Social Matching: A Framework and Research Agenda

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Social matching systems bring people together in both physical and online spaces. They have the potential to increase social interaction and foster collaboration. However, social matching systems lack a clear intellectual foundation: the nature of the design space, the key research challenges, and the roster of appropriate methods are all ill-defined. This article begins to remedy the situation. It clarifies the scope of social matching systems by distinguishing them from other recommender systems and related systems and techniques. It identifies a set of issues that characterize the design space of social matching systems and shows how existing systems explore different points within the design space. It also reviews selected social science results that can provide input into system design. Most important, the article presents a research agenda organized around a set of claims. The claims embody our understanding of what issues are most important to investigate, our beliefs about what is most likely to be true, and our suggestions of specific research directions to pursue.

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1. INTRODUCTION

People are social creatures—fundamentally so. We look for other people for a multitude of purposes: dating and eventually marriage, pursuing shared interests, addressing community issues, solving technical problems, or maybe just having a good conversation.

Sometimes we rely on the services of a matchmaker to help us find someone. You may be picturing a little old lady, nosy but wise, who can find just

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the right young man for your daughter. Of course, matchmaking isn't just for romance. Some people have mastered the art of giving dinner parties, starting by inviting the right group of people, then seating them appropriately, and even knowing how to introduce people with interesting conversational starters. Nor is matchmaking done just for social purposes. There are lots of guides to help professionals (especially the unemployed) network with each other to find new jobs and career opportunities.

People don't rely only on matchmakers to get together; they also use whatever technology is at hand. Teenagers, for example, have been especially enthusiastic and innovative users of communications technology, from landline phones to mobile phones and text messaging [Ling and Yttri 1999; Grinter and Eldridge 2001; Grinter and Palen 2002].

Using computer-based technology for social purposes raises a new possibility: semi-automated matchmaking. Where recommender systems have (partially) automated the everyday process of word-of-mouth sharing of opinions, social matching systems (partially) automate the process of bringing people together.

Over the past 5–10 years, both commercial systems and research prototypes have begun to explore the space of social matching systems. As in everyday practice, dating services were early and prominent entries—sites like match.com let people fill out questionnaires about themselves and what they're looking for in a romantic partner, apply algorithms to find matches, and provide ways for people to communicate with their suggested matches. The LoveGety device [Wired News 1998] comes in male and female versions and can be set in one of a few modes. The devices continuously broadcast the user's mode so when a male and female are within about 5 meters and are in the same mode, both their devices beep and flash.

Other social applications have emerged recently. Social network tools like Friendster and Orkut let users create intricate friendship networks, then use these networks for communication and meeting people. Meetup (meetup.com) allows people with a shared interest—from working on behalf of a political candidate, to practicing a second language, to showing off their Chihuahuas—to meet in person.

Researchers have explored many additional applications, including matching people as they browse the Web [Budzik et al. 2002], locating topic experts who are socially close to an information seeker [Kautz et al. 1997; McDonald and Ackerman 2000; McDonald 2001] and matching people who frequent the same physical locations [Terry et al. 2002].

While technological developments have brought issues of social matching within the scope of computer science and human-computer interaction, we are far from the first to take them on. For example, over the past century social psychologists have done countless studies of what attracts people to others as potential mates or friends (see Berscheid and Reis [1998] for an overview). The relevance of such work to the design of social matching systems should be plain: social matching systems embody (often implicitly) some folk social psychology of what attracts people to each other. For LoveGety, being of the opposite sex and in the same mode equals a match. Reflection suggests that our folk psychology intuitions may be too simplistic; social science results can provide a firmer foundation and practical design guidelines for social matching systems.

We are now in a position to lay out the plan of the article. First, we characterize social matching systems through a critical review of existing systems and previous research. We explain how social matching systems differ from recommender systems in general. Second, we review some relevant social science literature that can inform the design of social matching systems. Finally, we devote the bulk of the article to staking out a research agenda for the field organized as a set of claims. These claims embody our understanding of what issues are most important to investigate and offer many specific suggestions of research directions to pursue. We offer these claims to stimulate and focus research on social matching and present opportunities for newcomers to begin work.

2. SOCIAL MATCHING SYSTEMS: DEFINING THE TERRITORY

One could offer a simple definition of social matching systems: they're recommender systems that happen to recommend people instead of (say) movies or books or documents. This definition can be read as self-subverting, however: after all, book recommenders aren't treated as a separate class of systems than movie recommenders. Therefore (one might argue), social matching systems aren't anything special—they're not a natural kind.

We disagree. So, the first order of business for us is to explain why we consider social matching systems an interesting class of systems in their own right. We begin by reviewing a few essential features of recommender systems.

Recommender systems address the problem of information overload, that is, they help users choose from large sets of items of which they have no first-hand knowledge. Recommender systems use knowledge of users' preferences to identify small subsets of items they're likely to find interesting. The two main types of recommender systems are *collaborative* and *content-based*. Collaborative recommenders aggregate many users' preferences to recommend items to a target user. The automated collaborative filtering technique matches a target user with other users who have similar preferences, and then recommends items that these neighboring users rated highly and that the target user has not rated. Well-known collaborative recommenders include GroupLens and MovieLens [Resnick et al. 1994; Konstan et al. 1997], the Bellcore Video Recommender [Hill et al. 1995], Ringo/Firefly [Shardanand and Maes 1995], and Jester [Goldberg et al. 2001]. In contrast, content-based recommenders [Lang 1995; Lieberman 1997; Maes 1994; Mooney and Roy 2000] locate items that are similar to those a user has liked in the past. They typically apply techniques from machine learning to learn a user's preferences and techniques from information retrieval to select similar items to recommend.

Recent important papers include those by Herlocker et al. [2004] and Breese et al. [1998] on algorithms and evaluation, Terveen and Hill's HCI-oriented survey [2001], and Burke's analysis of hybrid recommender systems [2002].

Social matching systems recommend people to each other instead of recommending items to people. Recommending people fundamentally changes the

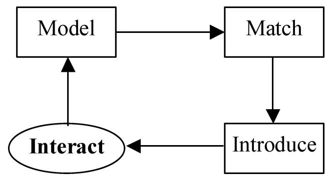

Fig. 1. A simple model of the social matching process. Social matching consists of four main steps: (1) modeling the set of users who can be matched, (2) matching users in response to an explicit request or implicit opportunity, (3) introducing matched users, enabling them to (4) interact with each other, either in a mediated space created by the system or through means of their own choosing. Note that the results of the process must feedback to the system, possibly causing it to updates its models.

game. Some amount of personal information about users is necessarily revealed. This makes for an inherently riskier interaction, and thus elevates issues such as privacy, trust, reputation, and interpersonal attraction to much greater importance. We elaborate on these issues throughout the article.

2.1 A Basic Model

To help make sense of the space of social matching systems, we present a basic process model that any such system must instantiate and identify a set of issues that such systems must address (see Figure 1).

Let's illustrate the model by walking through the paradigm example of a dating system. A system such as match.com builds a profile of users by getting them to answer a fairly lengthy sequence of questions on topics such as their profession, religious beliefs, cultural background, desire for a family, and what they're looking for in a romantic partner. It then applies some matching algorithm that embodies a model of compatibility between (in this case) romantic partners. The system gives people various ways to learn about potential matches, introduce themselves and interact with each other. The interaction techniques are all electronic—chat, email, and so on—and preserve user privacy unless and until users decide to reveal their identities. Users may update their profiles at any time (e.g., if they are not satisfied with the type of people they're being matched with).

This discussion highlights the following set of issues.

—*Profiling users*. What type of information does a system represent about its users, and how does it acquire this information?
—*Computing matches*. What is the system's model of what makes a good match? How does the system compute matches?
—*Introduction*. How are matching people brought together? What information does the system reveal about the people?
—*Interaction*. To what extent does the system facilitate interaction? Does interaction take place in a mediated space created by the system or do users interact as they see fit, including face-to-face?
—*Feedback*. How does the result of an interaction feed back to the user profiles? Can the system automatically update profiles or is it up to users to provide explicit feedback?

The research agenda elaborates upon these issues in depth. However, we next survey some representative social matching systems, highlighting which of these issues they focus on and the technical innovations they have introduced.

2.2 A Survey of Social Matching and Related Systems

Researchers have addressed a broad range of purposes for matching people and explored a diverse set of matching techniques. The following sections survey several distinct social matching approaches and related research areas.

2.2.1 *Social Recommenders for Information Needs.* Several research prototypes explicitly match people based on both their social relationship and an information need. Suppose Deborah is a computer scientist who's recently become interested in applying data mining techniques to genetic databases. She's not familiar with bioinformatics so she'd like to find an expert in the area who could direct her to some good introductory papers and perhaps answer some questions. Of course, she wants someone who's likely to answer and whose answers she'll find credible. A way to serve both of these goals would be to find a bioinformatics experts who also is socially close to her (e.g., a friend of a friend). Take another example: James is a software developer in a medium-sized financial services company who's working to add a new feature to some accounting software that he's not familiar with. He'd like to find another developer in the company who is familiar with the software and whom he knows.

ReferralWeb [Kautz et al. 1997] and Expertise Recommender [McDonald and Ackerman 2000; McDonald 2001] support scenarios like the ones presented. Considered together, they illuminate one path through the social matching design space.

First, both systems need two types of profiles, one concerning expertise and the other, social relations. Both systems obtain expertise information by data mining. ReferralWeb mines public Web documents for knowledge about potential experts. First, names are identified, then content analysis used to identify topics most associated with names is identified, and finally, co-occurrence of names (e.g., as coauthors of a paper) used to identify likely social relationships. Expertise Recommender acquires knowledge about who knows what by mining work products and byproducts within an organization like software source control systems and technical support databases. ReferralWeb also obtains social network information via data mining. While in principle such information can be obtained from many sources such as records of email exchanges or reply patterns in Usenet newsgroups, ReferralWeb obtains it from document co-authorship. That is, writing a paper together was evidence of a social relationship. On the other hand, social network information for Expertise Recommender is obtained through the successive pile sort method and observation techniques [McDonald 2003].

Both systems matched information seekers to an expert. Both are hybrid recommender systems [Burke 2002] in that they apply two different types of knowledge to recommend an expert. They use knowledge of topic expertise to identify people who are likely to be able to answer a question and apply knowledge of social relations to focus on the experts with the closest social relationship to the seeker.

To support the information seeker in introducing him or herself to an expert, ReferralWeb provids the *referral chain* showing a social path from the seeker to the expert. This can be used by the seeker both to assess the credibility of the expert and as a source of people who might introduce the seeker to the expert. Expertise Recommender does not offer any equivalent information. However, since it operats within a medium-sized organization, the assumption is that information seekers would likely know the recommended experts or know someone who could introduce them.

