Real World User Model: Evolution of User Modeling Triggered by Advances in Wearable and Ubiquitous Computing: State of the Art and Future Directions

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Real World User Model: Evolution of User Modeling Triggered by Advances in Wearable and Ubiquitous Computing

State of the Art and Future Directions

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Abstract

Over the last few years, user modeling scenery is changing. With the recent advancements in ubiquitous and wearables technologies, the amount and type of data that can be gathered about users and used to build user models is expanding. User Model can now be enriched with data regarding different aspects of people's everyday lives. All these changes bring forth new research questions about the kinds of services which could be provided, the ways for effectively conveying new forms of personalisation and recommendation, and how traditional user modeling should change to exploit ubiquitous and wearable technology to provide these services. In this paper we follow the evolution of user modeling process, starting from the traditional User Model and progressing to RWUM - Real World User Model, which contains data from a person's everyday life. We tried to answer the above questions and to present a conceptual framework that represents the RWUM process, which might be used as a reference model for designing RWUM-based systems. Finally, we propose some inspiring usage scenarios and design directions that can guide researchers in designing novel, robust and versatile services based on RWUM.

Keywords User modeling Ubiquitous computing Wearable technologies Adaptive systems Recommender systems Internet of things

1 Introduction

A personalised system maintains a model of the user and uses this model to adapt itself to the user's individual needs (Brusilovsky 2007). User modeling is the process of building this model. It is a cross-disciplinary research field that can be studied from the perspective of different disciplines: from Human-Computer Interaction (HCI) (Fischer 2001) to Artificial Intelligence (AI) (Webb et al. 2001), from psychology (Olson and Olson 1990) to philosophy (Giere 1986). While in HCI User Model represents the system builder's mental model of the user and has no explicit representation, in AI and personalisation research it deals in particular with the explicit representation of the model of a user (Kay 2008). This means that user modeling methods try to create digital representations of users, and use these models for calibrating and adapting the interface or the content of a system (Kobsa et al. 2001).

Methods, techniques and approaches to user modeling have always been subject to change along with the technological changes, as soon as new opportunities, challenges and techniques have arisen. For example, with the advent of the Web 2.0, people have started to use more extensively different Web applications such as Facebook and Twitter, generating and distributing personal and social information like interests, preferences and goals. All this information has been used to enrich the User Model. Also the Web of Data, with its enormous availability of information accessible in standard format, reachable and manageable by machines, opened new possibilities for user modeling. It allowed to enrich the knowledge about the user by extending it with more details about the items (books,

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movies, etc.) that she is interested in and by reasoning on them.

Another big recent change in the Web, with further implications on user modeling, was the arrival of the paradigm of Mobile Web, with the increased availability of mobile computing devices (smart phones, tablets, etc.) and the consequent ubiquitous diffusion of user data. Personalisation started to operate across many devices and information stores that constitute the user's "personal digital ecosystem" (Kay 2008). Nowadays, this pervasiveness of data is becoming more and more relevant with the advent of the so called Internet of Things (IoT) (Li et al. 2015; Whitmore et al. 2015). IoT allows to digitally connect everyday objects in the real world, making possible Wiser's vision of ubiquitous computing (Weiser 1998), which aims to bring intelligence to our everyday environments (also known as ambient intelligence (Mukherjee et al. 2009)). At the same time, wearable technologies with embodied sensors made it possible to gather a variety of personal data that was impossible to have before, related for example to people's physical states (e.g. blood glucose level) or psychological states (e.g. stress).

With such technological revolution, the amount and the type of data that can be collected about users are exponentially increasing, creating a constant stream of information that may reveal many aspects of their daily lives. Hence, interesting opportunities for user modeling arise, since User Model could be enriched with data concerning users' real-world characteristics and activities (e.g. regarding their body, habits, internal states etc.), and not only their Web behaviour. This could further support new forms of personalised and highly dynamic services directly integrated in the users' real lives: such services would adapt themselves almost in real-time depending on the ongoing users' internal states and external context. To stress the connection with real world, we call this new generation of User Models, *Real Word User Model* (RWUM). RWUM can be seen as an enrichment of the traditional User Model w.r.t. *coverage* (more data can be gathered and more user features can be modelled), *accuracy* (data reflect more accurately the users' behaviour) and *time and place* (potentially user modeling is present everywhere at any time).

In this scenario new research questions arise: what novel kinds of services and applications could be provided by this widespread availability of personal data in different domains? How user modeling process should change to exploit the opportunities offered by this new context?

Starting from these challenges, the paper will focus on the role of the ubiquitous and wearable technologies in the User Model enrichment. RWUM can be also seen as an evolution of the concept of Lifelong User Model (Kyriacou and Davis 2008), or better Lifelong Learner Model, envisioned by Kay (2008) before the real explosion of the new IoT world. Although Kay's work mostly focuses on learner models and their usage for personalisation in Intelligent Tutoring Systems (Nwana 1990), the vision of the Lifelong User Model inspired our present research. We tried to devote proper attention to the process of user modeling as a whole, with implications on recommendation and adaptation. More specifically, the main contributions of this article are the following:

- an overview on how user modeling process changed along with the changes in the Web, as well as with the spread of wearable and ubiquitous technologies, focusing on how the current trends are leading towards RWUM;
- a conceptual framework that represents the complete RWUM process and can be used as a reference model to design RWUM-based systems.
- some inspiring usage scenarios and research directions that can drive researchers in designing new services based on RWUM.

The article is structured as follows. Section 2 provides the background of the work: a technical overview on the research in the area of user modeling, focusing on the traditional methods and techniques for representing, reasoning about and evaluating User Models. Section 3 outlines a historical overview of user modeling process over the years, in order to better introduce RWUM in Section 4, which gives insights on how the aspects of the user modeling process could deal with the new challenges opened by ubiquitous and wearable technologies. Section 5 introduces a general high-level architecture which can be used for the design of RWUM, including the most relevant work related to RWUM. Section 6 describes some possible novel usage scenarios enabled by RWUM. Section 7 concludes the paper discussing open issues and opportunities arising with the introduction of RWUM.

2 Background on User Modeling

A *User Model* (UM) in Artificial Intelligence is a *data structure* with the characteristics of a particular user in a certain moment in time. *User modeling* (Brusilovsky 1996; Fink and Kobsa 2000; Kobsa et al. 2001; Brusilovsky 2007) is the process of creating, updating and maintaining a User Model. Starting from Kobsa et al. (2001), we identify the following phases in the user modeling process (see Fig. 1):

1. *User Model definition*
2. *data acquisition*
3. *inference of knowledge from data*
4. *representation of the User Model content*

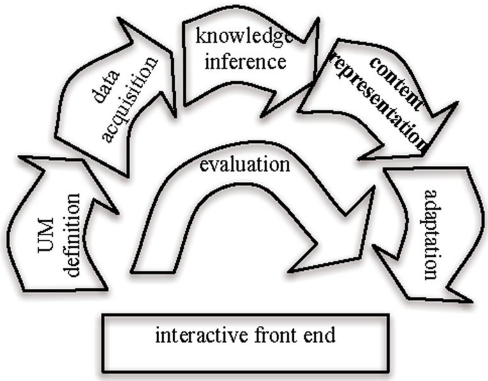

Fig. 1 User modeling process

5. *adaptation based on User Model data*
6. *User Model evaluation*

We provide essential details for each of the above phases in the rest of this section. We focus on information which will help the reader understand the development of RWUM and will find its counterpart in Section 4. A comprehensive study of all the techniques applicable in each phase is out of the scope of this article.

2.1 User Model Definition

In this phase the *data* to be modeled in a given scenario are defined. Traditionally, the following data can be incorporated in the User Model: *user data* (demographic data, user knowledge and skills, user preferences, user objectives (goals and plans), user affects (emotions, mood), user traits), *usage data* (observable usage, usage regularities) and *environment data* (software and hardware environment, location).

2.2 Data Acquisition

The information contained in the UM can be explicitly provided by the user (during the first usage of the system by filling forms (Petrelli et al. 1999; Janarthanam and Lemon 2014), or by rating items Miller et al. 2003; Wang et al. 2007) or implicitly obtained from raw data by inference processes (by unobtrusively monitoring the user's interactions Kelly and Teevan 2003).

The main source of raw data for traditional user modeling is the Web, where users leave a lot of traces (users' activities in browsing or in social networking sites Berkovsky et al. 2009; Shapira et al. 2013; Bhattacharya et al. 2014).

2.3 Inference of Knowledge from Data

The *analysis* of *Web traces* can provide training sets for machine learning algorithms which can create models of users' behaviour. Different *Machine Learning (ML) techniques* can be used for the scope (Zukerman and Albrecht 2001; Frias-Martinez et al. 2006). For example, the user's preferences can be captured from Web usage data by means of unsupervised approaches (e.g., k-means clustering Mobasher et al. 2000, fuzzy clustering Joshi and Krishnapuram 2000, association rules Chen et al. 2002), or supervised approaches (e.g., decision trees, Na¨ıve Bayesian classifier Zhu et al. 2003, Support Vector Machine (SVM) Ruvini et al. 2003).

Table 1 provides some examples from the state of the art of inference of user features starting from Web data.

