UMAP 2011

Workshop on

Adaptive Support for Team Collaboration

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Workshop on
Adaptive Support for Team Collaboration

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Motivation and Themes

The main aim of the Workshop on Adaptive Support for Team Collaboration (ASTC) has been to bring together researchers from different scientific fields and research communities to exchange experiences and discuss the topic of how collaboration within teams can be supported through the employment of adaptivity that is grounded on the characteristics of the teams and their individual members, their activities (which are increasingly data-intensive and cognitively complex) and social bonds. The workshop was structured around a number of main questions, including:

- How can we model teams as entities with their individual and collective characteristics, social evolution, maturity, etc?
- Which (types of activities) can be monitored during the collaboration process, and how can their significance be established?
- What types of interventions may have a beneficial effect on collaboration?
- What are the possible roles of a system in this respect?
- What are the effects of the application domain on the collaboration process, and on the ways in which this can be supported?
- What social and group processes are important for team collaboration and how can these be supported using UMAP techniques?

Programme Committee

We would like to thank the members of the workshop's Programme Committee for their invaluable support in making the ASTC 2011 workshop a successful and high-quality event: Liliana Ardissono (Università degli Studi di Torino, Italy), Rafael A. Calvo (University of Sydney, Australia), Michaela Cocea (Birkbeck College, University of London, UK), Ioannis Dimitriadis (University of Valladolid, Spain), Vania Dimitrova (University of Leeds, UK), Nikos Karacapilidis (Research Academic Computer Technology Institute, Greece), Judy Kay (The University of Sydney, Australia), Milos Kravcik (RWTH Aachen University, Germany), Eleni Kyza (Cyprus University of Technology, Cyprus), George Magoulas (Birkbeck College, University of London, UK), Gloria Mark (University of California, Irvine, USA), Estefanía Martín Barroso (Universidad Rey Juan Carlos, Spain), Judith Masthoff (University of Aberdeen, UK), Toshio Okamoto (University of Electro-Communications, Japan), Jose Palazzo M. de Oliveira (Federal University of Rio Grande do Sul, Brazil), Peter Sloep (Open University of the Netherlands, the Netherlands), Michael Sonntag (Johannes Kepler University, Austria), Marcus Specht (Open University of the Netherlands, the Netherlands), and Haibin Zhu (Nipissing University, Canada).

Keynote Talk

We would like to extend a special note of appreciation to Prof. Gloria Mark (University of California, Irvine, USA) for kindly accepting our invitation to deliver a keynote talk at the workshop, entitled "Collaboration in a Changing 21st Century Context".

Sponsoring and Support

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Collaboration in a Changing 21st Century Context*

Gloria Mark

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Abstract. Ever since Kurt Lewin over 60 years ago began to scientifically study groups, group characteristics have generally been treated as stable. However, groups instead should be viewed as dynamic and situational. I will highlight how the use of Information and Communication Technology (ICT) is changing the way that groups form, organize, and conduct work. I will draw on my research in distributed collaboration to illustrate how ICT is changing the notion of group scalability, sociability, membership, dynamics, coordination, mobility, and interaction. I will discuss challenges in supporting groups as collaboration becomes more commonplace on a global scale.

* Invited keynote talk.

Augmented Collaborative Spaces for Collective Sense Making: The Dicode Approach

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Abstract. Sense making is at the heart of cognitively complex and data intensive decision making processes. It is often conducted in collective spaces through exchange of ideas, discussions, analysing situations, and exploring alternatives. This position paper proposes a novel approach to facilitate collective sense making via a collaboration platform which (a) offers multiple views to collaboration (including forums, mind maps, and argumentation structure), and (b) provides intelligent support to understand sense making behaviour by employing user and community modelling techniques. The work is conducted in the framework of the EU funded Dicode project, developing intelligent services for data-intensive collaboration and decision making.

Keywords: Collective sense making, Collaborative workspaces, Intelligent support, User and community modelling

1 Introduction

This paper proposes a novel platform to augment the synergy between human and machine intelligence in complex decision making situations. Many collaborative decision making problems have to be solved through dialoguing and argumentation among a group of people [1, 2]. In such contexts, discussions for making sense of the issues, constraints, and options are usually conducted in an unstructured manner. Sense making is a "motivated, continuous effort to understand connections (which can be among people, places, and events) in order to anticipate their trajectories and act effectively" [3]. Therefore, sense making is an inevitable path in cognitively complex and data intensive decision making processes.

Dicode[1] (**D**ata-**i**ntensive **co**llaboration and **de**cision making), an EU Framework 7 project, sets out to tackle the above challenges for three use cases. The first use case concerns a team of scientists in clinico-genomic research. The second use case involves a group of radiographers, radiologists and clinicians in a trial of rheumatoid arthritis treatment. The third use case involves public opinion monitoring on the internet for a team of brand consultants to design a campaign.

[1] Dicode website is http://dicode-project.eu/

Argumentation, as seen in Dicode, is a common activity in collective sense making process. It is valuable in shaping a common understanding of the problem and can provide the means to decide which parts of the information brought up by the decision makers will finally be the input to the solution used. Argumentation may also stimulate the participation of decision makers and encourage constructive criticism. However, discovering the connections is mainly by using tacit knowledge and the value of this activity has been largely unacknowledged. Dicode aims to address the above by user-friendly multi-view collaboration workspaces, which facilitate the exchange and sharing of ideas, opinions, comments and resources between participants. While each collaborative workspace enables an individual or a team to visualise the connections between concepts and artefacts, keeping track of the rationale behind the decision points and redeploying the accumulated knowledge in new situations is itself potentially a cognitively complex process. Hence, intelligent support will be provided by exploiting the behaviour data captured in the usage logs and by adding semantics to the content shared.

This position paper outlines a multi-faceted approach to combine human and machine intelligence for collective sense making. Specifically, we will present a novel approach to design collaborative workspaces that facilitate sense making by combining multiple views – ranging from informal (unstructured) to formal (structured). Each view facilitates different sense making aspects. Furthermore, we present a proposal how collaborative workspaces can be augmented with intelligent support utilising adaptation techniques, namely user and community modelling.

2 The Dicode Project

The goal of the Dicode project is to facilitate and augment collaboration and decision making in data-intensive and cognitively-complex settings. It will exploit and build on the most prominent high-performance computing paradigms and large data processing technologies - such as cloud computing, MapReduce [4], Hadoop[2], Mahout[3], and column databases – to meaningfully search, analyze and aggregate data existing in diverse, extremely large, and rapidly evolving sources. Building on current advancements, the solution foreseen in the Dicode project will bring together the reasoning capabilities of both the machine and the humans. It can be viewed as an innovative workbench incorporating and orchestrating a set of interoperable services that reduce the data-intensiveness and complexity overload at critical decision points to a manageable level, thus permitting stakeholders to be more productive and concentrate on creative activities. Services to be developed are: (i) scalable data mining services (including services for text mining and opinion mining), (ii) collaboration support services, and (iii) decision making support services.

In this paper, the focus is on the collaboration support services which are realised via multi-view collaborative workspaces augmented with intelligent support for collective sense making.

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[2] Apache Hadoop Project http://hadoop.apache.org/
[3] Apache Mahout Project http://mahout.apache.org/

3 Multi-View Collaborative Workspace

In Dicode, three different views of collaboration workspaces (CW) are supported. These are summarised below:

- **Discussion-forum view:** In this view, the CW is displayed as a traditional *web-based forum*, where posts are displayed in an ascending chronological order. Users are able to post new messages to the collaboration workspace, which appear at the end of the list of messages. Posts may also have attachments to enable the uploading of files. Discussion-forum exhibits a very *low level of formality* and are mainly suitable to support *ideas sharing, exchange and collection*.
- **Mind-map view:** In this view, the CW is displayed as a *mind map* where users can interact with the items on the collaboration workspace. This view deploys a spatial metaphor permitting the easy movement and arrangement of items on the collaboration workspace (Fig. 1). Messages posted on the collaboration workspace in mind-map view can be one of the following types: *idea*, *comment*, *note* and *generic*. Files of any content type (e.g. pdf, jpg) can be uploaded to the CW. The set of available types can be configured and participating users will be able to define new ones. The mind-map view also provides a set of mechanisms through which: (a) items on the collaboration workspace can be related, and (b) new abstractions can be created. In particular, creation of relationships between items is facilitated by drawing directed arrows between items on the collaboration workspace. Visual cues can be used to convey semantics (e.g. red colour can indicate opposition, while green can indicate "in favour"; labels can be associated to arrows elucidating semantic relationships). Items on the CW can be aggregated, to allow a group of items to be treated as a single entity, and transformed into a single item creating new, composite items. The mind-map view aims at supporting *sense-making during data intensive and cognitive complex tasks*.

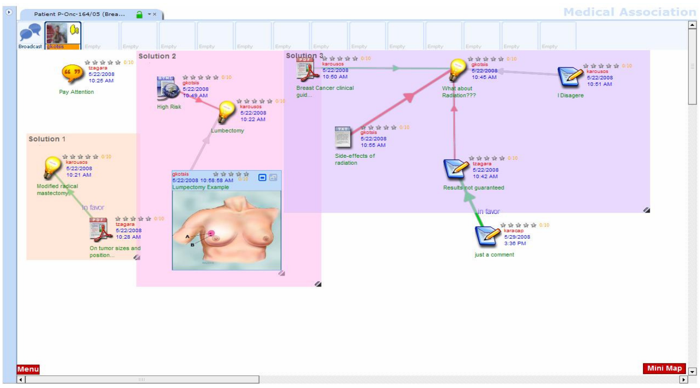

Fig. 1: Mind-map view of a collaboration workspace. Explicit relations can be created between collaboration items (arrows) or juxtaposed to express implicit/transient relationship.

- **Formal/Argumentation view:** The formal/argumentation view of the CW permits only a limited set of discourse moves for a limited set of message types whose semantics is predefined and fixed. Formal views of the collaboration workspaces exhibit a *high level of formality*. In particular, the formal view (Fig. 2) enables the posting of messages which can be of type *issue* (to indicate the decisions to be made) *alternative* (to represent potential solutions to the issues discussed) or *position* (to comment on alternatives or on other positions). Positions either support or are against alternatives and positions and their relationship are explicitly specified when users post them to the collaboration workspace. Files can be attached to positions to further support their validity. The formal view supports also the notion of preferences, used to weigh the importance of two positions and reflect the importance of one position over another. Decision making support algorithms (e.g. a voting or a multiple criteria decision making), which are associated with the CW, can take into consideration the relationships of positions as well as existing preferences and calculate which alternative is currently prevailing or which position has been defeated. The aim of the formal view is to *make the CW machine understandable* and to further support *decision making*.

Fig. 2: A formal view of the collaboration workspace shown in Fig. 1.

Every CW can be **transformed from one view into another** at any point in time by anyone participating in the collaboration. Such transformations are rule-based; a set of rules specifies how items in the source view are transformed into items of the destination view. All **discourse moves and contributions** that users create during their interaction in the CW are logged within Dicode in order to enable their further analysis by a variety of services. For each view, **log data contains** information related to the event that happened on the workspace and which includes:

- the collaboration workspace's ID and view where the event took place;
- the user's operation and the associated content (e.g. adding/updating/deleting an item, moving an item, creating relationships between items etc);
- the user who executed the operation;
- the date and time when the event occurred.

The log data in the CW will be used as an input for intelligent support algorithms.

