

DISI - Via Sommarive 14 - 38123 Povo - Trento (Italy)
<http://www.disi.unitn.it>

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Fausto Giunchiglia, Enrico Bignotti,
Mattia Zeni

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Fausto Giunchiglia
DISI - University of Trento
Via Sommarive, 9
I-38123 Povo (TN)
Email: fausto.giunchiglia@unitn.it

Enrico Bignotti
DISI - University of Trento
Via Sommarive, 9
I-38123 Povo (TN)
Email: enrico.bignotti@unitn.it

Mattia Zeni
DISI - University of Trento
Via Sommarive, 9
I-38123 Povo (TN)
Email: mattia.zeni@disi.unitn.it

Abstract—Context is a fundamental tool humans use for understanding their environment, and it must be modelled in a way that accounts for the complexity faced in the real world. Current context modelling approaches mostly focus on *a priori* defined environments, while the majority of human life is in open, and hence complex and unpredictable, environments. We propose a context model where the context is organized according to the different dimensions of the user environment. In addition, we propose the notions of *endurants* and *perdurants* as a way to describe how humans aggregate their context depending either on space or time, respectively. To ground our modelling approach in the reality of users, we collaborate with sociology experts in an internal university project aiming at understanding how behavioral patterns of university students in their everyday life affect their academic performance. Our contribution is a methodology for developing annotations general enough to account for human life in open domains and to be consistent with both sensor data and sociological approaches.

Keywords—Ontologies, Context modelling, Context annotation, Smartphone sensing, Behavioral trends

I. INTRODUCTION

Humans can only have a limited and partial view of the world at all times in their everyday life. This is what context is, i.e., “a theory of the world which encodes an individual’s subjective perspective about it” [6]. Hence, context modelling must account for this relation between the user and the context inferred from the environment. Currently, most works focus on controlled environments, e.g., smart homes [13]. The main limitation of these approaches is that they focus on *a priori* defined environments, which are limited in terms of complexity and known in advance. In other words, they focus on a *closed domain*, whereas humans experience is essentially in *open domains*. In open domains, unlike closed domains, it is impossible to predict, and hence model, how the world will present itself [7]. This requires managing, at run-time, unexpected obstacles and changes of the environment [9] and also deciding what is relevant to the state of affairs the user is in at that time [1].

We propose a model of context based on [6], organized according to the different dimensions of the environment. In addition, our model relies on the notions of *endurant* and *perdurant*. In formal ontology [5], *endurants* are “individuals wholly present whenever they are present, and that persist in time while keeping their identity”, e.g., buildings and people, while *perdurants* are “individuals composed of temporal parts”, e.g., events. These notions can then be used

to create an ontology accounting for the way perception guides how humans aggregate their description of their surrounding environment.

We apply and test our approach by collaborating with sociology experts and taking part to the SmartUnitn¹ project, which aims at recognizing behavioral patterns of students to see how their life style affects their academic performance. The collaboration with sociology experts provides us with useful insights on how to ground our methodology in real life and make our ontology more usable. The resulting contribution for the project is a questionnaire consisting of three lists of annotations mapped to our ontology for tracking the most salient triple of activity, locations and social relations, in accordance with sociological methodologies such as time use surveys [3].

The reminder of this paper is organized as follows. Section II provides our definition of (personal) context, while Section III explains the notions of *endurant* and *perdurant* contexts. Then, Section IV illustrates the process of adapting our ontology in a list of annotation for the internal university project. Section V presents the systems for administering the questionnaire, and Section VI describes works similar to ours. Finally, Section VII concludes the paper.

II. MODELLING CONTEXT

Consider an average occurrence in a student’s everyday life, such as a classroom with a teacher and students where a lesson is taking place. While these facts can be considered as objective, for each person in the room a different *context* is going on, focusing on certain elements, e.g., the teacher and the subject of the lesson, and ignoring others, e.g., the sound of the projector, the weather outside and so on.

