UNISINOS

Programa Interdisciplinar de Pós-Graduação em

Computação Aplicada

Mestrado Acadêmico

Natália de Arruda Botelho Navarro

SPONTANEOUS SOCIAL NETWORK:
CREATING DYNAMIC VIRTUAL COMMUNITIES
BASED ON CONTEXT-AWARE COMPUTING

São Leopoldo, 2016

UNIVERSIDADE DO VALE DO RIO DOS SINOS - UNISINOS
UNIDADE ACADÊMICA DE PESQUISA E PÓS-GRADUAÇÃO
PROGRAMA INTERDISCIPLINAR DE PÓS-GRADUAÇÃO
EM COMPUTAÇÃO APLICADA
NÍVEL MESTRADO

NATÁLIA DE ARRUDA BOTELHO NAVARRO

SPONTANEOUS SOCIAL NETWORK: CREATING DYNAMIC VIRTUAL COMMUNITIES BASED ON CONTEXT-AWARE COMPUTING

São Leopoldo
2016

Natália de Arruda Botelho Navarro

SPONTANEOUS SOCIAL NETWORK: CREATING DYNAMIC VIRTUAL COMMUNITIES BASED ON CONTEXT-AWARE COMPUTING

Dissertação apresentada como requisito parcial para a obtenção do título de Mestre, pelo Programa Interdisciplinar de Pós-Graduação em Computação Aplicada da Universidade do Vale do Rio dos Sinos – UNISINOS

Orientador: Dr. Cristiano André da Costa

Coorientador: Dr. Jorge Luis Victória Barbosa

São Leopoldo

2016

N322s Navarro, Natália de Arruda Botelho.
Spontaneous social network : creating dynamic virtual communities based on context-aware computing / Natália de Arruda Botelho Navarro. – 2016.
81 f. : il. ; 30 cm.

Dissertação (mestrado) – Universidade do Vale do Rio dos Sinos, Programa Interdisciplinar de Pós-Graduação em Computação Aplicada, 2016.
"Orientador: Dr. Cristiano André da Costa ; coorientador: Dr. Jorge Luis Victória Barbosa.”

1. Computação contextual. 2. Computação móvel. 3. Redes sociais on-line. 4. Computação ubíqua. I. Título.

CDU 004

Dados Internacionais de Catalogação na Publicação (CIP)
(Bibliotecário: Flávio Nunes – CRB 10/1298)

To my grandparents Anna Carolina Paula Leite de Arruda Botelho,
Gleci Cavalheiro Navarro, Mário Navarro (in memoriam), and
Paulo Maldonado de Arruda Botelho (in memoriam).

ACKNOWLEDGMENTS

First, I would like to thank my entire family for all the support and caring, especially my grandmothers, my aunts and uncles, my fiancée, my father, my mother, and my sister. I also thank everyone that, at some point in life, supported me and encouraged me to keep moving forward and to chase my goals. I thank my professor Dr. Cristiano André da Costa for all the advices, orientations and teaching. I also thank the professors, members and fellow students of the "Programa Interdisciplinar de Pós-Graduação em Computação Aplicada (PIPCA)". I thank my former colleagues at Getnet, and my professors and classmates at Senac that were a fundamental component to my career. Lastly, I would like to thank Santander Universities for financially supporting this work.

ABSTRACT

With the emerging of online social networks along with the worldwide diffusion of smartphones, context awareness has become an essential concept in the field of mobile computing. Recent efforts and relevant research regarding mobile social networks aim at connecting people in smart environments considering not only their social behavior but also their context. In this perspective, this work presents a novel Mobile Social Network (MSN) model called Spontaneous Social Network (SSN). The main scientific contribution of the SSN model is the possibility of creating social communities based on a combination of multiple contexts, including location, profile and data obtained from external online social networks. In the literature, we found several works that lack on the community grouping approach, on the aspect that they are either limited to a specific location, or do not fully support virtual social interactions. We develop a mobile application called Dino, to provide a glimpse of what an SSN based application would be. To evaluate our model we perform two experiments using the developed mobile client. First, we present hypothetical scenarios based on possible real-world SSN applications to measure users' perceived sense of community. The scenarios described are (1) music concert (2) sport event (3) shopping mall (4) conference or workshop (5) school or university. Second, we ask users to consider their real interests to assess our formed groups regarding their relevance and measure precision and recall of the groups' suggestions. We compute average values of 0.72 and 0.83 for precision and recall, respectively. The experiments' results to assess the proposed scenarios ascertain average values of agreement of 84% for sense of community, 80% for sense of belonging, 90% for social usefulness, 92% for member loyalty, and 81% for communities' ephemerality. Therefore, our evaluation depict that dynamic virtual communities formed by a SSN model based application would beneficially improve a social-aware virtual environment.

Keywords: context awareness, mobile social network, mobile computing, ubiquitous computing.

RESUMO

Com a emergência de redes sociais junto à difusão mundial de *smartphones*, ciência de contexto tornou-se um conceito essencial na área da computação móvel. Esforços recentes e pesquisas relevantes sobre redes sociais móveis visam conectar pessoas em ambientes inteligentes, considerando não apenas seu comportamento social, mas também seu contexto. Neste âmbito, este trabalho apresenta um novo modelo de rede social móvel, chamado rede social espontânea. A principal contribuição do modelo de rede social espontânea é possibilitar a criação de comunidades sociais baseadas na combinação de múltiplos contextos, incluindo localização, perfil e dados obtidos de outras redes sociais. Na literatura, encontramos alguns trabalhos que carecem na abordagem de formação de comunidades, no aspecto da limitação a localizações específicas ou em não suportar completamente interações sociais virtuais. Nós desenvolvemos um aplicativo móvel chamado Dino, para proporcionar uma visão do que seria uma aplicação baseada no modelo de rede social espontânea. Para avaliar nosso modelo, realizamos dois experimentos. Primeiro, apresentamos cenários hipotéticos baseados em possíveis aplicações para mensurar a percepção dos usuários quanto ao senso de comunidade. Os cenários descritos foram (1) evento musical (2) evento esportivo (3) *shopping center* (4) conferência ou *workshop* (5) escola ou universidade. Em sequência, pedimos que os usuários avaliassem as sugestões de grupos formados pela aplicação, considerando sua relevância em meio aos seus interesses. Então, medimos precisão e recuperação dos grupos sugeridos para cada usuário. Obtemos valores médios de 0.72 e 0.83 para precisão e recuperação, respectivamente. Como resultado dos experimentos para avaliar os cenários propostos, obtemos valores médios de concordância de 84% para senso de comunidade, 80% para senso de pertencimento, 90% para utilidade social, 92% para fidelidade de participação, e 81% para efemeridade das comunidades. Com isso, nossa avaliação retrata que comunidades dinâmicas formadas por uma aplicação baseada no modelo de redes sociais espontâneas poderiam aumentar beneficamente a utilidade de um ambiente virtual social.

Palavras-chave: ciência de contexto, redes sociais móveis, computação móvel, computação ubíqua.

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

API	Application Program Interface
CCE	Context-aware Crowdsensing Engine
CSS	Context-aware Semantic Service
DCO	Discover Connect Organize
FN	False Negative
FP	False Positive
GPS	Global Positioning System
IoT	Internet of Things
MCP	Mobile Context-aware Platform
MSN	Mobile Social Network
MSNP	Mobile Social Network in Proximity
NFC	Near Field Communication
OSN	Online Social Network
P2P	Peer-to-peer
SNS	Social Network Site
SOA	Service-oriented Architecture
SSN	Spontaneous Social Network
TN	True Negative
TP	True Positive
XMPP	Extensible Messaging and Presence Protocol

TABLE OF CONTENTS

1 INTRODUCTION

Along the years, commercial Social Network Sites (SNS) such as Friendster, MySpace, and Facebook, have shaped the business, cultural, and research landscape on social networks. The end of the 1990s introduced new social networking methods and many sites began to develop more advanced features for users to find and manage friends. Online Social Network (OSN) began to emerge with Six Degrees in 1997 and is current taken over by Facebook with over 1.39 billion monthly active users (FACEBOOK, 2015b). As of now, BOYD AND ELLISON (2007) define SNS as "web-based services that allow individuals to (1) construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with whom they share a connection, and (3) view and traverse their list of connections and those made by others within the system".

The evolution of mobile technology and wireless networking has stimulated social networks towards mobile computing (BEACH et al., 2008; SATYANARAYANAN, 2011; COSTA et al., 2014). Most OSNs regard their advancement into mobility as one of the key initiatives and a key to their growth (YANG et al., 2012). It is believed that Mobile Social Networks (MSN) will not merely be a simple extension of OSN, but it will revolutionize social networking by enabling anytime and anywhere social interaction, besides offering a higher degree of intelligence (ZHANG et al., 2013). As the mobile phone constantly accompanies people in their everyday lives, it is reasonable to take in consideration the user together with the environment as a whole. Mobile devices are capable of continuous sensing to obtain signals from the physical world with spatiotemporal information, which benefits the understanding of contexts where the user situates. Therefore, ubiquitous computing (WEISER, 1991) is essential for mobile computing because it represents the concept of computing everywhere integrated with the real world.

Context-aware applications, in this type of environment, have the capability to detect and adapt according to environmental data. In that perspective, context awareness (DEY, 2001) supports mobile computing to allow programs and services to react and adapt their behavior according to the circumstances. Therefore, there has been significant works into context modeling of physical nature such as space, time, activity, and so on (SCHUSTER et al., 2013; MAKRIS; SKOUTAS; SKIANIS, 2013). The most popular definition of 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" (DEY, 2001). Nonetheless, between the three entities defined by DEY (2001), in social computing (PARAMESWARAN; WHINSTON, 2007) the most important is the person. *Social context* refers to people, groups, and organizations with which an individual is interacting. Since sensors and devices are able to identify the person carrying the device along with the external environment, it can also sense information about people. Thus, the distinction between pervasive context and social context disappears, leading to the term *pervasive social context*:

> "Pervasive social context of an individual is the set of information that arises out of direct or indirect interaction with people carrying sensor-equipped pervasive devices connected to the same social network service." (SCHUSTER et al. 2013)

Due to advancements both in social context and context-aware pervasive environments, new concepts of social networks emerged. Temporary Social Network (NEJMA et al., 2014) is a social media that is not permanent online, meaning that the content is self-destructive and disappears once some rules are checked. Spontaneous and Ephemeral Social Network (LAFOREST et al., 2014; COSTA et al., 2014) is limited in time and space and dedicated to a single event, by linking people together to produce multimedia reports and contents in a collaborative way. Similarly, Ephemeral Social Network (CHIN, 2014) captures dynamic social networks at a particular point in time and place, allowing its members to interact and form virtual ties during an event. Serendipitous Social Network (JANG; CHOE; SONG, 2011) is a situation-centric network designed for supporting interactions to exchange relevant information in a timely fashion, mostly through interactions with unacquainted individuals. Semantics-based Mobile Social Network (LI; WANG; KHAN, 2011) discovers and automatically forms communities by the semantic analysis of users' profiles with similar interests based on their social behaviors (social profiles, interests, and hobbies). Spontaneous Social Network (COSTA et al., 2014) groups users to interact at any place or time, without the need of any pre-existing relation among them, opening new possibilities for employing assorted contexts as the basis for creating a social network.

Unlike traditional social networks in which social communities usually start from real-world relationships, these works approach context-aware groups' creation and management in pervasive environments. Especially in smart spaces, it is possible to create groups of users that cooperate effectively and successfully (WANG et al., 2010). Considering this, virtual environments enable users to create static or dynamic groups of interest to share common goals and tasks (LIMA; GOMES; AGUIAR, 2012).

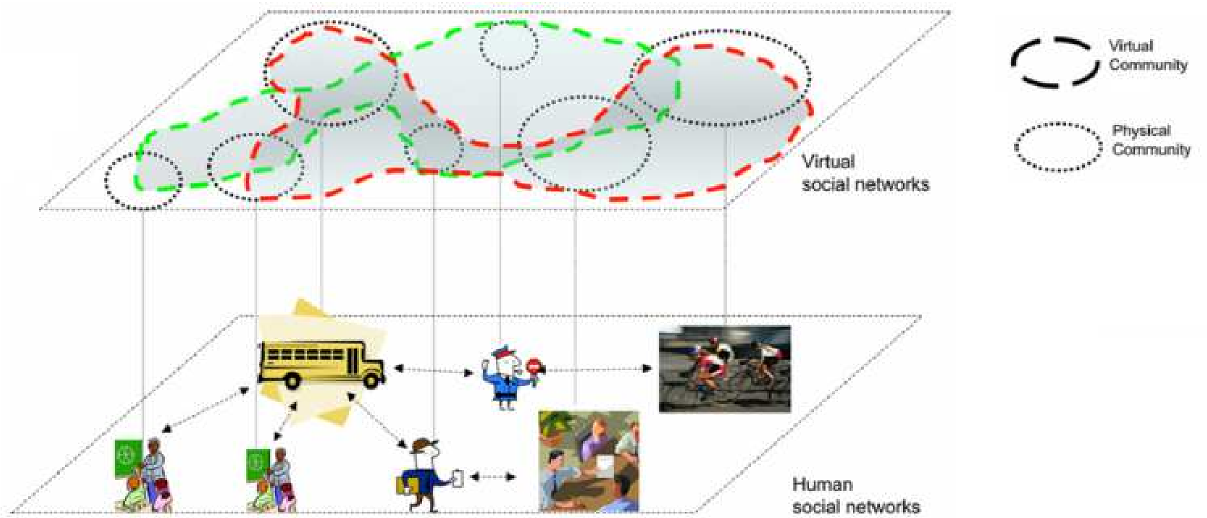
1.1 MOTIVATION

The proliferation of network-connected devices has led to a problem: given that most social network applications can create groups to share information with one another, which groups actually matter? Determining what constitutes a meaningful group depends on many aspects, such as performed tasks, community interests, goals to achieve, and so on. Mobile social communities (ZHANG et al., 2013) allow people to meet and communicate in a virtual space. The outcome of community grouping is to support social interactions or to provide personalized interest-based services or contents. For example, group-buying mechanisms allow people with the same interest to conduct a purchase together to achieve a discount (LIU et al., 2013).

As in real-world situations where people interact spontaneously over a specific subject of mutual interest, such as conferences, expositions, galleries, stadiums, and restaurants, a virtual layer enables people to communicate despite their physical location or displacement. Mobile communities can support social interactions in applications such as healthcare, transportation, environmental, travel, business, education, and so on. With social and context-aware services, conference participants can establish relevant business connections, universities can extend their services and learning contents to their students, stores and restaurants can offer personalized deals to their customers, companies can foster internal collaboration between employees, and individuals can find people with similar interests in virtual social environments. However, the duration in which it makes sense to group people in those situations may be unknown. In that way, devices must be able to materialize these opportunities without having to wait for requests, and recognize when those situations are no longer relevant for the user.

In spite of these challenges, we envision a model that will enable a wide range of spontaneous groups and instantaneous interactions among users and their environment using their mobile devices. This model extends what has being developed in our research group related to the topic of spontaneous social network (COSTA et al., 2014). The main contribution of this work is to group people that share common context in a dynamic way, meaning that they may or may not be aware of their similarity and still form a group. For instance, students that often practice a sport on same days but in different locations of a University campus can generate a suggestion of a group to play together. In the same way, co-workers can create a group for a monthly barbecue meeting. Furthermore, it is possible to provide context-aware services to those groups, as in, messages, map, calendar, share media content, fostering the interaction among people and creating a virtual extension of existent services. Afterwards, it is possible to go beyond the social connections of OSNs, generally based on existing social relationships, by stimulating social interactions among known or unknown people sharing interests and needs.

Figure 1. Virtual Communities



Source: Adapted from ARNABOLDI; CONTI; DELMASTRO (2014).

Nowadays, diverse social applications allow users to manually create and invite people to their groups. However, it is a challenge to suggest people to groups that already exist or to form new groups based on similarities. Figure 1 illustrates virtual communities and their interdependence on physical communities; that means location by itself is not a decisive factor to form a virtual community. Moreover, Figure 1 exposes a problem: Who is a member of each virtual community? On a daily basis, we are part of different communities over diverse situations; a context-aware approach can assist to detect groups dynamically formed by people.

1.2 RESEARCH QUESTION

Based on the established motivation, this work aims to answer the following research question:

"How would be a model to **group** people into **dynamic virtual communities** based on **multiple contexts**?"

A virtual community is the representation of a group of people that have something in common. One of this work's challenges is to detect contexts that could bring people together as a community, focusing on virtual communities to foster spontaneous interactions in a virtual environment. To adapt to users' transient interests over diverse contexts, people must be grouped into communities that consider similarities not only as static (i.e. permanent) attributes but also dynamic (i.e. modifies or evolves over time) attributes.

1.3 OBJECTIVE AND METHODOLOGY

The general objective of this thesis is to propose and evaluate a model to support the creation of dynamic virtual communities based on mobile devices and multiple contexts. The model represents people and communities, and employs a grouping mechanism to find context similarities among them. People can then compose a virtual community, allowing them to interact with each other and benefit from context-aware services.

This thesis is based on explanatory research followed by a controlled case of study. We aim at proving that social communities beneficially improve social usefulness in a virtual environment provided by a mobile social network application. We exploit a quantitative approach based on computing numeric metrics and variables with emphasis on comparing and discussing the obtained results (KITCHENHAM et al, 2002). To conduct the quantitative evaluation we apply a self-administered closed question survey, which means, a survey with predefined questions and answers that are answered by the participant and not by an observer (KITCHENHAM; PFLEEGER, 2002a). We elaborate the evaluation following the steps: (1) conceive questions and answers (2) define population sample (3) extract and compute results (4) discuss the results.

1.4 TEXT ORGANIZATION

This thesis is organized in seven chapters. The second chapter presents essential background concepts for the work. The third chapter describes related proposals and compares them considering relevant aspects for context-aware MSN applications. The fourth chapter details the SSN model and its four steps: gather, categorize, group, and interact. The fifth chapter presents the implementation of a mobile device based prototype. The sixth chapter details the evaluation methodology followed, the performed experiments and discussion of results. The seventh chapter concludes the thesis and enlightens future work for remained open questions.

2 BACKGROUND

This chapter describes some basic concepts related to this work in four sections. The first section provides a history background on online social networks and its evolution. The second section describes the main aspects of mobile social networks and points some of the most popular commercial applications. The third section details how context awareness and situation awareness can support and improve mobile social network applications. Finally, the fourth section, focus on the communities formed after sub-divisions of online social networks.

2.1 ONLINE SOCIAL NETWORKS

Online social networks (OSN), also called Social Network Sites (SNS), first introduced in the late 1990s, initially allowed members to search for people on the users' database and associate with others by adding them to their friends list. SixDegrees[1] was the first SNS launched, in 1997, but members alleged that there was little to do after accepting friend requests, causing the website to close in 2000. From 1997 to 2001, minor community websites began to combine profiles and friends managing tools, such as AsianAvenue[2], and MiGente[3]. Following, shortly after its launch in 1999, LiveJournal[4] included a one-directional connection in which people could mark others as friends to read their personal journals.

Afterwards, Friendster[5], launched in 2002, aimed at shortening friends-of-friends relationships, instead of introducing people to strangers with similar interests, which was mostly the focus of dating websites at the time (COHEN, 2003). However, the website experienced technical difficulties due to its rapid growth, frustrating users that reached seventeen million people by May of 2005 (MARWICK, 2005). To compensate the faulty servers, Friendster limited users from viewing only profiles of people who were four degrees away (friends-of-friends-of-friends-of-friends). To bypass the restriction and expand their reach, users began adding acquaintances or even random strangers, and started a massive wave of fictitious profiles of celebrities, iconic personalities, concepts and other entities. Users started using these fictional profiles, popularly called "fakesters", to find people they knew or with similar interests. The company disliked the practice and banished fake profiles, also accidentally deleting genuine users with non-realistic photos, which caused its popularity to fall out permanently in United States (BOYD; ELLISON, 2007).

