# ADAPTIVE FEEDBACK IMPROVING LEARNINGFUL CONVERSATIONS AT WORKPLACE

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**ABSTRACT**

This work proposes the definition of an Adaptive Conversation-based Learning System (ACLS) able to foster computer-mediated tutorial dialogues at the workplace in order to increase the probability to generate meaningful learning during conversations. ACLS provides a virtual assistant selecting the best partner to involve in the conversation and generating adaptive feedbacks for the dialog. Adaptive feedbacks are triggered by the concepts automatically extracted from the conversation texts, while their content is generated by querying the organizational knowledge represented by means of Semantic Web technologies. Lastly, Fuzzy Formal Concept Analysis is exploited to conceptualize domain knowledge.

**KEYWORDS**

Workplace Learning, Knowledge Extraction, Adaptive Educational System, Semantic Web, Fuzzy Formal Concept Analysis.

## 1. INTRODUCTION AND MOTIVATIONS

Workplace Learning represents the field of studies and researches related to effective and efficient solutions supporting learning and training processes within the work context and aiming at enhancing individual and organization performances.

Workplace Learning principles are described in several works. Among them, the authors of (M. Wang, et al., 2010) assert that Workplace Learning is *adult learning, organizational learning and knowledge management*. The related theories emphasize personal reflection, problem orientation and knowledge construction by means of social processes, models representing how organizations learn, approaches and practices exploited in order to identify, create, represent, and distribute knowledge for reuse, awareness and learning. Furthermore, in (P. Tynjälä and P. Häkkinen, 2005), the authors describe the main features of the Workplace Learning. First of all, it is mostly informal or non-formal (both intentional and incidental). Secondly, it is strongly contextualized in the sense that learning occurs in the environment in which skills and knowledge, that are object of learning itself, will be applied. In this scenario, conversation is considered an important tool to share, construct, create knowledge and learn as emphasized in (A. Soller, 2007). The authors of (I. Nonaka and H. Takeuchi, 1995) underline the importance of conversations in order to transform individual processes into organizational processes.

Moreover, conversations foster personal reflection and are typically driven by a well-defined learning objective. In this context, *technology enhanced learning* solutions are effective not only to support conversations (dialogues, discussions, etc.) but also to store knowledge, ideas and shared decisions. They can serve, at the same time, as a tool to support individual learning, sustain knowledge creation and construction, manage the organizational memory, share knowledge and develop mutual understanding (M. Wang et al., 2010). Generally, these systems are able to catch the knowledge of the domain experts to support learning and peer collaboration but they need methodical approaches for knowledge representation (W. Chen, 2006), otherwise they are focused, as *Adaptive and Intelligent Systems for Collaborative Learning Support (AICLS)*, on adapting the collaboration processes (I. Magnisalis et al., 2011).

With respect to the aforementioned systems, this paper proposes a novel approach to exploit organizational resources (kept *up-to-date* by the collective intelligence and represented by means of semantic models) in order to enhance and adapt peer learning activities.

Taking in consideration the relevant role of conversation at workplace for both individual and organizational learning and for knowledge management, this paper proposes a workplace learning system, based on semantic technologies, that implements the conversation-based learning approach. The main faced problems are: i) empowering conversations in order to facilitate the occurrence of learning by providing a mechanism to stimulate meaningful learning, and ii) exploiting conversations as a tool to link individual and organizational learning by tracing and reusing learningful conversations.