Fig. 1 shows this scenario as a knowledge graph, representing the personal context of an individual in the class. Each node represents an entity, e.g., the person and the room, 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 “Classmate”, respectively. Edges represent relations between entities, e.g., “Classroom” has two relations: “HasActivity” for “Lesson” and “In” for “Board” and “Desk”.

¹<http://trams.disi.unitn.it>

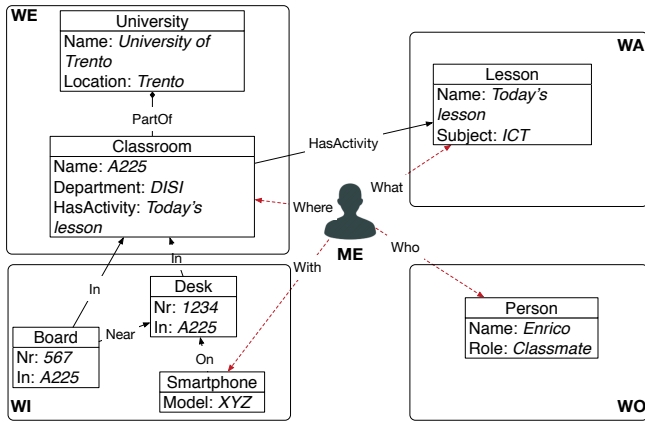


Fig. 1: The four dimensions of context, centered on the user.

We formalize the relation between context as a partial representation of the real world and the subject it is centered on from Fig. 1 as $MyWorld = \langle me, Cxt \rangle$ where:

- me is the person on which the context is centered on, represented as an entity with its attributes and relations.
- Cxt is the (real world) context of the person, aggregating different elements surrounding the user. As such, it is not the *global* view of the environment, but a *local* view encompassing an user centered subset.

In Fig. 1, the red arrows represent this relation between me and Cxt , since they link elements of the context directly to the person, e.g., the smartphone and the classroom the person is in.

Furthermore, we model Cxt as: $Cxt = WA \cup WE \cup WO \cup WI$, where:

- WA is the *temporal* context, i.e., the context generated from the question “**Wh**At are you doing?”. In Fig. 1, WA consists in the main activity taking place, i.e., the lesson.
- WE is the *spatial* context, i.e., the context generated from the question “**Wh**ErE are you?”. In Fig. 1, WE shows the most relevant location, i.e., the classroom.
- WO is the *social* context, i.e., the context generated from the question “**Wh**O are you with?”. In Fig. 1, WO focuses on user’s classmate Enrico.
- WI is the *object* context, i.e., the context generated from the question “**Wh**at are you w**It**h?”. In Fig. 1, WI covers two types of objects: furniture in the room, e.g., the board and the chair, and the user’s smartphone.

III. ENDURANTS AND PERDURANTS

In addition to dimensions, contexts account also for the fact that they aggregate based on points of view, i.e., that humans fundamentally use two elements to drive their representation: time and space. We account for this with the notions of *endurant* and *perdurant* contexts. According to [5], endurants are “individuals wholly present whenever they are present, and that persist in time while keeping their identity”, e.g., buildings and people, while perdurants are “individuals composed of temporal parts”, e.g., events. So the context can provide different representation of the same state of affairs depending

on which element is more important. For instance, consider the scenario described in Sec. II. In an *endurant* context, one could say “I’m in class”, implying a certain level of granularity within the building; in fact, saying “I’m at the university” would work too. In a *perdurant* context, one could say “I’m studying”, while other activities may be going on, e.g., somebody leaving or people discussing. The state of the world is the same, but the representation is different.

Fig. 2 extends the scenario described in Section II by taking a subset of the ontology based on [8]. This work proposes an ontology unifying human perception and knowledge representation, thus corroborating how contexts allow for different perceptions of the environment based on space or time. Notice that Fig. 2 is at the level of the entity classes from Fig. 1, and focuses only on WA and WE for clarity’s sake.

