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An infrastructure for Workplace Learning Analytics: tracing knowledge creation with the Social Semantic Server

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Abstract

In this paper, we propose the Social Semantic Server (SSS) as a service-based infrastructure for workplace and professional Learning Analytics (LA). The design and development of the SSS has evolved over 8 years, starting with an analysis of workplace learning inspired by knowledge creation theories and its application in different contexts. The SSS collects data from workplace learning tools, integrates it into a common data model based on a semantically-enriched Artifact-Actor Network and offers it back for LA applications to exploit the data. Further, the SSS design promotes its flexibility in order to be adapted to different workplace learning situations. This paper contributes by systematizing the derivation of requirements for the SSS according to the knowledge creation theories, and the support offered across a number of different learning tools and LA applications integrated to it. It also shows evidence for the usefulness of the SSS extracted from four authentic workplace learning situations involving 57 participants. The evaluation results indicate that the SSS satisfactorily supports decision making in diverse workplace learning situations and allow us to reflect on the importance of the knowledge creation theories for such analysis.

Notes for Practice

- We propose the Social Semantic Server (SSS) as a service-based infrastructure for workplace and professional Learning Analytics that focuses on the knowledge creation theories.
- We identify the requirements for the SSS and present its design and development.
- We evaluated the SSS by integrating a set of learning tools and Learning Analytics applications into the SSS and using it in four authentic workplace learning situations involving 57 participants.

Keywords

Learning Analytics, informal learning, workplace learning, Artifact-Actor Network, data infrastructure.

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1. Introduction

Workplace and professional learning happens across a multitude of formal and informal settings where professionals advance their competence, mostly in a self-directed manner. Learning can be a rather informal way of gaining knowledge and expertise by self-directed exploration and social exchange that is tightly connected to the processes and the places of work (Eraut, 2004). In contrast to formal education, workplace learning is often driven by personal interest or by problems that appear in the work context. It typically lacks a pedagogical design that guides the learning process (Kooken, Ley, & De Hoog, 2007). While professionals are also involved in more formal learning settings, such as trainings, these are commonly motivated from job-based demands and need to contribute to workplace performance. The fact that workplace learning is multi-episodic, happens across diverse contexts and is tightly coupled with the workplace poses several challenges for the design and development of technology that supports and analyzes workplace learning (Klamma, 2013).

In this paper, we particularly address challenges related to Learning Analytics (LA) in workplace settings. LA collects data about the learning processes and feeds it back to learners or trainers to support their decisions about their own or others' learning. LA at the workplace faces a number of particular challenges (Cardinali, 2015; Ruiz-Calleja, Dennerlein, Ley, & Lex, 2016; Ruiz-Calleja, Prieto, Ley, Rodríguez-Triana, & Dennerlein, 2017). For example, learners use a number of learning tools in a spontaneous and difficult-to-foresee way because learning does not follow a particular planned curriculum or pedagogical design. A number of such learning tools have been proposed to support particular workplace learning tasks, such as the creation of portfolios that allow tracing learning in multiple contexts (Krull & Leijen, 2015), or peer discussions to support help seeking (Santos et al., 2016). However, if we want to look at workplace and professional learning processes across different tools, contexts, and learning tasks, then LA needs to take a more holistic perspective.

In order to provide this more holistic picture for workplace LA it is required to coherently analyze data from several tools used for learning at the workplace. Some LA infrastructures have been proposed to collect, integrate and process data from several learning tools. While some of these proposals have been designed and tested in realistic situations (e.g. Renzel & Klamma 2013; Siadaty et al. 2012), most of them still focus on a limited number of learning tasks and tools. Additionally, such holistic perspective requires to rely on a careful analysis of existing learning theories, which is recognized as one of the major challenges in the LA community (Gašević, Dawson, & Siemens, 2015). For workplace and professional learning, this is even more critical because there is no curriculum or pedagogical design that may guide their analysis. Thus, a focus on a particular learning theory is crucial in order to guide the processes of collecting, managing and representing workplace learning data. Much too often, such theoretical claims remain implicit.

In a recent review, we analyzed existing proposals for workplace LA (Ruiz-Calleja et al. 2017). This analysis leads us to conclude that most of current proposals focus on theories that follow knowledge acquisition or participation metaphors (Paavola & Hakkarainen, 2005). In these cases, individuals are understood as the basic unit of knowing and learning (knowledge acquisition), or learning is seen as an interactive process of participating in cultural practices (participation). We see much less focus on the knowledge creation metaphor (Paavola & Hakkarainen, 2005), which considers learning as a joint development of objects of activity. This is especially true for LA infrastructures that allow tracing learning processes across several learning tools and contexts. This constitutes a significant problem because it means missing essential elements of a learning situation, such as how new knowledge is created or how innovation processes happen in communities. Considering that in order to keep a competitive edge in the current knowledge-based economy learning should focus on innovation, creative problem solving and knowledge creation (Peschl & Fundneider, 2014), this missing emphasis on knowledge creation metaphor in LA is especially troublesome.

To address these limitations, we propose to exploit the Social Semantic Server (SSS)(Dennerlein, Kowald, et al., 2015) as an infrastructure for workplace LA. This paper systematically derives the SSS requirements according to the knowledge creation theories, with a special focus on how data from different learning tools is coherently combined and offered back to LA applications. We also illustrate the support offered by the SSS across a number of different learning tools and settings and collect evidence for its usefulness from four evaluation studies. These studies allowed us to reflect on the importance of the knowledge creation theories for workplace LA.

The rest of the paper is structured as follows: first we summarize the state of the art related to workplace LA infrastructures; then we describe the SSS, whose evaluation is then presented and discussed; we end the paper by summarizing its conclusions.

2. Data infrastructures for Workplace Learning Analytics

The field of workplace LA is still in its early stage of development but its interest increased in the last few years (Ruiz-Calleja, Prieto, Ley, Rodríguez-Triana, & Dennerlein, 2017). Some LA projects, such as LACE[1], moved their attention to the workplace domain (Cardinali, 2015) and other workplace learning projects, such as Learning Layers[2], began to use LA to analyze and support learning processes (Ruiz-Calleja, Dennerlein, Ley, & Lex, 2016). These projects exploited LA techniques as a way to assess or support decision making in workplace learning processes. These proposals are implicitly or explicitly grounded by particular learning theories (Gašević, Dawson, & Siemens, 2015). We reviewed them following the three metaphors of learning -knowledge acquisition, participation and knowledge creation- defined by Paavola & Hakkarainen (2005). These metaphors can be understood as different lenses for the design or analysis of learning situations and are "closely connected to the way knowledge is understood in different conceptions of learning" (Paavola & Hakkarainen, 2005). The metaphors help us to understand the assumptions that guide the creation of existing LA applications and infrastructures, especially those assumptions related to how knowledge is represented.

Many LA proposals follow the knowledge acquisition metaphor. This metaphor assumes individuals as the basic unit of

[1] http://www.laceproject.eu/
[2] http://learning-layers.eu

learning. Hence, these LA applications commonly model the learners according to the knowledge they acquired (e.g. Ley & Kump 2013; Niemann & Wolpers 2014). Depending on the learning tools this knowledge may be stated as a set of competences (e.g. Krull & Leijen 2015) or as a set of topics were the learner is considered an expert (e.g. Ley & Kump 2013). These LA systems typically use ontologies to structure the data they manage (e.g. Nussbaumer et al. 2012; Siadaty et al. 2016b) or other formal conceptualizations of the learning domain, such as knowledge spaces (e.g. Ley & Kump 2013).

Other proposals (e.g. Rajagopal et al. 2016; Buckingham-Shum & Ferguson 2012) follow the participation metaphor, which assumes that learning happens by participating in cultural practices that shape cognitive activity in manifold ways. These LA applications focus on modeling learning communities and groups depending on their social behavior. Therefore, they create social networks to abstract the social interactions that occur in the tool. In many occasions, Social Network Analysis techniques are employed to extract the community's expertise about certain topics, or to detect communities (Klamma, 2013) and unconnected subnetworks in professional networks (e.g. de Laat & Schreurs 2013).