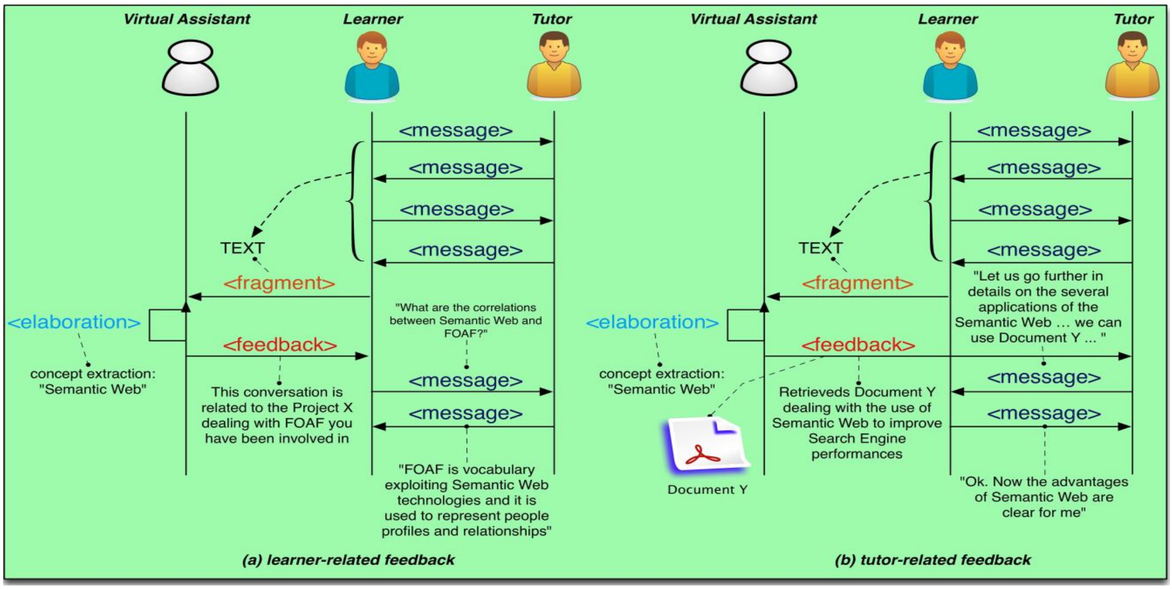


Figure 1. Learner-related and tutor-related feedback

The structure of this work is the following: section II provides an overview of the defined approach and a description of the adaptation strategy. Section III describes the general view and the most important details of the ACLS. Lastly, Section IV provides details about the evaluation of the proposed approach and some final remarks.

## 2. OVERALL APPROACH

The proposed approach lays on three pillars mainly enabling a virtual assistant that exploits the organizational knowledge in order to foster conversations by means of the provision of feedbacks for both learner and conversation partner.

The first pillar is represented by **computer-mediated conversations**. In our approach, conversations are dialogues between two participants, the tutor and the learner, who exchange messages through an instant messaging tools. A model for learningful conversations is defined in (D. Laurillard, 2009), where the author provides a framework for a conversational learning approach. This framework is conceptually structured into two levels, the lower and the upper. In the lower one, the learner masters the topics of learning while the conversation partner provides the experiential environment (e.g. delivery of learning resources) where the learning process is executed. In the upper level, the learner and the conversation partner are engaged in a dialogue by exchanging messages containing their understanding and representations of the topics obtained through the experience performed at the lower level and adapting their behaviours. Reflection occurs when the learner and the partner talk about what they are doing at the lower level. Adaptation occurs when they modify what they are doing at the lower label on the basis of their talk. Several types of dialogues (e.g. argumentation-based dialogues, tutoring dialogues, peer dialogues, and so on) can be instantiated, but this work, in particular, focuses on tutoring dialogues. The virtual assistant is committed to help the conversation partner in playing his/her tutor role.

The second pillar is represented by **the capability to generate adaptive feedbacks** able to foster conversations in order to increase the probability that meaningful learning occurs during dialogues. We adopt the definition of feedback reported in (V. J. Shute, 2008): *[...] feedback is defined in this review as information communicated to the learner that is intended to modify his or her thinking or behavior for the purpose of improving learning. And although the teacher may also receive student-related information and use it as the basis for altering instruction [...]*. In our proposal, feedbacks are generated by the virtual assistant that analyses a specific conversation fragment and queries the organizational knowledge for content that could foster the dialogue and help the learner to improve development of domain-specific knowledge and skills. Feedbacks are *adaptive*, in the sense that they are generated by considering the concepts that really emerge from the conversation fragment and *personalized*, in the sense that they take care of both learner and tutor roles and are tailored to prior knowledge and previous work experience of the learner. For the sake of simplicity, we divide feedbacks in two types: learner-related and tutor-related. The first ones are topic contingent feedbacks suggesting correlations among the topics to master and the learner's prior knowledge (V. J. Shute, 2008). The second ones are hints/cues/prompts about worked examples provided by the tutor (conversation partner) in response to automatic suggestions, produced by the system, concerning the existence (in the organizational knowledge) of documents, user-generated content, etc. that are related to the topics to master. The main idea is to build these feedbacks in the form of dialogue moves by exploiting classifications provided by the authors of (S. D'Mello et al., 2010) and (X. Lu et al., 2007). In this way, even if indirectly, the dialogue is adapted maintaining a common tutorial dialogue scheme.

