

S.LI.DES

Smart strategies for sustainable tourism in Lively cultural DESTinations

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Deliverable 3.2.1. Mobility Database

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Responsible Partner:	INSTITUTE FOR TOURISM		
Partners involved:	<p>LP – University of Cà Foscari (IT)</p> <p>PP1 - CISET (IT)</p> <p>PP2 - Ecipa (IT)</p> <p>PP3 - SIPRO Ferrara (IT)</p> <p>PP4 - City of Bari (IT)</p> <p>PP5 - City of Venice (IT)</p> <p>PP6 –CAST-University of Bologna (IT)</p> <p>PP7 – Institute for Tourism</p> <p>PP8- Craft College- Institution for adult education Subsidiary Rijeka</p> <p>PP9- Development Agency of the City of Dubrovnik-Dura</p> <p>PP10-Sibenik Tourist board</p>		

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1. Experimental Campaigns

The SLIDEs project copes with the problem of getting a quantitative measure of the tourist flows visiting an historical centre. The available statistical data give only an average qualitative information on the tourist flows present in an area and do not allow a quantitative measure of the effect of new initiatives to increase the tourist offer (like the pilot actions planned in te WP4). Moreover, in many cases the cities organize daily events that may attract large crowds and there is a necessity of getting the tourist flows data on short time intervals (i.e. daily data or hourly data to highlight the circadian rhythms) and of collecting data in real time to forecast the appearance of critical situations (i.e., overcrowding) and to apply safety policies. We proposed a solution to these problems by using a network of distributed sensors able to count the passing people through a virtual barrier along a road or the number of presences in a given area. The technologies used at this purpose are:

- 1) Wi-Fi/Bluetooth scanners record the presence or the passage of a mobile device in a given area that is connected to Wi-Fi network and associate an anonymous ID to each device.
- 2) The video analysis using cameras allows to count all people crossing virtual barriers of present in a monitored area.

The data quality is different in the two systems:

- 1) the Wi-Fi/Bluetooth scanners consider only a sample of the population in an area whose dimension depends on the antenna sensitivity, they do not distinguish the flows in different directions but since the ID associated to the device is unique, they are able to detect the residence times of a device in different locations and to reconstruct the mobility demand;
- 2) the video camera sensors use a software developed by the CAST UNIBO partner to count all the people passing in area distinguishing different directions by introducing virtual barriers or performing a crowd counting in case of a large areas like squares.

The sensors operation and quality of the recorded data are described in the next section.

The cities have made different choices according to their specific needs and the existence of other systems of monitoring people flows.

The Ferrara municipality decided to perform the data collection by means of 6 Wi-Fi/Bluetooth scanners that record the presence of a mobile device in the chosen area when the connection Wi-Fi or Bluetooth is switched on and associate an anonymous ID to each device. The location of the sensors in the Ferrara historical centre is shown in the Figure 1 The Wi-Fi/Bluetooth scanners consider only a sample of the population in an area

whose dimension depends on the antenna sensitivity; they do not distinguish the flows in different direction but since the ID associated to the device is unique that are able to detect the same device in different location and to reconstruct the mobility demand. We have decided to integrate the Wi-Fi presence data in the dynamics model since a preliminary analysis has shown a better quality of the Wi-Fi data with respect to the Bluetooth. The data are collected in the datahub and make available to the models. The sensor location has been chosen to consider the problem of detecting the mobility flows from the station and the parking areas near the historical centre and the presence the main POI of the Ferrara centre. The Figure 2 shows an example of the data recorded by the sensor located near the train station: the red curve refers to the presences recorded from 7/1/2021 and 10/01/2021, whereas the blue curve refers to the average presences in the two successive weeks at a time scale of 15 minutes. The Figure 2 highlights clearly the circadian rhythms of the use of the station area and difference among the days of the week. A fluctuation analysis points out the peculiarities of the presences of the considered day with respect to the expected average so that it would be possible to analyse the changes due to the realization of the pilot actions of the project comparing the measures collected during different periods. One of the results of the experimental campaign is to characterize the average use of the considered area during the different periods of the year to distinguish the presences of the visitors from the presence of residence and commuters and to study the changes in concomitance with specific tourist events or after the realization of new tourist initiative. The penetration of the mobile device sampling recorded by the sensors with respect to the total population present in the area will be estimate during the experimental campaigns (a rough estimate is $\sim 1/3$ of the total population). Ferrara municipality is also planning to extend the sensors systems beyond the SLIDES project.

