

A Rich Context Model Design and Implementation

Licentiate thesis
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Report No. 48, 2017
ISBN: 978-91-88357-62-5

Abstract

The latest developments of mobile devices include a variety of hardware features that allow for more rich data collection and services. Numerous sensors, Internet connectivity, low energy Bluetooth connectivity to other devices (e.g., smart watches, activity tracker, health data monitoring devices) are just some examples of hardware that helps to provide additional information that can be beneficially used for many application domains. Among others, they could be utilized in mobile learning scenarios (for data collection in science education, field trips), in mobile health scenarios (for health data collection and monitoring the health state of patients, changes in health conditions and/or detection of emergency situations), and in personalized recommender systems. This information captures the current context situation of the user that could help to make mobile applications more personalized and deliver a better user experience. Moreover, the context related information collected by the mobile device and the different applications can be enriched by using additional external information sources (e.g., Web Service APIs), which help to describe the user's context situation in more details.

The main challenge in context modeling is the lack of generalization at the core of the model, as most of the existing context models depend on particular application domains or scenarios. We tackle this challenge by conceptualizing and designing a rich generic context model. In this thesis, we present the state of the art of recent approaches used for context modeling and introduce a rich context model as an approach for modeling context in a domain-independent way. Additionally, we investigate whether context information can enhance existing mobile applications by making them sensible to the user's current situation. We demonstrate the reusability and flexibility of the rich context model in a several case studies. The main contributions of this thesis are: (1) an overview of recent, existing research in context modeling for different application domains; (2) a theoretical foundation of the proposed approach for modeling context in a domain-independent way; (3) several case studies in different mobile application domains.

Keywords

Context modeling, rich context model, mobile users, current context of the user, mobile sensors, multidimensional vector space model, contextualization.

Acknowledgments

Foremost, I would like to express my gratitude to my supervisors who made an enormous contribution to my academic, research and personal development and without whose support this thesis would not have been possible. I am sincerely thankful to my supervisor Professor Marc Jansen for the continuous support of my PhD study, for his patience, understanding, motivation, and immense knowledge. His guidance helped me in all the times of research and writing of this thesis. I would like to thank you for encouraging my research and for advises which allow me to grow as a researcher.

A special thanks to my second supervisor Professor Marcelo Milrad, for giving me a great opportunity to start my research career as a research fellow as part of the CeLeKT research group and continue as a PhD student. Thank you for your support, suggestions and comments that helped to gain a different perspective to my research area and improve my work. Thank you for your sense of humour and positive attitude.

I would like to thank Karin Siöö from Linnestudenterna, for your help and support of organizing and arranging the scenarios and participants (international students at Linnaeus University) for several case studies conducted in this thesis. Thank you for your valuable feedback that contributed to this work and helped to improve it.

Many thanks for help and support to my great colleagues and friends, in the Department of Media Technology and Computer Science. Appreciation goes to Maximilian Müller, Janosch Zbick, Nico Reski, Julia Bons, Didac Gil de la Iglesia and Konstantyn Kucher for feedback, comments and suggestions on my thesis, as well as for the proofreading. Thank you for interesting discussions that always inspired me and increased my motivation in investigating new use cases, scenarios and technologies.

Last but not least, I would like to thank my family: my parents Neonila and Oleksandr and my sister Olena for supporting me throughout writing this thesis and all my life. Thank you for everything.

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Chapter 1

Introduction

Personalization has become increasingly important within the mobile application domain due to the constant use of mobile devices by users in their everyday activities. Modern mobile devices provide a profound set of sensors and, together with Internet connectivity, possibilities for gathering different types of information about the user's current situation. This information characterizes the current 'context' of the user and helps to understand many user characteristics (e.g., what the user is going to do, what the user needs to perform his/her current action) in order to recommend relevant content/information to the user in the right time and place [1, 2]. The most commonly used definition of 'context' was introduced by Dey:

"Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves"[3].

Such a broad definition allows for the consideration of different types of information as context and, in some cases, makes it difficult to model context for a specific application domain. Without understanding the context and how context can be used efficiently, it may be difficult for a application developer to know which contextual information to use and what types of contextualized behaviors to support with his or her mobile application [3].

During the literature review, we found that most of the existing context-aware mobile frameworks provided personalizations rather than contextualizations for mobile applications. Personalization is based on the users' behaviors, application usage and provides recommendations to suit personal user preferences. Examples of personalization can be offering services or products based on the users' search history, earlier purchase or

favorite items (e.g., book author, movie director), and adapting a user interface based on the users' history of interactions with mobile applications [4]. On the other hand, contextualization aims to utilize sensors and technology to understand the current context of the user in order to better serve a specific user's needs. Examples of contextualized applications or services are location-based applications or services [5] that provide information useful and relevant to the user's current location, contextualized knowledge applications or services [6] to be used to support learners in a personalized and adaptive manner by using the context information, and contextualized learning services [7] to be used to provide personalized feedback to the learners. Contextualization may enhance personalization by using information about the users' situations to create a customized user experience.

In this thesis, we will investigate whether context information can enhance existing services and mobile applications by making them adaptable to the user's current situation. We present recent approaches used for context modeling and introduce an approach to be used for domain independent context modeling.

1.1 Motivation

The current context of a mobile user has often been limited to his or her current position, neglecting the possibilities offered by modern mobile devices of providing a much richer representation of the current user's context. Modern mobile devices provide possibilities to gather context information from different mobile sensors, including external sensors connected to the mobile device via Bluetooth, smart watch sensors, and activity tracker bands. In addition, this data can be extended and enriched by using additional web service APIs, which can provide a better understanding of the user's behaviors, needs, and current situation.

In recent years, an increasing interest has occurred in delivering personalized user experiences with highly contextualized content in order to improve the user's engagement and interaction with mobile applications. However, existing solutions lack contextual information related to specific user's needs or current situations in regard to supporting the user's decision-making process. We aim to improve the usability of context information during the design and development process of personalized and contextualized mobile applications.

Another interesting opportunity of using context information is to enhance current recommendation systems by integrating the user's context. Most recommendation systems use historical data about the user's interests and situations without considering the current context of the user when providing recommendations.

1.2 Problem Statement

One of the greatest challenges in context modeling is domain independence in the core of the context model. The context information depends on the application domain, but the modeling of the context can be independent from the application domain. However, current context modeling techniques [8, 9] do not support the modeling of context information for different application domains without changes in the core of the model. Therefore, this issue limits the usability of context modeling approaches in regard to the development of personalized and contextualized mobile applications in production mode. In addition, application developers must have theoretical and practical knowledge of context modeling approaches in order to know which approach is best for their target users and mobile applications.

Each mobile application or service can have different contextualization goals (e.g., make the application more personalized to the users' needs and goals, improve the existing application features, deliver information in the format convenient to the current users' context, improve the users' interactions and engagement with the application and more) that should be supported by a context model. In the existing context models, a lack of abstraction exists to deal with different purposes of contextualization with taking into account the mobile application domain and target users. Based on the contextualization goal different contextual information should be considered and analyzed in order to achieve this goal. Here, different data types of context information should be supported in n-dimension context spaces. To the best of our knowledge, no context modeling approach exists that can support the processing of different data types of contextual information.

Many researchers are working on developing a general solution for context modeling. However, a major problem with this type of model is its limited usability due to its applicability for a specific application domain. Most of the existing context models require additional changes in the core model that take time, effort, and framework knowledge. To summarize, a need exists in the context modeling approach to support the goal-based and domain-independent development of contextualized mobile applications.

1.2.1 Goal and Research Questions

The main goal of this thesis is to define a unified context modeling approach that allows modeling context in a domain-independent way. In order to achieve this goal, we design and explore the applicability and reusability of a Rich Context Model (RCM) in different application domains. It will lead to the development of a general context model that can be deployed as a cloud-based contextualized service that enables application developers to easily and quickly develop contextualized mobile applications. In contrast to existing approaches, our approach will improve the applicability of context modeling

techniques in the development of personalized mobile applications, preventing re-coding and redesigning based on the application domain and reducing implementation efforts.

For the purpose of fulfilling the goal, we need to answer the following research questions:

RQ1: How can we model the context in a domain-independent way for mobile applications?

RQ1.1: How can we handle different data types of contextual information and priorities for context information for different mobile scenarios?

RQ1.2: What are the common components of the abstract context model that allow modeling the context in a domain-independent way?

RQ2: What are the requirements for application developers to be able to develop contextualized mobile applications?

With RQ1, the thesis aims to empirically investigate the modeling of different contextual information during the context model design process. RQ1.1 is motivated to investigate approaches and methods used to handle various contextual information data types. With this research question, we aim to study the properties of a rich context model (RCM) under different levels of granularity. RQ1.2 aims to identify the main and common components of context modeling in domain independent way. Additionally, we aim to evaluate the proposed context model in several user studies focused on different application domains.

RQ2 focuses on defining the main requirements and efforts to use the contextualization approach for the development of contextualized mobile applications.

The target domains in this study are *mobile applications* or *scenarios* and *recommender systems*. The answers to the research questions are described in Chapter 5.

1.2.2 Research Methodology

The primary research methodology adopted to perform this work is based on the Design Science Research Methodology (DSRM) proposed in [10]. The methodology consists of six main activities, which are iterated and shown in Figure 1.1.

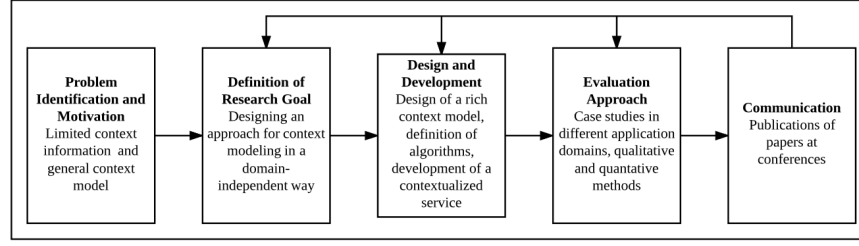


Figure 1.1 The design science research methodology applied in the thesis, based on [10]

We performed a *literature review* in order to obtain a complete understanding of current research efforts and problems in the field of context modeling for mobile applications. Based on the identified problems we defined the goal and research questions. Afterwards, we designed a unified context modeling approach to model context in a domain-independent way. In order to evaluate our context modeling approach we applied the *case study* method. Several case studies have been used in order to demonstrate the flexibility and reusability of the unified context modeling approach in developing contextualized mobile applications and recommender systems.

1.3 Contributions

Many researches have contributed to context modeling different techniques and context models [11, 12, 13]. These efforts have provided a foundation for modeling the context of a specific scenario or application domain. However, the significant challenge of context modeling is to model context in a domain independent way. This thesis contributes to this challenge as it provides:

- An overview of recent, existing research in context modeling for different application domains, including the pros and cons of the context models.
- A theoretical foundation of the proposed approach for modeling context in a domain-independent way. In contrast to the existing approaches, our approach has flexibility gained through an abstract context model that could be applied to different application domains without the need for a change in the core context model.
- Several case studies in different mobile and recommender application domains illustrate the usefulness and applicability of the proposed context modeling approach. With the help of our approach, application developers will be able to easily develop contextualized mobile applications for their target users and may raise the number of satisfied users, hopefully leading to an increase in the number of potential users.

1.4 Thesis Outline

The remainder of this thesis is organized as follows. In Chapter 2, we present an introduction to the contextualization of mobile users. First, we provide the existing definition of the context together with an argumentation about our definition of the context of a mobile user. Second, we provide an overview of the existing modern approaches and techniques for context modeling in the mobile application domain. For each approach, we discuss the pros and cons. We present a few examples of contextualization and personalization support for mobile users and discuss the relationship between contextualization and recommendation engines. We conclude Chapter 2 with a discussion of open issues related to context modeling for mobile users.

Chapter 3 presents the theoretical foundations of the designed context modeling approach for modeling context in a domain-independent way. Here, we provide the examples of contextual information and how the proposed approach can handle different types of this contextual information. We conclude Chapter 3 with a discussion on how our rich context model tackles the open issues (described in Chapter 2) and solves the research problem.

In Chapter 4, we present an overview of the three conference papers and one book chapter that contribute to the core of this thesis. We illustrate the different case studies that we used for validating the usefulness and reusability of the rich context model. Chapter 5 concludes this thesis with a discussion of the major contributions to the field of context modeling for mobile application domains and answers on the research questions. It also outlines on-going work and future work.

Chapter 2

Background: Toward the Contextualization of Mobile Users

In this chapter, we introduce the general background of the context definition, context modeling approaches, contextualization and personalization concepts. Based on the previous context definition we provide our definition of the context of mobile users. We give an overview of the recently used approaches for context modeling. One of the approaches related to context modeling is applied, extended, and evaluated in the following chapters. Additionally, the open issues related to the contextualization of mobile users are discussed at the end of this chapter.

2.1 Context Definition

A large number of definitions for the term ‘context’ have been found in the area of computer science. Dey and Abowd introduced the general definition that is most widely used:

“Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between the user and the application, including the user and the applications themselves” [3].

Based on this definition, researchers and application designers use different aspects of context information to target particular application domains. Due to the broad and general definition of context, it might be difficult for application developers to understand what types of information they should consider when attempting to support contextualization of mobile users. Therefore, a more detailed definition of context is needed in order to better understand the context of mobile users. In the domain of mobile applications, where modern

mobile devices have built-in sensors (e.g., GPS, accelerometer), use external sensors (e.g., heart rate sensor) connected to the mobile device via Bluetooth, utilize smartwatch sensors, activity tracker bands, and have access to the Internet, we defined context as:

“Any information that describes a situation of the user, not only received from different mobile sensors, which could be extended by additional web service APIs, but which also derive or use a meaningful interpretation of this information for the current user need.”

A number of applications use context for various purposes. For example, a context-aware system utilizes context to adapt the application’s behavior according to its environment of use [14, 15, 16] or improve its use and performance [17]. A recommendation system also utilizes context information to provide relevant information and/or service to the end-users with respect to his or her current tasks, situations or needs [18, 19]. Examples of using context in recommender systems can be found in the *tourism domain* (e.g., recommendations for points of interest to tourists based on context information, such as season, weather conditions, crowdedness, and travel length) [20, 21]; *mobile learning domain* (e.g., provide personalized learning resources based on the learner’s context and personal learning profile [22]); *restaurant recommendation domain* (e.g., recommend a place to eat based on the user’s location, historical information about visited cafes or restaurants, and time of the day [23]); *news recommendation domain* (e.g., the context-aware and content-based recommendation of news based on the user’s feedback and context, where context is described by device type, time of the day, day of the week, and historical information related to how and when the user consumed prior news from a news service [24]); and *museum domain* (e.g., connecting objects, places, and themes through mobile virtual museums [25]).

Many studies have shown the importance of the usage of the context information of users in different application domains. Context information varies from one domain to another, thus different approaches and methods are used for the modeling and processing of contextual information.

2.2 Context Modeling Approaches

Recently used approaches to context modeling can be broadly classified into three main categories: multidimensional context modeling approach, object-role-based models, and ontology-based models. A context model can be characterized by the following properties as defined in [26]: *type of formalism* (e.g., vector-, key-value-, ontology-, graph-, mark-up scheme-), *flexibility* (e.g., how the context model is bound to the application domain, how easy it is to replace or add new contextual information to the context model, whether it supports the priorities of the contextual information, whether it takes into account the user’s preferences), and *context granularity* (e.g., levels of

detailization of the context information supported in the model). These properties are discussed in the following approaches for context modeling.

Multidimensional context modeling approach. This approach was one of the first approaches proposed in [13, 27, 28] for generalized context modeling. The idea of this approach is to make a decision to which the context situation of the entity is the most relevant or similar. In this approach, different context situations are represented as individual examples in multidimensional space. The model classifies the entities based on their similarities to these examples [29]. Similarity is a decreasing function of distance between the entities and individual examples in a space [13]. Classical examples of these models are the Context Space Model (CSM) [30] and Vector Space Model (VSM) [31]. CSM operates on these two concepts from geometrical spaces: context state and situation spaces. The context state refers to the current state of the entity being modelled at a certain time based on the contextual information, while the situation space represents a real-life situation based on a collection of context states during a certain period of time. This modeling approach has shown good practical usage examples in developing context-aware mobile applications [32, 33] and in detecting anomalous behaviour in video surveillance [30].

VSM measures the similarities between the vector of the current context of an entity and the vectors of different context situations that are represented in multidimensional vector space. This approach is practically useful for modeling n-dimensions of context information and finds similarities even when some context information is missing. Additionally, this approach has ability to represent the characteristics of the context at different levels of detail. This approach has been used in providing similarity-based context aware recommendations [29] and content-based information retrieval (IR) applications [34]. VSM has been widely used for text/documents similarity in IR systems rather than in context modeling applications. Little research has been done on using VSM for mathematical representations of contextual information. The multidimensional representation of context information is good when applying complex data analyses [35, 36]. The main advantage of the multidimensional approaches is a general and unifying approach to model context for different application domains [8], which enables it to match users' context in real time.

Object-role based or object-oriented modeling approach. This modeling approach was adopted from the database modeling field [37]. Here, the context model language, which was based on Object-role Modeling Language (ORM), was developed to support the object-role based context modeling. This approach uses the concepts and advantages of the object-oriented approach. Here, the superclass represents the abstract context object (e.g., *ContextObject*) with abstract methods for processing the context information (e.g., *processData*). Then, each piece of context information (e.g., location, temperature and others) is inherited by the abstract *ContextObject*

class (e.g., *LocationObject*, *TemperatureObject*, *OtherObject*), which implements the abstract methods (e.g., *processData*) [38].

Another example of such approach are the Object Relational Database Management Systems (ORDBMS), which are used to model context and relationships between different contextual information [26]. The advantage of this approach is that it utilizes the combination of object-oriented and traditional relational concepts to model the context information.

Ontology-based models. These models have been widely used in the modeling of complex context situations. Using ontologies provides a uniform way for specifying the model's core concepts as well as an arbitrary amount of sub-concepts and facts, which enable contextual knowledge sharing and reuse in a ubiquitous computing system [39]. This can lead to a growing complexity for certain types of applications [14]. Since most of the existing ontology-based models require some additional changes in the core model in order to adapt and customize it for a specific application domain, their practical applicability is reduced in regard to mobile application development.

In order to analyze the approaches mentioned above, we applied the *Questions, Options, and Criteria* (QOC) schema [40]. The main elements of QOC are *Questions*: identifying key design issues; *Options*: providing possible answers on the *Questions*; and *Criteria*: for assessing and comparing the different *Options* [40]. The questions were created based on the properties defined in [26] (e.g., flexibility, type of formalism and others) as shown in Figure 2.1 and Figure 2.2.

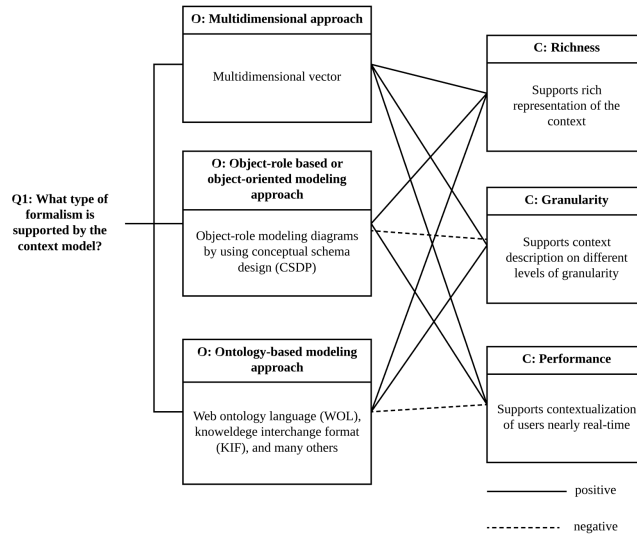


Figure 2.1 QOC diagram with approaches for context modeling

The *Options* represent a three context modeling approaches used to answer the created question Q1 (What type of formalism is supported by the context model?) and question Q2 (How context model is bound to the application domain?). A set of *Criteria* (i.e., *richness*, *granularity*, *performance*, *flexibility*, and *adaptability*) was defined based on the *Options*. As shown in the QOC diagram in Figure 2.1, the multidimensional approach supports more of the criteria in comparison to other approaches. In the next QOC diagram (see Figure 2.2), we analyze the *Criteria* (i.e., *flexibility* and *adaptability*). The *flexibility* criteria defines how flexible the core model is (i.e., how easy it is to replace or add new contextual information to the model), while the *adaptability* criteria defines how the context model can be adaptable to the user's priorities.

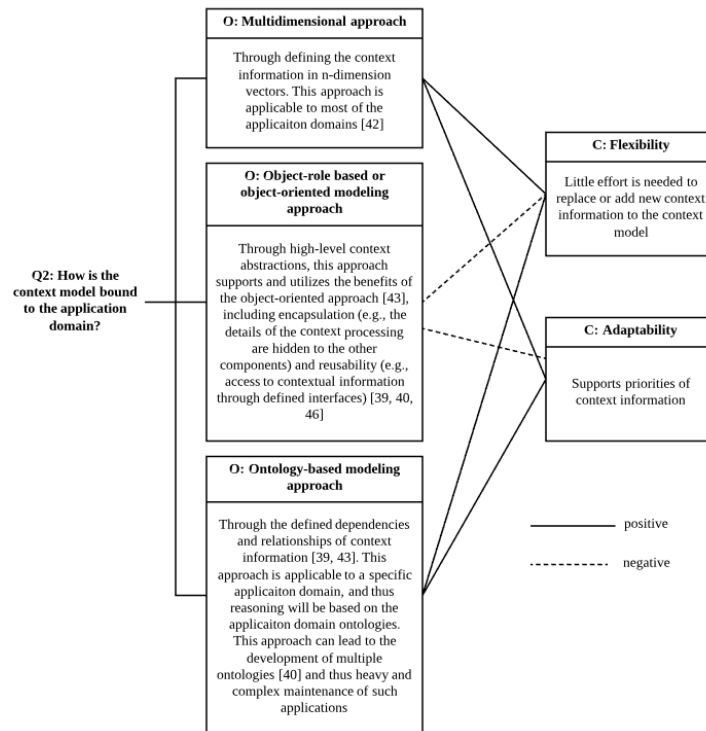


Figure 2.2 QOC diagram with flexibility and adaptability criteria for each context modeling approach

As shown in Figure 2.2, the object-role based approach is less flexible in comparison to other approaches (e.g., ontology-based and multidimensional approaches). The replacement or addition of new contextual information in the

context model is completed by inheriting the context objects from the high level of abstraction or defining new context objects manually. Thus, the complexity is increased in regard to structuring complex context data due to the increased inheritance of the context objects [41]. The ontology-based approach is flexible in regard to replacing and adding new context information as it adopts such information from other context ontologies or via reasoning (e.g., automatically derives new knowledge about the current context). However, reasoning is computationally expensive and, as it has many rules, it makes the language undecidable and decreases the application performance [41, 42]. Each of these approaches has its own pros and cons, as found in the literature and described in Table 2.1.