Other examples (e.g. Derntl et al. 2013; Southavilay et al. 2013) can be found that follow the knowledge creation metaphor, which deals with the collaborative and systematic development of common objects of activity. These LA applications model how learning materials and conceptual artifacts are collaboratively created (Schoefegger, Seitlinger, & Ley, 2010; Thüs, Chatti, Brandt, & Schroeder, 2015). The group of learners is taken as the unit of analysis, considering also their tools and common artifacts (Berendt, Vuorikari, Littlejohn, & Margaryan, 2014; Buckingham-Shum & Ferguson, 2012). Hence, interactions between learners and artifacts and the contexts in which these interactions happen are taken into account, creating a context-aware Artifact-Actor Network (AAN) (Ruiz-Calleja, Dennerlein, Tomberg, Ley, et al., 2015), which is then exploited to understand the evolution of the learners and artifacts (e.g. Fidalgo-Blanco et al. 2015; Thüs et al. 2015). It is typical for such systems to make use of folksonomies, thus enabling the introduction of new and unexpected terms or topics by the users (Schmidt et al., 2009). the amount of LA proposals that follow this metaphor is much lower than in the previous two. This is surprising because of the long history of knowledge creation theory (Nonaka, 1994), and its recognized importance in workplace learning and professional development in the knowledge society (Paavola & Hakkarainen, 2005).

Another restriction shared by all the LA proposals presented above is that they only collect and process data from a single application. Consequently, these proposals put less emphasis on reusability of the data they manage and the algorithms employed to manipulate this data. However, the LA vision goes beyond these restrictions (Siemens, Gašević, et al., 2011): learners, especially workplace learners, typically employ several tools in a way that is difficult to foresee. Researchers are therefore encouraged to develop open proposals that enable the integration of content and data from different sources. These proposals should also be extensible for third parties to integrate their own data sources and data processing techniques. Following this vision, several LA infrastructures were proposed to enhance the integration of data from several tools as well as the reusability of this data and the algorithms to process it (Duval, 2011) (see Table 1). Next, we will review these proposal.

Several authors proposed infrastructures that exploit the data collected by Learning Management Systems (LMSs) in formal learning contexts. LMSs successfully integrate data from different tools, but they structure learning processes according to a pre-described pedagogical design which commonly does not exist in workplace learning. Nonetheless, some authors exploit the data collected by LMSs for analysis that go beyond the pedagogical design. For example, Fidalgo-Blanco et al. (2015) use Moodle data to assess the individual contributions in teamwork activities. For this purpose they analyze the relationships between learners and between learners and learning artifacts inside each teamwork. They focus on a set of indicators to understand and assess how the team collaborated. Another very interesting proposal is Connected Learning Analytics (CLA) toolkit (Bakharia, Kitto, Pardo, Gašević, & Dawson, 2016). A distinguishing characteristic of CLA toolkit is that it collects data from social media applications (e.g. Facebook and Twitter) to analyze student behavior and student relationships. The authors applied CLA toolkit in different "student-facing LA" case studies (Kitto, Lupton, Davis, & Waters, 2017) to make learners reflect upon and change their learning behavior.

Other informal learning infrastructures integrate tools and support LA without the need of a pedagogical design. An example is the ROLE Sandbox[3], a widget-based Personal Learning Environment built on theories of self-regulated learning (Kravcik & Klamma, 2012). In Renzel & Klamma (2013), ROLE Sandbox log data was exploited to extract statistics and to define several social networks. The authors argued that directly analyzing Web log data has the advantage of guaranteeing data interoperability among different services without the need of developing new data standards. This solution technically enables the data sharing and processing, but Web log data does not include any kind of learning concepts, which hinders the integration and reuse of learning-specific information. In order to overcome this limitation, other technical frameworks and infrastructures were proposed. Two interesting examples are Contextualized Attention Metadata (CAM) framework (Schmitz, Wolpers, Kirschenmann, & Niemann, 2011) and Learn-B (Siadaty et al., 2012). Their aim is to enhance the collection, processing and offering of learning data. CAM framework is used to log activities from those tools that generate CAM records; the logs can then be offered for the analysis of the learning process. The CAM framework has already been employed for several purposes, which include learning object classification, competency detection, emotional state recognition and the detection of

[3] http://role-sandbox.eu

Table 1. Comparison of several infrastructures and frameworks for Learning Analytics.

	Functionality offered					Technical issues	
	Knowledge metaphor	Retrieves data from	Extensibility	Informal learning	Workplace learning	Data model	API
Fidalgo-Blanco et al.	K. creation	Moodle	Low	Partly	No	AAN	
CLA toolkit	K. creation	Social Media	High	Partly	No	Ontology-based	JSON-LD xAPI
ROLE Sandbox	Participation	ROLE widgets	Low	Yes	Partly	Social Network	REST
CAM framework	K. acquisition	Integrated tools	High	Yes	Partly	Ontology-based	
Learn-B	K. acquisition	Integrated tools	High	Yes	Yes	Ontology-based	
Apereo LAI	K. acquisition	xAPI tools	High	No	No	Ontology-based	xAPI
Watershed LRS	K. acquisition	xAPI tools	Low	Yes	Partly	Ontology-based	xAPI
SSS	K. creation	Integrated SSS	High	Yes	Yes	Context-aware AAN	REST

goals and intentions (see Schmitz et al. 2011). On the other hand, Learn-B is a service-based software environment designed to support self-regulated learning at the workplace. Learn-B was employed in several studies of the Intel-LEO project[4] for several purposes, such as assessing the impact of scaffolding practices in workplace environments (Siadaty, Gašević, & Hatala, 2016a,b). Following the knowledge acquisition metaphor of learning, both the CAM framework and Learn-B defined ontologies to structure activity logs. Both are also able to describe the contexts where the learning activities happens.

As several infrastructures were proposed, how to share data among them became a relevant problem. For this reason, open software and standards were promoted for Learning Analytics (Siemens, Gasevic, et al., 2011). In this regard, the Experience API[5] gained adoption as a *de facto* standard for the exchange of learning data. Its main idea is to define a common data format between learning tools and infrastructures to exchange information about learning events. According to Experience API each learning event is defined by a quadruple: a subject, a verb, an object and a context; while an ontology should be implemented to define the different elements of the quadruple. As an example, Bakharia et al. (2016) use JSON for Linked Data (JSON-LD) to define an extensible vocabulary for xAPI statements.

Some Learning Record Stores (LRSs) have also been proposed to collect and manipulate Experience API data. Examples of LRSs with an open license are Learning Locker[6] and Larissa[7]. Other initiatives built on top of them to create open infrastructures or tool-kits that can be adapted to different learning situations. Some examples are Starfish Analytics[8], Jisc Learning Analytics[9], and Apereo Learning Analytics Initiative (LAI)[10] (we included Apereo LAI in Table 1 as an example to represent this group of LRSs). These proposals support the collection and storage of xAPI data. They also offer some data analysis services and some user interfaces (e.g. SNA algorithms and Dashboards). These services and interfaces can be adapted to different learning situations or new services can be integrated into the toolkit. However, all these initiatives focus on formal learning and take an institutional perspective. An interesting example of an xAPI-compliant infrastructure that supports informal learning is Watershed LRS[11]. The data analysis of Watershed LRS again follows the knowledge acquisition approach in a rather individualistic way. Furthermore, it is a closed infrastructure, offered as a cloud service, that cannot be extended by third parties.

3. The Social Semantic Server

The Social Semantic Server (SSS) (Dennerlein, Kowald, et al., 2015) is an infrastructure that collects data from workplace learning tools and offers it back to be used by LA applications. It evolved during 8 years from a close analysis of workplace learning practices in different domains carried out in the MATURE project[12] (Ravenscroft, Schmidt, Cook, & Bradley, 2012). More recently it has been applied in the Learning Layers project[13] to support informal workplace learning (Ley et al., 2014) with a special focus on SMEs working in innovation-driven domains. Its theoretical roots lie in knowledge creation theories. Moreover, its design was based on a number of additional empirical studies, such as in-depth case studies of workplace and organizational learning (e.g. Kaschig et al. 2012) as well as a number of design-based research activities in several contexts (Dennerlein, Theiler, et al., 2015). These studies contributed to the understanding of how individual, group and organizational

[4] `http://intelleo.eu/index.php`
[5] `https://experienceapi.com`
[6] `https://www.ht2labs.com/learning-locker-community/overview/`
[7] `https://github.com/Apereo-Learning-Analytics-Initiative/Larissa`
[8] `https://www.starfishsolutions.com/home/starfish-enterprise-success-platform/starfish-analytics/`
[9] `https://www.jisc.ac.uk/learning-analytics`
[10] `https://www.apereo.org/communities/learning-analytics-initiative`
[11] `http://www.watershedlrs.com`
[12] `https://mature-ip.eu/`
[13] `http://learning-layers.eu`