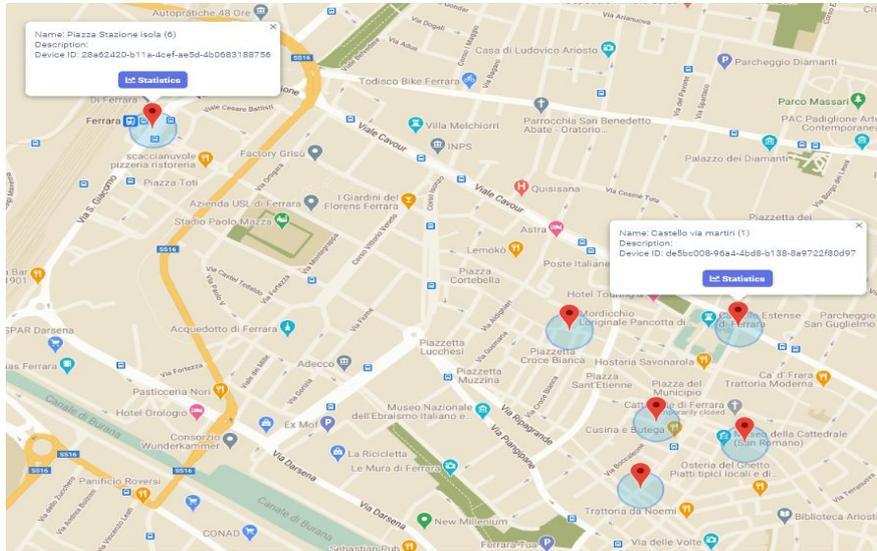


Figure 1: The dots show the location of the Wi-Fi scanner installed in the Ferrara historical centre to perform the experimental campaign

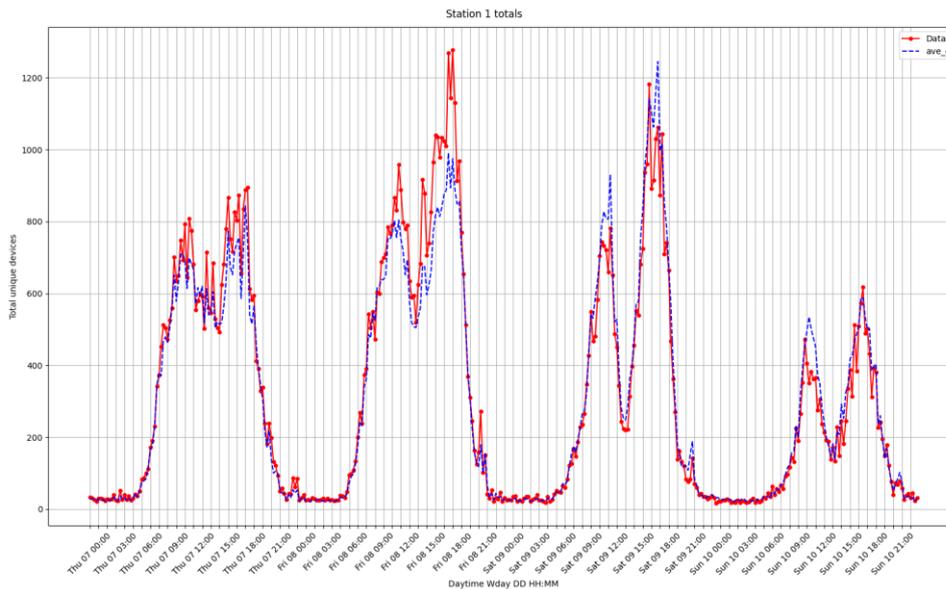


Figure 2: Example of presences recorded by the Wi-Fi sensor installed near the Ferrara train station at a time scale of 15 minutes

The red curve on Figure 2 shows the presences detected from 07/01/2021 to 10/01/2021 whereas the blue curve is the average presences during the two successive weeks.

More details are reported in the Simulations Report D3.5

The experimental campaign in Sibenik has been performed using video-camera analysis to detect the tourist flows. The map in Figure 3 shows the location of the video-camera positions at entry points for the tourist flows in Sibenik. The location of the four cameras has been decided in collaboration with the tourist agency of Sibenik.