Table 2.1 Analysis of the pros and cons of the context modeling approaches

Context modeling approach	Criteria			
	Richness (i.e., supporting different types of contextual information)	Flexibility	Granularity	Performance
Multidimensional approach	Pro: 1) Multi-dimensional vector space allows modeling context in n-dimensions Con: 1) Usually uses simple one metric similarity (e.g., Euclidean), which limits the use of this approach for different contextual data types	Pros: 1) Flexible in regard to adding or replacing the context dimensions 2) Supports priorities of context information (e.g., a context-depending weighting method for vector space model [31])	Pro: 1) Supports context granularity on different detailization levels [43] (e.g., sub dimensions, sub-sub-dimensions), such as location (e.g., country, town, region, place)	Pro: 1) Has high performance with complex contextual data analyses [36, 43].
Object-role based or object-oriented modeling approach	Pro: 1) Supports a high level of context abstraction [41]	Pros: 1) Supports analysis and design of the context in various stages	Con: 1) An approach to support context granularity on different	Unavailable

	<p>Con:</p> <p>1) An approach to handle different data types of contextual information should be designed and implemented</p>	<p>of the software engineering process [41]</p> <p>2) Reusability (e.g., access to contextual information through defined interfaces) [38, 44]</p> <p>Cons:</p> <p>1) Supports manually adding new contextual information to the model [45]</p> <p>2) Complexity is increased when structuring complex context data due to the increased inheritance of context objects</p>	<p>detailization levels should be designed and implemented</p>	
Ontology-based modeling approach	<p>Pros:</p> <p>1) Reasoning (e.g., automatically deriving new knowledge about the current context) [41, 44]</p> <p>2) Takes into account the dependencies between the entities that represents the context [38]</p>	<p>Pro:</p> <p>1) Possible to reuse existing domain-specific ontologies [44]</p> <p>Con:</p> <p>1) Due to the formal language of the approach (i.e., terminologies and taxonomies) when using</p>	<p>Pro:</p> <p>1) Supports context granularity for a specific application domain</p>	<p>Cons:</p> <p>1) The reasoning is computationally expensive [41]</p> <p>2) Its many rules make the resulting language undecidable and decrease application performance [41]</p>

	Con: 1) The lack of a common vocabulary in different domain-specific ontologies [39]	two or more domain-specific ontologies it could be found that two objects have different names but same meaning [46]. Such context modeling approach is difficult to verify.		
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The analyses of the context modeling approaches and survey results in [26] show that there is not yet a common solution for a general context model and that the context model should be chosen depending on the target application domain. The existing general context models lack applicability due to the requirement of specific language learning; because the specific, context-aware framework is not compatible with the technologies used; or because it is time-consuming to adapt the existing context models in order to support new contextualization features. A high level of abstraction for context representation and processing is necessary to define in order to support the development of multi-domain contextualized mobile applications. Therefore, in RQ1, we aim to explore the common components of the abstract context model that allow it to model the context in the domain independent way.

2.3 Contextualization and Personalization Support of Mobile Users

*Contextualization*¹ could also be understood as the process by which one makes sense of information based on the situation from which the information was collected. Using this definition, the contextualization of mobile users is a process that collects context information related to a user's current situation, processes it, and meaningfully interprets it in order to better understand the user's behaviors, needs, goals, and tasks. The features of the contextualization are specific to particular mobile applications. According to the literature, the following categories exist in regard to features that contextualization can provide:

¹ <https://www.wordnik.com/words/contextualization>

- the presentation of relevant content/information or service to a user [47] via location-based, context-aware mobile applications that can provide relevant information about the place where the user is located (e.g., a museum) based on the geolocation information gathered by the GPS sensor in the mobile device;
- a representation of the content/information in a suitable format [48] (e.g., changing the textual representation of the content/information to an audio representation when the user is moving, such as on a bus or train);
- an automatic execution of a service [47] (e.g., changing an application's brightness based on the user's environmental context, changing the mobile device to silent mode when the user is in a meeting, or using the automatic service discovery feature based on the user's location);
- automatic push notifications (e.g., when the user reaches a certain location, the application provides relevant information or services that might interest the user) [49].

These contextualization features make mobile applications more personalized and intelligent. The *personalization*² of mobile applications aims to provide personalized experiences based on the user's behaviors and preferences. Examples of personalization include offering services or products based on the user's search history, earlier purchases, or favorite items (e.g., author, movie director) and adapting a user's interface based on the user's history of interactions with mobile applications [4].

The personalization has become widely used in recommender systems. Traditional *recommender systems* provide recommendations that match users and items (e.g., services, products) [27, 50]. This type of recommender system provides the same recommendations of items to different users who used identical search queries without taking into account the user's interests, needs, and goals [51, 52]. The improved versions of such systems are *personalized recommender systems*, which provide recommendations based on the user's preferences and needs. However, most personalized recommender systems lack the context information in which the search query was performed [8, 50, 52, 53]. By knowing the current context of the user (e.g., his or her habits, behavior at certain time and location), it is possible to provide more relevant and accurate recommendations to better suit the user's needs, goals, and interests.

The use of context information is beneficial as it allows *context-aware personalized recommender systems* (CARS) to provide more personalized and meaningful information recommendation to users [18, 31, 32, 47]. CARS have been used in various application domains (e.g., e-commerce, e-health, e-learning) to facilitate the retrieval of relevant learning resources [50, 54, 55];

² <https://www.techopedia.com/definition/14712/personalization>

mobile applications with context-dependent and personalized recommendations [53]; social networks in order to provide relevant recommendations based on the shared opinions of the user's friends who have similar interests with the target user [56]; mobile tourism (m-tourism) with the use of mobile device capabilities to gather context information in order to enrich the tourism experience (e.g., recommending which attractions a user should visit based on the contextual information like weather conditions, user preferences, the traveling purpose, location and time [21, 57]); news recommendations based on the user's interests, preferences and location [58, 59]; and online dating services when matching users' profiles [60, 61]. However, most of the existing CARS either cannot efficiently combine different types of contextual information or suffer from high computational complexity [56].

Recommender systems have become increasingly attractive for mobile applications due to the access to the user information gathered by mobile device. Mobile recommender systems are a good example for utilizing a general context modeling approach in order to support different recommendation application domains (e.g., movie recommendation, recipe recommendation, restaurant or food recommendation).

2.4 Issues with the Context Modeling of Mobile Users

When it comes to the use of mobile devices for the support of contextualization, it is important to consider privacy, security issues, and data quality [62]. Personal data (e.g., location, health indicators such as heart rate, body temperature and others) should be used with the permission of the user and applications should provide some guarantee of privacy and security. The data quality of mobile sensors should be improved by using additional noise filtering algorithms or methods in order to prepare the data before it is processed and analyzed.

Another important issue for the contextualization of mobile users is the diversity of mobile devices, especially in regard to screen size and operating system. Here, the cross-platform mobile development approach is better to use for the development of contextualized mobile applications rather than the native development of several applications for each device platform.

Context information may have different data types and data structures, including numerical values (e.g., user's age), categorical values (e.g., gender, hobbies), Boolean values (e.g., user's state: moving/standing, inside/outside the building), object values (e.g., weather: temperature, humidity, air pressure; location: latitude/longitude), text data (e.g., the name of the location where the user is located, user's comments/feedback, user's interests). Thus, the context model requires an abstract component used to process the context as well as well-defined interfaces in order to handle the various types of context information.

Mobile applications should have constant Internet connection in order to complete the necessary computations outside of the mobile device so as to not use the mobile device's resources (e.g., processing power, battery). In addition, the data received from the mobile sensors can be enriched by using additional web service APIs (e.g., Google Places API, Open Weather API, News API) in order to retrieve additional information relevant to the current context of the user.

Based on the above issues, we have identified the initial requirements for the RCM [63], [64]:

- **Richness.** Contextual information can be collected from different sets of sensors and additional web service APIs. This information should fully describe each context dimension defined within the model. A number of dimensions exist that can be defined as main dimensions. These main dimensions can also contain sub-dimensions used to describe an entity in detail. Some sub-dimensions can depend on others. For example, the “environment” might be a main dimension and “weather conditions” might be a sub-dimension of the “environment”. Then, if the user is sitting inside a building, the “weather conditions” sub-dimension would not necessarily be used in the “environment” dimension.
- **Extensibility.** Various web services can provide information in different data formats, same as mobile sensors can provide different data formats, which is why a model should support common and often used data formats (e.g., JSON, XML). Supporting common and often used data formats for communications between different component in the context model can extend the context information by adding new web services or sensors to the model.
- **Flexibility.** Different contextual information may have various data types. For each data type (e.g., numerical, Boolean, text, date), the model should provide different evaluation algorithms. The model should flexibly define which context dimensions are important for which scenarios. In addition, the model should support the prioritization for each sub-dimension in order to achieve the best recommendation results.
- **Applicability.** This model should be easily reusable in different application domains where mobile devices are used as it enables the context dimensions to be reused or replaced in the RCM without additional effort.

2.5 Summary

In this chapter, we introduced our definition of context, which built on and described the context more explicitly than the definition found in the literature. The relationship between contextualization, personalization, and recommender systems was discussed. A literature review on recent and often used approaches for context modeling was performed and the pros and cons of

each approach were summarized. Previous works have shown that a common solution does not yet exist for a general context model. Therefore, the context model is bound to a specific application domain. They have also shown that a high level of abstraction is needed in order to support multi-dimensional context modeling. Based on the QOC schema, the multidimensional approach is better meet all criteria and has minimal amount of cons in comparison to other approaches. In addition, this approach has high performance and flexibility in terms of representing the context information at different levels of detailization. We agree with [29] that the greater the similarity between two context situations, the greater the similarity between the recommender items (i.e., information and product/service). Thus, the multidimensional vector space modeling approach was chosen for identifying the similarity between various context situations. Context information is important and necessary in order to provide highly personalized recommendations with respect to the user's situation and needs. The initial main requirements for context modeling of mobile users (i.e., richness, extensibility, flexibility, and applicability) have been defined.

Chapter 3

Theoretical Foundations: Toward a Rich Context Model

In Chapter 3, we present a *Rich Context Model* (RCM), which is based on the multidimensional context modeling approach. The motivation of the chosen approach for context modeling as a basis is described in Section 3.1. The modeling and processing of contextual information is described in Section 3.2. Section 3.3 presents the developed contextualized recommendation algorithm for matching the content to the user's current context.

3.1 Motivation

In the previous chapter, two examples of context models were described: *Context Space Model* (CSM) and *Vector Space Model* (VSM), which both represent multidimensional approaches for context modeling. The VSM is a well-known model used in *Information Retrieval* (IR) systems [34, 65, 66] and has been proven in practice for query documents, emotion classifications in text documents [67], and document clustering [68]. It was proposed by Salton in 1960 and first introduced in the System for the Mechanical Analysis and Retrieval of Text (SMART) project as a new retrieval model for representing text documents as vectors [69]. In the VSM, *documents* and *queries* are modeled as elements of a two-dimensional vector space [70]. Then, the *query vector* is matched with each *document vector* by using *similarity metrics*. The result is the list of all documents ordered by relevance to the query. The main disadvantage of this approach is that the terms/words in the document are treated independently [66, 70] and, therefore, context is lost in the document. Many researchers have developed different methods and approaches to overcome this problem with minimal modifications of the VSM [70, 71]. Thus, previous studies have shown the flexibility of the VSM in regard to extending its capabilities.

Based on the contextualization features described in Chapter 2, the main task of contextualization is to deliver the resource (e.g., information, content, service) that is relevant to the current context of the user. Relevance is one of the most important factors that should be considered in the contextualization process. Since the VSM has a similar task to the contextualization task (i.e., define the relevance of the documents to the user's query), its concepts can be applied to the contextualization process in order to ensure the relevance of the delivered information and service to the user's current context. For instance, the numbers of different information resources or services have been retrieved/used in various context situations. As such, the task of contextualization will be to define which information resource is the most relevant to the user's current context.

In addition, as contextual information is complex (e.g., some context information can be described using a single value (e.g., numerical data), while others are described using an array of values (e.g., categorical data, sequential data) or as an object, thus two dimensions may not be enough to describe the complex context situation of the user. Therefore, we suggest using the multidimensional approach when modeling complex contextual information.

3.2 Context Dimensions

We understand that the term *rich context* can encompass data received from different mobile sensors as well as how this data can be enhanced via external web service APIs in order to retrieve more detailed information, including current location (e.g., place, environmental information). Additional contextual information could consist of the noise level in the location where the user is currently located and his or her movement status (e.g., sitting, walking), which can be used to decide the most convenient representation format for the situation. For instance, if the user is walking to his or her job listening, via headphones, to an audio stream provided by a text-to-speech API, then an audio stream may be more convenient than reading information on the mobile device screen. Furthermore, information about the mobile device's platform allows for recommender mobile application to provide relevant information to the user's device. For instance, if users A and B share the same interest (e.g., mobile games) and user A has an Android device, while user B has an iPhone, then news about upcoming games for the Android platform would be more relevant to user A than user B [72].

Context information is modeled in dimensions where each dimension is multi-dimensional by itself. Each dimension represents a property of an entity. For example, context information about a user's device can be described by *device dimension* (e.g., internet connectivity type: WiFi; battery charge level: 90%; device platform: Android OS); *environment dimension* (e.g., weather conditions: rainy, 18°C; noise level: 15dB; location: inside the building; place: library; date and time: Monday, afternoon); *personal dimension* (e.g., age: 20-

years-old; gender: female; hobbies: watching movies, listening to music; interests: music, sports) (See Figure 3.1).

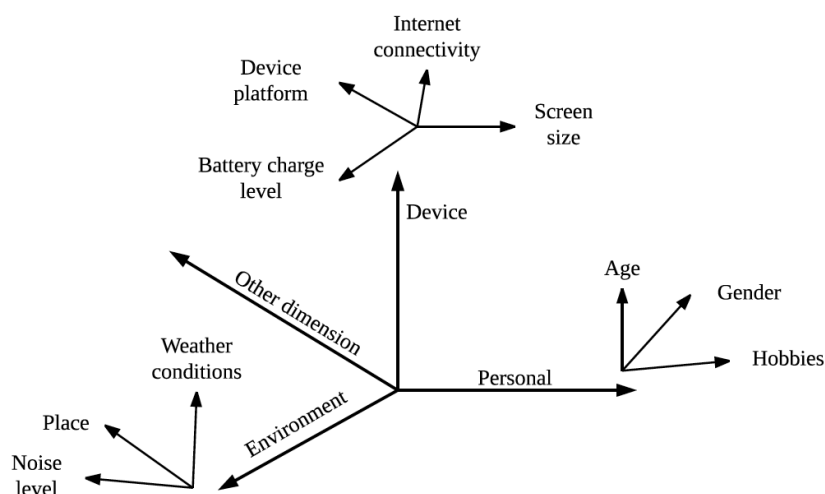


Figure 3.1 General context dimensions representation

Context data may contain different information about the user's situation depending on the application domain and which types of contextualization features (See Chapter 2.2.3) are supported in the mobile application. An example of different contextual information grouped into context dimensions and mobile sensors that can be used in the mobile learning (m-learning) domain is given in Table 3.1.

Table 3.1 Example of the context dimensions and mobile sensors in the mobile learning domain

Context dimension	Mobile sensors	Contextual information	Web services
Environment context	GPS	The type of place where the learner is located The nearest places to the learner's location The weather conditions when the learning environment is outdoors	Google Places API Free Weather API Google Sensors API
	Accelerometer	The learner's situation (e.g., sitting on the train or bus)	
	Digital compass	The learner's moving direction	

	Camera	Fast and easy access to the learning materials by scanning barcodes	QRCode Web Service
Device context		Screen size Battery charge level Internet connectivity	
Personal context		The learner's study program Passed courses Current courses Course timetable Assignments Grades Age Gender Interest in the program's courses	Facebook API Twitter API Moodle Web Service API

The datasets described in Table 3.1 are used to represent the rich context of mobile users in the m-learning domain. However, each application domain may replace or be added to any of the other context dimensions if necessary. For example, the location dimension is the most used contextual information in the recommender systems and location-based context-aware systems. However, in other application domains, such as online games, the context models are built without the location dimension since the current physical location of the players is not relevant to making recommendations.

Each context dimensions is used to support one or several contextualization features. For example, the *environment* and *device* context dimensions can be used for the representation of learning objects (e.g., like learning materials, content) in a suitable format for the learner's current situation, while the *personal* context dimension can be used for the representation of learning objects relevant to the learner's learning style, available time for study, and course program. An algorithmic and model-based approach for handling the rich context information of mobile users (i.e., the RCM) is described in the next section.

3.3 The Rich Context Model

The Multidimensional Vector Space Model (MVSM) is used as a basis for modeling multiple dimensions of the rich context of the user. Each dimension describes a property of an entity or the entity itself, where the entity can be an object, a person, or a situation. For example, in the m-learning application domain, the entity can be the representational format of Learning Object (LO) as described by the context information of the learner's situation. In this case,

the LOs in different formats (e.g., .pdf, .mp3) are described by contextual information (see Table 3.1) and represented in a MVSM (see Figure 3.2).

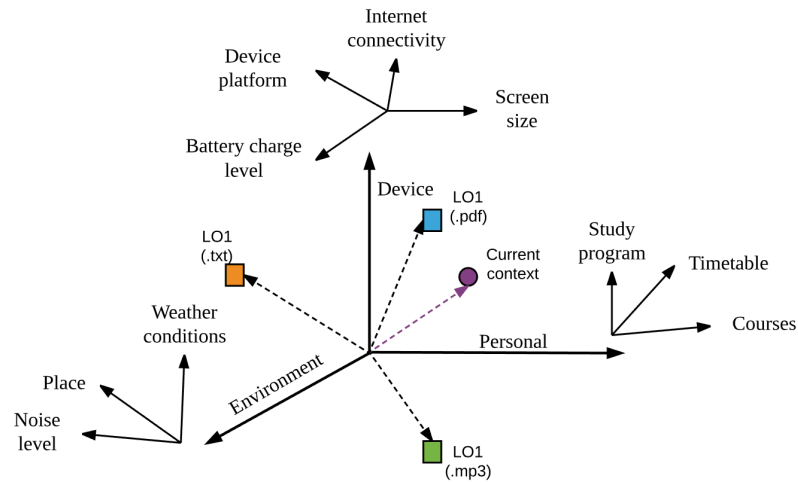


Figure 3.2 Learner's context representation in MVSM

In order to identify the relevant entity, the similarity of two vectors is measured: the vector describing the current rich context of the mobile user and other vectors describing the different available entity items. The similarity between the vectors can be calculated using a combination of different similarity metrics (e.g., Euclidian distance, Jaccard, cosine metrics). Then, the vector that has the closest distance to the point of the current rich context of the user defines the entity to recommend. This multidimensional approach provides flexibility in regard to processing different data types of contextual information by using different similarity metrics and other methods (i.e., latent-semantic analysis for the text data). The MVSM is used to represent complex context information with any number of dimensions. Any one of the dimensions can be replaced by any other dimension. The context information has various data types; therefore, different metrics and algorithms should be considered when attempting to process this data.

3.3.1 Similarity Metrics

Similarity metrics are used in order to define the vector that has minimal distance to the current context of the user. Each dimension of contextual information can be represented using different data types and value ranges. For instance, the temperature, noise level, battery level, and connection speed

might be represented as a decimal type, while the weather description might be represented as a Boolean type (e.g., cloudy: true/false, rainy: true/false, sunny: true/false). For the decimal type, a simple *Euclidean* distance can be used to measure the similarity between the current weather and a set of defined weathers in the MVSM. For instance, the *Euclidean* distance measures the similarity between two vectors of n dimensions by calculating the distance between their components. The value of distance d shows how much one object differs from another object (e.g., how much the current noise level in the café differs from the noise level in the library) [64, 73].

The environment context information related to moving/standing and outdoor/indoor can be represented as Boolean typed values. Here, the *Jaccard* metric for binary objects might be better suited than the *cosine* metric similarity or *Euclidean* distance because measuring the overlap between the sets of binary objects will provide more meaningful results than calculating the linear distance or cosine metric. In our case, the *Jaccard* similarity is defined as the size of the intersection of the context information described by Boolean values (here, the intersection means the components that are equal in both vectors) divided by the size of the union (here, all of the components described by Boolean values) of the corresponding vector. The higher the *Jaccard* distance is for two vectors, the more equal these two vectors.

As discussed above, the *Euclidean* distance gives us the absolute value for the distance between two objects represented as numerical values. In case of categorical values (e.g., place names) the concept of distance or similarity is not the same as for numerical values since they cannot be inherently ordered [74] (e.g., for a learner sitting in the café, we are interested in defining similar places to the café, not the nearest place to the café). The *cosine* metric similarity shows how similar or ‘close’ one piece of contextual information is to another one. Therefore, the *cosine* metric similarity could be also used to compare two categorical values of contextual information.

Based on the discussion above, different metrics could be used for different data types of contextual information. As an example, we proposed the combination of metrics and algorithms shown in Table 3.2.

Table 3.2 Example of the usage of different metrics and algorithms for processing contextual information

Contextual information	Data type	Metric categories
Weather description (e.g., cloudy, sunny, rainy), inside/outside the building, gender, hobbies	Array of Boolean (cloudy: 1 – true, 0 – false, sunny: 1 – true, 0 – false)	Jaccard distance
Age, weather temperature, Time of the day (morning, lunch, afternoon, evening, night)	Integer	Euclidean distance
Place (e.g., café, library)	Categorical	Cosine metric

Textual information	Long text/String	Latent semantic analysis, term frequency algorithm
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In order to combine these approaches and process contextual information, an algorithm should be designed. In this case, the output of the algorithm would be the suggested or recommended object (e.g., the entity) to be delivered to the mobile user.