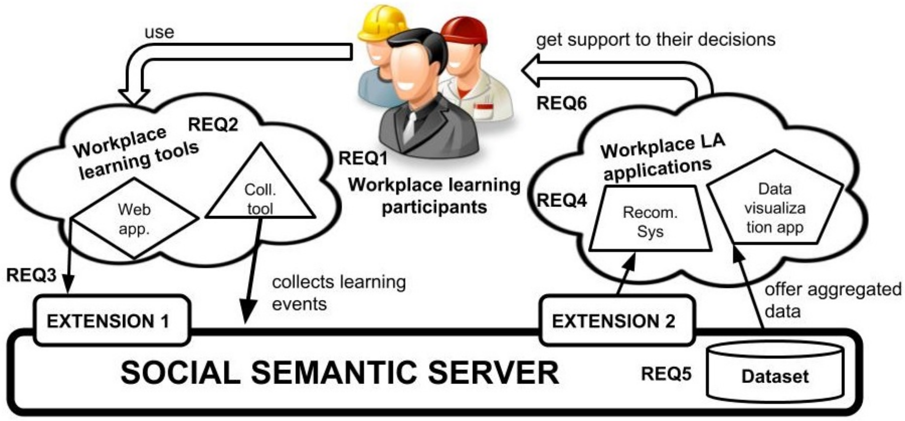

Figure 1. Potential scenario supported by the Social Semantic Server.

learning are intertwined in knowledge creation. To name just a few examples, it was found how professionals make sense of experiences and informally learn from them (Dennerlein et al., 2014), how help seeking happens in professional networks (Santos et al., 2016), or how organizations create boundary objects to facilitate knowledge sharing (Kaschig et al., 2012). The SSS was designed by deriving requirements from the tools and services needed to support these empirical studies.

3.1 Requirements for the Social Semantic Server

Figure 1 depicts a typical scenario of a workplace LA infrastructure. Workplace learning participants (e.g. workers or trainers) use a set of tools to learn at the workplace. The workplace LA infrastructure collects the learning events from these tools and creates a coherent dataset out of them. This data is then offered back to workplace LA applications to support the decision making of workplace learning participants based on their learning evidences.

The SSS has been evolved into an open-source infrastructure designed to address the knowledge creation metaphor for this type of scenarios. It is not restricted to a specific domain or activity, so it should support a wide range of workplace learning scenarios (**REQ3** in Table 2 and Figure 1), which may differ in the way they are enacted, in their number of participants and in their level of formality (Kooken, Ley, & De Hoog, 2007). Therefore, the SSS should be flexible enough as to be adapted to many different learning situations.

The SSS is meant to be used during normal activity in real work environments (**REQ2**). Hence, the SSS should be able to remove the inherent boundaries from the large variety of tools that are currently used for workplace learning (Kooken, Ley, & De Hoog, 2007). It is well known that in real work environments different tools are used for learning purposes (Cardinali, 2015). Hence, the SSS should collect the learning events tracked by different tools and integrate them (**REQ1**). It should also enable different integration strategies, as the technical aspects of these tools may also differ.

The data collected by the SSS should later on be offered back to LA applications (**REQ4**). Therefore, the SSS should offer a data access API for external applications. It would also be desirable for the SSS to allow the definition of new data APIs. Thus, the wide range of LA applications that are currently used for workplace learning (Ruiz-Calleja, Prieto, Ley, Rodríguez-Triana, & Dennerlein, 2017) could potentially exploit its data.

Other requirements related to how the SSS structures the knowledge derive from its focus on the knowledge creation metaphor (**REQ5**). As we showed in the previous section, the LA applications that follow this metaphor establish an Actor-Artifact Network. This AAN should be able to describe different relationships between actors and artifacts (e.g. resource creation or access). It is key for this metaphor to track the context in which interactions between learners, and between learners and artifact, take place. The special focus of knowledge creation on emerging knowledge also requires the SSS to represent different data structures in different levels of maturity (Ruiz-Calleja, Prieto, Ley, Rodríguez-Triana, & Dennerlein, 2017). Finally, as the SSS is meant to support decision making in workplace learning practices (**REQ6**), a positive impact on these practices is expected out of the exploitation of the data collected by the SSS.

3.2 Design and implementation of the SSS

3.2.1 SSS Data model

The requirements of the SSS data model are derived from its focus on the knowledge creation metaphor (REQ5), and the need to support the semantic integration of data collected from different learning tools (REQ3) with different levels of formality (REQ1). The basis of the SSS data model is an Artifact-Actor Network (AAN), in accordance with the analysis on LA applications that follows the knowledge creation metaphor. Therefore, the SSS can explicitly describe the relationships between learners,

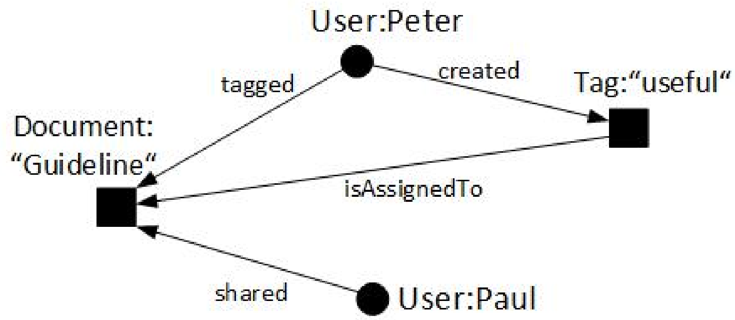

Figure 2. Example of an AAN from the SSS.

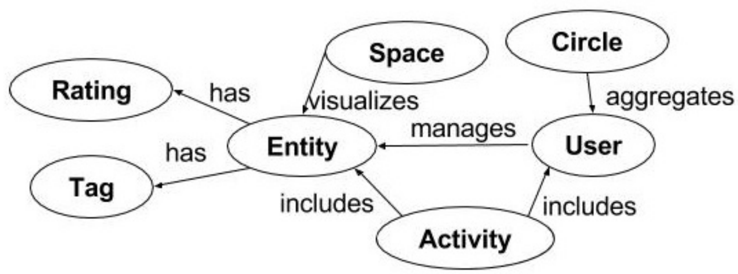

Figure 3. The SSS Core Ontology.

artifacts and between learners and artifacts. Furthermore, different types of relationships can be defined, thus giving a meaning to the connections among entities. Some contextual information (e.g. time or some keywords) can also be attached to the entities.

As an example, a typical situation in informal learning would be a worker (let's call him “Paul”) sharing a document that describes a guideline for a particular work process. A colleague (“Peter”) would find this document, mark it for his own use, and tag it as “useful”. In that case, the AAN will register four entities (both users, the document and the tag) and four relationships with three different meanings (“tagged”, “shared” and “isAssignedTo”). In addition, the relationships between the entities will include the time frame of the event and maybe some contextual information, such as the location or the tool employed for such event. Figure 2 graphically depicts the resulting AAN from this example.

This AAN can be seen as a high-level abstraction that offers a common data model to integrate data from multiple learning tools. However, the entities related to the AAN (actors, artifacts, relationships and contexts) should be semantically described if the semantic integration of data is required. For this reason the SSS includes a core ontology. This ontology is used to describe the entities in the AAN, their relationships and the parameters to define the context where these relationships happen. Hence, the data model of the SSS is based on a context-aware and semantically-enriched AAN.

Figure 3 represents the entities and the most important relationships in the SSS Core Ontology. The main entities to define nodes in the AAN are `User` and `Entity`. Users can be aggregated into `Circles` (i.e. an abstraction similar to Google+ Circles, to aggregate users into groups) and entities into `Spaces` (i.e. an abstraction similar to Dropbox spaces, to aggregate documents into folders). Then, some metadata can be attached to entities (`Rating` and `Tag`). Finally, the `Activity` is used to trace activities where users and entities are involved. Note that the SSS Core Ontology does not include a concept to define contexts because the parameters related to learning contexts highly depend on each specific situation. For example, in some situations the context is related to the metadata attached to the entity (e.g. tags), while in others it is related to the spaces where the entities are aggregated to.

This ontology can be later on extended to include additional concepts for specific learning situations. For instance, in order to describe the AAN depicted in Figure 2 the concept `Document` should be defined as a subclass of `Entity`, as well as the relationship `Shared`. In some other cases ontology extensions are used to define parameters to describe learning contexts, such as location. It should be noted that the SSS faces a well-known trade-off: ontologies are more expressive vocabularies than folksonomies and are used to model domains or to allow the semantic integration of several applications; however, they are sometimes not able to collect emerging knowledge, as they are more difficult to modify and evolve. For this reason, ontology extensions can provide further structure by semantically defining narrower concepts (e.g. different types of “artifacts”); but this semantic definition can also be avoided (e.g. defining a folksonomy of tags). Thus, the SSS can integrate data with different levels of formality (Ruiz-Calleja, Dennerlein, Tomberg, Ley, et al., 2015).

