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DISSERTATION

Titel der Dissertation

On Social and Technical Aspects of Managing Mobile Ad-hoc Communities

Verfasser

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angestrebter akademischer Grad

Doktor der Wirtschaftsinformatik (Dr. rer.soc.oec.)

Wien, im Oktober 2011

Studienkennzahl lt. Studienblatt:

A 084 175

Dissertationsgebiet lt. Studienblatt:

Wirtschaftsinformatik

Betreuer:

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Abstract

Social software encompasses a range of software systems that allow users to interact and share data. This computer-mediated communication has become very popular with social networking sites like Facebook and Twitter. The evolution of smart phones toward mobile computers opens new possibilities to use social software also in mobile usage scenarios. Since mobile phones are permanently carried by their owners, the support focus is, however, much stronger set on promoting and augmenting real group gatherings. Traditional client-server platforms are not flexible enough to support complex and dynamic human encounter behavior. Mobile encounter networks (MENs) which represent a mobile peer-to-peer platform on top of a short range wireless network promise better flexibility. MENs diffuse content from neighbor-to-neighbor in a spatial diffusion process. For physical group gatherings this is advantageous for two reasons. Direct device-to-device interactions encourage sharing of situation-dependent content. Moreover, content is not necessarily locked within friend groups and may trigger networking effects by reaching larger audiences through user mobility.

One disadvantage is, however, the high resource usage. We develop a social software framework for mobile ad-hoc groups, which partly solves this problem. This framework supports services for the management of group dynamics and content diffusion within and between groups. Social network analysis as an inherent part of the framework is used to adapt internal community states continuously with real world encounter situations. We hereby qualify interpersonal relationships based on encounter and communication statistics, identify social groups through incremental clustering and assign diffusion roles through position analysis. To achieve efficient content dissemination we make use of social diffusion phenomena. Other researchers have experimented extensively with the small world model as it proofs that people transfer knowledge based on local knowledge but are still capable of diffusing it efficiently on a global scale. Their approach is often based on identifying short paths through member connectivity. However, this scenario is not applicable in MENs as transfer time is limited in contrast to the wired Internet. Our approach is therefore based on the least effort transfer theory. Following Reagan et al., who first postulated this hypothesis, people transfer knowledge only if the transfer effort is within specific limits, which depends on different social and cognitive factors. We derive routing mechanisms, which are capable of distinguishing between different content complexities and apply information about peer's expertise and social network to identify advantageous paths and content transfers options.

We evaluate the feasibility of the group management and content transfer component with prototypes. Since labor settings do not allow to obtain information about large scale diffusion experiences, we also conduct a multi-agent

simulation to evaluate the diffusion capabilities of the system. Experiences from an earlier prototype implementation have been used to quantify the technical routing process. To emulate realistic community life, we assigned to each agent an individual daily agenda, social contacts and territory preferences specified according to outcomes from different urban city life surveys. During the simulation agents move on a city map according to these models and collect contact and content specific data. Analyzing the network topology according to small world characteristics shows a structure with a high tendency for clustering (friend networks) and a short average path length. Daily urban mobility creates enough opportunities to form shortcuts through the community. Content diffusion analysis shows that our approach reaches a similar amount of peers as network flooding but with delays in the beginning. Since our approach artificially limits the number of intermediates to central community peers more bandwidth is available during traveling and more content can be transferred as in the case of the flooding approach. Ordinary peers seem to have significantly fewer content replications if an unlimited cache is assumed proofing that our mechanism is more efficient. By varying the content type used during the simulation we recognize that time dependent content is better disseminated through frequent contacts and time independent content through random contacts. Performing a precision-recall analysis on peers caches shows that ordinary peers gain an overall better context precision, and central peers a better community recall. One explanation is that the shared cache approach leads to fewer content replacements in the cache as for instance the least recently used cache strategy.

Acknowledgements

I would like to thank all people who encouraged and supported me during my Ph.D. study.

Especially, I would like to express my heartfelt gratitude for my adviser Prof. Hlavacs for his inspiration, enthusiasm, patience and knowledge. My sincere thanks also go to Prof. Haring who made this thesis possible, and gave me detailed feedback and advices for my interdisciplinary research. Further, it is a pleasure to thank Prof. Gaspar-Ruppert who helped me to identify important social studies forming the basis for my research project.

Besides my advisers, I also would like to acknowledge the great support from Frank Busch who provided me the simulation tool and allowed me to enhance it for the evaluation of my research.

Last but not the least, I would like to thank my family and Encarna for their understanding and patience.

Vienna, October 2011

Bernhard Klein

Conventions

Throughout this thesis the following conventions will be used:

The plural “we” will be used throughout this thesis instead of the singular “I”, even when referring to work that was primarily done by the author.

The whole thesis is written in American English.

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1

Introduction

1.1 Potentials for Social Software

Formerly, interpersonal communication depended on direct *face-to-face* encounters. Thus, the communication range was limited to traveling capabilities. Modern communication technology has fundamentally changed the way we socially interact with others. Over years, Information and Communication Technologys (ICTs) has led to substantial improvements in our daily life and have effected it in the following ways:

- **Introduction of landline phones:** With the ability to communicate from distant places, locational settings lost their importance. Social life in neighborhoods vanished and has been increasingly replaced by *social networks* (social structure of personal contacts), established by common interests rather than geographic proximity. As a consequence people spend more time traveling to remote places.
- **Introduction of mobile phones:** Mobile phones enable *anywhere* and *anytime* communication through wide area wireless networks. Permanent accessibility eliminates the need for pre-planning, and meetings are more often decided spontaneously. Following Steinmüller [108], communication, mobility and flexibility correlate and form the basis of a new information society. This transition to *flexible* agendas, however, has side effects and leads to an increased coordination effort as last minute changes often occur. Several studies [3, 21] show that people recognize this flexibility as stress and sometimes even switch the mobile phone off to escape from it.

Belonging to a social group is critical for most humans. Group membership influences how people perceive themselves and how others think of them, gives them security and opens up opportunities for collaboration. Not surprisingly, ICT has been used early on to support social life in several ways:

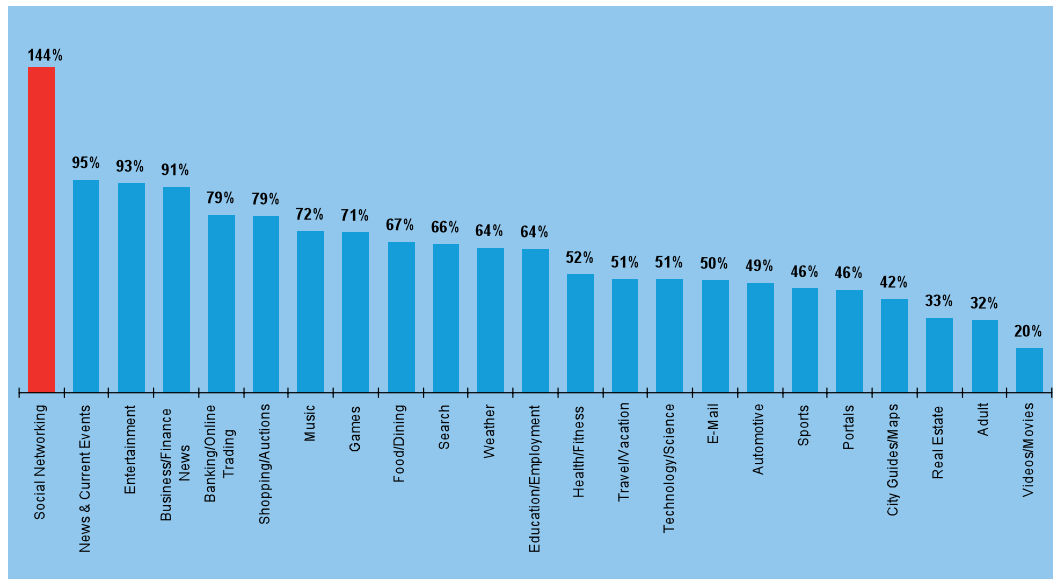


Figure 1.1: Increasing mobile social software popularity (Rocha [96]).

- **Virtual Communities:** With the rise of the Internet social software platforms that allow users to *interact* and *share* experiences became popular. Earlier systems focused on interest communities (e.g. wikis¹, forums² and blogs³) and newer developments on social network management, location based meeting support and microblogging. Microblogs are a form of mobile blog services which differ from traditional blogs in that its content is smaller and more frequently updated. Virtual communities fill the gap between mass media broadcasts and unilateral phone communication. They create community knowledge from the *bottom up* and shift the power from hierarchical organizations to networks.
- **Mobile Communities:** Following Heylen [55], “...people are increasingly living in a ‘mosaic society’ where they are disconnected from family, friends, neighbors and both local and national democratic structures.” With mobile social software *bilateral* communication capabilities of mobile phones can be extended to strengthen social networks of their owners. A study conducted by Rocha [96] confirms that social services in the year 2008 had the biggest growth with a 144% increase in comparison to other mobile Internet services (see Figure 1.1). Social software extends hereby the possibility of users in various ways (see Figure 1.2). People can use mobile phones to manage social networks, e.g., by broadcasting

¹Free Internet encyclopedia

²Internet message board

³Internet diary or commentary by an individual

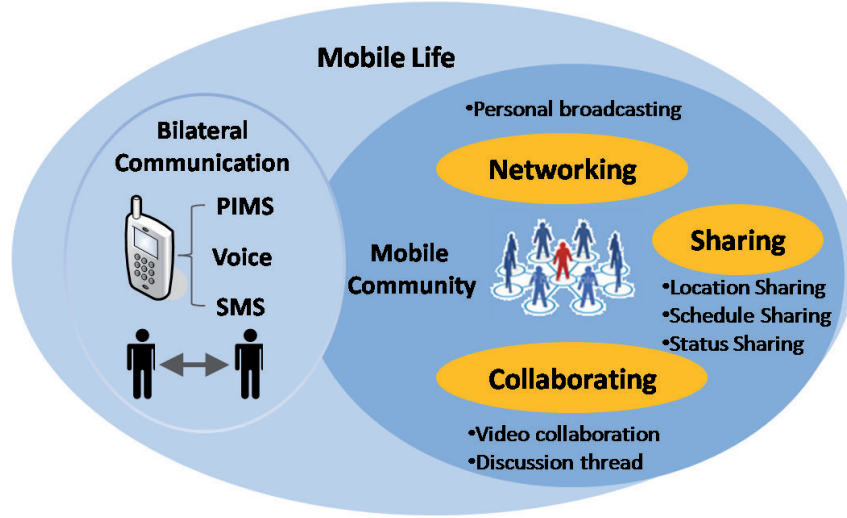


Figure 1.2: Extension of mobile phone capabilities with social software (Rhee and Lee [95]).

user interests, *maintain relationships*, e.g., by sharing of personal information like their whereabouts, daily schedules or the state information and *collaborate* with others through video conferences or group chats. Mobile social software focuses preferably on smaller social groups rather than large interest communities known from the Internet.

1.2 Challenges through the Sociotechnical Gap

In the early phases several attempts to create successful mobile social software applications failed. Many problems were related to hardware limitations of mobile phones during this time period. In a survey about the mobile Internet, Wellman [80] indicated that community applications are difficult to transfer on mobile phones since they require a large screen size. Another problem is related to the multilateral messaging which requires high bandwidth and consumes a lot of battery power. Following Ackerman [1] the problem of designing well accepted mobile social software lies even deeper in the interface between social behavior and technological support. As he states: “The *social-technical gap* is the divide between what we know we must support socially and what we can support technically.”

Ackerman argues further that humans have often very different backgrounds and motivations, which lead to *unpredictable* behavior. Individuals’ behavior may, for instance, depend on the friends’ interests, available mobility options, and aspects specifically related with the current user activity. Humans com-

pensate this complexity by reacting *immediately* and *frequently* on current environment conditions and feedback from others. Later Ackerman continues that support tools are much more rigid in the sense that they offer support often only for a predefined collaboration pattern. People who want to use this software have to adapt their behavior to the collaboration flow propagated by the tool. Moreover, human collaboration covers several aspects, including *coordination*, *communication*, *methodological* support and domain specific *knowledge* (see Borghoff and Schlichter [14]). Support tools cannot offer this variety and specialize on individual collaboration aspects.

The reason for this rigidity lies in the mobile infrastructure itself. The underlying system architecture but also the capabilities of applied technical components e.g. sensors, batteries and software limit the flexibility of social software services (Figure 1.3). Most commercial social software providers use *central* server platforms to host social software services which users can access with mobile clients. Although this infrastructure is easy to setup and maintain it may lead to following support problems:

- **Top-down information:** Although social software services and data are usually both hosted by one provider, users may still fail to capture the right content. Key word based queries are often not precise enough due to large contextual search spaces. Small screens additionally limit possibilities for hierarchical navigation and filtering services. As a result too much unfocused information is provided giving the user soon the impression of an *information overload*. The only possibility to tackle this problem is to separate false content in a lengthy interactive process.
- **Fixed distribution channels:** Since user generated content is often member dependent, operators sometimes offer *publish-subscribe* services to manage the information distribution within communities. Content distribution in publish-subscribe systems [13] is managed through message brokers which forward content to recipients who have previously subscribed to a specific topic or publisher. This restriction, however, may also introduce problems. For instance, information intended for a broader audience may only reach a smaller subset due to strict distribution policies. Newer applications allowing to query the general community domain, e.g., Twitter Trends⁴ proof that there is a need to have a more seamless diffusion model.

The recent trend to *decentralize* network infrastructures has brought important technical improvements. Routing functionality has moved to the edge shifting the power from the provider to the user. Overall this has introduced flexibility to the collaboration chain in following ways:

⁴iPhone Application from Wizag LLC, <http://friendsignal.com>

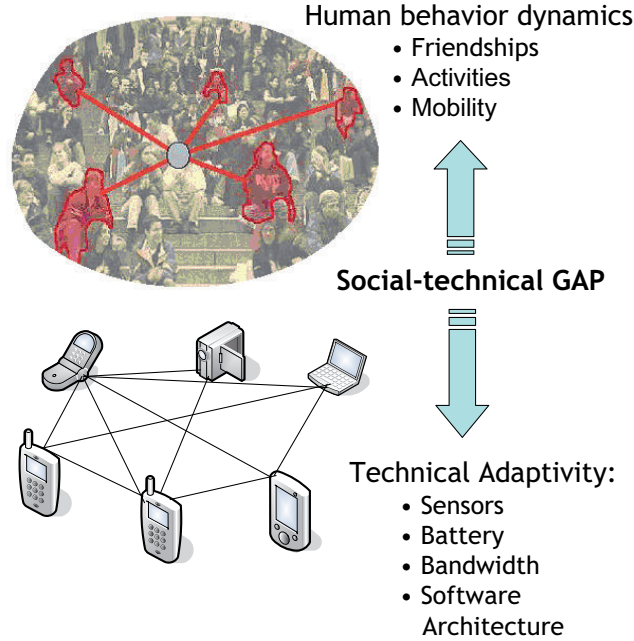


Figure 1.3: Understanding the social-technical gap.

- **Decentralized group management:** One important implication is that groups may be arranged in a decentralized manner. Each member may provide his own service to a group of users closely related to him. Nevertheless, the nature of publish-subscribe systems still does not permit him to do this in an ad-hoc manner required to adapt to physical group formations.
- **Decentralized content management:** User devices provide increasingly larger storages which can be used to offer community content directly from their devices. Lengthy up- and download activities reduce the overall collaboration process and give users stronger control about their content. Content in this decentralized infrastructure is still accessed in a pull manner which may be not satisfying in short term group formations.

1.3 Research Objectives and Scope

In this thesis, our goal is to develop a software framework for mobile ad-hoc groups. During the day people move between different communities and places. Support systems should augment the social life of community members. The delivery of community contents in a timely manner on mobile phones is hereby our key concern. This can be achieved by suggesting a meeting with friends being nearby, keeping them up to date about shared community activities

or simply by giving advices to people not familiar with their environment. Support systems may exploit data about community relations to route contents through frequent encounters or trusted contacts. Besides, such community systems may exploit urban dynamics, e.g., by utilizing the public transport system to propagate information about public events in this area. Additional technical infrastructure like public displays may be used to augment urban spaces and make social life in urban environments more convenient for their citizens. Figure 1.4 illustrates this complex interdependence between social life, urban spaces and mobile technologies.

As a basis for our framework we consider a *mobile encounter network* (MEN), which represents a mobile peer-to-peer system executed above a short range wireless ad-hoc network. One big advantage of MENs is that they require no infrastructure installations. Connections between peers are established through a decentralized wireless network. In such an intermittently connected network, peers need to store the content temporarily in order to forward it to other peers. This characteristic enables a *spatial diffusion* process as known, e.g. from rumor spreading. Following diffusion characteristics are hereby important for us:

- **Bottom-up information:** Information quality is reached as we receive preferable information from people whom we frequently meet and evaluate as important. The idea is based on the fact that humans continuously evolve their personal contact network according to cost-benefit rules. The *transitive* principle allows us to conclude that content carried by people within personal networks have a high potential to be of interest for other network members.
- **Open distribution process:** Traditional information systems based on publish-subscribe mechanisms are limited in their flexibility. Korhonen [65] calls this as the selectivity problems which he describes with following example:

”Basically, it may happen that the intended receiver of the information is not aware of the information being available, and the sender is not aware of whom to send to the information which is available.”

In MENs content is propagated in a spatial diffusion process for which previous subscriptions to specific content providers are not required.

A disadvantage of MENs is their high resource usage, which is a problem for mobile devices with limited capacities. Coordinating the content diffusion in communities requires a carefully chosen balance between egoistic and altruistic filter settings. While egoistic filter settings assure a high user acceptance,

1.3. RESEARCH OBJECTIVES AND SCOPE

altruistic filter settings guarantee high diffusion ranges. Several approaches exist to manage the diffusion process in encounter networks, e.g., based on managing precise *encounter schedules*. Most of them have not been designed for realistically *large scale* scenarios like urban environments. We therefore plan to follow a different approach, which we roughly describe as augmentation of the human knowledge transfer process.

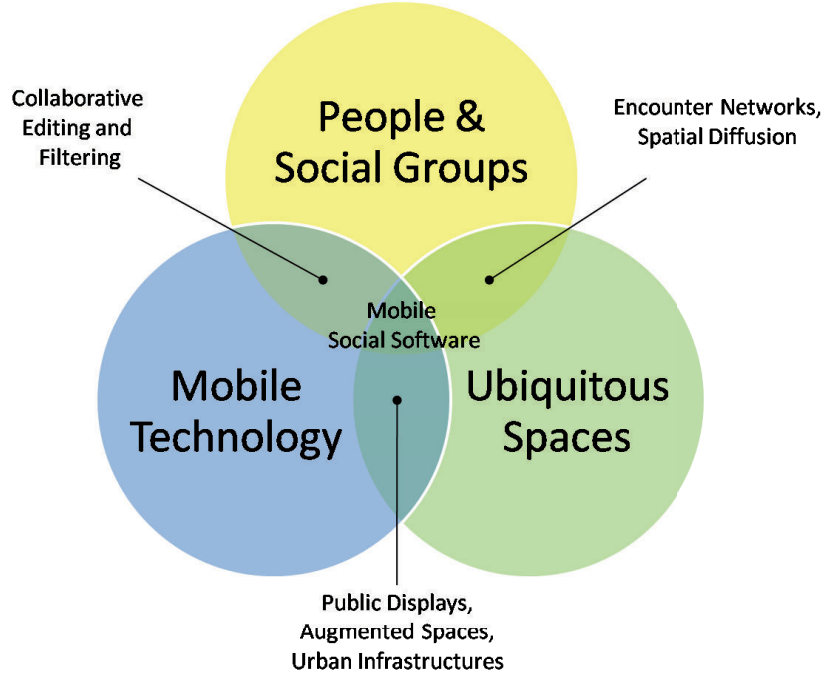


Figure 1.4: Different aspects of mobile social software.

- **Emulating the human knowledge transfer process:** Experiences show that humans are very efficient in transferring knowledge between them. They use *past experiences* and *common sense* to shape the knowledge transfer process. Thereby, they consider several social and contextual factors, including different knowledge related aspects, backgrounds of potential recipients, trustworthiness and reputation. We plan to emulate human knowledge transfer processes with a *socially-aware* diffusion algorithm. This approach limits transfers leads to less messaging effort (number of intermediate nodes) and to the same time creates higher cooperation incentives as forwarders are chosen based on the current interest and context situation.
- **Empowering of the human knowledge transfer process:** Moreover, human communication is generally restricted during traveling. Geser [43] summarizes these limitations as follows:

”... whole collectivities move together, so that intra-group communication can be maintained, communication has to be limited to the rather rare occasions when populations are densely aggregated at specific locations; communication codes have to be *standardized* and messages simplified in a way to be compatible with conditions of movement and/or wide and variable spatial dispersion.”

MENs establish *digital spheres* (see Kortuem et al. [69]) around their owners, and enable much better opportunities for message exchanges even during traveling. We envision that this creates a better integration between communities since humans have regular mobility patterns like the daily commute between home and work places. Even if brief encounters limit transfers to small content types, they can still be enough to produce global content summaries for specific interest communities dramatically enhancing community transparency. For instance, small descriptions about community events and recommendations could function as an incentive for the user to download dependent media content with wide area networks (WANs).

1.4 Research Approach and Methodology

Research on community support systems is generally a *cross-disciplinary* effort which encompasses computer science and sociology in the broader sense. Computer science is required as technical infrastructure with content management, repository systems and networking facilities. Social-psychological sciences are important to increase user acceptance of technical systems, as they provide models for cooperation dynamics and user interaction.

Analysis of the Social-Technical Gap

In the beginning of our project work, we analyze differences arising from the social-technical gap. We therefore conduct a literature analysis covering articles about social group theories and mobile technical infrastructures. Our intention is to collect data about following aspects:

- **Community behavior patterns:** Social behavior dynamics emerge from different perspectives. To deal with them successfully, it is important to classify behavior options. We separate random from repeated, individual from shared behavior and identify behavior chains. We derive characteristic community behavior patterns, which essentially represent *behavior abstractions* for group formation and knowledge exchange. Each of these patterns may contain *temporal*, *spatial* and *social* aspects. Our

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contribution lies hereby in the way how we formalize them. We define behavior patterns solely based on parameters, which a) can be obtained through sensor technology and b) which can be further processed through empirical algorithms.

- **Reference architectures:** Decisions on the architecture level limit the potential flexibility of social software systems. We inspect *centralized*, *decentralized* and *ad-hoc* infrastructures. Each of them has different strengths and weaknesses. We need to understand general temporal, spatial and social diffusion characteristics. The behavior of peer-to-peer systems is defined through *network protocols* and local *cache policies*. Protocols define a standardized way for peers to interact with each other and cache policies describe how content is temporarily stored at the peer. We survey both aspects to see how content diffusion is actually implemented.

Design of a Social Software Framework

The ad-hoc nature of mobile groups and the requirement to handle situation specific content require the extension of existing social software infrastructures. System adaptivity is hereby achieved by adding social intelligence to the infrastructure. In detail we plan the following enhancements to traditional MENs:

1. **Extension of peer architecture and protocols:** We start with the design of an abstract model of urban communities with descriptions for urban, social, and domain specific structures. We use this model to define *community overlays* representing virtual links between users describing community participation preferences. The primary use of overlays is the structuring and management of content indexes. Following this we derive a peer system architecture. This architecture includes both data and interaction relevant peer specifications. Peer *profiles* are used to store user and community specific data and to personalize user interactions. We design group formation and content exchange *protocols* with the goal of group consistency independent of particular group dynamics. Local *cache policies* are specified according to user and community specific relevance criteria.
2. **Representing realistic social information:** Social information represents knowledge about *social relationships*, *network positions* and *roles*. It is stored as static and dynamic data in peer profiles. Social network knowledge is represented through *sociometry*, introduced by Moreno [82], where humans represent nodes and relationships links between the nodes.

Node and link states can be semantically enhanced through *metadata* descriptions. Metadata include descriptions about user sociability and expertise, group roles in social groups, reputation and influence on other community members. To manage realistic peer and community states, we need to specify metadata sets with specific *metrics* allowing for continuous empirical evaluation. The data itself is obtained from location *sensors* e.g. GPS, *network* and *communication* specific data.

3. **Modeling community behavior:** The goal of any social software platform is to utilize group synergies and by this provide a benefit to the user. Thus we have to review individual behavior and look for cooperation potentials. *Social network analysis* is well suited to identify individual and collective behavior patterns. We define different ad-hoc group categories and derive adequate criteria for group boundaries. Existing *clustering* algorithms are reviewed and adapted to scarce resource requirements of mobile telephones.
4. **Development of opportunistic community diffusion:** A major problem for a distributed information system is content availability. In other words, content needs to be routed to the *edges* of the large scale urban community. Hereby, MENs can only rely on *local* network knowledge. To achieve this we have to alter existing social information processing technology. Rather than just describing social information, *executable* social knowledge has to be embedded in social software applications. By this, the information system can continuously adapt to realistic community states. Human knowledge transfer theories (see further details in Chapter 2) are used to define the information flow. We specify it with system loop representations and implement concrete information flow rules for routing algorithms.

Prototyping and Simulation

The community framework is evaluated through *prototypes* and a diffusion *simulation*. We extend a file sharing application implemented for Wi-Fi networks with community management services. To verify the framework feasibility we tested the prototype in different encounter scenarios with various content types. Since device calculations are less time consuming than device communications we use the experiments to improve the protocol design. In addition, we apply the performance experiences gained from the prototype to define technical parameters for the urban diffusion simulation. In this simulator, agents emulate human encounters following patterns observed in studies about social life and urban traffic. During the simulation, we record an encounter relationship graph and analyze the graph topology. We conclude opportunities for community collaboration and community size through

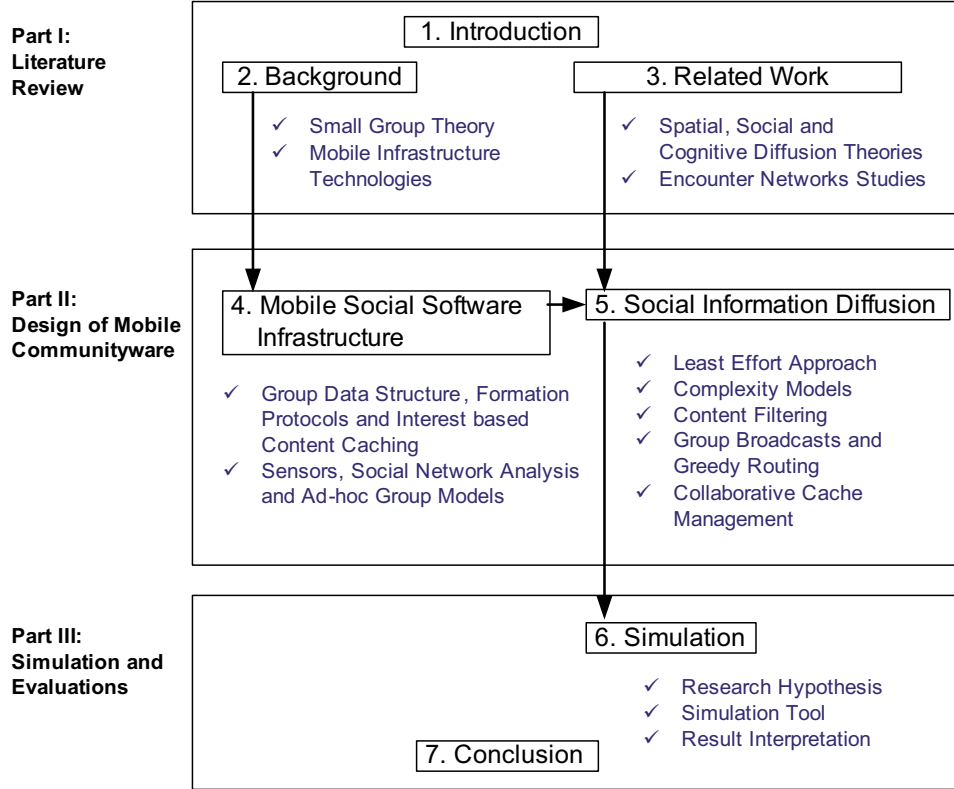


Figure 1.5: Chapter dependencies.

a *small world* analysis. In a second phase of the experiment, we emulate the content diffusion under realistic transmission conditions by specifying network bandwidths and content types. The diffusion efficiency is derived from the *messaging effort* and the observed number of content recipients. We gain further information about the content delegation within the community by applying a *precision/recall* analysis on the data collected by the agents. By comparing network potentials, diffusion efficiency and quality with reference systems, we are able to show benefits and limits of our approach.

1.5 Outline of Thesis

This thesis is logically divided into three parts. Figure 1.5 shows a structural overview of the thesis' chapters and dependencies which we will now elaborate further:

- Chapter 1: Introduction

This chapter motivates the enhancement of mobile phones with community applications. An information system for mobile groups is chosen as

CHAPTER 1. INTRODUCTION

the major research focus. We separate the problem in several subordinate problems and present the structure of our thesis.

Part I - State-of-the-art of Mobile Social Software. In the first part, we introduce and analyze basic social and technical concepts.

- Chapter 2: Background and Definitions

In Chapter 2 we review small group theories and identify important group formation and interaction concepts. We describe the correlation between social groups and territories, classify social groups according to their privacy and derive requirements for community support. On the technical side, we compare different infrastructures for mobile social software according to group formation, content management, diffusion characteristics and maintenance effort. We finalize this chapter by choosing an adequate infrastructure for mobile groups to be further used in this thesis. Presented infrastructure background and small group models together build the foundation for software framework in Chapter 4.

- Chapter 3: Related Work on Knowledge Diffusion

This chapter focuses on the analysis of social and technological knowledge diffusion concepts. We review different spatial, social and cognitive knowledge exchange theories to identify their diffusion characteristics. From this we draw conclusions about their applicability on diffusion systems. Research on ad-hoc routing systems can be classified in selective forwarding and cache management strategies. We present different reference architectures for spatial and social routing approaches and interest-/situation-aware cache approaches. All routing approaches are analyzed according to their diffusion potentials. Presented social diffusion phenomena are used for designing a collaborative content management mechanism for MENs in Chapter 5. Hereby we utilize experiences from diffusion and caching surveys with MENs to control the content flow.

Part II - Design of a socially-aware Community Framework. Part II represents the main part of the thesis. Here, we develop static and dynamic models for an ad-hoc community diffusion system required for the basic operation of mobile social software systems.

- Chapter 4: Mobile Social Software Infrastructure

The goal of this section is to design and implement a socially-aware community management framework. Therefore we extend traditional MEN

infrastructure with group management functions. We add group data structures and formation protocols according to the small group models discussed in Chapter 2. Social adaptivity is achieved through context sensors and real-time social network analysis. The social network analysis component identify behavior patterns and ad-hoc group formations. The system reacts on group state changes by triggering specific peer and protocol actions. We implemented a small framework prototype to evaluate the feasibility of our concept. The mobile infrastructures provides real-time social network data for the content diffusion mechanisms. The content diffusion mechanism described in Chapter 5 requires this data to shape the diffusion process according to the real-world encounter situation.

- Chapter 5: Realizing Social Information Diffusion

On-top of the socially-aware community infrastructure we employ social diffusion algorithms. We base our algorithm design on human knowledge transfer theories described in Chapter 3 and emulate them where they are satisfactory and extend them where they have limitations. Hereby, we envision that peers identify suitable diffusion paths and contents in an opportunistic manner. This allows us to deal with varying encounter durations by considering previously made encounter experiences of the peers. As diffusion theories reveal certain diffusion phenomena in large scale scenarios, we utilize specific temporal, social and spatial diffusion aspects to achieve global distribution efficiency. The design focus is set on keeping the number of content replications for each peer low and to the same time assure a high content quality for the user. The diffusion protocol is evaluated through an urban simulation in Chapter 6.

Part III - Simulation and Evaluation. Part III evaluates the effectiveness of the content dissemination algorithms for large-scale urban life scenario and concludes the thesis.

- Chapter 6: Simulation and Evaluation

We verify the feasibility of our ad-hoc peer-to-peer protocol through a small prototype implementation and test it with different content types. As the number of devices is limited in labor settings, we use a car traffic simulator with which we emulate the large scale urban encounter conditions. Agent movements in this simulator are choreographed according to empirical studies for time management, traffic and community behavior. During the simulation, each encounter (agent separated within a given minimum distance) triggers content exchanges following the diffusion protocol based on technical settings obtained from the framework

CHAPTER 1. INTRODUCTION

prototype. The simulator allows the data dissemination process to be tested with various parameters. Therefore, we repeat experiments with different user behavior, protocol and cache settings. During each simulation round data about peer connectivity, diffusion efficiency (number of messages) and the quality (situation and interest specifcness) of cached contents are collected and evaluated.

- Chapter 7: Conclusion and Further work

We summarize the major results, review and analyze their applicability to the area of mobile community support systems, and present our conclusions. At the end of the thesis, we give an outlook on open problems that have to be addressed in future research.

Part I

State-of-the-art of Mobile Social Software

2

Background and Definitions

Mobile and virtual community support systems are quite different from each other. While virtual communities emerge around *interests* and may get very large, mobile communities have a much more *private* character. People want to keep this personal content within their families, friend groups or work teams.

Mobile community support systems need functions supporting *group formation* and ongoing *group dynamics*. For this reason, the porting of desktop based support systems on mobile devices is not enough. Rather, new support services have to consider a closer embedding of support functionality in real life. New promising solutions lie in the application of *interdisciplinary* research disciplines, which view social computing as an inherent part of technical infrastructures.

In the following we present important background and definitions from social and mobile computing disciplines with the objectives to identify adequate support architectures. We are especially interested in small group theories from which we derive a minimal set of requirements for mobile support infrastructures. We conclude this chapter by comparing different technical architectures according to their applicability on informal groups.

2.1 Small Group Theories

Small group research deals with mobile groups and is part of broader sociology and social psychology research domains. The term was chosen to differentiate it from research about large statistical groups like ethnic groups. Small group research typically deals with topics like *group building*, *group composition* and *structure*, *intergroup relations*, *performance* and *conflicts*. Here we are particularly interested in group building processes and various classifications of mobile communities as we need to emulate them later to achieve adaptive community support systems. Social groups require spaces to meet. Hence, we analyze social but also spatial group aspects.

2.1.1 Social Groups

Following the American sociologist Georg Homans [56] people form their relationships based on individual cost-benefit analysis and the comparison of available alternatives. In the following, we present some factors influencing their decision:

- **Interest similarity:** Sharing interests is an important prerequisite to assure ongoing contacts. Griffitt and Veitch [47] could predict longtime relationships in social surveys if they knew the interests of the study participants in advance. A sufficient explanation may be given by the *social identity* theory [52] which states that people build their own identity often in dependence to others which they regard as important or meet frequently.
- **Neighborhood proximity:** *Social impact* theory [70] suggests that the impact of persons on each other decreases with the distance. Of course it is easier for people to interact with others nearby since traveling always represents an additional effort. A study [48] has proven that proximity is a better predictor for friendship than interest similarity.
- **Encounter familiarity:** Repeated contact between people creates more chances to interact with each other. With frequent encounters persons become more familiar with each other. *Familiarity* leads to more predictable relationships and after Zajonc [81] can even lead to liking of that person. When comparing the impact of interest similarity, proximity and familiarity, the latter is the strongest indication for possible relationships between people.

Group Development Models

Humans as social beings participate in groups and receive support and security from these. In some cases group participations create even new opportunities as specific tasks can only be achieved with help of others. Several models for group development exist. They can be divided according to their *life cycle*, *feedback* mechanism, *conflict compensation* and *evolutionary* progress. For us, life cycle oriented models are the most interesting as they describe specific development stages. Some well known models are Kurt Lewin's individual change process [72], Bruce Tuckman's stage model [115], Stewart Tubb's systems approach [114] and Fisher's theory of decision emergence in groups [39]. Exemplary, we present Bruce Tuckman's stage model. According to Tuckman, the lifespan of a group can be divided in five stages from its first formation until its final break up. For each stage Tuckman analyzed group relations and characteristic tasks. Below we summarize each stage briefly:

CHAPTER 2. BACKGROUND AND DEFINITIONS

1. **Forming:** In this phase people meet each other for the first time and learn more about each other. At this point, people are still insecure about their group participation.
2. **Storming:** Once people know more about each other, shared ideas about the group perspective are developed. Since group structures are still not established conflicts may often emerge.
3. **Norming:** In this stage group members establish rules, methodologies and delegate tasks between each other.
4. **Performing:** This stage is the most productive phase of the group. Group members reach a conclusion and implement the solution according to the group objectives.
5. **Break-up:** After the results have been achieved, the group dissolves again.

Classification of Social Groups

Below we characterize mobile groups based on well known social group classifications:

- **Primary and Secondary Groups:** An important criterion for group classification is the level of *intimacy*. The sociologist Charles Cooley [25] was the first to introduce the terms *primary* and *secondary* groups to differentiate between intimate and pragmatic group associations. A primary group is a group of people who have known each other for a very long time and trust each other. They share various interests and collaborate in several activities. Communication in primary groups is highly personal and intimate. Family members, longtime friends and very influential persons are good examples. Secondary groups are often *interest* based and have a clear benefit for their individuals. Their members leave if their benefit is not given. Consequently, relationships are rather temporary and members easily interchangeable such as in student groups or work teams. Both group types stay in contrast to public or statistical groups, which emerge randomly or share specific properties. Table 2.1 visualizes the difference between primary and secondary groups.
- **Formal and Informal Groups:** The purpose of a formal group is to perform certain activities together to reach a specific target. To improve their collaboration, these groups possess often an *organizational* structure. This structure enables formal groups to grow very large. Enterprises, associations or sports teams are good examples for this group category. Mayo [78] observed work in factories and observed that formal

2.1. SMALL GROUP THEORIES

	<i>Social Groups</i>	
<i>Interactions</i>	Primary	Secondary
Activities	Broad variety	Specialized Interests
Communication	Personal	Pragmatic
Duration	Long term	Often short term
Gratification	Long term	Immediate
Examples	Families and friends	Students and colleagues

Table 2.1: Comparison of primary and secondary groups.

organizations always overlay with informal social structures. Informal groups, in contrary, emerge spontaneously and are only bound through social relationships. As the effort to coordinate this type of groups rises with the group size, informal groups stay rather small. People in informal groups work together on the same task while in formal organizations people tend to delegate tasks due to efficiency reasons. Examples are the friend, student or work groups. Table 2.2 visualizes the difference between informal groups and formal organizations.

<i>Properties</i>	Informal groups	Formal organizations
Activities	Shared	Specialized
Membership	Personal aspects	Specific expertise
Size	Small	Often large
Structure	Often informal	Often hierarchical
Norms	General norms	Specific regulations
Communications	Informal	Formal and written
Examples	Friendly colleagues	Company organization

Table 2.2: Comparison of formal groups and formal organizations.

Wellman et al. [80] conducted a survey among Japanese youth to compare the difference between Internet and mobile phone based communication patterns. They found that social networks created through mobile phones consist largely of friend contacts in the direct neighborhood of the user. Social groups coordinated through mobile phones are, thus, highly *homogeneous* and display a high degree of *transitivity*. Following Granovetter [46] "Transitivity is the tendency of one's friends' friends to be one's friends as well." This phenomena is based on *taste similarity* caused through the time invested in relationships. In contrast, Internet based social groups emerge around interests and are location independent. Figure 2.1 a) shows the difference between interest based school community and mobile friend groups. By removing few ties from the Jefferson school community the network quickly disintegrates into local friend groups.

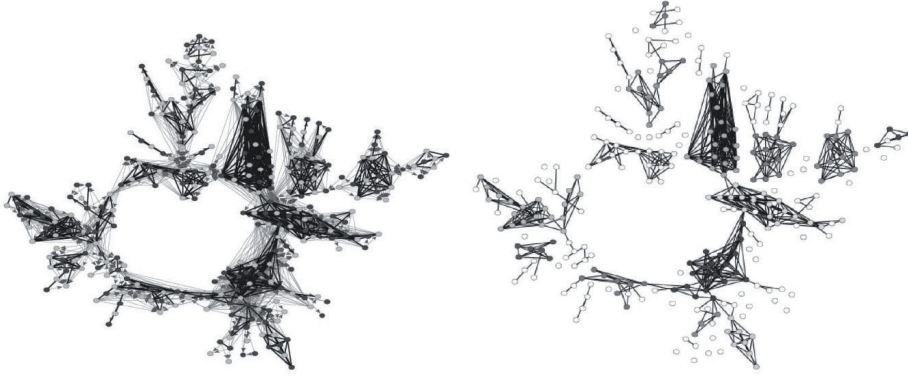


Figure 2.1: Jefferson High School: a) student network and b) friend groups (Bearman et al. [11]).

This shows how much stronger informal mobile groups can be in comparison to interest based communities.

2.1.2 Social Territories

Sommer [107] and Altman [4] introduced the concept of social territories. Their research looks on the relationship between social behavior and surrounded spatial environments. More specifically, Altman [4] suggested a classification of personal space similar to social groups in *primary*-, *secondary*- and *public* territories. As it can be seen in Table 2.3 these categories are determined through *usage duration*, *usage rate*, *control*, *ownership* and *personalization degree*. Primary territories are homes or private areas. Examples for secondary territories are libraries, concert halls and waiting rooms. Urban places, but also railway stations, airports and markets belong to the third category. The level of territorial control can easily be depicted from the way how people use their mobile phones. People, for instance, often have to turn off their mobile phones in primary and secondary territories due to possible disturbances, which are certainly less restrictive in public spaces.

	<i>Social Territories</i>		
<i>Properties</i>	Primary	Secondary	Public
Control	Strict	Weak	Open
Ownership	Permanent	Shared	None
Personalization	Strong	Partly	Few
Usage duration	Long term	Mid term	Short term
Usage rate	Permanent	Occasional	Temporary

Table 2.3: Comparison of territory characteristics (Altman [4]).

The following properties additionally characterize social territories (see Schultz-Gambard [103]):

- Geographic information: urban positioning and territory size
- Usage time information: permanent or temporary usage
- Social information: persons, groups or populations
- Diverse community functions
- Means of personalization and defense

2.2 Social Network Analysis

In this section, we present terms and methodologies commonly used to analyze social life of humans (see Figure 2.2). Researchers obtain data from involved actors to analyze the individual behavior, relationships and the surrounding social network. Data can be obtained through questionnaires, interviews or observations.

Any background information about persons like their interests, character or demographic data can help to understand why a person acts in a specific way.

Relationships between humans describe how people relate with others. Important survey aspects are related to the type of the relationship and its interaction patterns. Relationships can have short term or long term character. Accordingly we use relationships to exchange information, provide help or give monetary or other small scale support (see Wellman [122]). The most important interaction parameters are *relationship direction*, *strength* or the *distance*. Depending on the influence of individual persons, relationships may have directive character (e.g., in companies) or may be well balanced (e.g., friendships). The strength of the relationship describes the perceived intensity of that relationship. Some people we know only through third persons e.g., friends. The value of these friend-to-friend relationships decreases with the distance from the source and target person. It is expressed with the number of intermediates also often called hop count.