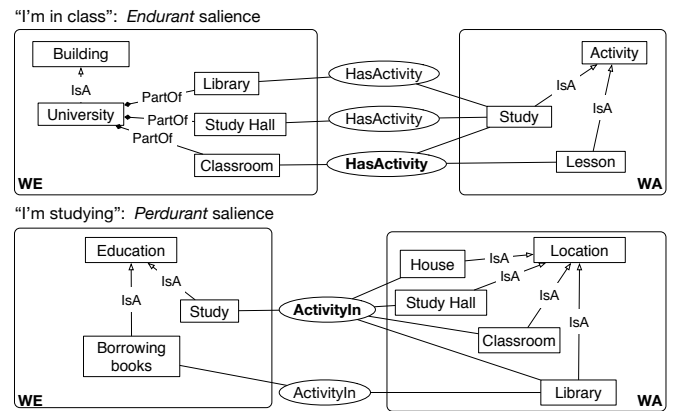


Fig. 2: The difference between the notions of *endurant* and *perdurant* when describing the context.

The two possible representations are as follows:

- **Endurant context:** since being in the classroom is more relevant, the activities to be performed are fixed: either studying or having a meeting are possible.
- **Perdurant context:** among the events, studying is more relevant, so the possible locations, and their granularity, are less relevant and there may be different types of locations.

Note that the relations (in bold) mapping locations and activities and vice versa, i.e., “**HasActivity**” and “**ActivityIn**” respectively, are not simply inverse functions, i.e., $ActivityIn = HasActivity^{-1}$ does not necessarily hold. In fact, in Fig. 2 in the case of *endurant* context “**HasActivity**” maps classroom to both “Study” and “Lesson”, whereas in the *perdurant* context “**ActivityIn**” maps “Study” to many more elements, i.e., “House”, “Study Hall”, “Classroom”, and “Library”. This shows that the structure changes depending on the viewpoint, since relations do not map to the same elements.

These phenomena affect the activity recognition process, since, depending on which context is active, the elements to be recognized and to be expected, along with possible services, change. For instance, in the case of *endurant* contexts, location

based services, e.g., sharing a location with friends, may be more relevant for a user.

IV. ANNOTATING CONTEXT

While general, ontologies are hard to use for real users. We solve this problem by mapping our proposed ontology to the state of the art in sociological approaches to obtain information by people. Time use surveys are particularly relevant approaches, since they are widely used to investigate a specific aspect of people’s time management, e.g., working, academic performance, and so on [3]. In fact, we based our modelling for activities on several time use surveys, especially the American Time Use Survey (ATUS) [14].

To test and apply our methodology, we interact with sociology experts in the SmartUnitn project for linking student behaviour and academic performance. Students are recruited via surveys and participate by signing a consent form allowing an application, described in Section V, is installed on their smartphones. The project lasts two weeks: during the first one, students need to answer a questionnaire on their day and must carry their phone with them for the collection of sensor data. The interaction with sociology experts in this project leads to an adaptation of our ontology to the experiment accounting based on these methodological considerations:

- 1) **Perdurant context:** Since activities are the main focus of this experiment, the context to be mapped to the annotations is a perdurant one. This allows us to mirror the relevance of activities, since events are the aggregating elements for perdurant contexts.
- 2) **From ontology to annotation lists:** Following the sociology experts inputs, to make the ontology usable it has to be adapted to a list of annotations, without any sort of hierarchy. In fact, a simpler, leaner presentation is more likely to elicit and engage the students’ answers, coupled with a controlled vocabulary for reducing possible ambiguities. In order to capture the most salient triple of location, activity and social relations [10], the annotations act as a list of possible answer for the corresponding questions, i.e. “Where are you?” (locations), “What are you doing?” (activities) and “Who is with you?” (social relations).
- 3) **No WI context:** In the case of this experiment, out of the four context dimensions, the sociology experts do not deem the WI context relevant. Thus, no mapping with the object context is required.
- 4) **Ordering of the questions:** According to the sociology experts, and in general for time use surveys [10], activities are more relevant than locations and social relation in the experiment. Thus, the ordering of the three question mirrors this hierarchy: activities first, locations second and then social relations.
- 5) **No locations and activities constraints:** In activity recognition, locations can often act as constraints for the activities performed there [12]; for instance, when in bathrooms, people take a shower instead of cooking. However, from a sociological point of view, constraints