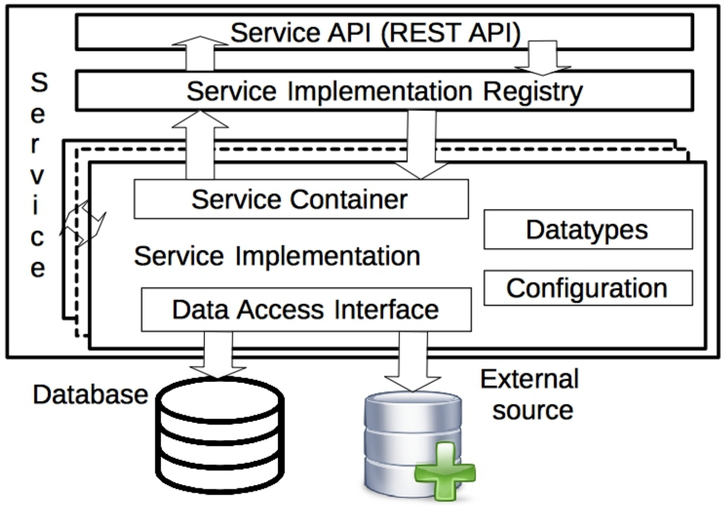

Figure 4. SSS Service architecture.

3.2.2 SSS Software architecture and implementation

The SSS software infrastructure should allow the integration of a wide variety of tools used for learning at the workplace (REQ3 and REQ2). It should also be flexible to be adapted to different informal learning situations (REQ1) and extensible, so new functionalities can be offered to data consuming applications (REQ4).

The SSS software architecture follows the Service Oriented Architecture (SOA) style (Earl, 2005). SOA promotes architectures based on the light integration of loosely coupled services that offer a granular functionality and can be orchestrated to provide a more complex one. SOA leads to flexible and modular architectures since services can be exchanged if needed. This is achieved by dividing the functionality of the SSS into fine granular services that can be easily maintained, reused, combined and replaced. Thus, by adding new services or configuring the existing ones, the SSS can be extended to offer additional functionalities or they can be adapted to specific learning scenarios.

Figure 4 depicts the architecture of each SSS service. Each service is composed by a set of `Service Implementations`, a `Service Implementation Registry` and a `Service API`. Each service may include several `Service Impleme ntations` (or just one) that offer the same functionalities in different ways. For example, a tag recommendation service may have two implementations, each of them based on different recommendation algorithms. Each service may define its own `Datatypes` and can have some `Configuration` parameters. In the previous example the configuration parameters define the data sources accessed by the implementations of the recommender service or the way each result is ordered. This way it is possible to modify the internal logic of the services (and adapt their functionality accordingly) without the need of any change in the `Service API`. Each `Service Implementation` also includes a `Data Access Interface`, which is used to access data sources. These data sources can be databases integrated to the SSS (e.g. MySQL), or external data sources (e.g. external applications that share their data to the SSS). The `Service Implementation Registry` mediates the communication between the `Service API` and the `Service Implementations`, deriving each API call to the corresponding implementation through its `Service Container`.

Figure 5 represents a possible configuration of the SSS software architecture. It can be seen that external learning tools submit their data to the SSS calling the `Activity service`, which traces the interaction between learners and resources. The data is then stored by the `Metadata services` (e.g. `Data Export Service`), which manage the datasets of the SSS. These `Metadata services` also offer abstractions - based on the AAN previously described - for other services to access the data. Thus, the data APIs implemented in the `Metadata services` wrap the interfaces of the underlying databases, which may vary depending on the data representation used (e.g. SQL, NoSQL or document-based representations). Thus, the implementation of the data model can be abstracted to fit the business logic of each particular service. This solution makes the SSS data layer to be scalable and adaptable. However, this solution does not take data-access performance as a requirement. The reason is that learning datasets are typically small in comparison to other domains, and current data stores offer enough data-access performance. While it is true that the implementation of the `Metadata services` may hinder such performance because it adds an extra software layer, our previous experience (see the first paragraph of section 3) shows that this does not represent a problem for the users or the software developers. Finally, the business logic of the SSS is composed of another collection of services. They can be `Simple services`, which serve one functionality (e.g. `Group Access Restriction`, which controls user restrictions) or manage some entity types (e.g. `Tag`, `Collections`, `Q&A`

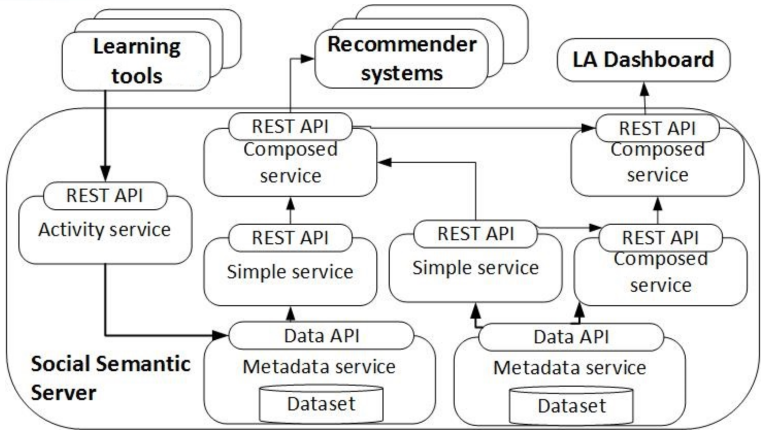

Figure 5. Possible configuration of the SSS software architecture.

or `Activity`). Others are `Composed services`, which exploit other services to provide their own functionality (e.g. `Search` or `Recommendations`). See Dennerlein, Kowald, et al. (2015) for additional details about these services.

As previously seen, the design of the SSS architecture promotes its flexibility and extensibility. Services can be composed and different implementations or configurations of the services can coexist. This way, the SSS can be adapted to different workplace learning situations. Furthermore, the SSS includes a set of services that can be exploited by several LA functionalities, such as the `Activity service` or the `Metadata services`, while the `Service API` is offered as a REST API.

Regarding the integration of learning tools and LA applications, the SSS supports two strategies. The first one is a loosely-coupled integration, where external applications make use of the SSS data API either to publish or to retrieve data. In these cases the functionality of the SSS does not need to be extended or modified, although an extension of the SSS may be required to enable the semantic integration of the data retrieved (i.e. new concepts may need to be defined). The second strategy is a tightly-coupled integration, where part of the functionality of the applications is developed as SSS services or as extensions of already-existing ones. It is sometimes the case that these new services need to define new API methods to offer new functionalities that could potentially be reused by other applications. Therefore, the SSS can be seen as a framework that facilitates the development of workplace LA applications (Dennerlein, Kowald, et al., 2015).

The implementation of the SSS architecture is based on microservices (Newman, 2005), which have emerged as a novel way to design software in form of services to promote the independence in their own deployment and to deal with technological heterogeneity. This independence of the services increases the flexibility of the SSS infrastructure, as some of them can be deployed and others can be integrated if needed. Furthermore, the loose-coupling of SSS services also enables their development by third parties and the integration of software frameworks inside the SSS. In fact, the current version of the SSS (which is coded in Java and available in our GitHub repository[14]) integrates the TagRec (Kowald, Kopeinik, & Lex, 2017) framework for the development of tag recommender algorithms.

4. Evaluation

In order to assess whether the SSS meets the requirements stated in the previous section, we developed a set of workplace learning tools that submit their data to the SSS, as well as LA applications that consume such data. We then used the SSS in authentic evaluation studies carried out in the Learning Layers project. Note that carrying out authentic studies that involve different stakeholders (Dewan, 2001) is typically applied for the evaluation of collaborative systems in education (e.g. Alario-Hoyos et al. 2013). Table 2 summarizes the SSS requirements and their relationships with the evaluation studies, the evaluation methods and the data sources.

4.1 Workplace learning tools integrated into the Social Semantic Server

We integrated into the SSS some domain-independent tools offered by third parties during the Learning Layers project. These tools were extended to submit data to the SSS or to make use of some of its services. One example is the web browser Chrome[15]. We developed a Chrome plugin (called Bookmarker (Ruiz-Calleja, Dennerlein, Tomberg, Ley, et al., 2015)) that allows to create, tag and submit bookmarks to the SSS from Chrome interface. We followed a similar strategy to integrate the blog editor Wordpress[16] with an extension called Attacher (Ruiz-Calleja, Dennerlein, Tomberg, Ley, et al., 2015). Attacher allows

[14] `https://github.com/learning-layers/SocialSemanticServer`
[15] `https://www.google.com/chrome/`
[16] `https://wordpress.com`

Table 2. Relationship between SSS requirements, evaluation studies, evaluation methods and data sources.

