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CAPSCombining Crowdsourcing and Crowdsensing to Infer the Spatial Context

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***Abstract*—How smartphones can empower users is a relevant topic in areas such as crowdsensing and crowdsourcing. However, to be able to harness users' knowledge requires accounting for their context and how it structures their understanding of the world. In this work, we propose to combine crowdsourcing and crowdsensing in the first of a series of experiments where we involve students to annotate their knowledge on their sensor data collected via a dedicated mobile application. We focus on the task of identifying WiFi networks in the university buildings as an initial step to obtain a better knowledge of students' location context. Results show that students were very accurate in their task and the potential benefits of combining the approaches from crowdsensing and crowdsourcing.**

***Index Terms*—Smartphones; Crowdsourcing; Crowdsensing**

I. Introduction

Given the increasing pervasiveness of smartphones in our everyday life, there is an ever growing interest in understanding how they can augment users life as individuals but also as collectives. The area of crowdsensing [1] explores the possibilities of leveraging on users as sensing nodes to collect and share their data for multiple purposes, especially in the paradigm of smart cities [2]. For instance, citizens can help understanding how to improve areas such as mobility, e.g., SenseMyCity[1], or characterization of WiFi deployment and configuration [3]. In addition to sensor information, human knowledge from users or collective of users is also invaluable in these fields of research, which can be treated as annotations of sensor data [4], [5], since it is unfeasible to rely on dedicated experts. In fact, recreating and understanding users experience is not an easy task [6]. The idea of relying on this "wisdom of the crowd", i.e., the intuition, popularized from [7], that collectives can provide more and better knowledge than individuals or even experts is at the base of crowdsourcing, which is progressively moving from only Web-based approaches to mobile devices [8].

However, involving humans to exploit their knowledge requires accounting for the fact that each person has his or her *context*, i.e., 'a theory of the world which encodes an individual's subjective perspective about it" [9]. Diversity in context may also lead to additional issues among humans, especially as a collective, whose context elements do not align. For instance, if a person were to communicate where he or she works to a person she just met, this person could reply with "I work in my office" but rather he or she will say something like "The University of Trento in Povo (TN)". As a counterexample, if a person's friend asks where he or she is, this person may still reply using " the University of Trento in Povo (TN)" but would rather prefer saying "I'm in my office". This situation shows that, depending on the context, a different output is enabled starting from the same real world, i.e., an office of the University of Trento.

In this work, we propose an approach that combines crowdsensing, concerning the collection of users' sensor data, and crowdsourcing, concerning users' annotations. We rely on the annotation methodology developed in [10], where annotations are built semantically to account for users' view of the world, thus conveying human knowledge in a continuous annotation process of their surroundings via smartphones. The users' annotations can then be exploited at the collective level in different types of real-life scenarios.

We tested this annotation approach with an experiment where we involved students in describing their everyday life. To do so, we relied on i-Log [11], a mobile application that allowed students to both annotate their experience but also collect sensor data from their smartphones.

As a preliminary result, we show how students collaborated in finding the Wifi networks of the University of Trento by annotating their presence in the university buildings, which accounts for crowdsourcing, while i-Log collected information about the WiFi networks, which accounts for crowdsensing, to infer their spatial context. The result is an accurate mapping of the routers in the University of Trento that provides the basis for context-aware spatial recognition.

The remainder of this paper is organized as follows. Section II summarizes our methodology for building annotations, while Section III presents the students experiment. Then, Section IV explains how we combined crowdsensing and crowdsourcing to develop a localization system. Section V describes related work and Section VI concludes the paper.

II. From Context to Annotations

In this work, we treat context is treated as the main representational tool that people use to make sense of their

[1] https://sensemycity.up.pt/

surroundings at a given moment. As an example, let us consider a Ph.D. student that is currently in an open space of her university where she has to attend a meeting with professor Fausto and her colleague Enrico.

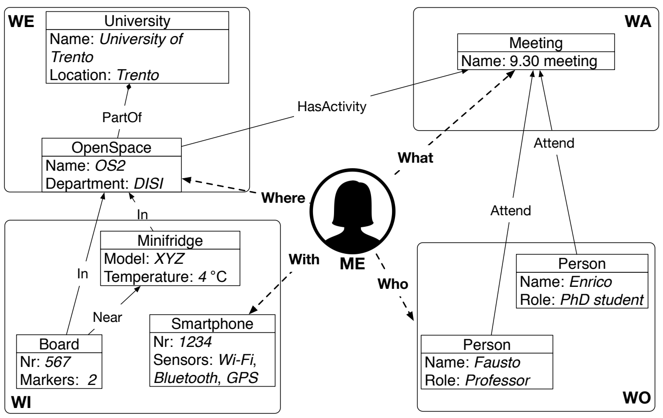

Fig. 1: A representation of a student's context.