From 2003 onwards, Friendster inspired a new category of OSN that helped people with same interests to meet and interact. SNS started to have very specific communities as targets, such as Dogster[6] and Catster[7] to let people create profile for their pets, MyChurch[8] to

[1] www.sixdegrees.com

[2] www.asianave.com

[3] www.migente.com

[4] www.livejournal.com

[5] www.friendster.com

[6] www.dogster.com

[7] www.catster.com

[8] www.themychurchapp.com

approximate Christian churches of their followers, and Couchsurfing[9] to arrange travelers meetings. Simultaneously, MySpace[10] expanded beyond former Friendster users. Because of its allowance of public profiles, bands started to join the website to create a connection with their fans, and local clubs to promote VIP passes and advertise among its clients. At this point, the SNS adherence was not limited to US, but worldwide. Friendster gained traction in the Pacific Islands, Orkut[11] became the first SNS in Brazil before growing rapidly in India, Hi5[12] reached smaller countries in South America and Europe, and Bebo[13] became very popular in the United Kingdom, New Zealand, and Australia (BOYD; ELLISON, 2007).

Launched in 2004, Facebook[14] started as a Harvard University SNS, expanding to other colleges in the Boston area, the Ivy League, and gradually most universities in Canada and the United States, and in September of 2006, to everyone of age 13 and older with a valid email address (FACEBOOK, 2015a). Facebook differentiate itself for letting outside developers build applications and for allowing users to personalize their profiles and interests with, for instance, movie preferences and chart travel histories (KIRKPATRICK, 2010). As the social media and user-generated content phenomena grew, websites focused on media sharing began implementing SNS features, for example, Flickr[15], Last.FM[16], and YouTube[17].

2.2 MOBILE SOCIAL NETWORKS

The first mobile version of Facebook, introduced in January of 2007, let users upload pictures directly from their phones, send and receive messages, update their profile status and search for other profiles (FACEBOOK, 2007). Currently including many other functionalities, it represents 1.19 billion monthly active users as of December 2014 (FACEBOOK, 2015b). However, mobile versions of OSNs are not considered truly MSN. Those MSNs are called hybrid because people can also access them from non-mobile devices such as PCs and laptops (JABEUR; ZEADALLY; SAYED, 2013).

In this perspective, MSN does not mean merely accessing an OSN through a mobile device that connects to the Internet; it has the capability to perceive context and connect people through a common physical context, such as co-location, co-encounter, and co-activity (CHIN; ZHANG, 2014). In that way, MSN is not a replacement of existing SNS but its complement. It combines distributed content sharing, social networks and pervasive computing together in order to provide an integrated experience that fuses physical and digital social interactions.

With the increasing diffusion of GPS and wireless networks on smart mobile devices, mobile applications can combine location and digital contents to social-aware functionalities.

---

[9] www.couchsurfing.com

[10] www.myspace.com

[11] orkut.google.com

[12] www.hi5.com

[13] www.bebo.com

[14] www.facebook.com

[15] www.flickr.com

[16] www.last.fm

[17] www.youtube.com

Mobile social network in proximity (MSNP) (CHANG; SRIRAMA; LING, 2015) and location-based social networks (CHORLEY; WHITAKER; ALLEN, 2015; ZHENG, 2011) can assist mobile users to interact with proximal people and perform various social activities such as search for new friends who have common interests, exchange content, and establish conversations. Typical applications include navigation systems and a combination of yellow pages and maps that usually provide the nearest points of interest to the user, as in Foursquare[18] and Yelp[19].

Foursquare, launched in 2009, enabled people to check-in at a location and share their status and photos with others. In 2014, Foursquare divided its functionalities between "local search" in Foursquare 8.0 and social location sharing in Swarm[20]. Foursquare 8.0 has both web and mobile versions that display personalized recommendations based on a number of factors, including the user's tastes and venue ratings. Swarm is a mobile application that lets users share their location with friends, and see where their friends are. The location sharing can be wide (by neighborhood or city), or specific by check-in to a specific location or venue. Swarm and Foursquare 8.0 work together to improve recommendations. Swarm check-ins helps Foursquare to understand users' preferred places. Similarly, in 2010, Yelp added check-in features to its places search and rating application. Additionally, Yelp users can make restaurant reservations, order delivery food, view hygiene inspection scores, make appointments at spas, find local businesses special offers, book hotels, and so on.

MSN applications found in the literature cover a very wide range of purposes and functionalities. VASTARDIS AND YANG (2013) divide them in six categories: social services, vehicular networks, wearable MSNs, healthcare services, social learning networks, and recommender systems. Similarly, HU et al. (2014) classify MSN applications in location-based, proximity-based, healthcare-based, profession and education, entertainment, and pervasive collaboration. Additionally, MSN application domain includes social networking services, game, travel, business, education, healthcare, dating, and road traffic (HU et al., 2014).

MAKRIS, SKOUTAS AND SKIANIS (2013) survey solutions that combine mobile computing and context awareness, as mobile and wireless systems appear as the most promising and challenging networking research area for employing context-aware functionalities. Context-aware platforms can provide a set of contextual information to the application that runs on the mobile device. Subsequently, based on such information, the MSN can gather and process the information, determine its value, and interact with the end-user. In addition, social network applications, explore users' personal and social information to enrich the original notion of context with social awareness (ARNABOLDI; CONTI; DELMASTRO, 2014).

2.3 CONTEXT AWARENESS AND SITUATION AWARENESS

Historically, WANT et al. (1992) introduced their "Active Badge Location System" in 1992, as one of the first context-aware applications. In literature, the term context-aware appeared in SCHILIT AND THEIMER (1994) for the first time. The authors described context as location, identities of nearby people, objects and changes to those objects. BROWN (1996) defined context to be the elements of the user's environment that the computer knows about.

[18] www.foursquare.com

[19] www.yelp.com

[20] www.swarmapp.com

DEY (1998) defines context as the user’s emotional state, focus of attention, location and orientation, date and time, as well as objects and people in the user’s environment. The most popular definition (DEY, 2001) distinguishes context on three entities: places, people, and things; and four categories of attributes describe each entity: identity, location, status (or activity), and time.

Context awareness can provide relevant information or service to the user, meaning that the provided information helps to better and easier perform a task in the current context. Derived from this definition, situation awareness (ENDSLEY, 1995; ENDSLEY; JONES, 2013) allows a better adaptation of information or services. A situation abstracts from the context dimensions by translating specific contexts (location, time, temperature, environment, number and list of available network devices) into logical situations. For instance, a work situation is not bound to a single location context, since a professional can be working at home or at different places. Therefore, it is necessary to qualify the information resulted from different context in higher-level way, called the user situation (eating in a restaurant, eating at home, working at home, working in the office).

Context awareness is a crucial issue in mobile applications and it is possible to improve the notion of context to provide a mobile user with information matching interests adapted to situation (BOUNEFFOUF, 2013). Situation awareness refers to the perception of the elements in the environment within time and space and the comprehension of their meaning (ENDSLEY, 1995). Situations often change; in order to adapt for each situation, applications must detect real-time changes on contexts and assume a corresponding set of preferences for each circumstance.

Knowledge-based are special examples of context-aware systems (BAKER et al., 2009). Many works (KIM et al., 2006; BOTTAZZI; MONTANARI; TONINELLI, 2007; LI; WANG; KHAN, 2011; ANEJA; GAMBHIR, 2015) employ ontologies to design a semantic-based model for context adaption. Moreover, semantic specification of context can assist users in realizing their tasks by recommending them to other users who share similar interests. Ontologies (GRUBER, 1993) express knowledge in a way that computers can do logical inferences, organize and classify definitions of a formal concept representation. Through logical inference, semantic-based social networks can come up with new relations out of the already existing ones between the social entities (WENNENBERG, 2005).

Users interact with the system within diverse contexts; therefore, preferences for items in one context may be different from those in another context. Context-aware recommender systems (ADOMAVICIUS et al., 2011) is an example of application that addresses that issue by considering not only a given item, but also the contextual information in which the user consumed that item. The ideal context-aware recommendation system considers user action with an appropriate context and effectively tailors the results for that given context (ADOMAVICIUS et al., 2011). For example, a restaurant recommender may determine that the user is going to a romantic date and filter out restaurants that tend to be noisy or without an adequate wine selection. Furthermore, recommender systems can be combined with content sharing platforms to group users with related interests in order to create virtual communities (FOELL et al., 2007).

Previous works approach context information supporting pervasive communities. PICO (KUMAR et al., 2003) is a framework to create pervasive communities that can collaborate proactively in areas such as telemedicine, military and crisis management, aiming to achieve a sequence of events that can lead to the creation of communities. MobiLife (COUTAND et al., 2005) provides community ubiquitous services by enabling group awareness, supporting group management and by facilitating trustworthy communications. HERMES (JOHN et al., 2006) demonstrates the use of context-aware in a company using context information of organizations, users and applications to trigger automatic selection of a conference tool. POPEYE (MEYER et al., 2008) project approached spontaneous virtual communities formed in a P2P fashion for collaborative work.

2.4 VIRTUAL COMMUNITIES

A community has several characteristics that distinguish it from a mere group of people. JONES (1997) conceptualized the notion of a virtual community based on the definition of a virtual settlement (a place, or cyber place, where a virtual community forms). He identified four necessary characteristics of a virtual community: interactivity, communicators, a publicly shared mediated communication place, and sustained membership. Similarly, PREECE (2000) defined a community as “people who interact for their own needs or perform special roles; a shared purpose such as an interest, need, information exchange, or service that provides a reason for the community; policies that guide people’s interactions; computer systems that support and mediate social interaction and facilitate a sense of togetherness”.

The interactive nature of virtual communities distinguishes them from a random virtual encounter of users. GARFINKEL (1994) notion of interaction has two important characteristics: temporal and contextual coherence. He specifies that interactions are temporally coherent if the degree of interaction is sustained over time, and contextually coherent if they have similar interaction context (e.g. time, location, people or objects associated with the interaction). When people become gradually aware of each other, through coherent interactions, a community begins to emerge.

Over SNS, there are plentiful user-generated content creation and exchange. From those interactions, derive social connections that are dynamic in nature as user interests can evolve due to, for instance, temporal (e.g. day of the week) or spatial (e.g. change in geographical position) reasons. These dynamic connections within a social domain build inner divisions of well-stablished networks. That leads to a topic of study in the social networking field, community detection (NEWMAN, 2006). Algorithms for community detection are closely related to clustering algorithms. However, despite their resemblance, community detection focuses on the pairwise relationship between network nodes, and more generally, the network topology (SUNDARAM et al., 2012).

Nonetheless, to detect coherent social communities successfully is a challenge that combines community extraction and social awareness. WANG et al. (2010) define social context as “the information relevant to the characterization of a situation that influences the interactions of one user with one or more other users”. Furthermore, group awareness refers to the use of context information related to a group that enables the provisioning of ubiquitous applications and services in order to address the group’s concerns and needs (COUTAND et al., 2005). Therefore, the formation of dynamic communities can support people to perform a common task and ungroup them after they achieve the joint objective. Moreover, through the context awareness of a given community it is possible to better understand groups’ collective interests and needs to personalize applications and services.

3 RELATED WORK

In this chapter, we discuss solutions that explore social groups in context-aware MSN applications. Section 3.1 details the literature review conducted. Sections 3.2 to 3.7 describe the related works elected from the review. We compare those works in the matter of community grouping, context awareness, and other aspects in section 3.8. At last, section 3.9 points research opportunities.

3.1 LITERATURE REVIEW

We performed a literature review following aspects of the method proposed by KITCHENHAM (2004). Considering the research question, we conducted a search on the Google Scholar[21] tool. We considered papers that fit the following criteria: (1) written in English (2) published between 2011 and 2015 (3) works that propose a context-aware MSN application. The terms used for the search were ("context-aware" OR "context awareness") AND ("mobile social network" OR "social network") AND ("virtual" OR "social" AND "community" OR "groups"). We discarded works that (1) superficially describe the proposed model; (2) do not present any social interaction feature; (3) do not present any community grouping feature; (4) are limited to opportunistic networks; (5) focus on data mining in social networks; (6) focus on trust or privacy or security aspects in social networks; (7) focus on people's social behavior in social networks.

3.2 FIND AND CONNECT (2013)

Find and Connect (CHIN et al., 2013) provides social networking among attendees at a conference or meeting. Users can find where the room, session, and people are on the map and then connect with people by adding them as a connection, sending them a message, or sharing an item. Its main functionalities are "Program and My Agenda", "Profile and Social Network", "Map", and "Messaging". The solution aims to employ resources in the physical environment to foster social networking. Particularly, the authors investigate two research questions: how social connections can be established and integrated with physical resources in a conference through positioning technology; and how physical proximity can affect and be affected by online social connections (CHIN et al., 2013).

CHIN et al. (2013) define the physical proximity between two users as an encounter. The encounter measurement algorithm considers the encounters' duration and frequency of occurrences. Such concept raised from the idea that some relationships are only relevant during a certain time, hence the indifference of people to bring these relations over to their OSN. Find and Connect also employs a recommendation algorithm to suggest possible interesting connections to the conference attendees. This algorithm considers the user relevant context: the encounter history; personal messages; user's interests; activity history; friends, following and followers; and the contents they have exchanged with other users. The application monitors social network activity during the conference and users can establish relationships by "Follow" or "Add Friend" or exchange their contact information by "Exchange contacts". The user's

[21] http://scholar.google.com.br/

position is monitored within every ten seconds, the encounter measurement is calculated every five minutes, and the friend recommendation algorithm is computed every ten minutes.

The system evaluation's results show that social connections that are reciprocal, such as friendship and exchanged contacts tend to be more relevant than a unilateral connection such as "following". Additionally, the frequency and greater physical proximity in encounter duration will increase the probability for a person to add someone as a friend or follow online. The future work suggested is to further study the effect of encounters on recommendations and determine the reasons why users add someone as a friend. Besides that, the authors idealize an algorithm for mining the encounters and discovering encounter patterns for identifying ephemeral social networks.

3.3 TOURIST-MSN (2014)

Tourist-MSN (ARNABOLDI; CONTI; DELMASTRO, 2014) is a real example of an MSN application developed on top of CAMEO (ARNABOLDI; CONTI; DELMASTRO, 2011). It allows tourists to create, collect, and share multimedia content related to geo-located points of interest through opportunistic communications among users' mobile devices. These multimedia posts are divided into categories (e.g. event, cultural visit, transportation) in which users can express their interests. Furthermore, the application also provides real-time communication through an opportunistic text chat identified by a title and a category within a limited group of users in close proximity.

Tourist-MSN disseminates over the network thought CAMEO's platform the title and category of each post and chat generated by the local user, and the user's interests in specific categories of posts and chats. Each node becomes aware of other nodes running Tourist-MSN in its current physical community and the list of available content. Even though each node maintains a historical profile of neighbors and content encountered in different physical communities, the management of a real-time chat is limited to the current physical community due to intermittent connectivity conditions characterizing opportunistic network (ARNABOLDI; CONTI; DELMASTRO, 2014). However, since the distribution of the posts results in an asynchronous content exchange, Tourist-MSN provides CAMEO with the utility function algorithm designed to implement the context and social-aware dissemination of posts among different physical communities.

Moreover, users can increase the content of a post by adding their own comments, and CAMEO distributes the content updates to interested nodes. CAMEO is also able to collect, manage, and reason upon multidimensional context information, derived both from physical and virtual worlds, characterizing the users profile, their social behavior, the available services and resources, and the surrounding environmental conditions. ARNABOLDI; CONTI; DELMASTRO (2011) expect to extend CAMEO in several directions, from the efficient management of heterogeneous context information to the implementation of services based on opportunistic computing.

3.4 SOCIETIES (2014)

SOCIETIES (DOOLIN et al., 2014) aims to bridge the virtual and real worlds by building purpose-driven communities of interest through its key concepts: Discover, Connect and Organize (DCO). The first step is to discover entities both in the physical or digital layer, such as individuals, communities, devices, resources, and services. The discovery system allows high personalization and context-aware use, enabling the detection of people with common interests without a dependence on OSNs. Next, a connection built between the relevant entities bridges the physical and the digital worlds. These connections can take many forms: person-to-person, person to group, person to object, and person to service. The final stage is to organize the communities. Table 1 describes the DCO stages for each aspect proposed.

Table 1. DCO stages

	Discover	Connect	Organize
Context awareness	Context sensing resources, user context values and available resources based on current context information	Users based on context similarity and users with relevant resources based on current and historic context information	Community lifecycles and membership based on context information of individual members and of the entire community
Learning	Individual and community preferences	Based on individual and community preferences	Community-level learning assists individuals in acquiring information and links from other community members
Privacy	Individuals and communities who will comply with user's privacy preferences	Privacy policy negotiation during connection for data obfuscation, micro-agreement, and privacy-aware social firewall	Privacy audit/assessment contributes to reputation, and enables organizational activities more informed
Trust	Trustworthiness of individuals, communities, services, and trustable entities in advance	Various entities based on individual and community trust assessment	Trust-based community membership management and trust-based community lifecycle (merging and splitting) based on trust relationships among members of existing communities
Community Orchestration	Potential communities and members	Individuals via community membership formation	Individuals into communities, form, merge, and delete communities and sub-communities
User intent	Individual and community intent	Establishing a community with users who share similar intent	Provides community intent-aware services, and takes actions on behalf of a community

Source: Adapted from DOOLIN et al. (2014)

DOOLIN et al. (2014) assert that pervasive community is inherently context-aware, therefore it can adapt to factors such as user's location, activity, environment, and others. Members of a pervasive community form a "community interaction space" and interact through their "cooperating smart space", which is, basically, their mobile device. Dynamic and hierarchical communities facilitate the formation of temporary and ongoing groups. For example, a temporary community can become a permanent community interested in a particular subject, and a hierarchical community can be a sub-group of a larger community.

Although the proposal is well detailed, so far its only real-world application is an automatic real-time interaction with social networks. The alignment occurs through pull and push, in which the first one is in charge of extracting and informing what is happening in the Social Web, and the second sends the pervasive community activity to update the user status in the social networks (e.g. Facebook, Twitter). The authors point that the platform applicability goes from the development of a full commercial community management system to allowing third-party entities to exploit all or parts of the system. Through external interfaces (APIs), for example, service providers would have the capability to create new highly intelligent community-based services, or to enhance existing services with richer information.

3.5 SMART CITY (2014)

HU et al. (2014) propose a multidimensional context-aware social network architecture aiming to development and usage of mobile crowdsensing applications. It integrates multidimensional flows of context-aware solutions to collect and elaborate contextual data, which can improve and personalize mobile services for crowdsensing, and allows creation of new crowdsensing applications. It provides a generic model to deploy, examine, and evaluate different context-aware solutions for mobile crowdsensing applications.

The proposal details how to communicate with the widely used social networks and ubiquitous sensors in the mobile ecosystem to obtain and make use of context-related data in context-aware applications. The proposed mobile context-aware platform (MCP) consists in three main components: a mobile service-oriented architecture (SOA) framework, a context-aware semantic service (CSS), and a multidimensional contextual data aggregation service. In the mobile ecosystem, the SOA framework works as a bridge between the MCP and the Vita cloud platform (HU et al., 2013).