may lead to a loss of valuable sociological data, e.g., students studying in places not explicitly designed for it, such as workplaces, bars or gyms. As a result, no constraints are imposed between the locations and activities annotation lists.

- 6) **Adding “Other”:** In time use surveys, the answer “Other” is a standard option with possible variations, e.g., the “n.e.c.” field (i.e., Not Elsewhere Classified) in the ATUS [14]. Methodologically speaking, this means that the possible activity, location or social relation is outside the research scope of the sociologist, so it does not matter; “Other” covers such cases [3]. Ontologically speaking, “Other” acts as an element of openness, i.e., as a placeholder node in the ontology to accommodate and expand new pieces of information to be added in time to an ontology.

The result of the mapping between our ontology and the sociological methodology for the experiment is three different lists of annotations. Notice that there is a decreasing level of granularity among activities, locations, and social relations in the mapping. In fact, since they are taken from a perdurant context, activities, being more relevant, are both more in terms of number of nodes and granularity than locations and roles.

- **Activities:** Fig. 3 shows the mapping of activities, i.e., the WA context, from the perdurant context and the question about activities. Here the annotations are adapted by the first tier of activities, especially for “Relax”, which maps to 4 annotations, i.e., “Hobbies”, “Cultural Activity”, “Other Free Time”, and “Social Life”. This coarseness in the mapping is due to the fact that, in order to capture high level patterns, activities are required to be very general. Furthermore, more detailed activities, as underlined by the sociology experts, would cause more cognitive load in terms of memory for students and force them to answer more questions to reach an unnecessary fine grained level of detail.

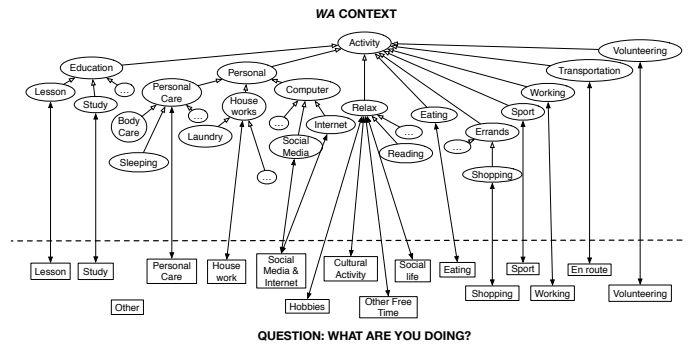


Fig. 3: The mapping from the WA context to the activities annotation list.

- **Locations:** Fig. 4 shows the mapping from the locations, i.e., the WE context, of the perdurant context to the question about locations. Here the mapping is almost one to one with the lowest tier, except for “Other University

place” and “Other Home”, since they group more specific types of buildings.

Notice that, even though “En route” is an activity, it refers to actual locations. So, if a student chooses it, then, instead of the options in Fig. 4, a list of means of transportation is provided and the question is “How are you travelling?”. The possible means of transportation are listed exactly as suggested by the sociology experts, i.e., “By Foot”, “By Bus”, “By Train”, “By Car”, “By Motorbike”, and “By Bike”.

