Chapter 4
Social Behavior in Mobile Social Networks: Characterizing Links, Roles, and Communities

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Abstract Mobile social networks are enabled by the emergence of mobile and ubiquitous applications, providing social networking and social media functionalities in diverse contexts. This chapter focuses on social behavior in mobile social networks: We first discuss different aspects of mobile social networks. After that, we briefly describe exemplary systems. Finally, we summarize recent real-world analysis results, especially focusing on links and contacts between individuals, characterization of their roles, and dynamics of communities in mobile social networks.

4.1 Introduction

Mobile social networks are usually created using pervasive and ubiquitous applications. In this way, mobile social systems help to bridge the gap between physical and online worlds, utilizing context awareness, pervasive computing, distributed computing, and sensor networks.

Mobile devices, such as smartphones or RFID tags coupled with appropriate ubiquitous and social applications, enable an integrated approach for both physical and digital social interactions. In that way, mobile social networking specifically includes networking options that are only possible on mobile and ubiquitous devices. It is important that mobile social networks are not restricted to networks provided by smartphone technology. For example, an RFID sensor network is one prominent kind of mobile social network that enables the capture, analysis, and processing of offline interactions in order to support social networking and provide sophisticated social services in ubiquitous environments.

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This chapter describes social behavior in such mobile social networks. We focus on different aspects in mobile social networks, and discuss its implementation. With regard to this, we also briefly describe exemplary systems in real-world application contexts: We briefly discuss the Conferator (Atzmueller et al. 2011a) and MyGroup (Atzmueller et al. 2012a) systems for supporting social networking in conferencing and workgroup contexts. Both systems apply active RFID technology that allows us to detect real-world face-to-face contacts, i.e., offline contacts in addition to contacts in (online) social networks. In this context, we summarize a number of exemplary analysis results of social behavior in mobile social networks, focusing on the characterization of links, roles, and communities.

The rest of the chapter is structured as follows. The next section provides an overview on social behavior in mobile social networks, focusing both on the social and the behavioral aspect. After that, we briefly summarize exemplary systems enabling mobile social networks. The following section discusses analysis results in the application context of the Conferator and MyGroup systems. Finally, we conclude with a summary and outlook on future work.

4.2 Overview

In this section, we briefly provide an overview on mobile social networks (and corresponding) systems, and sketch analysis options for social behavior in such networks. A detailed discussion of these aspects is provided in the subsequent sections. First, we start with a brief introduction to social networks and social media.

4.2.1 Social Networks and Social Media

Social networks and social media are key concepts for the analysis of mobile social networks. From a technical perspective, social networks typically consist of a set of actors (nodes) connected by links (edges). Usually, these relations are modeled as a graph. For example, we could consider friendship relationships or the "Follower" relationship in Twitter. Extensions consider multiple types of connections (links or relations) modeling the network as an (extended) hypergraph. From an analytic point of view, we can then analyze the networks using a number of techniques from the area of social network analysis (SNA) (Wasserman 1994).

With regard to social media, Kaplan and Haenlein define social media as a set of internet-based applications that apply principles of the Web 2.0 (Kaplan and Haenlein 2010). In this context, user-generated content plays a prominent role, that is, content being produced and shared by users online. In this chapter, we adopt a similarly intuitive definition, and consider social media as Internet-based systems and services in the ubiquitous Web that use and provide all kinds of social data of human interaction and communication. Both social media and mobile devices play an important role for connecting people through the social media artifacts. Therefore, we especially focus on social media that are being enabled by social mobile devices.

This also includes data from sensor networks, as long as the data is created by real users. Essentially, mobile social networks are enabled by mobile devices; however, we do not constrain these to just networks on mobile, but include special kinds of networks and applications that are specifically created by mobile devices.

