ADAPTIVE FEEDBACK IMPROVING LEARNINGFUL CONVERSATIONS AT WORKPLACE

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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 generating adaptive feedbacks, in the form of recommendations, for the conversation partners. The concepts extracted from the conversation texts trigger the recommendations, while queries on the organizational knowledge, represented by means of Semantic Web technologies, generate their content. Lastly, the Fuzzy Formal Concept Analysis is exploited to conceptualize domain knowledge.

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 (Wang *et al.*, 2010) assert that Workplace Learning is adult learning, organizational learning and knowledge management. The theories related to the first one emphasize personal reflection, problem orientation and knowledge construction by means of social processes. Moreover, the second one refers to the models representing how organizations learn (Argyris *et al.*, 1996). Lastly, the third one focuses on approaches and practices exploited in order to identify, create, represent and distribute knowledge for reuse, awareness and learning (Nonaka *et al.*, 1995). Furthermore, in (Tynjälä *et al.*, 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 will be applied. In this scenario, conversations are an important mean to share, construct, create knowledge and learn as emphasized in (Soller, 2007; Vandewaetere *et al.*, 2011). The authors of (Nonaka *et al.*, 1995) underline the importance of conversations in order to transform individual processes into organizational processes. Conversations foster personal reflection and typically are driven by well-defined learning objectives. Definitely, a conversation is a dialogic process (Van Aalst, 2009) involving a mentor and a mentee, that is useful to sustain acquisition of declarative knowledge (concepts, principles, ideas, theories), procedural knowledge (practical knowledge, knowledge on how-to-do, subject-specific skills, algorithms, subject-specific techniques and methods, criteria for determining when to use appropriate procedures), situational knowledge (knowledge about specific work situations). 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 (Wang *et al.*, 2010). For example, in the workplace context, conversations can be exploited as a training method able to link learning and working activities enable knowledge acquisition by fostering reflection, inquiry and deepening on specific issues support the development of specific capabilities. The dialogic mediation becomes a fundamental strategy to valorise the working practices and transform them into significant experiences in the professional sphere.

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 adaptive conversation-based learning approach (Park & Lee, 2003). The main faced problems are: i) empowering the adaptive dimension in 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.
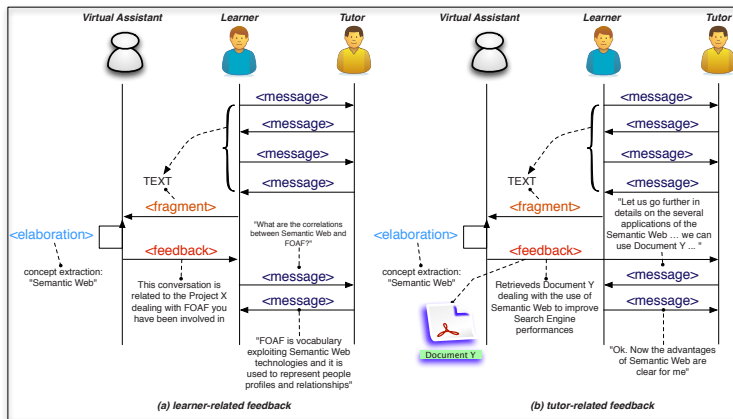

Fig. 1 - Learner-related and tutor-related feedback.

The adaptive conversation-based learning approach is realized as an *e-learning recommender system* (Chen *et al.*, 2005; Khribi *et al.*, 2008) where adaptive feedbacks are generated as recommendations (or suggestions). More in details, the adopted recommender system model is the well-known *item-based filtering* (Meteren *et al.*, 2000) that recommends items to users basing on the relations among the content of aforementioned items and the preferences of the user.

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 adaptive feedbacks, implemented as suggestions, for both the learner and the conversation partner.

The computer-mediated conversations represent the first pillar. In our approach, they are dialogues between two participants, the tutor and the learner,

who exchange messages through instant messaging tools.

A model for *learningful* conversations is defined in (Laurillard, 1996), where the author provides a framework for a conversational learning approach. This framework has two conceptual 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 one, 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 level based on 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.
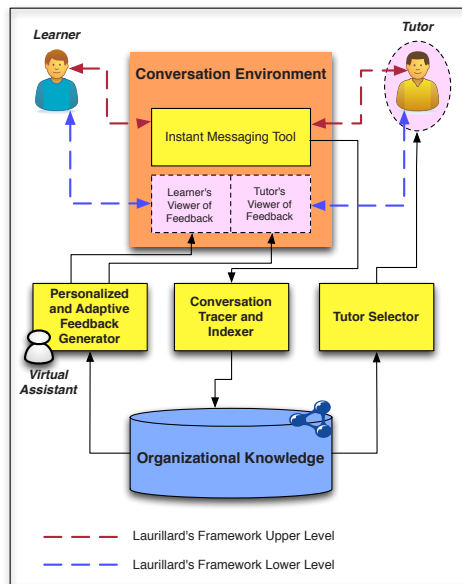

Fig. 2 - High-level architecture in ACLS.

