SociUM: Adaptation and Personalisation in Social Systems: Groups, Teams, Communities

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SociUM:
Adaptation and Personalisation
in Social Systems: Groups, Teams, Communities

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Introduction

Some of the most vigorous computing applications currently are social software environments. Collaborative work and learning technologies support social interaction, knowledge sharing, and collaboration in multi-user environments ranging from working in small groups or closely-knit teams to participating in online communities and forums. Social software is rapidly becoming an important part of mass culture by engaging users in creating, sharing, tagging, downloading, remixing, and rating content as well as in virtual worlds populated with other users. Social environments engage a broad range of users producing highly dynamic collections of resources. The difficulties that arise for individuals in such volatile environments are manifold: cognitive overload, unawareness of current trends in the community, and difficulties in finding their role in the group, ultimately reducing the effectiveness of the community to create, share, evaluate and evolve knowledge.

Therefore, in such environments, personalisation and adaptation are paramount to facilitating effective knowledge construction and information sharing and creating a trusting and motivating atmosphere for members of groups, teams and communities to share and work together seamlessly. Web 2.0 and related aspects will certainly play a major role for UM research in the near future, and we believe it is about the time for this workshop.

The main questions include: What adaptation goals may exist in social systems? What does it mean to adapt in a social context when everything changes due to the social dynamics (i.e. what is the scope and effect of adaptation)? How to derive models of groups, teams and communities in dynamically changing social environments taking into account individual participation, social relationships, social capital, trust, and motivation? What adaptation models can be adopted (e.g. filtering, recommendations, dynamic notification, visualisation) or have to be developed for social computing? What criteria can be used to measure the benefits of adaptation (e.g. team efficiency, level of participation, awareness)? How to evaluate social adaptation mechanisms (are experiments in real settings possible by controlling all factors in complex social environments or can simulations provide a feasible alternative and will they adequately model the world)?

The workshop attracted 14 submissions from Canada, France, Greece, Italy, Portugal, Spain, Switzerland, UK, and USA. Each submission was reviewed by at least two program committee members. Six papers were accepted as full-length and four as short-length. The accepted papers represent a variety of approaches, such as empirical studies, theoretical models, system design and implementation, and reviews discussing new trends. A range of topics are covered, from adaptive support for collaboration, community awareness, group and community modeling, social recommendations, knowledge sharing and emergent Web 2.0 applications.

June 2007

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On the Need for a Framework for Attentive Groupware Systems

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Abstract We present a combined perspective over groupware systems and attentive user interfaces to address the balance between the rising needs for collaboration and the rising costs of not paying attention and being interrupted. We introduce a framework that derives attentive devices from groupware mediation modes to take into account attentional phenomena. Finally, we demonstrate the framework’s role in a brainstorming tool, explain what the attentive devices do, and provide preliminary results from a pilot experiment.

1 Motivation

A continuing trend in groupware research aims at improving the sense of proximity within groups, whether by enabling geographically distant people to work together, or by supporting ongoing activities at different times. Researchers have been proposing several mechanisms to enhance group awareness by providing ever greater information about the presence and actions performed by people, e.g., radar views, multi-user scrollbars, and telepointers [1], and also by addressing social factors, such as context [2]. A main argument is that communication channels mediated by computers are relatively poor when compared with more natural settings, such as face-to-face meetings [3]. However, a problem with this trend is that it fails to recognise that sometimes more is less due to the limitations of the human attentive capacity, especially as we become surrounded with computers and, not necessarily useful, information [4].

During the late 1990s several researchers from the Human-Computer Interaction (HCI) field have became interested in Attentive User Interfaces (AUI), and since then this topic is gaining momentum, as evidenced by a special issue in the Communications of the ACM [4], and a second one in Computers in Human Behavior [5]. The prime motivation for AUI is the recognition that as the needs for information and communication rise so do the costs of not paying attention and being interrupted [4]. So, instead of assuming the user is always focused on the entire computer display, AUI negotiate the users’ attention by establishing priorities for presenting information.

Most research on AUI is directed towards single-user activity, the main assumption being that individual performance degrades with the number of simultaneous requests for attention. Therefore, researchers are enhancing input/output devices so that the user remains focused on a primary task without getting too much distracted by a secondary, typically unrelated, task, e.g., by using eye-trackers [6], statistical models of human interruptibility [7,8], displays that show information at various levels of detail [9], and other devices.

Regarding multi-user activity, the literature is mainly situated in video conferencing [10,11], making the study of attention in computer-mediated collaborative contexts a largely unexplored area. Moreover, the current emphasis is directed towards evaluating the enhanced input/output devices themselves, in contrast with determining the outcomes of using these devices in work settings. Furthermore, the convergence of groupware and AUI poses new challenges because of the differences between individual and group work, such as: a) people working in a group are exposed to more interruptions because they have to manage more information flows; b) instead of doing a single, extensive task, group members usually execute a series of intertwined tasks; and c) in group work the primary and secondary tasks are typically related and can both contribute to the shared goal.
Given this situation, we propose a framework for mediating attention in groups and put forward the possibility of using specialised, software-based, groupware devices to account for attentional phenomena. These attentive devices would work by manipulating the information flows supported by the groupware system, and since, in this work context, collaboration is mediated by computers, its use might mean that the group as a whole would be more attentive, and possibly more productive.

We explain the framework in Sect. 3, and in Sect. 4 we describe its application to an electronic brainstorming tool and provide some results from a pilot experiment. In Sect. 5 we conclude the paper with a discussion regarding our approach and with prospects for future work.

2 Related work

The study of the mediating role of computers on attention within groups is largely an unexplored research area, with the exception of video conferencing. Currently, the major part of the literature on AUI is focused upon single-user software (singleware). We will refer to both multi and single-user contexts to provide a more comprehensive picture of the systems and devices that address human attention in HCI.

2.1 Attentive groupware systems

GAZE is a groupware system developed to facilitate the detection of who is talking to whom in remote meetings [12]. It works by displaying photographs of users on the computer display, which can be rotated by intervention of eye-trackers placed in front of each user. For example, the photos might be rotated towards a photo of a user who is speaking. In this way, turn taking may be more natural and require less interruptions to determine who will speak next.

The GAZE-2 system was developed to overcome the technical limitations of the original GAZE and to support multiple conversations at the same time [10]. In GAZE-2 each user has three video cameras that capture the user’s face at slightly different angles; then, an automatic camera director chooses one video stream taking into account the direction where the user is looking at. As in the original GAZE, the representation of each user is rotated to reflect the focus of attention. Moreover, as the angle of rotation increases, the quality of the video stream is purposefully reduced to save network bandwidth. According to the authors, this technique is effective because it is based upon our own natural limitations concerning peripheral vision. Another feature of GAZE-2 is the automatic filtering of voices when multiple conversations are being held at the same time. Depending upon the user in focus, so is the respective audio stream amplified, and the other streams attenuated (but not eliminated). If the focus of interest suddenly changes, as sensed by the eye-tracker, the audio is again adjusted.

Recent work with groupware systems further explore the ideas in GAZE-2. For instance, eyeView supports large meetings by manipulating the size of the video windows and the voice volumes of each user on the group as a function of the current focus of attention [11].

2.2 Attentive devices on singleware systems

In contrast with groupware systems, several input/output devices have been tested on attentive interfaces for single-user applications, such as: a) sensors that detect the user’s focus of attention based upon eye-gaze and body orientation [6,13,14]; b) physiological sensors that assess the user’s mental workload by measuring heart rate variability, pupil dilatation, and eye-blink activity [15,16,17]; c) statistical models that determine adequate moments to interrupt and communicate with the user [7,8]; and d) displays that present information at various levels of detail, depending on the user’s focus of attention [9].

Regarding the use of eye-trackers to support human attention, applications include enlarging the graphical window which the user is currently focused on, controlling a robotic directional
microphone coupled to a video camera, to overhear a particular conversation taking place in a remote room, and detecting eye contact to automatically choose which electronic appliance should obey to voice commands [6]. Other applications use eye-gaze to position a cursor on the screen with minimal hand intervention [13] and to help a user read a book written in a foreign language [14].

Body orientation sensors have been tested in an office environment to regulate the transparency of cubicle walls (opaque when the user does not wish to attend requests from others) and to control noise cancellation in headphones [6].

Concerning physiological sensors, these have been used to assess mental workload, which, in turn, is considered a surrogate of the user’s attentional state. One study suggests using heart rate variability and electroencephalogram analysis to distinguish between at rest, moving, thinking, and busy states, and describes an automated regulator of notifications that can be installed on mobile phones [16]. Heart rate variability had already been used in the 1990s to assess conditions of excessive mental effort [17]. More recently, pupil dilatation has been used, in combination with hierarchical task models, to predict opportune moments to interrupt the user [15].

Another approach to detect the best time to interrupt the user is to apply statistical models that permanently estimate and balance the value of information with the cost of interrupting, based upon a stream of clues, such as, appointments on the personal calendar, past activities and work patterns, ambient noise, or body posture [7]. Statistical models have also been used to select the best predictors of interruptibility from a myriad of software sensors embedded in an integrated development environment [8].

Finally, we also refer to a special display that adjusts the level of detail in selected areas of the screen as a function of the user’s current visual focus of attention [9]. This effect has similarities with the GAZE-2 approach.

2.3 Discussion

Research in AUI, its applications and devices, is progressing in many directions. However, we argue that most studies are directed towards evaluating the devices per se, in contrast with determining the outcomes of using these devices in work settings. For example, to the best of our knowledge, the GAZE-2 system was evaluated through a user questionnaire that measured the self-perception of eye-contact and distraction, as well as changes in colour and brightness during camera shifts [10], but no attempt was made to determine if group work benefited. The same situation seems to occur with eyeView [11], which is still in an early stage of development.

Some studies do address the evaluation of AUI from the perspective of task execution, but are restricted to single-user activity. One study measured the effects of interruption on completion time, error rate, annoyance, and anxiety, and suggest that AUI should defer the presentation of peripheral information until task boundaries are reached [18]. In another study, the effectiveness and efficiency of users were evaluated as they performed two types of tasks under the exposure of four methods for coordinating interruption, and recommends that AUI should let users manually negotiate their own state of interruptibility, except when response time for handling interruptions is critical [19].

We note, however, that there are numerous differences in individual and group work that might reduce the external validity of current results. This opens an opportunity for doing research in groupware systems and AUI.

3 Framework for attentive groupware systems

The purpose of this framework is to conceptualise attentive groupware systems. Its underlying assumption is that group performance may improve by incorporating human attentional phenomena in attentive devices that adjust the groupware mediation (e.g., the information in circulation) as people carry out the collaborative tasks (see Fig. 1).
Performance evaluation of group work is outside of the scope of the framework but is strongly tied to its usefulness. In the next sections we look into the concepts of the framework.

3.1 Groupware mediation

Conceptually, the groupware system is at the centre of the group. It is a mediator that deals with all sorts of information that comes and goes between and among the users. Moreover, we assume that the users are restricted to using groupware to collaborate, e.g., when they are geographically distributed, since this is a challenging scenario for managing attention in groups.

Groupware mediation should support the notions of interdependence, for group planning, and mutual awareness, for situation assessment, which generate information that requires human attention in order for the group to make progress. Our strategy to characterise groupware mediation is to change the perspective over the information flows that we investigated in a previous study about shared workspaces [20]: instead of looking into the ways remote people collaborate, we analyse the corresponding mediation modes.

In the **explicit communication mode** the groupware receives information produced by a user and forwards it to one or more users, based upon an explicit request by the sender [3]. This may happen, for instance, when a user expresses a request for an object to the user who is holding it; another example is when an instructor provides online guidance to students for collaborative problem solving (illustrated in Fig. 2a\(^1\)). This mode can be supported by a groupware interface capable of multiplexing information from input devices to several output devices, e.g., a user typing on a keyboard and the other users seeing the text on their displays.

\[\text{U1} \downarrow \quad \text{U2} \quad \text{GM} \quad \text{U3} \quad \text{U4} \]

\[\text{GM} \quad \text{U2} \quad \text{GM} \quad \text{U3} \quad \text{U2} \downarrow \uparrow \quad \text{U4} \quad \text{GM} \quad \text{U3} \quad \text{U4} \]

(a) Explicit communication (b) Feedthrough (c) Back-channel feedback

In the **feedthrough mode** the groupware automatically reports actions executed by one user to several users [21]. This mode is essential because it provides group awareness and enables users to construct meaningful contexts for collaboration. For example, a graphical shared workspace may provide its users with information about the menu selections for each user who is manipulating objects. The groupware interface can support the feedthrough mode by capturing each user’s inputs and then multiplexing feedback information (replies to a single user) to the other

\[\text{GM} \quad \text{U2} \quad \text{GM} \quad \text{U3} \quad \text{U2} \quad \text{U4} \]

\[\text{GM} \quad \text{U3} \quad \text{U4} \]

\[\text{GM} \quad \text{U4} \]

\[\text{U1} \downarrow \uparrow \quad \text{U2} \quad \text{GM} \quad \text{U3} \quad \text{U4} \]

In Fig. 2, **GM** means groupware mediation and **Un** is user n.
users on the group (see Fig. 2b). Sophisticated schemes may consider delivering less information by manipulating the granularity and timing associated with the operations executed through the groupware [22]. Interestingly, the motivation for these schemes has been related to technical limitations, such as network bandwidth, but, in our view, the limitations of the human attentive capacity should also be accountable because the amount of information generated by the groupware may overtake us, and thus decrease group performance.

In the back-channel feedback mode the groupware captures unintentional information initiated by a user and directs it to another user to facilitate communication and to convey human states of attention. This may occur, for instance, when a listener says ‘uh-huh’ to indicate that s/he is following the speaker (see Fig. 2c). To capture this type of information the groupware interface can use attentive devices such as those described in Sect. 2, or use other sensors that take advantage of the information that is available to the groupware.

One of the concepts of the framework embraces specialised attentive groupware devices, but first we look into some phenomena related to human attention.

3.2 Attentional phenomena

Human attention is often associated with the selection of relevant information and simultaneous attenuation or discard of non-relevant data. It is a process that optimises the use of our limited cognitive resources so that we can perceive or act accurately and quickly [23,24,25].

Attention and consciousness are thought to be different processes: whereas attention covers the full spectrum of data that we manipulate (through our senses or memory), consciousness is confined to the information that we are currently aware of [25]. Furthermore, a recent study identifies scenarios in which attention might not give rise to consciousness and vice-versa [23]. This means that we may be scanning a computer display without noticing important information.

Over the decades, psychologists and cognitive scientists have been identifying the goals and limitations of human attention. Researchers should pick up this knowledge to invent and evaluate ways to support the goals and compensate the limitations.

Two of the main goals of attention are accuracy, to perceive specific objects and to execute particular tasks, and speed responding, to perceive objects or execute tasks after the presentation of a predictive cue [26]. Accuracy manifests itself when we successfully remove or attenuate the influence of extraneous and confusing information. The ‘cocktail party’ phenomenon—our ability to keep track of a conversation in a crowded room—is related to this goal [25,24]. Speed responding occurs when we are able to respond faster to anticipated events [26] and almost always involves a clear expectation of when to initiate the response [24].

An example of a groupware system that addresses attentional accuracy is GAZE-2 [10], which automatically regulates the sound volume of overlapping conversations according to the user’s current visual focus of attention. The effects on group performance have not, however, been evaluated, and more contexts of group work, besides remote meetings, may benefit from explicit support of human attentional goals. Regarding groupware support to speed responding, anticipation of upcoming events is actually quite possible in computer-mediated work because, as soon as the system detects user activity that may be pertinent to another user, it can signal that activity and also control the delivery time to create clearer expectations. For example, popular instant messengers provide anticipatory cues when users start typing a message.

Interestingly, human attention has its own limitations, in that it can fail to select the relevant information, or take too long. Moreover, some phenomena are known to occur even after tremendous training, such as the ‘attentional blink,’ which is a delay between paying attention to one object or task and attending to the next stimulus [27]. On the other hand, there is evidence that the response time to the second stimulus may be reduced if the time between attention switches is made longer and, in particular, constant [28]. This type of intervention should be performed by groupware systems to regulate the flows of information that each user is exposed to.
Another attentional phenomenon is ‘change blindness,’ which manifests itself when we fail to notice changes, even dramatic ones, such as a swap of the person with whom we were talking to just seconds ago. As long as the change matches the context, e.g., swapping of students during a brief encounter in a university campus, we may simply miss the difference [24]. If we do want to check if anything has changed, then we may have to engage in a very slow process of scanning the full picture before us. This happens because, although we can attend to four or five objects simultaneously, we can only detect one change at a time [29]. The consequences of ‘change blindness’ in people doing group work should be apparent. The notion of group lends itself to the creation of a social context and the existence of several people collaborating, i.e., contributing to the same shared goal, stimulates scenarios in which multiple changes may occur simultaneously. This creates the required conditions for people not noticing changes, which may reduce group performance because of the time needed to catch up. Groupware systems should, therefore, highlight changes to compensate this attentional limitation.

3.3 Attentive devices

The last concept of the framework comprehends the input/output devices that support the groupware mediation. We propose a classification that comprises awareness and coupling devices, which may themselves be manipulated by specialised attentive devices.

We define awareness input/output devices as devices dedicated to sensing and displaying information about the collaborative activity within the group, allowing users to construct a perceptual image of the work context. This information is usually designated ‘group awareness’ [3]. Many of such devices have been described in the literature [1,3], and indeed, we argued at the beginning of the paper that groupware research has been focusing on these devices.

The coupling input devices are used to loose the link between the actions executed by a user and the information that is passed on to the other users [30]. Two types of coupling control may be considered in groupware mediation: first, coupling may be exerted at the origin to specify what and when information produced or about a user should become available to the rest of the group; second, coupling may be applied at the destination to apply filters that restrict group awareness to some selected objects and actions.

Figure 3 illustrates that users may use their respective coupling input devices to control the outflow of information from both the input and output awareness devices. Note that coupling control does not apply to (single-user) feedback.

![Figure 3: Groupware input/output devices](image-url)

Coupling devices require manual discrimination and control of group awareness, thus penalising individual performance. However, this disadvantage is balanced by the capacity to limit the amount of information, which may improve attention within the group. This tradeoff sets the stage for introducing specialised attentive devices for groupware systems.
We propose a set of attentive devices that collect and combine information received from awareness sensors associated with each user, and that automatically manage the information that is delivered to the awareness displays, according to human attentional phenomena:

**Activity anticipator (AA)** Senses users’ actions, or lack of activity, that may affect group performance and delivers preliminary information (cues), to prepare users to be attentive to upcoming outcomes and to enable faster response times.

**Change emphasiser (CE)** Tracks awareness information available on each user’s display and highlights changes caused by the latest group activities, to attenuate the effects of the ‘change blindness’ phenomenon and to help users make faster situation assessments.

**Opportunity seeker (OS)** Senses activity on a user basis and seeks for opportune moments to deliver group awareness, such as when the user completes a recognisable subtask or after a brief period of inactivity, to enable faster response times to stimulus.

**Time separator (TS)** Intercepts the delivery of group awareness to the users, and introduces a constant delay, after which the hand over proceeds. The delay should be constant from the point of view of each user, and its purpose is to attenuate the effects of the ‘attentional blink’ phenomenon and to improve task switching performance.

Some of these attentive devices may be combined to achieve more complex manipulation of groupware mediation. For example, TS → CE highlights changes in group awareness collected by the time separator over a constant period of time, instead of as soon as they occur. However, some combinations may be incompatible, such as TS → OS because, in this case, of the contrast between the time separator and the opportunity seeker awareness delivery timing.

This set of attentive devices, which may include more devices in the future, should be applicable to groupware mediation in a broad range of collaborative scenarios; for example, in asynchronous groupware, the change emphasiser may be used to highlight differences between two discrete states of group work.

### 4 An attentive brainstorming tool

We applied the proposed framework to the design and development of an electronic brainstorming tool, in the context of a laboratory experiment for testing the effects on group performance caused by the attentive devices.

#### 4.1 Architecture and components

The attentive brainstorming tool is characterised by a client-server architecture, in which groupware mediation is performed on the server. The purpose of the clients, one per user, is to receive input from the users and pass it on to the server, to display group awareness as it becomes available from the server, and also to collect performance data, which is stored in a server log.

Groupware mediation is entirely supported in the feedthrough mode, i.e., the tool automatically distributes new ideas to all users, without requiring mechanisms for explicit or back-channel communication between or among the users. All users remain anonymous during the sessions.

In this work context, group performance depends on the number of ideas that the users put forward, and this, in turn, is related to the quantity of ideas that each user is able to attend to, in particular, ideas coming from the other users. The purpose of the attentive devices is to enable users to attend to more ideas, which may have a positive net impact on group performance.

The brainstorming tool implements all four attentive devices: a) the **activity anticipator** detects periods of group inactivity and alerts users that the session will soon end unless new ideas are put forward; it also signals when a user is typing an idea (see status bar in Fig. 4); b) the **change emphasiser** displays an horizontal line (shown in Fig. 4) that separates old and new ideas; when a user stops typing the separator line disappears after thirty seconds; c) the **opportunity seeker** waits for a user to stop typing to then display new ideas from the other users; and d) the **time separator** shows new ideas at constant time intervals, collected over periods of ten seconds.
4.2 Preliminary results

We now briefly describe a pilot experiment that we conducted in a university laboratory with a group of five male graduate students, gathered for a brainstorming session through the attentive tool. No other means of communication, such as speaking or gesturing, was allowed, to simulate remote collaboration. The session lasted for thirty five minutes and the topic was ‘for a better school.’ Our expectation was that this topic would induce many ideas, so as to create a scenario that demanded more attention from the users. The ideas did come, indeed, but at the cost of breaking the rules of brainstorming because the session was transfigured into a chat (as illustrated in Fig. 4; the average number of characters per idea was seventy two). We decided to continue the experiment for three reasons: a) to observe the users’ activity under the exposure of the attentive devices; b) to check if the attentive devices were working as expected; and c) to obtain performance data for posterior analysis.

We did not notice any unusual behaviour from the users, such as apprehension or frustration, and adaptation to the tool required no training. One of the attentive devices malfunctioned: the change emphasiser was not highlighting new ideas as expected, and we later found out that the cause was linked to faulty interactions with the time separator. There was also a minor glitch with the opportunity seeker in that between one and seven ideas slipped through to the display while users were typing an idea, which was not supposed to happen. We also detected that several key-press events in the performance log were recorded with the same time stamp for the same user, which probably indicates lack of timing precision.