4.2.2 Mobile Social Networks

In this chapter, we aim to sketch a more comprehensive view on mobile social networks, in contrast to earlier work (e.g., Humphreys 2008) that mainly considered the social network on the mobile, i.e., the mobile device as just another technical device for accessing the social network. We specifically include networking options that are only possible on mobile and ubiquitous devices. This includes, for example, sensor networks, and ubiquitous computational systems enabled by RFID sensor networks as one prominent kind of mobile social network.

For the characteristics of mobile social networks, we therefore consider different devices which enable systems utilizing such networks. Basically, these include all devices for connecting people, for example, mobile phones, and RFID or Bluetooth tags. Specific studies for these include those using cell phones (Miluzzo et al. 2008) and Bluetooth-enabled devices and sociometric badges (cf., Chin et al. 2012; Eagle and Pentland 2006; Zhuang et al. 2012), as well as passive and active RFID tags, e.g., the proximity tags developed by the SocioPatterns consortium (http://www.sociopatterns.org), (e.g., Alani et al. 2009; Barrat et al. 2010). We describe these in more detail below; we especially focus on these sensors because they are utilized in the exemplary Conferator and MyGroup systems also described below. These systems provide attractive technical options for analyzing social behavior in mobile social networks: compared to the other discussed technologies, the active proximity tags are able to detect "real" contacts, that is, real face-to-face contacts between individuals. If the tags are worn on the front of the body, proximity of two tags indicates a face-to-face contact of the actors. In the analysis section below, we will consider exemplary analysis results in the context of such networks. In contrast, many technologies implementing mobile social networks, e.g., based on Bluetooth, mainly consider the "co-location" of the contacts. In an offline scenario, a network can then be created, for example, using frequent encounters – however, only as a proxy for contacts.

4.2.3 Analysis of Social Behavior in Mobile Social Networks

Mobile social networks are often created during certain events, for example, during conferences, at work, or other group-based activities. During a conference, for example, social contacts form an essential part of the experience of the participants. In general, the term "networking" is used for describing the inherent processes in such interactions. Typically, there are different (implicit and explicit) communities present at such events, defined according to interests or membership to certain tracks or special interest groups. In order to enhance the participating experience, ubiquitous computing approaches, e.g., based on RFID-tokens, can provide dynamic adaptation options. Mobile social networks can then be utilized, for example, for recommendations, or explanations of the current user context.

In the following, we focus on the analysis of key actors, roles, and communities. For the analysis, we can consider the static and dynamic behavior in mobile social networks. For the static behavior, we can simply analyze the network structure and derive basic statistics and characteristics from these. As an overall summary, such an analysis usually provides first insights into the link structure and behavioral characteristics. Different network types, for example, can then be distinguished by the diameter, contact distribution, degree distribution, or mean connectivity of the contained nodes. Identifying different "roles" of nodes, and finding so called "key actors", has attracted a lot of attention, ranging from different measures of centrality (cf., Brandes and Erlebach 2005) to the exploration of topological graph properties (Gaertler 2004; Wongchokprasitti et al. 2010) or structural neighborhood similarities (Lerner 2005). For an analysis of the dynamic behavior, we can consider how the behavior changes and evolves during the event, i.e., the life cycle of the mobile social network. We can analyze time-based slices of the networks, for example, that is, snapshots of the network constructed using different time-thresholds for constructing the edges.

The analysis of communities intuitively considers densely connected subgroups of actors, represented as nodes in the social network. While there exist different definitions of communities, the above definition includes the core of most – focusing on the density of the connections within the community (Atzmueller and Mitzlaff 2011; Fortunato and Castellano 2007; Girvan and Newman 2002; Lancichinetti and Fortunato 2009; Newman 2004). In general, usually not only the density within the community is assessed, but the connection density of the community is compared to the density of the rest of the network (Newman 2004). Then, cuts between communities are established in such a way as to maximize the community evaluation function. For community-based roles, a prominent metric measures how much a node connects different communities (cf., Scripps et al. 2007; Chou and Suzuki 2010). It can be based on initially given community structures or on a probabilistic model.