2.4 Representation of User Model Content

The simplest way to represent a User Model is to use a flat model, a collection of variables and associated values, that can have the form of attribute-value pairs (De Bra et al. 1999), probability distributions (Carmagnola et al. 2008), fuzzy intervals (Cena et al. 2006), plain vectors (Lynda Tamine-Lechani Mohand Boughanem 2006), bags of words (Chen et al. 2010), Vector Space Models (VSM) (Musto 2010; Noia and Ostuni 2015)). When some aspects of the UM are more general and at a higher level than the others, these are best captured with a hierarchical structure representing relations between user characteristics, such as a tree or a directed acyclic graph like an ontology (Kim and Chan 2003; Liu et al. 2004; Heckmann et al. 2005; Razmerita 2007). Domain-dependent user features (interest or knowledge) can be matched to the domain concepts, by representing the UM as an *Overlay* over the domain structure. For each item in the domain, the user's current state with respect to that item is recorded (Brusilovsky and Millán 2007).

2.5 Adaptation Based on UM Data

The final goal of the user modeling process is to create a digital representation of the user to be used to customise a system. According to Kobsa et al. (2001), adaptation may occur at three different levels.

Adaptive presentation shows information to the user in a personalized way, according to her current level of knowledge, goals, etc. The content remains the same, whereas the layout and the modality of content representation change, such as in Fink et al. (1998), Haggerty et al. (2003). A similar approach can be found in Golemati et al. (2006), Nazemi et al. (2011), Bai et al. (2011), Bai et al. (2012), where the visualisation of content is adapted to the context of use.

Adaptive content selection means selecting the most relevant items for a specific user. Recommender systems are the most well-known type of such systems (Ricci et al.

Table 1 Examples of how to implicitly obtain user data from the analysis of Web traces

User data	Web traces	Techniques used for knowledge inference
Demographics	followed Twitter accounts (Volkova et al. 2016)	logistic regression
	tweets (Volkova et al. 2015)	log-linear models
	Facebook posts	hierarchical Bayesian models
Knowledge and Skills	interactive narrative experience (Rowe and Lester 2010)	dynamic Bayesian models
	CVs (Antunes 2008)	sequential pattern mining and constraint relaxations
	online surveys (Li and Yoo 2006)	Bayesian Markov Chain clustering clustering
	browsing content (Tang and McCalla 2002)	
Preferences		
opinions	comments (Pang et al. 2002)	Na¨ıve Bayes, maximum entropy classification, Support Vector Machine (SVM)
interests	tags in social networks (Yang et al. 2015)	tag normalisation algorithm
	pages visited (Kim and Chan 2003)	divisive hierarchical clustering
	search history (Daoud et al. 2007)	term-based interest building with ontology
	web usage data (Mobasher et al. 2000)	k-means clustering
	web behaviour (Joshi and Krishnapuram 2000)	fuzzy clustering
	annotated user logs (Zhu et al. 2003)	C4.5 algorithm and Na¨ıve Bayesian classifier
Objectives		
goals	interaction with Google (Ruvini 2003)	SVM
intentions	keywords and their conceptual generalisations (Chen et al. 2002)	association rules and modified na¨ıve Bayes classifier
Affects		
emotions	tweets (Volkova et al. 2015)	distant supervision and bootstrap noisy hashtag annotations for classification
mood	comments (Divya Vani and Suneetha 2015)	Feature selection with Naÿe Bayes classifiers
	tweets (Sadilek et al. 2014)	Fourier analysis and principal component analysis
Traits		
personality traits	tweets (Volkova et al. 2015)	log-linear models
	Facebook profile (Bachrach et al. 2012)	multivariate regression
	Twitter profiles (Golbeck et al. 2011)	regression analysis
Cognitive functions		
attention	web behaviour (Lagun and Agichtein 2015)	mixture of interactions and content salience model (MICS)
mental disorders	social behaviour (Shuai et al. 2016)	SVM
depression	Twitter posts (Choudhury et al. 2013)	SVM
mental health disclosure	Reddit content (Balani and De Choudhury 2015)	perceptron classifier

2010; Resnick et al. 1994; Linden et al. 2003; Adomavicius and Tuzhilin 2005; Su and Khoshgoftaar 2009). They can select items on the basis of their similarity with other items the user liked in the past (content-based) (Lai et al. 2003), or on the basis of similarity among users (collaborative filtering) (Miller et al. 2003). A special case of adaptive content selection is *contextual recommendations* (Micarelli et al. 2007), where the text displayed in the user's browser is used to retrieve related content.

Adaptation of structure or *navigation support* aim at helping users find information by adapting the way of presenting links to their features (Brusilovsky 2007), by means of different techniques, such as link ordering and hiding (Smyth and Cotter 2002; Brusilovsky and Pesin 1998), link annotation (Weber and Specht 1997), and link generation (Armstrong et al. 1995).

To provide adaptation based on UM data, Information Retrieval (IR) or Machine Learning techniques can be used.

Typical IR methods are Vectors of Terms, Bags of Words or Vector Space Model, where items and user profiles can be represented as weighted vectors computed using the TF-IDF formula (Breese et al. 1998). The match between items and the user profile can be computed using similarity metrics (e.g. cosine similarity): then, the most similar items to the user profile are recommended. ML techniques, instead, are used to learn a model (regression or classification) of the user's preferences by analysing the content of the items she rated (by means of Bayesian Network, SVM) Di Noia et el. 2012). The training set consists of item feature vectors labelled with ratings.

2.6 Evaluation

Personalised systems, due to their complexity, exhibit a need for a *layered-evaluation* (Paramythis et al. 2010), a combination of user-based and data-set based evaluation.

User-based evaluation involves end users in both formative and summative stages. Formative evaluations assess a model during its construction. They evaluate, for instance, if the UM contains the features that are relevant for the final recommendation. Instead, summative evaluations assess the worth of something completed. They evaluate, for example, the accuracy, the final users' opinions and satisfaction, and the coverage of the multi-source User Model. Both exploit qualitative techniques (usability tests, observational methods, interviews, card sorting, etc.), as well as quantitative ones (questionnaires, experiments, etc.), basically drawn from usability research (Fernandez et al. 2011).

Dataset-based evaluation. The most commonly measured aspect of personalisation quality is *accuracy of rating prediction*. Traditionally, the most popular metrics to measure it are error based metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). Despite the large adoption of error metrics, the accurate prediction of ratings does not imply the best top-N ranking of items (Bellog´ın et al. 2011; Cremonesi et al. 2010). More appropriate measures for evaluating top-N recommendation accuracy are precision-oriented metrics which take into account the ranked list of items, such as Precision, Recall and Normalized Discounted Cumulative Gain. Other measured aspects of recommendation quality are *diversity*, which measures how different the recommended items are w.r.t. what has been previously seen (metric: Intra-List Diversity (ILD)) (Ziegler et al. 2005), and *novelty*, which assess whether not only popular items were recommended. (metrics: Entropy-Based Novelty (EBN)) (Bellog´ın et al. 2010).

In Section 4, we will specify how each of these phases changes in the new context enabled by ubiquitous and wearable technologies.

3 User Modeling OverYears

In this section, we present a brief overview of the development of user modeling over the past years, which brings us ultimately to RWUM.

3.1 First Generation of User Modeling Systems

The first work on user modeling dates back to the early works of Allen, Perrault et al. (1978), Cohen and Perrault (1979) and Rich (1979), which inspired the development of numerous systems with different kinds of adaptation capabilities. These early proposals made no clear distinction between system components used for user modeling and components which performed other tasks.

One of the earliest approaches to user modeling was *stereotype user modeling* (Rich 1979). As explained in Section 2, stereotype-based systems map users' individual features to one or several equivalence classes, which are then used during the recommendation process. Grundy (Rich 1979) is the best known stereotype-based system, but other works also used stereotypes in different domains (Ardissono and Sestero 1995; Krulwich 1997; Zimmerman and Kurapati 2002).

3.2 Second Generation of UserModeling

Starting from 1990, it became evident that the user modeling component should be reusable for the development of user-adaptive systems (Fig. 2A).

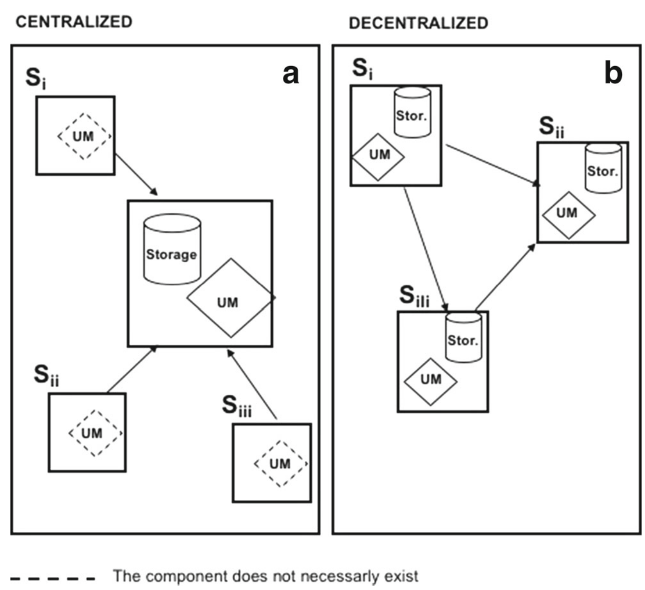

Fig. 2 Different user modeling architectures. We distinguish the *physical storage* of the UM, which physically maintains the user data (the cylinders in figure) from the *conceptualisation of the model*, which reflects how the UM component is conceived in terms of being shared or not (the diamonds in the figure)

The first step in this direction was the development of *generic user modeling systems* (also known as *user modeling shell systems*). According to Kobsa (2001), a generic user modeling system serves as a separate user modeling component of a system at runtime, and developers should simply fill it with the application-specific user modeling knowledge. Some examples are: UMT (Brajnik and Tasso 1994), TAGUS (Paiva and Self 1995), um (Kay 1995) and BGP-MS (Kobsa and Pohl 1995).