Fig. 1 shows the open space scenario as a knowledge graph, representing the student's context. Following our notion of context, it focuses only on certain elements of the real world and abstracts to a certain degree, e.g., being in a meeting and ignoring activities from other people in the office or the presence of a camera. Each node represents an entity, e.g., Fausto or her smartphone, with its respective attributes and their attribute values. For instance, attributes of Enrico in Fig. 1 are "Class", "Name", and "Role", and their corresponding values are "Person", "Enrico", and "PhD student", respectively. Edges represent relations between entities, e.g., "Enrico" has only one relation: "Attend" for "Meeting."

We formalize the structure of context as the following tuple:

$$Cxt = < me, WA, WE, WO, WI > \tag{1}$$

where:

- **me** is the person on which the context is centered, e.g., a student;
- WA is the Temporal dimension, i.e., the answer to the question "**W**h**A**t are you doing?". It accounts for all the most relevant activities for a person in the current context, e.g., attending a lesson;
- WE is the Spatial dimension, i.e., the answer to the question "**W**h**E**re are you?". It accounts for all the most relevant locations for a person in the current context, e.g., a classroom;
- WO is the Social dimension, i.e., the answer to the question "**W**h**O** are you with?". It accounts for all the most relevant people for a person in the current context, e.g., the teacher and classmates

In Fig. 1, the dashed arrows represent the relation between *me* and dimension entities, e.g., where the student is or the activity she is involved in, which are modeled as an ontology based on the general ontology in [12] unifying human perception and knowledge representation.

Ontologies can act as hierarchies of labels to be used as annotations. However, to be effectively adopted in real life scenarios, they are required to be deployable on mobile devices and easy to use. Thus, we present them to the users as time diaries, which are a popular type of self-report used in sociology to analyze human behavior. Time diaries are logs where respondents report activities performed, locations visited and people encountered during their day [13].

This presentation of ontological information in the form of time diaries consists of two main steps. Firstly, the most relevant time use classification standard must be agreed upon, considering whether it can be properly adapted and how well it covers the domain of investigation, e.g., occupation or student life. Secondly, the context dimensions to be covered must be chosen, i.e., locations, activities, and people. Then, the resulting ontologies must be adapted, with the help of sociologists, to the research scope and aim to become the closed entries of time diaries to be administered via smartphones.

The time diary used in this work was presented in [10], so we will omit the details on the building process. To summarize, it relied on the American Time Use Survey (ATUS) [14] to obtain an ontology consisting in over 80 candidate labels for three dimensions, each being a question to be asked: activities, locations, and people. Then, the second step led sociologists to reduce the total number of labels to 43.

TABLE I: The time diary from [10].

What are you doing?	**Where are you?**	**Who is with you?**
Lesson	Class	Alone
Study	Study Hall	Classmate(s)
Eating	Library	Friend(s)
Selfcare	Other University place	Roomate(s)
En route (*)	Canteen	Partner(s)
Social life	Bar/ Pub/etc	Colleague(s)
Social media & internet	Relative(s)	Other
Cultural Activity	Home	
Sport	Other Home	**(*) How are you travelling?**
Shopping	Workplace	By Foot
Hobbies	Outdoors	By Bus
Other Free Time	Gym	By Train
Work	Shop	By Car
Housework	Other Place	By Bike
Volunteering		Other
Other		

This process of adaptation was then performed on activities and social roles, resulting in the time diary shown in Table I. For each dimension, the available answers are the adaptation of concepts to coded entries and each question is mapped to the corresponding context dimension. "What are you doing?" represents activities (WA), "Where are you?" represents locations (WE), and "Who is with you?" represents social relations (WO); notice that no WI is present in this specific case because of the research scope. The link between the fourth question "How are you traveling?" and the "En route" activity, shown via an asterisk, represents that, although "En route" would qualify as an activity, it represents traveling habits, which refer to locations. If a user selects this option, then, instead of the "Where are you?" options, he or she will be able to indicate a mean of transportation.