3.3.2 Contextualized Recommendation Algorithm

This section uses the following terminology:

- **Definition 1 (Existing contextual information).** Information that can be provided by a mobile application, mobile device, and user (e.g., sensor data, event data as user-interactive data).
- **Definition 2 (Derived contextual information).** Information that is extracted or calculated based on the use of the existing contextual information (e.g., the place name where the user is located can be derived by using GPS data and a request to Google Places API, the user's activity can be recognized by using sensor data and an existing activity recognition service). Examples of sources for derived contextual information are web service APIs, open data APIs, and customized calculations, formulas or algorithms. Both *existing* and *derived* contextual information should be relevant to the contextualization goal and application domain.
- **Definition 3 (Contextualized entity).** Represents an object, a person, or a process that is the main target of the contextualization (e.g., an object: learning material, news, movie, service, application feature; a person: a user; a process: the user's behavior).

The MVSM assumes that, for each contextualized entity e_i , $i = 1, 2, 3 \dots n$, exists a vector of a contextualized entity $\vec{ce_i}$, $i = 1, 2, 3 \dots n$ in the vector space that represents it. Then, the set of all of the contextualized entity vectors $\{\vec{ce_i}\}$ is to be considered the space basis. The contextualized entity vector $\vec{ce_i}$ and current context vector \vec{c} consist of a set of multidimensional vectors $\{\vec{d_{1k}}, \vec{d_{2l}}, \vec{d_{3m}}, \dots, \vec{d_{po}}\}$, $k = 1, 2, 3 \dots s$, $l = 1, 2, 3 \dots r$, $m = 1, 2, 3 \dots t$, $p = 1, 2, 3 \dots y$, $o = 1, 2, 3 \dots x$, where $\vec{d_{1k}}$ is one of the possible context dimensions described in Table 3.1 (e.g., environment, device, personal).

A combination of metric similarities and other methods (e.g., data mining, text mining) is used to calculate the minimal distance between the vector of the current context of the user \vec{c} and vectors representing the contextual entities $\vec{ce_i}$. That is,

$$\vec{c} \cdot \vec{ce_i} = \min_{j=1 \dots i} \{sim(\vec{c}, \vec{ce_j})\}$$

where,

$$sim(\vec{c}, \vec{ce}_j) = \begin{cases} Euclidean_{dis} \left(\sqrt{\sum_{g=0}^p (\vec{d}_p - \vec{de}_{jp})^2} \right), & \text{if } \vec{d}_p, \vec{de}_{jp} \in R \\ Jaccard_{index} \left(\sum_{g=0}^p \frac{|\vec{d}_p \cap \vec{de}_{jp}|}{|\vec{d}_p \cup \vec{de}_{jp}|} \right), & \text{if } \vec{d}_p, \vec{de}_{jp} \in [0,1] \\ LSA \left(\sum_{g=0}^p lsa(\vec{d}_p, \vec{de}_{jp}) \right), & \text{if } \vec{d}_p, \vec{de}_{jp} \in \mathbb{C} \end{cases}$$

where lsa : latent semantic analysis function [15], R : real numbers, and \mathbb{C} : characters. \vec{d}_p is one of the dimensions of the current context and \vec{de}_{jp} is one of the dimensions of the contextualized entity e_j .

The context model $CM(\vec{c}, \vec{ce}_i, sim): e_j$ has the current context vector \vec{c} as an input parameter, contains the vectors of the contextualized entities \vec{ce}_i and a combination of the similarity measurements or algorithms: sim , and the output of the context model CM is a contextualized entity e_j that is most relevant to the current context of the user (see Figure 3.3).

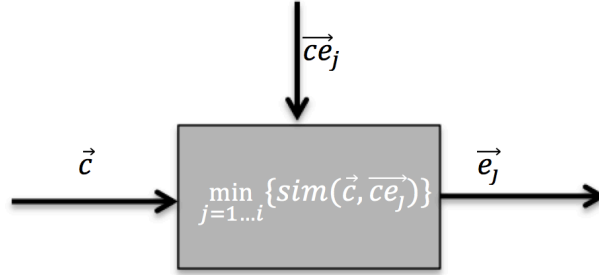


Figure 3.3 The mathematical representation of a rich context model

The contextualization task can be formulated as follows: given a current context and context knowledge data, find the relevant contextualized entity. Where the current context contains a combination of existing and derived contextual information in a current moment/time, the context knowledge data contains contextualized entities represented as vectors in the MVSM, and relevance is the satisfaction of the user's information/service need.

Our context model is a formal method that predicts the degree of relevance of an entity to a user's current context. A basic example of the context modeling process is shown in the Figure 3.4.

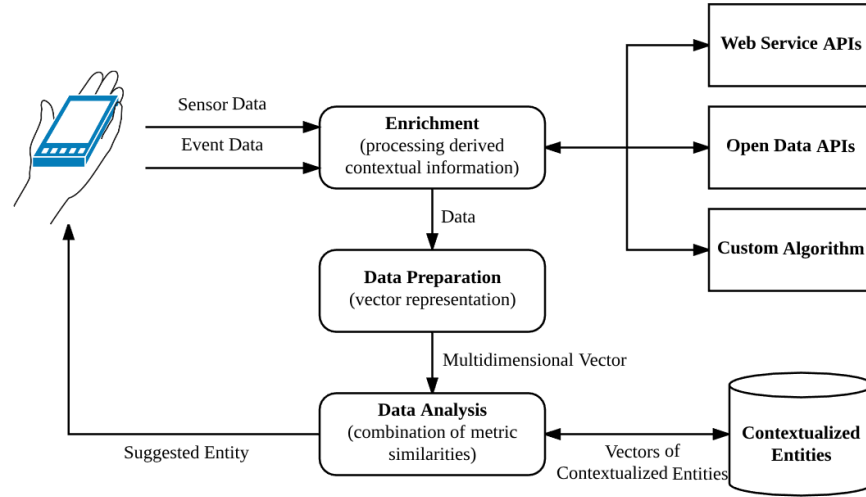


Figure 3.4 Diagram of the basic context modeling process

Based on the context modeling approach described in Sections 3.2 and 3.3, the main abstract components (see Figure 3.5) are identified in our context model.

- A *Mobile Application* is an application that collects data from mobile sensors or external sensors within some period of time and sends it to the *Resource Manager* component.
- The *Resource Manager* component receives the collected sensor data and extends it by performing get/post requests to external web service APIs (e.g., Free Weather API, Google Places API) and other sources (e.g., Open Data APIs), which allows to describe the user's situation in detail. The output of this component is a multidimensional vector of the current context of the mobile user.
- The *Context Manager* component receives as its input a multidimensional vector of the current context and requests the vectors represented in the MVSM from the Database component. The Database component contains the vectors of the contextualized entities created in the preparation phase. This component contains a collection of methods that can evaluate different data types of context information (e.g., the similarity metrics described in Section 3.31). For example, for the long text data type, the latent semantic analyses [75] technique can be used; for the short text data type, the usual indexing methods can be used for matching; and for the numerical data types, different metric similarities can be used. The matching context algorithm [76] is applied in order to define the best

matched contextualization object (e.g., learning material). The output of this component is a recommendation object (e.g., learning material, format of the learning material).

- The *Recommendation Manager* component is responsible for preparing the recommendation content and delivering it to the mobile application. For example, if the recommended object is an ‘MP3 format of learning material’, then the *Resource Manager* will request the learning material in MP3 format from the database and send it to the mobile application.

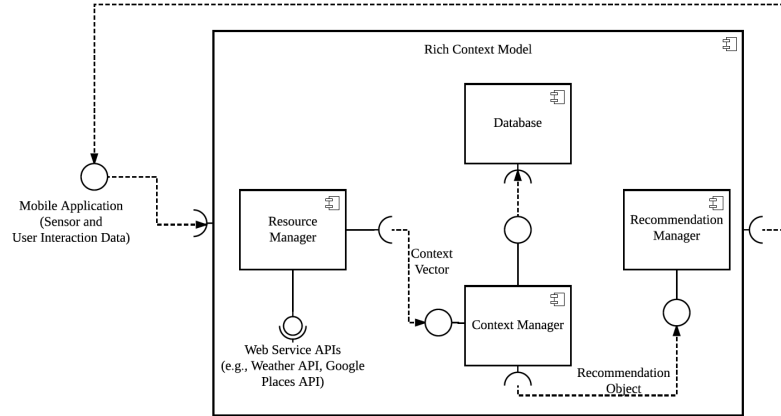


Figure 3.5 Component diagram of a rich context model

Two phases of the context modeling process can be identified: preparation and runtime phases. In the preparation phase, the multidimensional vector is created in the MVSM and represents an entity (e.g., can be any item, service, content, information) described by the defined contextual information (see Table 3.1). This contextual information can be obtained by using historical data, data provided by an expert of the application domain, or generated by the system. The preparation phase is executed once before to use the system in runtime. In the runtime phase, the multidimensional vector is created in the MVSM and represents the current context of the user as described by the contextual information collected and extracted by the *Resource Manager* component.

3.4 Discussion

In this chapter, we introduced a RCM to be used to model the rich context of the user, which was described using multiple dimensions and represented as a vector in a MVSM. The usage of a multi-dimensional approach allows for the design of a flexible context model, which can describe the complex context situation of mobile users. The proposed context model also provides a much

more detailed description of the user's context by using mobile sensors and additional web services than existing approaches.

The disadvantage of our RCM is that, for some particular scenarios, it may require a pre-study in order to identify and evaluate the necessary context dimensions used in our context model. Since the proposed approach uses a comparison of the current context of the user with objects that were consumed by others in similar context situations, a pre-study should be performed in order to create a database of different context situations (i.e., all of the contextualized entities first need to be contextualized so that they can be compared to the current context situation of the user). For example, in the news recommendation scenario, a pre-study evaluation of news should be performed before the usage of the news recommendation application [72]. This concern is part of the future work of this thesis; one of the possible ideas to address this concern could be to use machine learning algorithms to represent the contextualized entities in the MVSM.

Chapter 4

Publications Overview

In this chapter, we present information on the main publications that have contributed to this thesis. The evaluation for the proposed RCM has been performed in several application domains (i.e., mobile learning domain [64], people-to-people recommendation domain [77], and item-to-people recommendation domain [72]). The use of cloud-based mobile applications in m-learning scenarios was explored in [63]. The main contributions of this chapter have been published according to the following:

Publication I

A. Sotsenko, M. Jansen, and M. Milrad. Implementing and Validating a Mobile Learning Scenario Using Contextualized Learning Objects. *In The 22nd International Conference on Computers in Education (ICCE)*, Nara, Japan, pp. 522–527, 2014.

A detailed description of these efforts will be described in Section 4.1.1,

Publication II

A. Sotsenko, J. Zbick, M. Jansen, and M. Milrad. Flexible and Contextualized Cloud Applications for Mobile Learning Scenarios. *In Mobile, Ubiquitous, and Pervasive Learning*, Alejandro Peña Ayala, Ed. Springer International Publishing, pp.167-192, 2016.

The outcomes of this book chapter are described in Section 4.1.2

Publication III

A. Sotsenko, M. Jansen, and M. Milrad. Using a Rich Context Model for People-to-People Recommendation. *In 3rd International Conference Future of Internet of Things and Cloud Computing*, Rome, Italy, pp. 703-708, 2015.

This work is described in Section 4.2.1 and

Publication IV

A. Sotsenko, M. Jansen, and M. Milrad. Using a rich context model for a news recommender system for mobile users. *In Workshop Proceedings of the 22nd Conference on User Modeling, Adaptation, and Personalization*, Aalborg, Denmark, vol. 1181, pp. 13-16, 2014.

It is presented and discussed in Section 4.2.2.

4.1 Mobile Learning Application Domain

Substantial research in the field of m-learning has explored aspects of context modeling related to contextualized learning scenarios [78]. The m-learning domain utilizes the learner's context information because the learning happens outside of a traditional classroom and with the use of modern mobile devices. The use of mobile devices in learning opens many opportunities to investigate the learner's context situation in order to support a convenient and easy way to learn, independent of time and space (i.e., anywhere at any time). In the next two publications described in Section 4.1.1 and 4.1.2, we argue that a detailed contextualization of the learner based on the RCM (see Chapter 3) may provide benefits for m-learning scenarios.

4.1.1 LnuGuide Mobile Application

In order to evaluate the RCM, we implemented a m-learning scenario that allowed exchange students to be guided at Linneaus University in Växjö, Sweden, in order to get familiar with the campus and its prominent institutions [64]. In this scenario, the contextualization of the learners was supported by recommending a convenient format of learning material to the learner's current context. The learning materials were represented by different formats (i.e., MP3, PDF, PPTX, MP4) and described using different contextual information as shown in Table 4.1. This context information has been used to describe the format (e.g., .mp3, .pdf, .mp4, .html) of the LO in the MVSM.

Table 4.1 Context dimensions used in the LnuGuide application

Context dimension	Mobile sensor	Context information	Web service APIs
Personal context		- The user profile information in a corresponding Learning Management System (LMS)	Moodle Web Service API
Device context	Device-specific feature	- Battery level to define battery status	Cordova API

		- Screen size of the device (i.e., width, height)	
Environment context	GPS sensor	- To define the current place of the learner - To define the current weather conditions	Google Places API Open Weather API
	Accelerometer	- To define the movement status of the learner (e.g., moving, standing)	
	Digital compass	- To define the direction of the learner and navigate him or her to the corresponding station at the LnuGuide scenario example	
	Camera	- To scan QRcodes for indoor navigation	QRcode reader web service API

The implementation of the application was done in a platform independent manner in order to allow for a cross-platform deployment. The server-side implementation was done in Node JS for the main functionality of the mobile application. The client side was implemented using the jQuery Mobile framework, (see Figure 4.1). For persistency, a MongoDB database was used in order to natively store the JSON objects, which were used for the complete communication between the components of the system.

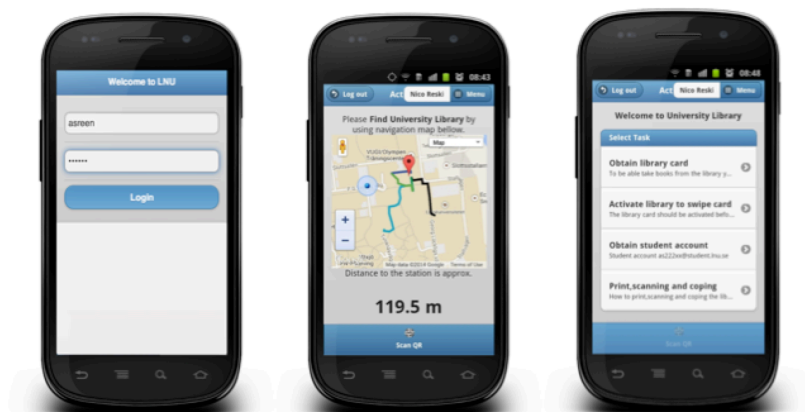


Figure 4.1 Examples of the user interface for the LnuGuide mobile app

An evaluation of the RCM was performed in order to investigate whether the contextualized version of the LnuGuide provided benefits compared to the implementation of the LnuGuide app without contextualization support. The study was performed using two groups of students: Group№1 (10 participants) performed the activities with the contextualization support, while Group№2 (12 participants) performed the activities without the contextualization support. For this study, we utilized two questionnaires provided by the Davis' Technology Acceptance Model (TAM) [79] that fit well with the study goal: Perceived Usefulness (PU) and Perceived Easy of Use (PEU) (as shown in Table 4.2 and Table 4.3). A 7-point Likert scale [80] was applied to each question.

Table 4.2 List of questions for the PU

№	PU Questions
Q1.1	The LnuGuide app helped me get to know my university.
Q1.2	The mobile support of the LnuGuide app helped me to familiarize myself quicker with the university.
Q1.3	The LnuGuide app addressed the important stations for my study at the university.
Q1.4	Using the LnuGuide app decreased my opportunities to understand the visited university stations.
Q1.5	The LnuGuide app helped me to understand the visited university stations in a sustained manner.
Q1.6	The LnuGuide app complicated my task in regard to getting to know my university.
Q1.7	Overall, I think that an app like LnuGuide was helpful when attempting to become familiar with my university.

Table 4.3 List of questions for the PEU

№	PEU Questions
Q2.1	I think the LnuGuide app was easy to understand.
Q2.2	The usage of the LnuGuide app appeared inflexible to me.
Q2.3	The LnuGuide app was easy to handle and reacted as expected.
Q2.4	The handling of the LnuGuide app was easy to understand.
Q2.5	It was hard for me to remember how to achieve the goals in the LnuGuide app.
Q2.6	Working with the LnuGuide app was exhausting.
Q2.7	Overall, I consider the LnuGuide app to be user-friendly.

In order to determine whether the contextualization support provided some statistically relevant improvement in regard to usefulness and easy of use, we analyzed the data gathered from the questionnaires. First, we calculated the total PU average as 4.83 in Group№1 and 4.69 in Group№2. For the PEU, the

total average was 5.03 for Group№1 and 4.2 for Group№2. In order to test these results for statistical significance, we conducted two independent samples t-tests. The results for the PU indicated no significant difference with regard to the total scores in Group№2. However, the results for the PEU showed differences in Q2.2, Q2.5, and Q2.6 regarding the total scores in Group№2 (see Figure 4.2).

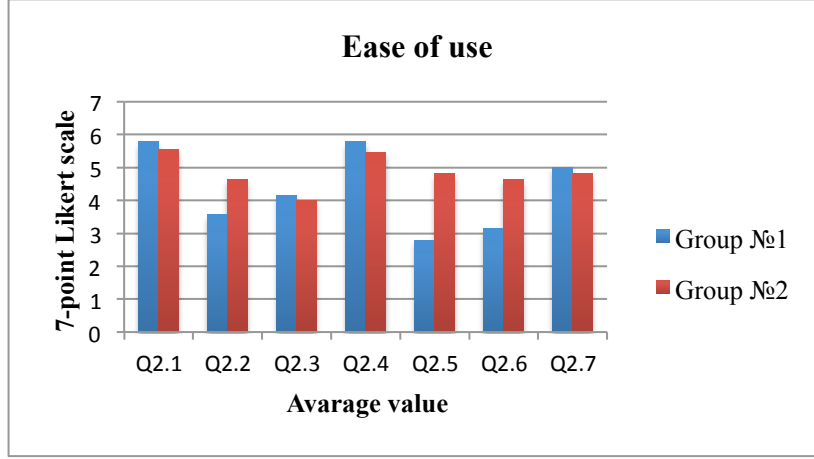


Figure 4.2 Average rating for the PEU questions

Therefore, we decided to conduct a t-test comparing the mean scores of Q2.2, Q2.5, and Q2.6 in Group№1 and Group№2. Since we had a relatively small group of participants ($N=25$), we decided to calculate the effect size offered in [9]. This test showed a significant difference in Q2.5 ($M=2.79$, $SD=1.67$) for Group№1 and ($M=4.82$, $SD=2.32$) Group№2; $t(13)=4.55$, $p=0.001$, $d=1.0$. For Q2.6 ($M=3.15$, $SD=1.7$) for Group№1 working with the contextualized LnuGuide application was significantly less exhausting then ($M=4.63$, $SD=2.1$) for Group№2; $t(13)=3.29$, $p=0.006$, $d=0.7$. The results for Q2.2 indicated a non-significant difference for Group№1 ($M=3.57$, $SD=1.5$) and ($M=4.63$, $SD=2.01$) Group№2; $t(13)=1.73$, $p=0.106$, $d=0.59$. All of the statistical tests were conducted with an alpha level of 0.01.

The standard deviation for Q2.2, Q2.5, and Q2.6 showed that the collected data for Group№1 were more coherent than in Group№2, indicating that using the contextualization model was well accepted. As an overall result of this experiment, we can conclude that the contextualized approach and standard approach had similar acceptances in regard to PU; however, the contextualized approach had better results in regard to acceptance with respect to the PEU. For example, for the students in Group№1, it was easier to remember the task and how to perform it than for the students in Group№2.

The questionnaire also contained general open text feedback about the LnuGuide app. In this section, the students mentioned its user-friendliness;

easy to use interface; and informative, easy to understand content as well as its slow network connection.

4.1.2 Cloud-based Contextualized Applications for Mobile Learning Scenarios

Cloud Computing (CC) solutions are often used to overcome some of the limitations of mobile devices, desktop computers, and servers, especially in regard to improving accessibility and interoperability [81]. One of the main advantages of using CC technologies with mobile devices is that it allows for the enhancement of the computational capabilities of these resource-constrained units, which, in turn, allows for rich user experiences [82]. Therefore, the enrichment of the learner's experiences and activities demands the development of personalized CC services. Context modeling techniques can be useful in the development of personalized, mobile, cloud-based services or applications for m-learning scenarios.

In [63], we described the main benefits of using a cloud environment in the teaching and learning process. We explored existing cloud-based services and applications for m-learning as well as how teachers or learners can use them. The context analysis of the learner's context required historical information to be stored and used. The learners generated different content (e.g., pictures, text) that also required storage and processing. In addition, the use of sensor data as contextual information required storage and processing in real-time. In this case, the processing of huge amounts of contextual information required additional computational resources, storage capacity, and flexible algorithms. Additionally, a cloud-based solution provides richer and more detailed descriptions of the user's context by using additional cloud-based services (e.g., Bluemix mobile services) with the power of CC (e.g., Amazon Elastic Map and Reduce service). The results of this book chapter were used in the initial stage of the development of a *Contextualization Service*, which is part of the on-going work described in Chapter 5.

4.2 Recommender Systems

Another domain where the contextualization approach can be applied is the recommender systems. Recommender systems have become an important application domain related to the development of personalized mobile services. Thus, various recommender mechanisms have been developed for filtering and delivering relevant information to mobile users. Usually, recommender systems consider many variables to do item-to-people or people-to-people matching. Therefore, in order to validate our flexible RCM in regard to handling various data types, priorities, and personal preferences, we performed a study in the people-to-people recommendation domain [77]

and proposed an approach for the item-to-people recommendation domain [72].

4.2.1 People-to-People Recommendation Domain

The Buddy Program is a program for exchange students to apply to have a buddy while studying at Linnaeus University in Växjö. The buddy is a Swedish student who wants to help newly arrived exchange students with their student life activities.