The flow of context-aware solutions in the mobile ecosystem consists of three steps: collection, processing, and utilization of contextual data. First, context-aware data collection is concerned with the acquisition of context information. The collection of raw data comes from different external sources and provides initial input regarding user's locations, activities, and environments. Each contextual data category derives from an equivalent raw sensing data, as shown in Table 2. The CSS component further processes and transforms the contextual data into semantic-based context information to improve the context awareness of the mobile crowdsensing applications.

Table 2. Sources of the contextual data

Raw sensing data		**Contextual data**	
Mobile data	Location data (GPS, WiFi, cell tower) Human interaction with phone (texting, calling) Activity data (accelerometer) Noise (microphone)	**Environment**	Temperature, humidity, pollution; Indoor, outdoor; Location (home, work, leisure, in transit).
Sensor data	Environment data (temperature, humidity, pollution) Health data from body sensors (heart rates, blood pressure, stress level)	**Personal activity**	Walking, running, sleeping; Emailing, texting, calling; Heart rate, blood pressure, stress level; Mobility pattern.
Online data	Facebook, Twitter (social relationships)	**Social**	Social relationships (friendship, connection); Online/offline social behaviors and activities.

Source: Adapted from HU et al. (2014)

The proposed CSS is a lightweight and generic solution for similarity computing for mobile devices. The method infers the similarity of two entities considering: (i) the distance (the length of the path) between two words, (ii) the depth of two words and the depth of their most specific common parent in the common ontology, and (iii) whether the direction of the path between the two words is changed. The ontology captures additional information that affects the interpretation of generic concepts. For example, when annotating a data of retail price with "U.S.", the value assigned to the currency modifier is "USD", and the value assigned to the taxes modifier is "not included".

The context-aware crowdsensing engine (CCE) can understand the semantics of the data collected by different mobile devices. Therefore, CCE can automatically process the context information and convert the data by using the context annotation of the mobile devices. For example, convert a retail price collected in United States to the corresponding information for a receiver located in Hong Kong. To fulfill the data conversion, CCE can select the appropriate conversion rules from a pre-specified conversion library based on the contexts of the source and receiver.

The Smart City prototype application demonstrates the crowdsensing functionality based on the proposed context-aware mobile platform. Two examples of crowdsensing requests are "What is the delicious food in Hong Kong?" and "Recommendations of branded clothing in Hong Kong". The CCE ascribes personal context information relevant to each request, for example, for a shopping recommendation: gender, stores frequently visited, preferred brands, average money spent. Further, the application pushes each request to people who have similar preferences as the requester, addressing them to an appropriate target group and leading to a relevant and accurate query result. Moreover, the authors remark that the platform supports RESTful web services, allowing developers to extend new functions to this application.

3.6 MOBILIS GROUPS (2011)

Mobilis Groups (LUBKE; SCHUSTER; SCHILL 2011) is a part of the Mobilis project (SCHUSTER; SPRINGER; SCHILL, 2010) that supports MSNs developers with a reusable toolkit providing functionality like direct and group communication, import contacts from existing social networks, location sharing, proximity detection, media sharing, and shared editing of XML objects. Mobilis Groups specifically approach the formation and management of location-based groups. A temporal restriction also composes the restriction for visibility of groups and ability to join them.

Within a group, people can see each other's profiles, send private messages or use the group chat, and share media files; outside a group, users can see other groups' members' profiles and add them as friends. The application also suggests new groups based on the user location and on the friends' groups. Combining the temporal and spatial restriction, the application creates interesting attributes for groups, for example, a group can be visible a certain time before an event, but people can only join and interact during the event. Specifically, each group has latitude and longitude attributes, and a radius as a geo-position limit, and a start time and end time. A privacy attribute defines if the group creator has to authorize new members to join the group or not. Foursquare integrates the solution as an external social network and can be used as a starting point to create groups based on places or venues.

The authors present an Android application prototype that uses XMPP for communication between client and server. However, they did not show an application evaluation. Moreover, future research points to the implementation and evaluation of dynamic groups. As the proposed work consider groups on fixed or static locations in which only the users represent a mobile component, the authors suggest expanding the location concept.

3.7 TALDEA (2014)

Taldea (NEJMA et al., 2014) is a community-centered application that helps users to access spontaneous communities and organize social exchanges between users in a geographic territory. The application employs an ontology-based model for describing formally a community, and its components and relations. Each community has a set of concepts describing physical or conceptual objects including interest, member, lifespan, service, location, content, and type. In the application, services support a group as a social entity the same as single user.

Taldea's hybrid architecture shares properties with both centralized and P2P architectures and takes advantage of both approaches. Two main components compose the platform. One is the Community Manager that interacts with the ontologies and has a set of services used to supply and extract knowledge from ontologies. The other is the Member Device that allows the user to discover and interact with the communities. The application has community-aware services that facilitate information exchange and communication; they vary according to the communities' properties and social context of the users.

The system has three initial functionalities: (i) recommendation, (ii) search or (iii) creation. The first one computes semantic similarity and recommends communities with the highest values of semantic similarity between the user's interests and the community's interests. The second lets users search for a specific community by formulating a natural language query. The third creates a spontaneous community with user-defined policies or predefined policies. Once connected to a community, users can view the community space and the list of available services (e.g. take picture or chat).

The authors describe a scenario for Taldea in a botanical park and cite use cases such as conferences, expositions, festivals, sport events, etc. However, they did not show an evaluation with users in a real-world environment. Moreover, as the proposed recommendation mechanism only considers the interest attribute, they suggest integrating spatial and temporal dimensions to the communities and services recommendation.

3.8 COMPARATIVE ANALYSIS

In this section, we compare the six aforementioned works. Table 3 summarizes the MSN solutions based on seven comparison aspects. We describe the criteria as following:

1) Community grouping: social recommendation (suggest friends, groups, places, contents, or services), or content-sharing (messaging, rates, comments, reviews, data or information exchange);
2) Context: spatial, temporal, personal, situational, social, or interests;
3) Profile: static, dynamic, or history-based;
4) Semantic-based similarity: yes or no;
5) Spatial scope: local or global;
6) Manual group creation: yes or no;
7) Architecture: centralized, distributed or hybrid.

The first comparison aspect is the community grouping purpose. As the outcome of community grouping is to perform social-aware recommendations of places, people, contents or services; or to help people socialize by providing functionalities for group communication, exchange of contents, rates, or opinions, we divide it into social recommendation and content-sharing. To compare the contexts considered by each solution, we delimitate context dimensions as spatial, temporal, personal, situational, social, and interests. Moreover, we categorize profile as static, dynamic, or history-based, in which the static is invariable, the dynamic changes from time to time and the history-based evolves along time. Semantic-based approaches are useful to categorize data retrieved from external sources; their effectiveness is given due to the heterogeneity of users' vocabularies, contents, social profiles, and so on. For that reason, we point the solutions that exploit ontologies as an auxiliary tool to infer similarity.

To assign the physical boundaries of a community, we consider BELLAVISTA, MONTANARI, DAS (2013) spatial scope definition of global and local. Furthermore, we distinguish the applications that let users manually create their own personalized groups. Additionally, we consider architecture as centralized, distributed or hybrid, as defined by VASTARDIS AND YANG (2013). The centralized architecture employs a remote server and end nodes deploying wireless infrastructure, cellular network, Wi-Fi, or similar technologies to communicate with each other or to access the remote service providers. The fully distributed architecture totally renounces centralized remote servers, employing cellular network to inter-communicate nodes. At last, the hybrid architecture is a combination of the other two, in which wireless communication are given through end nodes that can also access remote servers.

Table 3. Related works comparison

		MobilisGroups	Find and Connect	Taldea	Tourist-MSN	SOCIETIES	Smart City
Community grouping	Social recommendation	✓	✓	✓	✗	✓	✓
	Content-sharing	✓	✓	✓	✓	✗	✗
Context	Spatial	✓	✓	✗	✓	✓	✓
	Temporal	✓	✗	✗	✗	✓	✗
	Personal	✓	✗	✗	✗	✓	✓
	Situational	✗	✗	✗	✗	✓	✓
	Interests	✗	✓	✓	✓	✓	✓
	Social	✓	✗	✗	✗	✗	✓
Semantic-based similarity		✗	✗	✓	✗	✗	✓
Profile		Static	Static	Static	Static	Dynamic History-based	Static
Manual group creation		✓	✗	✓	✗	✗	✗
Spatial scope		Local	Local	Global	Local	Global	Global
Architecture		Centralized	Distributed	Hybrid	Distributed	Not described	Centralized

Source: Created by the author

The analyzed MSNs address the same functionality aiming at different real-world purposes. Find and Connect (CHIN et al., 2013) performs content-sharing and social recommendation, although restrained to the local scope of a conference. Similarly, MobilisGroups (LUBKE; SCHUSTER; SCHILL 2011) provides chat communication for every formed group and suggests new groups based on the users' location and their friends' groups. Otherwise, on a global scope, SOCIETIES (DOOLIN et al., 2014) and Smart City (HU et al., 2014) perform social recommendation but do not have any content-sharing functionality, which limits the social interactions. Tourist-MSN (ARNABOLDI; CONTI; DELMASTRO, 2014) employs opportunistic network to provide proximity-based messaging combined with location-based services and multimedia content sharing related to geo-located points of interest, while Taldea's (NEJMA et al., 2014) P2P chat explores semantic-based recommendation in a global scope but limited to only one context.

Context and profile change over time, that means, for instance, a user interest from yesterday may not be the same tomorrow; and a point of interest for a vacation during summer can be very divergent during winter (ADOMAVICIUS et al., 2011). The proposed solutions effectively employ context in MSN applications, however only two combine location and time contexts. MobilisGroups (LUBKE; SCHUSTER; SCHILL 2011) sets a spatial and temporal restriction, wherein the users can only join a group when they attend those criteria of being in a specific place at a specific time. SOCIETIES (DOOLIN et al., 2014) determine what is relevant at the current time (t), historically at (t − 1, t − 2 ...), and predicted at (t + 1, t + 2 ...).

When grouping people based on profile similarity and interests, people may want to form different communities over varied situations. In that way, grouping attributes may be customizable, in order to attend users' needs and tastes; MobilisGroups and Tadea allow users to create their own personalized context-aware groups. Besides, users should be able to choose which contexts to apply or not and to give them more or less relevance. As in SOCIETIES, relevance can be decisive to decide what to alert to a user at a specific time or place and differs from the typical "all or nothing" approach.

3.9 RESEARCH OPPORTUNITIES

Context awareness has become a fundamental requirement in the design of mobile and pervasive computing systems. It attempts to improve the life quality and the technological solutions experience to groups of people that share similar interests or habits. Nonetheless, currently, no context models have been developed to support the management of context for a dynamic community in large-scale systems (DOOLIN ET AL., 2013; CHANG; SATISH, 2015).

The architecture plays an important role in the success of the MSNs. HU et al. (2014) define hybrid architecture as an integration of the traditional Internet and opportunistic networks, and point it as future key research in MSN. PAUL; FAMULARI; STRUFE (2014) define hybrid architecture as a mixture of P2P and client-server infrastructure. VASTARDIS AND YANG (2013) assert that a hybrid approach can fully exploit the immense capabilities of MSNs, while low-range wireless communication and fully distributed platforms enable connection among mobile users to exchange data only when in proximity. Thus, compared to the conventional client-server architecture of MSNs, the hybrid approach has three additional capabilities: (i) opportunistic data exchange, (ii) multi-hop communications, and (iii) mobile opportunistic computing (HU et al., 2014). Another advantage of the hybrid architecture is that it can extend existing centralized MSN benefiting from the web-based approach and not suffering performance limitations caused by P2P structures.

While location is by far the most frequently used attribute of context, attempts to combine location to other context information and social functionalities have grown over the last few years. By combining user preferences and smart neighbor's discovery, context awareness can improve social interaction aspects. JABEUR; ZEADALLY; SAYED (2013) point adaptive discovery of friends or people sharing the same interest supporting dynamic changes in context and benefiting from historical information as one of the research challenges in mobile social network applications. Such strategy requires a fair amount of context information associated with social and interaction records to predict the user preferred people, services, and contents. Additionally, with the integration of the traditional communication into mobile social applications, users are constantly sharing, commenting, rating, among each other contents through social media and social networks. For that reason, it is fundamental to explore content sharing in MSNs along with social awareness.

Due to users' mobility in MSNs, it is difficult to assert their exact status at a specific time and location, since each user activities and interests are very diverse and depend on many unknown parameters. To address that, some works employ a semantic-based model to represent people and arrange them in groups based on shared attributes (LI; WANG; KHAN, 2011; HU et al. 2014; RAAD; CHBEIR; DIPANDA, 2010). Their effectiveness is given due to the heterogeneity of users' vocabularies, contents, social profiles, and so on. In addition, EAGLE et al. (2009) assert that a user's historical behaviors and locations is a powerful indicator of the user's preferences. Therefore, it is essential to design a semantic-based profile model that represents users' profile combined to past behaviors.

Many challenges related to context-aware communities remain open, such as its attributes and associations among groups (to create, merge, subdivide and terminate groups). Although recent projects provide a rich platform for context management, discovery mechanisms and personal preferences, they miss to take advantage of features for social collaboration in groups (LIMA; GOMES; AGUIAR, 2012). In other words, MSNs proposals still lack on some aspects while combining social features within a context-aware environment. Each analyzed proposal has its shortcomings; therefore, we delineate a combination of their strong points. We propose a community grouping mechanism employing a semantic-based model to match groups and people based on multiple contexts. The main purpose is to enable content sharing within a virtual community that is not restricted to the physical location and can be manually created or suggested by the application.

4 SPONTANEOUS SOCIAL NETWORK MODEL

In this chapter, we detail the SSN model in four sections. Section 4.1 presents an overview of the main concepts and key definitions. Sections 4.2 to 4.5 describe the SSN steps gather, categorize, group, and interact, respectively.

4.1 OVERVIEW

To provide an overview of the SSN model, we present five definitions that are essential for this work.

Definition 1. A social community is a group of people.

Definition 2. A dynamic social community is a social community that changes according to context.

Definition 3. A static social community is a social community that has a tendency to remain the same and not change according to different contexts (e.g. family).

Definition 4. A virtual community is the representation of a social community in a virtual-layer or application.

Definition 5. A spontaneous social network allows people with temporary context similarities to interact anywhere, anytime, without previously exchanging any contact information.

In this work, we focus on dynamic social community's grouping. We present a model to form and support spontaneous social relations in a virtual environment. The central purpose is to use the context as an integrator element to unite people. The objective is to form and manage social communities in a mobile application, in order to provide social functionalities and community-oriented services. In this way, through a set of contextual attributes, the application is able to suggest members, address relevant services, and more.

To form dynamic virtual communities, we must abstain from previous social relation or the exchange of any contact information (e.g. phone number, e-mail, OSN) among people. A SSN can exist in a controlled environment, such as a University. However, a SSN differs from previous Mobile Social Network in Proximity (MSNP) approaches in the matter that location is not the only determinant factor for group interaction. For instance, students can be located outside of the university campus (e.g. home) and still interact. Another difference is that in the SSN people can form dynamic social communities based on context similarities that are so far unknown by them. For instance, students that attend the same course in different schedules (e.g. morning, afternoon, evening) are engaged in the *same activity*, but tend to do not know each other because they are not classmates; therefore, no previous social relation exists between them. By forming a virtual community, they can share relevant content, collaborate, interact with each other, arrange meetings (e.g. a group of study), and so on. Nonetheless, a SSN can also exist independently of a controlled environment, as in sports games, events, concerts, conferences, and so on. For instance, people that are attending the same event are involved in the *same activity*. In this way, context similarities are temporary when activities have a specific duration and after that, those people will no longer share those contexts.

Figure 2. SSN Steps

Source: Created by the author

Figure 2 shows the four SSN steps to form and support the named dynamic virtual communities: gather, categorize, group, and interact. The first step consists on collecting contextual information regarding the user and the environment from external devices and sensors, such as smartphones, social networks, databases, application program interfaces (APIs), internet of things (IoT), global positioning system (GPS), near field communication (NFC) readers, etc. The second step is to categorize the collected data. To do so, we employ an ontology to determine the core context dimensions. Once categorized, it is feasible to process the contextual information by an algorithm. The SSN Grouping Mechanism algorithm computes the syntax similarity among ontology instances. By measuring the similarity, the algorithm is able to detect alike instances and group them based on their similarity degree. With the formed groups, an application layer can then provide virtual community services and contents, fostering social interactions.

4.2 GATHER

OSNs assign a profile to a person to describe contact information, personal interests, and so on. Relevant works approach aggregation of social web profiles into a single unified profile (ORLANDI; BRESLIN; PASSANT, 2012). Through social media profiles, it is possible to recognize social relations and virtual interactions on the expectancy to measure individuals' social tie (AIELLO; SCHIFANELLA; STATE, 2013). Through social tie measurement, encounters detection, and data synchronized from social networks it is possible to monitor people's social activities. With those techniques, it has been proven that people with similar social-demographic or behavioral characteristics are more likely to connect with each other. This principle, often called homophily (MCPHERSON; SMITH-LOVIN; COOK, 2001), is the tendency of individuals to associate with similar others, in other words, that similarity breeds connection. The homophily effect has been demonstrated across a variety of OSNs. The most important implication of this theory for social awareness is that people that have similar tastes are expected to interact with each other (CHIN; XU; WANG, 2013).

Studies on monitoring users in mobile computing systems have shown that it is possible to record the history of contexts visited by users and their actions performed in each context (DRIVER; CLARKE, 2008). However, contextual information originate from heterogeneous and distributed sources, which complicates reuse of implementation when sensors or data sources change. In addition, despite the massive amount of social data existent, each provider typically offers its own, proprietary, API for accessing its data. This lack of standards hampers integration between different social networking applications and the potential for mobile applications to accelerate social context exploration. Thus, not allowing service integration nor providing a unified communication. Therefore, it is a challenge to combine the named social activities extraction techniques with context acquisition, and it may require an additional step of integration following the collection.

In that perspective, we start by importing and synchronizing personal information from external OSNs. We intent to associate with other OSN profiles instead of creating a new one. Subsequently, through the synchronized OSNs, we are able to track dynamic information that the user is constantly generating in real time to complement their profile, such as shared contents, check in's, interactions with friends, visited places, events previously attended, hobbies engaged, etc. Our goal is to monitor user activities and preferences in different contexts to differentiate aspects that are static (i.e. independent of context) and dynamic (i.e. changes according to context and surroundings).

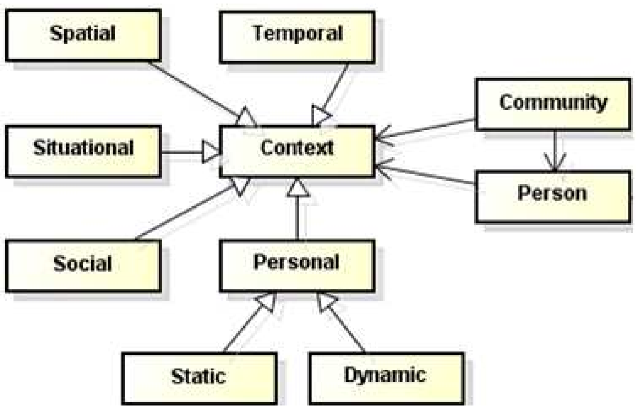
4.3 CATEGORIZE (SSN ONTOLOGY)

To categorize the contextual data collected, we define context dimensions as the core of the SSN ontology. According to NOY AND MCGUINNESS (2000), whenever possible we should reuse existing ontologies to describe our domain of interest. By extending ontologies such as UbisWorld (HECKMANN, 2006) and GUMO (HECKMANN, 2005), that model distributed user profiles and its relations with other people and the environment, it is possible to enhance such context dimensions.