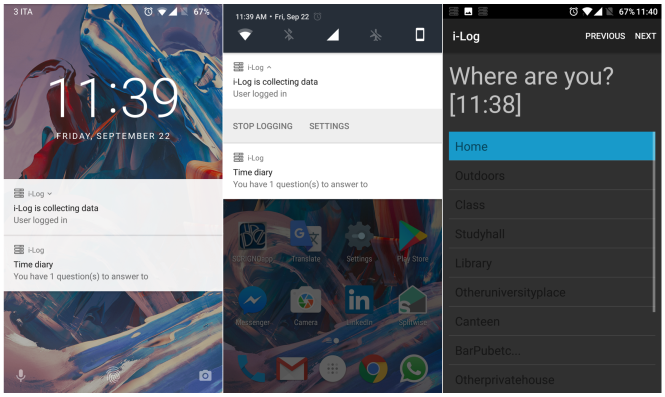

Fig. 2: i-Log is limited to a notification to tell the user that the data collection is ongoing and a second notification when a new question is made available.

III. The Experiment Design

The main aim of our experiment is to explore the combination of crowdsensing and crowdsourcing using semantic annotations. This experiment is the first in a series where the final goal is to develop personal assistant systems leveraging on technologies, such as smartphones, living in symbiosis with their users and capable of understanding the world as they do.

The experiment relies on a the i-Log mobile application [11] for two main functionalities. The first one is collecting data from up to 30 different sensors at the same time, be they hardware sensors (e.g., GPS and accelerometer) or software sensors (e.g., notifications and running applications). The second one is administering the time diary from Section II asking students to annotate their activities, location and social relations with predefined time intervals between questions, as shown in Figure 2. There is a dedicated backend infrastructure for storing and synchronizing the data. i-Log is designed to address configuration issues, by adapting its configuration both in terms of the internal specifications of each smartphone sensor and in terms of time diaries, e.g., changing their administration frequency. Furthermore, it grants user privacy from the data acquisition to the analysis process. It is also light-weight computation-wise by delegating all the CPU intensive tasks to the server side. In fact, the smartphone is only tasked with logging and synchronizing the data. An additional element of battery efficiency is adopting smart sensing strategies (e.g., GPS) to limit the battery consumption of the collection process.

The experiment involved 72 students selected among the ones enrolled at the University of Trento. The primary criterion for choosing students was that they had to have an Android smartphone with an Android version 5.0.0 or higher. This criterion is due to limitations of lower versions' smartphones in terms of computing efficiency and hardware sensors availability.

Students were asked to attend an introductory meeting on the experiment goals and how to use i-Log. After signing a consent form, they could install i-Log on their smartphones. Users were informed about all aspects of their personal information treatment in terms of privacy, from data collection to storage to processing. As customary for these type of experiments, before starting the data collection, we obtained the approval from the University of Trento ethical committee.

The experiment was divided into two weeks. During the first week, students were asked to answer a time diary on their smartphone, while i-Log was collecting sensor data in the background. The questions were administered every 30 minutes, but, to allow users to answer with ease, the questions could be answered with a delay of up to 150 minutes from when they were generated. If the students could not or did not wish to answer, the questions expired. During week 2, students were only required to have the application running for collecting sensor data since two weeks of questions were likely to discourage students in providing accurate answers.

The resulting 110 Gb dataset is a behavioral annotated dataset that exploits sociological insights from the very beginning and, in addition to sensor data and answers, it is also merged both with socio-demographic characteristics of students provided by the University of Trento.

IV. Combining Crowdsensing and Crowdsourcing

Among the various aspects that are relevant for understanding users, locations are extremely important, primarily to enable context-aware services. We illustrate the outcome of the crowdsourced task, within the general aim of our experiment, for students to identify the WiFi routers, crowdsensed with i-Log, within the University of Trento to detect their spatial context.

The first part of the process consisted in considering the annotations concerning the university, i.e., 'Class", "Study Hall", "Library", "Canteen", and "Other university place", in order to have windows of time that, according to students, represented when they were actually in the university. The total number of annotations is 3775, with "Class" having the highest amount of among all annotations (2767, i.e., 73.2%).

Out of all the 3775 annotations, to assess that students were actually in the university, we considered only those annotations having a corresponding physical location collected by the smartphone sensors via GPS or NETWORK providers at the time of the question generation. If the physical location fell within the shape of any university building, then the annotation was valid; this was the case for 91% of all the location points.