We used our RCM to match exchange students' preferences (e.g., hobbies, interests, age, country) with buddy preferences (e.g., age, preferred country). The context information for this scenario was modeled in three dimensions: *environment* (e.g., country, university), *personal* (e.g., gender, preferred gender of student or buddy, age), *interests* (e.g., hobbies; additional information about oneself). Each of the dimensions was multi-dimensional and provided different data types (e.g., hobbies is an array of strings, additional information about oneself is long/short text, and age is number) and priorities (e.g., gender has a higher priority compared to age, hobbies has higher priority than country). The main requirement for an expert who had been working with the Buddy Program for more than three years was that the collected student/buddy information was handled by the proposed application. The data was collected from exchange students and potential buddies via a web registration form. Different metrics were used for matching the students. For example, the usual Euclidean metrics were used for age and gender; Jaccard metrics was used for hobbies; and cosine metric with latent semantic analysis (LSA) was used for additional information provided as free text by the student or buddy.

In order to validate our RCM toward flexibility in regard to handling different data types with different similarity techniques, we performed two recommendation rounds. In the first round, 401 exchange students were recommended to 215 buddies. The matching results showed that 271 students were matched correctly; 68 students were matched incorrectly (i.e., big age difference, country not matched, student was assigned twice, or no hobbies in common); 62 students were matched by the system, but were moved by the expert to the non-matched list (from which 22 students were matched by the expert manually). Overall, the matching accuracy was 75%, which is a good result for the first trial. After analyzing the reasons for the incorrect matchings, several suggestions for improvements were proposed and implemented in the context model (e.g., the age difference between the buddy and student that has to range from one to five years was defined in the personal context dimension and the priority was defined for each country in the environmental context dimension). These suggestions for improvements were easily implemented due to the high flexibility of the RCM. The second round was then performed with the improvements in the system.

In the second round, another 85 exchange students were recommended to 64 buddies. The matching results showed that 56 students were matched correctly and 13 students were matched incorrectly (i.e., some buddies changed preferences, such as to have two students instead of three) due to issues not considered by the approach. Therefore, the quality of the matching was different when compared to the first round's matching results. In addition, in this round, 16 students were not matched and, as such, will receive a buddy in the next semester. Overall, the matching accuracy increased to 85%.

The expert provided positive feedback about using our system, both for the quality of the recommendations and the spent time as it saved about 40 hours for the expert.

The evaluation was performed by comparing the matching results obtained by the system and manual approach. In order to do this comparison, we introduced a questionnaire to both groups (i.e., Group 1: Students matched by the system and Group 2: Students matched manually) (see Table 4.4). The questionnaire was adapted from a study conducted by [83] and a 7-point Likert scale [80] was applied for each question.

Table 4.4 Questionnaire used for the evaluation of the BuddyProgram application

Category	Question
Recommendation accuracy	Q1: The buddy/student recommended to me matched my hobbies.
	Q2: The buddy/student recommended to me matched my gender preference.
Expectation	Q3: The buddy/student recommended to me was exactly what I expected.
	Q4: The buddy/student recommended to me fit well with my age.
Recommendation diversity	Q5: The hobbies of the buddy/student recommended to me are diverse/dissimilar.
Transparency	Q6: I understand why the buddy/student was recommended to me.
Overall satisfaction	Q7: To what extent has our matching met your needs?
	Q8: Overall, how satisfied are you with the buddy/student you have received?
	Q9: I would recommend this program to my friends.
	Q10: If you were to seek a student/buddy again, would you come back to our program?
Open questions	Q11: How enjoyable was your recommended buddy/student to do activities with?
	Q12: How easy was it to communicate with your recommended student/buddy?

The first two questions (Q1 and Q2) aimed at evaluating the recommendation accuracy of our approach. The second two (Q3 and Q4) aimed at defining the student's expectations of his or her buddy recommendation. The next question (Q5) asked for the diversity of the recommendation. This is a negative question where "one" equals extremely

like and “seven” equals extremely dislike. The next questions (Q6-Q10) asked about overall satisfaction. The last two questions (Q11 and Q12) were open text feedback. The questionnaire in Table 4.4 was given to the exchange students who received buddies during the autumn 2014 semester using our approach (Group1) and exchange students who received a buddy in the spring 2014 semester who were matched manually by an expert (Group2).

Ninety-nine exchange students in each group (total – 198) answered the questionnaire. In order to validate our questionnaire for reliability, we calculated Cronbach’s alpha [84] for Group1 (i.e., 0.895) and Group2 (i.e., 0.908). This alpha showed that the data provided by the students in both groups was reliable and valid. Figure 4.3 shows the average results of the questionnaire.

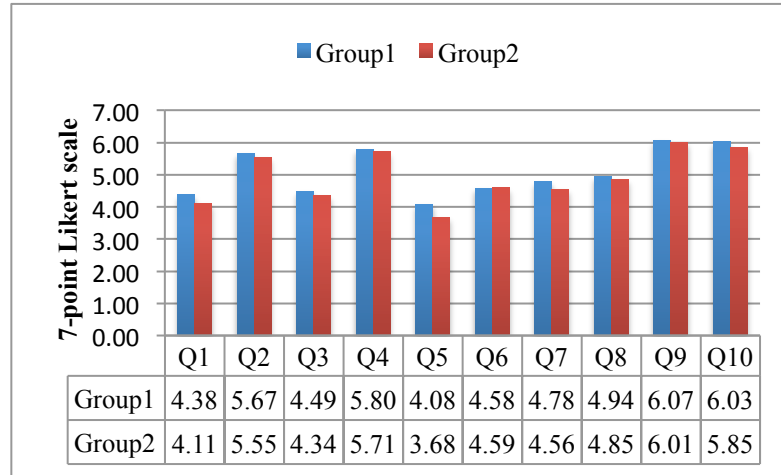
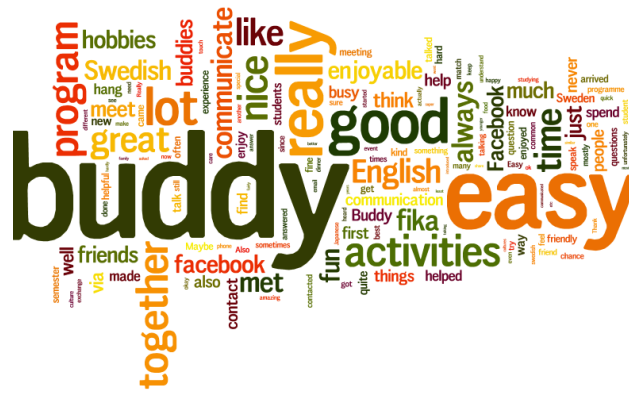


Figure 4.3 Average rating for the BuddyProgram application questionnaire

We calculated a paired sample t-test in order to compare the mean values between our approach (Group1) and the manual approach (Group2). The p-values obtained from the paired t-test did not show a significant difference between Group1 and Group2 ($p > 0.5$). This means that we retained the null hypothesis and our approach can provide recommendations with the same quality as provided by a human.

According to the average values for Group1 and Group2 are presented in Figure 4.3, the results are slightly better using our approach (Group1) when compared with the results obtained by the expert matching process (Group2).

Additionally, the most used words in the feedback provided by the students and buddies are shown in Figure 4.4. The overall feedback to those open-ended questions was positive based on the most frequently used words (e.g., buddy, good, easy, really, like, nice, together, activities, communicate; see Figure 4.4).



The goal of this study was to identify possible extensions of the RCM that could improve the recommendations and be reused in different scenarios. For example, priorities for the contextual information in regard to different levels of detalization were added as weights for each dimension or sub-dimension in the RCM. This feature allows us to define important context dimensions in different situations. For example, if one of the current context sub-dimensions with a high priority is unknown, then the RCM will consider, as the highest priority, the next sub-dimension that had less of a priority than the unknown one. Support of priorities in contextual information makes it possible to provide a good quality recommendation even if some of the context information is missing or not available.

We have applied our RCM to recommend the relevant content of news to the current context of mobile users [72]. News items are described by the contextual information presented in Table 4.5.

Personal context	Environmental context	Device context
Topics of interests Hobbies Country Activity Language	Place Direction Movement Date Time	Platform Battery level Internet connectivity

information about the activity in which the user is currently involved (e.g., doing sports, working) and/or *device dimension* (e.g., information about the device platform). The representation format of the news content was also considered. For instance, if the user was walking to his or her job listening, via headphones, to a news audio stream provided by a text-to-speech API, then an audio stream for the news may be more convenient in comparison to reading the news on the mobile device screen.

The context in which some news is suitable for a particular situation needs to be calculated. For instance, this could be done by using pre-executed evaluations where the users in different context have consumed different news. Afterward, the users' context information related to consumed news would be stored in the multidimensional vector space model (MVSM). Then, each news item could be represented as a vector in the MVSM (e.g., News1, News2).

In this RCM, we considered two requirements: to provide news content that is better suited to the user's current context and to provide a representation format that is most convenient to mobile users related to their situation. In order to identify the relevant content of the news, the *similarity* must be measured between two vectors: the vector describing the *current rich context* of the user and other vectors describing the different available news items. The similarity between the vectors can be calculated using *Euclidian* distance, *Jaccard*, and *cosine* similarity metrics. Based on our previous efforts [64], we considered a combination of the *cosine* and *Jaccard* similarity metrics in order to match the *current rich context* of the user to the content and representational format of the news. Here, we differentiated the Boolean data type of the contextual information (e.g., whether the user is currently moving – 1 or sitting – 0). For this type of Boolean data, we proposed to calculate the *Jaccard* similarity metrics in order to define the similar environmental contexts. The *cosine* metrics, which we proposed for the non-Boolean data, defines how similar the current context of the user is to another context in which some news was consumed. Since we needed to use different similarity measures, we ended up having a value for the similarity that is a vector itself. Thus, the final step for the identification of the news items to recommend is to calculate the closest distance to the point of the *current rich context* of the user and all available news items.

The proposed contextualized approach allows for real-time recommendations of news. The mobile application will collect the user's current context information, analyze it, and recommend relevant news accordingly in real-time.

4.3 Summary

In this chapter, we have provided an overview of our four main papers: m-learning domain [63, 64] and recommender systems domain [72, 77].

The m-learning scenario (i.e., LnuGuide app), which was used to guide exchange students at Linnaeus University, was designed in order to identify the possible benefits of rich contextualization support in an m-learning scenario. Positive comments and feedback from the students showed that the LnuGuide app with contextualization support was more convenient to use and beneficial in regard to achieving their goals (or performing tasks) easily. The evaluation also showed significantly better results for the contextualized approach, especially with respect to the acceptance of the PEU.

Current Cloud Computing technologies and services offer new possibilities for supporting the contextualization of users and providing personalized and adaptable services and applications that can enhance m-learning activities.

In the people-to-people recommendation domain, the aim was to validate the flexibility of our RCM in terms of handling different contextual information data types while taking into account personal priorities. The evaluation of the proposed RCM was performed in the student university network Buddy Program in Växjö. This study showed that no significant difference existed between our matching approach and the manual approach performed previously by an expert. The positive feedback from students and an expert has shown a usefulness of the system, especially in regard to saving time. In addition, the results also showed slightly better outcomes in almost all of matching criteria when compared to the manual approach, although it was not statistically significant. This result showed that an automatic matching mechanism using our approach performed just as good as an expert.

These results provide some initial evidence that our RCM is flexible enough to support different data types (e.g., numerical, Boolean, short text, long text) with different algorithms (e.g., metric similarities, defined rules, latent semantic analysis) in order to process the data and take into account the user's personal priorities/goals.

Chapter 5

Conclusions and Future Work

In this thesis, we presented a RCM that implements a unified context modeling approach, which considered the rich context of the user and allowed to model context in a domain-independent way.

The research of this thesis contributes to the state of the art with the following contributions:

- *Literature review.* A literature review of the existing and most used context modeling techniques and approaches was presented in Chapter 2. Previous research has shown that no common solution exists for a general context model, but the context model is bound to a specific application domain and a high level of abstraction is needed in the design in order to support multi-domain context modeling. Based on the QOC schema analysis, the recommendation has been done toward using a multidimensional context modeling approach as a starting point for creating a unified context modeling approach.
- *An abstract context model.* A RCM has been designed and proposed for modeling context for different application domains without making changes in the core of the model. The mathematical model and contextualized recommendation algorithm were presented in Chapter 3. The proposed approach supports the modeling and analysis of different data types of contextual information and represents the contextual information in different levels of detailization. The proposed design can be used to develop personalized and contextualized mobile applications.
- *Two case studies and proposed implications in several application domains.* This thesis presented two case studies in the domain of m-learning and recommender systems. These case studies illustrate the applicability and flexibility of using the proposed approach. They show the benefits of the contextualization approach for m-learners (e.g., more convenient to use and can easily perform the tasks) and significantly

better results in regard to being easy to use in comparison with a non-contextualization approach. The flexibility of the proposed approach has been evaluated in the people-to-people recommendation domain.

In this chapter, we first revisit the research questions in Section 5.1. Then, we describe, in detail, our ongoing work (see Section 5.2). Finally, we discuss the directions for future research efforts.

5.1 Research Questions Revisited

The main goal of this thesis was to identify the general context modeling approach to be used to model context and explore applicability and reusability in different application domains. In addressing this goal, we provided answers to the two research questions:

RQ1 How can we model the context in a domain independent way for mobile applications:

RQ1.1 How can we handle different data types of contextual information and priorities for context information for different mobile scenarios?

We investigated the modeling of different contextual information during the context model design. In order to handle the different data types, a combination of the various similarity metrics (e.g., cosine and Euclidean for numerical data, Jaccard for Boolean data) and algorithms (e.g., latent-semantic analysis for the text data) was proposed and supported by the RCM. Additionally, the RCM supported the priorities of the contextual information by adding additional weight from 0 to 1 to each context dimension.

RQ1.2 What are the common components of the abstract context model that allow modeling the context in a domain-independent way?

Based on the studies performed in the different application domains (i.e., m-learning, and recommender systems), we found that the most common components of the abstract context model are a mobile application through which to collect sensor and user interaction data and having a *Resource Manager* tasked with receiving the data from the mobile application and enriching it by using external web services (e.g., web service APIs, open data APIs). Additionally, the *Resource Manager* prepares the data as a multidimensional vector for further context analysis. The *Context Manager* implements the RCM and calculates the distance between the vector of the current context and the contextualized entities stored in the database. The *Recommendation Manager* prepares the recommendation item for the mobile user. All of these components allow to model the context for different application domains.

RQ2 What are the requirements for application developers to be able to develop contextualized mobile applications?

Based on the studies performed in this work, in order to use the contextualization approach, the following requirements must be met. For the mobile applications, they must have constant internet connectivity and access to the data from the sensors. For the application developer, he or she must have knowledge about the target users, what the application does (e.g., application features), and which context data is needed in order to provide the best recommendations for the target user.

In contrast to existing approaches, our approach attempts to improve on the applicability of the context modeling techniques in the development of personalized mobile applications and prevents recoding and redesigning a new context model repeatedly.

5.2 Ongoing Work

After designing the context model and implementing the recommendation algorithm, we are now targeting a general architecture that allows developers to more easily integrate our approach. Currently, we are implementing a cloud-based contextualized service for the development of contextualized mobile applications. With this service, application developers will be able to develop personalized mobile applications with minimal coding efforts. The main focus is on the architectural design of the service to make it flexible for usage in different application domains and support various contextualization goals.

We have chosen the microservices architectural approach [85], where each microservice represents one of the abstract components defined in Chapter 3.3.5. The microservices architecture is an approach used to develop an application or service as a set of small, independent services [85]. The *Contextualization Service* will provide the following features: a) a web application for modeling the context information for a specific application domain or scenario, b) the enrichment of the mobile data by using a combination of external context providers (e.g., Web Service APIs, mobile sensors, social media APIs, open data APIs) that are related to the application domain/scenario, and c) context analysis of the data that utilizes the rich context model. Then, when using the *Contextualization Service* application, the developer should:

- have knowledge of the mobile application's users and features,
- have knowledge of the goal of the contextualization,
- model the context information by using the *Contextualization Service*,
- provide the data in a form that the *Contextualization Service* can consume, and

- develop an approach in a mobile application for the representation of the suggestion results (e.g., notification, integrated in the mobile application as a part of the user interface).

Another ongoing direction is to explore other application domains where contextualization can help to improve the mobile applications, user experiences, and mobile services. One of the prominent areas for using context is big data analysis [86]. Therefore, we have chosen two use-cases: social network analysis and streaming data analysis. These cases will be described in more detail in the next sections.

5.2.1 Social Network Analysis

In today's society, the vast amount of data generated by users in social networks needs to be processed and analyzed. For example, on Twitter, there are more than 300 million tweets about events, news, opinions, and other information daily. This social network can be utilized in regard to exploring customers' needs, potential markets, customers' opinions, and customers' experiences with products.

Big data techniques can analyze a lot of data, but do not consider the meaning and knowledge of the data in the particular related application domain [87, 88]. Contextual data can be used to enrich big data by a) adding additional, important information that can be used to improve the quality of the data analysis; b) prioritizing particular aspects of the data analysis that can influence the prediction/recommendation results; c) helping to make correct observations from big data and utilize them in further data analyses; and d) helping to learn more about the users' behaviors or historic patterns, and current trends. Thus, context information is important in data analysis in order to provide better decision-making, predictions, and recommendations.

The proposed approach has been presented in [89]. The main idea of this approach is to extract the context of the tweet from the tweet metadata, extended by using additional Web Service APIs and process data by using the RCM integrated with a machine-learning algorithm in order to cluster tweets by their contextual similarity. The proposed approach in [89] can be used to order/structure tweets by context situation. Additionally, threads of tweets with different context could be identified and similar patterns could be discovered. Our approach tries to create clusters of context from Twitter data, in order to provide meaningful interpretations and understanding of the context of the tweets. In the future, it might be possible to analyze these clusters of tweets in context and discover additional contextual parameters useful to be analyzed further. Another interesting focus will be to use the advantage of clustering real-time streaming of tweets in order to derive more information about the context situation from several tweets that have a similar topic or are connected/relevant to each other. Thus, we believe that adding

context information related to tweets may bring new opportunities for designing advanced analytics services.

5.2.2 Streaming Data Analysis

Every second, a huge amount of data (e.g., event logs, sensor data, text data, web data) is generated by many applications (e.g., medical systems, transport systems, news applications, social media applications). These data are continuously generating a sequence of multidimensional data as so-called *data streams* and can be considered one of the big data sources. A challenge exists in regard to understanding streaming data and providing some meaningful use related to it for mobile users, applications, and services. The context modeling approach combined with mining the data stream may enrich the original data and help discover existing contexts in the streamed data. By knowing to which context a stream of data belongs, we would better understand the analytical results of context detection and be better able to build a reasonable story of usage behavior.

In the streaming data analysis, it would be interesting to explore the opportunities and issues related to discovering contextual information or parameters in real-time from streaming data. The approach based in combination of context modeling (i.e., MVSM) and data mining (i.e., unsupervised k-means clustering) approaches for grouping data into clusters of context. Each cluster represents some context X with some contextual parameters that can be used as additional information for further data mining techniques. By using a context modeling approach in big data analyses, we aim to improve the existing big data analytic services or build new context-driven analytic services.

Our approach can be applied to different mobile application domains and the outcomes can be used as follows: additional relevant input to other mining techniques (e.g., prediction analytics) and explanation of some concepts (e.g., user behavior) to provide some application/service adaptation. The main benefits of using our approach with data analysts are to enrich the data, which will lead to a better understanding of the data and better decision-making; to provide organizations with opportunities to improve their applications/services as related to the users' context (e.g., by adding contextual features to the application/service).

5.3 Future Work

In the future, we plan to focus on the architectural issues related to Contextualization Service (with implemented RCM) and the literature review of existing contextualization features for mobile applications. Second, we will design several evaluation scenarios in order to validate our approach. One of the scenarios will be used to investigate how the contextualization of LOs

influences the time to perform certain learning tasks. For doing this, first, we will extend the LnuGuide application (e.g., use iBeacons instead of QRcodes and add additional stations to the LnuGuide app and run a pilot study with more than 50 exchange students (divided into two groups, Group1: with contextualization approach and Group2: without contextualization approach). The evaluation will be done using questionnaires and interviews.

Another interesting scenario could be in the image recognition domain [90, 91]. The use case could be the contextualization of photos, where additional information about the user, environment, and social context could be tagged as additional metadata to a photo when the user is utilizing the mobile camera [92]. Examples of the application domain could be the contextualized sorting/ordering/managing/searching of photos (e.g., by place, event, social activity) or the tagged context information of the photos could be used as additional data for the image recognition approach.

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Appendix A

Publications

Publication I

A. Sotsenko, M. Jansen, and M. Milrad. Implementing and Validating a Mobile Learning Scenario Using Contextualized Learning Objects. *In The 22nd International Conference on Computers in Education (ICCE)*, Nara, Japan, pp. 522–527, 2014.

Publication II

A. Sotsenko, J. Zbick, M. Jansen, and M. Milrad. Flexible and Contextualized Cloud Applications for Mobile Learning Scenarios. *In Mobile, Ubiquitous, and Pervasive Learning*, Alejandro Peña Ayala, Ed. Springer International Publishing, pp.167-192, 2016.

Publication III

A. Sotsenko, M. Jansen, and M. Milrad. Using a Rich Context Model for People-to-People Recommendation. *In 3rd International Conference Future of Internet of Things and Cloud Computing*, Rome, Italy, pp. 703-708, 2015.

Publication IV

A. Sotsenko, M. Jansen, and M. Milrad. Using a rich context model for a news recommender system for mobile users. *Workshop Proceedings of the 22nd Conference on User Modeling, Adaptation, and Personalization*, Aalborg, Denmark, vol. 1181, pp. 13-16, 2014.

Implementing and Validating a Mobile Learning Scenario Using Contextualized Learning Objects

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Abstract: Substantial research in the field of mobile learning has explored aspects related to contextualized learning scenarios. Nevertheless, the current context of a mobile learner has been often limited to his/her current position, neglecting the possibilities offered by modern mobile devices of providing a much richer representation of the current learner's context. In this paper, we show that a detailed contextualization of the learner may provide benefits in mobile learning scenarios. In order to validate this claim, we implemented a mobile learning scenario based on an approach that allows for a very rich and detailed contextualization of the mobile learner. The scenario that we implemented allowed exchange students to be guided at Linnaeus University in Växjö, Sweden in order to get familiar with the campus and prominent institutions on it. We carried out a study including two groups; one that performed learning activities with contextualization support and one other without it. The results of our evaluation showed significantly better results for the contextualized approach, especially with respect to the acceptance of the Perceived Ease of Use.