Furthermore, the analysis of links within contact networks can be analyzed on a static or dynamic level, for example, considering link prediction (Liben-Nowell and Kleinberg 2003; Murata and Moriyasu 2007) on new or recurring contacts, their duration, and points in time (Scholz et al. 2012). This includes both static and dynamic properties of the social (contact) network.

4.3 Systems Enabling Mobile Social Networks

With regard to the analysis of mobile social networks, there have been several approaches. For example, Hui et al. (2005) describe an application using Bluetooth-based modules for collecting mobility patterns of conference participants.

Furthermore, Eagle and Pentland (2006) present an approach for collecting proximity and location information using Bluetooth-enabled mobile phones. Cattuto et al. (2010) applied proximity sensing in the Sociopatterns project. Isella et al. (2011a) conducted further experiments on a variety of contact networks obtained via RFID technology. In addition, Alani and colleagues, e.g., (Alani et al. 2009), also added contact information from social online networks in the live social semantics experiments. In Barrat et al. (2010), the authors analyze social dynamics of conferences focusing on the social activity of conference participants in those experiments. They analyze, for example, their activity in social Web platforms such as Facebook, Twitter, and other social media, together with status and their research seniority. These experiments have also extended their focus from conferences to schools (Stehle et al. 2011) and hospitals (Isella et al. 2011b) using the SocioPatterns proximity tags. Chin et al. present mechanisms using WLAN and RFID positioning, e.g., (Chin et al. 2012; Zhuang et al. 2012) for their Find & Connect system. The system aims at connecting conference participants using location-based proximity as a proxy for face-to-face encounters and online social networks. Encounters based on the location can be estimated for constructing the mobile social networks, which enable flexible support of participants at conferences using localization and online network techniques.

The Conferator system (http://www.conferator.org), a social conference guidance system, uses the same technical basis (RFID tokens with proximity sensing) as the Sociopatterns project for connecting people. Essentially, Conferator and MyGroup – a similar system for working groups – are two applications (Atzmueller et al. 2012a; Atzmueller et al. 2011a) using social media for collective intelligence. Conferator offers conference participants the option to organize and manage their social contacts during conferences. For this purpose, active SocioPattern RFID tags are applied that allow to localize participants and to collect their face-to-face contacts. For these, the system allows the setup of a complete profile, the management of their own social contacts, social networking to other participants, and the management and personalization of the conference schedule. A similar application, MyGroup (Atzmueller et al. 2012), allows the support of social communication in the context of working groups using social-interaction-awareness by utilizing the same technology.

Conferator has been applied at a number of conferences, for example at the LWA 2010, LWA 2011, and LWA 2012 conferences of the German association of computer science, and at the ACM Hypertext 2011 conference. MyGroup is continuously running in the Knowledge and Data Engineering research group at the University of Kassel, and has also been applied at a number of different events, e.g., at a software development code camp to enhance social interactions and communication in developing software. The applied data mining methods are based on the community mining and key actor analysis techniques described above.

Using the SocioPatterns proximity tags, the system is able to detect proximity contacts. Due to the technical ability of the tags to detect contacts between each other, Conferator detects face-to-face contacts between actors, if the tags are worn on the front of the body. Therefore, in contrast to other approaches that apply passive RFID, Bluetooth, or WLAN, the active proximity tags allow a relatively accurate detection of the location of participants and of their face-to-face contacts for constructing mobile social networks.

4.4 Analysis of Mobile Social Behavior

This section focuses on social behavior in mobile social networks, and describes analysis options on different levels: It summarizes specific methods and techniques that can be used to characterize user and social behavior, for role mining and characterization, as well as dynamic community identification.

In the following, we primarily focus on the analysis of social behavior in mobile social networks, and include exemplary results obtained by the analysis of networks of the Conferator and MyGroup systems at different events.