Tag	Requirement	Evaluation Studies	Evaluation methods	Data sources
REQ1	Supports LA in a wide range of learning scenarios	TT-14, CC-15, MR-15 and RW-16	Multiple authentic studies, mixed methods	SSS logs, interviews, questionnaires
REQ2	Integrates tools used for learning at the workplace	TT-14, CC-15 MR-15 and RW-16	Multiple authentic studies, feature analysis	Implementation of the SSS, SSS logs, LA applications
REQ3	Collects and integrates data from different tools	TT-14, MR-15 and RW-16	Multiple authentic studies	SSS logs
REQ4	Enables the consumption of its data by LA applications	LA applications development	Feature analysis	LA applications
REQ5	Focuses on knowledge creation metaphor	TT-14 and CC-15	Multiple authentic studies, mixed methods, feature analysis	Implementation of the SSS, interviews, LA applications
REQ6	The SSS data is relevant for analyzing and supporting learning practices	TT-14, CC-15, MR-15 and RW-16	Multiple authentic studies, mixed methods	SSS logs, interviews

blog editors to browse the resources (e.g. bookmarks) contained in the SSS from the blog editing interface, to access their corresponding URLs and to cite them in the blog posts. Attacher also registers in the SSS the blog posts published. A different strategy was followed to integrate Evernote[17] (Dennerlein, Kowald, et al., 2015). In this case a SSS Service was created to access Evernote API in order to semantically integrate into the SSS the notes taken by its users, thus turning Evernote into an external data source from which data can be imported to the SSS.

We also developed from scratch other learning tools that make use of the SSS. In these cases the SSS was exploited as a framework for the development of workplace learning tools that are tightly integrated into it (Dennerlein, Kowald, et al., 2015). This approach was followed by KnowBrain (Dennerlein, Theiler, et al., 2015), a collaborative resource hosting tool built on top of the SSS. KnowBrain exploits the SSS services to allow users to manage, tag and share resources, such as learning documents or bookmarks. Similarly, a set of three tools was developed to support informal learning in the healthcare domain, which is typically offered combined in one tool set that uses the SSS as a common back-end infrastructure. The first tool is Bits & Pieces (Dennerlein et al., 2014), a visual categorization tool to enhance individual and collaborative sense-making processes; it exploits the SSS to enable learners define semantic and contextualized relationships between learning artifacts. The second tool is Discussion Tool, a question & answer tool that offers an interface similar to a web forum (Dennerlein et al., 2014); it exploits the SSS to relate the resources created (questions and replies) and these resources to their authors and readers. The third tool is Living Documents (Bachl, Zaki, Schmidt, & Kunzmann, 2014), a collaborative text editor; it exploits the SSS to allow its users to access the resources registered in the infrastructure.

4.2 Learning Analytic applications that exploit the Social Semantic Server

In addition to the learning tools mentioned in the previous subsection, we developed a set of LA applications that exploit the data collected by the SSS. Specifically, we developed a visual dashboard and five recommender services, which offer typical functionalities of workplace LA (Ruiz-Calleja, Prieto, Ley, Rodríguez-Triana, & Dennerlein, 2017). The development of a bigger set of applications that offer other workplace LA functionalities is part of our future work.

4.2.1 SSS Dashboard

The SSS Dashboard (Ruiz-Calleja, Dennerlein, Ley, & Lex, 2016) allows end users to visualize and browse the data collected by the SSS. Specifically, the SSS Dashboard contains three visualizations: `filter events`, which represents the list of events collected by the AAN and allows users to filter them by their actors, by the artifacts involved or by the actions done; `Social network`, which represents a social network of the artifact-mediated relationships between the actors registered by the SSS; and `Tag Cloud`, which represents a tag cloud of the tags registered in the AAN.

These visual abstractions are suitable for learners and trainers to visualize "uptake relations", which have been defined as the smallest units of meaning making activities in knowledge creation (Suthers & Dwyer, 2014). For example, Figure 6 shows how the dashboard represents these meaning making activities by building a social network that is generated from the uptake relations arising from reciprocal contributions to a particular artifact. These uptake activities represent the use and reuse of certain tags when collecting and annotating learning materials. The directional social network, therefore, represents the subgroups of learners that have collaborated around the creation, use and enrichment of concepts. It also represents the subgroup of learners who have influenced others in this process.

The SSS Dashboard was implemented as a loosely-coupled application that consumes the data offered by the SSS. It simply gathers a .csv file from the `Data Export Service` API that contains the events registered in the AAN. This

[17] `https://evernote.com/`

Table 3. Main characteristics of the SSS evaluation studies.

Tag	Date	Location	Duration	Domain	Purpose	Users	Tools	LA Applications
TT-14	2014	Estonia	5 months	Education	Reflect on how to introduce technology in education	11	Chrome, Wordpress	SSS Dashboard
CC-15	2015	Austria	4 weeks	Research	Study of a state of the art	18	Knowbrain	3Layers, Most Popular
MR-15	2015	England	2 months	Medical practice	Making sense of their working experience	6	Evernote, Bits & Pieces, Discussion Tool, Living Documents	Most Popular, CF recommendation algorithm
RW-16	2016	Europe	5 months	Research	Plan and evaluate interventions	22	Evernote, Bits & Pieces, Discussion Tool, Living Documents	Most Popular, CF recommendation algorithm

implementation decision is not as efficient as extending the `Data Export Service` with a CRUD REST API to offer abstraction suitable for the Dashboard. However, we reduced our development time because we reused the `Data Export Service` extension developed for the recomendation algorithms (see next subsection). The current version of the Dashboard was implemented using Javascript and well known libraries, such as d3[18].

4.2.2 Recommendation algorithms

Other LA applications that exploit the data collected by the SSS are recommender services that take advantage of the TagRec (Kowald, Kopeinik, & Lex, 2017) framework integrated into the SSS. As part of this evaluation, we developed a set of recommendation algorithms that exploit the SSS data for different purposes: recommend learning resources (Seitlinger et al., 2015), recommend tags to be assigned to learning resources, and recommend people to interact with (Kopeinik, Kowald, Hasani-Mavriqi, & Lex, 2017).

Several recommendation algorithms are currently available. These include tag and resource recommendations based on recent or most popular resources (Kowald & Lex, 2016; Kowald, Seitlinger, Trattner, & Ley, 2014). Thus, these approaches rank the resources in the learning system based on popularity or recency (i.e. time since last usage). Another recommendation approach is based on collaborative filtering (CF) (Schafer, Frankowski, Herlocker, & Sen, 2007), which means that items of similar users are recommended. In the future, we also plan to extend this CF-based approach with a content-based approach as provided in the ScaR recommender framework (Lacic, Traub, Kowald, & Lex, 2015), which would allow us to not only incorporate similarities between users but also between resources (e.g. based on description texts or even full contents).

An algorithm that is especially designed to follow knowledge creation theory is the 3Layers tag recommendation approach (Seitlinger, Kowald, Trattner, & Ley, 2013; Kowald, Seitlinger, Kopeinik, Ley, & Trattner, 2013). It learns how a learner, or group of learners, categorizes resources. It traces the tags used for particular resources; later on, it dynamically builds an understanding of the semantic contexts over time. The algorithm then recommends tags that match a particular semantic context. This mirrors a situation where the interpretation of a resource (its semantic context) emerges from past artifact-mediated activity, rather than being predefined by an ontology of the domain.

The recommender services were implemented[19] as a micro-service in the SSS (`Recommendations`) service, which includes the TagRec framework. The `Data Export Service` was also extended in order to dynamically create a .csv file with the structure required by the framework, out of the data contained in the SSS database. This extension of the `Data Export Service` to offer the data as a .csv file did not take efficiency as a requirement. However, it managed to wrap the data contained in the SSS database to be offered to a service that takes .csv file as an input without the need of modifying such service. The `Recommendations` micro-service also defines new methods in the SSS API. As an example, it includes a method that provides a set of tags recommended and whose parameters are a user, a set of entities, a category, and a maximum number of tags to recommend. External applications (e.g. Knowbrain and Bits & Pieces) exploit this method to provide tag recommendations to their users.