User modeling servers maintain a User Model as a *centralised repository*, shared across several applications through a flexible client-server architecture (see (Kobsa 2001; Fink 2003; Kobsa 2007) for more details). Some examples are: DOPPELÄNGER (Orwant 1995), Learn Sesame (Caglayan et al. 1997), GroupLens (Konstan et al. 1997), LMS (Machado et al. 1999), Personis (Kay et al. 2002), MEDEA (Trella et al. 2003), Cumulate (Brusilovsky 2004), UMS (Kobsa and Fink 2006).

Despite the benefits of centralised user modeling systems, they show some potential weaknesses (Kobsa 2007). They are too restrictive and their well-defined rigid access points are a potential central failure point for data protection[1]. All these limitations have a negative effect on the performance (especially availability and scalability) of the applications relying on user modeling servers.

3.3 Third Generation of User Modeling

With the increased availability of mobile computing devices, people may own a personal smart phone, a tablet device and a portable computer, as well as use multiple fixed desktop computers (Kay and Kummerfeld 2013). This is even more valid in ubiquitous environments (Weiser 1998), where numerous unrelated sensors and devices acquire information about users Lorenz (2005). This caused a proliferation of user data on different platforms: combined with the limitations seen above, it led to a *decentralised UM setting*, where there is a collection of User Model fragments distributed among the systems the user interacts with. *Decentralised user modeling* investigates how to combine partial user data and make sense of them in a specific context (Vassileva 2001; Dolog and Vassileva 2005; Heckmann 2005). To this aim, semantic techniques are used in order to favour data integration.

As shown in Fig. 2B, in decentralised user modeling process applications have their own representation of the User Model.[2] They communicate directly in order to exchange user and domain data in a peer-to-peer manner.

A decentralised architecture might have the form of *User Model Agents*, specialised agents that represent the user and cooperate with the source of information to satisfy the user's requirements, allowing for a dynamic reconfiguration of the system's capabilities. Examples of distributed ubiquitous UM based on multiple agent activity can be found in Niu et al. (2003), Lorenz (2005).

Usually, decentralised user modeling solutions offer functionalities for mapping and integration of different knowledge models (Brooks et al. 2004; Mehta et al. 2005; Heckmann 2005; Dolog and Schäfer 2005; Zhang et al. 2006; Carmagnola and Dimitrova 2008; Cena and Furnari 2009).

4 Current Trends in User Modeling: Towards a Real World User Model

The advent of ubiquitous and wearable technologies, as seen in Section 1, makes the shift from centralised to decentralised setting even more relevant. Several types of personal data can now be collected via ambient and wearable sensors (*ubiquitous sensing* Puccinelli and Haeggi 2005; Sigg et al. 2015). Such data can be used for the creation of a User Model. From our perspective, this can be seen as the *fourth generation* of user modeling, which is based on real world data, requiring specific techniques and having the potential for providing novel personalised services to users. We call this model *Real World User Model* (RWUM in the rest of the paper) to stress the more important role of real world data w.r.t. web-based data. Due to the complexity of this new context, made up of different and heterogeneous forms of information, new challenges for user modeling arise, which have impact on all the phases seen in Section 2: from definition through acquisition, representation, inference and adaptation to evaluation.

4.1 User Model Definition

The exponential growth of user data coming from sensors allows for the modeling not only of the user's web behaviour, but also of her real-life behaviour. This is a groundbreaking advancement for User Model, which can now be enriched by this new kind of information. It was seminal with mobile devices, able, for example, to gather

[1]Their reliability can be increased by introducing mirrors or distributing the information across several servers (virtual centralisation of distributed User Models), where there is a unique User Model but different parts of it are separately stored on different servers (Kobsa and Fink 2006).

[2]Systems can also be implemented as *mixed solutions*, where the User Models are physically decentralised, while each system stores its User Models locally, referring to centralised model which includes the most used concepts in the domain, as in Berkovsky (2006), GUC (van der Sluijs and Houben 2006) and MEDEA (Musa and de Oliveira 2005).

user positions in real time by means of GPS. But with ubiquitous technologies it acquires even more strength giving the possibility to:

1. *provide empirical evidence* for interests and preferences, mainly inferred from user activities on the web;
2. *increase the coverage of the model*, modeling not only interests, goals, knowledge and preferences, but also human habits, physiological and psychological states, social relations.

4.1.1 Providing Evidence for Traditional Features

Regarding user data, usage data, and environment data, the basic types of information remain the same, but they are confirmed by data coming from real world and not only from interactions with digital systems.

4.1.2 Increasing the Coverage of the Model

Due to the novel data gathering modalities, further user features can be included in RWUM w.r.t. the ones listed in Section 2.1, all related to the user's real life:

– *user behaviour*: we distinguish *activities* i.e. actions the user performs in real world, occurring at an exact point in time (such as movements and tasks), and *habits* i.e. recurrent and repetitive sequences of actions (such as sleeping pattern, eating pattern, sedentary level, activity level, media usage, etc.);
– *physical states*: information about the user's physical and mental health obtained by tracking user's physiological parameters in a particular moment (such as blood pressure, temperature, glucose level, heart rate, etc.), as well as physical characteristics and problems persisting for a long period of time (chronic diseases such as sight problems, auditory problems, movement problems, etc.);
– *social relations*: data about the user's current contacts and relations with other people in the real world (e.g. people met during a day, number of visits to relatives in a week), that we called "encounters", and all the social connections that an individual has developed over time (her social network).

Environment data, also known as *contextual data*, in RWUM scenario become more and more important, since ubiquitous technologies provide new modalities for acquiring them. In this perspective, the notion of context may be expanded to embrace both the external (like characteristics of the environment, the locations the user has visited) and the internal (like the user's, tasks, emotions etc.) factors that may affect the user's behaviour (Prekop and Burnett 2003).

In this new context, where data may be seamlessly and continuously gathered by sensors for prolonged periods of time, we can distinguish *long term* user features, which refer to users' characteristics considered in a dilated time frame, from *short term* user features, which point to punctual users' aspects considered in a specific moment in time. Table 2 gives a snapshot of the RWUM user features, distinguishing between long and short term ones.

Thus, the RWUM is richer than a traditional UM, since it can contain different categories of data describing the user from different points of view. One of the advantages of having all these data is the possibility to analyse them in order to find aggregations, patterns and correlations among them, for example among physical states and context, or habits and chronic diseases, as well as to examine their evolution over time, e.g. through time-series analyses and detection of trends and seasonalities.

4.2 Knowledge Acquisition and Inference

Besides the traditional modalities of *Web traces analysis* seen in Section 2, ubiquitous and wearable technologies enable other automatic data gathering modalities, in particular:

– *behavioural observation method* used to identify the users' features by observing their externalised reactions, such as facial expressions and speech. This can be done by means of ambient intelligence technologies (sensor-based or vision-based), by using mobile sensors on smart phones and wearable devices, or by analysing how the user interacts with her personal devices;
– *physiological recording* used to identify user features by recognising the user's physiological changes with biosensors (often incorporated in wearable devices).

These new means enable the gathering of new types of data, impossible to be collected before. In the following, we describe, for each type of data, how it can be automatically obtained, with examples coming from the state-of-the art (see also Table 3). It is worthy noting that to be exhaustive is out of the scope of this section.