ReferralWeb does not provide any explicit support for the interaction process—seekers are expected to use whatever means they find appropriate to communicate with the experts. Expertise Recommender provides a simple instant messaging system for users who are logged into the system [McDonald 2000]. And since it operates within an organizational context, seekers typically have many ways to communicate with experts: face-to-face, email, phone, IM, and so on. Acting on a ReferralWeb recommendation could be trickier: a seeker might not have any contact information for the recommended expert and might have to rely on people in the referral chain to pass the query along.

2.2.2 *Information Systems with Implicit Social Matching.* Another class of systems moves further away from our first examples of social matching. Here the focus is on navigating information spaces to find desired facts. However, the spaces are constructed so that when users need information beyond that already recorded, pointers are provided to people who can help.

PHOAKS [Hill and Terveen 1996; Terveen et al. 1997] harvests recommended Web pages from Usenet news messages. Its interface also shows information about the messages in which Web pages were recommended, including the person who posted the message. Thus, PHOAKS first lets users find Web pages on topics they are interested in, then if they are particularly interested, they can explore further to find and contact the person who recommended a Web page.

The Designer Assistant [Terveen et al. 1995] organizes software design knowledge as a hierarchical series of questions. Designers traverse the hierarchy to get advice about their project. Each piece of advice is tagged with an *owner*, the person in the organization most familiar with that particular aspect of the software system. Similarly, Answer Garden [Ackerman 1994; Ackerman and McDonald 1996] organizes knowledge around a hierarchy of questions and answers; users traverse the hierarchy to locate their question and the corresponding answer. Questions and answers also are tagged with the domain expert who is responsible. If a question has not been answered, a user can email the question to the responsible expert.

PHOAKS, Answer Garden, and the Designer Assistant aim to satisfy user information needs and facilitate social interaction when their existing information spaces are inadequate. No explicit profiles of users are constructed; instead, users are matched through a shared interest in (or expertise about) particular information. This is related to social navigation, a topic that we explore further later in the article. These systems offer no particular support for introducing users other than the information context. In the Designer Assistant, for example, when a user was put in touch with an expert, it was specifically with regard to a particular piece of design knowledge. All three systems supported interaction through email. Answer Garden allows experts to remain anonymous so it mediates email queries from users. Since the Designer Assistant operates within an organization (like the Expertise Recommender), it provides complete contact information for experts so users can contact experts however they were most comfortable.

2.2.3 *Opportunistic Social Matching.* Another class of systems matches users opportunistically—that is, independent of a specific user request. Matching typically is based on shared interests, where users' interests are inferred by the system from their current activity or record of past activity.

Let's consider a typical scenario. Suppose Brian is browsing the Web for information about one of his favorite rock bands, The White Stripes. He becomes aware that about 10 other people are also reading Web pages about The White Stripes and is able to join in a chat room to talk about their favorite songs, live shows they've seen, and so on. I2I [Budzik et al. 2002] provides this functionality.

I2I profiles users by applying information retrieval techniques to a user's current Web document. This process identifies terms that represent the user's current interest. Whenever the user navigates to a new Web page, the system updates its profile. I2I matches users by applying text similarity metrics to cluster users who are browsing similar documents. In other words, users with similar interests are considered good matches. I2I enables interaction through synchronous chat between groups of users as well as instant messaging between pairs of users. This lets users maintain anonymity if desired. The context of the match—the set of documents being browsed by the users—is not revealed, but, in principle, it could be presented to the users as an introduction aid.

Several other systems are quite similar to I2I. Kalas [Svensson et al. 2001] is a social navigation system for recipes. Kalas organizes recipes into collections (based on type of cuisine, for example) and visualizes interaction history so users can identify the most popular collections. Users can gather around a collection, chatting with others who are there. Like Kalas, LiveMaps [Cohen et al. 2002] supports both social navigation and social matching, this time for Web browsing. Users can join a chat around a Web site, page, or even section of a page.

Other systems strike off in different directions. Yenta [Foner 1996] is a distributed agent-based system. Each user's individual agent examines documents in that user's file system to identify topics the user is interested in. Once each user's agent identifies his or her interests, the agents communicate to identify users who share interests: the more topics two users have in common, the more likely they are to be grouped together.

Social Net [Terry et al. 2002] matches users based on their position in physical space, not in virtual space. Users carried handheld devices that broadcast IDs using radio signals. Each user's device stores IDs of the user's friends and notices recurring patterns of copresence with unknown others. For example, your device might note that you are often copresent with another user (not on your friends list) and so will add this user's ID to your unknowns. Thus, physical proximity, rather than reading similar documents, is used to indicate shared interests. Social Net also looks for a mutual acquaintance who can introduce two people with shared interests who don't know each other. Every time two friends meet, their devices exchange lists of unknowns. If friend A is a friend of one of friend B's unknowns, then friend A will be prompted to introduce friend B and the unknown.

2.2.4 *Related Approaches.* Several other research areas are related to various aspects of social matching. Considering them briefly helps us to further define the scope of the field.

User modeling systems [Rich 1979; Kobsa 2001] create models of users in order to adapt system interaction to each user, tailoring the functionality that the system provides or customizing the information that is presented. Social matching systems need models of users—their interests, demographic and other personal features, and social ties—in order to match them.

Group recommenders provide information to a predefined group of people. PolyLens [O'Connor et al. 2001] recommended movies to self-defined groups of movie lovers. MusicFX [McCarthy and Anagnost 1998] selected music to play in a corporate fitness center based on the preferences of the people working out at a given time. And Neighborhood Window [McCarthy et al. 2003] used active badges to identify users standing in front of a large display, compute shared interests of these users, and then depicted them on the display.

Group recommenders take a group as given, then attempt to find relevant information (e.g., a movie recommendation) for the group. Social matching systems, on the other hand, must form groups by applying some notion of appropriate matching to a set of user profiles. However, group recommendation techniques are relevant to social matching; specifically, they offer guidance for the problem of computing an introduction for a group of matched users.

Online communities are social spaces built on technologies such as chat rooms, newsgroups, and bulletin boards where people go to discuss topics that interest them and to meet others. They are popular for interests such as hobbies, popular entertainment, technical information exchange, political discussion, and health and emotional support [Baym 1993; Preece 1998; Preece 1999; Sproull and Faraj 1997].

Social matching systems can facilitate the process of joining and participating in online communities, serving as zero-effort interfaces [Lieberman et al. 2001]. That is, users do not have to explicitly decide that social communication is an option nor find an appropriate community to join. Systems may create new social places for users with a shared interest. For example, I2I created a chat room for people browsing related Web pages. They also may recommend existing online communities [van Dyke et al. 1999].

Awareness systems [Dourish and Bly 1992; Fish 1993; Hudson and Smith 1996; Erickson et al. 1999] users allow to maintain awareness of and communicate with friends, family members, and colleagues. For example, Instant

Messaging systems let users specify buddies, keep users aware of their buddies' status (e.g., active vs. idle), and let users engage in text chats with their buddies.

The goals of social matching systems differs in two fundamental ways. They can introduce people who don't already know each other but have shared interests, and they can suggest specific opportunities to collaborate even among people who already know each other (e.g., two colleagues who hadn't realized that they were both attending the same large conference).

Social visualization systems convey information about the activity of an online community and individual community members. Such information can help users decide whether a community is one they'd like to join and identify members they'd like to communicate with. Donath et al. [1999], Sack [2000], and Smith and Fiore [2001] describe systems for visualizing the structure of various online communities. These systems can help in tracing threads, finding active posters, and identifying communication patterns between people.

Social matching and social visualization systems can both help users identify other people to communicate with. However, while social visualizations support the goal of finding someone to communicate with, social matching systems partially automate this process. Social visualization systems offer rich graphical representations of a social activity but leave interpretation and decision-making up to the users. Social matching systems, on the other hand, attempt to ease decision-making by identifying specific people a user may wish to communicate with and creating introductions to facilitate interaction.

Social navigation systems use social information to aid users in deciding where to go next in large, complex information spaces. Social navigation systems typically aggregate user data, allowing users to follow the most popular path. A prototypical application is logging all usage history through a Web site and using it to modify the display of pages to emphasize the most popular links and pages. Well-known examples include Dourish and Chalmer's foundational theoretical work [1994], systems by Dieberger [1997] and Wexelblat and Maes [1999] for Web navigation, and Kalas [Svensson et al. 2001].

In contrast to social navigation systems, social matching systems use identifiable user data to bring individuals together to facilitate communication and collaboration. Where a social navigation tool might aggregate download statistics on a music file-sharing site to help you find the most popular songs, a social matching tool could introduce you to other users who have downloaded the same type of music as you have, thus giving you the opportunity to talk with someone who shares your interests in music. The two approaches are complementary; thus it is natural to combine them into a single system. However, they do raise different challenges. For example, data visualization is important in social navigation since systems often modify information displays with social data to depict important items and well-traveled paths [Hill et al. 1992; Hill and Hollan 1994; Wexelblat and Maes 1999]. Social matching, on the other hand, takes a recommender system approach, filtering (potentially) large sets of people to identify those whom a user may want to communicate with. Further, privacy is a much bigger issue for social matching systems since social navigation systems, like recommender systems, may use social data in the aggregate.

3. SOCIAL SCIENCE BACKGROUND

While social matching systems raise a number of new research issues, the social sciences offer a wealth of results to draw on. The social sciences have long been interested in the relationships between individuals and the individual in relation to the group. Studies of social relations have been conducted in social settings that range from public social spaces, through a range of community settings, to the organizations in which people participate. Researchers have studied topics including interpersonal attraction, friendship, dating and mating, help giving, and group behavior.

This section discusses selected social science results which we draw on in stating our claims that follow. We emphasize work that bears most directly on how and why people come together, interact, and form relationships. Some results, for example, concerning interpersonal attraction, provide input into the problem of developing effective user profiles. Other results, for example, dealing with social settings and social structure, can guide the design of social matching models. Work on the conditions and motivations for group interaction help identify ways that a social matching system can facilitate interaction between matched users.

3.1 Interpersonal Attraction

There is a vast amount of social psychological literature on interpersonal attraction. Berscheid and Reis [1998] give an extensive overview; Kandel [1978] and Hill et al. [1976] are examples of specific studies. Prior research has identified three types of factors that predict interpersonal attraction: personal characteristics, demographics, and familiarity.

3.1.1 *Personal Characteristics.* They say that beauty is in the eye of the beholder. Lots of the characteristics that attract people to each other—personality, friendliness, character, trustworthiness, sense of humor, and physical attractiveness—are similar. Judgments about physical beauty and appealing personality are a function of cultural and social norms. Individuals with similar personal characteristics are likely to be attracted to each other. In the language of recommender systems, personal characteristics function as tastes or preferences that one individual may have about another. While there are cultural regularities, people's tastes differ. For example, one person's good sense of humor is another's obnoxious silliness.