For the static analysis, we mainly include common methods of social network analysis, providing overview statistics and centrality measures in the contact graph of the respective mobile networks. Furthermore, these can also be extended to a time-based analysis, considering different contact lengths of these networks. This bridges the path to more dynamic analysis, concerning the evolution of the networks. We consider individual behavior with regard to role characterization and provide examples of role patterns, before we describe an analysis of social behavior using link prediction methods. Furthermore, we discuss community mining, and provide examples of different community characterizations.

4.4.1 Characterization of Key Players

In social networks, key players are actors that are important for the network in terms of connectivity, number of contacts, and the paths that are passing through the corresponding node. There is a broad range of applications concerning the identification and characterization of key players. It can be applied for prestige and reputation mining, for identifying hubs in the network and for social monitoring. The assessment can happen on different layers. We can consider the network as a whole for discovering individual roles (Wasserman 1994). Additionally, we can consider roles in specific communities (Gaertler 2004). Finally, descriptive pattern mining and characterization can be applied for both layers, (e.g., Atzmueller et al. 2011b; Atzmueller and Mitzlaff 2011; Atzmueller and Puppe 2008; Macek et al. 2012).

For the first case, standard social network analysis (SNA) methods can be applied for analyzing the complete network structure (Wasserman 1994), for example for determining the mean path length between nodes, or for discovering the diameter of the network. Additionally, on the level of the whole network we can determine different centrality measures, in order to identify important nodes or hubs (Atzmueller et al. 2012b; Wasserman 1994). Examples are given by the degree centrality as the

Table 4.1 Exemplary results of characterizing non-organizers and PhD students at the LWA 2010 conference (Atzmueller et al. 2012b) using different centrality measures. The table shows the lift of the pattern comparing the fraction of non-organizers and PhD students covered by the pattern p compared to the fraction of the whole dataset, the size of the pattern extension (number of described non-organizers/PhD students), and the description itself. *Clo*, *eig*, *deg*, *bet*, and *str* denote the closeness, eigenvector, degree, betweenness, and weighted degree centralities, respectively with the values *low, medium, high*

Target	#	Lift	p	Size	Description
Non-organizer	1	1.06	0.88	51	*clo* = {*low*; *medium*}
	2	1.05	0.87	61	*eig** = {*low*; *medium*}
	3	1.04	0.86	59	*deg* = {*low*; *medium*}
	4	1.10	0.92	12	*clo* = {*low*; *medium*} AND *deg* = {*high*; *medium*}
	5	1.12	0.93	30	*clo* = {*high*; *low*} AND *eig** = {*low*; *medium*}
PhD-student	1	1.07	0.54	59	*bet* = {*high*; *low*}
	2	1.07	0.54	48	*str* = {*high*; *low*}
	3	1.14	0.58	26	*deg* = *high*
	4	1.31	0.67	12	*bet* = {*high*; *low*} AND *eig** = *high*
	5	1.38	0.70	20	*deg* = *high* AND *bet* = {*high*; *low*}
	6	1.58	0.80	10	*deg* = *high* AND *bet* = {*high*; *low*} AND *eig** = {*high*; *low*}

number of connections to the neighbors of the node, the betweenness centrality as the number of shortest paths of all node pairs that go through a specific node, or the closeness centrality that considers the length of these shortest paths. For the degree and betweenness centralities, high values indicate a higher importance, while the reverse is true for the closeness centrality (Wasserman 1994).

As an example, we can consider the contact network of the LWA 2010 conference that was obtained using the Conferator system (Atzmueller et al. 2012a, 2011a). In the network, we can observe higher centrality values for professors compared to other groups, for example, post-docs and students. An exception is given by the betweenness centrality, for which the post-docs showed the highest scores (cf. Atzmueller et al. 2012b). In these results, these findings indicate the potential influence in hierarchical relationships, for which the post-docs are contained in many shortest paths between the participants, and thus seem to have a very important function as bridges.