User demographics

Mori et al. (2010) present an approach for automatically constructing a User Model of daily life. In particular, they propose a method that predicts a User Model by using features based on users' offline behaviour, their environment, as well as their online activities and the web-contents they interact with. Specifically, they model a town visitor, capturing her data (in terms of the shops the user visited and the physical characteristics of the environments she goes through, such as noise, congestion, weather, and

Table 2 RWUM features wrt traditional UM features (the features with * are not present in Kobsa's model)

User data	Trad. UM	Short term	Long term
Demographics	yes	address, job, marital status, etc.	name, date of birth, etc.
Knowledge and skills	yes	concepts known, particular skills	learning styles, general capabilities
Preferences	yes	opinions, whises	interests, tastes
Objectives	yes	goals	plans
Affects	yes*	emotions	mood
Cognitive functions	yes*	cognitive states (e.g., level of attention orientation, etc.)	cognitive skills personality traits
Behaviour	no	activities	habits
Physical states	no	physiological parameters (blood pressure, etc.)	chronic diseases
Social relations	no	encounters	social network

Table 3 Technologies for automatically gathering RWUM data

User data	Technologies for behavioural observation	Technologies for physiological recording
Demographics	ambient sensors (Mori et al. 2010)	
Knowledge and Skills	eye tracker (Cole et al. 2013)	
Preferences	sensors (Karami et al. 2016; Khalili et al. 2009) smartphone use (Liao et al. 2015)	
Affects		
emotions	camera-based facial recognition(Affectiva 2017) sensors and camera (frustration) (Kapoor et al. 2007)	wearable sensors (Guo et al. 2013) wearable sensors (Kapoor et al. 2007)
mood	mobile phone use (LiKamWa et al. 2013)	i-textile devices (Valenza et al. 2013)
Cognitive functions		
cognitive states	ambient network (attention) (Shi et al. 2014)	
cognitive skills	sensors (cognitive impairment) (Hodges et al. (2010; Dawadi et al. 2013)	
Behaviour		
activities	sensors (Turaga et al. 2008; Karami et al. 2016) camera (Aggarwal and Ryoo 2011; Cristani et al. 2013) location-based technologies (Liao et al. 2005; Ashbrook and Starner 2003)	smartphone sensors (Reyes-Ortiz et al. 2016; Dernbach et al. 2012; Anguita et al. 2012)
habits	camera (Rashidi et al. 2011; Huang et al. 2014) smartphone use Liao et al. (2015), Liao et al. (2004), Shoaib et al. (2015), Cao et al. (2010)	
Physical states		
physiological parameters	camera (Stone and Skubic 2013)	blood pressure monitor (H2care 2017) diabetes monitor (Medtronicdiabetes 2017)
chronic deseases	sensors (Robben et al. 2014)	
Social relations		
encounters	mobile network (Yoneki et al. 2009) camera for 1st person view (Fathi et al. 2012; Gan et al. 2014) mobile phone use (Matic et al. 2012)	
social network	wi-fi (social ties) (Bilogrevic etal. 2013)	mobile phone sensors (Hsieh and Li 2014)

temperature) by using ambient sensors and by obtaining additional information coming from her blog posts. Starting from these features they predict visitors' age, gender, marital status, residential area, occupation, and interests, by using SVM.

User knowledge and skills

Cole et al. (2013) present an approach for inferring users' levels of domain knowledge from their interactive search behaviour without considering the content of queries or documents. They model the users' information acquisition processes during search by only using eye movement patterns, making visible a correlation between the individual's cognitive effort, due to the reading activity, and her degree of domain knowledge. To predict the user's knowledge they construct exploratory regression models.

4.2.1 Short Term User Features

User affects
Emotions

Guo et al. (2013) present a pervasive and unobtrusive system for sensing human emotions, inferred by the recording, processing, and analysis of the Galvanic Skin Response (GSR) of human bodies. Differently from traditional multi modal emotion sensing systems, they recognise human emotions with the single modularity of GSR signal, which is captured by wearable sensing devices. A comprehensive set of features is extracted from GSR signal and fed into supervised classifiers for emotion identification, using Sequential Floating Forward Selection (SFFS) techniques.

Kapoor et al. (2007) present an automated method which assesses if a learner is about to become frustrated in Intelligent Tutoring System environment. The data was gathered using channels of information offering affective cues: a pressure sensing chair, a pressure mouse, a wristband with a wireless skin conductance sensor, a video camera for offline coding and the Blue-Eyes camera to record elements of facial expressions. The assessment method is based on Gaussian process classification and Bayesian inference.

User cognitive functions
Cognitive states

Shi et al. (2014) investigate the classification of FM radio signal fluctuation for monitoring the attention of individuals moving toward a static object. Changes in a person's walking speed, direction, and orientation have been identified as the best indicators of attention. They extract features for attention monitoring from changes in FM signals, continuously broadcasted by an FM radio station. Then, they merge the extracted features and distinguish between various attention classes using a decision tree and a k-NN classifier.

Stone and Skubic (2013) exploit an environmental camera, the Microsoft Kinect, for capturing habitual, in-home gait measurements for risk assessment. They exploit a probabilistic methodology for generating automated gait estimates over time from the Kinect data. The approach makes the assumption that each resident will create a cluster, or mode, in the dataset, representing their typical, in-home, habitual gait. These clusters are modelled as Gaussian distributions in the four-dimensional (4-D) feature space. The basic procedure is to fit a Gaussian mixture model (GMM) with the number of distributions K equal to the number of residents in the apartment to the dataset.

User behaviour
Activities

Anguita et al. (2012) present a system for human physical activity recognition using smart phone inertial sensors, such as accelerometers. They are used to classify a set of physical activities (standing, walking, laying, walking, walking upstairs and walking downstairs) by processing inertial body signals through a supervised ML algorithm for hardware with limited resources. This method adapts the standard SVM and exploits fixed-point arithmetic for computational cost reduction.

Reyes-Ortiz et al. (2016) present the Transition-Aware Human Activity Recognition system for the recognition of physical activities through smart phones. Their method combines inertial sensors for body motion capture, an ML algorithm for activity prediction and a filter of consecutive predictions for output refinement. The method targets real-time classification with a collection of inertial sensors, while addressing issues regarding the occurrence of transitions between activities and the presentation of unknown activities to the learning algorithm. This is accomplished by combining the probabilistic output of consecutive activity predictions of a SVM with a heuristic filtering approach.

Social relations
Encounters

Gan et al. (2014) exploit wearable cameras in order to reconstruct the human social interaction spatial structure. They use the constraints from the available first-person view cameras to estimate the spatial location and orientation of each observed individual. They then reconstruct the social interaction structure from multiple first-person views, where each of them contributes to the multifaceted understanding of the social interaction.

Matic et al. (2012) make use of sensing capabilities of phones to detect social interactions between people and analyse their social context. They avoid using dedicated hardware to recognize social interactions, since additional devices that users are not familiar with might influence natural users' behaviour and thus their social interaction patterns. The work shows that two parameters that can be detected through mobile phone sensing, namely interpersonal distance and relative body orientation, provide a solid basis for inferring social interactions. In particular, for estimating the distance between two mobile phones they use supervised learning, i.e. RSSI (received signal strength indicator) analysis.

4.2.2 Long Term User Features

User preferences
Interests

Karami et al. (2016) describe how to infer users' interest starting from users' activities detected by ambient sensors in a smart home. To this aim, semi-supervised learning algorithms and Markov-based models are used to determine the user's preferences by combining observation of the acquired data and user feedback on decisions taken by automation.

Khalili et al. (2009) aim to learn the user's service preferences in a smart environment (e.g. music and ambient lighting) by observing her states and learning from her feedback. System image sensors are used to obtain a richer description of the user's pose and activity through the analysis of images via computer vision techniques. Then, reinforcement learning (RL) is applied.

User affects
Mood

LiKamWa et al. (2013) present a smart phone software system, *MoodScope*, which infers the mood of its users based on how the smart phone is used. Compared to smart phone sensors that measure acceleration, light, and other physical properties, *MoodScope* is a "sensor"' that recognises the user's mental states. It analyses usage history (number of phone calls, SMSs, emails, application usage, Web visits, unique clustered location records) as coarse indicators of routine activities. Applications are monitored based on the usage of the ten most frequently used applications, while browser activities are grouped by unique URL domains. They cluster the time-series of location estimates using the DBSCAN clustering algorithm, which allows to count user visits to each approximate location.

Valenza et al. (2013) propose a monitoring platform which consists of a comfortable sensorised t-shirt that can acquire the inter-beat interval time series, the heart rate, and the respiratory dynamics for long-term monitoring during the day and overnight. Specific signal processing techniques and artificial intelligence algorithms (feature extraction, feature reduction strategy) are applied to analyse the data, in order to correlate dysfunctions involving the autonomic nervous system (ANS) and mood. For example, a feature projection method (PCA - Principal Component Analysis) is applied in order to retain the most important information from all features.

User cognitive functions
Cognitive skills

Dawadi et al. (2013) introduce a ML-based method for assessing activity quality in smart homes. They validate the approach comparing automated assessment of task quality with direct observation scores. They also assess the ability of ML techniques to predict an individual's cognitive health based on these automated scores. In particular, they use both supervised techniques, in which a ML algorithm learns a function that maps the sensor-derived features to the direct observation scores (SVM with sequential machine optimisation and bootstrap aggregation or bagging to learn the mapping) and unsupervised techniques, which use data characteristics to identify natural boundaries between activity performance classes.

User behaviour
Habits

Liao et al. (2015) present Smart Diary, a smart phone based framework that analyses mobile data to infer, predict, and summarise people's daily activities, such as their behavioural patterns and lifestyles. Smart Diary is able to make inferences and predictions based on a wide range of information sources, such as the phone sensor readings, locations, and interaction history with the users, by exploiting a sustainable mining model (MC). It considerably decreases system complexity by decomposing inference tasks into multiple MCs, capable of handling heterogeneous sensing data with the appropriate techniques (e.g. Naïve Bayes or Decision Tree method). Moreover, the model can be integrated with logic rules defined by users to express short-term, mid-term, and long-term event patterns and predictions. They also develop a feedback loop so that users can provide optional opinions on the generated diaries, and the system can learn continuously over time to improve its diary generating capabilities.

Huang et al. (2014) propose a method for recognising abnormal habits. In particular, they propose a multi-camera positioning algorithm which improves the positioning accuracy by combining head location with posture recognition. Moreover, they suggest a new recognition algorithm which detects the abnormal habits by clustering the data obtained from combining key points' duration histogram with the information of ISUS (intelligent space for understanding and service).

