SNAP4CITY
www.snap4city.org
www.snap4solutions.org

KM4CITY
www.km4city.org

Data Analytics and Artificial Intelligence

Nov. 2023, Course, Part 4
https://www.snap4city.org/944
https://www.snap4city.org/577

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DIGITAL TWIN SOLUTIONS TO SETUP SUSTAINABLE DECISON SUPPORT SYSTEMS AND BUSINESS INTELLIGENCE

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

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

SNAP4CITY

KM4CITY

SNAP4 Appliances and Dockers Installations

100% OPEN SOURCE

SMARTCITY EXPO WORLD CONGRESS
7-9 November 2023, Barcelona, Spain
Visit Snap4City in Hall 1

Data Analytics and Artificial Intelligence

Data Analytic

EU GDPR COMPLIANT

PEN Test Passed

Powered by FIWARE

SNAP4CITY on EUROPEAN OPEN SCIENCE CLOUD MARKETPLACE

Nov. 2023, Course, Part 4

https://www.snap4city.org/944
https://www.snap4city.org/577

Node-RED

SCALABLE SMART ANALYTIC APPLICATION BUILDER FOR SENTIENT CITIES

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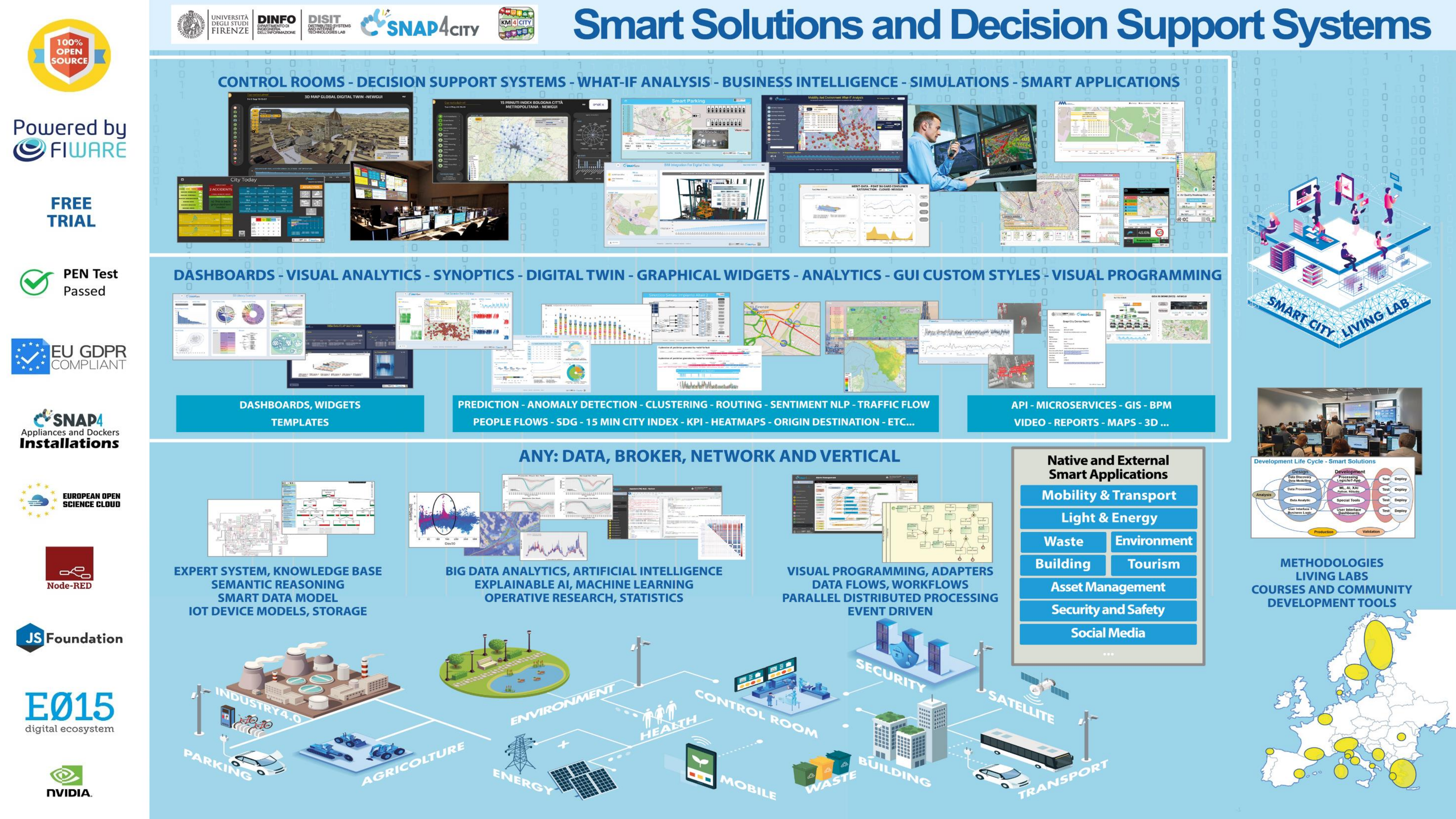
Smart Solutions and Decision Support Systems
100% OPEN SOURCE
Powered by FIWARE
FREE TRIAL
PEN Test Passed
EU GDPR COMPLIANT
SNAP4 Appliances and Dockers Installations
EUROPEAN OPEN SCIENCE CLOUD
Node-RED
JS Foundation
E015 digital ecosystem
NVIDIA
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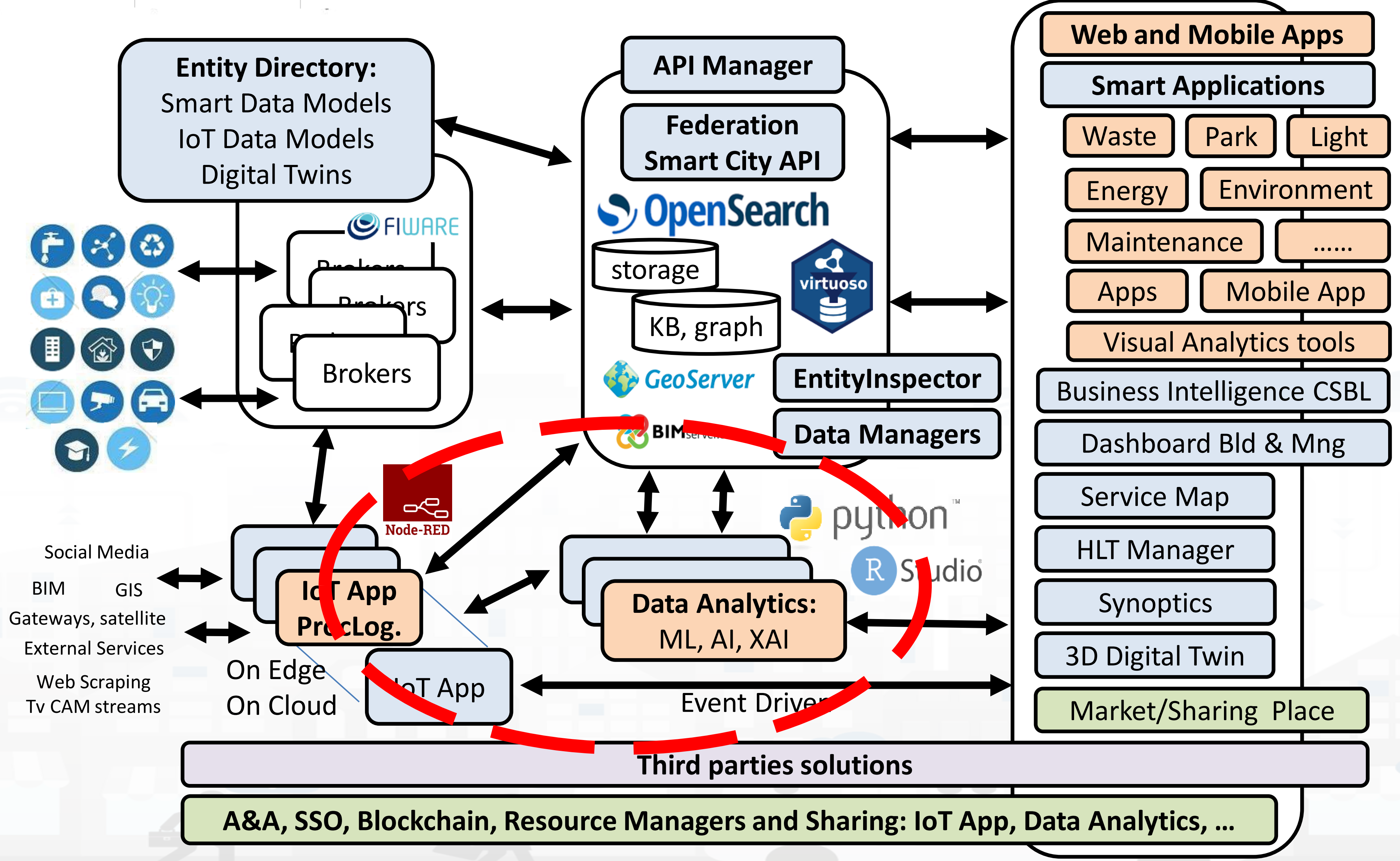
SNAP4CITY
KM4CITY
CONTROL ROOMS - DECISION SUPPORT SYSTEMS - WHAT-IF ANALYSIS - BUSINESS INTELLIGENCE - SIMULATIONS - SMART APPLICATIONS
DASHBOARDS - VISUAL ANALYTICS - SYNOPTICS - DIGITAL TWIN - GRAPHICAL WIDGETS - ANALYTICS - GUI CUSTOM STYLES - VISUAL PROGRAMMING
DASHBOARDS, WIDGETS
TEMPLATES
PREDICTION - ANOMALY DETECTION - CLUSTERING - ROUTING - SENTIMENT NLP - TRAFFIC FLOW
PEOPLE FLOWS - SDG - 15 MIN CITY INDEX - KPI - HEATMAPS - ORIGIN DESTINATION - ETC...
API - MICROSERVICES - GIS - BPM
VIDEO - REPORTS - MAPS - 3D ...
SMART CITY LIVING LAB
ANY: DATA, BROKER, NETWORK AND VERTICAL
EXPERT SYSTEM, KNOWLEDGE BASE
SEMANTIC REASONING
SMART DATA MODEL
IOT DEVICE MODELS, STORAGE
BIG DATA ANALYTICS, ARTIFICIAL INTELLIGENCE
EXPLAINABLE AI, MACHINE LEARNING
OPERATIVE RESEARCH, STATISTICS
VISUAL PROGRAMMING, ADAPTERS
DATA FLOWS, WORKFLOWS
PARALLEL DISTRIBUTED PROCESSING
EVENT DRIVEN
Native and External Smart Applications
Mobility & Transport
Light & Energy
Waste
Environment
Building
Tourism
Asset Management
Security and Safety
Social Media
...
Development Life Cycle - Smart Solutions
METHODOLOGIES
LIVING LABS
COURSES AND COMMUNITY
DEVELOPMENT TOOLS
INDUSTRY4.0
ENVIRONMENT
HEALTH
CONTROL ROOM
SECURITY
SATELLITE
PARKING
AGRICOLTURE
ENERGY
MOBILE
WASTE
BUILDING
TRANSPORT

Tech Arch



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IoT Data Models
Digital Twins
FIWARE
Brokers
Brokers
Brokers
API Manager
Federation
Smart City API
OpenSearch
storage
KB, graph
virtuoso
GeoServer
EntityInspector
Data Managers
Node-RED
python
R Studio
Social Media
BIM
GIS
Gateways, satellite
External Services
Web Scraping
Tv CAM streams
IoT App
ProcLog.
On Edge
On Cloud
IoT App
Data Analytics:
ML, AI, XAI
Event Driven
Web and Mobile Apps
Smart Applications
Waste
Park
Light
Energy
Environment
Maintenance
……
Apps
Mobile App
Visual Analytics tools
Business Intelligence CSBL
Dashboard Bld & Mng
Service Map
HLT Manager
Synoptics
3D Digital Twin
Market/Sharing Place
Third parties solutions
A&A, SSO, Blockchain, Resource Managers and Sharing: IoT App, Data Analytics, …

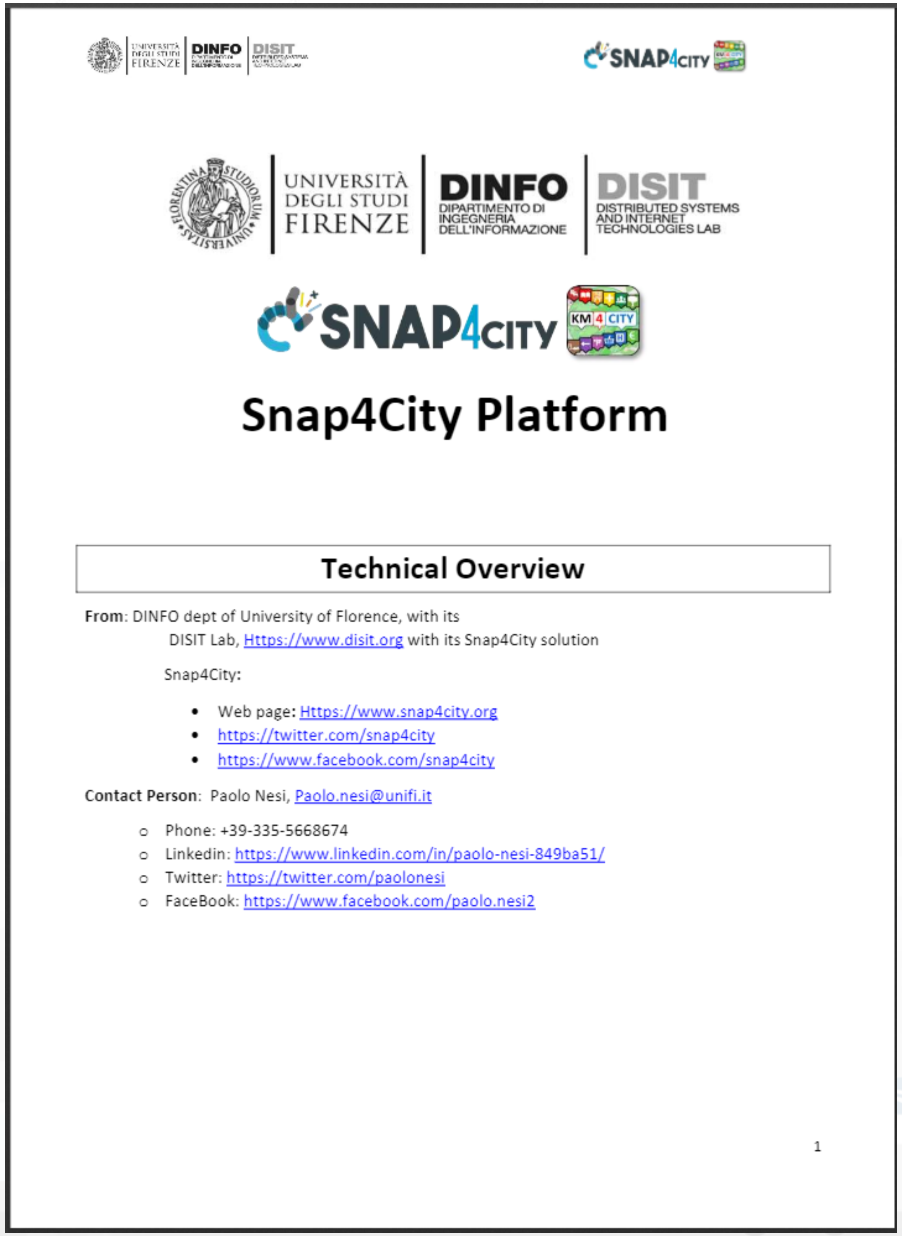
https://www.snap4city.org/944

On Line Training Material (free of charge)

1st part	2nd part	3rd part	4th part	5th part	6th part	7th part	8th
Overview	Dashboards	IOT App, IOT Network	Data Analytics	Data Ingestion processes	System and Deploy Install	Smart City API: Web & Mob. App	Design and Develop Smart Solutions

Note on Training Material

- **Course 2023**: https://www.snap4city.org/944
  - Introductionary course to Snap4City technology
- **Course** https://www.snap4city.org/577
  - Full training course with much more details on mechanisms and a wider set of cases/solutions of the Snap4City Technology
- **Documentation** includes a deeper round of details
  - Snap4City Platform Overview:
    - https://www.snap4city.org/drupal/sites/default/files/files/Snap4City-PlatformOverview.pdf
  - Development Life Cycle:
    - https://www.snap4city.org/download/video/Snap4Tech-Development-Life-Cycle.pdf
  - Client Side Business Logic:
    - https://www.snap4city.org/download/video/ClientSideBusinessLogic-WidgetManual.pdf
- **On line cases and documentation**:
  - https://www.snap4city.org/108
  - https://www.snap4city.org/78
  - https://www.snap4city.org/426



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SNAP4CITY

Snap4City Platform

Technical Overview

From: DINFO dept of University of Florence, with its DISIT Lab, Https://www.disit.org with its Snap4City solution

Snap4City:

- Web page: Https://www.snap4city.org
- https://twitter.com/snap4city
- https://www.facebook.com/snap4city

Contact Person: Paolo Nesi, Paolo.nesi@unifi.it

- Phone: +39-335-5668674
- Linkedin: https://www.linkedin.com/in/paolo-nesi-849ba51/
- Twitter: https://twitter.com/paolonesi
- FaceBook: https://www.facebook.com/paolo.nesi2

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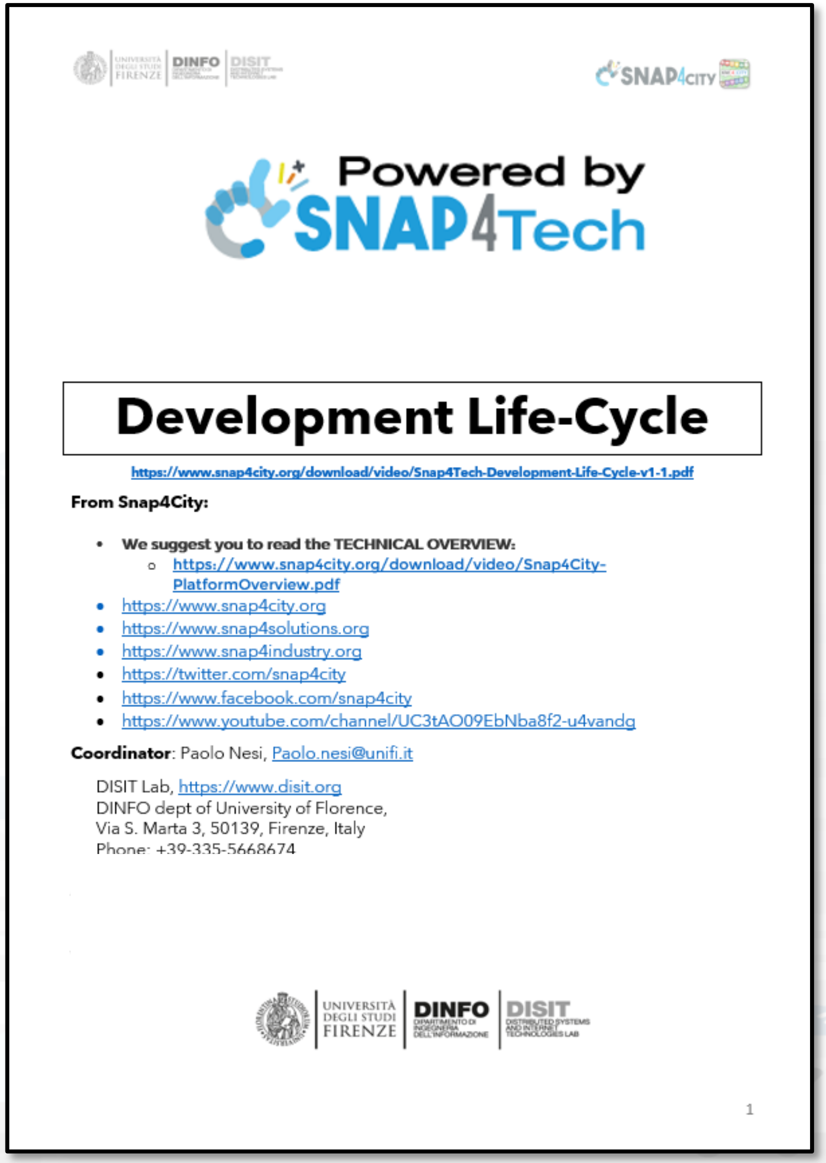
Tech Overview

- https://www.snap4city.org/drupal/sites/default/files/files/Snap4City-PlatformOverview.pdf

Development

https://www.snap4city.org/download/video/Snap4Tech-Development-Life-Cycle.pdf


Powered by SNAP4Tech

Development Life-Cycle

https://www.snap4city.org/download/video/Snap4Tech-Development-Life-Cycle-v1-1.pdf

From Snap4City:

- **We suggest you to read the TECHNICAL OVERVIEW:**
  - https://www.snap4city.org/download/video/Snap4City-PlatformOverview.pdf
- https://www.snap4city.org
- https://www.snap4solutions.org
- https://www.snap4industry.org
- https://twitter.com/snap4city
- https://www.facebook.com/snap4city
- https://www.youtube.com/channel/UC3tAO09EbNba8f2-u4vandg

Coordinator: Paolo Nesi, Paolo.nesi@unifi.it

DISIT Lab, https://www.disit.org
DINFO dept of University of Florence,
Via S. Marta 3, 50139, Firenze, Italy
Phone: +39-335-5668674

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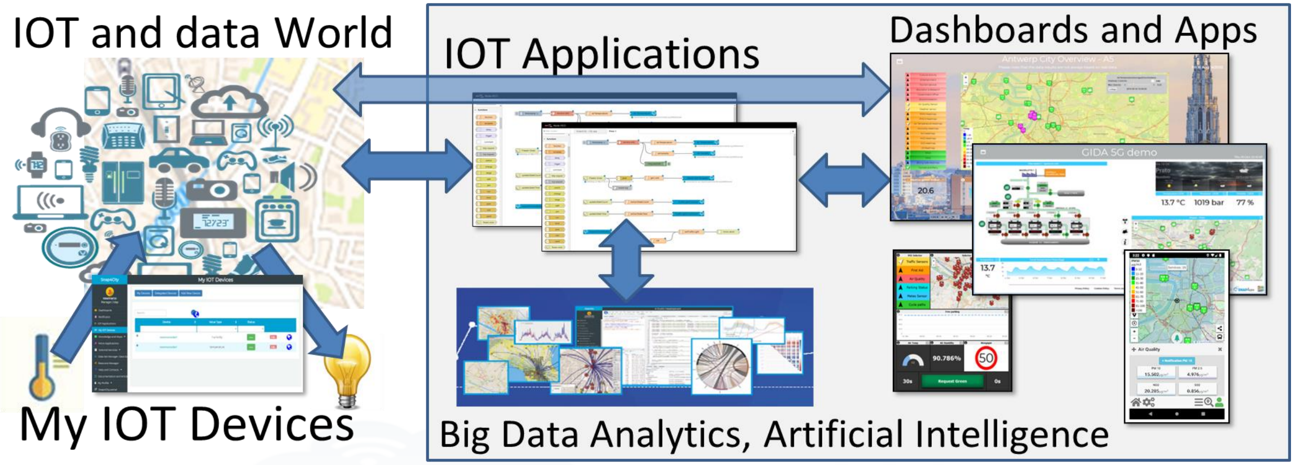
Free Trial

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

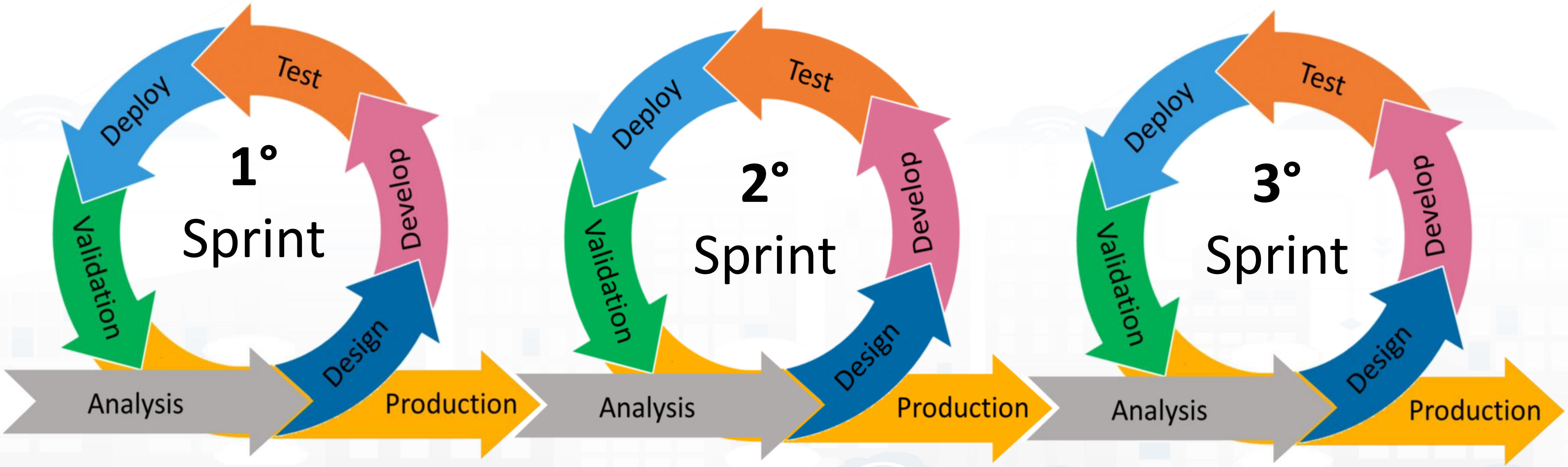


IF you need to go more in deep you can ask us to pass at the next Role becoming full AreaManager with full rights of development, also for Data Analytics, machine learning, etc.

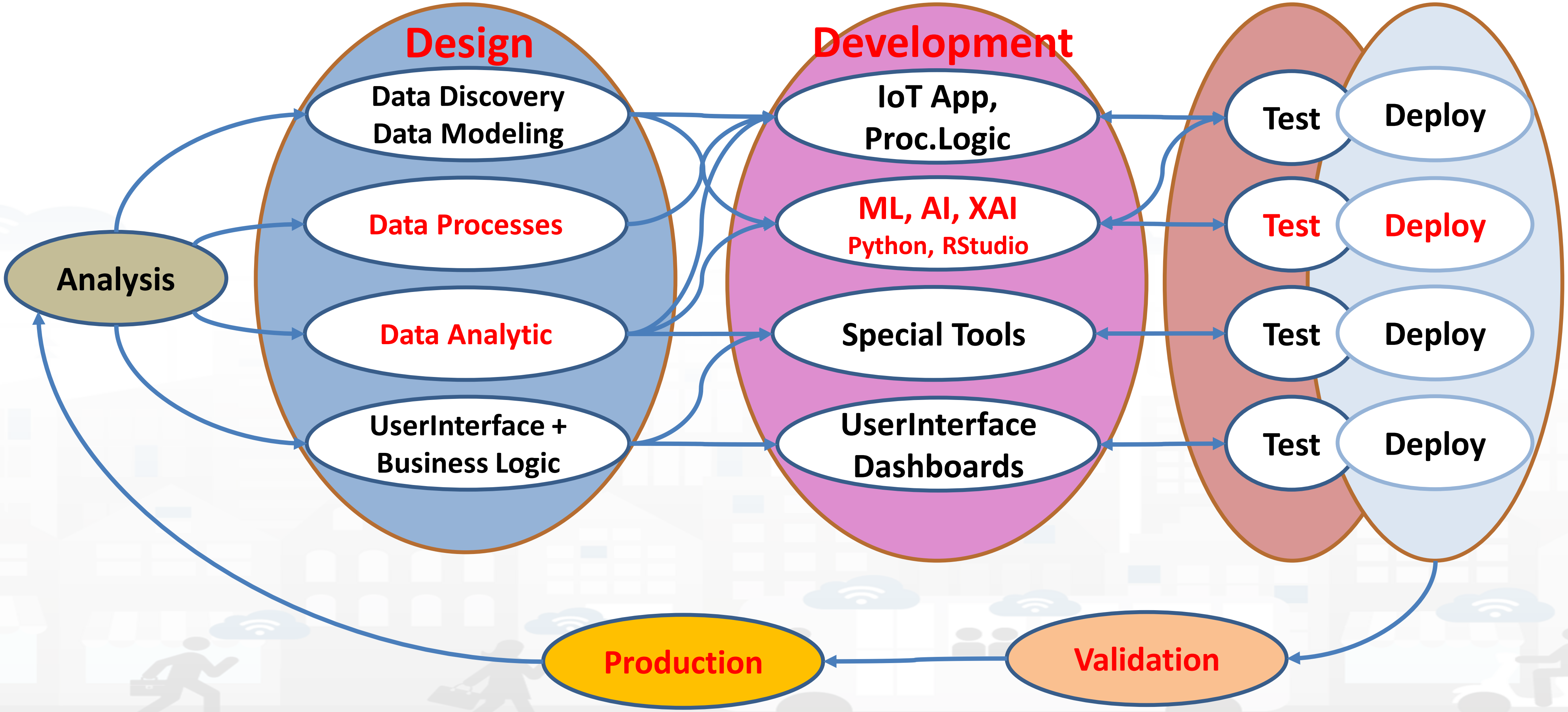
Agenda of forth part

- Why and Where use DA, AI and XAI General Life Cycle
- Data Processing
- What is Data Analytics, DA and Artificial Intelligence, AI
- List of the most relevant available DA and AI Solutions
- Predictions and Anomaly detections
- Computing: Higher Level Types Data and their representations
- How AI/XAI, and Life Cycle
- Using DA, AI, XAI in Snap4City infrastructures
  - Data Analytics ←→ IoT App / Proc.Logic
- Decision Support Systems and What-If Analysis
- Routing, Multimodal Routing, Dynamic Routing
- Business Intelligence and Visual Analytics
- Training Material

Agile Development Life Cycle by sprint Smart Solutions



Development Life Cycle Smart Solutions

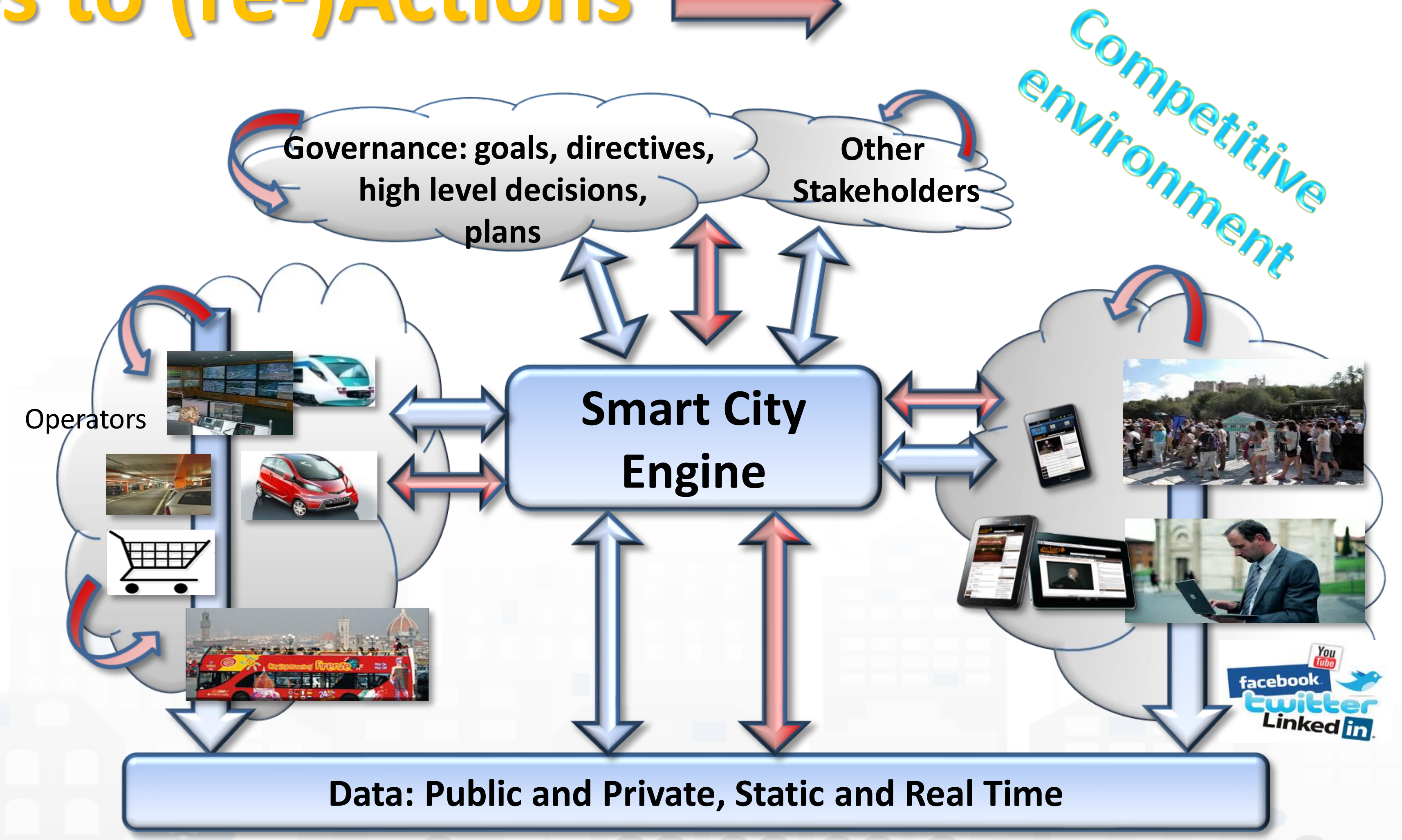


TOP

Why and Where use DA, AI and XAI → General Life Cycle

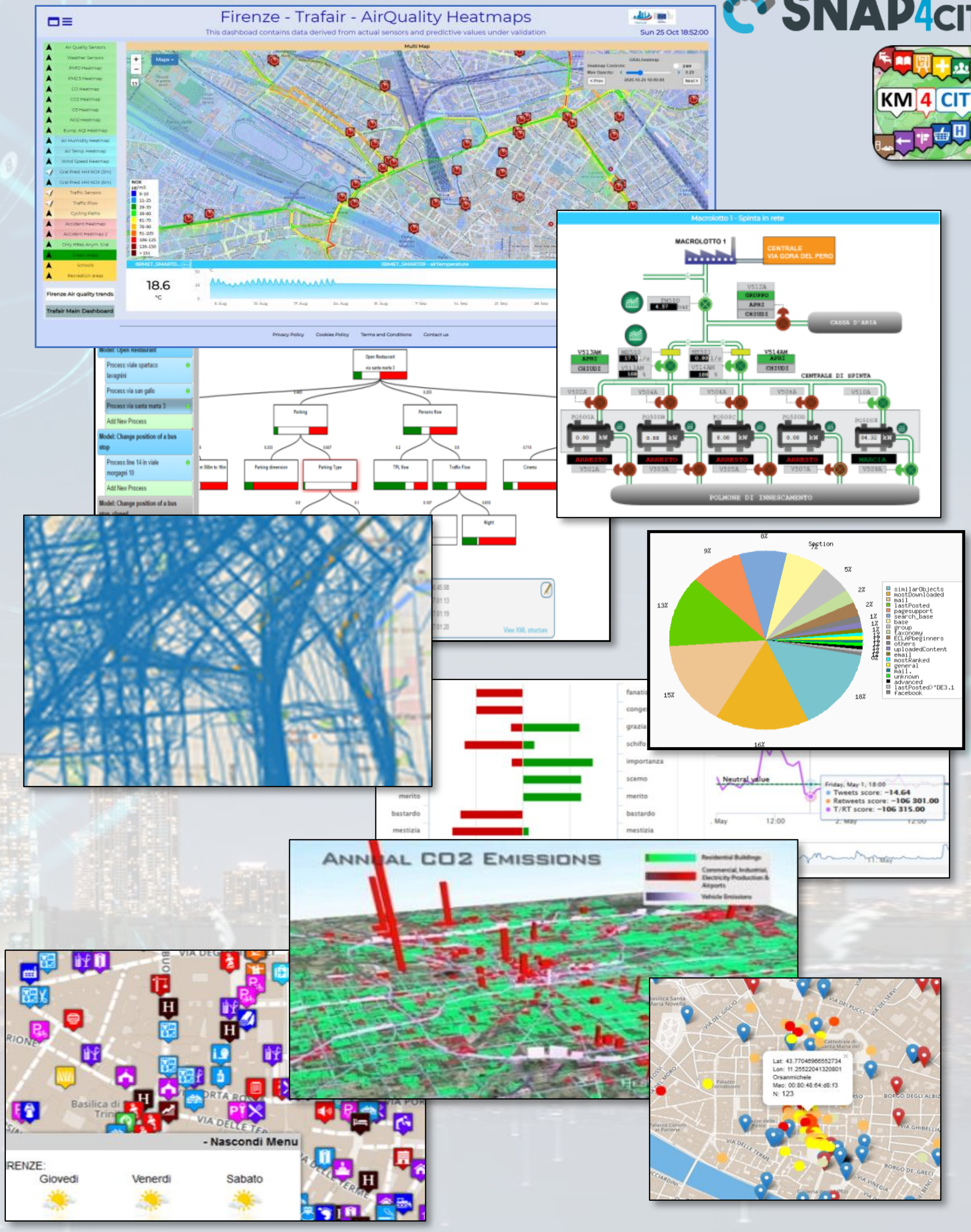
From Strategies to (re-)Actions

- Analyze
- Alerting, Early Warning
- Support Decision makers
- Plans
- Prescriptions
- Inform
- Suggest
- Engage
- Research



Data Driven Decision Support

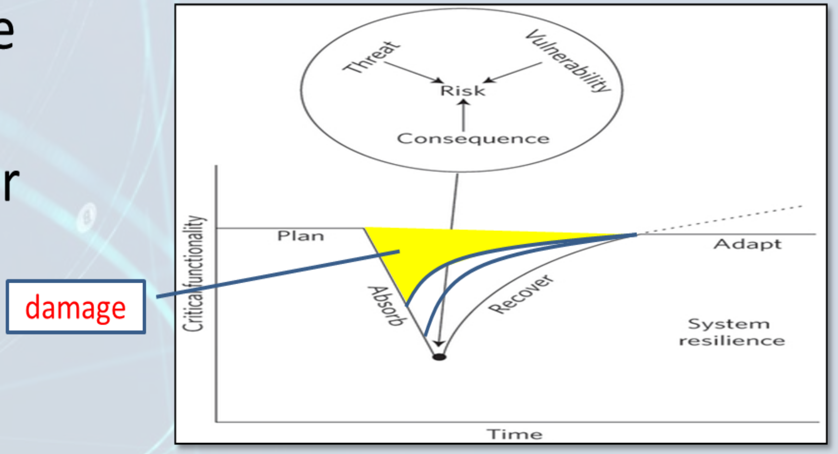
- Decision Support system
- Assessment / Strategies
- Data Rendering,
  - visual analytics, business intel..
- Data Analytics, ML, AI
- Data aggregation, Storage, indexing
- Data Ingestion

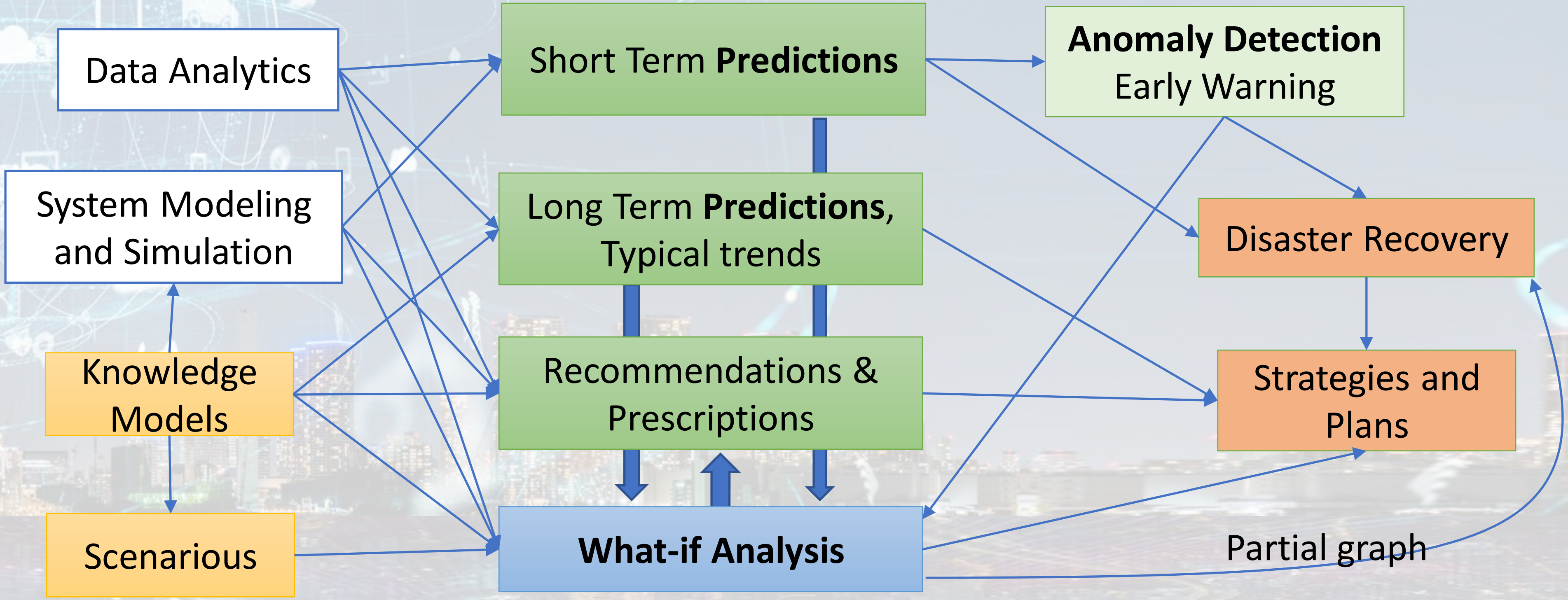


Snap4City Analytics

- Decision support systems
- Improvement of life quality
- Sustainable Solutions
- Reduction of costs
- Risk Assessment
- Resilience

Prepare
Absorb
Recover
Adapt

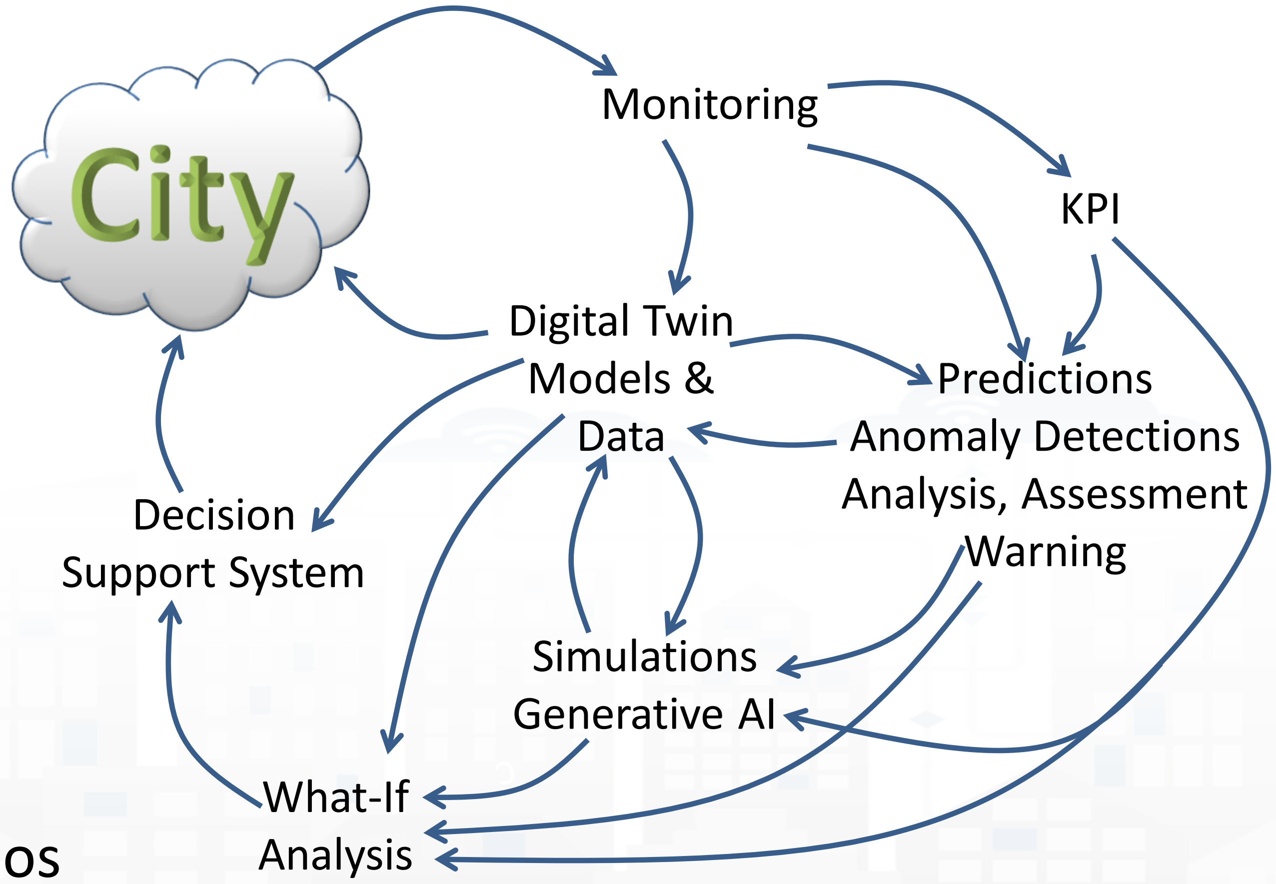




Decision Support System
Targeting Indicators: Quality of Life, PUMS, SUMI, KPI, SDG, 15MinIndex,…

Main tasks

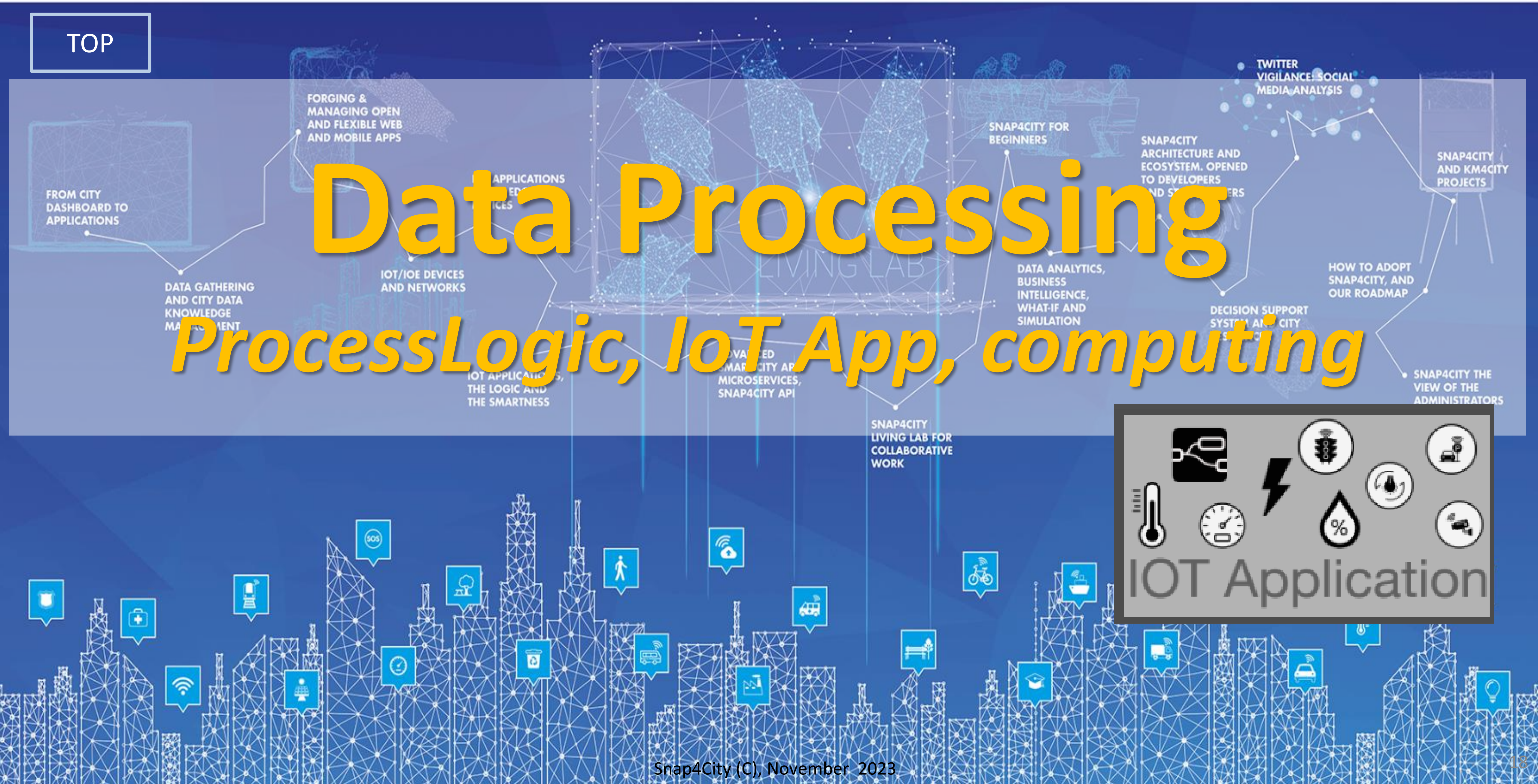
- **Controlling Status: management, and operational**
  - Monitoring via KPI
  - Computing predictions vs KPI
  - Anomaly detection
  - Neuro-Symbolic analysis
  - Risk assessment
  - Early warning on critical conditions
- **Making plan: tactic and strategic, medium and long range**
  - Simulation & predictions
  - Generative AI Prescriptions, scenarios
  - Resilience to Unexpected unknows
  - What-if analysis wrt scenarios



TOP

Data Processing

ProcessLogic, IoT App, computing



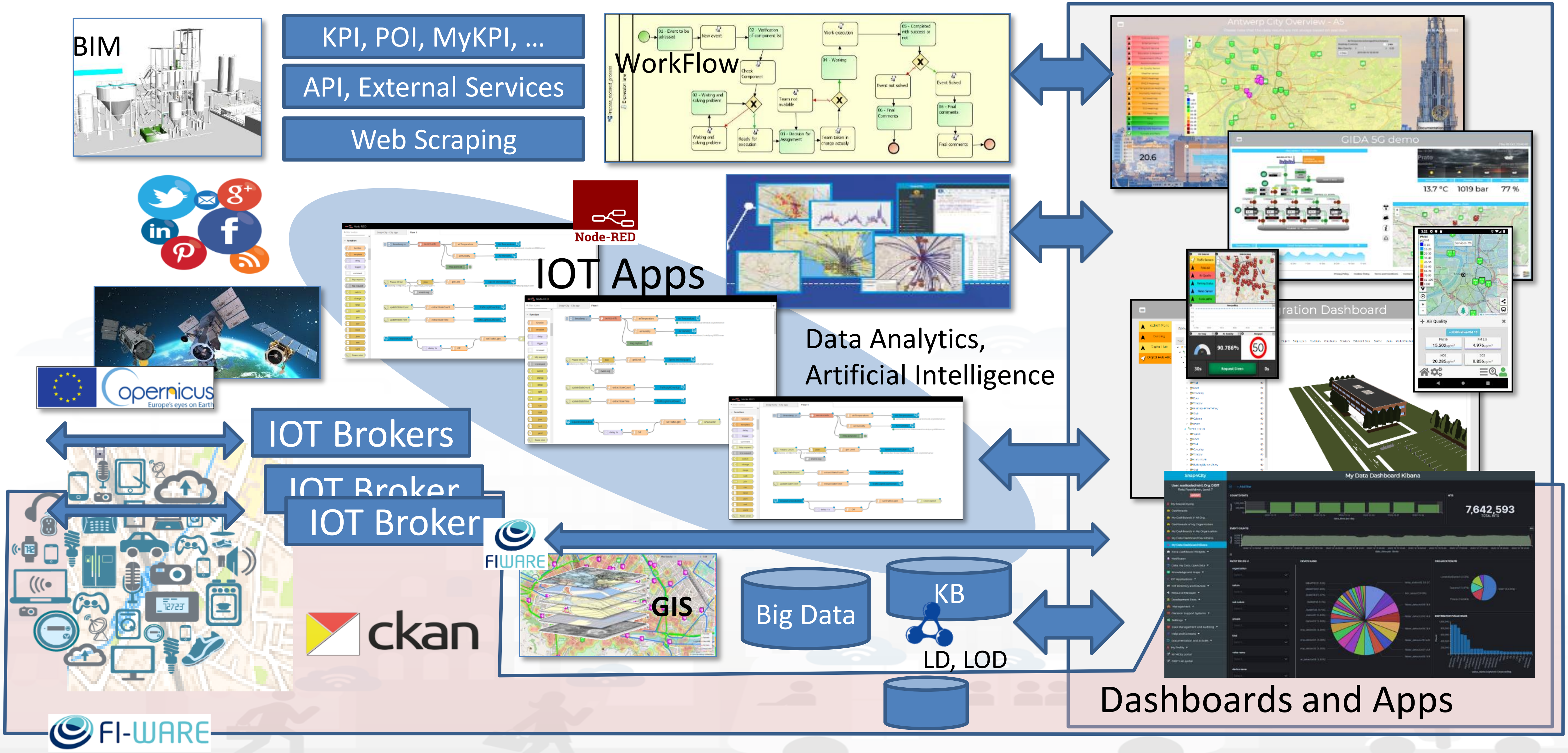
In This Section

- Data Processing, definition
- Computing KPI & Indexes
- Traffic flow data
  - Computing Traffic Flow In/out of the city
  - Computing CO2 from traffic flow data
- Computing quality of Public Transportation

Definition: Data processing

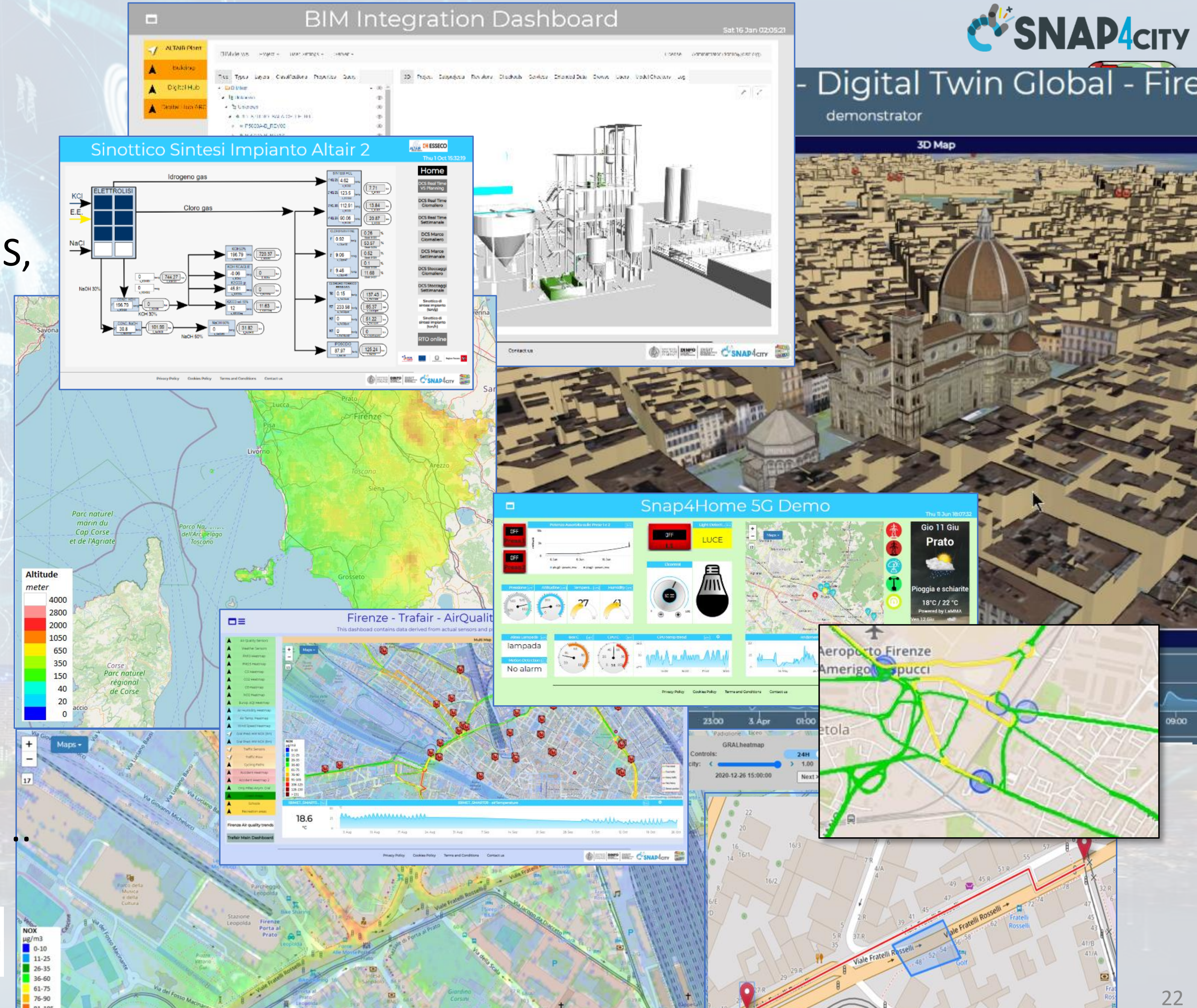
- **Data Processing:** transformation of data into meaningful information through various operations and manipulations.
  - make informed decisions, and support various business processes
  - **Via:** collecting, data entry, organizing, analyzing, interpreting data to extract insights, validation, sorting, filtering, aggregation, computing indexes, calculation, and reporting.
  - → convert data into a more usable and valuable form for further analysis or decision-making purposes.
- ***Snap4City provides support for implementing Data processing:***
  - *Proc.Logic / IoT Apps: on cloud and on Edge*
  - *Python processes in containers or on Edge*
  - *R Studio processes in containers, on server, on premise*

Concept


BIM
KPI, POI, MyKPI, …
API, External Services
Web Scraping
WorkFlow
Node-RED
IOT Apps
Data Analytics,
Artificial Intelligence
copernicus
Europe's eyes on Earth
IOT Brokers
IOT Broker
IOT Broker
FIWARE
GIS
Big Data
KB
LD, LOD
ckan
Dashboards and Apps
FI-WARE

High Level Types

- POI, IOT Devices, shapes,..
  - FIWARE Smart Data Models,
  - IoT Device Models
- GIS, maps, orthomaps, WFS/WMS, GeoTiff, calibrated **heatmaps**, ..
- **Satellite data, ..**
- **traffic flow**, **typical trends**, ..
- **trajectories**, events, Workflow, ..
- **3D Models**, BIM, Digital Twins, ..
- **OD Matrices** of **several kinds**, ..
- Dynamic icons/pins, ..
- Synoptics, **animations**, ..
- KPI, personal KPI,..
- social media data, TV Stream,
- **routing**, multimodal, constraints, ..
- **decision scenarios, ….**
- etc.



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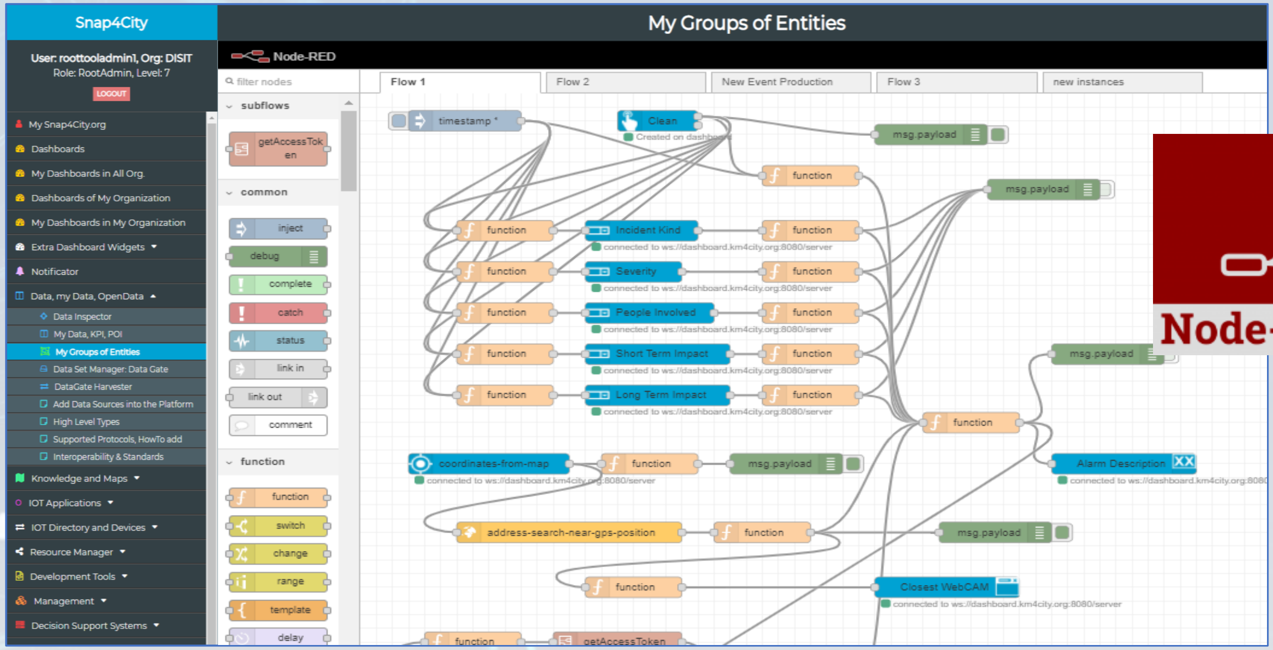
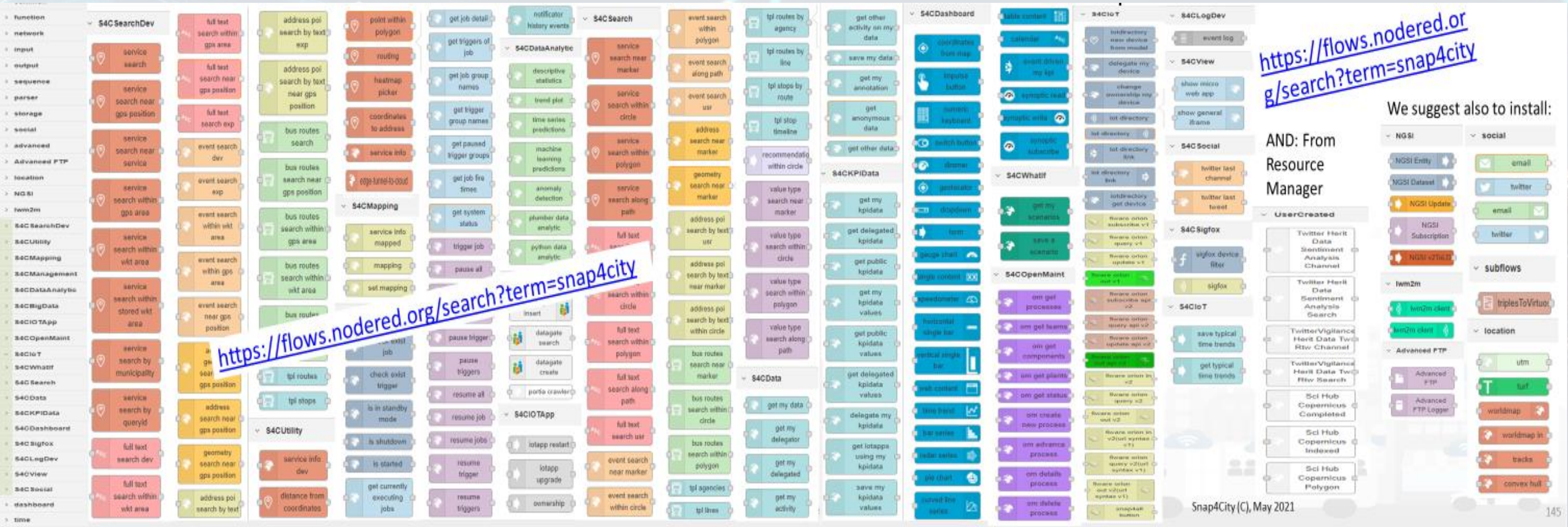
Ingestion, aggreg. → exploitation

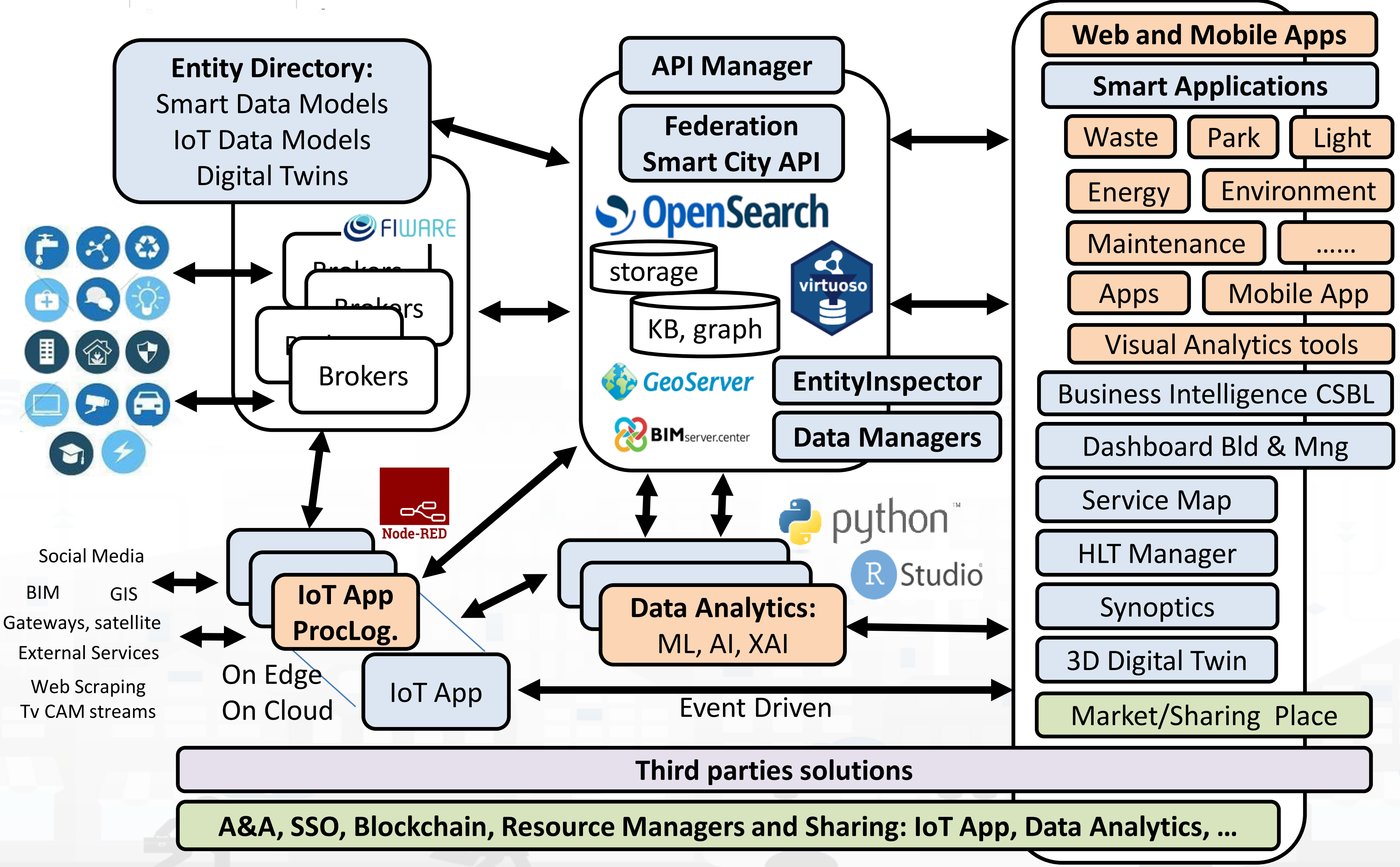
- **IoT App Visual Programming, no coding**
  - **Data transformation**
  - **Integration, Interoperab.**
  - **Scripting Data Analytics, AI..**
  - **Data ingestion**
  - **Business logic**



- **Edge and Cloud**
- **MicroServices** data d develop via visual language Node-RED



Tech Arch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EntityInspector
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Web and Mobile Apps
Smart Applications
Waste
Park
Light
Energy
Environment
Maintenance
……
Apps
Mobile App
Visual Analytics tools
Business Intelligence CSBL
Dashboard Bld & Mng
Service Map
HLT Manager
Synoptics
3D Digital Twin
Market/Sharing Place
Node-RED
Social Media
BIM
GIS
Gateways, satellite
External Services
Web Scraping
Tv CAM streams
IoT App
ProcLog.
On Edge
On Cloud
IoT App
python
R Studio
Data Analytics:
ML, AI, XAI
Event Driven
Third parties solutions
A&A, SSO, Blockchain, Resource Managers and Sharing: IoT App, Data Analytics, ...

TOP

Computing, kpi & Indexes

indicators

Pollutant	Averaging period	Objective and legal nature and concentration	Comments	WHO guidelines Concentration	WHO guidelines 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	

- **United Nations Sustainable Development Goals, SDGs** (for which cities can do more to achieve some of the 17 SDGs, https://sdgs.un.org/goals);
- **15 minutes cities** (where primary services must be accessible within 15 minutes on foot);
- **objectives of the European Commission** in terms of pollutant emissions for: NO2, PM10, PM2.5 (https://environment.ec.europa.eu/topics/air_en);
- **PUMS: mobility and transport vs wnv**
- **SUMI: mobility and transport vs env**
- **ISO indicators: city smartness, digitization. Tech level**
- ….

Global Vs Local


UNITED NATIONS
SUSTAINABLE DEVELOPMENT GOALS
1 NO POVERTY
2 ZERO HUNGER
3 GOOD HEALTH AND WELL-BEING
4 QUALITY EDUCATION
5 GENDER EQUALITY
6 CLEAN WATER AND SANITATION
7 AFFORDABLE AND CLEAN ENERGY
8 DECENT WORK AND ECONOMIC GROWTH
9 INDUSTRY, INNOVATION AND INFRASTRUCTURE
10 REDUCED INEQUALITIES
11 SUSTAINABLE CITIES AND COMMUNITIES
12 RESPONSIBLE CONSUMPTION AND PRODUCTION
13 CLIMATE ACTION
14 LIFE BELOW WATER
15 LIFE ON LAND
16 PEACE, JUSTICE AND STRONG INSTITUTIONS
17 PARTNERSHIPS FOR THE GOALS
SUSTAINABLE DEVELOPMENT GOALS

Sustainable Development Goals (SDGs) - Obiettivi di sviluppo sostenibile

RAPPORTO 2021

Istat Istituto Nazionale di Statistica

1 SCONFIGGERE LA POVERTÀ — 21 indicatori

9,4% persone in **POVERTÀ ASSOLUTA**

2 SCONFIGGERE LA FAME — 16 indicatori

15,8% **COLTIVAZIONI BIOLOGICHE** su **SUPERFICIE AGRICOLA** utilizzata

3 SALUTE E BENESSERE — 37 indicatori

66,5% **COPERTURA VACCINALE ANTINFLUENZALE** età 65+

4 ISTRUZIONE DI QUALITÀ — 34 indicatori

26,9 **POSTI** autorizzati negli **ASILI NIDO** e servizi integrativi per la prima infanzia per 100 bambini di 0-2 anni

5 PARITÀ DI GENERE — 17 indicatori

49,6 **DONNE VITTIME DI VIOLENZE** segnalate al numero di pubblica utilità contro la violenza e lo stalking 1522 per 100.000 donne

6 ACQUA PULITA E SERVIZI IGIENICO-SANITARI — 18 indicatori

58,0% **ACQUA EROGATA** agli utenti sulla immessa in rete

7 ENERGIA PULITA E ACCESSIBILE — 12 indicatori

18,2% **ENERGIA DA FONTI RINNOVABILI** sul consumo finale lordo di energia

8 LAVORO DIGNITOSO E CRESCITA ECONOMICA — 28 indicatori

62,6% tasso di **OCCUPAZIONE** (20-64 anni)

9 IMPRESE, INNOVAZIONE E INFRASTRUTTURE — 26 indicatori

3,6% **OCCUPATI** con posizioni specializzate sulle **ICT**

10 RIDURRE LE DISUGUAGLIANZE — 15 indicatori

177.254 **NUOVI PERMESSI DI SOGGIORNO** rilasciati

11 CITTÀ E COMUNITÀ SOSTENIBILI — 32 indicatori

28,3% persone che vivono in **ABITAZIONI SOVRAFFOLLATE**

12 CONSUMO E PRODUZIONE RESPONSABILI — 26 indicatori

2,5% **IMPRESE** che redigono bilanci e/o **RENDICONTAZIONI AMBIENTALI** e di **SOSTENIBILITÀ**

13 LOTTA CONTRO IL CAMBIAMENTO CLIMATICO — 15 indicatori

7,1 **EMISSIONI** di CO_2 e altri gas clima alteranti tonnellate per abitante

14 LA VITA SOTT'ACQUA — 4 indicatori

65,5% **COSTE** marine **BALNEABILI**

15 LA VITA SULLA TERRA — 21 indicatori

31,7% **AREE FORESTALI** in rapporto alla superficie terrestre

16 PACE, GIUSTIZIA E ISTITUZIONI SOLIDE — 19 indicatori

105,5 **DETENUTI** in istituti di detenzione per 100 posti disponibili

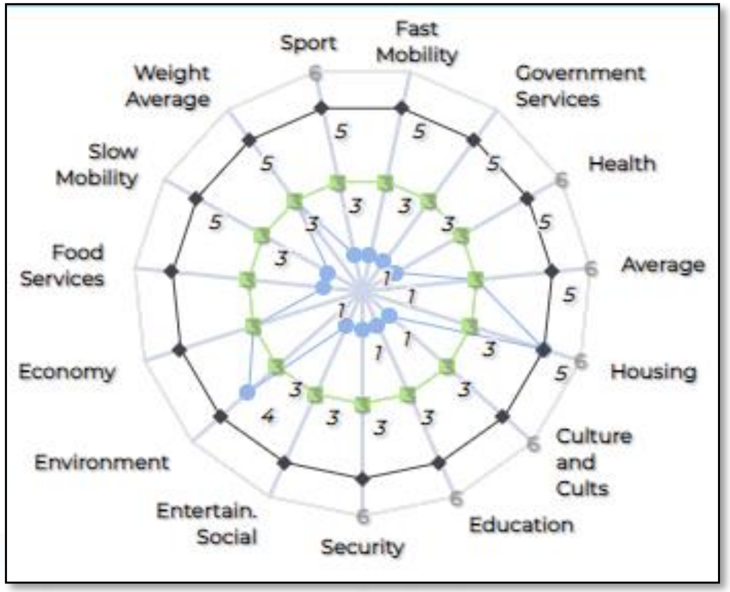
17 PARTNERSHIP PER GLI OBIETTIVI — 9 indicatori

0,22% **AIUTO PUBBLICO ALLO SVILUPPO** come quota del reddito nazionale lordo

... tutti gli altri indicatori sono presenti nel Rapporto 2021

Indicators, KPI, etc.

- Can be **formally defined or not**
  - Italian PUMS is not fully formally defined
  - SUMI is formally defned
  - SDG is not formally defined
- In any case they are **based on SubIndicators / SubIndex**
  - They can and have to be evauated with ***some formulas*** and compounded to obtain the general indicator, and the formulas should be validated
  - To use the SubIndicator/Index is a way to reduce the problem and complexity



Concept 15MinIndex

Assessing in each point of the area (city or rural) the capability of providing services ad 15 Min walking distance for the city users

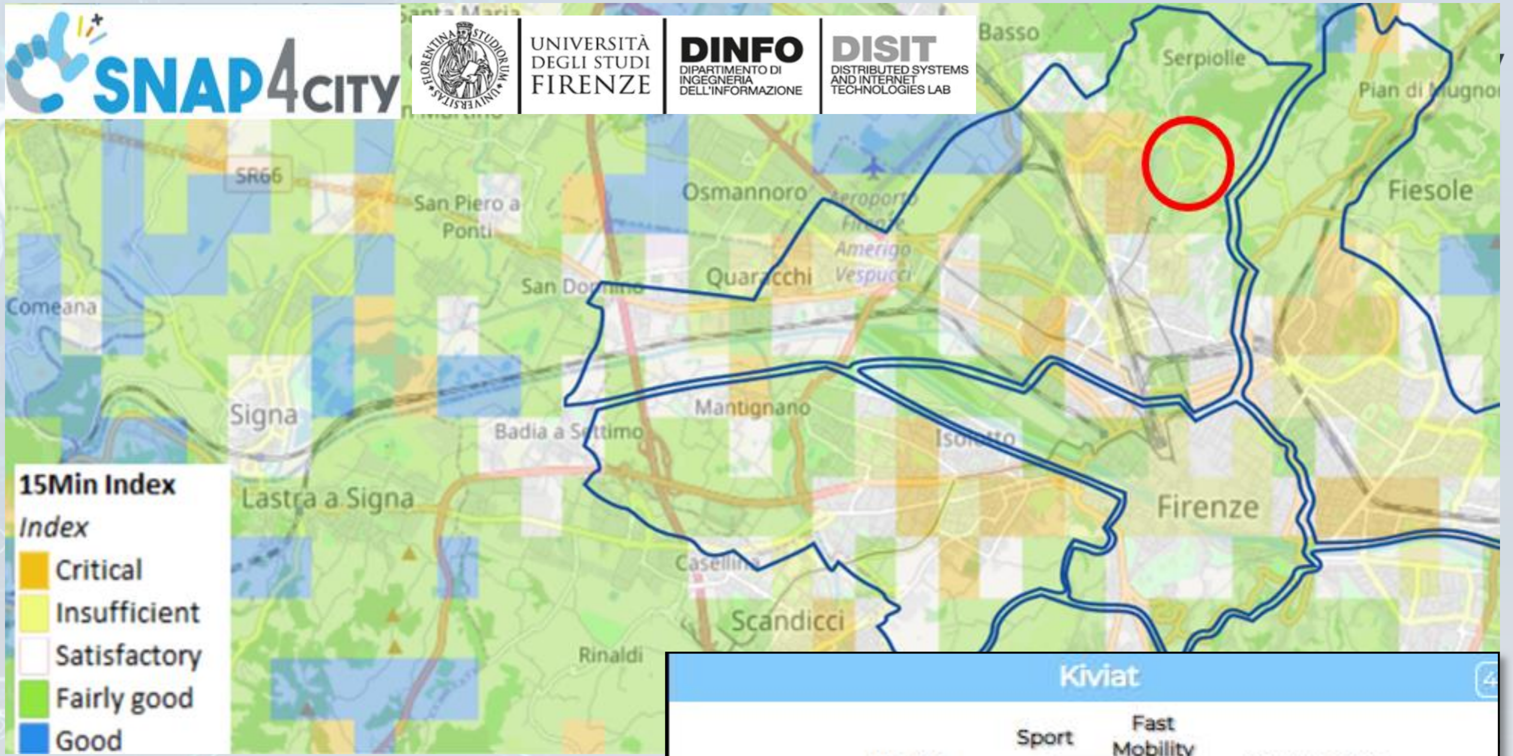
- Several different approaches from early Carlos Moreno concept
- Several different subindexes

Carlos Moreno Functions	Li et al., 2019	15MinCityIndex subindexes
living		Housing viability
	Gov	Govern Services
		Safety Services
		Culture and Cults Services
		Environment Quality
	Roads	Slow Mobility Services
		Fast Mobility Services
	[Medical]	Sport Services
working		Economy/ sustainability
	pension	
commerce	commerce	
	dining	Food Services
healthcare	medical	Health Services
education	edu	Education Services
entertainment	entertainment	Entertainment Services

15MinCityIndex

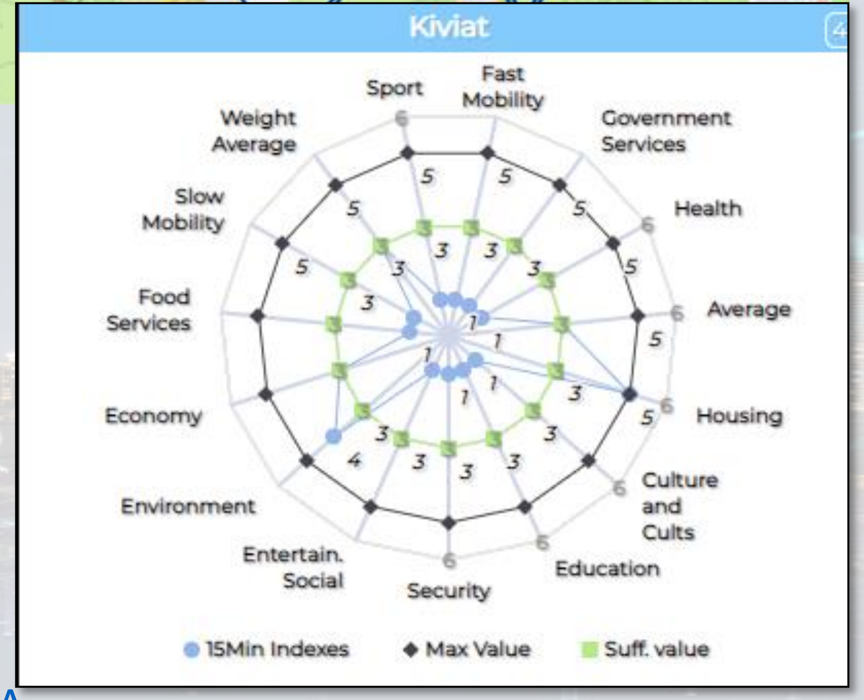
What would support my neighborhood to become a 15-Minute City?

Using the Open Data:
We developed a data analytic tool based on municipal and national open data to assess services adequacy for people living in each 15 minutes areas of the city.



Good public transport services: bus, new tram line, train stations, cycle paths.

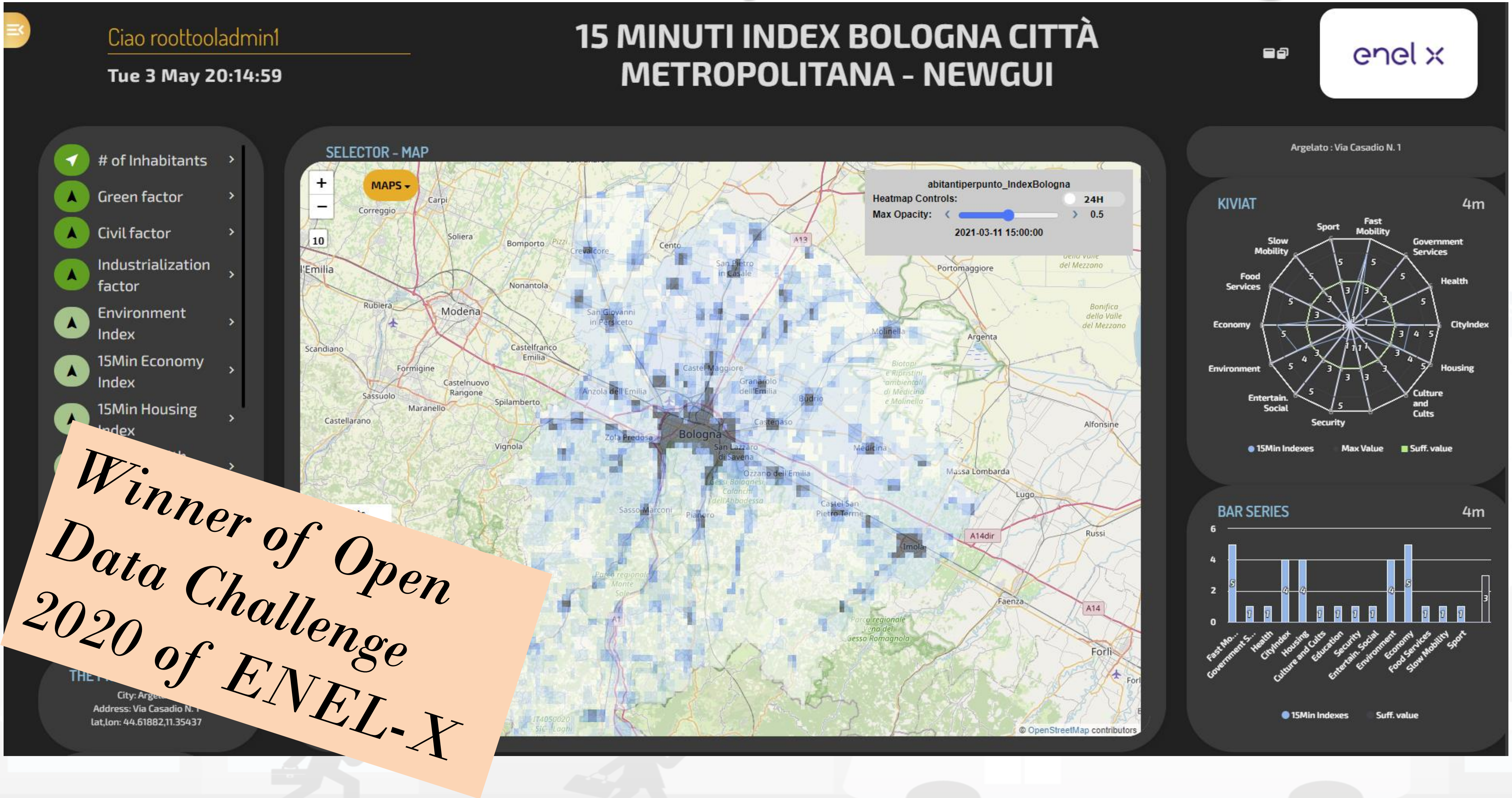
The tool supports the becoming of a 15-Minute city evaluating the service level in various domains.



Careggi/Rifredi is a relevant district in Florence because of hosting the main Florence/Tuscany hospitals Careggi and Meyer, but also university headquarters and many other workplaces.

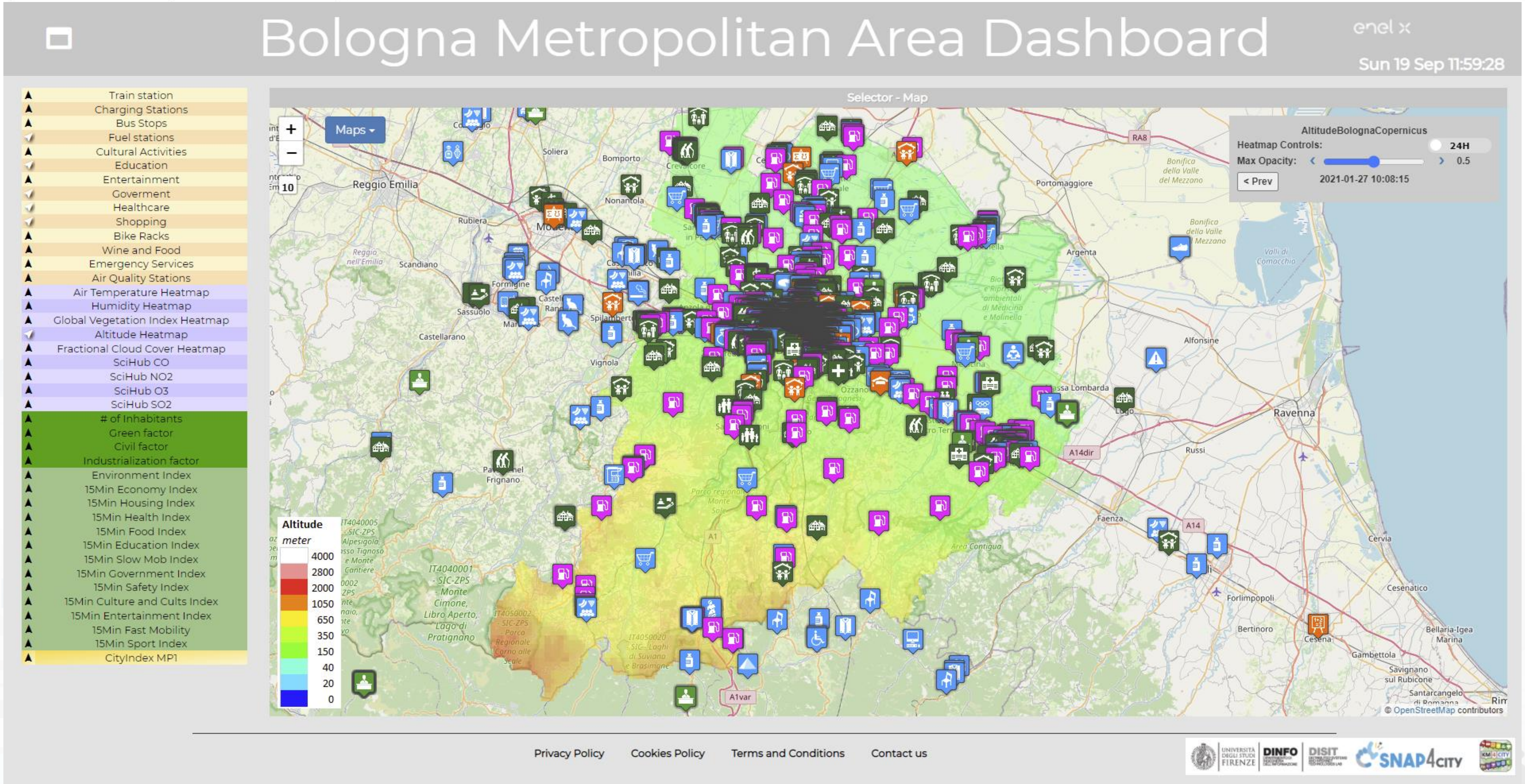
https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MjkzOA==

15MinCityIndex on Bologna



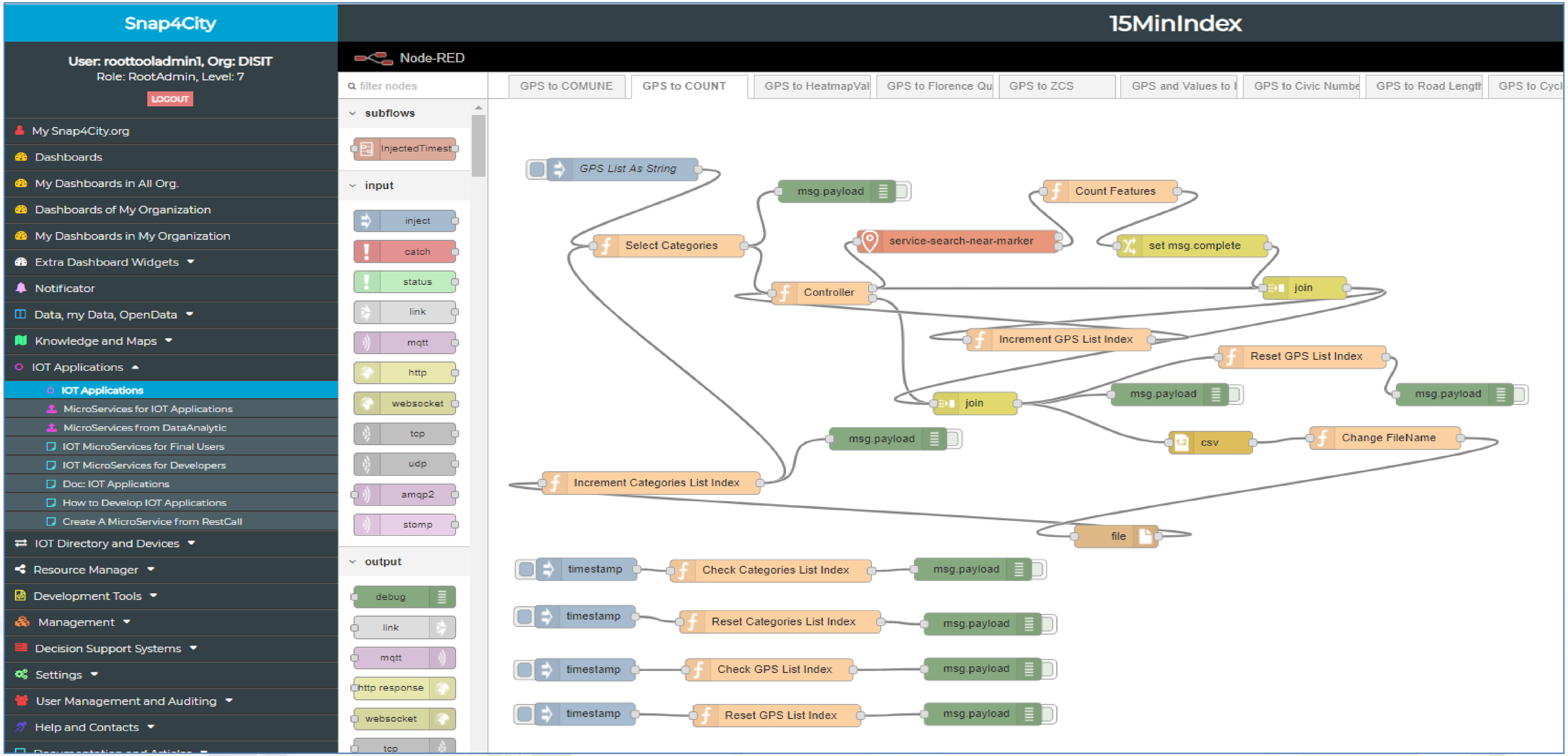
Winner of Open Data Challenge 2020 of ENEL-X

https://www.snap4city.org/dashboardSmartCity/view/Baloon-Dark.php?iddasboard=MzQxMg==



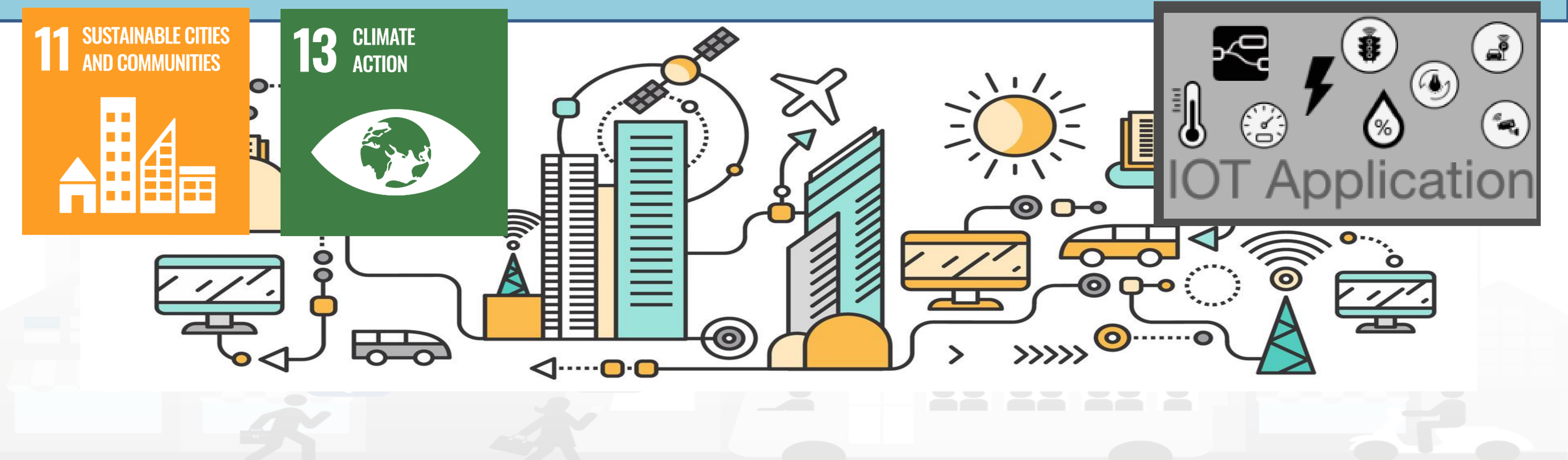
https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MzA1OA==

IoT App....