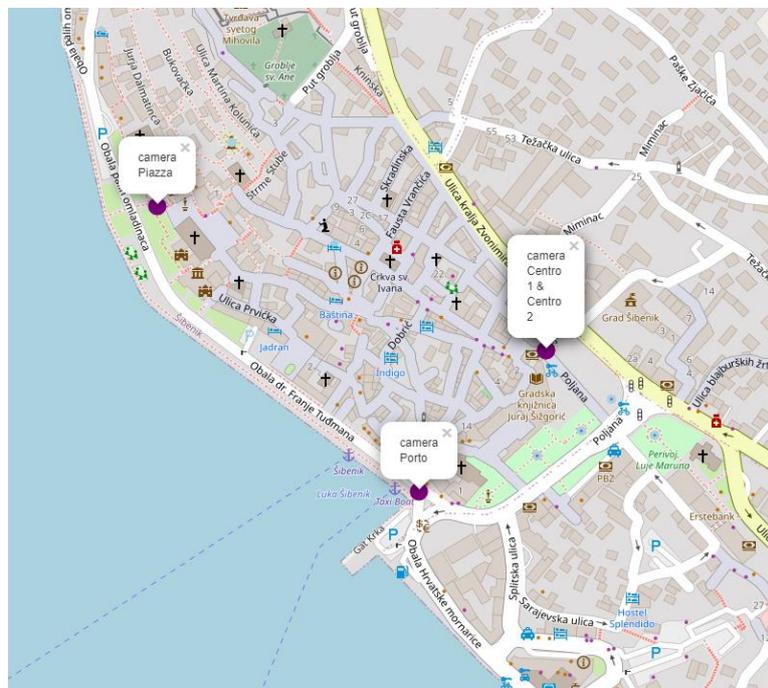


Figure 3: Location of the four video cameras installed in Sibenik to measure the tourist flows

The videos are collected on a dedicated server and they are analyzed in real time by a software developed by the Cast-Unibo unit of the SLIDES project. In this way we are able to count how many individuals are present in each area monitored by the camera, to tracking their trajectories and to count how many individuals are crossing some virtual barriers in a given time interval. The video cameras have been installed in

December 2020 and the system starts to be operative from January 2021, but the tourist flows are absent due to the COVID-19 pandemic. The system operation is described in the next section.

The experimental campaign in Dubrovnik has been implemented by using a system to detect the presence of a mobile phone connected to the Wi-Fi access points present in the city. This system integrates the video camera system that is just present in the city at the entrances of the historical centre and allow to get information on a larger area both on the tourist presences at different points of interest (to each connected device it is associated an anonymous id) and on the mobility agenda (i.e., the presence of the same device at different points at different times). The distribution of the monitored Wi-Fi access points is shown in Figure 4. As it is shown by the figure, due to the presence of multiple access points in some location we have performed a clustering procedure for the data analysis.



Figure 4: The red circles show the location of the Wi-Fi access points able to detect the presence of mobile device Wi-Fi connected in the Dubrovnik historical centre to perform the experimental campaign

In Figure 5 we give an example of the total unique presences recorded by the sensors during some days of January 2021: the data are actually recorded by the SLIDES datahub and the comparison between the presences during winter and the presences in summer would allow to measure the visitors flow in the area.

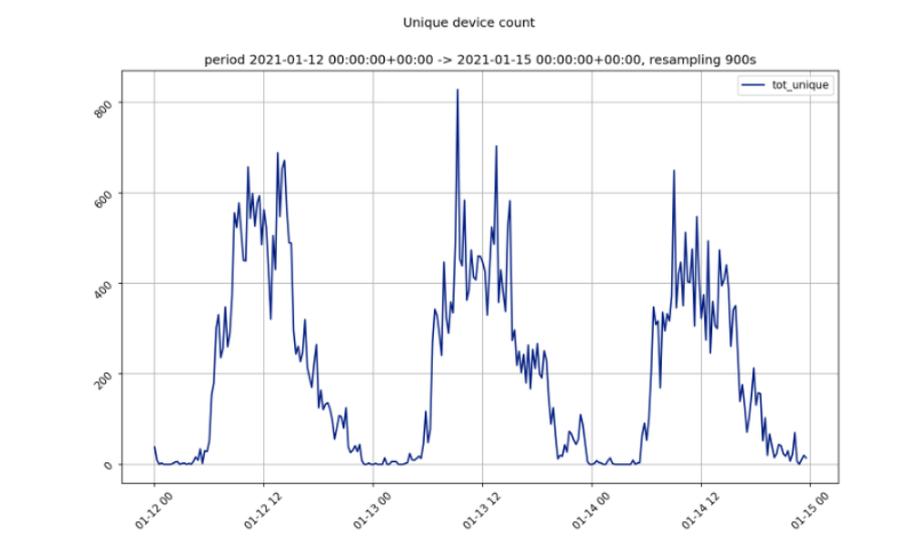


Figure 5: Total unique presences recorded by the Wi-Fi access points in Dubrovnik during three days of January 2021

The data on Figure 5 are consistent with the flow recorded by the video cameras installed at the entrances of the historical city.