Physical states
Chronic diseases

Robben et al. (2014) present an approach for longitudinal ambient sensors monitoring for functional health assessments. By using ambient sensors, it is possible to analyse health trends. The health metrics comprise self reported data such as demographic data, comorbidities, physical functioning ((I)ADL), self-perceived health status, psychological and social functioning, and health-related quality of life. These are inferred through ambient sensors, and by analysing inactivity, indoor activities and loneliness. A location extraction algorithm is applied to the data. Based on the sensor events it can infer the location of the resident, where it is assumed that she is within a location until a sensor in another area is triggered. Subsequently, the time spent in a location is calculated for each hour, resulting in a 5*24-dimensional feature vector for each day. Such data can be used for further trend analysis. Two methods are presented: the first is simply plotting the time spent in a location per day as a function of time, therefore losing information on the daily structure; the second is reducing the dimension of the feature vector by performing principal component analysis (PCA) on the complete data matrix.

Social relations
Social network

Campos et al. (2016) presents the development of a prediction model of social isolation in older adults by exploiting Ambient Intelligence (AmI) and Social Networking Sites. The goal was to identify attributes that have a correlation with social isolation. These attributes correspond to social activities performed by older adults that can be monitored by AmI and SNS's, such as time spent inside the house, time spent outside and mobile phone communication. In order to obtain the first subset of relevant attributes, the J48 classification algorithm was applied to the full dataset. Then, the subset obtained was assessed using Chi-Squared and InfoGain methods with the Ranker method for evaluation of attributes, Correlation-based Feature Selection method with BestFirst and Greedy Stepwise for evaluation of the sets of attributes.

All this information is mostly in form of raw data, thus requiring some kinds of processing to be transformed into user features. Examples of the inference methods used by some of the state-of-art works are then presented in Table4.

4.3 Representation of User Model Content

How to represent data in the User Model strictly depends on the type of data considered. Since the majority of data that can now be exploited in the RWUM are huge amounts of raw information, model-based approaches are often used. When we have to integrate different data sources in order to make complex inference and to provide them to third parties, it is necessary to label data in a common manner. This can be achieved by using shared standards for the representation of both the raw data coming from sensors and the inferred data in the User Model. Unfortunately, such standards are not still widely used: this entails a proliferation of data formats, which are very heterogeneous w.r.t. the syntax and semantics, making data integration a tricky task that requires strenuous efforts. To this aim, ontologies (Guarino 1998) can be used, since they can solve the possible data value and schema conflicts coming from different data sources. Data value conflicts happen at the level of instances, whereas schema conflicts happen among classes of the ontology. When using ontologies for representing user data, it is possible to reuse the User Model across different applications. This can be achieved by agreeing on a unique ontology used by all the applications, or by mapping or harmonising different ontologies.

4.4 Adaptation Based on UserData

The RWUM has notable implications on adaptation and recommendation, since the possible applications of such enriched User Model are wider w.r.t. traditional User Model. We will follow again Kobsa's (Kobsa et al. 2001) classification of adaptation presented in Section 2.

Regarding the *adaptation of presentation and modality* and the *adaptation of structure*, RWUM-based adaptation is not different from traditional UM-based adaptation. The input and output modalities could be chosen by the system according to the user's preferences, needs and expertise. As time goes by, the system could learn the best interaction modalities to communicate with the user. What changes in ubiquitous contexts is that input and output modalities (from textual to visual, from vocal to gestural, etc.) are more numerous than in the traditional web context, and thus more opportunities for adapting interaction arise. For example, an ecosystem based on RWUM could automatically transform visual information into audio messages when the user is engaged in cognitively-demanding tasks.

Regarding the *adaptation of content*, we can make some more interesting considerations regarding novel opportunities offered by RWUM.

More accurate recommendation. First of all, RWUM offers the possibility to improve the content based and collaborative filtering approaches, grounding in empirical evidences the user's preferences. Hence, traditional adaptation mechanisms can be extended to become more effective by taking into account not only the user's experience in

Table 4 Techniques used by some state-of-the art work to infer user data from usage data

Work	User data to infer	Usage data	ML techniques
Short term features			
Mori et al. (2010)	demographics	user's activity in the city	SVM
Karami et al. (2016)	interest	user's activities at home	Markov model
Khalili et al. (2009)	interest music	user's pose and activity at home	reinforcement learning
Cole et al. (2013)	knowledge	eye movement patterns	exploratory regression model
Anguita et al. (2012)	physical activities	user's movements	SVM
Reyes-Ortiz et al. (2016)	physical activities	body motion	SVM
Guo et al. (2013)	emotions	galvanic skin response	supervised classification (SFFS)
Shi et al. (2014)	attention	gait (speed, direction, orientation)	decision tree, kNN classifier
Stone and Skubic (2013)	physical states	gait	Gaussian mixture model
Gan et al. (2014)	social relations	conversation	search-based structure recovery method
Yoneki et al. (2009)	social relations	meeting among people	K-quiques
Long term features			
Liao et al. (2015)	life style	locations, phone usage	multiple mining models (decision tree, Na¨ıve Bayes)
Huang et al. (2014)	habits	head location, posture	recognition algorithm
LiKamWa et al. (2013)	mood	phone usage	cluster
Valenza et al. (2013)	mood	physiological parameters	PCA, MLP techniques
Dawadi et al. (2013)	cognitive functions	(quality of) home task	SVM
Robben et al. (2014)	physical states	ADL, location in a house	PCA
Walsh et al. (2014)	physical states	home activities	linear discriminant analysis
Campos et al. (2016)	social relations	time spent at home or outside, mobile phone communication	decision tree
Matic et al. (2012)	social relations	phone usage	RSSI

digital world (i.e. the conventional user modeling paradigm), but also her relevant experience (of this user or of similar users) in the physical one (Abel et al. 2012). Data coming from real world can be used as validation of web-generated inference. As an example, collecting users' movements using GPS might confirm that the interests inferred from the Web were correct. To the authors' knowledge, there are no works in the literature that exploit RWUM to this aim yet.

Enriched user similarity. It is possible to enrich the notion of user similarity used in Collaborative Filtering (CF), where it only depends on having rated the same items similarly. Here, this notion can become a wider concept, including similar habits, similar movement patterns, etc. For example, the authors in Zheng et al. (2010) improve activity recommendations, by pulling many users' data together and by applying CF to find like-minded users and like-patterned activities at different locations. There are a few approaches that exploit CF in real-world recommendations within ubiquitous scenarios (Zhao et al. 2014; Zhang et al. 2013). However, they aimed at improving IoT service provision and not at using real world data to improve user similarity.

Wider range of recommendations. With the employment of RWUM we can obtain a wider range of recommended items. Examples of items with low complexity and value are: news, books and movies, whereas examples of more complex and higher value items can range from laptops to financial services, jobs and travel itineraries. With RWUM items can also be goals to be achieve, activities to be performed, services to be used Zhao et al. (2014), Zhang et al. (2013).

Real-time recommendation. With RWUM it should be possible to provide recommendations at the right time and in the right place, suggesting alternatives based on the user's actual context. This is an evolution of traditional context-aware systems (Abowd et al. 1999), especially w.r.t. the accurateness and appropriateness of the recommendations provided, since the recommender could consider both the user's external context conditions, and the internal ones, both in the long term and in the short term. The system could give suggestions in the form of real-time advices related to the user's ongoing behaviour, as well as her current physical, emotional and mental states, also adapted to her external environment. For example, it could recommend to stop studying when the noise in the environment is too high and the user's level of stress is rising too much: the recommender could propose to go out for a short walk, given the good weather outside. Few works in the literature exploit RWUM to this aim. We can cite (van Hage et al. 2010), a real-time adaptive routing system that implements a mobile museum guide for providing personalised tours tailored to the user's position inside the museum, as well as to her interests.

Emotional recommendations. Continuous tracking of emotional states could enable recommendations based also on users' unconscious preferences and wishes, better supporting their decision making process and their choices during their everyday activities. It could make suggestions without relying on their rational thinking, but exploiting their visceral tastes (Zheng et al. 2013; Costa and Macedo 2013). This could happen, for example, before buying something in a store, or when choosing a book to read, or a friend to call. Since emotion-based recommendations might be closer to what users really want and feel, they would be more inclined to follow them. The challenge here is to provide recommendations based on the user's current emotions, which could be detected by wearable technologies (see for example (Guo et al. 2013)).

Cognitively-based recommendations. With cognitive data, such as levels of attention, interests, mental workload, etc., it could be possible to provide recommendations on the work tasks to be prioritised, or on the learning topics to be studied, improving working and learning activities. To the authors' knowledge, there are no works in the literature that exploit RWUM to this aim yet.

Goals recommendations. The system could set long-term goals based on the user's past behaviour and on predictions of how it will likely evolve in the future. It should provide recommendations triggered by the user's current condition, suggesting what kinds of actions and changes the user should put in place to meet the set goals. In this way, the system would act as a "personal coach", able to set short-term goals for specific situations in relation to long-term goals. This is a clear shift from how traditional recommender systems and user modeling use goals. Usually, they try to learn users' goals in order to adapt recommendations to them (Drachsler et al. 2009; Barua et al. 2012; Barua et al. 2014). Instead, we want the recommender system to suggest the user new goals to be reached.

