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EU GDPR COMPLIANT

PEN Test Passed

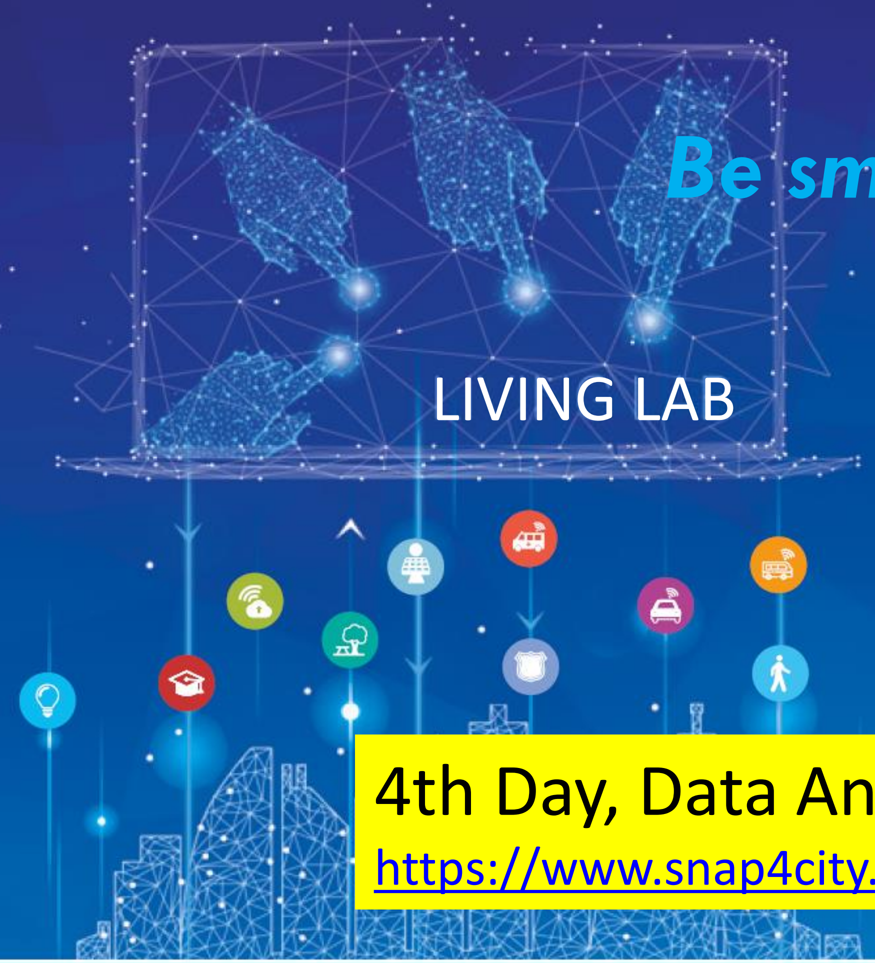
SNAP4CITY on EUROPEAN OPEN SCIENCE CLOUD MARKETPLACE

SNAP4 Appliances and Dockers Installations

SNAP4CITY

KM4CITY

Be smart in a SNAP!



4th Day, Data Analytics, Nov 2019

https://www.snap4city.org/501

SCALABLE SMART ANALYTIC APPLICATION BUILDER FOR SENTIENT CITIES

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SNAP4CITY

KM4CITY Powered by

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

https://www.Snap4City.org

100% OPEN SOURCE

4th Day, Data Analytics, Nov 2019

https://www.snap4city.org/501

Paolo Nesi, paolo.nesi@unifi.it

https://www.Km4City.org

https://www.disit.org

General Overview of the full Course

- **1st Day:** *General overview (1 day, 6 hours)*
- ***2nd Day:*** *Dashboards, how to build and manage them (4 hours)*
- ***3rd Day:*** *IOT Applications development, IOT Devices, IOT Networks (4 hours)*
- ***4th Day:*** *Data Analytics, in R Studio, In Python, how to integrate with IOT Applications (4 hours)*
- ***5th Day:*** *Data Ingestion, Data Warehouse, ETL Development, Data Gate, IOT Device Data ingestion, etc.. (5 hours)*
- ***6th Day:*** *Snap4City Architecture, How To Install Snap4City (3 hours)*
- ***7th Day****: Smart city API (internal and external) Web and Mobile App development tool kit (4 hours)*

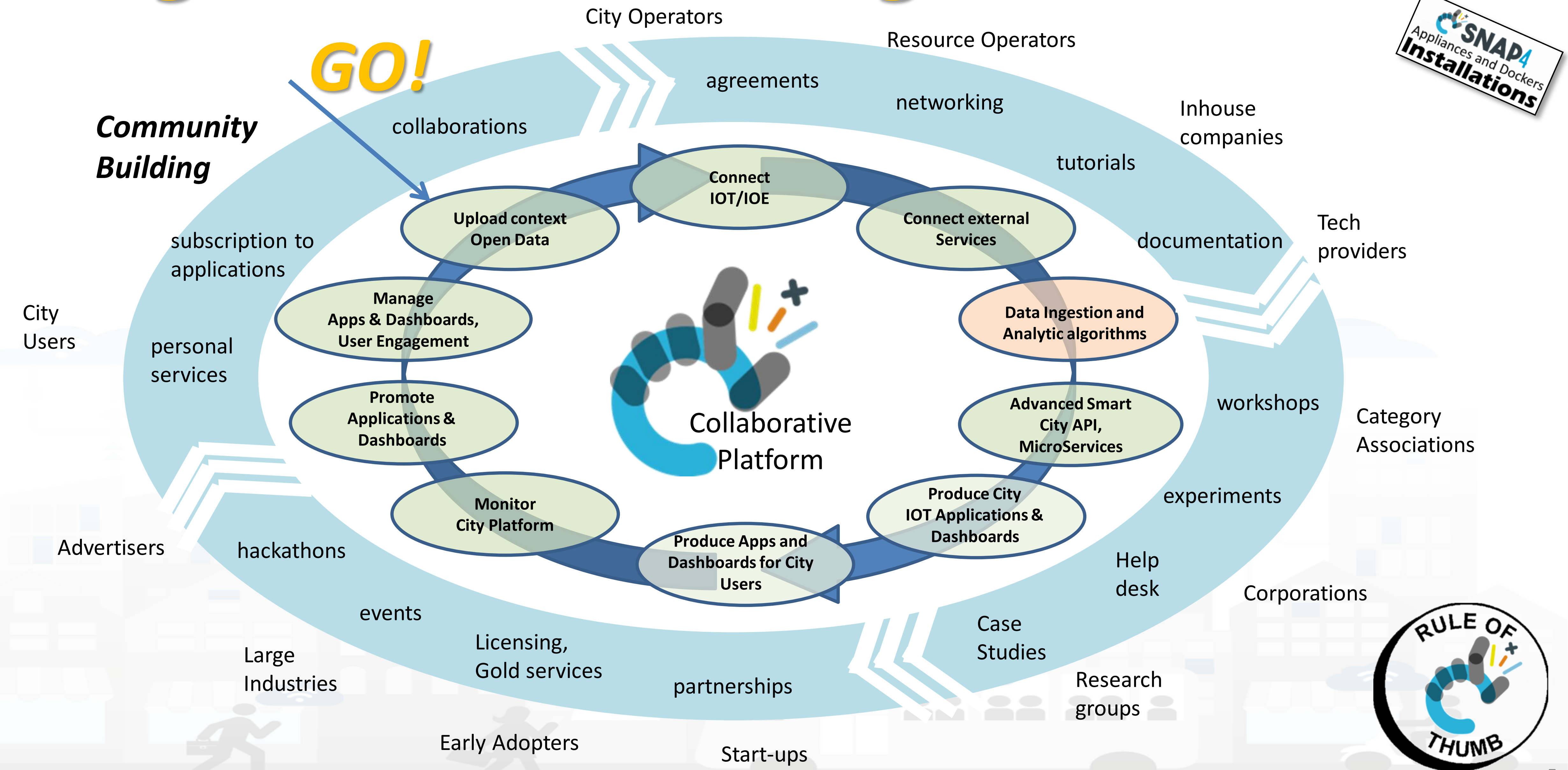
A number of the training sections include exercitations

Updated versions on: https://www.snap4city.org/501

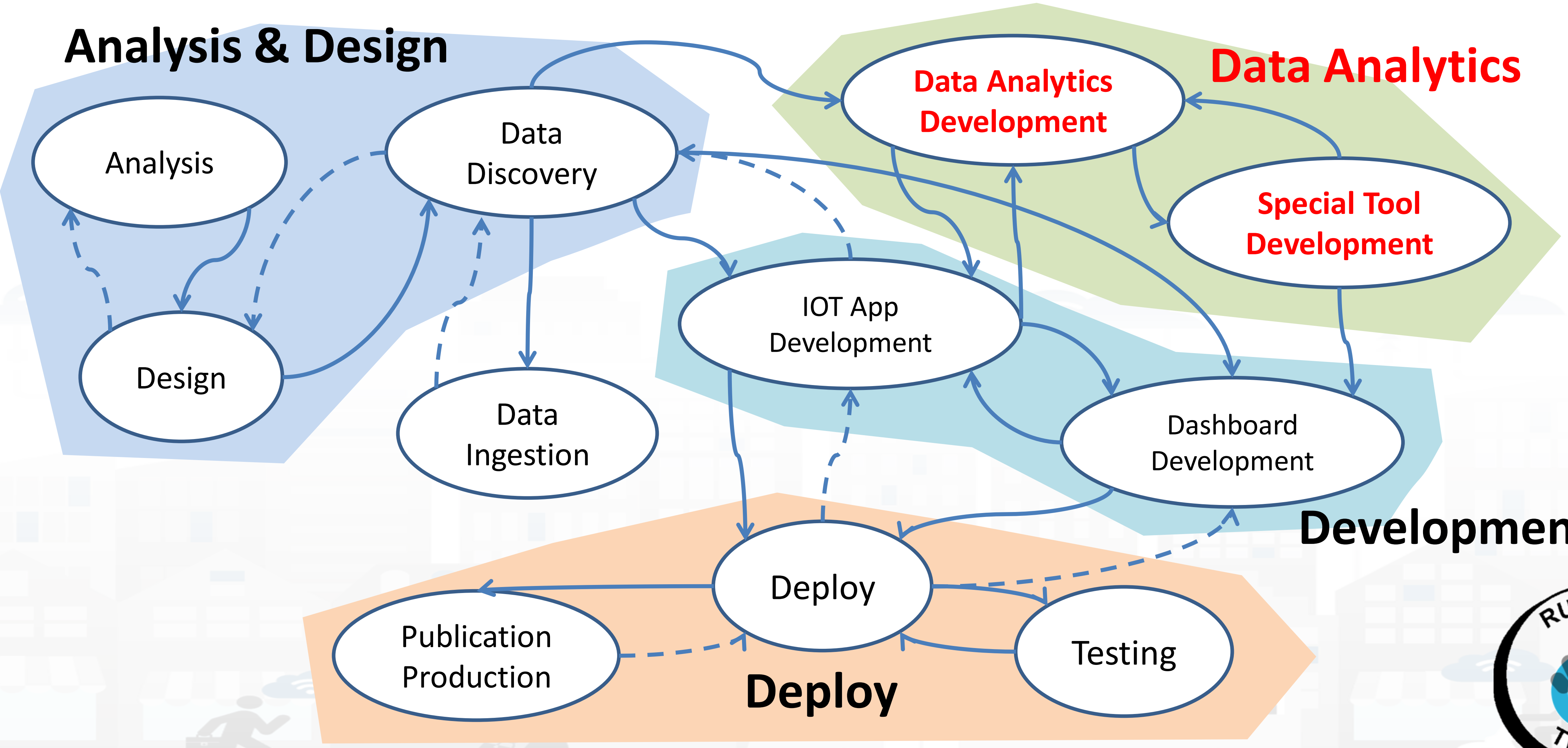
4th day Agenda

- GO **Data Analytics: Examples from Snap4City**
  - GO – Smart parking: Predictions
  - GO – User Behavior Analysis, via Wi-Fi, OD, Trajectories
  - GO – Recognition of Used Transportation means
  - GO – Traffic Flow Reconstruction, from Traffic Sensors Data
  - 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 **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

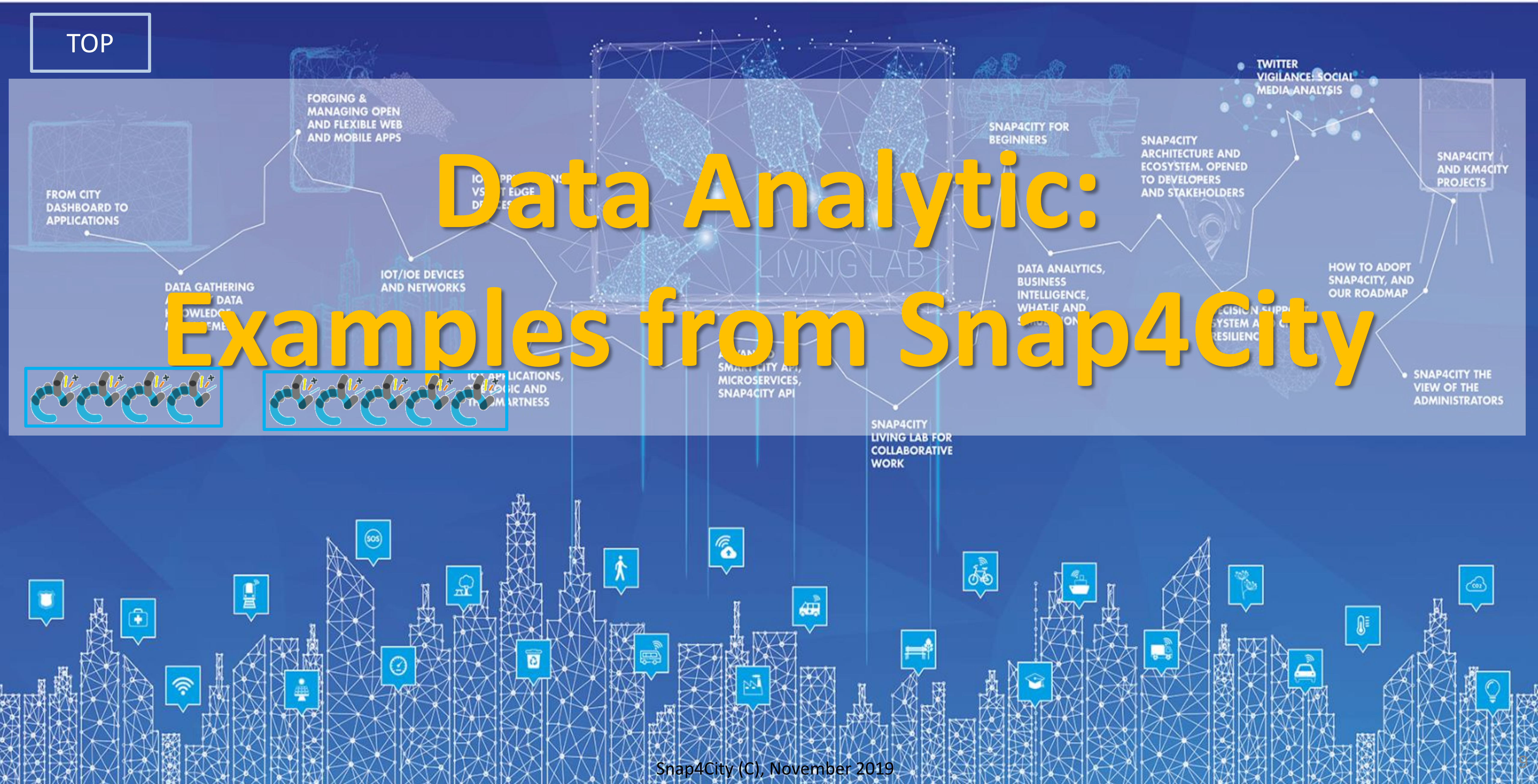
• Easy.	non programmer level
• Moderate.	Some JavaScript rudiment coding
• Good.	JavaScript programming
• Golden.	Programming in R Studio
• Professional.	Exploiting Smart City API
• Excellent.	Developing Full IOT Applications, Dashboard and Mobile Apps

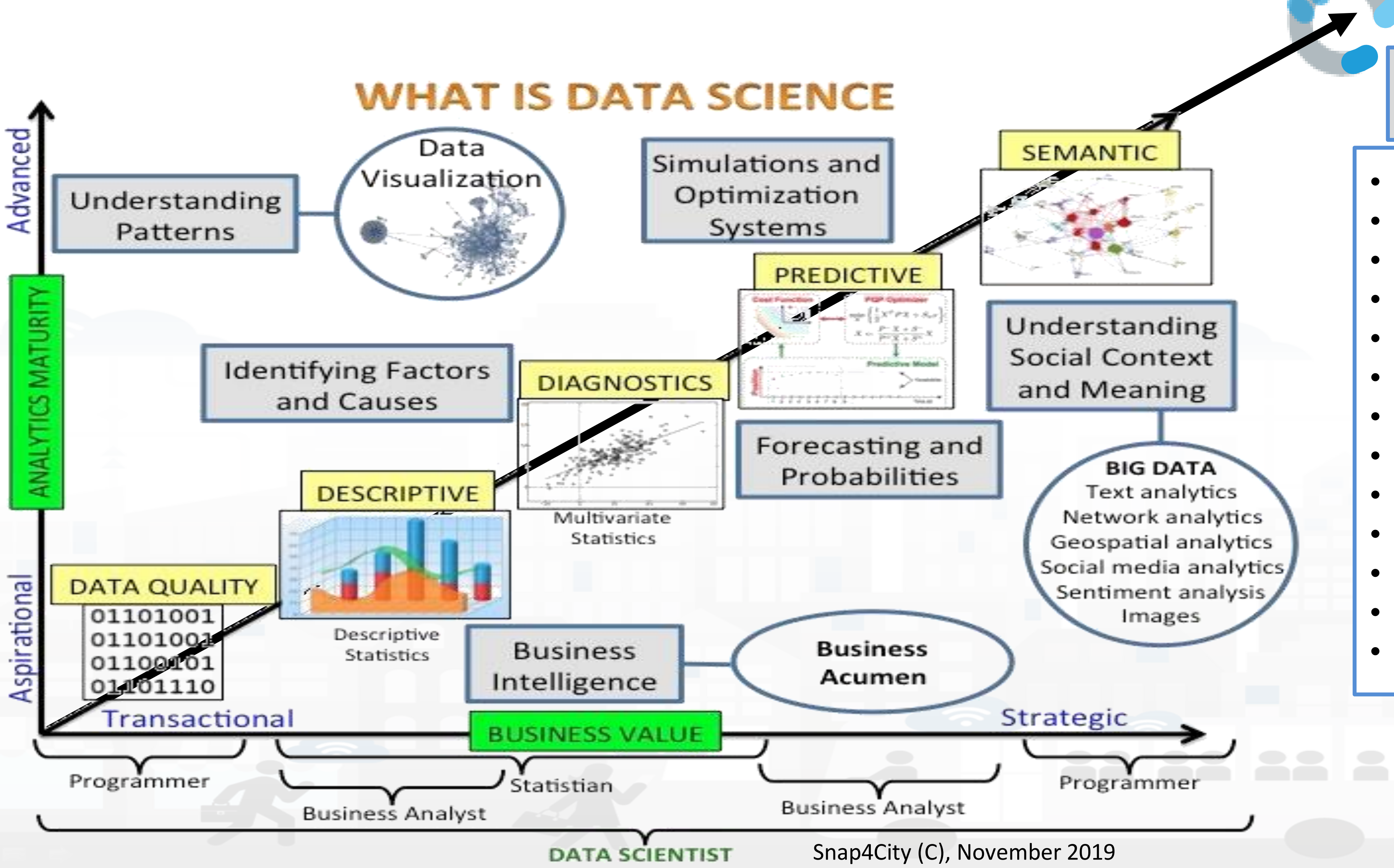
Self Training main path

- **Please start a fully guided training cases:**
  - 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

TOP

Data Analytic: Examples from Snap4City





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
- ....

DATA ANALYTICS

- Traffic flow reconstruction from sensors and other sources: parking predictions: wi-fi people flow prediction and reconstruction
- What-if analysis, dynamic routing, origin destination matrices production from a large range of sources
- Analysis of the demand vs offer of mobility according to public transportation and multiple data sources
- Resilience and risk analysis
- Early warning computation
- Accidents heatmaps
- Traffic flow predictions
- NOX pollution prediction on the basis of traffic flow, 48 hours see
- Pollution prediction at 48 hours, every hour
- User engagement for sustainable mobility
- User’s behaviour analysis, data reconstruction and calibration
- Tracking fleets, people, devicesOBD2 support
- People flow analysis from PAX Counters
- Social media analysis on specific channel, specific keywords: see Twitter Vigilance, for NLP and Sentiment Analysis, SA
- Data quality assessment, prediction, anomaly detection
- Maintenance prediction and costs predictions
- ReTweet proneness, retweet-ability of tweets
- Audience prediction to TV channels and physical events

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Disappearing Data Analytics

SNAP4CITY	Antwerp					Helsinki								Where				RULE OF THUMB
	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.
  – **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
  – **Trajectories** of people flow
  – **Traffic Flow** reconstruction
  – **Origin Destination Matrices**
  – **Simulations**: demand vs offer

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,….)

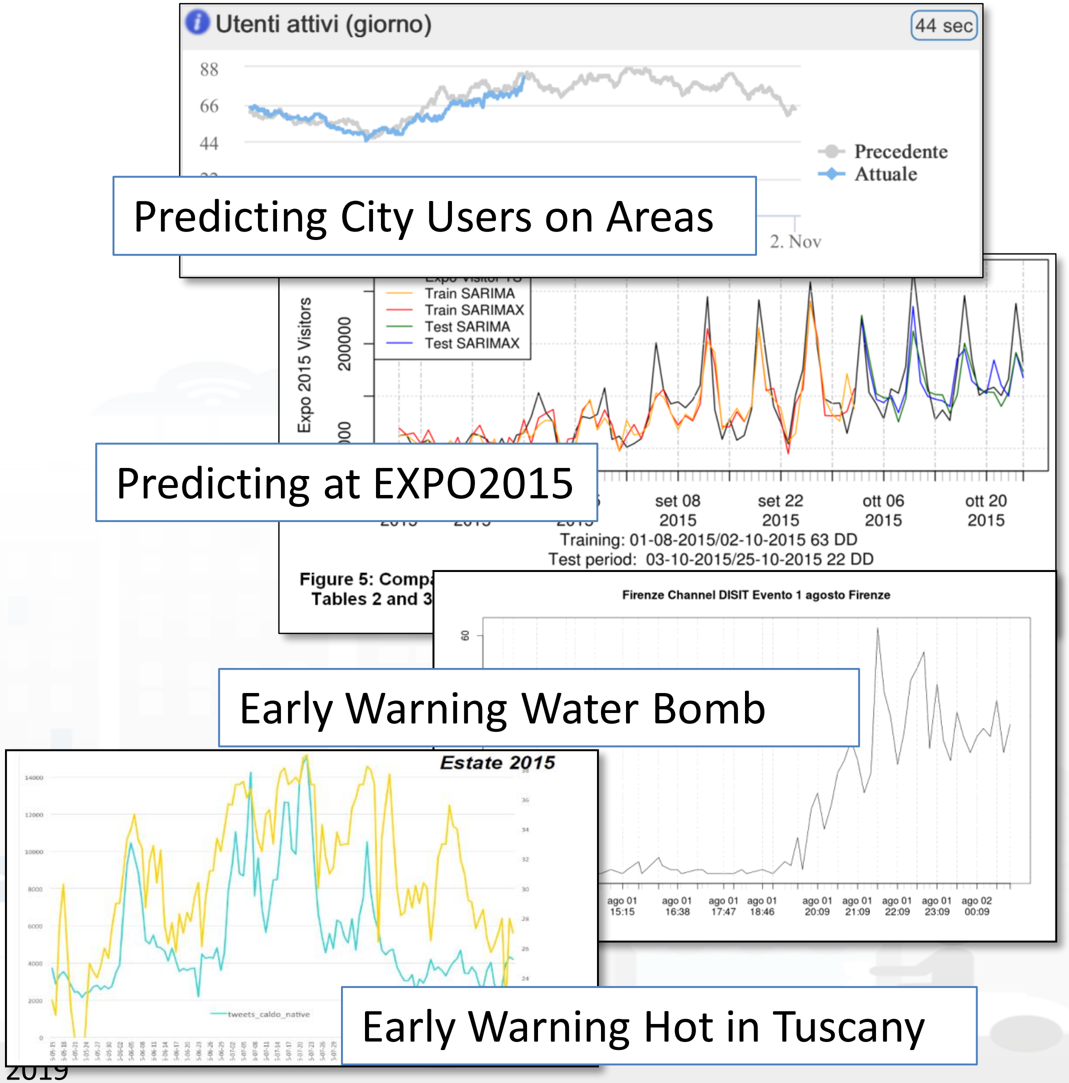
- **Weather and environment, quality of life**
  - **Weather forecast/condition** (Weather forecast)
  - **Air quality Pollution** (pollution sensors, PM10, PM2.5, NOX, etc.)
  - **Pollination** (Pollination sensors)
  - **Alerting on Air quality for multiple parameters** (Prediction of parameters time slots, notification)
  - **Information Heatmaps for weather and air quality** (air quality sensors, heatmaps, prediction)
  - **Air quality indexes, and forecast** (…………………

Snap4City and Data Analytic (summary)

- **Data Analytics** in Snap4City 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, what-if analysis, smart routing, heatmaps, etc.
- **can be developed** in:
  - R Studio / Tensor Flow, MapReduce, Java, Python, ETL, IOT Applications
- **can 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) and mid Term (1 week)
- **Data Analytics**: ML, 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)

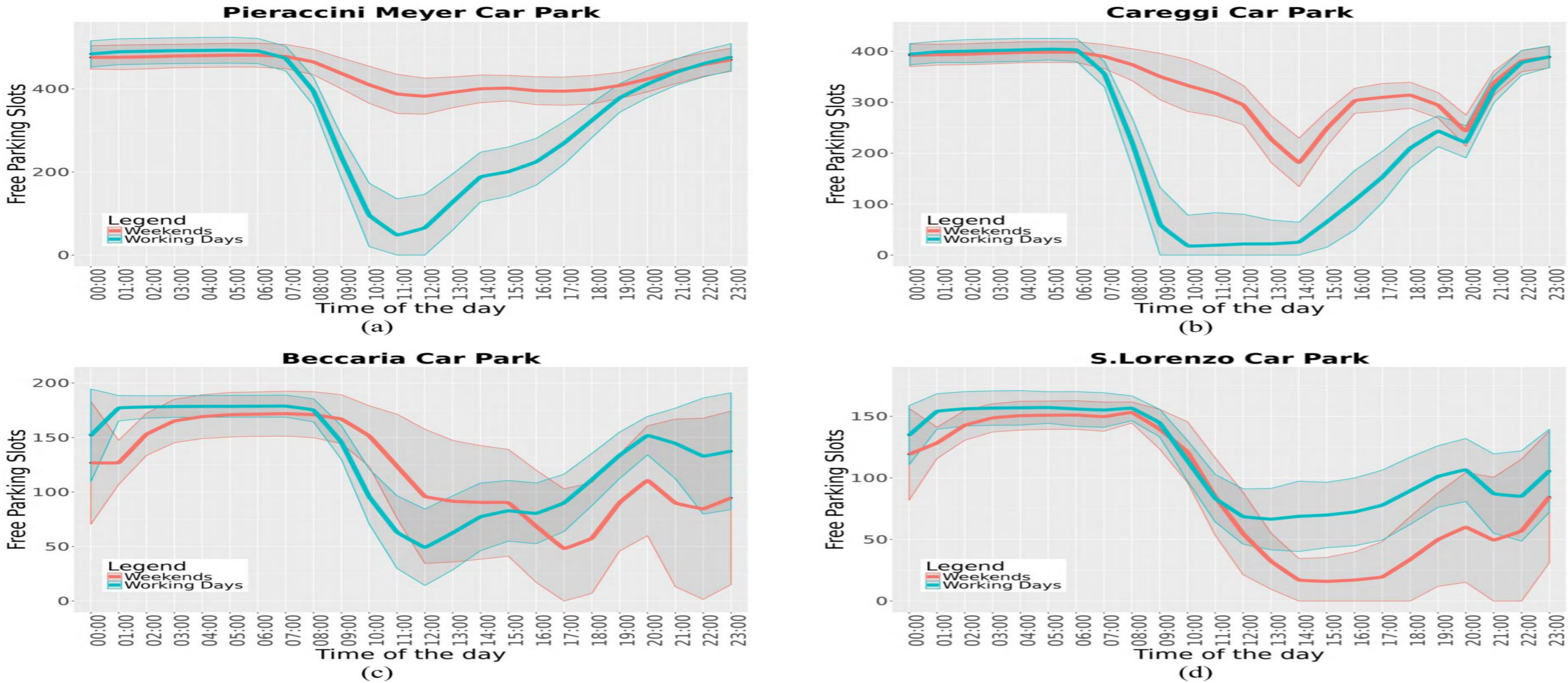
- R Studio Development
- TC7.2 - R Studio for Analytics, exploiting Tensor Flow
- TC7.4 - From R Studio process to MicroService for IOT application, data analytics, machine learning
- TC7.5 - Developing Data Analytics Processes
- US7. Data Analytics and related integration aspects

TOP

Smart Parking: predictions


autostrada
FIESOLE
SIENA

Free Parking space trends

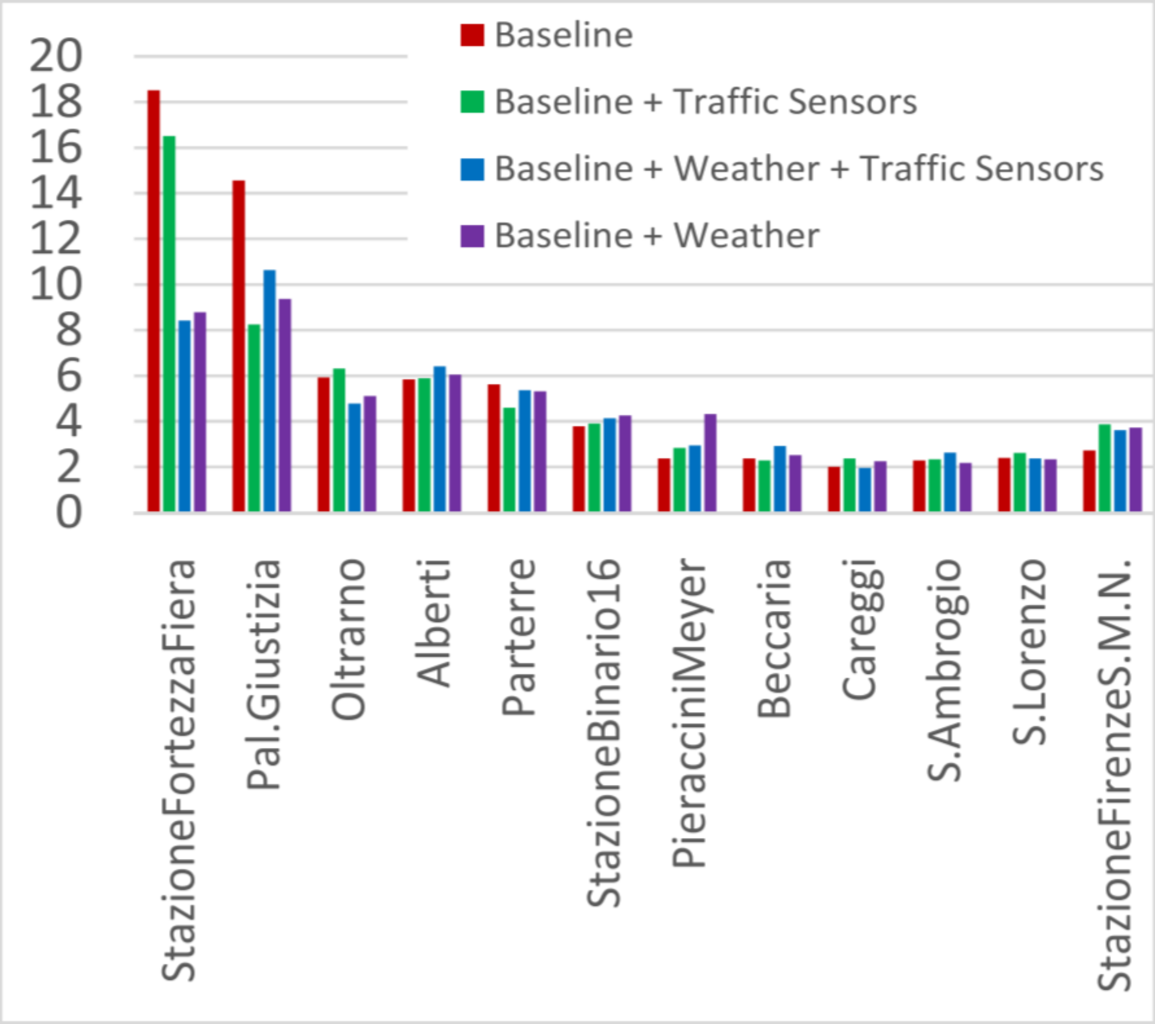


12 parking areas in Florence

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

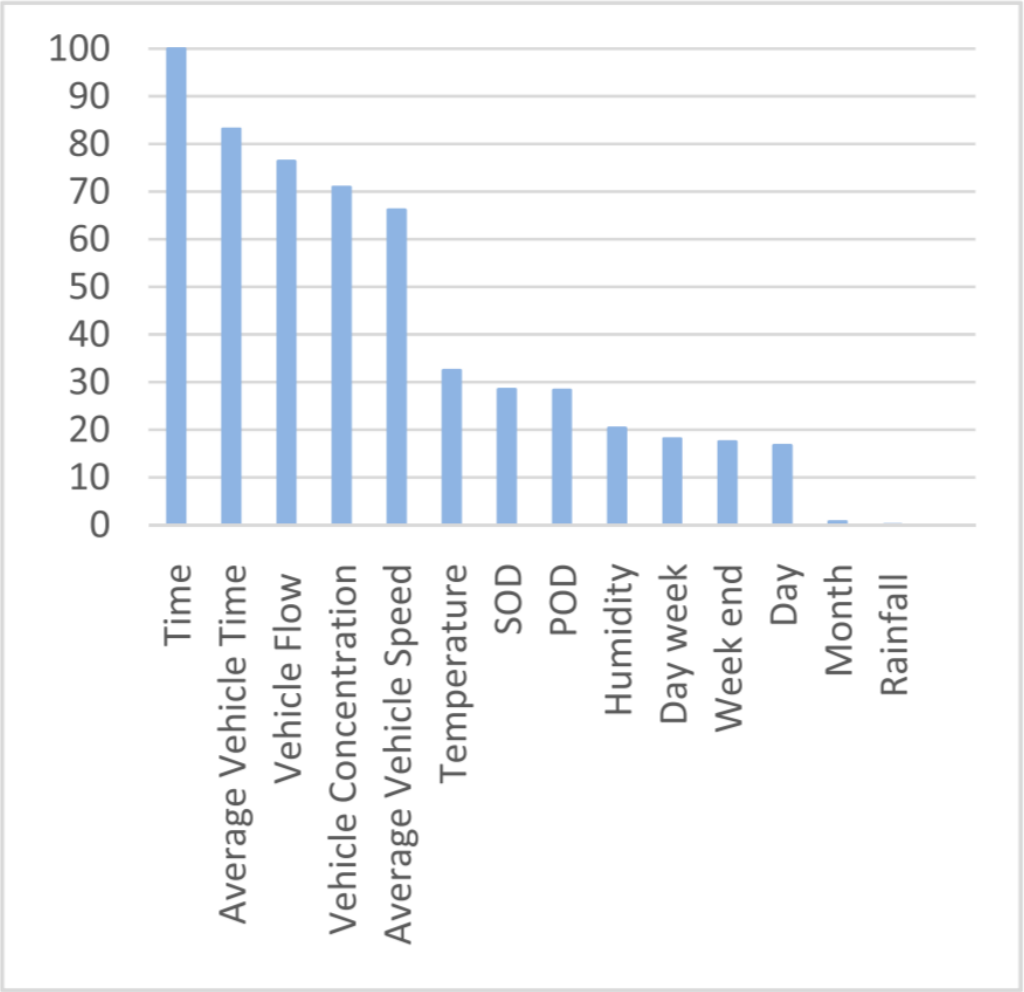


Free Parking PREDICTIONS

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

Relevance of Variable



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

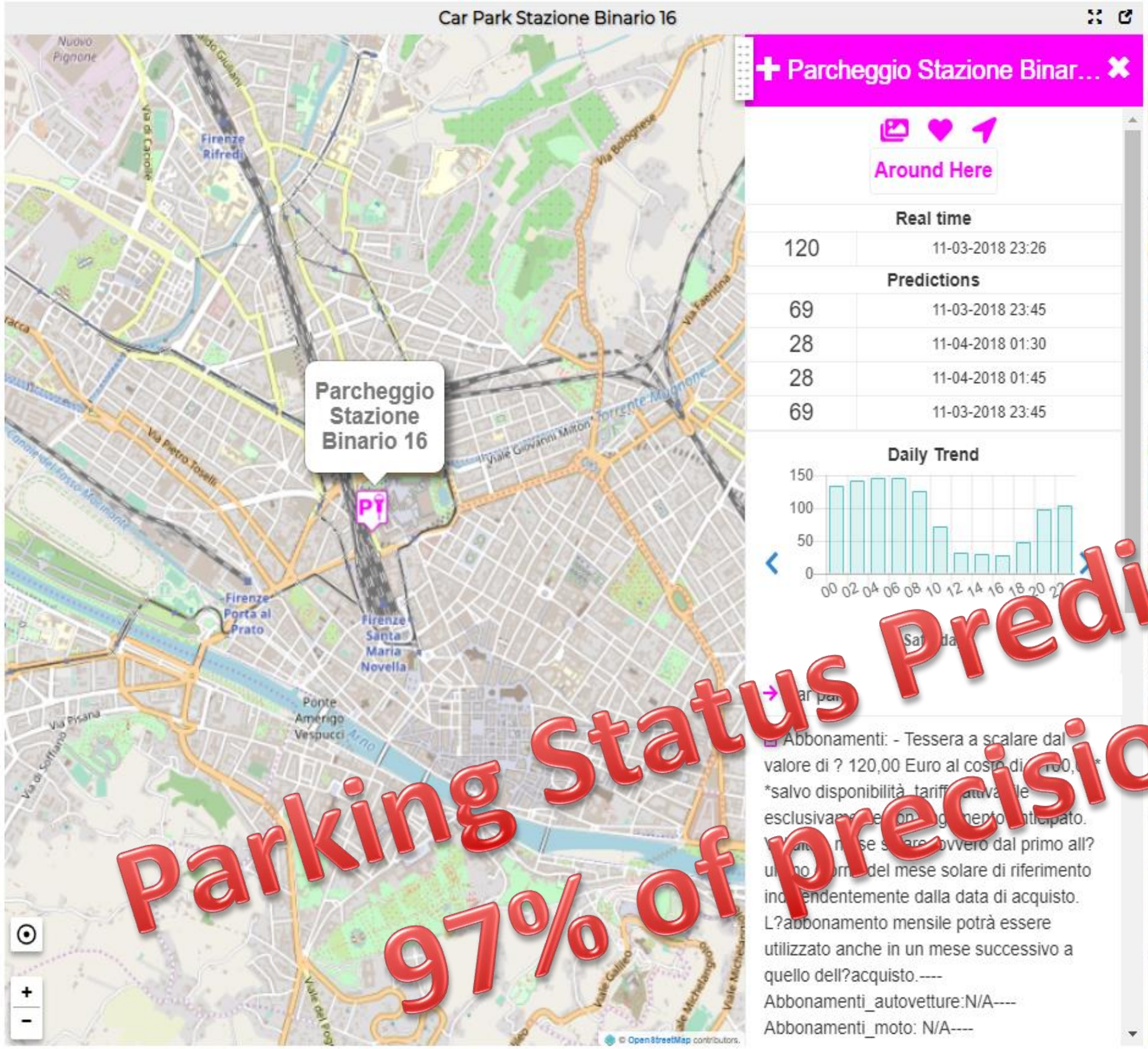
Active on Mobile Apps as:

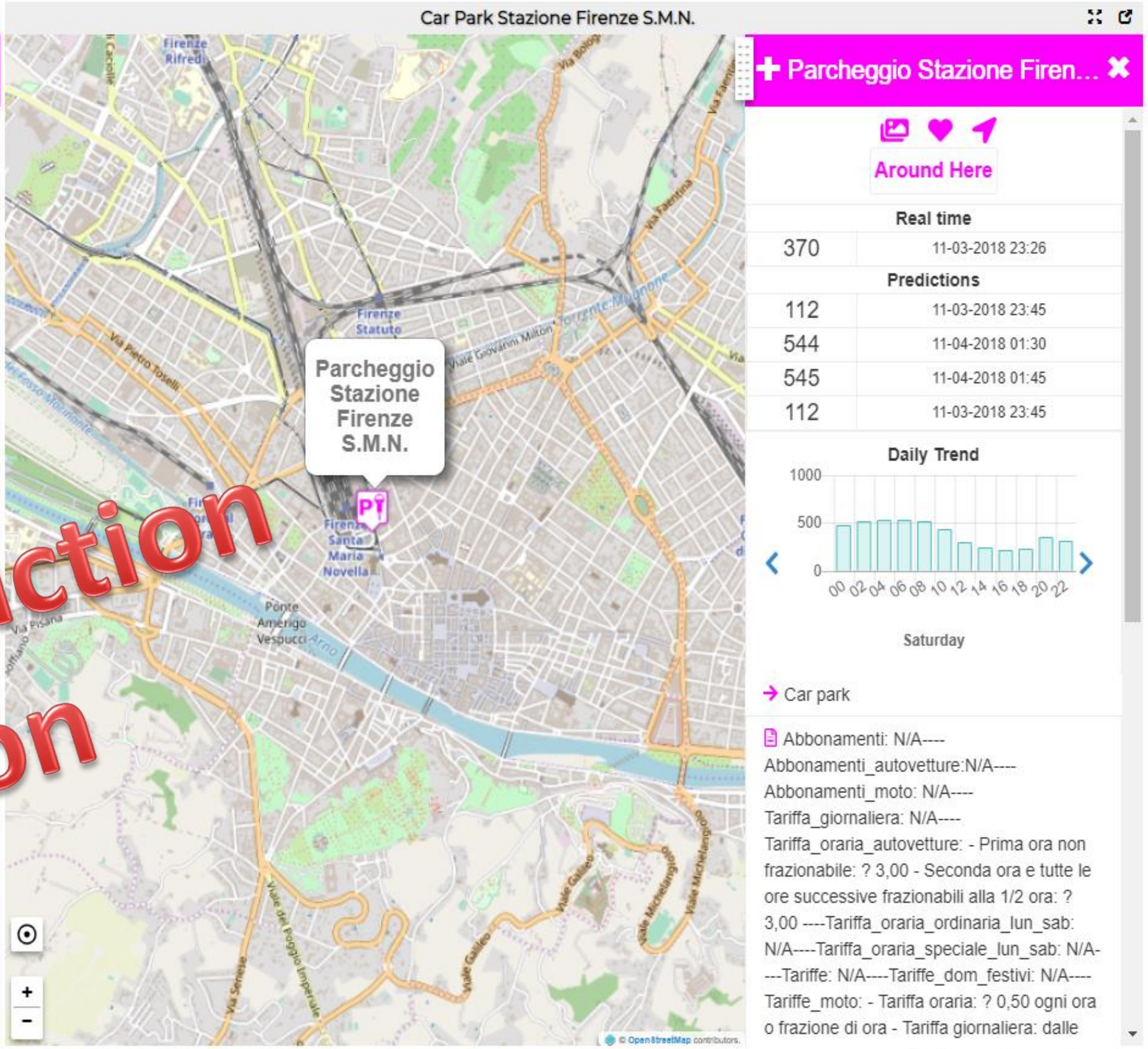
- «Firenze dove cosa»
- «Toscana dove cosa»

Precision: 97,5%

Monitoring Station for Parking

Sat 3 Nov 23:39:55





Parking Status Prediction

97% of precision

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

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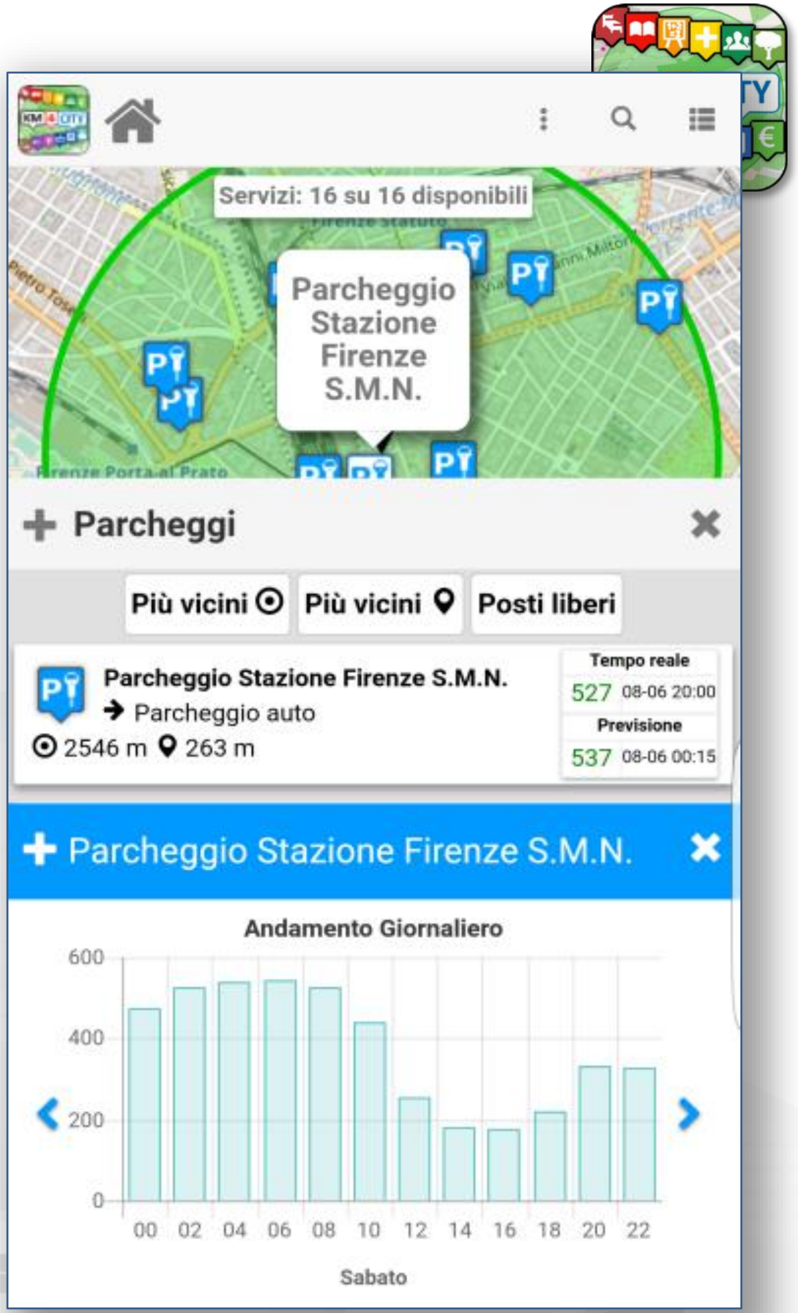
Predictions on Parking

- 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/

IEEE Access

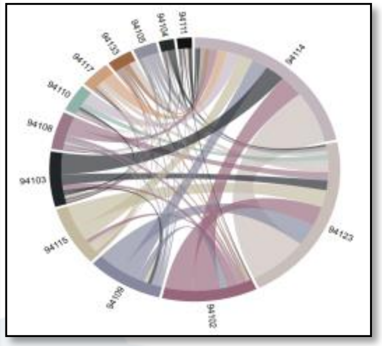


TOP

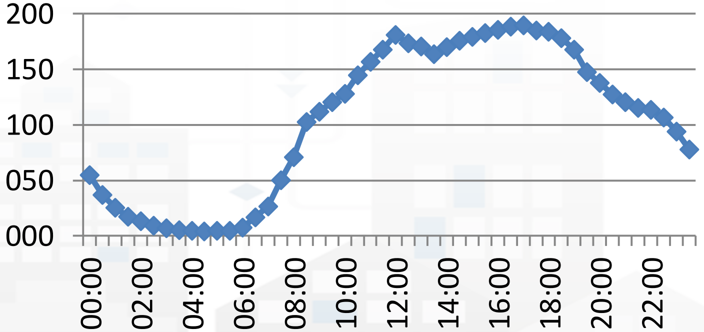
User Behaviour Analysis via Wi-Fi, OD Matrices, Trajectories

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**
  - **…….**



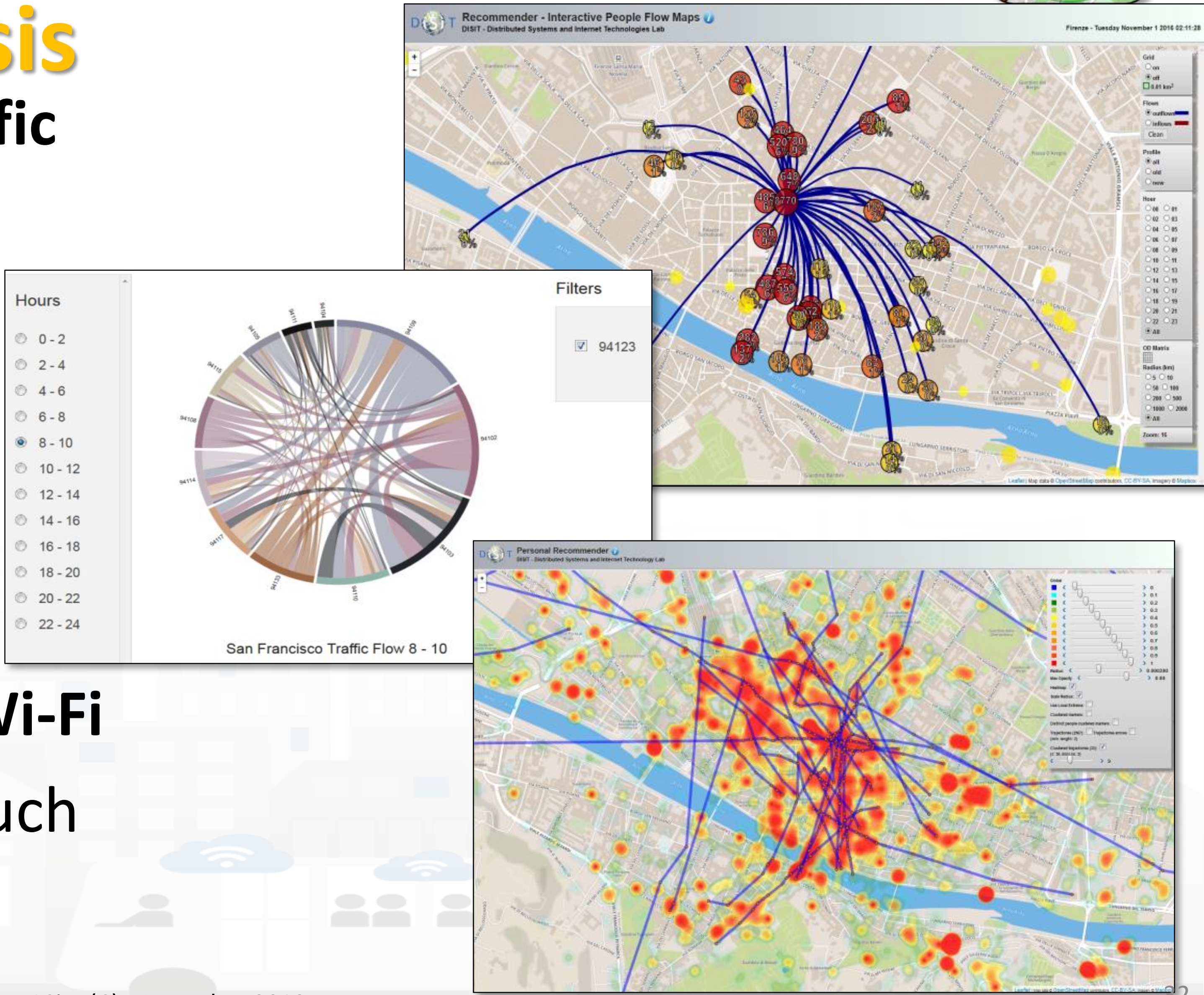
- Daily trends
- OD matrices
- Trajectories
- Prediction models



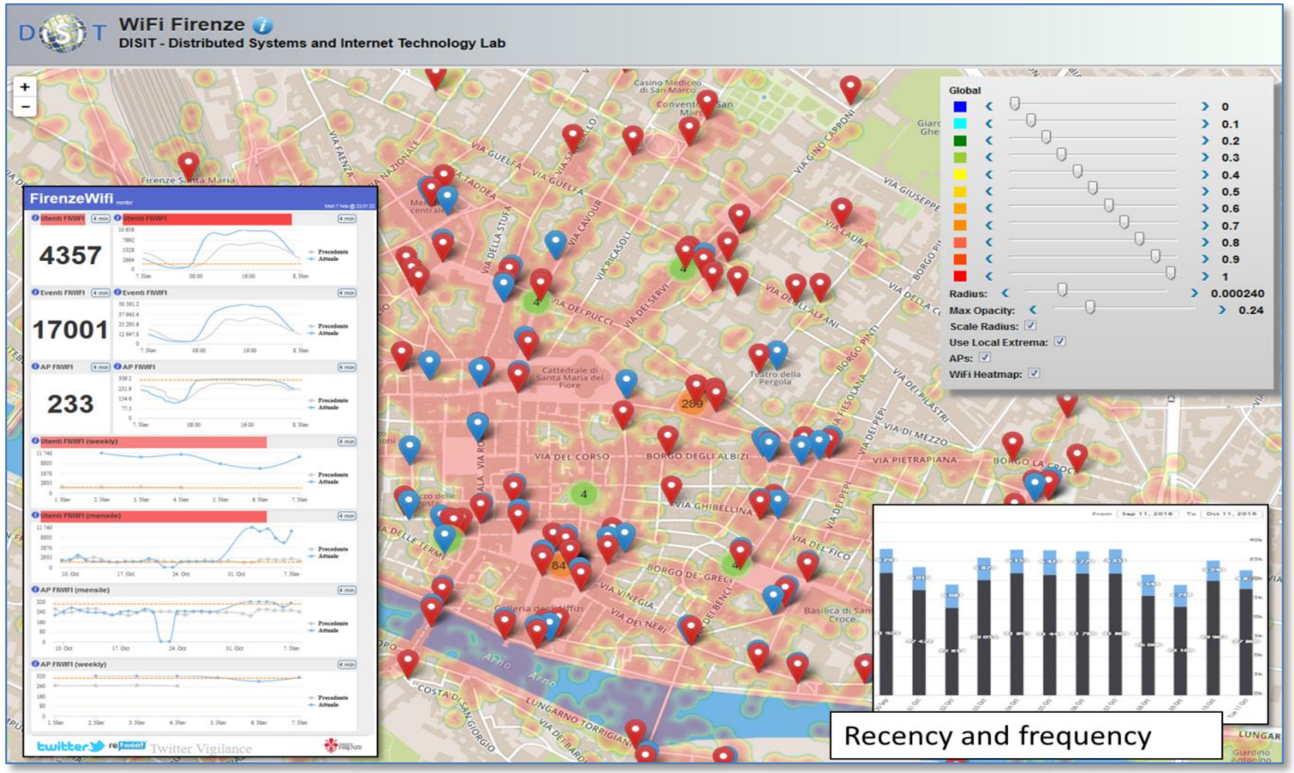

1007
GEST
904
1016

User Behaviour Analysis

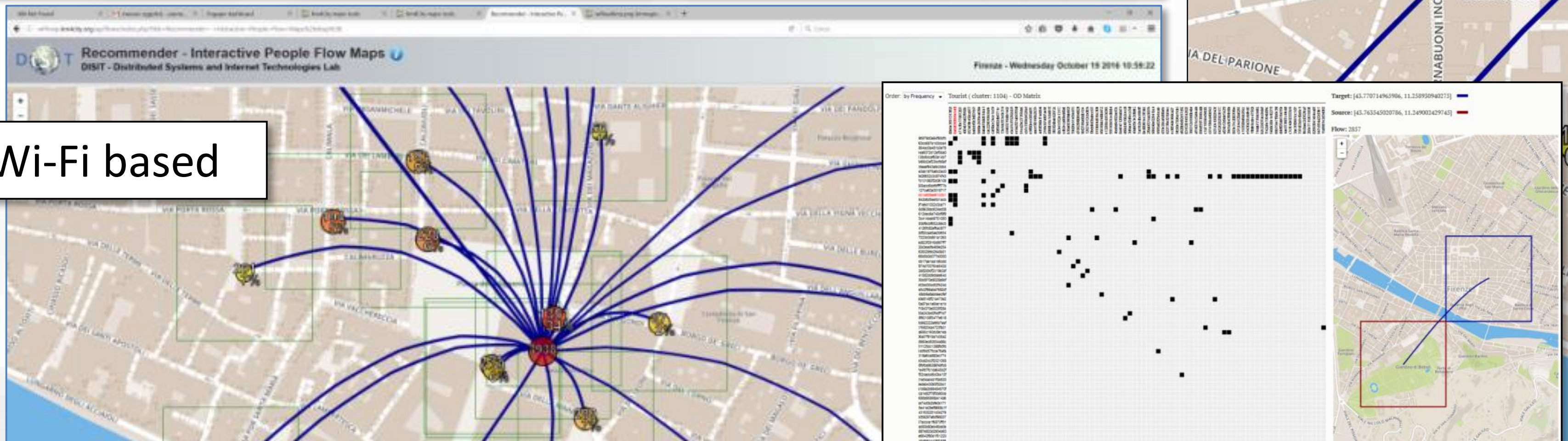
- **Monitoring movements by traffic flow sensors**
  - Spires and virtual spires
- **Monitoring movements from Mobile Cells**
  - Unsuitable for precise tracking and OD production
- **Monitoring movements from Wi-Fi**
- **Monitoring movements** and much more from mobile Apps