4 Intelligent Support

Intelligent support will **augment the multi-view CWs** with machine intelligence to understand and facilitate collective sense making. Intelligent support will be provided at two levels:

- *Understanding collective sense making*. This will include user/community profiling, e.g. identifying user characteristics, discovering links between individuals, identifying common topics; discovering patterns of behaviour such as silos or dominance, extracting situations parameters.
- *Facilitating collective sense making*. This will include interface augmentation (e.g. adding visual signals to help establish situational awareness) or suggestions in the form of messages (e.g. to facilitate the exchange of ideas, point at useful patterns, highlight important situation aspects).

The following subsections propose our approach to implementing the first level of intelligent support, i.e. understanding collective sense making behaviour. This will be achieved by three functions (section 4.3) which employ descriptive machine learning and data mining algorithms and meet the key objectives as stated in section 4.2. The following section outlines how the CW log data will be enriched with semantics for user and community modelling.

4.1 Input: Augmented CW Log Data

Intelligent support will be based on the log data from the CWs which include mind mapping graphs, discussions, arguments and comments. In addition, the users' meta-data, including the users' navigational behaviour as recorded in the usage logs, as well as the searching behaviour of the users in the collaborative workspace, will be used to characterise the users and derive a user profile for each user in the community. Semantic enrichment of the user profiles is achieved by considering semantic data sources, such as domain ontologies (to identify the domain topics discussed), as well a collaboration and decision making ontology developed in Dicode (to take into account the user roles and to link sense making to decision making steps).

4.2 User and Community Modelling

Intelligent support in Dicode is underpinned by a mechanism for user and community modelling which will be outlined here. It is envisaged to be used by intelligent services which augment the CW in Dicode. For instance, a recommendation mechanism in Dicode will be able to use the output of the community modelling functions to direct to 'items' in the CW, e.g. a data set, a set of relevant discussions, a topic of interest to search for. Furthermore, the users of the CW can be pointed to a set of discussions that occurred in different times but belong to a certain topic of interest.

Objectives. The following four main objectives can be perceived for the community modelling and user profiling functions:

- **O1:** Detect topics of community discussions in the collaborative workspace.
- **O2:** Identify key characteristics of the users in the community from available data about the users, i.e. unstructured data, semantic annotations, meta-data, and use these characteristics to shape the user profile for each user within the community.
- **O3:** Quantify the strength of each characteristic for discovery of connections.
- **O4:** Discover clusters of users and interesting patterns in user behaviour by applying descriptive data mining functions, i.e. cluster analysis and association mining on the derived user profiles.

4.3 Outline of the Main Algorithms

This section will outline how **descriptive machine learning and data mining**, such as cluster analysis and association rule mining, can be applied for user and community modelling. We will group them into three main functions.

Function 1: Clustering Unstructured Data for Topic Detection

Purpose (O1). The main purpose of this function is to discover the main topics of the unstructured data, i.e. community discussions, arguments, using descriptive data mining methods, i.e. cluster analysis.

Input. Unstructured data that community users create within the collaborative workbench, as part of their collaboration activities. These include the discussion and arguments that occurred between the community users in the workbench. All the available parts of the discussions can be utilized by the function, i.e. the title of the discussion thread, main discussion body, replies by other users, tags that collaborating users attach to the discussion.

Processing. The input data will be processed as follows:

- Pre-process the input unstructured data and transform it into a term weight document matrix to be used as input for cluster analysis.
- Using the pre-processed matrix, build and train a clustering model that segments the discussions into distinct groups (clusters) based on the similarities and distances between the discussions.
- Using the profiles of the discovered clusters, detect the topic of each cluster of discussions based on the frequency of occurrence by considering the most occurring terms that occur in each cluster.

Output. There are two types of output produced by this function:

- *Clusters of discussions*, where each discussion instance will be assigned a cluster id to identify to which discovered cluster of discussions it belongs to.
- *Cluster profiles*, including the number of discussions that belong to each cluster and the most significant terms that belong to each cluster based on the frequency of occurrence.

Function 2: Deriving Key User Characteristics and Generating User Profiles

Purpose (O2 & O3). The purpose of this function is to derive the key characteristics that describe each user within the community, and weight these characteristics for every user to reflect the significance of each characteristic. These weighted user profiles will be accumulated in a community model.

Input. Data input to this function include: (a) Discussion topics that are detected using the first function described above; (b) User meta-data available from the logs and meta-data derived from the other components of the collaborative workbench, including the discussions, arguments, i.e. the author of the main body of the discussion and the authors of the replies to the main body, the mind mapping graphs, and the meta-data available from the searching behaviour in the workspace. (3) The characteristics derived from the unstructured data, i.e. topics, and the meta-data can be semantically enriched by the collaboration and decision support ontology, relevant domain ontologies, and open lexical resources, i.e. Wordnet.

Processing. This function will process the input data as follows:

- *Identify user characteristics* within the community from the available input data.
- *Compute weighted interests in the identified topics* - for each identified characteristic, the function will compute a numerical weight for each user profile that represents the significance (importance) of this characteristic to that user within the community.
- *Build a user–characteristic matrix* that could be input to further descriptive data mining functions (cluster analysis and association mining).

Output. The output of this function is a community model that includes a user profile for each user. Each user profile represents the weights of the identified characteristics for each user within the community.

Function 3: Discovering Patterns in the User Profiles

Purpose (O4). The purpose of this function is to discover hidden patterns in the user profiles for further support to collaboration and decision making, using descriptive data mining techniques.

Inputs. The input to this function is mainly the community model (user profiles) derived by the second function

Processing. This function will process the input data as follows:

- Apply *cluster analysis* methods on the derived user profiles within the community model to discover the user clusters and the user cluster profiles.
- Apply *association mining* methods on the derived user profiles within the community model to discover association hidden patterns within the user characteristics.

Output. This function mainly produces three outputs: (a) Clusters of user profiles, where each user profile instance will be assigned a cluster id to identify to which discovered cluster of user profiles each user belongs to. (b) Cluster profiles, including the number of user profiles that belong to each cluster and the characteristics' values for the average user profile, i.e. cluster centroid, for each discovered cluster. (c) Discovered hidden association patterns, including frequent characteristic-sets that list those significant characteristics that are obtained frequently by the same users, and the hidden association rules underlying these sets.

5 Related Work

The approach proposed in this paper has two main innovative aspects: (a) a new way to facilitate sense making using multiple linked views of collaborative workspaces; and (b) a novel application of user and community modelling to get an understanding of collective sense making behaviour.

Over the years, a number of systems have been developed aiming to support the process of sense making which include Debatepedia [5], Parmenides [6], ClaiMaker [7], TruthMapper [8] and Cohere [9]. Despite their powerful features, each of these systems provides only a fixed level of formality lacking the ability to adapt their environment to the needs of the collaboration. In Dicode, collaborative workspaces build on and extend the notion of spatial hypertext, which has been proposed as an alternative to navigational and semantic organisation of resources [10]. Spatial hypertext employs a spatial metaphor to organize information aiming at taking advantage of the user's visual memory and pattern recognition. Due to its ability to express ambiguity as well as transient and implicit relationships between information, it is an effective way to support information triage, i.e. the process of sorting through relevant materials and organizing them to meet the needs at hand[11]. While most existing hypertext systems permit only a single user to organize the information (e.g. VIKI [12], WARP [13]), approaches to bring spatial hypertext into the collaborative realm have only recently started to emerge [14]. Dicode will make a contribution to this stream by exploiting spatial hypertext for collective sensemaking in cases when humans need to process large volumes of heterogeneous data.

Recent research trends look at intelligent ways to support the effective functioning of close-knit communities through personalization and adaptation techniques. Modelling users within a community provides the grounds for generating group recommendations [15]. One method to support that is through detecting the topics that the collaborating users show interests in. In [16] Cheng and Vassileva derived topics of users' interests based on the resources shared by them within the community, where a reward factor is calculated to measure the relevance of each contributed resource to the topics derived. In [17], Bretzke and Vassileva modelled users' interests based on how frequently and recently users have searched for a specific area from a particular taxonomy. User relationships are then determined based on the resource downloading behaviour. A more recent approach by Kleanthous and Dimitrova [18][19] employs the metadata of the shared resources along with an ontology representing the community context and derives a semantically relevant list of interests for every user.

In Dicode, we aim to further enhance the existing topic detection approaches by exploiting a hybrid machine learning, text data mining, and semantic enrichment approach. Using as input community discussions, mind-mapping activities, and relevant ontologies, we aim to discover topics of interests that are buried within the diversity of unstructured and semi-structured contents produced by the collaborating members in the multi-view collaborative workspaces. Detected topics will then be exploited to facilitate collective sense making within the community members.

A community model can be analysed to automatically detect patterns which can be used to decide when and how interventions to the community can be done [20]. It has been shown that community patterns based on these processes can be derived from the community graph. For example, [19] have identified community patterns related to processes linked to effective knowledge sharing, such as transactive memory (how members' knowledge is related), shared mental models (shared understanding of the common goal), and cognitive centrality (influential members).

Similarly to Kleanthous and Dimitrova's work on semantically-enriched relationship detection, we will exploit semantics and ontologies to enhance the log data from CWs and get richer input about what is happening in the community. However, the community modelling approach in Dicode will take the modelling further by exploiting descriptive data mining approaches, including output from (i) statistical member segmentation, i.e. group profiles, where members assigned to the same group share a similar behavioural profile, as well as output from (ii) association rule mining, i.e. lists of the frequently co-occurring behavioural activities of the community members, in order to further improve the community pattern discovery tasks. Discovered patterns will also be used to further augment the multi-view CW for enhanced collective sense-making, knowledge sharing, and group recommendations.

6 Conclusions

We have set out an ambitious goal to exploit the synergy of machines and humans in complex cognitive situations that require making decisions involving large volumes of data. We are starting to unravel the aspects of this synergy. While data mining techniques (i.e. machine intelligence) can be exploited to process data and discover trends and patterns, human intelligence is needed to make sense of the data and take decisions. The process of sense making involves discovering connections, deriving patterns, generating alternatives, weighting possibilities. People perform these tasks in an intuitive manner using tacit knowledge. Our ultimate goal is to capture, preserve, and reuse this tacit knowledge by providing collaborative workspaces for collective sense making. In turn, we will exploit machine intelligence to analyse the human behaviour in the collaborative spaces in order to get a better understanding of the collective sensemaking process, facilitate important aspects, and support future human sense making (e.g. exploiting patterns applied earlier).

Currently, we are developing the CWs following a generic approach, which will enable the same approach to be applied to diverse use cases. The illustrations in this paper were from the exemplification of the multi-view space for a Breast Cancer research group embarking on an analysis to discover any common characteristics or trends that could be deducted from recent studies which used high-throughput technologies such as microarrays and next-generation sequencing. We plan to apply the approach presented here to support sense making in a clinical trial of Rheumatoid Arthritis treatment where a team of medical practitioners examines large data sets and analyses the effectiveness of the treatment on patients. In addition, the log data from the CWs is being analysed in line with the functions presented in here to augment CWs with intelligent support.

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An Activity Awareness Visualization Approach Supporting Context Resumption in Collaboration Environments

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Abstract. In the research on Computer Supported Cooperative Work, activity awareness is considered a key feature for the coordination of users' activities. We propose a model for the visualization of recent activity awareness information organized at two abstraction levels: (a) the upper level, represented as a tag cloud, provides a general view of the degree of activity occurred in the user's collaborations. (b) the lower level is a detailed view of the occurred events, structured on the basis of the user's activity contexts. The results of a user study show that the adoption of the proposed solution is preferable over a standard awareness space providing a direct access to complete awareness information.