Information about individual relationships may be of limited use in respect to community research. More important in this case is the analysis of social networks into which humans are embedded. Moreno [82] developed an analysis method based on *graph analysis*, allowing the structural analysis of social networks. In his model persons represent *nodes* and *relationship* links between them. Evaluations are based on the assumption that specific network topologies enable or disable certain behavior options. Network topologies can

CHAPTER 2. BACKGROUND AND DEFINITIONS

be calculated from standard parameters. These parameters focus on the entire graph, specific regions or individual actors.

Important global network parameters are their *size* and *structure*. The overall network size is defined by the largest distance between any pair of network members. Often network size is also called network *diameter*. Networks can show different levels of structuring and thus may or may not favor different activities. For instance, hierarchies support knowledge diffusion, while network oriented topologies encourage network cooperation.

One way to reveal the diffusion efficiency of networks is to calculate their *average path length*. This parameter is defined as the average number of hops for the shortest paths calculated for all possible relations in the network. This parameter should not be confused with the network size (see for a more formal definition Equation (6.6)). Information about the network structure can be derived from the amount of *clusters*, their *density* and *cohesion*. The network density specifies the ratio of actual to all potential relationships (see a more detailed definition in Section 6.4). Hereby, it is important that network density and size are associated as the density decreases with increasing size of the network. Together with the network density researchers often obtain the network cohesion. The network cohesion expresses the reciprocity ratio of all relationships (see Definition 7.7 in Chapter 7). This value can be thought of as a measurement of cooperation, as it stands for the tendency toward forming cohesive subgroups.

Informal hierarchies in communities emerge from heterogeneous member popularity. The *node degree* of a network member is defined as the number of connections it has to other nodes and should not be confused with the node connectivity. The degree distribution describes how node degrees are distributed over the community. Most human generated networks e.g. Internet communities have a characteristic distribution which approximately follow the a power law distribution. More information about this can be read in Section 3.1.2. Most nodes in such a scenario have a low degree and only few selected hub nodes have a high degree.

These superior members in communities can be identified through centrality measures. The network centrality describes to which extent a node is in the center of a community network. Leading community members of the community (also often referred as opinion leaders) represent the center of a community. Obviously, nodes with a high network centrality posses also large network ranges (reachable proportion of network). The centrality of a network graph can be expressed in different ways, among them are Freeman's *centrality measurements* [41, 40] like the *degree*, *closeness* and *betweenness* centrality. The degree centrality describes the number of node links upon a node and expresses the probability that content can be collected by that node. Closeness centrality describes the mean distance to all other nodes. This value is of-

ten used as an indicator about how much time is required to diffuse content from this node to other nodes. Betweenness centrality describes the number of shortest paths through the node and gives a hint how important this node is as a bridge to other communities.

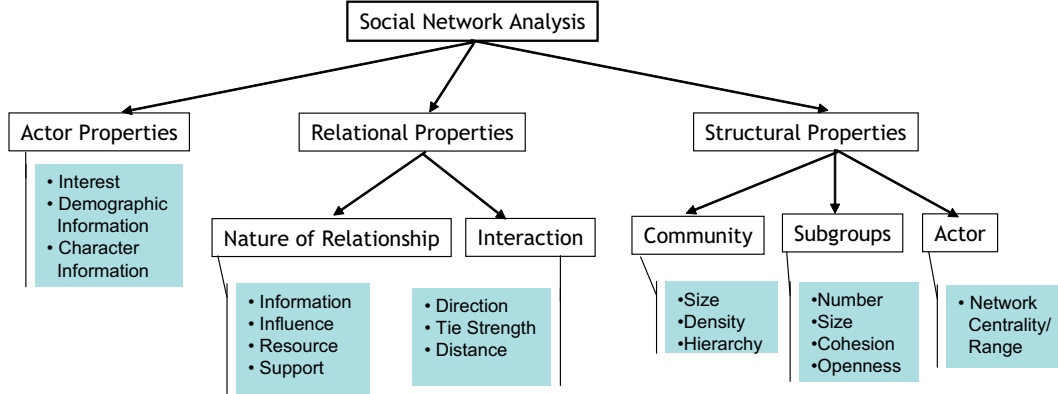


Figure 2.2: Properties of social networks.

2.3 Mobile Support Infrastructure

Community support systems for mobile groups require a distribution system for situation specific contents which target small user groups often only for a short time. This imposes a big challenge to the information system, since distribution processes are seldom efficient. Recently several mobile support infrastructures came up, which differ strongly in the way content is distributed. Below we compare traditional Client-Server (C/S) platforms, to *Mobile Peer-to-Peer network (MP2P)* applications and *Mobile Encounter Networks (MENs)*. Here the focus is set on group formation capabilities, supported content types, diffusion characteristics and platform deployment and administration issues.

2.3.1 Content Distribution Network (CDN)

Commercial mass media content today is mostly delivered through content distribution networks. A content distribution network represents a network of content servers which are placed close to the recipient. With a “close” distance we mean that the number of forwarding steps in the Internet from the intermediate content provider to the consumer is minimized. The overall objective of this approach is to improve the service quality for the user. With content we refer to wide variation of downloadable objects like real-time streams, media files and documents but also applications or services.

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Traditional CDNs are implemented as client-server networks but more recent systems use peer-to-peer networks as an underlying technical infrastructure. While a single provider distributes content to a community of consumers in a client server system, peer-to-peer systems allow users to become content provider and consumers. Both technical infrastructures are presented in more detail in the following Sections 2.3.2 and 2.3.3. Peer-to-peer systems improve content distribution because they allow the integration of heterogeneous content sources which strengthens the role of user generated contents. But also for mass media content delivery situations, peer-to-peer systems show certain benefits. In concurrent download situations which are typical for mass media sources, service quality improves with every user participating in the download process, as they alone provide their own resources.

CDN providers optimize the content delivery process based on the content server location which is often dynamically adapted to the current content popularity. For the provider, costs are reduced due to lower overall bandwidth costs and users benefit from better perceived service quality e.g., based on reduced download times. This quality improvement is a prerequisite to deliver a complete new level of high quality content.

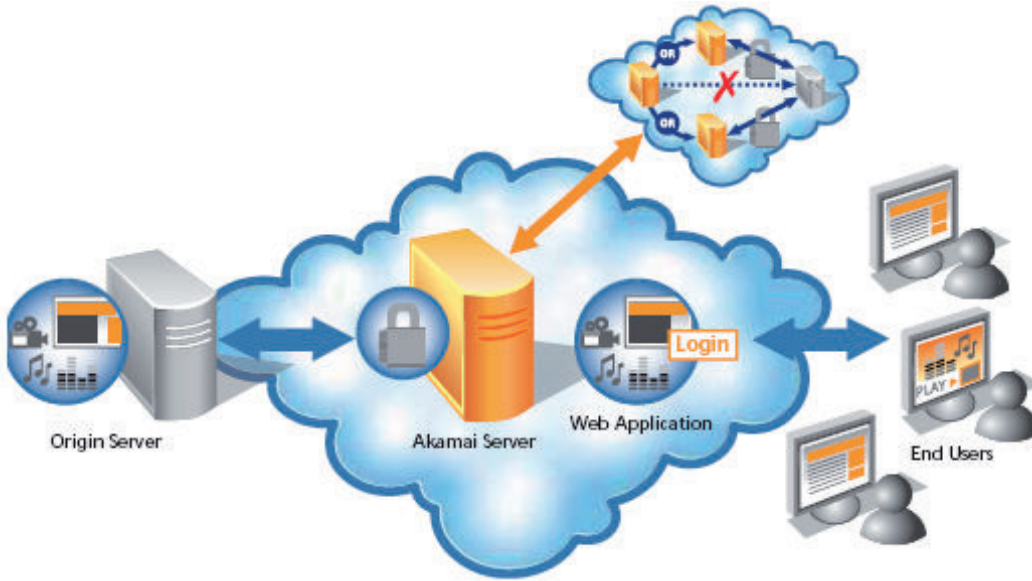


Figure 2.3: Content delivery network (Barnaba [10]).

2.3.2 Client-Server (C/S) Platforms

Most commercial community support platforms hosted today by telecommunication operators represent C/S architectures. C/S platforms are *easy to*

2.3. MOBILE SUPPORT INFRASTRUCTURE

deploy and *community content* can be controlled through a central entity. Mobile versions of Facebook¹ and Twitter² are good examples for this platform type. The communication between server and client is managed through wide range *cellular networks* based on the General Packet Radio Service (GPRS) or the Universal Mobile Telecommunications System (UMTS) protocol or short range Wireless Fidelity (Wi-Fi) networks (see Figure 2.4). Application servers offer general purpose community services like user profile, information and communication services. User profiles provide general information about users and are often used by applications to manage user personalization settings. Users access these services through mobile phones. In some cases, they have to install *small applications*, offering *basic screen handling* to *access or author* community content. To avoid lengthy installations some community operators replace clients with browsable web pages.

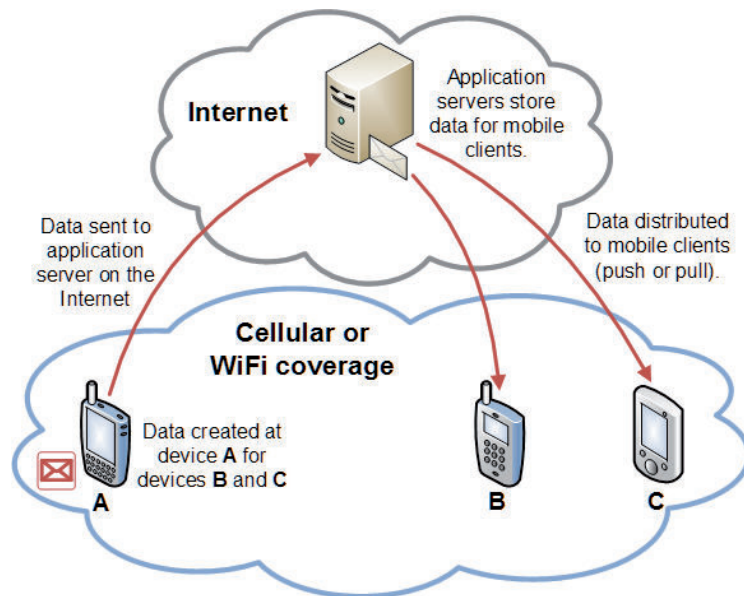


Figure 2.4: Mobile client-server architecture (Earl [85]).

Group management is provided through publish-subscribe services. Group leaders (or ordinary members) may publish content in these groups. All subscribed members are subsequently informed through notification services and may retrieve the content if they wish. User experiences show that GPRS protocols with bandwidths up to 115 kbit/s are only practical for smaller file types like text messages but suffer seriously from larger media like audio or video. For this reason, UMTS with bandwidths of up to 384 kbit/s are often more

¹See <http://mobile.facebook.com>

²See <http://twitter.com>

appropriate. Experiences from a Twitter survey [61] show that users use content attachments to deal well with these bandwidth limitations. Attachments have the advantage that they can be downloaded separately in a situation where better download conditions exist. For our mobile community scenario, C/S architectures have only a limited use. First, with increasing popularity central servers become often bottlenecks or may even fail completely if technical problems occur. Second, publish-subscribe systems require predefined group specifications and thus cannot exploit ad-hoc group formations. Another disadvantage results from the hierarchical diffusion approach which does not allow the consumption of nearby information sources.

2.3.3 Mobile Peer-to-Peer Systems (MP2Ps)

With increasing Internet traffic service operators started to develop load balancing measures. One way to achieve this is to push content closer to the recipient with peer-to-peer content distribution technologies. According to Schollmeier's definition [34] the strength of peer-to-peer networks lies especially in resource sharing:

Definition 2.1 (Peer-to-Peer Network [34]) *A distributed network architecture may be called a Peer-to-Peer (P2P) network, if the participants share a part of their own hardware resources (processing power, storage capacity, network link capacity, printers,...). These shared resources are necessary to provide the service and content offered by the network (e.g. file sharing or shared workspaces for collaboration). They are accessible by other peers directly, without passing intermediary entities. The participants of such a network are, thus, resource (service and content) providers as well as resource (service and content) requesters (Servant-concept).*

This content sharing process follows a certain life cycle from content *creation, sharing, discovering, transfer* and *success confirmation*. To share content between peers, peers start *advertising* their resources in the peer community through peer profiles. *Profiles* contain metadata about the identity and the characteristic of that peer. This includes information about a peer's content, expertise and preferences. Since peers belong to specific persons this data is often augmented with demographic user information. The subsequent communication between peers is managed through peer *protocols*. Peer-to-peer protocols enable a common understanding between peers and assure consistent execution states for each participating peer throughout the sharing process. Each peer evaluates incoming messages and triggers specific actions if the message has been correct. Collected contents are stored in the local *cache* of the peer. Since a cache's storage space is rather limited, *cache policies*

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coordinate the removal of unused contents in regular intervals from the storage. These policies are often designed in a way that peers evolve individual expertises over time. In robust environments peers construct shared content summaries (often also referred as content indexes) to ease content discovery and provide a complete transparent knowledge space. In a centralized architecture, these content summaries are maintained in a single peer (e.g. Napster [57]), whereas in a fully distributed architecture like the Gnutella system [57], they are distributed among all peer members. In hybrid architectures like the FastTrack system [31], indexes are maintained by a small group of super peers which are usually equipped with superior hardware. Figure 2.5 shows a centralized architecture of the Bittorrent file sharing system³ [90], in which index providers (trackers) are used to coordinate download activities.

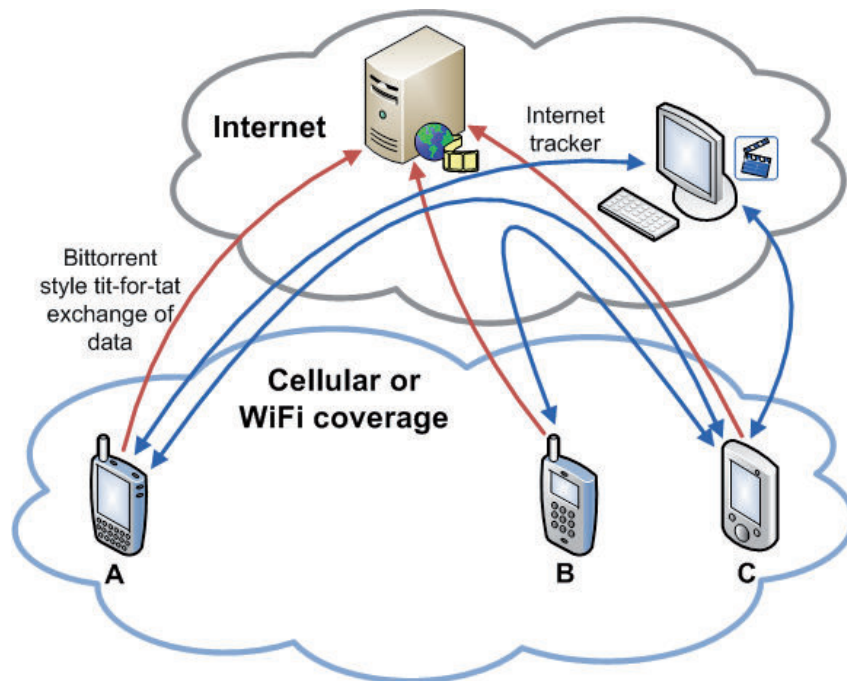


Figure 2.5: Mobile peer-to-peer scenario (Earl [85]).

In mobile usage scenarios peer-to-peer networks are executed on top of wireless networks. Wireless connections between devices are established through wide area wireless networks. In a dynamic mobile environment content index management reaches its limits, because additional administrative network traffic is needed to keep them up to date. At a certain point the benefit of having search indexes may not be given any more and be replaced with a simpler query flooding approach. This abandonment of index maintenance traffic is, however, traded with decreased transparency and higher traffic demands

³See <http://www.bittorrent.com>

during querying. To avoid flooding of the entire network peers use a routing parameter which limits the number of forwarding hops in the network. Wireless networks have to deal with high network dynamics and unreliable transfer bandwidths. According to a survey conducted by Hößfeld et al. [38], a given minimal bandwidth has to exist to make file sharing work on mobile devices. Because of this high traffic demands GPRS networks are often insufficient. Hößfeld et al.'s measurements have shown that GPRS can only be used to share small text files. Mobile media, e.g., photo, audio and small video recordings can effectively be shared only over UMTS networks. To circumvent these physical restrictions telecommunication operators used mobile proxies. Mobile proxies represent a virtual cache for mobile phones and stay on line even if the mobile phone has no reception or has run out of battery. With the increasing popularity of content sharing between users direct device-to-device exchanges become more important for the operator. In UMTS networks one can expect bandwidths up to 384 kbit/s, whereas newer HSDPA networks may offer up to 7,2 Mbit/s data transfer rates in theory and more realistically up to 3.6 Mbit/s. This bandwidth limitation results from heterogeneous up- and download bandwidths representing a potential bottleneck for any peer-to-peer application. In near future LTE wireless systems may solve this problem as they promise to offer even up to 300 Mbit/s. In comparison to UMTS or HSDPA, LTE supports various bandwidths (from 1,4 MHz to 20 MHz) and as such can more flexibly deal with varying traffic demands. Rich multimedia content transfers between devices are managed through *multiple source downloads*. This technique splits the stream into different packages, transfers them in parallel through different paths and aggregates them again at the recipient according to the logical order of the media stream. Another problem according to Nurminen et al. [7] are heterogeneous traffic patterns in peer-to-peer networks caused through *lurker effects*. Lurking describes the observation that only a small group of people in a community provides contents, whereas the majority consumes those only. In contrast to the fixed Internet heterogeneous traffic patterns are a big problem for resource restricted mobile devices. To solve this problem, Nurminen et al. suggest to balance the traffic artificially and reduce the traffic where possible. One way to balance the traffic between peers is to group peers according to their content expertise. Load balancing is then achieved by sharing content summaries between each group member, allowing them to respond to queries on behalf of another, e.g., if it is overloaded with other requests. Nurminen et al. call this approach Parallel Index Cluster (PIC). Besides that Nurminen et al. observed that quite a few query requests were sent through unpromising paths over peers with different expertise than that of the query request. They therefore proposed a more content aware routing approach, which adapts the number of forwarding hops to the expertise of the currently traversed peer. In other words, routing paths are

extended if the peers fit with the query request and shortened otherwise. This approach of course assumes that peers with similar expertise are in the close neighborhood. Making this assumption for context sensitive content is not a problem, since the content relevance decreases usually with the distance.

Although high network traffic and related energy usage are a major disadvantage of peer-to-peer systems it is still worth mentioning some important advantages. Whereas a server based content distribution platform targets in the majority mass content, peer-to-peer networks have proven useful to share so called long tail content resources intended for small audiences. Since the value for situation aware content raises in mobile usage scenarios this is an important advantage. Furthermore, creating this big amount of situation aware content cannot be achieved by a single provider. Peer-to-peer networks encourage collaborative creation processes and move more power back to the user community.

2.3.4 Mobile Encounter Networks (MENs)

The biggest drawback of earlier presented architectures is that those cannot diffuse content between collocated devices. This is different for peer-to-peer systems based on a short range wireless network like Bluetooth or Wi-Fi. Bluetooth has a range from 10-100 meters and Wi-Fi around 20-200 meters. Content exchanges in such networks can only happen if the ad-hoc wireless networks of all involved devices overlap (see Figure 2.6). Kortuem et al. [69] describe the content transfer process as follows:

“With the advent of Personal Area Network (PAN) technologies our mobile and wearable device can participate with us in face-to-face interactions. PANs⁴ establish communication links among physically close mobile devices. We can interpret this as if a PAN creates a digital sphere (aura) around every person. The extension of this aura depends on the transmission range of the wireless transceivers and can range from a few inches to several feet. When two individuals come in close physical proximity or meet face-to-face their respective auras overlap enabling their personal mobile devices to interact. At that point, the devices can exchange information and access each others services. On the other hand, when these individuals separate and their auras no longer intersect, connections between their devices are broken and inter-device communication is no longer possible.”

Because of this transfer characteristic Kurhinen et al. [66] called them Mobile Encounter Networks. According to the authors, the big advantage of

⁴Wireless ad-hoc network like Infrared and Bluetooth

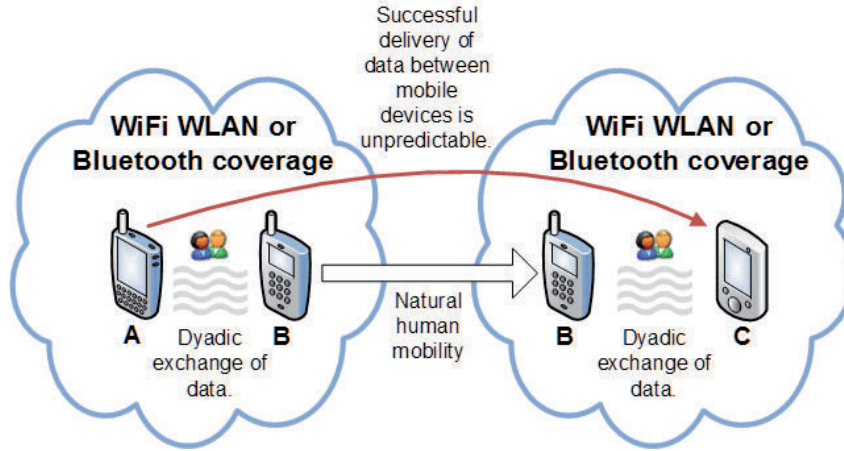


Figure 2.6: Encounter network model (Earl [85]).

MENs is that they require no infrastructure as node addresses are assigned in an ad-hoc manner only within the current transmission range. Therefore, complex routing over a large distance as it has been described for MP2P is impossible. In contrast to MP2Ps, content in MENs is exchanged in a *push* rather than in a *pull* manner (see Kurhinen et al. [66]). This process has to be as transparent as possible to the user, as content transfers should not be noticed and run autonomously in the background of the user. Peer profiles thus not only have the function to provide information about peer identity but also to filter for suitable content exchanges.

Contents in MENs are distributed in a *spatial* manner from neighbor to neighbor. Diffusion speed and reach depend hereby on the encounter and mobility characteristic of their users (see Kurhinen et al. [66]). Usually contents are spread fast in the beginning and start to lower down when more people have received it already (see Figure 2.7). This process is comparable with rumor spreading where the value of information decreases the more people have heard about it. A comparison with local content broadcasts shows that MENs are advantageous, as they continue to spread the content in far distant areas (see survey conducted by Bai and Helmeý [6]) as long as the content resides in the cache.

The network bandwidth lies around 4-700 kbit/s for Bluetooth and for WLAN. However, when it comes to available bandwidth the limited time frame of encounters in MENs is often the bigger problem to consider. The majority of encounters are short, e.g., a typical pass-by situation may last not more than a few seconds. This often limits content exchanges to not more than a few hundred kilobytes. For the exchange of mobile multimedia content like photos, audio and video recordings this is usually not enough. To avoid the bandwidth problem, Kortuem et al. suggested in [68] to exchange *references*

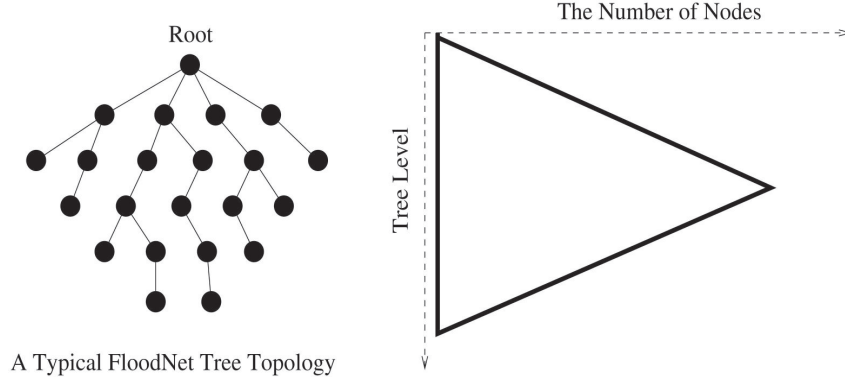


Figure 2.7: Flooding characteristic (Jiang et al. [62]).

to larger contents instead of exchanging the content itself. To proof this, they created a community application for the exploration of music trends. Their music service exchanges play lists based on the Moving Picture Experts Group Layer-3 Audio (MP3) format between their members.

Mobile encounter networks buffer content ahead of potential content requests because networks are *intermittently* disconnected and a content source may not be available when it is needed. Since local caches are in comparison to the virtual knowledge space several orders of magnitude smaller, cache replacement policies focus on keeping the most up to date and thus, relevant contents. Mobile *proxies* provided from telecommunication operators enable cache extensions and a continuous download through the Internet (see Figure 2.5) even if the short range networks have become unavailable. Altogether, the biggest advantage of MENs is their spatial diffusion character. Spatial diffusion flourished on the distribution of context aware contents and limit network traffic to peers with a high probability to carry relevant contents.

2.4 Summary

In this chapter, we presented the theoretical foundation for mobile community support systems and discussed potential community architectures.

The challenge of supporting mobile groups in urban settings lies in their unpredictable character. Although such informal groups are highly dynamic, humans do not act completely spontaneously and base their decisions on previously made experiences. We identified following group formation patterns: The probability to form social relationships with others increases if people follow similar interests, live in the neighborhood, and encounter each other repeatedly. We classified urban communities according to their cohesion in public, acquaintance and friend groups. Equivalently, we distinguish meet-

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ing places between public, protected and private territories. Social network analysis techniques can be used to identify social groups and meeting places.

To support informal groups, mobile support infrastructures need to be highly flexible, adapt their group boundaries continuously and enable direct interactions between their members. To identify the best possible architecture for mobile community support systems we compared C/S systems with MP2P systems and MENs. C/S systems represent the preferred architecture for telecommunication operators as they are easy to deploy and content sharing is easy to control. Since people demand very specific niche information, providers realized that content cannot be generated by a single entity. MP2P systems solve this problem and support collaborative content generation through direct peer-to-peer interactions. High bandwidth usage, however, remains an unsolved problem. The advantage of MEN infrastructures lie in their spatial diffusion process well suited for the diffusion of context dependent content. Content push rather than pull strategies in MENs are also more advantageous in unstable mobile networks. Varying encounter times, however, limit their exchanges to small and uncritical contents.

Altogether, MENs seem to be the most promising architecture for mobile community support systems, because content is transferred direct between peers and thus, enable bottom up information diffusions. One disadvantage of MENs is, however, their high resource usage caused through the content flooding. Consequently, a more intelligent approach has to be found. In the next chapter, we will analyze patterns of human knowledge spreading and compare existing MEN methodologies for information diffusion. Based on these outcomes we envision identifying more economic diffusion approaches for MENs.

3

Related Work on Knowledge Diffusion

A common design challenge for any social support system is the social-technical gap. Jonathan Gurdin describes in [50] different organizational challenges related to social dynamics in digital communities. These include the problem of *complex interfaces* due to integration of application and social functionalities, possible *disruption of social processes*, need for *exception management* to allow for improvisation, *disparity of effort and benefit* of community management, the necessity to reach a *critical mass* to make communityware attractive, and difficulties to evaluate *communityware success*. On the technical side, Diacui et al. [12] identified the creation of *member awareness*, *group coordination*, *content sharing* and *synchronization* and system *scalability* as major technical challenges. Summing up, support systems have to compensate dynamic and situation specific human behavior and at the same time provide community information for the user in a scalable and transparent way.

MENs represent a good starting point for the design of a mobile community support infrastructure as they unify social and technical aspects. Content exchanges in MENs depend on real world encounters and on technical parameters of the ad-hoc network. In the following literature survey, we analyze in Section 3.1 knowledge diffusion theories and use results to identify promising knowledge spreading phenomena. We then review in Section 3.2 MEN experiments after their applied routing mechanism to see how knowledge spreading patterns can be realized through routing protocols in MENs. We summarize our literature analysis in Section 3.3 and highlight most promising approaches.

3.1 Knowledge Diffusion Theories

The proximity of people has been identified as a critical factor for knowledge transfers (see Lorentzen [76]). Proximity is hereby seen as a concept with various dimensions, including *geographic*, *social* and *cognitive proximity*. Geographic proximity refers to the physical possibility to interact with others during an encounter. Social proximity covers the willingness to share knowledge according to the trust they have in each other. Cognitive proxim-

ity describes the shared background that enable people to understand each other. We present theories which describe spatial, social and cognitive aspects of human knowledge transfer processes.

3.1.1 Spatial Dimension of Diffusion

Several researchers have studied spatial diffusion phenomena in the area of innovation adoption, skill acquisition and disease spreading (see Rogers [97]). Disease and knowledge spreading are comparable as both are transferred through direct contact but of course with different efficiency.

Euclidean Space Model

In general, knowledge diffusion has a strong geographical component. Jaffe [60] and later Acs et al. [2] showed, for instance, that collocated corporations are influenced by local and global knowledge flows. Consequently, innovation diffusion depend to a large extent on the geographic closeness of other research companies. The importance of people, spaces and goods decreases with the distance, largely because communication and interaction possibilities are increasingly limited. In other words, geographic spaces structure urban communities in regional areas with different specialization.

Spatio-temporal Compression

Human mobility leads to a stronger mixing of urban societies leading to a change of the situation to a certain extent. This observation is also often referred to as *spatio-temporal compression* effect, as more people can be contacted in the same time as without travel. Tatem et al. [110] researched on the connection between human travel and disease spreading. The close synchronization between travel patterns and occurrences of disease outbreaks proved that travel significantly extends spreading efficiency. With a rise of the average travel distance in recent years (see traffic survey from Schönfelder et al. [5]), this correlation has become even more important. For an increasing proportion of the society, traveling has become an essential part of their work life and represents an important quality factor in spare time (see Torre and Rallet [112]). Mobility can be distinguished in short term daily mobility e.g., commute to work places or long term mobility when people change their living places. Short term mobility depends on available urban infrastructures (e.g. service and transportation offer). Their daily travel path represents a long term result of an effort-benefit calculation and explains why daily mobility patterns keep fairly constant over time (See Hammer and Scheiner [116]). Figure 3.1 visualizes a sample mobility pattern of an individual, in which the strength of the green color correlates with the visiting duration. Both, increasing ranges

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of human mobility patterns and their predictability make human mobility an important diffusion factor.



Figure 3.1: Daily travel patterns (Schönfelder et al. [5]).

Central Places Theory

Settlements of cities have begun at strategic important places and have grown as they have attracted more people. Central places often remain important because they provide better supply services for their surrounding neighborhoods.

Porta et al. [22] speculated that the *hierarchical* structure of urban systems is an important factor that influences spatial diffusion. To proof this, they conducted several experiments in Bologna, Italy. Hereby, they derived the place centrality in a similar way as Moreno did it for the analysis of social networks. Equivalently, they created a *street graph* model exemplary taken from Bologna in which nodes represent intersections and streets the edges between them. Previous experiments [26] have shown that betweenness centrality distinguishes central more efficiently from edge places than degree or closeness centrality. Figure 3.2 a) shows a visual representation of the betweenness value. Light colors in this graph represent central and dark less central places.

For the evaluation of the service quality the authors used a kernel density. A kernel density estimation represents a non-parametric way of estimating the probability of a given system variable. Here the densities represent the number of provided service offers per square meter (For more details see [89]). In Figure 3.2 b) the dark red color represent places with a dense service offer whereas light colors represent places with rather sparse service offers. By comparing

CHAPTER 3. RELATED WORK ON KNOWLEDGE DIFFUSION

the betweenness value from the street graph with the density a strong correlation between both parameters is obvious. Dense urban populations obviously encourage service specialization and their exchange. We conclude from this that central places play an important role for knowledge diffusion.

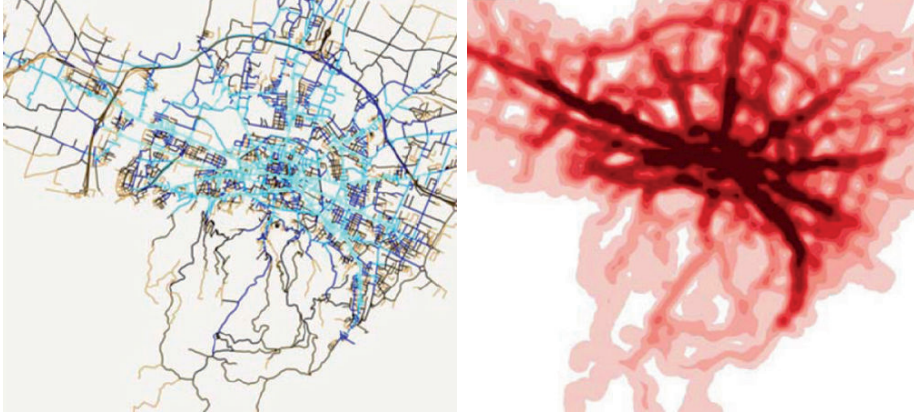


Figure 3.2: Visual representation of a) the spatial betweenness centrality and b) the kernel density of Bologna (Porta et al. [26]).

Urban Overlay Theory

Modern communication and transport technologies sustainably influenced social life in urban environments. People nowadays maintain increasingly more relations independent of the distance but based on specific properties, which are important for them. This of course is only possible since communication and travel efforts are increasingly smaller. In a world where relations depend less on geographic aspects, urban structures lose importance. Following Noller and Ronnenberger [83] the result of this development is a new *relational* model of perception, where social and spatial relations emerge only based on their semantic meaning for humans. Sassen [102] argues that the scattering of urban centers leads to an *overlay structure* which integrates different *local*, *national* and *global* layers. People not only communicate through their overlays but also exchange goods, services and money. Castells [19] sees a similar development but claims that such virtual layers are also highly *volatile*. Accordingly, he distinguishes between *privileged* and *peripheral* spaces whose role emerges for a short term and changes after a while again. A development which was certainly stimulated with the rise of mobile phones. Communication technologies create opportunities for the construction of overlay networks, which integrate urban communities.

3.1.2 Social Dimension of Diffusion

Besides the spatial diffusion of information, transfers can also be facilitated through social networks. Researchers have analyzed structural aspects of surrounding social networks like the tendency toward clustering or positing of important members. From this they are able to draw conclusions how diffusion relates to social parameters.

In the following, we present the *small world* theory as a main model to proof human behavior economics and other dependent theories explaining how this diffusion efficiency can be achieved.

Small World Theory

Humans are able to share knowledge in societies efficiently only with their *common sense*. To proof this Milgram [113] carried out a letter sending experiment in which he asked people in the Midwest (Omaha, Nebraska and Wichita) to send a letter to a recipient in Massachusetts. He chose these specific locations because he assumed that they represent a large distance in a spatial and social sense. In the unlikely case that the person knew the recipient they were instructed to send it directly to the person, in all other cases people should forward the letter to persons who they thought could know the recipient.

After receiving the letters Milgram analyzed the results. Not surprisingly only a small part of the letters (64 of 296) finally arrived at the destination, because some intermediates refused to forward the letter. Milgram analyzed the paths of those letters which have reached their destination and observed that all letters were sent within *six forwarding steps* (see relationship distance in Section 6.2.2). The letter sending process was obviously efficient in the sense that no letter exceeded this specific number of forwarding hops. This is surprising because people participating in this experiment had in the majority only local knowledge to make their forwarding decision.

This ascertains that bottom up diffusion systems work efficiently, even if the system can only utilize information from entities participating in current encounters (see Section 2.3.4).

Weak Tie Hypothesis

Granovetter conducted a similar experiment, in which he wanted to reveal how people find new jobs. During a long term survey [46] in New Jersey, he found that most jobs were not found through work- or friend networks, but rather through *acquaintances*.

This is insofar surprising as we spend significant less time with acquaintances. Based on this observation Granovetter analyzed the background knowledge of each study participant. It became clear that people to whom we have

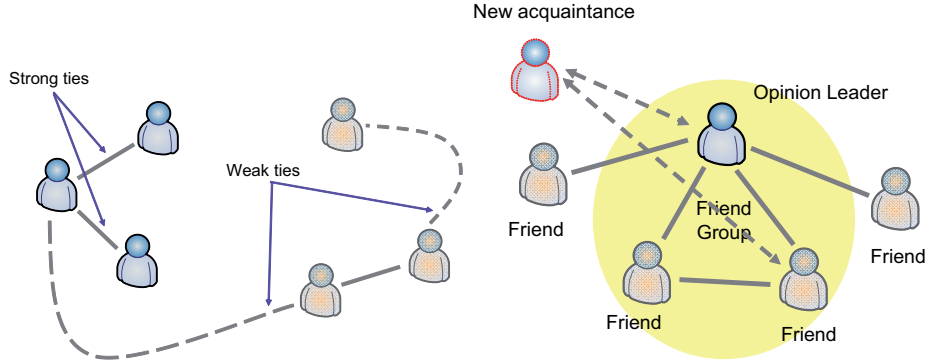


Figure 3.3: Social phenomena: a) weak tie bridges and b) preferential attachment.

frequent contact have a much higher probability to share the same information and are thus not well suited to give job recommendations. On the other side, people who we meet seldom are often embedded in friend networks which have access to different knowledge sources. Following Granovetter, acquaintances function as a crucial *bridge* between social groups (knowledge pools) in urban societies (see Figure 3.3 a)). Since acquaintances represent only weak links, knowledge between social groups spreads much slower than within social groups.

Theoretical Models

Watts and Strogatz [119] were the first to develop a theoretical model to explain the small world phenomena. In their opinion, the high forwarding efficiency was achieved through randomly selected shortcuts in the community.

They proved their assumption by constructing a lattice (see Figure 3.4) in which nodes were initially connected through neighbor relationships in the left lattice. In this structured graph reaching a node on the opposite site takes a maximum path length. By *rewiring* some paths randomly (lattice graph in the middle) this path length could be dramatically reduced. This result also backs the weak tie hypothesis of Granovetter. In the opposite, forwarding information to local neighbors in a *random* graph (right lattice) requires more forwarding steps as in a *structured* graph in which all neighbors are directly connected. Hence, structured graphs are better suited for local content exchanges.

Watts and Strogatz concluded from the that the efficiency behind the small world model originates from clustering tendency of human societies and randomly created shortcuts between these subgroups.

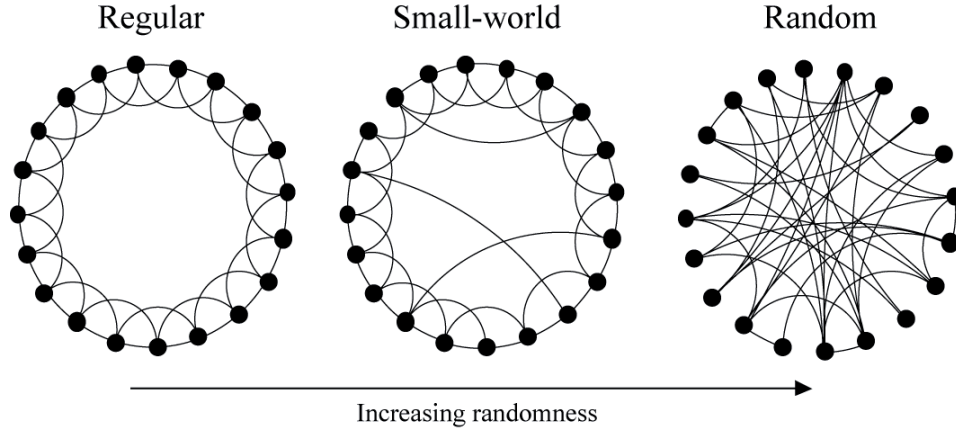


Figure 3.4: Theoretical small world model (Watts and Strogatz [119]).

Scale-free Networks

Barabasi et al. defined the model of *scale free* networks [8], as an explanation for efficient knowledge sharing in social networks. Many human made networks like web pages, science models, engineering systems, biological systems, citation structures have a scale-free network character.

According to the authors' observation people prefer relationships to others who are already well connected. The authors called this effect *preferential attachment*. Networks which are progressively constructed like this follow in principle a power law. Power law distributions have typically long tails in the end.

The right graph in Figure 3.5 shows this degree distribution. It illustrates well that only few members evolve as highly connected opinion leaders. The left graph in Figure 3.5 illustrates the integration potential of scale free networks based on the example of air traffic routes in the United States. If knowledge is distributed through these highly connected nodes the number of required forwarding steps to reach the community edge can be significantly reduced. As a conclusion diffusion systems being aware of social hierarchies transfer knowledge more efficiently.

3.1.3 Cognitive Dimension of Diffusion

Although geographic and social proximity enables physical and virtual contact, both are not sufficient if cognitive proximity does not enable them to share and understand this knowledge.

To proof the importance of this factor Reagans et al. [93] observed the transfer process directly and discovered that people do not use all available opportunities for knowledge transfer. They concluded that transferring knowl-

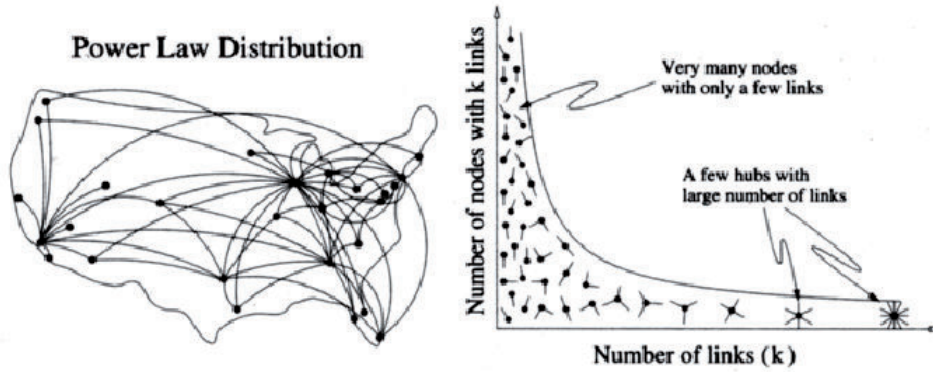


Figure 3.5: Power law distribution of scalefree networks (Barabasi et al. [8]).

edge represents some *effort* for helping others to understand the knowledge. More specifically, three factors determine a successful transfer: the *relationship quality*, *cognitive capacity* and the surrounding *social network*. To quantify the exchange process they distinguished *codified* and *tacit* knowledge and discussed different enabling factors, which make it more likely that tacit knowledge can be transferred between two parties. Codified knowledge refers here to explicit knowledge which is easy to communicate, while tacit knowledge belongs to the implicit knowledge of a person which is difficult to share with others through language codes. *Strong relations*, *group collaboration*, *central network positions* and a high *background overlap* make the exchange of complex and diverse knowledge more likely. Figure 3.6 gives an overview how different enabling factors influence the human knowledge transfer process. Subsequently, we describe how each factor benefits the diffusion process:

- **Common Knowledge:** People learn knowledge by combining existing experiences with new facts. Accordingly, Reagan et al. in [93] state:

”An implication is that it is easier for knowledge to transfer from the source to a recipient when the source and the recipient have knowledge in common. Consequently, knowledge is more likely to be transferred between people with similar training and background characteristics.”