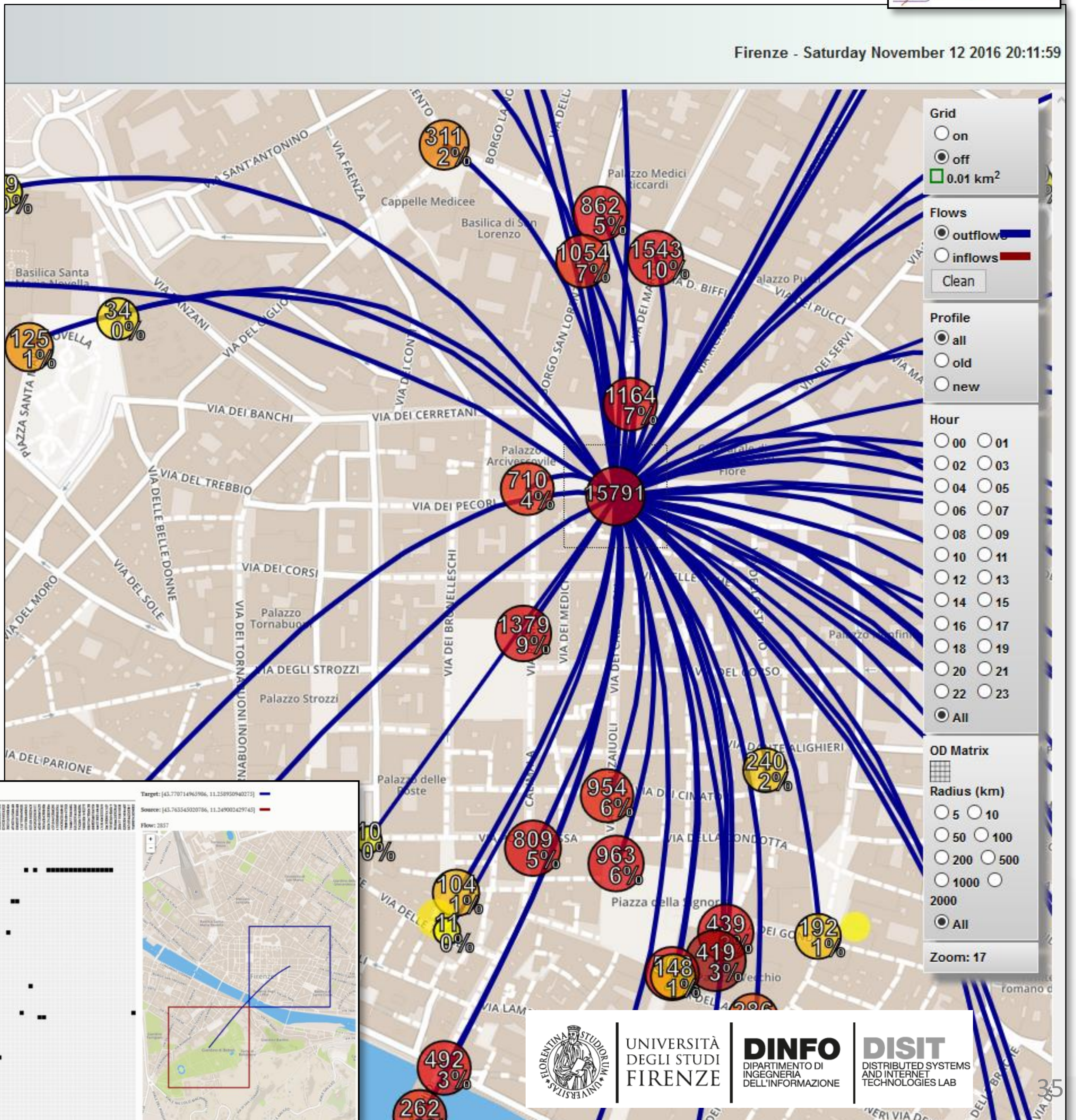
Origin Destination Matrix Estimation



Recency and frequency

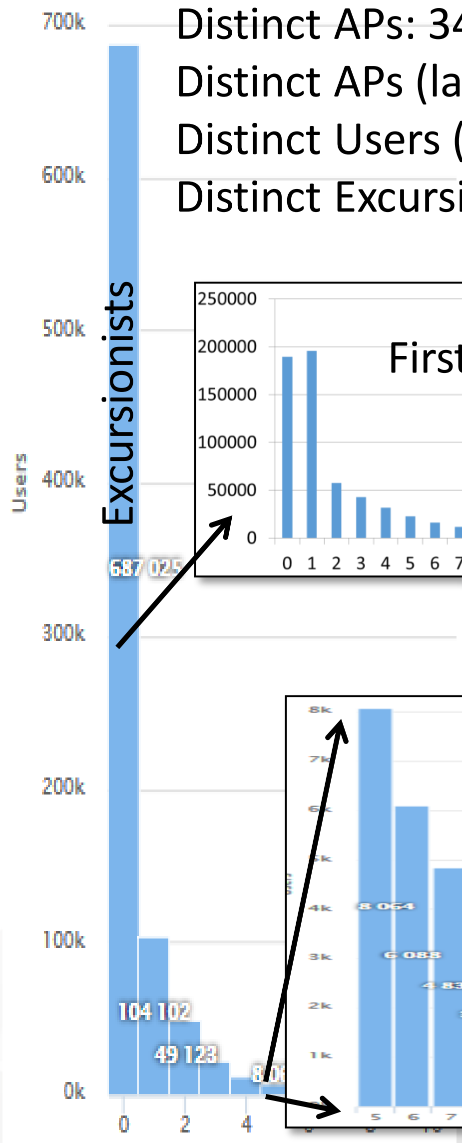


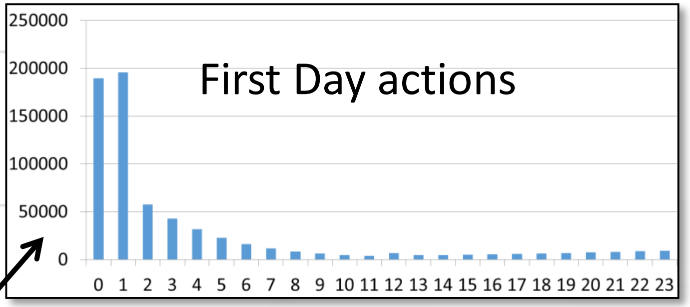
Wi-Fi based

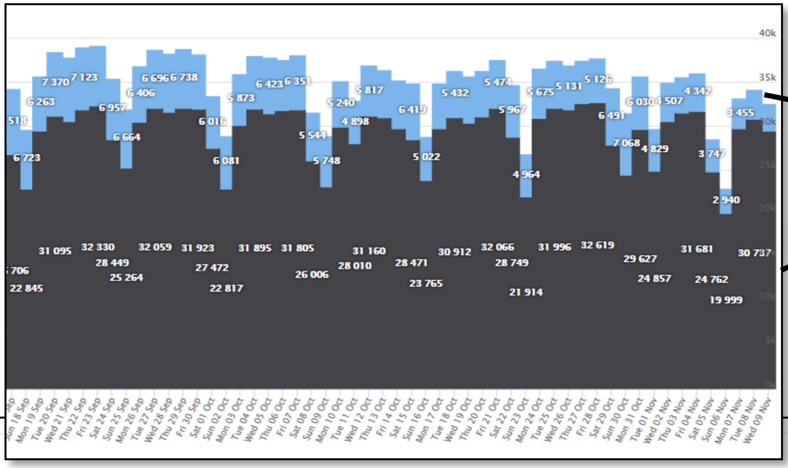


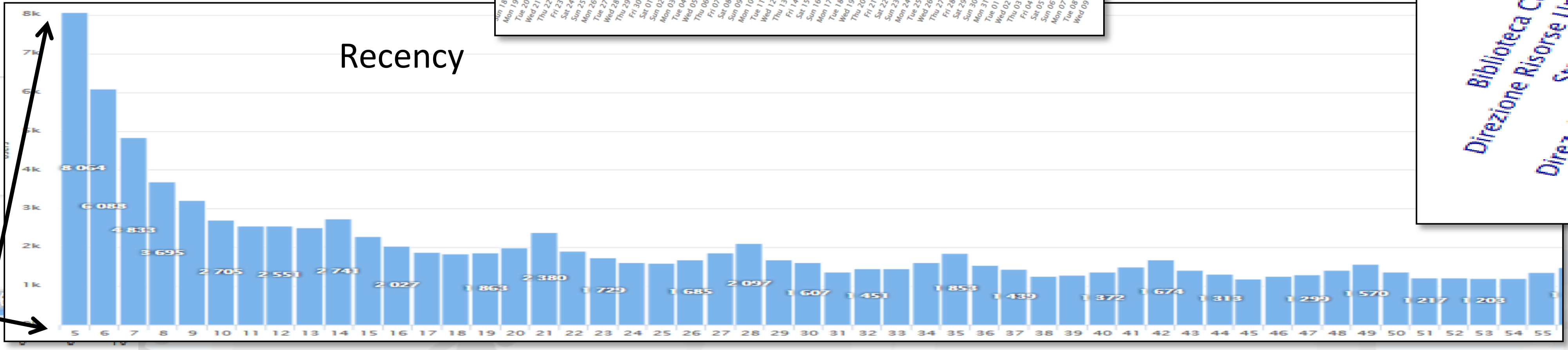
User Behaviour Analysis

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

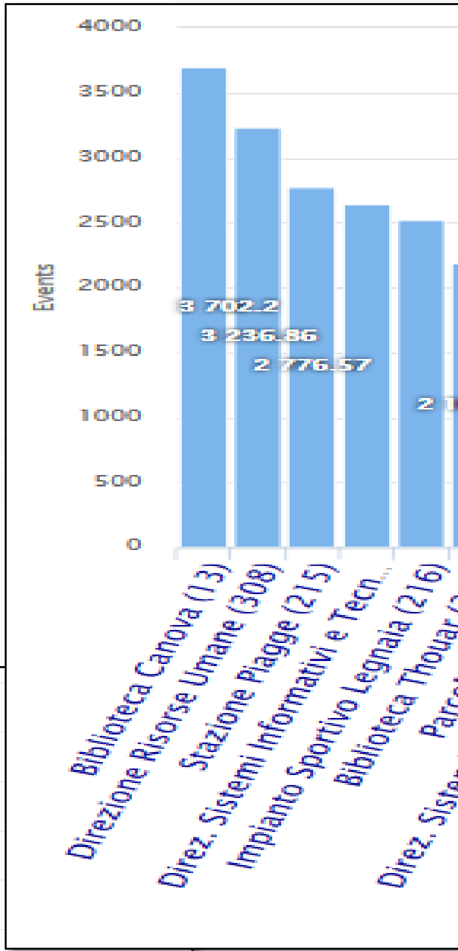








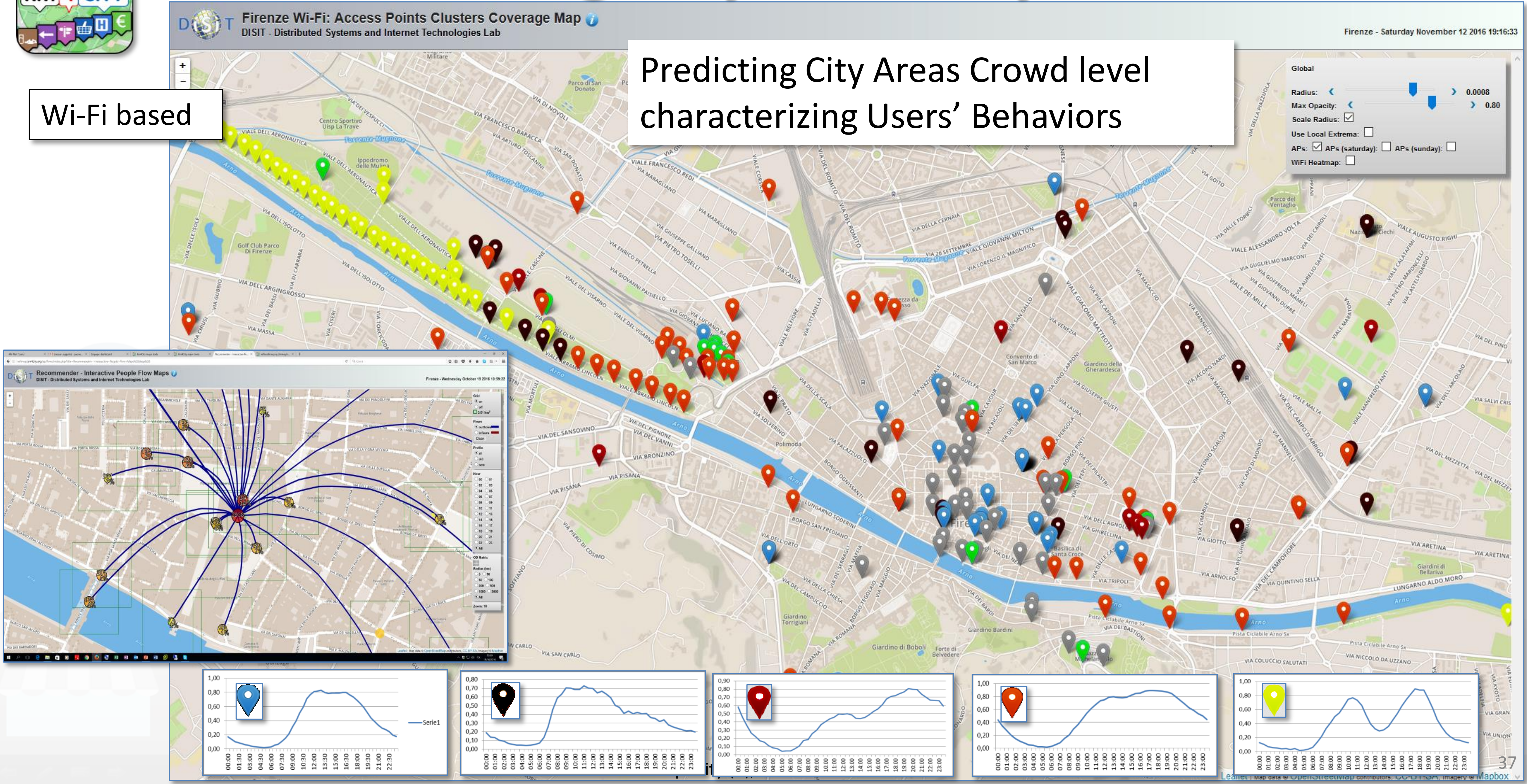
Where



Characterizing City Areas by User Behavior

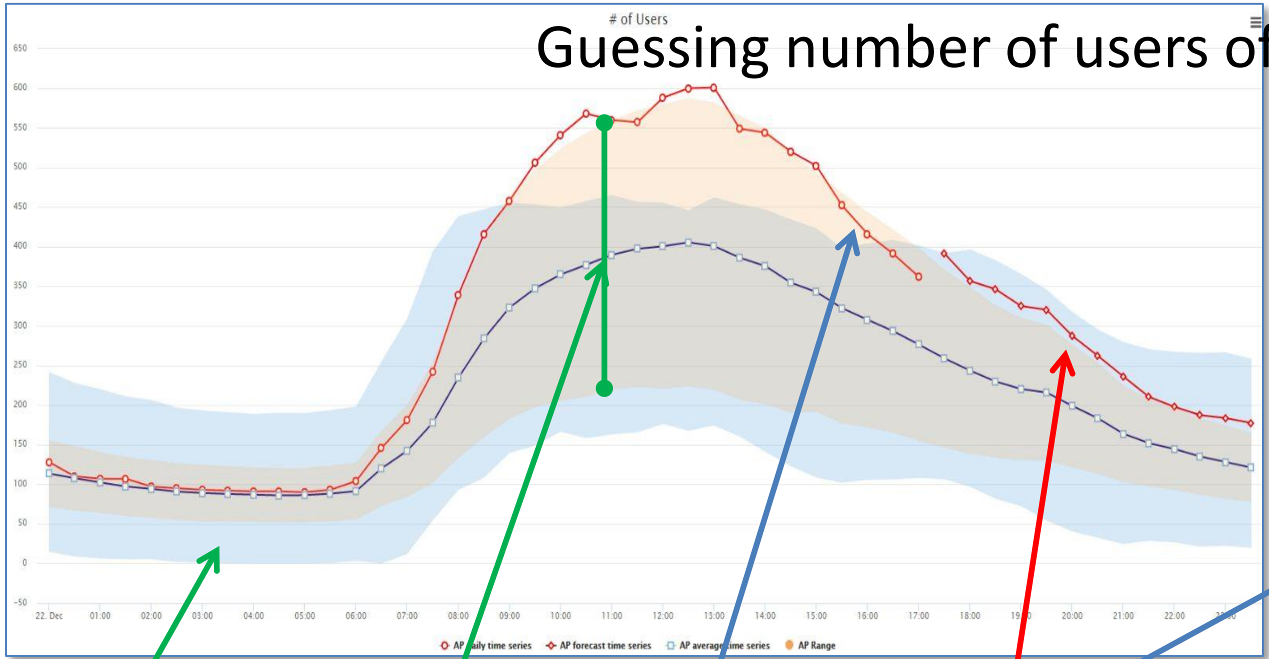
Wi-Fi based

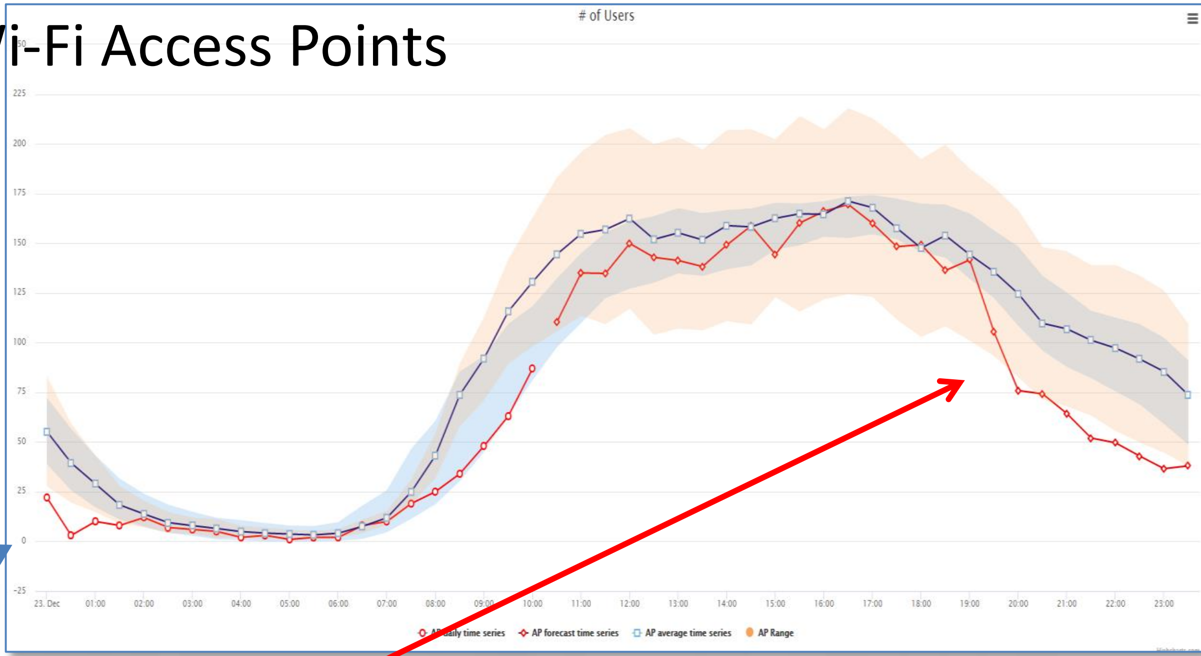
Predicting City Areas Crowd level characterizing Users' Behaviors



Prediction and Identification of Anomalies

Guessing number of users of Wi-Fi Access Points





Cluster confidence

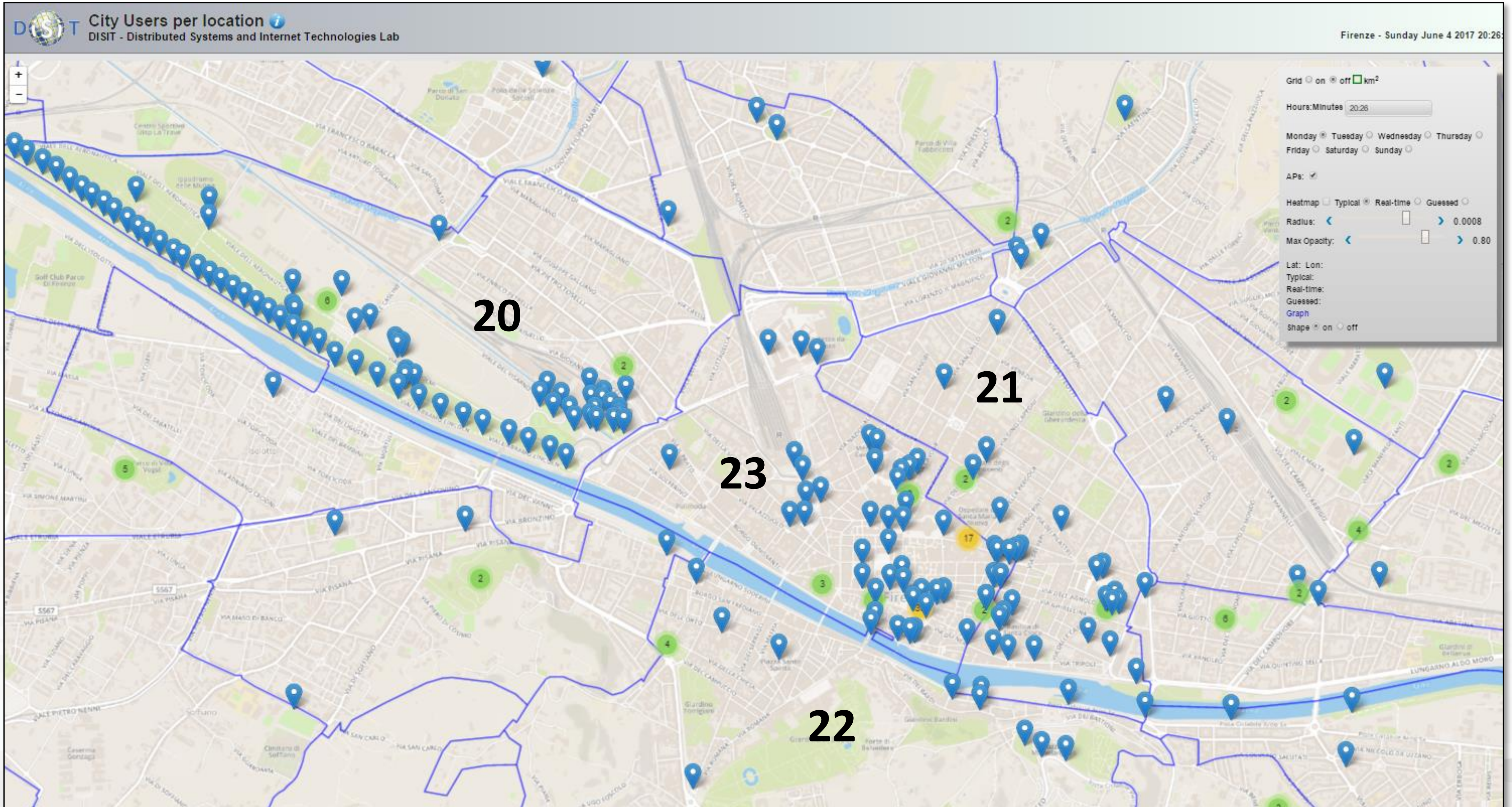
AP average and confidence

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%

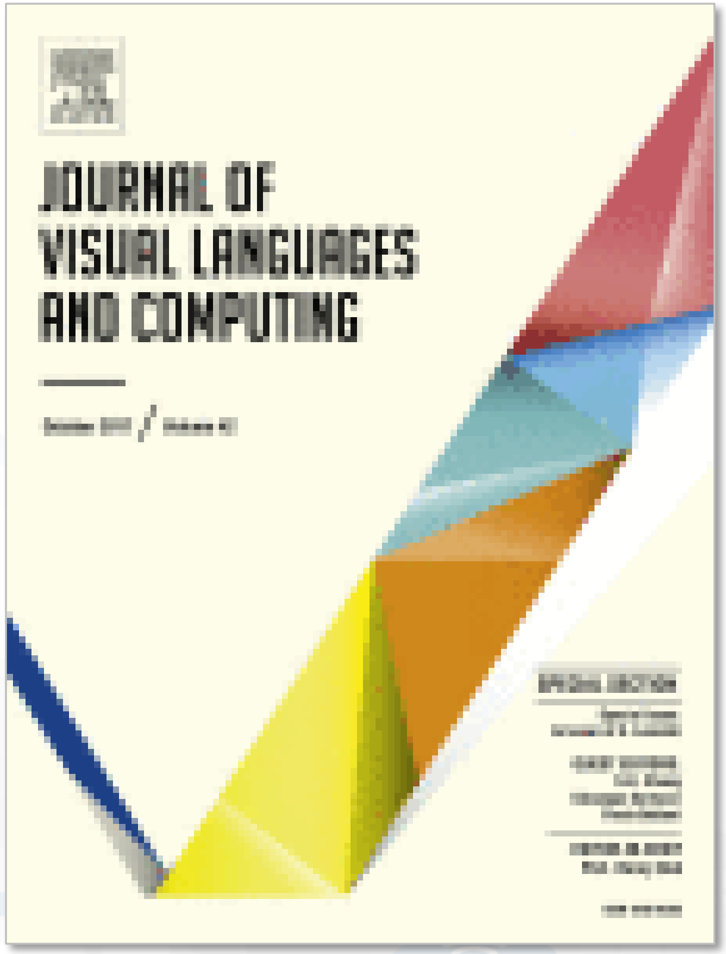
Firenze Wi-Fi vs ACE



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

ELSEVIER



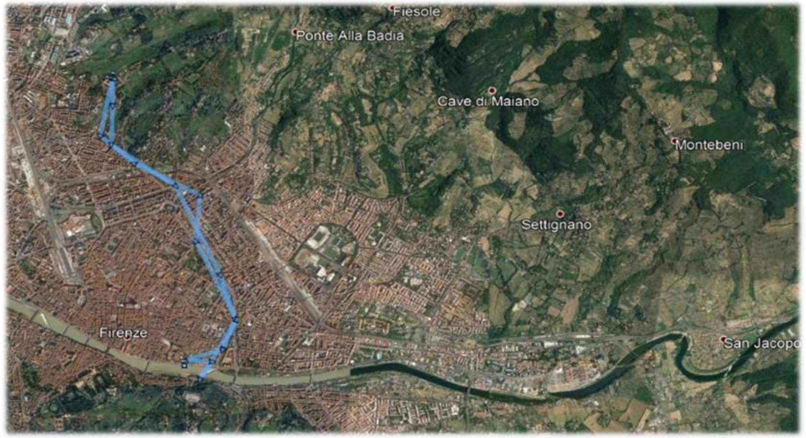
TOP

Recognition of Used 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

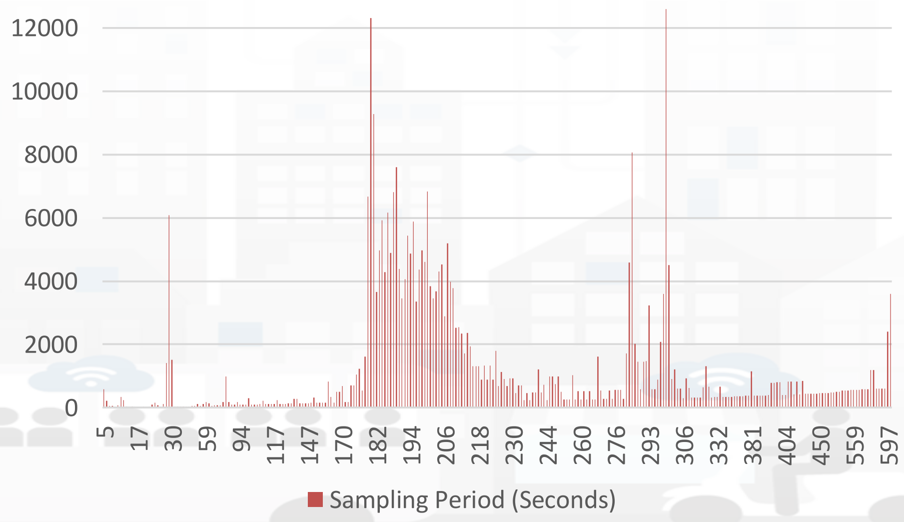
Note that:

- ***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

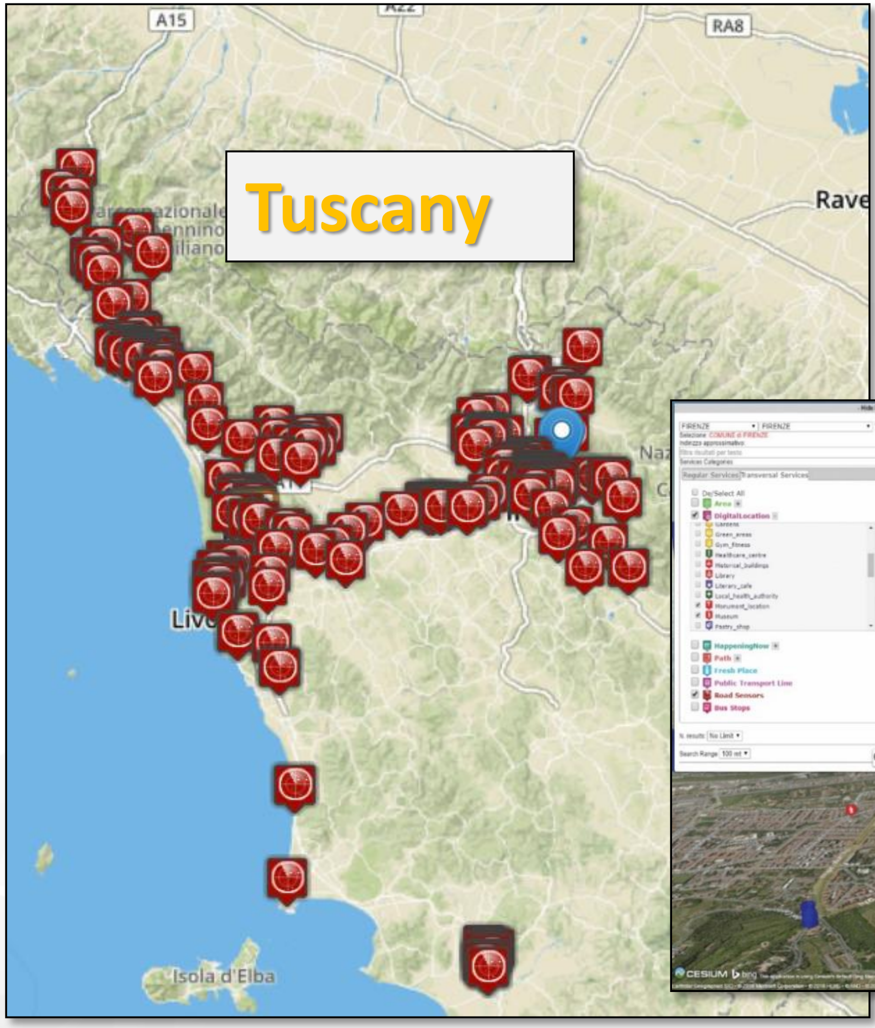
Traffic Flow Reconstruction from Traffic Sensors Data

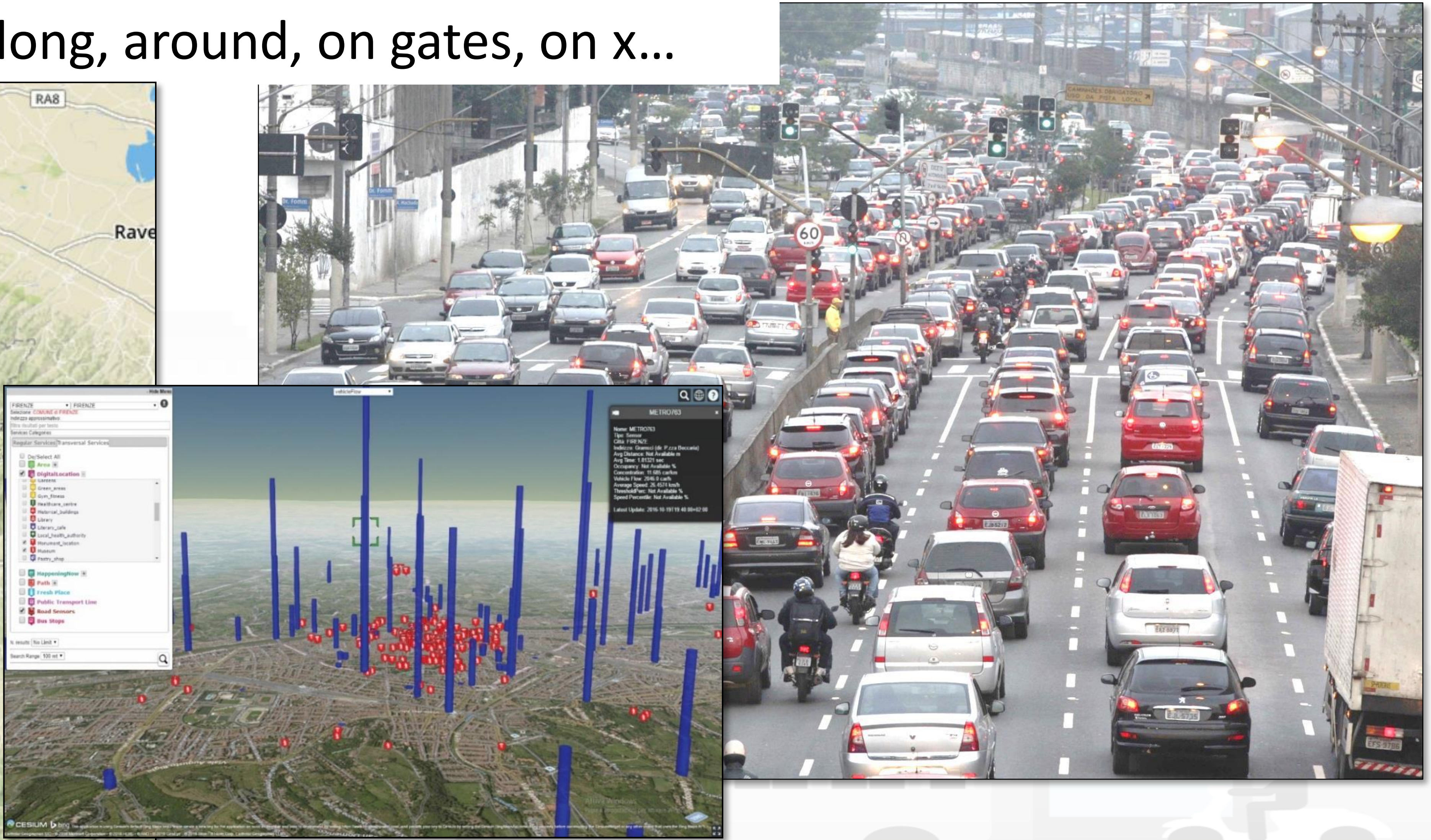

60

Traffic Flow Tools

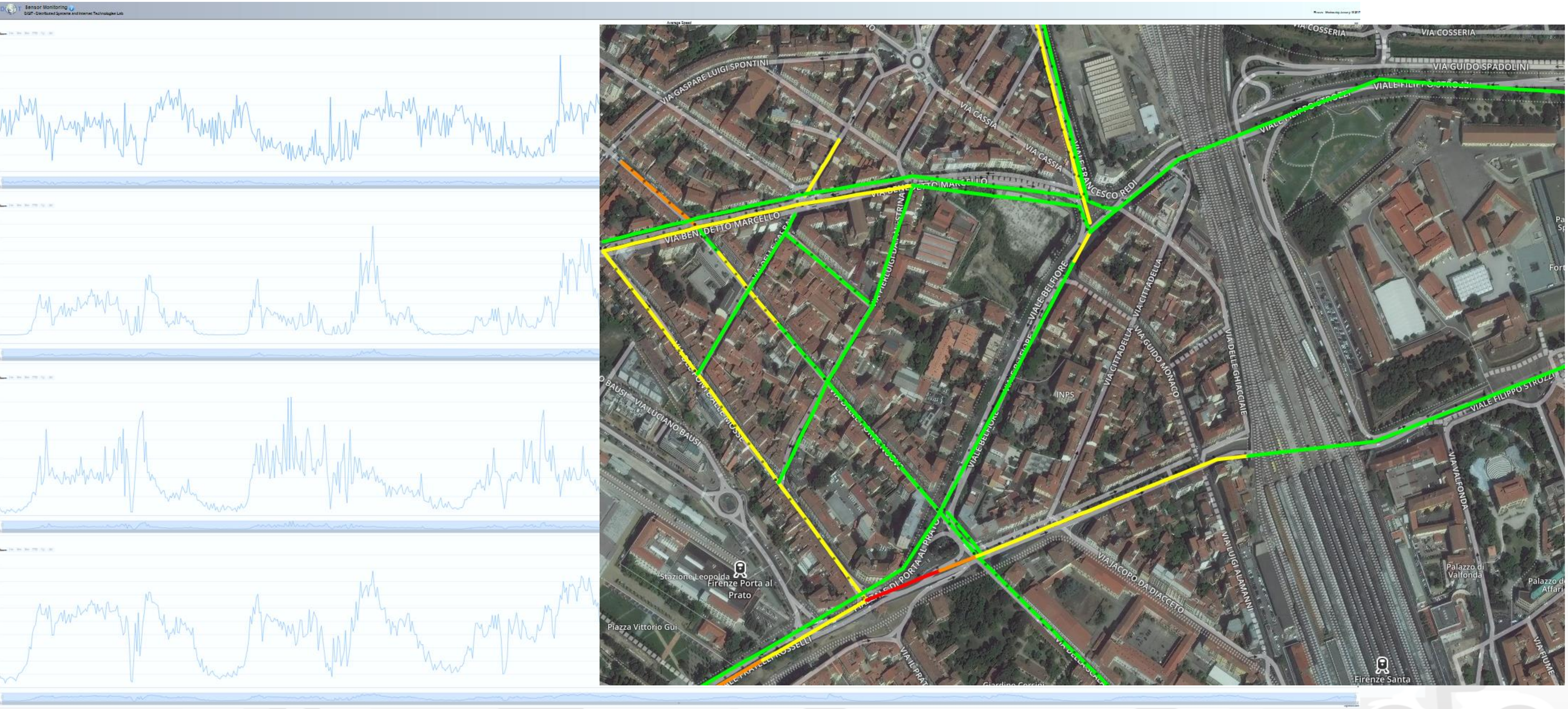
Spire and Virtual Spires (cameras), Bluetooth, ...

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





Traffic Flow data



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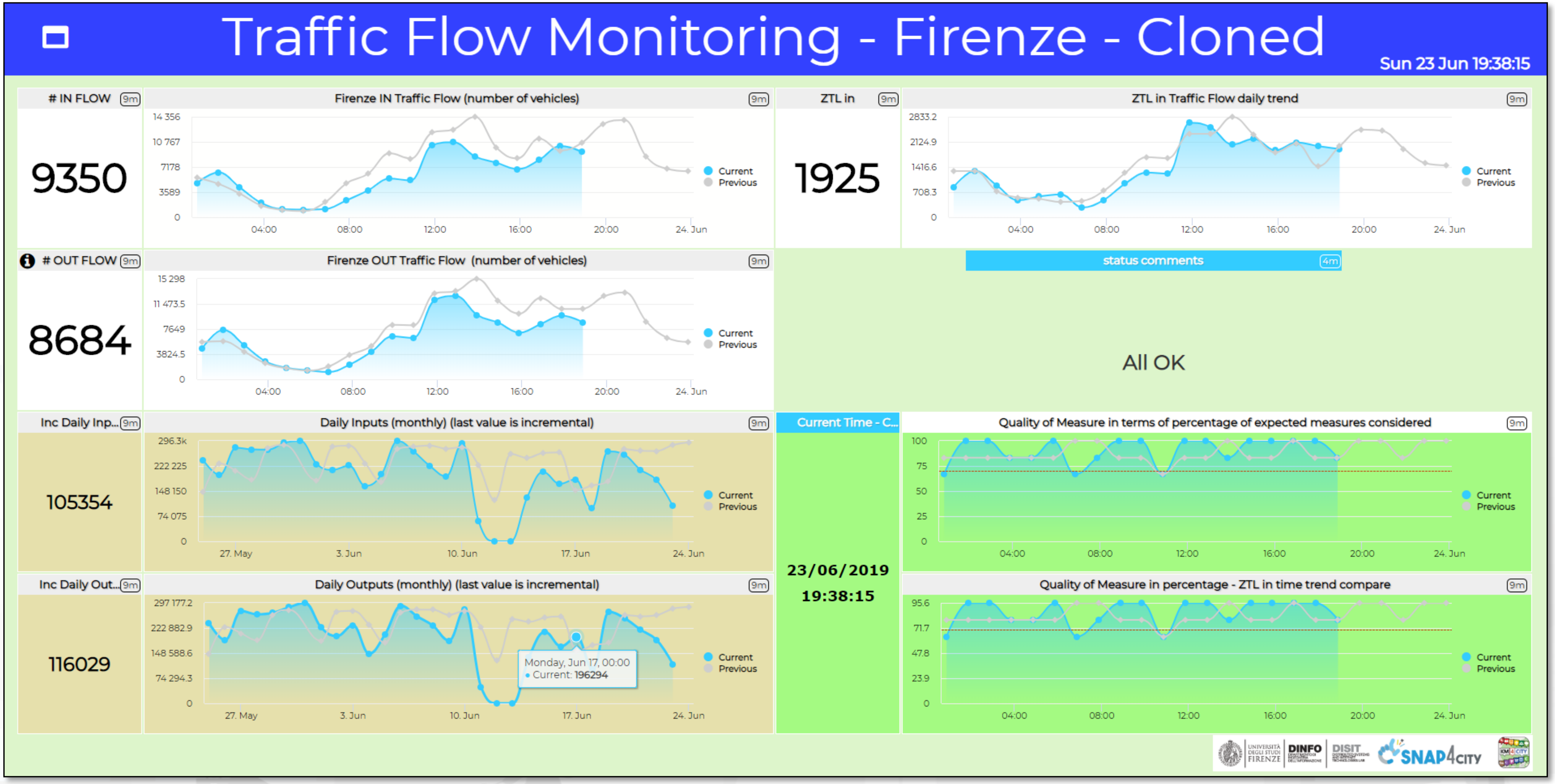
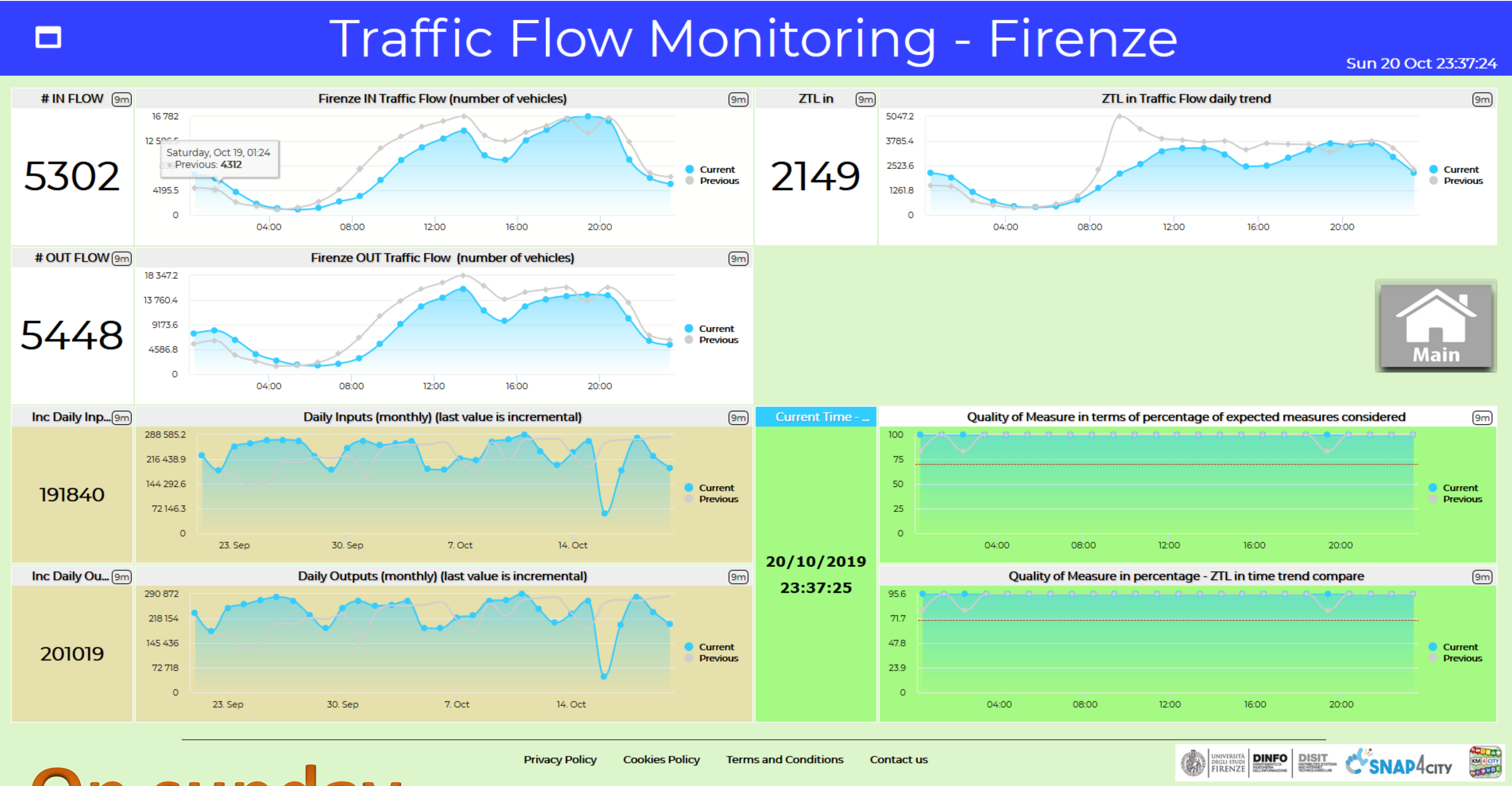


https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTc2MQ==



Traffic Flow Monitoring - Firenze
Sun 20 Oct 23:37:24
IN FLOW 9m
5302
Firenze IN Traffic Flow (number of vehicles)
Saturday, Oct 19, 01:24
Previous: 4312
Current
Previous
ZTL in
2149
ZTL in Traffic Flow daily trend
OUT FLOW
5448
Firenze OUT Traffic Flow (number of vehicles)
Main
Inc Daily Inp...
191840
Daily Inputs (monthly) (last value is incremental)
Current Time - ...
20/10/2019
23:37:25
Quality of Measure in terms of percentage of expected measures considered
Inc Daily Ou...
201019
Daily Outputs (monthly) (last value is incremental)
Quality of Measure in percentage - ZTL in time trend compare
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On sunday

Traffic Flow Reconstruction

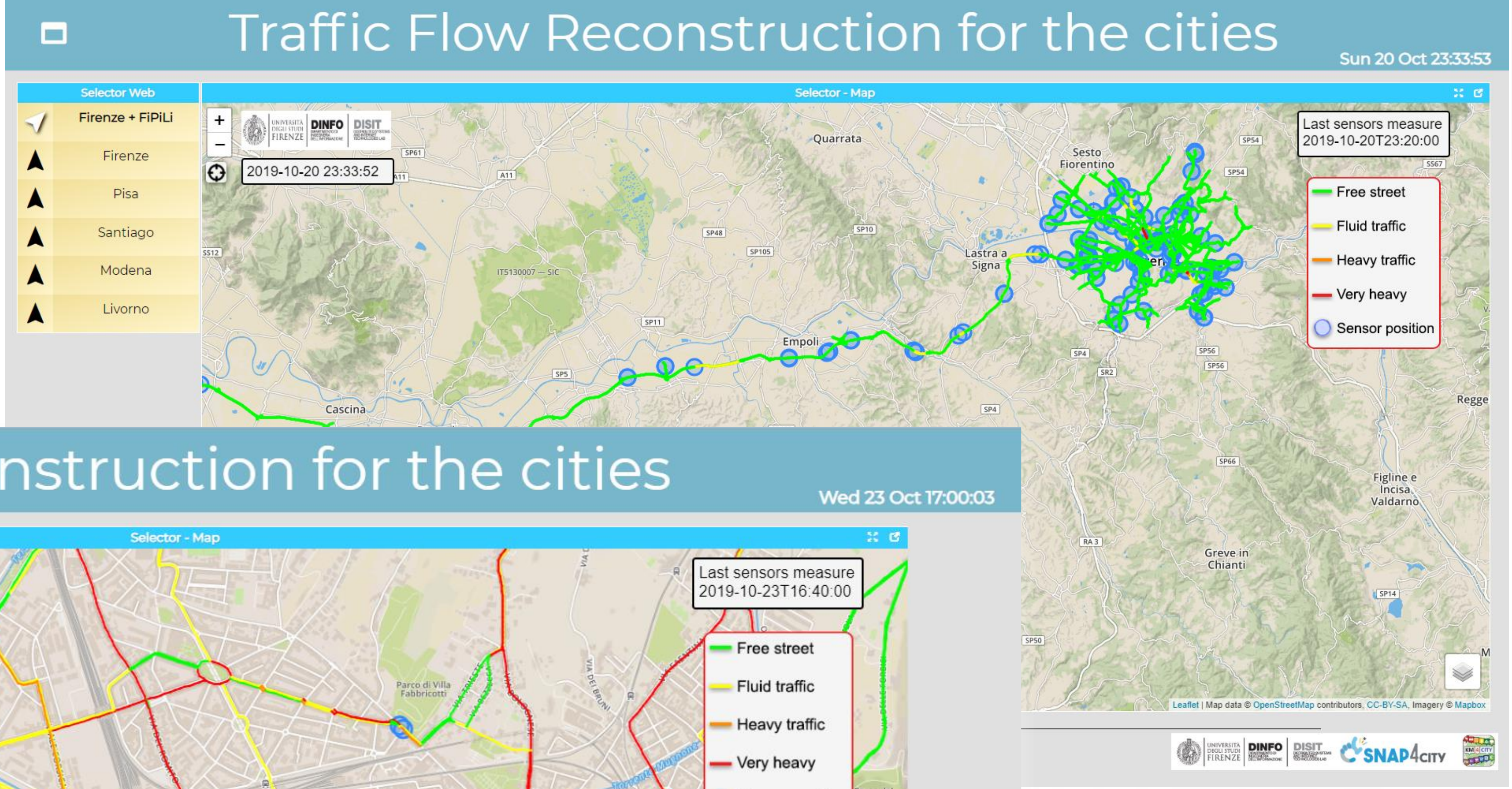
Firenze
FiPiLi
Pisa
Modena

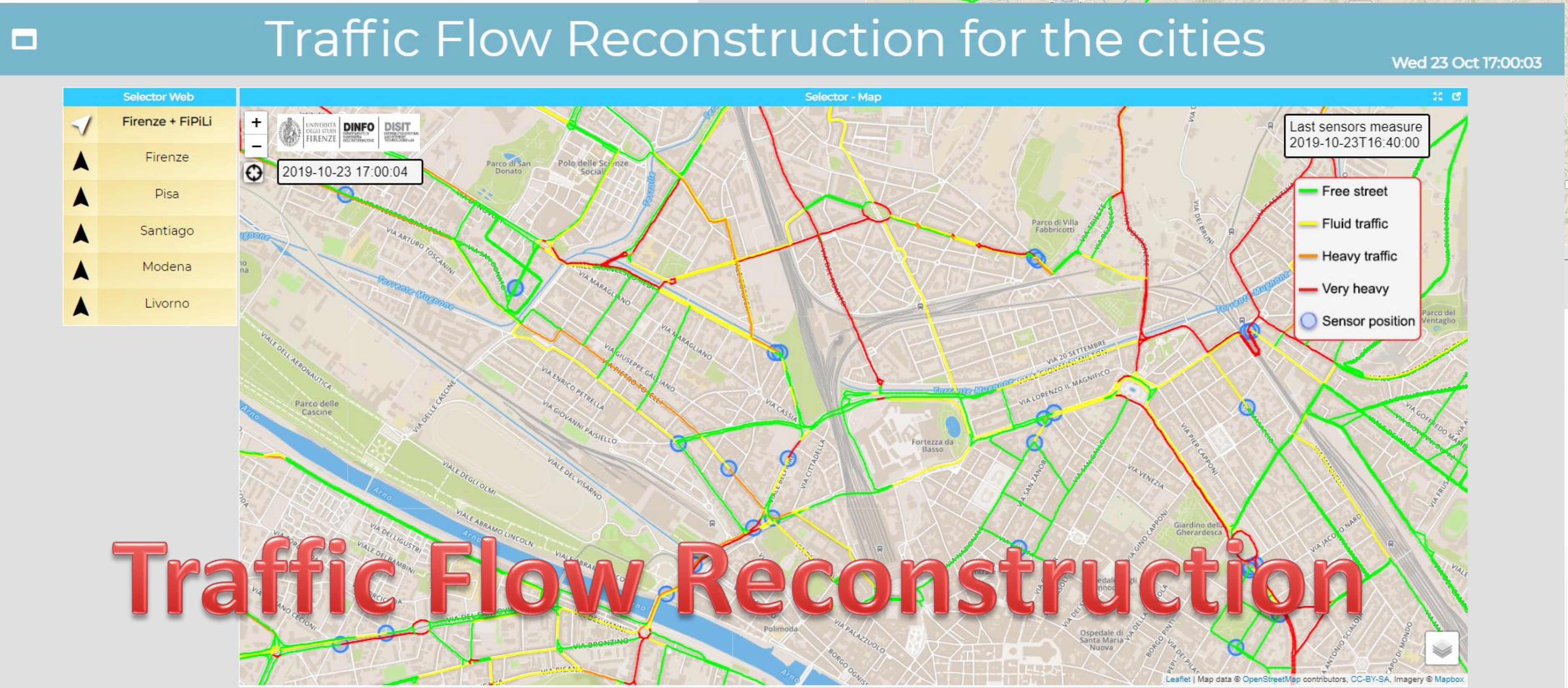
real time

http://firenzetraffic.km4city.org

http://firenzetraffic.km4city.org/new.html

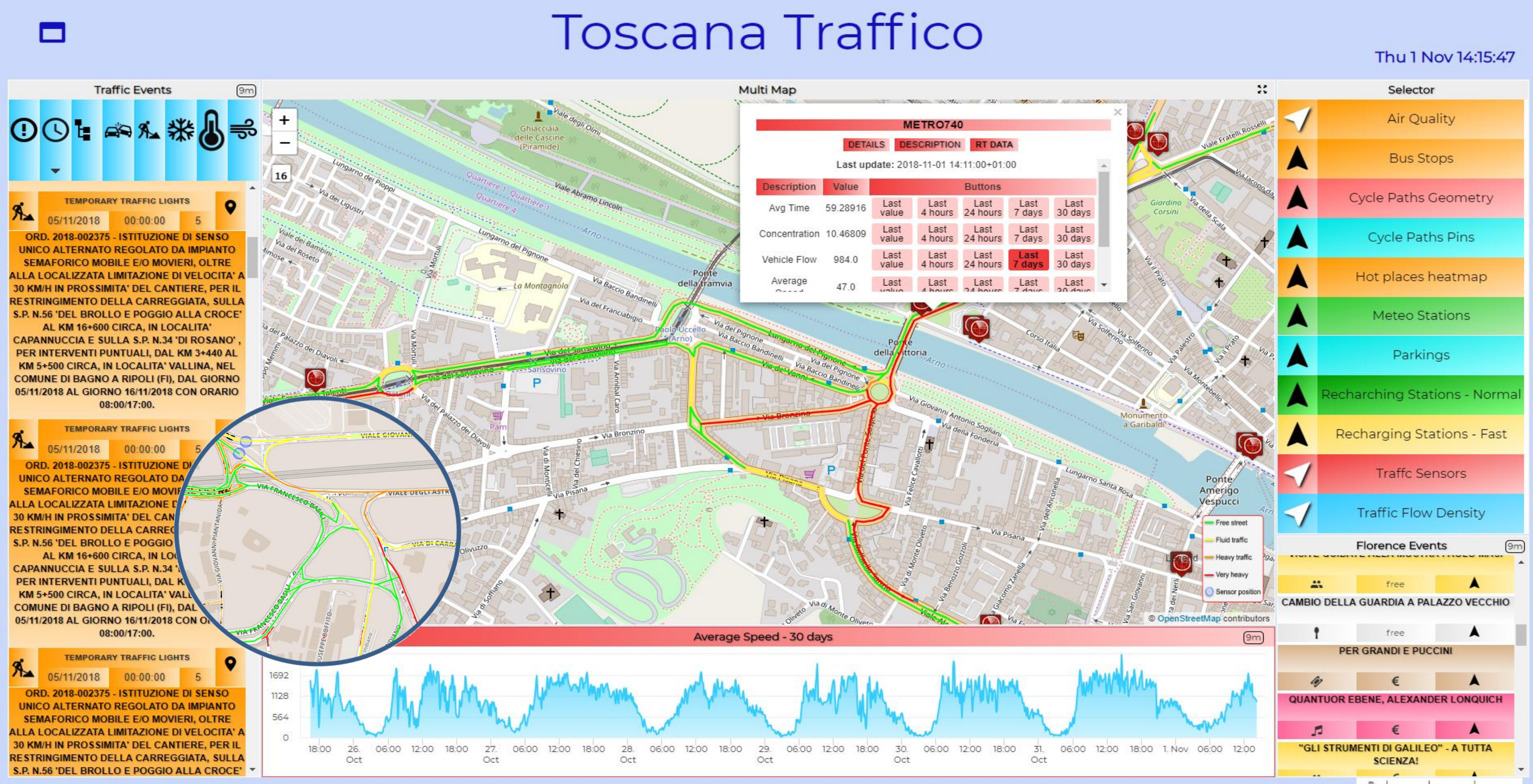
http://firenzetraffic.km4city.org/newSensors.html





Traffic Flow Reconstruction

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



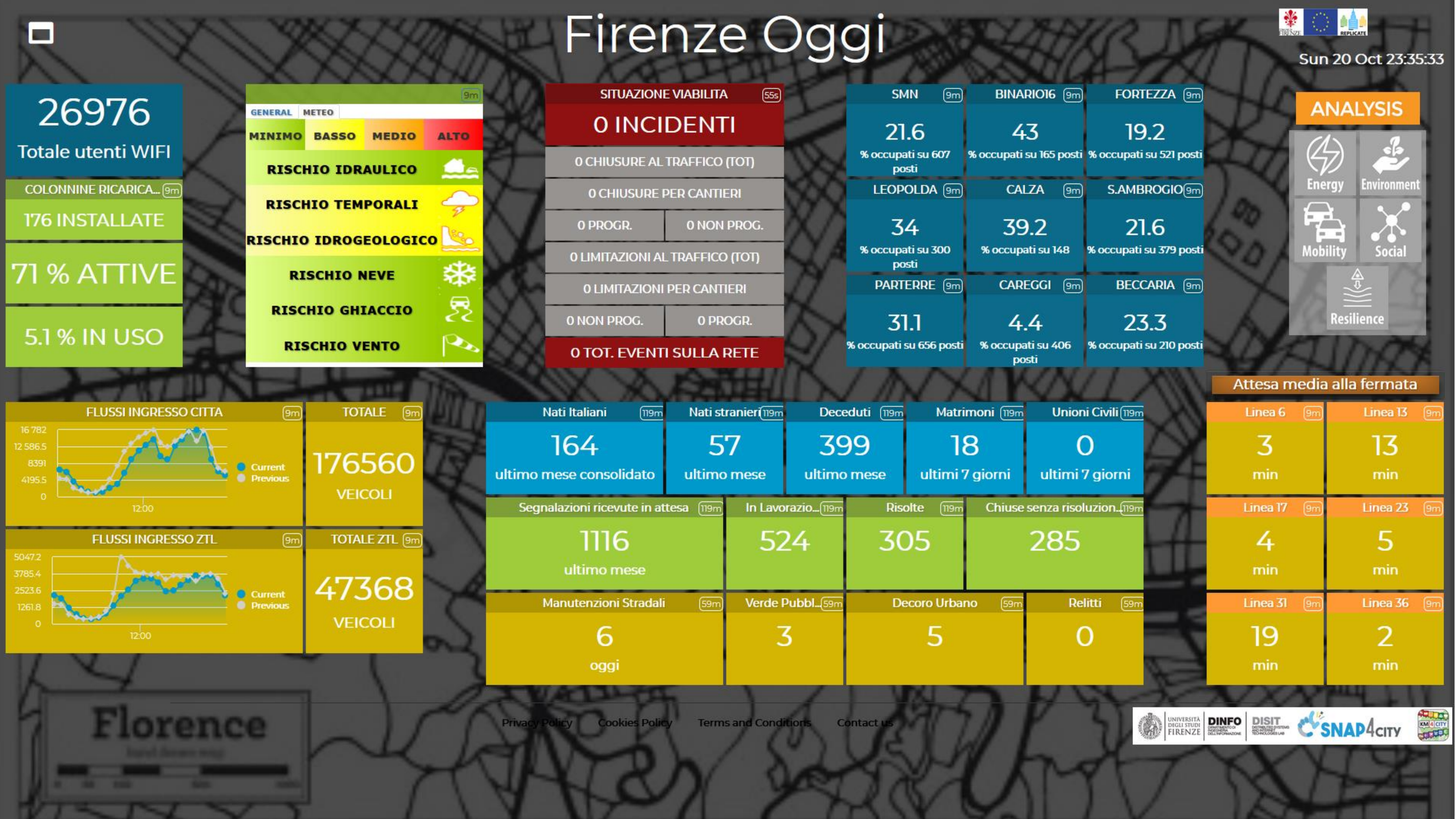
https://main.snap4city.org/view/index.php?iddasboard=MTE5MQ==