Keywords: activity awareness support, workspace awareness, collaboration environments, Web 2.0.

1 Introduction

The research on groupware and Computer Supported Cooperative work describes awareness support as a key feature for collaborative environments, in order to enable users to maintain an up to date view of their collaborations. In particular, [1] introduces the *activity awareness* concept to represent "the awareness of project work that supports group performance in complex tasks".

Activity awareness support involves notifying the user about many different types of information, concerning collaborators, artefacts to be manipulated, actions performed by others, pending tasks, etc. Thus, a major issue to be addressed is that of preventing the user from being overloaded by an excessive amount of data to be inspected (i) while (s)he operates in the collaboration environment, and (ii) every time (s)he resumes the state of an activity context; e.g., after having been out of office for some time.

The risk of overloading users was evident in former collaboration environments; e.g., see [2]. However, nowadays it is even more problematic, as private and corporate users are increasingly using online services to carry out their activities by exploiting the ubiquitous environment offered by the Internet [3, 4]. Therefore, for each user, the number of private and shared activity contexts to be handled in parallel, and the amount of awareness information to deal with, are much larger than before.

In order to support an efficient resumption of the state of the user's collaborations, we propose a two-level model for the visualization of recent awareness information which provides a synthesis of the evolution of the user's activity contexts, from which the details of the occurred events can be retrieved on demand. The idea is that of enabling the user to quickly understand the degree of activity occurred in her/his collaborations in order to decide whether some of them deserves to be inspected in detail. For this purpose, we have designed the higher visualization level as a tag cloud (the Awareness Cloud) whose nodes

– represent activity contexts and users, depicting the level of occurred activity in the selected time interval by means of their relative size in the cloud;
– are direct links to projections of the awareness space handled by the collaboration environment, focused on specific activity contexts/users. These projections form the lower visualization level and support a direct access to recent awareness events from particular perspectives.

These two views complement the thorough information provided by standard awareness spaces by enabling the user to access information incrementally and in a focused way.

We conducted an experiment with end users to assess how people interacted with these views. The results revealed that, in terms of improved users' performance, our designed Awareness Cloud represents an added value to an awareness space structured on the basis of the user's activity contexts because it helps users to quickly access the information required to answer specific information needs.

In the following, Section 2 presents our visualization model. Section 3 describes the user study we carried out and discusses its results. Section 4 compares our proposal to the related work and Section 5 concludes the paper.

2 Presenting Recent Activity Awareness Information

The provision of awareness information is challenging: on the one hand, push technologies can be employed to notify users about the occurred events, e.g., via Instant Messages or e-mail. However, they can generate interruptions possibly having a disruptive effect on users' attention and emotional state [5]. On the other hand, as discussed in [6], users acknowledge notifications as disruptive, yet opt for them because of their perceived value in providing awareness. Moreover, as reported in [7], users are observed to frequently switch among different activity contexts, with a consequent effort in resuming the state of the contexts they enter.

One way to address the trade-off between keeping users up-to-date about the evolution of their collaborations and interrupting them is the provision of an incremental access to awareness information. In fact, this solution gives a flavor of what has happened in the users' activity contexts and supports a quick access to the details they need, on demand. The visualization model we propose follows this approach and is thus proposed as an awareness layer to be superimposed over a standard awareness space, in order to provide views on such space, focused on the recent past and on specific information needs. As such information is not enough to reconstruct the complete history of a collaboration, our visualization model assumes the existence of a separate awareness space presenting the long-term event history. See [8] for a proposal of how such a space could be organized.

2.1 Context-dependent Management of Awareness Information

For each user of a collaborative environment, the awareness events to be visualized concern actions performed by her/himself, or by her/his collaborators, while they use the business services integrated in the environment. In order to support a structured, context-dependent presentation of information to the user, our visualization model makes two main assumptions:

- The user's activity contexts are explicitly modeled, as well as the collaboration groups associated to such contexts.
- The awareness events generated by the services integrated in the collaboration environment are classified in their reference activity contexts, so that they can be managed in a structured awareness space reflecting the user's collaborations and private activities.

Fig. 1. Awareness cloud of a user of a collaboration environment (user utntest1@gmail.com).

As described in [9, 10], we represent the user's private and shared activity contexts at different granularities, considering the following types of contexts:

- *Collaboration sphere*: this is a thematic group, similar to a virtual community, used to keep in touch with each other. For instance, the "family" sphere could be defined to keep track of the communication concerning the user's family.
- *Activity frame*: this is a more or less structured project, which a user can define in order to collect artefacts of interest around a topic and manage activities aimed at reaching a goal, possibly in collaboration with other users. For instance, an activity frame could represent a work project aimed at preparing a conference paper.
- *Task*: this is used to specify and carry out the execution of an activity, possibly shared with other users; e.g., writing a section of the above mentioned conference paper. A task may include artefacts to be manipulated and can have a deadline. Tasks are created within activity frames and can be related to each other according to partial order relations, in order to coordinate the execution of complex activities.

[9] and [10] present a framework for the development of user-centered service clouds supporting an explicit management of contexts and the consequent classification of awareness events. The visualization model proposed here builds on that architecture but could be applied to a different one, as long as it guarantees the association of awareness events to actors and contexts.

2.2 Two-level Presentation of Awareness Information

We propose to visualize the recent activity awareness information for a user in the Awareness Cloud. This is a tag cloud which shows the degree of activity occurred in the user's private and collaboration contexts during the time interval selected by the user.

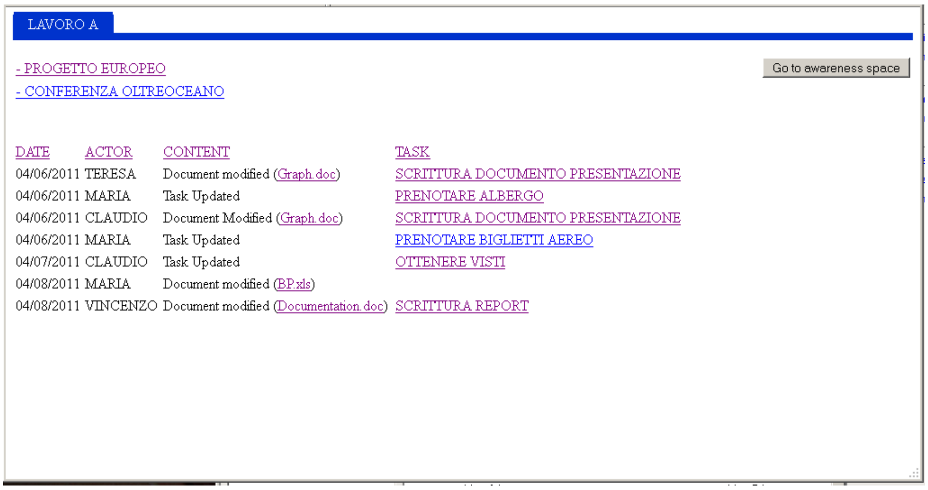

Fig. 2. Detailed views on awareness information concerning context "LAVORO A".

As shown in Figure 1, the Awareness Cloud for a user U is organized as follows:

- The nodes represent four types of entities: *user* nodes are associated to U's collaborators; e.g., see node CLAUDIO. *Collaboration sphere*, *activity frame* and *task* nodes are associated to the user's collaboration spheres, activity frames and tasks, respectively. For instance, node LAVORO A represents a collaboration sphere.
- The relative size of each node in the cloud represents the degree of activity in the selected time window and depends on the number of associated awareness events that have been collected in the collaboration environment. Specifically, user nodes visualize the degree of activity of the represented users *within U's activity contexts*, as the operations performed by users in other contexts cannot and must not be disclosed to the user. The other types of nodes summarize the degree of activity occurred in the contexts they refer to.
- The user can specify the starting and end time of the interval for the generation of the cloud in order to visualize the evolution of her/his activity contexts along time.

Moreover, a “catch up” button enables the user to refresh the cloud by setting the starting time to the current time. This is useful when the user is not interested in the recent event history any more.

Thus, for each user, a dynamic awareness cloud is generated, which reflects the activity contexts (s)he engages in and the selected time interval.

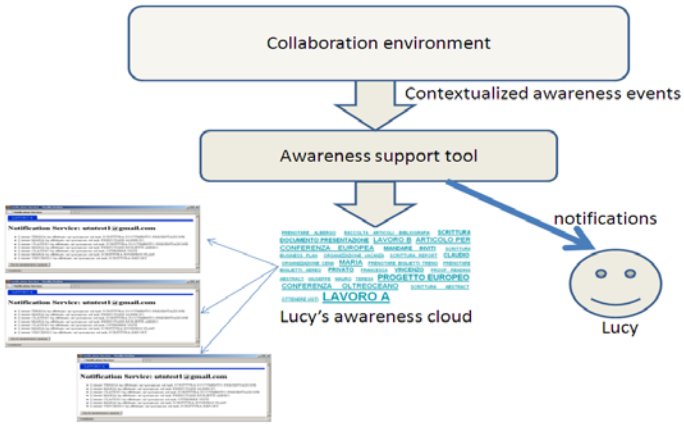

Fig. 3. Architecture of the collaboration environment supporting activity awareness.

Each node of the cloud is linked to a view on the main awareness space of the collaboration environment which shows the related awareness events in detail. Each view is indeed a projection of the awareness space, focused on the context represented by its source node in the Awareness Cloud and on the time interval selected for the generation of the cloud. Specifically, the page linked to a user node displays the list of events describing the actions performed by the represented user. Moreover, the page linked to an activity context node displays the list of events occurred in that context.

Figure 2 shows the event history associated to node LAVORO A of the awareness cloud: in order to support the navigation of events, these can be sorted by date, actor, content and task (in fact events are managed as structured objects, with features, within the collaboration environment. Notice that, if the context associated to a view includes any nested contexts (in this case, PROGETTO EUROPEO and CONFERENZA OLTREOCEANO, which are two activity frames defined within the LAVORO A collaboration sphere), the page includes links which the user can follow in order to visualize the events concerning such nested contexts. Thus, the projections on the awareness space are hierarchical.

It should be noticed that the cloud includes a maximum number of 40 elements to be visualized at each time because, as discussed in [11], a cloud with too many tags can be puzzling and hard to read. Should more than 40 elements be eligible for visualization, those with least elements would therefore be dropped. The user can however personalize the cloud by suppressing nodes in order to avoid the visualization of users and/or activity contexts (s)he is not interested in. Moreover, we are extending the cloud generation model in order to allow the user to specify high-priority nodes, associated to users and/or contexts which the user wants to monitor with particular attention. Such nodes will not be dropped from the cloud and will be depicted in a different color for easy identification.

We integrated our visualization model in a collaboration environment developed by exploiting the Personal Cloud Platform (PCP) [9], which supports the development of customized collaboration environments by integrating heterogeneous software components in order to answer specific functional needs. Figure 3 shows the overall system architecture and highlights the generation of the Web pages according to our proposed model (integrated in the Awareness Support Tool of the environment). The PCP enables the user to specify her/his collaboration spheres and to synchronize heterogeneous business services accordingly. Moreover, it offers the Collaborative Task Manager (CTM, [10]) for the management of activity frames and tasks and for the classification of the awareness events generated by the user's actions in the related activity contexts. The CTM offers a User Interface which enables the user to interact with business services (e.g., to create or manipulate artefacts) within a specific activity context and to classify awareness events in the appropriate activity contexts.