For a more detailed analysis, Table 4.1 summarizes exemplary analysis results focusing on the characterization of different status roles given a set of network properties (cf. Atzmueller et al. 2012b). Here, we focus on the application of descriptive pattern mining (Atzmueller et al. 2011b, 2012), that is, in identifying certain subgroups that are exceptional with respect to a certain property of interest. In our case, this property is given by a high share of a certain role, for example, “non-organizer” and “PhD student”. We observe, for example, that extreme values, i.e., sets of high and low centrality values, are also very significant for distinguishing PhD students. As expected, the combination with other strong influence factors increases the precision of the patterns (indicated by the lift parameter). The most descriptive factors for the non-organizer role are given by the closeness, eigenvalue centrality, and the

Table 4.2 Exemplary role influence patterns (Scholz et al. 2012) for the Hypertext 2011 conference measuring the mean duration of recurring contacts. The column "Lift" shows the relative increase of the mean of the subgroup described by the factors in the "Description" column compared to the mean of all attendees

#	Lift	Mean	Size	Description
1	2.10	5,944.17	6	PhD AND low affiliation
2	1.52	4,297.15	26	Low affiliation
3	1.09	3,089.00	6	Session chair AND professor
4	1.08	3,038.67	21	PhD candidate
5	1.06	3,003.93	14	PhD
6	0.87	2,461.25	8	Session chair
7	0.82	2,326.18	11	Professor

degree, for which lower values than those of the organizers are measured. However, if we consider combinations of factors, we observe, that there are subgroups with regard to the non-organizer role, for which extreme values, e.g., the closeness together with the eigenvalue centrality, yield a significant increase in characterization power.

4.4.2 Characterizing Roles and Links

A related analysis to the identification of key players and according "status" roles is the characteristic behavior when establishing links. This is an analysis relating to link prediction, i.e., the prediction of new links between nodes in a network. Fundamental work in this area has been done by Liben-Nowell and Kleinberg (2003), considering standard network proximity measures, which has also been extended to weighted variants (Murata and Moriyasu 2007).

For analyzing influence factors for link prediction in mobile social networks, we consider the prediction of new and recurring links. In the following, we specifically consider human contact networks obtained using the Conferator system, and summarize results concerning the analysis of contacts patterns in those social networks, and their underlying mechanisms (cf. Scholz et al. 2012). Homophily (Rosvall and Bergstrom 2007), for example, is a classic topic of social network analysis. Similar to the RFID-based setting, Eagle and Pentland (2006) and Zhou et al. (2009) presented an analysis of proximity information collected by Bluetooth-based devices, similar to Xu et al. (2011), relating this to online social networks.

Table 4.2 shows exemplary results (cf. Scholz et al. 2012) of a descriptive link prediction analysis at the Hypertext 2011 conference in the form of characteristic patterns (Atzmueller et al. 2009; Atzmueller and Puppe 2008) that describe certain subgroups of the conference participants. The table shows combinations of influence/role factors that are significantly correlated with the duration of recurring contacts at the conference. In the table, we observe, for example, that people with a low affiliation, i.e., participants that are new to the conference, are still very active after the first day, i.e., on day 2 or 3 of the conference. Furthermore, being a session chair and being a professor increases the mean duration of contacts by 10 %, while considering the single factors separately decreases the duration (by 13 % and by 18 % respectively).

4.4.3 Characterization of Communities and Roles

Community mining (Lancichinetti and Fortunato 2009; Leskovec et al. 2010; Newman 2004; Newman and Girvan 2004) in social networks aims at discovering and analyzing (cohesive) subgroups, clusters, or communities that are "densely" connected with each other in a network. Standard techniques for the mining of communities include graph-based approaches (Girvan and Newman 2002), clustering according to features of the nodes, or pattern-mining techniques for optimizing a community evaluation function (Atzmueller and Mitzlaff 2011). The core idea of the evaluation function is to apply an objective evaluation criterion; for example, the number of connections within the community compared to the statistically "expected" number based on all available connections in the network, and to prefer those communities that optimize the evaluation function locally (Atzmueller and Mitzlaff 2011), or globally (e.g., Girvan and Newman 2002; Lancichinetti and Fortunato 2009).