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

Quality of Public Transport



Firenze Oggi
Sun 20 Oct 23:35:33
26976
Totale utenti WIFI
COLONNINE RICARICA... 9m
176 INSTALLATE
71 % ATTIVE
5.1 % IN USO
9m
GENERAL
METEO
MINIMO
BASSO
MEDIO
ALTO
RISCHIO IDRAULICO
RISCHIO TEMPORALI
RISCHIO IDROGEOLOGICO
RISCHIO NEVE
RISCHIO GHIACCIO
RISCHIO VENTO
SITUAZIONE VIABILITA 55s
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 9m
21.6
% occupati su 607 posti
BINARIO16 9m
43
% occupati su 165 posti
FORTEZZA 9m
19.2
% occupati su 521 posti
LEOPOLDA 9m
34
% occupati su 300 posti
CALZA 9m
39.2
% occupati su 148
S.AMBROGIO 9m
21.6
% occupati su 379 posti
PARTERRE 9m
31.1
% occupati su 656 posti
CAREGGI 9m
4.4
% occupati su 406 posti
BECCARIA 9m
23.3
% occupati su 210 posti
ANALYSIS
Energy
Environment
Mobility
Social
Resilience
Attesa media alla fermata
FLUSSI INGRESSO CITTA 9m
16 782
12 586.5
8391
4195.5
0
12:00
Current
Previous
TOTALE 9m
176560
VEICOLI
FLUSSI INGRESSO ZTL 9m
5047.2
3785.4
2523.6
1261.8
0
12:00
Current
Previous
TOTALE ZTL 9m
47368
VEICOLI
Nati Italiani 119m
164
ultimo mese consolidato
Nati stranieri 119m
57
ultimo mese
Deceduti 119m
399
ultimo mese
Matrimoni 119m
18
ultimi 7 giorni
Unioni Civili 119m
0
ultimi 7 giorni
Segnalazioni ricevute in attesa 119m
1116
ultimo mese
In Lavorazio... 119m
524
Risolte 119m
305
Chiuse senza risoluzion... 119m
285
Manutenzioni Stradali 59m
6
oggi
Verde Pubbl... 59m
3
Decoro Urbano 59m
5
Relitti 59m
0
Linea 6 9m
3
min
Linea 13 9m
13
min
Linea 17 9m
4
min
Linea 23 9m
5
min
Linea 31 9m
19
min
Linea 36 9m
2
min
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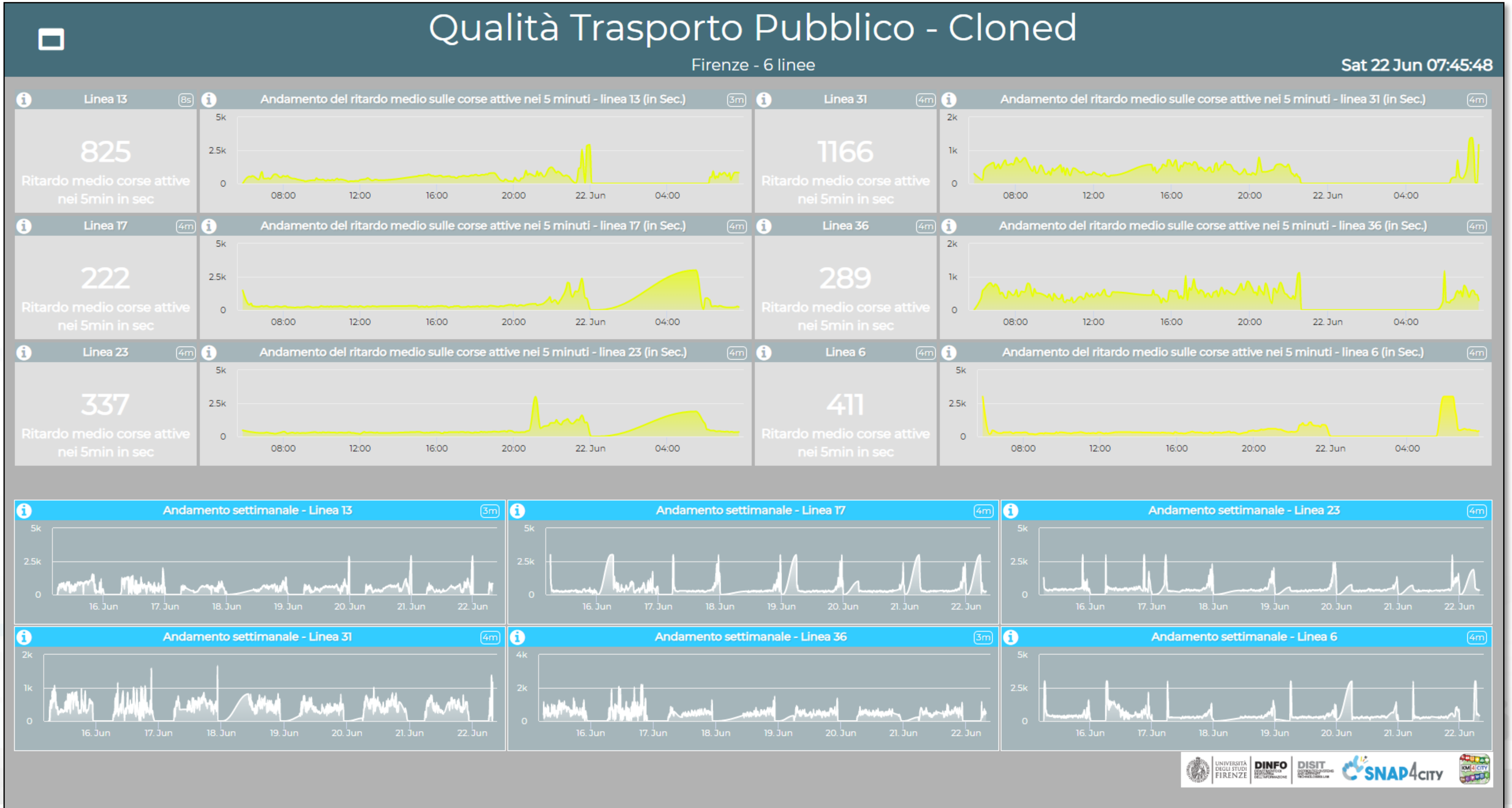
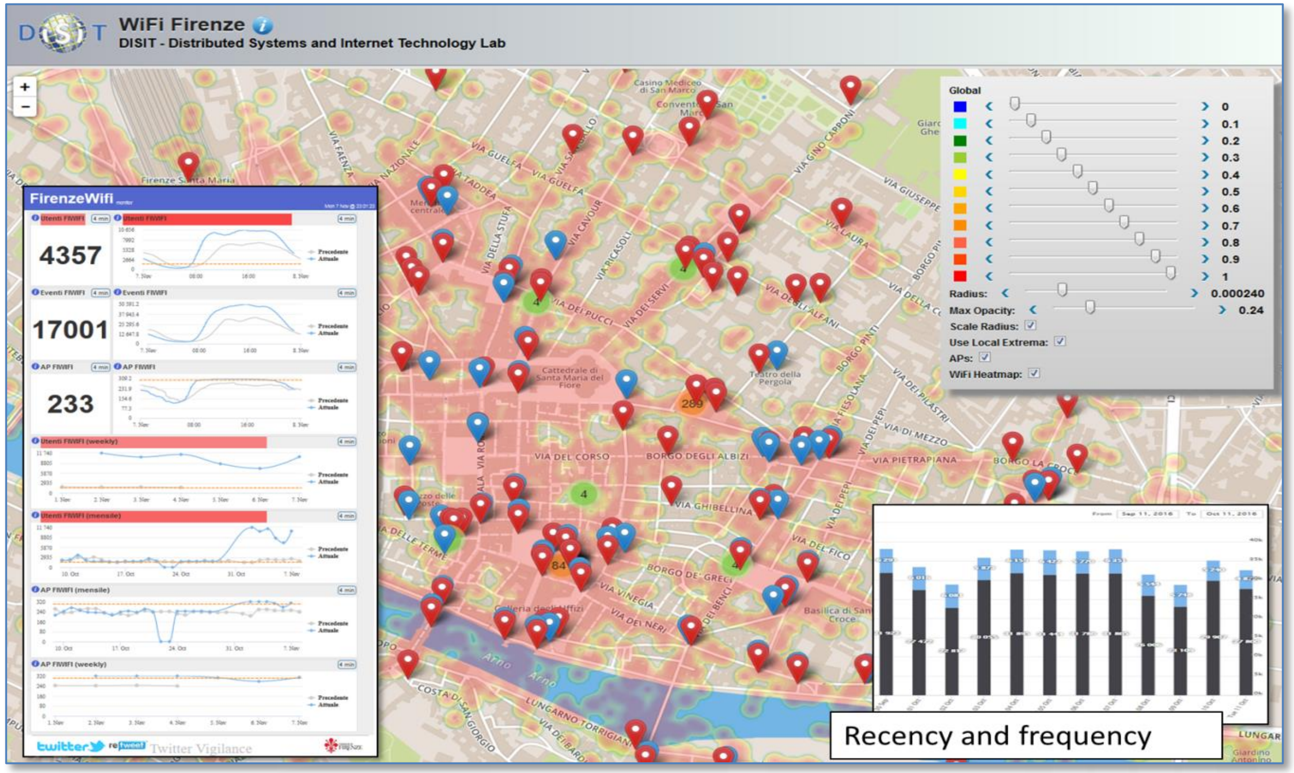


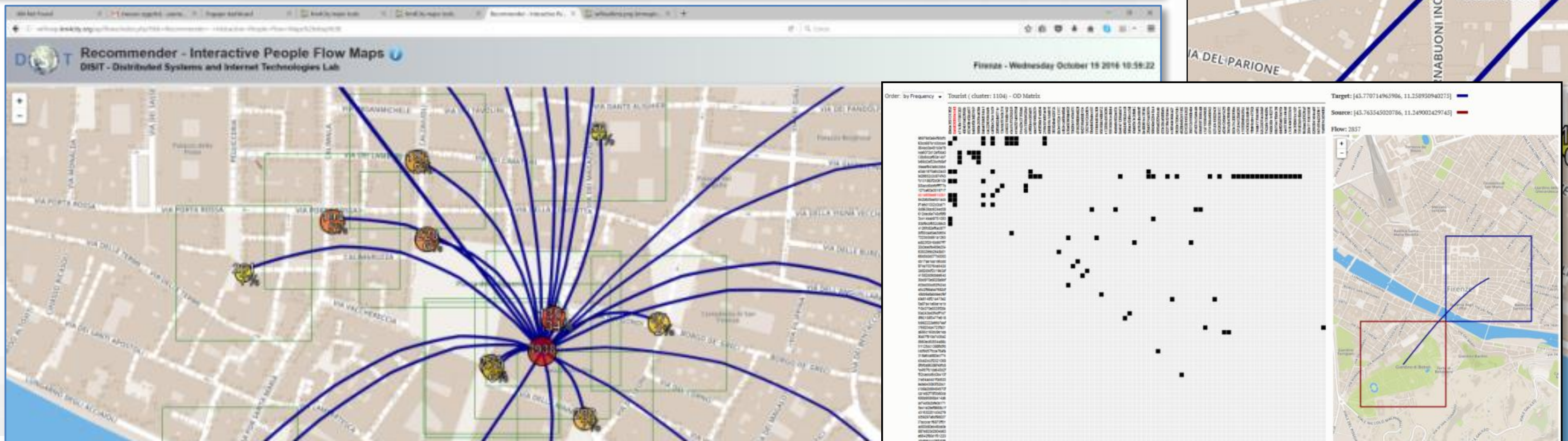
Qualità Trasporto Pubblico - Cloned
Firenze - 6 linee
Sat 22 Jun 07:45:48
Linea 13
825
Ritardo medio corse attive nei 5min in sec
Andamento del ritardo medio sulle corse attive nei 5 minuti - linea 13 (in Sec.)
Linea 31
1166
Ritardo medio corse attive nei 5min in sec
Andamento del ritardo medio sulle corse attive nei 5 minuti - linea 31 (in Sec.)
Linea 17
222
Ritardo medio corse attive nei 5min in sec
Andamento del ritardo medio sulle corse attive nei 5 minuti - linea 17 (in Sec.)
Linea 36
289
Ritardo medio corse attive nei 5min in sec
Andamento del ritardo medio sulle corse attive nei 5 minuti - linea 36 (in Sec.)
Linea 23
337
Ritardo medio corse attive nei 5min in sec
Andamento del ritardo medio sulle corse attive nei 5 minuti - linea 23 (in Sec.)
Linea 6
411
Ritardo medio corse attive nei 5min in sec
Andamento del ritardo medio sulle corse attive nei 5 minuti - linea 6 (in Sec.)
Andamento settimanale - Linea 13
Andamento settimanale - Linea 17
Andamento settimanale - Linea 23
Andamento settimanale - Linea 31
Andamento settimanale - Linea 36
Andamento settimanale - Linea 6

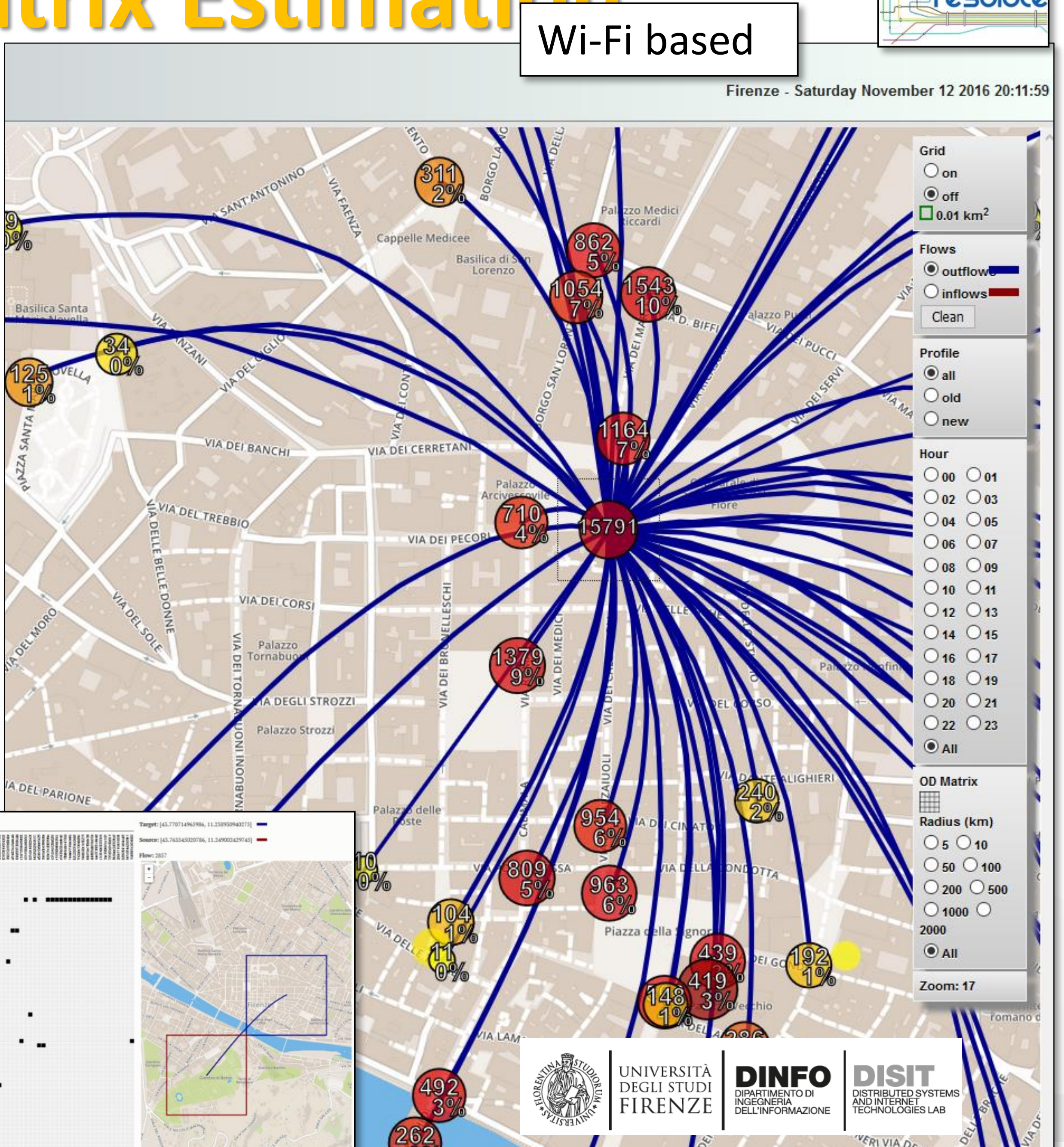
TOP

Origin Destination Matrices

Origin Destination Matrix Estimation







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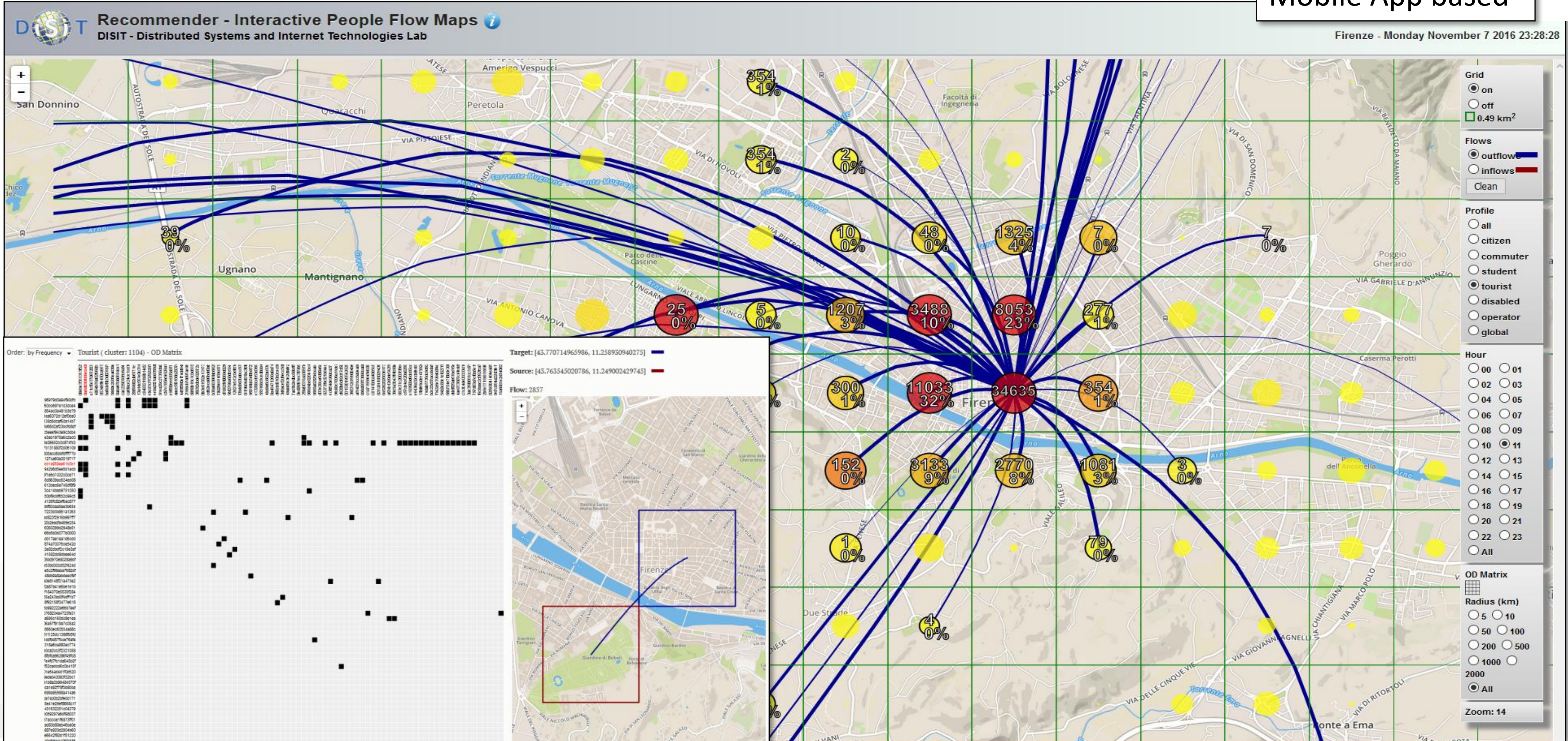
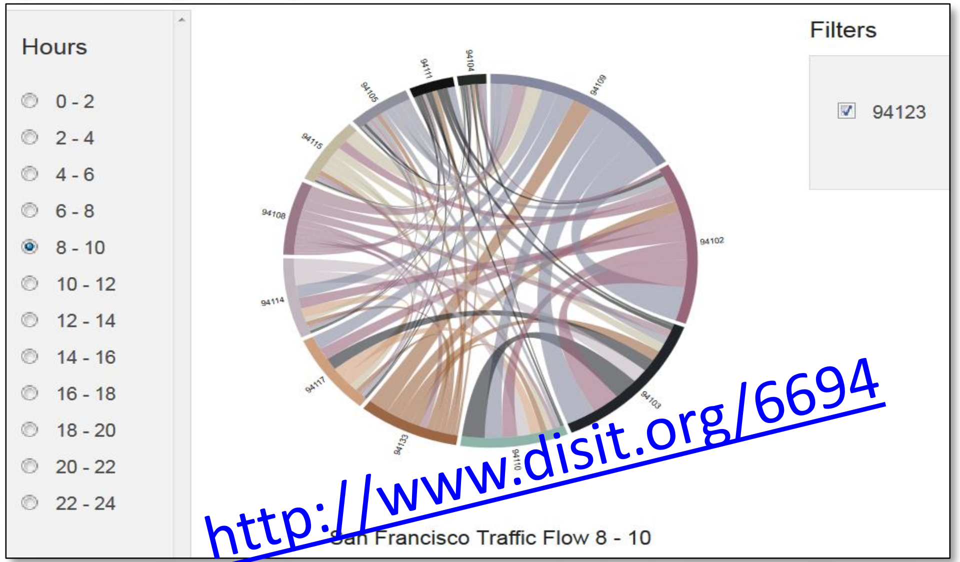
Scalable multiresolution OD matrix

Mobile App based

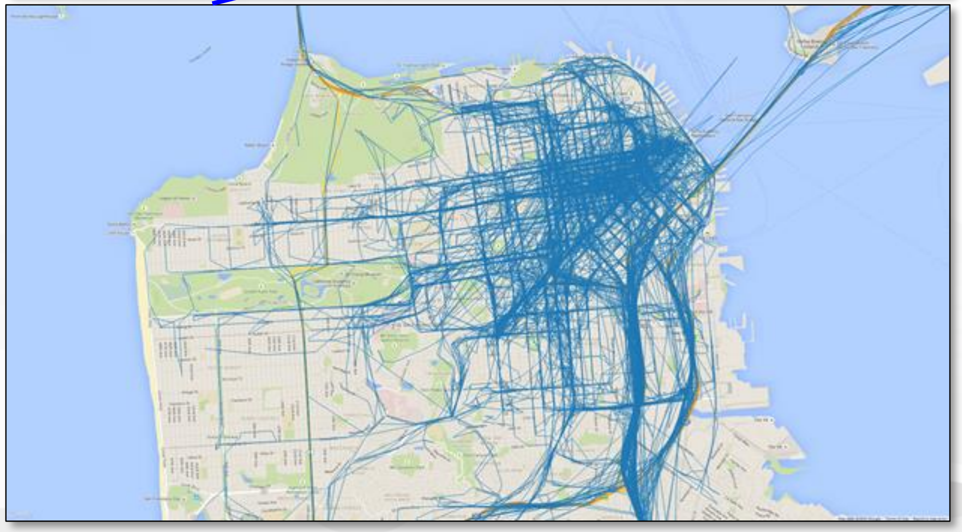


Traffic and People Flow Assessment

- **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

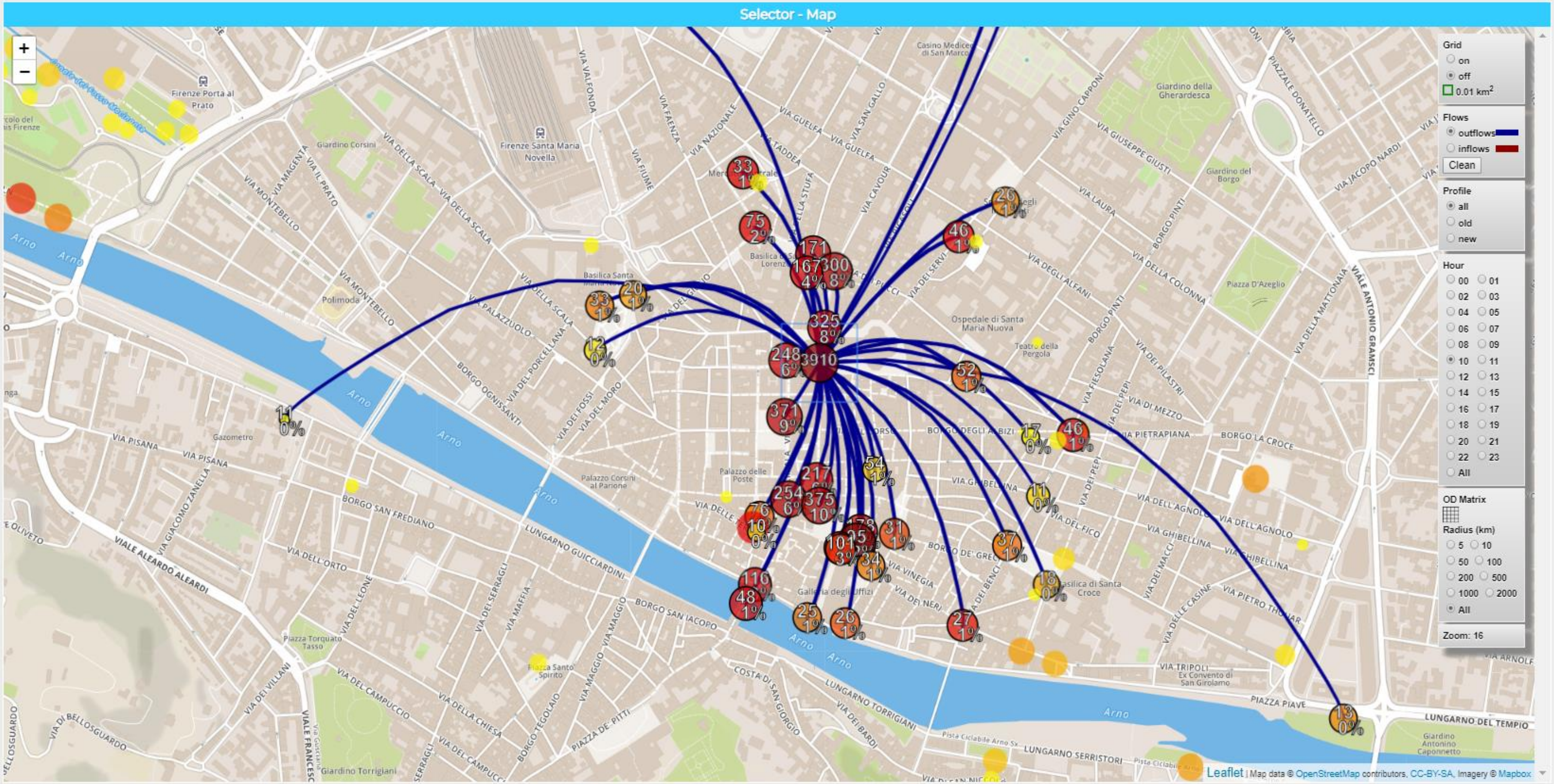


http://www.disit.org/6694



Life in Toscana: Dashboard

Sun 20 Oct 23:44:05



- Line of Transport
- Public Transport
- Travel Plan
- Traffic Flow FIPILI
- Air Quality
- Weather
- Origin Dest. Matrix
- Typical Trajectories
- **People Flow WIFI**
- People Flow KM App
- Cultural Activities
- Forum Discussion
- CAM
- Ponte Vecchio
- Real Time Busses
- Main

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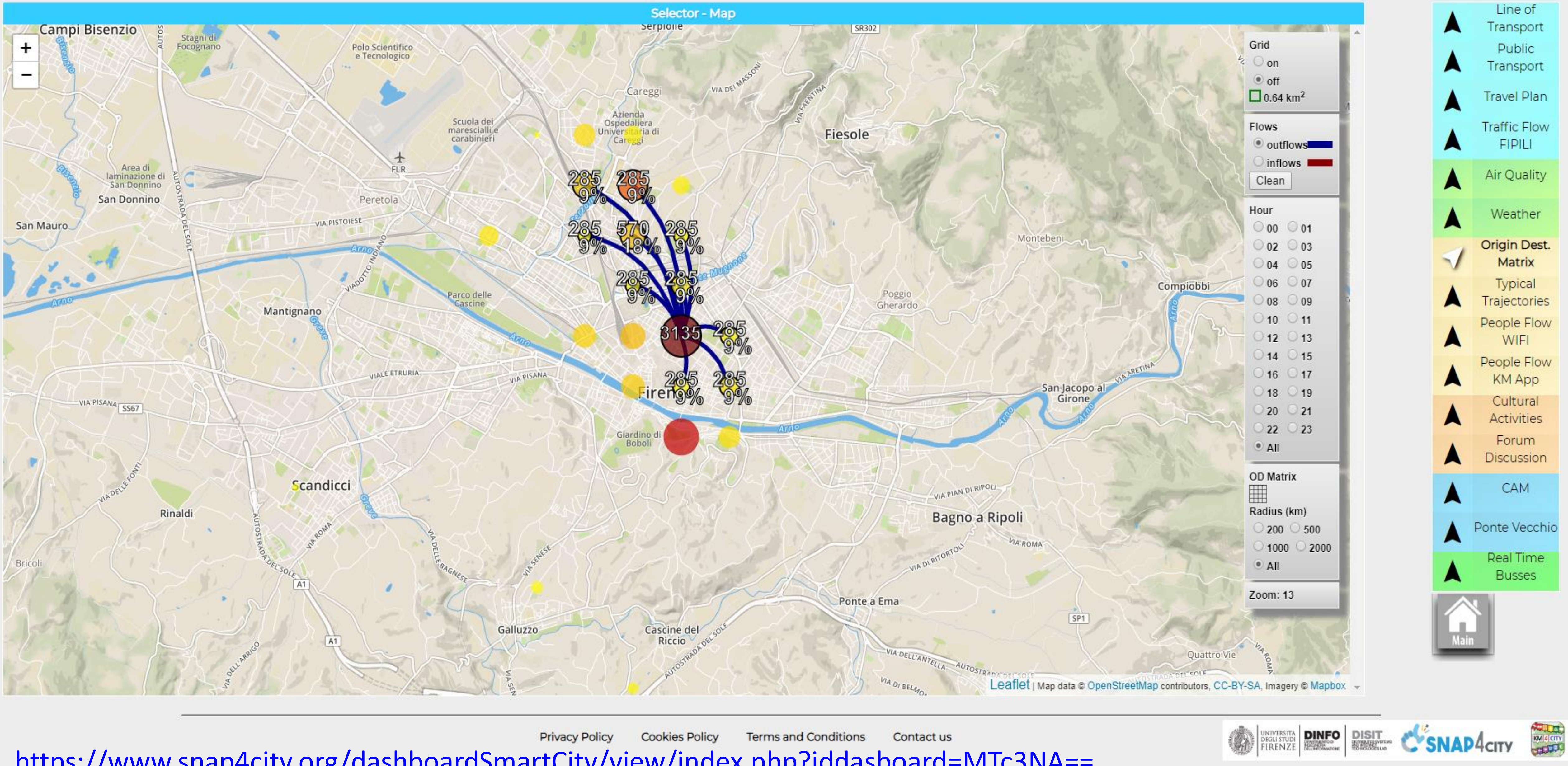
Life in Toscana: Dashboard

Sun 20 Oct 23:40:25



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

The Life of Antwerp

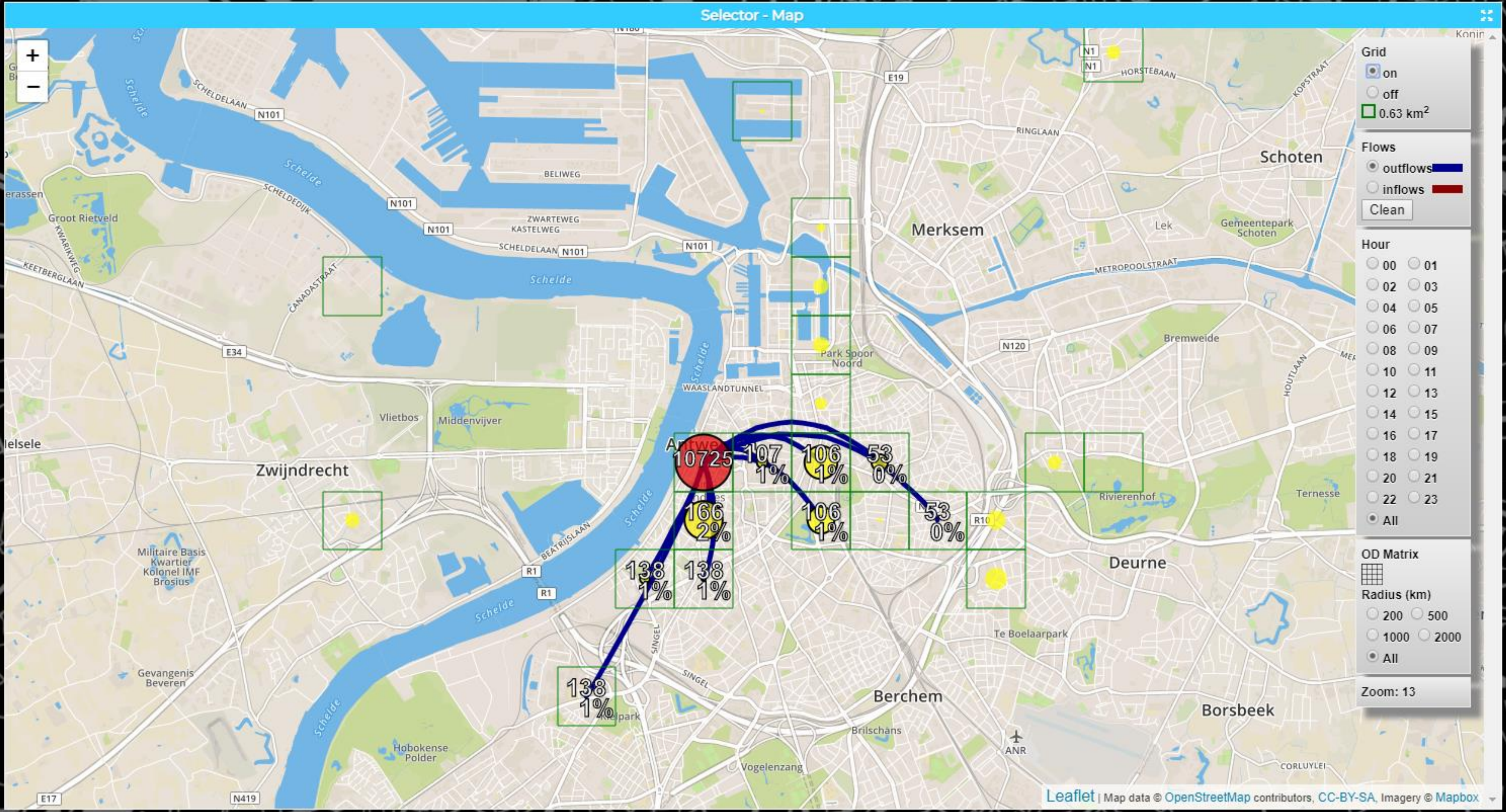
Please note that the data results are not always based on real data.

Sun 20 Oct 23:42:07

- Shopping: POI
- Wine and Food: POI
- Discovery Antwerp
- Point of Interest
- 3D view POI
- Routing on Antwerp
- Line of Transport
- Public Transport
- Safe On Bike
- Tunnel and Ferry
- Twitter Vigilance
- Twitter Vig. Real Time
- Air Quality
- Weather
- **Origin Dest. Matrix**
- Typical Trajectories
- Forum Discussion

Documentation

Survey

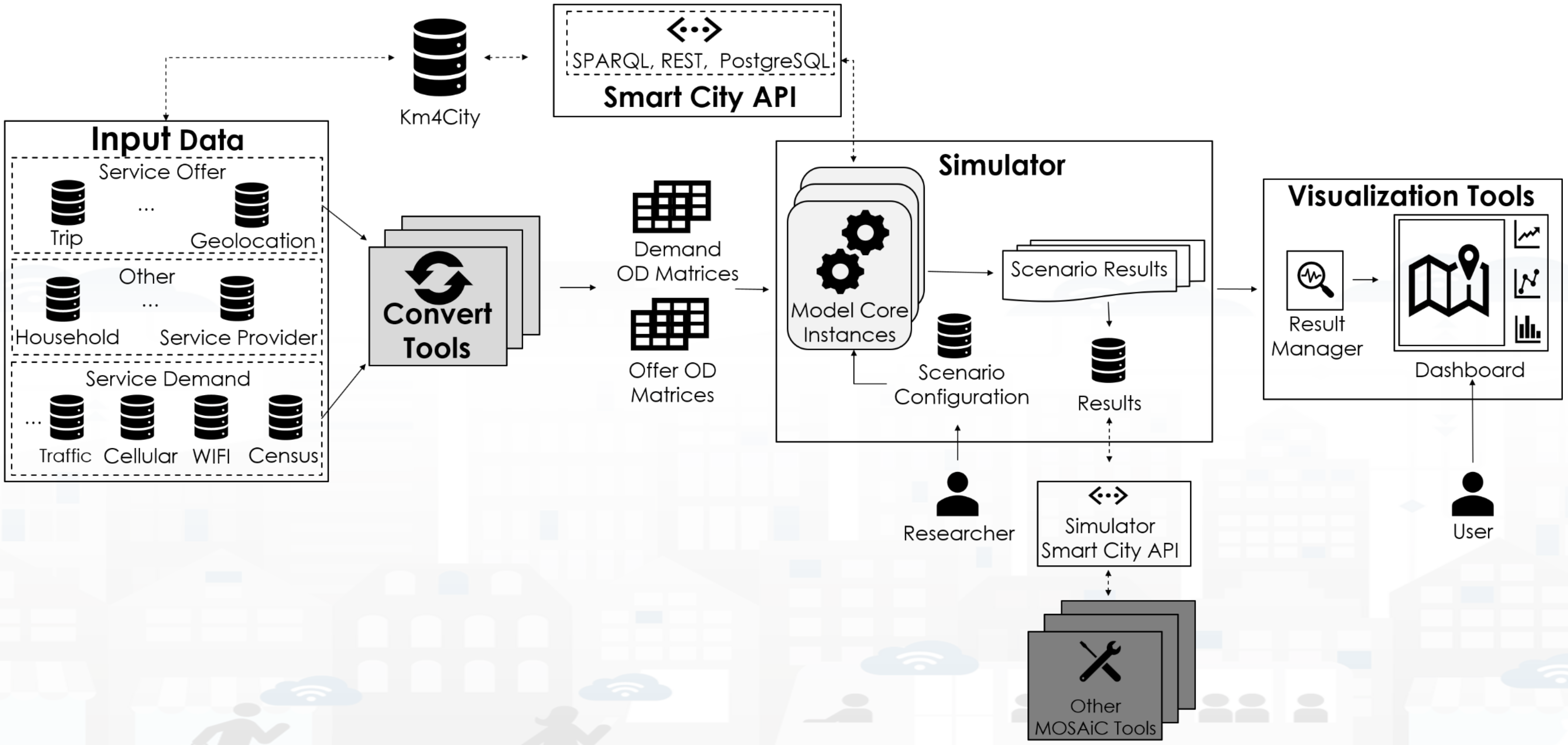


https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTcwNg==

TOP

Demand of Mobility vs Offer of Transportation

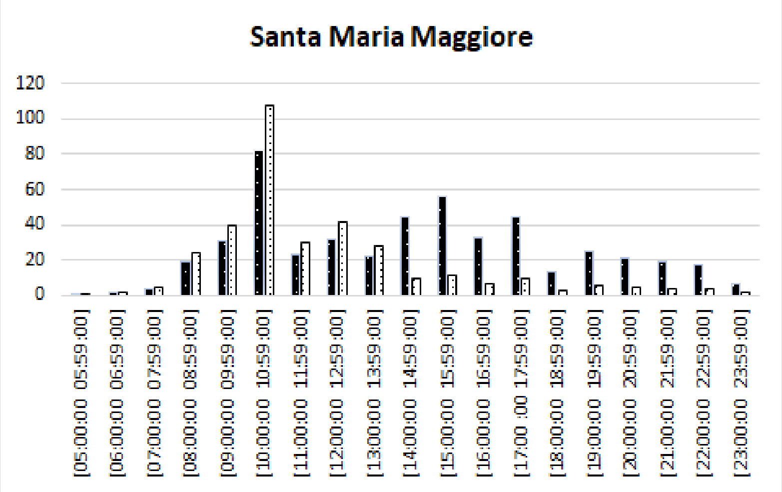
Demand vs Offer of Mobility Analysis

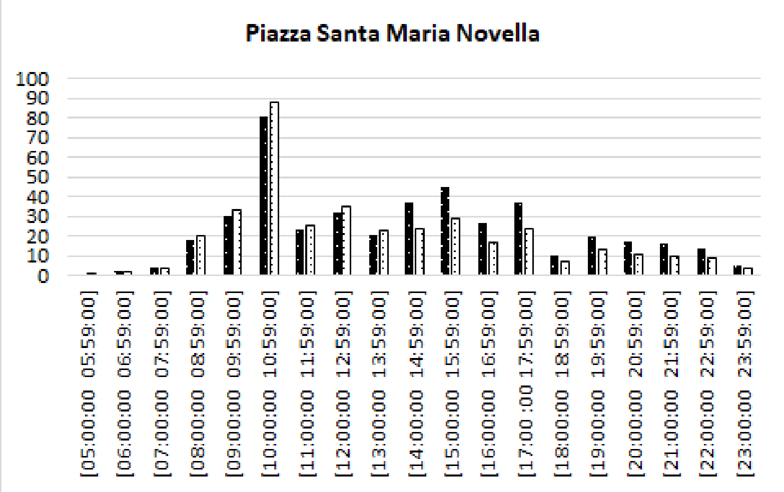


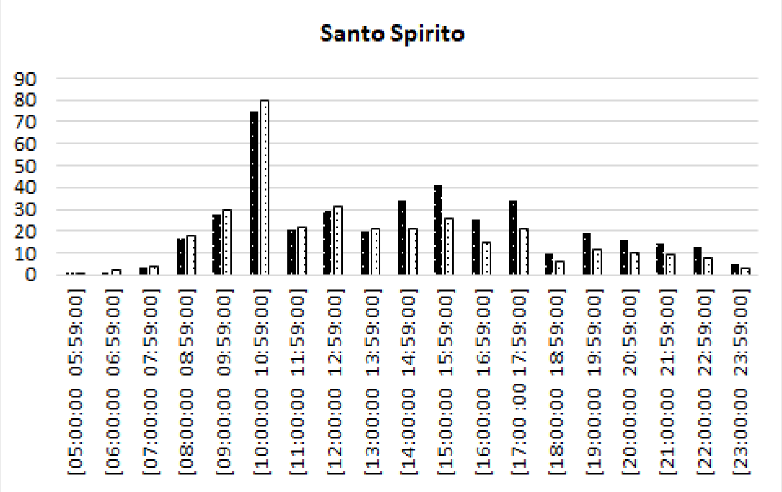
What can produce the Analysis tool

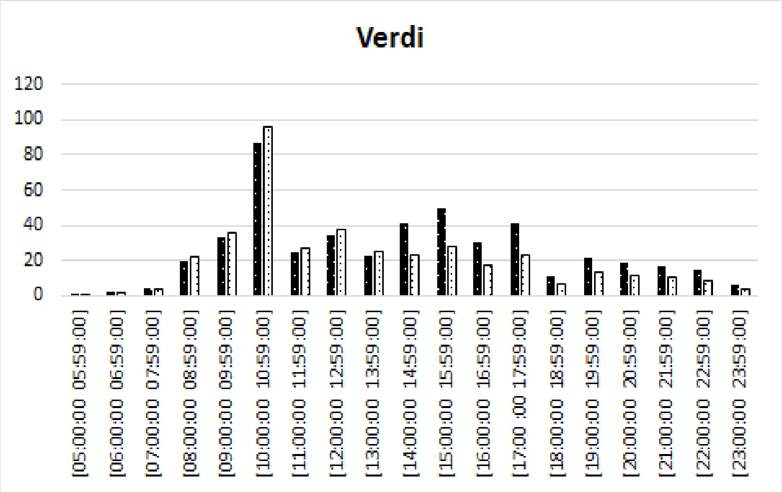
- Identification of critical Bus Stops over time
- Identification of critical courses of bus lines, over day and week
- Effects of changing the position of Bus Stops, courses and line schedules, bus size, etc.
- Effects of changing the contextual conditions:
  - The opening of shopping centers, cinemas,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

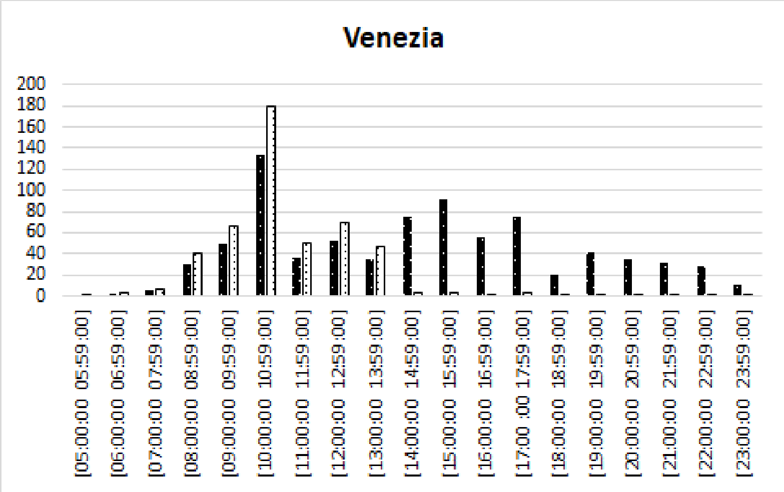
Pick-ups (black bars) and drop-offs (white bars) for the six selected stops

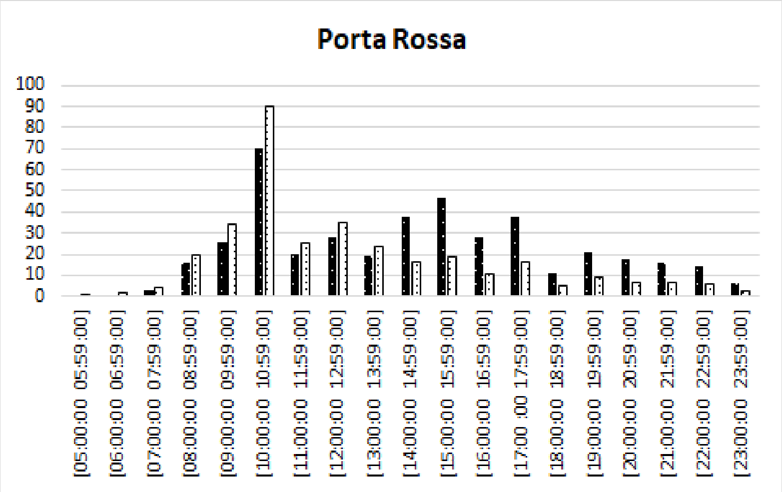


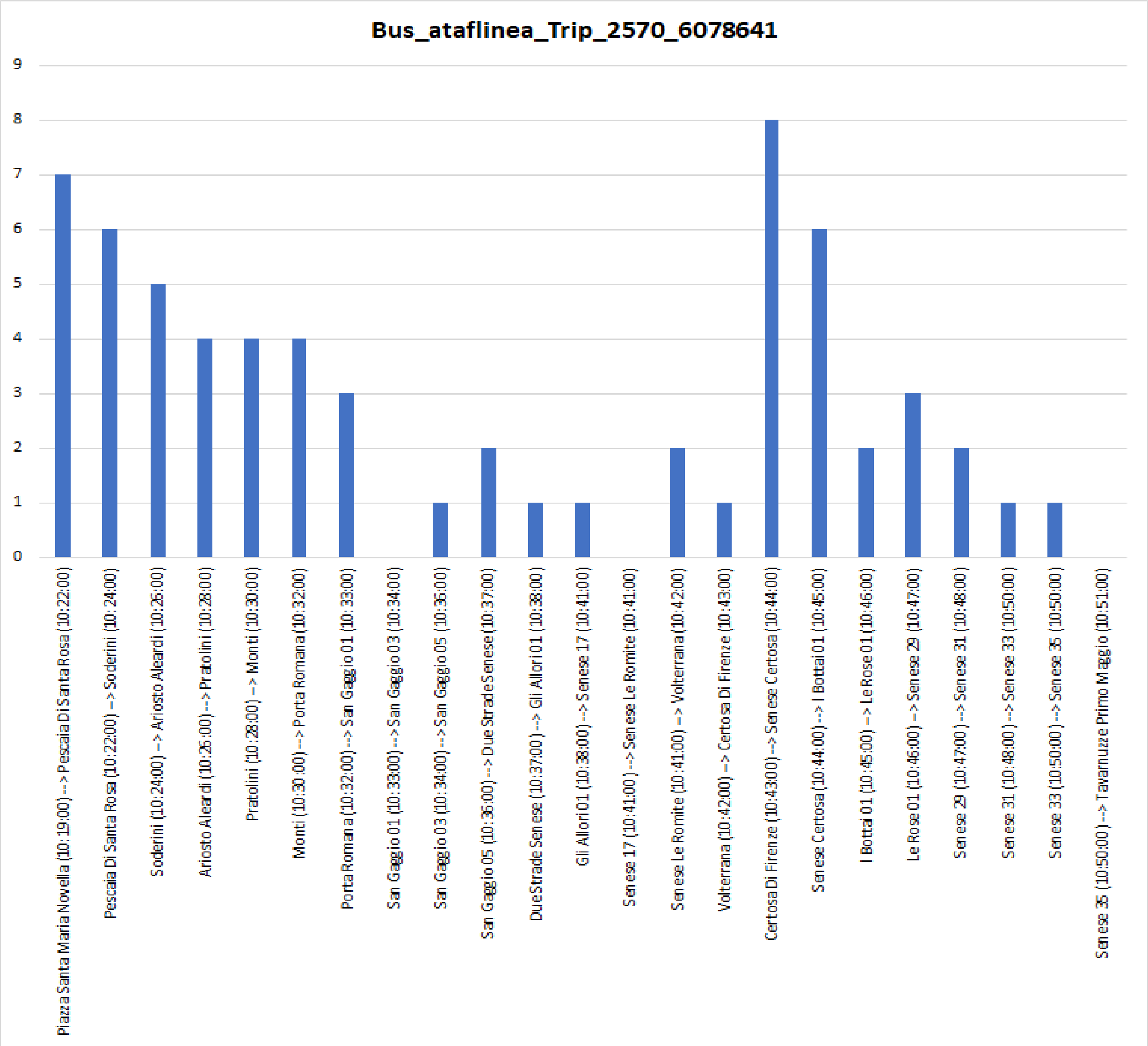


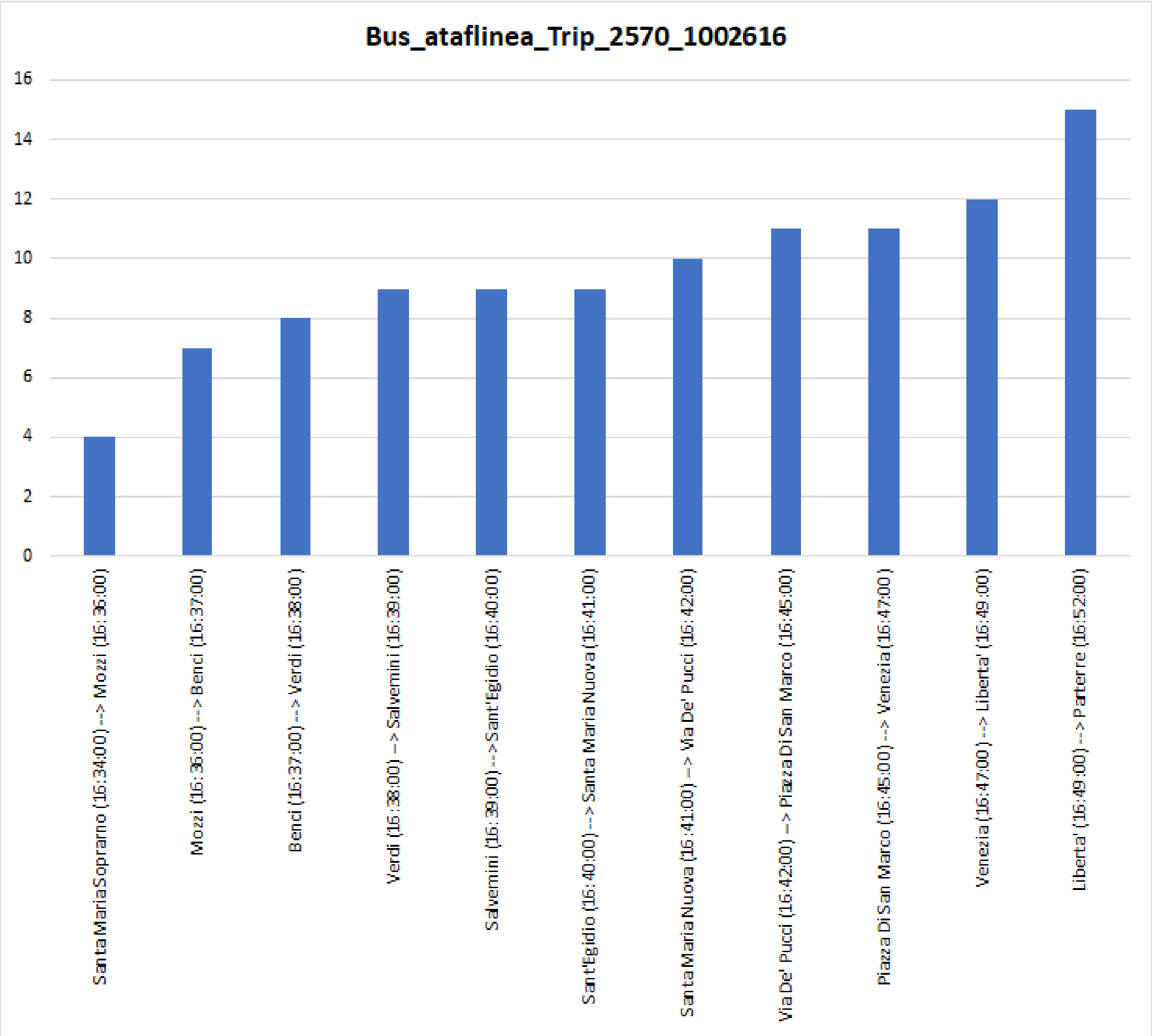









Bus_ataflinea_Trip_2570_6078641
9
8
7
6
5
4
3
2
1
0
Piazza Santa Maria Novella (10:19:00) --> Pescaia Di Santa Rosa (10:22:00)
Pescaia Di Santa Rosa (10:22:00) --> Soderini (10:24:00)
Soderini (10:24:00) --> Ariosto Aleardi (10:26:00)
Ariosto Aleardi (10:26:00) --> Pratolini (10:28:00)
Pratolini (10:28:00) --> 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
16
14
12
10
8
6
4
2
0
Santa Maria Soprano (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)

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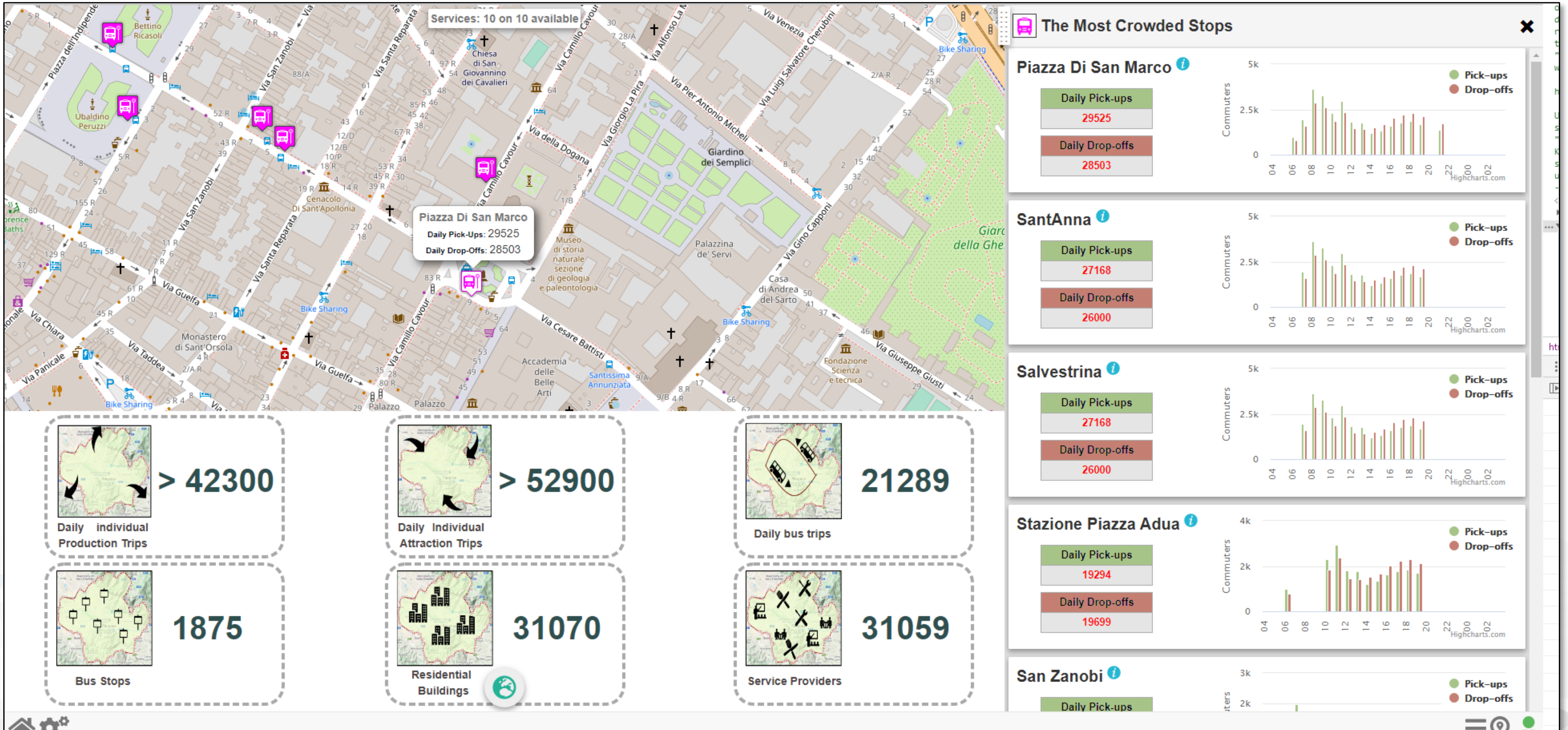
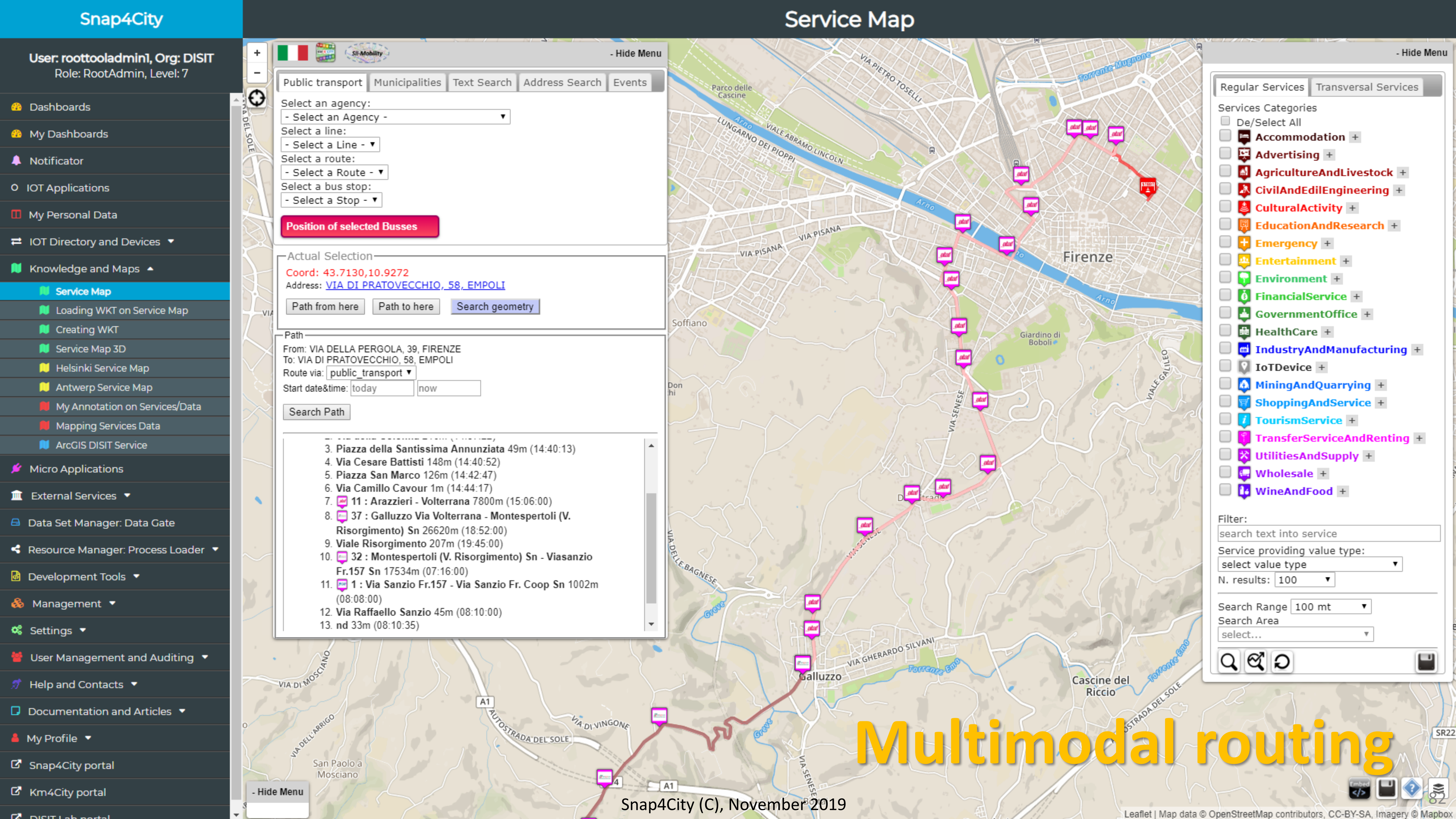
Bus Stop Analysis: identification of criticalities