Snap4City
15MinIndex
User: roottooladmin1, Org: DISIT
Role: RootAdmin, Level: 7
LOGOUT
My Snap4City.org
Dashboards
My Dashboards in All Org.
Dashboards of My Organization
My Dashboards in My Organization
Extra Dashboard Widgets
Notificator
Data, my Data, OpenData
Knowledge and Maps
IOT Applications
IOT Applications
MicroServices for IOT Applications
MicroServices from DataAnalytic
IOT MicroServices for Final Users
IOT MicroServices for Developers
Doc: IOT Applications
How to Develop IOT Applications
Create A MicroService from RestCall
IOT Directory and Devices
Resource Manager
Development Tools
Management
Decision Support Systems
Settings
User Management and Auditing
Help and Contacts
Node-RED
filter nodes
subflows
InjectedTimest
input
inject
catch
status
link
mqtt
http
websocket
tcp
udp
amqp2
stomp
output
debug
link
mqtt
http response
websocket
tcp
GPS to COMUNE
GPS to COUNT
GPS to HeatmapVal
GPS to Florence Qu
GPS to ZCS
GPS and Values to I
GPS to Civic Numbe
GPS to Road Length
GPS to Cycl
GPS List As String
msg.payload
Count Features
Select Categories
service-search-near-marker
set msg.complete
Controller
join
Increment GPS List Index
Reset GPS List Index
msg.payload
join
msg.payload
csv
Change FileName
msg.payload
Increment Categories List Index
file
timestamp
Check Categories List Index
msg.payload
timestamp
Reset Categories List Index
msg.payload
timestamp
Check GPS List Index
msg.payload
timestamp
Reset GPS List Index
msg.payload

TOP

Traffic Flow Data




60
km/h

Vehicle Flow

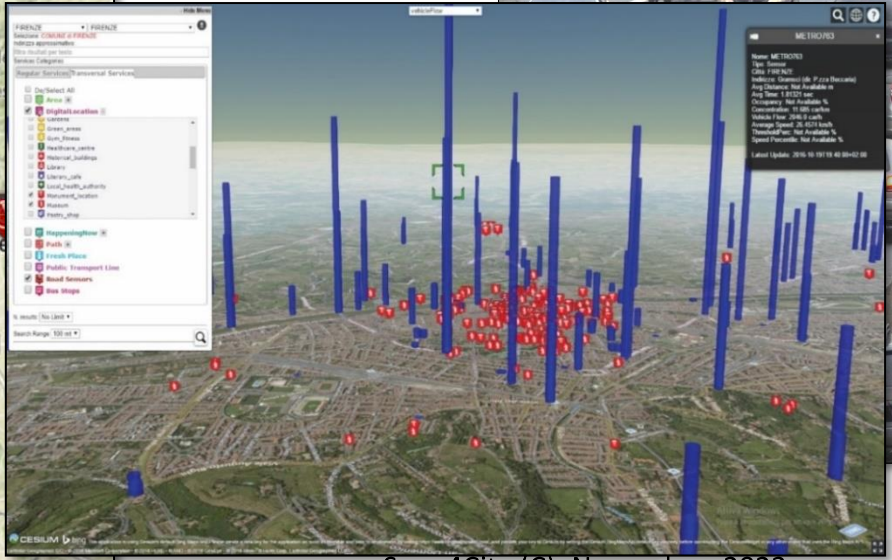
– Traffic Flow data can be used for a number of applications:
  - Traffic Flow Analysis and reconstruction
  - What-if-analysis
  - forecasting of pollutants
– The main problem is the need of consistent data:
  - Traffic Flow sensor are not 100% reliable
  - There could be some problem in data acquisition process

providing **PREDICTIONS** can be useful to improve quality of service

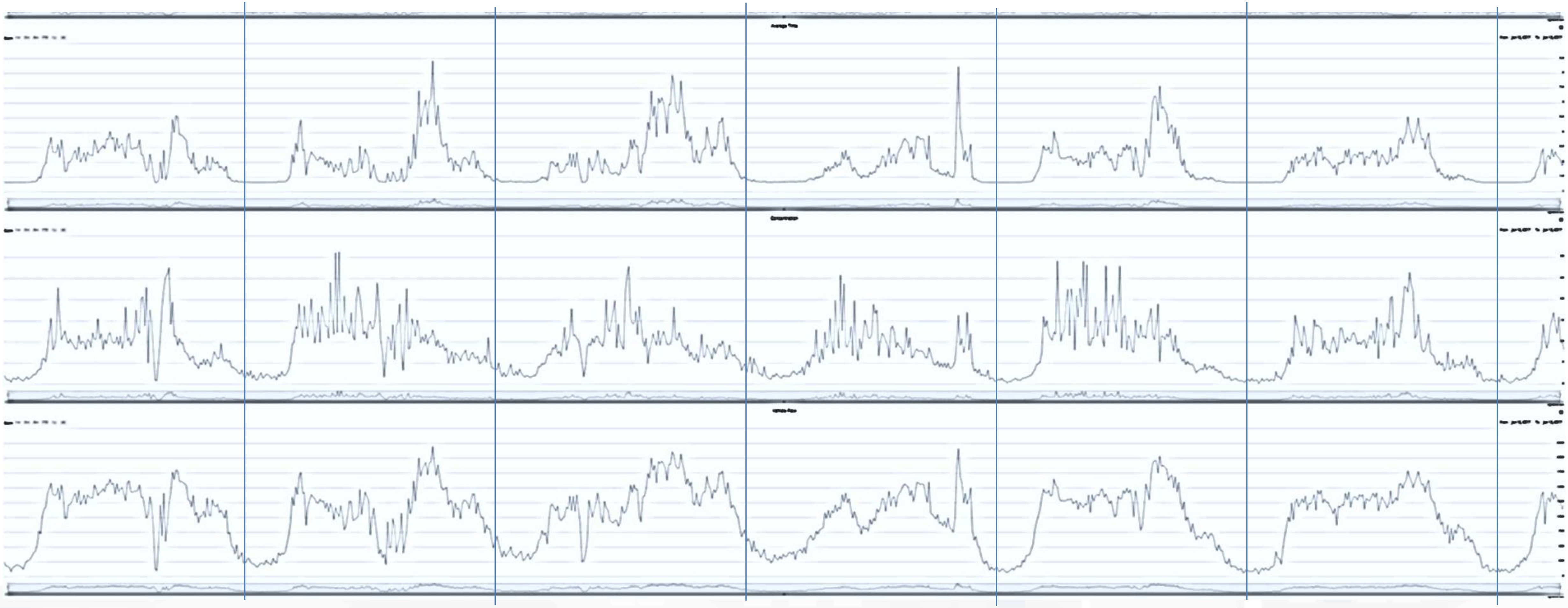
Traffic Flow Tools

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

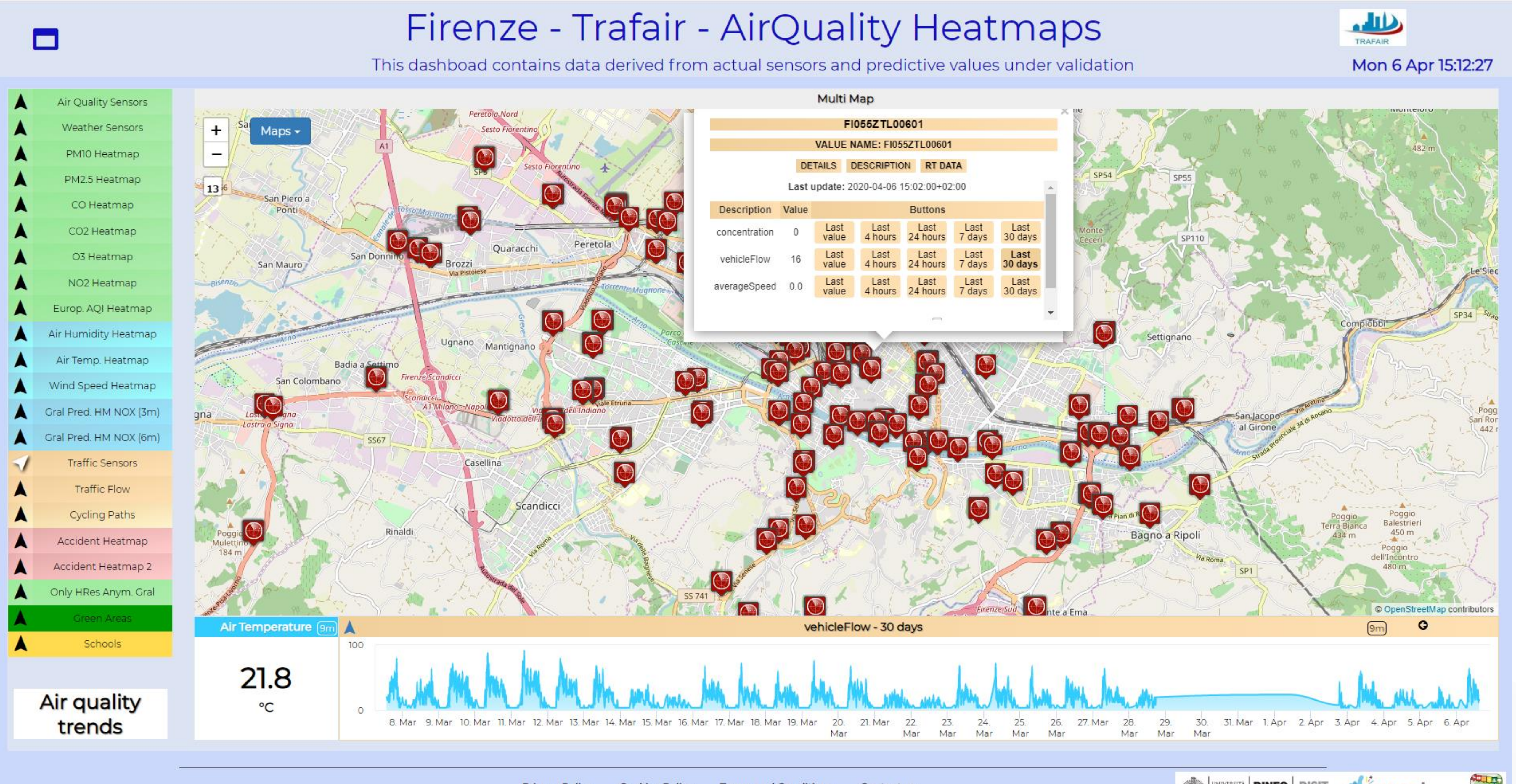
Specifically located: along, around, on gates, on x…



Traffic Flow data



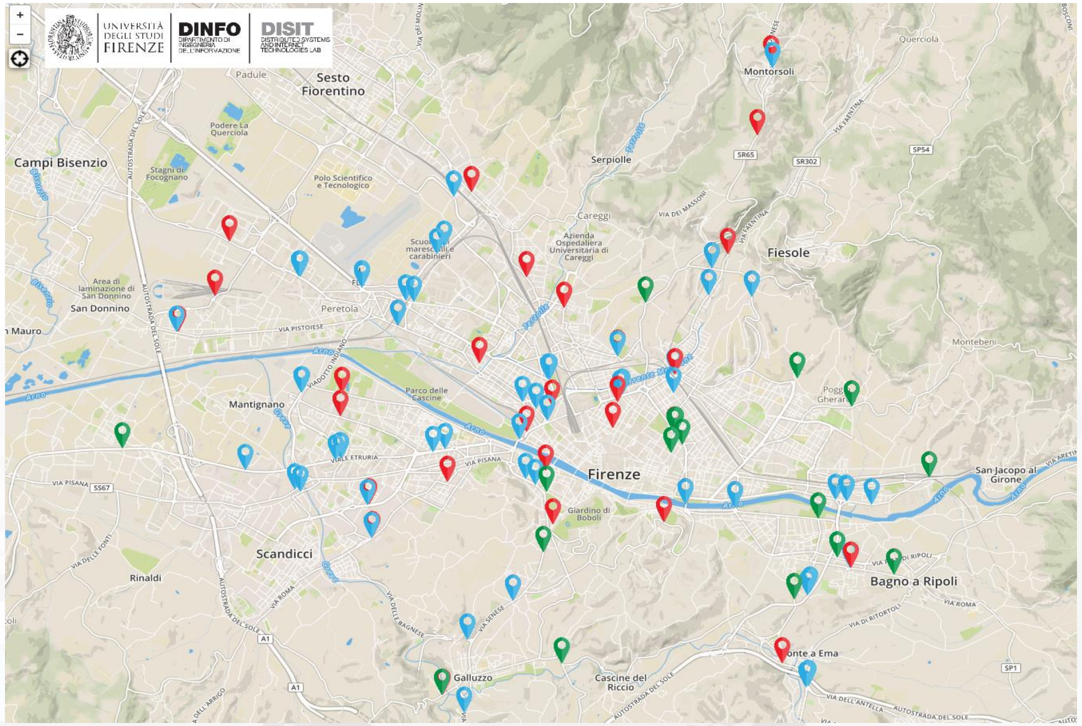
- Day by day traffic flow, on the week data from 3 sensors



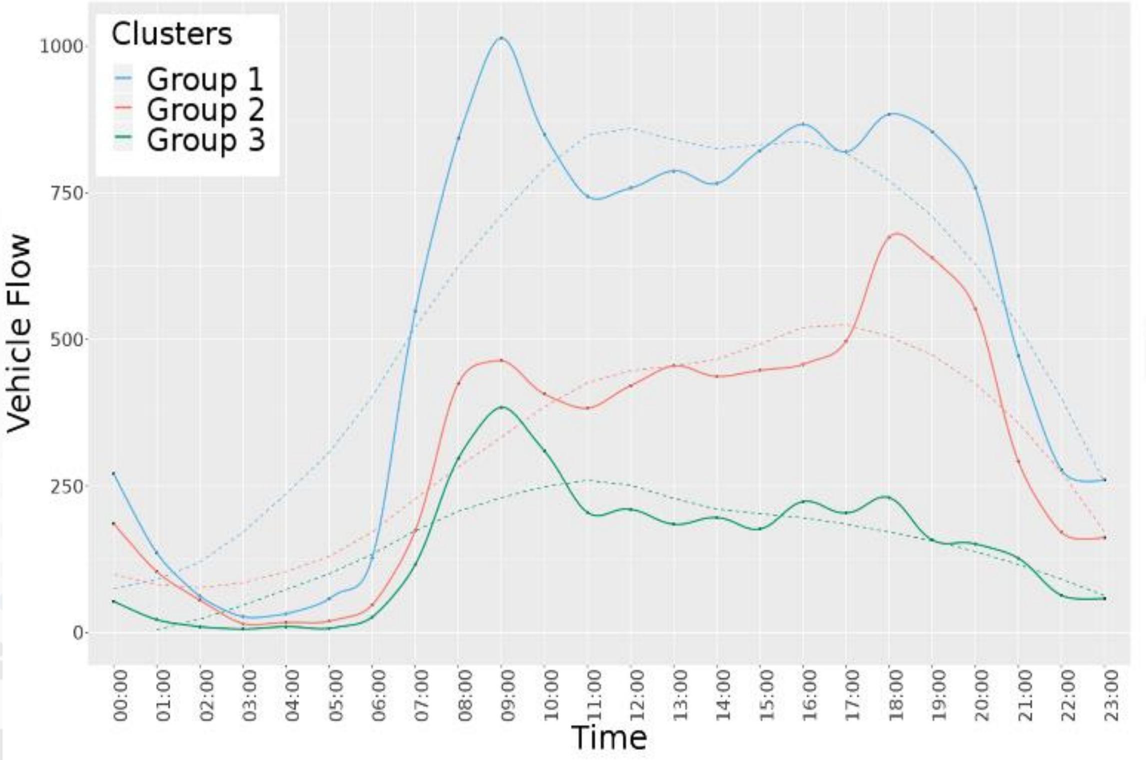
https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MTUzMg==

Traffic Flow Data Analysis

Map of the traffic sensors location per cluster in Florence municipality



Hourly median vehicle flow trends per cluster



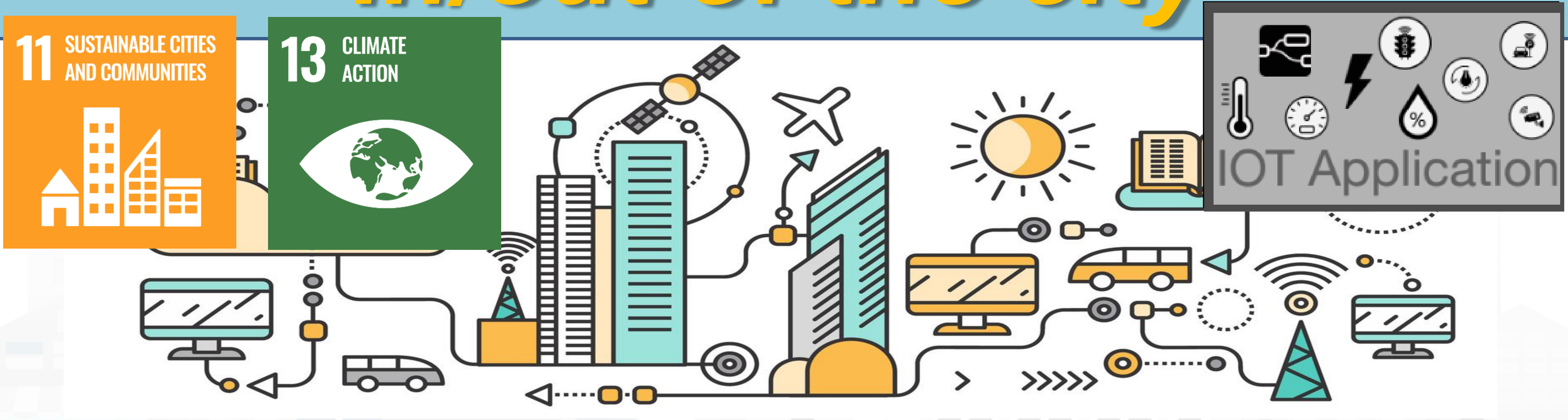
Example of Volume of data

- Sensors: 150
- Variables per sensor: 15 + datetime, etc.
  – Bytes per sensor per message: 150 Byte
- Days per year: 365
- Hours in the day: 24
- Samples for hour: 6, one each 10 minutes
- → 150*365*150*24*6 = 1.127 GB

- More: Platform factor: number of replicas, indexing, etc…
  – May range from 100 to 2000 Byte per Variable

TOP

Computing Traffic Flow
In/out of the city



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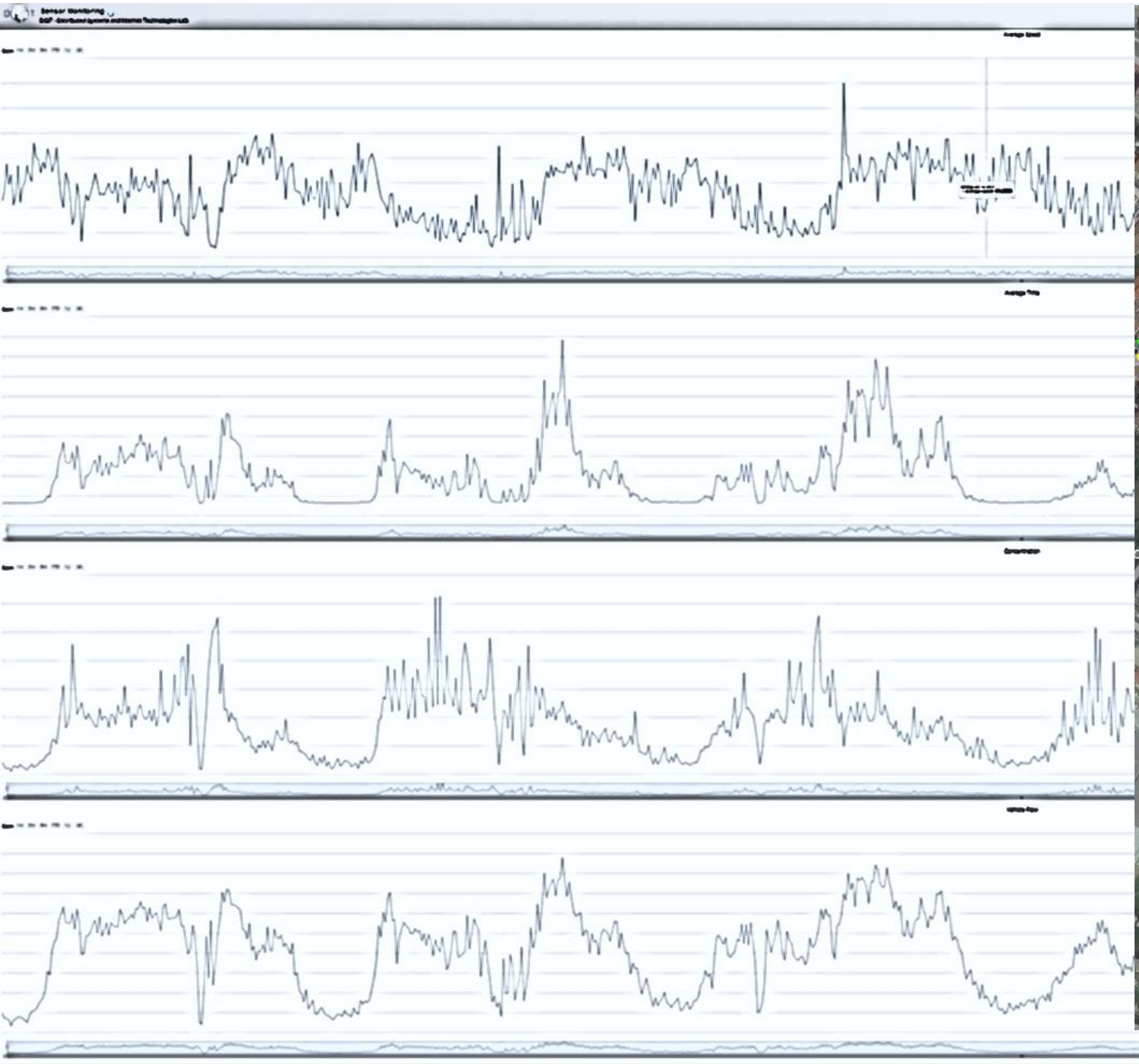
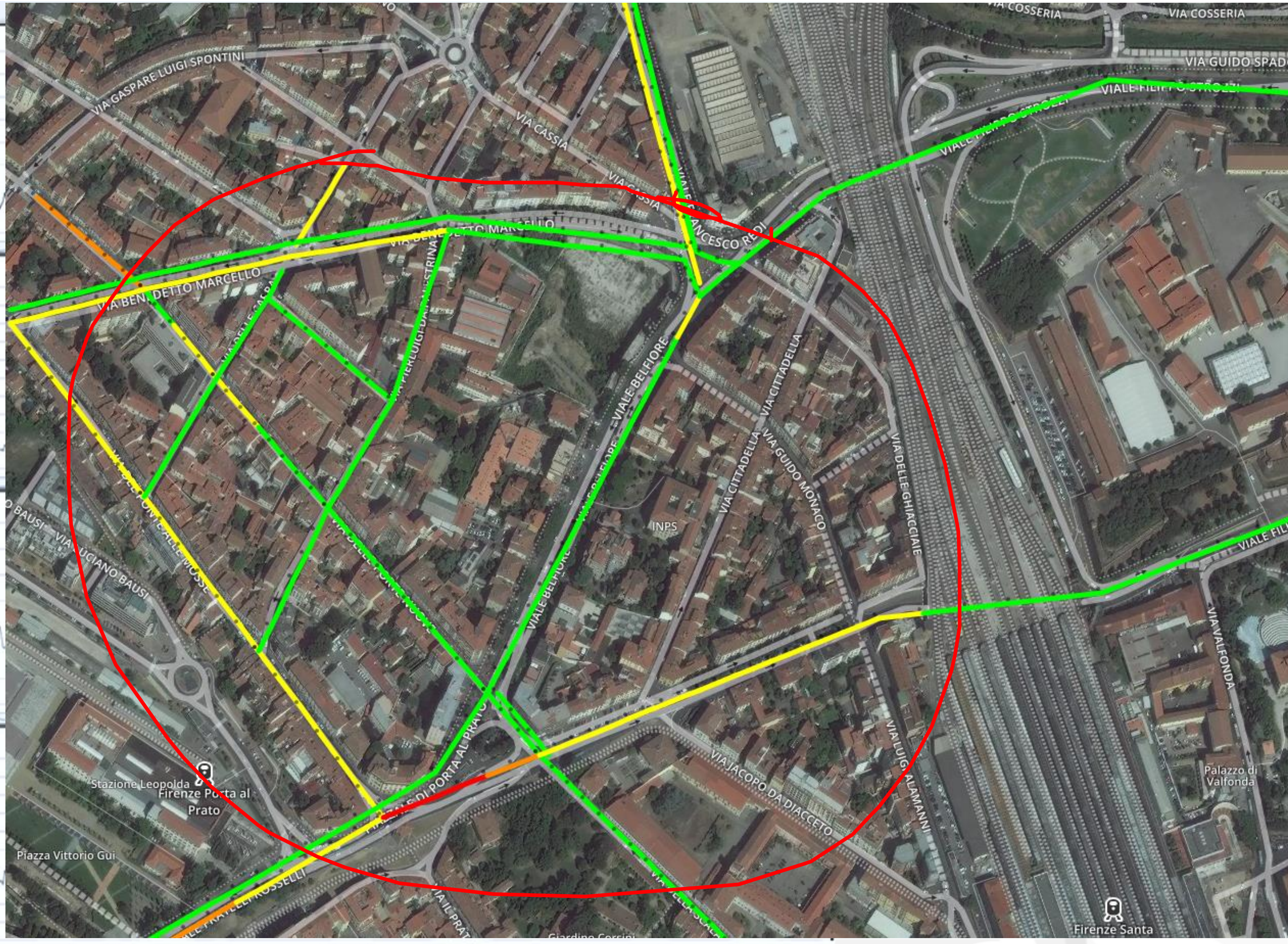
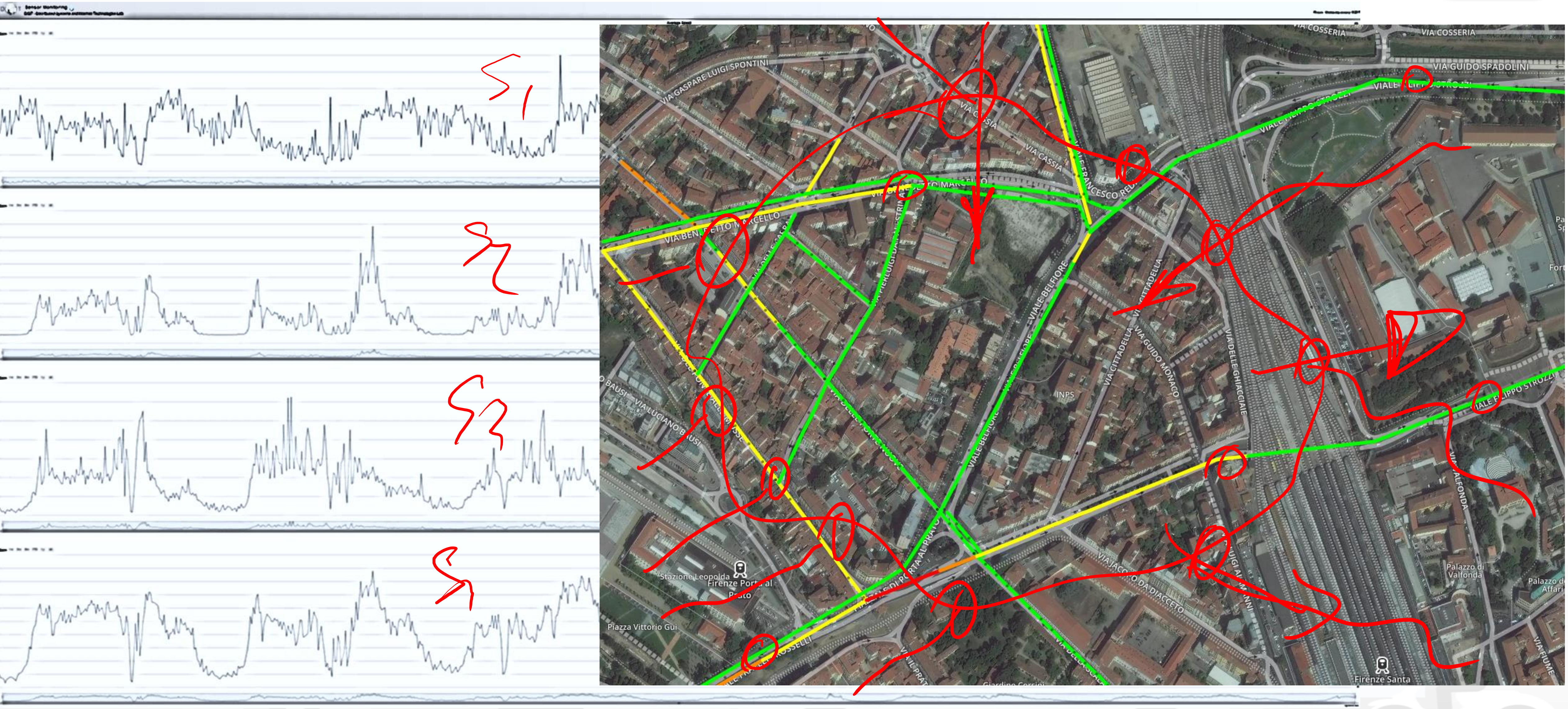
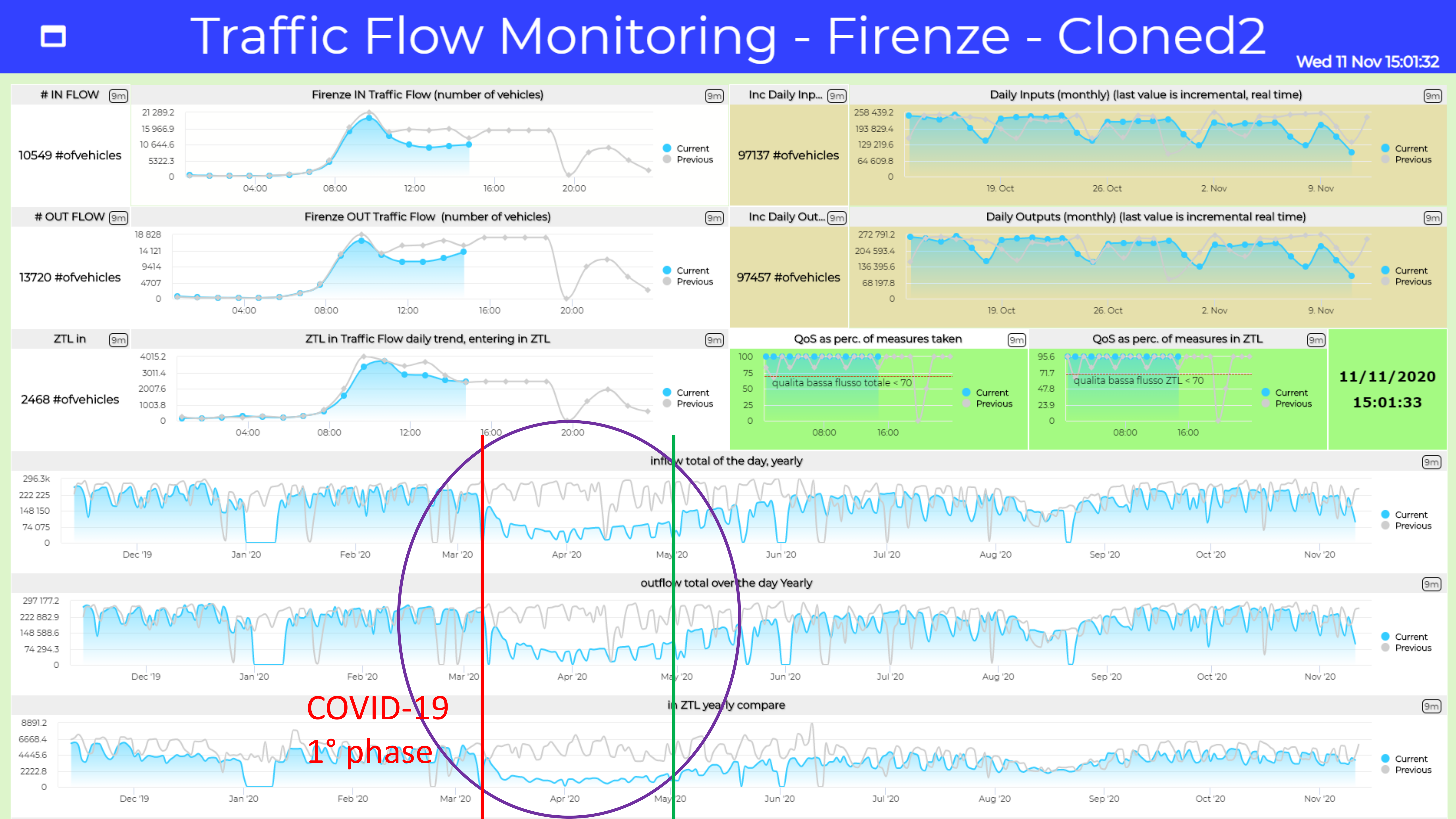
Traffic Flow data





Traffic Flow data

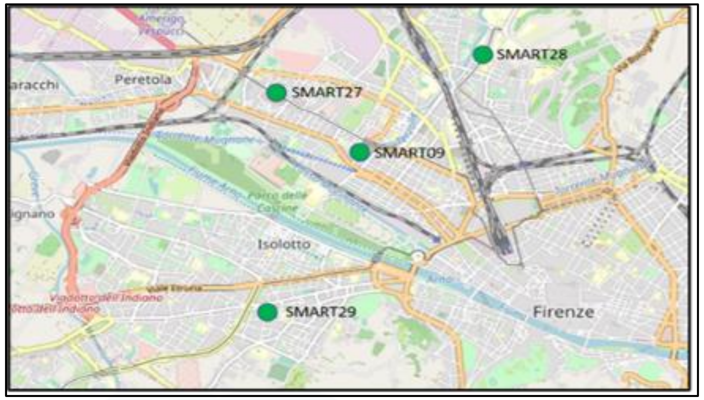




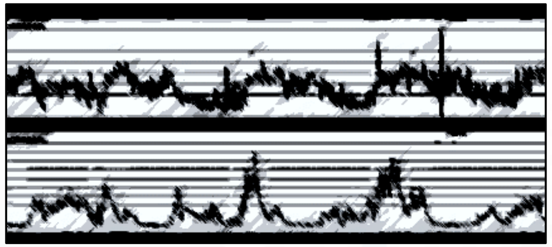
Traffic Flow Monitoring - Firenze - Cloned2
Wed 11 Nov 15:01:32
IN FLOW
10549 #ofvehicles
Firenze IN Traffic Flow (number of vehicles)
Inc Daily Inp...
97137 #ofvehicles
Daily Inputs (monthly) (last value is incremental, real time)
OUT FLOW
13720 #ofvehicles
Firenze OUT Traffic Flow (number of vehicles)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

Computing CO2 from traffic Data

Estimating City Local CO2 from Traffic Flow Data



- CO_2 sensors are very expensive and thus few



- Traffic Flow is one the main source of CO_2
- Most of the cities have many sensors on traffic flow
- **Dense estimation of CO_2 into the city** is very useful to know to target the EC limits/KPI

S. Bilotta, P. Nesi, "Estimating CO2 Emissions from IoT Traffic Flow Sensors and Reconstruction", Sensors, MDPI, 2022. https://www.mdpi.com/1424-8220/22/9/3382/

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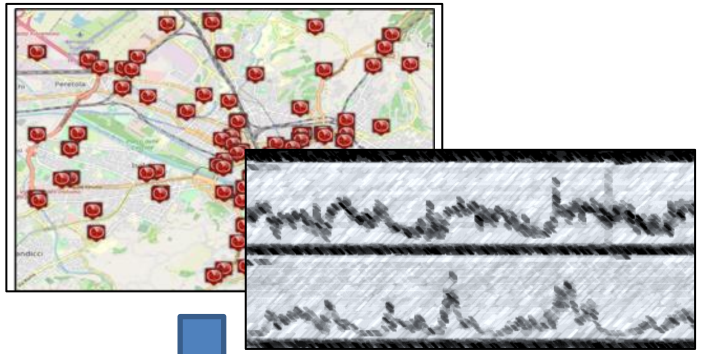
Estimating City Local CO2 from Traffic Flow Data



Computing Traffic Flow into CO2 sensor area

Traffic Flow data

- Traffic Flow is one the main source of CO2
  - K1: Fluid Flow
  - K2: Stop and Go
- **Dense estimation of CO2 into the city** is very useful to know to target EC's KPIs

11 SUSTAINABLE CITIES AND COMMUNITIES

13 CLIMATE ACTION

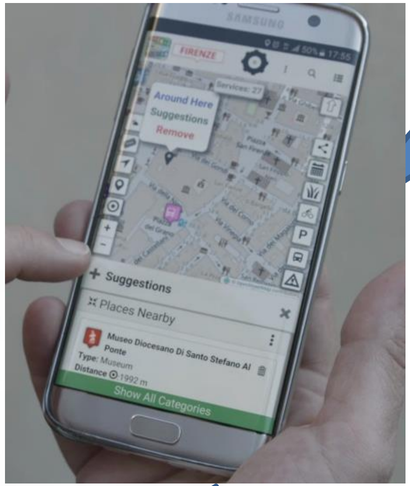
Computing CO2 on the basis of traffic flow data

CO2 estimation

S. Bilotta, P. Nesi, "Estimating CO2 Emissions from IoT Traffic Flow Sensors and Reconstruction", Sensors, MDPI, 2022. https://www.mdpi.com/1424-8220/22/9/3382/

Computing Quality of Public Transportation

How much confident is the guess for bus arrival



Assessment and prediction

Customer satisfaction

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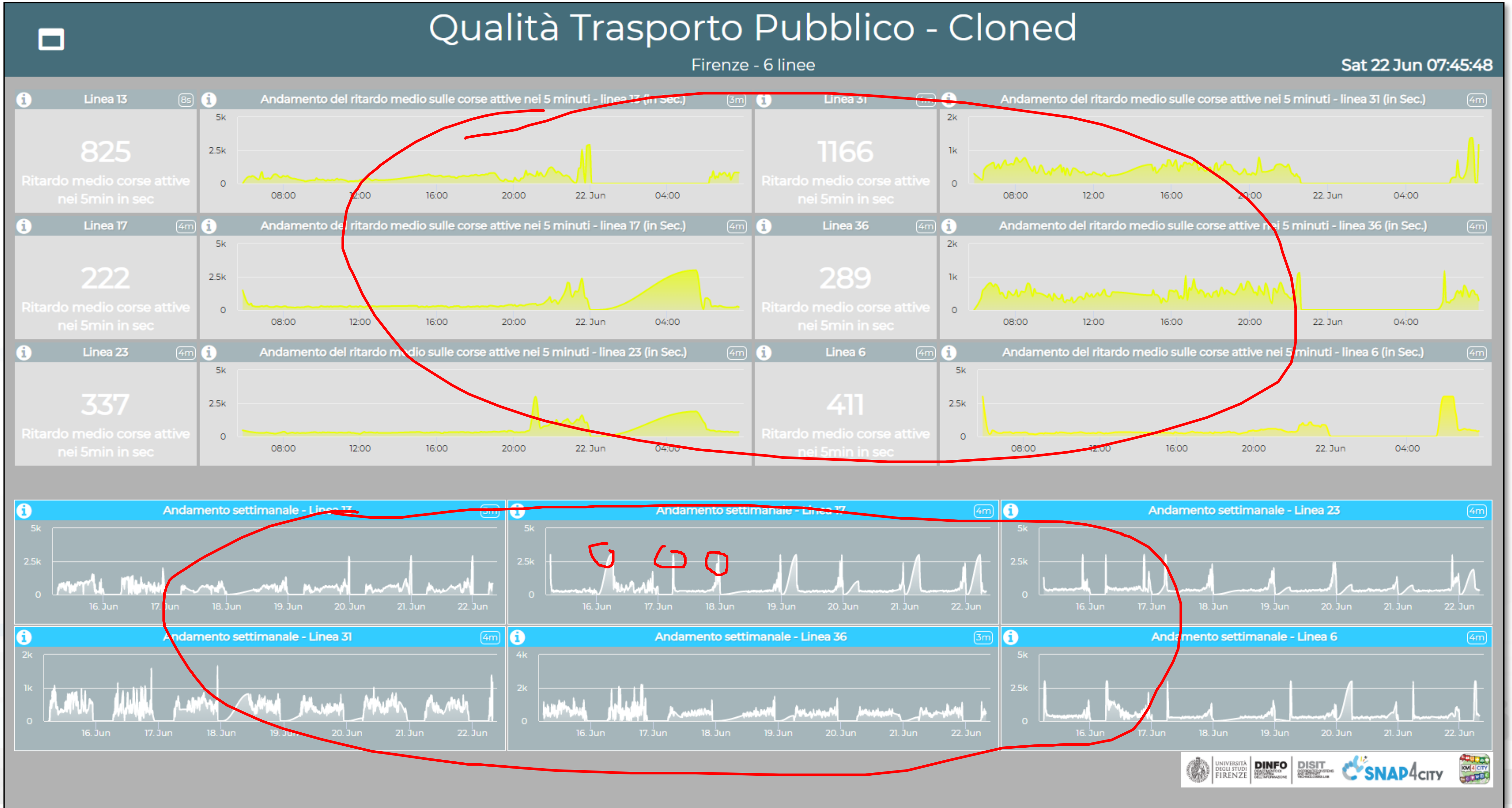

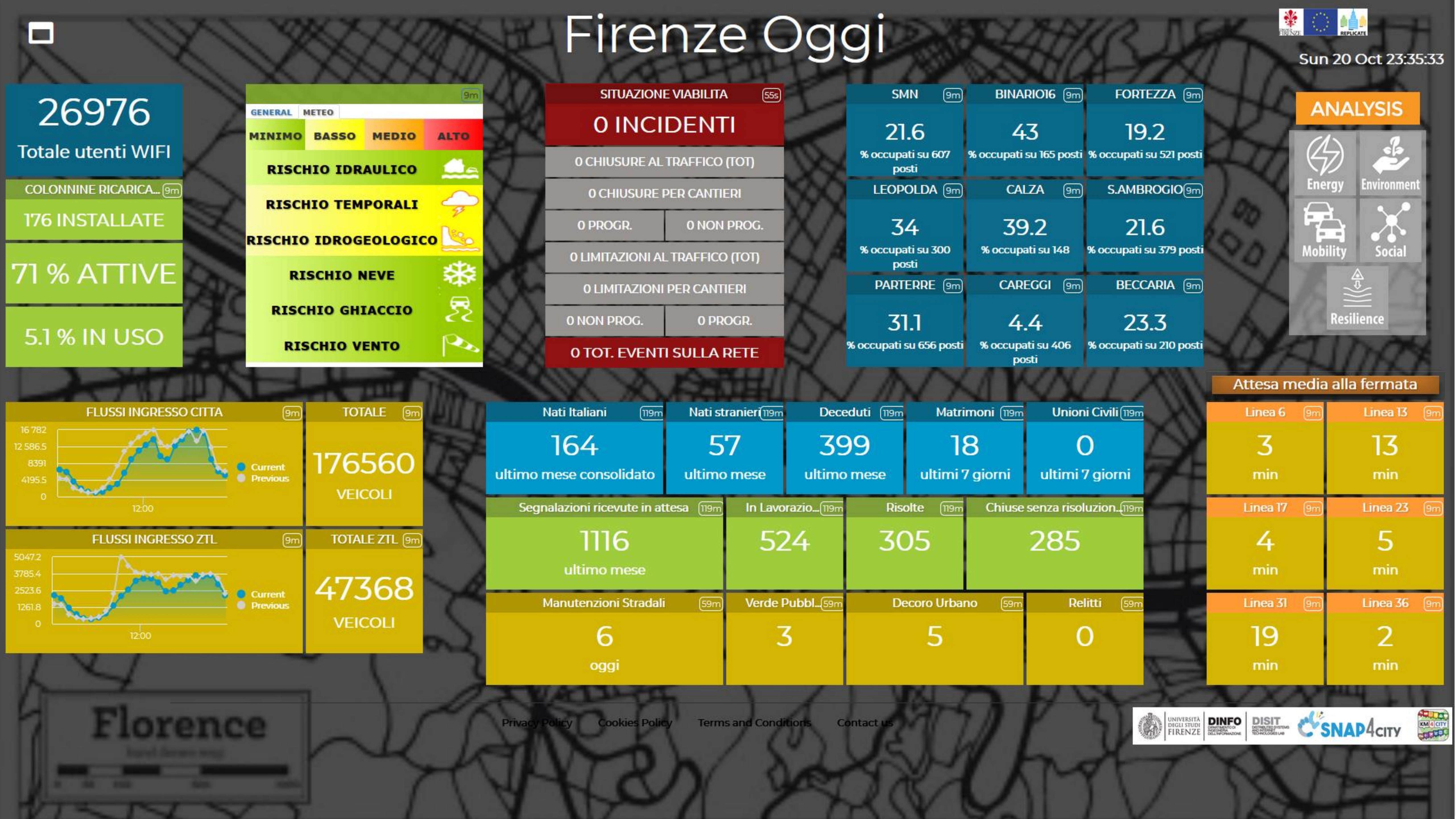

Firenze Oggi
Sun 20 Oct 23:35:33
26976
Totale utenti WIFI
COLONNINE RICARICA... 9m
176 INSTALLATE
71 % ATTIVE
5.1 % IN USO
9m
GENERAL METEO
MINIMO BASSO MEDIO ALTO
RISCHIO IDRAULICO
RISCHIO TEMPORALI
RISCHIO IDROGEOLOGICO
RISCHIO NEVE
RISCHIO GHIACCIO
RISCHIO VENTO
SITUAZIONE VIABILITA 55s
0 INCIDENTI
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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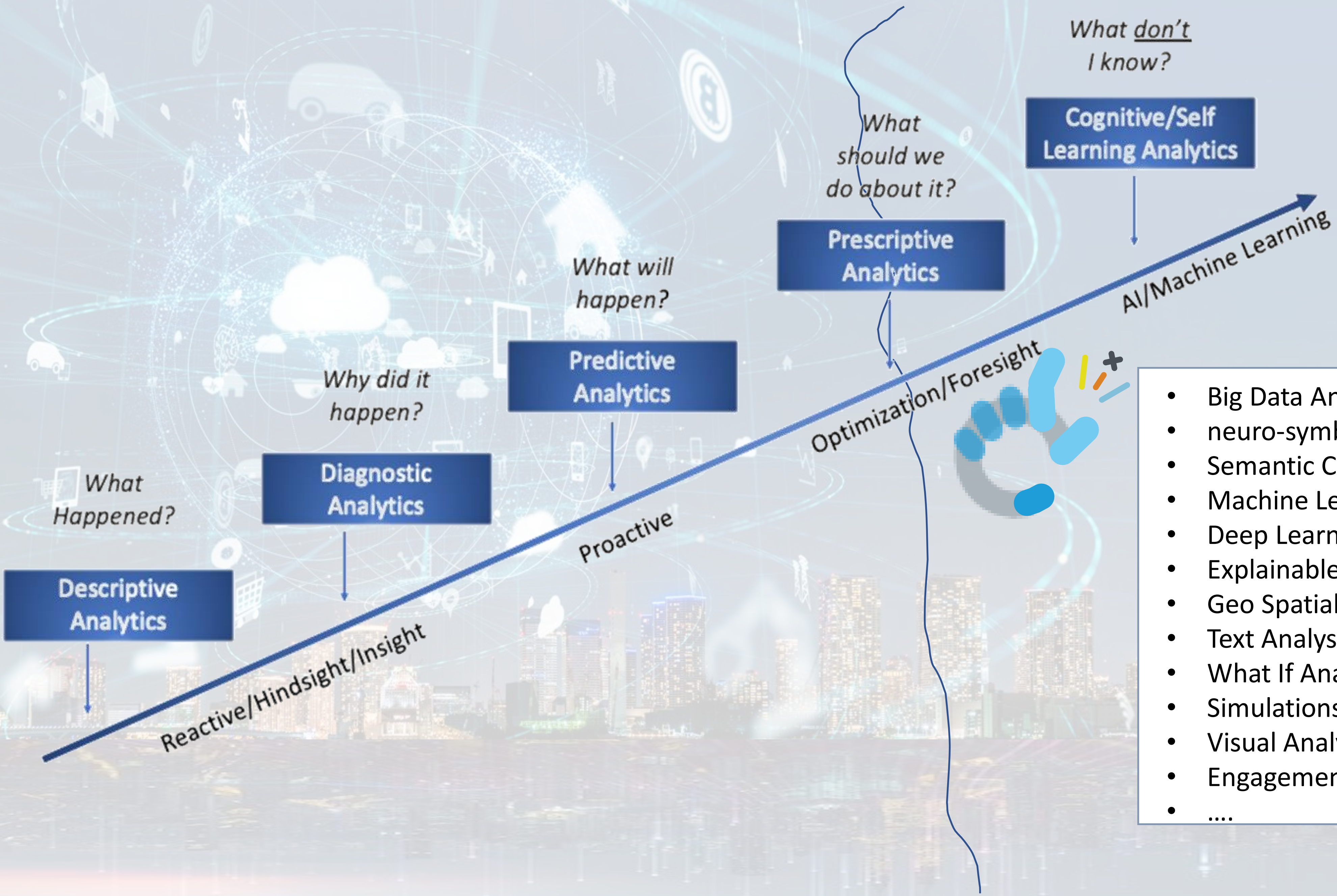
TOP

What is Data Analytics, DA and Artificial Intelligence, AI

Data Analytics

- **examining data** to
  - uncover patterns, trends, and insights that can be used to make informed decisions.
  - extracting meaningful information from data and typically involves statistical analysis, data mining, and visualization techniques.
- **Data analysts** use tools like tables, data base queries, and programming languages to process and analyze data, identify correlations, and create reports.
- ***Snap4City provides support for implementing DA on:***
  - *Proc.Logic / IoT Apps: on cloud and on Edge*
  - *Python processes in containers or on Edge*
  - *R Studio processes in containers, servers, premise, etc.*



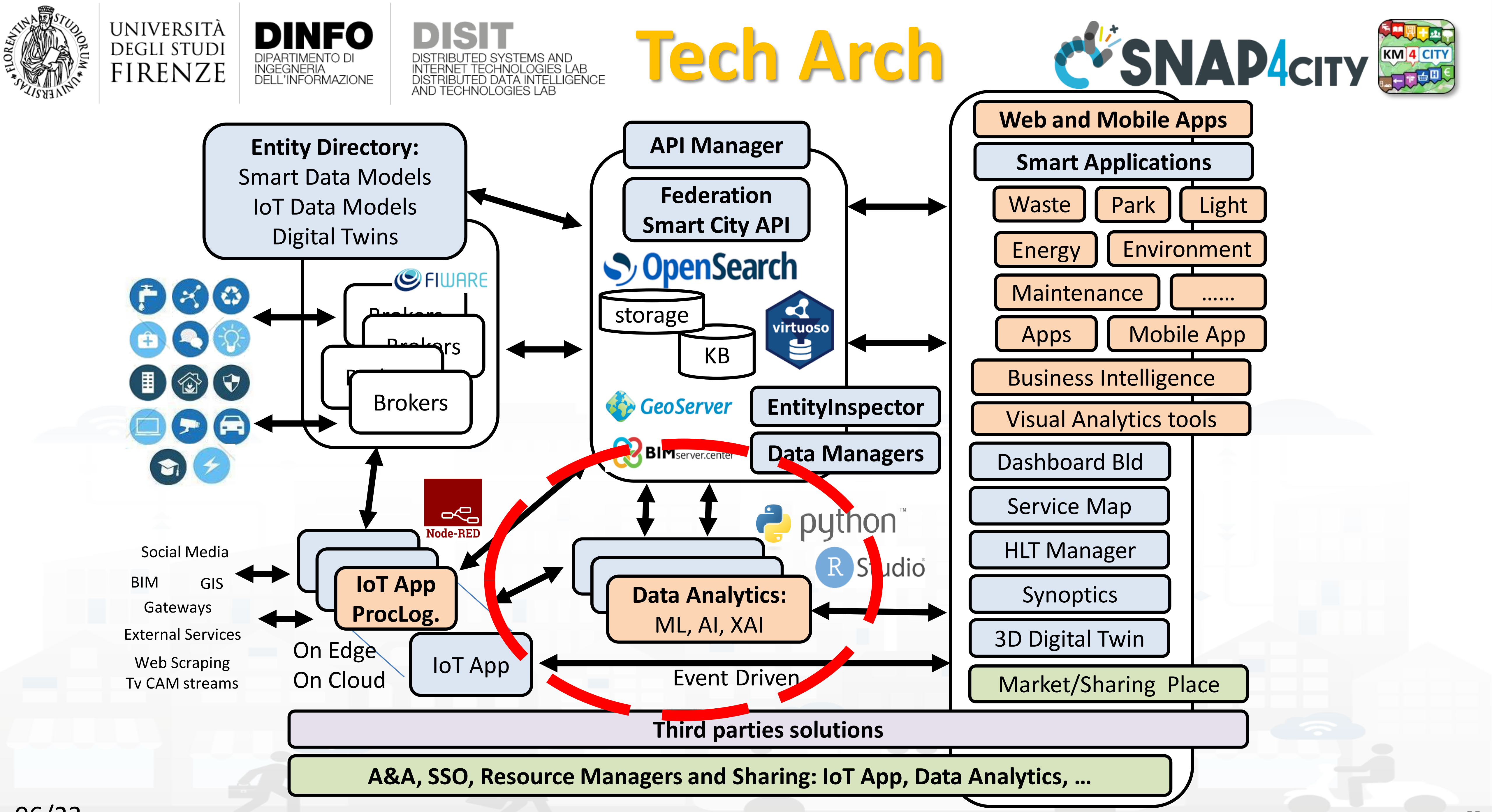
Sentient and active processes

- Big Data Analytics
- neuro-symbolic
- Semantic Computing
- Machine Learning
- Deep Learning
- Explainable Artificial Intelligence
- Geo Spatial Reasoning
- Text Analysis, Sentiment Analysis
- What If Analysis
- Simulations, Optimization
- Visual Analytics
- Engagement Analysis
- ….

Advanced Computing

- **cutting-edge technologies**, techniques, and methodologies to solve complex computational problems that are beyond the capabilities of traditional computing approaches.
  - optimization problems, pattern recognition, natural language processing
  - **Via:** artificial intelligence (AI), machine learning, high-performance computing (HPC), big data analytics, and cloud computing.
  - **On:** massive volumes of data, complex simulations, computationally intensive tasks
  - → accelerate problem-solving, and enable breakthroughs in scientific research, engineering, business intelligence, and other domains.
- ***Snap4City provides support for implementing AC:***
  - *Python processes in containers, servers, etc.*
  - *R Studio processes in containers, servers, etc.*

Tech Arch

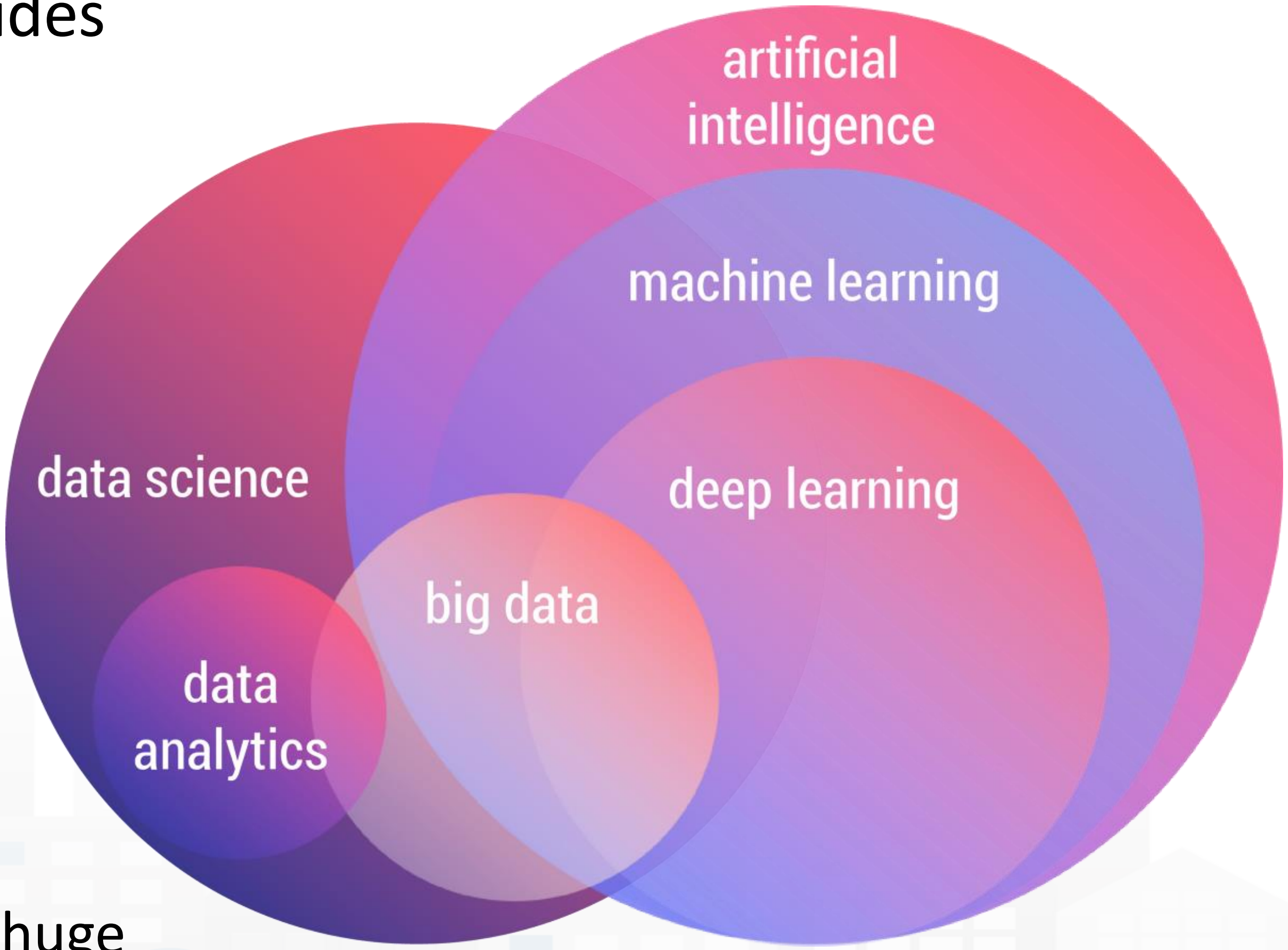


06/23

Snap4City and DA and AC (summary)

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

- **Artificial Intelligence** usually also includes
  – Code, learn and reasoning
  – Semantic computing, Knowledge Bases
  – Neuro-symbolic reasoning
  – Decision Support Systems
  – Problem solving
- **Machine Learning** usually includes
  – Learn without coding
  – Predictions, decisions (classifications)
  – Supervised or not
  – NLP, vision, pattern recognition
- **Deep Learning** usually includes
  – Capability to learn complex patterns on huge amount of data
  – Specialized ML solutions



Snap4 Solutions and Technologies

- **Indexes, KPI, Indicators**
- **Predictions: short, long, very long:**
  - traffic, parking, people flow, maintenance, land sliding, NO2, etc.
  - 3D Flow prediction: Pollutant (NOX, NO2, …)
- **Anomaly detections, critical condition detection:**
  - early warning, recovery, etc.
- **Simulation and optimization**
  - Traffic Flow reconstruction
  - Routing, multimodal routing, constrained dynamic routing, etc.
  - Public transportation load
- **What-IF analysis** (simulation + predictions + data + scenarious)
- **AI: technologies: operating research, ML, AI, XAI, DL, NLP:**
  - Semantic computing, neuro symbolic
  - RF, XGBoost, BRNN, RNN, SVR, MLP, …
  - DNN, LSTM, CNN-LSTM, Autoencoders, BERT, …
  - Clustering: K-means, K-Medoid, …
  - XAI: Shap, variations, Lime, ..
- **Based on several computational models**:
  - trajectories, OD matrices, Typical Time Trends, etc.

to cope with

- *any data, format*
- *any channel, protocol*
- *any AI/ML*
- *any place*
- *online development*
- *multi-tenant*
- *Secure, PENTest*
- *GDPR, privacy*
- ***→ low costs***
- ***→ easy to evolve***

https://www.snap4city.org/download/video/course/p4/

Lesson Learnt for Recipes

RULE OF THUMB

- **Data identification and finalization**:
  - Collection of data, acquisition of data from provider, construction of data
    - easy to use data or surrogated data ?
  - Data quality ?
    - To work and produce results any way even in presence of Missing and poor quality data
- **Computation Models** depending on the case
  - Statistics, Optimisation
  - Simulation and computation, or mixt
  - Identification of the most effective ML/AI techniques to obtain:
    - the best possible results with respect to the state of the art
    - reasonable results with the accessible data
    - the reasonable and cheers results compromise
  - ML/AI techniques: training and execution
- **Data Representation Models and tools**

- ***Before** entering into how to do it, it is better to see some examples*

TOP

List of the most relevant Snap4City DA and AI Solutions

Available DA / AI Solutions on Snap4City

- **Mobility and Transport**
- **Environment, Weather, Waste, Water**
- **City Users Behaviour and Social analysis**
- **Energy and Control, Security, …..**
- **Tourism and People**
- **Security and Safety**
- **High Level Decision Support Solutions**
  - **Asset management**
  - **Resilience and Risks Analysis**
- **Low level Techniques**

https://www.snap4city.org/download/video/DPL_SNAP4SOLU.pdf

https://www.snap4city.org/download/video/course/p4/

Mobility and Transport

- **Predictions** for: traffic flow, smart parking, smart bike sharing, people flows, etc. (ML, DL)
- **What if analysis**: routing, traffic flow, demand vs offer, pollutant, etc. (Simulation + ML)
- **Traffic flow reconstruction** from sensors and other sources (simulation + ML)
- **Public Transportation**: Ingestion and modelling of GTFS, Transmodel, NeTEx, etc. (DP)
  - Analysis of the **demand mobility vs offer transport** of according to public transportation and multiple data sources (Simulation)
  - Assessing **quality of public transportation** (analysis)
- **Accidents** heatmaps, anomaly detection (analysis, ML)
- **Tracking fleets**, people, via devices: OBU, OBD2, mobile apps, etc. (DP)
- **Routing** and multimodal routing (multistop travel planning), constrained routing, dynamic routing (DA)
- Computing **Origin Destination Matrices** from different kind of data (analysis, DP, DP)
- Computing **typical trajectories** on the basis of tracks (analysis, ML)
- Computing Messages for Connected drive (DP)
- Slow and Fast Mobility **15 Minute City Indexes** (analysis, DP, …ML)
- Computing and comparing traffic flow on devices and at the city border (analysis)
- **Typical time trends** for traffic flow and IoT Time series. (analysis, ML)
- **Impact of COVID-19** on mobility and transport
- Computing **SUMI, PUMS**, etc. (mainly DP)
- **Definition of Scenarios:** traffic, road graph, conditions, etc.
- Etc

Environment and Weather

- **Pollutant Predictions: short, long and very long term** European Commission KPIs
  - NOX, PM10 pollution on the basis of traffic flow, 48 hours (ML, AI, DL)
  - Cumulated NO2 average value over the year, ……. (ML, AI, DL)
- **Computation of CO2** on the basis of traffic flows (DP), computing emission factor (DA)
  - each road for each time slot of the day
- **Prediction of MicroClimate** conditions for diffusion (ML, AI)
  - NO2, PM10, PM2.5, etc.
- **Prediction of landslides**, 24 hours in advance (AI, DL)
- **Heatmaps production**, dense data interpolation (DP) for
  - Weather conditions: temperature, humidity, wind, DEW
  - Pollutants and Aerosol: NO, NO2, CO2, PM10, PM2.5, etc.
- **Impact of COVID-19** on Environmental aspects (DP)
- Optimisation of **waste collection** schedule and paths (DP, ML)
- Computing **SDG, SUMI, PUMS**, .. (mainly DP)
- Etc.

City Users Behaviour, Safety, Security and Social Analysis

- **People detection and classification**: persona, strollers, bikes, etc. (ML, DL)
- **people counting and tracking**, head counting, people trajectories (via thermal cameras, ML, DL)
- **People flows prediction** and reconstruction, (ML, DL)
    - Wi-Fi data, mobile apps data, Mobile Data, etc.
- **User's behaviour analysis**, **People flow analysis** from PAX Counters and heterogenous data sources (ML, AI)
    - origin destination matrices, hot places, time schedule,
    - Recency and frequency, permanence, typical trajectory, etc.
- **Computing User engagement and suggestions** for sustainable mobility (Rule Based, ML)
- **Social media analysis** on specific channel, specific keywords: see Twitter Vigilance,
    - Reputation, service assessment: MultiLingual NLP and Sentiment Analysis, SA
    - Tweet proneness, retweet-ability of tweets, impact guessing
    - Audience predictions on TV channels and physical events, locations
    - Prediction of attendance of events and on attractions
- **Virtual Assistant construction, LLM, NLP, Sentiment Analysis (DL, NLP)**
- **Video management System integration for security**
- **15 Minute City Index** , etc. (modeling and computability)
- Computing **SDG**, etc., (DP)
- Etc

Energy

- **Monitoring Energy Consumption in single building, area and per zone**
- **Matching Energy consumption with respect to the actual usage**
- **Computing Roof orientation for Photovoltaic installations**
- **Simulation of Photovoltaicc installations** to identify the best parameters of size and storage
- **Smart Light management**, unicast and multi cast management, smart light controlled by **traffic flow data**
- Collecting and managing **Communities of Energy**
- Monitoring Energy provisioning on **recharging station**
- Optimization of battery life
- Computing **KPI**
- Etc.

Energy and Control, Security

- **Smart Light Solutions:** monitoring luminaries, profiling luminaries, managing error conditions (DP)
- Design by Simulation of **Photovoltaic Plants**: using real statistical data from the area (ML, Dp)
- **Energy Community**: Energy Districts (in Italy, CER) (ML, DP)
  - Monitoring, design and simulation of energy community
- Monitoring and controlling **recharging stations, recharging poles**
- Monitoring **energy production and consumption** over: plant, building, floors, offices, server rooms, etc.
- Monitoring **healthiness of Smart City Network of devices**
- Monitoring **critical areas** for: people, traffic, boats, etc.
- Etc.

High Level Decision Support Systems

- **Management and strategies**
  - **Estimation of KPI** and local indexes
  - **Anomaly detection and Early warning** computation
  - **What-if analysis**, dynamic routing, origin destination matrices production from a large range of sources
  - **Planning and Monitoring** renovation works via objective KPIs
  - **Managing Maintenance** and teams
  - **Predictive Maintenance** and costs predictions: chemical plant, vehicles, boats
- **Resilience and Risks Analysis**
  - **Resilience analysis** wrt European Guidelines on Resilience of critical infrastructure, and transport systems
  - **Risk analysis:** natural and non natural disaster

Low level Techniques

- **Time Series**
  - **Time Series Anomaly detection: any kind**
  - **Data quality** assessment and control: any kind
  - short and long term **prediction: any kind**
  - **Interpolation/extrapolation** of Data on regular grid for calibrated heatmaps
- **Semantic Reasoning**
  - **Ontology Modelling** and integration, expert system construction
  - **Knowledge modelling** and reasoning on RDF stores: spatial, temporal, relational
- **Matrices, Images, Maps and 3D Digital Models**
  - Conversion of **Satellite data images** into regular ground images
  - **Extraction information** from **Orthomaps, LIDAR**, etc., regarding city structures
  - **3D Digital Twin** of Cities and Objects: pattern extraction, 3D model reconstruction

1 NO POVERTY · 2 ZERO HUNGER · 3 GOOD HEALTH AND WELL-BEING · 4 QUALITY EDUCATION

- ***15 Minute City Index:***
  - 13 subindexes: energy, slow mobility, fast mobility, housing, economy education, culture and cults, health, entertainment, gov, food, security…

10/22

7 AFFORDABLE AND CLEAN ENERGY

- Monitoring and Prediction of energy consumption
- Stimulating: Bike sharing, e-bikes, car charge, etc.

9 INDUSTRY, INNOVATION AND INFRASTRUCTURE

- Industry 4.0 integrated solutions
- Decisions Support Systems
- Process optimization, control
- Predictive maintenance

11 SUSTAINABLE CITIES AND COMMUNITIES

- Smart City infrastructure: monitoring and resilience, long terms predictions
- Effective and Low cost smart solutions
- What-if analysis, Simulations
- Origin Destination matrices computation

12 RESPONSIBLE CONSUMPTION AND PRODUCTION

- business intelligence tools for decision makers
- Reduction production costs
- Monitoring resource consumption
- Optimization of Waste Collection

13 CLIMATE ACTION · 15 LIFE ON LAND

- Monitoring and Predicting: NO2, NOX, CO2, Traffic flow, pollutant, landslide, waste, etc.
- Traffic flow reconstruction
- Demand vs Offer of Mobility analysis

16 PEACE, JUSTICE AND STRONG INSTITUTIONS

- Shortening justice time
- Anonymization and indexing legal docs.
- Prediction of mediation proneness
- Ethical Explainable Artificial Intelligence

Disappearing Data Analytics

	Antwerp					Helsinki								Where				
SNAP4CITY	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		POI, OSM
Routing: pedestrian				X	x			X	X	X	X	X	x	X				OSM
Routing: pedestrian quite				X	x			X	X	X	X	X	x	X				OSM
Routing: private vehicles	X		X	X		X		X	X	X	X			X	X			OSM
Routing: Multimodal Public Transport				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	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	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	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
Comparsision: Enfuser, Gral, Real Time							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	Snap4City Mobile App
Hot Places in Smart Zone	X	X	X	X										X		X	X	Snap4City PAXcounters
Services Suggestions on mobiles										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

Data Analytics for targeted users
Via specific Tools and Visual Analytics

TOP

Predictions and Anomaly detections

Data Analytic

Predictions

- **Computing predictions**
  - **Why?**
  - **They can be always computed**?
    - Time series, time trends, seasonality, etc.
  - **Which data are needed?**
  - **Precision needed and precision which can be obtained?**
  - **Computational costs?**

Management

Tactics/strategy

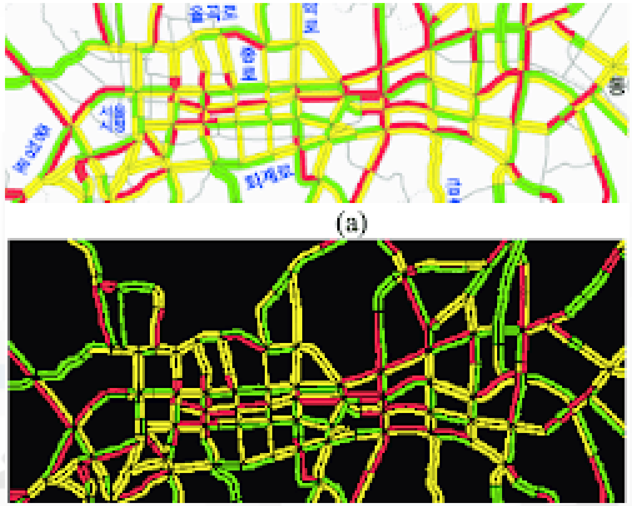
- **Technically:**
  - **Time range**, in most cases they are defined such as:
    - Short: 5-15 Minutes; Mid: 30-45 minutes;
    - Long: 1 day, week; very long: weeks / months / years
  - **Computational Model needed ?**

Why Computing Predictions

- if I know how many people will attend an event
  - I can **detect anomalies** earlier if an unexpected event will occur, intervene
  - I can **organize** better services, cleaning and preventive security
  - I can **inform, mitigate, plan**, **save money and time**, etc.
- Other Cases:
  - **Traffic** → pollutant, luminaries, city plan, be prepared critical conditions
  - **Parking** → inform in advance the users**,** save money and time, ….
  - **Energy** → be prepared for critical conditions
  - **Pollutant** → to avoid taking taxes, planning trips, etc.
  - **Waste** → save money and time, ……….

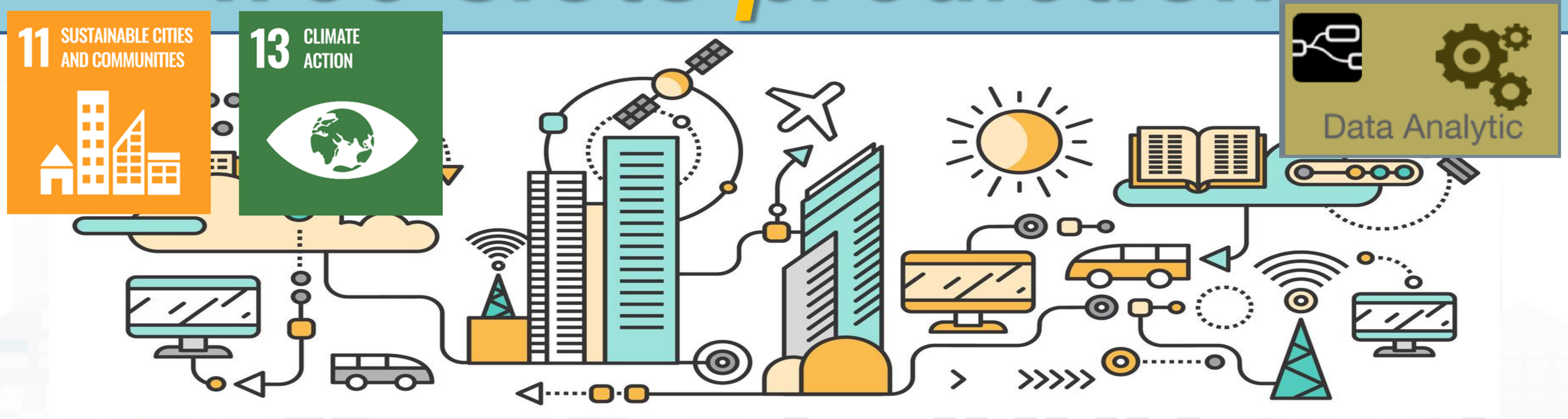
Predictions

- **For Cases:**
  - Free parking slots
  - Free bikes, and free slots on bike racks
  - Pollutant: NOX, NO2, CO2
  - Land Slide
  - People behavior
  - Energy consumption
  - Waste production
  - Etc.
- **→ Anomaly Detections**


(a)

TOP

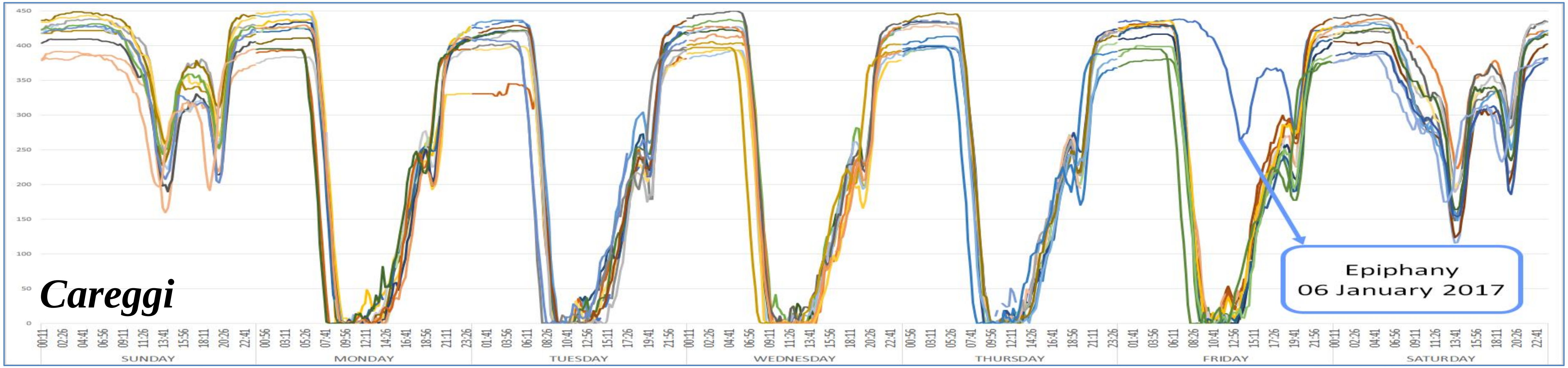
Smart Parking: free slots predictions

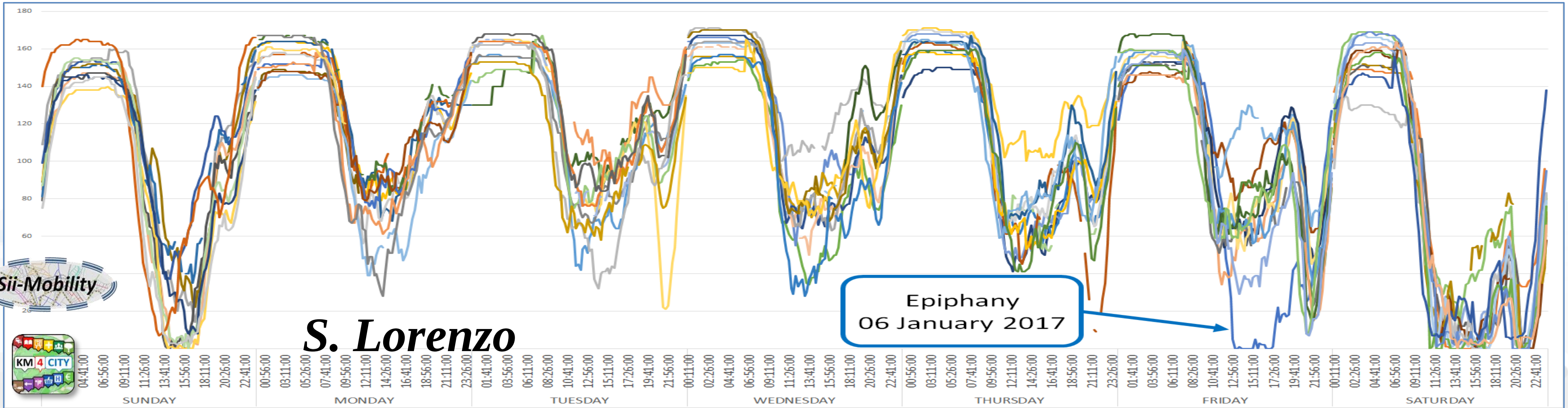



autostrada
FIESOLE
SIENA
AREZZO - FORLI'

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

Free Parking space trends





Sii-Mobility

UNIVERSITÀ DEGLI STUDI FIRENZE

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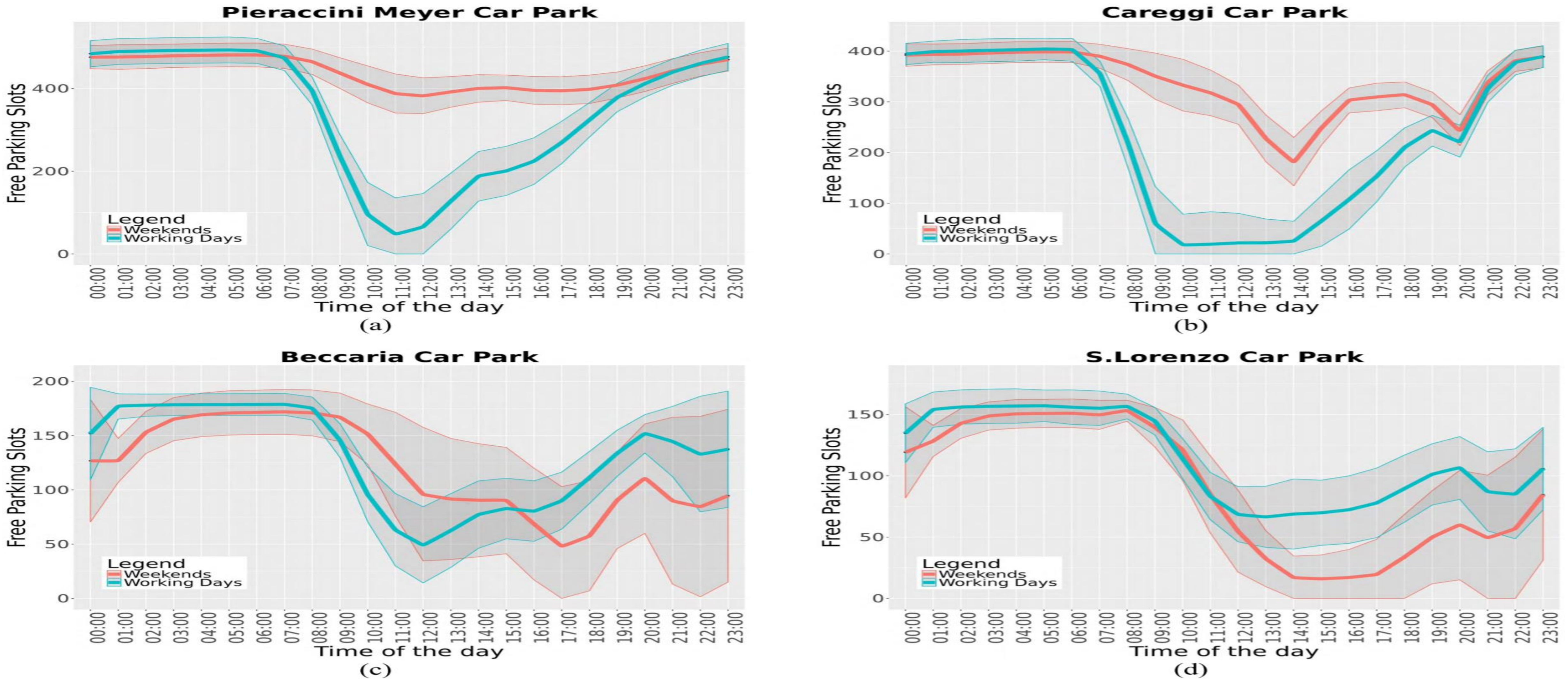
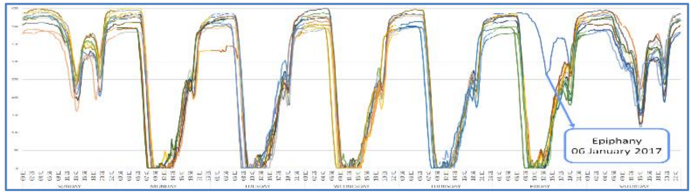
DISIT DISTRIBUTED SYSTEMS AND INTERNET TECHNOLOGIES LAB

Free Parking space trends



12 parking areas in Florence

I would arrive to surely Park in 45 Minutes??

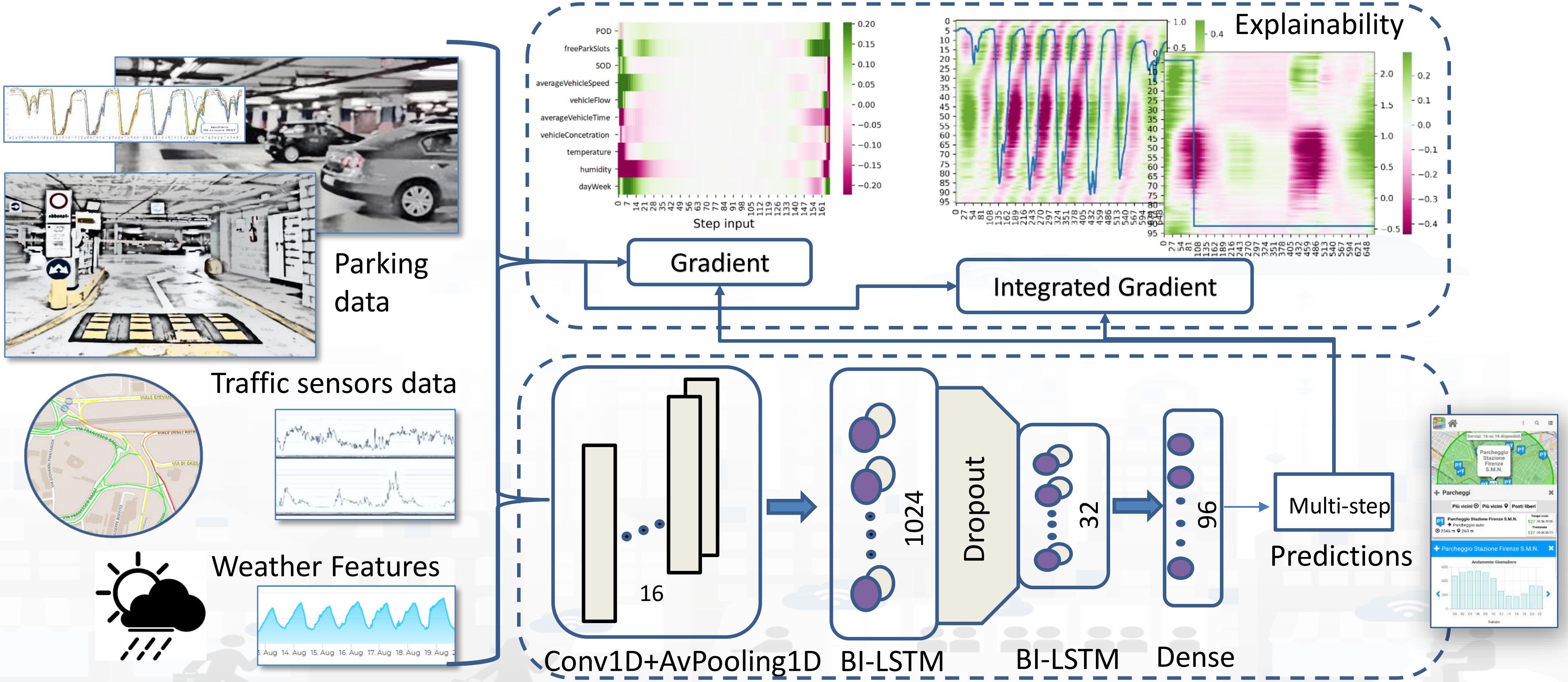


Category	Features	Description of features variable
Baseline features of free slot data	Free parking slots	Real number of available slots recorded every 15 minutes
	Time	Hours and minutes
	Month	Month of the year (1-12)
	Day	Day of the month (1-31)
	Day week	Day of the week (0-6)
	Weekend	0 for working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

Artificial Intelligence Predictions

97% of precision

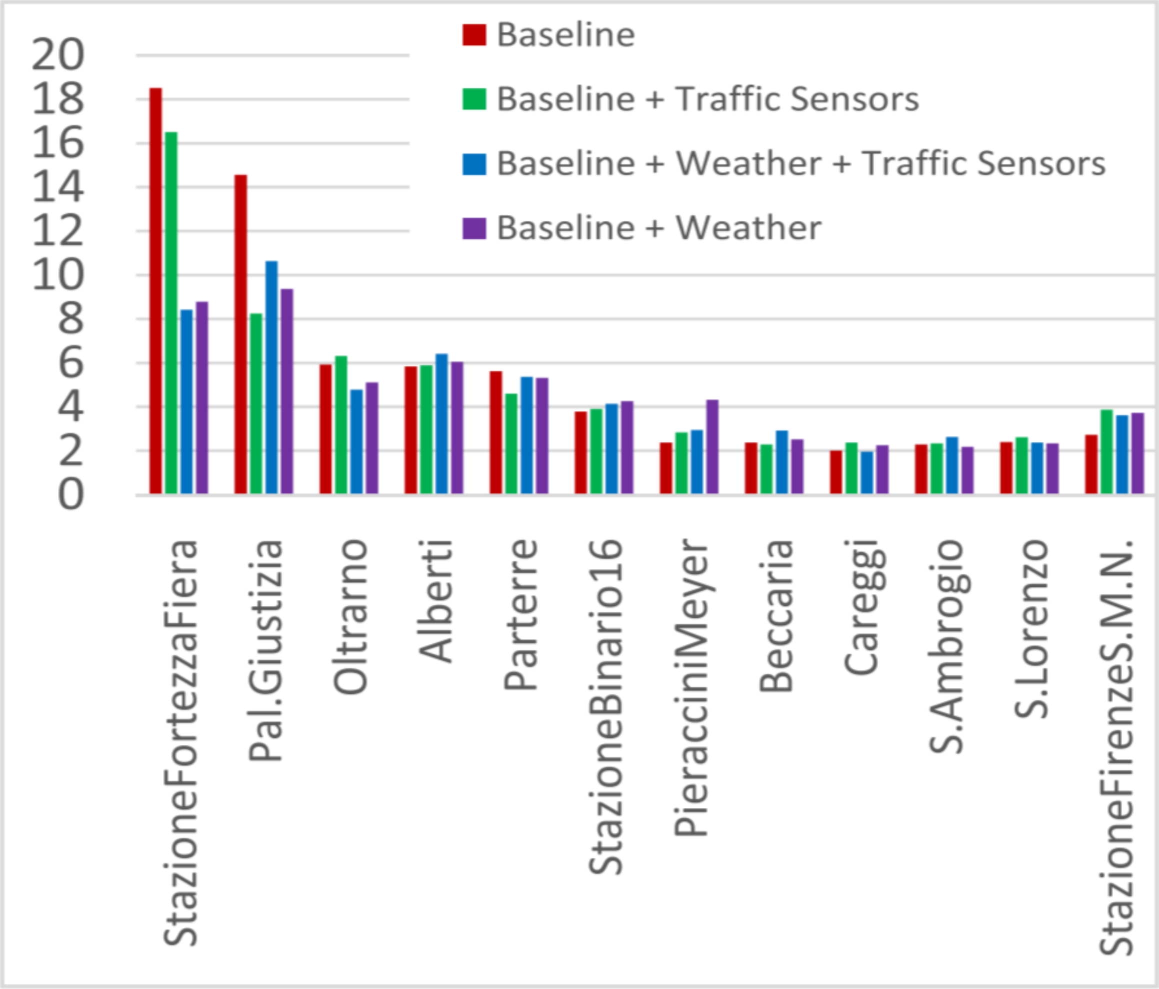
Deep Learning AI to surely Park!



Free Parking PREDICTIONS

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

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



ML models

The best selected models for the purpose have been:

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

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

Best compromize

Active on Mobile Apps as:

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

Precision: 97,5%

Smart Bike

Free Bike predictions

11 SUSTAINABLE CITIES AND COMMUNITIES

13 CLIMATE ACTION

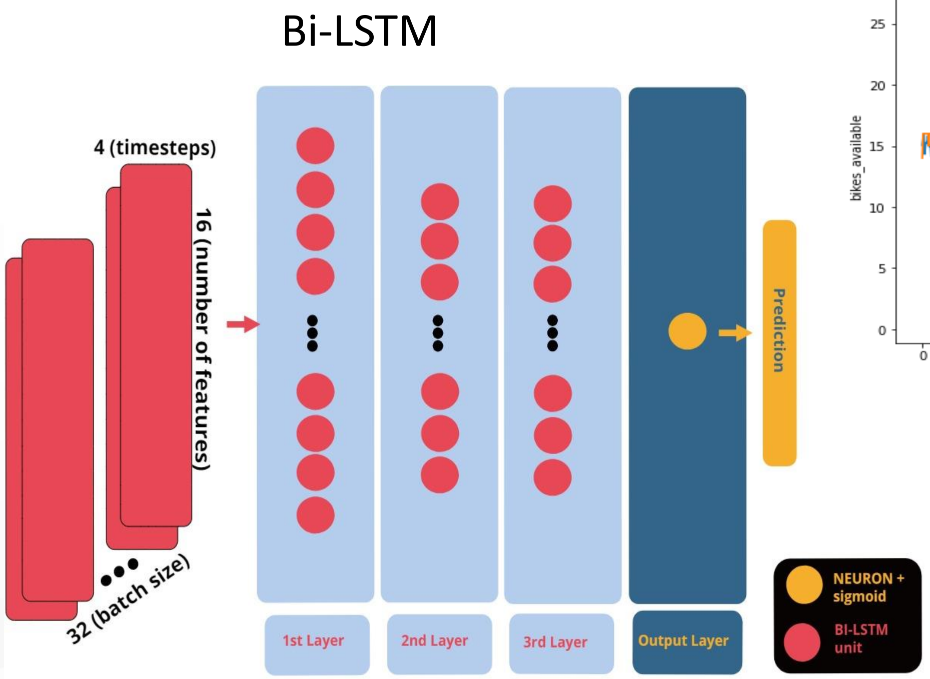
Data Analytic

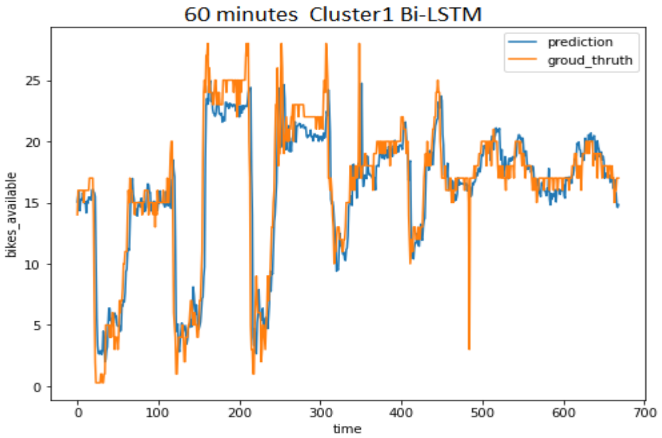
Bike Sharing

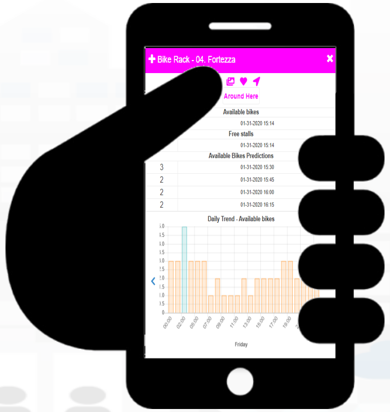
– Pros:
  - Eco-friendly
  - Prevent traffic congestions
  - Reduce the probability of social contacts in public transports
  - Regular bikes or e-bikes
– Problems:
  - Irregular distribution of bikes on racks/areas
  - Difficulty of knowing in advance their status with a certain degree of confidence
    – available bikes at a specific bike-station
    – free slot for leaving the rented bike

→ providing **PREDICTIONS** can be useful to improve quality of service

Deep Learning for Short-Term Prediction of Available Bikes on Bike-Sharing Stations



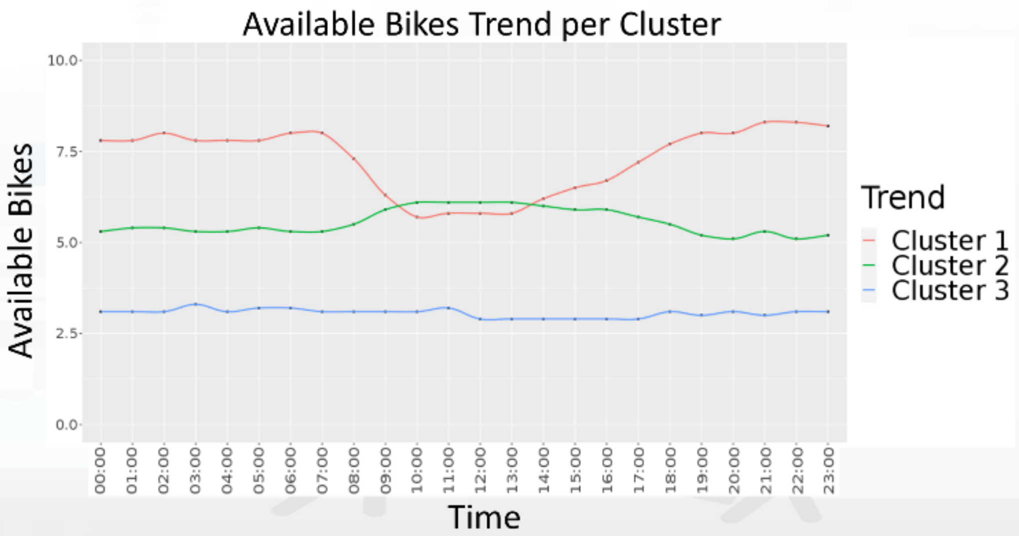


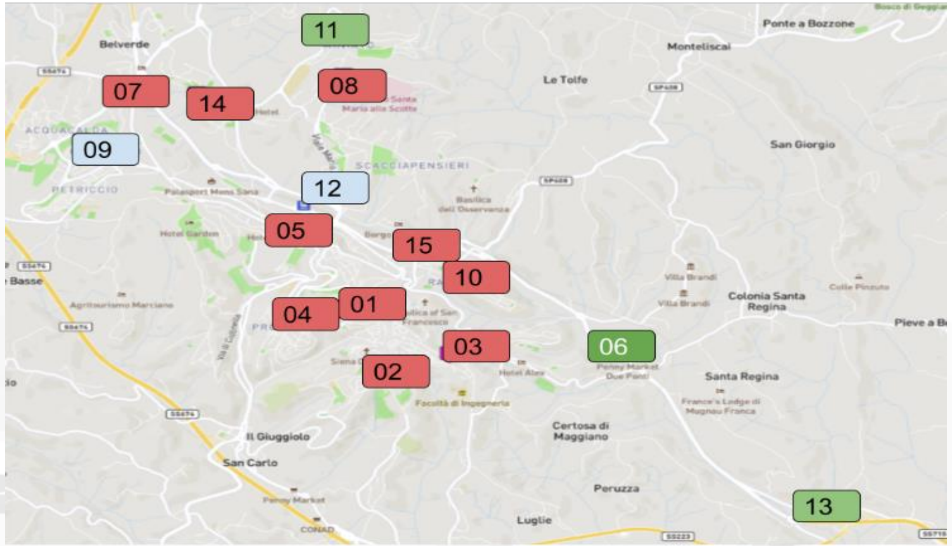


E. Collini, P. Nesi and G. Pantaleo, "Deep Learning for Short-Term Prediction of Available Bikes on Bike-Sharing Stations," in *IEEE Access*, vol. 9, pp. 124337-124347, 2021, doi: 10.1109/ACCESS.2021.3110794.
https://ieeexplore.ieee.org/abstract/document/9530580

Clustering

- A **clustering** approach has been applied in order to classify Pisa and Siena stations based on their mean trend H24 of bikes availability
  - This is also correlated to the typical services in the neighbourhoods
- **K-means** clustering method has been applied to identify clusters
  - The optimal number of clusters resulted to be equal to **3**, and it has been identified by using the **Elbow criteria**





Features

Category	Feature	Description
target	#Available Bikes	Number of available Bikes
Baseline-Historical	Time	The observation time hh-mm-ss
	month	Month of observation {1-12}
	Day Of The Week	Day of the week {1-7}
	Weekend	1 if the observation day is Saturday of Sunday, 0 otherwise
Differences Over Time	dP	the difference between the number of available bikes in the observation day (d) at the time slot t and the number of available bikes during the previous time slot (t-1) of the previous day (d-1)
	dS	the difference between the number of available bikes in the observation day (d) at the time slot t and the number of bikes during the successive time slot (t+1) of the previous day (d-1).
	PwAB	the number of available bikes of the previous week (d-7) in the same time slot (t).
Real-time weather and weather forecast	Temperature	Air temperature at the observation time, in °C
	Max Temperature	Forecast of max temperature of the observation day, in °C
	Min Temperature	Forecast of Min temperature of the observation day, in° C
	Humidity	Humidity of the hour prior to the observation time, in percentage
	Rain	mm of rain registered in the hour prior to the observation time
	Pressure	Pressure at the observation time, in millibar (mb)
	Wind Speed	Average wind speed registered in the hour prior to the observation time, in km/h
	Cloud Cover Percentage	Cloud Cover Percentage at the observation time

Analysis of the state of the art (Phase)

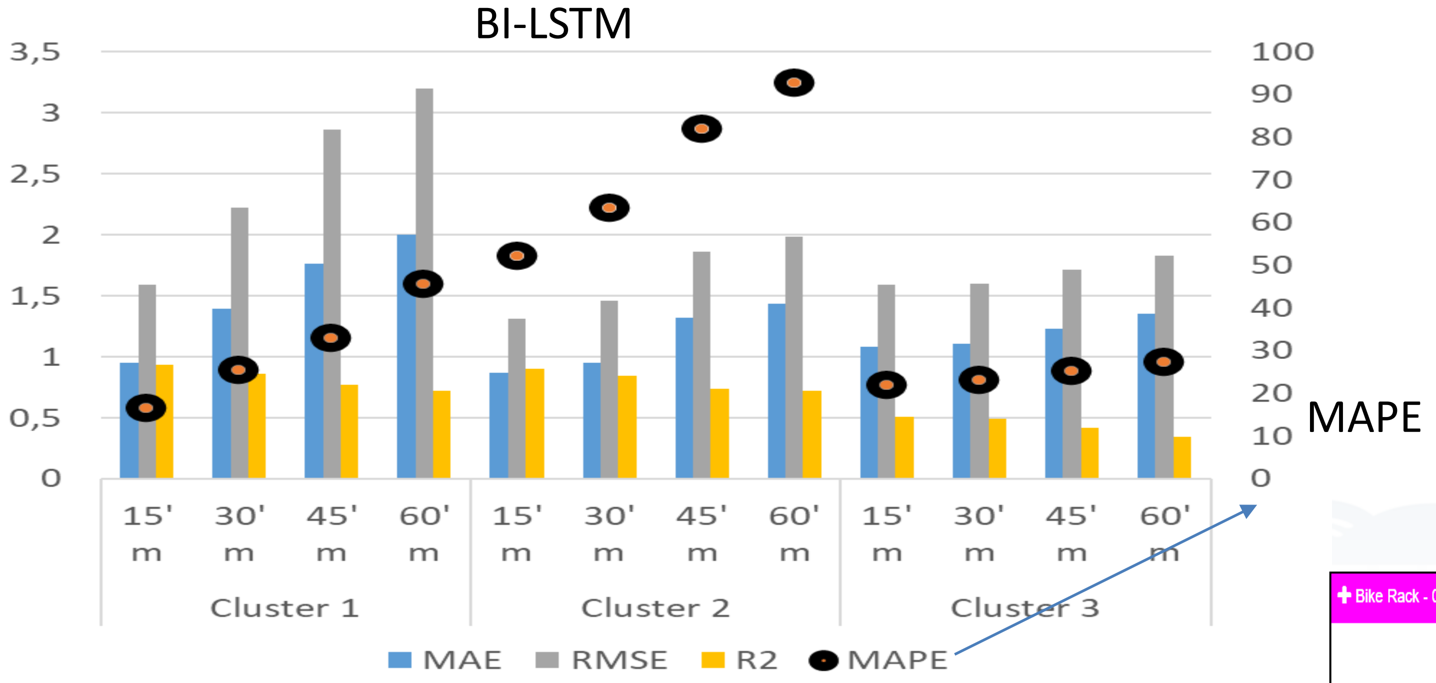
TABLE I

COMPARISON OF RELATED WORK SOLUTIONS, WITH MAIN ATTENTION TO DEEP LEARNING ASPECTS AND BETTER RESULTS.