3 Tests

3.1 Description

We conducted an experiment to evaluate the impact of the introduction of the Awareness Cloud on users' experience. We wanted to test a hypothesized causal relationship between the introduction of the Awareness Cloud on top of an awareness space structured on the basis of the user's activity contexts (henceforth, context-aware awareness space) and people's performance during a task.

Our research question was *"Does a context-dependent tag cloud modify the level of performance of the users with an activity awareness space?"*. If the answer is positive, which case can give best results?

Hypothesis (Ha): The introduction of a custom tag cloud to enhance a context-dependent activity awareness space (i.e., an awareness space structured on the basis of the user's activity contexts) will improve users' performance on an awareness information seeking task, in terms of execution times and number of errors.

Sixteen volunteers participated as participants in this experiment (10 men and 6 women). All participants were students or staff within the University of Torino and performed the test for free, without any reward.

The experiment had a single-factor, between-subjects design. Two treatments were applied - one experimental treatment and one base-case control treatment. The experimental treatment consisted in a context-dependent activity awareness space enhanced with an Awareness Cloud, while the context-dependent awareness space alone was reputed as the base-case.

Each treatment condition was considered as an independent variable. Participants' performance was considered as a dependent variable and was calculated considering two objective measures: number of committed errors and time needed to complete the task. Participants were divided into two groups of eight people, and each group received one single treatment. Such design was aimed at preventing side effects such as practice and fatigue. Users were also given two questionnaires: one before the task, the other after task completion. The first questionnaire was meant to evaluate users' background about collaborative applications. The second questionnaire was meant to evaluate users' opinion on the adopted User Interface solution.

The experimental task was designed as an information recovering and comprehension one, simulating a typical, asynchronous reception of awareness information in a collaboration environment. Users in both groups were briefed about their scenario before the beginning of the task: as participants of three different collaboration groups, they had received awareness information regarding other users' activities, that was still to be read. Such information was collected in a structured list (the activity awareness space), where each event-related element was organized on the basis of its originating activity context; the recent activity awareness consisted of 13 events. Users were then asked to answer six questions, whose answers could be found by navigating the events. Questions 1, 2 and 4 were general, quantitative oriented ones, such as "who is the most active user in a certain task"; questions 3, 5 and 6 were more specific, as for example "list every task and collaboration sphere a certain user is involved in".

All participants used the same activity awareness space for this purpose. The only difference between the two treatments was the presence (or the absence) of the Awareness Cloud, combined with the visualization of recent events. Users within the experimental treatment group could therefore access particular "projections" of the awareness space by clicking on the corresponding node of the Awareness Cloud. Each user was also given information about the nature of their (simulated) collaborations, such as names of collaboration groups, projects, tasks and involved users. Such instructions were available to participants as a reference throughout the whole experiment. Each participant was engaged in testing activity for a period of about 15 minutes.

3.2 Results and Discussion

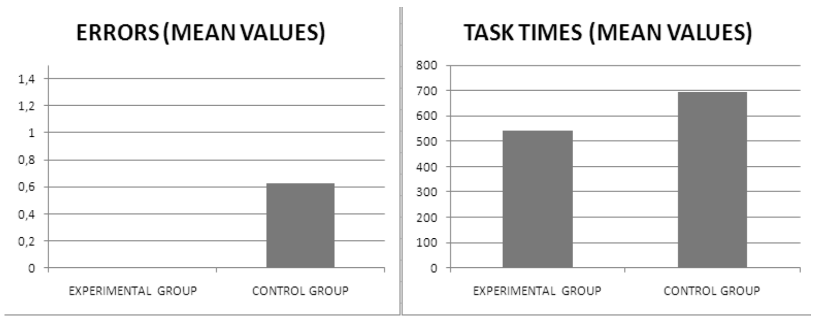

Fig. 4. Test results.

The first questionnaire was aimed at measuring the level of practice each user had with collaborative applications, within two different environments: workplace and private life. Each user could choose between four non-decreasing levels of practice, ranging from 0 to 3. Results showed no significant difference in the level of practice each user had with collaborative applications in both environments.

Figure 4 shows the results of the user tests. The figure is split in two parts, and both parts show mean values for the two treatments: the values are referred to the number of errors and execution times (in seconds) respectively, and are defined on the y-axes; the x-axes identify the treatment group.

We used an unpaired Welch's t-test (which does not assume equal variances) to analyze collected data. An alpha level of 0.05 was used to make decisions of significance. We found a significant effect either for number of errors ($t = -2.38$, $p = 0.049 < 0.05$) and for execution times ($t=-3.15$, $p = 0.011$), that lead us to reject null hypothesis of no difference between the treatments, and to accept our hypothesis: the introduction of the Awareness Cloud lead to an improvement of users' performances.

In the second questionnaire we asked users to evaluate their own experience with the User Interface they operated with: awareness space plus Awareness Cloud for experimental group, awareness space alone for control group. Each user could choose between seven non-decreasing levels of satisfaction, ranging from 0 to 6. The experimental group expressed a mean value of 5,81 for their UI (st.dev = 0,55), while the control group expressed a mean value of 5,31 (st.dev = 1,02).

The results of this experiment revealed that the introduction of the Awareness Cloud significantly improved users' performance, in terms of times of execution and number of errors. First-hand observations of participants behavior in this experiment lead us to grasp two aspects that may explain these results:

- The Awareness Cloud proved itself as very easy to understand and to use, and showed a good level of integration with the awareness space. Indeed, the users of the experimental group were left free to choose arbitrarily whether to adopt it or not, but every one of them (even those who did not know what a tag cloud was) opted for its use since the first question.
- The Awareness Cloud allowed users to express fast and precise queries by clicking on the desired nodes, with a User Interface that was valued as "practical, good and interesting". Navigating into the awareness space in isolation did not prove itself as immediate and error-proof as the Cloud: users of the control group who did not commit errors tended to spend more time doing their tasks, probably due to the need of verifying their choices with more accuracy.

Users indicated as a major drawback of the Awareness Cloud the fact that it made hard to spot nodes with a very low density of events: while it could be much faster to identify high density elements (specifically, groups of users and highly active tasks), those written with the smallest font (such as low activity tasks) might get lost among the crowd. This aspect is typical of a tag cloud [11] but could be addressed by supporting a personalized configuration of the cloud, based on the user's interests. Specifically, we plan to enable the user to configure the Awareness Cloud by specifying which elements (s)he wants to monitor with most attention. When the cloud is generated, such elements will then be displayed with a different color (e.g., red instead of traditional light blue) and would never be omitted when the cloud is too large.

4 Related Work

Most groupware and project management tools only offer standard awareness spaces which show the list of occurred events organized by collaboration group; e.g., BSCW [12]. Other systems, such as CANS [13], support the presentation of awareness events in different formats (such as lists and tables), but events are classified by group/shared directory. Furthermore, [14] proposes a radar view of awareness events, which are only classified by source application.

In [2], AwarenessMaps are proposed to provide the members of shared workspaces with an overview of users and documents: "the PeopleMap shows an array of pictures of active users fading out over time; and the DocumentMap provides a schematic overview of the structure of a shared workspace and indicates recent changes." Moreover, [15] introduces a pictorial representation of incoming e-mails (Info-Lotus), divided in groups and sub-groups in order to represent conversation threads. Our proposal makes a step forward in this direction by visualizing the recent awareness information at different granularity and abstraction levels. The *granularity* aspect concerns the generality of the activity context to be considered and is motivated by the fact that users engage in different types of collaborations, such as thematic groups (e.g., small or large virtual communities), more or less structured projects, and specific tasks. The *abstraction* aspect enables the user to receive a synthesis of the evolution of her/his activity contexts and to select the contexts to be inspected in detail.

Recently, the research about collaboration in online communities has focused on activity awareness in order to inform users about who is active in the topics of interest of the community, which kind of contribution has been provided, and similar. For instance, [16] proposes a "star" view of users, aimed at showing their degree of activity in the community. Moreover, [17] proposes a visualization of activity awareness in CiteULike, which exploits radial time bands to show the time period during which the user/group activity (or the activity on a topic) has occurred. Our proposal differs from those works because, besides modeling individual users and groups, we model the user's activity contexts. Specifically, the visualization we propose enables the user to assess the state of her/his collaborations or to focus on aspects, such as a particular task.

5 Conclusions

This paper has described a visualization model supporting the incremental access to activity awareness information in a collaboration environment. Our model presents the awareness information at different levels of detail in order to provide the user with a general view on what has recently happened in her/his collaborations, and enable her/him to retrieve detailed information on specific activity contexts. A user study showed that the adoption of the proposed solution is preferable over a standard awareness space providing a direct access to complete awareness information.

Before concluding, it is worth mentioning that the model presented in this paper is the first step towards the development of an adaptive awareness support service enabling users to receive a personalized view of the information they need, depending on their interests and activities. In fact, the current model for the generation of the Awareness Cloud is only based on the user's activity contexts and on the selected time interval for the visualization of information. Personalized clouds could be generated by enabling the user to explicitly select "high-priority" contexts (as proposed in Section 2), but also by tracking the user's interests across activity spaces along time, and by dynamically configuring the Cloud in order to focus it on the most relevant ones; e.g., see [18] for a similar approach applied to notification management. In our future work, we plan to extend our awareness model towards the provision of adaptive workspaces which tailor both the presentation of information (e.g., awareness information) and their services to the dynamics of the collaboration activities carried out by users; e.g., see [19].

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Scaffolding Collaborative Learning Opportunities: Integrating Microworld Use and Argumentation

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Abstract. This paper presents our research efforts to support students' collaborative process when learning mathematics and science as they interact in microworlds and engage in discussions and structured arguments. From a pedagogical perspective, the system provides students with an environment to explore challenging problems and encourages them to collaborate. The collaboration takes place in a discussion environment that is integrated with microworlds, allowing students to discuss and argue with one another and share their rationales and insights. The challenge of this work lies in providing students, teachers, and researchers with coherent, unified feedback within the system as a whole. To accomplish this, the system must combine and analyze student actions across tools, and results of those actions. We conclude that the integration of these two types of software tools provides a solid foundation for intelligent analysis of student collaboration.

Keywords: Collaboration, intelligent support, microworlds, argumentation, discussion

1 Introduction

Technological advances and research in technology-enhanced learning (TEL) have enabled at least two ways in which computer-based environments can support the way students learn mathematics and science. The first is through Exploratory Learning Environments (ELEs) including microworlds and simulations, which hold the promise of making abstract ideas concrete and manipulable [1, 2]. The second is through computer supported collaborative learning (CSCL) and particularly dialogue and argumentation [3, 4, 5] which provide students the means to engage in discussions and structure arguments.

The work presented here attempts to blend these two approaches to learning by integrating ELEs with a discussion and argumentation environment, thus enabling the possibility to learn in ways that were not previously possible. Some prior steps have been taken in this direction; for instance, the CoChemEx project explored the combined use of a virtual laboratory environment with a collaborative discussion environment, finding that scripted use of the integrated environment was easier for students than a non-scripted environment [6]. The Rashi project also experimented with combining tools for data exploration and argument construction in a collaborative context, finding that the addition of collaboration increased the amount of student effort within the system [7].