TOP

Modal & Multimodal Routing for Navigation and Travel Planning



Multimodal routing

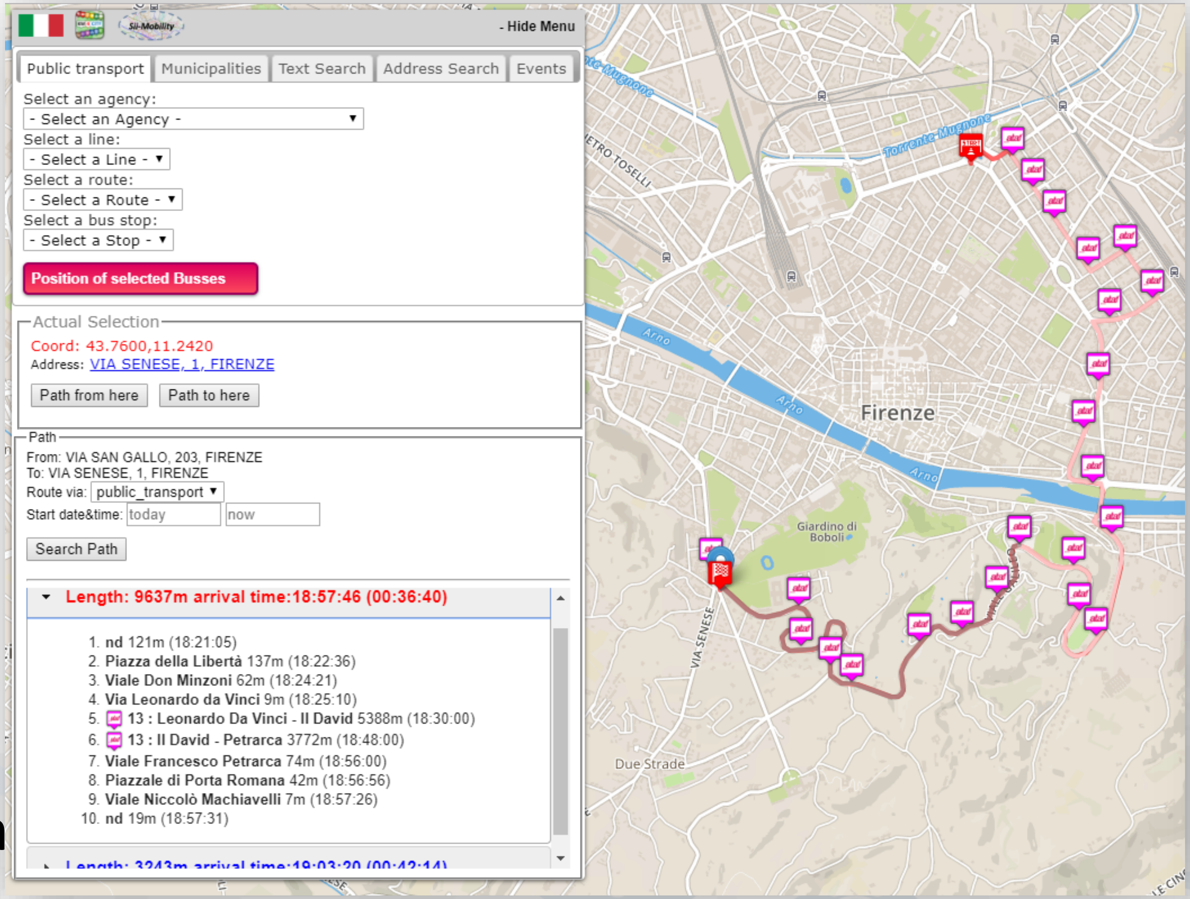
Routing and Multimodal Routing

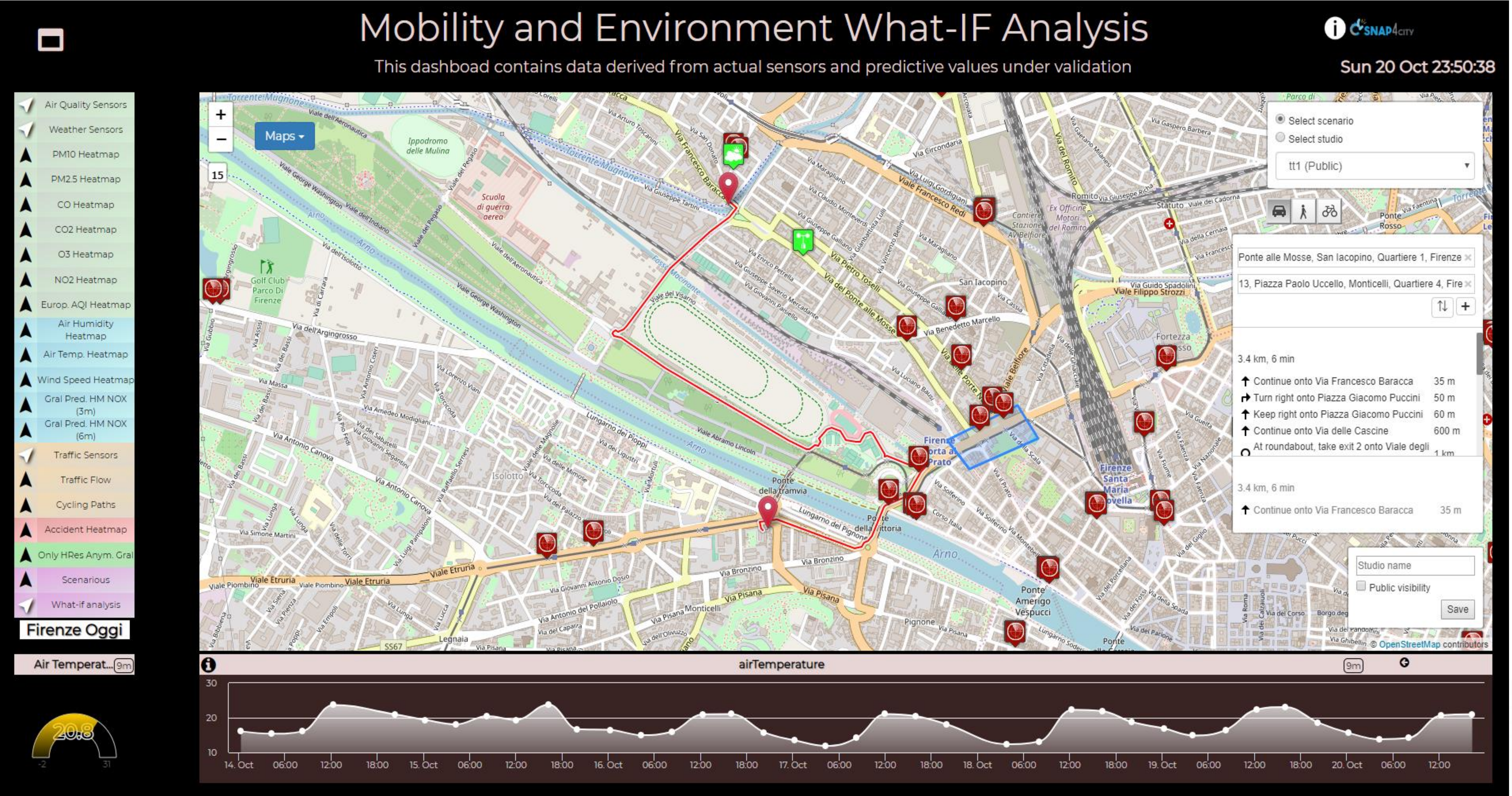
Modes:

- 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





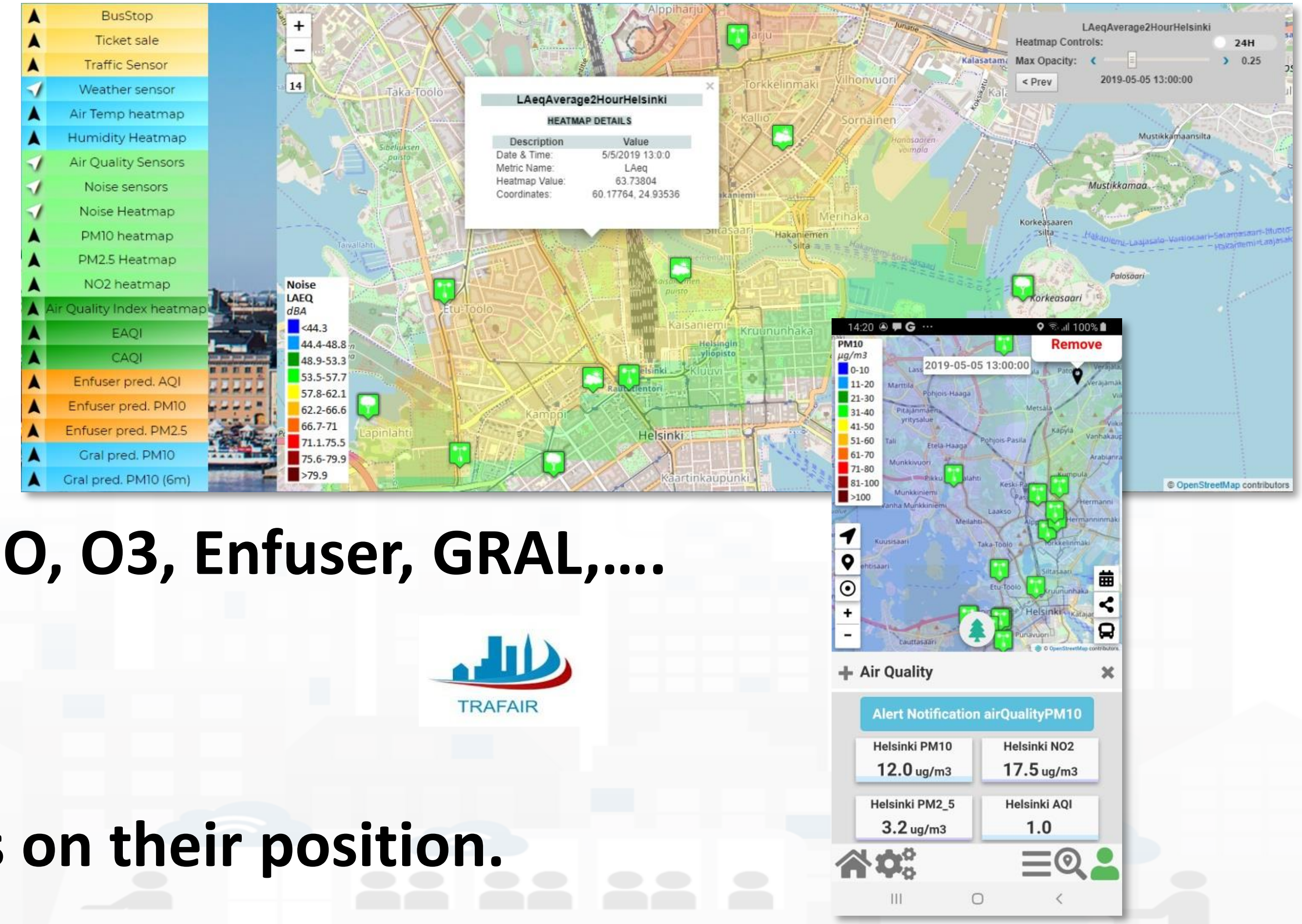
https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MjE5MA==

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

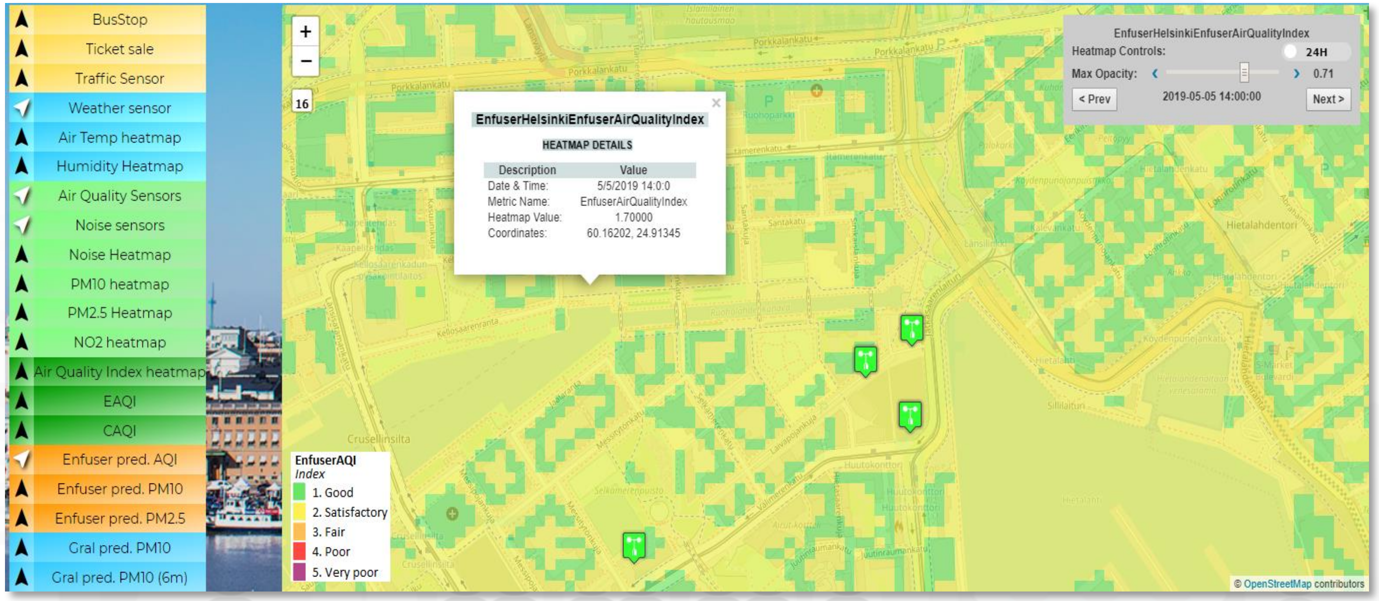


Environmental ENFUSER Predictive Measures

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



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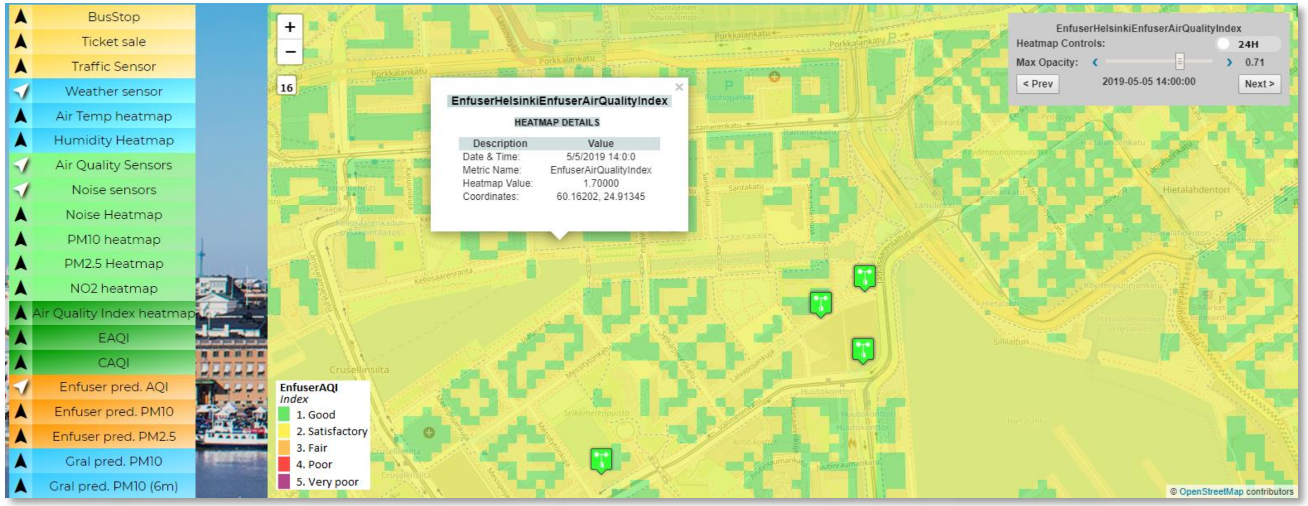
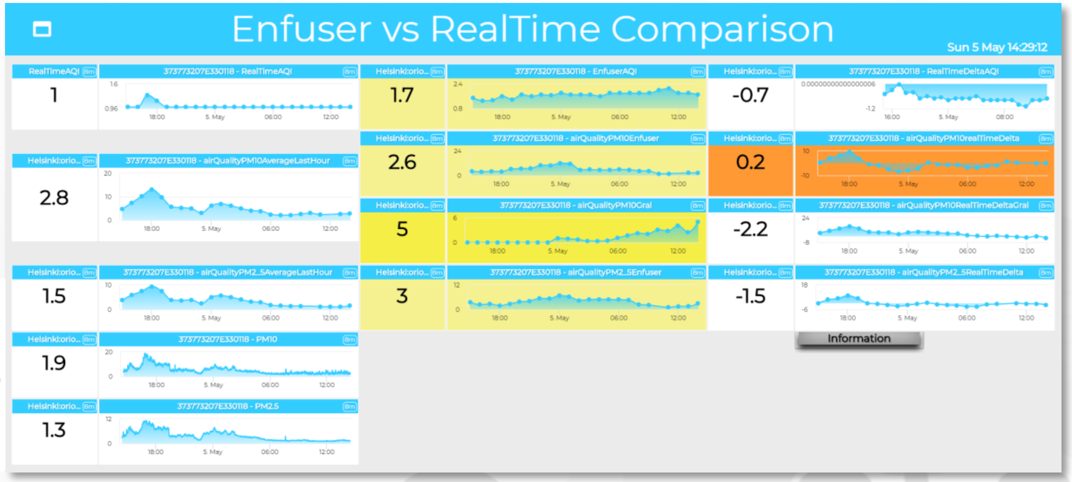
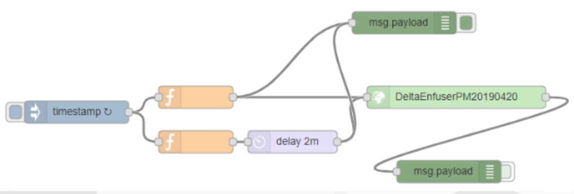
Data Analytics: Enfuser predictions

- **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

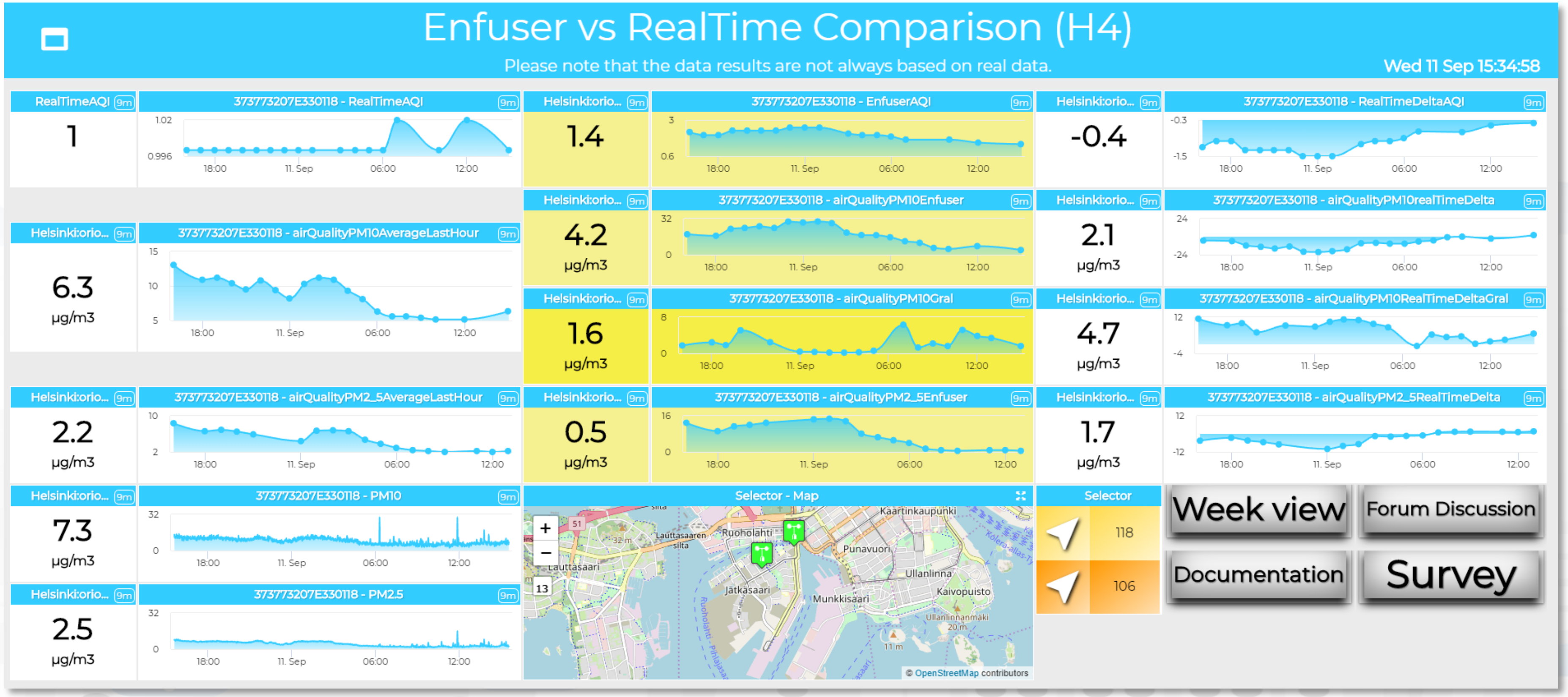






Comparative Dashboard

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

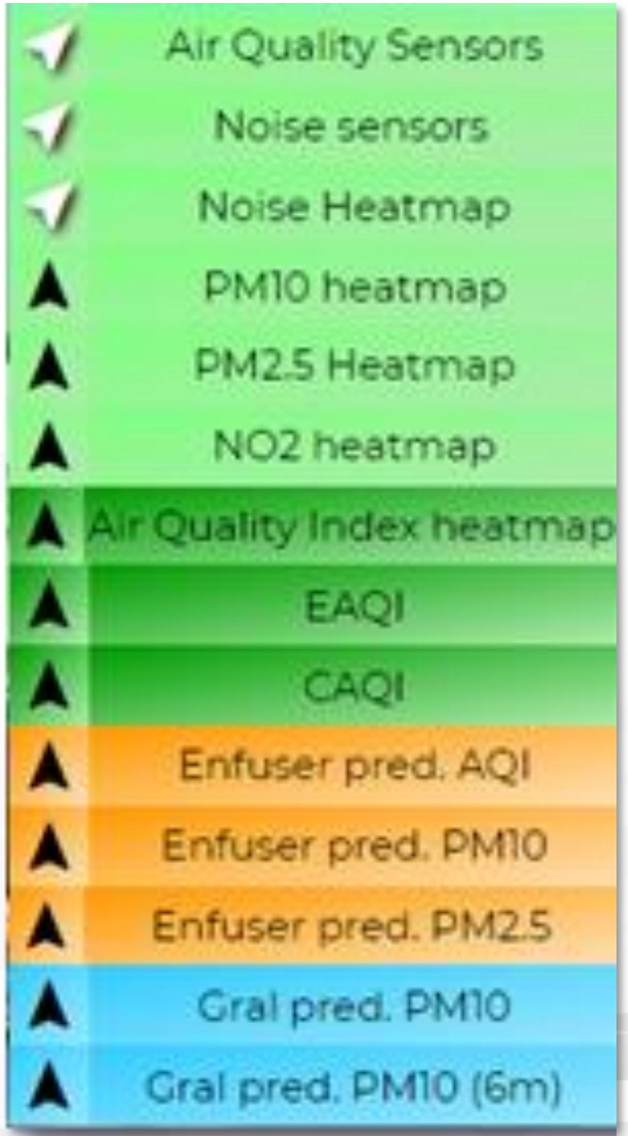


https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTczMg==

Data Analytics: AQI estimations

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

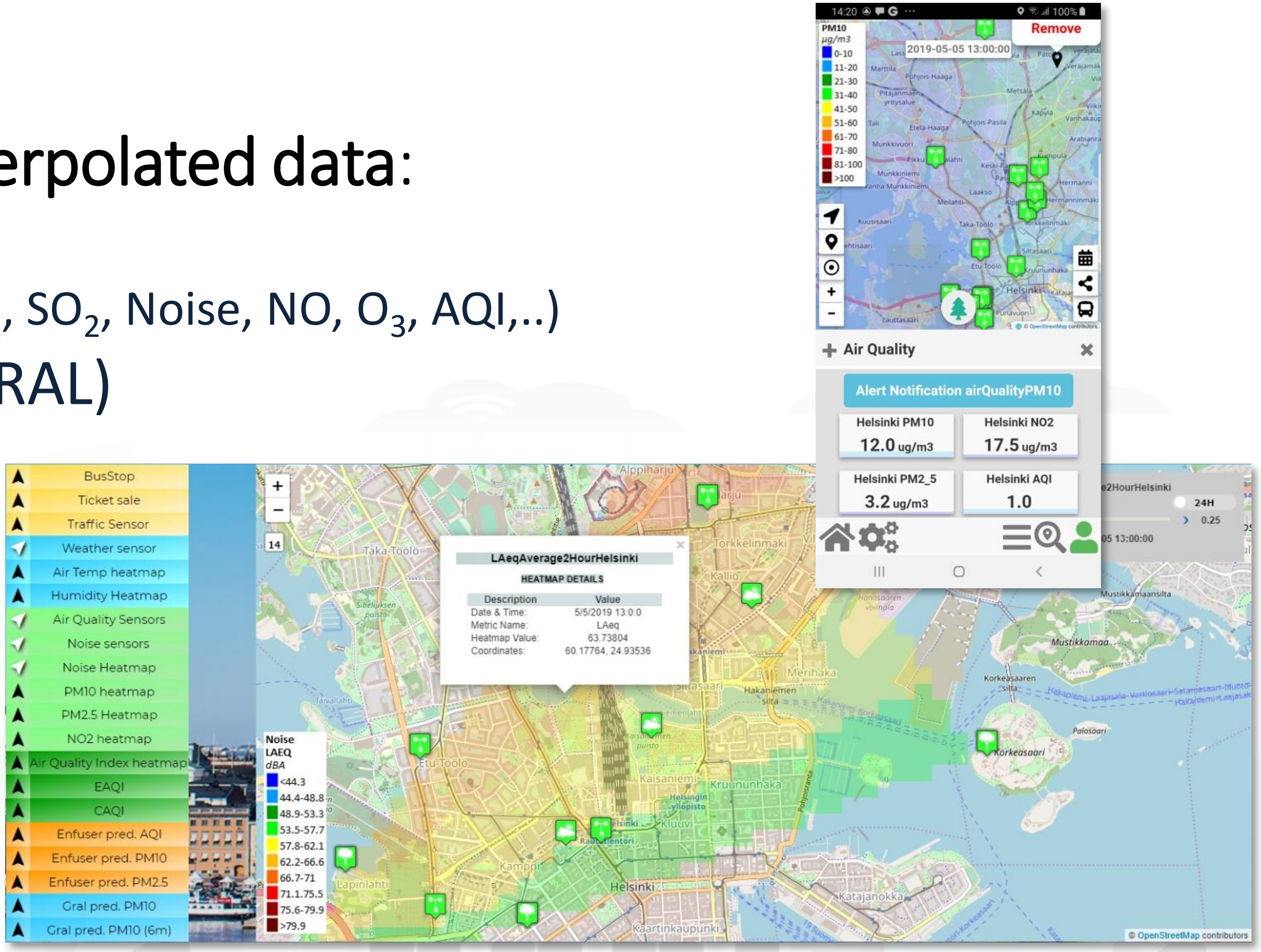
- **AQI estimation via Rstudio and IOT App:**
  - **EAQI, European Air Quality Index**
  - **Enfuser AQI for Delta,**
  - **CAQI**
  - **Their corresponding Heatmaps**



Environmental Heatmaps

Calibrated heatmaps based on **Interpolated data**:

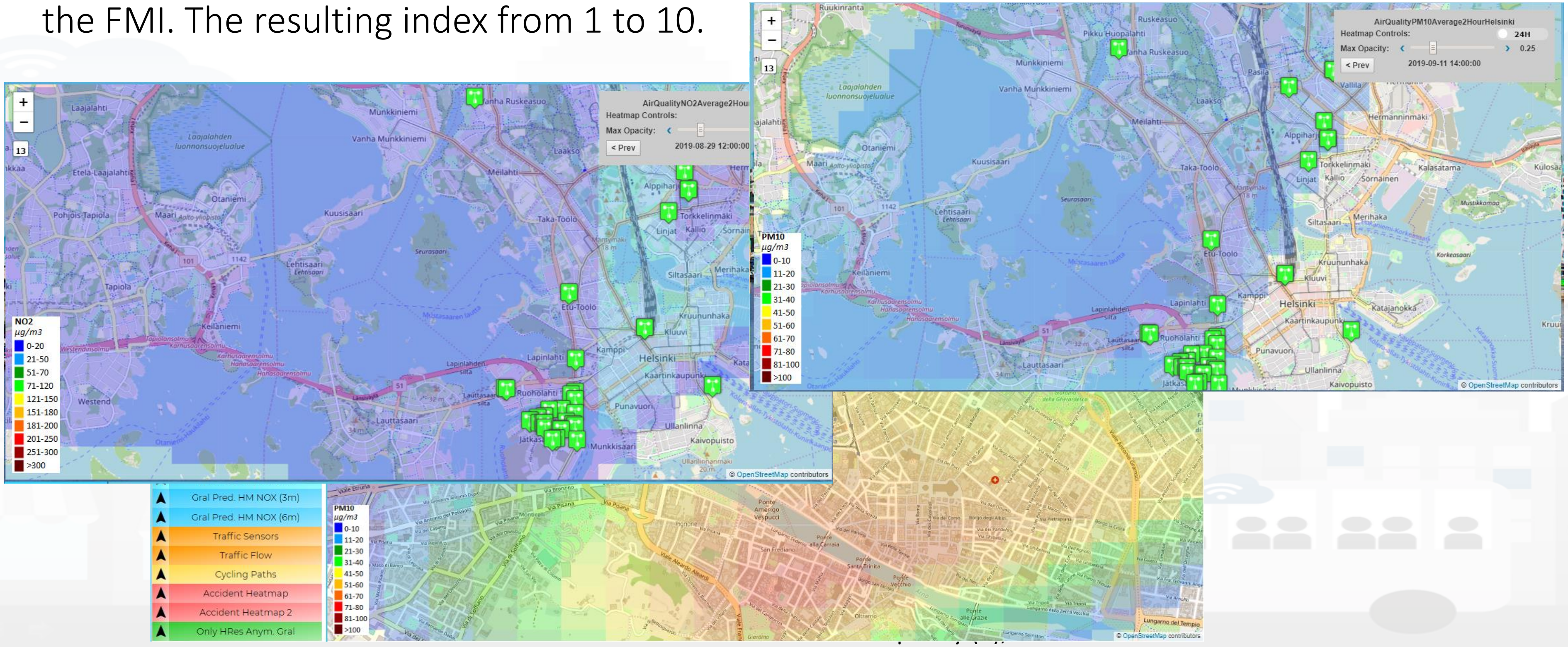
- **Real time** measures (PM_{10}, $PM_{2,5}$, NO_2, SO_2, Noise, NO, O_3, AQI,..)
- **Predictive** measures (ENFUSER, GRAL)
- From **200x200** to **4x4** m
- Hourly concentration
- Any programmed Color map
- Animations over H24
- Picking values in any place
- On Web and Mobile App



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.



- BusStop
- Ticket sale
- Traffic Sensor
- Weather sensor
- Air Temp heatmap
- Humidity Heatmap
- Air Quality Sensors
- Noise sensors
- Noise Heatmap
- PM10 heatmap
- PM2.5 Heatmap
- NO2 heatmap
- Air Quality Index HeatM.
- EAQI HeatM.
- CAQI HeatM.
- Enfuser pred. AQI
- Enfuser pred. PM10
- Enfuser pred. PM2.5
- Gral pred. PM10
- Gral pred. PM10 (6m)
- PM10 Jätkäsaari
- PM2.5 Jätkäsaari
- EAQI Jätkäsaari
- Appreciated POIs

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**

www.airqualitynow.eu

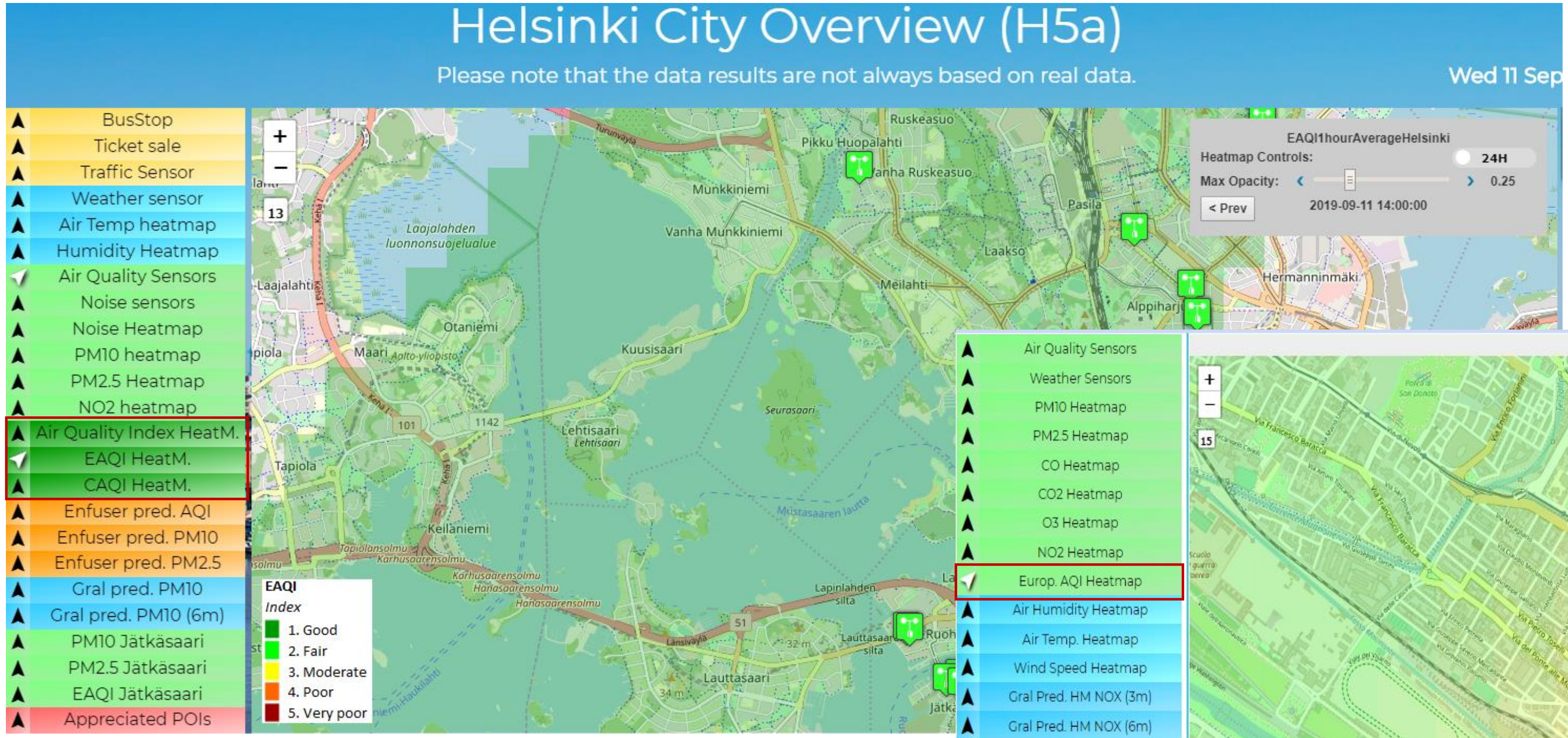
Qualitative name	Index or sub-index	Pollutant (hourly) density in µg/m^3			
		NO_2	PM_{10}	O_3	$PM_{2.5}$(optional)
Very low	0–25	0–50	0–25	0–60	0–15
Low	25–50	50–100	25–50	60–120	15–30
Medium	50–75	100–200	50–90	120–180	30–55
High	75–100	200–400	90–180	180–240	55–110
Very high	>100	>400	>180	>240	>110

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**.

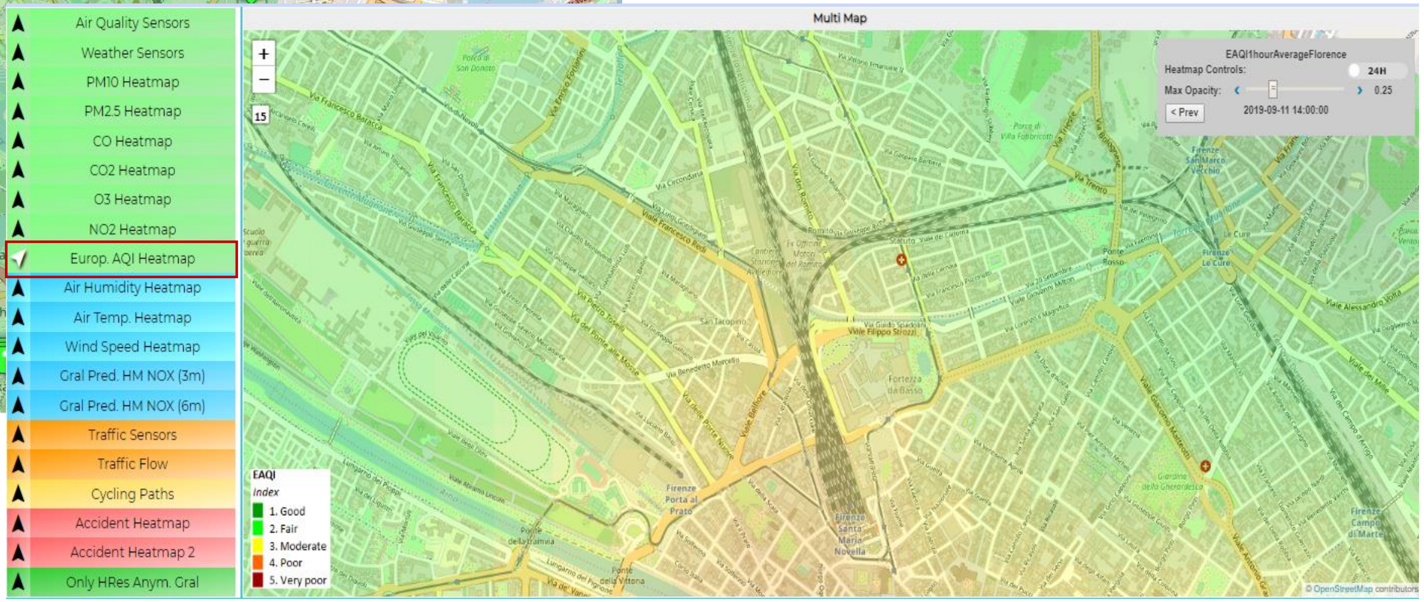
Legend of Environmental data:
https://www.snap4city.org/drupal/node/435

AQI Indexes estimation Heatmaps

Hourly pollutant concentration



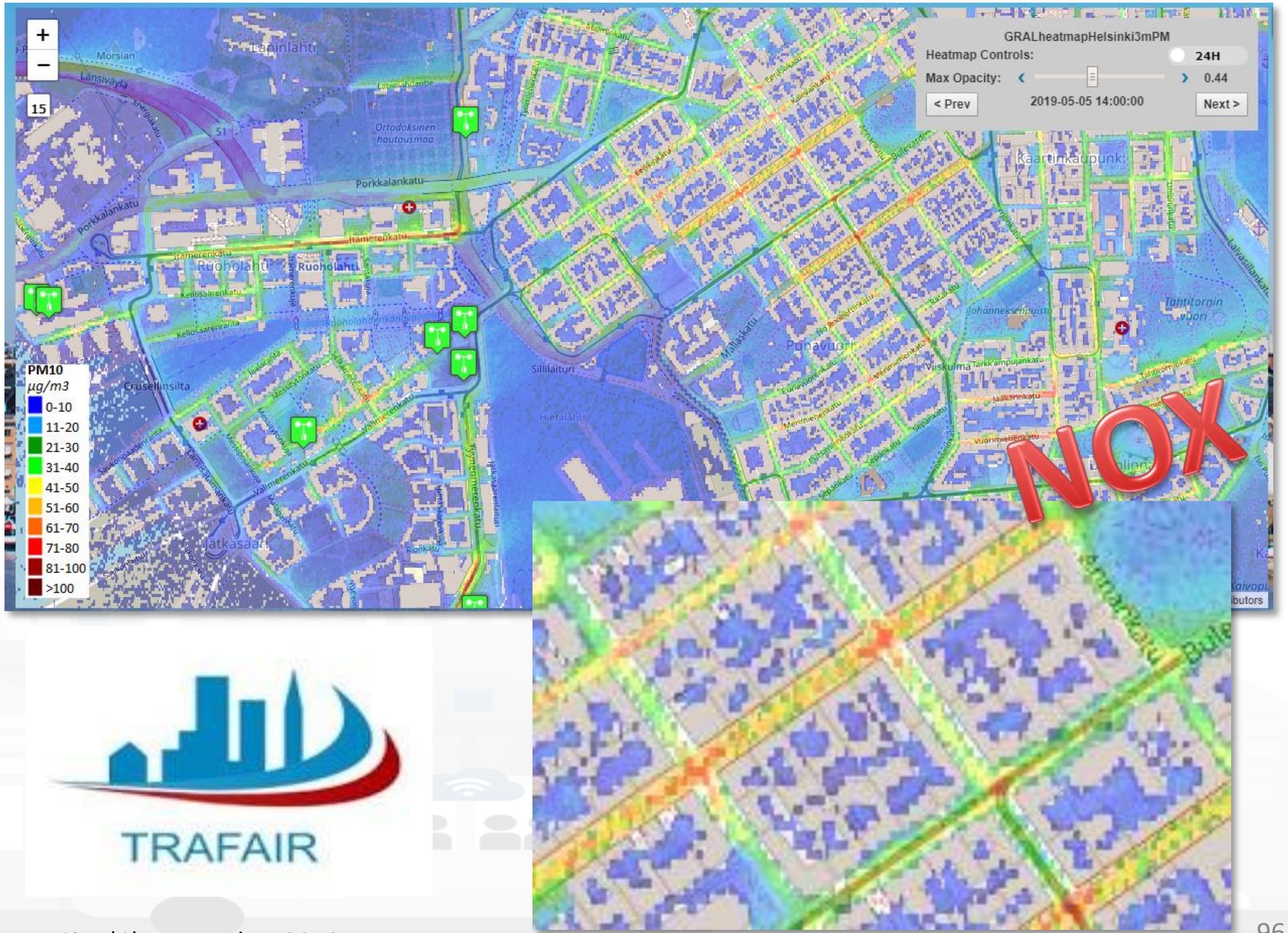
https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTQwNg==



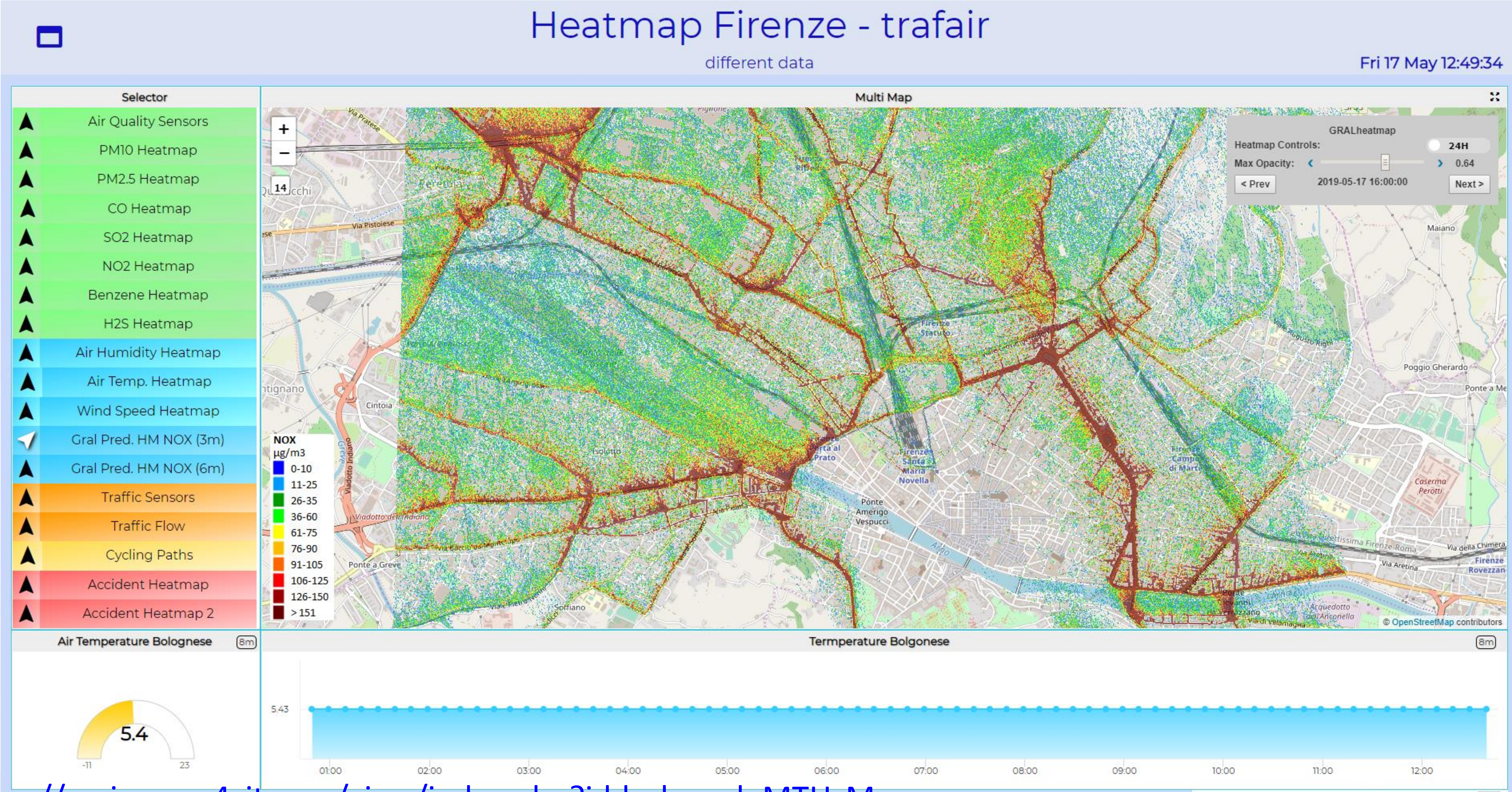
https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTUzMg==

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

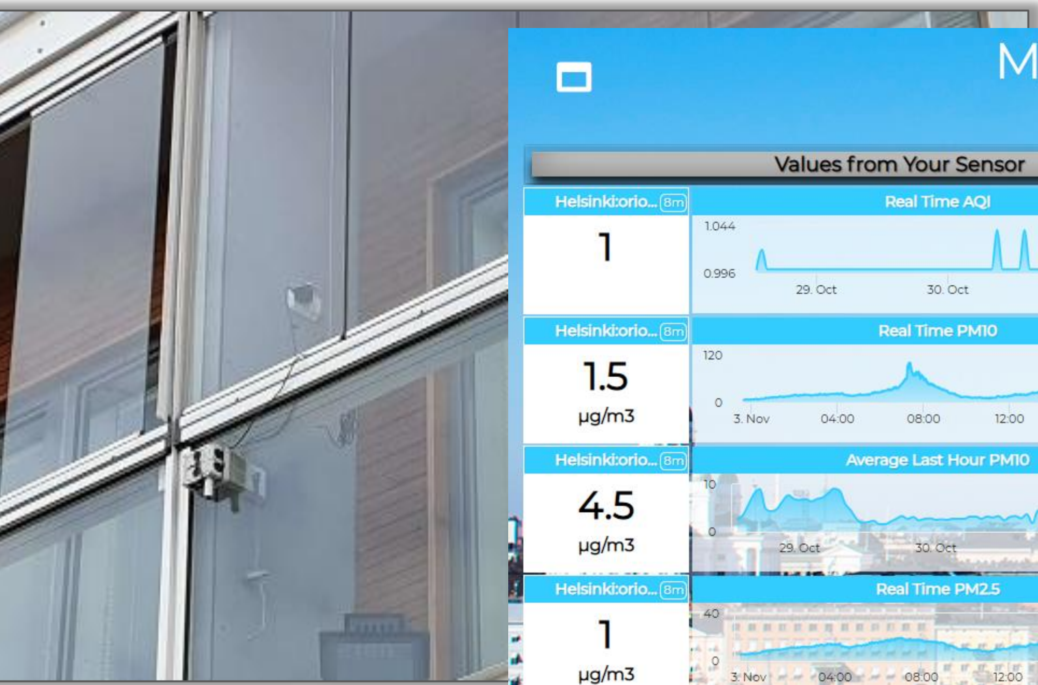


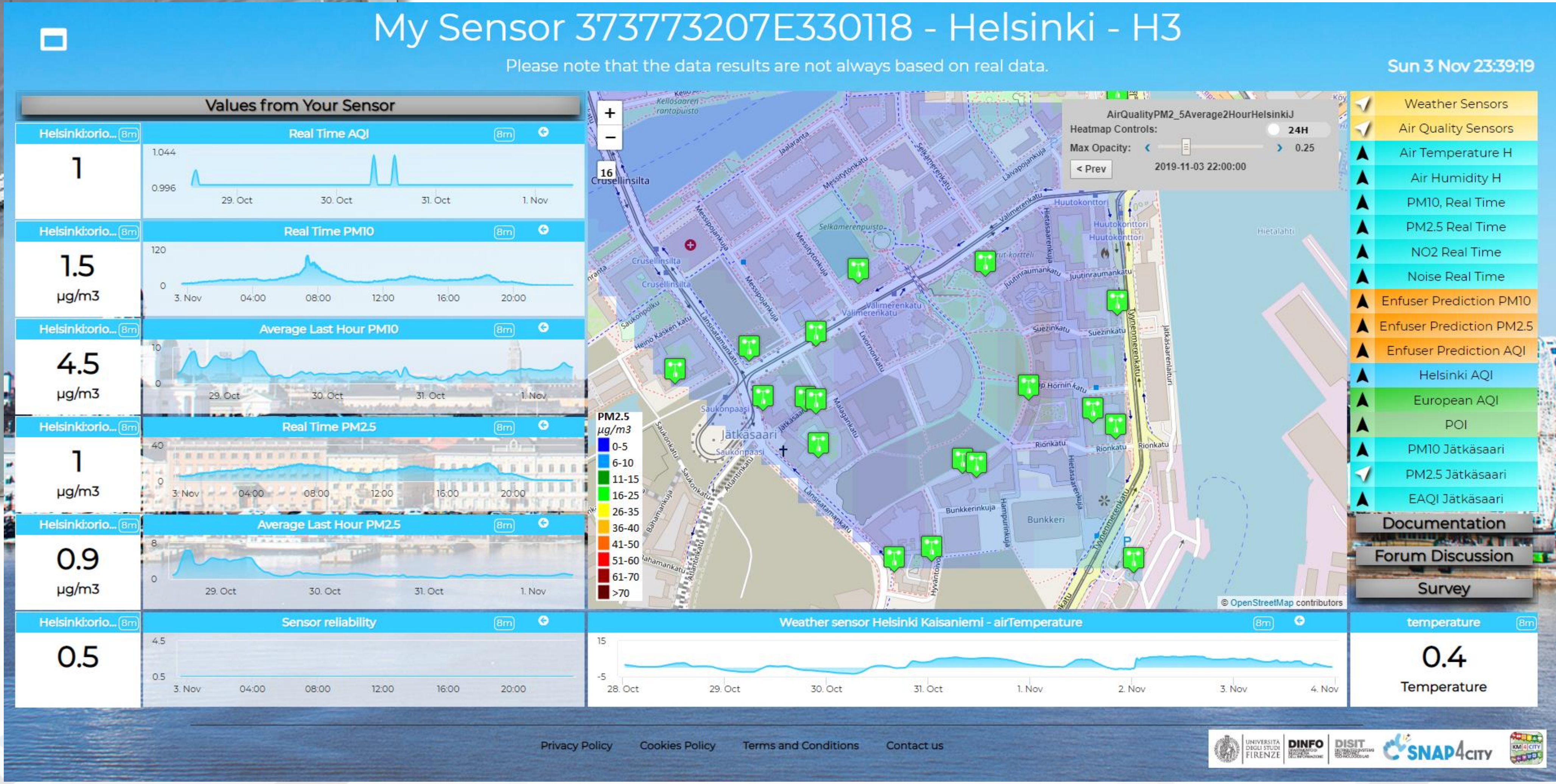
TRAFAIR



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

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.