In the context of mobile social networks, the discovered communities can then be applied, for example, for recommendations (Boratto et al. 2009; Gargi et al. 2011; Farzan and Brusilovsky 2007) or for personalization of intelligent systems (Boratto et al. 2009; Farzan and Brusilovsky 2007; Wongchokprasitti et al. 2010). In such cases, the community assignment can be made explicit, or the information about other members of the community can be used implicitly for the adaptation of the application. We focus on patterns characterizing specific community-oriented roles (Scripps et al. 2007), that is, how well certain participants are able to bridge communities, for example. Before that, we first focus on a time-based analysis considering how the social behavior measured by the length of contacts evolves during the LWA 2010 conference, using data obtained by the Conferator system. Both techniques can be applied in a recommendation setting, for example, for recommending people in interest-based communities, or for identifying influential bridges between different communities – based on the mined patterns.

For the time-based analysis, we utilized the MOSES algorithm (McDaid and Hurley 2010), and considered different time slices corresponding to different minimal contact lengths. Summarizing the setting in Atzmueller et al. (2012), we were able to use four different communities corresponding to special interest groups present at the conference, as a ground truth of interest-based communities. For the analysis, we considered their interactions with regard to different minimal conversation lengths (i.e., contact length between participants for their face-to-face conversations). In the following, we discuss exemplary results in this setting. Concerning our mobile social network of conference participants, the community results in