Keywords: mobile learning scenarios; learning objects; contextualization; cross-platform development

1. Introduction

With the growing population of mobile devices, especially smartphones and tablet PCs¹, also their usage in mobile learning scenarios increased tremendously. A significant amount of research has been conducted in recent years, providing both, new technological approaches and pedagogical scenarios to support learning. According to O'Malley et al., (2003) mobile learning can be defined as "any kind of learning when the learner is not at a static or fixed location, or when the learner takes advantage of mobile technologies". For the purpose of this study, we understand mobile learning as learning that occurs outside of a traditional classroom and when the learner uses a mobile device in order to perform some tasks in the context of the learning activity. The context of the learner may include different contextual information about the environment, device, user's needs and interests. Mobile learning scenarios that take into account the learning context are called contextual mobile learning (Chuantao, Bertrand, & Rene, 2009). The mobile device allows collecting user's current context information, e.g., by collecting data from various sensors, to provide a convenient and easy way of learning independent of time and space (anywhere and anytime).

In order to investigate whether a richer contextualization model, as described in (Sotsenko, Jansen & Milrad, 2013a; Sotsenko, Jansen & Milrad, 2013b) really provides benefits to mobile learning scenarios, we developed a guided tour activity at our university, both with and without contextualization support. The objective of this study was to understand if the implementation including contextualization support provides significant differences with regard to an implementation without that support. The results of these efforts are described in this contribution.

The rest of the paper is organised as follows: next section provides a short overview about the current state of the art. Afterwards, a description of the implementation of our scenario is provided,

followed by the presentation of the results of our evaluation. In the last section, we conclude by discussing our results and providing some ideas for future lines of research.

2. State of the art

The experiment carried out by Hung et al., (2014) shows that using multimedia content of Learning Objects (LO) is more convenient and satisfactorily than just LOs in textual form. Approaches utilizing multimedia LOs can be used in mobile learning scenarios, e.g., for data collection in science education (Vogel, 2013), for quizzes with access to learning content (Geisler & Jansen, 2011) and/or field trips (Giemza A. , Bollen, Jansen, & Hoppe, 2013). in which mobile devices assist the learners in a convenient and efficient way. For instance, Wang et al., (2012) have developed a context-aware mobile application for navigating university campus maps in which personalized maps show important and relevant buildings, e.g., providing services to students. The results of this experiment indicate that a contextualized approach could improve its usefulness and navigation efficiency. Unfortunately, in this research contextual support only consisted of GPS location information and the user needed to specify the type of buildings/services he/she have been interested in. Moreover, no indoor navigation support was provided and the application was implemented only for the iOS platform. Another multimedia based mobile application is the Mytilene E-guide (Kenteris & Economou, 2011), implemented as a tourist guide allowing users to select certain content and to download an application for an appropriate mobile platform. The advantage of this app is its ability to also work in an offline mode while, at the same time; a disadvantage is that it was not implemented as a cross-platform application. In the work discussed in this paper, we present a cross-platform mobile app with contextualization support for which a much richer context model was used not just relying on the current user's location. The scenario that we implemented allowed exchange students to be guided at the Linnaeus University (LNU) in Växjö, Sweden in order to get familiar with the campus and prominent institutions on it. Therefore, the app provides relevant information about the university, its campus, cafes and other facilities. Here, the mobile app provides different activities, subdivided in to different tasks that allow foreign exchange students to get familiar with their new university.

3. Implementation

This section describes the implementation of a mobile application utilizing the contextualization approach described in (Sotsenko, Jansen, & Milrad, 2013a), implementing a three dimensional (environment, device and personal context) vector space model in which LOs' are represented. The context data is collected by: a) accelerometer, to define the movement (e.g. moving, sitting/standing) of the user; b) GPS location, to define the current place by using Google Places API; c) GPS location, to define the current weather condition; d) battery service, to define the battery status; e) screen size (width, height); f) camera, to confirm user location by scanning QR codes (e.g., for indoor navigation); and g) the user profile in a corresponding Learning Management System (LMS), to define users with similar interests. All LOs' to be used are stored in different media formats (.pdf, .html, .mp3, .mp4) in a standard LMS (Moodle) in order to make them accessible to the app.

The implementation of the app was done in a platform independent way (Sotsenko, Jansen, & Milrad, 2013b), for allowing a cross-platform deployment. The server-side implementation was done in Node JS for the main functionality of the mobile app. The client side is implemented by using the jQuery Mobile framework, allowing for the creation of user-friendly mobile interfaces. For persistency, a MongoDB database was used in order to natively store JSON objects, used for the complete communication in the system. Additionally, to collect the information about the current context of the user we used additional Web Services: a) Free Weather API provides the current weather condition for the location of the user; b) Google Places API provides the information (e.g. name, type, image, etc.) of current place of the user. These two types of data have been necessary in order to provide an appropriate description in the rich context model; c) Moodle Web Service extension (Piguillem, et al., 2012) allowing access to the LOs' that we provided to users as main learning content in the app; and d) a QR code service used for reading QR codes in order to identify the current location of the user in an indoor scenario.

3.1 Description of LnuGuide mobile application

The following sub-section describes the main functionality of the LnuGuide mobile app. At the login view, the user should login with a username and password from the LMS. The main view (Figure 1) is responsible for helping users to navigate in the activities. The Google Maps API v3 along with the Google Places API are used in order to provide an easy and convenient navigation. For inside navigation, the QR code service was used in order to determine the current position of the user.

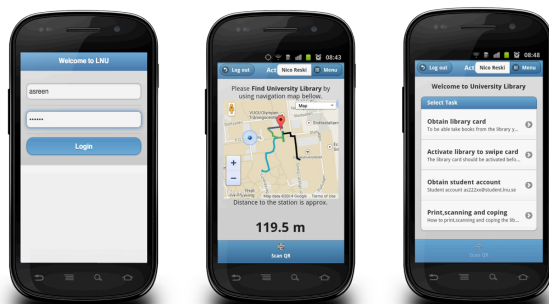


Figure 1. Screenshots of login and main view in LnuGuide app

The activity lists the tasks that a user can choose within his/her current station. Based on the user's current location the application will provide different tasks that are retrieved from a database. The task view shows the learning material in an appropriate format, according to the current context of the user. The profile view allows filling and saving the users' profile, e.g., with data like a picture by taking a photo, the study program of the learner, interests and hobbies. In order to facilitate collaboration between students the real-time chat is provided by application. The application determines other users with similar interests that are of the database and applies a filter to just show which users are currently online.

3.2 Description of the Learning Scenario

Mobile learning scenarios can be designed for guiding mobile learners to gain information about their current learning environment and how to work in it. For instance, students can learn about how to use the different services at the university library (e.g. registration in the library, usage library card, etc.) if he/she is inside the university library. Another example might be that students can be guided to learn how to print and scan papers by using universities printing system. The scenario described in this paper was designed for allowing international exchange students to familiarise with LNU and to learn about the different facilities and services available on campus. The Student Guide activity contains three stations (e.g. University Library, Administration Building and a café on campus) where students can get useful information to facilitate his/her "student life" (e.g. obtain the library or student card, to be able scan and print at Library, etc.). Each station provides a number of tasks, where, e.g., the app will provide information on how to scan documents at the library including instructions that the user should easily be able to perform. In this scenario, the LOs represent learning materials describing certain tasks that need to be carried out by the students.

4. Evaluation

An evaluation was performed to address the following research question: does the contextualized version of the LnuGuide provide benefits compared to the implementation of the LnuGuide app without contextualization support? In order to investigate this, we carried out a study including two groups of students; one group performed the scenario with contextualization support (Group№1) and a control group without contextualization support (Group№2).

4.1 Participants

The participants of the study were 25 exchange master students arriving to LNU on January 17th 2014 and invited via a Facebook event to participate in the Student Guide Activity during the universities' orientation week. The participants were divided into two groups where the Group№1 had fourteenth students and Group№2 eleven students.

4.2 Description of Study

The participants were enrolled in the course in our Moodle system manually with username and password. Before the Student Guide Activity started, a Samsung Galaxy S3 mobile device with the installed LnuGuide app and headphones has been provided to each one of the participants.

The Group№1 with contextualization support performed the different tasks of the activity in 45 min.. Below, we provide a short example of the type of contextualization support provided by the app. For example, the task "How to use the library card in order to be able to gain access to computer facilities at the university and enter universities buildings at any time?" Considering the current context of the user: user is walking near the university library and the weather condition is cloudy with the temperature -4C and his/her mobile device charged with 90% and with 3G connection. The learning material would be provided in audio format because light conditions are too bad for video and during movement it is probably not convenient to consume a text-based format. Considering a different context of the user: user is standing inside the university library and his/her mobile device charged with 40% and with Wi-Fi connection, the learning material would be presented in text format due to the low battery load, the different lightning conditions and the user not moving.

The Group№2 without contextualization support performed the activity also in 45 min. Here, different tasks provided the material only in text format and without taking into account the current context of the user. After the activity finished, participants from both groups were provided with the questionnaires including additional open feedback text questions.

4.3 Limitations

According to a previously performed pilot test with a few students, we defined that 45 min should enough to complete all tasks that were part of the university guide scenario. Still, in our final study, the external students complained that 45 min was not enough to perform all tasks. The overall number of students ($N=25$) resulted from the fact that we implemented the first prototype of the LnuGuide application in order to validate our approach, test and improve the application before running a larger study. At the end, the different number of students in the groups did not significantly influence the results of the quantitative analysis.

4.4 Study Results

The evaluation was conducted using questionnaires according to the Davis' Technology Acceptance Model (TAM) (Davis, Bagozzi, & Warshaw, 1989). From this set of questionnaires, we haven chosen two that fit well with our aims: the Perceived Usefulness (PU) and the Perceived Easy of Use (PEU). A seven-point likert scale (Likert, 1932) was applied for each question. The questions have been adapted (Giemza A. , Bollen, Jansen, & Hoppe, 2013) to our study. In order to determine whether or not the increased contextualization support provides some statistically relevant improvement, we deeply analyzed the gathered data from the questionnaires. First of all, we calculated the total average for the Perceived Usefulness to 4.83 in Group№1 and 4.69 in Group№2. For the Perceived Ease of Use the total average is 5.03 for Group№1 and 4.2 for Group№2. In order to test these results for significance, we conducted an independent-samples t-test for the PU and for the PEU. The results for PU indicate a not significant difference with regard to the total scores in Group№2. Still, the results for PEU show differences in question 2.2, 2.5 and 2.6 regarding the total scores in Group№2. So, we decided to conduct a t-test comparing the mean scores of questions 2.2, 2.5 and 2.6 in Group№1 and Group№2. Since we had a relatively small group of participants ($N=25$), we decided to calculate the

effect size offered by (Cohen, 1988). This test shows a significant difference in the question 2.5 ($M=2.79$, $SD=1.67$) for Group№1 and ($M=4.82$, $SD=2.32$) for Group№2; $t(13)=4.55$, $p=0.001$, $d=1.0$. In the question 2.6 ($M=3.15$, $SD=1.7$) for Group№1 significantly less then ($M=4.63$, $SD=2.1$) in Group№2; $t(13)=3.29$, $p=0.006$, $d=0.7$. Results for question 2.2 indicates non-significant difference for Group№1 ($M=3.57$, $SD=1.5$) and ($M=4.63$, $SD=2.01$) for Group№2; $t(13)=1.73$, $p=0.106$, $d=0.59$. All statistical tests have been conducted with an alpha level of 0.01.

4.5 Discussion of Results

The results for the Perceived Usefulness show almost no difference between the two groups, which is not surprising since the scenario and the provided learning content was the same for both groups. Figure 2, shows the average values both for the group using the contextualization approach (Group№1) and the control group (Group№2). From the t-test results we found that there are not significant differences for question 2.2. Furthermore, the corresponding Cohen's effect size (Morgan, 2002) value ($d = .59$) suggests a high significance. Still, significant differences could be found in question 2.5 indicating that using the LnuGuide mobile app with contextualized approach is less exhausting than the LnuGuide mobile app without contextualization. Here, the corresponding Cohen's effect size value ($d = 1.0$) also suggests a high significance. Furthermore, the results from question 2.6 show that with rich contextualization support, it was easier for the students to remember how to perform certain tasks within the provided scenario. Last but not least, here, the corresponding Cohen's effect size value ($d = 0.7$) suggested medium significance. Therefore, it could be said that the implementation based on the rich contextualization support is easier to use.

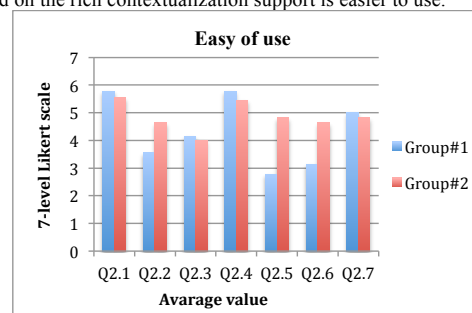


Figure 2. Average rating for PEU questionnaire

5. Conclusions and Future Work

The mobile learning scenario to guide exchange students at Linnaeus University was designed to identify the possible benefits of a rich contextualization support in a mobile learning scenario. The cross-platform LnuGuide mobile application was developed using jQuery Mobile, Node JS and Web Services, providing a stable and reliable technology stack for the development of cross-platform apps. Positive comments and feedback from the students showed that the LnuGuide app with contextualization support is more convenient to use and beneficial in order to achieve their goals (or to perform the tasks) easily. The evaluation also showed significantly better results for the contextualized approach, especially with respect to the acceptance of the Perceived Ease of Use. The results of the study provide some new insights with regard to the usage of the multi dimensional vector space model for modeling user's context for a mobile context based recommender system. The contextualization allows adaptation of the LO's format and the delivery of the LO's to mobile devices according to the user's context in order to keep learner's concentration and convenient study in anywhere and anytime. Our next research steps include a modification of the contextualization support to expand it to mobile health scenarios, where the usage of contextual information provided an important opportunity to create new personalized mobile healthcare applications. Additionally, we

plan to refine our approach on how to provide LOs' in different multimedia formats and to further improve the contextualization mechanisms.

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Chapter 7

Flexible and Contextualized Cloud Applications for Mobile Learning Scenarios

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Abstract. This chapter describes our research efforts related to the design of mobile learning (m-learning) applications in cloud computing environments. Many cloud-based services can be used/integrated in m-learning scenarios, hence there is a rich source of applications that could easily be applied to design and deploy those within the context of cloud-based services. Here, we present two cloud-based approaches - a flexible framework for an easy generation and deployment of mobile learning applications for teachers, and a flexible contextualization service to support personalized learning environment for mobile learners. The framework provides a flexible approach that supports teachers in designing mobile applications and automatically deploys those in order to allow teachers to create their own m-learning activities supported by mobile devices. The contextualization service is proposed to improve the content delivery of learning objects (LOs). This service allows adapting the learning content and the mobile user interface to the current context of the user. Together, this leads to a powerful and flexible framework for the provisioning of potentially ad-hoc mobile learning scenarios. We provide a description of the design and implementation of two proposed cloud based approaches together with scenario examples. Furthermore, we discuss the benefits of using flexible and contextualized cloud applications in mobile learning scenarios. Hereby, we contribute to this growing field of research by exploring new ways for designing and using flexible and contextualized cloud based applications that support mobile learning.

Keywords: Mobile learning, contextualization, contextualized service, cloud computing, cloud-based services, context modeling.

Abbreviations

ICT	Information and communication technologies
CC	Cloud computing
LO	Learning object
MVSM	Multi-dimensional vector space model

RCM	Rich context model
TEL	Technology enhanced learning
UI	User interface

7.1 Introduction

The use and integration of information and communication technologies (ICT) in the field of education is constantly increasing. In classrooms, a trend of a transition from traditional teaching methods to digital supported education can be identified [1]. There are some indications that the introduction of the latest ICT developments in classroom settings can improve the quality of teaching and learning [2].

Recent developments in the field of technology enhanced learning (TEL) have led to a renewed interest in new learning approaches and technologies that can be widely used and adapted for different forms of learning. Currently, mobile devices are used in everyday life activities. m-Learning has been defined as the process of learning with the use of mobile devices to access the educational resources, services from any place and any time where the learner takes advantages of the learning opportunities offered by mobile technologies [3]. Mobile technologies can facilitate learning outside the classroom in order to enhance the learning experience [4]. Also, learning materials are no longer limited to traditional materials like books [5]. A challenge that arises with the growing role of mobile technologies in the field of education is the importance to provide end-users, in particular teachers, with the possibility to author and deploy their own mobile applications [6] as they usually do not have the technical and programming skills to develop mobile applications suiting their requirements. Thus, one area of concern that developers and researchers are exploring is how to give end-users the possibility to create and author their own mobile applications.

Mobile learning activities offer also learners opportunities to independently explore processes that involve the gain of knowledge and own experience. Here, the context of the learner plays an important role in supporting the interactions between mobile devices and the environment in which the learning is taking place. By using contextual information, learners can be supported or advised via a mobile application in order to help them to find a solution for the given problem in the real world. Therefore, new ways of interpretation and the consideration of contextual information of mobile learners are necessary.

Currently, cloud computing (CC) solutions are often used to overcome some of the limitations of mobile devices, desktop computers or server systems, especially to improve accessibility and interoperability [7]. In this chapter, we explore and present how novel uses of cloud computing can contribute with some advancements to the field of TEL. CC increases the flexibility of modern applications while at the same time improving security aspects such as availability, data storage or communication. Furthermore, one major aspect in CC solutions is the accessibility of the provided services through a standardization of interfaces. With respect to learning scenarios, a different perspective to these abstracted features of CC services (referred to in this

chapter as cloud services) provides new ways to conceptualize and deploy emerging services such as contextualization and flexible authoring tools.

Flexible and contextualized mobile applications can be used as entry points for value-adding functions both in formal and informal learning settings, remote and co-located situations and in synchronous or asynchronous scenarios. Using cloud-based services allows increasing flexibility, availability and the accessibility of services through standardized methods, and additionally it allows the usage of off-the-shelf software, which saves implementation efforts and development time. Informal learning scenarios can particularly benefit from this approach, as it allows for an easier contextualization of the learning experience, which is still a hot topic, in the domain of mobile learning.

In this chapter, we address how the field of TEL has been affected by CC technologies by reviewing several studies and applications. The benefits of using cloud-based services for the development of new personalized mobile learning applications and services are described. In section 7.2, we provide arguments about using cloud computing technologies for developing flexible and personalized m-learning applications and services. Section 7.3, firstly presents and discusses relevant efforts connected to the use of CC for educational purposes, and already existing cloud-based services for supporting the development of m-learning applications for students and teachers. Secondly, we provide a few examples on how to support the contextualization of learners by using mobile devices and CC capabilities. The following section 7.4 describes our cloud-based solutions is Contextualized Service. Section 7.4 follows by describing the proposed services provided by a Contextualized Service with several examples on how they can be used for developing m-learning applications. In Section 7.5 we describe two scenario examples in order to investigate the advantages and benefits of using cloud-based services for suggested contextualized approach. Section 7.6 concludes the chapter by providing a summary and a discussion of ideas for future directions of research and development.

7.2 Motivation

Currently, Cloud Computing solutions have been focused more on the using CC capabilities to create a learning environment for a specific lab, course, assignment or lesson [8] rather than adding new possible capabilities by using existing ones [7]. For instance, using the CC power for processing vast amount of data about the learner's situation, scalability for supporting a large amount of students, flexibility in using different available services - all these together provide new opportunities to create a learning environment that will be adapted to the current learner's needs and situation. These examples are not only taking the advantages of the ubiquity of the CC to support mobile learning but also shows additional functions and services that can be implemented and used to improve TEL activities [9].

One of the main advantages of using CC technologies together with mobile devices is to enhance the computational capabilities of these resource-constrained units in

order to provide rich user experiences [10]. Therefore, the enrichment of the learner's experiences and activities it demands the development of personalized CC services.

7.2.1 Cloud-based Services for Teaching

There are a number of cloud-based services that provide opportunities for teachers to create virtual desktop environments with preconfigured software and learning resources [8]. Those services provide an access to different software applications (e.g., Scilab, R) in order to flexibly organize a learning environment for any group of students. However, there are no cloud-based services that can provide opportunities for teachers to design their own learning scenarios (e.g., field trips) and deploy them in a cloud as a mobile learning application and finally distribute it among students. Moreover, not all teachers have knowledge about how to configure cloud environments for a certain learning environment. We think that cloud-based solutions should be more flexible in terms of easy and fast configuration of learning scenarios for teachers, and to deploy them as mobile applications for students.

There are many cloud-based services that provide ubiquitous computer power, processing and storage capabilities together with different software applications to support learning environments suitable to a certain student's learning task [11]. However, few research efforts have been carried out towards supporting an adaptation of cloud-based learning services to the current learner's needs and situation in order to improve the learning performance. Furthermore, it is desirable to support the convenient format representation of learning materials, to define learning problems/difficulties and to evaluate the learning progress. We think that the most salient CC features (e.g., scalability, high availability, flexibility) provide opportunities to create highly personalized services that can be beneficially used both for teachers and learners.

7.2.2 Benefits of Using Cloud-based Services

In this sub-section we describe some of the benefits for learners and teachers with regard to mobile applications running in a CC environment:

- Learners can run different software applications on their mobile devices anytime and anywhere. Teachers can provide different software applications available in a cloud environment without additional installation efforts and cost. Additionally, teachers can test a variety of apps from different providers to find out which ones are best for them.
- Teachers can create learning repositories for sharing learning resources among students; Learners have access to these resources anytime and from any device [10]. Additionally, it saves the cost of learning materials [12]. Since, students and teachers can share learning e-books, video tutorials with each other in a cloud.
- Using CC technologies can increase learners' engagement and interactions with mobile learning applications by enhancing features and functionalities of mobile devices [13].