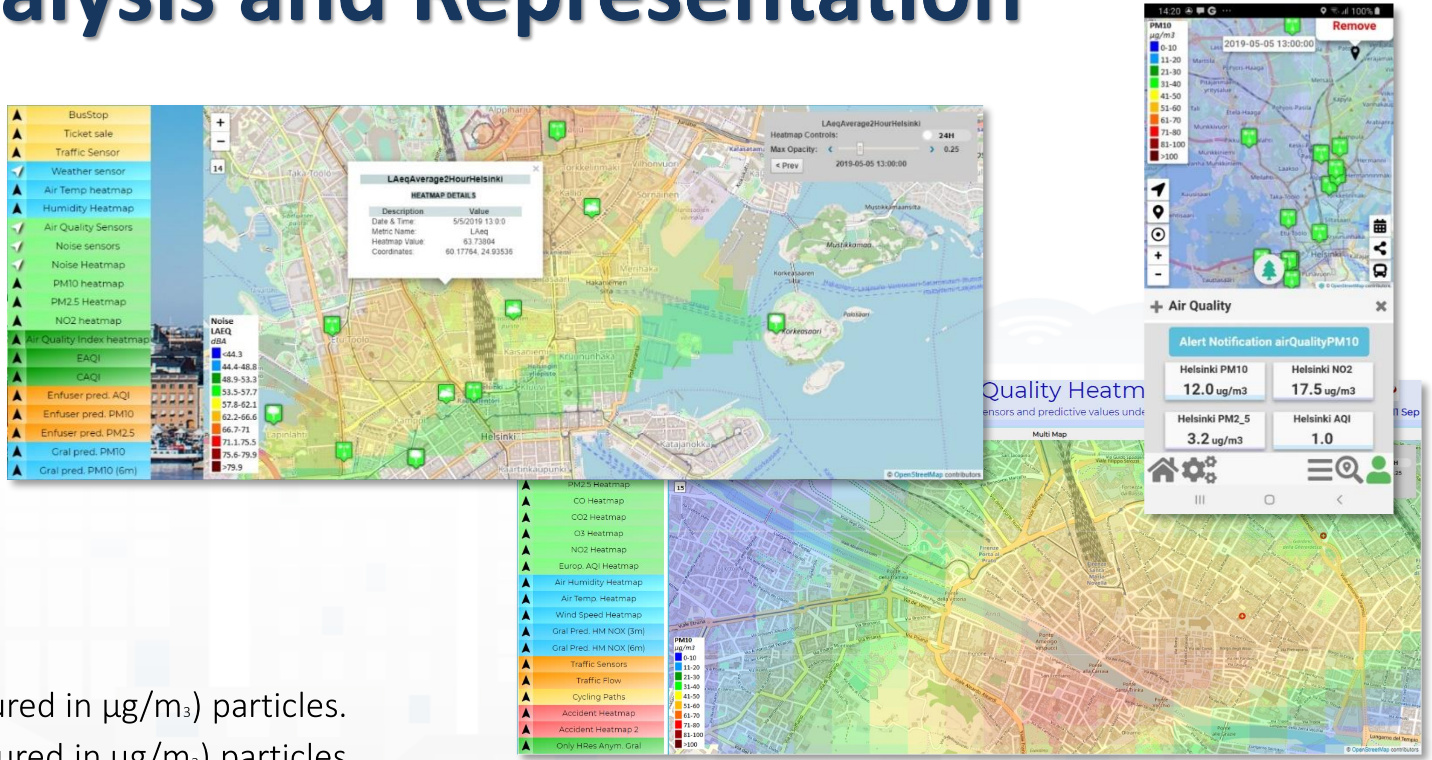
Data have been collected from:

- 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 $\mu g/m_3$) particles.
- **$PM_{2,5}$:** real time pollutant levels in air in terms of $PM_{2.5}$ (measured in $\mu g/m_3$) particles.
- **NO_2:** real time pollutant levels in air in terms of nitrogen dioxide (measured in $\mu g/m_3$).
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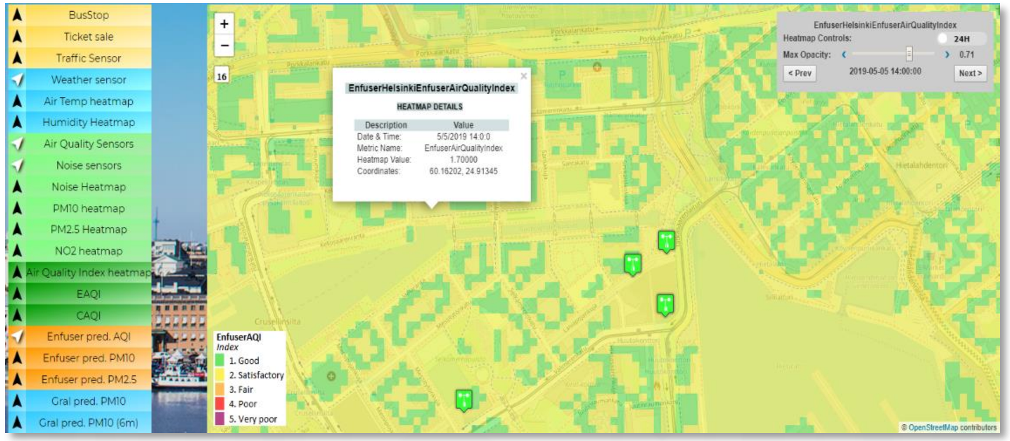
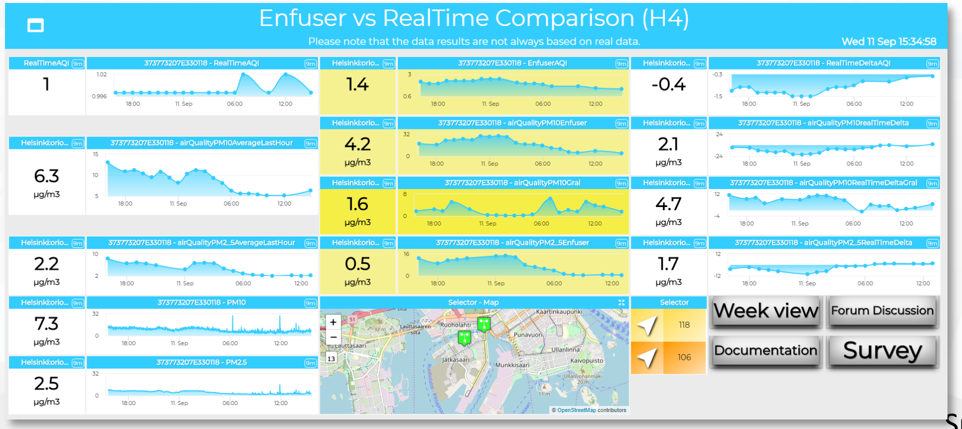
- **European Air Quality Index** (EAQI): measurements of up to five key pollutants supported by modelled data determine the index level that describes the current air quality situation at each monitoring station.
- **Common Air Quality Index** (CAQI): is defined away from roads (a "background" index). 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

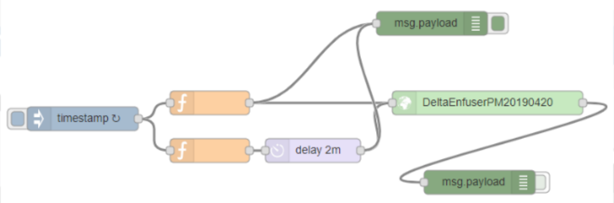
Environmental Predictive Measures:

- **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



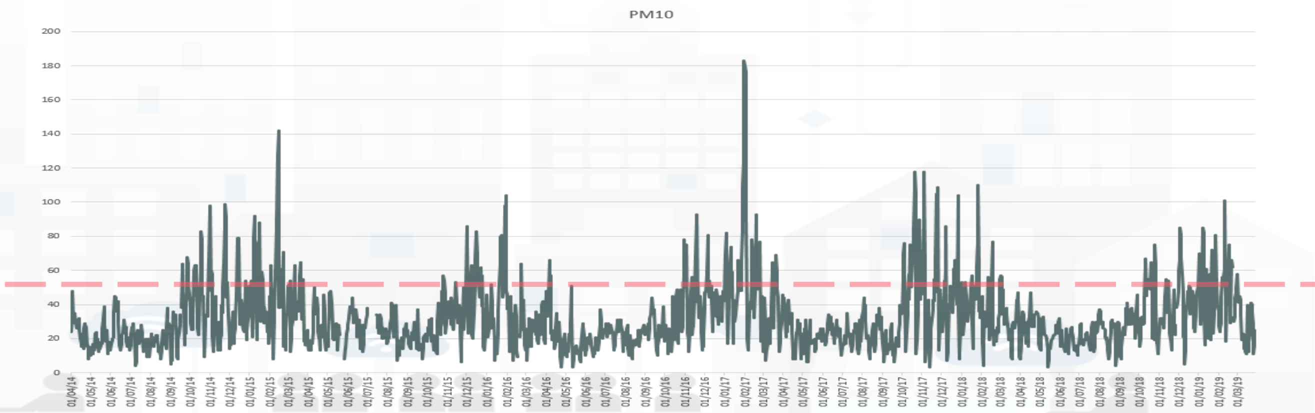
TOP

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	

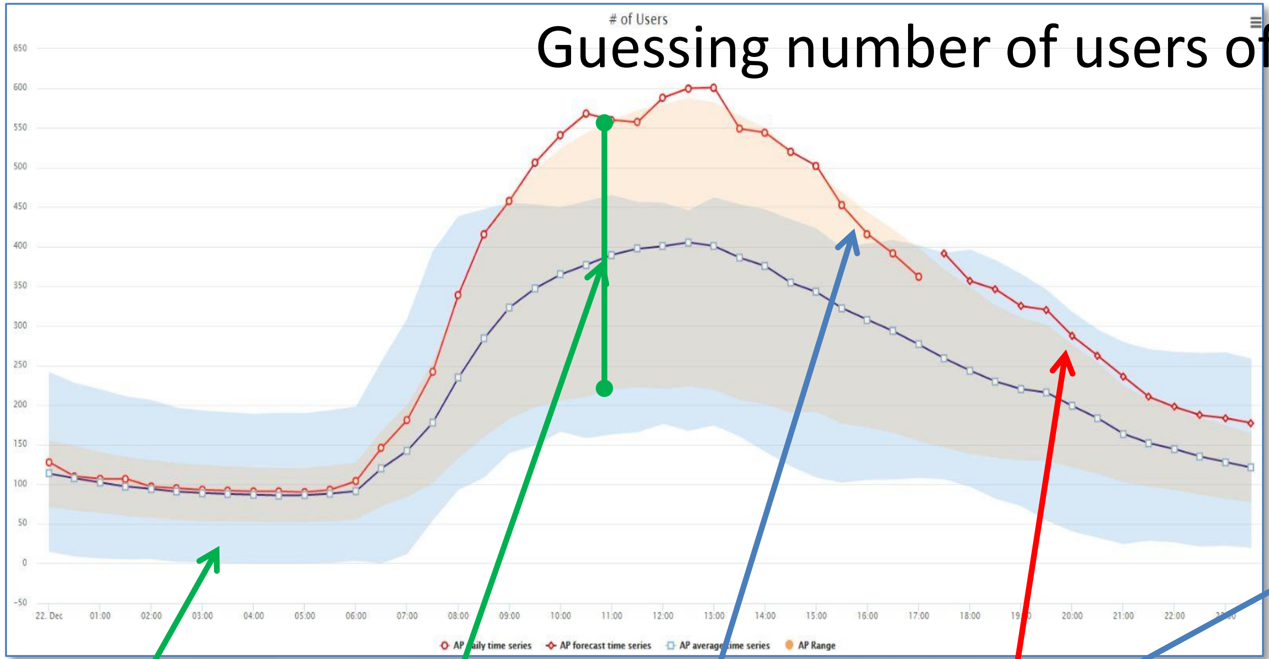


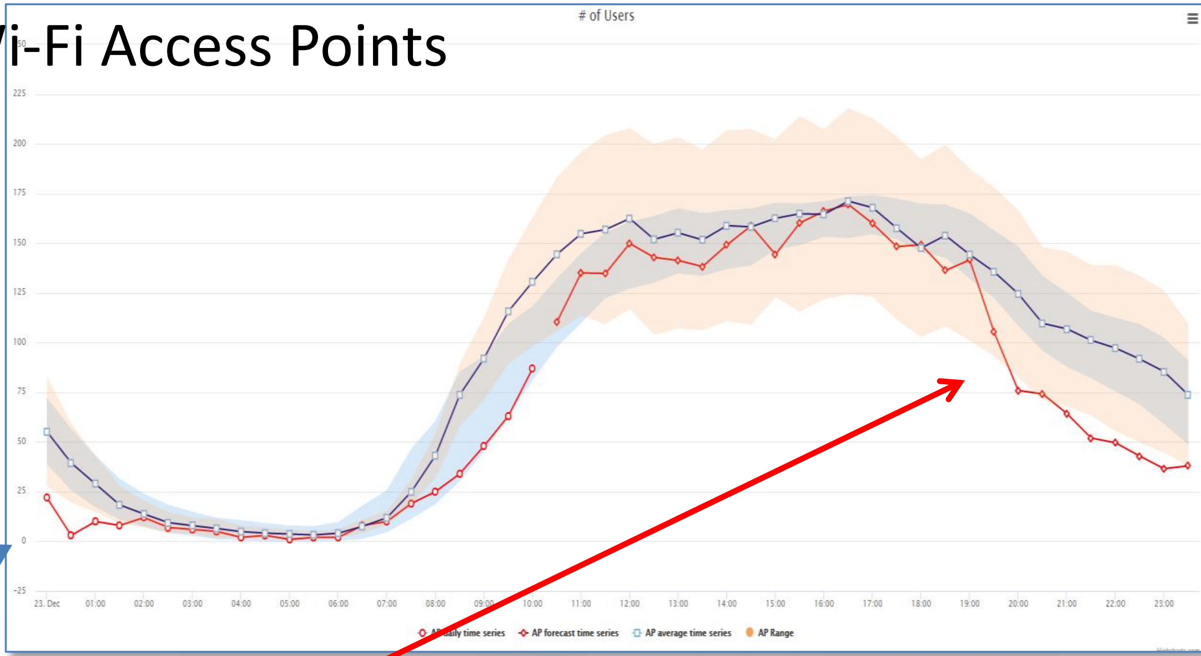
TOP

Anomaly Detection

Prediction and Identification of Anomalies

Guessing number of users of Wi-Fi Access Points





Cluster confidence

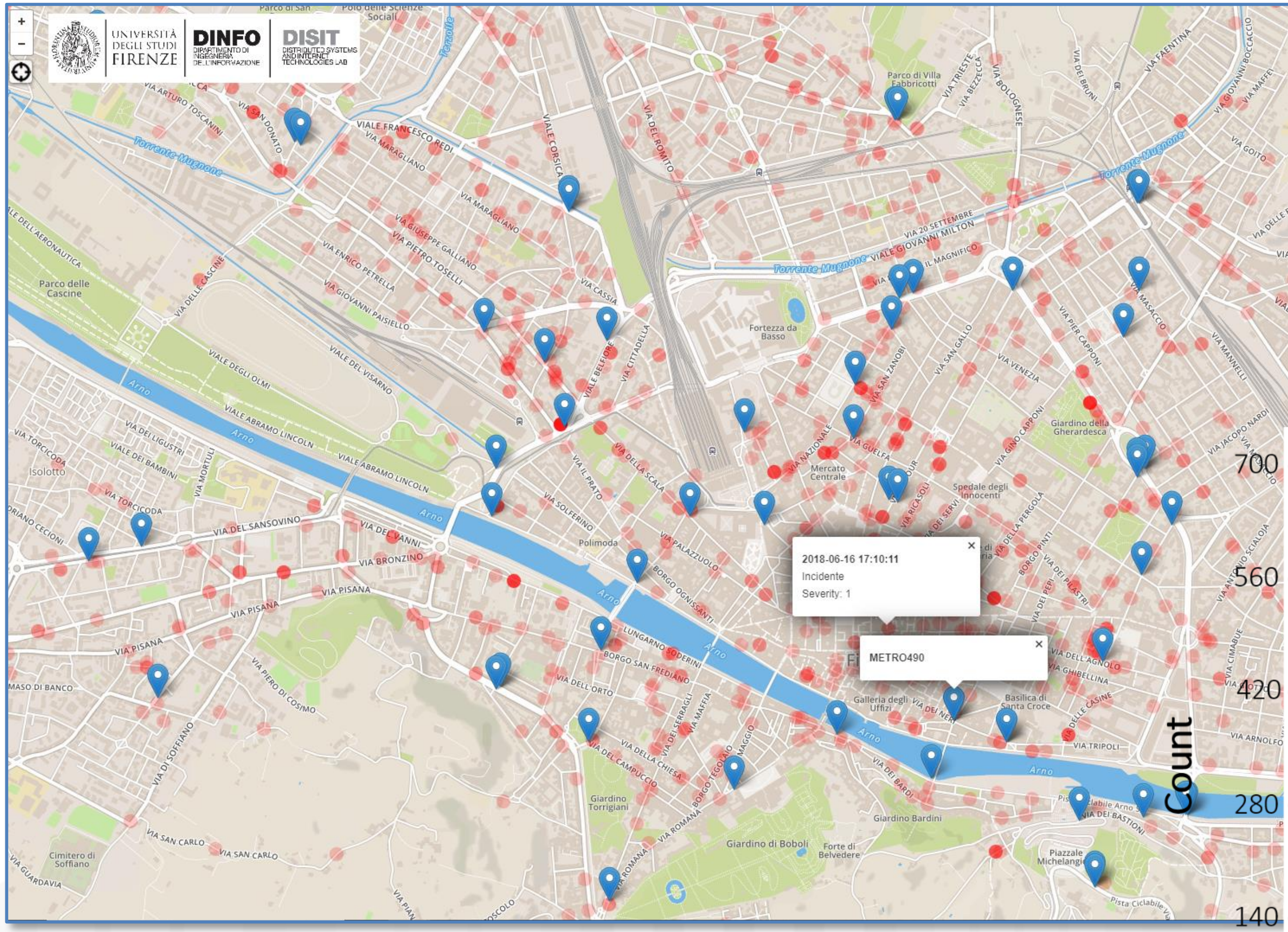
AP average and confidence

Actual AP trend for today

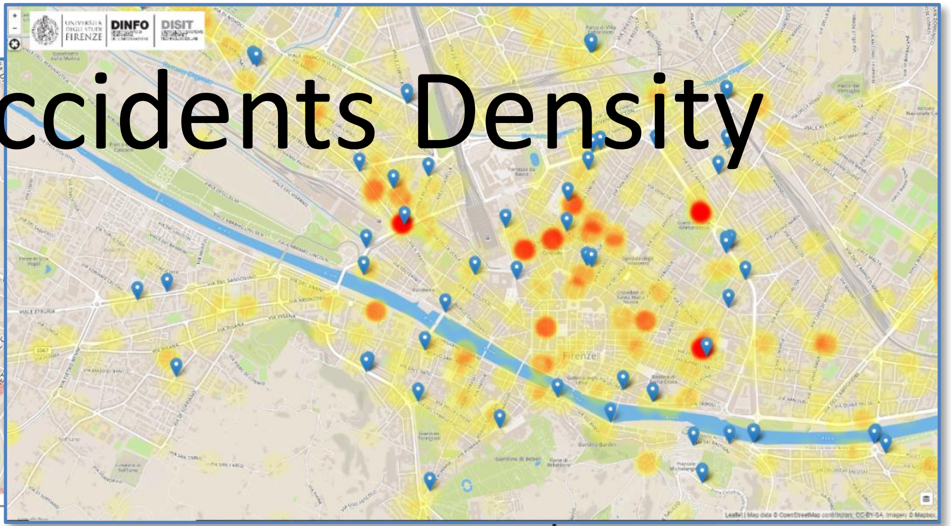
AP prediction for the next time slot in the day on the basis of past weeks

Predictive precision of the 95%

Anomaly Detection

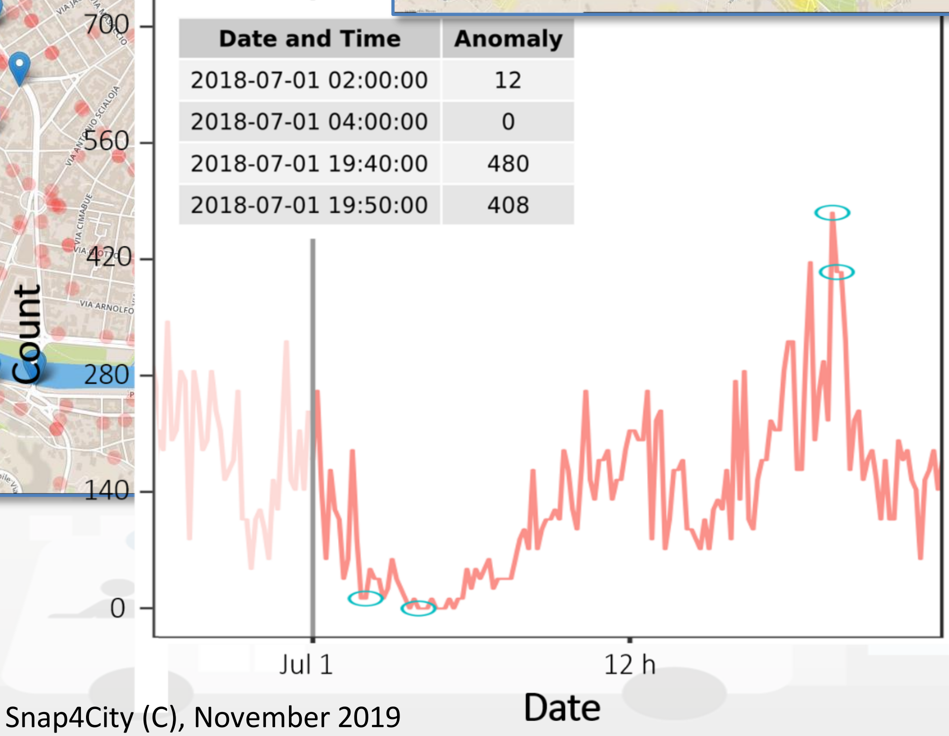


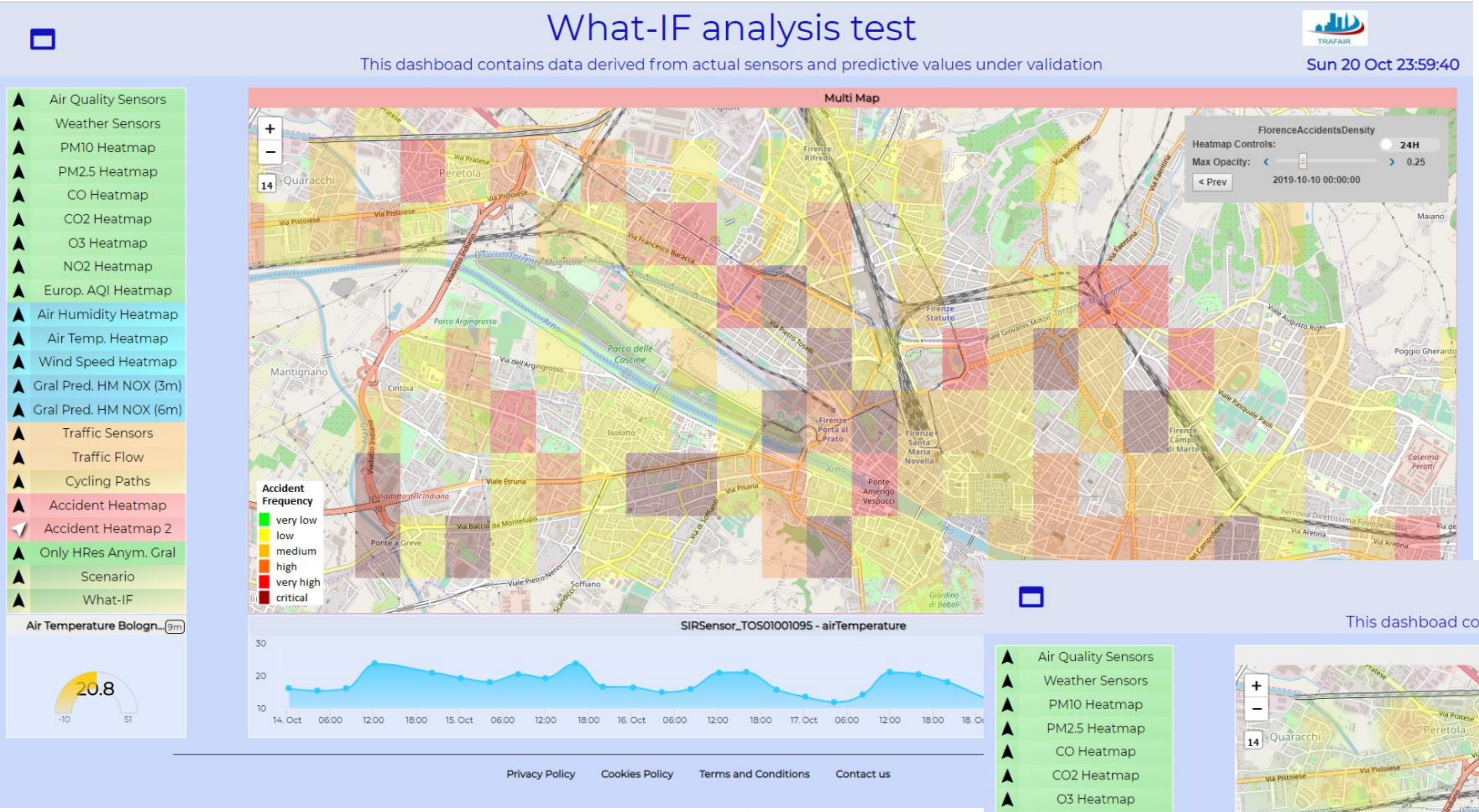
Accidents vs Traffic

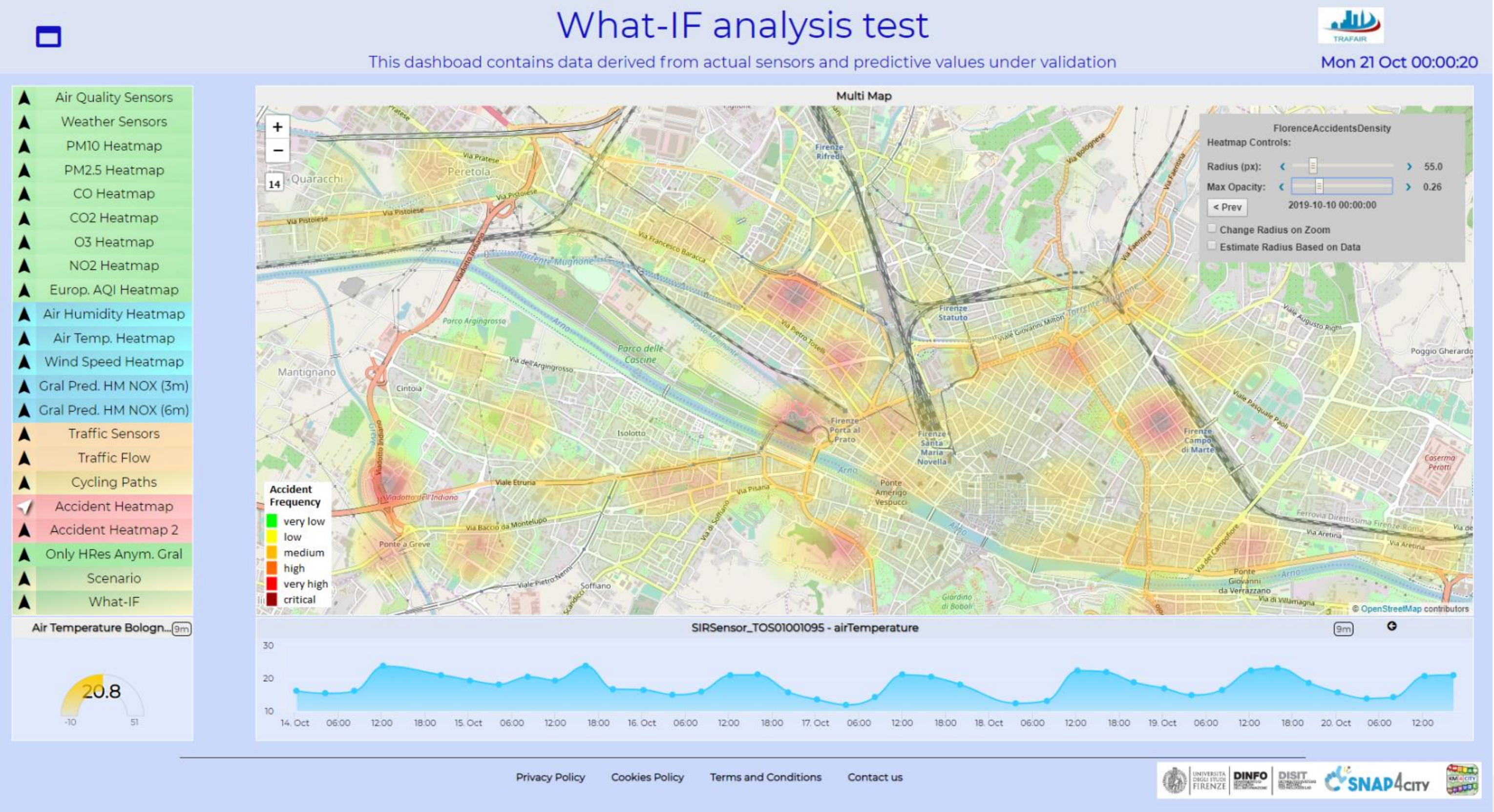


Accidents Density

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

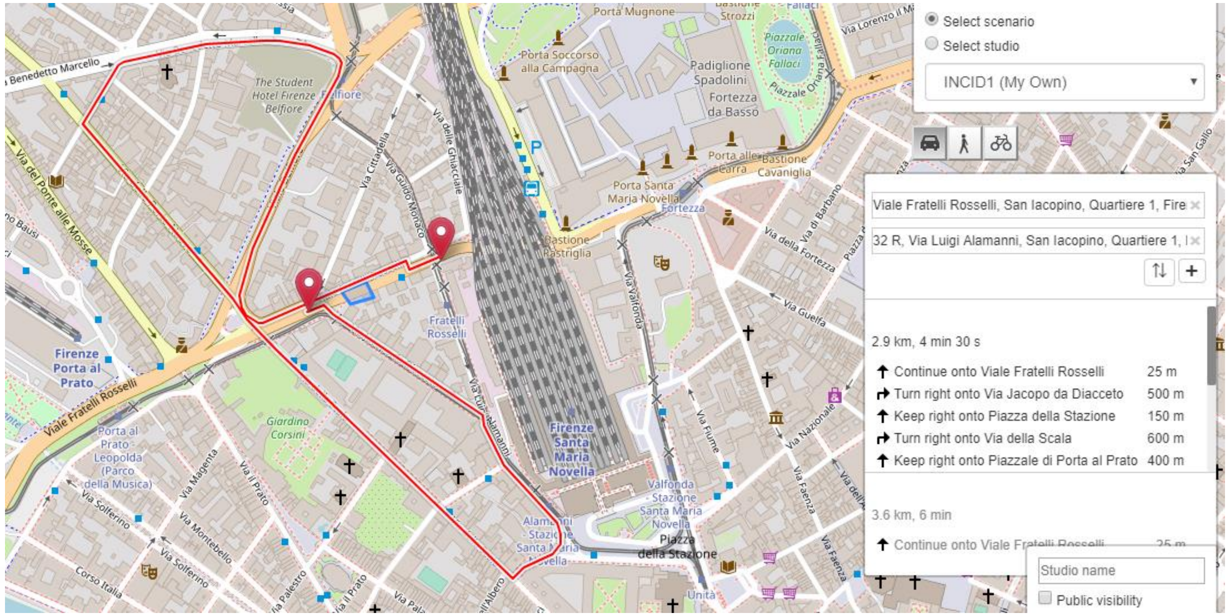
What-If Analysis

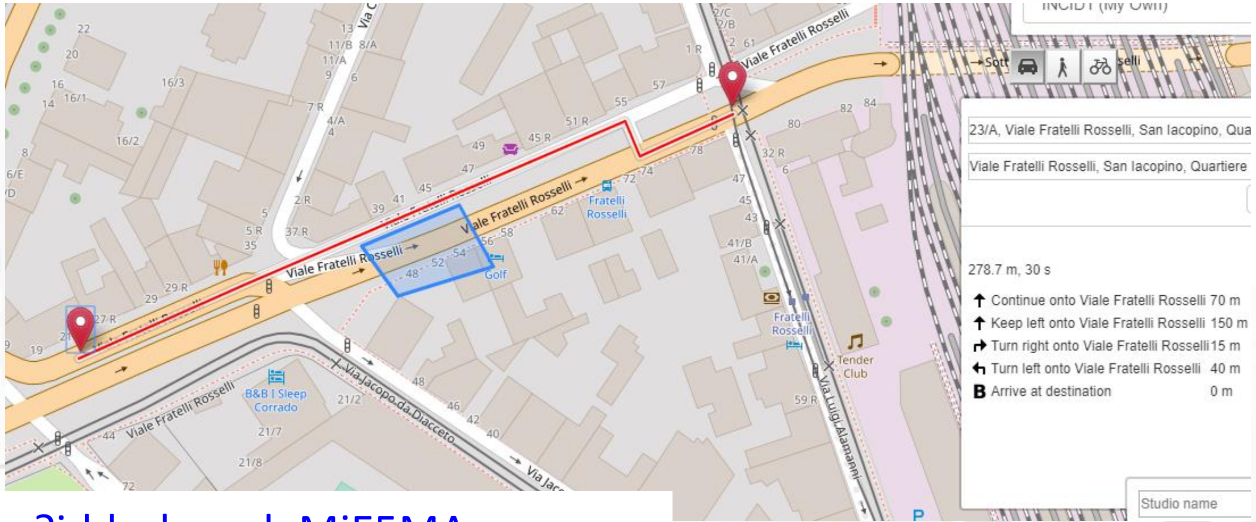
Accidents and elements blocking Points and Shapes taken into account for:

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

Assessment on the basis of changes:

- Mobility demand assessment
- Mobility Offer assessment



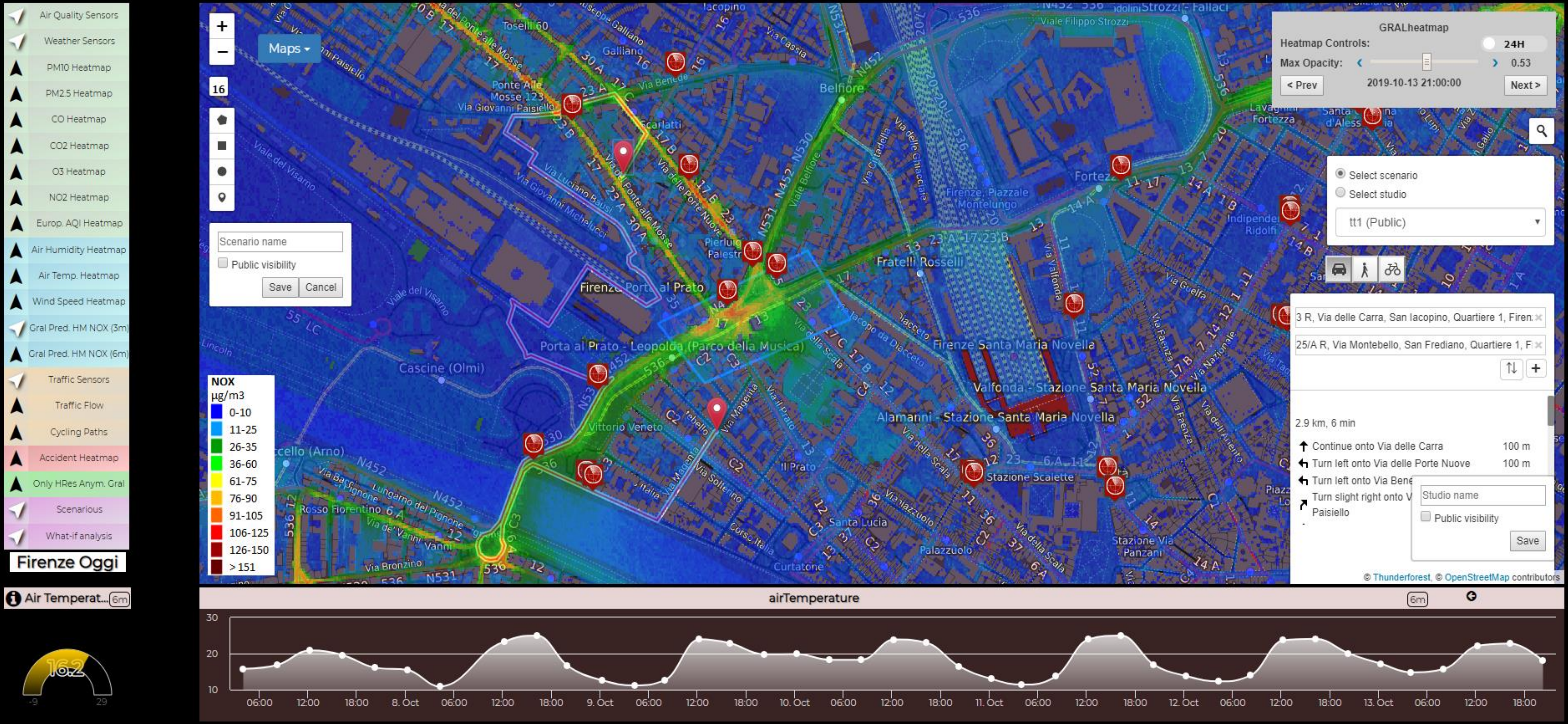


https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MjE5MA==

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



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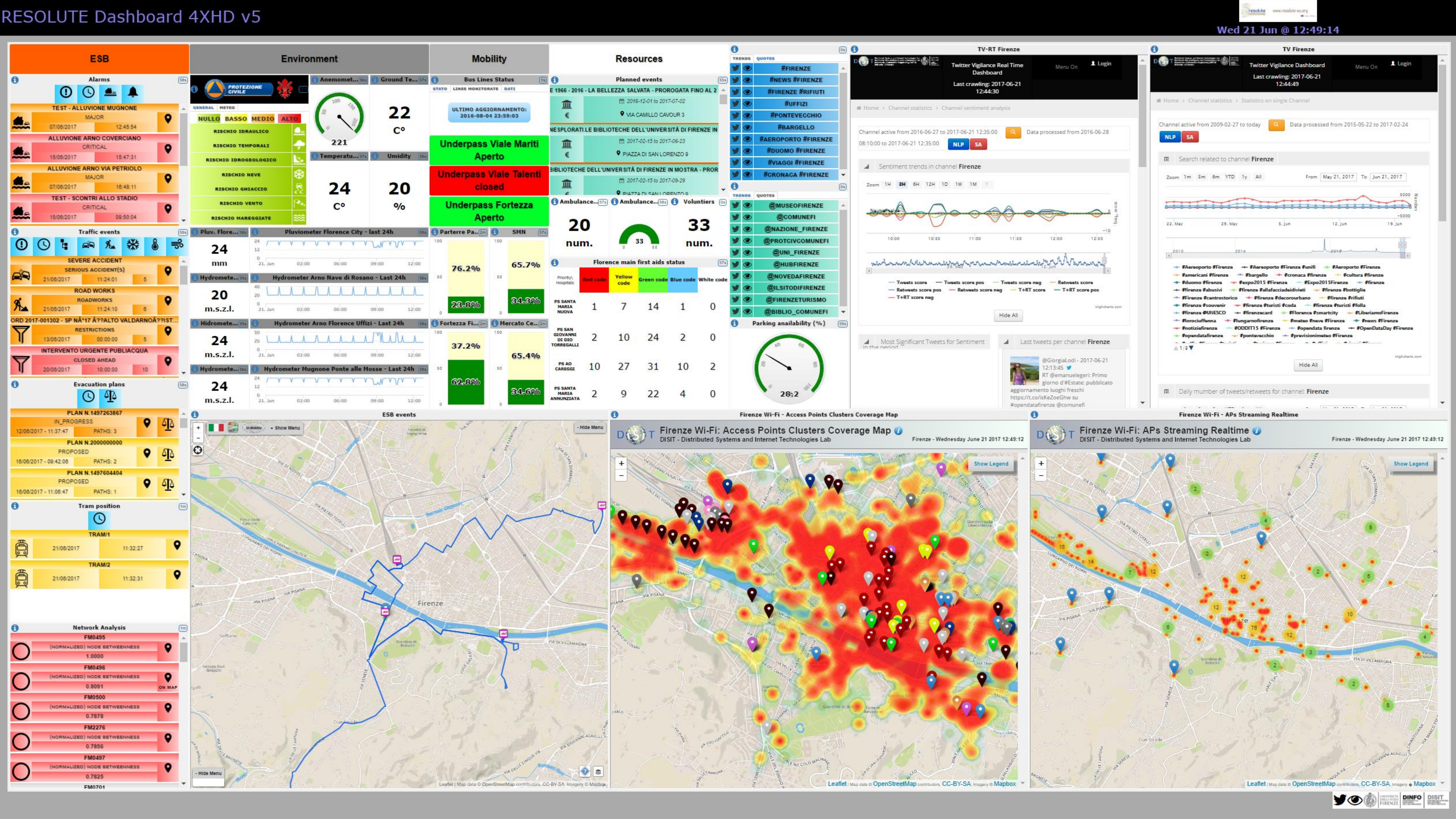
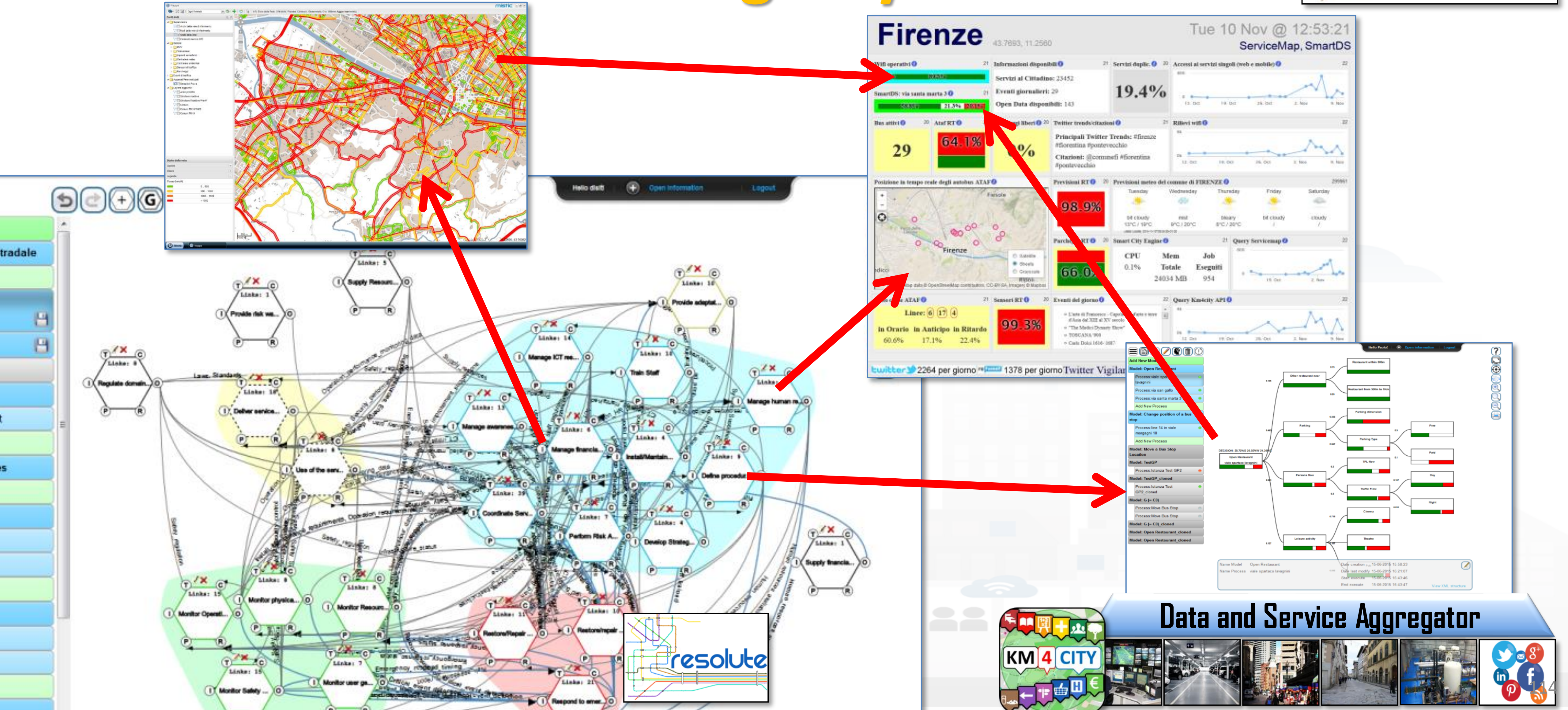

RESOLUTE Dashboard 4XHD v5
Wed 21 Jun @ 12:49:14
ESB
Environment
Mobility
Resources
Alarms
TEST - ALLUVIONE MUGNONE
MAJOR
ALLUVIONE ARNO COVERCIANO
CRITICAL
ALLUVIONE ARNO VIA PETRIOLO
MAJOR
TEST - SCONTRI ALLO STADIO
CRITICAL
Traffic events
SEVERE ACCIDENT
SERIOUS ACCIDENT(S)
ROAD WORKS
ROADWORKS
RESTRICTIONS
INTERVENTO URGENTE PUBLIACQUA
CLOSED AHEAD
Evacuation plans
PLAN N.1497263867
IN_PROGRESS
PLAN N.2000000000
PROPOSED
PLAN N.1497604404
PROPOSED
Tram position
TRAM/1
TRAM/2
Network Analysis
(NORMALIZED) NODE BETWEENNESS
PROTEZIONE CIVILE
NULLO BASSO MEDIO ALTO
RISCHIO IDRAULICO
RISCHIO TEMPORALI
RISCHIO IDROGEOLOGICO
RISCHIO NEVE
RISCHIO GHIACCIO
RISCHIO VENTO
RISCHIO MAREGGIATE
Anemometer
Ground Temperature
221
22 C°
Temperature
Umidity
24 C°
20 %
Pluviometer Florence City - last 24h
24 mm
Hydrometer Arno Nave di Rosano - Last 24h
20 m.s.z.l.
Hydrometer Arno Florence Uffizi - Last 24h
24 m.s.z.l.
Hydrometer Mugnone Ponte alle Mosse - Last 24h
24 m.s.z.l.
Bus Lines Status
ULTIMO AGGIORNAMENTO: 2016-08-04 23:59:03
Underpass Viale Mariti Aperto
Underpass Viale Talenti closed
Underpass Fortezza Aperto
Parterre
SMN
76.2%
23.8%
65.7%
34.3%
Fortezza
Mercato Centrale
37.2%
62.8%
65.4%
34.6%
Planned events
Ambulance
Voluntiers
20 num.
33
33 num.
Florence main first aids status
Red code
Yellow code
Green code
Blue code
White code
PS SANTA MARIA NUOVA 1 7 14 1 0
PS SAN GIOVANNI DI DIO TORREGALLI 2 10 24 2 0
PS AO CAREGGI 10 27 31 10 2
PS SANTA MARIA ANNUNZIATA 2 9 22 4 0
#FIRENZE
#NEWS #FIRENZE
#FIRENZE #RIFIUTI
#UFFIZI
#PONTEVECCHIO
#BARGELLO
#AEROPORTO #FIRENZE
#DUOMO #FIRENZE
#VIAGGI #FIRENZE
#CRONACA #FIRENZE
@MUSEOFIRENZE
@COMUNEFI
@NAZIONE_FIRENZE
@PROTCIVCOMUNEFI
@UNI_FIRENZE
@HUBFIRENZE
@NOVEDAFIRENZE
@ILSITODIFIRENZE
@FIRENZETURISMO
@BIBLIO_COMUNEFI
Parking availability (%)
TV-RT Firenze
Twitter Vigilance Real Time Dashboard
Sentiment trends in channel Firenze
TV Firenze
Twitter Vigilance Dashboard
Search related to channel Firenze
ESB events
Firenze
Firenze Wi-Fi - Access Points Clusters Coverage Map
Firenze Wi-Fi: Access Points Clusters Coverage Map
DISIT - Distributed Systems and Internet Technologies Lab
Firenze - Wednesday June 21 2017 12:49:12
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

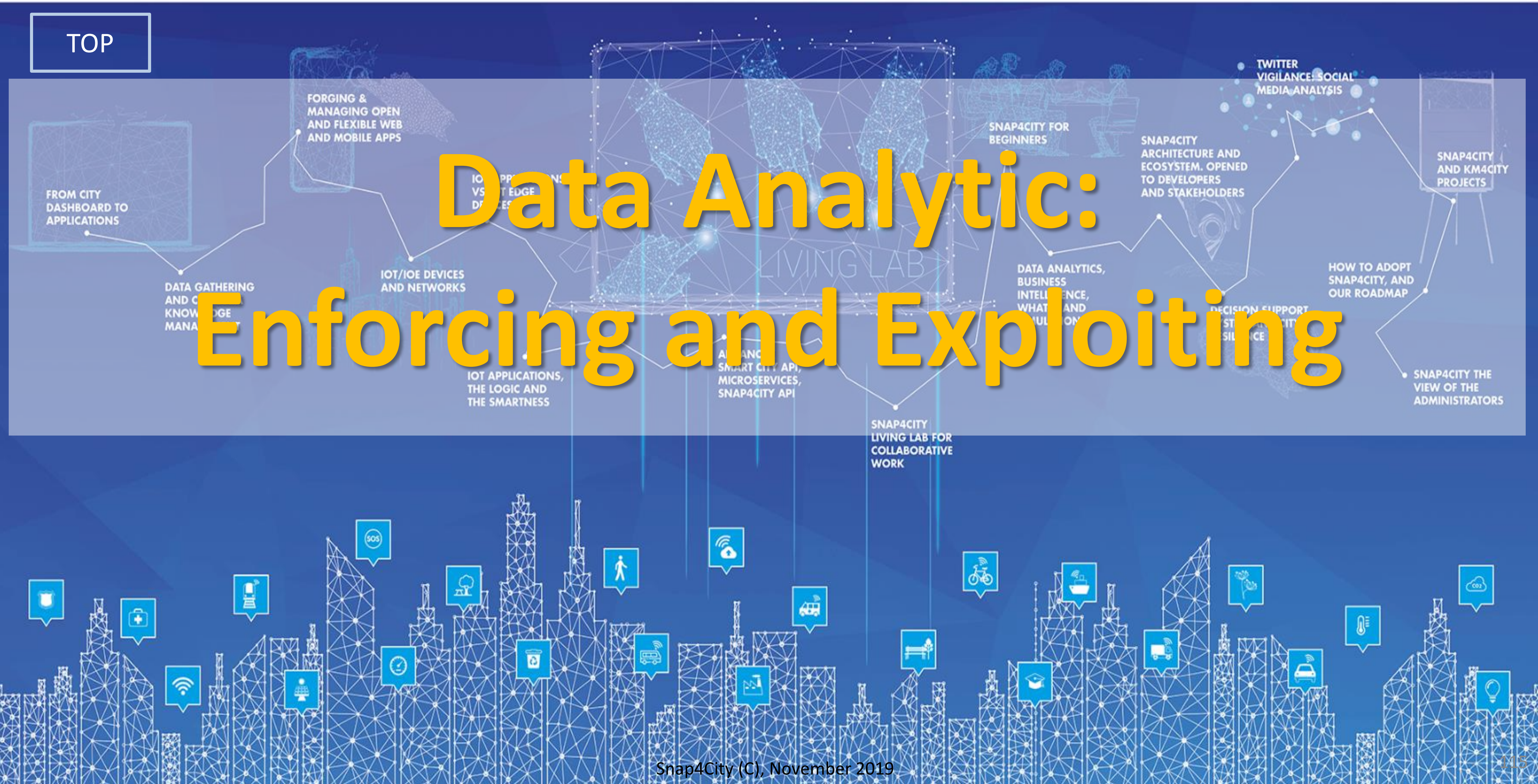
UNIVERSITÀ DEGLI STUDI FIRENZE | DINFO DIPARTIMENTO DI INGEGNERIA DELL'INFORMAZIONE | DISIT DISTRIBUTED SYSTEMS AND INTERNET TECHNOLOGIES LAB

Dashboarding City Resilience

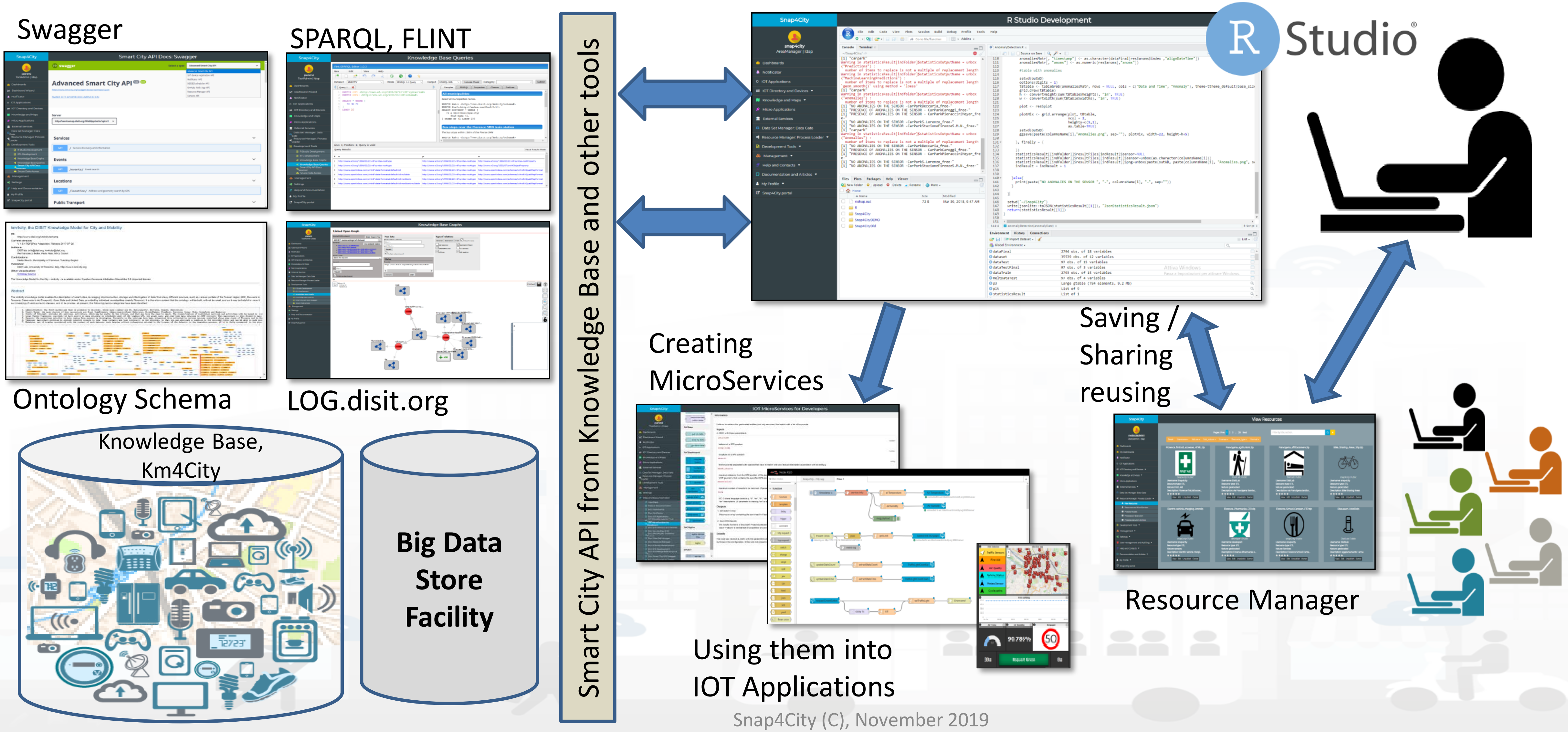


TOP

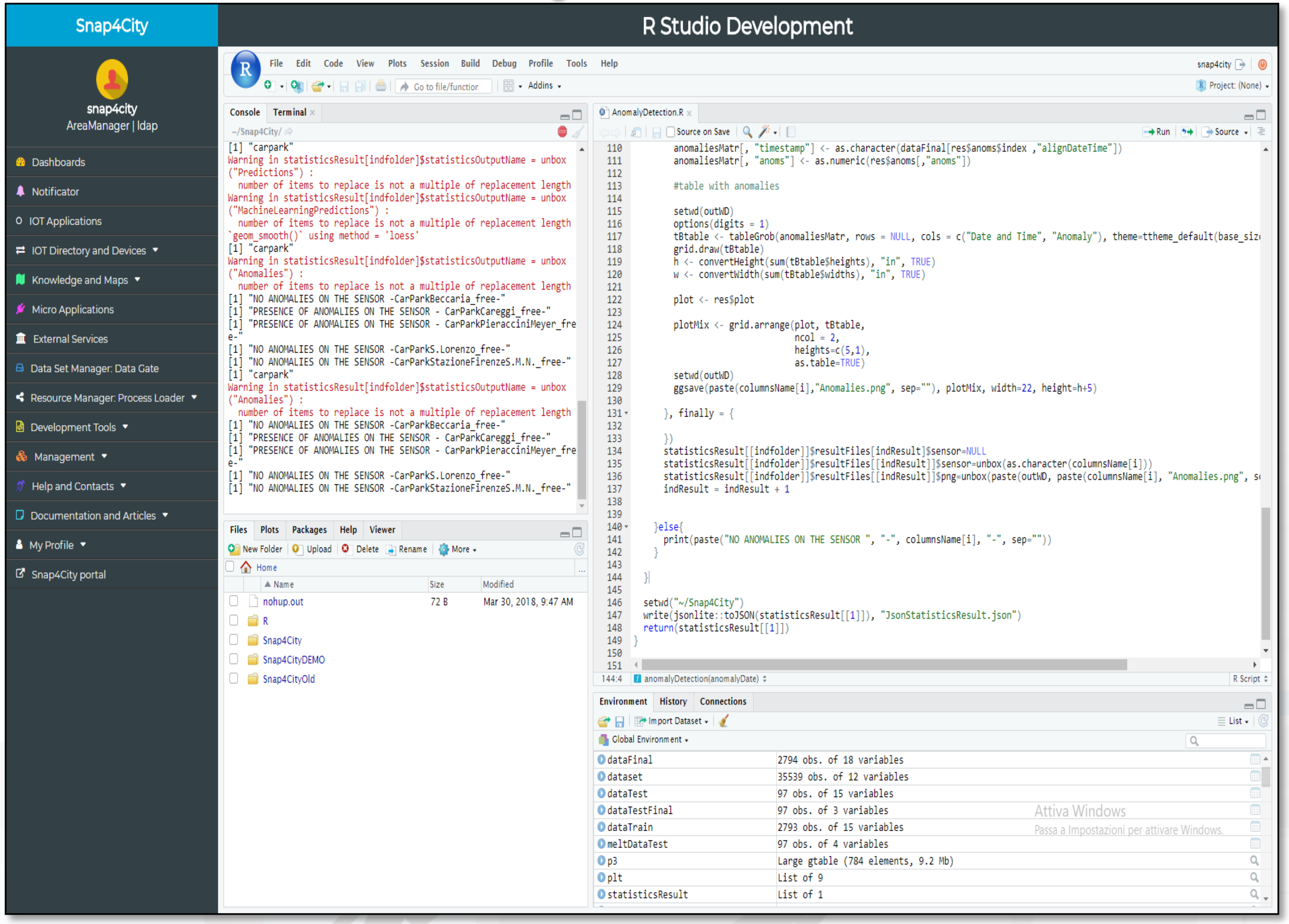
Data Analytic: Enforcing and Exploiting



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



Developer in R Studio + Tensor Flow



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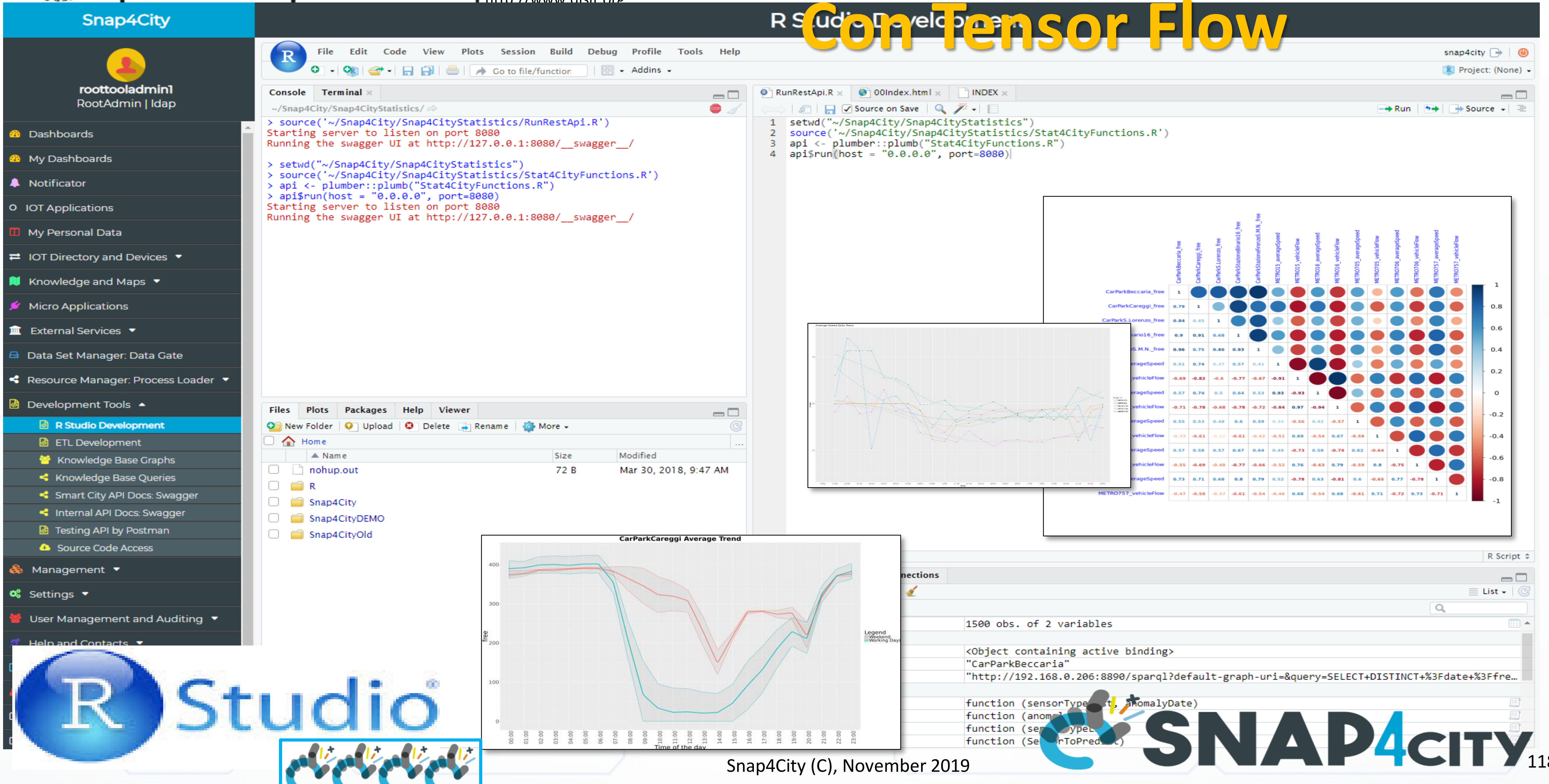
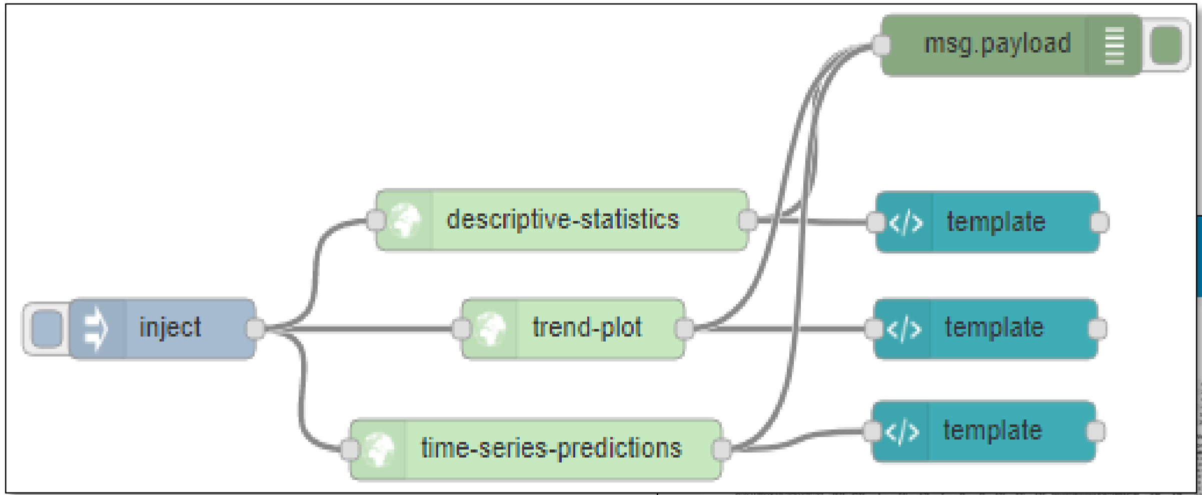
DISIT DISTRIBUTED SYSTEMS AND INTERNET TECHNOLOGIES LAB
http://www.disit.org