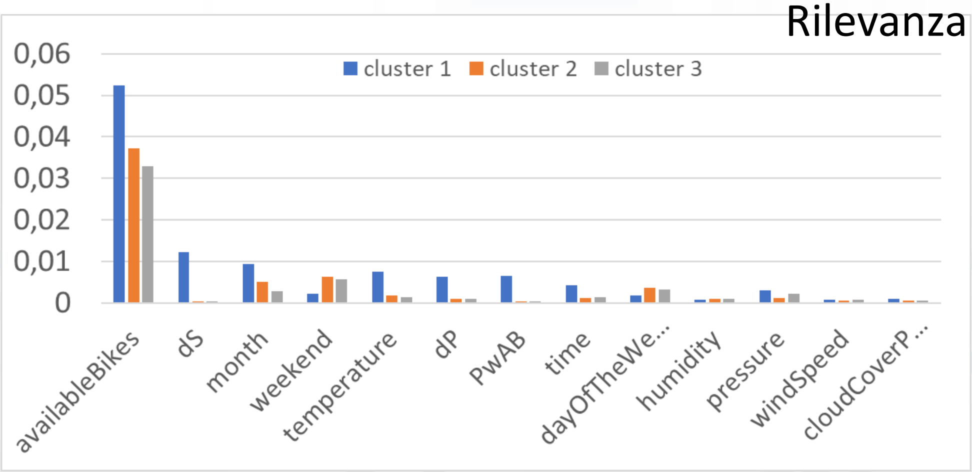
citation	Target	Features	Dataset	Model	Reported Best Resutls
[25]	1h, 2h, 3h bike rentals and returns	Bike rented, Bike returned, Avg temperature, Wind speed, Sky cover, Rain, holiday or Sunday, time, weekday, month, year	ThessBike	RF, XGBoost, GB, DNN	RF / Rentals / returns; MAE 0.85 / 0.82; MSE 2.77 / 2.76; RMSLE 0.46 / 0.46; R2 0.64 / 0.63
[24]	Hourly Bike number change in station	Usage features, spatial features, temporal features	Citi Bike dataset July – August 2017	XGBoost tree, RF, DNN	XGBoost tree: MAE 1.8159; AP 0.7085
[26]	1h rental bikes rented	Rental bikes rented, Weekend/weekday, Day of the week, Holidays, Functional/non functional, Temperature, Humidity , Windspeed, Visibility, Dew Point, temperature, Rainfall, snowfall	Seoul (South Korea)	RF, SVM, k-Nearest neighbours (KNN), Classification and Regression Trees (CART)	RF results: R2 0.88; RMSE 216.01; MAE 130.52; CV 30.63; PI 0.73
[27]	Hourly rental bike demand	Temperature, Humidity, Windspeed, Visibility, Dewpoint, Solar radiation, Snowfall, Rainfall, number of bikes rented per hour, date information.	Seoul (South Korea	LR, XGBoost, SVM, Boosted Trees, XGBoost Trees	XGBoost results: R2 0.92; RMSE 174.68; MAE 109.89; CV 24.92
[28]	Long terms predictions	Timestamp, count of new bike shared, temperature, humidity, windspeed, weather code, is holiday, is weekend, season	London	LR, RF, XGBoost, SVM, AB, BGR	RF results: MAE 0.04; MSE 0.01; RMSLE 0.03; R2 0.95
[23]	1h number of rider...	Number of riders, Season, year, month, hour, day, holiday, weekday, working, weather...	Rental Company...	DNN	80% accuracy

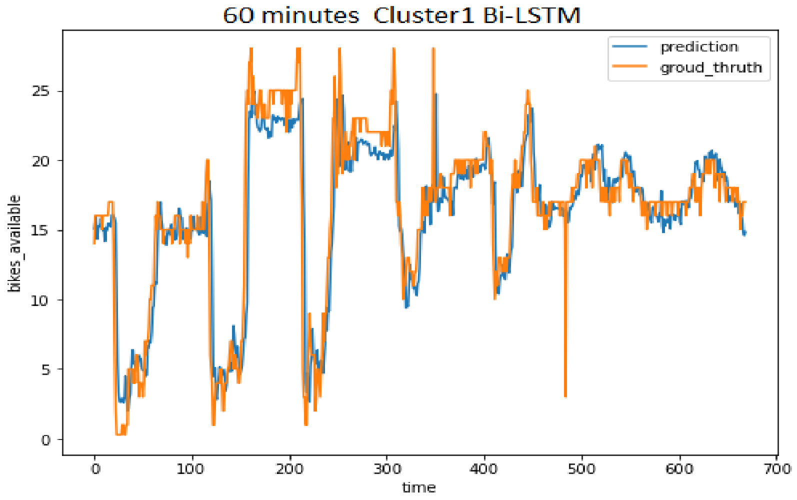
Siena Bike Sharing

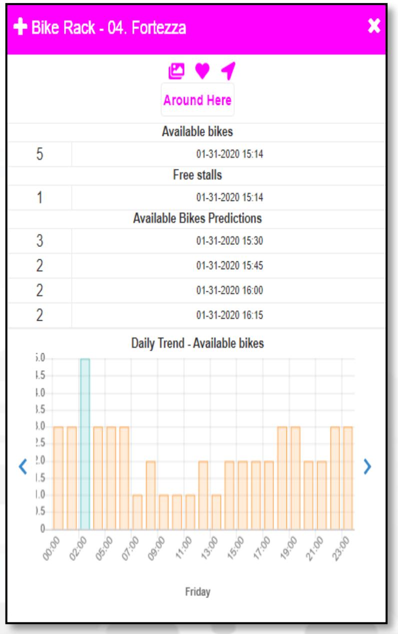
- For each Bike Rack, Prediction of the number of
  - available bikes in sharing
  - free slots for leaving the bike



Rilevanza







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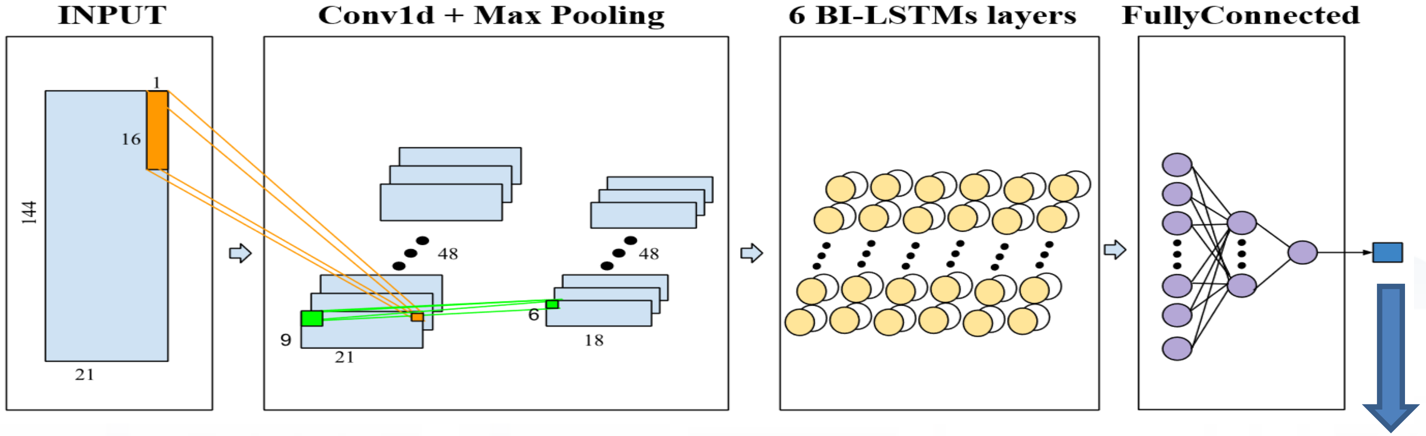
Traffic Flow Prediction

Short-Term Prediction of City Traffic Flow via Convolutional Deep Learning

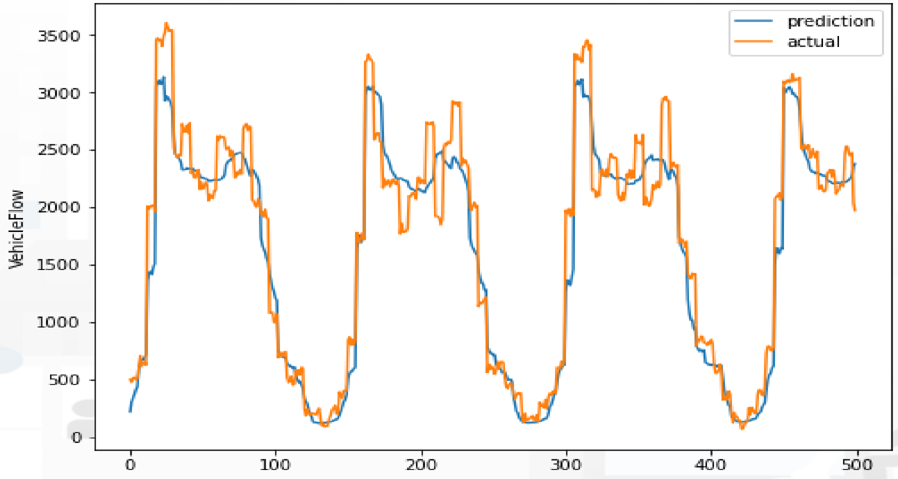


Urban data:

- Date-time
- Traffic
- Temporal
- Seasonality
- Pollution
- Weather

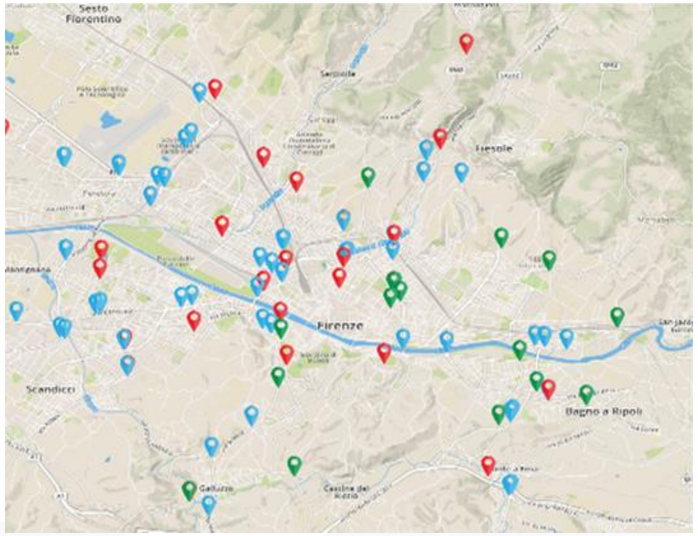
RF
XGBOOST
DNN
LSTM
BI-LSTM
Autoencoder BI-LSTM
Attention CONV-LSTM
CONV-BI-LSTM

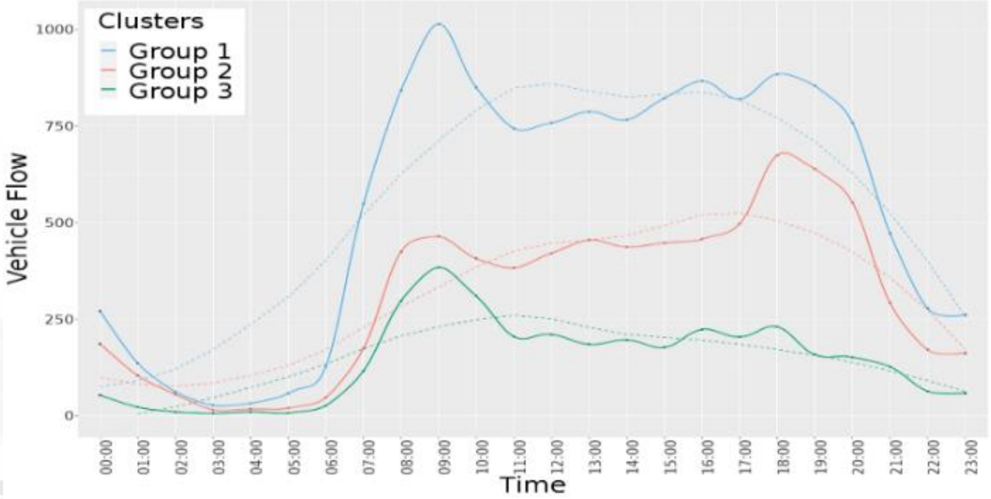
CONV-BI-LSTM



Clustering traffic flow sensors

- The clustering has been performed on the basis of the time trend H24, considering the normalized vehicle flow measures.
- The optimal number of clusters turned out to be 3 and it has been identified by using **elbow** criteria
- **K-means** clustering method has been applied to identify clusters
  - The optimal number of clusters resulted to be equal to **3**, and it has been identified by using the **Elbow criteria**





Best compromize

Selected Features

Category	Feature	Description
Traffic Trafplus	Traffic Flow	Real number of vehicles recorded every 10 minutes
	AverageSpeed	Average speed of vehicles (Km/h)
	Concentration	Number of vehicles in terms of road occupancy (%)
DateTime	timeOfTheDay	Time of the day {1, 144}
	dayOfTheYear	Day of the year {1, 366}
seasonality	dayOfTheWeek	Day of the week {1,7}
	Weekend	0 for working days, 1 else
	Year	The year of the observation
Temporal	Previous observation's difference of the previous week (dP)	the difference between the number of vehicles in the observation day (d) at the time slot t and the number of available vehicles during the previous time slot (t-1) of the previous day (d-1)
	Subsequent observation's difference of the previous week (dS)	the difference between the number of vehicles in the observation day (d) at the time slot t and the number of vehicles during the successive time slot (t+1) of the previous day (d-1).
	Previous week observation ($PwVF$)	the number of vehicles of the previous week (d-7) in the same time slot (t).
Weather	Air Temperature	City temperature one hour earlier than Time (°C)
	Humidity	City humidity one hour earlier than Time (%)
	Pressure	City pressure one hour earlier than Time (millibar mb)
	Wind Speed	City wind speed one hour earlier than Time (KM/h)
AirPoll	CO	Concentration of CO one hour earlier than Time
	NO2	Concentration of NO2 one hour earlier than Time
	O3	Concentration of O3 one hour earlier than Time
	PM10	Concentration of PM10 one hour earlier than Time
	PM2.5	Concentration of PM2.5 one hour earlier than Time

Best Model for traffic flow prediction

- With a temporal target of 1h, which is the most critical short-term prediction slot ensemble learning techniques such as **Random Forest** (RF) and **Extreme Gradient Boosting Machines** (XGBOOST) are powerful techniques that must be considered for this type of problem.

- Regarding the deep learning techniques for this research project it has been proposed a new architecture **CONV-BI-LSTM** that will be compared to other solutions as **Deep Neural Network** (DNN), Deep **LSTM**, Deep **BI-LSTM** Neural Network , **Autoencoder BI-LSTM**, and an **attention-based CONV-LSTM** to assess the research question of which will be the best AI architecture for the problem of short-term prediction of vehicle flow based on this case study.

Analysing Features vs ML/AI Models

Chose the best model and/or the best compromise

ID	Features adopted in the model						Median value of MAPE for prediction results by technique								min
	Date time	Traf plus	Temp oral	Season ality	Air poll	weath er	RF	XGBO OST	DNN	LSTM	BI-LSTM	Autoenco der BI-LSTM	Attention CONV-LSTM	CONV-BI-LSTM	
C1	Y	Y	Y	Y	Y	Y	29.342	34.552	42.754	49.407	34.865	34,708	37,059	31.365	29.342
C2	Y	Y	Y	Y	Y	N	29.682	35.545	43.400	49.832	35.870	35,707	39,506	35.613	29.682
C3	Y	Y	Y	Y	N	Y	28.782	34.441	35.465	36.824	31.555	32,998	33,179	30.894	28.782
C4	Y	Y	Y	Y	N	N	30.935	35.373	38.942	35.383	30.564	32,969	35,713	32.485	30.564
C5	Y	Y	Y	N	Y	Y	29.776	34.469	33.425	42.301	39.865	37,167	35,161	36.897	29.776
C6	**Y**	**Y**	**Y**	**N**	**Y**	**N**	**29.598**	**35.547**	**33.865**	**36.792**	**35.097**	35,322	29,923	**25.981**	**25.981**
C7	Y	Y	Y	N	N	Y	29.421	33.711	31.377	34.736	40.510	37,110	30,741	30.106	29.421
C8	Y	Y	Y	N	N	N	31.245	34.414	32.026	37.823	40.662	37,538	31,263	30.500	30.500
C9	Y	Y	N	Y	Y	Y	29.626	36.919	42.187	**37.068 [38]**	34.297	35,608	36,651	**31.115**	29.626
C10	Y	Y	N	Y	Y	N	29.964	35.802	47.201	41.334	34.743	35,272	40,658	34.116	29.964
C11	Y	Y	N	Y	N	Y	29.785	35.976	45.451	44.756	41.620	38,798	37,345	29.240	29.240
C12	Y	Y	N	Y	N	N	31.262	35.792	36.040	37.228	32.727	34,259	32,701	29.363	29.363
C13	Y	Y	N	N	Y	Y	29.431	35.935	34.448	35.829	34.619	35,277	32,287	30.126	29.431
C14	Y	Y	N	N	Y	N	29.764	36.374	36.203	43.510	35.744	36,059	33,015	29.827	29.764
C15	Y	Y	N	N	N	Y	29.972	35.423	31.526	46.201	37.209	36,316	32,919	34.313	29.972
C16	Y	Y	N	N	N	N	**30.960 [14]**	34.235	30.338	**37.068 [23]**	**38.082 [39]**	**34,235[45]**	**29,455[46]**	**28.573**	28.573
C17	Y	N	Y	Y	Y	Y	29.281	34.503	72.909	64.557	48.685	41,594	51,026	29.144	29.144
C18	Y	N	Y	Y	Y	N	30.184	35.350	59.458	68.127	46.874	41,112	44,810	30.163	30.163
C19	Y	N	Y	Y	N	Y	28.711	34.316	45.679	46.211	33.404	33,86	37,125	28.571	28.571
C20	Y	N	Y	Y	N	N	31.211	34.784	51.603	45.188	48.643	41,713	40,862	30.122	30.122
C21	Y	N	Y	N	Y	Y	30.689	35.774	36.428	48.608	40.092	37,933	34,801	33.175	30.689
C22	Y	N	Y	N	Y	N	30.505	36.165	37.337	61.168	34.420	35,292	34,385	31.434	30.505
C23	Y	N	Y	N	N	Y	30.036	34.779	37.583	64.341	51.063	42,921	33,455	29.328	29.328
C24	Y	N	Y	N	N	N	32.629	34.312	36.849	53.854	41.912	38,112	33,257	29.665	29.665
C25	Y	N	N	Y	Y	Y	28.766	35.906	71.829	65.565	54.403	45,154	52,023	32.218	28.766
C26	Y	N	N	Y	Y	N	30.008	37.317	67.870	49.366	46.880	42,098	53,256	38.642	30.008
C27	Y	N	N	Y	N	Y	28.986	35.218	57.938	50.333	59.419	47,318	43,298	28.658	28.658
C28	**Y**	**N**	**N**	**Y**	**N**	**N**	**31.068**	**35.878**	**66.634**	**50.957**	**55.096**	45,487	47,097	**27.561**	**27.561**
C29	Y	N	N	N	Y	Y	29.301	37.532	38.325	40.677	50.303	43,917	35,554	32.784	29.301
C30	Y	N	N	N	Y	N	29.323	37.284	37.149	48.801	55.064	46,174	34,721	32.294	29.323
C31	Y	N	N	N	N	Y	29.964	36.331	34.638	56.157	45.016	40,673	35,293	35.049	29.964
C32	**Y**	**N**	**N**	**N**	**N**	**N**	**29.281**	**34.574**	**33.028**	**57.961**	**44.977**	39,775	29,320	**25.612**	**25.612**

Quite good model, RF
1 data source
Easy to compute and manage

Best model
1 data source
CONV-BI-LSTM

Comparing performance

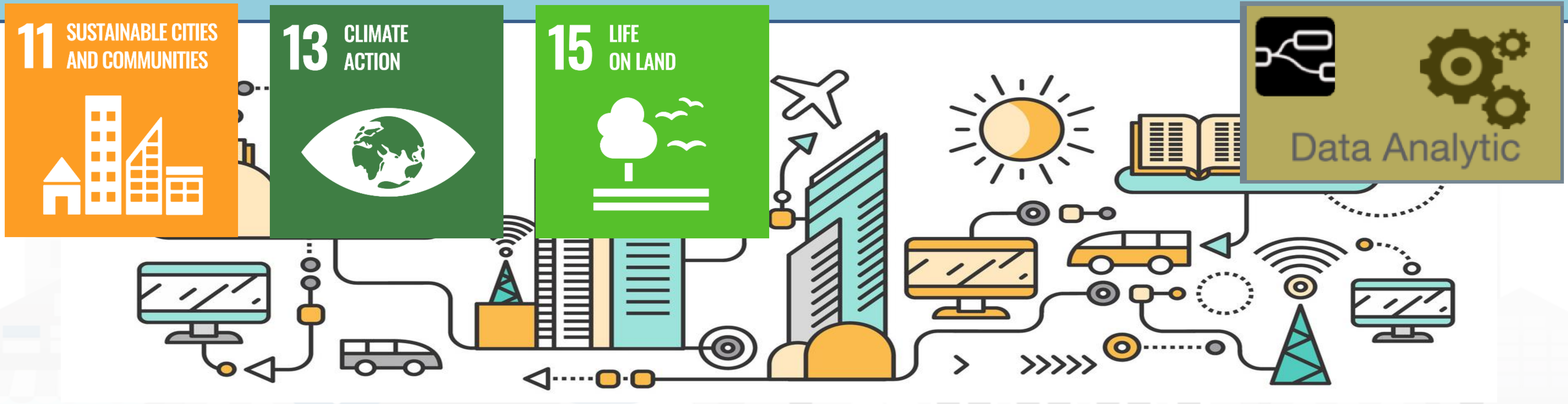
	Training execution		Prediction execution (s)
Processing time	Duration (s)	Max GPU	
RF	14.681	On CPU	0.023
XGBOOST	4.352	On CPU	0.002
DNN	748.431	25%	0.056
LSTM	527.623	40%	0.017
BI-LSTM	681.874	42%	0.021
Autoencoder BI-LSTM	3240.564	38%	0.033
Attention-based CONV-LSTM	2579.248	41%	0.023
CONV-BI-LSTM	353.672	39%	0.102

Please take note of the wide difference from the training and the execution times

Best compromize

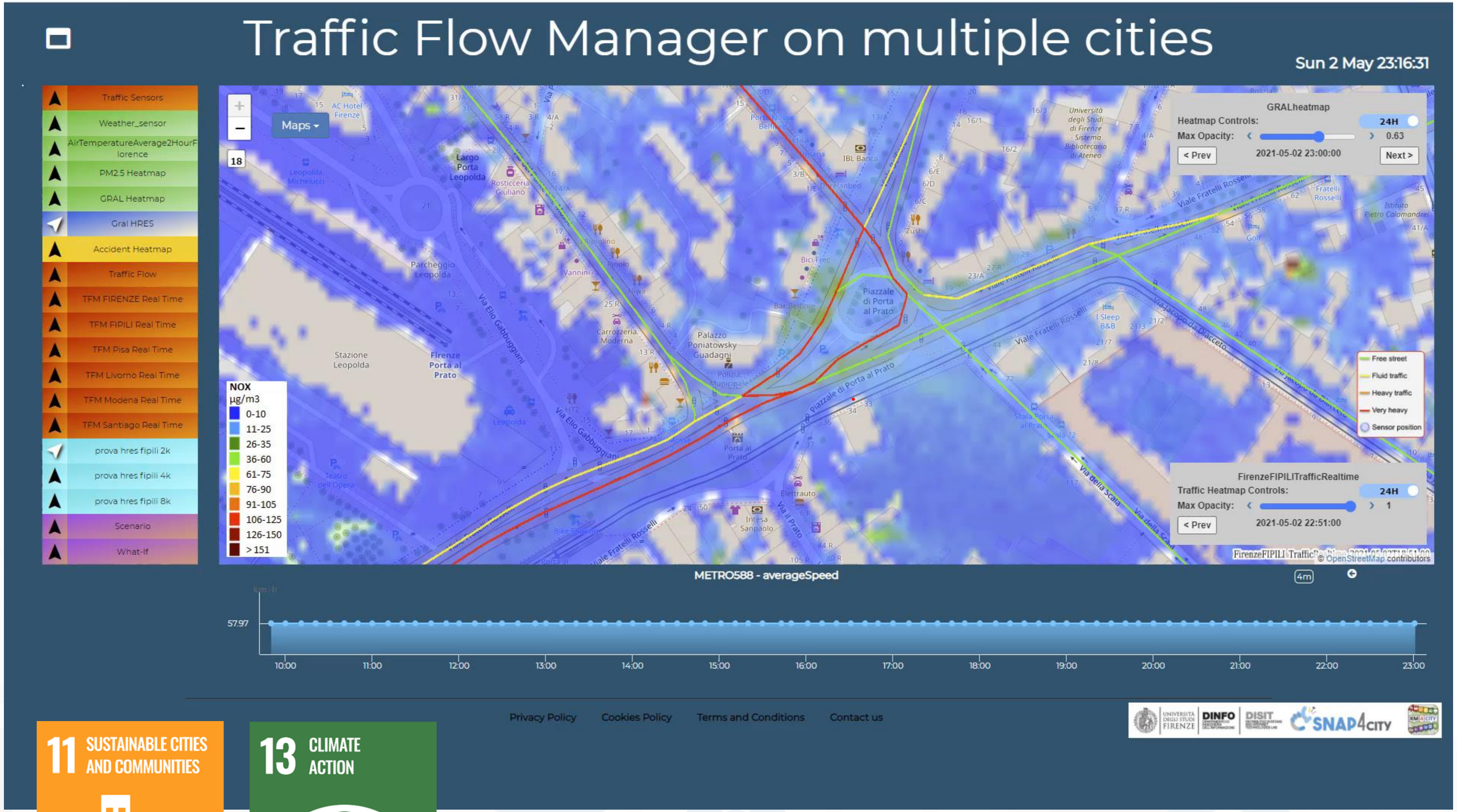
TOP

1-48 Hour prediction of NOx

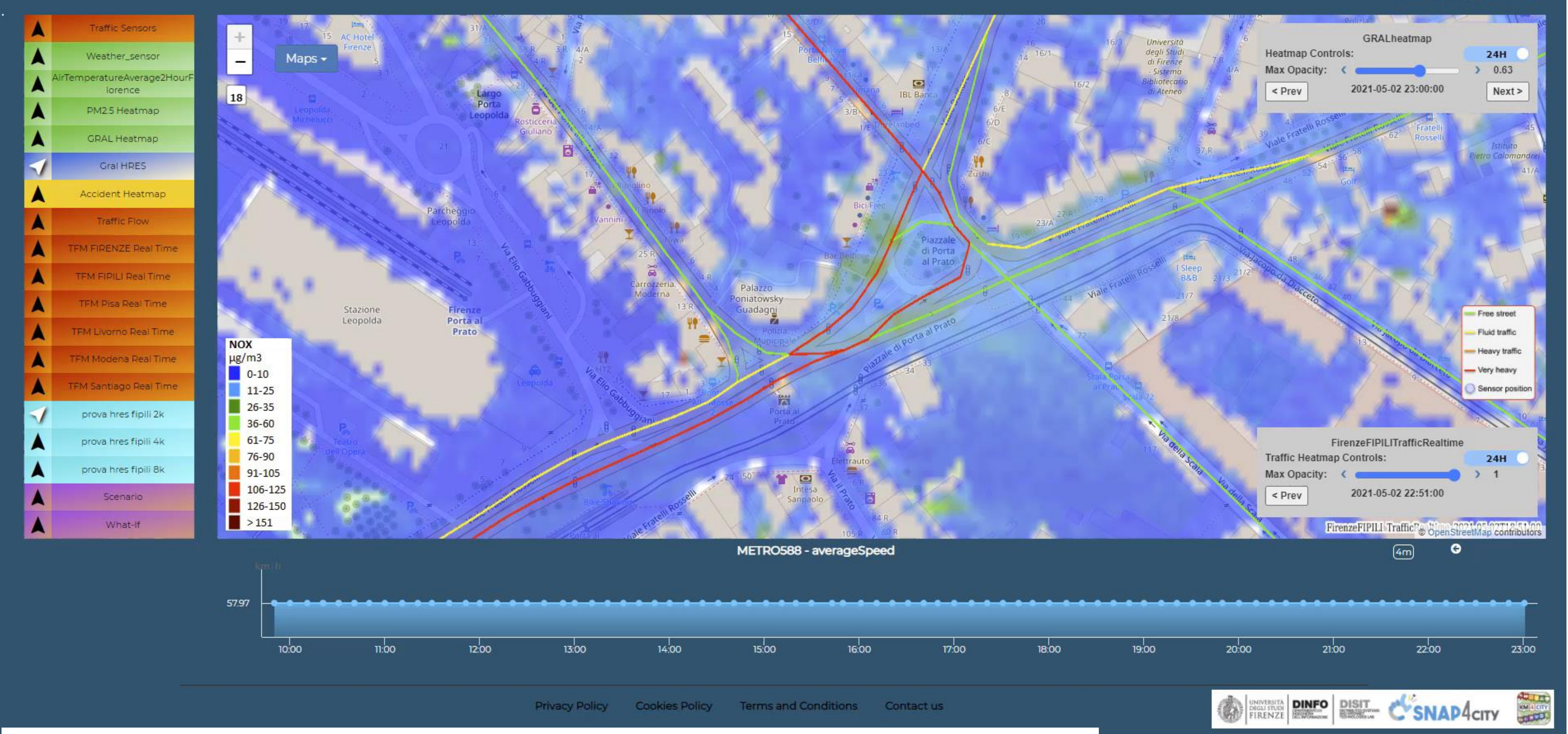


Environment

- **Prediction**
  - **NOX Pollutant** diffusion on the basis of Traffic Flow (prediction), weather and 3D structure
  - **NO2 progressive average** (Long term)
- **Project:**
  - **Trafair** CEF EC
  - Mixed solutions of Fluidinamics modeling and AI



Traffic Flow Manager on multiple cities



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

How it works: NOX predictions

Road Graph

3D City Structure

Traffic Flow Predictions

Weather Forecast: Temp, wind…

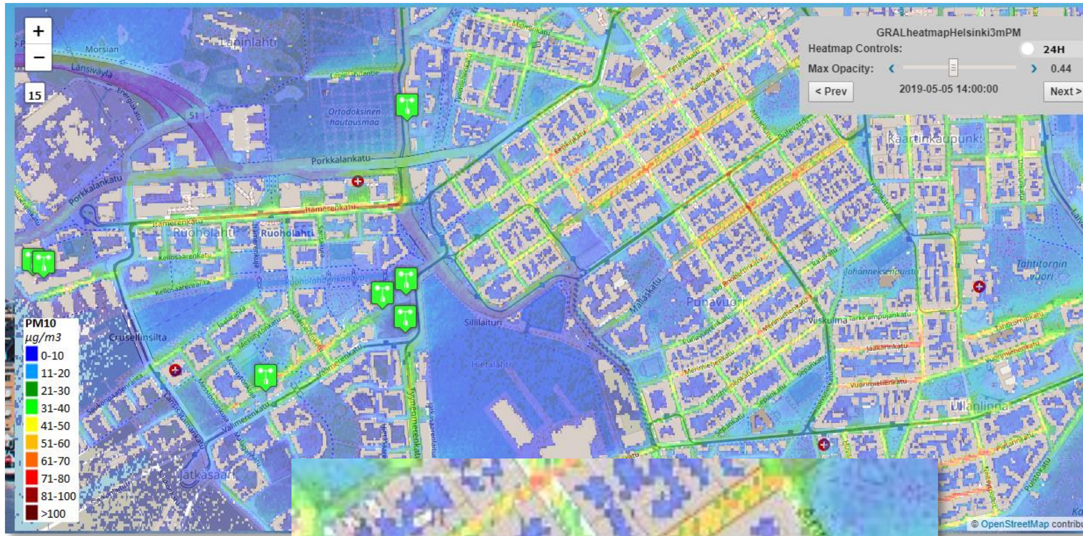
Particles Flow Simulation

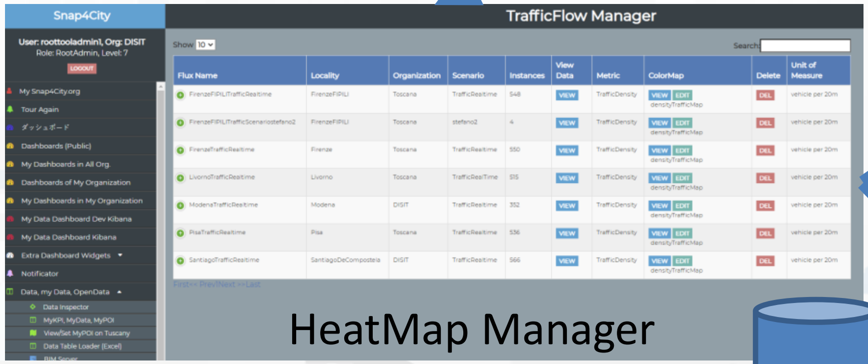
Heatmap

JSON

JSON

WMS



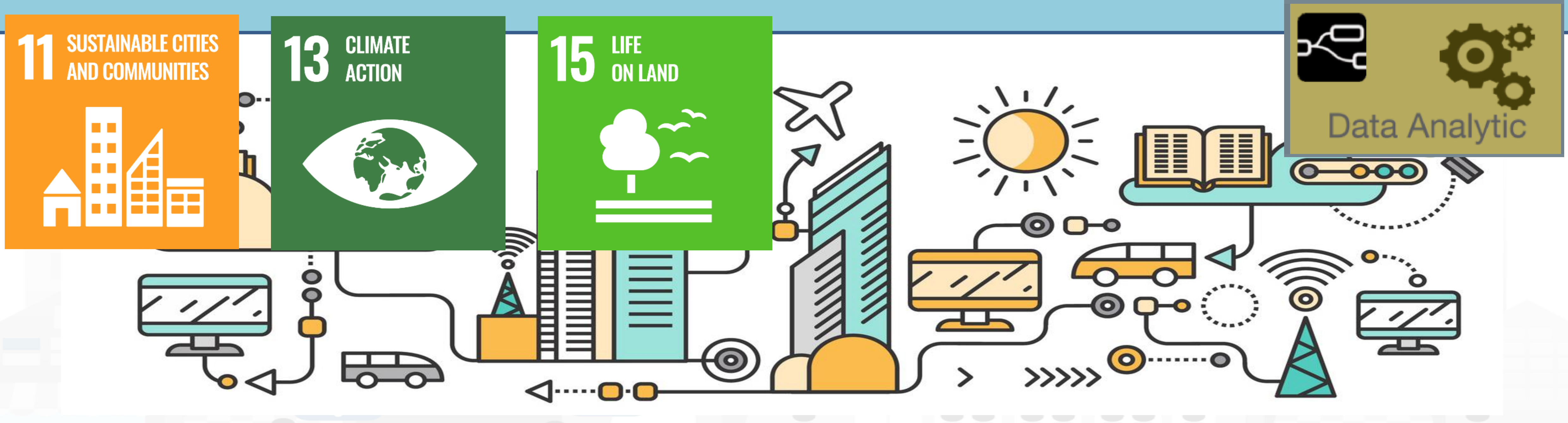


HeatMap Manager

GeoServer

TOP

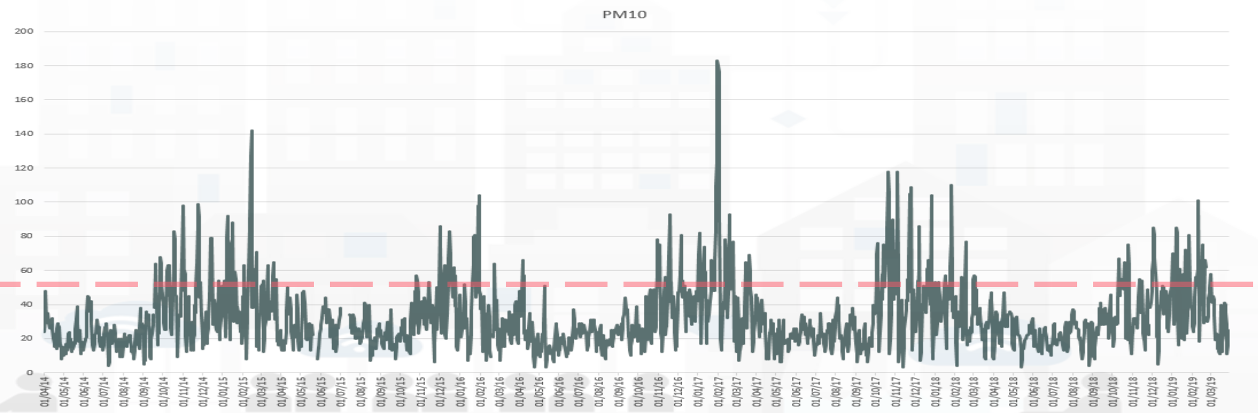
Long Term Prediction of Annual Mean of NO2 index of EC



Predicting Air Quality

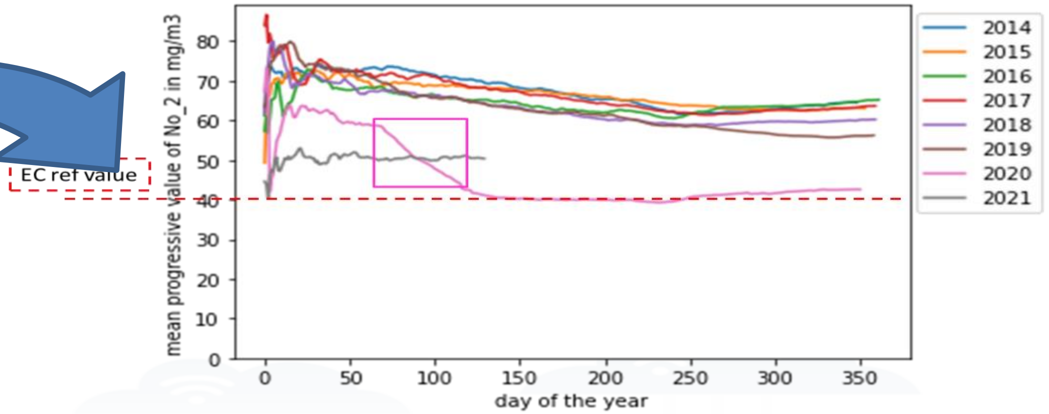
- European Air Quality Directive
- Predicting critical days
  - PM10 with an accuracy of more than 90% and precision of 85%;
  - PM2.5 with an accuracy of 90% and precision greater than the 95%.
- Simulating Long terms values
  - For long terms predictions

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	

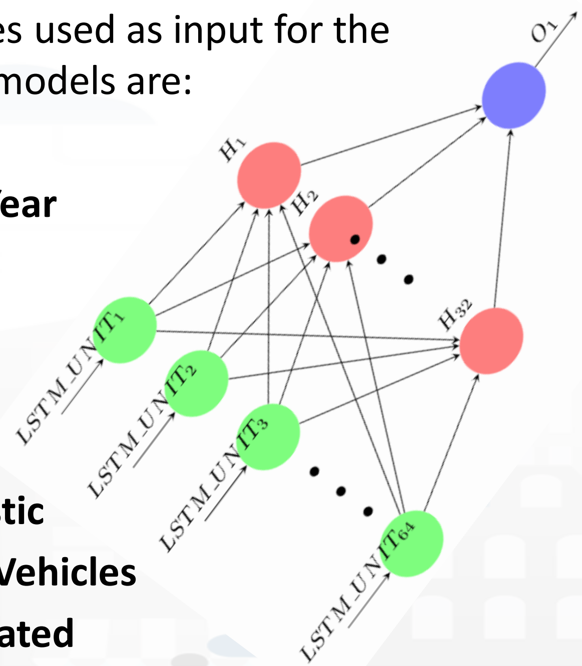


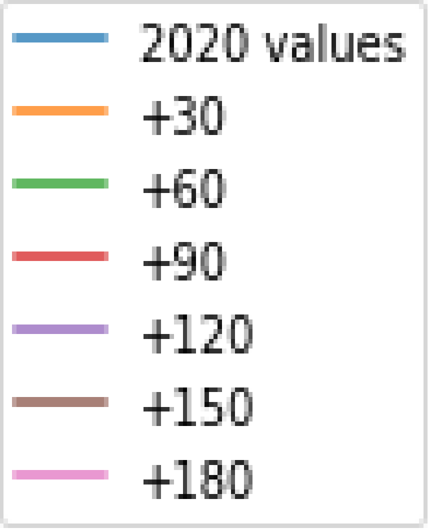
Predicting EC's KPI on NO2 months in advance

Deep Learning Long Terms Predictions of NO2 mean values, From 30 to 180 days in advance



- The features used as input for the predictive models are:
- Month
- dayOfTheYear
- NO2
- Tmean
- Humidity
- windMean
- NoxDomestic
- numberOfVehicles
- NO2cumulated
- NO2progresseveMean
- numberOfVehiclesCumulated





11 SUSTAINABLE CITIES AND COMMUNITIES
13 CLIMATE ACTION

	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	
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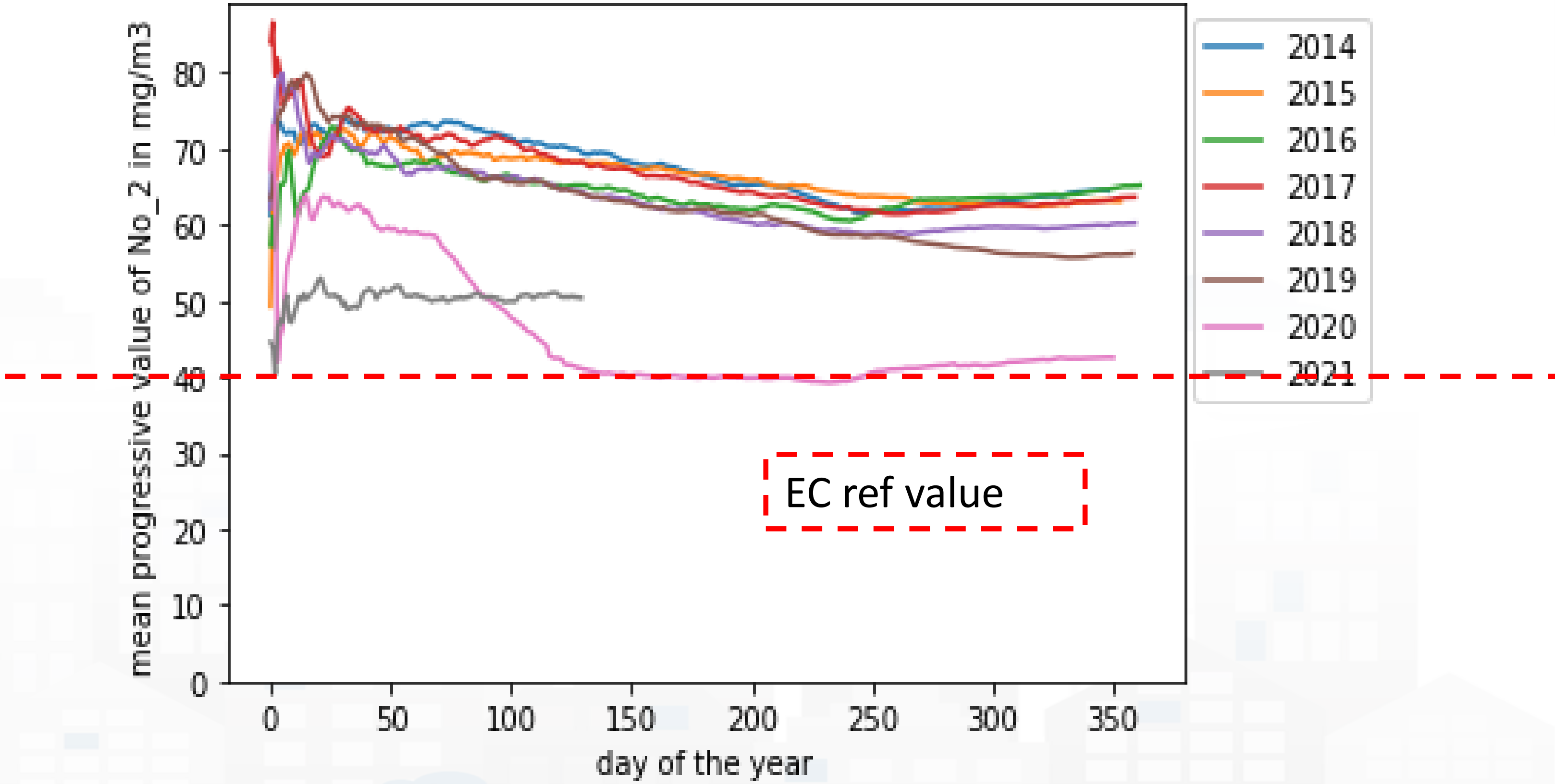
NO_2	One hour	Limit value, 200 µg/m³ (*)	Not to be exceeded more than 18 times a calendar year	200 µg/m³ (*)	
NO_2	Calendar year	Limit value, 40 µg/m³		40 µg/m³	

Actual Time Trend of the mean progressive NO2

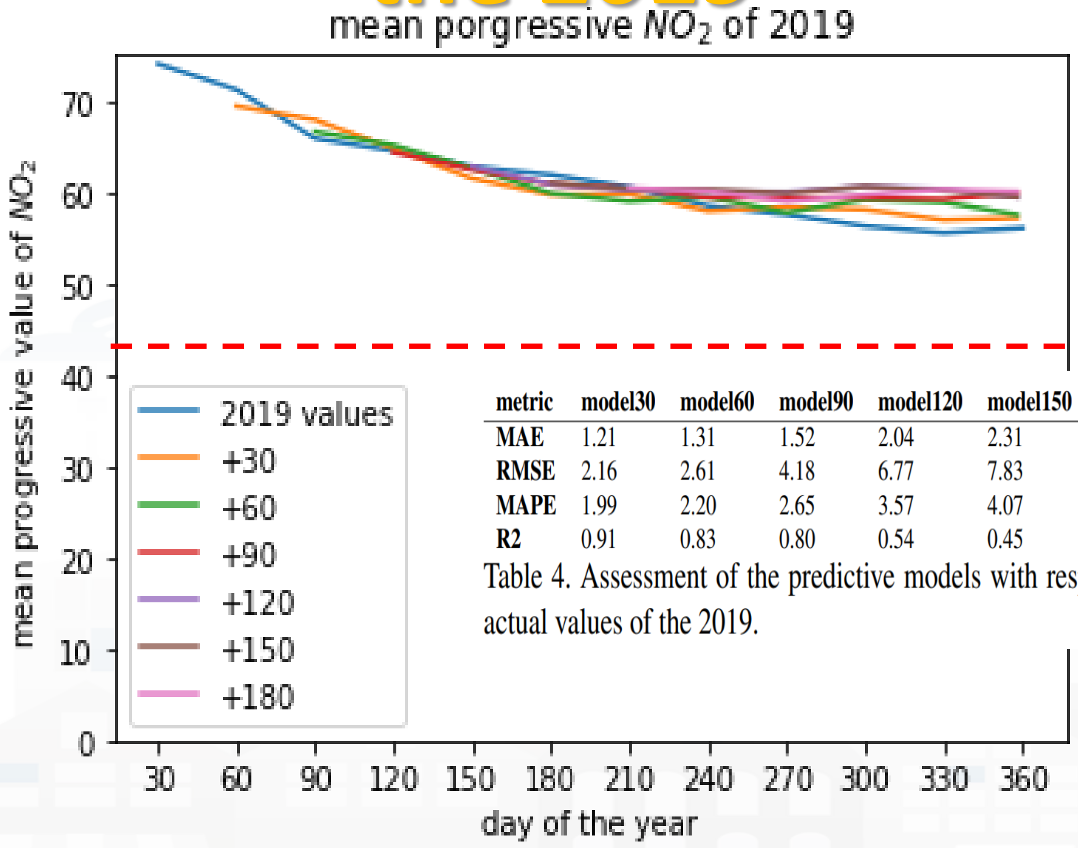
- The data used refers to the years from 2014 to 2020.
- Training set 2014 – 2017
- Test set 2019



Using data since 2014

Very long term predicting Mean NO2:

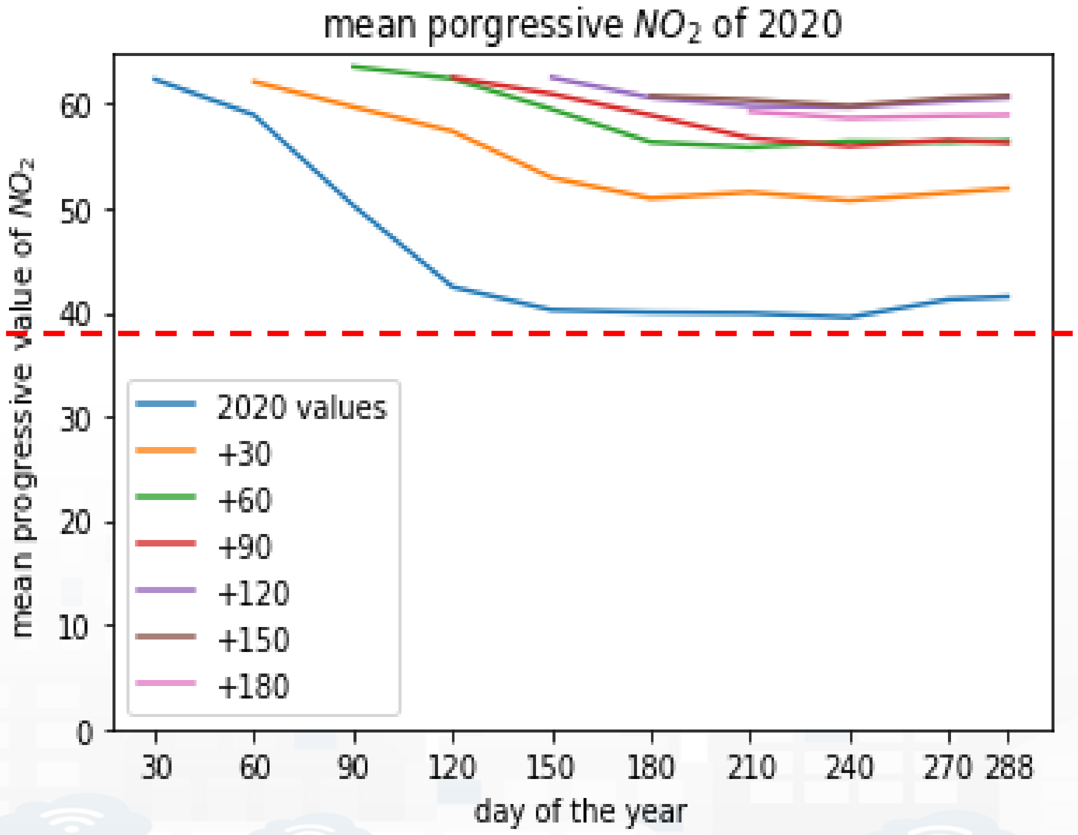
the 2019



metric	model30	model60	model90	model120	model150	model180
MAE	1.21	1.31	1.52	2.04	2.31	2.37
RMSE	2.16	2.61	4.18	6.77	7.83	7.93
MAPE	1.99	2.20	2.65	3.57	4.07	4.18
R2	0.91	0.83	0.80	0.54	0.45	0.14

Table 4. Assessment of the predictive models with respect to the actual values of the 2019.

the 2020



EC ref value

Deep Learning Approach

TOP

Predicting Land sliding

Landslide Prediction

Rainfall induced landslide is one of the main geological hazard in Italy and in the world.

- Worldwide based on the study [1] of Natural Hazards and Earth System Sciences
  - from 2004 to 2016, 55997 people were killed in 4862 non seismic landslide events worldwide
  - The same authors identified rainfall as the main the triggering factor of 79% of non-seismic landslides.
- In Italy based on the ISPRA report:
  - 19.9% of the Italian territory is at risk of landslides (59981km^2)
  - Tuscany is among the regions with the largest areas at risk (26%)

Accurate short-term **PREDICTIONS** (1 day in advance) of landslides can be extremely important and useful, in order to both provide local authorities with efficient prediction/ early warning and increase the resilience to manage emergencies.

[1] Froude, M. J. and Petley, D. N.: Global fatal landslide occurrence from 2004 to 2016, Nat. Hazards Earth Syst. Sci., 18, 2161–2181, https://doi.org/10.5194/nhess-18- 2161-2018

Scenario

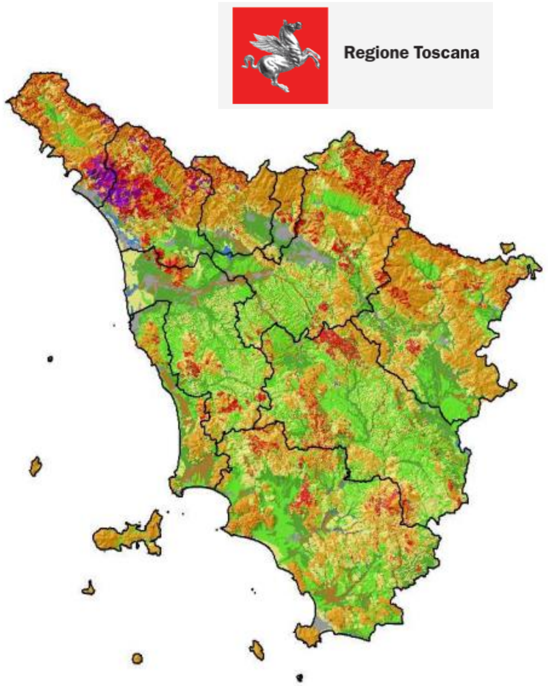
- The solution and its validation have been performed by using data collected in in the area of the **Metropolitan City of Florence** with
  - 41 Municipalities
  - 3514 Km^2 of Surface Area
  - altitude between 100-1000 above the sea level
  - land predominantly of deciduous forests and cultivated areas
  - 1.5 M inhabitants
- The data history covers the years 2013-2019 with a total of **341** landslide events

Prediction | Susceptibility

per municipality

dynamic hazard heatmaps

Useful for early warning systems	Useful for long term land usage planning
static + dynamic features	static features based
Can be computed daily	1 or 2 times per year



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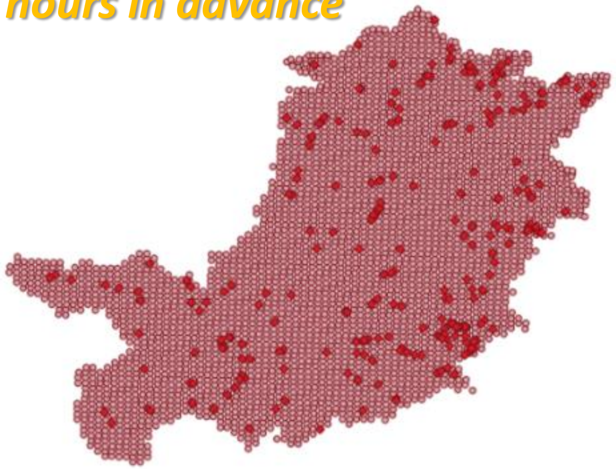
DISIT DISTRIBUTED SYSTEMS AND INTERNET TECHNOLOGIES LAB DISTRIBUTED DATA INTELLIGENCE AND TECHNOLOGIES LAB

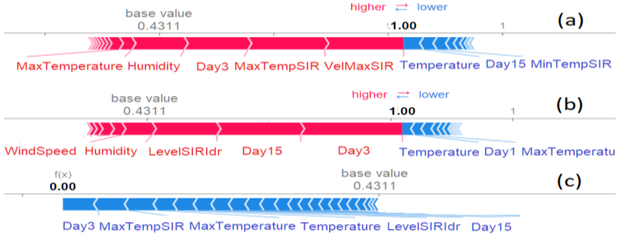
11 SUSTAINABLE CITIES AND COMMUNITIES
13 CLIMATE ACTION
15 LIFE ON LAND

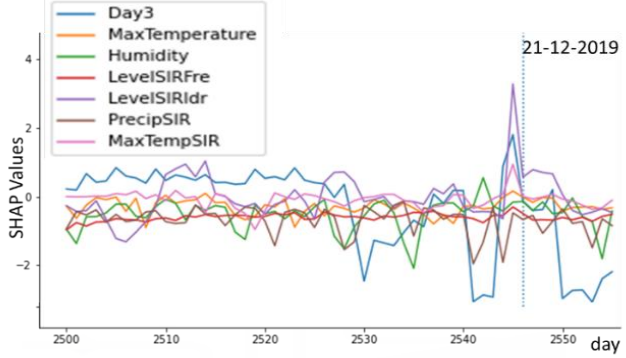
SNAP4CITY

Predicting Land slides

24 hours in advance







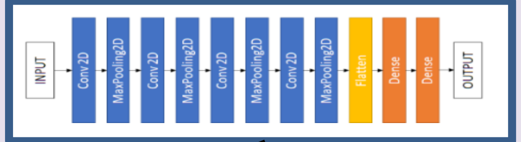
Dataset Construction

Previsional Model

Dataset Construction

Model training And validation

Model



Data

SNAP4City Advanced APIs

landslide DB

Real Time data from Field: rain, weather, etc.

Processes Ingestion

Big Data Storage and KB

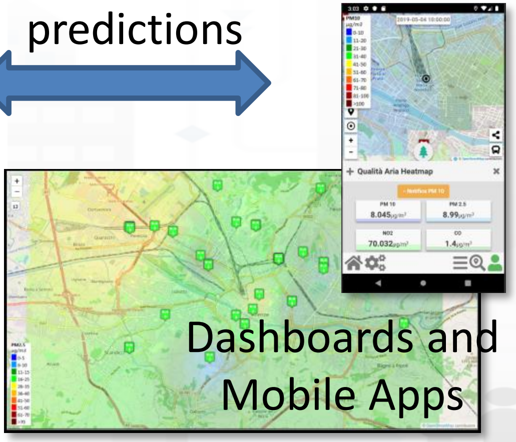
Predictions

Model execution Shap Assessment

Data Analytics IOT App Management

predictions

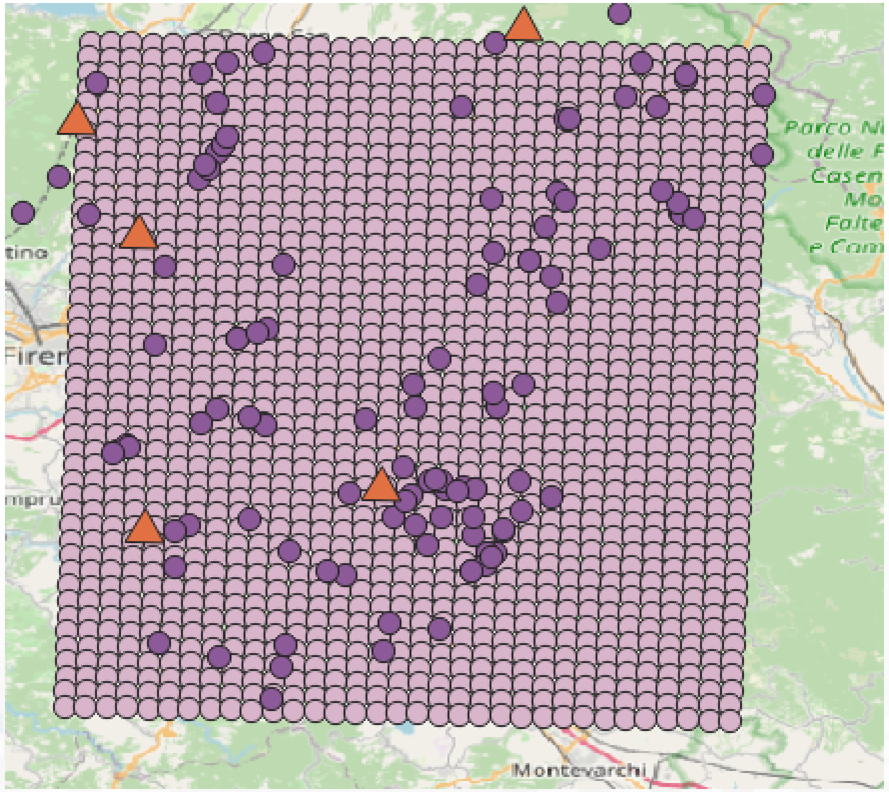
Snap4City Servers and Tools: Dashboard manager, Heatmap manager, GeoServer, Smart City API.



Dashboards and Mobile Apps

E. Collini, L. A. I. Palesi, P. Nesi, G. Pantaleo, N. Nocentini and A. Rosi, "Predicting and Understanding Landslide Events with Explainable AI," in *IEEE Access*, doi: 10.1109/ACCESS.2022.3158328.
https://ieeexplore.ieee.org/abstract/document/9732490

Features as Predictors: static + dynamic data



● landslide events ▲ rain gauges ● grid

Feature	Description	Unit	Example
Date	Observation date, in the format YYYY-MM-DD	Day	2013-01-14
Latitude	Latitude of the area, EPSG:4326 format	Deg	43.86239
Longitude	Longitude of the area in the EPSG:4326 format	Deg	11.51586
Altitude	Altitude of the area	m	467.204
Slope	Acclivity of the area	%	45.942
Vegetation	Vegetation of the area	%	0.262
Ground	Soil type at the event site (class UCS)		223-Oliveti
Day1	Rainfall on the day before the observation	mm	12.453
Day3	Rainfall on the 3 days preceding the observation	mm	15.072
Day15	Rainfall on the 15 days preceding the observation	mm	16.160
Day30	Rainfall on the 30 days preceding the observation	mm	51.515
Temperature	Mean Temperature on the observation day (IlMeteo.it)	°C	6.965
MinTemperature	Minimum temperature on the observation day (IlMeteo.it)	°C	2.99
MaxTemperature	Maximum temperature on the observation day (IlMeteo.it)	°C	9.942
Humidity	Humidity (average) on the observation day (IlMeteo.it)	%	92.96
WindSpeed	Average wind speed on the observation day (IlMeteo.it)	Km/h	5.991
VelMedSIR	Average wind speed on the observation day (SIR)	m/s	0.9
VelMaxSIR	Maximum wind speed on the day of observation (SIR)	m/s	1.8
LevelSIRFre	phreatimetric data on the observation day (SIR)	m	-4.34
LevelSIRIdr	Water (river) level recorded on the observation day (SIR)	m	0.8
PrecipSIR	Precipitation on the observation day (SIR)	mm	0
MinTempSIR	Minimum temperature on the observation day (SIR)	°C	0.5

Data Analytic Solutions

- Aiming at creating an early warning can be traced back to the estimation of areas presenting a high probability of landslide event occurrence in the **next day**, as in this case.

- On the basis of the above-described dataset, a number of techniques to predict landslide events has been tested:
    - Random Forest, **RF**
    - eXtreme Gradient Boosting, **XGBoost**
    - Convolutional Neural Network, **CNN**
    - Autoencoders, **AE**
    - decisional algorithm **SIGMA**

Comparing Predictive Model Architectures

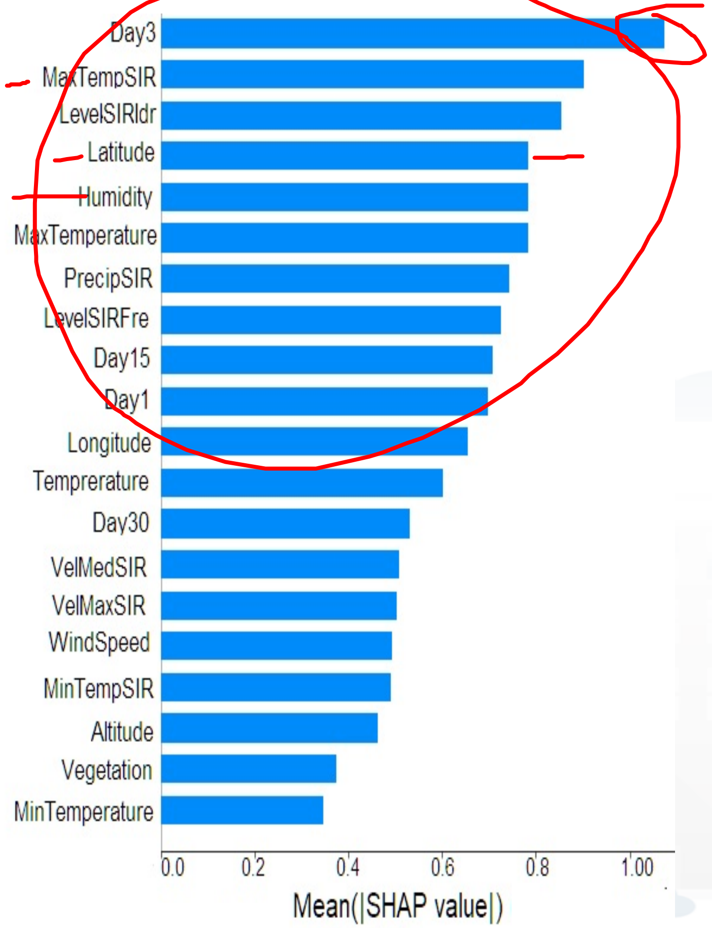
- The considered dataset is composed of about 9 million estimations, among which 2342 positive events (labeled with Value = 1)
- The dataset was divided into two groups: training set (80%) and test set (20%)

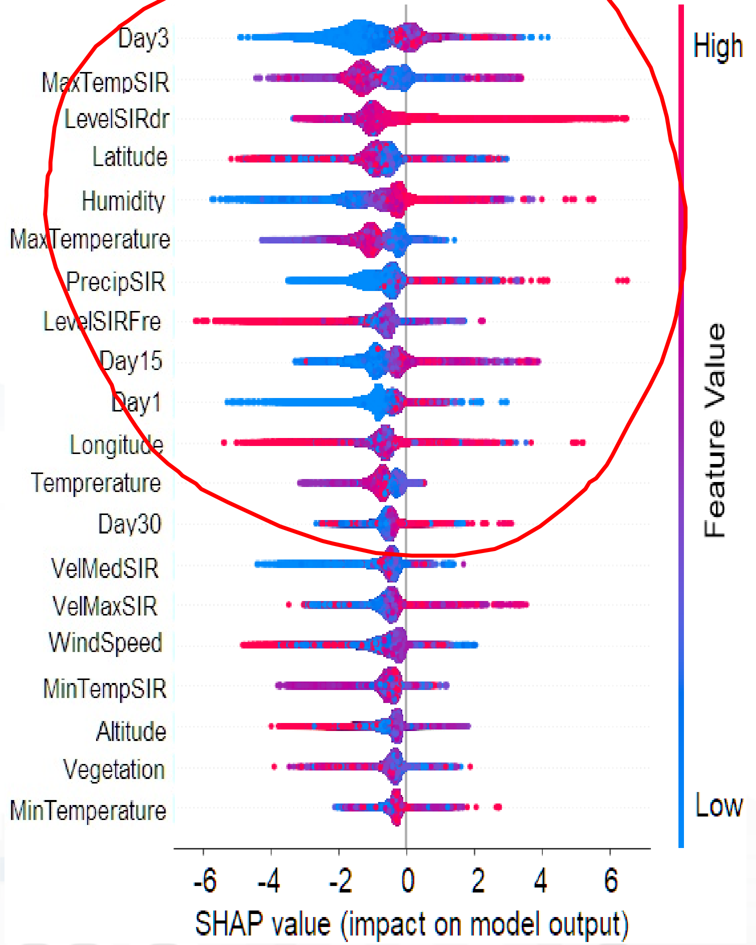
TABLE III COMPARISON OF RESULTS OBTAINED USING MODELS FOR SHORT TERMS PREDICTION OF LANDSLIDES, BEST RESULTS IN BOLD.

Model	XGBoost	RF	CNN	Auto encoder	SIGMA
MAE	**0.000173**	0.000334	0.000600	0.009218	0.004169
MSE	**0.000173**	0.000334	0.000259	0.009218	0.004169
RMSE	**0.0131**	0.0182	0.0160	0.0960	0.064572
Accuracy	0.99	0.99	0.99	0.99	0.99
Sensitivity	**0.79**	0.36	0.24	0.19	0.06
Specificity	0.99	0.99	0.99	0.99	0.99
TSS	**0.78**	0.35	0.23	0.18	0.05
PfA	**0.01%**	0.02%	**0.01%**	0.11%	0.39%
Precision	0.63	0.35	0.33	**0.64**	0.003
F1 score	**0.70**	0.36	0.27	0.29	0.007
MCC	**0.70**	0.36	0.28	0.35	0.01
OA	**2.40**	1.72	1.55	1.64	1.02
Kappa	**0.70**	0.36	0.27	0.29	0.01
AUC	0.89	0.68	**0.99**	0.92	0.53

Comparing Predictive Model/architectures

Model	XGBoost	RF	CNN	Auto encoder	SIGMA
MAE	0.000173	0.000334	0.000600	0.009218	0.004169
MSE	0.000173	0.000334	0.000259	0.009218	0.004169
RMSE	0.0131	0.0182	0.0160	0.0960	0.064572
Accuracy	0.99	0.99	0.99	0.99	0.99
Sensitivity	0.79	0.36	0.24	0.19	0.06
Specificity	0.99	0.99	0.99	0.99	0.99
TSS	0.78	0.35	0.23	0.18	0.05
PfA	0.01%	0.02%	0.01%	0.11%	0.39%
Precision	0.63	0.35	0.33	0.64	0.003
F1 score	0.70	0.36	0.27	0.29	0.007
MCC	0.70	0.36	0.28	0.35	0.01
OA	2.40	1.72	1.55	1.64	1.02
Kappa	0.70	0.36	0.27	0.29	0.01
AUC	0.89	0.68	0.99	0.92	0.53





Global Explainable AI
- Feature relevance

- Red: positive, blue: neegative;
- vs intensity and impact

Local Explainable AI - understanding the single event

- The local explanation puts in evidence the features which provided major contribution to the prediction
- For example considering Figure10a, the value of VelMaxSIR, MaxTempSIR, Day3 and Humidity contributed significantly to the classification of the observation as a l**andslide event**

FIGURE 10. Local feature relevance via SHAP, as interpretation of events in terms of feature values: (a) and (b) are events with predictions of landslide, (c) a no landslide event.

Local Explainable AI - understanding the single event

The trends of the SHAP values of the most relevant features have been plot with respect to the time/days.

It can be noted that in coincidence of the day before the event, most of the SHAP values of the relevant features assumed a relevant value at the same time. And in particular for this event: **LevelSIRIdr, Day3 and MaxTempSIR**.

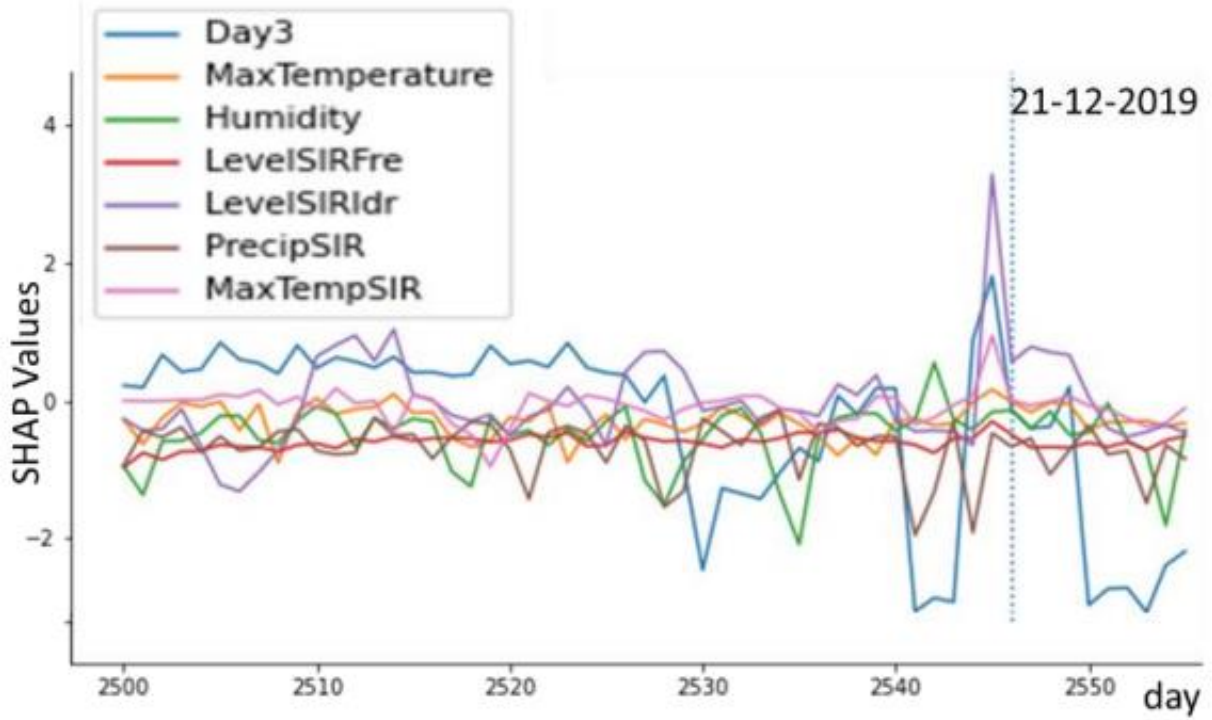


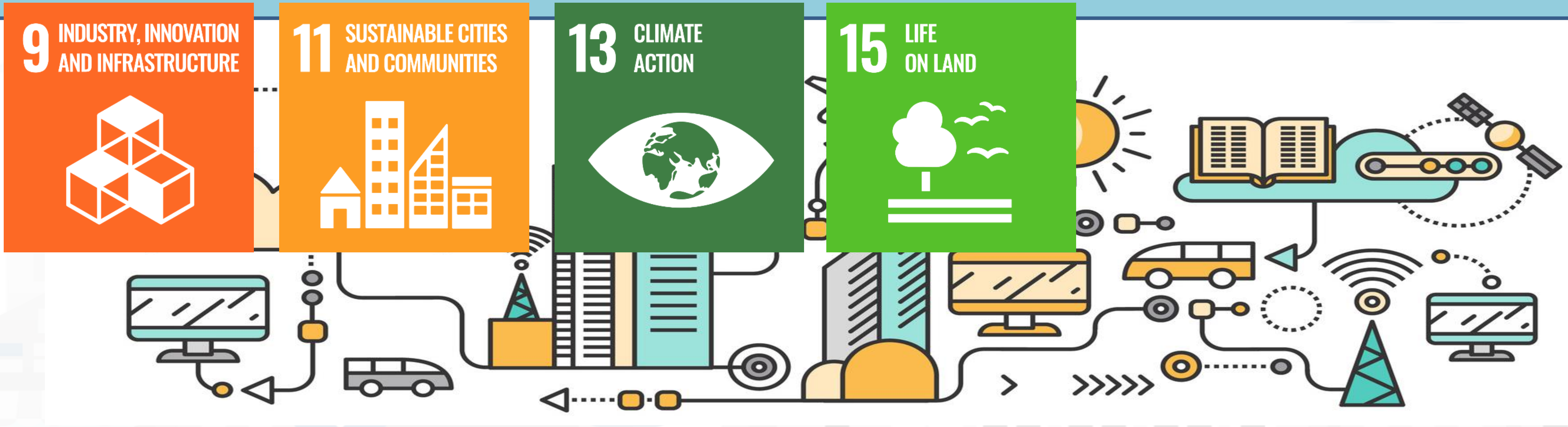
FIGURE 11. Time trend of SHAP values of most relevant features around the landslide event of 21-12-2019: values estimated by using data collected in the neighboring area of the event.

Consideration

- **The problem of landslide event prediction** has been addressed, for early warning specific to the case study in the Metropolitan City of Florence, using
  - static land description,
  - dynamic features as rain fall, temperature, wind, etc.
- **Numerous AI solutions has been compared**
  - **t**he best performing architecture has been XGBOOST
- **XAI: based on Shapley** additive explanation (SHAP), global and local, derived relevance:
  - rain the last 3 days, max temperature in the previous day, lever of water in the river
  - land static features are preconditions for landslide, while they are not efficient in creating an early warning system.
- **Computationally**: predictions can be assess every day,
  - susceptibility map usually are computed 1 or two times per year.
- **Prediction** models can prevent disaster
  - susceptibility map are mainly used for taking decision on planning.

TOP

Predicting Presences to major events



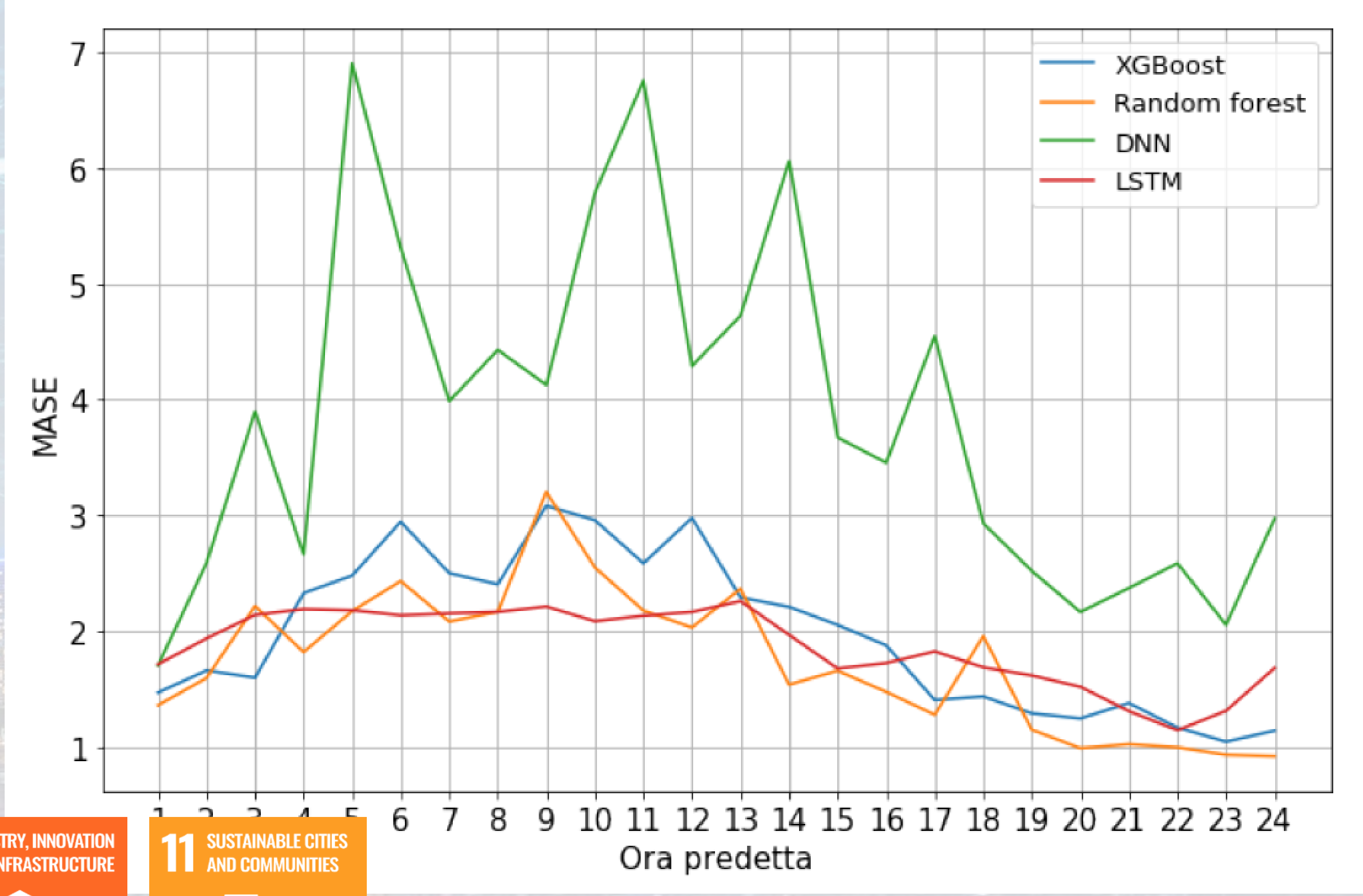
Twitter Vigilance

Pont du Gard: data analytics

- Prediction of the number of sold tickets 24 hours in advance

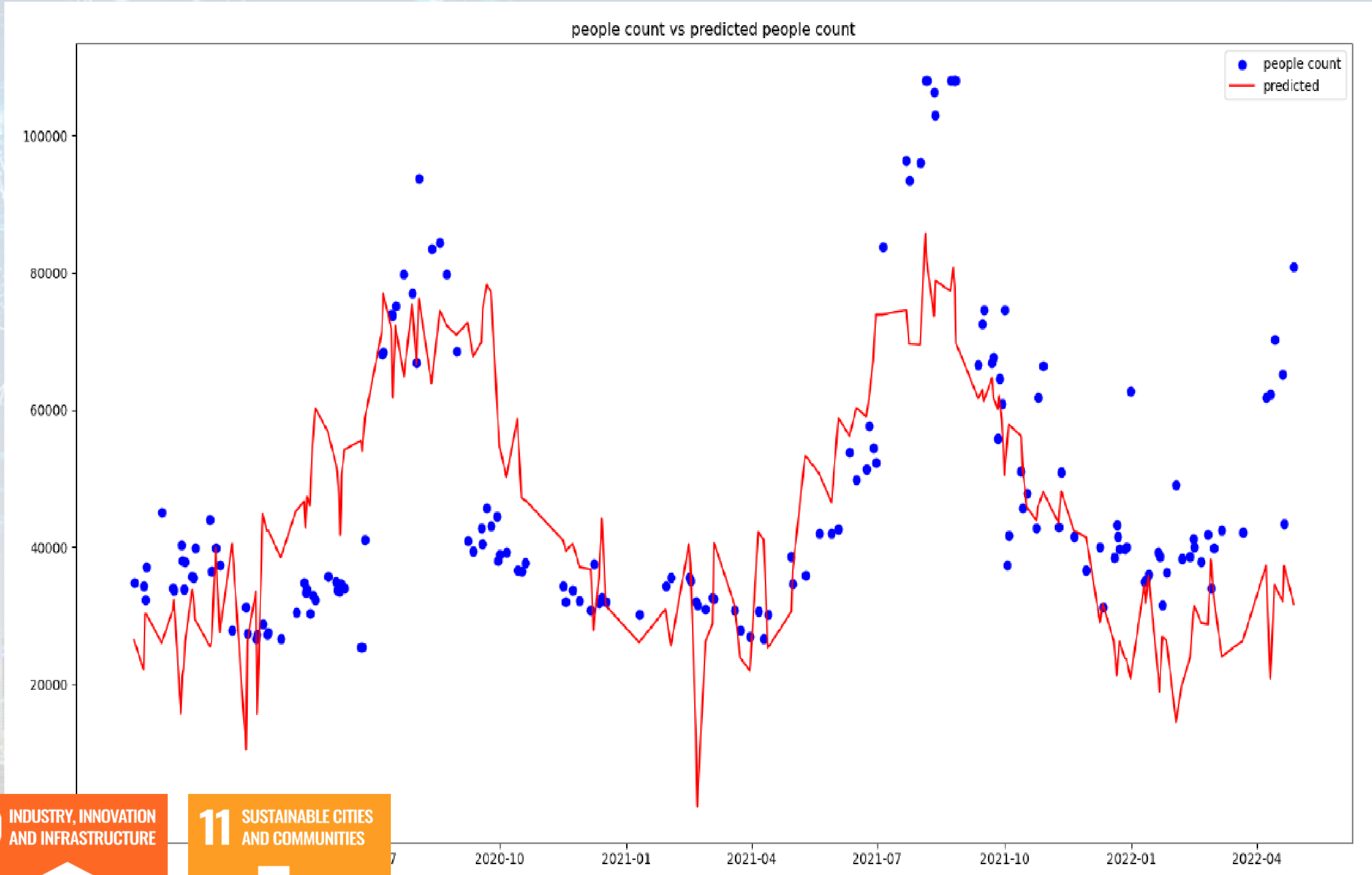
- Using:
  - Historical data
  - Weather conditions
  - Social Media

Twitter Vigilance



Dubrovnik: Data Analytics

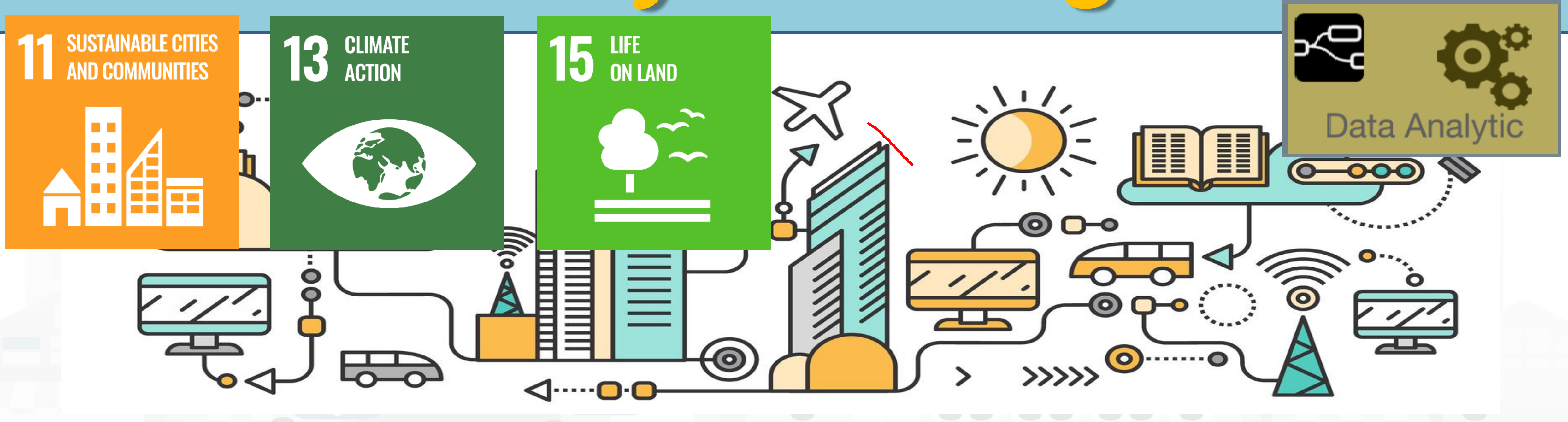
- Assessing impact of advertising
- Prediction of presences on the basis of
  - Social Media Twitter Vigilance
  - weather conditions
  - Historical data



Twitter Vigilance

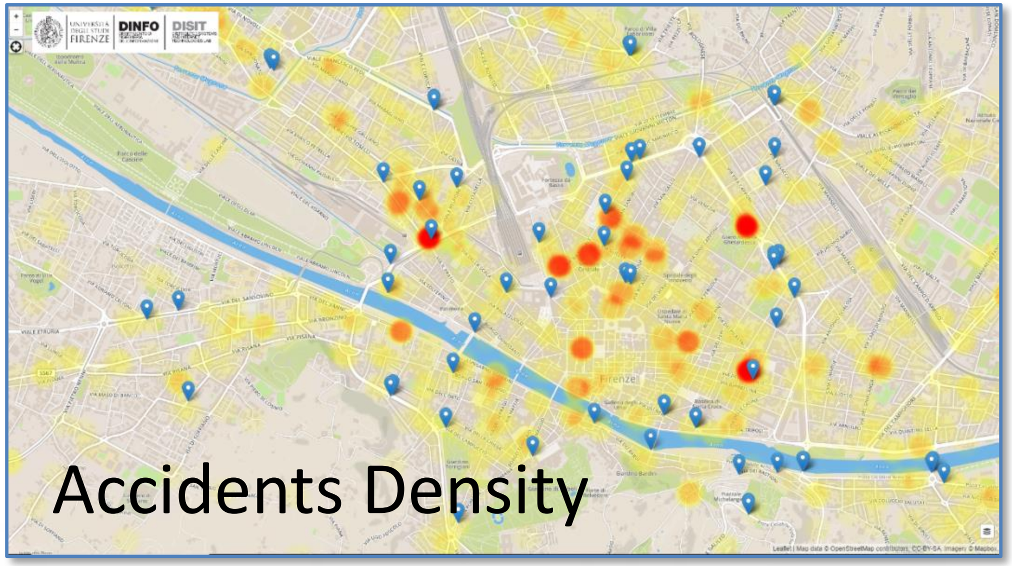
TOP

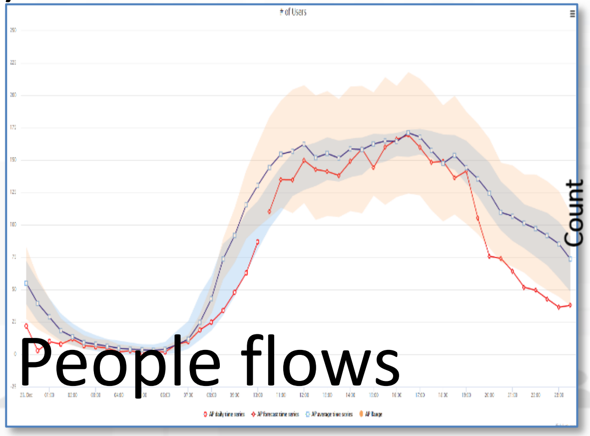
Anomaly Detection
Early Warning

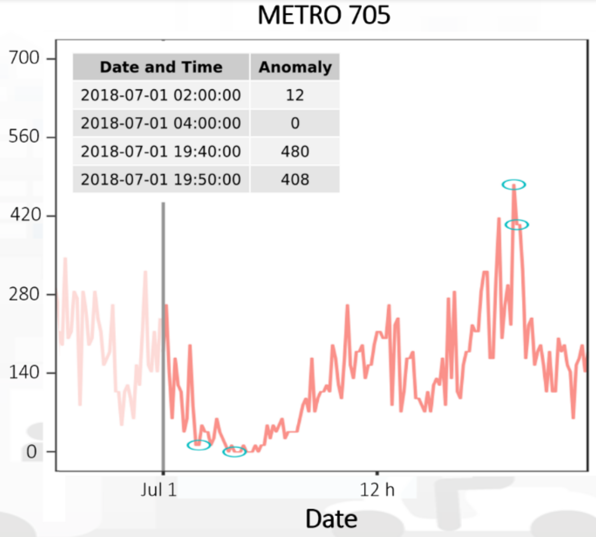


Anomaly Detections

- About the IoT Devices status
  - Eventual problems on IoT Devices, connections, etc.
- About People Flows and Density
  - Early warning of the ineption of critical events
- About traffic flow
  - Early warning on eventual incidents, or on the inception of critical conditions on the traffic (e.g., a reduction in viability, a broken bus, ..)
- About....
  - Early warning, early detection of problems,
- Recurrence analysis
- Causal Analysis



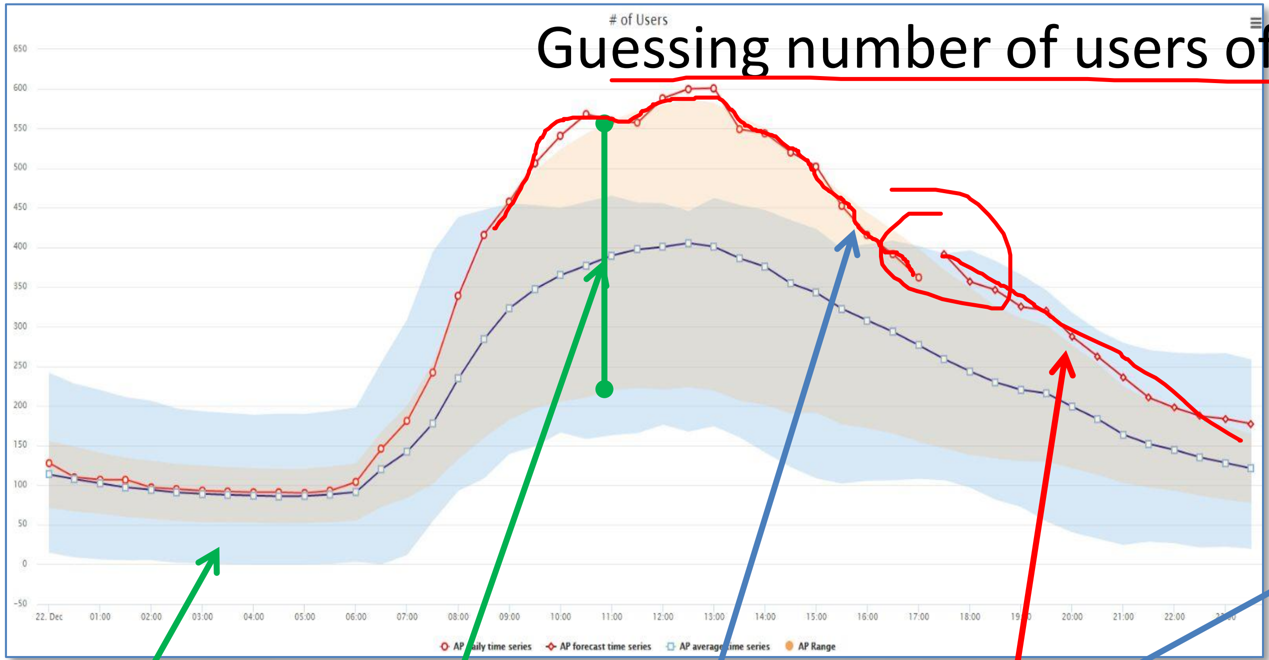


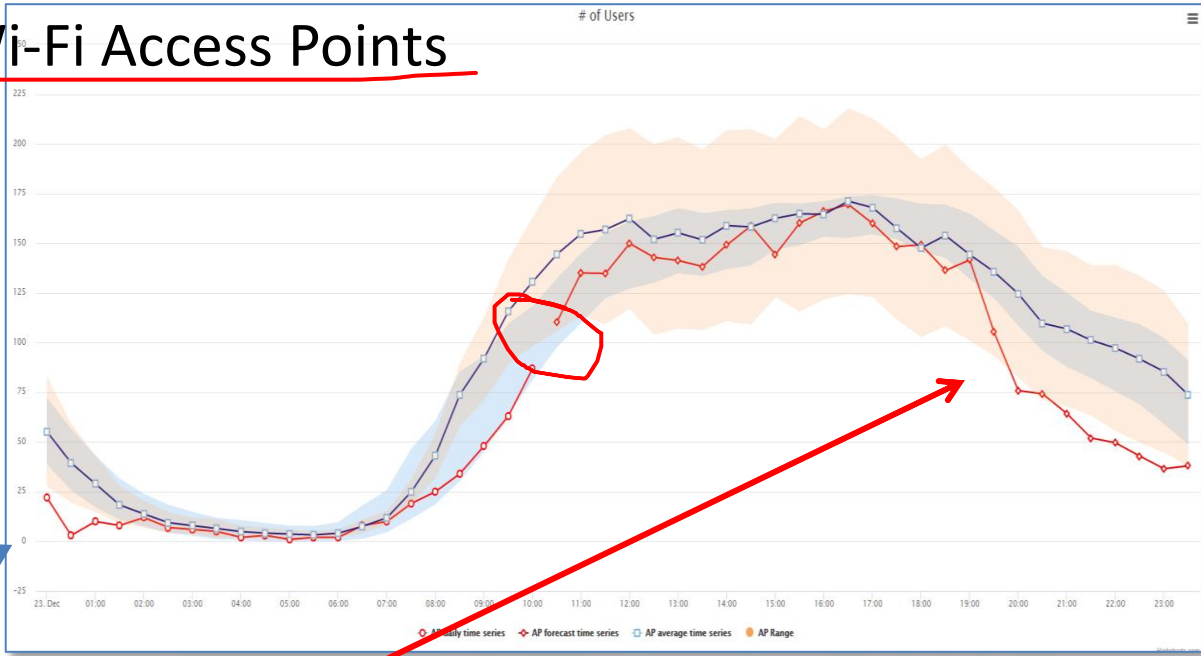


Date and Time	Anomaly
2018-07-01 02:00:00	12
2018-07-01 04:00:00	0
2018-07-01 19:40:00	480
2018-07-01 19:50:00	408

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

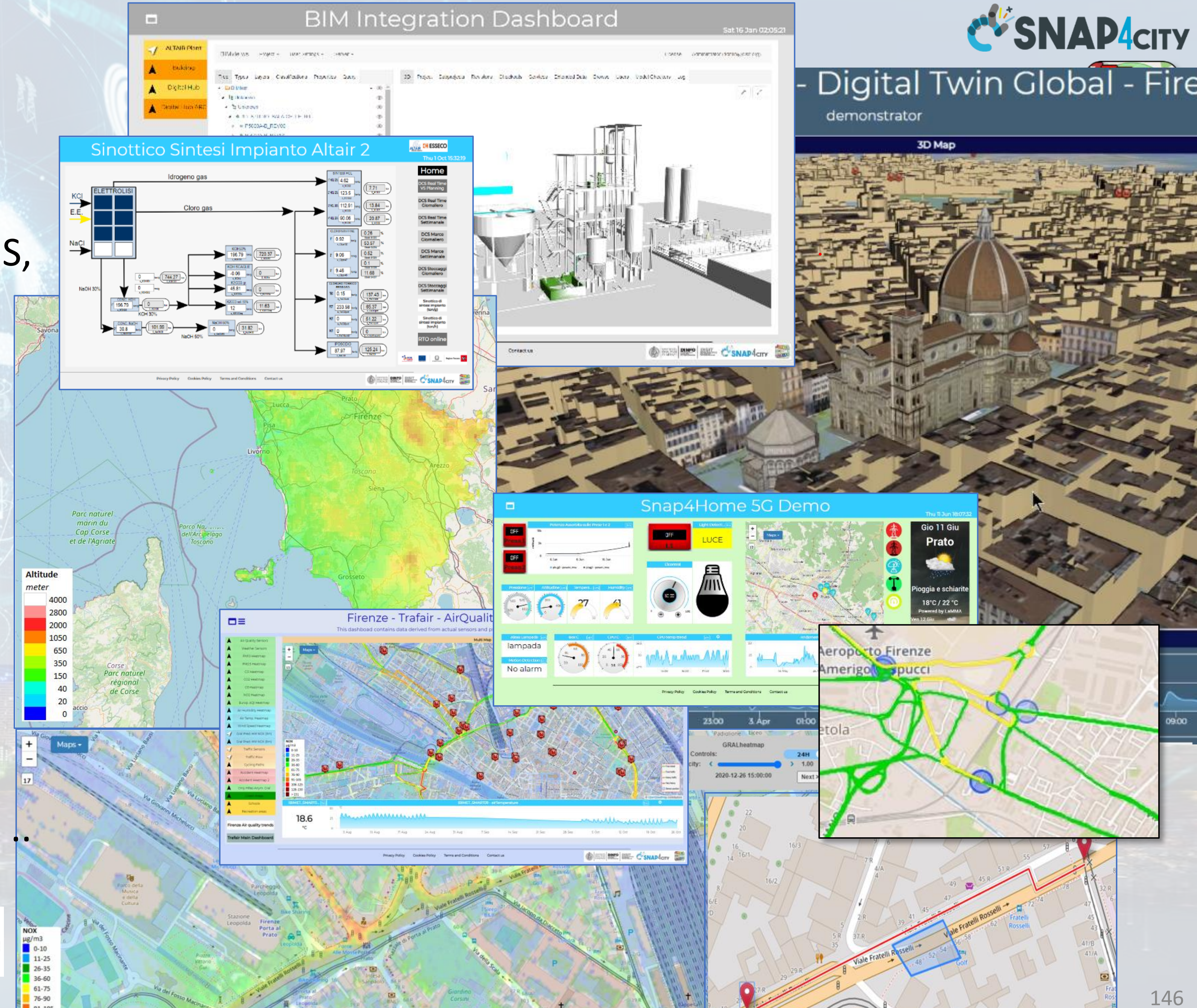
Predictive precision of the 95%

TOP

Computing: High Level Types Data and their representations

High Level Types

- POI, IOT Devices, shapes,..
  - FIWARE Smart Data Models,
  - IoT Device Models
- GIS, maps, orthomaps, WFS/WMS, GeoTiff, calibrated **heatmaps**, ..
- **Satellite data, ..**
- **traffic flow**, **typical trends**, ..
- **trajectories**, events, Workflow, ..
- **3D Models**, BIM, Digital Twins, ..
- **OD Matrices** of **several kinds, ..**
- Dynamic icons/pins, ..
- Synoptics, **animations**, ..
- KPI, personal KPI,..
- social media data, TV Stream,
- **routing**, multimodal, constraints, ..
- **decision scenarios, ...**
- etc.



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Why computing Higher Level Types

- They are a more **direct representations for the decision makers**
  - fast awareness of the situation
  - fast reaction and decision making

- **High Level Types and their representations**
  - Traffic Flow and animations
  - Heatmaps and animations
  - Origin Destination Matrices, ODM; and animations
  - Trajectories, ….
  - Digital Twin and 3D digital representation of the city
  - User behavior representation
  - Typical trends, different time spam
  - etc.

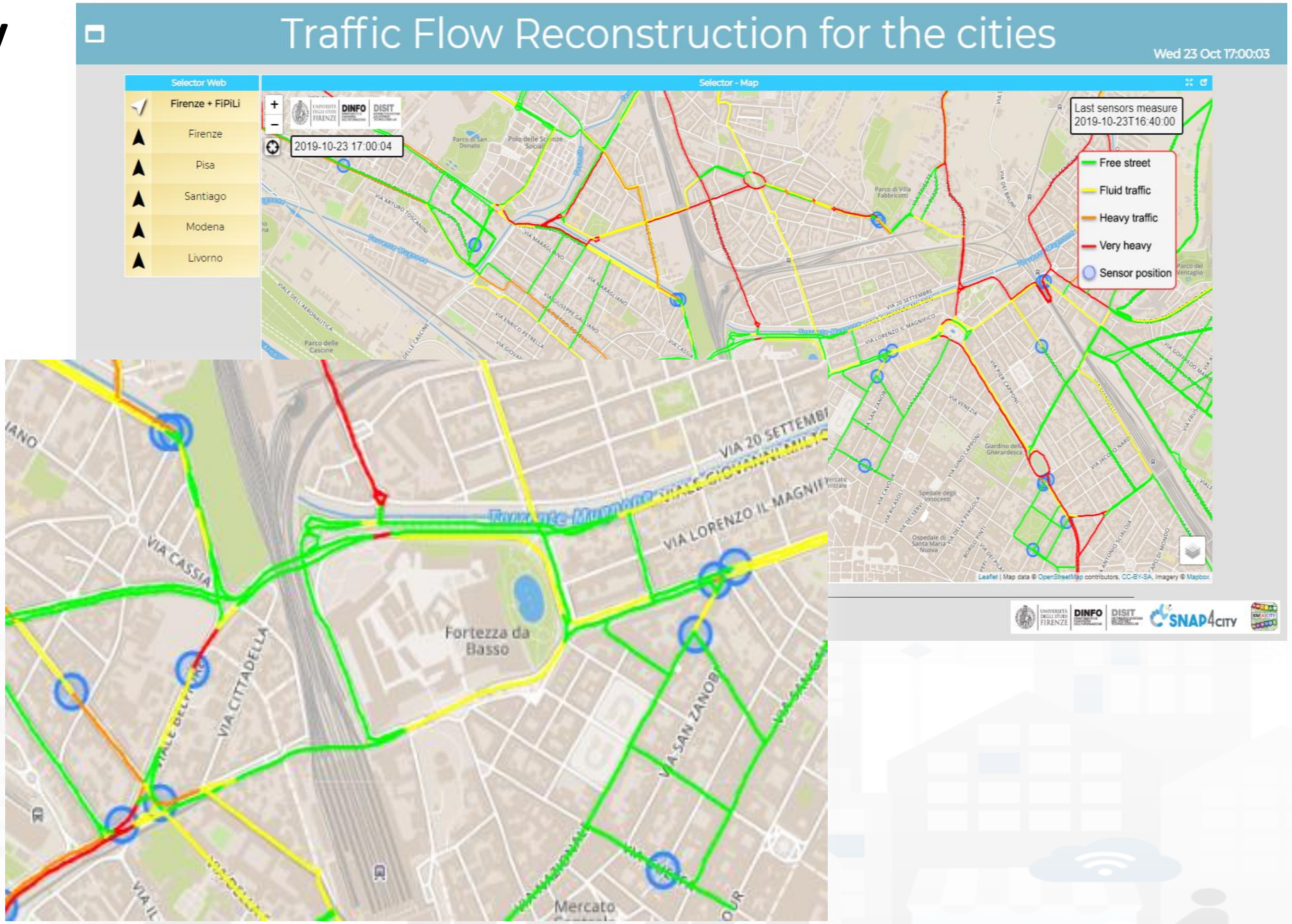
TOP

Traffic Flow Reconstruction from Traffic Sensors Data

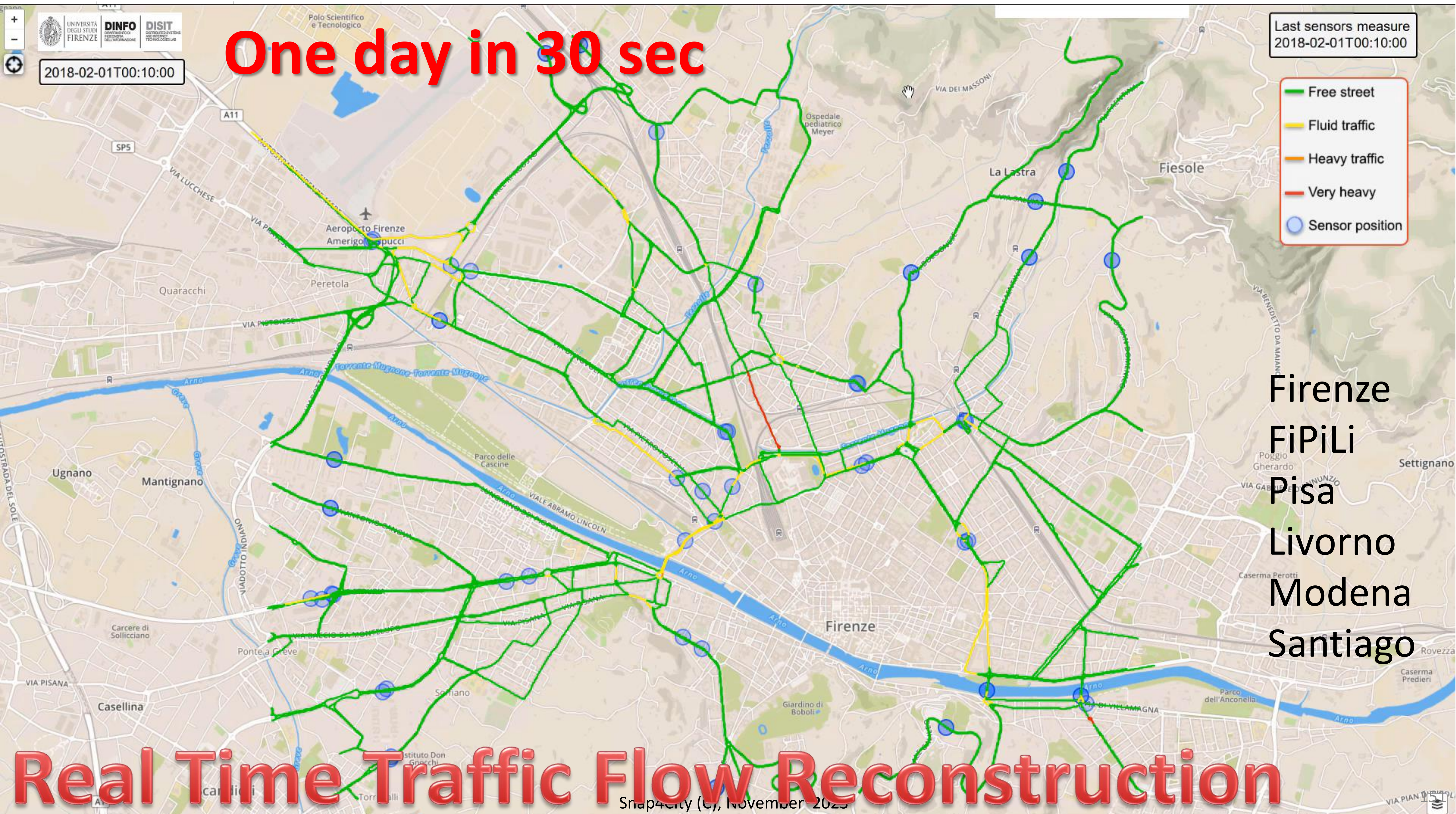
Data Analytic

Why Dense Traffic Flow Reconstruction ?

