# The 3A Interaction Model and Relation-Based Recommender System: Adopting Social Media Paradigms in Designing Personal Learning Environments

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*To my grandmother,*
*Najibé Beyrouthy*

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# Abstract

We live in a rapidly changing digital world marked by technological advances, and fraught with online information constantly growing thanks to the Internet revolution and the online social applications in particular. Formal learning acquired in traditional academic and professional environments is not by itself sufficient to keep up with our information-based society. Instead, more and more focus is granted to lifelong, self-directed, and self-paced learning, acquired intentionally or spontaneously, in environments that are not purposely dedicated for learning.

The concept of online Personal Learning Environments (PLEs) refers to the development of platforms that are able to sustain lifelong learning. PLEs require new design paradigms giving learners the opportunity to conduct autonomous activities depending on their interests, and allowing them to appropriate, repurpose and contribute to online content rather than merely consume pre-packaged learning resources.

This thesis presents the 3A interaction model, a flexible design model targeting online personal and collaborative environments in general, and PLEs in particular. The model adopts bottom-up social media paradigms in combining social networking with flexible content and activity management features. The proposed model targets both formal and informal interactions where learning in not necessarily an explicit aim but may be a byproduct. It identifies 3 main constructs, namely actors, activities, and assets that can represent interaction and learning contexts in a flexible way. The applicability of the 3A interaction model to design actual PLEs and to deploy them in different learning modalities is demonstrated through usability studies and use-case scenarios.

This thesis also addresses the challenge of dealing with information overload and helping end-users find relatively interesting information in open environments such as PLEs where content is not predefined, but is rather constantly added at run time, and differ in subject matter, quality, as well as intended audience. For that purpose, the 3A personalized, contextual, and relation-based recommender system is proposed, and evaluated on two real datasets.

# Résumé

Nous vivons dans un monde digital, évoluant rapidement, marqué de progrès technologiques importants, et riche en information en ligne en continuelle croissance grâce à Internet en général, et aux outils sociaux en particulier. L'apprentissage formel acquis dans des environnements académiques et professionnels traditionnels n'est en soi pas suffisant pour progresser dans notre société de l'information. De plus en plus d'importance est accordée à l'apprentissage autorégulé, acquis volontairement ou spontanément, dans des environnements qui ne sont pas explicitement dédiés à l'apprentissage.

Le concept d'environnement personnel d'apprentissage en ligne (PLE) se réfère au développement de plateformes en mesure de soutenir la formation continue. Les PLEs requièrent de nouveaux paradigmes donnant aux apprenants l'opportunité de mener des activités autonomes dépendantes de leurs propres intérêts, et leur permettant de s'approprier et de contribuer à différentes sources d'information en ligne, plutôt que de simplement consommer des ressources d'apprentissage préétablies.

Le modèle d'interaction 3A est présenté dans cette thèse. Il s'agit d'un modèle de conception flexible visant les environnements personnels et collaboratifs en ligne en général, et les PLEs en particulier. Le modèle proposé adopte l'approche « bottom-up » des media sociaux pour combiner des services de réseaux sociaux avec des outils flexibles de gestion d'activités et de contenus partagés en ligne. Le modèle vise les contextes d'interaction formels aussi bien qu'informels où l'apprentissage ne constitue pas nécessairement un objectif explicite mais peut être un résultat indirect. Il identifie 3 principaux concepts, les acteurs, les activités, et les artefacts

(ou ressources) pouvant représenter les contextes d'interaction et d'apprentissage de manière flexible. L'applicabilité et l'utilité du modèle d'interaction 3A pour la conception de PLEs et leur mise en œuvre dans différentes modalités d'apprentissage sont démontrées par des études d'utilisabilité ainsi que des scénarios d'utilisation.

Cette thèse aborde aussi le défi de faire face à la surcharge d'informations et d'aider les utilisateurs de plateformes en ligne à découvrir des ressources relativement intéressantes dans des environnements ouverts, tels les PLEs, où le contenu n'est pas prédéfini, mais plutôt dynamiquement crée et modifié, et se distingue en termes de qualité, thème, et public cible. À cette fin, le service 3A de recommandation personnalisé, contextuel, et relationnel est proposé et évalué sur deux bases de données réelles.

**Mots-clés:** modèle d'interaction 3A, médias sociaux, environnement personnel d'apprentissage, gestion de connaissance, interactions sociales, contextes d'interaction, contexte, modèles conceptuels centrés sur l'utilisateur, extraction de données, système de recommandation en ligne, personnalisation, contextualisation, apprentissage continu, apprentissage formel, apprentissage informel, travail collaboratif assisté par ordinateur, apprentissage collaboratif assisté par ordinateur.

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## *Introduction*

## 1.1 Research Context

### *1.1.1 Technology-Enhanced Collaboration and Learning*

In 1945, as World War II was coming to an end, Vannevar Bush, calling for the exploitation of science for knowledge sharing and human progress rather than destruction, revealed his wish for a collective memory device that could be used with high speed and flexibility to store, connect and share published work, communications, in addition to personal trails. He named it "memex" (Bush, 1945). Memex can be considered as the first reference to devices aimed at supporting social interactions as well as sustaining personal and collaborative learning.

Hiltz and Rheingold employed the term "online community" (or "virtual community") to express the feelings of kinship detected among people in online spaces (Hiltz, 1984; Rheingold, 1993). Subsequent researches interested in the design and evaluation of community platforms refer to online

community as "people who come together for a particular purpose, who are guided by policies (including norms and rules) and supported by software" (Maloney-Krichmar & Preece, 2005).

In 1984, Irene Greif and Paul M. Cashman introduced the term CSCW (Computer- Supported Cooperative Work) during a workshop on the use of technology to support people in their work (Grudin, 1994). CSCW can be defined as the study of "Groupware" tools and their psychosocial effects. "Groupware" denotes the concrete technological tools, services, and techniques that make "the user aware that he is part of a group" and coordinate "things so that users can "see" each other, yet do not conflict with each other" (Baecker, Grudin, Buxton, & Greenberg, 1995). Since then, extensive research has been carried out in the field of CSCW addressing how computer systems can support collaboration and activities coordination. As an example, (Sherman, 1995) discusses how maintaining an electronic journal and expressing reflections in a news group motivates students to participate in groups' discussions and improves their critical thinking.

Research in a related field namely CSCL (Computer-Supported Collaborative Learning) also started in the 90s. A situation is considered as collaborative when it involves peers working together towards the achievement of a shared goal and is usually characterized a symmetry in action, level of expertise, and status. "Collaborative learning" can be defined as a situation where particular forms of interactions among people, such as disagreement or explanation, could potentially take place and, as a result, initiate different learning mechanisms (Dillenbourg, 1999). The research in CSCL focuses on how technology can help trigger these types of social interactions and learning mechanisms.

Content management systems (or CMS) aim at supporting end-users in managing and sharing data by allowing access control based on roles, and defining workflow management (Bergstedt, Wiegreffe, Wittmann, & Moller, 2003). Also abbreviated as CMS, Course management systems offer a set of tools for publishing online course material, and facilitating course management and teaching in situations that involve diverse student interactions (EDUCAUSE, 2003).

Learning management system (or LMS) is defined as a framework concerned with all aspects of the learning process (Watson & Watson, 2007), incorporating learning content management systems (or LCMS) within it (Greenberg, 2002) and covering course administration, tracking and reporting, assessment of individual and organizational learning, in addition to delivery and management of instructional content (Gilhooly, 2001).

### 1.1.2 The Web 2.0 Online "Movement" and the Rise of Social Media

In the early 2000s, five decades after Vannevar Bush published his article "As we may think", the Web 2.0 online "movement" started to emerge concretizing the way Tim Berner's Lee had originally envisioned the "WorldWideWeb" (Scott, 2000). The precursors of this "movement" are *LiveJournal*[1], a Website founded in 1999 and allowing people to publish their diary or "blog", *Wikipedia*[2], a free, Web-based and multilingual encyclopedia launched in 2001 and editable by any online user, as well as *Friendster*[3], a Website founded in 2002 for connecting with friends. Thereafter, similar sites emerged such

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[1] http//:www.livejournal.com
[2] http://www.wikipedia.org
[3] http://www.friendster.com

as *LinkedIn*[4], and *Orkut*[5], which benefit today from worldwide popularity. The shift from the "Read Web" to the "Read Write Web" or the Web 2.0 "movement" was just about to begin; the Web, has become a participation platform where users are no longer passive "consumers" but active "contributors" thanks to user-centered design, low learning curves, simple authoring and editing of online content using wikis, interactive information sharing, free open-source software, and social networking (O'Reilly, 2005).

Since then, interactive sites promoting user-generated content (or UGC) along with social networking, and referred to nowadays as social media sites (Herzog, 2008), have become increasingly popular. A Nielsen report published in March 2009 states that 2/3 of the global Internet population visits social networks. The report also indicates that social networks and blogs form together the fourth most popular online sector, ranking ahead of personal emails and having a growth rate which is more than double that of any of the other four major sectors which are namely: "search", "general interest portals and communities", "software manufacturers" and "email" (The Nielsen Company, 2009). *Wikipedia* has now over 15 million articles, 3.3 of which are written in English. According to a study published in Nature in 2005, Wikipedia "comes close to Britannica in terms of accuracy of its science entries" (Giles, 2005). *Flickr*[6], a popular photo sharing Website, has over 4 billion pictures (Champ, 2009). In March 2010, *YouTube*[7], a social Website intended for sharing, rating and commenting videos online, had over 100 million videos viewed every day,

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[4] http://www.linkedIn.com
[5] http://www.orkut.com
[6] http://www.flickr.com
[7] http://www.youtube.com

and reported 24h hours of videos, uploaded every minute (Physorg, 2010). *Facebook*[8] reports having more than 400 million active users who interact with more than 160 million groups, pages and events, and share every month more than 25 billion pieces of content such as notes, photo albums, blog posts and Web links. 50% of these users connect daily to the platform (Facebook, 2010).

Digital natives, N-gen ("N" denoting native and "gen" generation) or D-gen ("D" denoting digital) are all terms referring to the young generation of people who "grew up digital", and are immersed in technology in their daily lives (Brown, 2002). Digital natives have a short attention span, and hardly accommodate for de-facto authorities, top-down hierarchical structures at work, and lecture-style courses (Prensky, 2001). Also, referred to as Generation Y ("Y" denoting why), they are characterized by being technology savvy, image-driven, expressive, keen on social networking and teamwork, and good at multi-tasking (Wilson & Gerber, 2008).

The popularity of social media has pressured academic institutions and professional organizations to embrace it in order to better cope with our digital world. Enterprise 2.0 is a term referring to the adoption and the spreading of bottom-up social media that connect employees of the same enterprise, and go beyond enterprise boundaries to reach other enterprises, partners as well as clients (McAfee, 2006). In the same way, e-Learning 2.0 refers to the application of social media in education (Downes, 2005; Wever, Mechant, Veevaete, & Hauttekeete, 2007). As a concrete example, several institutes and universities such as Massachusetts Institute of Technology

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[8] http://www.facebook.com

(or MIT)[9], Open University[10], Oxford[11], Stanford[12], and University of California, Berkeley[13], have joined and contributed to iTunes U, an educational media "store" launched in May 2007. *iTunes U* gathers digital content with limited access, in addition to more than 250,000 free videos, lectures and audio files added or authorized by educators, and made available to "all lifelong learners all over the world" (Apple, 2010).

### 1.1.3  *Technology-Enhanced Lifelong Learning*

To cope with today's fast changing world, learning should be pursued *actively* throughout life and not just be merely acquired in early life stages within standard educational systems. "Lifelong, lifewide, voluntary, and self-motivated" (Government of Ireland Stationery Office, 2000) learning refers to the activities that people conduct during their lifetime, to develop knowledge, skills and competences, motivated by personal, social as well as employment reasons (Aspin & Chapman, 2007; Griffin, 1999). Lifelong learning is about learning anything, anywhere, anytime and anyway. It encompasses formal, non-formal and informal learning. Formal learning refers to intentional learning that occurs in structured contexts, and often leads to a formal recognition (e.g. diploma, certificate). Non-formal and informal learning, on the other hand, take place in environments that are neither essentially learning-oriented, nor structured in terms of learning objectives, material, time, or support (Colardyn & Bjornavold,

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[9] http://Web.mit.edu
[10] http://www.open.ac.uk/
[11] http://itunes.ox.ac.uk
[12] http://www.stanford.edu
[13] http://berkeley.edu

2004). Different from non-formal learning, informal learning is accidental or spontaneous, and occurs over the lifetime period (Cross, 2006; Faure, et al., 1972).

Traditional CMSs and LMSs are not suitable for lifelong learning. In fact, these systems are usually characterized by a hardcoded asymmetry in user rights and a pre-structured content that follows a central anticipated plan (Twidale, Wang, & Hinn, 2005; Wilson, Liber, Johnson, Beauvoir, & Sharples, 2007). To better address the requirements of lifelong learning, there is a need to shift from traditional CMS and LMS *applications* particularly focused on formal interactions and learning, to personal learning *environments* (PLEs) that can target institutional and self-directed, intended and unintended learning. The concept of PLEs is based on the idea that learners must be given the opportunity to decide their own learning goals, control their learning spaces, and interact with each other during the learning process (Van Harmelen, 2006). In a PLE, there ought to be no inherent distinctions in terms of user capabilities and no pre-assumed hierarchy; everyone can be a producer, consumer, publisher, reviewer and "administrator". Learners should be able to create, share, modify, annotate, review and most importantly repurpose learning artifacts ranging from books to Weblogs, videos, podcasts and discussion archives (Downes, 2007). I adhere to this vision of PLEs and in this thesis I rely on it.

Successfully sustaining lifelong learning with online PLEs requires developing and adopting new design patterns, models and prototypes that can substitute for prevalent LMS design models (Downes, 2010; Wilson, Liber, Johnson, Beauvoir, & Sharples, 2007).

Developing personalized recommender systems for PLEs also constitutes an important challenge. PLEs can be classified

as "open corpus" environments (Brusilovsky & Henze, 2007). In a PLE, relationships between knowledge artifacts are not necessarily known beforehand, as it is the case in traditional hypermedia systems; instead, they can emerge, evolve and expand during run time. In addition, in online platforms where everyone is a "consumer" and a "producer", contributions differ in quality, style, subject matter, target audience, composition, and reliability. In such environments, it is important to offer personalized recommendations that can drive learners' attention to potentially interesting resources depending on their implicit or explicit interests, in order to trigger formal and informal learning opportunities while avoiding information overload (Rafaeli, Dan-Gur, & Barak, 2005; Tang & Mccalla, 2003).

## 1.2   Research Challenges

This thesis addresses two main challenges related to the development of successful PLEs for lifelong learning and recognized by the academic community:

- The challenge of **developing new design models and prototypes for online PLEs** to better support lifelong learning.

- The challenge of **building personalized recommender systems, embedded in open PLEs** to avoid information overload, and trigger learning opportunities by recommending relatively interesting knowledge artifacts.

## 1.3 Contributions

The thesis addresses the above challenges by developing a design model and a recommender system applicable for online PLEs and summarized hereafter:

**The 3A interaction model**
The 3A interaction model targets online environments supporting social interactions, knowledge sharing and management, as well as formal and informal learning. The model adopts a user-centered and bottom-up approach prevailing in social media design. It is based on the following design principles deemed important for developing successful PLEs:

- Building on previous CSCL and CSCW theories while staying at a right level of formalism and abstraction for facilitating implementation;
- Representing interaction and learning contexts in a flexible way;
- Supporting both formal and informal learning scenarios;
- Combining social networking with flexible bottom-up content and activity management services;
- Supporting the development of online communities whose role is important in supporting personal and collaborative learning;
- Incorporating social media features known to motivate active participation and social interactions.

The 3A interaction model distinguishes three main constructs (Actors, Activities and Assets). Each of these constructs can serve as a starting point for social interactions, personal and collaborative learning. Unlike prevalent CMS and LMS design paradigms, the proposed model allows spontaneously sharing knowledge assets without necessarily associating them with a learning unit serving a predefined learning objective. In the same way, individuals enter the system as "equal" actors, with no inherent hierarchy of roles.

## The 3A personalized, contextual, and relation-based recommender system:

The proposed recommender is built on top of 3A interaction model and serves two purposes in an online PLE:

- Increasing the work and learning efficiency by ordering entities in a workspace according to their global popularity and most importantly their predicted importance to the target user and his or her context;
- Inducing new interaction and learning opportunities by recommending new and potentially interesting actors, activity spaces, and assets depending on the target learner's context.

To fulfill these two purposes, the system adopts a relation-based approach where the target learner's interests and preferences are inferred unobtrusively from his or her previous interactions.

## 1.4   Thesis Outline

The next chapters describe and discuss the thesis contributions and the associated research methodologies. They can be summarized as follows:

**Chapter 2** presents the 3A interaction model. It describes how the model was developed following a participatory design approach. Then, it discusses how social media helps address challenges reported by earlier CSCL and CSCW research. Moreover, it presents the proposed interaction model, identifies its main constructs, and explains how it builds on previous CSCL and CSCW theories while explicitly incorporating social media patterns known to motivate participation and facilitate social interactions. The chapter gives a literature overview positioning the proposed model with respect to several existing ones.

**Chapter 3** presents *elogbook[14];* a PLE based on the 3A model and discusses its deployment in a formal learning environment consisting of a practical hands-on course given at *EPFL[15]*. The chapter discusses the results of two consecutives experimental studies of *elogbook's* acceptability as a PLE that follows the bottom-up social media approach in aggregating learning resources and involved actors, facilitating data sharing and management, as well as supporting students' interactions. The study sheds light on the usage of social media features such as tagging in education. In addition, the chapter gives an

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[14] http://elogbook.epfl.ch
[15] http://www.epfl.ch

overview of similar studies touching on the use of social media in education. The chapter also illustrates through a use-case scenario how a PLE based on the 3A model can be used in less formal and more self-directed learning contexts. Finally, the chapter is concluded with a summary of the study findings and a discussion of its limitations.

**Chapter 4** presents the 3A personalized, contextual, and relation-based recommender system. The chapter explains how the recommender system relies on the 3A interaction model to identify significant relations and interactions in the workspace and model them in a heterogeneous multi-layer graph. Then, it describes how a modified version of the original pagerank algorithm is applied to achieve multi-relational, contextualized and personalized ranking where actors, activity spaces, and assets are ranked based on their global importance, as well as their connectedness to the target user's network and context. In addition, the chapter illustrates the recommendation approach using reduced-scale cases. The chapter also compares the adopted recommendation approach to other approaches proposed in the literature.

**Chapter 5** discusses two experiments conducted on real datasets in order to evaluate the 3A recommender system. The first experiment served as an illustrative application and a preliminary evaluation of the 3A recommender system. It was performed in the context of the research network of the *Palette*[16] European project (FP6, IST programme) and involved data related to collaborative deliverables production and work package memberships. The second experiment was carried out

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[16] http://palette.ercim.org/

on a large and publically available Epinions[17] dataset. The experiment indicates that the proposed recommendation approach that combines ratings, trust, and authorship relations yields more relevant results than a user-based collaborative filtering method.

**Chapter 6** summarizes the research work presented in this thesis reviewing its main contributions, and discusses future research.

*"It is not the strongest of the species that survive, nor the most intelligent, but the one most responsive to change"*

*Charles Darwin*

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[17] http://www.trustlet.org/wiki/Extended_Epinions_dataset

# Chapter 2
## *The 3A Interaction Model*

## 2.1 Introduction

Traditional CMSs and LMSs cannot adequately support lifelong learning. This is mainly due to their prevalent design paradigms that draw a hardcoded distinction between "teacher" and "student" rights. Students usually have single predetermined roles and share the same homogenous learning context. They are expected to achieve the same learning goals within the same period. Moreover, learning content is pre-packaged in learning units, has a restricted visibility scope (usually limited to the course duration), and is isolated from the outside world. Sometimes, courses cannot even be shared within the same LMS (Wilson, Liber, Johnson, Beauvoir, & Sharples, 2007).

To successfully address lifelong learning, educational systems need to become part of an external system accounting for learning inside and outside formal academic environments

(Taylor, 2004). Best described as a **PLE**, such a system should cover formal, non-formal and informal learning situations. PLEs should enable learners to control their own learning processes in order to improve the learning quality (Naeve, Nilsson, Palmér, & Paulsson, 2005). For instance, a PLE is expected to allow learners to appropriate and repurpose knowledge artifacts depending on their self-directed activities.

This chapter presents and discusses the **3A interaction model** intended for online environments supporting social interactions and knowledge management in both formal and informal contexts. The proposed model takes its roots from existing CSCW and CSCL theories. At the same time, it follows a "minimalist design" (Wenger, 1998), remains at appropriate formalism and abstraction levels to ease implementation.

The 3A interaction model is particularly suited for **guiding and describing the design of PLEs**, as it is based on the design principles considered crucial for building successful platforms for lifelong learning. These PLE design principles are discussed hereafter. First, PLEs should support formal and informal learning scenarios. Second, they should define interaction contexts in flexible ways including explicitly delimited and implied ones. Third, they need to combine social networking facilities with content and activity management systems from the perspective of the *individual* rather than the *institution* (Atwell, 2006). Fourth, activity and content management should be designed in a flexible and bottom-up way accounting for formal and non-formal, structured and unstructured learning situations. Additionally, content management in PLEs requires a design where learning objects are "free-floating" and "conversational" (Downes, 2010). In other words, their usage does not have to be anticipated nor

strictly embedded within a course unit; instead, it depends upon the object's affordances and spontaneous appropriation, and occurs in an open interactive environment linking individuals to content. Fifth, PLEs should support online communities, and in particular communities of practice. Communities of practice (CoPs) are defined as a group of individuals who choose to collaborate on a regular basis in order to learn and improve their practices related to a shared passion or topic of interest (Wenger, 1998). CoPs are considered to play a key role in fostering knowledge sharing and learning (LaContora & Mendonca, 2003). This triggers the motivation to sustain their initiation and evolution in professional and educational environments (Stanoevska-Slabeva & Schmid, 2000). Last but not least, PLE frameworks should embrace the social media practices of knowledge "democratization" encouraging active participation and facilitating information dissemination, as well as social interactions.

The rest of the chapter is organized as follows. Section 2.2 explains how the model was developed following a participatory design approach. Section 2.3 summarizes the influence of CSCW and CSCL theories on the proposed model. Section 2.4 discusses how social media can help address challenges pointed by early CSCW and CSCL research. Section 2.5 describes the 3A interaction model with an emphasis on its social media explicitly modeled facets. Section 2.6 consists of a related literature review. Section 2.7 discusses questions related to the 3A model. Section 2.8 concludes the chapter.

## 2.2 Participatory Design Approach

The 3A interaction model was developed following the participatory design approach adopted in the *Palette* European Project (FP6, IST programme)[18].

*Palette* aimed at supporting individual and organizational learning in Communities of Practice (CoPs) by delivering a set of innovative and interoperable services along with use-case scenarios. *Palette* services were expected to help CoPs converge towards a comprehensive representation of practices, support discussions between CoP members, improve practices by facilitating knowledge exploration and sharing within and outside the CoPs, as well as provide easy procedures for reifying and creating new practices.

The participatory design approach adopted in *Palette* can be described as follows: teams of designers, developers, and CoP representatives were formed. CoPs representatives were responsible for conducting face-to-face meeting, interviews and questionnaires with CoP members in order to learn how they function, and identify their requirements (Charlier & Daele, 2009). Two examples of reported CoPs needs are presented hereafter.

