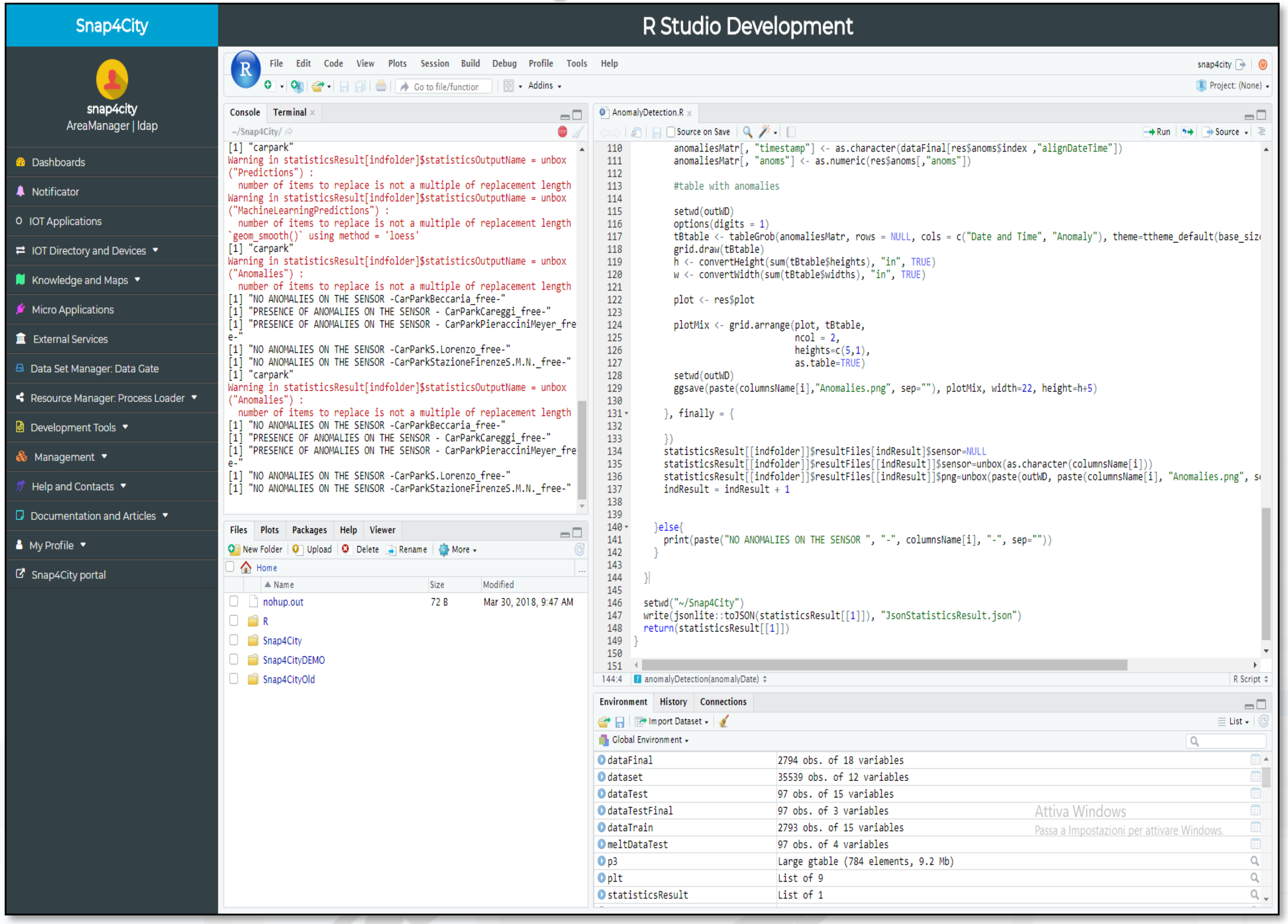
Data Analytic: Enforcing and Exploiting



Data Analytics Dev. in R Studio and/or Tensor Flow



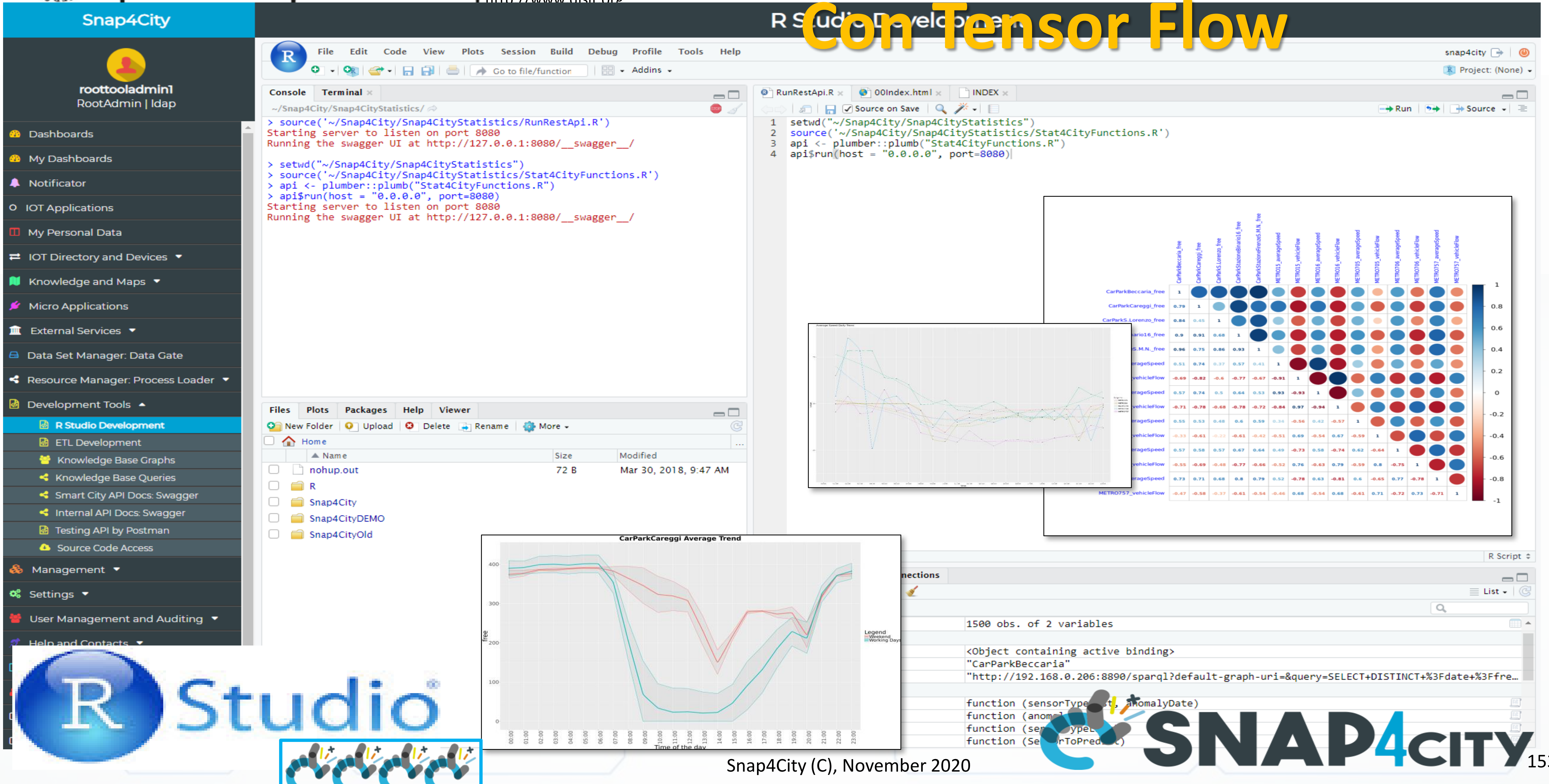
Developer in R Studio + Tensor Flow



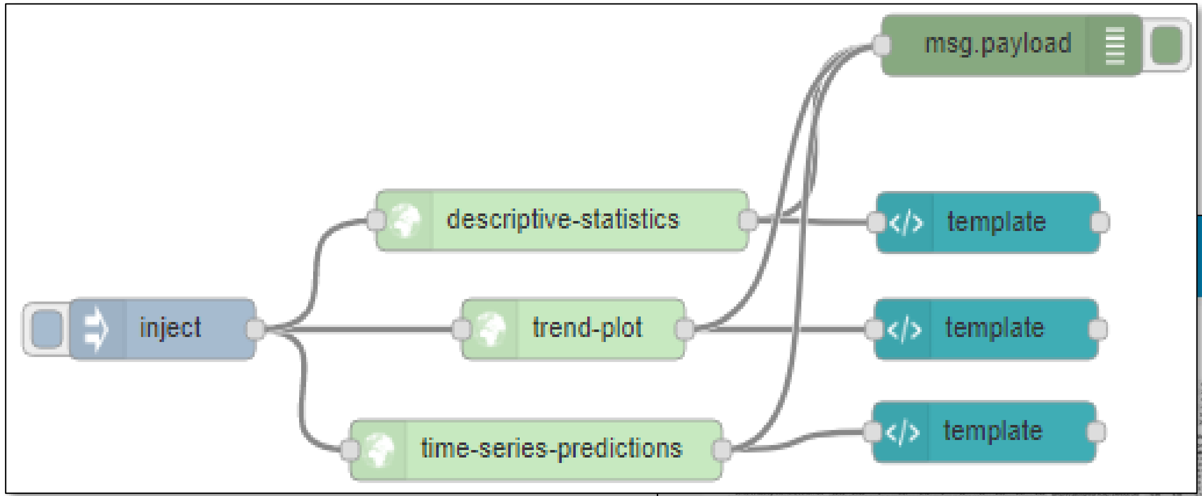
Data Analytics in R Studio

Con Tensor Flow

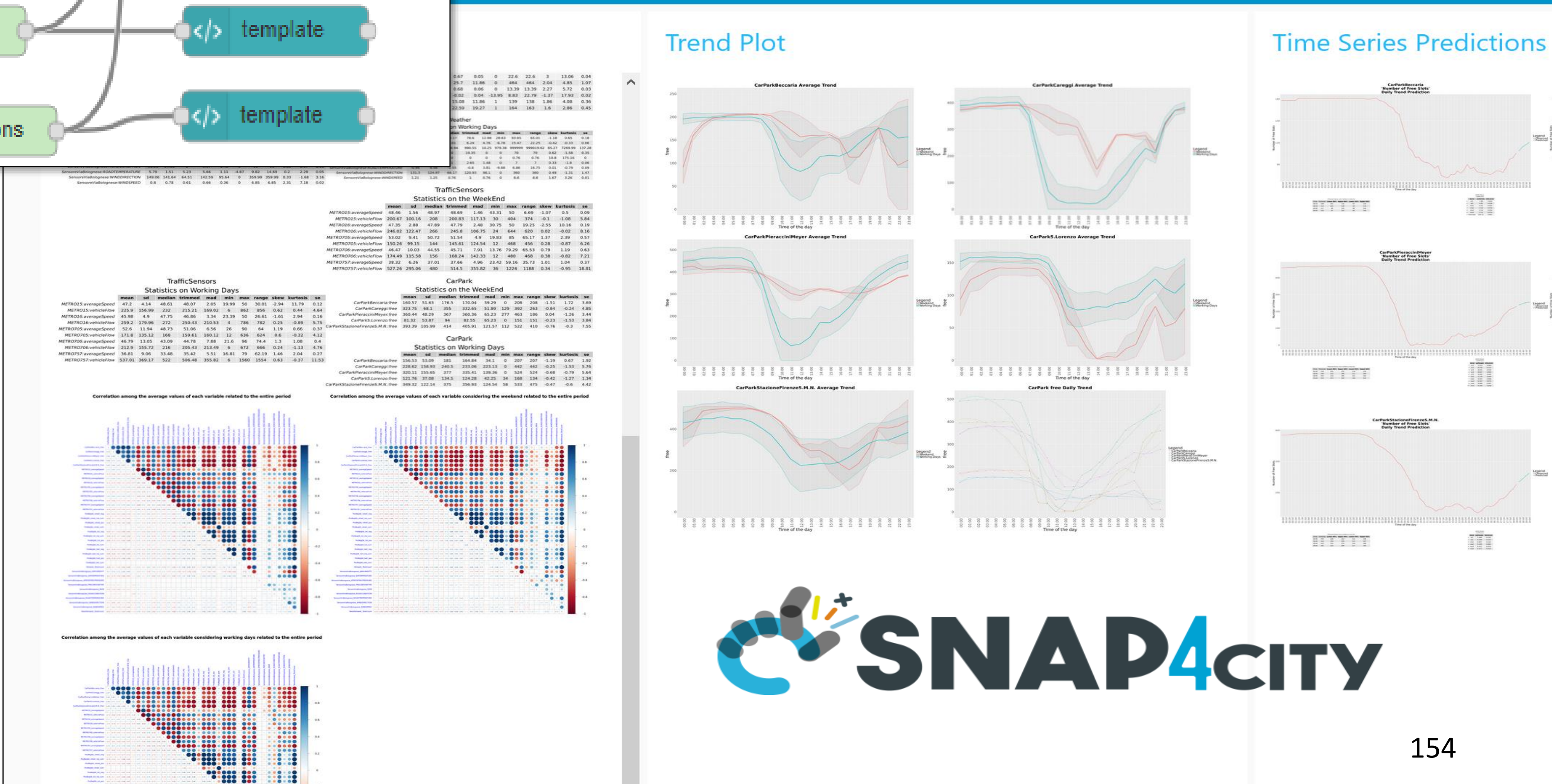
UNIVERSITÀ DEGLI STUDI FIRENZE | DINFO DIPARTIMENTO DI INGEGNERIA DELL'INFORMAZIONE | DISIT DISTRIBUTED SYSTEMS AND INTERNET TECHNOLOGIES LAB http://www.disit.org



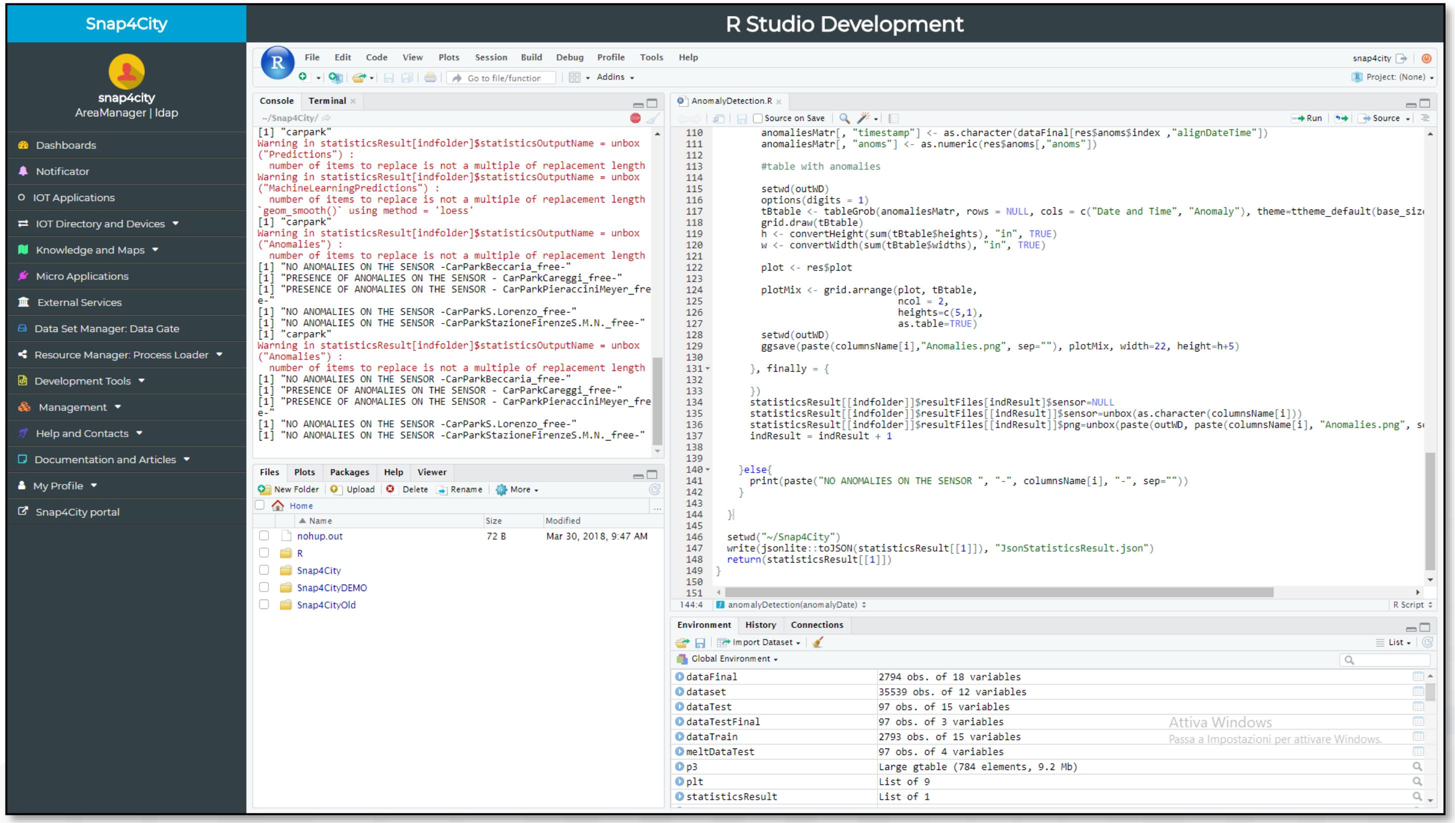
From R studio data analytics to MicroService

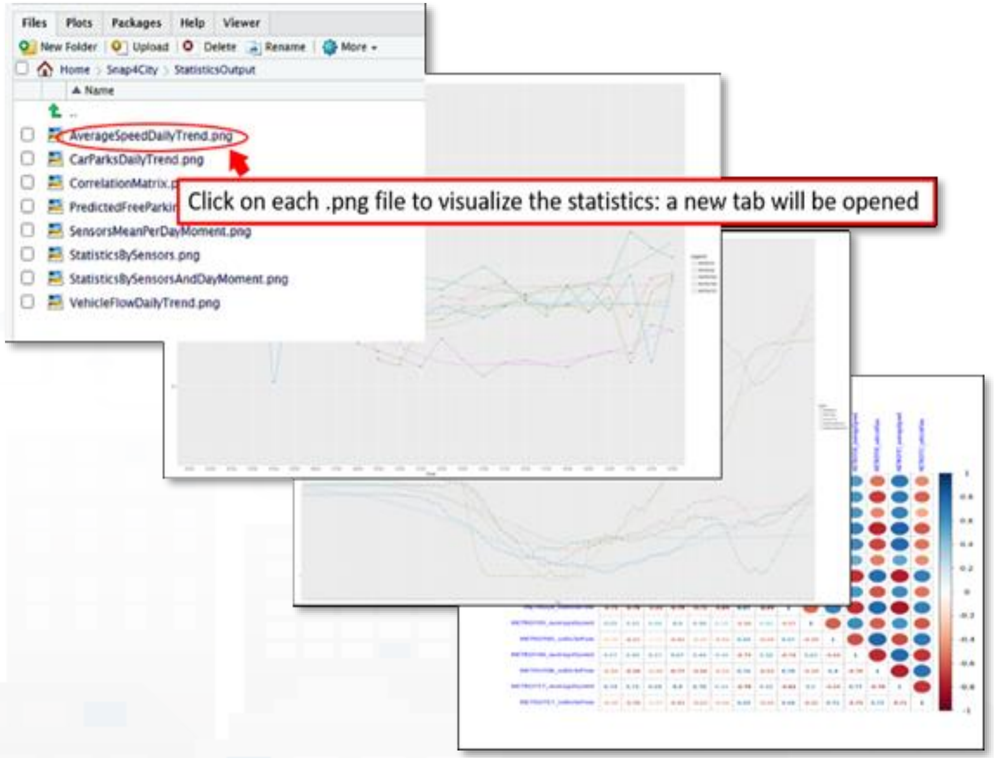


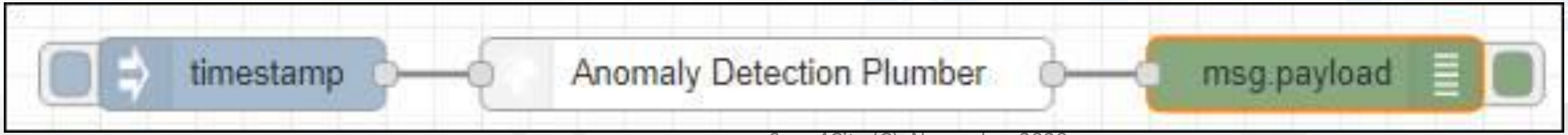
R Studio algorithms are automatically transformed into MicroServices for your IOT Applications



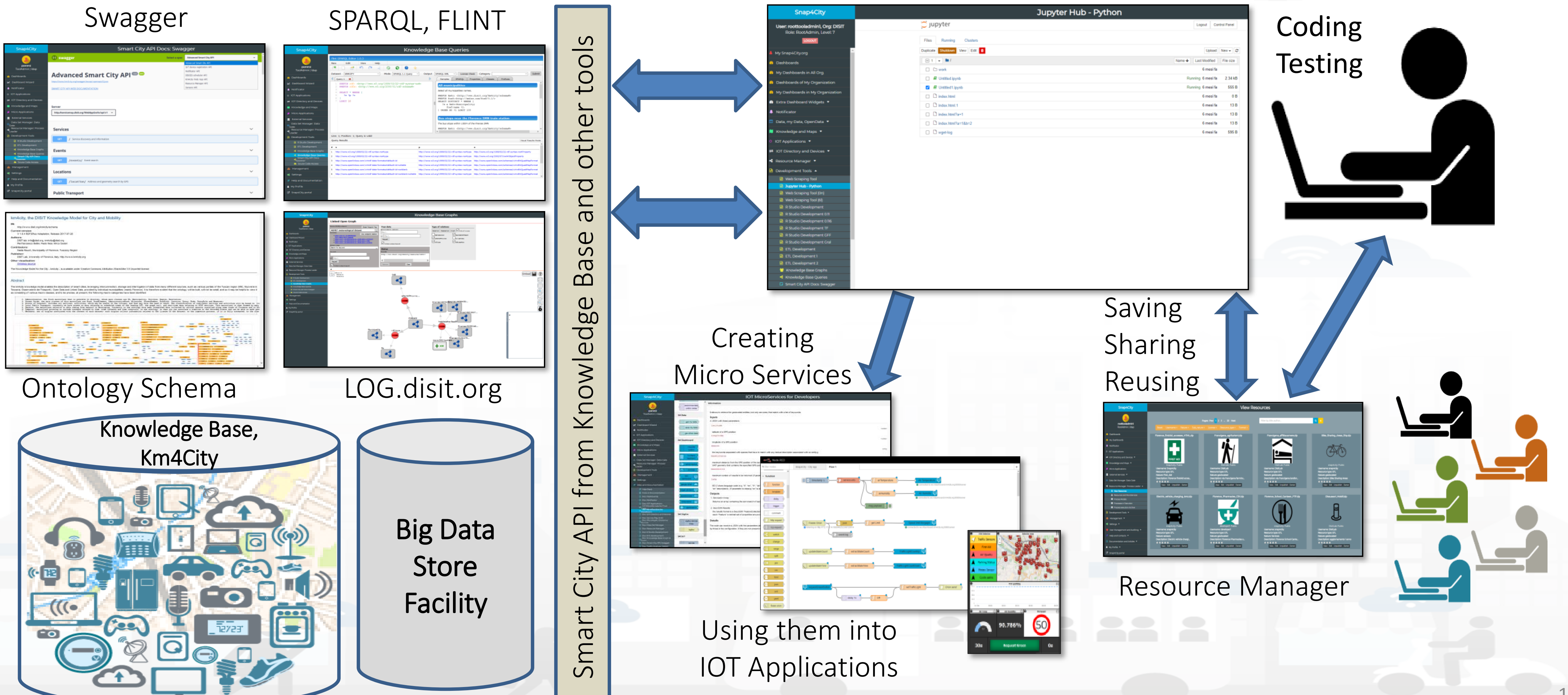
Developing in R Studio and/or Tensor Flow





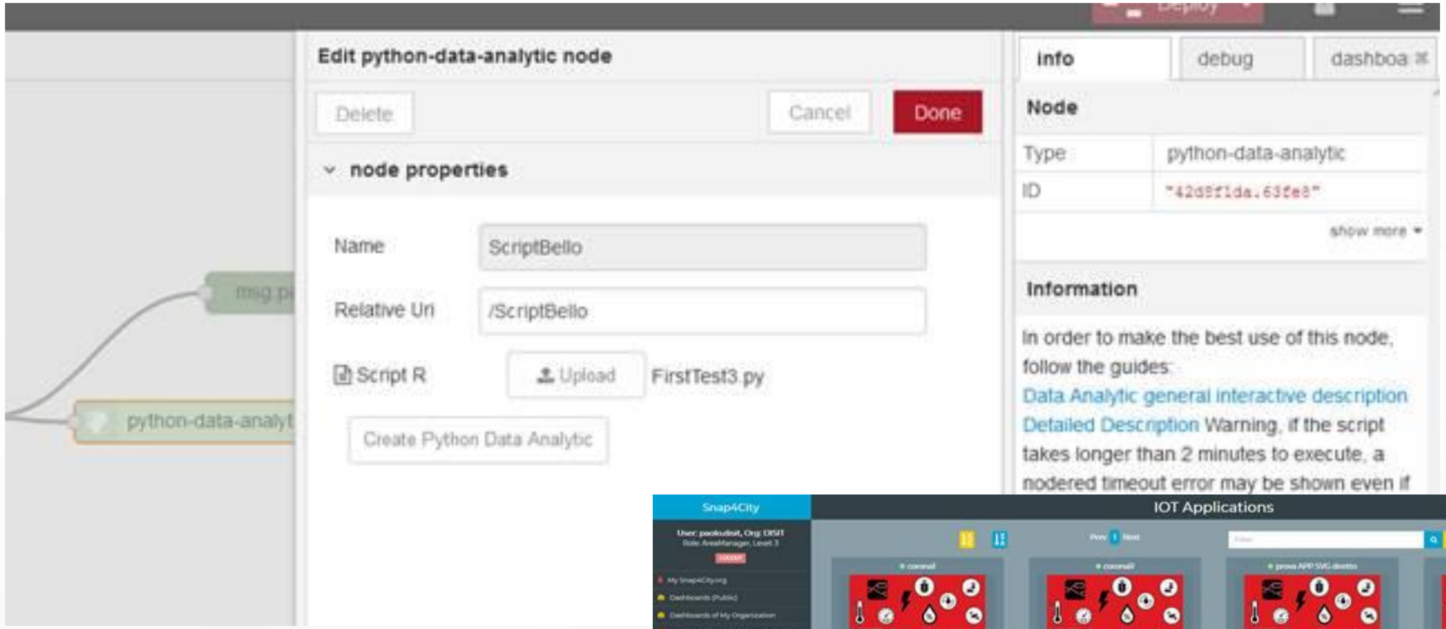


Data Analytics Development in Python, python

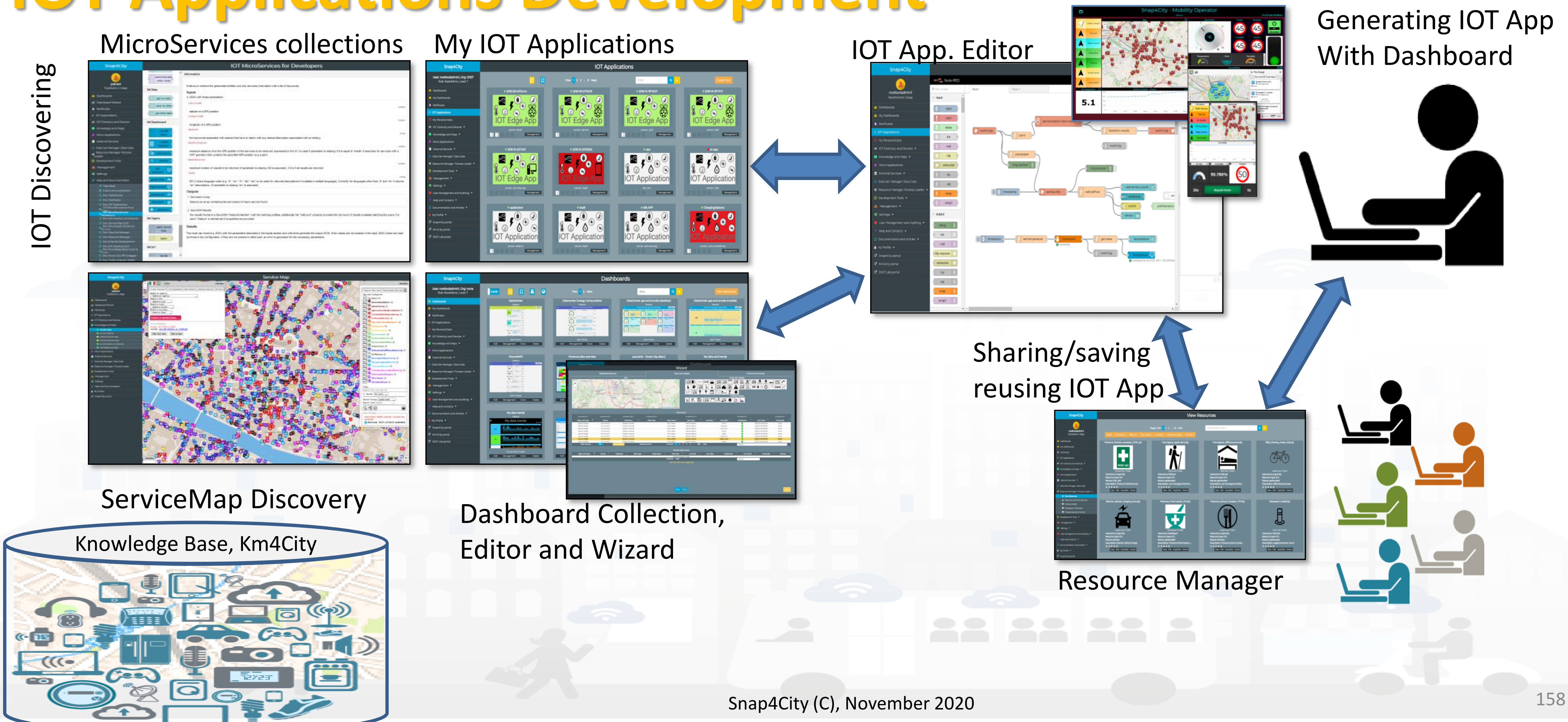


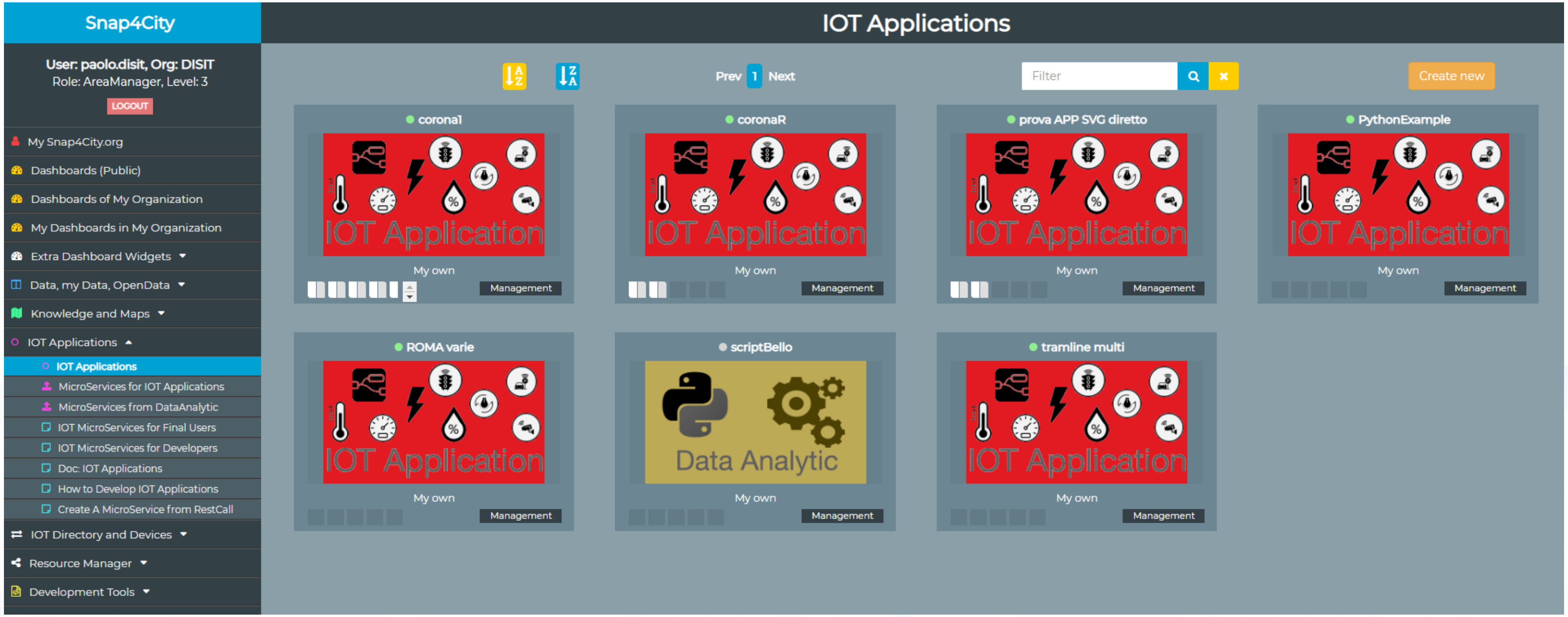
Python process

- Develop Python code exploiting Flask calls
- Test on local for the Call
- Test on Cloud for API
- Deploy via IOT App



IOT Applications Development

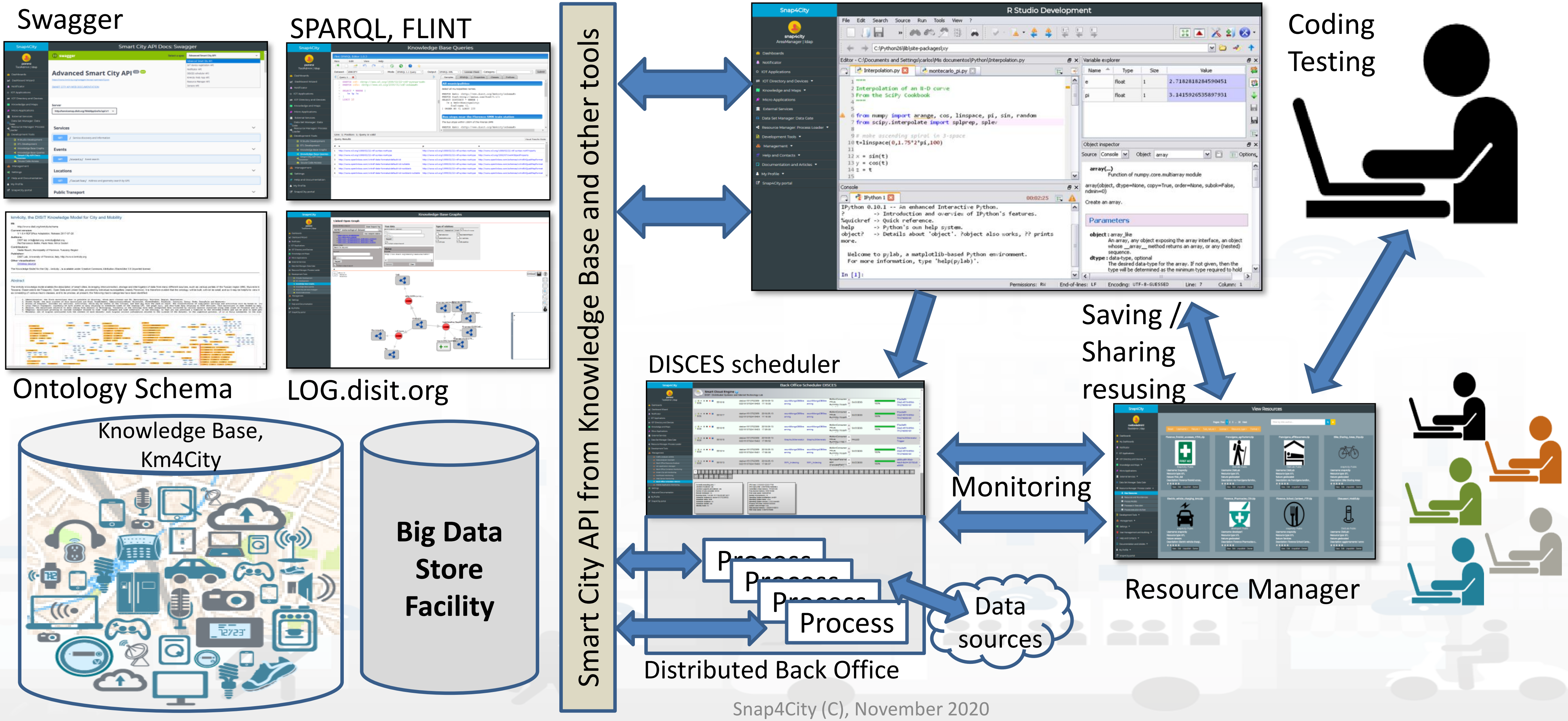




More information

- [HOW TO: develop DataAnalytic in Python and manage them via IOT App]()

Data Analytics Dev. in Java



TOP

How to work with R Studio in Snap4City

TOP

How to work with R Studio in Snap4City

Data Manipulation using RStudio

1. How to download Real-Time data using APIs

2. How to manipulate data

3. How to create 

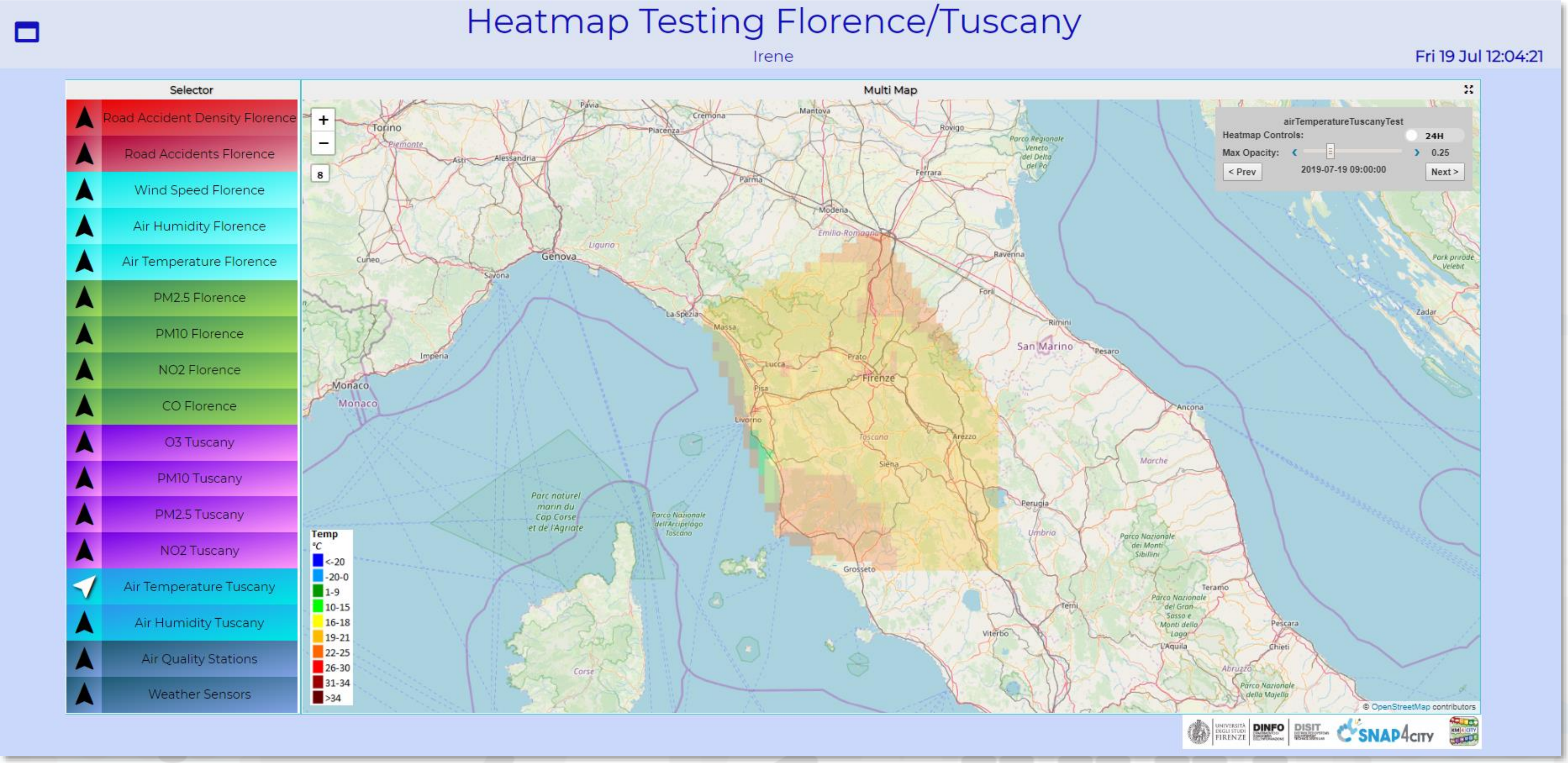
DEMO Section 1

UNIVERSITÀ DEGLI STUDI FIRENZE | DINFO DIPARTIMENTO DI INGEGNERIA DELL'INFORMAZIONE | DISIT DISTRIBUTED SYSTEMS AND INTERNET TECHNOLOGIES LAB | SNAP4CITY

TOP

Real Time Data Analytics using R Studio. Exploitation in IOT Applications

Heatmap Visualization



https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTI2OA==

Real Time Data Analytics and Heatmaps creation using RStudio

1. How to create a *plumberized* R script:

    - How to download Real-Time data using APIs
    - How to save heatmaps using APIs

2. How to create an IOT Application for Real-Time Data Analytics:

    - How to upload the R script and create a plumber instance

3. How to visualize the created heatmap in a dashboard

Real Time Data Analytics using R Studio

How to create a *plumberized* R script - 1

PLUMBER is an **R** package that generates a web API from the **R** code you already have.

- Step 1 - *Plumberize* the code:

```
#' @get /TuscanyHeatmap
#' @serializer unboxedJSON
```

❖ In order to send a response from R to an API client, the object must be *serialized* into some format that the client can understand (JSON format).

Note that, **@get** and **@serializer** annotations must to be put on the top of the code.

Any comments must not be inserted before the annotations or between them and the R function.