More details are given in the Simulation Report D-3.5.

In the city of Venice, there are installed ~40 people and flow counter sensors that collect real time data in the framework of the Smart Control Room project (see Figure 6). These data will be available for the tuning of the Visitors' Mobility Models developed in the SLIDES project thanks to an agreement with the Venice Municipality for a period that will be defined when the social restriction due to COVID-19 pandemic will be finished and the tourist flows restart in Venice. The SLIDES project activities have been integrated with the Smart Control Room activities by implementing the possibility of performing a real time crowd counting in San Marco Square using the installed video cameras to complete the information recorded by the distributed

sensors on the road network. The video analysis will be performed by the same algorithms developed by the CAST-UNIBO partner based on a deep learning neural network (see next section). In Figure 7 we show an example of the counting detection from the video analysis in San Marco Square (the video has been recorded before the restrictions of social activities due to the COVID-19 pandemic).

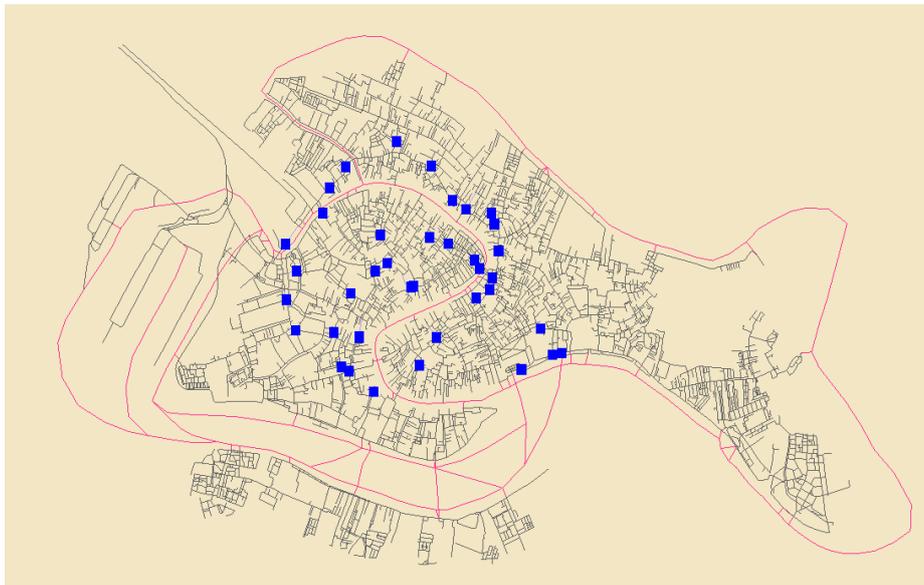


Figure 6: The blue square denotes the position of the people and flow counters installed in Venice in the framework of the Smart Control Room project



Figure 7: Example of crowd counting in San Marco Square in Venice: the number is an id associated to each detected individual and the curves denote the reconstructed trajectories from the video analysis

The city of Bari has decided to take advantage from the installed video cameras between the station and the historical centre by upgrading these systems to people flow sensors. The location of the video cameras available for upgrading to people counting sensors is shown in Figure 8. The system is completed by a server that collects the videos and perform a real time data analysis. The measures will be collected at the SLIDES dashboard and made available for further analysis and for the model simulations.