HECKMANN (2005) presents UbisWorld as a collection of concepts and models for location, time, interaction and context that are prepared for ontological representation. UbisWorld describes most aspects of the real world, such as locations, people, objects, and their properties. Instead of using one ontology for all aspects, UbisWorld is composed of specialized partial ontologies, which are, the physical, the spatial, the temporal, the activity, the situation, and the inference ontology that models the computational and intelligent behavior in ubiquitous computing environments.

HECKMANN (2005) representation divides the user model dimensions in three parts (auxiliary, predicate, and range), which directly influences on the GUMO structure. It focuses on the modeling of user model auxiliaries, predicate classes, and special ranges. Usually, the auxiliaries lead to domain-dependent predicates that require additional general-world knowledge. That means a more detailed domain is needed to further describe people's interests or knowledge on particular areas, such as sports, music, movies, etc. In that case, any subject in the world could fit as people's interests, preferences, or knowledge. In this work, we focus on describing contextual representation of people individually and as part of a community. As HECKMANN (2005) representation of context goes way beyond our needs, for scope limitation, we suggest that extended ontologies restrain to the core dimensions.

Figure 3. SSN Ontology Core



Source: Created by the author

The SSN Ontology Core, presented in Figure 3, describes five context dimensions for person and community: spatial, temporal, personal, social, and situational. The dimensions involve the environment in which people situate, activities performed, subjects of interest, personal characteristics, and so on. Moreover, we assign contexts to a person and to a community separately, to determinate that context is not the same for a person within a community and when separate as a single individual. At least one dimension must be elected to define a community context, potentially being combined with others. Typically, a community is built from the combination of different contexts with Boolean operators, such as “AND”, “OR”, and “XOR”. Following, we briefly describe each context dimension and exemplify an existent referent ontology for extension:

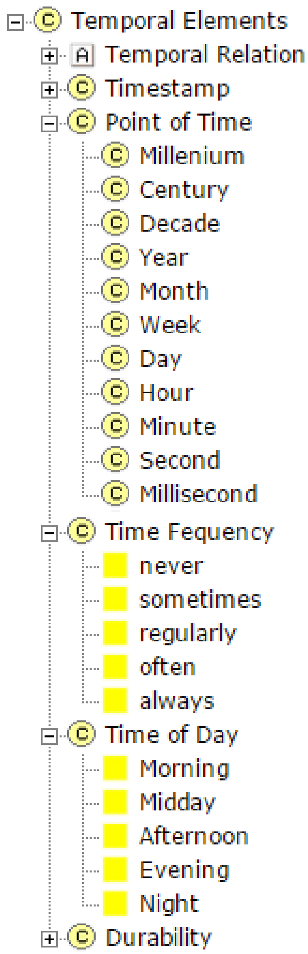
- *Spatial:* to describe the environment we consider attributes of GUMO class Physical Environment (i.e. noise level, temperature, level of wind, weather, humidity, light level). The spatial context mostly defines *location*, which can be a single point (e.g. a venue) or a perimeter (e.g. a city). If the community does not have a location, it means that the other contexts can still prevail independently of where the members are physically located. To represent location, we demonstrate two classes. First, UbisEarth contains a wide set of classes to describe locations on Earth, as shown in Figure 4 (a). Second, UbisWorld Spatial Elements subclass Location describes specific locations such as buildings or venues, as shown in Figure 4 (b).

Figure 4. (a) UbisEarth (b) UbisWorld Spatial Elements

Source: HECKMANN (2015).

- *Temporal:* represents the time dimension. For the community, it can detail when the community is mostly active, for instance, Wednesday mornings, every weekend, or a specific date as an event on December 15th of 2016. UbisWorld Temporal Elements represents that, as shown in Figure 5.

Figure 5. UbisWorld Temporal Elements



Source: HECKMANN (2015).

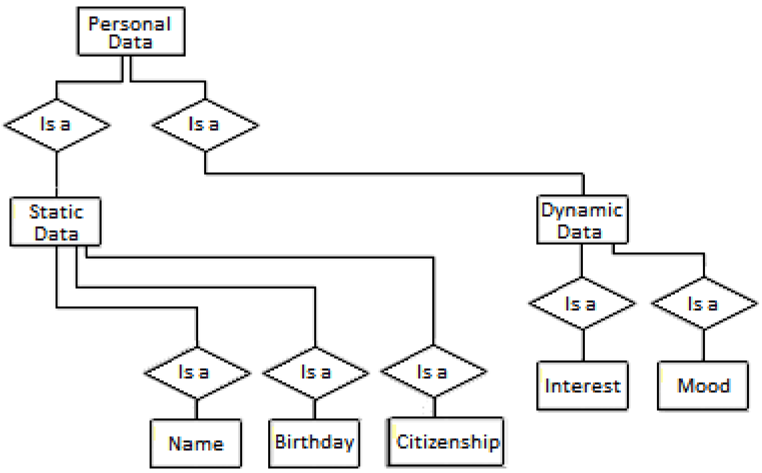
- *Situational:* represents the situation. That means, for instance, one or more actions performed on that context. The purpose is to describe the situation and distinguish them from related subjects of interest. The main activity in a store is shopping, and its subjects of interests depend on the store department (e.g. clothes and shoes). Similarly, in a sports event the situation could be "practicing baseball" so people will not join if they are interested in other activities, or in attend a different type of sport event. In that way, by specifying the situation (or performed activity) we avoid subject mismatches. To represent situation in the SSN ontology, we exemplify UbisWorld Spatial Purpose, as shown in Figure 6.

Figure 6. UbisWorld Spatial Purpose

Source: HECKMANN (2015).

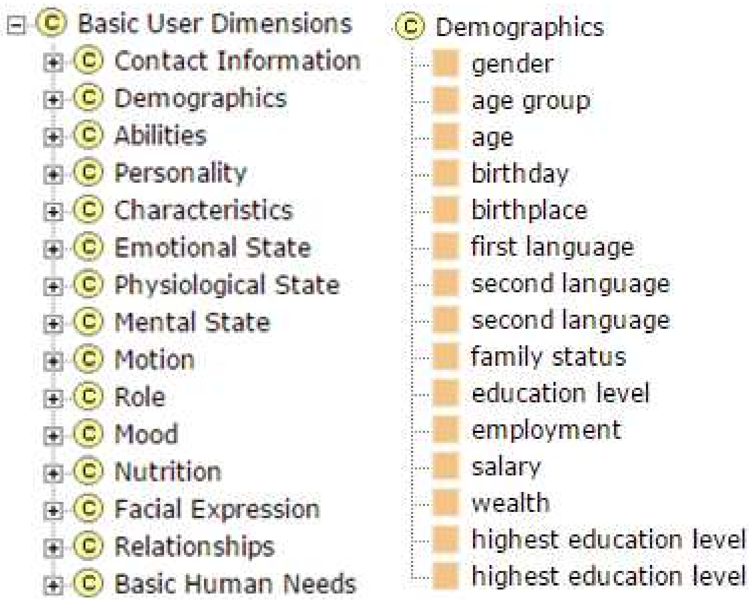
- *Personal*: the personal dimension is divided in two sub-classes, static and dynamic. Following the concept of static and dynamic profile attributes, shown on Figure 7, the personal static ontology classes represent permanent aspects of a person, and the personal dynamic ontology classes detail ephemeral aspects.
- *Personal Static*: details demographics, personal information, and characterizes relevant attributes of a person to the community. It is highly decisive for the community formation because it describes the expected member for each community. When the personal context is considered, it is assumed that a user with that characteristic is more likely to join that community. For example, a nightclub community can define the personal age attribute as above eighteen or twenty-one. GUMO Basic User Dimension is meant to describe every aspect of personal characteristics. Figure 8 (a) shows the Basic User Dimensions top-level classes and Figure 8 (b) shows the attributes of the Demographics class.

Figure 7. Static and Dynamic Personal Data



Source: Adapted from WEIßENBERG, GARTMANN, VOISARD (2006)

Figure 8. (a) GUMO Basic User Dimensions (b) Demographics



Source: HECKMANN (2015).

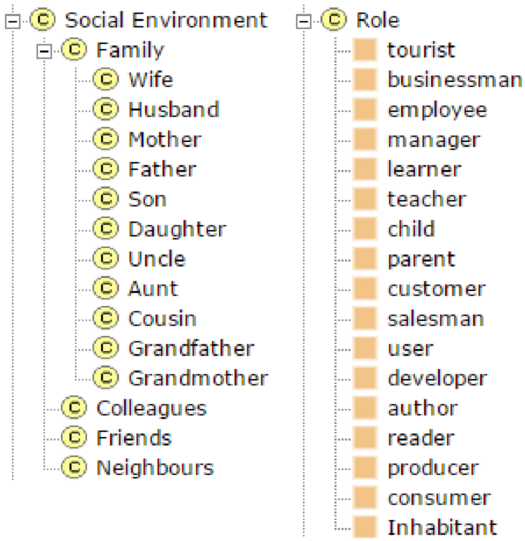
- *Personal Dynamic*: represents attributes of a person or community that may change over time. For instance, a person interest in "artificial intelligence" will match a community with "intelligent agents" subject. Similarly, a person that often attends matches of a particular sport's team will possibly be interested in a community that debates about that team. To describe interests we consider GUMO Domain Dependent Dimensions' class Interest, and the Amazon Ontology. Figure 9 (a) shows a high-level view of the Interest class and Figure 9 (b) shows the Interest sub-class Film. Figure 9 (c) displays the top-level classes of the Amazon ontology.

Figure 9. (a) GUMO Domain Dependent Dimensions (b) GUMO Film (c) Amazon Ontology

Source: HECKMANN (2015).

- *Social*: regards the social relation between two or more people, or within a community, meaning the possible social relation among its members. Figure 10 (a) shows the GUMO Social Environment class, and Figure 10 (b) shows other possible social roles.

Figure 10. (a) GUMO Social Environment (b) Social Roles



Source: HECKMANN (2015).

4.4 GROUP (SSN GROUPING MECHANISM)

The SSN ontology represents the context of a person or a community with a set of concepts. A simple way to match people and communities would be to match their corresponding instances. However, profile matching on instance level can be very sensitive to vocabularies. Mapping the concepts and instances of the shared ontology is a way to overcome that issue. In that way, a vector of concepts representing contexts is assigned to an instance of person or community, as defined by Equation 1.

$$instance_A = \{C_a, C_b \ldots C_n\} \qquad \textbf{(1)}$$

Given two instances summarized as collections of concepts, the initial similarity between instances is defined by Equation 2, where A and B are two instances, the common concepts between A and B is the intersection of the two sets of concepts, divided by the union between A and B, and *t* is a given threshold. The instance A is said to be somehow similar to B when $iSim(A, B) \geq t$.

$$iSim(A, B) = \left(\frac{A \cap B}{A \cup B}\right) \geq t$$
$$t = (0 \leq t \ \leq 1) \qquad \textbf{(2)}$$

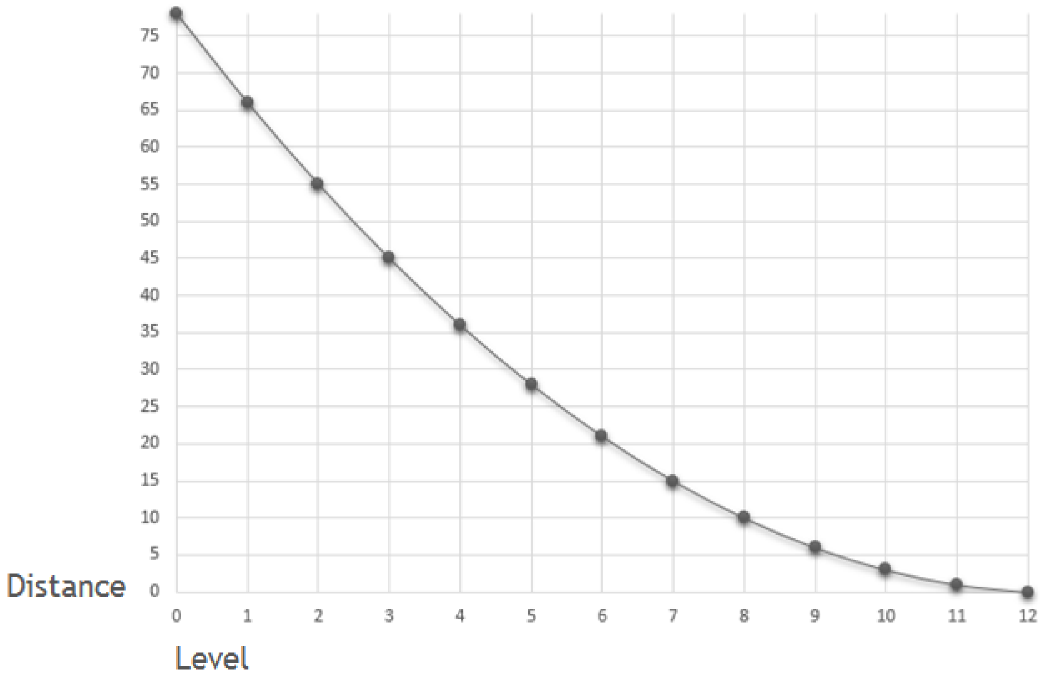
After identifying instances with initial similarity, we can further compute their similarity. A natural way to estimate similarity in a taxonomy is to measure the distance between concepts to which the compared instances belong. In other words, taxonomy distance measures the similarity between the instances' concepts. This means that closer the concepts are in the taxonomy, more similar they are. However, in a taxonomy, the closer to the root the more generic the information is, and further the concepts are from the root the more specific information they hold. Therefore, to determine the similarity of two concepts we complement the taxonomy distance measuring the nodes' depth in the ontology hierarchy. In that way, less distance on lower levels of the taxonomy will significantly increase similarity. For instance, in a book domain, the concepts "Programming" and "Software" (with common ancestor "Computer Science") are more similar than "Medicine" and "Computer Science" (with common ancestor "Subject"), even though the path distance between "Programming" and "Software", and "Computer Science" and "Medicine" have the same length. In short, two instances are more similar when they have a common ancestor in a deeper level.

The semantic distance between two different concepts C_a and C_b in a given ontology is defined by Equation 3, where C_p is the common ancestor of C_a and C_b in the hierarchical ontology, and C_{root} is the root of the ontology tree. *Depth* is the literal distance between two nodes, and *max* is the higher value of a set.

$$dis(C_a, C_b) = \frac{\sum depth(C_p, C_{root})}{\max(\sum depth(C_a, C_{root}), \sum depth(C_b, C_{root}))} \tag{3}$$

Considering the aforementioned semantic distance measure, Figure 12 shows the relation between concept level and taxonomy distance, in which the x-axis represents level and the y-axis represents distance. It demonstrates that the distance between concepts decreases as their depth level on the ontology increases, exemplifying a twelve level taxonomy. As the comparison is based on a common ontology, all the distances can be pre-computed so the results can be obtained faster on future computation. Additionally, following ontology principles of extension, our similarity measurement supports the increase of concepts (i.e. classes).

Figure 11. Graph of the relation between distance and level



Source: Created by the author.

We define instances similarity as the summation of the distribution between the elements of two given instances, divided by the total amount of elements. Equation 4 defines the similarity between two instances of a common given ontology, where s*im* returns a degree of similarity between zero and one, where *one* stands for perfect match or identical instances, and *zero* for a bad match or entirely different instances.

$$
\begin{gathered}
sim(A,B) = \frac{\sum dis(A \times B)}{|A| + |B|} \\
sim(A,B) \in [0 \ldots 1] \\
sim(A,B) = 1 \rightarrow A = B \\
sim(A,B) = 0 \rightarrow A \neq B
\end{gathered} \tag{4}
$$

For flexibility matters, we assign a weight for each concept. These weights determine the relevance of each concept on the final similarity, defined by Equation 5. When using weights, the similarity between two instances is defined by Equation 6. The weighted semantic similarity assigns a weight for each concept in the set of the compared instances concepts.

$$
\begin{gathered}
W_A = \{w_{1,}w_2 .. w_n\} \\
\mathrm{w} \in [1 \ldots w]
\end{gathered} \tag{5}
$$

$$
sim(A,B) = \frac{\sum dis(W_A * A \times W_B * B)}{\sum W_A + \sum W_B} \tag{6}
$$

While computing the similarity between two instances, a matrix holds the degree of similarity for each pair of concepts from each instance. A set of concepts identify the most relevant concepts between those two entities. If the similarity computed for two instances is greater than similarity threshold t_a and t_b, the instances are considered similar. The higher the similarity between A and B, the harder to find further matches for them. The matrix defined by Equation 7 holds the similarity measure of concepts between instances A and B. Equation 8 defines the relevant concepts between instances A and B, where *t* is a given threshold. The use of a threshold avoids taking pairs with undesired similarity degree.

$$
mSim(A,B) = sim(A \times B) \tag{7}
$$

$$
rel(A,B) = mSim(A,B) \geq t \tag{8}
$$

For example, given A and B as A = {C1, C4, C6} and B = {C1, C2, C3, C4}, their similarity will be computed as a matrix shown by Equation 9. Given a hypothetical matrix of similarity shown by Equation 10 and considering a threshold 0.8, the Equation 11 represents the relevant concepts between A and B. Therefore, to find similar instances to A and B, it is possible to compute the similarity between that set of concepts and another instance, as $sim(rel(A,B),C)$.

$$sim(A \times B) = \begin{Bmatrix} dis(C1, C1) & dis(C1, C4) & dis(C1, C6) \\ dis(C2, C1) & dis(C2, C4) & dis(C2, C6) \\ dis(C3, C1) & dis(C3, C4) & dis(C3, C6) \\ dis(C4, C1) & dis(C4, C4) & dis(C4, C6) \end{Bmatrix} \quad (9)$$

$$mSim(A, B) = \begin{Bmatrix} 1.0 & 0.5 & 0.1 \\ 0.9 & 0.8 & 0.8 \\ 0.7 & 0.5 & 0.3 \\ 0.5 & 1.0 & 0.9 \end{Bmatrix} \quad (10)$$

$$\begin{gathered} rel(A, B) = \{C1, C2, C4, C6\} \\ t = 0.8 \end{gathered} \quad (11)$$

4.5 INTERACT (SSN APPLICATION)

The interaction layer purpose is to represent the formed groups' in a virtual layer, and to support social interactions within those groups. Thus, the application must exploit the grouping mechanism accordingly. We point two possible ways to employ the grouping mechanism:

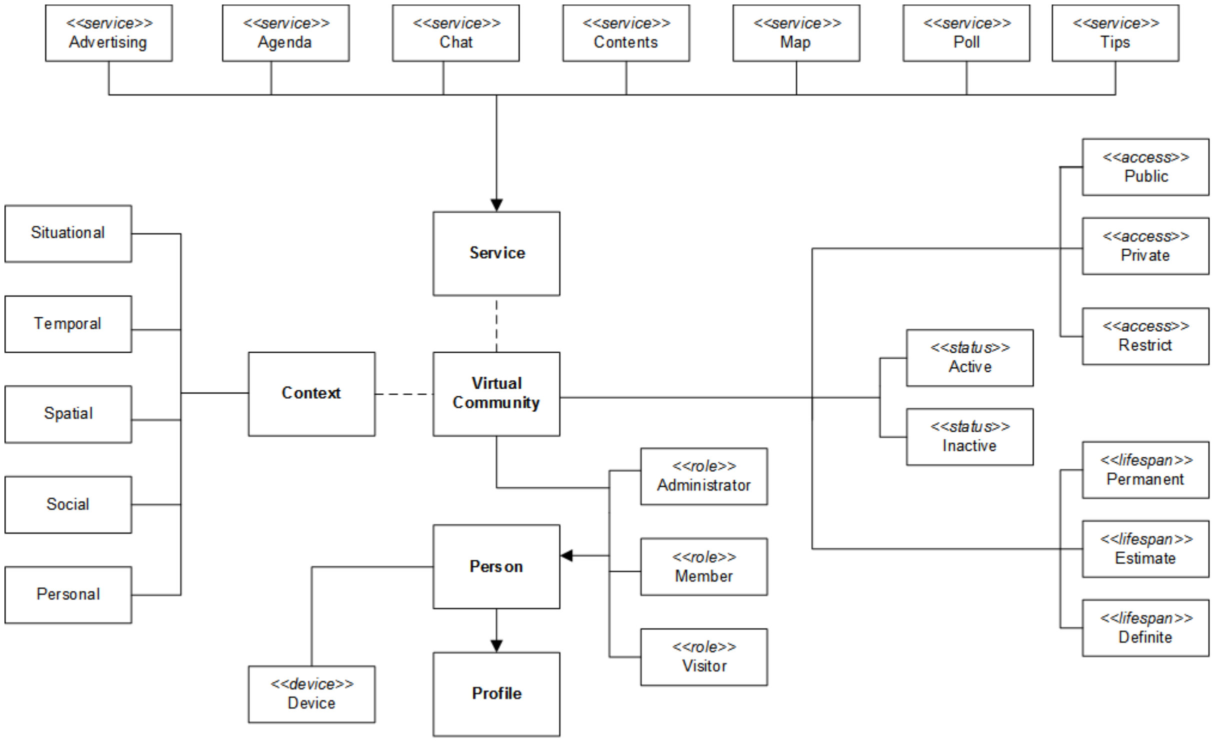
- Identify people with specific requested context;
- Identify similar contexts among people.