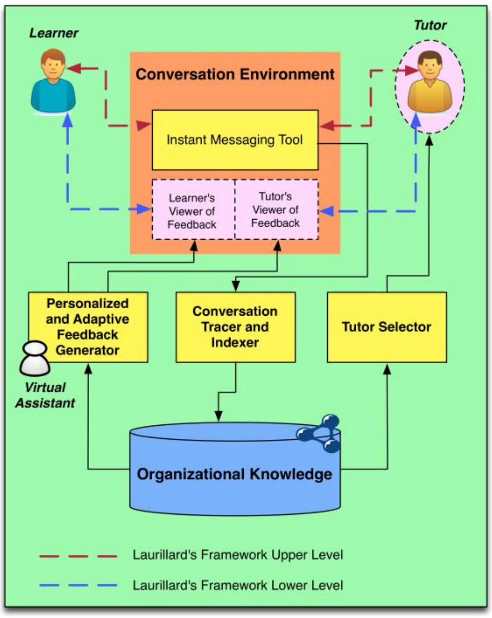


Figure 2. Learner-related and tutor-related feedback

The third pillar is represented by **the exploitation of the organizational knowledge** in order to support computer-mediated conversations as well as other processes. In this paper we refer to the organizational knowledge as the set of all types of knowledge existing in a specific organization, for instance, tacit knowledge in the minds of workers, embedded knowledge in procedures, explicit knowledge recorded in artefacts (e.g. documents, etc.) and in information systems (e.g. information about the competences of each workers (N. Capuano et al., 2011), etc.), and so on. In our approach the organizational knowledge is represented by means of a model (see section III-A for further details) exploiting the Semantic Web stack[1].

The so represented organizational knowledge is mainly useful to accomplish three objectives. The first one is to enable search for suitable conversation partners among all the available human resources in the organization. The second one is to enable search for resources (e.g. documents, user generated content, task

[1] http://www.w3.org/2001/sw/

and project information, and so on) useful to generate personalized and adaptive feedbacks fostering learningful conversations (in this case the virtual assistant, once extracted the concepts from the conversation fragment, uses SPARQL1.1[2] to query the organizational knowledge and provide content to construct feedbacks). The third one is to enable storage and correlation of learningful conversations with the existing knowledge in organization in order to foster reuse. For a further description of the overall approach, Fig. 1 shows the two types of feedbacks and how they support adaptation of the conversation by providing suggestions to the learner (Fig. 1a) and to the tutor (Fig. 1b).

# 3. ADAPTIVE CONVERSATION-BASED LEARNING SYSTEM

Our ACLS implements the approach described in II. The high level architecture of it is presented in fig. 2.

## 3.1 Structuring the Organizational Knowledge

Modelling and representing the organizational knowledge are two of the most important tasks related to the definition of the ACLS architecture.

In particular, the technologies adopted to represent the organizational knowledge come directly from the W3C Semantic Web vision. This choice guarantees a layer of interoperability and cooperation among applications (or apps), the fundamentals to build knowledge-based applications, the chance to use a standard query language like SPARQL1.1, the possibility to integrate and reuse existing ontologies, vocabularies and metadata to model several aspects of the organisational knowledge, the capability to support reasoning, inference and so on.

If the Semantic Web provides us with a set of methodologies, languages and technologies useful to represent the organizational knowledge, an effective and efficient organizational knowledge model is needed. The solution for the aforementioned issue is provided by the ARISTOTELE Project[3], where the organizational knowledge is presented as Organization Linked Data structured in three layers as depicted in 3 that provides only a fragment of the whole model. Firstly, the upper layer consists of several linked ontologies (described by using RDFS/OWL/OWL2[4]) used to model the organization key concepts (ontology classes). Secondly, the lower layer consists of the instances of the classes we can find in the upper layer. Lastly, the middle layer is made of a set of lightweight ontologies used to classify and organize the lower layer elements. Lightweight ontologies (described by using SKOS[5]) can be connected each other in order to correlate concepts (at the same layer) and instances (at the lower level).