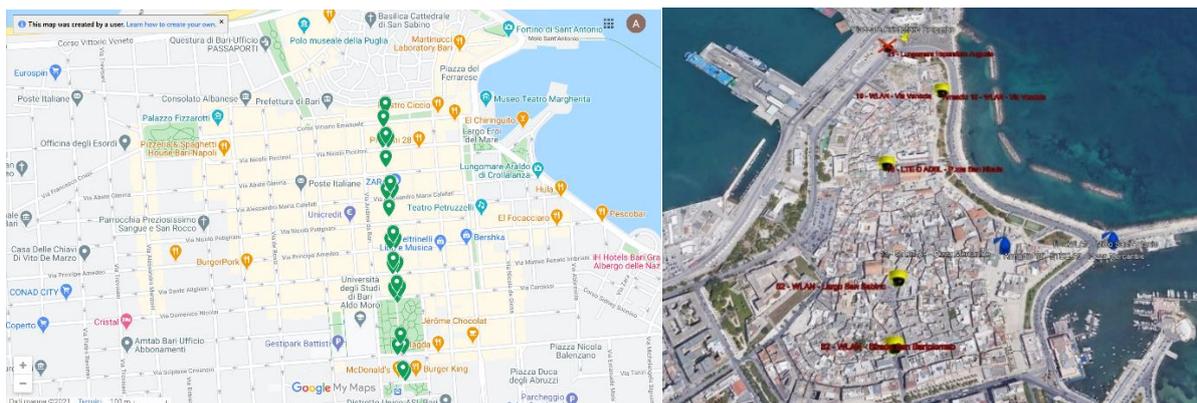


Figure 8: The markers indicate the location of the video cameras available to perform people counting in Bari: the left picture shows the cameras location along via Sparano (the main pedestrian area between the

station and the historical centre), whereas the right pictures show other cameras available in the historical town

2. Mobility data from video camera and Wi-Fi sensors

The Cast Unibo partner has developed a software package able to analyze the video streams from different IP cams distributed in a city at key locations to estimate the crowd flow and people presence. Our task is to count the number of people in the video and detect if they are crossing an arbitrary placed imaginary barrier which tells us if the people are entering or leaving the interested area. We will explicitly illustrate the system operation using the video cameras installed in Sibenik (see Figure 3).

Each camera has been set to monitor a given area that is shown in the following pictures:



Figure 9: Center 1 (Centro 1)



Figure 10: Center 2 (Centro 2)

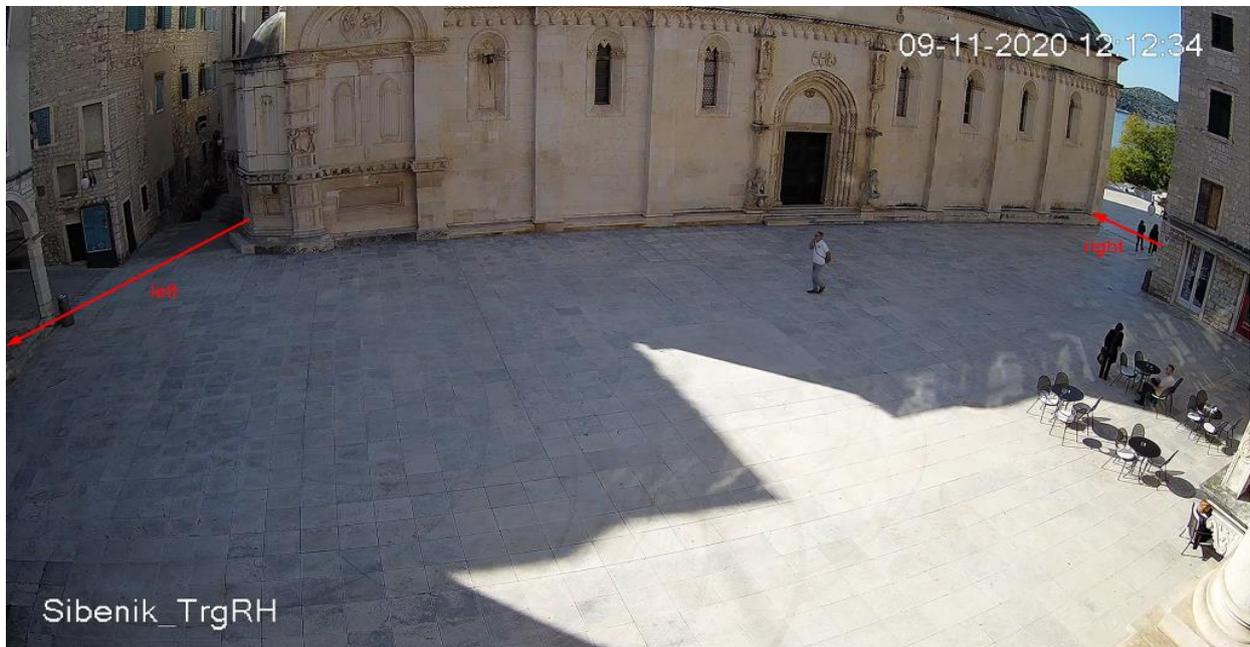


Figure 11: Square (Piazza)