- Making decision on mobility and transport solutions → what if analysis
- Controlling pollution
- Dynamic Routing for Firebrigade, Ambulances, general public
- Planning Public Transportation routing



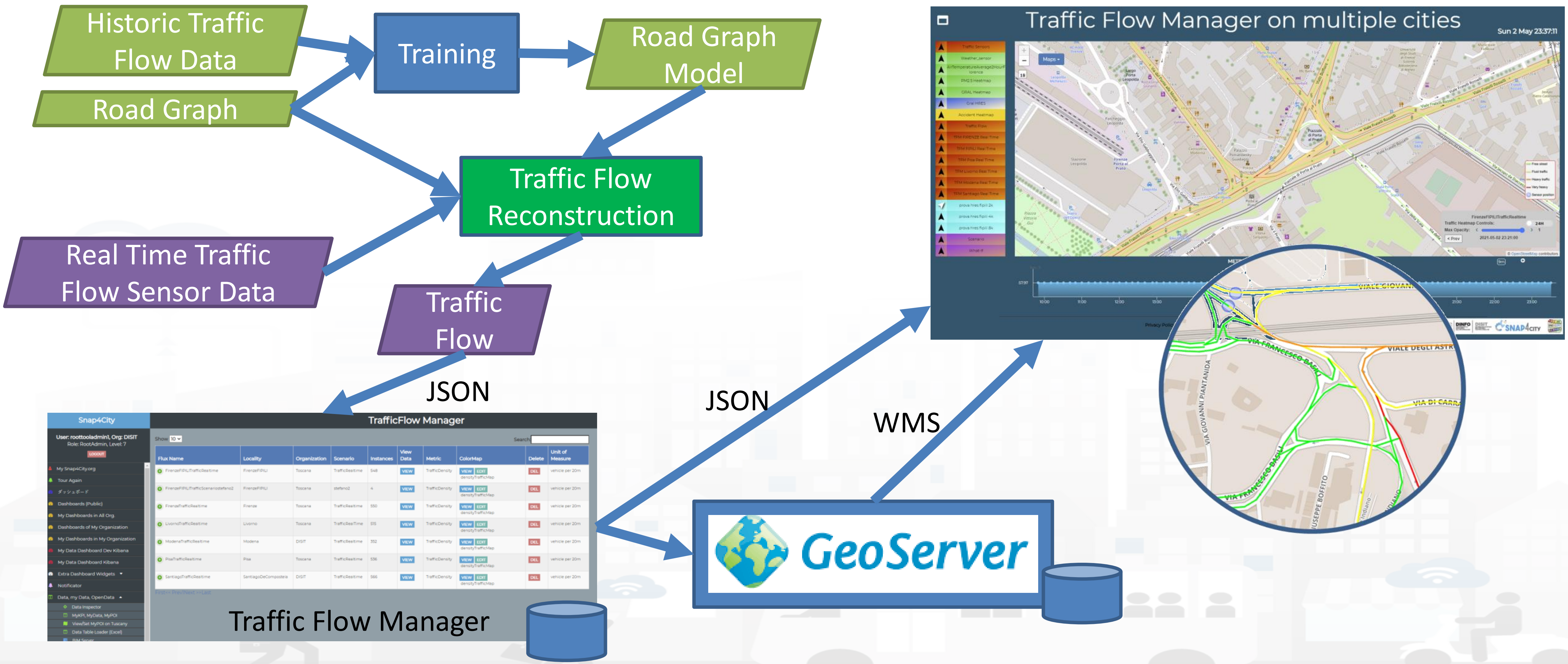
One day in 30 sec



Firenze
FiPiLi
Pisa
Livorno
Modena
Santiago

Real Time Traffic Flow Reconstruction

How it works: Traffic Flow Manager



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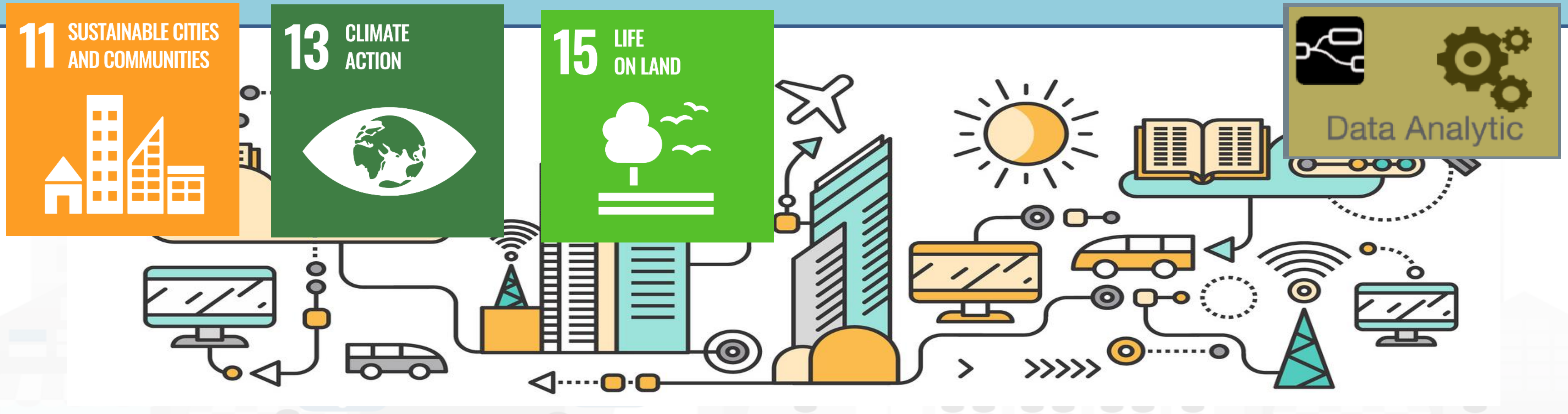
Heatmaps and animations

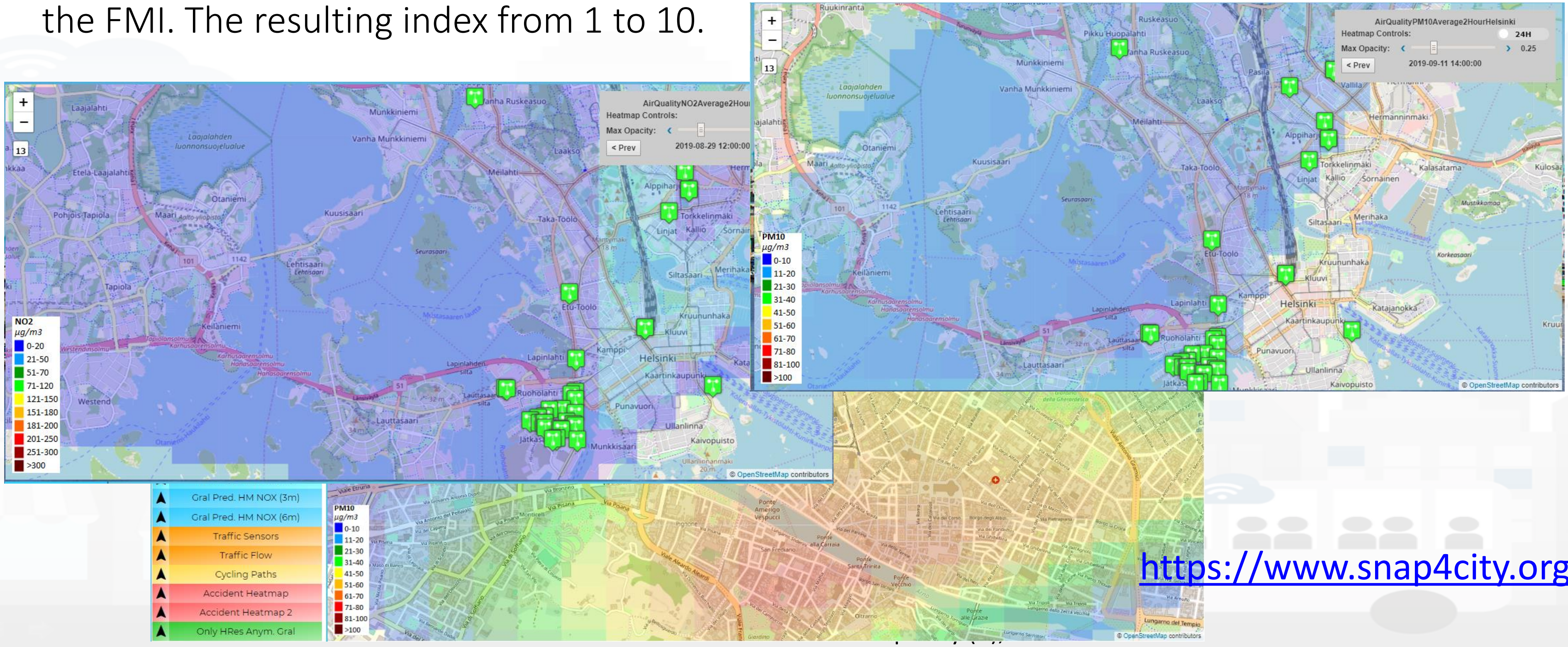


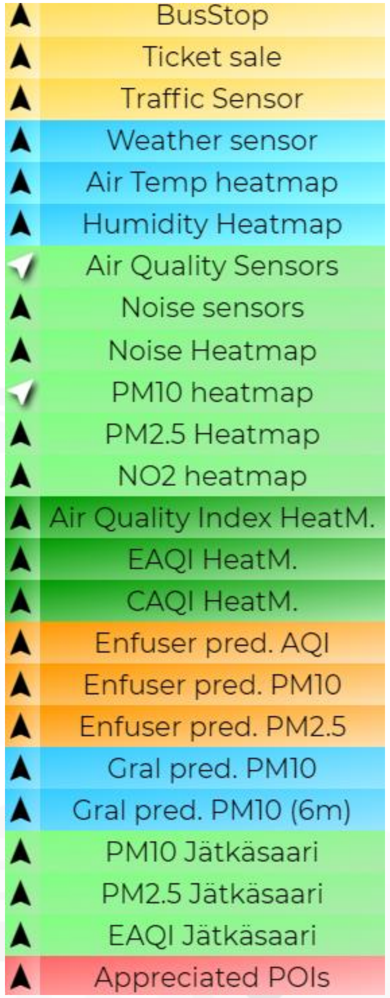
Devices data

- **Air Quality sensors are**
  - Collected on scattered positions
  - Not all sensors have sull set of data, complexity of computing AQI
- **AirQuality Services**
  - AirQuality indicators independent on the sensors' position, in any GPS position of the area
  - **Multiple data:** PM_{10}, $PM_{2.5}$, CO, CO_2, SO_2, O_3, H_2S, NO, NO_2, NO_x, air temperature, air humidity, velocity of wind speed, dew point, etc.
- **Applications**
  - Control Room Rendering
  - Alerting on specific personal GPS locations
  - Constrained routing for: runners, walking with baby, people with pulmonary problems,
  - Mobile Phone Rendering, this means to have thousands of users active at the same time, and a reasonable memory consumption in the server.

Environmental Real Time Measures

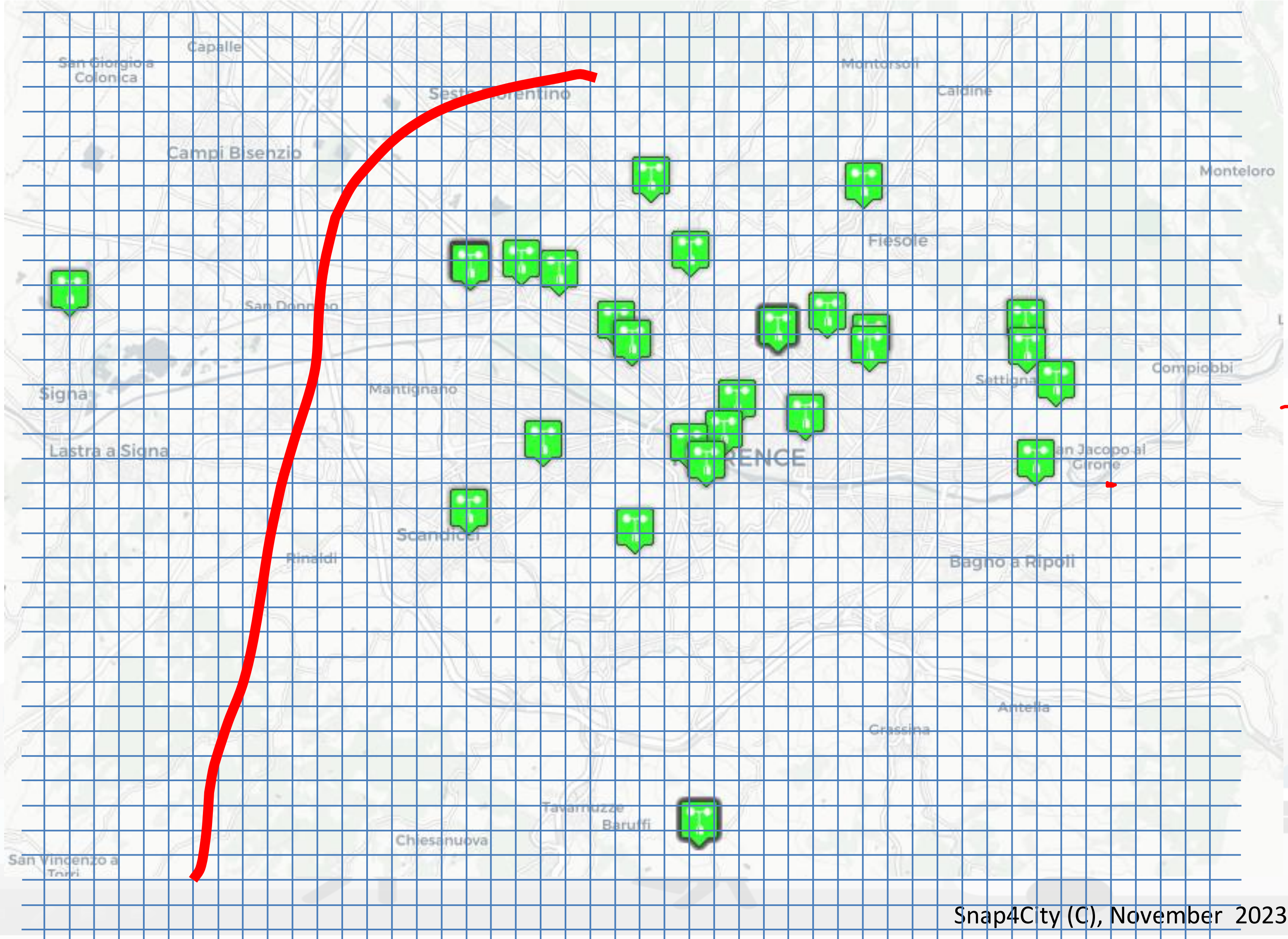
- **Noise:** real time noise levels (measured in dBA).
- **PM$_{10}$:** real time pollutant levels in air in terms of PM$_{10}$ (measured in µg/m$_3$) particles.
- **PM$_{2,5}$:** real time pollutant levels in air in terms of PM$_{2.5}$ (measured in µg/m$_3$) particles
- **NO$_2$:** real time pollutant 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.





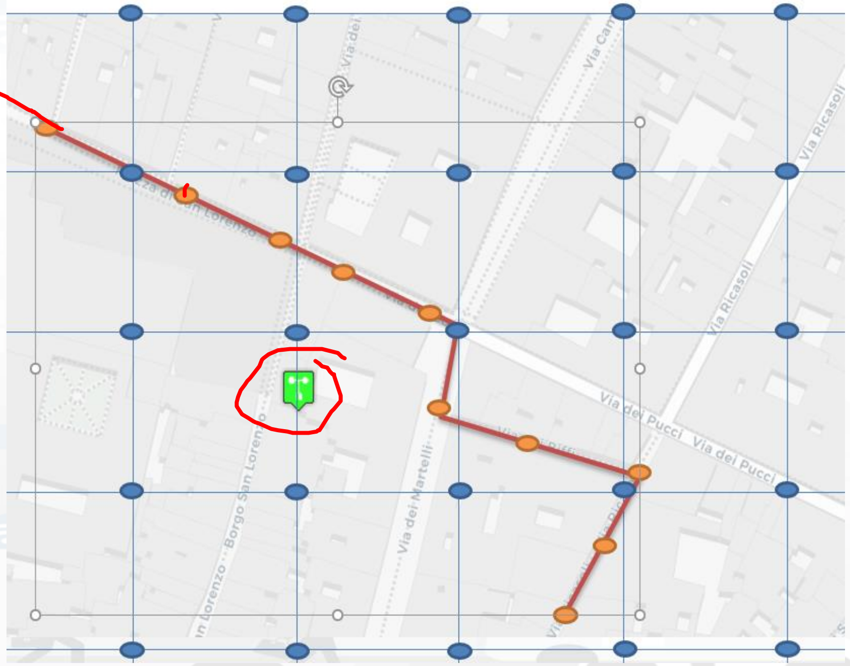
https://www.snap4city.org/435

The GRID density is never enough



4x4 meters grid is really too expensive

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



AQI Indexes estimation via R studio and IOT App

European Air Quality Index **EAQI**

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

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

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

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

Common Air Quality Index **CAQI**

http://www.airqualitynow.eu

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

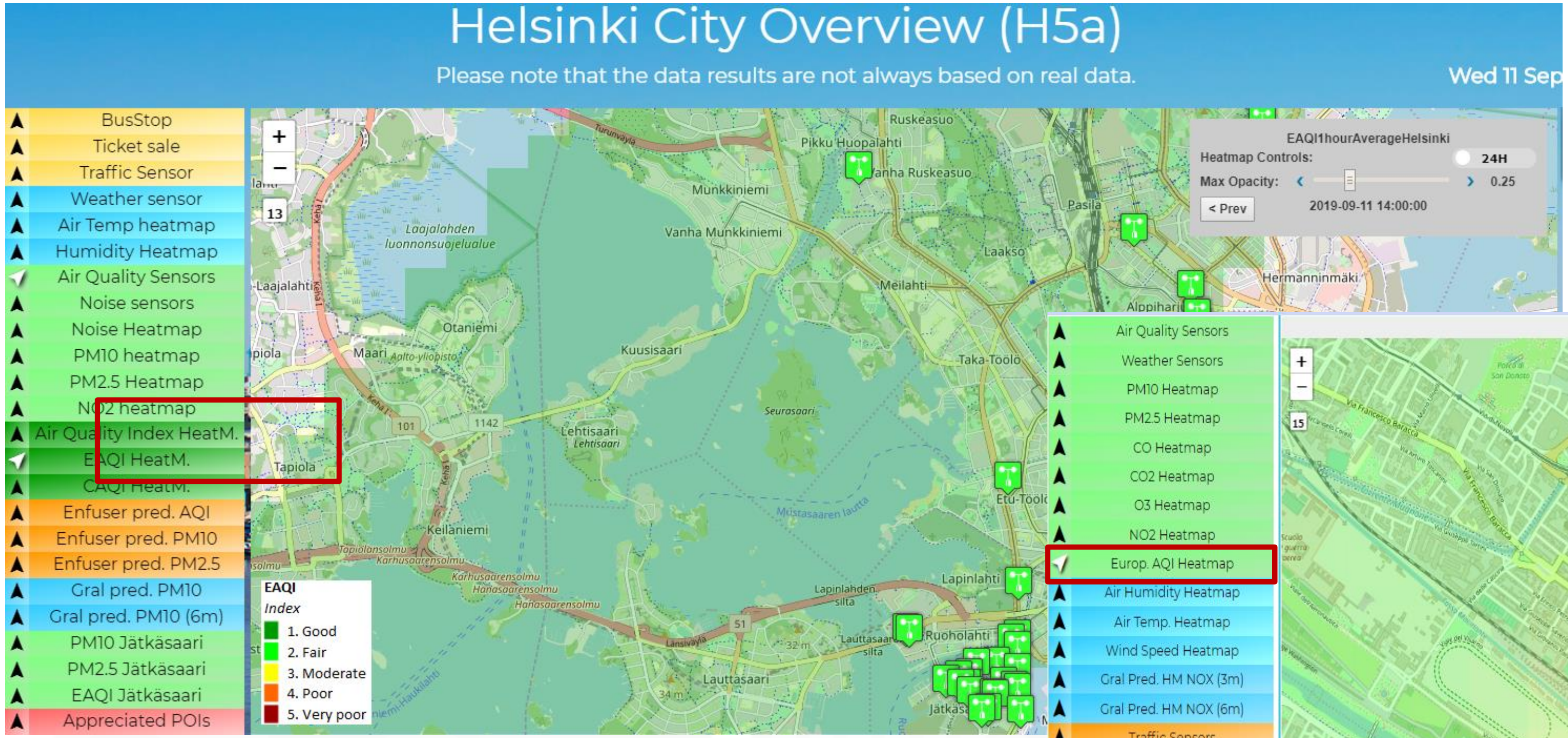
The index is defined away from roads (a "background" index). **CAQI** is computed on the basis of **NO_2, $PM_{2,5}$, PM_{10}** and **O_3**.

Legend of Environmental data:

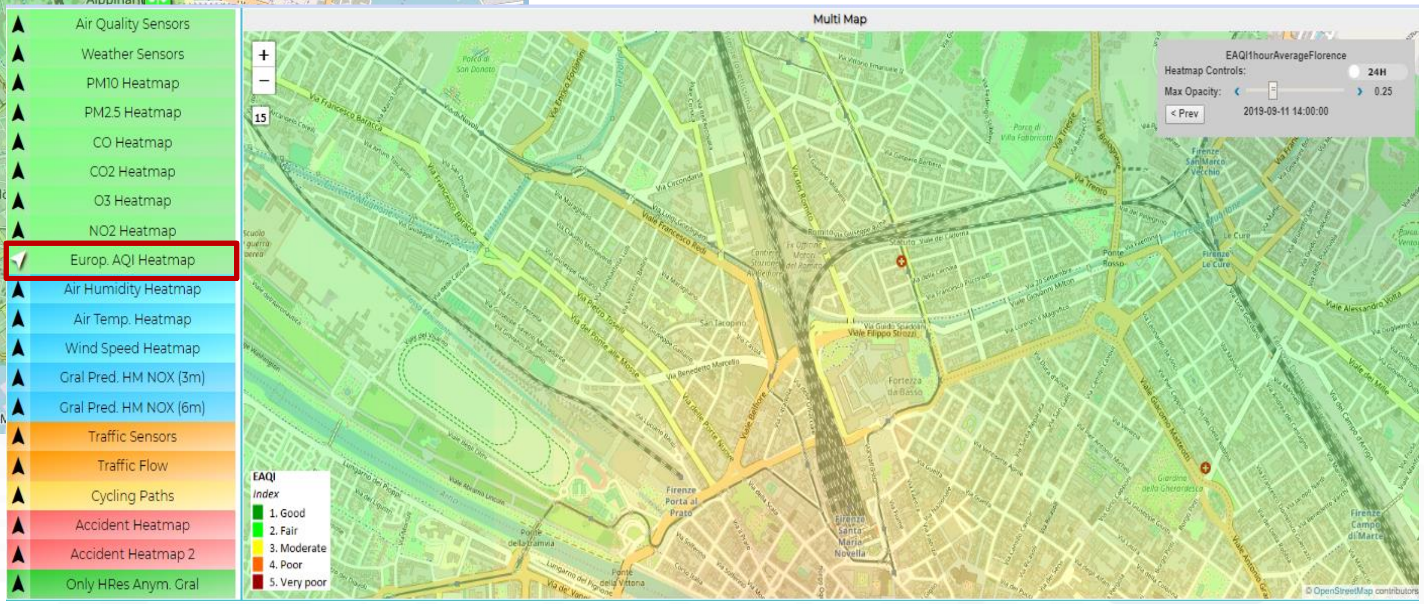
https://www.snap4city.org/435

AQI Indexes estimation Heatmaps

Hourly pollutant concentration



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



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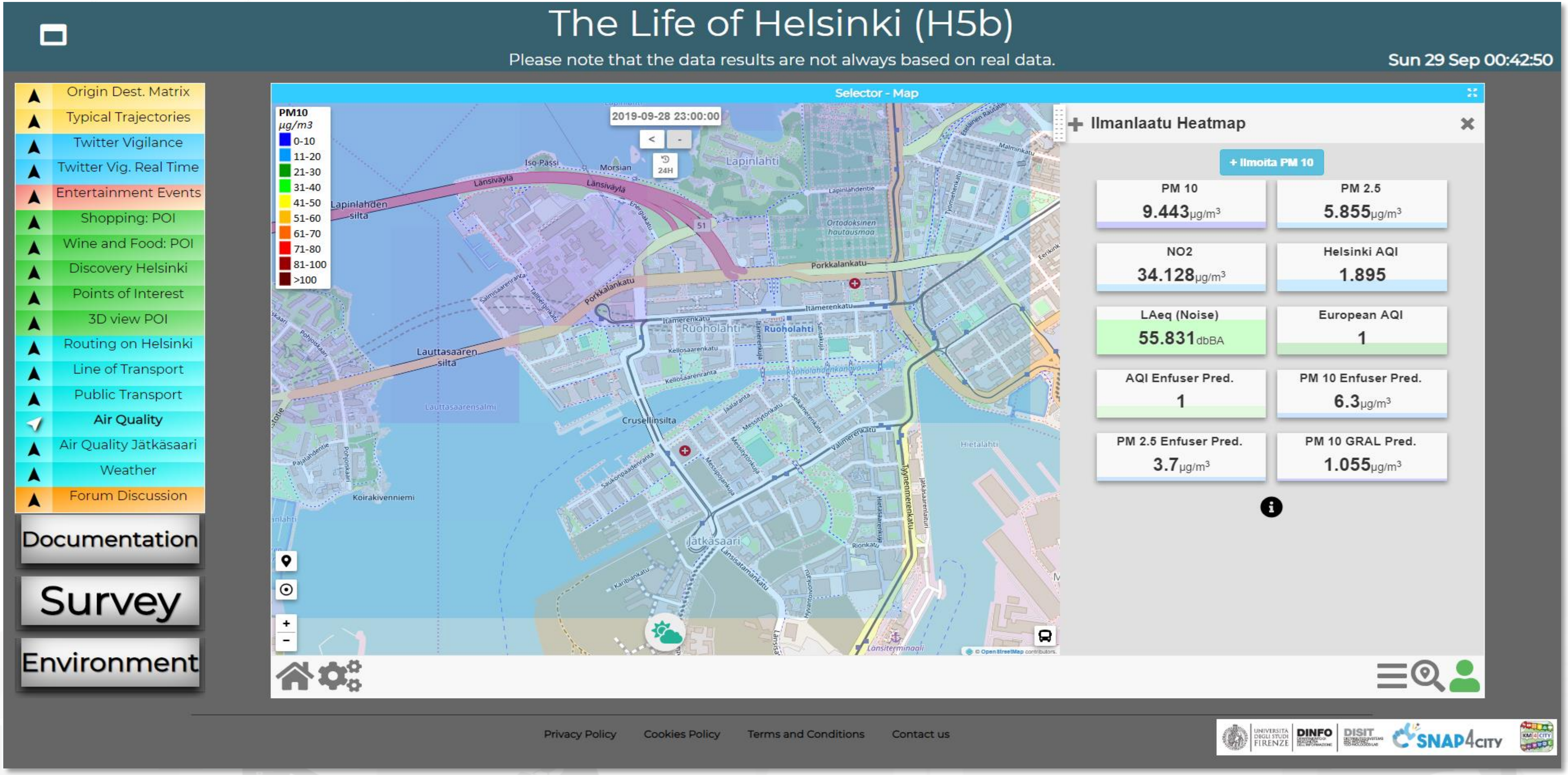
Helsinki



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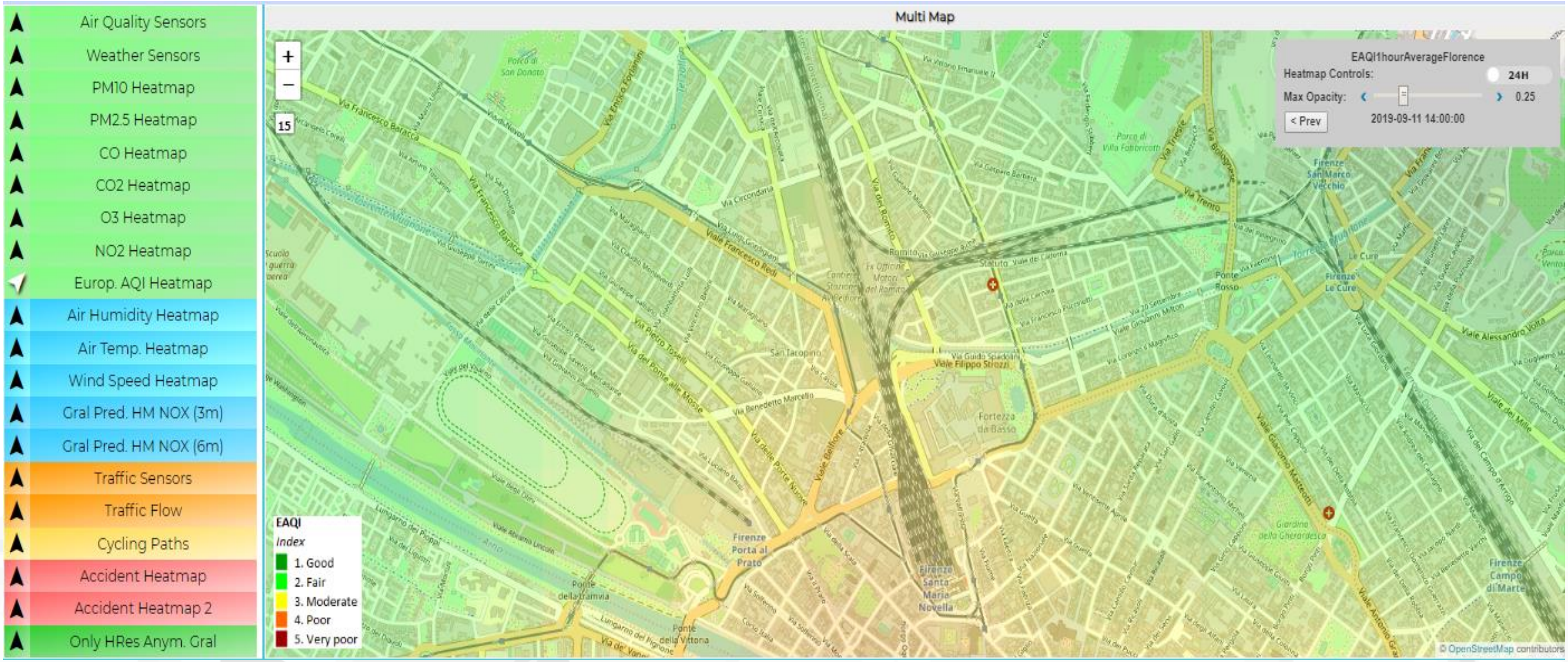
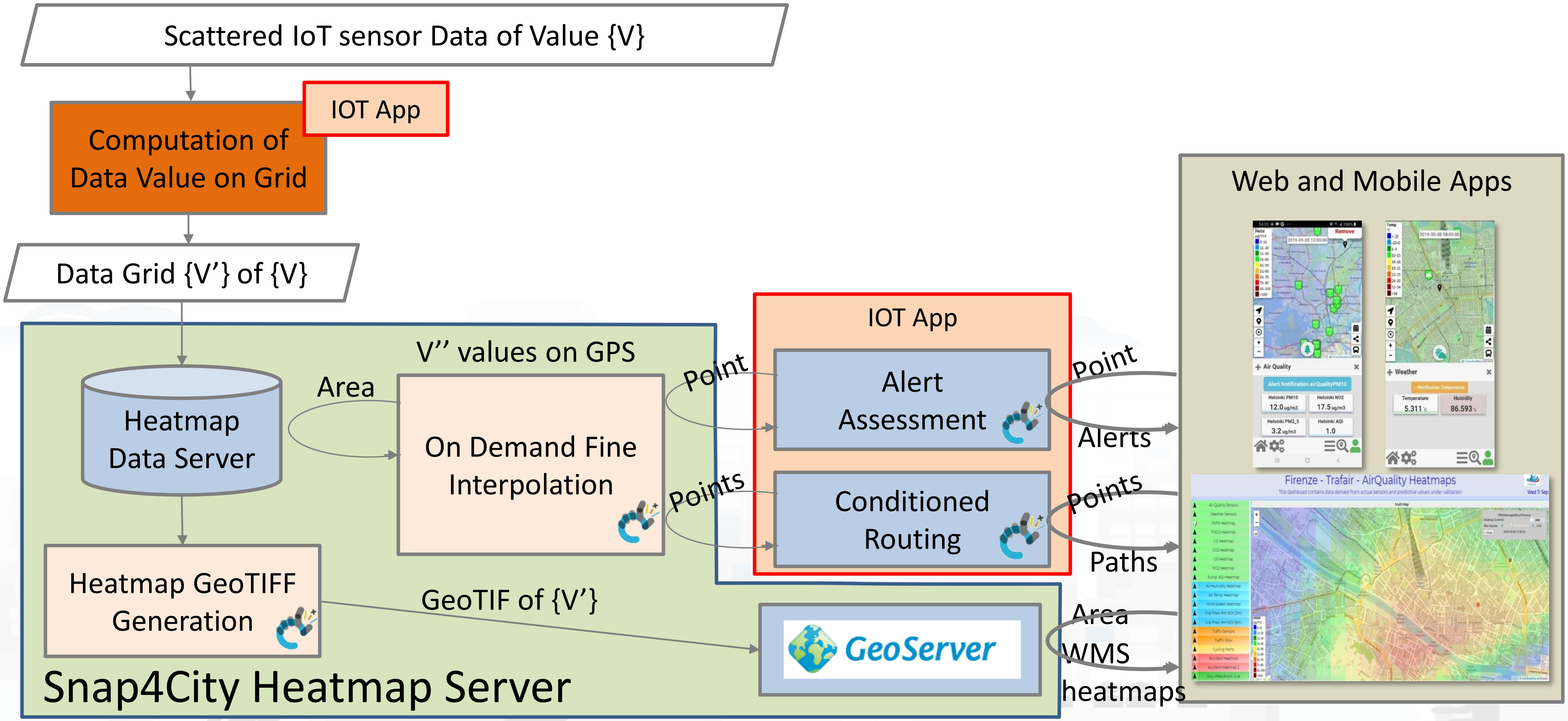
EAQI Heatmap and sequence

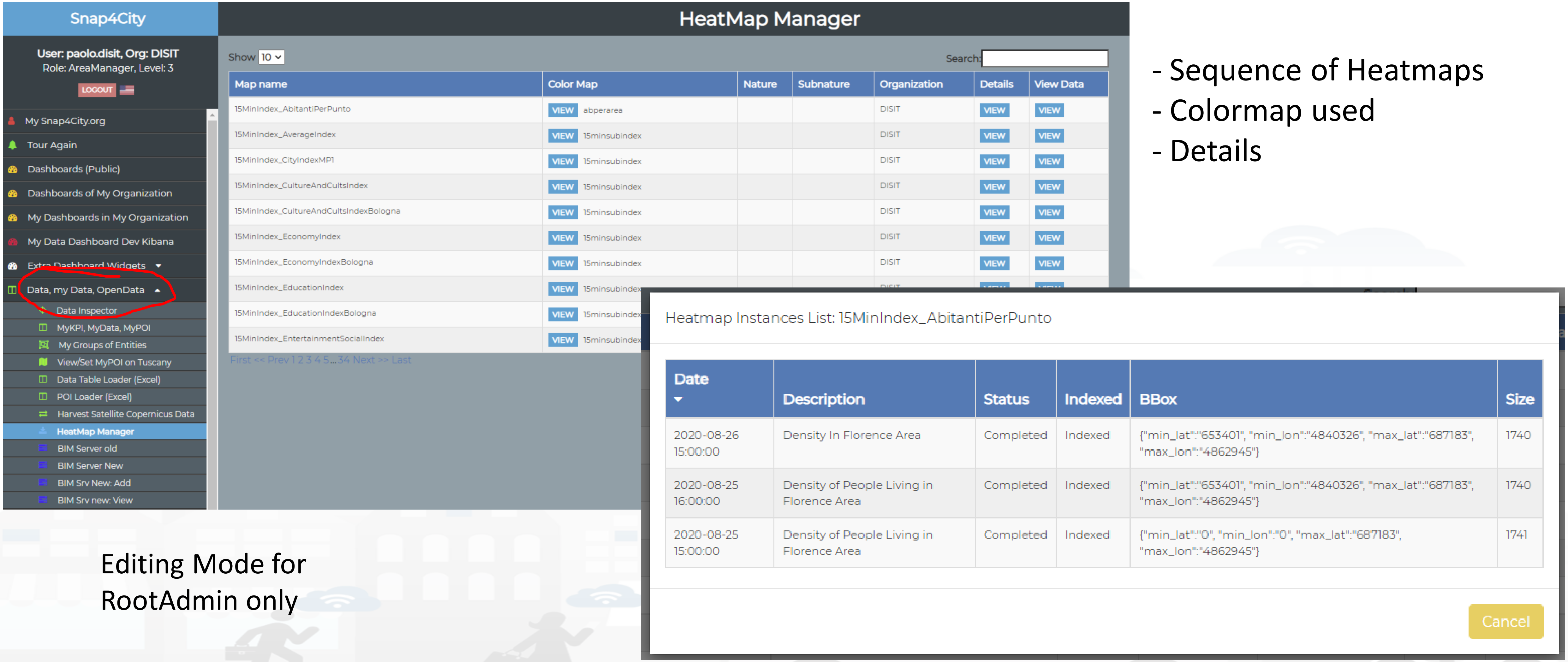


Workflow



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

HeatMap Manager (Area Manager view)



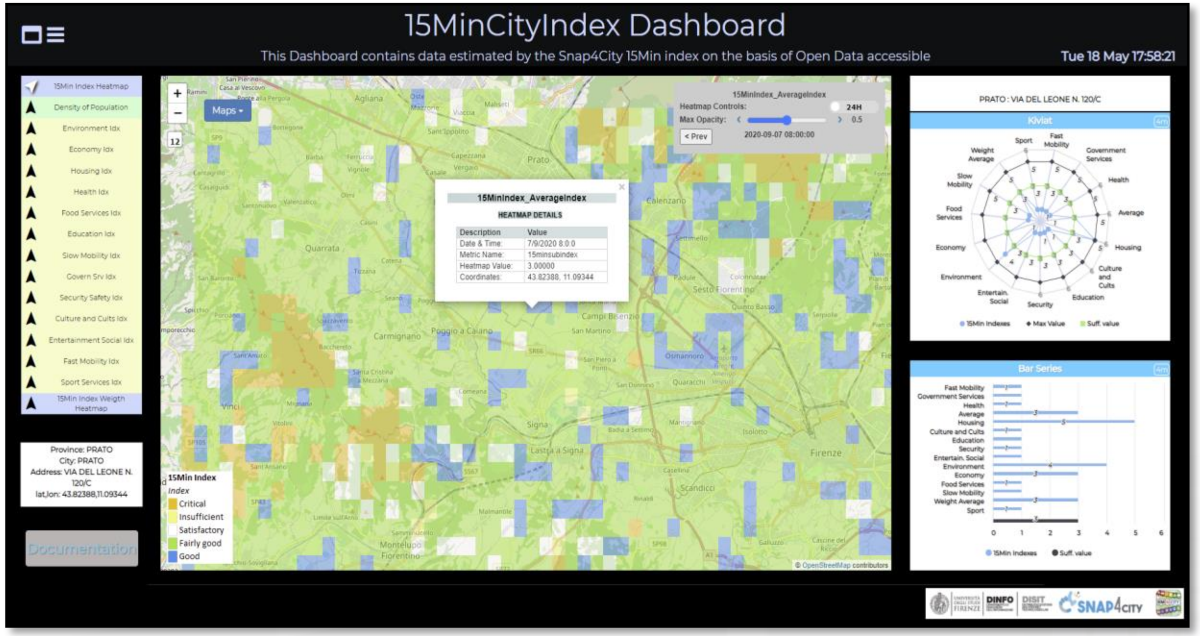
Map name	Color Map	Nature	Subnature	Organization	Details	View Data
15MinIndex_AbitantiPerPunto	VIEW abperarea			DISIT	VIEW	VIEW
15MinIndex_AverageIndex	VIEW 15minsubindex			DISIT	VIEW	VIEW
15MinIndex_CityIndexMP1	VIEW 15minsubindex			DISIT	VIEW	VIEW
15MinIndex_CultureAndCultsIndex	VIEW 15minsubindex			DISIT	VIEW	VIEW
15MinIndex_CultureAndCultsIndexBologna	VIEW 15minsubindex			DISIT	VIEW	VIEW
15MinIndex_EconomyIndex	VIEW 15minsubindex			DISIT	VIEW	VIEW
15MinIndex_EconomyIndexBologna	VIEW 15minsubindex			DISIT	VIEW	VIEW
15MinIndex_EducationIndex	VIEW 15minsubindex					
15MinIndex_EducationIndexBologna	VIEW 15minsubindex					
15MinIndex_EntertainmentSocialIndex	VIEW 15minsubindex					

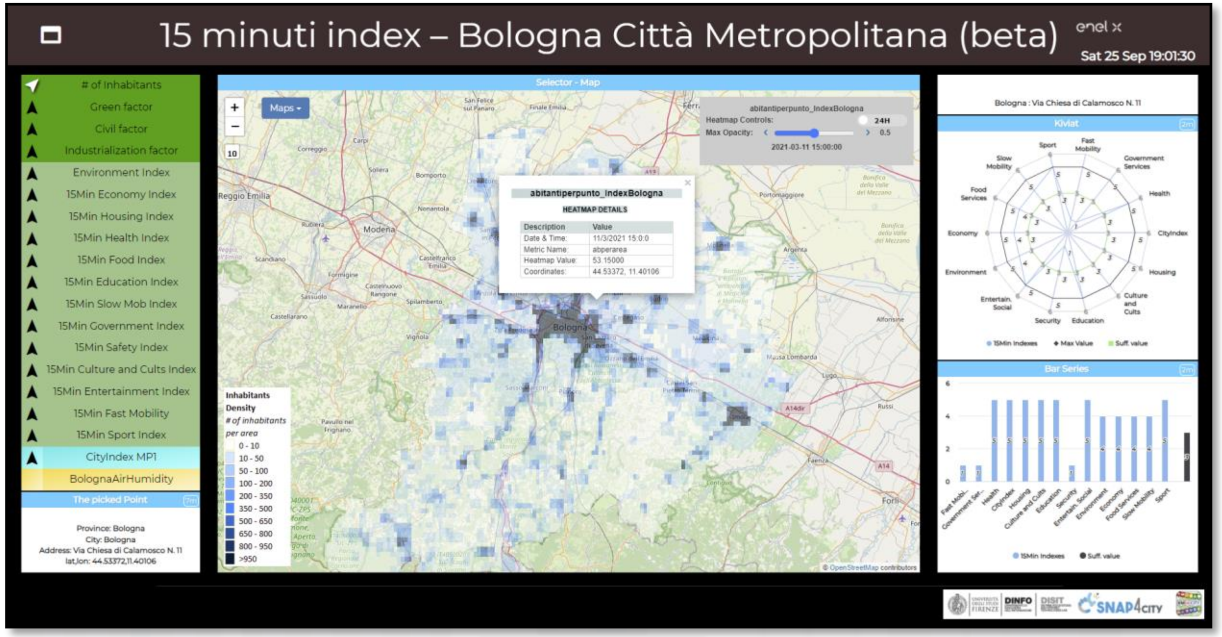
Date	Description	Status	Indexed	BBox	Size
2020-08-26 15:00:00	Density In Florence Area	Completed	Indexed	{"min_lat":"653401", "min_lon":"4840326", "max_lat":"687183", "max_lon":"4862945"}	1740
2020-08-25 16:00:00	Density of People Living in Florence Area	Completed	Indexed	{"min_lat":"653401", "min_lon":"4840326", "max_lat":"687183", "max_lon":"4862945"}	1740
2020-08-25 15:00:00	Density of People Living in Florence Area	Completed	Indexed	{"min_lat":"0", "min_lon":"0", "max_lat":"687183", "max_lon":"4862945"}	1741

- Sequence of Heatmaps
- Colormap used
- Details

Editing Mode for RootAdmin only

15MinCityIndex





[FLORENCE metro city](https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MjkzOA=)

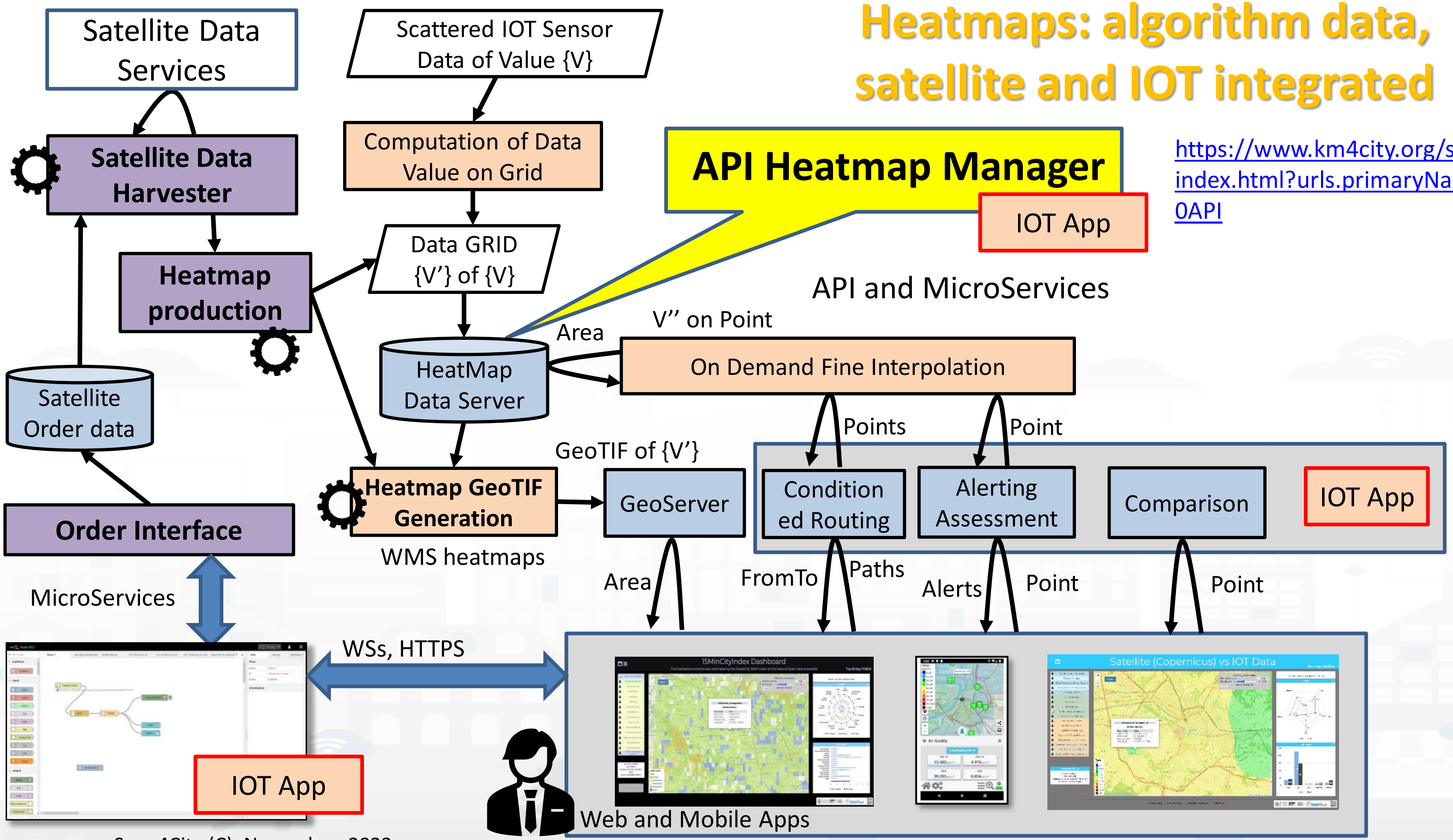
https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MjkzOA=

[Bologna metro city](https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MzA1OQ==)

https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MzA1OQ==

Heatmaps: algorithm data, satellite and IOT integrated

https://www.km4city.org/swagger/external/index.html?urls.primaryName=Heatmap%20API



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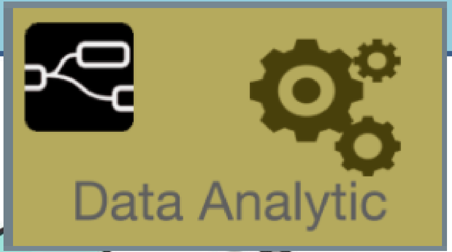
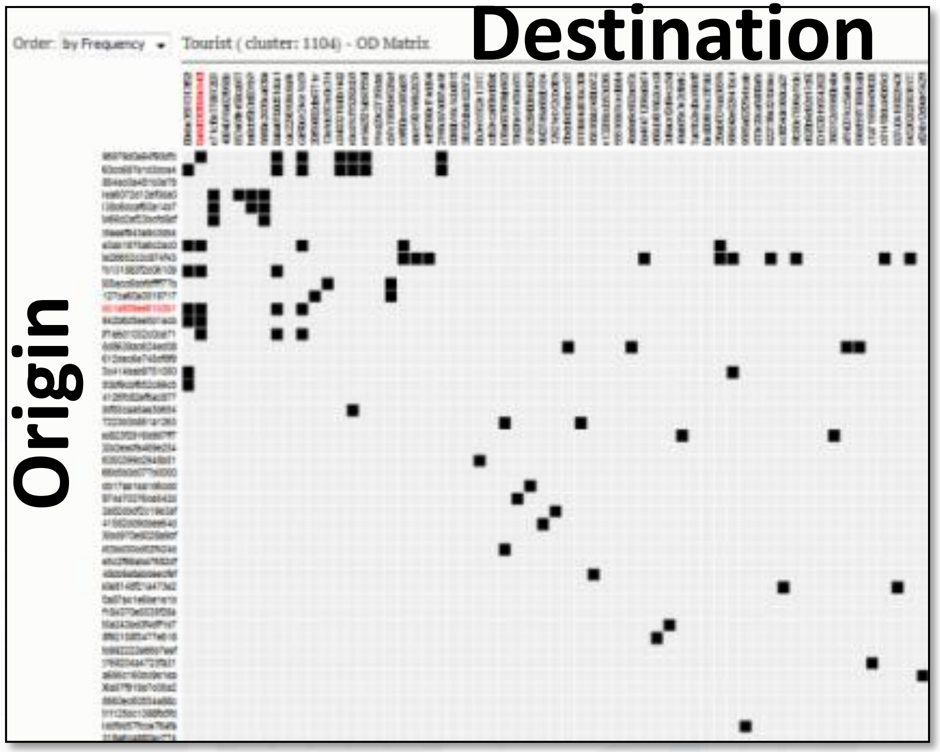
TOP

Origin Destination Matrices and Trajectories



Origin Destination Matrices

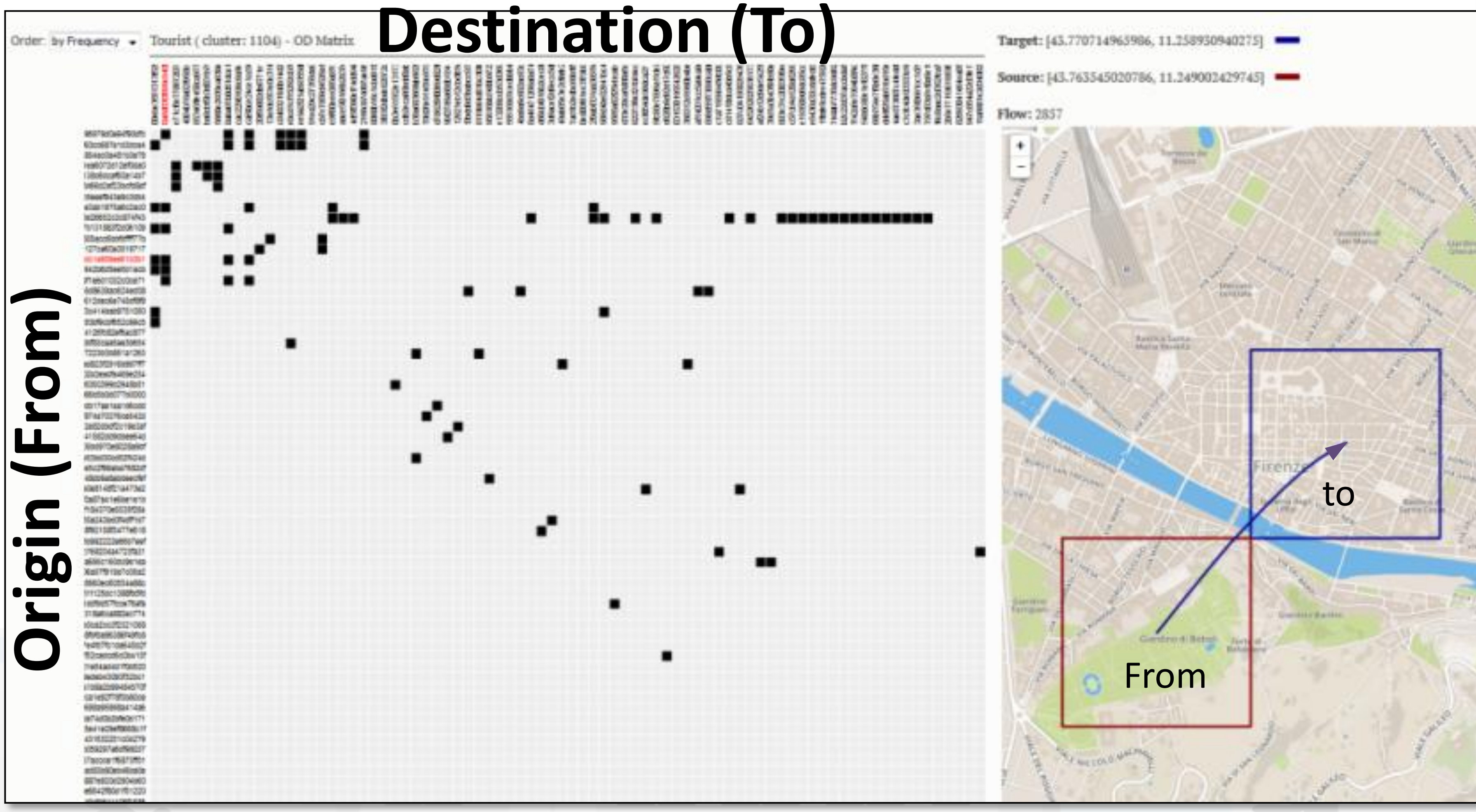
- **computed** from several kinds of data
  – Census Data
  – Cellular Mobile Data
  – Mobile App Data **trajectories**
  – OBU from vehicles **trajectories**
  – Composition of multiple sources: ODM + Trj
- **may represent:**
  – Demand of mobility
  – Offer of transportation



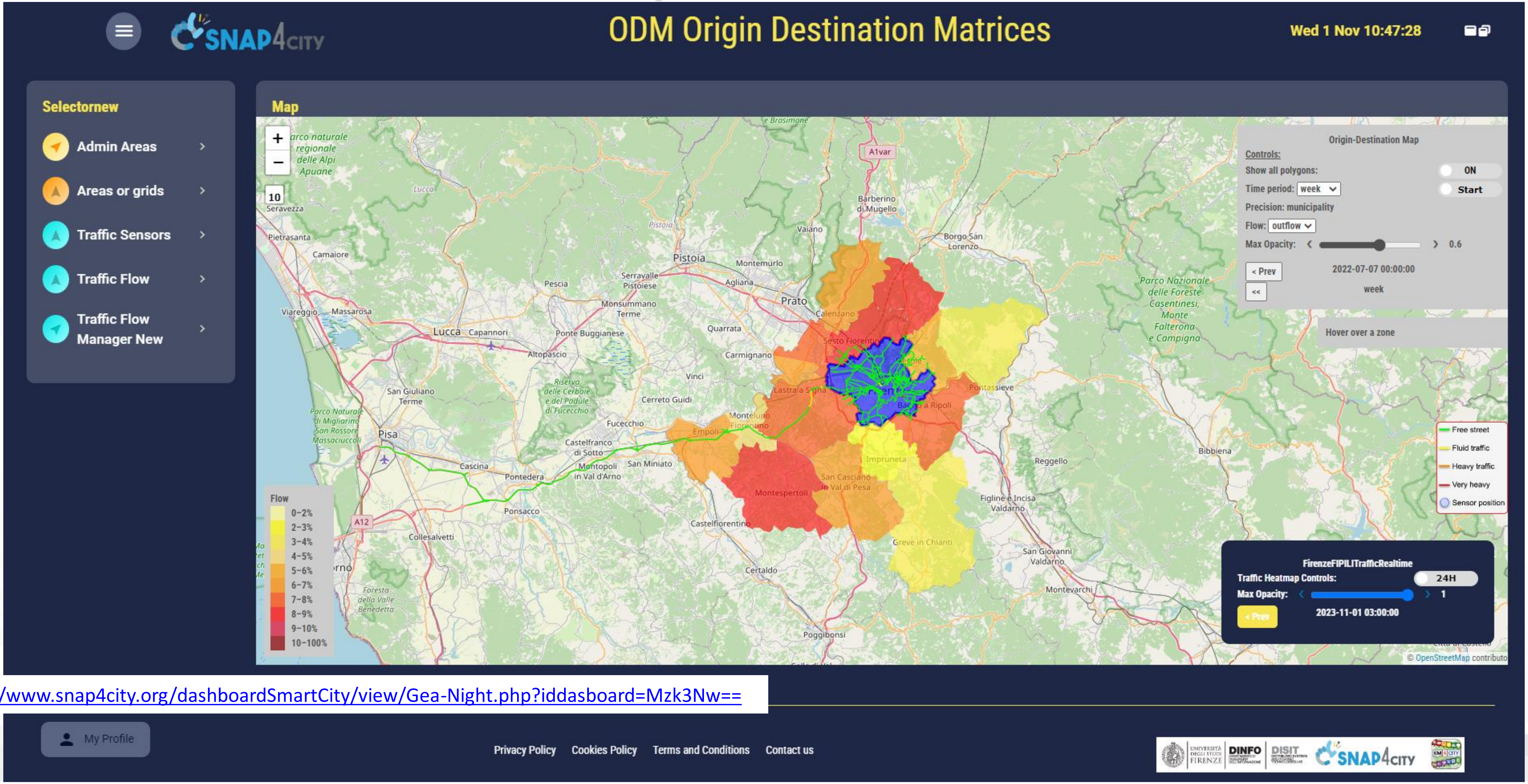
- **refer** to different area kinds for Origin and of Destination
  – Different kinds of OD areas
  – Different kinds of temporal resolutions → animations
    - Hourly, daily, weekly, monthly, etc…

OD Matrices, ODM

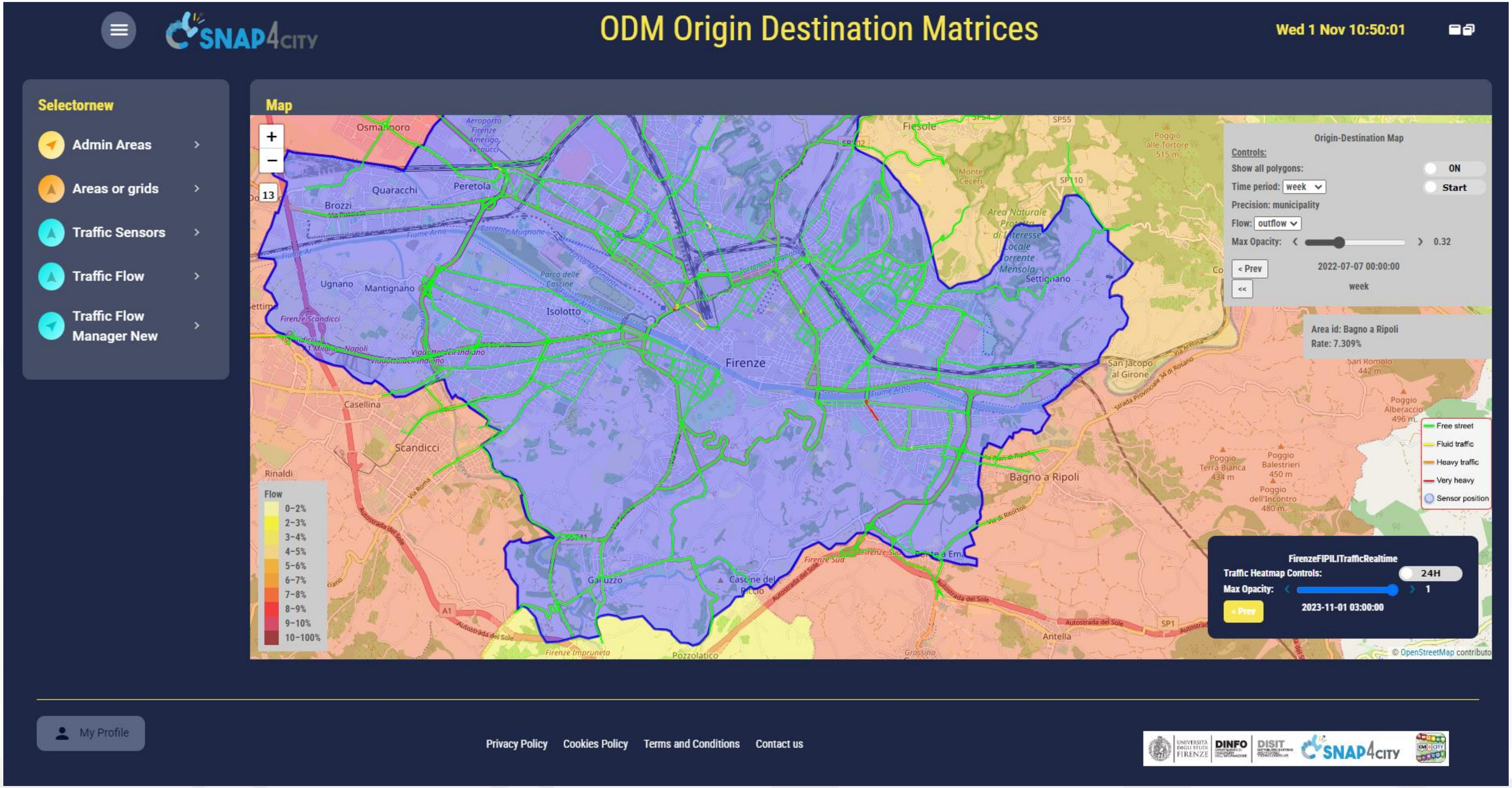
- Origins and destinations
  - Any area of the zone
  - From to
  - To from
- By inflow or outflow
- By temporal slice
  - Hour, day,…
  - Series by hour, day, etc.
- By user profile:
  - Age, nationality,
  - Commuter, citizen, etc.
- By motivations
- By travel means:
  - car, bike, walk..
- By extraction technique
- By civic area VS segmented GPS area
- ….



ODM, Traffic Flow

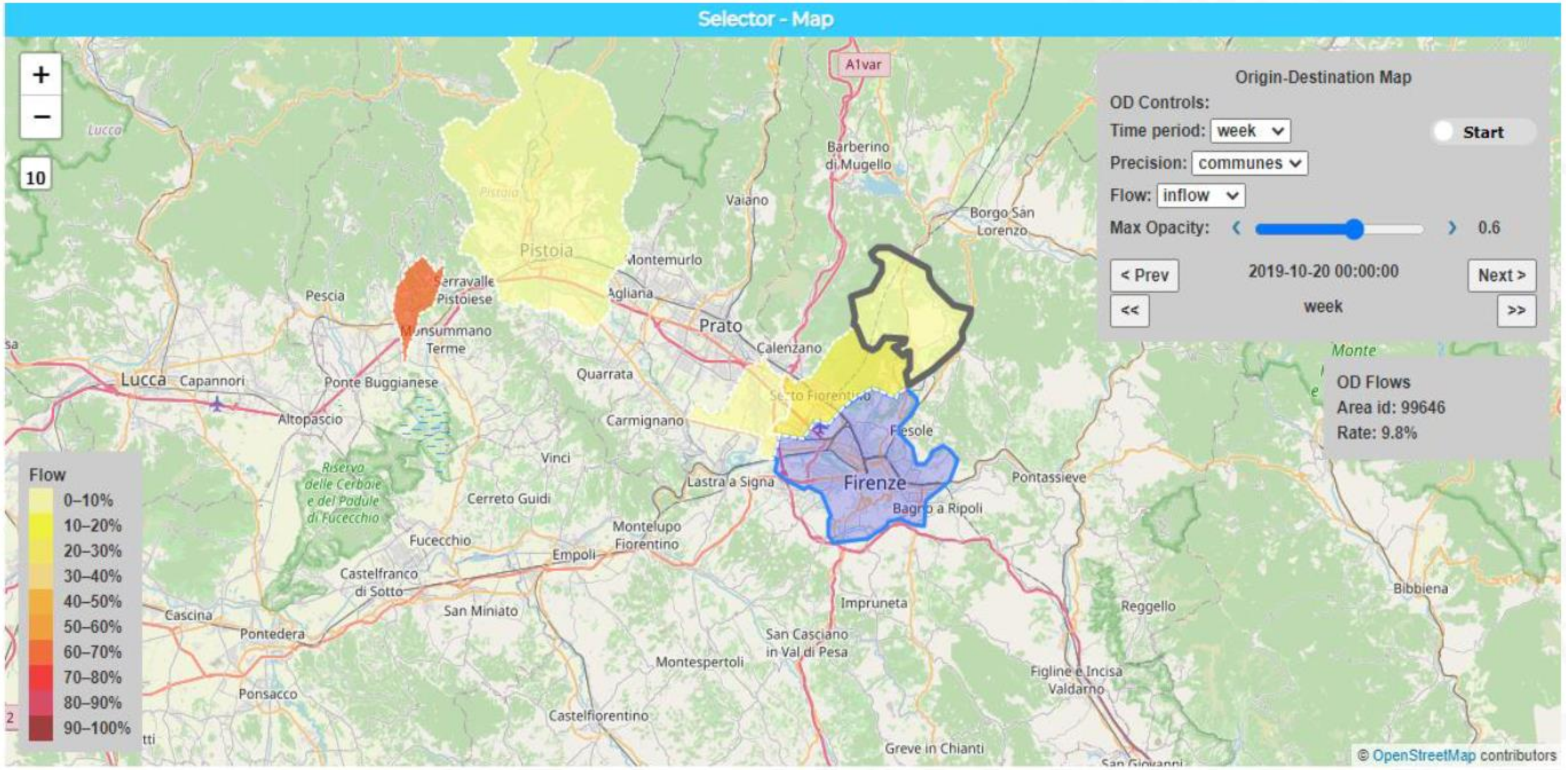


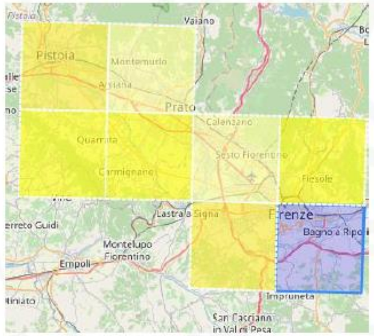
https://www.snap4city.org/dashboardSmartCity/view/Gea-Night.php?iddasboard=Mzk3Nw==

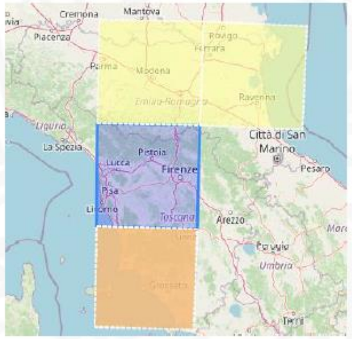


ODM Origin Destination Matrices
Wed 1 Nov 10:50:01
Selectornew
Admin Areas
Areas or grids
Traffic Sensors
Traffic Flow
Traffic Flow Manager New
Map
Origin-Destination Map
Controls:
Show all polygons:
ON
Time period: week
Start
Precision: municipality
Flow: outflow
Max Opacity:
0.32
< Prev
2022-07-07 00:00:00
week
Area id: Bagno a Ripoli
Rate: 7.309%
Flow
0-2%
2-3%
3-4%
4-5%
5-6%
6-7%
7-8%
8-9%
9-10%
10-100%
Free street
Fluid traffic
Heavy traffic
Very heavy
Sensor position
FirenzeFIPILITrafficRealtime
Traffic Heatmap Controls:
24H
Max Opacity:
1
< Prev
2023-11-01 03:00:00
Firenze
Bagno a Ripoli
Scandicci
Fiesole
My Profile
Privacy Policy
Cookies Policy
Terms and Conditions
Contact us

Different Origin Destination Matrices





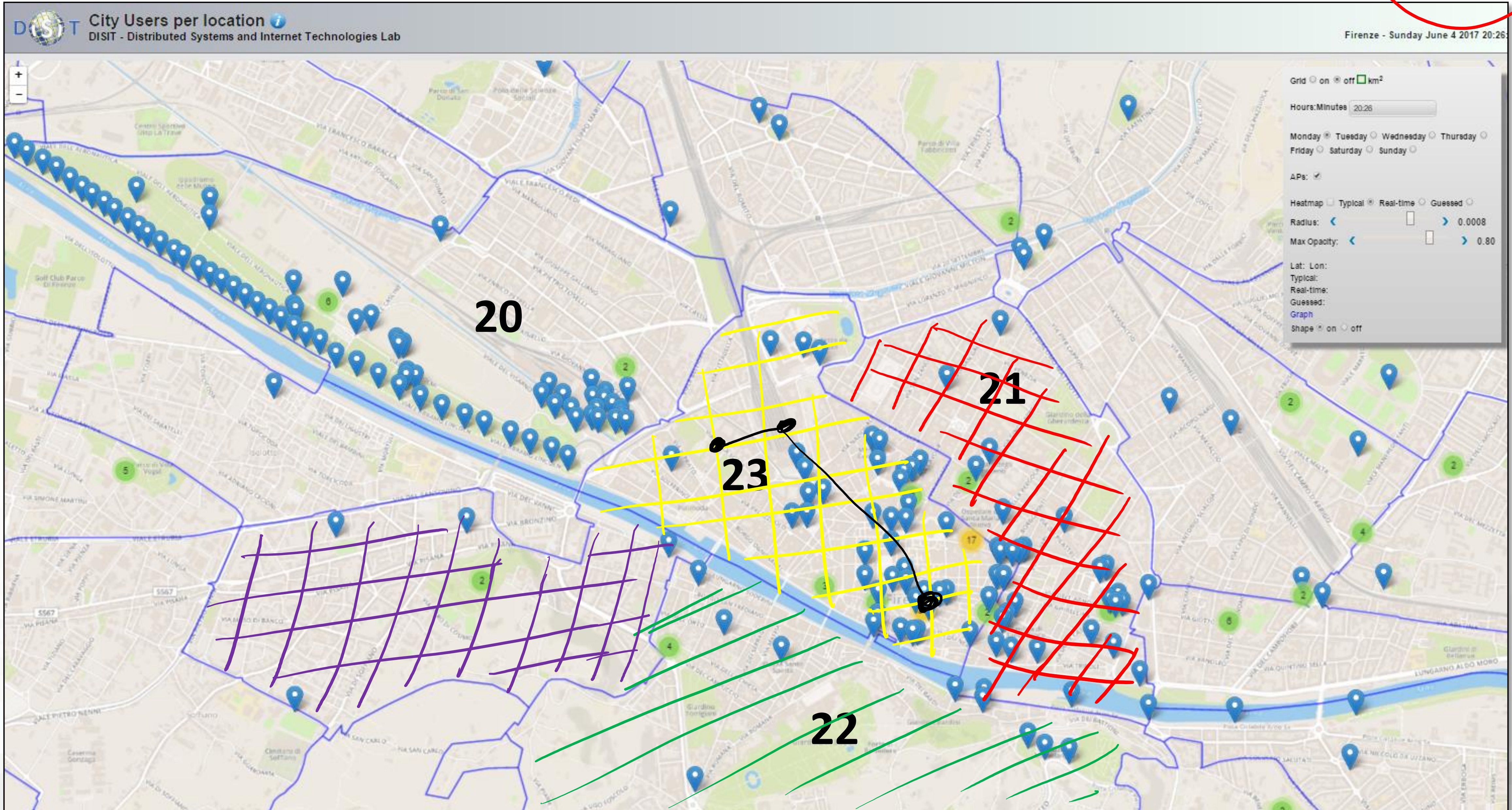


- **Get specific value**
- **Time window**
- **Opacity**
- **Animation**
- **Inflow/outflow**
- **Sequence of OD matrices: next/prev**

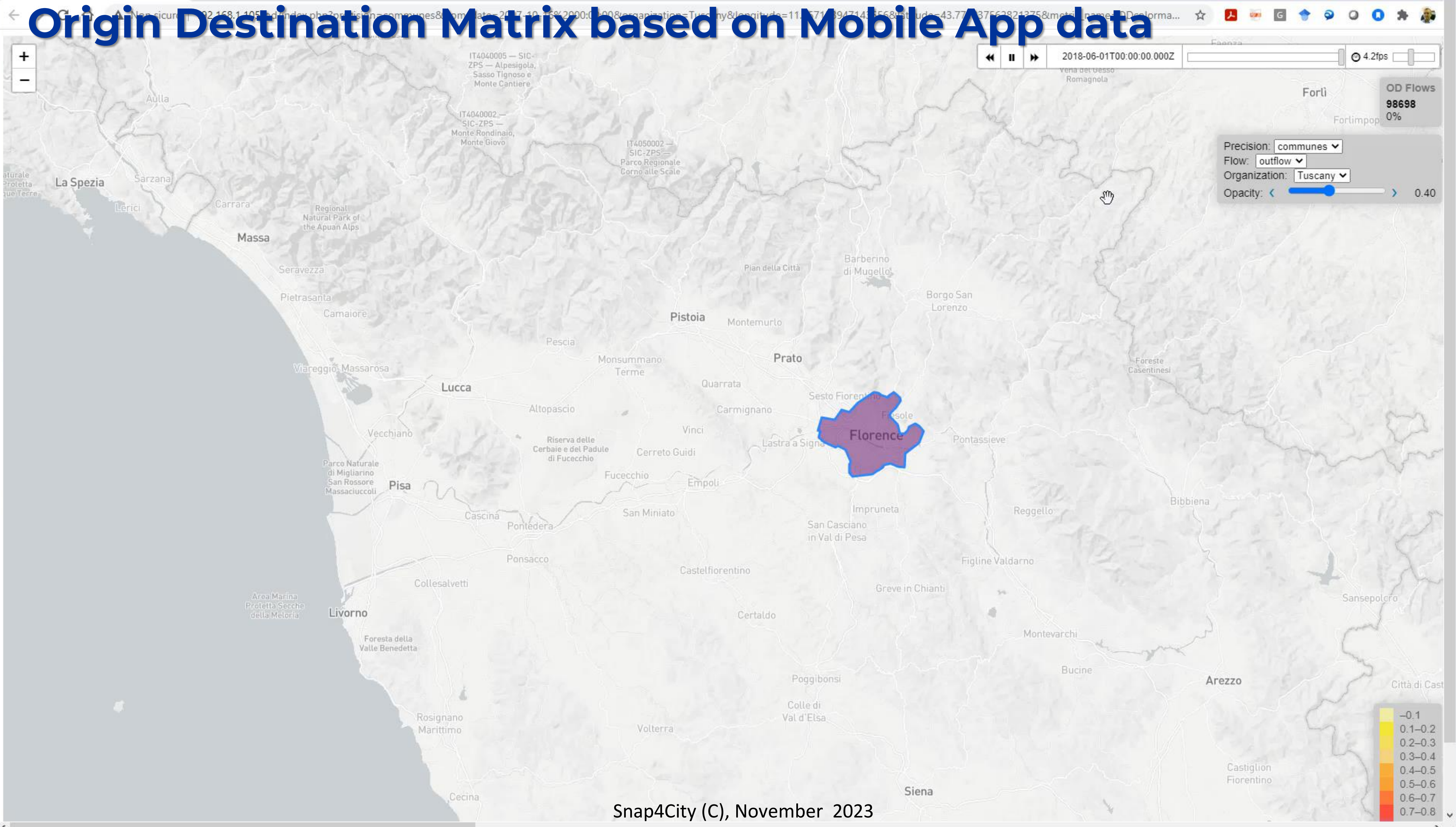
shapes

- **Shapes**: city, region, territories, etc.
  - GADM https://gadm.org/ , and ACE
- **Squared** MGRS:
  - 1m, 10m, 100m, **1Km, 10Km, 100Km**

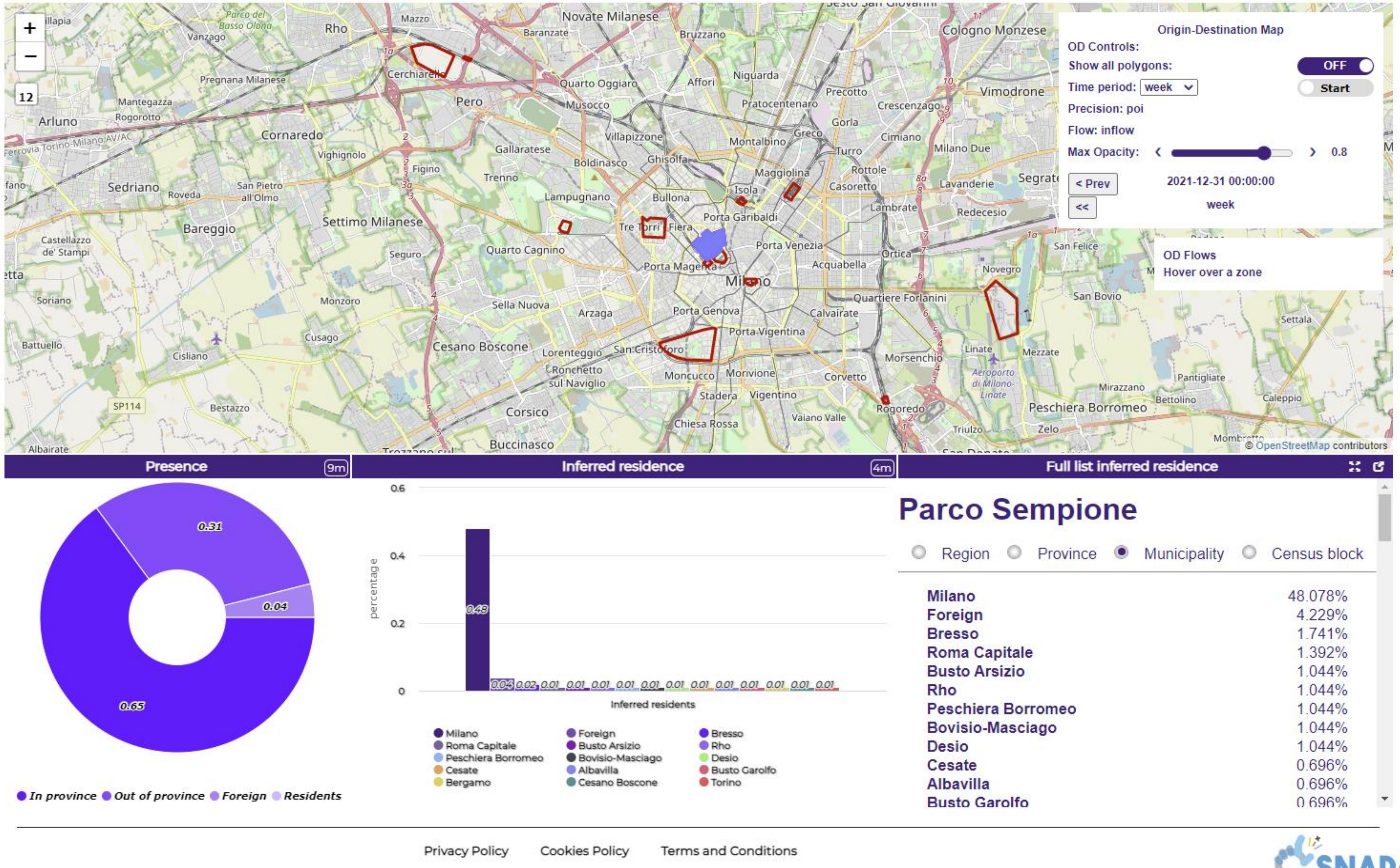
Firenze Wi-Fi vs ACE



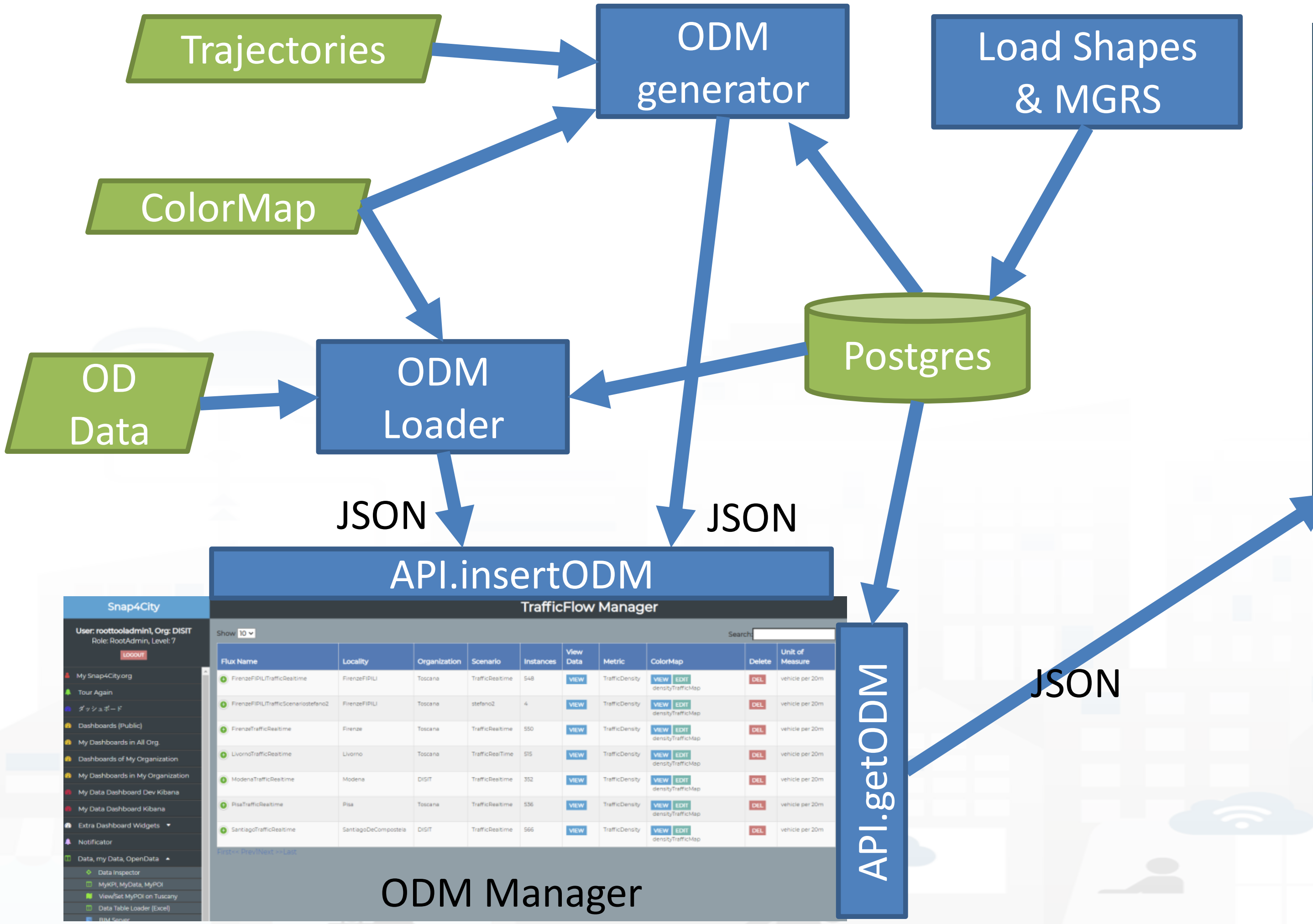
Origin Destination Matrix based on Mobile App data

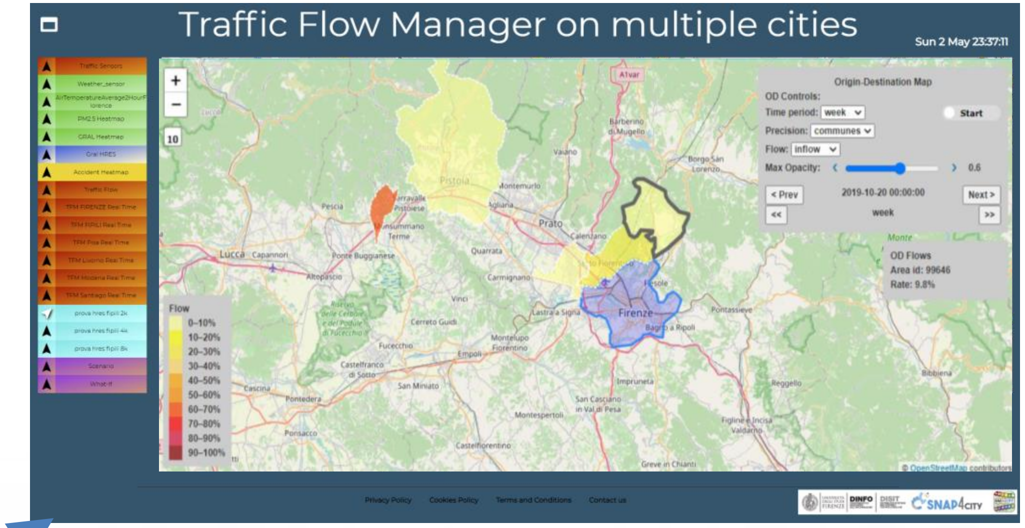


ODM Visual Analytic on Milan Area



How Origin Destination Manager works

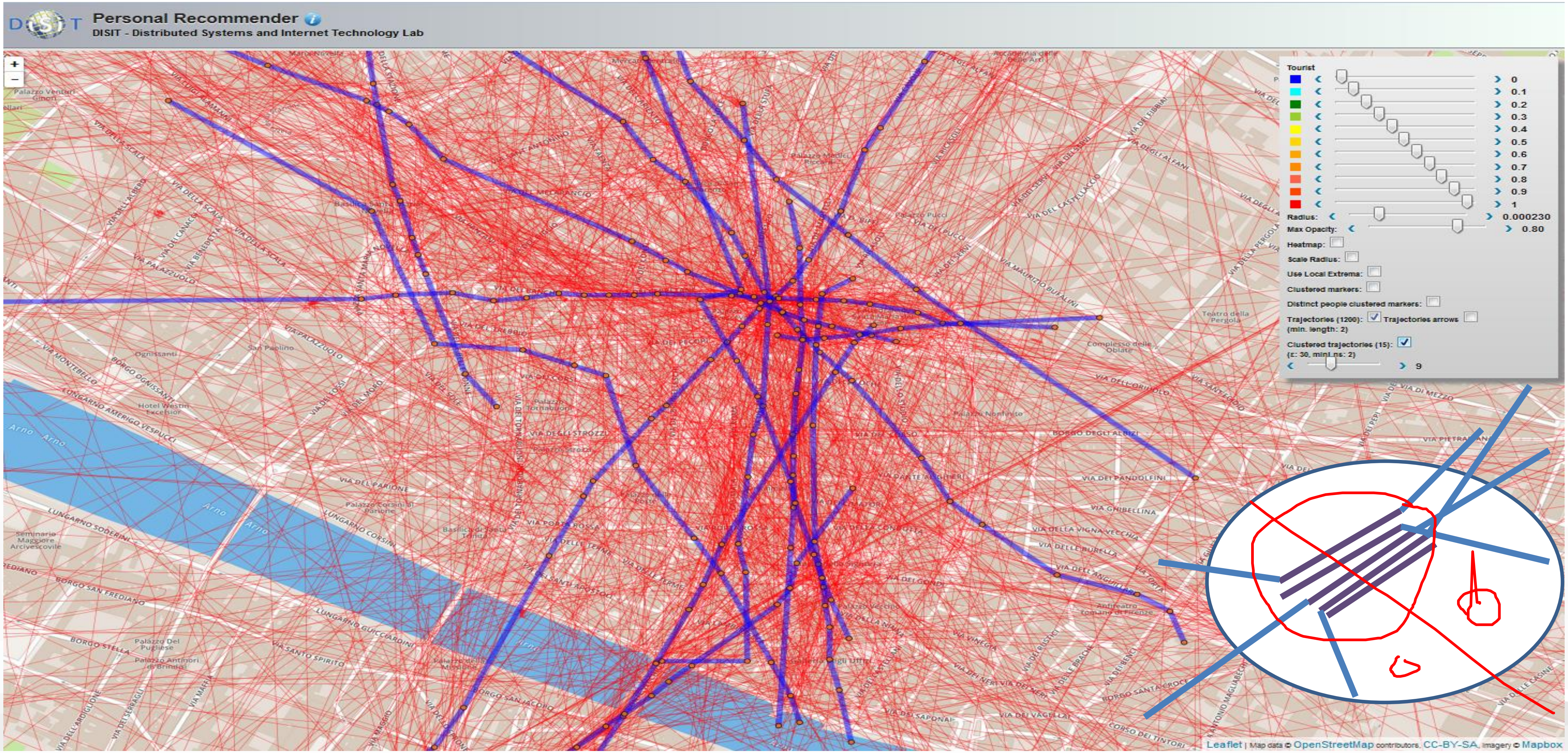




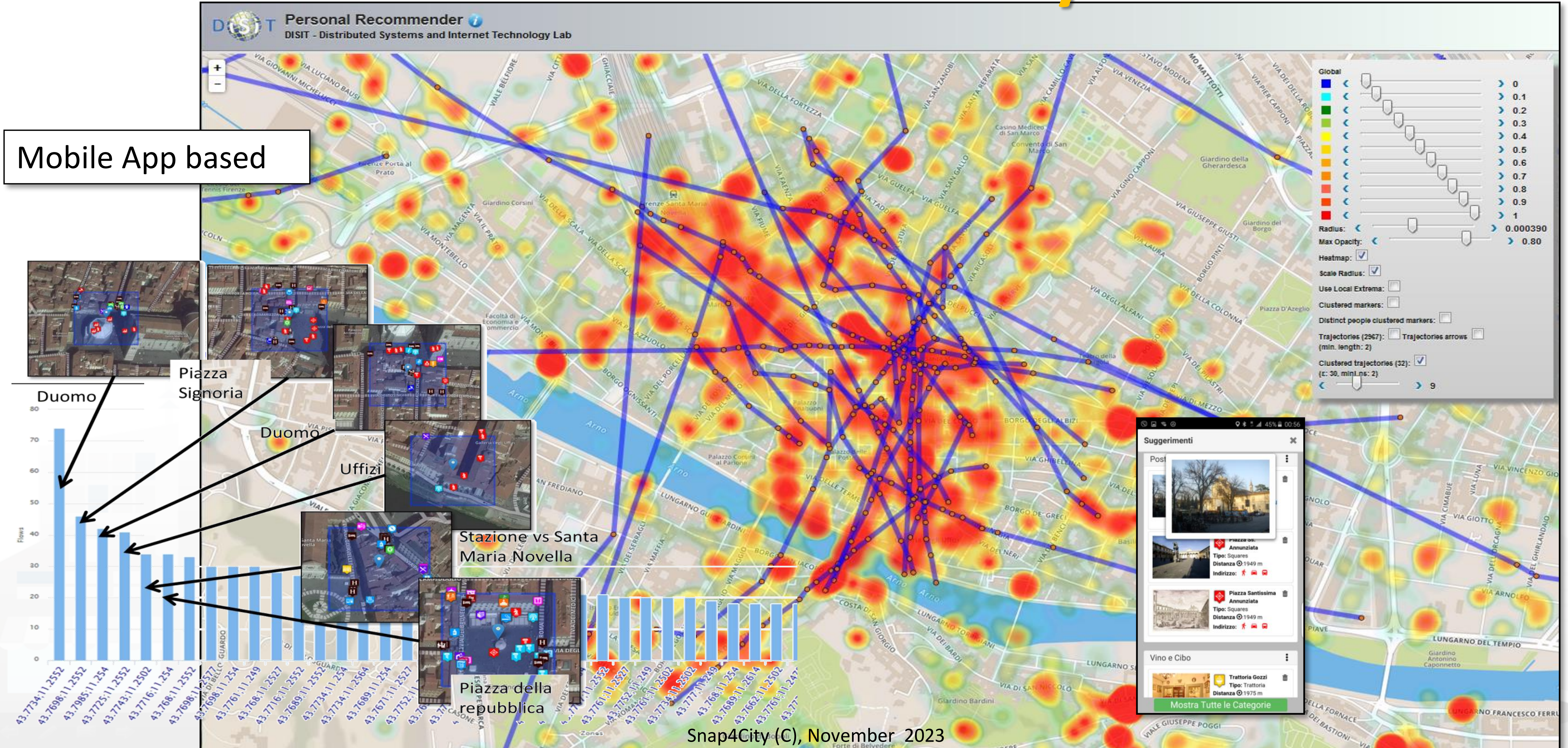
Postgress loaded for

- **Shapes**: city, region, territories, etc.
  - GADM https://gadm.org/ , and ACE
- **Squared** MGRS:
  - 1m, 10m, 100m, **1Km, 10Km, 100Km**

Cluster di Trajectories



User Behavior Analyzer



TOP

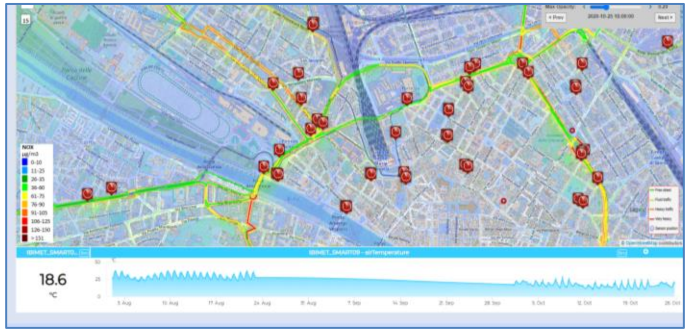
Digital Twin and 3D Digital Representation of the City

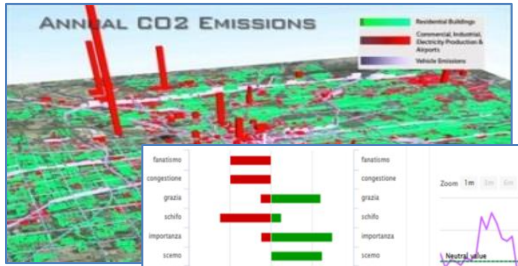
11 SUSTAINABLE CITIES AND COMMUNITIES

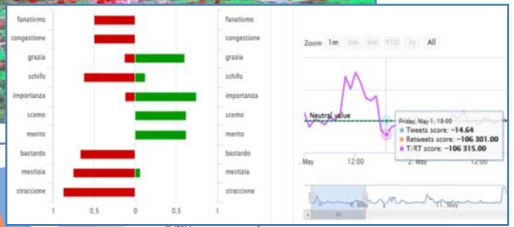
Data Analytic

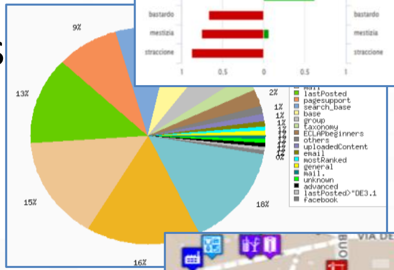
Digital Twin

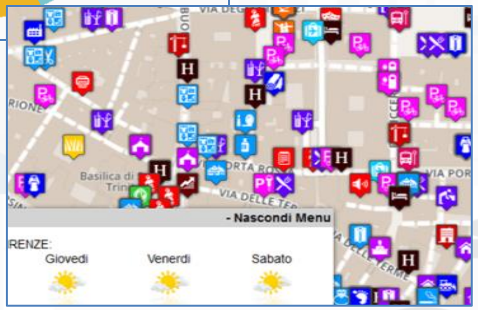
- **Digital Twin**
  - **Connected** with real systems
  - **Modelling** aspects: structural, visual, informative, real time data sensors (context), POI, functional, resources, etc.
  - **Integration:** AI/XAI techniques, simulations, users' needs, etc.
- **Utility to**
  - Experiment via simulations and analysis by case
    - Reduction of costs to experiments new solutions
    - Share the possibilities with city users
  - Virtual Representation
    - Easier to understand the context, review from multiple points of view
  - Who
    - Discussion with city users, decision makers
    - Support: decision makers, proposers of solutions

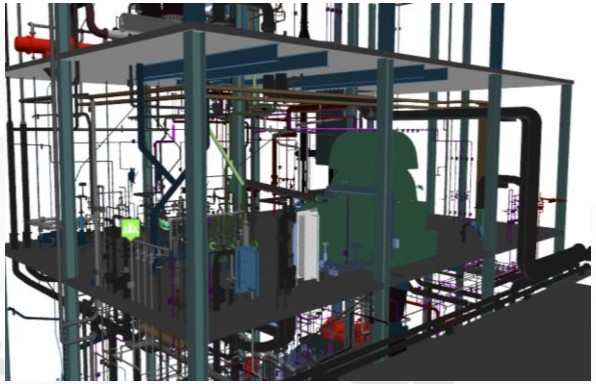


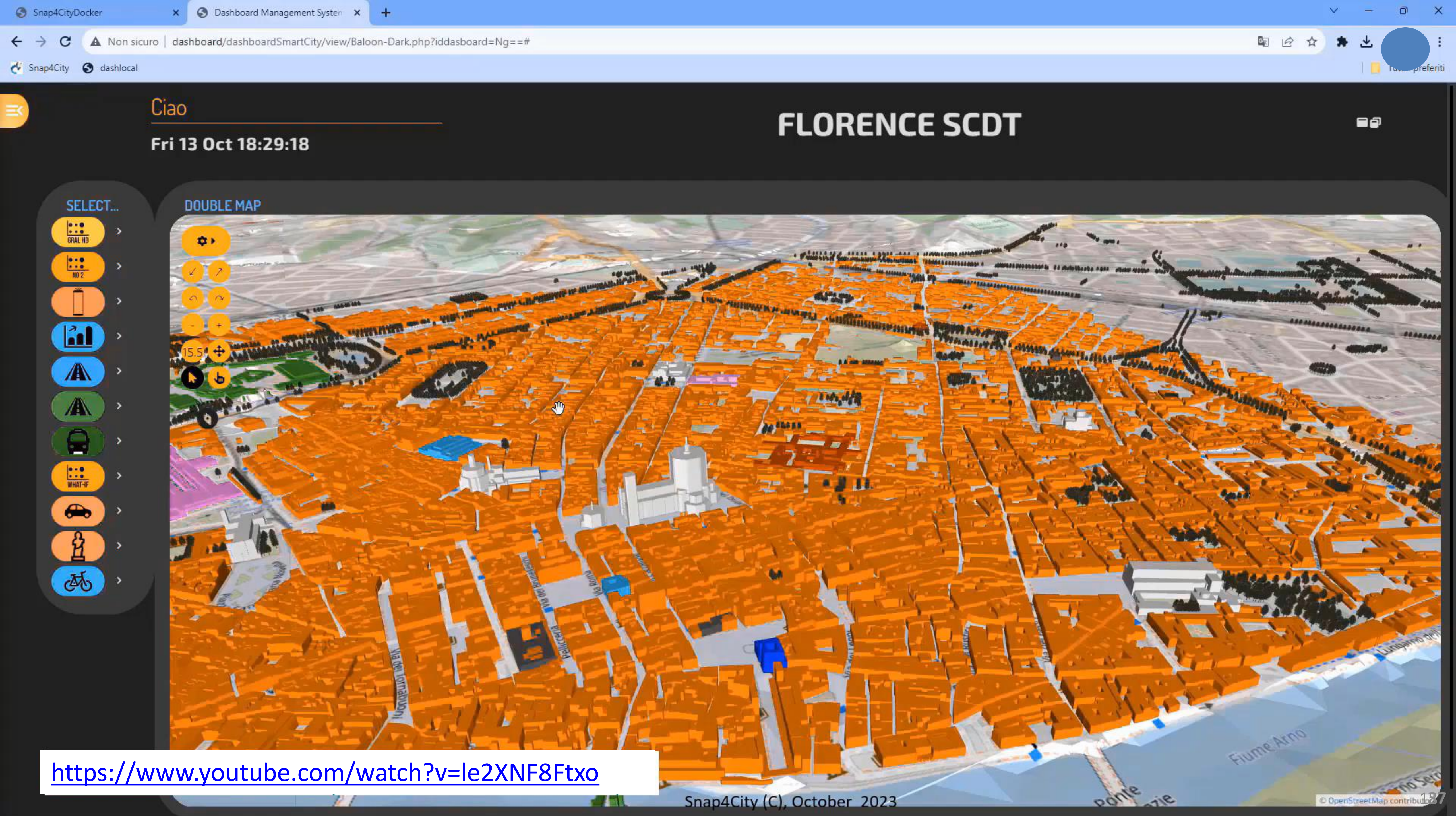










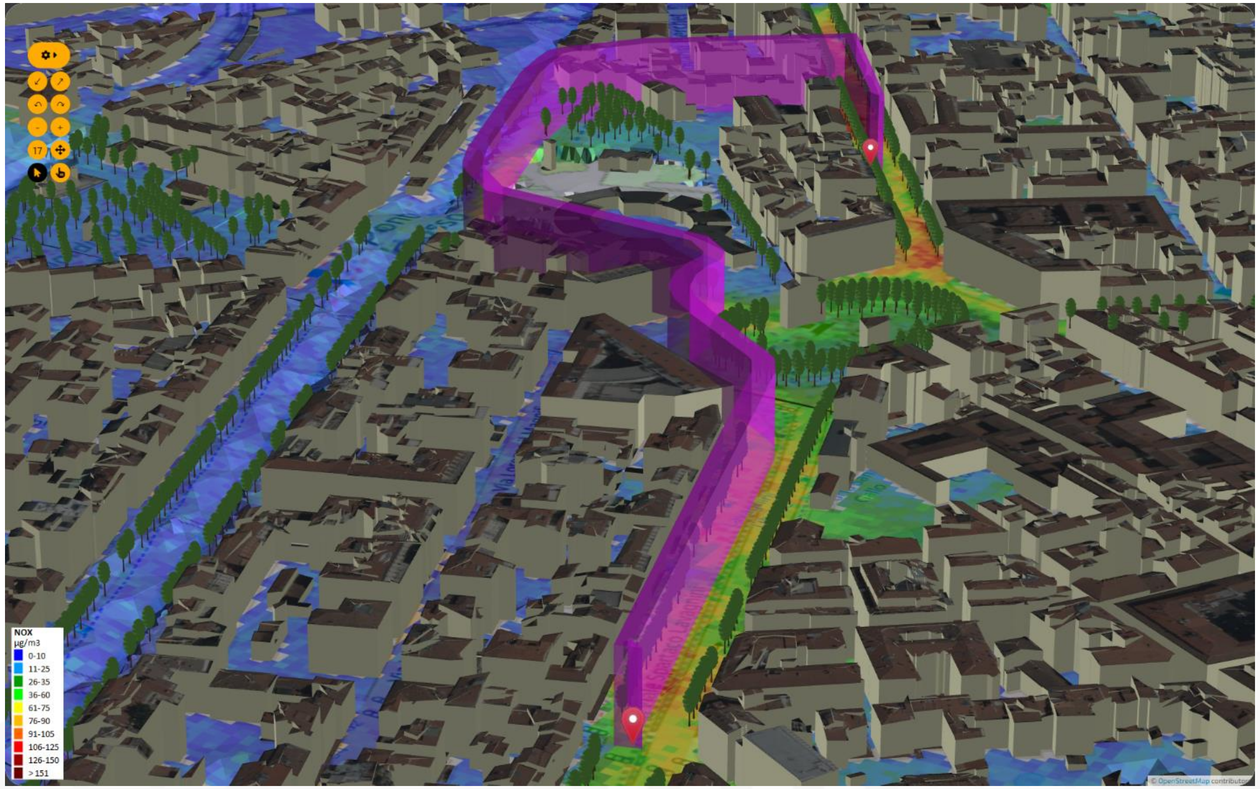


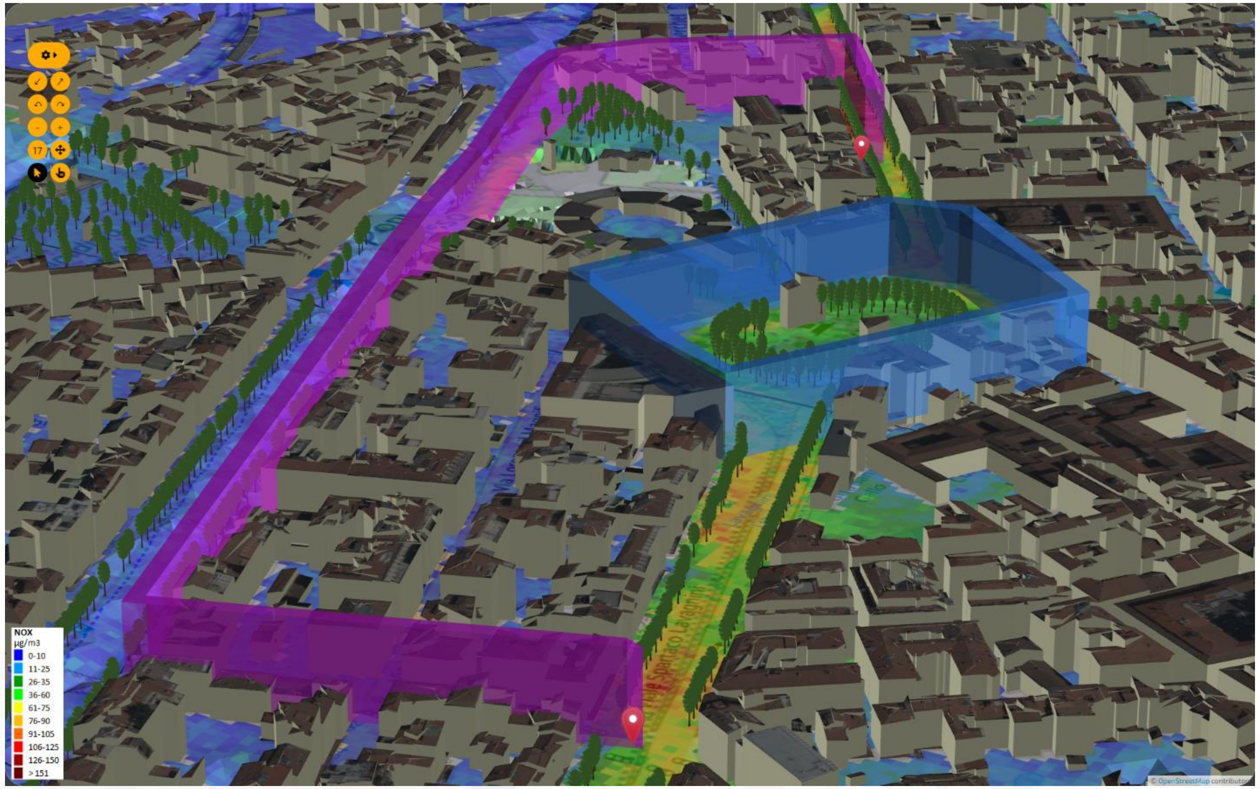
https://www.youtube.com/watch?v=le2XNF8Ftxo

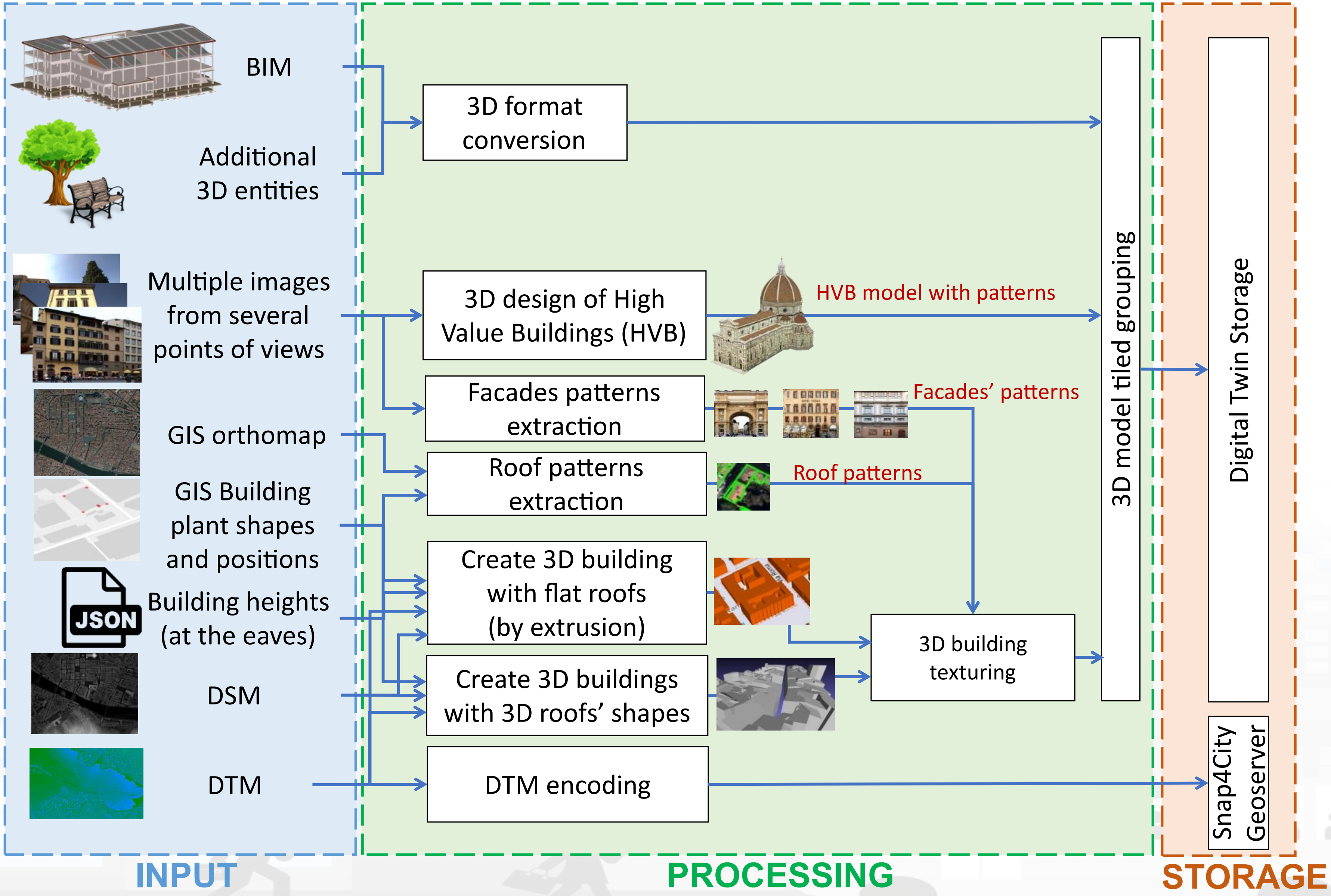
Global City Digital Twin

- **Real Time Rendering Maps with 3D City Digital Twin**
  - Full control:
    - pan, zoom, tilt, rotation, etc.,
    - simulation of light conditions: over the daylight and night
    - Plus Full control with right button and wheel of the mouse
  - Full control of pre-setting for direct show specific condition when loading
  - Section modality to pick the single Building or part of it, and to start a navigation towards other views, via relationships managed by an IoT App of reference
- **3D City Construction is an comprehensive and scalable process**

Dyamic Routing in 3D space






BIM
Additional 3D entities
Multiple images from several points of views
GIS orthomap
GIS Building plant shapes and positions
JSON
Building heights (at the eaves)
DSM
DTM
3D format conversion
3D design of High Value Buildings (HVB)
HVB model with patterns
Facades patterns extraction
Facades' patterns
Roof patterns extraction
Roof patterns
Create 3D building with flat roofs (by extrusion)
Create 3D buildings with 3D roofs' shapes
3D building texturing
DTM encoding
3D model tiled grouping
Digital Twin Storage
Snap4City Geoserver
INPUT
PROCESSING
STORAGE

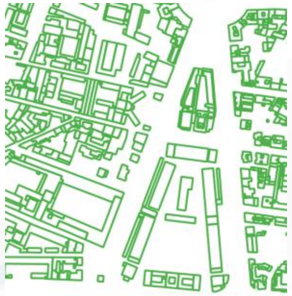
Interacting with 3D City Digital Twin

- You can see in the 3D model
  - Terrain model defining the level of the terrain and of the building
  - Generic Buildings, high value buildings, HVB (e.g., Dome, Palazzo Vecchio, etc.), facades, roofs, etc.
  - Sky pattern: sun, cloudy, etc.
  - Orthomaps below the buildings, by selection
  - Heatmaps, over orthomaps, and below buildings:
    - temperature, traffic, pollutant
  - Cycling paths and other shapes, polylines
  - Traffic Flows: as crests shaping the traffic flow density in high and color according to color map
  - POI, Sensors: PopUps to see real time data
  - Pillars reporting in 3D the values of specific sensors: temperature, traffic flow, people counting, pollutant, etc.