- **Tie Strength:** The more people interact with each other the more efficient gets their communication. To support this idea Reagan et al. cited a study from Hansen [51]:

”Hansen, in his analysis of team performance, found that team performance increased as a function of the strength of connections from the team to the broader organization and

3.1. KNOWLEDGE DIFFUSION THEORIES

also as a function of the kind of knowledge being transferred by the team. Furthermore, team performance was higher when strong ties were used to transfer tacit knowledge. Based on these findings, Hansen concluded that a strong tie facilitated the transfer of tacit knowledge more than it facilitated the transfer of codified knowledge. He concluded that *strong ties should be used for the transfer of tacit knowledge and weak ties for the transfer of codified knowledge.*”

- **Group Cohesion:** Group cohesion describes the solidarity that people feel toward a group and their members. Strong cohesion reduces the appearance of egoistic behavior, because the group as a whole creates synergies and delivers benefits for everyone. To show this benefit, Reagan et al. referred to a study about friendships of hotel managers and their implications conducted by Ingram and Roberts [59] in Sidney:

”Hotel managers embedded in friendship networks (i.e., managers connected to each other through a dense web of third-party friendship ties) shared customers and best practices, which increased the profitability of their hotels. One explanation for the observed effect is that friendship networks promote knowledge transfer, allowing managers facing similar market conditions to learn from each other’s experience.”

- **Network Range:** Network range or centrality describes the integration of a single member in a given community. Reagan et al. in [93] argued that people with a high network range have better access to different ”knowledge pools” than those with fewer connectivity. To support this hypothesis, they referred to a study undertaken by Reagan and Zuckerman [94], where they described to which extent project members in research departments can transfer complex ideas to other departments in the enterprise:

”Collaboration among scientists with different external contacts bridged gaps, or ”structural holes” in the network outside the team. People at opposite ends of a structural hole have access to distinct knowledge and information. Bridging structural holes in the external network enabled the scientists to access and share with each other diverse knowledge, resulting in greater creativity and innovation, thereby improving the team’s overall productivity.”

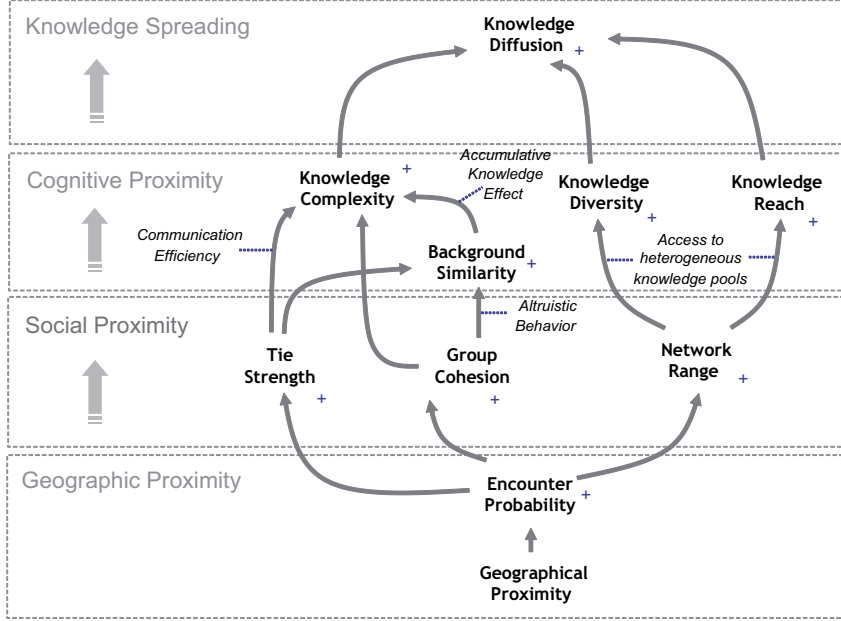


Figure 3.6: System loops of least effort knowledge transfer.

This diffusion theory is probably the most important one, as it considers parameters, which are directly correlated with the diffusion process. A big challenge of MENs lies in comparison to support systems of the wired Internet in the limited transfer bandwidth. The bandwidth depends heavily on the encounter characteristic. This effort based transfer hypothesis allows us not only to select suitable content providers but also to identify contents of a given type which are most likely transferred successfully during the encounter.

3.2 Encounter Network Studies

Jones and Ward [63] proposed a classification that separates epidemic diffusion approaches based on the methodology to reduce the network traffic. Generally two major approaches can be distinguished. First, nodes may not use every encounter for content forwarding and select only those that promise a high diffusion impact (in the following called *selective forwarding* approach). As bandwidth in MENs is limited this approach may be advantageous over a longer time. The second approach assumes that nodes carry several contents with different importance for the user. Cache policies may in the interest of the user purge less relevant content with more relevant content (in the following called *cache management* approach). Since cache space in mobile devices is a scarce resource this approach leads in long term to better results for the user.

Below we present selective forwarding strategies that exploit node mobil-

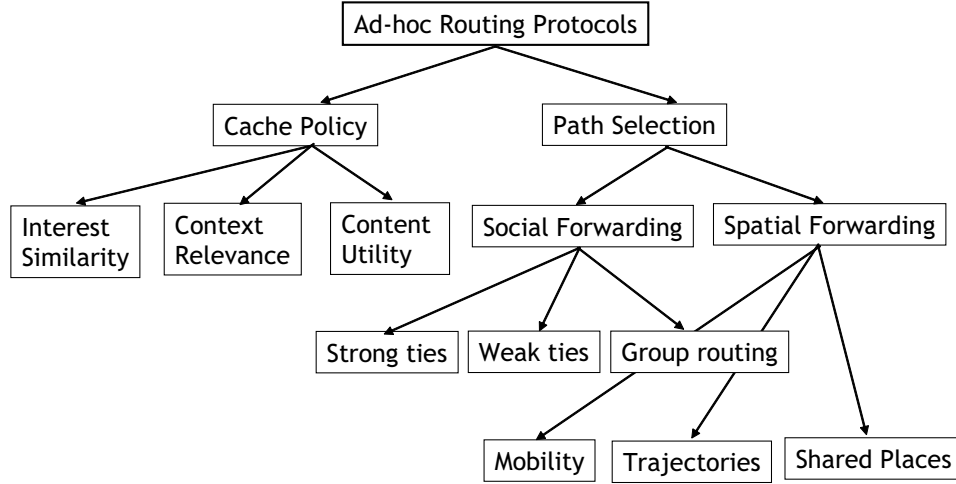


Figure 3.7: Classification of MEN protocols.

ity, social networks of nodes and conclude this section by presenting cache management approaches for different content types.

3.2.1 Mobile and Spatial Approaches

Spatial forwarding approaches were extensively researched in the area of sensor and ad-hoc networks. Node mobility is an important factor to improve content diffusion based on the spatio-temporal compression effect presented in Section 3.1.1. More advanced research work has concentrated on specific properties of node mobility patterns.

Exploitation of Random Mobility

Shah et al. [104] proposed a three-tier architecture called DataMule to improve information spreading within ad-hoc networks with relative low costs. In DataMule agents move *randomly* around to gather information from a fixed sensor network and drop it finally at a base station. The advantage of such an approach is that no infrastructure is required. Experiments proved that if enough mobile nodes and cache space is available the setup is even more robust in terms of content availability than a traditional fixed sensor network approach. Drawbacks of this approach are potential latencies caused through the random collection of data.

As the geographic reach of social networks is limited (see Section 2.1.1) the exploitation of node mobility is the only reasonable way to diffuse content in large scale urban environments. According to Section 2.3.4 this approach is especially interesting if suburban areas with sparse populations have to be reached.

Node Selection based on Spatio-temporal Trajectories

Other more complex node selection strategies were developed for point-to-point routing protocols, which deliver content to a specific target. This type of protocol tries to reduce the distance to the target with every content exchange. Unfortunately, large scale content routing is difficult due to node mobility. It requires a location service which stores in a distributed database all available node positions. These positions have to be updated and communicated whenever the network topology changes.

Grossglauser and Vetterli [49] present the Exponential Age SEarch (EASE) approach which exploits the *distance effect* of two or more departing nodes. This theory states that nodes require a more precise information about the location of the destination node the closer they come to it to make appropriate routing decisions. As a replaced measure for the precision functions the duration of the last encounter with the destination. The authors hereby assume that nodes in this environment are well mixed and move with a continuous speed. In other words, instead of continuously communicating node locations between nodes, nodes record encounters from all nodes in the community and base their routing decisions on the encounter history of all involved nodes. Figure 3.8 visualizes such an encounter situation. Together with the node identifier each node (node number four and nine) stores the time and location of their encounters. Host nodes then continuously try to select nodes with a more recent encounter time till the target is finally reached. The authors tested their protocol with different mobility patterns including the random way point and compared the relative transmission cost with the transmission costs of the shortest path route. This cost ratio decreased gradually and stabilized at a rather small level. Obviously their approach showed also good scaling behavior with at least 1000 tested nodes.

This greedy routing approach progressively tries to reduce the distance to the target, but it relies on a community assumption (well mixed node population) which cannot be assumed for realistic urban settings. Still, with a suitable metrics applied on community diffusion, e.g., based on node connectivity greedy diffusion has the potential to improve diffusion efficiency.

Node Selection based on Shared Territories

Another way to avoid location services is to exploit *shared territories* of community members. Such an approach is based on the assumption that users do not randomly move around in cities but rather visit frequently specific social meeting places.

Gosh et al. [44] developed a protocol which they called Sociological Orbit aware Location Approximation and Routing (SOLAR) protocol. In their scenario, peers record personal territories which they call hubs together with the

3.2. ENCOUNTER NETWORK STUDIES

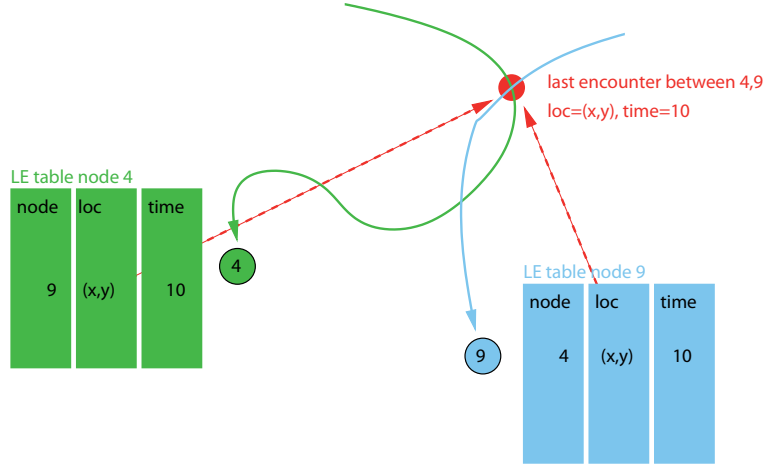


Figure 3.8: Encounter phase of last encounter algorithm (Grossglauser and Vetterli [49]).

visiting probability and *average stay duration*. Figure 3.9 shows a representation of the mobility profile (here called *social orbit*) of two peers 1 and 2. Both peers share the territory (hub) 3. Peers carrying a content for a destination can transfer the content in this territory. Even if the peer is not available during the time other peers may cache it and forward the content to the destination later whenever it visits the territory. Since people do not often change their territories maintaining mobility profiles requires much less effort than tracking the current position of a peer. Propagation of content to a specific target is then based on a collaborative process between acquainted peers. During encounters peers exchange their mobility profiles whenever the encountered peer has not been seen before or its mobility profile has been updated meanwhile. By this, peers gradually learn more about available community members and territories in the urban environment. Packet forwarding itself then represents a multi step process. First peers need to identify *territories* frequently visited by the destination. If this information is not available they start a multi-hop discovery process in the community to get this information from potential close acquaintances of the destination peer. In case, the destination peer receives this query it responds with a message containing its mobility profile together with the currently visited territory. Then, the source node makes a copy of the content and tries to forward it to the current territory of the destination peer or if not available to each territory of it. Hereby, the source peer does not directly forward the content to the remote destination but to its direct neighbors. More specifically it forwards the content to k neighbors with a higher delivery probability than itself or k neighbors with the second highest delivery probability. The delivery probability is calculated from the mobility profile. It depends on what territories neighbors share with the destination, or even more

specific on the visiting probability of the destination. If no neighbors exist, the peer caches the content for a predefined timeout period and purges the content then. The system was verified through a simulation emulating a 1000×1000 square mile area with 15 different territories within $500 m^2$. The peer moving speed was set to 10 m/s and the trace period was set to 3000 seconds. Their experiments proved that both territory size and transmission range influence the impact. In comparison to other epidemic routing approaches like Prophet, their solution showed shorter delays.

As territories of forwarding peers have to overlap geographic distribution ranges are likely to be limited. This approach is still very interesting as overlapping territories represent places where content can easily be duplicated to an entire group of people.

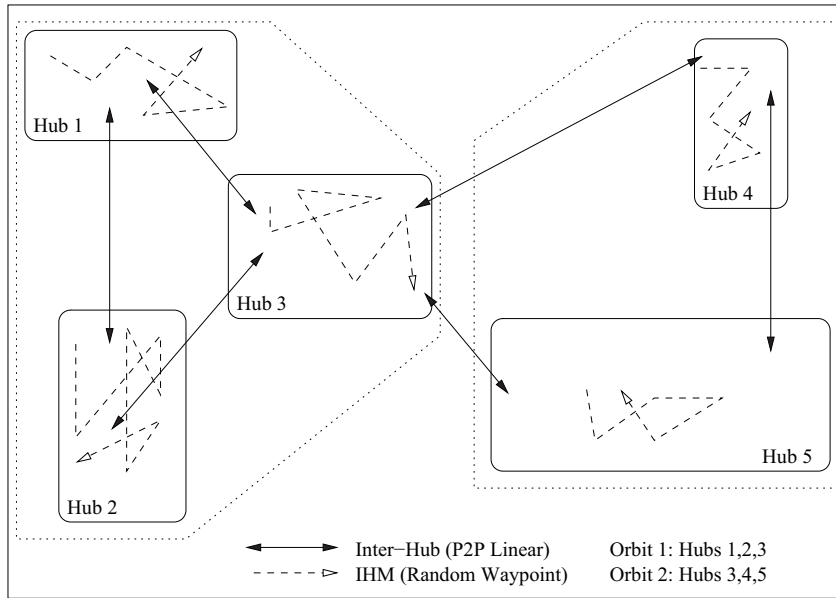


Figure 3.9: SocialOrbit spatial routing schema (Gosh et al. [44]).

3.2.2 Social and Group based Approaches

Since encounter histories allow the forecast of potential node transfers, several publications explored how social network knowledge could be used to select advantageous intermediate nodes. Solutions are ranging from analyzing the encounter history, member reputation, and group affiliations. In the following we present three extensions to epidemic routing protocols which additionally exchange sociological network information during the encounter phase.

Node Selection based on Encounter Familiarity

Lindgren et al. [74] observed that frequently encountered nodes usually also have better delivery probabilities. Based on this idea, they created a *probabilistic* encounter system called Prophet. In Prophet peers monitor encounters and update their encounter history (number of encounters within a given time frame) in their contact list. During the encounter, peers exchange their contact lists and forward content if the counterpart has a higher delivery probability. Since the number of peers with direct contact to the target can be very limited, the authors also utilize the *transitive* nature of social relationships. Peers exchange information about their *friend-of-friend* relationships and recalculate the delivery probability according to possible acquaintance chains constructed through intermediate nodes. A sample encounter situation is shown in Figure 3.10 in which node pairs C/D (graph a) and B/C (graph b) encounter each other frequently (see the contact list). Node A possesses content for node D but the direct delivery probability is very low. When node A encounters node B (graph c), content gets forwarded because the delivery probability between node B and node D is higher. Lindgren et al. verified the Prophet routing protocol through simulation, in which agents randomly move on a plane field. In an assumed area of $1500\text{ m} \times 300\text{ m}$, fifty nodes randomly placed visited a sequence of predefined areas during the simulation. After a warm up phase in which delivery forecasts were calculated, peers started exchanging messages to a randomly chosen destination and recorded delivery abilities, delays and messaging efforts. Results showed that the cache size has a great impact on the performance. With a messaging system like Prophet twice as many messages reach their target as with epidemic diffusion.

Their simulation results show that selecting intermediates after their encounter history reduces the messaging effort to a specific recipient. This scenario can be extended to content diffusion in communities if the delivery probability is differently calculated. We envision, e.g., a calculation in which the encounter familiarity for specific node is replaced with a more general decision factor like the overall node popularity in the community.

Node Selection based on Social Hierarchies

Lynch et al. [58] exploit the *scale-free* character of the small world theory to design a social routing protocol. Following their scenario societies are structured in local and global communities. Figure 3.11 shows a typical content forwarding scenario from a given source (node at the left bottom) to a specific destination (node at the upper right). Such a source node first forwards the copy of the content to more popular people in its community till it reaches a person who is well connected with other communities e.g., like a postman. This *bridge* node (in the figure the large node at the edge of the subordinate

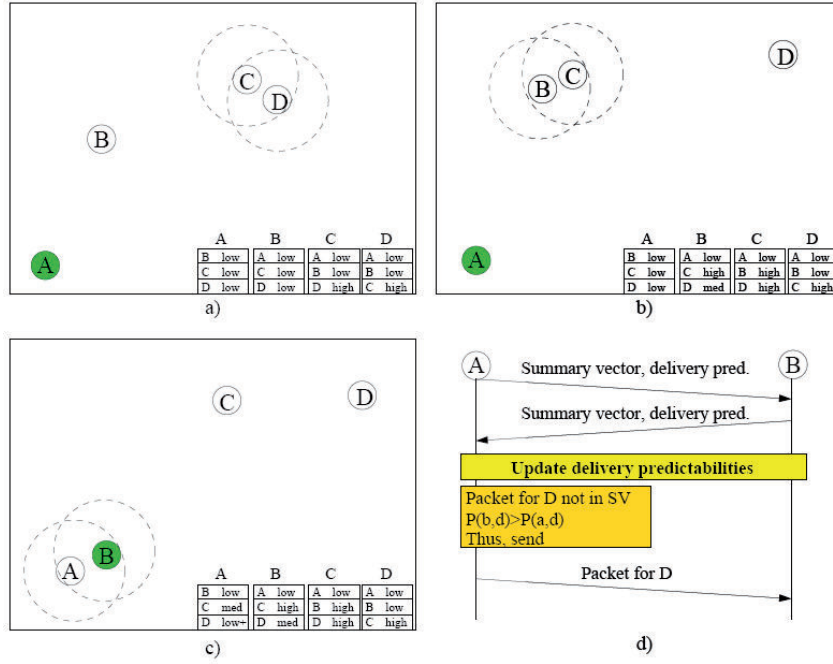


Figure 3.10: Probabilistic routing schema (Lindgren et al. [74]).

community colored in gray) then hands the content over to a member of this community. In this community the content is again forwarded to the local group leader who will finally send it to the destination.

Lynch et al. implemented this scenario with a *greedy* routing approach, where nodes with a higher popularity are continuously chosen until the highest degree node is reached within the community and then progressing to lower degree nodes until the target is reached. Hereby they distinguish between local and global routing scenarios. For content routing within local communities they introduce a mechanism which they call *rank* routing based on node degrees in a temporal community network. A similar mechanism was designed also to forward content between communities which they called *degree* routing. The difference between both is that degree routing uses average node degree values accumulated over a longer period of time. The assumption hereby is that longer intervals provide a better approximation of global node degrees values. Both mechanisms are complemented with a *label* mechanism which helps to identify members which belong to a specific community. The Bubble protocol unifies all above discussed routing mechanisms.

Their protocols were evaluated based on recorded mobility and encounter traces taken from different real world communities. These traces are often also known as Rumridge Reality, Infocom05, Infocom06 and Hong Kong datasets and describe member dynamics of communities with varying hierarchical structure. The results showed that Bubble algorithms require less messages than

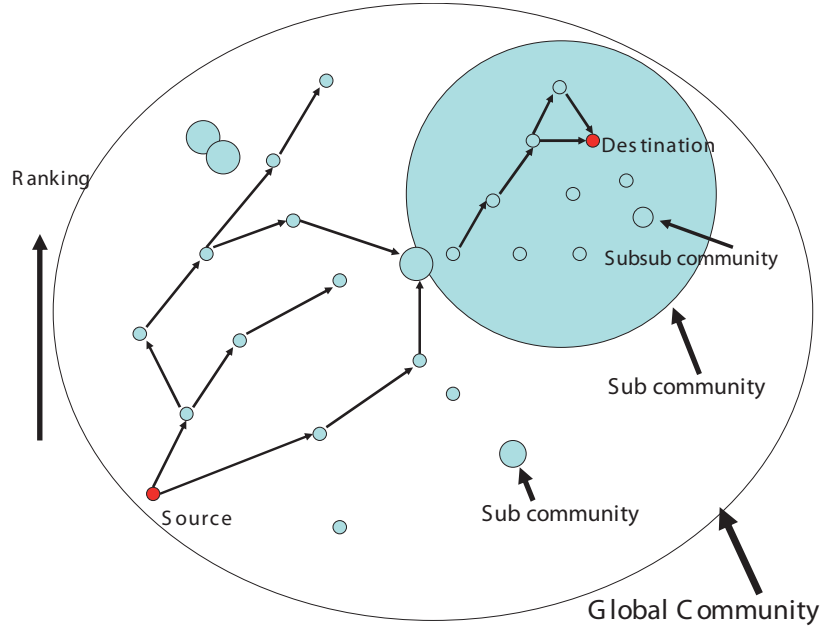


Figure 3.11: Social routing schema (Hui et al. [58]).

Multiple-Copy-Multiple-Hop (MCP) approaches and still deliver contents quite reliably. MCP describe a type of multi-hop routing protocols which forward multiple content copies with a predefined hop count to a given destination. Both greedy routing approaches work well in mixed societies but reach their limits in complete distributed datasets as the Hong Kong dataset, where people were selected without social correlation. As a reference Bubble can only deliver four messages out of hundred while traditional epidemic routing still delivers 40%. The Label strategy has the lowest impact of all new routing approaches but seems to work well in combination with greedy approaches.

The Bubble routing protocol differs from the Prophet approach, as it considers not only bilateral relationships but also surrounding communities. In case peers maintain no direct contact with the recipient, the connectivity of central members in a community can be utilized to identify content recipients faster. Besides the fact that this routing scenario is much closer related to a community diffusion approach we also think that it is more effective. In larger communities identifying transitive relationships is difficult and the exploitation of central members may become a more reasonable strategy.

Node Selection based on Network Centrality

Daly et al. [28] applied the weak tie hypothesis (previously discussed in Section 3.1.2) to improve routing decisions in intermittent connected networks. Following this hypothesis bridge nodes have a stronger capability to connect

different social groups and thus, is a key element of an efficient content diffusion. A common approach to identify *bridge* nodes is through centrality calculations such as Freeman's betweenness centrality. Usually for these types of calculations all community members are considered. To limit calculation effort, Daly et al. proposed to limit calculations to the *ego-networks* of participating peers. To justify this approach, they compared global and local calculated betweenness values and proved their strong correlation. Based on these results they proposed the SimBet routing protocol, which considers not only the *betweenness centrality* but also the *interest similarity* to the target node for routing. The similarity is again based on the transitive principle of human networks and is measured as separation degree (also called hop count) to the target node. The authors simulated their protocol with a realistic sequence of encounters recorded in log files during the Massachusetts Institute of Technology (MIT) reality mining project. Throughout the simulation trace, the number of message deliveries, end-to-end delay, average hop number and forwarding effort were recorded. A comparison with epidemic routing and the Prophet routing protocol was conducted. The SimBet routing protocol performed better than the Prophet routing protocol, and achieved only 60 % more delay than epidemic routing. The advantage of SimBet routing is, however, obvious when comparing the message effort. SimBet routing claims to reduce the effort more than 33 times against simple epidemic routing protocols.

The SimBet routing approach extends the idea of Bubble routing in several ways. First it targets specifically the routing in larger scale scenarios as it is based on the weak tie hypothesis from Granovetter. Instead of relying on the local degree centrality measure it uses the global betweenness measure which has proven highly effective to identify leaders in the large scale societies. Through these designated members, we assume that content in urban societies can be highly effective spread. Hence, we see the SimBet point-to-point routing protocol as a starting point to design a socially-aware community diffusion protocol.

3.2.3 Interest and Context based Approaches

Knowledge management in MENs is a collaborative effort since individual peers can only store a small portion of the entire community space. Because of this, peers specialize usually in certain domains. Content, fitting their interest is cached and less relevant content forwarded to their neighbors. Aspects like finding the right balance between egoistic and altruistic approaches are important to achieve a continuous information flow. In the following we present three approaches to show how cache policies can influence knowledge building in communities.

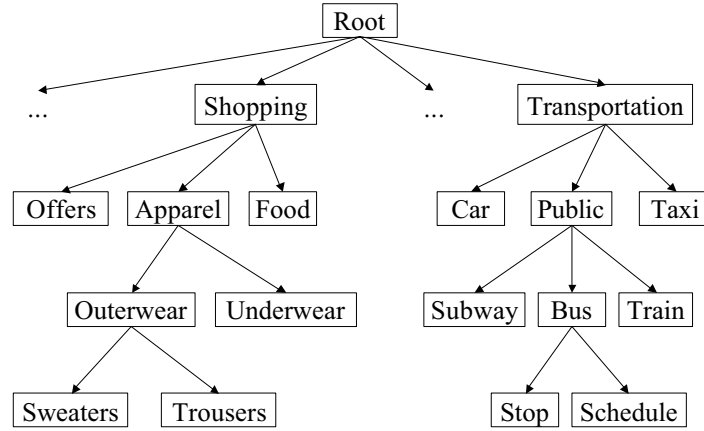


Figure 3.12: Interest routing based on taxonomies (Buchholz et al. [16]).

Content Filtering based on User Interests

Heinemann et al. [54] implemented an ad hoc information management system called iClouds which spreads content either through one-hop *content broadcasting* or *node mobility*. In their scenario devices periodically scan their environment and in case new devices have been identified, content between both devices are synchronized. Content synchronization is achieved by *matching* content *have-* and *wish-lists* with the counterpart. Similar contents are identified through a semantic matchmaking process, which compares metadata descriptions from different content objects. In distributed systems such matchmakes are not easy to achieve as metadata descriptions are provided from different content producers. The authors resolved this problem through the application of community *taxonomies*. Figure 3.12 shows an example taxonomy for shopping and transport community topics. Each domain is ordered in a hierarchical fashion, in which domain level of specialization increases with the tree depth. This approach allows a flexible assignment of domains to more abstract levels in case, e.g., no content is found within the original domain level. Tests were conducted with a prototype based on a Toshiba Pocket PC e740 (Windows CE) with integrated 802.11b cards. Experiences show that iClouds works well to discover specific contents from people nearby, but query formulation represents a challenge due to small screens of the mobile device.

For us this approach is a good example for how content matchmaking between two entities can still be achieved, even if their interest specifications differ from each other. Interest matchmaking is an important measure for content to reduce resource waste in MENs.

Content Filtering based on Spatio-temporal Relevance

Wolfson et al. [124] explored the problem how situation-aware information could be collected with mobile devices. They created an information system for managing free parking spaces in cities. In their scenario cars driving around and looking for a parking lot would receive information which guides them to the closest parking place. Information about available parking lots are generated from a parking meter and sent out via an ad-hoc network. Cars function as intermediate peers which can catch and transfer content between other cars encountered during the traffic. Such content has a specific *spatio-temporal relevance*, whereas perceived value for the content decreases with proximity to the parking space described in the content and the lifetime when this information was generated. Content selection is achieved by sorting cache content in the order of their situation relevance and remove the least relevant content in case the cache is full. The calculation of the situation relevance goes back to the idea that user situations and free parking spot events represent specific points in three dimensional space, where the x-axis represents a time line and the y/z-axis a geographic space. The relevance can be then be determined by calculating the Euclidian distance between these two points.

Their approach was verified by simulating a distributed parking lot management system. In this scenario cars would keep information about available parking space and exchange it with other cars. The intention hereby is to reduce the time to find free parking lots. After the initial publication of an available parking space the number of content copies referred with this information has rapidly increased. It decreased again after the car has reached a specific distance to the parking slot or if the note publication has reached a certain age. Increasing travel ranges, travel speed, population density and cache memory lead to faster fluctuations of the notes within the peer caches.

This opportunistic content routing approach works perfectly for situation-aware content, as it keeps content within spatial and time based boundaries. This diffusion behavior assures that peers outside this range who are not interested in this type of local content do not have to deal with it and can save resources.

Content Filtering based on Content Utility

Datta et al. [29] managed content exchange according to it's utility value. The value of content depends hereby not only on personal preferences but also on the availability of this content in the community. The authors implemented a system called autonomous gossiping, indicating the self-organizing nature of their system. In their scenario content items compete among themselves for cache memory similar to the context based diffusion mechanism described above. Utility is defined through the *interest similarity* and the overall *content*

availability within the community. According to the utility value, content is either *migrated*, *replicated* or *deleted*. Content is generally transferred if another device with higher hospitality has been encountered and the content is not widely available. If the content is intended for a specific target and has not reached it yet, it is, however, always migrated. If this content has a high utility rating and is not completely distributed yet then peers not only migrate but also replicate it to raise content availability in the community. The content gets finally deleted if neighboring nodes have already received the content and are not interested in it anymore. This diffusion approach was simulated within $1000 \text{ units} \times 1000 \text{ units}$ (a square) area. 20 mobile nodes with three different randomly chosen territories continuously traveled between those territories and exchanged contents, whenever they encountered other nodes. Precision-recall analysis (See Section 6.2.4 for a more detailed explanation) revealed that autonomous gossiping performs well as it continuously increases the cache relevance for their users. In contrast to above presented solutions, this mechanism explicitly supports additional altruistic content diffusion if the content is sparsely distributed within the community.

Previously discussed routing approaches from Heinemann et al. and Wolfson et al. work well for popular contents. However, it is equally important in community systems to preserve contents, which are less frequently requested. Datta et al. use different forwarding strategies consider the content availability in the direct proximity of a source peer. We will use their utility based approach as a sample to design a sustainable diffusion strategy for community contents.

3.3 Summary

In this chapter, we presented different human diffusion theories and technical research work describing state-of-the-art routing approaches in MENs.

More specifically, we analyzed social and spatial aspects of human knowledge propagation. The small world theory proofs that the knowledge transfer process between humans is surprisingly efficient on a larger scale, even though humans base their forwarding decision only on local knowledge. Several researchers analyzed this phenomena and found different explanations. According to Watts and Strogatz random shortcuts between subgroups are important to limit average path length within communities. Following Barabasi the existence of social hierarchies in human societies and the way how humans utilize them for knowledge transfers is another explanation of short paths in human societies. In large scale scenarios spatial dominate social diffusion factors. Human mobility is a major enabling factor for knowledge distribution, especially in sparsely populated environments. According to Porta et al. central place

CHAPTER 3. RELATED WORK ON KNOWLEDGE DIFFUSION

locations are even more important factor in densely populated areas. As knowledge transfer processes also represent a certain acquisition effort Reagan et al. introduced different knowledge complexity levels. Complex knowledge requires adequate background knowledge for involved partners and explains why some opportunities were not used. Table 3.1 gives a brief overview of all discussed diffusion theories and compares them according to their type (social, spatial or cognitive approach), temporal data range (historic versus real time data), applied methodology (e.g. compression/virtualization effect, exploitation of social and urban hierarchies, random or weak tie forwarding and awareness of transfer effort) and observed impact scope (local or global influence).

We classified spatial diffusion approaches in selective forwarding and cache management approaches. Selective forwarding approaches can be further separated in social and spatial strategies. As social routing approaches, we presented Prophet, a representative for strong tie routing and SimBet for routing over weak tie connections. Both use social transitivity to identify adequate target nodes. In contrast to Prophet, SimBet routing focuses on larger scale scenarios as it uses explicitly bridge nodes to route content between acquaintance groups. Both proofed to be advantageous against simple epidemic approaches and SimBet routing even exceeded the efficiency of Prophet. Bubbles, another social routing protocol, represents a mix of the previous approaches and a group based routing approach. Although its reach is limited in contrast to SimBet routing still seems to be more efficient in neighborhood networks as it builds upon the behavior heterogeneities of humans. Finally, we investigated spatial routing protocols. An early prototype called DataMule used node mobility to become more independent of static infrastructures. Experiments revealed that diffusion efficiency depends on the cache size and has to be paid with delivery latencies. The last encounter approach utilizes spatio-temporal correlation of encounters. Interestingly the forwarding algorithm is independent of node velocity levels and works well in communities whose members meet each other repeatedly. The final experiment is SolarOrbit which forwards contents based on the territory information of peers. Intermediates are selected after their probability to have shared territories with the target. All three approaches are advantageous against simple epidemic diffusion approaches. Among the cache management approaches we presented the interest based, situation-aware and utility-aware caching approaches. The iClouds system matched interests through taxonomies to assure that heterogeneous interest descriptions would still be comparable. The opportunistic diffusion mechanisms proposed by Wolfson et al. manages cache content based on situation fitness. This policy keeps diffusion in within certain ranges, depending on the traffic density and mobility characteristics. Autonomous gossiping considered not only individual caches but also the distribution situation within the community and thus, could differentiate between pure forwarding and replication

strategies. Table 3.2 gives a brief overview of all discussed publications and compares them according to type (social, spatial and semantic algorithms), target specification (point-to-point versus community diffusion focus), utilized peer component (path selection versus cache management component), applied methodology (e.g. peer mobility degree, last encounter characteristic, spatial hubs, familiarity and transitivity of relationships, group labels, interest/context/utility based filtering approaches) and observed impact (local versus global influence).

The small world theory builds the foundation for a large scale content routing mechanism in MENs which can only use local knowledge for their content forwarding. Social and spatial diffusion theories describe how short diffusion paths within communities can be identified. A more recent study by Reagan et al. has shown that the consideration of encounter experiences goes not far enough and instead the complete context of the encounter situation has to be considered. Therefore, we consider to create a social diffusion mechanism based on the least effort transfer hypothesis. This theory is based on a compound knowledge transfer scenario which integrates several traditional social knowledge transfer theories depending on the encounter situation. In order to reflect user's mobility it is necessary to expand this scenario on spatial knowledge transfer theories such as the central places theory. Before we can realize our MEN based diffusion algorithm we develop in Chapter 4 a model for a socially-aware community support model on which social diffusion theories such as the least effort theory can be executed. An concrete implementation of the community support system is attached in the appendix A. In a second stage we realize the least effort content transfer algorithm by modifying and extending existing MEN projects in Chapter 5. The SimBet, Bubble routing and the SolarOrbit experiment describe how social and spatial diffusion theories can be implemented in MENs. To apply them the point-to-point routing focus has to be adapted to an advanced community diffusion strategy. The Bubble group addressing schema can be used to load balance diffusion tasks amongst group members. Content filtering research outcomes such as from the IClouds or the opportunistic routing system can to the greatest possible extent be re-used but are also expanded to create more sophisticated cache approaches.

THEORY	TYPE	DATA RANGE	METHODOLOGY	SCOPE
Compression Effect	Spatial	Urban Topology	Spatio-temporal compression	Global
Urban Overlays	Spatial/Virtual	Technology	Virtualization	Global
Central Places	Spatial	Urban Topology	Population Hierarchy	Local
Small World	Social	Network Topology	Shortcuts, Clustering	Global
Weak tie Hyp.	Social	Network Topology	Bridge Member	Global
Global Eff. Hyp.	Social	Network Topology	Social Hierarchy	Local
Transfer Hyp.	Social/Cognitive	Encounter Situation	Transfer effort	Local

Table 3.1: Comparison of communityware case studies.

SYSTEM	TYPE	TARGET	COMPONENT	METHODOLOGY	SCOPE
DataMule	Spatial	Community	Path Selection	Mobility	Global
EASE	Spatial	Individual	Path Selection	Last Encounter	Local
SocialOrbit	Spatial	Individual	Path Selection	Spatial Hubs	Local
Prophet	Social	Individual	Path Selection	Familiarity, Transitivity	Local
SimBet	Social	Individual	Path Selection	Centrality, Distance	Global
Bubble	Social	Individual	Path Selection	Rank, Labels	Global
iClouds	Semantic	Community	Cache Policy	Interest	Global
Opportunistic R.	Semantic	Community	Cache Policy	Context	Local
AutoGossip	Semantic	Community	Cache Policy	Interests, Utility	Global

Table 3.2: Comparison of encounter network prototypes.

Part II

Design of a socially-aware Community Framework

4

Mobile Social Software Infrastructure

In this chapter we define a social software framework for an information system focusing on mobile ad-hoc groups. Based on the infrastructure analysis conducted in Section 2.3, we decide to build our platform on MENs. Since MENs distribute content through direct content transfers, they are well qualified to unlock and share public content in ad-hoc group formations. Their drawbacks are varying bandwidths and a high resource usage during the diffusion process. Our idea is to improve the diffusion efficiency of MENs by providing additional functions for peer collaboration.

Some researchers have developed similar frameworks such as the PROEM framework from Kortuem et al. [67]. PROEM offers a grouping service for peers that allows the execution of shared services. In contrast to their approach, we envision not only to add group administration capabilities but also to embed social intelligence as an essential part of the infrastructure. Group management requirements are formulated in accordance to existing small group theories. Patterns in group formation and behavior, function as a role model for the specification of group properties and for the design of group formation protocols. As a result physical group formations can be emulated with the technical infrastructure in real time. By utilizing group synergies, we expect

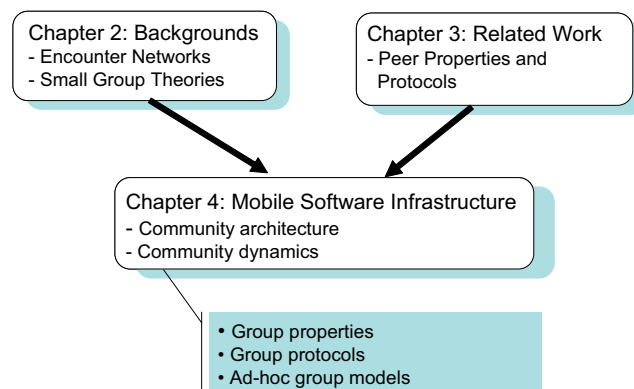


Figure 4.1: Chapter dependencies.

that system scalability can be dramatically improved.

We begin the chapter by outlining our basic cooperation concepts in Section 4.1. An overview about the peer architecture is provided in Section 4.2. It includes components for community related profiles described in Section 4.2.1, group formation protocols in Section 4.2.2 and cache management approaches in Section 4.2.3. The group dynamics management component is explained in Section 4.3. We provide statistical methods to calculate relational data in community graphs (see Section 4.3.1), social network analysis methodologies to identify group clusters (see Section 4.3.2) and position analysis to assign roles in communities in Section 4.3.3. We conclude the chapter with a short summary about all achieved mobile infrastructure capabilities.

4.1 Basic Community Concepts

People who install the software framework on their mobile device belong automatically to a virtual urban community VC . This virtual community is organized by a domain hierarchy D and maintains data about community members U , meeting places T , and available contents C . Each member contributes to the community with their social contacts $\{u_1, \dots, u_n\} \in U$, knowledge about their personal territories $\{t_1, \dots, t_n\} \in T$ and specific community contents $\{c_1, \dots, c_n\} \in C$. By subscribing to specific community topics of a given domain hierarchy $\{d_1, \dots, d_n\} \in D$ the user agrees that the community infrastructure handles content exchanges between devices in the background of the user.

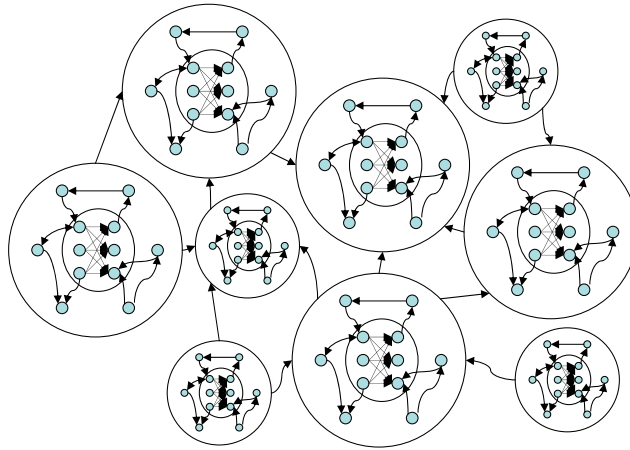


Figure 4.2: Small world network topology (Figure taken from NEC Research Institute website).

Content is either generated by the user or collected from third parties. In tra-

ditional MENs content spreads in a bottom-up manner from device to device. The human tendency toward clustering separates urban societies into smaller subgroups, which are loosely connected. Figure 4.2 schematically illustrates this structure of an urban society. In such networks knowledge starts spreading within groups, then between groups before it finally reaches isolated members. This characteristic pattern opens opportunities for better collaboration during the diffusion process:

- **Social ad-hoc groups (SG):** Group gatherings may be used to share knowledge and evaluate it together. The software framework could emulate group formations by establishing connections between devices and identifying group formation based on member profiles. Ongoing group interactions can easily be augmented with shared community services. But more importantly, members in social groups may specialize in specific diffusion tasks and thus reach a better system scalability.
- **Social overlay networks (SON):** One reasonable specialization scenario would be to exploit central positions of opinion leaders and use them to disseminate content across group boundaries. A diffusion chain spanning a large portion of the community could be formed through vertical social networks. Another diffusion factor in MENs is the member mobility. Community members with superior mobility characteristic may complement the social overlay groups and promote diffusion capabilities even further. The software framework could automatically identify other opinion leaders or highly mobile members in the environment of the user, e.g., during the daily commute to the workplace and exchange important information between the devices. This approach is comparable with a top down approach whose efficiency results from the reputation of opinion leaders in their community. Since overlay networks are highly heterogeneous they can also be used to efficiently address community discoveries. Various discovery approaches have been addressed in several previous investigations by other researchers and are, thus, omitted from this thesis.

4.2 Peer System Architecture

Peers offer common functions for creating, publishing, recommending and discovering community contents. These functions are provided through the content management component that also handles the persistent storage of content in the local repository. An overview about the underlying peer system architecture is given in Figure 4.3. Limited storage size of the local repository requires a continuous replacement of contents in the repository. When users publish a content object it becomes accessible for other community members.

4.2. PEER SYSTEM ARCHITECTURE

In a distributed community system content is not only provided from the local repository but also from devices of other community members. Since peers are only intermittently connected, the local repository functions as an temporary cache for a later content access by the user. The communication between devices is managed through standardized communication protocols (see epidemic peer-to-peer protocol). Protocols regulate the order and the type of messages exchanged, and by this assure consistent community states. Device-to-device messaging is executed over a wireless networking layer which shields functional from technical routing aspects. Physical connections are managed through ad-hoc networks like Bluetooth or Wi-Fi.