In the first one, the application submits a set of contexts and receives the people that match the requested context, or that are most similar with it. In the second one, the application submits a set of people for the grouping mechanism to identify one or more sets of similar contexts among them. By receiving one of the two outputs, the application parts to represent the virtual communities the Grouping Mechanism has identified.

The Grouping Mechanism has the possibility to employ weights to contexts. However, those weights must be set by the user or by the application, according to their needs. For instance, an application focused on grouping people in proximity could set a higher weight to the location context. Similarly, an application focused on foreign language conversations could set a higher value for personal contexts such as nationality and languages attributes. Additionally, an application that lets users create their own groups could provide the flexibility to each user to set their own weights to contexts that they consider more relevant to the group. The application or the user can dispense the appliance of weighs; in that case, every context would have the same weight.

The application must be able to support the interactions of the formed groups' members in a virtual layer. Figure 12 presents the SSN application model, its entities organization and attributes. The virtual community is the center of the model. The attributes that define a virtual community are general information, access control policy, lifespan, and context. The general information consists in name, description, and a welcome message that may contain personalized content for the members' first access. The roles are administrator, member and visitor. The administrator is the person that first created the community, this role has full access for editing the community's attributes, removing any content and blocking users; more than one administrator may be assign. Members have no additional privileges other than interacting and accessing services. Visitors have limited privileges defined by the administrator. Every person that forms a virtual community has a role and a profile.

Figure 12. SSN Application Model



Source: Created by the author

The lifespan defines an expiration date for the community. It may be (i) permanent (or unknown) in which it never expires; (ii) estimate when a precisely date is not applicable, but an approximate date or interval of dates; or (iii) definite when there is an exact date (or date and time) to expire. The access policy controls users' permission to join the community. A public community allows members and visitors to interact and collaborate openly. One or more administrators control a private community, and they decide if it does or does not allow the entrance of visitors. At last, a restrict community has a set of people allowed to join and is led by an administrator.

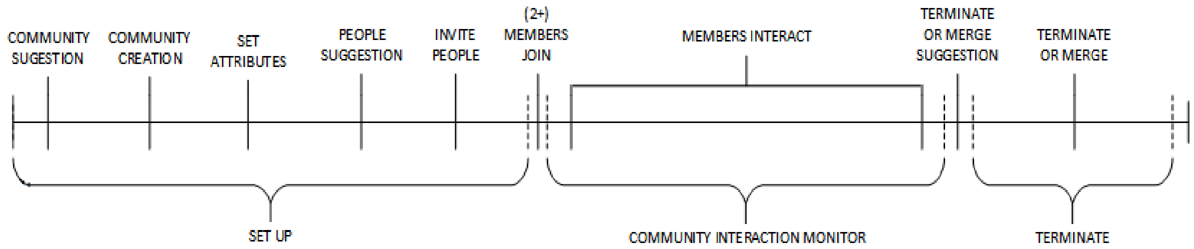
A community is *active* when its members are interacting and *inactive* when they are not. After being inactive for a certain time, a suggestion to finalize the community is sent to the administrator. Although a virtual community can exist without people, there would be no interaction, therefore characterizing it as inactive. However, for instance, a public community for an open-air park that has no members during the night would not terminate if it has members and interactions during the day.

A SSN may offer many services to its users. Depending on the service purpose, it may or may not suit for a virtual community. The SSN application model contains some initial services, yet many others can be included. Following, we list some services samples:

- Advertising: a section for publishing ads, either personal or professional, for offering virtual or real services
- Agenda: a calendar schedule sorted by date and time;
- Chat: text messaging communication;
- Contents: multimedia content sharing, such as pictures, audio and video;
- Map: displays relevant locations such as people, venues, and pinpoints;

- Poll: questions with multiple choice answers and votes counting;
- Tips: comments or short messages providing hints and tips.

Figure 13. Virtual Community Lifetime



Source: Created by the author

Figure 13 shows the virtual community lifetime stages. First, the set up can start by a system suggestion or manually. The user sets the community's attributes, taking the system suggestion or creating its own. Then, according to the selected contexts and attributes, the system will provide an initial suggestion of people for that community. The administrator can request people suggestion at any later moment. After receiving the suggestion, the creator can choose to invite the suggested people or others manually. The second stage is when the community comes to life. After two or more people join the community, they can start to interact and benefit from services. In this stage, new members can join at any time. While active, a component monitors users' interactions to detect when the virtual community becomes inactive. When inactive for a certain time, if there is one or more administrators, they will receive a suggestion to terminate or merge the community; if not, the members will receive a notification. On the terminate stage the system looks for similar active communities, and suggests a migration of the members to a similar active community. This process is called community merge. If no other similar community was found, the community will simply proceed for deletion.

5 IMPLEMENTATION

In this chapter, we detail the implementation of a SSN prototype, called Dino. We point the technologies and tools that we used during the implementation phase. We also detail the artifacts produced for the client application, and the Facebook taxonomy designed.

5.1 Dino

To collect personal and contextual information we used the Facebook social network. We employed OAuth[22] authentication for Facebook login. Additionally, an application page must be associated to the login, Figure 14 shows Facebook's Dino App page. To have access to users' profiles, they must grant the set of requested permissions on the login, as seen on the example on Figure 15. A privacy policy is also mandatory to enlighten users about the uses of their personal information. Following, Facebook provides the Graph API[23] for querying information contained on the profiles.

Figure 14. Dino's Facebook App

Source: Created by the author

Figure 15. Dino's Facebook login permission

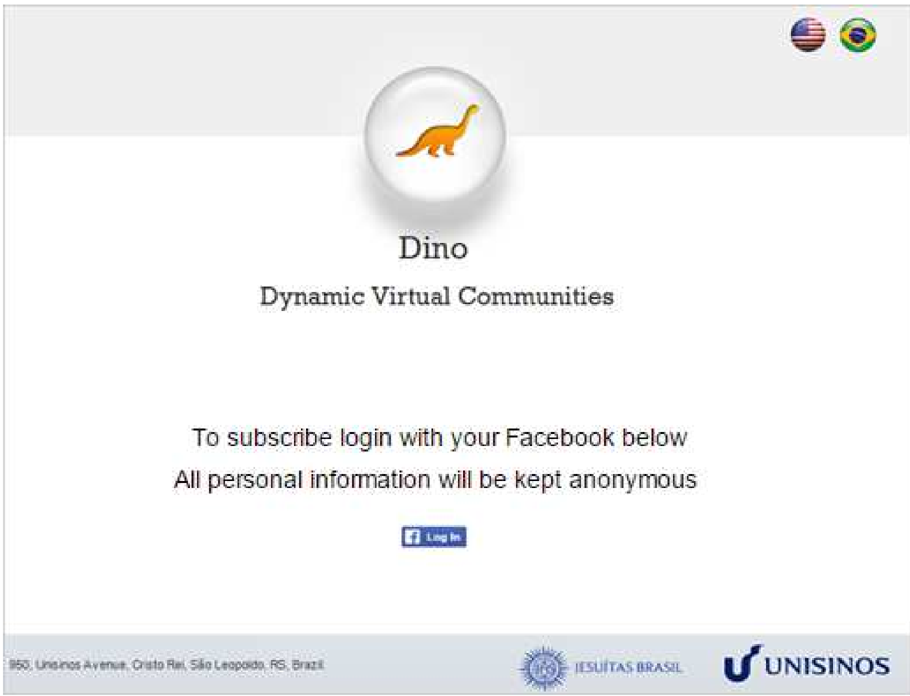
Source: Created by the author

[22] https://developers.facebook.com/docs/facebook-login

[23] https://developers.facebook.com/docs/graph-api

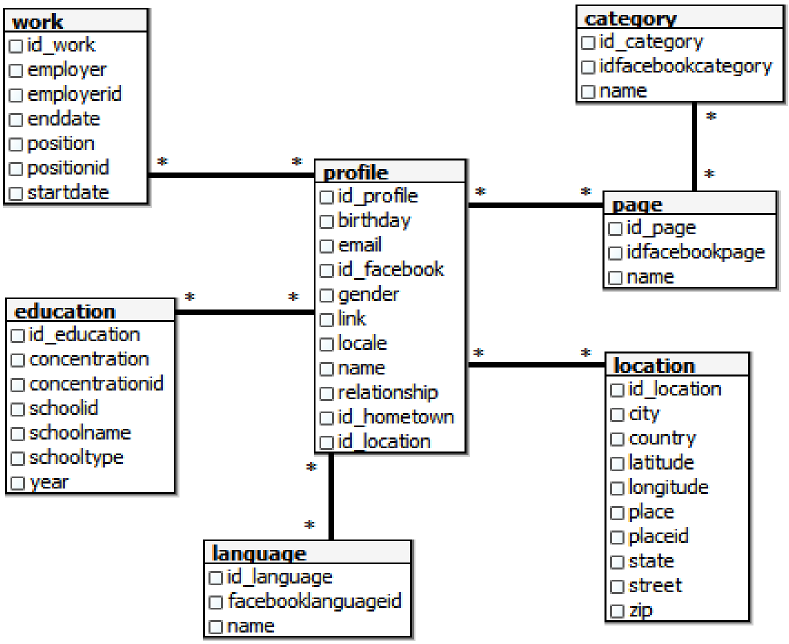
We developed a web client for users to login with their Facebook account, shown in Figure 16. The client fetches the logged profile, transforms its data into Java[24] objects, and stores it into a Postgres[25] database. Figure 17 shows the SSN database structure.

Figure 16. Dino web client



Source: Created by the author

Figure 17. SSN database structure



Source: Created by the author

---

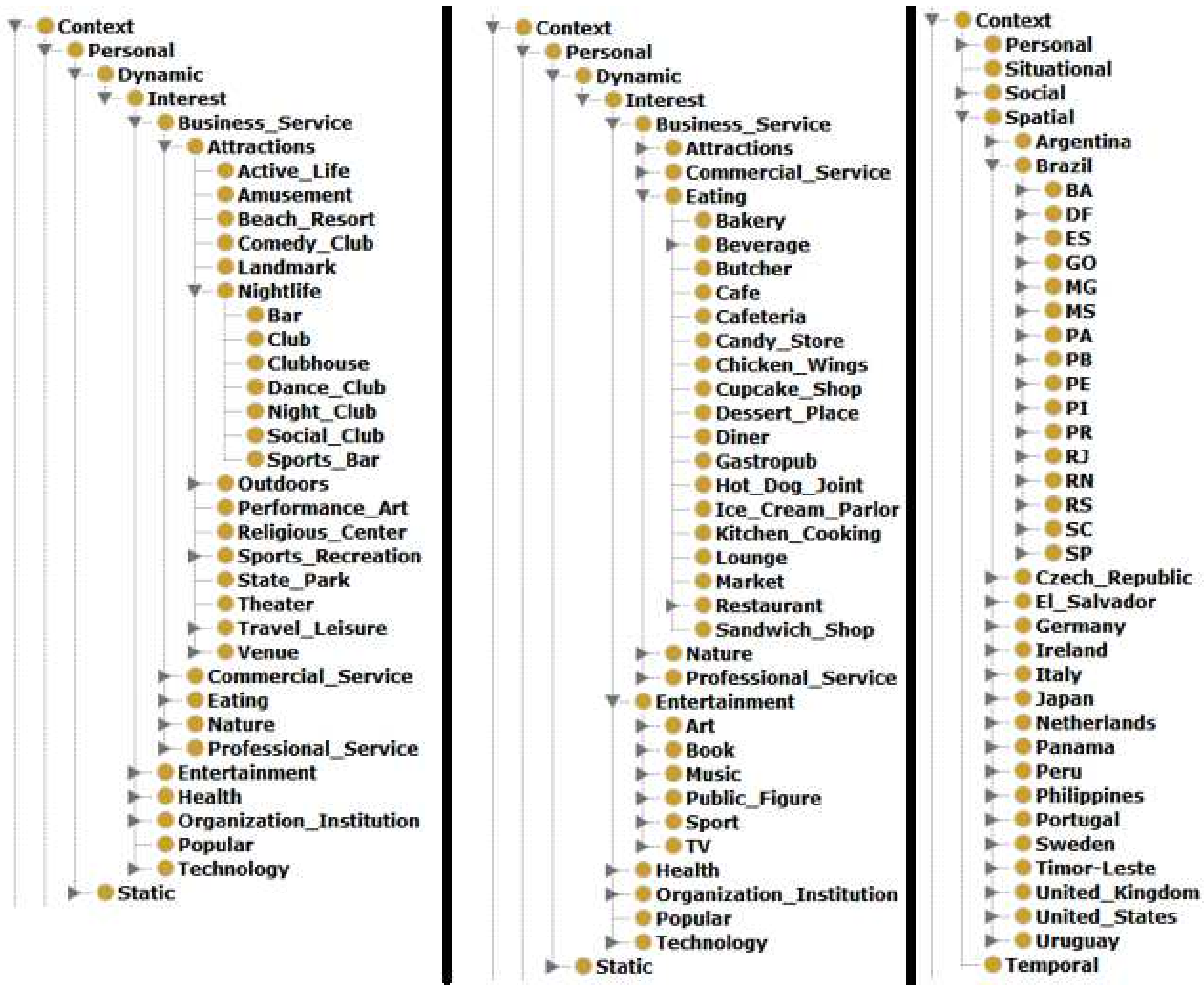
[24] www.java.com

[25] www.postgresql.org

To categorize the contextual information we employ the SSN Ontology core in conjunction to a Facebook taxonomy developed for the application. The Facebook taxonomy describes the pages categories, to represent people's dynamic interests based on their profiles' "Likes", and represents the "Check-ins" into spatial context. Figure 18 (a) and (b) show some of the interests' classes mapped. Figure 18 (c) shows some of the spatial context classes. Figure 19 (a) shows some of the personal static context classes. Figure 19 (b) shows social context classes. For scope limitation, we only kept in the ontology classes that have at least one instance, that means, for example, not all known languages or countries are in the ontology.

We developed a convertor using the Jena[26] library to transform raw data stored in the database into ontology instances. The conversion happens after the Facebook profile is imported to the SSN database. The convertor turns each Facebook profile entry into a RDF Person instance.

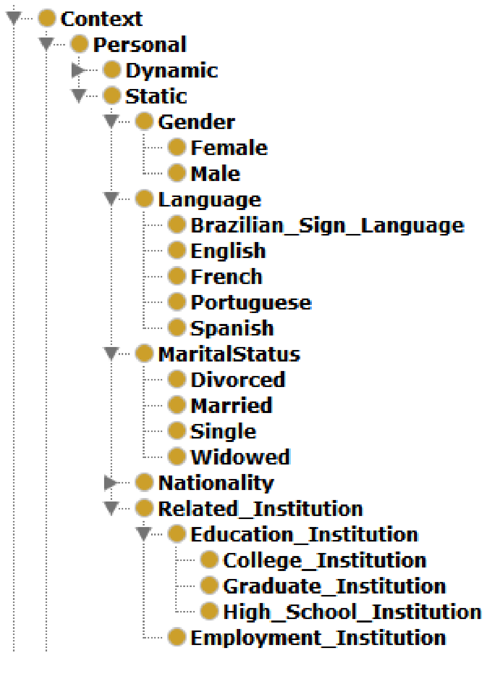
Figure 18. (a) (b) Dynamic Interest classes (c) Spatial Context classes



Source: Created by the author

[26] jena.apache.org

Figure 19. (a) Personal Static Context classes (b) Social Context classes



Source: Created by the author

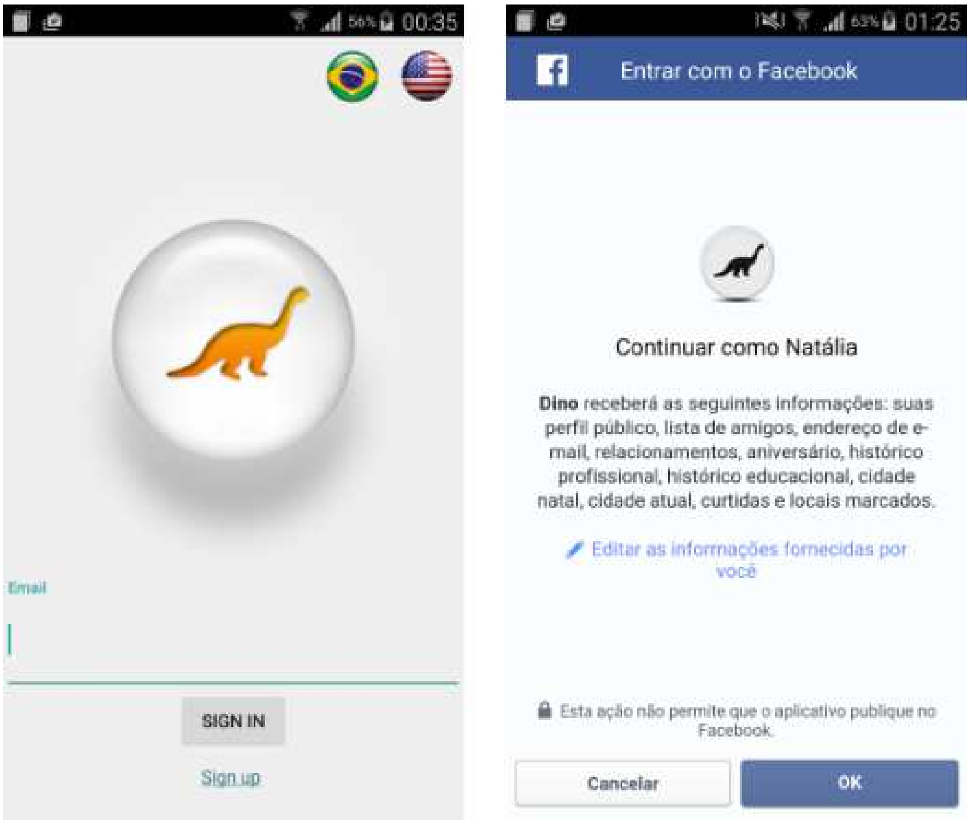
Afterwards, the grouping mechanism is able to form groups based on context similarities. The grouping mechanism algorithm works on top of the SSN Ontology and uses the instances of Person to compute their context similarity. We implemented a web service in Java to provide the computed results for the application client.