Table 1 shows a summary of the performance data that were collected by the brainstorming tool. We randomly assigned colours to the five users, but unfortunately two of them were given the same colour during the configuration of the tool, so we exhibit only results for three users. The total number of ideas contributed during the session, for the five users, was 244. User ‘orange’ received all of the ideas, but the other two users received less because the session ended before the time separator could deliver the last remaining ideas. This should cause no problem in practice. The rightmost column in Table 1 shows the number of seconds of non-typing activity
Table 1: Results from the pilot experiment

<table>
<thead>
<tr>
<th>User</th>
<th>Produced ideas</th>
<th>Received ideas</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td># Typing s/idea</td>
<td># Processing s/idea</td>
</tr>
<tr>
<td>Green</td>
<td>65 17m 09s 15.3</td>
<td>240 6m 03s 1.5</td>
</tr>
<tr>
<td>Red</td>
<td>42 10m 40s 9.3</td>
<td>234 6m 40s 1.7</td>
</tr>
<tr>
<td>Orange</td>
<td>68 20m 49s 18.4</td>
<td>244 5m 05s 1.2</td>
</tr>
</tbody>
</table>

immediately after the reception of ideas, divided by the total number of ideas that the user received throughout the entire session. By adding the values in this column, on a per user basis, to the average number of seconds to type an idea, a total of between 10–20 seconds is to be expected for situations in which the user types a contribution in reaction to an idea that s/he received from another user. We will use these findings to fine-tune the attentive devices, e.g., the time separator, in future experiments.

5 Conclusion and future work

The study of the mediating role of computers on human attention in remote collaboration settings is largely an unexplored research area. While current trends keep aiming at conveying ever greater awareness information about the group, we suggest a route that explicitly recognises the limitations of the human, and therefore the group, attentive capacity. This route is consistent with AUI research and we argue that the existing body of knowledge should extended into the groupware field. To this end we introduce a framework for attentive groupware systems and hypothesise that group performance improves with the use of specialised attentive devices.

Many questions remain unanswered: does group performance significantly improve? What attentive devices are best suited for different collaborative scenarios? Can groups be made larger while remaining attentive and productive? We are addressing some of these questions with an attentive brainstorming tool and, beyond the pilot experiment described in this paper, we are setting up laboratory experiments with groups of five people, where we measure group performance—number of ideas produced, average time to type an idea, duration of non-typing activity, and other dependent variables—in terms of each attentive device, using multiple comparisons with repeated measures and non-parametric statistical analysis. The road is open for many more experiments and applications.

References

Abstract. This research indicates how information retrieval activity is a social process helping to foster a network of organizational expertise. After describing knowledge management practices in a distributed research and development laboratory we identify recent introduction of Experts' Retrieval Software. A four steps model RESONER: Information Retrieval, Caring (social support), Negotiation, and Reification is suggested. This model specifies DemonD an ERS relying on transparent profile construction based on user's activity, community's participation and shared documents. DemonD eventually encourages the emergence of informal knowledge networks and competencies awareness in a distributed context.

Keywords: Collaborative Information Retrieval, profile, virtual teams, expert retrieval systems, knowledge management.

1. Introduction and context description

In previous work on Distance Education, we analyzed peer communities emergence during a 16 weeks web based course at the University of Central Florida [2]. This study, focusing on the importance of social ties in distance education, offered one conclusion. Students join or create learning communities to seek help but mainly to overcome isolation feeling that arises in distance education. Distance learners we interviewed shared the need of information or contact retrieval services to assist them in their learning process. We formulate the assumption that Distance Education and distributed teamwork share similarities. In fact, in a professional context, individuals usually have to work with remote colleagues or clients. Recurrent introduction of new technologies and collaboration necessity allow the constitution of projects team globally distributed. For this research, we apprehended the challenges of a Research and Development laboratory, of 80 persons, in a French telecommunication company. In a highly competitive market, the organization decided to consistently invest in R&D projects. The laboratory that we observed is distributed in France among three cities: Grenoble, Sophia Antipolis and Caen. Its mission is to identify, conceive and support the sale of telecommunication services for businesses.

Information Retrieval is a critical task for researchers. Employees we interviewed emphasized the need for computing tools to identify and communicate with topic experts. The laboratory previously attempted two strategies in order to create and share organizational information in such a distributed context.

First, they produced an exhaustive knowledge database, trying to externalize and share explicit knowledge. Intranet's folders were also utilized to share content among coworkers. Yet, interviewed employees revealed that the knowledge database was usually obsolete and shared folders not accessible (privileges needed to be granted on each folder) and folder's content was not properly indexed.

Conscious about the shortcomings of such a systemic approach of knowledge management, the organization deployed communities of practice [7]. The 'not-so-informal' communities shared a virtual collaborative workplace and face to face member's meetings were scheduled monthly. Yet, this second strategy also turned out to be unsatisfactory. Employees were reluctant to ask/share information with individuals they never met. Indeed, working for the same company and in the...
same field of activity doesn’t justify for community members to share their knowledge with other colleagues.

The objective of this work is then to validate a hybrid information retrieval model. This model relies on transparent profiling techniques to match a knowledge demand with one or many knowledge offers. This model helps specifying DemonD a groupware dedicated to collaborative information retrieval and favoring the emergence of a lightly structured information network. After reviewing previous research on knowledge management and expert retrieval services, we describe the collaborative information retrieval model RESONER and its implementation in an artifact named DemonD (Demand&responD).

2. Related work

Knowledge management is usually comprised of: externalization, capture, indexation, and presentation of organizational knowledge. This method substitutes an access to a knowledge database for a contact with the topic’s expert. Unlike content, which is perishable and quickly become obsolete, experts’ informal networks are rather permanent in R&D context. We assert that the real value of information systems is connecting people to people and encouraging them to share their expertise rather than collecting and storing de-contextualized information. In fact, [4] evidenced that individual looking for information usually explore and contact personal communications prior to using documents or knowledge bases. Information technologies contribute to sharing and constructing knowledge in distributed organizations thru specific systems named: Expert Retrieval Systems (ERS). Multiple ERS (Expert Retrieval Systems) have been deployed but usually failed for two reasons. First, ERS do not take in consideration the importance of informal social networks in the construction of knowledge. Second, ERS do not let final users manage their profiles and participation. We select and compare three famous ERS: Referral Web, Agilience and Answer Garden 2.

2.1. Referral Web

Referral Web [5] is an ERS created in AT&T labs. User's profile is constructed based on keywords extracted from web pages or shared documents where individual's name exists. Social network is also drawn based on co-occurring names on published research, public documents or organization chart. Individual utilizing referral web select the reach of his request and the number of hopes between him and knowledge offer.

Mapping users interactions and position on a social network is interesting yet problematic. In fact, user's knowledge is frequently not present on documents only but should encompass a list of other sources such as online participation on discussions groups for instance.

2.2. Agilience

Agilience relies on sent email messages to create user's profile. During initiation phase, emails are analyzed and significant words extracted and compared to an existing taxonomy. User is able to manage his profile by adding or deleting keywords. To retrieve pertinent individuals, users send an email with a description of his request. The content of the message is analyzed by Agilience that returns back a list of documents, a list of individuals and a list of individuals able to forward the request to other potential respondents. Requests and responses are leveraged to accurately define user's profile.

Relying exclusively on email, Agilience is a translucent solution for distributed Knowledge Management. Yet, Agilience conceptualize knowledge construction or sharing as a dialogue between a demand and an offer. In reality, knowledge usually emerges from collaboration between multiple individuals. The creation of a dedicated collaborative workspace could definitely enhance this solution.
2.3. Answer Garden 2

Answer Garden 2 [1] follows the realization of an earlier version ERS. AG2 relies on a multi agent system to select a recipient for a request. AG2 replicates progressively user's request based on recipient's proximity, privileging first near-by contacts. Recipients are invited to cooperate on specific discussions groups with instant messaging and emails functionalities.

This powerful ERS presents a major constraint for end-users. Individuals do not control the reach of their request. In fact, AG2 retransmits the request without prior approval.

In conclusion, the description of three ERS (Agilience, Referral Web and AG2) presents three challenges that need to be addressed. First of all, user's profiling must be extracted from heterogeneous sources (documents, user's activity, social networks…). Second, a knowledge exchange should take place in a collaborative environment, with multiple participants. Finally, user must be able to manage the reach of his request and ensure privacy, especially in R&D teams depicted in the introduction.

3. RESONER Model

When considering the activity of information retrieval as a social practice, we are interested in a network, slightly structured, whose principal objective is the transmission of knowledge. The Actor Network Theory accurately describes such association of heterogeneous resources (individuals, documents, discussions…) [6]. This theory suggests that social networks does not pre-exist and shall be created to achieve a task. In opposition to the solitary information retrieval activity, we suggest a collaborative approach [3]. We are focusing on information retrieval activity as a social process in order to build an organizational network of expertise. The information seeking process is not restricted to content retrieval / distribution but initiate a negotiation between demander and giver. It is followed by the capitalization of exchanged information and the social structure utilized. The recurrence of the exchanges of information supports the constitution of mutual aid (caring) network and eventually the emergence of an information community.

4. DemonD – a groupware for collaborative information retrieval

DemonD, is specified with model RESONER and comprised of four main functions: Initialization & Information Retrieval - Diffusion - Negotiation – Capitalization.

5. Initialization & Information Retrieval

User's profile is built with the "Profiler" algorithm and consists of a list of weighted keywords also named tags. In order to follow the first recommendation of 2.3, user's profile is extracted from multiple sources and updated when individual utilizes this ERS. Corporate Information System directly provisions socio demographic data including (name, address, email, phone, occupation…). Individual also declares a list of competency (keywords) complementing his profile. To enrich his profile, individual also shares a set of documents (curriculum vitae, publications, patents) with the rest of the community. Recurrent keywords are extracted from these documents and enhance user's profile.

User can also create workgroups known as a list of contacts. DemonD utilized this activity of group creation to extract recurrent keywords from group member's profiles. Such keywords are also utilized to complement user's profile.

Individual are able to add or delete tags (keywords) on any resources on DemonD (his/others profile, his/others documents, discussions). Various tags utilized are added to individual's profile.

In conclusion, user's profile is constructed from heterogeneous sources. Each keyword is weighted based on its frequency.
6. **Diffusion**

During an information retrieval activity, DemonD suggests to the information seeker heterogeneous resources such as documents, ongoing discussions and pertinent users. Users are sorted according to the cont@ctrank, an algorithm compiled with the following criteria (knowledge, proxy, participation, reputation).

- The first criterion – knowledge, suggests profiles (extracted from Profiler cf. 4.1) containing words directly matching seeker's requests. Tags are weighted according to their sources and provide the cont@ctrank with a coefficient.
- The second criterion, proxy, indicates user's ability to forward a request to recipients not previously suggested by DemonD. It is calculated by the size of non-redundant contacts between demander and various respondent(s).
- Participation criterion indicates the number of times a recipient has responded to requests in the past.
- Reputation criterion compiles positive or negative former recipients’ participations.

![](image1.png)

**Fig 1.** DemonD's transparent profiling

7. **Negotiation – Capitalization**

For the negotiation step of DemonD, the recipients selected are invited to provide a collaborative answer on a dedicated workspace. Such workflow follows the third challenge of ERS (cf. 2.3). Validation takes place with peer reviewing and grading other member's answers. During the last phase (capitalization), the solution validated by the community is inserted in the organizational knowledge base. Information network constructed previously is also available on DemonD.

Human caring such as mutual aid or trust facilitates the emergence of such information networks. To support caring in DemonD, we utilize a four phases model (awareness, receiving, responding, remaining) previously developed and tested in a distance education context [2].

![image2.png](image2.png)

**Fig 2.** Potential Recipients sorted with Cont@ctRank

In order to follow the second recommendation (cf. 2.3), knowledge seekers manage the reach of their requests by selecting one or many recipients.
8. Perspectives

We collected qualitative data that reflect potential uses of DemonD, apprehended by end users. We interviewed 40 researchers who reacted positively to DemonD's approach of collaborative information retrieval. In order to suggest potential usage of the ERS, we simulated a geographically distributed company willing to export "nanotechnologies" in China. DemonD's workflow appeared coherent to most surveyed users and seemed to avoid the three limits identified in previous work (cf. 2.3). Yet two challenges need to be addressed shortly.

First, the collaborative tagging approach, critical in DemonD (users tags their/other's documents, their/other's profiles…), must be assisted. In fact, tagging might create inaccuracy (noise) if it does not rely on a semi-structured ontology. Furthermore, tagging is time consuming and not yet included in worker's practice. To respond to this challenge, we are contemplating the possibility to suggest tags based on user's context and shared documents.

Second, the naïve sharing assumption embedded in DemonD must be leveraged by proper incentives. Users usually leverage their personal network of information. Sharing knowledge with unknown co-workers must be secured (in terms of intellectual property) and encouraged. To respond to this challenge, we included a "confidential" functionality to restrain and control information diffusion. We also gave active user's visibility on DemonD.

A new version of DemonD is currently in progress and will be deployed in the laboratory depicted in the introduction, between May and July 2007. Quantitative data will then be collected based on user's improved effectiveness when utilizing this Collaborative Information Retrieval Groupware

References

Open Group Learner Modeling, Interaction Analysis and Social Visualization

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Abstract. This paper argues that a new and very interesting area is forming from the merge of three research streams originating in different areas: open learner modeling, interaction analysis and social visualization. The paper reviews the most notable work in these areas from the viewpoint of the purposes for opening the model and whether it is opened to the learner/user or to the teacher/moderator. Several versions of the Comtella online learning community are used to demonstrate how depending on the purpose in mind, data to represent in a learner (group) model is chosen and an appropriate visualization is designed to stimulate social comparison and reciprocation.

1 Introduction

Open (Bull et al, 1995), externalized (Paiva, 1995), scrutable (Kay, 1999) learner modeling has been an active direction in user modeling for over a decade now. Most of the works in this area focus on one-to-one systems aiming to open the learner model to the learner. With some notable exceptions, e.g. (Mazza & Dimitrova, 2004) not much has been done so far for multi-user systems, like collaborative learning systems, e-learning systems and online learning communities.

The area of group or community modeling is still young. Group models can represent interactions among members of a group, individual contributions or relationships, or collaboration activities, stages, phases and processes (Soller, 2001). Just like opening up individual models, opening group models to the users offers many advantages. It can help learners reflect on their progress in the group context, understand the problems others face (Vassileva et al. 1999). By externalizing the social model of the group, certain social norms are enforced and certain user behaviours are observed (Sun and Vassileva, 2006; Vassileva, submitted).

In the realm of Computer Supported Collaborative Learning (CSCL) and Computer Supported Collaborative Works (CSCW), where researchers traditionally steer away from Artificial Intelligence and User Modeling (UM), a stream of research called “interaction analysis”, has been very active recently. The goal is using statistical and data-mining techniques to analyse the interactive/collaborative activities in the group and to represent the results in some appropriate way to the teacher/moderator. Researchers in CSCW from the Human-Computer Interaction community have produced a stream of work on social visualization, aimed at revealing a view of the other users and their activities in the community to the users, so that they can self-regulate behaviour accordingly. In fact these researchers are doing open group modeling.

There is an obvious link between interaction analysis (IA) in CSCL/CSCW and Community Visualization (CV) in the CSCW/HCI areas and Open Group Modeling (OGM) in Artificial Intelligence in Education (AIED)/UM areas and the researchers working in these areas can learn from the experience of the others. For example, the question of how to represent visually the information from the user/group model or the results of interaction analysis in a way that it is understandable and useful is common for HCI, CSCL/CSCW and AIED/UM. Also common is the fundamental question which data to open (visualize) depending on the pedagogical or moderator goals.
The goals of the paper are to suggest a link between these research streams of OGM, IA and CV and to suggest that opening group user models should be done carefully and pragmatically, with a purpose in mind. The next section reviews the purposes for which OGM, IA and CV have been used. The third section discusses several versions of the Comtella online learning community as examples, to demonstrate how depending on the purpose in mind, data to represent in a learner (group) model is chosen and an appropriate visualization is designed to open the model to the learners.

2 Open Group Modeling, Interaction Analysis and Visualization

A brief overview of the Learner Modelling for Reflection (LeMoRe) examples, listed at http://www.eee.bham.ac.uk/bull/lemore/index.html shows the following main purposes for using open learner models:
- ensure the learner’s awareness of her progress towards her learning goals (Brusilovsky & Sosnovsky, 2005), and stimulate reflection (Bull & Pain, 1995), (Zapata-Rivera & Greer, 2004), (Mabott & Bull, 2004), (Kay & Lum, 2005), (Mitrovic & Martin, 2002), (Papanikolau et al, 2003).
- provide a way for the learner to annotate (Zapata-Rivera & Greer, 2004) or correct errors in the learner model and thus involve the user in construction of the user model (Bull & Pain, 1995), (Papanikolau et al, 2003) or engage the user in dialogue / argument (Dimitrova, 2003)
- provide for the teacher an ongoing evaluation of the learner’s performance (Zapata-Rivera & Greer, 2004)

A variety of representations have been proposed for visualizing the learner model, from fairly standard visualization tools such as charts and bars (Mitrovic & Martin, 2002), (Bull & McEvoy, 2003), graphs representing concept maps (Mabott & Bull, 2004), or Bayes nets (Zapata-River & Greer, 2004), verbal (Bull & Pain, 1995), (Dimitrova, 2004), to quite innovative ones, using subtle emphasis in tags/concepts (Kay & Lum, 2005) and haptic interfaces (Lloyd & Bull, 2006).

Work on group learner modeling since the late 1990ies originated from interaction analysis in CSCL (Soller, 2001, 2004, Soller et al, 2005). Various techniques have been used in interaction analysis, varying in complexity from simple statistics, to complex stochastic (e.g. Markov) or task-models, leading to the creation of models of the group activity (discussion, task collaboration, problem-solving). Until recently, interaction analysis in CSCL/CSCW has been done mostly to serve the teacher or the moderator of the community or discussion forum with the following purposes:
- provide the teacher with an overview of the learners’ progress so that she can take remedial actions or carry out evaluation (Barros & Verdejo, 2000), (Mazza & Dimitrova, 2004)
- provide a model of collaborative activities for the teacher so that she can influence the process and make it more productive (Soller, 2001), (Harrer et al, 2006).
- provide the teacher with an overview of the interactions in the group, e.g. if someone is isolated or dominating the discussion (Brace-Govan, 2003), (Bratitsis & Dimitracopoulou, 2006), (Brooks et al, 2006), (Collins & Berge, 2001).

In the HCI/CSCW community results of interaction analysis were used to create visualizations aimed at the users to stimulate reflection and self-regulation. When visualization is directed to end-users, one has to consider some general design guidelines developed in the visualization community. They are aimed at reducing cognitive overload, increasing the usability and exploiting psycho-physiological properties of human vision. The choice of metaphor is very important, since an appropriate metaphor is intuitive to use and doesn’t require a complex legend for interpretation. Applying a hierarchical structure and using a composable layout and visual sets are always helpful, when designing information-compact visualizations for large networks. Proper use of location and color contraction of visual components will successfully attract attention. Richly expressive information visualization is difficult to design and rarely found.

Most of the existing visualizations are based on some sort of graph representation where users are represented as nodes with various sizes and various locations depending on their actions or relationships. Sociograms have been used often to represent social networks or interaction networks in
online communities (Brooks et al. 2005). These visualizations are shown to the learners/users for the following purposes:
- increase knowledge awareness and reflection of learners during problem solving (Margaritis et al., 2006, Bratistis & Dimitracopoulou, 2006).
- provide social awareness about the other learners’ existence or actions (Erickson & Kellogg, 2003, Viegas & Donath, 1999) and contributions (Bretzke & Vassileva, 2003, Sun & Vassileva, 2006) to encourage social norms and participation.

Erickson (2003) came up with a list with guidelines for designing social visualizations. For example, one of them states that the information showed in the visualization does not necessarily have to be very detailed and exact. In most of the cases, it is better just to give the user a general idea, and even in some cases a certain level of misrepresentation may be beneficial. Also, customization should be avoided; all users should see the same thing. In this way they feel more responsible for their actions, since they know that others see what they do.

From this overview it is clear that there is a variety of ways and techniques to create group models, and to open and visualize these models to users, both teachers / moderators and learners /participants. The pedagogical or moderation (social engineering) purpose is the main defining factor in choosing what to model and how to open / visualize the model. The next section presents several simple open community models and the corresponding visualization designed with the same main purpose, but with different emphasis in the desired activities. The Comtella community was chosen as an example, since the model is fairly simple technically and this allows focusing how the chosen purpose defines what user data to show and how.

3 Designing Community Visualization: the Comtella Experience

The Comtella community (http://umtella.usask.ca/um) has evolved through four versions since its initial design in 2003. It started as a decentralized P2P system for sharing academic articles (as .pdf files) among research lab members (graduate students and faculty). Ensuring participation and a stream of original contributions has always been the paramount goal. Our main hypothesis was that using a social visualization we can achieve an awareness of the existence of other users and of their contributions, and this will trigger social norms such as social comparison and reciprocation. With this purpose in mind, we decided what information we needed to keep about users in their individual models and what the community model will look like. The visualization was designed to present in an intuitive and attractive way to view the information contained in the model (Bretzke & Vassileva, 2003). Simplicity and aesthetics were our guiding principles in choosing a representation metaphor and in the graphics design. An ugly, boring, complex, and hard to understand visualization will not be used and won’t have motivational effect. For this reason, unlike most existing visualizations, we did not try to pack as much information as possible using standard visualization tools, such as graphs, charts, or trees. We used a star sky as a metaphor (see Table 1) where each user that was online at the moment was represented with a star with visual parameters reflecting participation aspects of the user (Sun & Vassileva, 2006).

The second, third and fourth versions of Comtella supported students in an undergraduate class to do their coursework (find online materials relevant to the class). To guarantee availability of the shared materials, we needed to ensure simultaneous presence of all peers and their shared files, which was impossible with a P2P architecture. Therefore all next versions were centralized. The users shared links (URLs) of papers instead of files. In the second version we had to step back to a poorer and more simplistic graphical representation. This was necessitated by specific pedagogical purposes (to encourage social comparison on a regular basis, in different activities, and for each topic of the class), and by user feedback from the previous version which pointed to the need of less ambiguous graphical language (the users weren’t able to distinguish between the smooth differences in the sizes of stars and the different colours). The second version of the visualization (Sun & Vassileva, 2006) used circles instead of stars, so it was simpler to generate on request. Interactivity was deemed important by the instructor, since she wanted to encourage social comparison with respect to several participation dimensions: bringing new articles, downloading (and presumably reading) articles from others, logging in the system frequently. Since the system was centralized, it was possible to aggregate the
models and display all users, not just those currently online. This strengthened the motivational effect, since users didn’t feel alone, and the sizes of stars were consistent, not relative to who is online, as in the first version.

The experience with the second version (Sun & Vassileva, 2006) showed that some of the pedagogical goals, for example, encouraging social comparison along different activities, were not achieved with the interactive design. The students did not use the interactive features of the visualization and accessed only the default view. In response, we introduced a combined measure of contribution and classified the users in four classes (memberships): plastic, silver, bronze and gold, each shown with a different colour star in the visualization. The details about the algorithm of classification are presented in (Cheng & Vassileva, 2005, 2006). Encouraging users to contribute high-quality papers and to rate papers became the most important goal. Therefore, we introduced a new feature in the user model, called “reputation” which was based on the ratings that the user’s contributions have received from others. It was necessary to find a way to visualize the reputation of users, which made us extend the graphical language by introducing “brightness” of each star. The attractiveness of the visualization turned out to be very important too. We used computer graphics software to generate more realistic stars with certain parameters (size, colour, brightness, and type).