In contrast to traditional peer-to-peer systems, peers may form communities with the intention to collaborate on the content diffusion process. The least effort routing logic utilizes data from the group dynamics management component and content from the content repository to efficiently route content between devices. Such a peer community represents a group with a shared set of attributes, e.g., interests. A *group dynamics management* component identifies appropriate group gatherings through the means of social network analysis. *Social network analysis* is based on behavioral data about collocated peers. Peers store this behavior specific data in peer profiles which are stored in a specific profile repository (see the user, mobility, social and content profile repository in Figure 4.3). Profiles can be manually adjusted by the user through a profile administration component but also maintained through the device through context sensors (see context sensing component in the figure). More information about socially-aware community management is provided in Section 4.3.

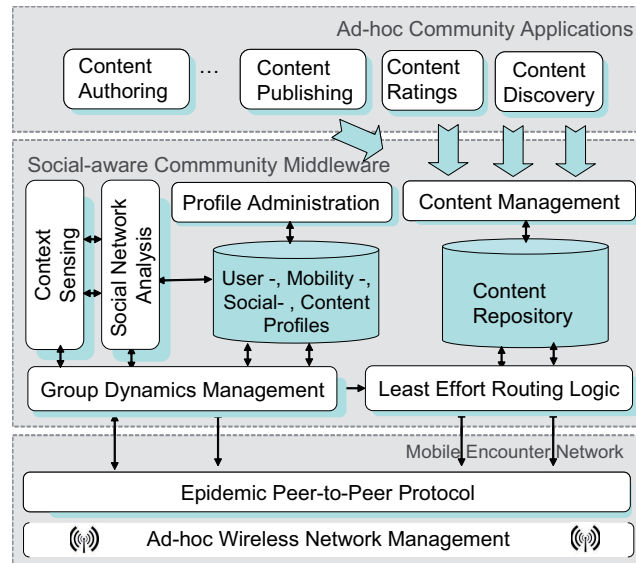


Figure 4.3: Community architecture.

In the following we describe data structures and algorithms required to manage peer communities. We specifically elaborate on

- the *peer profile model* to store behavioral user data and peer specific information.
- the *community protocol model* which defines the exchange of administrative data between peers, e.g., about peer properties, group formation and content transfers.
- the *local cache management* required to assure that users have access to relevant community content.

4.2.1 Peer Profile Model

Peer profiles store characteristic descriptions of a peer. For instance an adequate user profile Pf^u may store user names, interests and contact data. With this data users can identify specific peers in a larger community or personalize peer functions.

In addition to static user data, profiles may store dynamic behavior data. This data could include information about specific activity routines but also related social and spatial behavior patterns. Humans switch eventually between different communities and territories according to their current activity interest. Storing these type behavior patterns makes sense, because they represent the result of a long term cost/benefit calculation (see Section 2.1.1) and thus, stay fairly robust over time.

For efficiency reasons users cannot keep a complete overview of the urban community. They rather specialize in those aspects closely related to them. Each user consequently maintains his own social and spatial community networks and expertise. We extend user profiles by adding ego-centric representations of spatial, social and semantic community networks. Following definition for ego-centric networks is provided from the my personality project:

Definition 4.1 (Ego-centric network [109]) *Ego-centric networks are personal networks which contain a single entity (ego), together with all connected entities (alters), and links between the alters.*

All visited territories together describe the mobility profile of a user. For instance, users may leave their home and go to their offices and later to a sports center. We introduce following notation for the mobility profile:

Definition 4.2 (Mobility Profile) *Given is a user $u \in U$. A mobility profile for a given user is ego-centric spatial network graph $Pf^m(u) = (T_u, P_u)$ where*

- T_u represent a set of frequently visited territories of the user u , and
- P_u represent a set of paths between these territories.

A more detailed specification for territorial properties will be provided in Sections 4.3.1 and 4.3.2. Not all territories are equally important to the user. The possibility to separate between randomly and intentionally visited territories can help to personalize the community system for the user. One way to achieve this is to allow users to rate individual territories. Since this process can get very tedious for the user we provide in Section 4.3.1 better automated approaches.

Moreover, people encounter various other community members during the day. For instance, people encounter colleagues at their work, friends in their spare time and their family at home. These contacts describe the social network of a user. More formally, we denote the following notion for social profiles:

Definition 4.3 (Social Profile) *Given is a user $u \in U$. A social profile for a given user is ego-centric social network graph $Pf^s(u) = (F_u, Rel_u)$ where*

- F_u represent a set of friends, who the user frequently encounters, and
- Rel_u represent a set of social relations between the user and friends and between friends.

For each person users may specify additional contact details. Some people we encounter randomly, others we would like to visit because they are important to us. It is thus desirable to qualify the relationship intensity. Community systems aware of these differences can identify important persons in a crowd of users and give them a higher priority during the execution. A quick solution again is to allow user to rate their contacts. In Section 4.3.1 we will present models that allow us to derive relationship information from sensor data making the system less dependent on user inputs.

To enable autonomic exchanges, it is necessary to match content according to content subscription and publication lists. Based on the result missing remote content is identified and exchanged between the partners. This approach follows the example of the iClouds project presented by Heinemann et al. [53]. Matchmaking between user interests and available contents is achieved through a hierarchical domain structure which is defined as below:

Definition 4.4 (Community Taxonomy) *We call D a hierarchical tree of topics, in which the abstraction level decreases with the tree depth. Each tree node represents a specific community interest domain d , which is uniquely identified through the path from the root of the tree to the tree node.*

Assuming that each user $u \in U$ has subscribed to different topics of a given community taxonomy $d_1, d_2, \dots, d_n$ and stores content $c_1, c_2, \dots, c_n$ in the local repository $Cache_p$ then we define the Content Profile as follows:

Definition 4.5 (Content Profile) *Given is a community taxonomy D , a user $u \in U$ and the peer cache $Cache_u$ of the user. Then a content profile of a user u is a tuple $Pf^c(u) = (D_u, C_u)$ where:*

- D_u is a subscription list which contains all topics $\{d_1, d_2, \dots, d_n\} \in D_u$ with $D_u \subseteq D$ in which user u is interested.
- C_u is a publication list of all contents which the user wants to contribute to the community. The contents referred in the publication list represent a public subset of all contents in the local cache $C_u \subset Cache_u$. The publication list is a set of summarized content descriptions with $\{\text{resume}(c_1), \text{resume}(c_2), \dots, \text{resume}(c_n)\} \in C_u$.

The function $\text{resume}(c)$ returns a content summary including a unique identifier and all metadata descriptions associated with the content object c . More information about content summary descriptions are provided in Section 4.2.3.

Information about community interests can be provided through manual configuration. Several publications, e.g., [88, 123, 32] describe how content discoveries can be applied to identify user interests. Most mechanisms are based on extracting information about the query domain and frequency to determine the interest focus.

4.2.2 Community Protocol Model

Peer-to-peer protocols are used to coordinate activities between peers. Our focus of interest lies in particular on activities for group formation and content spreading. As a role model for the group formation process, we take Tuckman's group development model presented Section 2.1.1. Following this model, we classify group collaborations in five progress stages starting with *peer encounters and profile exchanges*, *the group formation*, *role delegations*, *index construction* and finally the *transfer of contents* between the members. Based on each community development stage, a specific chain of activities is initiated by the peer. Through mutual profile exchanges peers learn about their capabilities. Based on individual capabilities each peer analyzes its surrounding community (see social network analysis techniques in Section 4.3) and determines possible communities and leaders. This ongoing communication ends of course when a peer leaves the group. Figure 4.4 shows the final protocol structure. The standard message structure for our community system has the following form:

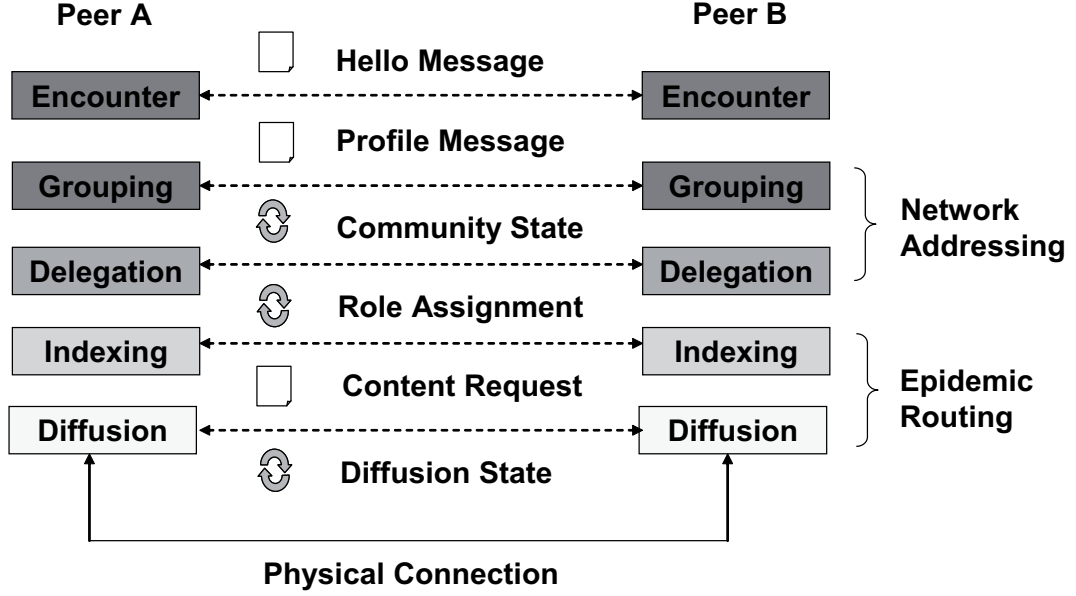


Figure 4.4: Community exchange protocol.

Message 4.1 (General Message Format) *The message format describes a senderID or receiverID as a unique identifier of the sending and receiving peer, MID as unique identification of the message, and msgdata as message body, then the message is defined as quadruple $Mtype(senderId, receiverId, MID, msgbody)$.*

In the following we present individual protocol messages in the chronological order of the protocol stack as extension of the general message format defined above:

1. **Community Identification:** Peers initially scan their environment for new peers. Each peer periodically announces their presence with a Hello message of the following format:

Message 4.2 (Hello Message) *Each Hello message msg_{hello} contains a unique peer identifier PID based on the mac address of the device and a time stamp $time_{pf}$ for the last profile modification.*

In case the encountered peer has not been discovered before or the profile data of that encountered peer is outdated, peer profiles are requested from the peer with a profile request message. The response message has the following format:

Message 4.3 (Profile Message) *Given is a user $u \in U$, the user profile $Pf^u(u)$, mobility profile $Pf^m(u)$ and social profile $Pf^s(u)$ of the user u . Then the profile message is a triple $msg_{pf} = (Pf^u(u), Pf^m(u), Pf^s(u))$.*

According to the protocol, detected peers transfer their profile data within a predefined time period. As a result of this phase, we assume that peers know about the capabilities of all colocated peers. In the next phase, peers are assigned to groups.

2. **Group Dynamics Management:** The group formation process follows the following pattern. First, all peers select a unique group initiator e.g., based on the smallest mac address (hardware address of the device network adapter).

- **Group initialization:** The leader node creates a preliminary group specification. It contains a unique group identifier, group constraints, a group interest focus, and leader- and member lists containing the leader node. Group constraints define the conditions required to join the group. A more formal definition will be provided in Section 4.3.2. The interest focus of a group is provided by the group initiator and may be specified according to its current activity domain. All public contents from the group leader related to the interest specification of the group build the initial group publication list. Finally, the node announces the group through invitation-broadcasts to all members that potentially qualify for that group. This message contains group data of the following form:

Message 4.4 (Invitation Message) *Each invitation message msg_{inv} describes a group of users $G = (GID, GCSTR, L_g, M_g, D_g, C_g)$, where*

- GID represents the unique identification of the group. Optional a group name and description could be provided,
- $GCSTR$ represents a list of constraints which define membership conditions. More information about possible group types and correlated constraints will be provided in Section 4.3.2,
- M_g describes the list of group members with $M_g \subset U$,
- L_g specifies the list of group leaders $L_g \subseteq M$ currently coordinating group membership administrations,
- D_g provides the group subscription list $D_g \subseteq D$ and
- C_g describes the group publication list.

- **Joining and leaving groups:** On receiving a group invitation message, the receiver node checks the group constraints. If the node is interested to join the group, it sends the following join message containing user-, interest- and content data (see Definition 4.5):

Message 4.5 (Join Message) *Following an invitation message, invited nodes respond with a positive or negative join message. The join message msg_{join} includes the user identifier UID of the node intending to join the group identified through the GID identifier, the positive or negative join acknowledgment ack and its content profile (see Definition 4.5) filtered according to the activity focus D_g of the group g if the join message is positive.*

$$msg_{join} := \{UID, GID, ACK\} \cup \begin{cases} \emptyset & \text{if } ACK \neq true \\ Pf_g^c & \text{if } ACK = true \end{cases} \quad (4.1)$$

$$Pf_g^c := \{\{d \mid d \in D_u \cap D_g\}, \{c \mid c \in C_u \wedge dm(c) \subseteq D_g\}\} \quad (4.2)$$

where $dm(c)$ is a function which returns domains closely correlated with the content object c .

After receiving a positive join message the leader node updates his membership list M_g , adds subscription preferences to the shared subscription list D_g and extends the group content summary C_g with content descriptions of joining peers. Group memberships could be deferred for various reasons, e.g., if the user is on a black list, topics do not match well, or the group gets too large. All memberships are periodically renewed to verify if individual members are still reachable. This is necessary because peers may spontaneously leave the group. The resulting group data structure has finally the form $G(GID, GCSTR, L_g, M_g, D_g, C_g)$ with

$$D_g = \bigcup_{u \in M_g} D_u \text{ and } C_g = \bigcup_{u \in M_g} C_u \quad (4.3)$$

- **Leader migration:** After the group has been formed it may happen that the leader needs to leave the group or a more adequate leader has been discovered. In both cases new leaders have to be selected and group data transferred between both nodes. After the completion of the migration step, all other member nodes are notified about the change. More information about leader selection procedures is provided in Section 4.3.3. The migration message has the following format:

Message 4.6 (Migration Message) *Given is a leader node u , a group g with a member list M_g , shared subscriber D_g and content summary list C_g . If a new leader node v has been identified, the group data structure is transferred $u \xrightarrow{G} v$ and all group members are informed about the leader change. The migration message for a given user $x \in M_g$ has the following format:*

$$msg_{mig} := \begin{cases} \{M_g, D_g, C_g\} & \text{if } role(x) = \langle Leader \rangle \\ \{u, v\} & \text{if } role(x) \neq \langle Leader \rangle \end{cases} \quad (4.4)$$

3. **Content Management:** Each peer maintains a subscription list and a publication list for the contents currently stored in the local cache. This data structure can be based on a binary data structure as known from bloom filters¹ to reduce the space overhead associated with the summary vector.

- **Index Construction:** Whenever the community interests or cache contents of a group member have changed the group leader is notified about it with a new content profile. Hereby each member peer filters the content profile according to the group domain specified earlier in the group invitation message. The message format is as below:

$$msg_{cms} := \{\{d \mid d \in D_u \cap D_g\}, \{c \mid c \in C_u \cap dm(c) \subseteq D_g\}\}$$

where $dm(c)$ is a function which returns domains closely correlated with the content object c .

- **Content Exchange:** In contrast to a bilateral content exchange, group leaders match accumulated group subscription with group publication lists. The result of this comparison is list of missing contents which are then individually requested from the leader and distributed within the entire group. More information about broadcast process is given in Section 5.3.3. In the following we specify the message format for the content diffusion.

Message 4.7 (Request-for-Download Message) *Given is a content profile $Pf(u)^c$ for a user u . Each Request for Download message msg_{req} contains one or more content requests identified through CID , where $CID \in Pf(u)^c$.*

Message 4.8 (Content Download Message) *Given is a content profile $Pf(u)^c$ for a user u . Each Content Download Message msg_{doc}*

¹See http://en.wikipedia.org/wiki/Bloom_filter

contains one or more content with identifier CID , where $CID \in Pf(u)^c$.

Message 4.9 (Download Confirmation Message) *Given is a content profile $Pf(u)^c$ for a user u . Each Download Confirmation Message msg_{ack} contains one or more boolean retrieval success confirmations with $ack \in \{true, false\}$ transcoded as parameter value pairs of the form $\langle CID, ack \rangle$, where $CID \in Pf(u)^c$.*

This pairwise communication protocol allows peers to learn about member's capabilities, enable group collaborations and empower the dissemination of contents through limited broadcasts. This specific protocol design keeps the number of peer interactions small and to the same time assures that available encounter durations are best possible utilized through a stepwise knowledge increase between peers.

4.2.3 Local Cache Management

People often use mobile content to describe environments, physical objects, persons or events. An unknown author makes following comparison to illustrate the potential of mobile content:

“Mobile phones can be envisioned as sensors for the urban community, generating community contents, whenever it is relevant for the rest of the community. With people commenting on existing contents, a realistic picture of the urban community is created.”

Community systems provide a virtual knowledge space for this kind of real-world knowledge. Figure 4.5 shows a typical community data model for community systems. To identify adequate community content, content items are usually associated with specific community topics and with corresponding authors. Following Rantanen et al. [92] people refer to content differently in public aggregations and social groups. In social groups users evaluate the value of a given content item through the reputation of the author or recommender. In public aggregations where people cannot trust each other, people can only rely on contextual factors. In other words, the content value depends strongly on the situation fitness. Content filtering is achieved by comparing content metadata with the user's situation. The user situation is characterized by its current location, time and activity domain. Metadata descriptions specify semantic, spatio-temporal properties of real-world events described in the content:

Definition 4.6 (Content Summary) *Given is a community taxonomy D . Then each content object c is described through a quintupel $c = (CID, D_c, Time, Loc, Author)$, where:*

- *the content identifier CID represents the unique identification of content object, required to avoid replicated content downloads.*
- *a set of topics $D_c \subset D$ describe the content item semantically. This is needed to filter content related to the current activity of the user.*
- *the time stamp $Time$ indicates the described event time,*
- *a location coordinate Loc indicates the described event location,*
- *the person $Author$ describes the originator of the content document and is used to limit content diffusion to potential recipients.*

In contrast to traditional C/S based systems content in MENs is stored in a distributed manner. Peers store content temporarily to forward it to others and distribute the content throughout the urban community. Cache management policies order content after a given relevance function and purge the least important content if the cache has reached its size. A commonly used cache policy is the least recently used strategy. This policy replaces outdated contents with more recent contents. For community systems it is more important to collect contents according to user interests. Therefore, we filter content according to interest similarity (see Section 3.2.3). For this, semantic peer contents (e.g. classified by keywords) are compared with the interest profile of the user (see Section 4.2.1), and their relevance is calculated with the Pearson coefficient:

Definition 4.7 (Interest Similarity [15]) *Given interest profile for a user u and a semantic description for content object c , then user u and the content item c have at most one preference rating $w^d(u)$ or $w^d(c)$ respectively for each community domain d . Based on the sample mean $\bar{w}_u$ or $\bar{w}_c$ and standard deviation δ_u or δ_c for each interest profile of user u and semantic description for the content item c the similarity weight between a user u and content item c is defined by the Person correlation coefficient as:*

$$sim^{Pear}(u, c) = \frac{\sum_{m=1}^d (w^d(u) - \bar{w}_u)(w^d(c) - \bar{w}_c)}{\delta_u \delta_c} \quad (4.5)$$

This coefficient returns values between -1 and +1, whereas -1 refers to opposite tastes and +1 to the same taste of both users.

Such a cache policy increases the motivation for users to participate as a content forwarder in a peer-to-peer network, because content is collected according to their own egoistic interests. This policy has to be extended in a community scenario, because group members delegate diffusion tasks between each other. In Section 5.3.4, we will enhance the interest based caching policy to satisfy specific content needs for group leaders and ordinary members.

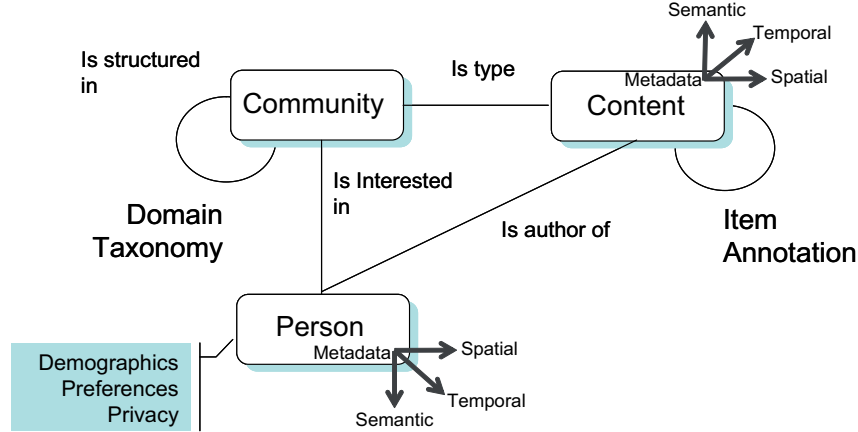


Figure 4.5: Traditional community data model.

4.3 Group Dynamics Management

The degree to which the technical infrastructure aligns with the physical encounter situation decides about a successful synergy exploitation. Due to high group dynamics, group management with human intervention is likely to fail. Group formations thus should better be controlled by the infrastructure itself.

Mobile phones offer a lot of sources to obtain information about the current user environment (see Figure 4.6). Imaginable sources are location data taken from GPS sensors, information about user interests from user profiles, temporal event information from calendar applications, proximity data from other Bluetooth or Wi-Fi devices and finally communication relevant data from previous SMS conversations. For the collection of context data we consider an application like the context logger application from Raento et al. [91]. This application collects event data from different context sensors and stores them in log files for further processing. To minimize the effect for the user analysis processes can be started, e.g., in periods when the device is in an idle state.

This continuous adjustment process is best explained with a regulatory system shown in Figure 4.7. A regulatory system uses feedback mechanisms to control its execution. Therefore, the system has to interact with several infrastructure components including context sensors, social network analysis and

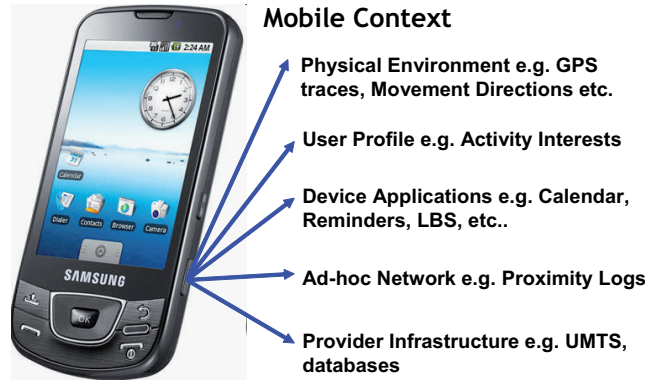


Figure 4.6: Contextual information sources for mobile devices (Raento et al. [91]).

group dynamics management components. Context sensors collect data about the user environment. This data is interpreted to derive significant behavior information, e.g., about a friend encounter. Social and spatial profiles are updated accordingly. Simultaneously, real-time community graphs are constructed. These graphs are augmented with additional social profile data to obtain realistic relationship information between the peers. Potential group formations are identified through social network analysis. The group dynamics management component compares the link state of the wireless ad-hoc network with detected group formations and triggers actions to synchronize them. Peers may, for instance, issue a group invitation or join messages. Subsequently, member roles are assigned according to a prior executed position analysis. The task of the group dynamics management component is, hereby, to assure that all peers maintain always consistent community states. The measurement interval (control section) represents the time period in which the environment may change. Keeping this interval short leads to better group boundary precision but also requires more energy.

In the following, we describe methods and models for community analysis. These include the

- analysis of *behavior patterns* and preferences.
- definition of *community models* like social groups and networks
- definition of *community roles* separating leading from ordinary members.

4.3.1 Analysis of Human Behavior Patterns

Whereas peers in peer-to-peer systems are generally treated as equal, socially-aware systems base their execution on human behavior heterogeneities. Imprecise behavior descriptions very likely have a negative impact on the execution

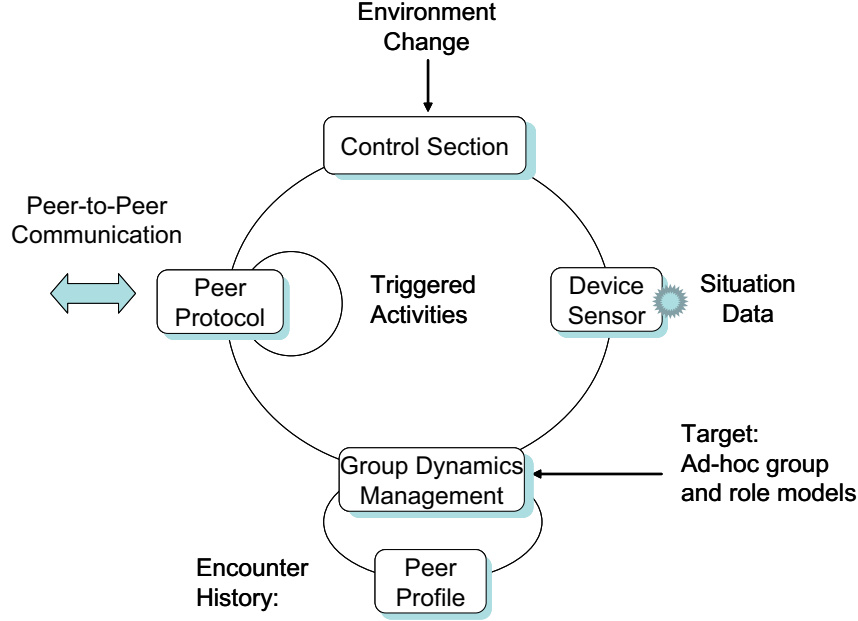


Figure 4.7: Regulatory system of social community adaptivity.

of the entire system. Users, therefore, often can customize community application through user ratings (see Section 4.2.1). These user ratings change over time and are generally tedious to maintain. Our goal is to replace user ratings with metrics automatically obtained from context sensors. Such metrics have also the advantage that they are in general more objective as user ratings. Of course, this sensor data collection should happen in an unobtrusive manner so that mobile application usage is not negatively affected.

Community behavior can be characterized through activity preferences, personal territories and social networks. Logging applications like those of Raento et al. store context events in log files as a series of *event/time* value pairs. By applying statistical approaches, e.g., by counting of event occurrences or by calculating the accumulated time per event, we are able to derive patterns of *semantic*, *spatial* and *social* behavior. Following Wellman [121], event occurrences per time can better deal with aging effects in comparison to the total number of accumulated events. By this, the system becomes better aware of long term behavior modifications but also requires more energy for behavior analysis.

It is possible to extract visiting characteristics for specific territories from mobility log files. We are able to distinguish randomly, occasionally and frequently visited territories just by event counting. Assuming that the social software uses a positioning system, then a place visit can be defined as below:

Definition 4.8 (Place Visit) *A place visit represents an event where the position system of the social software detects one or more location points within*

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a given personal territory stored in the mobility profile Pf^m of a given user.

Hereby, it is assumed that a territory possesses a certain reach defined through a boundary line. More information about territories is provided in Section 4.3.2. Although visiting statistics may not always correlate well with the perceived territory importance it is still good enough as a first hand indicator. Hence, we replace territory ratings used in the mobility profile (see Definition 4.2) to distinguish personal from random territories with a quantitative metric for the visiting probability:

Definition 4.9 (Place Significance) *Given is a user u who visits a social territory st N times and stays for a duration d_i within a given time frame Δt to follow community activities of the domain d . Then the place significance $p_{u,st}^d$ for a given social territory st and can be measured in two different approaches:*

- duration of a visit to a place: $\hat{p}_{u,st}^d = \frac{\sum_{i=1}^N d_i}{\Delta t}$
- the frequency of visits: $\tilde{p}_{u,st}^d = \frac{N}{\Delta t}$

Assuming that Th_{stay} is a stay time threshold value for one of the above properties, then a social territory st is significant for the user u if $p_{u,st}^d \geq Th_{stay}$.

People who we meet often or with whom we pursue certain activities together are more important than people who we encounter randomly. Originating from this idea we replace the subjective concept of relationship intensity (see Definition 4.3) used in the social profile with a quantitative measure for tie strength based on human encounters. Assuming that the social software uses an ad-hoc network and continuously scans the environment for new devices in the proximity of the user then an human encounter can be defined as below:

Definition 4.10 (Human Encounter) *A human encounters is given if two or more devices owned by community members are within the reception range of their ad-hoc networks and are able to establish communication links between the devices.*

Based on this notion of a human encounter we further define the tie strength criteria as below:

Definition 4.11 (Tie Strength) *The tie strength $rel_{u,v}^d$ describes the statistical relationship quality between two people u, v for a given activity domain d , where the peers encounter each other N times for a duration of d_i within a given time period Δt . Then encounter and interaction related parameters can be used to measure the tie strength:*

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- *accumulated interaction duration*: $\widehat{rel}_{u,v}^d = \frac{\sum_{i=1}^N d_i}{\Delta t}$
- *interaction frequency*: $\widetilde{rel}_{u,v}^d = \frac{N}{\Delta t}$

Assuming Th_{fam} is a familiarity threshold for one of the above parameter types, then we define a relationship between a person u and v as a strong friend relationship, if $rel_{u,v}^d \geq Th_{fam}$ is true, otherwise we call it a weak relationship.

With this approach social and spatial community relationships can be frequently processed and updated. It is important to mention that the above threshold values (Th_{stay} and Th_{fam}) are domain dependent and not easily selected. Large threshold values mean long learning periods, and small values may not reliably separate random from routine behavior. Wrong pattern detection later reduces the chance to exploit group synergies effectively and even may render the community infrastructure useless for the user. Further semantics about community relationships can be revealed through their space-time characteristics (See the Reality Mining Project from Eagle and Pentland [33]). For instance, people who we meet during the day are probably workmates, whereas people who we meet in the evening are more likely friends or belong to the family. A similar interpretation can be applied for the space-time characteristics of place visits.

4.3.2 Definition of Community Models

Heterogeneous community behavior lead to cluster building in urban communities. A well established approach to identify group formations is based on graph analysis. Moreno presented an approach to map real world community interactions on a network graph (we presented this approach earlier in Section 6.2.2). We follow this approach to construct a network graph that illustrates the current encounter situation among people. Hereby, we fall back on the specification of a human encounter provided in the previous section. Collocated persons following this specification build the nodes in the graph. Such nodes can be detected by proximity scans, e.g., from Bluetooth ad-hoc networks. Relations between the nodes are derived from tie strength measures stored in the social profile. More formally we define the encounter network graph as following:

Definition 4.12 (Encounter Network Graph) *Given is a set of encounters E and a set of relationships R between them. Then an encounter network graph $EN = (E, R)$ is a network diagram where encounters E represent nodes in the graph, ties R between them symbolize functional ad-hoc network connections whereas the tie strength is determined by the overall interaction history.*

Moreno constructs his social network graph based on the results from an empirical survey. In contrast to Moreno, we update this graph periodically with real-time sensor data. This allows us to obtain an up-to-date image of the encounter situation for a given user. A common way to identify potential group formations in a network graph is based on clustering analysis. The cluster analysis is a statistical methodology which differentiates data into smaller subsets based on specific cluster conditions. Note, that these cluster conditions are equal with the group constraints specified in the group invite messages in Section 4.2.2. In order to assure exact group boundaries, this clustering analysis has to be repeated with every modification of the graph topology. A detailed description about the clustering algorithm is presented in Section 4.3.4.

In the following, we will derive formal cluster conditions for mobile communities. Informal ad-hoc group formations as we envision them for our community infrastructure are *location dependent*. This location dependency results from the coverage range of ad-hoc networks needed to exchange messages between the devices. According to the community concepts presented in Section 4.1 users belong to a virtual community as soon as they register to available community topics. Humans who randomly meet at a shopping center or who visit an opera event are a good example for such a random interest aggregation. More formally we define a random *interest aggregation* (*agg*) as the following:

Definition 4.13 (Random aggregation) *An aggregation of users is called a random interest aggregation, if all members U in the group share a minimal amount of interests within a given similarity threshold Th_{sim} and are within the reception range of the ad-hoc network Th_{rec} .*

$$AGG(U, Th_{sim}, Th_{rec}) = \{u, v \in U \mid (dist^{Eucl}(u, v) < Th_{rec}) \wedge (sim^{Pear}(u, v) \geq Th_{sim})\} \quad (4.6)$$

where $sim^{Pear}(x, y)$ is a function used to determine the interest similarity between two users u and v (see Definition 4.7) and $dist^{Eucl}(u, v)$ is a function which calculates the Euclidian distance between two geographic location points representing the whereabouts of users u and v

$$dist^{Eucl}(u, v) = \sqrt{\sum_{i=1}^2 (u_i - v_i)^2} \quad (4.7)$$

In contrast to random aggregations, informal group gatherings rely on interpersonal relations. Wellman showed that group gatherings coordinated through mobile phones in general are highly transitive (see Section 2.1). People often

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follow specific interests, live in the close neighborhood and meet each other quite frequently. In other words, such group relationships can be predicted from users interest similarity, territory proximity and contact familiarity (see Section 2.1.1). A *social group* (*sg*) in a mobile community scenario is an ad-hoc group of people who fulfill at least the following criteria:

Definition 4.14 (Social Group) *A group is called a social group, if all members U in the random aggregation (see Definition 4.13) share minimal amount of interests within a given similarity threshold Th_{sim} and maintain strong relationships with each other exceeding a given familiarity threshold Th_{fam} .*

$$SG(U, Th_{rec}, Th_{sim}, Th_{fam}) = \{u, v \in U \mid (dist^{Eucl}(u, v) < Th_{rec}) \wedge (sim^{Pear}(u, v) \geq Th_{sim}) \wedge (rel(u, v) \geq Th_{fam}) \} \quad (4.8)$$

where $dist^{Eucl}(u, v)$ is a function which calculates the Euclidian distance between the two geographic location points representing the whereabouts of users u and v (see Equation 4.7), $sim^{Pear}(x, y)$ is a function used to determine the interest similarity between two users u and v (see Definition 4.7) and $rel(u, v)$ is a function describing the tie strength between two persons u and v who perform a specific activity of a given domain d together (See Definition 4.11).

Territories function as meeting places for social groups. They go beyond a geographic location by having a specific range and a specific social meaning. Territories often provide a physical infrastructure made for specific activities like sport centers or restaurants. Following Altman, these meeting places may have public character or be restricted to a certain group of people. Some of the territories may be located in privileged locations close to the urban center, others at suburbs. These requirements can be formalized accordingly:

Definition 4.15 (Social Territory) *Given is a community taxonomy D . Then a social territory is a social meeting place described through the triple $t = (TID, c, r, rank, d)$ where*

- *TID is a unique identifier,*
- *the centroid c and radius r describe a circle encompassing the territory boundary,*
- *$rank$ describes the spatial territory centrality, and*
- *d represents the usage domain of the territory with $d \in D$*

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In Section 3.1.1 we presented a study from Porta et al., which compared the correlation between available service density and various centrality measures. The closest correlation to the service density was observed for the betweenness centrality measure. Calculating the betweenness centrality for individual territories can, however, not be done without a street network graph e.g., provided from a map service. A street network graph is best described through following formal description:

Definition 4.16 (Street Network Graph) *Given is a set of territories T and a set of paths P between them. Then a street network graph $SNG = (T, P)$ is a network diagram where territories T represent nodes in the graph, ties P between them symbolize streets between territories whereas the tie strength is determined by the distance.*

Following Port et al. [89] urban spaces are structured in smaller neighborhoods and are usually connected through larger streets. Following Tomko et al. [111] "the urban partition into suburbs represents an overlaying functional structure over the basic structure of the street network." Freeman's formula for the betweenness centrality does not consider structural holes and thus, goes not far enough. As a consequence Tomko et al. suggest an extended ranking scheme which introduces the betweenness centrality of suburbs as an additional parameter. They define an experiential ranking $rank(i, d)$ based on a betweenness calculation for an individual location i in a given neighborhood together with betweenness value for the entire suburb d as follows:

Definition 4.17 (Place Centrality Rank [111]) *Let i denote a street in the street network, D a set of suburbs in the city, D^i the suburbs intersected by street i , d_j^i a suburb of D^i , C_i^{Bet} the betweenness centrality value of the street i , C_d^{Bet} the betweenness centrality of the suburb d , $Pd_k d_l$ the number of shortest paths linking to suburbs d_k and d_l of D , $Pd_k d_l(d_j^i)$ the number of shortest paths linking two suburbs d_k and d_l that contains d_j^i . We can then define $C_{d_j^i}^{Bet}$ as follows:*

$$C_{d_j^i}^{Bet} = \sum \frac{Pd_k d_l(d_j^i)}{Pd_k d_l} \quad (4.9)$$

The $rank(i, d)$ for a named street i in the hierarchy of the street network based on the betweenness centralities of the street network and the suburb partition of space is then defined as follows:

$$rank(i, d) = \sum C_i^{Bet} \times C_{d_j^i}^{Bet} \quad (4.10)$$

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Vertical overlay networks are another very important concept discussed in Section 4.1. An overlay network is a virtual network built on top of social communities (see Figure 4.8). Their purpose is to encourage content transfers across group boundaries and to ease community discoveries.

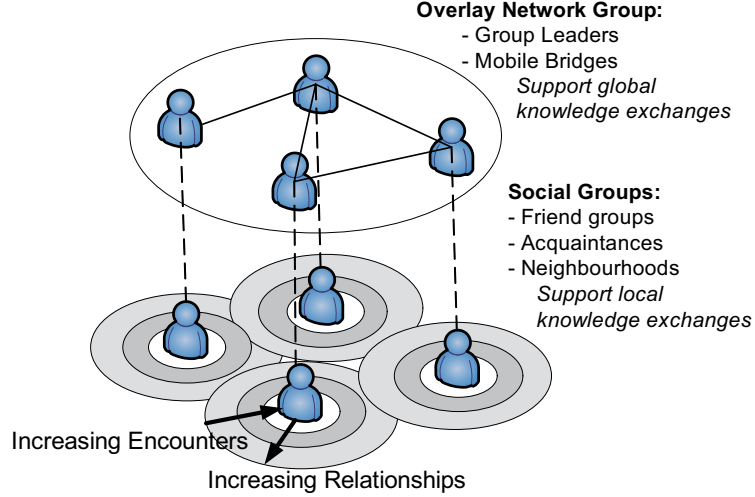


Figure 4.8: Social community heuristics.

Overlay networks are fundamentally different from social groups. While social groups require homogeneity and coherence, overlay networks have to be as diverse and open as possible. Overlay networks do not fulfill immediate information needs of individual community members but try to improve the overall community transparency. Because of this altruistic character communication should be kept to a minimum. Therefore, we limit the membership of overlay networks to superior connected group members as a representative for their social groups.

Central group members frequently meet a small number of homogeneous people and thus, have rare or no contacts to other groups (see Figure 4.8). According to the weak tie hypothesis presented in Section 3.1.2, acquaintances who are located at the edge of social groups function as a bridge between those groups. As such they have generally a better position to contact people with heterogeneous background. More formally we define a social overlay network as below:

Definition 4.18 (Social Overlay Network) *Given are two users $u, v \in U$. An social overlay network is then a collocated group of persons within the reception range Th_{rec} of the ad-hoc network, who either maintain indirect relationships to an acquaintance with less than Th_{acq} referral relationships, or people with whom we share a given amount of interest Th_{sim} but to whom they do not have a relationship.*

$$\begin{aligned}
 SON^{soc}(U, Th_{acq}, Th_{rec}) = & \{u, v \in U \mid (role(u) \wedge role(v) \wedge leader) \wedge \\
 & (dist^{Hops}(u, v) \leq Th_{acq}) \wedge \\
 & (dist^{Eucl}(u, v) < Th_{rec})\}
 \end{aligned} \tag{4.11}$$

where $role(u)$ is a function which returns the last role of a user in a social group, $dist^{Hops}(u, v)$ is a function which represents the separation degree between two people u and v and $dist^{Eucl}(u, v)$ a function describing the Euclidian distance (see Equation 4.7) between two users u and v .

Unfortunately, acquaintances emerge from friend-of-friend relationships with a high degree of separation. For an efficient knowledge transfer between groups this is not sufficient. We therefore complement weak tie contacts with a group of so called familiar strangers, introduced by Milgram. Familiar strangers are people who are repeatedly encountered but with whom no social relationship is maintained. They share some common characteristic like the neighborhood or travel paths. In contrast to humans, mobile devices can exchange small content even during brief encounter situations (see Geeser [43]). Using such random encounters during traveling for content transfers becomes, therefore, an interesting option to enhance community transparency. Accordingly, we define a semantic overlay network as below:

Definition 4.19 (Semantic Overlay Network) *Given are two users $u, v \in U$. A semantic overlay network is then a collocated group of persons within the reception range Th_{rec} of the ad-hoc network, who either maintain indirect relationships to an acquaintance with less than Th_{acq} referral relationships, or people with whom we share a given amount of interest Th_{sim} but to whom they do not have a relationship.*

$$\begin{aligned}
 SON^{mob}(U, Th_{sim}, Th_{rec}) = & \{u, v \in U \mid (role(u) \wedge role(v) \wedge bridge) \wedge \\
 & ((sim^{Pear}(u, v) > Th_{sim}) \wedge (rel(u, v) = 0)) \wedge \\
 & (dist^{Eucl}(u, v) < Th_{rec})\}
 \end{aligned} \tag{4.12}$$

where $role(u)$ is a function which returns the last role of a user in a social group, $sim^{Pear}(u, v)$ is a function used to determine the interest similarity between two users u and v (see Definition 4.7) and $rel(u, v)$ is a function describing the tie strength between two persons u and v who perform a specific activity of a given domain d together (See Definition 4.11) and $dist^{Eucl}(u, v)$ a function describing the Euclidian distance (see Equation 4.7) between two users u and v .

The high transitive character of mobile groups guarantees a distinct clustering process. Such strong coherent groups are well qualified for shared community service and promise high synergy exploitation. Vertical overlay groups complement social groups and establish content exchange above the group boundary. The strong heterogeneous composition of vertical overlay groups demands highly personalized content exchanges between their members.

4.3.3 Definition of Community Roles

Community collaborations are controlled through individual role assignments. Community roles describe the authority distribution in the community. Researchers proposed different role assignment strategies for ad-hoc networks. One of the most simple assignment strategies is based on numerical principles. In Section 4.2.2 we presented such a strategy where group leaders were selected after a minimal mac address. Another possibility is a selection based on technical capabilities, e.g., process speed, memory size and most importantly battery lifetime. Technical approaches are very useful for the administration of larger ad-hoc groups.