3D Map Texturing

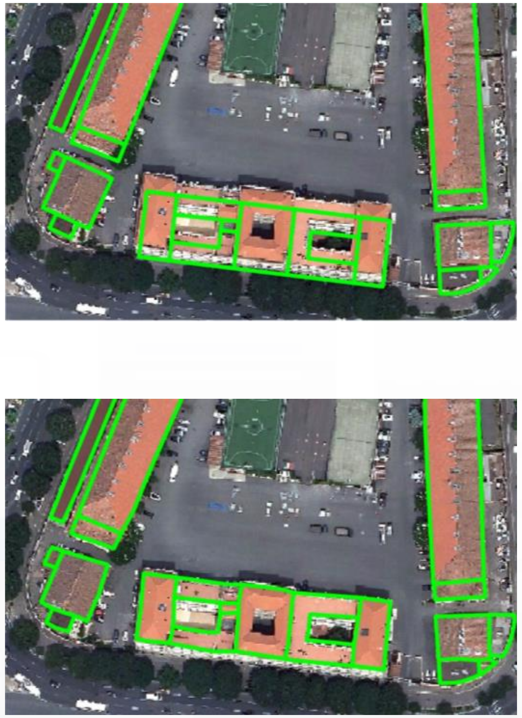
HVB inclusion

Orthomaps

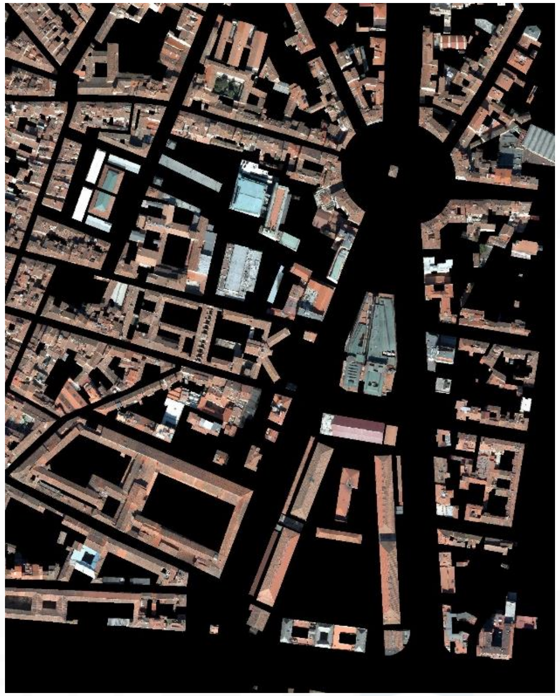


Building shapes

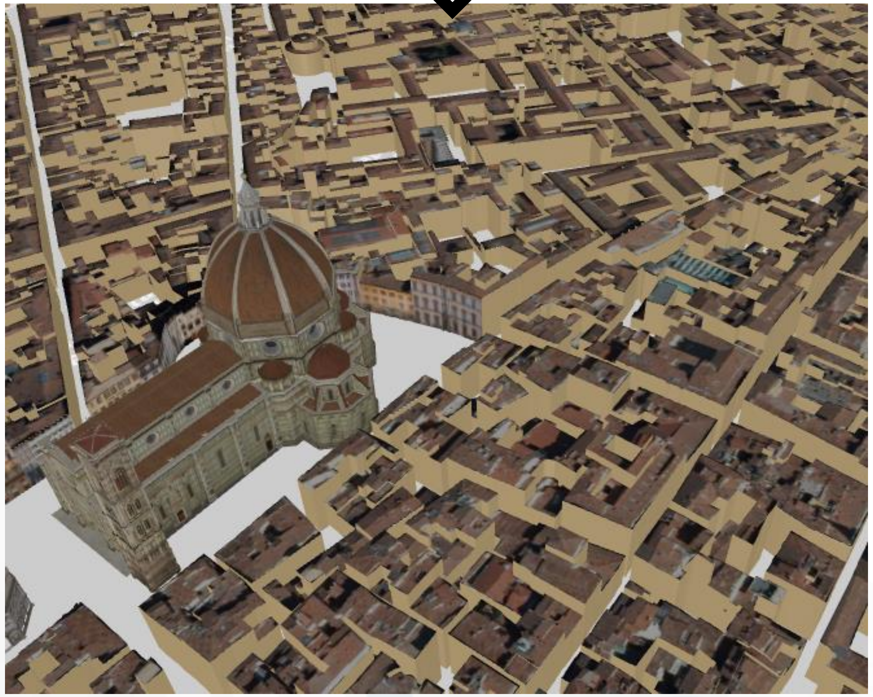
Input



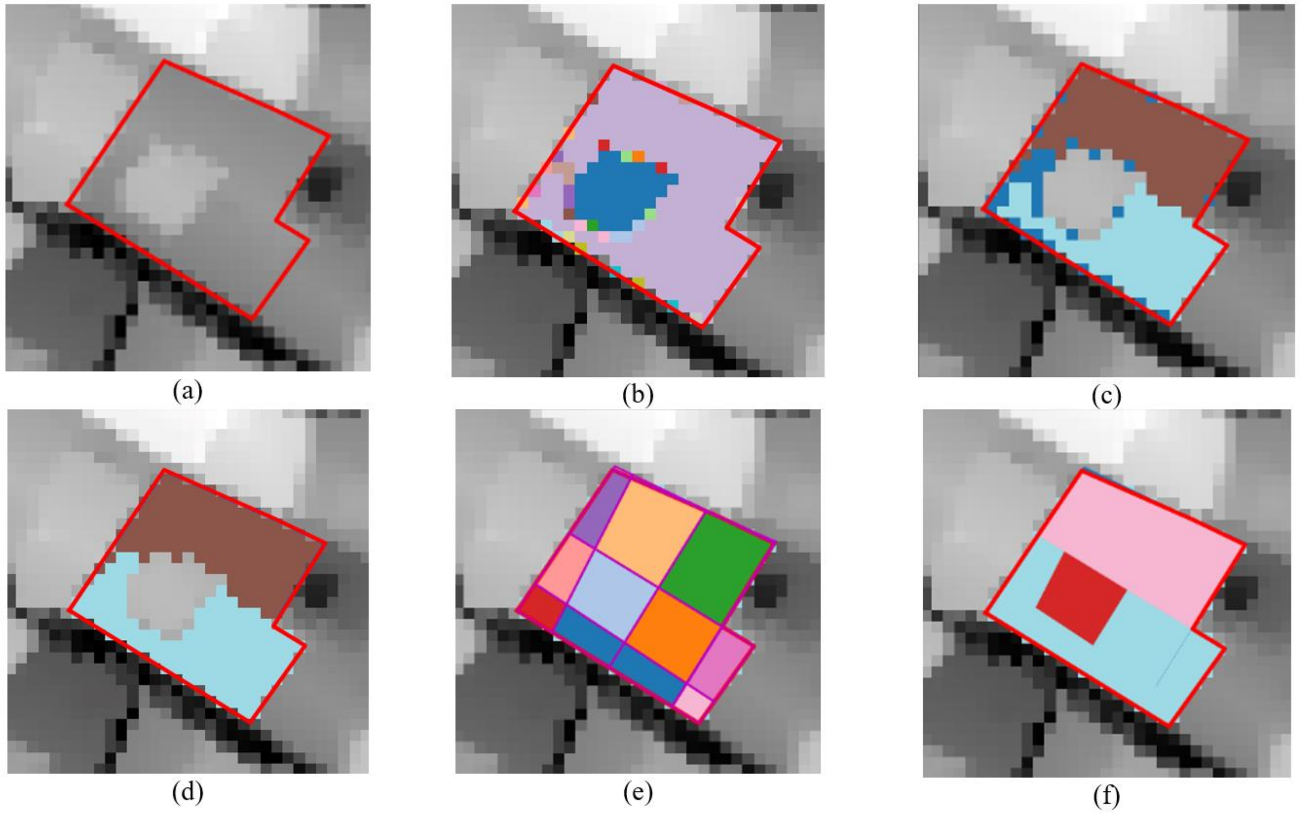
Deep network alignment

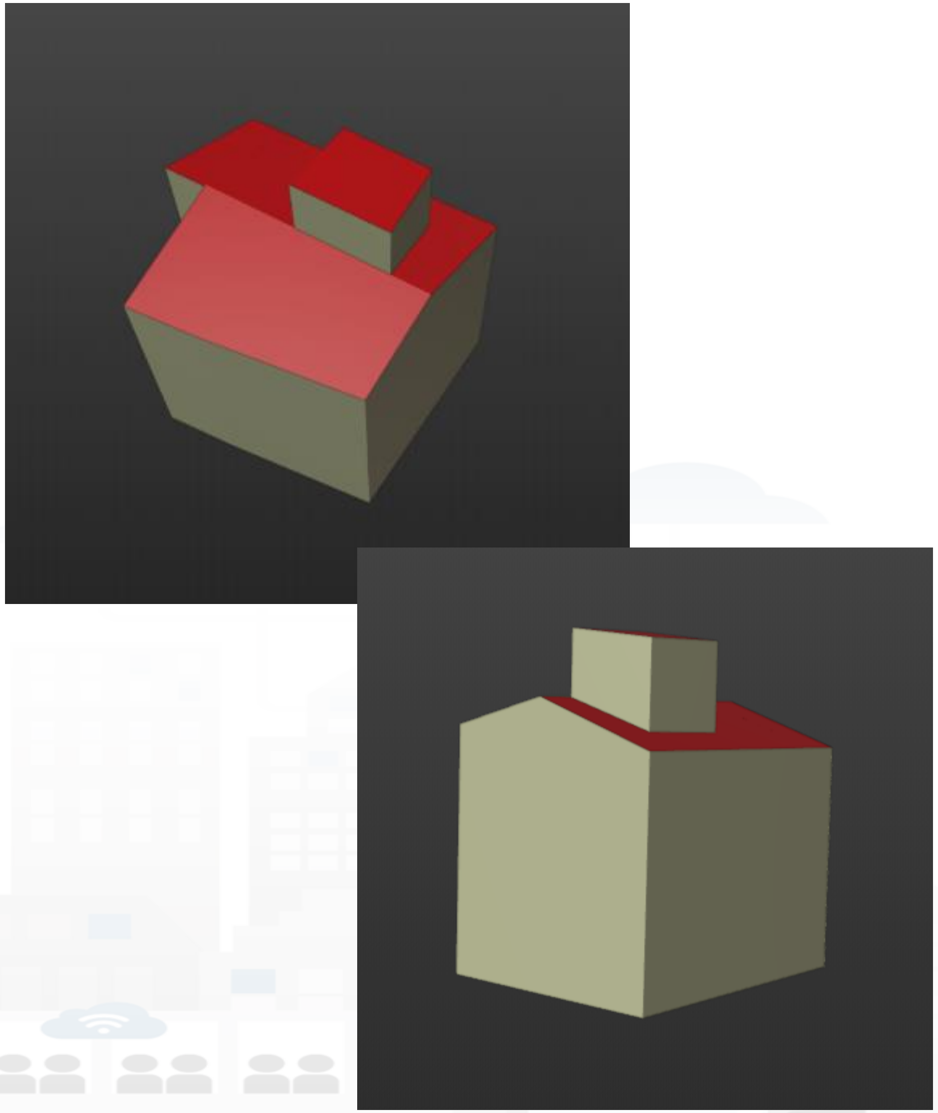


Rooftop texture extraction and warping

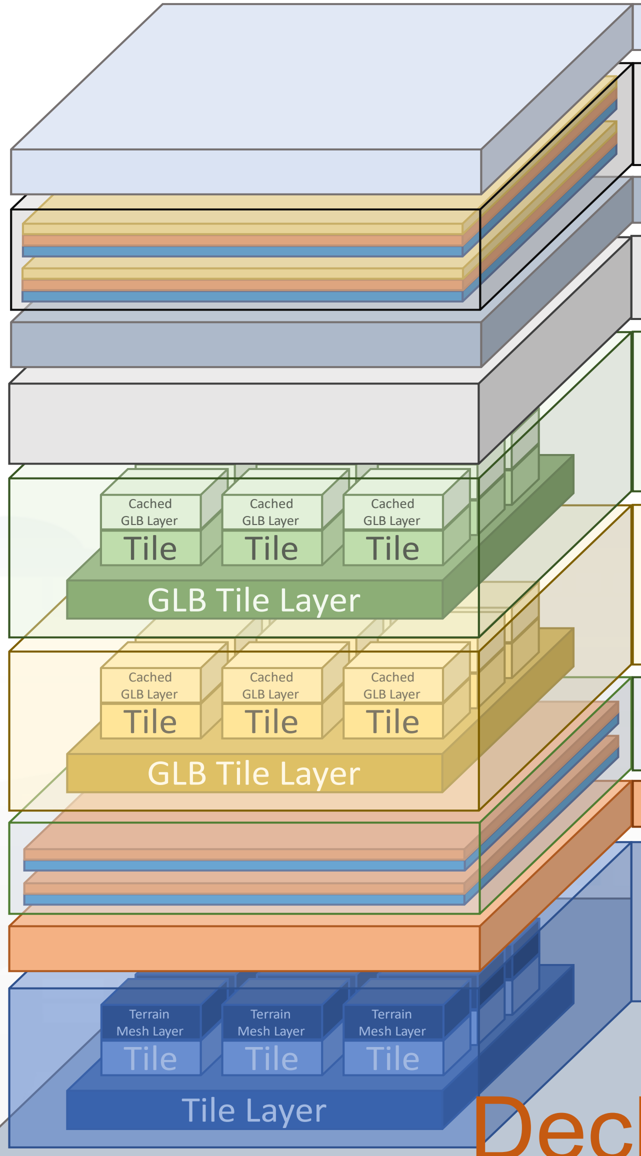


Final textured 3D map





Computational steps of the pipeline to obtain building model with 3D roof from LiDAR based DSM data. (a) input DSM with superimposed the building shape polygon in red, (b) initial output of the region growing clustering, (c) an intermediate step of the plane-cluster expansion, (d) the final plane-clusters, (e) rooftop planar patches, (f) planar roof segments obtained after fusion of the planar patches.



IconLayers: array of layers used to show PINs for IoT sensors, POI, SVG.

Sensor3DLayers: array of layers composed by Scatterplotlayer, ColumnLayer, and TextLayer. Used to represent 3D pillars.

CrestLayers: array of layers used to represent the 3D Traffic Crests

WhatIfLayer: used to show the results of a What-If analysis. It includes a PathLayer, a GeoJSONLayer, and an IconLayer.

TreeLayer: used to present the trees (and eventually other additional 3D entities). It is implemented with the same layer structure of the BuildingLayer.

BuildingLayer: to show the Realistic Buildings. As for the 3D terrain a tiled solution is adopted using CachedGLBLayers instead of TerrainMeshLayer. When using the monolithic approach, different layers are used (see text).

BusLayers: array of layers. Each one is composed by a PathLayer and an IconLayer. Used to represent the bus lines

PathLayers: array of layers used to display cycling paths

ManagedTerrainLayer: used to display the 3D terrain with Orthomaps, Heatmaps, etc. In the case of flat terrain, this layer is substituted with a series of tiled BitmapLayers (see text).

DeckGL Layered Structure

OCULUS


Perspective
Lit
Show
Scrivi qui per eseguire la ricerca
6°C
19:09
30/11/2022


Perspective
Lit
Show

OCULUS

https://www.youtube.com/watch?v=Rcf_B2_GOio

Exploiting Google API with Snap4City engine

- Select any city/locality and see if 3D Representation of your city is Available
- Snap4City redendering and distribution engine allows to
  - – Optimize distribution of data
  - – Integrate any kind of data on Digital Twin with 3D tileds of Google
    - PIN, IoT Data
    - Traffic Flows
    - Cycling paths
    - 3D shapes superimposed
    - Etc.

Snap4City Digital Twin Engine and data + 3D Google Data

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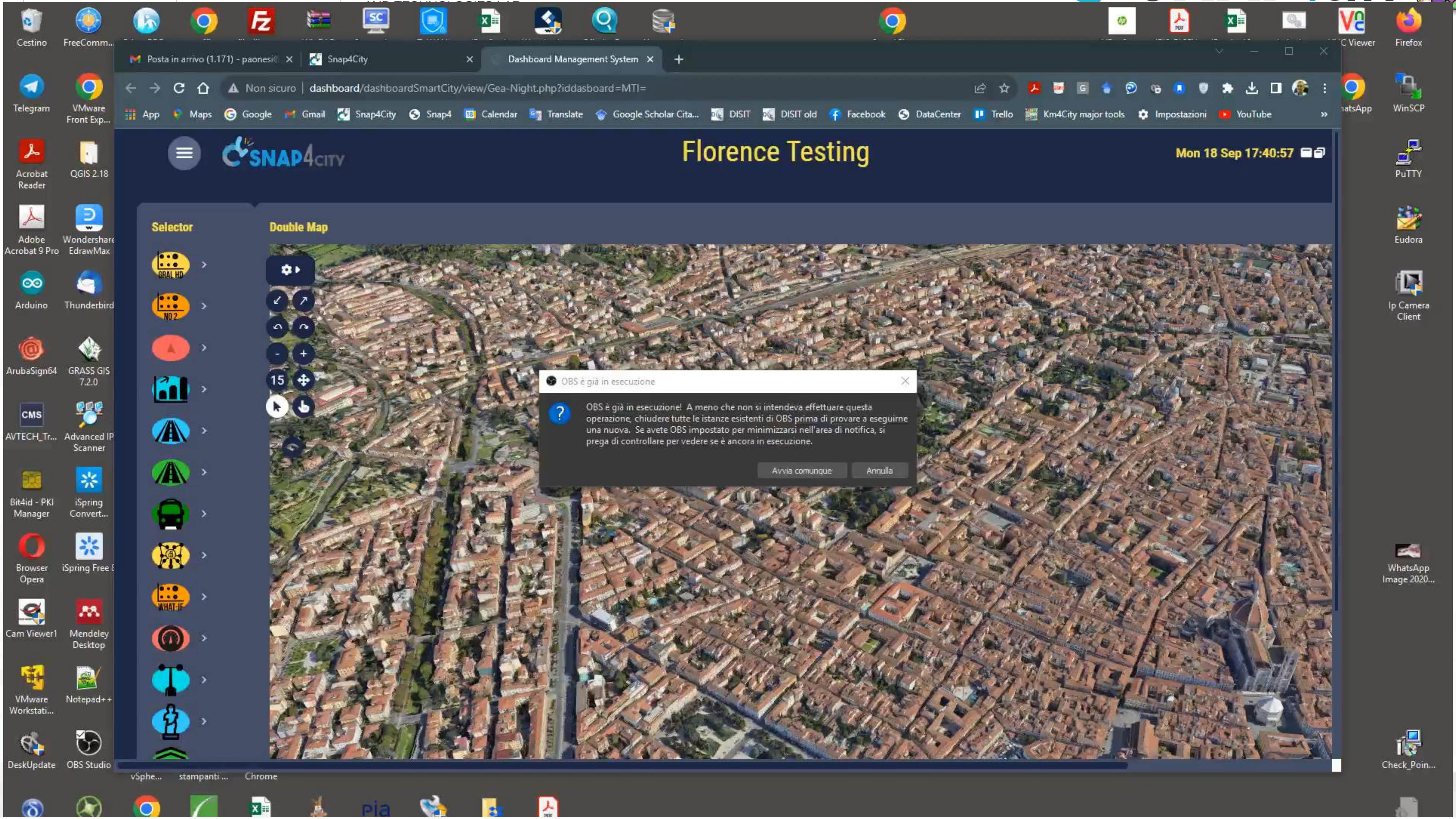
DINFO DIPARTIMENTO DI INGEGNERIA DELL'INFORMAZIONE

DISIT DISTRIBUTED SYSTEMS AND INTERNET TECHNOLOGIES LAB DISTRIBUTED DATA INTELLIGENCE

Firenze

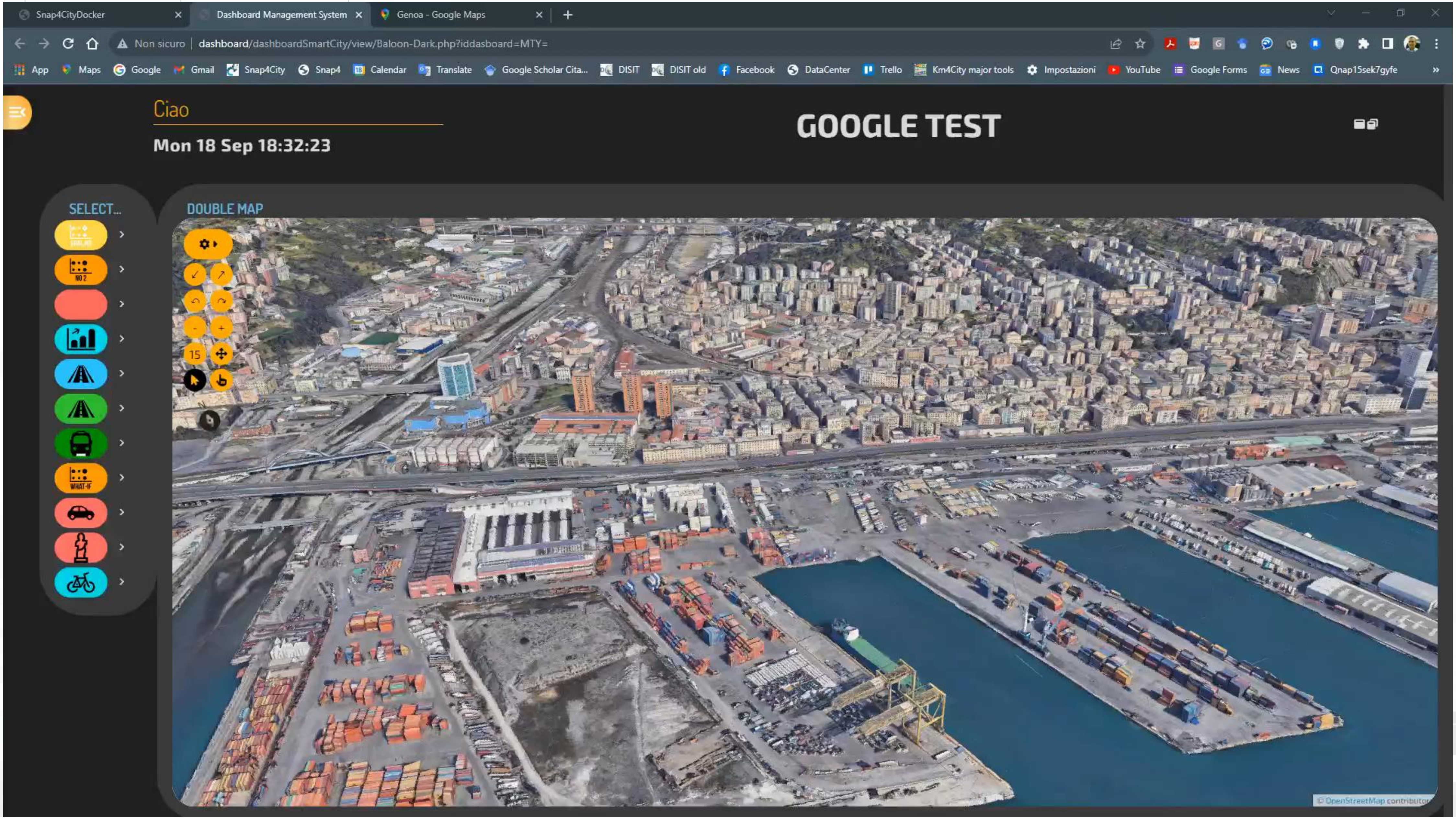


UNIVERSITÀ DEGLI STUDI FIRENZE

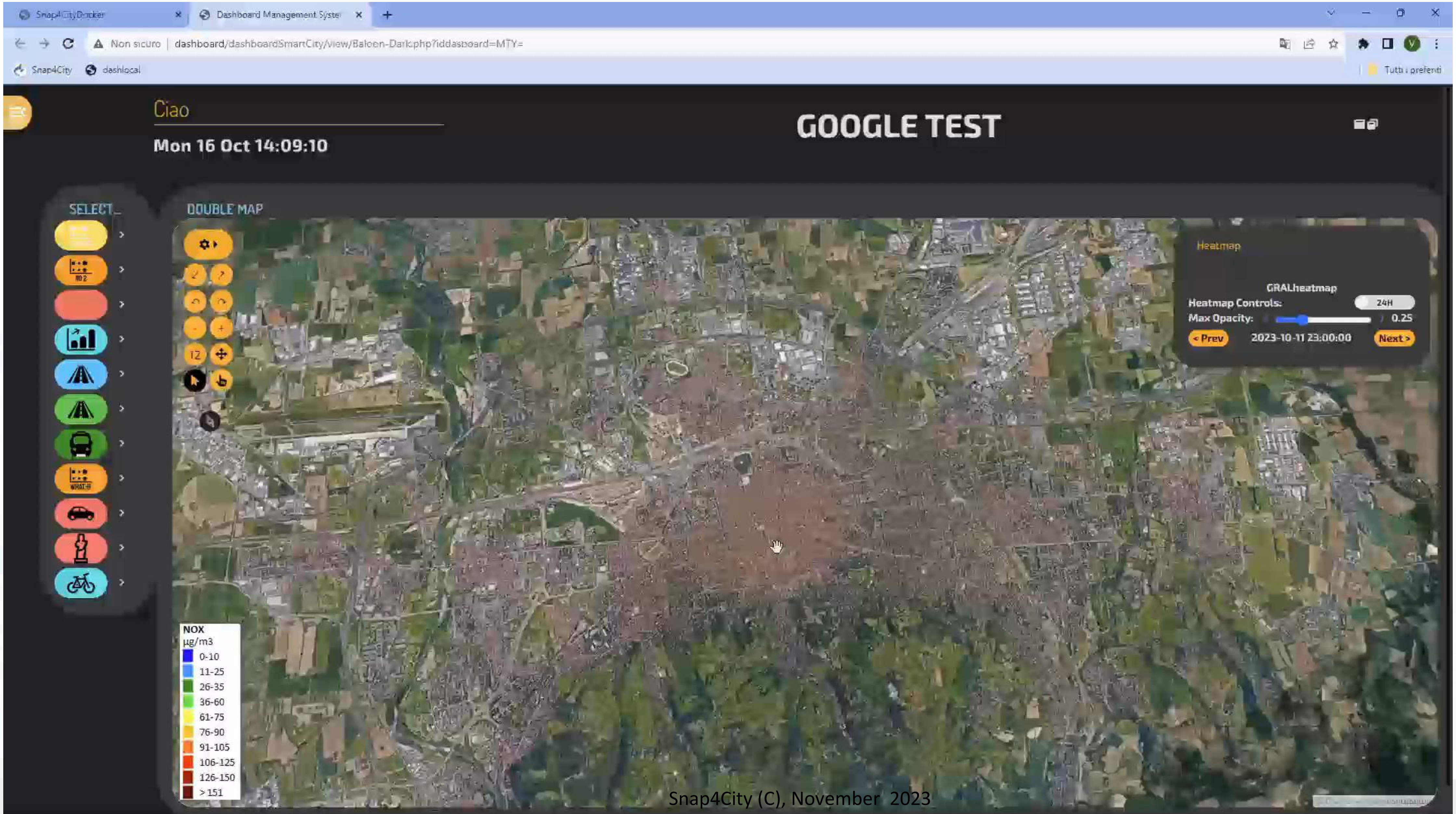
DINFO DIPARTIMENTO DI INGEGNERIA DELL'INFORMAZIONE

DISIT DISTRIBUTED SYSTEMS AND INTERNET TECHNOLOGIES LAB DISTRIBUTED DATA INTELLIGENCE AND TECHNOLOGIES LAB

Genova

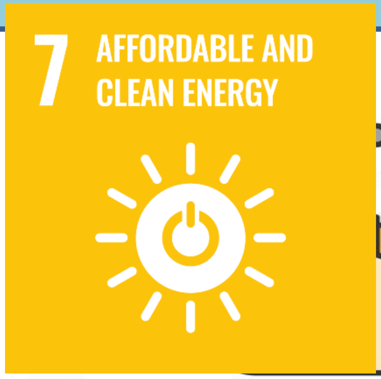


Bologna

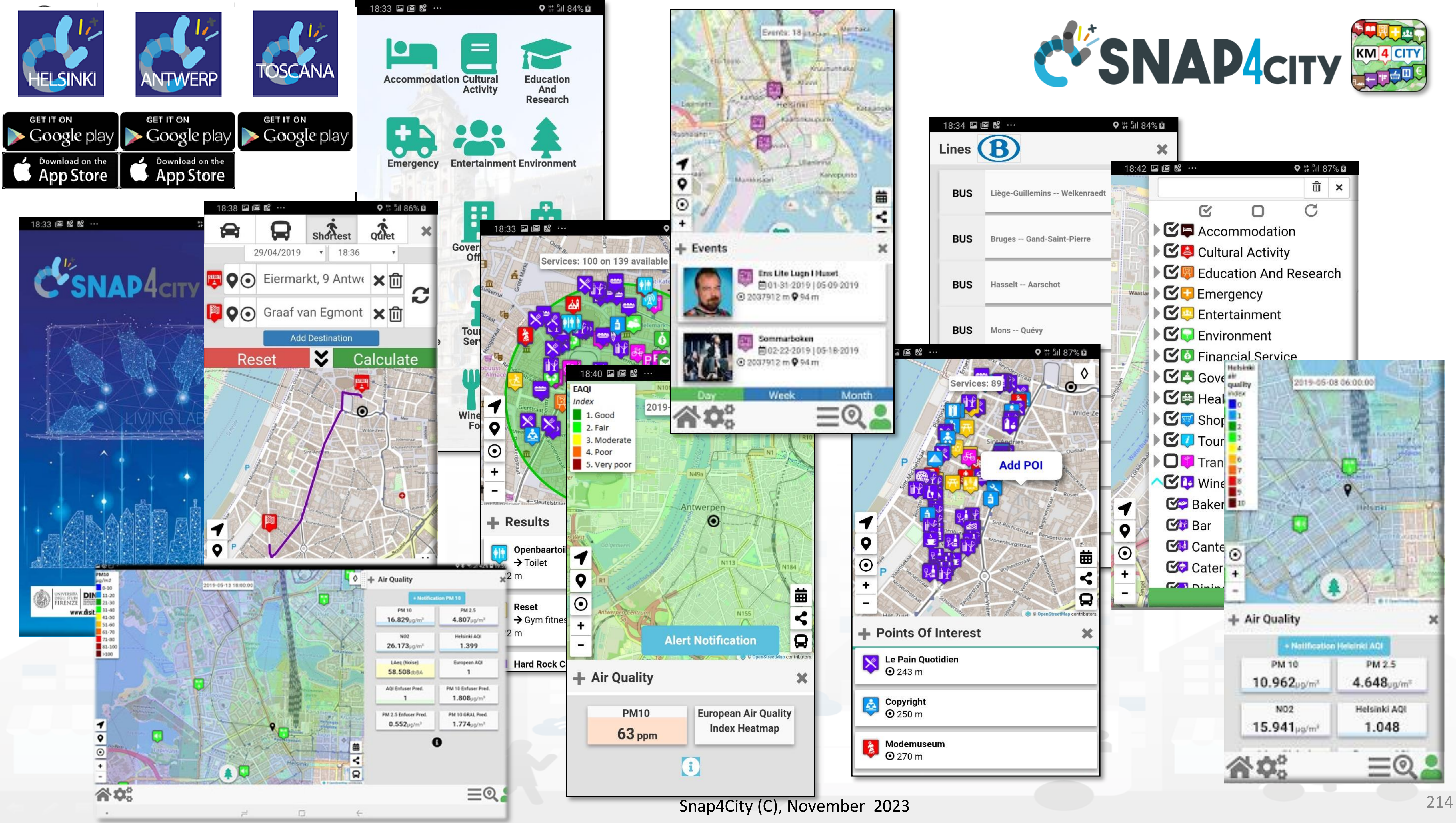

Dashboard Management System
Ciao
Mon 16 Oct 14:09:10
GOOGLE TEST
SELECT...
DOUBLE MAP
Heatmap
GRALheatmap
Heatmap Controls:
24H
Max Opacity:
0.25
< Prev
2023-10-11 23:00:00
Next >
NOX
µg/m3
0-10
11-25
26-35
36-60
61-75
76-90
91-105
106-125
126-150
> 151

TOP

User Behaviour Analysis: Trajectories, Heatmap, typical…



Data Analytic


HELSINKI
ANTWERP
TOSCANA
GET IT ON Google play
Download on the App Store
SNAP4CITY
KM4CITY
Accommodation
Cultural Activity
Education And Research
Emergency
Entertainment
Environment
Events
Lines
BUS Liège-Guillemins -- Welkenraedt
BUS Bruges -- Gand-Saint-Pierre
BUS Hasselt -- Aarschot
BUS Mons -- Quévy
Shortest
Quiet
Eiermarkt, 9 Antwe
Graaf van Egmont
Add Destination
Reset
Calculate
Services: 100 on 139 available
Results
EAQI Index
1. Good
2. Fair
3. Moderate
4. Poor
5. Very poor
Antwerpen
Alert Notification
Air Quality
PM10
63 ppm
European Air Quality Index Heatmap
Services: 89
Add POI
Points Of Interest
Le Pain Quotidien
243 m
Copyright
250 m
Modemuseum
270 m
Financial Service
PM 10
10.962
PM 2.5
4.648
NO2
15.941
Helsinki AQI
1.048
Day
Week
Month

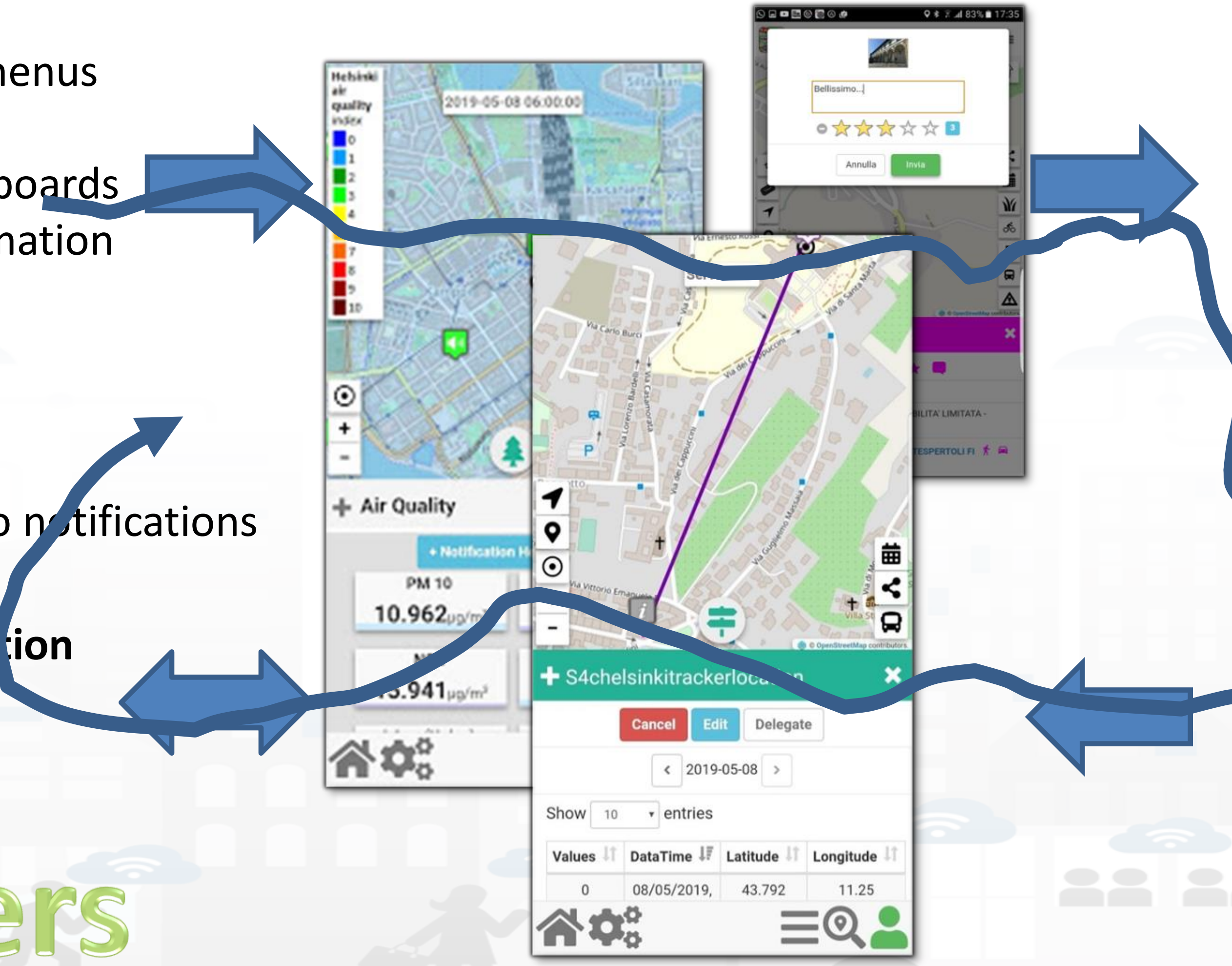
The App is a Bidirectional Device

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

Produced information

- Viewed ?
- Accepted ?
- Performed ?
- …

Users



Derived information

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

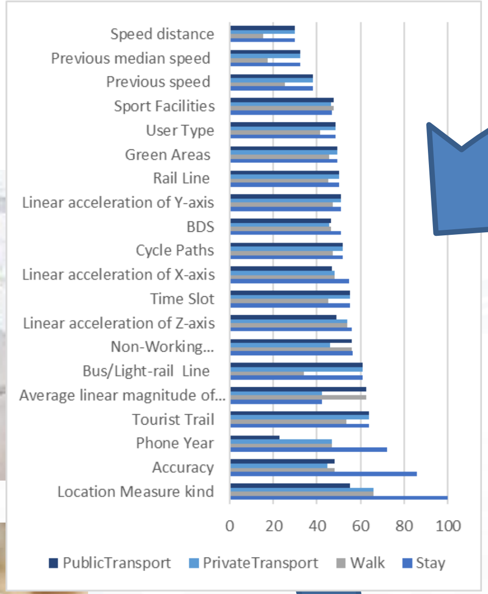
Produced information

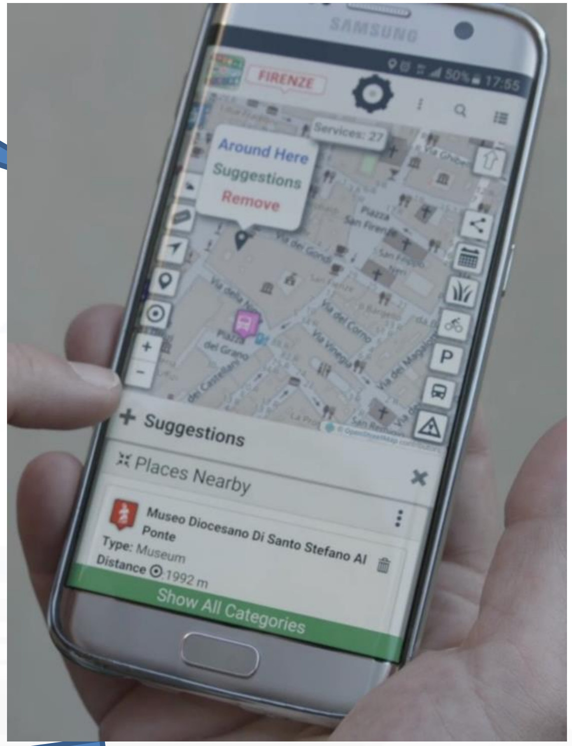
- Suggestions
- Engagements
- Notifications
- …

System

To propose suggestions and Engage city user

we need to know how they are moving





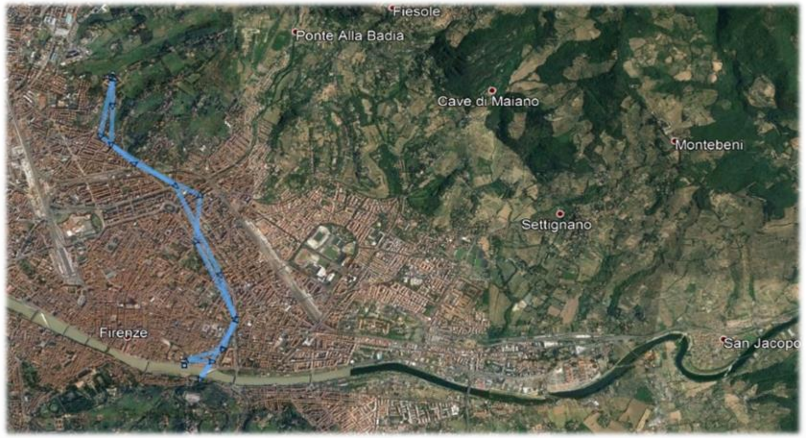
Artificial Intelligence Classification

Suggestions

Automated Classification of Users' Transportation Modality in Real Conditions

Variables taken into account:

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



Dataset:

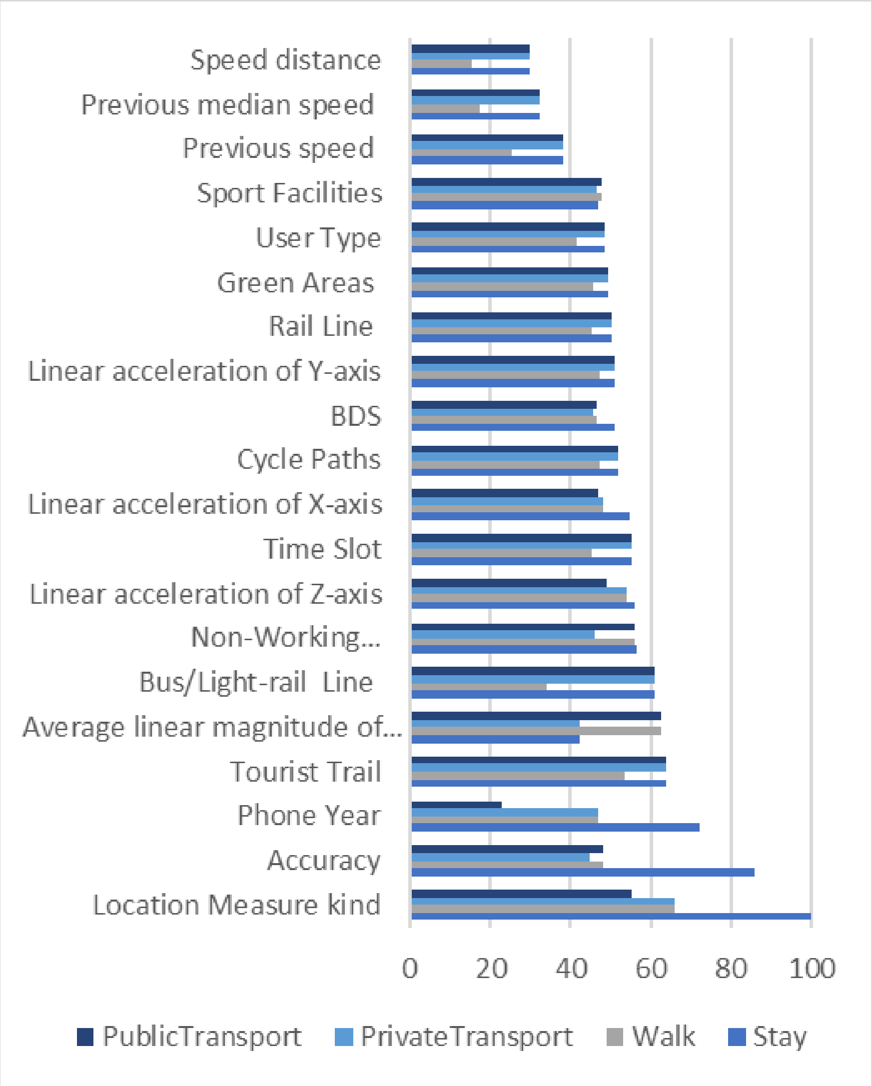
- 30K observations
- 25 variables
- 38 different users
- 30 different kinds of devices
- 4 classes (Stationary, Walking, Private Transport, Public Transport)

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

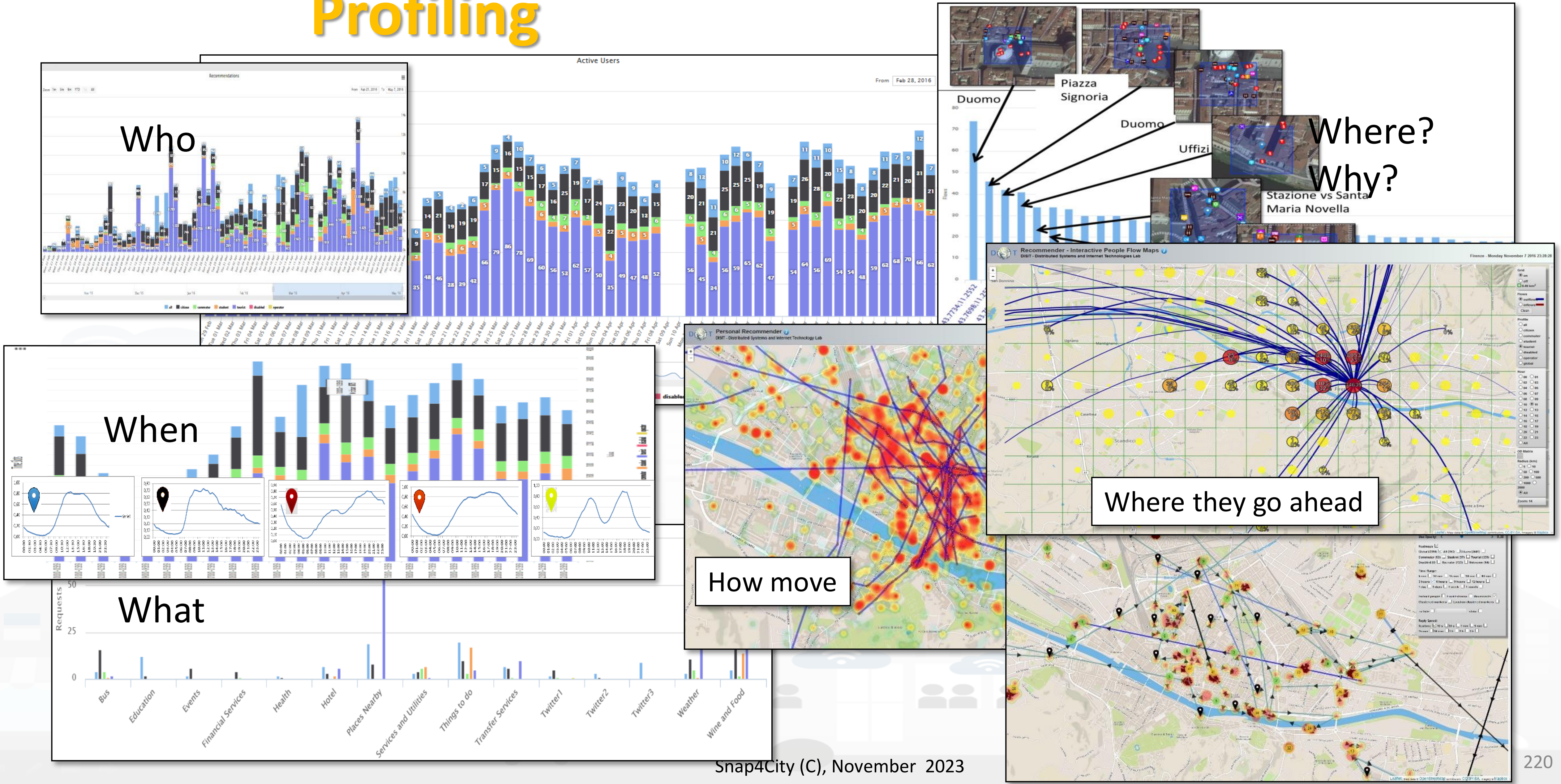
Note that, *each user have used the mean of transport of his/her own preference*. When the mode of transport is changed, the user was asked to notify the change to the App for creating the learning set and for validation.

Feature relevance



Model features categories	Extra Tree Model results			
	Accuracy %	Precision %	Recall %	F_1 Score
Baseline and GPS	91.0	68.2	75.1	0.714
Baseline and GPS + proximity	92.4	73.9	69.1	0.715
Baseline and GPS + proximity + Accelerometer	92.6	81.4	74.4	0.777
Baseline and GPS + proximity + Temporal window	94.9	80.5	78.7	0.787
Baseline and GPS + proximity + Accelerometer + Temporal window	95.3	82.7	86.9	0.847

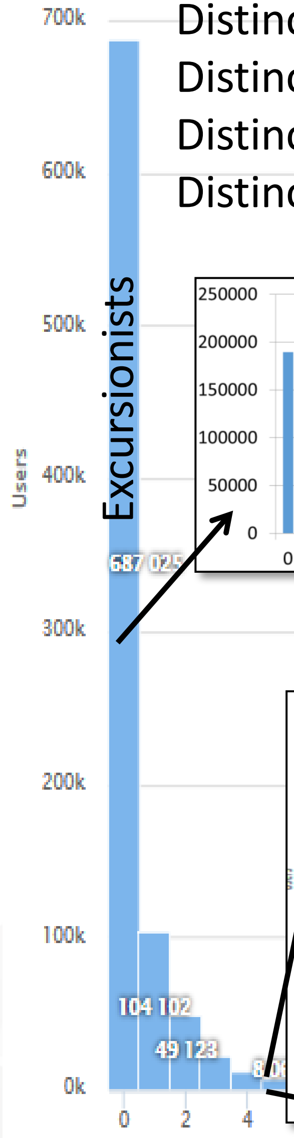
User Behavior Analyser for Collective Profiling

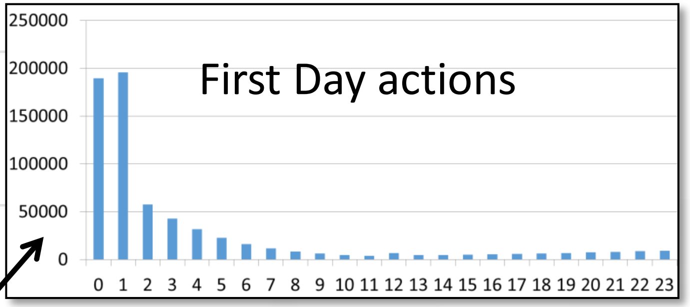


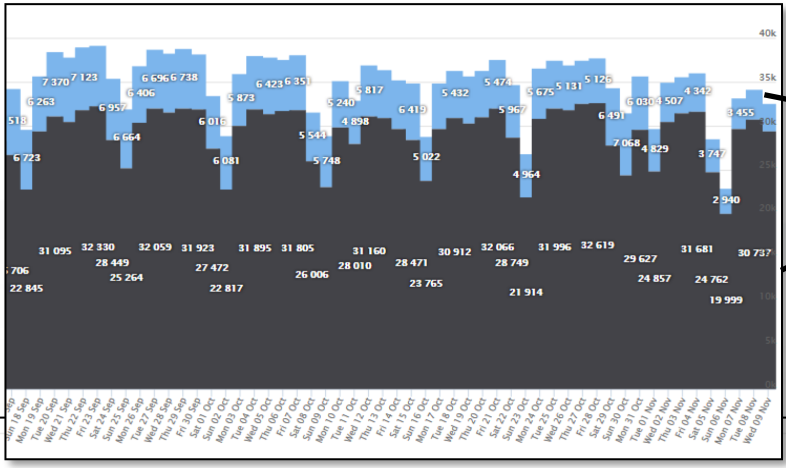
User Behaviour Analysis

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

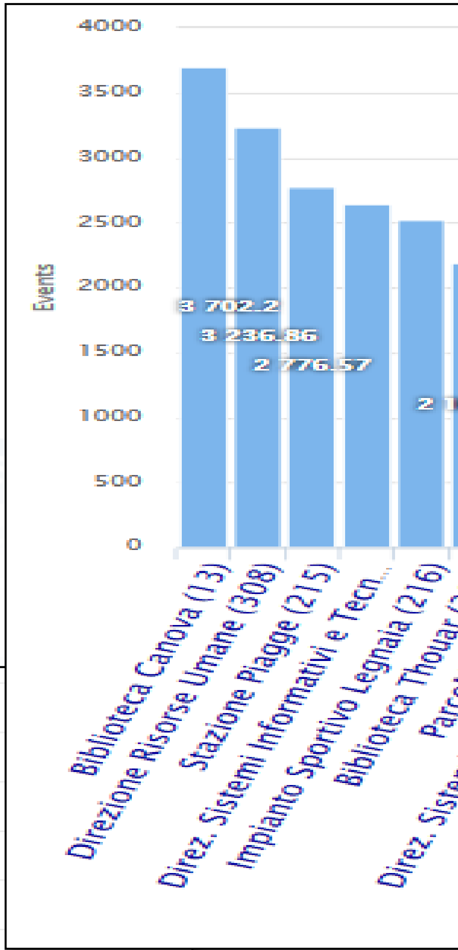
About the 15% of the peoples passing by

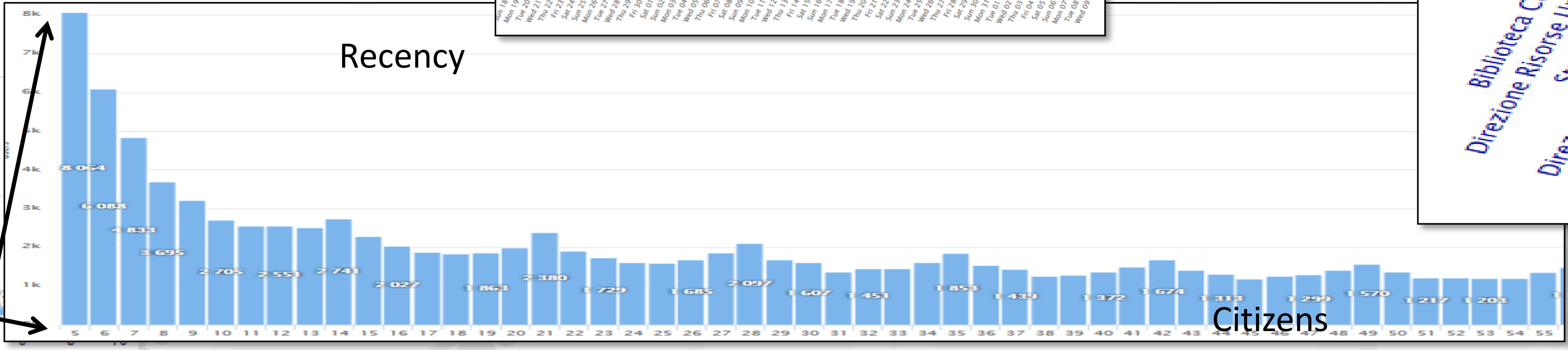






Where

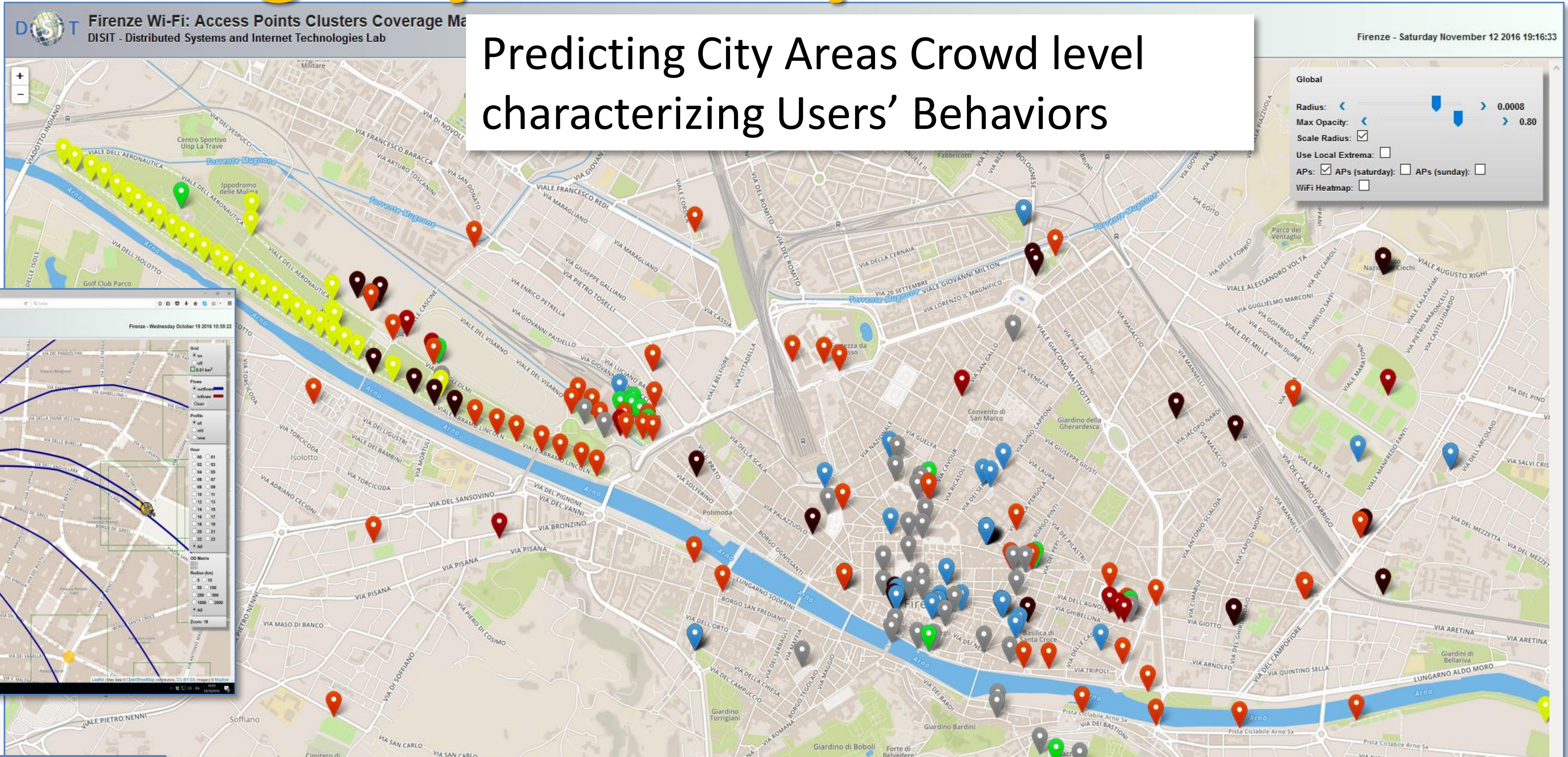


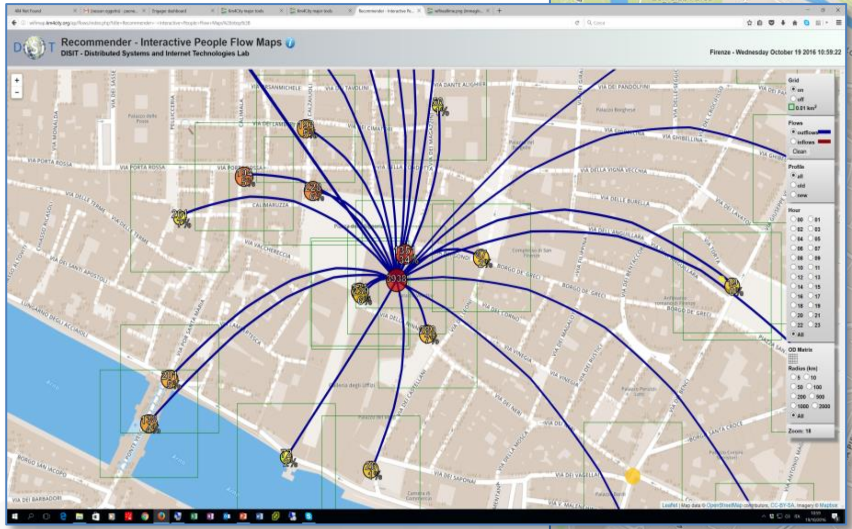


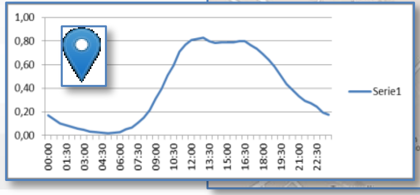
Characterizing City Areas by User Behavior

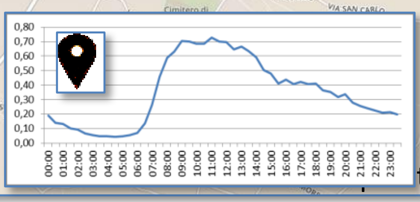
Wi-Fi based

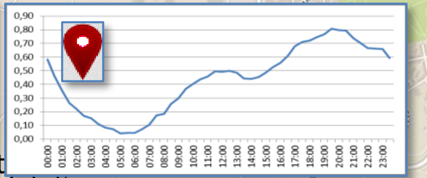
Predicting City Areas Crowd level characterizing Users' Behaviors

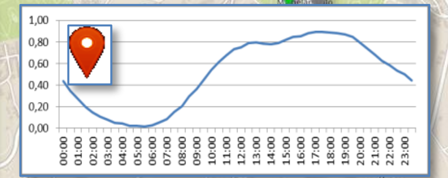


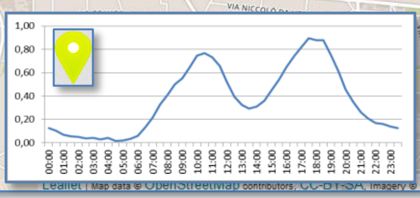




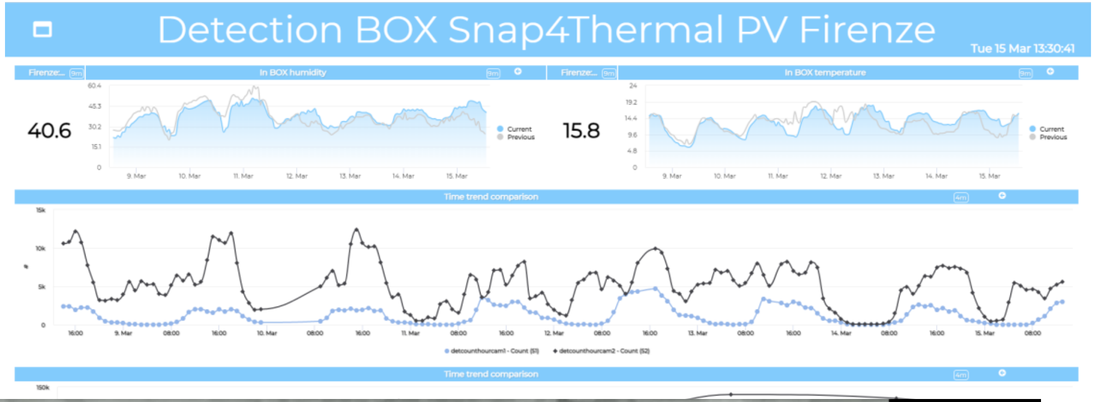








A view and data from the Thermal Camera



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SNAP4INDUSTRY

https://www.snap4city.org/dashboardSmartCity/view/Gea.php?iddasboard=MzM3Ng==

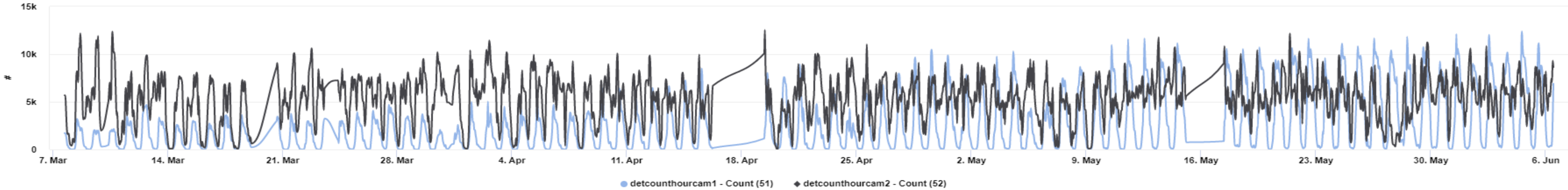
SNAP4CITY

Detection BOX Snap4Thermal PV Firenze

Thu 30 Mar 23:55:16

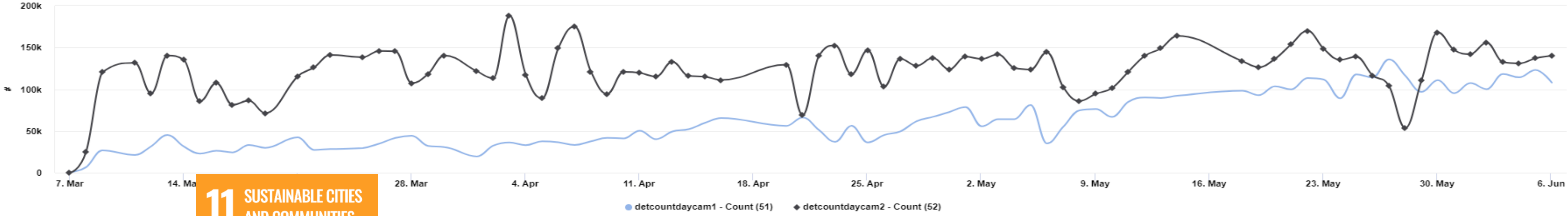
Time Trend Comparison

4m



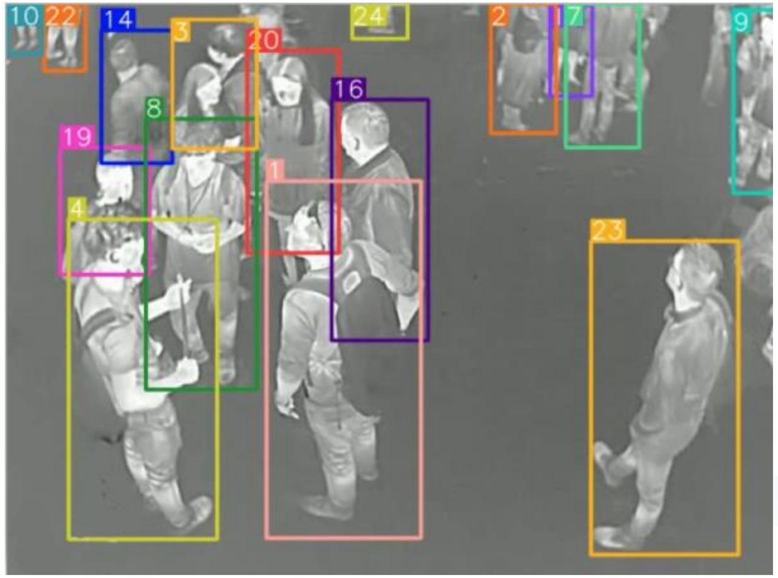
Time Trend Comparison

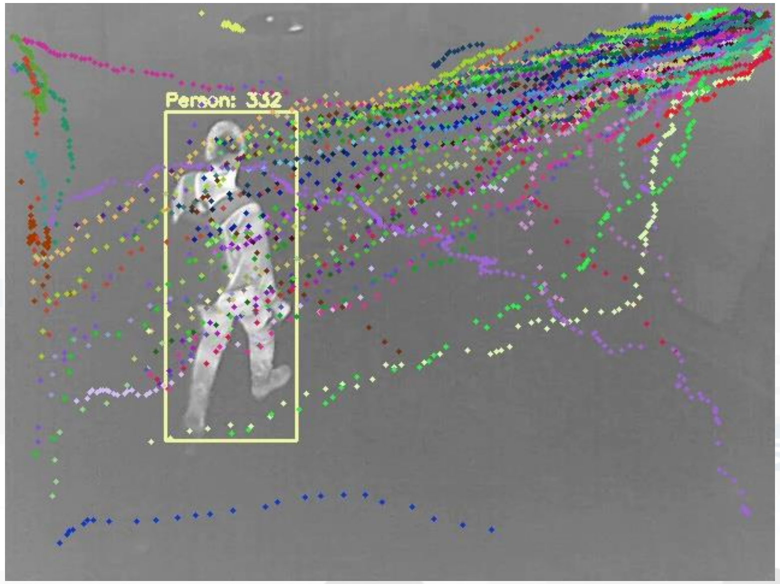
4m



11 SUSTAINABLE CITIES AND COMMUNITIES

People Counting and Tracking



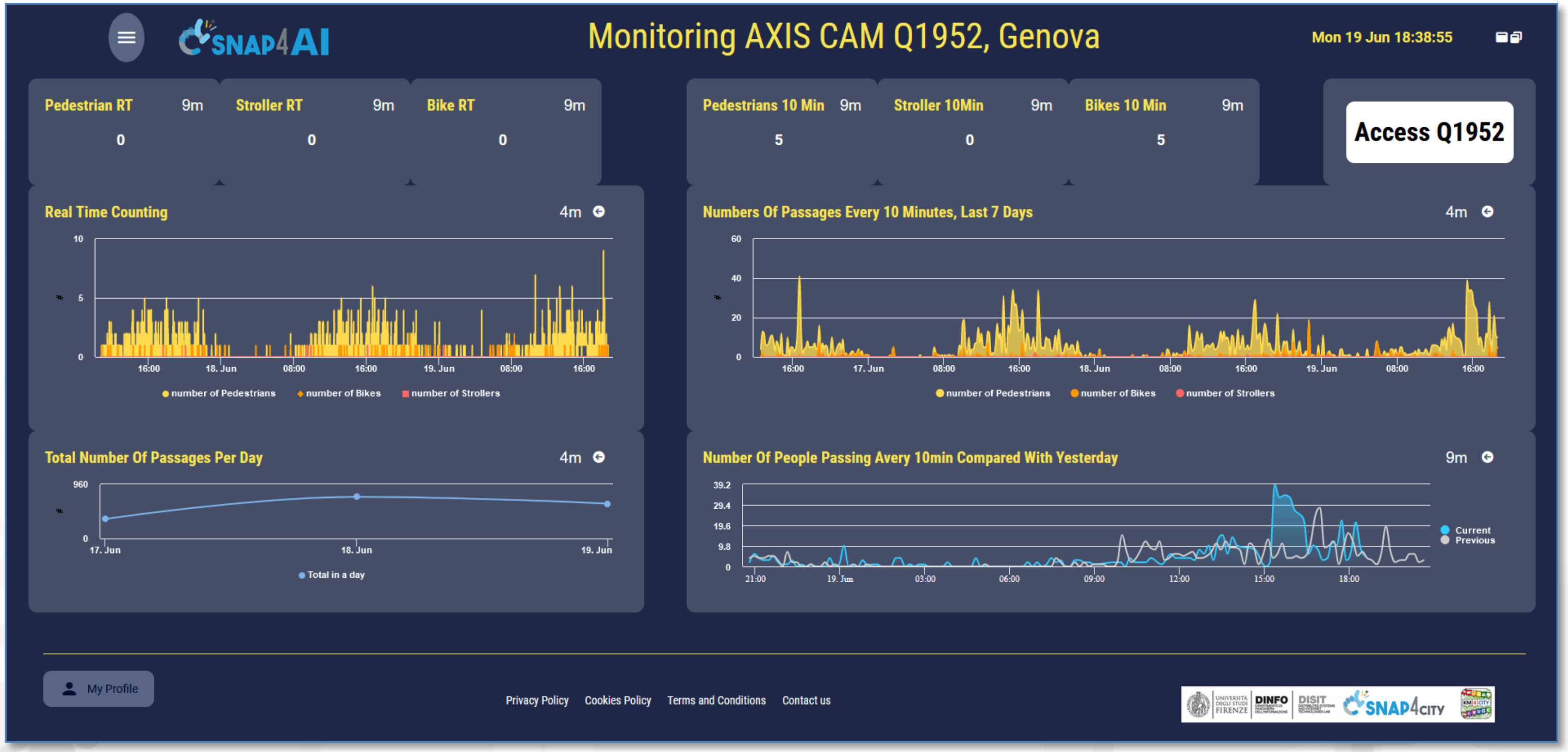


11 SUSTAINABLE CITIES AND COMMUNITIES

3X

Monitoring Passages AXIS Q1952

- Genova: Ocean Race, 2023



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SNAP4CITY

TOP

Typical Time Trends

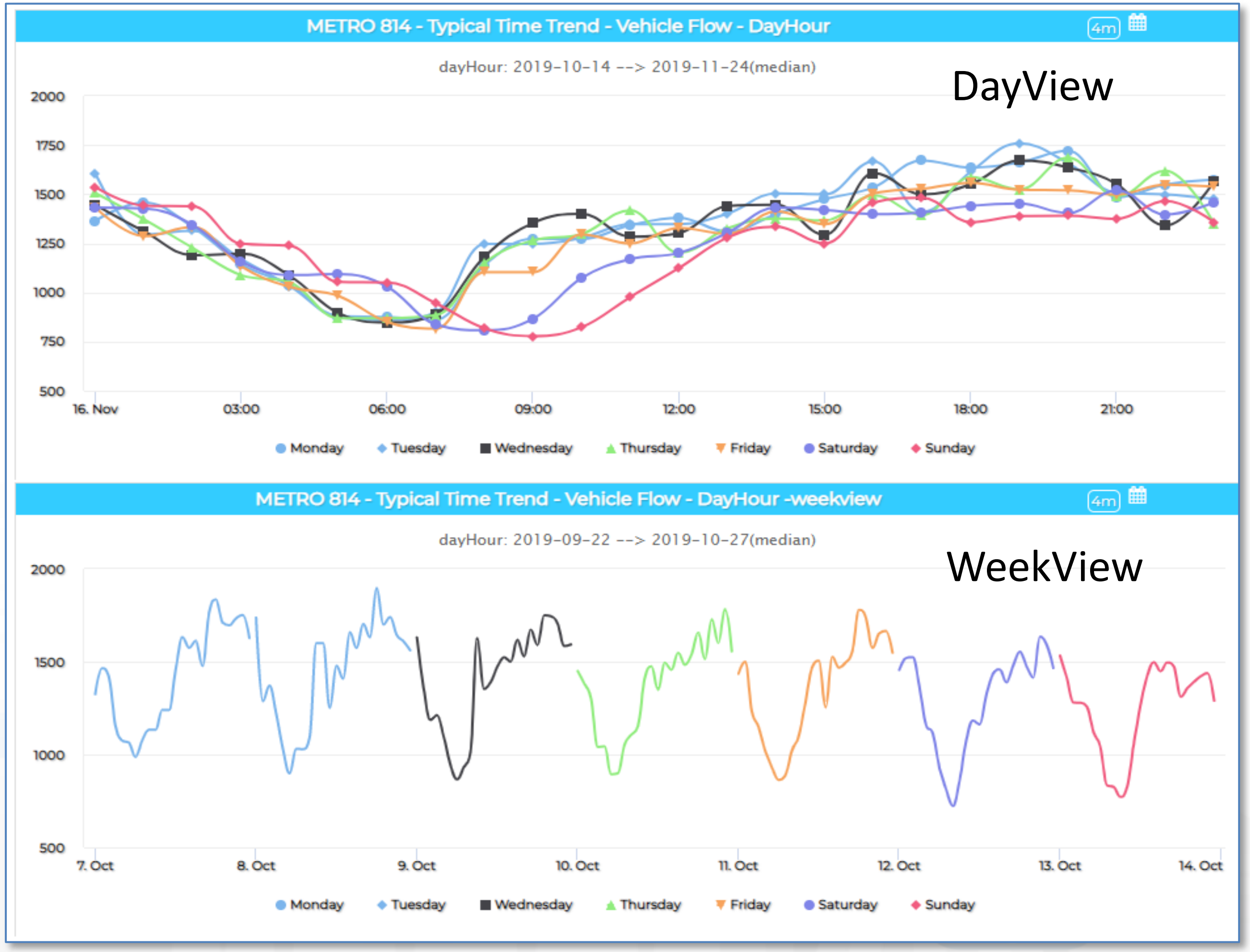
11 SUSTAINABLE CITIES AND COMMUNITIES

13 CLIMATE ACTION

Data Analytic

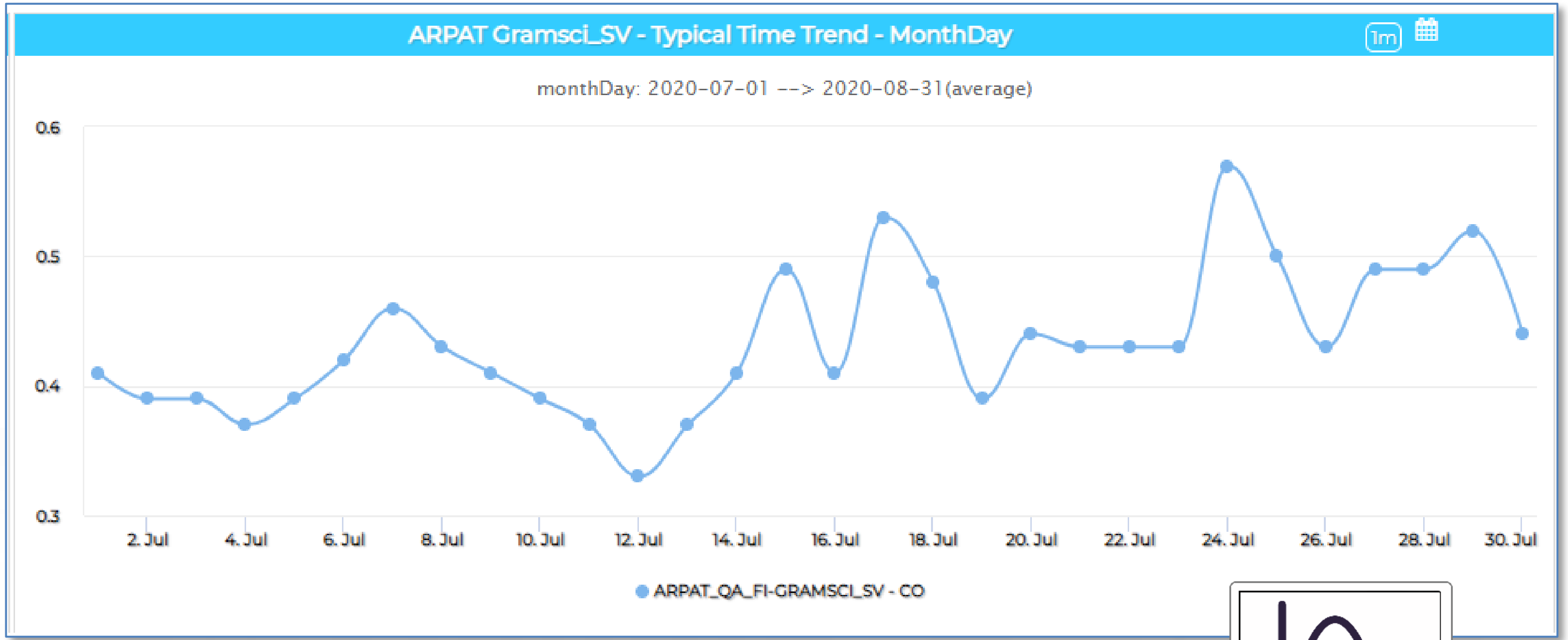
Typical Time Trend

- They:
  - **need to be computed in advance** on the basis of a Time Serie variable, and a reference period of computation.
  - **represent typical trends of: min, max, average, median**
  - You can change the data on view
- **Formats**:
  - **DayHour**: 7 time trends, one for each day of the week, each hour, 24 values.
    - As DayView or WeekView, start monday
  - **MonthDay**: a value per day, 30 values of the month.
  - **MonthWeek**: a value per day aligned to week days: 28 values, 4 weeks.
    - 1st Monday of the month
    - 3rd Friday, etc.