The second pillar is 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 (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, a virtual assistant analyses a specific conversation fragment and queries the organizational knowledge to generate feedbacks with content that could foster the dialogue and help the learner to improve development of domain-specific knowledge and skills (Corno, 2008; Mangione, 2013). Feedbacks are adaptive, in the sense that the virtual assistant generates them by considering the concepts that really emerge from the conversation fragment, and personalizes them by taking care of both learner and tutor roles, 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 (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 (D'Mello *et al.*, 2010) and (Lu *et al.*, 2007). In this way, even if indirectly, the dialogue is adapted but it maintains a common tutorial dialogue scheme (Gaeta *et al.*, 2013).

The third pillar is 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, it includes 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 (Capuano *et al.*, 2011), etc.), and so on. In our approach, the organizational knowledge is represented by means of a model (see section "Structuring the organizational knowledge" 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 and project information) 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 que-

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

[2] http://www.w3.org/TR/sparql11-query/

ry 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 recommendations (suggestions) to both learner (Fig. 1a) and tutor (Fig. 1b). The proposed approach differs from a typical *recommender system* providing *item-based filtering* for the following reasons:

1. The user preferences are modelled as users' prior knowledge and context (concepts elicited from the conversation fragment text);
2. The recommendations are further personalized with respect to the conversation role (learner or peer/expert peer/tutor);
3. The recommendations are generated by using a semantic representation (Boticario *et al.*, 2011) of the organizational knowledge.

Lastly, the provided approach enables two different adaptation strategies. The first one, based on the construction and provision of adaptive feedbacks, is a micro-adaptation strategy (for details, see the following sections). The second one, based on the dynamic selection of the conversation partner, is a macro-adaptation strategy (for a brief discussion, see the end of this paper). Feedbacks, suggestions and adaptation trigger and improve cognitive processes in the people involved in this kind of learning activities. The learner receives stimulus on these processes and goes in the reflection on what he/she is talking about with his/her dialog partner (Miranda *et al.*, 2013).

3 Adaptive Conversation-Based Learning System

Our ACLS implements the approach described in the previous section "Overall approach". Fig. 2 shows the high-level architecture of ACLS.

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 ARISTO-TELE Project[3] provided a solution for the aforementioned issue, where the organizational knowledge appears as Organization Linked Data structured in three layers as depicted in Fig. 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 (Gaeta *et al.*, 2011) that are representative for the organizational knowledge. For this aim, we exploit the framework described in (De Maio *et al.*, 2012) that is based on a fuzzy extension of the Formal Concept Analysis (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.

The goal of the first step is to construct a Fuzzy Formal Context, i.e. a matrix

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[3] http://www.aristotele-ip.eu

[4] http://www.w3.org/TR/owl2-overview/

[5] http://www.w3.org/2004/02/skos/

showing the relationships between the keywords extracted from the input documents and the documents. It extracts the set of keywords from the documents; it filters them (by eliminating non-informative words by using stopword lists), normalizes them (by means of stemming and POS-tagging) and enriches them 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 is one of the keyword in the enriched set) is calculated by using the TF-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). The Lattice is a mathematical model of the knowledge embedded in the input documents. Moreover, it is 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 (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 is 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 using the lightweight ontologies.

Definitely, the lightweight ontologies can evolve by exploiting a similar process based again on FFCA.
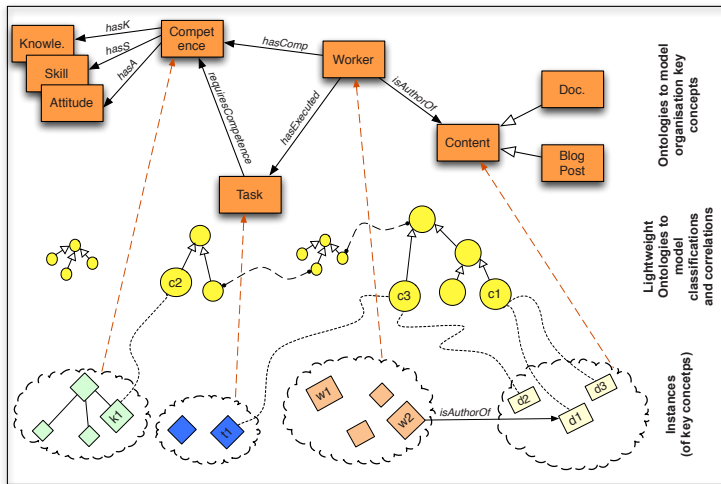
Fig. 3 - Three layers of structured Organisational Knowledge (Organisational Linked Data).