Doctoral group Lancaster was a CoP involved in *Palette* and located within the Doctoral Programme for practitioners in further and higher education, Department of Educational Research, Lancaster University. Its members include lecturers, educational developers, as well as e-Learning professionals. Most of them are based in the UK and Ireland and few in the United Arab Emirates. Lancaster's observers and representatives reported the community's urge for a formalized and systemized archived system, an easier access and more

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[18]http://palette.ercim.org/

intuitive format for discussions, an easy access to the documents in the virtual learning environment with possibility of versioning documents such as thesis presentation, and finally to have a tool that tells students to submit their work and that lets tutors give online feedback.

Learn-Nett, on the other hand, is an educational Community of Practice where students from different European Universities learn collaboratively by conducting joint projects. This CoP expressed its need to find traces of students' learning and evaluate its training accordingly. In addition, Learn-Nett needed an easy mechanism to conduct discussions, collect exchanged practices, and sustain currently "orphan activities" such as task sharing. In addition, the online platform used by Learn-Nett back then, offered one single space involving all tutors and students. Tutors expressed their need for a private space to discuss things among themselves. The option of having different spaces with different scopes of visibility is also useful for students who sometimes had the impression that tutors are "spying on them". This is a good example, of how some collaborative tools impose sometimes inflexible labels and preplanned rigid structures, not taking into account that they might need to dynamically change their social behavior, and smoothly move back and forth from one social context to another and have different levels of information sharing. As it will be explained in details later in this chapter, the 3A model follows a bottom-up approach that does not enforce any rigid structure or default hierarchy of roles. End-users should be able to define both: activity spaces having a hierarchical distribution of rights and activity spaces having completely flat structure and where all members share equal rights. In addition, the same person can be a "guide" or "tutor" in one space and a "learner" or simply a "member" in another (Naeve, 2001). Just as tutors

can create an activity space dedicated for a particular course and governed by specific access rules, students are also entitled to create their own activity spaces, within or outside the course space, and define their own sharing rules.

After having identified CoPs requirements, CoPs representatives discussed them with designers and developers who suggested different models and services. Then, CoP specific use-case scenarios were developed to illustrate how the proposed models and services address the needs of different *Palette* CoPs. Then, more "generic" scenarios were developed, showing how CoPs activities related to knowledge reification, content management, debate, and animation of CoP life, can be supported by relying on interoperable services serving different purposes (i.e. multi-media authoring, support of debate, activity management, sharing and notification) (Esnault, Daele, Zeiliger, & Charlier, 2009).

## 2.3   Influence from CSCW and CSCL Theories

The 3A interaction model takes its roots from two theories adopted in CSCW to understand how people interact with one another in studied collaboration contexts. They are Activity Theory and Distributed Cognition.

On the one hand, **Activity theory** takes the "activity" as its main unit of analysis. Every activity involves subjects, who use tools to produce and transform mediating artifacts. The latter carry in them the intention behind the activity's existence and the continuation. Every activity is positioned in a historical context, and consists of several conscious actions that should be performed in order to achieve the main goal. With practice, actions themselves turn into quasi-automatic operations.

Inversely, operations can become actions requiring a conscious effort (Jonassen & Rohrer-Murphy, 1999).

On the other hand, **Distributed Cognition** tries to understand how cognitive systems are organized in order to reach cognitive achievements. An activity is described in its socio-cultural-technical context by identifying its processes, how they are controlled and understanding how its representational states are created, transformed and propagated. While the first theory is rhetorically powerful because it names its constructs (community, subject, rules, division of labor), the second zooms into the low-level processes of a system, a characteristic particularly significant for designers. Nonetheless, **one cannot obtain system requirements directly from either of these two theories** (Halverson, 2002).

Inspired by Activity Theory, the 3A model is activity-centric and focuses on naming constructs. This facilitates the constructs' manipulations and the model's discussions between field researchers, designers, developers and end-users. The 3A model further increases its descriptive and application power by accounting for how its basic concepts are exactly related. By this, the 3A model facilitates the communication between cognitive scientists that study the collaboration context, designers that derive system requirements from field studies, and target end-users expected to use the system. On the other hand, the 3A model takes from the Distributed Cognition theory the idea of looking at the general socio-technical context rather than focusing the theory only around the subject itself. This can be best understood in the next section, in which the constituents of the 3A interaction model are described.

The 3A model is also influenced by two learning theories, namely constructivism and connectivism. **Constructivism** perceives learning as a byproduct of experiences and

interaction with people and content (Greg, 2010). In "constructivist classrooms", students are considered as thinkers who have their own mental models, and who try to understand and learn through hands-on problem solving and engagement in constructive dialogues. In addition, the curricular is tailored according to students' prior knowledge instead of being standardized, and the students' assessment is interwoven with the learning process and achieved using portfolios plus presentations (Brooks & Brooks, 1999).

Last but not least, in his article entitled "a learning theory for a digital age", Siemens explains how **connectivism** combines the network, chaos, and self-organization principles. Siemens argues that chaos, a "cryptic form of order" (Stewart, 1989), initially introduced as a mathematical concept acknowledging the connection of everything with everything, can be regarded as "the new reality for knowledge workers". While constructivists consider that learners complete tasks in order to *create* meaning, chaos as a science believes that learners seek the right connections between sources of information, and form useful information patterns in order to *find* the hitherto-existing meaning. People achieve lifelong learning by creating, maintaining, extending and strengthening their personal network composed of people with similar interest, groups, systems and specialized information sets (Siemens, 2004).

## 2.4   From CSCW and CSCL Tools to Social Media

In 2002, Clay Shirky adopted the term "social software" mentioned earlier in (Rockwell, 1997), as he was looking for "something that gathered together all uses of software that

supported interacting groups, even if the interaction was offline". He had intentionally not opted for "groupware" because the term "had become horribly polluted by enterprise groupware work". Also, he did not choose "collaborative software" because it "seems a sub-set of groupware, leaving out other kinds of group processes such as discussion, mutual advice or favors, and play" (Allen, 2004). Today, the expression "social software" is used interchangeably with "social media" to denote the set of interactive websites that are based on Web 2.0 technological foundations and encourage UGC (Kaplan & Haenlein, 2010).

Ironically, in the same year, Joe McCarthy and Elizabeth Churchill "half-jokingly" described *CSCW* as "Computer Supported Cooperative Whatever". In 2004, Bonni Nardi claimed: "CSCW is about play too" (McCarthy, 2006). Likewise, a paper published in CSCL 2005 and entitled "CSC*: Computer Supported Collaborative Work, Learning and Play" suggests accounting for unplanned appropriation of resources rather than explicitly enforcing in the CSCL system particular learning scenarios. The paper also discusses designing applications that can simultaneously target in contexts including work, formal learning and play (Twidale, Wang, & Hinn, 2005). This raises the question of how is social software related to CSCW and CSCL research, or how can it be positioned with respect to these fields?

Social software can be considered as a new "era", in the field of "CSCWhatever", which, by taking a different perspective and adopting a bottom-up approach, has "democratized" and "popularized" the domain, and considerably contributed to overcoming the problems identified by CSCW research (El Helou, Gillet, & Yu, 2007; Koch, 2008). To better elucidate this stand, identified challenges and

lessons learned from early CSCW and CSCL research related to designing collaborative software, are summarized. Then, the bottom-up democratic approach of recent social media is described, shedding light on how it helps overcome these challenges.

### 2.4.1  Lessons Learned from CSCW research

The problem of **low participation** and lack of personal incentives was a major problem in early collaborative applications. To illustrate this problem, Grudin gave as an example, the task of scheduling a meeting (Grudin, 1988). This is mainly the scheduler's task. Nevertheless, it would be made easier if other community members maintain an electronic calendar, even if they do not perceive a direct personal benefit in doing so. Two conditions should be checked to ensure their collaboration and ease the scheduler's task. First, collaborative tools used for maintaining a shared calendar should be uncomplicated, easy-to-use and effortless. Second, **incentives that stimulate active participation and encourage interaction** with others through collaborative tools should be triggered.

Ackerman identifies the necessity of shifting to **flexible, nuanced and contextualized CSCW apparatus** just as human behavior is "flexible, nuanced and contextualized" (Ackerman, 2001). In the same way, Dourish argues that when it comes to collaborative systems, flexibility is a critical usability factor. He focuses in particular on the need to support the evolution in groups' behavior, nature and composition (e.g. membership, distribution of roles). Following this principle, he identifies the problems of the traditional CSCW systems where groups are more or less forced to adapt their behavior to the tool, in the

lack of a tool capable of adapting to their behavior. As a matter of fact, a dynamic reconfiguration of these systems as groups evolve over time is not possible. According to the author, this is mainly because they have internalized the notion of "group processes", focused on very specific tasks, and ignored the dynamic changes in roles assignments over time (Dourish, 1992).

CSCW and CSCL researchers stress the importance of awareness in collaborative workspaces. Awareness is defined as "an understanding of the activities of others, which provides a context for one's own activity" (Dourish & Belloti, 1992). Despite identifying awareness as a crucial requirement for successful collaborative work, researchers have also recognized that excessive notifications might have adverse effects such as a decrease in productivity (Spira & Feintuch, 2005). Therefore, an important challenge is to deliver tunable, **context-dependent, and personalized awareness services**.

### 2.4.2 *Social Media: a User-Centered Bottom-up Philosophy in Practice*

Social media can be considered as "democratization" and folks' appropriation of collaborative software. Its user-centered bottom-up approach whose characteristics are described hereafter, play an important role in overcoming challenges reported by earlier CSCW researchers.

Social media successfully triggers active participation, and fosters UGC, social interaction, as well as information dissemination. First, social media applications are usually free of cost and accessible by simple addressing links. In addition, they require minimal registration information (consisting usually of an email and a password), have low learning curves, and offer interactive user-friendly interfaces. With respect to

developing interactive interfaces and improving the user experience, Web 2.0 technologies such as AJAX[19] play a particularly important role if applied properly (Garrett, 2005). Second, collaborative authoring is made easy and quick through the spreading of blogs and wikis. The first wiki software (*WikiWikiWeb*) was created in 1995 and in the early 2000, wikis started to be increasingly used as collaborative tools (Cunningham, 2002). One example is *Wikipedia*, the free open-source encyclopedia that has over 15 millions articles written by online users. Furthermore, in social media online content is organized based on UGC. For instance, folksonomy denotes the Web 2.0 way of classifying content using tags created and shared by people (Liccardi, et al., 2007). Third, social media are particularly tailored for social networking and information sharing. For instance, *Flickr*[20] is intended for sharing photos, *Facebook* for social networking and sharing resources such as photo albums, and Web links with friends, del.icio.us[21] for managing and sharing bookmarks. Fourth, simple features such as rating, liking/disliking, commenting, tagging, social bookmarking (i.e. *Digg*[22]), and linking people or online resources such as videos ("related" videos in *YouTube*, people in *LinkedIn* or *Facebook*) together facilitate social networking and social interaction around shared artifacts.

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[19]AJAX (Asynchronous JavaScript and XML) combined technologies exchange data asynchronously with the server to respond to a user's request. This avoids freezing the current Webpage and allows the user to continue interacting with it while waiting for the server's response. Then, rather than re-uploading the page, only parts of it are updated based on the server's response, thus speeding the system's overall response time.

[20] http://www.flickr.com
[21] http://delicious.com
[21] http://digg.com/

Moreover, social media facilitate information sharing and aggregation across different sites by relying on lightweight specifications such as RSS (Real Simple Syndication or Rich Site Summary) (Pilgrim, 2002).

Another factor that has substantially contributed to the success of social media lies in the new techniques of designing and spreading technology (Boyd, 2007). In fact, social software applications rely on "extreme" participatory design policies where users play a major role. Applications are deployed at an early stage with basic and simple features. From there, based on how early-bird users used the system's basic functions, interacted with its initial interface, and reacted to it by providing different feedback forms (i.e. reported bugs, critiques, suggestions), designers and developers improve the interface, modify existing features, and add news ones. This is how the application evolves over time with users being involved directly and indirectly in the ongoing design and implementation processes. Not surprisingly, (Schwen, 2003) recommends user-centered and rapid prototyping design for supporting online CoPs.

Furthermore, the social software bottom-up philosophy builds upon the natural emergence of social networks based on bottom-up individual decisions rather than top-down initiatives. Users enter the system as individual actors and not as pre-labeled members of a rigid organizational or institutional structure. Then, they can form self-organized communities or deliberately join existing ones. Self-organization refers to the spontaneous formation of well organized structure, patterns, or behaviors, from random initial conditions" (Rocha, 1998).

Last but not least, today's collaborative applications and networking platforms that fall under the umbrella of social media pay attention to awareness. For instance, *Facebook*

allows users to tune news feeds and notifications according to their own preferences.

To summarize, by adopting a user-centered bottom-up philosophy and by relying on Web 2.0 technologies, social media applications have successfully overcome several problems identified by earlier CSCW studies achieving by that a higher acceptability and a better user experience than traditional groupware. Studies related to social software have started to appear in the CSCW literature (Lampe, Ellison, & Steinfield, 2006).

## 2.5   The 3A Interaction Model

The 3A interaction model is a design model intended for online platforms that offer social networking, community support, in addition to bottom-up content and activity management features (El Helou, Gillet, Salzmann, & Rekik, 2009). The model is well suited to the design of PLEs supporting lifelong learning. It can also serve as a basis for building lightweight specifications to exchange data across different online platforms. Furthermore, it is user-centric, and explicitly embeds social media features known to trigger social interaction and participation incentives, such as rating and tagging online content.

In this section, the 3A interaction model is described in detail, explaining its main constructs and their inter-relations, its social media explicitly embedded features, its flexible sharing rules, and finally its awareness aspects.

### 2.5.1   Description

The 3A interaction model consists of three main constructs also referred to hereafter as concepts or entities. Before discussing

these constructs illustrated in Figure 1, it is worth noting that an instance belonging to any construct type is described using the following attributes: title, description, creation date, last modification date, status, and *URL*.

First, the concept of *Actor* represents any entity capable of initiating an event in an online platform. An actor can consist of a person or an agent that sends requests on behalf of him or her. For instance, a Doodle[23] widget[24] that sends a request for adding a date to a shared calendar, and an experimentation tool that saves measurements as assets in an activity space are considered as actors.

Second, the concept of *Activity* is borrowed from Activity Theory. It is based on the idea that individuals and communities conduct activities in order to achieve their goals. For instance, members of a CoP gather in a community's main activity space with "sharing good practices" as their chief objective. Activity spaces can either be strictly **personal or collaborative**, depending on their purpose of creation. Additionally, they can be dynamically and smoothly **repurposed** depending on how their usage evolves over time. For instance, an actor can decide to create a personal activity space where he or she collects, manages and annotates assets related to a topic of interest. Then at some point, he or she can choose to invite other actors to access the space transforming it from a personal data repository to a collaborative one where interactions around shared assets can take place, and a community around the topic(s) of interest can emerge. **Each activity is conducted within its dedicated space where roles**

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[23]http://www.doodle.com
[24] In computer programming, a widget is a visual container embedded in an online application's graphical user interface and able to directly interact with specific data.

**are assigned to involved actors**. A role consists of a label and a set of rights. In a community space, **roles** guide members in finding their place in the community, and learning how they could contribute to it. As an example, the main activity space of the Automatic Control laboratory course given at EPFL involves "students", "tutors", "course assistants", "technical assistants" and "simulation tools". Roles change from one context to the other. For example, students taking the course mentioned above can create their own spaces where they define their own rules, deciding who is allowed to access their space and what actions he or she can perform in it. **An application based on the 3A model, should be flexible enough to account for both hierarchical and flat spaces, and allow space structures to be easily changed over time if required**. For instance, a community space can evolve from a flat structure consisting of only one main activity space, to a more fine-grained structure where different community activities are classified and explicitly mapped to sub-spaces. Furthermore, an activity can have a plan of deliverables or "**expected assets**" with concrete submission and evaluation deadlines, specific evaluators and submitters (selected on an individual or role-dependent basis). This is particularly useful in e-Learning environments, project management and learning communities such as Lancaster or Learn-Nett.

Third, the concept of *Asset* includes any kind of resource that is produced, shared, annotated, or transformed by actors. In the vocabulary of Activity Theory, it mediates the relation among community members, and between them and their final product. The proposed definition includes textual documents, images, audio and video files, discussion threads and wiki pages. Unlike traditional LMS and CMS where knowledge objects are organized within learning units and their usage

anticipated, in the 3A model, assets can exist outside the scope of activity spaces; they can be shared directly among actors without having to belong to an activity space or fall under the umbrella of reaching an explicitly stated objective. Indeed, they can at any time be posted in one or more activity spaces, grouped together in a bottom-up way using tags, or explicitly related to other assets. This approach increases the learning flexibility and encourages the spontaneous appropriation of resources (Twidale, Wang, & Hinn, 2005).

Every 3A entity (or combination of 3A entities) can be considered as a starting point and a **context** for planned or spontaneous interactions, collaborative work, and personal as well as collaborative learning. Indeed, there can be different levels of interaction contexts, ranging from those explicitly delimited by actors to those implied from their personal and collaborative actions. For instance, a community space constitutes an explicit context, for potential interactions and learning, revolving around the community's practices, involving its actors, shared assets as well as eventual sub-activity spaces. On the other hand, two or more actors commenting the same asset could also form an implicit interaction context involving them, the asset in question, its owner and other contributors. Identifying interaction and learning contexts is crucial in PLEs and is indeed more challenging than in traditional CMSs and LMSs. This is mainly because PLEs are not confined to preplanned collaborative scenarios occurring within rigid and closed spaces. Instead, it also accounts for smoother forms of interactions between actors, activity spaces, and assets, occurring in open spaces and involving intended or unintended learning situations. Therefore, it would be helpful to define the learner's current context with the 3A entities, and then adapt the way

information is represented in the PLE depending on this defined context. More specifically, actors, activities as well as assets can be ordered and filtered depending on their relevancy to the delimited context so as to avoid information overload. This is discussed further in chapter 4.

Figure 1 illustrates the 3A model, showing its 3 main constructs and examples of what they could consist of. *SALT* and *CRUD* actions trigger time-stamped events involving actors, activities and/or assets. *CRUD* is an acronym used in relational databases or at the user interface level to refer to the four main actions of Creating, Reading, Updating and Deleting that could be performed on actors, activity spaces, and assets. *SALT* (Share, Assess, Link, Tag) is an acronym introduced in (El Helou, Li, & Gillet, 2010) to account for social media features explicitly represented in the 3A model. These features are discussed in details in the following section. Figure 2 consists of a more detailed representation of how the 3A main constructs and sub-constructs are inter-related.
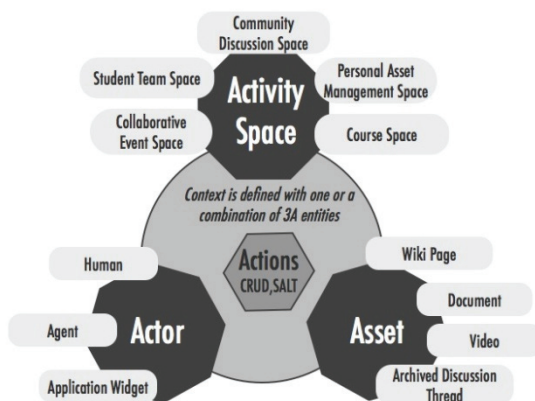


Figure 1: The 3A main constructs of the 3A interaction model
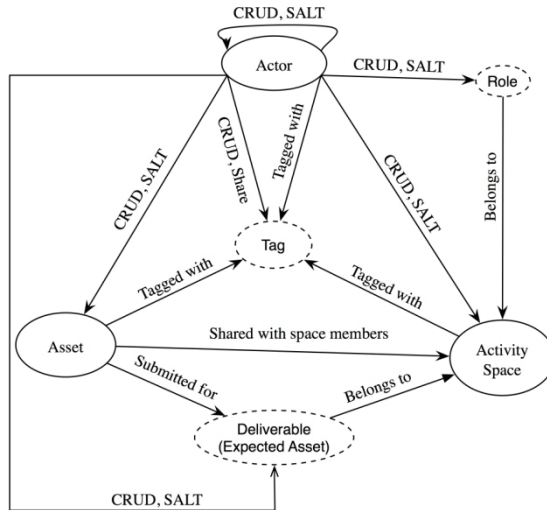
Figure 2: Entity relations in the 3A interaction model

## 2.5.2   *Incorporating Social Media Features: SALT*

As noted, **SALT** (Share, Assess, Link, Tag) is an acronym describing social media features explicitly represented in the 3A model. These features encourage opinion expression and active participation, and facilitate bottom-up information management. Actors, activity spaces, and assets of the 3A interaction model can be shared, assessed, linked and tagged.

First, the model accounts for different **sharing** levels, designed after a careful examination of the different sharing policies adopted in formal learning platforms such as *Moodle*[25], and informal social media applications such as *Facebook*, *Google Groups*[26], *LinkedIn*, *Doodle*, and *Elgg*[27]. Sharing policies and access rules are discussed in section 1.6.3.

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[25]http://moodle.org
[26]http://group.google.com

Second, in the realm of social media, **assessing** content can either be quantitative (rating or voting) or qualitative (commenting, bookmarking). Giving users the opportunity to easily contribute and express their views leads to a better appropriation of the collaborative platform and increases their motivation to collaborate with others. Moreover, a direct advantage of having such features is generating relation-based recommendations whereby metadata resulting from *SALT* actions are exploited in order to bring to the surface relevant actors, activities and assets based on how and by whom they have been *"salted"*. The 3A recommender system that is based on this approach is discussed in chapter 4.

Third, **linking** or relating actors, activities, and assets is popular in many social media applications: related videos in *YouTube*, friends in *Facebook*, colleagues in *LinkedIn*, related products on *eBay*[28]. In formal and informal learning, linking helps discover connected actors, relevant activity spaces, and related assets. Following the 3A model, actors can create uni-directional and bi-directional links between 3A entities. As a rule, public links or relations need to be approved by the owner(s) of involved entities before taking effect. Even though the model accounts for a set of meaningful link types such as "sub-space" between spaces and "friends" or "colleagues" between actors, it does not enforce one single link type with a specific meaning. Instead, it leaves it optional for actors to explicitly describe the relation between entities linked together. By default, a neutral link type, namely "related", is adopted. Actors can also define new link types and make them public so that others can reuse them. User-defined links do not have to be "understandable" by the system. Nevertheless they are

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[27]http://elgg.org
[28] http://www.ebay.com

meaningful to users, and can be directly exploited by them to manage and cluster 3A entities as well as define access lists as it is explained in section 2.5.3.

Last but not least, Compared to the traditional way of classifying files into folders, **tagging** can serve as a bottom-up organization approach where users organize and cluster information depending on its type and content, by giving it one or more label(s) using a vocabulary of their own (Etches-Johson, 2006). When a 3A entity belongs to multiple categories or touches on several distinct topics, it is more practical to tag it with different tags than put it (or put an alias of it) in each of the corresponding folders. Additionally, using tag-based search and tag clouds, learners and tutors can discover actors, activities and assets relevant to specific topics of interest. Tagging actors have also proven to be useful in formal contexts. For instance, in an IBM study, employees were allowed to tag each other's profile page (Farrell, Lau, Nusser, Wilcox, & Muller, 2007). The study shows that employees used tagging to make others aware of a colleague's competences that did not always coincide with his or her position in the company. Finally, sharing tags facilitates the gradual emergence of folksonomy helping a community to incrementally build a common vocabulary and externalize its shared memory. The 3A model distinguishes between two types of tagging. The first one is "content tagging". It consists of labeling an entity by describing its content using one or more keyword(s). The second tagging category is intended for describing the type of a 3A entity rather than its actual content. For instance, an asset can consist of a "discussion archive" or a "project deliverable". In the case of activities, defining their type help identify the level that researchers, designers and/or users are considering at any point in time, and facilitates

activity management in a "open corpus" environment such as a PLE. As an example, the main activity space dedicated for the community can be tagged as "community". A sub-activity space created within the same community and dedicated for specific discussions can be tagged as a "topic discussion". Tags can be shared and reused by different actors helping actors and communities to gradually build a shared vocabulary as noted earlier.