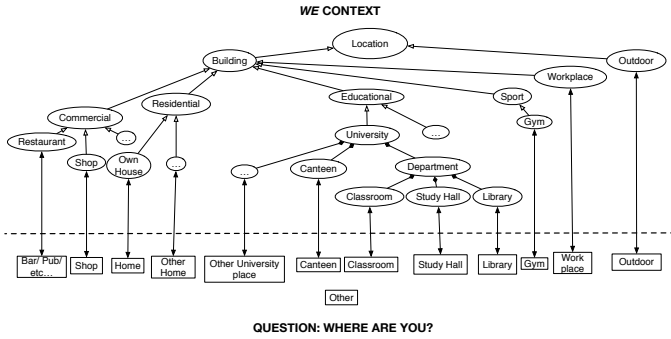


Fig. 4: The mapping from the *WE* context to the locations annotation list.

- **Social relations:** In the case of social relations, unlike locations and activities, the mapping is one to one, since they are a simple list in our current version of the *WO* context, as shown in Fig 5.

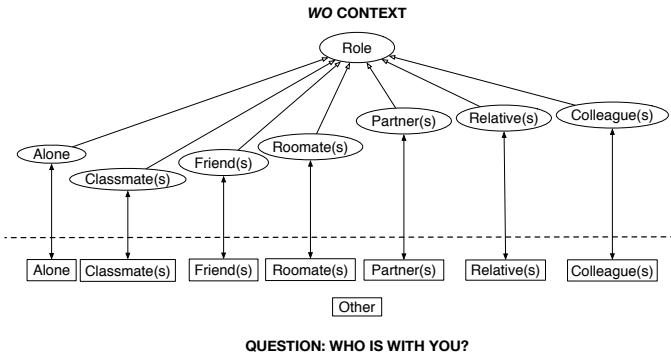


Fig. 5: The mapping from the *WO* context to the social relations annotation list.

The three lists of annotations compose the questionnaire to be administered to students, shown in Fig. 6. Each list of answers is the mapped set of annotations from Fig. 3, i.e., activities answering the question “What are you doing?”, Fig. 4, i.e., locations answering the question “Where are you?” and Fig. 5, i.e., social relations answering the question “Who is with you?”. The link between the fourth question “How are you travelling?” and the “En route” activity is shown via an asterisk at the end of the latter.

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

Fig. 6: The questionnaire for the experiment

V. DATA COLLECTION AND ANNOTATION

In order to administer the questionnaire to the users and collect the answers we rely on the i-Log [20] infrastructure conveniently modified. It consists of a front-end mobile application and a back-end system that work in symbiosis to infer the user’s context and provide personalized services accordingly. The system collects 29 streams of personal data from the user mobile device. The streams consist of data collected by the sensors inside the device, e.g. the GPS and the accelerometer, plus additional streams that log other events such as screen on/off, Wi-Fi networks available, and so on. All these sensor data are then processed in the back-end and mapped to the corresponding dimension of the context to aid the recognition in the user’s state of affairs. The main difference from the original implementation in [20] is the possibility to receive feedback from the users about what they are doing as answers to a questionnaire. They function as actual annotations on top of which elaborate the collected sensor data. These annotations then allow us to perform the mapping between the sensor data and the elements of the context. For example, once the user is asked “Where are you?”, we can map the high level answer “Home” with the GPS coordinates and the name of the Wi-Fi Network connected to the phone, among others. From that moment on, we can consider the Home location mapped to the specific values of the sensor data, e.g. “Latitude”: 11.237635, “Longitude”: 42.487252 and Wi-Fi Network name: “Home”. Thus, we can discover patterns that will help in inferring the user context in all the possible situations.

Figure 7 shows how the questionnaire is administered to the users in i-Log. Notice that each of the questions displayed is actually composed by the three of questions from Figure 6, i.e., i.e. “Where are you?” (locations), “What are you doing?” (activities) and “Who is with you?” (social relations), and the question is saved only if all three questions are answered. At a fixed time interval, a new notification pops up (Figure 8) displaying a message informing the student that a new question is available. In time use surveys, the standard timing to be covered by questionnaire is usually 10 or 15 minutes

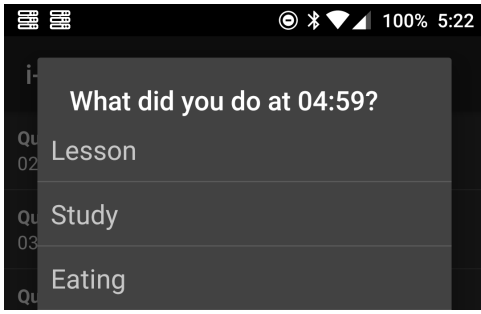


Fig. 7: (Partial) screenshot of the questionnaire on the user’s mobile device.