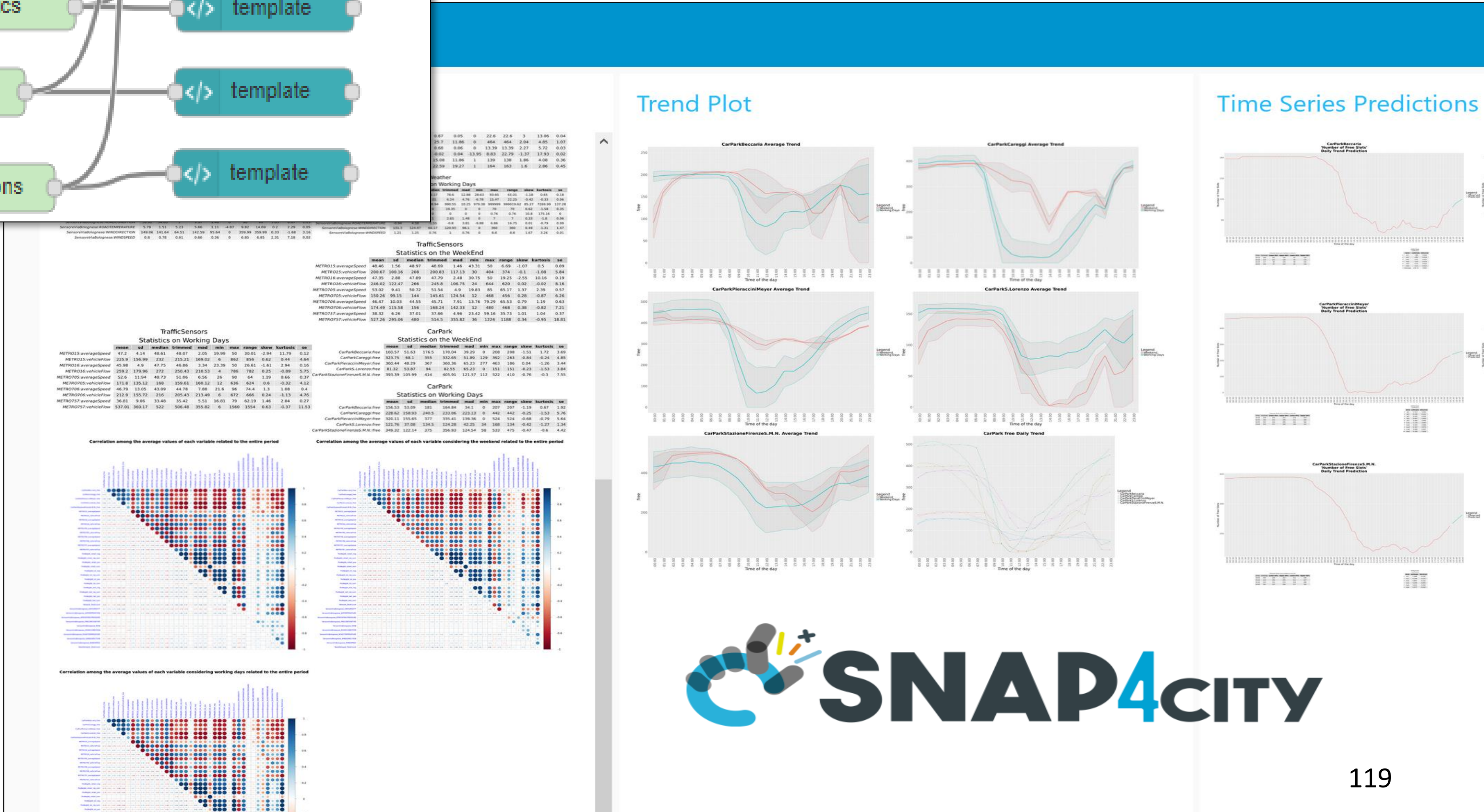
Data Analytics in R Studio
Con Tensor Flow



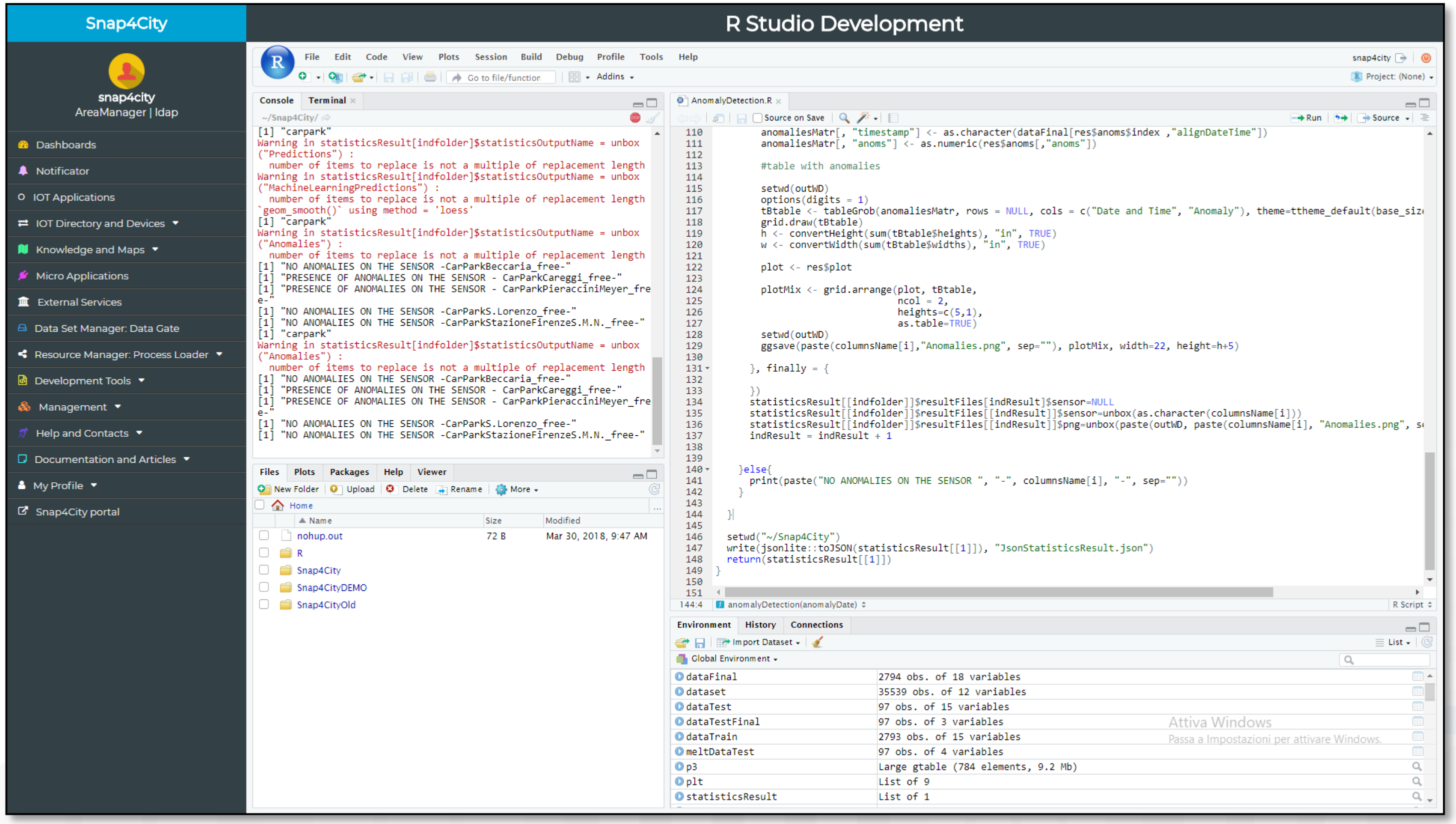
From R studio data analytics to MicroService

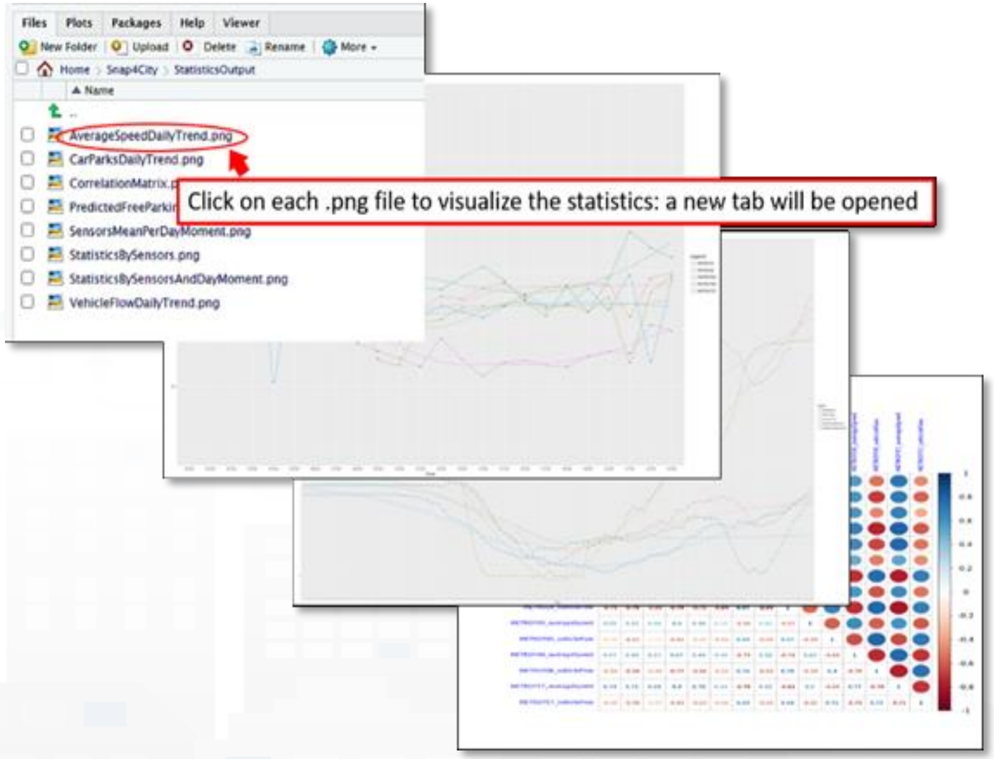


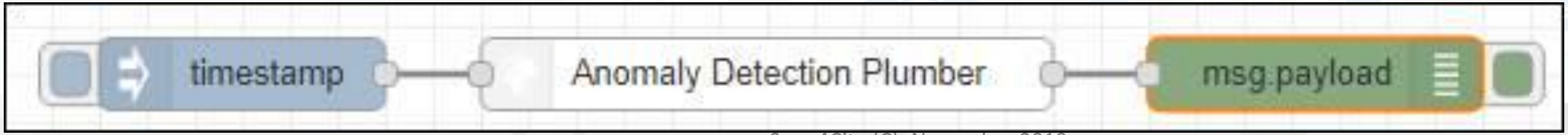
R Studio algorithms are automatically transformed into MicroServices for your
IOT Applications



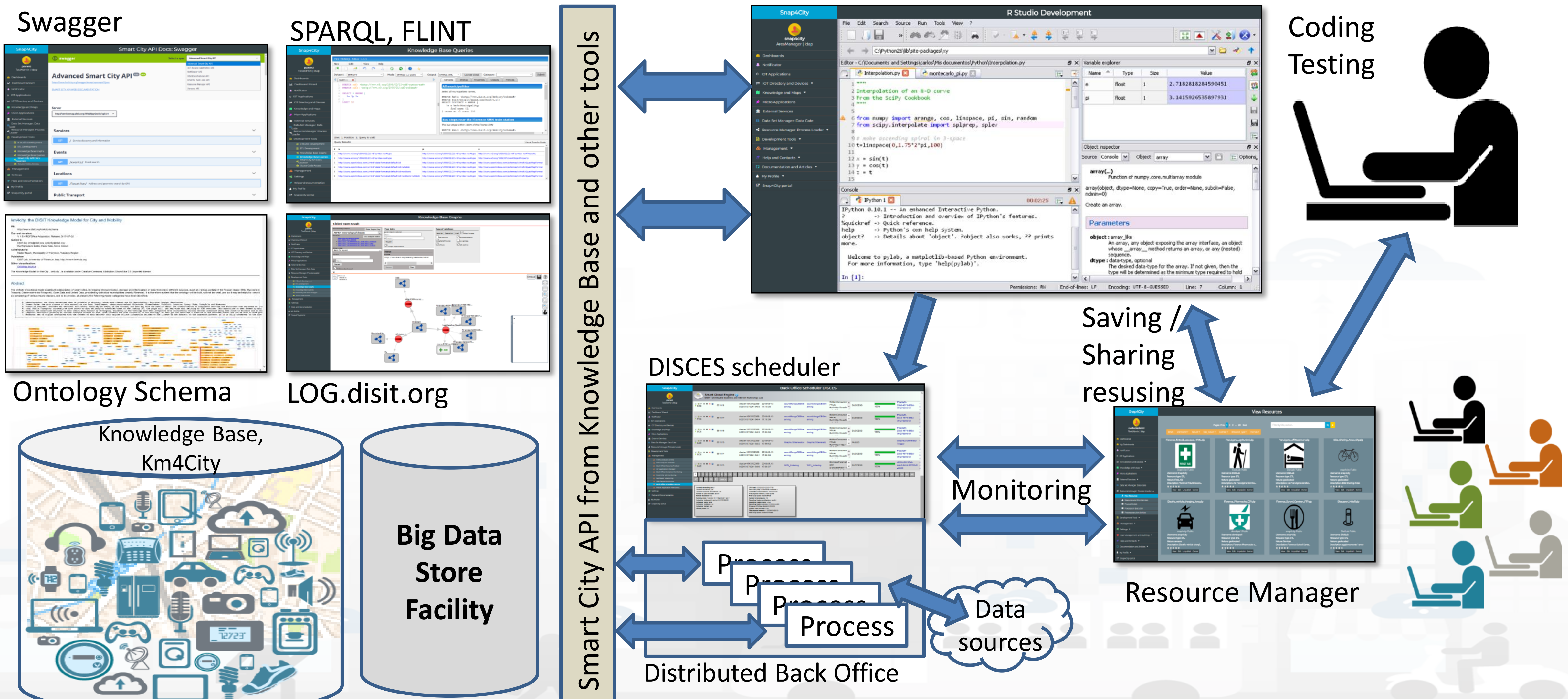
Developing in R Studio and/or Tensor Flow







Data Analytics Dev. in Java, Python, ..



TOP

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

Real Time Data Analytics using RStudio

1. How to create a Data Analytic Node based on R Script (*plumberized*):
   - How to download Real-Time data using Smart City APIs
   - How to save heatmaps using Heatmap APIs
2. How to create an IOT Application for Real-Time Data Analytics:
   - How to upload the R script and create a Data Analytic Node 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.

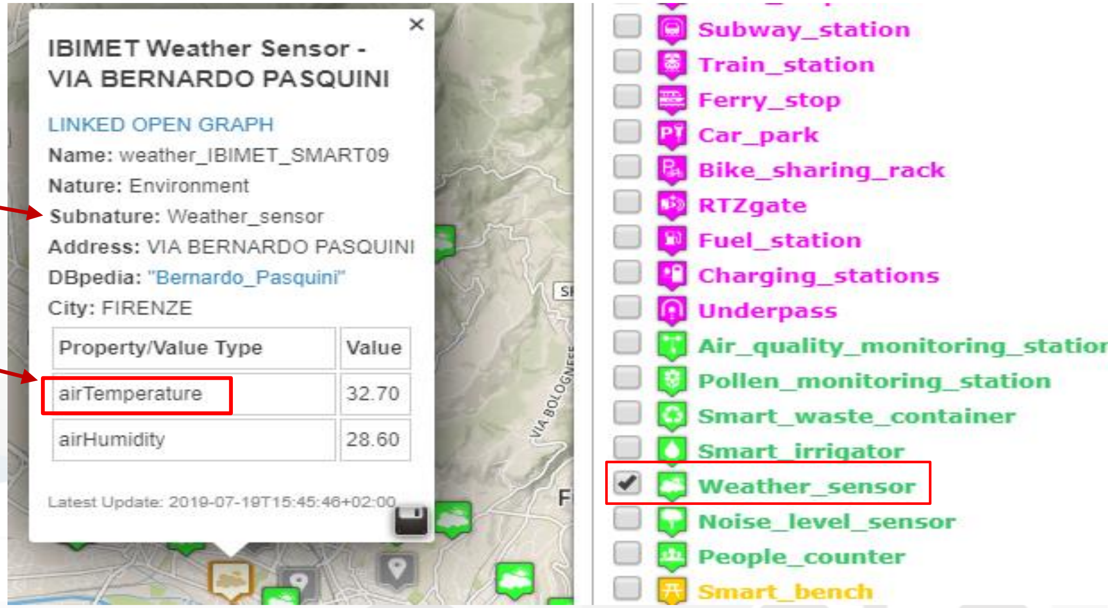
Real Time Data Analytics using R Studio

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 = "2019-07-23T10:00:00"
fromDateTime = "2-hour"



https://www.snap4city.org/dashboardSmartCity/management/iframeApp.php?linkUrl=https%3A%2F%2Fservicemap.snap4city.org%2F&linkId=map1link2&pageTitle=Service%20Map%20(Toscana)&fromSubmenu=kmlink

Real Time Data Analytics using R Studio

How to download Real-Time data using API - 1

- 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=
                42.5024797334869;8.19580078125;44.6061127451739;13.422546386718
                &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 download Real-Time data using API - 2

https://servicemap.disit.org/WebAppGrafo/api/v1/?selection=42.67897316354954;9.95403229581 4045;44.00523270268637;12.06340729581 4045&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 download Real-Time data using API - 3

- 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/?serviceUri="http://www.disit.org/km4city/resource/IBIMET_SMART11"&fromTime=2-hour&toTime=2019-07-23T10:00:00

Real Time Data Analytics using R Studio

How to download Real-Time data using API - 4

- 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
```

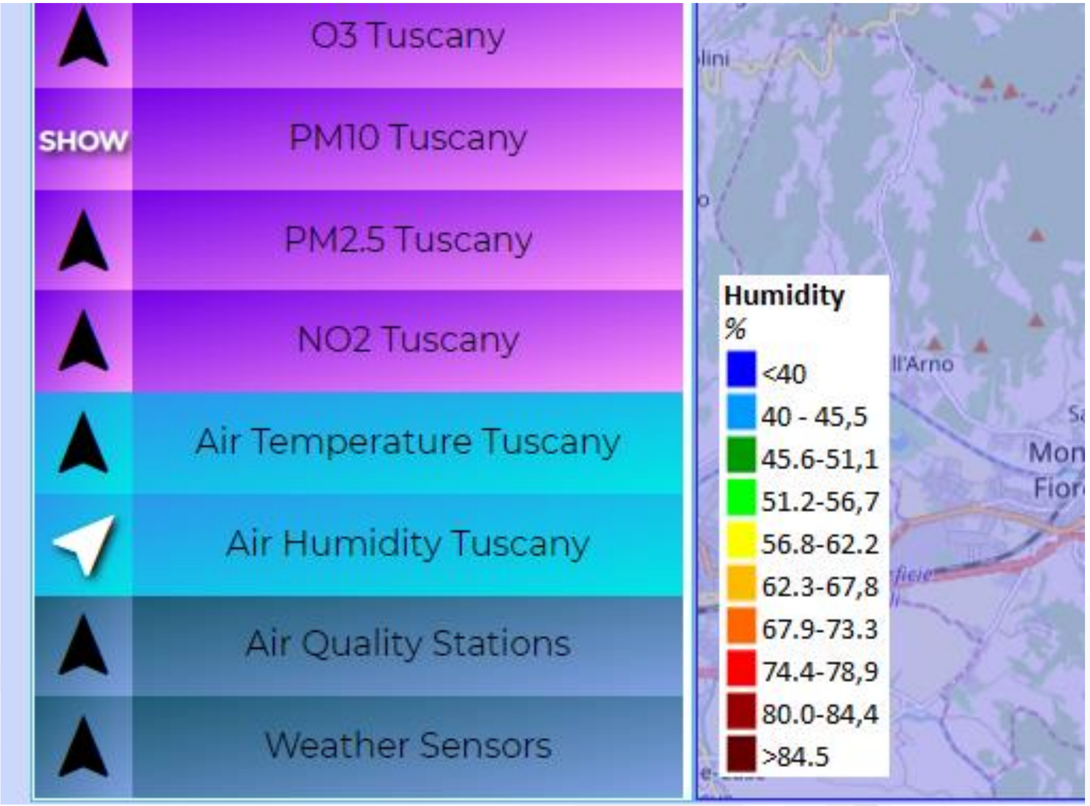
Real Time Data Analytics using R Studio

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

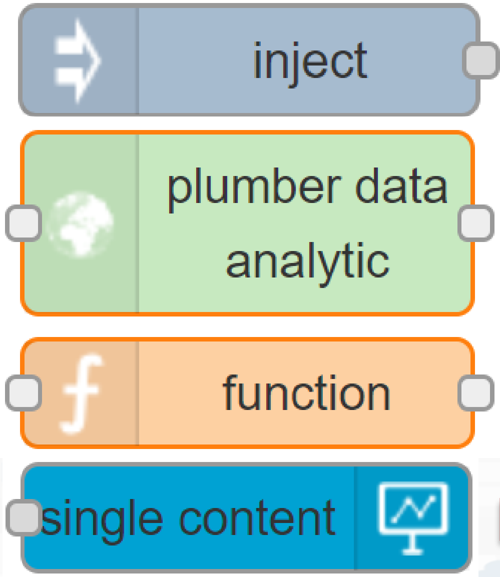
JSON Array Format example

[
{
"mapName": "airTemperatureTuscanyTest",
"metricName": "airTemperature",
"description": " Air Temperature heatmap … ",
"clustered": 0,
"latitude": 43.1,
"longitude": 11.1,
"value": 25.5,
"date": "2019-07-23T10:00:00Z"
"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

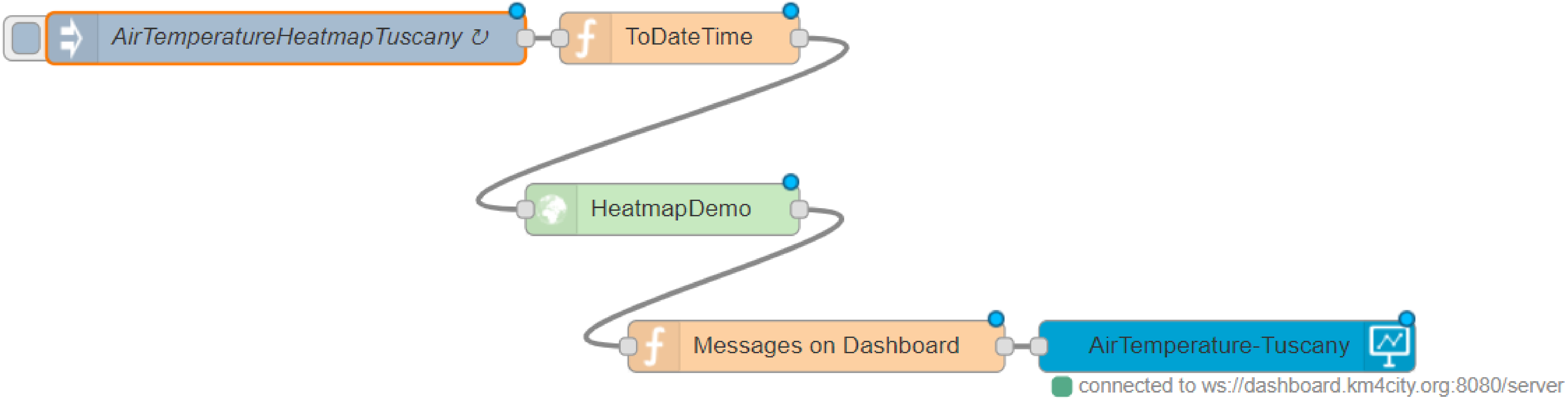
To upload the R script and create a plumber instance

To visualize strings/numbers/html on a dashboard

To execute JavaScript code on output messages

IOT App for Real Time Data Analytics

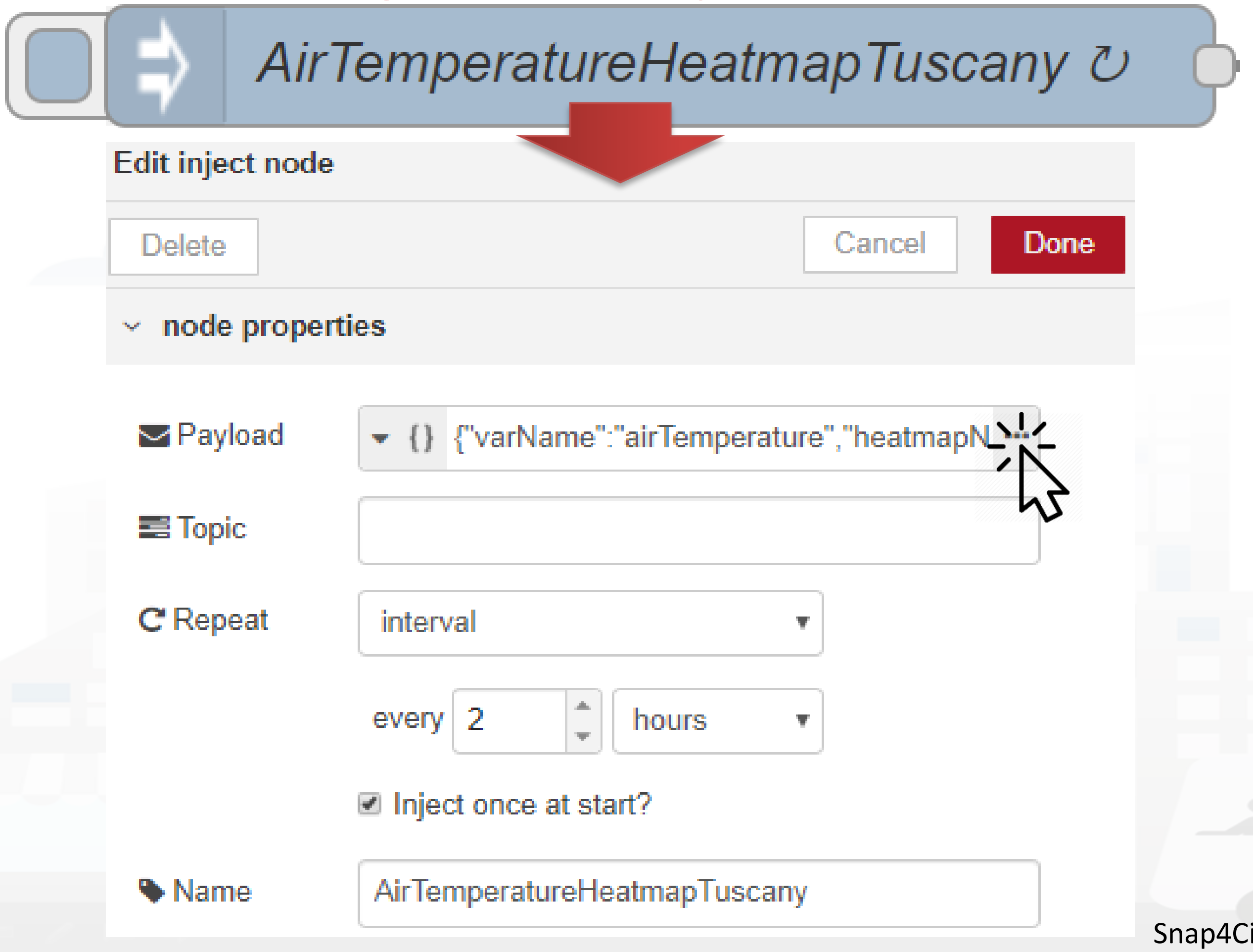
How to create a Data Analytics IOT Application



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):

ToDateTime

Name: ToDateTime

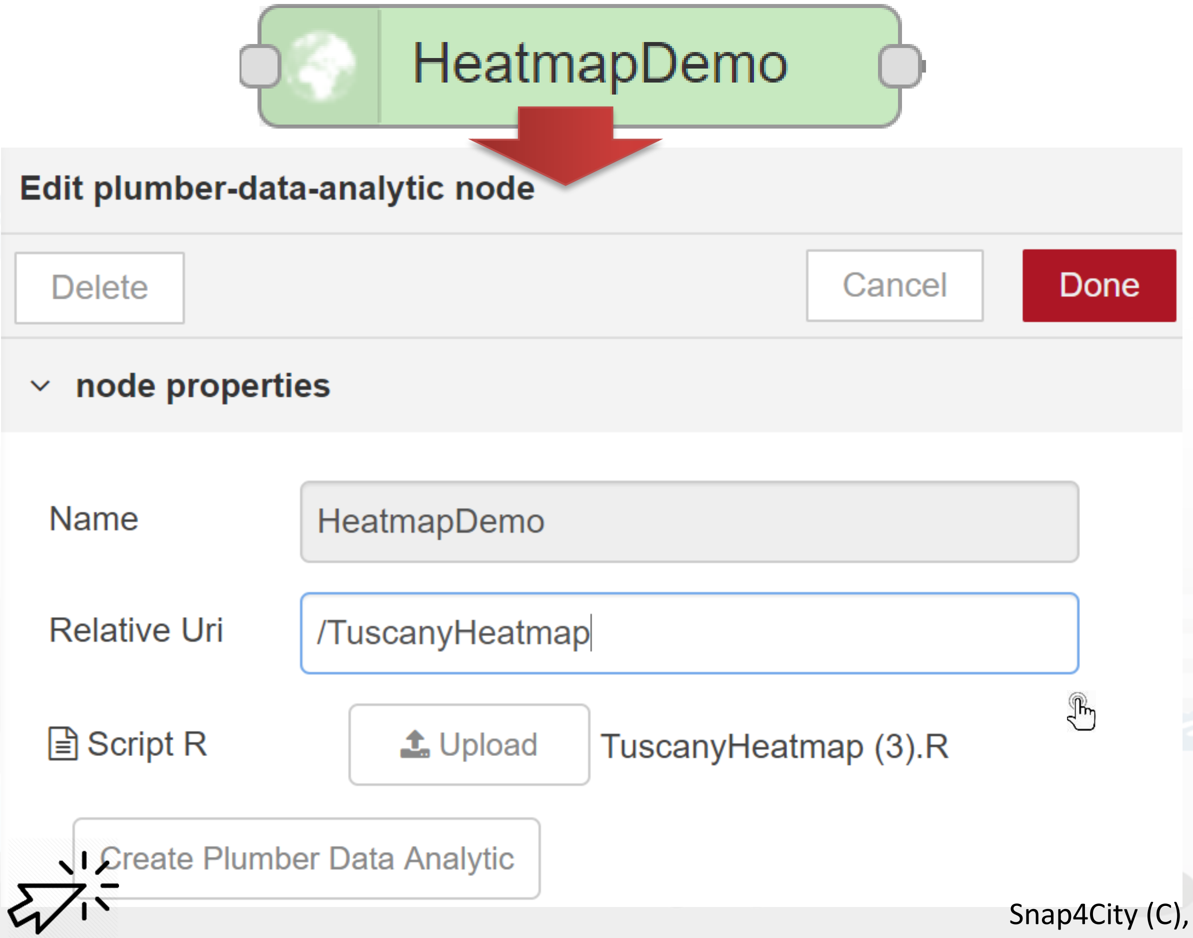
Function

```
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:

AirTemperature-Tuscany

connected to ws://dashboard.km4city.org:8080/server

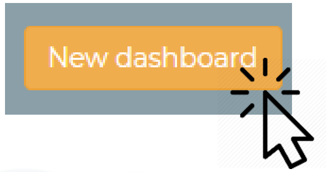
Dashboard Name: Check Data Analytics Tuscany — Create New

Widget Name: AirTemperature-Tuscany

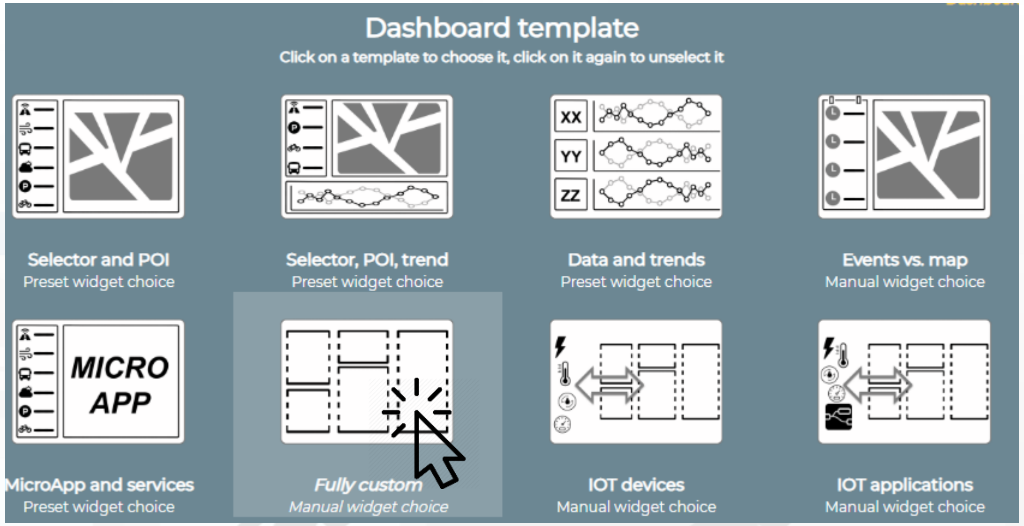
Edit Dashboard | View Dashboard

Wizarded Heatmap Visualization

1. Create a New Dashboard from Dashboard (Public)

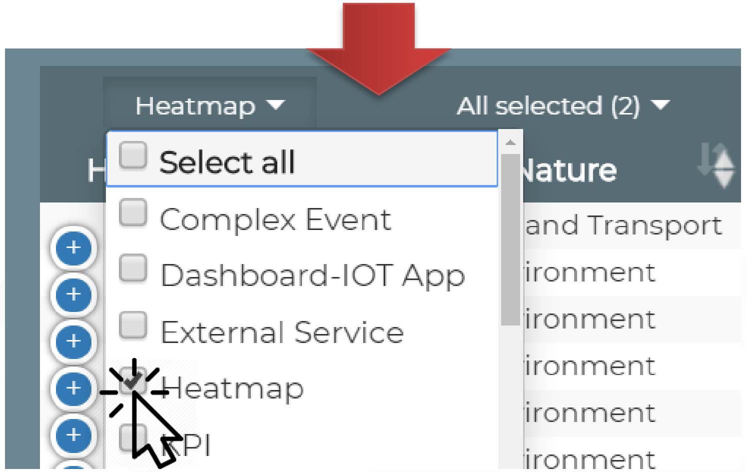


2. Insert a Dashboard Title and select a Dashboard Template

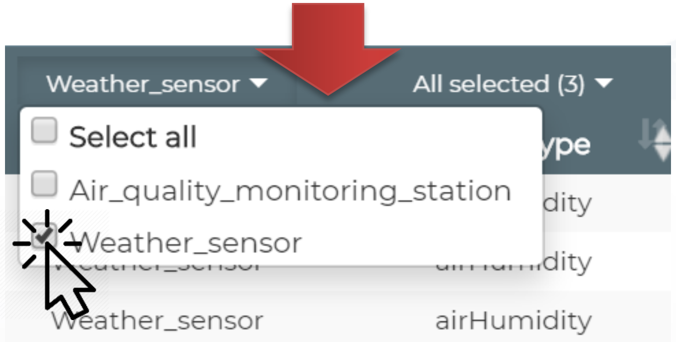


Wizarded Heatmap Visualization

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



4. Select the Sensor Category (Subnature)

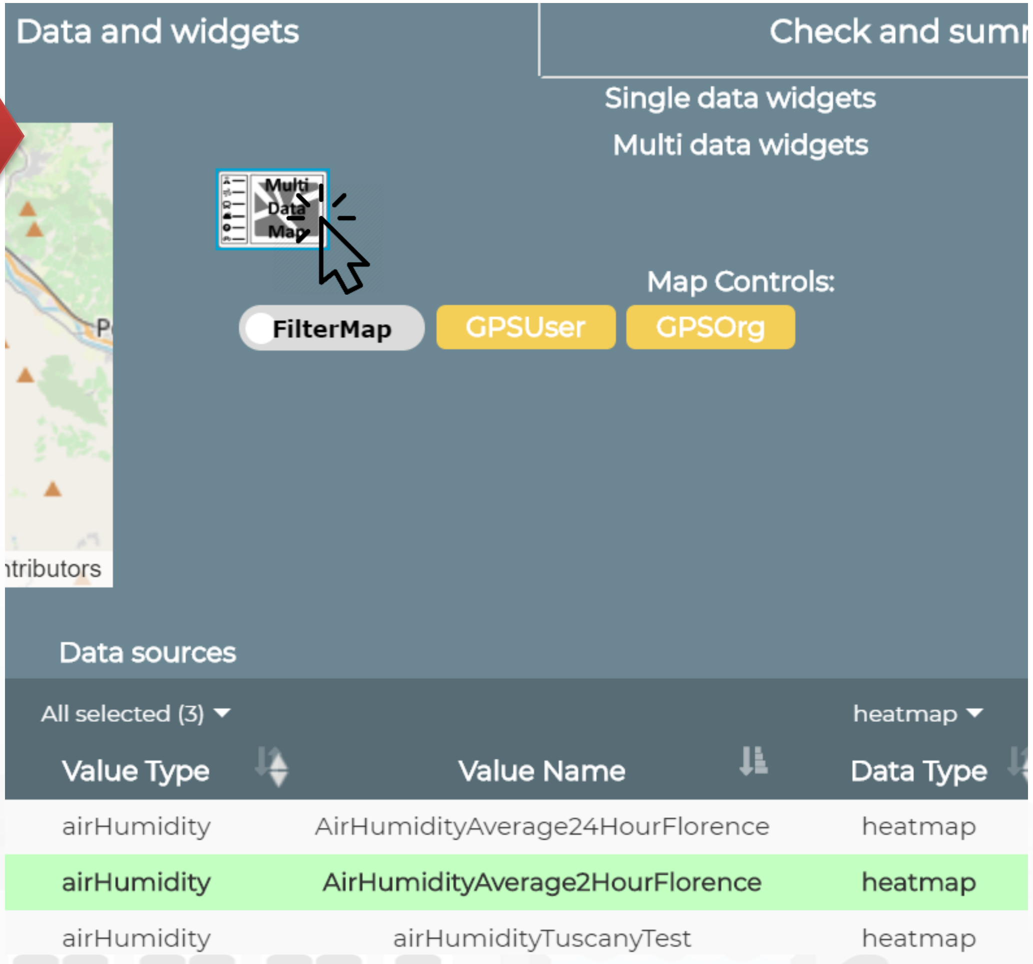


5. Select the measure (Value Type) and the Heatmap Name (Value Name)

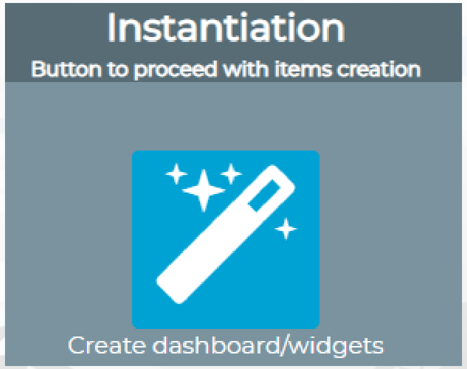
All selected (3)		heatmap	
Value Type	Value Name	Data Type	Last Date
airHumidity	AirHumidityAverage24HourFlorence	heatmap	2019-04-08 13:27:52
airHumidity	AirHumidityAverage2HourFlorence	heatmap	2019-07-22 13:00:00
airHumidity	airHumidityTuscanyTest	heatmap	2019-07-22 12:00:00

Wizarded Heatmap Visualization

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

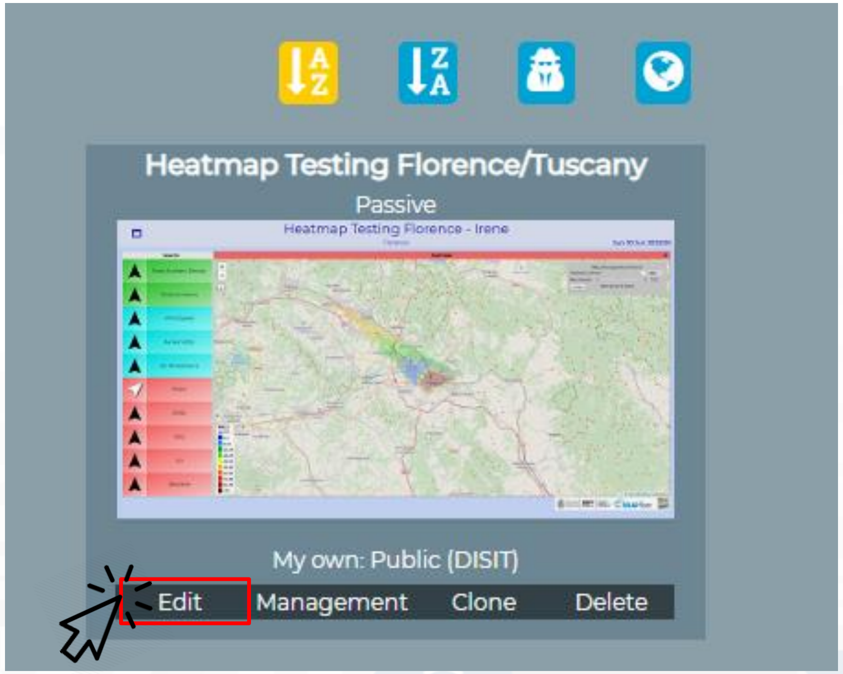


7. Select the instantiation button to proceed with items creation

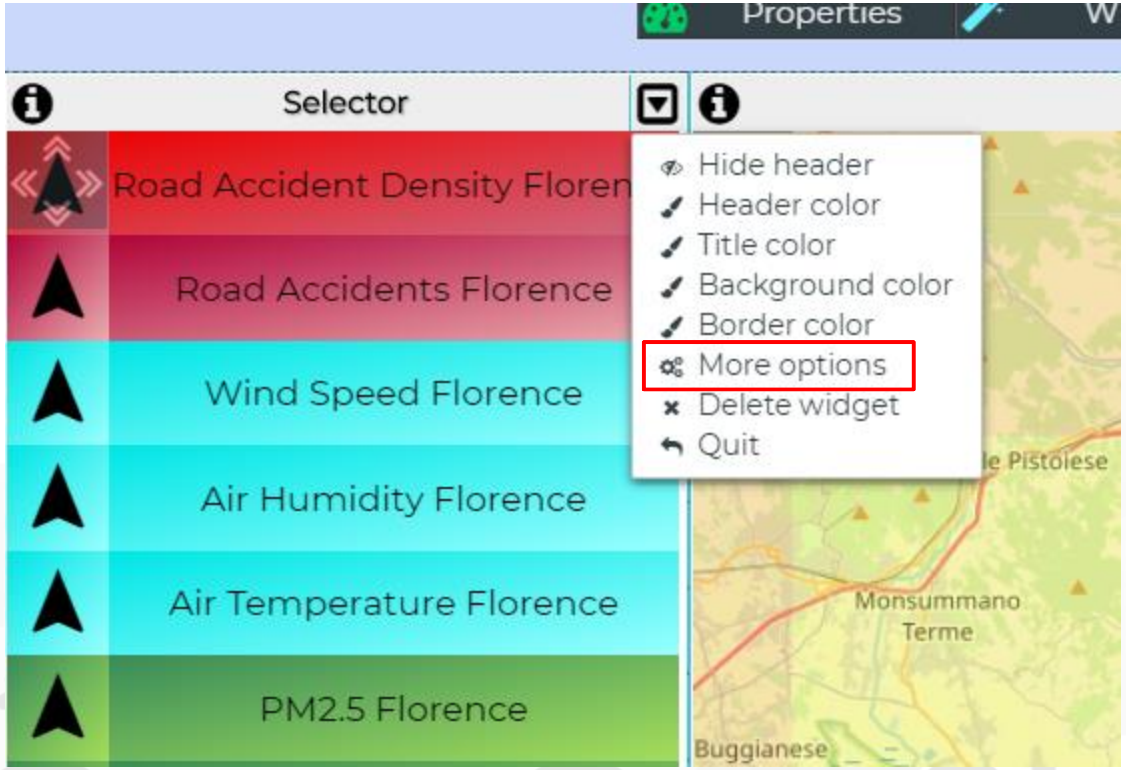


Manually Heatmap Visualization

1. Select a Dashboard and click on Edit

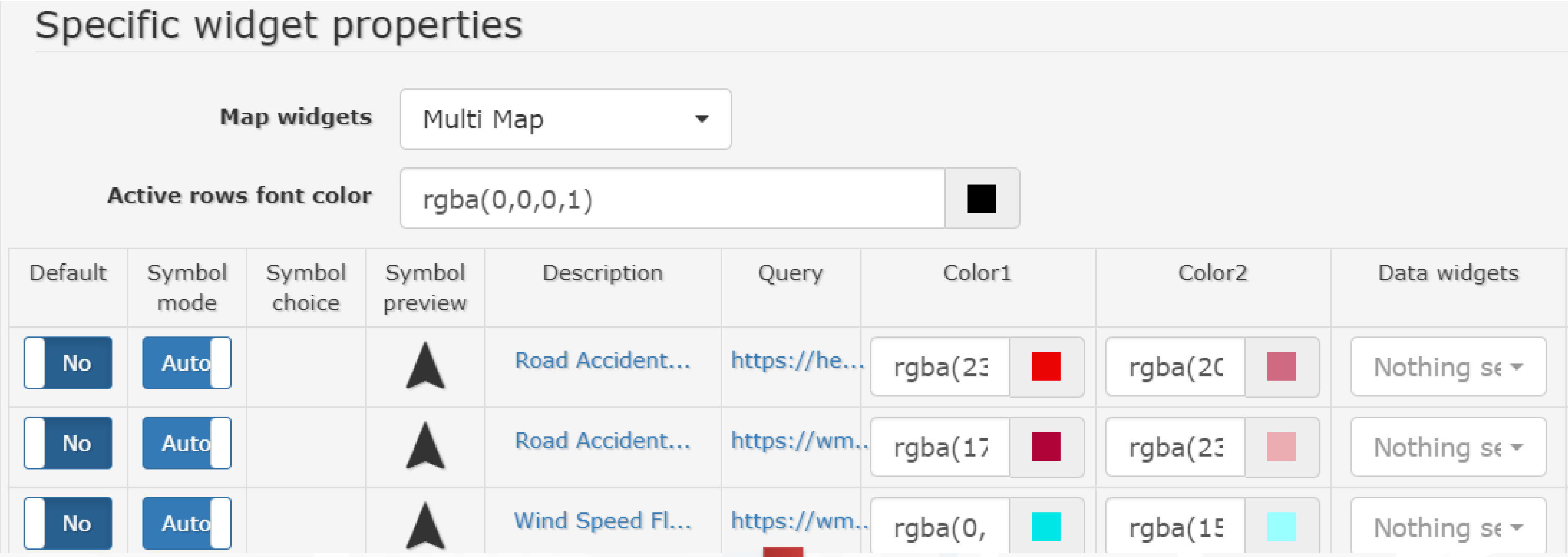


2. Select on More Options to modify the widget properties



Manually Heatmap Visualization

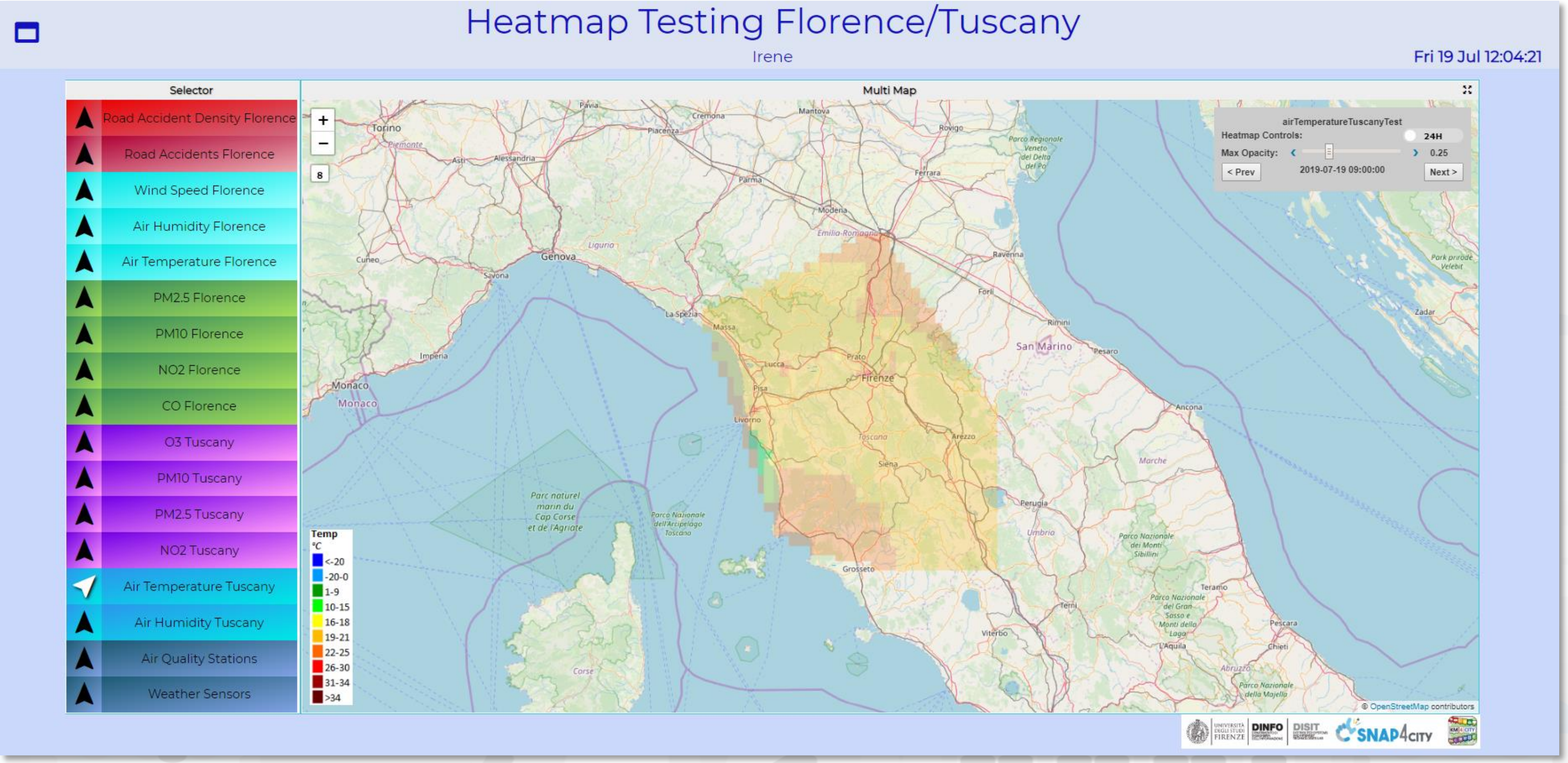
3. Change the Query to visualize the new heatmap



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

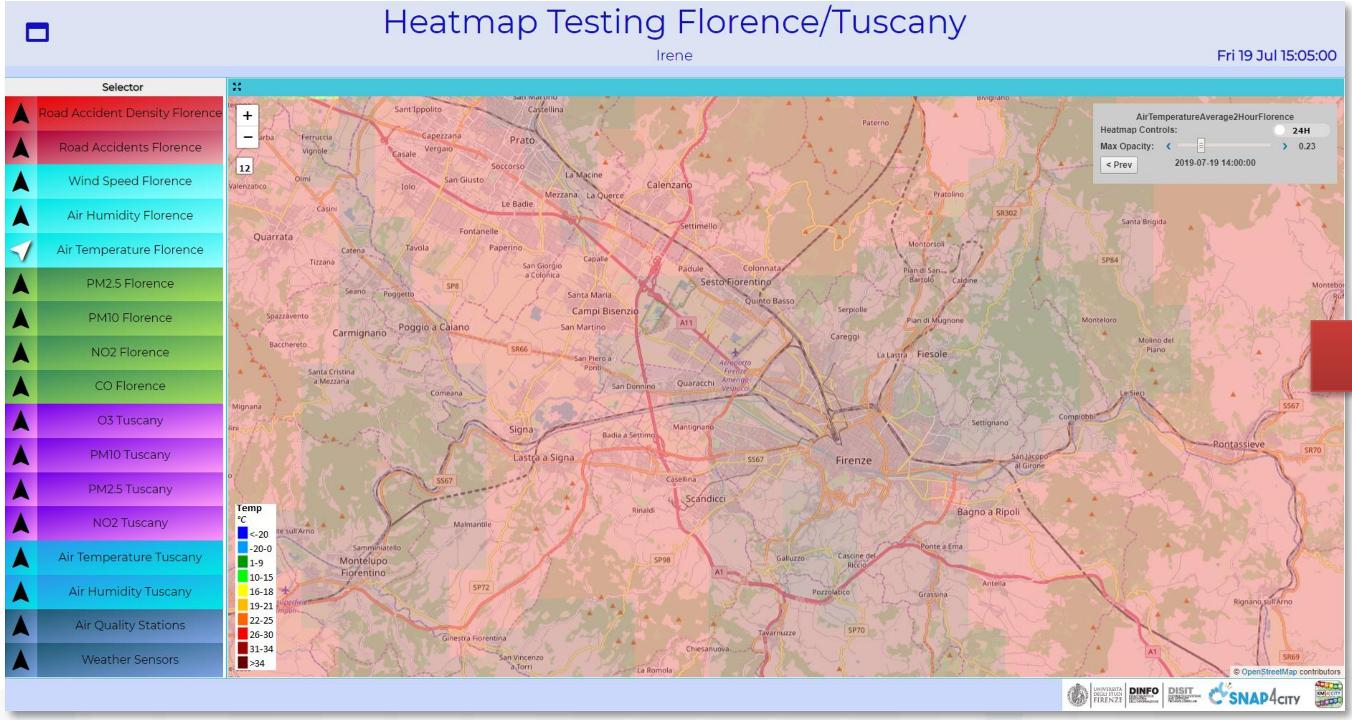
https://wmsserver.snap4city.org/geoserver/Snap4City/wms?service=WMS&layers=airTemperatureTuscanyTest

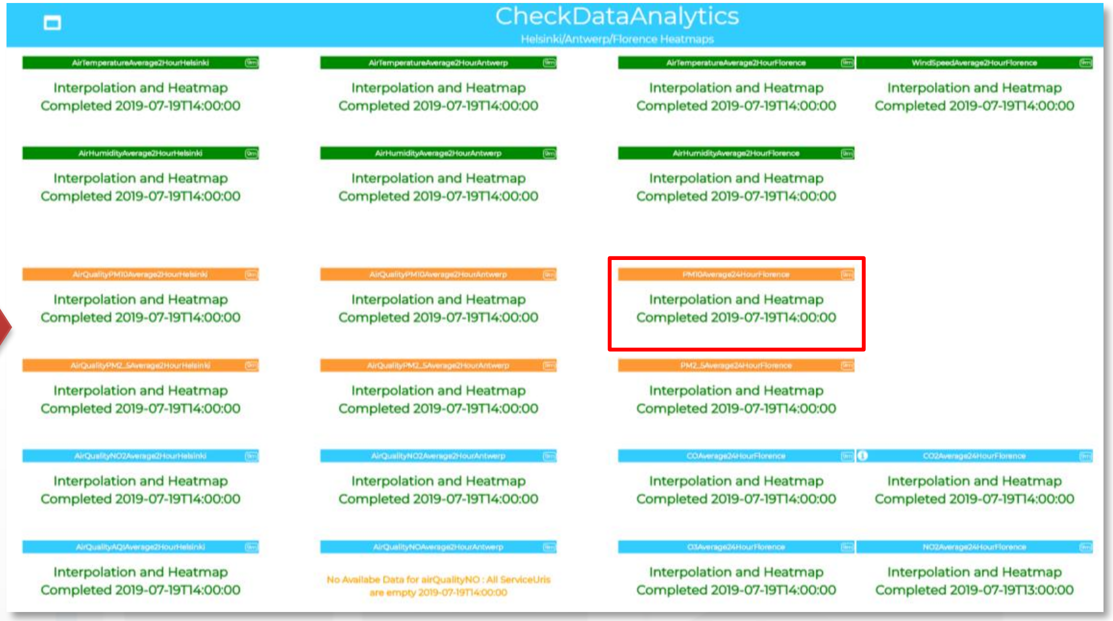
Heatmap Visualization



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

Heatmap Visualization and Heatmap Status Check on Dashboards





https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTc3MQ==

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

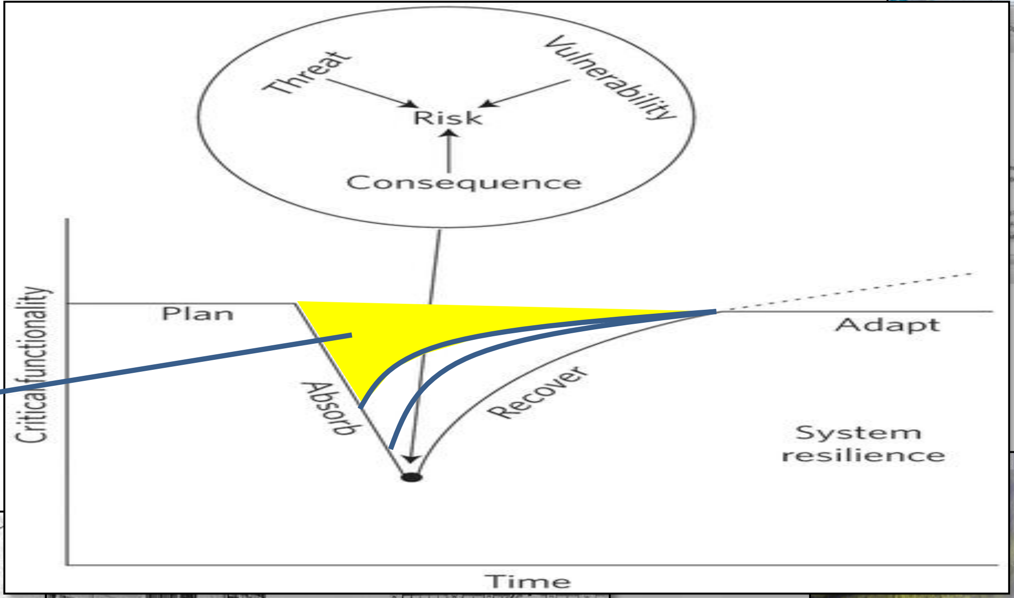
DECISION SUPPORT SYSTEM AND CITY RESILIENCE