Real Time Data Analytics using R Studio

How to create a *plumberized* R script - 2

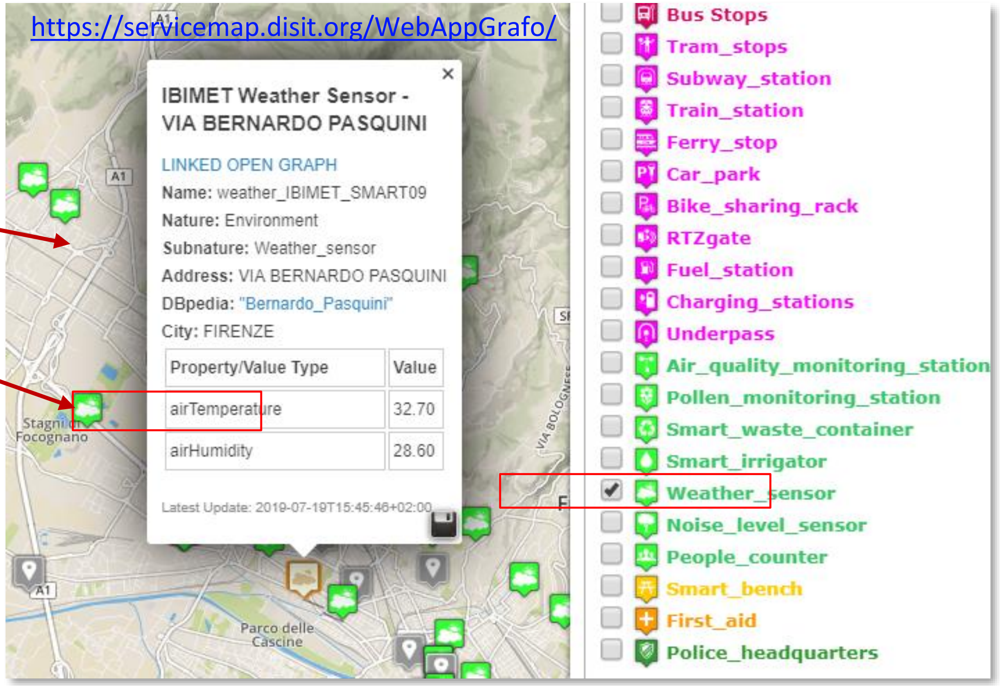
- Step 2 - Create an R function with the same name of the **@get** parameter:

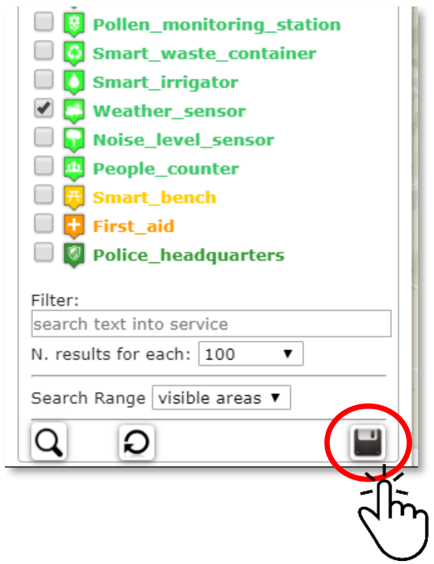
```
TuscanyHeatmap <- function(sensorCategory, varName, fromDateTime, toDateTime, heatmapName){
```

heatmapName = “airTemperatureTuscanyTest”

sensorCategory = “Weather_sensor”
varName = “airTemperature”

toDateTime = “2020-04-14T10:00:00”
fromDateTime = “2-hour”





Real Time Data Analytics using R Studio

How to create a *plumberized* R script - 3

- Step 3 - Upload All Service Uris (sensor stations) from service map in the area of interest:

```
query <- paste("https://servicemap.disit.org/WebAppGrafo/api/v1/?selection=
                42.5024779733486 9;8.19580078125;44.6061127451739;13.422546386718 7
                &categories=",sensorCategory,
        "&maxResults=0&maxDists=0.1&format=json",sep="")

sensorCategoryJson <- fromJSON(query) #jsonlite package

suri <- sensorCategoryJson$Services$features$properties$serviceUri #serviceUri
```

Real Time Data Analytics using R Studio

How to create a *plumberized* R script - 3

https://servicemap.disit.org/WebAppGrafo/api/v1/?selection=42.67897316354954;9.95403229581404 5;44.0052327026863 7;12.06340729581404 5&categories=Weather_sensor&maxResults=0&maxDists=0.1&format=json

```
"http://www.disit.org/km4city/resource/IBIMET_SMART11"
"http://www.disit.org/km4city/resource/IBIMET_SMART04"
"http://www.disit.org/km4city/resource/IBIMET_SMART13"
"http://www.disit.org/km4city/resource/IBIMET_SMART06"
"http://www.disit.org/km4city/resource/IBIMET_SMART17"
"http://www.disit.org/km4city/resource/IBIMET_SMART33"
"http://www.disit.org/km4city/resource/IBIMET_SMART33"
"http://www.disit.org/km4city/resource/IBIMET_SMART25"
"http://www.disit.org/km4city/resource/IBIMET_SMART24"
"http://www.disit.org/km4city/resource/IBIMET_SMART30"
[…]
```

Real Time Data Analytics using R Studio

How to create a *plumberized* R script - 4

- Step 4 - Upload data related to a specific time interval (fromTime/toTime) for each Service Uri:

```
sensorData <- vector("list", length(suri))
for (i in 1:length(suri)){
  temp=c()
  #api to upload the realtime data
  api <- paste("https://servicemap.disit.org/WebAppGrafo/api/v1/?serviceUri=",
                suri[i],"&fromTime=",fromDateTime,
                "&toTime=",toDateTime,sep="")
  sensorCategoryData <- fromJSON(api)
```

```
https://servicemap.disit.org/WebAppGrafo/api/v1/?serviceU
ri="http://www.disit.org/km4city/resource/IBIMET_SMART11"
&fromTime=2-hour&toTime=2020-04-14T10:00:00
```

Real Time Data Analytics using R Studio

How to create a *plumberized* R script - 5

- Step 5 – Data manipulation and data Interpolation…

… After data manipulation and interpolation we obtain something like this:

```
    long      lat    value
11.24686 42.76616 39.87238
11.30287 42.76616 39.54115
11.35888 42.76616 39.20993
11.41489 42.76616 38.87870
11.47090 42.76616 38.54747
11.52691 42.76616 38.21624
11.58292 42.76616 37.88501
[…]
```

Interpolated values

Real Time Data Analytics using R Studio

How to save heatmaps using API - 1

- Step 6 - Create a R list:

```
interpolatedHeatmap=list()
interpolatedHeatmap$attributes=vector("list", dim(interpolatedData)[1])
interpolatedHeatmap$saveStatus=list()

for(i in 1:dim(interpolatedData)[1]) {

  #list
  lat = as.numeric(interpolatedData[i, "lat"])
  long = as.numeric(interpolatedData[i, "long"])
  meanObs = interpolatedData[i, "value"]

  listAttribTemp = list("mapName"=heatmapName,  "metricName"= metricName,
                      "description"= paste("Average from",fromDateTime,"to",toDateTime,sep=" "),
                      "clustered"= 0, "latitude"=lat, "longitude"=long,
                      "value"= meanObs, "date"= paste(toDateTime, "Z", sep=""), "org"="DISIT")

  interpolatedHeatmap$attributes[[i]]=listAttribTemp
```

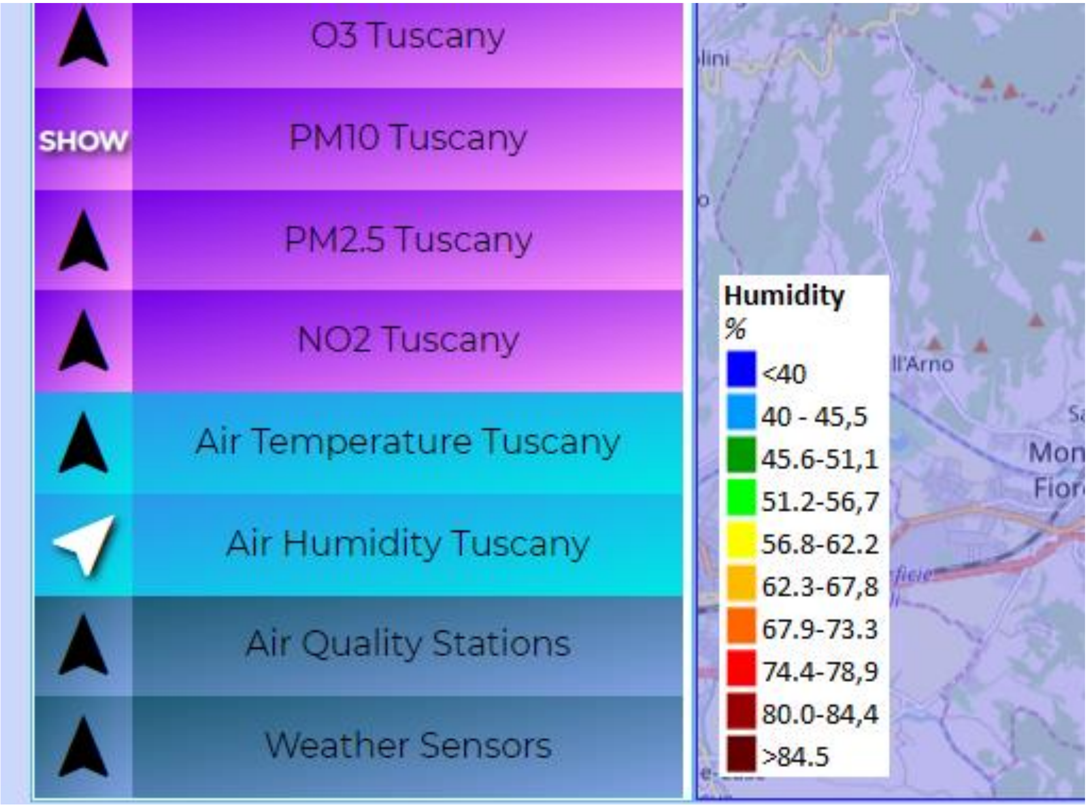
Real Time Data Analytics using R Studio

How to save heatmaps using API - 2

Note that, the "metricName" identifies the legend for each heatmap and the colour scale to be used.

It corresponds to the *varName* of the R function except for PM10 and PM2.5 measurements:

- "HighDensityPM10"
- "HighDensityPM25"



Real Time Data Analytics using R Studio
How to save heatmaps using API - 3

- Step 7 - Transform the R list in a Json and save heatmap data using API:

```
request_body_json <- toJSON(interpolatedHeatmap$attributes, auto_unbox = TRUE, digits = 10)

resultPOST <- POST(url = "http://snap4city:disit2019@192.168.0.59:8000/insertArray",
                   body = request_body_json,
                   encode = "json", add_headers("Content-Type" = "application/json"))
```

[...]

```
apiFinal <- paste("http://192.168.0.59/setMap.php?mapName=",heatmapName,
                  "&metricName=",metricName,
                  "&date=",paste(toDateTime, "Z", sep=""),
                  "&completed=", completed,  sep="")
resultPOST <- GET(url = apiFinal)
```

Real Time Data Analytics using R Studio

How to save heatmaps using API - 4

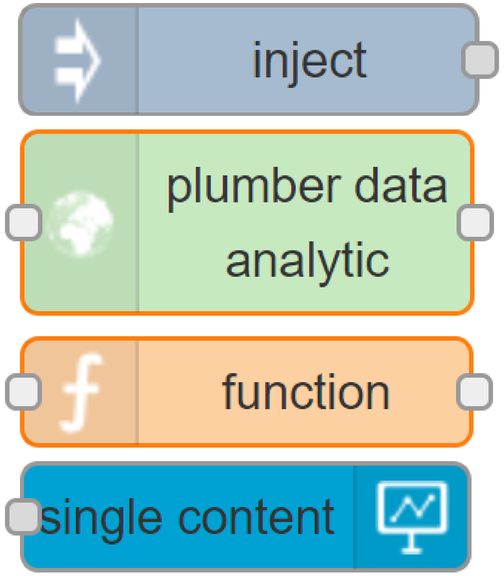
JSON Array Format example

[
{
"mapName": “airTemperatureTuscany",
"metricName": "airTemperature",
"description": " Air Temperature heatmap … ",
"clustered": 0,
"latitude": 43.1,
"longitude": 11.1,
"value": 16.5,
"date": "2020-04-14T10:00:00Z"
"org": "DISIT"
}, { […] }]

IOT App for Real Time Data Analytics

How to create a Data Analytics IOT Application

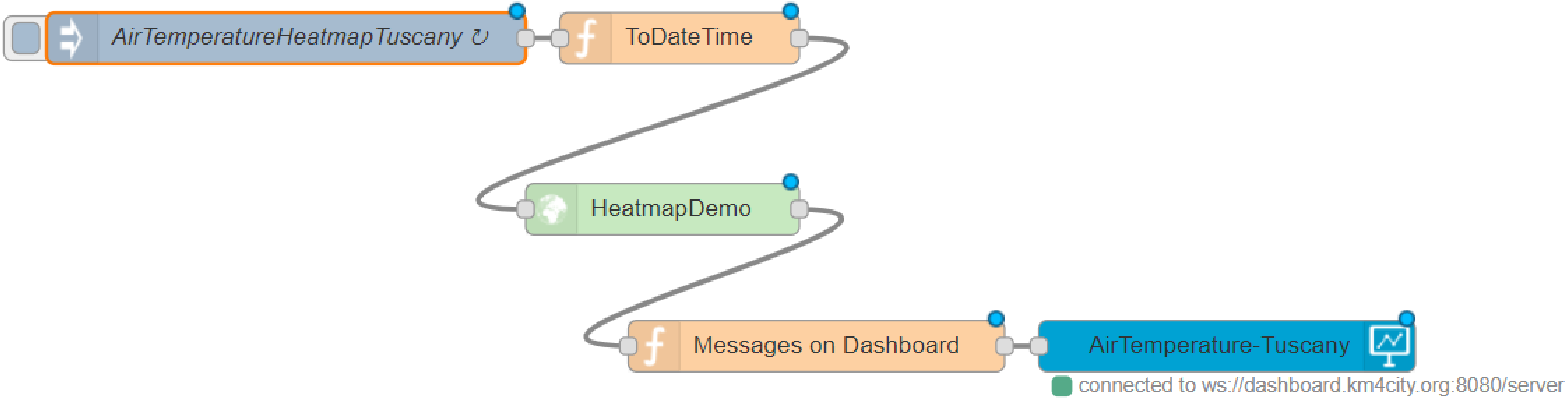
What we need:



- To insert the R function parameter
- To upload the R script and create a plumber instance
- To visualize strings/numbers/html on a dashboard
- To execute JavaScript code on output messages

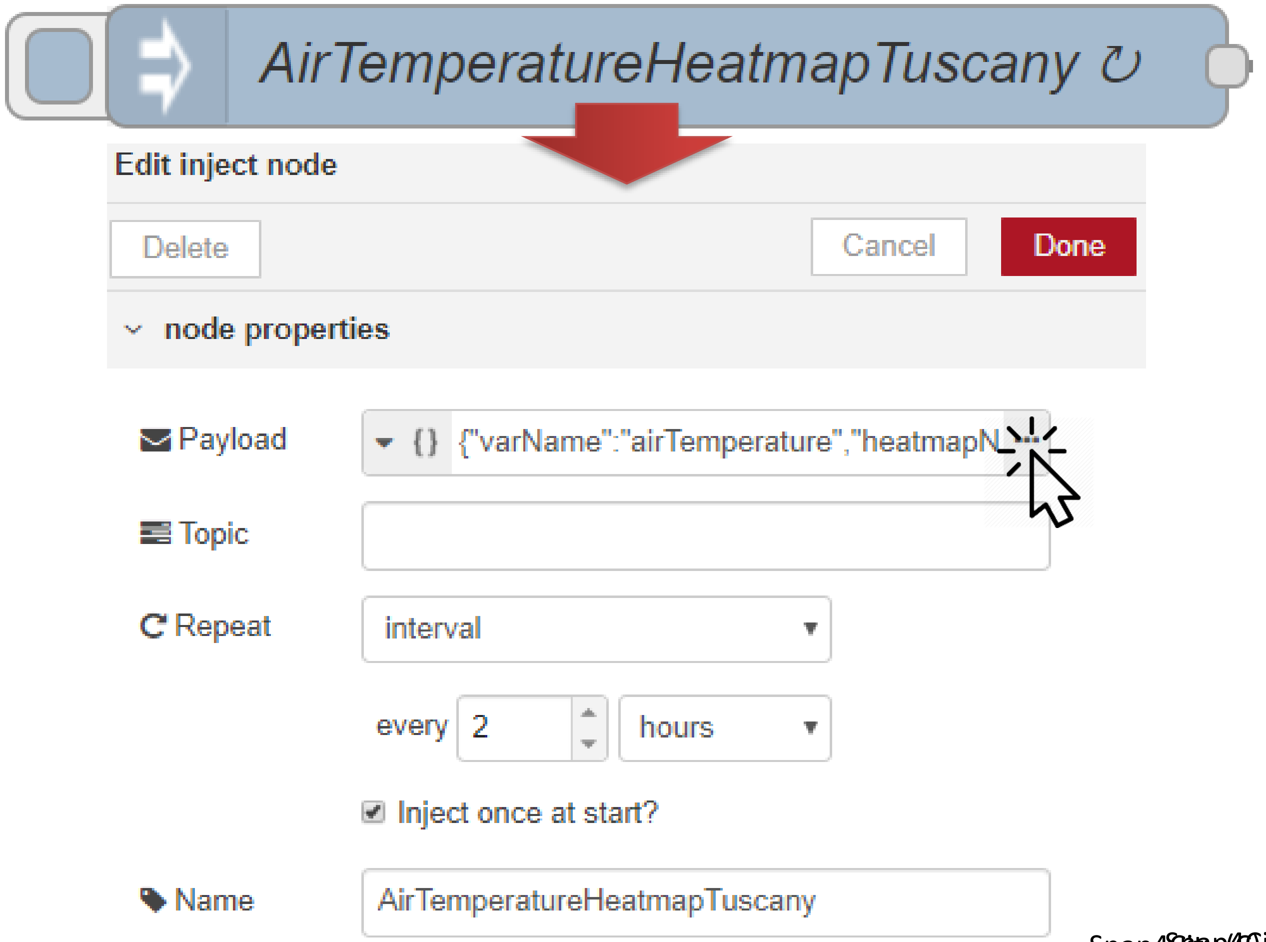
IOT App for Real Time Data Analytics

How to create a Data Analytics IOT Application



IOT App for Real Time Data Analytics
Nodes Configuration – Inject Node

How to configure the **inject** node:



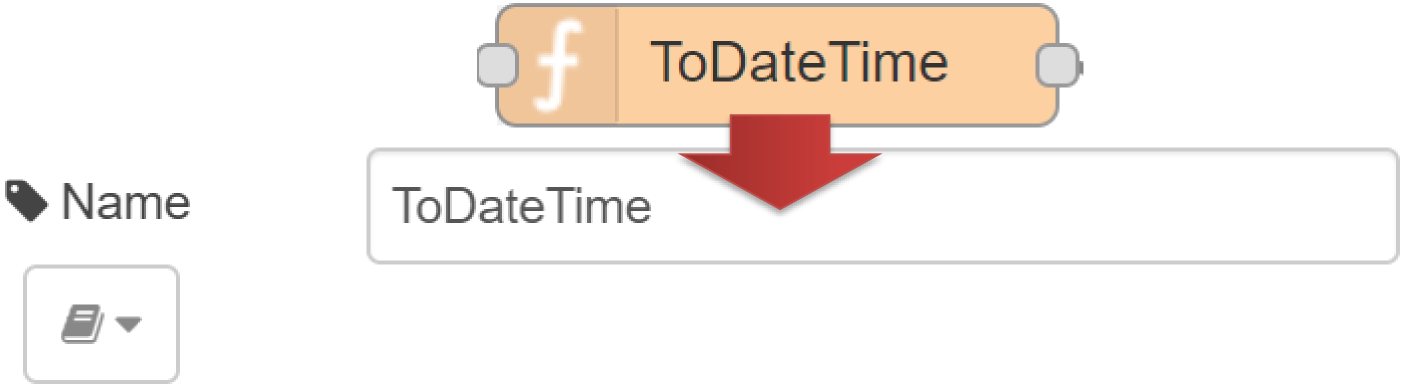
The JSON Format of the Payload property has the same notation of the R function parameters:

{ "varName": "airTemperature",
"heatmapName":
"airTemperatureTuscanyTest",
"fromDateTime": "2-hour",
"sensorCategory": "Weather_sensor"
}

IOT App for Real Time Data Analytics

Nodes Configuration – Function Node for Date and Time

- Before configure the plumber data analytic node is necessary to execute a JavaScript code to dynamically update the date ("toDateTime" parameter):



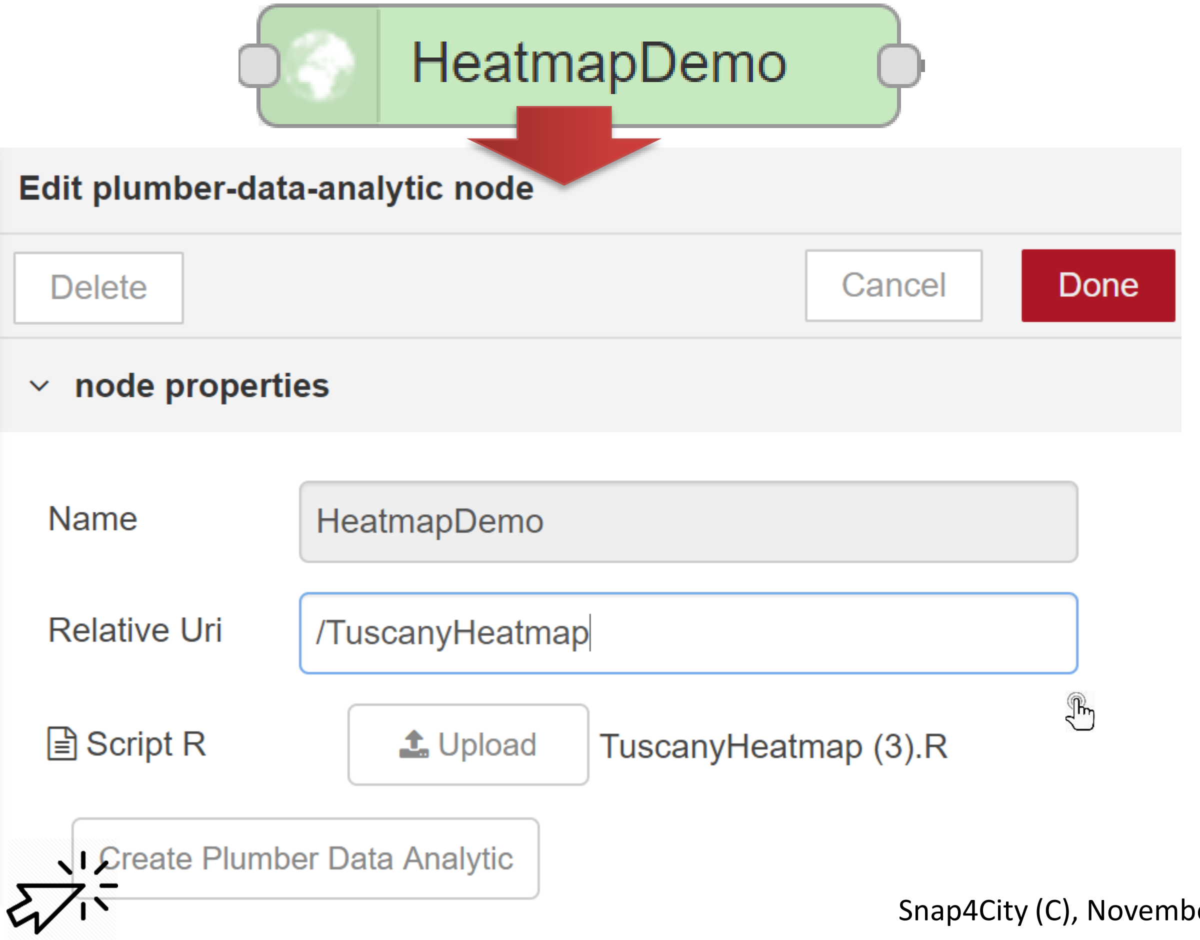
Function

```
msg.payload.toDateTime =
new Date(new Date().getTime() +
7200000).toJSON().substring(0,13)+(":00:00");
return msg;
```

IOT App for Real Time Data Analytics

Nodes Configuration – Plumber Data Analytic Node

How to configure the **plumber data analytic** node:



Relative Uri is the same of the R @get annotation:

```
#' @get /TuscanyHeatmap
```

IOT App for Real Time Data Analytics

Nodes Configuration – Function Node for Messages on Dashboard

- Before configure the single content node is necessary to execute a JavaScript code to visualize the status of the heatmap:

Messages on Dashboard

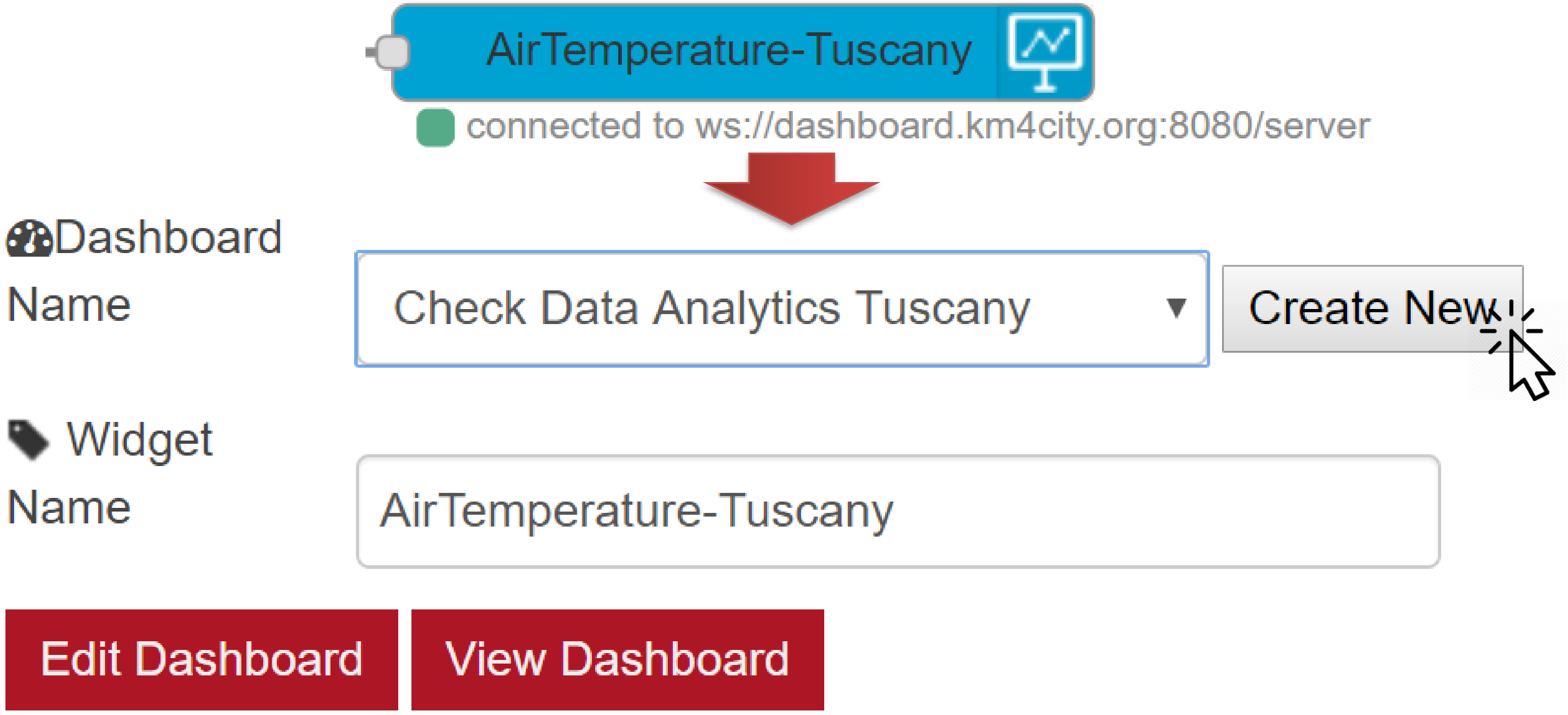
Function

```
msg.payload=msg.payload.message+" "+msg.payload.dateTime;
if(msg.payload.indexOf("Completed")!= -1){
    msg.payload ="<span style='color:green;'>"+
    msg.payload + "</span>"
} else  if (msg.payload.indexOf("No Availabe Data") != -1){
     msg.payload ="<span style='color:orange;'>"+
     msg.payload + "</span>"
}
return msg;
```

IOT App for Real Time Data Analytics

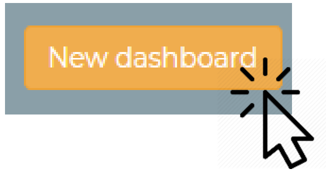
Nodes Configuration – Single Content Node

How to configure the **single content** node:

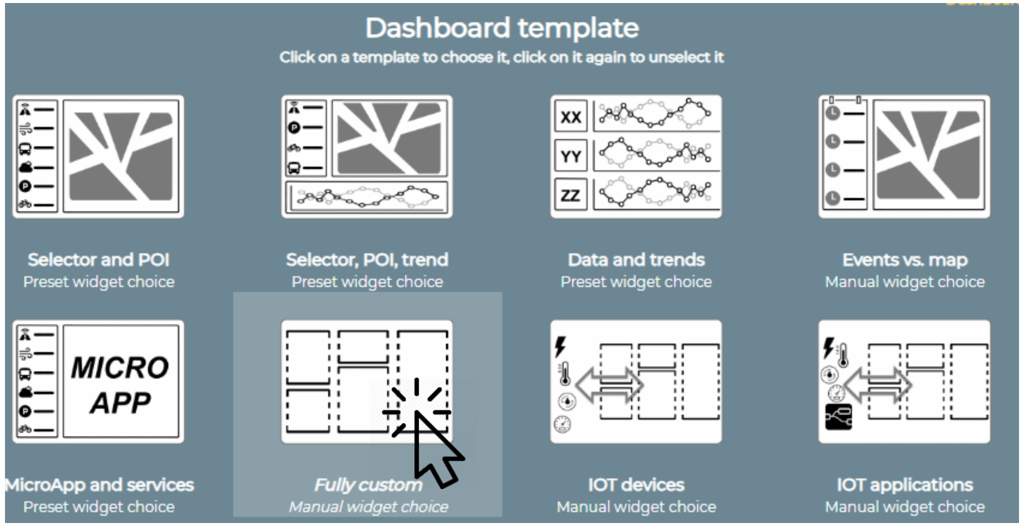


Wizarded Heatmap Visualization

1. Create a New Dashboard from Dashboard (Public)

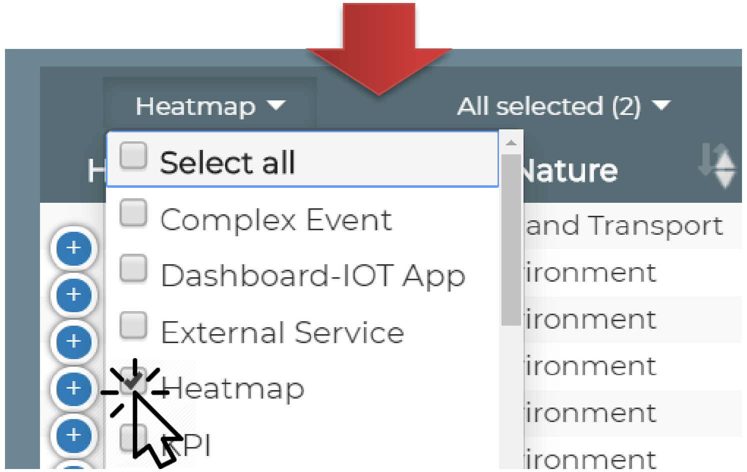


2. Insert a Dashboard Title and select a Dashboard Template

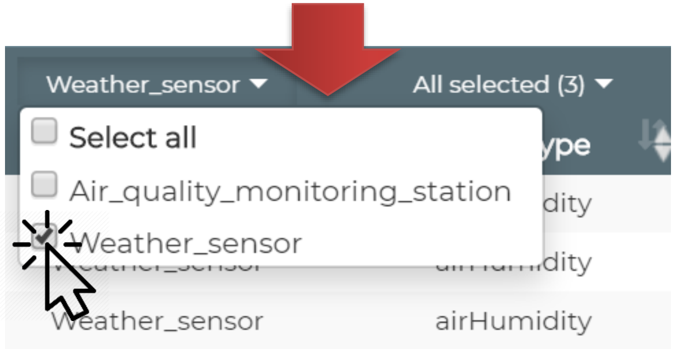


Wizarded Heatmap Visualization

3. Select the Heatmap box as High-Level-Type



4. Select the Sensor Category (Subnature)

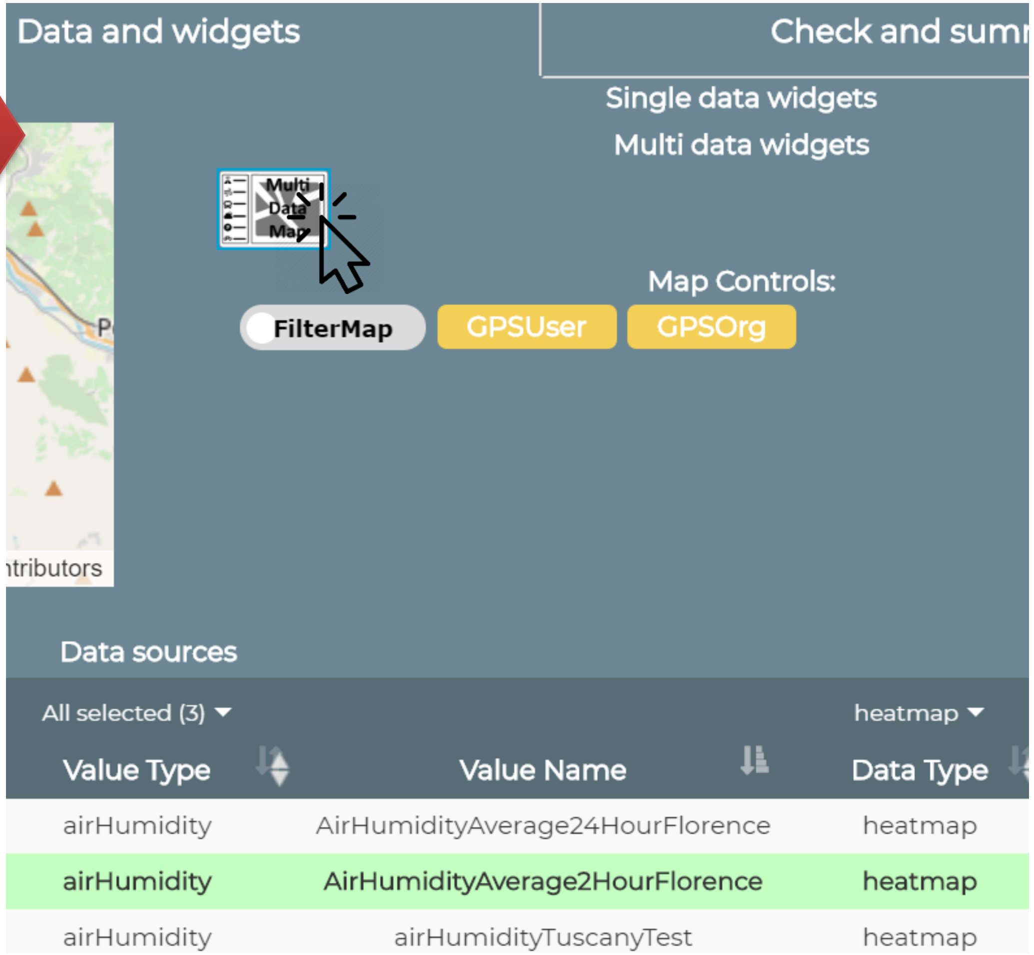


5. Select the measure (Value Type) and the Heatmap Name (Value Name)

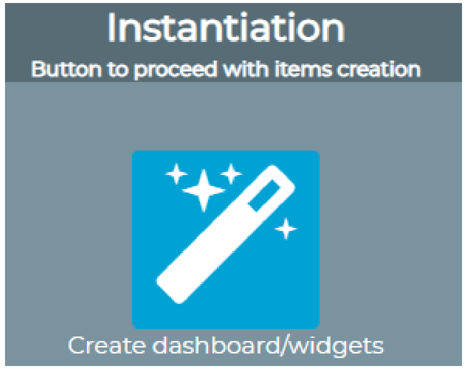
All selected (3)		heatmap	
Value Type	Value Name	Data Type	Last Date
airHumidity	AirHumidityAverage24HourFlorence	heatmap	2019-04-08 13:27:52
airHumidity	AirHumidityAverage2HourFlorence	heatmap	2019-07-22 13:00:00
airHumidity	airHumidityTuscanyTest	heatmap	2019-07-22 12:00:00

Manually Heatmap Visualization

6. After the Heatmap selection, select the Multi Data Map button and click on next



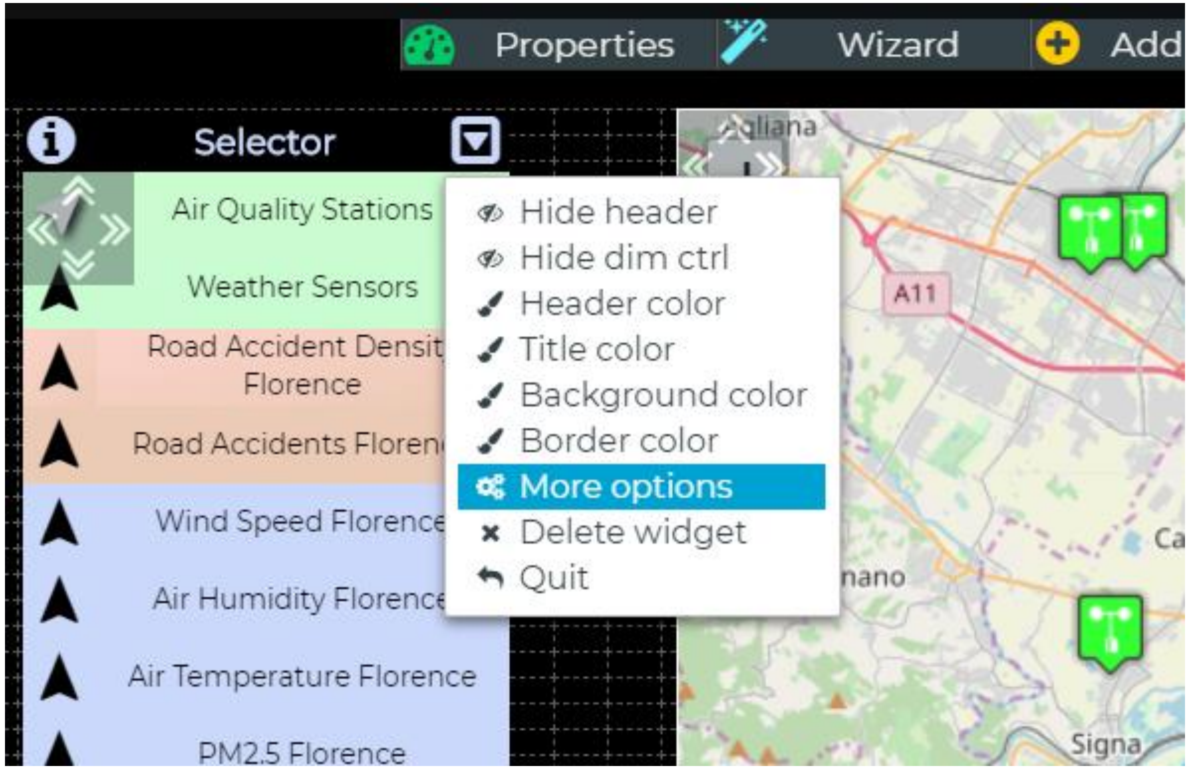
7. Select the instantiation button to proceed with items creation



Manually Heatmap Visualization

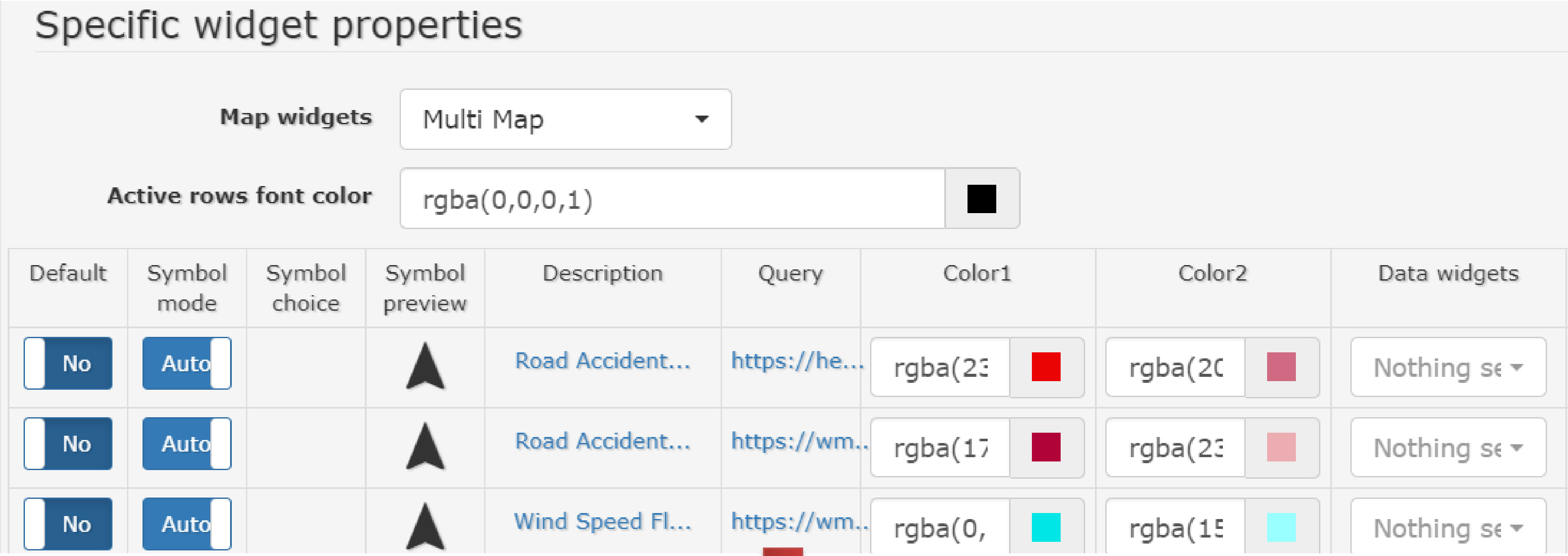
1. Select a Dashboard and click on Edit

2. Select on More Options to modify the widget properties



Manually Heatmap Visualization

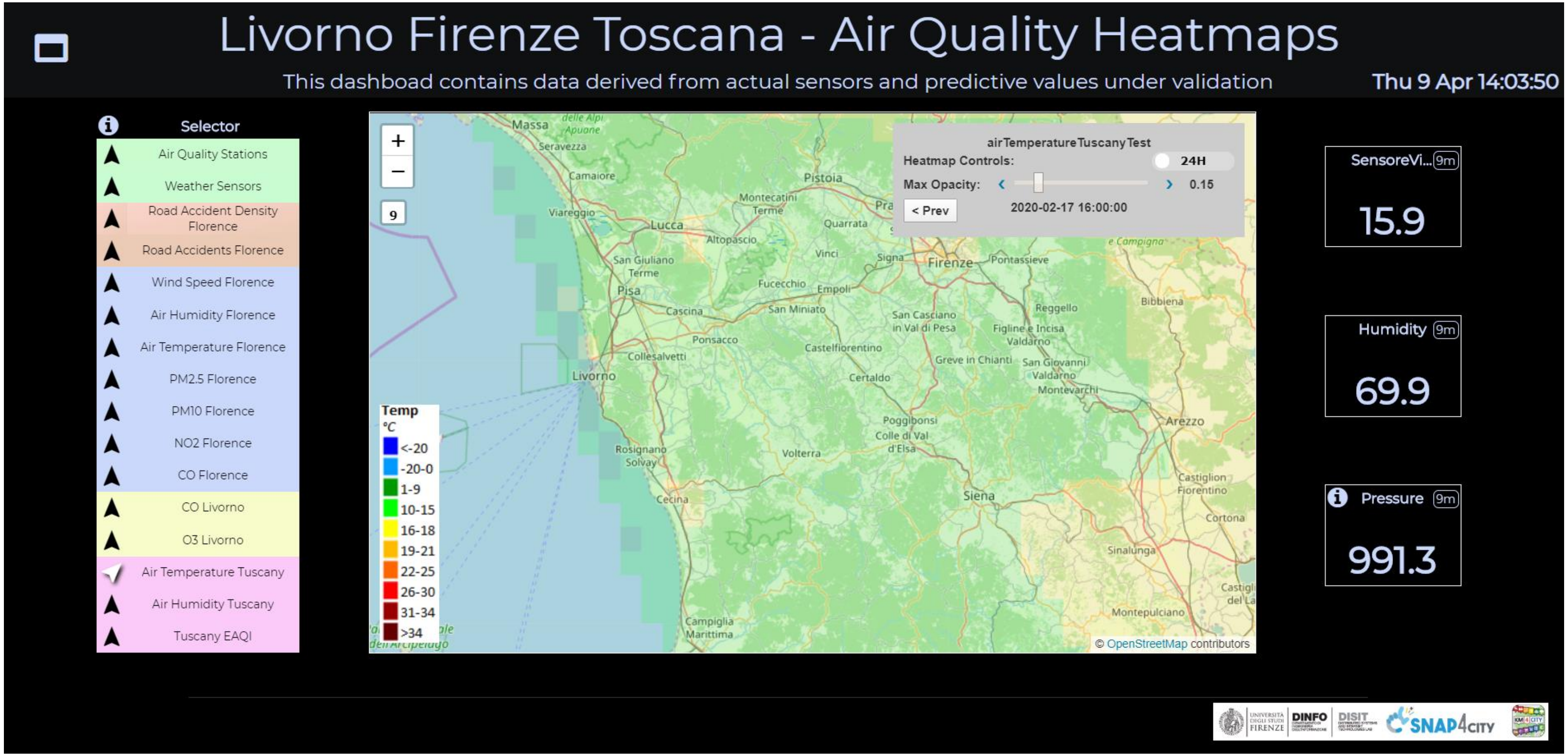
3. Change the Query to visualize the new heatmap



https://wmsserver.snap4city.org/geoserver/Snap4City/wms?service=WMS&layers=heatmapName

https://wmsserver.snap4city.org/geoserver/Snap4City/wms?service=WMS&layers=airTemperatureTuscanyTest

Heatmap Visualization



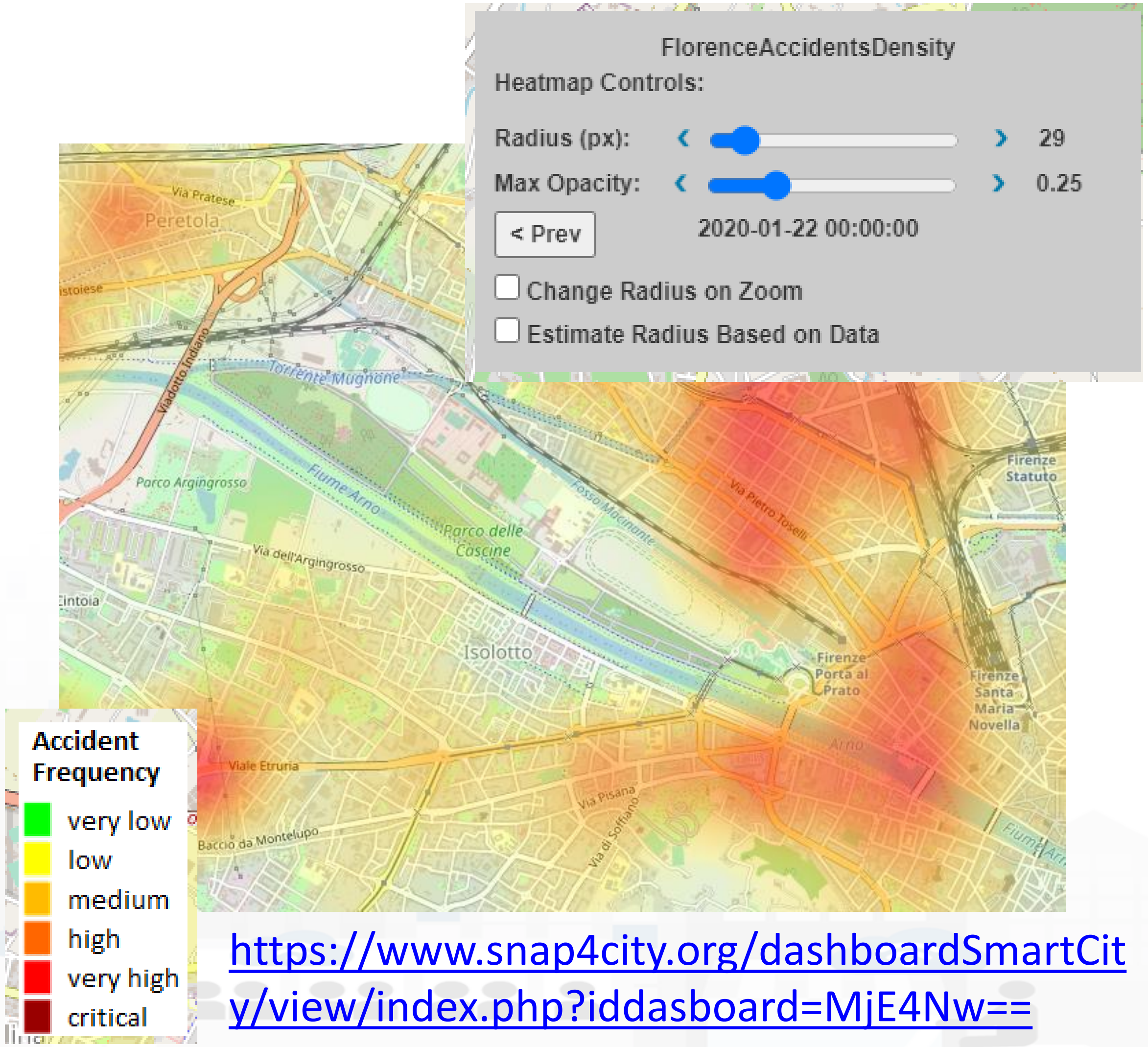
https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTI2OA==