Early ethnographic work by Waller [1937] investigated attraction in courtship and dating. Waller describes the many complex social cues that individuals use when determining how another individual rates when making a decision to make or accept an invitation for a date. Its relevance for us is to reinforce the point that user goals must be considered in the matching process, specifically in guiding the characteristics to consider and suggesting how to weigh them.

3.1.2 *Demographics.* Demographic features are more objective than personal characteristics: age is not in the eye of the beholder, and you either have a college degree or do not. Ethnic background, gender, marital status, profession, and income are other demographic features. Such features often correlate with people's attitudes and values so people use them as visible signals that someone shares their values and attitudes. Demographic features have been shown to correlate with interpersonal attraction [Fischer et al. 1997; Fischer 1982].

Social matching systems face the problem that demographic information that is obvious in face-to-face interaction is (for better or worse) not obvious online. An experiment by Cosley et al. [2003] found (1) users both seek out and disclose much demographic information, and (2) users appear to be sensitive to some demographic factors even when they aren't explicitly disclosed. Pairs of subjects completed an online game-playing task. Demographic factors—particularly education level, age, and gender—affected the quantity and quality of conversation even when the factors were not explicit. Further, many subjects asked about and offered information such as their age, physical location, and family status.

3.1.3 *Familiarity.* The amount of exposure people have to each other strongly influences the likelihood of interpersonal attraction. Whyte [1956] presented early results on the role of proximity in friendship development. His study used physical proximity to stand in for exposure. The rationale for this is that people who are physically proximate are likely to frequently meet and interact. Whyte showed that families who lived near to each other were more likely to develop friendships.

Work places studies also have shown the importance of familiarity with proximity again serving as a proxy. Kraut et al. [1990] showed that proximity of offices strongly correlated with collaboration. Aspects of familiarity also influence online interaction. Studies have shown that exposure can lead to strong relationships; however, the lower bandwidth of social information that online channels carry makes relationships take longer to develop [Walther 1992; Walther et al. 1994; Parks and Roberts 1998].

3.1.4 *Discussion.* The different types of interpersonal attraction are somewhat related. While most prior research attempts to focus on one factor at a time, researchers also realize that the social world is more complex. For example, proximity in a neighborhood is often related to economic standing. But it is unclear whether familiarity (through proximity) and socio-economic similarity are enough to overcome serious differences in personality.

Some research suggests ways that different types of factors may be combined. Verbrugge [1977] talked about the meeting and mating phases of relationship formation. First, people who encounter each other in their daily rounds are likely to be quite similar demographically—in effect, social contexts such as places of work, commuter trains, churches, and community groups serve as filters. From this pool of already similar candidates, people tend to form friendships with those who most share their values and interests. Finally, factors like a group's size and the specificity of its focus also are known to influence people's commitment to a group and the extent of their participation.

3.2 Influence of Social Setting

The setting of a relationship often influences how the relationship develops. Social settings influence people's behavior, and behavior influences the attributions people make about each other.

Goffman [1961] points to the importance of roles in daily life. One role may be dominant in a particular setting, but people may flexibly step into other roles at any time. For example, the role of father or mother is assumed mostly in the context of the home and family, whereas the role of manager is prominent in the context of work and place of business. However, modern technology and work practices cause roles to blur. For example, a manager may need to play the role of father in the workplace if his child visits him or school calls because of an incident involving his child.

Studies of friendship by Jackson [1977] found that the context in which a friendship is formed—at work vs. the community one grew up in, for instance—influences the dimensions along which similarity is highest. For example, friends made at work are more similar in their occupation level and economic standing than in ethnicity. In other words, people orient to different aspects of potential friends in different settings.

Other researchers also have studied the special context of the workplace. Since working relationships exist to accomplish tasks, factors such as skills and successful task outcomes are more important, while disclosure of personal information is less important [Gabarro 1990, p. 79]. However, task-centered relationships exert their own influence on relationship development. Completing a task successfully can lead team members to like each other more [Farris and Lim 1969] and promote greater satisfaction and team cohesion [Staw 1975]. Further, there is much evidence that the "more similar two people are in background and attitudes, the easier and more satisfying a task-based relationship will become" [Gabarro 1990, p. 102].

3.3 Social Structure

Social structures that knit individuals and constitute groups are a resource for computing matches. A social network is one such structure. The idea is simple: a social network is a graph that represents people and relationships between them. An area of sociology called structural analysis has formalized the concept, using mathematical graph theory to represent and analyze concepts such as the strength of social ties, central and peripheral social roles, information flow, and access to resources [Freeman 1998; Granovetter 1973; Wasserman and Faust 1994].

Like any research discipline, social network theorists must bound the social group of interest. Kinship, geographic boundaries, organizational divisions, participants in a specific online chat room, and contributors to a Usenet news group all have been used to define groups for social network studies. For example, Wellman [1997, 2001] has analyzed computer-mediated communication to show that relational ties over computer networks are essentially the same as social networks established in face-to-face settings.

In the whole network approach, the researcher attempts to identify all relationships among members of a group of interest. Whole network analyses have been used to identify patterns of information seeking as well as key individuals (gatekeepers) whose level of network connectivity make them effective in bridging between people who do not know each other [Allen 1977; Garton et al.

1997]. Whole network analyses have consistently revealed that the social and information seeking structure of organizations rarely follow formal organizational divisions. The whole network approach has also been used to identify who provides informal technical support to whom [Eveland et al. 1994].

In contrast, the egocentric approach takes an individual and her relations as the main focus of analysis. Research by Nardi et al. [2002] used egocentric networks to point out how individuals purposely activate their weak ties [Granovetter 1973] to achieve workplace and social goals. From an individual perspective, strong ties and weak ties are used and activated as necessary.

3.4 Motivation for Participation in Groups

Another large body of work has studied the problem of collective action. Sometimes referred to as social loafing [Karau and Williams 1993], or the tragedy of the commons [Hardin 1968; Ostrom 1990], the basic problem is that people contribute less effort when they work with others than when they work alone, and thus take more than their fair share of common resources. This relevance of this problem to our concerns is that simply bringing people together in a group does not guarantee participation: maybe no one will chat or post messages or answer questions, and the group will be stillborn.

The basic attack on this problem is to identify factors that motivate people to give more effort. Karau and Williams [1993] summarized the social loafing literature to derive a model that predicts various motivational factors such as making group members care more about the group and group outcomes and making them believe their effort matters to group outcomes. Kraut [2003] discussed the relevance of this work to CSCW, including identifying specific ways to bring about possible motivations. For example, creating a group whose members have similar interests will tend to make the group more attractive, and emphasizing to group members their unique skills or knowledge will tend to make them believe their efforts matter. In work following this approach, Ludford et al. [2004] experimented with discussion groups, and Beenen et al. [2004] experimented with a recommender system community. Both found that telling users something unique about their relationship to a topic motivated participation.

3.5 Conditions for Cooperative Action

Theoretical analysis of cooperative behavior yields important findings for system design. Kollock [1996] stated several fundamental requirements for cooperative behavior: (1) people must be likely to meet again in the future (else why behave constructively?), (2) people need to be able to identify each other (so being able to change online pseudonyms easily is problematic (see Friedman and Resnick [2001]), and (3) people need information about how others have behaved in the past (to decide whether to believe and trust them). In light of these requirements, exchanges between people whether commercial or informational, flirtatious or serious are more likely to succeed when they take place in online social spaces where both identities and interaction history persist.

On the Internet, these principles are visible in reputation systems. Users of online trading sites like EBay must be able to trust each other even if they've never traded with each other before: this is where the notion of a reputation comes in. Take an example: suppose Rahul is interested in Superman comics from the 1940s. He browses EBay and discovers that someone named Lex is selling a particular issue Rahul has been looking for with an asking price of $200. Should Rahul engage in a transaction with Lex? If Rahul sends the money, will he receive the comic? How soon will he get it? Will it be in the condition that Lex described? By creating mechanisms to answer such questions, reputation systems allowed the trickle of online trading to become a flood. People rate those they've bought from or sold to, and these ratings are publicized so that anyone considering a transaction can see how others have rated the other party on past transactions. As Resnick et al. [2000] put it, "reputation systems seek to establish the shadow of the future to each transaction by creating an expectation that other people will look back on it", thus encouraging good behavior.

4. RESEARCH AGENDA

Prior sections explored a range of concepts and issues concerning social matching. In this section, we outline a research agenda for the field, organized around a set of claims [Erickson 2003].

The claims address both social and technical concerns. Some of the claims are implicit in previous work; we simply present them and trace through their consequences. Other claims derive from our experience in recommender systems and social matching (e.g., Terveen et al. [1997], McDonald and Ackerman [2000], McDonald [2001], Terveen and Hill [2001], Amento et al. [2003], Cosley et al. [2003], McDonald [2003], Ludford et al. [2004]) and our intuitions about productive research directions to pursue. They also are motivated by our reading of the relevant social science literature.

We expect some of the claims to be controversial, and we cannot prove that any of them are true. We have formulated them to cover the issues we think are most important, to capture our intuitions about what is most likely to be true, and to articulate interesting questions that are worthy of additional research. Our most ambitious goal is to form the research agenda for the field of social matching. More modestly, we aim to stimulate discussion and identify opportunities for newcomers to the field.

We will cover the following claims in detail:

CLAIM 1. *Social matching systems need to use—and users will be willing to supply—relatively sensitive personal information.*

CLAIM 2. *Social matching algorithms necessarily embody a model of what makes a good match; making that model explicit leads to better matches.*

CLAIM 3. *Social networks are a useful tool for social matching. While whole (population-based) networks are problematic, egocentric (user-centered) networks offer several promising uses and raise interesting research challenges.*

CLAIM 4. *Creating effective introductions between users is crucial, but requires balancing the effectiveness of the introduction and the disclosure of personal data.*

CLAIM 5. *Size does matter for a social matching system but not as much as you might think.*

CLAIM 6. *Designers must consider possible contexts of interaction between matched users.*

6(a) *Properties of online spaces constrain the possibility for developing interpersonal relationships and group ties.*

6(b) *Interacting physically offers greater rewards and risks than interacting in a virtual space; when this is an option, systems must support users in exercising this option safely.*

CLAIM 7. *User feedback for a social match must be relative to a specific role or context; obtaining feedback is much harder than getting user ratings for books, movies, music, etc.*

CLAIM 8. *Evaluations of social matching systems should focus on users and their goals.*

The following discussions of each of the 8 claims provides the context for our research agenda.

CLAIM 1. *Social matching systems need to use—and users will be willing to supply—relatively sensitive personal information.*

Personal information ranging from personality attributes and religious beliefs to demographic data is highly sensitive. People are rightly concerned about how such information is handled by computational systems. Consistent with this attitude, Burke's survey [2002] of recommender system techniques dismisses recommender systems that categorize users based on demographic features as "likely to remain rare", since the "data most predictive of user preferences is likely to be information that users are reluctant to disclose".