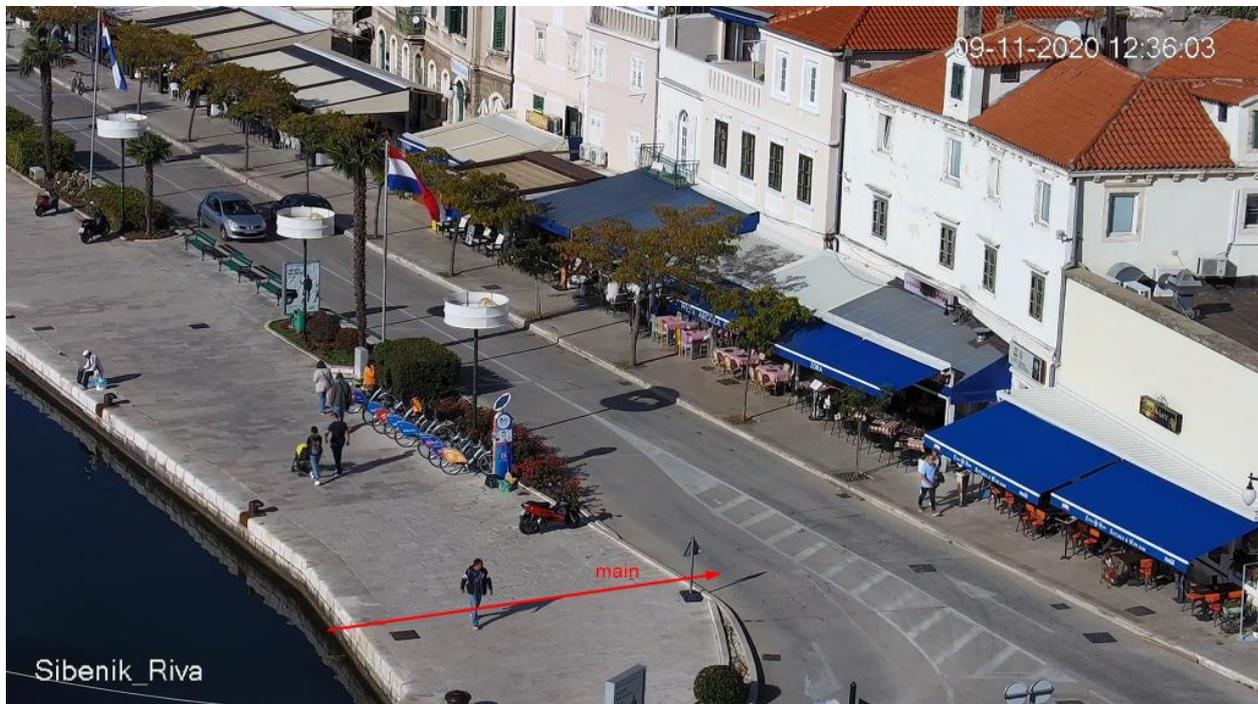


Figure 12: Harbor (Porto)

The red arrowed lines represent examples of virtual barriers location that are used by the system to count how many people are crossing the area in a given time interval. As illustrated in the *Square camera*, it is possible to set more than one barrier for each camera. The video analysis program works like a service constantly running in the background in a dedicated server that collects the videos. It is composed of three main blocks: the video buffers acquisition, the detection neural network, and the trackers. Every minute (or any set time interval) the service performs the people counting on the current video buffers and writes the results on files.

2.1. Video acquisition

When the service starts a thread is spawned for each camera, with the purpose of constantly grabbing the video frames. Every camera has a separate video ring buffer of set length (for example 200 frames, which correspond to 10 seconds since the cameras run at 20fps). This way every buffer always contains the last frames of video information.

2.2. Detection neural network

We use a deep neural network called YOLO to perform people detection and counting in the frames. You Only Look Once is a state-of-the-art, real time detection system. Given the video buffer as input, this network divides each frame into regions and predicts bounding boxes and class probabilities for each region. These bounding boxes are weighted by the predicted probabilities, and the optimal box and class is then decided.