TOP

Different Heatmap Models
A comparison and features

Gaussian vs WMS heatmap settings/calls

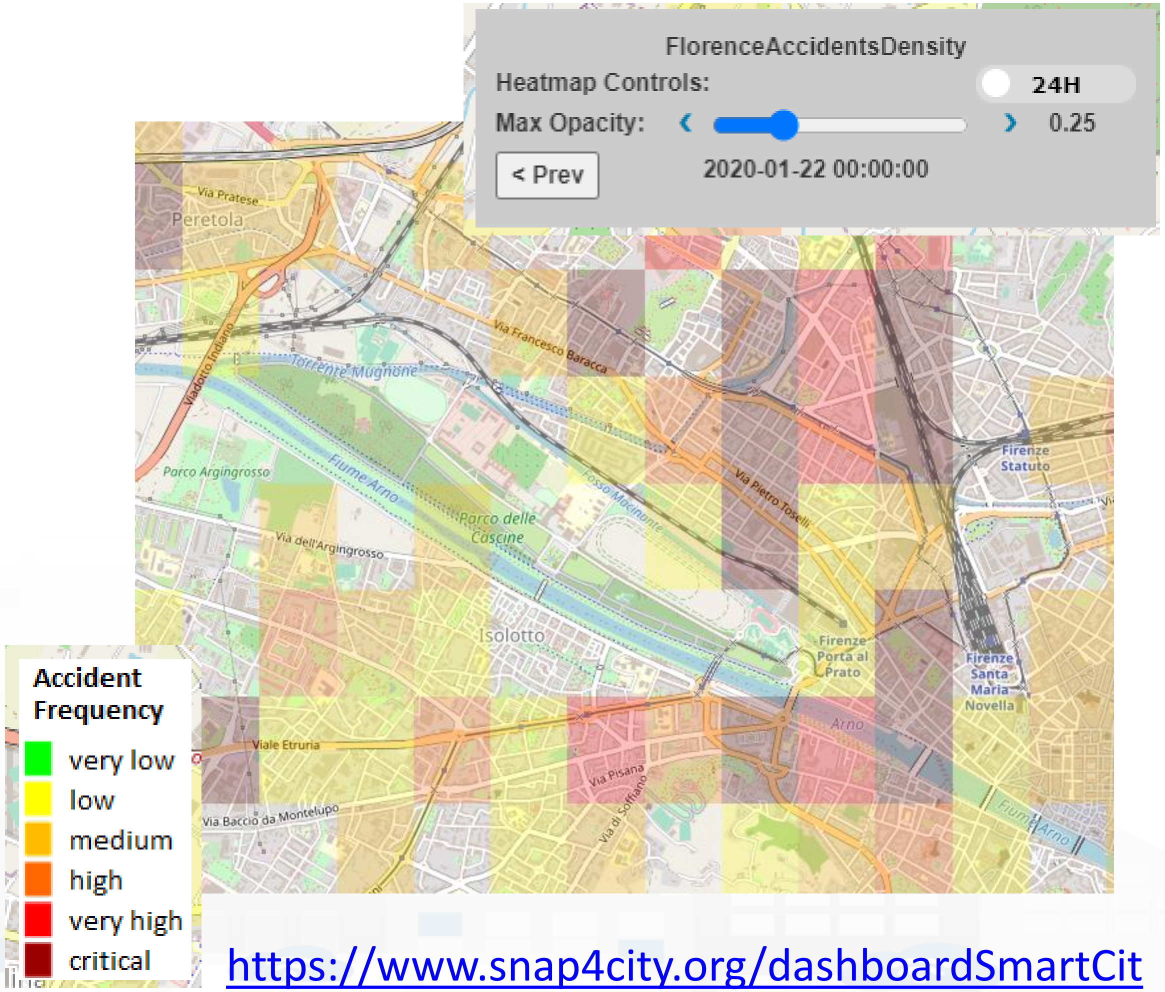
- https://heatmap.snap4city.org/heatmap.php?dataset=15MinIndex_HousingIndex
  - GPS coordinates (points)
  - Metrics to be defined into the Dashboard table
  - Legenda of colormap in PNG to be uploaded if not standard
  - Heatmap non calibrated, created on client. Data provided from Heatmap server, some limitations on the number of points since the heatmap is created on client side
- If data are on Heatmap Server, the data Piker from Heatmap is accessible



https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MjE4Nw==

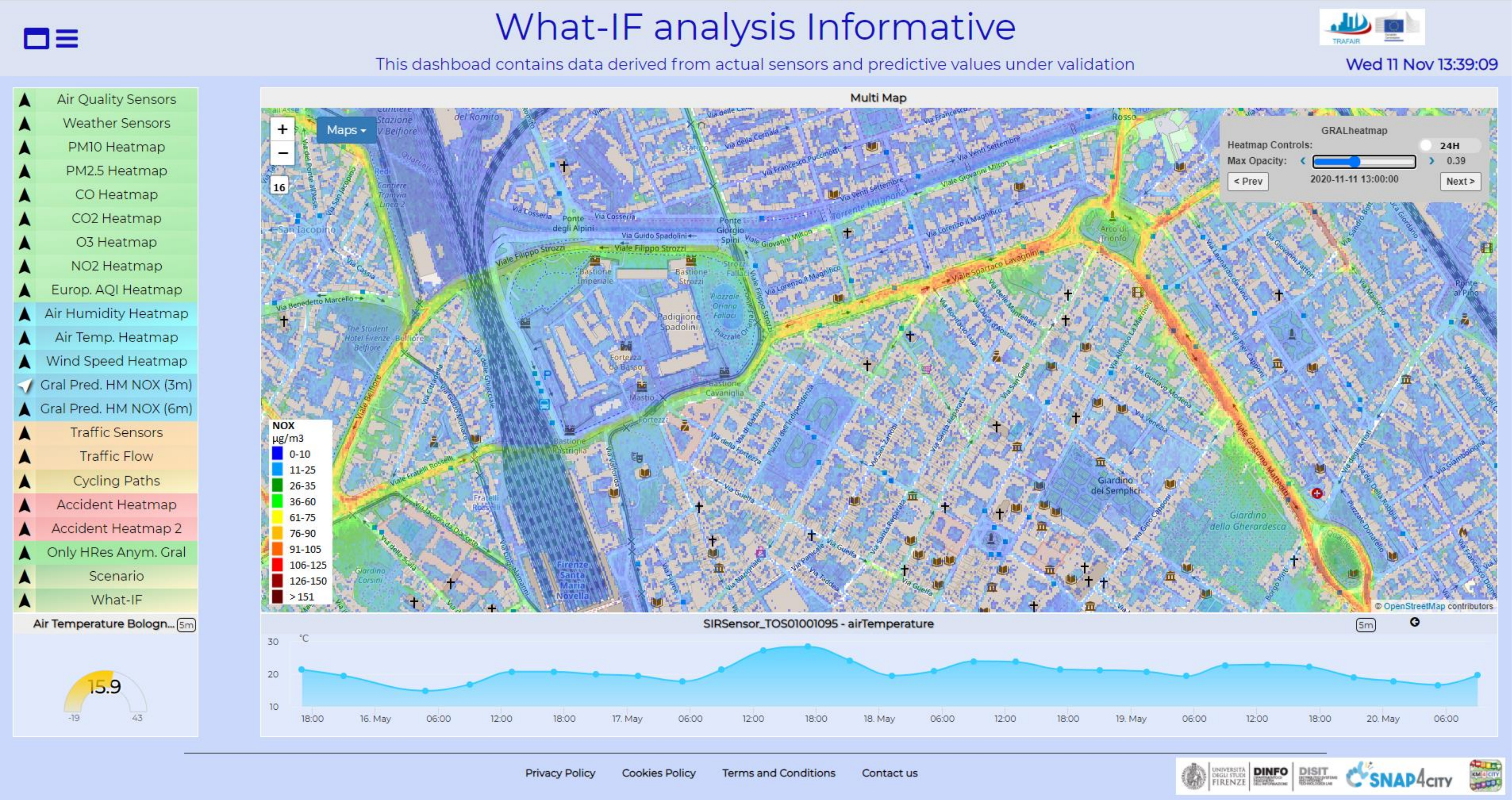
Gaussian vs WMS heatmap settings/calls

- https://wmsserver.snap4city.org/geoserver/Snap4City/wms?service=WMS&layers=15MinIndex_HealthIndex
  - UTM coordinates (points, grid size, etc.)
  - Legenda of Colormap in PNG to be uploaded if not standard
  - Heatmap built as Tiled Images in GeoTIFF and provided from GeoServer
- It is possible to create Heatmap on GeoTiff without loading data on Heatmap Server



https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MjE4Nw==

WMS heatmap



https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MjE4Nw==

R studio Development documentation (self training)

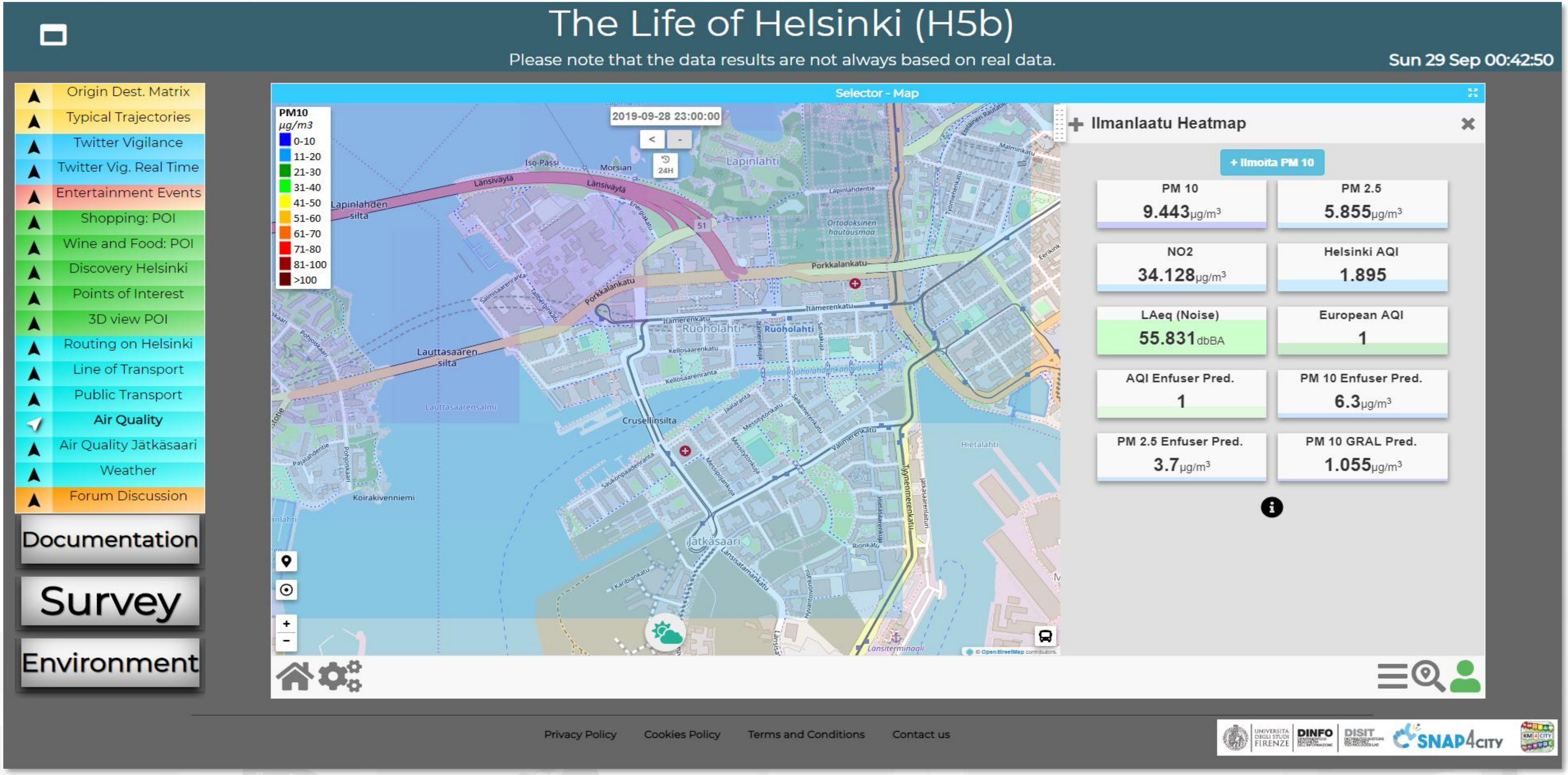
https://www.snap4city.org/dashboardSmartCity/management/iframeApp.php?linkUrl=https%3A%2F%2Fwww.snap4city.org%2Fdrupal%2Fnode%2F25&linkId=25link&pageTitle=Doc:%20R%20Studio%20Development&fromSubmenu=handddocLink

- TC7.1. Exploiting data analytics and machine learning in IOT Applications as MicroService
- TC7.2. R Studio for Analytics, exploiting Tensor Flow
- TC7.3. Download data from AMMA (Application and MicroService Monitor and Analyser), ResDash (Resource Dashboard) and DevDash (Development Dashboard) tools
- TC7.4. From R Studio process to MicroService for IOT application, data analytics, machine learning
- TC7.5. Developing Data Analytics Processes
- TC7.6. How to get data from API into R studio
- TC7.7. How to Save resulting data via API from R studio
- TC7.8. Example of how to CreateLastValuesMean.R
- TC7.9. CreateHourlyAvgTrendPerDay.R
- TC7.10. CreateHeatmap.R
- TC2.31 - Create Data Analytic Flow
- TC2.32 - Make Your Data Analytic Flow Public

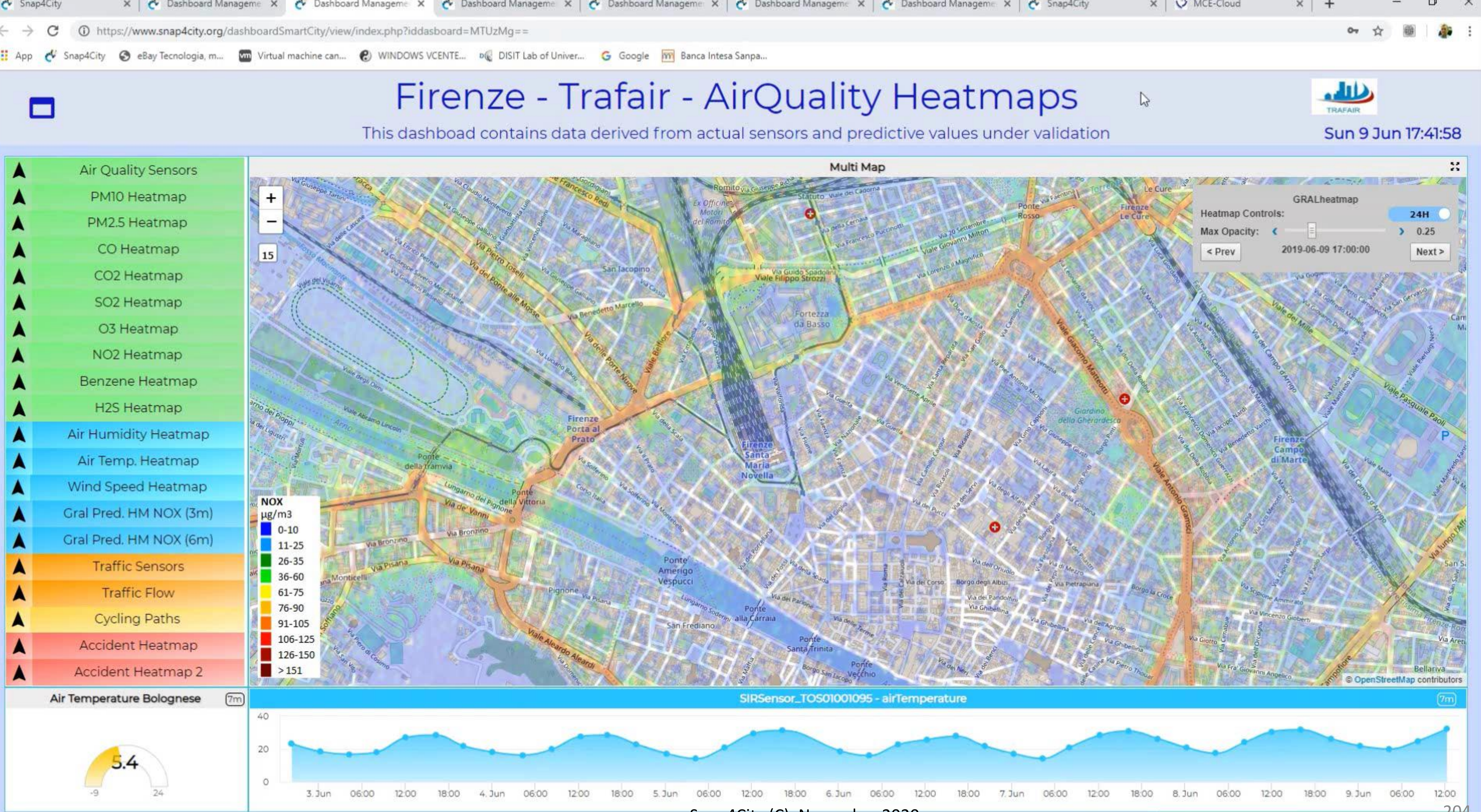
TOP

Dynamic Heatmap Exploitation on the Front-End Tools

Helsinki



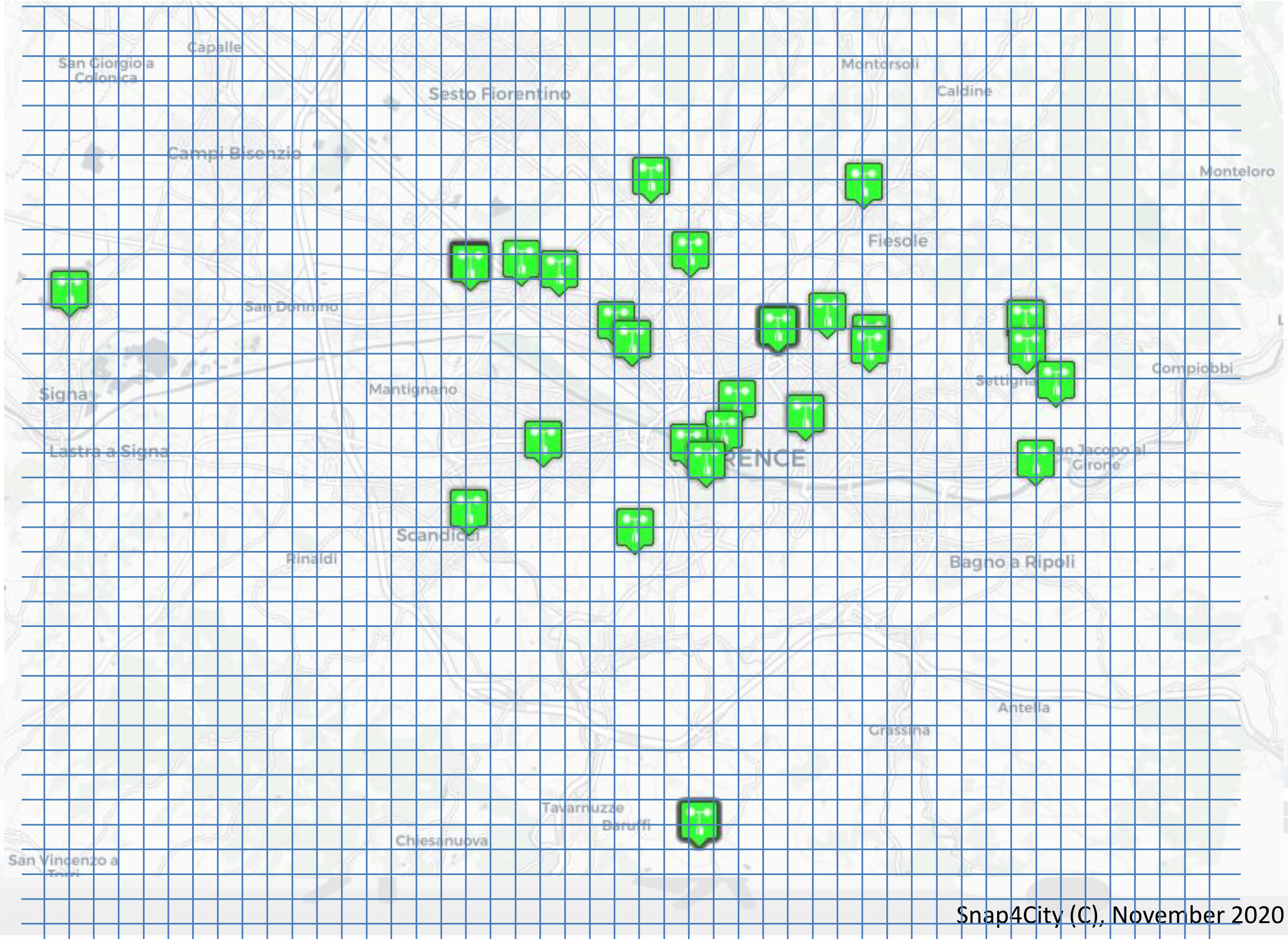
https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTc1Mg==


Firenze - Trafair - AirQuality Heatmaps
This dashboad contains data derived from actual sensors and predictive values under validation
Sun 9 Jun 17:41:58
Air Quality Sensors
PM10 Heatmap
PM2.5 Heatmap
CO Heatmap
CO2 Heatmap
SO2 Heatmap
O3 Heatmap
NO2 Heatmap
Benzene Heatmap
H2S Heatmap
Air Humidity Heatmap
Air Temp. Heatmap
Wind Speed Heatmap
Gral Pred. HM NOX (3m)
Gral Pred. HM NOX (6m)
Traffic Sensors
Traffic Flow
Cycling Paths
Accident Heatmap
Accident Heatmap 2
Multi Map
GRALheatmap
Heatmap Controls: 24H
Max Opacity: 0.25
< Prev 2019-06-09 17:00:00 Next >
NOX µg/m3
0-10
11-25
26-35
36-60
61-75
76-90
91-105
106-125
126-150
> 151
© OpenStreetMap contributors
Air Temperature Bolognese
5.4
SIRSensor_TOS01001095 - airTemperature

Services

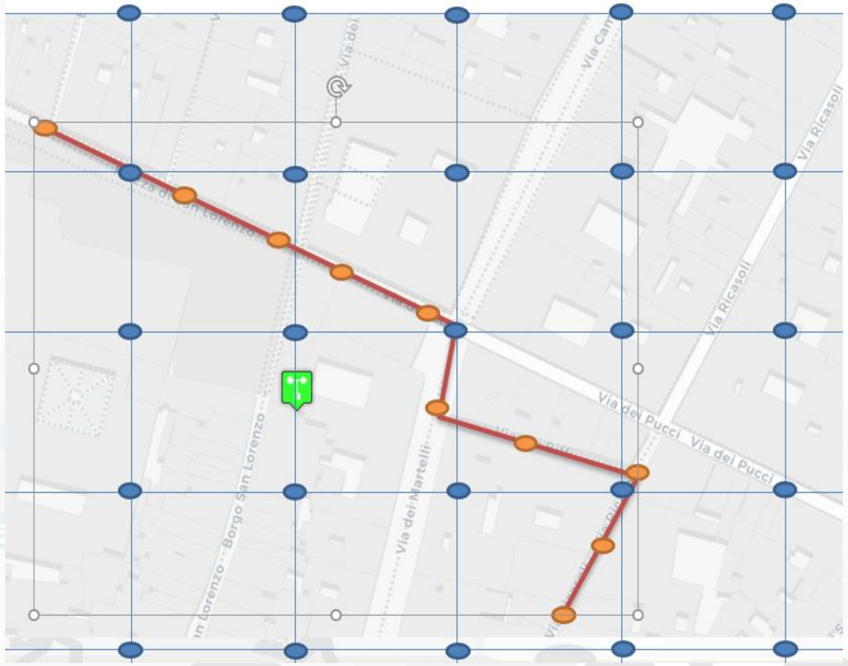
- **Air Quality sensors are**
  - Collected on scattered positions
- **AirQuality Services**
  - AirQuality indicators independent on the sensors' position, in any GPS position of the area
  - **Multiple data:** PM_{10}, $PM_{2.5}$, CO, CO_2, SO_2, O_3, H_2S, NO, NO_2, NO_x, air temperature, air humidity, velocity of wind speed, dew point, etc.
- **Applications**
  - Alerting on specific personal GPS locations
  - Constrained routing for: runners, walking with baby, people with pulmonary problems,
  - Control Room Rendering
  - Mobile Phone Rendering, this means to have thousands of users active at the same time, and a reasonable memory consumption in the server.

The GRID density is never enough

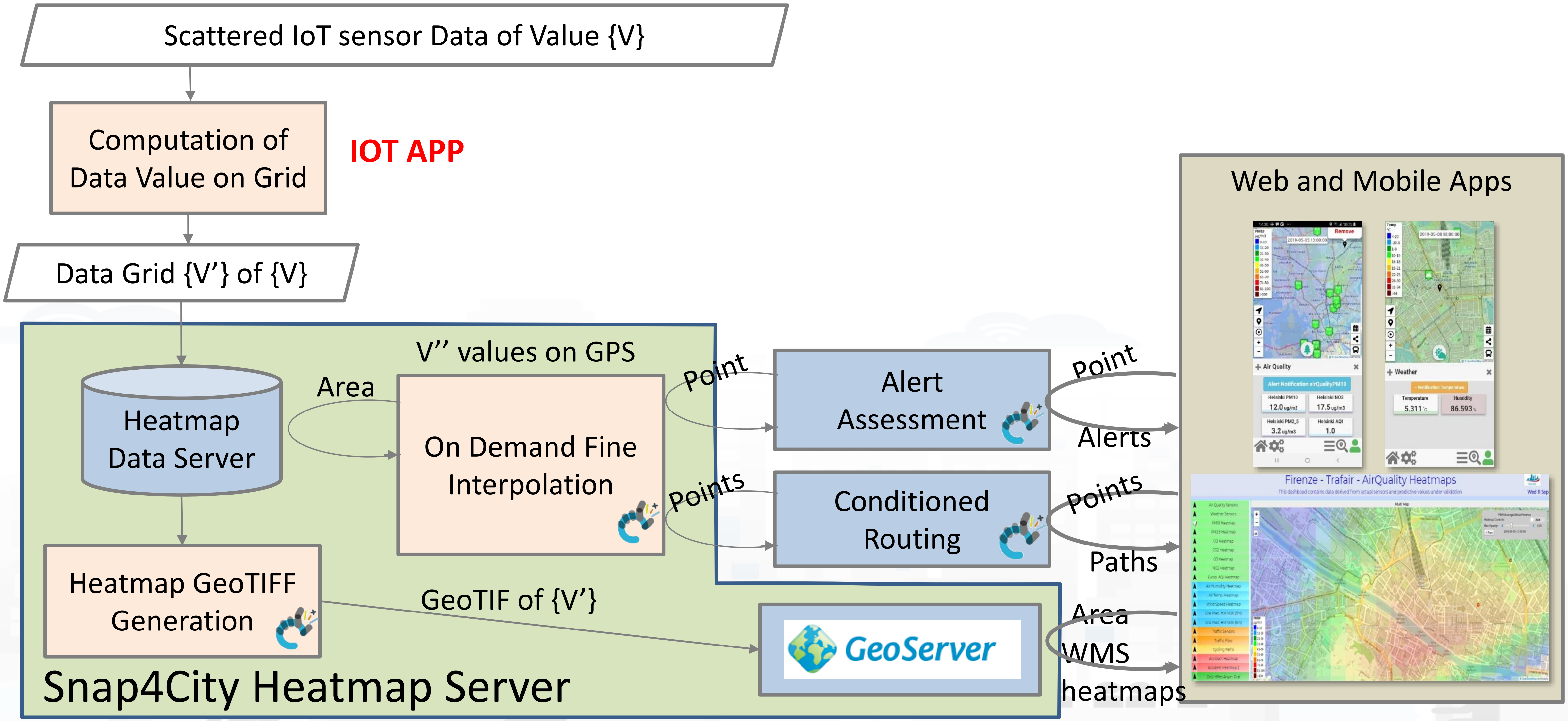


4x4 meters grid is really too expensive

1000x1000 area (small town)
4x4mt * 10 variables * 24 hours per day
→ 3.8 Billions of data

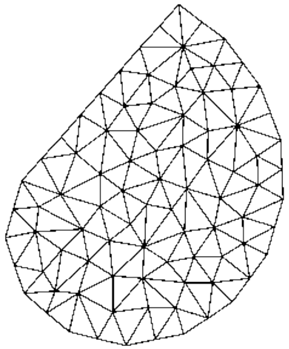


Workflow



Scattered IoT sensor Data of Value {V}
Computation of Data Value on Grid
IOT APP
Data Grid {V'} of {V}
V'' values on GPS
Area
Heatmap Data Server
On Demand Fine Interpolation
Point
Points
Alert Assessment
Conditioned Routing
Heatmap GeoTIFF Generation
GeoTIF of {V'}
GeoServer
Snap4City Heatmap Server
Web and Mobile Apps
Point
Alerts
Points
Paths
Area
WMS
heatmaps
Firenze - Trafair - AirQuality Heatmaps

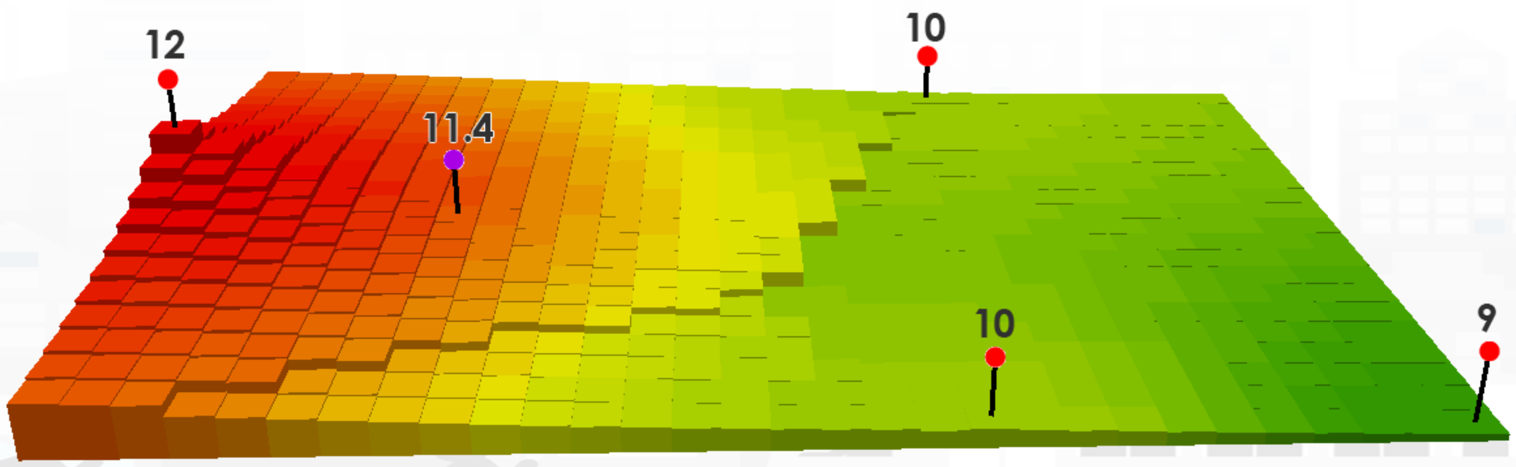
Bivariate Interpolation Method [Akima]



- Steps for irregular data
  - *triangulation* (i.e., partitioning of the area into a number of triangles) of the *x-y* plane
  - *selection* of several data points that are closest to each data point (sensor) and are used for estimating the partial derivatives;
  - *organization* of the resulting data with respect to triangle numbers;
  - *estimation* of partial derivatives at each data point;
  - *computation of* the interpolation at each output point.

Inverse Distance Weighting, IDW Method

- It is a deterministic mathematical method widely used in the geoscience.
  – the interpolated value at the location (x, y); z_i is the observed value; d_i is the Euclidean distance between the point i and the interpolated point; and w_i is the weight for the point each point $(x_i, y_i\ )$ and (x, y)



Validation via Error Estimation

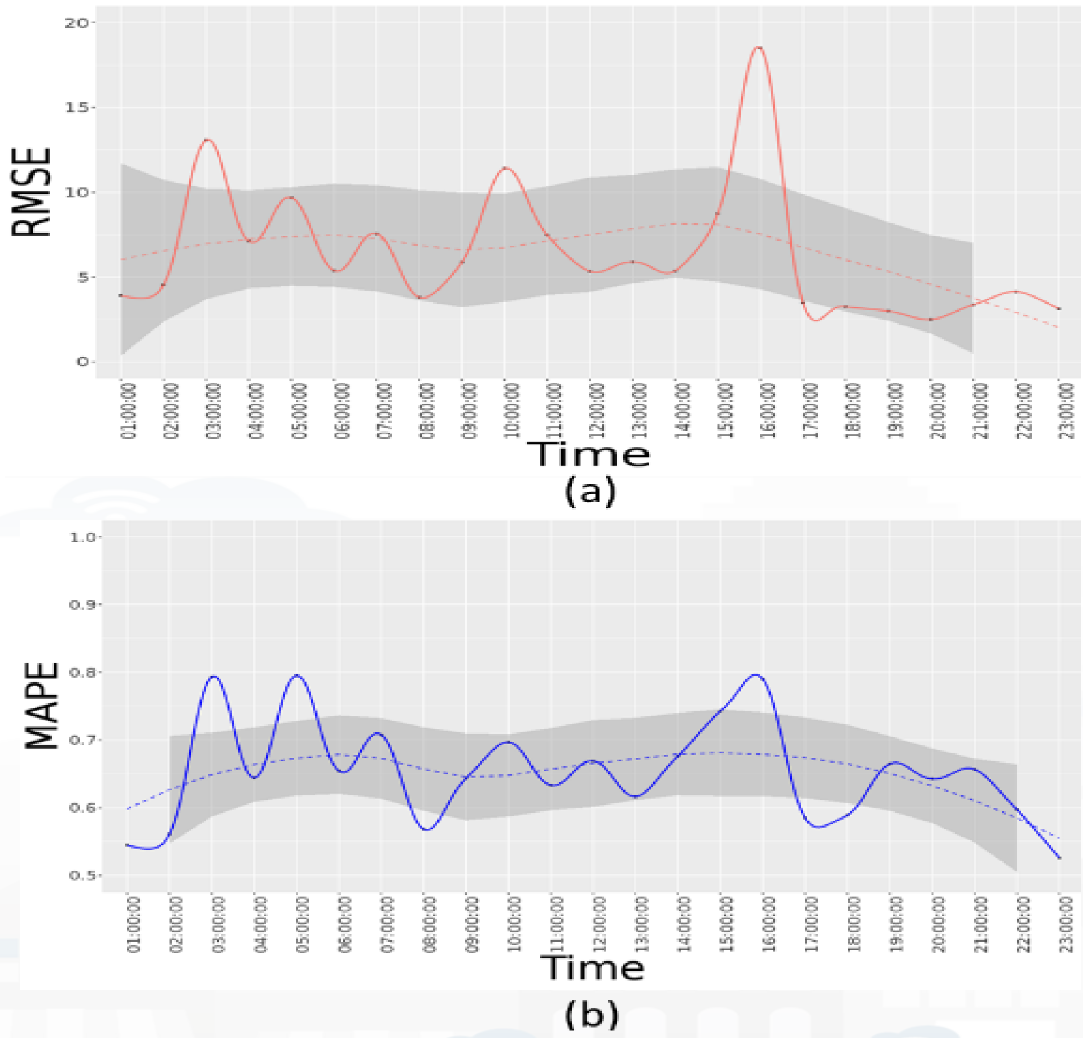
- alternate exclusion of selected air quality sensor in contributing to the model and using the excluded as true value for validation in that point on the basis of the estimation performed exploiting all the others.

Error Measures	Akima	IDW
MAPE	**0.69**	0.79
RMSE	**8.90**	12.20
MAPE-we	**0.60**	0.95
MAPE-wd	**0.70**	0.93
RMSE-we	**8.60**	10.70
RMSE-wd	**9.70**	17.00

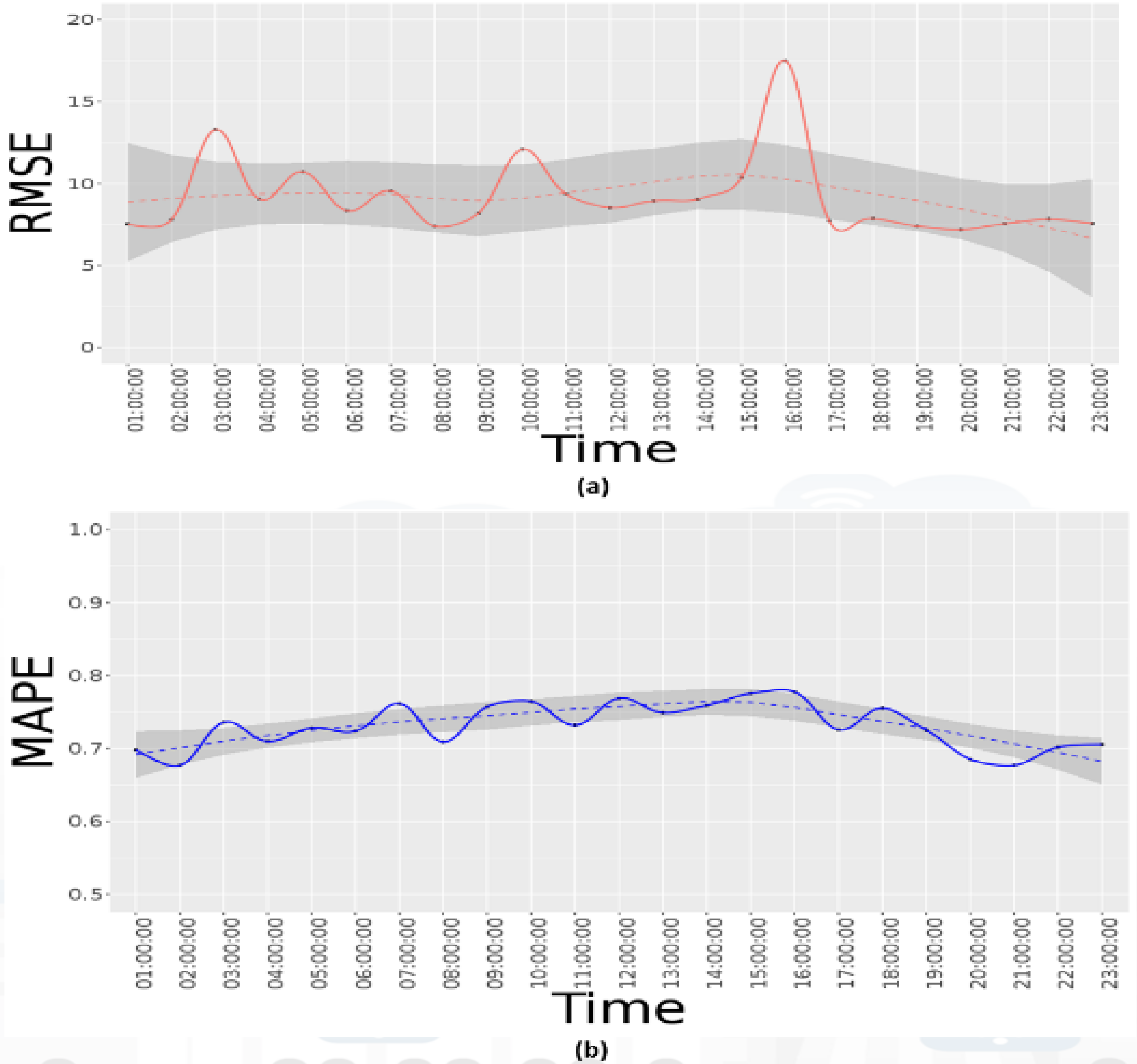
mean absolute percentage error (MAPE)

root mean squared error (RMSE)

Error Trends



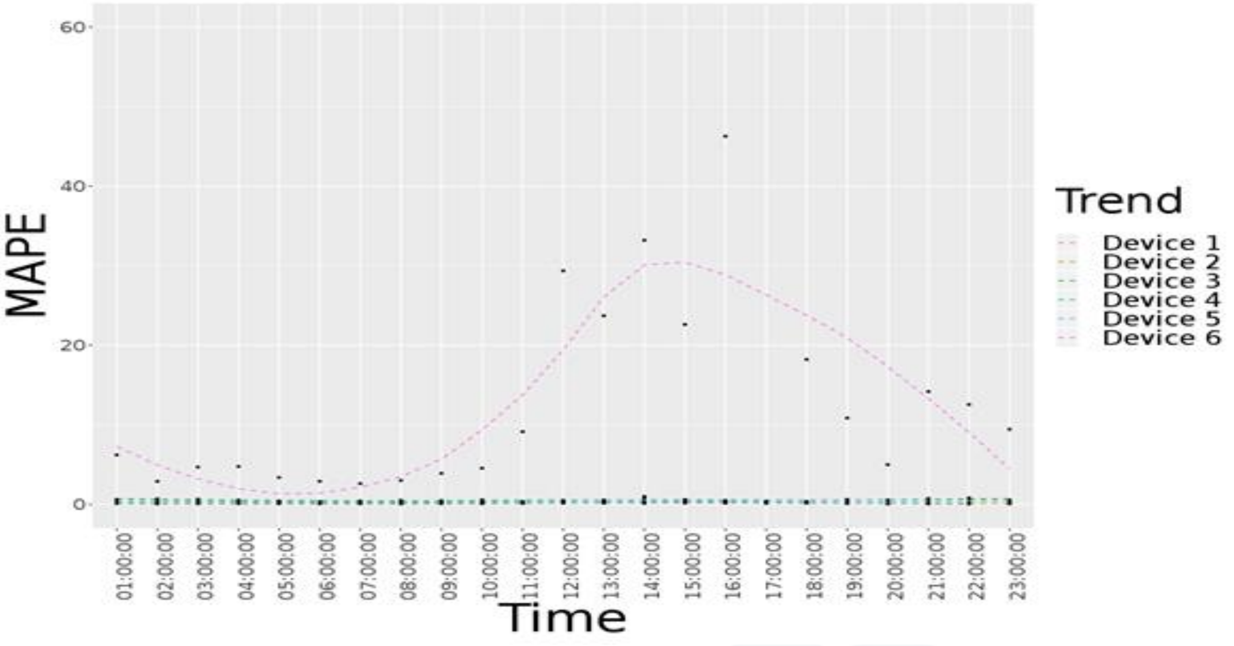
PM_{10} working days RMSE (a) and MAPE (b) per time slots (Akima Method)



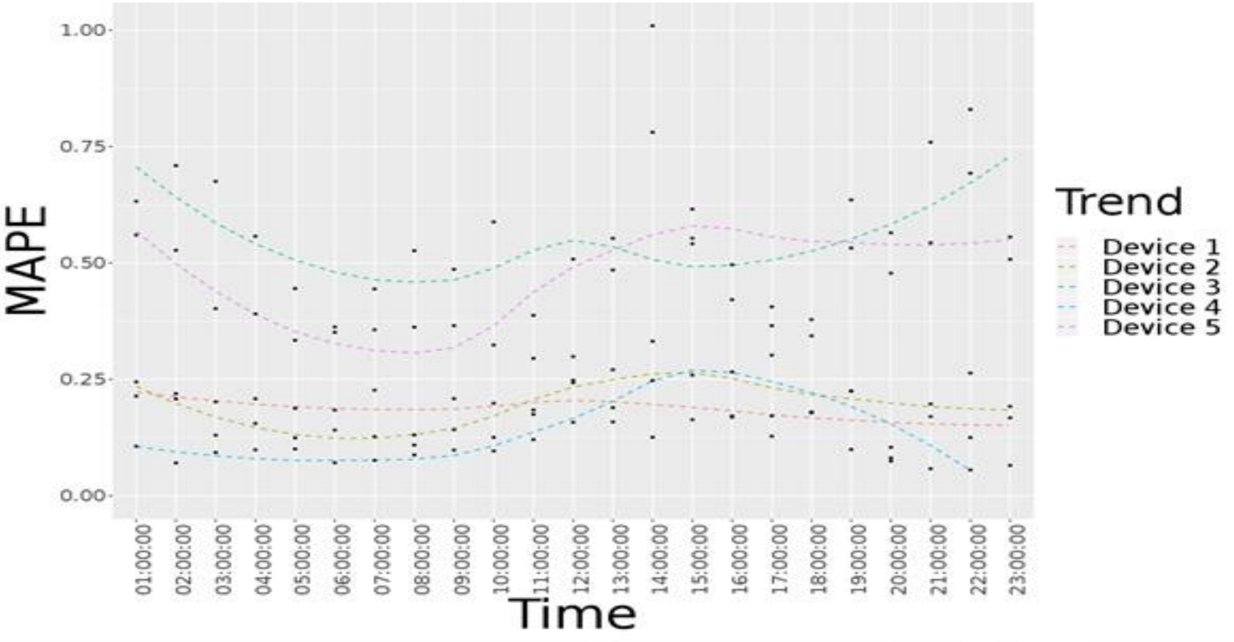
PM_{10} working days RMSE (a) and MAPE (b) per time slots (IDW Method)

Detecting dysfunction on devices using error detection

- Air Quality PM_{10} working days interpolation error trends per hour in terms of mean absolute percentage error for
  - (a) six personal devices including the device with a dysfunction;
  - (b) five personal devices



(a)



(b)

Considerations

- In order to **satisfy the requirements** reported above:
  - Provide Sensor value in any GPS point, for implementing alerts and other applications (routing), rendering on mobile and control room web pages
- What:
  - Two methods have been implemented
  - A scalable architecture has been defined and implemented to provide these services to several thousands of users
- The selection of the best method has been performed on the basis of and error assessment in which Akima solution has been better ranked.
- The Solution can be also used for detecting eventual dysfunction of specific IOT Devices in the same area, for example for bad positioning, turned off, etc.