### 2.5.3    *Sharing Policies and Access Rules*

Individuals and CoPs require an easy mechanism of controlling who has access to their profile information, activity spaces, and assets, as it was observed during the *Palette* participatory design process.

Publicizing knowledge artifacts or restricting to some or all CoP members should be left as **options** for CoP members depending on the information at hand. Moreover, dynamic "reconfiguration" of access rules related to actor profiles, activity spaces, and assets should be kept easy. As a first impression, these requirements can be seen as contradicting with the very basic principle of CoPs, which is of course practice sharing. Nevertheless, giving the possibility to define community boundaries and having different levels of information sharing helps nurture the community identity among its members (Resnick, 2002). In addition, limiting the visibility scope of some entities to only concerned actors contributes to reducing information overload.

The **sharing policies** recommended by the 3A interaction model and applying for actor profiles, activity spaces, and assets are discussed hereafter:

**<u>Access and Contribution Policies for Activity Spaces:</u>**
As far as **invitees** are concerned, any actor can join a *public activity space*, while only explicitly invited actors can join a *private activity space*. Entitlements to join activity spaces can either be *unconditional* or *conditional* upon belonging to a dynamic list of actors. The dynamic invitee list is chosen by the activity space owner(s). It can consist of actors related to the space owner(s) with a specified relation type such as "colleagues" or it can contain all members of a particular activity space (holding any or one particular role). *A dynamic invitation implies that involved actors will loose their rights over the activity space when they no longer belong to the dynamic list, which entitled them to this space invitation.*
With respect to access rights and participation policies,

A survey of existing applications supporting collaborative spaces leads to identifying 3 main types depending on **access and participation conditions**:

- In an activity space of *type I*, all invitees are offered a full view. In addition, they can acquire their assigned role and participate in the activity space without necessarily having to confirm their membership. This is the simplest and most open activity space type.

- In an activity space of *type II*, full view is granted to all invitees. However active participation is restricted to those who accept to join it. In other words, assigned roles and associated rights take action only after having confirmed membership.

- In an activity space of *type III*, only a *preview* is granted to its invitees, while full view and participation are left for confirmed members.

Table 1 consists of a classification of different platforms according to the taxonomy described below (i.e. depending on the participation and access policies offered and the possibility to have public or private spaces, as far as the intended audience is concerned).

TABLE 1: A CLASSIFICATION OF ACCESS AND PARTICIPATION POLICIES

| Space Type / Space Invitees | Type I *Full view and participation allowed to all invitees, Confirming membership is not required* | Type II *Full view for all invitees, Participation restricted to confirmed members* | Type III *Preview for all invitees, Full view and participation restricted to confirmed members* |
|---|---|---|---|
| **Public** *Open to everyone* | Elgg "wire" | Elgg, Moodle, Forums in general, Google Groups (Public option) | LinkedIn |
| **Private Space** *Restricted to explicitly invited actors* | Doodle | Google Groups (Announcement-only) | Elgg Moodle LinkedIn Google Groups (Restricted) |

According to the 3A model, **participation** in an activity space is achieved by doing *CRUD* and *SALT* actions within it. Regardless of the space type, only space **owner**(s) are allowed delete the activity space and set access and participation rules and. In addition, they can remove data and metadata resulting from *CRUD* and *SALT* actions performed in their own spaces

such as posted assets. The space creator is automatically assigned the role of "owner" and can share this role with other individuals and groups if he or she wishes it. Also, it is up to the owner(s) to decide what invited actors can do in his or her activity space. This is achieved by assigning to every invited actor or dynamic list of actors a role involving a label and a set of rights. To ease activity space management, an automatic "contributor" role is attributed to every activity space. Indeed, activity space "owners" can choose to use this role or define other ones with a different label and rights combination. The "contributor" role has rights over all *SALT* actions and a subset of *CRUD* ones (only create and read). In other words, contributors can access, share, rate, comment, link and tag the activity space and its content. Sharing the activity space means inviting other to join it. Choices taken regarding the default "contributor" role, apply to the three activity space types discussed above. *The difference is that in an activity space of type I, invited actors can directly perform actions associated with their assigned role. While in the other two cases, actors first need to confirm membership in order for their assigned role to take effect and be able to actively participate in the activity space. While the invitation status is still pending, invitees of "type II activity spaces" are granted a full view of the activity space while invitees of "type III activity spaces" only a get a preview.*

**Access and Contribution Policies for Actors:**
Access and participation rights for actors and assets are managed in similar ways to those for activity spaces. Each actor can decide who can access and "*salt*" his or her own profile. He or she can grant these rights to everyone. Alternatively, he can restrict access to specific actors chosen on

an unconditional personal level or a conditional one dependent upon belonging to dynamic actor lists such as "friends" or "colleagues". By default and following usual conventions, everyone is granted a preview of the profile, and only directly related actors are permitted to access the full profile and "*salt*" it. Actors can of course disallow contributions to their own profiles by disabling *SALT* actions. They can also delete at any point in time their complete profile or simply metadata resulting from *SALT* actions performed by others.

**Access and Contribution Policies for Assets:**
Finally, similar rules apply to accessing and contributing to assets. The asset creator can decide to share "ownership" rights with other actors. The asset owner(s) can allow everyone, specific actors, or specific lists of actors to access and/or "*salt*" his or her asset. As it is the case for actors and activity spaces, only owners can delete it. They can also remove asset-related metadata resulting from *SALT* actions.

### 2.5.4 *Awareness*

Awareness is essential for successful collaboration (Carroll, Rosson, Convertino, & Ganoe, 2006). Awareness of past and current actions in a community, guides members' decisions, influence their course of actions. For instance, a recent study shows that visualizing awareness cues of participation stimulates students' exchange, and encourages them to actively engage in their group activities (Janssen, Erkens, Kanselaar, & Jaspers, 2007).

Several types of awareness are proposed in the CSCW literature (Chen & Gaines, 1998; Gross, Stary, & Totter, 2005; Gutwin & Greenberg, 2002; Gutwin, Stark, & Greenberg,

1995). Nutter & Boldyreff, 2003). A list of the most common ones is provided below:

- **Informal awareness** concerns the general knowledge of who is around and what he/she is doing. It has been pointed out as enabling spontaneous interaction.
- **Presence awareness** involves information about the status of users. This information indicates each user's availability, and willingness to collaborate with others. It helps trigger online interactions.
- **Task awareness** involves information about the aim of a task, its requirements and how it fits within a bigger plan.
- **Social awareness** concerns the information that a person maintains about others on a social or conversational level. It includes issues like the degree of attention and the level of interest of a person.
- **Group-structural awareness** involves information about participants' roles and responsibilities, their positions on an issue and the overall group processes.
- **Historical awareness** concerns the knowledge of how artefacts resulting from collaboration have evolved in the course of their development.
- **Workspace awareness** concerns the up-to-the-minute knowledge about others' interaction within a shared workspace. This includes knowledge about the workspace in general, information about other participants' interactions with the shared space and the artefacts it contains. While informal awareness considers a broad system-wide context, workspace awareness is relevant only within the context of a specific collaborative environment. Several elements are relevant to this type of awareness: *presence* (is

anyone in the workspace?), *identity* (who is participating?), *authorship* (who is doing what?), *action* (what are the participants doing?), *action history* (how did that operation happen?), *artefact history* (how did this artefact reach this state?), etc.

The adopted awareness types are not considered as independent; instead, they can overlap in a collaborative platform. With respect to the 3A model, **asset-related awareness requires** historical and workspace awareness. This involves usage notifications and statistics regarding assets shared on a personal basis or at a collaborative level such as posting a new asset or accessing and "*salting*" already existing ones. Moreover, the status attribute of an asset, can tell whether it is still "in production", "submitted" or "evaluated". **Actor-related awareness** involves social, presence and informal awareness. The status attribute of an actor serves that purpose. There can be default platform-understandable statuses such as "busy, offline, and online" and actors should still be able to create new ones. Actor-related notifications also include notifications of actions performed on actor profiles such as tagging, linking and rating it. Last but not least, **Activity-related awareness** encloses task-based, group-structural and workspace awareness. In that, space members should be informed of their role, tasks and responsibilities. In addition, they should be made aware of the changes occurring within their activity space (as a result of a *CRUD* or *SALT* action) such arrivals of new members, postings of new assets or approaching dates for submitting "expected" assets (El Helou, Tzagarakis, Gillet, Karacapilidis, & Yu, 2008; El Helou, Gillet, Salzmann, & Rekik, 2009).

## 2.6 Related Literature Review

Several guidelines, design patterns, models and frameworks targeting general-purpose and educational collaborative platforms can be found in the literature.

(Kollock, 1998) discusses design principles for online communities. He stresses the importance of promoting members' ongoing interaction, making them aware of actions undertaken in the community, providing them with a coherent sense of space, allowing them to decide its boundaries and customize norms and rules of interaction, in addition to permitting identity persistence. The 3A model covers the aspect of identity persistence by representing each community member as an individual actor having intrinsic and contextual attributes and related entities. Moreover, as it was described earlier in the chapter, each community has its main collaboration space where it can define its own set of collaboration and access rules, ranging from completely open and flat structures to more organized ones where multiple roles and various access rights are defined. In addition, interaction is promoted by the incorporation of *SALT* features as discussed earlier.

In (Guerrero & Fuller, 1999) design patterns for collaborative systems are also proposed. Seven main candidates are selected after an examination of existing development tools (sessions, users, roles, events, objects, repositories, and views) and two others (environments and floor controls). Similar to the 3A model, roles are assigned over repository objects (space assets) giving users different rights over data. Default common roles are also identified (readers, writers, and coordinators). The 3A model uses a general concept referred to as an activity space where users are

assigned different roles with specific rights. Compared to the design patterns suggested by Guerrero and Fuller, the activity space encapsulates the concepts of "repository", "session" and "environment" as described in the cited paper. An activity space can serve as a repository where assets are posted, shared and annotated. It can also serve as discussion space or session where membership is enforced. In addition, just as an environment can have multiple sessions, a main activity space can enclose different subspaces serving several purposes. Furthermore, multiple separate spaces can co-exist.

Preece identifies two keys factor for the success of online communities: sociability and usability. On the one hand, sociability involves aspects related to social interactions mediated by information and communication technologies (ICTs) such as community purposes, interaction policies, social capital, trust and reputation. Preece argues that the initial community's sociability is affected by the choices that developers make concerning the online community's purpose, people and policies. On the other hand, usability addresses questions related to how useful, efficient, safe and effective the collaboration medium is. For instance, choosing whether or not to impose a registration policy is a matter of sociability, while deciding how exactly to present the policy at the interface level is a question of usability. Futheremore, the author presents access, navigation, information design and social interaction support as key usability factors for online communities (Preece, 2000).

More recently, the C4P model is presented in (Hoadley & Kilner, 2005). It focuses on how learning occurs in communities of practice and addresses learning needs in collaborative systems. The framework has four inter-connected purposeful components namely: content, connections,

conversation and context. It also states that knowledge objects (assets) can be shared, linked to other related ones. The 3A model is influenced by the design models discussed earlier and comparable to the models described above. Nevertheless, its particularities lie in the fact that it gives a detailed description of its constructs and their interconnections and describes the actions that can be performed focusing specifically on social media ones (*SALT*).

Furthermore, the PIKM (personal information and knowledge management) framework was presented in (Jiang & He, 2007). It focuses on seven main principles: "accessing, evaluating, organizing, analyzing, conveying, collaborating with, and securing information and knowledge" It involves four major modules. To start with, the first one is the *Collaboration Workspace Module* where subjects, individuals, institutions and groups join their efforts towards one common objective. According to PIKM, collaboration sponsors create workspaces in order to conduct private and professional collaborations and store related resources and tools. Second, the *Personal Profile Module* where people hold different identities (depending on the workspace) and store personal information and/or information pointers related to their knowledge. Third, the *Knowledge Network of Practice* consists of a linked map where profiles are linked through workspaces. Lastly, the *Platform Module* is related to environments and tools that help fulfill each of the seven principles stated above. The *Collaboration Workspace Module* is highly comparable to the concept of activity space in the 3A model and the idea of holding different roles in different workspaces (the Personal Profile Module) is also similar. Nonetheless, no detailed description of space types, potential collaborative actions, multiple identities and

access rights are provided. In addition, the inter-connection between the different modules is not clearly stated.

As far as the educational modeling is concerned, (Reigeluth & Garfinkle, 1994) calls for reforming educational systems so that they become flexible and account for learner-defined goals. (Koper & Tattersall, 2004) present the *Learning Network* (or *LN*) model allowing self-directed learners get a global overview of proposed learning activities and recommended learning paths and decide for themselves what path to take according to their learning objectives. Learning paths consist of *targets* that consist of a set of *Activity Nodes* (or *AN*s) and allow reaching certain *competency* levels. An *AN* is described with metadata, and can be achieved following a predefined sequence. In addition, it can consist of courses, workshops, conferences or other learning resources serving different objectives. Every *AN* is designed as an *unit of learning package* that is describable using the IMS Learning Design Specification and that defines the activity *roles* and *environments* consisting of a set of resources (or references to resources) required to complete the activity (Koper & Olivier, 2004). What the two models have in common is that they are both designed with the idea that actors conduct activities to reach specific goals and can take different roles in different activities. Nevertheless, three important differences can be underlined. First, even though the *LN* model allows actors to choose their own learning activities, it is not clearly stated whether they can suggest activities and learning assets themselves. Second, in the *LN*, resources are necessarily part of an explicit activity, and are either prepackaged in learning unit or added at runtime. On the other hand, in the 3A model actors can directly share and interact with "free-floating" assets without having to connect them to an activity space or link

them to a explicitly stated objective. This higher flexibility and reduced formalism in describing how actors interact with assets is believed to be more suitable for informal learning scenarios and the spontaneous appropriation of knowledge objects. In addition, the possibility to create activity spaces and define different rules and visibility scopes by any end-user gives more freedom to learners and involves them more actively in the self-directed learning process. Last but not least, the 3A model explicitly accounts for social media features such as linking, rating, tagging, and sharing that encourage contributions and interactions. On the other hand, the 3A interaction model does not explicitly model competences. Still, tags can be used to describe actor's competence in general, and roles can be used within an activity space to distinguish between "experts" and "novices" in the context of this particular activity.

In (Wilson, Liber, Johnson, Beauvoir, & Sharples, 2007) alternative design patterns in order to shift from traditional virtual learning environments (VLEs) to PLEs are proposed. According to the authors, the traditional approach of forcing a predefined asymmetric roles structure (i.e. "tutors" vs. "students"), homogenizing learning context and isolating learning content is not suitable for lifelong and lifewide learning which is expected to be cross-organizational, continual and ubiquitous taking place anytime and anywhere whether at the workplace, at home or in leisure places. This is why they recommend designing flexible and symmetrical access rights, adopting tags and smart groups rather than hierarchical folders, relying on "lowest common factors" (i.e. such titles, tags, ratings and comments). Moreover, they advocate using lightweight Web 2.0 specifications such as RSS and creative

common[29] licenses to bring together heterogeneous information resources, rather than strictly adhering to educational standards (i.e. IMS[30], SCORM[31]).

(Mödritscher & Wild, 2009) discuss the Mupple prototype and infrastructure that targets PLEs and aims at facilitating end-user development as well as achieving semantic interoperability. It is based on a domain-specific language referred to as LISL that allows a learner to associate an action with a particular tool and a corresponding outcome. Mupple does not model assets and communities, nor does it incorporate social media features.

Finally, as it is mentioned earlier the 3A model can be used as a basis for building lightweight specifications to exchange data across different PLEs and online platforms in general. As far as social sites are concerned, in 2007, Google released OpenSocial, a common API to facilitate interoperability across social sites (OpenSocial, 2010). The OpenSocial data specification 1.032 released in March 2010 contains the following main data objects: person, group, and message as well as additional ones such as media item and album consisting of a collection of media items (video, image and sound). There can be private, invitation-only, public and personal groups (used by people as personal friends list). A media item or a message corresponds to an asset in the 3A model. Moreover, depending on its aim, an activity space can either be collaborative and involve several people with potentially different roles, or personal and serve as a private list

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[29] http://creativecommons.org
[30] http://www.imsglobal.org
[31] http://en.wikipedia.org/wiki/Sharable_Content_Object_Reference_Model
[32] http://opensocial-resources.googlecode.com/svn/spec/1.0/Social-Data.xml#Activity

of actors or a collection of assets. An important aspect of the 3A model worth including in a common API for social sites or PLEs in particular is the bottom-up, social, and interactive metadata resulting from *SALT* actions. This allows gathering feedback; reflections and opinions related to asset, activity and actor across different platforms and eventually use them in recommender systems.

## 2.7   3A model Discussion

The 3A interaction model raises open questions requiring further research and experimentation. In addition, it is expected to evolve depending on how platforms based on it will be perceived and exploited by end-users. One related discussion concerns the usage of tags, roles, and links. The question is whether they have overlapping or distinct usage contexts. The current view on which the 3A model is based is explained hereafter knowing that it can change as a result of future usability studies. While tags are used to describe an entity with one or more expressions, links are used to describe the aspect(s) in which two entities are related. Indeed, two entities sharing the same tags are implicitly related. Moreover, social tagging is in some situations more powerful than linking. This is typically the case when two assets for example share topics in common, but actors aware of one of them, do not know about the second's existence. Thus, the two assets in question cannot be explicitly connected together using links. Still, if different actors tag these assets using similar expressions, tag-based search helps discover their relationship making actors aware of only the first one, learn about the second, and vice versa. This tag-based approach of discovering resources is particularly important in PLEs, where knowledge objects and

their relationships are not predetermined (as it is the case in traditional LMS), but are instead gradually added, connected and remixed at any point during the collaboration and learning processes. Even though what can be achieved with links can also be achieved with tags, the former feature is considered as a specific way of explicitly relating two entities, while the latter is primarily meant to describe and classify a particular entity. In addition, while tagging an entity requires specifying at least one descriptive keyword, linking necessitates designating the related entities leaving their relationship's naming *optional*. One can argue that to group different entities, one can also rely on spaces. This is dependent upon the user's preferred style in organizing resources; either he or she can follow the traditional folder-based metaphor by grouping similar resources in one space, or can adopt a bottom-up approach by putting the same tags on similar resources. One advantage of the tag-based approach is that when a resource belongs to more than one category, it is easier to tag it with the corresponding distinct keywords then to post it in different spaces. In addition, it is expected that space creation is more appropriate in situations where actors want to gather people around a specific topic in an activity space, to conduct discussions and form a community. Last but not least, the specificity of roles compared to links and tags remains to be discussed. Roles can be defined as dedicated links that exclusively connect actors to spaces, in order to define actors' position in a space *and* grant them access rights. While using links serves a general purpose and is optional, using roles is a requirement for inviting members to join an activity space. Compared to tags, assigning roles can be considered as tagging actors *in context*; tags describe the general attributes inherent to an actor, and roles describe his or her rights and responsibilities that are specific to one activity

space and can change from one space to the other (Ren, Kraut, & Kiesleri, 2007). In addition, unlike links and tags, roles in the 3A interaction model carry with them a set of rights defining what an actor can do in a space. A last remark regarding the usage of these different features is that it is dependent upon the user's subjective judgments and habits. This is why there is always a trade-off between giving enough possibilities to accommodate different styles rather than imposing one way of doing things, and the principle of parsimony along with the concern of not confusing users with too many overloading features. Clearly, it is only through careful usability studies including observations, action analysis, interviews, questionnaires and data logging (Holzinger, 2005) that the expected usage of different features will be verified and perhaps unexpected ones identified. In this perspective, a PLE based on the 3A model was designed and applied in an educational context, and two usability studies covering among other things the usage of tags in formal learning environments, were conducted. The studies are described and discussed in the next chapter.

Finally, a last matter worth discussing is the extent to which the 3A model's descriptive ability is suitable for formal learning. For instance, in the current version, actor competences can be represented in two ways: general ones can be described using private and public tags, while activity-specific ones can be described by creating different roles to distinguish between experts and novices. Should competences, competence levels and related activity prerequisites be modeled in more explicit and built-in way? If so, how could this be done, whilst adhering to the PLE design principles of self-direction, flexibility, symmetry of action as well as bottom-up association and spontaneous appropriation of resources?

Further research involving comparative usability studies will hopefully help in addressing these questions.

## 2.8 Conclusion

This chapter presented and discussed the 3A interaction model that guides the development of knowledge management and "CSCWhatever" platforms in general, and online PLEs in particular. The model is based on design principles identified as crucial for building PLEs for lifelong learning. It builds on CSCW and CSCL theories. At the same time, it eases implementation thanks to its descriptive and application powers.

The proposed model identifies 3 main entities: actors, activities and assets, and allows a flexible representation of context. A single or a combination of 3A entities represents a starting point for planned and unplanned interactions, and a potential context for personal and collaborative learning. Depending on the situation at hand, interaction and learning contexts are either explicitly defined by users, or implied from their current actions. The model combines social networking with flexible content, activity and community management, and provides guidelines for sharing policies. Finally, it integrates social media features. Grouped under the *SALT* acronym, these features encourage active contribution and social interactions, and facilitate bottom-up knowledge management in "open-corpus" environments.

*"Do not quench in your aspiration and your imagination; do not become the slave of your model"*

*Vincent Van Gogh*

# Chapter 3
## *Application of the 3A Interaction Model in Designing Social Media and online PLEs Supporting Formal and Informal Learning*

## 3.1 Introduction

The exploitation of social media to support informal as well as formal learning is gaining more and more interest, mainly because social media successfully trigger contribution incentives, foster user-generated content, and facilitate user interactions via blogging, sharing videos and commenting online material (Mason & Rennie, 2007; Farrell, Lau, Nusser, Wilcox, & Muller, 2007; Rollett, Lux, Strohmaier, Dosinger, & Tochtermann, 2007).

*eLogbook*[33], is a PLE platform implemented based on the 3A interaction model. It offers social networking, flexible community support, in addition to bottom-up asset and activity

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[33] http://elogbook.epfl.ch

management features. It incorporates *SALT* features that trigger active participation and social interactions, and allow a bottom-up classification of 3A entities. During the 2008 and 2009 spring semesters, *eLogbook* was deployed and evaluated in a formal learning environment, more specifically in the context of a laboratory course on automatic control given at EPFL. Two related usability studies were conducted over two consecutive spring semesters.

This chapter discusses the role of *eLogbook* and its actual usage in the laboratory course, demonstrating the applicability of PLEs based on the 3A interaction model in formal learning environments and shedding light on the impact of social media in education by discussing how students used the *SALT* features during the course. The chapter also presents a use-case scenario illustrating how PLEs based the 3A interaction model can support less formal and more self-controlled learning contexts.