Since social groups are rather small we propose a role system which is stronger correlated with real-world communities. After all, a highly important aspect in human societies and in diffusion networks is to which extent actors can control the information flow in the community. Unfortunately, roles in informal groups are not as evident as in institutions where they are explicitly assigned. In MENs' content diffusion capabilities depend on social and spatial aspects. Accordingly, we define the following community roles using structural principles:

- **Opinion leaders in social networks:** The position in social networks clearly limits or enables interaction possibilities of an actor. One way to identify social network positions are centrality measurements as described earlier in Section 6.2.2. A study from Seung Hwan (Mark) Lee [71] has shown that among the Freeman's centrality measures, the betweenness centrality correlated best with real opinion leaders in acquaintance networks. Opinion leaders are then determined by identifying the user with the highest betweenness value:

Definition 4.20 (Opinion Leader) *For a social group $SG := (U, Rel)$ of users U and relations R the group leader is:*

$$leader^{SG} : C^{Bet}(leader^{SG}) = \max_{u \in U}(C^{Bet}(u)) \quad (4.13)$$

where the function $C^{Bet}(u)$ represents the social betweenness centrality for a given user u defined as

$$C^{Bet}(u) = \sum_{\substack{a \neq u \neq b \in U \\ s \neq t}} \frac{\sigma_{st}(a, b; u)}{\sigma_{st}(a, b)} \quad (4.14)$$

The σ_{st} represents the number of shortest paths between two users a and b , and $\sigma_{st}(u)$ describes a subset which passes through the user u .

- **Mobile bridges in sparse urban networks:** The second diffusion aspect in MENs is the spatial mobility. Following the spatial diffusion theories presented in Section 3.1.1, two aspects influence knowledge diffusion. Knowledge diffusions benefit from the spatio-temporal compression effect caused from human mobility and from the increasing availability of densely populated areas close to the urban center. Both aspects affect content diffusion differently. More formally we identify mobile bridges after a spatial diffusion impact (SDI) factor for a user u with following formula:

Definition 4.21 (Mobile Bridge) For a social group $SG := (U, Rel)$ of users U and relations R the group bridge is:

$$bridge^{SG} : SDI(bridge^{SG}) = \max_{u \in U} (SDI(u)) \quad (4.15)$$

Where $SDI(u)$ describes an indicator for the spatial diffusion impact for a given user u and is calculated from the mobility range and the average territory centrality as follows:

$$SDI(u) = \alpha \times range(u) + \beta \times \sum_{t \in T_u} \frac{rank(t, (d(t)))}{|T_u|} \quad (4.16)$$

where $range()$ is a function used to calculate the mobility range of user u and the $rank()$ is a function to calculate the spatial betweenness centrality of a territory in the mobility profile (see Definition 4.17). An auxiliary function $d(t)$ is used to determine the suburb of a given territory t . α and β represent additional correction factors used to influence the impact of mobility ranges and territory centralities.

Following Schönfelder and Axhausen [5] mobility ranges are calculated through the minimum spanning tree MST of all personal territories stored in the mobility profile. We derive the minimum spanning tree from the center points of each territory as below:

Definition 4.22 (Mobility Range) *Given is an undirected street graph $STG = (T, P)$, where each path $p = (i, j) \in P$ has an associated weight $w(i, j)$ describing the distance between the territories $i, j \in T$. Furthermore there exists a subgraph $MST = (T, P')$ of STG with $P' \subseteq P$, which connects all territories of STG . The mobility range of a given user u is then given by all distances of the minimum spanning tree defined through following formula:*

$$range(p) = \sum_{(i,j) \in MST_G} dist(i, j) \quad (4.17)$$

We considered a role system for in-group and intra-group coordination. Hereby, we distinguish between opinion leaders, mobile bridges and ordinary members. Roles are assigned according to social and spatial capabilities. Social capabilities are determined through a position analysis in the encounter network graph and spatial capabilities by analyzing the mobility path of a user. Both can be calculated with a minimal effort even on resource limited mobile devices.

4.3.4 Applying Clustering Mechanisms

After defining a suitable cluster heuristic in Section 4.3.2, we describe suitable clustering techniques. Clustering describes a process of assigning objects with similar properties to a cluster. This assignment process uses similarity measures to determine the equivalence between two or more entities. Several clustering methodologies exist but not all are suitable for resource restricted mobile devices. Incremental clustering approaches work well for our scenario as they avoid large data sets. Many clustering algorithms require a declaration of the final amount of clusters prior to its execution. This information cannot be provided because social behavior is fairly unpredictable. We therefore extend partition and density based clustering approaches to enable dynamic cluster identification.

- *Partition based algorithms* start by assigning each item to an individual cluster and stepwise merge them based on given similarity metrics. Since mobile groups are highly transitive this type of clustering algorithms work well for the identification of ad-hoc groups. As adequate

equivalence metrics we imagine the interest similarity or the degree to which acquaintances overlap.

- *Density based clustering* is based on the idea that items accumulate at certain points. Since people who visit a given territory move between a fixed boundary this approach may work well for spatial clustering. This type of algorithms first identify central items, and progressively assign new items to that cluster by expanding the reach from the center. The process ends if a predefined cluster density is not reached anymore.

In the following, we describe the applied social and spatial clustering approaches in more detail.

Social Clustering Approach

We derive our social clustering algorithm from the *k-clique* clustering algorithm (see Palla et al. [87]). The assumption behind the algorithm is that members with similar tastes also frequently interact with each other. Cliques are identified based on a social network graph. A social network graph describes a community of members in which links describe the relationships between them. A *k-clique* is a complete subgraph of size *k*, in which all *k* members are connected with each other. Higher *k* values mean stronger coherent groups. The *k*-value is predefined and cannot be changed during the clustering process. Experiences show, however, that reasonable *k* values are between three and six (see Eiesland [36]). In our scenario the clustering process is managed in a distributed manner. Each node identifies suitable member groups and shares them with other collocated nodes. First nodes add their friends and expand these group by adding further acquaintances who represent friend-of-friends of all original group members.

To enable incremental clustering progress states have to be maintained. Each peer manages encounter lists *E*, friend lists *F* and its current activity domain *d*. Context sensors are used to obtain real-time information about the environment and monitor social behavior. Table 4.1) shows an example context log file containing proximity -, communication and location logs. For each new encounter $v \in E$ the clustering algorithm will be initiated and the group state modified accordingly. The group state is given by a triple $G(SG, L_g, M_g)$ (see Section 4.2.2). Hereby, *SG* represents the clique cohesion criteria (*k*-factor), *L_g* a set of group leaders and *M_g* a set of group members. The clustering process itself has to be seen as an ongoing process which has to update internal community states, whenever peers join or leave the neighborhood. This process goes through several stages including relationship evaluation, determination of local communities and role assignments:

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```
// Proximity log
20140555T108410 devices: 0034577970 [NameY]
20140555T108450 devices: 0034766f70 [NameY] 0010eea08829 [NameZ]
20040555T108470 devices: 0034576760 [NameY] 0010eea08829 [NameZ]
```

Table 4.1: Example device proximity logfile.

1. First, each peer updates the relationship status of the encountered peer and separates friend from stranger encounters. The relationship quality $rel_{u,v}^d$ is measured through time based parameters as specified in Equation 4.11. If the encountered peer does not already belong to the friend list F_v and the total encounter time (or average frequency) exceeds a certain familiarity threshold Th_{fam} then the peer is added to the friend list of the peer.
2. In a second stage, the peer adds all direct friends to the local group. Therefore, the peer creates an intersection $E \cap F$ and adds all overlapping encounters. Following this step, the peer checks if local group members have friends in the remaining encounter group. Usually this is achieved by intersecting local group members with the friend list of the collocated node $M_g \cap F_v$. The acquaintance is added to the local group, if at least k overlaps exist.
3. At this stage, all participating peers may still have different views on their local groups. Thus, both peers exchange data about their local communities and verify in an iterative process if these group members could also be added to their local group. Each peer checks for all members of the local group M_v if members have k acquaintances in their local group M_g . If this condition is met, the node is added to the local group.
4. In the final stage, new group roles are assigned to each group member. Role assignments follow the approach described in Section 4.3.3. Each group appoints one opinion leader and one mobile bridge. Both nodes manage the content diffusion between groups. The group member with the highest betweenness centrality (See also Equation 4.13) is chosen as an opinion leader in the group, whereas a group member with the best spatial diffusion properties (See also Equation 4.15) is selected as a mobile bridge.

Spatial Clustering Approach

Several authors [105, 75] published papers for *incremental* clustering of user mobility traces. We have chosen an algorithm from Kang et al. [64], which allows the identification of *arbitrary shapes*. It is based on the assumption that

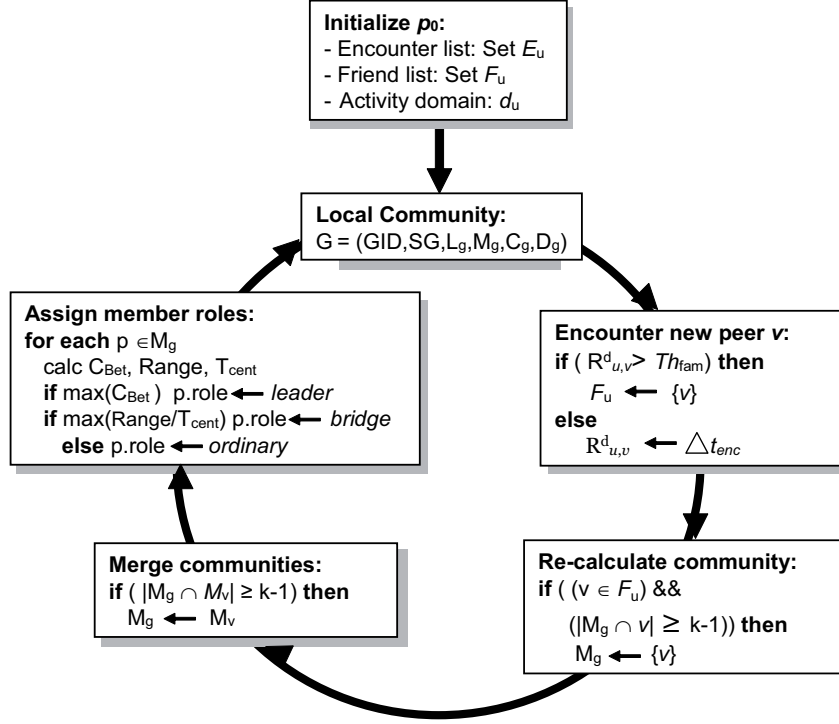


Figure 4.9: Social clique identification algorithm.

humans spend significantly more time at places that are important for them. Since their location tracking system periodically records the current position of the user, more location points are accumulated for frequently and longer visited places. To discover these places Kang et al. use a density based clustering technique. Following their model, certain patterns of location points can be traced back to specific user activities. If one wants to identify places from a set of location points it is necessary to remove those location points related with a relocation activity from one place to another. This separation between travel - and place specific activities is done by collecting location points for a specific time interval and calculating the their mean location observed during this interval. By comparing this location data with the mean locations from previous intervals, place movements are easily identified by measuring the distance between them. Whenever new user movements are detected all previously collected location points are assigned to new place structure and later added to the mobility profile of the user.

Kang's position technology uses available WLAN hotspots to derive the current user location. This approach works well in urban centers and indoor scenarios. As we need to identify personal territories from the entire urban space, including suburbs, we prefer to use a location technology with global coverage like GPS. This decision requires some modifications to the algorithm

to meet the specifics of the GPS system. First, GPS signals are lost if no direct sights to satellites exist e.g., if people enter a building. In this case, the GPS device produces erroneous data, which has to be detected and corrected by restoring the last valid location. Error detection can be done by verifying the signal with reasonable validity ranges. Another problem is that GPS location points do not occur continuously and may randomly jump due to a bad satellite connection. This may happen especially if users move close to high buildings in urban centers. These jumps in a series of location points have to be filtered out, to avoid misinterpretations. This can be done by analyzing the continuous progress of location points. If the distance between location points jumps in an unexpected manner (exceptional case) these location points can be dropped from the mobility trace. If in contrary a larger amount of location points changes its progress then this can be interpreted as a change in the user activity.

During the execution of the GPS receiver, a logging application records mobility traces *Path* of the form represented in Table 4.2. The spatial clustering algorithm takes this mobility trace as input and produces a set of user territories T (see Definition 4.15 in Section 4.2.2) as an output. During the clustering process location points are taken one by one from the mobility trace and used for further calculation. Detected territories are then compared against the territories stored in the mobility profile of the user and added if a new territory has been identified, otherwise their data is merged with existing territory description. The algorithm maintains three variables, including the last valid location *loc*, a new obtained location point from the mobility trace *locPt*, a temporary cluster structure C_{temp} which intermediately stores a series of location points and a temporary territory structure t_{temp} which contains data about a significant user territory. Figure 4.10 displays a schema of the clustering algorithm. In the following, we describe the clustering algorithm in more detail:

1. In a first step plausibility checks are done on all obtained location points from the mobility trace. In case an invalid location point has been detected the last valid location is restored. We execute validity checks by observing the signal and compare its progress with reasonable validity ranges. If the progress exceeds a reasonable limit we restore the GPS data with the last valid GPS reading *loc* as seen in the subroutine *validity check* in Figure 4.10.
2. In a second step, the algorithm has to check if the current location point refers still to a visited territory or is already part of a new user movement from one territory to another. This is done by calculating the movement distance and time delay from the currently observed series of location points (see subroutine *calculate peer velocity* in Figure 4.10). If these user movements represent normal wandering within a given territory then

```
// Mobility Traces
$GPGGA,000000,174356.410,4810.7257,N,01618.9279,E,1,06,2.0,268.9,M,,,0000
$GPGGA,000000,174436.408,4810.7249,N,01618.9283,E,1,05,2.0,268.5,M,,,0000
$GPGGA,000000,174446.407,,,,,0,00,50.0,,M,,,0000
...
$GPGGA,000000,174506.406,,,,,0,00,50.0,,M,,,0000
$GPGGA,000000,174526.405,4810.7204,N,01618.9353,E,1,05,2.0,276.2,M,,,0000
```

Table 4.2: Example mobility trace logfile.

these location points are added to a temporary cluster C_{tmp} . If the new location point exceeds a given distance threshold Th_{vel} then the temporary cluster is closed (see subroutine *detect peer movements* in Figure 4.10). At this stage, we assume that the user starts moving again, and all new location points are purged from the mobility trace as long as their distance stays over this velocity threshold Th_{vel} , otherwise a new temporary cluster structure is started.

3. After the temporary cluster has been closed, the total stay time is calculated as the time difference between the last and first collected location points (see subroutine *significant territory?* in Figure 4.10). If the total stay time exceeds the stay time threshold Th_{stay} the detected place is considered to be a significant territory of the user. In this case, the data is copied to a temporary territory structure t_{tmp} . In the case the place stay time has not been long enough to identify this place as an important user place the temporary data structure C_{tmp} is dropped and a new temporary cluster with the last location point is created.
4. The next step is to integrate this new territory with the mobility profile of the user. Therefore, all previous detected territories of the mobility profile are verified to check if an overlap with the new territory exists (see subroutine *familiar territory?* in Figure 4.10). This overlap is calculated by checking if the centroid point of the temporary place structure is embedded in reference territory. If the new territory is supposed to be familiar to the user then both territories are merged. During the merge process place centroids and boundary nodes are re-calculated. Further compression can be achieved by removing all inner location data keeping only the boundary line of that territory. Otherwise, if the place has never been visited before, this place is added to the mobility profile as a new personal territory (see subroutine *unfamiliar territory?* in Figure 4.10).

After peers have completed the clustering process every peer knows it's favorite personal territories, potential local community and role assignments.

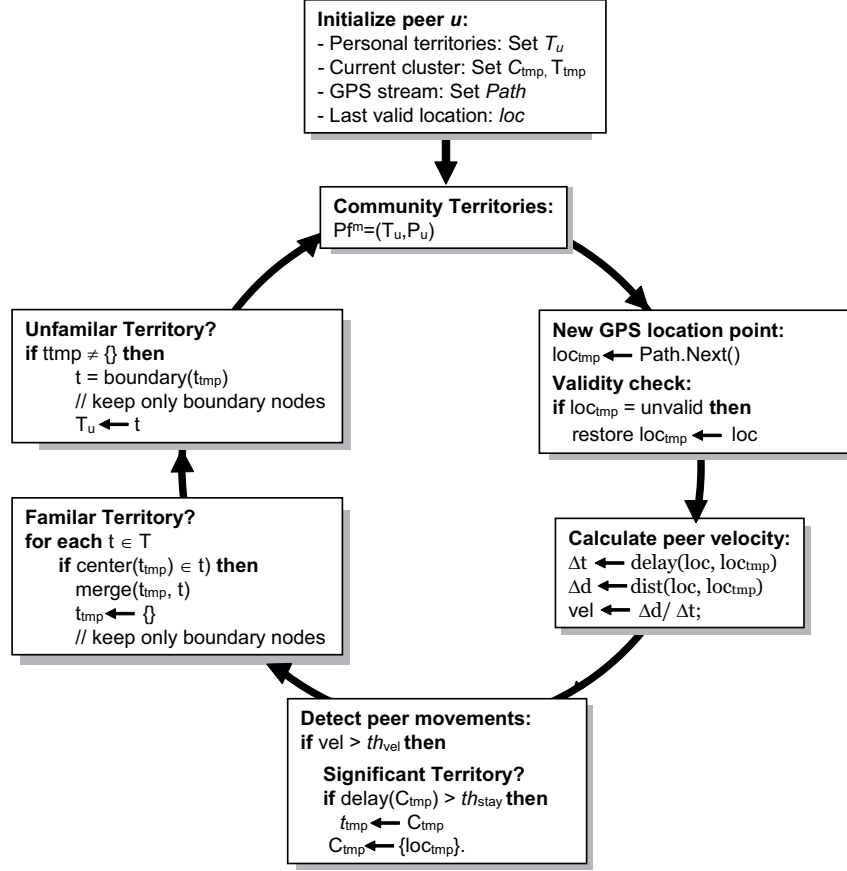


Figure 4.10: Social territory identification algorithm.

4.4 Summary

In this chapter, we created a socially-aware software infrastructure based on MENs. First, we enhanced a peer system architecture with adequate group structures, formation protocols and cache management policies. Each community member maintains its own ego-centric view on the urban community with social networks, personal territories and expertise. During an ad-hoc group formation members share their individual views and generate a shared semantic, spatial and social group structure. Pairwise communication protocols include extensions for profile exchanges, group formations and content transfer processes. The chosen protocol design keeps the number of required peer interactions small. Contents in mobile systems have often a strong correlation with the physical environment. Spatio-temporal metadata and interest based caching mechanisms enable situation aware content access and expertise delegations in the group.

Secondly, we provided mechanisms to enable infrastructure adaptivity in a self organizing manner. Although human behavior is fairly complex people

still develop routines over time, which can be exploited to adapt information systems. New sensor technologies allow to obtain data about the user environment. To achieve computable relationship measurements, we replaced intensity based parameters with time-based values. Based on this data we construct real-time community graphs. Different social network analysis techniques are used to identify peer clusters and role positions. The high transitive character of mobile groups promises several opportunities to offer shared community services. Social and spatial overlay networks lead to high transitivity in the urban community. We assigned inter- and intra-group roles based on users social and spatial capabilities. We choose incremental clustering approaches to keep data and processing requirements small enough for mobile devices. We adapted k -means and density based clustering approaches with dynamic termination criteria based on group coherence and stay probability. System adaptivity is achieved by comparing the wireless network topology with social community states and trigger adequate actions at the peer. Network calculations are based on local data and can, thus, easily be processed by mobile devices. Short sensing intervals from several minutes guarantee up to date boundary detections but also require more energy. Applied threshold values are often domain dependent and thus, not easy to select.

The mobile social software infrastructure delivers important social data necessary to control community diffusion. Surveys about human knowledge diffusion have shown that efficient large scale dissemination can be achieved solely through common sense decision making. In the following chapter, we will revisit social diffusion theories to define content routing algorithms based social phenomena. We direct the diffusion process through routing and filtering methods for MENs presented in Chapter 3.

5

Realizing Social Information Diffusion

The distributed nature of mobile encounter systems (MENs) requires a well coordinated community diffusion mechanism on-top. A reliable diffusion approach must reach the entire community within a given number of forwarding steps.

Managing global network information in dynamic environments is difficult, because the amount of traffic needed to maintain this information often outweighs the benefit. Simple flooding based approaches represent often a better solution. However, they tend to consume a lot of resources, which is a problem for resource restricted mobile devices. Although several point-to-point routing protocols for ad-hoc networks deal with this problem (see examples in Sections 3.2.3, 3.2.2 and 3.2.1), they consider only homogeneous and sometimes even unlimited transfer links between peers. In MENs the transfer bandwidth depends strongly on the encounter duration which may vary between less than a minute up to several hours a day.

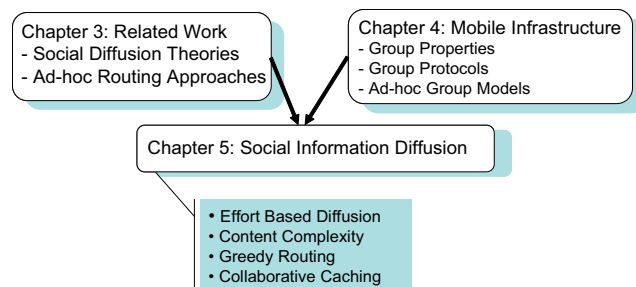


Figure 5.1: Chapter dependencies.

In this chapter, we identify new solutions to improve the epidemic diffusion process of traditional MENs by exploiting human behavior economics. Human routine behavior is a result of a long term decision making process, for which a practical balance between costs and benefits has been achieved. Sociologists have analyzed rumor spreading patterns and found highly effective processes based on common sense decision making (see diffusion theory overview presented in Section 3.1). Therefore, we extend the protocol of our

socially-aware support infrastructure (see Section 4.2 and Chapter 4.3) with an additional content routing layer, which emulates diffusion processes following human knowledge transfer theories. The assumption is that we cannot only reduce *download failures* but also enhance the *distribution reach*.

We start in Section 5.1 with a short overview about characteristic diffusion problems observed for encounter networks. Then, in Section 5.2, we compare social and technical diffusion scenarios to identify important overlaps and a starting point for technology transfer. In Section 5.3, we give an initial view how an effort based diffusion approach can be designed. We introduce in Section 5.3.1 different complexity levels for community content. In Section 5.3.2 and Section 5.3.3 we define node and content selection schemes to control the content diffusion between peers. In Section 5.3.4 various collaborative caching approaches are presented. Previous content diffusion models are implemented for opinion leaders, mobile bridges and ordinary members in Section 5.4. We conclude the chapter with a short achievement summary.

5.1 Epidemic Diffusion Problems

Designers for content diffusion mechanisms for MENs have to deal with several problems:

- **Local navigation:** Peers in MENs cannot rely on a global address management service. Routing decisions are solely based on local knowledge. Gossiping approaches use fewer resources in contrast to network flooding but are also not very efficient. For efficient content forwarding, it is important to identify superior nodes, which are well connected. According to a study from Thomas W. Valente [117], knowledge spreading through opinion leaders outperforms bottom up rumor spreading.
- **Varying bandwidth:** A surveillance study [20] has shown that human encounters have power law character, meaning that most of the encounters are short termed and only few have a longer duration. Because of this, current MEN solutions are only applicable to small content types. This represents of course an unreasonable limitation for mobile encounter networks, since longer encounter situations exist but cannot be used.
- **Memory limitation:** Local peer caches are several levels smaller than the virtual content space managed by MENs. Peers depend on a continuous content flow to keep users up to date with the latest contents. Since people follow several interests during the day, short term cache strategies may not lead to long term knowledge building.

On the other side, mobile information systems should provide rich and dynamic content for their users and deliver to all members interested in a

particular content within the urban community. The success of community applications depends on networking effects. With every new node subscribing to the community, the number of connections rises non-linearly. This population increase leads, in consequence, to more community interactions which again raise the overall content quality. The total amount of shared contents represents the community knowledge, and therefore, is important to attract new members.

5.2 Social and Technical Diffusion Analogies

Both, knowledge and content transfers depend on physical encounters. The limited coverage range of ad-hoc networks requires that people stay close together for the establishment of wireless communication links. While humans have to interrupt their personal activities for an inter personnel conversation, mobile devices can handle the transfer without significant user interventions. This has the advantage that random encounters, e.g., made during traveling can be used for content transfers.

Human knowledge spreading and content propagation in MENs rely on local knowledge. Humans use their knowledge about others to decide what type of knowledge is being transferred. An important role plays trust, which naturally limits the amount of information exchanged. Technical systems have to emulate this user experience by gathering information about encounters through context sensors. The quality of the raw sensor data depends on the capability of the sensor. In addition, this data has to be repeatedly evaluated in a time and energy consuming process. Hence, it can be expected that MENs perceive human encounters less accurate and often with a certain delay.

The control methods for human knowledge - and technical content transfers are comparable. Both have to deal with limited transfer bandwidths and thus, have to prioritize diffusion activities. As a consequence, people preferably communicate with those that are important to them and transfer knowledge according to their skills. Similar to humans, peers in MENs control content exchanges by node and content selections. Because of the limited transfer bandwidth, it makes sense to attach priorities to content objects, and transfer the important or the smaller ones first. By this bandwidth is preserved and download failures can be significantly reduced. Cache policies are used to keep the most relevant content and purge least relevant. Such a cache specialization leads to fewer content replacements. The longer content objects reside in the cache, the more they add to the reach of the diffusion process.

5.3 Least Effort based Cooperation Principle

Several diffusion approaches based on small world networks have been implemented by other researches. Their strategy focused mainly on identifying short paths in broadband networks. Efficient diffusion paths in MENs depend, however, not only on the network topology but also on available bandwidths. Consequently, short paths may differ significantly from each other in both scenarios.

Extending traditional routing methodologies with an effort based diffusion approach is promising. Effort based mechanisms filter content according to the qualification of an encounter situation to transfer content. Situations where content downloads cannot be completed, consequently, occur less likely. As a basis for this diffusion protocol we take the least effort transfer hypothesis described in Section 3.1.3. This theory classifies knowledge in different complexity levels and identifies various enabling factors that empower content transfers between two people.

In Section 5.2 we proved that social and technical transfer scenarios are indeed very much comparable. An obvious solution is to identify and exploit these enabling factors for content diffusion. Before this can be achieved it is necessary that MEN infrastructures become aware of the social environment of the user. The mobile social software infrastructure functions as a basis for a socially-aware community diffusion system. This platform monitors peers and tracks group formations. But more importantly, it delivers the social data in real-time with which potential diffusion mechanisms can be controlled. Continuous feedback loops guarantee an appropriate interpretation of physical encounter situations. In addition, the implicit decision making process of humans has to be mapped on precise forwarding algorithms, which can be executed by machines. Technical control mechanisms are used to emulate human diffusion phenomena. According to our survey about encounter systems in Section 3.2 content diffusion in MEN can be controlled through means of *content filtering*, *node selections* and *cache management* mechanisms. We adapt content exchanges to the capabilities of the recipient, select superior nodes as intermediate nodes and apply collaborative cache approaches for a better usage of the collective knowledge space.

5.3.1 Classifying Content after Complexity Levels

Following Colbert et al. [23], people in unfamiliar environments look preferably for *orientation* support, while people in familiar environments are more interested in getting updates about *ongoing activities* in their communities. Community descriptions can help to improve user orientation, while more complex dynamic content types promise a better solution to stay informed about ongoing activities.

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As bandwidth is crucial for successful content transfers between peers, we propose this parameter as major complexity classification criteria. General descriptions about people, places, and events can be downloaded in one single transmission. The assumption is that this content type can always be downloaded even in brief encounter situations e.g., when people pass each other randomly during the commute from one place to another. As such we count them to a simple content type. community recommendations represent a special form of descriptive content, which contain popularity ratings of those objects they are referred with. MENs are generally well suited for the distribution of small content types.

The concept of discourse related content reflects a content item, which is part of a larger discourse structure and cannot be downloaded independently without significant loss of its meaning. Such a dynamic content is much more important for mobile usage scenarios since this type of media has a stronger expressiveness. Frequent content updates assure on the one hand that people are more accurate informed and on the other hand that a more complex content presentation can be provided. Examples for dynamic content is any type of event coordination, community voting, progress reports and context adaptive content. Unfortunately dynamic content requires a certain *interactivity* between the peers and imposes high requirements on the download process. It, thus, may fail more often. This dependency exists also for *multimedia* files like mobile music, videos, or photos which may be *truncated* during the download in smaller pieces and make only sense if these pieces are later put together in the right order. For this reason dynamic content is often transmitted through wide area networks which guarantee download bandwidths. Accordingly, we define content in relation to the community scenario based on functional aspects:

Definition 5.1 (Content Complexity) *Given is a content object $c = \{c_1, c_2, \dots, c_n\}$ of n dependent items and a complexity classification with $\{C^{simple}, C^{complex}\}$ for simple and complex content types. Then we classify the content as $C^{complex}$ if $n > 1$ dependent items exist, otherwise we categorize the content as C^{simple} .*

Figure 5.2 summarizes the different aspects of user contents. Content ratings differentiate important from less important content. Metadata descriptions are used to filter content according to the user situation. Content filtering reduces the number of necessary interactions with which content can be accessed by the user. Finally, content is classified according to its transfer complexity. This classification leads to a better exploitation of encounter situations and helps to avoid download failures.

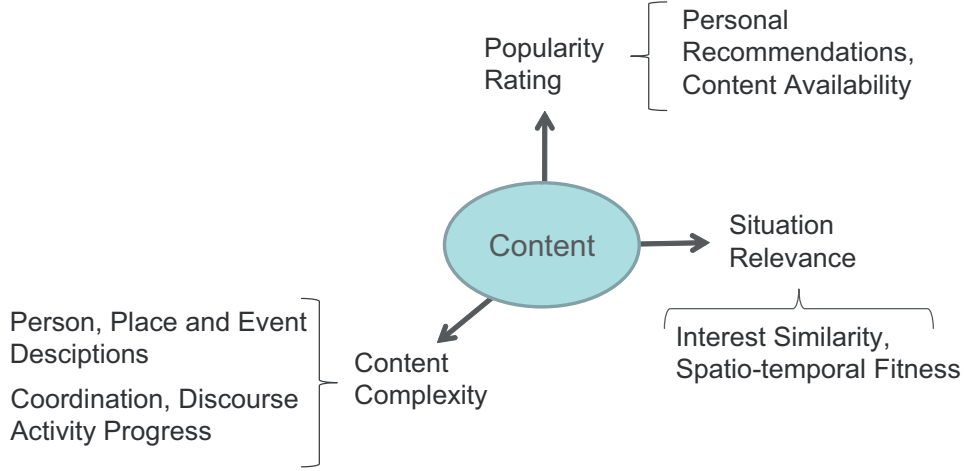


Figure 5.2: Content complexity schema.

5.3.2 Complexity aware Content Filtering

After defining a new complexity model for community contents, we now design a content filtering mechanism. Our goal is to adapt content transfers to the capabilities of the recipient. We expect a reduction of download failures and fewer content replications. Both represent unnecessary and costly bandwidth wastes, which should be avoided.

The least effort knowledge transfer hypothesis is based on the observation that not all knowledge transfers are equally complex. Almost all encounter situations can be used to transfer descriptive content types. Following Reagan et al. several enabling factors are responsible for promoting knowledge transfer processes between humans. Only, if such enabling factors can be observed during an encounter, discourse related content types can be transferred. Strong relationships between humans promote the transfer of tactile knowledge. This type of relationship indicates frequent encounters often for a longer duration between the people and finally leads to a more efficient communication between them. Since human encounters have power law character (see Section 5.1) only few encounters have a longer duration. Besides that, the surrounding network enables or restricts the content diffusion. Dependent on the network position, humans may gain diffusion advantages. Well embedded group members can benefit from group synergies, or have access to diverse knowledge if they frequently move between groups. Finally, also expertise related factors influence the knowledge acceptance as associative learning strategies can be applied. In the following we define these set of enabling factors more formally:

Definition 5.2 (Enabling Constraints) *Given are two users $u, v \in U$, who share a minimal amount of interests within a given similarity threshold Th_{sim} , maintain strong relationships with each other exceeding a given familiarity*

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threshold Th_{fam} , and are member of a social group SG (see Definition 4.14). Then based on the content transfer $u \xrightarrow{c} v$, the enabling factors are represented through following constraints:

- Strong tie constraint: $rel^d(u, v) \geq Th_{fam}$
- Group membership constraint: $u, v \in SG$
- Network range constraint: $role^d(v) \equiv Leader^{SG}$
- Mobility range constraint: $role^d(v) \equiv Bridge^{SG}$
- Background similarity constraint: $sim^{Pear}(u, v) \geq Th_{sim}$

where $rel^d(u, v)$ is a function describing the tie strength between two persons u and v who perform a specific activity of a given domain d together (See Definition 4.11), $role(u)$ a function which returns the last obtained role of a user u in a social group SG with the group focus of $d \in D$ and $sim^{Pear}(u, v)$ is a function used to determine the interest similarity between two users u and v (see Definition 4.7).

Matchmaking mechanisms required for the filtering of descriptive or discourse related contents are implemented as simple if/then rules, where potential encounter situations represent the condition and applied content filters the corresponding action. It makes sense to prefer discourse related content transfers whenever the opportunity exists, because occasions to transfer discourse related content happen quite rarely. More formally we define filter rules as following:

Definition 5.3 (Complexity Filtering) Given is a set of enabling factors E (see Definition 5.2), a set of contents C and a user $u \in U$. Then the content filter logic for opportunistic content transfers is described through a quadrupel $Filter = (Ef_u, F, C_u, Rule)$, where

- Ef_u is a set of enabling factors $Ef_u \subseteq Ef$ observed during the encounter with user u .
- F is a set of content filters $F = \{C^{simple}, C^{complex}\}$ (see Definition 5.10)
- C_u is the publication list of all contents which the user u wants to contribute to the community. The publication list is a subset of all contents in the local cache $C_u \subset Cache_u$.

- Rule is a set of matchmaking rules of the form

$$\text{if } \langle e \rangle \text{ then } \text{filter}(C_u, f) \quad (5.1)$$

with $e \in E_u$, $f \in F$ and $\text{filter}(C, f) \Leftrightarrow \{C^f \subseteq C \mid \forall c \in C^f \text{cp}(c) = f\}$ where the function $\text{cp}(c)$ returns the content complexity classification (see Definition 5.10) of a content object c .

Figure 5.3 shows a decision tree for the matchmaking algorithm. Content transfers are only conducted if an interest overlap between the counterparts exist. According to Section 4.1 we foresee rich content exchanges in social groups and simple content exchanges through overlay network groups. If the system detects strong tie contacts between peers, no matter if it is a bilateral or a multilateral connection it will always trigger complex content transfers according to the least effort transfer hypothesis. This makes sense since people in familiar environments require fewer descriptive contents to improve their orientation. If encountered peers maintain only weak relationships with their neighbors, only simple content types can be exchanged between them. If these peers maintain relationships to a broader portion of the community this diffusion scenario is still very important. Opinion leaders or users with extraordinary mobility patterns belong to this group of people. In this case peers may establish content flows between groups leading to a better community integration.

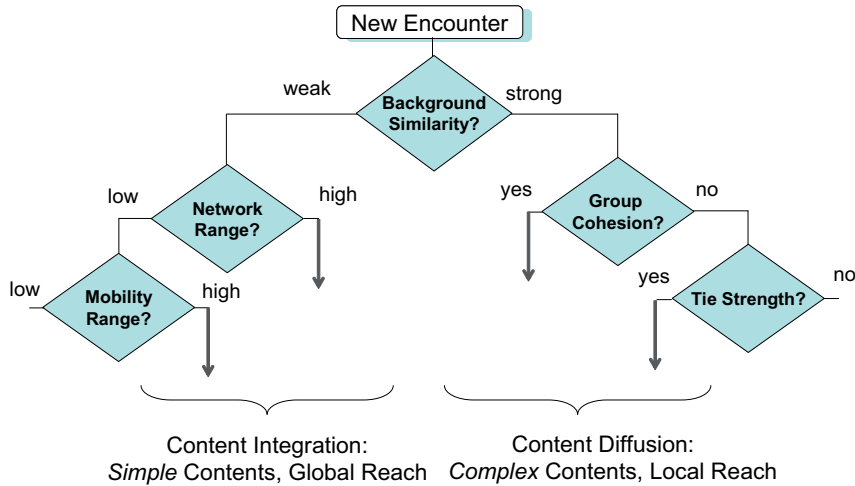


Figure 5.3: Least effort protocol overview.

5.3.3 Small World Dissemination Approach

The small world theory has proven that short paths can be found through human "common sense" decisions (see Section 3.1). This confirms that central diffusion infrastructures are not needed to distribute information efficiently within the urban community.

A scalable routing mechanism has to exploit such a small world network topologies in a best possible way. Small world networks consist of loosely connected neighborhoods and even smaller subgroups. Efficient routing mechanisms should provide horizontal and vertical diffusion approaches. Horizontal diffusion approaches benefit from group synergies during short range content broadcasts and vertical diffusion strategies utilize hierarchical structures of urban societies. In the following, we explain both approaches in more detail.

Exploiting Group Broadcasts

Assuming that group boundaries can be maintained in real-time, then group broadcasts have the advantage that all group members can be reached within a single hop. In a serial content diffusion scenario, the process takes more time because each member needs to be contacted individually. But, if the group management process fails the diffusion algorithm has to suffer from time out problems due to unidentifiable recipients (see protocol description in Section 4.2.2).

The group broadcast process is executed as follows: First, peers with new or modified content send these to the group leader. The group leader has a queue for incoming messages and processes each message one after the other. To verify that this content follows the shared interest of the group, the leader compares this content item with the group subscription list and continues with the process only if a positive match exists. In a subsequent step content ratings are updated. The group leader updates content ratings by calculating the average value from all individual ratings provided by users from the same role level or overrides the rating if the new rating comes from a leading community member. The process is finished by broadcasting the content object to all group members.

Exploiting Social Hierarchies

Human generated networks follow often a power law distribution. Power law curves are characterized through long tails in the end. A common approach to navigate along such hierarchies are greedy routing approaches. This specific distribution scenario of scale free networks leads to knowledge forwarding chain toward the center. Content dissemination based on a greedy approach gets even more effective as higher connected members are reached earlier.

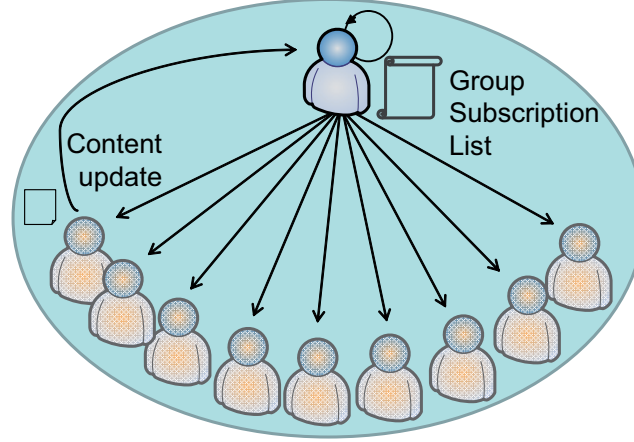


Figure 5.4: Efficiency improvements through content broadcasts.

Moreover, from the characteristic long-tail character we conclude that only a small group of super spreaders is responsible for the majority of knowledge transfers and others contribute only minor. Therefore, it makes sense to target especially this group of super spreaders. This reduces the overall message amount but still achieves a comparable high diffusion impact. After content has reached these central members, they disseminate these again to members according to their expertise. Generally, a greedy routing approach can be specified as below (definition adapted from Li et al.):

Definition 5.4 (Greedy Routing Logic [73])) *The greedy diffusion logic based on the opportunistic connected graph is described through a quadrupel $GR = (U, C, w, \geq)$, where*

- U is a set of users $\in ON$,
- C a set of content of a specific type,
- w a weight measure mapping encounter links to a positive value representing the network range difference between the encountered peers and
- $\geq$ an order function.

Navigation in social networks

Onnella et al. [86] verified the power law character of human communication networks. They constructed a calling graph from the data provided by Telecommunication providers where people represent nodes and calling patterns describe the edge between them. Through a cluster and opinion leader analysis, they could show that only few people emerge as opinion leaders and interconnect urban societies with their calls.

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From this, we conclude that the identification of opinion leaders is crucial to establish community wide communication across social groups. Adequate diffusion algorithms use opinion leaders to disseminate descriptive content types which give users at least the opportunity to explore remote areas of the urban community. A greedy routing approach between opinion leaders can be established by comparing the centrality parameters of the local and remote user. Based on this local hierarchy, content is forwarded if the collocated peer is better connected. Focusing on increasingly better connected peers gradually improves diffusion efficiency. This approach is comparable to SimBet or Bubble routing but focuses on diffusion efficiency rather than on concrete targets.

A valid calculation for the betweenness centrality has to be based on the entire community graph. The centrality parameters used for the position analysis in Section 4.3.3 are limited to the members of a local group. Daly et al. (SimBet approach) refer to a publication from Marsden [77] who investigated how sociometric and ego-centric betweenness measures relate to each other. Sociometric calculations are based on the entire community graph whereas ego-centric calculations consider only the local portion of the graph which centers around the actor. Despite the fact that both measures lead to different values, he showed that their ranking was similar in a given network. Hence, ego-centric betweenness value calculations can replace sociometric betweenness calculations.

Therefore, we reuse the previous centrality calculations executed to determine role assignments in groups. We define a social greedy routing approach by applying the betweenness centrality as cost function and define the algorithm as below:

Definition 5.5 (Social Greedy Routing) *Given is an overlay network group SON^{soc} (following Definition 4.18) and a quadruple $(M, C^{simple}, C^{Bet}, \leq)$, where*

- M represents a set of acquainted opinion leaders (See Definition 5.5) with $M \in SON^{soc}$,
- C^{simple} represents a subset of all descriptive content types (see Definition 5.10) available in the overlay network group SON^{soc} ,
- C^{Bet} is a weight function representing social betweenness of a given user u in the social overlay network SON^{soc} (See Definition 4.20),
- $\leq$ represents an order functions which describes the popularity distribution within the social overlay network SON^{soc} .

Then a user $u \in M$ forwards content to another user $v \in M$ in greedy manner, if peer v is better connected than u :

$$C^{Bet}(u) \leq C^{Bet}(v) \quad (5.2)$$

Navigation in urban networks

With increasing reach of the urban community, social contacts are getting less likely. See also the observation from Onnela et al. who concluded that phone communication is not suited to spread information on a larger scale. In other words, greedy routing in acquaintance networks ends when "local" opinion leaders are reached. To avoid this trapping of the information flow it is essential to add alternative diffusion routes for large scale scenarios. Following Watts and Strogatz's rewiring experiment, random encounters have the potential to create additional shortcuts in the urban community (See Section 3.1.2).

According to the finding from different spatial diffusion theories in Section 3.1.1 user mobility and place centrality influence spatial diffusion. In the following we present two surveys, which verify the power law character for human travel behavior and urban street topologies. Barabasi et al. [45] analyzed the travel behavior of people by obtaining data about the nearest antennas used during the call. The graph in Figure 5.5 b) displays the probability of phone calls (y-axis) in correlation with covered distances in km (x-axis) during the call. From the progression Barabasi et al. concluded that only very few travelers travel over large distances (even between countries) whereas the majority does not leave their direct neighborhoods. Another spatial study conducted by Porta et al. [26] took map data of a given city and constructed a street network graph from this. For each position in the graph, they calculated the betweenness centrality measure and compared this with the availability of city services, e.g., the number of shops at this location. Figure 5.5 a) illustrates the correlation between the service offer and the spatial betweenness. The authors concluded from the graph progression that only very few people live in privileged areas, whereas the majority has to take longer travel distances into account in order to access similar urban services.

The outcomes of both surveys suggest that superior spreaders can be identified through their personal territories and mobility characteristics. Similar to the previous case, they should be preferably used to empower descriptive content exchanges between community members. This leads to a better community transparency as this type of contents enables further community discoveries. Identifying the right content forwarder is, however, a challenge, since persons randomly encountered possess no encounter history. The people who participated in the letter sending experiment from Milgram were confronted with a similar problem. They compensated missing contact information with

5.3. LEAST EFFORT BASED COOPERATION PRINCIPLE

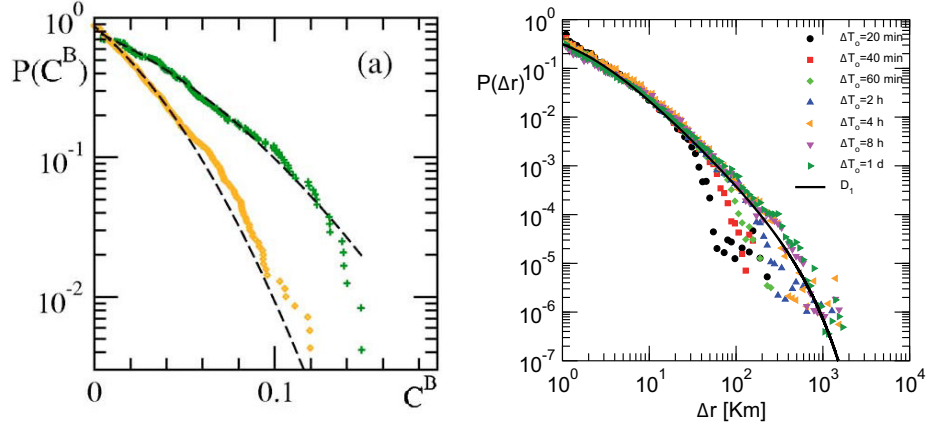


Figure 5.5: Observed Power Law effects in a) urban street networks and b) travel behavior of phone users.

additional context data. We speculate that by combining spatial behavior data with data about human backgrounds e.g., community interests adequate content forwarders could be selected. Similar community interests also assure that people will tolerate intermediate content storage on their devices required to disseminate the content within the community. A greedy routing mechanism can then be established after following scenario. Whenever two people belonging to this advanced spreader group, encounter each other they initially exchange mobility and content profiles to gain contextual data about the peer. If an interest overlap exists peers would start comparing their territorial and mobility properties and forward content if the encountered peer promises to diffuse the content more efficiently. Analogically we enhance our greedy routing logic with the following spatial routing method:

Definition 5.6 (Spatial Greedy Routing) *Given is a semantic overlay network SON^{sem} (following Definition 4.18) and a quintuple $(M^{son}, C^{simple}, sim^{Pear}(), SDI(), \leq)$, where*

- M represents a set of bridge peers (See Definition 4.21) with $M \in SON^{sem}$,
- C^{simple} represents a subset of all descriptive content types (see Definition 5.10) available in the overlay network group SON^{sem} ,
- $sim^{Pear}(u, v)$ is a similarity function between two peers u and v , as defined in (see Definition 4.7).
- $SDI(u)$ is a weight function representing the mobility potential for an individual member u of the overlay network group SON^{sem} (see Definition 4.22 and 4.17).

- $\leq$ represents an order functions which describes the mobility distribution within the semantic overlay network SON^{sem} .

If bridge user u encounters randomly another bridge user v with similar interests (within a given similarity threshold Th_{sim}):

$$sim^{Pear}(u, v) < Th_{sim} \quad (5.3)$$

Then a user $u \in M$ forwards content to user $v \in M$ in a greedy manner, if peer v has better mobility potential SDI than u :

$$SDI(u) \leq SDI(v) \quad (5.4)$$

5.3.4 Shared Cache Management

With increasing knowledge complexity it makes sense that people in communities specialize on specific topics. A similar situation exists for MENs where content diffusion often goes along with content replications occupying costly cache space.

Because of this, cache policies need to find a reasonable balance between egoistic and altruistic storage policies. Less frequently accessed content should be delegated to other group members, who access the content more often. The goal is to increase the time content objects remain in their caches. The longer content resides in the cache, the more they add to the reach of the diffusion process. Or seen from the other side, if objects are soon flushed out of peer caches, they will not be transported far.

Following Rulke [98] group members can be roughly divided into *generalists* and *specialists*. Whereas generalists are responsible for the information exchange with other groups (vertical content delegation), specialists focus on expertise building within the group (horizontal content delegation). In the following sections we explain the motivation behind both delegation approaches and derive appropriate cache policies for MENs.

Vertical Content Management Policies

Daft and Lengel [27] analyzed the differences between these two knowledge acquisition strategies. They used the equivocality reduction theory [120] from Weick to explain the vertical knowledge delegation behavior of generalists. After this theory, managers in enterprises collect information about their competitive environment, and assess it with the intention to reduce uncertainties for their employees and to provide clear directives for their employees. This process of outside information collection and filtering through managers is also illustrated in Figure 5.6 (left side).

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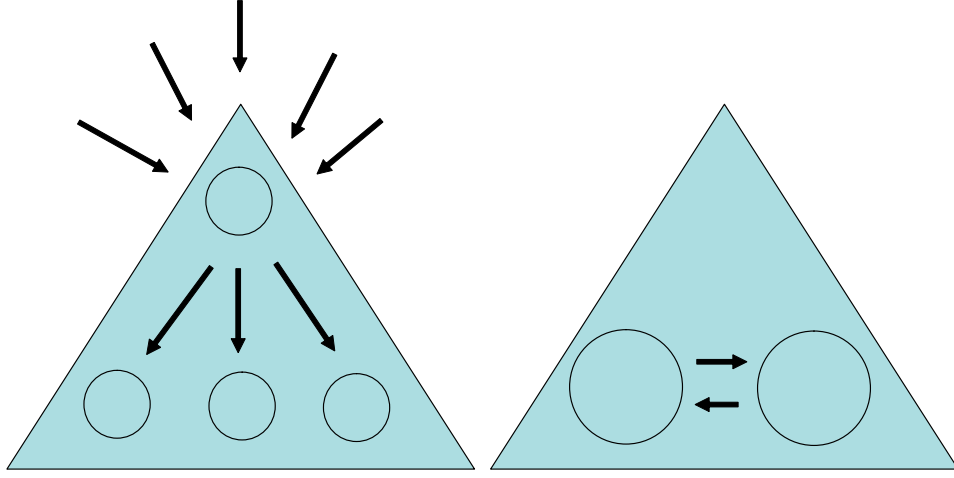


Figure 5.6: Horizontal and vertical caching (Daft and Lengel [27]).

A similar knowledge transfer process is also imaginable in an urban communities. A network of group leaders can be used to exchange the most important content between communities. To raise the overall content quality in the entire urban community, group leaders should preferable spread well accepted contents. In other words collaborative content ratings can be used to reduce content equivocality in the urban community. Hereby, we foresee different cache strategies for *social* and *mobile bridges*.

A bridge between social groups and may be used to share personal content relevant for a specific neighborhood. Since social groups remain rather small, content ratings largely depend on the reputation of the recommender. People with high reputation in groups usually also have strong influence on their members. Content ratings can be collected explicitly by assigning ratings by the user or implicitly by reading or discarding the content. Accordingly, we define a reputation based rating approach for group leaders (see Definition 5.5) as below:

Definition 5.7 (Reputation Cache Policy) We define the cache relevance $R^{Rep}(c, u)$ as seen by individual u (embedded in a social network with the reputation expressed through the betweenness centrality $C^{Bet}(u)$ (see Equation 4.14)) of an information object c matching with the user interest $sim^{Pear}(c, u) \geq Th_{sim}$ (see Definition 4.7) that was given the rating w by u to be

$$R^{Rep}(c, u) = \begin{cases} \alpha \times C^{Bet}(u) + \beta \times w(c) & \text{if } sim^{Pear}(c, u) \geq Th_{sim} \\ 0 & \text{if } sim^{Pear}(c, u) < Th_{sim} \end{cases} \quad (5.5)$$

Public community content on the other side is spread mainly through random encounters. Because of this, previous evaluation approaches based on the

group hierarchy cannot be applied. Such a potentially large base of random users, however, justifies the application of statistical methods for content evaluation. Statistical approaches are based on the calculation of mean ratings, whose values depend on the number of potential content recipients. The value of a content item is hereby determined by the number of replications available in the community. Since peers are not aware of the global knowledge space, availability of contents has to be determined through a local monitoring process. Wang et al. [118] suggested a fully distributed solution based on buddy content tables which dynamically count with every content download the availability of a specific content item. Users measure the local popularity of given content items in respect to their local social networks. This approach requires no extra communication and can be stored in a memory efficient way. Consequently, we define for mobile bridges (see Definition 4.21) popularity rating based on a peer-to-peer evaluation approach to avoid the need for central infrastructures as follows:

Definition 5.8 (Popularity Cache Policy) *We define a statistical cache relevance measure $R^{Pop}(c, p)$ independent of individual ratings for an information object c that fits to the user profile p with a similarity of $Sim^{Pear}(c, p)$ (see Definition 4.7) and was already downloaded $Pop(c)$ times within the community and has the relevance*

$$R^{Pop}(c, p) = \begin{cases} Pop(c) & \text{if } sim^{Pear}(c, p) \geq Th_{sim} \\ 0 & \text{if } sim^{Pear}(c, p) < Th_{sim} \end{cases} \quad (5.6)$$

where we assume a distance based similarity measure between the content object and the interest profile containing N subscribed community domains is $Sim^{Pear}(c, p)$ (see Definition 4.7). Since similarity increases with feature vector closeness, we assume a negative α for the relevance function!

Horizontal Content Management Policy

The right graph in Figure 5.6 shows the knowledge delegation process between group members. An straight forward delegation approach is based on content filtering according to user's interests (see also Section 4.2.3). In mobile community systems such semantic content filtering must always be accompanied by a situation-aware approach to make the content access more efficiently. Wolfson et al. identify content that is closely bound to the current user situation by calculating the relevance through the spatio-temporal distance between the user and the event described in the content object as follows:

Definition 5.9 (Situation Relevance [124]) *Given is a situation space describing time and location separation degrees. The relevance of a content object*

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described through the quintupel $c(CID, D_c, Time_c, Loc_c, Author)$ to a user described through the tuple $u = (UID, D_u, Loc_u, Time_u)$ who retrieves the content object with current timeliness and with a given profile similarity sim^{Pear} (see Definition 4.7)

$$\Delta t = |time(u) - time(c)| \quad (5.7)$$

in time units, and distance

$$\Delta d = \sqrt{(loc(u)^x - loc(c)^x)^2 + (loc(u)^y - loc(c)^y)^2} \quad (5.8)$$

from the user location Loc_u to the event location Loc_c of the content object c , can be described as follows:

$$R^{New} = \begin{cases} -\alpha \cdot \Delta t - \beta \cdot \Delta d & \text{if } sim^{Pear}(u, c) \geq Th_{sim} \\ 0 & \text{if } sim^{Pear}(u, c) < Th_{sim} \end{cases} \quad (5.9)$$

where α, β are non-negative (constant) weight factors. Bigger ratios α to β are applied for content domains which stay only for a short period of time up-to-date.

As people participate in several communities over the day and they are specializing in *multiple* community domains. In such a case, content cached for previous community meetings may be overwritten with content from other community meetings. This content replacement, however, is undesirable, since content from both communities may be equally important to the user. One way to solve this content purge-out problem is to extend the cache policy. Instead of focusing on the temporary user situation we consider all communities in which the user participates. These communities are stored as territory definitions in the mobility profile of the user. Assuming that content items describe a specific location, relevant communities are identified by calculating the distance to the community territory. The content relevance is then calculated based on the properties for the nearest community. We assure content relevance through the fact that only relevant community territories are stored in the mobility profile. In this case, the content relevant for community reminder services can be identified by changing the meaning of d in Definition 5.9 as follows:

Definition 5.10 (Mobility Path Distance) We look at all territories $t \in Pf^m$ taken from the profile Pf^m of the peer. This profile is a summary of past activities of a peer and describes the knowledge gathered by the system about the places the user has relations to. Each territory t is represented by its

center of mass $center(t)$. Then the distance d in Equation 5.9 for computing the relevance of an event c that is attached to a place $loc(c)$ is calculated as

$$d = \min_{t \in Pf^m} (dist^{Eucl}(loc(c), center(t))), \quad (5.10)$$

i.e., d denotes the distance between the place of the event c to the nearest center of a territory of the user.

5.4 Implementation of Diffusion Tasks

Applying the previous defined diffusion mechanism in real-world scenarios requires additional steps to assure fairness and robustness. Small distant ad-hoc networks often lead to frequent interruptions of digital links between the devices. The device has to recalculate the community state wasting important energy and time. This problem can be avoided by enhancing encounter list management. If peers do not only log the mac-address but also the last encounter time, they can easily block peers that have just recently been re-discovered. Algorithm 1 shows how redundant encounters can be blocked from the diffusion process. Before peers may again engage in a diffusion process, peers check the last encounter time of that peer and check if the duration between both encounters is above a predefined blocking period Δt_{block} . Blocking periods of several hours up to one day are reasonable assuming that community information is not time critical.

Algorithm 1 Pseudocode for encounter redundancy management

Require: Set E_u , Num Δt_{block}