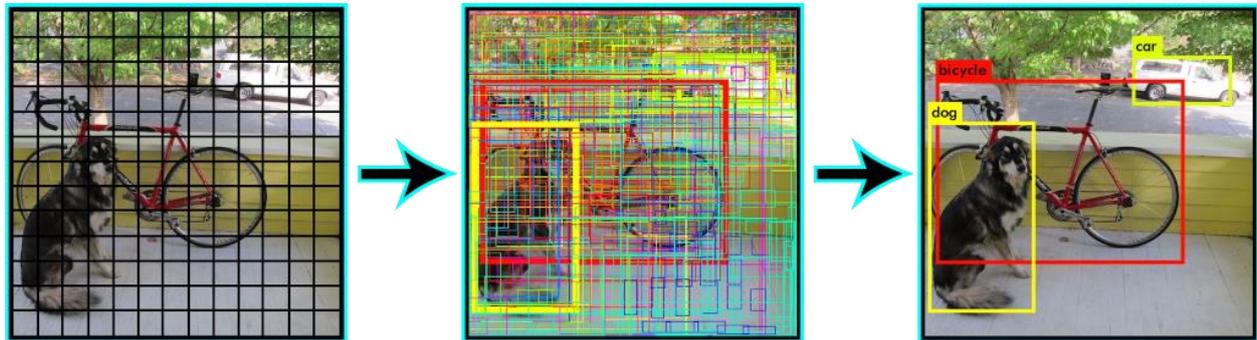


Figure 13: Bounding boxes

In this case we only care about people detections, but the network can work on bicycles or cars too just as well.

2.3. Tracking

We use the DeepSORT algorithm to perform tracking on the people detections. DeepSORT is a barebones implementation of a visual multiple objects tracking framework based on rudimentary data association and state estimation techniques, with integrated appearance information based on a deep appearance descriptor. It is currently trained to track only people.

Once this is done, every person gets a unique label and can be counted when crossing the barriers, leading to flow estimation: in this way it is also possible to get information on the individual velocity when crossing the area to understand the people behavior in case of crowding.

We illustrate an example of a live version of the program working real-time on the *harbor* camera, with the total counting shown in the upper left corner of the image (in red). In compliance with the privacy law, the

service version doesn't show a visual output of the video, but only stores the data output for further analysis and the integration in the visitor's mobility model.



Figure 14: Real time people counting at Sibenik's Riva

2.4. Data output

The detection and tracking data are written in .json files with the following structure:

```

cam_Centro2_1611777540.json
1 {
2   "cam_name": "Centro2",
3   "timestamp": 1611777540,
4   "datetime": "210127 205900",
5   "counter": {
6     "MEAN": 2.6,
7     "MAX": 4,
8     "MIN": 1
9   }
10 }
  
```

For each camera we write a file output for the detection data in a given interval, which reports the mean, minimum and maximum number of people detected in the video buffer, and a file output for the tracking part, which reports the number of people which crossed the barriers in the video buffer. Both files also contain the exact time and date when the service performed the task. The service writes these files for each camera and every set time interval (in this example it's 1 minute and these files were written at 20:59:00 of the 27/01 so the next ones were written at 21:00:00). The data are stored in a datahub for further analysis.

The program settings can be greatly tweaked to best adapt to the user needing: the number of frames in each buffer, the time between detections, the position and number of the barriers, and many other parameters for the detection and tracking.

The code can be found at <https://github.com/physycom/slides>.

2.5. Dubrovnik data

Dubrovnik municipality provided access to the log database of a system of wifi routers scattered across the town center which are used as hotspots for a series of public wifi networks. In this way the various events related to the interaction between any nearby wifi device and the routers, such as connection/disconnection/data transfer, are recorded in an anonymized form along with the relevant metadata

(timestamp, geodata, anonymous device id, ...). An example of such raw data is depicted in the following picture:

```
{
  "networkId": "N_659777345409800961",
  "deviceSerial": "Q2KD-Z2JC-Y7WM",
  "deviceName": "",
  "deviceMac": "e0:cb:bc:8d:69:d8",
  "devicePublicIp": "195.29.30.146",
  "deviceStatus": "online",
  "deviceLanIp": "192.168.200.4",
  "deviceLat": 42.64037,
  "deviceLng": 18.11075,
  "deviceAddress": "Pred Dvorom 3",
  "deviceModel": "MR42",
  "deviceFirmware": "wireless-25-11",
  "eventOccurredAt": "2021-01-18T08:52:52.930023Z",
  "eventOccurredYear": "2021",
  "eventOccurredMonth": "01",
  "eventOccurredDay": "18",
  "eventOccurredHour": "08",
  "eventOccurredMinute": "52",
  "eventType": "disassociation",
  "eventDescription": "802.11 disassociation",
  "eventClientId": "k2f3ed4",
  "eventSsidNumber": 0,
  "eventSsidName": "DUMUS",
  "eventDataRadio": "0",
  "eventDataVap": "0",
  "eventDataClientMac": "78:D7:5F:DD:F0:66",
  "eventDataChannel": "1",
  "eventDataDuration": "1562.308380621",
  "eventDataFullConn": "923.711340238",
  "eventDataIpResp": "923.711340238",
  "eventDataIpSrc": "10.47.62.212",
  "eventDataHttpResp": "928.659793839",
  "eventDataArpResp": "0.029990628",
  "eventDataArpSrc": "10.47.62.212",
  "eventDataDnsServer": "10.128.128.128",
  "eventDataDnsReqRtt": "0.009996876",
  "eventDataDnsResp": "1.819431427",
  "eventDataDhcpFailed": "1",
  "eventDataAid": "1947031354",
  "eventClientDescription": ""
}
```