From the aforementioned purposes of the grouping mechanism, we chose to implement the one to form groups for a person, individually. That means, for a given user, we form the groups according to the user context and profile interests, resulting in the more suitable groups for that person within the domain. The domain in case are the people that subscribed to our research project, although it could be any other domain or users database. Other possible and similar approach, would be, for instance, recursively form groups within the domain, and notify users that they are potential members to join those groups.

We developed the Dino Android[27] client to display the imported Facebook profile and the groups formed by the grouping mechanism to the users. Figure 20 (a) shows the application login screen and Figure 20 (b) the Facebook login permission. Figure 21 (a) and (b) display examples of attributes imported from Facebook to Dino.

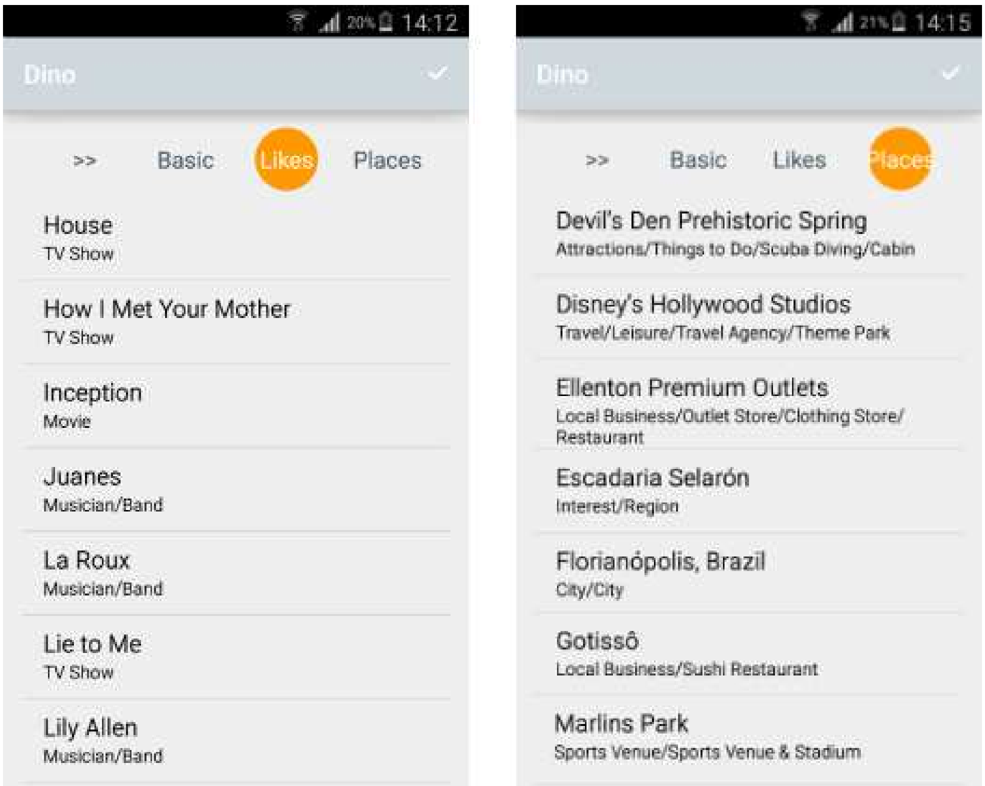
[27] www.android.com

Figure 20. (a) Dino App login screen (b) Facebook login permission



Source: Created by the author.

Figure 21. (a) Likes imported from Facebook (b) Places imported from Facebook



Source: Created by the author.

6 EVALUATION

In this chapter, we present the model evaluation. We divide our evaluation in two parts, we evaluate specifically the grouping mechanism, and we evaluate other aspects of the SSN separately. Section 6.1 details the evaluation methodology followed. Section 6.2 describes the performed experiments. Section 6.3 presents the experiments results and final discussion.

6.1 EVALUATION METHODOLOGY

To evaluate the SSN Model, we follow two approaches. First, to evaluate the grouping mechanism we perform an evaluation to measure precision and recall of the communities' suggestions. Second, to evaluate the main contributions and other aspects of the SSN, we perform an experimental evaluation to assess the relevance of the virtual communities in a controlled environment, measuring the users' perceived sense of community.

6.1.1 GROUPING MECHANISM EVALUATION

In recommender systems research, it is assumed that a recommendation is successful if and only if the recommended item is beneficial, or if and only if the item matches the target user's preferences. Which means, the objective of a recommender system is to generate suggestions that will be accepted by the user, and to filter interesting items (OLMO; GAUDIOSO, 2007). One way to evaluate that is to measure the algorithm's capability to recommend good items (GUNAWARDANA; SHANI, 2009). Therefore, to evaluate the outcome of our algorithm we adopted two commonly used metrics: precision and recall (BUCKLAND; GEY, 1994). In literature, information retrieval and recommendation systems are two areas that mostly employ precision and recall metrics on their evaluations. In the social networking field, we found several works (RAAD; CHBEIR; DIPANDA, 2010; HÖNSCH, 2011; ASABERE et al, 2014; KIM et al., 2014) that also employ precision and recall metrics.

Table 4. Classification of items' output

	Recommended	Not recommended
Relevant	True Positive	False Negative
Not relevant	False Positive	True Negative

Source: Created by the author

Precision measures a recommender algorithm's ability to show only useful items, while recall measures the coverage of useful items achieved, that means, the capacity to obtain the most useful items available. In other words, precision metric answers "how many recommended items are relevant", and recall metric answers "how many relevant items are displayed". There are four possible outputs for an item, as shown in Table 4. An interesting item that is recommended to the user is a true positive (TP), an uninteresting item that is not recommended to the user is a true negative (TN), an interesting item that is not recommended to the user is a false negative (FN), and an uninteresting item that is recommended to the user is a false positive (FP). Those outputs compose precision and recall metrics, respectively seen in Equations 13 and 14 (BUCKLAND; GEY, 1994). Therefore, a more reliable recommender algorithm reduces the number of false negatives in order to achieve high values of recall, and decrease false positives in order to obtain higher precision values.

$$Precision = \frac{tp}{tp + fp} \tag{12}$$

$$Recall = \frac{tp}{tp + fn} \tag{13}$$

We follow an approach remarked by GUNAWARDANA AND SHANI (2009) for evaluating precision and recall for multiple test users. To recognize relevant and irrelevant elements, we ask users to assign a positive or negative rate for a list of groups. HÖNSCH (2011) and ASABERE (2014) compare their recommendation algorithms outcome with randomly generated recommendations. Following this approach, we mixed random groups with genuine matches made by our grouping mechanism. We then verify which groups would have been suggested or not for that given user. We consider true positives relevant suggested groups, false positive irrelevant suggested groups, true negative irrelevant groups not suggested, and false negative relevant groups not suggested. We compute precision and recall curves for each user, and then average the resulting curves over users.

6.1.2 VIRTUAL COMMUNITIES EVALUATION

To evaluate community grouping based on multiple context, we must consider a large amount of users in different contexts to form social communities. To acquire an extent number of profiles and personal information, a suitable method is to import datasets obtained from existing OSNs such as Facebook (HOSSMANN et al., 2011). RAAD; CHBEIR; DIPANDA (2010) combine a profile generator with a profile retriever in an evaluation of a similarity measure between Facebook and LinkedIn profiles.

It is possible to produce hypothetical scenarios for many users to conduct an evaluation within a diversity of contexts. BIANCALANA et al. (2013) present a set of fictitious contexts to users and ask them to judge a restaurant recommendation. The contexts include aspects of transportation method (e.g. by car, by foot, by subway), weather (e.g. raining, sunny), type of meal (e.g. lunch, dinner), and time (e.g. opening and closing hours). The users rate the recommendations as zero (non-significant), one (significant), and two (very significant). Moreover, BOLDRINI et al. (2010) simulate context to test properties of the designed solutions on a larger scale. In short, simulation allows the authors to focus on the social aspects of the evaluation and reduce difficulties such as network congestion and sensor transmission errors. These conditions cannot be guaranteed in real environments, also due to the influence of several external parameters. Another advantage of simulation is the possibility of defining accurately the involved parameters, guaranteeing the repeatability of the experiments.

MARTÍNEZ et al. (2002) and CHIN et al. (2013) perform experiments with similar objectives as ours. MARTÍNEZ et al. (2002) perform an evaluation with 120 students divided in 40 students of three different courses of a university. The case of study was performed using a tool for automatic logs processing of social network analysis, combined with a general qualitative evaluation. Social collaborative aspects among students (e.g. discussions, sharing information, and solving doubts) were analyzed with metrics (e.g. density, degree of centrality, and frequency). CHIN et al. (2013) evaluate a proximity-based social network with 120 people in a conference. They analyze users' behavior by monitoring the social activity of attendees and presenters with a mobile application. They evaluate the relation between encounters based on physical proximity and virtual connections (add as friend) formed.

Considering the aforementioned works, we propose experimental scenarios to evaluate the SSN model. We must evaluate the relevance of the social communities formed. To do so, we employ a measure of sense of virtual community (BLANCHARD, 2007). Sense of virtual community defines members' feelings of membership, identity, belonging, and attachment to a group that interacts primarily through electronic communication. BLANCHARD (2007) demonstrates how sense of community in virtual communities has increased content validity and sensitivity over the traditional measures. Moreover, sense of belonging is a crucial feature for participation in virtual communities because no involvement or participation would occur if it were absent (LIN, 2008). Therefore, we also consider sense of belonging to be an appropriate measure for virtual community relevance evaluation. Lastly, none of the previous mentioned works considers dynamic virtual community as subject of study. Thus, we added some questions to measure the users' sense of the virtual communities' ephemerality.

Our evaluation assesses the relevance of the formed communities for each user. However, we do not consider all determinants factors of successful virtual communities present in the literature; we singly focus on the sense of virtual community. We loosely based our questionnaire on BLANCHARD (2007) and LIN (2008) works, slightly adapting the questions to better fit our experiments (e.g. "Using the virtual community gives me the opportunity to recommend ideas to other virtual community members." was modified to "This virtual community would give me the opportunity to recommend ideas to other members"). Additionally, for simplicity matters for the users' point of view, we standardized the using of the words "community" and "virtual community" to "group". Following, we enumerate the metrics' categories and their respective questionnaire questions:

- SENSE OF VIRTUAL COMMUNITY

Q1: Other members and I would want the same thing from this group.

Q2: I would feel at home in this group.

Q3: It would be very important for me to be a member of this group.

Q4: I would have questions that this group could answer.

- SOCIAL USEFULNESS

Q5: This group would give me the opportunity to recommend ideas to other members.

Q6: This group would help me to form warm relationships with other members.

- SENSE OF BELONGING

Q7: I would enjoy being a member of this group.

- MEMBER LOYALTY

Q8: I believe it would be worthwhile for me to be in this group.

Q9: I would be willing to participate in this group's discussions.

Q10: I would be willing to communicate with other group members.

- EPHEMERALITY

Q11: I believe this group would have a deadline.

Q12: I believe this group would only be relevant for a specific time span.

Q13: I would quit this group whenever I think it would not be relevant for me.

Q14: I believe this group would not depend on the location of its members to exist.

Q15: I believe different people would join and quit this group over time.

Q16: I would quit this group whenever it becomes inactive.

6.2 EVALUATION SETUP

We used the mobile application Dino to perform the proposed evaluation. The client allows us to provide an interface for the users to glimpse what a real SSN application would be. We built a beta testing (PRESSMAN, 2001) environment for the evaluation and users performed a quantitative assessment. The objective is to evaluate possible scenarios, services and functionalities offered by the SSN from a human perspective. We defined two experiments considering a diversity of contexts to analyze the application suitability and effectiveness. For population sampling we employed opportunity sampling (also called accidental sampling or convenience sampling), a non-probabilistic sampling method (KITCHENHAM; PFLEEGER, 2002b), by promoting the research project on social media and asking for participants volunteers who were available and willing to take part.

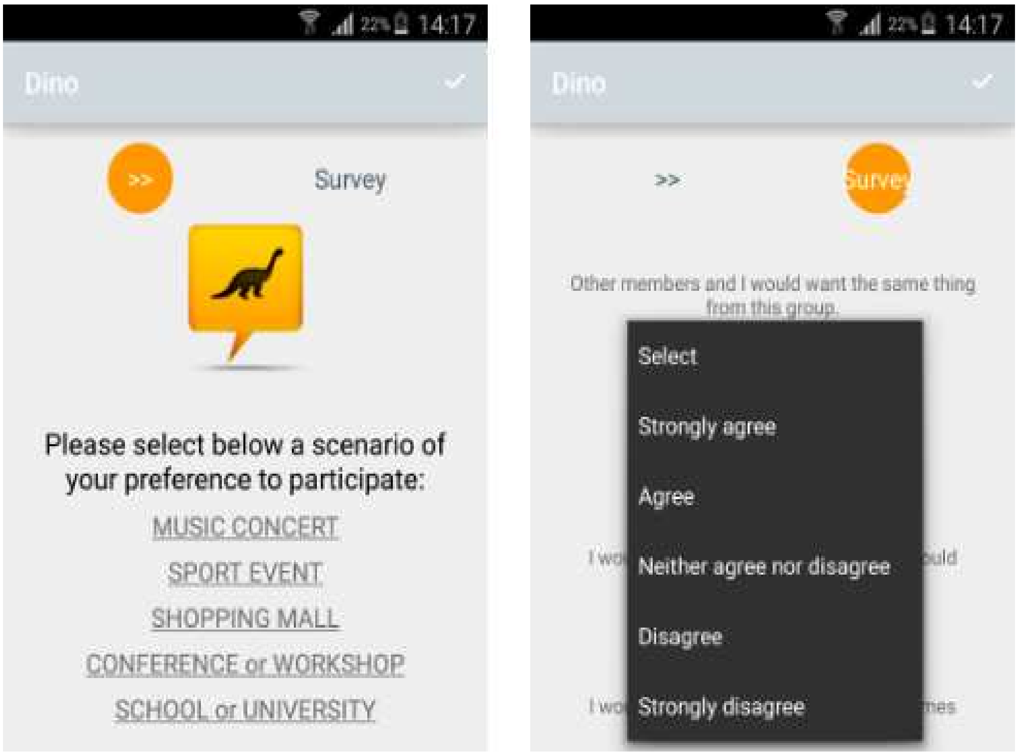
On our first experiment, we present hypothetical scenarios in real-world situations that could employ an SSN application. We demonstrate the applicability of a SSN prototype by describing use cases scenarios in (1) music concert (2) sport event (3) shopping mall (4) conference or workshop (5) school or university. Figure 22 (a) shows the application screenshot in which the user choses one of the possible scenarios. The user then answers a survey considering the chosen scenario. The survey answers follow the Likert scale (LIKERT, 1932) of five degrees: strongly disagree, disagree, neither agree nor disagree, agree and strongly agree. Figure 22 (b) shows the survey answers options. The scenarios are described in the application as following:

1. Music Concert: “Imagine you are at a concert of a band or singer that you like. You find out that you can be a member of a virtual group to interact and communicate with other people that are at the concert. By being a member of this group, you can find your friends from social networks that are also attending the concert. Additionally, you can find information about the concert venue and surroundings, and special contents for the fans attending the concert, like promotions, contests, polls, rewards, souvenirs, etc...”
2. Sport Event: “Imagine that you are watching a match of a team or athlete that you like. You find out that you can be a member of a virtual group to interact and communicate with other people that are watching the game. By being a member of this group, you can find your friends from social networks that are also watching the game. Additionally, you can find special information for who is watching the game at the stadium, statistics about the match and the players, polls, contests, souvenirs, etc...”
3. Shopping Mall: “Imagine that you are at a shopping mall. You find out that you can be a member of a virtual group to interact and communicate with other people that are also at the mall. By being a member of this group, you can find your friends from social networks that are also at the mall. Additionally, you can

find specific contents for mall clients such as additional information about stores and restaurants, comments and ratings from other customers about products and services, interactive maps, discounts, etc...”

4. Conference or Workshop: “Imagine that you are attending a conference or workshop (live or virtually through audio or video). You find out that you can be a member of a virtual group to interact and communicate with other people that are attending the same conference. By being a member of this group, you can find your friends from social networks that are also attending the conference. Additionally, you can find special information about the conference, such as additional information about the talks, presenters and sponsors, polls, etc...”
5. School or University: “Imagine you are a student of a school or university. You find out that you can be a member of a virtual group to interact and communicate with other students. By being a member of this group, you can find your friends from social networks that are students in the same school. Additionally, you can find students with similar interests as you, to create debates, exchange class material, form study groups, etc. You can also find information about classes and professors, campus events, consult the library, etc...”

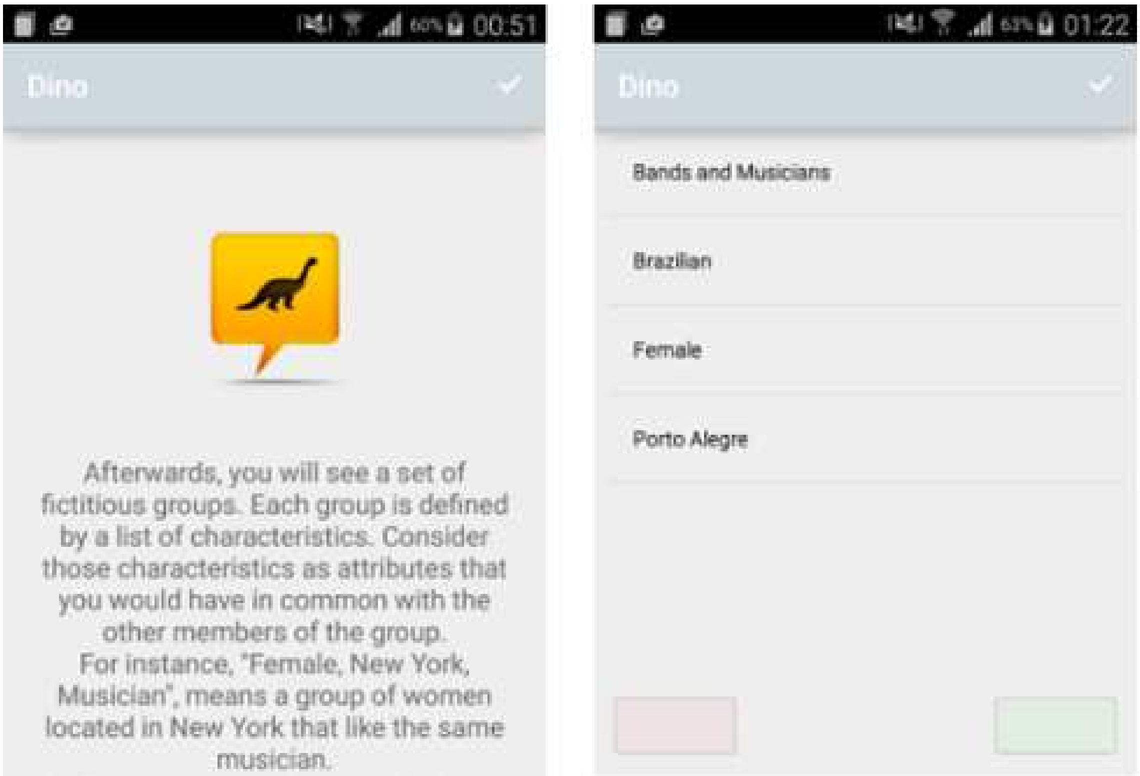
Figure 22. (a) Survey scenarios (b) Survey answer options



Source: Created by the author.