After this step, we collected the WiFi networks recorded by the i-Log application. More in detail, i-Log was designed to collect all the available WiFi networks every minute for all the users. Among all these millions of values, we extracted only those networks that were collected 15 minutes before and 15 minutes after the time of when the students' location was collected. The result is a list of 103,094 WiFi networks, each one having the MAC address, the name and the signal strength mapped on the corresponding buildings, as shown in Table II. Among all these networks, there are 3013 unique MAC addresses and 789 unique SSID (network names). The reason for this disparity is that all the routers in the university

TABLE II: Networks, with their respective MAC addresses and names, of the University of Trento buildings.

Building	Total Networks	Variable	Unique Networks
Computer Science	36077	Address	563
		Name	117
Biology	11990	Address	367
		Name	91
Natural Sciences	7995	Address	173
		Name	32
Humanities	12336	Address	614
		Name	142
Sociology	7269	Address	378
		Name	114
Law	1130	Address	50
		Name	5
Economics	15914	Address	534
		Name	229
Engineering	10383	Address	334
		Name	59

propagate a wireless signal with the SSID unitn or unitn-x, while each of them has a different MAC address. For this work, we kept only the 50 most common unique MAC addresses per building and the 10 most common WiFi names. In fact, due to the distance of detecting a WiFi network, there were multiple networks sensed only once by one or few people in the crowd of students; we treat these networks as outliers.

By considering these networks, which are localized by checking their time of the location collection, we could attach a set of WiFi networks to each building of the university where students were during the experiment. The buildings belong to the faculties of Humanities, Economics, Law, Sociology, Engineering, Computer Science, Natural Sciences, and Biology.

The result is a map representing buildings with their corresponding WiFi networks, which allows us to locate the students within any university building without the need on leveraging on the GPS location or forcing students to be connected to a WiFi network. This result is a huge advantage since the GPS is known to be the highest energy demanding smartphone sensor [15], while being connected to a WiFi usually requires the user interaction. Localizing student through the WiFi networks detected with their device is particularly important in our scenario since we discovered that our sample, most of the time, was keeping the GPS sensor and the WiFi connectivity off. Our approach also works in this case and allows us to locate them unobtrusively and continuously since Android allows applications to detect nearby WiFi networks even if the interface is off.[2]

The idea is that the more data collected by the students as a crowd, the more accurate the localization of students as individuals will be in the next experiments since it leads to a more complete and representative list of buildings and their respective WiFi routers. Furthermore, the crowdsourcing component of the annotations allows us to infer the location even if the user is not collecting the GPS location.

To evaluate our solution, we decided to train on half of the students (35 out of 70) and then test on the remaining half.

[2]https://goo.gl/m56xRc

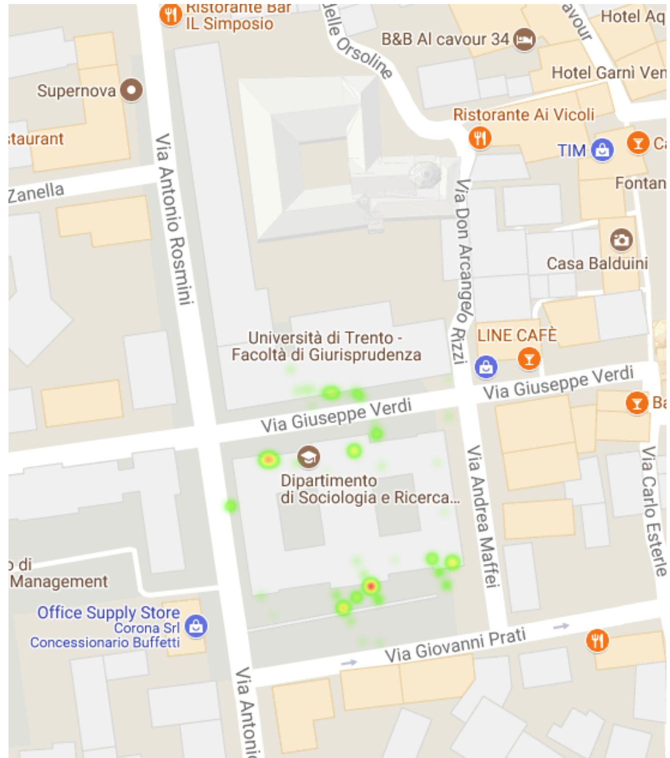

Fig. 3: MAC addresses for the Sociology building.

The splitting has been done randomly and, for every iteration, we tested the results are similar. For the test phase, we adopted the following procedure:

- We generated a list of WiFi networks composed of address, name, and building for each of the 35 students.
- We looped over every point, searching the corresponding name/address of the WiFi network in the list building/WiFi as designed above.
- For every match, we compared the expected label collected by the user with the label associated with the same WiFi network by the crowd.
- We then counted the correct matches to define a percentage of accuracy for each user.