Finally, from student feedback in the two versions described above (Sun & Vassileva, submitted) we realized that in a learning community an important form of participation is reading the shared resources, not only contributing new ones. Encouraging users who aren’t active contributors, but nevertheless participate by “lurking” and read the resources shared by others required a very different approach, which was experimented in the fourth Comtella version. This version had the paper sharing functionality from the previous versions, but emphasized discussion and rating of contributions. The motivation approach here was no longer based on social comparison. There were two purposes: to emphasize visually the social reward received by users who contribute good quality postings through the ratings of others and to stimulate the development of reciprocal relationships among the users, i.e. stimulate cooperation instead of competition. To achieve the first purpose, the postings of users were visualized in different shades of the orange to purple spectrum (representing “hot” or “cold”) depending on the ratings they have received. Each act of rating changed the colour of the posting a little bit, bringing an aesthetic reward to the user who gives the rating. Viewing the list of discussion postings, one could immediately see which the “hot” ones were. This brought satisfaction to the author and was useful for the community since it made finding good stuff easier. For the second purpose, the main idea was that if users were aware explicitly about who was reading and rating their postings, this could stimulate reflection and they might be tempted to read and rate their postings. In this way the lurkers would be pulled to participate and would get as reward the appreciation (in the form of ratings) from the other community members.

To achieve these two purposes, we did not need to keep an individual model of contributions for each user anymore. Instead we created a community model representing the relationships between every two users, each with two parameters expressing the visibility of user B from the point of view of user A and the other parameter showing the opposite, the visibility of user A from user the point of view of user B. The values of these parameters were updated every time when user A reads or rates posting by user B or the opposite. In a reciprocal relationship these parameters will have equal values. When one of the users is a lurker, she will be involved mostly in asymmetric relationships with other users. Visualization designed to show the asymmetry brings a spotlight on the lurker and stimulates reflection in both parties involved.

Table 1 shows the purposes, community user models and visualizations deployed in each of the four versions of Comtella discussed above.
Table 1: The Purposes, Community Models and Visualizations in Comtella.

<table>
<thead>
<tr>
<th>Purpose</th>
<th>Community Model</th>
<th>Visualization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Version 1 - P2P-Based community for sharing academic papers (Bretzke &amp; Vassileva, 2003)</td>
<td>Aggregation of individual models (in one database), each with its own participation metrics: - number of shared original files, - number of re-shared downloaded files) - inter-personal relationships: represented as the balance of contributed-downloaded files. The interests of users are modeled explicitly in the individual model. Only the models of users that are currently online can be aggregated in the community model (the others are unavailable). Individual model is updated directly after each action, no historical data is kept.</td>
<td>Central server generates visualization from data received from distributed servents. Users – shown as stars Individual contribution – size of star (analog) Sociability – shown with different color (blue star – taking user, red star – giving user) Clicking a star shows on the left side of the window all shared files (and their topics). Groups (galaxies) of stars show communities interested in a given topic Position of star on screen is random Visualization shows only the stars of users currently online. No way to see the past contributions.</td>
</tr>
</tbody>
</table>
**Version 2:** centralized P2P system supporting students in a presence class to share class-related online resources (Sun & Vassileva, 2006).

<table>
<thead>
<tr>
<th>Feature</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Encourage higher number of contributions for each topic (week)</td>
<td>Aggregate of individual user models kept in one database. Each individual user model is organized according to 2 dimensions, to represent contributions for different topics and different types of contributions (new papers, shared downloads, logins, number of ratings given, comments, reads). Users classified into 4 participation levels for each dimension. Individual model contains a flag variable “online”. All participation data is kept with timestamp</td>
</tr>
<tr>
<td>Encourage users to compete in specific topics and for different kinds of participation</td>
<td>Quality of contributions not represented in user model</td>
</tr>
<tr>
<td>Most important – current topic and bringing new papers</td>
<td>Interactions between users (whose paper the user reads and who reads the papers submitted by the user) are kept in the individual user model</td>
</tr>
<tr>
<td>Important to see everyone (both online and offline users)</td>
<td>Individual users ➔ circles Individual contribution level ➔ size of star (discrete - 4 levels) State of a circle: filled – on line users, empty circle – offline users Visualization provides different “Views”: - by topic - by participation type User can pick a View interactively Default view – for current topic (week) and “original contributions” User can see community participation for previous topics (weeks) Visualization does not represent the quality of contributions / participation Colour is not used Position of circles is fixed -sorted in order of decreasing contribution The “balance” in the interactions between users are displayed in the list of search results (below) not in the social visualization: S/he owes me I owe her/him</td>
</tr>
<tr>
<td>Important to see progress in time</td>
<td>Not important to encourage quality of contributions</td>
</tr>
<tr>
<td>Not important to encourage quality of contributions</td>
<td>Rating – not considered important</td>
</tr>
<tr>
<td>Sociability isn’t very important</td>
<td>State of a circle: filled – on line users, empty circle – offline users Visualization provides different “Views”: - by topic - by participation type User can pick a View interactively Default view – for current topic (week) and “original contributions” User can see community participation for previous topics (weeks) Visualization does not represent the quality of contributions / participation Colour is not used Position of circles is fixed -sorted in order of decreasing contribution The “balance” in the interactions between users are displayed in the list of search results (below) not in the social visualization: S/he owes me I owe her/him</td>
</tr>
</tbody>
</table>
**Version 3** centralized web-based online community for sharing class-related papers (URLs) (Sun, 2005).

<table>
<thead>
<tr>
<th>Same as in Version 2, however: Important to encourage quality of contributions - papers - ratings</th>
<th>Aggregate of individual user models stored in one database. Users are classified into 4 classes along the following dimensions: - number of original contributions, - reputation – computed from the quality of contributions (from other users’ ratings). - status (combined measure of participation from quantity and quality of contributions). No relationships or balance of give-take computed in the model.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not important to encourage comparison for single activities</td>
<td></td>
</tr>
<tr>
<td>Sociability – not important</td>
<td></td>
</tr>
</tbody>
</table>

![Comtella](attachment://comtella.png)

User selects topic (category) for which a view is shown. Users represented as stars with a fixed position with different:
- **size** (number of new contributions)
- **brightness** (reputation)
- **colour** (status)
- **state** (eclipsed – offline, clear – online).

**Version 4** Comtella – Discussions supporting a presence class (Webster & Vassileva, 2006).

<table>
<thead>
<tr>
<th>Important to encourage reciprocity between users. Participation is expected to increase as a result of two factors: - becoming aware of other people reading and rating your postings; - satisfaction of the ratings that your</th>
<th>A group user model fed by individual actions of users. Reciprocity between each couple of users is represented as a measure of “opaqueness/ transparency”. The actions of user A on contributions of user B increase the transparency of B to A, but don’t</th>
</tr>
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</table>

![Community visualization](attachment://community_visualization.png)

Community visualization shows the two directions of reciprocity on a XY-graph from the viewpoint of the user looking at the visualization. X – how close the viewer is to other users from their point of view, Y – how close are others from the viewer’s point of view.
postings receive from the community. Not important to encourage participation explicitly. Topic of interest is not important. affect the transparency of A to B. The ratings given by users to the postings become a kind of a group model. No measures of participation / activities kept for individual users. No topics represented in the user model. Only the “closeness” and the “symmetry of relationship” between the viewer and other users is shown, not any other information. The main interface of the application – the display of discussions shows the collectively accumulated ratings by the postings as “hot” or “cold”. It is also a kind of group model visualization, but focused on the contributions, not on the users.

4 Conclusions

This paper argues that a new and very interesting area is forming from the merge of three research streams originating in the areas of AIEd/UM, CSCL, and CSCW/HCI: open learner modeling, interaction analysis and social visualization. The amount of data resulting from collaborative and social systems is prohibitively large and one has to make very careful choices as to what features to include in the group model depending on the purpose the open model plays and the constraints that the chosen visualization metaphor poses. The goal should never be showing as much information as possible; whatever information is opened to the learners/users should be there with particular purpose in mind. Aesthetical considerations are also important to attract users to view the visualization.

References


Community-based Conference Navigator

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Abstract. As the sheer volume of information continues to grow, information overload challenges users in many ways. Large conferences are one of the venues suffering from this overload. Faced with several parallel sessions and large volumes of papers covering diverse areas of interest, conference participants often struggle to identify the most relevant sessions to attend. We have designed a community-based conference navigator system that uses social navigation support to help conference attendees schedule\textsuperscript{1} the most appropriate sessions and make sure that the most important papers are not overlooked. The system collects the wisdom of the community in order to guide individuals making decisions about attendance at papers presented at a large conference. The paper presents the design and a preliminary evaluation of the system.

Keywords: Information overload, community-based personalization, adaptive navigation support

1 Introduction

As the sheer volume of information continues to grow, information overload challenges users in many ways. Large conferences are one of the venues suffering from this overload. Faced with several parallel sessions and large volumes of papers covering diverse areas of interest, conference participants often struggle to identify the most relevant sessions to attend. Conferences organized by the Association for the Advancement of Computing in Education (AACE) such as E-Learn\textsuperscript{[6]}, and ED-Media\textsuperscript{[7]} are a clear example of large conferences with diverse collections of papers. To tackle the planning problem, AACE makes the schedule of the conference available on the web several weeks before the conference and also offers a personal scheduler system to help conference attendees plan their conference beforehand. The schedule and the planner provide the title and abstract of each paper. However, given the large number of papers (more than 500 articles in 15 parallel sessions in the latest E-Learn conference) without any navigation support, it is a challenge for the conference attendees to find what interests them and not miss any interesting presentations. Informally, conference attendees are accustomed to seeking each other’s advice in order to find relevant papers. However, at a large conference with hundreds of attendees, it is very difficult to find people with similar interests. To address this problem we have designed a community-based conference navigator system that formalizes the process of advice-seeking from people with similar interests. The system uses community-based adaptive navigation support to help conference attendees schedule the most appropriate sessions and make sure that the most important papers are not overlooked. The system is designed as an adaptive service layer covering the AACE conference program and schedule. It adds the wisdom of the community to the system in order to help individuals make decisions.

The remainder of this paper is structured as follows. In section 2 we review related work on community-based personalization. In Section 3 we describe our community-based conference navigator system. Section 4 describes our preliminary evaluation of the system. Section 5 concludes with a discussion of future directions for research in this area.

\textsuperscript{1}Throughout the paper we use the term “schedule” to indicate planning to attend. We use the term “plan” when someone explicitly plan to attend a talk using the AACE planner.
2 Community-Based Personalization

Over the last decade, a range of information systems have looked at how community-based personalization can help users find their way in a rapidly expanding information space. Community-based personalization is mainly offered through social information access technologies. These technologies capitalize on the natural tendency of people to follow direct and indirect cues about the activities of others; for example, we often prefer restaurants that appear to attract lots of customers and our movie preferences are often informed by the opinions of others.

Pioneering work on social information access from the early 90’s attempted to formalize this social tradition in two ways: collaborative filtering and history-enriched environments. Collaborative filtering attempted to propagate information items between users with similar interests. This technology enabled a social form of information filtering and recommendation. For example, the innovative collaborative filtering system GroupLens [4] allowed the cross-recommendation of NetNews articles. In contrast, history-enriched environments attempted to make the aggregated or individual actions of community users visible to others, mainly to facilitate social navigation through a given information space. For example, the ‘Read Wear and Edit Wear’ system [2] visualized the interaction history a document developed between its authors and readers, enabling third parties to quickly locate the most-viewed or -edited parts of a document. More recently, the set of social information access technologies has been extended by the advent of social search and social bookmarking systems. Social search systems such as I-SPY [5], attempt to help new searchers by harnessing past successful searches by similar users, promoting results that have proved successful during these sessions. Social bookmarking systems such as WebTagger [3] applied tagging to help new users locate useful information that has already been discovered and classified by others. Information access using social tagging systems was recently popularized by such systems as del.icio.us and Flickr. Knowledge Sea II [1] is an elaborated example of social browsing. It was developed to help students within one course discover the most useful pages in multiple open corpus textbooks. It supports information access through search, visualization, and browsing and guides the users with extended footprint-based and annotation-based social navigation support.

3 Community-based Conference Navigator

![Conference Navigator Login Page](image)

**Fig. 1.** Conference Navigator Login Page

To explore the problem of conference planning, we have developed a community-based conference navigator system for the E-Learn conference organized by AACE. This system uses community-based adaptive navigation support to help conference attendees schedule the most appropriate sessions and to make sure that the most important papers are not overlooked. The
The system is built as an adaptive layer of service over the AACE conference planning system, which allows the conference attendees to browse the entire program and plan their own schedule. The service tracks different activities of the community, including the scheduling of papers and allows users to add comments to papers. The activities are used to update the community profile accumulating over time—the “wisdom” of the community. This “wisdom” in turn is made available to all community members through adaptive icon annotations that attract attention to papers that are popular within a certain community.

To use the service, a user needs to first choose a community. If the desired community does not already exist, they can create their own community. In the current system, an expert in the field created a list of communities related to E-Learn conference; however, this is not necessary for the system and the system allows the user to create their own community. Fig. 1 presents the login page to the system. As can be seen in the figure, the system provides two access options: “Schedule Browser”, and “Personal Schedule Planner.” Both methods are augmented with community-based support as described in the following section.

3.1 The Schedule Browser

The schedule browser helps users to locate papers that are popular within the community. The AACE schedule browser allows users to search the schedule by topic, date, and keyword in within the author, title, organization, country, or abstract. Our schedule browser “hijacks” the results returned from the AACE search and provides community-based navigation support by augmenting the search results with visual cues (icons). The visual cues represent different community activities such as annotation, reading or adding a paper to one’s personal schedule.

![Schedule Browser](image)

Fig. 2. Schedule Browser

Fig. 2 presents the overall view of schedule browser with community-based navigation support. The results shown in the figure are the list of the papers presented on the first day of the conference, which includes 77 papers. The current user is looking at this result as a member of the “Social Learning” community. Community information is shown at the top right of the window. Papers that are scheduled by members of the community are augmented with footprints.
icons. While navigating and checking the papers, the user can add annotations to visited papers and mark them as relevant or irrelevant to the interests of the community. Users’ annotations are represented by a sticky note icon. The overall attitude of the community about the relevance of the paper is represented by a thumb-up or thumb-down icon.

The first, third, and fifth papers in the list shown in Fig. 2 are augmented with community information. The footprints icon added to the first and third results signifies that those papers are scheduled by members of the “Social Learning” community. The thumbs-up icon added to these two results recommends these two papers to the community. However, the fifth item is not annotated by any footprints icon, which means that no one from the “Social Learning” community has added the paper to their schedule and the thumbs-down icon is another indication that the paper is not relevant to the “Social Learning” community.

Anyone who is interested in viewing papers from the viewpoint of several communities is able to switch to a different community at anytime. A link at the top left allows the user to change the community at anytime. In this way, the user will view the same set of results, but they will be augmented for a different community.

3.2 Personal Schedule Planner

AACE provides a personal code to all registered attendees so that they can use the personalized schedule planner. The schedule planner provides the user the ability to search the conference schedule, similar to the schedule browser. Users can search by topic, date, or keyword. Next to the link to each paper returned in the search results, there is an option to add the paper to one’s personal schedule, as shown in Fig. 3. All the scheduled papers can be viewed in the “My Schedule” section of the interface. Once the paper is added to the schedule, the “Add” option will be replaced by the “Remove” option—allowing the user to edit his/her personal schedule.

Fig. 3. Personal Schedule Planner
Our system synchronizes authentication with the AACE without the need to know any personal data. When a paper is added to or removed from the personal schedule it is tracked by our system as well. As a result, we have information about all papers scheduled by each member of the community and we can use this information to provide navigation support. While checking and planning the schedule, users are also able to annotate the paper and mark it as relevant or irrelevant to the interests of the community. The same community-based navigation support as the “Schedule Browser” has is provided for the schedule planner, as shown in Fig. 3. Previously scheduled papers are annotated with a footprints icon and papers with users’ annotations are emphasized by adding a sticky note icon. Papers found relevant by the community are annotated with a thumbs-up icon while ones found not relevant by the community are annotated with a thumbs-down icon. The navigation support in the planner view allows the user to plan their session attendance with the help of a community with similar interests. The users are able to locate relevant papers and make sure to attend important presentations. Therefore, community-based navigation support improves the personal planner while the planning actions of each member of the community feed into the collection of community wisdom at the same time.

3.3 Annotation Feature

As mentioned in the previous section, our system incorporates an annotation feature which allows the users to annotate papers while browsing, or planning the schedule and let the user mark the paper as relevant or irrelevant to the interests of the community. When the user clicks on a search result returned by the AACE search, a detailed page about the paper is presented which includes the title of the paper, information about the authors, and the abstract of the paper. Our system adds the annotation feature to these paper information pages as a frame on the right side of the window. Fig. 4 presents an information page along with the annotation feature. As shown in the figure, previously written community annotations are shown at top of this frame and information is also given about how many members have scheduled to attend the paper.

![Fig. 4. The annotation feature](image)

An annotation is a free-format note that will be associated with the related paper. The user has the option to share the note with everyone who uses the system (Public option) or to limit it to one community (Community option). Along with the free-format note, the user can recommend the paper to the community if she finds it relevant or otherwise mark it as not relevant. As described in previous sections, this information is used to provide navigation support and guide other members of the community.
3.4 Community-Based Navigation Support

The main personalization functionality of our system is its social navigation support. This support is provided by augmenting links to papers presented to the user during search and browsing, with visual cues reflecting the activities of the community. Appropriate visual cues represent different activities of the community and the level of color within each icon represents the magnitude. Filling an action with a higher level of color represents a higher magnitude for that action. Icons with various levels of color are shown in Table 1.

Table 1. Visual cues providing community-based navigation support

<table>
<thead>
<tr>
<th>Activity</th>
<th>Icon</th>
</tr>
</thead>
<tbody>
<tr>
<td>Planning</td>
<td>![Planning Icon]</td>
</tr>
<tr>
<td>Annotation</td>
<td>![Annotation Icon]</td>
</tr>
<tr>
<td>Overall attitude</td>
<td>![Overall attitude Icon]</td>
</tr>
</tbody>
</table>

For example, the height of the color in the footprints icon represents the magnitude of scheduling; i.e., the number of community members who have scheduled to attend the paper. Higher levels represent that a higher number of members of the community scheduled that paper. To give more weight to early scheduling events, the levels increase logarithmically. The maximum level depends on the number of members in the community. We would assign the maximum level to a paper which is scheduled by half of the members of the community. The range of each level is specified using the following formula

\[
\text{range}(i) = \left( \frac{\text{Max}^{i+1} - \text{Max}^i}{2} \right)
\]

where \( \text{Max} = \frac{\# \text{of community members}}{2} \)

Similar to footprints icons, different filling levels are used for sticky note icons, representing the different densities of community annotations, with higher levels representing larger numbers of annotations. Since the number of annotations is limited, we assigned levels directly based on the number of values as shown in table 2.

Table 2. Assignment of annotation icon

<table>
<thead>
<tr>
<th>Number of Users’ Notes</th>
<th>Icon</th>
</tr>
</thead>
<tbody>
<tr>
<td>One</td>
<td>![One Note Icon]</td>
</tr>
<tr>
<td>Two to five</td>
<td>![Two to Five Note Icon]</td>
</tr>
<tr>
<td>More than five</td>
<td>![More than Five Note Icon]</td>
</tr>
</tbody>
</table>

When the user mouses over an icon, detailed information about the annotations including the total number of annotations, the number of members recommending it, and the number of members finding the paper not relevant are presented to the user. If the paper is generally found to be relevant by a larger proportion of community members, the paper is augmented with a thumbs-up icon and if it is not found relevant by a larger proportion of community members, it is augmented with a thumbs-down icon.

3.2 Activity Summary

Another important feature of the system is the ability to view the summary of activities for each community. At the top right corner of all pages there is a link to check the summary of community activities. The summary page shows all pages annotated by the community, the top 5 pages scheduled by the community, and the top 5 papers accessed. There is an option to view all scheduled and all accessed papers as well. Each paper is linked back to its description page which includes the abstract of the paper. Similar to previous views, the links in the view are also annotated with visual cues. The annotated papers are augmented with annotation icons, as
described above, which shows the density of annotation and the overall attitude of the community towards the paper. Scheduled papers are also augmented with the footprints icon which represents the number of members scheduled to attend the paper. Fig. 5 presents a sample view of the summary of activities completed by the “Social Learning” community.

Fig. 5. Summary of activities by the “Social Learning” community

4 Preliminary Evaluation

To evaluate our community-based conference navigator system, we ran a user study at the latest E-Learn conference. As mentioned before, E-Learn is one of the conferences organized by AACE, which provides an online schedule and planner to attendees, several weeks before the conference. Each year, E-Learn features about 500 articles, which are organized in about 15 parallel sessions. We created several communities related to the conference and advertised the system one week before the conference, through email to the members of these communities who were attending the conference. We also prepared a flyer and advertised the system throughout the conference. We asked participants to plan the conference using the system. The participants were also asked to respond to a questionnaire which was designed to evaluate the community-based support features of the system. We collected the questionnaire at the end of the conference. The questionnaire included 7 short questions. The sample questions are shown in Fig. 6.

Unfortunately, our study was damaged by a technical problem. We expected the main use of system to happen during the second day (after the first day was spent advertising the system). However, due to a local earthquake, there was a power outage during the whole second day of the conference. While the conference was able to continue, the attendees were not able to use
computers. As a result, we collected only seven attendee responses to our questionnaire. Out of these seven responses, six used the system extensively and one did not use the system (so we discarded the responses from that user). As a result, the collected data presented below should be tempered with an understanding of the sample size. A more elaborated study needs to be carried out for a better understanding of the system.

<table>
<thead>
<tr>
<th>2. While browsing or planning the schedule</th>
<th>While planning your schedule</th>
<th>While locating interesting papers</th>
</tr>
</thead>
<tbody>
<tr>
<td>presence of any type of community</td>
<td>a. Strongly agree</td>
<td>a. Strongly agree</td>
</tr>
<tr>
<td>annotations</td>
<td>b. Agree</td>
<td>b. Agree</td>
</tr>
<tr>
<td>presence of positive type community</td>
<td>c. Neutral</td>
<td>c. Neutral</td>
</tr>
<tr>
<td>annotations</td>
<td>d. Disagree</td>
<td>d. Disagree</td>
</tr>
<tr>
<td>presence of negative type community</td>
<td>e. Strongly disagree</td>
<td>e. Strongly disagree</td>
</tr>
<tr>
<td>annotations</td>
<td></td>
<td></td>
</tr>
<tr>
<td>presence of footprints (sign of scheduling by members of the community)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3. How useful did you find the following navigational cues? Put letters into table.

4. The ability to provide comments for the community is very useful.

5. The ability to read comments from the community is very useful.

Fig. 6. Sample questions

A set of questions was asked about the usefulness and attractiveness of social annotations. The result is shown in Fig. 7. As shown in the figure, all users noticed the social annotations and 80% of them found the social annotation very useful in planning the conference and locating the most interesting papers. Generally, the users also found the ability to provide comments and read others’ comments to be very useful.