On our second experiment we present groups to the user and ask them either they would or would not join the given group. For user-friendly matters, the groups are displayed as a list of categories. The categories represent the last edge in the SSN Ontology tree. For instance, the category “Bands and Musicians” originates from a Personal Dynamic Interest context, although the entire ontology tree nor any parent classes are displayed for the user. Figure 23 (a) shows the screenshot of the instructions for the second experiment. The complete description is “Afterwards, you will see a set of fictitious groups. Each group is defined by a list of characteristics. Consider those characteristics as attributes that you would have in common with the other members of the group. For instance, 'Female, New York, Musician', means a group of women located in New York that like the same musician. Or 'Technology, Los Angeles, Business' means a group of people located in Los Angeles that have interests in technology and business. Considering your real interests, please tell us which groups you would like to join, hypothetically. To do so, select positive (green), or negative (red) for each group. Keep in mind that not every group would be adequate for you. In that way, if you like the characteristics presented, press GREEN. Otherwise, if you do not feel related to the characteristics of the group, press RED." Figure 23 (b) shows a screenshot of an example of a list of categories of a group, similar to the one mentioned on the instructions.

Figure 23. (a) Instructions for the experiment (b) Example of group.



Source: Created by the author.

To perform the second experiment, we formed groups within the research project volunteers using a 0.8 threshold. Table 5 summarizes the amount of entries for each entity that composes the Facebook profiles collected. Table 6 shows the demographics of the 65 collected profiles regarding gender, age and nationality. Figure 24 displays a graph provided by the Facebook API to control the number of users' access into the app, it shows the total of Facebook logins in the period of the experiments, with a peak of 65 logins in December.

Table 5. Collected entities

Entity	Entries
Profile	65
Language	5
Employment	153
Education	116
Page	3153
Page Category	335
Place	702
City	170
State	49
Country	19

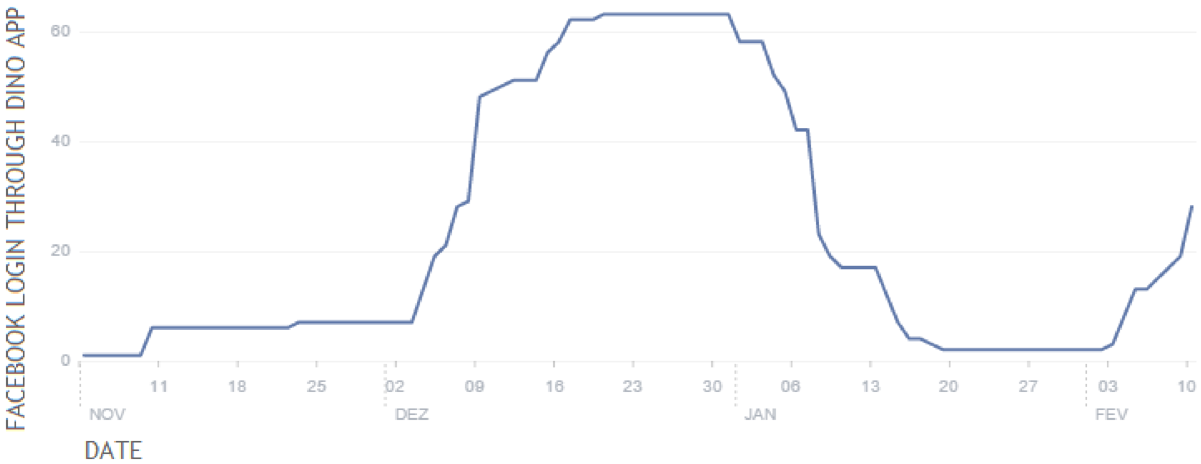
Source: Created by the author.

Table 6. Profile Demographics

Characteristic		Total	Percentage
Gender	Male	32	49%
	Female	33	51%
Age	Under 20 years old	2	3%
	Between 20 and 30 years old	38	59%
	Over 30 years old	25	38%
Nationality	Brazilian	60	92%
	Other	5	8%

Source: Created by the author.

Figure 24. Total of Facebook Logins through Dino App by date



Source: Adapted from Dino App Facebook Analytics.

6.3 EXPERIMENTS RESULTS AND DISCUSSION

The first experiment had 31 participants. Each participant answered 16 questions considering one of the aforementioned scenarios. Table 7 shows the distribution of the chosen scenarios among participants. Figure 25 summarizes the total of answers for each survey question. Figure 26 displays the percentages of answers for each survey question.

Table 7. Number of participants by scenario

Scenario	Participants	Percentage
Music Concert	15	48%
Sport Event	7	23%
Shopping Mall	1	3%
Conference or Workshop	2	6%
School or University	6	20%

Source: Created by the author.

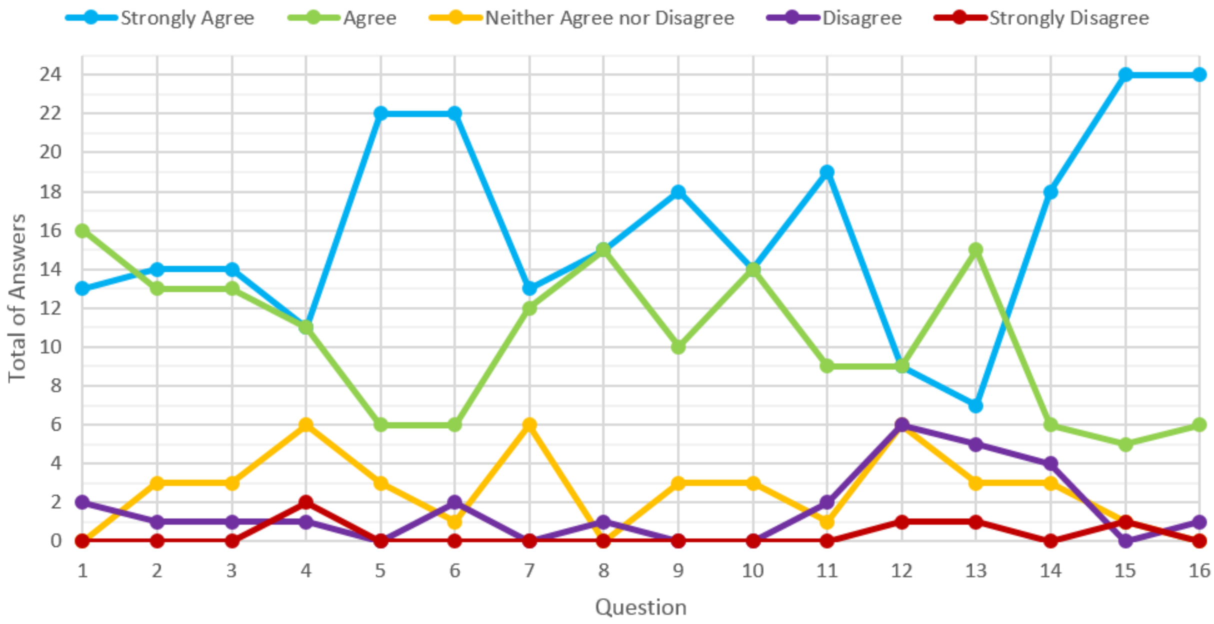
We observe that question 12 had the second lowest “Strongly Agree” (29%) and the highest “Disagree” (19%) percentages. Question 12 asks if the user believes that the group would only be relevant for a specific time span. Therefore, we understand that either people do not clearly see a time frame for the groups, or they might believe that the group would always be relevant. However, Question 11 asks if people believe the group would have a deadline, and only 9.67% answers do not agree, while 90% agree or strongly agree. Therefore, we conclude that people do see a deadline for the group, but they think the group would still be relevant even after the deadline.

Question 13 has the lowest “Strongly Agree” (22%) and the second highest “Disagree” (16%) levels. Question 13 asks if people would quit the group whenever it is no longer relevant for them. Therefore, we understand that either people would not quit the group even if it is not relevant, or they do not believe that the group would stop being relevant for them. By analyzing questions 12 and 13, we believe that people do not see relevance as an ephemeral factor on the proposed scenarios. However, Question 16 had 96% “Strongly Agree” or “Agree” answers. Question 16 asks if people would quit the group whenever it becomes inactive. Therefore, we also conclude that people would rather quit a group that is inactive than a group that is no longer relevant for them.

Questions 4 and 5 form the “Social Usefulness” metric, they had both 90% of “Strongly Agree” or “Agree” answers. Therefore, we conclude that an SSN application would be socially useful for the proposed scenarios. Questions 8, 9, and 10 regard “Member Loyalty”. Considering the three questions together, only 6.45% participants do not agree with the affirmatives. Thus, we conclude that people would have a strong sense of loyalty on the suggested scenarios.

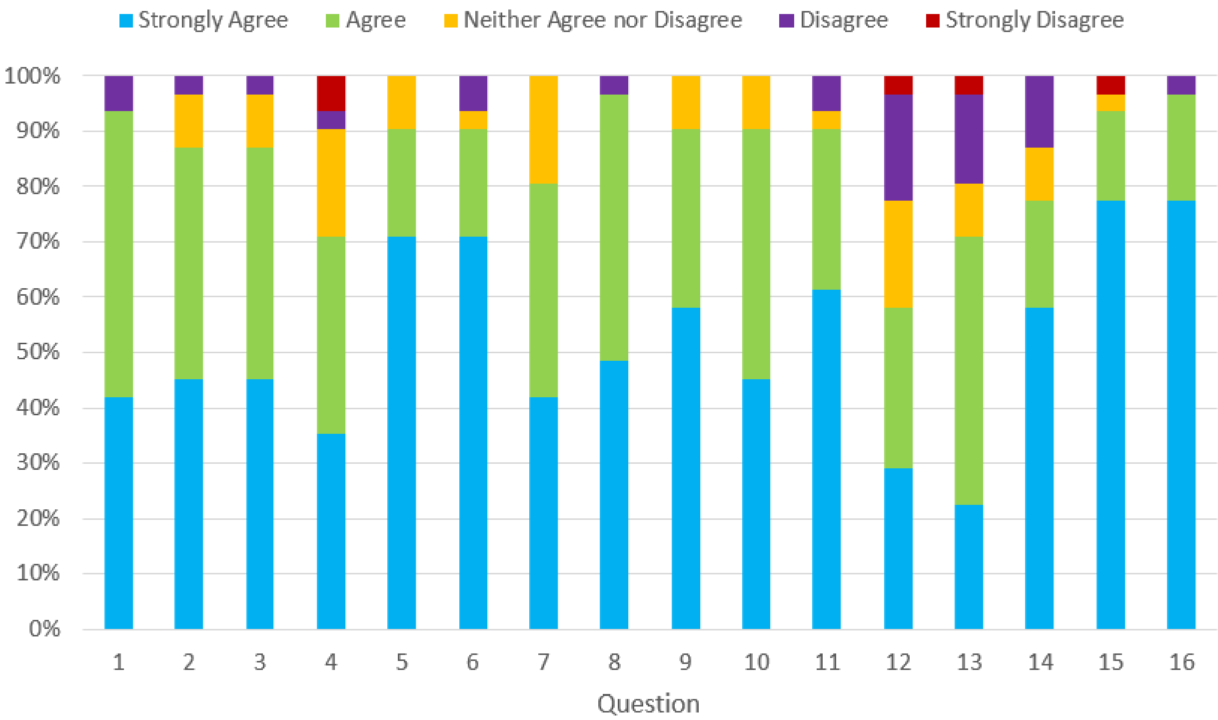
Questions 1 to 4 and 7 evaluate the “Sense of Community” and the “Sense of Belonging” of the users towards the group. The affirmatives had 93%, 87%, 87%, 70%, and 80% of agreement, respectively. The question with the lowest percentile of agreement (70%) asks if people believe that they would have questions that other members of the group could answer. Therefore, 30% of the participants do not believe that other members could answer questions they might have. We believe that this could be for two reasons: (1) users believe that they would not have questions in the context of the given scenario, or (2) they do not fully trust on unknown people's expertise to answer their questions. Despite the percentile of disagreement on question 4, we conclude that people would also have a strong sense of community and belonging on the proposed scenarios.

Figure 25. Total of answers for each question



Source: Created by the author.

Figure 26. Percentages of answers for each question



Source: Created by the author.

The second experiment had 22 participants. Table 8 shows the computed values for TP, FN, FP, TN measures, and precision and recall metrics for each participant. In addition, Table 8 shows the amounts of groups evaluated and genuine generated groups suggestions for each user. However, as seen on Table 8, seven users did not receive any group suggestion made by the grouping mechanism, which invalidates the experiment because we cannot measure precision or recall over those users. We then consider 15 valid experiments.

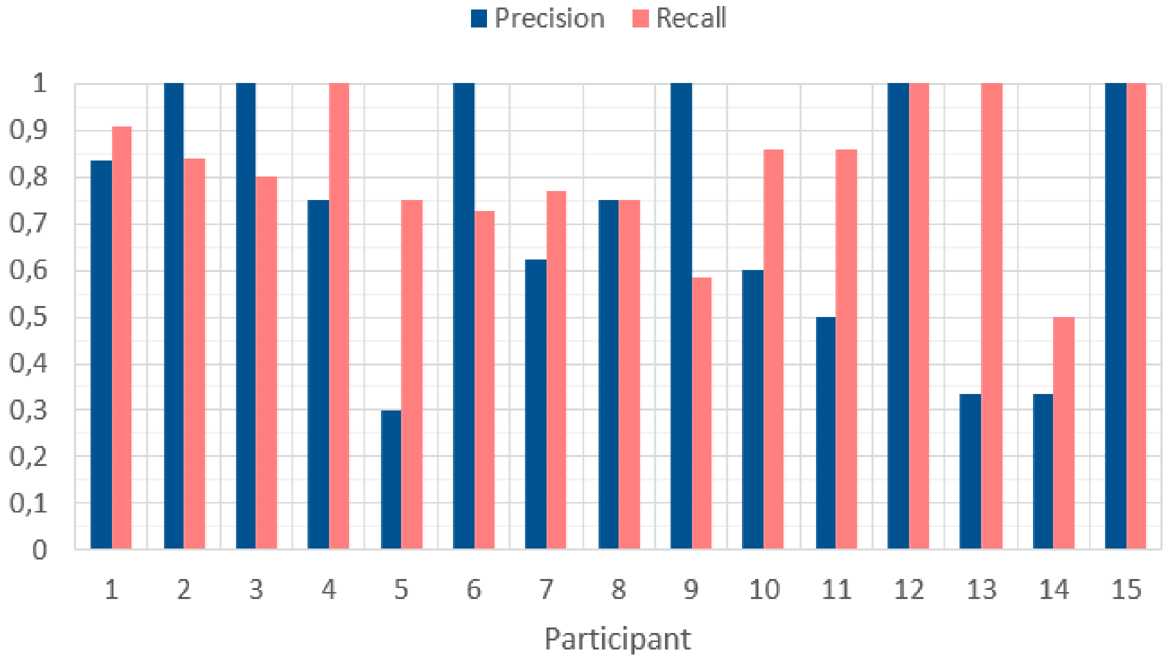
Table 8. TP, FN, FP, TN, precision, and recall computed by participant

Participant	TP	FN	FP	TN	Groups evaluated	Groups suggested	Precision	Recall
1	10	1	2	2	15	12	0.83	0.90
2	21	4	0	0	25	21	1.00	0.84
3	4	1	0	3	8	4	1.00	0.80
4	6	0	2	3	11	8	0.75	1.00
5	3	1	7	5	17	10	0.30	0.75
6	8	3	0	2	13	8	1.00	0.72
7	10	3	6	2	21	16	0.62	0.76
8	3	1	1	4	9	4	0.75	0.75
9	7	5	0	1	13	7	1.00	0.58
10	18	3	12	22	55	30	0.60	0.85
11	6	1	6	7	20	12	0.50	0.85
12	4	0	0	3	7	4	1.00	1.00
13	1	0	2	1	4	4	0.33	1.00
14	1	1	2	2	6	4	0.33	0.50
15	12	0	0	5	18	12	1.00	1.00
16	0	0	0	2	2	0	-	-
17	0	0	0	1	1	0	-	-
18	0	4	0	2	6	0	-	-
19	0	0	0	2	2	0	-	-
20	0	6	0	1	7	0	-	-
21	0	5	0	2	7	0	-	-
22	0	1	0	1	2	0	-	-

Source: Created by the author.

Figure 27 displays precision and recall metrics computed for each valid participant. We calculate an average value of 0.73 and 0.82 for precision and recall, respectively. We observe that only one participant had both precision and recall values under 0.51, which represents 6.6% of the sample. In contrast, precision or recall reached ten times the highest value (1.00), which represents 33% of the sample.

Figure 27. Precision and recall by participant



Source: Created by the author.

Due to the lack of other metrics in our experiments such as f-measure, or comparing precision and recall for different sets of groups, or sets of users, we are incapable to confront our results with other works. However, precision and recall metrics by themselves are able to answer the questions "'how many recommended items are relevant", and "how many relevant items are displayed", respectively. Therefore, we state that, in these experiments, our grouping mechanism was capable to form an average of 73% relevant groups, and our application was capable to add 9% relevant groups, totalizing an average of 82% relevant groups displayed for the users.

Due to the absence of suggested groups for some users, we notice a strong need to expand the experiments with variable thresholds. Varying the threshold would aim to determine a more adequate value based on, for instance, each person's contextual information data coverage. Thus, we suggest further efforts focused on automatic detection of optimal threshold for the grouping mechanism. In sequence to the users' first approval of an SSN application on the proposed scenarios, we recommend experiments with domain-specific focus to evaluate each scenario separately. Besides, we envision the development of a complete application that would be able to support virtual interaction within the formed groups, or export those groups to other social applications.

We judge necessary expressive efforts to employ techniques of social context information acquisition. The lack of standards for manually input data hampers the exploration of the user-based information available over social networks. For instance, we observe that Facebook categories on Facebook Pages are not always consistent with the real-world entity being described on the page. For this reason, sometimes the virtual representation of real-world attributes is distorted, which affects our final goal to reproduce real-world communities in a virtual environment. We also went through difficulties to conceive semantical attributes conversion. We believe that applying better semantic information extraction techniques would help ease this problem.

By improving the semantical information extraction and conversion, it would be possible to explore other social networks and platforms. Many other OSNs, such as LinkedIn[28], Twitter[29], Instagram[30], provide significant information regarding the users' context. Additionally, we point technological limitations to discover some of Facebook data, such as date and time attributes of Facebook posts.

We remark the possibility to enrich contextual information imported into the application, which would directly affect the quality of the formed groups. The model has the capability to receive even more information than what was utilized by the Dino client. Moreover, although the model is able to describe dynamic attributes, we did not manage to collect context information in a dynamic way. It is necessary to expand the model to, for instance, dynamically attribute weights for contexts according to a detected situation that the user encounters.

We asked the participants to say if they would or would not join a group based on their personal interests; however, the groups were formed based on data imported from Facebook only. Thus, it may be possible that Facebook profiles do not reflect people's real interests plentifully. Therefore, we point a remain open question, concerning the mismatch of users' virtual profile with their real interests. In addition, we remark another remain open question, regarding the similarity among the contexts considered to form a group. We noticed that some groups did not have a coherent similarity from a human perspective, which may affect people's judgment when deciding either to join or not the given group.