[3]. For this application, in accordance with the sociology experts, this timing is increased to 30 minutes. Based on their inputs, this increase ensures that students are less likely to be annoyed and enough time passes for detecting salient activities to be meaningful. The application has been designed so that the student can answer immediately or answer at a later time. Questions that are not immediately answered are put in a FIFO queue. The sociology experts decided to allow a maximum of $N=5$ questions to be present at the same time in the queue. This means that a student can avoid answering for a maximum of 2 hours (e.g., question1:1PM, question2:1.30PM, question3:2PM, question4:2.30PM, question5:3PM). If a new question is generated (e.g., question6:3.30PM), it is put in the queue after question5 and question1 is discarded because it expired.

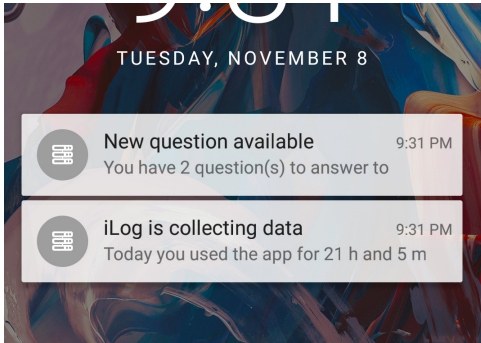


Fig. 8: Screenshot showing the two notifications provided by i-Log: (1) the first one showing that the logging is in progress and (2) the second one showing that some questions are available for answering.

Equation 1 shows how the total time a question lasts in the system and is available for answering:

$$Q_{TIME} = INTERVAL \times (N - 1) \quad (1)$$

Although the project is still ongoing, we can already show some preliminary results obtained from a subset of users (21, while the final project consists of 76 students) from a reduced time window of 5 days, shown in Table I. From the first row is it possible to see that the generated annotations

are 1130 in total, 74.77% of which are answered while the remaining 285 are left unanswered. From the answered ones,

No. of annotations	Answered 845 (74.77%)		Not answered 285 (25.23%)			
Location accuracy	95.65%					
Δ_A (in sec)	0-5	6-10	11-15	16-20	21-25	26-30
	16,8%	43,6%	17,6%	9,0%	4,6%	8,1%
Δ_{QA} (in min)	0-16	17-33	34-66	67-100	101-133	134-166
	33,2%	17,7%	21,7%	13,0%	9,8%	4,3%

TABLE I: Preliminary results from a subset of students participating in the project.

we calculated the correctness between the annotations and the actual locations, e.g., “Home” and “Via Roma 1” or GPS coordinates, since they are the easiest to check directly with the students; the accuracy rate is 95.65%. Finally, rows 3 and 4 provide an analysis of the answer behaviour of the student in terms of timing. Row 3 shows the time needed to complete an annotation, i.e., Δ_A , from the moment the student selects a question until all three questions are answered. 60.4% of the annotations are filled in less than 10 seconds, while none of them took more than 30 seconds. Since students do not receive incentives, 30 seconds response rate can be considered more than enough time for a question interval of 30 minutes. On the other hand, row 4 shows the time delay between the question notification and the student’s reply, i.e., Δ_{QA} . Here, 50.9% of the annotations were filled within 30 minutes, meaning that the reply came before a new question appeared; we consider this close to real time answering. Moreover, the 72.6% of the annotations were provided within 60 minutes, i.e., when there were less than two questions available. Notice that the choice of answering all the questions at once just before the earliest one expires was discouraged by the sociology experts, since it may lead to more errors in reporting; in fact, only 4.3% of the questions were answered this way.