High Density Real-Time Air Quality Derived Services from IoT Networks

- C. Badii, S. Bilotta, D. Cenni, A. Difino, P. Nesi, I. Paoli, M. Paolucci, Sensors, Vol.20, 2020, N.18, ISSN 1424-8220
- DOI 10.3390/s20185435
- https://www.mdpi.com/1424-8220/20/18/5435/pdf

TOP

Engaging City Users toward a Virtuous Behaviours (real time)

The App is a Bidirectional Device

- GPS Positions
- Selections on menus
- Views of POI
- Access to Dashboards
- searched information
- Routing
- Ranks, votes
- Comments
- Images
- Subscriptions to notifications
- ….

Produced information

- Accepted ?
- Performed ?
- …

Users

Derived information

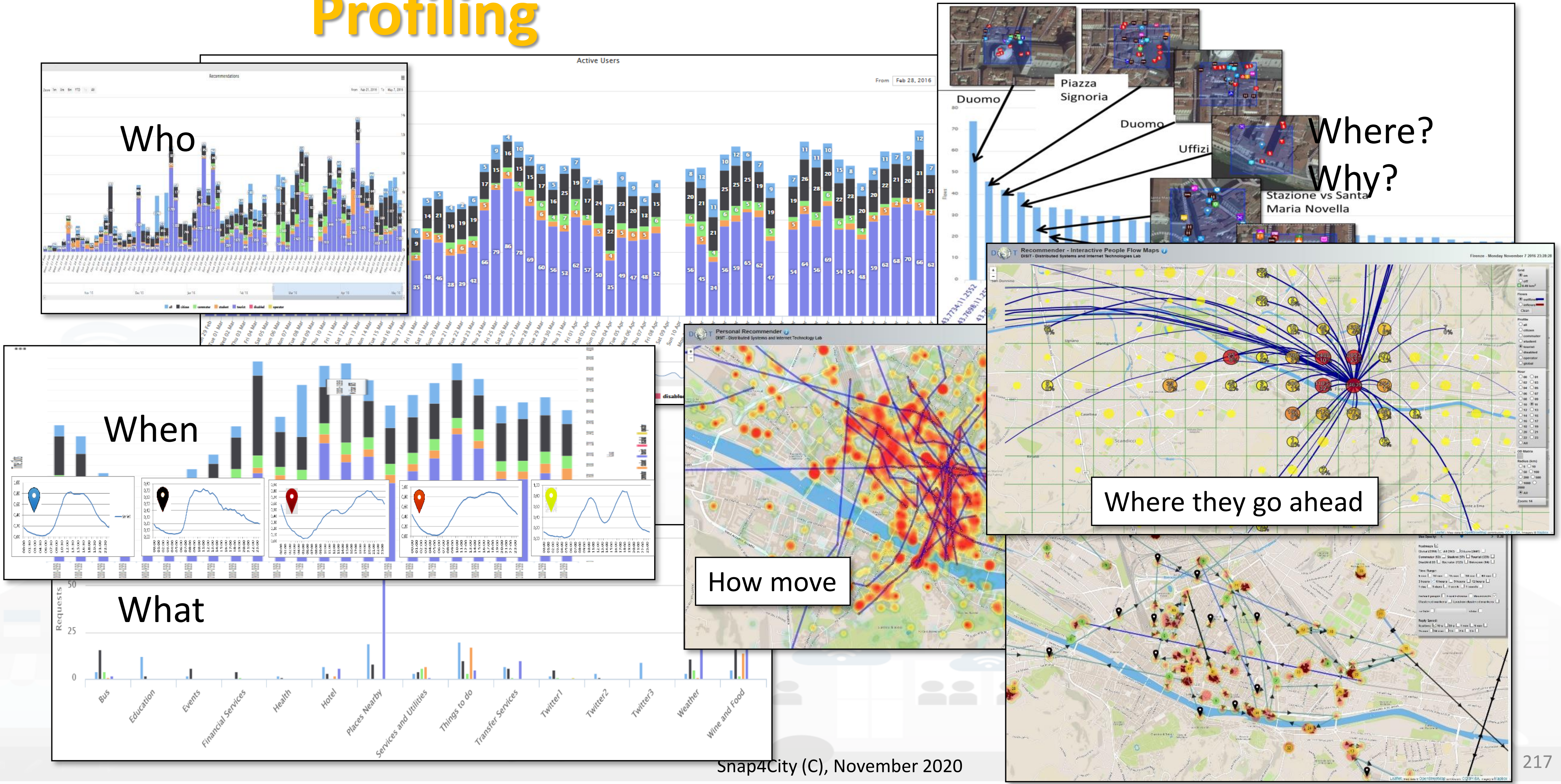
- Trajectories
- Hot Places by click and by move
- Origin destination matrices
- Most interested topics
- Most interested POI
- Delegation and relationships
- Accesses to Dashboards
- **Cumulated Scores from Actions**
- Requested information
- Routing performed
- …..

Produced information

- Suggestions
- Engagements
- Notifications
- …

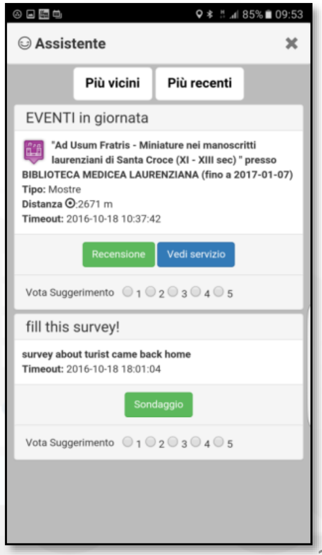
System

User Behavior Analyser for Collective Profiling

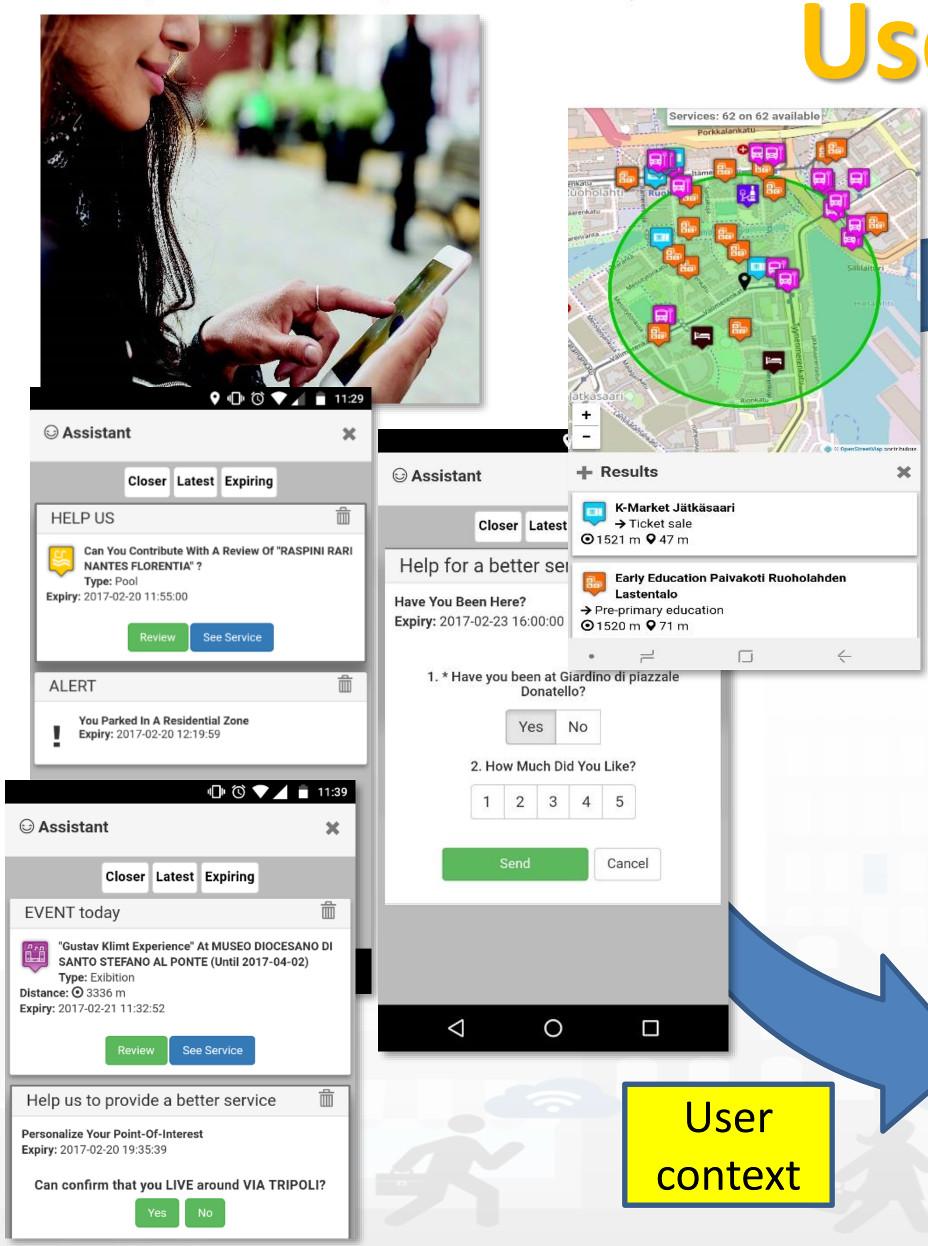


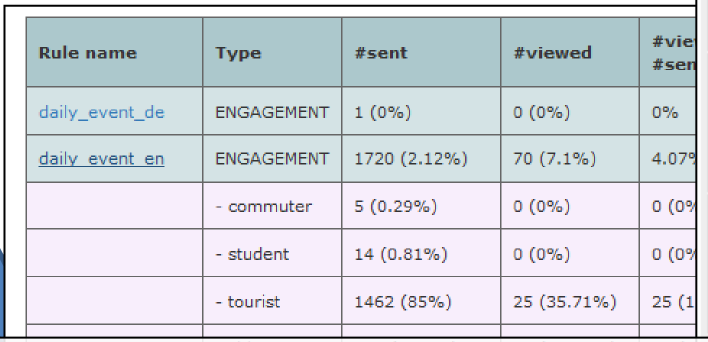
Profiled Engagements to City Users

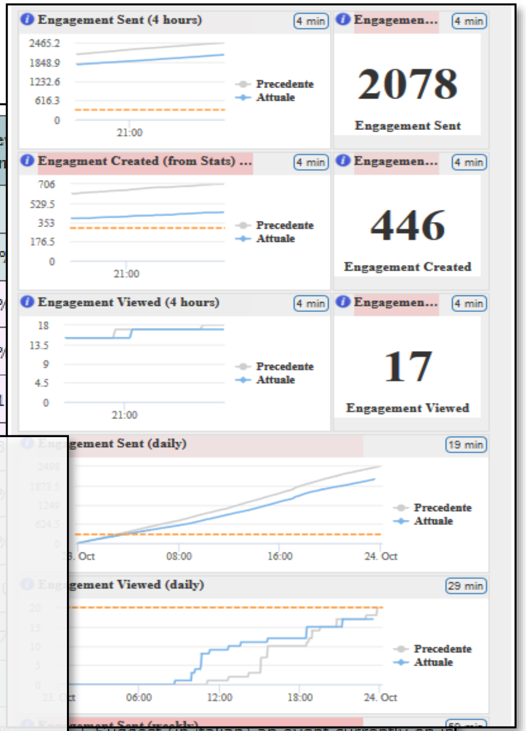
- The users are profiled to learn habits:
  - Personal POI, paths, Mobility habits
- Information and engagements sent to the users are programmed according to the context and user behavior to:
  - Stimulate virtuous habits
  - More sustainable habits
  - More healthy habits, etc.
  - Get feedbacks
  - Provide bonus and prices, …..
  - Send alerts, ….



Users' Engagement







Inform

- Air Quality forecast is not very nice
- You have parked out of your residential parking zone
- The Road cleaning is this night
- The waste in S.Andreas Road is full

Engage

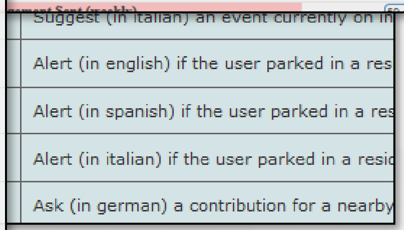
- Provide a comment, a score, etc.

Stimulate / recommend

- Events in the city, services you may be interested, etc..

Provide Bonus, rewards if needed

- you get a bonus since you parked here
- We suggest: leave the car out of the city, this bonus can be used to by a bus ticket



Rules

User context

City context

Engaging City Users

- **Mobile Applications** can use Advanced Smart City API to collect data about the city usage by the city users via a signed consent
- It can be used for sending engagements to them such as to:
  - **Inform**
    - You have parked out of your residential parking zone
    - The Road cleaning is this night
    - The waste in S.Andreas Road is full
  - **Engage**
    - Please Provide a comment, a score, etc.
  - **Stimulate / recommend**
    - Events in the city, services you may be interested, etc..
  - **Provide Bonus**
    - Since you have parked here you can get 1 Bonus
    - We suggest you to leave the car out of the city, this bonus can be used to buy a bus ticket


Sii smart.
Sii-Mobility!
In palio per te
Carnet multicorsa Cap e voucher per:
Sii smart.
Sii-Mobility!
Scarica, viaggia, vinci!
Dal 15 aprile al 15 luglio scegliere il trasporto pubblico ti premia!
Scarica l'app "*Toscana dove, cosa*", guadagna punti viaggiando in autobus e vinci tanti fantastici premi!
Per maggiori informazioni visita il sito info.sii-mobility@org
TOSCANA
cpt
MIUR
UNIVERSITÀ DEGLI STUDI FIRENZE
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In palio per te
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FARMACIE COMUNALI PISA
Ci Prendiamo cura del tuo benessere
ZONE CITY
MULTISALA ODEON
TEATRO DI PISA


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TOSCANA
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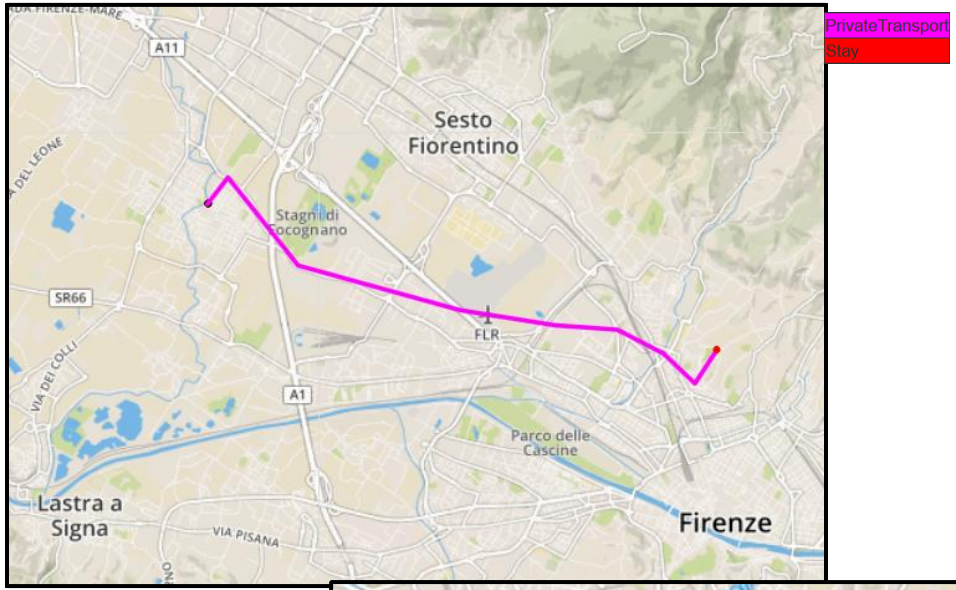
REWARDING'S RULES

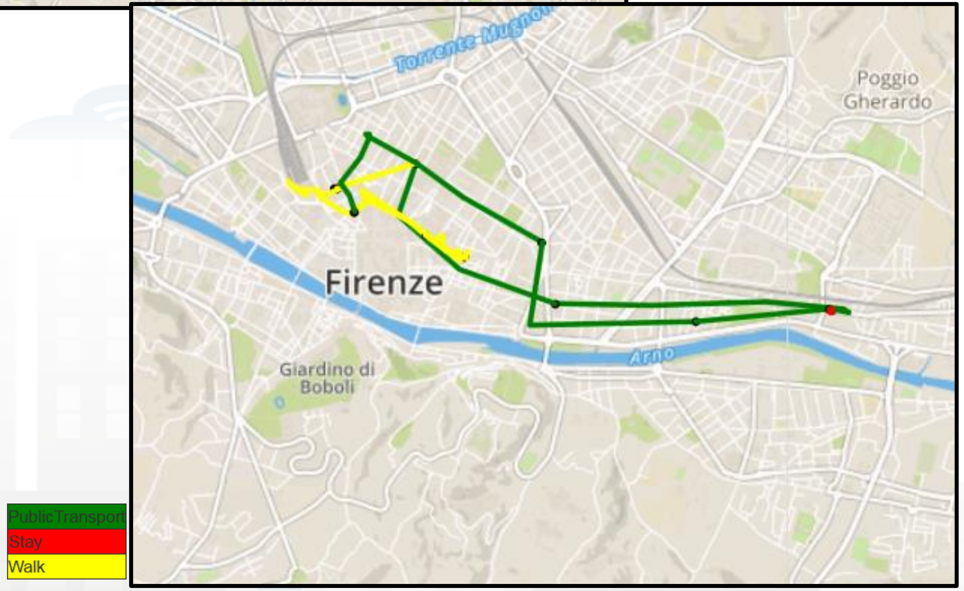
- **ASSISTANCE**
- If public transport is detected after bus line suggestion on trajectory usually made on private transport → 10points
  - Why don't you take the bus line 4 in Piazza Marconi to reach your workplace? You save money, you respect the environment and you will be stress free for not worry about parking!
- Once a day, if public transport is detected after suggestion on an alternative bus line availability →3points
  - Why don't you take the bus line 4 that stop just 50 meters far from you? You save money, you respect the environment and you will be stress free for the traffic jam!
- If public transport is detected for at least 30(?) minutes a day → 1point

- **ENGAGEMENT**
- Survey on commuter and their preferred way of mobility → 1point
  - How many minutes you usually commute to go to work? How do you rate the service?
- Feedback on public transport →1point
  - Which current public transport are you using? Are the service in line with your expectation?
- Comments/Photo/Rate or survey on POI (public transport) →1point
- Survey on use of the App after N days or for tourist coming home → 1point
- Feedback on PPOI or mobility → 1point

WALLET / PROFILE

- On homepage
  - How many points have been distributed?
  - How many rewards has been already delivered?
  - How many rewards are still available?
  - How many CO2 has been saved?
  - How many km our users made this week?





CURRENT NUMBERS

- 50 engagement's rules in 5 languages
  - (surveys, feedbacks, suggestions, assistances)
- From1° September 2016
  - Produced 322.900 engagements on 4270 users
- From 1° July 2017
  - 233 registered users with email (154 via social)

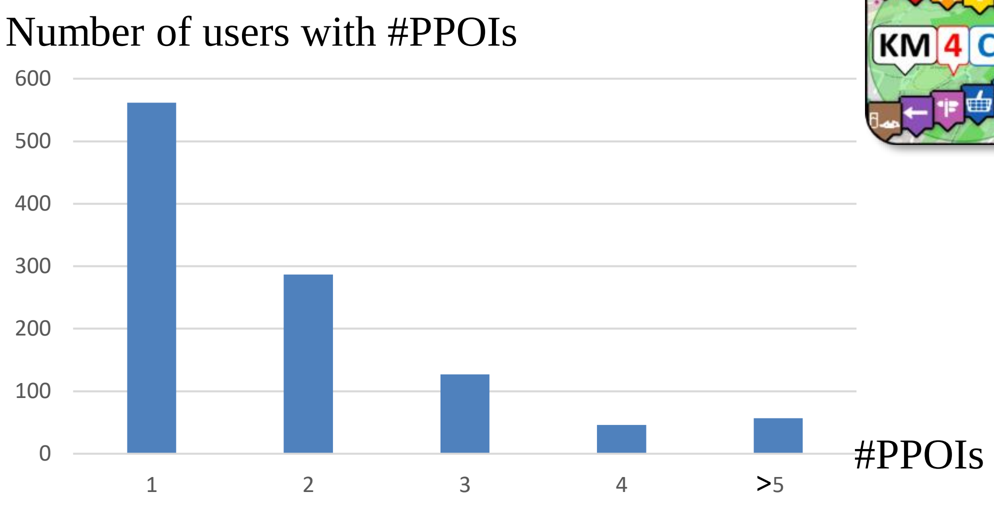
From: 2016-08-01 00:00:00
To: 2017-05-26 11:19:52
Refresh

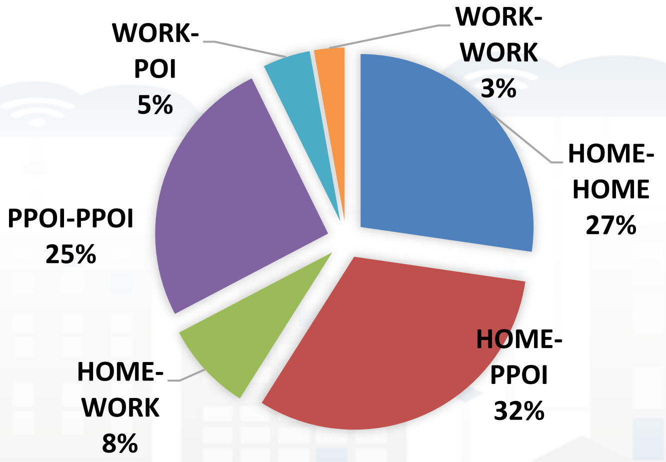
Rule name	Type	#sent	#viewed	#viewed on #sent	#executed	#executed on #viewed	Description
confirm_ppoi_home_de	ENGAGEMENT	4 (0%)	1 (0.03%)	25%	0 (0%)	0%	Ask (in german) a confirmation of the position of user's HOME
confirm_ppoi_home_en	ENGAGEMENT	90 (0.03%)	0 (0%)	0%	0 (0%)	0%	Ask (in english) a confirmation of the position of user's HOME
confirm_ppoi_home_es	ENGAGEMENT	13 (0.01%)	1 (0.03%)	7.69%	1 (1.04%)	100%	Ask (in spanish) a confirmation of the position of user's HOME
confirm_ppoi_home_fr	ENGAGEMENT	1 (0%)	0 (0%)	0%	0 (0%)	0%	Ask (in french) a confirmation of the position of user's HOME
confirm_ppoi_home_it	ENGAGEMENT	1794 (0.69%)	97 (2.97%)	5.41%	16 (16.67%)	16.49%	Ask (in italian) a confirmation of the position of user's HOME
confirm_ppoi_school_it	ENGAGEMENT	45 (0.02%)	1 (0.03%)	2.22%	1 (1.04%)	100%	Ask (in italian) a confirmation of the position of user's SCHOOL
confirm_ppoi_work_en	ENGAGEMENT	15 (0.01%)	0 (0%)	0%	0 (0%)	0%	Ask (in english) a confirmation of the position of user's WORK
confirm_ppoi_work_it	ENGAGEMENT	368 (0.14%)	37 (1.13%)	10.05%	7 (7.29%)	18.92%	Ask (in italian) a confirmation of the position of user's WORK
daily_event_de	ENGAGEMENT	105 (0.04%)	19 (0.58%)	18.1%	0 (0%)	0%	Suggest (in german) an event currently on in Florence
daily_event_en	ENGAGEMENT	2115 (0.81%)	66 (2.02%)	3.12%	0 (0%)	0%	Suggest (in english) an event currently on in Florence
dai							
dai							
dai							
mo							
mo							
mo							
mo							
mo							

parking_it	ASSISTANCE	659 (0.25%)	75 (2.3%)	11.38%	0 (0%)	0%	Alert (in italian) if the user parked in a residential parking zone
shoot_a_photo_de	ENGAGEMENT	604 (0.23%)	4 (0.12%)	0.66%	0 (0%)	0%	Ask (in german) a contribution for a nearby point-of-interest
shoot_a_photo_en	ENGAGEMENT	11159 (4.29%)	37 (1.13%)	0.33%	0 (0%)	0%	Ask (in english) a contribution for a nearby point-of-interest
shoot_a_photo_es	ENGAGEMENT	2140 (0.82%)	11 (0.34%)	0.51%	1 (1.04%)	9.09%	Ask (in spanish) a contribution for a nearby point-of-interest
shoot_a_photo_fr	ENGAGEMENT	2880 (1.11%)	4 (0.12%)	0.14%	0 (0%)	0%	Ask (in french) a contribution for a nearby point-of-interest
shoot_a_photo_it	ENGAGEMENT	216479 (83.29%)	976 (29.88%)	0.45%	14 (14.58%)	1.43%	Ask (in italian) a contribution for a nearby point-of-interest
spent_time_en	ENGAGEMENT	53 (0.02%)	14 (0.43%)	26.42%	0 (0%)	0%	Ask (in english) a confirmation of the position of user's POI
spent_time_it	ENGAGEMENT	1192 (0.46%)	175 (5.36%)	14.68%	15 (15.63%)	8.57%	Ask (in italian) a confirmation of the position of user's POI
	- commuter	24 (2.01%)	2 (1.14%)	8.33%	0 (0%)	0%	
	- student	131 (10.99%)	11 (6.29%)	8.4%	2 (13.33%)	18.18%	
	- tourist	238 (19.97%)	59 (33.71%)	24.79%	0 (0%)	0%	
	- citizen	665 (55.79%)	122 (69.71%)	18.35%	10 (66.67%)	8.2%	
	- operator	26 (2.18%)	5 (2.86%)	19.23%	1 (6.67%)	20%	
	- all	155 (13%)	23 (13.14%)	14.84%	2 (13.33%)	8.7%	
survey_turist_de	ENGAGEMENT	179 (0.07%)	15 (0.46%)	8.38%	1 (1.04%)	6.67%	Propose (in german) a survey to turist after they left Florence
survey_turist_en	ENGAGEMENT	966 (0.37%)	13 (0.4%)	1.35%	2 (2.08%)	15.38%	Propose (in english) a survey to turist after they left Florence
survey_turist_es	ENGAGEMENT	115 (0.04%)	2 (0.06%)	1.74%	0 (0%)	0%	Propose (in spanish) a survey to turist after they left Florence
survey_turist_fr	ENGAGEMENT	51 (0.02%)	2 (0.06%)	3.92%	0 (0%)	0%	Propose (in french) a survey to turist after they left Florence
survey_turist_it	ENGAGEMENT	1006 (0.39%)	42 (1.29%)	4.17%	6 (6.25%)	14.29%	Propose (in italian) a survey to turist after they left Florence

CURRENT NUMBERS

- From 1° September 2016
  - Detected 2108 PPOIs on 1080 users
    - 437 HOME
    - 285 WORK
    - 34 SCHOOL
    - 1350 EXTRA
  - 130 PPOIs are feedbacked
  - 460 survey responses
- From 1° August 2017
  - Built 524 Markov Networks about user’s trajectories

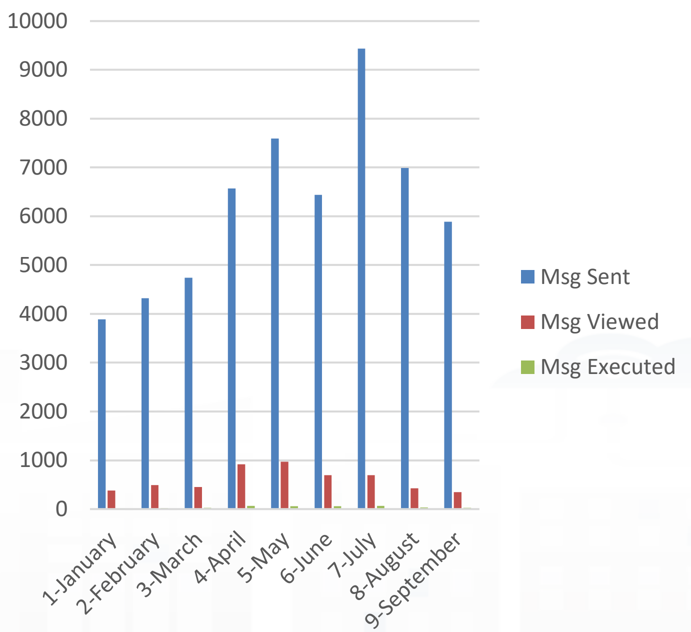


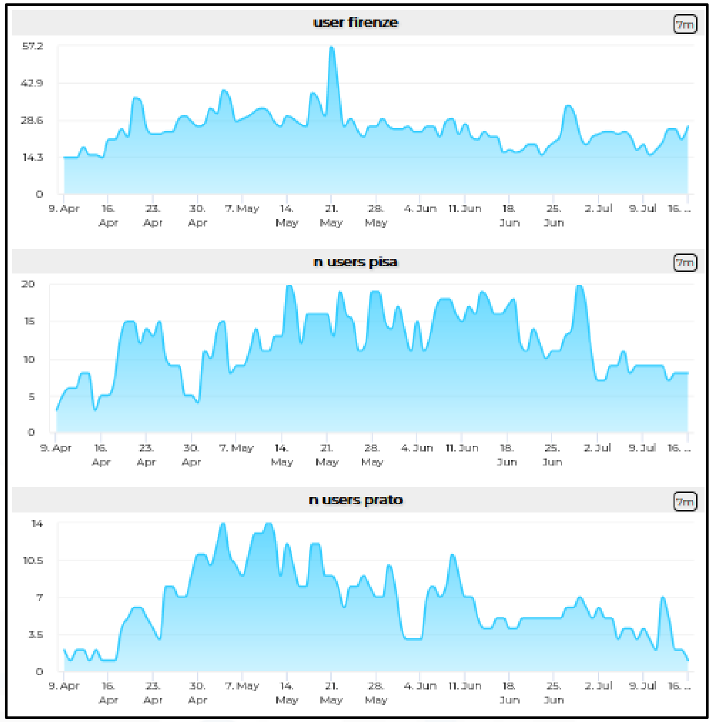


Validation of user Engagement

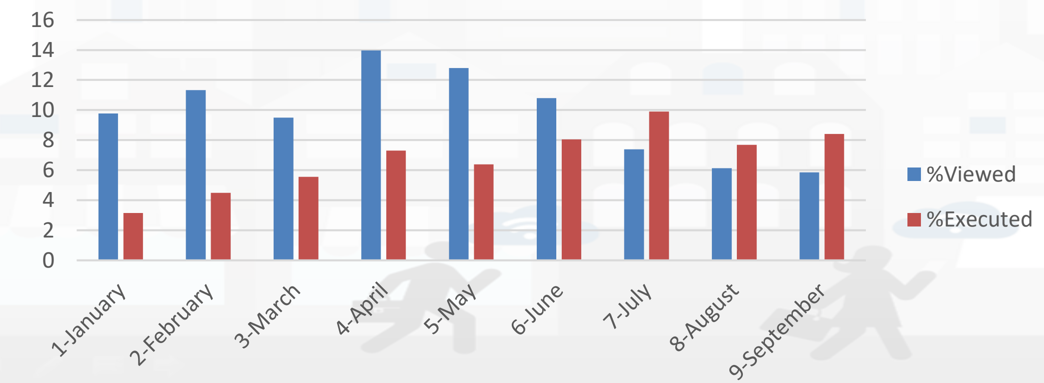
Months	Msg Sent	Msg Viewed	Msg Executed
1-January	3888	380	12
2-February	4319	489	22
3-March	4739	450	25
4-April	6567	918	67
5-May	7594	972	61
6-June	6437	695	55
7-July	9432	697	69
8-August	6988	429	73
9-September	5885	345	49
Total	55849	5375	433

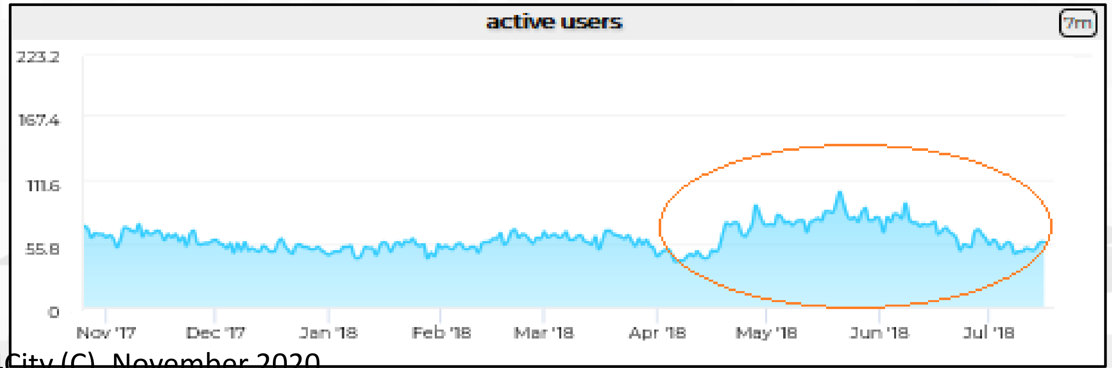
#Msg





%Msg



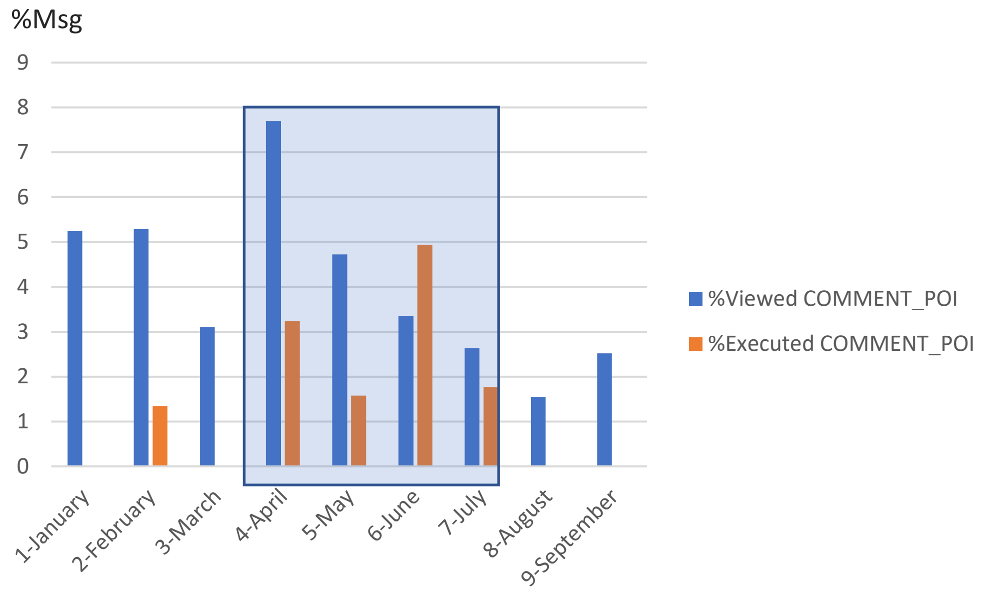


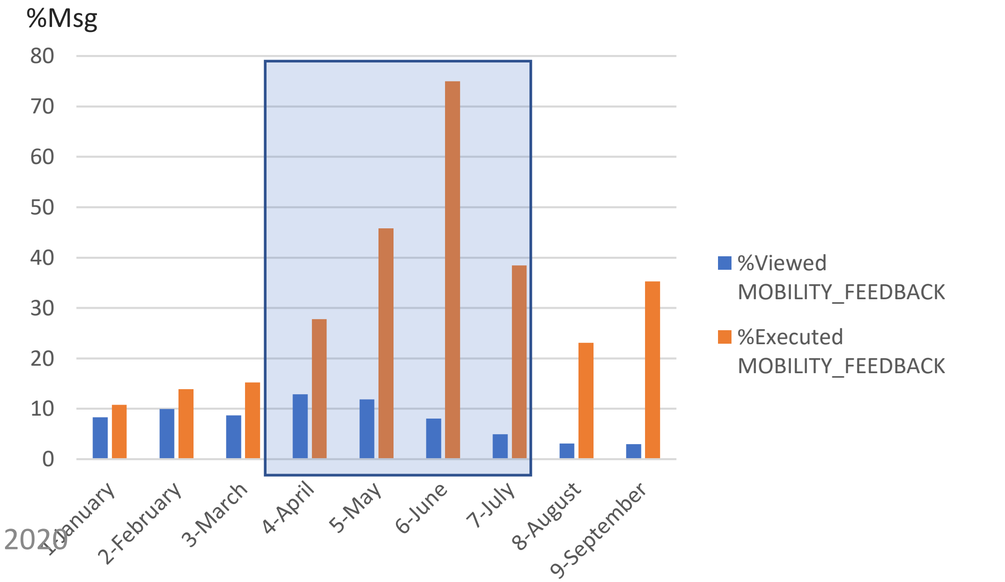
User Behaviour Analysis

VALIDATION

- **During the PILOT new rules has been added (30 on a total of 80) and mostly all of them are still online**
- COMMENT_POI: requires more user interaction and not very contextualized (POI proximity) → higher rate of sent, lower rate on execution
- MOBILITY_FEEDBACK: requires less user iteration and very contextualized (user in MOBILITY) → normal rate of sent, high rate on execution

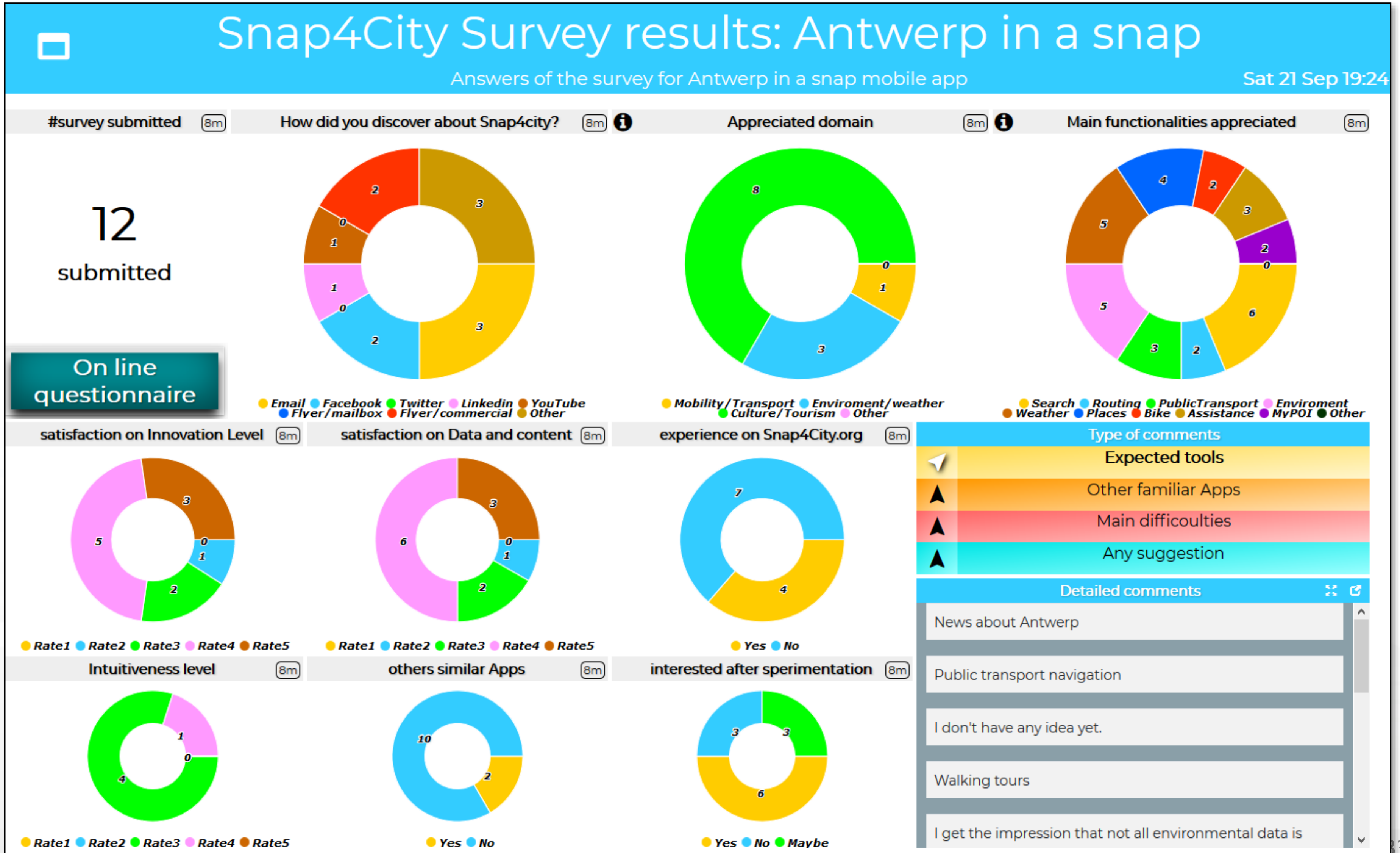
	Msg Sent	Msg Viewed	Msg Executed
COMMENT_POI	21632	804	15
MOBILITY_FEEDBACK	5378	371	94





https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTc2OQ==

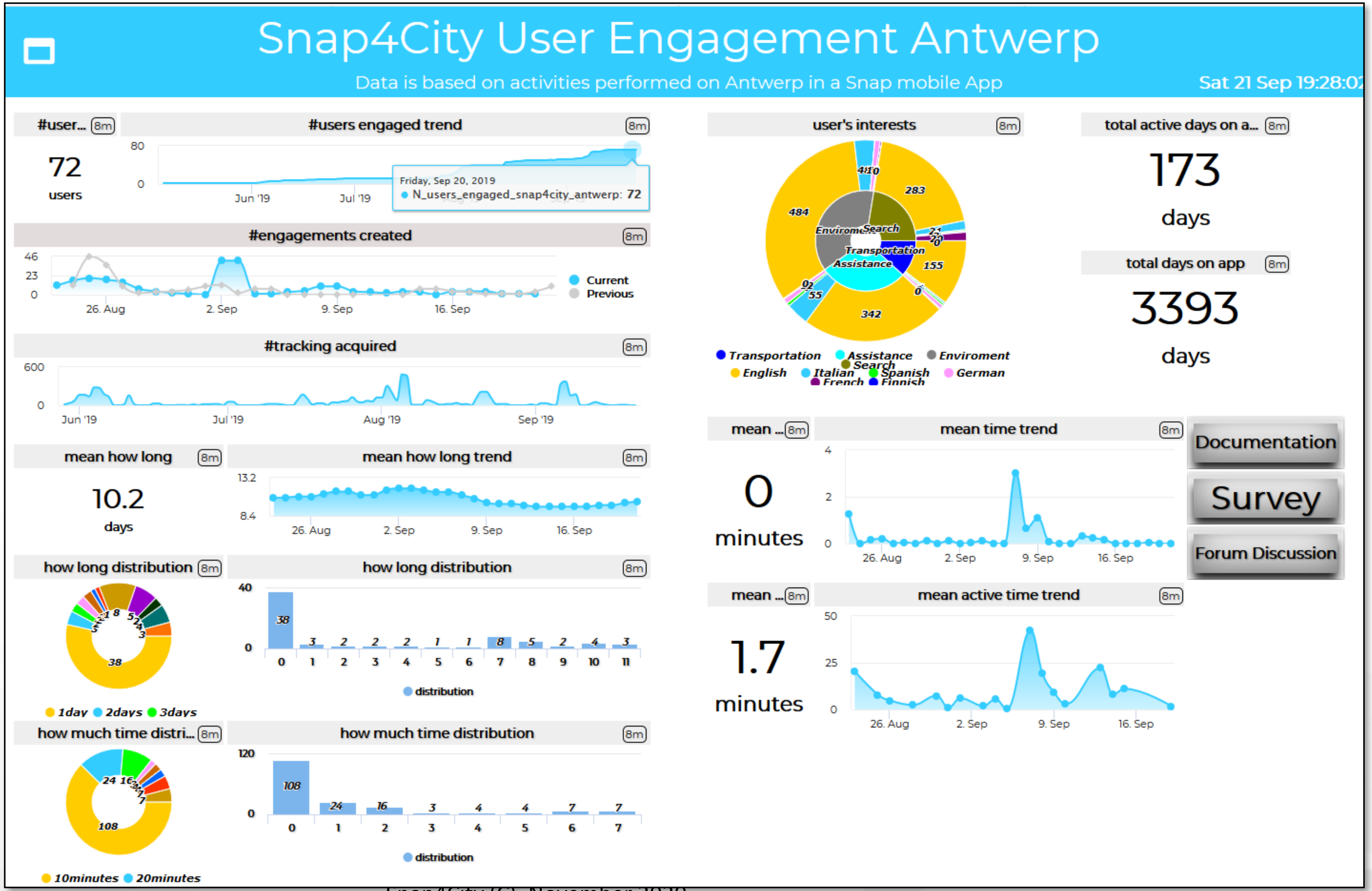
Dashboard created to monitor in real time the answers to the survey provided on the Mobile App directly by the Engagement tool



https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTc1OQ==

Dashboard monitoring the Mobile App:

- Collecting the clicks
- Describing the community of users in terms of the profile aspects
- Measuring the time spend, and topics of interest of the users, etc.