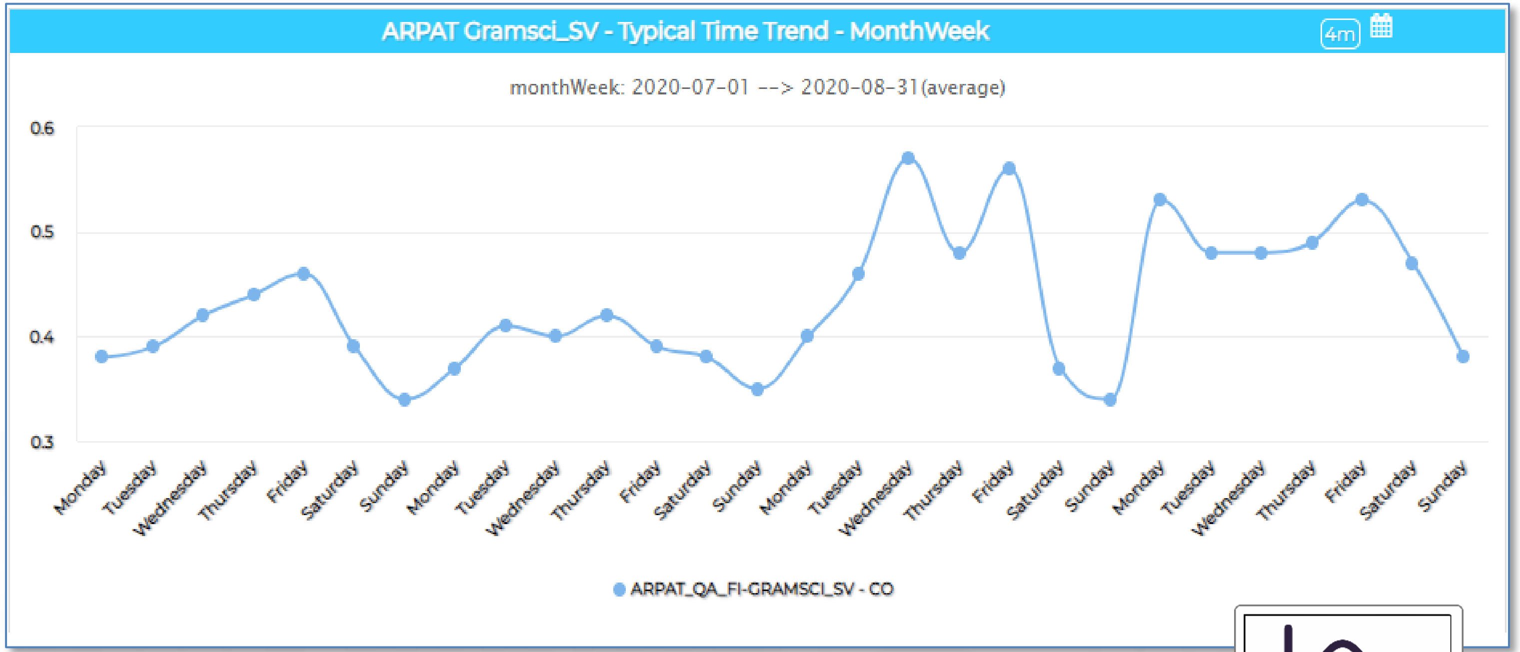
https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MzA4NA==

TTT: Month Day



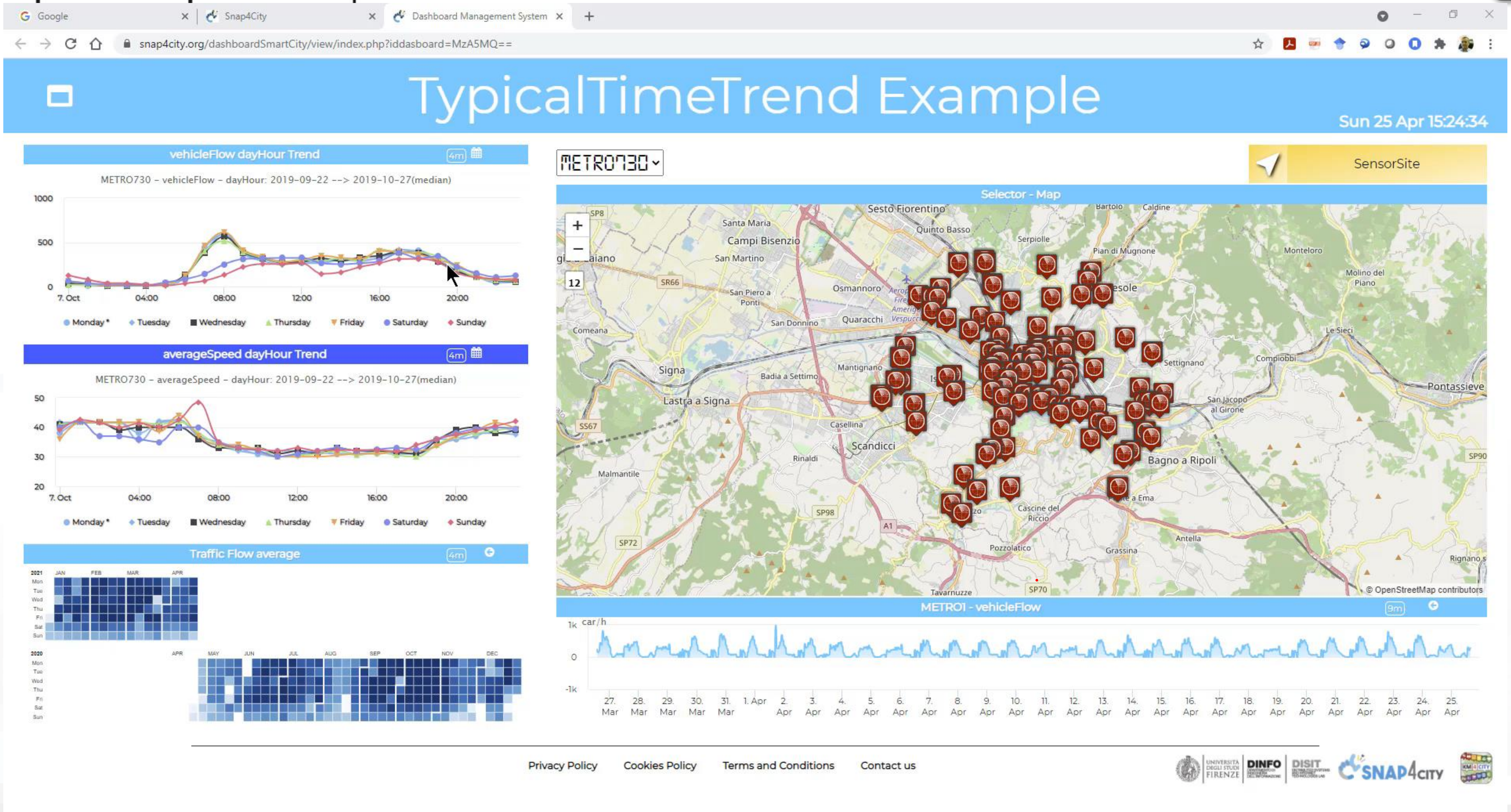
- **MonthDay**:
  - a value per day,
  - 30 values of the month.
  - Aligned from the first day of the month
  - computed on the basis of a Time range: from-to including that date
    - e.g.: 2 months
    - As min, max, average, median
    - You can change the data on view

TTT: Month Week



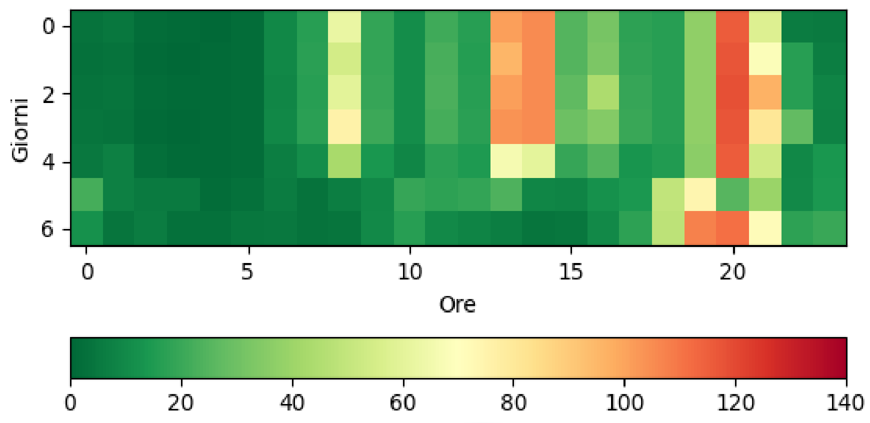
- **MonthWeek**:
  - a value per day,
  - 30 values of the month.
  - Aligned from the first Monday of the first week of the month
  - computed on the basis of a Time range: from-to including that date
    - e.g.: 2 months
    - As min, max, average, median
    - You can change the data on view

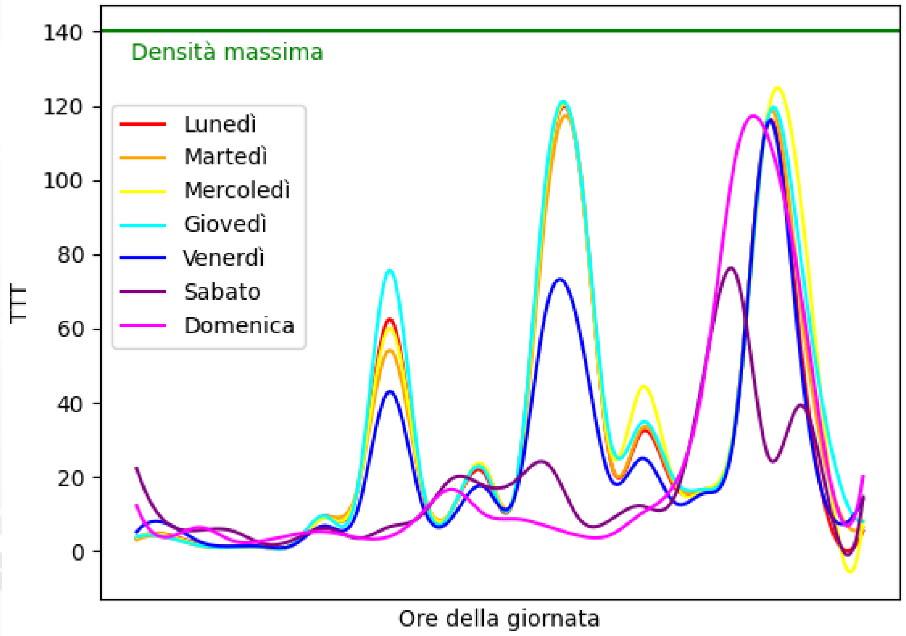
Typical Time Trends



Typical Time Trends

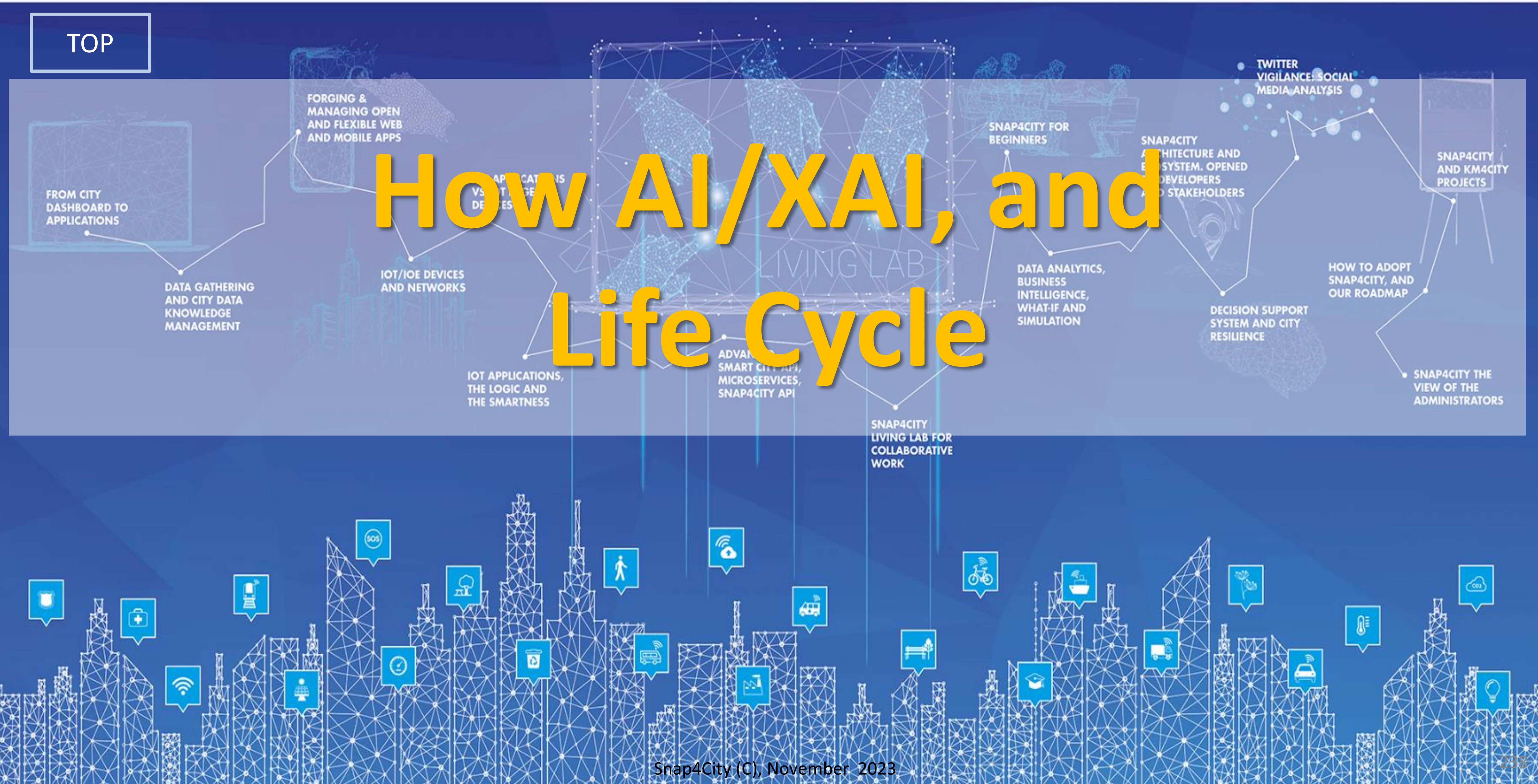
- They can be used for:
  – Computing traffic flow reconstruction
  – Long terms predictions
  – Scenarios and conditions
  – Semaphores conditions
  – Smart Lights conditions





TOP

How AI/XAI, and Life Cycle



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SNAP4CITY KM4CITY

Development

https://www.snap4city.org/download/video/Snap4Tech-Development-Life-Cycle.pdf

Powered by SNAP4Tech

Development Life-Cycle

https://www.snap4city.org/download/video/Snap4Tech-Development-Life-Cycle-v1-1.pdf

From Snap4City:

- **We suggest you to read the TECHNICAL OVERVIEW:**
  - https://www.snap4city.org/download/video/Snap4City-PlatformOverview.pdf
- https://www.snap4city.org
- https://www.snap4solutions.org
- https://www.snap4industry.org
- https://twitter.com/snap4city
- https://www.facebook.com/snap4city
- https://www.youtube.com/channel/UC3tAO09EbNba8f2-u4vandg

Coordinator: Paolo Nesi, Paolo.nesi@unifi.it

DISIT Lab, https://www.disit.org
DINFO dept of University of Florence,
Via S. Marta 3, 50139, Firenze, Italy
Phone: +39-335-5668674

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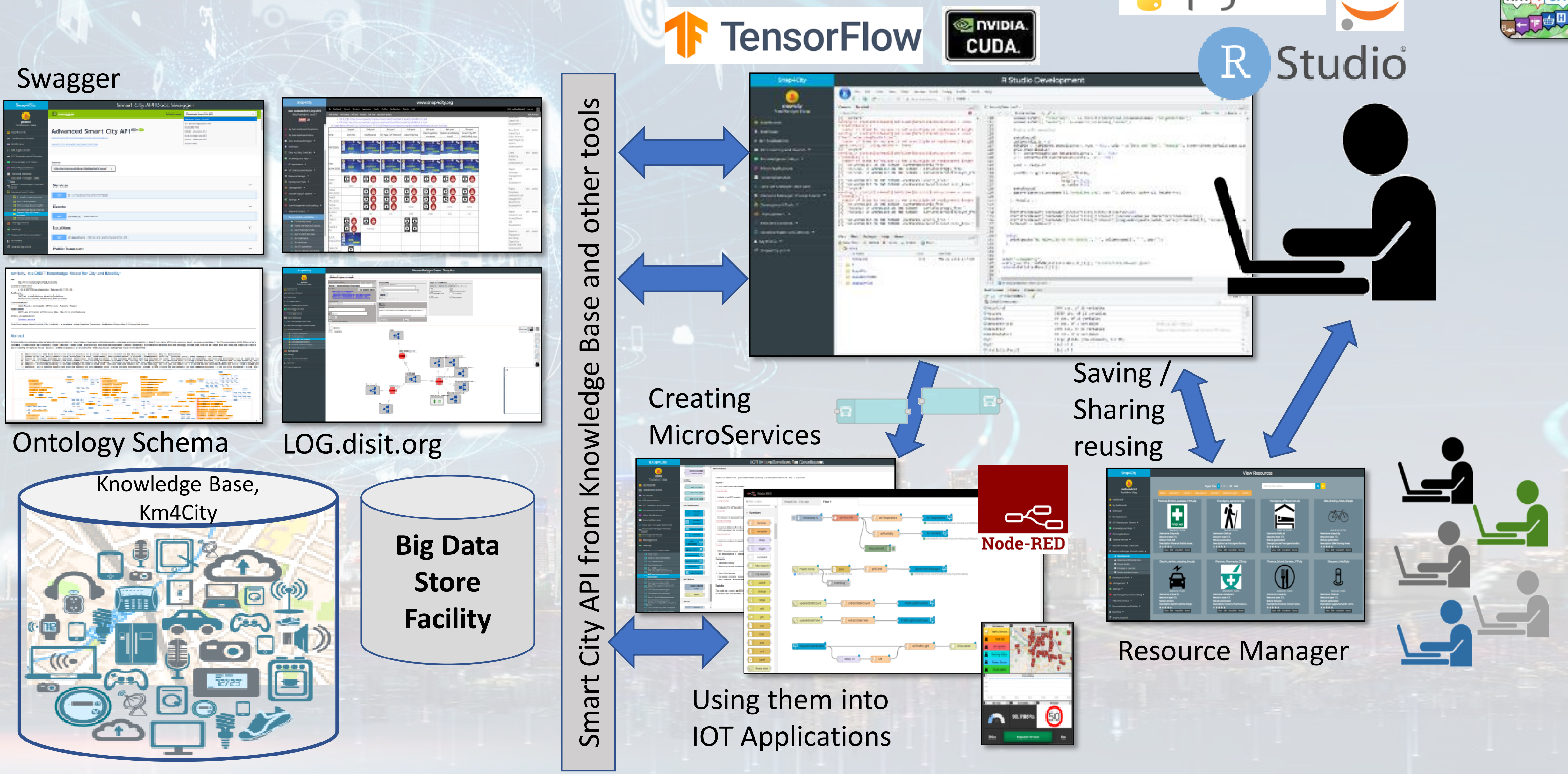
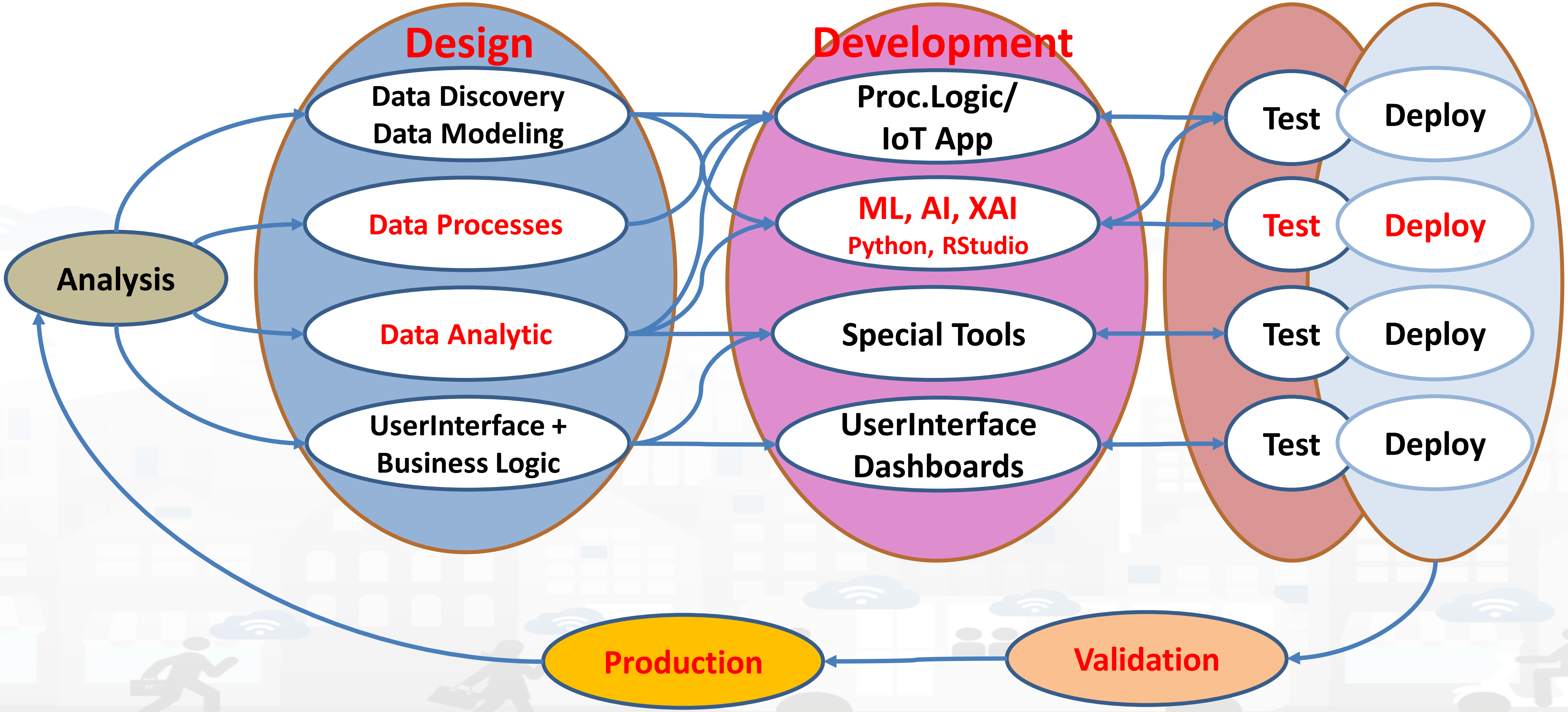
1

Data Analytics on Snap4City platform



Development Life Cycle Smart Solutions

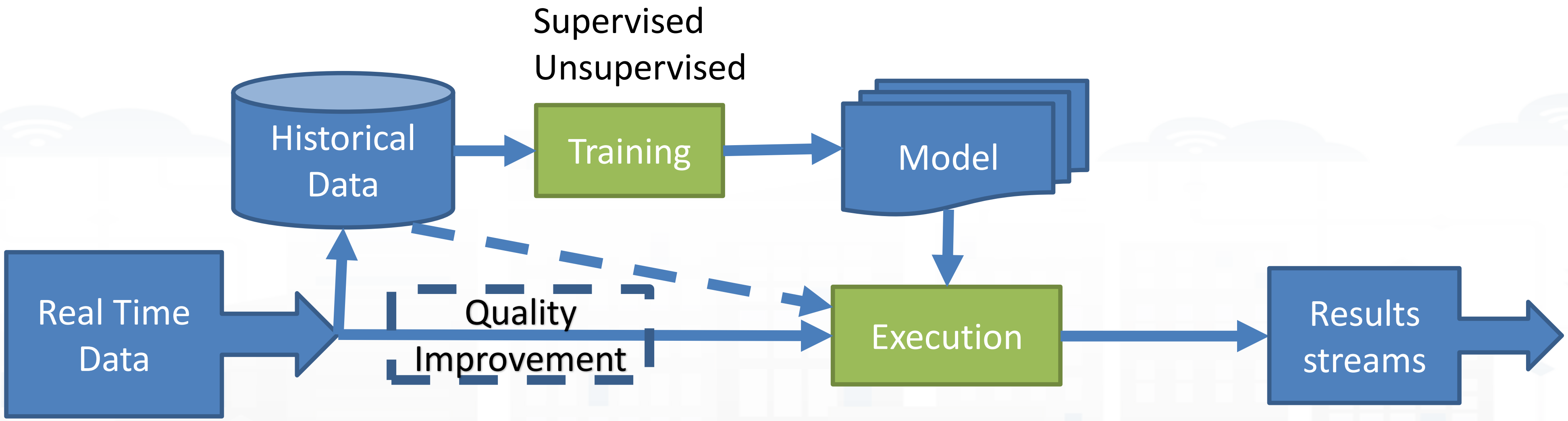


Data Analytics Life Cycle

RULE OF THUMB

- **Problem analysis**, business requirements
- **Data Discovery**, Data Licensing, ingestion, and acquisition
- **Data set preparation**, transformation, identification of features, normalization, scaling, imputation, feature engineering, etc.
- **Target Assessment Model Definition**
  - Identification of metrics for the assessment, KPI
- **Screening on Models/Techniques, for each Model/Technique or for the selection Model/Technique** perform the
  - ***Model/Technique Development/testing , also hyper-parametrization***
- **Best Model selection among those tested**
  - If needed reiterate for different parameters, features, etc.
  - Comparison with state of the art results on the basis of KPI/metrics
  - Needs of Explainable AI solutions: global and local
- **Deploy best Model in production, monitoring in production**

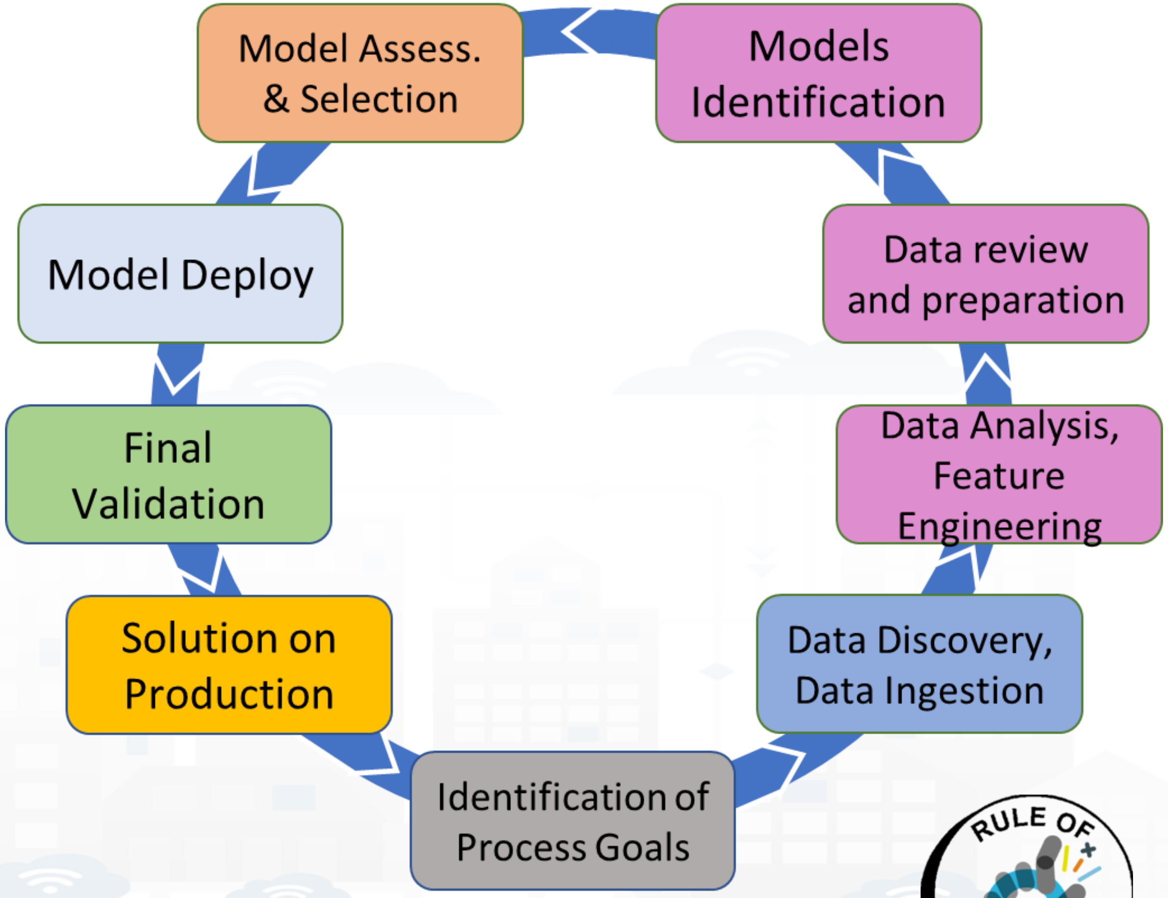
Simplified Training and Deploy process



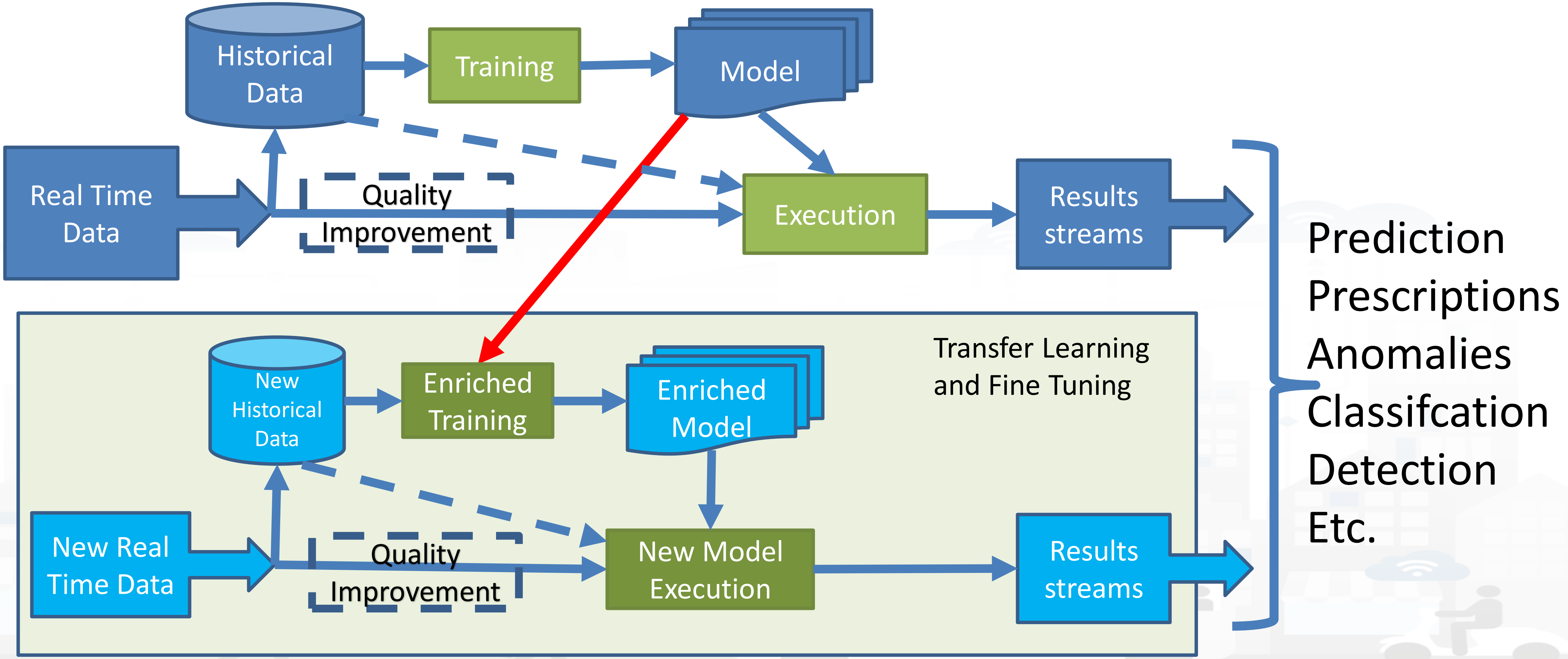
Prediction
Prescriptions
Anomalies
Classifcation
Detection
Etc.

Model/Technique Development/testing

- **Identification of Process goals and Planning**
  - Which goals
  - How to compute, which language
  - Which environment, which libraries
- **Data Discovery and Ingestion (from the general life cycle)**
- **Data Analysis: feature engineering, feature selection**
- **Data review and preparation for the model**
- **Model Identification and building: ML, AI, etc….**
  - **Training**
  - **Tuning hyperparameters when possible**
- **Model Assessment and Selection**
  - **Validation in testing**
  - **Assessment** on a set of **metrics** depending on the goals: global relevant and feature assessment
  - **Assessing computational costs**
  - **Impact Assessment, Ethic Assessment** and incidental findings
  - **Global and Local Explanation via Explainable AI techniques**
- **Model Deploy and Final Validation**
  - **Optimisation** of computation cost for features, if needed reiterate
- **Solution on Production (security, scalability, etc.)**



Simplified Deploy of Transfer Learning Model



AI/ML Requirements

AI/ML desired requirements

RULE OF THUMB

- **Reliable**: capable to produce results in reliable manner, repeatable in operative conditions
- **Trustworthy**: capable to behave such as your best expert, that you can trust
- **Not Biased**: not influenced by some preconcept neither based on some data that can structurally for definition influence the decisions/results!
  - Identified **Goals** of the model can be biased (e.g., approach the solution logistically or predicting a value)
  - **Data Set** for training can be biased (e.g., including variables which can discriminate wrt law/regulations)
  - **AI architecture** can be biased (e.g., selecting one that can see only a specific aspects, reducing the solution space, not addressing non linearity, preprocessing data losing a part of information),
- **Ethical**:
  - **Data Ethics**: to address the ethical non bias aspects on data
  - **AI Ethics (DA Ethics)**: to address the ethical non bias aspects on Data Analytics process from training, to model selection and assessment
  - **Incidental Finding**: what happen if the results or partial results provide hints on unexpected aspects
  - **Etc….**
- ***→ → AI Regulation of EU Act, AI Act:***
  - ***https://digital-strategy.ec.europa.eu/en/policies/european-approach-artificial-intelligence***

Data Analytics vs Data Law

RULE OF THUMB

- **Respect Data Sovereignty**:
  - data are subject to the laws and governance structures of the nation (*Jurisdiction*) where they were collected
  - Specific licenses can be modelled and the development tools enabling the development of AI must guarantee
- **Privacy, Respecting GDPR in Europe, other Acts on other countries**: a set of guidelines and techniques
  - **Anonymization**: several kind of approaches, from drastic to those that preserve the: statistical validity, semantics, etc.
  - **Encryption**: of personal data
  - **Decoupling** of data and personal identification data
  - **Channel protection**: SSL, TLS, etc.
  - **Signed Consent**: not any more of Informed Consent, signed per data type
    - Usage of data have to be provided by the user, for each single data type
  - **Data Types**: any kind of user's data, which could be exploited , reused, sold, etc.
  - Any **data start as private** data.

AI Explainability

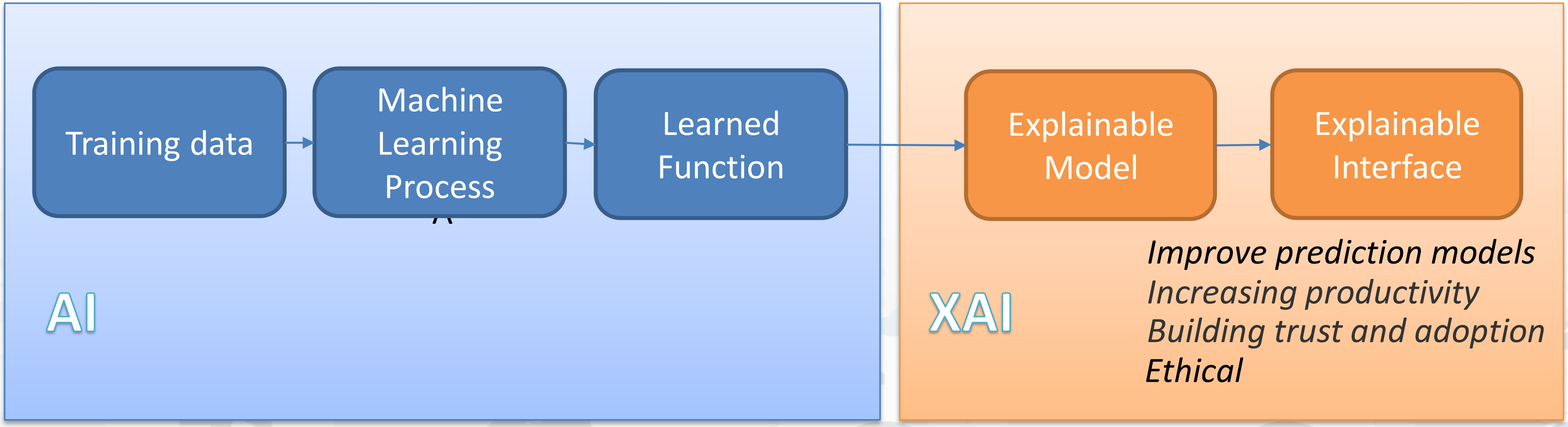
RULE OF THUMB

- **Global Explainability, GE**
  - Given the features adopted in some ML/AI solution, the GE is a description of relevance or important of those features in the production of all the results.
  - The Relevance/Importance is estimated by taking into account the typical impact/incidence of features values on the estimation of results (prediction, classification, etc.)
- **Local Explainability, LE**
  - Given the features adopted in some ML/AI solution, the LE is a description of relevance or important of those features in the production of a specific result, by case.
  - The LE Relevance is estimated by taking into account the specific impact/incidence of a feature value on the estimation of a specific result (prediction, classification, etc.)
- **A number of tools can be used for example:**
  - SHAP, Shapley Additive Explanations

XAI: Explainable artificial intelligence

Data Analytic

Explainable artificial intelligence (XAI) is a set of processes and methods that allows human users to comprehend and trust the results and output created by machine learning algorithms.



White Box vs. Black Box Models

A **white-box** model is explainable by design. Therefore, it does not require additional capabilities to be explainable:

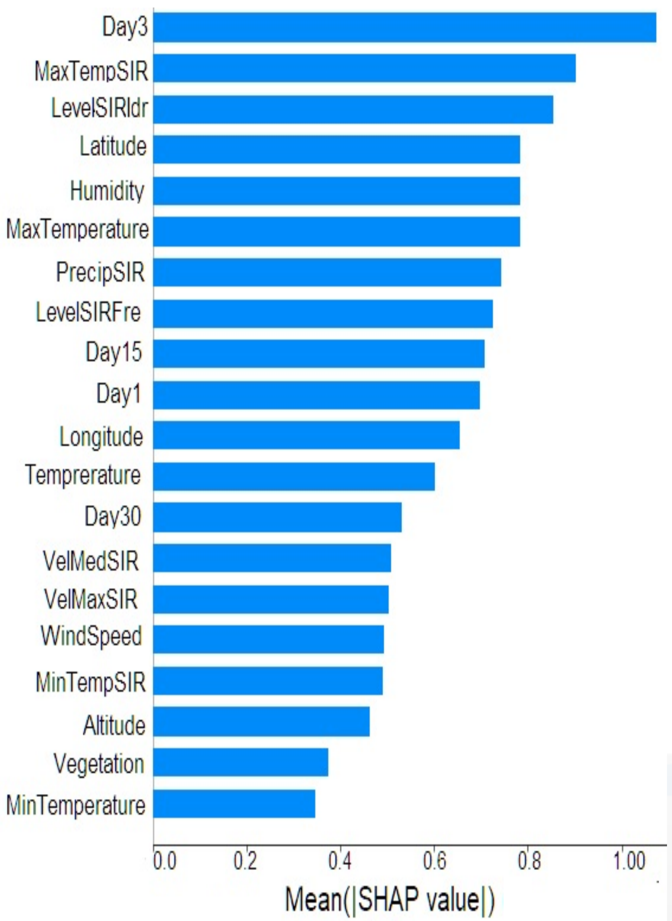
- Linear regression,
- Logistic regression,
- Decision Tree,
- Naive Bayes,
- KNNs
- ……………………

A **black-box model** is not explainable by itself. Therefore, to make a black-box model explainable, we have to adopt several techniques to extract explanations from the inner logic or the outputs of the model.

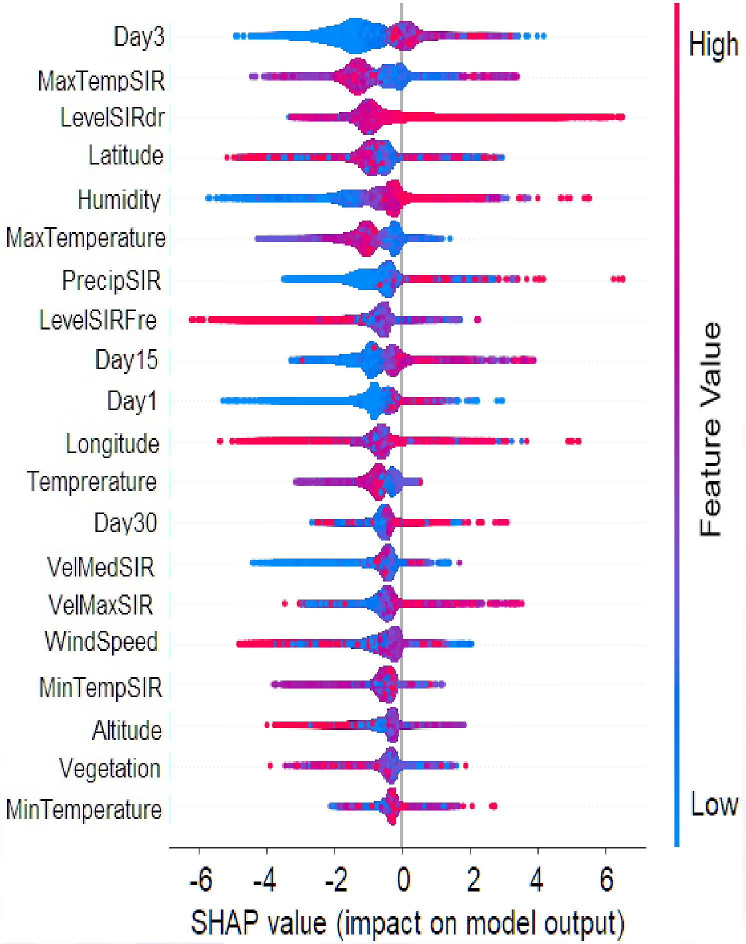
- CNN, DNN, …
- LSTM
- ……………………

SHAP Global interpretability

```python
with tf.device('/device:GPU:0'):
    explainer = shap.TreeExplainer(MODEL)
    shap_values = explainer.shap_values(X_train)
```



shap.summary_plot(shap_values, features_names, plot_type="bar")

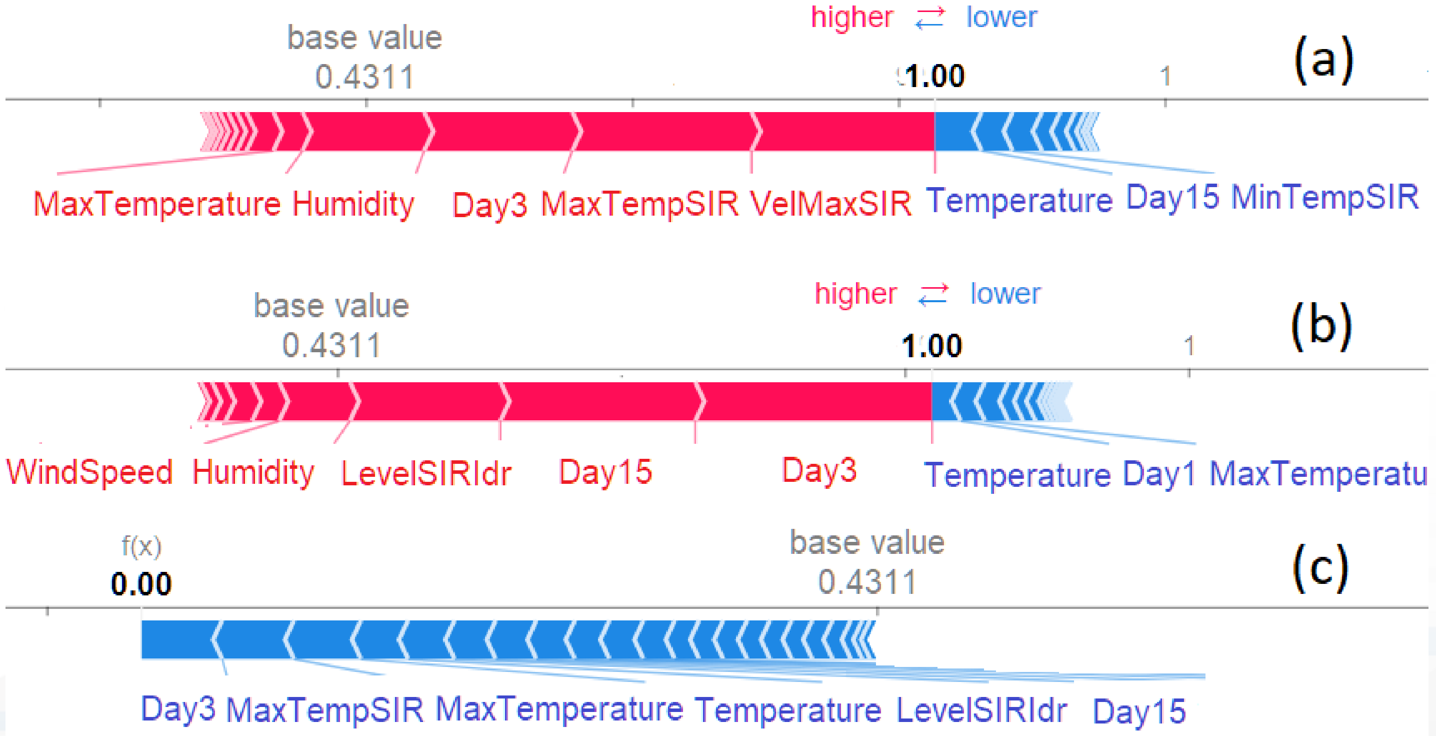


shap.summary_plot(shap_values, X_train,features_names)

•***Feature importance***: Variables are ranked in descending order.
•***Impact***: The horizontal location shows whether the effect of that value *is associated with a higher or lower prediction*.
•***Original value***: Color shows whether that variable is high (in red) or low (in blue) for that observation.
•***Correlation***: A *high* level of “Day3” or “PrecipiSIR” content has a high and *positive* impact on the classification. The “high” comes from the red color, and the “positive” impact is shown on the X-axis.

SHAP: Local interpretability

```
with tf.device('/device:GPU:0'):
    explainer = shap.TreeExplainer(MODEL)
    shap_values = explainer.shap_values(X_train)
```




```
shap.force_plot(explainer.expected_value,
shap_values[7,:],fields)
```

The ability to explain each prediction, is a very important promise in an explainable AI.

(a) value of VelMaxSIR, MaxTempSIR, Day3 and Humidity contributed significantly to the classification of the observation as a landslide event.

(b) values related to rainfall in the last days, LevelSIRIdr and Humidity given a relevant contribution to the landslide event prediction.

(c) the value of features: Day3, MaxTempSIR, MaxTemperature, Temperature and LevelSIRdr have been determinant for the classification of the observation into a no landslide event.

TOP

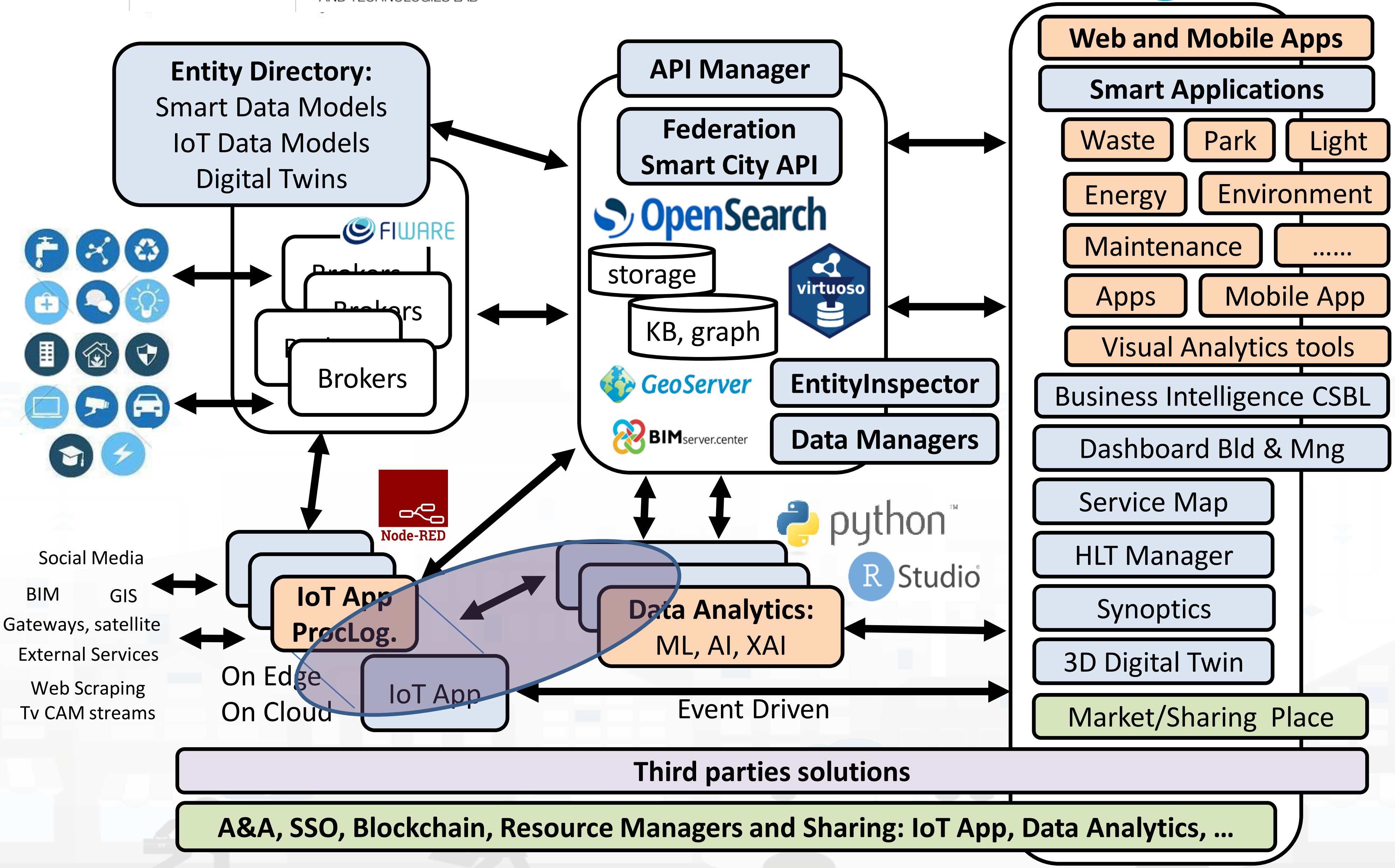
Using DA, AI, XAI in Snap4City infrastructures

Data Analytics ←→ IoT App / Proc.Logic

Data Processing for different purposes on Snap4City

- **Node-RED** Proc.Logic → see Part 3 and 5
  - On Cloud and/or on Edge
- **Python or R-Studio** → see this Part 4
  - On Cloud
  - On Premise on special hardware with NVIDIA boards, HPC infrastructures, etc.
  - On Edge is needed also with Node-RED

Tech Arch


Entity Directory:
Smart Data Models
IoT Data Models
Digital Twins
FIWARE
Brokers
API Manager
Federation
Smart City API
OpenSearch
storage
KB, graph
virtuoso
GeoServer
BIMserver.center
EntityInspector
Data Managers
Node-RED
python
R Studio
Social Media
BIM
GIS
Gateways, satellite
External Services
Web Scraping
Tv CAM streams
IoT App
ProcLog.
On Edge
On Cloud
IoT App
Data Analytics:
ML, AI, XAI
Event Driven
Web and Mobile Apps
Smart Applications
Waste
Park
Light
Energy
Environment
Maintenance
……
Apps
Mobile App
Visual Analytics tools
Business Intelligence CSBL
Dashboard Bld & Mng
Service Map
HLT Manager
Synoptics
3D Digital Twin
Market/Sharing Place
Third parties solutions
A&A, SSO, Blockchain, Resource Managers and Sharing: IoT App, Data Analytics, …

IoT App / Proc.Logic

- Storage → IoT App / Proc.Logic
- External Service ←→ IoT App / Proc.Logic
- Dashboards ←→ IoT App / Proc.Logic

Part 3

Node-RED

- Data Analytics ←→ IoT App / Proc.Logic

Part 4

- Broker → Storage
- IoT App / Proc.Logic → Broker
- Broker → IoT App / Proc.Logic
- IoT App / Proc.Logic → Storage

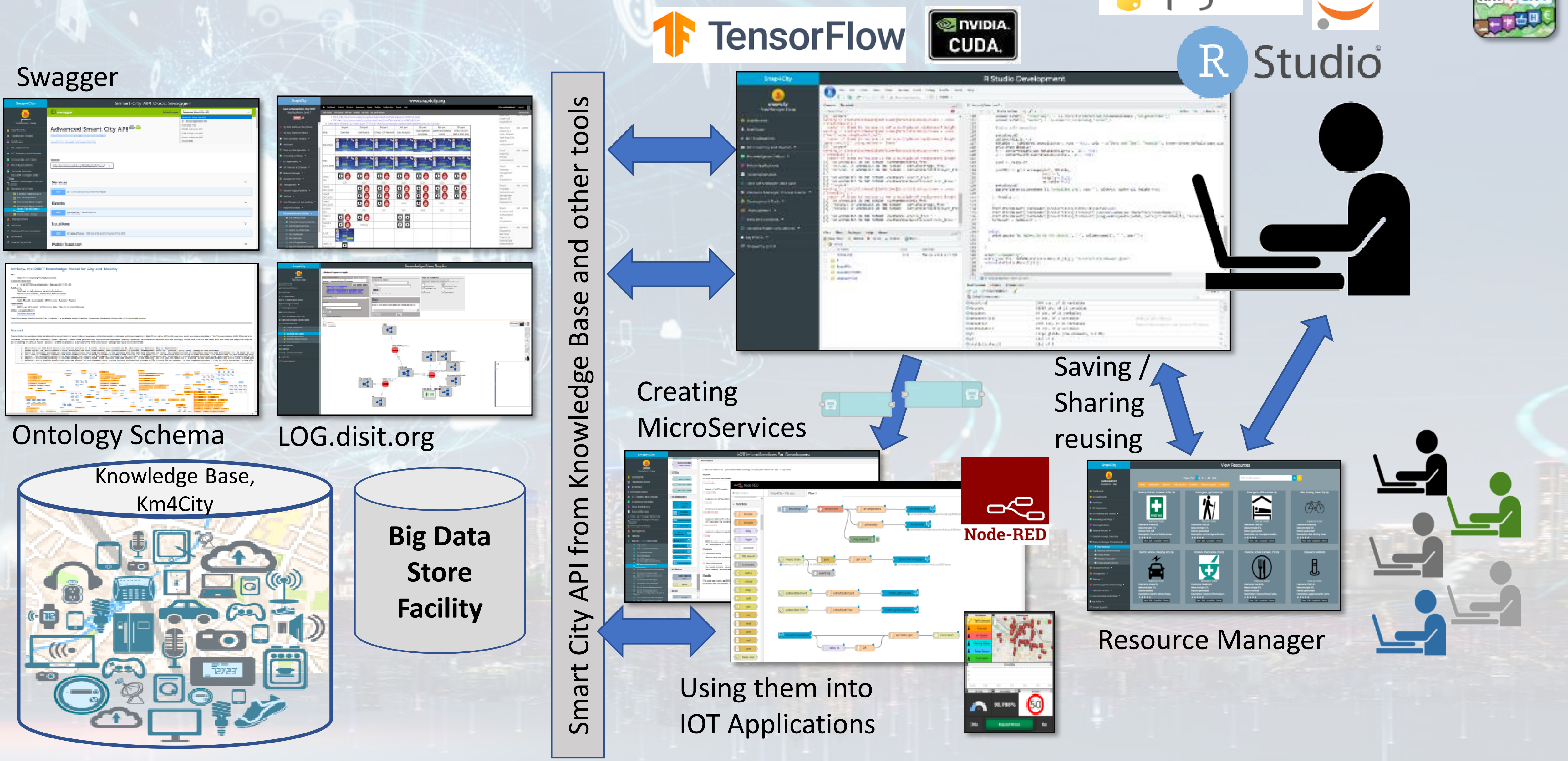
Part 5

TOP

DP, for DA, AI, XAI on Container an Example

Data Analytics ←→ IoT App / Proc.Logic

Data Analytics on Snap4City platform



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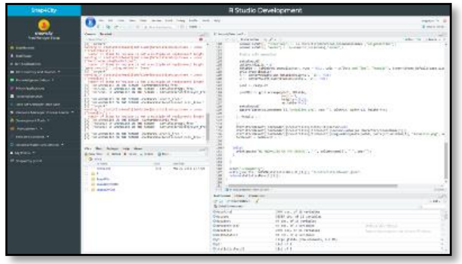
Development

SNAP4CITY

python jupyter

SNAP4CITY



API

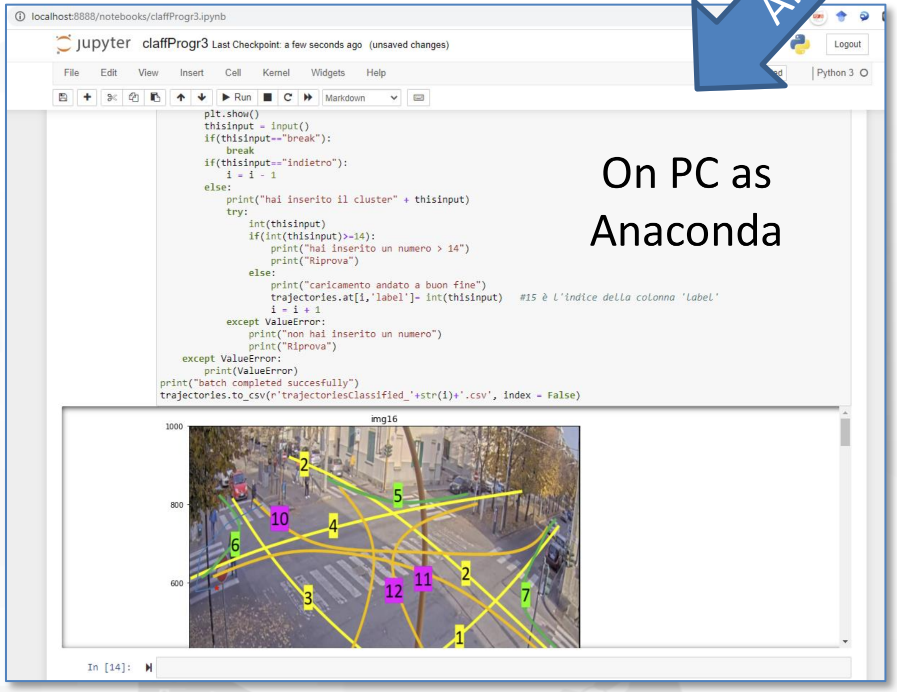
Big Data Store Facility

docker

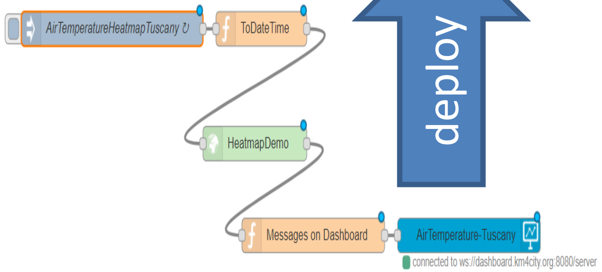
Data Analytic

API

On Server
Or
On PC



On PC as Anaconda



deploy

Once finalized

File.py
AI Model
Mapping
Data..

ZIP

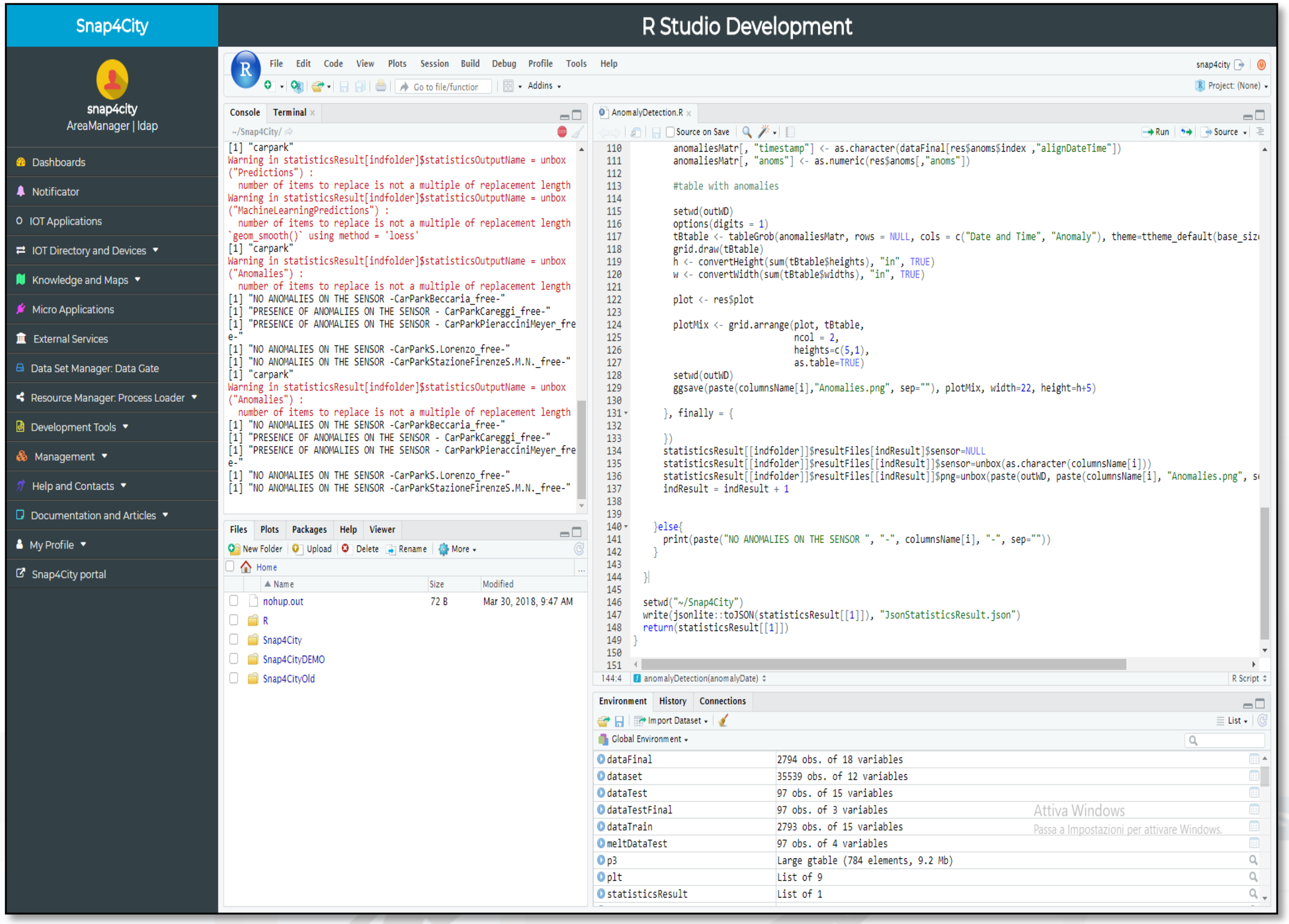
Load
File.py
or .zip

python data analytic

To make the .PY usable as MicroService you need to adapt it to get and send data in/out with Node-RED from a Container.
If you provide a .zip file the main .py inside has to be called doScript.py

1

Developer in R Studio + Tensor Flow



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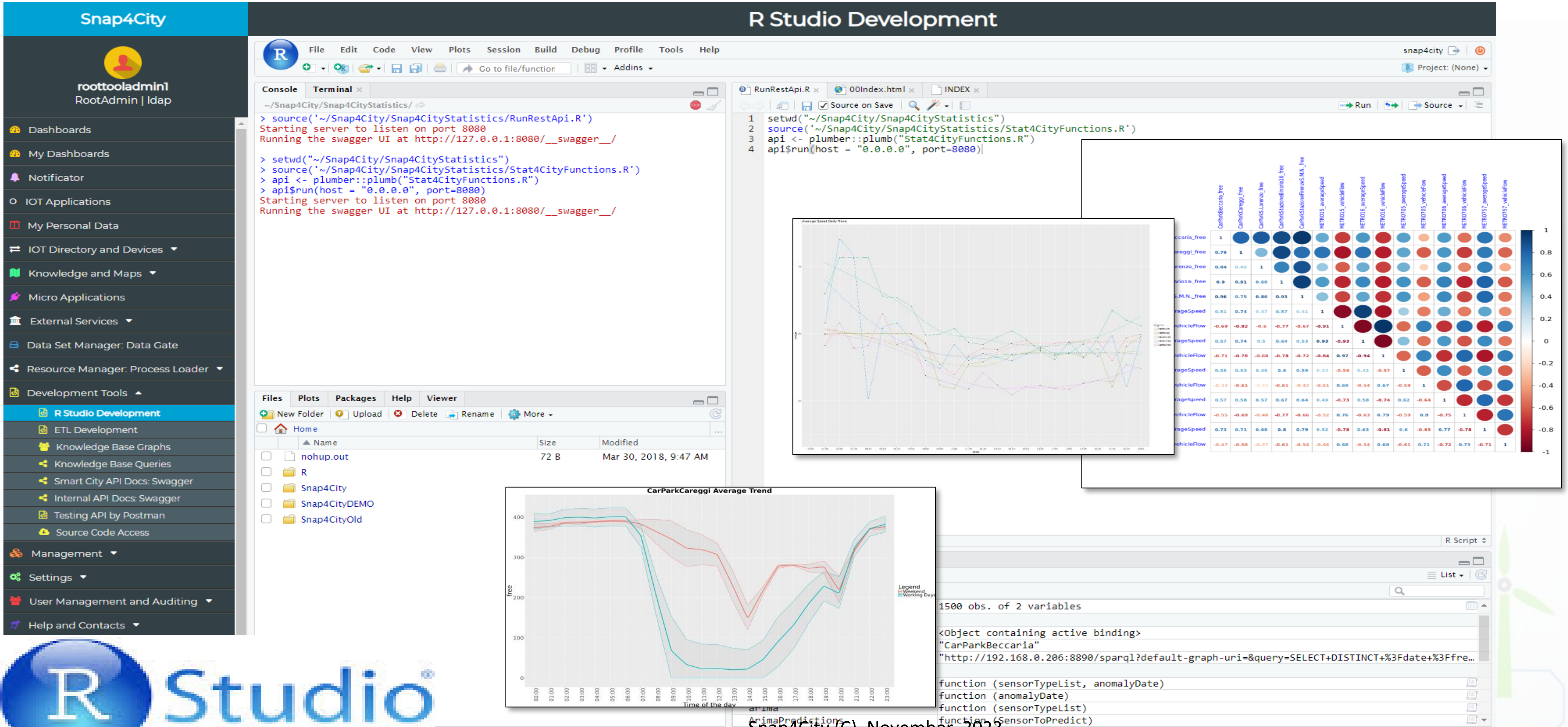
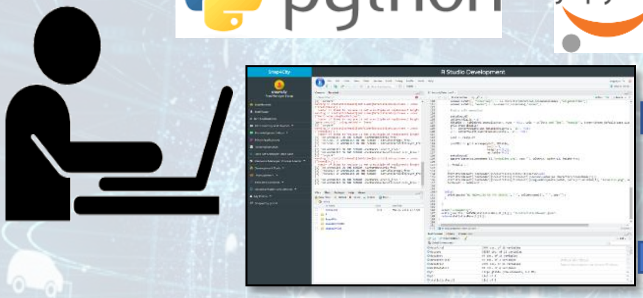
Data Analytics in R Studio Con Tensor Flow

1

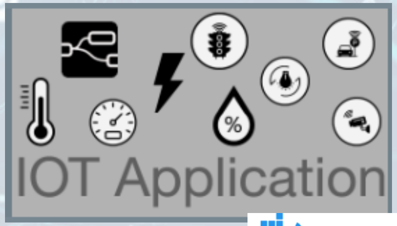


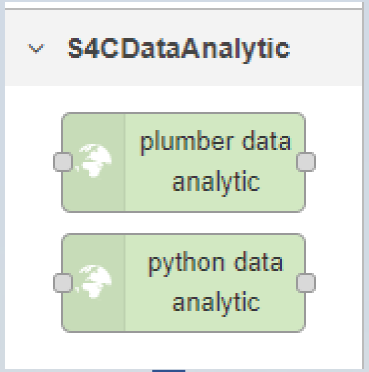
RStudio

Data Analytic Container

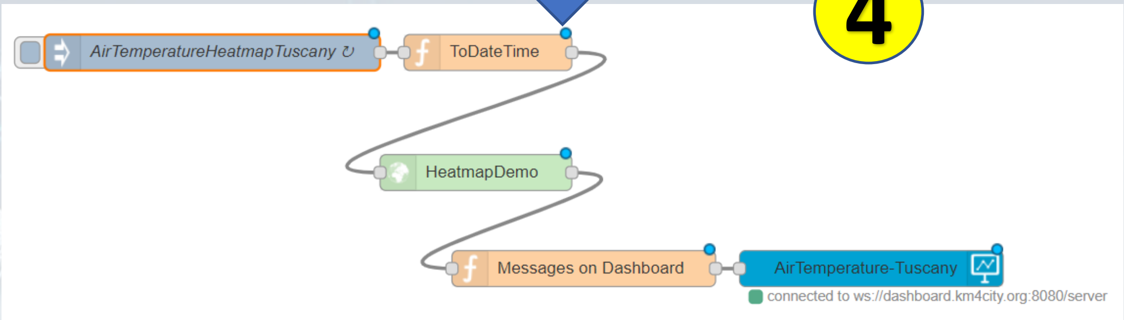


2 Open an Advanced IoT App / Node-RED





3 Use Snap4City Data Analytic Node, and load in the code you developed.



4

1 Develop .py **or** .r program on (i) Snap4City platform online, or (ii) your Development Machine.

The code has to respect the guidelines provided for creating API.

The API are called as a MicroService

For example see:

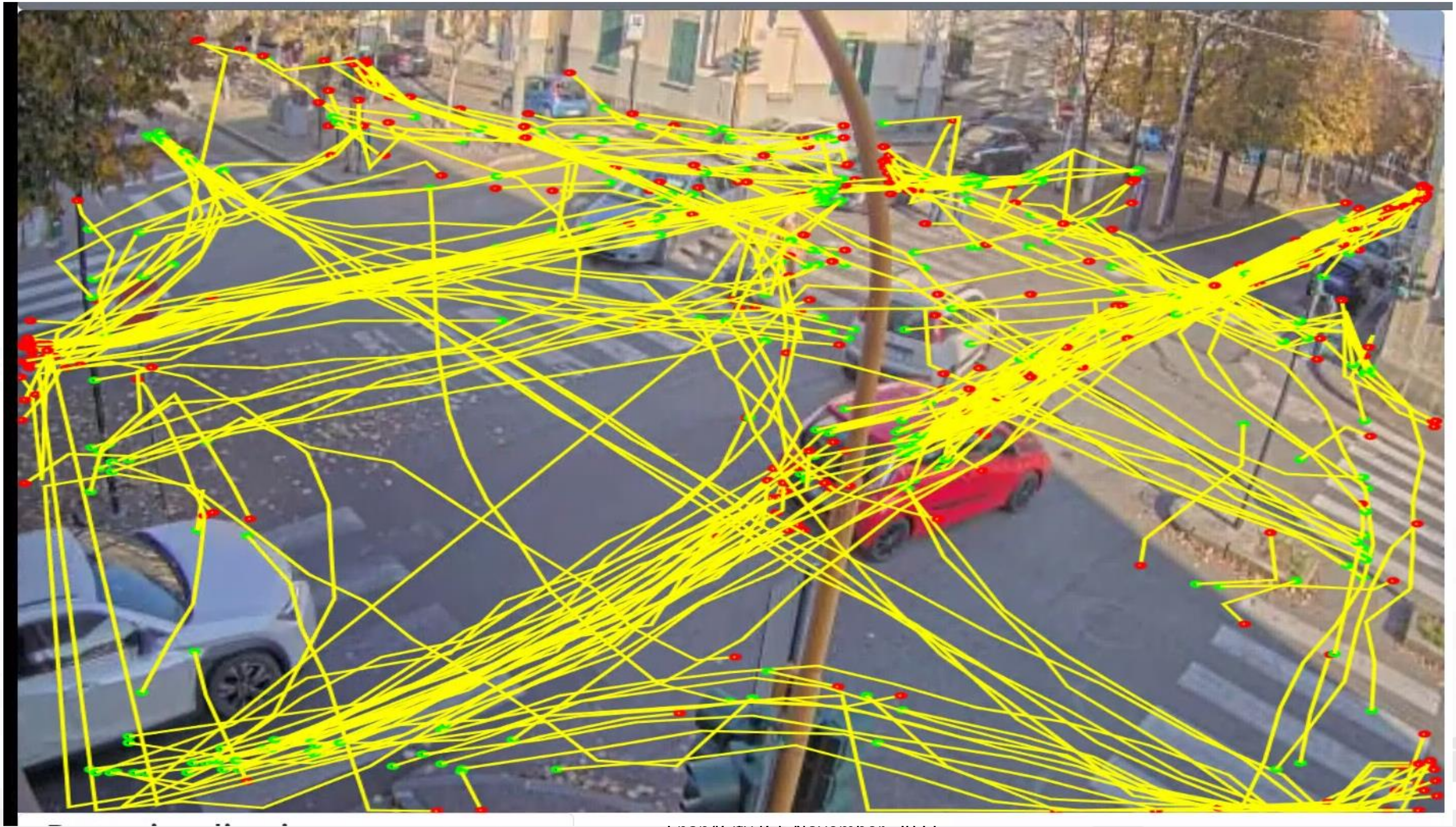
https://www.snap4city.org/641

https://www.snap4city.org/645

5 Deploy the IoT App → Snap4City Container Manager based on Marathon/Mesos is creating a Container for your Data Analytic code

Data Analytic

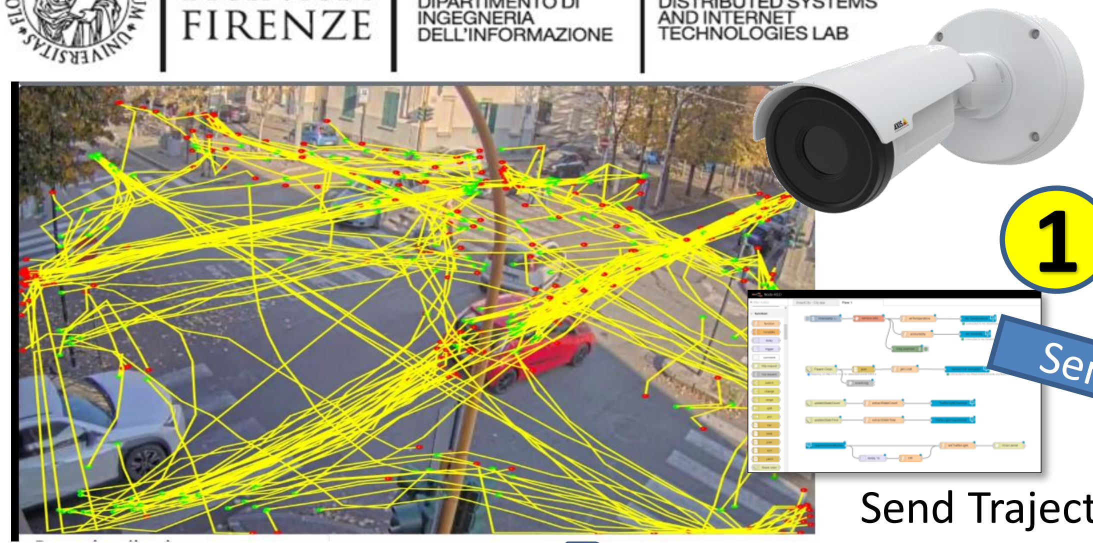
Data Analytic



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

AXIS COMMUNICATIONS

SNAP4CITY



IoT edge on TV Camera

1

Send Trajectories

Send data to Broker

2

IOT Broker

Device: CrossVenaria2 with trajectories

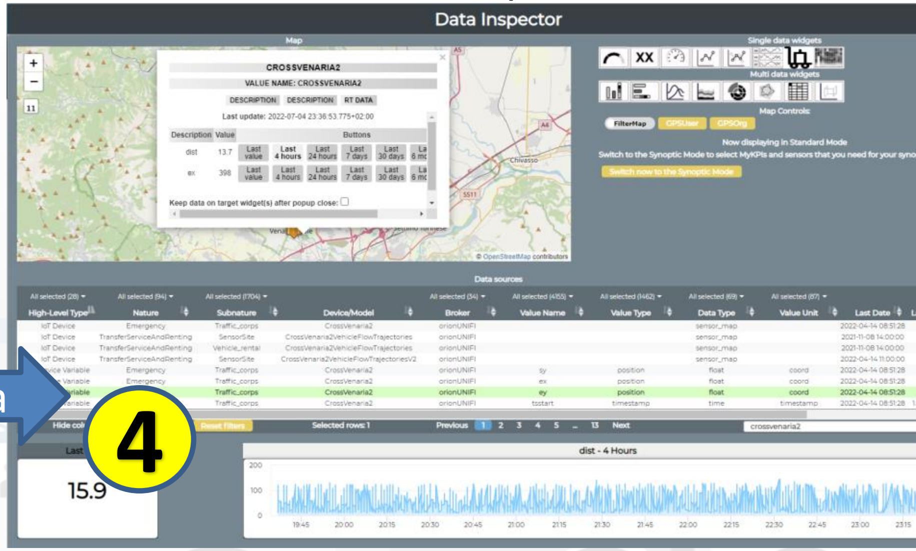
SNAP4CITY

3

Save data

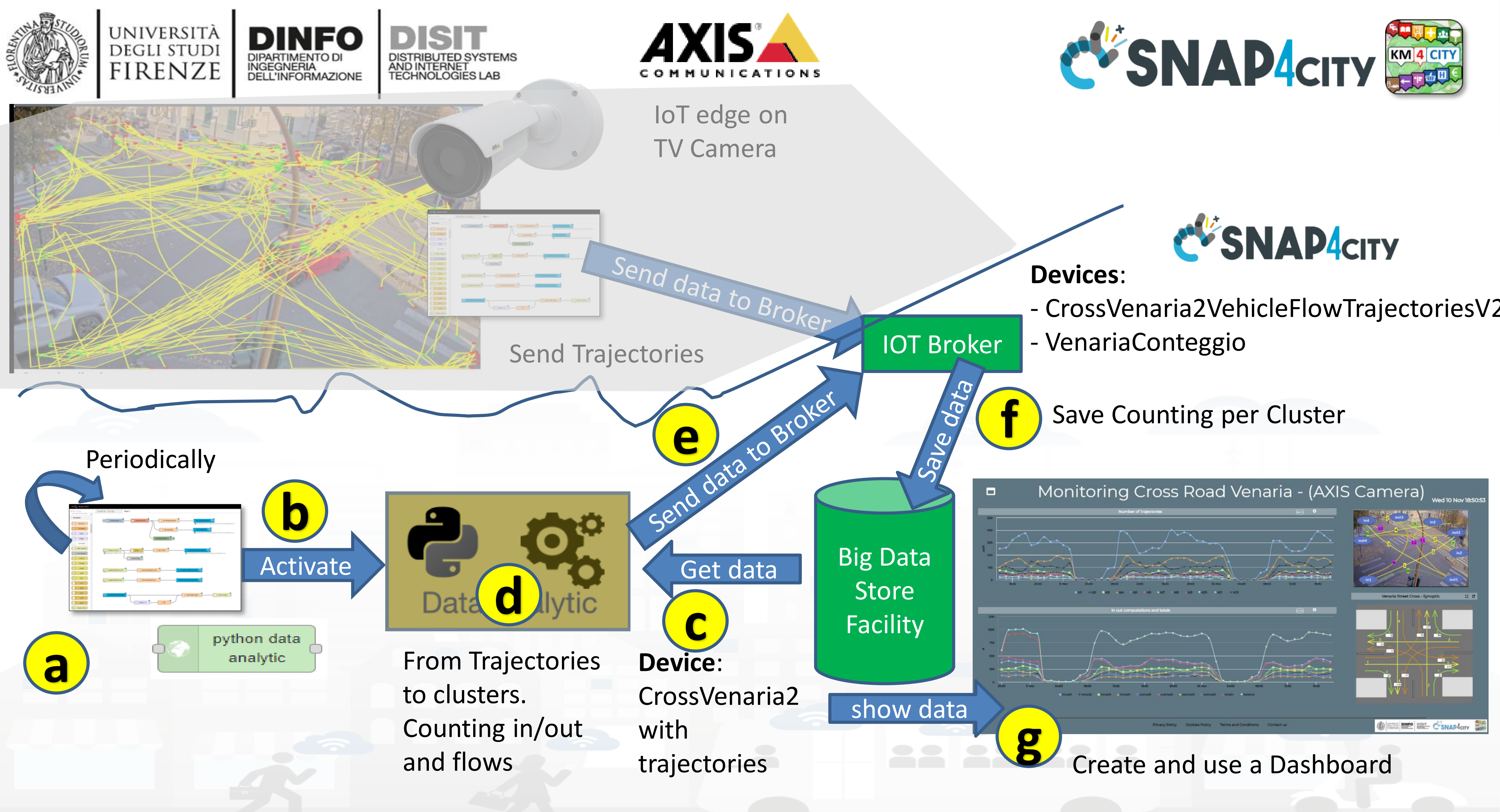
Big Data Store Facility

Data Inspector

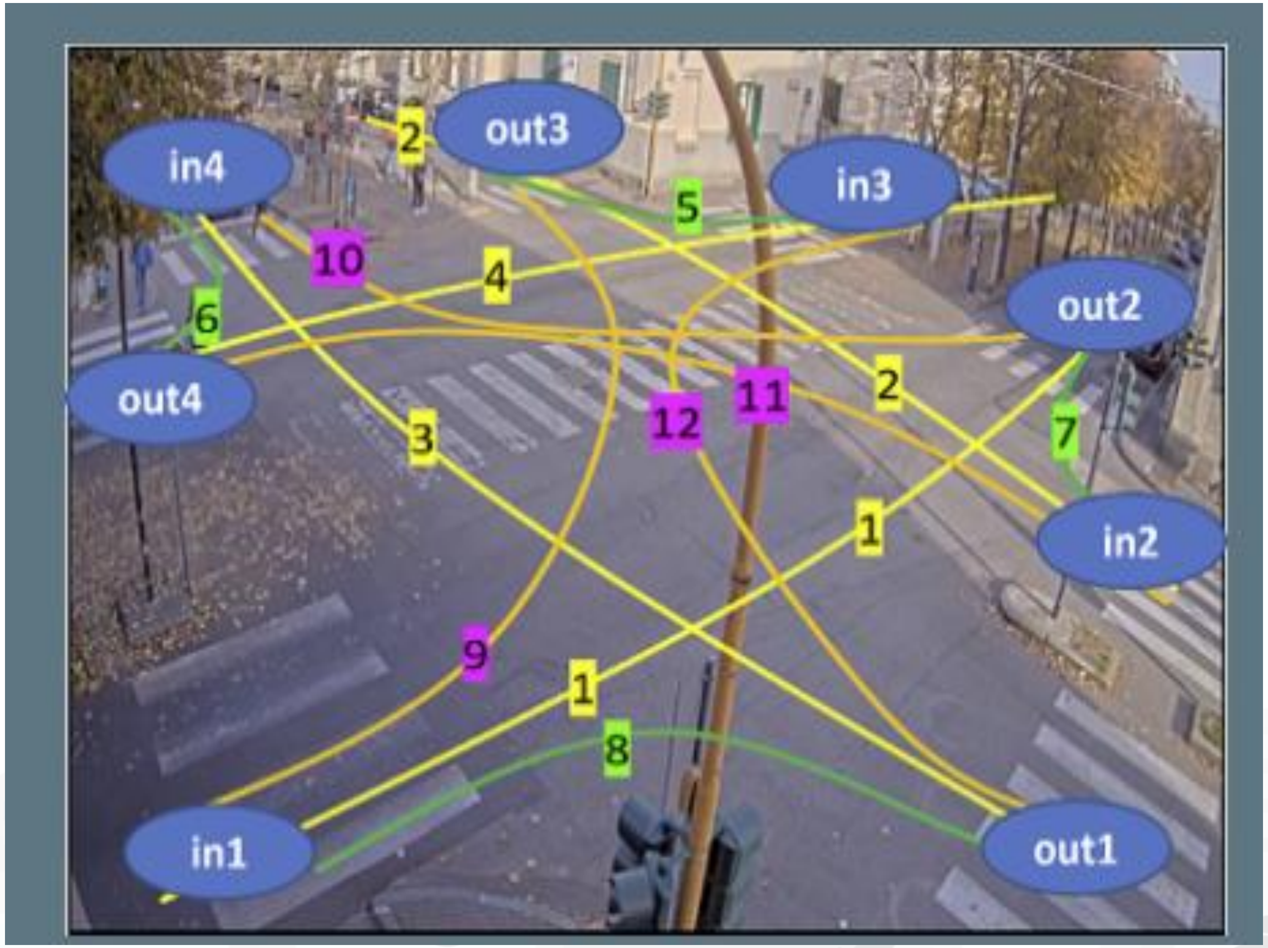


show data

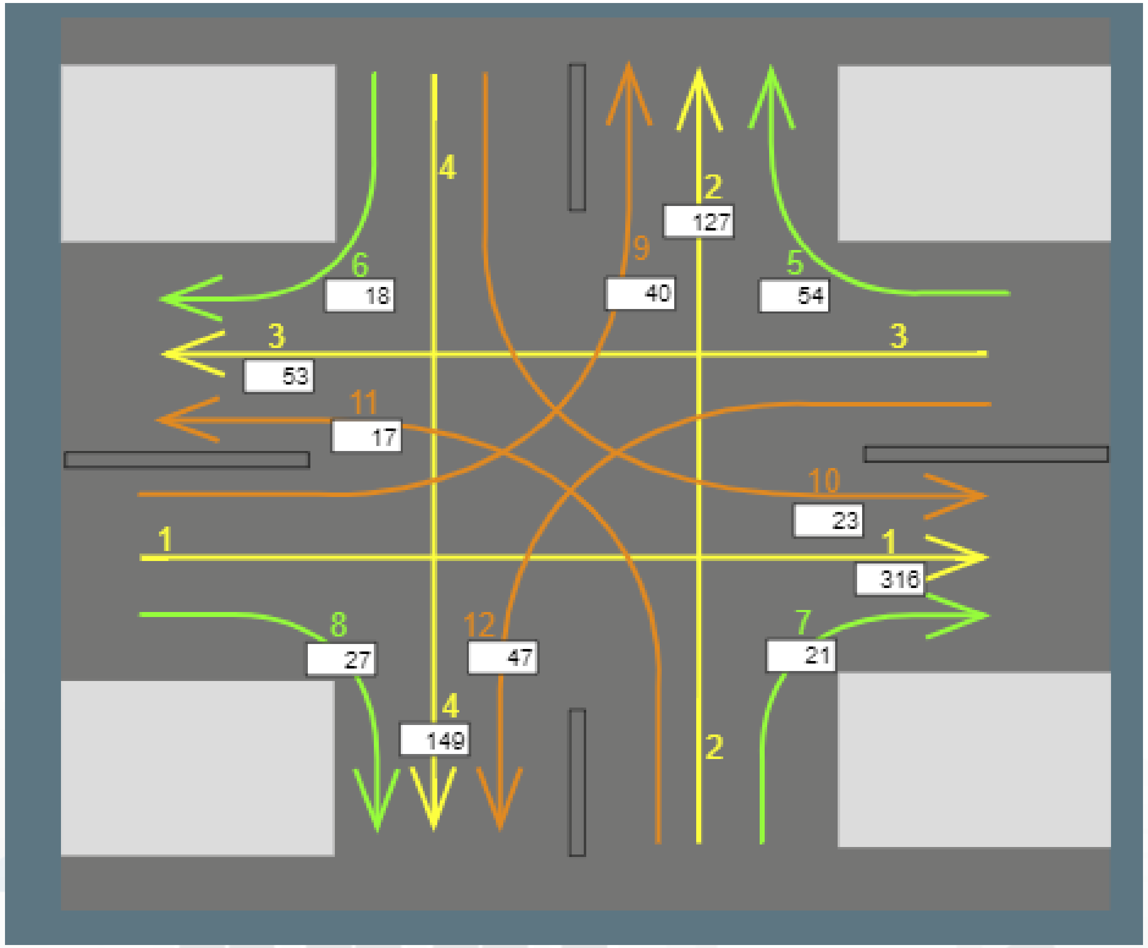
4


UNIVERSITÀ DEGLI STUDI FIRENZE
DINFO DIPARTIMENTO DI INGEGNERIA DELL'INFORMAZIONE
DISIT DISTRIBUTED SYSTEMS AND INTERNET TECHNOLOGIES LAB
AXIS COMMUNICATIONS
SNAP4CITY
IoT edge on TV Camera
Send data to Broker
Send Trajectories
IOT Broker
Devices:
- CrossVenaria2VehicleFlowTrajectoriesV2
- VenariaConteggio
f
Save Counting per Cluster
Save data
e
Send data to Broker
Periodically
b
Activate
Data Analytic
d
Get data
c
Big Data Store Facility
Monitoring Cross Road Venaria - (AXIS Camera)
a
python data analytic
From Trajectories to clusters. Counting in/out and flows
Device: CrossVenaria2 with trajectories
show data
g
Create and use a Dashboard

Real time Clustering: legenda and synoptic



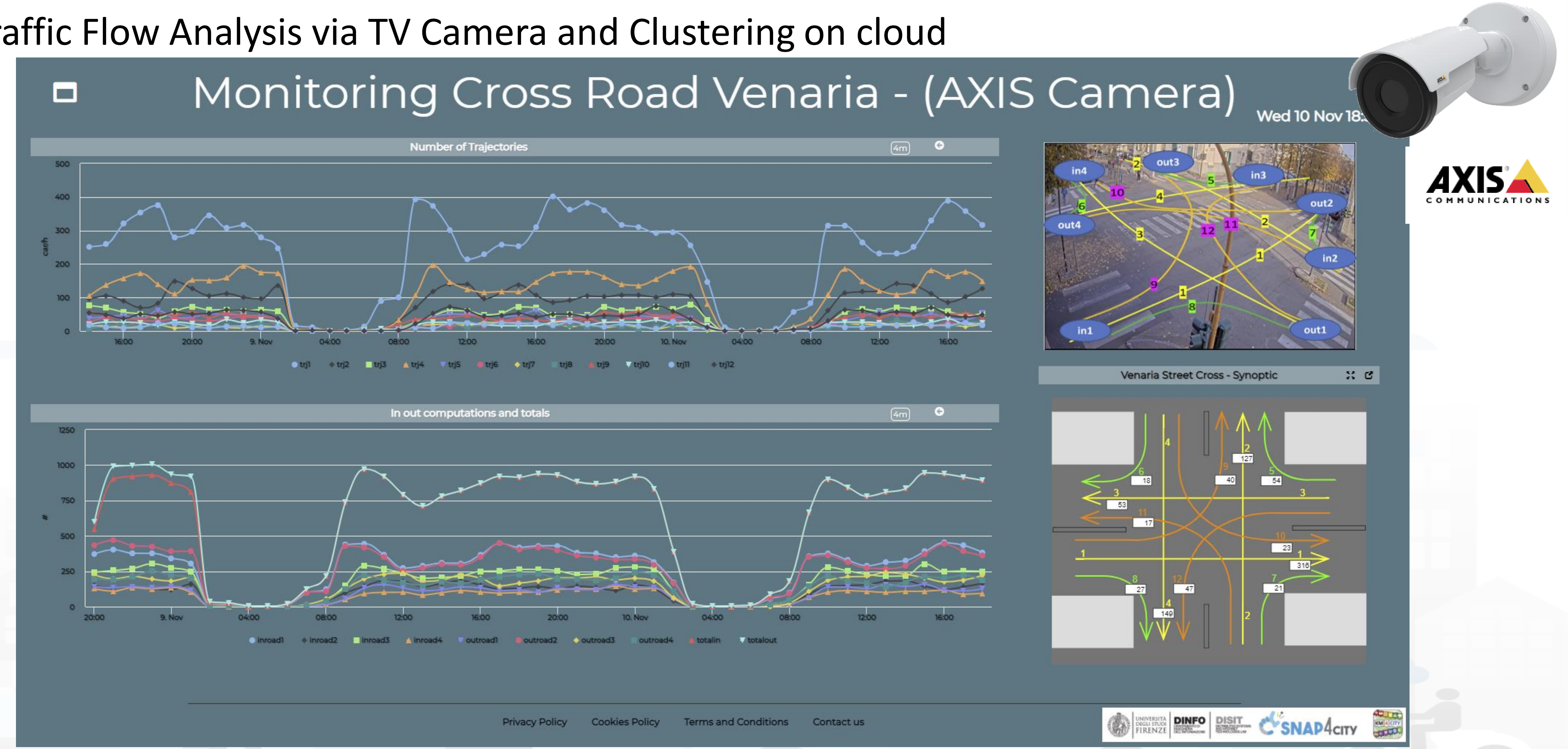
Legenda



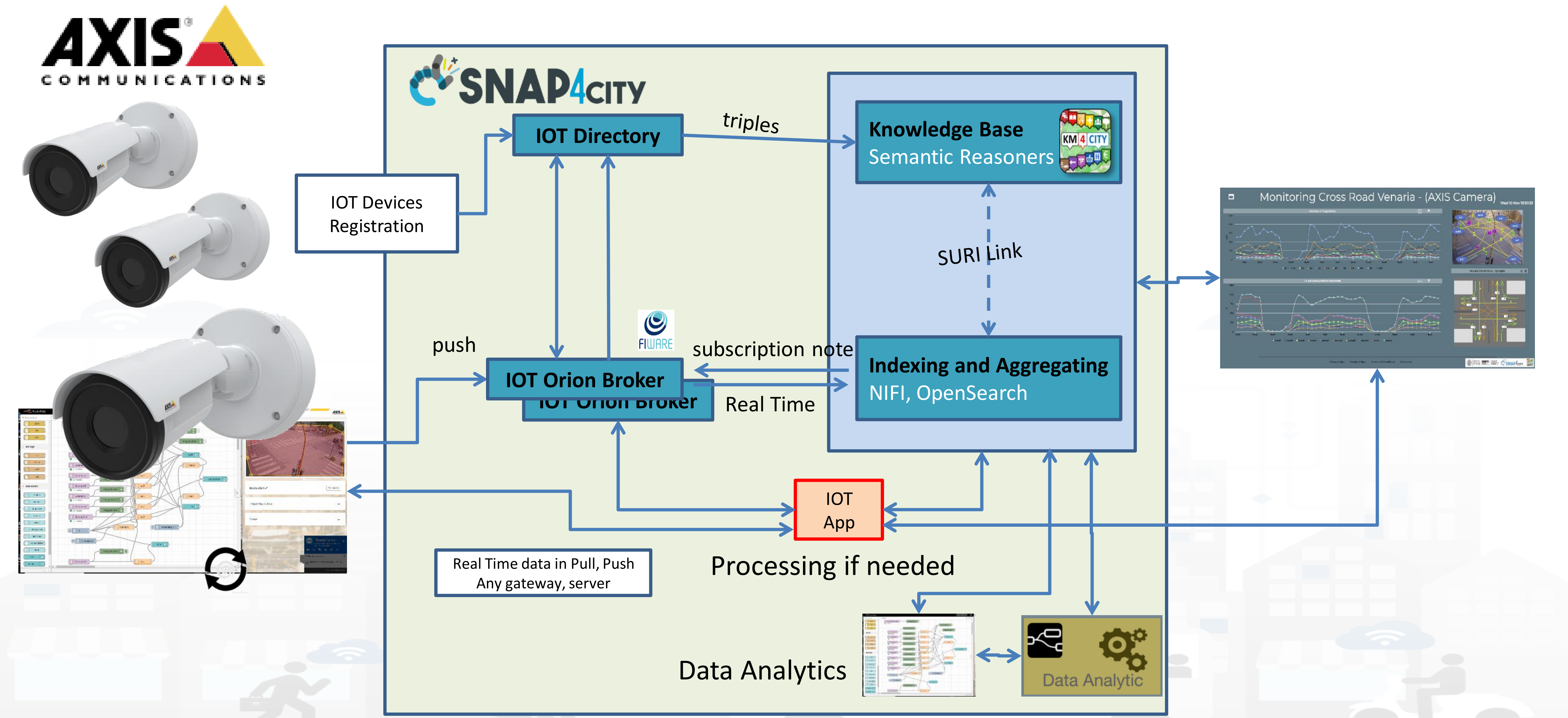
Synoptic with real time data

An example

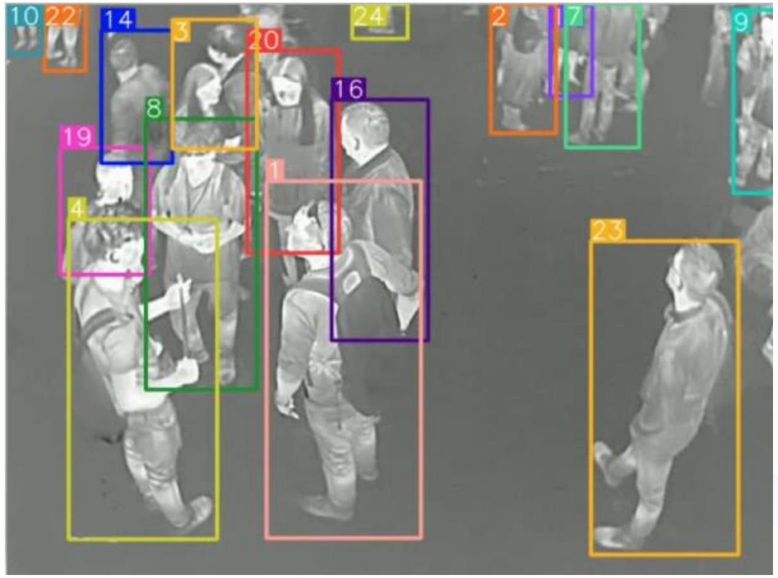
Traffic Flow Analysis via TV Camera and Clustering on cloud

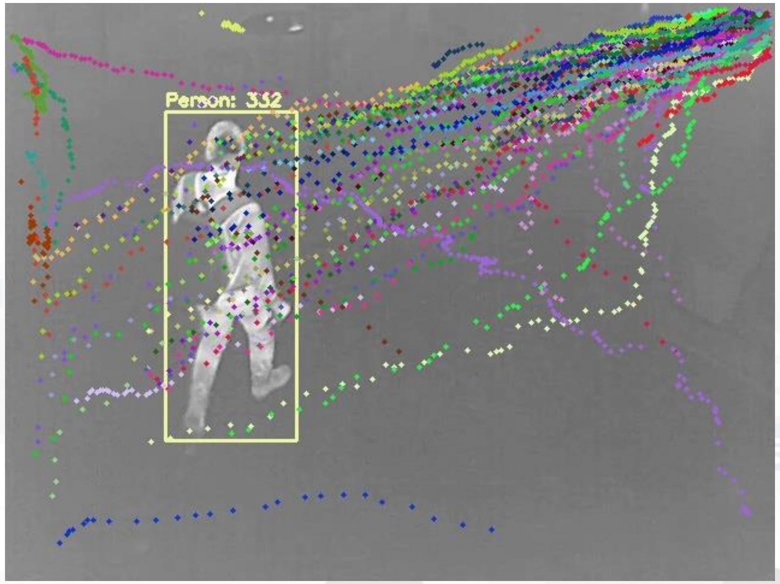


Managing TV Cam



People Counting and Tracking



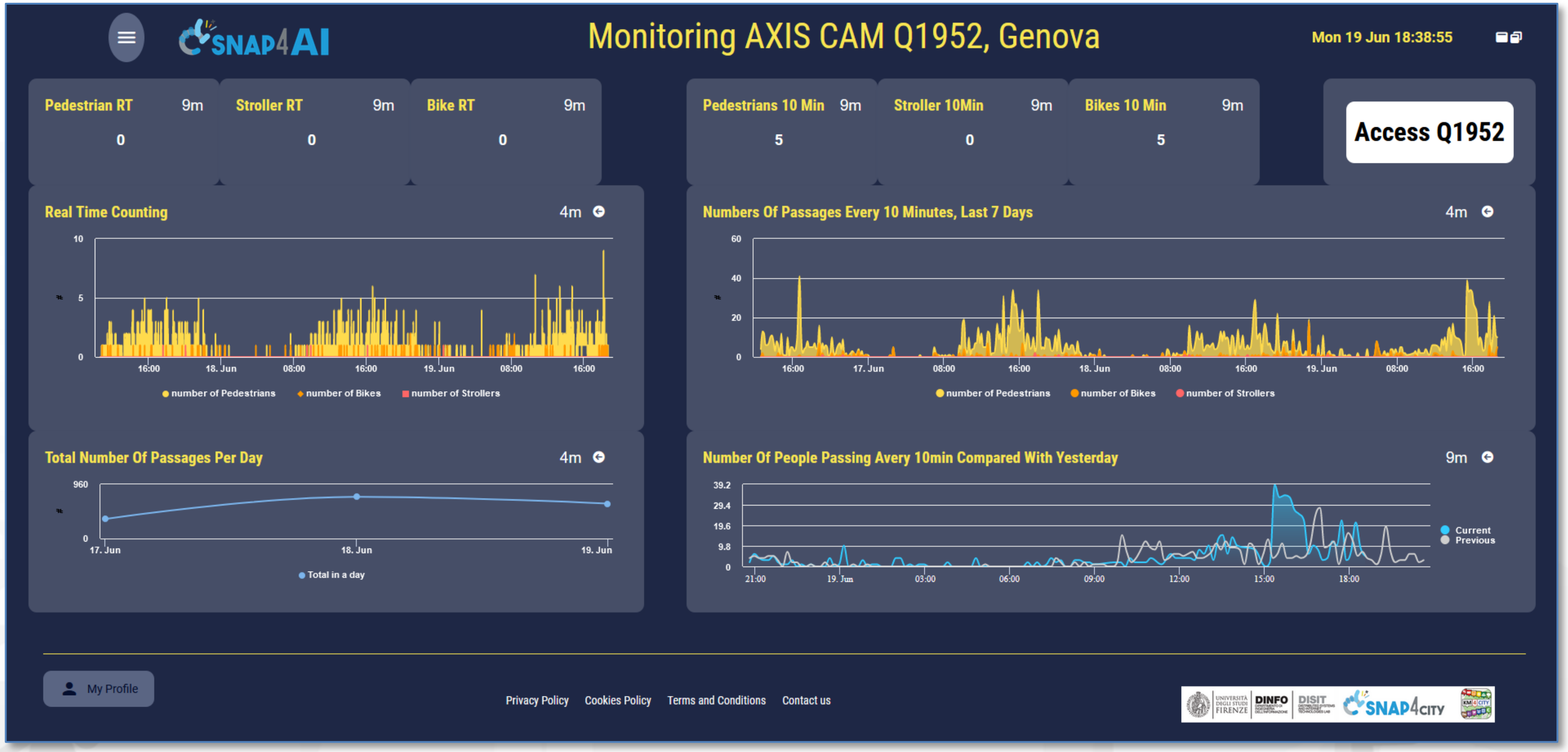


11 SUSTAINABLE CITIES AND COMMUNITIES

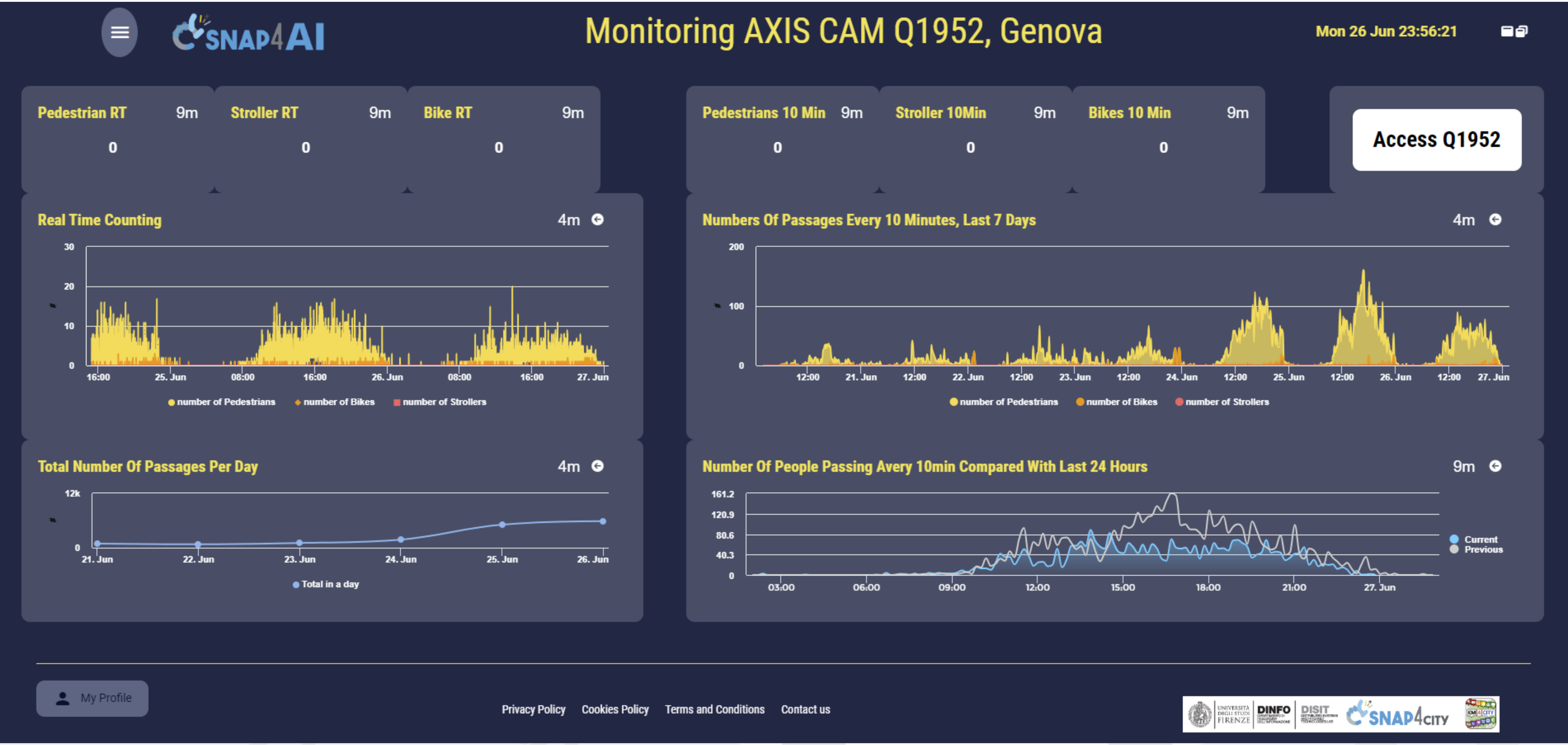
3X

Monitoring Passages AXIS Q1952

- Genova: Ocean Race, 2023



11 SUSTAINABLE CITIES AND COMMUNITIES


Monitoring AXIS CAM Q1952, Genova
Mon 26 Jun 23:56:21
Pedestrian RT 9m 0
Stroller RT 9m 0
Bike RT 9m 0
Pedestrians 10 Min 9m 0
Stroller 10Min 9m 0
Bikes 10 Min 9m 0
Access Q1952
Real Time Counting 4m
number of Pedestrians
number of Bikes
number of Strollers
Numbers Of Passages Every 10 Minutes, Last 7 Days 4m
Total Number Of Passages Per Day 4m
Total in a day
Number Of People Passing Avery 10min Compared With Last 24 Hours 9m
Current
Previous
My Profile
Privacy Policy
Cookies Policy
Terms and Conditions
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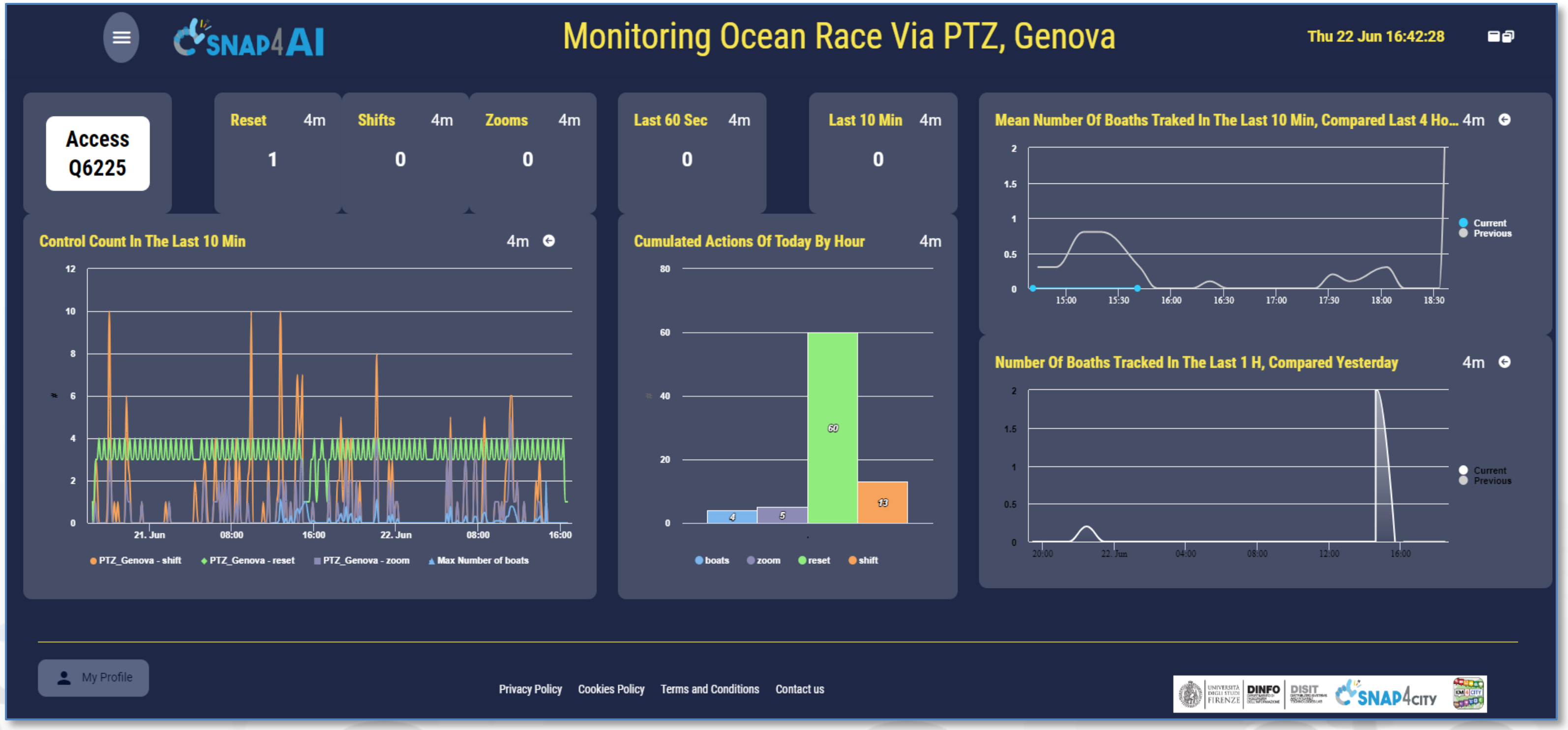
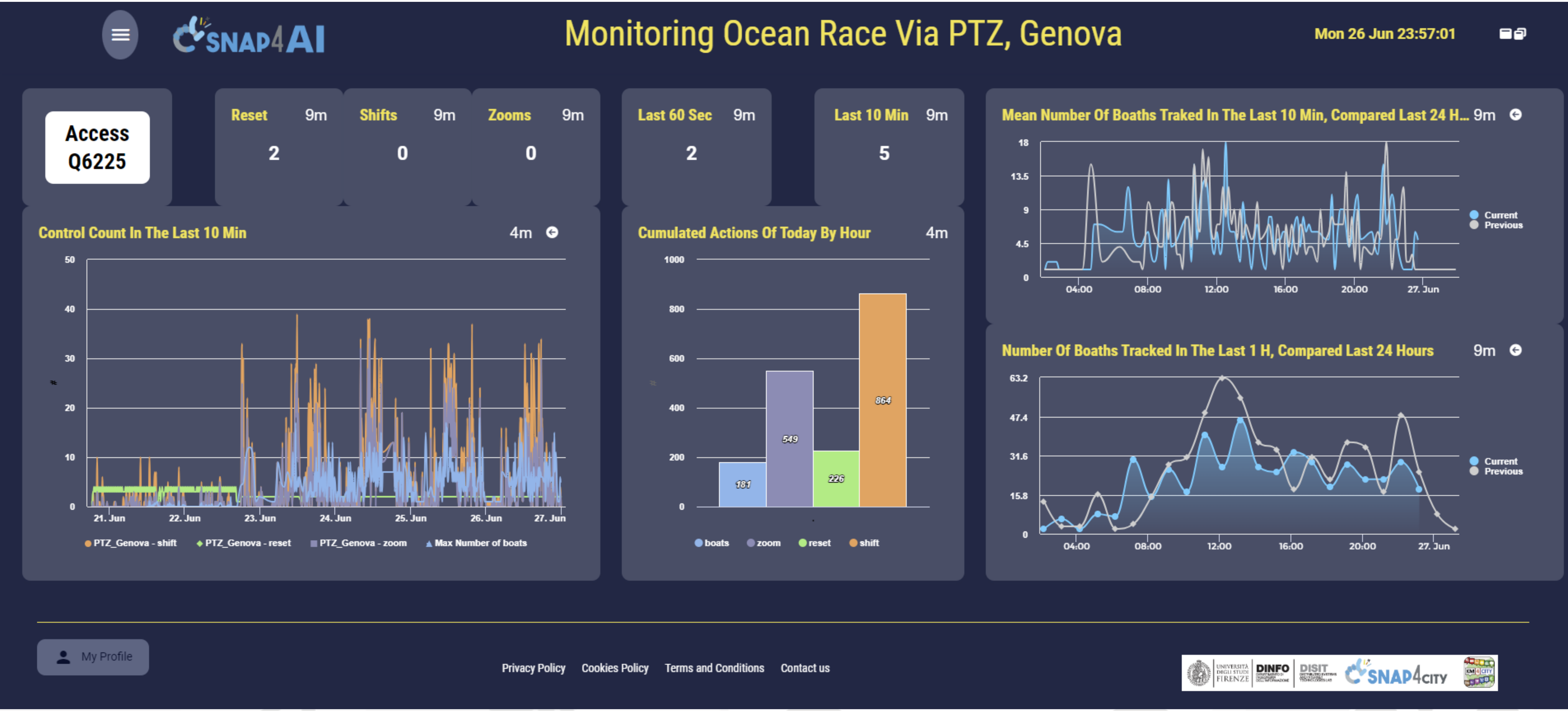
Monitoring Boats
AXIS Q6225

- Genova: Ocean Race, 2023





SNAP4AI
Monitoring Ocean Race Via PTZ, Genova
Mon 26 Jun 23:57:01
Access Q6225
Reset 9m 2
Shifts 9m 0
Zooms 9m 0
Last 60 Sec 9m 2
Last 10 Min 9m 5
Mean Number Of Boaths Traked In The Last 10 Min, Compared Last 24 H... 9m
18
13.5
9
4.5
0
04:00
08:00
12:00
16:00
20:00
27. Jun
Current
Previous
Control Count In The Last 10 Min 4m
50
40
30
20
10
0
21. Jun
22. Jun
23. Jun
24. Jun
25. Jun
26. Jun
27. Jun
PTZ_Genova - shift
PTZ_Genova - reset
PTZ_Genova - zoom
Max Number of boats
Cumulated Actions Of Today By Hour 4m
1000
800
600
400
200
0
181
549
226
864
boats
zoom
reset
shift
Number Of Boaths Tracked In The Last 1 H, Compared Last 24 Hours 9m
63.2
47.4
31.6
15.8
0
04:00
08:00
12:00
16:00
20:00
27. Jun
Current
Previous
My Profile
Privacy Policy
Cookies Policy
Terms and Conditions
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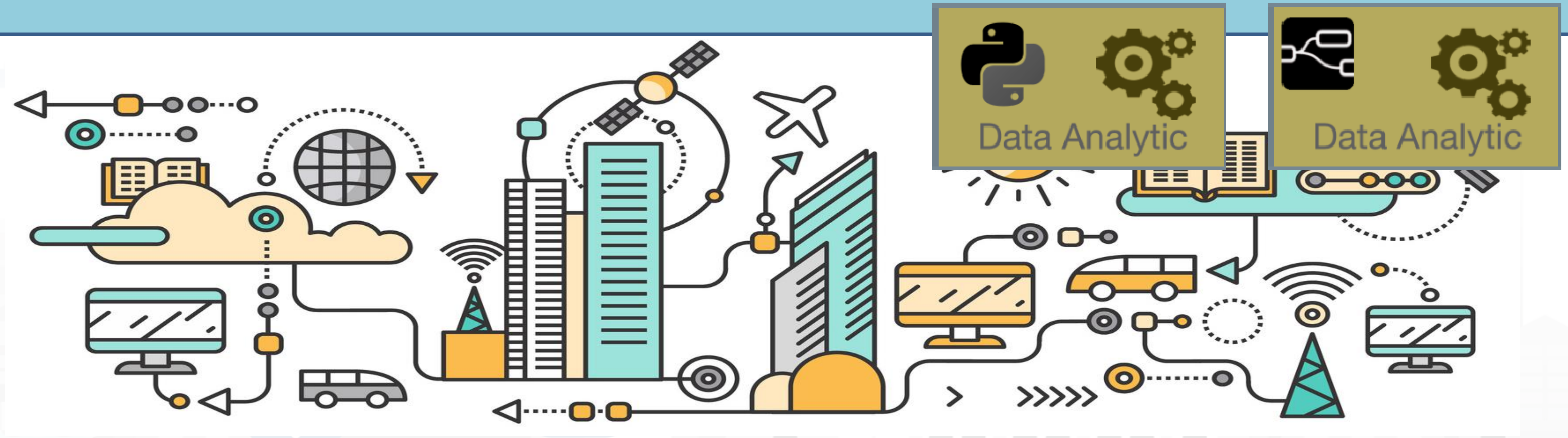
DP, for DA, AI, XAI on Container vs Proc.Logic: Python/RStudio



VIDEO

WorkShop
working with Data Analytics on Node-Red
using the SCAPI

- R data retrieval from a public sensor in a specific window of time
- Python data retrieval from a private sensor in a specific window of time

Min - Mean - Max computing

https://www.youtube.com/watch?v=axAR6u4suQU

WorkShop
working with Data Analytics on Node-Red
using the SCAPI

- R data retrieval from a public sensor in a specific window of time
- Python data retrieval from a private sensor in a specific window of time

Min - Mean - Max computing

Device selection

- You can choose between a multitude of Devices inside the Snap4City Platform
- A useful online user interface is available at http://servicemap.km4city.org/WebAppGrafo/
- Or you can of course use your devices created in the platform

For this workshop we have identified two sensors:

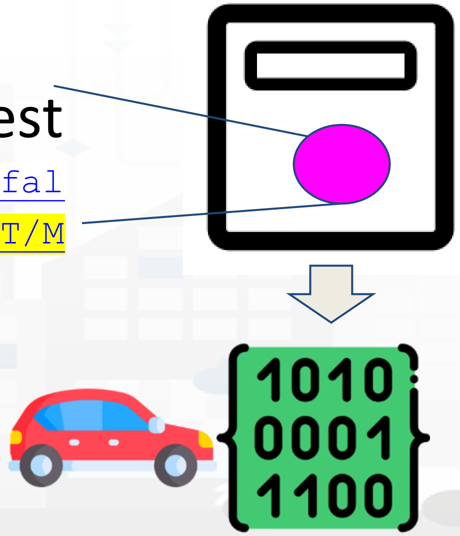
- a public one whose service_uri (the link identifier of the resource) is `http://www.disit.org/km4city/resource/iot/orionUNIFI/DISIT/METRO762`

- a private one accessible through an authentication procedure whose service_uri is `http://www.disit.org/km4city/resource/iot/orionUNIFI/DISIT/118907.682_485819.390-Plastic`

SCAPI ?