More in details, the ontologies at the upper layer describes the semantics of domain-independent concepts in organization like Task, Competence, Worker, Content, Document, BlogPost, etc. that are implemented as OWL classes. Whilst, the middle layer defines conceptualizations for domain-dependent knowledge in a specific organization. For instance, the main research topics the organization deals with are modelled as instances of skos : concept and organized in semantic structures like taxonomies or conceptual maps.

It is clear that the middle layer is more dynamic than the upper layer, in the sense that the lightweight ontologies (as we have defined them) can evolve in the time if, for instance, a new research field is activated or new project artefacts are indexed in the Document Management System (DMS) of the organization. Instead, the probability that a concept (like, for example, Document or Task) changes in the upper layer is very low. The construction of the lightweight ontologies implementing the middle layer is a critical and difficult task.

The idea is to generate the aforementioned ontologies by exploiting textual data embedded in documents (M. Gaeta et al., 2011) that are representative for the organizational knowledge. For this aim we exploit the framework described in (C. De Maio et al., 2012) that is based on a fuzzy extension of the Formal Concept Analysis (Q. T. Tho et al., 2006). The objective of the above mentioned framework is building a taxonomical conceptual structure starting from a collection of text documents. The framework defines an ontology generation workflow consisting of three main steps: **text processing**, **fuzzy data analysis** and **ontology building**.

[2] http://www.w3.org/TR/sparql11-query/
[3] http://www.aristotele-ip.eu/en/project/svc/entry/0/196/4/aristoteleproject.html
[4] http://www.w3.org/TR/owl2-overview/
[5] http://www.w3.org/2004/02/skos/

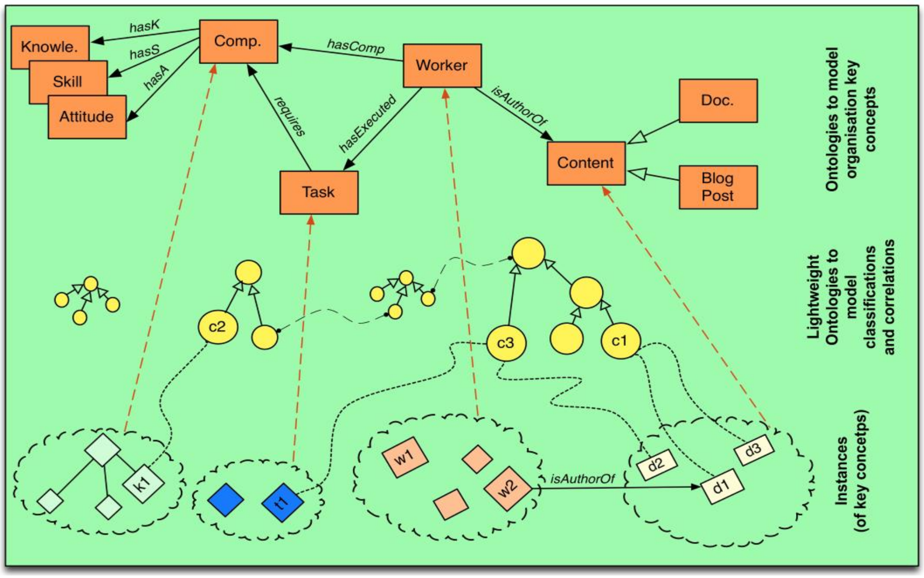


Figure 3. Three layers of structured Organisational Knowledge (Organisational Linked Data)

The goal of the first step is to construct a *Fuzzy Formal Context*, i.e. a matrix showing the relationships between the keywords extracted from the input documents and the documents.