4.5 Evaluation

Within the RWUM framework, there is a need to mix qualitative with quantitative assessments in a layered , where it is assumed that she is within a location until a sensor in another area is triggeredevaluation approach (Paramythis et al. 2010) even more than in a traditional UM context.

Quantitative forms of evaluation are needed to assess whether the specific aspects of the RWUM are accurate, as well as whether the whole model matches with the real characteristics of the user. Since the RWUM can be used for a variety of purposes, the accuracy should be particularly evaluated in accordance with the specific goals for which the RWUM is used in a particular context. For example, using the physiological part of the RWUM for providing health advices requires a higher level of accuracy of the recommendations given than when this part is used for providing suggestions on running training programs to amateur athletes.

The relations with the other parts of the RWUM and the accuracy of the overall model should also be considered, in order to prevent contradictions and drawbacks in the recommendations provided. Since the RWUM directly impacts on the user's everyday life, by allowing for recommendations on users' real behaviour, its effects are far more varied, and somehow unpredictable, than those of the traditional UM: they depend on the changing context in which the user is situated in a given moment. Such mutability requires evaluation techniques that go beyond the mere assessment of accuracy, diversity and user satisfaction, thus requiring qualitative techniques such us contextual inquiries and ethnographic research that may enable an "in the wild" evaluation (Johnson et al. 2012). For example, the recommendations provided on the basis of the RWUM may be accurate *per se*, but they may negatively affect the user. For example: i) they might not be provided at the right time or in the right place, thus interrupting the user's current activity or being out of context (e.g. recommending to relax to reduce the current state of stress when the user is actually at work, thus increasing the stress level as a result of not being able to escape the situation); ii) they might jeopardise the user's privacy or be socially inappropriate (e.g. they may make visible information that the user does not want to disclose to others); ii) they might not sufficiently consider the other aspects of the user (e.g. they may correctly recommend to eat a large amount of sweets to the user, even if she has health problems related to high glucose levels).

To assess such matters, it is necessary to ask users to extensively report how the RWUM and the recommendations enabled by it have affected their everyday lives, or directly observe through ethnographic techniques the impact that such elements have on their activities.

5 Conceptual Framework for RWUM

We can now outline our vision of RWUM and point out its distinctive features, aiming to provide a conceptual model for it.

5.1 RWUM Definition

A RWUM is a User Model with the following characteristics:

- *real world-based*: it contains real world data gathered by environmental and wearable sensors;
- *integrated*: it can provide a comprehensive view of a user, whereby different aspects are not separated but correlated to discover new relations among them previously unknown;
- *interactive*: it can be accessed by users through different interaction modalities (graphical visualisations, vocal interfaces, etc.)
- *open*: it is accessible to other applications;
- *lifelong*: it can contain data about long periods of time.

To be defined as RWUM, a UM should have at least the first feature, i.e. it should be based on real world data. As a consequence of this feature, other characteristics can be derived for RWUM:

- *rich*: it has a greater coverage of user features. In principle, it could contain data about the whole real life of a person;
- *accurate*: by working with real world data, which provide more objective and direct information w.r.t. Web data; it can be used to have confirmation of information obtained from digital behaviour;
- *unobtrusive*: by using sensors, it may obtain data in a transparent way, without interfering with users' life;
- *up-to-date*: due to the usage of sensors, it contains updated data gathered in a continuous way.

A RWUM can be seen as a *multilayer structure* (Fig. 3) containing different levels with increasing complexities:

- *Level 1* contains usage and environment raw data gathered from environmental sensors, as well as raw physiological user data from wearable sensors;
- *Level 2* contains short-term user data inferred from level 1;
- *Level 3* contains long-term user data inferred from level 2;
- *Level 4* contains correlations among all the user data, usage data and environment data.

Notice that level 4 might exist also directly over level 2, without the need to distinguish between short and long term features.

To move from one level to another, the system should make use of reasoning and inference mechanisms, usually exploiting machine learning techniques and ad hoc algorithms, to infer new features and find correlations.

Moreover, a RWUM can be used in the following three ways (not exclusive):

1. to provide advanced *adaptive services*, also in real time. This is mandatory in order to speak about user model;
2. to provide *data interaction modalities* to users. In principle, it could be possible to adapt the interaction modalities (how to provide data, such as visual/vocal etc.) and data provided (how to present data, which data to present) to the user's features
3. to provide *data to other applications*: simple raw data (level 1), elaborated data (level 2 and 3) or correlations (level 4).

5.2 Possible Architectures for Implementing the RWUM Model

There are several aspects to be considered in order to effectively implement a RWUM in an application. Ultimately, the goal is to provide the system with capabilities to gather, maintain, and support reasoning on user data in order to deliver adaptive services and/or interaction modalities to the user and/or data to other systems. Thus, there is a need for a mechanism that can:

1. manage input data, thus collecting data from the user's context (usage and environment data).
2. create the RWUM:
   - reason on raw data to infer user data;
   - reason on data to find correlations;
3. use the RWUM to provide as output:
   - personalised services to the user;
   - interactive modalities to access the data, such as data visualisations to the user;
   - user data (raw or elaborated) to other applications.

To the authors' knowledge, so far there are no systems capable of dealing with all these aspects together. Existing systems implement only some features of RWUM. We provide now some examples, categorised according to their architectures.

5.2.1 Centralised Services for Adaptive Applications

A possible implementation of RWUM is a centralised architecture (Section 3 1), where the system collects user data in a central repository that provides data to other (adaptive) systems (Fig. 4). The centralised system should be in charge of:

1. data gathering;
2. data integration;
3. data inference;
4. interaction with data (for example through visualisation).

We now describe existing state-of-art centralised systems that implement some RWUM features.

Kay (2008) provides a framework for creating *lifelong learner modeling*. Data for learner modeling, or the so

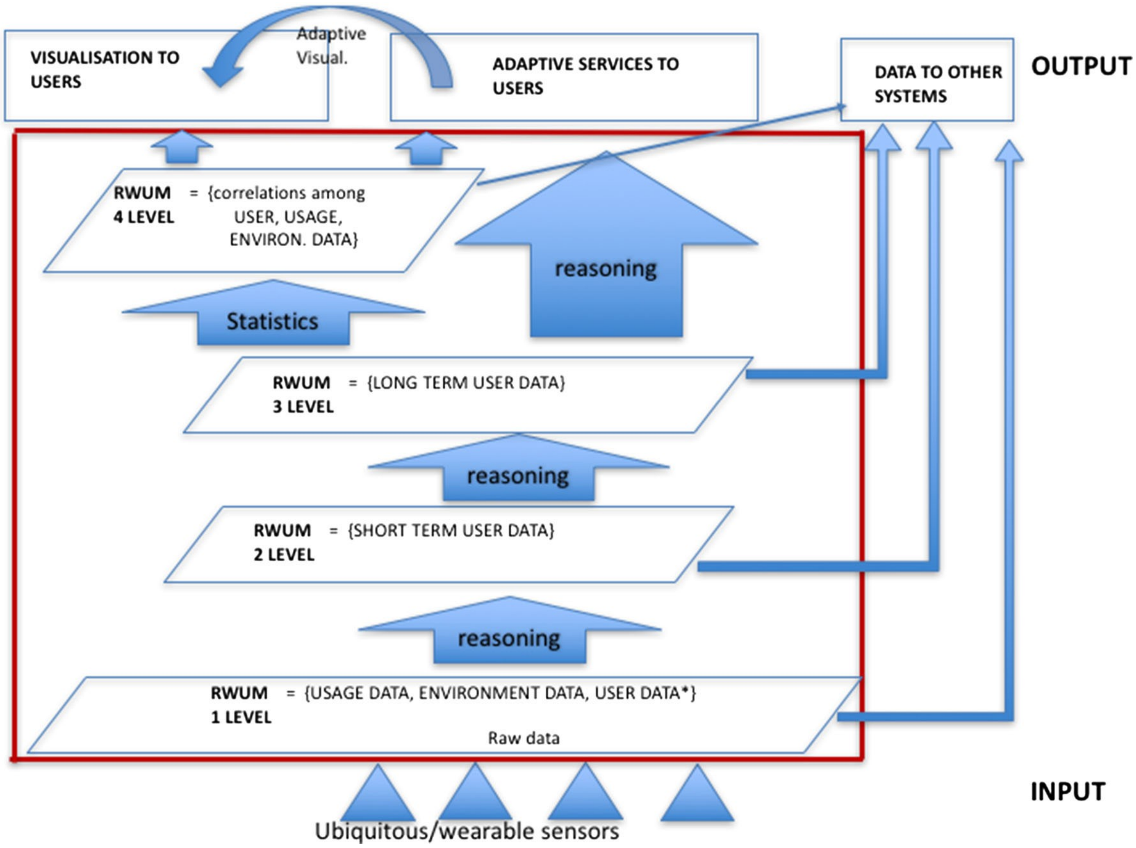

Fig. 3 RWUM conceptual framework. Notice that user data* in the first level are mainly raw physiological data, that should be somehow elaborated to be be used in the UM

called *evidence*, can be obtained from wearable sensors, interactive learning activities, Web trace analysis and explicit information provided by the user (e.g. goals). These data are fragmented across many devices and used to reason on them to create a complete User Model. This kind of lifelong User Model could serve as a repository for user information to be used during the learning process by other applications, such as intelligent tutoring systems.