Fig. 7. Users' attitude toward the usefulness and attractiveness of social annotations.

Another set of questions asked the users about the usefulness of each visual cue while planning and browsing. The results are shown in Fig. 8. It is interesting to observe that the general presence of users’ annotation is not as useful as other social cues, which is an expected result. Users are more interested in knowing whether the paper is found relevant or not-relevant by other members. Consistent with this result, the importance of negative comments is the same as the
importance of positive comments. This means that knowing a paper is relevant or not relevant influenced the users’ decisions about the paper. The results also show that the footprints icon, representing scheduling information, is the most useful icon. This is a rather expected result since there is a stronger level of interest in scheduling.

![Fig. 8](image.png)

**Fig. 8.** Usefulness of visual cues while planning and browsing the schedule

## 5 Conclusion & Future Work

The current work presents our design for a community-based conference navigator system that collects the wisdom of the community in order to guide individuals making decisions about attendance at papers presented at a large conference. We have presented the design and a preliminary evaluation of the system. As mentioned before, a more elaborate study is required to validate whether the system is useful in guiding conference attendees. We plan conducting future studies in upcoming AACE conferences. Moreover, we are looking into integration of our system with the AACE system instead of as an add-on system. True integration of the systems would improve the visibility of our system and also enable us to add more functionality to the system. For example, it is currently not possible to plan to attend a paper from the activity summary page since our system does not have any access to AACE planning. This would be an important additional functionality for the users. Another limitation of the current implementation is scheduling a paper for more than one community. Since our system uses AACE planning and AACE only allows scheduling a paper once, it is not possible to schedule the same paper for different communities. A true integration of these two systems will help to address these limitations.

## References

Abstract. Social tagging is a kind of social annotation by which users label resources, typically web objects, by means of keywords with the goal of sharing, discovering and recovering them. In this paper we investigate the possibility of exploiting the user tagging activity in order to infer knowledge about the user. Up to now the relation between tagging and user modeling seems not to have been investigated in depth. Given the widespread diffusion of web tools for collaborative tagging, it is interesting to understand how user modeling can benefit from this feedback.

1 Introduction and State of the Art

With the beginning of the new millennium, the Web has seen a big transformation which led to the explosion of the so-called “social software” and to the definition of a new paradigm of the Web, the Web 2.0\footnote{http://www.oreillynet.com/pub/a/oreilly/tim/news/2005/09/30/what-is-web-20.html}. This new paradigm offers users several ways to participate in the creation of web content: it makes easy and stimulating the process of tagging (labeling resources by means of keywords), inserting new contents, sharing objects, providing comments and so on. These activities are typically defined as “social” or “collaborative” annotations.

In the last two years several projects have been developed in the field of adaptive systems. For example, Ahn et al. [1] use social annotation to improve information visualization by presenting visual indicators that provide information about user and group annotations to resources; Bateman et al. [3] propose a framework for integrating social tagging into a natural language ontology. Finally some works make tags themselves the object of adaptation, e.g. Xu et al. [8].

Up to now nobody seems to have exploited tag annotation in order to enrich and extend the user model. van Setten [7] provide some ideas about how information systems can adapt themselves using annotations to support users in finding the information they need. Moreover, they indicate that this profile can then be used for recommendation, using techniques as collaborative filtering or case based reasoning. This is indeed a way of tags, but it would be even more interesting to semantically analyze tags and reason on them in order to infer new knowledge about a specific user.

The aim of our work is quite to understand how tags can be used for user modeling, and specifically how tags can be useful to increase and improve the knowledge of an adaptive system about users. This work moves from a recommender system, iCITY [4], a web-based multi-device application that provides suggestions on cultural events in the city of Turin, and allows users to tag the events. Events are classified on the basis of a domain ontology, and suggestions are based on user model and user location, and the user interface is adapted to the device being used.

The paper is structured as follows. In Sec. 2 we analyze reasoning on the action of tagging, and on the content of tags. We also present a test we carried out to support our analysis. Finally Sec. 3 concludes the paper and presents some open issues.
2 Reasoning on Tags

Tags can be useful in increasing and optimizing the knowledge of an adaptive system about a user. What we want to investigate in this first part of the section is the relevance of tagging (meant as the action led by a user when adding tags), showing how and why this action could represent an important feedback for user profiling.

Thus, we start analyzing the user model of iCITY and, in particular, the user dimensions that could be inferred from the action of tagging:

i) user’s interactivity level, namely the measure of how much the user interacts with the system. It is related, on the one hand, with the willingness of the user to interact with the application, and, on the other hand, with the real possibility of the user to interact with it. The action of tagging seems to be a relevant indicator of the user interactivity level, since it requires some effort to accomplish it, compared to the other user actions;

ii) user’s organization level, which identifies the attitude of the user in organizing and categorizing things. In all the tagging services available on the web, the main motivation for user to tag is to satisfy the need of organizing resources in a personal way in order to better visualize, store and retrieve them later;

iii) user’s interest in a content, if a user spends time in selecting or inserting tags on a specific item she is probably interested in the item.

Now, we want to investigate the chance to reason on the semantics of specific tags inserted by the user in order to enrich the user model by refining the value of existing user features and inferring new user features. To accomplish such a goal, the following three main tasks seem to be necessary.

1) Categorization of tags. In order to explore how iCITY users tag events and, consequently, how this knowledge can be exploited for user modeling, we carried out an initial evaluation. We selected a list of events from the RSS channel that feeds iCITY\(^2\), to simulate the tagging activity on the web site.
We chose 15 events belonging to different categories (art, theatre, cinema, music, books), and then we set the items in three homogeneous groups to be presented to three different groups of users. We selected 39 users choosing them between students (23 subjects), researchers working in our departments (10 s.), relatives and friends (6 s.).
We organized the experimental tasks as follows: we showed each user a printed list containing 5 events and their description, and we asked them to tag them. They could freely write their own tags (up to 5 tags for event) or choose them from the words contained in the event description (the reason of this second option is that iCITY suggests also the tags automatically extracted from the event description). We collected 217 tags and we analyzed them in an inductive way, following the principles of the Grounded Theory [6]. The main two categories emerged from our analysis are the following: **proposed tags** (tags derived from the event description): 76% of tags and **free tags** (not derived from the description): 24% of tags.

We then analyzed tags taking also into account other properties related to the tagged event. Thus other categories emerged: **specific tags** (tags that add some specification about the event): 61.19%; **generic tags** (tags that classify the event in a more general dimension): 22.37%; **contextual tags** (tags about the context of the event: location, time, etc.): 13.24%; **synonym tags** (tags that are synonyms of terms in the event description): 2.74%; **invented tags** (e.g. unhyphenated compound words like “PicassoExhibition”): 2.17%.

Considering the gap between our test and the real online service iCITY provides, the next step of our analysis has been to integrate the classification obtained by our test with the categories that could not be detected with it. Thus, first of all we included the categories **Subjective tags** (tags that express user's opinion and emotion) and **Organizational tags** (tags that identify personal stuff).

Then, we took into account the types of tags suggested by iCITY, which suggests tags on the basis of i) the most popular tags in the community; ii) the most used tags previously inserted by

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\(^2\) http://www.torinocultura.it/
the user, and iii) the tags recommended on the basis of the user model features combined with the event description. As a consequence, our classification is extended with the following three categories: Most popular tags, Most used tags and Recommended tags. These categories will be taken into account as subclasses of the general class Proposed tags.

2) How to automatically analyse tags. At this point of our analysis, the main problem to face with is how to transform all the above categories into information processable by machine in order to reason on them. According to the above tags classification, some tags can be analyzed exploiting the iCITY events ontology, other categories of tags can be detected on the basis of the user behaviour, but a better solution might be analyzing tags by mean of a natural language ontology, such as WordNet3.

In the following we provide, for each category of our classification, some ideas of how to analyze them:
- proposed tags/free tags: this is the easiest category to detect, since the categories are based on the user selections and the proposed selections are controlled by the system. Thus, it is possible to check if the tags come from the system’s inference (recommended tags), if they come from the most used tags of the user, if they belong to other users (most popular tags), if they are inserted for the first time from the user (free tags), and in this specific case also if they do not belong to the WordNet dictionary (invented tags);
- generic/specific tags: for each event, tags are recognized as “general” if they are mapped on the upper categories of the iCITY ontology; “specific” if they are mapped on instances or lower concepts of WordNet related to the categories of the ontology;
- synonym tags: inserted tags are compared with WordNet vocabulary in order to identify synonyms of the word used in the description of the specific event;
- contextual tag: by means of the WordNet vocabulary, iCITY tries to discover whether the tag is related to the context of the event. It is possible only for tags with a well-defined format (e.g. time) or tags which represent instances of previously identified as contextual concepts in WordNet (e.g. location-based concepts);
- subjective tags: these tags express user's opinion and emotion, and, again, they can be identified by means of WordNet.
- organizational tags: these tags can be used to organize events and thus it is difficult to recognize them by using WordNet. Tags can be assumed to be organizational if the same user uses them with a high frequency.

Finally, we also consider the meaning of the tag: WordNet can return the category to which the tag belongs and this could be useful in order to discover whether the tag pertains to the same category of the event. E.g., a user could tag a movie like “Ray”, about the Ray Charles’ life, with the tag “jazz”, which is a lower concept of WordNet category three. A final remark to this section regards a big problem we have not taken into account up to now. It is the possible polysemy of tags, which can make difficult the use of WordNet. For discussions about that see Dix, Levialdi and Malizia [5].

3) Matching between tags and user model dimensions: starting from the above described classification of tags, we then analyzed how each tag category can be relevant for user modeling dimensions. In the following we provide a description of it.

If the user selects one of the proposed tags, we can infer a medium level of participation in the tagging activity; we can also assume a low level of knowledge on the content and a medium level of organization (maybe she could be not so interested in well categorizing the events). All these inferences are weak since the user behaviour could be due as well to slackness or to the fact that she simply found the right tag among those ones suggested by the system.

Analyzing more specifically the type of the proposed tags, if the user selects the most popular tags we can weakly infer that she trusts the other people of the community and that she conforms herself to the general thought (conformism). While if she always uses the same tags after some interactions, we could infer a propensity to regular habits (orderliness). Finally, if the user selects

3 http://wordnet.princeton.edu/
tags recommended by the system, we could infer a high level of trust in the system. On the contrary, if the user uses a lot of free tags, we can make other assumptions.

Her knowledge in the topic is probably medium-high, because inserting free tags requires a specific knowledge in the area. It could also mean a high creativity, a great participation in the tagging activity (because using personal words requires more effort than to simply selecting from suggested tags) and a high level of organization.

The last three values are even higher when the free tag is an invented one. If the user uses specific words, this could indicate a great knowledge in the topic; but, on the contrary, if she uses generic words, this does not necessarily imply a low knowledge. In fact, if the generic words are appropriate, it could mean a high knowledge that allows using high abstract concepts.

The use of synonyms could imply again a good knowledge in the topic and a high level of creativity; while contextual tags could mean that the user has high practical knowledge probably derived from a direct participation at event, and thus a high interest in it.

The meaning of the tag could reveal some cross-categorization, that could reveal a high knowledge in the event. Finally, organizational tags express a high attitude to organization and creativity and subjective tags reveal a tendency to personalize the interaction.

3 Conclusion and Future Work

In this paper we have analyzed the possible contribution that the analysis of tagging activity can bring to user modeling. In particular we have proposed some possibilities of reasoning that can be performed in order to infer new knowledge about the user. On this account we have started to implement some of our proposals in iCITY, a tagging system which provides recommendations about cultural events.

The next step is to verify these hypotheses with a deep evaluation. On this account we have started to implement some of our proposals in iCITY, a tagging system which provides recommendations about cultural events. A final consideration regard how user modeling could furthermore benefit from the analysis of tagging. All the hypotheses we presented in this paper follow a rule-based approach and are applied to each user independently from others. A further possibility of analysis could be, exploiting the techniques of collaborative filtering, case based reasoning, etc. in order to find similarities among users. However finding similarities between users on the basis of the tagged items is not the same as finding similarities on the basis of rated items. What we obtain in the second case is a set of users that share common interests, while in the first case we obtain a set of users that share a common way of categorization, a common “code”, a common mental view of items. Depending on the meaning of the inserted tags, this common mental view could also reveal common interests, but this implication is not always true. Furthermore we are investigating the possibility of exploiting the list of tags publicly available in the accounts (express through URLs) of the web communities the user belongs to, since most of them make the list publicly available in some xml-based syntax. By importing such tags (and to map them onto the domain ontology) it would be possible to enrich and extend the user model and consequently improve and refine recommendations.

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Abstract. Social networks are becoming increasingly important for a wide number of applications. This is in particular true in the context of the Web 2.0 movement where a number of Web-based applications emerged – termed social networking applications or services – that allow the articulation of social relationships between individuals thus creating social networks. Although Web 2.0 applications are a popular and characteristic class of such applications they are not the only representatives that permit such functionality. Applications in the Personal Information Management domain exhibit similar characteristics but have never been mentioned in the context of social networking. The increasing number and diversity of such applications makes their study, analysis and evaluation from a systems point of view critical and important as their study may help identify relationships that are useful when attempting to represent a community. In this paper we outline a framework for analyzing applications that permit the construction of social networks. Our main focus is on the abstractions and mechanisms that a number of applications provide to facilitate the building of such networks.

1 Introduction

The advent of the so-called Web 2.0 movement raises the level of abstraction of user information. Web 2.0 emphasizes on user participation, trusting the individual and community forming [1] and in this context “information about users” reaches first class status. The explicit concept of a user in the Web 2.0 approach is dictated primarily by the desire of the representative systems to facilitate community building. One characteristic class of Web 2.0 applications that make user abstractions one of their main focus are social networking applications. Those applications allow the creation of explicit social relationships between individuals. Motivated by social network theories [2, 3] their purpose is to establish social networks that facilitate the process of finding people that share common interests. Currently the use of social networks in some application domains is rising in popularity representing an evolutionary step in replacing the user model component of applications with a social network model component [4, 5]. Such trend requires investigating how social networks can be represented in order to best solve the problem at hand.

In this paper we survey a number of applications that permit the creation of social networks in order to investigate how the notion of social network is currently modeled, implemented and taken into consideration when providing services by some known applications. Focusing on the provided mechanisms, the survey takes a look not only at a representative set of of Web 2.0 applications but also applications from the area of personal information management that nevertheless provide means to express relationships between individuals. The survey is by no means complete and does not go into much detail but aims at giving first insights on what trends exist with respect to the available...
mechanisms of network building. As the use of social networks is a new but promising approach to service provision the study of existing applications may help identify opportunities and challenges.

Characteristic applications of Web 2.0 included in our survey are Friendster (friendster.com), LinkedIn (linkedin.com), and MySpace (myspace.com). Besides those we also analyzed Apple Address Book [6], an application from the area of Personal Information Management (PIM) [7] for managing contact information. Although PIM applications have never been termed as social networking applications, their emphasis on expressing relationships between individuals is what makes them relevant to our research.

2 Analysis

2.1 Abstractions and Syntax

In this section we discuss which abstractions and which syntax are used to build the community as well as user profiles. The basic abstraction in Address Book is card. It represents an individual or company and is the “node” abstraction. There are two main abstractions that are used for structuring: groups and associations. Groups can be a collection of cards (i.e., references to cards) or other groups. A special type of groups are so-called smart groups. They are defined by search queries on all stored cards which get executed when the group is opened.

Associations can be set by entering a person’s name into a designated field within a card as reference. References to companies do not work. No link object is stored. The reference is implicit and made explicit on activation. Even though references to other cards can be set easily by entering the associated person’s name, we expect groups as the main structure in Address book.

Equivalent to Address Book, LinkedIn, Friendster, and MySpace promote with user profiles “node” abstractions. They all allow to associate any two user profiles. Those connections are bidirectional. This is different to unidirectional associations in Address Book, which can be possibly dangling (i.e., one endpoint of the association is missing). In LinkedIn and MySpace the creation of associations are based on invitations, such that a connection is established as soon as one person accepts the request of another one.

MySpace differentiates between “friends” and “top friends”. The user can chose up to 24 friends as top friends. This is relevant for the presentation. Additionally to associative connections to other user profiles, Friendster and MySpace support the notion of groups. A group aggregates a set of user profiles and can be created by anyone. Groups may be either public or private.

2.2 Semantics

In Address Book groups (including smart groups) and associations are typed. Every group has a name and every association a type. Custom names or types are possible. The application is not aware of the implied semantics. It is exclusively the user for whom semantics plays a role.

Whereas Address Book provides customizable semantics to the user, the other analyzed applications only support very simple or not typed associations. All associations in Friendster and MySpace are named friends relationships. However, MySpace is aware of “top friends” and displays those before others. Because there is no further differentiation of friends, this term yields to be semantically meaningless, especially when considering that both Friendster and MySpace are targeted primarily at capturing personal relationships. Groups in Friendster and MySpace are not typed.

LinkedIn uses simple and untyped connections. Since LinkedIn’s application domain is primarily business, connections denote primarily business relationships. Explicitly typing relationships, however, is not supported.
2.3 Interpretation and Awareness

We reach awareness, such as group or network awareness, through interpretation and computation. One example are the so-called smart groups in Address Book. These groups are defined by queries which are computed and updated on the fly. They may show different results over time. For example, a smart group may show all people who’s birthday will comes up within the next 30 days. Associations to cards are also computed on the fly at traversal time, based on the given names. The application is group aware (i.e., it is aware of all members of a group). Furthermore, it finds duplicated entries by comparing names. However, understanding semantics (e.g., association types or group names) is not supported and exclusively at the user’s side.

Almost all analyzed applications support asynchronous notification services that help making users aware of events that happen and may be of interest to them. Friendster allows the notification of first degree friends when a user creates new groups. LinkedIn automatically notifies users in case new profiles match some aspects of their profiles, such as, the institution from which they graduated. Users may then browse through those new profiles. In case a user updates his/her profile, LinkedIn allows the notifications of all members with whom the user is associated with. LinkedIn allows users to see profiles that are within the reach of a shortest path of three degrees.

Finally, LinkedIn is also capable of finding common friends of two users. In MySpace users may optionally receive notifications when their profile is added to a users favorites. Moreover, MySpace also notifies users in case their profile, blogs or their resources they upload (such as images and videos) receive comments. Additionally, MySpace notifies users on the number of users that have viewed their profile, without revealing their identity though. Almost all applications provide presence indicators (i.e., users can see whether other users with which they are associated are currently online or not).

2.4 Presentation and Visualization

Address Book’s main window provides three sections: A list of groups, a list of group members of the selected group, and one section for displaying the data of a selected card. Double clicking on an name entry opens an additional window with the card’s content. Group and group member list are sorted alphabetically, the latter by last or first name, depending on the given preference settings.

LinkedIn, Friendster, and MySpace are accessed through WWW browsers. The main unit displayed are profiles, one at a time. Visualization of associations are held simple. Users may choose which part of their profile will be visible to others. MySpace presents friends as a sequence of display name and attached picture, representing the associated profile. A click traverses the association. “Top friends” take the first places, but are not especially marked to be recognized by others.

2.5 Type

Address Book is based on a business card metaphor. As with collecting real business cards, there is mostly one person involved in managing them. The point of view therefore is strongly personal. Only those entries that are relevant for the user will be added.

LinkedIn provides the user in the beginning with an ego-centric view of the network. Every user may see the network only through his/her own connections. Yet, divergence from this subjective view is the ability to see profiles with which a user is not directly connected but rather indirectly through his/her connections. As LinkedIn, Friendster and MySpace do not provide whole network maps to the user. The point of view on the network is ego-centric from the currently opened profile. Any profile can act as an entry point for further browsing through the network.

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3 The display name can be freely chosen by the user. It appears on MySpace and can be seen by everyone.
2.6 Size

Cards, groups, and associations are created in Address Book by a single user. This follows a business card metaphor. Therefore, we expect a small number of cards, possibly less than 1,000. When Address Book acts as a LDAP client, the accessible number of accessible contact information (i.e., “cards”) may increase immensely. LDAP search results can be added to a group by drag & drop. The cards get instantiated in the local database. The LDAP search result, however, is not part of the actual structure, since it cannot be connected in any way but instantiating entries locally.

The other applications are built for millions of users. Therefore, networks can become very large. We are not aware of any maximum size for networks in LinkedIn, Friendster, or MySpace. LinkedIn, however, suggests a minimum network size for each user (called “core group”) of 45 people.

2.7 Growth

Address Book’s structure grows by creating new entries. This is usually done by a single user.

For the other analyzed services, networks grow intrinsically by making relationships of type friend to already networked user profiles. Every user specifies his/her own relationships. An invitation based scheme provides the mechanism to create new relationships. An relationship is established only when both peers have accepted the invitation.

2.8 State and Modifications

We expect only a small number of structure changes in Address Book, because the application is made mainly for individual use. Therefore, the structure is rather static. Structure modifications are easy to make. Adding cards to groups is done by drag & drop, associations are inserted or removed by adding the name of the associated card. Backspace removes selected cards from a group or from the database. Smart groups are updated automatically. This may cause a structure change even on modifications on a card’s data.

LinkedIn, Friendster, and MySpace show a very dynamic network state. Due to millions of users, profiles as well as relations are constantly added or changed. Modification to the network, however, can only be accomplished by modifying the user’s own connections.

3 Discussion and Conclusion

The raise of the WWW made it possible to provide a platform for collaboration and connectivity. Therefore it is logical that the Web facilitates social software. This can be experienced especially with what is under the umbrella of “Web 2.0” [8].

There has been research done on the ethnographic aspects of social software services (e.g., [9]) as well as on it as a means for communication compared to other tools (e.g., [10]). However, a detailed and general description or classification of how those applications model communities or users is still missing.

We developed criteria which allow us to classify applications regarding their support for community building. We have shown that the community and user models of the surveyed Web-based applications (LinkedIn, Friendster, MySpace) appear similar. Apple Address Book compares to them, however, is more diverse on some criteria than the others.

In general, LinkedIn, Friendster, and MySpace are more restricted and simpler than Address Book with respect to structuring. This is true for syntax as well as semantics. For instance, Address Book
provides less restrictions for connections between cards. They are unidirectional, whereas the other
surveyed applications support only bidirectional links. Another example is the freedom in Address
Book to choose arbitrary names or types for groups or relationships in Address Book, whereas the other
services provide generic and predefined typing for connections.

Even though Address Book supports connections between cards, its main focus rests upon the use
of groups as a means for expressing social relationships. Groups are very flexible and include also smart
groups for on-the-fly computation. The other applications support also groups, however, their main
focus are relationships between individual users.

The size and growth of the networks also differ. While Address Book is made primarily for a single
user organizing his/her or her private contacts, the Web-based applications support millions of users
in connecting their profiles to others.