Our results show that for every iteration (where each iteration creates a different split of the users) accounting for the WiFi MAC address with routers having a unique MAC address, 85% of the students obtained an accuracy higher than 95%. In the case of the WiFi SSID, since it is shared among multiple routers and buildings, the accuracy unsurprisingly drops to $\sim 30\%$.

What follows are some images to show how the crowdsourced and crowdsensed data used in combination can be used to locate the WiFi networks within the university buildings. The images represent a heatmap, where the more the network concentration the more the color tends to red. Figure 3 shows where the crowd located the MAC addresses for the Sociology faculty. Notice that the results, in this case, are noisy because the department of Sociology and Law are one

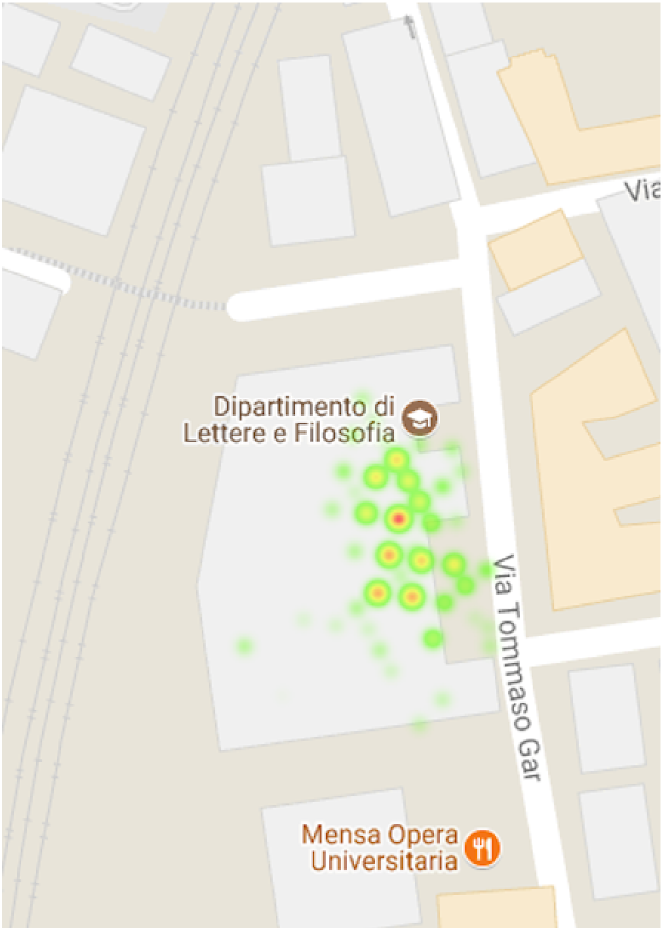

Fig. 4: MAC addresses for the Humanities building.

opposite the other within 20 meters. Since WiFi networks can be sensed more than 100 meters away, it is reasonable that students from one faculty could collect the WiFi networks of the other. Figure 4 shows a more definite distribution of WiFi networks for the Humanities building. In this case, there are no other university buildings nearby, and the result is much neater. Finally, Figure 5 shows the location of the WiFi networks where the SSID is equal to unitnx. As expected, all the buildings of the University of Trento can be identified. Starting from the left, which represents downtown Trento, we can identify the faculties of Humanities, Economics, Law, and Sociology. Moving towards the right, we reach the suburbs of Mesiano, where the faculty of Engineering is, and, slightly further to the right, Povo, where the faculties of Natural Sciences, Biology, and Computer Science are.

V. Related Work

Our work is at the intersection between crowdsourcing [8] and crowdsensing [1]. Among the works from these two areas, the most similar one to ours is [6], which focuses on the best approach to elicit annotations from 37 users while describing their traveling habits. With respect to this work, we treat users as collectives and also have some heuristics to assess users' reliability. Focusing on our experiment and the annotation of WiFi, some similar works use crowdsensing. SensLoc [16] groups WiFi or other types of location related information, e.g., GPS, into clusters that correspond to specific semantic areas in an energy efficient way. Pazl [3] is a mobile crowdsensing based indoor WiFi monitoring system that addresses the issue of locating measurements employing a hybrid localization mechanism that combines pedestrian dead reckoning with WiFi fingerprinting. [17] exploited crowdsensing, e.g., traveling on public transports and measuring the received signal levels, to obtain the WiFi characterization and monitoring of Edinburgh. Our main difference with respect to these works is the addition of annotations and also here some form of control to ensure that users provided the expected data. With respect to the semantic annotation of significant locations (or places), there has been considerable work in trying to address this issue. For example, the PePe field study [18] examined conditions and characteristics of semantics given by users to different locations, while [19] argues that semantics typically depend on the "role" of the person. In the case of University building, this might be less important as the names used by people are likely to be similar regardless of their role.