For social matching systems, however, we argue (1) that personal information is necessary, and (2) there is evidence that users will be willing to provide it.

Our discussion of interpersonal attraction reminded us of an obvious point: the attractiveness of other people (for whatever purpose) greatly depends on their personal characteristics, from physical features to sense of humor to age and education, among many others. We further note that popular online dating services ask users to fill out extensive personal profiles that cover sensitive topics from religion to sex and just about everything in between. This suggests the action of a personal information-for-value proposition. In other words, users will be willing to provide personal data to the extent that they receive benefits from doing it.

Studies of user attitudes about disclosing personal data in e-commerce transactions give more reason for optimism. Ackerman et al. [1999] surveyed nearly 400 Internet users about their attitudes toward online privacy. The amount of concern varied across people for different types of data and under different scenarios. The authors identified three levels of concern: (1) privacy fundamentalists (17%) who were generally unwilling to disclose any type of personal data under any circumstances, (2) the pragmatic majority (56%) who had specific concerns and specific strategies for addressing their concerns, and (3) the marginally concerned (27%) who were willing to provide personal data in nearly any circumstances. This study suggests that a suitably designed system (e.g., with a reasonable, clearly stated data usage policy) would be acceptable to a large segment of Internet users, that is, all of the marginally concerned and many of the pragmatic majority.

Follow-up research paints an even more optimistic picture. Spiekermann et al. [2001] not only surveyed attitudes about disclosing data but also studied actual behavior in an e-commerce interaction. Experimental subjects engaged in an e-commerce dialogue in which some of the questions asked for personal information related only marginally to the task. Large majorities of the subjects answered nearly all of these questions—most strikingly, even the privacy fundamentalists answered about 86%. Apparently users perceive enough benefit from engaging in the dialogue with the system that they are willing to disclose personal information.

Research Questions

1. Which specific personal data raise the largest user privacy concerns (e.g., economic status Race Political leanings)?
2. When does the sheer volume of personal information collected begin to raise privacy concerns?
3. Can demographic data be effectively mined or inferred to create a demographic user profile?
4. What role is there for personal information like demographics in a social matching system used within an organization?

CLAIM 2. *Social matching algorithms necessarily embody a model of what makes a good match; making that model explicit leads to better matches.*

A social matching system necessarily embodies a model of who should be matched, even if that model is not made explicit. Clearly, what counts as a suitable match depends on the context and user goals. Designers should be explicit about their models and base them on empirical results from the social sciences where possible. This will make systems less opaque to users, clearly scope the conditions under which the system is appropriate to use, facilitate clearer evaluations, and enable subsequent research that can build on established results. We consider several examples.

As we mentioned, several systems assume that people are interested in casual chat with others who share their interests in a given topic. Is this true? Yes, but not the whole truth. Referring back to our presentation of social science results, recall that people generally are attracted to similar others. Interest similarity certainly is one facet of this. However, there are many others key aspects, including demographics and task considerations. To illustrate, consider a popular U.S. cult TV show, Buffy the Vampire Slayer. The show's fan base included large numbers of teenage girls. Perhaps more surprisingly, the show also attracted a great amount of academic attention. So, if you are a 15 year old girl browsing her favorite fan site, how likely are you to want to chat with a middle-aged scholar interested in an upcoming conference (c.f., http://www.slayage.tv/SCBtVS/index.htm)?

Social Net implicitly claims that people would like to meet others with whom they've been physically colocated. Sociological results lend some support to this claim. For example, Verbrugge's observations [1977] suggest that people who encounter each other in their daily rounds are likely to be quite similar. That is, if you share a commuter train with someone, there's a good chance you live in similar neighborhoods, have similar work and career circumstances, and have comparable education and socioeconomic status. And people tend to make friends (mate) with those that they meet the most. Whyte [1956], too, showed the role of physical proximity in friendship formation. On the other hand, Milgram's familiar stranger concept [1977] reminds us that people necessarily remain unacquainted with the vast majority of people who share their daily rounds; one simply doesn't have the time or energy to interact with or care about most of these people and so they remain strangers.

Expertise Recommender and Referral Web both draw on social network concepts to recommend experts. The designers took on not only the issue of who has particular expertise, but also issues such as whether an information seeker is comfortable approaching a particular person with a question, and who is likely to respond to the seeker. Social networks, particularly with the organizational focus of Expertise Recommender, model relationships that allow such questions to be (approximately) answered.

Finally, the work by Ludford et al. [2004] and Beenen et al. [2004] shows the utility of applying models that predict how to motivate contribution to a group activity.

Research Questions

1. Once designers use explicit social models to build their systems, what are the additional costs and benefits of making these models available to end users?
2. Are some social models better than others for certain social matching tasks? How can a model be matched to the task?
3. When complex social models are implemented in code, it will be difficult to implement all parameters of the model; how can designers identify the most important parameters to include?
4. How should models be communicated in the academic literature so that we can effectively share and build on a base of working knowledge?

CLAIM 3. *Social networks are a useful tool for social matching. While whole (population-based) networks are problematic, egocentric (user-centered) networks offer several promising uses and raise interesting research challenges.*

We believe that social network models will be useful for social matching systems even though there are challenges in applying a social science modeling technique to system design. The analyst does not face the same problems as users and designers. Our claim discusses prospects and issues for applying both whole and egocentric networks.

Recall that a whole network represents all relations between individuals in a population such as members of an organization. Ideally, the network combines data from all members. That is, the strength of the relationship (if any) between members A and B is based on everyone's opinions of that relationship. We question the utility of the whole network approach for social matching for several reasons.

First, systematic evaluation has demonstrated that whole network representations diverge from individual users' expectations [McDonald 2003]. In a comparison task, users identified specific cases where a whole network led to someone being recommended as a socially close expert whom they did not consider particularly close. Users see this as a fatal flaw: I want expert X recommended to me only if I think he is socially close to me not because the members of my organization in general think so. In other words, personal social networks are needed.

Second, we are cautious about approaches where large networks or long referral chains are visually presented to users as decision aids [Sack 2000; Smith and Fiore 2001; Kautz et al. 1997]. These systems are based on the intuition that users can extract information about the existing nature of relationships through visual processing of the network. However, people's ability to use and interpret social network diagrams has not been established. In particular, it has not been established that social network diagrams help users select others with whom to interact. Indeed, informal evidence from several system evaluations [Nardi et al. 2002; McDonald 2003] suggests that users do not find social networks intuitive or easy to use.

In contrast to whole networks, we claim that egocentric networks offer significant potential for social matching. There are rather complicated experiences, complications, and opportunities here so we trace through them in some detail. First, we consider the utility and limits of the simplest possible egocentric network. Second, we discuss how aggregating simple egocentric networks adds utility, while raising interesting challenges. Finally, we consider issues involved in acquiring relationship data for network modeling.

By a simple egocentric network, we mean one that represents data about the relationships of a single person, the ego. ContactMap [Nardi et al. 2002; Whittaker et al. 2004] is one system that builds and uses such networks. It processes a user's email archives to identify candidate individuals to add to the user's egocentric social network. It also offers a visual interface where users select and organize the individuals in their network. The interface facilitates awareness and recall of these individuals. Evaluation showed that users found value in how the system could identify patterns of infrequent communications or clusters of communication with similar email addresses, as well as allowing users to organize groups around personally relevant factors. Systems like ContactMap may support maintenance and activation of weak ties [Granovetter 1973; Nardi et al. 2002].

One of the great appeals of social networks is the access they provide to information and resources. Suppose Frank is evaluating Darla, a job applicant who has just received her computer science degree from the University of North Dakota. He doesn't have any contacts at the university, but he recalls that his friend Sharon was a professor there for years before joining his lab. He asks Sharon if she still has contacts in the department, and she responds by recommending her old colleague James, the director of undergraduate studies. Frank now has found a friend of a friend who can provide the necessary information, an evaluation of a job applicant. The great thing about a friend of a friend is that such a person is more likely to be able to give you new knowledge or provide different resources, and you have a mutual acquaintance who can introduce the two of you and serve as a social conduit that makes the interaction more likely to succeed.

We have just discussed the value of paths in a social network of length 1 (friends) and 2 (friends of friends). This begs the question what about longer paths? Here we are skeptical. When there are two or more intermediate parties, there is no one mutual acquaintance, no one person to do the introductions and grease the social wheels as needed. In a path Alice-Ben-Chuck-Dan, Alice would have to get Chuck—whom she doesn't know, and who doesn't have any obligations to her—to introduce her to Dan, yet another person she doesn't know. Alternatively, Ben could try to serve as a bridge to Dan, but there is no relationship between the two of them, either. In short, someone would need to make a set of decisions about introducing a person he knows to one he doesn't. This is unusual and awkward in everyday life.

We should note, however, that social networks aren't static. Perhaps Alice asks Ben to introduce her to Chuck. After interacting with Chuck for awhile, she then is comfortable enough to ask him to introduce her to Dan. In other words, in response to her need, she extended her social network. This is common, and a system must be able to update its models to capture such changes.

Systems face the problem of how to acquire information about social relationships. The dominant approach in the commercial world today is simple: ask users to tell you their friends. Popular sites like Friendster, Orkut, and LinkedIn operate this way. Any user can assert a relationship with any other user. The system records relationships and provides functions such as network browsing and messaging.

An alternative to the explicit entry approach is data mining. Various systems have explored techniques for discovering social relationships. ContactMap mined patterns of communication in email; ReferralWeb mined co-occurrences of names in Web documents; Adamic and Adar [2003] mined links between home pages and comembership in mailing lists.

Data mining and explicit entry approaches have different strengths and weaknesses and raise different issues. First, users must do explicit work in the explicit entry approach, while none is required in the data mining approach.

Second, the approaches to privacy are quite different. For example, Friendster and Orkut make all relationship data public: everyone can see everyone else's connections. If you don't like this, you don't use the system. For data mining approaches, on the other hand, this may not be an option. If a private information source like email archives is mined, then revealing relationships is very problematic. Even if a public source like the Web is mined, the extraction and repurposing of information may require special care.

Third, the two approaches differ in how details of a relationship are captured. For example, the public nature of relationship data in Orkut and the symmetric nature of links may exert social pressure to accept new friends, perhaps distorting the reality of social relationships. Also, while one can rate the strength of a relationship, such judgments are difficult to make. Data mining approaches, in contrast, have the potential to discover subtle details of a relationship. Email analysis, for example, can reveal that person A has a much closer (email) relationship to B than to C, and even that A's relationship to B is stronger than B's to A.

Research Questions

1. How accurate are algorithms for mining social networks? How do such networks compare to those collected by explicit user entry or techniques?
2. How can egocentric social networks be combined? How can different tie strengths be represented and shared among different users?
3. What do users infer from social network visualizations? What social network visualizations are effective and for what tasks?
4. For what tasks, if any, will people cross more than three edge connections in their social network?
5. How can a system recommend new connections within a network that users may be interested in making?