- The Snap4City API allows you to formulate requests to get different results based on your needs
- The documentation is accessible at: https://www.km4city.org/swagger/external/index.html
- Under Services it is possible to retrieve data from a specific device
  - identified by its service_uri
  - specifying the temporal windows fromTime - toTime
- regarding the public traffic sensor it is reported below the GET request

https://servicemap.disit.org/WebAppGrafo/api/v1/?maxResults=10000&lang=en&geometry=false&format=json&serviceUri=http://www.disit.org/km4city/resource/iot/orionUNIFI/DISIT/METRO762&realtime=true&fromTime=2021-04-14T00:00:00&toTime=2021-07-13T08:04:21



Private Device Data Retrieval

1) for accessing a private device data you'll need to have an

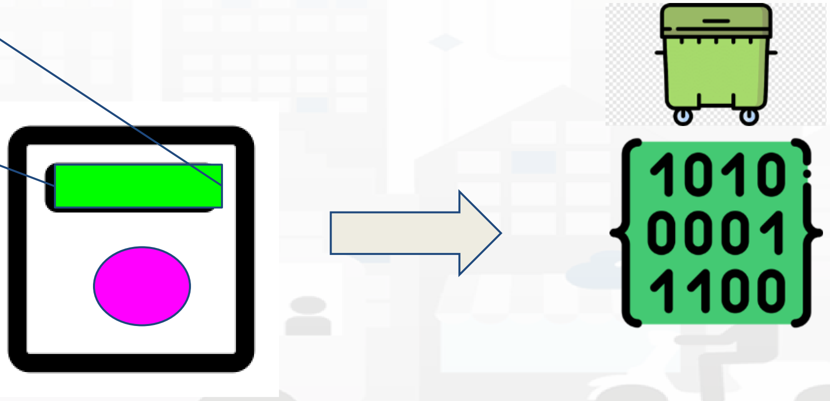
ACCESS TOKEN

2) to get the access_token you'll to make a POST request specifying the username and password of the owner of the resource or the delegated ones.

```
url = "https://www.snap4city.org/auth/realms/master/protocol/openid-connect/token/"
data = {"client_id": client_id,"grant_type":"password","username":utente,"password":password}
r=requests.post(url, data)
```


```
{
  "access_token":"eyJz93a...k4laUWw",
  "token_type":"Bearer",
  "expires_in":86400
}
```


3) same get request for the one of the traffic sensor, but with the additional header with the access_token



HANDS ON!

"toTime": "2021-07-13T08:04:21",
"fromTime":"2021-07-01T08:04:21",

Min - Mean - Max computing

"start_date" : "2021-01-21T00:00:00",

"end_date" : "2022-03-09T00:00:00",

Sources for the example

- IoT App / Proc.Logic
  - https://www.snap4city.org/download/video/course/p4/flussoWorkshop-DA-AI-2023.zip
- Example in Python
  - https://www.snap4city.org/download/video/course/p4/PythonScriptPrivateDataRetrievalAndStatistics.zip
- Example in RStudio
  - https://www.snap4city.org/download/video/course/p4/RscriptPublicDataRetrievalAndStatistics.zip

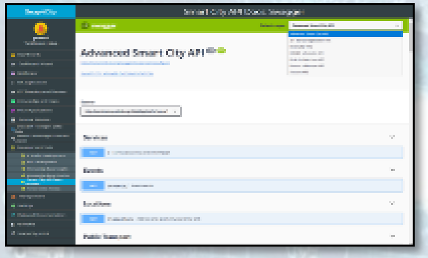
TOP

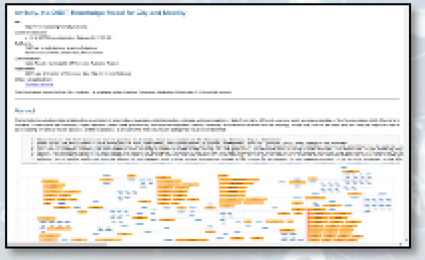
DP, for DA, AI, XAI on Premise, Specific Hardware

Data Analytics on Snap4City platform
Dev on Premise, Custom

TensorFlow · NVIDIA CUDA · python · jupyter · R Studio

Swagger





Ontology Schema

LOG.disit.org

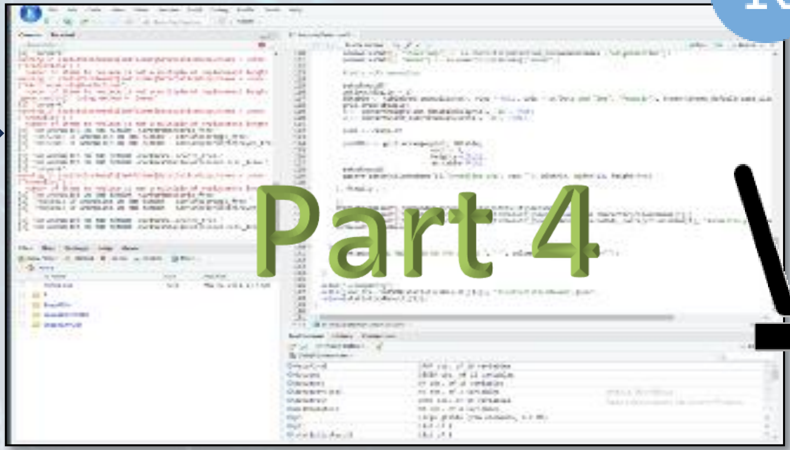
Knowledge Base, Km4City

Big Data Store Facility

Smart City API from Knowledge Base and other tools

SCAPI

NGSI



Saving / Sharing reusing

SCAPI

NGSI

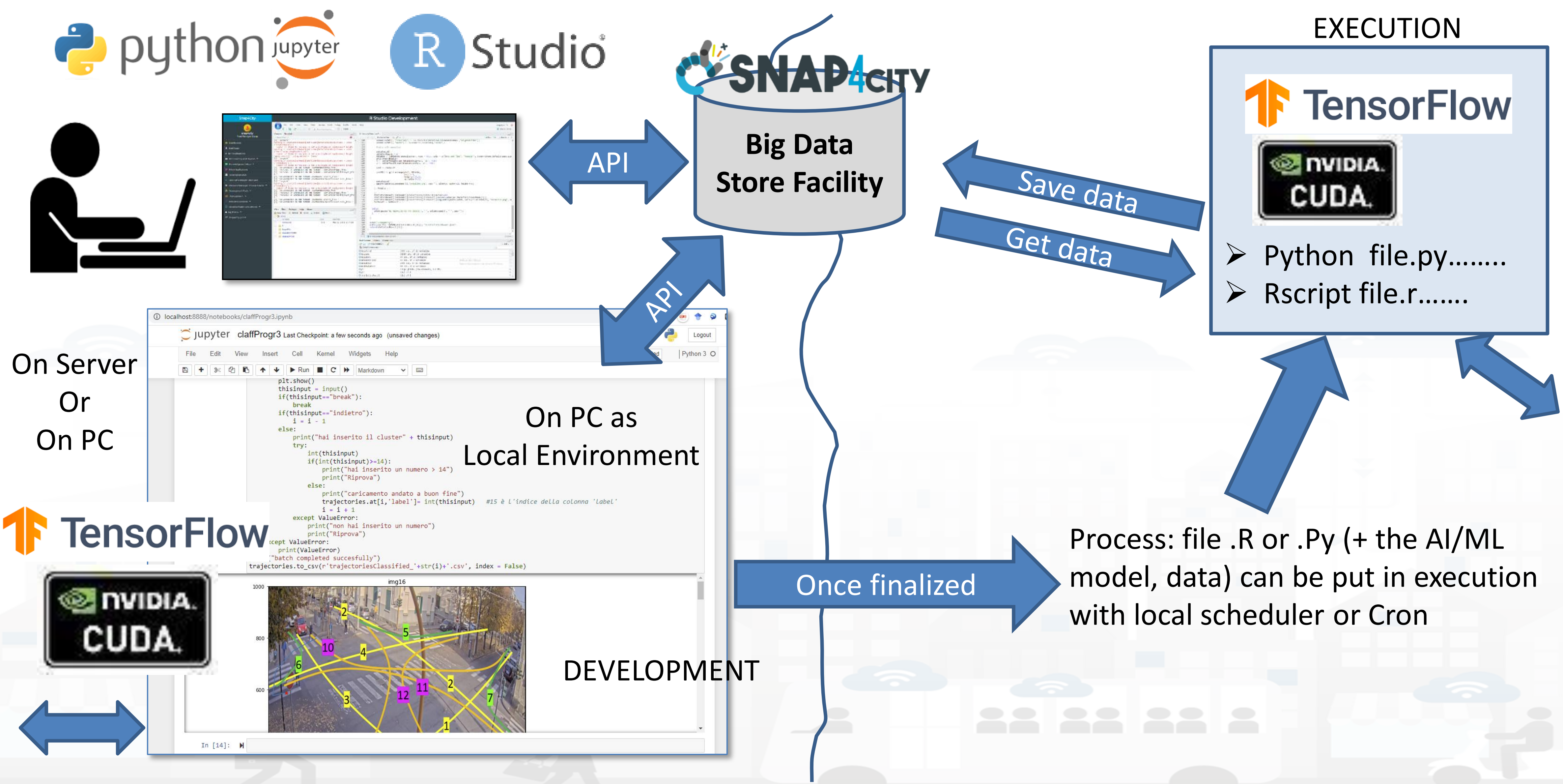
TensorFlow

NVIDIA CUDA

- Python *file.py* ....
- Rscript *file.r* ....

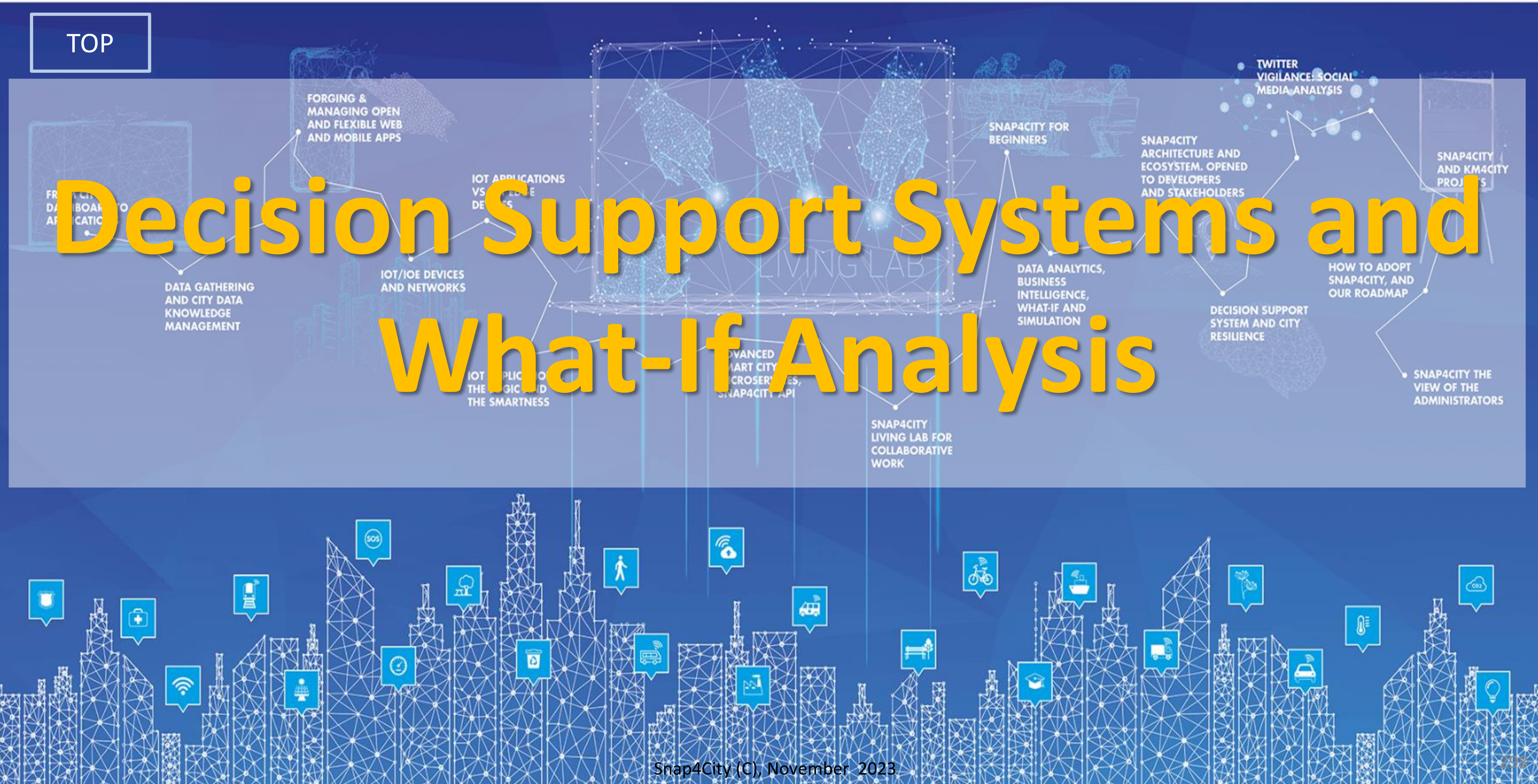
Resource Manager

Development



TOP

Decision Support Systems and What-If Analysis

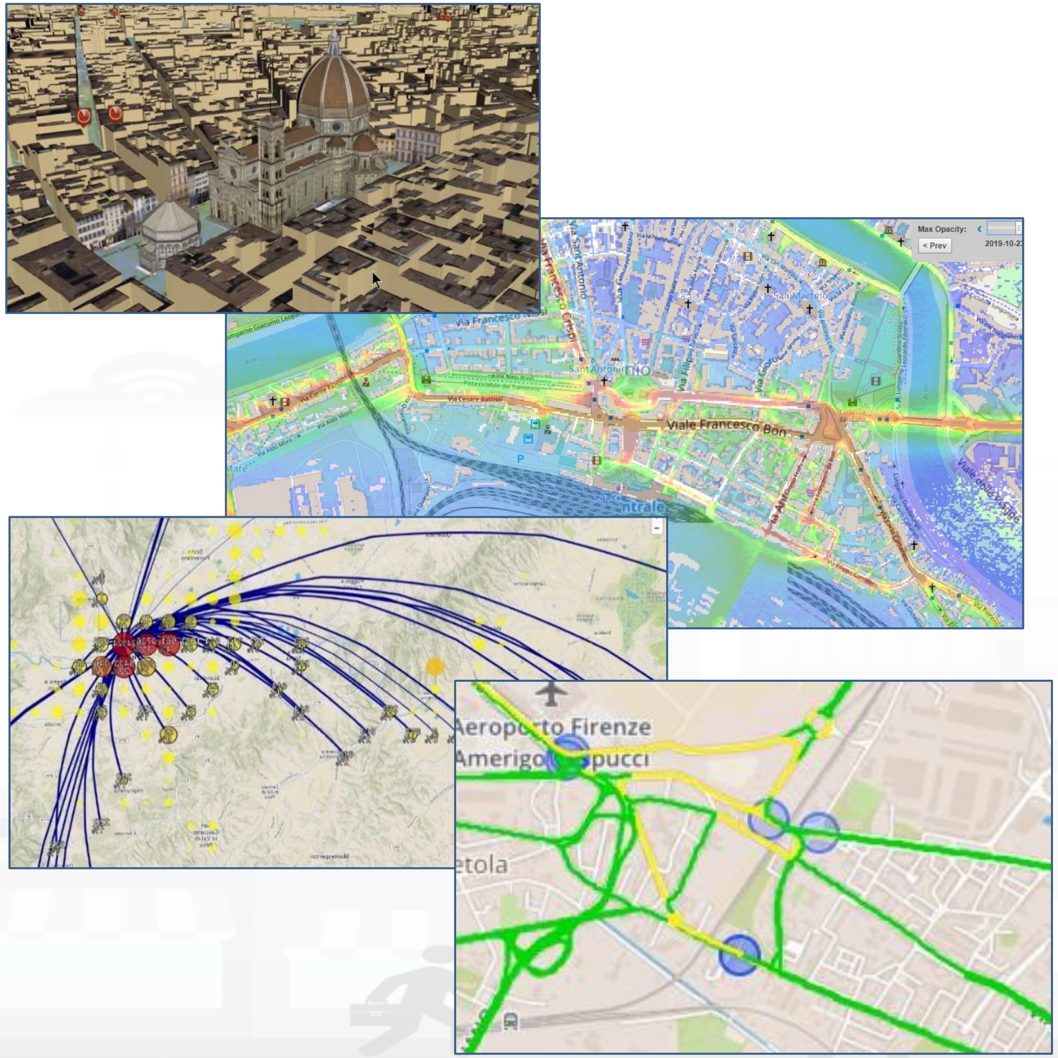


Public Spaces as Critical Infrastructures

- The City is a system of systems for city users
  - Cascading effects
- **Transport** networks
  - Main means for rescue teams, food, water, etc.
- **Communication**, ICT infrastructure
  - TV cam, switches, cyber,
- **Energy** networks
  - power supply for health, cyber systems, etc.
- **Hospitals** networks
- Aggregation areas

https://www.snap4city.org/download/video/DPL_SNAP4SOLU.pdf

Smart City Digital Twin



Digital representation of the city with…

- Intuitive platform
- Any Data TYPE, any data source, any protocol
- Data storage seamless
- Data analytics –> artificial intelligence, AI/XAI
- Data Ethics, AI Ethics, GDPR
- Data Representation
- Key performance Indicators
- What-IF analysis – Simulation, prediction, 2D/3D
- Operation, planning tactic and strategic
- Collaborative and shared representation
- Sustainable, shared, open source 100%

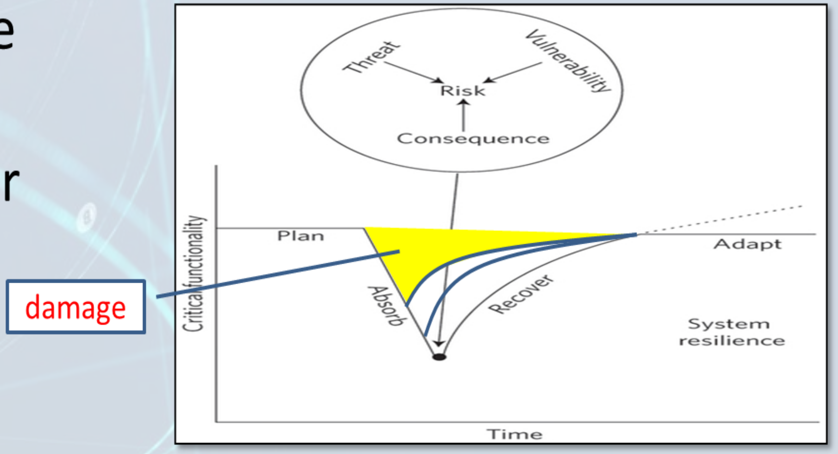
Complex and heterogeneous information, interoperability

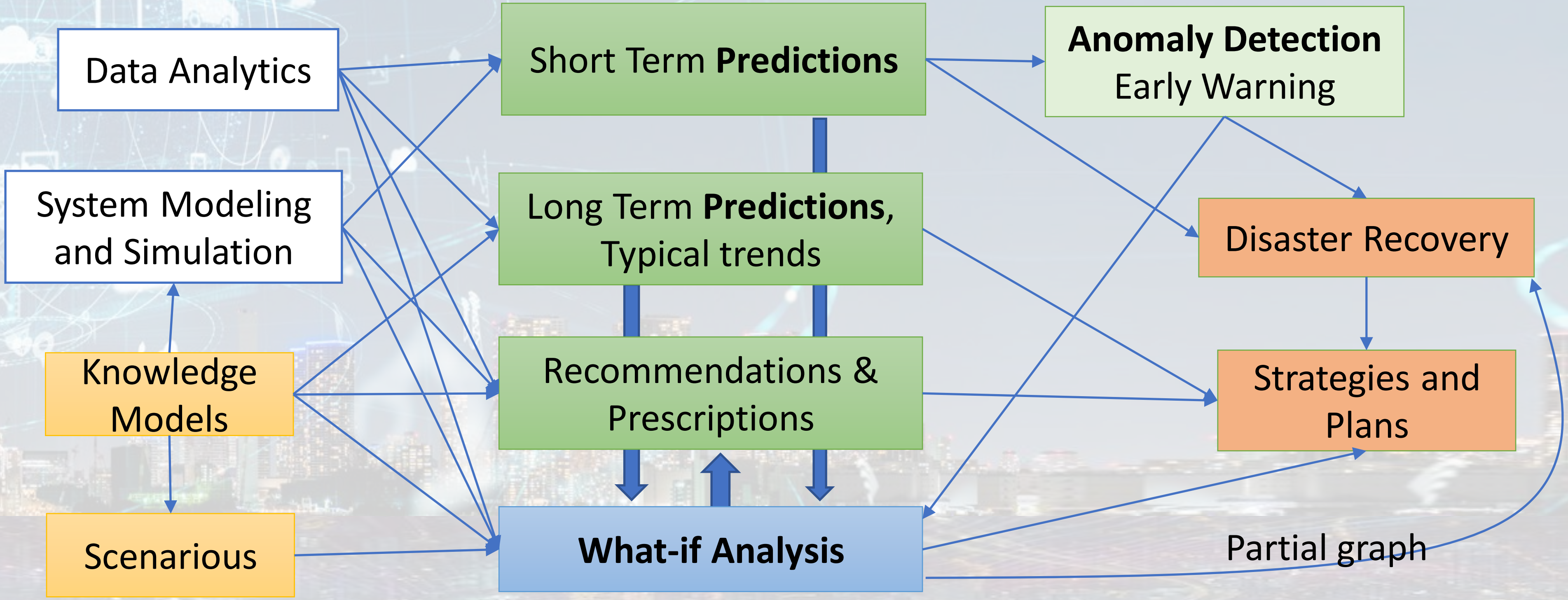
- GIS, ITS, AVM, IoT, BIM, CKAN, etc.
- Satellite services
- MaaS, lastmile delivery HUBs
- etc.

Snap4City Analytics

- Decision support systems
- Improvement of life quality
- Sustainable Solutions
- Reduction of costs
- Risk Assessment
- Resilience

Prepare
Absorb
Recover
Adapt

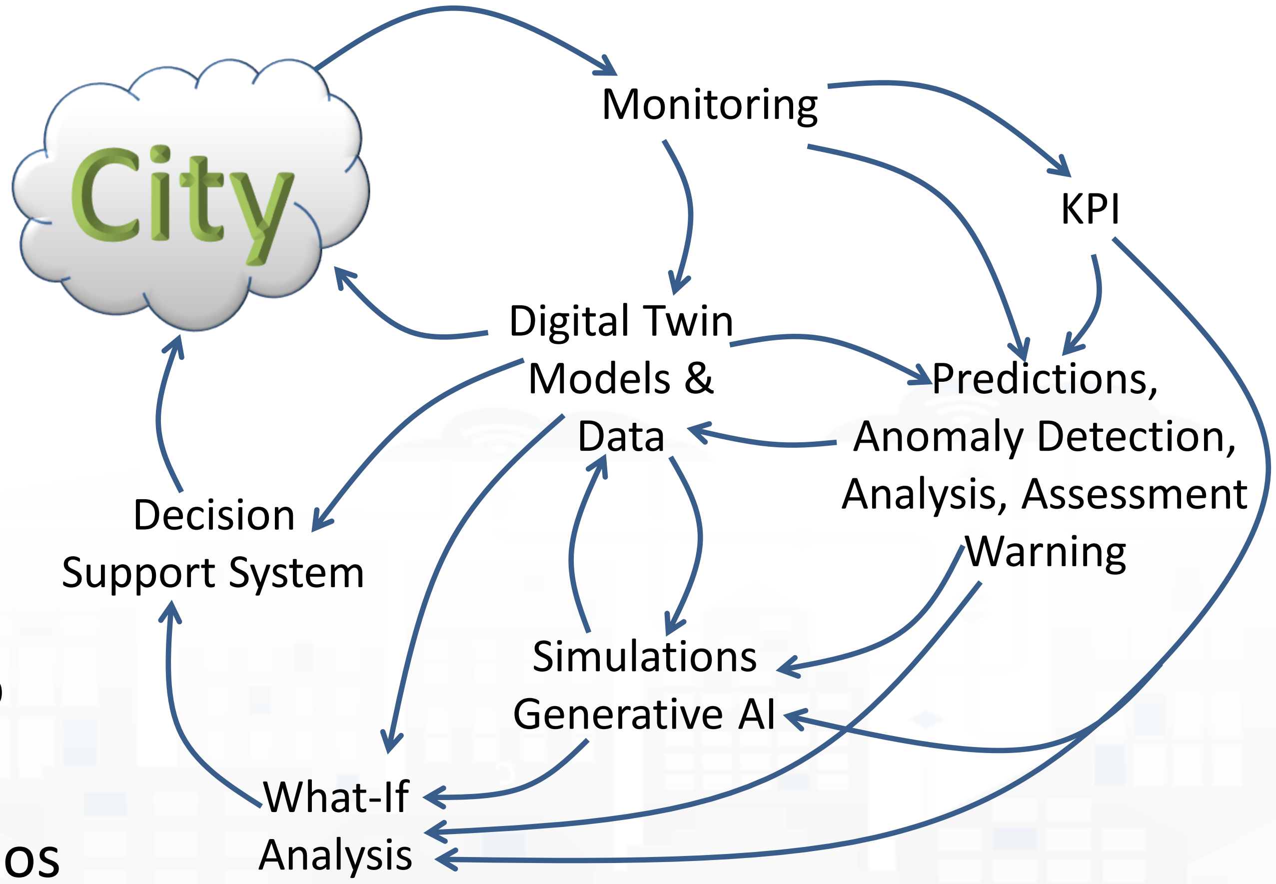




Decision Support System: neuro-symbolic reasoning
targeting Indicators: Quality of Life, PUMS, SUMI, KPI, SDG, 15MinIndex,…

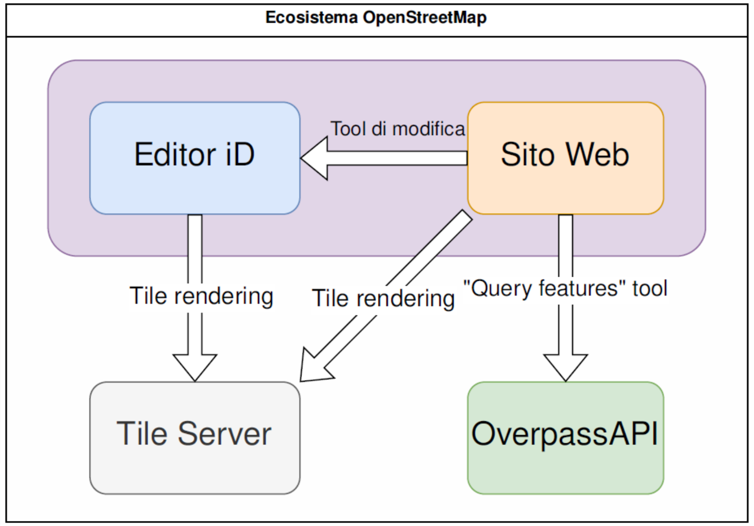
Main tasks

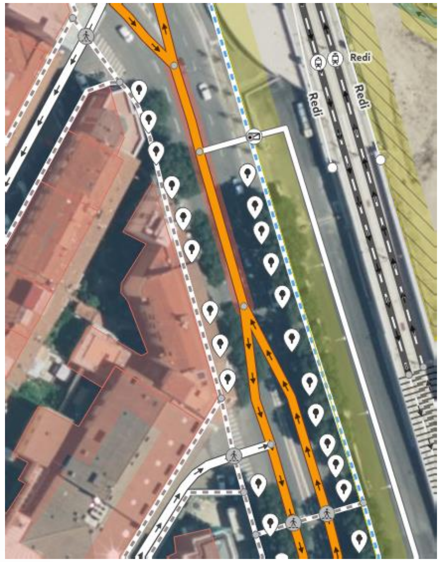
- **Controlling Status: management, and operational**
  - Monitoring via KPI
  - Computing predictions vs KPI
  - Anomaly detection
  - Neuro-Symbolic analysis
  - Risk assessment
  - Early warning on critical conditions
- **Making plan: tactic and strategic, medium and long range, micro/macro**
  - Simulation & predictions
  - Generative AI Prescriptions, scenarios
  - Resilience to Unexpected unknows
  - What-if analysis wrt scenarios

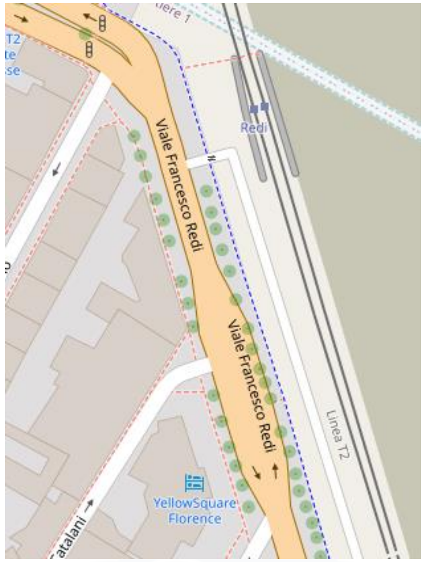


Tactic and/or Strategic Planning

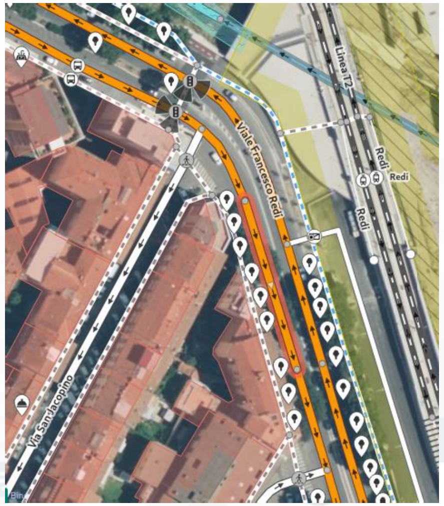
Correction of road graphs which is present on OSM

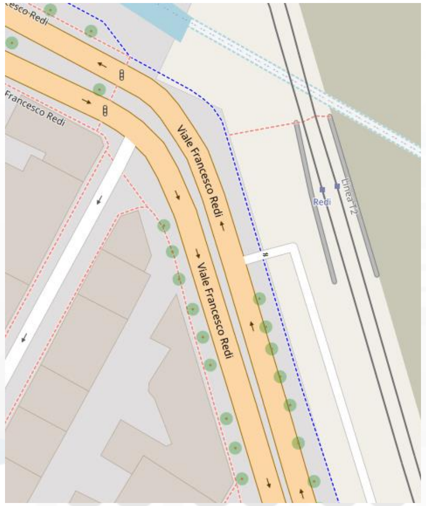






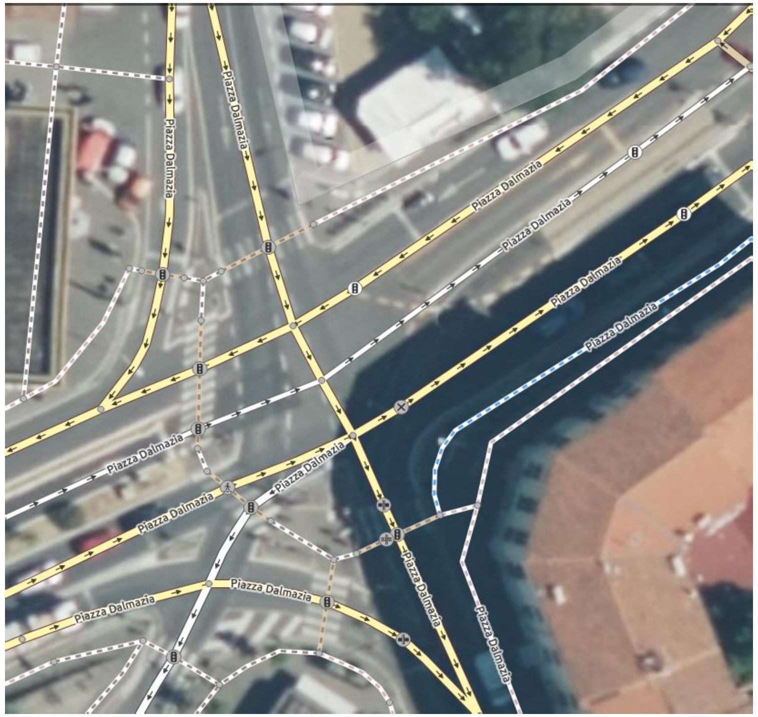
OSM data with non clear double bidirection lane on Viale Redi, Florence.
Editing OSM data and present Tiles



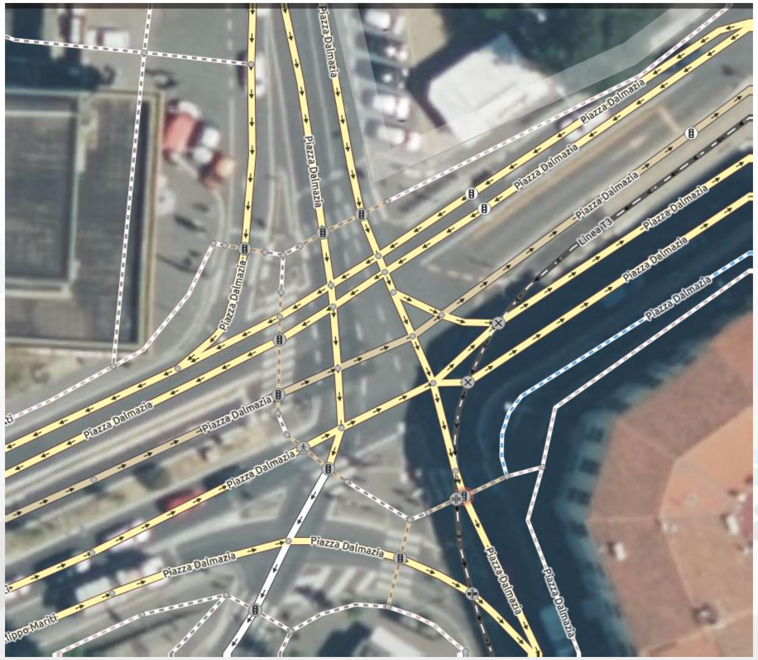


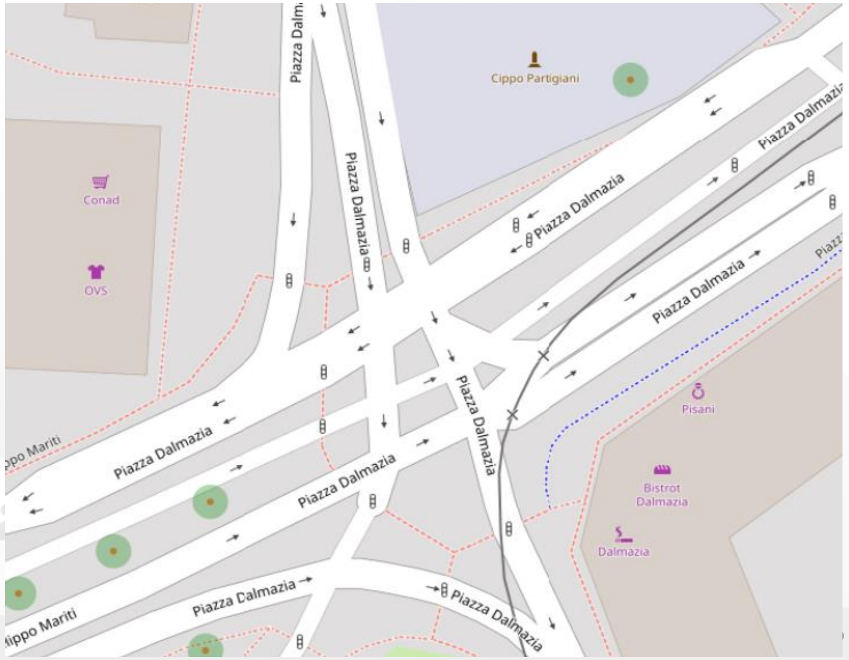
After Corretion of OSM data defining a clear double bidirection lane on Viale Redi, Florence.
Regeneration of the TILEs for the maps

OSM data with non correct viability in Piazza Dalmazia, Firenze



After Correction of OSM data defining a correct viability of Piazza Dalmazia, Florence. Regeneration of the TILEs for the maps






SIGNORVINO

Control Room

What-If Analysis

Available data and techniques	What happened	What is going on now	What is going to happen	What-If: what is going to happen if a scenario occurs in the future	Which is the best solution
Historical Data, HD	Yes	No	No	No	No
Real Time Data, RTD	No	Yes	No	No	No
HD + RTD + Short term Predictions, STP(.)	Yes	Yes	Yes	No	No
HD + RTD + Analytical Model, AM(.) + Scenario Model, SM(.)	Yes	Yes	Yes	(Yes)	No
HD + RTD + Short and Very Long Term Predictions, SVLTP(.) + AM(.) + SM(.) + Simulation, S(.)	Yes	Yes	Yes	Yes	No
HD + RTD + SVLTP(.) + AM(.) + SM(.) + S(.) + KPI(.) based Decision	Yes	Yes	Yes	Yes	Yes

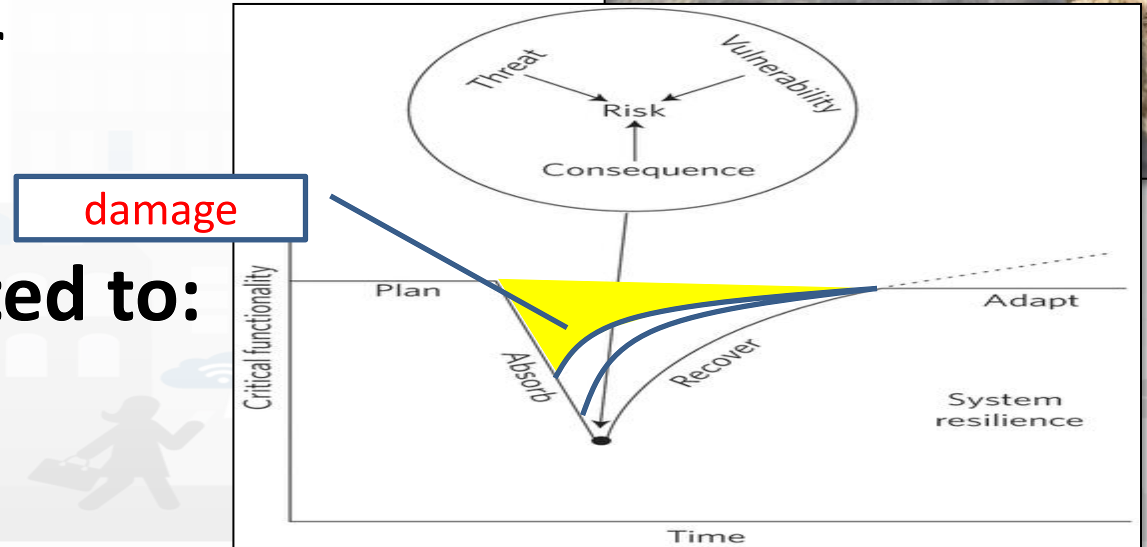
Early Warning, Detection

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

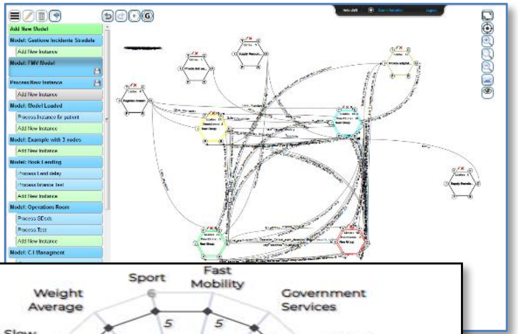
Impact:
- Early warning, faster reaction
- Increased resilience

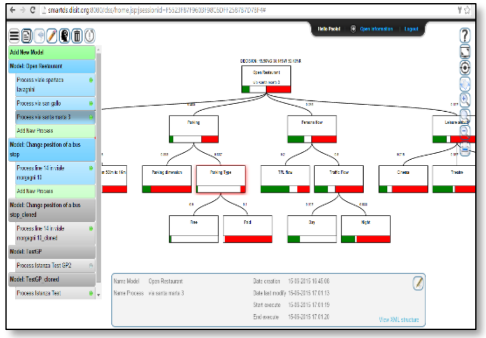
Several metrics related to:
- Volume of retweets
- Sentiment analysis

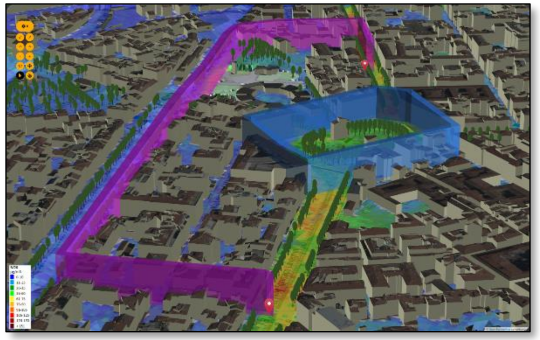
Prepare
Absorb
Recover
Adapt

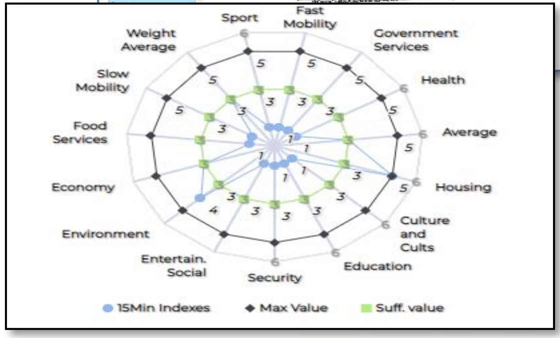


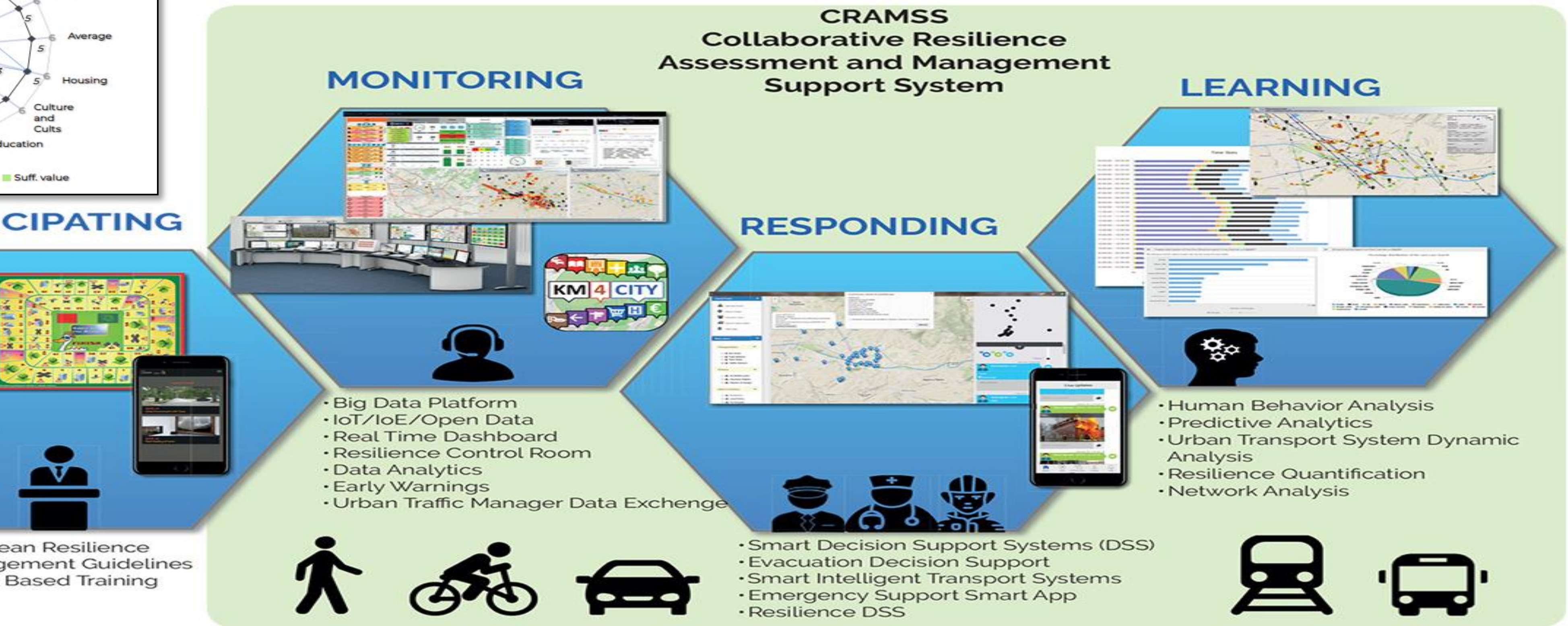
ERMG: European Resilience Management Guide





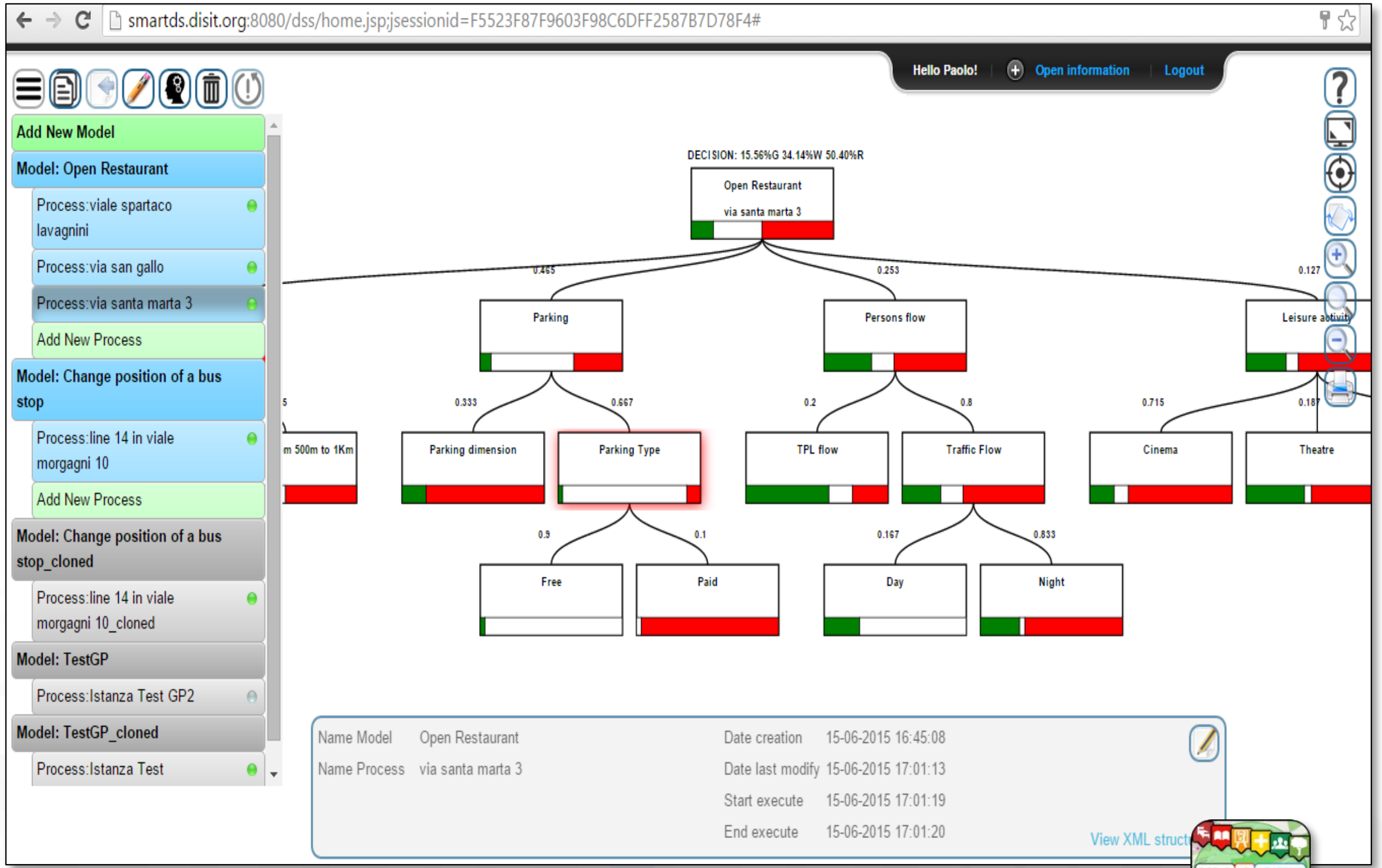






Smart Decision Support , system thinking

- **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, …



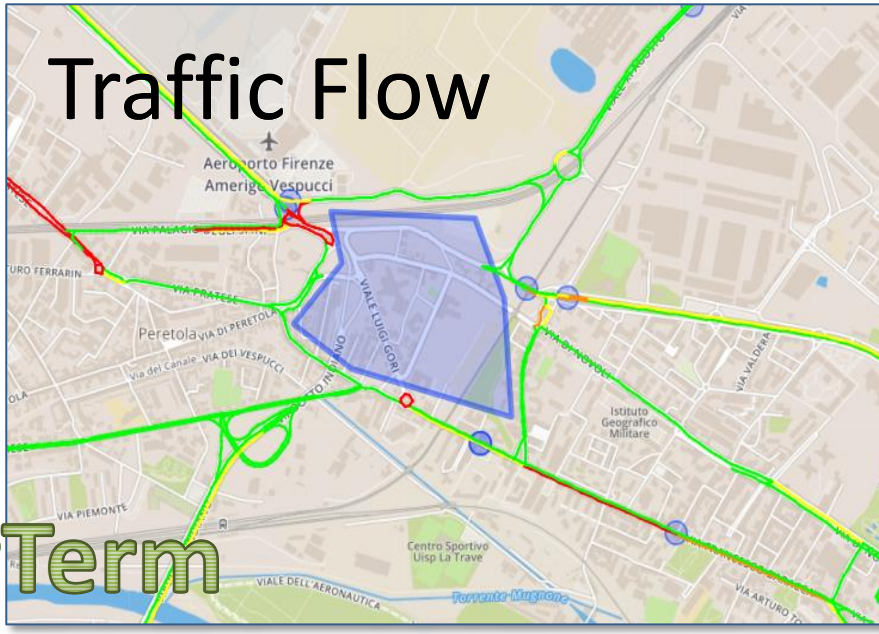
http://smartds.km4city.org

TOP

WHAT-IF Analysis

Decision Support Systems, What-if

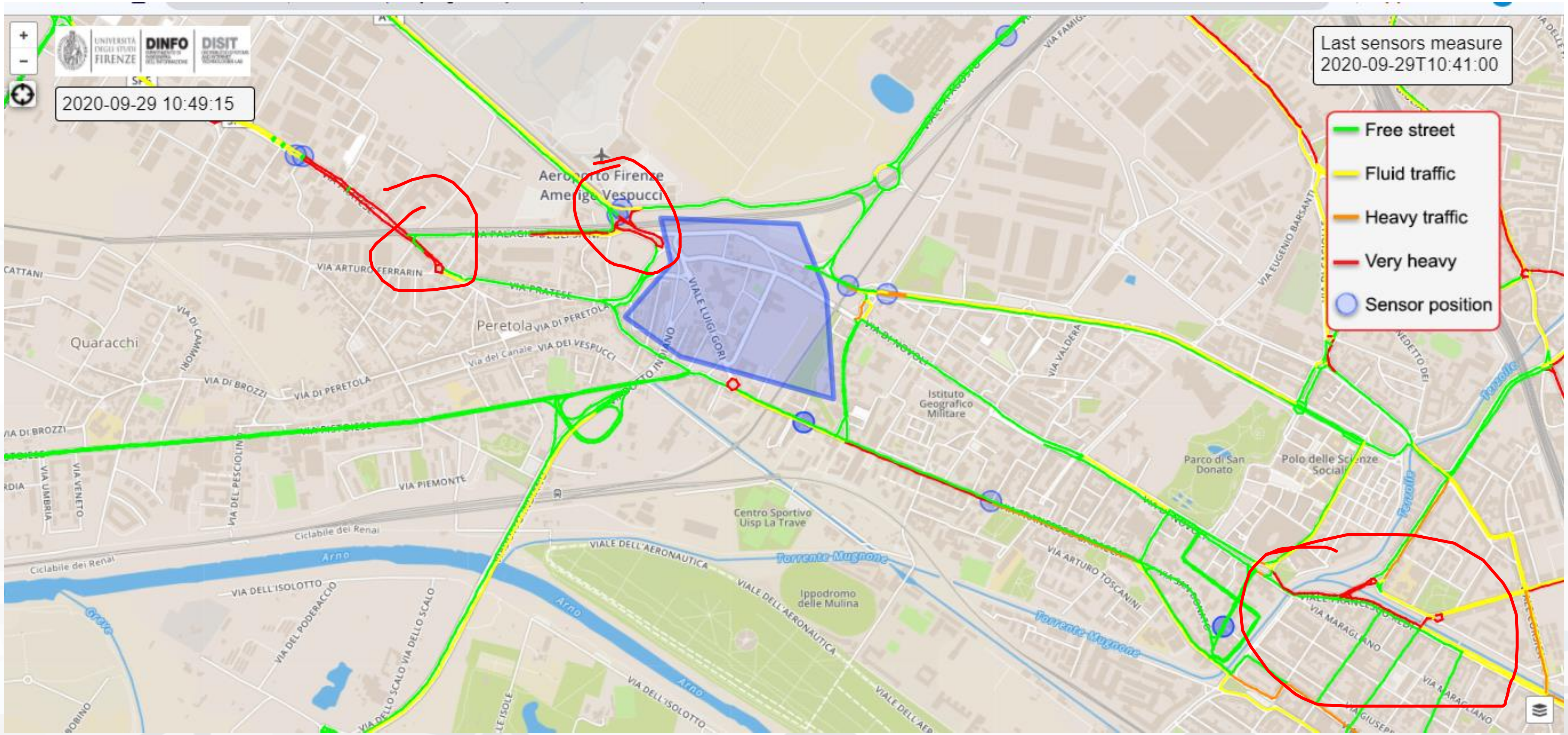
- **Event planning, via what-if analysis**
  - Change in the graph structure of the city
  - Impact on the flow of people and vehicles
  - Adaptation: public transport, traffic, pedestrian management, etc.
- **Immediate reaction to natural events or not**
  - Everything is ready and updated in real time
  - Each view is contextualized in terms of data: descriptive and prescriptive
- **Digital Twin**
  - More detail in the context integrated data
  - Greater realism in deductions and representations
  - Less fragmentation and non-uniformity in the views to support decisions



LongTerm

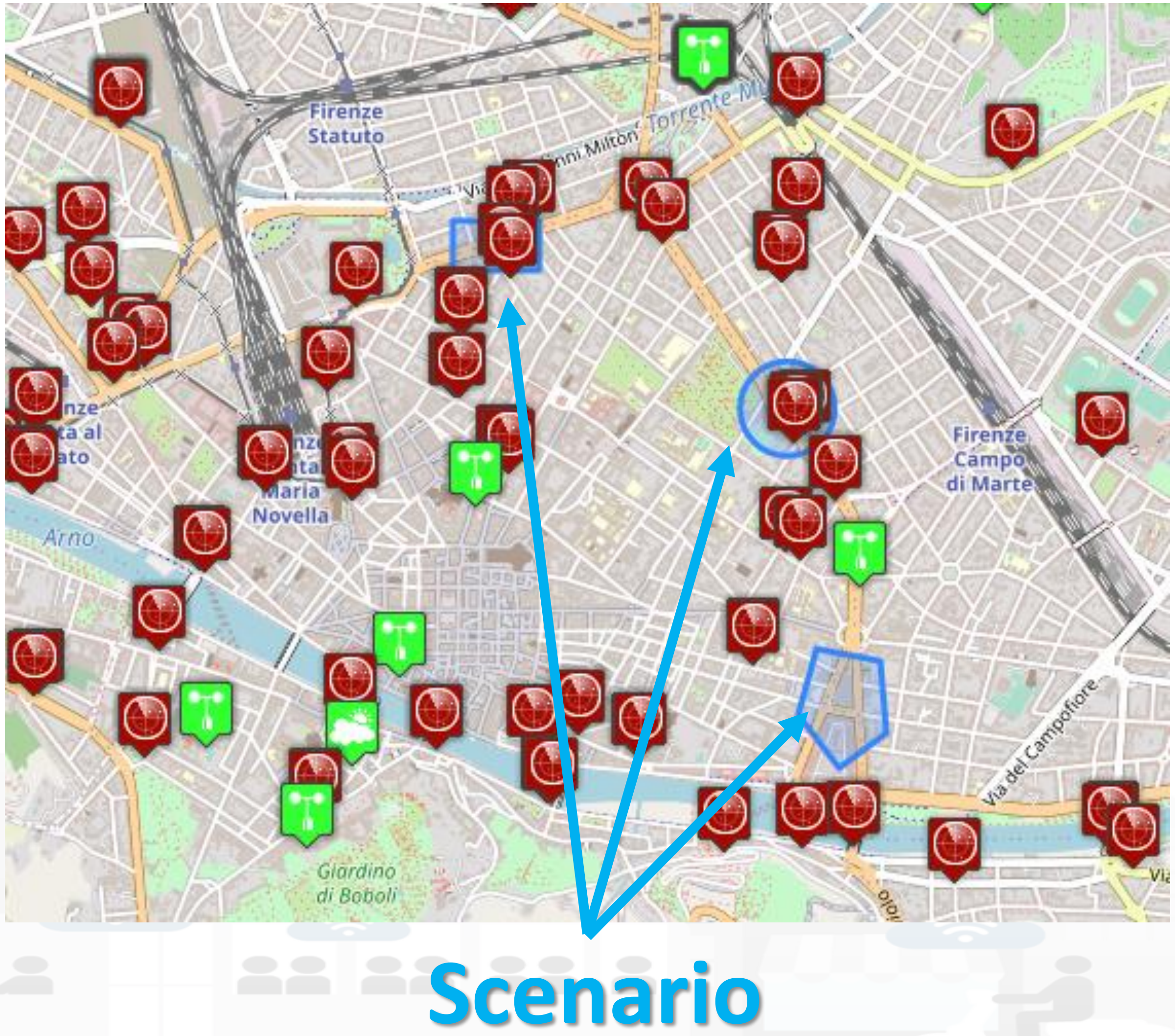
ShortTerm

Computation of Traffic Flow Evolution, cascade effects



What-If Analysis Concepts

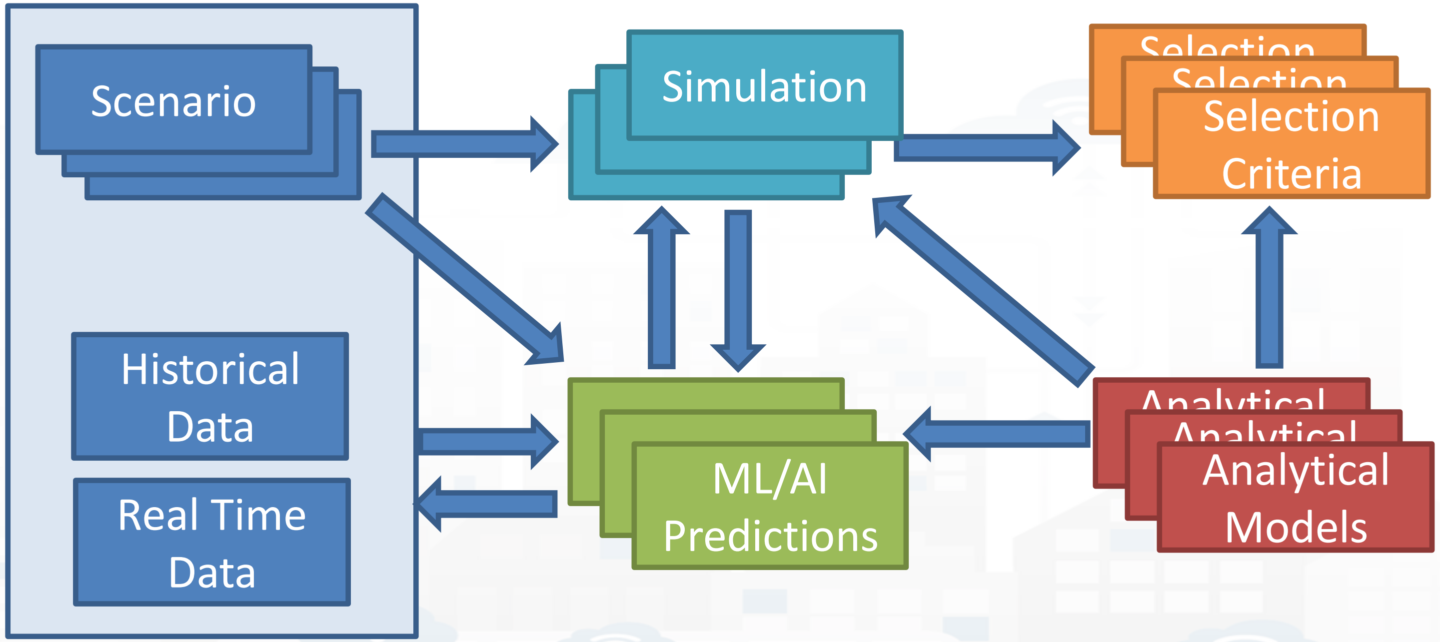
- What is going to happen at Services if certain conditions/cases are going to occur
- Formalize: Conditions/cases, Services
- Scenarios of Cases+Services Vs Solutions are Studios
- You can define, save, load:
  - Scenarios and Studios



What-if: what is going to happen if …. this and that

- **What is going to happen at:**
  - People, Economy, Society, ..
  - Traffic, Pollutant, Parking, structures
  - Equipment, .. …
- **if certain unexpected events would occur**
  - Scenario definition
  - Guessing future data…
- **Taking into account**
  - Historical Data
  - Real Time Data
  - Contextual data

Decision Support System
KPI, Optimization
Visual Analytic: animations



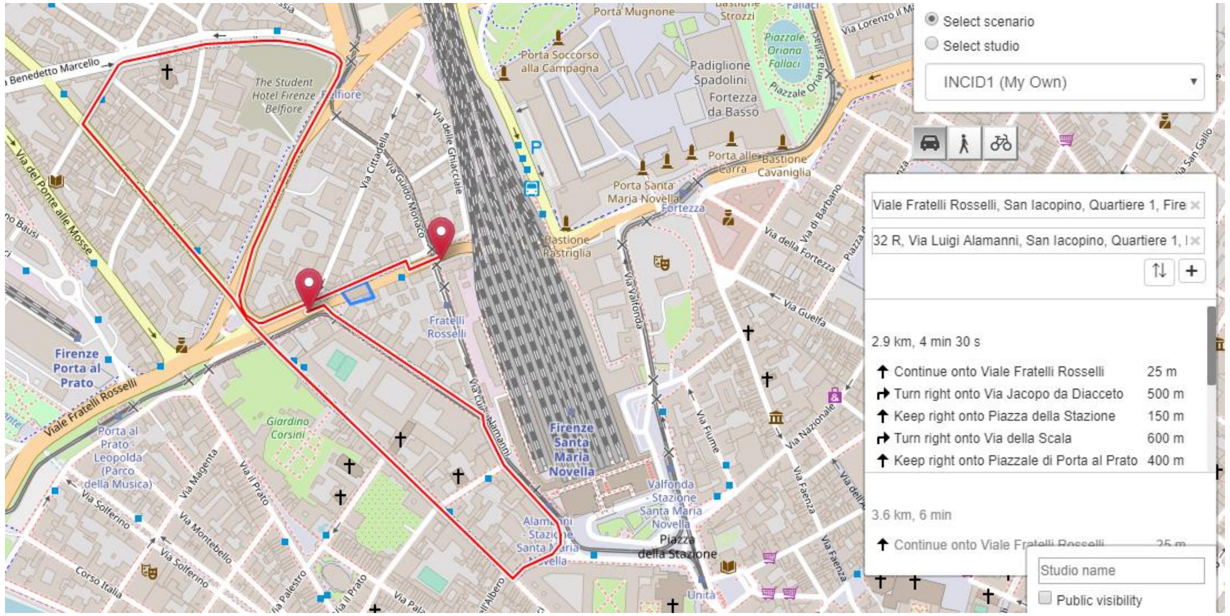
What-If Analysis

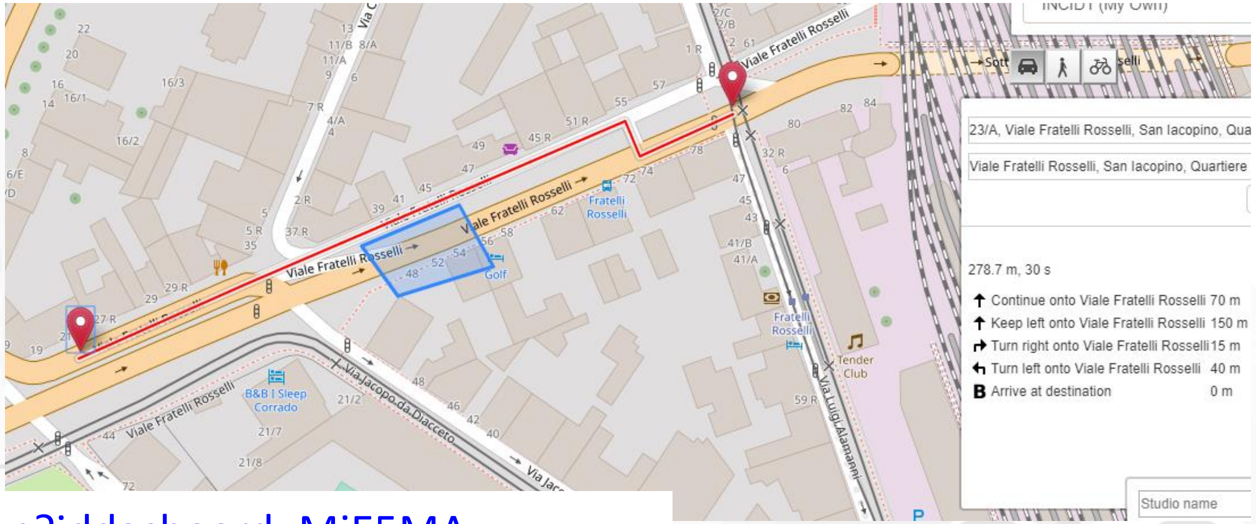
Accidents and elements blocking Points and Shapes taken into account for:

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

Assessment on the basis of changes:

– Mobility demand assessment
– Mobility Offer assessment

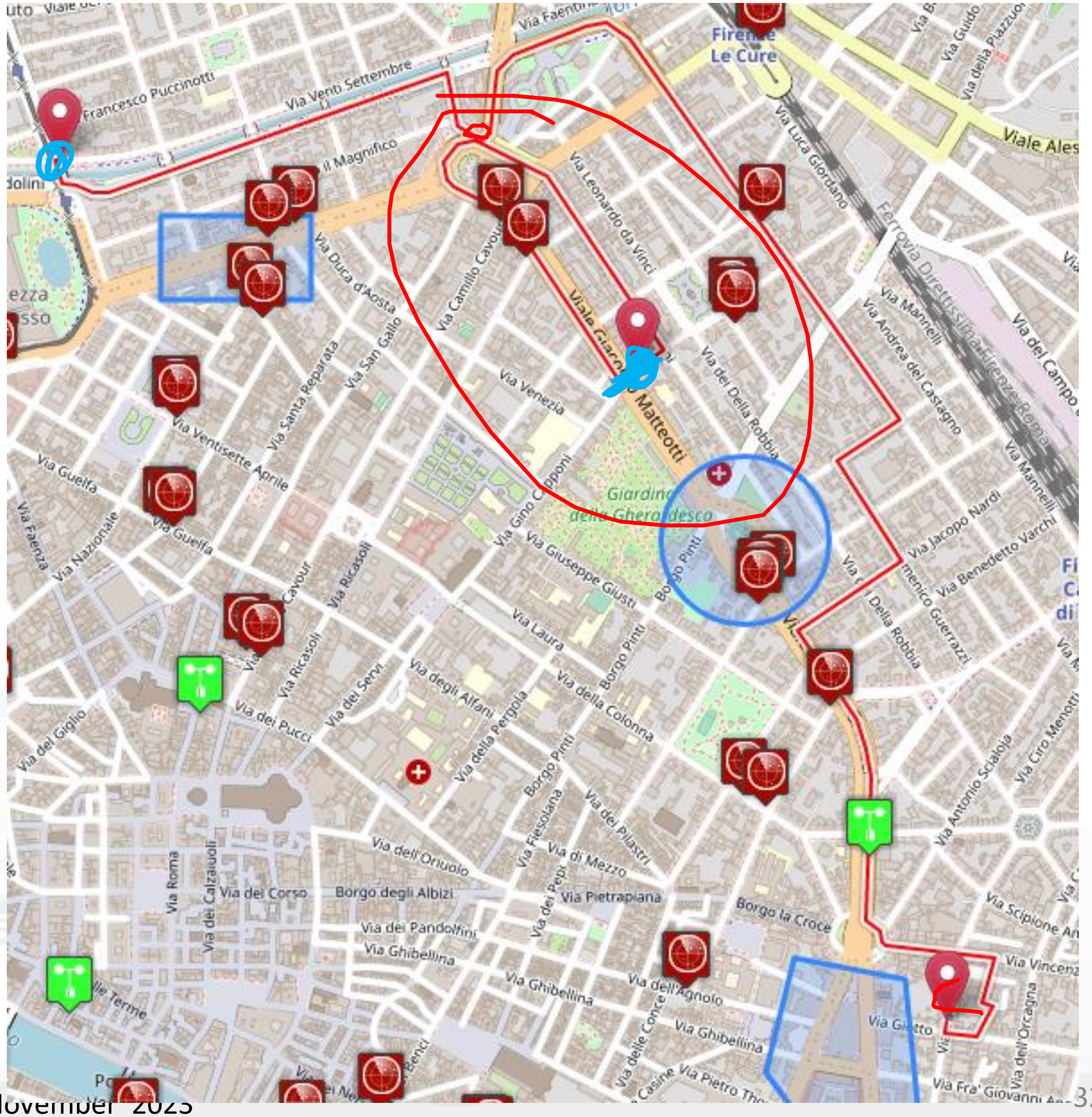




https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MjE5MA==

Impact on Routing

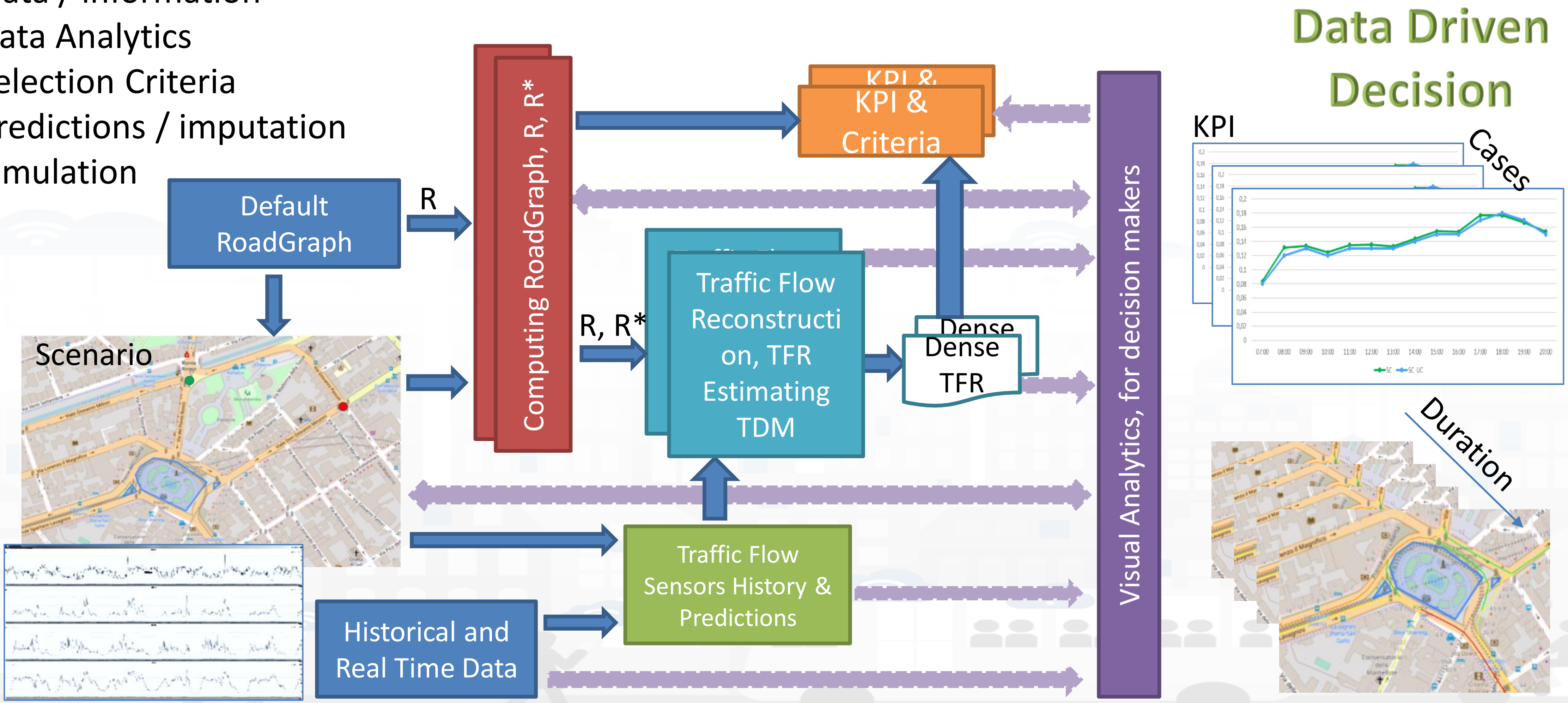
- Scenario with multiple shapes
- Conditional Routing
  - – avoiding areas or
  - – reducing traffic in those areas
  - – Multiple stop points



What-if: Simulation for Traffic Flow

At the same color corresponds the same area:

- Data / information
- Data Analytics
- Selection Criteria
- Predictions / imputation
- Simulation



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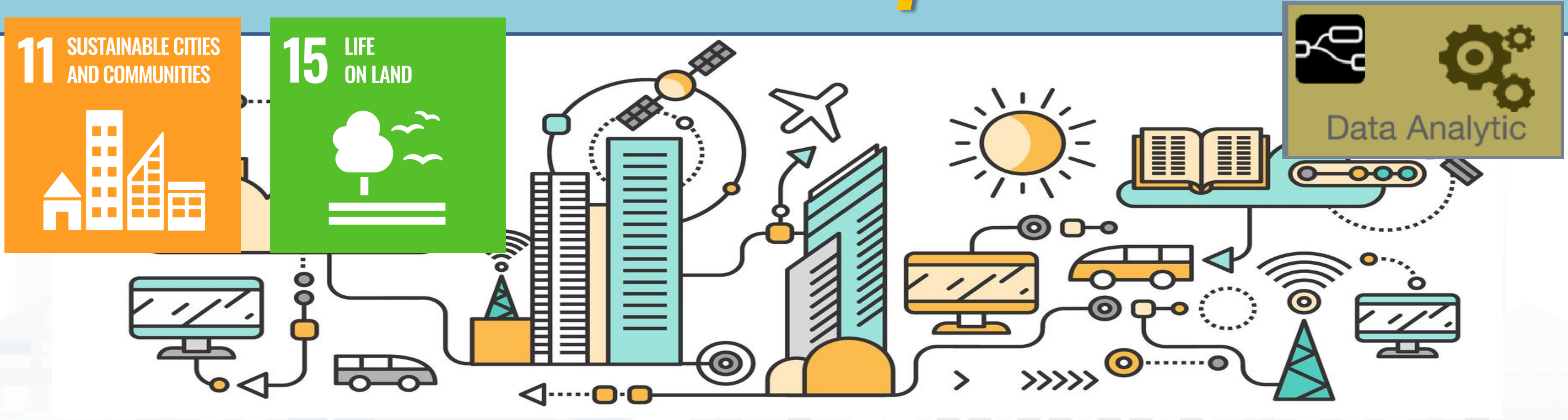
TOP

DORAM: Demand of Mobility vs Offer of Transportation



DORAM

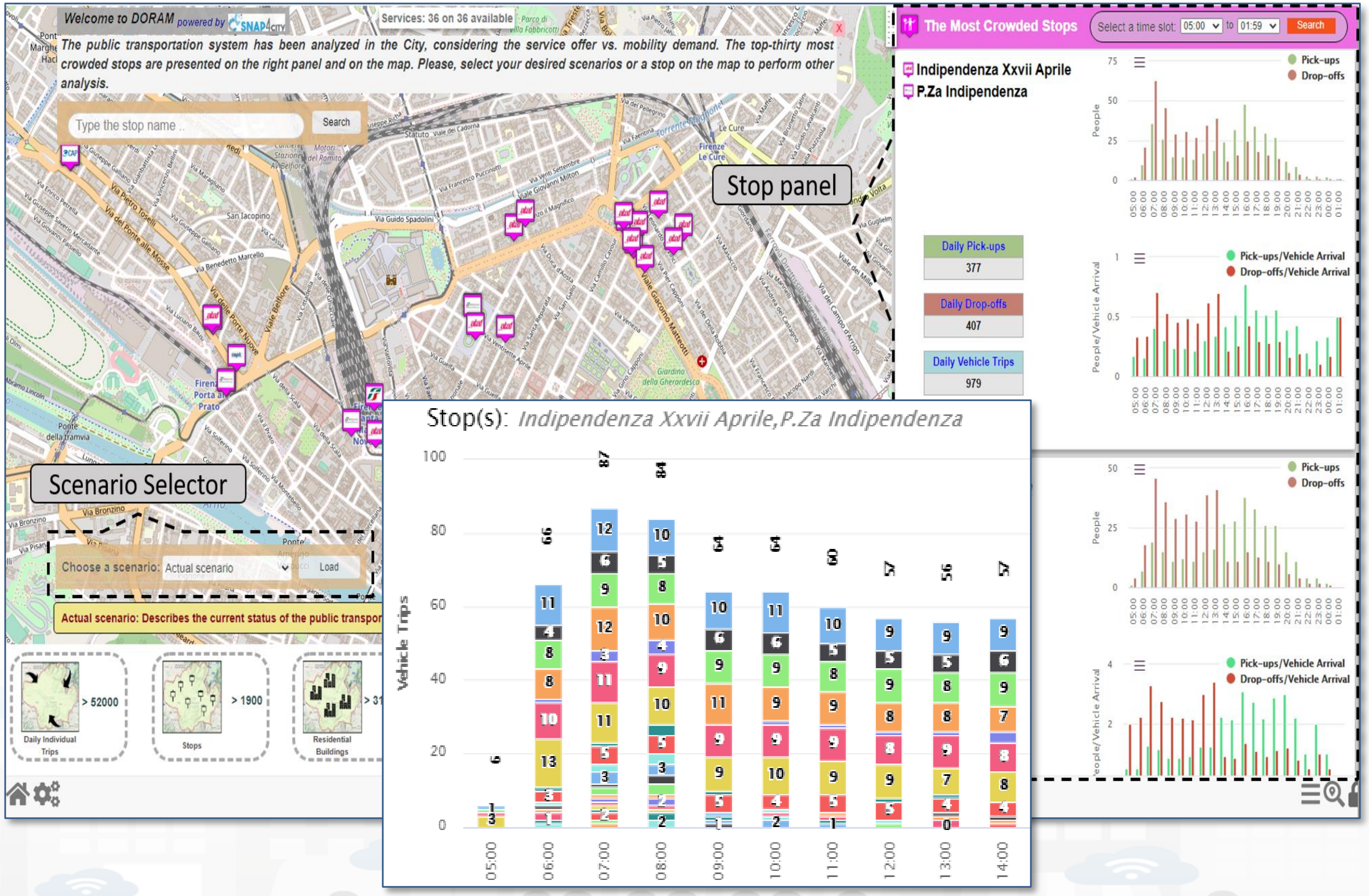
Analysis of

- **Demand** of Mobility
  - Action Based
  - Via OD matrices, several kinds
  - POI, city structure, etc.