The rest of the chapter is organized as follows. Section 3.2 presents *eLogbook*. Section 3.3 presents the formal learning environment in which *eLogbook* was adopted and describes the role of *eLogbook* in this learning context. Sections 3.4 and 3.5 discuss the usage and the perceived usefulness of *eLogbook* as a PLE allowing to represent the course structure, centralizing the access to aggregated actors (students, tutors and machine agents), activities, and assets, in addition to offering bottom-up content management and interaction features. Section 3.6 introduces *Graaasp*[34], *eLogbook*'s successor, and portrays a less formal use-case scenario where a graduate student employs a PLE based on the 3A model during his PhD studies. Section 3.7 consists of literature review focusing on the impact of social media on education. Section 3.8 concludes the chapter.

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[34] http://graaasp.epfl.ch

## 3.2   *eLogbook*: a Platform Based on the 3A Model

The *eLogbook* platform is a freely accessible Web-based PLE deployed by EPFL. It aims at supporting knowledge management and collaboration and enhancing personal and collaborative learning. It is based on the 3A interaction model developed during the *Palette* project taking into account CoPs requirements. Hence, it can simultaneously serve as a flexible community and activity management system, a social networking site, as well as a data repository for producing, managing and sharing assets. In this section, its context-sensitive interface, which embeds pertinent awareness cues and offers multiple functionalities while keeping the same overall skeleton is presented.

### 3.2.1   *A Context-Sensitive Interface*

The *eLogbook* context-sensitive interface consists of a central element surrounded by three main areas respectively dedicated to actors, activity spaces, and assets (Gillet, El Helou, Rekik, & Salzmann, 2007). When an entity is selected as the contextual element (also referred as focal or central element), its related entities are displayed in the surrounding areas with a specification of how they are related. Consequently, just by changing the type of the focal point from an actor to an activity space or an asset, the interface can serve different purposes, while maintaining the same layout structure. As an example, Figure 3 shows a snapshot of the *eLogbook*'s context-sensitive interface where the focal entity is an actor: associated actors are listed to the left, related activity spaces are listed in the top area, and owned or accessible assets are displayed to the right. As illustrated in Figure 3, the central area includes a rich-text description of the focal entity that can

be easily updated thanks to an embedded wiki. The contextual or focal entity can be rated, commented, tagged and linked to other entities. It can also be shared according to the 3A model sharing policies described in the previous chapter. Following the 3A model bottom-up approach, all actors can create and manage their own activity spaces. There is no single administrator and no built-in hierarchy of rights; every actor is in charge of his or her own personal and collaboration activity spaces and decides to share full, partial, or no responsibility with others. Awareness "cues" of different types are seamlessly incorporated in every area through using symbolic icons, different colors and changing the ordering of the displayed entities. For example, "expected assets" or deliverables with earlier deadlines are highlighted in red and appear on the top of the list as it is illustrated at the bottom of Figure 5. The latter shows a case where the context is an activity space that aims at facilitating the management of a semester project by aggregating involved actors, related discussions, tasks, and resources. For privacy reasons, names and pictures are blurred in all the illustrative *eLogbook* snapshots.
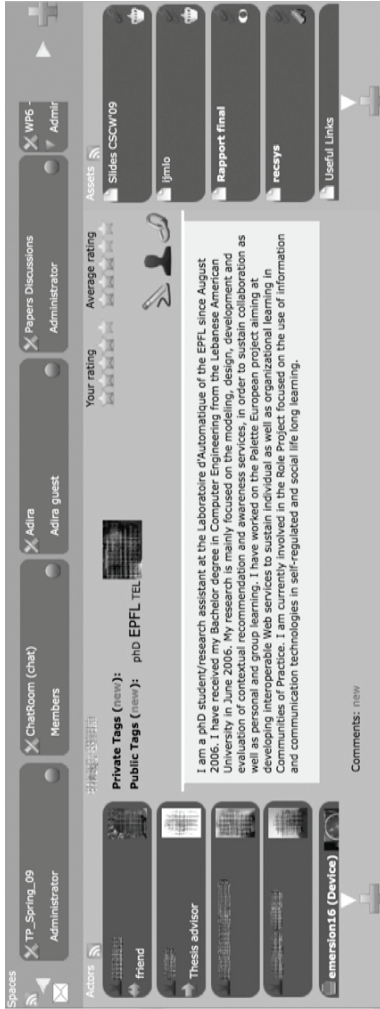
Figure 3: Context-sensitive view (context is an actor)
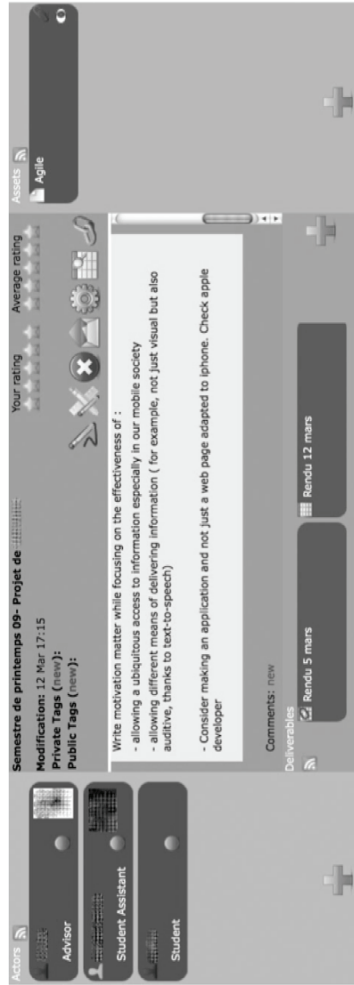


Figure 5: A section of the context-sensitive view (context is an activity space)

*Names and figures are blurred for privacy reasons*

### 3.2.2 Embedded Awareness cues

Awareness cues of different types are seamlessly incorporated in the *eLogbook* context-sensitive interface. Table 2 lists some of those cues, describes how they are displayed and relates them to one ore more awareness types defined in the literature and summarized in the previous chapter. Awareness display means involving colors and symbolic icons are complemented by explanatory texts appearing on mouse over.

TABLE 2: EXAMPLES OF AWARENESS CUES

| Awareness Cues | Display | Awareness Types |
|---|---|---|
| User statuses | When the user is online, the "status" icon turns green. | Presence awareness |
| Reminder of deliverables deadlines | Deliverables with close deadlines are listed first and highlighted in red. Those with future deadlines appear next. Already submitted ones appear last in grey. | Task awareness |
| Rights over assets | Use of Icons: An "editor" is indicated with a pen. An "owner" is indicated with a crown. A "reader" is indicated with an eye. | Historical awareness |
| A space invitation's response | The role button changes its color depending on whether the invitation is still pending, was refused or accepted. | Group-structural, Workspace awareness |
| Activity Space Roles | The role appears under the actor's name. The role'are listed using different icons. | Group-structural, Task awareness |
| Average rating per entity | Displayed below the central item's name using stars. | Workspace awareness |
| Tag list per entity | Display size is proportional to tag usage frequency. | Workspace awareness |

## 3.3 Application and evaluation of *eLogbook* in a formal learning environment

*eLogbook* was used for two consecutive years in the context of a laboratory course given at EPFL and evaluated following the technology acceptance model (TAM). According to TAM, the perceived usefulness and ease-of-use of a particular technology decide how users will accept and use it. Davis defines a technology's perceived usefulness as "the degree to which a person believes that using a particular system would enhance his or her job performance", and perceived ease-of-use as the degree to which a person believes that using a particular system would be free from effort" (Davis, 1989). Usability is used to denote the *ease* with which people can use a technology in order to reach a certain goal.

This section describes the formal learning environment in which *eLogbook* was applied. The section also discusses results related to:

- The usage, usability, and usefulness of *elogbook* as a PLE platform aggregating 3A entities involved in the formal learning environment;
- The usage, usability, and usefulness of *elogbook* as a PLE platform supporting interactions, discussions, content sharing, and content management, with a focus on the usage and usefulness of its *SALT* features.

### 3.3.1 Application Context

In 2008 and 2009, undergraduate students enrolled at EPFL were invited to use *eLogbook* for one semester, in the context of an automatic control laboratory course. The course, itself, is a hands-on practical course that aims at studying

experimentally the behavior of dynamical systems. It is organized in 3 different modules to be carried within a total of 14 hours. The work is carried out collaboratively in self-selected groups of 2 to 4 students. Collaborative work increases the sense of responsibility and motivates students to actively participate in the learning experience (Tinto, 2000). In order to perform the planned experiments, students are supposed to connect through an applet to remote machines, as shown in Figure 6. They also have available a tool called *SysQuake Remote* for analyzing the saved measurements in the time and frequency and domains. Each group is expected to hand in a report at the end of the semester, and every student should pass an oral examination.
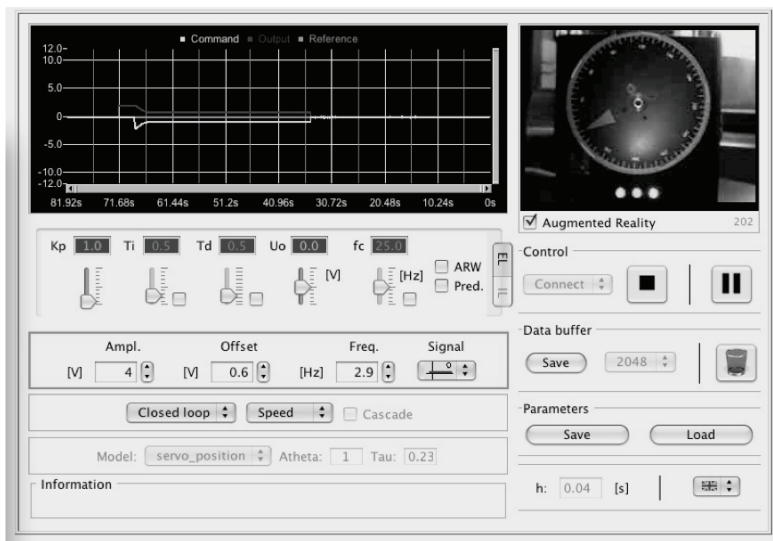


Figure 6: Remote experimentation with a servo-motor.

The number of students who took the course during the spring 2008 semester was 90. Since *eLogbook* was used for the

first time within the course, only the 20 mechanical engineering students taking the course were selected for its first evaluation. Students involved in the study were not forced to use *eLogbook* during the laboratory course; they could still share files, communicate with each other, and connect to the applet or to *SysQuake Remote* without relying on *eLogbook*.

### 3.3.2    Role of eLogbook

*eLogbook* can be considered as a central platform aggregating course activities, actors (including human actors, remote machines and visualization tools), and assets. In addition to centralizing access to the course resources, *eLogbook* offers bottom-up content management facilities allowing to store, share, manage and interact with different types of assets (i.e. online course material, measurements, snapshots, discussion archives) through rating, commenting, linking, and tagging them. It also allows representing and structuring the short-term course community. This is achieved by creating a main activity space that contains a description of the course objectives and gathers students, assistants, and tutors, and to creating activity spaces that are dedicated for teamwork and controlled by the students.

From the 3A interaction model perspective, the learners that are working together, along with the teaching assistants are all involved in a mother activity aimed at achieving the course's learning goals. Following this, an activity space called "TP" ("Travaux Pratiques" which translates in English to "Practical Sessions") dedicated for this mother activity is created in *eLogbook*, with the roles "student", "teaching assistant", and "technical support" distributed among its members. Figure 7 displays the main activity space labeled "TP" to which all

students, tutors, and teaching assistants were invited. A description of the "TP" was added to the space wiki, and useful documentations such as an introduction to *SysQuake Remote* were also posted as assets in the space. The description and the tasks related to each of the 3 courses modules were also made available. Subspaces of the main "TP" space were created to allow the different student groups to conduct their intra-group activities; they could access the remote machines assigned to them to run experiments together, save, share, annotate and discuss measurements, in addition to collaboratively writing the final group report. A teaching assistant was assigned to every group. Based on the 3A model's definition of actors, the applets allowing each group to connect to its assigned machines and conduct remote experiments were considered as actors, and were made available in the group's activity space. In an attempt to centralize the access to the different resources, assets that consisted of MATLAB files could be open with the *SysQuake Remote* tool directly from *eLogbook*.

The introductory session was divided into two parts: during the first part, the tutor explained how to connect to remote machines using an applet, and during the second part, a teaching assistant presented *eLogbook* very briefly focusing mainly on how it connects to the applet and how it could be used in the context of the course. A short screencast on how to use *eLogbook* to connect to the applet, save screenshots, and share them with other students was made available. It is worth noting that the screencast does not detail all the possible features that could be used in *eLogbook* such as searching, tagging, rating and linking assets and activity spaces.

Figure 7: Section of the TP activity space dedicated for the course

## 3.4 Evaluation and Discussion of *eLogbook's* Adoption in 2008

The results of the usability study related to the adoption of *eLogbook* are discussed in (El Helou, Salzmann, Gillet, & Yu, 2009). The study involved questions related to the usability of *eLogbook*'s context-sensitive interface. It also addressed questions related to the usefulness and usability of *eLogbook* as a PLE allowing tutors to easily represent the course structure, and offering students a centralized access to all 3A entities involved in the course along with the possibility to manage their own collaborative learning spaces as well as produce, share, and annotate online content using social media features. The evaluation methods included a survey consisting mostly of 7-point preference scale questions (with 18 respondents in 2008 and 81 in 2009), interviews conducted with 7 students, along with an analysis of students' logged actions throughout the semester. This section focuses on findings related to the usage of *eLogbook* as a PLE used by students to access aggregated 3A entities involved in the formal learning

environment, conduct discussions, manage their collaborative spaces, as well as produce, share, and interact with content using the available *SALT* features.

### 3.4.1   *Usage of eLogbook as a PLE aggregating 3A entities*

All but one student to whom *eLogbook* was introduced had activated their account. Moreover, 68.4% of them used *eLogbook* between 3 and 21 days during the semester. This suggests that *eLogbook* usage was not confined to the 3 face-to-face module sessions. Figure 8 shows the number of students connected to *eLogbook* during semester days. The straight line corresponds to the oral exam date while the three circles correspond to the 3 regular module days. The resulting graph shows usage peaks corresponding to the days during which the 3 modules were scheduled. An increase in the number of connections during the pre-exam period can also be observed. This highlights the actual usage of *eLogbook* as a PLE centralizing access to the course resources.
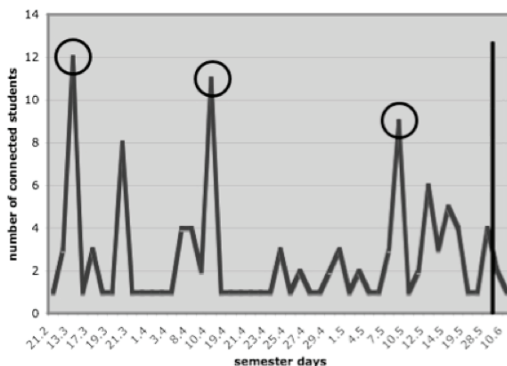


Figure 8: Students' daily connections

The maximum number of students connected, even during peak days was no more than 12 out of 20. Knowing that students usually work in pairs during the laboratory hours and run experiments from the same PC, this number is indeed satisfactory. With this in mind and to better evaluate *eLogbook*'s stickiness factor throughout the semester, its usage within groups is examined. A student group is considered to have used *eLogbook* for completing a particular module if at least one of its members was connected to *eLogbook* on one of the days scheduled for that module. The result was that, except for one group who did not use *eLogbook* during the third module, all groups used it to fulfill tasks related to the three modules. In 55% of the cases, no more than 50% of group members were simultaneously connected to *eLogbook*, which confirms the tendency to work in pairs on the same PC.

Some kind of group **"contagion effects"** was underlined. *eLogbook*'s usage frequency was consistent among members of the same group. The student decision of adopting the platform is influenced and dependent upon his or her group's satisfaction with it. If at least one group member is comfortable using the tool, he or she will drive his or her group towards using the tool, and other members will catch up with him or her. Inversely, a member having had an unpleasant experience with the tool can confer his or her dissatisfaction to other members of his or her group, and this will negatively affect the tool's adoption by the group. To illustrate, the only group that did not use *eLogbook* during the last module consisted of two members who did not use it more than two times over the semester. Inversely, each student of the most active group in *eLogbook* used it on more than 8 days throughout the semester.

To sum up, usage statistics show that *eLogbook* was indeed used throughout the course as a central point of access to the

applet and visualization tools, the modules' description as well as the teams' workspace. Still, it is important to find out why *eLogbook* was not convincing enough for the 6 students who did activate their account but used *eLogbook* only once or twice thereafter and why one group abandoned the usage of *eLogbook* during the third module. Evaluating the usage of *eLogbook* for content management and sharing helped identifying some usability problems.

### 3.4.2 Usefulness and Usability of eLogbook as a Content Management Platform offering SALT Features

During a remote experimentation, students save, share, visualize, and analyze measurements. They also adjust related parameters. This is a prerequisite for understanding the material, preparing the report and getting ready for the oral defense. The applet offers several options for saving measurements; students could choose to send them by email, or download them to the local disk or save them in *eLogbook*. This section reports the findings related to the role of *eLogbook* as **a central content management platform** and sheds light on the perceived usefulness and ease-of-use of its asset production, sharing, management, and classification features.

According to the results summarized in Table 4, 80% of the students who answered the questionnaire have created and saved files using *eLogbook*. The logged data reveals that a total of 177 assets were created, with an average of 12.6 assets per student and a standard deviation of 9.6. This means that approximately 66% of the students created between *3* (12.6-9.6) and 22.2 (12.6+9.6) assets. This high standard deviation can be explained by the fact, as it was mentioned earlier, that students worked most of the time in pairs using a single PC and a single *eLogbook* account. Assets were produced

collaboratively from a single student account and then shared with others. 71.2 % of the assets were produced in the applet, and shared in *eLogbook*. The remaining 28.8% consisted of snapshots taken with *SysQuake Remote*, in addition to module summaries and reports created in *eLogbook*.

Figure 9 shows an example of an asset posted in a collaborative activity space.

Only 42% of the created assets were shared with other group members. Most likely, measurements were subject to a selection process and only the best ones were shared at the end of the session. Using the easy collaborative authoring feature (wiki associated with each asset), students could add discussions and comments related to their experiments while preparing for the final report. For instance, Figure 10 shows an asset belonging to the C3 group with its measurements attached and its description added in the asset wiki.



Figure 9: A snapshot of an asset produced in module 2
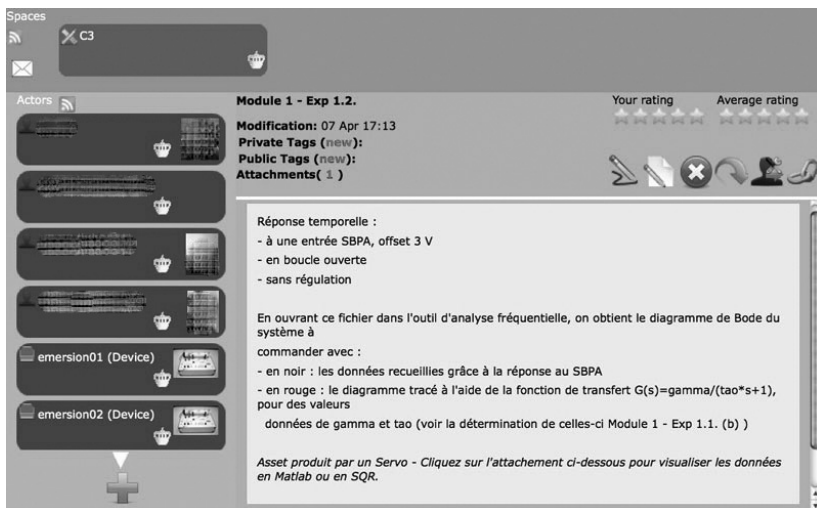
Figure 10: An asset posted in the collaborative space of group C3

Table 3 summarizes the **sharing policies** adopted by the students. In the table, groups are sorted in increasing order according to their group size. The different stripes, from the darkest to the lightest, correspond to the percentage of assets posted in a group, shared with group members having a particular role, sent to group members individually, made public, and posted in a subspace of the group space respectively. Regardless of the group size, the most frequently used sharing method was posting it inside the group space or subspaces. Interestingly, the C1 group used a sharing option, which was not introduced to the students: sharing assets within a group, but on a role-dependent basis. In their case, assets were only shared among "students"; teaching assistants were not granted an access right over the assets in question.
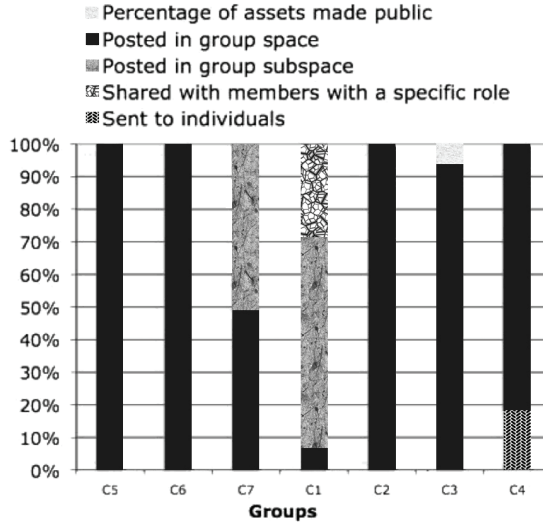
With respect to **asset management and classification features**, half of the students gave a negative response to the question of whether they quickly found what they were looking for. During the interview, students were asked whether they often scrolled down the list to find assets; they all answered positively and said that it was not easy to find their assets in *eLogbook*. This clearly indicates that the main difficulty was in organizing and finding assets. *eLogbook* did offer an option to search by keyword; for every search query, names, description and tags would be checked to find a keyword match. Nonetheless, the questionnaire, interviews, and analyzed logs, all confirm that not a single student used the search button available in the context-sensitive view. As a matter of fact, the 7 interviewed students did not even notice that a search button existed. *eLogbook* did offer annotation and classification features. For instance, it was possible to classify assets in a

bottom-up approach by simply tagging them. Even though this feature was not shown in the video, tags were listed right under the name of the center element. In addition, assets produced from the applet, were all automatically tagged as "measurement" or "parameter" files in order to highlight the *eLogbook* tagging feature, and allow students to differentiate between measurements and other types of assets. Nevertheless, according to the questionnaire results, only 41.17% mentioned that they had annotated their assets using *eLogbook*. The examination of the logged data shows that annotation was often limited to leaving some comments and description in the asset wikis; no tags and very few ratings were observed. When interviewed students were asked why they did not use tags, three answered that they do not really know what a "tag" is and how it could be used. After interviewers explained what a tag stands for and how it could be used, students stated that had they known this earlier, they would have definitely relied on it especially that they had a real problem in classifying and finding their assets. The remaining students answered that they were acquainted with other traditional top-down approaches such as creating folders and posting assets inside them. But even though, there was a possibility to create a subspace for that purpose, only two groups adopted this approach. In fact, it was not intuitive for the remaining students, to make the connection between the notion of a space for grouping assets and the concept of "folder". Since the bottom-up tagging approach was not common and the top-down approach not intuitive, students came up with an alternative: they named their assets in very specific ways and then scrolled down the long list to find them. In Group C3 for instance, assets were named as follows: "Module 1 - Exp 1.1. (a), Module 3 - exp 1.2.(a), [Old] Module 2 - Exp 2.2.1., [New] Module 2 - Exp

2.2.1". 5 out of the 7 observed groups adopted group-specific naming conventions.