The set of keywords is extracted from the documents, filtered (by eliminating non-informative words by using stopword lists), normalized (by means of stemming and POS tagging) and enriched by inserting the synonyms of all words in the set. The relationship value (in the range [*0,1*]) in a matrix cell (*g,m*) (*g* is one of the input documents and *m* one of the keyword in the enriched set) is calculated by using the TD-IDF technique (term frequency inverse document frequency) and represents an evaluation of the measure of strength of the relationship. The goal of the second step is to analyse the *Fuzzy Formal Context* by means of *Fuzzy Formal Concept Analysis* (*FFCA*) and transform the matrix into a *Fuzzy Concept Lattice* (nodes in the lattice are called *Fuzzy Formal Concepts*) that is a mathematical modelling of the knowledge embedded in the input documents and, moreover, it can be considered an alternative and more informative representation of the matrix. Lastly, the goal of the third step is to transform the Fuzzy Concept Lattice into a taxonomy structure by executing some rules. In our approach we use a SKOS-based representation of the final taxonomy instead of the OWL-based representation adopted in (C. De Maio et al., 2012). SKOS is more suitable than OWL when the objective is to organize large collections of objects and provide a lightweight intuitive conceptual modelling. At the end of the process, the obtained SKOS structures represent the aforementioned lightweight ontologies. It's important to underline that the documents, used as input of the ontology construction process, are already related to their respective concepts in the SKOS structures.

New documents, as well as other artefacts, can be subsequently classified (by manual and/or automatic operations) by the lightweight ontologies.

Definitely, the lightweight ontologies can evolve by exploiting a similar process based again on *FFCA*.

## 3.2 Activation of a Context-Steered Conversation and Selection of a Suitable Tutor

First of all, it is important to remark the role of the context in which the conversation is activated. The learning scenario we consider in this work is the context-steered learning (A. Schmidt and S. Braun, 2006) where a worker has been committed to execute a specific task (an instance of the *Task* class) that requires a specific competence (an instance of the *Competence* class) that must be developed (fully or partially) by means of the execution of a tutorial conversation. Now, the context is defined as the set of all concepts (nodes of the lightweight ontologies) that are directly linked to the needed competence or to its parts (knowledge, skills or attitudes).

The so defined context is useful to select a suitable conversation partner. This selection is one of the most important operations enabled by the Organizational Linked Data and is realized by using SPARQL queries. In order to find suitable partners (peers, experts, tutors) among all the workers in the organization our approach takes into account, their competences (see classes *Competence*, *Knowledge*, *Skill* and *Attitude*), work experiences (see *Task* class) and produced artefacts (see *Content*, *Document* and *BlogPost* classes).

For instance, it is possible to write a query to find all the workers with *Software Engineering* and *Tutoring* competences in order to reinforce the tutor role. Moreover, it is also possible to relax the constraint on *Tutoring* competence and search only for *Software Engineering* competence to have a peer-based conversation. With respect to the architecture presented in Fig. 2, the module responsible for finding a suitable tutor is the **Tutor Selector**.

## 3.3 Feedback Generation

Once the lightweight ontologies are generated and deployed, we have two types of elements linked to them: the set $D(c)$ of all documents and the set $E(c)$ of all elements that are instances of classes *Content* (or its subclasses) and *Task*. The main idea is using a search engine like Lucene[6] to index all the elements in the set $D(c)$ and finding matches among a conversation fragment $T$ (extracted by means of the Instant Messaging Tool presented in Fig. 2 by exploiting the *MoreLikeThis* function provided by the Lucene API).

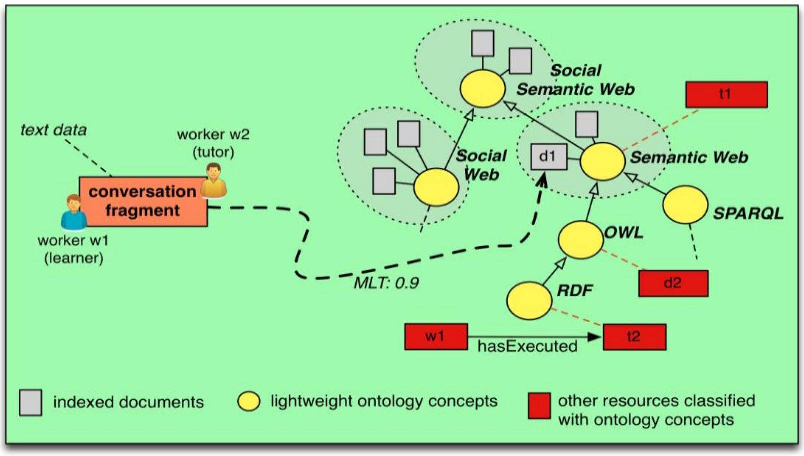


Figure 4. Matching example

The virtual assistant invites the tutor to provide prompts, hints or cues by using worked examples retrieved from the documents, blog posts, wiki articles, task/project information and so on. The idea is that the tutor has the competence to mediate the aforementioned artefacts and use them as learning content. Furthermore, the virtual assistant suggests the learner to reflect on (or to ask the tutor for details about) the correlation among his/her previous work experience, represented by the retrieved elements and his/her understanding of the current conversation fragment.