Integration of discussion and exploratory learning environments has the potential to provide unique learning opportunities. Students can support each other by sharing domain knowledge (a form of peer tutoring), and students arguing about their work can promote deeper understanding than the students could gain working independently. However, there is a large potential for confusion, or missed opportunity when students are working in different tools and with different conceptual knowledge. The unique aspect of this work is our attempt to use an intelligent support system to recognize differences in student's knowledge, and to support the movement between different tools in such a way that students gain the benefits of peer support and argumentation about constructed knowledge.

This work is being done within the context of an EU-funded project (Metafora[1]), which aims to provide a holistic environment in which students will collaboratively plan and organize their work, as well as collaborate in solving challenges and problems over a relatively long time period.

This paper presents a particular use case in mathematics and introduces the challenges that we face in our efforts to analyze students' collaborative process while they interact in a mathematical microworld and simultaneously have the opportunity to engage in discussions and structured arguments. In the microworld, called eXpresser, students construct patterns of repeated building blocks of square tiles and their associated algebraic rules, as described in more detail in the next section. Underlying this goal, the main objective is to promote students' appreciation of the power of algebra [8, 9].[2] In parallel, students engage in discussions in LASAD[3], a web-based argumentation tool that enables groups of learners to discuss their work in a structured way [10, 11]. LASAD is a collaborative, shared workspace containing a graphical argumentation environment and a chat tool. Students use this space to share ideas and organize their thoughts as they learn new concepts, and discuss or argue.

Both of these tools have analysis agents that can provide intelligent support. Several computational components analyze students' interaction in eXpresser and a rule-based system offers suggestions or hints designed to help them complete the task they are undertaking [12]. The LASAD tool offers a generic framework for feedback [11] and a rule-based system that offers advice on the structure of arguments, such as whether "claims" are supported by "facts" and "questions" are answered with "answer" objects. The output from these analyses can be combined to offer feedback that supports collaboration and helps students make progress while they grapple with the challenge.

The Metafora system incorporates these tools (as well as other tools not mentioned here), providing communication and control abilities across tools. The tools, and their associated intelligent support components, are linked both through interface elements

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[1] http://www.metafora-project.org

[2] eXpresser was developed in the context of the MiGen project (see http://www.migen.org)

[3] http://cscwlab.in.tu-clausthal.de/lasad/

and data sharing components. Each tool records lower-level events (termed indicators) that note instances or summary of student activity, and higher-level events (termed landmarks) that note a significant accomplishment or evaluation of student work. An overall analysis component analyses these events to identify situations where intervention might encourage peer support or shared knowledge evaluation. To concretize the purpose, architecture, and usage of the system, section 2 presents a specific use case to illustrate how students might work within the system, and how the system might respond. Section 3 discusses our generic cross-tool analysis approach and section 4 concludes that this approach of integration and analysis across tools provides a solid foundation for supporting student collaborative process.

2 The Integrated Microworld and Discussion Environment in Use

This scenario is meant to highlight the potential benefits and challenges of integrating microworld and argumentation tools in a pedagogically meaningful way. We seek to demonstrate how analysis from the individual tools can be combined to recognize when students should be prompted to use a specific tool, and how they might be prompted to do so.

The challenge given to students in this scenario is to use eXpresser to derive algebraic rules that correspond to structures of their own design, and are general across variable values. Specifically, in eXpresser, students construct their own models made of square tiles. These models contain variables that can be changed dynamically to test their structural generality. For example, Fig. 1 shows a student's construction of a model that is comprised of two patterns, the red and the green. The red pattern (made of a building block of 2 tiles) is repeated horizontally 5 times. In an effort to make the model general and animate it, the student specifies that the green pattern (made of a building block of 5 tiles) is repeated 'one more time' than the red building block. To achieve this, the student creates a variable called 'gaps' to represent the number of gaps in the model. In order to color the model, the student has to specify algebraic expressions that represent the number of tiles in each pattern and subsequently define the model rule that represents the total number of tiles in the model. It is evident that the same model can be constructed in different ways, leading to different model rules. The description of the task and the classroom culture encourages students to construct structurally different models.

Subsequently, a collaborative task encourages students to discuss the correctness and equivalence (or not) of their derived rules. It challenges students to read, deconstruct and match their rule with their own model as well as with their partner's model. In previous work we have established the benefit of these collaborative tasks in that they provide students with opportunities to reflect on their interaction with the system and develop strategies that allow them to justify the correctness and equivalence of their rules [13]. We now envision that students are given this task within the Metafora system, which provides access to both the eXpresser and LASAD tools. The students can use LASAD to share and discuss their models with the other students in a group. Ultimately, the goal is for the students to reach an agreement and understanding of the importance and usage of algebraic rules.

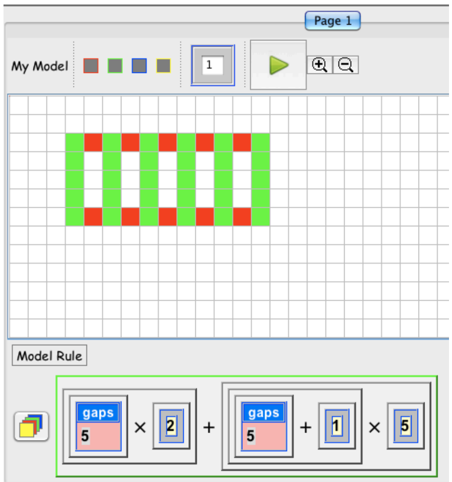

Fig. 1. A student's construction in eXpresser and its rule: a quasi-algebraic representation of the total number of tiles in the model.

As students are working individually at the beginning, the analytic tools of eXpresser look for landmarks, i.e. significant points that demonstrate important information about a student. One situation that might occur is that Student A achieves the landmark of creating a "general rule." The analytic tools of eXpresser recognize and report this event to the analysis channel in the Metafora framework. The Metafora analysis agent recognizes that Student B has not yet reached this landmark. The LASAD tool reports any sharing of models over the analysis channel as well, so the system can recognize that the two students have not discussed this model. Thus, we have a situation where Student A has reached an understanding that could be helpful if shared with Student B. If the system took no action, Student B might struggle a bit in doing her own generalization, or Students A and B could potentially discuss their findings and share knowledge on their own. However, if Student B continues to struggle, and Student A doesn't communicate her model with Student B, the system could suggest to Student A that she share her work with Student B and they discuss. Additionally, or alternatively, this information can be conveyed to the teacher who can take appropriate decisions.

Here we see some of the pedagogical benefits of linking the individual workspace with a group discussion space. Rather than relying entirely on automated feedback from within the microworld, we can exploit the advantages of collaboration to encourage students to help each other. Similar tactics for encouraging students to help one another have been suggested in prior work on the Rashi project where the system used an expert knowledge base to recognize differences between student knowledge and would then elicit conversation about these differences [14]. Likewise, in the Metafora system, we can recognize differences in landmarks for students, and encourage discussion in this context.

The Metafora analysis agent then monitors indicators (the lower level events such as messages sent and statements created in the argument space) logged from the LASAD tool to the analysis channel of the Metafora framework. When the analysis agent recognizes that the model has been shared, and that a sufficient amount of conversation has occurred, the system suggests to Student B that she re-visit her model with the aim of reaching this landmark with her own solution. As the analysis system for LASAD matures for this specific application, LASAD itself could offer landmarks, such as recognition that the students have “shared knowledge”, or “reached agreement”. This is a challenge to be addressed, and can refer to earlier work in the ARGUNAUT project in which graph and text matching techniques were used to identify certain critical exchanges between students [15]).

Finally, after some time passes in which both students are moving between discussion and microworld environments, the analysis agent in the eXpresser system reports that student B has created her own general model, attaining the same landmark as originally attained by student A. Since the analysis agent is now aware that both students have achieved the landmark “general rule”, the system refers both students to the discussion environment (if they are not both there), and prompts them to discuss questions like “How are your models different?”, or “Convince each other that your models are correct?”. Fig. 2 shows an example of the discussion that follows in LASAD. Both students provide arguments that, in their opinion, justify the correctness of their rule. However, in Student A’s opinion, Student’s B argument (*Box 4*) does not explain clearly why the rule is correct. Having been challenged, Student B provides a further explanation (*Box 12*) that demonstrates a better understanding of the microworld affordances and a growing appreciation of some algebraic concepts (e.g. by writing “even if the number changes the rule is always correct”).

The LASAD analysis agent can analyze this discussion of differences and correctness, looking for patterns such as “lack of consensus”. Again, here we see the benefit of combined systems, knowing that both students have reached the landmark (creating a “general” rule) allows the system to predict that they should reach consensus on the correctness of each model. We also see the major challenges offered by such a task, in recognizing a lack of consensus. The LASAD feedback agent employs rule-based pattern recognition using information such as the types of boxes used (e.g. claim, argument, explanation) and linkage between them, as well as limited text analysis (keywords, etc.) in an attempt to recognize patterns of argumentation. Once user data has been collected, this work can be extended using proven machine-learning techniques applied to similar discussion environments [15]. At least initially, the system is not likely to be precise enough in this type of decision to directly prompt interaction with students; rather, a message to a moderating teacher could be used to prompt her to offer advice and support. For example, if the system recognizes a “lack of consensus” on the correctness of a model that eXpresser has reported as being correct in a landmark, the system can report this situation to the teacher. If the teacher agrees with the diagnosis, or finds the situation interesting in any significant way, she can then intervene in the discussion helping students appreciate what has been preventing them from reaching consensus and promoting more effective collaboration.

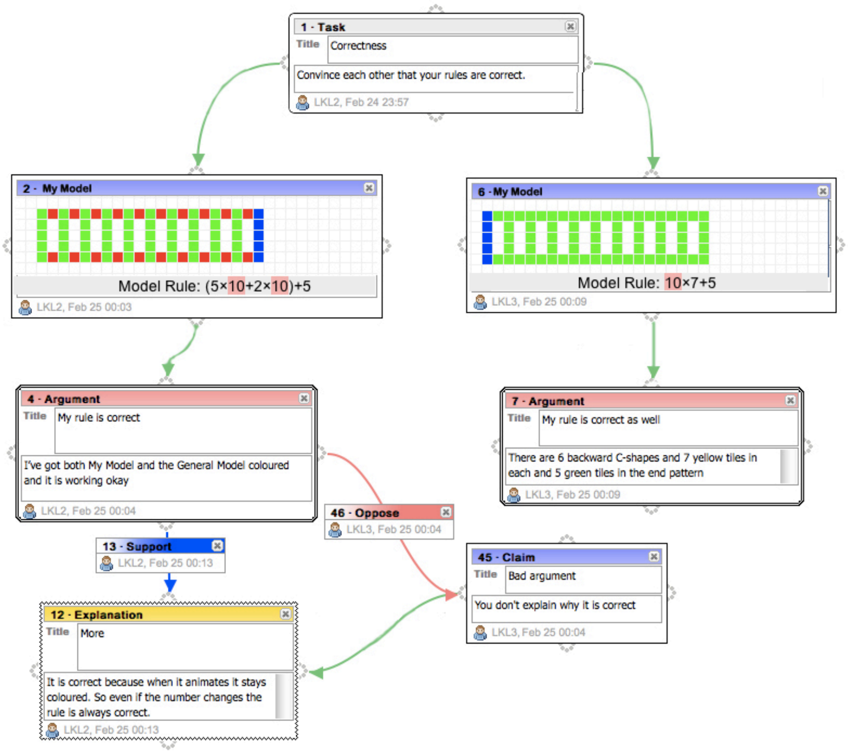

Fig. 2. An example of a LASAD discussion where students discuss the correctness of their eXpresser models.