CLAIM 4. *Creating effective introductions between users is crucial, but requires balancing the effectiveness of the introduction and the disclosure of personal data.*

In everyday social interaction, making good introductions is an art. A key issue is deciding what information to include in the introduction. How much should be revealed? What information is relevant to the context (e.g., a dinner party or a professional meeting)? How much should be left to the parties to discover for themselves through conversation? Should any private information be mentioned?

Introduction is crucial for a social matching system because it sets the context for interaction: users are told something they have in common or why the system considered them a good match. Introducing users raises two challenges: the technical challenge of computing effective introduction information, and the social challenge of maintaining sensitive personal user information.

The technical challenge for some systems is that the matching process does not yield information that can be used for introductions. Consider Social Net. Social Net matches users based on recurring patterns of colocation, then handles introductions in an ingenious way by passing the task off to a mutual acquaintance of two people who have been matched. However, Social Net does not give the mutual acquaintance any information to use in making the introduction. So, if Charles is supposed to introduce Alice and Barbara, he is not told anything about where they've been colocated. So even if he is able to figure out some way to introduce them, it's unlikely to correspond to the reason the system matched them.

Social Net could be enhanced to provide such information. It would have to record the physical location(s) two users shared, not just that they were within a certain proximity. This also would distinguish between the quite different situation of two people who have been together multiple times in one location from two people who have been together in multiple distinct locations. Further, in order to craft a meaningful introduction, the system would need location labels (e.g., Boalt Hall), not just physical coordinates (e.g., latitude and longitude). Taking these steps would enable Social Net to meet the technical challenge of computing introduction information.

Computing an introduction for matched users can build on techniques for explaining system advice. Past research has shown that this is not an easy task: often the system's reasoning process is opaque or there are many possible explanations. Clancey [1987] detailed how the Guidon expert system had to be reengineered to generate explanations, and Herlocker et al. [2000] enumerated and evaluated various possible explanations for a recommender system. Group recommendation algorithms [O'Connor et al. 2001] also are relevant.

Once the technical challenge is surmounted, the harder problem remains, that is, the social problem of maintaining sensitive personal data. Again, Social Net provides an example. Suppose Alice and Barbara have been copresent at the European Grind coffeehouse between 4 and 6 pm and at the Kitty Kat Club between 12 and 2 am. Which information should be used to introduce them? Even the mutual acquaintance method doesn't solve the problem as Alice and Barbara might not want Charles to know where they've been. We propose several different techniques that may address this problem.

First, matching and introductions based on public information are less likely to raise privacy concerns. Web pages and Usenet posts are two examples of public information. Therefore, ReferralWeb's referral chains, which are based on co-authorship relations mined from public sources, are unproblematic. Note, however, that whether someone has visited a Web page is not public information. Therefore, a system like I2I that matches based on visits to Web pages must be more careful.

As an aside, we note that even the use of public information may raise concerns. Companies might aggregate data from different public sources to attempt to learn something new about a potential customer. A credit agency might attempt to decide whether to offer someone a loan or an insurance agency might decide whether to offer someone a policy. Users may rightly feel that this inference process has led to the discovery of sensitive personal information that has harmed their interests.

A second simple and minimal technique for preserving privacy is opting in. If users explicitly state that they are willing to disclose to others the Web page they are visiting, the music they're listening to, and so on, this is some assurance. (Note that projects such as FOAF (http://www.foaf-project.org/) let users create machine-readable representations of personal information. To the extent such representations are used, users retain control over both whether to participate and what information is disclosed.)

However, we are skeptical that users will give blanket access to their information. For example, users might be willing to disclose their interest to others when they're browsing the Web for recreational interests but not when they're browsing a competitor's Web site to develop a business strategy. We suggest a technique that gives users greater control, match previewing. When a system computes a match, it can notify each user what information would be disclosed (e.g., Someone else shares your interest in The White Stripes), and it would be up to users to decide whether they wanted to proceed with the match. The match would proceed only if both users agreed. To accommodate users who browse sensitive information regularly, the system might offer the option to ban certain topics from ever being used in a match.

This proposal is similar to Hong and Landay's [2004] approach to the disclosure of location information in ubiquitous computing applications. When a user's location is requested (e.g., to be displayed as part of a status line in an enhanced Instant Messenger client), the user may decline, allow once, or specify a range of circumstances under which a location request from the requesting user will be granted. In the latter case, a particular situation prompted the user to state a general rule.

Research Questions

1. What types of information are most important for crafting an effective introduction between two people?
2. Can a system use a mutual acquaintance as an effective way of introducing two others? Will the bridging person even take that action?
3. When does aggregation from public data sources lead to inference of sensitive personal information? How can a system inform users of the contents of their profiles and give them control over the contents?
4. What do users infer from exceptional events ("He always shows me his current location, but right now he's hidden it; he must be doing something interesting")? What are the privacy implications?
5. Can users judge the consequences of rules for matching and introduction, that is, when the rules may impact their privacy?

CLAIM 5. *Size does matter for a social matching system but not as much as you might think.*

For social matching systems, there are two points where the number of users is an issue: first, the total users of a system (potential matches), and second, the number of users brought together in a match.

Typically, more total users are better since this makes it more likely that good matches can be found for any given user. However, more users are not always required. Recall that Expertise Recommender operated within a small organization, a company with just over 100 employees. Yet evaluations showed that users considered its recommendations generally accurate and useful [McDonald 2001]. Indeed, evidence suggests that expertise is quite contextually specific, and therefore that expertise location is more likely to be successful when the scope of the match is limited appropriately [McDonald and Ackerman

1998]. Further, systems that operate within an organization benefit from the significant similarity and shared context of the users. Thus, small organizations are good candidates to benefit from at least one class of social matching systems, expertise recommenders. More generally, Shirky [2004] argues for the importance of systems that operate within a small, well-defined context and incorporate knowledge of the context directly into their design. He offers examples developed within a university, including a system for rating professors, one for coordinating purchases, and another for commenting on video art.

Concerning the number of users actually brought together in a match, smaller group sizes typically are appropriate. For many user goals (assuming an effective matching model and algorithm), users do not want to be matched with lots of others. For example, most people only want to date one other person at a time and probably only want to browse a fairly limited number of potential matches before picking one or a few to contact. Even in situations where group interaction is desired, say a chat about a shared interest, too large a group leads to conversational confusion and overload.

Research Questions

1. When do social matching systems require large user populations to be effective, and when can they work effectively within limited populations?
2. What factors, for example, user goals, prior relationships, overlap in interests influence effective size for a matched group?
3. To what extent do social matching systems face the critical mass system of groupware systems [Grudin 1994]?

CLAIM 6. *Designers must consider possible contexts of interaction between matched users.*

6(a) *Properties of online spaces constrain the possibility for developing interpersonal relationships and group ties.*

6(b) *Interacting physically offers greater rewards and risks than interacting in an online space; when this is an option, systems must support users in exercising this option safely.*

We distinguish between two main contexts for interaction: online, in virtual spaces, and face-to-face, in physical space. Finer-grained distinctions also can be made, for example, private vs. public physical places or intraorganizational vs. public virtual spaces.

User goals for a social interaction can differ. A person may be interested in just a casual chat or in getting a specific question answered. On the other hand, sometimes people are looking to develop a lasting relationship, either purely social or professional.

The work on cooperative interaction by Kollock [1996] and others shows that developing real, trusting relationships requires the "shadow of the future" [Resnick et al. 2000]. People must be able to see and understand past actions of others and must have the expectation that their current actions will be visible to others in the future. Thus, Claim 6(a) tells us an online space must support these properties for people to be able to develop a real relationship. Anonymous exchanges in ephemeral spaces (e.g., chat rooms that disappear when the last participant leaves) offer little chance for people to form meaningful relationships, personal or professional.

System designs are moving in this direction. Synchronous technologies such as chats and instant messaging that initially were ephemeral now often allow for conversational histories to be stored and accessed. This happened with the asynchronous medium of Usenet news, too. People once thought of their messages as eventually fading out of sight. Yet the emergence of DejaNews (now part of Google) in the mid-1990s turned Usenet into a permanent, globally searchable record of social interaction.

We suggest one promising research direction involving opportunistic social matching systems. Currently, systems like I2I place users into dynamically created chat spaces. The advantage is that, in principle, the system can create as specific a match as possible. For example, if enough people are reading documents about The White Stripes, they can be matched; if a few people are reading documents about The White Stripes and a few reading about each of a handful of other contemporary garage rock bands, they could be matched, and so forth. That is, the granularity of the match is not predetermined. However, there is a problem. It is not immediately obvious how to offer both opportunistic matching and persistent social spaces.

Here is one approach: dynamically cluster users in ephemeral groups, but link these ephemeral groups to one or more closely-related persistent social places. For example, garage rock fans could be given an ephemeral chat room that contains links to several relevant Usenet groups or Web-based discussion forums. The metaphor is a dynamic, ephemeral foyer or lobby to a persistent room. Initial and casual chat could occur in the chat room with users moving to a persistent forum for more substantial exchanges. This idea is related to systems like Butterfly [van Dyke et al. 1999] that recommend online conversations whose text matches a user query.

Claim 6(b) reminds us that the most desirable social interaction usually takes place between people who are physically colocated, talking, gesturing, and sharing all the rich informational and affective cues available in face-to-face conversation. But it also reminds us that face-to-face interaction is riskier: not only might one become embarrassed or inarticulate, one could even be in danger. We all have heard about predators meeting people on the Internet, luring them into meeting, then kidnapping or murdering them. So what obligation, if any, does the designer of a social matching system have to help users minimize the risks involved in meeting face-to-face?

First, a system obviously should not reveal any personal information about a person without that person's consent; Claim 4, on introductions, goes into detail about this. Second, a system can provide ways for users to converse anonymously online with the decision to reveal personal information or arrange meetings left up to them. This functionality is provided by all online dating systems.

People are good at finding ways to combine online and physical interaction. There is a great opportunity for systems to provide new types of support for this. Meetup.com is a Website that lets people arrange physical meetings. It gained large a amount of attention in late 2003 and early 2004 because of its use in the US Presidential campaign, but it is widely used for topics other than politics, too. Meetup is very popular with people who want to practice conversational Japanese (http://japanese.meetup.com), show off their Pugs and meet other Pugs and their owners (http://pug.meetup.com), and meet with fellow knitters (http://knitting.meetup.com). A key feature of meetups is that they happen in public places such as coffee shops, bookstores, and libraries. This greatly minimizes the risk of meeting strangers.