TOP

DECISION SUPPORT SYSTEM AND CITY RESILIENCE

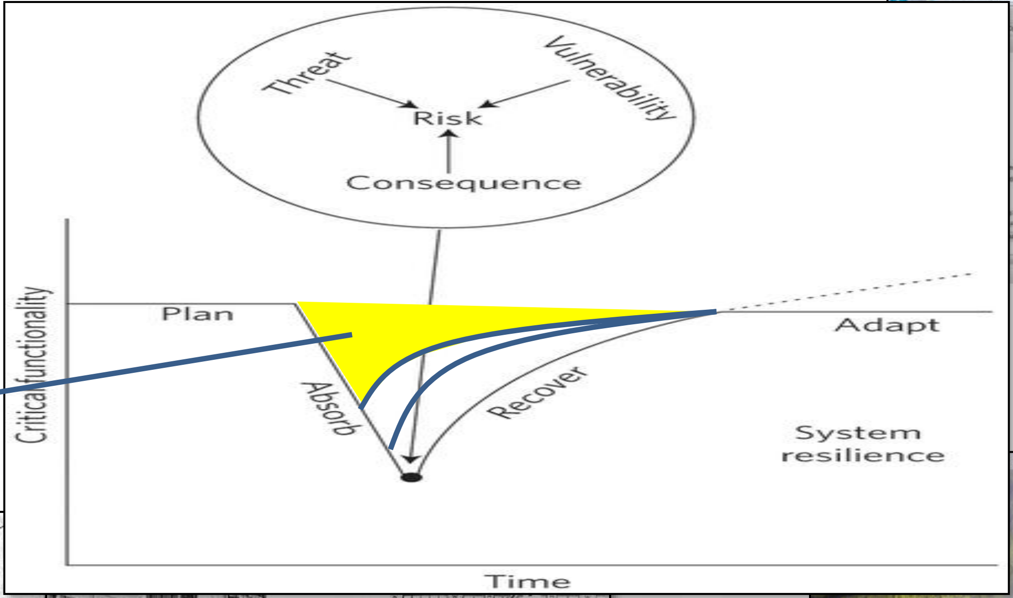

SIGNORVINO

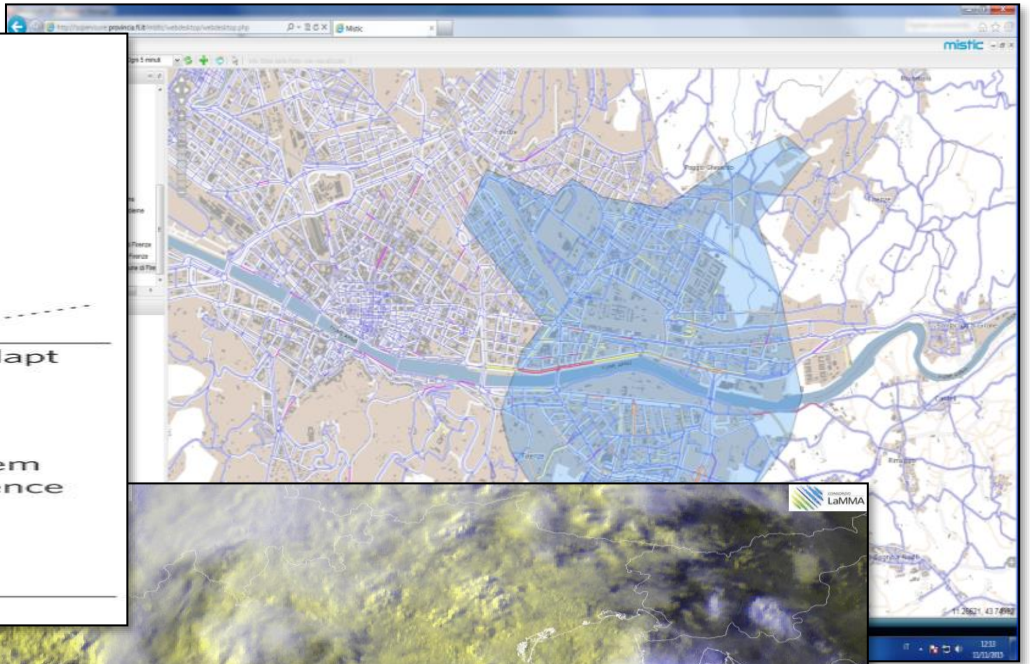
City Resilience

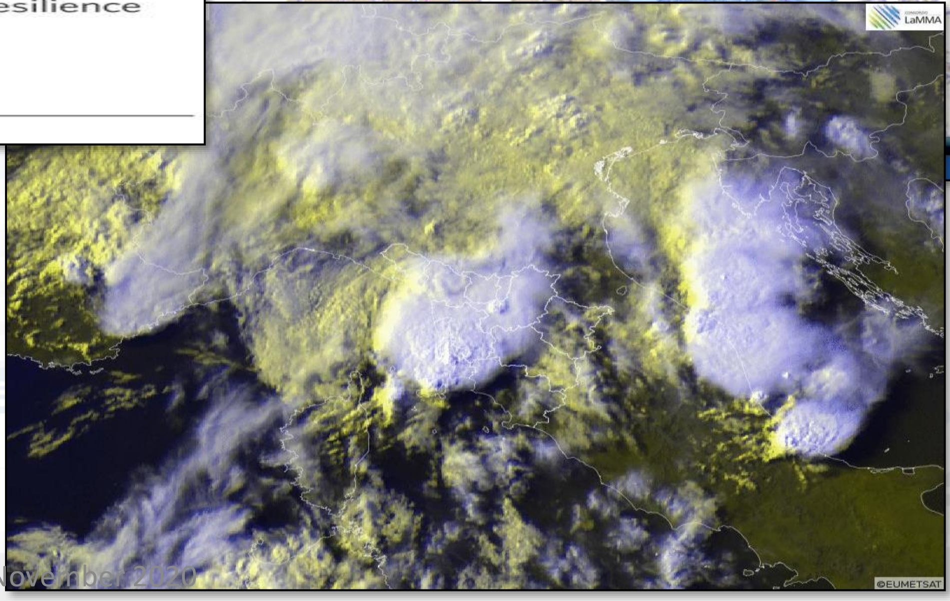
Early Warning, Detection

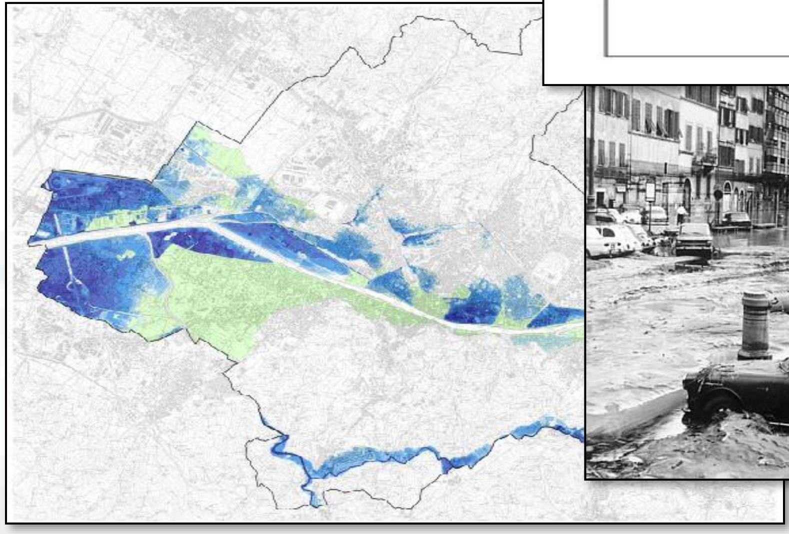
Prepare
Absorb
Recover
Adapt

damage









Early Warning, Detection

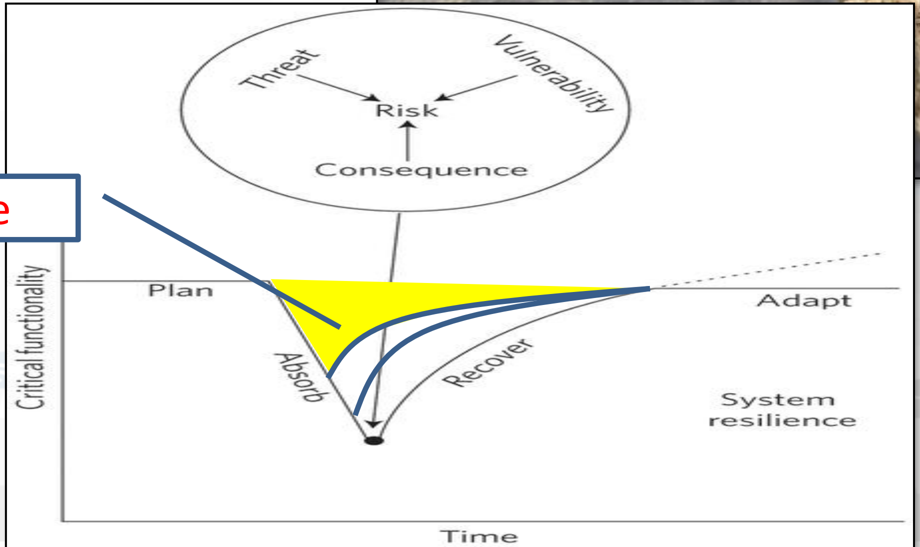
Issue:
- Detection of critical condition
- Not easily detected with other means

Impact:
- Early warning, faster reaction
- Increased resilience

Several metrics related to:
- Volume of retweets
- Sentiment analysis

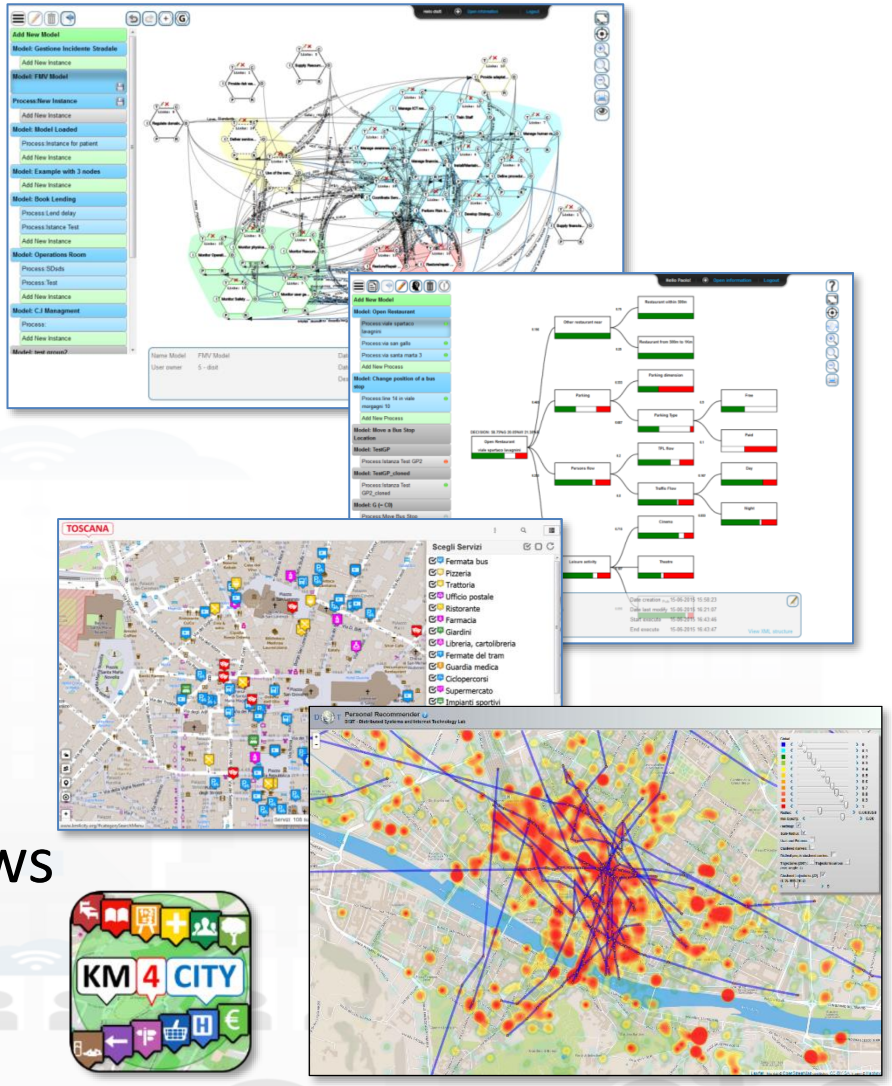
Prepare
Absorb
Recover
Adapt

damage



Main Approach

- Three main layers
- Complex System modeling: function, processes, resources, time, events, etc.
  - Functional Resonance Analysis Method, FRAM
  - Resilience Analysis Grid, RAG
- Decision Support System, DSS
  - System Thinking, Goal Models
  - Risk analysis
  - UTS/ITS decision supports
- Data, big data access and exploitation
  - Data Analytics, Internet of Things, sensors, flows
  - People flow and behavior
  - Social Media

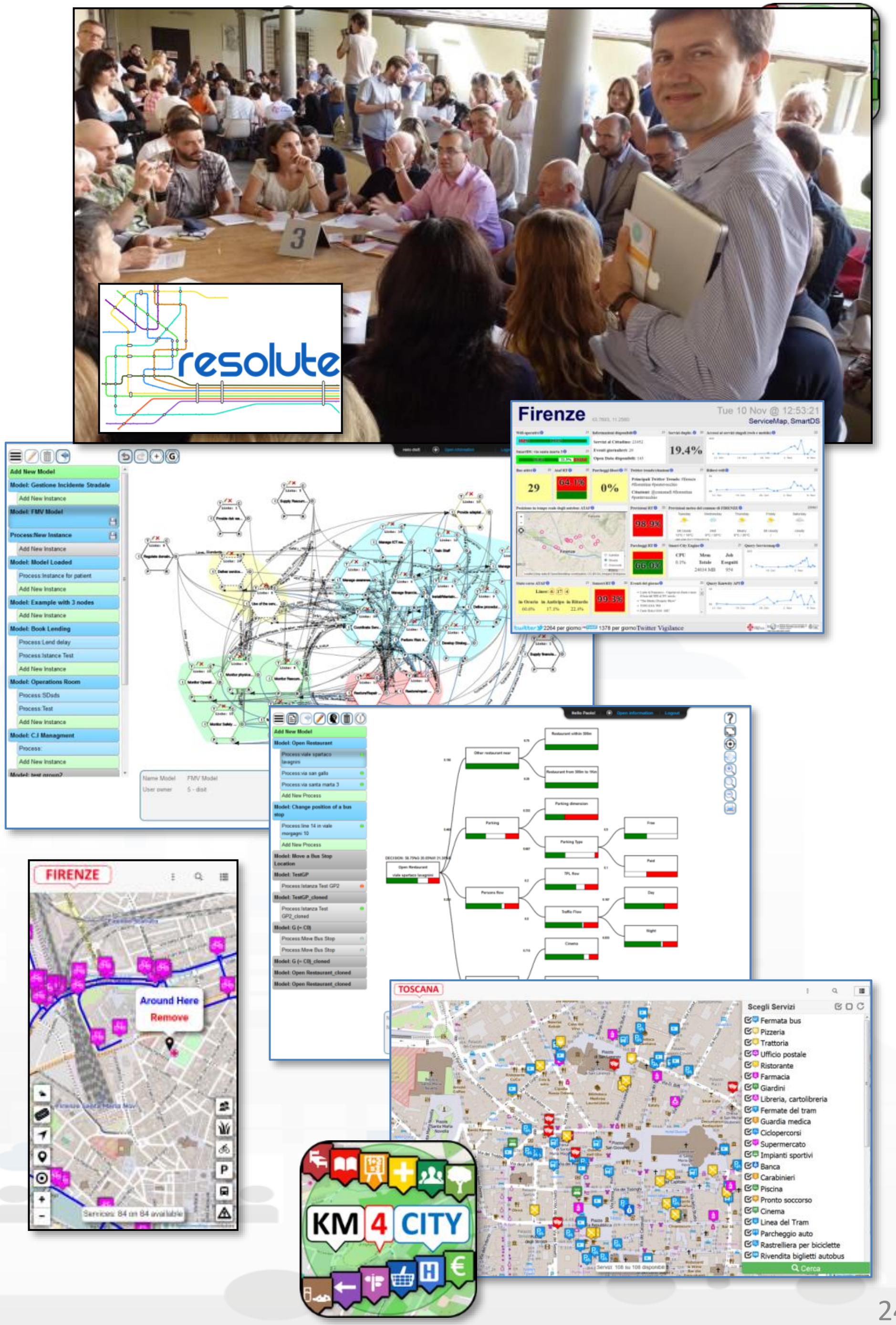


ERMG: European Resilience Management Guide

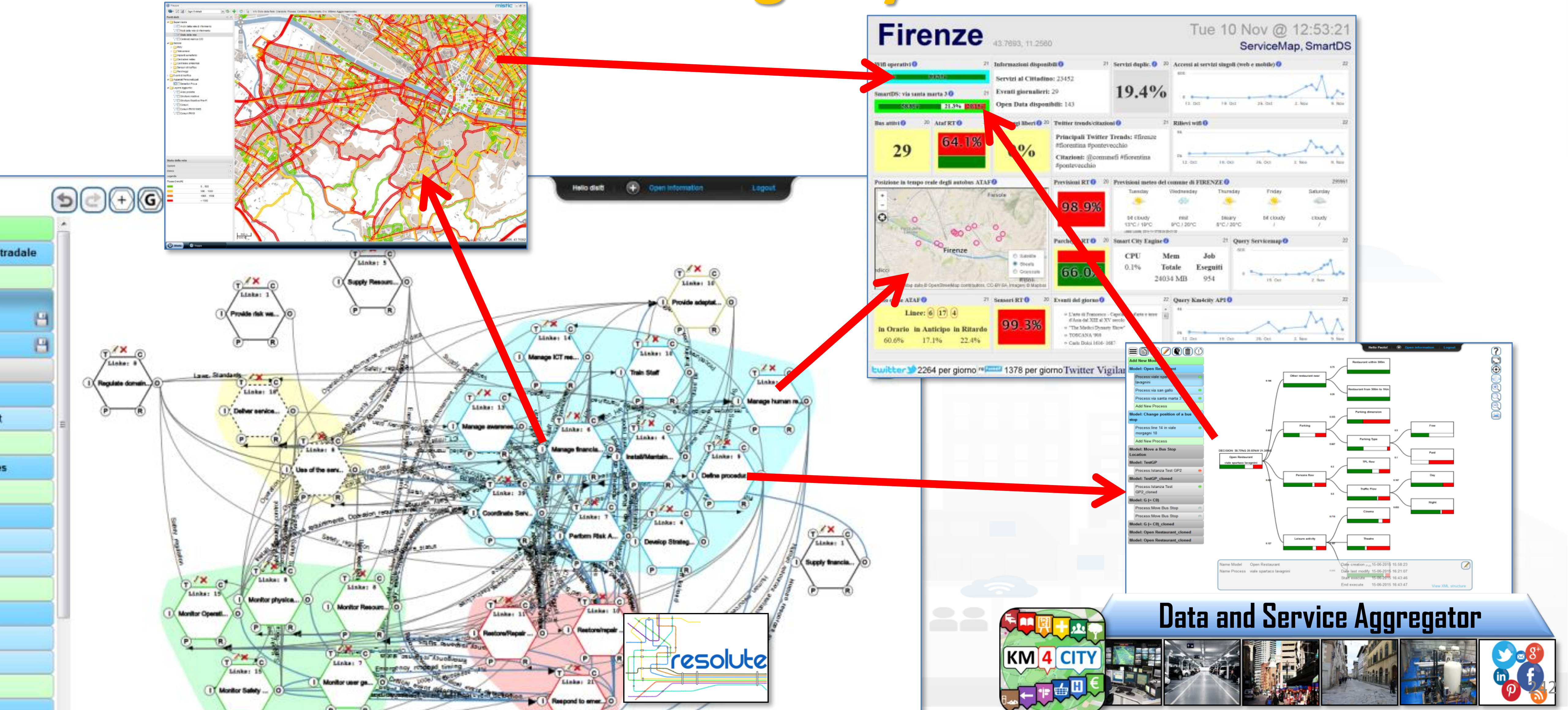
http://www.resolute-eu.org/

Improve city resilience, reducing risks and decision support

- **assessing** city **resilience** level
- **improving** city **resilience**, providing objective hints
- **improving** city users **awareness** with personal city assistants and participatory tools



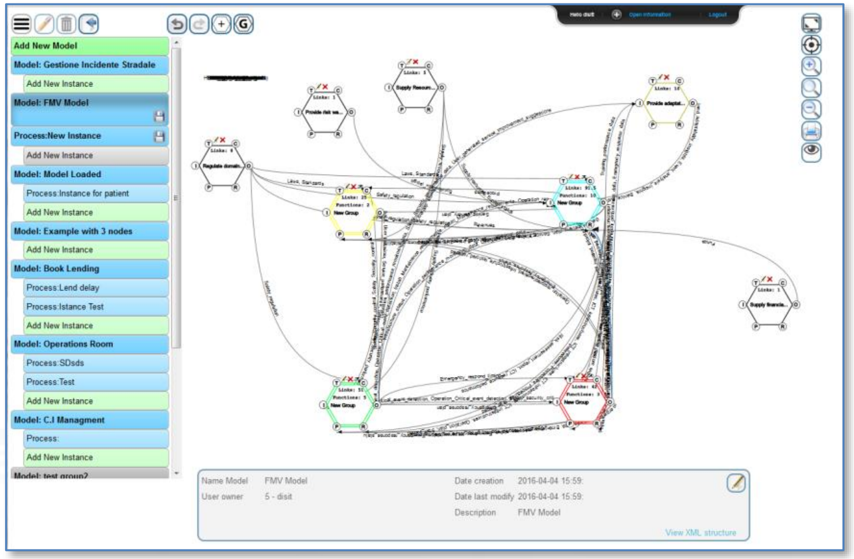
Dashboarding city resilience

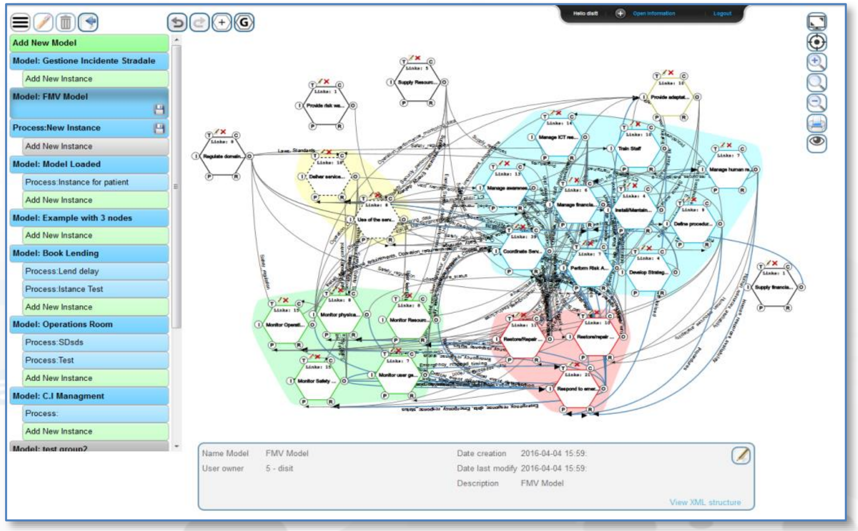


ResilienceDS Tool

http://resilienceds.km4city.org

- **FRAM Model**
  - Macro FRAM processes
  - Metrics for Process complexity assessment
  - Operational Semantic for executing FRAM model
  - Connection with SmartDS
  - Connection with BigData open to multiple sources of data and workgroup results, Km4City
- **Collaborative work, web tool**
- **Open for all**
- **Validated on ERMG: European Guidelines**



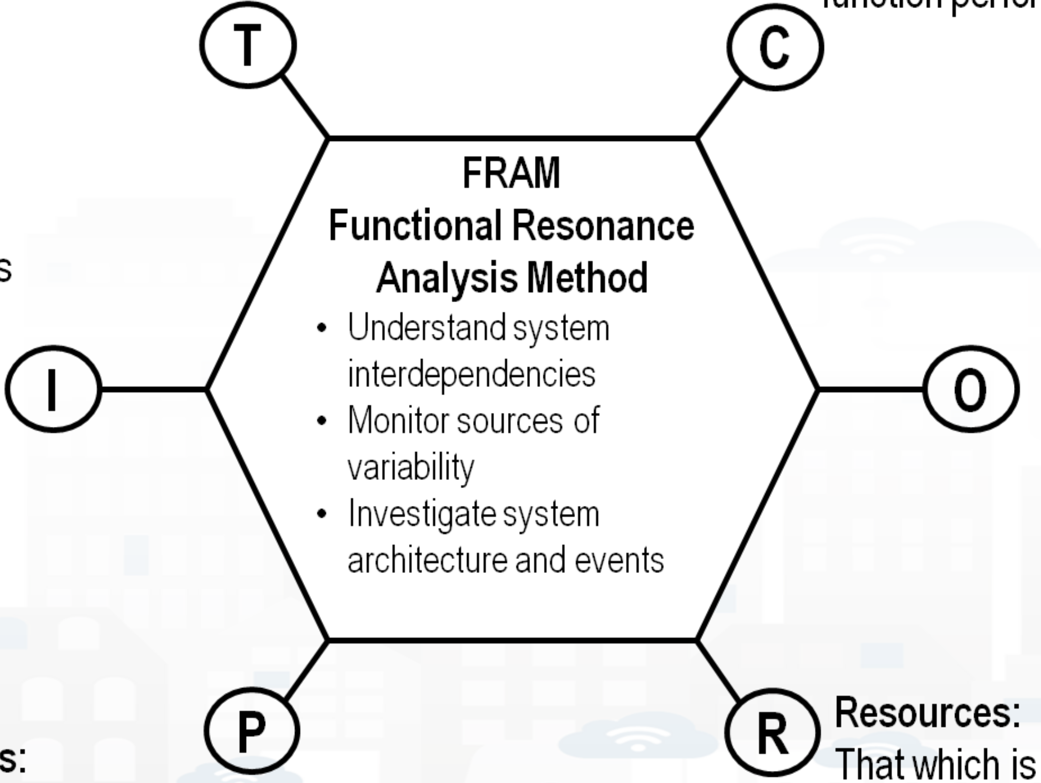


Functional Resonance Analysis Method

Time:
This is simultaneously a resource and a constraint

Controls:
That which supervises or adjust function performance

Input:
That which engages function operation and is used to produce the function output



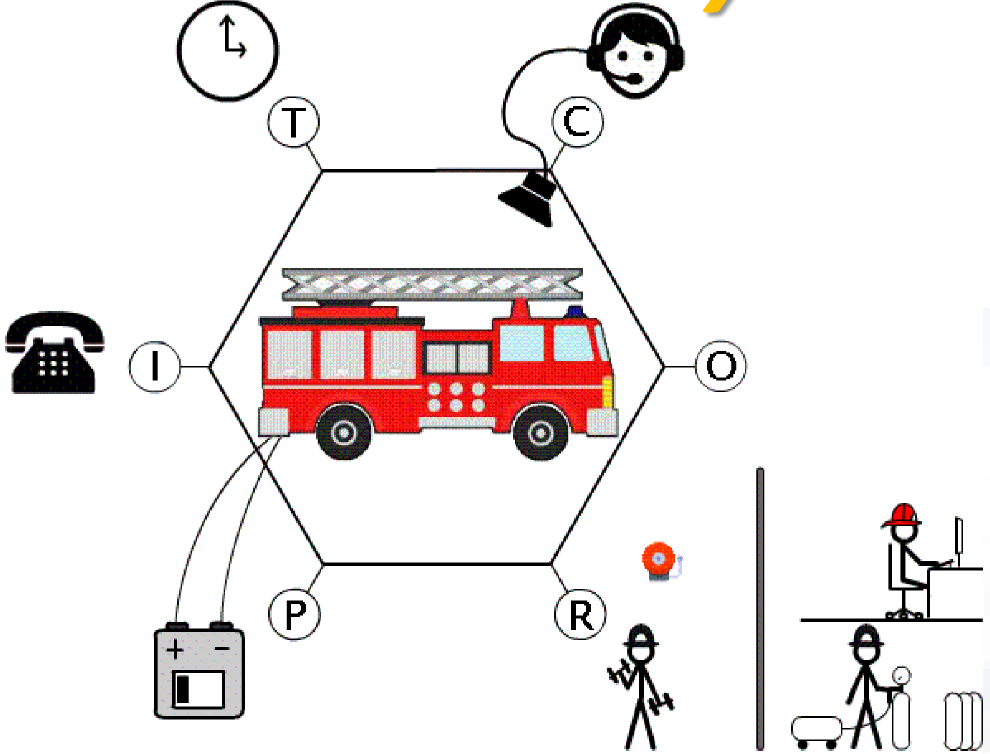
Output:
That which is produced by the function and becomes the input for other functions

Preconditions:
System conditions that must be met before function can be carried out

Resources:
That which is needed and/or consumed by the function to process the input

Fram Model: *Functional Resonance Analysis Method*

- Success and failure are equivalent in the sense that they both emerge from performance variability.
- Variability, intended as a way for people to adjust tools and procedures to match operating conditions.
- Emergence of either success or failure is due to unexpected combination of variability from multiple functions.
- The unexpected “amplified” effects of interactions between different sources of variability are at the origin of the phenomenon described by functional resonance.



resolute

- Success and failure are equivalent in the sense that they both emerge from performance variability.
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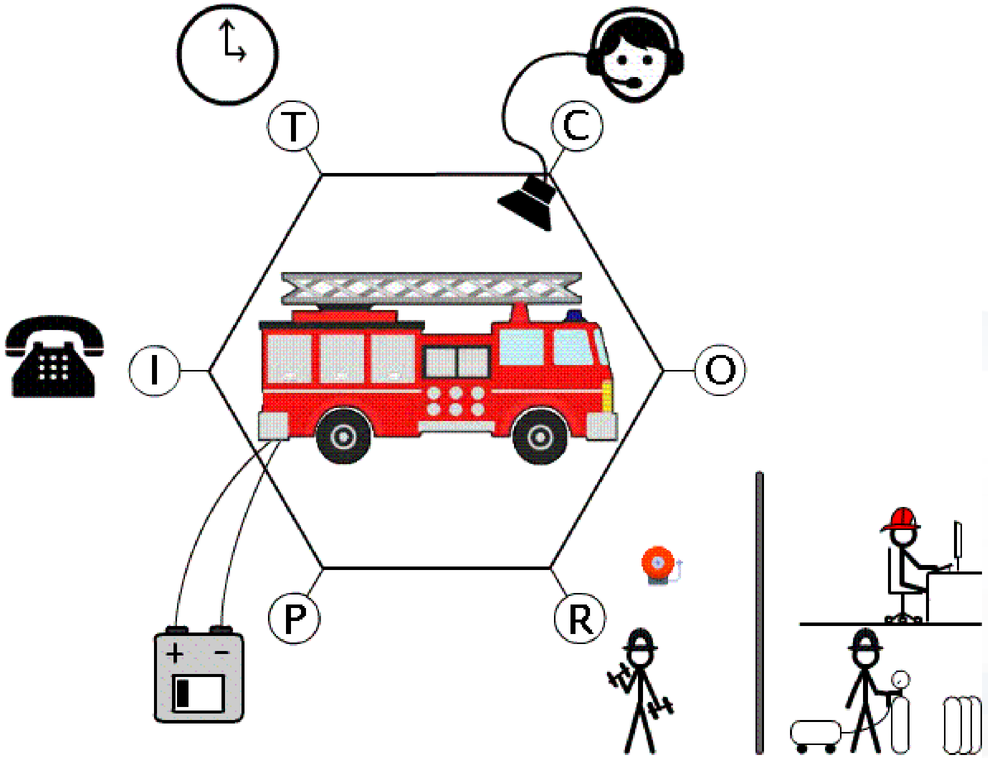
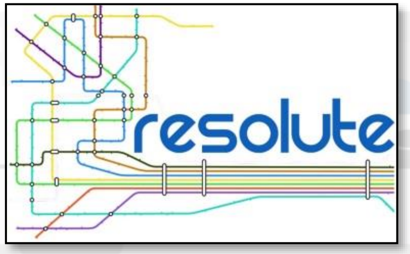
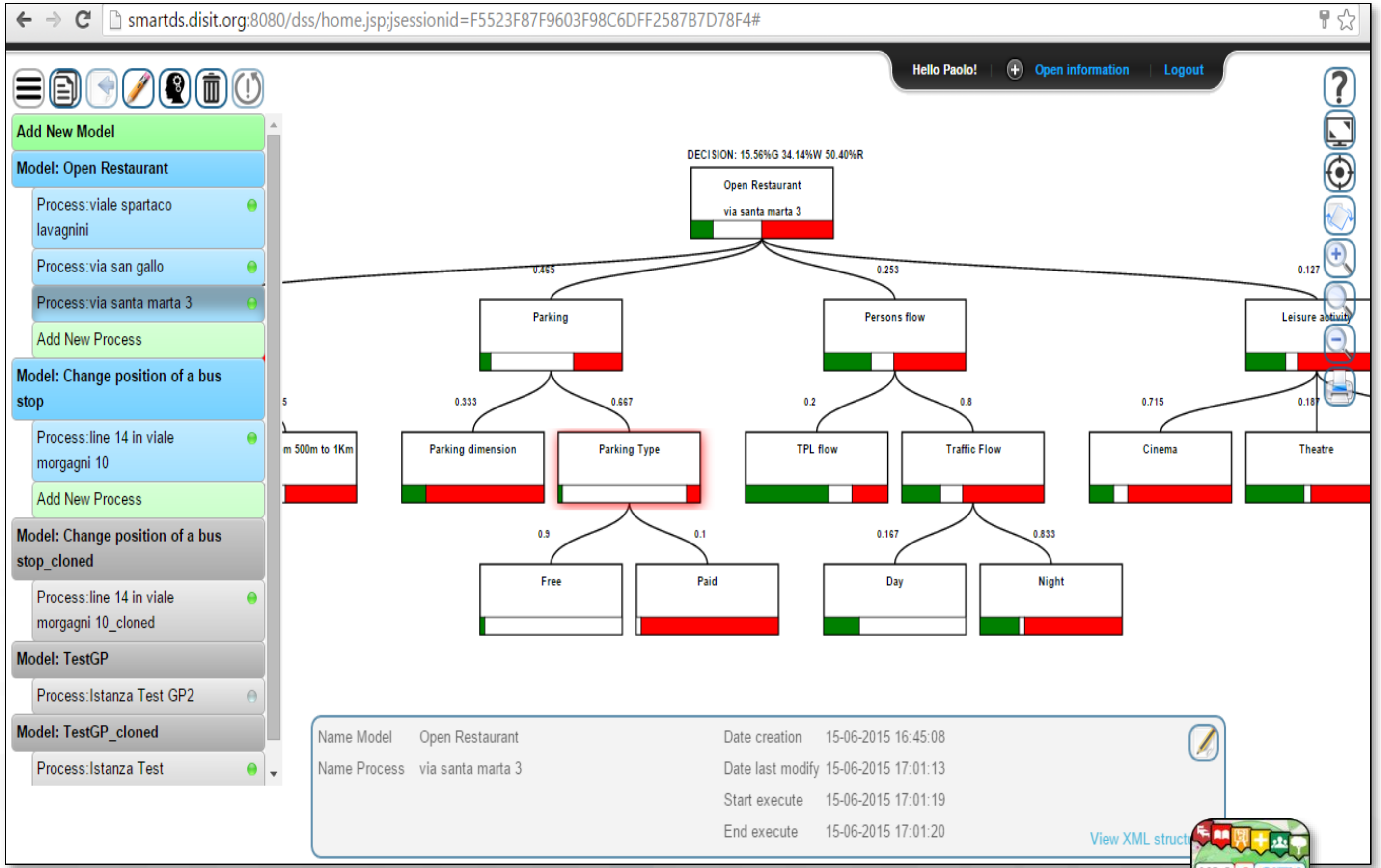




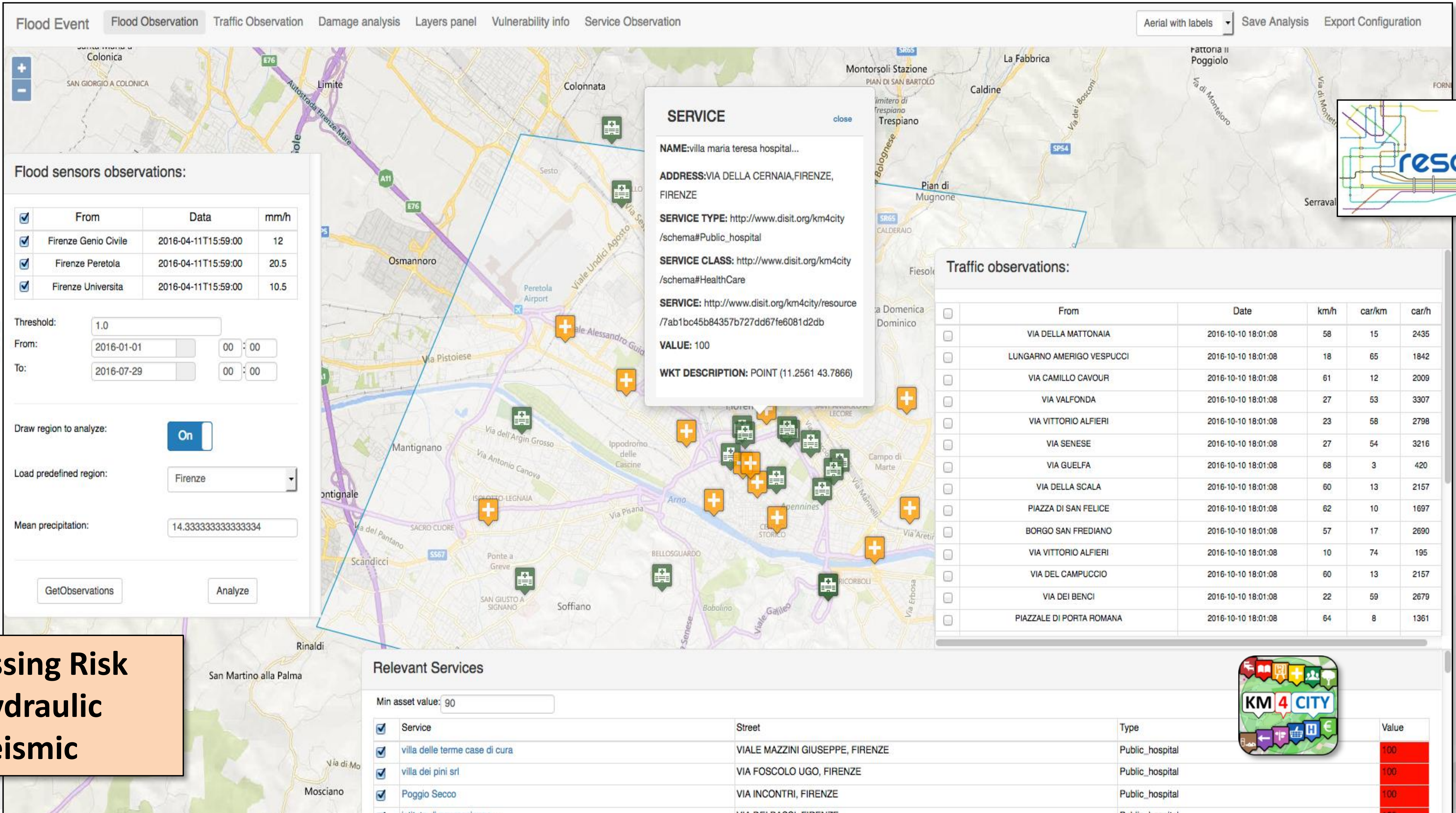
Smart Decision Support , system thinking

- **Smart Decision Support System** based on System Thinking plus
- Actions to city reaction, resilience, smartness, ...
- Enforcing Mathematical model for propagation of decision confidence..
- Collaborative work, ...
- Processes connected to city data: DB, RDF Store, Twitter, etc.
- Production of alerts/alarms
- Data analytics process
- Twitter Processes
- reuse, copy past, ...



http://smartds.km4city.org

Risk Assessment

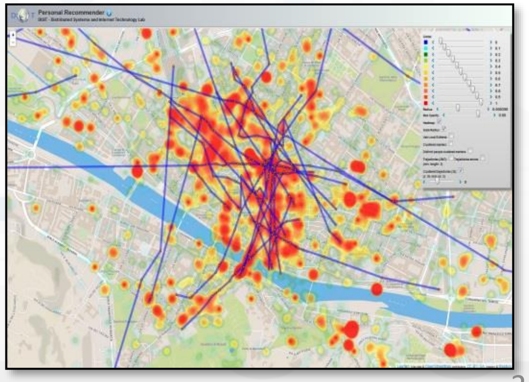


Assessing Risk

- hydraulic
- Seismic

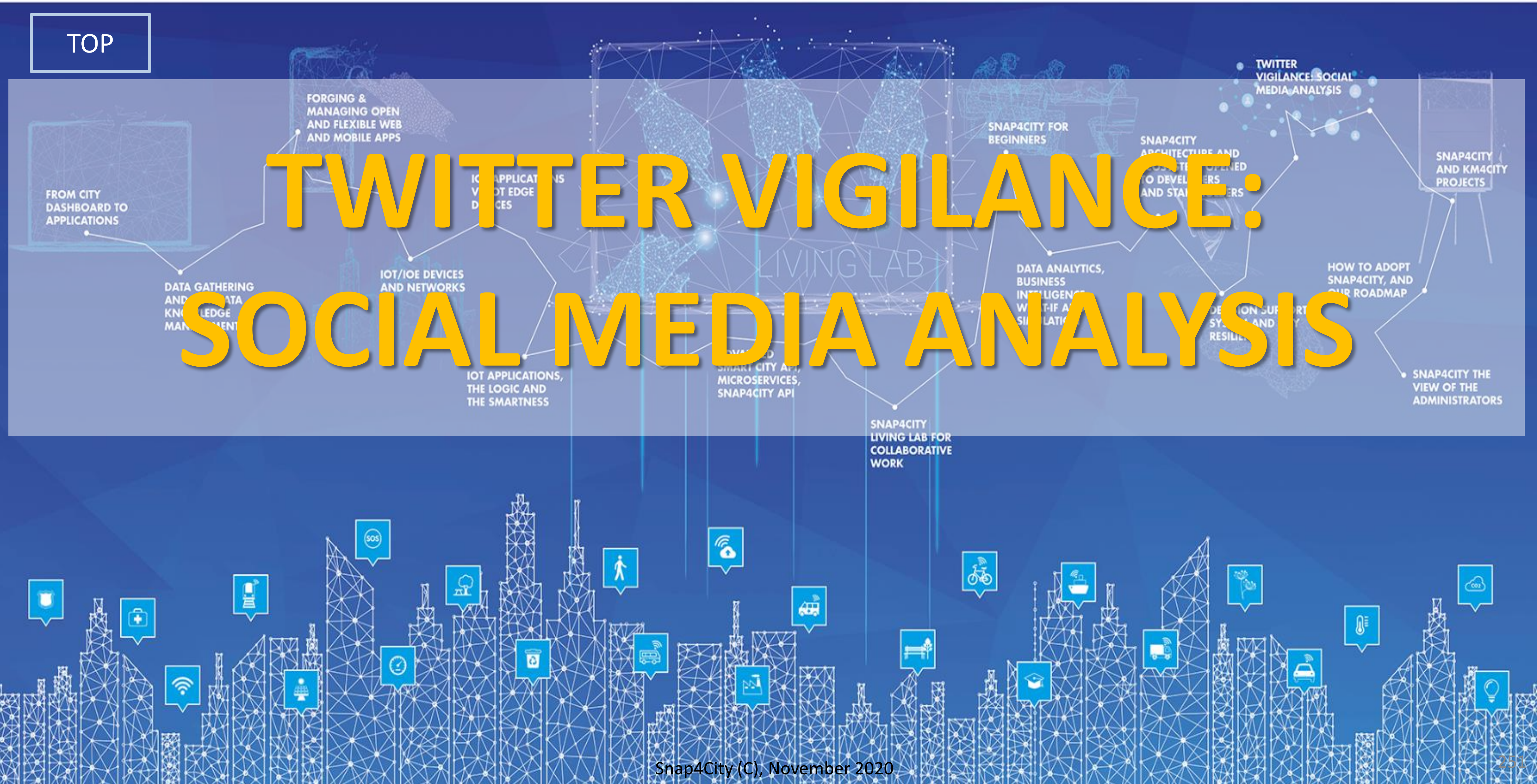
Mobile Emergency

- Personalized menu for Operators
- Providing information and suggestions to citizens
  - Civil Protection Page
  - Twitter Info
  - Geolocalized Info
- Tracking people and operators flows
- Collecting information from citizens
  - Comments
  - Images



TOP

TWITTER VIGILANCE: SOCIAL MEDIA ANALYSIS



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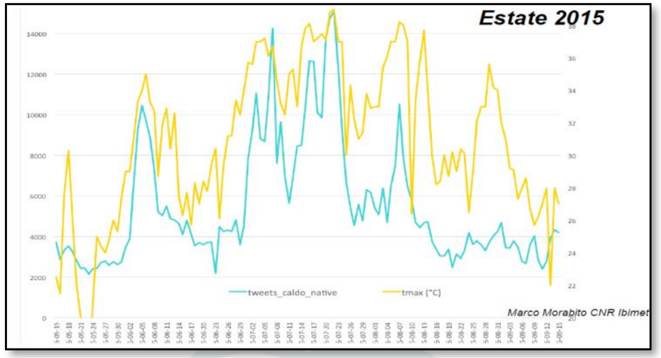
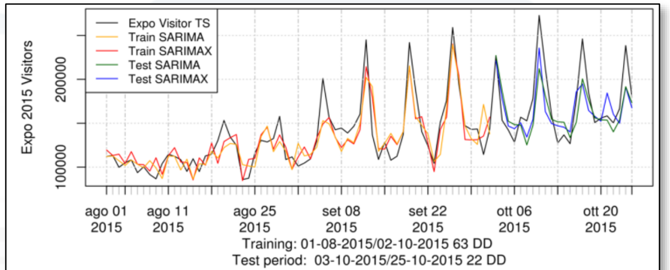
Twitter Vigilance

resolute

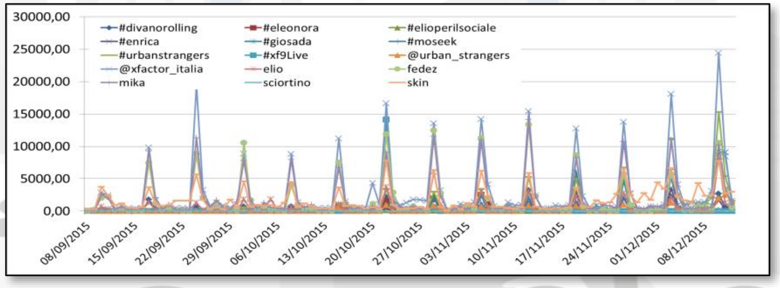
Prediction/Assessment

- Football game results as related to the volume of Tweets
- Number of votes on political elections, via sentiment analysis, SA
- Size and inception of contagious diseases
- marketability of consumer goods
- public health seasonal flu
- box-office revenues for movies
- places to be visited, most visited
- number of people in locations like airports
- audience of TV programmes, political TV shows
- weather forecast information
- Appreciation of services





Training: 01-08-2015/02-10-2015 63 DD
Test period: 03-10-2015/25-10-2015 22 DD
Figure 5: Comparison among the selected predictive models discussed and presented in Tables 2 and 3 with respect to the real number of visitors. Both training and validation periods are reported.