All these observations draw the conclusion that Address Book is made for detailed and feature-rich
structuring of cards, syntactically as well as semantically. This is possible due to its focus on one user
only and a rather small collection of cards. It can be assumed that the user know most (possibly all)
of the people who are part of his/her Address Book. This allows to provide the user with the freedom
of arbitrary typing relationships or groups. Most awareness and interpretation of semantics is put into
the user’s hands.

The surveyed Web-based applications provide highly “anonymous” networks and profiles. It is
impossible for a single user to know all others. Users may even connect to people they do not know,
because they are drawn by their user profile, etc. The vast number of users makes it difficult to provide
them with a unified semantics that everyone understands the same way or with a more sophisticated
syntax. Semantic and syntax for modeling communities are kept very simple.

Our conclusions allow us to classify or compare social relationship applications. We will use them
as a means to identify flaws in representing social relationships and improve existing applications to
become more efficient tools.

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Considering Web 2.0 Technologies within an Ecology of Collaborations

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Abstract. In this paper we argue that the value and usage of Web 2.0 technologies should be viewed within a context of the total pattern of workplace collaborations and interactions. We present empirical results from three field studies which show that a typical workday for information workers involves managing multiple collaborations and interactions and rapid switching between collaboration contexts. Web 2.0 technologies will expand even more people’s circle of contacts in the workplace as companies are sanctioning the use of blogs, wikis, video sharing sites, and other social Internet technologies. We argue that adaptive systems need to provide support for the integration of social Internet technologies into a work environment where people rapidly switch contexts, so that people can manage information overload.

Keywords: multi-tasking, attention management, collaboration, Web 2.0 technologies.

1 Introduction

Web 2.0 technologies have been changing the landscape of interaction and collaboration. Yet to date there has been little consideration of how such social technologies can be integrated into the workplace. The purpose of this paper is to position the role of Web 2.0 technologies vis-à-vis an ecology of collaborations in the workplace. In workplace collaborations, individuals are involved in numerous networks, communities, and collaborations that they must manage. An ecology of collaborations refers to all the different relationships among collaborating partners and their tasks, and their environment. In this paper we stress that understanding the role of Web 2.0 technologies in the workplace involves considering how these technologies can integrate into people’s complete pattern of collaborations and interactions. Web 2.0 technologies expand the borders of the workplace collaborative environment.

It is a common tendency in the field of CSCW and related areas to consider the role of technologies in supporting only a particular collaboration or type of collaboration. Generally, collaborative work has been studied in terms of a single unit: e.g., a collocated team collaboration [25, 10], distributed team collaboration [17] or an organizational department [17, 20]. However, such a perspective fails to
consider that people are involved in a myriad of collaborations and interactions throughout the workday. We will present empirical results from a series of studies conducted over the last three years that will bolster the argument that the typical workday for people consists of continual switching and juggling among multiple collaborations and interactions.

The capability of Web 2.0 technologies to provide easy access to a social digital environment is at the same time its very nemesis. The challenge is how to harness the power of participating in multiple social interactions and work collaborations without being overwhelmed by information and social demands. The fear of information overload is not a new problem. In fact, in 1959, before the age of the Internet, Gertrude Stein lamented that “Everybody gets so much information all day long that they lose their common sense.” The difference though is that researchers are now starting to systematically study this problem and recognize that information and interactions can be properly managed so as not to be overwhelming.

1.1 Information overload and collaboration

Influenced by the vast number of technologies available to access information and people, recently researchers in the fields of HCI, CSCW, and management science have started addressing the topic of interruptions and multitasking in technology-rich work environments. However, studies have been conducted even before IT and email played a major role in the workplace. These studies first brought attention to how managers distribute their time between multiple activities [13, 22, 18]. Studies conducted after IT (especially email) became a major influence in the workplace have also confirmed that people manage multiple activities [7, 19, 3].

Participating in multiple workplace activities with multiple collaborations inevitably leads to interruptions. Recently there has been an interest in understanding how interruptions affect people’s ability to perform their tasks in the workplace. In general, these studies have shown that the nature and complexity of interruptions and the tasks affect performance (see [11], for a review). There are times when interruptions are more acceptable than others, such as at natural breaking points [1]. Interruptions are not always detrimental. Some studies found interruptions to be beneficial [7, 19], e.g. as an opportunity to interact with others [21].

Taking all these studies together, we maintain that it is not only interruptions that tax an individual [6], but especially the process of frequently switching activities. Web 2.0 has only recently become the subject of empirical studies. Most of these studies have focused on the usability of Web 2.0 technologies and an individual’s motivations for using them (e.g. with blogs [15] and social networks [2]). A recent annual workshop is bringing attention to the impact of wikis [26]. Yet a topic that still remains relatively unstudied is the effects of Web 2.0 technologies on our current work activities. Even without considering Web 2.0 technologies, there have been for several years now widespread use of varied media for accessing information and colleagues and managing activities (cell phones, email, IM, blackberries, PC’s, PDA’s, voicemail, paper, post-it notes, etc.). While the potential benefits in designing Web 2.0 technologies to empower workers is real—a recent study on social bookmarking in the workplace shows that such tools can help manage both personal
and corporate needs [15]—there are also challenges such as discerning, in the context of multiple possible audiences (internal teams, potential customers, family, etc.), what content is appropriate in corporate blogs [6]. What we also need to understand better is how even more and faster access to information and colleagues, as enabled by Web 2.0 technologies, will affect workplace collaborations.

Though Web 2.0 technologies are a tremendous benefit to collaboration we advocate understanding the nature of how these technologies can fit into the overall ecology of workplace collaborations. As a starting point for a discussion of such effects, we present research on how people typically switch tasks and interactions and experience interruptions in the workplace. We then will discuss how adaptive systems can benefit people in using Web 2.0 technologies in light of these results.

2 Research Setting and Methodology

In this paper we will present empirical results of three field studies, ongoing since 2004, that have examined how people multitask in the workplace. The fieldsites have several things in common. First, they are all medium to large-size high-technology companies. Second, all employees work in a very IT-rich environment. Third, all employees at the fieldsites are knowledge workers, which refers to the fact that their primary task is dealing with information.

Fieldwork was conducted at three different companies in the southwestern U.S. Data was collected for the first two studies over a thirteen month period. Data for the third study, which is ongoing, has been collected since March 2006. The first company, called “A”, provides information technology, accounting and financial services as an outsourcer for a major bond investment manager. Two teams were studied, one in charge of maintaining the financial systems, and one in charge of maintaining different transactions and accounting systems. The second company, “B”, specializes in providing process reengineering solutions and software systems for small and medium sizes medical practices. The third company, “C”, provides expertise on scientific and technical issues for its customers. 24 people participated in the study from company “A” (14 were from one team and 10 were from the other team). Twelve people participated from company “B”. To date, data has been collected from 18 people from company “C,” though data from only 10 informants has so far been analyzed.

2.1 Methodology

All studies were based on two main ethnographic techniques: participant observation and long interviews. A “shadowing” observation technique was used to capture as much detail as possible, similar to previous time management studies [19, 22]. The researcher observed the informant in her cubicle or office and followed her, whenever possible, to meetings or other activities. Whenever the individual performed an action such as typing in a Word document, making a phone call, or writing down a note on her planner, the researcher annotated the time (to the second) and other details of the event. Interactions with others were also documented, including details about the
topic of the conversation, documents used and persons involved. Clarification questions were asked at the end of the day.

Each person was observed for three and a half days. The first half-day was used to become familiar with their activities and working style. For the next three days, all informants’ activities were timed and recorded, averaging 26 hours per informant. A two-hour semi-structured post-interview was conducted which focused on e.g., informants’ activity management strategies. Documents were collected such as email printouts, project descriptions, and software specifications. Other data was also collected, e.g. photos of desks, photocopies of documents, printouts of screen shots showing file folders and calendaring tools.

The data was triangulated using qualitative and quantitative methods. Grounded theory [23] was used to derive conceptual categories, such as types of contexts. The time-stamped data was quantitatively analyzed. Further details on the methodology and study setting can be found in [5, 6, 8, 24].

3 Results

The field sites can all be characterized as fast-paced changing environments with multiple interactions occurring face-to-face, on the phone and online. In companies A and B, our intent was to understand the extent to which people switched among devices, tasks and interactions with people. In company C, the focus was primarily to understand the extent to which people switched interactions.

3.1 Multitasking in the workplace

We first present results on multitasking. To measure the extent that people switched tasks, the data was coded into events defined as any continuous use of a device or engagement in an interaction with other individuals (e.g. phone conversation, using a spreadsheet with the PC, writing documents, or talking “through the wall”). Following Sproull [22], it was considered that in any particular event neither the structure nor the content changes. The average amount of time that the informants spent in any event was calculated, i.e. the continuous use of a device or in a continuous interaction, before switching to another event or being interrupted. Table 1 shows the average amount of time per event for each person, averaged over all their observations for three days.

The following was left out of the calculation: 1) formal meetings, as it was reasoned that people are “prisoners” of a meeting, the length determined by factors beyond their control, and also 2) “other” events (personal and unknown). The data reveals that multi-tasking is done to a surprising extent: every three minutes on the average (3 min., 5 sec. in Table 1) people switch events throughout their workday. For more details see [6, 8].
### Table 1. Average continuous time spent on events before switching or being interrupted (hour:min:sec).

<table>
<thead>
<tr>
<th>Events</th>
<th>% entire day</th>
<th>Avg. Time/Day (sd)</th>
<th>Avg. Time/Event (sd)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Using phone¹</td>
<td>7.6</td>
<td>0:39:48 (0:29:10)</td>
<td>0:03:02 (0:01:28)</td>
</tr>
<tr>
<td>Using email</td>
<td>8.3</td>
<td>0:43:31 (0:20:27)</td>
<td>0:02:04 (0:00:42)</td>
</tr>
<tr>
<td>Using PCs²</td>
<td>27.8</td>
<td>2:26:21 (1:08:23)</td>
<td>0:02:30 (0:00:45)</td>
</tr>
<tr>
<td>Using paper documents/books</td>
<td>6.6</td>
<td>0:34:51 (0:25:10)</td>
<td>0:01:50 (0:00:52)</td>
</tr>
<tr>
<td>Using other tools³</td>
<td>0.8</td>
<td>0:04:02 (0:03:55)</td>
<td>0:01:15 (0:00:43)</td>
</tr>
<tr>
<td>Talking through the walls</td>
<td>1.7</td>
<td>0:8:46 (0:10:29)</td>
<td>0:01:06 (0:01:14)</td>
</tr>
<tr>
<td>Interacting with people in their own cubicle</td>
<td>8.3</td>
<td>0:43:45 (0:29:37)</td>
<td>0:04:29 (0:02:49)</td>
</tr>
<tr>
<td>Going to other cubicles</td>
<td>12.4</td>
<td>1:05:24 (0:37:40)</td>
<td>0:08:21 (0:03:27)</td>
</tr>
<tr>
<td>Formal meetings</td>
<td>14.3</td>
<td>1:15:21 (1:00:12)</td>
<td>0:42:56 (0:19:11)</td>
</tr>
<tr>
<td>Personal</td>
<td>11.2</td>
<td>0:59:11 (0:26:13)</td>
<td>0:33:32 (0:27:40)</td>
</tr>
<tr>
<td>Unknown</td>
<td>1.0</td>
<td>0:05:15 (0:08:59)</td>
<td>0:05:09 (0:09:05)</td>
</tr>
<tr>
<td>All events (except Formal meetings, Personal, Unknown)</td>
<td>73.5%</td>
<td>0:48:19 (0:53:05)</td>
<td>0:03:05 (0:02:51)</td>
</tr>
<tr>
<td>All events total</td>
<td>100%</td>
<td>0:47:51 (0:51:48)</td>
<td>0:09:40 (0:17:19)</td>
</tr>
</tbody>
</table>

¹ Includes time spent on cell phones
² Includes both PCs and financial terminals – does not include email.
³ Other tools include: handheld calculator, planners, and address books

### 3.2 Interruptions in the workplace

It was discovered that interruptions can be external or internal (cf [14]). An internal interruption refers to when one interrupts oneself of their own volition. For example, someone might be typing on a document, and for no obvious reason to the observer, the person stops and then turns to make a phone call. An external interruption refers to when there exists an observable environmental condition that motivates switching, such as a phone call, or a person entering one’s office. Table 2 shows data from companies A and B: actions that were associated with internal interruptions of the informants (e.g. making a phone call or leaving the cubicle) as well as sources of external interruptions (e.g. a person enters the cubicle).

The results show that people were almost as likely to interrupt themselves as to be interrupted by others. Most interruptions concerned interactions with other people (69.72%), either face-to-face, or using a communication technology (telephone or email). The category of “leaving the workspace” was not considered as interactions, as this could involve personal business as well as interacting with another person. Email was a significant source of both internal and external interruptions, making up over 20% of all interruptions [6].

### Table 2. Average number and types of interruptions per day per informant.
<table>
<thead>
<tr>
<th>Type</th>
<th>Average Interruptions per day (s.d)</th>
<th>% within Interruption type</th>
<th>% of all Interruptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internal</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Checking/Using Paper Docs</td>
<td>0.33 (0.49)</td>
<td>3.48</td>
<td>1.52</td>
</tr>
<tr>
<td>Checking/Using Computer</td>
<td>2.70 (2.36)</td>
<td>28.19</td>
<td>12.29</td>
</tr>
<tr>
<td>Talking through the wall</td>
<td>0.82 (0.95)</td>
<td>8.03</td>
<td>3.50</td>
</tr>
<tr>
<td>Phone call</td>
<td>1.28 (1.43)</td>
<td>13.29</td>
<td>5.80</td>
</tr>
<tr>
<td>Email use</td>
<td>1.28 (1.47)</td>
<td>13.29</td>
<td>5.80</td>
</tr>
<tr>
<td>Leaves workspace</td>
<td>3.24 (2.29)</td>
<td>33.72%</td>
<td>14.70</td>
</tr>
<tr>
<td>Internal total</td>
<td>9.60 (6.13)</td>
<td>100%</td>
<td>43.60%</td>
</tr>
<tr>
<td>External</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>New email notification</td>
<td>3.17 (2.26)</td>
<td>25.65%</td>
<td>14.47</td>
</tr>
<tr>
<td>Person arrives</td>
<td>5.65 (2.78)</td>
<td>45.69%</td>
<td>25.77</td>
</tr>
<tr>
<td>Status on terminals</td>
<td>0.81 (0.54)</td>
<td>1.31%</td>
<td>0.74</td>
</tr>
<tr>
<td>Phone ringing</td>
<td>2.25 (1.18)</td>
<td>18.17%</td>
<td>10.25</td>
</tr>
<tr>
<td>Voice message light</td>
<td>0.11 (0.31)</td>
<td>0.62%</td>
<td>0.35</td>
</tr>
<tr>
<td>Call through wall</td>
<td>0.96 (1.16)</td>
<td>7.32%</td>
<td>4.13</td>
</tr>
<tr>
<td>Reminder notification</td>
<td>0.15 (0.22)</td>
<td>1.23%</td>
<td>0.69</td>
</tr>
<tr>
<td>External total</td>
<td>12.36 (4.00)</td>
<td>100%</td>
<td>56.40%</td>
</tr>
<tr>
<td>Total</td>
<td>3.33</td>
<td>100%</td>
<td>61.65%</td>
</tr>
</tbody>
</table>

### 3.3 Interactions in the workplace

Table 3. Time spent interacting through different mediums, N=10. (hour:min:sec) (sd).

<table>
<thead>
<tr>
<th>Interaction Type</th>
<th>Avg. time/interaction</th>
<th>Avg. time/day</th>
<th>% all interactions</th>
</tr>
</thead>
<tbody>
<tr>
<td>F2F</td>
<td>0:02:41 (0:06:32)</td>
<td>0:52:27 (0:45:01)</td>
<td>28.40</td>
</tr>
<tr>
<td>Email</td>
<td>0:01:06 (0:01:35)</td>
<td>0:25:00 (0:28:19)</td>
<td>13.98</td>
</tr>
<tr>
<td>IM</td>
<td>0:00:48 (0:01:12)</td>
<td>0:01:20 (0:04:03)</td>
<td>0.74</td>
</tr>
<tr>
<td>Meeting</td>
<td>0:33:47 (0:30:25)</td>
<td>1:10:33 (1:26:45)</td>
<td>38.35</td>
</tr>
<tr>
<td>Paper</td>
<td>0:01:27 (0:01:35)</td>
<td>0:02:55 (0:06:51)</td>
<td>1.60</td>
</tr>
<tr>
<td>Phone</td>
<td>0:02:39 (0:03:15)</td>
<td>0:25:36 (0:28:35)</td>
<td>14.11</td>
</tr>
<tr>
<td>CM</td>
<td>0:02:10 (0:02:52)</td>
<td>0:05:08 (0:14:08)</td>
<td>2.82</td>
</tr>
<tr>
<td>All types but “Meeting”</td>
<td>0:01:56 (0:04:14)</td>
<td>1:52:29 (1:33:15)</td>
<td>61.65</td>
</tr>
</tbody>
</table>

Similar to the results found with multitasking, Table 3 shows that people also switch interactions very frequently. If we disregard the interactions spent in formal meetings (using the same reasoning that people are “prisoners” of formal meetings), then interactions can be regarded as fleeting, switching continually between interactions and work. Though people spent about two hours a day interacting with others, the average time spent in an interaction of any type was 1 min. 56 sec.

People spent the longest in face-to-face interaction and next longest on the telephone. Interactions conducted over the Internet (on average, each IM lasts about 48 sec. and each email lasts 1 min. 6 sec.) can be characterized as short and fleeting.
In general, people have preferences for particular types of technologies used in different networks or groups. See [24] for further details of the study.

4 Implications for Web 2.0 Technologies

Thus, what we can infer from these results are several things:
1) People multitask to a great extent, typical of daily work, switching tasks on the average every three minutes. This result occurs irrespective of a person’s work role.
2) Peoples’ workdays are also characterized by interruptions from various sources. People are almost as likely to interrupt themselves as to be interrupted by others.
3) Similarly, interaction in the workplace is characterized as occurring in short segments and people continually switch in and out of different networks, groups, and communities throughout the workday.

Perhaps the last result is the most relevant for thinking about the impact of Web 2.0 technologies. Web 2.0 technologies are inherently social. They afford the capability of accessing more people in more capacities than ever previously imaginable. While a particular emphasis on the social possibilities of having a system available to anyone who has Internet access has been tapped with Web 2.0 (e.g., social bookmarking through del.icio.us and collaborative online article picking through digg.com), how this affects workers in their everyday lives has largely been ignored.

Web 2.0 technologies are changing the ecology of collaboration, increasing our access to people and information. Take the case of RSS feeds. It is extremely easy to subscribe not only to single RSS feeds, but to clusters of RSS feeds, such as clusters of news organizations or blogs. This access increases our sphere of interruptibility. We discovered that by far, most interruptions are due to interactions with other people, either computer-mediated or face-to-face. Already it is not only our colleagues within our various workplace networks, groups and communities who interrupt us (see Table 3), but interruptions are now stemming from far expanded groups and networks, formed, for example, through blogs, wikis, and folksonomies. These groups can be leveraged by RSS feeds which can inform us spontaneously when new information or new contacts appear.

Increased access to more circles of people alone may not create a problem. But there is an associated expectation with social technologies: when a message is sent, the target should respond to the message in a timely manner. This type of reciprocity is expected especially in email and IM, but also now in social Internet technologies such as wikis. The opportunities are abundant for forming social networks on the Internet through a greater choice of media channels. The web beckons us to join these networks and we maintain them through reciprocal expectations.

4.1 Adaptation to multiple working spheres

Where does this lead us? There are two basic questions that we need to answer when considering how best to use social Internet technologies in the workplace: when and what? The when can be answered by considering how technology can enable our information to adapt to the current sphere of work that we are engaged in. As
described earlier, interruptions may not all be detrimental, and in some cases can be beneficial. One informant at company A described interruptions as *interactions* when they matched the current work one was involved in, and as *disruptions* when they didn’t. In the latter case, people had to switch their attention to a different sphere of work, at a cognitive cost. The informants all reported multitasking as stressful and reported difficulties in reorienting back to work that had been interrupted.

Mark and Poltrock [9] discovered that the adoption of a collaborative technology could best be explained at the level of a unit of a group’s work practice, what they termed a *working sphere*. Each sphere of work has a unique constellation of colleagues, collective experience, organizational and environmental conditions, and set of tasks. Thus, a sphere of work is bounded by dimensions: the task, the people involved, the timeline, and though boundaries of working spheres may be fuzzy, in general, people can distinguish their working spheres from one another.

In these studies described in this paper, the informants frequently spoke about their work not in terms of lower-level tasks such as phone calls but in terms of their working spheres, e.g. “the Clear Quest app”. A working sphere can be defined as a set of interrelated events, which shares a common goal, involves the communication or interaction with a particular set of people, involves unique resources and has a unique time framework. Each working sphere might use different documents, reference materials, software, or hardware. Examples of working spheres might include a training effort for new UNIX programmers, an implementation of a new feature in a compliance module, a trip to a regional Park for a team, or the documentation of modules.

Thus, what we propose is a system that can adapt information to the context of the working sphere at-hand. This approach emphasizes that people are not involved in a single working sphere but in an entire ecology of multiple spheres of work and interactions, or rather multiple contexts. These working spheres (and associated interactions) switch continually throughout the day. Gonzalez and Mark [6] found that people switched working spheres every 10.5 minutes on the average. The goal of such an adaptive approach is that interruptions and information would be targeted so that their context matches that of the working sphere that one is currently involved in.

How can a working sphere be identified for purposes of designing an adaptive system? It was found that people, in interviews, were very good at reporting the working spheres that they were involved in. The working spheres reported by the informants validated those identified through observation [6], [8].

An adaptive system could detect the working sphere that one is currently involved in (e.g. through documents or applications that are being used, through interactions, or even keywords). The system could then signal to colleagues whether one is interruptible or not, depending on whether the interruption topic matches the current working sphere. For example, if a person wanted to interrupt their colleague about the Clear Quest project they could determine whether their colleague was currently working on that project. If so, then it would be beneficial to interrupt them. If not, they could wait until they notice that their colleague is working on that project. Privacy implications could be addressed by creating a rough level of granularity. For example, a signal might simply indicate whether one is interruptible for a particular working sphere request without revealing what one’s current working sphere is. Such a system could also help people manage self interruptions (which are almost as often
as external interruptions). It could, for example, indicate to users when web information might be relevant to their current working sphere.

The what question can be answered if we can understand what patterns of technology best fit a particular working sphere. In the study done with company C, we discovered certain patterns of technology use, with particular workplace networks and communities. For example, in their our business units, people used a combination of media: face-to-face, email, IM, stationary (paper-based communication), phone, and a knowledge management system, whereas with colleagues in professional networks, people used only email and paper-based communication. Some social Internet technologies may fit a type of collaboration or working sphere better than others. The point is that we need to better understand through research the types of technologies that are best suited for which working spheres. Our data showed that people generally follow patterns of using certain technologies for working spheres. Wikis, or blogs, e.g., may support work in some working spheres better than others.