### 3.4.3  Usability and Usefulness of eLogbook as a Discussion Platform

According to logged data, *eLogbook* was mainly used as a shared repository of assets, but not as a means for communication outside laboratory hours. Apart from two students who left comments for each other within the *eLogbook* space, all the remaining students relied on email or a combination of email and voice in order to communicate with each other and with the teaching assistants. In subsequent *eLogbook* releases, a contextual chat feature that allows archiving discussions as assets and "*salting*" them was integrated in order to encourage and centralize students' discussions enhancing by that personal and collaborative learning.

## 3.5  Evaluation and Discussion of *eLogbook's* Adoption in 2009

Prior to its usage in the spring semester 2009, *eLogbook* was subject to few improvements based on the evaluation results of the previous year. Three measures were taken to help overcome the asset management and classification problems reported by students in 2008. First, the position and design of the search button were changed. Second, the usefulness of the tagging features in classifying assets was emphasized during the introductory session. Third, the notion of "folder" and "space" to group assets was explicitly stated.

Regarding the evaluation method, no interviews were conducted but the students filled the same questionnaire as the

previous year, at the end of the semester with two questions added, one regarding the usage of the new discussion feature and one regarding the perceived usefulness of the search feature by students who had used it.

A total of 128 students were registered for the course. This time, the evaluation involved all the students. They were distributed into 46 groups having each a corresponding group space in *eLogbook*. 93.6% activated their account and were distributed into 45 groups.

### 3.5.1   Usage of eLogbook as a PLE aggregating 3A entities

Compared to the previous year, the percentage of students who used *eLogbook* between 3 and 21 days during the semester increased from 68.4% to 90%. In addition, apart from one group whose members did not even activate their account, all other groups used *eLogbook* to complete the three modules. According to the questionnaire, 18.75% of students were neutral and 33.3% agreed with the statement that the direct access to the modules, the applets and other tools from *eLogbook* was helpful. A technical problem that considerably slowed down the connection to *eLogbook* especially in the beginning of the semester is believed to have affected *eLogbook*'s acceptance.

The second evaluation of *eLogbook* helped verify the "**contagion effects**". Again in 2009, only one group did not use *eLogbook* during the modules and indeed none of its members actually activated their accounts. In all the other groups, all the members have activated their accounts, and in 64% of the groups, all members were connected more than 3 times to *eLogbook*. This shows that the attitude of a group member vis à vis a tool influences other member's behavior and decision to use the tool.

### 3.5.2 Usefulness and Usability of eLogbook as a Content Management Platform offering SALT Features

A considerable improvement in *eLogbook*'s acceptability and usage as a data repository can be concluded from the examination of logged data and related questionnaire answers. Table 2 compares questionnaire results related to the usage and usefulness of *eLogbook* for content management.

TABLE 4: COMPARING QUESTIONNAIRE RESULTS IN 2008 AND 2009

| Questions | Answers in 2008 | Answers in 2009 |
|---|---|---|
| Did you share files with other people using *eLogbook*? | Yes: 64.7% | Yes: 64.6% |
| Have you used *eLogbook* to annotate your files (by tagging, rating, and editing the wiki)? | Yes: 41.2% | Yes: 65.8% |
| Have you used the "search" button? | Yes: 0% | Yes: 40.74% |
| If yes replied positively to the previous question, was it useful? ( questions added in 2009) | NA | Yes: 72.72% |

A total of 1267 assets were created by 70.9% of the students, and 85% of them consisted of measurements and snapshots sent from the applet. As illustrated in Figure 11, bigger groups created on average more assets than smaller groups. In Figure 11, groups are ordered by increasing group size and number of created assets. Averages corresponding to the 3 different groups categories are drawn with horizontal dotted lines. The number of assets created in groups of size 2 ranged between 4 and 41 assets with an average of 22.15, in groups of size 3 it ranged between 16 and 42 with an average of 29, while in groups of size 4 it ranged between 24 and 81 with an average of 40.6.
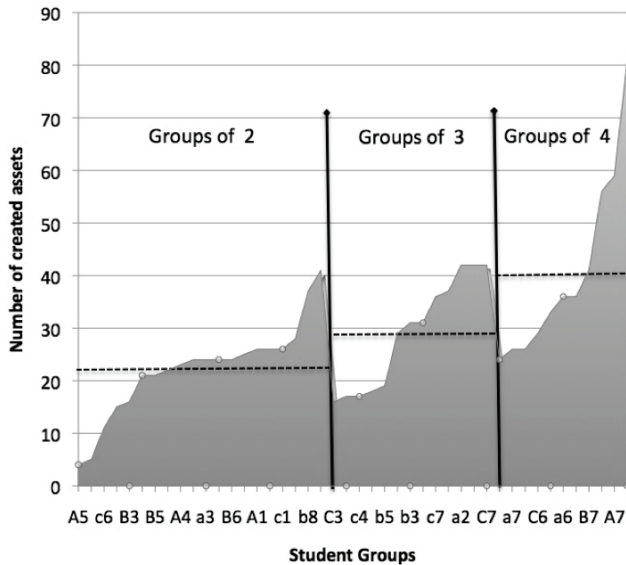
Figure 11: Total number of assets created per group

As far as **asset management** is concerned and unlike the first year, students did rely on tagging and comments to describe and differentiate their measurements. According to the questionnaire, 64.63% of the students found the *eLogbook* annotation scheme useful (tagging, commenting, and rating). Based on logged data, a total of 204 tags were created and used 522 times. On average each tag was used 2.56 times with a standard deviation of 6.02. Only 5 tags were reused more than 15 times across different groups. (e.g.: module1, module2, tp1). Within groups, students sometimes tagged their measurements with the name of the person who took it; this partially explains why very little tag sharing took place across groups. As an illustration, Figure 12 consists of a tag cloud where the tag size is proportional to its usage frequency by the students.
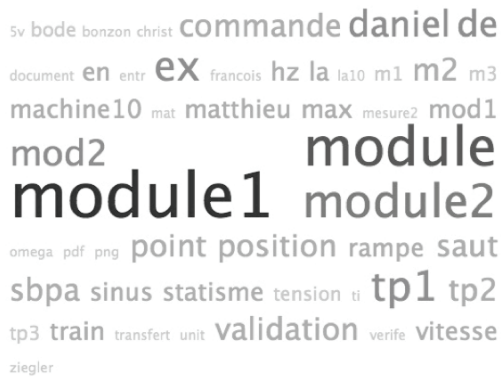
Figure 12: Tag Cloud

As far as other *SALT* features are concerned, 33.33% of the groups used comments and 17.78% of them rated their assets. This is not surprising, as rating in the context of the automatic control laboratory course has no true added value apart from potentially serving to distinguish between good and bad measurements. As students most often erase their bad measurements, it was not really common to use rating for that purpose. Finally, an important improvement with respect to the previous year is connected with the use of the search feature. According to the questionnaire, 40.7% of the students used it and among them 72.72% found it useful.

### 3.5.3 Usability and Usefulness of eLogbook as a Discussion Platform

With respect to the usage of *eLogbook* as a discussion platform, the public chat room accessible to all students taking the course was not used at all. One the other hand, examining logged data reveals that 66.67% of the students used private chat spaces during lab hours. Nonetheless, most chat messages were sent during the first session when students were discovering

*eLogbook* and much less frequently during the semester. Several messages were not directly related to the course (e.g. "is this really a chat?"). A few were destined to the teaching assistants in order to schedule appointments with them. The fact that the latter did not respond via *eLogbook* is believed to be one of the factors that lead the students to opt for another communication mean to reach them. On the other hand, according to the questionnaire results, 28.39% of the students used email to discuss laboratory work with their group members outside laboratory hours, 32.1% communicated with one another mainly face-to-face, while only 3.7% used *Skype* or *MSN* and 1.2% used *eLogbook* for that purpose. The remaining students relied on a combination of the different communication means.

It is hypothesized that embedding a user-friendly chat in a PLE facilitates students' discussions and encourages them to address questions to one another or to the tutor. In addition, being able to use a contextual conversational tool, available from the same environment used for sharing learning material and assigned tasks, helps trigger and capitalize discussions in context. As learners are more used to their proper environments, it might be useful to incorporate existing tools (*Skype, MSN*) but this carries with it a bigger risk of distraction. The context is which the usability study discussed in this chapter was conducted does not actually help in verifying this hypothesis. In fact, the course is only limited to the 3 modules that span over a relatively short period of time, and do not necessitate sufficient collaborative work and discussions outside its regular 14 hours to be able to test the usefulness of a PLE-embedded contextual chat feature.

## 3.6 An Imaginary PhD Journey through a PLE Platform Based on the 3A Model

This section aims at presenting how *Graaasp*[35], another PLE based on the 3A interaction model can support interaction and learning in a less structured and more autonomous context than a single short-term academic course. For that, a scenario is presented showing how *Graaasp* can help a PhD student organize his or her learning spaces as well as discover and interact with actors, collaborative activity spaces, and assets relevant to his or her research interests triggering by that learning opportunities.

Compared to *eLogbook*, *Graaasp* offers an improved contextual navigation and makes user-generated actions easier to find and execute. For instance, creating links between entities, posting an asset in a space, or inviting an actor to join it can be done via a simple drag and drop action. *Graaasp* also puts more emphasis on the non-human 3A actor, bringing together widgets and services from other online platforms (Bogdanov, El Helou, Gillet, Salzmann, & Sire, 2010).

A use-case scenario is presented hereafter in order to illustrate the potential role of *Graaasp* in sustaining interaction and learning for PhD candidates in TEL (Technology-Enhanced Learning) (Gillet, El Helou, Joubert, & Sutherland, 2009). The scenario involves an imaginary person, namely Peter, who has just started his PhD in the TEL field. Peter is invited by his colleagues to register in *Graaasp*. Just like social media applications, *Graaasp* has a low entry barrier; registration only requires a valid email and a password. With time, Peter's profile will gradually be completed. Having liked the platform's context-sensitive and interactive interface as

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[35] http://graaasp.epfl.ch

well as its different social media features, Peter invites his PhD advisor to discover it.

Peter types in the search field keywords describing his research interests: "trust and reputation in social media". In response to Peter's quest, the system proposes a list of relevant actors, activity spaces, and assets. For instance, *Graaasp* proposes a *LinkedIn* group activity space entitled "Social Media". Peter decides to join it. Subsequently, *Graaasp* uses the *LinkedIn*'s application programming interface (API) to send Web services request on behalf of Peter. Furthermore, the system returns relevant documents plus discussions threads saved and annotated in *Graaasp*, embedded YouTube videos involving conference talks on trust and reputation in social media, in addition to external papers from the IEEE and ACM digital libraries or the STELLAR open archive[36]. Last but not least, *Graaasp* also recommends a list of actors that are keen on the requested topic, ordered by relevancy and reputation. The list includes PhD candidates and senior researchers working on topics relevant to Peter's quest, having written relevant papers and/or participated in relevant group activities. When the recommended actor is logged in to *Graaasp*, the system shows presence awareness in order to encourage social interactions. Moreover, Peter is also asked whether he wishes to be notified of any new activity spaces and assets relevant to "Trust and Reputation in Social Media". Peter responds in the affirmative.

In the mean time, a professor creates a public activity space called "Privacy and trust in the realm of Web 2.0". Peter is notified of space's creation, and decides to become a member. He takes the role "PhD candidate". His membership is

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[36] http://oa.stellarnet.eu/

announced to other members. A senior "PhD candidate" takes the initiative of opening a conversation with him giving him hints on how to start learning about the field as well as references to assets (i.e. discussions, papers, online course notes) and activity spaces that can best introduce him to the field. They also speak about the PhD process in general. Seeing that the discussion is interesting, Peter decides to save it as an asset, post it in the activity space and tag it with "tips for beginners", "TEL", "PhD in TEL". It will serve as a reference to him and other PhD candidates. Afterwards, Peter is notified of the creation of a sub-activity space within "Privacy and trust in the realm of Web 2.0" dedicated to a summer school. The latter's main topics and its application details are described in the space wiki. A plan for expected assets is created, specifying submission and evaluation deadlines. By a simple click, Peter downloads the submission deadline to his calendar. He intends to work hard to be able to develop his knowledge in the field, submit a position paper and eventually participate in the summer school.

After a discussion with Peter, his advisor decides to create an activity space to better follow-up Peter's progress and discuss his research work. They define for this activity a plan of expected assets. First, Peter is expected to read material related to TEL, raise and discuss the challenges that he thinks are important to consider and solve. These discussions are to be submitted as assets for the thesis advisor. Once the submission is done, the advisor is notified by the system. Subsequently, the advisor reviews and comments the submitted asset prior to a face-to-face meeting. After the meeting, Peter uploads a minutes of meeting report and links it to the asset that triggered the discussion.

Towards the end of his PhD, Peter types in the search field 'PhD dissertation'. Since actors do not only include humans but also agents and tools, *Graaasp* proposes AWSOME Dissertation[37], an online project that other users have registered as a tool and tagged with the keywords 'PhD dissertation'.

As Peter's profile is gradually completed, and as he uses the collaboration platform more frequently, the recommendations rendered by the system become more and more personalized. As a matter of fact, when the system suggests actors, activity space and assets to Peter depending on his working context, it draws on information about Peter's previous interactions to discover his interests and preferred networks.

Figure 13 consists of a mock up of the *Graaasp* interface, showing as current context an activity created by Peter and is entitled "Peter's PhD Research Follow up" (central left-hand side). The activity's aim is described in the space wiki followed by comments. The contextual 3A entity can be selected from the *Favorites* or the *Clipboard* area by clicking on the corresponding rectangle. It can also be chosen from the results of a search query and from related entities. Once an entity is selected as current context, related entities explicitly associated with it are automatically displayed in three dedicated columns (central right-hand side). The current context can then be changed to one of the displayed related entities. Hence, *Graaasp* can be seen as a contextual browser showing in a single screen all the relevant information aggregated by the user in the current context. New relations can be created by dragging and dropping entities or by clicking on the relevant grey rectangles. In addition to displaying explicitly related entities, recommendations of external ones can be provided

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[37] http://awesome.leeds.ac.uk

taking into account their potential relations with the current context and their relative importance (bottom left-hand side). By clicking on any rectangle, the user automatically triggers a change in context and an update of related interface components.



Figure 13: Recent mockup of the *Graaasp* interface

## 3.7   Related Literature Review

As it is mentioned earlier, "e-Learning 2.0" refer to the application of social software in education (Downes, 2005). It accounts for a shift from traditional LMS mediums used to store course material and conduct mandatory discussions, to lifelong learning platforms where different knowledge resources such as course material, blogs, podcasts, and archives of unplanned discussions are aggregated, shared and

augmented in a bottom-up approach for future exploitation. Despite the promising role of applying social media in education (Liccardi, et al., 2007; Page & Ali, 2009; Solomon & Schrum, 2007), e-Learning 2.0 is still in its early phases and has not yet gained in popularity. A previous study shows that the most popular medium adopted in formal learning contexts for distant communication is still the email, and that wikis and blogs are not yet widely used (Anderson T. , 2006). Another study (Wever, Mechant, Veevaete, & Hauttekeete, 2007) on the role of social software in education reveals that students often use social software for sharing media files with their friends, but rarely for educational purposes. The authors of this study argue that for social software to be adopted in education, new learning models and fine-tuned tools with clear added values are needed. A recent study that explored the usage of social bookmarking in education, states that only 3 of the 59 subjects involved in the study knew about social bookmarking prior to the course (Farwell & Waters, 2010). Nevertheless, authors report that once exposed to social bookmarking, people involved in the study preferred it over CMS, mainly because of the ease of the technology, the variety of online up-to-date material and the possibility to see their overall rating.

## 3.8 Conclusion

This chapter demonstrated the applicability of the 3A interaction model for developing online platforms supporting formal and informal learning. Two platforms based on the 3A interaction model, namely *eLogbook* and *Graaasp*, were presented. The application of *eLogbook* in a formal learning environment is discussed. A use-case scenario showing how *Graaasp*, which offers an improved contextual interface

compared to *eLogbook*, can support less structured and more self-directed learning contexts is also presented.

The formal learning context in which *eLogbook* was applied consisted of a laboratory course in higher education. *eLogbook* served as an aggregator bringing actors (e.g. students, teaching assistants, tutors, measurement tools, experimentation devices), learning activities, and shared assets (measurements, documentations, reports) together. It provided flexible activity management services giving students a sense of control and responsibility over their own activity spaces. Additionally, it offered social media features that facilitate content management and encourage contributions and interactions. Usability studies were conducted in order to assess the usage, usability and usefulness of *eLogbook* in this formal learning environment and examine the role of social media in education. The first study involved a small sample of students who took the course in spring 2008, while the second one involved the 120 students who took in spring 2009. In the two cases, quantitative and qualitative evaluation methods were combined together in order to assess *eLogbook*'s usability and usefulness in a formal learning context where it served as a personal and collaborative learning platform aggregating 3A entities and offering content management features. Unfortunately, interface usability problems, namely the difficulty in organizing and finding assets during the first year, and the slow server responsiveness during the second year, are believed to have negatively affected the students' experience with *eLogbook*.

The application of *eLogbook* in a formal learning environment suggests that it might be essential to explain to target groups how social media features such as tagging or social bookmarking can be used in the context of their work. Such explanations would then increase the chances of

employing *SALT* features and hopefully benefit from them in professional and academic environments where people are not yet used to relying on them.

The two studies discussed in this chapter were conducted in the context of a course that only consists of 3 hands-on modules to be completed in only 14 hours. Despite the fact that the course involves collaborative work, it does not trigger considerable discussions and reflections nor does it necessitate significant personal and collaborative engagement outside the modules. Further longitudinal and comparative studies involving other formal learning contexts need to be conducted. When feasible, studies should involve courses that span over a longer period and require students to be actively engaged in personal and collaborative learning by seeking, collecting, sharing and interacting with potential learning assets. This will complement the findings discussed in this chapter, validate the usefulness of 3A model-based PLEs in supporting personal and collaborative learning in formal contexts, and assess the role of social media in education. Finally, another interesting challenge is designing online experiments that aim at studying the impact of 3A model-based PLEs on non-formal and informal learning.

*"We have built our education system on the model of fast food, where everything is standardized."*

*Sir Ken Robinson*

# Chapter 4
## *The 3A Personalized, Contextual and Relation-Based Recommender System*

## 4.1  Introduction

We live in an age of information abundance best described as the "Information Overload Age" (Ram, 2001). It is an age distinguished by a fast-changing knowledge society (Burch, 2005; Hargreaves, 2003), and fraught with information thanks to the rapidly evolving technological advances, the Internet revolution, as well as the exponentially popular social media that particularly facilitated the production, distribution and consumption of digital content. Today, more than anytime before, the society is challenged to constantly and actively acquire knowledge in order to stay up-to-date. Moreover, it is confronted with adverse information overload effects such as stress, anxiety, and reduced work efficiency at a personal as well as an organizational level (Heylighen, 1999; Wilson T. ,

2001). Personalized recommender systems are instrumental in overcoming the problem of information overload as they help online users find relatively interesting information, services and products (Good, et al., 1999; Im & Hars, 2007; Mulvenna, Anand, & Büchner, 2000). In PLEs supporting formal and informal learning, recommender systems play a particularly important role. As a matter of fact, they can filter information according to "soft" and significant context boundaries (Wilson , Liber, Johnson, Beauvoir, & Sharples, 2007) avoiding by that the learner gets saturated in an open environment where shared content that differ in quality, target audience, size, as well as subject can be added, annotated and repurposed at any time, and most importantly help in finding appropriate knowledge artifacts and learning activities depending on learner interests (Drachsler, Hummel, & Koper, 2008; Koper & Tattersall, 2004; Tang & McCalla, 2009).

This chapter discusses the **3A personalized, contextual and relation-based recommender system** that is built on top the 3A interaction model and can be embedded in an online PLE to simultaneously recommend actors, activities and assets (El Helou, Gillet, Salzmann, & Sire, 2009). The proposed system serves two purposes. First, it can recommend an ordering of existing entities in a workspace according to their predicted importance to the target user and his or her context, thus increasing the working efficiency. Second, it can recommend new actors, activities and knowledge assets depending on the target user's interest, hence triggering new collaboration and learning opportunities.

To unobtrusively pursue these two aims, the proposed recommender system relies on significant 3A inter-relations. These inter-relations result from previous *CRUD* and *SALT* actions that involve actors, activities, as well as assets. Such

relations incorporate shared evaluation metadata consisting of user-generated ratings, bookmarks, tags and reviews and recognized as particularly useful for recommender systems (Vuorikari & Berendt, 2009). The 3A ranking algorithm that takes its roots from the original pagerank algorithm exploits the 3A inter-relations in order to rank 3A entities according to their popularity in the neighborhood of the target actor and his or her context.

The rest of the chapter is organized as follows. Section 4.2 discusses the recommendation approach. Section 4.3 presents the original pagerank algorithm and describes how it is modified to achieve personalized, contextual and multi-relational ranking. Section 4.4 illustrates the algorithm using reduced-scale cases. Section 4.5 consists of a literature review. Section 4.6 concludes the chapter with a summary and a discussion of the proposed recommender system.

## 4.2   Recommendation Approach

The objective is to develop a ranking algorithm able to order the 3A entities (i.e. actors, activity spaces, and assets) according to their importance to a target actor and his or her specific context. In order to leverage the entities' relative importance, the proposed approach relies on the target user's established relations and past actions. This is motivated by two main reasons. First, studies have shown that when it comes to assessing and filtering the information at hand, people are highly influenced by their trusted networks of friends and colleagues (Geyer, Dugan, Millen, Muller, & Freyne, 2008). Second, early studies have revealed that people are not always ready to explicitly express their preferences and priorities. As a matter of fact, people perceive such actions as being extrinsic to their work and requiring extra effort (Grudin, 1988). Thus, in

order to leverage the relative importance of actors, activities and assets, the system relies on implicit indicators embedded in the target actor's past interactions with the collaborative environment.

The relation-based approach adopted to achieve personalized and contextualized ranking by exploiting significant 3A inter-relations, consists of four main steps discussed hereafter: graph construction, context definition, importance computations and ranked lists extraction.

### 4.2.1   Graph Construction

The proposed recommender system models significant 3A inter-relations in a heterogeneous and multi-relational directed graph. The graph is formed taking as nodes the actors, activity spaces, and assets that the target user is allowed to access, and as edges the inter-relations between them. Intermediary entities such as roles and tags are also incorporated in the graph as nodes, depending on the relations considered and the level of granularity worth keeping track of. For instance, it might be significant to give different importance weights for space owners and regular members. For that, it is important to include "role" as an intermediary node between spaces and actors, instead of connecting an activity space directly to its members, losing in the graph the information related to their role.

Each bidirectional relation (such as "friendship" between two actors) is translated into two directed edges. Additionally, some initially unidirectional relations are complemented by another edge going in the opposite direction, in such a way that the two nodes involved in the relationship reinforce one another. For instance, transforming the initial one-way authorship relation between an asset and its author into two

directed edges in opposite directions has two benefits. On the one hand, the edge going from the author to his or her asset allows actors in the author's network to reach this asset through its author. On the other hand, the edge going in the opposite direction (i.e. from the asset to the authors) allows actors that fall on the asset in question, to reach its author and from there discover other potentially interesting assets also written by him or her. In the same way, if an actor frequently participates in a community's activity space, not only does this relation imply the actor's interest in the discussion space, but it also indicates his or her importance to the community. In other words, if one would like to know what's happening within the collaborative space, it is worth recommending this active participant to him or her.