- Students might use different portable devices during the learning process therefore m-learning applications should be accessible on all of them. Cloud-based services provide the possibility to run learning applications on multiple devices (e.g., tablets, mobile devices, etc.), as long as the device has an internet access [10, 13].
- Scalable storage capacity and processing power allow developing m-learning applications to support large numbers of students [2, 14–16].

One of the possible drawbacks of using CC in the field of TEL is that it requires specific technological skills to configure different learning environments for a lesson, study, and lab that not all teachers may have [17].

The suggested cloud-based solutions we are proposing, namely the web-based framework and the Contextualized Service pose new challenges. In the case of the web-based framework, the system should be used by a significant amount of users. Since no programmer needs to be involved in the process of generating mobile applications, the potential of the existence of a massive amount of applications is given. One potential solution to address this issue is the deployment of the components, in this case, the mobile application, in a cloud-based system. As mentioned before, cloud-based systems provide benefits with respect to scalability and reliability.

In the case of information contextualization, the processing of huge amount of contextual data requires additional computational resources, storage capacity and flexible algorithms for analyzing these data sets. A cloud-based solution allows providing richer/more detailed descriptions of the user's context by using additional cloud-based services together with the power of CC (e.g., Amazon Elastic Map and Reduce service). Furthermore, it allows using contextual data from different mobile learning scenarios for providing recommendations based on historical data.

To address the challenges mentioned above the following research questions have been formulated and they serve as the foundations that guide our efforts:

- *How can a cloud-based solution improve the contextualization approach for mobile users in learning scenarios?*
- *Which cloud-based services can be used for supporting a contextualization approach for mobile users in learning scenarios?*

In the next section, we present an overview of related research efforts in this domain.

7.3 Related work

Traditional m-learning applications have limited access to learning resources [13, 18], limited offline data usage support, data sharing and social-technical issues for teamwork [19]. Cloud-based learning applications can help to solve/overcome these limitations. For example, a rich mobile multimedia cloud-based service enables access rich multimedia content from any mobile device or platform [15]. Using a service-oriented system, “Teamwork as a Service” (TaaS) [19], allows improving and facilitating social collaboration and learning activities for learners' team, and the Microsoft Mobile Apps provides possibility to use offline data when there are network issues. Addi-

tionally, the applications provide much richer availability of services in terms of data size, faster processing speed and saving battery life [13].

Context-aware m-learning applications require processing a vast amount of contextual data as well as to store this contextual data for further processing. Therefore, context-aware m-learning applications can benefit of using CC technologies [12, 14]. For example, the Amazon Elastic storage can be used for collecting and storing sensor data gathered from mobile devices while Microsoft Azure Machine Learning Service can be used for processing and analyzing a historical contextual data in order to make recommendations to the learner and to support him/her in different context situations.

One of the main advantages of CC capabilities is in supporting context-aware learning activities for both individuals and in groups of learners. Here, the context data should be collected and processed from several learners' mobile devices to provide a real-time feedback to the group of learners. Such m-learning applications can use cloud-based services to monitor e.g., a mood in the group, the performance of the group, the communication and learning flow in the group while they performing of a certain learning activity, how students interact with a learning material [20] by using e.g., educational and learning analytics service [21]. Current context-aware m-learning applications do not have enough computation power and resources to support context-aware learning activities for groups of learners.

In order to investigate in more details which existing cloud-based services and applications can be used in m-learning domain, several studies together with cloud service providers have been reviewed and they are described in the following subsection.

7.3.1 Classification of Cloud-computing Services and Applications

Cloud computing offers different available services, software applications and resources for processing a huge amount of data, reducing cost and increasing flexibility and mobility of information [13]. The widely used technologies, such as social networks together with mobile sensors data, CC and Internet connectivity makes it possible to provide personalized learning through mobile device [10]. Up to now, several cloud-based services have been suggested to adapt the delivery of learning objects on mobile devices including text-to-speech solution for learners in the move [22], support of geo-collaboration for situated learning activities [13, 23]. The work carried out by [23] uses combinations of different cloud services to support new forms of TEL activities with adaptation to the learner's style. The current solutions are based on using learning analytics techniques [24] for processing students' learning activities to predict learner's performance or issues by e.g., monitoring the logs in a cloud. Other challenges described in [10] address problems related to learners that can combine various applications on their mobile devices (e.g., Calendar, Editor, Notes) to configure a personalized cloud learning environment that utilize content and services available from the cloud for their individual needs. Based on the cloud services classification provided in [7] we describe bellow already existing cloud-based services and applications and how they can be used in mobile learning scenarios.

Cloud-based Communication Services. They are utilized for supporting learner-teacher and learner-learner interactions on a remote or co-located mode. Learners use different types of collaboration and therefore use different applications or tools to satisfy their needs and goals. For example, for group/team collaboration the most used technologies either social networks applications (e.g., Facebook Chat, Twitter) or chat-based applications (e.g., Skype, Viber, WeChat) for interaction between their group/team members. For asking questions about a certain problem/issue or answering with a solution for the given problem/issue usually a question and answer sites (e.g., stackoverflow.com, mathoverflow.net) are used by learners, and for collaborative paper working a set of tools (e.g., the Google Apps for Education Suite [25]) can be used to simultaneously communicate and work in the team/group. For learner-teacher communication learners usually prefer to use email services (e.g., Mailbox, CloudMagic Email) or learning platforms' forums (e.g., Moodle forum). In case of mobile learning scenario the mentioned above communication services can be used either through cloud-based mobile applications (e.g., ZOOM Cloud Meetings, the Google Apps for Education Suite is available for tablets and phones) or cloud-based mobile services (e.g., Push notifications). The efforts carried out by [26] show that cloud-based communication services can help teachers to know the current learner situation and to improve the communication between them.

Cloud-based Repository Services. They are used to store, share and retrieve learning materials or resources in the cloud. The most popular examples of such services, just to mention some of them, are Dropbox, OneDrive, Box, Amazon Cloud Drive, Google Drive that available on iPhone and Android mobile platforms. Learners can use these tools to perform different tasks. For example, Dropbox is used for sharing, accessing different types of files between other learners, while the Box application supports additionally a group work, including assigning tasks and tracking file versions for each team member. This example can be used e.g., to evaluate the contribution and the performance either of the group of learners itself or individual learner in the group. Such services allows accessing the large number of LOs via mobile through Internet at anywhere and anytime. Hence, depending on the file size of LO and Internet connection it might take some time to get it. Therefore, such services as DropBox, OneDrive, Google Drive offers offline accessing and viewing files on the mobile device due to Internet connectivity issues. But those files that should be accessed in offline mode should be specified in the application in advanced and in online mode. This offline feature allows for learners learning in anywhere (e.g., sitting in the train, in the park) and anytime with their mobile devices. The added value for teachers is to share the learning resources among a large number of students/learners; tracking both the learner's individual contribution, task's responsibility, performance and the group work of learners itself. The added value for learners is to accessing the learning resources and sharing their own resources, materials, work between other learners.

Cloud-based Single-Specialized Services. They are utilized for learning or working on a task that is related to a specific application domain. For example, for learning supported by audio or video stream processing or for playing and creating digital content anywhere and anytime with a mobile device. Two of the most known single-

specialized services are the AutoCad 360, which offers viewing, editing and sharing AutoCAD files via a mobile device. Other example are the Adobe Slate, Premiere Clip and Voice Services, which allow learners turn any document into a visual storytelling that can be used in museums or field trips. In addition to sharing, and editing a video/audio files, the CyberLink's Mobile App Zone provides the possibility to take a picture of live presentation lecture slides and turn them into PDF files on the mobile devices. An additional example is the Quick Graph application for visualizing plots with high quality 2D and 3D mathematical expressions.

Cloud-based Processing Services. They allow analyzing and processing big data sets with different processing algorithms and methods. Such services allow to support learners in real-time during the performing of a certain learning activity through monitoring learners' interactions with a learning environment and a mobile device. Another example is to analyze and process the log files after a learning activity is finished in order to investigate and understand the workflow and its outcomes by using e.g., learning analytics services. This feature enables teachers to analyze the weak and strong aspects of a certain learning activity and offers the possibility to improve it. This could also lead that students can get real-time feedback and support that helps them to successfully perform learning activities.

Most of the above described cloud-based services provide an API that can be used as an additional service or combination of services to develop novel custom cloud-based applications for mobile learning scenarios.

7.3.2 Mobile Cloud-computing Services and Applications

Mobile cloud computing is the combination of mobile application, CC and Internet connectivity aiming to enhance computational and interactional capabilities of mobile devices towards rich user experience [10]. Many cloud providers offer a huge variety of services for mobile devices called as "Mobile back end as a Service" (MbaaS) (e.g., Microsoft Windows Azure Mobile Services, AWS Mobile Services). The main available services for development of mobile cloud-based applications are presented in Table 7.1.

Table 7.1. Examples of mobile Cloud-based Services

Cloud provider	Platform SDK's	Database	Analytics	Cloud Functions/ Services
Microsoft Windows Azure Mobile Services	Windows Phone 8, Android, iOS, HTML5	SQL, MongoDB	Mobile Analytics with Capptain	Push Notifications
AWS Mobile Services	Android, iOS	Amazon DynamoDB	Custom analysis, Amazon Mobile	Push Notifications, Data Streaming, AWS Lambda

			Analytics Reports	
Oracle Cloud Mobile Ser- vices	Android iOS	Oracle Database	Oracle Analytics	Push Notifications
IBM Bluemix Mobile Cloud Services	Android, iOS, Hybrid, Node.js	DB2, Cloudant NoSQL DB, SQL	IBM Em- beddable Reporting, SPSS ana- lytics	Push Notifica- tions, Language Identifi- cation, Machine Translation, Per- sonality Insights, Speech to Text, Text to Speech, Visual Recogni- tion, Presence Insights and more

The examples of MbaaS services described in Table 7.1 allow for developing and deploying web-based, native or hybrid mobile applications and running them on multiple devices. Learners can have different mobile platforms to use cloud-based m-learning applications. Furthermore, if the Internet is temporally unavailable, learners still can continue working on their mobile devices locally and the changes made will be synchronized in the cloud when Internet will be available.

The Push Notification service allows to easily pushing data to the right users at the right time on the mobile devices. Notifications can be sent to a single device, or a group of devices based on their subscriptions. Depending on the learning scenario this service can be used to support individual learner or group of learners while performing a certain learning activity. In addition to the Push Notification service, IBM's BlueMix mobile cloud service offers a number of services that can be used to develop m-learning applications. For example, the Language Identification Service allows detecting the language in which input text is written while the Machine Translation Service enables to translate text from one language to another. This latest service can be useful for supporting a multi-language communication on forums where a student can write a text message on his/her native-speaking language and it's language will be automatically identified and translated to the student's receiver native-speaking language.

Service providers can easily add and expand their service offerings. Multiple services from different providers can be integrated easily through the cloud to meet today's complex user demands and increase users' engagements with m-learning applications.

7.3.3 Advantages of Mobile Cloud-computing Services

In this sub-section, we describe how mobile cloud-computing services can be used to support learning activities, to overcome obstacles related to mobile learning and to enhance learners' engagement with m-learning applications:

- Context-aware learning: supports context-aware learning activities for learners. For example, providing learning resources for learners by recommending the appropriate content to users based on an intelligent analysis of the learners' behaviors and their learning outcomes [27]. The CloudAware framework offers context adaptation features through *Jadex* middleware with a combination of agent-, service-, and component oriented engineering perspectives [28]. Another interesting feature for mobile application development is the creation of a function that is executed in response to an event (e.g., notifications, messages, image uploads) and it has been introduced in AWS Lambda Addrs. Those functions are written in NodeJs framework that invoked in synchronous manner and receive the context information of the application data (e.g., name, build, version and package), device data (e.g., manufacturer, model, platform), and user data (e.g., a client id) as part of the request. This feature allows to easily create rich, adaptable and personalized responses to in-app activities.
- Security: The mobile application security service enables to provide or block any devices and/or users by using additional user authentication [29]. Additionally, it provides possibility to configure the access, sharing settings and protect personal data. Most cloud computing providers offer flexible and reliable backup and recovery solutions [30].
- Accessibility: m-learning systems typically include different kinds of multimedia resources helping learners to be more engaged and interested in collaboration [31, 32]. The efforts carried out by [32] provide the Learning Cloud framework, where users can work on different operating systems for mobile devices, and in that way students and teachers can access the cloud-based platform simultaneously from any location, at any time. Another study carried out by [31] has used a cloud-based learning platform to support distance learning and to provide an increased quality of e-learning. In m-learning scenarios like field trips, where students are taking photos by using their mobile cameras to collect some information and data about the learning environment, it is necessary to have some storage capacity and search/retrieve mechanism. Here, for example the photos can be stored and processed directly into the cloud instead of mobile device [33].

There are also advantages for teachers having cloud based applications to manage everything from documents to students' attendance and grades [34]. For example, with the TeacherKit application teachers can organize classes and manage students' activities easily. With the SchoolTube application teachers can upload educational videos for students. Another example is the Edmondo application where teachers, students and parents are connected to collaborate on assignments, discover new resources and more. However, there are still no cloud-based services that provide possi-

bilities for teachers to design their own m-learning applications and to distribute them to students on multiply mobile platforms.

Cloud services for learning scenarios can be used for both in formal and informal learning settings, remote and co-located situations and in synchronous or asynchronous scenarios [35]. The combination of different cloud services, sensors information, storage capacity and cloud computation power provides new opportunities to develop flexible and highly personalized cross-platform m-learning applications.

7.3.4. Limitation

In this section, we presented an overview with regard to the possibilities and potential that different CC environments and methods can have within the field of TEL. We are aware that a lot of different applications and services are listed within this section. To describe each one of them in more detailed fashion would be out of scope of this chapter, therefore we leave it to the reader to investigate the mentioned applications/services/methods and leave the description at the current abstraction level.

7.4 Contextualized Cloud-Based Services and Web-based Authoring Framework

In order to address our research questions, we present in this section two cloud-based solutions that are strongly connected. We present first a flexible *Web-based Framework* to enable teachers to compose and deploy their own mobile applications to perform mobile learning activities. Additionally, we present a *Contextualization Service* that has been developed in order to improve the content delivery of learning objects. This service allows adapting the representational format of the learning content and the mobile user interface to the current context of the user.

7.4.1 Web-based Framework

There are many learning activities that are connected to tasks that include data collection, analysis and visualization; our proposed framework offers to take advantage of the internal sensors available at modern mobile devices. The fact that the framework is realized in a cloud based environment, tackles the previously mentioned challenges in terms of scalability and reliability.

The presented web-based framework, *mLearn4web*, comes with an authoring tool, where teachers can design mobile applications for instance for field trips scenarios. Additional to the authoring tool, *mLearn4web* consists of two more components that are all purely based on web-technologies: a mobile component to perform learning activities and a visualization component that offers analyzing methods of the data that has been generated by the mobile component.

A major challenge in the field of TEL is the fact that teachers often do not have the technical skills that are required to create applications that can fits their pedagogical

needs. Often, they need to consult with researchers and/or developers to create or adjust applications to their specific requirements, which is not only inconvenient for the teachers but also generates additional work for researchers/developers. Therefore the mentioned authoring tool allows designing mobile applications by using simple and well-known interaction methods like drag and drop. In our case, the mobile applications consist of a number of screens and the authoring tool can modify the content and functionalities within a screen. The authoring tool is divided into three areas: a screen area; a content area; and an element area. In the screen area, users can add/delete screens and change their appearance order by dragging a screen to a new position. Users can add functionalities and content to screens of a mobile application by dragging pre-defined elements from a list to the content area. This includes the access of certain internal sensors of mobile devices like camera, microphone or GPS. Furthermore it is possible to add the following elements: an instruction that allows providing text information; a textarea that allows users to enter text on a mobile device; a multiple choice element where it is possible to pose a multiple choice questions and the user can pick an answer at the mobile device; a numerical input field; and a date input field that allows to enter a date in the proper format. Fig 7.1 illustrates the functionalities of the authoring tool.

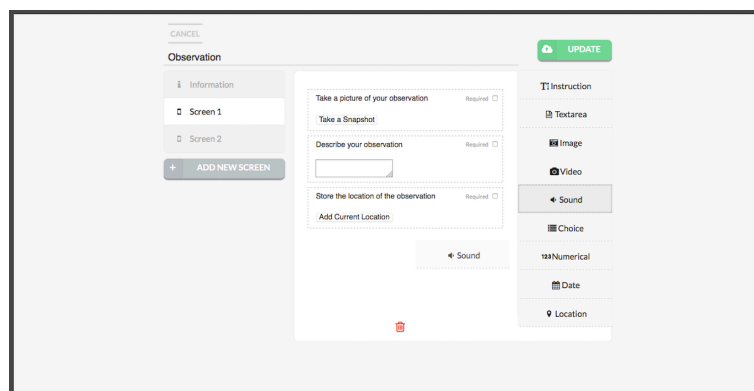


Fig. 7.1. Screenshot of the authoring tool

The authoring tool allows even non-technical skilled users to easily generate mobile applications that have the functionalities fitting their needs. After the design process is finished a mobile application is automatically deployed and available as a web-application. The fact that all components are based on web-technologies allows the easy deployment in CC environments like OpenShift. Since no developers/researchers are involved in the process, the potential of having a huge amount of mobile applications is given. Therefore, the mobile application is deployed in a CC environment. Fig. 7.2 shows examples of how the mobile application looks like.



Fig. 7.2 Examples of the mobile application

We have conducted several studies [36–38], and the outcomes of our efforts indicate that teachers without technical knowledge could generate and deploy mobile application fitting their specific needs. Of particular interest is the fact that even though some teachers had troubles in the beginning to deal with the functionalities of the framework, managed at the the end to design and deploy mobile applications and repeated the process without having much troubles [36]. This shows that the system is not only easy to use but also has a high learnability factor.

The third component of mLearn4web (Fig. 7.3), the visualization component, processes data that is generated during the usage of the mobile application. This allows teachers and students to reflect upon learning activities performed with the mobile application.

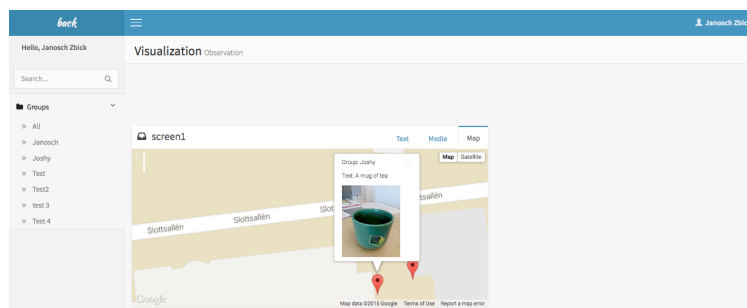


Fig. 7.3 The visualization component of mLearn4web

Datasets that are generated by the mobile application can be brought into context to each other. For instance, if GPS data and a picture are collected at the same screen, it is likely that they are contextually connected. Therefore, a map is offered, where the marker shows the picture that is also available. However, there is more potential for

presenting contextualized information. It is for example possible to use existing web-services to gather more information and to aggregate to the data generated by the mobile application. For instance, if GPS data is available, it is possible to add information about the surrounding environment or weather to the visualization.

7.4.2 Contextualized Service

The *Contextualized Service* is a service that provides personalization for mobile applications to the current context of the user. Particularly, it supports personalized interactions with a mobile device in order to meet the user's needs and goals. The main goal of personalization is to improve the user experience by taking advantages of contextual information in order to provide adequate services. Examples of contextualized services are location based services [39] that provide useful and relevant information to the current users' location; contextualized knowledge services [40] for supporting learners in a personalized and adaptive way by using the context information; contextualized learning services [41] for providing a personalized feedback in learning support. Based on our previous research work [42], the contextualization of learners could vary from one learning scenario to another. Unlike in a traditional learning environment, in a mobile learning environment, interactions with the learning applications are performed across a variety of contexts. Therefore, it is very important to identify the learners' needs, goals and expected outcomes to provide them with relevant contextualized services. For example, in a location-related learning scenario the relevant content should be provided to the learner at the right place and time (e.g., museums, field trips). Below we describe three features that personalized mobile learning applications should have while providing a contextualized service.

Contextual Content Representation. This feature allows adapting the format of LOs to the current learner's situation. We describe the learner's situation by contextual data gathered from mobile sensors, additional external Web Service API's, social networks and store it in a database in the cloud. Utilizing a cloud service with large storage capacity for collecting, storing and processing the contextual data provides the possibility to use not only real-time contextual data but also historical users' contextual data that can improve the prediction of the format of LO that is best suited to the current context of the learner. For predicting the relevant content of the LO the proposed flexible *rich context model (RCM)* [42] has been used. The main difference of having RCM on the cloud is that allows to store and process a vast amount of contextual data, to support a large number of mobile users and to use additional cloud based services to enrich the contextual data. This feature can be used in different mobile learning scenarios to provide convenient support to the learning processes anywhere and at anytime.

Contextualized User Interface. This feature allows adapting user interface (UI) elements of a web-based mobile application to the current context of the user (e.g., light/dark colors in the themes, predictable input form elements, adaptable UI elements). This allows making the interaction with a mobile device adaptable to the current context of the user. For example, provide convenient volume of the mobile device (e.g., make it lower/upper) by taking into account the noise level of the device

environment and position of the device, user's activity, place and time. Another good example is an application called Star Walk¹ application, which uses mobile camera, compass, location and augmented reality that allows learning and exploring the information about the universe by holding the phone at the night sky. Another example can be a contextualized keyboard for learning chemistry through mobile application (e.g., ChemCalc²) or for having personalized keyboard application called SwiftKey³ that delivers smart predictions and fast typing. Another example is a personalized application launcher that organizes the application bar with the most used mobile applications in a certain time, place and day (e.g., the user is at a school then the application bar shows only thus applications that was often used by user at the school).

Contextual Notifications. This feature allows users to make their mobile devices more personalized according to their current needs and interests. For example, a student is interested on buying a particular thing, then the application sends him/her the discounts/offers related to this object, depending on the users' leaving place for taking into account the delivery costs or using the local shops. Additionally, reminders of duties, course schedule, etc., can be sent as notifications to the mobile device in a suitable format (e.g., the voice notification, the image notification, the text notification). In the case of mobile learning scenarios, this feature can be used for guiding students in learning environment such as field trips or visits to thematic parks or museums. The described three features above can be implemented as a set of micro services and integrated in the micro service architecture as shown in Fig. 7.4.