```

1: while  $GetHelloMsg(p)$  do
2:   if  $(v \notin E_u \vee (T_{curr} - p.LastEnc()) > \Delta t_{block})$  then
3:      $requestProfile(v)$ 
4:   end if
5: end while

```

To save time during the diffusion process, each peer constructs a content summary (see Algorithm 2). Of course this has to be rebuild if new content is added or removed from the cache. Content summaries are individually generated according to the diffusion role of the peer.

Encounters may end abruptly and the diffusion process may not be finished. In this situation it is important that some peers are not discriminated from others. A better distribution fairness can be achieved by limiting the number of content transfers between peers. Therefore, we introduce a parameter $Download_{max}$ which defines the maximum amount of content items exchanged

5.4. IMPLEMENTATION OF DIFFUSION TASKS

Algorithm 2 Pseudocode for content summary generation

Require: Set $Cache_u$, Set C_u , Num $Complexity$

```

1: while  $GetContentMsg(v)$  do
2:    $add(Cache_u, c)$ 
3:    $cleanCache()$ 
4:   for all  $c \in Cache_u$  do
5:     if  $IsOfType(c, Complexity)$  then
6:        $C_u \leftarrow c$ 
7:     end if
8:   end for
9: end while

```

between devices. Another problem is that some content items are more relevant than others and should be delivered first. Because of this we order content requests according to the relevance of the requesting peer, in decreasing order. If peers are not able to finish the download process they still can be sure to have retrieved the most relevant items.

Algorithm 3 Pseudocode for managing fair content exchanges

Require: Set E_u , Set $Cache_u$, Set $CReq_u$, Num $Download_{max}$

```

1: while  $GetSummaryMsg(v)$  do
2:   for all  $c \in CReq_v$  do
3:     if  $c \notin Cache_u$  then
4:        $CReq_u \leftarrow c$ 
5:     end if
6:   end for
7:   if  $|CReq_u| > 0$  then
8:      $sort(CReq_u, R^{rep}, Order.Desc)$ 
9:      $filterLength(CReq_u, Download_{max})$ 
10:     $requestContents(CReq_u)$ 
11:   end if
12: end while

```

The content diffusion process in communities is a collaborative effort in which people participate with different roles. We therefore extend *opinion leader*, *mobile bridge* and *ordinary member* roles by assigning to them specific diffusion responsibilities. In the following subsection, we describe each diffusion role in more detail.

5.4.1 Opinion Leader

Opinion leaders enable intra group communication by participating in social overlay networks (see Definition 4.18 in Section 4.3.2). These overlay networks are used to route user specific content to leading group members in a greedy manner (see Definition 5.5 in Section 5.3.3). By this, content becomes increasingly stronger filtered, the closer it move to the community center (see Definition 5.7 in Section 5.3.4).

The content diffusion algorithm is divided into two main parts. In the first part, opinion leaders build the social overlay network. Each peer hereby maintains an encounter list E , a friend list F and a social overlay list SON^{soc} . The second part describes the content diffusion between overlay members. Peers determine initially missing remote content by comparing the publication list C_v of the remote peer with their own cache $Cache_u$ and request appropriate content $CReq_u$ from their collocated peer.

Algorithm 4 (Acquaintance overlay algorithm) shows resulting interactions between two encountering *group leader* peers:

1. If a peer u enters the reception range of another peer v they start exchanging hello messages to verify if they have encountered before.
2. If the peer is new, both peers start exchanging their social profile Pf^s and calculate their position in the local community on each side (see line 1-5).
3. If one of the peers fulfills the criteria formulated in the greedy algorithm (see line 6 - 13) then they start the exchange of the content summary C_u , specified above.
4. Each peer then matches the content summary of the encountered peer C_v with their own cache $Cache_u$ to identify missing content items (see line 14 - 25).
5. If new content has been identified from the remote peer, the peer starts formulating content requests $CReq_u$ in the decreasing relevance order *Order.Desc*. Since both peers maintain social relations with each other, they can use the author reputation R^{rep} to judge the relevance of missing content and sort the order of content requests accordingly.
6. After replying with a content request $CReq_u$ to the originating peer, the peer starts with the download process (see line 26 - 32). For safety reasons, peers confirm the reception of each content item and continue with the downloading process.

If peers move out of the transmission range before the entire download is finished, it is imaginable that content downloads are continued through 3G connections (*wide area network*) based on the address registered during the encounter.

5.4.2 Mobile Bridge

Similar to opinion leaders, mobile bridges form semantic overlay networks (see Definition 4.18 in Section 4.3.2) to enable large scale content transfers. Content between mobile bridges is routed in a greedy manner. The routing hierarchy between mobile bridges is established based on the expected spatial diffusion impact (see Definition 5.5 in Section 5.3.3). Since mobile bridges encounter each other randomly, trust between peers cannot be assumed. Because of this, ratings based on content popularity replace personal content recommendations to distinguish relevant content (see Definition 5.7 in Section 5.3.4).

The diffusion process is managed in a manner similar to opinion leaders. For the management of semantic overlay networks peers keep lists for node encounters E , friends F_u and social overlays SON^{sem} . Furthermore, each peer maintains a cache $Cache$ and a corresponding publication list C . Based on the exchange of content profiles peer request missing remote contents and exchange adequate content requests $CReq$.

Interactions between two encountering *mobile bridge* peers follows the pattern shown in Algorithm 5:

1. If a new peer enters the reception range of another they start exchanging hello messages msg_{hello} to verify if they have encountered before and block each other from further interactions if this is the case.
2. Otherwise both peers start exchanging their mobility profile Pf^m and calculate their community state on each side (see line 1 - 5).
3. If the encountered peer fulfills the requirement formulated in the greedy routing algorithm and the peer has larger mobility ranges or belongs to the super spreader group then both peers continue with the exchange of their content summaries C_u , specified above (see line 6 - 13).
4. Each peer matches the content summary of the encountered peer with their own cache $Cache_u$ to identify missing content items.
5. If new content has been identified on the peers starts formulating content requests $CReq_u$ in the decreasing relevance order $Order.Desc$ (see line 14 - 25). Since both peers maintain no social relations with each other they can only use statistical metrics like the overall content popularity R^{pop} to judge the relevance of missing content.

6. After sending the content request vector back to the originating peer, peers start their download process (see line 26 - 33).

5.4.3 Ordinary Member

Most of the peers (compare the lurker effect in virtual communities [84]) do not qualify as leading group members but still have an important function to create and collect new unrated content from their neighborhood. Since the combined storage space of ordinary peers surpasses the storage volume of leading member peers it makes sense that unrated content is stored in ordinary members' caches. Over time new content will be evaluated by all group members and popular content is forwarded toward central members of the subgroup. Central members share this content with other subgroups as it was described in Sections 5.4.1 and 5.4.2.

Ordinary members may engage in the diffusion process following two different scenarios as described in Algorithm 6:

- **Discovery of third party content:** In unfamiliar environments, people may share *location specific information* to increase environment awareness. Location specific information belongs to the simple content type and can easily be exchanged between devices even in brief encounter situations. The chance to satisfy personal content requests raises with an increasing number of people participating in the diffusion process.
 1. Users initiate manually an environment discovery process, which starts with *periodic query broadcasts* (see line 1 - 10). The query is of the form $(loc, time, act)$ together with desired location Th_{cent}^{ST} , time $Th_{actuality}$ and similarity Th_{sim} thresholds.
 2. Peers receiving the discovery query will create a situation specific content summary and reply to the requester (see line 11 - 26). Content summaries are generated according to the Algorithm 2 with the difference that contextual filters are applied.
 3. Peers that receive these content summaries align these again with their cache to determine missing remote content (see line 27 - 32).
 4. If missing remote content was discovered, content requests are generated in *descending relevance* order (see line 33 - 38). Since surrounding peers maintain no trust able relationships with each other, content relevance is determined through context filtering. This filtering approach applies the situation relevance formula specified in Definition 5.9.

5. Peers that receive a content request reply with the transferral of requested content (see line 39 - 45). Fair content sharing is achieved through limiting content exchanges to the maximum amount

$Download_{Max}$.

- **Dissemination of group content:** To exploit group synergies within groups, group leaders coordinate content disseminations. Peers joining a group attach to the join message also their subscription and content summary lists. Since peers participating in a social group maintain strong tie contacts it makes more sense to route preferable dynamic content, e.g., about shared group activities.

Based on these data, group leaders generate *shared subscription* and *content summary* lists. The latter is redistributed again within the group to give all group members the opportunity to reply to outside content queries and thus, enforce *load balancing*.

During the group encounter leader nodes try to synchronize member knowledge as follows:

1. First, a group leader generates content requests in *descending* relevance order. Content relevance is based on the *timeliness* of the content item and the number of *missing content* items. The group leader broadcasts content request in the following to all group members.
2. Group members receiving content requests from the group leader again match them against their cache and *broadcast* missing content within groups if it has not been broadcasted before (see line 39 - 45).

5.5 Summary

Network flooding in MENs is not adequate for resource restricted devices as it consumes too many resources. On the other side, missing global addresses and the varying bandwidth problem make the design of routing protocols in MENs a challenging task.

Studies presented in Chapter 3 have proven that humans can spread rumors effectively solely on common sense decision making. Therefore, we took human knowledge diffusion theories as a raw model for content diffusion in MENs. We solved the varying bandwidth problem by adapting content diffusion to the current encounter situation. We introduced a descriptive and discourse related content to differ between different transfer complexities. According

to the *least effort theory*, we then route discourse related contents preferably through strong tie contacts or strong cohesive groups. Well integrated persons or persons with extraordinary mobility patterns were used to route descriptive contents, which allow the exploration of the entire community.

Human societies follow the small world model and as such show tendencies toward clustering and possess a scale-free member distribution. To keep the number of hops needed to reach the entire community small we apply a mix of group broadcasts and greedy routing approaches. Limited broadcasts have the advantage that all group members can be reached within one hop distance. Following the centrality theory content is first forwarded to the center of the community and then redistribute again to those members who show interest in these contents. By reaching central members in early diffusion phases the number of hops can be significantly reduced. To motivate community participation outside social groups, we select intermediate peers due to their community interests. For the protocol implementation, we further enhance the routing logic to gain a more robust and fair diffusion. This is achieved by limiting the number of content exchanges to a predefined value and exchange the content in decreasing relevance order. By this, peers that disconnect early still have the maximum benefit from the encounter.

Since frequent content purge outs reduce the probability that content gets spread within the community, we delegate expertise between group members according to their capabilities. Peers in this scenario collect content of their interest and forward remaining content to other group members. An exception is formed by group leader or bridge peers. They focus on the collection of popular content items with the goal to spread this high quality content later to other subgroups of the urban community.

A major drawback of this socially-aware diffusion approach is that content adaptation is solely based on content types and not on the exchanged content amount. Future solutions could consider, for instance, the energy balance or the number of available intermediates to adapt the number of exchanged content items more appropriately. After defining the software framework we will in the next chapter analyze the capabilities of our approach and verify if our original goals have been met. Since labor settings cannot replace large-scale tests, we use urban simulations to verify efficiency and effectiveness of our approach.

Algorithm 4 Pseudocode for the acquaintance overlay algorithm

Require: Set F_u , Set SON^{soc} , Set $Cache_u$, Set $CReq_u$

```
1: while  $GetHelloMsg(v)$  do                                ▷ exchange of hello message
2:   if  $v \notin F_u$  then
3:      $requestProfile(v)$ 
4:   end if
5: end while

6: while  $GetProfileMsg(v)$  do                                ▷ exchange of peer profile
7:   if  $v.Role \equiv Leader \wedge sim^{Pear}(u, v)$  then
8:     if  $(u.C^{Bet}() \geq v.C^{Bet}())$  then
9:        $SON^{soc} \leftarrow v$                                 ▷ used for discovery queries
10:       $requestSummary(v)$ 
11:    end if
12:  end if
13: end while

14: while  $GetSummaryMsg(v)$  do                                ▷ exchange of content summary
15:   for all  $c \in C_v$  do
16:     if  $c \notin Cache_u$  then
17:        $CReq_u \leftarrow c$ 
18:     end if
19:   end for
20:   if  $|CReq_u| > 0$  then
21:      $sort(CReq_u, R^{rep}, Desc)$ 
22:      $filterLength(CReq_u, Download_{Max})$ 
23:      $requestContents(CReq_u)$ 
24:   end if
25: end while

26: while  $GetRequestMsg(v)$  do                                ▷ exchange of simple content
27:   for all  $c \in CReq_v$  do
28:     if  $c \in Cache_u$  then
29:        $sendContent(c)$ 
30:     end if
31:   end for
32: end while
```

Algorithm 5 Pseudocode for the overlay management algorithm

Require: Set F_u , Set SON^{sem} , Set $Cache_u$, Set $CReq_u$

```

1: while GetHelloMsg( $v$ ) do                                ▷ exchange of hello message
2:   if  $v \notin F_u$  then
3:     requestProfile( $v$ )
4:   end if
5: end while

6: while GetProfileMsg( $v$ ) do                                ▷ exchange of peer profile
7:   if  $v.Role \equiv Bridge \wedge sim^{Pear}(u, v)$  then
8:      $SON^{sem} \leftarrow v$                                     ▷ used for discovery queries
9:     if ( $u.SDI() \geq v.SDI()$ ) then
10:      requestSummary( $v$ )
11:    end if
12:   end if
13: end while

14: while GetSummaryMsg( $v$ ) do                                ▷ exchange of content summary
15:   for all  $c \in CReq_v$  do
16:     if  $c \notin Cache_u$  then
17:        $CReq_u \leftarrow c$ 
18:     end if
19:   end for
20:   if  $|CReq_u| > 0$  then
21:     sort( $CReq_u, R^{pop}, Desc$ )
22:     filterLength( $CReq_u, Download_{Max}$ )
23:     requestContent( $CReq_u$ )
24:   end if
25: end while

26: while GetRequestMsg( $p$ ) do                                ▷ exchange of simple content
27:   for all  $c \in CReq_v$  do
28:     if  $c \in Cache_u$  then
29:       IncreaseRating( $c$ )
30:       sendContent( $c$ )
31:     end if
32:   end for
33: end while

```

Algorithm 6 Pseudocode for the ordinary member diffusion algorithm

Require: Set E_u , Set F_u , Set SG_u , Set $Cache_u$, Set $CReq_u$