Similarly, Ling and Yttri [1999] give fascinating accounts of how Norwegian teenagers incorporate new technology into relationship formation. They describe three phases. It may begin with a chance encounter among different groups of friends in a public space, perhaps resulting in the exchange of cell phone numbers. Then a boy and girl might move to one-on-one interaction via text messaging and cell phone conversation. This lets them get to know each other at a safe distance and postpone the risks involved in moving the relationship to another level. Finally, if there is mutual interest and comfort, the relationship moves back to face-to-face interaction, again in a public space, either one-on-one or with a few friends (double dating).

The risk involved in a meeting can be decreased by matching within a constrained context. In current work, the first author is exploring the use of matching within an organization such as a church or synagogue, work group, or neighborhood group. These organizations can be large enough that people don't know each other personally so matching is useful. Further, people are likely to trust others who share their organizational affiliations [McKnight et al. 1998] and may be more likely to engage in interactions. From a social psychological perspective, this is exploiting group identity to form personal bonds [Prentice et al. 1994].

Research Questions

1. How can we combine the benefits of opportunistic social matching and persistent online spaces?
2. How can a system provide support for novel and flexible combinations of physical and online interaction? What social cues can a system provide to facilitate transitions between physical and online interaction?
3. What are the benefits and drawbacks of constraining social matching to operate within a specific organizational context?
4. Are there technical means or social norms that can make physically situated social matching safer for users?

CLAIM 7. *User feedback for a social match must be relative to a specific context; obtaining such feedback is much harder than getting user ratings for books, movies, music, and so on.*

Based on a profile of user preferences in a domain, a recommender system predicts items a user will like. Users may rate any of the predicted items, giving the system additional information about their preferences. The tight loop between expressing preferences, building profiles, computing recommendations, receiving recommendations and rating more items is essential to the success of recommender systems.

Social matching systems should be able to use a similar feedback loop. After users are matched, they can indicate their happiness with the match so the system can update user profiles and social models as necessary. However, the contextual nature of human activity raises some complications.

Goffman [1961] reminded us that people play different roles at different times, for example, father, manager, friend. Jackson [1977] found that the context in which a friendship is formed leads people to orient to different personal factors. Together, they imply that one person's rating of another—feedback concerning their desirability as an actual or potential match—must be relative to a specific role or context.

This distinguishes social matching systems from recommender systems in general. In systems that recommend products like movies or books, items are given a single rating. For example, a movie might be rated from 1 to 5 stars. It certainly is possible to conceive of a movie along multiple dimensions such as story, acting, and special effects, and researchers have discussed this idea. However, it has not been tried widely, and initial experiments by The GroupLens research group at The University of Minnesota showed that rating movies on multiple dimensions yielded no benefits.

In contrast, consider some different ways a person might be judged, for example, as a teacher, mentor, a trader of Grateful Dead tapes, or a potential rock-climbing partner. We argue that a single rating of the person would not suffice: a person can be better or worse, more or less trustworthy in each of these ways. Some roles are closely related, while others are quite distinct. For example, when looking for a rock-climbing partner, factors such as physical skill and strength, the ability to stay calm under pressure, and loyalty to one's partner are important. A person may have more chance to show these off in other outdoor sports than in his role as a churchgoer. If so, this means that an evaluation of the person formed in the former context would be more relevant than one formed in the latter.

It is an interesting and open issue how portable the ratings or reputation a user earns within one context is to other context. Surely the reputation one earns on EBay should be transferable to other online trading sites (ignoring competitive barriers for the moment), but should it be transferable to a newsgroup on the Perl programming language?

This claim also emphasizes the importance of making user goals for a match and the system's model of what counts as a good match explicit. It is easiest to do this when a system operates in a focused domain. Consider EBay, which supports the process of buying and selling goods. A buyer is a good match for a seller when she wants to purchase something he has to sell. Further, the parties to a transaction must trust each other to fulfill their side of the bargain. Thus, feedback is relatively straightforward: did the other party fulfill his or her obligations? Was the item in the described condition? Was it sent on time?

However, sometimes a social matching system serves more complicated user goals and thus getting feedback is harder. Let's illustrate with Jake, a user of an online dating system. Jake creates a profile and eventually is matched with someone else, say Rose. Sadly for Jake, he doesn't consider the match a success. What can he do to let the system know so he'll get better matches in the future? To begin, he must indicate which aspects of the match were unsatisfactory; in other words, he must indicate what about Rose he didn't like. Was it her sense of humor, politics, religious beliefs, or what?

Let's be precise. Although we're talking of things about Rose that Jake didn't like, the system must update its profile of Jake so that it can make better matches for him in the future. An effective way to do this would be to present the various aspects of the model to Jake, let him indicate which ones were problematic (e.g., sense of humor) and adjust them accordingly. This adjustment could consist of two things: the system could change its profile of Jake, for example, that he does not like people with a sarcastic sense of humor, or change the weights it assigns to various factors in computing a match, for example, by adding weight to the compatibility (or lack thereof) in sense of humor. Such changes to the parameters of the social model might apply just to a single user or to all users.

Details of the context, the meaning of feedback, and the way feedback is gathered can make it more difficult to get good feedback. The discussion by Resnick et al. [2000] on EBay's feedback system is very instructive. After a seller and buyer engage in a transaction, they can give each other a score (1, 0, or −1) and leave written comments. Each person's score and comments are public to any EBay user. Resnick notes several reasons why honest feedback is hard to come by. First, since feedback is public, people often negotiate with each other before posting negative feedback. One party may even blackmail the other, threatening to post bogus negative feedback unless the other agrees to post positive feedback. The feedback system leads to this behavior by making ratings public and making it clear that the other party's performance is being rated.[1]

In contrast, our example of Jake and Rose suggests techniques that may allow better feedback to be obtained by making it clear to users that it is their own profiles that need to be updated, or keeping feedback private when possible. Research is necessary to determine when these techniques are applicable. For example, EBay users must be able to see the reputation of other users before engaging in a transaction with them. And it would be unfair for users to be unable to see their own reputation in case they had received bogus negative feedback.

Research Questions

1. How portable should reputations be? What data representations and adaptation techniques are required to allow reputation portability?
2. When obtaining feedback for a match (actual or potential), how can the system determine which aspects of the match deserve the credit or blame?

[1]This is analogous to a problem in explicit social network systems like Friendster that we mentioned in Claim 3. Each user's network is publicly visible which often influences users to accept people as friends when they might not really be friends. Making social behavior visible is not the solution to every socio-technical dilemma or trade-off. In these two examples, making behavior public has caused some unusual consequences.

3. How can a system determine what action to take in response to user feedback, for example, when to update its profile of a user and when to update the parameters of its social model?
4. What design techniques and policies increase the chance of a system obtaining honest feedback from users?
5. In an organizational setting, feedback or ratings of workers in a social matching system (like an expertise recommender) could be confused with performance evaluations. How can this be avoided or mitigated?

CLAIM 8. *Evaluations of social matching systems should focus on users and their goals.*

The essential evaluation metric for a social matching system is whether or not users achieve their goals. Some goals are more information-oriented and objective, for example, finding someone who can answer a particular question. Some goals concern recreation, leisure, or socializing, for example, finding someone you enjoy talking to. User goals should be made explicit, and systems should be evaluated with respect to these goals.

Focusing the evaluation of social matching on users and their goals should be natural. After all, users already are central since the system's function is to match users. However, the dominant approach to evaluation within related fields is different. A social matching system is a sort of information-retrieval system, as systems like I2I and Yenta make explicit. IR systems traditionally were evaluated in ways that abstracted away from real users engaged in real tasks (although there are exceptions, see Turpin and Hersh [2001] for examples). Queries were defined for a given document collection, a set of people determined which documents were relevant to each query, then systems were evaluated in terms of how many relevant documents they returned (recall) and how many of the documents they returned were relevant (precision). Precision and recall serve as objective ways to compare different IR algorithms.

Recommender systems are commonly evaluated using offline analysis with a database of ratings. The ratings of some items by some users are (temporarily) removed from the database. Based on the remaining ratings, the system predicts the ratings those users would have given those items. The difference between the real ratings and the system prediction is then computed. A popular metric is the Mean Absolute Error, or MAE, which measures the average absolute deviation between predicted and actual ratings. MAE can serve as an objective way to compare different recommender algorithms.

As a field matures, standards become important. Commonly accepted task definitions, datasets, and metrics allow researchers to tell when progress is being made and identify opportunities for improvement [Whittaker et al. 2000]. Social matching needs appropriate metrics that consider factors such as the estimated accuracy of a match and the size of a matched group, and that measure them relative to some notion of user goals.

Objective metrics are good as far as they go. However, there is much they don't tell us, for example, it is not clear that increases in precision, recall, or MAE lead to any perceptible user benefits. Turpin and Hersh [2001] conducted a study in which subjects used two different IR engines, one of which was significantly more accurate than the other. Yet, in both cases, subjects were about as successful in completing their tasks. Swearingen and Sinha [2001, 2002] found that several properties of a recommender system, such as the availability of explanations for recommendations, significantly affected user ratings of the system. See Herlocker et al. [2004] for additional discussion of these issues.

Qualitative and quantitative methods, including surveys, interviews, observations of use situations, and instrumented code are suitable evaluation techniques. We particularly recommend the use of scenario-based evaluations [Carroll and Rosson 1992]. In this approach, evaluation is centered around topic areas and problems that are specific to the subjects' tasks and organizational setting. This approach was used in evaluating the Expertise Recommender. Extensive fieldwork characterized the organizational setting and user goals to be addressed by the system [McDonald and Ackerman 1998]. A set of scenarios was extracted from the field observations and study artifacts and used as the basis for several evaluations [McDonald 2001, 2003]. The scenarios provided a catalyst for the users to inspect, reflect on, and evaluate the information the system provided.

Research Questions

1. What are appropriate objective metrics for evaluating social matching systems? Are there equivalents of precision, recall, and MAE?
2. How can usability evaluation methods be used to create more realistic evaluations of social matching systems?

5. CONCLUSION

Social matching systems are a type of recommender system that bring people together rather than recommend items to people. They offer great potential to increase social interaction and foster collaboration among users within organizational intranets and on the Internet as a whole. Yet despite this potential, social matching systems are not well-established; indeed, there is not even a generally recognized name for the field. Thus, it is not surprising that the intellectual foundations, the nature of the design space, the set of key research challenges, and the roster of appropriate methods are all ill-defined.

This article begins to remedy this situation. We defined the scope of social matching systems by distinguishing them from recommender systems in general and situating them with respect to related fields. We reviewed literature from the social sciences that is relevant to the design of social matching systems. Finally, we stated a research agenda for the field organized around a set of claims. These claims embody our understanding of what issues are most important to investigate, our beliefs about what is most likely to be true, and our suggestions of specific research directions to pursue. We offer these claims to stimulate and focus research on social matching and present opportunities for newcomers to begin work. We are pursuing this research agenda ourselves, and we hope this article will encourage others to do so as well.