With respect to the architecture presented in Fig. 2, the module responsible for finding a suitable tutor is the **Personalized and Adaptive Feedback Generator**. Feedbacks for the learner and the tutor are provided by means, respectively, of the **Learner's Viewer of Feedback** and the **Tutor's Viewer of Feedback** shown in the high-level architecture. Table 1 provides a mapping between the generated feedbacks and the interaction patterns in tutorial dialogues (X. Lu et al., 2007) (S. D'Mello et al., 2010).

[6] http://lucene.apache.org/core/

Table 1. Mapping feedbacks on dialogue patterns

| *Feedback* | *Pattern* | *Content* |
|---|---|---|
| Suggesting *personal reflection* on integration among conversation topics and learner's prior knowledge. | Student-tutor. | Set *A*. |
| Suggesting *questions* (to the tutor) about integration among conversation topic and learners' prior knowledge. | Student-tutor. | Set *A*. |
| Suggesting *specific prompting* by instructing with worked examples coming from real and concrete work experiences. | Tutor-student. | Set *B*. |

## 3.4 Knowledge Reuse

In ACLS, conversation threads are traced and indexed to satisfy a possible need to reuse them in informal or non-formal learning experience. In order to foster reuse, conversation threads are represented by using SIOC[7]. SIOC may be easily integrated with the upper layer ontologies of the Organizational Linked Data because they share the same Semantic Web stack. In particular, we use some extensions of SIOC (e.g. *sioct:ChatChannel* and *sioct:InstantMessage* that are sub-classes of *sioc:Forum* and *sioc:Post*) to model a conversation session and individual messages. With respect to our work, the most important properties of the *sioct:InstantMessage* class are topic and content.

The first one enables to link a conversation message with a *SKOS:Concept*. This is, de facto, a way to index messages and threads by means of lightweight ontologies at the middle layer of the Organizational Linked Data. The second one stores textual data of a message. Thus, a Social Semantic Web process is deployed: conversations produces messages and threads represented in SIOC that are classified with respect to the concepts in the lightweight ontologies and become retrievable through SPARQL queries. The quality of the conversation messages and threads can be evaluated by means of social rating or by assessing learners after the conversations.

# 4. EVALUATION AND FINAL REMARKS

In order to emphasize the rationale of the feedback generated by the ACLS with respect to the objective of improving the meaningfullness of learning during tutorial dialogues, Fig. 5 provides the rules used to define the feedbacks.

Table 2. Rules used to generate the feedbacks and their rationale

| Rule | Description | Rationale |
|---|---|---|
| 1 | Connecting learner's prior knowledge with new one | People learn better when unfamiliar material is related to familiar knowledge and when they ask questions |
| 2 | Connecting learner's prior experience with new knowledge | People learn better when they organize and connect new concepts with already acquired ones |
| 3 | Enriching explanation with expert's concrete work experiences | People learn better when worked examples are presented in the context of a familiar situation |
| 4 | Exploiting organisational resources as learning content | People learn better with guidance rather than by pure discovery |

In brief, according to (R. E. Mayer, 2008), the generated feedbacks try to stimulate *generative processes* (e.g. organizing and integrating knowledge) which are those, among the cognitive processes, able to produce meaningful learning. Furthermore, generative processes are sustained also by the defined Organizational Linked Data in the sense that the Semantic Web structures, and in particular the explicit use of the lightweight ontologies, help the learner to organize the knowledge and integrate the new one with the prior

[7] http://rdfs.org/sioc/spec/

one. Unlike what the other systems usually do, the proposed approach pays attention to both the domain knowledge and the cognitive processes raised from the partners' interactions but it doesn't need any expensive modelling activity. Both the approach and the ACLS will be experimented in the next months in the ARISTOTELE Project activities.

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