With respect to

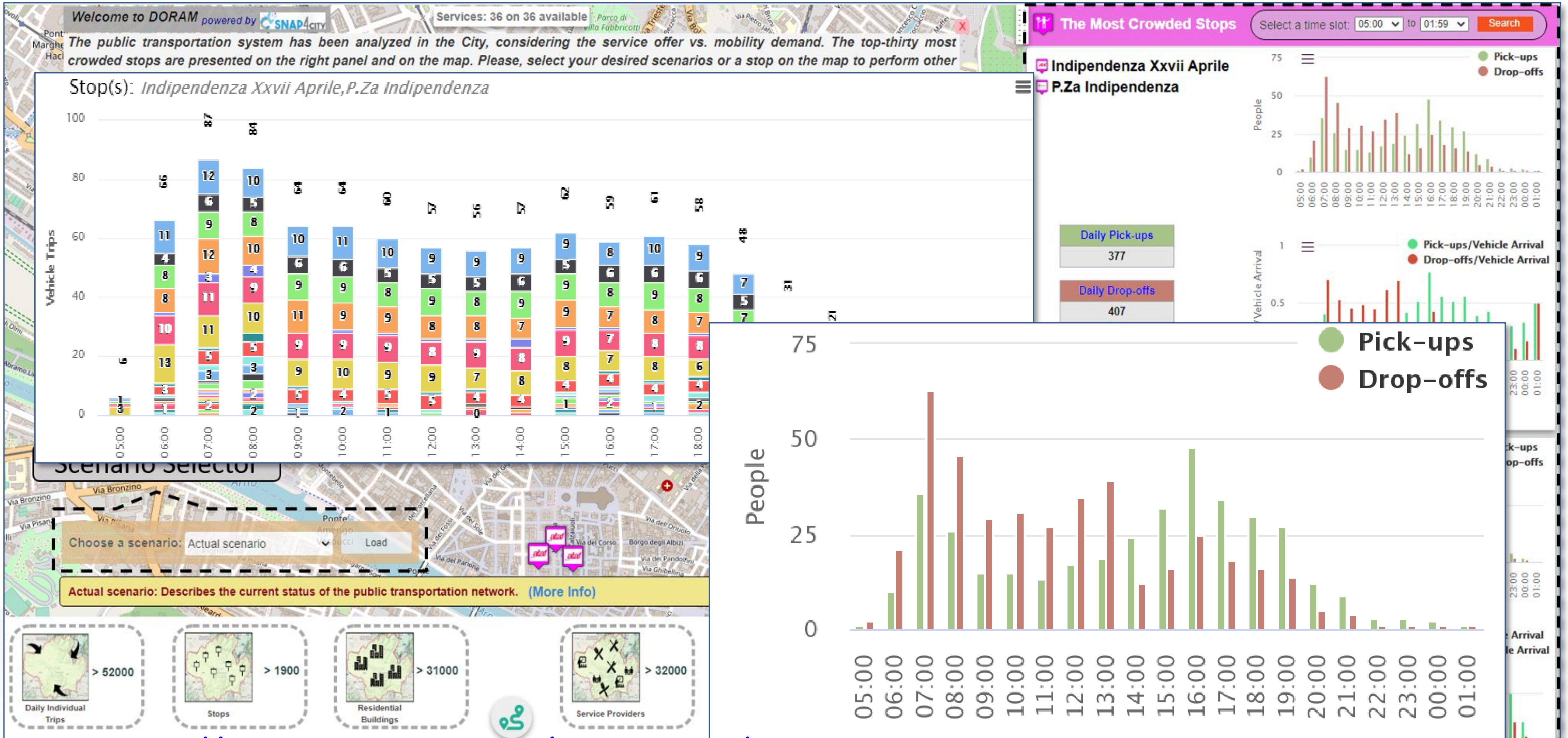
- **Offert** of Transportation:
  - Public services
  - Private services
  - Multiple agencies
  - GTFS

Critical Busses, busstops, paths, rides, etc.



https://www.snap4city.org/odanalyzer/#b

DORAM



https://www.snap4city.org/odanalyzer/#b

DORAM

Action based using Snap4City Knowledge Base

DORAM - Demand OfffeR Analyzer for Mobility

Citizen Mobility demand and habits, real time traffic

Service offer (GTFS)

https://www.snap4city.org/odanalyzer/#b

analysis of the offer vs demand (DORAM)

GTFS variation to improve the efficiency of the service

City Mobility Operator(s)

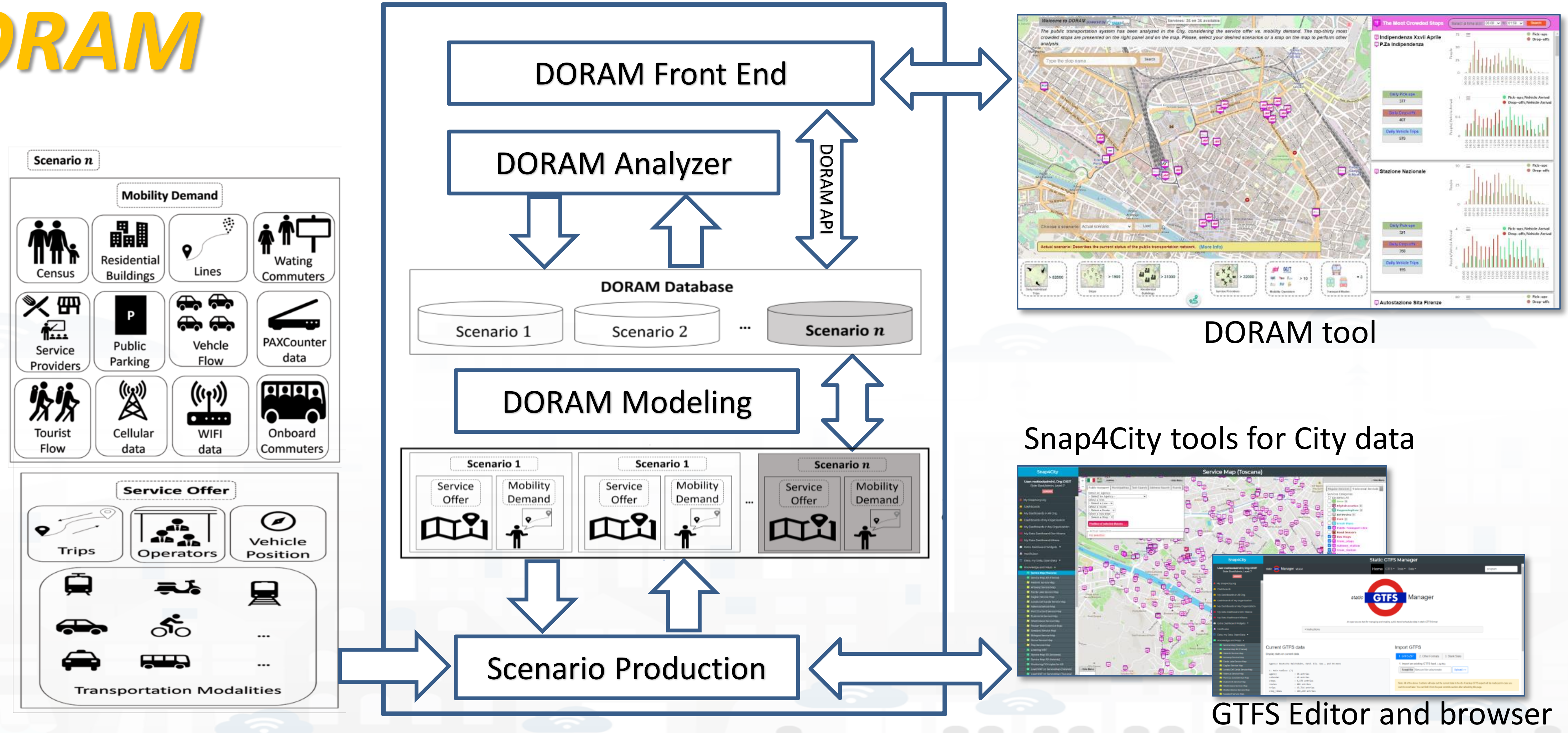
Planned Bus/Tram/Train/ etc. stops/trips and timetables (GTFS)

What can produce the Analysis tool by KPI

- 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..
  - Changes on city structure and paths
  - Size of the buses

https://www.snap4city.org/odanalyzer/#b

DORAM



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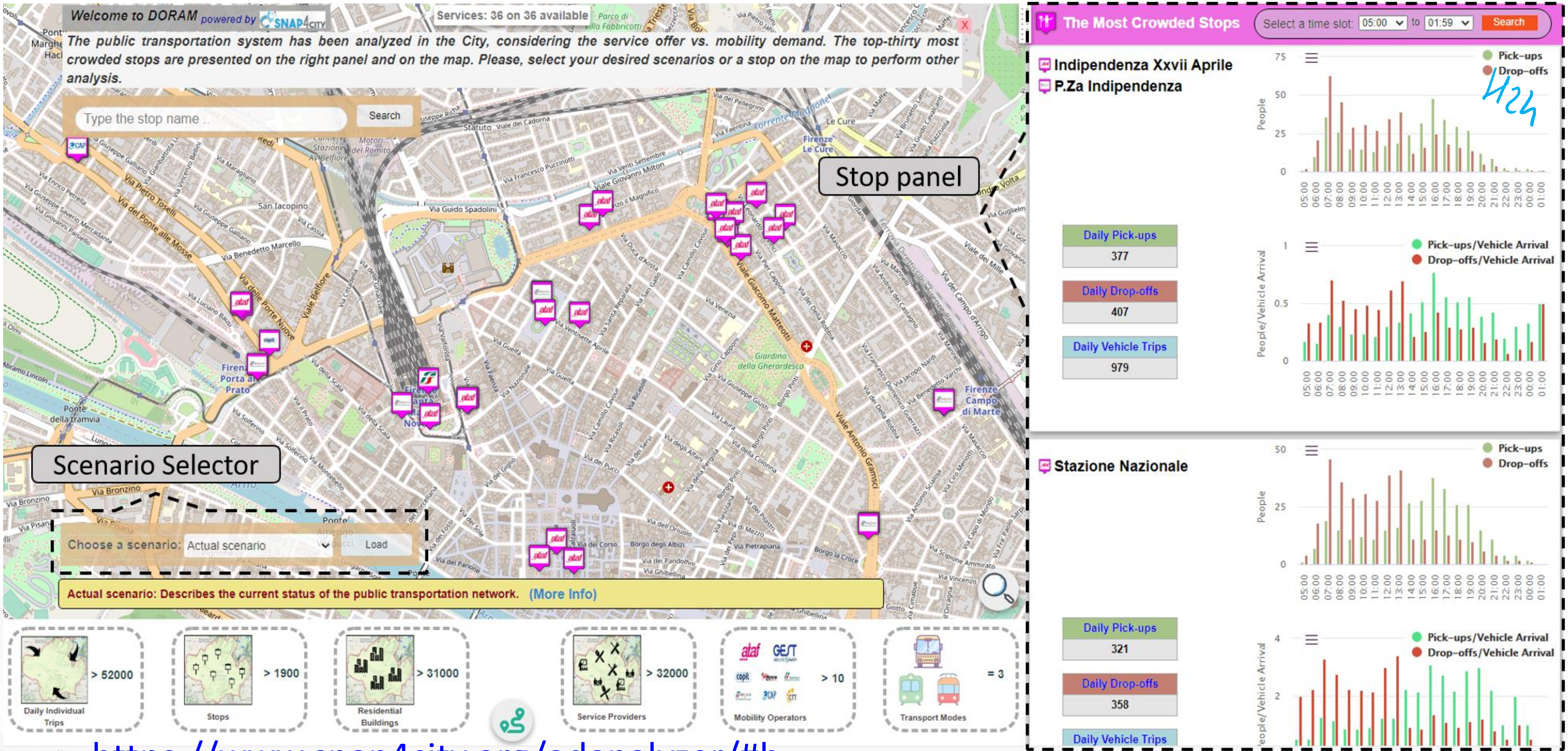
DORAM



https://www.snap4city.org/odanalyzer/#b

TOP

Routing, Multimodal Routing, Dynamic Routing

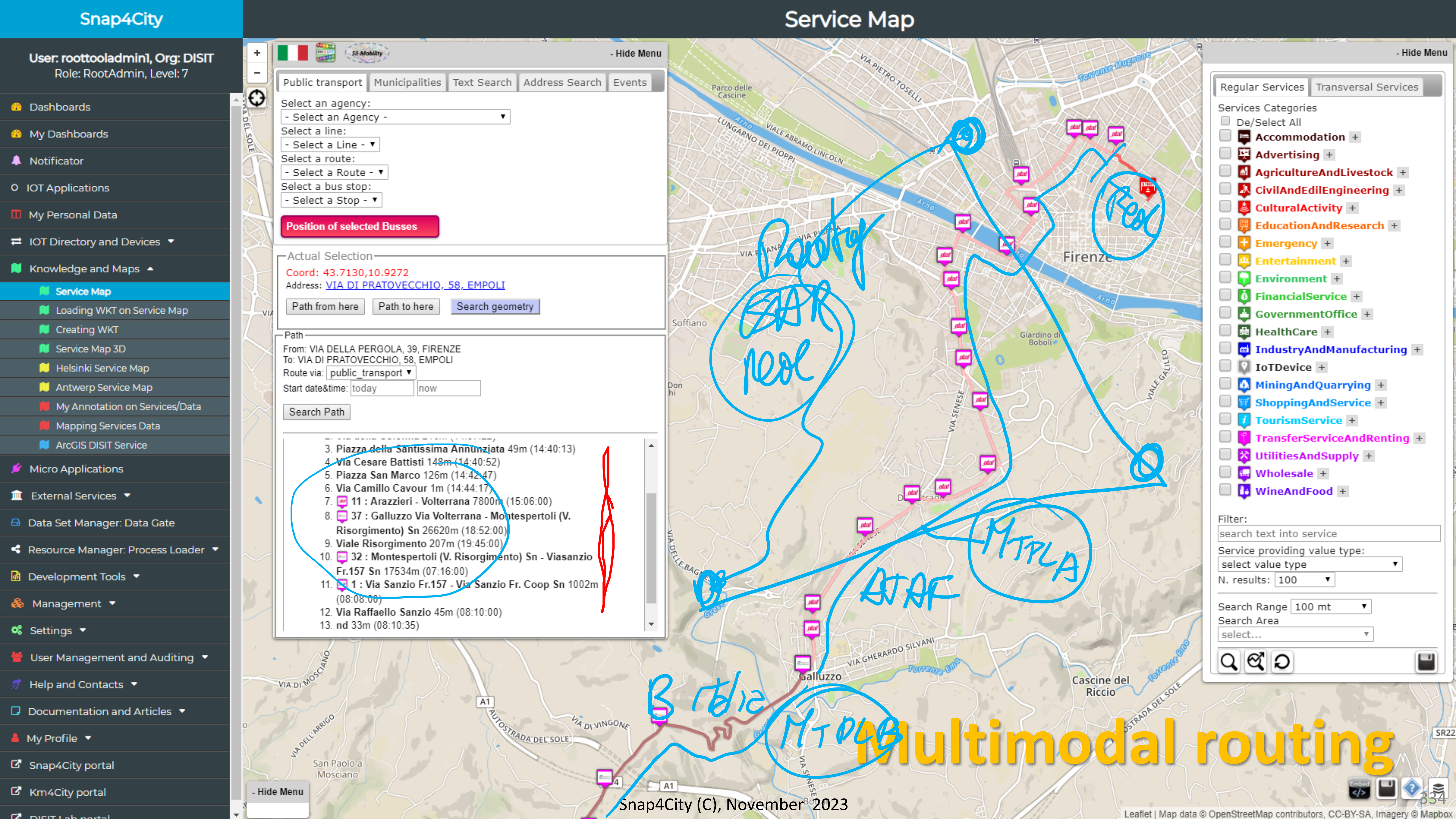
11 SUSTAINABLE CITIES AND COMMUNITIES

15 LIFE ON LAND

Data Analytic

Routing

- **Routing**: From XX to YY, Travel means:
  - private as cars, bike, pedestrian, public transport ..
  - Public: busses, tramway, train, etc.
- **Multimodal routing**: public travel means (busses, train, metro, etc.), pedestrian, etc.
- **2D and 3D routings**
- **Taking** into account:
  - Multiple intermediate points
  - Constraints/preferences:
    - size of roads, pollutant, traffic flow, obstacle/barriers, noise
    - Limitations on paths per travel means / vehicle kind
- **Dynamic Routing** enabling the addition of constraints on the user interface. For example: *barriers and/or selecting constraints*



Multimodal routing

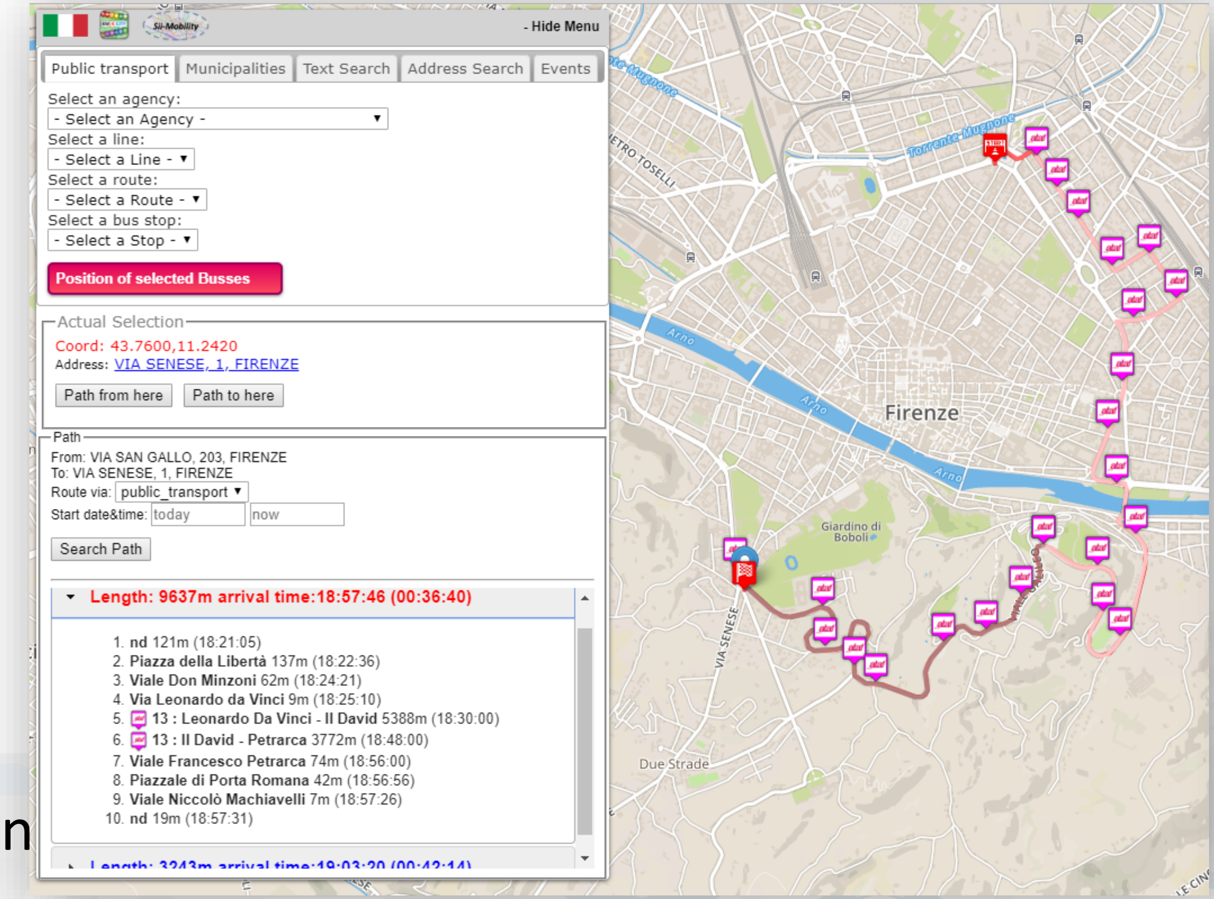
Routing and Multimodal Routing

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



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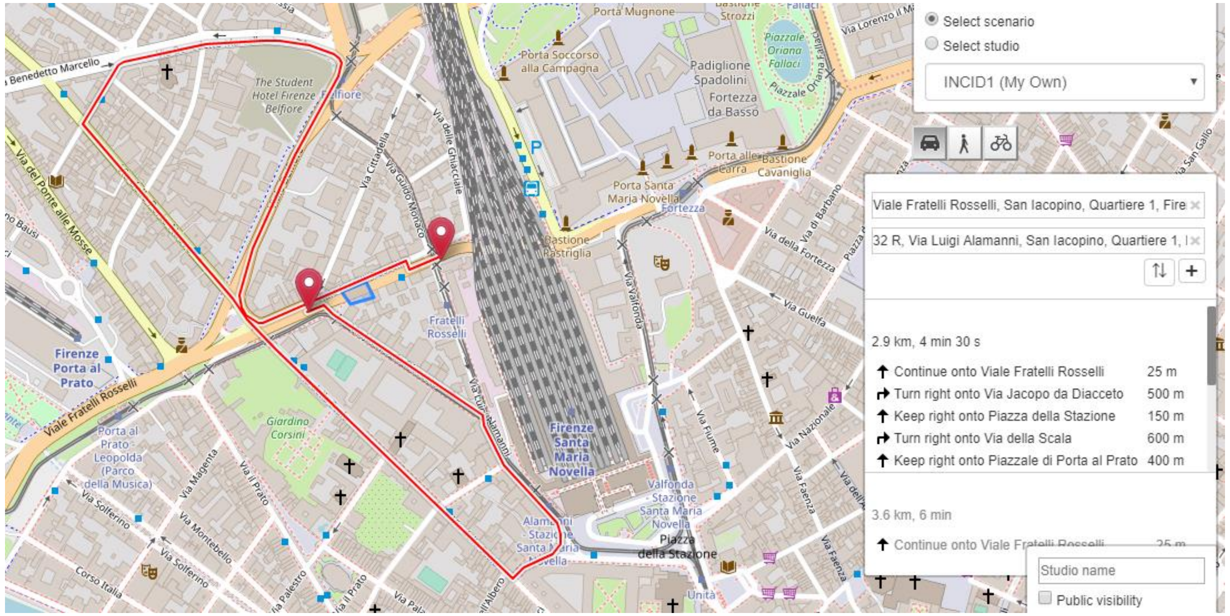
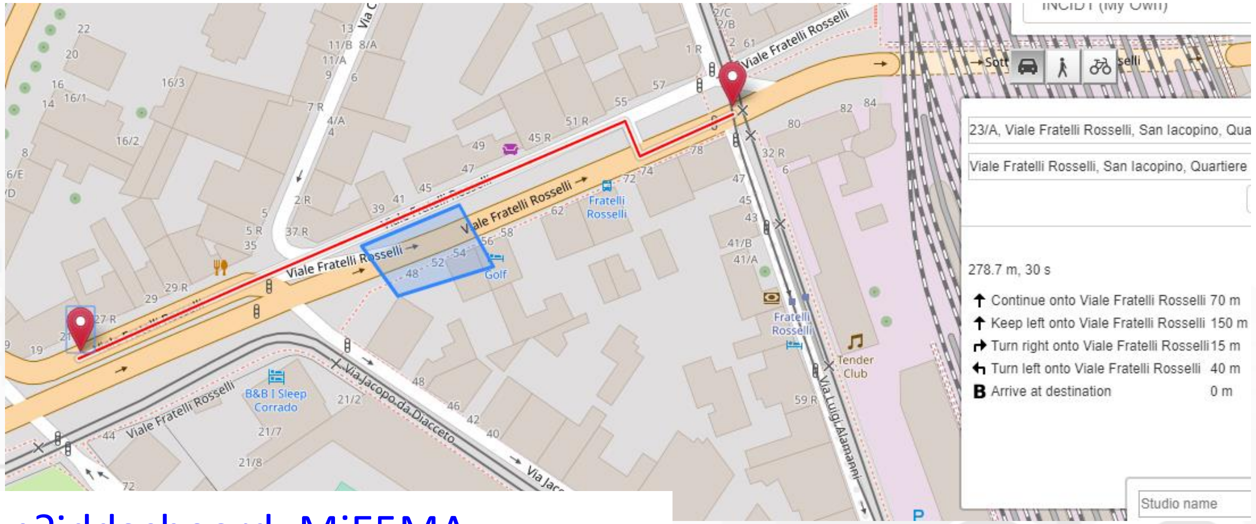
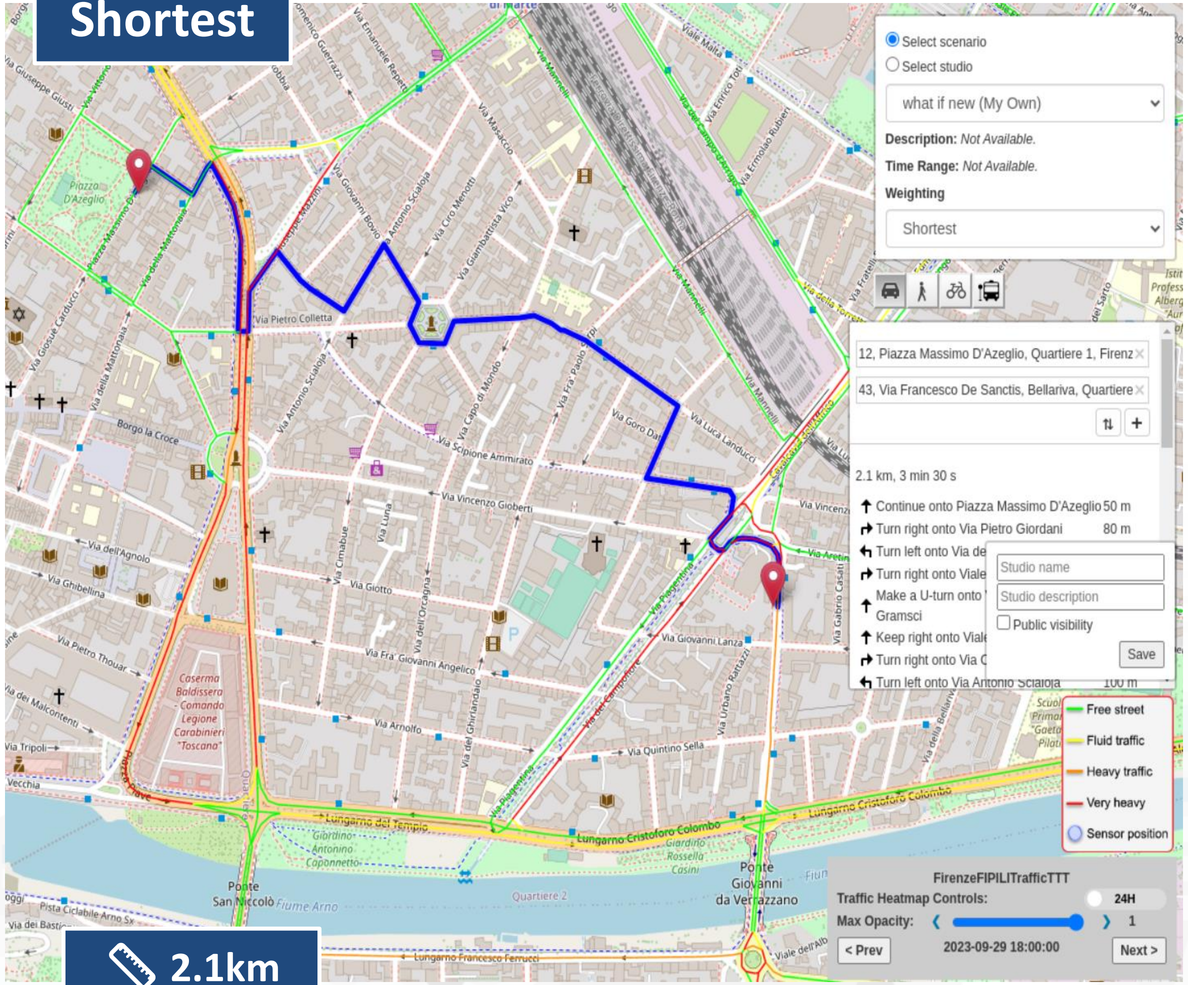




https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MjE5MA==

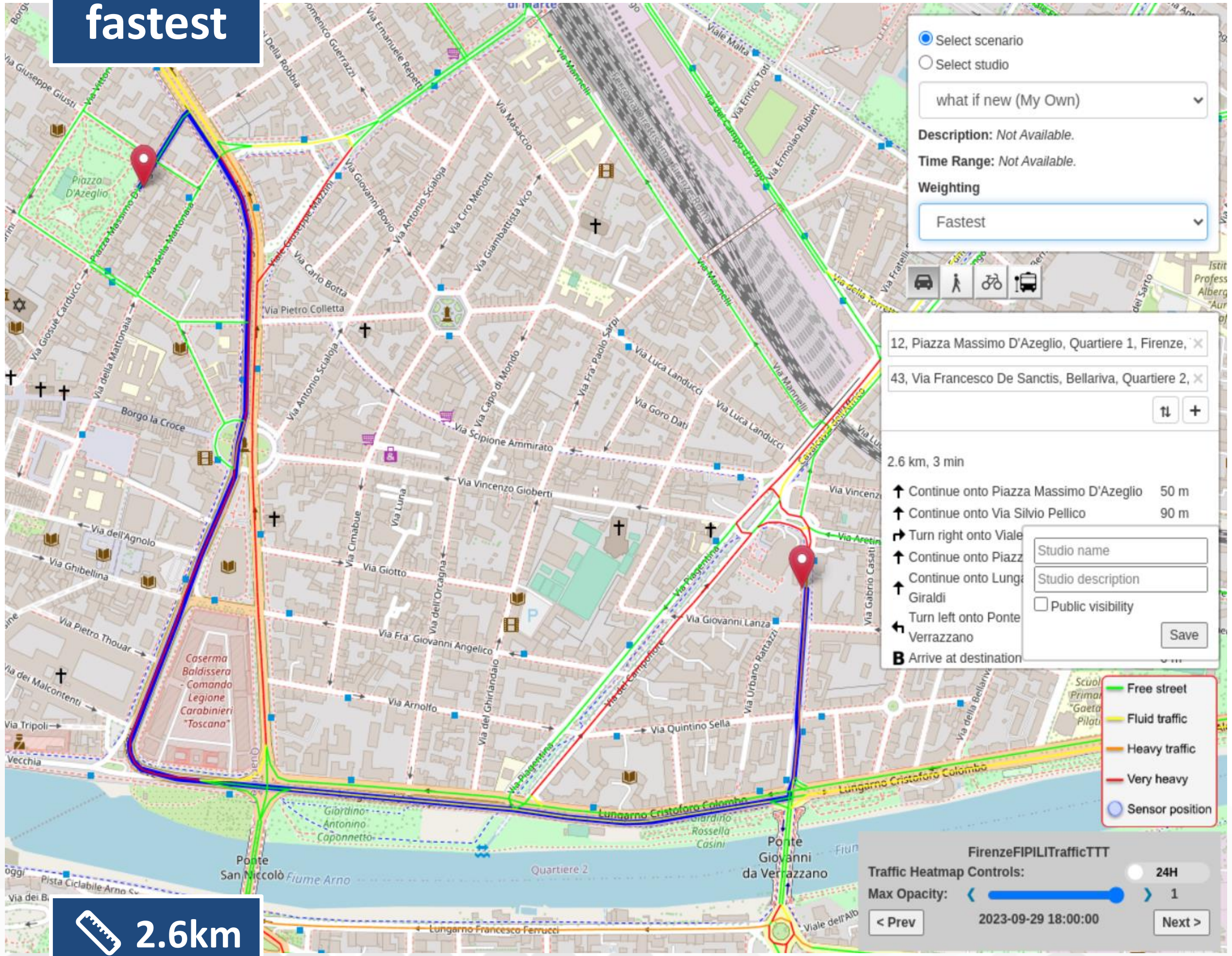
Constrained Dynamic Routing: Traffic Flow

Shortest



2.1km
3min 30s

fastest



2.6km
3min

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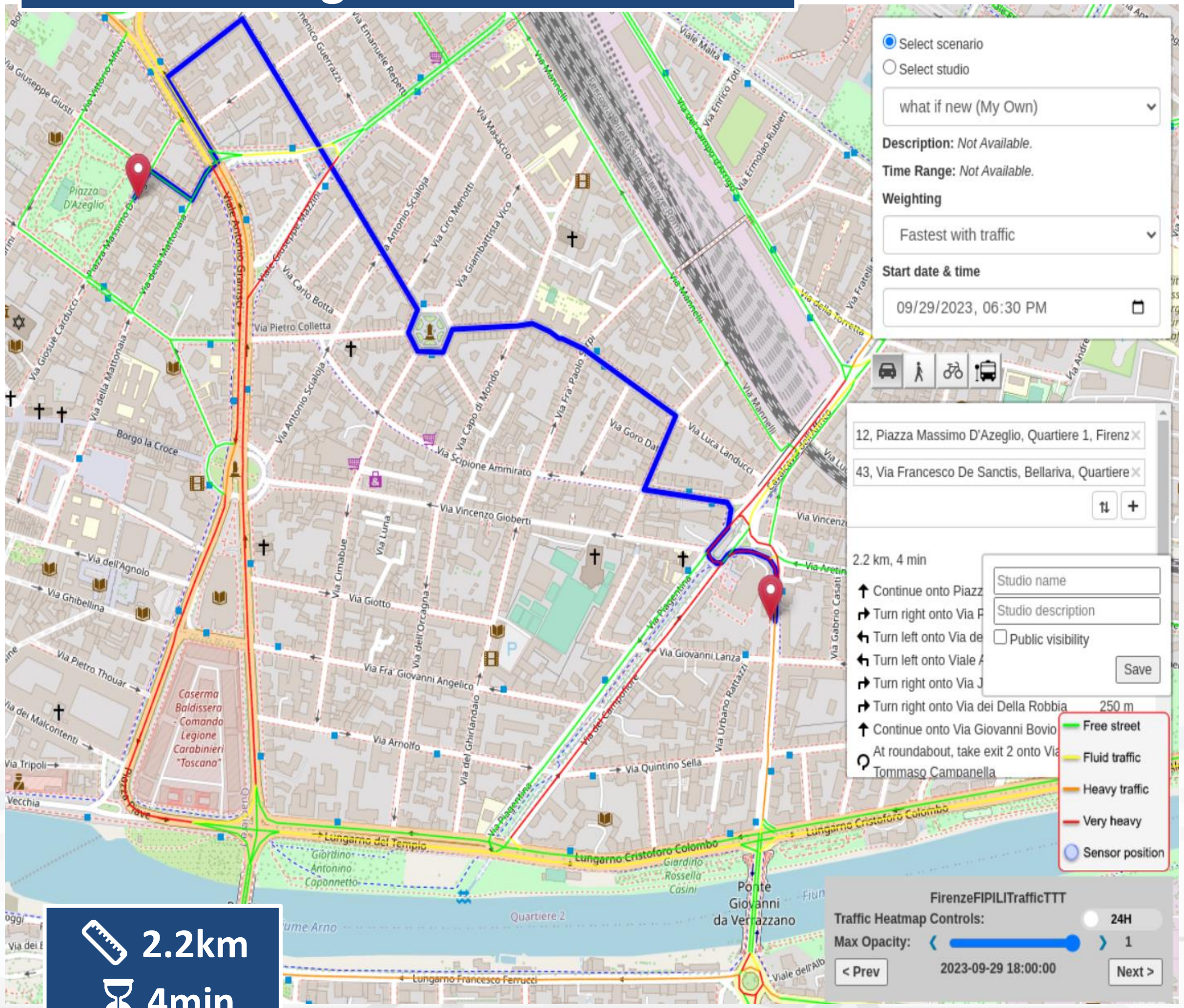
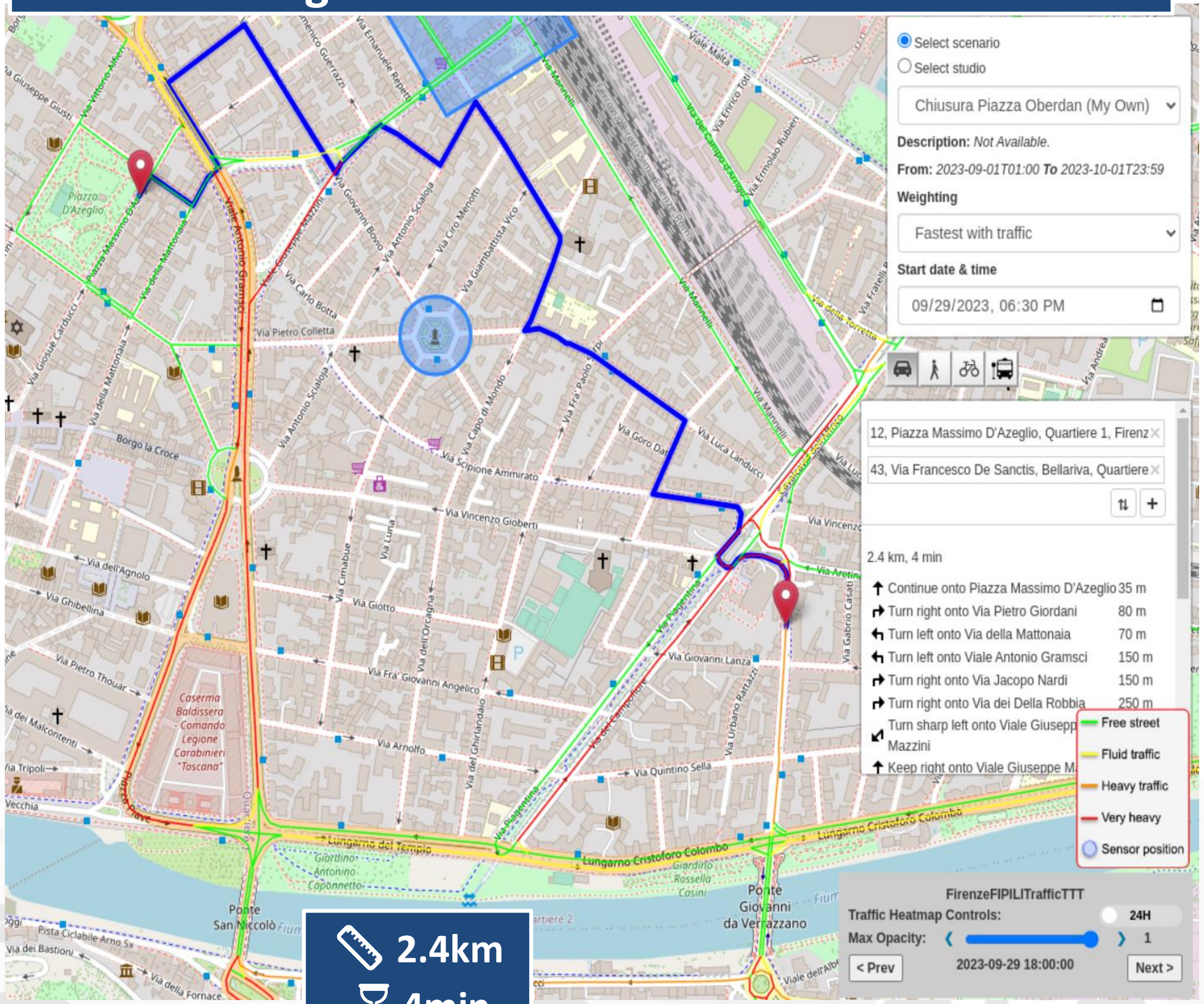
Constrained Dynamic Routing: Traffic Flow

Fastest taking into account traffic



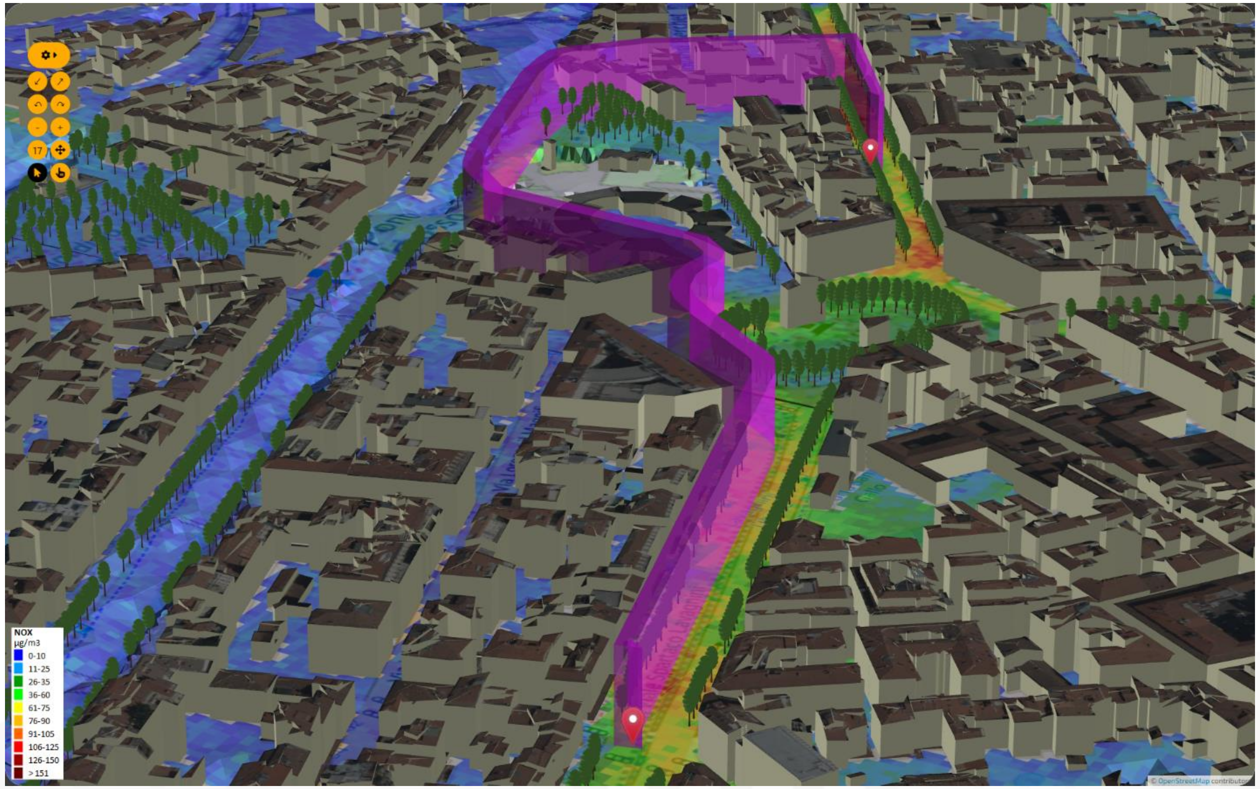
2.2km
4min

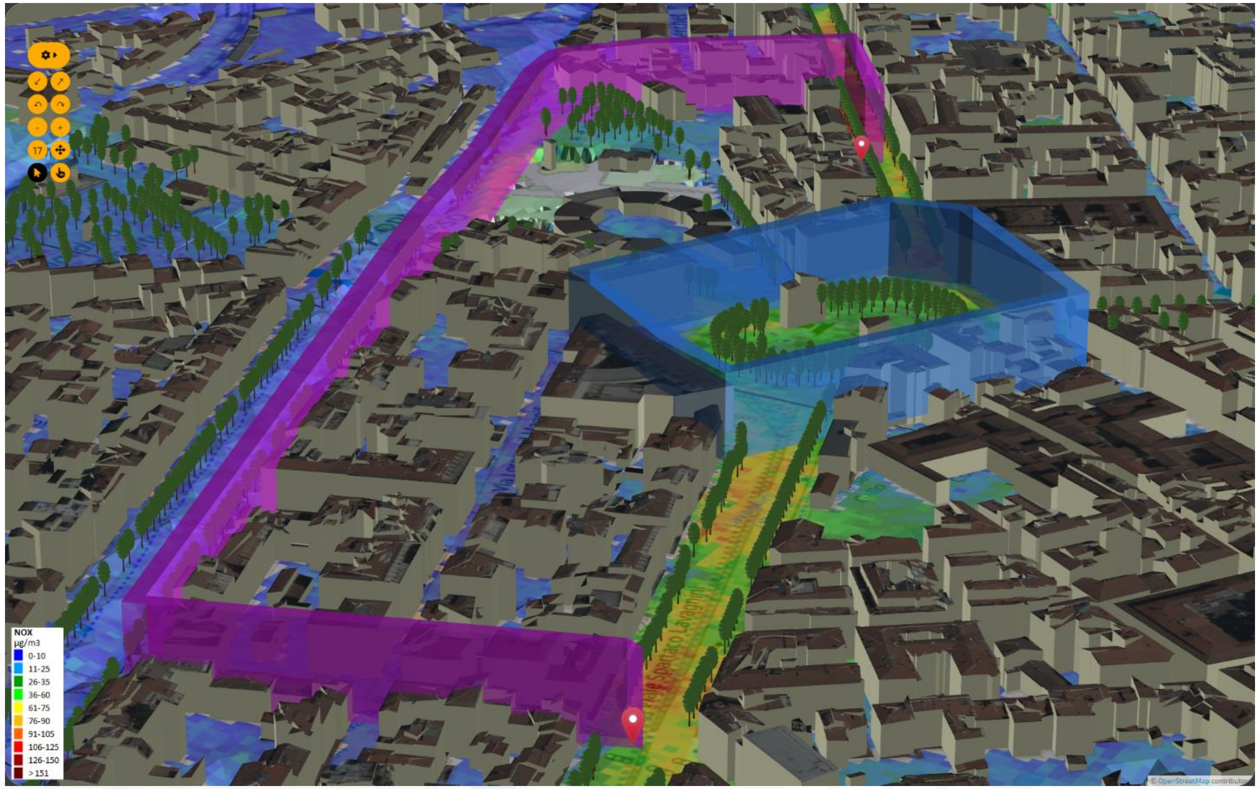
Fastest taking into account traffic and blocked areas



2.4km
4min

Dyamic Routing in 3D space





TOP

Predictive Maintenance

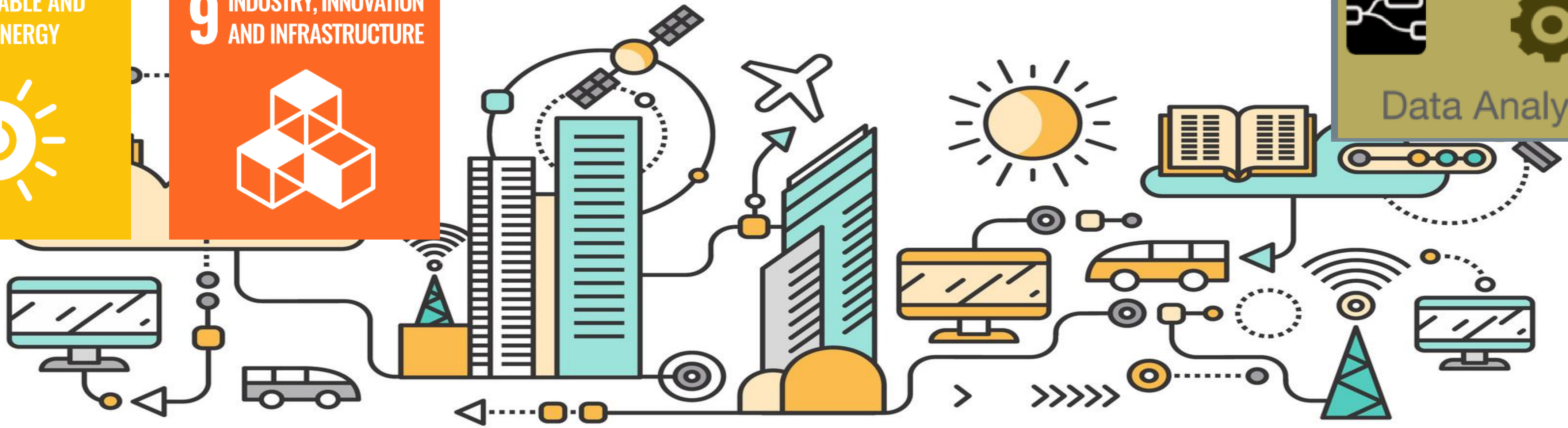
TOP

Predictive Maintenance

7 AFFORDABLE AND CLEAN ENERGY

9 INDUSTRY, INNOVATION AND INFRASTRUCTURE

Data Analytic

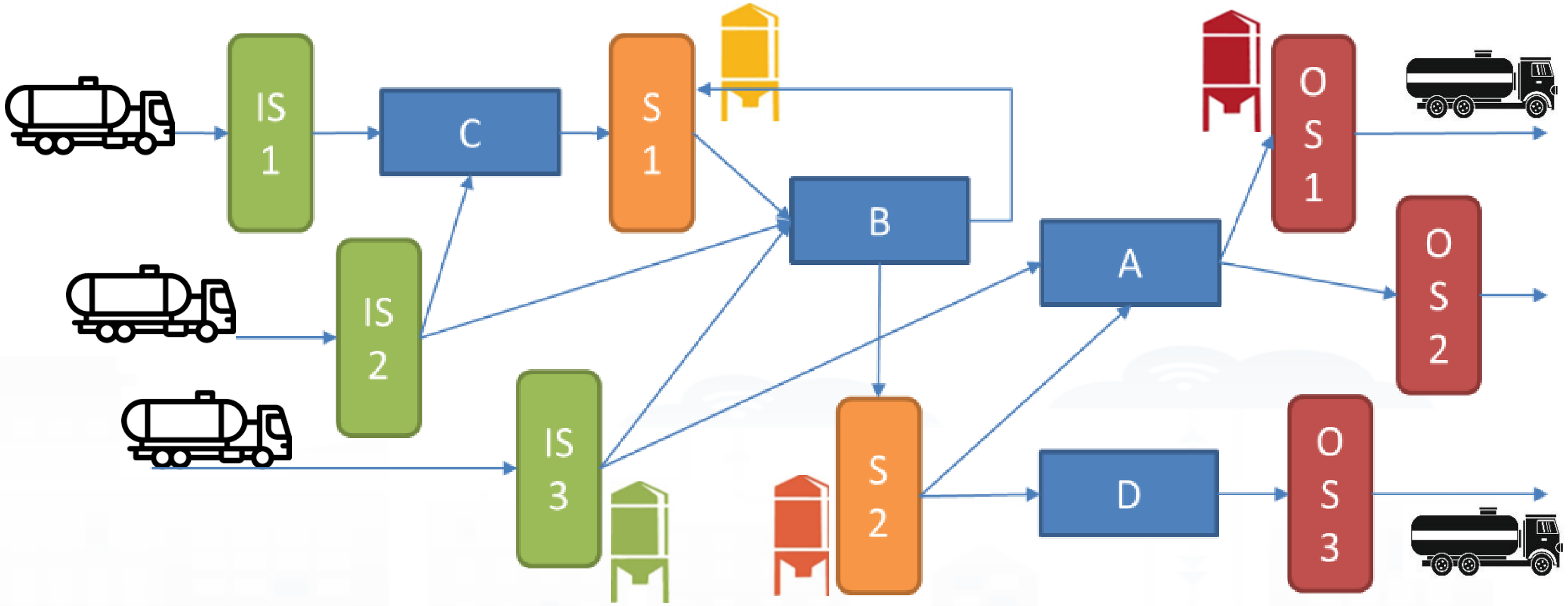


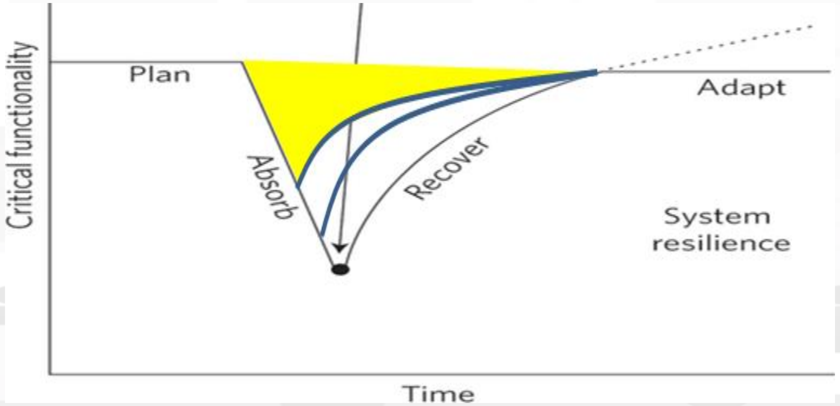
Industry 4.0

- **ALTAIR SODA-4.0 project**
  – maximize the efficiency and productivity of plants, reducing downtime
  – in order to improve competitiveness in the market
- **Goals and drivers:**
  – Business intelligence tools on maintenance data
  – predictive maintenance approach into the whole control and management systems Predictive models for engagement
  – predict plant failures 60 minutes before it happens
  – Provide indications on the area of failure via XAI

Complex cause-effect realtionships

- **Elements:**
  - Machines: A…C
  - Storage: silos…
  - Flows:…
- **Dependencies**
  - Cascade effects
- **Early warning**
  - Reduction of costs
  - Recovering from failure is more expensive than correcting in advance
  - Possible advanced replan and reschedule: secondary solutions





Workflow

Data acquisition Production - Maintenance

Feature selection, Feature engineering

CNN-LSTM Training

Validation AI Model

Classification Model

CNN-LSTM Engine

F/NF

Explainable/XAI (Shap)

{features (t)}

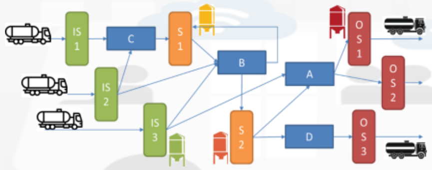
Business Intelligence for Maintenance

integration of workflow management system for maintenance with general control systems and data flow

Decision making on more cases

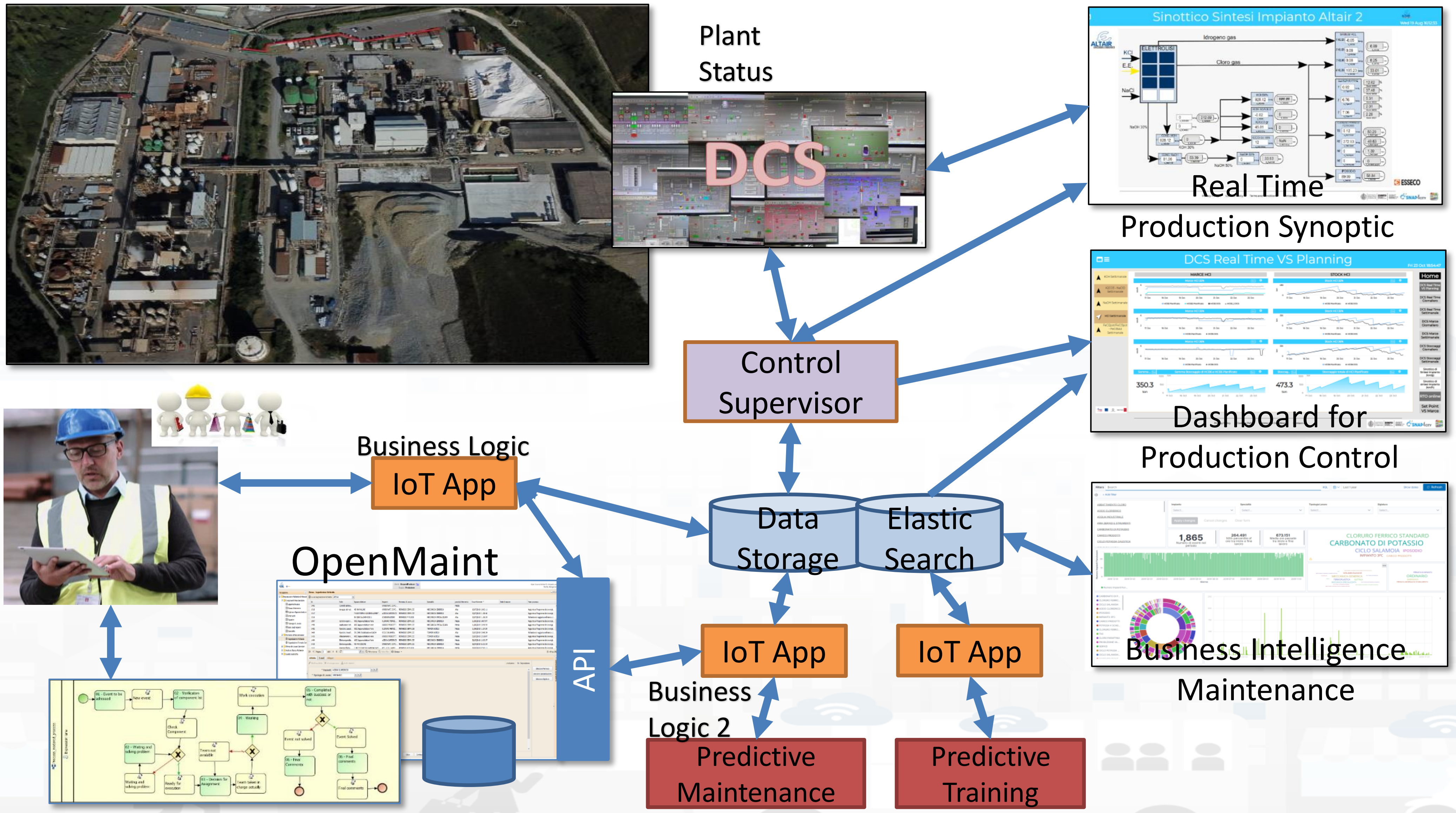
KPI

Structure of the plant



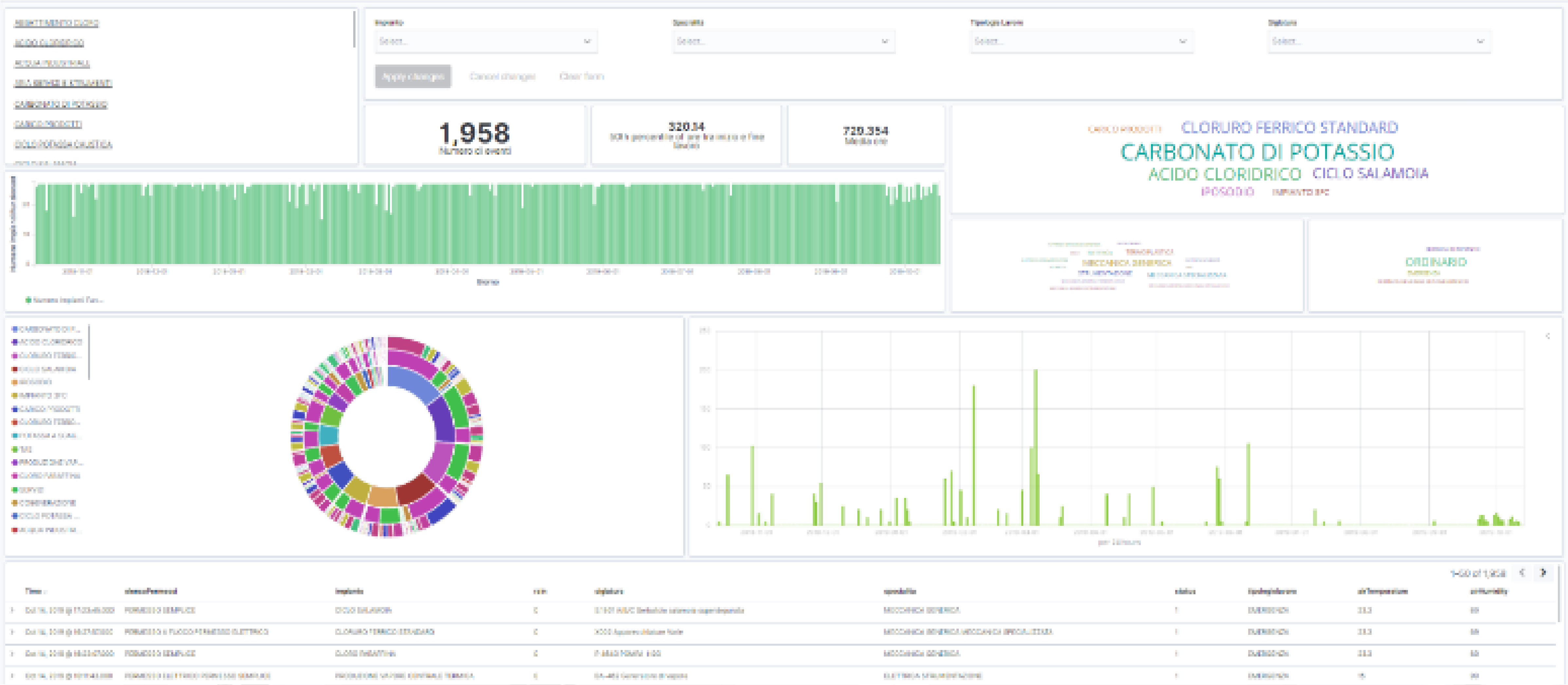
CNN: Convolutional NN
LSTM: Long Short-Term Memory
(deep learning model)

Solution



Plant Status
DCS
Sinottico Sintesi Impianto Altair 2
Real Time Production Synoptic
DCS Real Time VS Planning
Dashboard for Production Control
Control Supervisor
Business Logic
IoT App
Data Storage
Elastic Search
Business Intelligence Maintenance
OpenMaint
API
IoT App
IoT App
Business Logic 2
Predictive Maintenance
Predictive Training

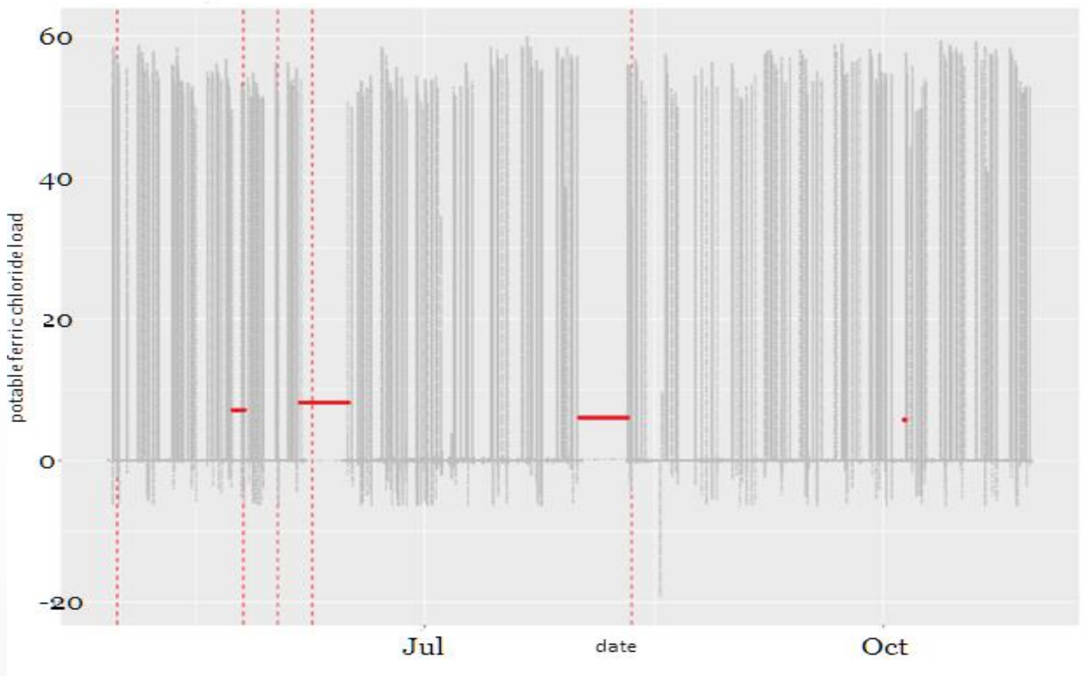
Business Intelligence



Production:
- 1-minute observation from 2020-04-28 to 2021-01-04
- 343.183 observations for 147 features/variables
- production, storage, status, several temperatures of elements, gear plants, process/safety parameters, chemicals compounds produced

Fault:
- List all the details: event datetime, Permission List, Plant, Signature, Specialty, Status, Job Type, Air Temperature, air humidity and rain
- Ticket and stop classification as "GENERAL PLANT STOP", "ORDINARY", "PLANT STOP" and "EMERGENCY "

Example of a failure



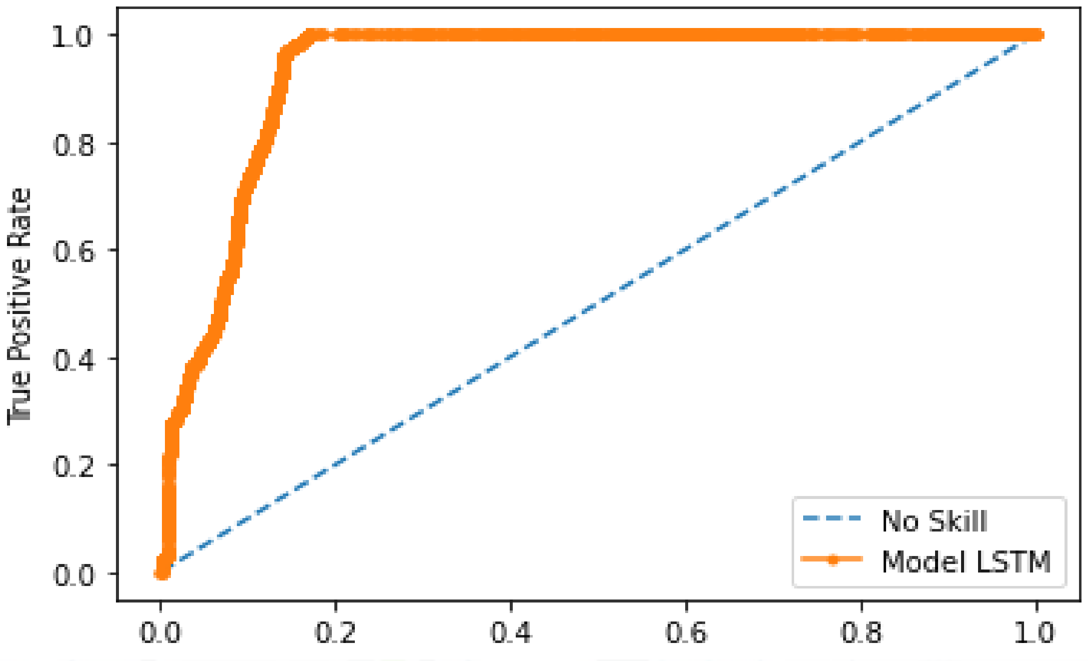
Overview Features

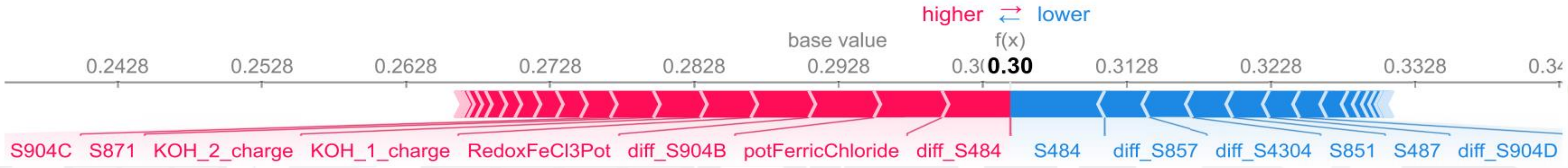
Feature	Plant	Description	Unit of measure
TempreactoreR4001 - TempreactoreR4002 - TempreactorR4003	chlorine paraffins (CPS)	reactor temperature indication	°C
S904A - S904B - S904C	Potable Ferric std	Storage level indication	%
S4304	chlorine paraffins (CPS)	Storage level indication	%
standardFerric Chloride	Potable Ferric std	flow rate measurement and totalization	m3
potFerricChloride	Potable Ferric Chloride	flow rate measurement and totalization	m3
S904E - S904D	Potable Ferric Chloride	Storage level indication	%
QuantNaOHperBatchNaClO - QuantNaOHBatchNaClO_2	NaOH KOH	flow rate measure and totalization	lt – m3
ConversionNaOH - ConversionKOHlinea1	NaOH KOH	electrolysis load adjustment (production)	kA
KOH_1_charge - KOH_2_charge	NaOH KOH	flow rate measure and totalization	m3
S487 - S484 - S5104	NaOH KOH	Storage level indication	%
hypo sodium	sodium hypochlorite	quantity of material produced	m3
S851 - S852 - S854 - S856 - S857	sodium hypochlorite	Storage level indication	%
S871	HCl	Storage level indication	%
RedoxFeCl3Pot	Ferric Chloride std	potential measure redox Ferric Chloride	mV

Preditive capabilities

- Deep Learning: LSTM, CNN-LSTM approached
- Explainable AI: Identification of possible causes of fault

	Precision %	Recall %	F_1 score %
weighted avg	0.90	0.92	0.90

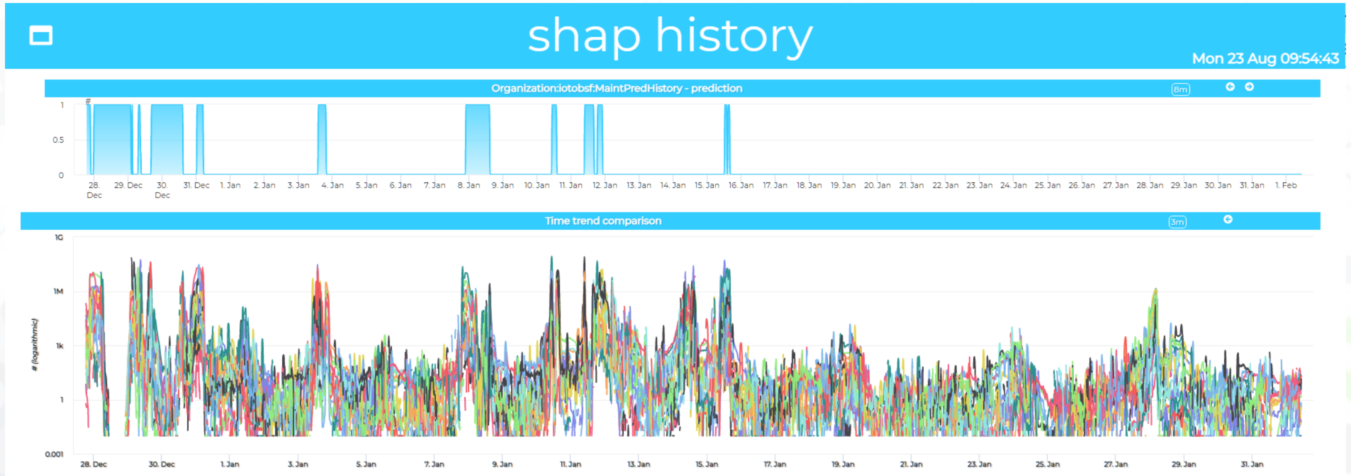




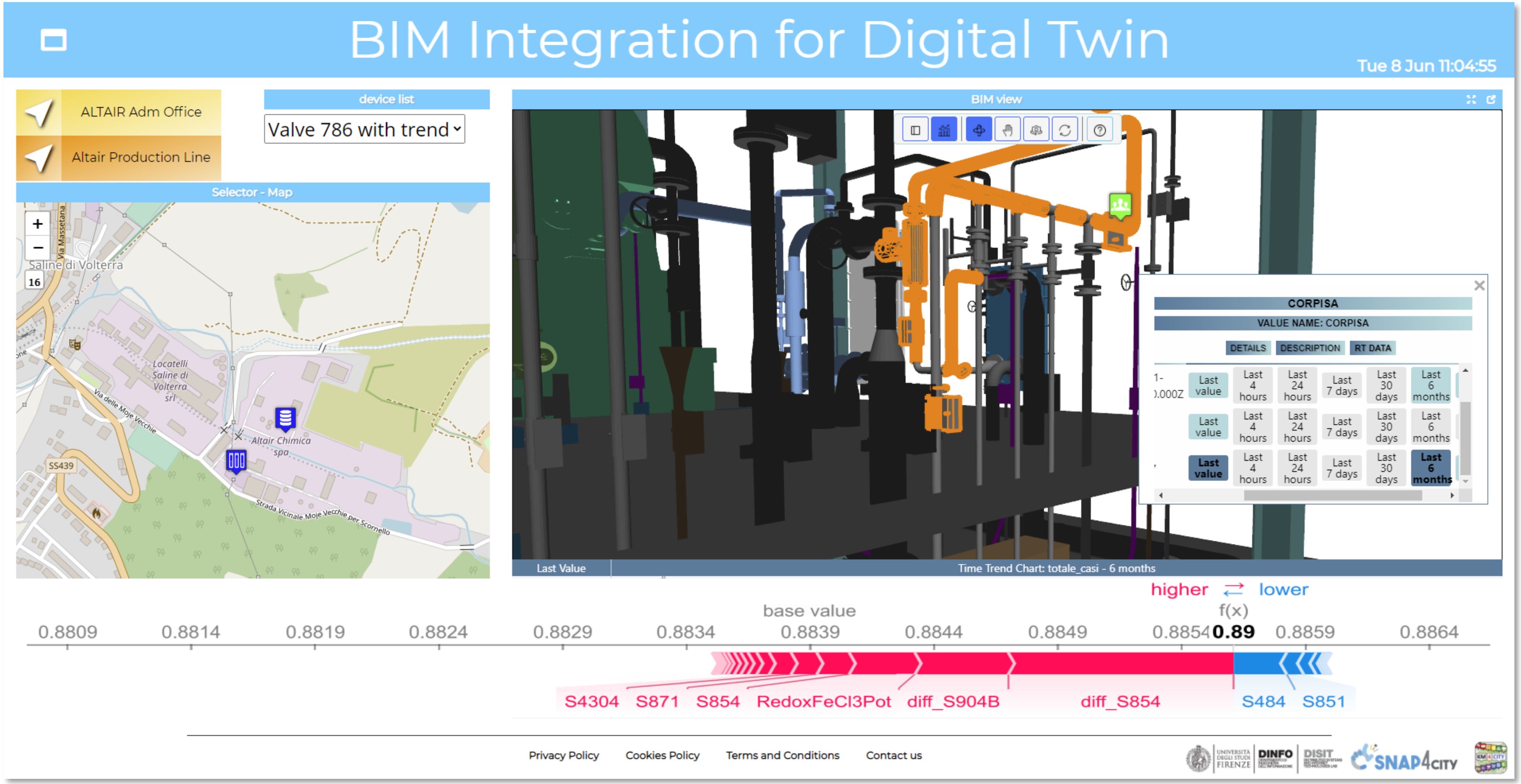
Explainable/XAI - CNN-LSTM (SHAP)

Explanation of prediction generated by model for fault

Explanation of prediction generated by model for normality



Digital Twin Local, 3D vs Real Time Data



Considerations

- results shown an average Accuracy of 91.8% and an average F1-score of 90%, which are very satisfactory results
- Explanation of the predictions provides suggestions for the maintenance teams in terms of areas of intervention.
- Large renovation of the production infrastructure.

EN.TE.R.PR.I.S.E.

(**EN**hanced **TE**chnological **R**&D of new **PR**oducts and Processes for **I**nnovation, **S**mart factory and green **E**conomy)

Administrative Data from AS400

Real Time Data, Historical, Events from DCS

Unique National Energy Costs (PUN)

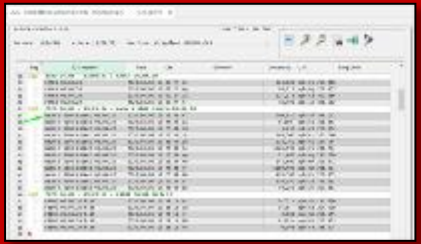
OPC UA

Big Data Analytics Artificial Intelligence Engine

SNAP4INDUSTRY

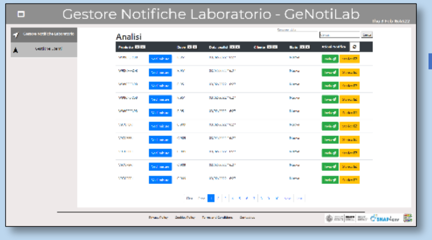
ALTAIR CHIMICA

Analytical Data from the product quality Lab (LIMS/SAM)



SNAP4

GeNotiLab



POR CreO REGIONE TOSCANA
UNIONE EUROPEA
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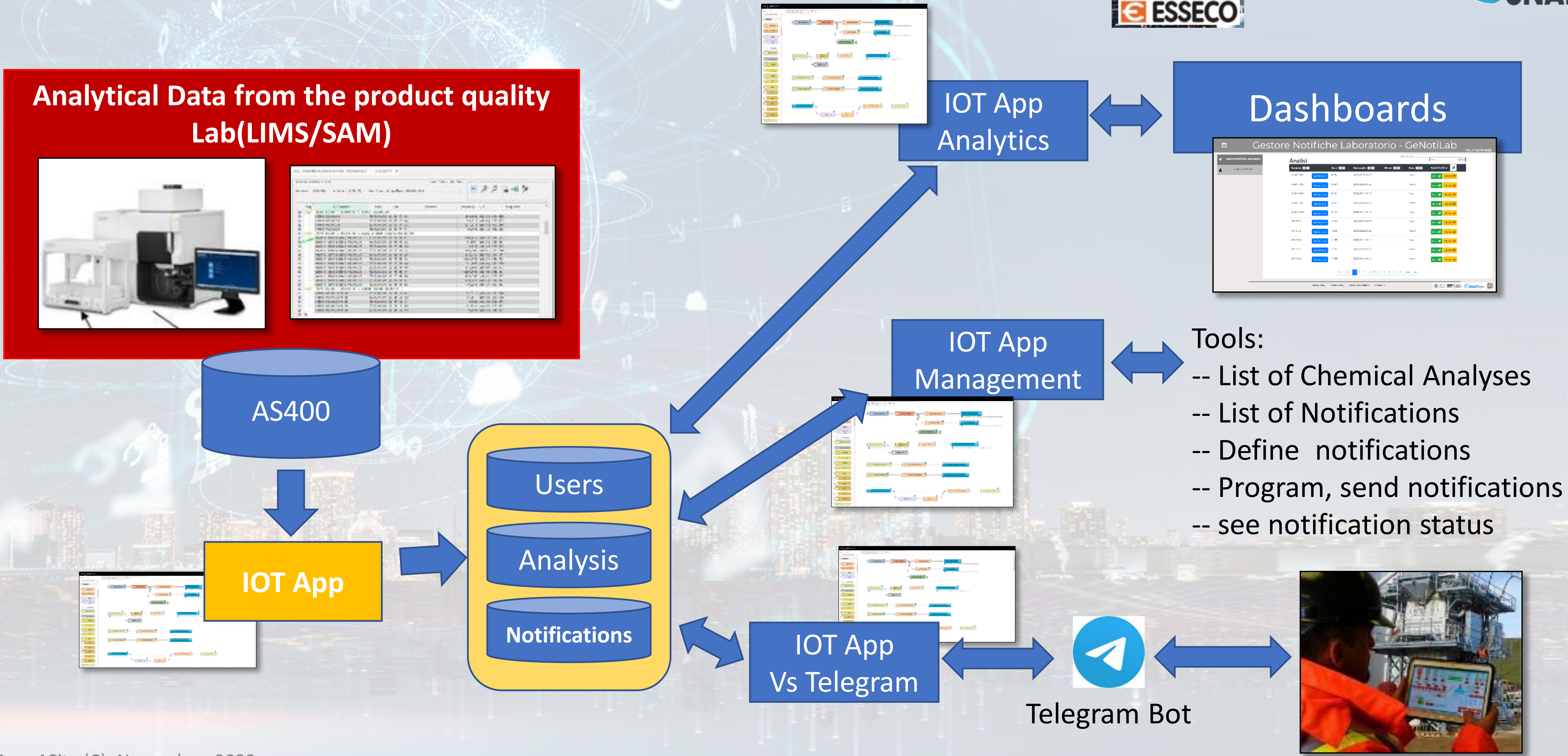
Regione Toscana

GeNotiLab Architecture for ALTAIR



What you can find in the former course

In addition in the former course you can find:

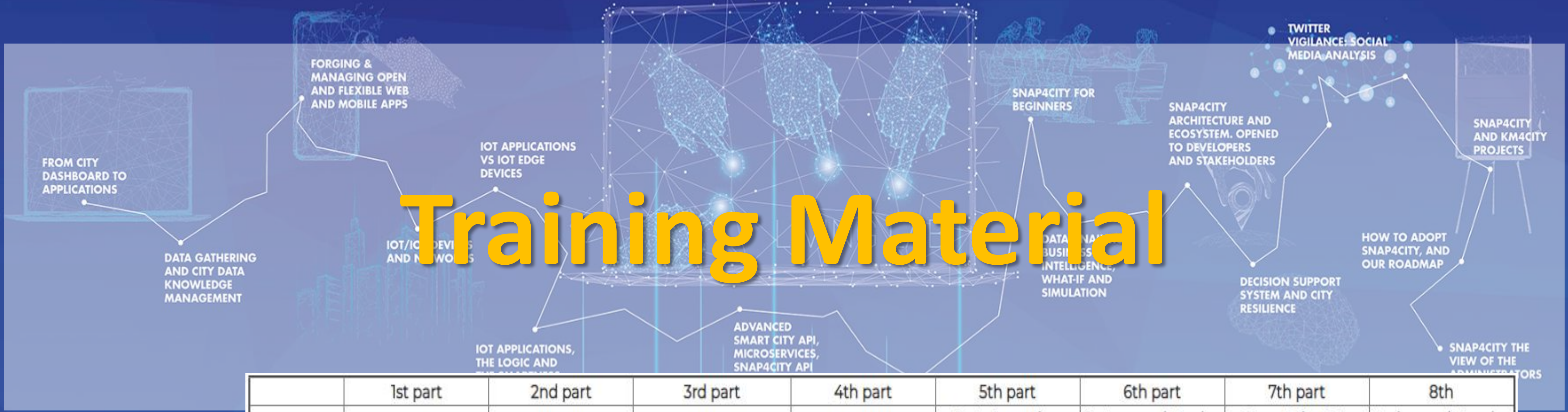
https://www.snap4city.org/577

- Detecting and Counting People
- Recommendations for retail
- Predictive Maintenance
- Time Series Analysis and Characterization
- GeoTIFF management vs Heatmaps
- Heatmap modeling and generation
- User Engagement
- Decision Support Systems, SmartDS, System Thinking
- Decision Support System, FRAM
- Social Media Analysis: Twitter data (prediction, early warning, reputation)
- Impact of COVID-19

https://www.snap4city.org/944

On Line Training Material (free of charge)

1st part	2nd part	3rd part	4th part	5th part	6th part	7th part	8th
Overview	Dashboards	IOT App, IOT Network	Data Analytics	Data Ingestion processes	System and Deploy Install	Smart City API: Web & Mob. App	Design and Develop Smart Solutions
							
							



Training Material

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what	Overview	Dashboards	IOT App, IOT Network	Data Analytics	Data Ingestion processes	System and Deploy Install	Smart City API: Web & Mob. App	Design and Develop Smart Solutions
PDF 2022								
Interactive (2022) with video and animations								


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SNAP4CITY
CAPELON
3D MAP GLOBAL DIGITAL TW


3D MAP GLOBAL DIGITAL TWIN
Wed 16 Nov 17:03:10
VEHICLEFLOW - 7 DAYS

Note on Training Material

- **Course 2023**: https://www.snap4city.org/944
  - Introductionary course to Snap4City technology
- **Course** https://www.snap4city.org/577
  - Full training course with much more details on mechanisms and a wider set of cases/solutions of the Snap4City Technology
- **Documentation** includes a deeper round of details
  - Snap4City Platform Overview:
    - https://www.snap4city.org/drupal/sites/default/files/files/Snap4City-PlatformOverview.pdf
  - Development Life Cycle:
    - https://www.snap4city.org/download/video/Snap4Tech-Development-Life-Cycle.pdf
  - Client Side Business Logic:
    - https://www.snap4city.org/download/video/ClientSideBusinessLogic-WidgetManual.pdf
- **On line cases and documentation**:
  - https://www.snap4city.org/108
  - https://www.snap4city.org/78
  - https://www.snap4city.org/426

Snap4City

Switch To New Layout (Beta)

User: paolo.disit, Org: DISIT
Role: AreaManager, Level: 3

LOGOUT

- My Snap4City.org
- Tour Again
- www.snap4solutions.org
- Dashboards (Public)
- Dashboards of My Organization
- My Dashboards in My Organization
- My Data Dashboard Dev Kibana
- Extra Dashboard Widgets
- Data Management, HLT
- Knowledge and Maps
- Processing Logics / IOT App
- Entity Directory and Devices
- Resource Manager
- Development Tools
- Management
- Decision Support Systems
- Deploy and Installation
- Help and Contacts
- Documentation and Articles
- My Profile
- Km4City portal
- DISIT Lab portal

Snap4City

Home | How and Why To Use it | Tools | Tutorials and Videos

Home / Tutorials and Videos / Welcome: how to start using Snap4City for beginners

Welcome: how to start using Snap4City for beginners

We suggest you:

Congratulations! You have really contributed to Snap4City and successfully passed all first levels!

You have reached a level in which you can contribute with competence to the city improvement and smartness. We hope you interested in helping other users in conquering higher levels on the city smartness ranking, and provising of smart services to all city users!
So that we could be interested in engaging and elevating your role in the Snap4City community as coordinator of thematic groups, for example on **Mobile APP development**, **Dashboard** on Mobility, **IOT Application** Development, etc., according to your preferences.

Please contact **paonesi@gmail.com** !

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- Development Life Cycle: https://www.snap4city.org/download/video/Snap4Tech-Development-Life-Cycle.pdf
- Client-Side Business Logic Widget Manual: https://www.snap4city.org/download/video/ClientSideBusinessLogic-WidgetManual.pdf
- Booklet Data Analytics, Snap4Solutions: https://www.snap4city.org/download/video/DPL_SNAP4SOLU.pdf

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

Username: paolo.disit

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-Any-

Training on Tools and Platform

Powered by www.km4city.org

FIWARE Node-RED

Sii-Mobility

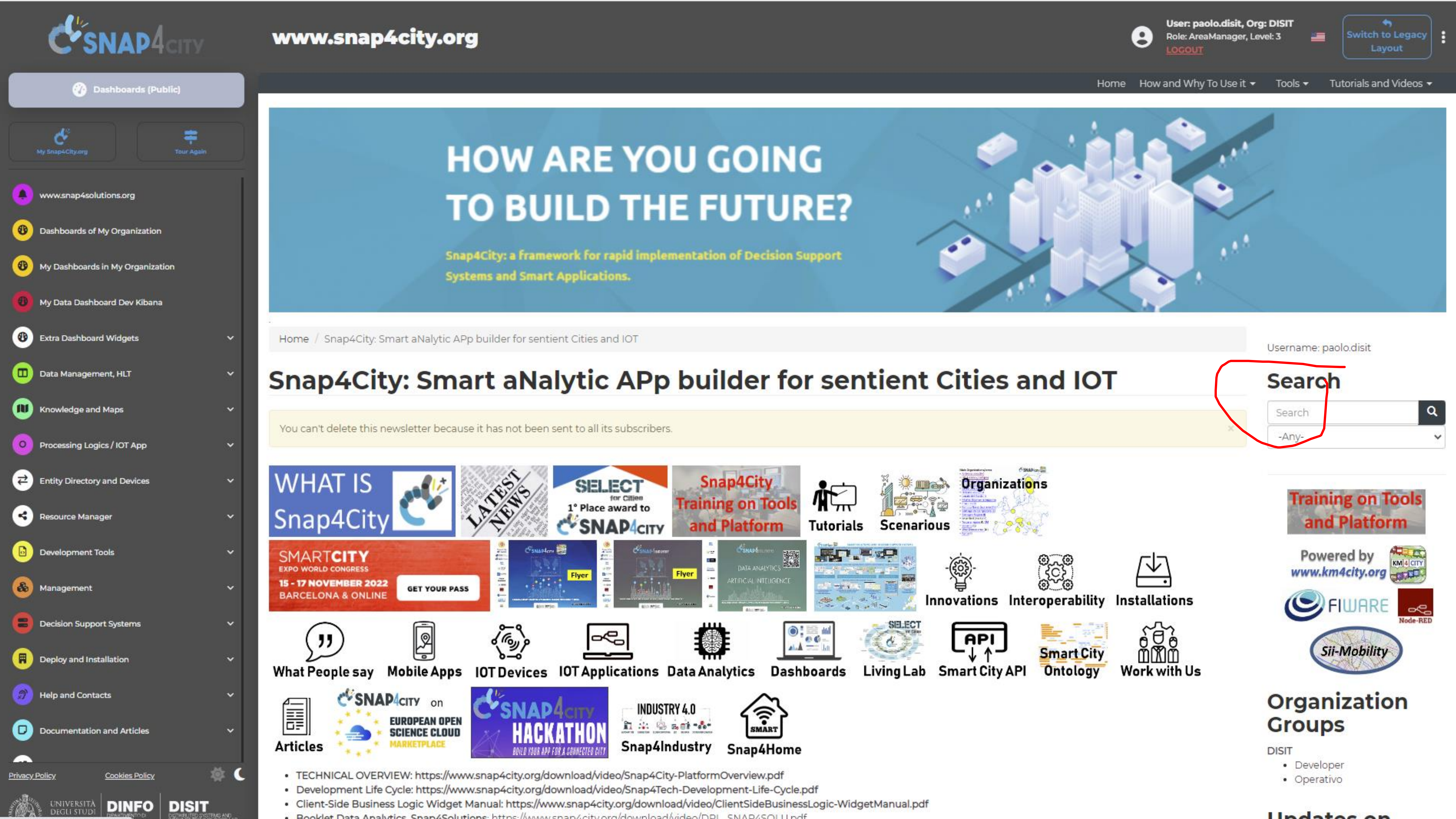
Organization Groups

DISIT
- Developer
- Operativo

Updates on Tools

Training Course Snap4City - 2023 Edition new
drupaladmin

Snap4City Newsletter of April 2023 new
roottooladmin1


www.snap4city.org
User: paolo.disit, Org: DISIT
Role: AreaManager, Level: 3
LOGOUT
Switch to Legacy Layout
Dashboards (Public)
My Snap4City.org
Tour Again
www.snap4solutions.org
Dashboards of My Organization
My Dashboards in My Organization
My Data Dashboard Dev Kibana
Extra Dashboard Widgets
Data Management, HLT
Knowledge and Maps
Processing Logics / IOT App
Entity Directory and Devices
Resource Manager
Development Tools
Management
Decision Support Systems
Deploy and Installation
Help and Contacts
Documentation and Articles
Privacy Policy
Cookies Policy
Home
How and Why To Use it
Tools
Tutorials and Videos
HOW ARE YOU GOING TO BUILD THE FUTURE?
Snap4City: a framework for rapid implementation of Decision Support Systems and Smart Applications.
Home / Snap4City: Smart aNalytic APp builder for sentient Cities and IOT
Snap4City: Smart aNalytic APp builder for sentient Cities and IOT
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WHAT IS Snap4City
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Snap4City Training on Tools and Platform
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Organizations
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FIWARE
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Developer
Operativo
TECHNICAL OVERVIEW: https://www.snap4city.org/download/video/Snap4City-PlatformOverview.pdf
Development Life Cycle: https://www.snap4city.org/download/video/Snap4Tech-Development-Life-Cycle.pdf
Client-Side Business Logic Widget Manual: https://www.snap4city.org/download/video/ClientSideBusinessLogic-WidgetManual.pdf
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2023 booklets

- Smart City

https://www.snap4city.org/download/video/DPL_SNAP4CITY.pdf

- Industry

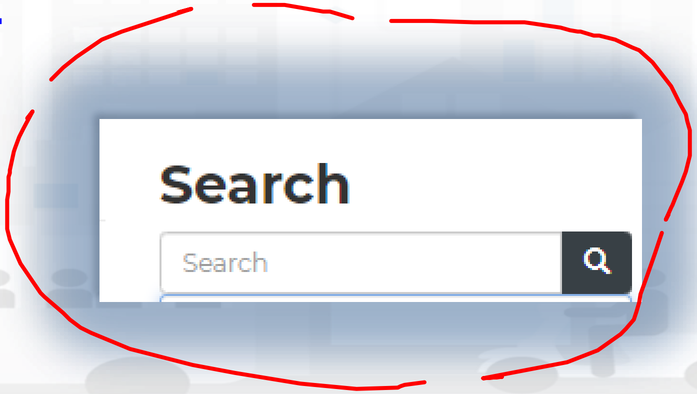
https://www.snap4city.org/download/video/DPL_SNAP4INDUSTRY.pdf

- Artificial Intelligence

https://www.snap4city.org/download/video/DPL_SNAP4SOLU.pdf

The Platform

- **Free Registration on Snap4City.org**
  - Please select DISIT ORG to be sure to access at the examples
  - Most of the cities / tenant are private and they do not left much visible
- **What you get** is probably the 10% of what is on the platform ☺
- **Training**: https://www.snap4city.org/577
- **Scenarious**: https://www.snap4city.org/4
- **Publications**: https://www.snap4city.org/426
- **WEB pages**: https://www.snap4city.org/78
- ***SEARCH on the right side***



Tech. Overview

- https://www.snap4city.org/drupal/sites/default/files/files/Snap4City-PlatformOverview.pdf

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SNAP4CITY KM4CITY

Snap4City Platform

Technical Overview

From: DINFO dept of University of Florence, with its DISIT Lab, Https://www.disit.org with its Snap4City solution

Snap4City:

- Web page: Https://www.snap4city.org
- https://twitter.com/snap4city
- https://www.facebook.com/snap4city

Contact Person: Paolo Nesi, Paolo.nesi@unifi.it

- Phone: +39-335-5668674
- Linkedin: https://www.linkedin.com/in/paolo-nesi-849ba51/
- Twitter: https://twitter.com/paolonesi
- FaceBook: https://www.facebook.com/paolo.nesi2

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SNAP4CITY

Development

https://www.snap4city.org/download/video/Snap4Tech-Development-Life-Cycle.pdf

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Development Life-Cycle

https://www.snap4city.org/download/video/Snap4Tech-Development-Life-Cycle-v1-1.pdf

From Snap4City:

- **We suggest you to read the TECHNICAL OVERVIEW:**
  - https://www.snap4city.org/download/video/Snap4City-PlatformOverview.pdf
- https://www.snap4city.org
- https://www.snap4solutions.org
- https://www.snap4industry.org
- https://twitter.com/snap4city
- https://www.facebook.com/snap4city
- https://www.youtube.com/channel/UC3tAO09EbNba8f2-u4vandg

Coordinator: Paolo Nesi, Paolo.nesi@unifi.it

DISIT Lab, https://www.disit.org
DINFO dept of University of Florence,
Via S. Marta 3, 50139, Firenze, Italy
Phone: +39-335-5668674

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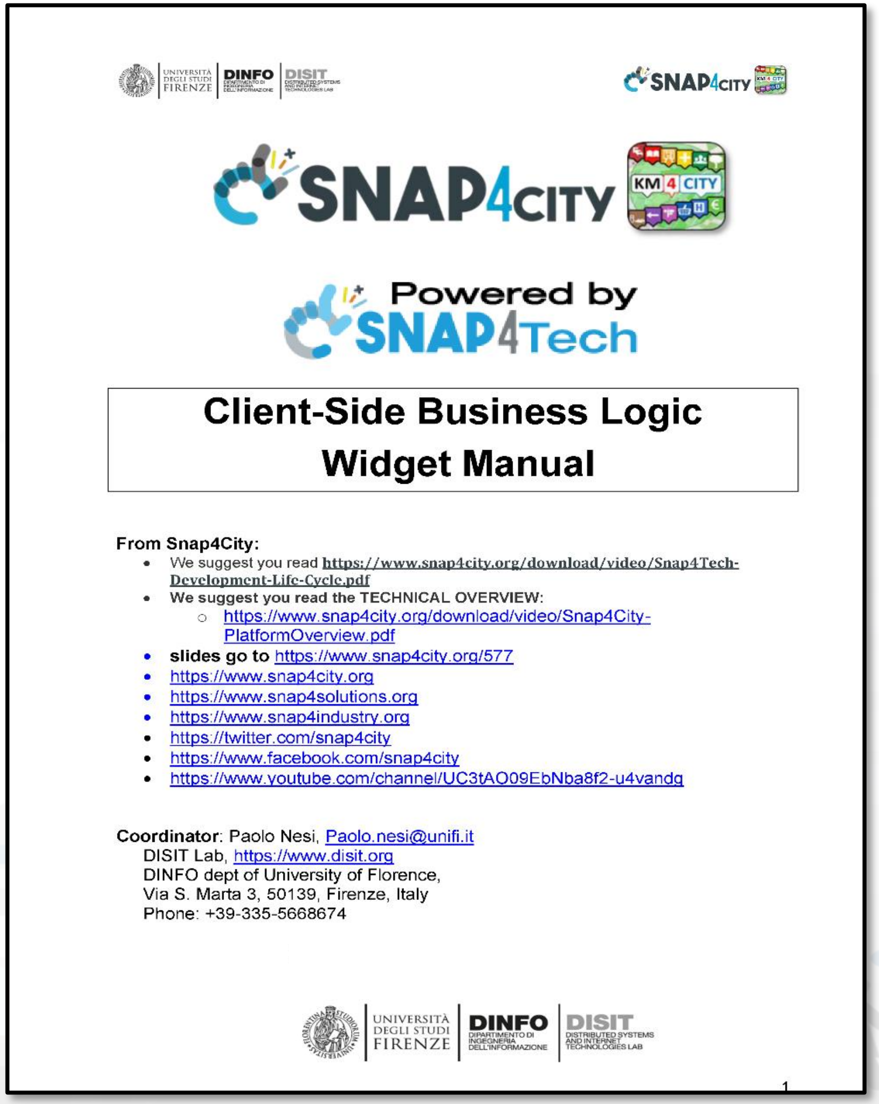
CSBL

Client Side Business Logic


Client-Side Business Logic
Widget Manual

From Snap4City:
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- slides go to https://www.snap4city.org/577
- https://www.snap4city.org
- https://www.snap4solutions.org
- https://www.snap4industry.org
- https://twitter.com/snap4city
- https://www.facebook.com/snap4city
- https://www.youtube.com/channel/UC3tAO09EbNba8f2-u4vandg

Coordinator: Paolo Nesi, Paolo.nesi@unifi.it
DISIT Lab, https://www.disit.org
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https://www.snap4city.org/download/video/ClientSideBusinessLogic-W df


FIWARE
Open APIs for Open Minds
FIWARE IMPACT STORIES
SMART CITIES AND SMART INDUSTRY
Snap4City: FIWARE powered smart app builder for sentient cities
With the contribution of
UNIVERSITÀ DEGLI STUDI FIRENZE | DINFO | DISIT

Commercial Overview

FIWARE

- https://fiware-foundation.medium.com/snap4city-fiware-powered-smart-app-builder-for-sentient-cities-acfe24df49d5
- https://www.snap4city.org/drupal/sites/default/files/files/FF_ImpactStories_Snap4City.pdf

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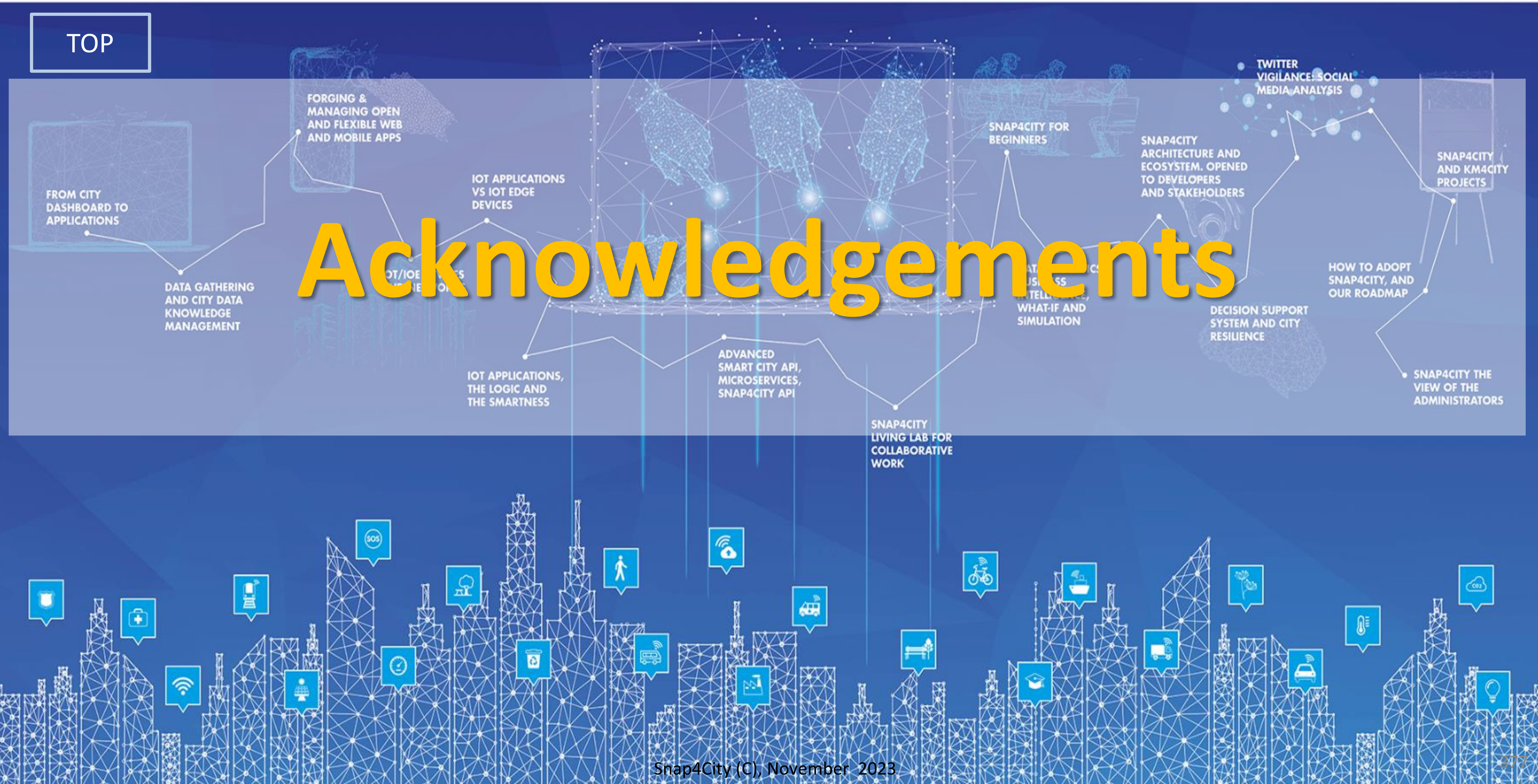
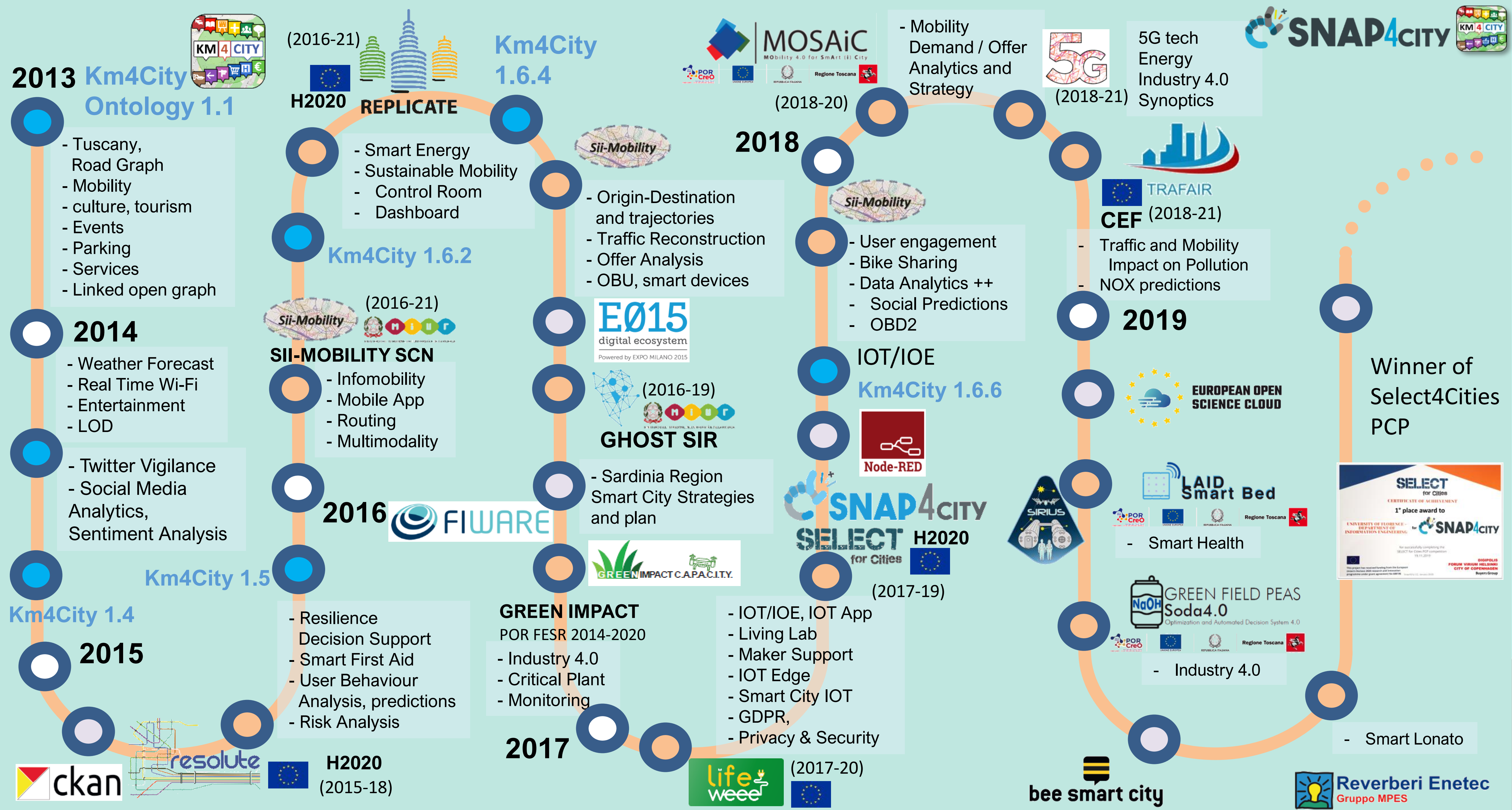
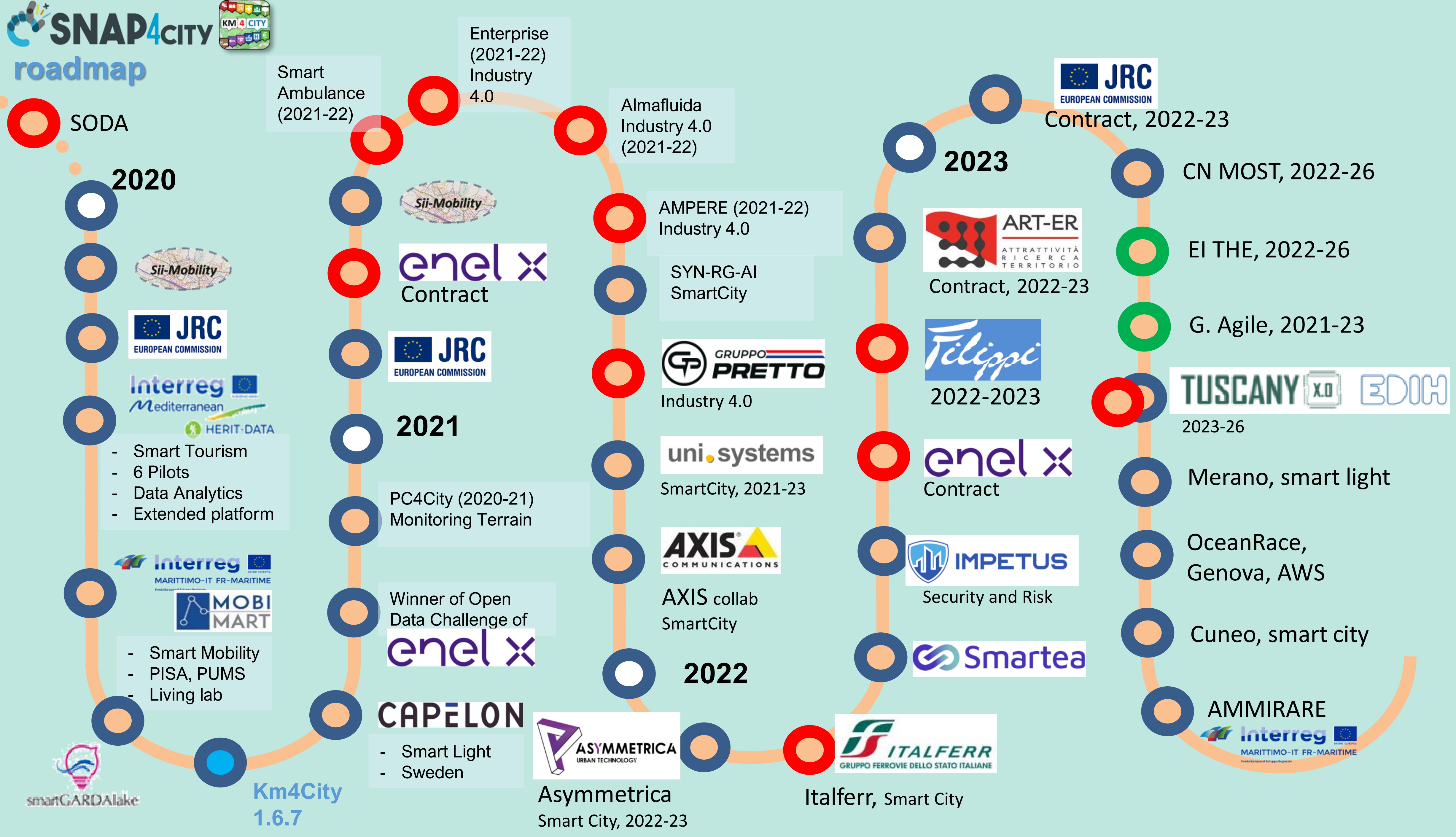
Acknowledgements





DISIT lab roadmap vs model and tools' usage


SNAP4CITY
KM 4 CITY
roadmap
SODA
2020
Sii-Mobility
JRC
EUROPEAN COMMISSION
Interreg
Mediterranean
HERIT-DATA
- Smart Tourism
- 6 Pilots
- Data Analytics
- Extended platform
Interreg
MARITTIMO-IT FR-MARITIME
MOBI MART
- Smart Mobility
- PISA, PUMS
- Living lab
smartGARDAlake
Km4City 1.6.7
Smart Ambulance (2021-22)
Enterprise (2021-22) Industry 4.0
Sii-Mobility
enel x
Contract
JRC
EUROPEAN COMMISSION
2021
PC4City (2020-21)
Monitoring Terrain
Winner of Open Data Challenge of
enel x
CAPELON
- Smart Light
- Sweden
Almafluida Industry 4.0 (2021-22)
AMPERE (2021-22) Industry 4.0
SYN-RG-AI SmartCity
GRUPPO PRETTO
Industry 4.0
uni.systems
SmartCity, 2021-23
AXIS COMMUNICATIONS
AXIS collab
SmartCity
2022
ASYMMETRICA URBAN TECHNOLOGY
Asymmetrica
Smart City, 2022-23
ITALFERR
GRUPPO FERROVIE DELLO STATO ITALIANE
Italferr, Smart City
2023
ART-ER
ATTRATTIVITÀ RICERCA TERRITORIO
Contract, 2022-23
Filippi
2022-2023
enel x
Contract
IMPETUS
Security and Risk
Smartea
JRC
EUROPEAN COMMISSION
Contract, 2022-23
CN MOST, 2022-26
EI THE, 2022-26
G. Agile, 2021-23
TUSCANY X.0 EDIH
2023-26
Merano, smart light
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SMARTCITY EXPO WORLD CONGRESS

7-9 November 2023, Barcelona, Spain

Visit Snap4City in Hall 1

Appliances and Dockers **Installations**

CONTACT

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

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

www.snap4city.org

Email: snap4city@disit.org

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