There is an increasing number of applications specifically designed to allow users to annotate their own sensor data. [5] proposed the idea of "mission", i.e., a sequence of selecting activity class and device position as well as performing the activity. Over 35,000 activity data were gathered from more than 200 users over 13 months. However, only the accelerometer of the participants' smartphones was collected. [4] presented an annotation system using multi-sensory streams for daily activity. It segments each day in a small set of meaningful events which the user has to annotate with multiple tags categorized by activity, place, and people, e.g., eating in a restaurant with friends. However, the system has only been evaluated by one volunteer. The major difference with respect to our work is our interdisciplinary methodology for building annotations.

Our definition of context is quite different from that usually found the pervasive computing community (see [20] for a survey). To us, context is an intermediate representation layer which bridges the human and machine representations of the world, rather than an aggregation mechanism exploited by machines to reason about sensor data [20]. As such, our notion of context does not need to represent uncertainty. We implement reasoning by representing context as an ontology and by exploiting efficient Modal/Description Logic inference engines [21], [22].

VI. Conclusions

In this work, we proposed to combine elements from two increasingly overlapping areas, i.e., crowdsourcing and crowdsensing. The approach relies on an annotation process built on the notion of context to account for human input, which is at the base of crowdsourcing, and that can be used in real life crowdsensing scenario. We evaluated this approach in a first experiment where users were supposed to annotate their

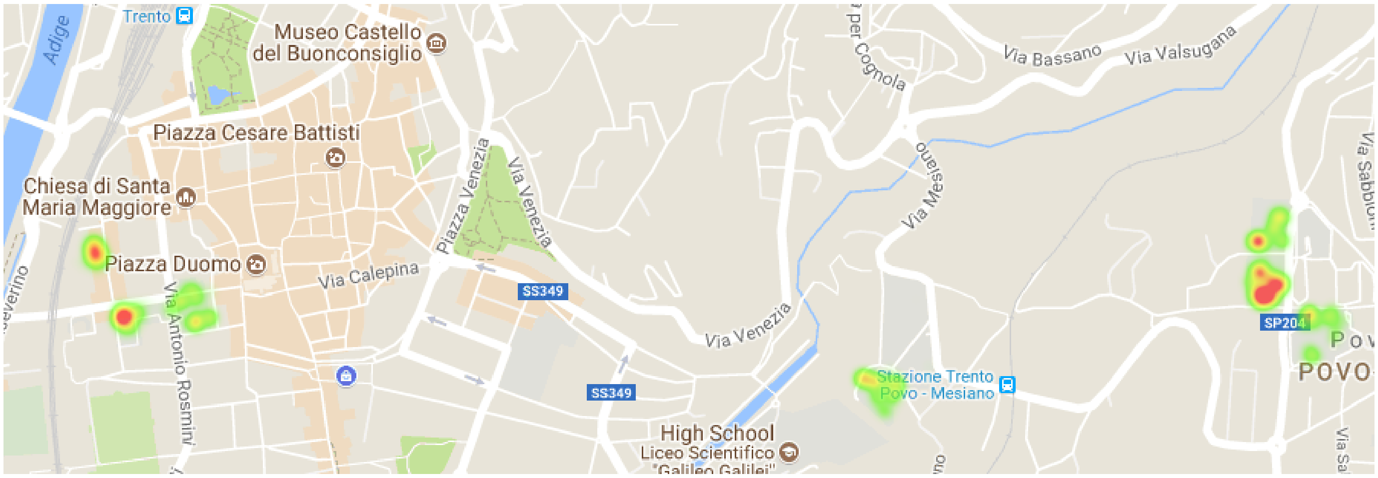

Fig. 5: WiFi networks with SSID unitnx for the University of Trento.

everyday life, focusing on their task as a collective to identify WiFi networks in the University of Trento. The annotations allow us to build crowdsensed and crodwsourced knowledge that can be exploited in new iterations of the experiment to enable context-aware recognition of activities and social relations. Although preliminary, our results show that students were very accurate in their annotation task and that there is a potential in hybrid approaches. Future experiments will involve more participants and last for a longer period of time.

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