5 Conclusion

The goal of this paper is to propose an approach for managing information and interactions so that the information available through Web 2.0 technologies can enhance work rather than overload it. This approach is based on the notion of considering work and interactions in terms of a workplace ecology. The ecology consists of the totality of the different working spheres and relationships that people pass in and out of throughout the workday. Switching between working spheres can be triggered by events in the environment or even by internal causes, which we have yet to understand. As a first step, we suggest identifying people’s working spheres and to use this as a basis for delineating context. Web 2.0 technologies offer tremendous potential for increasing social contacts and interaction, and even documenting our current lives. Accessible anywhere, with a small learning curve, Web 2.0 is becoming increasingly attractive to corporations. But we must at the same time harness the power so as to wisely integrate them into our work and not succumb to Gertrude Stein’s fear of losing our common sense from all the information.

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References

Trust is a popular and much disputed topic in various research communities. This paper attempts to integrate existing knowledge on trust into a simple computational model. The model incorporates the impact of direct experiences, reputation, stereotypes, empathy and user characteristics on trust. We present the results of two exploratory experiments testing and improving aspects of the model.

1 Introduction

Trust has been extensively studied in fields as varied as economics [13,17], business and marketing [8,24], politics, e-commerce [1,14,41], psychology [7,42,50], sociology [27], medicine, nursing [15], and computing science [10,11,19,39,40,44]. Whilst many definitions of trust have been proposed, none has been agreed upon. However, there have been some good efforts in inventorizing the different definitions, and trying to distill what characterizes trust and what different dimensions there are to it [15,29]. As noted by [29], different researchers have defined different types of trust. Based on their review, [29] defined six types of trust. Trust in this paper is closest to the one they called Trusting Beliefs, defined in [29] as “the extent to which one believes (and feels confident in believing) that the other person is trustworthy in the situation”, with trustworthy defined as “willing and able to act in the other person’s best interests”. The computational model provided in this paper will make our view on trust more explicit.

Trust is key to long-term relationships [22], and user trust has been shown to affect the success of a system, in terms of increasing sales, users’ likelihood to stay with and return to the system [8], use of information provided [32], and users’ willingness to pay more [1]. A computational model of trust is particularly useful when an adaptive system interacts with a community of users (like a group recommender system does). Simply optimizing trust is then not possible: actions aimed to increase the trust of some users may well decrease the trust of others. An accurate trust model would allow tailoring of system actions (such as selected appearance for an embodied agent, empathetic explanations, items) to maintain the trust of all users. In a social system, models of users’ trust can also be used when facilitating interactions between users.

Many factors influence the trust of an agent \( x \) in another agent \( y \). In this paper, we will consider the following: (1) direct experiences of \( x \) with \( y \), (2) indirect experiences, namely the reported experiences of others (often referred to as reputation [40]), (3) intuitions of \( x \) about \( y \) based on stereotypes, (4) empathy between \( x \) and \( y \), and (5) characteristics of \( x \). Sections 2 and 4 discuss these factors, and incorporate them into a simple computational model of trust. Sections 3 and 5 report on two experiments that investigate some of the issues arising from the modelling and propose improvements. Section 6 concludes this paper.

2 Modelling direct experience and reputation

2.1 Direct Experience. “You have seen me act well”

We will denote the impact of direct experience \( d \) on the trust of \( x \) in \( y \) as \( \text{Impact}_{\text{Dir}}(x,y,d) \). We assume \( d \) to be a numerical objective measure of agent \( y \)’s performance, with negative \( d \) indicating poor performance. Trust declines when errors occur [33]. However, the size of the error does not seem to be proportional to the decline in trust, with small errors having a larger than expected effect [20, 25]. We assume that the effect on trust of good performance is similar. We define
Impact_{Rep}(x,y,t) = -\lambda^* + \mu^* d, \text{ if } d<0; \quad \lambda^* + \mu^* d, \text{ if } d>0; \quad 0, \text{ if } d=0

with parameters $\lambda^*, \lambda^*$ (both $>0$) modeling the decline/increase in trust occurring with unsatisfactory/satisfactory performance independent of how poor/good the performance was, and $\mu^*, \mu^*$ (both $\geq 0$) modeling how much the extent of the bad/good performance contributes.

The existing trust of $x$ in $y$ (called $t_{xy}$) may affect the impact of $y$’s performance on the trust placed in it. It has been hypothesized that the stronger the emotional bond between those in a trust relationship, the less likely contrary behavioral evidence will weaken the relationship [27]. So, we assume poor performance will have less impact if the existing trust is higher. Similarly to the treatment of assimilation in [28], we define

$$\text{Impact}_{Dir}(x,y,t) = \text{Impact}_{Rep}(x,y,t) + (t_{xy} - \text{Impact}_{Rep}(x,y,t)) \times \varepsilon,$$

with $0 \leq \varepsilon \leq 1$.

Parameter $\varepsilon$ models the extent to which $x$’s existing trust in $y$ influences $x$’s judgement of $y$’s performance: with $\varepsilon=0$ there is no such influence, with $\varepsilon=1$ $y$’s performance has no impact at all.

### 2.2 Reputation. “You have heard that I act well”

The impact of a trust report $t$ by agent $z$ to agent $x$ about agent $y$ clearly needs to depend on the difference between $t$ and $t_{xy}$ ($x$’s existing trust in $y$). After all, there should be no impact if this difference is zero. Additionally, the trustworthiness of reporting agent $z$ ($t_{xz}$) may influence the impact of the trust report. This effect is described in detail in [18], who propose to propagate trust along chains². Table 1 shows seven options for defining Impact_{Rep}(x,y,z,t_{xz},t_{xy}) which differ in the way $t_{xz}$ is used. In the first three options (1A-1C), $t_{xz}$ needs to reach a threshold in order for there to be any impact, but once that threshold is reached, the size of the impact is independent of $t_{xz}$. In the latter options, the size of the impact also depends on $t_{xz}$ (normalized by the maximally obtainable trust $t_{max}$). Parameter $\kappa$ is a trustworthiness threshold, e.g., in Option 1A, if $z$ is trusted more than $\kappa$ then $z$’s report is taken into account, otherwise it is ignored. Parameter $\phi$ (0 $\leq \phi \leq 1$) models an agent’s propensity to contagion by others’ beliefs: with $\phi=0$ trust reports have no impact at all, with $\phi=1$ they override the existing trust. We will explore which option is better in Experiment 1.

### Table 1. Seven options for defining Impact_{Rep}(x,y,z,t_{xz},t_{xy})

<table>
<thead>
<tr>
<th></th>
<th>Parameter</th>
<th>Conditions</th>
<th>Impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>A</td>
<td>$\phi \times (t-t_{xy})$</td>
<td>if $t_{xz} &gt; \kappa$</td>
</tr>
<tr>
<td></td>
<td>B</td>
<td></td>
<td>if $t_{xz} &gt; t_{xy}$</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td></td>
<td>if $t_{xz} &gt; \kappa$ and $t_{xz} &gt; t_{xy}$</td>
</tr>
<tr>
<td>2</td>
<td>A</td>
<td>$\phi \times (t-t_{xy}) \times (t_{xz} / t_{max})$</td>
<td>if $t_{xz} &gt; \kappa$</td>
</tr>
<tr>
<td></td>
<td>B</td>
<td></td>
<td>if $t_{xz} &gt; t_{xy}$</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td></td>
<td>if $t_{xz} &gt; \kappa$ and $t_{xz} &gt; t_{xy}$</td>
</tr>
<tr>
<td></td>
<td>D</td>
<td></td>
<td>Always</td>
</tr>
</tbody>
</table>

Often an agent will have multiple experiences with another agent, some of which may be direct and some indirect. This may lead to problems when the existing trust differs a lot from the trust reported by another agent. For instance, suppose agent $z$ reports distrust in $y$, while $x$ trusts $y$, then it is possible that $x$ may start liking and trusting $z$ less (instead of or in addition to decreasing trust in $y$). This corresponds to ideas from Congruity theory [36] in the area of persuasion. We will denote the impact on an agent $x$’s trust in $z$ of the trust $t$ in a third agent $y$ reported by $z$, given existing trust $t_{xz}$ and $t_{xy}$ as Impact_{RepGiven}(x,z,y,t_{xz},t_{xy}). We define

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1 In fact, two types of trust are involved in reputation: the trust placed in $z$ is trust as a recommender of other agents (e.g. recommend a plumber), while the trust in $y$ is trust as performer of some task (e.g. plumbing). Here, we do not explicitly mention the domain of trust, but the model can be easily modified to do this.

2 In [18], the situation is even more complicated, as they incorporate $x$ getting a recommendation of $w$ from $y$ who in its turn got the recommendation from $z$ etc.
$$\text{Impact}_{\text{RepGiven}}(x, z, y, t_{xz}, t_{xy}) = -\rho - \tau \times |t - t_{xy}|, \quad \text{if} \ |t - t_{xy}| > \xi.$$  

with $\rho$ modeling the decline in trust occurring when there is a larger than $\xi$ discrepancy between $t$ and $t_{xy}$ independent of how large this discrepancy really is, and $\tau$ modeling how much the extent of the discrepancy contributes. We have not yet incorporated $t_{xz}$ into this formula. We will investigate this further in Experiment 1 below.

The situation may well be more complicated than modelled. The question arises whether agents should remember the trust reports. For instance, suppose $x$ started trusting $y$ because it was told that $y$ was trustworthy by $z$ whom it trusted at the time. Suppose that later experience shows $z$ is not trustworthy. Should $x$ now remember that its trust of $y$ was based on its trust of $z$ and revoke its trust in $y$? Similarly, suppose that $x$ was told $w$ was trustworthy by $v$, but later experience shows $w$ is not trustworthy. Should $x$ now reduce its trust in $v$? For simplicity reasons, in this paper we have decided not to use a memory of trust reports. We intend to investigate this issue further in future.

### 3 Experiment 1: Reputation

#### 3.1 Experimental Design

Twenty-six subjects participated in the experiment (16 male, 10 female, average age 32.5, stdev 9.6). All subjects were associated with the computing science department. Each subject was given two scenarios: in each, they were told their trust in two people (say Z and Y, names differed per scenario), using a scale from 1 (very untrustworthy) to 10 (very trustworthy). Next, they were told how much Z trusts Y. Subjects rated how trustworthy they now regarded Z and Y. The two scenarios were the same except that one scenario (H) would have a higher initial trust rating of Z than the other (L). The order of the scenarios was randomized.

Subjects were split into groups for three experimental conditions (G1, G2, G3), using different initial trust ratings for Z and Y, and a different rating for Z’s reported trust in Y. See Table 2 for details. We used a combination of a within- and a between-subjects design. The two scenarios within each group will be used to investigate whether a higher trust in Z leads to a higher impact of Z’s trust in Y. Group G3 differed from G1 by having a very low rating for Z’s reported trust in Y. The difference between these two groups will be used to explore the impact on both trust in Y and Z of a large difference between the reported trust and the existing trust. Group G2 differed from G1 by having a low rating for the existing trust in Z in one scenario (4, so untrustworthy) compared to a high rating in a scenario in G1 (10, so very trustworthy). This will be used to explore whether a threshold $\kappa$ is used, and how low trust in Z affects the impact of the trust report.

### Table 2. Trust ratings used in each experimental condition and in each scenario, and results

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Z Rating</th>
<th>Y Rating</th>
<th>Z’s Trust in Y</th>
<th>1A</th>
<th>1BC</th>
<th>2A</th>
<th>2BC</th>
<th>2D</th>
<th>Z’s Trust</th>
<th>Y’s Trust</th>
<th>Z’s Trust</th>
<th>Y’s Trust</th>
</tr>
</thead>
<tbody>
<tr>
<td>G1 L</td>
<td>7</td>
<td>7</td>
<td>5</td>
<td>-2$\phi$</td>
<td>0</td>
<td>-1.4$\phi$</td>
<td>0</td>
<td>-1.4$\phi$</td>
<td>6.6 (.7)</td>
<td>6.4 (.7)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>G1 H</td>
<td>10</td>
<td>7</td>
<td>5</td>
<td>-2$\phi$</td>
<td>0</td>
<td>-1.4$\phi$</td>
<td>0</td>
<td>-1.4$\phi$</td>
<td>9.4 (1.1)</td>
<td>5.6 (.5)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>G2 L</td>
<td>4</td>
<td>7</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>-0.8$\phi$</td>
<td>0</td>
<td>-1.4$\phi$</td>
<td>3.7 (.5)</td>
<td>6.8 (.4)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>G2 H</td>
<td>7</td>
<td>7</td>
<td>5</td>
<td>-2$\phi$</td>
<td>0</td>
<td>-1.4$\phi$</td>
<td>0</td>
<td>-1.4$\phi$</td>
<td>6.8 (.4)</td>
<td>6.6 (.5)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>G3 L</td>
<td>7</td>
<td>7</td>
<td>1</td>
<td>-0$\phi$</td>
<td>0</td>
<td>-4.2$\phi$</td>
<td>0</td>
<td>-4.2$\phi$</td>
<td>6.2 (1.1)</td>
<td>5.7 (1.5)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>G3 H</td>
<td>10</td>
<td>7</td>
<td>1</td>
<td>-0$\phi$</td>
<td>0</td>
<td>-4.2$\phi$</td>
<td>0</td>
<td>-4.2$\phi$</td>
<td>9.7 (.5)</td>
<td>4.8 (2.2)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3 Telling people their trust on a 1-10 scale may seem unnatural, but is a good simulation of how reputations are often given in an on-line system where users do not know each other. Of course, telling people how much they trust somebody does not necessarily create the same situation as when this degree of trust has arisen through real experiences. However, it seemed a good way to ensure everybody started with the appropriate degree of trust. We will try to do more direct experiments in future.
For each scenario, we calculated the predictions of the options given in Table 1. We had to make some assumptions to do this, as these options contain parameters. For trustworthiness threshold \( \kappa \), we assumed \( 4 < \kappa < 7 \). Parameter \( t_{\text{max}}=10 \), as this is the maximal trust available on the scale given to subjects. The trust ratings provided, together with this value of \( \kappa \), resulted in no differences between the predictions of options 1B and 1C, and no differences between 2B and 2C.

### 3.2 Results and Discussion

Table 2 shows the results of the experiment. Over all subjects, trust in Y decreased in both types of scenario (one sample t-tests, \( p<.005 \)). Comparing this to the predictions by the modelling options in Table 2, this clearly conflicts with 1BC and 2BC. So, it seems that the existing trust in Z being smaller than or equal to that in Y is not resulting in subjects ignoring the trust report. However, there are exceptions: four subjects did indeed mention an effect of the equal trust in Z and Y. For two this resulted in no impact of the trust report: e.g., “Z’s opinion will not affect mine since I trust Z and Y at the same level”. The other two reduced their trust in both Y and Z: e.g. “One of the two is less trustworthy than I thought but I do not know who, so I’m hedging my bets”.

There is also qualitative evidence that subjects used a trust threshold (as advocated in options A). Four subjects mentioned distrust of Z (when it was 4) as a reason for not changing trust in Y: e.g., “I don’t trust Z enough for him to change my opinion”. However, another subject pointed out that trust in Y might suffer slightly nevertheless as “maybe there is […] some side of him I need to be aware of”. A value of the threshold \( \kappa \) between 4 and 7 seems to correspond with the behaviour and comments of many subjects. However, one subject seemed to put the threshold higher than 7: “I didn’t totally trust Z anyway, so would use my own judgement about Y”. Another three subjects (in G2) indicated that their trust would not be affected by the opinions of others, which may also be caused by using a threshold higher than 7 (the highest score for Z’s trust in G2).

Over all subjects, trust in Y decreased more in the scenario with the higher trust in Z (paired t-test, \( p<.02 \)). Four subjects mentioned their high trust in Z (when it was 10) as a reason for changing trust in Y: e.g., “because I have such a high trust in Z I agree with him in his views”. The degree of trust in Z clearly affects the impact of the trust report. So, the results correspond better with the predictions by options 2A,D than those by option 1A.

Comparing groups G1 and G3 (which only differed in reported trust), the trend is for a higher decrease in trust in Y when Z reports a lower trust (means of 1.4 versus 2.2 for the high trust scenario, .6 versus 1.3 for the low trust scenario). However, the groups are too small for statistical significance. Nevertheless, the data seems to suggest that the decrease is not simply proportional to the trust reported by Z. If it were, we would have expected the decrease to be three times as large in G3 as in G1, which it clearly is not. So, while options 2A and 2D seem best from the ones we proposed above, we change our modelling of ImpactRep\((x, y, z, t_{xy}, t_{xz})\) within those conditions to:

\[
(-\omega + \varphi(x(t-t_{y}))))(t_{xz}/t_{\text{max}}), \text{ if } t \leq t_{xy}; \quad (\omega + \varphi(x(t-t_{y}))))(t_{xz}/t_{\text{max}}), \text{ if } t > t_{xy}; \quad 0 \text{ otherwise, with } \omega>0
\]

Over all subjects, trust in Z decreased in both types of scenario (one sample t-tests, \( p<.01 \)). So, the discrepancy between Z’s reported trust in Y and the existing trust in Y leads indeed to a decrease in trust in Z. This is substantiated by the qualitative data. Four subjects (three in G1 and one in G2) defended lowering their trust in Z with reasons like “If Z does not share my trust in Y then I trust Z less”, “Because […]Z does not share my view about Y”, “Z maybe correct but it is strange he tells me this; it might be some animosity between him and Y”, and “If Z denigrates Y, I would be unsure if I could trust Z myself”. Comparing groups G1 and G3 (which only differed in the size of the discrepancy between the trust report and Y’s existing trust), we did not find any difference in the decrease in trust in Z (the trends for the Low and High Trust scenarios are even in directions opposite to each other). So, a discrepancy leads to a decrease in trust, but the size of the

---

4 A different scale is used than in the model, where a negative number indicated negative trust. A value of \( 4 \leq \kappa \leq 7 \) corresponds to \(-1.5 \leq \kappa \leq 2 \) on the model’s scale. The scale difference does not matter for our results.
discrepancy does not seem to greatly matter. Therefore, we simplify our modelling of
Impact\textsubscript{RepGiven}(x,z,y, t_{xz}, t_{xy}) to
\[ \text{Impact}\textsubscript{RepGiven}(x,z,y, t_{xz}, t_{xy}) = -\rho, \quad \text{if } |t - t_{xy}| > \xi \]
As we found that a discrepancy of 2 already leads to a decrease in trust, it seems that $\xi < 2$.

Over all subjects in all groups, we found no significant difference between the decrease in trust
in Z between the two scenarios (mean decrease in trust is .4 for the higher trust scenarios, and a
very similar .5 for the lower ones). So, there does not seem to be a need of using $t_{xz}$ in the
calculation of Impact\textsubscript{RepGiven}(x,z,y, t_{xz}, t_{xy}).

Four subjects (one in G2 and three in G3) said that they needed evidence to back up the trust
reports. As one of them put it: “Unless Z tells me a specific story about something Y did, I’m
unlikely to revise my trust in Y”. Note that this subject gave this reason when Z had a trust score
of 7, not for the other scenario when the trust score was 10. Also, in G3 the trust report is 1, very
far from the original trust, so this might require more evidence.

4 Modelling stereotypes, empathy, overall trust and user characteristics

4.1 Stereotypes. “You presume that I act well”

With neither direct nor indirect evidence at its disposal, an agent may still assume that another
agent will act well, based on ‘intuitions’. This is similar to humans drawing conclusions about
people on first sight, like some managers who decide within seconds whether to reject an applicant
having come to interview. A number of factors influence this feeling:

- **Appearance.** People studying web credibility for various domains (like finance, health, and
  travel websites) have found a remarkably high influence on credibility of user interface issues
  (like usability, cool colour tones, balanced layout, or adding a formal author photograph)
  [9,12,21]. In a sense, one could regard the interface as the cloths of a computer programme.
  Fogg et al [12] hypothesize that people assume more effort has gone into making a sleek
  website, and that therefore the author has more to lose by acting badly.

- **Category-based trust.** Humans may trust people belonging to a certain social or organisational
  grouping more, without necessarily being aware of this bias [24]. For instance, they may place
  more trust in females (as found by [34] who hypothesised that this may be due to role
  differences) or doctors. Category-based trust seems similar to “presumed credibility” mentioned
  by [11] as one of four types of credibility, and illustrated with a negative view of the
  trustworthiness of car salesmen.

- **Expertise.** Outwardly signs of expertise may increase trust. For instance, it has been found that
giving a computer the label of “specialist” made it more credible (as reported in [11]). This is
related to so-called role-based trust [24]; if somebody has a certain role in an organisation (i.e. a
job title), then people assume they know how to do that job and therefore may trust them more.

We assume that this stereotypical effect on trust happens initially, when the agents first meet. So, it
suffices to model it in the initial trust of an agent in another agent, before any (direct or indirect)
experiences. We denote the trust produced by y’s appearance as T\textsubscript{Appearance}(y), by y’s category
membership as T\textsubscript{Category}(y), by y’s expertise as T\textsubscript{Expertise}(y), and the initial trust of x in y due to
stereotyping as Initial\textsubscript{Trust}(x,y). We define

Initial\textsubscript{Trust}(x,y) = \psi_1 T\textsubscript{Appearance}(y) + \psi_2 T\textsubscript{Category}(y) + \psi_3 T\textsubscript{Expertise}(y), \quad \text{with } \Sigma \psi_i = 1 \text{ and } \psi_i \geq 0

with $\psi_i$ modelling the relative influence of the factors. T\textsubscript{Appearance}, T\textsubscript{Category}, and T\textsubscript{Expertise}
are clearly domain and user-interface dependent. Defining them further is outside the scope of this
paper. We are currently investigating the influence of appearance and expertise on trust in the
context of a persuasive health-advice system [34]. We expect that the system designer will
optimize its user interface to have as high an initial trust value as possible. Our model requires this value, as it affects the impact of a user’s subsequent experiences. So, some of its factors may need to be determined as part of the design process.

4.2 Empathy “We understand each other”

Another factor that influences trust is empathy: “one’s ability to recognize, perceive and directly experientially feel the emotion of another” (Wikipedia). Empathy can partly be seen as having a stereotypical influence: for instance, empathy based on some types of similarity (like gender, ethnicity and age) may be visible at first sight, so may impact trust even before the trustee has experienced the trustor’s behaviour. However, it can also evolve over time. Empathy does not only exist between humans: it is possible to achieve empathy in a computer environment [37], and it has been shown that making artificial support agents empathetic helps [23, 3]. Empathy depends on:

• Similarity between the trustor and the trustee. Empathy is strongest between people who identify similarities with others or who share experiences [16]. People with the same gender, same occupation, who are close in age, and use similar expressions are more likely to detect others’ feelings accurately [16]. If other people are like ourselves we infer they have the same level of trustworthiness [31]. Trust can be fostered by the development of shared common experiences and a group identity [6].

• Accurate prediction by the trustee of the trustor’s feelings and supportive response. Both empathic accuracy [16] and supportive response (responding compassionately to another person’s distress, [4]) had significant influence on online interpersonal trust [10], but inferring alone was not sufficient, there was a need to be supportive as well.