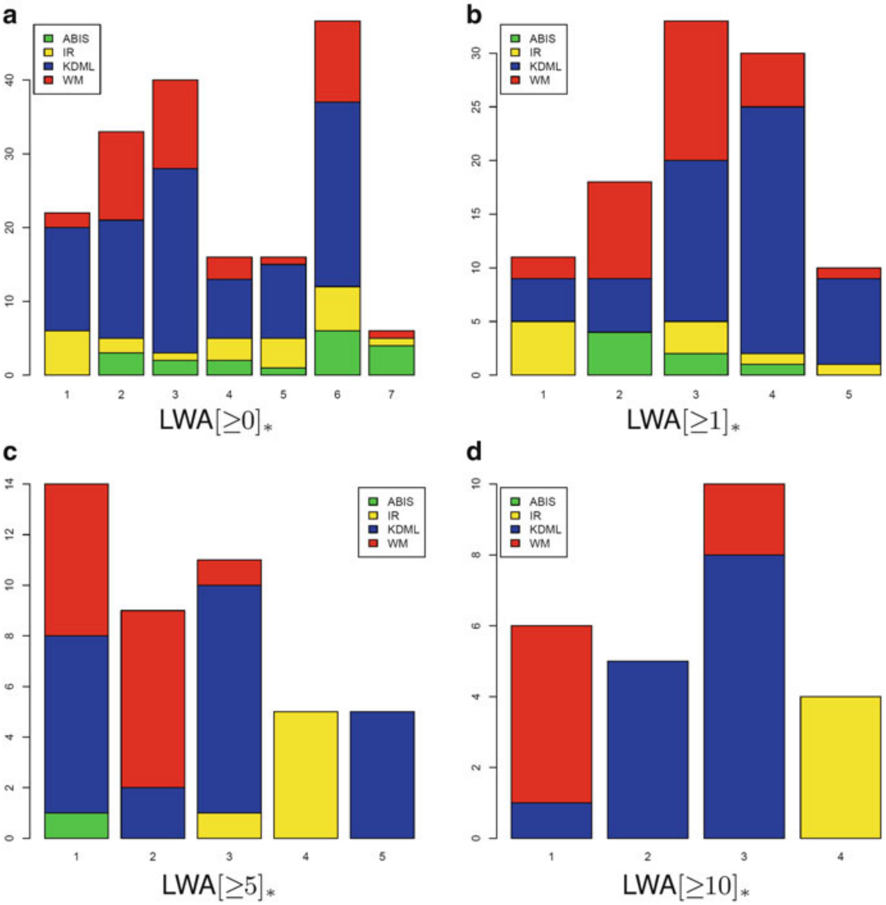

Fig. 4.1 Exemplary community detection results (Atzmueller et al. 2012), for different minimal conversation lengths (in minutes), using the MOSES algorithm (McDaid and Hurley 2010). The different communities are colored according to their special interest track distributions

Fig. 4.1 suggest that the communities tend to focus more on the special interest groups with an increasing minimum conversation length threshold. The communities start with a mixture of different interest groups, but concentrate more and more on special sub-communities. These findings suggest the trend that more specialized sub-communities of the special interest groups are mined. This is especially significant for higher minimal conversation length thresholds, see Fig. 4.1. In summary, this community-oriented analysis suggests, that participants actually tend to interact more frequently with members of their own special interest group for longer conversations.

Role mining with regard to communities mainly considers the relations between the communities for a specific actor. Scripps et al. (2007) present a method for

Table 4.3 Exemplary results (Macek et al. 2012) of pattern analysis at the Hypertext 2012 conference for describing individual roles using pattern mining and subgroup discovery. The patterns are described by (combinations) of properties of the participants, e.g., being session chairs or having a strong affiliation to the Hypertext conference

Min. contact length: 180 sec					
#	Target	Lift	Share	Size	Pattern
1	Ambassador	1.47	0.63	8	SessionChair = true
2	Ambassador	0.98	0.42	12	Affiliation = strong
3	Bridge	1.05	0.29	7	Country = Netherlands
4	Bridge	1.83	0.50	6	SessionChair = true AND Affiliation = strong
5	Bridge	1.53	0.42	12	Affiliation = strong
6	Bridge	1.38	0.37	8	SessionChair = true

assessing roles considering the membership in the communities and the potential to bridge or to connect different communities. In this way, different actor profiles concerning their centrality prestige and their community importance can be derived. Chou and Suzuki (2010) present a similar method considering a set of given communities for such a community-oriented analysis.

While the above methods mainly focus on the network and community structure, a simple characterization or description is usually not provided by standard methods for role and community mining. To this end, the characterization of actors and their roles is provided by descriptive pattern mining techniques (e.g., Atzmueller et al. 2011a, b; Atzmueller and Lemmerich 2012) that utilize different centrality measures and allow the characterization of role-specific nodes given different centrality measures. In this way, roles can get an intuitive interpretation given the network characteristics as depicted in Table 4.3, where we see exemplary results from the Hypertext 2011 conference (Macek et al. 2012). The table describes the community-oriented roles by different conference-oriented properties. In both cases, the VIKAMINE tool (Atzmueller and Lemmerich 2012) for pattern mining and subgroup analytics was applied for obtaining these characteristic patterns. They can then be inspected in a detailed context, for example, or they can be described by representative instance prototypes (cf., Atzmueller and Puppe 2008).

4.5 Conclusions

Pervasive and ubiquitous applications, in addition to the advances in technology, have created a number of options for mobile social networking. This chapter has presented different aspects of mobile social networks, and the emerging social behavior in those, especially focusing on roles, the creation of links, and social behavior in communities. We have summarized different exemplary systems, and discussed related analysis results. Then, ultimately, the analysis and understanding of such phenomena bridges the gap to collective intelligence (Malone et al. 2009;

Mitchell 2009), and provides different options for making use of the collected information (and derived knowledge) for integrating it into smart ubiquitous and social systems.

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