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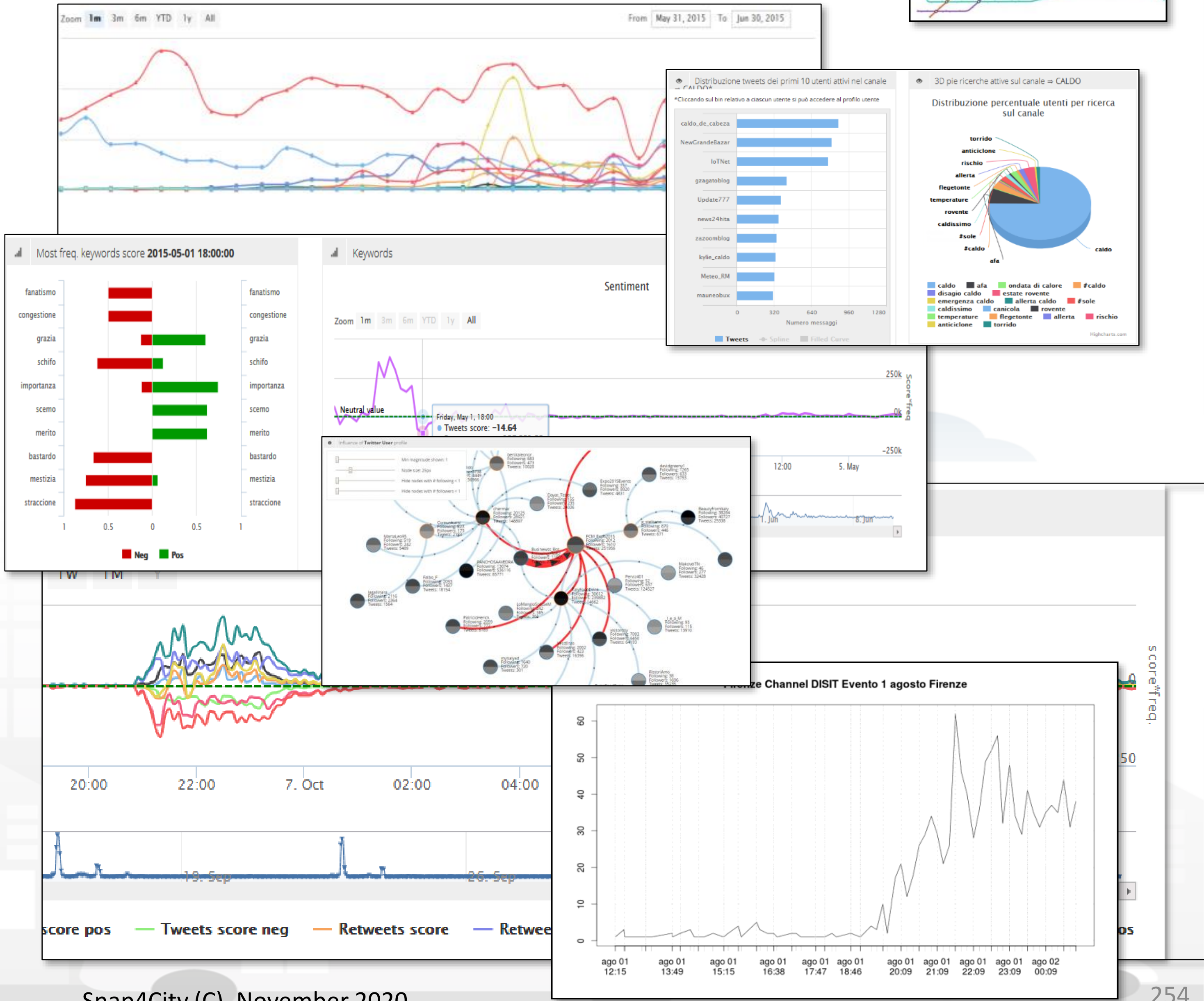
Twitter Vigilance

- http://www.disit.org/tv
- http://www.disit.org/rttv
- Citizens as sensors to
  - Assess sentiment on services, events, …
  - Response of consumers wrt, …
  - Early detection of critical conditions
  - Information channel
  - Opinion leaders
  - Communities
  - Formation
  - Predicting volume of visitors for tuning the services



Twitter Vigilance

Twitter Vigilance in Numbers

- **Used by several users:**
  - UnivFirenze, LAMMA, IBIMET, ARPAT, Master on Big Data, …
- **Active since** Aprile 2015
- **3 platforms for automated**:
  - Daily collection: statistical direct analysis and sentiment analysis
  - Real time collection and statiscal, sentiment analysis
  - Full faceted indexing: thus enabling search on collected tweets
- **All: precomputation of basic metric opening the activities of deep analysis**
- More than 350 million of tweets in the storage: ready on Hadoop cluster
- More than 250 channels
- More than 450 search activities daily
- From 400.000 to 4 Million of tweets per day.

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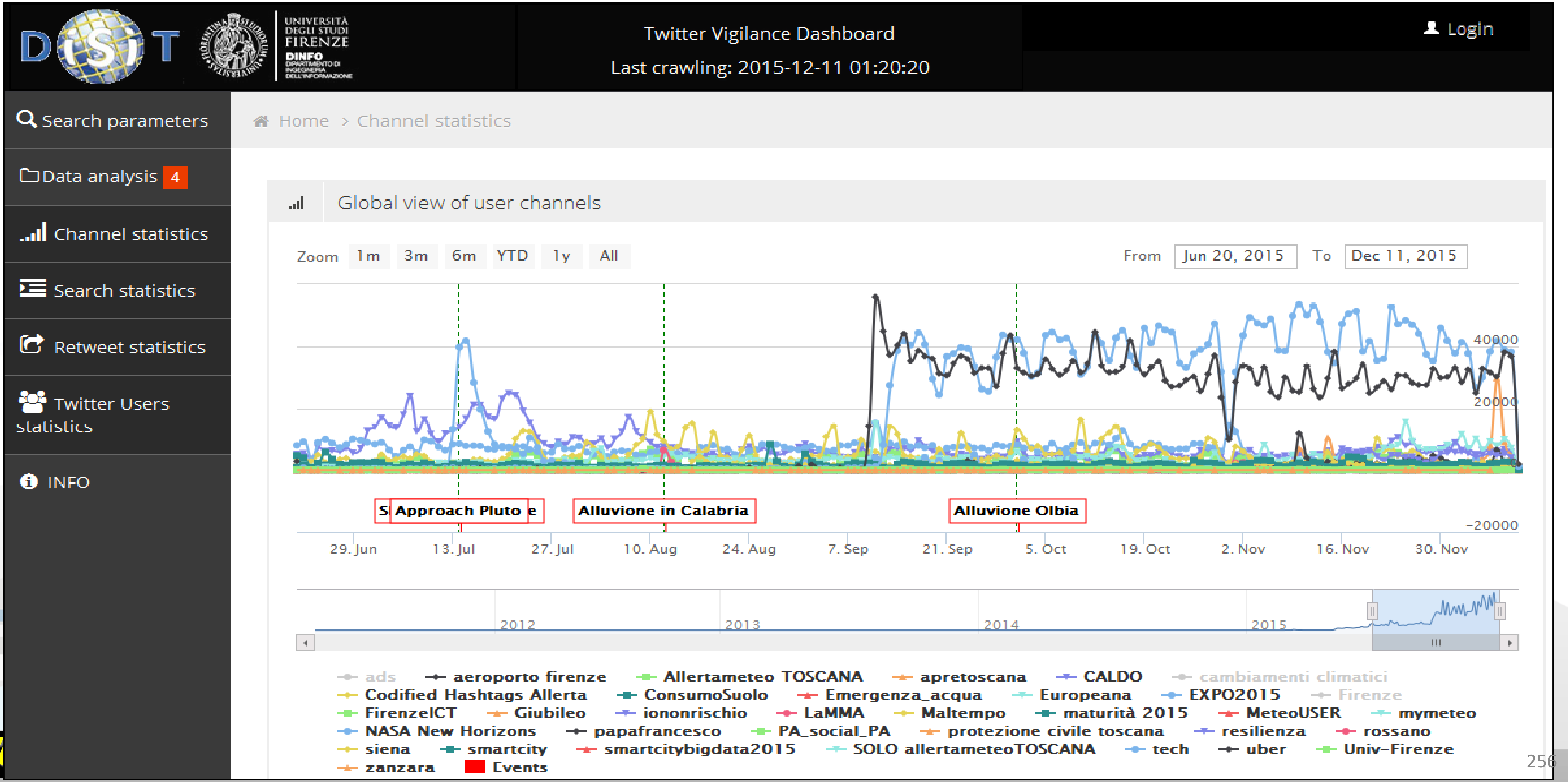
DISIT DISTRIBUTED SYSTEMS AND INTERNET TECHNOLOGIES LAB

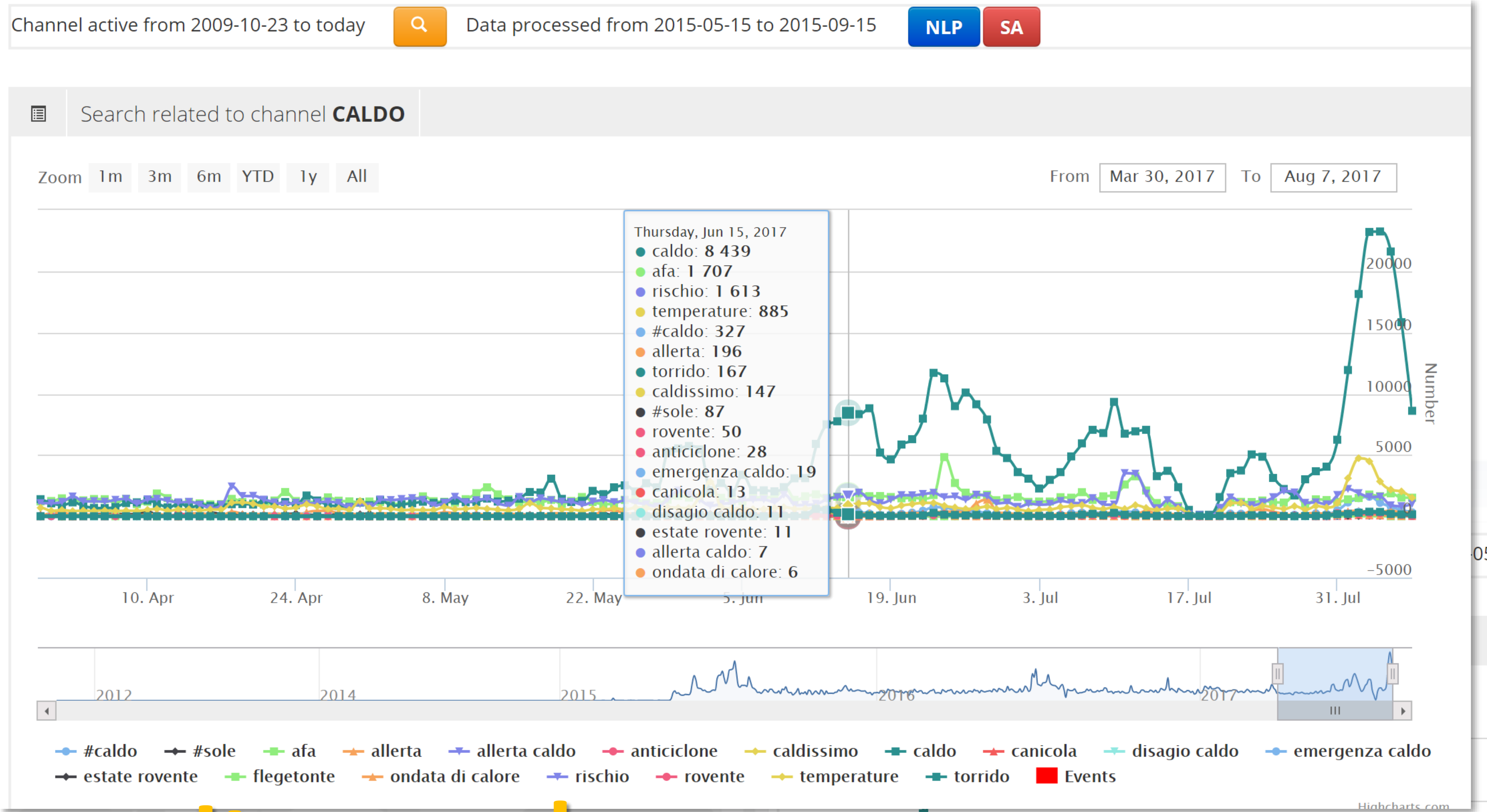
http://www.disit.org

Several Channels

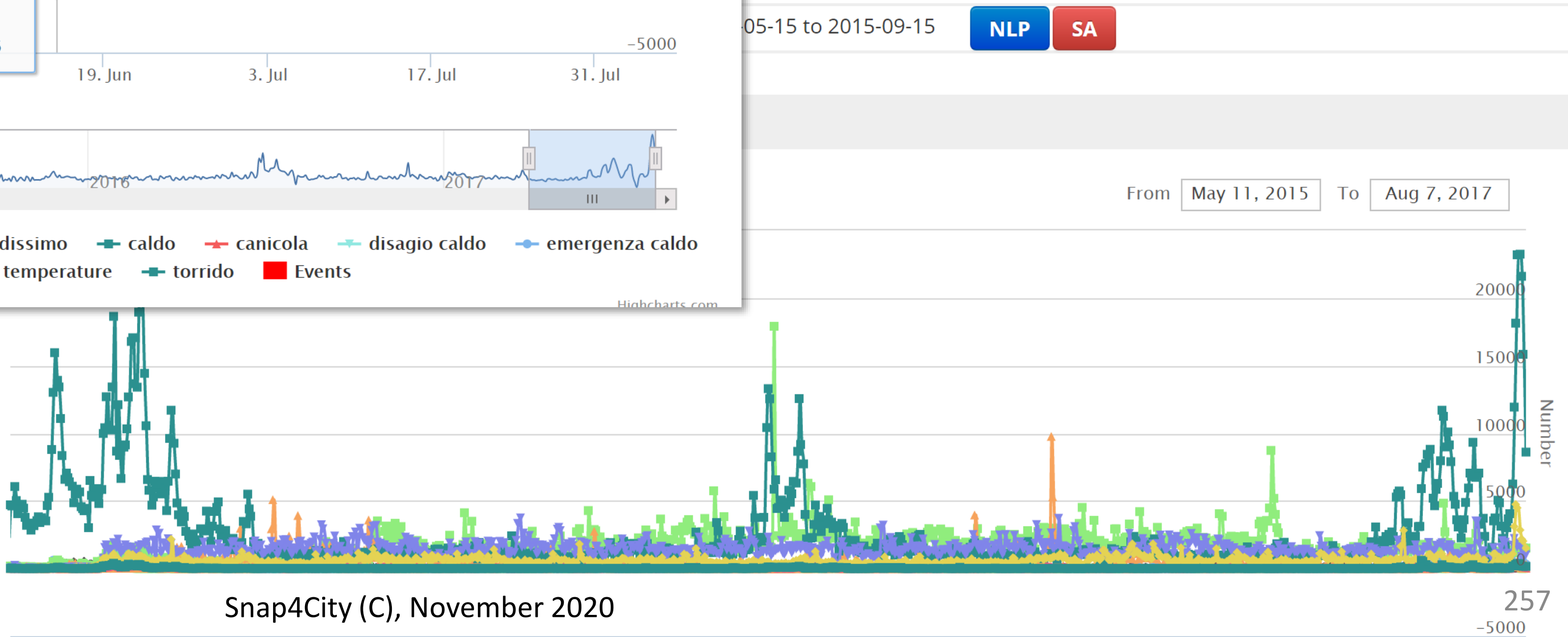
Sii-Mobility



A Channel



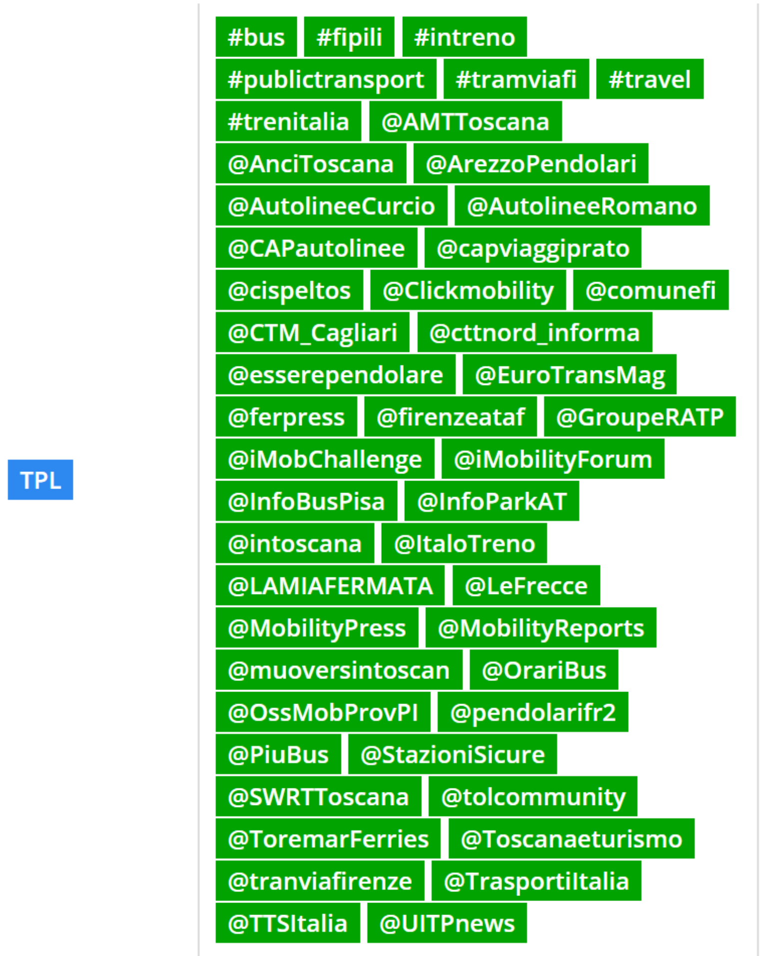
Its searches



Twitter Vigilance

Twitter Syntax for Searches

- String substring: Caldo
- Hashtag: #Caldo,
- Citations: @CivilProtection, @paolonesi
- From users: From:@paolonesi
- Etc.
- ….ANDed and ORed



Metrics' Kinds

- **Volume Metrics**
  - Number of TW, number of RTW
- **User Metrics**
  - Number of distinct users
  - Number of followers, following
- **NLP and SA metrics**
  - Counting word, adjective, noun, verbs, ….
  - Estimating SA, weighting with SentiWordNet (extended to Italian)
- **High level metrics (compositing all the other metrics)**
  - Addition of metrics..
  - Ratio among metrics, e.g.: num of TW/num of RTW,…
  - Cumulated metrics over time, e.g.: number of TW in the last X days..

- All: (i) per day, per hour, etc. (ii) per channel, per search
- Recently: we added the possibility of using metrics as firing conditions for alerts and bot on Twitter.

Problem addressed

Strong Limitations of the Search API of Twitter

- minimizing the number of searches on the basis of the user requests:
  - different users with their queries request tweets already requested by others
- Recovering of parent Tweets from Orphan reTweets taken in the searching process

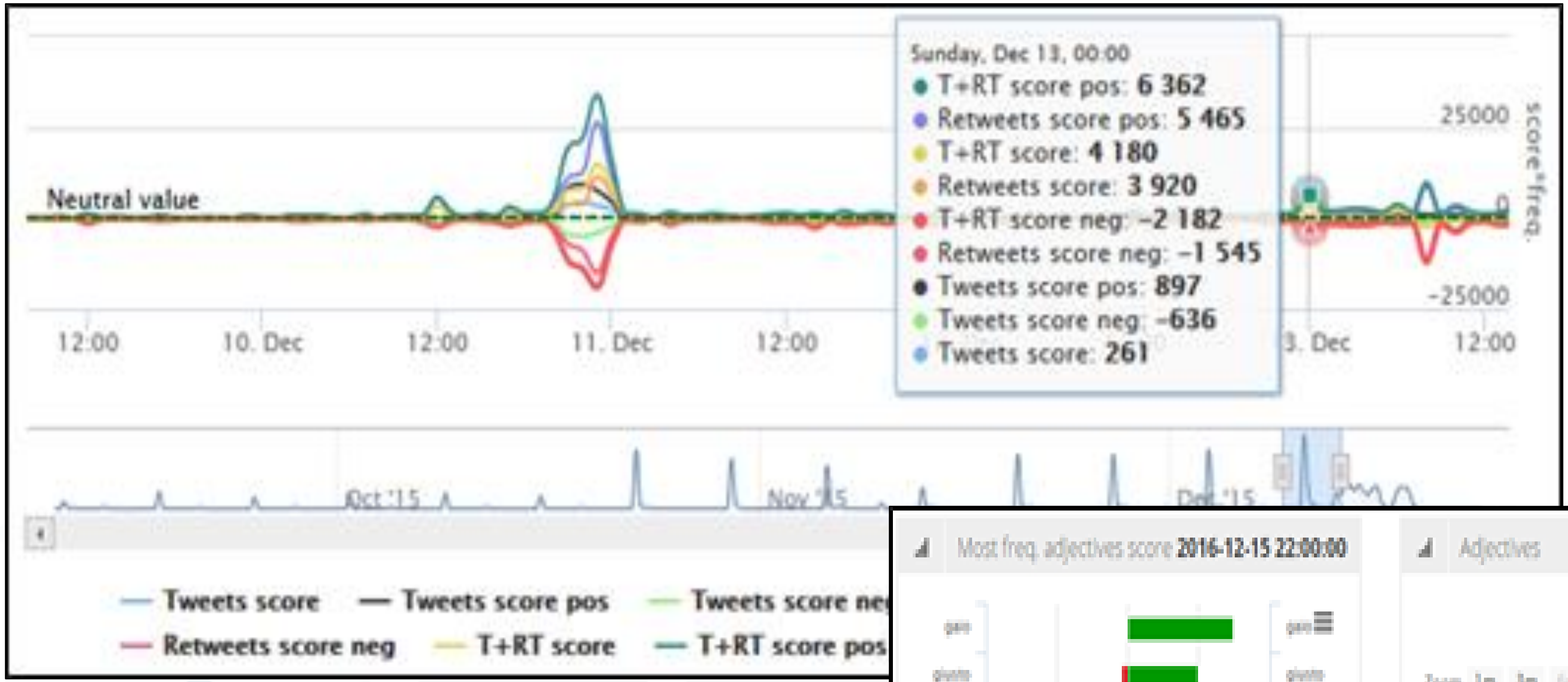
Analytics:

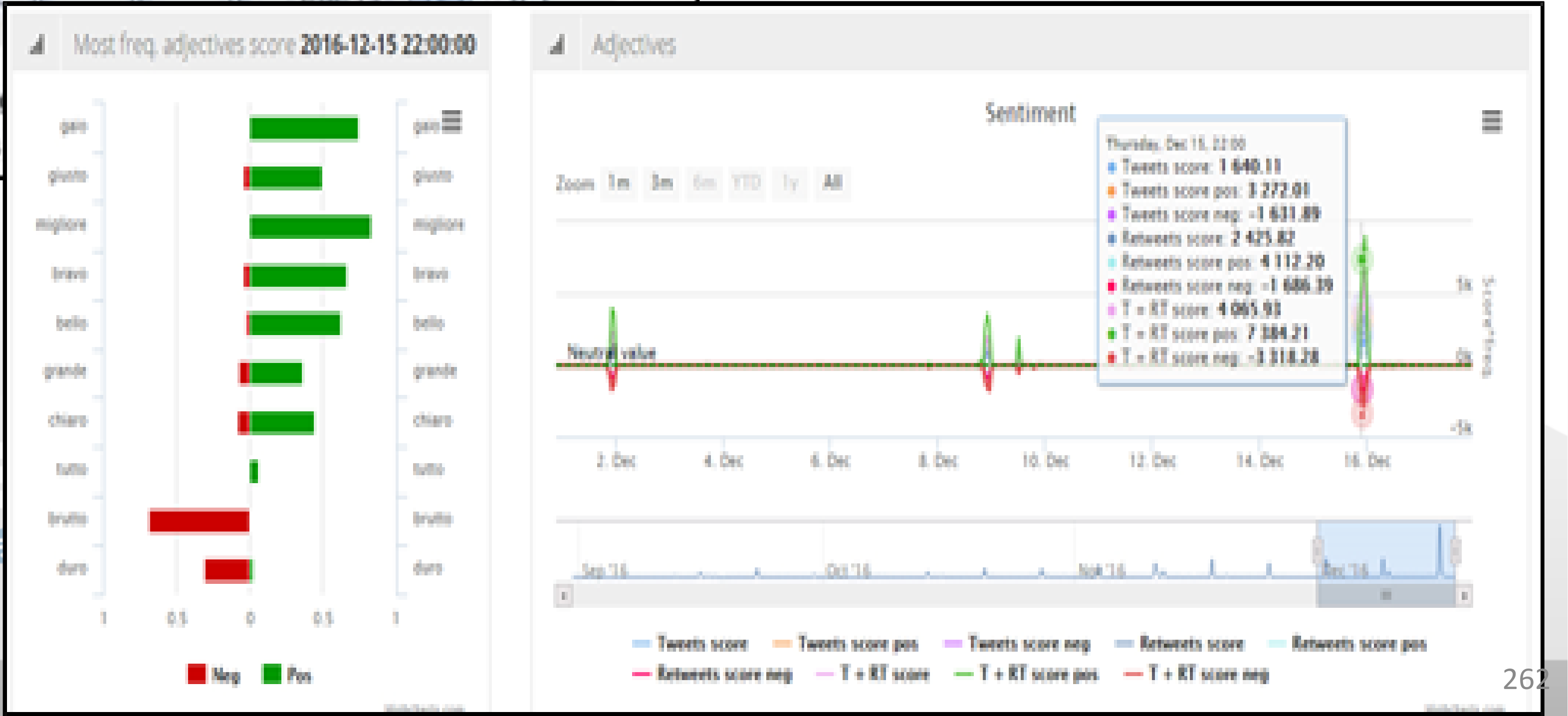
- High performance solution based on HDFS, Hadoop for NLP and SA, exploiting MapReduce programming model
- Estimating the network of influencer
- Computing metrics and prediction in real time.

TOP

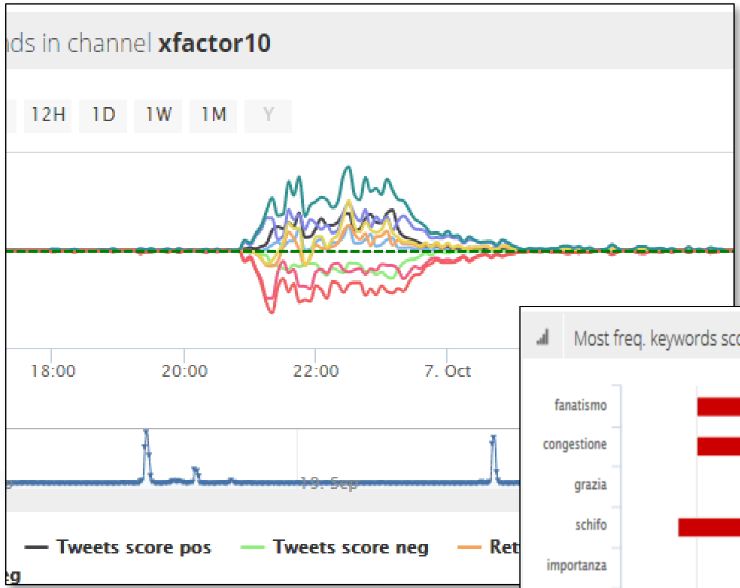
Sentiment Analysis

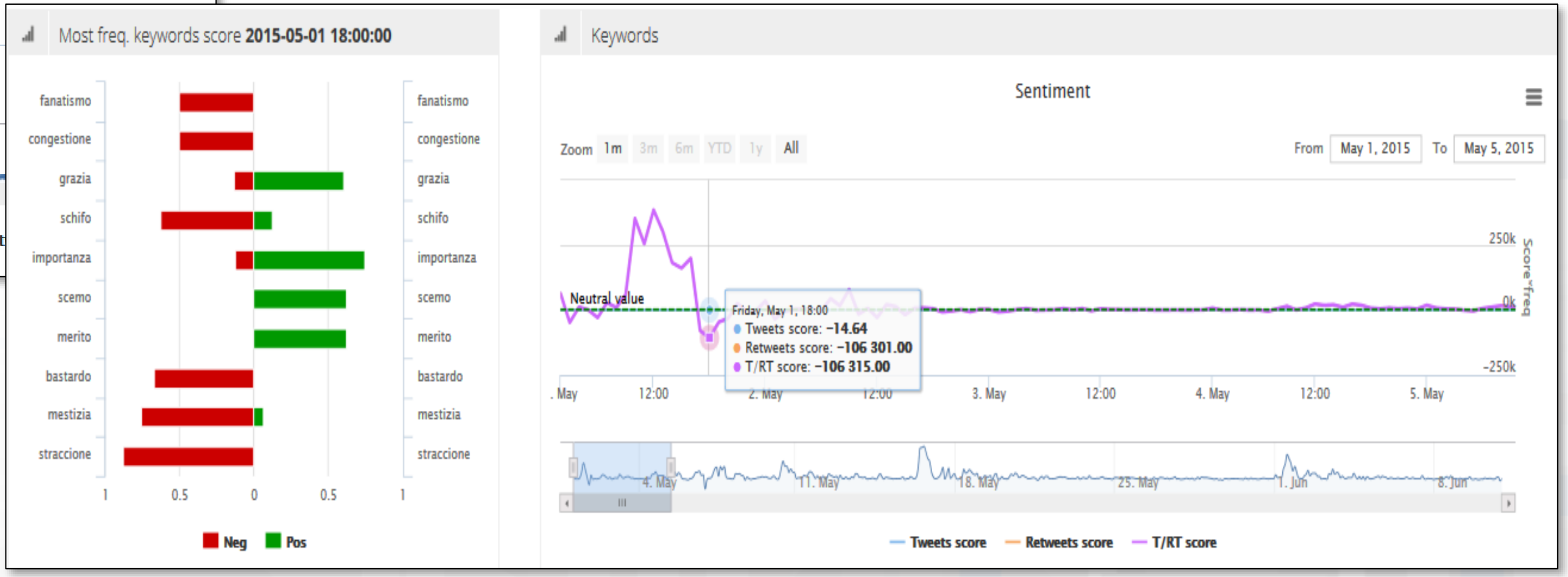
Sentiment Analysis



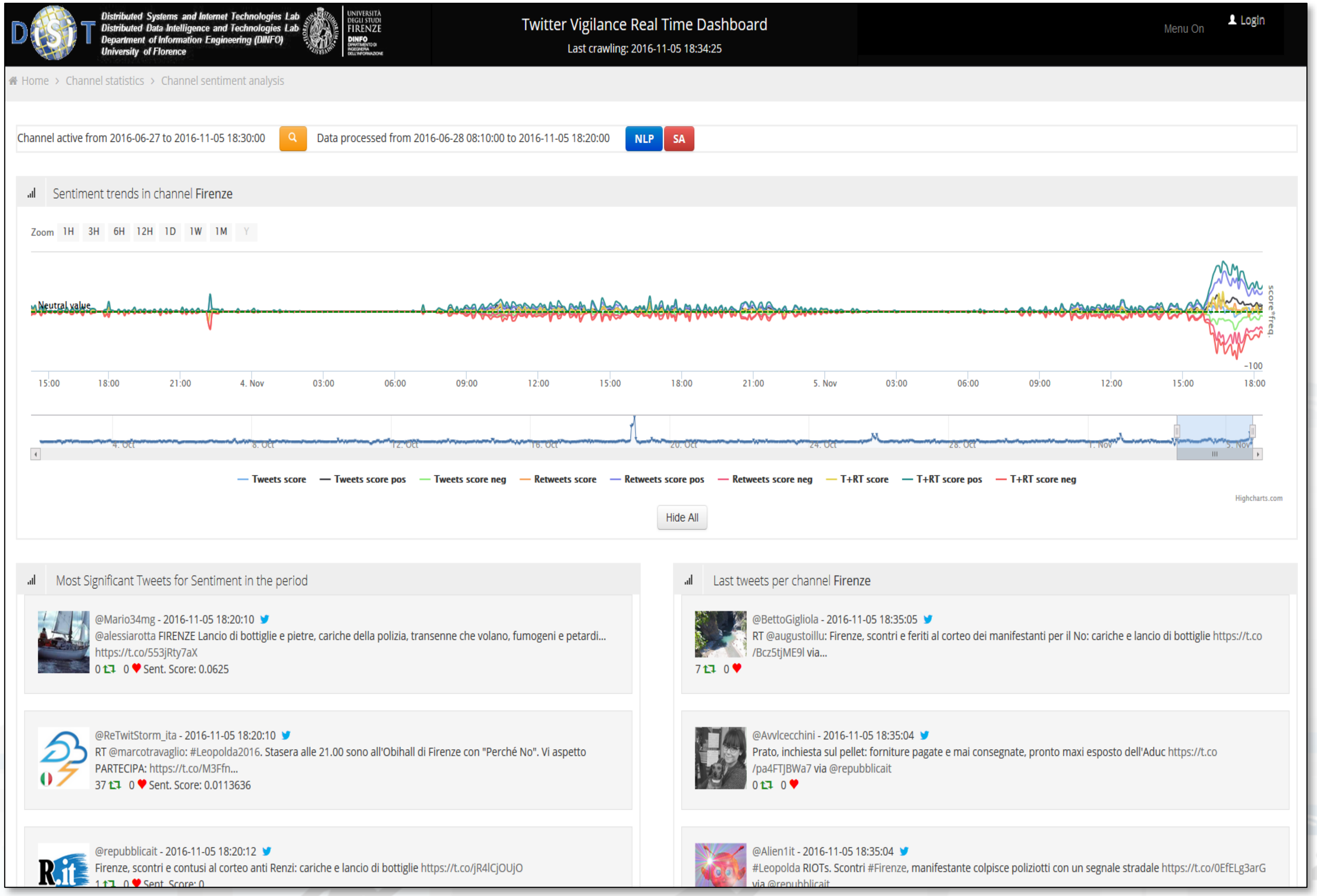


Twitter Vigilance

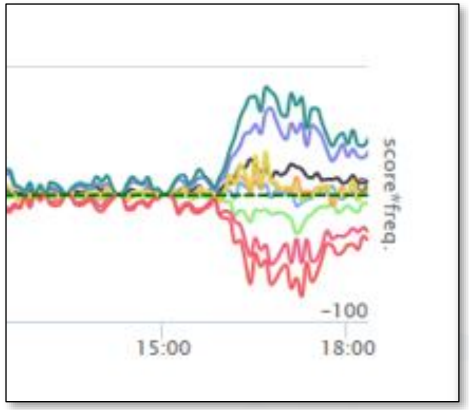

ds in channel xfactor10
12H 1D 1W 1M Y
18:00 20:00 22:00 7. Oct
Tweets score pos
Tweets score neg

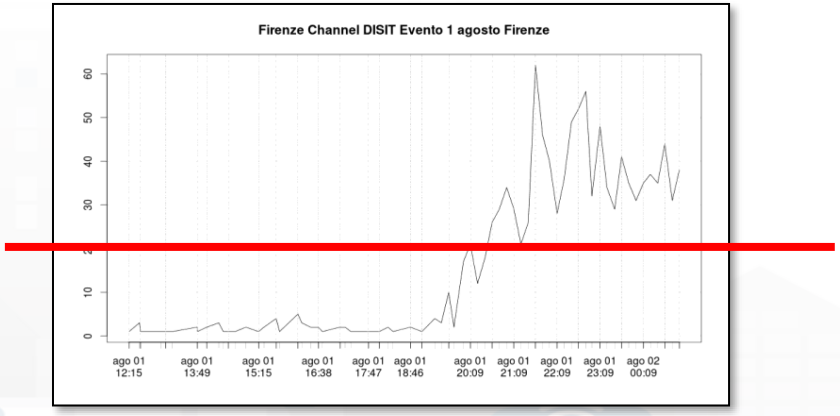

Most freq. keywords score 2015-05-01 18:00:00
fanatismo
congestione
grazia
schifo
importanza
scemo
merito
bastardo
mestizia
straccione
Neg
Pos
Keywords
Sentiment
Zoom 1m 3m 6m YTD 1y All
From May 1, 2015 To May 5, 2015
Neutral value
Friday, May 1, 18:00
Tweets score: -14.64
Retweets score: -106 301.00
T/RT score: -106 315.00
250k
0k
-250k
Tweets score
Retweets score
T/RT score

Real Time Twitter Vigilance, Early Warning



Sentiment Analysis



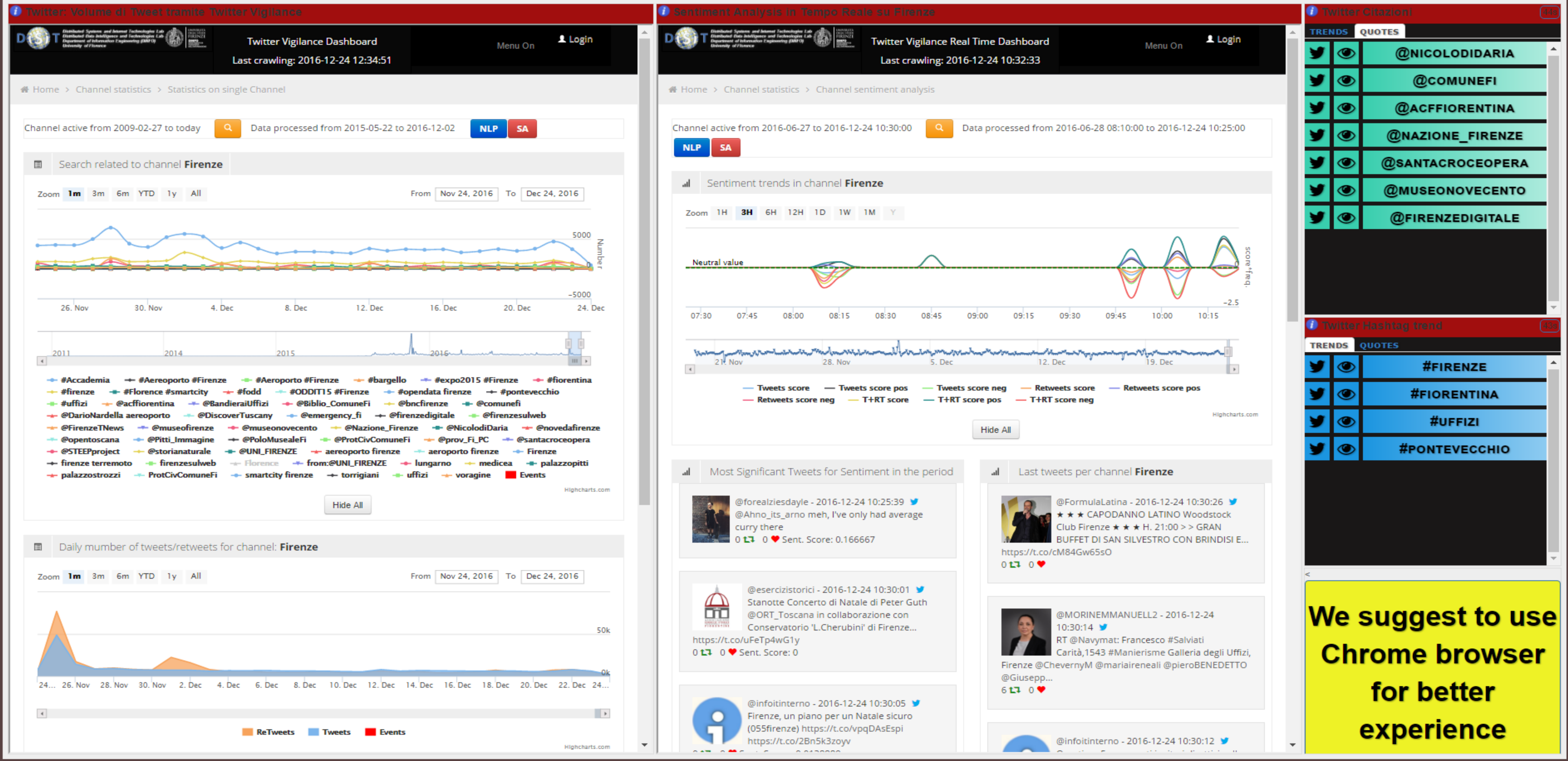


Twitter Vigilance

Twitter Vigilance su Firenze

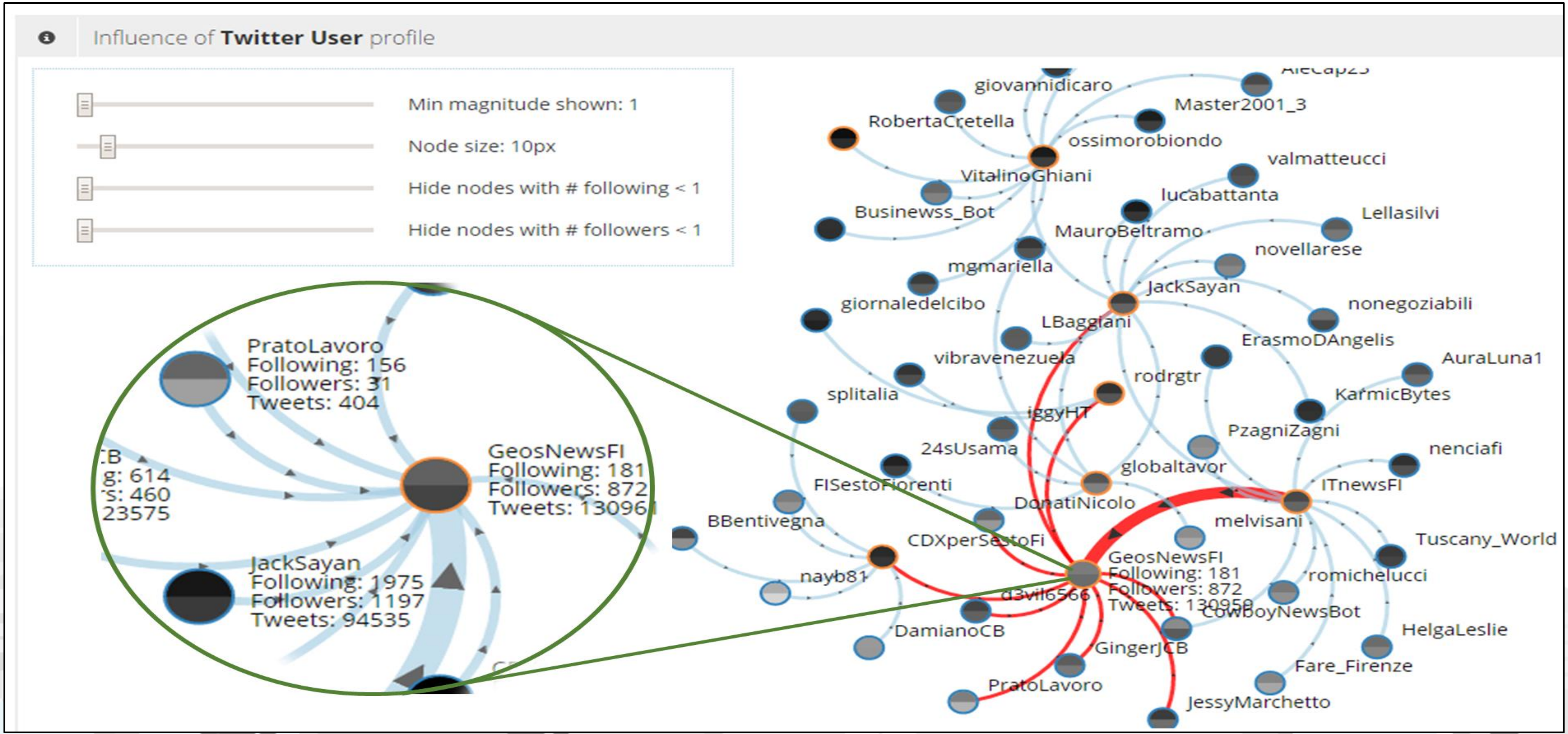
(sperimentale)