The fields tagged with “device” are related to the routers whereas the ones tagged with “event” are related to the connected device activity.

2.6. Ferrara data

Ferrara municipality installed a distributed system of wireless sniffers which are able to record the presence of nearby devices of this kind through the collection of handshake messages. The sniffers are equipped with a wifi and a Bluetooth module and are therefore capable of detecting both types of devices.

An example of the raw data provided by each station is depicted in the following figure:

```
{
  "mac-address": "dd5d346d73f95ee24fd50ee54d83f858ae81bcf873bef4ec216d4d5911e1e057",
  "power": -81,
  "station_id": "test_10",
  "timestamp": "1606739585.093794",
  "date_time": "2020-11-30 13:33:05.093794+01:00",
  "coordinates": [
    20.4,
    30.2
  ],
  "random": true,
  "station_name": "test_10",
  "kind": "wifi",
  "kind_en": "wifi",
  "city": "Ferrara"
}
```

3. Raw Data Storage and Processing

Raw data are mirrored inside the project own data lake in real-time. Every 1 minute a scheduled series of server-sided process query for the raw data from each source and store them in a MongoDB database.

Raw data are then processed in order to extract some features of interest and perform some analysis:

- unique counters of devices for time interval, along with a daily basis average performed on a moving time window to include seasonal trends;

- origin/destination statistical matrix;
- device behavior analysis, which enables the distinction between static and passing devices;
- penetration factor, an estimate for the inferred number of people from the subset of the connected devices.

These quantities in turn are used as parameters for the nowcasting and forecasting models as illustrated in detail in the model section.

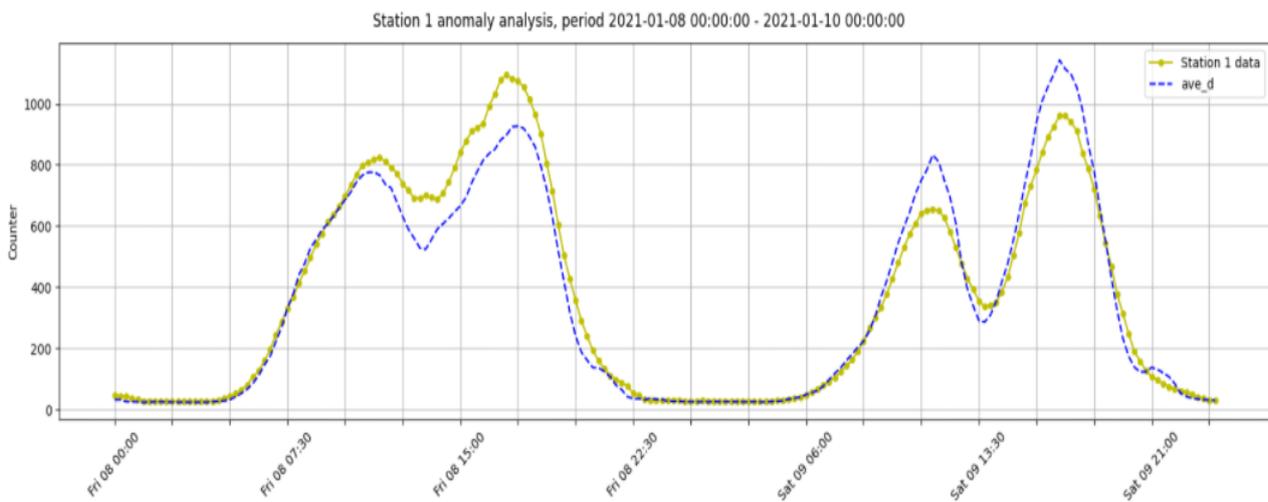


Figure 15: Station 1 anomaly analysis