```

1: while OnUserRequest(MODE) do                                ▷ exchange of hello message
2:   mode  $\leftarrow$  MODE
3:   while mode do
4:     if counter + 1 > period then
5:       counter  $\leftarrow$  0
6:       createQuery(loc, Thloc, time, Thdelay, act, Thsim)
7:       broadcast(query)
8:     end if
9:   end while
10: end while
11: while GetDiscoveryQuery(requestor, v) do                    ▷ exchange of peer profile
12:   if v  $\in$   $F_u$  then
13:      $SG_u \leftarrow v$                                           ▷ member of social group
14:     sel  $\leftarrow$  Random(1, | $SG_u$ |)                            ▷ gossiping
15:     requestSummary(vsel, Activity)                          ▷ activity related content
16:   else
17:     sel  $\leftarrow$  Random(1, | $E_u$ |)                            ▷ gossiping
18:     requestSummary(vsel, Situation)                          ▷ navigational content
19:     while v  $\in$   $E_u$  do
20:       p.Duration  $\leftarrow$  p.Duration + 1
21:       if p.Duration  $\geq$  Thfam then
22:          $F_u \leftarrow v$ 
23:       end if
24:     end while
25:   end if
26:   sendSummary(requestor)
27: end while
28: while GetSummaryMsg(p) do                                ▷ exchange of content summary
29:   for all c  $\in$   $CReq_u$  do
30:     if c  $\notin$   $Cache_u$  then
31:        $CReq_u \leftarrow c$ 
32:     end if
33:   end for
34:   if | $CReq_u$ | > 0 then
35:     sort( $CReq_u$ , Rrep, Desc)
36:     filterLength( $CReq_u$ , DownloadMax)
37:     requestContent( $CReq_u$ )
38:   end if
39: end while
40: while GetRequestMsg(v) do                                ▷ exchange of community content
41:   for all c  $\in$   $CReq_u$  do
42:     if c  $\in$   $Cache_u$  then
43:       sendContent(c)
44:     end if
45:   end for
46: end while

```

Part III

Simulation and Evaluation

6

Simulation and Evaluation

During the design of the mobile community platform we verified individual concepts by implementing real prototypes. One prototype was used to test functions for ad-hoc group management and content sharing. Another was used to verify spatial and social clustering algorithms to detect user territories and friend groups. Both prototypes proved the soundness of our concept.

Prototypes, however, reach their limits when it comes to the measurement of protocol efficiencies. Experiments can only be executed with a limited number of devices. Such laboratory settings do not allow us to observe important large-scale diffusion effects.

A common technique to evaluate peer protocols is network simulation. We simulate an urban scenario with a heterogeneous distributed society and observe the content diffusion process to draw meaningful conclusions from it. In the following chapter, we describe a set of experiments used to explore characteristic information spreading patterns emerging from our least effort transfer protocol and compare them with traditional reference systems.

We first describe in Section 6.1 our research approach and briefly state our research hypotheses. Then, in Section 6.2 we will introduce our simulation model, and related model abstraction approaches. Moreover, we define experiment scenarios, reference systems and measurement criteria. Finally, in Section 6.3 we present our results according to our postulated research hypotheses and compare them with well known reference models and systems.

6.1 Research Approach and Hypotheses

Our goal is to evaluate information spreading in MENs with means of computer simulation. Simulation plays an important role for protocol evaluation. However, most peer-to-peer communication scenarios use the open space model. The open space model describes a model simplification where all peer links are equally weighted. This type of simulator typically concentrates on the evaluation of correct protocol sequences or the influence on network topologies. We cannot apply this category of simulators, because our community

system explicitly exploits human behavior heterogeneities (heterogeneous link conditions).

We therefore decided to implement our own simulator, which can emulate urban community life and in addition adds an subsequent layer for the simulation of our mobile community infrastructure. Through simulation, we would like to explore three major diffusion characteristics (see Figure 6.1):

- **Encounter characteristics:** Human encounters represent a prerequisite to transfer content between peers. As people generally encounter only a small portion of the community it is important to find out more about the potential coverage reach. Can such a distributed platform integrate large-scale urban communities or is the content exchange limited to small friend networks? Another important question is to what extent humans in urban communities cooperate together? To solve this questions we intend to construct an encounter network graph (see Definition 4.12) to analyze the community diffusion potential. For a realistic representation of peer encounters, several studies about human life are considered. A clear picture about diffusion potentials can be obtained through a small world analysis. The *small world network analysis* will be explained in more detail in Section 6.2.2 and 6.2.4.
- **Diffusion dynamics:** Moreover, we are interested in analyzing how contents realistically spread within the community network. Experiences from implemented prototypes provide us with information how content forwarding has to be technically parametrized. Issues like protocol design and latency play here an important role. Content diffusion depends not only on the encounter situation but also on the content available at this point of time. By emulating the diffusion process (see Section 6.2.2) we determine information about the diffusion efficiency (see Section 6.2.4) by observing the content reach (number of content recipients) and the required transfer effort (number of content transfers).
- **Expertise distribution:** From the information retrieval perspective, community infrastructures have to deliver content efficiently but also effectively. Diffusion effectivity is achieved by delegating community expertise between their members and route the right content to them. We qualify contents according to models used for commercial social software. More information about content management issues is provided in Section 6.2.2. We conduct a *precision-recall* cache analysis on all contents stored in the cache throughout the simulation period. Adequate cache policies avoid knowledge overlaps with the goal to increase the overall community space and content availability. Information about applied content measurements is given in Section 6.2.4.

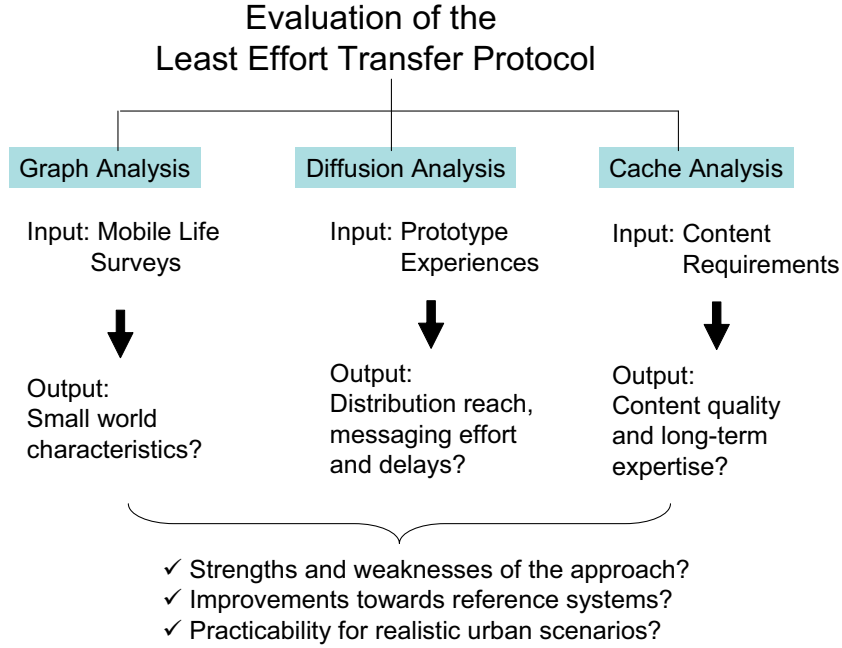


Figure 6.1: Evaluation approach.

6.1.1 Analysis of Encounter Characteristics

Diffusion in large-scale scenarios depends more on spatial than on social diffusion aspects. Spatial diffusion itself is largely achieved through human mobility. Daily travel is dominated by the commutes from home to work places and vice versa. Despite the fact that leisure traveling occurs only sporadically people may still travel far to visit friends or other spare time locations. As human traveling goes along with a multitude of intentional and random contacts, we speculate that the resulting community network network may cover the entire city area. More formally we hypothesize:

Hypothesis 1: Daily mobility assures a citywide community integration.

In peer-to-peer infrastructures like our envisioned social software, peers function equally as content consumer and provider. The diffusion efficiency in such systems depends on a complicated balance between personal interests and altruistic community behavior. People maintain regular relationships with social groups, including family, friends and workmates. This allows efficient content distributions on a local scale. If community members share similar interests people are more willing to forward contents to other community members, which they may even not know personally. Random encounters made during traveling may come from far distant places. If used for content transfers they enable bridges to far distant community edges. Consequently, we offer the following hypothesis:

Hypothesis 2: Encounter networks have capabilities for local and global information transfer!

6.1.2 Analysis of Diffusion Dynamics

The performance of any flooding based system depends on the number of neighboring peers. With increasing density the probability for content retransmission, however, rises. Better coordinated systems where few peers control the information flow in the system can lower the number of retransmissions. Retransmission increase the system reliability but to the same time represent also a resource waste. Keeping retransmissions to a minimum is therefore advantageous. We formulate the following hypothesis:

Hypothesis 3: Bottom-up diffusion approaches are more sensitive to retransmissions than hierarchical diffusion approaches, and therefore are less efficient.

More specifically bandwidth is especially limited in group formations occurring during traveling, where people continuously join and leave the group. Controlling the information flow in travel groups is crucial to achieve an acceptable content diffusion reach. Members with high member connectivity produce more encounters in later stages than fewer connected peers. However, it is not easy to answer if peers excluded from the diffusion process will receive content in a later stage as no concrete encounter schedule exists. We derive the following hypothesis:

Hypothesis 4: Restricting access to travel aggregations to peers with superior mobility properties and adequate expertise leads to wider community reach with occasional delivery delays.

For the mobile community, we distinguish between different types of content: general content which describes, e.g., global community events, and context aware content, which represents a situation specific selection of information. We are interested to find out which specific encounter characteristic encourages or limits content spreading. Context dependent content loses its relevance if the user moves out of the context scope. Content availability can only be achieved through frequent content updates. Since delivery of general content is less time critical, frequent publishing cycles are not required. In this case, the network range is a major factor for distribution. Consequently, we formalize our last efficiency hypothesis:

Hypothesis 5: Different encounter patterns support different content categories.

6.1.3 Analysis of Expertise Distribution

Traditional caching policies based on short term content access patterns do not reflect human routine behavior. Content withdrawn from the cache through

such policies may be missed in a later point of time. Content quality suffers from this, as we cannot assume to catch the content in time when it is needed. Responding to this problem in Section 5.3.4 we suggested a caching policy which continuously collects information augmenting routine behavior of the user. Such a cache strategy reduces storage overlaps within groups, and consequently, we formalize the following hypothesis:

Hypothesis 6: The consideration of mobility patterns for caching increases the context precision and the content lifetime.

This situation is different for content which targets no specific user group. In this case, content items are relevant for all members and finally take a lot of collective storage space, as all members need to reserve space for similar content. The amount of community storage space is important as it guarantees a certain content variety. Storage space savings can only be achieved if group representatives store content on behalf of others. Adequate representatives are mobile bridges as they have a high integration potential. We formulate the following hypothesis:

Hypothesis 7: The consideration of the peer connectivity improves the community recall.

6.2 Planning and Execution of Experiments

Following the hypothesis formulation we will now describe the urban simulator. We first provide details about the underlying simulation model, then we describe a series of experiments, and finally define measurement criteria and reference systems, with which we are able to evaluate the behavior of the system.

6.2.1 CitySim Simulator

As a basis for our diffusion emulations we extended the CitySim traffic simulator implemented as a master thesis by Frank Busch [17]. CitySim is based on map data of San Francisco and manages the traffic in a round based process, where each car is moved according to traffic rules in every round.

To simulate urban city life, we extended the tool with individual and social human behavior models on top of the traffic model to achieve realistic group formation and interaction patterns throughout a emulated day. To analyze human knowledge transfer among community members, we added another abstraction layer above the human behavior model which represents a data structure used to emulate a simplified peer-to-peer file sharing system. Each human is represented through an agent whose behavior model is shown in Figure 6.2. Every day each human follows a certain routine defined through a

sequence of activities. Every activity change goes along with a move to a new territory, whose travel path and place are defined in the environment model. During the execution, the agent cooperates with other agents defined in the social model. In the following, we describe the abstraction process for each of the models in more detail.

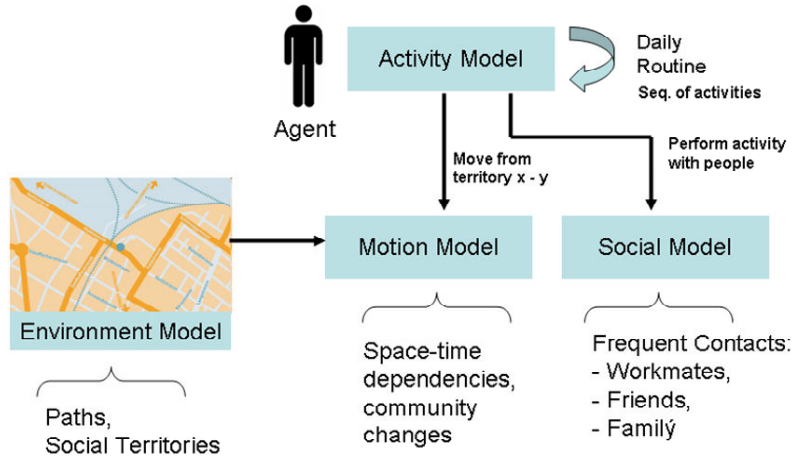


Figure 6.2: Correlations between behavior determinants.

Modeling of City Environment

As an environment model we used digital map data representing the city of San Francisco. San Francisco is the 4th biggest city in California with about a 600 km^2 range and a population density of 6.151 inhabitants per km^2 . The map is modeled through a graph containing 15799 street segments and 9411 intersections, covering an area of approximately 1250 m by 900 m. To specify in the map community territories with a certain usage character, we integrated additional land usage information. We distinguish between four different location types, including residential- recreation-, shopping- or industrial areas. The area that does not belong to these four types is referred as “other area”. Generally, land usage information is public available from government organizations on address basis. However, this information may be outdated. Instead of modeling land usage by addresses, we assign the same usage domain by neighborhoods. As place usage diversity leads to higher chances of obtaining knowledge from several knowledge pools, we argue that this simplification step where neighborhoods are homogenized will lead to fewer optimal diffusion situations and therefore, will not artificially improve the experiment.

Modeling of Dynamic Behavior

Dynamic agent behavior is defined through shared community activities executed at specific community territories, and the mobility required to travel between community territories. Activities are specified through their type and their temporal information like starting and end times. For the experiment they can be distinguished into work, shopping, leisure and home related activities. For each activity we assign activity durations specified according to time usage studies published by San Francisco government [100, 99]. Exact values are specified in Table 6.1. To emulate different arrival and stay times we randomize the average arrival time and duration within a time frame between several minutes up to two hours.

Given the activity - territory correlation, there are usually popular locations which people tend to visit more often than others. We model such behavior by assigning different weights to them according to the probability of choosing such a destination from that area. Work places and home places are fixed. Shopping and leisure places may vary from time to time according to an assumed variety seeking behavior. Moves between locations happen according to predefined traffic settings (see Table 6.1 for motion speed) and follow shortest paths between given community territories. This computation is achieved using the Dijkstra algorithm [30] implemented as part of the traffic simulation. Travel distances generally vary a lot, depending on their mode of transportation and trip purpose. Longest travel distances are accepted for leisure purpose, second for the daily work commute and least distances are accepted for shopping activities. A study about commuting traffic in Vienna revealed that major traveling to workplaces occurs within 10 km and only in rare cases exceed more than 50 km. We emulate this distribution of travel ranges within the agent's trip model.



Figure 6.3: Example of a static and a dynamic simulation.

Modeling of Social Behavior

Human behavior depends not only on personal interests but also on surrounding social networks. In our simulation each person has social relationships with other persons. Such social networks include neighbors, relatives, workmates and spare time-friends. Group affiliations are generated by assigning the same territory to a group of people. These territories represent also physical group boundaries.

To model group formations realistically, we used findings from a dairy study about spare time behavior published from Martin Colbert [23]. The average size of rendezvous observed during the diary study was about 3.6 people per rendezvous. The majority of rendezvous have been bilateral meetings. Altogether, Colbert recorded for 33 % bilateral meetings, 20 % for meetings with three persons, 13 % for meetings with four persons, 16 % for meetings with 5 persons and 18 % for meetings with 6 or more people. Since the effort to arrange meetings raises with the group size people prefer obviously smaller rendezvous.

A similar study for family statistics [101] was taken to specify family groups. We modeled social groups according to these distributions and limited upper groups size as presented in Table 6.1. An exception is noted for enterprises whose size may get very large due to artificial organizational structures. For the experiment, we limited their size, as enterprise organizations are less mixed due to office infrastructures. We argue that smaller territory populations will reduce the possibilities to exchange content and therefore do not artificially improve experiment results.

PARAMETER	SYMBOL	UNIT	VALUE
Simulation Time	t	ticks	1 day $\approx$ 2000 ticks
Population	p		200, 500, 1000, 2000
Activity Duration		hour	5(home), 5(work), 1(shopping), 1.4(leisure)
Motion Speed	v	km/hour	0, 50
Group Size		max size	5(home), 12(work), 6(leisure)
Document Size	size	kb	1(Text), 8(Photo), 40(Music)
Cache size	C	Items	1, 50, 100, 200
Detection Interval	tick	sec	30
Transmission Range	r	meter	200-500
Bandwidth	w	Kb/s	35
Exchange Overhead	Bf	byte	1 kb

Table 6.1: Simulation input parameters and their values.

6.2.2 Simulation Methodology

We simulate urban life from one to several days. Community behavior of the peers is emulated after a round based schema common for protocol evaluations. The parameters used for the simulation are listed in Table 6.1. During each round peers are moved according to their activity state and collective behavior model. The simulator calculates the encounter situation of each peer and realizes content diffusions according to the encounter situation. All activities and execution states for each experiment are protocolled in log files before the simulator resumes. The simulation tool supports graph analysis to evaluate encounter potentials and diffusion analysis for measuring support infrastructure capabilities. In the following, we describe both research methodologies in more detail.

Encounter Graph Analysis

We analyze the encounter potential by mapping encounter situations on a social network graph as suggested by K. A. Zweig [127] and later evaluate it with social network analysis technique.

1. **Generating urban communities:** Initially, the simulator generates the activity model for each peer, defines peer groups and assigns adequate group territories. In a second step, the simulator will distribute agents to their home locations. Home addresses are allocated randomly within residential areas and are as such more or less equally distributed. This a model of the reality works well since homes are not clustered in one residential area. In early diffusion phases content spreading is more difficult. We argue that if content diffusion works well in this scenario, it will work even better in scenarios where peers are clustered as perhaps found in many real settings. Due to the necessary simulation effort it is generally not possible to simulate large population sizes, e.g. tens of thousands of peers. Instead the number of peers is limited to the values given in Table 6.1. Since a small number of peers again represents fewer encounter opportunities, we conclude that our results are some kind of a lower bound for evaluating the content diffusion effectivity, and content diffusion in real world scenarios is expected to work even better than in the simulated scenarios.
2. **Construction of encounter graphs:** During the experiment peers move according to their dynamic behavior model and whenever new peers are encountered the encounter graph (see Definition 4.12) is extended. The resulting graph mirrors the entire encounter history of all peers during the experiment. Technical aspects of the encountering process are defined later in the Section 6.2.3.

3. **Social network analysis:** After the experiment, we analyze the graph with social network analysis technique to explore network potentials. This analysis includes evaluations about network density, clustering and average path lengths.

Content Diffusion Analysis

A drawback of the graph analysis is that situation specific data like the available transfer bandwidth during the encounter is lost. As our social diffusion mechanisms depend on opportunistic forwarding decisions, we emulate above the encounter model the content exchange process between peers and measure resulting diffusion efficiency and quality.

1. **Generating social network knowledge:** Since our diffusion algorithms utilize social network knowledge to improve diffusion decisions, we create these in a two phase approach. A preliminary simulation round is used to generate social network knowledge, and subsequent rounds are used to emulate the diffusion process. The creation of the agent models and the population of the urban community follow hereby exactly the same steps as previously described in the encounter graph analysis.
2. **Content management aspects:** Prior to the execution of the experiments a specific set of contents is generated for each agent. These content generation is handled differently for diffusion efficiency and diffusion effectivity experiments. For the first category of experiments, one single content item is assigned to one randomly chosen peer. For the second category, we populate the caches of all peers with randomly chosen content domains. Each content item describes a distinct community event at a specific time and location, which is valid within the urban area and the duration of the experiment (see also Section 4.2.3). Subsequently, we configure community diffusion according to the diffusion scenarios described in Section 5. These include specifications for the content types and settings for content propagation and caching. After starting the experiment, community members exchange contents between each other. The overall success of the diffusion process depends on the availability of each member in the entire diffusion chain.
3. **Empirical evaluation of efficiency and effectivity:** Diffusion progress in any flooding based systems depend on the position of initial source peers and on the initial content composition of peer's cache. During the experiment different parameters for content propagation and cache quality are recorded. Because of the previously mentioned dependency we repeat the experiments n times with randomly chosen content source

peers or respectively randomly populated content caches. Each run results in an estimate x_i for the efficiency or cache quality, resulting in n estimates. The estimate for the true propagation efficiency or cache quality is then given by the average $\bar{x}$ of the n results. For both experiments the question arises how large n must be such that $\bar{x}$ or $\bar{y}$ is a good estimate for the real efficiency or effectivity, respectively. We therefore calculate the standard error σ of the single results, and then the standard error of the mean $\bar{x}$ is given by $\sigma_n = \sigma/\sqrt{n}$. From the normal distribution, it is known that 95% of the values lie within a range of 2σ away from the mean. If we want the estimation error to be less than 5% with a probability of 95 %, then $2\sigma_n/\bar{x} \leq 0.05$, which yields:

$$n \geq \left(\frac{2\sigma}{0.05\bar{x}} \right)^2$$

6.2.3 Configuration of Diffusion Scenarios

Initially, we run experiments for a theoretical scenario for which we assume unlimited bandwidths. Content items are opportunistically exchanged whenever peers are in contact with each other. To account also for more realistic scenarios, it is essential to consider technical parameters like memory size and network bandwidths.

Technical Scenarios

For the simulation of the technical scenario we assume that the time for data processing is several orders of magnitudes smaller than the delay through air traffic. Because of this, emulated technical delays depend solely on the protocol structure and bandwidth limitations. When peers exchange content between each other delays can occur during the device discovery $t_{discovery}$, community formation $t_{grouping}$ and data transmission $t_{download}$. For each of these protocol phases we explain factors influencing the delays:

- **Device discovery:** Peers discover their environment periodically. In order to save energy, the time frame between two discoveries cannot be too short. During each round, the simulator evaluates all occurring encounter situations. The discovery period is limited up to Δt of 40 seconds.

Following the protocol specification in Section 4.2 the discovery process is separated in two phases. Peers exchange hello messages to announce their presence, and transfer profile messages to learn more about the neighboring peer. As both operations require less time than the total time period between the discovery periods, additional time for connection

creation and closing can be ignored. The discovery interval finally equals the total discovery time (see Equation(6.1):

$$dt_{discover} = \Delta t \quad (6.1)$$

- **Community formation:** During the group formation process, content summaries from all group members are collected to create a group content summary. Binary data structures like bloom filters can be used to save memory. The size of the bloom filter depends on the maximum amount of content assumed to be stored on a mobile devices. This is typically not more than several kB but may grow in future. The calculation of group time (see Equation 6.2) depends on the size of the community G and the transferred index size $|Idx|$. Since social groups and overlay groups are rather small the group formation process scales well:

$$dt_{grouping} = \frac{|Idx| \times |G|}{bw} \quad (6.2)$$

- **Content transmission:** Since content is forwarded through an epidemic process, we have to calculate the amount of new content for each member in the groups. For this calculation we further have to consider a specific media format with a given media size following the rule of Equation 6.3. The data transmission speed bw is chosen to be 3.5 Mb/s - 5.5Mb/s. The size of each content object ms varies in dependence of the media type. As media type we distinguish between text messages (up to one kB), photos (up to 40 kB) and time based multimedia like mobile music (up to 20 MB) and video files (up to 40 MB). We further assume that the encounter duration during regular group meetings is long enough for complex content downloads. Whereas during traveling, encounter durations are limited due to missing opportunities for collective travel. This makes bandwidth a scarce resource:

$$dt_{transfer} = \frac{ms \times |G| \times |docs_{diff}|}{bw} \quad (6.3)$$

As we take performance parameters from implemented prototypes we make initial tests to see what kind of mobile content types can be routed in different encounter situations. We distinguish between simple text content, photos and small music files with storage size specified in Table 6.1. We further survey the influence of radio transmission ranges varying from Infrared, Bluetooth, and WLAN ranges with assumed ranges given in Table 6.1. The goal is to identify lower and upper bounds for content diffusions to see how realistic they are and describe situations in which wide area network support is required.

Least Effort Knowledge Transfer Scenarios

The simulator implements different social diffusion processes. In order to inspect specific protocol behaviors the diffusion process is controlled through various parameters for content filtering (see Sections 5.3.1, 5.3.2), content routing (see Section 5.3.3) and content caching (see Section 5.3.4). This allows us to apply the following techniques to influence the content diffusion:

- **Topology Control:** The influence of specific nodes on the diffusion process can be detected by excluding nodes with specific properties. By removing nodes from the surrounding community network, we control the network topology. By varying exclusion parameters between the diffusion experiments, the diffusion impact for this specific node category can be derived. The nodes to be excluded are chosen according to their mobility characteristics, community centrality and interest similarity. For a better visualization of the diffusion impact, we start by removing nodes with the potentially largest diffusion impact and progressively enhance this list with less important nodes.
- **Replication Control:** For the least effort diffusion approach, we assume different content complexities (see Definition 5.10). In our simulation we emulate simple content with *time independent* content and dynamic content with *time dependent* content. This time limitation expresses the dependency toward a specific content provider e.g. for a transmission for one community discourse. In case the validity duration of that content has been exceeded, content will reside in peer caches but will not distribute further through node encounters.
- **Expertise Control:** Before experiments start, content caches are prepared (see also Section 6.2.2) in a predefined manner. To observe long term content delegations between peers all peer caches are filled with random contents. Such a random assignment leads to a specific distribution of interest domains. Since peers implement different cache policies content becomes finally re-delegated. Analyzing the domain distribution after the experiment allows us to draw conclusions on the effectivity of the caching algorithm.

6.2.4 Measurement Criteria

During our experiments several network quality, diffusion efficiency and cache quality parameter are collected for later evaluation.

Network Quality Parameter

The topology of encounter graphs reveals important information about community diffusion potentials. For our analysis, we assume an encounter graph $G = (V, E)$ consisting of a set of vertices V and a set of edges E between them. An edge e_{ij} connects a vertex i with a vertex j . In real life encounter graphs are not completely connected and structural holes in the graph may lead to individual neighborhoods. For this reason, we define a neighborhood N for a vertex i as direct neighbors as follows:

$$N_i = \{v_j | (e_{ij} \in E) \wedge (e_{ji} \in E)\}.$$

Diffusion potentials depend on the graph connectivity (also called network density) and on its small world characteristics introduced by Watts and Strogatz. Small world characteristics are calculated based on two parameters, the characteristic path length and the clustering coefficient. We briefly describe these measurements but more details are available for further reading in following source [8]:

- **Network Density.** This measurement [24] describes the degree of connectivity for a given graph. We use this parameter to find out, if we are able to integrate individual neighborhoods into one urban community, despite the fact that the community infrastructure represents finally a distributed system.

Measurement 1: The graph density $G_{density}$ describes the proportion of reachable ties to the total number of ties. Structural holes in the graph limit the reachability of individual nodes to $|N_i|$. The overall graph density $\bar{G}_{density}$ represents then the average proportion of reachable to the total number of ties n for each node in the network. Since edges in encounter graphs are symmetric the total number of ties is $\frac{n(n-1)}{2}$, where n is the total number of nodes with $n = |V|$. Altogether we derive the formula for the overall graph density as below:

$$\bar{G}_{density} = \frac{\sum_{i \in V} 2(|N_i|)}{n \times (n - 1)} \quad (6.4)$$

- **Average Path Length.** The average path length [8] describes realistic separation degrees between nodes in an encounter graph. Separation degrees are a good indicator for the number of hops needed to reach graph edges.

Measurement 2: In a fully connected graph, the average path length G_{APL} describes average distances for the shortest paths between two nodes divided by all edges in that graph. Assuming that the distance of short paths

6.2. PLANNING AND EXECUTION OF EXPERIMENTS

is defined through the function $\text{dist}()$, and the total number of edges is $\frac{n(n-1)}{2}$ then G_{APL} is

$$G_{APL}^N = \frac{\sum_{v_i, v_j \in V} \text{dist}(v_i, v_j)}{n \times (n-1)} \quad (6.5)$$

In graphs with structural holes, the overall average path length is the average path length for all neighborhoods and isolated nodes. Since real isolated persons rarely exist we estimate for these a worst case scenario. We take as an appropriate path length for isolates nodes $PL_{isolated}$, the length for regular graphs (e.g. half of all available graph vertices V). Further we use $\bar{G}_{density}$ to determine the proportion of isolated nodes in the encounter graph and derive following global average path length $\bar{G}_{APL}$:

$$\begin{aligned} \bar{G}_{APL} = & \bar{G}_{density} \times \sum_{v_i \in V} \frac{\sum_{v_j \in N_{v_i}} \text{dist}(v_i, v_j)}{|N_{v_i}|} + \\ & (1 - \bar{G}_{density}) \times PL_{isolated} \end{aligned} \quad (6.6)$$

- **Cluster Coefficient.** This measurement [119] describes the tendency toward clustering of a given graph. Clusters are important to exploit group synergies and to achieve a scaling community infrastructure, for instance, through the utilization of shared services.

Measurement 3: Within a neighborhood, the clustering coefficient G_{CC} describes the proportion between edges to vertices within the neighborhood and all possible edges (including edges outside the neighborhood). Let x be a vertex with a set of neighboring vertices N_x and a function $e(i, j)$ returning true if the vertices i and j are neighbors and false otherwise. Then we derive for an individual node the following clustering coefficient condition:

$$G_{CC}^x = \frac{\sum_{v_i, v_j \in N_x} |\{e(i, j)\}|}{|N_x| \times (|N_x| - 1)} \quad (6.7)$$

Following Watts and Strogatz the average clustering coefficient $\bar{G}_{CC}$ for all nodes is given as the average for all clustering coefficients for each vertex:

$$\bar{G}_{CC} = \frac{\sum_{v=1}^N G_{CC}^v}{N} \quad (6.8)$$

Diffusion Efficiency Parameter

The diffusion efficiency describes the throughput of the community system. We hereby assume a mobile community C of peers p with caches of size s . We further assume that the diffusion starts from a source peer p^s , includes a total of $n = |C|$ peers and results in a set of empty peers $p_\emptyset$ and peers with content p_c . System efficiency is then measured with three different parameters: the diffusion reach, diffusion reliability and the delivery timeliness. In the following, we introduce these parameters briefly:

- **Diffusion Reach.** To measure the reach of the diffusion mechanism we simply count the number of peers who received content during the experiment.

Measurement 4: This distribution ratio $D_{distribution}$ expresses the proportion of nodes, which received the contents in contrast to the total number of nodes N which could possibly receive the content.

$$D_{distribution} = \frac{\sum_{i=1}^N |p_{i,c}|}{N} \quad (6.9)$$

- **Diffusion Reliability.** In flooding based systems diffusion reliability is equivalent with the number of reoccurring opportunities to receive the same content (duplicated content) during the experiment. Since epidemic exchange protocols filter duplicated content, it is important to de-activate this filter and assume infinite peer caches for this type of experiments.

Measurement 5: Assuming that the community contains content of different type of topics, then the diffusion reliability $D_{reliability}^i$ for an individual node i is calculated as the sum of all download opportunities per document type C_t divided through the number of topics t present in the cache of node i .

$$D_{reliability}^i = \frac{\sum_{t \in topics} C_t}{\sum_{t \in topics} |t_i|} \quad (6.10)$$

The overall diffusion reliability for the entire system is then build through the average value for all nodes N :

$$\bar{D}_{reliability} = \frac{\sum_{n \in N} D_{reliability}^n}{N} \quad (6.11)$$

- **Diffusion Timeliness.** In some scenarios, timely content delivery is important and timeliness is an important parameter to know. The shorter the delay the more appropriate is the diffusion mechanism for urgent content.

Measurement 6: Assuming that the diffusion delay of a specific content is defined through the difference between the time t of the first reception of a given content at node n ($t = T_{n,k}$) and the time of initial content provision ($t = 0$) leading to the delay of $T_{n,k}$. Then we specify the diffusion timeliness D_{delay} for a node n for all available content present in the cache C_n as follows:

$$D_{\text{delay}}^n = \frac{\sum_{k=1}^{C_n} T_{n,k}}{C_n}.$$

The overall timeliness is then characterized by the average $\bar{D}_{\text{delay}}$ over all respective delays D_{delay}^n of all N nodes:

$$\bar{D}_{\text{delay}} = \frac{\sum_{n=1}^N D_{\text{delay}}^n}{N}. \quad (6.12)$$

Cache Quality Parameter

Each mobile peer can only store a small portion of the virtual content space (see also Section 6.2.2). Because of this, it is important that the community middleware collects content, which is relevant for the user. This diffusion effectiveness is usually measured by a precision-recall analysis. We accompany these measurements with a measure for a storage locality as this is an important indicator for expertise building. In the following, we describe briefly these measurements but more details can be read in following source [35].

- **Context Precision.** The context precision [106] describes the accuracy of situation aware content retrieved through the community infrastructures [106].

Measurement 7: We assume a cache with n documents retrieved through encounters during the experiment. Further we assume that of these n documents, $r \leq n$ are relevant to the user. The context precision $Q_{\text{precision}}^i$ of node i is defined as the ratio between the number of relevant objects $C_{r,i}$ in the cache of node i to the total number of objects in the cache $C_{c,i}$ of node i :

$$Q_{precision}^i = \frac{C_{r,i}}{C_{c,i}}. \quad (6.13)$$

Simply put, $Q_{precision}^i$ is the percentage of useful information in the cache of node i . The overall precision is then characterized by the average $\bar{Q}_{precision}$ over all precision values $Q_{precision}$ of all N nodes:

$$\bar{Q}_{precision} = \frac{\sum_{i=1}^N Q_{precision}^i}{N}. \quad (6.14)$$

- **Community Recall.** This measurement [106] is used to analyze the overall cache quality, by measuring the completeness of the cache process in comparison to the overall virtual knowledge space.

Measurement 8: The community recall Q_{recall} of node i expresses the completeness of the cached (relevant) documents $C_{r,i}$ in the cache of node i in relation to the number A_r of all relevant documents within the community:

$$Q_{recall}^i = \frac{C_{r,i}}{A_r}. \quad (6.15)$$

The overall recall is then characterized by the average $\bar{Q}_{recall}$ over all respective lifetimes Q_{recall}^i of all N nodes:

$$\bar{Q}_{recall} = \frac{\sum_{i=1}^N Q_{recall}^i}{N}. \quad (6.16)$$

- **Content Locality.** The community locality $Q_{locality}$ is a metric which describes the average lifetime of objects in the nodes. The longer objects remain in caches, the higher the locality gets. This measurement is important as it expresses the quality of knowledge concentration at the peer.

Measurement 9: Assume an object o_k that has been transferred to the cache of node i and has remained there for the time $T_{i,k}$. When observing the lifetimes of $|C_i|$ such objects in the cache C_i , the average lifetime T_i of the objects in the cache of node i is then

$$Q_{locality}^i = \frac{\sum_{k=1}^{N_i} T_{i,k}}{|C_i|}. \quad (6.17)$$

The overall locality $\bar{Q}_{locality}$ is then characterized by the average $\bar{T}$ over all respective lifetimes T_i of all N nodes:

$$\bar{Q}_{locality} = \frac{\sum_{i=1}^N T_i}{N}. \quad (6.18)$$

6.2.5 Reference Systems

For a better result assessment, we compare our strategy with other approaches. We compare the encounter network graph to other well researched theoretical graphs, and the content diffusion characteristic to traditional epidemic routing and caching approaches applied in MENs. In the following, we describe the intended reference systems in more detail:

1. **Comparison to theoretical graphs:** Several sociologists have created theoretical graphs and analyzed them extensively in order to draw conclusions about real world scenarios. For instance, Barabasi and Bonabeau [9], Erdoes and Renyi [37] and also Watts and Strogatz [119] have analyzed regular and random graphs.
 - *Regular graphs* are strongly structured and as such have a high clustering coefficient. Analysis has shown that high clustering is appropriate for information exchange in local neighborhoods. Members participating in different groups and working on different tasks require only local knowledge and benefit from this network topology. The biggest disadvantage of this kind of network is the long average path length, which makes global communication almost impossible. Watts and Strogatz [119] visualized the idea of regular graphs with a connected network ordered through a circular topology shown in Figure 6.4 a). This circular topology is typical for communication between neighbors.
 - In contrast, *random graphs* are created spontaneously often without planning. Missing topology structures do not allow local group communication. Since nodes are randomly connected several shortcuts exist in the community. These shortcuts finally lead to a short average path length. Short community paths enable in few communication steps information spreading to a broad majority of the

community. Watts and Strogatz visualized random graphs with a circle structure in which individual peers are randomly connected, as shown in Figure 6.4 b).

2. **Epidemic Systems:** Encounter networks use a simple opportunistic diffusion process, which results in network flooding.

- In a *flooding* based systems content gets finally forwarded to all reachable nodes in the network. Forwarding happens from step-wise from neighbor to neighbor whose number of forwarding steps depends on the community size. The spreading reach is usually controlled through lifetime counters (TTL) which are reduced with every forwarding step. If the lifetime counter reaches zero the diffusion process comes to an end. For the CitySim simulator we choose an endless lifetime to observe the maximum diffusion reach. A major drawback of a flooding based system is its extensive resource usage.
- *Gossiping* represents simple energy aware extension to a flooding based system. Instead of forwarding content to all neighbors, individual nodes are randomly selected. Energy is saved by choosing only a small amount of possible nodes for content propagation. For the simulation we limit content forwarding to one single member per group encounter. The overall performance of gossiping systems is, however, slower. As many systems are not time critical this approach is often used as a more efficient alternative to network flooding.

3. **Least Recently Used (LRU):** Content which has been used recently is often more appropriate than content used a long time ago. Cache replacement policies exploit this data locality to improve the access time.

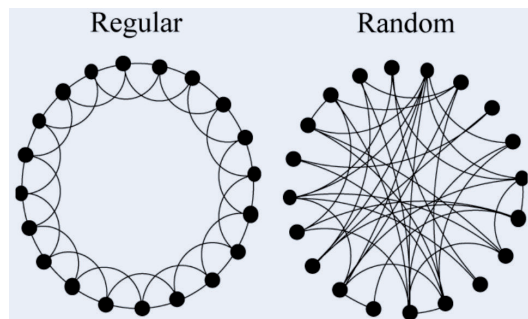


Figure 6.4: Theoretical network models a) regular b) random networks (Watts and Strogatz [119].)

The term locality describes the circumstance that the same content is accessed more frequently in short time frames. This is equivalent with an increased probability for future content demand. Such cache mechanisms monitor service access patterns to optimize their retrieval. A well known cache management strategy is the least recently used replacement policy. Caches applying this policy track the time of the last content access and order it so that the least accessed content can be accessed first.

We remark that more complex diffusion and caching algorithms like the opportunistic resource exchange project from Wolfson et al. [124] exist. An extensive state-of-the-art analysis for encounter based diffusion and caching algorithms is provided in Section 3.2. However, rebuilding those for verification was dropped due to the effort to rebuild them in the simulator.

6.3 Discussion of Results

For our experiments we emulate a population varying between 200 and 2000 citizens for an imagined one day period (represents 2000 ticks). The emulated population is several levels smaller than the realistic scenario. We argue that the topology of the community network has a higher influence on the diffusion characteristic than the population density. We think further that a one day simulation period is enough to show the basic characteristics since the daily user mobility has usually a much larger impact on the diffusion behavior than human's variety seeking behavior.

In a series of three experiments, we first analyze the encounter characteristics, proceed with the examination of the diffusion process, and finally, observe the caching behavior of individual peers.

6.3.1 Urban Encounter Experiments

During the first series of experiments, we derive a time-independent encounter network graph constructed from encounter events as described in Section 6.2.2. To show that the population distribution has only a minor influence on the overall encounter network graph we alternate home locations for each agent with every new experiment. We execute the experiment for a small population of 200 people and repeat the experiment according our calculation for the empirical evaluation in Section 6.2.2. The error bars show the variation of graph measurements observed due to varying home locations. The encounter network graph is used to obtain information about the network connectivity and local and global routing capabilities.

Average Connectivity and Network Density

Figure 6.5 a) shows the development of the average peer connectivity and Figure 6.5 b) the number of total isolates of the constructed encounter graph.

Average peer connectivity: The average peer connectivity is measured as percentage of the encountered persons to the entire experiment population. This graph shows a steady increase (in stepwise manner) of the average connectivity, till it reaches the maximum average connectivity of 12 percent of the simulated population. Steps in the connectivity curve occur, because urban traffic occurs in specific time frames, e.g., when cars commute to their workplaces in the morning and back to their homes in the evening.

Total isolates: This measure represents an inverted measure of the network density $\bar{G}_{density}$ defined in Equation 6.4. The percentage of isolated nodes in respect to the total population decreases fast and leaves after a quarter of the simulation period (one day) no node unconnected. This clearly shows that daily commuter traffic, e.g., from home to work places creates enough opportunities to interconnect the urban community. Only very circular roads in San Francisco connect different neighborhoods in San Francisco. Although these roads were constructed for high traffic capacities they still often represent the bottleneck in urban street networks. The traffic accumulation on these roads leads to a highly mixed population. In real life we cannot assume that all nodes actively participate in mobile communities. But the fact that the curve for isolated nodes decreases much faster (almost three times as much) as individual nodes in average increase their connectivity gives us a certain tolerance to members currently not using this social software.

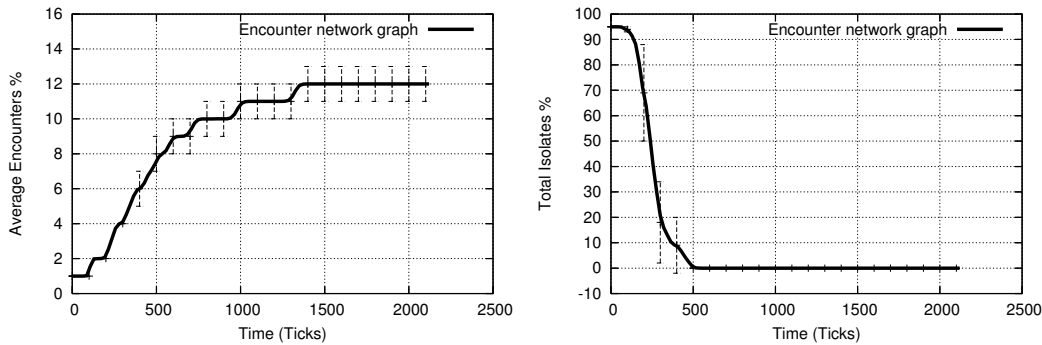


Figure 6.5: Encounter graph analysis: a) individual connectivity b) community connectivity.

Local and Global Exchange Capabilities

Figure 6.6 shows the progression of different small world parameters for the derived encounter network graph. On the right side we see the development

of the average path length $\bar{G}_{APL}$ (See Definition 6.6) and on the left side the development of the clustering coefficient $\bar{G}_{CC}$ (See Definition 6.8) for the given trace period of one day.

Clustering coefficient: The clustering coefficient starts with a value of 20 % and increases slightly with a maximum value of 24 %. In realistic scenarios clustering coefficients are observed from few percent up to 50 % (see Watts and Strogatz [119]). We compare the curve with regular graphs described in Section 6.2.5. Regular graphs are highly structured. The strong organizational structure is still beneficial for establishing efficient local information flows and as such are a major means to generate community scalability. Encounter graphs have clustering coefficients of only a slightly less degree. We explain this as people frequently meet with others sharing similar activities, e.g., workmates, family and friends.

Average path length: The average path length declines fast and finally reaches a bottom at close to 1. To understand the progression of this curve we compare it to random graphs (see Section 6.2.5), for which diffusion characteristics have been well studied. Random graphs are randomly connected with no tendency toward clustering. This type of graph has a minimum diameter, and requires only a small number of hops to cross the community. Our encounter graph exhibits comparable small path lengths. We explain this with shortcuts created through the urban traffic that integrate different social groups or neighborhoods. Simulating larger populations will certainly lead to a higher average path length. But it will still be lower than the path lengths observed for communication networks (see the analysis about mobile phone networks conducted by Onnela et al. presented in Section 5.3.3) as shortcuts are frequently generated.

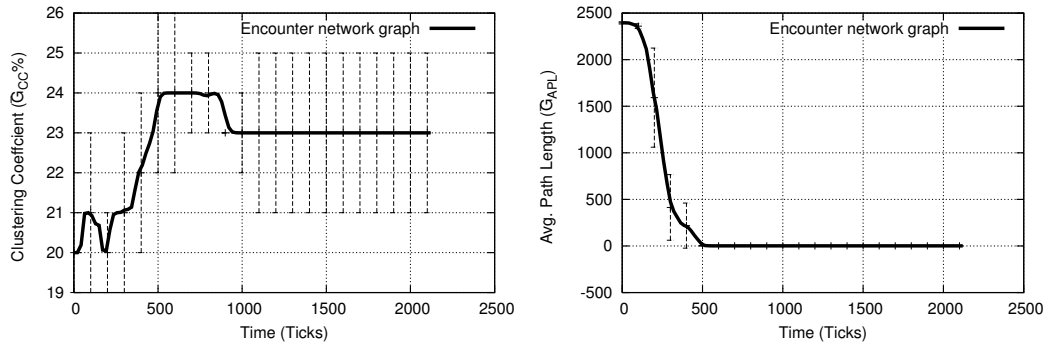


Figure 6.6: Small world encounter patterns: a) clustering coefficient and b) average path length.

Based on these results we accept hypothesis one and two. Above experiments have proven that encounter graphs show a similar small world characteristic as

already known for caller graphs. The existence of friendship relations guarantees instant content disseminations in small groups. But even more important, urban commuter traffic can be utilized to integrate urban communities on a larger scale. This is possible because traffic generates many opportunities to forward content through random contacts.

6.3.2 Download Efficiency Experiments

After analyzing the potentials for content diffusion based on the community graph, we start with realistic content diffusion experiments. In these experiments, we compare routing scenarios with different node - and content selection strategies. Our goal is to compare the outcomes of the *least effort* routing logic with traditional flooding or gossiping approaches. For this, a technical set-up scenario based on experiences from a previously implemented prototype is considered (see parameters defined in Section 6.2.3). The content size was set to 40kb representing small media files. The experiments are conducted with a population of 200 and later with 1000 people for verification. Since content diffusion heavily depends on the initially selected content source, we reiterate the experiment according to the empirical evaluation requirements in Section 6.2.2 with randomly selected source peers. The error bars describe the 95 % confidence intervalls for the diffusion progress observed during the experiments. Besides measuring the content spreading we collect data about the messaging effort (measured through content duplicates) and delivery delays.

Improvements through Topology Control

Hence, we conduct two experiments during which we measure the diffusion reach $D_{distribution}$ (see Definition 6.9) and diffusion reliability $\bar{D}_{reliability}$ (see Definition 6.11) for the least effort transfer protocol. Deliver reliability and large scale coverage are both mandatory to achieve long term user acceptance. We compare both results with flooding and gossiping systems in order to asses the benefit through our approach.

Diffusion Reach: Figure 6.7 b) displays the development of the diffusion reach (expressed through the number of encountered persons) for the trace period of approximately one day specified in time ticks. All three curves show a continuous increase of the content distribution for the peer community, whereas the *flooding* case represents the optimum community penetration. As *gossiping* does not forward content to all neighbors (only to a randomly selected neighbor) the diffusion reach is the lowest from all three of them. The curve representing the least effort diffusion approach follows in early phases the progression of the gossiping approach. However, the curve increases much steeper after the first half of the simulation period (1000 ticks). We argue that this

is the phase where all bridge peers encounter coworkers at their offices and distribute their content to ordinary group members. At the end of the simulation period both, network flooding and the least effort diffusion approach show similar results. This shows that the bottom up spreading approach in the flooding case is best suited if content has to be spread quickly. In case certain delays are acceptable the top down approach of the least effort diffusion mechanism is equivalently effective as the flooding approach, but with the important difference that fewer resources are used.

Diffusion Reliability: Figure 6.7 a) shows the distribution of content duplicates within the urban community. For the *least effort diffusion* approach, we observe that most peers have only a small number of duplicates (less than five), and only few peers (approximately ten of a given population of 200 persons) a larger number of duplicates (up to 10 duplicates). We explain this distribution of duplicates with the network centrality of individual peers. With increasing centrality, peers in the community are better connected and have a higher probability to obtain content duplicates. The duplicate distribution of *gossiping systems* has a comparable progression but a smaller number of nodes has few duplicates (up to five) and slightly more nodes have twenty and more duplicates. This is in great contrast to *flooding systems*, where the number of duplicates follows a normal distribution pattern where the biggest number of nodes have collected 40 duplicates. The flooding case seems to produce the largest number of duplicates, whereas the least effort diffusion and the gossiping approach seem to be comparable. Obviously, our least effort diffusion approach trades peers with a large number of duplicates against peers holding significant fewer duplicates. Only a small group of opinion leaders maintains the majority of diffusion contacts, whereas ordinary have only two or three content retransmissions in average. This small number of retransmissions for ordinary peers is desirable. In case members do not currently use the social software peers still have further opportunities to catch the content. All this shows that the top down diffusion strategy behind the least effort diffusion protocol seems to work well.

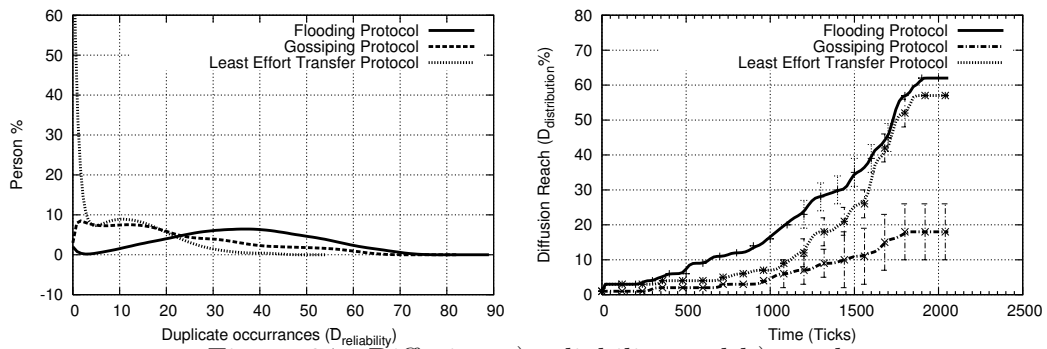


Figure 6.7: Diffusion a) reliability and b) reach

Improvements through Replication Control

For the second reiteration of the experiment, we compare diffusion efficiency of simple and complex content types through weak and strong relationships. Time-independent content is hereby used as a metaphor for simple content and time-dependent content as a metaphor for more complex content.

Time-independent content: Figure 6.8 describes different content diffusion scenarios for the propagation of simple content. The graph on the left side shows the influence of random and on the right side of frequent encounters. Both graphs display on the vertical axis the diffusion reach $D_{distribution}$ (see Definition 6.9) and on the horizontal axis the simulation time given in tick units. To visualize the influence, we repeated the experiments with decreasing number of intermediate peers. By this methodology, the sensitivity toward intermediate reduction for both scenarios can be compared. If we look on both graphs, we observe that the distance between graphs is larger for the random encounter scenario. Obviously time independent content shows a higher sensitivity if they are forwarded through random encounters. In other words, forwarding this content through randomly encountered nodes has a bigger diffusion impact as forwarding the same type of content through friend networks. We explain this with the fact that friends typically reside in close proximity and as such are less applicable to spread the content. On the other side randomly selected peers may come from different regions and may travel across far distances.