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REFERENCES

ALLEN, T. J. 1977. *Managing the Flow of Technology*. MIT Press, Cambridge, MA.

ACKERMAN, M. S. 1994. Augmenting the organizational memory: A field study of answer garden. In *Proceedings of the Conference on Computer Support Cooperative Work (CSCW'94)*. Chapel Hill, NC. ACM Press, 243–252.

ACKERMAN, M. S. AND MCDONALD, D. W. 1996. Answer Garden 2: Merging organizational memory with collaborative help. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work (CSCW'96)*. 97–105.

ACKERMAN, M. S., CRANOR, L. F., AND REAGLE, J. 1999. Privacy in e-commerce: Examining user scenarios and privacy preferences. In *Proceedings of the ACM Conference on Electronic Commerce (EC'99)*. 1–8.

ADAMIC, L. A. AND ADAR, E. 2003. Friends and neighbors on the web. *Social Netw. 25*, 3 (July), 211–230.

AMENTO, B., TERVEEN, L., HILL, W., HIX, D., AND SCHULMAN, R. 2003. Experiments in social data mining: The TopicShop system. In *ACM Trans. Comput.-Hum. Interact. 10*, 1, 54–85.

BAYM, N. 1993. Interpreting soap operas and creating community: Inside a computer-mediated fan culture. *J. Folklore Res. 30*, 143–176.

BEENEN, G., LING, K., CHANG, K., WANG, X., RESNICK, P., AND KRAUT, R. 2004. Using social psychology to motivate contributions to online communities. In *Proceedings of the ACM Conference on Computer-Supported Cooperative Work*. To appear.

BERSCHEID, E. AND REIS, H. T. 1998. Attraction and close relationships. In *The Handbook of Social Psychology*. D. T. Gilbert, S. T. Fiske, and G. Lindzey, Eds. Oxford University Press 193–254.

BRADNER, E. AND MARK, G. 2002. Why distance matters: Effects on cooperation, persuasion and deception. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work (CSCW'02)*. 226–235.

BREESE, J. S., HECKERMAN, D., AND KADIE, C. 1998. Empirical analysis of predictive algorithms for collaborative filtering. In *Proceedings of the 14th Conference on Uncertainty in Artificial Intelligence (UAI'98)*. G. F. Cooper and S. Moral, Eds. Morgan Kaufmann, San Francisco, CA. 43–52.

BUDZIK, J., BRADSHAW, S., FU, X., AND HAMMOND, K. J. 2002. Clustering for opportunistic communication. In *Proceedings of the International WWW Conference*. Honolulu, HA.

BURKE, R. 2002. Hybrid recommender systems: Survey and Experiments. *User Model. User-Adapt. Interact. 12*, 4, 331–370.

CARROLL, J. M. AND ROSSON, M. B. 1992. Getting around the task-artifact cycle: How to make claims and design by scenario. *ACM Trans. Inform. Syst. 10*, 181–212.

CLANCEY, W. J. 1987. From Guidon to Neomycin and Heracles in twenty short lessons. *The AI Magazine 7*, 3, 40–60.

COHEN, D., JACOVI, M., MAAREK, Y. S., AND SOROKA, V. 2002. Livemaps for collection awareness. *Int. J. Hum.-Comput. Stud. 56*, 1, 7–23.

COSLEY, D., LUDFORD, P., AND TERVEEN, L. 2003. Studying the effect of similarity in online task-focused interactions. In *Proceedings of ACM Conference on Supporting Group Work (GROUP'03)*. To appear.

DIEBERGER, A. 1997. Supporting social navigation on the World Wide Web. *Int. J. Hum.-Comput. Stud. 46*, 6, 805–825.

DONATH, J., KARAHALIOS, K., AND VIEGAS, F. 1999. Visualizing conversations. In *Proceedings of the Hawai International Conference on System Science (HICSS-32)*. Maui, HI.

DOURISH, P. AND BLY, S. 1992. Supporting awareness in a distributed work group human factors. In *Proceedings of ACM Conference on Human Factors in Computing Systems (CHI 92)*. 541–547.

DOURISH, P. AND CHALMERS, M. 1994. Running out of space: Models of information navigation. In *Proceedings of Computer-Human Interaction (HCI'94)*.

ERICKSON, T., SMITH, D. N., KELLOGG, W. A., LAFF, M. R., RICHARDS, J. T., AND BRADNER, E. 1999. Socially translucent systems: Social proxies, persistent conversation, and the design of 'babble'. In *Proceedings of Computer-Human Interaction (CHI'99)*. ACM Press.

ERICKSON, T. AND KELLOGG, W. A. 2000. Social translucence: An approach to designing systems that mesh with social processes. *ACM Trans. Comput.-Hum. Interact. 7*, 1, 59–83.

ERICKSON, T. 2003. Designing visualizations of social activity: Six claims. In *Extended Abstracts of Computer-Human Interaction (CHI'03)*.

EVELAND, J. D., BLANCHARD, A., BROWN, W., AND MATTOCKS, J. 1994. The role of "help networks" in facilitating use of CSCW tools. In *the Proceedings of the ACM Conference on Computer-Supported Cooperative Work (CSCW'94)*. 265–274.

FARRIS, G. F. AND LIM F. G., JR. 1969. Effects of Performance on leadership, cohesiveness, influence, satisfaction, and subsequent performance. *J. Appl. Psych. 53*, 490–497.

FISCHER, C. 1982. To *Dwell Among Friends: Personal Networks in Town and City*. University of Chicago Press, Chicago, IL.

FISCHER, C. S., JACKSON, R. M., STUEVE, C. A., GERSON, K., AND JONES, L. M. 1977. *Networks and Places: Social Relations in the Urban Setting*. Free Press, New York, NY.

FISH, R. S., KRAUT, R. E., ROOT, R. W., AND RICE, R. E. 1992. Evaluating video as a technology for informal communication. In *Proceedings of the ACM Conference on Human Factors in Computing Systems (CHI'92)*. 37–48.

FONER, L. 1996. A multi-agent referral system for matchmaking. In *Proceedings of the 1st International Conference on the Practical Application of Intelligent Agents and Multi-Agent Technology*. (April) London, UK. 245–261.

FREEMAN, L. 1998. Computer programs in social network analysis. *Connections 11*, 26–31.

FRIEDMAN, E. AND P. RESNICK. 2001. The social cost of cheap pseudonyms. *J. Econom. Manage. Strat. 10*, 2, 173–199.

GABARRO, J. J. 1990. The Development of Working Relationships. In *Intellectual Teamwork*. J. Galegher, R. E. Kraut, and C. Egido, Eds. Lawrence Erlbaum Associates. 79–110.

GARFINKEL, H. 1967. *Studies in Ethnomethodology*. Prentice-Hall.

GARTON, L., HAYTHORNTHWAITE, C., AND WELLMAN, B. 1997. Studying online social networks. *J. Comput. Mediated Comm. 3*, 1 (June).

GOFFMAN, E. 1961. *The Presentation of Self in Everyday Life*. Anchor-Doubleday, New York, NY.

GOLDBERG, K., ROEDER, T., GUPTA, D., AND PERKINS, C. 2001. Eigentaste: A constant time collaborative filtering algorithm. *Inform. Retrieval J. 4*, 2, 133–151.

GRANOVETTER, M. 1973. The strength of weak ties. *Amer. J. Sociol. 78*, 6, 1360–1380.

GRINTER, R. E. AND ELDRIDGE, M. 2001. "y do tngrs luv 2 txt msg?" In *Proceedings of 7th European Conference on Computer Supported Cooperative Work (ECSCW'01)*. (Sept.) Bonn, Germany. 18–20. 219–238.

GRINTER, R. E. AND PALEN, L. 2002. IM in teenage life. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work (CSCW'02)*. (Nov.) New Orleans, LA. 16–20. 21–30.

GRUDIN, J. 1994. Eight challenges for developers. *Comm. ACM 37*, 1, 93–104.

HARDIN, G. 1968. The tragedy of the commons, *Science*. *162*, 1243–1248.

HERLOCKER, J., KONSTAN, J., AND RIEDL, J. 2000. Explaining collaborative filtering recommendations. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work (CSCW'00)*.

HERLOCKER, J., KONSTAN, J. A., TERVEEN, L. G., AND RIEDL, J. T. 2004. Evaluating Collaborative Filtering Recommender Systems. *ACM Trans. Inform. Syst.* (Special Issue on Recommender Systems Algorithms, and Evaluation). *22*, 5–53.

HILL, C. T., RUBIN, Z., AND PEPLAU, L. A. 1976. Breakups before marriage: The end of 103 affairs. *J. Social Issues 32*, 1, 147–168.

HILL, W. C., HOLLAN, J. D., WROBLEWSKI, D., AND MCCANDLESS, T. 1992. Edit wear and read wear. In *Proceedings of Computer-Human Interaction (CHI'92)* (May) Monterey, CA. 3–9.

HILL, W. C. AND HOLLAN, J. D. 1994. History-enriched digital objects: Prototypes and policy issues. *The Inform. Soc. 10*, 2, 139–145.

Hill, W. C., Stead, L., Rosenstein, M., and Furnas, G. 1995. Recommending and evaluating choices in a virtual community of use. In *Proceedings of Computer-Human Interaction (CHI'95)* (May) Denver, CO. 194–201.

Hill, W. C. and Terveen, L. G. 1996. Using frequency-of-mention in public conversations for social filtering. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work (CSCW'96)* (Nov.) Boston MA. 106–112.

Hong, J. I. and Landay, J. A. 2004. An architecture for privacy-sensitive ubiquitous computing. In *Proceedings of The 2nd International Conference on Mobile Systems, Applications, and Services (MOBISYS'04)*.

Hudson, S. and Smith, I. 1996. Techniques for addressing fundamental privacy and disruption tradeoffs in awareness support systems. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work (CSCW'96)*. 248–257.

Jackson, R. M. 1977. Social structure and process in friendship choice. In *Networks and Places: Social Relations in the Urban Setting*. Fischer et al., Eds. Free Press, NY. 59–78.

Kandel, D. 1978. Similarity in real-life adolescent friendship pairs. *J. Personal. Soc. Psych. 36*, 306–312.

Karau, S. J. and Williams, K. D. 1993. Social loafing: A meta-analytic review and theoretical integration. *J. Personal. Soc. Psych. 65*, 4, 681–706.

Kautz, H., Selman, B., and Shah, M. 1997. ReferralWeb: Combining social networks and collaborative filtering. *Comm. ACM 30*, 3.

Kobsa, A. 2001. Generic User modeling systems. In *User Modeling and User-Adapted Interaction* 2nd Ed. Kluwer, 49–63.

Kollock, P. 1996. Design principles for online communities. *Harvard Conference on the Internet and Society*. Also published in *PC Update 15*, 5 (June 1998), 58–60.