3 Generic Cross-Tool Analysis

We have described a scenario in which an integrated microworld-discussion system could potentially provide great benefit to collaborating students. The integrated system can use the accumulated data across the tools to determine, for instance, when one student or another has reached a landmark. This can be a cue for the successful student to help the other student.

We now discuss our initial ideas on creating a system that can handle the above-mentioned situation in a generic manner, working also in the context of different challenges, with different kinds of microworlds, and potentially different types of discussion environments, in a standardized manner. In this way, we describe how the analysis agent for the overall Metafora system can recognize and take action to create the scenario described above.

First, the intelligent analysis components of the separate tools must share information, in particular analysis and abstraction of student actions, which allows for unified analysis of the integrated learning system. The systems remain highly separated, with each individual tool running from its own server. The over-arching Metafora system maintains multiple communication channels for the interaction between tools: an analysis channel where tools' analysis components can report indicators and landmarks; and a command channel, where the system can instruct tools to display specific states or offer feedback to a specific end-user. The server logs and analyzes data coming in from the analysis channel, and provides commands to the tools based on this analysis.

Each tool reports processed information about the current users to the Metafora system (indicators and landmarks), and receives feedback information from the system to be presented to a user or a group of users. The challenge for the analysis agent on the Metafora server is to decide what is relevant information for the given task and tools. In the example above, we see that one relevant piece of information from the microworld is the generation of a landmark, in this case the accomplishment of the high-level task "creating a general rule". The discussion environment can provide other pertinent pieces of information by generating indicators of student activity: in this case indicators showing discussion of the artifacts involved in this landmark (e.g. references to the "general rule" model that have been shared in discussion). Considering the generated landmark, we can allow it to act as a phase judgment consisting of three phases, as presented in Table 1. Here we see that the landmark defined by the microworld helps define when and how the system encourages students to use the discussion tool.

Table 1. Cross-tool feedback. The system will encourage a certain behavior, according to the given landmark, and the tool in which students are currently engaged.

<table>
<tr><th>Landmark has been Noted For…</th><th>Feedback in Microworld</th><th>Feedback in Discussion</th></tr>
<tr><td>Neither student</td><td>Provide students microworld-specific feedback</td><td>Prompt students to use the microworld to explore task</td></tr>
<tr><td>Only Student A</td><td colspan="2">Prompt students to discuss Student A's microworld state</td></tr>
<tr><td>Both Students</td><td>Prompt a discussion of differences between solutions</td><td>Provide students discussion-specific feedback</td></tr>
</table>

4 Conclusions

We propose that the combined analysis of individual activities (individual students' actions in a microworld) and collaborative activities (discussion of the microworld activities between students) can lead to productive intelligent support. The information provided by individual components can be used to define phases of work and recognize opportunities for productive collaboration. One major challenge of employing the approach described here is to generalize beyond the specific use case above. We have offered insight for a specific scenario between two tools and two users. Table 1 is the beginnings of a generic way of considering the state of individual tools in a more global way by the Metafora system. Future work includes scaling this type of support over multiple tools, in particular, to encompass different microworlds, and larger groups of students. Another major challenge, related to the first, is defining an abstraction layer that is able to capture and represent a variety of indicators and landmarks. Furthermore, such an abstraction layer must represent the connections between landmarks. For instance, in the example provided, there is a need for the landmark achieved by Student A to be linked to the need of a similar landmark for Student B.

With this effort, we also suggest a path that fellow researchers might follow in attempting to introduce collaborative activities into their current systems, or combine current systems to create collaborative workspaces. We suggest that single-user environments can be integrated with collaborative workspaces by adding small components to communicate student state information with external systems. We also demonstrate how current intelligent feedback agents can be integrated and extended to work with information across multiple tools by using simple message passing with a common language and data format. Such an approach can offer a solid foundation for taking many currently independent and specialized tools and creating a collaborative workspace that can offer holistic, intelligent support to students. Furthermore, such an approach can provide useful information to teachers and support them in their efforts to help students. Future work includes defining and implementing a teacher interface and interaction that will allow teachers to access and respond to such information, building off of previous similar efforts in the Argunaut and MiGen projects [15, 16].

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Team Formation for Research Innovation: The BRAIN Approach

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Abstract. Recently trends show that innovative research requires multidisciplinary teams. This brings forth the importance of team formation for innovation. In order to successfully identify who has to be in a specific team and what constitutes potentially successful multidisciplinary team collaboration, social processes important for team formation for innovation have to be understood. Based on this, technological approaches that can support these processes can be defined. This paper outlines key processes regarding team formation for innovation, following psychology and social sciences literature. We then present the BRAIN approach on forming multidisciplinary teams for innovation, which addresses some of the aspects identified in the literature. The paper revisits the current state of the BRAIN application, and recommends future work where user modelling, adaptation and personalisation approaches can be used to address the limitations identified

Keywords: Team formation, Expertise browsing, Intelligent support

1 Introduction

Recent trends in science and engineering require collaborative research by multidisciplinary teams. Funding organisations have acknowledged that innovation coming from addressing complex problems requires teams from multiple disciplines working together and approaching a problem from different perspectives. Thus, universities and research institutes set as strategic objectives to foster the development of multi- and cross- disciplinary collaboration teams. Institutional repositories which store researcher publications, projects, interests, form a valuable source for fostering multi-disciplinary team formation. However, such repositories are mainly used in a 'traditional' way as separate databases that provide information on demand. We consider here support to help establishing multi-disciplinary teams within an institution which function in virtual settings.

Multidisciplinary teams of people who collaborate with the purpose to create innovation have been defined by Peter Gloor [1] as "*a cyberteam of self-motivated people with a collective vision, enabled by the Web to collaborate in achieving a* *common goal by sharing ideas, information, and work*". There is an agreement in the literature that people in innovation teams have diverse knowledge and work towards a common goal. However, very little is done to support the formation of multi-disciplinary entities, which includes identifying who to be in a specific team and what constitutes a potentially successful multidisciplinary team. Hence, social processes important for team formation for innovation have to be identified.

A broad literature exists on processes and theories for supporting team formation in general. However, there is little work focusing on what processes are important when supporting team formation with respect to innovation. In this paper, we are reviewing the relevant literature of psychology and social sciences to identify what are the important processes that need to be supported at the early stages of team formation for innovation, and what tools can be used in facilitating these processes in a system.

Based on the relevant work presented in section 2, section 3 will define requirements for supporting team formation for innovation. Section 4 will present a tool developed within a UK project which aimed at Building Research and Innovation Networks (BRAIN). The BRAIN tool supports multidisciplinary team formation for innovation. Section 5 will discuss how user modelling, adaptation, and personalisation (UMAP) techniques can be incorporated in future work following BRAIN to better facilitate team formation. Section 6 will then conclude this paper.

2 Relevant Work

2.1 Social Processes Important for Team Formation for Innovation

The requirements and processes that need to be supported when forming a team depend strongly on the purpose of the prospective team. In this section we discuss social processes important for the formation of multidisciplinary teams for research innovation (i.e. creating new ideas or finding new solutions to challenging problems).

Mohammed and Dumville (2001) developed a framework pointing at the importance of the development of shared mental models, the facilitation of information sharing, and the support of transactive memory between team members [2]. This stressed the need for pulling information from multiple disciplines, and identified several crucial processes for successful teams. **Team mental models** provide members with a shared, organised understanding and mental representation of knowledge about key elements of the team's environment or topic of interest. **Information sharing** helps team members to shape and organise their ideas around a topic of common interest. Without information sharing the team cannot function and reach the required level of team (shared) mental models needed. Shared information can also help in reshaping the team when new ideas not previously known to the team come in for discussion. **Transactive memory** [3] concerns the members' awareness of what knowledge is possessed by whom in the team; and refers to members' ability to use peers' memory (expertise) as an extension of their own memory (expertise).

More recently, Paletz and Schunn (2010) have reviewed literature from psychology and social sciences with respect to multidisciplinary team formation for innovation and creativity purposes [4]. They propose a social-cognitive framework describing the social and cognitive processes important when a multidisciplinary team is formed for the purpose of innovation. The framework proposes two stages:

- **Stage 1: Divergent thinking** - which takes place at the formation of the team and involves pulling information and knowledge from multiple directions and various interpretations according to the members' own understanding of the topic;
- **Stage 2: Convergent thinking** - where members share the information and knowledge collected, discuss upon finding a common ground, and agree on what will be followed by the team.

Different social and cognitive processes are involved in each stage of this framework. At **Stage 1**, **knowledge diversity** is considered important and is associated with team innovation. Through this divergent thinking in interdisciplinary teams, discussions are generated which, in turn, increases the drive towards novelty and complex thinking. For this to happen though, the group should have sufficient participation in **information sharing**. At this stage peripheral members who hold unshared information play a vital role in the success of the team. Without enough participation and unique information to be shared within the group there will not be innovation. **Formal roles** within the team may concern expertise and/or power structures and enable **transactive memory** among members to be developed. Thus formal roles created in the team are influencing team discussion via their associated communication norms.

At **Stage 2**, the team narrows and selects options based on what has been brought in and discussed among the members. In this way, the team identifies the most promising ideas to be followed to achieve innovation. The development of **shared mental models** among members is vital, as members crate a common understanding of the ideas and processes involved and what has to be done to achieve the team's goal. **Knowledge diversity** also plays an important role here, in the sense that information from different disciplines must continue to flow in the team but at this point members should be able to interpret this information with a shared view.

Relevant reviews carried out in organisational psychology and team performance [3], [5], [6] confirm that **knowledge diversity** has been positively associated with team innovation at organisational level [7]. Similarly, **information sharing** among team members has proven to be very important for creativity and for generating discussions within the team [8]. Other important aspects identified include establishment of **formal roles** and development of team **transactive memory** [3].

The next section will discuss techniques that can be used in computer systems for supporting important processes for team formation for innovation.

2.2 Techniques to Support Team Formation for Innovation

Identifying, analysing and supporting collaborative innovation networks, is one of the key research areas relevant to team formation for innovation. There is not much work reported on this aspect, but the following approaches can be viewed as an initial attempt to build technologies for the above purpose.

Danowski [9] combines semantic text mining, social network metrics and visualisations in an attempt to identify collaborative innovation networks in an organization. In his paper the web is used to extract relevant documents about employees in a college department. The method of proximity co-occurrence indexing [10] is then used to extract **connections** between people based on department and relevant interests that appeared in the network. Standard **social network analysis** metrics (e.g. density, centrality) are used to obtain networks of similar actors, extract centrality measures and other quantitative similarity metrics. **Visualisations** combined with **statistical analysis** have been used in order for the networks to be externalised and the results of the constructed network presented to the team.

A similar approach is followed by Gloor et al. [11] where email and other computer logs are analysed in order for potential collaborative innovation networks to be identified and supported. Once the relationships (networks) are extracted (based on text mining), a **social network visualisation tool** is used to convey the network to the team. Since the results are directed graphs, density, betweenness centrality and group degree centrality metrics are used to analyse the extracted networks.