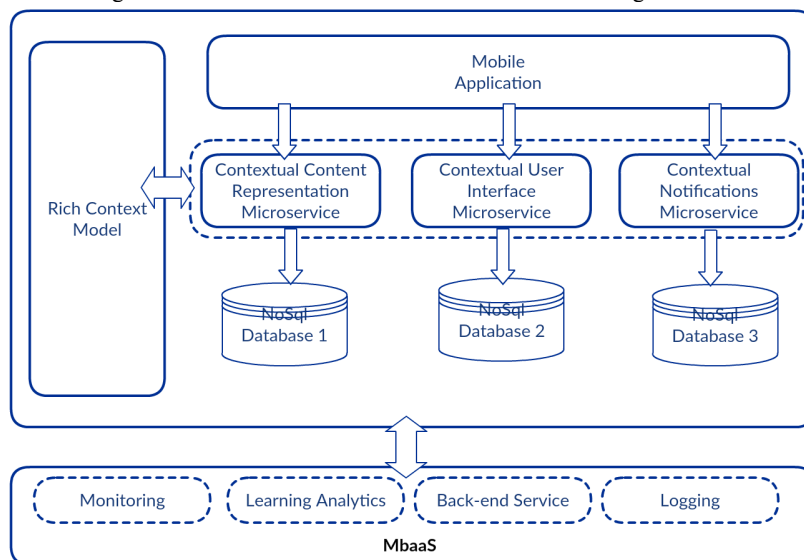


Fig. 7.4 The proposed architecture overview for Contextualized Service

¹ <https://itunes.apple.com/en/app/star-walk-5-stars-astronomy/id295430577?mt=8>

² <https://itunes.apple.com/us/app/chemcalc/id499955745?mt=8>

³ <https://swiftkey.com/en/>

It is shown in Fig. 7.4 that each feature is implemented as a micro-service and it has its own database in order to use it independently from the scenario point of view. The micro-services architecture is an approach for developing an application or service as a set of small independent services [43]. The main advantages of using a micro-service approach are scalability (e.g., scaling a certain feature instead of whole application), maintainability (e.g., easy to maintain since each micro-service implements a single feature/functionality), flexibility in distribution of the resources for each micro-service (e.g., the single function as *analyze contextual data* will need more computational resources than the *collect contextual data* function) and extensibility in adding new features/functions by increasing/adding/implementing additional micro-services. Then, different features provided by the Contextualized Service can be used independently from the scenario point of view. For example, one learning scenario can use only the *contextual content representation* feature while another one only *contextual notifications* depending of the nature of the activity. Furthermore, the service is flexibly in a way that allows adding new features as an independent micro service and uses it in combination with others. The proposed service is deployed in a cloud environment for supporting contextualization of mobile users in real-time. In our case, the *rich context model* has been utilized [42] to support these features.

7.4.3 Rich Context Model

The *rich context model* we are using is a model that handles the rich context of a mobile user. Here, the rich context is a data set received from different mobile sensors available on the device. Moreover, this data can be enhanced by using external Web Services (e.g., Google Places API) to retrieve more detailed information about the context of the mobile user (e.g., weather condition, nearby services) [42]. An example of different context dimensions and mobile sensors that can be used in different mobile learning scenarios is given in Table 7.2.

Table 7.2 Example of context dimensions and mobile sensors in m-learning scenario

Context dimension	Mobile Sensors	Contextual information	Web Services
Environment context	GPS	The type of place where the learner is located; the nearest places around the learner's location; the weather conditions when the learning environment is outdoor;	Google Places API, Free Weather API
	Accelerometer	The learner's status (sitting in the train, bus etc.);	

	Digital Com- pass	The learner's direction	
	Camera	Fast and easy access to the learning materials by scanning barcodes, qr codes; the type of place by taking picture of place where learner is located	QRCode Web Service
Device context		Screen size, Battery Charge, Internet con- nectivity	
Personal context		Interests, Language, Country	Facebook API, Twitter API

There is no use for sensors if the data will not be processed and analyzed. Context analysis techniques allow processing these data and providing a meaningful interpretation. The available contextual data is evaluated by the use of a multidimensional approach that provides richer representation of the user's context [44]. Each dimension describes a property of an entity or the entity itself, where the entity can be an object, a person or a situation. This enables the RCM to consider various data types of the contextual information and to use different approaches to evaluate and analyze the data. Another example of what can be achieved with the RCM is the identification of a context similar to the user's current context in order to provide relevant recommendations. In addition, a suitable format for the representation of the learning materials can be recommended with the RCM by taking the environmental context information into account. Here, the learning objects (LOs) in different formats are described by contextual information provided in Table 2 and represented in *multidimensional vector space model (MVSM)* as shown on Fig. 7.5.

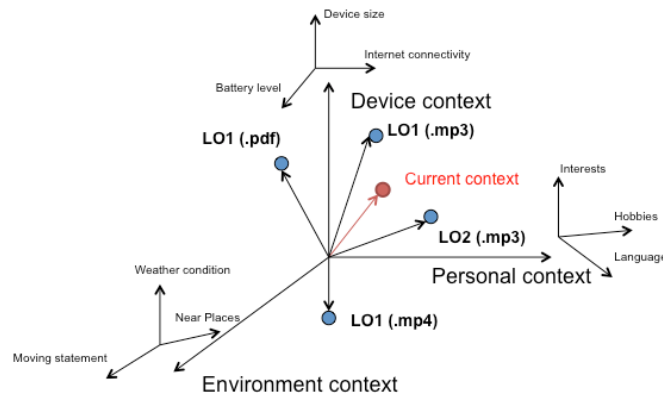


Fig. 7.5 Context representation in MVSM

Then, in order to define the best-suited format of a LO, the distance between the vector of the current context of the user and the vectors at the MVSM is calculated by using the combination of different metrics similarity (cosine distance, Euclidean distance, Jaccard distance, etc.). The vector that has minimal distance to the vector of current context of the user defines the best-suited format of LO.

The context information has various data types and therefore different metrics similarity or algorithms should be considered to process this data. As an example, we used the combination of different metrics and algorithms that are shown in Table 7.3.

Table 7.3 Examples of usage different metrics and algorithms for processing contextual information

Contextual information	Data type	Metric similarity/ algorithm
Hobbies	Array of Boolean (1 – has hobby, 0 – does not have hobby)	Jaccard distance
Age	Integer	Euclidean distance
Movement statement, outside/inside the building	Boolean	Jaccard distance
Additional Information	Long text /String	Latent semantic analysis

Having a generic approach for context modeling is very important, because different learning scenarios may have dissimilar properties describing an entity itself and therefore different dimensions in a context model. A technical infrastructure to support this is outlined in Fig. 7.6. The major task performed by this infrastructure is to provide a certain abstraction for the context dimensions in order to allow an automatic and flexible configuration in the RCM.

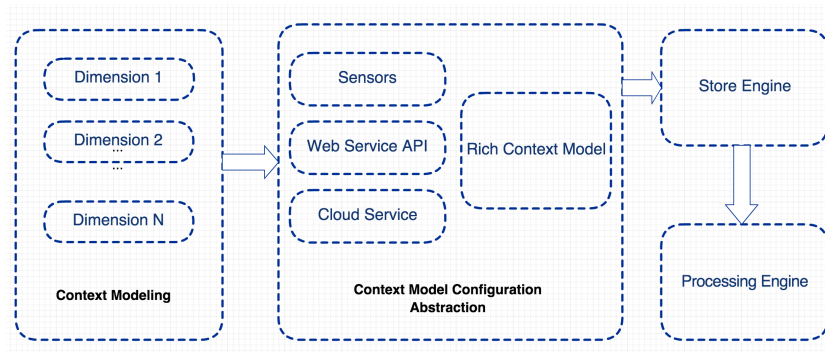


Fig. 7.6 Architecture overview for RCM configuration

In this architecture, the *Context Modeling* component is responsible for defining the context dimensions that should be used for a certain scenario. The web-based application proposed to configure these context dimensions and can be used by an

expert. We define *an expert* as a person (e.g., teacher) that has a wide body of knowledge in relation to subject matter that is at the core of the learning scenario in which the Contextualized Service will be used.

The developed web application allows visually adding/removing context dimensions and sub dimensions. After adding all the required dimensions into the scenario, the expert can export the context modeling results into a JSON file. This JSON file is an input for our contextualized approach and it is required for the usage of the Contextualized Service. Then the *Context Model Configuration* block has an abstraction for the context dimensions and it is responsible for the configuration of RCM. After the RCM is configured it can be used for collecting, storing and processing contextual data. We think that an expert in a certain learning scenario should define the context dimensions as he/she has best knowledge about it. This makes our contextualized service flexibly in terms of supporting different context models for different learning scenarios.

The model supports different recommendation types, e.g., relevant learning objects and convenient representational format of LOs, and can therefore be extended by others types of recommendations. Additionally, it supports different levels of granularity of the context. This is achieved by the flexibility of the RCM to include/exclude the context dimensions. It supports using priorities for different contextual information. The latest is achieved by using additional weights for each context sub-dimension according to the user's preferences. This in theory allows the RCM to provide better and more convenient services for mobile users. The main difference between our RCM and similar approaches is the flexibility that it allows for describing a complex contextual situation. Our approach has the potential to improve the usability of mobile devices in order to enrich the current context of the users.

For some learning scenarios it might be the case when an expert does not know which context dimensions should be considered in order to achieve good recommendation results. We suggest two possible solutions (a) to perform a pre-study in order to identify and evaluate the necessary context dimensions used in our context model. Since the proposed approach uses the comparison of the current context of the user with objects that were consumed by others in a similar context situation, the pre-executed study should be performed in order to have the database of different context situations; (b) to collect contextual data for different context's situations and apply machine learning algorithms (e.g., vector support machine) to define which contextual data should be used to classify different contexts' situations for a certain learning scenario.

7.5 Scenario Examples

This section presents two scenario examples: (a) using the *mLearn4web* framework in a m-learning scenario and (b) using the Contextualized Service with the *LnuGuide* mobile application. The *mLearn4web* is a web-based framework that allows users without programming skills to design and deploy mobile learning activities [36]. The *LnuGuide* is mobile application that supports exchange students while they are ex-

plore the university facility services on the campus. The purpose of these designed scenarios is to outline the advantages and benefits for learners and teachers while using the *mLearn4web* framework with the *Contextualized Service* in a cloud environment.

7.5.1 *mLearn4web*

The *mLearn4web* is a web-based framework designed in [37] for creation and deploying mobile learning activities. It consists of three main components: an authoring tool that was described in Sec 7.4.1, a mobile application and a visualization tool. These components can be used to support the three phases that are described in [45] which together provide one of the most prominent examples of a mobile learning activity: a field trip. The authoring tool offers support for the “pre-trip phase”, where the preparation of the field trip takes place. The mobile application offers support to the actual field trip. The visualization tool supports the “post-trip phase” in which the debriefing and analysis of the field trip takes place. In this field-trip scenario, these are the units of interest for the RCM. For instance, in the “pre-trip phase” the teacher defines which kind of data should be collected in a certain learning activity. Then, these collected data (e.g., images, location, textual comments, numerical values) could be considered as a part of the contextual information and stored at the RCM. Here, the RCM will represent the collected data by contextual information as described in Table 7.2. Then, the result of the contextualization will be the delivery of interested and relevant information about the learning environment to the current context of the learner. For instance, when the learner will reach a certain place, the application will show the most relevant objects and data gathered by other learners in the similar context situation. This might allow for learners to find out more information about the learning environment or do not miss important and useful pieces of information that related to a particular location/place. This information can be delivered with the help of contextual notification services provided by the Contextualized Service.

In order to tackle the issues related to scalability, we have deployed the *mLearn4web* in a cloud environment. Having the *mLearn4web* application in a cloud allows automatically deploying the resulting designed mobile learning activities into the cloud. This may turn out to a powerful and flexible framework for the provisioning of (potentially ad-hoc) learning scenarios.

7.5.2 *LnuGuide*

Mobile learning activities can be designed for guiding mobile learners [46] to gain information about current learning environment and how to work in it. For instance, students can learn how to use the different services at the university library (e.g. registration at the library, using the library card, etc.) if he/she is on site. Another example might be that students can be guided to learn how to print and scan articles by using the university printing system.

The *LnuGuide* mobile learning scenario was designed and developed for exchange students to get familiar with campus and prominent institutions and services on it [42]. The *LnuGuide* activity contains three stations (e.g. University Library, Administration Building and a café on campus) where students can get useful information to facilitate his/her “student life” (e.g. obtain the library or student card, to be able to scan and print at Library, etc.). Each station provides a number of tasks, where for instance the app will provide information on how to scan documents at the library including instructions that the user should easily be able to perform.

In this particular scenario, the contextualization of learners is supported by recommending a convenient format of learning material that is suitable to the learner’s current context. Each learning material has been represented by different formats (MP3, PDF, PPTX, MP4) and described by contextual information in the RCM. Here, the following three main context dimensions were used: *personal*, *device* and *environment* context.

Additional cloud-based services as *Speech to Text* and *Text to Speech* (Table 7.1) Services can be used to provide convenient representation format of LO to mobile device instead of having and storing the LOs in an audio format (e.g., MP3). The *LnuGuide* application requires having reliable Internet connection during the performed learning activity. Therefore, the cloud-based offline support service can be used to overcome this issue and increase the student’s concentration level on performing a certain task without interruption (e.g., Internet connection not available). Additionally, the exchange students come from different countries and therefore speak different languages. Then by using a Language Identification Cloud Service, the *LnuGuide* application can be adapted to the students’ native speaking language. Moreover, the analyses of log files can be replaced by the use of rich analytics cloud services for monitoring the students’ performance. These described features provide possibilities to improve the usability and personalization of the *LnuGuide* application.

7.5.1 Responses for the Research Questions

In order to address the research questions formulated in the beginning of the chapter two scenario examples of using (a) the *mLearn4web* framework and (b) the Contextualization Service in a cloud were proposed. These examples show that the cloud-based solutions have the potential to improve the contextualization approach by adding new available cloud services to provide more highly personalized applications. Furthermore, storing more contextual data to improve recommendations, by monitoring user’s interactions with application to increase their engagement with the app and the understanding of users’ current needs can also help to increase the level of personalization. Additionally, it allows using different algorithms (e.g., machine learning algorithms) for processing contextual data and providing recommendation to the user in real time. The described examples also show that the most useful cloud-based services such as the Learning Analytics Service, Logging Service and Monitoring Service provide new opportunities for designing novel services. All of them provide the possibility to gather more information about the current context of the learner in order to provide him/her better recommendations.

7.6 Conclusions

This chapter described and discussed different cloud-based services and solutions used for educational purposes. These can provide contextual support for mobile learners. Additionally, we presented the most popular cloud-based applications and services used by teachers and learners. Overall, this chapter presented (a) a flexible web-based framework, mLearn4web, to enable teachers to compose and deploy their own mobile applications to perform mobile learning activities and (b) a contextualized service to improve the content delivery of learning objects on mobile devices. This service allows for adapting: (1) the learning content and (2) the mobile user interface to the current context of the user. For the realization of the contextualization approach, a rich context model deployed in a cloud-based environment has been utilized. The combination of the two cloud-based approaches described in this chapter provide a powerful flexible framework that can enhance the learning experience for both, teachers and students.

Our future efforts towards the refinement and improvement of contextualized services include the development of additional mobile learning applications with a focus on personalization and the use of data analytics to increase students' motivation, performance and engagement. Current cloud computing technologies and services offer new possibilities for supporting the contextualization of users and for providing personalized and adaptable services and applications that can enhance mobile learning activities.

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Using a Rich Context Model for People-to-People Recommendation

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Abstract—In this paper we present an approach for People-to-People recommendations based on a Rich Context Model (RCM). We consider personal user information as contextual information used for our recommendations. The evaluation of our recommendation approach was performed on a social network of students. The obtained results do show a significant increase in performance while, at the same time, a slight increase in quality in comparison to a manual matching process. The proposed approach is flexible enough to handle different data types of contextual information and easy adaptable to other recommendation domains.

Keywords—rich context model; people-to-people recommendation; matching;

I. INTRODUCTION

People-to-people recommendation techniques are very important in different application domains, such as online dating, friend recommendation in social networks and job agencies where matching has been done between employer and employee [10] and many others. Matching people with other people is a difficult task in online social networks. In particular, because both sides of the matching process should be satisfied to meet their needs and preferences.

The main purpose of this paper is to study the performance of a rich-context model approach for people-to-people recommendation in a university students network in comparison to a manual content-based profile matching method. The advantages of our recommendation approach are: (1) the considerations of both user personal preferences and priorities, (2) recommendation results at least comparable to a human matching approach by hand (3) and flexibility in using in the different application domains.

This paper is organized as follows: section II describes related work in this domain and different approaches for people-to-people matching. Additionally, the advantages and disadvantages for each method are shortly described and discussed. Furthermore, the argumentation of the proposed approach is provided at the end of section II. Section III presents and describes design issues related to our proposed rich context model implementation. Additionally, the implementation of the proposed matching approach is described. Section IV describes our scenario and the presentation of our evaluation. Afterwards, Section V ends the

paper and presents our conclusions and possible lines of future work.

II. RELATED WORK

Many studies have been conducted in matching people-to-people in domains such as online dating and friend recommendation in social networks [1,2,3]. In the next subsections, we provide an overview about the current state of the art for people-to-people recommendation together with examples from domains such as online dating and friend recommendations.

A. General people-to-people recommendation approaches

The most used matching algorithms can be categorized in four main approaches: content-based algorithm [4], collaborative filtering [5], hybrid matching algorithm [6,7,8] and context-based algorithm [2,3,9]. The *content-based algorithm* matches people based on the user profile description. Such algorithms have advantages in defining explicitly the priorities of matching (e.g., hobbies are very important for person A and should be prioritized but the country from which the matched person B comes from is not important, etc.) and the disadvantage of lacking user information about his/her current interests. Therefore, *collaborative filtering* techniques help to identify the user's characteristics such as current interests, hobbies, how social and active a person is, etc. and to provide recommendations based on their interaction in social networks or dating systems. Here, the main advantage of such an approach is on the identification of inexplicit characteristics of the user profile. Hence, the limitations of such an approach are some people use social networks everyday while some people use it just once a month or even not use social networks at all (e.g., Facebook, Twitter, etc.), and therefore the historical data might be not be enough to provide a proper recommendation. Additionally, such an approach cannot provide recommendations for new users of the system [5]. The *hybrid approach* uses a combination of content-based and collaborative filtering algorithms [6,10] to provide people-to-people recommendation. Here, the advantage of this approach is overcoming the disadvantages of content-based approach and the collaborative filtering approach to provide the best matching result. Examples of such algorithms are data manning [11], semantic analysis [12], rule-based algorithms [1], etc. However, there is a problem on defining the priorities for each

algorithm output and how to combine outputs in an efficient way.

The content-based approach is better suited to recommend people that are unknown to each other, while collaborative filtering is better to fit known people [10]. The hybrid approach is used to improve either the content-based approach or collaborative filtering approach to provide successful recommendation of people in social networks through friend of friend recommendation. Content-based approaches usually use similarity metrics for matching user's profiles while the most used metric is a cosine similarity metric [2,8,9]. However, the information about the user's profile can have different data types (e.g., numerical for age, boolean for e.g., has or has not food allergy, enum for gender – male or female, textual for hobbies and interests, etc.) and using only similarity metrics for numerical data types limits the approach. Therefore, current content-based approaches lack on flexibility in terms of supporting different data types of the user profile to provide recommendations taking into account as much information about user profile as possible. Moreover, most of them lack of personalized support in recommendations of friends or partners according to the user's preferences and goals.

In recent years, using contextual information in recommendation engines has become more and more popular [2,3,6,13]. Here, *context-based approaches* are used to match people based e.g., on their current geolocation/position. For example, mobile applications such as Happn, Stepout, OkCupid Dating match people that have passed several times the same locations/places or are situated close to the user's location. The advantages of context-based approaches here are to easily and fast find a friend nearby you, more friends compare to common friends approach and better/improved ranking of recommended results [2,13]. Current approaches use geolocation containing time information [6,9,13], personal information [6,8,10], social context information [5,7] as additional contextual information tags. Several other efforts have also added contextual information into content-based, collaborative filtering [3] or hybrid approaches [2]. Most context-based approaches in the friend recommendation systems or online dating systems use one (e.g., physical or personal context) or two dimensions (e.g., combination physical with personal context or physical with social context) for the user's context.

B. Recommendation approaches in the online-dating domain

Recent techniques for matching people in dating web sites focus on analyzing the user's temporal behaviour, sending messages, reply behaviour of users and interactions in social networks, etc [4,14,15]. The main problem in such systems is that a big list of recommendations results are provided to the user and a large amount of time is required to review all recommended profiles in order to find a person whom he/she might be interested in. A study carried out by [16] examines the need of ranking and relevance mechanisms for people matching in online dating systems. In contrast to this, our approach allows ranking the results and recommends only people who fitted the most matching criteria, without considering the people with matching fewer criteria. We will describe our approach in more details in the section III.

C. Friend recommendation approaches

The example of the context-based approach is a context-graph matching [9] where the nodes are users and edges are similarities between contexts of users. Such an approach provides quite fast recommendations neglecting the growing amount of users in social networks. The follow-up work in [2] used physical context (location and time) together with personal context (user's interests, profile) and social interactions in social networks to recommend new friends. This approach calculates a relevance vector, between the user and his/her potential friends that he/she has met several times in the same place and time, by using the Jaccard similarity measure. Additionally, this approach allows defining manually the user's priorities for different preferences (e.g., hobbies, interests, etc.). However, it is not clear how they apply the Jaccard similarity measure for different data types of contextual information (e.g., for places, messages and interactions in social networks etc.). Additionally, it is not clear how easy the approach could be adapted to different, still similar, recommendation domains. Another example by [6] showed good results for friend recommendations in social networks by using contextual information with ontology graph modelling. This approach focuses on how to define the relationships between users in social networks in order to group them into different communities (e.g., friends in school, university, etc.), but it neglects user's priority preferences.