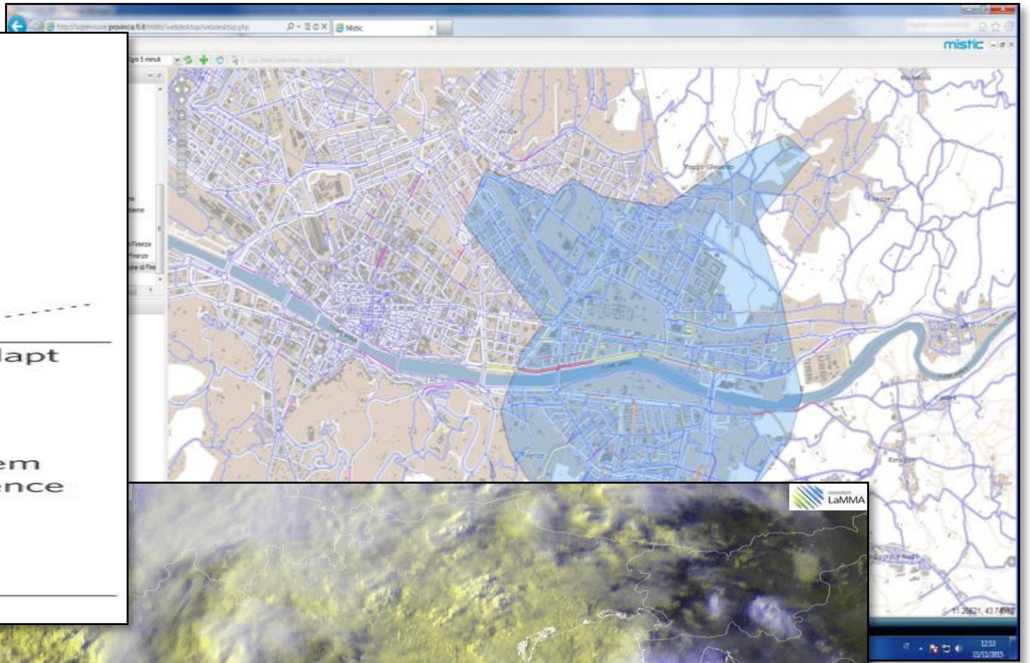

SIGNORVINO

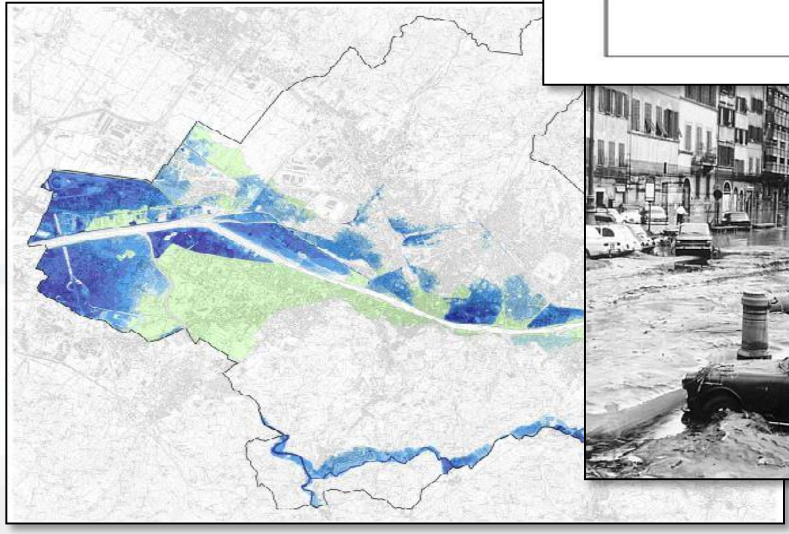
Early Warning, Detection

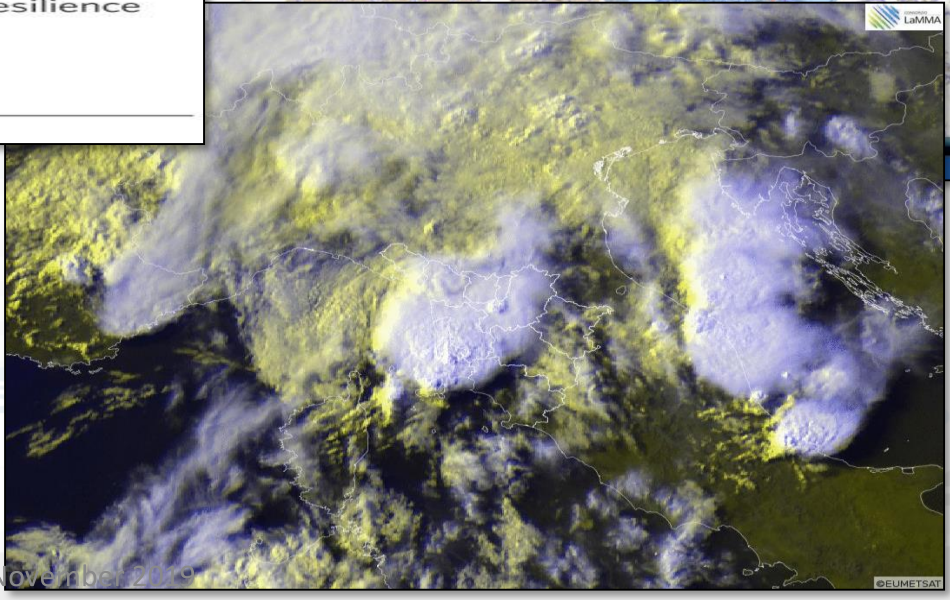
Prepare
Absorb
Recover
Adapt

damage









Early Warning, Detection

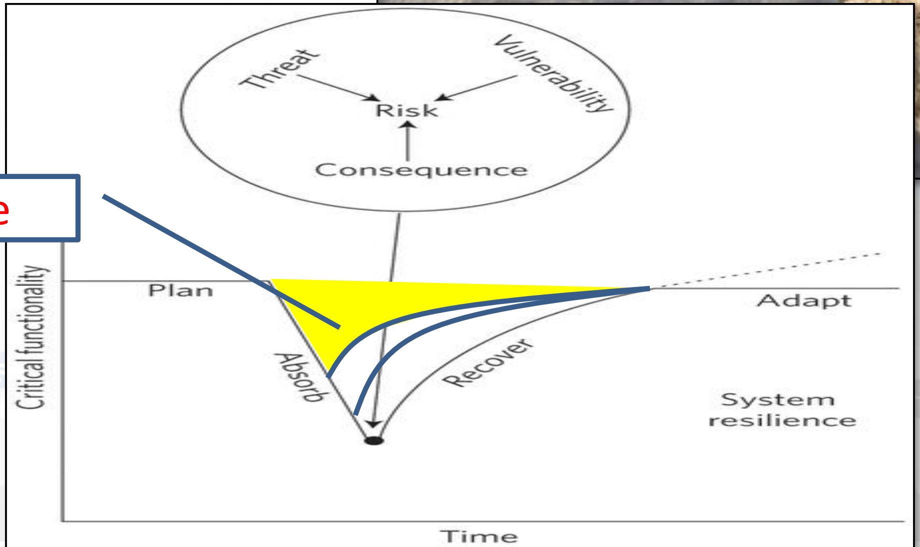
Issue:
- Detection of critical condition
- Not easily detected with other means

Impact:
- Early warning, faster reaction
- Increased resilience

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

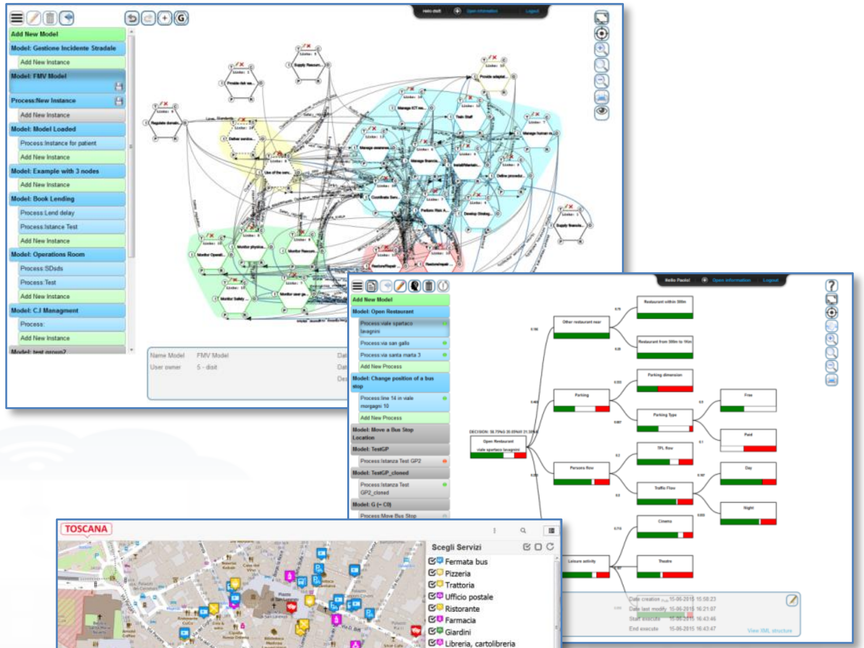
Prepare
Absorb
Recover
Adapt

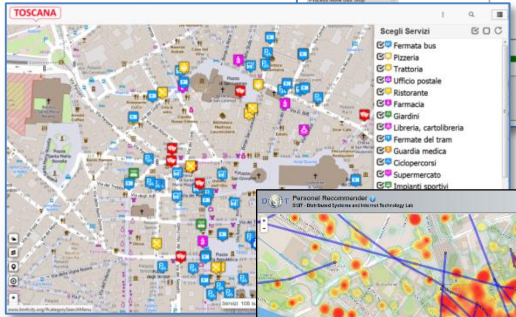
damage

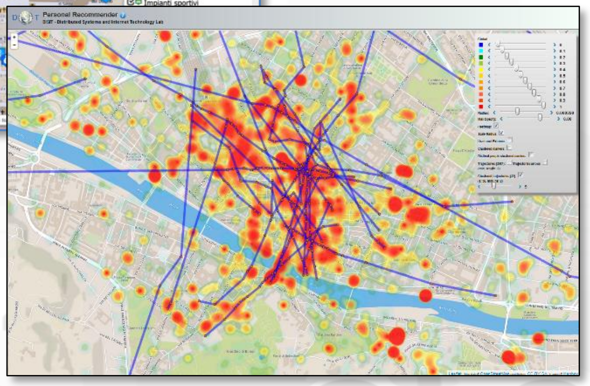


Main Approach

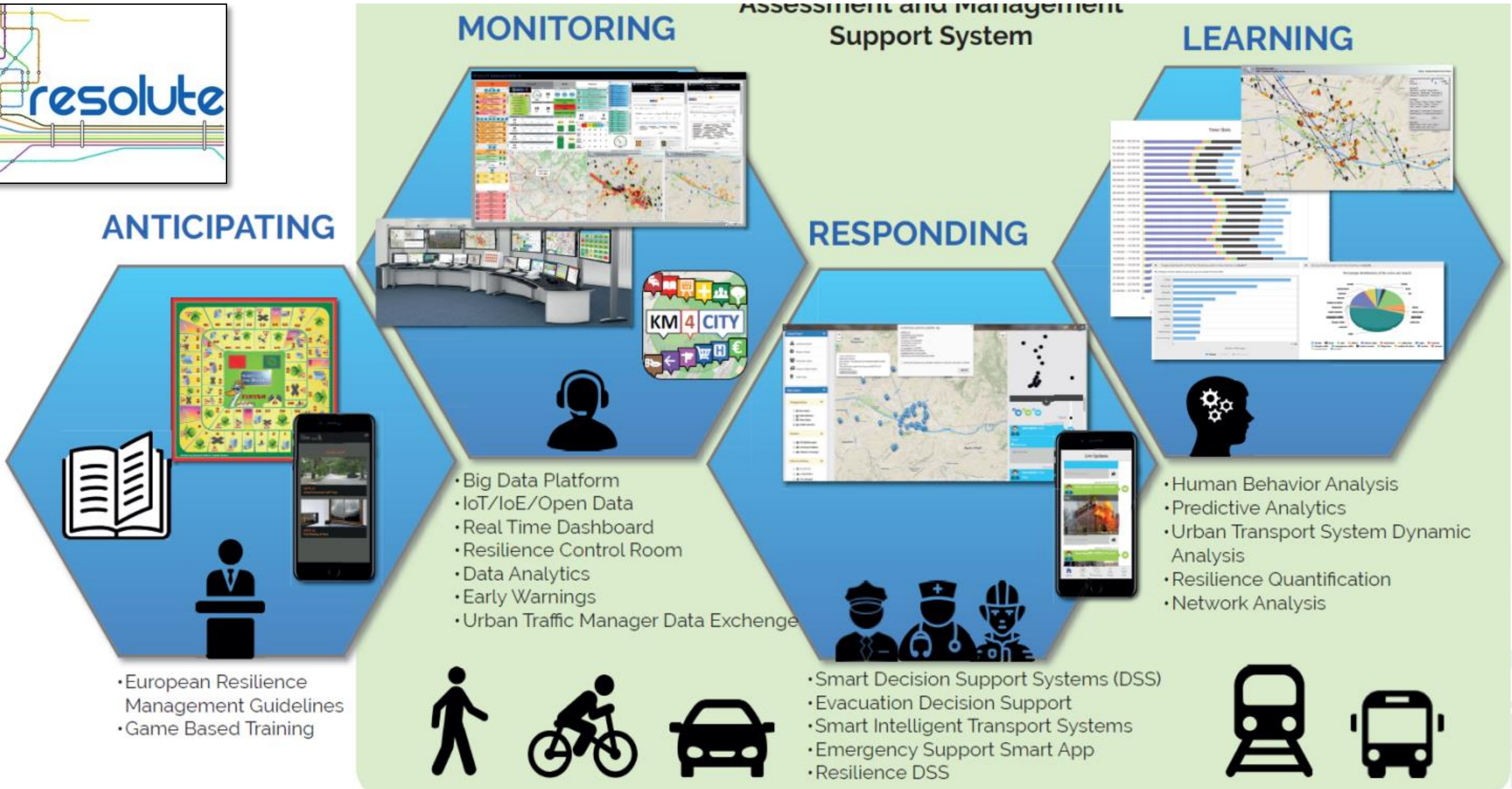
- Three main layers
- Complex System modeling: function, processes, resources, time, events, etc.
  - Functional Resonance Analysis Method, FRAM
  - Resilience Analysis Grid, RAG
- Decision Support System, DSS
  - System Thinking, Goal Models
  - Risk analysis
  - UTS/ITS decision supports
- Data, big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





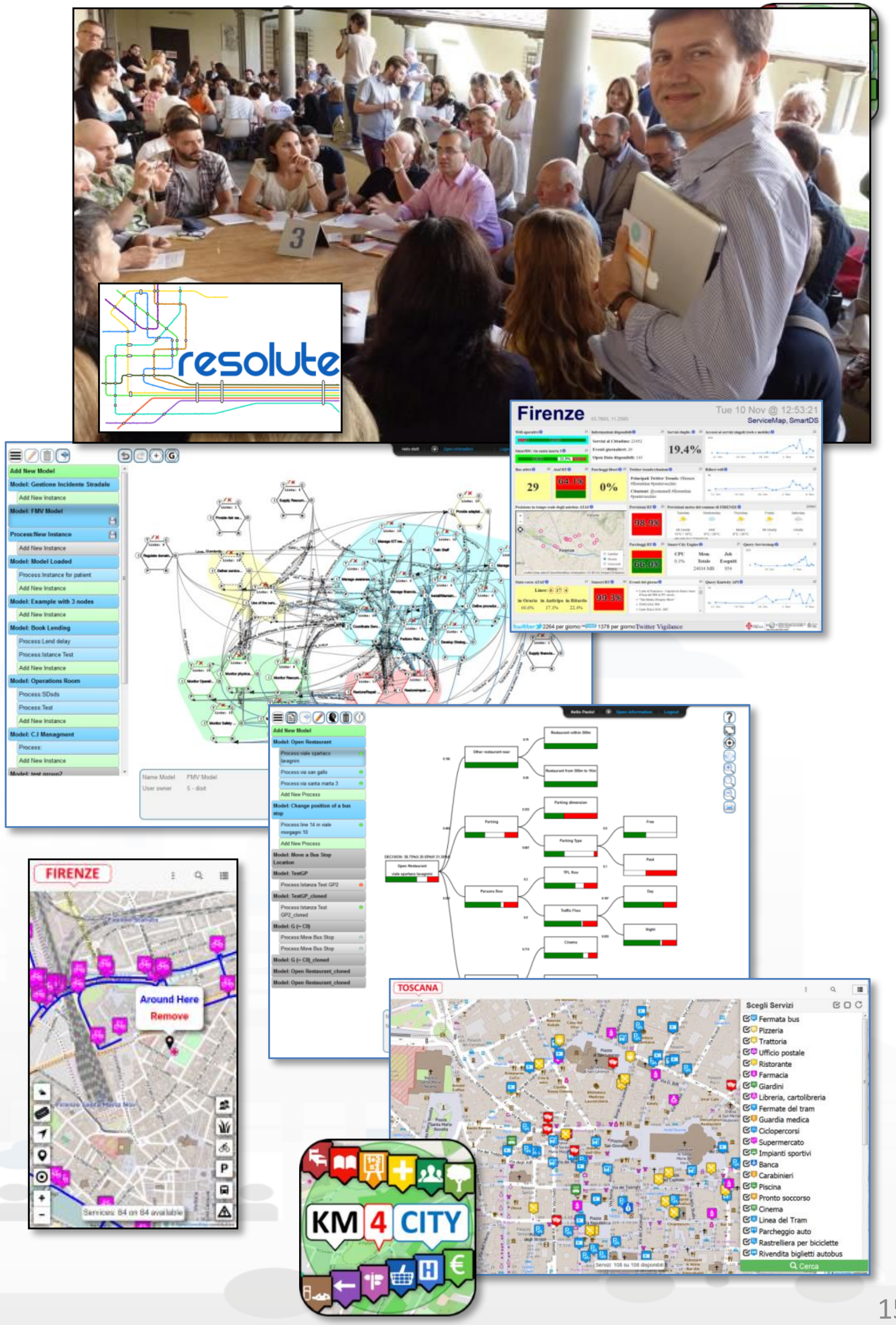


ERMG: European Resilience Management Guide



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



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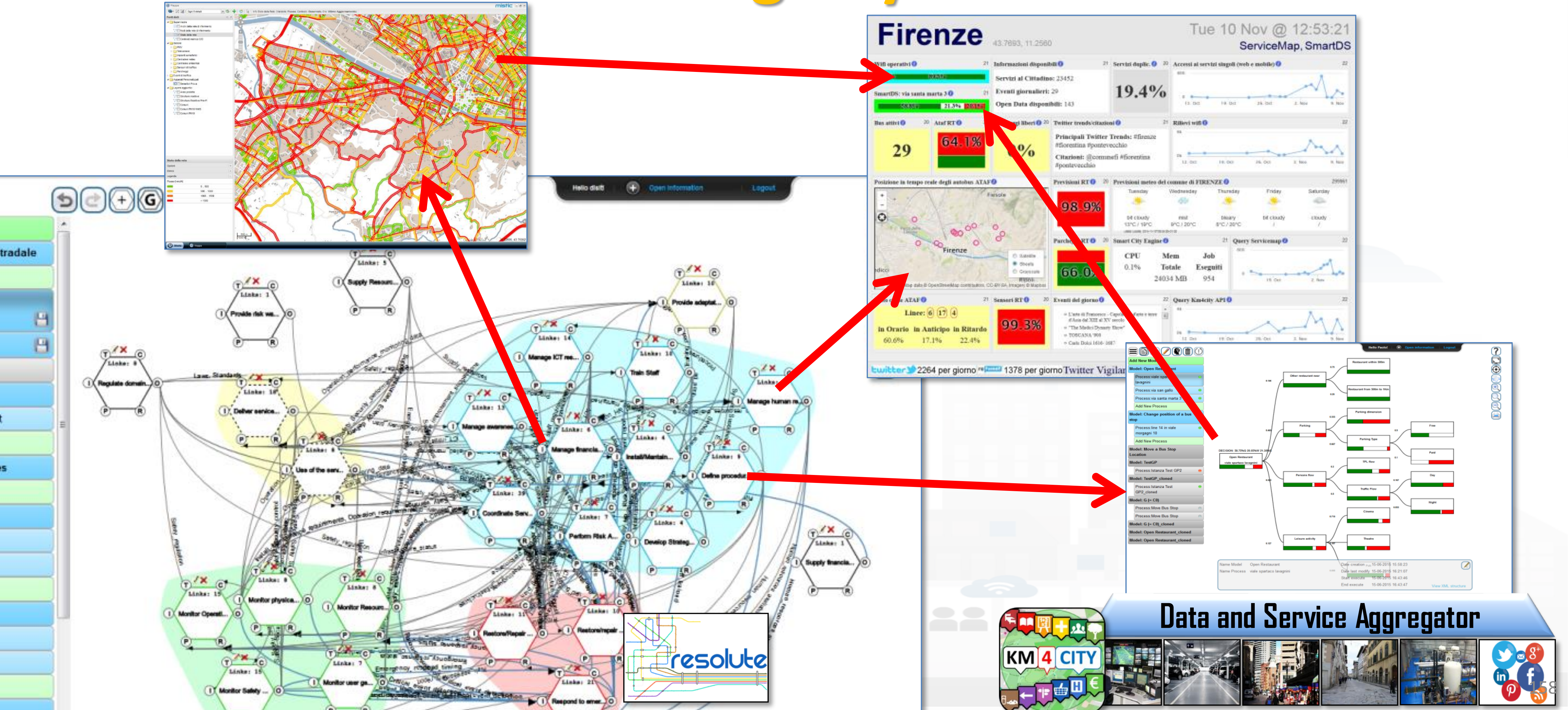
SNAP4CITY

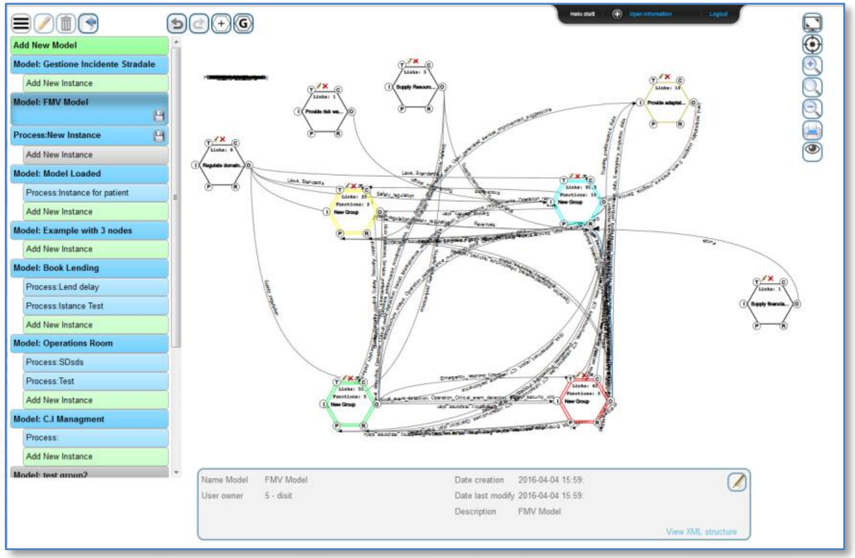
Dashboarding city resilience

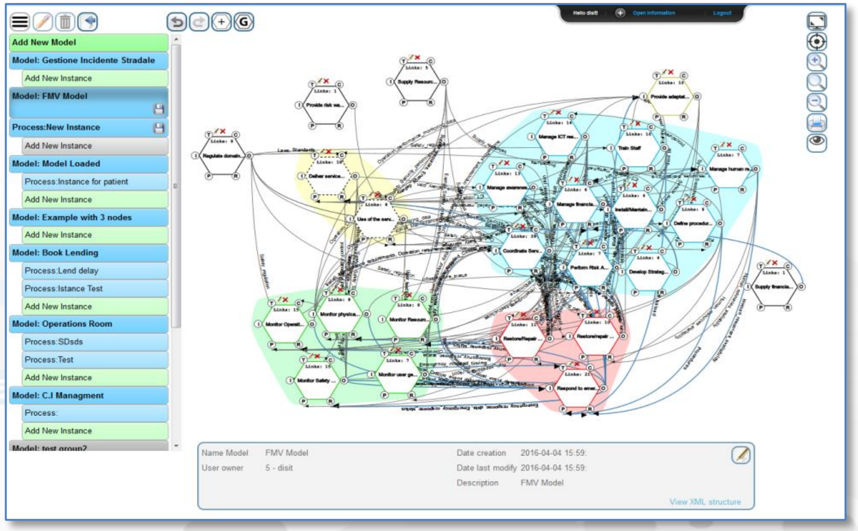


ResilienceDS Tool

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**



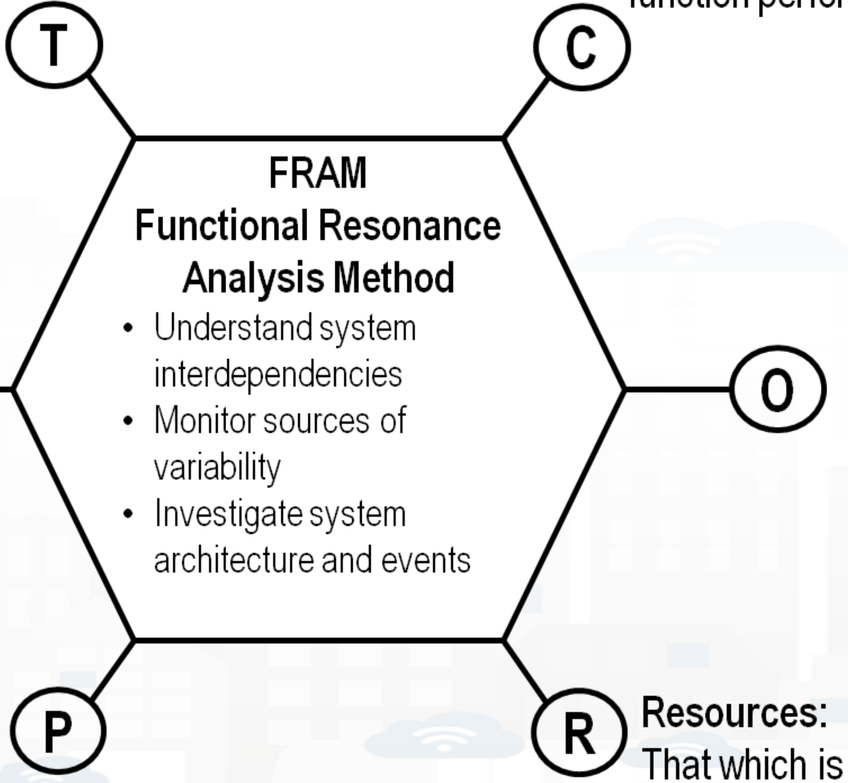


Functional Resonance Analysis Method

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



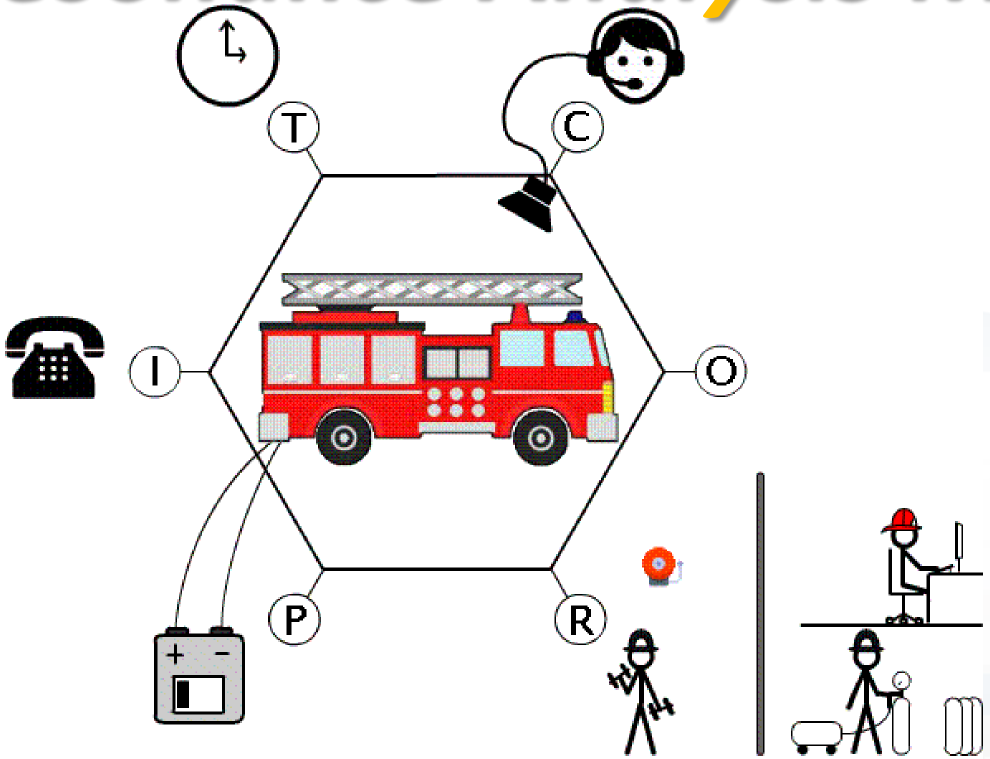
Output:
That which is produced by the function and becomes the input for other functions

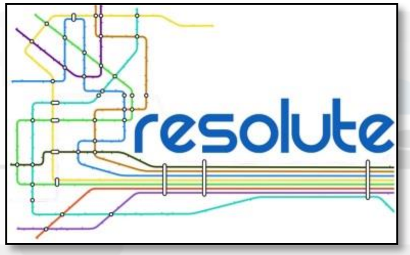
Preconditions:
System conditions that must be met before function can be carried out

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.





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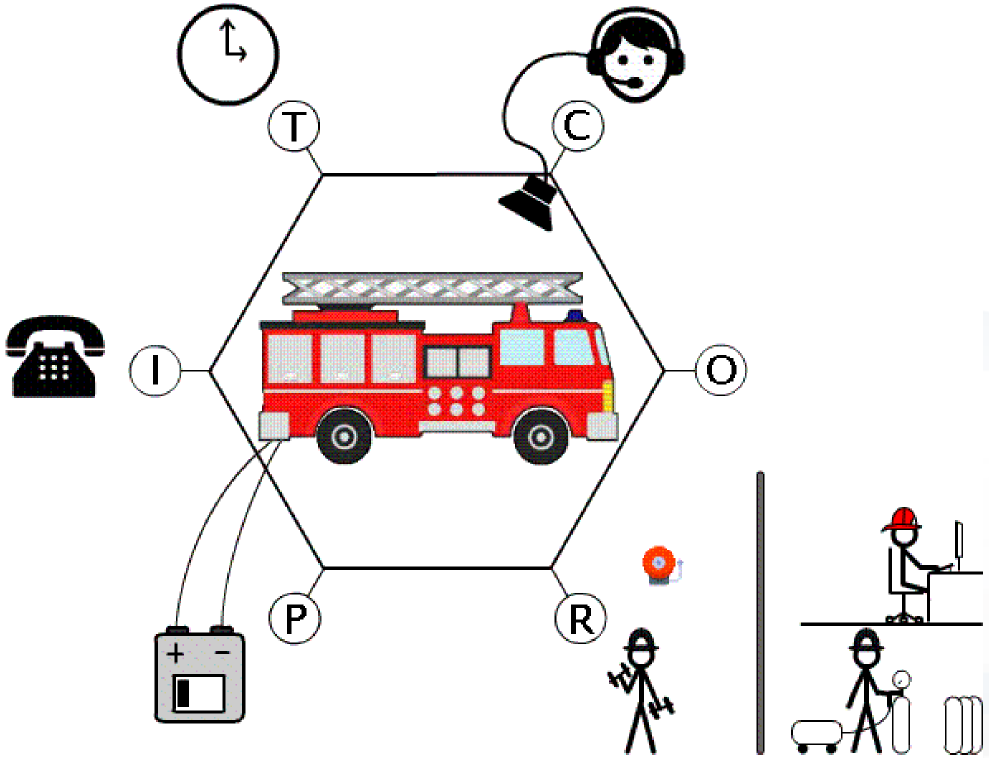
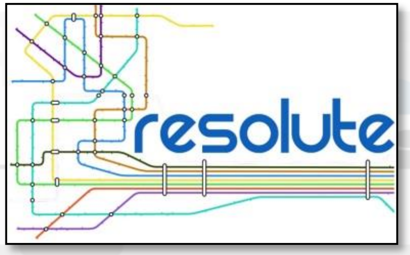
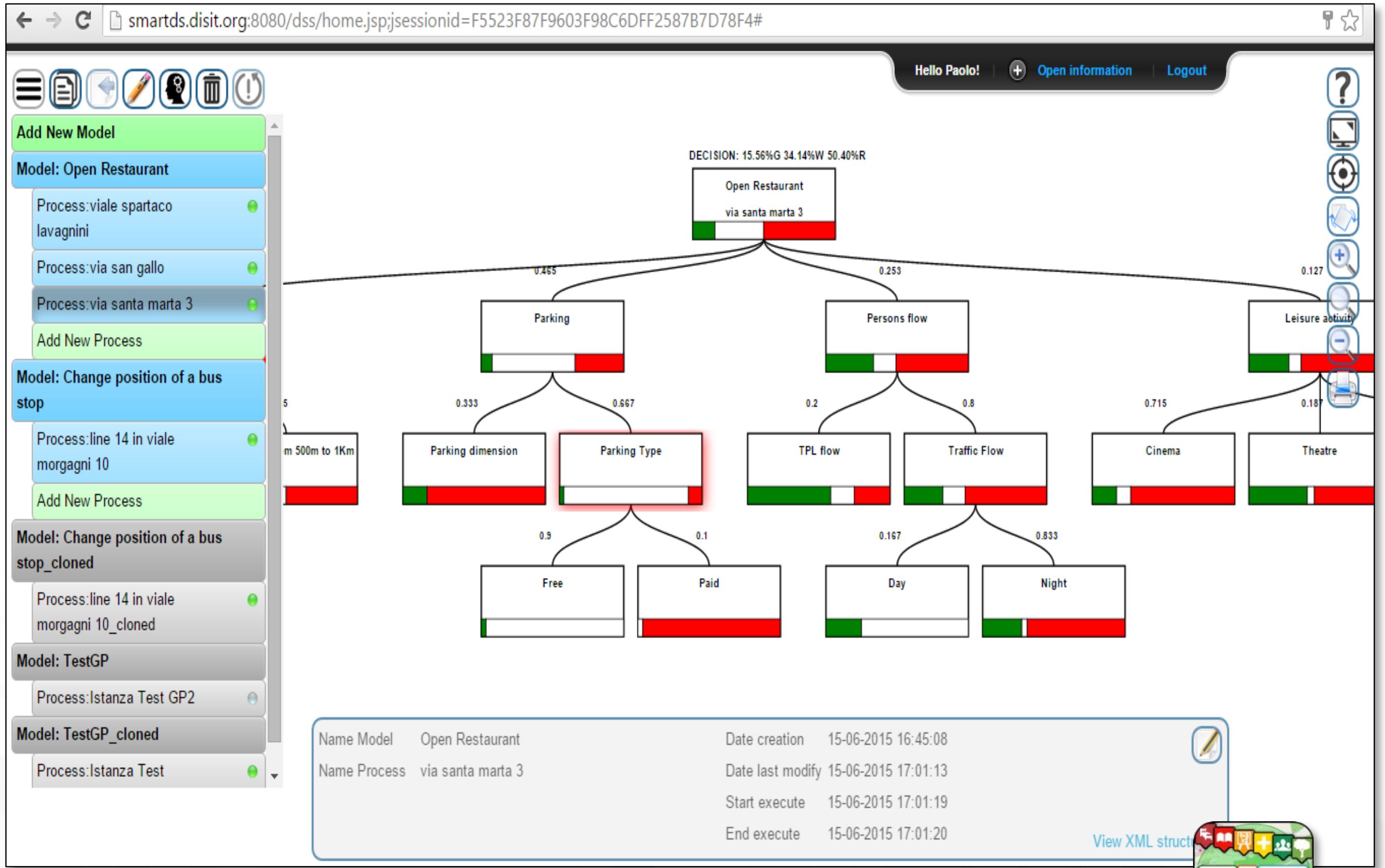




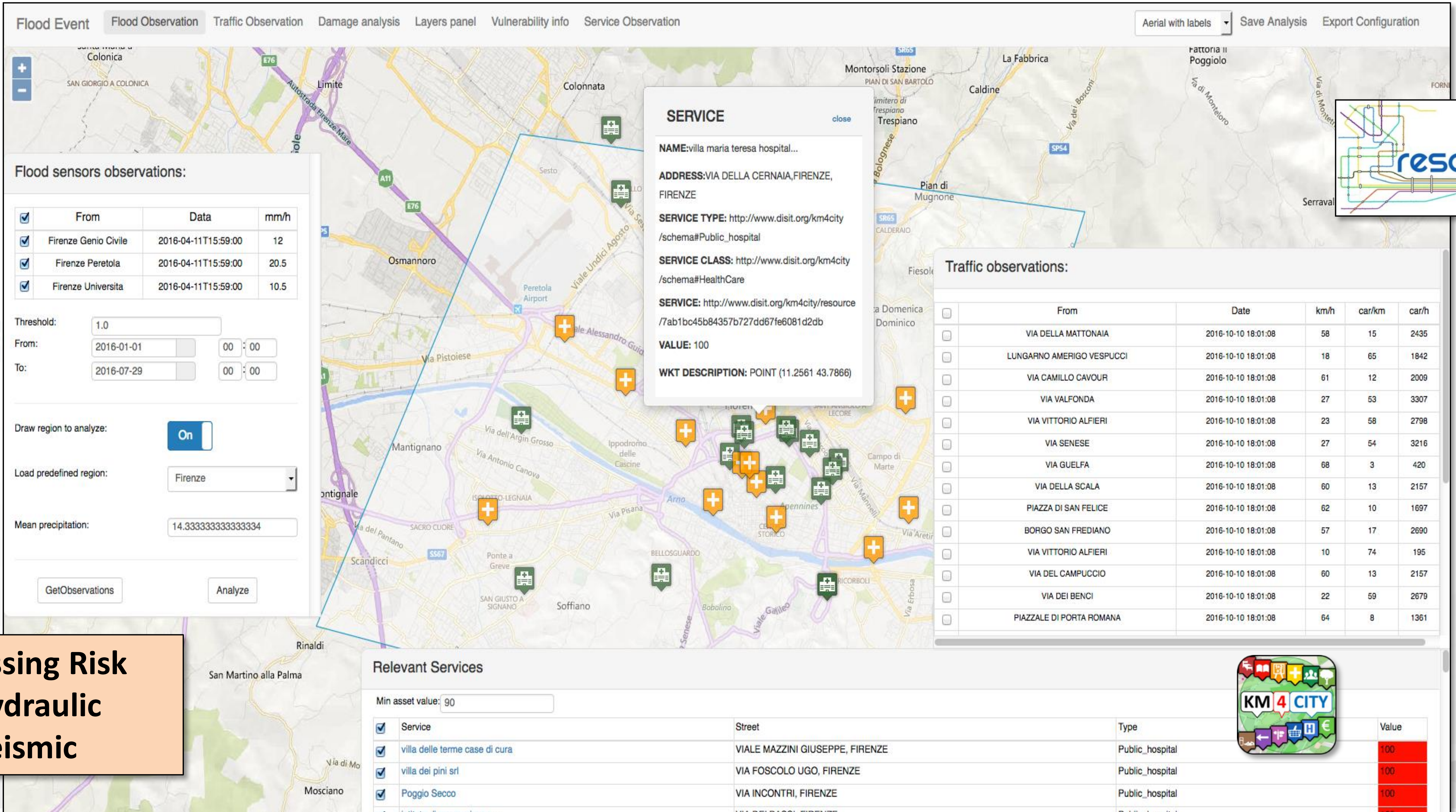
Smart Decision Support , system thinking

- **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

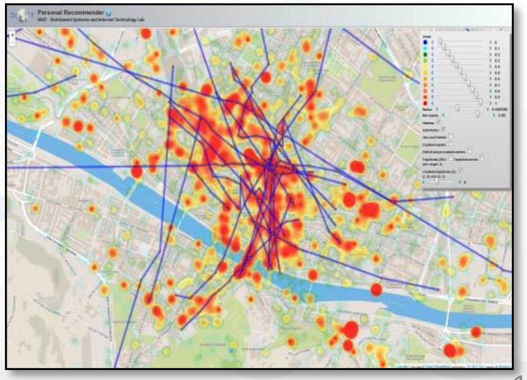


Assessing Risk

- **hydraulic**
- **Seismic**

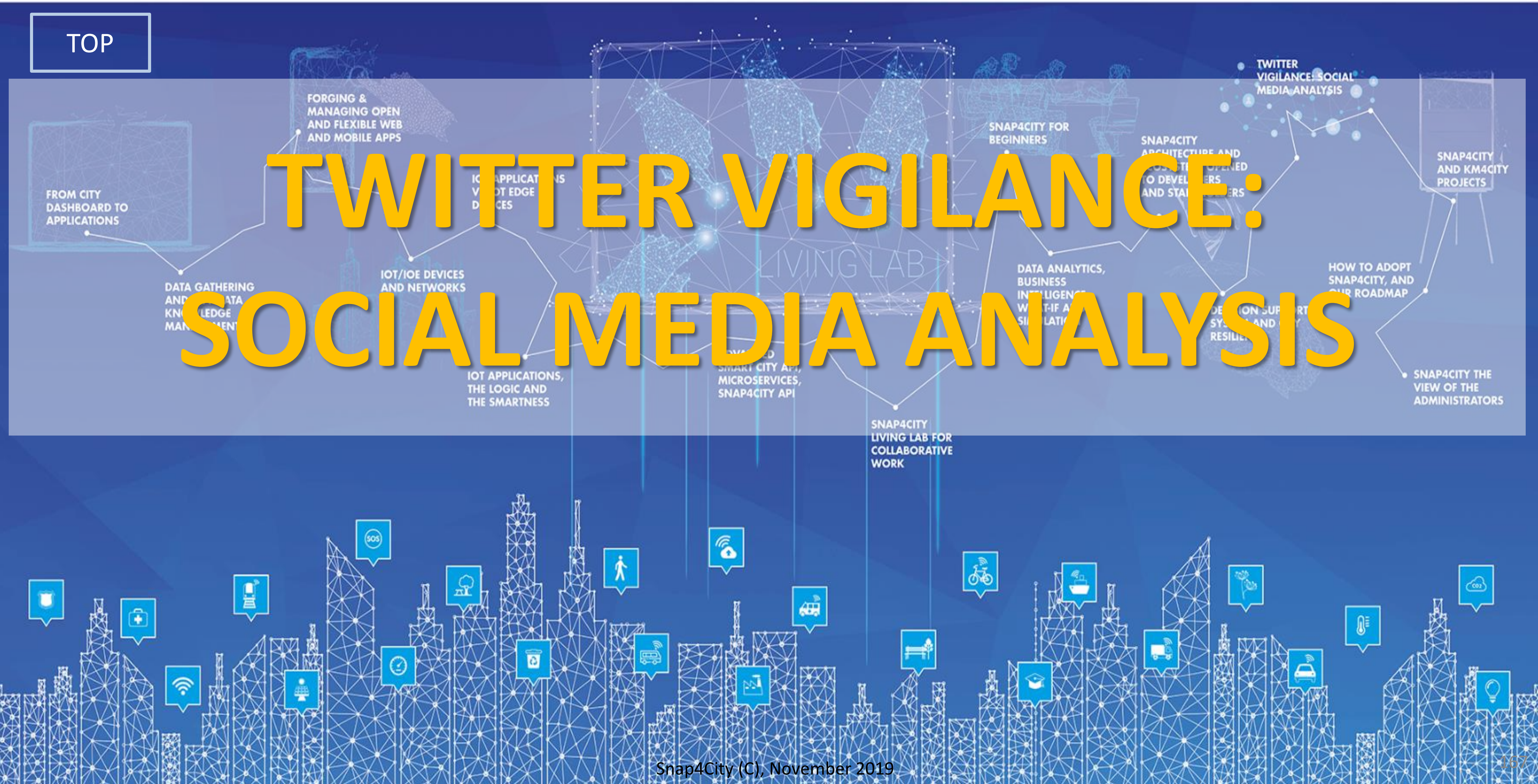
Mobile Emergency

- 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

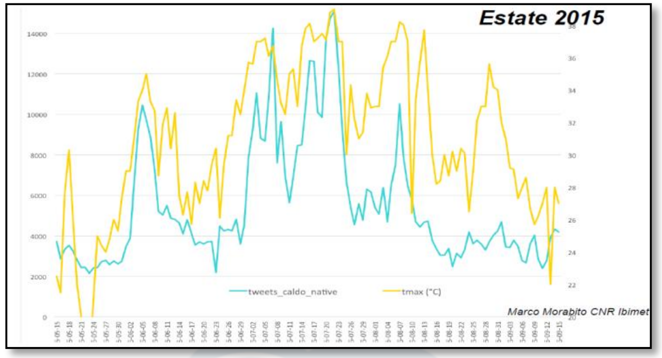
TWITTER VIGILANCE: SOCIAL MEDIA ANALYSIS



Twitter Vigilance

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



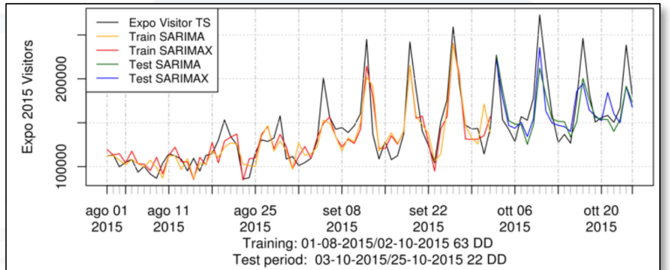
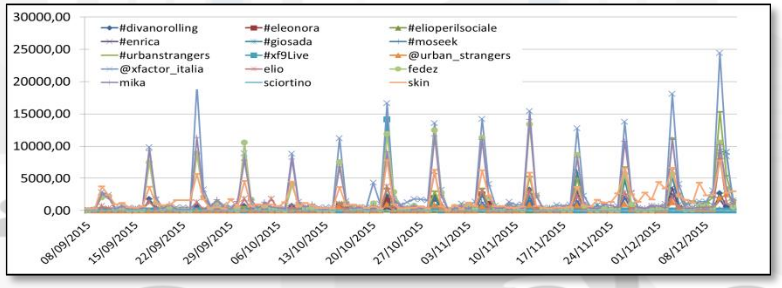
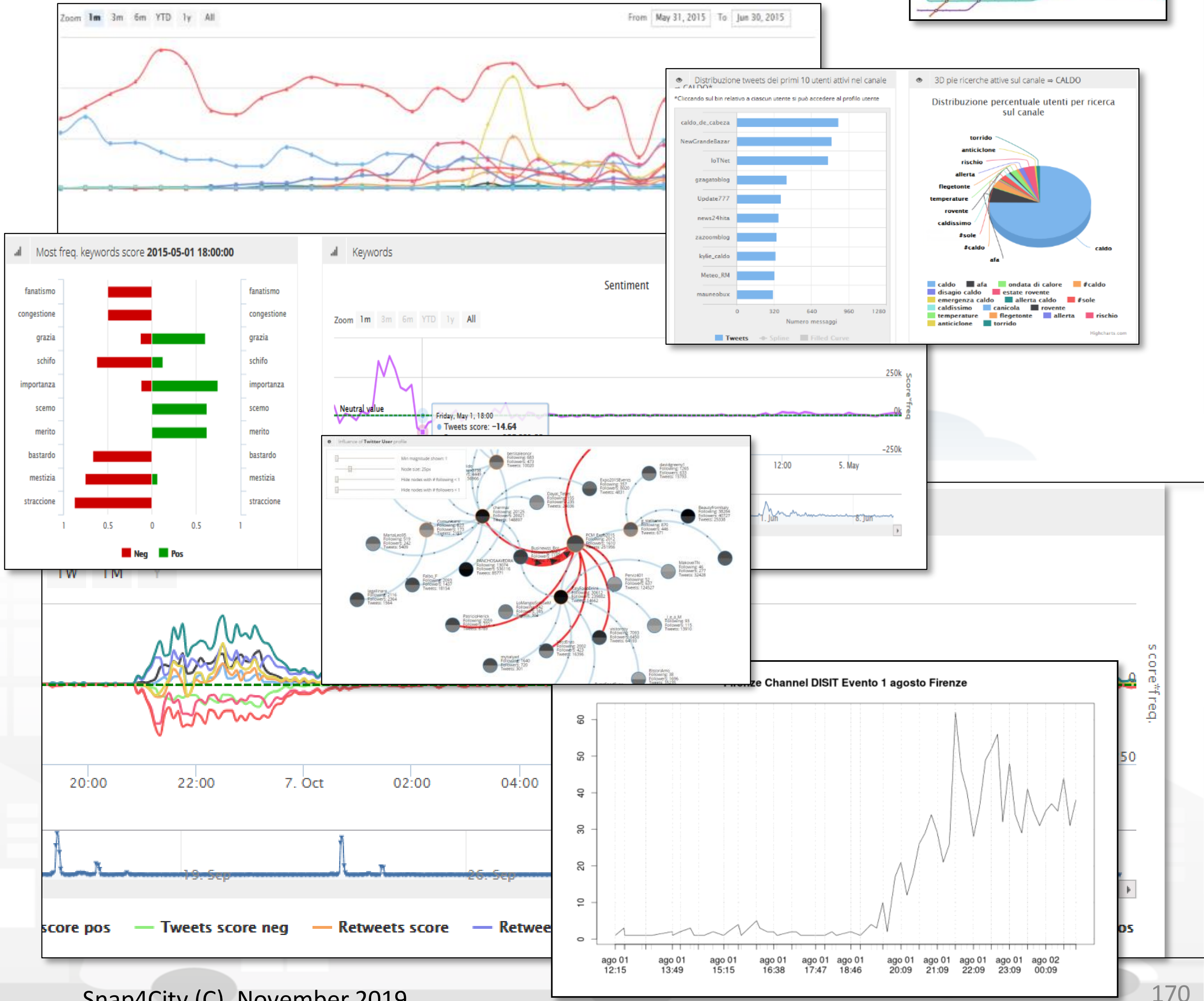


Figure 5: Comparison among the selected predictive models discussed and presented in Tables 2 and 3 with respect to the real number of visitors. Both training and validation periods are reported.



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

Early warning, detection

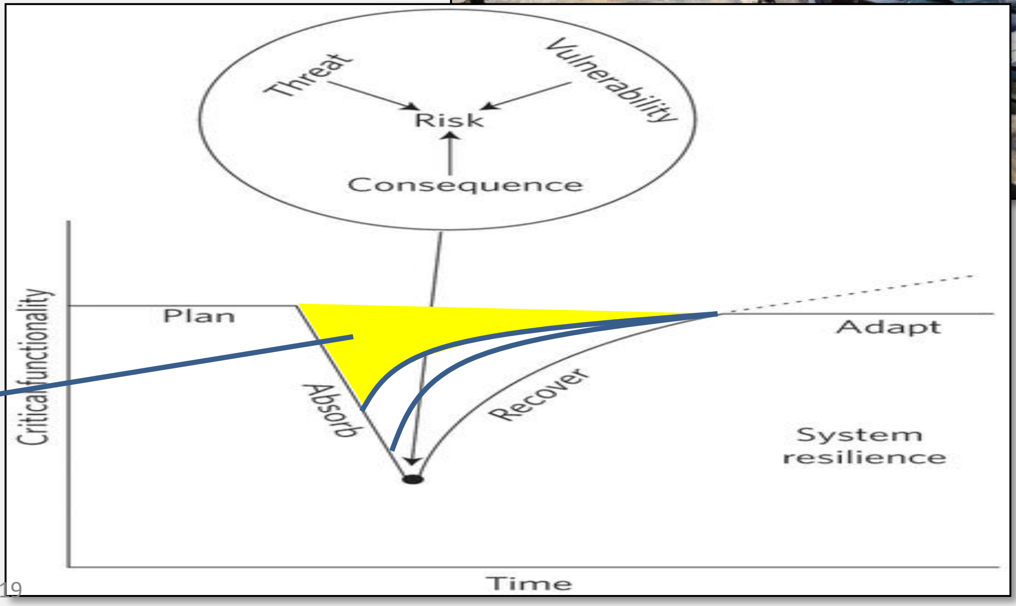
resolute

City Resilience

- **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



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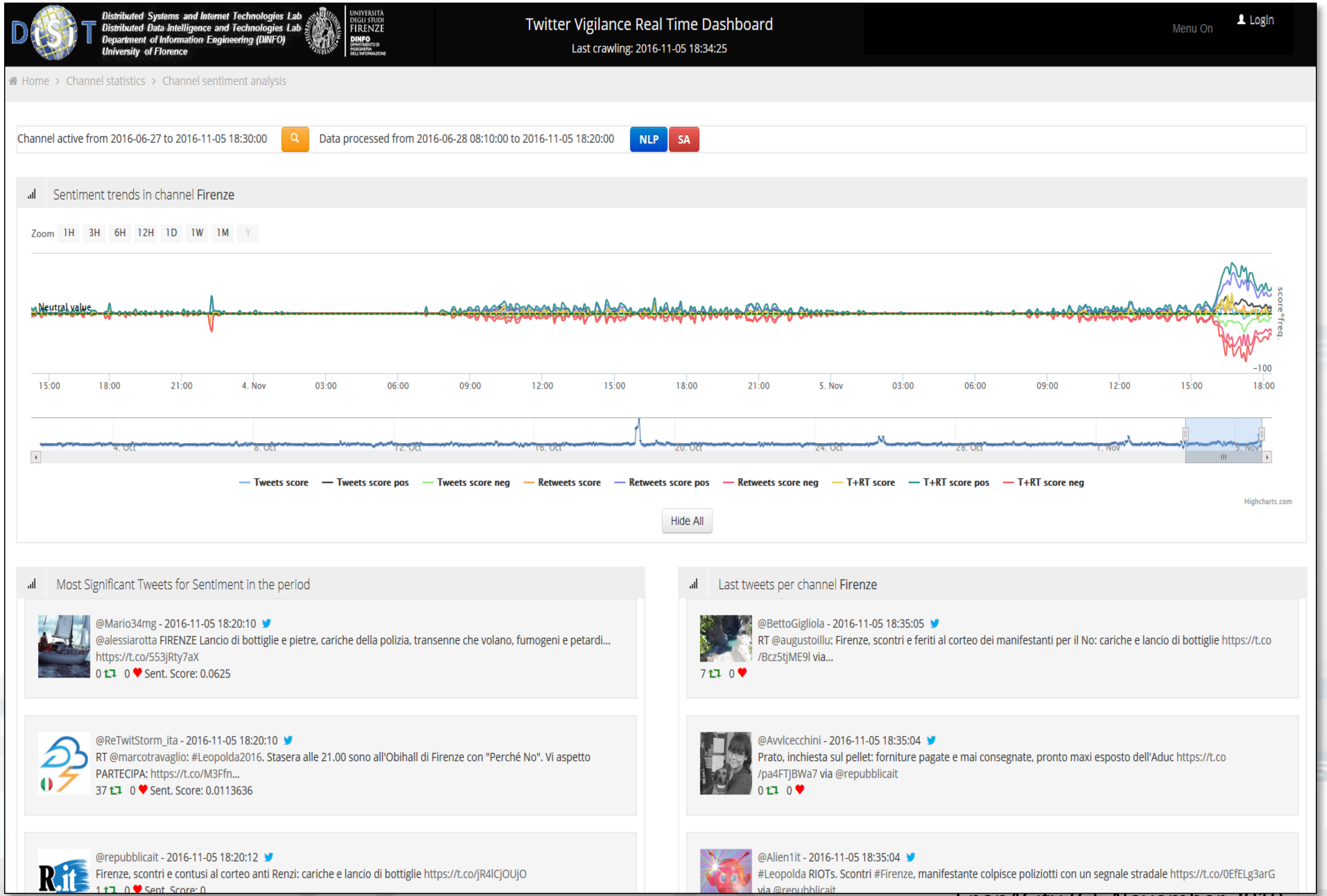
Twitter Vigilance

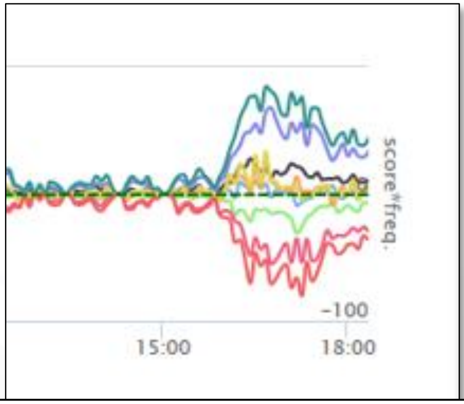
resolute

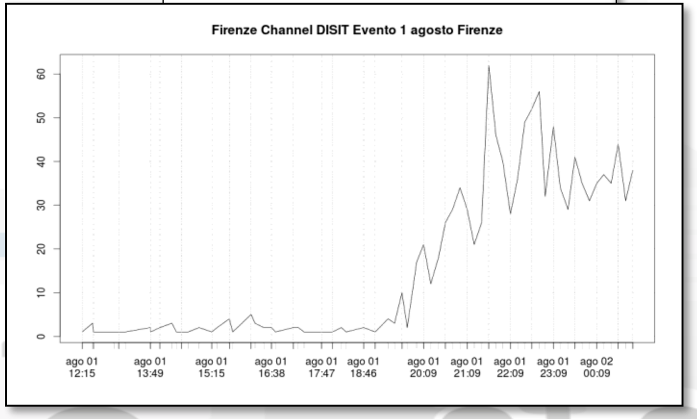
Twitter Vigilance RT: sentiment analysis