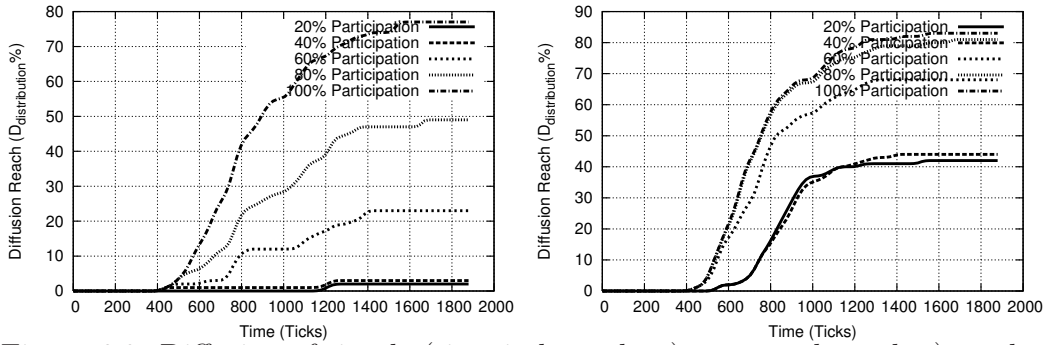


Figure 6.8: Diffusion of simple (time independent) content through a) random and b) friend groups.

Time-dependent content: The situation is completely different for time dependent content as seen in Figure 6.9. On the left side we show the diffusion increase by adding random contacts as intermediates and on the right side by adding intermediate friend nodes. Both graphs display on the vertical axis the diffusion reach $D_{distribution}$ (see Equation 6.9) and on the horizontal axis the simulation time given in tick units. This time we observe that the distances between graphs are larger for the friend encounter scenario. Obviously, time

dependent content has a higher sensitivity within friend networks. In other words, forwarding time dependent content through friend groups has a bigger diffusion impact than the dissemination through strangers encountered, e.g., during traveling. Discourse related content is time dependent and requires fast spreading in short time frames. Only friend relations have high interactivity and as such are able to refresh this time dependent content repeatedly. Similarly, as friends meet typically for a longer duration, this encounter category is more practicable for longer discourse related content. The early achievement of maximum diffusion levels is caused through the limited time frame discourse related content stays valid.

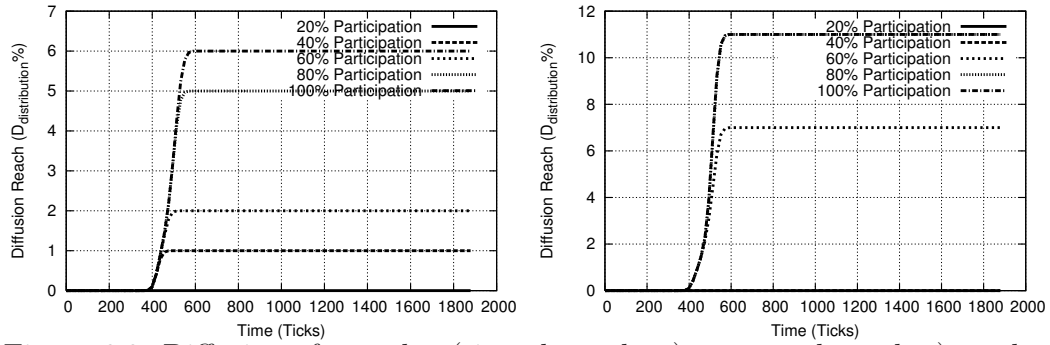


Figure 6.9: Diffusion of complex (time dependent) content through a) random and b) friend groups.

Summing up, topology control seems the appropriate mean to empower encounter based diffusions. We accept hypothesis 3 and 4 under the condition that vertical overlay groups are used to manage global content exchanges. These utilize not only community bridges but also random peers with superior mobility characteristics. Obviously, the relationship between source and destination nodes influences what type of content can be routed through this channel. As expected, weak or random encounters limit content diffusion to descriptive content and confirm Granovetter’s weak tie hypothesis. Friendship relations, however, seem to support discourse related content exchanges, correlate better with the global efficiency theory. Therefore, we support hypothesis 5 and conclude that content adaption has the potential to reduce download failures.

6.3.3 Cache Management Experiments

In the last series of experiments, we analyze how cache management influences knowledge delegation within urban communities. For the experiment, we separate between context-aware and traditional community content. Content objects store additional metadata like spatio-temporal properties but also data

about user ratings. As for the cache policies, we distinguish between vertical and horizontal cache approaches (see Section 5.3.4). Leading members manage information exchanges between groups through a rating based cache policy. In contrast, ordinary members gather content through a mobility path based cache policy to identify preferably content closely related to their communities. We compare our cache policy with the least recently used (LRU), and a situation (SIT) aware cache policy inspired by the parking lot information system designed by Wolfson et al. presented in Section 3.2.3. For the experiments we use a population of 1000 people. With the start of the experiment, all caches are randomly populated with content. During the experiment, we observe the progress of the knowledge building process. Hereby, we assume a theoretical diffusion scenario with unlimited bandwidth to gain clear view on the content delegation. The result depends on the original composition of the caches whose variation depends on the assumed cache size of 200 content items. To account for effects resulting from different initial contents we repeat the experiment according to the empirical evaluation requirements in Section 6.2.2 of the predefined cache size. All collected precision/recall measurements are averaged. The error bars in the following graphs represent data points with 95 % confidence intervals of applied effectivity measurements.

Horizontal cache management for ordinary members

We first analyze the content delegations between peers for context-aware content. The content quality for contextual content is measured with the context precision $\bar{Q}_{precision}$ (see Definition 6.14). Figure 6.10 a) compares the context precision progression for the LRU policy described in Section 6.2.5, the SIT policy based on a spatial-temporal relevance function defined in Equation 5.9, and our mobility path (PATH) aware cache policy based on the relevance function defined in Equation 5.10.

Least recently used cache policy: The context precision for the LRU policy stays at an initial minimum close to zero. This cache policy focuses only on the timeliness of the content and is not able to cache content according to spatial aspects. By looking on Figure 6.11 which shows the development of the cache locality $\bar{Q}_{locality}$ (See Definition 6.18) one can see that the LRU policy frequently replaces content, which can be seen as a sign that no expertise can be built up.

Situation based cache policy: The SIT policy rises slightly and then stays roughly around a context precision value of 15. This value represents a mean value which is determined by the content density assumed for this experiment. Increasing the content density would lead to an increase of the mean context precision. This policy, however, ignores that people are interested into several topics during the day and thus replaces content, which has been collected

for previous activities. However, if we compare the development of the cache locality then we can see that content stays slightly longer in the cache as spatial parameters also contribute to the content relevance and people are not permanently moving around. But still, the content stay time in the cache remains too short to gain a higher context precision. We conclude from this that this cache strategy does not go far enough and has to consider the user context to be more effective.

Mobility path based cache policy: The context precision for the PATH approach rises steadily until it reaches a maximum level around 60. The upper bound of 60 is again limited by the content density, however, this time the cache policy also considers other activity domains and thus finally reaches a much higher context precision than those achieved from the situation based cache policy. Content for this cache scenario is only replaced if it is outdated or collected content is more precise. Because of this they are more successful in continuously building up knowledge according to the interest profile of the user. A higher average content stay time in Figure 6.11 proofs this.

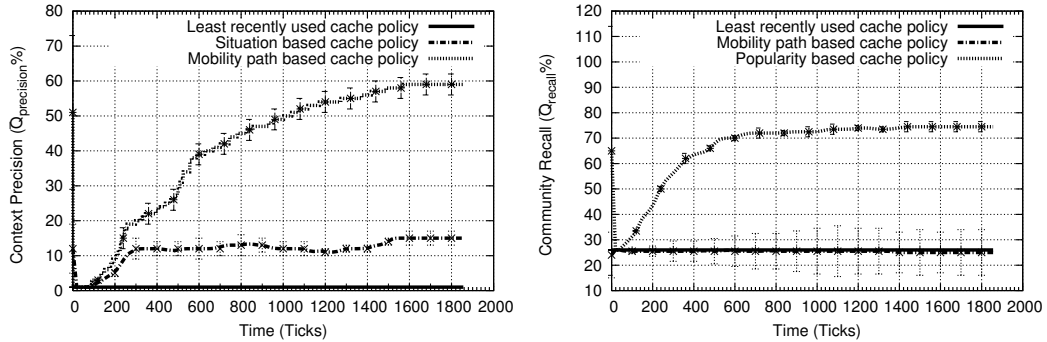


Figure 6.10: Cache analysis based a) context precision and b) community recall parameters.

Vertical cache management for leading members

We complement this experiments with evaluations targeted on community content without contextual metadata. The content quality for this content type is best measured with the community recall measure $\bar{Q}_{recall}$ (see Definition 6.16). Figure 6.10 b) compares the community recall again for the LRU, the PATH, and the content popularity (POP) aware cache policy, which is based on the relevance function defined in Equation 5.6.

Least recently used and mobility path based cache policies: Both the LRU and the PATH policy start with an initial value of around 25. This value represents a mean distribution of highly rated content available in all caches after the initial preparation phase of the experiment. During the experiment, the curve

for the LRU or PATH strategy wanders slightly around these initial values and does not change very much. Both cache strategies do not consider content ratings in their relevance functions. This explains why the community recall stays nearly on the same level during the experiment.

Popularity based cache policy: In contrast to the LRU and PATH strategy, the community recall in the POP cache policy increases further and finally outrages the recall of several degrees. We conclude that the maximum recall value from the POP policy is finally limited through the cache size. We explain this improvement by the ability of this cache policy to spread globally valid content between groups. As community recall describes the portion of relevant content of the virtual community cache, this strategy improves the total retrieval of relevant content.

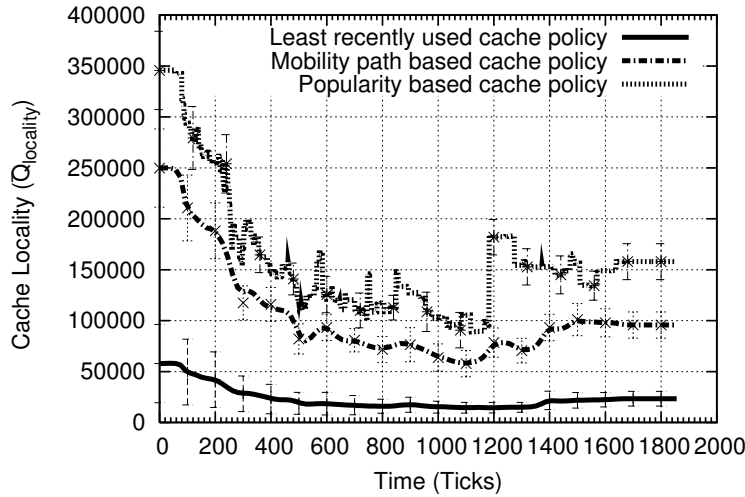


Figure 6.11: Impact on cache locality.

We accept the last two hypotheses 6 and 7. Our PATH policy is well suited to acquire community knowledge within the close neighborhoods. Its caching policy leads to a steady knowledge increase in those community domains related with user's interests. Equivalently, our POP cache approach clearly increases the community recall. Both cache strategies increase the content availability in the social group. This finally can also be tracked back to the enhanced cache storage times observed during the experiment. Because of this we support both hypotheses.

6.4 Summary

In this chapter we verified our community framework and its content diffusion mechanism. We used the CitySim traffic simulator as a basis to emulate

the diffusion process. The agents used in this simulator were enhanced with additional spatial and social models. To achieve a realistic urban life scenario we specified these models according to the data of public available urban life surveys. Moreover, we applied experiences from a technical prototype to parametrize the technical diffusion process.

We started our simulation with experiments analyzing the community network. After the simulator has distributed randomly agents on the map, agents moved according to previously specified spatial and social models. Recorded encounter events were used to construct an encounter network graph. The graph analysis revealed a tendency toward clustering and a short average path length. Short paths were created through random encounters made during traveling. In addition, these results indicate potentials to exploit group synergies and community networking.

In a second series of experiments we evaluated characteristic diffusion patterns. Therefore, we assigned a content source randomly to an individual agent and observed the subsequent content propagation. The least effort transfer protocol outperformed gossiping systems by far and reached finally comparable results as a flooding based system. A decrease of the diffusion reach in early stages and a strong increase later again can be explained by the fact that diffusion in critical situations is limited to agents with a high network range. In other words, few opinion leaders coordinate the diffusion process in the community. This leads to less content retransmissions and the diffusion process itself becomes more sustainable. Moreover, we analyzed the complex correlation between content types and relationship strengths and studied its influence on the diffusion process. We repeated these experiments with different content types and observed the effect of withdrawing friends or random encounters from the diffusion chain. Comparing the graphs reveals the following correlations: Simple contents are better spread through random encounters, as more potential forwarders exist. The situation is different for complex contents which require ongoing retransmissions. In this case the frequent contact of friend encounters is more advantageous.

For the third series of experiments we analyzed the knowledge delegation capability of our system. A shared caching approach has been implemented for the community framework which distinguishes different cache policies according to the group role. Caching algorithms should provide a transparent overview of the community and to the same time allow content specializations. We measure the quality of the community overview through community recall parameters and the degree of content specializations in the cache through context precision parameters. The PATH approach outperforms according to its precision values traditional approaches (LRU and SIT) since multiple user interests are considered for knowledge building. Traditional approaches like the LRU cache policy replace contents solely after temporary valid properties like

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the last access time and thus purge contents related with previous executed activities. Simultaneously, the POP cache policy gained a significant higher community recall as the reference systems. This shows that this policy constructs over time a highly relevant community overview by collecting preferable highly popular contents. Both cache approaches lead in comparison to traditional cache policies (LRU and SIT) to less content replacements which can be interpreted as a sign for a more sustainable knowledge building strategy.

7

Conclusion and Further Work

In this thesis, we developed an information system for mobile ad-hoc groups. Our research work is based on an interdisciplinary framework integrating different views from computer science and social sciences. After summarizing the contributions of this thesis, we conclude with a future outlook on promising research directions.

7.1 Major Achievements

The contribution of this thesis was the development of an ad-hoc information system for mobile groups. The dynamic character of mobile communities demanded the development of an encounter based support infrastructure. Our attempts show that the use of social metaphors for content diffusion in mobile peer-to-peer networks is promising. In comparison to flooding or gossiping based approaches, the application of the least effort knowledge transfer hypothesis can help to adapt diffusion strategies to the current community situation. We could decrease the messaging effort (content duplicates), and improve the overall content quality on group and member level. In the following list, we summarize these contributions in relation to our problem definition:

- **Small group and mobile infrastructure background:** A major problem for community support systems results from the existing gap between social behavior and technological systems. Social behavior is complex and highly dynamic, technical systems are less flexible and focus on individual behavior aspects. Fortunately, humans develop routine behavior for efficiency reasons. Based on a cost benefit analysis people create preferences for specific activities, territories and communities. We classified social groups in primary and secondary groups and found comparable patterns for spatial territories. The intention was to use this classification later to derive adequate ad-hoc community models. The observation from Wellman that mobile groups are highly transitive is encouraging as group boundaries can be identified more easily. Above

that, we divided support architectures into content distribution networks, client-server platforms, peer-to-peer systems and mobile encounter networks. Most commercial systems are based on client-server architectures since these are easy to deploy. The trend to interact increasingly in smaller groups empowers mobile peer-to-peer systems. A new type of support technology represent MENs which are completely independent of any installed infrastructure. As content transfers happen directly between devices MENs represent the best choice to support mobile ad-hoc groups.

- **Design patterns for a social diffusion system:** For the design of a community diffusion service, we conducted a literature survey. Knowledge diffusion depends on spatial contact, social relations and cognitive factors. The small world theory has shown that people are able to forward content efficiently to far distant places without knowing the entire community. The Prophet project builds upon friend relations to forward content to a given destination. On a larger scale, weak tie relationships have a higher potential to integrate local neighborhoods. The SimBet project exploits this phenomena and outperforms Prophet in a direct comparison. Another explanation for the small world efficiency is given through the scale free character of human networks. The Bubble routing mechanisms uses local and global ranking mechanisms to exploit this degree distribution. In combination with a group based routing mechanism the authors could show that this approach is highly efficient. Human mobility is another important factor to increase spatial contact within urban communities. Several research projects examined how the mobility of individual peers can increase the diffusion efficiency. The DataMule project uses mobile entities to randomly collect data from a sensor network. A comparison with a static sensor network proved that these mobile collectors outperform static collection approaches as long as they possess sufficient cache space. In the SocialOrbit project researchers aimed at replacing a peer-to-peers routing mechanism through a territory based routing approach. This has the advantage that not only friends but also familiar strangers can be used to deliver the content to the intended recipient. Experiments proved a significant improvement toward traditional routing approaches. The design of a diffusion system requires not only to identify efficient paths but also to limit content replications. The iCloud project and an parking place information system filter content according to semantic and spatio-temporal content meta data. Both projects proved that content spreading can be controlled and still reach their targets. A limitation of the previous presented design approaches is the rather simplistic content model behind them and the fact that these diffusion approaches do not consider varying bandwidths of MENs. A possible

solution is given by the least effort transfer hypothesis which states that humans transfer knowledge only within a reasonable effort. This approach considers not only the network topology but also the relationship strength and the background of involved partners.

- **Socially-aware mobile community framework:** Mobile encounter networks represent the best architectural choice to support bottom up content diffusions. The biggest challenge for a distributed support infrastructure is platform scalability. We envision to solve this problem by enabling collaborations between peers. We provided data structures for group administration and shared community services. In our framework, peers maintain their own spatial, social and semantic view on urban communities and share these during the group formation process. Pairwise communication protocols assure consistent group states between all peers at anytime. From sensor raw data, we derive statistical measures, which allow us to identify and evaluate behavior patterns. We use this data to create real-time encounter graphs, which function as input for social network analysis components. With social network analysis techniques the platform is able to adapt community states to the current encounter situation. More specifically we apply cluster and position analysis to identify group boundaries and delegate member roles.
- **Socially motivated diffusion and caching algorithms:** Due to varying bandwidth conditions we require an effort based approach to manage the content diffusion in MENs. As a role model for content diffusion we choose the least effort transfer hypothesis. Following this hypothesis, knowledge exchanges depend on various enabling factors that ease the transfer process. For instance, people with high network ranges increases knowledge building in communities through a better access to broader variety of knowledge. People who maintain strong relationships with each other communicate more efficient and as such can transfer more complex knowledge. Finally, humans with similar backgrounds have less problems understanding new knowledge. Content diffusion in human networks and MENs have several aspects in common. This allowed us to transfer several diffusion concepts to the technological domain. Similarly, to classifying knowledge in codified and tacit knowledge we introduced a content complexity schema which distinguishes content in descriptive and discourse related content types. Discourse structures are more complex and can only be transferred in specific encounter situations. According to the relationship strength, encounters are either used to route simple or discourse related contents. Through this adaption process, the bandwidth is better used and downloads failures are less likely. A big challenge for any distributed system is the creation of an integrated view on the

urban community. To solve this we established content flows between groups. We realized this by forming overlay networks based on members with superior network and mobility ranges. By this, descriptive contents are disseminated over larger distances, enabling more community members to query for more details. Moreover, overlay networks are accompanied with an additional group broadcast mechanism which allows for efficient content sharing in social groups. Since humans act often in groups we delegate knowledge between group members according to their role. Leading members cache preferably popular contents and ordinary members contents related with daily routines. This approach aims at creating the best possible community overview and to the same time allow for group specific specializations.

- **Evaluation of the community framework:** Our community framework was evaluated through technological prototypes and with a simulation of the content diffusion. In Chapter 6 we simulated our framework based on structural and dynamic network aspects. We emulated an urban environment by extending a traffic simulation tool. To achieve realistic behavior scenarios, we equipped agents with fixed social behavior models constrained through empirical surveys for time-management, traffic and social life. We proved that the exploitation of group synergies and the application of social diffusion phenomena could significantly increase the content quality (precision-recall) and to the same time considerably lower the messaging effort (content duplicates) in comparison to state-of-the-art encounter networks. Through numerous experiments, we depicted the following elementary behavior characteristics:
 - **Community networking:** The topology of the encounter graph shows that graph construction follows social principles. A major integration factor is the urban traffic. During traveling people encounter frequently others. Such random encounters create community shortcuts and lead to short average path lengths. Diffusion systems may reach the entire community in reasonable time frames. Since these random encounters may origin from far distant locations, community edges are likely to be well integrated. Another important aspect is the clustering tendency of humans. We meet regularly with different social groups e.g. family, friends and colleagues. High average clustering coefficients indicate the high potential for shared community services.
 - **Topology control:** For our diffusion experiments we established overlay groups to forward content in time critical situations like traveling and social groups to broadcast contents between group members. Experiments show that such overlay groups reduce the

overall messaging effort significantly and still reach comparable results to network flooding. This reduction in the messaging effort can be explained through limiting content diffusions to members with superior network ranges. By this, more contents can be exchanged in short term and second, higher diffusion potentials exist on a long term perspective since these type of bridge nodes are better connected within the remaining community.

- **Replication control:** The aim of this experiments was to explore the complex correlation between content types and encounter relationships. The higher sensitivity of diffusion graphs showed clearly that descriptive contents are better routed through random contacts and complex content through frequent contacts. Matching of content complexities according to encounter capacities is crucial to reduce download failures. In other words, in brief encounter situations we limit content exchanges to simple descriptive community content and in long-lasting meeting situations we allow the exchange of more complex contextual or discourse related content.
- **Cache control:** The goal for the design of cache replacement policy was to extend the average stay time of content in the cache. Applying a popularity aware cache policy for leading group members and a mobility path based policy for ordinary groups members delivers both a high context precision and high community recall values. Both cache policies outperform traditional cache approaches as they minimize costly content replacements and thus achieve a stronger knowledge concentration. These frequent content replacement from traditional cache policies is caused by the fact that temporary parameters, e.g. last access time, are used to calculate the relevance of that content.

Summing up, social adaptive content sharing systems based on MENs are well suited to manage content exchanges in mobile ad-hoc groups. Such systems opportunistically forward content whenever people encounter each other. In contrast to broadcast systems, they require no infrastructure, achieve wider diffusion ranges through peer mobility and are less sensitive to uncooperative community members. Their disadvantage, however, is the high resource usage typical for all kinds of diffusion based systems. We solved this problem by applying an effort based diffusion approach. This diffusion mechanism is based on the least effort transfer hypothesis. The derived algorithms tolerate varying encounter situations and avoid download failures by identifying the right content category for diffusion. Further, we keep the messaging effort to a minimum by exchanging content only between superior community members in critical situations. This assures optimal content exchanges between groups

even in highly dynamic travel situations and to the same time enables better long term diffusion due to the fact that these members are better embedded in the urban community. Ordinary members receive these contents in less time critical situations and thus do not waste unnecessary bandwidth. Although messaging is dramatically reduced in comparison to simple flooding, our least effort approach delivers high content results. Although other publications may target analogical diffusion problems, this thesis represents the first comprehensive solution for a mobile ad-hoc group information management mechanism, which includes social behavior detection, ad-hoc group formation and large-scale diffusion mechanisms.

7.2 Directions for Future Work

Methods and algorithms presented in this thesis represent a powerful foundation for the development of mobile social software applications on the basis of a socially-aware infrastructure. Nevertheless, many challenging research issues remain to be solved. We present briefly additional support problems and outline potential starting points for future research.

- **Dynamic adoption of content exchanges:** A major drawback of our diffusion protocol lies in the rough adaption process itself. Currently, adaption is based on the decision on what content type is to be forwarded. More flexibility can be achieved if the adaption process can regulate the amount of content to be exchanged, which is currently fixed and predefined by community operators. All factors that limit the shared bandwidth are suitable parameters to control the content amount to be exchanged. These are, for instance, the size of detected populations in reception range of the device, moving speed, available amount of content and average content size. Wolfson et al. developed a nice mechanism to adapt the relevance threshold on technical parameters in [125]. We think that this could be a good starting point for further research.
- **Diffusion oriented cache strategies:** Storage space on the mobile device is costly, and thus has to be maintained with care. Assessing the value of content is not trivial and may depend on other diffusion related aspects. For instance, users may perceive the value of content higher if it is not easy to access. In some cases, it may be important to keep certain content in the community, even if it is not frequently accessed. Adding diffusion related factors to the cache mechanism may add value to the entire community. People could function temporarily as intermediates if it is important to disseminate the content and withdraw it as soon as central persons have reached the content or it is stored in some alternative

public storage. Yin and Cao [126] developed a method for cooperative caching which could deliver interesting ideas in this direction.

- **Energy aware technologies:** A recent study reveals that network communication has the biggest impact on battery life of mobile devices. If the battery of the device is running low the device should reduce communication with other devices and transfer its diffusion role to other community members with better capacities. Also it is not necessary that the device is permanently online. Since the device knows the daily schedule of the user it may be useful to periodically power it off if no further content exchanges are expected and power it on, for instance, after a relocation to a new user territory. Zhi-yan et al. published a useful paper [18] about existing energy aware diffusion strategies in wireless sensor networks.
- **Prioritized epidemic diffusion:** In community systems, it is often necessary to transfer content with a higher priority for example in emergency situations. This content should be transmitted anytime, even if it does not match the relevance criteria of users. In order to avoid conflicts with user interests, this content should spread quickly and not remain longer in the cache than necessary. This can be achieved by waiving the requirement to replicate content. The autonomous gossiping project [29] follows a similar approach and could function as a starting point for further research.
- **Privacy enhanced technologies:** User profiles as we envision them for our system store behavior related data, which may be critical to share. To assure user privacy it is important to share only information that is currently needed. Profile data structures, therefore, should be advanced and structured in privacy layers. Moreover, protocols need to be extended so that data privacy always correlates with the familiarity of the encountered peer. Friksen and Golle [42] worked on a project to protect social network knowledge. We think this is a good starting point to advance this idea.

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List of Variables

AGG	A set of constraints defining a random aggregation limited by the reception range of ad-hoc networks of involved parties' mobile devices. – Page(s) 75
$Author$	Author or recommender of a given content object c . – Page(s) 70
C	A set of community contents representing the entire knowledge of the virtual urban community. – Page(s) 61, 97
CID	A unique content identifier. – Page(s) 70
$C^{Bet}(t)$	The spatial betweenness centrality parameter for a given territory t in a given street graph network. – Page(s) 80
$C^{Bet}(u)$	The social betweenness centrality parameter for a person u in a given social network. – Page(s) 80, 81, 99
C_d^{Bet}	The spatial betweenness centrality for a given suburb d . – Page(s) 80
$C^{complex}$	A content object classification for a complex composite content object. – Page(s) 97
C^{simple}	A content object classification for a simple content object. – Page(s) 97
C_g	The group publication list of a group g . – Page(s) 65
C_u	The content publication list of a user u describing all contents he or she is interested to share within the virtual urban community. – Page(s) 63
$Cache_u$	The local cache of a user u containing all private and public contents. – Page(s) 63
$Complexity$	A specification for the content complexity degree. – Page(s) 93
D	A set of community interest domains available in the virtual urban community. – Page(s) 61
D_c	A set of correlated community domains used to classify the content object c in a semantic manner. – Page(s) 70
D_g	The group interest subscription list of a group g . – Page(s) 65
D_u	The community subscription list of a user u containing all topics he or she is interested in. – Page(s) 63
E	A set of encountered users including random and frequent contacts. – Page(s) 75
EN	The encounter network graph describes the social network behind a given encounter situation. – Page(s) 75
Ef	A set of constraints representing enabling factors easing the content dissemination between peers. – Page(s) 94
F	A set of friend contacts who a given user frequently encounters. – Page(s) 63

List of Variables

G	An administrative data structure to maintain group formations. It includes data about the group identification, constraints, leader- and member lists and group subscription and publication lists. – Page(s) 65
$GCSTR$	This property describes the group type e.g. a social group category, defined through a set of group constraints. – Page(s) 65
L_g	A set of group leaders of a group g . – Page(s) 65
Loc	Spatial metadata description for a given content object. – Page(s) 70
M_g	A set of group members of a group g . – Page(s) 65
ON	A set of constraints defining a overlay network group for the purpose of community discoveries. This artificial group is quite heterogeneous and merges members after their community role. – Page(s) 61
P	A set of paths connecting social territories. Since territories are correlated with specific communities they describe also potential community traversals. – Page(s) 63
P	A set of peers. – Page(s) 97
Pf^c	Content matchmaking profile for a given user. This profile contains user's community topic subscriptions and a content publication list. – Page(s) 63
Pf^m	Mobility profile of a given user containing frequently visited territories. – Page(s) 63
Pf^s	Social profile of a given user, containing a list of frequent encountered community member contacts. – Page(s) 63
Pf^u	The user profile used to describe some characteristic data about a given user e.g. his or her name and contact information. – Page(s) 63
$R^{New}(u, c)$	Situation relevance of a given content object c , which describes to what extent the content fits to the current user situation given by spatio-temporal and semantical settings of the user u . – Page(s) 102
$R^{Pop}(c, u)$	Relevance of a content object c defined after the overall content popularity in the ego-network of the user u . – Page(s) 102
$R^{Rep}(c, u)$	Relevance of a content object c determined after the social status of the content author or recommender. – Page(s) 102
Rel	A set of social relations between community members. – Page(s) 63
$Rule$	A set of content routing rules which filter content according to their content compositness based on the availability of enabling diffusion factors. – Page(s) 94

SDI	A parameter defining the spatial diffusion impact caused through user mobility and the centrality of frequently visited territories. – Page(s) 80
SG	A set of constraints defining a social group based on member familiarity, interest similarity and collocation. – Page(s) 61
SNG	The street network graph described through streets as edges and crossing roads as nodes. – Page(s) 80
T	A set of social territories belonging to the virtual urban community. – Page(s) 61
$Time$	Temporal metadata description for a given content object. – Page(s) 70
U	Set of users, who participate in the virtual urban community maintained through the social software framework. – Page(s) 61
VC	The virtual urban community maintained through the software framework. – Page(s) 61
$\sigma_{st}(u, v)$	A set of short paths between two users u and v . – Page(s) 80
$\sigma_{st}(u, v, x)$	A set of short paths between two users u and v through a given user x . – Page(s) 80
$bridge^G$	Group bridge role of a group g . – Page(s) 61
c	A single content item. – Page(s) 70, 93
$center(t)$	A function that describes the centroid location of a given territory t . – Page(s) 102
$dt_{discover}$	Estimated time duration needed to discover peers. This parameter is used to specify technical settings of the urban simulation. – Page(s) 127
$dt_{grouping}$	Estimated time duration needed to form a group. This parameter is used to specify technical settings of the urban simulation. – Page(s) 127
$dt_{transfer}$	Estimated time duration needed to transfer content between peer group members. This parameter is used to specify technical settings of the urban simulation. – Page(s) 127
$leader^G$	Group leader role of a group g . – Page(s) 61
$loc(c)$	A function that describes the location referred or described by the content object. – Page(s) 102
md	Describes the distance $dist$ between the location referred by the content and the centroid of the closest user territory. – Page(s) 102
$p^d(u, t)$	This parameter describes the significance of territory t for a specific activity d perceived by the user u . In a certain aspect, this parameter describes the probability of a user to visit this place. – Page(s) 73

List of Variables

$range(u)$	The mobility range of the user u defined through the minimal spanning tree of his or her all frequently visited territories. – Page(s) 80
$rel^d(u, v)$	The relationship strength between two people u and v in respect to a shared activity domain d . – Page(s) 73
$w^d(c)$	A weight property describing to which extent the content object c fits to a community domain d . – Page(s) 70
$w^d(u)$	A weight property describing to which extent a given user u is interested in a community domain d . – Page(s) 70

List of Thresholds

Th_{acq}	Acquaintance Threshold. Used to describe maximum separation degree of acquaintances. – Page(s) 79, 80
Th_{fam}	Familiarity Threshold. Used to separate stranger from friend contacts. – Page(s) 75, 77, 95
Th_{leader}	Super Popularity Threshold. Used to identify social super spreaders. – Page(s) 99
Th_{mob}	Super Mobility Threshold, Used to identify mobile super spreaders. – Page(s) 99
Th_{rec}	Receptionrange Threshold. Used to describe the ad-hoc network range. – Page(s) 76, 79, 80
Th_{sim}	Similarity Threshold. Used to identify similar interests or expertise. – Page(s) 76, 77, 95
Th_{stay}	Staytime Threshold. Used to identify significant places. – Page(s) 74, 75

List of Messages

<i>msg_{ack}</i>	Download acknowledge message. After the content transfer process, peers confirm the positive or negative reception of that content. – Page(s) 65
<i>msg_{cms}</i>	Content matchmaking message, contains information about peer's publication list and subscription list. – Page(s) 65
<i>msg_{doc}</i>	Content broadcast message, used to transfer a set of content items between two or more peers. – Page(s) 65
<i>msg_{hello}</i>	Hello message, used to identify neighboring peers. – Page(s) 65
<i>msg_{inv}</i>	Group invite message. Leader nodes issue this message to form groups. – Page(s) 65
<i>msg_{join}</i>	Group join message. Ordinary peers send this message to apply for group membership. – Page(s) 65
<i>msg_{mig}</i>	Leader migration message. If a leader node has to leave a group group related administrative data is with this message transferred to an alternative leader node. – Page(s) 65
<i>msg_{pf}</i>	Profile exchange message, contains peer content, contact and territory information. – Page(s) 65
<i>msg_{req}</i>	Content request message, used to request missing remote content. The message contains a set of content identifiers form the publication list of a given peer. – Page(s) 65

List of Measurements

$D_{distribution}$	Diffusion reach. This diffusion efficiency measure describes how many members of the community have been reached during the experiment. – Page(s) 131
$\bar{D}_{delay}$	Diffusion timeliness. This diffusion efficiency measure describes the average delivery delay to nodes in comparison network flooding. – Page(s) 132
$\bar{D}_{reliability}$	Diffusion reliability. This diffusion efficiency measure describes how many alternative possibilities nodes have to catch the same content in case it has been switched off before. – Page(s) 132
$\bar{G}_{APL}$	Overall average path length. This graph measure is used to determine how many forwarding hops are needed to reach the community edge. – Page(s) 130
$\bar{G}_{CC}$	Overall clustering coefficient. This graph measure is used to determine how efficient content can be distributed in local groups. – Page(s) 130
$\bar{G}_{density}$	Network density. This graph measure describes how well community members are connected. – Page(s) 129
$\bar{Q}_{locality}$	Overall cache locality. This cache quality parameter describes how often cache content is replaced in the cache for more relevant content. – Page(s) 134
$\bar{Q}_{precision}$	Overall context precision. This cache quality measure describes how well all contents of the cache relate to the peers interest peer profile. – Page(s) 133
$\bar{Q}_{recall}$	Overall community recall. This cache quality parameter describes to what extent peers have collected relevant content in respect to the overall relevant content of the community knowledge space. – Page(s) 133

Abbreviations

C/S

Client-Server – Page(s) 31, 32

GPRS

General Packet Radio Service – Page(s) 32

GPS

Geographic Position System – Page(s) 18

ICT

Information and Communication Technology – Page(s) 11

LRU

Least Recently Used Cache Policy – Page(s) 141

MCP

Multiple-Copy-Multiple-Hop – Page(s) 51

MEN

Mobile Encounter Networks – Page(s) 31

MIT

Massachusetts Institute of Technology – Page(s) 52

MP2P

Mobile Peer-to-Peer network – Page(s) 31, 36

MP3

Moving Picture Experts Group Layer-3 Audio – Page(s) 37

MST

Minimal Spanning Tree – Page(s) 82

P2P

Peer-to-Peer – Page(s) 33

PAN

Personal Area Network – Page(s) 35

PATH

Mobility Path based Cache Policy – Page(s) 142

PIC

Parallel Index Cluster – Page(s) 35

POP

Popularity based Cache Policy – Page(s) 143

SIT

Situation based Cache Policy – Page(s) 141

SMS

Short Messaging Service – Page(s) 72

UMTS

Universal Mobile Telecommunications System – Page(s) 32, 33

WAN

Wide Area Network – Page(s) 16

Wi-Fi

Wireless Fidelity – Page(s) 32

Glossary

Ad-hoc Protocol

Protocols describe conventions how technical devices communicate with each other. They regulate the order of message exchanges and their exact formats. Typically they provide functions for session management, network routing, addressing and other physical aspects. Ad-hoc protocols are specifically designed for ad-hoc wireless networks. Since ad-hoc networks cannot rely on global addressing additional communication is required to periodically scan the environment for new devices, exchange data about device's identity and arrange a temporary network topology. – Page(s) 39

Bandwidth

The bandwidth describes the flow capacity of telecommunication systems. Larger bandwidths result usually in a higher performance of the distributed system. This data capacity is usually measured in size per time units e.g. bits per second (bps). – Page(s) 126

Codified and Tacit Knowledge

Sociologists classify human knowledge in different complexity levels. A common classification is the separation in codified and tacit knowledge. Codified knowledge describes explicit knowledge which can easily be shared between humans. Tacit knowledge refers to implicit knowledge, e.g. human experiences or skills. This type knowledge is difficult to transfer between partners because it cannot be formulated easily. – Page(s) 24, 44

Ego-networks

A social network is a social structure which describes different types of social relationships between people. An ego-centric network provides a hierarchical view on such a social network which starts from a specific node representing the center in the structure. – Page(s) 27, 63

Epidemic Diffusion

Epidemic diffusion describes the characteristic spatial diffusion pattern that can be observed in human populations. Typical scenarios are knowledge and disease spreading. Spreading is hereby achieved through direct contact and depends on different factors like the population density, the infection or currance rates. Epidemic diffusion models are often used to analyze ad-hoc networks to forecast potential diffusion impacts. – Page(s) 50

Global Positioning System

A positioning system which uses satellites to detect the current user position. Locations are determined by measuring the signal travel time to different satellites. GPS receivers allow location measurements within several meters. – Page(s) 173

Greedy Routing

Nodes that apply greedy routing progressively try to reduce the distance to the destination with every forwarding step. The forwarding decision is based on local network information with the hope to reach a global target. The biggest drawback of this routing approach is the possibility to get trapped in a local maxima unable to proceed to its intended global destination. – Page(s) 90

Informal Groups, Mobile Groups or Ad-hoc Groups

Informal groups are social groups, which emerge spontaneously, stay together for a certain time and dissolve often quickly. – Page(s) 24

Intermittent Connected

This term refers to a sporadically connected network in contrast to a fixed network with clear end-to-end paths. A good example represent mobile ad-hoc networks where transmitters have limited coverage and potential recipients continuously enter or leave their wireless networks. – Page(s) 52

Load Balancing

A methodology used to delegate tasks between equivalent system components. This is usually achieved through a separate controller unit which monitors the load of individual entities and if necessary forwards tasks to other components in order to achieve a better effort balance for each system component. As a result the overall system performance usually increases. – Page(s) 35

Network Flooding

Network flooding belongs to the category of broadcast based diffusion protocols. In such a network all nodes can act as receiver and transmitter. Content is forwarded to all collocated nodes except that node from which it was originally received. As a result of this process all reachable nodes in the network finally learn about this content. In real world flooding systems replicated contents are avoided with special techniques and the diffusion reach is controlled by limiting the number of forwarding steps. The biggest disadvantage of network flooding is its high resource usage. – Page(s) 36

Opinion leader

Opinion leaders have a high reputation in their communities and thus influence the knowledge building process in groups. Opinion leaders play an important role for the introduction of changes in communities as they provide a role model for others. – Page(s) 90

Opportunistic Routing

Opportunistic routing is usually applied in highly dynamic networks, where static route maintenance cannot be made or is too costly. Nodes are selected based on their availability and on shortest path predictions. Available algorithms can be classified after their technique to calculate shortest paths and the way how they are coordinated. An example represents spatial routing where the next forwarding node is selected with the goal to reduce the distance to the target node. The biggest drawback is the potentially very small progress toward the destination. Experiences show that opportunistic routing works well in densely populated areas where node redundancy can be exploited. – Page(s) 55

Overlay Network

An overlay network is a virtual network on-top of a physical network. Overlays describe different connection scenarios between nodes through virtual connections, usually to improve their management or content access. For example, index structures of peer-to-peer networks are usually managed through an overlay network. – Page(s) 90

Peer Cache

The cache in computer science is a component that stores temporarily data for future access, introduced to improve the overall system performance. In peer-to-peer networks a cache represents the local storage of the peer required to efficiently share content with other peers. Cache policies define what type of content is removed first if the cache reaches its limits. A well known cache policy is the least recently used strategy which replaces older with more up to date content. – Page(s) 37

Probabilistic Systems

A probabilistic diffusion system uses deduction logic to manage content diffusions. Such an approach works especially well in highly dynamic networks where encounter uncertainty is replaced with probabilistic security. For instance, nodes in such systems may monitor local network interactions to predict efficient diffusion paths through the identification of superior nodes with high network connectivity. The biggest disadvantage lies in their increase of computational efforts for each involved entity. – Page(s) 50

Publish-Subscribe Services (P/S)

P/S services refer to a messaging mechanism which matches content providers with consumers. Content providers classify contents in various topics to which consumer express interest by subscribing to them. Subscribers may register to several content sources and thereby receive a smaller amount of the overall contents. – Page(s) 14

Scalability

A situation with increasing system load usually leads to a performance decline. Scalable systems work still well in a larger scenario. They avoid critical situations by adding progressively resources to the systems or delegate tasks to other sub components. – Page(s) 39

Single- and Multi-hop Routing

Content in ad-hoc networks usually spreads directly between peers (single hop). To extend the transmission range intermediate peers may function as additional forwarding relays (multi hop). Such an approach is, however, more complex and requires a collaboration between peers. The benefit of this approach is an extension of the transmission range up to several kilometers. – Page(s) 35

Social Network Analysis

Social network analysis is a methodology to determine social properties through the means of graph analysis. It assumes that human behavior is limited or enabled through the social network surrounding the person. Social networks are made of nodes representing people links describing previous interactions between them. Several standard graph measures are used to analyze behavior options for individual members or the entire community. – Page(s) 29

Social Software

Social software describes a type of software, which offers people features to manage their social networks through the Internet. Characteristic features include functions for describing oneself, a list of favorite friends, message boards, buddy lists, on line chats and photo galleries. – Page(s) 60

Software Framework

A software framework represents an basic conceptual architecture needed to solve a specific problem. Their description often includes a set of tools, components and data repositories. – Page(s) 60

Super Spreader

A term used in network research to describe members with extensive

contacts to other community members. Frequently named examples are politicians or traveling sales men. Such members play a crucial role for rumor and disease spreading. – Page(s) 90

Wearable Computing

Mobile and Wearable Computing describes a computer science discipline which deals with special problems related with mobile devices. Wearable devices represent a specialization which can be worn on the body e.g., as part of clothing. Mobile computing scenarios are usually closer correlated with the real world and as such focus often on human behavior support. – Page(s) 35

Wireless Networks

Wireless networks are computer networks, which use radio waves instead of a cable infrastructure to communicate to other remote places. They can be separated in infrastructure based telecommunication networks and infrastructure less ad-hoc networks. Network protocols on the physical layer manage the data transfer between devices and assure communication consistency. – Page(s) 174

Zusammenfassung

Soziale Software beschreibt eine Klasse von Anwendungen, die es Benutzern erlaubt über das Internet mit Freunden zu kommunizieren und Informationen auszutauschen. Mit zunehmender Leistungsfähigkeit mobiler Prozessoren verwandeln sich Mobiltelefone in vollwertige Computer und eröffnen neue Möglichkeiten für die mobile Nutzung sozialer Software. Da Menschen Mobiltelefone häufig bei sich führen, können vergleichbare mobile Anwendungen stärker auf ihre unmittelbare Umgebungssituation zugeschnitten werden. Mögliche Szenarien sind die Unterstützung realer Treffen und damit verbundenen Mitgliederinteraktionen. Client-Server-Plattformen, die dabei häufig zum Einsatz kommen wurden allerdings nie für solche hochflexiblen Gruppensituationen konstruiert. Mobile Encounter Netzwerke (MENE) versprechen hier mehr Flexibilität. Ein MEN stellt eine mobiler Peer-to-Peer-Plattformen dar, das über ein kurzreichweitiges Funknetz betrieben wird. Mit diesem Netzwerk werden Beiträge über einen räumlichen Diffusionsprozeß von einem mobilen Endgerät zum nächsten verbreitet. Das hat zwei entscheidende Vorteile: Zunächst ist der direkte Nachrichtenaustausch besser geeignet zur Verbreitung von situationspezifischer Information, da die Informationsrelevanz mit ihrer Entfernungsabnahme abnimmt. Gleichzeitig können aber auch Inhalte, die für einen breiten Interessenskreis bestimmt sind über Mitglieder mit herausragenden Mobilitätscharakteristik in weit entfernte Gebiete transportiert werden.

Ein Nachteil ist jedoch der hohe Ressourcenverbrauch. Zur Lösung dieses Problems entwickeln wir ein Rahmenwerk zur Unterstützung mobiler ad-hoc Gruppen, das es uns erlaubt, Gruppensynergien gezielt auszunutzen. Dieses Rahmenwerk bietet Dienstleistungen zur Verwaltung der Gruppendynamik und zur Verbreitung von Inhalten an. Mittels soziale Netzwerkanalyse wird die technische Infrastruktur ohne notwendige Benutzereingriffe kontinuierlich an die reale Umgebungssituation angepasst. Dabei werden mögliche Beziehungen zwischen benachbarten Personen anhand früher Begegnungen analysiert, spontane Gruppenbildungen mit Clusterverfahren identifiziert und jedem Gruppenmitglied eine geeignete Rolle durch eine Positionsanalyse zugewiesen. Eine Grundvoraussetzung für eine erfolgreiche Kooperation ist ein effizienter Wissensaustausch innerhalb einer Gemeinschaft. Wie die Small World-Theorie zeigt, können Menschen Wissen auch dann effizient verbreiten, wenn ihre Entscheidung nur auf lokaler Umgebungsinformation basiert. Verschiedene Forscher machten sich das zu nutze, indem sie kurze Verbreitungspfade durch eine Verkettung hochvernetzter Mitglieder innerhalb einer Gemeinschaft konstruierten. Allerdings lässt sich dieses Verfahren nicht einfach auf MENE übertragen, da die Transferzeit im Gegensatz zu dem drahtgebundenen Internet beschränkt ist. Unser Ansatz beruht daher, auf der von Reagan et al. vorgestellten Least Effort Transfer-Hypothese. Diese Hypothese besagt, dass Menschen Wissen nur dann weitergeben, wenn sich der Aufwand zur Infor-

mationsübertragung innerhalb bestimmter Grenzen bewegt. Eine erfolgreiche Wissensübertragung hängt in diesem Fall vom Hintergrundwissen aller Beteiligten ab, was wiederum von unterschiedlichen kognitiven und sozialen Faktoren abhängt. Entsprechend leiten wir ein Diffusionsverfahren ab, dass in der Lage ist, Inhalte in verschiedene Komplexitätsstufen einzuteilen und Datenübertragungen an die vorgefundene soziale Situation anzupassen.

Mit einem Prototyp evaluieren wir die Machbarkeit der Gruppen- und Informationsmanagementkomponente unseres Rahmenwerkes. Da Laborexperimente keinen ausreichenden Aufschluß über Diffusionseigenschaften im größeren Maßstab geben können, simulieren wir die Beitragsdiffusion. Dazu dient uns eine Verkehrssimulation, bei der Agenten zusätzlich mit aktivitätsbezogenen, sozialen und territorialen Modellen erweitert werden. Um eine realitätsnahe Simulation zu gewährleisten, werden diese Modelle in Übereinstimmung mit verschiedenen Studien zum Stadtleben generiert. Der technische Übertragungsprozess wird anhand der Ergebnisse einer vorangegangenen Prototypuntersuchung parametrisiert. Während eines Simulationslaufes bewegen sich Agenten auf einem Stadtplan und sammeln Kontakt- und Beitragsdaten. Analysiert man anschliessend die Netzwerktopologie auf Small World-Eigenschaften, so findet man eine Netzstruktur mit einer ausgeprägten Neigung zum Clustering (Freundschaftsnetzwerke) und einer überdurchschnittlichen kurzen Weglänge. Offensichtlich reicht die Alltagsmobilität aus, um ausreichend viele Verknüpfungen zwischen Gemeinschaftmitgliedern zu bilden. Die nachfolgende Diffusionsanalyse zeigt, dass vergleichbare Reichweiten wie bei einem flutungsbasierten Ansatz erzielt werden, allerdings mit anfänglichen Verzögerungen. Da unser Verfahren bei einem Ortswechsel die Anzahl der Informationsübermittler auf zentrale Gruppenmitglieder begrenzt, steht mehr Bandbreite für den Datenaustausch zur Verfügung. Herkömmliche Mitglieder (ohne Leitungsaufgaben) tauschen Inhalte vornehmlich in zeitunkritischen Situationen aus. Das hat den positiven Nebeneffekt, dass im Cache erheblich weniger Kopien aussortiert werden müssen. Wechselt man während der Simulation die Beitragskategorie so erkennt man, dass zeitabhängige Inhalte besser über regelmässige Kontakte und zeitunabhängig Inhalte durch zufällige Kontakte verbreitet werden. Eine abschliessende Precision-Recall Analyse zeigt, dass herkömmliche Gruppenmitglieder eine bessere Genauigkeit (Precision), und zentrale Mitglieder eine bessere Trefferquote (Recall) im Vergleich zu traditionellen Ansätzen besitzen. Eine Erklärung dafür ist, dass der von uns gewählte gruppenbasierte Cacheansatz zu weniger Säuberungszyklen aller Gruppenmitglieder führt und somit nachhaltiger ausgerichtet ist.

Curriculum Vitae



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