Elliott et al. (2009) provide a general architecture for life-long user modeling which can collect, store and process data from various data sources. The aim is to capture the heterogeneous data streams about various aspects of a person's life as a single stream and extract the relations among such aspects: this would improve Collaborative Filtering and Content-based recommendation of information relevant to people's everyday lives. This architecture consists of four main components: (i) Life Long User Modeling (LLUM) API, (ii) Life-Log repository, (ii) modeling component, and (iv) recommendation component. LLUM API enables data gathering from various individual devices and provides recommendations accounting for temporal and contextual conditions. The Life-Log repository is automatically updated for any device and exploited by using ontologies.

ARBUT (Hohwald and Frias-Martinez 2010) is a scalable architecture which can process huge amounts of heterogeneous sensor data and produce complex User Models for large numbers of users in timely manner. It is based on MapReduce, a framework for processing big amounts of data in parallel using a cluster of computers. This architecture can generate both short and long term User Models. It employs reusable components which contain functions used to compute the user modeling features and which can be shared in various application domains. The architecture has four main components: (i) *Sensor Data* coming from one or more sources and available as a set of files; (ii) *User Metamodel* which describes all the components of the User Models at a high level; (iii) *User Modeling Library* which contains the functions needed to generate different User Models; and (iv) *User Modeling Generator* which applies the User Metamodel to the sensor data and generates the User Models.

PersonisAD (Assad et al. 2007) is a framework which models people, sensors, devices and places and allows other applications to access this information. The PersonisAD framework can be used as a foundation for the development of context-aware applications. Two examples of such applications are: MusixMix, which chooses background music according the preferences of the people present in a room, and MyPlace, which helps people find other people in a building by providing personalised information about the place.

5.2.2 Decentralised Architecture

It is possible to have pure decentralised solutions, with no centralised system, as in Fig. 4B. Along this line, Dim et al. (2015) proposes an approach for allowing the development of UMs (and also RWUM) from reusable components. In particular, they propose developing and maintaining small, standard and reusable multipurpose building blocks that may be integrated into more abstract UMs as needed. They use the metaphor of information pendants (info-pendants) made of information beads (info-beads) and their connecting threads (info-links). More specifically, an info-bead is a standalone and encapsulated module that uses inputs or default data to infer a new piece of information about a user, and possibly delivers this information to service applications or to other info-beads linked to it. An info-pendant is a composition of info-beads, where data flow from one or more info-beads to another info-bead, invoking the other's inference process. Thus, an info-bead can comprise first, second and third level of RWUM, while an info-pendant can be seen as our fourth level.

Table 5 compares all such systems/approaches with respect to the RWUM features they implement.

5.3 Discussion

The choice of the architecture to be implemented relies on the features of the application exploiting RWUM. If it manages sensitive personal data (such as health-related data), decentralized solutions should be preferred wrt to centralized ones. In fact, one of the main drawbacks of centralised solutions (Kobsa 2007) is having a central failure point for data protection. Moreover, when the application needs a specific knowledge base, again a decentralized solution is to be preferred. In fact, it is difficult to find a centralized solution capable of storing and delivering extremely specific knowledge needed only by that particular application. Thus, in this case it should implement its own proprietary UM.

At the same time, the development of all the RWUM-related capabilities requires a strong effort in terms of architecture building and knowledge modeling, which is not achievable for all the applications aiming at providing RWUM-based adaptive services.

A possible solution could be that a centralized system is in charge of the effort of the creation and management of the RWUM, being then used by a set of adaptive systems with their own internal UMs (Fig. 4). A mediation component (based on ontologies) between the format of centralised RWUM and the UMs of the adaptive applications is needed. To this aim, an existent mash-up platform may act as a centralized system. A mash-up platform has the functionalities for gathering data from different sources, homogenizing them, reasoning on them and providing visualisations to the user Bentley et al. (2013). It does not explicitly implement any User Model, since it collects user data not for adaptation but only to create a unique repository for diverse personal information coming from scattered sources. However, it has *in nuce* some RWUM features (i.e. the capability to gather and aggregate user data) that may be used by other systems to provide adaptation. Nowadays, there is a large availability of such mash-up systems, both in the commercial domain (e.g., Google Fit[3], Apple Health[4], Tictrac[5], Headsup health[6], Beeminder[7]) and in the research community (Medynskiy and Mynatt 2010; Bentley et al. 2013; Rapp et al. 2017).

6 Possibile Usage Scenarios

In this section, we provide some examples of exploitation of RWUM in different usage contexts, in order to see possible concrete applications of such a model.

6.1 Sport

Mark has been running for years. He always planned his sport activities by dedicating time and effort to personally set his goals and trainings, but the results were somehow unsatisfactory. He thought of relying on the advises of a professional trainer, but the costs and the idea of not having control upon his own exercises have always prevented him from going in this direction.

Now he has a new application that exploits his RWUM to support him in his training activities. Thanks to the RWUM the application knows his habits, for example his working hours, how much he had exercised in the past, his food tastes, as well as his physiological parameters and how they evolved over time. The application has set for him a long-term training goal based on these data. Thinking that this objective is somehow not sufficiently ambitious, Mark "converses" with the application, setting its RWUM toward higher levels of motivation and willingness to improve his physical condition. Now, the application has defined a new long-term goal with which Mark completely agrees.

[3]https://www.google.com/fit/
[4]http://www.apple.com/it/ios/health/
[5]https://www.tictrac.com/
[6]https://www.headsuphealth.com
[7]https://www.beeminder.com

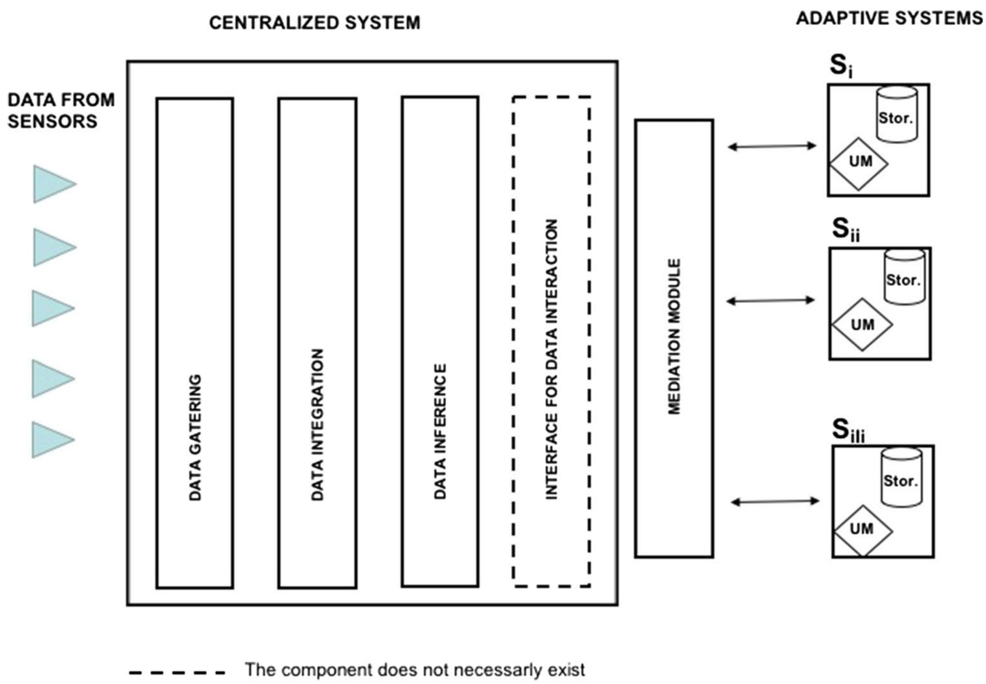

Fig. 4 High-level architecture of a centralised system (such as a mash-up) plus many adaptive applications

On the basis of such goal, the application has also defined a personalised plan to achieve it, setting a series of short-term objectives that are automatically adapted depending on Mark's context. The application provides him with just in time recommendations to support him in his training. For example, the application adapts the length of the path for his evening run depending on how well he slept the night before, how much he ate during the day, how much he improved in the last weeks. During the run, the application sends him contextual suggestions on the pace he has to maintain, depending on the weather, his current hearth rate and level of fatigue. Not only, it also suggests the paths depending on his mood, the current traffic conditions, and his preferences. For example, it recommends him to change his usual route, when it detects that Mark is stressed by the noise of the road next to which he is running, prompting an alternative path on the map, quite at that hour. During the day, it also provides suggestions on the food to eat and how much he should sleep to maximise the performances in the following day. For example, it recommends not to order pasta at the restaurant in the evening, and to take easily digestible food instead, since the next morning he has a scheduled training.

6.2 Cultural Heritage

Elena often visits museums and art expositions, but she is almost always unsatisfied with her experience. She is not interested in everything, moreover she rarely has the attention and the willingness to read about what she is seeing. The result is that such experiences, although exciting in their premises, are always disappointing in their concrete realisation.