3.2 Activation of a context-steered conversation and selection of a suitable tutor

First, it is important to remark the role of the context where the conversation happens. The learning scenario we consider in this work is the context-steered learning (Schmidt *et al.*, 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 the set of all concepts (nodes of the lightweight ontologies) directly linked to the needed competence or to its parts (knowledge, skills or attitudes). The so defined context is useful to select a suitable tutor among the workers of the organization. The selection of the tutor (conversation partner) is one of the most important operations enabled by the Organizational Linked Data. This operation is realized by using SPARQL queries in order to find suitable tutors, among all the workers in the organization, with respect to 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 conversation among peers. 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

In this section provides the rules of ACLS for generating suggestions during conversations in order to sustain a micro-adaptation process.

Once the lightweight ontologies are generated and deployed, we have two types of elements linked to them: $D(c)$ and $E(c)$. The first one is the set of all documents $\{d_1, d_2, ..., d_n\}$ in the DMS correlated to the concept c of the lightweight ontology L by means the FFCA process. Moreover, the second one is the set of all elements $\{e_1, e_2, ..., e_m\}$ that are instances of classes *Content* (or its subclasses) and *Task* correlated to the concept c. They have been linked to the concept c of the ontology L by means of some manual or automatic classification process. Let us also define the following functions:

- $G(c) = \{g_1, g_2, ..., g_k\}$ is the set of all concepts directly linked with c in L;
- $E(c,u) = \{e_1, e_2, ..., e_l\}$ is the set of all instances of classes *Content* (or its subclasses) and *Task* authored or executed by the worker c;
- $C(d) = \{c_1, c_2, ..., c_h\}$ is the set of all concepts correlated to the document d in the FFCA process.

The main idea is that for each L in the organizational knowledge and for each c ϵ L it is possible to use a search engine like Lucene[6] to index all the elements in the set $D(c)$. Now, it is possible to exploit the *MoreLikeThis* function provided by the Lucene API that allows finding the matches among a conversation fragment T (extracted by means of the Instant Messaging Tool presented in Fig. 2) and the indexed documents. *MoreLikeThis* returns a list of value $sim(T,d)$ (in the range *[0,1]*). The higher value of the list represents the best match found, i.e., the document that is more similar to the conversation fragment. The *similarity* is calculated by transforming the textual data of the documents and the textual data of the conversation fragment into term vectors (with TF-IDF values) and then calculating the similarity measure on them.

Once, document d with higher similarity value is identified, it is possible to obtain the associated concepts $C(d)$. Being T similar to d, we can assert that the conversation fragment T can be conceptualized with the set $C(d)$. In other words, the meaning of the considered conversation piece is defined by means of the concepts $\{c_1, c_2, ..., c_h\}$. Now, it is possible to construct the following sets:

$$A = \bigcup_{c \in C(d)} E(c)$$
,

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

$$B = \bigcup_{c \in C(d) \cup \overline{G}} E(c, learner)$$

,

where
$$\overline{G} = \bigcup_{c \in C(d)} G(c)$$
.

Using the sets A and B it is possible to generate both tutor-related and learner-related feedbacks. In particular, the virtual assistant invites the tutor to provide hints or cues by using worked examples retrieved from the elements of A that are documents, blog posts, wiki articles, task/project information related to the concepts elicited by the conversation fragment text. In A we can find contents retrieved by all available organization sources. The generated suggestions can improve learning because people learn better when:

1. Worked examples are presented in the context of familiar situations (tasks and projects dealing with conversation concepts);
2. Receive an adequate guidance (organization contents – dealing with conversation concepts – are mediated by the conversation partner with "Tutoring" and/or "Teaching" competences and become part of the experiential environment of the conversation).