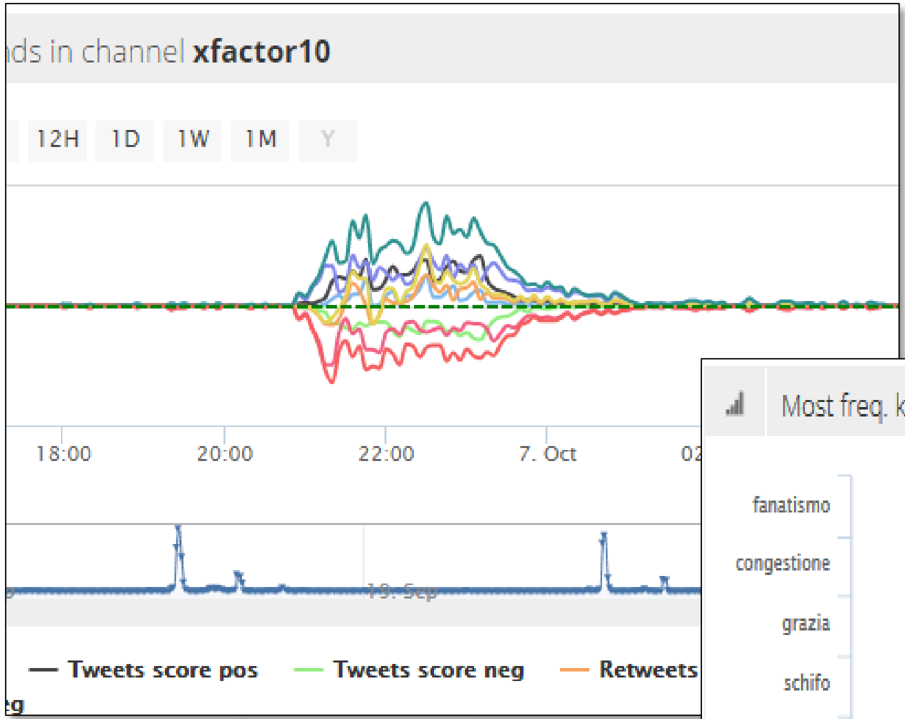
Real time

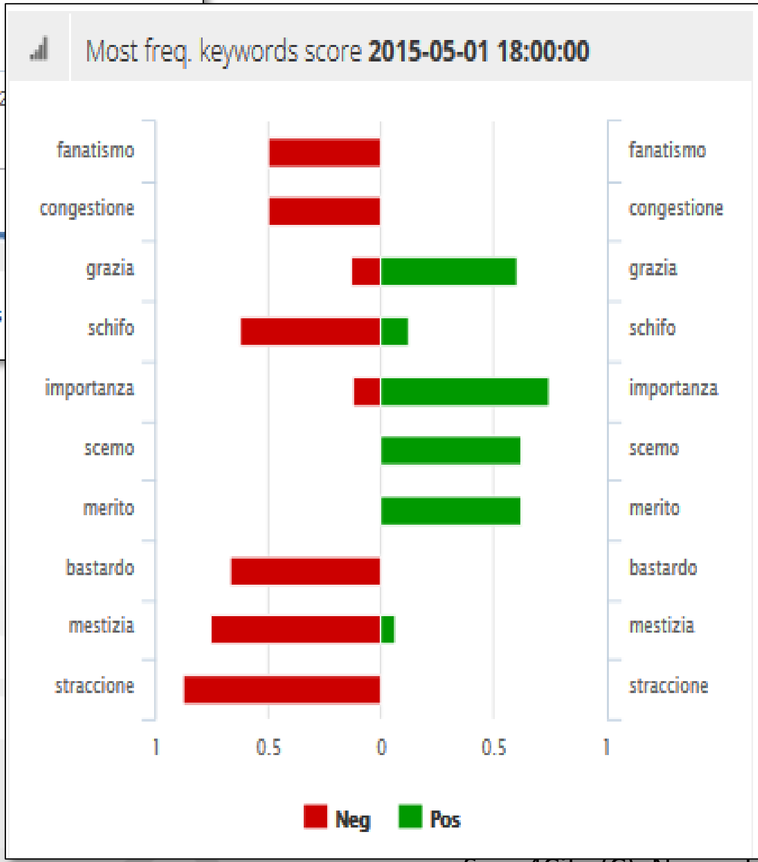
Early Warning

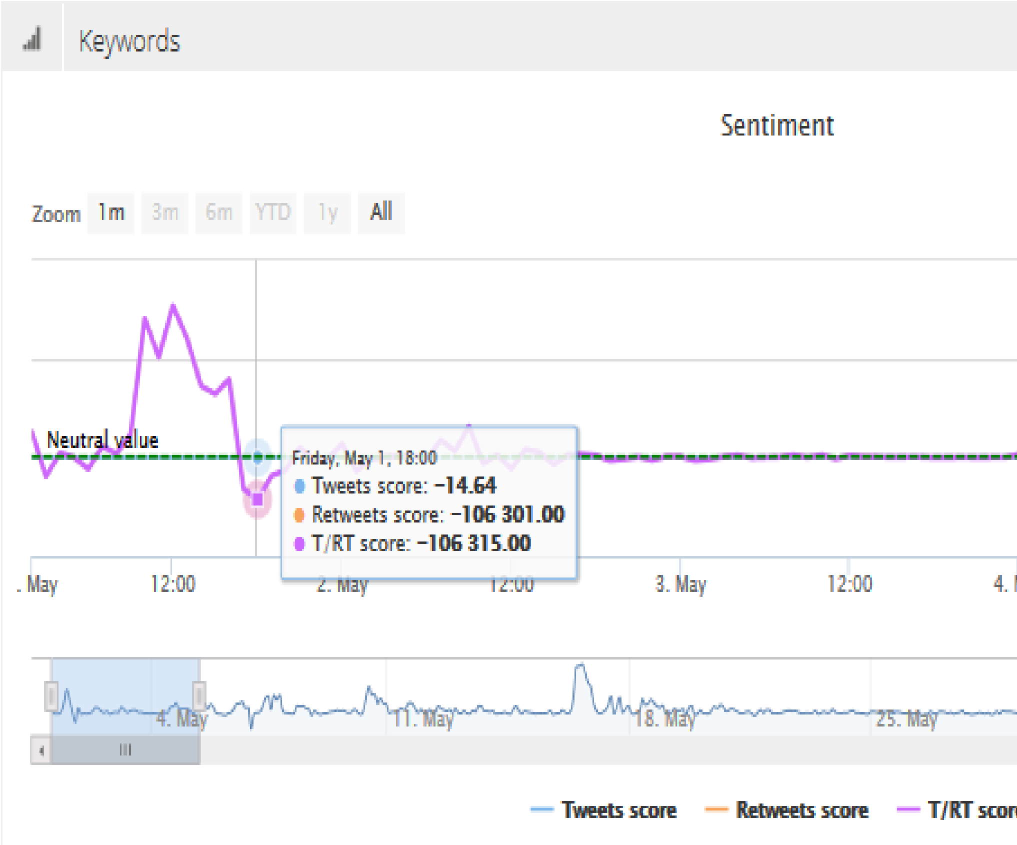




Sentiment Analysis







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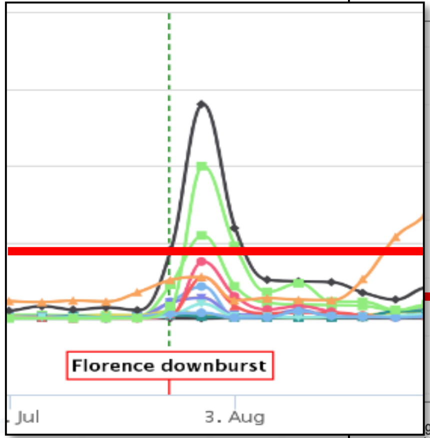
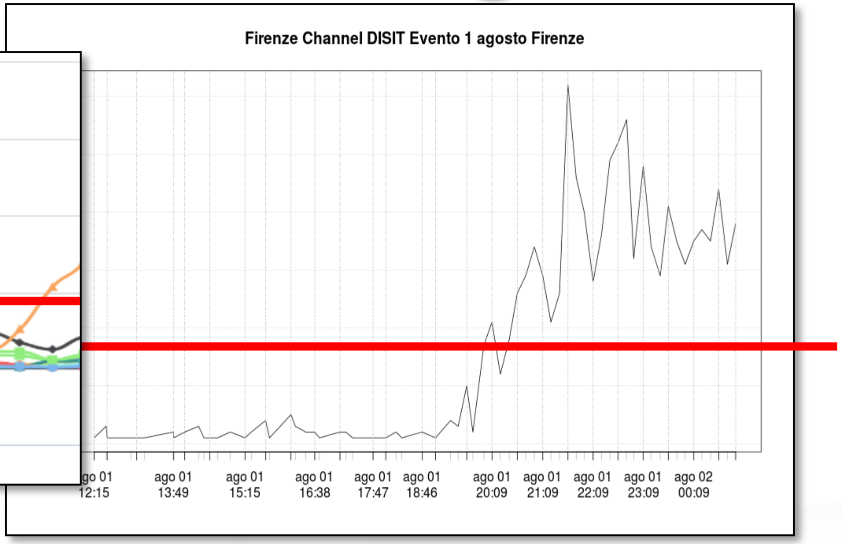
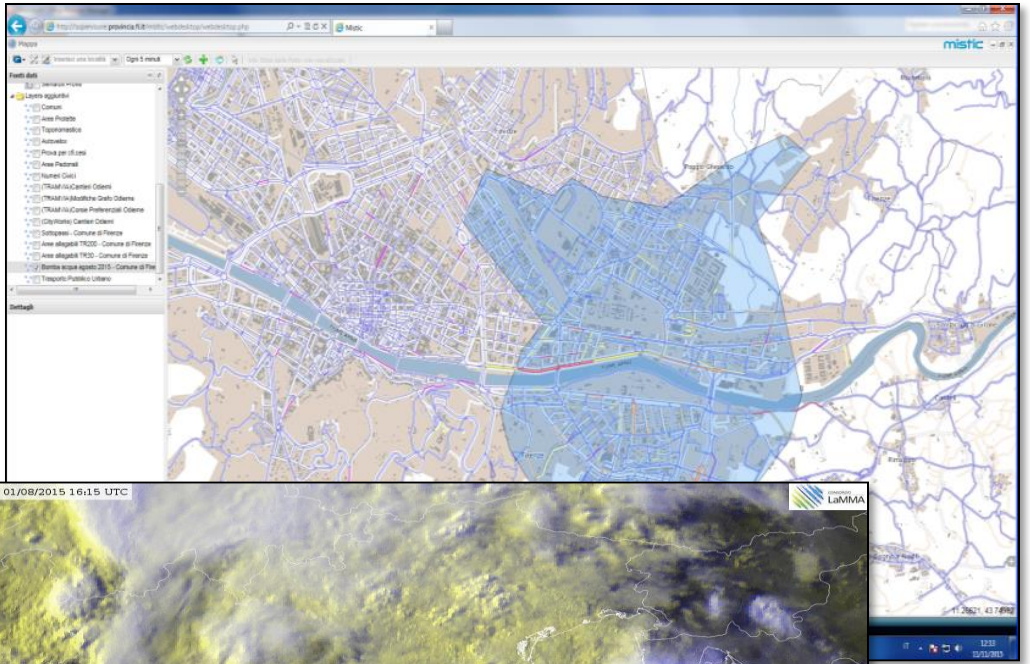
Early Warning

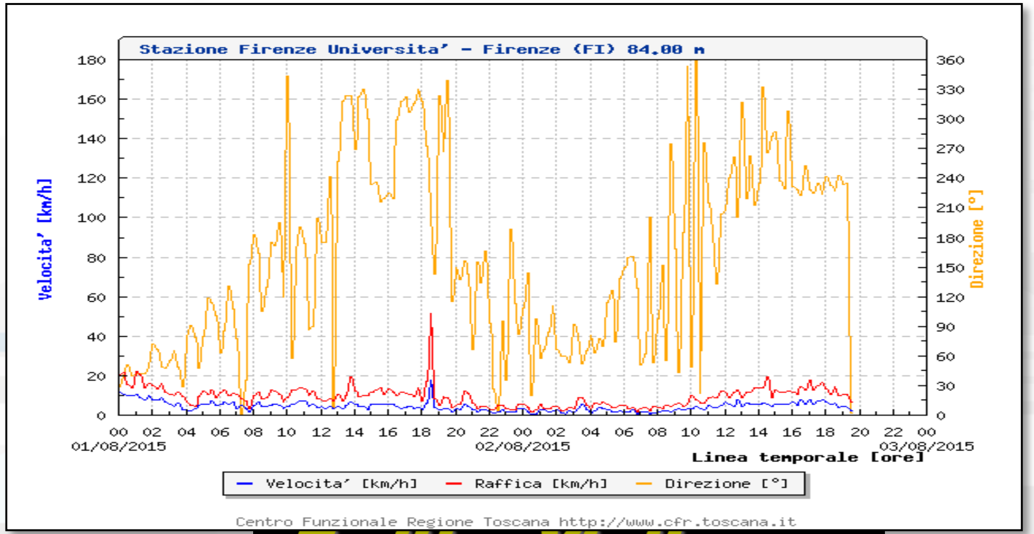
Twitter Vigilance and Water Bomb

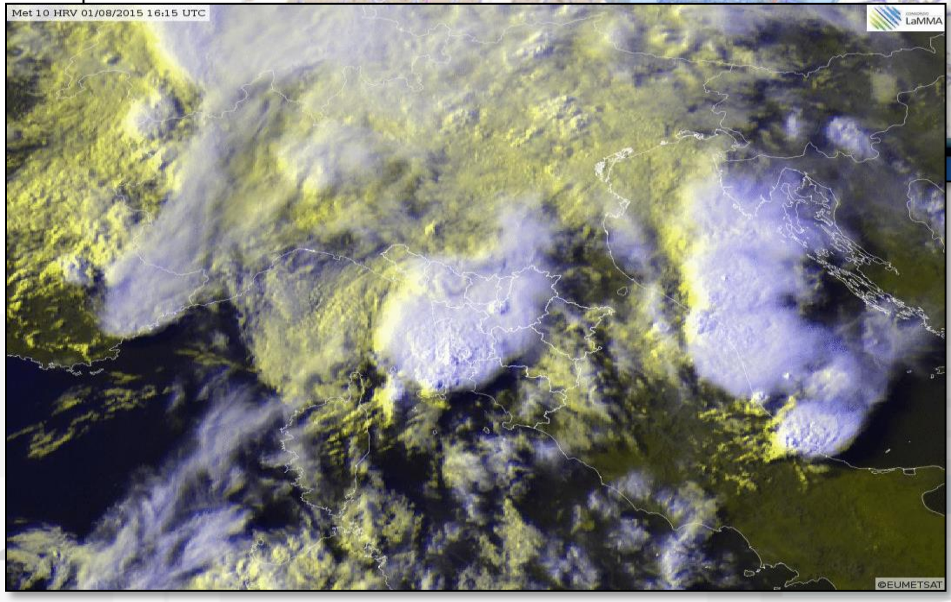
resolute









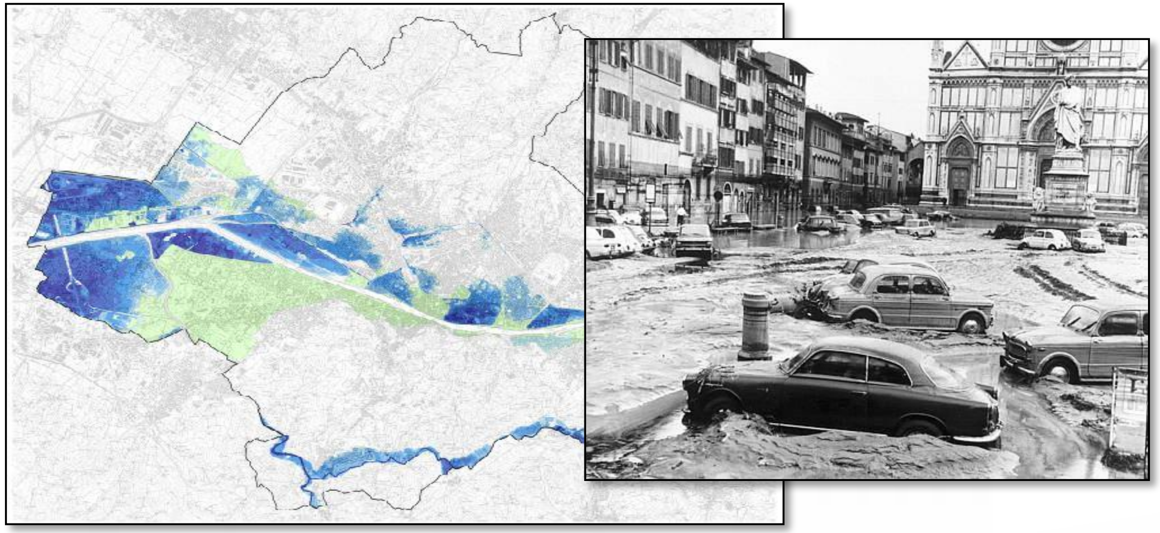


Twitter Vigilance

City Resilience ERMG

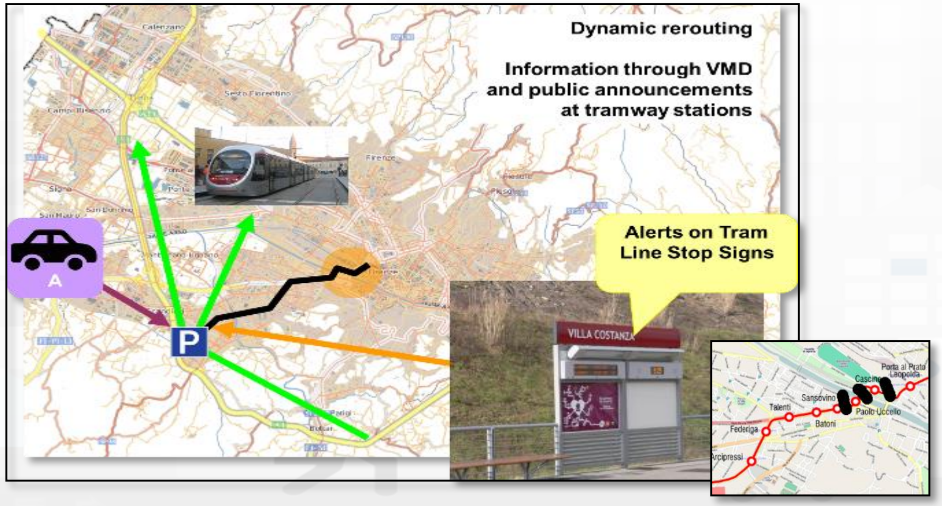
Case Study D

200 years probability Arno flooding



30 years probability Arno flooding

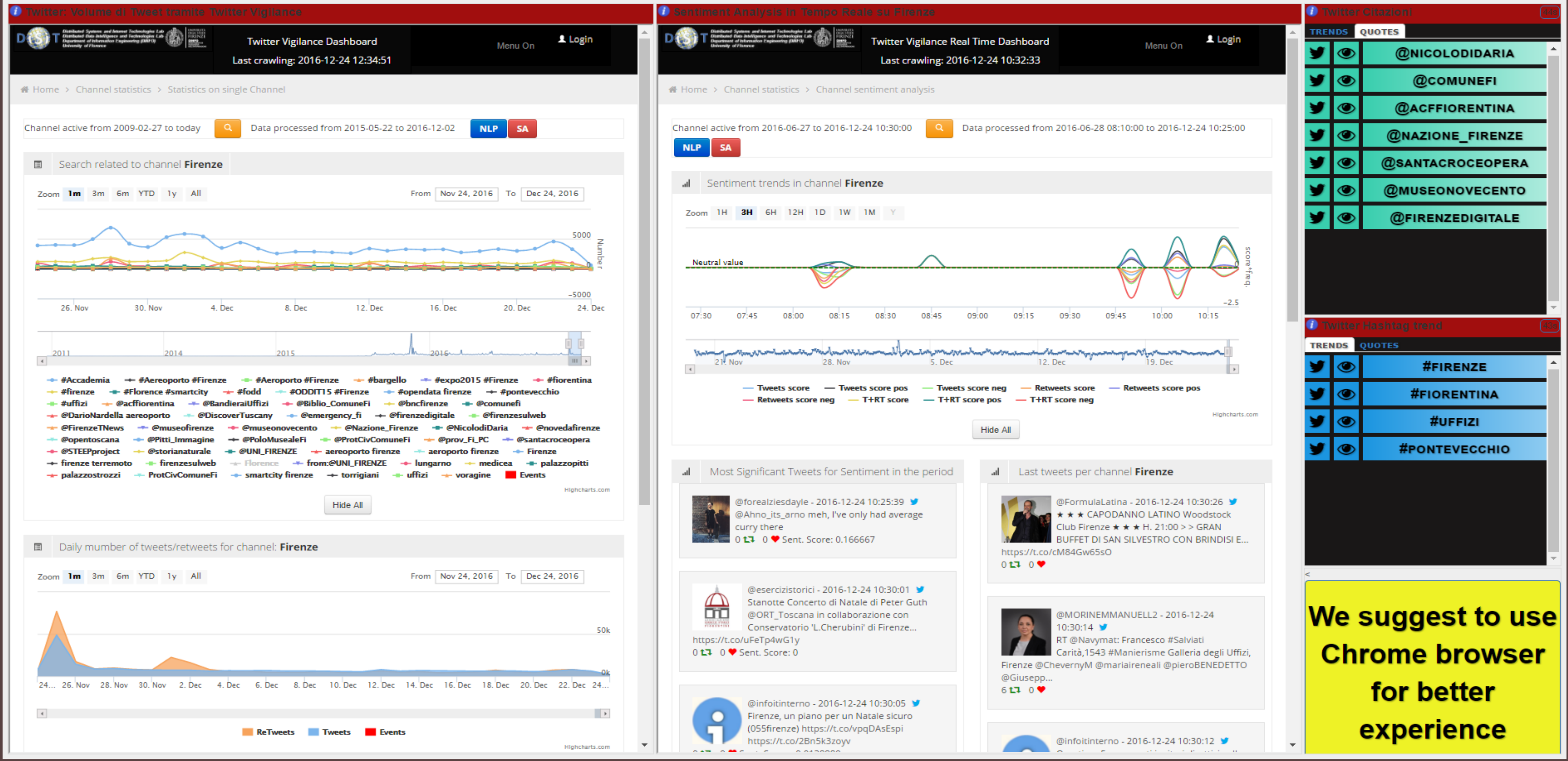
Arno Flood Impact on Tram Line & Traffic



Water bomb (down burst) in South Florence

Twitter Vigilance su Firenze
(sperimentale)

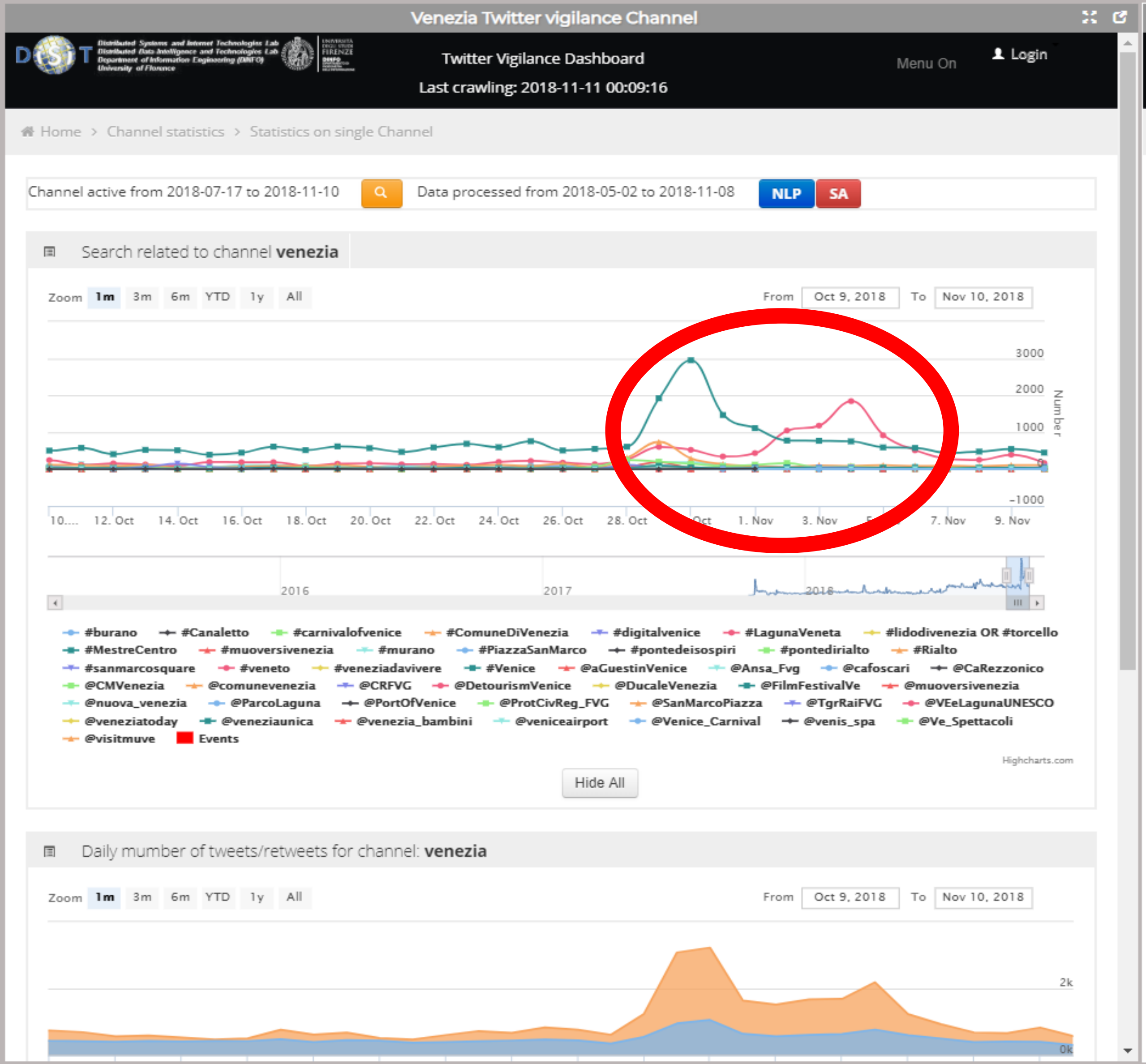
Sat 24 Dec @ 10:37:57

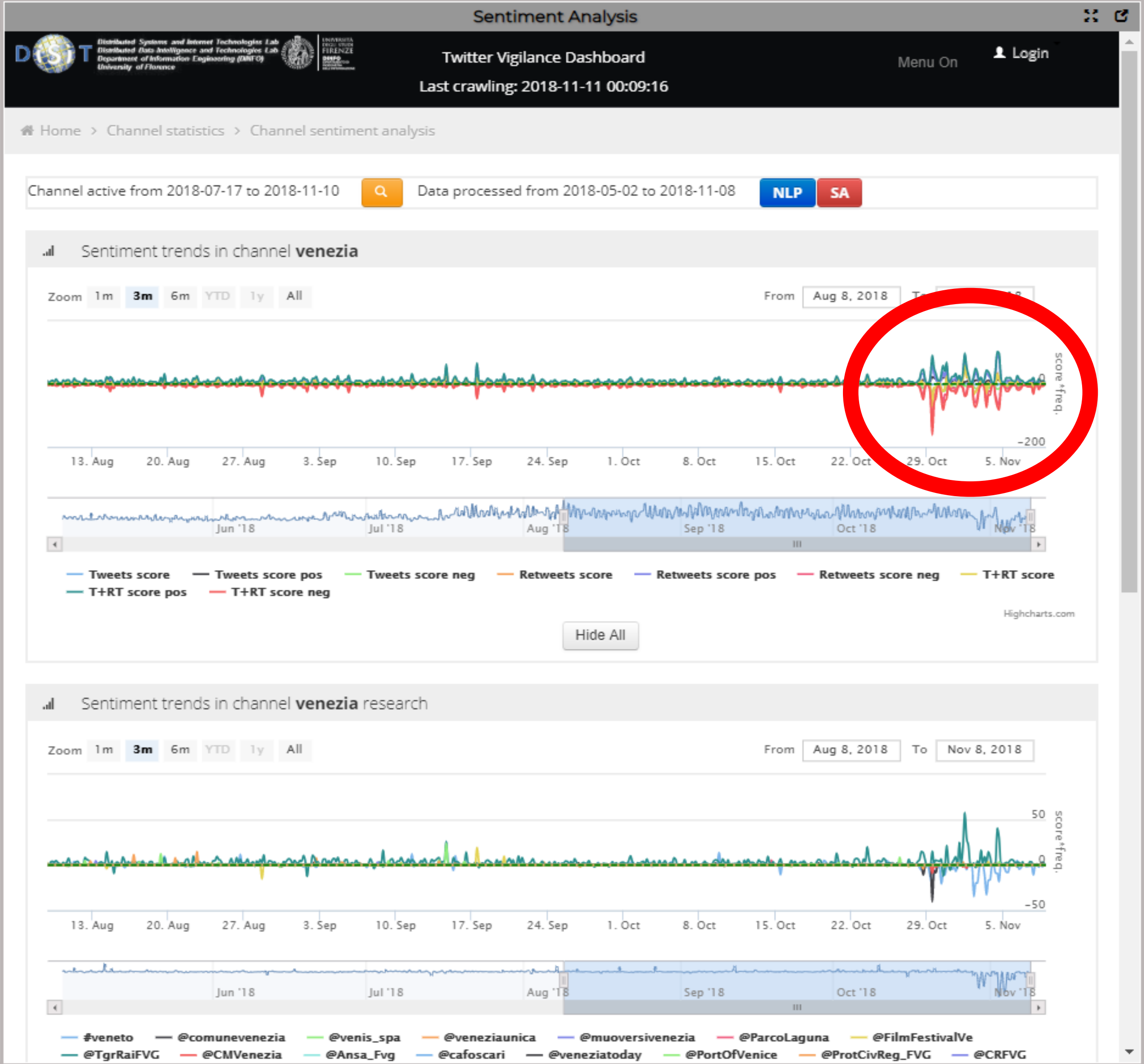


We suggest to use Chrome browser for better experience

Venezia Social - Twitter Vigilance

Sun 11 Nov 00:09:40

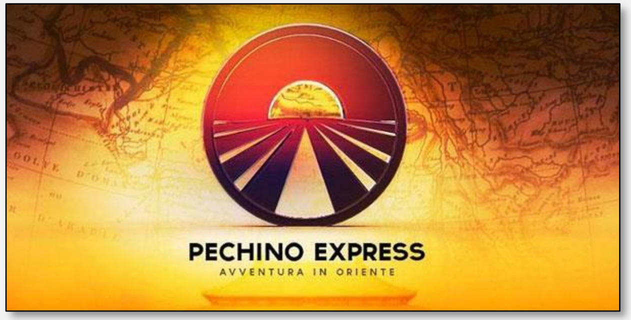




https://main.snap4city.org/view/index.php?iddasboard=MTIxOA==

Predicting Audience on Social intensive TV show

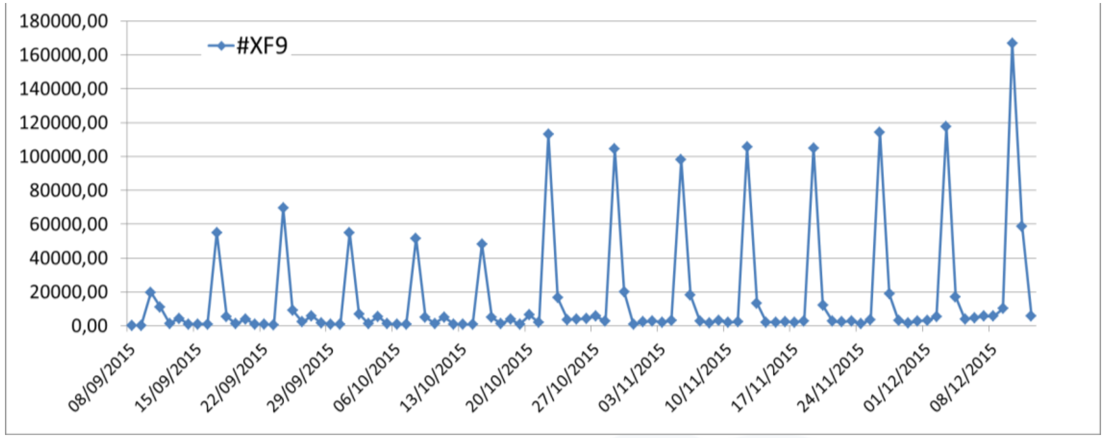
- **Issue:**
  - **How to predict the number of people following a TV reality show in life**
- **Impact:**
  - **Making Advertising, promotion**
  - **Valorizing advertising**
  - **Adjusting the show**
- **Several metrics related to**
  - **Structure of volume of TW, RTW**
  - **Features of the tweet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

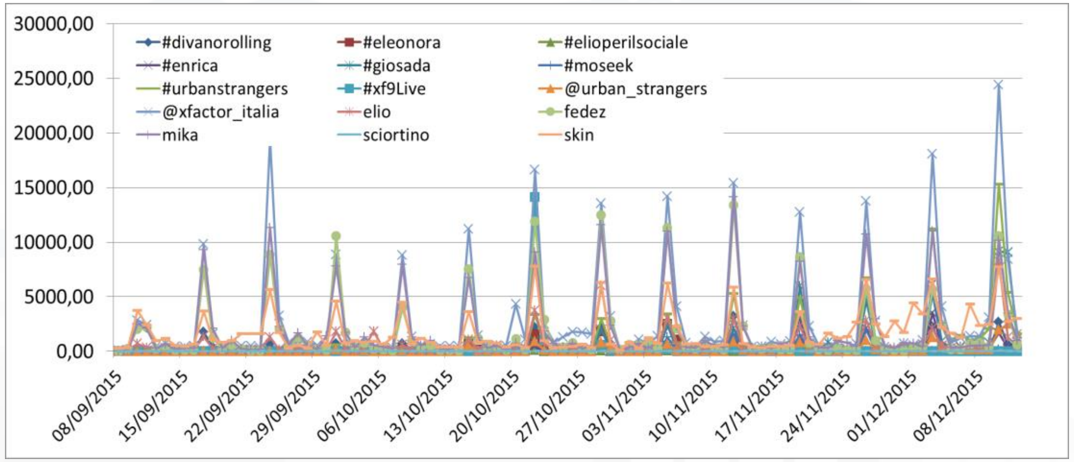


- Periodic events
- Specific rules
- Strong influence and user engagment
- Audience can vote
- Audience espress appreciation and rejects
- .. Similar to the presence at large and log terms event, such as EXPO2015

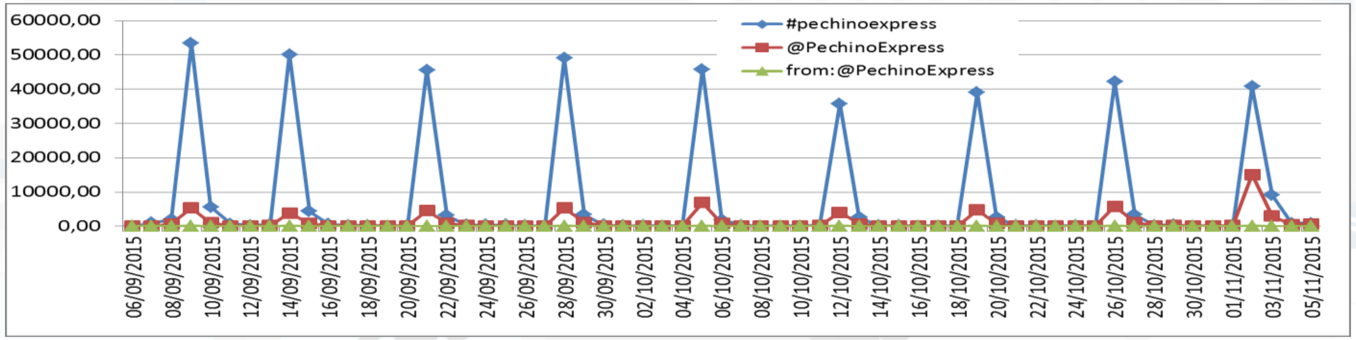
Predicting Audience: X-Factor, PechinoExpress, …

- 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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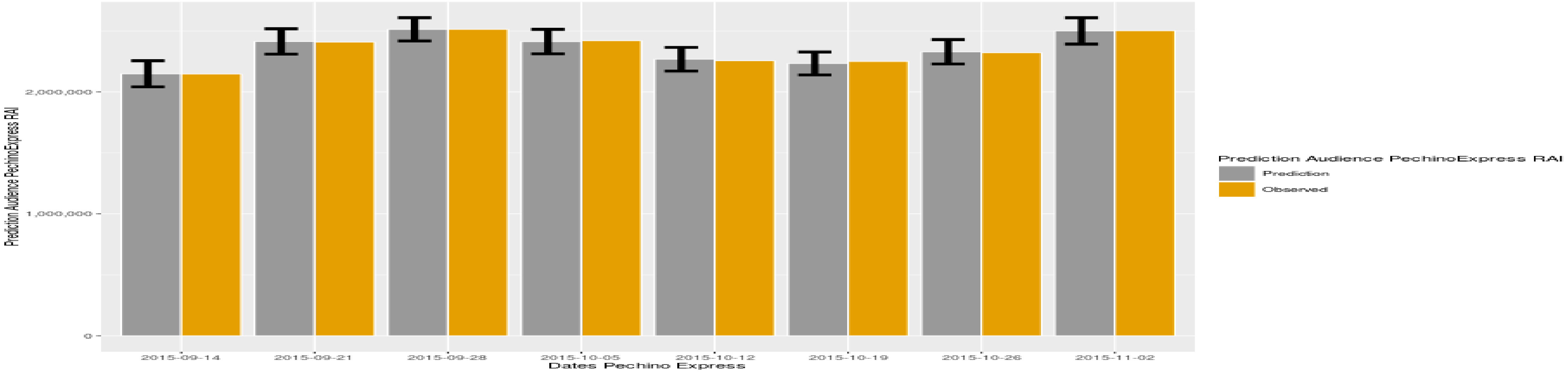
Details of Predictive Models Validities

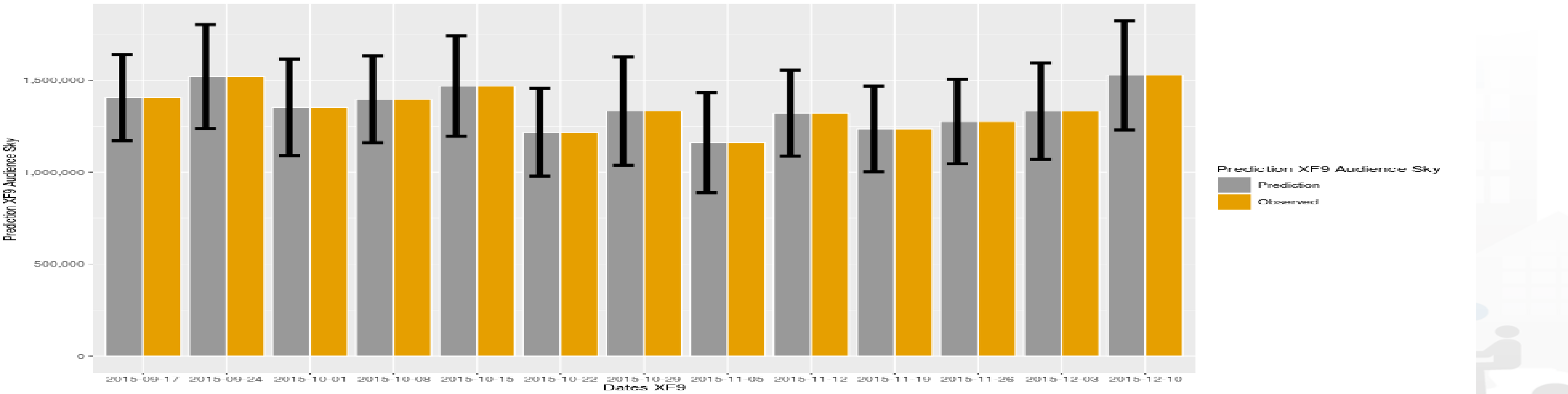
Metrics collected over the 5 days before the event.		X-Factor 9 - Model				Pechino Express - Model			
		Coeff	Std Err	t-val	p-val	Coeff	Std Err	t-val	p-val
Total number of tweets + retweets on main hashtag	β_1	-73.48	58.49	-1.256	0.2494	-954.3	64.69	-14.750	0.0045
Total number of tweets on main hashtag,	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			

Case Study B

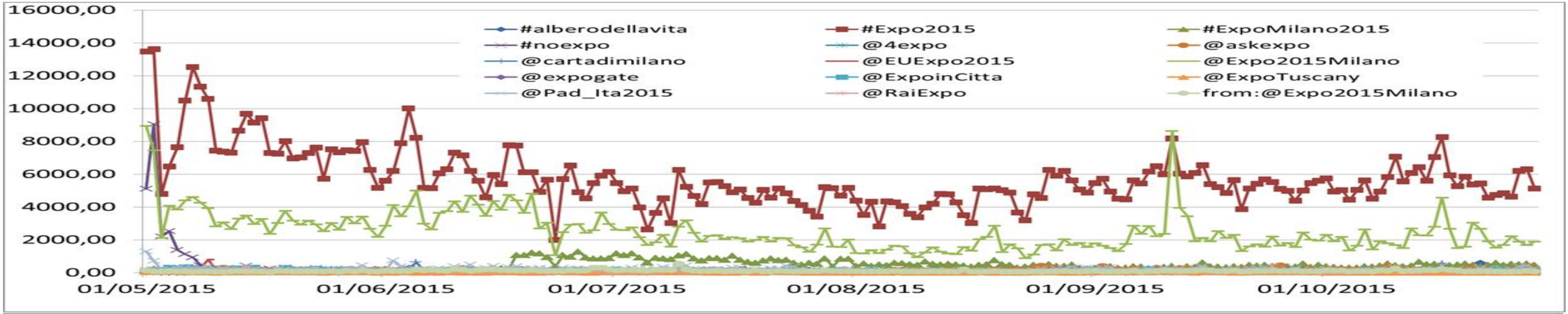
Predicting Confidence

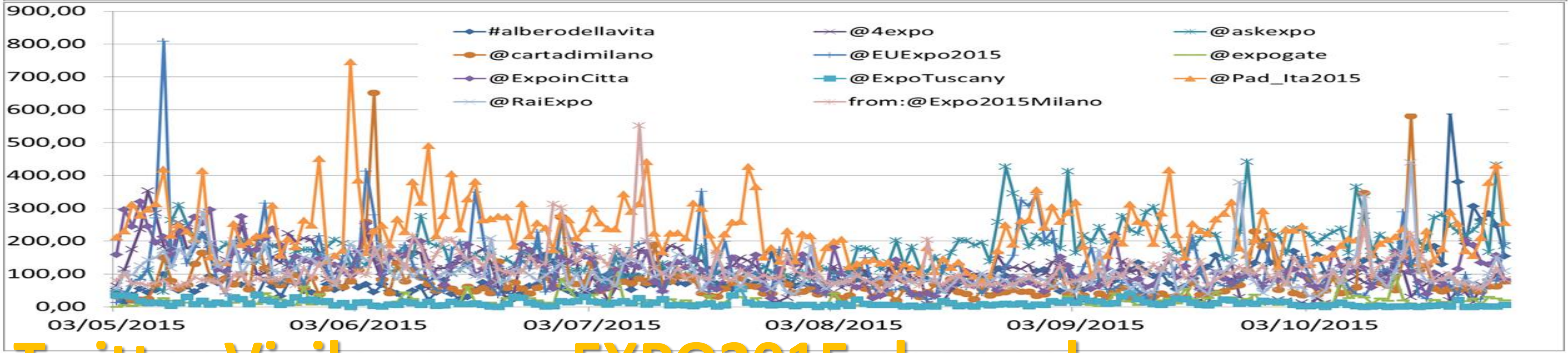
Case Study B





Predicting EXPO2015





Twitter Vigilance on EXPO2015 channel

Twitter Vigilance

Case Study B2

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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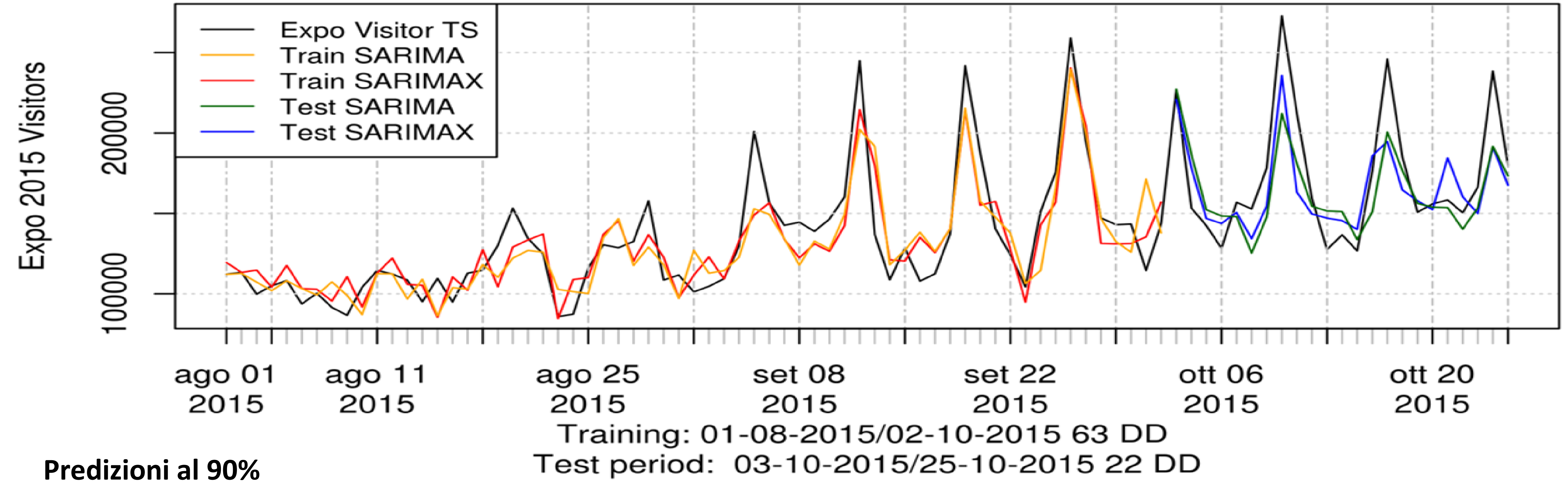
Twitter Vigilance monitoring and predictions



Predizioni al 90%

Precision: 96%

Twitter Vigilance on EXPO2015 channel

Predicting volume of visitors for tuning the services

retweetCount	message
531	dozens of cars burned down during #noexpo protest in #milan http://t.co/vtacp8mpkq http://t.co/llsgtqtpjt
342	rt @aut_omnia: black bloc used smoke bombs to blind cops, then changed clothes, dropped gear and slipped into crowd. genius. #noexpo http:/â€
337	black bloc used smoke bombs to blind cops, then changed clothes, dropped gear and slipped into crowd. genius. #noexpo http://t.co/2972qxcxkq

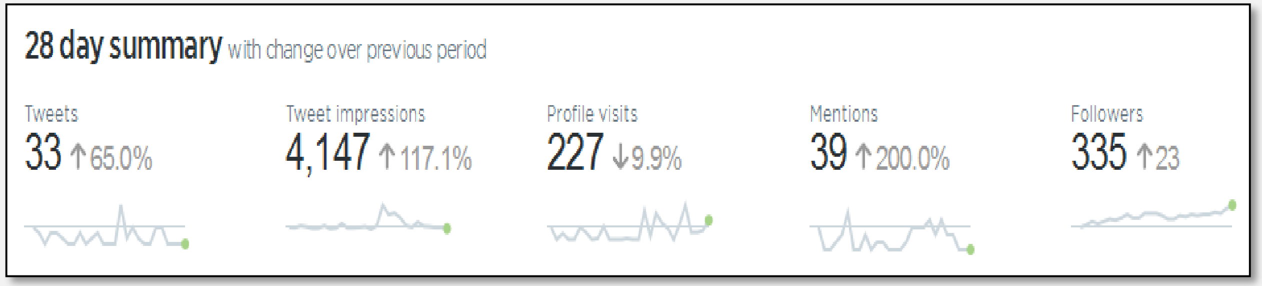
Twitter Vigilance

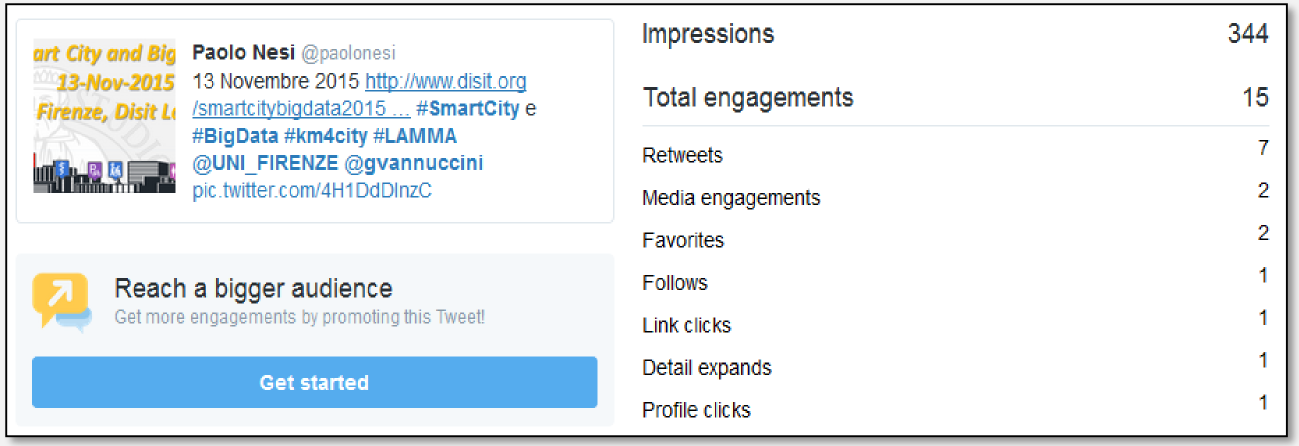
DISIT Lab, Distributed Data Intelligence and Technologies
Distributed Systems and Internet Technologies
Department of Information Engineering (DINFO)
http://www.disit.dinfo.unifi.it

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





Case Study C

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Department of Information Engineering (DINFO)
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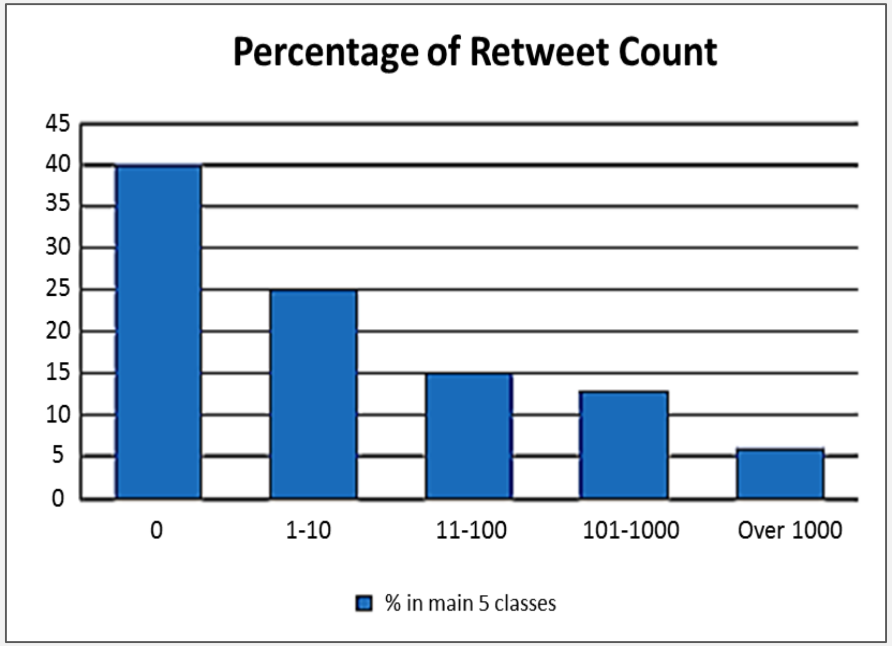
Tweet proneness Metrics

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

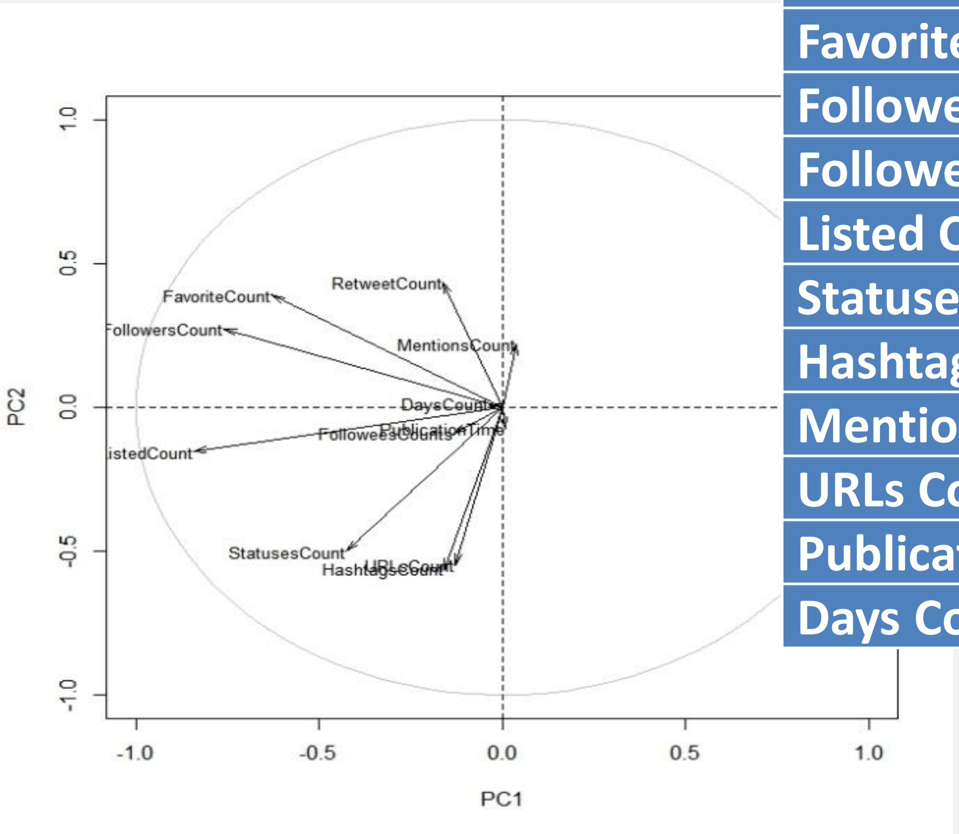
Data sets:

- 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

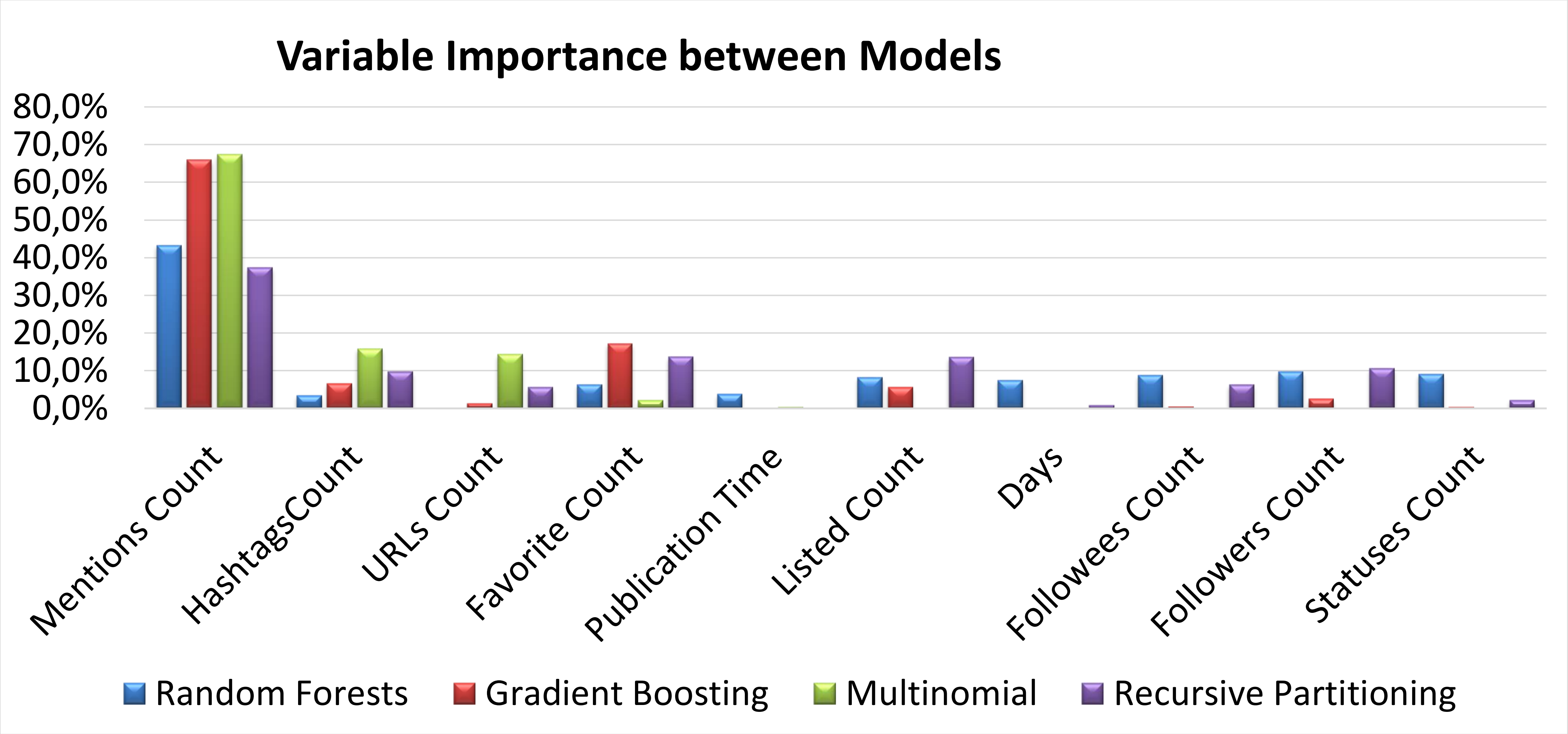
Classifier Models	Accuracy	Precision	Recall	F_1 score	Processing Time in sec.
Recursive Partitioning (Stat)	**0.6807**	**0.8512**	**0.7767**	**0.8122**	**180**
Random Forests (ML)	0.6884	0.8601	0.7866	0.8217	198968
Gradient boosting (ML)	0.6796	0.8534	0.7731	0.8113	64448
Multinomial Model (Stat)	0.6411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



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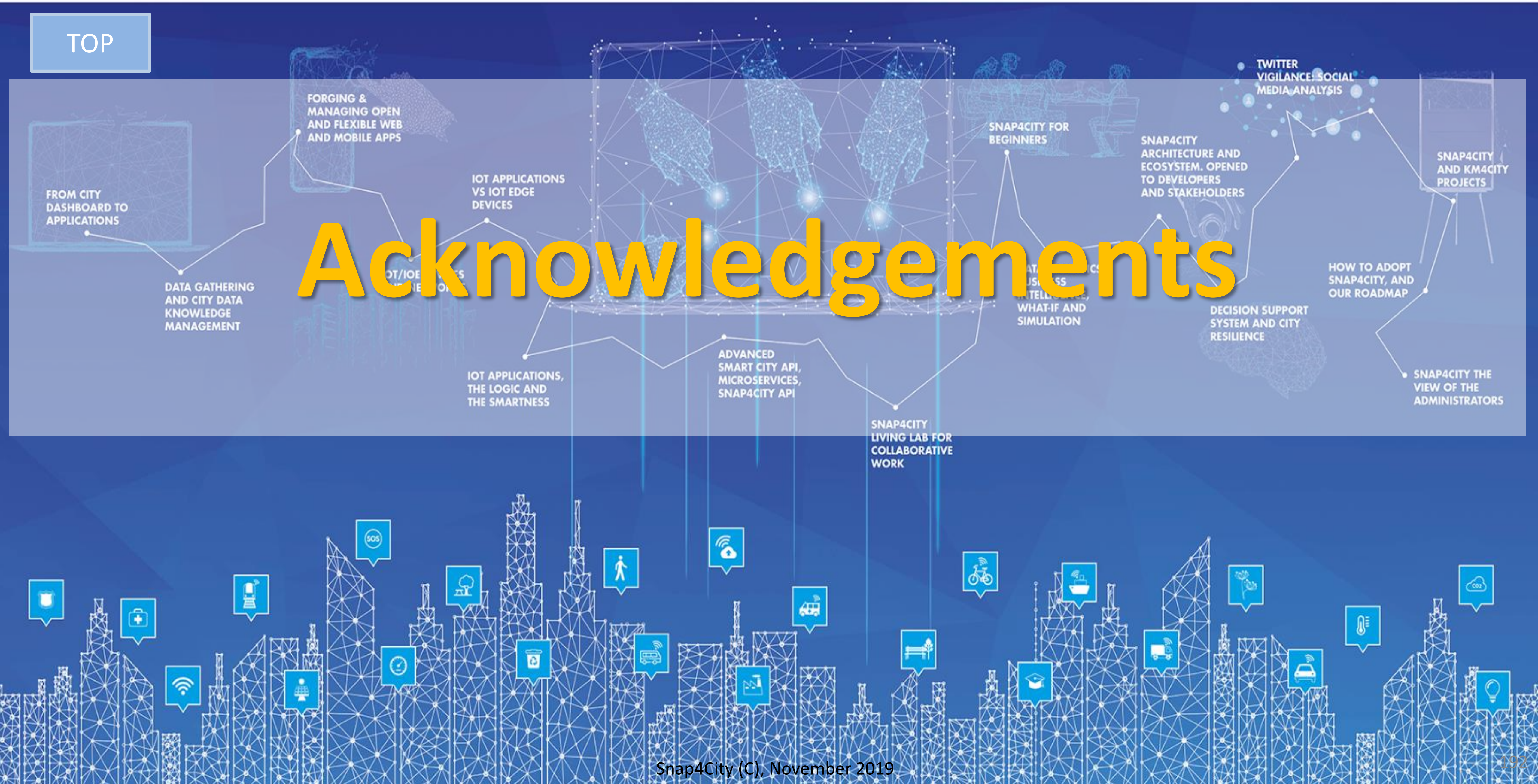
Acknowledgements



Snap4City managed to provide a maximum of information, flows, in depth analysis with the data provided.

There is no other platform that collects all city actors together.

The City officials and ICT officials were impressed with the performance of the Platform when loading the heavy, "resource-" demanding applications and dashboard.

The technical level of the Platform and its strong points such as the way real-time data is used, the algorithms, data clean-up possibilities of the Platform, presented data and information is state-of-the-art and impressive.

The data handling throughout the Platform is considered as one of the strong points in the Platform and of an extremely sophisticated level.

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- Thanks to the European Commission for founding. All slides reporting logo of **Snap4City** https://www.snap4city.org **of Select4Cities H2020** are representing tools and research founded by European Commission for the **Select4Cities** project. **Select4Cities** has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation Programme (grant agreement n° 688196)
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- **Km4City** *is an open technology and research line of DISIT Lab exploited by a number of projects. Some of the innovative solutions and research issues developed into projects are also compliant and contributing to the Km4City approach and thus are released as open sources and are interoperable, scalable, modular, standard compliant, etc.*

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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
- Events
- LOD

ckan

- Twitter Vigilance
- Social Media Analytics, Sentiment Analysis

Km4City 1.4

2015

Km4City 1.5

resolute (2015-18) H2020
- Resilience Decision Support
- Smart First Aid
- User Behaviour Analysis, predictions
- Risk Analysis

E015 digital ecosystem
Powered by EXPO MILANO 2015

- Sardinia Region Smart City Strategies and plan

FIWARE

GREEN IMPACT CAPACITY

2016

Sii-Mobility (2016-19)
SII-MOBILITY SCN
- Infomobility
- Mobile App
- Routing
- Multimodality

Km4City 1.6.2
- Smart Energy
- Sustainable Mobility
- Control Room Dashboard

(2016-21) H2020 REPLICATE

Km4City 1.6.4
Sii-Mobility
- Origin-Destination and trajectories
- Traffic Reconstruction
- Offer Analysis
- OBU, smart devices

(2016-19)
GHOST SIR

Km4City 1.6.6 IOT/IOE
Sii-Mobility

Node-RED

SNAP4CITY

SELECT for Cities H2020 (2017-19)
- IOT/IOE, IOT App
- Living Lab
- Maker Support
- IOT Edge
- Smart City IOT
- GDPR
- Privacy & Security

life weee (2017-20)
- Smart Waste

2017

TRAFAIR CEF (2018-21)

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

2018
- 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

POR CreO, Regione Toscana

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

- Traffic and Mobility Impact on Pollution
- NOX predictions

2019

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