In many university social networks, students potentially arrive from all over the world, also from countries in which the usage of social networks might not be allowed. Additionally, exchange students that applied for a study program do not have a student account to be registered to the university social network before they will arrive there. Therefore, using only a collaborative filtering or hybrid approaches within a social context is not enough and applicable for friend recommendation due to the fact that all exchanges students are new to the system and historical data of their interactions in the university social network does not exist. The information about the student's location is not relevant for recommending a friend to an exchange student, because the study place is pre-defined (a city where the university is located) and will not change during the study period. Additionally, exchange students and local students are not in the same location during the matching/recommendation process. The recommendation should be done before the exchange student will arrive to study at the university. Therefore, the physical context is not important in such use-cases. Hence, the personal context information is very important to consider in friend-to-friend matching. To the best of our knowledge, there is no method that can provide matching based on the current user's goal. The user's goal depends on user's current context. For example, user A would like to improve his/her spanish language skills, therefore he/she is interested in finding a Spanish friend B and does not want to consider friends from other countries even if they match perfectly with respect to other factors. Another example, user A is going to study next semester in country N at university M and therefore, currently he/she is interested to find a friend B that lives in country N and studies at the university M (or even nearby) and does not take into account the gender preferences, age, mother tongue, language skills, etc. Furthermore, in the next semester he/she will be not

interested in finding a friend in country N with university M because he/she will be in another contextual situation. Therefore, using recommendation approaches based on historical data about the users might not cover all features mentioned above. With our approach, these issues can be handled beneficially according to the user's current goals. Furthermore, our approach is flexible in terms of taking into account user's current goals, preferences with priorities and is at the same time extendable towards different matching algorithms to support different data types of contextual information.

III. OUR APPROACH

We used our *Rich Context Model* (RCM) [17] to match buddy's context situation with student's personal context information. In our previous study [17], we used RCM to recommend best-suited formats of learning objects to students according to his/her current context. There, we used several similarity metrics (e.g., combination of cosine similarity metric with Jaccard distance) for matching numerical and Boolean data types. Hence, in this study we show that our RCM is flexible enough in processing additional data types (e.g., short and long text) and supporting user's priorities/preferences for each context dimension or sub-dimension.

A. Scenario Description

The Buddy Program in the city of Växjö (VXO), Sweden is organized by Linnestudenterna and Växjö International Students (VIS) organizations at Linnaeus University (LNU) for the last 4 years. A buddy is a person that helps exchange students in different life activities. A student is an exchange student that comes to Sweden for studying one or two semesters at LNU, Campus VXO. Approximately, there are 800 exchange students coming to LNU every year. Previously, the expert who did all the matching manually was collecting all data about buddies and students from e-mails. The data model for the data that should be collected from potential buddies and students is provided by an expert that has several years of experience in matching students with buddies manually. The data that we are collecting from students and buddies is described in the next subsection.

B. Context Dimensions

In this study, we consider personal information as contextual information and divided it into three main domains as shown in TABLE I. The *location context* contains information about student's original country, the university in which he/she studies, the list of preferred countries from which the buddy wants to receive a student. The *demographic context* describes student's/buddy's age, gender and preferred gender of student/buddy. For example, for gender data there are two options "Female" or "Male", and for preferred gender of students there are several options "Does not matter", "Female", "Male", and in case the buddy wants to have more than one student, then he/she can chose "Female and Male" meaning at least 1 Female and 1 Male student as shown on TABLE II.

TABLE I. CONTEXT DIMENTIONS

Location context	Demographic context	Personal context
Country	Gender	Hobbies
University	Age	Additional information about buddy/student
Preferred country of student	Preferred gender of buddy/student	

TABLE II. DATA TYPES OF CONTEXT DATA

Context data name	Data Type	Sub-dimensions
Hobbies	Array of String	["Hiking", "Reading", "Watching movies", etc.]
Gender	Enumerated value	"Female", "Male"
Preferred gender of buddy/student	Enumerated value	"Does not matter", "Female", "Male", "Female and Male"
Country	String	e.g., "Australia"
Preferred country of student	Array of String	["Austria", "Germany", "Australia", "Japan", "Undefined", etc.]
Additional information about buddy/student	Short or long text	e.g., buddies described which student they want or described yourself. Students describe about yourself.

Additionally, each sub-dimension has different priorities for different buddies. For example, if a buddy/student specified a preferred gender, then it has the highest priority. If no gender preference has not been specified then the gender does not have priority. Some buddy specified additional information about the student from a particular university. In case, there is no such student, then the priority by university should not be considered. Another example is when some buddy wants to meet with students from different countries, then they are specifying the list of countries in which first two/tree countries have highest priority compared to the forth/fifth country, etc. Moreover, if the buddy/student has not specified any preferences (e.g., country is "undefined", gender is "does not matter", etc.), then the system will match with default priorities. For instance, the minimum age difference is 5 years, at least 3 hobbies should be in common, they should have similar description about themselves in additional information dimension, etc.

Another example could be that for a buddy it does not matter from which country the student comes from, but he/she specified in additional information which language the student should have as a native language. By knowing the country, the system can define the student's native language. Then, students that can speak the specified language have highest priority compared to other students. The additional information can contain information either about the student/buddy him-/herself or preferences description (e.g., a student that speaks English or a student who studies at some university in South Korea, etc.).

C. Similarity Metrics

To implement all of those features, we defined for each dimension a similarity metrics and an algorithm for processing contextual information. We used the *Jaccard distance* for matching students with the buddy hobbies. Since, there is a big variety of hobbies, the list of general hobbies is predefined in the system and represented as a vector of Boolean values (e.g., 1 – student/buddy chose some hobby, 0 – does not chose some hobby, etc.). Therefore, we used the *Jaccard distance* measure to define how many hobbies students have in common, where the values 1 represents that both students have same hobbies, and 0 – students do not have any hobby in common. In case student/buddy could not find his/her hobby in the predefined list, then he/she can write this in Additional information field. The *Euclidean distance* was used for gender and age information. The age has numerical data type, and to define the main difference between the student's and the buddy's age the Euclidean distance was used. By default, the difference should be 5 years as a minimum.

The *cosine similarity* metric was used as an output of Latent Semantic Analyze (LSA) [18] technique for matching short or long text specified in additional information. Students are from different countries and have their own style of writing/describing their interest and hobbies with similar but not same words. Therefore, the LSA technique allows defining similar texts not only by same words but also by semantic meanings of the words. The *defined rules* were used for preferred country matching. Here, the first three countries have bigger priority than the other countries defined in preferred country list.

D. Matching Algorithm

We calculate a vector of metrics similarities described in the previous section. For instance, the vector of the location context $L(l_1, l_2, \dots, l_n)$, demographic context $D(d_1, d_2, \dots, d_n)$ and context of interests $I(i_1, i_2, \dots, i_n)$. Then, we calculate vector similarities between buddy's vector $v(L, D, I)$ and each student vector $v'(L', D', I')$ represented in a multidimensional vector space model (MVSM), e.g., $sim_L(sim_{l_1}(l_1, l'_1), sim_{l_2}(l_2, l'_2))$, etc. In order to take into account the different priorities of contextual information, we defined for each sub-dimension a weight w (e.g., $sim_L(w_1 + sim_{l_1}, w_2 + sim_{l_2})$, etc.). The possible values of w are 1 – has priority, 0 – does not have priority. For example, the buddy specified preferred country, and is therefore not interested from which university the student comes from, then the location vector similarity $sim_L(1 + sim_{l_1}, 0 + sim_{l_2})$ where sim_{l_1} is a value calculated by *defined rules* for preferred country, the interests vector similarity is $sim_I(w_1 + sim_{i_1}, w_2 + sim_{i_2})$, where sim_{i_1} is the *Jaccard distance* between buddy's and student's hobbies, sim_{i_2} is *cosine metric* as output of LSA technique for matching additional information about buddy and student. Then, the best-suited student is defined by the vector in the MVSM that has the minimal distance $d_{min}(sim_L, sim_D, sim_I)$ of all similarity vectors.

Algorithm 1. The algorithm of recommending the best-suited student to the buddy (Fig. 1).

for each buddy in buddy_list do

```
similar_students[buddy] = [];
for each student in student_list do
    distances[student] = similarity(student, buddy);
end for
similar_students[buddy] = sort_desc(distances);
end for
```

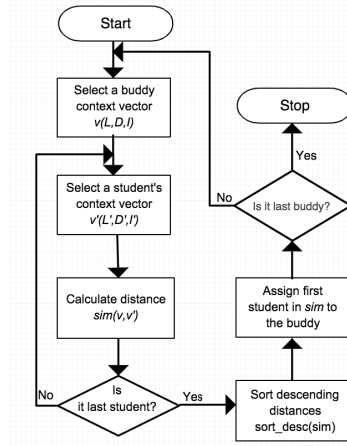


Fig. 1. Algorithm for matching buddies with students

E. Implementation

The contextual data sets were collected via web application forms, where each student and buddy provided relevant information about the birthday, country, gender, hobbies, etc. Fig. 2 below illustrates the web application form.

Fig. 2. Example of web application form for exchange students

The web application form for buddies (See Fig. 3.) is slightly different from the student's application form, since buddies can choose preferred student's country and the number of students they would like to support.

The implementation on the client side was performed by using frameworks like jQuery and Twitter Bootstrap, allowing the creation of a user interface supported by different browsers and devices. The server side was implemented by using

NodeJS and a MongoDB database was used for communication throughout the system by JSON objects. The Admin page is implemented for the expert where she/he can download a list of applied students/buddies in an Excel sheet.

Fig. 3. Example of web application form for buddies

Additionally, it allows to do CRUD operations of the data provided by students/buddies and to match all buddies or one by one automatically.

IV. EVALUATION

Each autumn semester approximately 500-exchange students applied to have a buddy while in the spring semester 300 exchange students apply. Accordingly, every semester there are between 150-300 buddies that apply to become a buddy for one or a couple of exchange students. We introduced our recommender system to the Buddy Program organizers and checked whether it is able to provide results of similar quality as the recommendations done before manually. This study investigates whether our approach can provide a good buddy recommendation based on personal priorities and preferences compare to a manual matching mechanism.

A. Participants

The exchange students are going to study at LNU and the buddies are Swedish or International students that already studied or are studying at LNU, Campus VXO.

B. Description of Study

Each exchange student and buddy had applied to the program via the web application form described in the previous section. 395 exchange students and 234 buddies were matched by our system for the Autumn semester 2014. In order to compare matching results obtained by the system and the manual approach, we introduced a questionnaire shown in TABLE III. adapted from a study conducted by [19]. A seven-point likert scale [20] was applied for each question. The questionnaire described in TABLE III. was given to exchange students that received a buddy during the autumn semester 2014 by using our approach (Group1) and exchange students that received a buddy in the spring semester 2014 that were matched manually by an expert (Group2). The first set of questions aimed to evaluate the recommendation accuracy of our approach. The second set of questions aims at defining the

student's expectation of the buddy recommendation given to him/her.

TABLE III. QUESTIONNAIRE

Category	Question
Recommendation Accuracy	Q1 The buddy/student recommended to me matched my hobbies.
	Q2 The buddy/student recommended to me matched my gender preference.
Expectation	Q3 The buddy/student recommended to me was exactly what I expected.
	Q4 The buddy/student recommended to me fit well to my age.
Recommendation Diversity	Q5 The hobbies of the buddy/student recommended to me are diverse/dissimilar.
Transparency	Q6 I understood why the buddy/student was recommended to me.
Overall Satisfaction	Q7 To what extent has our matching met your needs?
	Q8 In an overall, how satisfied are you with the buddy/student you have received?
	Q9 I would recommend this program to my friend.
	Q10 If you were to seek a student/buddy again, would you come back to our program?
Open questions	Q11 How enjoyable was recommended buddy/student to do activities with?
	Q12 How easy was to communicate with recommended student/buddy?

The next question asks for the diversity of the recommendation where 1 – extremely like and 7 – extremely dislike are the boundaries. The next questions ask about overall satisfaction. The last two questions are open text feedback to gather general comments.

C. Study Results

The 99 exchange students (from Group1 and Group2) have answered the given questionnaire. First of all in order to validate our questionnaire for reliability, we calculated Cronbach's alpha [21] for Group1 – 0.895 and for Group2 – 0.908. This alpha shows that the data provided by students in both groups are reliable and valid for further statistic analysis. Secondly, during a statistical analysis a null hypothesis H_0 "There is not a difference between the matching performed by an expert and the proposed matching algorithm" has been formulated. We calculated paired samples t-test in order to compare mean values between our approach (Group1) and manual approach (Group2). The p-values obtained from the paired t-test do not show a significant difference between Group1 and Group2 ($p \geq 0.05$). The latest means that we retain the null hypothesis and our approach can provide recommendations with the same quality, as a human would do. Furthermore, according to average values (See Fig. 4), the results are slightly better using our approach (Group1) if compared with the results obtained by the expert matching process (Group2). Additionally, the results, as shown in Fig. 4, indicate that the system matched very well the preferred gender, age and hobbies. Additionally, the expert provided a positive feedback about using our system, both for the quality of the recommendations that it saves about 40 hours for expert to do a recommendation. Furthermore, the system was easy

and simple to use. On the X-axis the questions for questionnaire are shown (see TABLE IV.) and the Y-axis represents the average results of the 7-level Likert scale. TABLE IV. depicts in more detail the average values for Group1 (our approach) and Group2 (manual approach).

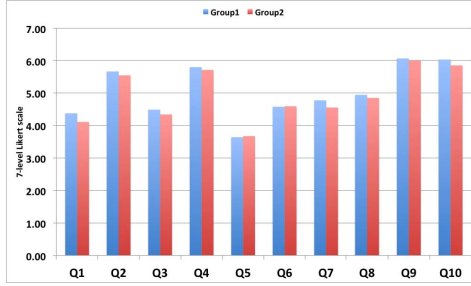


Fig. 4. Average rating

TABLE IV. EVALUATION RESULTS

Avg.	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
Gr1	4,4	5,8	4,5	5,8	3,6	4,58	4,8	4,9	6,1	6,0
Gr2	4,1	5,5	4,3	5,7	3,7	4,59	4,6	4,8	6,0	5,8

V. CONCLUSIONS

The aim of this study was to validate the flexibility of our RCM in terms of handling different data types of contextual information while taking into account personal priorities. The evaluation of the proposed RCM was performed at the student university network Buddy Program in Växjö. The results of the study have identified no significant difference between our matching approach and a manual one performed previously by experts. However, our results have also shown slightly better outcomes in almost all matching criteria compare to the manual approach, although not statistically significant. This shows that an automatic matching mechanism using our approach performs as good as an expert. These results provide some initial evidence that our RCM is flexible enough to support different data types (numerical, Boolean, short and long text) with different algorithms (metric similarities, defined rules, latent semantic analysis) for processing those data and taking into account personal priorities/goals in comparison to the similar approaches. Summing up, the following contributions can be highlighted: (a) we show that our flexible RCM can support different data types of contextual information (b) we report an evaluation of RCM with 99 students (Group1 and Group2) and show that the performed was as good as a matching done by an expert. The outcome of our results also confirms the flexibility of our proposed RCM and it shows that it can be used as a general approach that can be applied to various recommender systems in a variety of domains [17]. The positive feedback from students and the expert has shown the usefulness of the system, especially by saving a lot of time spent on the

manually matching process. As part of our future work, we plan to provide a service that could flexibly be configured for different scenarios or application domains.

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Using a Rich Context Model for a News Recommender System for Mobile Users

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Abstract. Recommender systems have become an important application domain related to the development of personalized mobile services. Thus, various recommender mechanisms have been developed for filtering and delivering relevant information to mobile users. This paper presents a rich context model to provide the relevant content of news to the current context of mobile users. The proposed rich context model allows not only providing relevant news with respect to the user's current context but, at the same time, also determines a convenient representation format of news suitable for mobile devices.

1 Introduction

Nowadays, people use mobile devices in very different situations independent of time and space in order to search and to retrieve relevant information about their needs and interests. Recommendation systems have become more and more popular for mobile devices due to the use and availability of various mobile information services [1]. Here, modern mobile devices provide a profound set of sensors and, together with Internet connectivity, rich possibilities to present relevant information with respect to the users' current context. Several studies have been conducted in order to provide personalized news recommender systems [2,3]. However, a number of challenges have been identified related to the accuracy of the news with relation to the mobile user's context and the proper format in which this content should be delivered. Most systems have limited information about the context of the mobile users and they require explicit data input about the features of the mobile device without taking into account mobile limitations (e.g. screen size, connectivity type, battery status). Work carried out by [4] shows that recommender systems can provide better quality of news and movies recommendations if additional contextual information is taken into consideration. Therefore, one of the key challenges for providing relevant news in a convenient representation format within different mobile user's environments is to conceptualize a rich context model. From this perspective, we agreed with the research efforts carried out by [5] that claim that context models should be generic and abstracted in order to reuse it in different recommendation domains.

This contribution presents a rich context model for mobile users to be applied for news recommender systems. The paper is organized as follows. Section two describes which contextual information can be used in order to describe the rich context of

mobile users. Additionally, it describes how different content of news might or might not be relevant for mobile users in a variety of contexts, also with respect to their representation format. In Section three we describe the context model for handling the rich context information. Finally, our last section concludes the paper and describes future lines of work.

2 Defining Rich Context for Mobile Users

We understand the term *rich context* as data received from different mobile sensors and how this data can be enhanced by using external Web Services (e.g. Google Place API) in order to retrieve more detailed information including among others the current location (e.g. place, environmental information, etc.). Rich contexts may also include personal information like topics of interests, hobbies, profession, etc. The information about the user's interests and hobbies can be used to describe his/her topics of interests of news items. Additional contextual information could consist of the noise level in the place where the user is currently located and his/her movement status (e.g. sitting, walking, etc.) can be used to decide about the most convenient representation format related to the news content that best suit mobile devices. For instance, if the user is walking to his/her job place listening to an audio stream provided by a text to speech API reading out the news and listening to with headphones can be more convenient in comparison to reading on the mobile device screen. Furthermore, information about the platform of the mobile device allows providing relevant news information to the user's device. For instance, if users A and B share the same interests e.g. for mobile games, if user A has an Android based device while user B has an iPhone, the news about upcoming games for the Android platform will be more relevant to user A than user B.

We classify the current context of the user into three major dimensions: the *environment context* (e.g. place, noise level, date and time, etc.), his/her *personal context* (e.g. topics of interests, hobbies, profession, etc.) with information about the activity in which the user is currently involved (e.g. doing sport, working, etc.) and/or *device context* (e.g. information about device platform). All these dimensions of rich contextual information, as illustrated Table 1, can be extracted with help of mobile sensors and existing additional Web Services.

Table 1. Dimensions of rich contextual information.

Personal Context	Environment Context	Device Context
Topics of interests	Place	Platform
Hobbies	Direction	Battery Status
Country	Movement	Internet connectivity
Activity	Noise level	
Language	Date	
	Time	

For instance, the location can be gathered from GPS sensor and the current user's location could be identified by using Web Services like the Google Places API. Another example of using GPS sensor is getting local news related to the user nearest

place by using additional web service e.g. YourStreet API or Google News API. The information about the platform of the mobile device can be obtained by using e.g. Cordova API. Information about user's hobbies, age, language, country, profession can be collected from the different social network API's, e.g. through a social network login, in order to provide better recommendation results.

All the data sets described in Table 1 are used to represent the *rich context* of mobile users. The context model supports extendability of the sub-dimensions of the context information described in Table 1 and can therefore be used in different recommendation domains by considering different context parameters. The amount of relevant news related to one topic could be different in different contexts, e.g., if the user is sitting on a train, then he/she might want to read among a number of different news sources, while during a physical exercise (e.g. jogging) the user might want to get the news just from his/her favorite news site. An algorithmic and model based approach for handling rich context information of mobile users, the *Rich Context Model (RCM)*, is described in the next section.

3 Description of the Proposed Rich Context Model

RCM is a context model for the handling of *rich context* information provided by mobile users. As described in our previous work on context modeling [6], we decided to use a *multi-dimensional vector space model* (MVSM) as the approach for modeling rich contexts of mobile users. The context in which some news are suitable for a particular situation needs to be calculated. For instance, this could be done by pre-executed evaluation where the users in different context have consumed different news. Afterwards, the users' context information of consumed news is stored in the MVSM. Then, each news item could be represented as a vector in the MVSM (e.g. News1, News2). Furthermore, each context dimension is in itself multidimensional in order to allow the description of an almost unlimited amount of dimensions in the RCM, e.g. environment context includes information about the place, noise level and user movement, etc.

In this model, we considered two requirements: the first one is to provide news content that is better suited to the user's current context and the second one is the representation format of the news that is most convenient to mobile users, again, according to his/her current situation. In order to identify the relevant content of news, the *similarity* is measured between two different vectors: the vector describing the *current rich context* of the user and other vectors describing the different available news items. The similarity between vectors can be calculated by e.g. Euclidian distance, Jaccard and cosine metrics. Based on our previous efforts [6], we consider the combination of *cosine* and *Jaccard* similarity metrics in order to match the *current rich context* of the user to the content and representational format of the news. Here, we differentiate Boolean data type of the contextual information e.g., if the user is currently moving (e.g. the user is sitting in the library – 0; the user is running or walking in the park – 1) or outside/inside (e.g. the user is inside of the café, library or outside in the park, stadium, etc.). For this kind of Boolean data we propose to calculate the Jaccard similarity metrics to define similar user's environment context.

The cosine metrics, which we propose for non-Boolean data, defines how similar the current context of the user to another context in which some news was consumed. Since we need to use different similarity measures, for Boolean and non-Boolean data types, we end up have a value for the similarity that is a vector itself. Thus, the final step for the identification of the news items to recommend is to calculate the closest distance to the point of the *current rich context* of the user and all available news items.

The outcomes from the proposed *rich context model* could be used for organizing relevant data with other tools to provide some classification and sentiment analyses (e.g. clustering relevant topics or categorizing users by their interests in Tweeter [7]). Especially, it allows for a flexible definition of what kind of context dimensions should be considered. Furthermore, the proposed contextualized approach allows a real time recommendation of news. The mobile application will collect the user's current context information, analyze it and recommend relevant news accordingly in real-time. Hence, the pre-executed evaluation of news should be performed before the usage of the news recommendation application.

4 Conclusions and future work

In this paper we have presented an approach for providing news recommendations based on the current context of mobile users and the format in which the news items can be represented. The proposed rich context model supports the adaptation of relevant information delivered to users of mobile devices. Our future research will be focused on the evaluation of the proposed approach in a number of practical scenarios.

References

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