4.3 Evaluation studies

Due to the complexities of introducing and evaluating workplace learning technology, it was not feasible to evaluate all requirements of the infrastructure in one single study. Hence, we conducted four evaluation studies to collect evidence for each of the six requirements described in the previous section. These studies cover different domains, different goals and happened in different countries. We particularly focused on uptake events and on how the infrastructure traced and supported them, as these are clear indications of collaborative knowledge building. Table 3 summarizes the most important characteristics of the evaluation studies, while further information is provided next.

[18] `http://d3js.org/`
[19] `https://github.com/learning-layers/TagRec/`

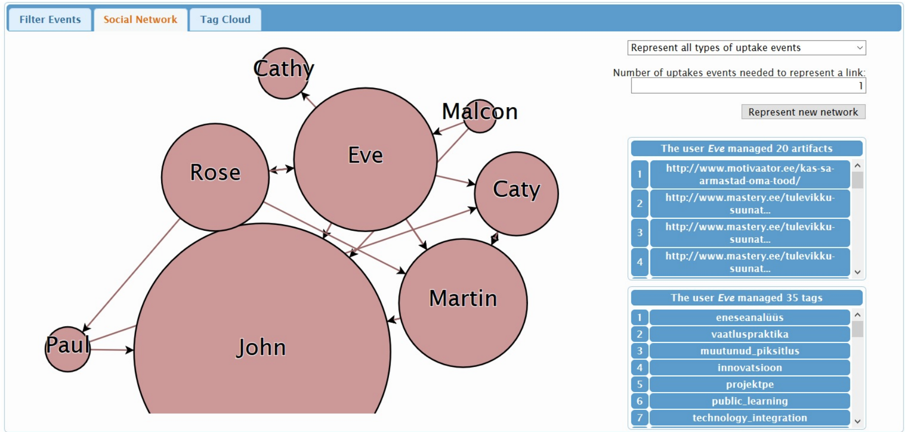

Figure 6. SSS Dashboard interface: Social Network Visualization out of the data collected in TT-14.

4.3.1 Professional teacher training course (TT-14)

The first evaluation study was done in a professional teacher training course (**TT-14** in Tables 2 and 4.3) held at Tallinn University (Estonia) between September 2014 and January 2015. It tests the SSS Dashboard in an authentic experience where learners use multiple workplace learning tools (**REQ3** and **REQ2**) and evaluate its support to understand learning processes (**REQ1** and **REQ6**) according to the knowledge creation metaphor (**REQ5**). Here we focus on the role played by the SSS, while additional details are reported at Ruiz-Calleja et al. (2016).

Learning context and participants: The main purpose of the course is to help teachers reflect on how to introduce new technologies and pedagogical techniques into their classes. Therefore, they had to address real problems and opportunities at their workplace. A group of 10 professional teachers ("learners" from now on) attended the course and were guided by a trainer. As part of the course activities, the learners were asked to browse the Web looking for resources that could extend or contrast the information provided by the trainer. Using these resources they were asked to write blog posts where they reflected about their own teacher practice and how to introduce new technology in their own classrooms. Each learner wrote 10 blog posts and they shared them with the rest of the learners. They used Chrome as a web browser to search and discover web resources that would help them in the design of their teaching. These resources were submitted as bookmarks to the SSS with the support of Bookmarker extension. As a blog editor they used Wordpress. The Attacher plugin was installed to facilitate the access to bookmarks published on the SSS.

SSS Configuration: A simple configuration of the SSS was required for this study as all the learning tools and LA applications are loosely-coupled integrated. The service `Tag` was exploited by Attacher and Bookmarker to submit learning resources attaching them some contextual metadata. Attacher also uses the `Search` service to search for resources, and the SSS Dashboard the `Data Export Service` to extract the AAN from the SSS. Regarding the data model, a folksonomy of tags was created during the study, but there was no need to define new semantic concepts. Hence, it was not necessary to extend the Core Ontology of the SSS.

Data collection and analysis: Once the training course was over, one of the learners and the trainer used the SSS Dashboard to visualize the data collected by the SSS. Figure 6 represents the Social Network interface of the SSS Dashboard (the name of the learners were changed). The functionality of the SSS Dashboard was explained to them and, after that, six tasks were proposed for them to accomplish with the dashboard. The tasks emerged from the learning procedures defined by the three learning metaphors (e.g. "Detect which interests two learners share in common" or "Identify learning topics that are surprising or unexpected to you"). Once they finished, a semi-structured interviewed was carried out to further understand their opinion about the dashboard and how useful they found the graphical abstractions offered (e.g. "if the SSS Dashboard was available during the course, what would you use it for?"). The participants' interactions with the SSS Dashboard, their voice while using and the interviews were recorded. Later on, two researchers listened the recordings and extracted their most important aspects.

Resulting AAN: During 5 months 8 of the learners frequently used Chrome and Wordpress while other 2 hardly used these tools since they were not active in the course. The SSS coherently combined the data from Chrome and Wordpress and a total amount of 320 events were registered. Out of these events, the SSS created an AAN that contained 11 actors, 53 resources and 116 tags.

Main study results: Both the trainer and the learner were able to accomplish the six tasks proposed using the SSS Dashboard. Both of them agreed that by using it they could better understand the learning process. Interestingly, they understood the collaboration among learners as a process mediated by artifacts (trainer while using the Dashboard: "*as a trainer I would be worried because these two learners did not reused artifacts from others and they do not share information to others*").

During the interview, both of them agreed that the SSS Dashboard was a useful application. However, the trainer found it interesting to understand the learning process (trainer when interviewed: "*an average trainer would use it to understand what is going on in the course*"), while the learner reduced its potential use to the identification of relevant learning artifacts or to find potential collaborators (learner when interviewed: "*I would use the dashboard to find out if there are learners that use the same resources as me and to get an overview of the resources used by others*").

4.3.2 Collaborative digital curation (CC-15)

The second evaluation study was conducted as part of a collaborative digital curation scenario (**CC-15**) coordinated from Austria in September 2015. The aim of this study was to test the tag recommender services in a real work environment (**REQ1** and **REQ2**) and to compare the support provided by a frequency-based MostPopular and the 3Layers algorithms (**REQ5**), as well as the benefit offered to the participants (**REQ6**). Part of the results have been published in Seitlinger et al. (2017).

Learning context and participants: As part of their job 18 professional researchers ("users" from now on) explored the topic "smart workplaces" during four weeks in order to collaboratively describe a state-of-the-art overview. These researchers belonged to two universities from two European countries. They coordinated themselves to collect and share topic-relevant resources (i.e. web pages or text documents), sharing at least four every week. For this purpose they used Knowbrain, which allowed them to upload, classify, tag and share resources. Each resource was related to a category (out of six predefined ones) that classified the resources according to their topics, and annotated with free tags. The users were supported in the process of tagging resources by means of a tag recommender service integrated into Knowbrain, which suggested seven tags to describe each resource depending on the category selected for the resource. These recommendations were extracted from two algorithms that exploited the data from the SSS: either 3Layers or the frequency-based MostPopular. One of the assumptions of the study was that 3Layers recommendations would be more suitable for creative group work as they would pick up and feed back emergent topics more quickly than MostPopular recommendations.

SSS Configuration: Knowbrain is a learning application tightly integrated into the SSS whose complex functionality uses the following SSS services (Dennerlein, Kowald, et al., 2015): `Recommendations`, `Gardening Knowledge Structures`, `Collections`, `Q&A`, `Search`, `Tag`, `Data Export Service`, `Activity` and `Group Access Restriction`. Knowbrain submits data to the SSS through the `Collections`, `Q&A` and `Tag` services. This data is later on exploited by the recommender services (`Recommendations` service). They extract the AAN from the `Data Export Service` and offer the tag recommendations through an extension of the SSS API. Additionally, the SSS Core Ontology was extended to define two new types of entities (`File` and `Image`). Other two concepts were introduced: `Collection`, to aggregate entities; and `Friend`, to allow the explicit relationships between users.

Data collection and analysis: We analyzed the Knowbrain and SSS logs to understand the tag recommendation and selection during the study. We measured the support of each recommendation algorithm by means of the F1 score (Power, 2011), which is calculated based on the number of accepted recommendations of a tag and the number of times the tag was recommended to the users. We used the F1 score since it a simple and commonly-employed metric that considers both the precision and recall of the recommendations, thus providing a more robust evaluation procedure. We also analyzed the timestamps of the log entries to understand how the tag assignments evolved in Knowbrain and which tags were uptaken by which users.