Konstan, J. A., Miller, B. N., Maltz, D., Herlocker, J. L., Gordon, L. R., and Riedl, J. 1997. GroupLens: Applying collaborative filtering to usenet news. *Comm. ACM 40*, 3, 56–58.

Kraut, R. E., Egido, C., and Galegher, J. 1990. Patterns of contact and communication in scientific research collaboration. In *Intellectual Teamwork*. J. Galegher, R. E. Kraut, and C. Egido, Eds. Lawrence Erlbaum Associates. 149–171.

Kraut, R. 2003. Applying social psychological theory to the problems of group work. In *HCI Models, Theories and Frameworks: Toward A Multidisciplinary Science*. J. M. Carroll, Ed. Morgan Kaufman, New York, NY. 325–356.

Lang, K. 1995. Newsweeder: Learning to filter netnews. In *Proceedings of the 12th International Conference on Machine Learning*. 331–339.

Lieberman, H. 1997. Autonomous interface agents. In *Proceedings of Computer-Human Interaction (CHI'97)*. Atlanta, GA. 67–74.

Lieberman, H., Fry, C., and Weitzman, L. 2001. Exploring the Web with reconnaissance agents. *Comm. ACM 44*, 8, 69–75.

Ling, R. and Yttri, B. 1999. Nobody sits at home and waits for the telephone to ring: Micro and hypercoordination through the use of the mobile telephone. Telenor Report. Available at http://www.telenor.no/fou/program/nomadiske/articles/08.pdf.

Ludford, P., Cosley, D., Frankowski, D., and Terveen, L. G. 2004. Think different: Increasing online community participation using uniqueness and group dissimilarity. In *Proceedings of Computer-Human Interaction (CHI'04)*.

Maes, P. 1994. Agents that reduce work and information overload. *Comm. ACM 37*, 7, 31–40.

McCarthy, J. F. and Anagnost, T. D. 1998. MusicFX: An arbiter of group preferences for computer supported collaborative workouts. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work (CSCW'98)*. 363–372.

McCarthy, J. F., Nguyen, D. H., Rashid, A. M., and Soroczak, S. 2003. Proactive displays and the experience UbiComp project. *Ubicomp 2003 Adjunct Proceedings*.

McDonald, D. W. and Ackerman, M. S. 1998. Just Talk to me: A field study of expertise location. In *Proceedings of the ACM Conference on Computer-Supported Cooperative Work (CSCW'98)*. 315–324.

McDonald, D. W. and Ackerman, M. S. 2000. Expertise recommender: A flexible recommendation architecture. In *Proceedings of the ACM Conference on Computer-Supported Cooperative Work. (CSCW'00)*. 231–240.

McDonald, D. W. 2000. Supporting nuance in groupware design: Moving from naturalistic expertise location to expertise recommendation. Unpublished dissertation, University of California, Irvine, Irvine, CA.

McDonald, D. W. 2001. Evaluating expertise recommendations. In *Proceedings of the International Conference on Supporting Group Work (GROUP'01)*.

McDonald, D. W. 2003. Recommending collaboration with social networks: A comparative evaluation. In *Proceedings of the ACM Conference on Human Factors in Computing Systems (CHI'03)*. 593–600.

McKnight, D. H., Cummings, L. L., and Chervany, N. L. 1998. Initial trust formation in new organizational relationships. *Academy Manage. Revi. 23*, 3, 473–490.

Milgram, S. 1977. *The Individual in a Social World*. Addison-Wesley, Reading, MA. 51–53.

Mooney, R. J. and Roy, L. 2000. Content-based book recommending using learning for text categorization. In *Proceedings of the 5th ACM Conference on Digital Libraries*. San Antonio, TX. 195–204.

Nardi, B. A., Whittaker, S., and Schwarz, H. 2002. NetWORKers and their activity in intensional networks. *J. Collab. Comput. (1–2)*. 205–242.

Nardi, B. A., Whittaker, S., Issacs, E., Creech, M., Johnson, J., and Hainsworth, J. 2002. Integrating communication and information through contact map. *Comm. ACM 45*, 4, 89–95.

O'Connor, M., Cosley, D., Konstan, J. A., and Riedl, J. 2001. PolyLens: A recommender system for groups of users. In *Proceedings of the European Conference on Computer Supported Cooperative Work (ECSCW'01)*. Bonn, Germany 199–218.

Ostrom, E. 1990. *Governing the Commons: The Evolution of Institutions for Collective Action*. Cambridge University Press, Cambridge, UK.

Parks, M. R. and Robert, L. D. 1998. Making MOOsic: The development of personal relationships online and a comparison to their offline counterparts. *J. Soc. Person. Relation. 15*, 517–537.

Preece, J. 1998. Empathic communities: Reaching out across the web. *Interactions* 32–43.

Preece, J. 1999. Empathic communities: Balancing emotional and factual communication. *Interdiscipl. J. Hum.-Comput. Interact.* 12, 1, 63–77.

Prentice, D. A., Miller, D. T., and Lightdale, J. R. 1994. Asymmetries in attachments to groups and to their members: Distinguishing between common-identity and common-bond groups. *Personal. Soc. Psych. Bull. 20*, 5, 484–493.

Resnick, P., Iacovou, N., Suchak, M., Bergstrom, P., and Riedl, J. 1994. GroupLens: An open architecture for collaborative filtering of netnews. In *Proceedings of the ACM Conference on Computer-Supported Cooperative Work (CSCW'94)*. Chapel Hill, NC. 175–186.

Resnick, P., Zeckhauser, R., Friedman, E., and Kuwabara, K. 2000. Reputation Systems. *Comm. ACM.*

Rich, E. 1979. User Modeling via stereotypes. *Cognitive Science 3*, 329–354.

Sack, W. 2000. Conversation Map: A content-based usenet newsgroup browser. In *Proceedings of the International Conference on Intelligent User Interfaces (IUI'00)*. 233–240.

Shardanand, U. and Maes, P. 1995. Social information filtering: Algorithms for automating "word of mouth". In *Proceedings of Computer-Human Interaction (CHI'95)*. Denver CO. 210–217.

Shirky, C. 2004. Situated software. Available at http://www.shirky.com/writings/situated_software.html.

Sinha, R. and Swearingen, K. 2002. The role of transparency in recommender systems. *CHI'02 Conference Companion*.

Smith, M. A. and Fiore, A. T. 2001. Visualization components for persistent conversations. In *Proceedings of the ACM Conference on Human Factors in Computing Systems (CHI'01)*. 136–143.

Spiekermann, S., Großklags, J., and Berendt, B. 2001. E-privacy in 2nd generation e-commerce: Privacy preferences versus actual behavior. In *Proceedings of the ACM Conference on Electronic Commerce (EC'01)*. 38–47.

Sproull, L. and Faraj, S. 1997. Atheism, sex, and databases: The net as a social technology. In *Culture of the Internet*. S. Kiesler Ed. Erlbaum, Publishing 35–52.

Staw, B. M. 1975. Attributes of the 'causes' of performance: A general alternative interpretation of cross-sectional research on organizations. *Organiz. Behav. Hum. Perform. 13*, 414–432.

Svensson, M., Höök, K., Laaksolahti, J., and Waern, A. 2001. Social navigation of food recipes. In *Proceedings of Computer Human Interaction (CHI'01)*. 341–348.

SWEARINGEN, K. AND SINHA, R. 2001. Beyond Algorithms: An HCI perspective on recommender systems. *SIGIR 2001 Workshop on Recommender Systems*.

TERRY, M., MYNATT, E. D., RYALL, K., AND LEIGH, D. 2002. Social net: Using patterns of physical proximity over time to infer shared interests. *Extended Abstracts of the ACM Conference on Human Factors in Computing Systems*. 816–817.

TERVEEN, L. G., SELFRIDGE, P. G., AND LONG, M. D. 1995. Living design memory: Framework, implementation, lessons learned. *Hum.-Comput. Interact. 10*, 1, 1–38.

TERVEEN, L. G., HILL, W., AMENTO, B., MCDONALD, D., AND CRETER, J. 1997. PHOAKS: A system for sharing recommendations. *Comm. ACM 40*, 3, 59–62.

TERVEEN, L. G. AND HILL, W. Human-computer collaboration in recommender systems. In *HCI in the New Millennium*. J. Carroll, Ed. Addison Wesley.

TURPIN, A. AND HERSH, W. 2001. Why batch and user evaluations do not give the same results. In *Proceedings of the 24th Annual ACM SIGIR Conference on Research and Development in Information Retrieval*. 17–24.

VAN DYKE, N. W., LIEBERMAN, H., AND MAES, P. 1999. Butterfly: A conversation-finding agent for Internet relay chat. In *Proceedings of the International Conference on Intelligent User Interfaces*. (Jan.).

VERBRUGGE, L. M. 1977. The structure of adult friendship choices. *Social Forces 56*, 2 (Dec.).

WALLER, W. 1937. The rating and dating complex. *Amer. Sociol. Rev. II* (Oct.). Reprinted in Silverstein, H. Ed. The Sociology of Youth: Evolution and Revolution. 1973 Macmillan, New York, NY. 284–292.

WALTHER, J. B. 1992. Interpersonal effects in computer-mediated interaction: A relational perspective. *Comm. Res. 19*, 52–90.

WALTHER, J. B., ANDERSON, J. F., AND PARK, D. W. 1994. Interpersonal effects in computer-mediated interaction: A meta-analysis of social and antisocial communication. *Comm. Res. 21*, 460–487.

WASSERMAN, S. AND FAUST, K. 1994. *Social Network Analysis*. Cambridge University Press, Cambridge, UK.

WELLMAN, B. 1997. An Electronic Group is Virtually a Social Network. In *Culture of the Internet*, S. Kiesler, Ed. Lawrence Erlbaum. 179–205.

WELLMAN, B. 2001. Computer networks as social networks. *Science 293*, 2031–2034.

WEXELBLAT, A. AND MAES, P. 1999. 'Footprints: History-rich tools for information foraging'. In *Proceedings of Computer-Human Interaction (CHI'99)*. 270–277.

WHITTAKER, S., TERVEEN, L. G., AND NARDI, B. A. 2000. Let's stop pushing the envelope and start addressing it. *Hum.-Comput. Interact. 15*, 2–3, 75–106.

WHITTAKER, S., JONES, Q., NARDI, B., CREECH, M., TERVEEN, L., ISAACS, E., AND HAINSWORTH, J. 2004. Using personal social networks to organize communication in a social desktop. *ACM Trans. Comput.-Hum. Interact. 11*, 4, 445–471.

WHYTE, W. H. 1956. The *Organization Man*. Simon and Schuster, New York, NY.

WIRED NEWS 1998. Love: Japanese style. http://www.wired.com/news/culture/0,1284,12899,00.html.

WIRED NEWS. 2004. Brits going at it tooth and nail. http://www.wired.com/news/wireless/0,1382,62687,00.html.

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