### 4.2.2   Context Definition

Whether the 3A ranking algorithm is used for ordering entities already known to the target actor or recommending new ones, it is crucial to take his or her context into account. Context is "any information that can be used to characterize the situation of any entity", an entity being a person, place or object relevant to the user's interaction with the application (Dey, 2001).

Context can be measured by relying on implicit interest parameters consisting of users' activities and interactions combined with explicit parameters such as tags (Vuorikari & Berendt, 2009).

Based on the above definitions and on the 3A model's taxonomy, the context is represented at any point in time by a set of 3A main entities (i.e. actors, activity spaces or assets), in addition to intermediary ones (e.g. tags) directly involved in an action performed by the target actor. When an actor performs a search, all tags and entities having attributes (e.g. title,

description) that match the search keyword(s) are considered as contextual nodes. Alternatively, when the target user chooses a specific actor, activity space or asset to interact with, all directly related entities constitute the context. For instance, when the selected entity is an activity space, then its members, assets, roles, and directly related activities constitute its context. The algorithm is then expected to bias results towards the context, as it will be explained in section 4.3.3, in such a way that entities that have strong connections to contextual nodes get an important ranking. This will lead to suggesting new relevant entities to the target actor depending on the strength of their connection to contextual nodes.

### 4.2.3   Importance Computation

Once the graph is formed and the context defined, the ranking algorithm detailed in section 4.3 is applied on the graph. It is based on the following key idea of the original pagerank algorithm: *a node is important if and only if many other important nodes point to it*. With respect to the 3A recommender system, the idea can be extended and reformulated as follows:

**A node is relatively important to a particular set of nodes (representing the target user and the context) if and only if many important nodes connected to this root set, via important relation types, point to it.**

### 4.2.4   Ranked Lists Extraction

Separate lists of actors, activities, and assets are extracted whilst respecting their relative order in the original heterogeneous list. In addition, when the aim is to recommend

new entities rather than prioritizing those that are already in a target actor's workspace, entities that have a direct connection to him or her are skipped. These items are more likely to appear first in the recommendation list. Even though it is definitely not beneficial to include them in the recommendation list, they are needed during the ranking process to reach related nodes that the target actor is not aware of.

## 4.3  3A Ranking Algorithm

In this section, the original pagerank algorithm is presented. Then, the modifications required for achieving personalized, contextualized, and multi-relational ranking are described. Finally, the algorithm's convergence and the actual rank vector computation method are discussed.

### 4.3.1  Original Pagerank Algorithm

The 3A ranking algorithm described in this chapter is influenced by the original pagerank algorithm that was developed by Page and Brin for ranking hypertext documents for Google (Page, Brin, Motwani, & Winograd, 1998). The pagerank algorithm is based on the idea that if the owner of a page $j$ links to a page $i$, he/she is implicitly indicating that page $i$ is important. It follows that the more incoming links page $i$ has, the more it is considered as globally important because many pages are linking to it. In addition, if authors of "authoritative" pages link in their turn to other pages, then they also confer importance to the latter.

This idea is illustrated in Figure 14, which represents an imaginary link structure between pages belonging to different Web sites. "ECTEL" is the node that has the biggest number of incoming connections, which makes an authoritative page. In

its turn, it confers importance to "EATEL" and "PLE". "EATEL" scores best because an authoritative node ("ECTEL") points to it and in addition, it is linked to by Prolearn Academy which links back to it reinforcing each other's rank.
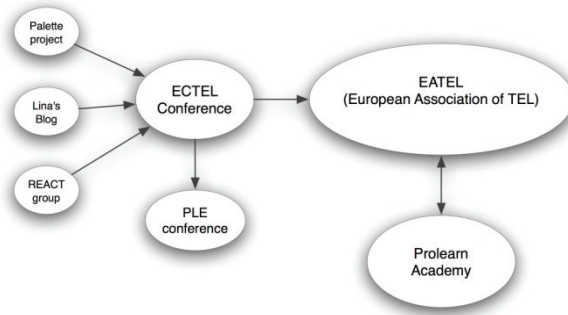


Figure 14: Illustration of the pagerank algorithm

The iterative probability equation that translates the algorithm's key idea is described hereafter.

A node's conferred importance is divided equally among all the other nodes it points to. Let N denote the total number of Web pages, OutDegree(j) the total number of outgoing links from a page (or node) j. A transition matrix $T(N \times N)$ is defined such that, each entry $T_{ij}$ is equal to $1/\text{Outdegree}(j)$ if $j$ points to $i$, and 0 otherwise.

Dangling pages are pages with no outgoing links such as "PLE" and "Prolearn" in Figure 14. These pages do not confer any importance to other nodes. To solve this issue, they are considered to link to all nodes in the graph with an equal probability. For that, a matrix $D(N \times N)$ is defined such that all entries are 0 except for the dangling columns where entries are equal $1/N$.

A random jump parameter $\lambda$ is introduced to avoid situations where nodes of a graph component form an importance "sink". This would have been the case for example, if ECTEL and EATEL were not connected in the graph above, leading to two disjoint graph components. $\lambda$ defines the probability of randomly falling on a page, and ensures that no page will have a zero rank and that every page is reachable from any other one. On the other hand, the damping factor $d$ represents the probability to follow page links instead of jumping on a random page. Given this, starting with an equal rank of $1/N$ to all nodes, the probability equation of landing on a node $i$ (or rank of a Web page $i$) at each iteration given the ranks of the previous iteration $k$, is given by:

$$p_i^{k+1} = \frac{\lambda}{N} + d\sum_{j=0}^{N}(T_{ij} + D_{ij})p_j^k \text{ with } \lambda, d > 0; \lambda + d = 1 \qquad Eq.1$$

Eq.1 can be understood as a Markov chain where states are pages and the transition between states depends on the link structure of the Web. It can be interpreted as the probability for a random surfer to land on a page or node $i$ starting at any node with an equal prior probability, following random links with a probability of $d$, and randomly jumping on a page with a probability of $\lambda$.

It is worth noting, that since the damping factor $d$ is less than 1, the further the nodes are from one another, the less influence they will have on each other's rank.

### 4.3.2   Multi-Relational Ranking

Unlike the graph of hypertext documents of the original pagerank algorithm, the social graph of the 3A model involves

heterogeneous nodes (i.e. actors, activity spaces, and assets) related by different types of edges that are not necessarily equally important. In such a multi-relational graph, when the surfer falls on a node, he or she can choose to follow different types of relations. For instance, if an actor is looking for an expert on a particular topic, he or she can search among his or her friends and "friends of friends" for actors whose profiles match his or her interest. He or she can also choose to traverse different activity spaces, choose one that is relevant to the topic, and from there reach actors who have actively contributed to the space and/or posted interesting resources. In the same way, given two papers that are equally relevant to a topic, an actor might prefer to first check the one that has been posted or given a top rating by a related actor, than the one that have been simply tagged by the same trusted actor. Clearly, the probability to fall on interesting nodes depends upon the probability that the adopted way (combined ways) will lead to them.

In order to take into account the existence of different link types with potentially different importance weights, the original algorithm is modified as follows. The complete multi-relational network is viewed as a combination of separate sub-networks each connecting nodes with one specific edge or relation type. Let $E$ denote the set of all types of edges. An inner transition matrix $T^e(N \times N)$ and a corresponding weight $w_e$ are defined for each edge type $e \in E$, where $w_e$ is interpreted as the probability for a target actor to follow links within the sub-network $e$, or in other words fall on nodes connected by relations of type $e$. Nodes that do not have outgoing links within a sub-network (locally dangling nodes) are considered as linking to all nodes in the sub-network with an equal probability. For that, a matrix $D^e(N \times N)$ is defined

for each type of relation $e$ such that all entries are 0 except for the dangling node columns where entries equal $1/N$. Then, the iterative stationary probability equation of landing on a node $i$, is given by:

$$p_i^{k+1} = \frac{\lambda}{N} + d\sum_{e \in E}\left( w_e \sum_{j=0}^{N} (T_{ij}^e + D_{ij}^e)p_j^k \right) \qquad Eq.2$$

$$\text{with } \sum_{e \in E} w_e = 1; \ \lambda, d > 0; \ \lambda + d = 1$$

The transition matrix $T^e$ is defined depending on the type of relation it corresponds to. When it comes to relations representing one-time events such as joining a space or relating two assets, $T^e$ is similar to the transition matrix of the original pagerank algorithm. Let OutDegree$_e(j)$ be defined as the number of edges of type $e$ outgoing from $j$, then the entry $T_{ij}^e$ between $i$ and $j$ can be written as:

$$T_{ij}^e = \left\{ \begin{array}{cc} \dfrac{1}{\text{Outdegree}_e(j)}, & \text{if } j \text{ points to } i \\ \\ 0, & \text{otherwise} \end{array} \right\}$$

Relations resulting from events that can be repeated over time such as updating an asset or accessing a workspace are treated in a slightly different way. Let $R_{ij}^e$ be defined as the number of events of type $e$ that have occurred between $i$ and $j$. Then, the probability to jump from $j$ to $i$ is equal to $R_{ij}^e$ normalized by the total number of outgoing relations of type $e$ with $j$ as source node.

$$T_{ij}^e = \begin{cases} \dfrac{R_{ij}^e}{\displaystyle\sum_{k \in N} R_{kj}^e}, & \text{if } j \text{ points to } i \\ 0, & \textit{otherwise} \end{cases}$$

The "rating" relation type is also handled differently. In this case, the probability to fall on an item $i$ rated by actor $j$ is equal to the corresponding rating value divided by the sum of all ratings issued by actor $j$ and having a value higher than his or her average rating value. In this way, poorly rated assets are not reachable from an actor. It is also useful to first normalize users' ratings by applying Gaussian or decoupling normalization (Manouselis & Costopoulou, 2008). Let $\bar{v}_j$ denote the average rating given by $j$ and $v_{ij}$ the rating value given by $j$ to $i$, then $T_{ij}^e$ can be written as:

$$T_{ij}^e = \begin{cases} \dfrac{v_{ij}}{\displaystyle\sum_{k \in N} v_{kj}}, & \text{if } v_{ij} \geq \bar{v}_j \\ 0, & \textit{otherwise} \end{cases}$$

Finally, in order to take into account the evolution of the graph over time, one can define significant time frames, and then group relations not only according to their nature or type but also according to the time frame during which they occurred, giving a higher relative weight to more recent ones.

### 4.3.3 Personalized and Contextual Ranking

(White & Smyth, 2003) show how pagerank could be extended to rank nodes according to their relative importance to a root

set of nodes. For that, the initial probability equation is changed in such a way that the random surfer starts at the root set with adequate prior probabilities, follows links with a probability of $d$, jumps to random nodes with a probability of $\lambda$, and goes back to the root set with a probability of $\beta$ (where it restarts again). This change results in a bias towards the root set and the nodes strongly connected with it (because of the iterative process). During their experiment, authors used a value of 0.3 for $\beta$ while acknowledging that the choice is inherently subjective and dependent upon the objective, nature and structure of the graphs considered.

Borrowing from their work, the 3A ranking algorithm can be contextual and personalized. In other words, ranking can be biased towards the target actor and his or her context. To do so, two parameters $\beta_c$ and $\beta_u$ are introduced. $\beta_c$ represents the probability to jump back to the contextual nodes and $\beta_u$ the probability to jump back to the target actor. Also, in order to speed up the algorithm's convergence to the stationary rank vector, the initial probability is set to 0 except for contextual nodes. Let $N'$ be the number of contextual nodes, then each of them receives an equal initial probability of $1/N'$. Also, let $R_c$ represent the set of contextual nodes and $p_c$ a variable equal to $1/N'$ for contextual nodes, and 0 otherwise. In addition, let $u$ denote the target actor's node and $p_u$ a variable defined such that it is 0 for all nodes except $u$. Then, the complete iterative stationary probability equation of landing on node $i$ is given by:

$$p_i^{k+1} = \frac{\lambda}{N} + \beta_u p_u + \beta_c p_c + d \sum_{e \in E} \left( w_e \sum_{j=0}^{N} (T_{ij}^e + D_{ij}^e) p_j^k \right) \qquad Eq.3$$

with $\sum_{e \in E} w_e = 1; \; \lambda, d, \beta_c, \beta_u > 0; \; \lambda + d + \beta_c + \beta_u = 1;$

$$p_c = \left\{ \begin{array}{ll} \frac{1}{N'}, & if \; i \in R_c \\ 0, & otherwise \end{array} \right\}; \; p_u = \left\{ \begin{array}{ll} 1, & if \; i = u \\ 0, & otherwise \end{array} \right\}$$

To make sure that no node that is highly connected to the user but irrelevant (or not enough relevant) to the context gets a high rank, $\beta_u$ should be made considerably smaller than $\beta_c / N'$. This ensures that nodes that are relevant to the context (i.e. contextual nodes and those strongly connected to them) achieve top ranks. Moreover, among these nodes, those strongly connected to the target actor and to nodes important to him or her achieve better ranking than others. For instance, if two assets, namely $a$ and $b$, are equally relevant to the context, but a target actor's colleague has already accessed $a$, then $a$ will receive a higher rank than $b$.

To summarize, Eq.3 can be interpreted as the probability to fall on a node in the graph, starting within a set of contextual nodes, following different types of links with a probability of $d$ (each with a probability of $w_e$), jumping to random nodes with a probability of $\lambda$, jumping back to the target actor with a probability of $\beta_u$, then going back to one of the contextual nodes with a probability of $\beta_c$ (and restarting again).

### 4.3.4 Rank Vector Existence, Uniqueness and Computation

This section explains how the rank vector whose components are the importance rankings of all graph nodes is obtained. Let

$C(N \times N)$ be a matrix such that all row elements are zero except those corresponding to contextual nodes where entries are equal to $1/N'$, and $U(N \times N)$ a matrix having all rows equal to 0, except the one corresponding to the target actor that is equal to 1. Also, let $1(N \times N)$ denote a matrix of 1s. Then, the complete matrix $M$ representing the random walk can be written as follows:

$$M = \frac{\lambda}{N}1 + d\sum_{e \in E} w_e(T^e + D^e) + \beta_u U + \beta_c C \qquad Eq.4$$

The rank vector $I$ containing the importance rank of each node $i$ can then be written as follows:

$$I^{k+1} = MI^k \qquad Eq.5$$

According to Eq.5, $I$ is an eigenvector of $M$ corresponding to the eigenvalue 1. To prove the existence and uniqueness of the rank vector $I$, important properties of the matrix $M$ are discussed hereafter. To start with, each column in $M$ sums to 1 and all entries are positive (in other words every node is reachable from every other ones, thanks to the random jump parameter), thus $M$ is stochastic, irreducible and primitive. As a result, and according to the Perron-Frobenius theorem, $M$ has one positive eigenvalue that is greater (in absolute value) than all other eigenvalues, and one positive eigenvector corresponding to it. Consequently, it is guaranteed that the matrix-free power method will converge to $I$, the unique leading eigenvector corresponding to the dominant eigenvalue and containing the importance rankings of all graph entities as it is the case for the original pagerank algorithm (Langville &

Meyer, 2003). Authors of the original pagerank algorithm report that with a value of *d* close to 0.85, only 50 to 100 iterations are enough to reach a good approximation of *I* for the Web graph involving billions of hyperlinks (Page, Brin, Motwani, & Winograd, 1998).

This chapter does not address issues related to space and time complexity or graph and rank update frequency. Still, a fully scalable future implementation can take advantage of reported experiments and proposed solutions related to scaling personalized pagerank (Fogaras, Rácz, Csalogány, & Sarlós, 2006; Haveliwala, Kamvar, & Jeh, 2003; Jeh & Widom, 2003).

## 4.4 Illustration Using Reduced-Scale Cases

### 4.4.1 *Illustration of Personalized and Contextual Ranking*

In this section, a reduced-scale case is used to illustrate and verify how ranking can be biased towards the target actor and his or her context. The corresponding simulated graph is displayed in Figure 15. The algorithm is computed four times under different conditions, in order to illustrate global, contextual, personalized, and personalized contextual ranking respectively:

- First, to illustrate **global ranking**, the algorithm is computed with **neither contextual nor target nodes**. Since no bias towards the target actor or the context is needed, $\beta_c$ and $\beta_u$ are set to 0. In this case, the algorithm will behave as the original pagerank algorithm ranking nodes based on their overall "popularity". The algorithm's parameter values are then set as follows: $d = 0.85$, $\lambda = 0.15$, $\beta_c = 0$, and $\beta_u = 0$. The resulting rankings are listed as follows, in decreasing order of importance: {1, (6, 7), 2, (3,5),

(8,9), 4}. As expected, the more incoming links from important nodes, a node has, the higher ranking it achieves. Even though the most "popular" node (node 1) links to (or "votes") for nodes 2, 3, and 5, nodes 6 and 7 rank better than the three of them. This is due to the fact that a node's conferred importance is normalized by the number outgoing links it has as discussed in section 4.3.1. For example, node 1 *divides* its conferred importance equally to nodes 2, 3 and 5. One factor that makes node 6 achieve the second best ranking is that it links to node 8 links which *exclusively* links back to it.
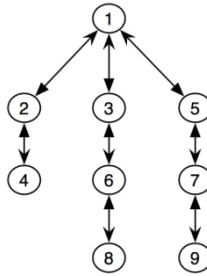


Figure 15: First simulated graph

- Second, to illustrate **contextual ranking,** nodes 1 and 4 are selected as contextual nodes. Their ranking is boosted at every iteration by $\beta_c / 2$. The algorithm's parameters that should sum to 1 are then chosen as follows: $d = 0.65$, $\lambda = 0.05$, $\beta_c = 0.3$, and $\beta_u = 0$. The node order becomes: {1, 4, 2, (3,5), (6,7), (8,9)}. Unlike the previous case node 2 now ranks better than nodes 6 and 7 because it is closer to the context.
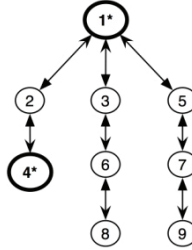
Figure 16: First simulated graph with contextual nodes

- Third, to illustrate **personalized ranking**, node 8 is set as the target node and boosted by $\beta_u = 0.3$ at every iteration as it was done for contextual ranking. The algorithm is rerun taking $d = 0.65$, $\lambda = 0.05$, $\beta_c = 0$, and $\beta_u = 0.3$. The node order becomes: {8, 6, 3, 1, 2, 5, 7, 4, 9}. Nodes are ranked not only according to their global "popularity" but also and more importantly according to their proximity with the target node. This is how node 3 for example ranks now higher than nodes 2, 7 and 5 because it is closer to the target node. Even though the same mechanism is used to achieve personalized and contextual ranking, each case is first illustrated individually to be able to compare later how results change when the algorithm is simultaneously contextualized and personalized.
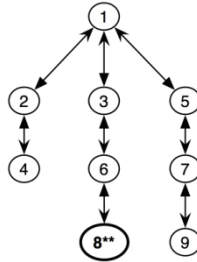
Figure 17: First simulated graph with a target node

- Finally, to illustrate how **personalized and
  contextualized** ranking is achieved, the algorithm is
  recomputed with both contextual and target nodes.
  More specifically, node 8 is chosen as the target node,
  and nodes 1 and 4 constitute the contextual set. To
  illustrate this, the following scenario can be imagined.
  Node 8 represents an actor looking for
  recommendations on a specific topic. Node 1 and 4
  refer to entities relevant to the topic, and therefore
  constitute together the search context. In this case, the
  aim is to rank elements according to the strength of
  their connection to the context giving better ranks to
  those among them that are closer to the target user and
  his or her strongly connected nodes. In order to give
  priority to nodes connected to contextual nodes and the
  target actor, both $\beta_u$ and $\beta_c$ should be nonzero.
  Parameters values are chosen as $d = 0.65$,
  $\lambda = 0.04$, $\beta_c = 0.3$, and $\beta_u = 0.01$. Nodes are then
  ranked as follows: {1, 4, 2, 3, 5, 6, 7, 8, 9}. Node 3
  achieves a higher rank than 5. In fact, they both have
  the same "global" popularity, they and are both equally
  connected with the context. However, node 3 is also
  indirectly connected to the target node through node 6.

It is worth mentioning that reducing the difference between $\beta_c$ and $\beta_u$ makes nodes strongly connected to the target one rank better than those more related to the context but not as close to the target node. As an example, node 6 will rank better than nodes 3 and 5 when parameters are set as follows $d = 0.65,\ \lambda = 0.05, \beta_c = 0.2,$ and $\beta_u = 0.1$.
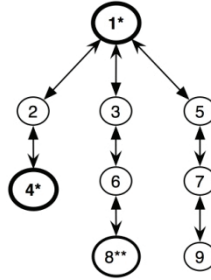


Figure 18: First simulated graph with target and contextual nodes

### 4.4.2 Illustration of Personalized, Contextual, and Multi-relational Ranking

Figure 19 shows a simulated reduced-scale network involving *actors, activity spaces* and *assets* respectively delimited with bold, dashed and normal lines. In addition, 4 different relations are considered: *actor-asset authorship*, *actor-activity space membership*, *actor-asset access,* and *actor-actor connection.* In the corresponding graph, to every bidirectional or unidirectional relation, two edges are created the first in the same direction as the initial relation and the second in the opposite one in order to insure that the two nodes mutually reinforce one another as discussed in section 4.2.1.
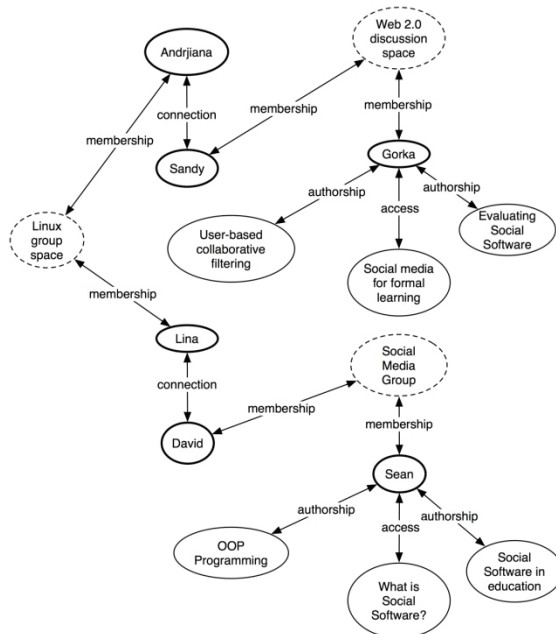
Figure 19: Second simulated graph

In order to illustrate multi-relational ranking as well as contextual and personalized ranking, the algorithm is computed under the following different conditions:

- First, to achieve **global uni-relational ranking**, the algorithm is run treating all relations the same and with neither contextual nor target nodes. The parameters values used are: $d = 0.85$, $\lambda = 0.15$, $\beta_c = 0$, and $\beta_u = 0$.

- Second, to illustrate **multi-relational ranking** is recomputed using the weights distribution specified in Table 5 and the same parameter values as in the first case (i.e. using $\beta_c = 0$, and $\beta_u = 0$ since here again no contextual or target node are specified). The most important relationship is asset authorship, followed by

space membership and actors connection, which count twice more than a simple asset access.