Resulting AAN: 18 users participated in the study. A total amount of 2654 user events were registered, out of which the SSS created an AAN that contained 18 actors, 122 resources, 263 unique tags, 701 relationships between tags and resources and 6 categories. The recommender services made extensive use of this AAN; there were 183 recommendation events with a total amount of 1281 tags recommended.

Main study results: The score obtained by the 3Layers algorithm (F1-score = 0.34) was higher than the score obtained by the frequency-based MostPopular (F1-score = 0.27). These results show that the recommendations offered by the 3Layers algorithm have a bigger influence on the users behavior than a popularity-based one. We assume this was the case because 3Layers better reflected the shared interpretations that emerged in the group as a result of their creative group work. We could also notice its impact by the capability of the 3Layers algorithm to rise awareness of topics once they are introduced into the users community. For example, the tags `wellbeing` and `social involvement` were marginal tags at the time they were introduced. These tags represented new concepts introduced in the learning community and were recommended by the 3Layers algorithm (and not by the Most Popular algorithm), making them to be quickly taken up by other users.

4.3.3 Healthcare professionals meaning making (MR-15)

The third evaluation study was part of a three-year design-based research project that aimed at developing workplace learning tools for interdisciplinary healthcare (HC) professionals. It was conducted at the participants' daily work from October to November 2015. The aim of the study was to assess whether the SSS can collect and integrate data from multiple tools (**REQ3**) that are employed to support informal learning while working (**REQ1** and **REQ2**). The benefit of the data collected to the participants will also be assessed (**REQ6**).

Learning context and participants: The study involved six English HC professionals (2 doctors, 1 practice manager, 1 office supervisor, 1 administrative and 1 IT support manager). During the study, the HC professionals used a toolset that included four tools integrated into the SSS. These tools supported the collection, categorization and formalization of informal learning experiences: Evernote helped recording informal learning experiences by taking multimedia notes; Bits & Pieces facilitated sense-making of the notes taken with Evernote; Discussion Tool supported parallel discussions and promotes the professional engagement in sense-making processes; and Living Documents supported the formalization of the conclusions. In addition, Bits & Pieces exploited two of the recommender algorithms integrated into the SSS: time-based recommender, which recommended tags to annotate learning artifacts; and a collaborative filtering algorithm, which recommended resources (e.g. Evernote notes) created by other professionals.

SSS Configuration: In this study the SSS configuration is more complex as four learning tools are involved. For the tight integration of Bits & Pieces two new services (`Learning Episode` and `Category`) were needed. These services categorize and contextualize learning resources in an abstraction called `Learning Episode`, defined as a new entity type in the SSS Ontology. Discussion Tool is also tightly integrated to the SSS. It exploits services such as `Q&A`, `Entity` or `Tag`. Although no new service was needed for this integration, the SSS Ontology was extended with the entity type `Discussion` and the relationship `Like`. The other two applications involved simply registered in the SSS the documents managed by their users. For this purpose two new services were required: `Data Import` to access Evernote API, and `Living Document` to retrieve documents written by Living Document. These services also defined new entity types: `Mail`, `Evernote note` and `LivingDoc`.

Data collection and analysis: We conducted questionnaires and semistructured interviews with the professionals to evaluate the impact of the recommender services for supporting informal learning. The questionnaire addressed the appropriation of functionalities and asked for their evaluation in form of open questions; the interviews focussed on how the tools were used and on their impact when learning and working. We analyzed the data following Mayring's inductive qualitative content analysis (Mayring, 2014): first, we transcribed the interviews; second, we paraphrased the contents; and, third, we extracted categories to iteratively discover structure such as use cases, working functionalities and corresponding reasoning in the data. We also analyzed the SSS logs to describe the resulting AAN and to quantify the tag recommendations.

Resulting AAN: The SSS registered 8345 user events and 151 resources imported from Evernote and Bits & Pieces. The resulting AAN contained 6 actors, 306 resources (145 bits used in episodes, 29 discussions related to 36 discussion entries from Discussion Tool, 13 documents from Living Documents and 48 learning episodes from Bits & Pieces), 31 tags and 71 categories. Based on this AAN tag recommendations were computed, which led to 12 accepted recommendations.

Main study results: In the analysis of the qualitative data, we found out that they all followed the informal learning process from tracing experiences, organizing and discussing them and finally transforming outcomes into a shared report. The support of the SSS as an infrastructure to share, categorize and evolve annotated learning resources among four different tools was key for the learning process. In addition, the SSS integrated the data collected from the four tools and offered it to the recommender algorithms. However, these recommender algorithms did not play a major role in this particular scenario. One of the reasons is that the resource recommendations were rather happening on a personal level by having bits added by colleagues than using the ones provided by the system. The seldom use of the tagging functions and the limited number of tags registered in the system lowered the impact of the tag recommendations. We claim that the seldom use is due to their lack of experience with similar tools and functionalities, which hides the additional value of tagging resources. However, some of the users appreciated the tags when searching for resources (HC professional: *"I use tags and things like that because I think obviously if [...] everybody's got a lot more diverse tags it would be very useful to search on, I like that"*). Despite this, the professionals stated in the interviews that the recommendation of tags eases the process of tagging and that they can see how they potentially help to arrive at a professionally agreed vocabulary.

4.3.4 Collaborative Planning of research work (RW-16)

The fourth evaluation study was also part of the three-year design based research project reported in MR-15. In this case, the SSS supported a group of researchers from March to July 2016 to coordinate their work related to the planning of research interventions, the evaluation of the data gathered and the reflection about the results obtained. In a similar way as MR-15 pilot, we assessed if the SSS can collect and integrate data from multiple tools (**REQ3**) that are employed to support informal learning while working (**REQ1** and **REQ2**). We also evaluated the impact of the data collected to support their learning practice (**REQ6**).

Learning context and participants: This study involved 22 researchers who belonged to 10 different institutions and collaborated in a European project. During the study the researchers used the SSS and the same tool set described in the MR-15 pilot study. They used Evernote, Bits & Pieces, Discussion Tool and Living Documents to communicate and to coordinate their activities. These tools supported the individual and collaborative collection, sensemaking, sharing and formalization of ideas.

SSS Configuration: The SSS configuration is exactly the same as in the MR-15 evaluation study.

Data collection and analysis: As it was the case in the MR-15 pilot, we quantitatively analyzed the SSS logs to describe the resulting AAN and to quantify the tag recommendations. We also analyzed the log files to detect uptake events where tags were introduced and reused by another user. Thus, we assessed the impact of the recommender services to support collaborative learning,

Resulting AAN: The SSS registered 182.911 user events and 293 resources imported from Evernote and Bits & Pieces. The resulting AAN contained 40 actors, 1056 resources (259 bits used in episodes, 75 discussions related to 96 discussion entries from Discussion Tool, 49 documents from Living Documents and 29 learning episodes from Bits & Pieces), 688 tag assignments of a total of 301 distinct tags and 132 categories. Based on this AAN tag recommendations were computed, which led to 102 accepted recommendations.

Main study results: The log analysis shows that the researchers followed a similar learning process as MR-15 pilot study: tracing experiences, making sense and discus them, and transforming outcomes into reports. Again, the SSS infrastructure provided a key support to this learning process as it allowed sharing data and documents across the applications. In this pilot study the learners made an extensive use of tags. These tagging events were facilitated by the recommender service, which also promoted the uptake of tags. In fact, 88 tag-uptake events were registered involving 67 unique tags. As we have shown in previous studies, these uptake events can facilitate the establishment of shared understanding in the sense-making process (Dennerlein, Seitlinger, Lex, & Ley, 2016; Ley & Seitlinger, 2015).

4.4 Discussion of the evaluation findings

4.4.1 Accomplishment of the SSS requirements

Support for informal and formal scenarios from different domains (REQ1). The diversity of learning and LA applications integrated into the SSS allowed to support LA in a wide range of workplace learning scenarios and contexts. In fact, our evaluation studies range from formal scenarios in a professional training course (TT-14) to others completely informal (MR-15 and RW-16) where participants had the opportunity to use the learning tools in authentic working conditions. The flexibility of the SSS -promoted by its micro-sevice-based architecture and its data model- was key to support these scenarios, as different services and ontology extensions were required.

Integrates tools used for learning at the workplace (REQ2). The SSS collects and integrates data from workplace learning tools that differ both in their functional and their technical characteristics. These tools range from general-purpose and independent ones that exploit the `Activity Service` (e.g. Wordpress (TT-14)), those that require a new service for collecting their data (e.g. Evernote (MR-15 and RW-16)), and those purpose-specific tools tightly integrated into the SSS (e.g. Knowbrain (CC-15)). The extensibility of the SSS -again promoted by its micro-sevice-based architecture-, the different integration strategies and the flexibility of the SSS data model made it possible to collect data from a wide variety of tools.