• Trustor liking the trustee. Likability is mentioned by [8] as a factor for predictability and intentionality. Buyers are more confident of their predictions about someone they like [46] and attribute favorable motives to them [43]. Liking has been found to be highly correlated with interpersonal trust [10]. It has also been argued that trust breeds trust; the trustee showing trust in the trustor making the trustor reciprocate that trust [30]. This may be linked to likeability, with likeability increasing with trust given.

We incorporate the initial empathy due to similarity into our definition of InitialTrust:

\[
\text{InitialTrust}(x,y) = \psi_1 T\text{Appearance}(y) + \psi_2 T\text{Category}(y) + \psi_3 T\text{Expertise}(y) + \psi_4 \text{Similarity}(x,y)
\]

We denote the impact on an agent x’s trust in y of an empathic experience f given existing trust \(t_{xy}\) of x in y as \(\text{Impact}_{\text{emp}}(x,y,f,t_{xy})\). We assume f to be a number, with a negative number denoting a negative empathic experience. A negative empathic experience may be, for instance: a bad reaction of y to x’s emotions, behaviour by y that shows dissimilarity to x, or behaviour that makes x like y less (e.g. rudeness). Mapping such behaviour onto an objective number is a complicated problem, which is outside the scope of this paper. Obviously, it depends on the interface: the way the agents interact with each other, and how much emotion they can portray and recognize.

We expect that the effect on trust of empathic experiences is similar to that of direct experiences and trust reports, with a small empathic experience having a higher than proportional impact. Also, we assume that assimilation effects happen, just as in the case of direct experiences. Therefore, we treat the impact of empathic experiences the same as direct experiences, and define

\[
\text{Impact}_{\text{emp}}(x,y,f,t_{xy}) = \text{Impact}_{\text{dir}}(x,y,f,t_{xy})
\]

4.3 Modelling overall trust

We denote the trust of x in y after a sequence of experiences \(\text{exps}\) as \(\text{Trust}(x,y,\text{exps})\). We assume that trust behaves like affective states: so, as in [28], it decreases over time, is averaged over experiences, and the impact of a new experience depends on the existing trust. We define:
We are not certain whether the minus sign before \(-4.4\). Incorporating user characteristics “You trust in general in this area”

It is likely that most of the parameters in our definitions are user dependent. For instance, others was determined using the test in [50] which consists of eight statements to be rated on a 5-

Twenty-three subjects participated in the experiment (74% male, average age 33, stdev=9.4, all associated with the computing science department). First, subjects’ general propensity to trust others was determined using the test in [50] which consists of eight statements to be rated on a 5-
point Likert scale. Secondly, subjects rated their expertise in computing and in five tasks (choosing pop music to listen to, classical music to listen to, wine to buy, a house to buy, and movies to watch) using a 7-point Likert scale (from “little expertise” to “a lot of expertise”). Thirdly, subjects rated how much they would trust a recommender system for each of these tasks using a 7-point Likert scale (from “very low trust” to “very high trust”). Finally, subjects rated for recommender systems in general, how much their trust would be influenced by their own experiences with the system (Exp), its reputation (Rep), and the extent to which they understood how it works (Tr). They also indicated whether this would differ for the systems mentioned.

5.2 Results and Discussion

Table 3 shows the results. Using Pearson, we found no significant correlation between subjects’ GP and subjects’ trust in the various recommender systems (correlations were all positive and small, around .2). We did, however, find significant correlations between subjects’ trust in the various recommender systems, for instance trust in recommendations of pop was correlated to trust in recommendations of classical music ($r=.7$, $p<.001$), wine ($r=.8$, $p<.001$), houses ($r=.5$, $p<.05$), and movies ($r=.9$, $p<.001$). So, though we did not find an impact of GP, there may well be an impact of general propensity to trust recommender systems. So, in the model we replace GP with a general propensity to trust the systems in question (GPS).

<table>
<thead>
<tr>
<th>GP</th>
<th>Expertise</th>
<th>Trust in recommender system</th>
<th>Influenced by</th>
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<tbody>
<tr>
<td></td>
<td>Pop</td>
<td>Clas</td>
<td>Win</td>
</tr>
<tr>
<td>23.1</td>
<td>4.0</td>
<td>3.2</td>
<td>2.9</td>
</tr>
<tr>
<td>(4.6)</td>
<td>(2.0)</td>
<td>(1.9)</td>
<td>(1.6)</td>
</tr>
</tbody>
</table>

We found no significant correlations between subjects’ expertise in a topic and their trust in a recommender system on that topic (correlations were all positive and small). Some of the literature discussed earlier indicated that more expertise would lead to lower trust. Indeed, one subject mentioned “I would sooner trust a system on topics about which I have no strong opinion/background knowledge, such as wine”. However, in the overall results, we clearly did not find this, and the trends are even in the opposite direction. Therefore, we have decided to remove the effect of user expertise on the general propensity to trust in the given circumstances.

We had assumed that subjects’ trust in a system recommending houses would be lower, as houses have a high financial and emotional value. Indeed, four subjects explicitly mentioned attributing more trust to a system recommending smaller items. However, the overall results did not confirm this (trust in recommenders of houses and classical music was quite comparable). Maybe this is because the risk a user takes is low: they would go and see a recommended house anyway before buying it. Given the results, we do not incorporate item value into the model.

As shown in Table 3, subjects expected that their trust would indeed be influenced by direct experiences, reputation, and system transparency. They thought direct experiences and transparency would be more important than reputation (pairwise t-tests, $p<.001$ and $p<.05$ respectively). Five subjects indicated this would differ a lot depending on the domain of the recommender system, and ten thought it would differ a little. One subject mentioned that reputation and transparency would be more important for domains about which they knew little. Another said transparency was more important for high value recommendations (like houses). A third thought music is more a matter of taste than houses, and that therefore reputation would be more useful for a house recommender than a music recommender. The latter is an interesting point, and it is likely we will need to make parameters in the model domain dependent. Our results also mean that transparency needs to be incorporated in the model.

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5 A confounding factor is that there may be differences between subjects in using rating scales.
6 Conclusions

Despite the vast literature on trust across disciplines, there is a lack of simple computational models of trust that incorporate the range of factors affecting trust. Some computing researchers have presented conceptual models, merely showing the relationship between trust factors (e.g. [5,9,41]). Others, in the field of multi-agent systems, have proposed computational models, but the overview in [44] shows that they model only some factors of trust: ten of the twelve trust models mentioned model only direct experiences and reputation (with four only modelling one of these). The other two incorporate part of what we called stereotypes. The existing models also seem to model at a far more complicated level (using networks of reputation as in [18]). None of them incorporates all the factors discussed here (e.g. they do not incorporate something like ImpactRegGiven). As trust can be seen as a special case of impression formation, research by social psychologists on predicting people’s attitude changes (e.g. information integration theory [1]) is also relevant even though not explicitly addressing trust. We already used ideas from Congruity Theory [36]. We intend to produce a comprehensive comparison with existing approaches.

This paper has presented a first step towards a simple, domain independent, computational model of user trust incorporating the main factors affecting trust from the cross-disciplinary literature. We have opted for quantitative equations, rather than trying to model cognitive processing. Clearly more work is needed in this area, and various aspects of the model need to be investigated (and validated) in more detail. For instance, Experiment 1 only looked at negative trust reports, so needs extending to positive ones. To turn the equations into algorithms, parameter values need to be determined, using experiments and user interaction. We would also like to show how this work can be applied to various domains, such as a recommender system domain.

References

Modelling Ontology-based Multilayered Communities of Interest for Hybrid Recommendations

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Abstract. This paper describes a strategy that automatically identifies Communities of Interest (CoI) from the tastes and preferences expressed by users in personal ontology-based profiles, and presents early experiments that evaluate how these CoI can be applied to recommend annotated items combining several content-based collaborative recommendation techniques. Specifically, we have experimented with a set of synthetic profiles generated from data of the well-known IMDb and MovieLens repositories. The obtained results show the feasibility of our CoI identification and recommendation approaches.

Keywords: community of interest, ontology, user profile, content-based collaborative filtering.

1 Introduction

Communities of Interest (CoI) are groups of people who share common interests or passions. However, it is very often the case that the membership to a community is unknown or unconscious. In many social applications, a person describes his interests in a profile to find people with similar ones, but he is not aware of other related interests that might be useful to find those people. In these cases, a strategy to automatically identify CoI might be very beneficial [1].

The issue of finding hidden links between users based on the similarity of their preferences is not a new idea. In fact, it is the essence of the well-known collaborative recommender systems [6], where items are recommended to a user based on his shared interests with other users, or according to ratings of items given by similar users. In typical approaches, the comparison between users is done globally, in such a way that partial, but useful similarities may be missed. For instance, two people may have a highly coincident taste in cinema, but a very divergent one in sports.

We propose a novel approach towards building multilayered CoI by analyzing the individual preferences of users, described in ontology-based profiles, and broken into potentially different areas of personal interest. Like in previous approaches [5], our method builds profiles of user interests for specific concepts in order to find similarities among users. But in contrast to prior work, we divide the profiles into clusters of cohesive interests, and based on this, several layers of CoI are found.

Depending on the current context, only a specific subset of the segments (layers) of a profile should be considered to establish his similarities with other people, enabling more accurate and context-sensitive results in recommendation processes. Thus, as an applicative development of our clustering and CoI building methods, here we evaluate empirically several content-based collaborative filtering models that retrieve annotated items according to a number of synthetic user profiles generated with data from MovieLens1 and Internet Movie Database2 (IMDb) repositories.

The rest of the paper has the following structure. Section 2 describes the ontology-based knowledge representation, upon which our personalised content retrieval processes are built. The proposed clustering technique to build multilayer CoI is presented in Section 3. The exploitation of the CoI to perform content-based collaborative filtering is explained in Section 4. Section 5 describes the experiments conducted to evaluate the proposals, and Section 6 includes some conclusions.

2 Personalised Ontology-based Content Retrieval

Our approach uses explicit user profiles. Working within an ontology-based personalisation framework [3], preferences are represented as vectors \( u_m = (u_{m,1}, u_{m,2}, \ldots, u_{m,K}) \) where \( u_{m,k} \in [0,1] \)

---

2 Internet Movie Database, IMDb, http://imdb.com/
measures the intensity of the interest of user \( u \in \mathcal{U} \) for concept \( c_i \in \mathcal{O} \) (a class or an instance) in a domain ontology \( \mathcal{O} \). Similarly, the items \( d_j \in \mathcal{D} \) in the retrieval space are assumed to be annotated by vectors \( d_j = (d_{j,1}, d_{j,2}, \ldots, d_{j,K}) \) of concept weights, in the same vector-space as user preferences.

With the above knowledge representation, we use a retrieval model that works in two phases. In the first one, a formal ontology-based query is issued by some form of query interface (e.g. NLP-based) formalising a user information need. The query is processed, outputting a set of ontology concepts that satisfy it. From this point, the second phase is based on an adaptation of the classic vector-space IR model [2], where the axes of the space are the concepts of \( \mathcal{O} \), instead of text keywords. The query and each item are thus represented by vectors \( q \) and \( d \), so that the satisfaction of the query is computed by the cosine measure \( \text{sim}(d, q) = \cos(d, q) \).

The above model is then adapted to include a matching algorithm that provides a personal relevance measure \( \text{pref}(d, u) \) of an item \( d \) for a user \( u \). This measure is set according to the semantic preferences of the user and the semantic annotations of the item based again on a cosine-based vector similarity \( \text{sim}(d, u) = \cos(d, u) \). In order to bias the result of a search (the ranking) to the preferences of the user, this measure has to be combined with the query-based score without personalisation \( \text{sim}(d, q) \) defined previously, to produce a combined ranking [3].

Additionally, we perform a semantic preference spreading mechanism, which expands the initial set of preferences stored in user profiles through explicit relations with other concepts in the ontology. Based on Constrained Spreading Activation (CSA) strategies [4], the expansion is self-controlled by applying a decay factor to the intensity of preference each time a relation is traversed, and applying constraints (threshold weights) during the spreading.

3 Multilayered Communities of Interest

It is commonly accepted that people who are known to share a specific interest are likely to have additional connected interests. We assume this hypothesis here as well, in order to cluster the concept space in groups of preferences shared by several users.

We propose to exploit the links between users and concepts to extract relations among users and derive semantic social networks according to common interests. Analyzing the structure of the domain ontology and considering the preference weights of the user profiles we shall cluster the domain concept space generating groups of interests shared by several users. Thus, those users who share interests of a specific concept cluster will be connected in the network, and their preference weights will measure their degree of membership to each cluster. Specifically, a vector \( c_k = (c_{k,1}, c_{k,2}, \ldots, c_{k,M}) \) is assigned to each concept vector \( c_i \) present in the preferences of at least one user, where \( c_{k,m} = u_{m,k} \) is the weight of concept \( c_k \) in the profile of user \( u_m \). Based on these vectors a classic clustering strategy is applied. The obtained clusters represent the groups of preferences (topics of interests) in the concept-user vector space shared by a significant number of users, and each user can be assigned to a specific cluster. The similarity between a user’s preferences \( u = (u_{m,1}, u_{m,2}, \ldots, u_{m,K}) \) and a cluster \( C_q \) is computed by:

\[
\text{sim}(u, C_q) = \frac{\sum u_{m,k} \cdot c_{i,k}}{|C_q|} \tag{1}
\]

where \( c_k \) represents the concept that corresponds to the \( u_{m,k} \) component of the user preference vector. The clusters with highest similarities are then assigned to the users, thus creating groups of users with shared interests.

In this scenario, the concept and user clusters can be used to find emergent, focused semantic CoI. Taking into account the concept clusters, user profiles are partitioned into semantic segments. Each of these segments corresponds to a cluster, and represents a subset of the user’s interests that is shared by the users who contributed to the clustering. By thus introducing further structure in profiles, it is possible to define relations among users at different levels, obtaining a multilayered network of users. The resulting semantic CoI have many potential applications. For example, they can be exploited to the benefit of content-based collaborative filtering recommendations, not only because they establish similarities between users, but also because they provide powerful means to focus on different semantic contexts for different information needs.
4 Hybrid recommendations

Collaborative filtering (CF) applications adapt to groups of people who interact with the system, in a way that single users benefit from the experience of other users with which they have certain traits or interests in common. We believe that exploiting the relations of the underlying CoI which emerge from the users’ interests, and combining them with semantic item information can have an important benefit in CF recommendation. Using our multilayered CoI proposal, we present two hybrid recommendation models that generate ranked lists of items. The first model (labelled UP) is based on the profile of the user to whom the list is delivered. The second model (labelled NUP) outputs lists disregarding the profile. This can be applied in situations where a new user does not have a profile yet, or when the preferences in a profile are too generic for a specific context. Additionally, we consider two versions for each model: a) one that generates a unique ranked list based on the similarities between the items and all the existing clusters, and, b) one that provides a ranking for each cluster. We thus study four different strategies, UP (profile-based), UP-q (profile-based, considering a specific cluster $C_q$), NUP (no profile), and NUP-q (no profile, considering cluster $C_q$).

In the following, for a user profile $u_m$, an item vector $d_n$, and a cluster $C_q$, we denote by $u_{m,k}$ and $d_{n,k}$ the projections of the vectors onto cluster $C_q$, i.e. the $k$-th component of $u_m$ and $d_n$ is $u_{m,k}$ and $d_{n,k}$ respectively if $c_k \in C_q$, and 0 otherwise.

Model UP. The profile of a user $u_m$ is used to return a unique list. The score of an item $d_n$ is computed as a weighted sum of the indirect preferences based on similarities with other users in each cluster. The sum is weighted by the similarities with the clusters.

$$
\text{pref}_m(d_n, u_m) = \sum_q \text{nsim}(d_n, C_q) \sum_i \text{nsim}_q(u_m, u_i) \text{sim}_q(d_n, u_i)
$$

where:

$$
\text{sim}(d_n, C_q) = \sum_{c_k \in C_q} \frac{d_{n,k}}{\|d_n\|\sqrt{|C_q|}}, \quad \text{nsim}(d_n, C_q) = \sum_i \text{sim}(d_n, C_q)
$$

are the single and normalized similarities between the item $d_n$ and the cluster $C_q$, and:

$$
\text{nsim}_q(u_m, u_i) = \cos(u_m^q, u_i^q) = \frac{u_m^q \cdot u_i^q}{\|u_m^q\| \|u_i^q\|}, \quad \text{sim}_q(u_m, u_i) = \sum_j \text{sim}_q(u_m, u_j)
$$

are the single and normalized similarities at layer $q$ between users $u_m$ and $u_i$, and:

$$
\text{sim}_q(d_n, u_i) = \cos(d_n^q, u_i^q) = \frac{d_n^q \cdot u_i^q}{\|d_n^q\| \|u_i^q\|}
$$

is the similarity at layer $q$ between item $d_n$ and user $u_i$.

Model UP-q. The user’s preferences are used to return a ranked list per cluster, obtained from the similarities between users and items at each cluster layer. The ranking that corresponds to the cluster for which the user has the highest membership is selected.

$$
\text{pref}_q(d_n, u_m) = \sum_i \text{nsim}_q(u_m, u_i) \text{sim}_q(d_n, u_i)
$$

where $q$ maximizes $\text{sim}(u_m, C_q)$.

Model NUP. The profile of the user is ignored. The ranking of an item $d_n$ is determined by its similarities with the clusters and the profiles of users within each cluster. The ranking that corresponds to the cluster the user is most close to is selected.

$$
\text{pref}(d_n, u_m) = \frac{1}{M-1} \sum_q \text{nsim}(d_n, C_q) \sum_{i \in m} \text{sim}(d_n, u_i)
$$

Model NUP-q. The user’s preferences are ignored, and a ranking per cluster is delivered. The ranking that corresponds to the cluster the user is most close to is selected.

$$
\text{pref}_q(d_n, u_m) = \frac{1}{M-1} \sum_{i \in m} \text{sim}_q(d_n, u_i)
$$
5 Experiments

The MovieLens database is one of the repositories most referenced and evaluated by the Recommender Systems research community. In its large public version, it consists of approximately 1 million ratings for 3,900 movies by 6,040 users on a 1-5 rating scale. It is in turn based on the Internet Movie Database (IMDb) that contains a catalogue of every pertinent detail about a movie, such as the cast, director, shooting locations, languages, soundtracks, etc. In our experiments, we have explored the combination of both sources of data. Specifically, we exploit some of the IMDb information to produce ontology-driven, content-based user profiles (described in Section 2) from the MovieLens ratings. For such purpose, we have defined a domain ontology describing the fundamental concepts involved in IMDb, including classes such as movies, actors, directors, genres, languages, countries, keywords, etc., and relations among them. Then we have parsed the IMDb content (as publicly available in text form), and converted it to an OWL KB, based on the aforementioned movie ontology. Semantic user preferences are then built from the MovieLens ratings by means of a number of transformations exploiting the generated IMDb KB.

5.1 Generating User Profiles from MovieLens ratings and IMDb data

Let \( i_{n1}, i_{n2}, \ldots, i_{nN_m} \) be the \( N_m \) items (movies) rated by user \( u_m \) and let \( r_{m1}, r_{m2}, \ldots, r_{mN_r} \in [1,5] \) be the corresponding ratings. We define the weight of movie \( i_n \) for user \( u_m \) as:

\[
w_{mn} = \frac{r_{mn}}{5} \in (0,1] 
\]

For each user \( u_m \), we measure the relevance of the different movie features by summing the weights of the movies in which these features appear.

\[
w_{mf} = \frac{1}{N_m} \sum_{n \in \text{features}(i_n)} w_{mn} 
\]

Taking into account all the movies rated by a user, the feature weights obtained with the previous formulas could be taken as initial semantic user preferences. However, we noticed that we had to filter an appropriate proportion of the features to be included in the final profiles as follows. After we expanded the features, we found that some of them appeared in the user profiles with too many instances, while others with very few. For instance, we observed that in general the initial user profiles contained lots of keywords and very few directors. Furthermore, we obtained a lot of weights with values very close to 0, too low to be considered significant or reliable. According to the cumulative distributions, for each feature, we selected the number of instances that covers approximately 90% of the feature values distribution. By applying this criterion, the resulting user preferences included the 8 top-weighted genres, 3 countries, 15 actors and 3 directors per movie.

5.2 Evaluating the hybrid recommendation models

Conventional recommender algorithms are modelled as ratings estimators. They receive a set of existent user ratings as input and predict new ratings for unseen items. In this context, it is easy to measure the effectiveness of the models if we use evaluations based on the Mean Absolute Error (MAE), i.e., the mean of the absolute differences between the ratings \( r_{w,a} \) and their predicted values \( p_{w,a} \):

\[
MAE = \frac{1}{M} \sum_{m=1}^{M} \frac{1}{N_m} \sum_{n=1}^{N_m} |r_{m,a} - p_{m,a}| 
\]

However, since our recommender models have been defined under a personalised content retrieval framework that generates rankings with values in [0,1], and aiming to make comparisons with MovieLens ratings, we saw the need to convert our recommendations into 1-5 scale ratings. To tackle this issue, we used again the cumulative distributions. In Figure 1 we show the cumulative distributions \( F \) and \( G \) of the real MovieLens ratings and the values obtained with our recommenders. To normalize each predicted value \( p_{m,a} \) we first map its cumulative probability \( G(p_{m,a}) \) into the equivalent cumulative probability \( F(r_{m,a}) \) in the rating value distribution. Then, we calculate its inverse value \( F^{-1}\left(G\left(p_{m,a}\right)\right) \) to extract the corresponding rating \( r_{m,a} \):

\[
r_{m,a} = F^{-1}\left(G\left(p_{m,a}\right)\right) 
\]
Once the rating transformations are defined, we are able to evaluate our recommenders by measuring their MAE. To this end, we built the models with 100 users and considering 10% to 90% of their ratings. The rest of their ratings were used for testing. The results are shown in Figure 2.

It can be seen that the user profile-based cluster-oriented UP-\(q\) model appears to be an appropriate hybrid recommender strategy, outperforming the base line established by our content-based recommender.

6 Conclusions and Future Work

In this work, we have presented an approach to automatically identify Communities of Interest from ontology-based user profiles. Taking into account the semantic preferences of several users, we cluster the ontology concept space, obtaining common topics of interest. With these topics, preferences are partitioned into different layers. The degree of membership of the obtained sub-profiles to the clusters, and the similarities among them, are used to define links that can be exploited by collaborative filtering techniques. Early experiments have been done applying the emergent CoI to a variety of novel semantic content-based collaborative filtering strategies showing the feasibility of our clustering strategy. However, more sophisticated experiments need to be performed in order to properly evaluate the recommendation models.

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Semantic-Enhanced Approach for Modelling Cognitive Relationships in Virtual Communities

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Abstract. Effective virtual communities appear to be an exceptional approach, which bring together people from diverse background and provide support for knowledge sharing. A common misconception though, is to believe that a VC will be effective when people and technology are present. This work examines computational means for providing personalised support tailored to the needs of a VC rather than supporting individual members. Based on 4 processes identified as important for successful knowledge sharing in closely-knit communities, we propose a computational framework that includes the extraction of a community model and the deployment of that model to provide support adapted to the whole community. This paper will present the initial formalization of the input data, along with an initial attempt to define relationships and centrality of community members.