Sat 24 Dec @ 10:37:57



We suggest to use Chrome browser for better experience

Influence Network



Twitter Vigilance

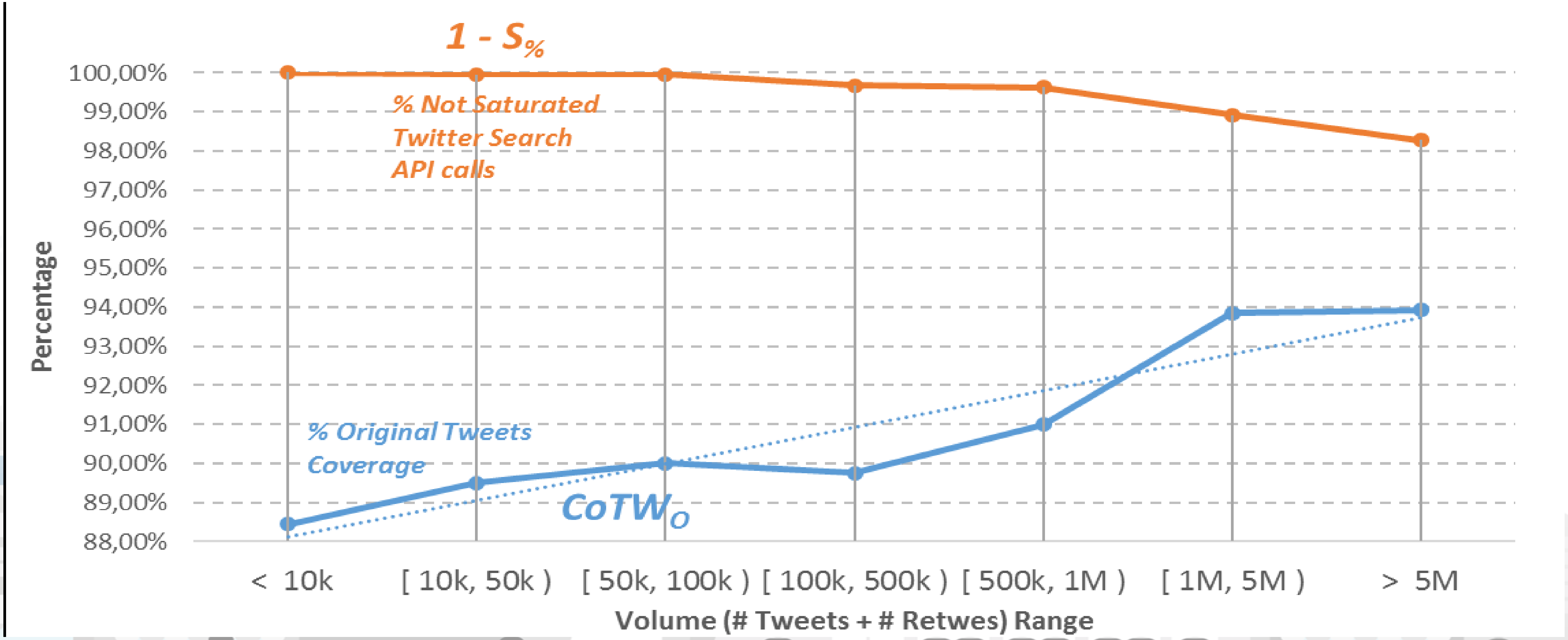
TOP

Reliability in collecting tweets

Efficiency in retrieval

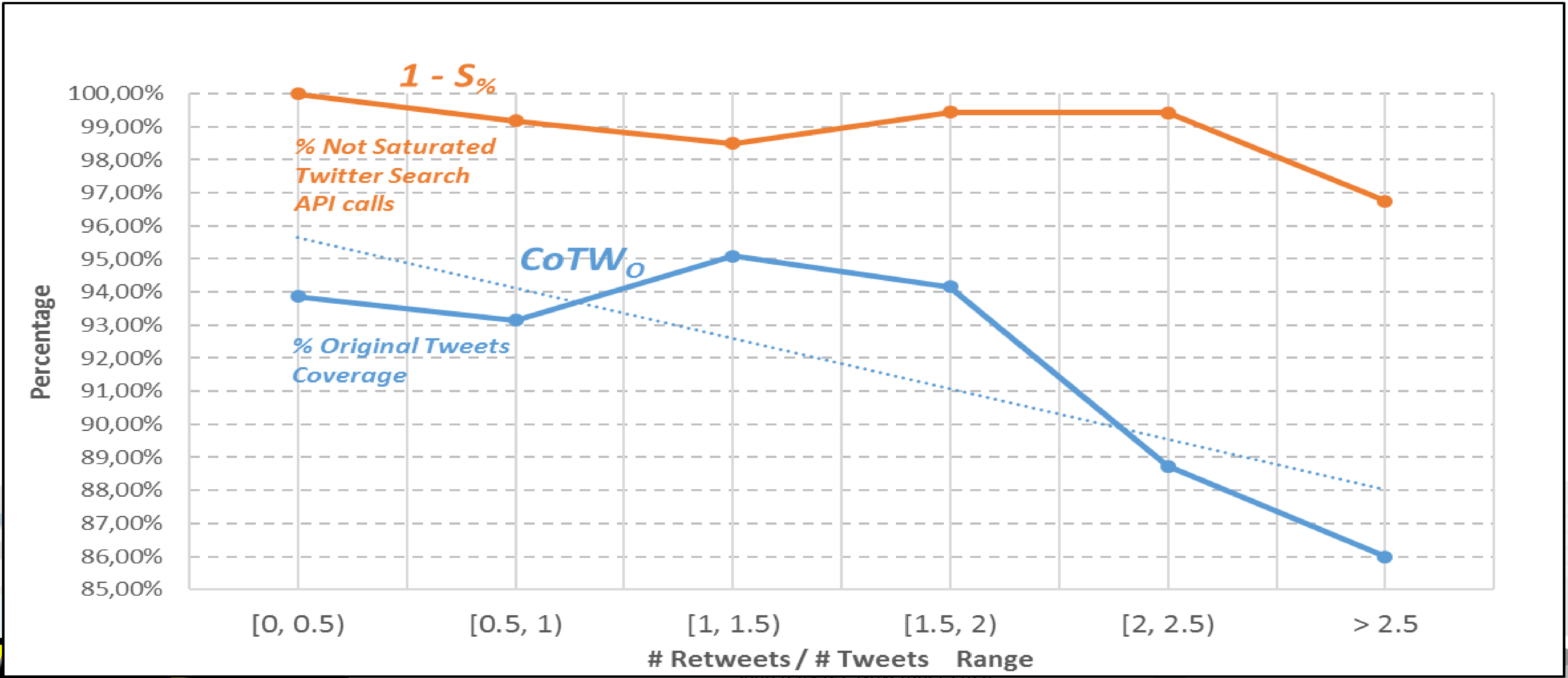
Posts Volume (Tweets + Retweets) Range	*# Recovered Original Tweets*	*# Missing Original Tweets*	*% Original Tweets Coverage ($CoTW_O$)*	*# Twitter Search API requests*	*# Saturations on Twitter Search API requests*	*% Saturations on Twitter Search API requests ($S_{\%}$)*	*% Not-Saturated Twitter Search API requests (1-$S_{\%}$)*
< 10k	18571	2033	89,05%	124299	1	0,00%	100,00%
[10k, 50k)	130051	13716	89,45%	399170	100	0,03%	99,97%
[50k, 100k)	96171	10278	89,31%	123804	165	0,13%	99,87%
[100k, 500k)	997833	86755	91,31%	849062	1589	0,19%	99,81%
[500k, 1M)	930646	61632	93,38%	439956	1998	0,45%	99,55%
[1M, 5M)	6454463	439628	93,19%	2787485	31585	1,13%	98,87%
> 5M	14714124	899035	93,89%	4509184	64284	1,43%	98,57%

Original Tweets coverage and Twitter Search API



Twitter Vigilance

Dependance on RTW/TW ratio



TOP

Tweets as Early Warning

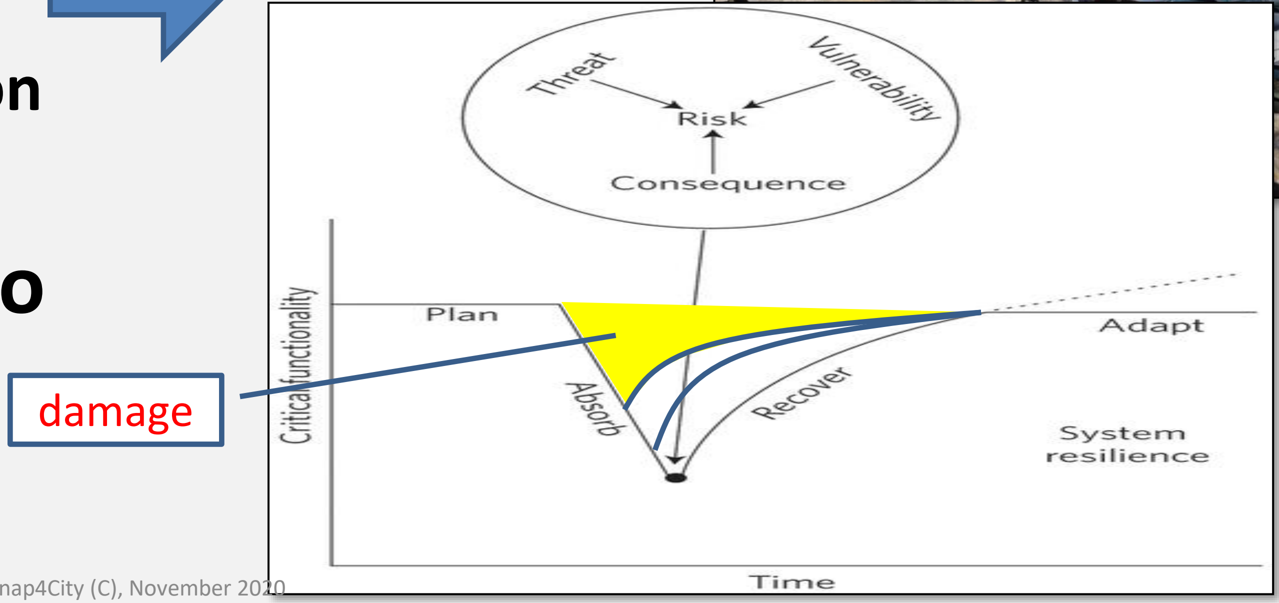
Early warning, detection

resolute

- **Issue:**
  - Detection of critical condition
  - Not easily detected with other means
- **Impact:**
  - Early warning, faster reaction
  - Increased resilience
- **Several metrics related to**
  - Volume of retweets
  - Sentiment analysis

City Resilience

Prepare
Absorb
Recover
Adapt



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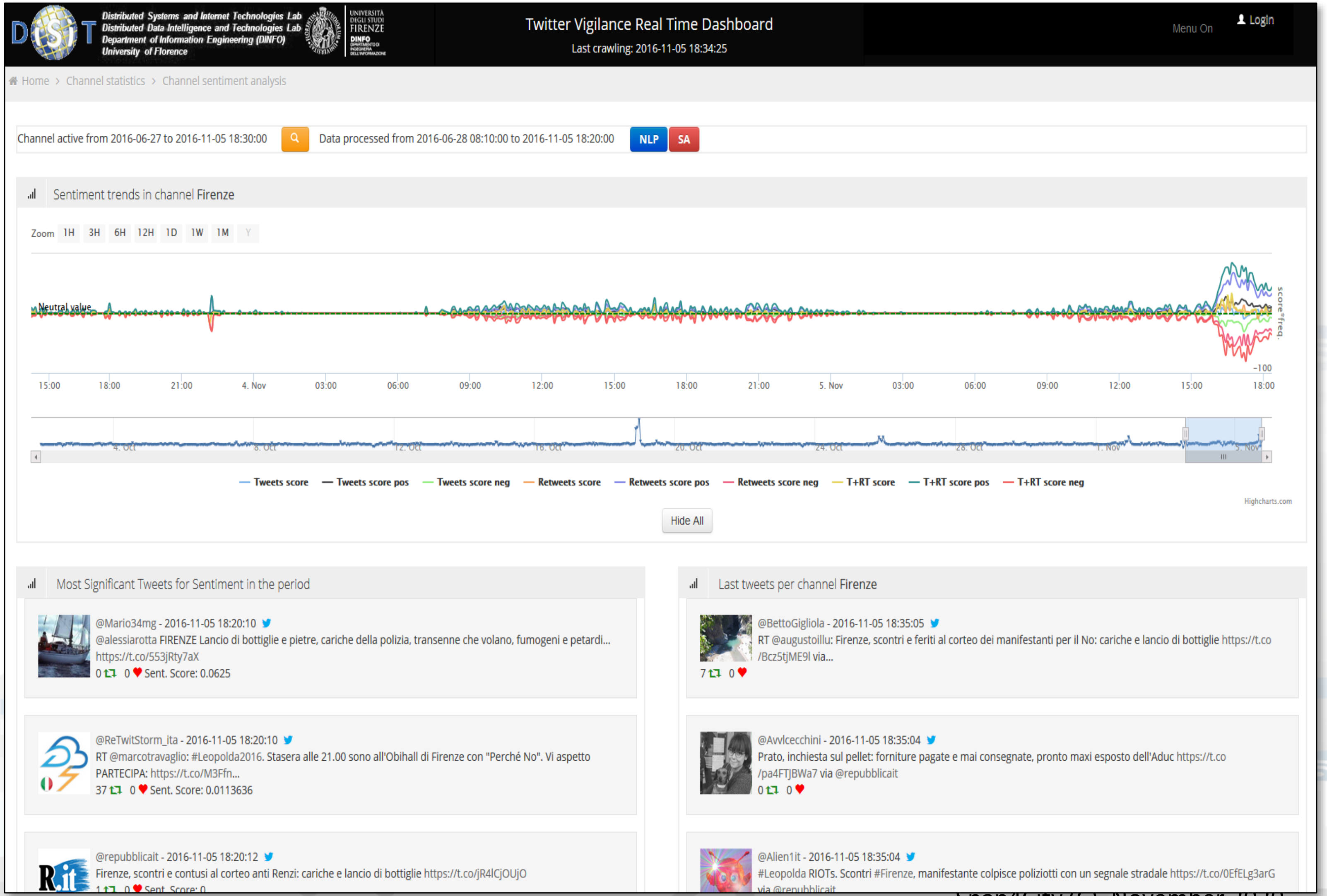
Twitter Vigilance

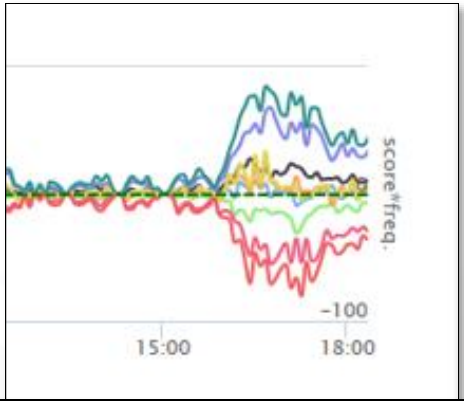
resolute

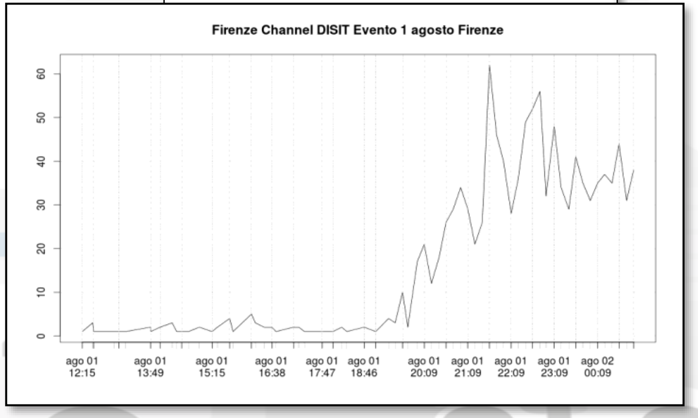
Twitter Vigilance RT: sentiment analysis



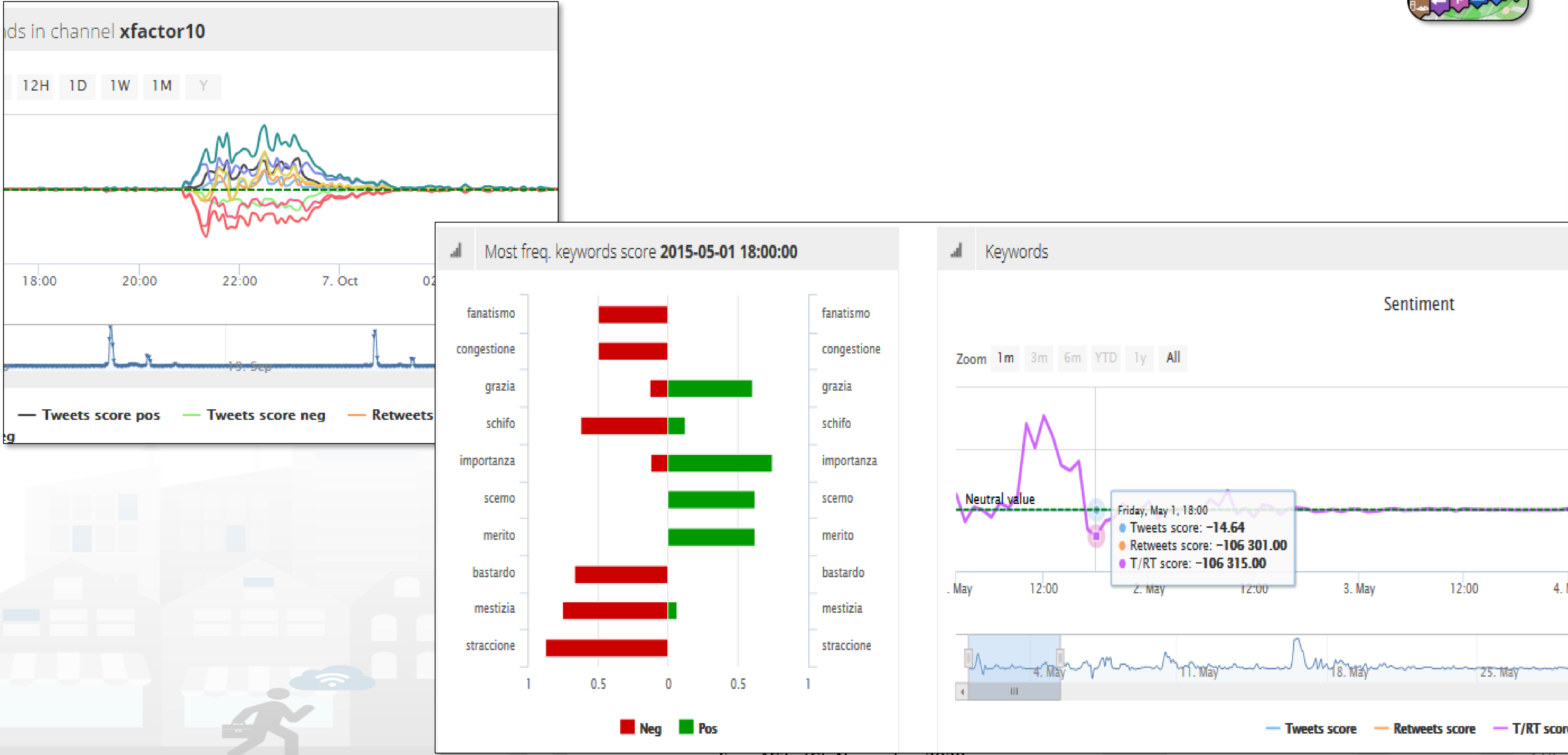
Real time

Early Warning

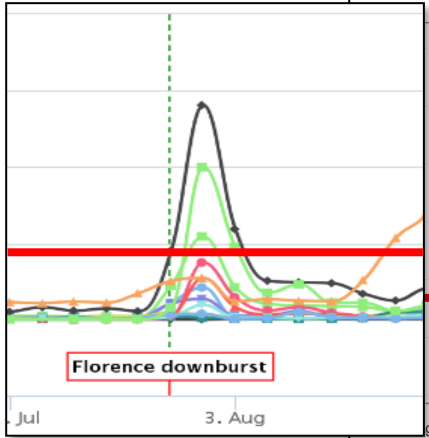


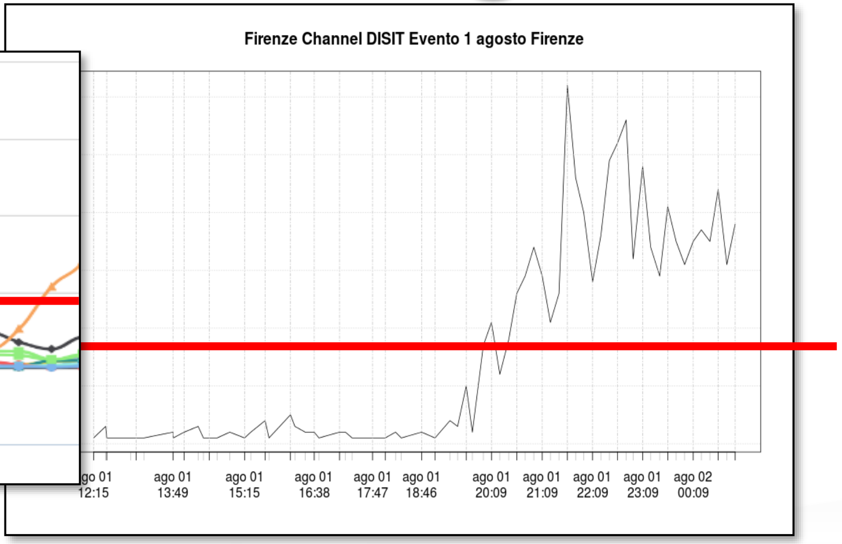


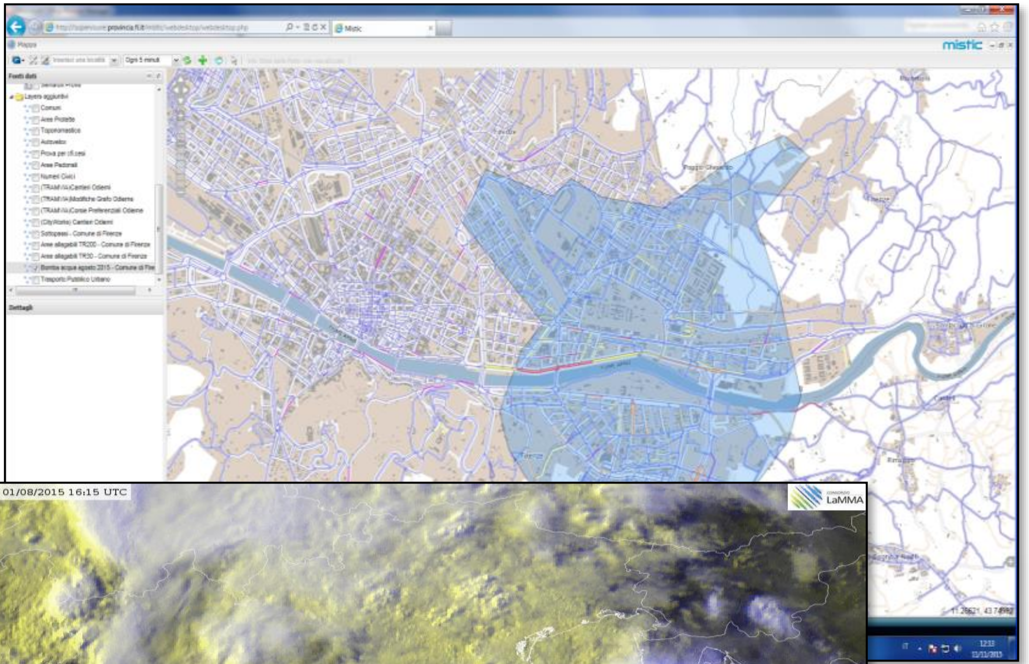
Sentiment Analysis

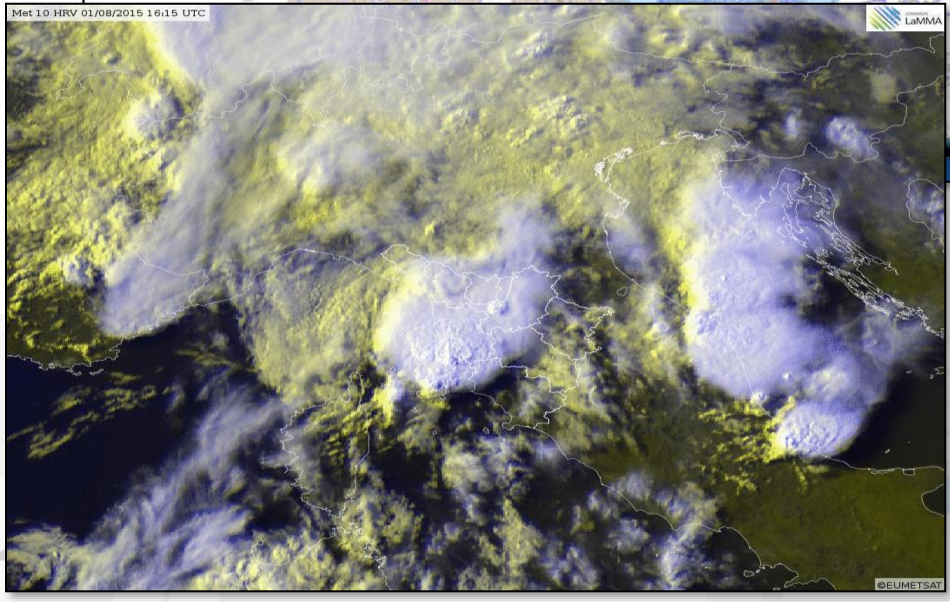


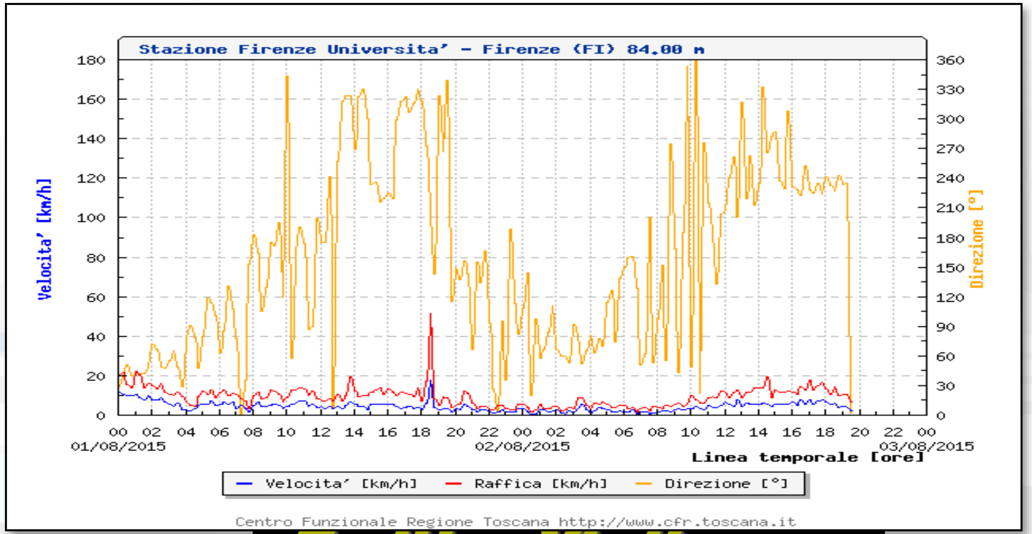
Early Warning
Twitter Vigilance and Water Bomb







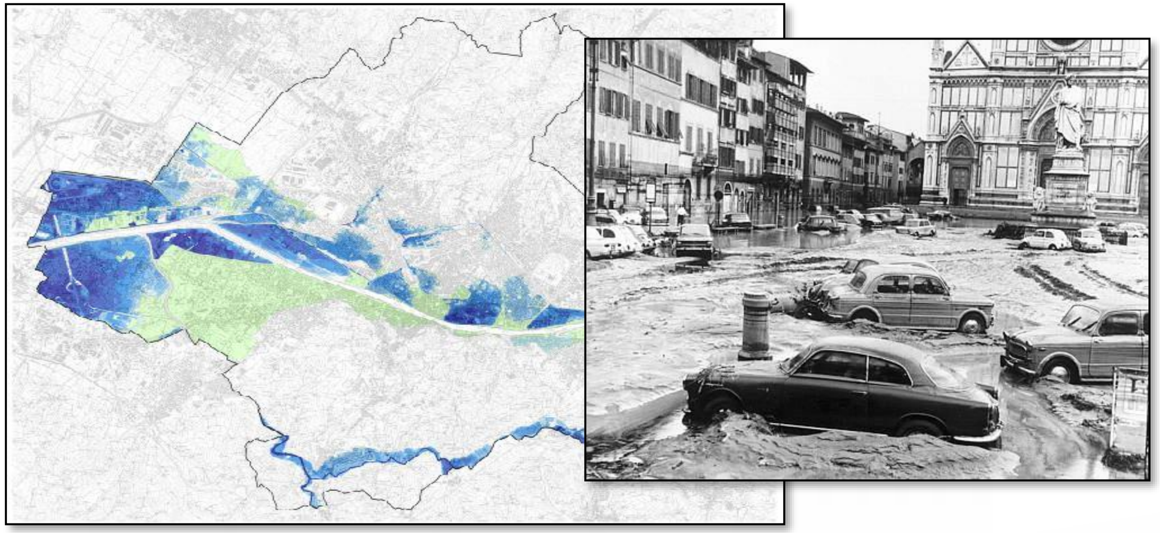




Twitter Vigilance

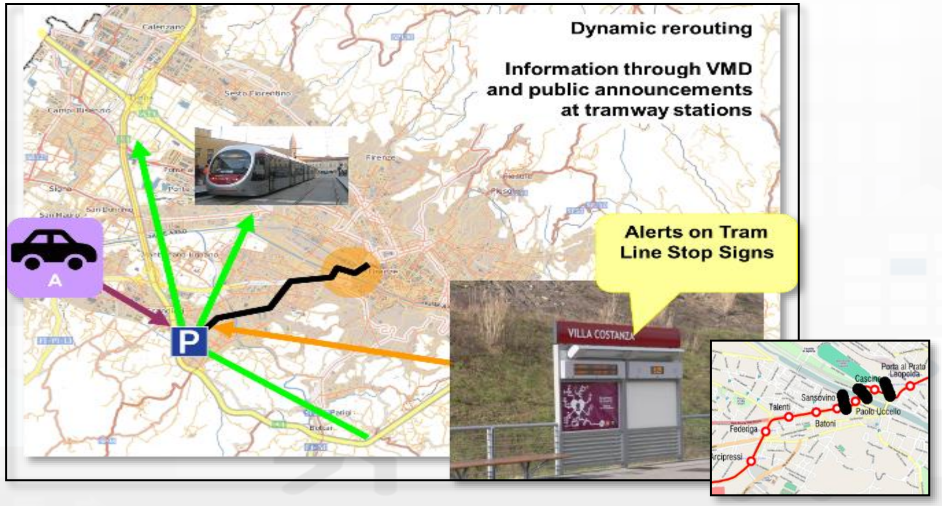
City Resilience ERMG

200 years probability Arno flooding



30 years probability Arno flooding

Arno Flood Impact on Tram Line & Traffic

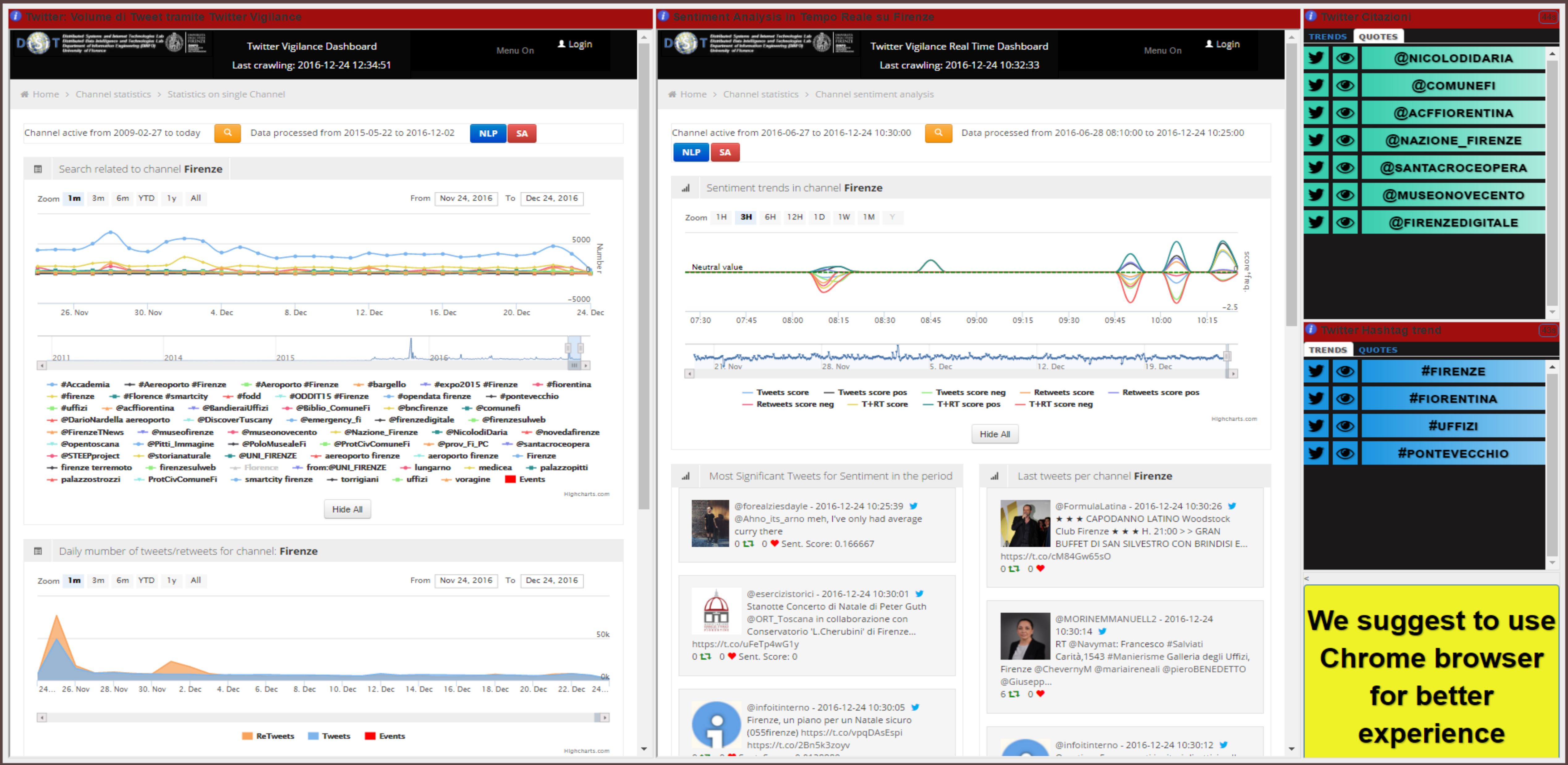


Water bomb (down burst) in South Florence

Case Study D

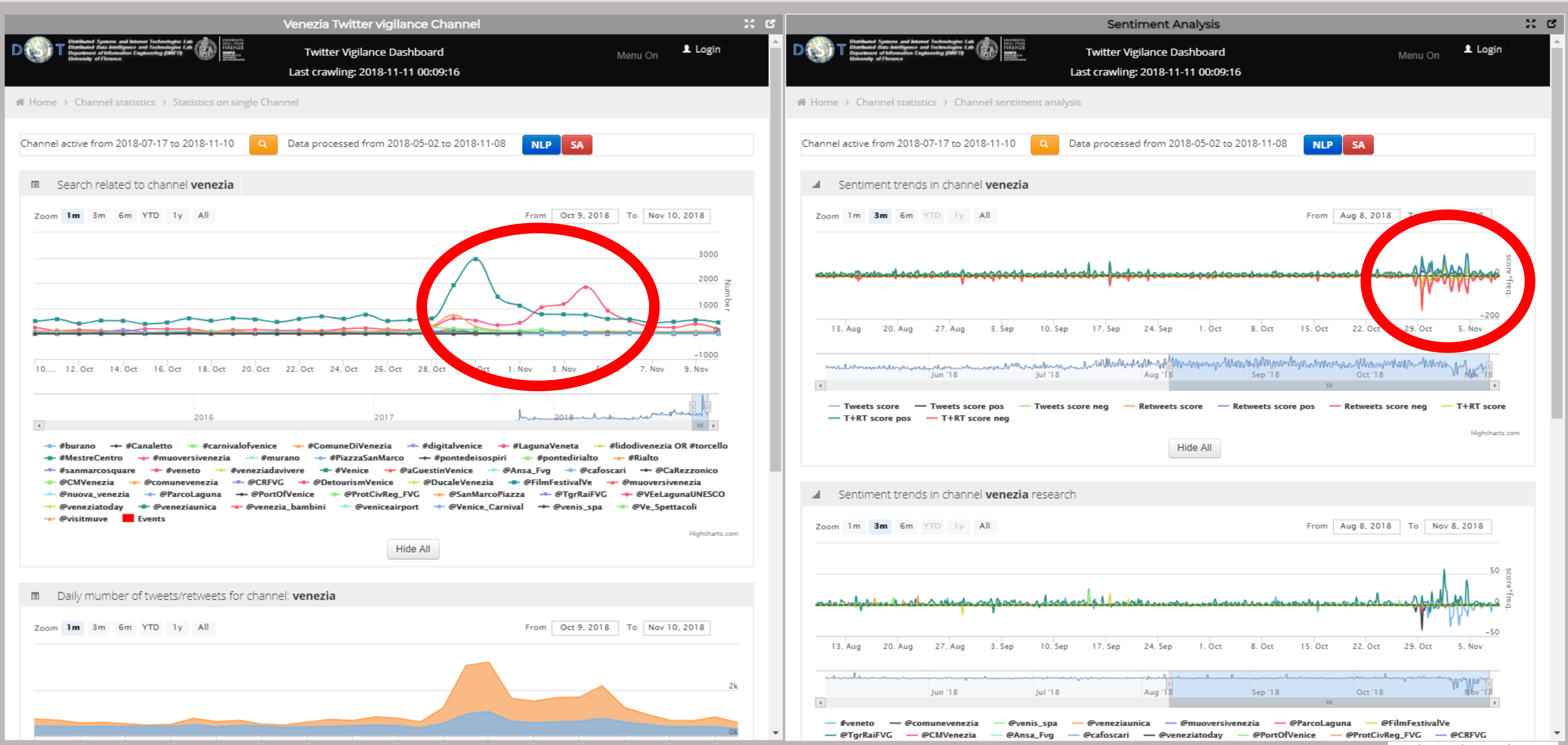
Twitter Vigilance su Firenze
(sperimentale)

Sat 24 Dec @ 10:37:57



Venezia Social - Twitter Vigilance

Sun 11 Nov 00:09:40



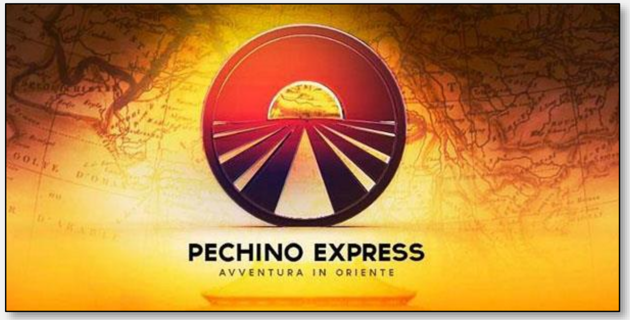
https://main.snap4city.org/view/index.php?iddasboard=MTIxOA==

TOP

Reliability Audience on TV programs

Predicting Audience on Social intensive TV show

- **Issue:**
  - **How to predict the number of people following a TV reality show in life**
- **Impact:**
  - **Making Advertising, promotion**
  - **Valorizing advertising**
  - **Adjusting the show**
- **Several metrics related to**
  - **Structure of volume of TW, RTW**
  - **Features of the tweet authors**
  - **Relationships ….**



- Periodic events
- Specific rules
- Strong influence and user engagment
- Audience can vote
- Audience espress appreciation and rejects
- .. Similar to the presence at large and log terms event, such as EXPO2015

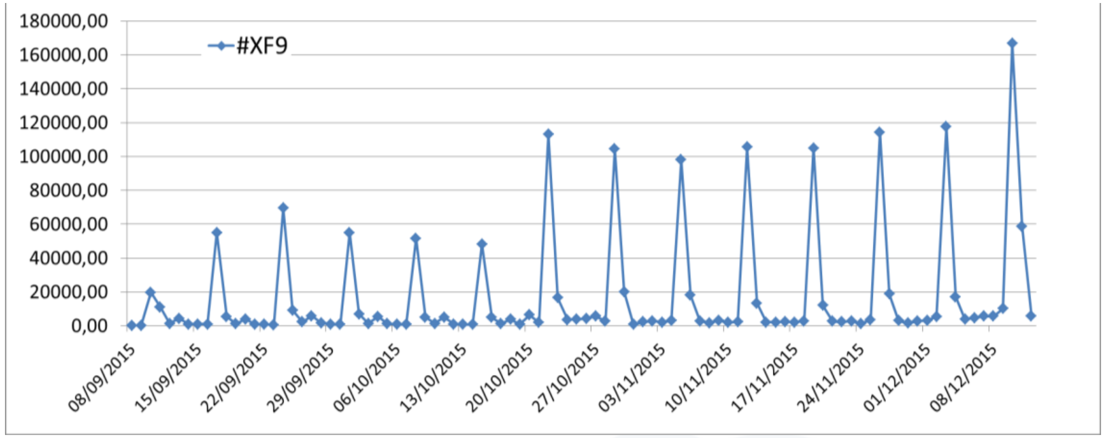
Twitter Metrics

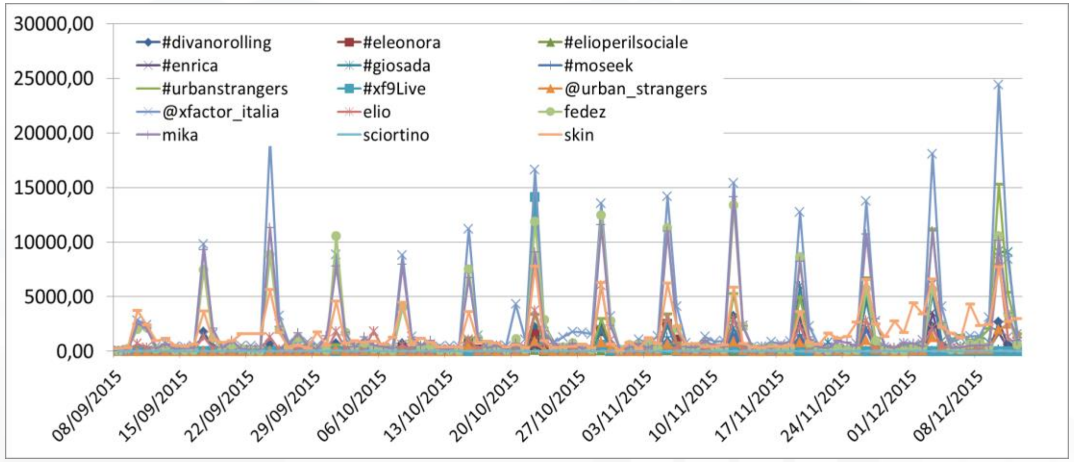
- TW: Number of Tweets per **Search/Channel** (as called Volume) , per day, per hour
- RTW: Number of ReTweets per **Search/Channel**, per day, per hour
- NRT/TW: ratio from ReTweets and Tweets per **Search/Channel**, per day, per hour
- NumSearch: number of Tweets including the Search per **Channel,** per day, per hour
- Sentiment Analysis Score per **Search/Channel**, per day, per hour
- Num of xxxxx

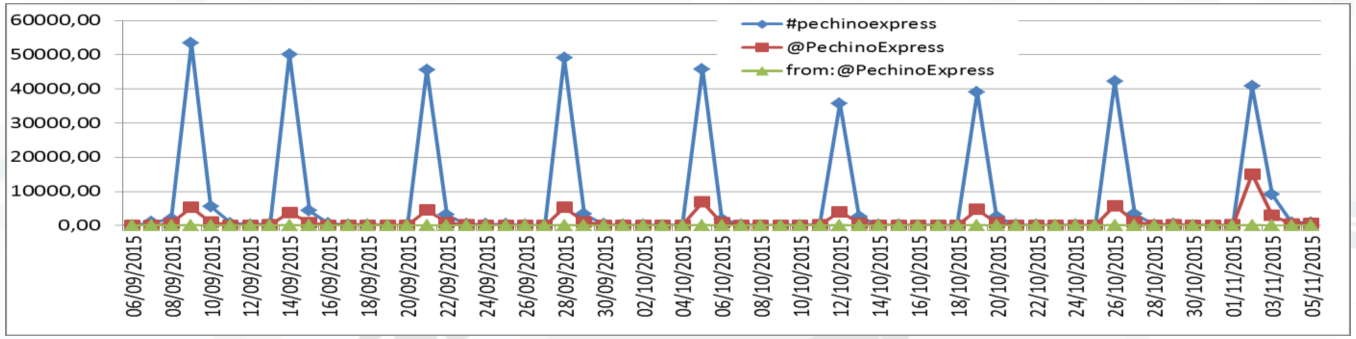
Predicting Audience: X-Factor, PechinoExpress, …

- Trend of TW and RTW for X-Factor 9
  - Several searches
- Similar model for other Social Intensive TV shows
  - See below Pechino Express

$$x_t = \beta_1 z_{1,t} + \beta_2 z_{2,t} + \beta_3 z_{3,t} + \cdots + \beta_k\, z_{k,t} + n$$