Concerning supporting innovation through team collaboration, Angehrn et al. have developed a tool using Web 2.0 technologies to support knowledge exchange, taking into account the social, emotional and psychological needs of individual team members [12]. The development of InnoTube took into consideration the elements of collaboration, knowledge sharing, reciprocal trust, recognised ownership, network visualisations, reinforcing and enlarging innovation stakeholders' networks. The purpose of this tool is to foster the creation of connections among community members, between members and content created, and stimulate participation. In order to achieve these, InnoTube is using the SLATES (Search, Links, Authorship, Tags, Extensions, Signals) paradigm[13]. It considers effective **search** as vital in supporting the creation of teams for innovation, as well as providing **visualisations and awareness techniques** with respect to relationships between actors and artefacts in the team/community. **Collaborative authorship** support tools are also important when participants are drafting reports/proposals together, as well as providing the option to use tags in associating the available content. Extensions, for example **recommendations** for further reading or relevant videos, are also a good complement when a member is looking at a specific artefact in the team's virtual space. These features were built and evaluated in a car manufacturing company. They were proved to improve the communication of ideas and were appreciated by the participants.

3 Essential Requirements and Processes for Supporting Team Formation for Innovation

The primary purpose of the above review was to inform the derivation of essential requirements and the identification of processes to be supported when forming teams for innovation. In this work, we focus on the formation of teams at their very early stage. Thus, following [4], we extracted processes and structures that need to be supported at this early stage of team formation[1]. The following processes and tools

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[1] We acknowledge the importance of processes that need to be supported at a later stage, when the team has been formed and is functioning (shared mental models, trust etc.). However, our research focuses primarily the early stage of the team formation.

need to be kept in mind when new systems are developed aiming at providing support for team formation for innovation.

Social Processes:

Disciplinary and knowledge diversity: In order for innovation to be achieved and for members to creatively collaborate, different perspectives must come in place [4]. Consequently, members must have diverse backgrounds and bring in the team their own knowledge and point of view [3]. In this way, the team has a holistic viewpoint and with knowledge coming from different disciplines, problem solving becomes easier and prospects for innovation to be achieved increase.

Formal Roles: Power, knowledge and tasks roles have to be clearly defined in the team in order for members to have an understanding of what is expected of them as an input, and also to be able to identify who can be of help in the team if a situation arises [3], [4], [5], [6]. That is, if an expert is needed on a specific subject, members should be able to know who is holding that expertise in the team. This relates to transactive memory which is proven to be positively linked with the performance of a team [3]. Power roles are also important and need to be identified and supported early in the formation of the team [4]. For example, a team coordinator or facilitator responsible for organising the activities, tasks, and setting deadlines, needs to be clearly identifiable and known to team members.

Information Sharing: Sharing of information by all members is essential to ensure that information flows in the team, and perspectives from every discipline involved, are heard.

Enabling Technologies:

Search Tools (people and information): Searching for people who can compose a team and work on a specific project is very important process, should be supported. Similarly, searching for relevant reports, academic papers and other resources is equally important in order for someone to get an understanding of what the others in an organisation have been working on, and judge the relevance of their expertise to a current open call for an interdisciplinary project.

Connections/Relationships Discovery Tools: Members should be provided with the relevant tools to help with identifying connections and relationships that exist between team members, as well as other people in the network. In this way, composing a team of members who come from different disciplines but have common interests will be easier and more efficient.

Social Network Analysis Tools: Social network analysis allows for meaningful information to be extracted and similar groups of people to be identified within large networks of people. Possible similarities between people in the network can be identified to help with the team formation. Furthermore social network tools provide potential members with facilities to discuss, share thoughts, and in to an extent to collaborate by sharing resources and ideas in a common collaboration platform.

Visualisations: Visualisations can be used to provide static or dynamic images of connections and relationships between people either because of a similarity in interests, in research areas, or because they have previously collaborated or co-authored a paper. If a team needs to be formed for a given project, relevant people across the organisation will be discovered, and given the opportunity to join the team.

The next section will provide a brief description of how the BRAIN application, designed and built for supporting multidisciplinary team formation for innovation, took into consideration some of the processes and techniques discussed above.

4 The BRAIN Project and Tool

This work is carried out as part of the Building Research and Innovation Networks (BRAIN[2]) project, funded under the UK JISC Virtual Research Environments Programme. The BRAIN project aimed at facilitating the building of teams of researchers to enable the accumulation of collective intelligence and innovative outputs when participants from different areas engage in joint initiatives.

To illustrate the importance of BRAIN, we will consider two scenarios:

- Recently there was a research call funded jointly by the Science and Social Science Research Councils in the UK on the theme of "Energy and Communities". The call involved subject areas ranging from environmental science, civil engineering and computer simulation through to psychology, sociology, economics and politics. A research institution wants to respond to the call by forming a multi-disciplinary team who will generate an innovative idea to be put in a joint proposal. The key challenge is to identify who should be involved, and what facilities would support the development of a proposal.
- A similar, but less clearly defined requirement arises when trying to identify groupings or clusters of researchers that may have the potential of working together or where the objective is to identify sub-disciplines within a larger area, but where the connecting themes are not known in advance. Examples concern finding connections between specific research groups and wider groupings of researchers for the purpose of the Research Evaluation Framework (a UK–based research assessment exercise that reviews research across higher institutions, and requires the institutions to present coherent research streams).

In order to meet the above scenarios and following the requirements outlined in Section 3, the BRAIN project developed a tool. It allowed us to evaluate and identify what more is needed by users who are involved in cases like those presented above. We will briefly outline next the BRAIN tool[3].

In the implementation phase of BRAIN, we wanted to include the basic functionality that required from a system to facilitate team formation for innovation (Fig 1). At first, the user is presented with the **user input panel** and is allowed to search for a topic, using *keyword search* or perform a *person search* through the data available. Data extracted from the **university databases**, describing researchers' expertise, interests, publications and projects previously or currently working on.

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[2] http://project-brain.org/

[3] A more detailed description of the system has been presented at [11].

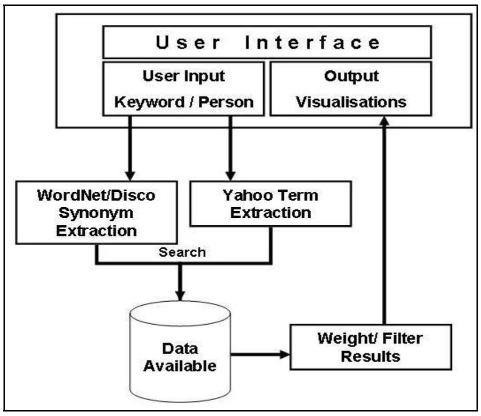

Fig. 1. The main components of the BRAIN tool and their interactions.

The **keyword search facility** implemented based on a simple string matching of the search word provided by the user, within the available data. Synonyms were then extracted using WordNet[4] and Disco[5] facilities and a checkbox facility provided for the user to choose a synonym according to preference. Selected synonyms were used for extracting commonalities between the keyword entered and the data at hand.

For the **person matching facility**, the Yahoo Term Extraction service[6] was used.

Filtering/weighting results is one of the components in determining commonality. This approach was not a necessity for the keyword search. However, for the person search this was an important consideration. Two techniques were used to tackle this problem. The first was the use of a stop list which filtered out certain words or phrases which were adjudged not to be useful in establishing connections, and was used after the stage of keyword expansion. For example, words like "research" and "university" are obviously too general to be used. The second technique used was to provide a user with a selectable filter parameter which would exclude terms which generated over a specified number of person matches. This allows searches to be run, and then this parameter adjusted depending on the results.

In this way, a user can became aware of his *similarities* with researchers from other *disciplines* with *diverse knowledge*. The system functionality allows the user to see the items responsible for a displayed connection. The output is stored in other formats that can be exported into other applications for analysis and **visualisation** (Fig 2).

The functionality of the system was evaluated continuously using personal interviews and focus groups allowing users to comment and advise us on what more was needed when forming teams. The next section will revisit the BRAIN tool using the processes and tools identified as important (Section 3). We will discuss what more can be done and how UMAP approaches can help in building systems, like the BRAIN too that facilitate multidisciplinary team formation for innovation.

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[4] http://wordnet.princeton.edu/

[5] http://www.linguatools.de/disco/disco_en.html

[6] http://developer.yahoo.com/search/content/V1/termExtraction.html

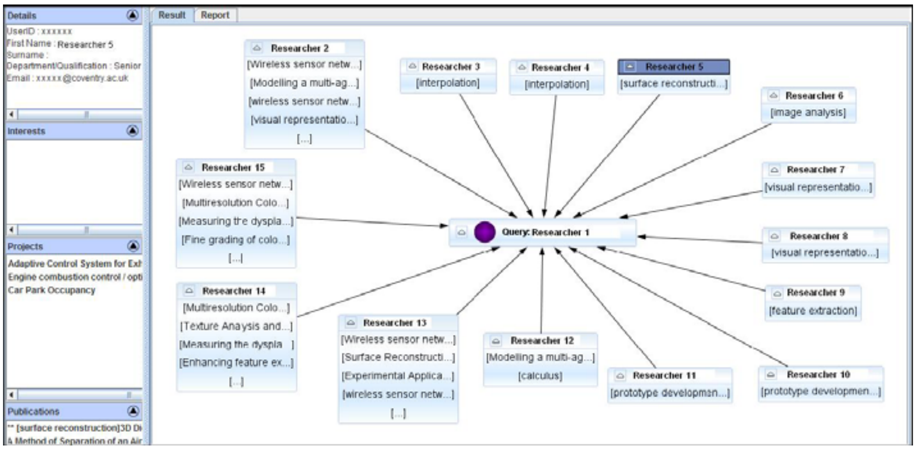

Fig. 2. Visualisation output of a typical person connection[7] search performed in BRAIN.

5 Future Extension of the BRAIN Tool

The process of forming a team of people who will collaborate and achieve innovation is very complex and needs to be carefully engineered. BRAIN attempted to address this problem by providing basic tools that allowed university academics to search and find information about colleagues who worked, or who are interested in specific areas and form teams. BRAIN provided support in the formation of team in terms of *knowledge diversity* by providing a **search tool** available to the interested parties that allowed searching based on key terms that represent specific research areas. This information has been presented as **graph visualisations** showing to people their *connections* with each other in terms of knowledge and interests. Although this can be considered as a first step towards supporting multidisciplinary team formation for innovation, more is needed for the support to be effective. An important lesson learned from the BRAIN evaluation is that people tend to remain focused on their everyday group interactions, failing to interact with, and bring, a different perspective in their research which might provide them with the added advantage and drive them closer to innovation.

Further extensions: User modelling, adaptation and personalisation techniques can be exploited to improve the effectiveness of the BRAIN tool. User models can be used to hold information about individuals that will be connected to, and automatically updated according to, the university's databases. **Open user models** [14] can be used allowing in this way individuals to view and edit their user model accordingly to ensure that up-to-date and accurate information is held by the system. Algorithms can be developed to enhance the existing search tools and allow to automatically extract **semantic connections** [15] based on the information stored in

[7] The names of the researchers returned as output have been removed and anonymised accordingly for data protection purposes.

the user model, and relevant to the knowledge and interests of a member. This tool will provide the backbone for **personalised notifications** [16, 17] to be generated, which will include information on connections, similarities or relations a member has with others in the network. These notifications can be sent to a given member if requested and allowing him to view the output in a **dynamic graph visualisation** [18]. Extended tools will allow a member to contact another member, if necessary, by clicking on that member's name in the graph.