1. Introduction

Virtual communities (VC) where people with common interests communicate electronically, share information, and construct knowledge [3] are becoming very popular recently. In a broad sense, virtual communities vary from loosely structured to closely-knit ones. An open, loosely structured community involves a large number of people with diverse interests, membership control is generally not imposed, and there are no restrictions of the interaction with the community information space. Examples of this kind of communities, such as Del.icio.us, MetaCafe, or web-blog communities like MetaFilter, are widely available on the web. In contracts, closely-knit communities involve a smaller number of people and usually exist in relatively well defined organisational or educational settings. This kind of communities are characterised with a common purpose (that can be identified by the participants or by a facilitator), shared interests among all members, commitment to the sharing of information and generation of new knowledge, high level of dialogue, interaction and collaboration, and equal participation. Closely-knit VCs have controlled membership for accessing the community’s space and resources. People from outside the community cannot access or view the resources exchanged between members or interact with the environment. To register people must be invited by an existing member, and have to provide at least a valid email address accessible by all members.

This work considers support for effective knowledge sharing in closely-knit communities. Examples of such communities include, to mention a few, groups of researchers sharing resources on a particular topic, students sharing materials within an online course, members of an organisation sharing documents and maintaining a joint repository. There are a variety of tools to support such communities (c.f. the review in [14]), from general knowledge sharing tools, e.g. BSCW [27] which provides basic support for cooperative work, to tailor-made tools to support specific tasks, e.g. ConDOR [7] which supports collaborative writing and construction of open educational resources. However, studies show that conventional tools do not provide adequate support for the effective functioning of online communities [5]. Such support requires a good understanding of what is happening within a community and what processes influence the success

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1Del.icio.us is a social bookmarking website. The primary use of del.icio.us is to store bookmarks online, which allows people to access the same bookmarks from any computer and add bookmarks from anywhere: http://del.icio.us/

2Metacafe is one of the world's largest online video broadcasters with a global audience of 17 million unique visitors: http://www.metacafe.com/

3MetaFilter is a weblog that anyone can contribute a link or a comment to: http://www.metafilter.com/
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of knowledge sharing. In this line, personalisation and adaptation can play a crucial role, as illustrated, for example, by user modelling approaches applied to web-groups [2, 17, 24].

However, personalisation approaches focus mostly on offering support tailored to the needs of individual members. There is little research that examines how user modelling approaches can be utilised to facilitate the effective functioning of a community as a whole [14]. Although, notable successes have been demonstrated for motivating participation [2], there is no systematic study how to exploit user modelling methods to offer support tailored to the effective functioning of a VC as an entity by facilitating the processes which can influence knowledge sharing.

The goal of this research is to define a computational framework for providing holistic support adapted to the needs of a closely-knit VC. The first step in our study was identifying processes related to effective knowledge sharing based on research in Organisational Psychology. Then, following the general architecture of user-adaptive systems, we derived the architecture of a computational framework, the core of which is a community model. This paper presents algorithms for extracting a key component of the community model, namely cognitive relationships between members. We will first outline community processes that have to be supported and will present the architecture of our framework (Section 2). Appropriate formalisation of the input is essential for deriving a computational model of a VC, and will be described in Section 3. Section 4 will outline algorithms for modelling relationships, and Section 5 will illustrate their application for modelling centrality. Finally, we will present the current status and will discuss future plans.

2. Framework for Personalised Support for Knowledge Sharing in VC

2.1 Community Processes to be Supported

Studies in Organisational Psychology point out that effective teams and groups operating in the boundaries of an organisation build transactive memory, develop shared mental models, establish cognitive consensus, and become aware of who their cognitively central and peripheral members are [9, 11, 12, 14, 20, 25]. Since we are dealing with closely-knit communities with characteristics similar to those of groups and teams [26], the above processes can also be applied to a broader context to inform what support should be provided to a VC.

Transactive Memory (TM) deals with the relationship between the memory system of individuals and the communication that occurs between them [10, 25]. Wegner [25] points out that transactive memory is concerned with “the prediction of group and individual behaviour through an understanding of the manner in which group processes and structures information”. The focus is on encoding, storage and retrieval of information. TM and the development of a TM system is important for the effective functioning of teams, groups, and closely-knit communities [9, 11, 20, 25]. Transactive memory helps community members to divide responsibilities for different knowledge areas and be aware of one another’s expertise. To illustrate, assume that member A’s memory can act as an extension of member B’s memory. If B is aware of what A knows, he/she should be able to benefit from A’s knowledge and the information A possesses.

Shared Mental Models (SMM) are defined as the “team members’ shared, organised understanding and mental representation of knowledge about key elements of the team’s relevant environment” [20]. Studies confirm that collaborative knowledge exploitation can be improved if group members have a shared understanding of the environment, situation and task at hand [8]. One of the main objectives of community formation is through knowledge sharing and communication to develop a shared understanding of the context in which community members act, and to create a shared understanding of the world [19, 22].

Note that there are other processes that can influence the successful functioning of a community, e.g. trust and social factors. Our study focuses on cognitive aspects, where TM, SMM, CCs and CCen are crucial.
Cognitive Consensus (CCs) deals with shared conceptualisations between members and shared understanding of the meaning concepts encapsulate [20, 21]. The idea is for the members to agree, or be aware of the different definitions behind a concept and come to an agreement of how a term is used inside a given community.

Cognitive Centrality (CCen), considers the importance of the contribution of individual members with regard to the community’s context. Members who share a significant amount of valuable information for the whole community become cognitively central and play a vital role in the functioning of a community. On the other hand, peripheral members can sometimes hold unique knowledge which can be crucial for effective knowledge sharing [16].

Further discussion with example scenarios illustrating the four processes in VC is given in [15].

2.2 Framework
The main assumption of our research is that providing adaptation tailored to the community as a whole by promoting the building of TM, development of SMM, establishment of CCs and identifying CCen inside the community can improve the functioning of a closely-knit VC. Based on this, and following the general architecture of user-adaptive systems presented in [13], we have outlined a framework for holistic personalised support to VCs which includes two parts: (a) acquisition of a community model that represents the whole community and focuses on aspects related to TM, SMM, CCs and CCen, and (b) application of the community model to offer adaptive support and improve the functioning of the community (see Fig 1).

![Fig. 1. Architecture of a computational framework to provide holistic support to closely-knit VC.](image)

2.3 Community Model
The community model will represent the whole community, including members, relationships, and topics of interest. It will consists of individual user models, a relationships model, model of the community’s context, lists of popular and peripheral topics, and a list of cognitively central members. The main components of the community model are illustrated in Fig 2.

Individual User Models for every member of the community will be maintained. They will include user interests, type of participation (e.g. uploading resources, initiating discussions), how cognitively central that member is, what relationships he/she has with other members in the community, and personal hierarchies of folders and resources created by that member.

Relationship Model will represent the following types of cognitive relationships which can exist between community members: ReadRes(i,j) – member i reads resources uploaded by member j, ReadDisc(i,j) – i reads discussions initiated by j, UploadSim(i,j) - i and j upload similar resources, InterestSim(i,j) - i and j have similar interests, and ReadSim(i,j) – i and j read similar resources.
Community Context is important to judge the cognitive centrality and influence of community members. Context as a term has been used to serve different purposes [4]. With regard to VC, context is most often considered as the general area of interest for the whole community [28]. This can be represented as a list of topics [1] or a more complex structure linking topics to an ontology. The latter approach is followed in this paper, and is discussed in Section 3.2.

Popular and Peripheral Topics are identified according to the topics of the resources uploaded, and the discussions initiated. The popular topics list will hold the first $n$ most popular topics within the community. The peripheral topics list will hold the $m$ least popular topics of the community. Having these two lists will help us in identifying the cognitively central members of the community along with defining the cognitive centrality of a particular member.

Cognitively Central Members are influential to the rest of the community. When problems with knowledge sharing are detected, these members can be prompted to take corresponding actions. The list of the most cognitively central members will be used for generating adaptive support.

2.4 Adaptive Support
Adaptive support to the community will be based on the application of the community model and will be designed with respect to the four processes – TM, SMM, CCs, and CCen. This will lead to the implementation of push factors for both newly joining members (newcomers) and existing members (oldtimers), for instance pop-up messages with useful information (e.g. welcome message, list of important members, interesting topics, relevant resources). Different colour or size of letters can be used to emphasise relevant topics in the community’s common interface. Self-tracking of folders can also be allowed so a meaningful organisation can be done. Useful information about the task at hand, along with information to promote awareness in the community, can help members to integrate and motivate them to contribute to the community. Community evolution and resource organisation will be monitored, appropriate actions will be undertaken when problems are detected, e.g. suggesting the location for a resource, encouraging members to engage in discussions when cognitive consensus is missing, pointing at interesting peripheral topics, using cognitively central members to influence the knowledge sharing process.

The remaining sections of this paper will outline initial algorithms for the first component of the computational framework – extracting a community model from semantic-enhanced data about the functioning of a VC.

3. Formalisation of the Input

Formalisation of the input data is the first step towards the implementation of the community model because it describes the input for the community modelling algorithms. We will consider a conventional structure of log data stored by knowledge sharing applications. In addition, semantic features, such as metadata and an existing ontology will be exploited.
3.1 Community Environment
The community environment contains the elements related to the functioning of a knowledge sharing community, and includes a list of members $M$, set of resources $R$, set of folders $F$ organised in a hierarchical structure $H_F$, and a set of discussions between members $D$.

The community environment $E$ will be defined as $E \equiv \{M, R, F, H_F, D\}$.

$E$ is not stable, it is changing over time by actions performed on it, including:
- join_community – a member is registering to the community
- leave_community – a member is leaving the community
- create_folder – a new folder is created by a member
- upload_resource – a new resource is uploaded in the environment
- rate_resource – a member is assessing a resource
- download_resource – a resource is downloaded from the environment
- add_resource_description – a new description is added to a resource
- add_folder_description – a new description is added to a folder
- initiate_discussion – a new discussion is posted
- reply_discussion – a new reply is posted to an open discussion

The above actions can cause the environment to evolve, e.g. topics to change or members to move into the periphery or the centre of the community. We consider that the actions will be recorded in log data which will be analysed periodically in order to extract a community model and detect changes in the community environment.

The log data will also include information about members, resources, and folders. When a member $m \ (m \in M)$ joins the community, information about their name, email address and date of joining is recorded. Thus, members will be represented as $m \equiv \{mName, mEmail, mDateJoin\}$.

A resource $r \ (r \in R)$ will be represented as tuple $r \equiv \{RCreatedData, RMetadata\}$, where $RCreatedData$ is information created by the member who uploads the resource, while $RMetadata$ is metadata associated to this resource.

A user creates $rCreatedData \equiv \{rFolder, rName, rDescription, rRating, rCreator, rDate, rAssessor, rReader\}$, where $rFolder$ is the folder storing the resource; $rName$ is the name of the resource (as given by the creator, and may be different from the original title of the resource); $rDescription$ denotes a set of resource descriptions $rDescription \equiv \{rd_1, m_1, rd_2, m_2, \ldots, rd_n, m_n\}$, where $\langle rd_k, m_j \rangle$ is the description $k$ given by member $j$; $rRating$ is a number which is the average rating given to that resource by community members, $rAssessor \equiv \{\alpha_1, m_1, \alpha_2, m_2, \ldots, \alpha_n, m_n\}$ where $\alpha_k, m_j$ represents the assessment $k$ given by member $j$; $rCreator$ is a member ($rCreator \in M$), who is the creator of the specific resource; the $rDate$ is the date the resource was uploaded; $rReader$ records the access to the resource by community members, $rReaders \equiv \{m_1, r_1, m_2, r_2, \ldots, m_n, r_n\}$ where $m_j, r_k$ indicates that resource $k$ has been read by member $j$.

$RMetadata$ concerns formal metadata. We will follow Dublin Core which is the basic and most conventional standard for online resources. $RMetadata$ will be either extracted$^5$ or provided by the user upon uploading the resource. The following elements have been selected from Dublin Core metadata: $\{Title, rAuthor, rSource, rKeywords, rDatePublish\}$, $rKeywords \equiv \{k_1, k_2, \ldots, k_n\}$ is used for comparing resources, as described below.

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$^5$ A tool that can be used is SAmgI - open source software for automatic metadata extraction developed at the department of Computer Science, Katholieke Universiteit Leuven.
Each folder $f$ ($f \in F$) is represented as tuple $f : \{\text{Title}, \text{Creator}, \text{Description}, \text{Date}\}$, where title is given by the creator, date registers when the folder was created, and the descriptions given to that folder may by from different members $\text{Description} : \{[d_1, m_1], [d_2, m_2], \ldots, [d_n, m_n]\}$, where $[d_k, m_j]$ indicates that description $k$ is provided by member $j$.

Discussions between members will also be considered for deriving a community model. A discussion $d$ is described as $d : \{\text{Topic}, \text{Originator}, \text{Contributor}\}$, where $\text{Topic}$ is the topic given by the member $\text{Originator}$ who initiated the discussion, and $\text{Contributor} : \{m_1, m_2, \ldots, m_n\}$ records the members who have contributed to the posting.

### 3.2 Community Context and Ontology

As mentioned in Section 2, we will use an ontology to maintain the community context. The relevance of an uploaded resource to the community will be checked against the context by using the ontology to determine the value that resource has for the community. Furthermore, the ontology will be used to identify similarity between resources and to detect cognitive discrepancies between members.

We consider that an existing ontology $\Omega$ will be exploited. $\Omega$ consists of classes organised in a hierarchical structure. Each class has properties and instances. There are relationships between classes and instances. For each class $c$, we define its neighbourhood $\mathcal{N}_c$ which represents a set of all classes and instances with which $c$ has a relationship. Subsequently, $\mathcal{N}_c$ of a given class includes the parent and children classes, its siblings or any other classes and instances linked with a relationship to that class. The neighbourhood enables us to consider close concepts and will be used for considering relevance between resources and similarity between users.

### 4. Definition of Relationships

The types of relationships between community members considered in our research have been listed in Section 2. Here, we define these relationships and derive methods for their calculation.

#### 4.1 ReadRes and ReadDisc Relationships

$\text{ReadRes}(i, j)$ and $\text{ReadDisc}(i, j)$ types of relationships are based on the fact that resources uploaded or discussion messages created by member $j$ are read by member $i$. Formulas (1) – (3) define the algorithm for calculating $\text{ReadRes}(i, j)$, $\text{ReadDisc}(i, j)$ relationship is calculated in the same way but considering discussion data. Let us denote $N_{i \leftarrow j}^{\text{Res}}$ to be the number of resources uploaded by member $j$ and read by member $i$. If $N_{i \leftarrow j}^{\text{Res}}$ is greater than or equal to a threshold $\sigma_\text{Res}$ (a constant that can be tuned according to the community) then a $\text{ReadRes}(i, j)$ relationship exists, i.e.

$$N_{i \leftarrow j}^{\text{Res}} \geq \sigma_\text{Res} \Rightarrow \text{ReadRes}(i, j)$$

(1)

The strength value of that relationship $|\text{ReadRes}|$ will be equal to the sum of all the values of the resources uploaded by $j$ and read by $i$, according to their context relevance, as given in (2):

$$|\text{ReadRes}(i, j)| = \sum_{i=1}^{N_{i \leftarrow j}^{\text{Res}}} V_i$$

(2)

Context relevance is calculated as follows. For each resource, we keep its keywords $R\text{Keywords}$ as mentioned in a previous section. For each keyword, $k_i$ we identify, based on the
ontology, its neighborhood $N_c$. The neighborhood of each keyword is then added into $T: \{N_{c_1}, N_{c_2}, N_{c_3}, ..., N_{c_n}\}$ where $n$ is the total number of keywords for a given resource. Now, the value of a resource can be defined based on the ontology which represents the community context. Having the list of keywords for a resource and $T$, a bag of words (BOW) algorithm [23] can be employed to calculate the similarity between the two lists of terms, which will determine the value of the resource. Let us denote the similarity between two lists $a$ and $b$ with $\text{Sim}(a, b)$. Then, the value of a resource is calculated by applying formula (3):

$$V_{r_i} = \text{Sim}(R\text{Keywords}_i, T) \quad (3)$$

### 4.2 ReadSim and UploadSim Relationships

ReadSim$(i, j)$ and UploadSim$(i, j)$ will be calculated by using again a BOW [23] algorithm.

We will consider Keywords for a resource uploaded by member $i$ and rKeywords for a resource uploaded by member $j$. Using the ontology, the neighborhood $N$ for every keyword can be extracted. By combining the concepts extracted for each keyword, we will derive an extended list of concepts related to each resource. These lists can be compared to find the similarity between them. Consequently, the values for ReadSim$(i, j)$ and UploadSim$(i, j)$ can be calculated as follows.

Let us denote the similarity value between the resources uploaded by member $i$ and the resources uploaded by member $j$ with $V^{(r, r)}_{\text{sim}}$. It is calculated by comparing the neighbourhood of the key words of which resource, as shown in (4):

$$V^{(r, r)}_{\text{sim}} = \text{Sim}(N^1_c, N^2_c) \quad (4)$$

The value of the relationship $|\text{ReadSim}|$ is the sum of all the similarity values for all resources:

$$|\text{ReadSim}| = \sum V^{(r, r)}_{\text{sim}} \quad (5)$$

$|\text{UploadSim}|$ is calculated similarly by considering all resources uploaded by two members.

### 4.3 InterestSim Relationship

The similarity between members’ interests is important for promoting transactive memory among community members. InterestSim$(i, j)$ relationship represents the similarity of interests between member $i$ and member $j$. To derive interests of a member, we consider the resources he/she has uploaded. Using the keywords rKeywords for each resource uploaded by a user, his/her interests can be captured in the form of a folksonomy. This enables us to link each user with a list of words, where each word has weight. For example, the interests of a member $i$ will be represented with a list of words $L_i$, where every word $k$ has weight $w(L_i, k)$ which indicates the frequency of $k$ in the list $L_i$. If $w(L_i, k)$ is greater than a threshold $\sigma_1$, $k$ is added to the interests of $i$ denoted with $1_i$, (6).

$$w(L_i, k) \geq \sigma_1 \Rightarrow k \rightarrow 1_i \quad (6)$$

$1_i$ will be presented as the member’s personal folksonomy. Following the same algorithm, a vector with words representing the personal folksonomy for member $j$ will be derived. The similarity between both vectors is calculated with BOW algorithm [23], and the value of interest similarity between the two users is calculated.

$$|\text{InterestSim}| = \text{Sim}(1_i, 1_j) \quad (7)$$
5. Centrality

Considering the relationships between members, we can define each member’s centrality within the community following centrality measurement in social networks. Freeman, [6] describes three types of centrality in social networks based on graph connections: degree centrality of a member is measured with the number members he/she is connected to; centrality of betweenness is based on the frequency with which a member connects two other members (the main point here is that that a member with high centrality of betweenness is controlling the communication inside the social network); closeness centrality represents how depended a member is to other members if he/she needs to pass a message to other members in the network (i.e. it deals with the distance of a given point to all other points in a graph). We currently work on the adaptation of algorithms for calculating centrality in social networks for defining centrality based on cognitive factors measured with the four types of relationships presented in Section 4.

Consider the relationships graph derived by applying the formulas from Section 4. We will illustrate the calculation of degree centrality, $C_D$, seen as the direct relationships a member has with another member in the community. $C_D$ has already been applied by [18] in their attempt to identify relationships in the context of CSCL. Note that the definition of $C_D$ in this paper, adds up towards the extraction of CCen, but the two are not the same. $C_D$ of a member $j$ can be measured according to his/her relationships with the other members of the community. In (8) we can see the original formula as presented in [6]. $a(m_i, m_j)$ is equal to 1 if there is a relationship between point $m_i$ and point $m_j$ and is equal to 0 otherwise.

$$C_D(m_j) = \sum_{i=1}^{n} a(m_i, m_j)$$ (8)

In our case, $a(m_i, m_j)$ is the value of each type of relationship between two members and is represented as $a_z(i, j)$, where $a_z$ is the relationship type. If a certain type of relationship (e.g. ReadRes), does not exist then the value is 0. Thus, the values of all the relationship types between two members are added, and then all $a_z(i, j)$ are added for a member $j$ to get his/her $C_D$. This is calculated in (9).

$$C_D(j) = \sum_{i=1}^{n} \sum_{z=1}^{5} a_z(i, j) \quad i \in M \quad n = |M|$$ (9)

6. Implementation and Future Work

The above algorithms are being implemented for extracting a community model based on tracking data from an existing closely-knit virtual community of some 25 researchers with common interests working together on joint research projects and sharing documents with the BSCW system. BSCW is a general tool for cooperation over the web which supports the main knowledge sharing activities, such as upload, download, search for resources, synchronous and asynchronous communication, and version control [27]. The main topic of interest of that community is Semantic Web Personalisation. Sub-topics include Ontologies, Metadata, Applications (E-Learning, Geographic Information Systems, Cultural Heritage), etc.

The log data collected from BSCW, which was the main source for the formalisation of input described in Section 3, records the interaction within the VC for nearly three years. The BSCW log data provides information about folders, resources and members, and records the events that cause changes to the community environment $E$, as outlined in Section 3. This community is not
functioning effectively, and some of its problems can be related to TM (members are unaware of what others’ interests and specialisation is, newcomers are not integrated in the community, oldtimers become inactive), SMM (the goal and benefits are unclear), CCs (there is no common agreement what terms mean which results in poor resource organisation, data duplication, clumsy search), CCen (there are members who possess key expertise and can be influential in the community but these members are not much engaged for improving the effective functioning of the community). We expect that the community modelling algorithms we are developing will be able to automatically detect such problems.

To validate the algorithms for extracting a community model the layered evaluation approach of adaptive applications will be applied. In order to check whether the model is complete and the elements included reflect the characteristics of the community we will use two methods. Firstly, the problems detected by the community model will be confirmed with members of the community. Secondly, we intend to use simulated data to check if the model can detect correctly users’ characteristics and relationships. This will enable us to answer one of the key questions of our research - how to extract a computational model to represent the functioning and evolution of VC as a whole. We will then be able to examine how to utilise a community model to provide support for the development of TM, building of SMM, establishment of CCs and identification of CCen. Finally, we will deploy the personalisation algorithms to extend an existing VC system - ConDOR [7] - which is built at the School of Computing, University of Leeds.

This paper presents initial steps towards the development of a community model. The relationships algorithms defined here form a major part of the community model extraction, and are crucial for modelling community centrality. The work is part of an ongoing PhD project which is expected to contribute to the user modelling and adaptive learning systems research communities with: (a) a novel framework for holistic personalised support in VC, (b) a mechanism for extracting and maintaining a community model based on the 4 processes, and (c) deployment of the community model to provide holistic support to a VC.

References