A filter applied on the set A could provide only contents coming from the experience of the conversation partner. This could facilitate the tasks of the conversation partner and allow him/her to only deal with already known material. 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 elements of the set B and his/her understanding of the current conversation fragment. These aspects can improve learning because people learn better when:

1. Unfamiliar material is related to familiar knowledge;
2. They organize and connect new concepts (elicited from the conversation fragment text) and the already acquired ones for the learner.

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 interaction patterns in tutorial dialogues (D'Mello *et al.*, 2010; Lu *et al.*, 2007).
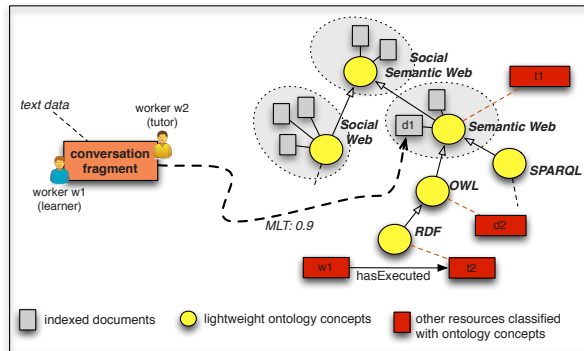
Fig. 4 - Example of conceptualization.

The Semantic Web stack used to model and represent computationally the organizational knowledge also allows the graphic representation of concepts and relations among them. This representation can further help learners (during the conversations) to organize and connect knowledge by supporting their cognitive processes.

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 between 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 Selection of the conversation partner

The selection of the conversation partner happens by querying Organisational Linked Data (where ontological schemas and instances represent workers' profiles and competences) and searching for a colleague who has already acquired the knowledge needed by the worker.

As described in (Gaeta *et al.*, 2012), the three profiles that are requested (for workers) to participate in the conversations are illustrated in the Table 2.

The selection of the conversation partner takes care of availability, timing and also costs and benefits for the organization.

Table 2
CONVERSATION PARTNERS' PROFILES

Profile	Description
Peer	A worker who has already acquired the knowledge related to the learning objective, but with no work experience on it.
Expert Peer	A worker having the characteristics of a Peer and having carried out work activities related to knowledge linked to the learning objective.
Tutor	A worker having the characteristics of the Expert Peer and having teaching and/or tutoring competences.

In particular, the selection of a less valued profile (e.g. a *Peer* wrt an *Expert Peer*) represents a lower cost for the organization. Instead, the selection of a more valued profile (e.g. a *Tutor* wrt an *Expert Peer*) represents a higher cost for the organization. On the other hand, it is reasonable to think that the quality of the learning process is higher in the second case than the first case. In order to balance the cost/benefit function, authors of (Gaeta *et al.*, 2012) propose a macro-adaptation strategy based on *scaffolding & fading approach* (Fischer *et al.*, 2013).

3.5 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 an individual of s*kos:Concept*. This is a way de-facto 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 (Mangione *et al.*, 2012): 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.

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

As in the Bloom's taxonomy for learning goals, a learning approach may follow the cognitive process in terms of:

1. *Knowledge*: Recall data or information.
2. *Comprehension*: Understand the meaning, translation, interpolation, and interpretation of instructions and problems.
3. *Application*: Use a concept in a new situation or unprompted use of an abstraction.
4. *Analysis*: Separates material or concepts into component parts so to understand its organizational structure.
5. *Synthesis*: Builds a structure or pattern from diverse elements.
6. *Evaluation*: Make judgments about the value of ideas or materials.

The rules to generate feedbacks are in the following Table 3.

Table 3
RULES USED TO GENERATE FEEDBACKS

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

The proposed approach meets both regulating and individualization dimensions, turns the point of view to the constructivism and allows student to be more involved in receiving suggestions, analysing feedback, controlling actions, looking for useful (and *learningful*) material so to reach the pointed out learning goals.

4 Software Prototype and Experimentation

In order to validate the above defined approach, a software prototype has been developed. In particular, as already asserted previously, the Apache Lucene library (version 4.6.0) has been adopted. In particular, in a preliminary phase, FFCA is launched on the available documents. This phase produces a SKOS taxonomy (see Fig. 5) and a set of associations among documents and SKOS concepts.
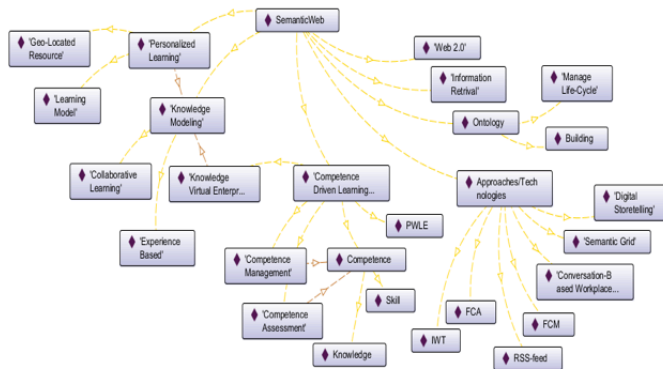
Fig. 5 - The generated SKOS taxonomy.