VI. RELATED WORK

One direct comparison with our work from an application point of view is the SPHERE annotation tool used in the SPHERE challenge.² The main difference is the domain of application: we have an open domain, while the SPHERE tool, although providing an “Outside” location, does not. Our annotations also cover social roles, which are missing in the SPHERE tool. Since we only focus on the most salient activity, location and role for the student at the time of the question, we do not allow for multiple activities, which is possible with the SPHERE tool. Also, it constraints the activities depending on the location, unlike the application in the experiment.

In terms of experiment on students life there are three works similar to ours. [16] proposes the StudentLife app for assessing several dimensions of the everyday life of a class of 48 students across a 10 week term at Dartmouth College, while the SmartGPA study [17] shows that there are some correlations between the GPA and behavioral patterns extracted from smartphone data in [16]. Before these works,

²<http://www.irc-sphere.ac.uk/sphere-challenge/home>

the Reality Mining dataset [4] was built to explore smartphones capabilities for investigating human interactions. Our main differences are the ontological nature of our annotations, together with the addition of sociological inputs, e.g., students participating to SmartUnitn belong to different departments, noted by [17] as a possible improvement.

However, the main area of related works is context modelling, starting with CoBrA [2], an agent-based infrastructure, designed for campus space, capable of performing several context operations such as modelling, reasoning, and knowledge sharing. CONON [18] focuses on modelling locations by providing an upper ontology and lower domain-specific ontologies organized into a hierarchy. PiVOn [11] consists of four independent ontologies (users, environment, devices, and services), used to describe smart environments. The users perform tasks that have a goal and use some services, while the device ontology defines specifications of devices. Lastly, the environment ontology represents the position of objects and their type of location. CaCONT [19] defines several types of entities, focusing on locations. It provides different levels of abstraction for specifying information about the location of entities, e.g., GPS and location hierarchies. Our main novelty with respect to these works is that our methodology for modelling context is consistent with and accounts for both sociological approaches and sensor data for activity recognition, in addition to the notions of enduring and perdurant contexts; admittedly, the Mining Minds Context Ontology [15] shows some similarity with these notions in its context model. In fact, contexts are defined as a triple of locations, activities and emotions, that in turn are grouped according to an aggregating element, e.g., amusement, housework, commuting and so on, which could be further differentiated as enduring or perdurants. Finally, several works in ontology based activity recognition use ontologies to model contexts or elements such as activities of daily living within smart homes. Among many recent works, see [13] for a review, [12] is close to ours, since it uses an ontology, built on the Pal-SPOT ontology³, for modelling activities and other contextual data, and also assumes outdoors. Overall, our main difference with these works is the type of domains they are focused on — they assume *closed* domain, while we assume *open* domains.

VII. CONCLUSIONS

In this work we proposed a modelling of context based on [6], divided according to the different dimensions of the environment. In addition, we introduced the notions of enduring and perdurant, accounting for how humans use space or time as the main criterion to aggregate their context. We applied and tested our approach by taking part to the SmartUnitn project, where we collaborated with sociology experts. Our general contribution is a methodology for developing annotations general enough for open domains and aligned with both sensor data and sociological approaches.