TABLE 5: WEIGHTS DISTRIBUTION FOR GRAPH RELATIONS

| Node 1 | Node 2 | Relation | Weight |
|--------|--------|----------|--------|
| Actor | Actor | Connection | 2/9 |
| Actor | Asset | Access | 1/9 |
| Actor | Asset | Authorship | 4/9 |
| Actor | Activity | Membership | 2/9 |

- Third, to illustrate **contextual ranking**, a set of contextual nodes is selected involving all nodes related to "social software". The algorithm is recomputed with $d = 0.65$, $\lambda = 0.05$, $\beta_c = 0.3$, and $\beta_u = 0$  and using the same weights distribution as in the previous case.
- Last but not least, to illustrate **personalized and contextual**, and see how in the same context, results change depending on the target actor, Lina then Andrijana are chosen as target nodes. The algorithm is recomputed for each of the two actors using the same contextual nodes, the weights distribution specified in Table 5, and the following parameter values: $d = 0.65$, $\lambda = 0.04$, $\beta_c = 0.3$, and $\beta_u = 0.01$ .

Table 6 shows the raw rankings list returned from the different computations described above. In the table, "EW" stands for equal weights, "DW" for different weights, "Pers." for personalized and "Cont." for contextual.

In **global ranking**, where all relations are treated in the same way, all assets achieve the same rank. Nevertheless, when **relations are weighted** according to Table 5, the two assets that were authored by Gorka, namely "User-based collaborative filtering" and "Evaluating social software" rank better than the

asset "Social media for formal learning" he simply accessed. The same applies for the two assets "OOP programming" and "Social software in education" that were written by Sean; they both now achieve a higher rank than the one Sean accessed ("What is Social Software"?).

When **contextual ranking** is introduced, contextual nodes (those marked with an asterisk in Figure 19) and those strongly connected to them find their rankings improved at the expense of all other ones. For instance, unlike previous cases, the two assets "OOP programming" and "User-based collaborative filtering", respectively authored by Sean and David get the lowest ranks among all other assets because they are not contextual nor sufficiently close to the context.

Finally, when the algorithm is **personalized** for Lina then for Andrijana, the results returned illustrate how given the same context, ranking varies from one actor to the other. When the algorithm is biased towards Lina, David, who has so far shared the same rank as Sandy, appears now before her in the recommended list. In fact, these two actors are equally popular at the overall level and are connected with the same strength to different contextual nodes. This is why they ranked in the same way in the two previous cases. Nevertheless, when the target actor is Lina, David ranks better than Sandy, because Lina knows him. As a result, all nodes that are connected with him receive higher rankings than the ones connected to Sandy, given that they are equally "popular" with respect to the context. **The underlying assumption is that Lina will trust more an information source authored or accessed by first or second-degree connections than ones that are equally relevant but coming from unknown sources.** Examples of how rankings are affected by personalization are discussed hereafter. Sean and Gorka achieved the same rank when only

global ranking was considered. In terms of contextual relevance, they have both authored two contextual assets and read one. The only difference is that Sean is directly connected to David, who shares a first-degree connection with Lina. This makes him rank better than Gorka when recommendations are personalized for Lina. Similarly, the asset "Social software in education" also ranks better than "Evaluating social software". In fact, these two assets are equally important in terms of "overall popularity" and they are both contextual. However, "Social software in education" was written by Sean, who shares a space with David, who knows Lina. For similar reasons, the rankings are inverted when Andrijana is chosen as the target actor.

TABLE 6: HETEROGENEOUS RANKED LISTS IN DECREASING ORDER OF IMPORTANCE

| Global EW Ranking | Global DW Ranking | Cont. DW Ranking | Pers. Cont. DW Ranking For Lina | Pers. Cont. DW Ranking For Andrijana |
|---|---|---|---|---|
| Sean *0.4937* | Sean *0.3799* | Social Media group * *0.3553* | Social Media group * *0.354111* | Web 2.0 disc. space* *0.354111* |
| Gorka *0.4937* | Gorka *0.3799* | Web 2.0 disc. space* *0.3553* | Web 2.0 disc. space* *0.353315* | Social Media group * *0.353315* |
| Social Media group *0.2407* | Social Media group *0.2752* | Evaluating Social Soft.* *0.333* | Social Soft. in edu. * *0.333136* | Evaluating Social Soft.* *0.333136* |
| Web 2.0 disc. space *0.2407* | Web 2.0 disc. space *0.2752* | Social Soft. in edu. * *0.333* | Evaluating Social Soft.* *0.331349* | Social Soft. in edu. * *0.331349* |
| Sandy *0.2374* | Linux *0.2458* | Social media for formal l.* *0.3116* | What is Social Soft.* *0.310189* | Social media for formal l.* *0.310189* |
| David *0.2374* | User-Based CF *0.2319* | What is Social Soft.* *0.3116* | Social media for formal l.* *0.310185* | What is Social Soft.* *0.310185* |
| Andrijana *0.2358* | Evaluating Social Soft. *0.2319* | Sean *0.2964* | Sean *0.293105* | Gorka *0.293105* |
| Lina *0.2358* | OOP prog. *0.2319* | Gorka *0.2964* | Gorka *0.293041* | Sean *0.293041* |
| Linux group *0.2353* | Social Soft. in edu. *0.2319* | Sandy *0.1545* | Lina *0.176681* | Andrijana *0.176681* |
| User-Based CF *0.1398* | Sandy *0.2290* | David *0.1545* | David *0.157521* | Sandy *0.157521* |
| Evaluating Social Soft. *0.1398* | David *0.2290* | User-Based CF *0.1512* | Linux group *0.152078* | Linux group *0.152078* |
| OOP prog. *0.1398* | Andrijana *0.2266* | OOP prog. *0.1512* | Sandy *0.152075* | David *0.152075* |
| Social Soft. in edu. *0.1398* | Lina *0.2266* | Linux group *0.1493* | OOP prog. *0.148763* | User-Based CF *0.148763* |
| Social media for formal l. *0.1398* | Social media for formal l. *0.1960* | Andrjiana *0.1415* | User-Based CF *0.148754* | OOP prog. *0.148754* |
| What is Social Soft. *0.1398* | What is Social Soft. *0.196* | Lina *0.1415* | Andrijana *0.139375* | Lina *0.139375* |

## 4.5 Related Literature Review

Many studies on recommender systems for Web applications can be found in the literature. In particular, several recommender systems specifically dedicated to learning environments are proposed (Anderson, et al., 2003; Rafaeli, Barak, Dan-Gur, & Toch, 2004; Manouselis, Vuorikari, & Van Assche, 2007). With respect to the adopted recommendation approaches, most of the existing systems use traditional collaborative filtering where items are recommended based on how "like minded" people rated them (Perkowitz & Etzioni, 2000). Some combine collaborative filtering with content-based filtering where items are recommended if they are similar in content to items the target user has previously liked (Torres, McNee, Abel, Konstan, & Riedl, 2004). Others use ontology-based filtering that define sequencing rules, model the fine-grained learner's preferences and competences, and compare them against the characteristics of the learning resource (Shen & Shen, 2004). This approach is usually computationally expensive and restricted to one domain. In addition, compared to the 3A model that simultaneously ranks actors, activities and assets, most of these cited systems are concerned with recommending learning resources only. Only a few also recommend people such as Altered Vista (Recker, Walker, & Lawless, 2003) and learning activities such as Cyclades (Avancini, Candela, & Straccia, 2007). The difference between Altered Vista and the 3A recommender system is that the former requires explicit and active user input, while the latter rely on user networks and previous actions as implicit preference indicators. On the other hand, Cyclades recommends folders and users using content-based filtering in addition to rating-based measures for finding similar folders. The 3A recommender system proposes a more general

framework that does not only rely on ratings and folder ownerships but also exploits other 3A inter-relations and evaluation metadata to leverage user preferences. In particular, relying on Web 2.0 evaluation metadata such as tags, reviews and ratings is not yet widely used in recommender systems targeting learning environments.

As far as recommender systems targeting general-purpose Web 2.0 applications are concerned, several rely on tagging and social bookmarking behavior (Gulli, Cataudella, & Foschini, 2009; Symeonidis, Nanopoulos, & Manolopoulos, 2008). For instance, TC-SocialRank (Hotho, Aschke, Schmitz, & Stumme, 2006) presents a link-based algorithm for folksonomy systems that ranks users, bookmarks and shared resources taking into account temporal and user-clicks information. In addition, several recommendation algorithms that rely on both user ratings and social networks (e.g. friendship and/or trust network) are proposed in the literature (Walter, Battiston, & Schweitzer, 2009; Ben-Shimon, Tsikinovsky, Rokach, Meisles, Shani, & Naamani, 2007). The difference with the 3A ranking algorithm is that its underlying graph is heterogeneous and multi-relational; it is not limited to actors related by a monolithic relation but also incorporates different node types and combines diverse relations. This is due to the fact that the 3A model targets collaborative environments where users can undertake more actions than merely tagging, bookmarking or rating and where recommendation is not limited to resources such as movies or documents but also extends to people and activity spaces. Therefore, more generalized interaction models and recommendation algorithms are required to be able to infer user interests and preferences from significant inter-relations between actors, activities and assets.

Recommender systems that adopt graph-based approaches and link-analysis algorithm already exist in the literature. (Huang, Chung, Ong, & Chen, 2002) presents a graph-based recommender system for digital libraries where a two-layer graph is used to represent similarity in content between books, similarity in demographic information between people as well as "purchase" relation connecting people to books. Then, the recommendation task consists of traversing the graph to find weighted paths from the target person to different books. Just as in the 3A recommendation model, first-degree associations (in that case, with books that users have already purchased) are only used to lead to other ones and are skipped in the final recommendation list. The difference with the 3A model is that the latter is applied in a different context and exploits social networks and user interactions. In addition, the 3A model ranks entities by applying a personalized and contextualized version of the original pagerank algorithm based on global and local popularity measures rather than a graph-search technique. On the other hand, (Wang, Yuan, & Qi, 2008) propose a graph-based approach that combines different object types linked by diverse relations. It relies on a random walk algorithm based on pagerank to compute the importance of objects in an educational portal. In addition, a more general framework called fusion also based on a random-walk algorithm and combining inter and intra-links among multiple-type objects is introduced in (Xi, et al., 2004). Nevertheless, none of these two papers addresses the issue of having different weights for different relation types, neither do they personalize or contextualize rankings. Finally, with respect to personalizing recommendations in working and learning environments, a personalized activity prioritization approach that identifies different types of users' actions and exploits them using a

Support Vector Machine model is presented in (Li, Muller, Geyer, Dugan, Brownholtz, & Millen, 2007). The 3A recommendation algorithm presented in this paper also identifies and exploits different types of user actions. Nevertheless, it does not only rank existing activities but also actors and assets. More importantly, it also aims at recommending new entities. In addition, the 3A model allows defining different weights for the different relations considered. Last but not least, unlike the activity prioritization approach discussed above, the 3A ranking algorithm takes into account the target user's context.

## 4.6 Conclusion

This chapter presented the personalized, contextual, and relation-based 3A recommender system that can simultaneously rank actors, activities and assets in a PLE. The proposed system can help overcome the problem of information overload and sustain lifelong learning in two ways. First, it helps learners manage their learning spaces and improves their work efficiency by prioritizing existing entities according to their relative importance to the target actor and his or her context. Second, it can induce new collaboration and learning opportunities by driving the learner's attention to new actors, activities and assets relevant to his or her context.

To do so, the proposed recommender system relies on the 3A interaction model to identify significant 3A inter-relations worth exploiting in the recommendation process as implicit interest and preference indicators. Then, the recommender system applies a contextual and personalized link-analysis algorithm based on pagerank to rank entities according to their global and more importantly their local "popularity", which depends on the target actor and his or her context.

The choice of relations' importance weights has so far been done based on intuitive assumptions, in addition to empirical analysis where different weights combinations are tried in context, and the ones yielding best rankings adopted. One idea worth exploring in future research is involving users in identifying and deciding what relations are more important than others or letting them define their own preferences. Future research should also address the algorithm's sensitivity to its different parameters. Finally, analyzing requirements for a fully scalable implementation of the proposed recommender system in an online environment is also an important topic for future work. This includes covering questions such as how to store the multi-layered and heterogeneous recommendation graph, and how to implement the ranking algorithm in a scalable way that allows updating rankings at run-time as the target user shifts from one context to another. Fortunately, previous research related to scalable implementations of personalized pagerank can be very helpful with that respect.

*"We are leaving the age of information and entering the age of recommendation"*

*Chris Anderson*
*(The Long Tail, 2006)*

# Chapter 5

## *Evaluation of the 3A Personalized, Contextual and Relation-Based Recommender System*

### 5.1 Introduction

The 3A recommender system presented in chapter 4, aims at helping end-users of online personal environments avoid information overload and find interesting actors, activity spaces, and assets depending on their context. Following the 3A interaction model taxonomy, the 3A recommender system identifies significant interactions between the 3A constructs and models them in a heterogeneous and multi-layer graph. Then, a personalized, contextualized, multi-relational, ranking algorithm is applied to simultaneously order actors, activity spaces, and assets taking into account their global and most

importantly their local importance relative to target actor and current context.

This chapter discusses two online experiments carried out with the 3A personalized, contextual, and relation-based recommender system.

The rest of the chapter is organized as follows. Section 5.2 presents the algorithm's application and its evaluation in the context of the *Palette* European Research Project. Section 5.3 discusses the evaluation carried out on a large and publically available Epinions[38] dataset. Results indicate that the proposed recommendation approach that exploits the trust and authorship relations between users performs better than user-based collaborative filtering. Section 5.4 concludes the chapter with hints on future work.

## 5.2   Evaluation using data from *Palette*

### 5.2.1   *Objective*

The experiment described in this section serves as an illustration and a preliminary evaluation of the proposed recommender system in the context of knowledge management and collaborative work. The two main purposes of the proposed recommender system constitute the hypotheses of this experiment.

- **Hypothesis I**: the algorithm improves work efficiency by ranking actors, activities and assets according to their predicted relative importance to the target actor and his or her context.
- **Hypothesis II**: the algorithm induces new collaboration and learning opportunities. This is

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[38] http://www.trustlet.org/wiki/Extended_Epinions_dataset

achieved by accurately recommending to each actor, 3A entities (actors, activities and assets) that are relevant to his or her context, and that, otherwise he or she would not have been able to discover especially when it comes to "open corpus" environments fraught with information.

## 5.2.2   Dataset description

As an illustrative example of the algorithm's applicability and as an evaluation of the two hypotheses discussed above, an experiment is conducted using data belonging to the *Palette* project research community. The exploited data is composed of 106 researchers, 65 deliverables, 9 work packages (or WPs), and 19 institutions. For each work package or institution an activity space is generated in *eLogbook*. Researchers are attributed different roles in the different activity spaces. The roles labelled "WP Leader", "WP Deputee Leader" and institution's "Main Representative" are created with "owner" rights in their corresponding activity spaces. Each WP contains a list of deliverables. Each deliverable has one or two managers, a list of contributors, and a list of evaluators. Deliverable managers are responsible for managing the deliverable's production and submitting it. Keywords associated with each deliverable are treated as tags, but there is no trace of who among the contributors has added the keyword. Apart from the BSCW[39] that was used as a repository of deliverables, no collaborative application for aggregating the project knowledge capital and enhancing interactions and discussions related to WPs was used. This limits the number of relations to explore between entities. The *Palette* network

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[39] http://public.bscw.de/

structure and the different types of connections considered are shown in Figure 20 hereafter. From the thickest to the thinnest, edges represent relations having a weight of 4/21, 2/21 and 1/21 respectively. Having submitted or authored a deliverable is considered to be two times more important than being a WP leader, and four times more important than having evaluated a deliverable and being a WP member. Section 1.2.5 discusses this choice regarding the relative importance of the considered relations.
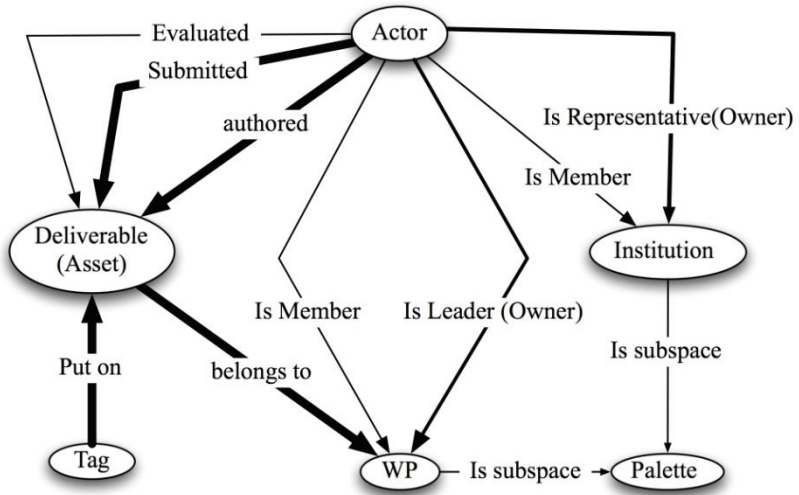


Figure 20: The Palette network structure

### 5.2.3   General Evaluation Methodology

The evaluation of the 3A recommender system in the context of *Palette* was conducted towards the end of the project. Therefore, it was carried out using a post-collaboration survey as it was done in (Campbell, Maglio, Cozzi, & Dom, 2003). The survey was addressed to all *Palette* researchers via the

main project's mailing list. 20 out of the 106 researchers replied to the questionnaire. To answer each question, the user had to drag elements from a suggested list and drop them into the result field as shown in Figure 21. Depending on the question, the suggested list consisted either of WPs or of the 106 *Palette* members displayed in alphabetical order. For privacy reasons, researchers name are blurred in Figure 21. The next two sections describe how different questions helped verify hypothesis *I* and *II* respectively, and discuss related results.



Figure 21: A snapshot from the online questionnaire (*Names blurred for privacy reasons*)

## 5.2.4 Preliminaries: Evaluation Metrics

*Precision* and *recall* are two widely used evaluation metrics used in information retrieval. While precision measures the

usefulness of a ranked list, recall measures its completeness. They are defined as follows:

$$\text{Precision} = \frac{\text{Number of relevant items returned}}{\text{Total number of items returned}} \; ;$$

$$\text{Recall} = \frac{\text{Number of relevant items returned}}{\text{Total number of relevant items}} \; .$$

*Precision at n* consists of measuring the number of relevant items returned at cutoff points instead of the entire list. For instance, a precision at 10 measures the number of relevant items within the first top 10 items returned.

*R-precision* is a special case of precision at *n*. It measures the precision at cutoff *R* where *R* is the total number of relevant items. In other words, it measures how many relevant items are returned at a cutoff point equal to the actual number of relevant items(Javed A. Aslam & Yilmaz, 2005).

$$\text{R-precision} = \frac{\text{Number of relevant items returned in the top } R \text{ list}}{R \text{ (the total number of relevant items)}}$$

A value of *R*-precision equal to 1 means a perfect ranking in terms of relevance and completeness. However, a very low value of *R*-precision cannot be interpreted in terms of ranking completeness, because there might be relevant items returned beyond point *R*.

### 5.2.5 Evaluation Metrics and Results Discussion for Hypothesis I

According to hypothesis I, the algorithm is expected to give the highest rank to entities strongly related to the target actor (i.e.

the user or actor for whom the recommendation is intended). The more an actor is active in a specific WP, the higher the rank of this WP is expected to be.

To verify this hypothesis, each *Palette* researcher was asked to rank each WP according to his or her perceived activity in it (an administrative WP that had no deliverables related with the *Palette* research work was omitted). Then, the algorithm was run once for every *Palette* researcher that answered the questionnaire taking him or her as target user. Parameters were then set as follows: $d = 0.65$, $\lambda = 0.05$, $\beta_c = 0$, and $\beta_u = 0.3$. $\beta_c$ was 0 because no contextual nodes were chosen. In a more general case where interactions between actors outside *Palette* were also recorded in the same online environment, it would be necessary to define a context with the 3A entities involved in *Palette* (project members, shared assets and WPs). However, in this experiment, all the data exploited was related to *Palette*, so there was no need to contextualize rankings. On the other hand, $\beta_u$ was chosen as non-zero so that *Palette* WPs are ranked for each target user according to their relative importance to him or her and not just their global one. In addition, the value chosen for $\beta_u$ was the same as the one used in (White and Smyth, 2003) to bias pagerank towards a set of roots nodes, as discussed in the previous chapter.

The Spearman correlation coefficient (Lehmann & D'Abrera, 1998) is used to measure the extent to which personal and automatic WPs ranking are correlated. A very good average Spearman correlation of 0.915 with a standard deviation of 0.15 was obtained for the 20 people who answered the questionnaire. *Therefore, the recommender system was able to accurately order WPs according to their importance to every researcher considered by exploiting data related to membership in WPs and joint deliverables production.*

It is worth noting that this high correlation was obtained after having adjusted the relative importance of the 9 different relations such that having managed or contributed to a deliverable is two times more important than being a WP leader, and four times more important than having accessed or evaluated a deliverable as illustrated in Figure 20. At first, different combinations of relation weights were tried. The best average correlation with personal rankings of WPs was achieved with the combination discussed above. This is consistent with the fact that internal evaluators were not in the same WP as the deliverable(s) they had reviewed. Thus, results confirm that when it comes to assessing one's activity in a WP or expertise on a related topic, researchers consider having contributed to a WP's deliverable as more important than having evaluated it. In general, similar experiments where different combinations of relations' weights are tried on the same training set and compared in terms of predictions' accuracy can help discover what relative ordering of relations is best suited for the dataset at hand.

Also to test the first hypothesis, researchers were asked to choose among the 106 *Palette* researchers the top 10 researchers with whom they have interact the most. For each researcher who replied to the questionnaire, the algorithm was computed taking him or her as target actor. The recommendation quality was measured for every target actor using the *R-precision* measure. The top 10 researchers chosen by each target actor to answer the above question are considered as the relevant items ($R$=10). Averaging the measures obtained for the 20 researchers having replied to the survey yields an average *R-precision* of 0.52 with a standard deviation of 0.17.

This low correlation can be explained by the fact that available data is limited to the collaboration within WP and around the joint production of deliverables. Within the same WP, people do not necessarily contribute equally to all deliverables nor collaborate evenly with one another. *A trace of the member's discussions around the different deliverables would also have helped to better identify for every researcher, the actors with whom he or she had collaborated the most during the project. This brings us to the important benefits of adopting usable online platforms that combine social interactions with content and activity management features. These platforms help centralize and capitalize community knowledge. As a byproduct, recommender systems can exploit richer information to improve the recommendation quality.*

### 5.2.6 *Evaluation Metrics and Results Discussion for Hypothesis II*

To validate hypothesis II, members were asked to recommend researchers from the *Palette* network for an imaginary learner wanting to learn on four different topics (namely 'Awareness', 'Usability', 'Semantic Web', 'Interoperability'). These topics were chosen because *Palette* researchers have worked on them during three years within different WPs. A total of 24, 35, 36 and 31 different actors were respectively cited for keywords 1, 2, 3 and 4.

Contextual ranking was computed for each topic taking as context all the WPs and deliverables whose tags, names and descriptions match the topic. No target actor was specified since the imagined learner is not within the *Palette* network. Thus, in this case, parameter values were set as follows: $d = 0.65$, $\lambda = 0.05$, $\beta_c = 0.3$, and $\beta_u = 0$. *R*-precision is used to evaluate the algorithm's ranking. The top 10 most

recommended researchers according to the questionnaire results were considered as relevant actors ($R$=10). The $R$--precision is then calculated by counting the number of relevant actors returned by the algorithm for each topic at cut-off 10. An average $R$-precision of 0.73 was obtained.

The algorithm relies on the participation in WPs and the collaborative production and evaluation of deliverables. Additional information such as the deliverables update frequency and the researchers' individual involvement in the different topics discussed would have probably helped to better differentiate the actors' contribution and expertise levels with respect to the different topics considered.