According to the processes and tools discussed in section 3, once the relevant people have been identified, a **communication tool** [12] should be in place, synchronous and/or asynchronous, where people will be able to contact each other in order for a team to start forming. This is especially important since the team is interdisciplinary and members have diverse knowledge. Being able to discuss and argue upon different ideas and opinions will allow them to make better selection of the best ideas to take forward.

In order for collaboration to lead to the generation of innovative ideas, the team has to set *formal roles* [5], [6]. Each member must have a role based on knowledge, experience, or status and work on tasks relevant to this role. This can be done through internal team communication that requires input from all potential members. Knowing who knows what in the team and who can perform better in what task will allow the development of *transactive memory* and allow better collaboration to take place [3].

In supporting initial collaboration among the interested members, tools for *information/knowledge sharing* [2], [4] should be in place. **Adaptation techniques** can be utilised to allow members to view relevant information according their role and task in the team and allowing filtering out all the irrelevant activity, reducing in this way information overload. **Personalised awareness techniques** can be used to allow people to know what is happening in the team by choosing what activity they want to be aware of. **Personalised messages or visualisations** can be featured to provide this kind of awareness to team members.

The above techniques have already been implemented and their effectiveness has been evaluated in user-adaptive systems with different purposes. We argue that these techniques could be exploited for team collaboration for innovation, and corresponding evaluation studies should be conducted to evaluate the suitability of the tools in this application context.

6 Conclusions

The paper has identified what social sciences and psychology consider as important ingredients that can be supported in team formation for innovation. An attempt has been made by other systems, as well as the BRAIN project, to provide support to prospective teams of members that collaborate towards innovation. The paper points out that technologies have yet a lot more to offer. Using adaptation techniques for supporting multidisciplinary team formation for innovation is a research area, yet to be explored. There are opportunities for researchers to work and innovate by applying existing techniques to a new area that needs the vision, as well as the maturity of a technologically advanced domain like UMAP.

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Designing Tabletop-Based Systems for User Modelling of Collaboration

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Abstract. Tabletops offer a new form of interaction and create new possibilities for small groups of people to collaborate and discuss tasks aided by the shared use of digital materials and tools. The collaborative affordances of tabletops make them suitable for many uses in public spaces as well as in more restricted environments such as workplaces and learning settings. This creates new opportunities for improving collaboration, particularly by capturing data that can be used to model the nature of the interactions and to present this model to the users in a form that will facilitate improved collaboration. It is timely to establish principles for designing tabletop-based systems in a manner that can facilitate such modelling. These principles should support effective use of data mining tools to create group collaboration models. In this paper, we outline theoretical design principles based on a careful analysis of the nature of tabletop datasets and collaboration.

Keywords: interactive tabletops, group modelling, collaborative learning, collocated collaboration, machine learning

1 Introduction

Interactive tabletops offer a new medium for supporting collocated collaboration. They provide a shared environment for small groups of people to work together, making use of digital materials based on collaborative activities. A well recognised role of tabletops is that they offer new means of interaction with special affordances for small groups. A less recognised possibility is to exploit the user's digital footprints as people make use of the tabletop. These footprints, along with the verbal communication and contextual information related to the users, have the potential to provide new opportunities to build models of their collaborative processes.

Collaboration is critical in a range of areas, from the workplace to learning spaces. However, learning to collaborate effectively is difficult, partly because it involves a long term development of skills. In addition, new collaboration contexts, working with different people and complex tasks, require finer grained monitoring of the collaboration and learning how to make it effective [1]. This means that collaborators need to be able to monitor the effectiveness of the group as a whole and their individual performance as part of the team. One approach that has proven effective in covering such a need is to promote social translucence, an external representation that mirrors objective measures of the group work to help them to be aware on their collaborative process and monitor whether their actions match what they intended [2].

The idea of reflecting overview information back to collaborators by exploiting the huge quantity of data generated by their interactions is not new. Research on user modelling has emphasised the potential of using machine learning techniques to monitor learners' collaborative processes and build adaptive tools that can intercede to make such learning process more productive [3]. Even though the development of collocated collaboration skills is very important in the classroom and beyond, most of the research work on adaptation in collaboration has focused on the use of e-learning tools (e.g. chat, forums, IM, email). However, e-learning and face to face environments are not two separate domains. Nowadays, students are immersed in both experiences: virtual and real worlds. They interact via email or chat, but also have moments in which they have to work face to face. The benefits that tabletops offer to this vision lie in the provision of support during the instants when students have to create understanding in real world settings.

Our work aims to create new tabletop tools to exploit the activity logs and feed them into user models in order to provide adapted support, so that the collaborative process can be more effective and the individuals in the group can each learn to improve their own performance. Currently, there are many tabletop interfaces but it is timely to establish principled approaches to design the key features that should define these learning systems. These range from the design of the tabletop setting to specific user interface features. We propose a top-down approach in which the design of these principles mandates what data should be captured and how it should be exploited to build a model of the group's interactions. Figure 1 shows the elements of our approach. This starts with choosing adequate theories of small group collaboration since they indicate the key elements of effective collaboration and learning. These theories should define the ideal goals and drive the design of the collaborative setting. For example, if we choose to measure symmetry of knowledge based on the definition given by Dillenbourg [4], the system should be designed to capture elements that can give insights on each learner's understanding about a given topic. However, even when these theories establish the ideal aims, the technology tradeoffs between the scope of what is possible to capture and the associated cost bounds the system design.

The rest of the process consists of exploiting the electronic footprints that can be captured as people interact at a tabletop and transform them into a useful data source for these goals. To do this, we consider three elements: *capture of useful data*; *mining the data* to transform it into a set of models of collaboration; and interfaces that make use of these models to offer *adapted feedback* to the group. In this paper, we focus on outlining generic principles for capturing and mining data in tabletop-based learning systems. Further exploration on specific user interface design elements and ways to access to the user models is mandatory, but the details are not important at this stage.

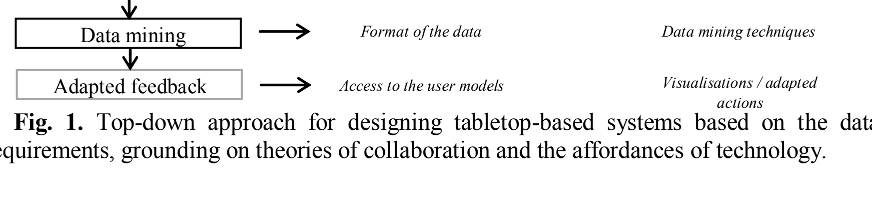

Fig. 1. Top-down approach for designing tabletop-based systems based on the dataset requirements, grounding on theories of collaboration and the affordances of technology.

2 Principles for Capturing Data

Special attention should be given to the architecture of the tabletop-based setting to make the collection of data useful and successful. Next, we outline the key principles of tabletop-based settings design capturing data effectively considering both the learning theories and technology affordances.

Capture speech/video information. The analysis of peer communication is very important for analysing the collaborative processes and it should be instrumented in tabletop settings. The data that is useful to capture depends on the collaborative learning theories underpinning the system. It can include just the *presence* of voice to measure the participation of learners [5] or more detailed information like tone, volume or, as most learning theories state is crucial, the speech content [4]. Current solutions to record verbal interactions in collocated settings range from the use of individual wearable audio recorders to the use of directional microphone arrays. Detection of affective states in learners may also be considered by exploiting video and sensors information [6].

Identify users (authorship of actions*).* As the collaborative setting becomes more sophisticated, and the provision of certain types of adaptation are required, identifying users' actions becomes mandatory for updating the model of the group [7]. Current solutions for identifying the authorship of each touch on the tabletop include high-priced hardware devices such as the DiamondTouch[1] or encumbering learners by attaching gadgets to their hands (e.g. gloves or pens). There are also software based solutions that constraint the design of the collaborative task, such as the assignment of roles, resource ownership, personal territories, fixed production lines or individual lenses [5].

Interconnection with other devices. In collaborative environments learners can make use of multiple devices. Interconnected devices provide added speciality and flexibility for specific tasks that come up during a collaborative session [8]. The interconnection of all these as sources of information, can potentiate the use of tabletops as a shared device in which all group members can work at the same time contributing each to the group task. An example of this is using a digital whiteboard to brainstorm ideas to afterwards store the results on a personal device or share them on the tabletop to its revision.

Integration with services. Tabletop applications can also be integrated within a larger scale system that can give continued support to the learning process of the students. Current online e-learning and project management tools support asynchronous collaboration in the form of wikis, chat and forums. Using tabletops as an added interface to these pre-existent online collaboration tools can extend the collaboration facilities provided by these services and compensate the lack of face to face collaboration of the e-learning environments [9].

[1] MERL- Diamond Touch.: http://www.merl.com/projects/DiamondTouch/

3 Principles for Formatting and Mining Tabletop Data

Once the datasets are collected from the tabletop and before starting to use data mining tools, the data has to be transformed into a suitable format for data mining techniques. In this section, we propose a number of principles to ease the formatting of the data according to the data mining requirements and the theoretical goals.

Define the logging granularity. The lowest level in which the tangible actions on the tabletops can be recorded corresponds to logging the coordinates of each touch point on the tabletop. Analyses of learners territoriality can be conducted using this raw data. However, higher-level data logs, such as activity dependent information (e.g. move object, press a button, delete an element), should be logged to get meaningful insights on the strategies followed by groups. Besides, it could be required to set up even higher-levels of abstraction by giving meaning to sets of basic actions based on heuristics specifically created for the task. For example, basic actions, such as dragging objects, inserting text or resizing images, in conjunction can be related with higher level group strategies like brainstorming, agreement, or formalisation of a solution.

Add user and contextual data. The user model of a group working at the tabletop can be enriched by the incorporation of learner information that is *normally* beyond the boundaries of the system, such as personal details or outcomes reached in related academic activities [10] (e.g. the familiarity between group members, parts of each learner model or the marks of previous assignments). Additional data can also be generated by other systems related to the tabletop application (e.g. vertical displays, smart-phones, laptops) [11] or if the tabletop is used after other technologies [12]. A possible solution to ease the formatting of the data is to adhere to a common user modelling framework which can give support to multiple services.

Define the focus of attention. The raw tabletop log data can contain detailed contextual information about each action that users perform and it is normally formatted as a very long sequence of events. It is very important to define the focus of attention of the user modelling to capture and format the adequate contextual data to fulfil the learning goals. Researchers on collaborative learning or the learners' facilitators can specify this focus of attention. It can be directed to specific users, the spatial position of resources, types of users or the disposition of learners around the tabletop. For example, if the analysis is focused on the resources present at the tabletop the dataset should identify and keep track of such resources along with the stream of events.

Define the format of the data according to the data mining technique. Finally, the data need to be extracted in the required format of the data mining technique to be used. This is important because different algorithms need might require specific contextual information. For example, sequential pattern mining algorithms need data formatted as a detailed sequence of elements. Other techniques might require the historical status of the objects at the tabletop to measure the progress of the group.

4 Conclusion

Tabletops are an emerging form of interactive device for small group collaboration, in educational and other settings. In order to design adaptive applications in collocated settings where horizontal tabletops are present, it is crucial to establish the design principles required by user modelling and machine learning techniques –two core scaffoldings to offer such adaptation. We discussed a number of elements that should be addressed by the architecture of collaborative tabletop systems. We look forward to explore the possibilities of tabletops as supporters of learning and hope this position paper can initiate a discussion regarding the technology and social issues that must be addressed towards the provision of adapted support through tabletops.

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