³<http://everywarelab.di.unimi.it/palspot>

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REFERENCES

- [1] P. Bouquet and F. Giunchiglia, "Reasoning about theory adequacy: a new solution to the qualification problem," *Fundamenta Informaticae*, vol. 23, no. 2, 3, 4, pp. 247–262, 1995.
- [2] H. Chen, T. Finin, and A. Joshi, "An intelligent broker architecture for context-aware systems," *PhD proposal in computer science, University of Maryland, Baltimore, USA*, 2003.
- [3] B. J. Claessens, W. Van Eerde, C. G. Rutte, and R. A. Roe, "A review of the time management literature," *Personnel review*, vol. 36, no. 2, pp. 255–276, 2007.
- [4] N. Eagle and A. S. Pentland, "Reality mining: sensing complex social systems," *Personal and ubiquitous computing*, vol. 10, no. 4, pp. 255–268, 2006.
- [5] A. Gangemi, N. Guarino, C. Masolo, A. Oltramari, and L. Schneider, "Sweetening ontologies with dolce," in *International Conference on Knowledge Engineering and Knowledge Management*. Springer, 2002, pp. 166–181.
- [6] F. Giunchiglia, "Contextual reasoning," *Epistemologia, special issue on I Linguaggi e le Macchine*, vol. 16, pp. 345–364, 1993.
- [7] —, "Managing diversity in knowledge," in *IEA/AIE*, 2006, p. 1.
- [8] F. Giunchiglia and M. Fumagalli, "Concepts as (recognition) abilities," in *Formal Ontology in Information Systems: Proceedings of the 9th International Conference (FOIS 2016)*, vol. 283. IOS Press, 2016, p. 153.
- [9] F. Giunchiglia, E. Giunchiglia, T. Costello, and P. Bouquet, "Dealing with expected and unexpected obstacles," *Journal of Experimental & Theoretical Artificial Intelligence*, vol. 8, no. 2, pp. 173–190, 1996.
- [10] M. Hellgren, "Extracting more knowledge from time diaries?" *Social Indicators Research*, vol. 119, no. 3, pp. 1517–1534, 2014.
- [11] R. Hervás, J. Bravo, and J. Fontecha, "A context model based on ontological languages: a proposal for information visualization." *J. UCS*, vol. 16, no. 12, pp. 1539–1555, 2010.
- [12] D. Riboni and C. Bettini, "Cosar: hybrid reasoning for context-aware activity recognition," *Personal and Ubiquitous Computing*, vol. 15, no. 3, pp. 271–289, 2011.
- [13] N. D. Rodríguez, M. P. Cuéllar, J. Lilius, and M. D. Calvo-Flores, "A survey on ontologies for human behavior recognition," *ACM Computing Surveys (CSUR)*, vol. 46, no. 4, p. 43, 2014.
- [14] K. J. Shelley, "Developing the american time use survey activity classification system," *Monthly Lab. Rev.*, vol. 128, p. 3, 2005.
- [15] C. Villalonga, O. Banos, W. A. Khan, T. Ali, M. A. Razaq, S. Lee, H. Pomares, and I. Rojas, "High-level context inference for human behavior identification," in *International Workshop on Ambient Assisted Living*. Springer, 2015, pp. 164–175.
- [16] R. Wang, F. Chen, Z. Chen, T. Li, G. Harari, S. Tignor, X. Zhou, D. Ben-Zeev, and A. T. Campbell, "Studentlife: assessing mental health, academic performance and behavioral trends of college students using smartphones," in *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 2014, pp. 3–14.
- [17] R. Wang, G. Harari, P. Hao, X. Zhou, and A. T. Campbell, "Smartgpa: how smartphones can assess and predict academic performance of college students," in *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 2015, pp. 295–306.
- [18] X. H. Wang, D. Q. Zhang, T. Gu, and H. K. Pung, "Ontology based context modeling and reasoning using owl," in *Pervasive Computing and Communications Workshops, 2004. Proceedings of the Second IEEE Annual Conference on*. Ieee, 2004, pp. 18–22.
- [19] N. Xu, W. S. Zhang, H. D. Yang, X. G. Zhang, and X. Xing, "Cacont: a ontology-based model for context modeling and reasoning," in *Applied Mechanics and Materials*, vol. 347. Trans Tech Publ, 2013, pp. 2304–2310.
- [20] M. Zeni, I. Zaihrayeu, and F. Giunchiglia, "Multi-device activity logging," in *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication*. ACM, 2014, pp. 299–302.