Now Elisa is using a new device that employs her RWUM for enhancing her museum visits. The device automatically detects her arousal, attention and mood. Depending on such parameters it provides specific kinds of information about the artwork she is going to see, as well asrecommendations

Table 5 Comparison of existing centralized and decentralized approaches in relation to the presence of RWUM features

	Multilayer				Interact	Open	Lifelong
	1 level	2 level	3 level	4 level			
(Kay 2008)	√	√	√	√	√	√	√
(Elliott et al. 2009)	√	√	√	√	√	√	√
(Hohwald and Frias-Martinez 2010)	√	√	√	-	-	√	?
(Assad et al. 2007)	depends on the application	√	-	-	√	√	√
(Dim et al. 2015)	√	√	√	-	√	-	-

on how to continue the visit. For example, the device recognises her level of attention and on the basis of that adapts the interaction modalities to the given information. Only when she is willing to extensively study the arguments, the device delivers textual details about the piece she is looking at. Otherwise, the device provides audio-visual information trying to stimulate her attention. Moreover, if the device detects that Elisa is really bored by what she is seeing, it suggests going to another room, where she could likely find something interesting for her (on the basis of her art preferences known by the RWUM). Thus, by knowing her mood states during the visit, the device is capable of suggesting different paths depending on her changing emotions. In this way, it is able to keep her attention high and to provide her with a memorable experience.

6.3 Health

Frank has just recovered from a stroke and now he is trying to return to his normal lifestyle. However, he needs to take many medications and to follow various instructions.

The new health system that he is using implements a RWUM that knows everything about his health history, as well as his habits and preferences. It helps him not to forget to take his medications, reminding him to take them right after he wakes up. Moreover, the system knows the various situations in which Frank may not adhere to his health regime. For example, when he goes out with his friends, it knows that Mark is inclined to drink alcohol at the restaurant: then, it provides him with contextual suggestions to substitute it with other drinks that he likes. The system also knows the different factors that may affect his health, and acts to reduce their impact on e.g. his blood pressure, his cholesterol level, his stress level. For example, when his degree of stress is raising too much it recommends an activity making him relax, among those that he likes. If Frank is in his office, the app suggests that he goes for a walk taking a snack at the bar. Such suggestion is delivered by taking into consideration all the food he has eaten during that day and in the last week, as well as his current glucose level, in order to give an advice that may be acceptable for him, without being harmful for his health.

6.4 Ageing

Asia has just got retired and in the last few months she noted a decline in her memory and attention level. She bought a new device that uses her RWUM to provide her with personalised cognitive and physical trainings on the basis of her daily activities. Depending on her current daily tasks and the current level of attention and arousal, the device provides her with different physical and mental exercises. For example, when it recognises that her attention is below a certain threshold while she is watching the TV, it prompts her to do an exercise related to the content displayed on the screen. Moreover, it proposes memory trainings connected with her daily activities and objects of her daily living. For example, it asks her to remember the exact sequence of the meals she had the last week. Slowly, Asia not only improves objectively, but she also increases her sense of self-efficacy, becoming aware that she can recover and maintain a high level of cognitive functioning.

6.5 Learning

Erika is at the second year at university, where she studies medicine. However, lately she encountered some learning difficulties, resulting in poor performances at the exams.

However, the new app she is using, which employs her RWUM , is actually helping her. First of all, the app suggested some similar students to her, in terms of studying habits (e.g. similar time of the day in which they study), and complementary skills (she is quite bad in mathematics, but very good in chemistry), who she can study with. This allowed her to receive some help from her peers.

Moreover, the app has set a series of personalised mid-term goals to support her in the preparation for her next exam. The learning program requires Erika to study for a certain amount of time each day until the day of the exam. Such a load is based on her habits, her current knowledge and her learning abilities. The app also provides exercises based on her progresses. Both the study program and the exercises are constantly redefined depending on the circumstances, as well as on her improvement, attention, and compliance. For example, if one day Erika cannot study for five hours, as it was defined, the app redistributes the study load across her entire program. Likewise, if at a certain time her cognitive load is too high, she is tired, or she is studying in a very noisy environment, the app recalculates the difficulty of the exercises that are given to her, lowering the request.

7 Discussion and Conclusions

Here we provide a discussion about how RWUM impacts on *traditional open issues* of the user modeling field.

Traditionally, user modeling has the problem of *privacy protection* of user data (Schreck 2003). This problem is still present in the new scenario, being potentially even more serious, since a lot of data collected by wearable devices are sensitive (think about mood or physiological parameters, as well as everyday movements). Morever, they are often stored without the user's awareness. Thus, users should have the possibility to decide which data should be shared or kept private, and which applications should be allowed to use them. Moreover, individuals should be the owners of their aggregated data (Kay and Kummerfeld 2013). The recommendations based on RWUM may violate the user's privacy as well. For example, they could be socially inappropriate (e.g. they may make visible the information that the user does not want to disclose to others). Thus, the adaptive system should devote a special attention to the context in which the recommendations will be provided.

A related problem is the *lack of control* users have upon their User Models (Barua et al. 2013). A proposed solution is to made the User Model content *scrutable*, i.e. to allow users to see how the User Models are designed and implemented, to be in control of the information they contain, the processes used for personalisation and how the information is used in various applications (Kay and Kummerfeld 2013; Wasinger et al. 2013). The possibility to interact with User Model data through different modalities and in an adaptive way is one of the key features of a RWUM. In this way, users might become aware of the data collected by the system and this may increase their level of self-awareness (Burke et al. 2011).

Regarding recommendations, a common issue is *the cold start problem* (Schein et al. 2002), which happens at the beginning of an interaction with a given system, when it does not have enough user data to provide effective recommendations. One solution is to gather data about the users from other sources (e.g., networking systems, other recommenders) (Fernández-Tobías et al. 2012). Gathering data from real world could be a further effective way to solve this problem, finding missing values and increasing the coverage of the User Model with new user features.

Another common problem in recommender system is the *lack of diversity in the results* (Adomavicius and Kwon 2012), i.e. the results of recommendations are often very similar to each other. Gathering data from real world to find similar users according to specific features, as well as new items to be recommended, can help to mitigate this problem.

Finally, the *contextual appropriateness* of the recommendation is another possible issue. In fact, even if accurate in principle, push modalities for providing recommendations can interrupt the user's activities, or can be out of context or socially inappropriate. This is especially true for RWUM-based recommendations, which aim at impacting on the user's real life. Thus, adaptive interruption modalities should be implemented (Arroyo and Selker 2003; Stouffs 2002).

We conclude the paper with the description of the most important *challenges* in a RWUM scenario, which can open up new research horizons.

Granularity of the model. What is the appropriate granularity for the concepts modeled in the RWUM and for the data to be collected? Not all the aspects contained in the RWUM may need the same level of detail: they could vary depending on the applications used or the user's goals, as well as on specific constraints due to the data collection modalities. For example, for a food recommender aimed at suggesting a healthy diet, it would be useful to use information about the user's preferences about single food ingredients; whereas for a system used for suggesting restaurants in the tourism domain, it would be more reasonable to use data about the user's preference about specific kinds of cuisine. Thus, the RWUM should provide the possibility to select the data level granularity most appropriate to a specific aim or domain.

Conflict resolution. How to decide which are the most important features in the User Model in order to provide the most effective recommendation? How to solve some recommendation data trade-offs? For example, how to choose between the preference of the user for cakes and her insulin problems in providing food recommendations? Such issues should always be considered and the RWUM should give the user the opportunity of setting priorities and importance hierarchies among her goals. Moreover, it should give the possibility of resolving conflicts, by allowing, for example, the definition of rules.

Granularity of the visualisation. How to make such a complex User Model scrutable? It is not feasible to present all the data to the user, since it could cause information overload. This problem is strictly related to the granularity of the collected data. For example, not all the data about the user's blood pressure should be provided to her. How should the data be presented? At which level of aggregation? When should the data be updated? A solution could be to change the data to be visualised according to the specific application that is using them, and/or the user's features (e.g. goals or expertise), and/or the specific context in which she is cast. Also the interaction modalities should be adapted to the user's features and context.

Interoperability of user data. Which data could be made available to other applications? Users should be able to use all their personal data (or a subset of them related to a specific tracked parameter) in other systems. This data interoperability would supply the systems with additional information about the user, enabling supplementary personalised services. For example, data about her food preferences could be provided to a health recommender or to a tourist recommender, but not to a social networking web site. Users should be left free to decide which kind of data to provide, for what purposes and for how long, in a sort of a controlled personalisation.

Novel recommendation modalities. As seen in Section 4.4, there are a lot of novel opportunities for recommendation that are not currently exploited in all their potentials, such as using RWUM to provide more accurate recommendations, real-time recommendations and cognitive-based recommendations. In principle, such knowledge could be exploited to make forecasts on the user's goals, behaviour and preferences. We can think of smart adaptive systems able to predict what would be useful for users, by simulating the future evolution of their data and setting the right goals to be reached based on such prediction.

Holistic modeling. RWUM can be holistic, thus representing a complete picture of a user. Moreover, it can capture salient aspects about the user over very long periods of time and handle changing interests over time, according to a lifelong user modeling vision (Kay 2008). However, this raises many practical issues: when can a model be considered completed? Which are the costs in terms of physical computation and user's acceptability of such ideas? Such problems are similar to those that are currently emerging in lifelogging research (Chowdhury et al. 2015).

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