Collecting and integrating data (REQ3). The evaluation studies TT-14, MR-15 and RW-16 included learning processes where the SSS collected and coherently integrated data from multiple learning tools to offer it back to Learning Analytic applications. The data model managed by the SSS played a major role for the data integration: the AAN is a flexible structure that allows to relate different concepts, while the SSS Core Ontology offered a high-level abstraction common to many learning tools that enabled to describe the entities of the AAN.

Supports Learning Analytics applications (REQ4). The development of LA applications showed how the data collected by the SSS can be exploited by LA applications. We exemplified it by integrating a visual dashboard and a set of recommender algorithms. These LA applications do not only offer different functionalities, but they also follow different approaches to consume the data from the SSS: while the SSS Dashboard was implemented as an external application that simply retrieves the SSS data from the `Data Export Service` API, the recommender algorithms were implemented as micro-services that extend the SSS functionality and offer a new data API that other applications (Knowbrain and Bits & Pieces) exploit. Again, the SSS flexibility was key to enable several integration strategies for its data consumption. It is also noteworthy that, due to the reduced number of participants, these studies do not assess whether the LA applications could exploit larger amount of data collected by the SSS. However, a previous study (Kowald et al., 2015) shows how 3Layers and MostPopular algorithms could satisfactorily exploit data from 10,000 users imported to the SSS from several social tagging systems.

Supports the knowledge creation metaphor (REQ5). The studies we conducted offer clear evidence for the focus on the knowledge creation metaphor by the SSS to support workplace LA. In TT-14 the SSS Dashboard supported learners and trainers to understand the learning process from the knowledge creation point of view. Both identified how artifacts were co-developed and how knowledge emerged inside the community. We obtained first evidence that trainers appreciated the visualization of shared artifacts and how learners contributed to them.

CC-15 showed that the 3Layers recommender algorithm provided more accurate results than an algorithm that offered the most popular results in a certain period. 3Layers also facilitated the introduction of new concepts into the community of learners as it also recommended newly introduced tags even if they were not the most common tags. 3Layers recommendations therefore better reflected the situation of creative group work (Seitlinger et al., 2017) which evidences the algorithm's foundation in knowledge creation theories.

In MR-15 and RW-16, the infrastructure supported knowledge maturation as it helped learners move through a collaborative learning process across several tools. Learners started with the collection of ideas, then could share them and finally were able to formalize them. The SSS, and more specifically its data model, played a central role in making objects of activity available across tools and in allowing the tracing of interactions with those objects: first, the explicit relationships between the entities enabled the detection of uptake events and co-creation processes; second, the flexibility of the AAN allowed to introduce new artifacts and tags and to dynamically learn the participants' shared categories over time. The limited number of participants in the evaluation studies limits the generalizability to these findings to larger communities of learners; it would be interesting to assess the support provided by the SSS to knowledge building in organizations, or even in cross-organizational networks, where innovation is more likely to happen.

Providing data that is relevant for analyzing and supporting learning practices (REQ6). Finally, we exemplified the impact of the SSS on workplace learning practices. In TT-14 the data facilitated the comprehension of the learning process by a trainer and a learner. As they only used the SSS Dashboard once the course was over, it did not have a direct influence on such process. However, they understood the dashboard as a useful application and the trainer explicitly said that she would have intervened if she had seen it during the course. In CC-15 the SSS data influenced the users when tagging resources, helping them to co-create conceptual artifacts and to introduce new ones into the learning community. A tag recommender based on knowledge creation achieved higher acceptance than one based on popularity only. In MR-15 the SSS supported a two year design-based research project that resulted in new tools and practices of healthcare professionals. The SSS allowed individual collection and formalization of learning experiences, sharing them and collaboratively working on them. Due to the limited use of the tagging system and the resource recommendations, the SSS data had little impact on the users in this study. On the other hand, RW-16 showed how an informal learning process supported by a similar technical configuration was enhanced by the tag recommender services. However, it remains to be seen whether recommender services are an effective way to exploit the data. Another open question is how to increase their impact on workplace learning processes, especially on the more informal ones that entail a larger number of learners. In this regard, we are currently starting a large scale study on the use of the recommender services in the healthcare domain.

4.4.2 An AAN to support knowledge creation metaphor

We started this paper from the assumption that a technical infrastructure that supports LA needs to start from an understanding of what learning is, how it takes place and how it can be supported. The SSS has its roots in the conception of learning as a knowledge building and maturing process, and is therefore rooted in an understanding of knowledge as a dynamic and social process of co-construction and creation (Ravenscroft, Schmidt, Cook, & Bradley, 2012). The evaluation studies that we have conducted have shown several knowledge creation and maturing activities that have been traced and supported. Our experience also shows that the knowledge creation metaphor provides a special challenge for the design of LA infrastructures. Such infrastructures should offer enough flexibility -both in its software architecture and its data model- as to allow for knowledge to emerge from individual and collaborative activities.

Uptake has been described as the smallest unit in collaborative learning that can be observed as an interaction (Suthers & Dwyer, 2014). In our evaluation studies, uptake occurred at several places. In RW-16, for example, several learners contributed ideas to shared collections. Reuse of tags occurred in CC-15 and RW-16. A powerful analytic framework has been created in the past years that allows interactions to be analyzed in "contingency graphs" (Suthers & Dwyer, 2014). With the uptake framework, a big step has been made towards making collaborative learning activity traceable for LA. While the uptake framework exists as an analytical tool that allows post-hoc analysis of learning data, with the SSS, we provide the technical means to trace and represent uptake events in life systems and feeding back this data to learners and trainers.

Once the infrastructure focuses on challenging scenarios of knowledge creation, we found it easier to support use cases that are more in line with other metaphors. For example, the SSS also includes recommender services that are more related to knowledge acquisition, such as time-based recommenders, or participation, such as collaborative filtering. Another example is the exploitation of SSS data to create a social network graph representation that shows community membership and centrality of members (Ruiz-Calleja, Dennerlein, Tomberg, Pata, et al., 2015), thus following the participation metaphor.

5. Conclusions and future work

This paper proposes to exploit the SSS as an infrastructure for workplace LA that follows the knowledge creation metaphor. For this purpose, we firstly derive the requirements for an infrastructure that complies to knowledge creation theories. We then designed and developed the SSS as a micro-service-based infrastructure whose data model is based on a semantically-enriched and context-aware AAN. Its evaluation entailed the integration of several learning tools that submit their data to the SSS and some LA applications -a visual dashboard and a set of recommender services- that exploit its data. This evaluation also comprised four authentic workplace learning scenarios where 57 participants were satisfactorily supported by the SSS.

Two characteristics of the SSS are key for its support to workplace LA. First, the flexibility of its software architecture allows to adapt it to a wide range of learning scenarios by configuring the micro-services that are deployed. It also allows different integration strategies for learning tools and LA applications. Thus, it is possible to collect data from external tools and to develop new services to provide additional functionality (e.g. tag recommendation) that can be exploited by external LA applications. The second key characteristic is its data model. The AAN allows to describe contextualize uptake events. Furthermore, it allows to describe the entities of the AAN with different degrees of formality, allowing both the semantic integration of data, using ontologies, and the description of emerging knowledge, using folksonomies.

Our research suffers from the limitations that are common when addressing learning at workplace. As workers learn in a self-direct way, any technology that supports this learning needs to seamlessly fit existing practices that may vary dramatically in different domains and organizations. Hence, samples sizes of studies are usually small and it is commonly difficult to assess how technology would be adopted in large networks of learners. We addressed these challenges by employing an iterative, design-based research strategy that collects evidence over a number of iterations and across different contexts. In this paper, we reported four of such studies. Together with the previous empirical studies that have also mentioned, these should allow us to build up converging evidence of the utility of our general approach over time, although the scalability of our proposal reminds to be assessed.

Our future work will focus on further exploiting the SSS for workplace LA in real scenarios. We are currently working on a large scale study that includes the use of recommenders in the healthcare domain. We will also promote the development of a wider collection of LA applications that make use of the SSS data. We plan to encourage the community of learning tool developers to adopt the SSS by making it compliant with the Experience API. The xAPI could be supported by developing a new `Metadata service` and a new `Activity service`. The development of such services, and their corresponding APIs, would be facilitated if we use as a dataset a Learning Record Store with an open licence. Finally, we will explore the potential use of the SSS data to support additional LA services, such as the automatic detection of learning needs in communities of workers.

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