The data exploited in this experiment consisted of a small dataset. Nevertheless, applying the 3A recommender algorithm in this context illustrated how it can be used in collaborative environments to fulfill its main objectives as described in section 5.2.1. The experiment also served to verify how the proposed recommendation approach would perform on real data. It shows that representing different 3A interactions in a heterogeneous and multi-relational graph, and applying a modified version of pagerank that computes global and local importance by biasing results towards the target actor and the context as described in chapter 4, yields consistent and meaningful rankings on real data.

## 5.3   Evaluation using Epinions dataset

### 5.3.1   Objective

This experiment aimed at verifying how the proposed algorithm would perform on a large and rich dataset. In particular, the objective is to verify whether the 3A recommender system approach of combining different types of

user interactions in a multi-layer graph and computing rankings based on a personal and contextualized version of pagerank is able to yield relevant results.

### 5.3.2 Compared Recommendation Approaches

Three different top-*N* recommendation approaches were used in this experiment:

- A user-based collaborative filtering approach exploring ratings
- The 3A recommender system exploiting trust relations and ratings
- The 3A recommender system combining all available relations

**The User-Based Collaborative Filtering Method:**
User-based collaborative filtering (referred hereafter as CF) relies on similar ratings behavior to make rating predictions. CF computes the similarity in rating behavior between users. Then, it predicts the rating of an asset unrated by a target user, based on how similar users have rated it.

In this experiment, the similarity in rating behavior $sim(x, y)$ between two actors $x$ and $y$ is calculated using the cosine-based similarity measure (Adomavicius & Tuzhilin, 2005). Let $S_{xy}$ denote the set of all items co-rated by $x$ and $y$, $sim(x, y)$ is given by:

$$sim(x, y) = \frac{\sum_{i \in S_{xy}} r_{x,i} r_{y,i}}{\sqrt{\sum_{i \in S_{xy}} r_{x,i}^2} \sqrt{\sum_{i \in S_{xy}} r_{y,i}^2}}$$

The predicted rating $r_{x,i}$ of an item $i$ unrated by a target actor $x$ is computed using the weighted average of all ratings

given by users in $S_{xy}$ for an item $i$. Let $r_{y,i}$ denote the rating given by user $y$ to item $i$ respectively. The predicted rating $r_{x,i}$ for a target user $x$ is given by:

$$r_{x,i} = \frac{\sum\limits_{y \in S_{xy}} sim(x,y)\, r_{y,i}}{\sum\limits_{y \in S_{xy}} sim(x,y)}$$

In this experiment, items rated by the top 50 most similar actors to a target user and unrated by the target actor are aggregated, and sorted according to their predicted rating $r_{x,i}$ and then their frequency of occurrence (McLaughlin and Herlocker, 2004).

## The 3A Recommender System:

Two different versions of the 3A recommender system are applied: one, which exploits trust and ratings relations, and one, which exploits all available ones (trust, ratings, authorship and topic information). The experiment does not involve contextualization. In order to personalize rankings towards every target user, parameters were adjusted as follows: $d = 0.75$, $\lambda = 0.05$, $\beta_c = 0$, and $\beta_u = 0.245$.    Ranks    were obtained using the power method with 6 iterations.

An explanation of how the 3A recommender system exploits the Epinions dataset to deliver personalized recommendations is given hereafter.

The predicted relative importance of a target actor in an asset increases if related actors have authored it, tagged it, or gave it a high rating value. This is achieved as follows. The target actor's rank is boosted at every step by $\beta_u$. Consequently, and unlike the original pagerank algorithm that only considers the nodes' global popularity, nodes that are

directly and indirectly connected to the target actor are boosted at every step. Actors trusted by the target actor will rank better than others because they are directly connected to the target actor. They will in turn confer importance to actors they trust, and to assets they authored, rated, or tagged. In the same way, assets and actors linked to tags used by the target actor will also achieve higher ranks than others. Figure 22 illustrates how this approach applies to the Epinions dataset.
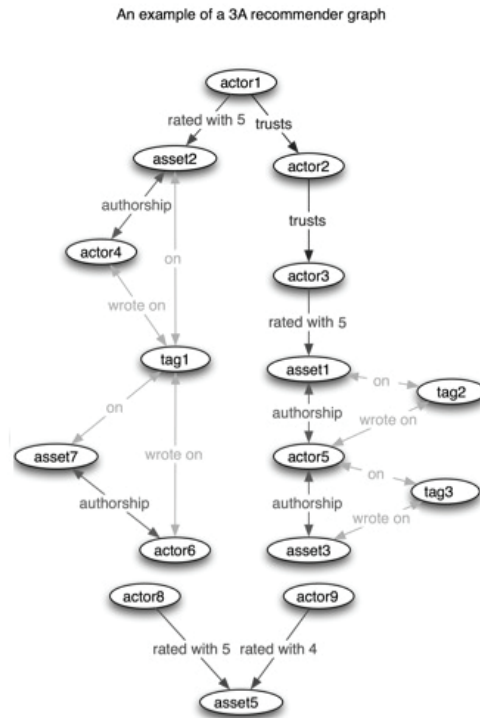
An example of a 3A recommender graph



Figure 22: Graphical illustration of the 3A recommendation graph for Epinions dataset

Actor1 trusts actor2 and the latter trusts actor3. Considering that trust is transitive (with a decay factor) and knowing that actor3 had rated asset1 with 5/5, actor2 is also expected to like asset1. When authorship information is also taken into account, it is possible to predict the potential interest of actor1 in asset7. In fact, asset7 is about the same topic as another asset highly rated by actor1 (namely asset2). When actor3 is the target actor, asset3 receives a high rank. This is because actor3 had previously given a top rating for another asset of the same author (namely asset1). Unreachable nodes from actor3, such as asset5 receive much lower but non-zero ranks depending upon their global popularity.

### 5.3.3   Dataset Description

The extended Epinions dataset was chosen, as it was the only large and rich publicly available dataset with social networks information in addition to authorship data. The initial dataset is composed of three separate files respectively containing:

- *Trust/distrust information* with a total of 717,129 trust and 124,244 distrust statements (ignoring people who trust themselves). The set involves 114,222 users with 69,608 having issued at least trust statement and 87,909 having received at least one.
- *Ratings information* with 13,668,319 ratings issued by 120,492 actors on a total of 755,760 reviews.
- *Reviews authorship and topic information* involving 1,560,144 reviews by 326,983 authors and 200,953 different topics.

The original dataset was reduced to a smaller one for computational reasons, and more importantly, to ensure a reasonable validation taking into account the adopted

evaluation methods and the ranking approaches compared in this experiment. The evaluation method, which will be explained in details later in this chapter, consists of randomly withdrawing user ratings and trying to predict them. Since reviews with no ratings cannot be evaluated in this way, they were excluded from the dataset along with their authorship information. Even though these unrated reviews could have enriched the 3A recommender system, the collaborative filtering method used as a comparison basis cannot make any prediction on them. Actors that share trust information but have not made any rating were also not considered. Distrust information between actors was also ignored, knowing that none of the ranking approaches exploits them. Moreover, since the 3A recommender system considers only ratings values greater or equal to the average, ratings with values less than 3 out of 5 were ignored in the dataset used during the evaluation. Knowing that a bias towards high rating values in Epinions rating distribution has already been reported in (Massa & Avesani, 2007), and that in this dataset in particular, ratings that are below the average only constitute 2.34% of the total ratings, removing them is not expected to affect the performance of user-based collaborative filtering in any substantial way. Figure 23 illustrates the bias towards favorable reviews in the initial Epinions dataset.

The resulting dataset involves 113,364 actors, 602,309 trust statements, 744,075 rated reviews (47.6% of initial total reviews), 13,348,412 ratings (97.7% of initial total ratings) and 102,652 different topics. Figure 24 shows a mapping of the Epinions data into the 3A model, in which reviews are considered as assets, and subjects or topics are treated as tags. *The unidirectional or bi-directional relations that are translated into bi-directional edges in the graph are displayed*

*in italic*. The relationships between actors, assets and tags are shown along with their relative weight.
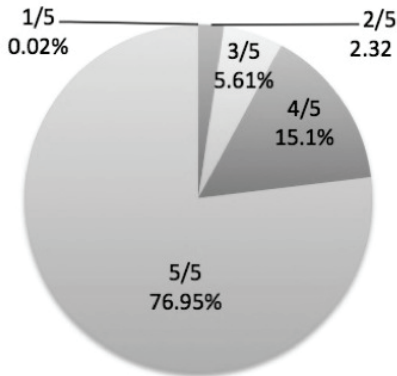


Figure 23: Ratings' distribution per rating value

Weights were chosen empirically taking into account the importance of the different relationships as well as the total number of edges in their corresponding sub-networks. In the Epinions dataset used in this experiment, the ratings' sub-network involves a total of more than 13 millions outgoing links while the authorship network contains a total of 744,075 links. On average, an actor has rated 117.7 reviews and written 5.3 reviews. Considering that on average an actor has considerably more ratings than authored reviews, the weights chosen for ratings and authorships relations are 0.5 and 0.1 respectively. Increasing the weights of rating relation types reduces the normalization penalty that strongly affects nodes with too many outgoing links (Fujimura, Inoue, & Sugisaki, 2005). This choice does not mean that an actor will confer more importance to an asset he or she authored than one he or she rated. On average, an authored asset will be conferred 4.4 times more importance than an asset rated by the same actor.
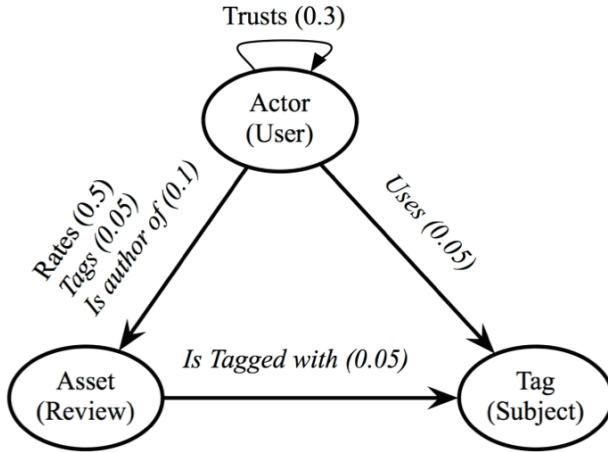
Figure 24: The Epinions network structure

### 5.3.4 *Evaluation Method and Metrics*

To compare the performance of the 3 *top-N* recommendation algorithms described above in terms of results accuracy, an evaluation approach similar to the one proposed in [Jamali and Ester, 2009] is used. The *leave-one-out* method is adopted. It consists of withdrawing a rating and trying to predict its rank using the remaining data. In our experiment, random ratings for 4000 randomly selected users are withdrawn one by one. Two constraints are however respected during the random selection process:

- Users that have at most 2 rating are excluded. This is due to the fact that user-based collaborative filtering cannot make any predictions for these users, after one rating is withdrawn.
- Only top-rated assets by an actor are selected (Jamali & Ester, 2009). If a user's maximum rating is 4 (or 5), then assets he or she rated less are not considered. This

ensures that in the ideal situation where predictions are 100% accurate, the top-rated asset will appear first in top-$N$ recommended list for the actor who rated it.

Recall (or hit-ratio) is commonly used to measure the accuracy of a top-$N$ recommended list for a target user (Karypis, 2001; Kim, Ji, Kim, & Jo, 2007). A hit occurs every time a withdrawn rating for a user appears in the *top-N* recommended list for that user. For each of the three recommendation algorithms used in this experiment, recall is computed by dividing the number of hits achieved, by the total number of withheld ratings. A recall value equal to 1 indicates that the considered algorithm successfully recommended within the top-$N$ list items whose ratings were withheld and a recall value of 0 indicates that the algorithm was not able to recommend any of them.

### 5.3.5 Results

Figure 25 shows the average recall value achieved by the three different ranking algorithms for different values of $N$ (10,50,100, and 500). Evaluating the algorithm's performance with also big values of $N$ is explained by the fact that the dataset involves around 13 millions ratings, and there are significantly more items than users in the dataset. For $N$=10, CF performs slightly better than the 3A ranking algorithm when only rating and trust relationships are taken into account, despite the fact that the latter uses more information. A slight improvement of user-based collaborative filtering over trust-based recommendation algorithms is also reported in other experiments and explained by the fact that the evaluation is biased in favor of collaborative filtering (Jamali & Ester, 2009; Walter, Battiston, & Schweitzer, 2009). Users do not

necessarily rate the same elements as the people with whom they have issued trust statements. When the 3A recommender systems combines trust, authorship, rating information and computes ranking based on the 3A-ranking algorithm, it achieves a better recall than user-based collaborative filtering for small as well as large values of *N*. By exploring more relations, *the 3A recommender system delivers more accurate predictions and covers more users*, especially cold-start ones (i.e. those who have very few ratings). The Epinions dataset used in this experiment has 58.2% users who have done at most 5 ratings. Merely relying on rating behavior is not suitable for the large portion of users who have done very few ratings.
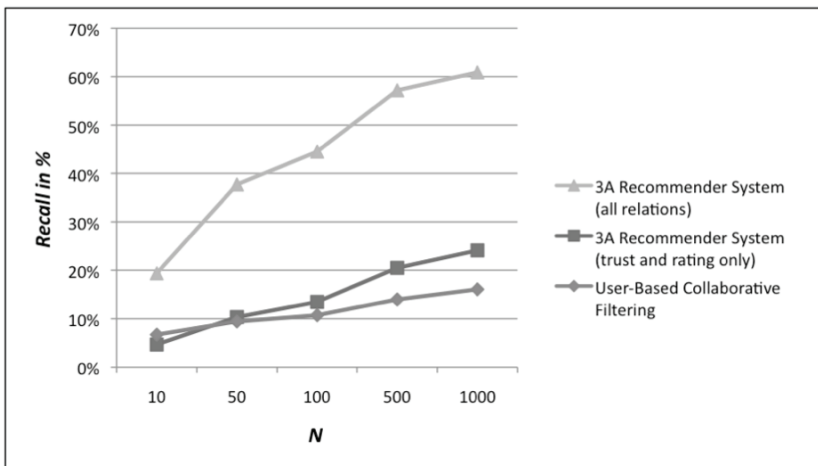


Figure 25: Average recall achieved by the different ranking approaches

## 5.4 Conclusion

This chapter discussed the findings of two experiments involving the 3A recommender system.

The first one was carried out in the context of the *Palette* research community. It served as an illustration of how the proposed recommender system can be applied in online environments for knowledge management, collaborative work and learning, in order to serve two purposes: increase work efficiency and induce new interaction and learning opportunities. This experiment involved a qualitative feedback from 20 users who replied to a post-collaboration survey. Its context is strongly tight with collaborative work and learning. Nevertheless, the exploited data was relatively small and limited to records related to WP memberships and deliverables' production. It was not possible to get traces of social interactions and assets (other than deliverables) exchanged between researchers throughout the project. The experiment is still very helpful in showing how the 3A recommender system yields consistent and meaningful rankings on real data.

The second experiment was conducted offline on a large and rich dataset containing trust, rating, and authoring information. It showed that the presented approach that exploits more relations than merely ratings and ranks entities according to their global as well as their local popularity, outperforms a traditional user-based collaborative filtering algorithm that was used as a comparative basis and relied on similar rating behavior to predict interest.

For future research, it would be useful to conduct more offline as well as online experiments involving end-users and carried-out in large and rich datasets.

*"You will have to experiment and try things out for yourself and you will not be sure of what you are doing. That's all right, you are feeling your way into the thing."*

Emile Carr

# Chapter 6
## *Conclusions*

Lifelong learning is both a necessity and an opportunity in a digital world that revolutionized the way we communicate information, interact with each other, share knowledge, educate ourselves, work, and play. Structured learning acquired in bricks and mortar academic and professional environments and leading to a formal recognition needs to be complemented with self-directed non-formal and informal learning that can occur anytime and anywhere.

Online PLEs are centered on the individual rather than the institution and aim at supporting lifelong learning in all its forms, structured and unstructured, intended and unintended. To be able to adeptly sustain all end-users in learning anything, anywhere, and anytime, PLEs need to follow bottom-up social media approaches engaging everyone actively in the process, and considering them as both potential knowledge consumers and producers. PLEs should also combine social networking facilities, with flexible content and activity management systems. Unlike traditional CMSs and LMSs, shared content should not be restricted to an anticipated plan, and the system should not intrinsically embed asymmetric roles. In addition, learners must be able to initiate their own personal and collaborative activity spaces based on their self-defined learning goals. In addition, PLEs should incorporate personalized recommender systems that help learners manage their learning spaces by ordering existing entities according to their predicted importance and their contextual relevance. More importantly, PLE-embedded recommender systems should induce new interaction and learning opportunities by making learning aware of actors, activities, and assets potentially

interesting to target learners. Recommendations are particularly important in an environment where contributions are neither restricted nor predefined, but are rather dynamically added and repurposed, and differ in quality, intended audience and topics. In that, they help learners in managing their own learning spaces in addition to choosing the activities worth participating in, the right people to connect to, and the right resources to interact with.

## 6.1 Contributions

This thesis addressed two main challenges related to the development of suitable PLEs for lifelong learning. The first concerns developing design models, prototypes and software prototypes for PLEs. The second corresponds to building personalized recommender systems targeting PLEs. Related contributions can be summarized as follows:

**The development of the 3A interaction model**
The 3A interaction model guides the design of online environments supporting social interactions and knowledge management. The proposed design model is particularly well suited for PLEs targeting lifelong learning; it is based on design principles discussed in chapter 2 and recognized as crucial for developing platforms that can sustain knowledge management, formal, non-formal and informal learning. The proposed model distinguishes three main constructs, namely actors, activities and assets. It describes their inter-relations focusing on *SALT* features, and gives guidelines for related sharing policies. A 3A entity (or a combination of 3A entities) can be exploited to explicitly represent structured interaction contexts. More importantly, any 3A entity can be spontaneously appropriated and connected with other ones,

thus forming a smooth context for informal interactions and learning.

The proposed model can also serve as a basis for building data specifications and common API leading to interoperable online personal and collaborative environments.

## The implementation of an innovative online PLE based on the 3A interaction model

*eLogbook* is the first platform based on the 3A model. It offers social networking, community support along with flexible content and activity management services. It provides *SALT* features that encourage active participation, trigger social interaction, allow bottom-up information management, and facilitate peer-to-peer recommendations. Thanks to its context-sensitive interface, it works as a contextual aggregator bringing together actors, activities, and assets and allowing an easy shift from one interaction or learning context to another.

## The application of 3A-model based PLEs in learning contexts

Two consecutive usability studies were conducted in order to assess *eLogbook*'s usage and acceptance in a formal learning environment, as a proof-of-concept of the 3A model applicability in such environments. The conducted studies shed lights on how social media features are exploited in education. Similar to more recent studies cited in chapter 2, this study indicates that in order to benefit from the promising utility of social media features in educational and professional environments, it is valuable to provide end-users with guidelines on how to apply them in these contexts.

The applicability and usefulness of the 3A interaction model in less structured and more self-directed learning contexts, is illustrated through a use-case scenario involving *Graaasp*, *eLogbook*'s successor.

## The development of the 3A personalized, contextual, and relation-based recommender system

The proposed recommender system serves two main purposes. It makes target users aware of potentially interesting 3A entities, thus triggering interaction and learning opportunities. It recommends an ordering of existing entities, thus facilitating quick access and efficient resource management.

To achieve its two main objectives, 3A personalized, contextual, and relation-based recommender system exploits 3A interactions between actors, activities and assets to unobtrusively infer actor interests and preferences, and rank entities according to their global and local importance. Local importance is relative to the target actor and his or her context as defined in section 4.2.2.

The 3A recommender system is perfectly appropriate to open PLEs environments. It relies on user actions and resulting *SALT* metadata to provide personalized and contextualized simultaneous recommendations of actors, activity spaces, and assets that are popular with respect to the target actor and the current context.

## The illustrative applications and evaluations of the 3A recommender system on real datasets

The 3A recommender system was evaluated the context of the *Palette* European project research network. The recommender system was used to rank work packages activities and researchers according to their predicted relative importance to

each target user, as well as suggest a list of research for an imaginary learner wanting to learn on different topics related to the project. To this end, the system was fed with data related to membership in work packages and contribution to deliverables production and evaluation. This evaluation involved 20 researchers who filled a post-collaborative questionnaire. The good correlation between the algorithm's ranked lists and the corresponding target users' list suggests that the proposed recommender system would achieve a good performance if applied in collaborative work and learning environments.

The 3A recommender system was also evaluated using a large and publically available Epinions dataset. This validation shows that the proposed recommendation approach that combines ratings, trust, as well as authorship relations, and ranks entities based on global and local importance, performs better in terms of predicting user ratings than a user-based collaborative filtering approach.

## 6.2 Future Research Directions

The adoption of PLEs based on the 3A interaction model in formal and informal learning contexts as well as the study of the impact of social media on formal learning constitute important topics for future research. Another challenge is related to the development of common API and data specifications in order to achieve interoperability between different PLEs.

With respect to the proposed recommender system, future research should further analyze the algorithm's sensitivity to its different parameters. It is also important for future research to carefully examine the time factor in recommendations, and address questions related to when it is appropriate to decay old actions with respect to new ones, and how best to do it.

Implementing the 3A recommender system on a large scale and being able to update recommendations online is also an important challenge requiring further investigations. It would also be interesting to explore and apply other ranking algorithms on the 3A recommendation graph and compare based on ranking accuracy, in addition to other aspects such as novelty and serendipity.

Finally, several challenges related to recommender systems in TEL in general should be addressed. They involve but are not limited to maintaining and sharing appropriate evaluation datasets, in addition to designing suitable evaluation frameworks. These frameworks should include online experiments involving users in the evaluation process and aim at studying the impact of different recommender systems on the learning experience. Another important usability issue concerns finding adequate ways to display recommendations, and be able to update recommendations taking into account users' input and feedback. Finally, privacy and transparency concerns should also be examined. There are actions such as rating and commenting that actors deliberately want others to learn about, and others such as visiting others' profiles that actors may neither wish others to learn about nor would accept that a recommender system exploits them.

*"When one has finished building one's house, one suddenly realizes that in the process one has learned something that one really needed to know in the worst way - before one began."*

*Friedrich Nietzsche*

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# Curriculum Vitae

## Personal Information:

Full Name: Sandy El Helou
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## Education:

**2001-2006, Lebanese American University (LAU)**
Bachelor in Computer Engineering (with emphasis on Communication)

## Awards & Honors:

The LAU President Award in June 2006 for having graduated with the highest cumulative GPA in the School of Engineering & architecture.

## Work Experience:

Currently involved in the ROLE European Project (FP7 project) focused on the use of information and communication technologies in self-regulated and social life long learning.

Participated in the Palette European Project (FP6, IST programme) aimed at developing a set of interoperable Web services to sustain collaboration and cooperation for communities of practice.

# Publications:

**El Helou, S.**, Gillet, D., Salzmann, C.. The 3A Ranking System: Contextual, Personalized & Simultaneous Recommendation of Actors, Activities & Assets. Journal of Universal Computer Science, Special Issue on Context-Aware Recommendations. In press.

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**El Helou, S.**, Tzagarakis, M., Gillet, D., Karacapilidis, N., and Yu Man, C. Participatory Design for Awareness Features: Enhancing Interaction in Communities of Practice. In Proceedings of the 6th International Conference on Networked Learning.