[28] linkedin.com

[29] twitter.com

[30] instagram.com

7 CONCLUSION

In this work, we propose a model to create and support social communities formed based on context similarities. The SSN model supports social functions such as interacting with other people and sharing contents, and provides a virtual layer of services. People form a virtual community using context information to compose a SSN. A grouping mechanism forms social communities among people that have common interests and share similar context. The SSN model brings the following possibilities: (1) group people with a combination of contexts, (2) represent them in a virtual environment, (3) provide them services, and (4) support social interactions among them.

The main scientific contribution of SSN is the formation of groups based on a combination of multiple contexts. On top of creating a virtual representation of those groups into a spontaneous social network, our model provides a layer of services for fostering the interaction within those groups. The model brings the possibility of creating dynamic virtual communities of users based on a combination of different context, including, location, social network data, activities, domain-specific data, profiles and any other modeled information in the system. We decided to do not approach any sharing functionality due to the expressive amount of commercial applications that provide virtual content exchange.

As an additional scientific contribution, we published a paper (NAVARRO et al., 2015) as product of this thesis. The paper presents the general concepts of the SSN model, and its main contribution, the possibility of creating dynamic social networks based on a combination of multiple contexts-aware data. Besides, in the mentioned work, we compare and discuss related MSN proposals, detail the SSN application model, and describe use case scenarios placed in a university campus.

Our work differs from related proposals in that we do not impose physical boundaries to virtual groups. Differently from MSN proposals found in the literature, we do not restrain communities to a specific location, for instance, friends that often practice a sport on same days but in different locations can generate a suggestion to play together. In this way, we combine a context-aware grouping mechanism with social-aware community services.

We develop a mobile application called Dino, to provide a glimpse of what an SSN based application would be. To evaluate our model we perform two experiments using the developed mobile client. First, we present hypothetical scenarios based on possible real-world SSN applications to measure users' perceived sense of community. The scenarios described are (1) music concert (2) sport event (3) shopping mall (4) conference or workshop (5) school or university. Second, we ask users to consider their real interests to assess our formed groups regarding their relevance as positive or negative. We then measure precision and recall of the groups' suggestions for each user.

Our evaluation depict that dynamic virtual communities formed by a SSN model based application would beneficially improve a social-aware virtual environment. We computed average values of 0.73 and 0.82 for precision and recall, respectively. Therefore, we state that, in these experiments, our grouping mechanism was capable to select 73% relevant groups, and our application was capable to display more 9% relevant groups, totalizing an average of 82% relevant groups for the users. The experiments' results to assess the proposed scenarios ascertain average values of agreement of 84% for sense of community, 80% for sense of belonging, 90% for social usefulness, 92% for member loyalty, and 81% for communities' ephemerality.

We observe a meaningful need to ascertain an optimal threshold for the grouping mechanism. We suggest expanding the experiments to relate variable thresholds to, for instance, people's contextual information coverage, or the dimension of the considered domain. We notice that the more similar the people that compose the domain are, the easily it is to form groups within it. Therefore, in a wider or larger domain, a higher threshold may apply. In addition, we point further efforts into social context information acquisition, semantical extraction and conversion, and extension of the covered social networks and platforms. Employing such techniques would enrich the explored contexts used to form groups.

We suggest further efforts to determine the accuracy of people's virtual profile regarding personal aspects, since we cannot guarantee the truthfulness of the information extracted. Thus, remains open a question concerning the mismatch of users' virtual profile with their real interests. Furthermore, we noticed that some groups did not have coherent attributes from a human perspective, hence, it brings another remain open question regarding the similarity among the contexts considered to form a group. Lastly, we identify a research opportunity to expand the model to, for instance, dynamically attribute weights for contexts according to a detected situation that the user encounters.

REFERENCES

ADOMAVICIUS, G; MOBASHER, B. RICCI, F.; TUZHILIN, A. Context-Aware Recommender Systems. 2011. Association for the Advancement of Artificial Intelligence, pp. 67-80.

AIELLO, L. M.; SCHIFANELLA, R.; STATE, B. Reading the source code of social ties. 2014. In Proceedings of the 2014 ACM conference on Web science, pp. 139-148.

ANEJA N.; GAMBHIR, S. Geo-Social Semantic Profile Matching Algorithm for Dynamic Interests in Ad-hoc Social Network. 2015. IEEE International Conference on Computational Intelligence & Communication Technology, pp. 354-358.

ARNABOLDI, V.; CONTI, M.; DELMASTRO, F. Implementation of CAMEO: a context-aware middleware for opportunistic mobile social networks. 2011. IEEE Int. Symposium World of Wireless, Mobile and Multimedia Networks, IEEE Computer Society, pp. 1-3.

ARNABOLDI, V.; CONTI, M.; DELMASTRO, F. Cameo: a novel context-aware middleware for opportunistic mobile social networks. 2014. Pervasive and Mobile Computing, vol. 11, Elsevier, pp. 148-167.

BAKER, N; ZAFAR, M; MOLTCHANOV, B; KNAPPMEYER, M. Context-Aware Systems and Implications for Future Internet. 2009. Towards the Future Internet, pp. 335-344.

BEACH, A; GARTRELL, M; AKKALA, S.; ELSTON, J. ET AL. WhozThat? evolving an ecosystem for context-aware mobile social networks. August 2008. IEEE Network, vol. 22, no. 4, pp. 50-55.

BELLAVISTA, P.; MONTANARI, R.; DAS, S. Mobile social networking middleware: a survey. August 2013. Pervasive Mobile Computing, vol. 9, no. 4, pp. 437-453.

BIANCALANA C.; GASPARETTI, F. An approach to social recommendation for context-aware mobile services. 2013. ACM Transactions on Intelligent Systems and Technology, vol. 4, no. 1, pp. 1-31.

BLANCHARD, A. L. Developing a Sense of Virtual Community Measure. 2007. Cyberpsychology & Behavior, vol. 10, no. 6, pp. 827-830.

BOLDRINI, C.; CONTI, M.; DELMASTRO, F.; PASSARELLA, A. Context- and social-aware middleware for opportunistic networks. 2010. Journal of Network and Computer Applications, vol. 33, no. 5, pp. 525-541.

BOTTAZZI, D.; MONTANARI, R.; TONINELLI, A. Context- Aware Middleware for Anytime, Anywhere Social Networks. 2007. IEEE Intelligent Systems, Vol. 22, pp. 23-32.

BOUNEFFOUF, D. Situation-aware approach to improve context-based recommender system. 2013.

BOYD, D. AND ELLISON, N. Social network sites: Definition, history, and scholarship. October 2007. Journal of Computer-Mediated Communication, vol. 13, no. 1, pp. 210-230.

BROWN, P.J. The stick-e document: a framework for creating context-aware applications. 1996. Proceedings of the Electronic Publishing, Palo Alto, pp. 259-272.

CHANG, C.; SRIRAMA, S. N.; LING, S. Mobile social network in proximity: taxonomy, approaches and open challenges. 2015 International Journal of Pervasive Computing and Communications, vol. 11, no. 1, pp. 77-101.

CHIN, A.; XU, B.; WANG, H. Who should I add as a friend? A study of friend recommendations using proximity and homophily. 2013. Proceedings of the 4th International Workshop on Modeling Social Media.

CHIN, A.; XU, B.; WANG, H.; CHANG, L. Connecting People through Physical Proximity and Physical Resources at a Conference. 2013. ACM Transactions on Intelligent Systems and Technology, vol. 4, no. 3.

CHIN, A. AND ZHANG, D. Mobile Social Networking: An Innovative Approach. Springer New York. 2014.

CHORLEY, M. J.; WHITAKER, R. M.; ALLEN, S. M. Personality and location-based social networks. 2015. Computers in Human Behavior, vol. 46, pp. 45-56.

COHEN, R. Livewire: Web sites try to make internet dating less creepy. July 2003. Available on <http://asia.reuters.com/newsArticle.jhtml?type=internetNews&storyID=3041934>

COSTA, C. A.; ZAUPA, D.; BARBOSA, J. L. V.; RIGHI, R. D. R.; CAMARGO, J. DAROIT, N.; YAMIN, A. C. A spontaneous social network based on mobile devices. 2014. Social Network Analysis and Mining, vol. 4, no. 1, pp. 158.

COUTAND ET AL. Context-aware group management in mobile environments. 2005. 14th IST Mobile &Wireless Communications Summit Germany, 2005.

DEY, A.K. Context-aware computing: the CyberDesk project. 1998. Proceedings of the AAAI, Spring Symposium on Intelligent Environments, Menlo Park, CA, pp.51–54.

DEY, A. K. Understanding and Using Context, Personal and Ubiquitous Computing. 2001. Special Issue: Situated Interaction and Ubiquitous Computing, vol. 5, no. 1.

DOOLIN, K.; TAYLOR, N.; CROTTY, M.; RODDY, M.; JENNINGS, E.; ROUSSAKI, J.; MCKITTERICK, D. Enhancing Mobile Social Networks with Ambient Intelligence. 2013. Mobile Social Networking: An Innovative Approach, pp. 139-163.

DRIVER C. AND CLARKE, S. An application framework for mobile, context-aware trails. 2008. Pervasive Mobile Computing, vol. 4, pp. 719-736.

ENDSLEY, M. R. Situation Awareness Misconceptions and Misunderstandings. 2015. Journal of Cognitive Engineering and Decision Making, vol. 9, pp. 4-32.

ENDSLEY, M. R. AND JONES, W. Situation awareness. 2013. The Oxford Handbook of Cognitive Engineering, pp. 88-108.

ENDSLEY, M. R. Toward a theory of situation awareness in dynamic systems. 1995. Human Factors, vol. 37, pp. 32-64.

FACEBOOK. 2007. Available on <https://www.facebook.com/notes/facebook/facebook-your-phone/2228532130>

FACEBOOK. 2015a. Available on <https://www.facebook.com/legal/terms/>

FACEBOOK. 2015b. Available on <http://newsroom.fb.com/company-info/>

FOELL, S.; BOESSLING, P.; LINNER, D.; RADUSCH, I.; STEGLICH, S. Self-organizing pervasive online communities. 2007. Eighth International Symposium on Autonomous Decentralized Systems. pp. 403-410.

GARFINKEL, H. Studies in Ethnomethodology. Cambridge, U.K.: Polity, 1994

GRUBER, T. A translation approach to portable ontology specifications. 1993. Knowledge Acquisition, vol. 5, pp. 199-220.

HECKMANN, D. Gumo – the general user model ontology. 2005.

HECKMANN, D. Ubiquitous user modeling. 2006.

HECKMANN, D. UbisWorld. 2015. Available on <http://ubisworld.org/ontology/>

HOSSMANN, T.; LEGENDRE, F.; NOMIKOS, G.; SPYROPOULOS, T. Stumbl: Using Facebook to collect rich datasets for opportunistic networking research. 2011. IEEE International Symposium on a World of Wireless, Mobile and Multimedia Networks, pp. 1-6.

HU ET AL. Vita: A Crowdsensing-Oriented Mobile Cyber Physical System. 2013. IEEE Transactions on Emerging Topics in Computing, vol. 1, no. 1, pp. 148-65.

HU ET AL. Multidimensional Context-Aware Social Network Architecture for Mobile Crowdsensing. 2014. IEEE Communications Magazine, vol. 52, pp. 78-87.

JABEUR, N.; ZEADALLY, S.; SAYED, B. Mobile social networking applications. 2013. Communications of the ACM, vol. 56, no. 3, pp. 71-79.

JANG, H.; CHOE, S. P.; SONG J. Exploring Serendipitous Social Networks: Sharing Immediate Situations among Unacquainted Individuals. 2011. In Proceedings of MobileHCI, pp. 513-516.

JOHN, A.; KLEMM, R; MANI, A.; SELIGMANN, D. HERMES: A Platform for Context-Aware Enterprise Communication. 2006. In Proceedings of PerCom Workshops, pp. 62-69.

JONES, Q. Virtual-communities, virtual settlements & cyber-archaeology: A theoretical outline. 1997. J. Comput. Mediated Commun., vol. 3, no. 3, pp. 35-49.

KIM, M.; JUNG, Y; LEE, J.; KIM, M. Context-Based Cooperation Architecture for Ubiquitous Environment. 2006. LNCS, Ubiquitous Computing Systems, vol. 4239, pp. 171-182.

KIRKPATRICK, D. The Facebook effect: The inside story of the company that is connecting the world. 2010. New York: Simon and Schuster.

KITCHENHAM, B. A. Procedures for Performing Systematic Reviews. 2004. Departament of Computer Science, Keele University.

KITCHENHAM, B. A. AND PFLEEGER, S. L. Principles of survey research: part 3: constructing a survey instrument. 2002a. ACM SIGSOFT Software Engineering Notes, vol. 27, no.2, pp. 20-24.

KITCHENHAM, B. A. AND PFLEEGER, S. L. Principles of survey research: part 5: populations and samples. 2002b. ACM SIGSOFT Software Engineering Notes vol. 27, no.5, pp. 17-20.

KITCHENHAM, B A., ET AL. Preliminary guidelines for empirical research in software engineering. 2002. Software Engineering, IEEE Transactions, vol. 28, no. 8, pp. 721-734.

KUMAR M., ET AL. PICO: A Middleware Framework for Pervasive Computing. 2003. IEEE Pervasive Computing, vol. 2, no. 3.

LI, J.; WANG, H.; KHAN, S. A semantics-based approach to large-scale mobile social networking. 2011. Mobile Networks and Applications, vol. 17, no. 2, pp. 192-205.

LIKERT, R. A Technique for the Measurement of Attitudes. 1932. Archives of Psychology 140, pp. 1-55.

LIMA, C.; GOMES, D.; AGUIAR, R. Pervasive CSCW for smart spaces communities. March 2012. IEEE International Conference on Pervasive Computing and Communications Workshops, pp. 118-123.

LIN, H. Determinants of successful virtual communities: Contributions from system characteristics and social factors. 2008. Information & Management, vol. 45, pp. 522-527.

LIU, Q.; MA, H.; CHEN, E.; XIONG, H. A Survey of Context-Aware Mobile Recommendations. 2013. International Journal of Information Technology & Decision Making, vol. 12, no. 1, pp. 139-172.

LUBKE, R; SCHUSTER, D; SCHILL, A. Mobilisgroups: Location-based group formation in mobile social networks. 2011. Second IEEE Workshop on Pervasive Collaboration and Social Networking, pp. 502-507.

MAKRIS, P.; SKOUTAS, D. N.; SKIANIS, C. A Survey on Context-Aware Mobile and Wireless Networking: On Networking and Computing Environments' Integration. 2014. IEEE Communications Surveys & Tutorials, vol. 15, no 1.

MARWICK, A. I'm a lot more interesting than a Friendster profile: Identity presentation, authenticity, and power in social networking services. October 2005. Internet Research 6.0, Chicago, IL.

MCPHERSON, M.; SMITH-LOVIN, L.; COOK, J.M. 2001. Birds of a feather: Homophily in social networks. Annual review of sociology, vol. 27, pp. 415-444.

MEYER, E.M.; WICHMANN, D.; BÜSCH, H.; BOLL, S. Location-based mapping services to support collaboration in spatially distributed workgroups. 2008. 4th International Conference on Collaborative Computing: Networking, Applications and Worksharing.

NAVARRO, N. A. B.; COSTA, C. A. ; BARBOSA, J. L. V. ; RIGHI, R. R. A Context-aware Spontaneous Mobile Social Network. 2015. Proceedings of 2th IEEE International Conference on Ubiquitous Intelligence and Computing (UIC 2015), pp. 85-92.

NEJMA, G. B; ROOSE, P.; DALMAU, M.; GENSEL, J.; GHORBALI, M. A. Taldea a Spontaneous Community-aware Application in Pervasive Environment. 2014. International conference on selected topics in Mobile and Wireless Networking, vol. 40, pp. 123-128.

NEWMAN, M. AND GIRVAN, M. Finding and evaluating community structure in networks. 2004. Physical review, vol. 69, no. 2, pp. 1-16.

ORLANDI, F.; BRESLIN, J.; PASSANT, A. Aggregated, Interoperable and Multi-Domain User Profiles for the Social Web. 2012. Proceedings of the 8th International Conference on Semantic Systems, pp. 41-48.

PAUL, T.; FAMULARI, A.; STRUFE, T. A survey on decentralized Online Social Networks. 2014. Computer Networks, vol. 75, pp. 437-452.

PARAMESWARAN, M.; WHINSTON, A. B. Social Computing: An Overview. 2007. Communications of the Association for Information Systems, vol. 19, pp. 6-30.

PREECE, J. Online Communities: Designing Usability and Supporting Sociability. New York: Wiley, 2000.

PRESSMAN, R. S. Software Engineering: A Practitioner's Approach (5th ed.). 2001. McGraw-Hill Higher Education.

RAAD, E.; R. CHBEIR, AND A. DIPANDA. User Profile Matching in Social Networks. 2010. 13th International Conference on Network-Based Information Systems, pp. 297-304.

SATYANARAYANAN, M. Pervasive computing: vision and challenges. 2001. IEEE Personal Communications, vol. 8, no. 4, pp. 10-17.

SCHILIT, B. N. AND MARVIN, M. T. Disseminating active map information to mobile hosts. 1994. IEEE Network, vol. 8, no. 5, pp. 22-32.

SCHUSTER, D.; A. ROSI, M. MAMEI, T. SPRINGER, M. ENDLER; F. ZAMBONELLI. Pervasive social context: taxonomy and survey. 2013. ACM Transactions on Intelligent Systems and Technology, vol. 4, no. 3.

SCHUSTER, D; SPRINGER, T; SCHILL, A. Service-based Development of Mobile Real-time Collaboration Applications for Social Networks. 2010. First International Workshop on Communication, Collaboration and Social Networking in Pervasive Computing Environments (PerCol), Mannheim, Germany.

SUNDARAM, H.; LIN, Y.; CHOUDHURY, M.; KELLIHER A. Understanding Community Dynamics in Online Social Networks. 2012. IEEE Signal Process. Magazine, pp. 33-40.

VASTARDIS, N AND YANG, K. Mobile social networks: architectures, social properties, and key research challenges. 2013. IEEE Communications Surveys & Tutorials, vol. 15, no. 3, pp. 1355-1371.

WANG, Z.; ZHOU X.; YU Z.; WANG H.; NI, H. Quantitative evaluation of group user experience in smart spaces. 2010. Cybernetics and Systems, vol. 41, no 2.

WANT, R.; HOPPER, A.; FALCAO, V; GIBBONS, J. The active badge location system. 1992. ACM Transactions on Information Systems, vol. 10, no. 1, pp. 91-102.

WEISER, M. The computer for the 21st century. 1991. Scientific American, vol. 265, no. 3 pp. 94-104.

WEIßENBERG, N.; GARTMANN, R.; VOISARD, A. An ontology-based approach to personalized situation-aware mobile service supply. 2006. Geoinformatica, vol. 10, no. 1, pp. 55-90.

YANG, K.; CHENG, X.; HU, L.; ZHANG, J. Mobile social networks: state-of-the-art and a new vision. 2012. International Journal of Communication Systems, vol. 25, pp. 1245-1259.

ZHANG, D.; YU, Z.; GUO, B.; WANG, Z. Exploiting Personal and Community Context in Mobile Social Networks. 2013. Mobile Social Networking: An Innovative Approach, pp. 109-138.

ZHENG, Y. Location-based social networks: users. 2011. Computing with Spatial Trajectories, pp. 243-276.