Twitter Vigilance

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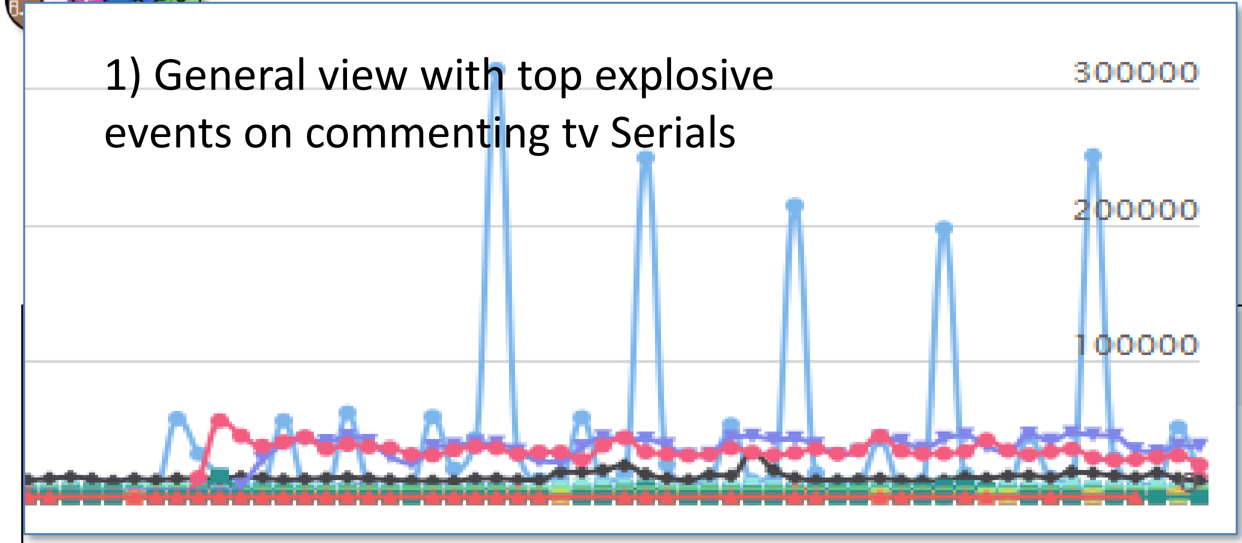
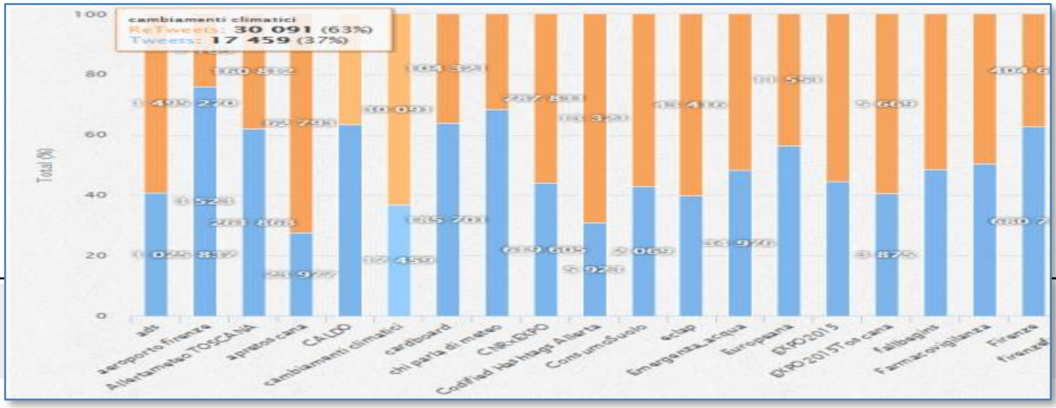
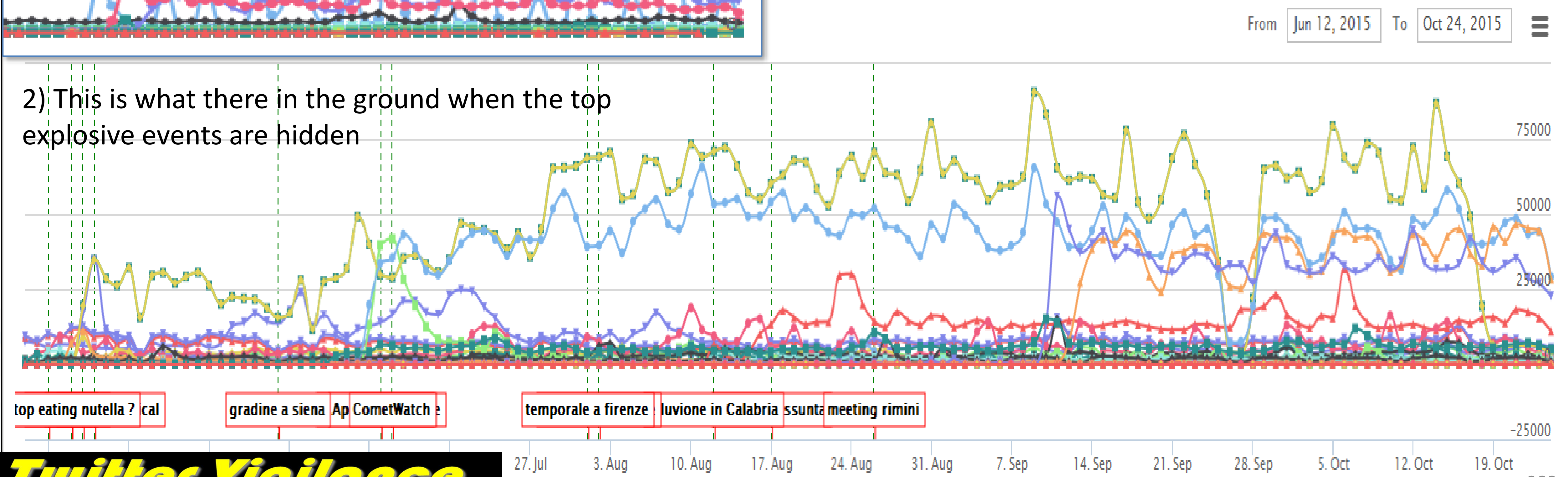
All Channels (private information)

1) General view with top explosive events on commenting tv Serials





2) This is what there in the ground when the top explosive events are hidden

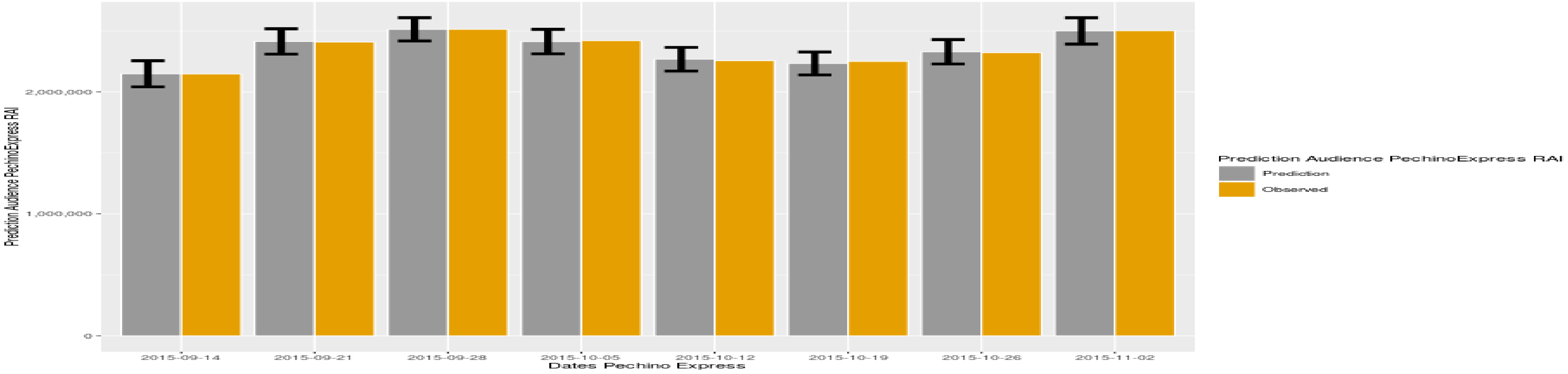


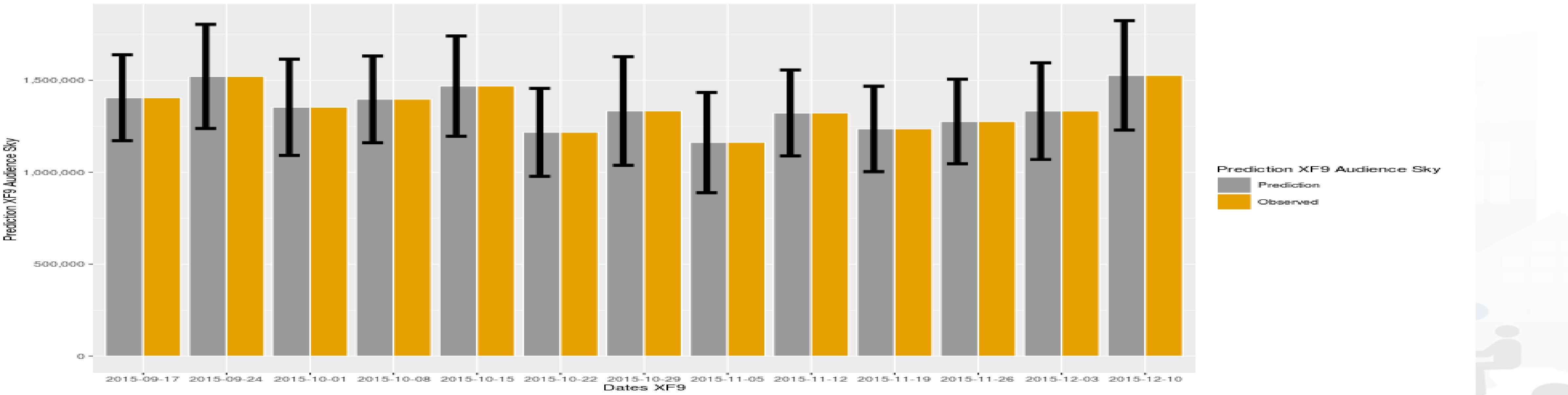
Twitter Vigilance

Details of Predictive Models Validities

Metrics collected over the 5 days before the event.		X-Factor 9 - Model				Pechino Express - Model			
		Coeff	Std Err	t-val	p-val	Coeff	Std Err	t-val	p-val
Total number of tweets + retweets on main hashtag	β_1	-73.48	58.49	-1.256	0.2494	-954.3	64.69	-14.750	0.0045
Total number of tweets on main hashtag,	β_2	122.7	70.27	1.745	0.1244	4144	284	14.590	0.0046
Ratio between: number of RTW/TW on main hashtag,	β_3	1358851	462704	2.937	0.0218	937920	80946	11.590	0.0073
UnqURetweet	β_4	264.3	153	1.728	0.1277	2175	345.6	6.293	0.0243
FUnqUsers	β_5	-214.9	132.5	-1.622	0.1488	-1640	270.6	-6.061	0.0261
Intercept	n	-762730	627238	-1.216	0.2634	-2560461	401675	-6.374	0.0237
R squared		0.727				0,995			
RMSE		66467				8851			
MAE		55589				6805			
AIC		340				182			
TV broadcasting company		Sky				RAI			
Weeks		13				9			
millions of registered tweets on Twitter Vigilance		1.625				0.455			

Predicting Confidence





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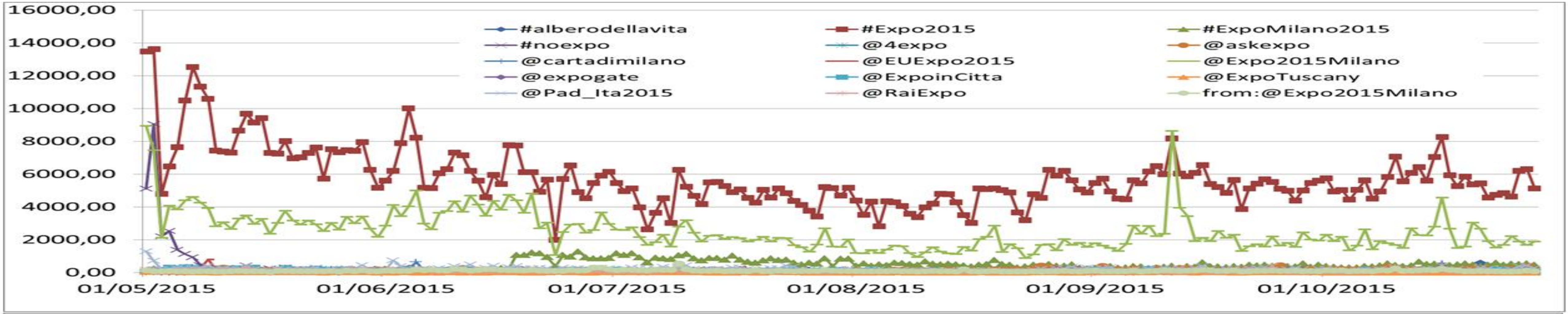
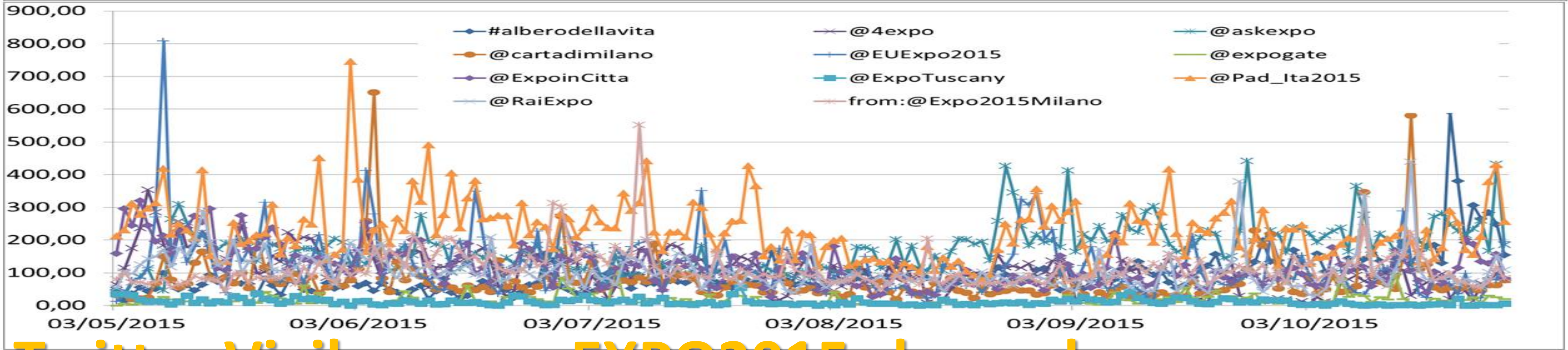
Reliability presences to major events

Predicting EXPO2015





Twitter Vigilance on EXPO2015 channel

Twitter Vigilance

Twitter Metrics

- TW: Number of Tweets per **Search/Channel** (as called Volume) , per day, per hour
- RTW: Number of ReTweets per **Search/Channel**, per day, per hour
- NRT/TW: ratio from ReTweets and Tweets per **Search/Channel**, per day, per hour
- NumSearch: number of Tweets including the Search per **Channel,** per day, per hour
- Sentiment Analysis Score per **Search/Channel**, per day, per hour
- Num of xxxxx

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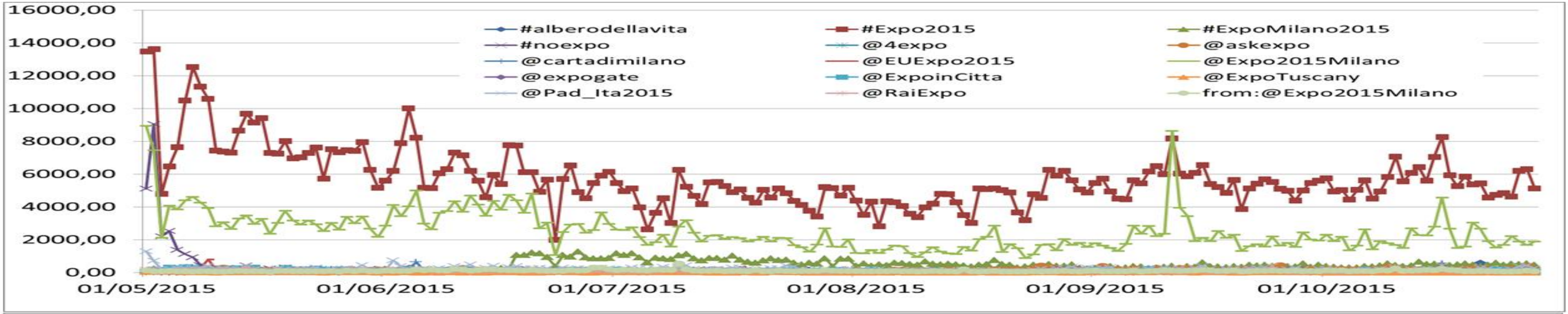
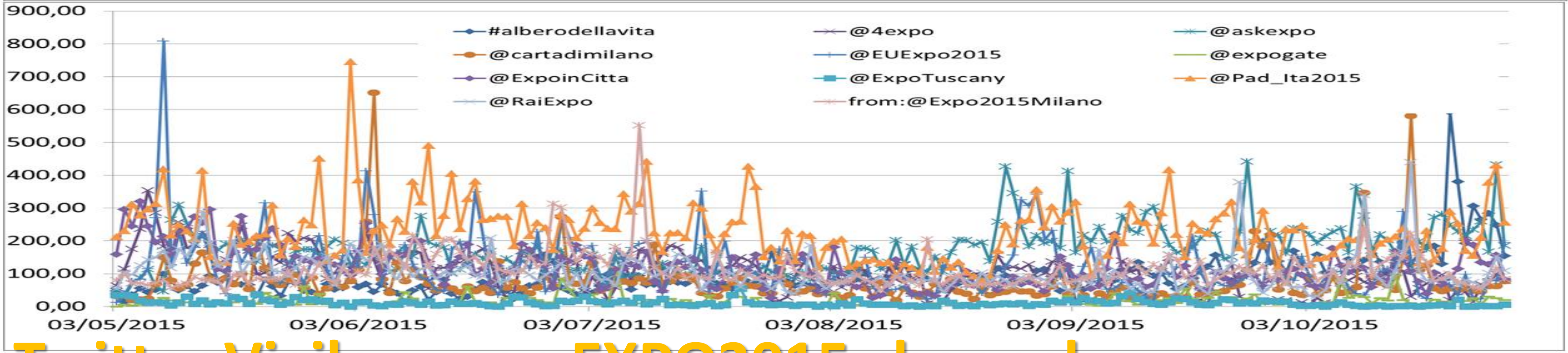
Predicting presences at events

Predicting EXPO2015

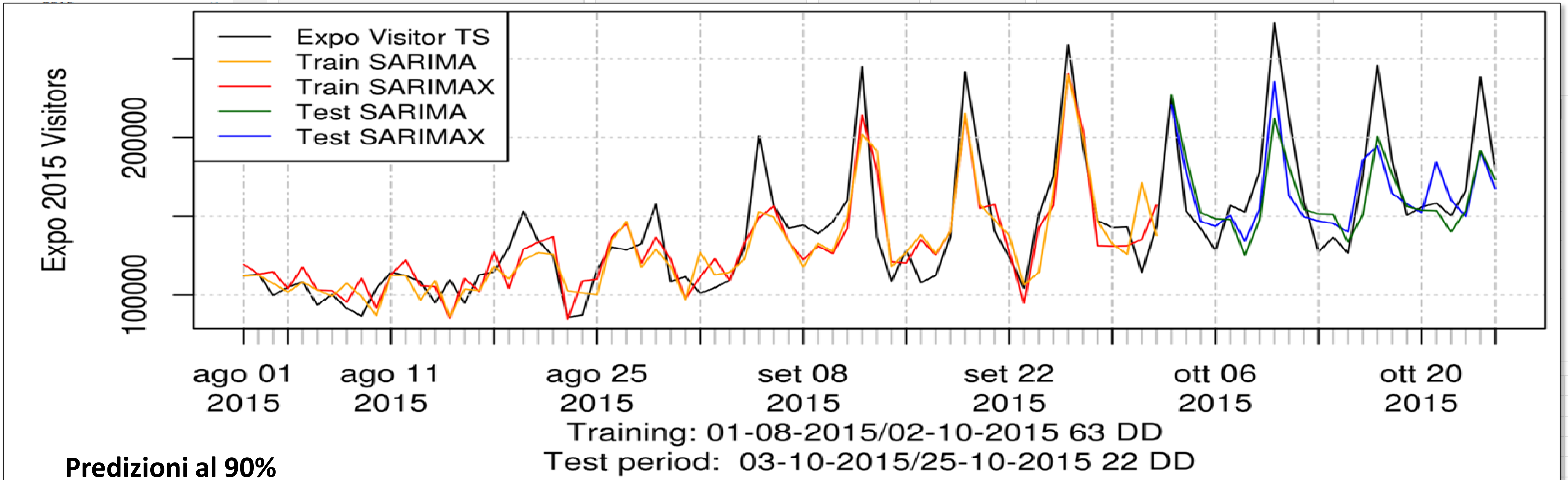




Twitter Vigilance on EXPO2015 channel

Twitter Vigilance

Twitter Vigilance monitoring and predictions



Predizioni al 90%

Precision: 96%

Twitter Vigilance on EXPO2015 channel

Predicting volume of visitors for tuning the services

Twitter Vigilance

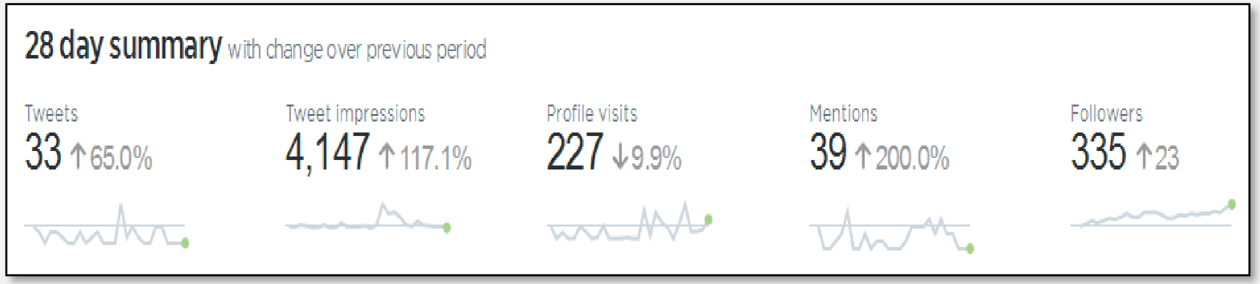
TOP

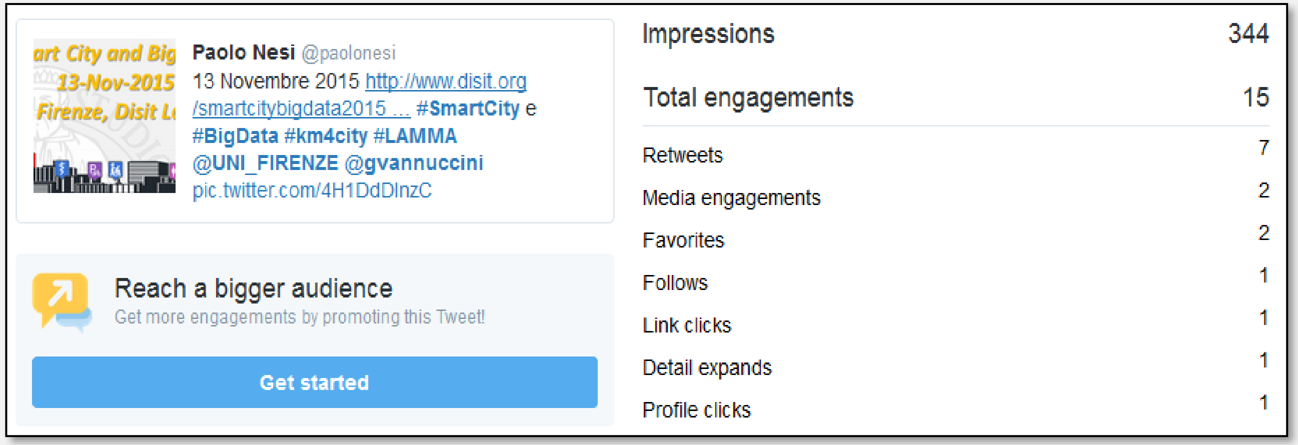
Predicting reTweet Proneness

Predicting the reTweet Proneness

- **Issue:**
  - How to understand if a tweet has a good probability of being retweeted?
- **Impact:**
  - Advertising, promotion, training
- **Several metrics related to**
  - Structure of the tweet
  - Features of the tweetting author
  - Relationships ….

Twitter Analytics



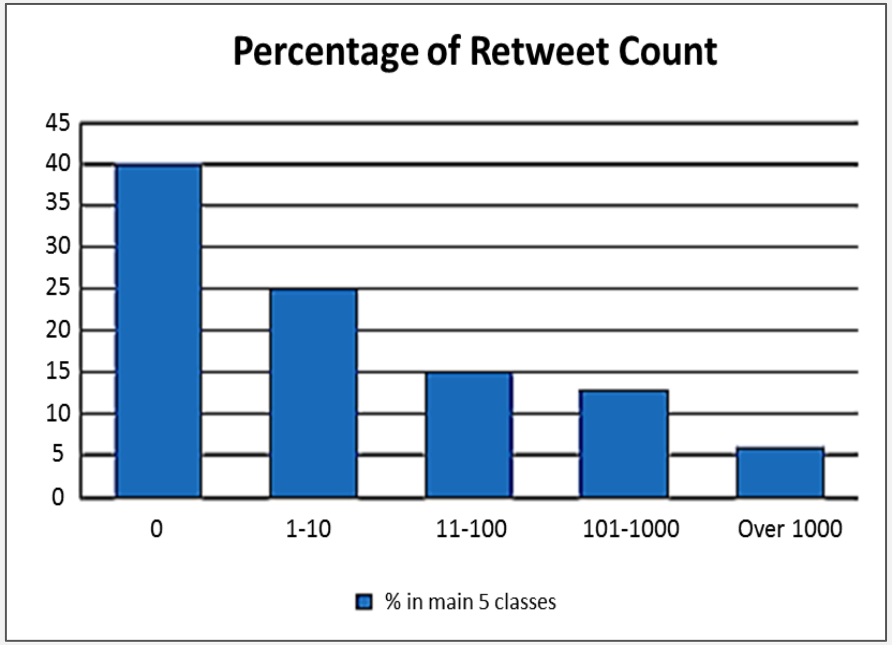


Tweet proneness Metrics

Tweet metrics	
URLs Count	# of URLs in the tweet
Mentions Count	# of mentions/citation of Twitter users in the tweet
Hashtags Count	# of hashtags included in the tweet
Favorites Count	# of favorite obtained by the tweet
Publication Time	Local hour H24 in which the tweet has been published in the day according to the author' local time.
Author of Tweet metrics	
Days Count	# of days since the tweet's author created its Twitter account
Statuses Count	# of tweets made by the tweet's author since the creation of its own account
Author Network metrics	
Followers Count	# of followers the author of the tweet
Followees Count	# of friends the tweet's author is following
Listed Count	# of people added the tweet's author to a list

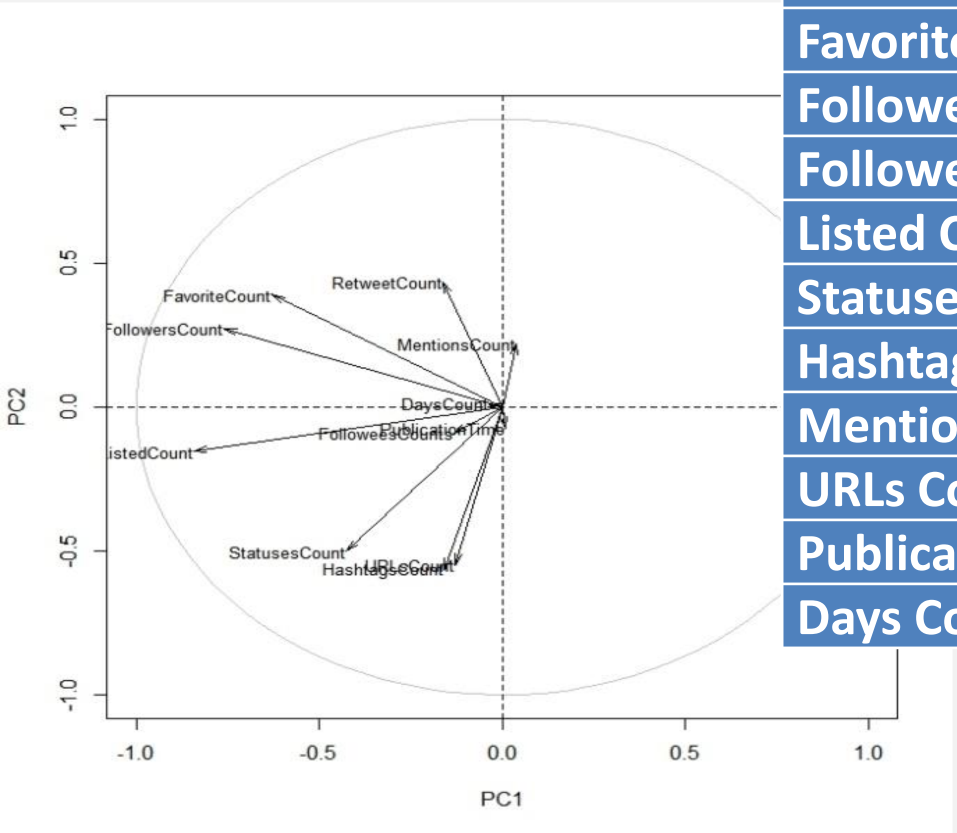
Data sets:

- 100 Million of Tweet
- 500 K
- 100 K



reTweet proneness: assessment

- PCA



Metrics	PC1	PC2	PC3	PC4	PC5
Retweet Count	-0.1623	0.4346	0.1635	-0.0026	-0.1009
Favorites Count	**-0.6294**	0.3908	0.1922	-0.1128	-0.1880
Followers Count	**-0.7599**	0.2736	0.0522	-0.0983	-0.0857
Followees Count	-0.1336	-0.0907	**-0.4627**	-0.2494	0.1182
Listed Count	**-0.8431**	-0.1549	-0.0498	0.1500	0.1871
Statuses Count	-0.4256	**-0.5016**	-0.3781	0.2795	0.2410
Hashtags Count	-0.1585	**-0.5661**	0.4377	-0.0517	0.0309
Mentions Count	0.0394	0.2194	0.0786	-0.1607	**0.7697**
URLs Count	-0.1288	**-0.5483**	0.2539	-0.3388	-0.3248
Publication Time	0.0076	-0.0728	0.3639	**-0.5186**	0.3707
Days Count	-0.0370	0.0070	**-0.5072**	**-0.6604**	-0.1691

reTweet proneness: Classification methods

- Statistic classifications vs machine-learning methods
- 80% of training data set, 20% of testing data sets; 500K data set
- → Recursive partitioning procedure models (RPART), good compromise for Big data problems

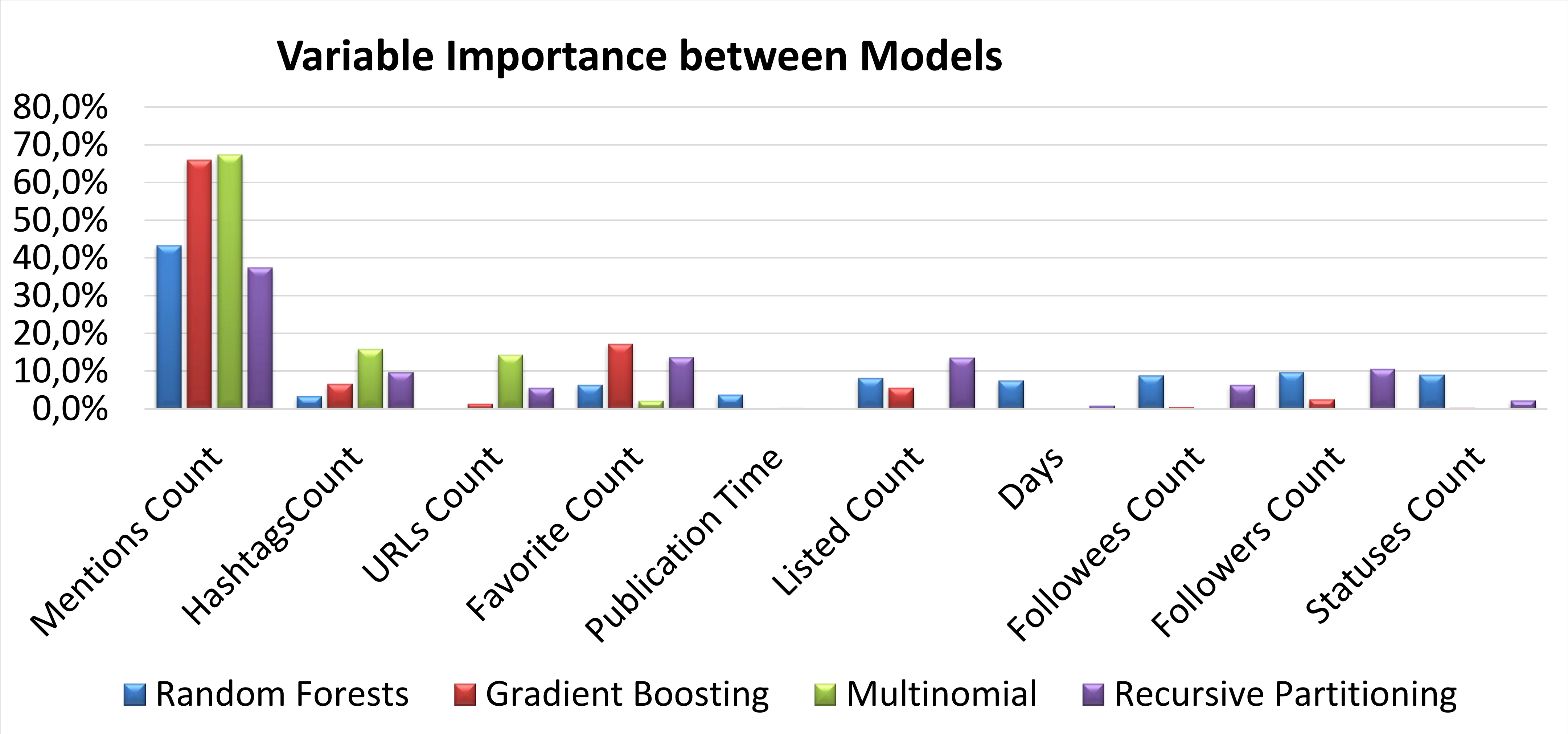
Classifier Models	Accuracy	Precision	Recall	F_1 score	Processing Time in sec.
Recursive Partitioning (Stat)	**0.6807**	**0.8512**	**0.7767**	**0.8122**	**180**
Random Forests (ML)	0.6884	0.8601	0.7866	0.8217	198968
Gradient boosting (ML)	0.6796	0.8534	0.7731	0.8113	64448
Multinomial Model (Stat)	0.6411	0.8367	0.7245	0.7765	31576

reTweet proneness (RPART), 100M

Assessment drivers	Degree of Retweeting Classes				
	0	1-100	101-1000	1001-10000	Over 10000
Sensitivity	0.7737	0.8105	0.3142	0.0208	0.0136
Specificity	0.9132	0.6694	0.9199	0.9996	1.0000
Positive Predictive Value	0.8564	0.6256	0.3752	0.7345	0.8488
Negative Predictive Value	0.8579	0.8382	0.8975	0.9485	0.9915
Prevalence	0.4007	0.4053	0.1328	0.0526	0.0086
Detection Rate	0.3100	0.3285	0.0417	0.0011	0.0001
Detection Prevalence	0.3620	0.5251	0.1112	0.0015	0.0001
Balanced Accuracy	**0.8435**	**0.7399**	**0.6170**	0.5102	0.5068

Accuracy	0.6815
Accuracy 95% Confidential Interval (min, max)	(0.6813, 0.6817)
Recall	0.7737
Precision	0.8564
Kappa	0.4922

Predictive models VS metrics relevance



Citations and self training

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- V. Grasso, A. Crisci, M. Morabito, P. Nesi, G. Pantaleo, I. Zaza, B. Gozzini, "Italian codified hashtags for weather warning on Twitter–who is really using them?." Advances in Science and Research 14 (2017): 63-69. http://www.adv-sci-res.net/14/63/2017/asr-14-63-2017.pdf

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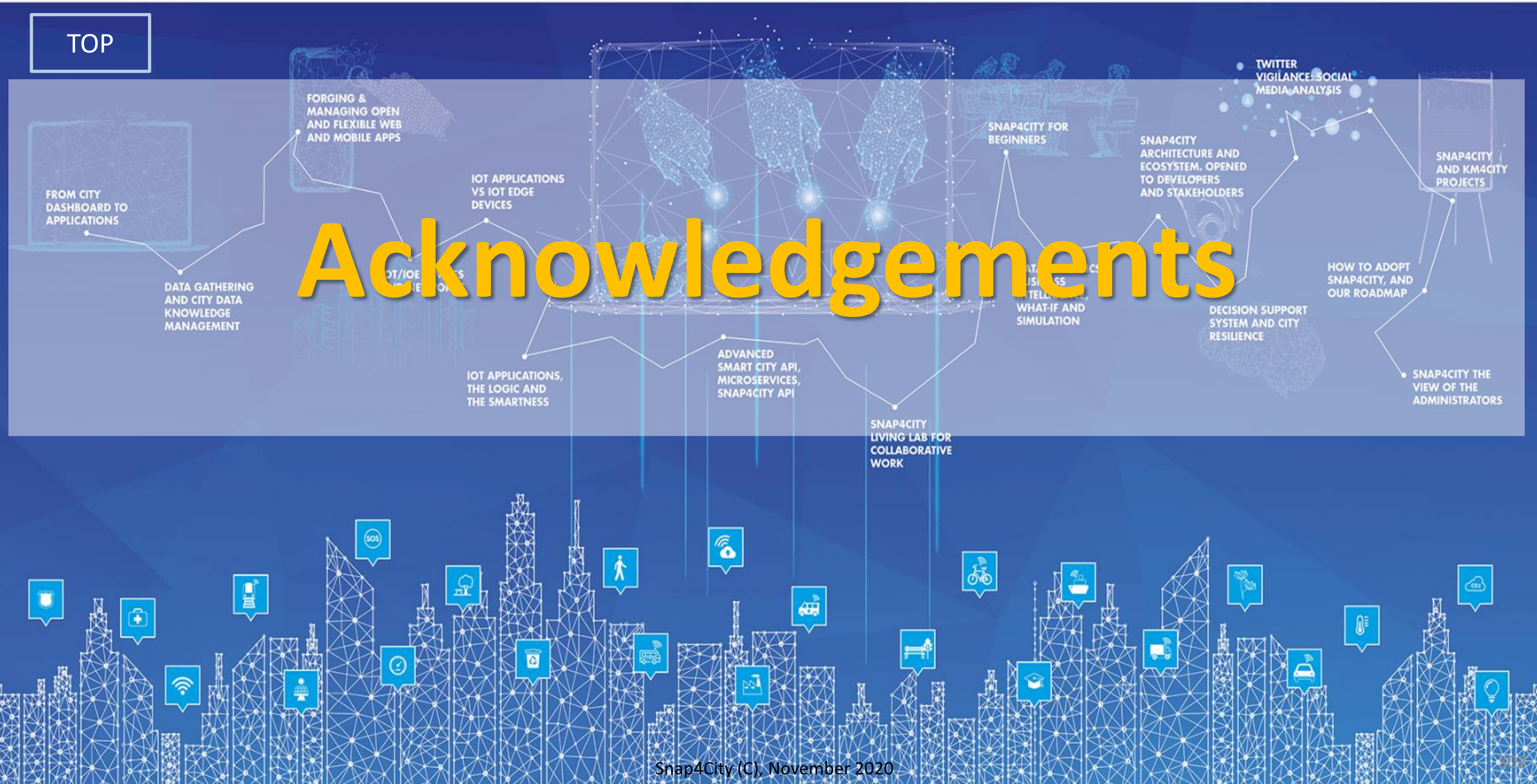

DISIT lab roadmap vs model and tools' usage

2013 Km4City Ontology 1.1
- Tuscany, Road Graph
- Mobility
- culture, tourism
- Events
- Parking
- Services
- Linked open graph

2014
- Weather Forecast
- Real Time Wi-Fi
- Entertainment
- LOD

- Twitter Vigilance
- Social Media Analytics, Sentiment Analysis

Km4City 1.4

2015

ckan

resolute H2020 (2015-18)

Km4City 1.5

- Resilience Decision Support
- Smart First Aid
- User Behaviour Analysis, predictions
- Risk Analysis

2016 FIWARE

Sii-Mobility (2016-21)
SII-MOBILITY SCN
- Infomobility
- Mobile App
- Routing
- Multimodality

Km4City 1.6.2

(2016-21) H2020 REPLICATE
- Smart Energy
- Sustainable Mobility
- Control Room
- Dashboard

Km4City 1.6.4

Sii-Mobility
- Origin-Destination and trajectories
- Traffic Reconstruction
- Offer Analysis
- OBU, smart devices

E015 digital ecosystem
Powered by EXPO MILANO 2015

(2016-19) GHOST SIR

- Sardinia Region Smart City Strategies and plan

GREEN IMPACT C.A.P.A.C.I.T.Y.

GREEN IMPACT
POR FESR 2014-2020
- Industry 4.0
- Critical Plant
- Monitoring

2017

life weee (2017-20)
- Smart Waste

- IOT/IOE, IOT App
- Living Lab
- Maker Support
- IOT Edge
- Smart City IOT
- GDPR,
- Privacy & Security

SNAP4CITY
SELECT for Cities H2020 (2017-19)

IOT/IOE
Km4City 1.6.6
Node-RED

2018

Sii-Mobility
- User engagement
- Bike Sharing
- Data Analytics ++
- Social Predictions
- OBD2

MOSAiC
MObility 4.0 for SmArt (i) City
(2018-20)
- Mobility Demand / Offer Analytics and Strategy

5G (2018-21)
5G tech
Energy
Industry 4.0
Synoptics

CEF TRAFAIR (2018-21)
- Traffic and Mobility Impact on Pollution
- NOX predictions

2019

EUROPEAN OPEN SCIENCE CLOUD

SIRIUS

AID Smart Bed
- Smart Health

GREEN FIELD PEAS
NaOH Soda4.0
Optimization and Automated Decision System 4.0
- Industry 4.0

bee smart city
- Smart Lonato

Reverberi Enetec
Gruppo MPES

- PCP Award

SELECT for Cities
1° place award to SNAP4CITY

2020

Interreg Mediterranean
HERIT-DATA
- Smart Tourism
- 6 Pilots
- Data Analytics
- Extended platform

Interreg MARITTIMO-IT FR-MARITIME
MOBI MART
- Smart Mobility
- PISA, PUMS
- Living lab

smartGARDAlake

- CAPELON
- Sweden

2021

…2022

Main running instances

- Sii-Mobility → mobility and transport, sustainability
- REPLICATE → ICT, smart City Control room, Energy, IOT
- RESOLUTE → Resilience, ICT, Big Data
- GHOST → Strategies, smart city
- TRAFAIR → Environment & transport
- MOSAIC → mobility and transport
- WEEE Life → Smart waste, environment
- Smart Garda Lake → Castelnuovo del Garda
- 5G → Industry 4.0 vs SmartCity
- Green Impact → Industry 4.0, Chemical Plant
- SmartBed (laid → smart health
- Green Field Peas (soda) → Industry 4.0, Chemical plant
- MobiMart and PISA Agreement → data aggregation, mobility and transport, Living Lab
- Lonato del Garda → smart parking, environment
- Herit Data → tourism, culture and management
- ISPRA JRC → site management and services
- Capelon (Sweden) → smart light solutions

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DISIT thanks to

Herit Data: Tourism and Mng. https://herit-data.interreg-med.eu/
Snap4City: IOT/IOE smart city www.snap4city.org
Trafair: CEF project with several Cities http://trafair.eu/
Mosaic: Mobility and transport model
Km4City: http://www.km4city.org
REPLICATE H2020, SCC1, EC flagship
 http://replicate-project.eu/
Sii-Mobility SCN MIUR: http://www.sii-mobility.org
Feedback: retail and GDO Big Data analytics
5G with 3G-Wind, Open Fiber, Estra
Coll@bora Social Innovation, MIUR:
 http://www.disit.org/5479
RESOLUTE H2020, EC:
 http://www.resolute-eu.org
TRACE-IT, RAISSS, TESYSRAIL, …
Mobile Emergency:
 http://www.disit.org/5404

Trace-IT

RAISSS

Further readings

https://www.snap4city.org/108

- HOW TO: create a Dashboard in Snap4City
- HOW TO: add a device to the Snap4City Platform
- HOW TO: add data sources to the Snap4City Platform
- HOW TO: define privacy rules for personal data, produced by the end-users own device
- HOW TO: Develop Smart Applications, Snap4City development Life Cycle
- HOW TO: HLT vs Ingestion, and HLT vs Widgets
- HOW TO: Develop an IOT Application for Data Ingestion
- HOW TO: Upload data into Knowledge Base, ServiceMap (triple upload)
- HOW TO: Create as set of Devices with BulkProcessing
- HOW TO: Create an IOT Device Model
- HOW TO: Create an IOT Device Instance from IOT Directory tool

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CONTACT

DISIT Lab, DINFO: Department of Information Engineering
Università degli Studi di Firenze - School of Engineering

Via S. Marta, 3 - 50139 Firenze, ITALY
https://www.disit.org

www.snap4city.org

Email: snap4city@disit.org

Office: +39-055-2758-515 / 517
Cell: +39-335-566-86-74
Fax.: +39-055-2758570