Subsequently, during the second phase, the set of documents has been indexed by means of the Lucene *StandardAnalyzer*. Moreover, the "stopwords" have been eliminated. Each document has been indexed by considering its content (for this experimentation only the executive summary has been considered), their associated SKOS concepts (obtained in the previous phase), filename and title. The second phase ends with the creation of a knowledge base that is ready to be used.

For the third phase, five conversation threads have been simulated. Each thread has been provided, as input, to the *MoreLikeThis* method of Lucene. This method returns a "similarity" score between the text, in the thread and all the indexed documents. Only the results with "similarity" score greater than a given threshold (in this case, the value 0.1 has been identified) have been considered.

Lastly, in the fourth phase a subset of concepts is associated to the analysed conversation thread. All the concepts associated to the documents whose "similarity" score was greater than the identified threshold have been considered. Since each concept can be contained in more than one document, starting from this preliminary set of concepts, a new score is computed with the following formula:

$$score(c) = \frac{\sum_{d}^{D} sscore(d,c)}{freq(c)}$$

More in details, to identify which concept each document treats, a cumulative score for each concept is calculated. This score is the mean of the "similari-

ty" scores. It is calculated by adding the score of all the documents treating that concept and dividing this by the frequency, i.e.: how many times this concept is present in the filtered set of documents.

The following figures provide the results generated by the prototype for five different experiments.
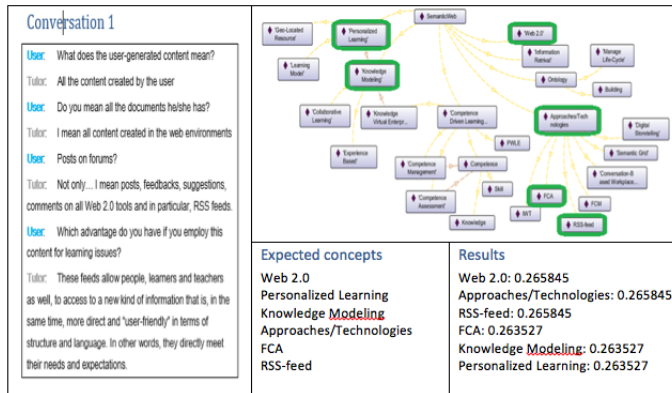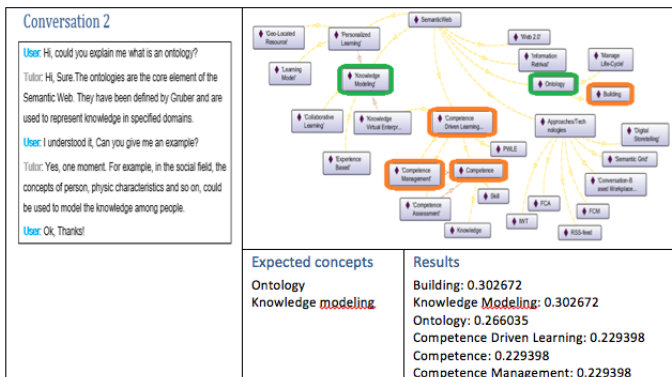

Fig. 6 - Experiment results (1/5).

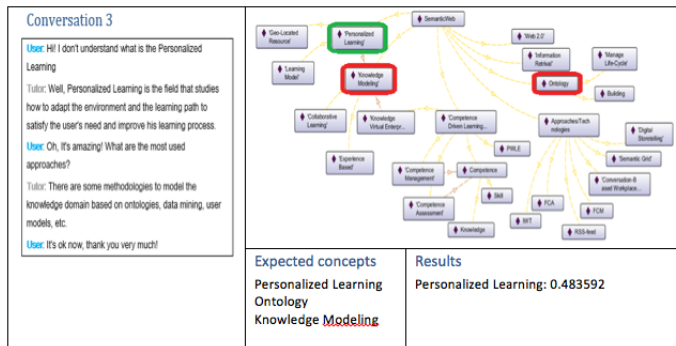Fig. 7 Experiment results (2/5).
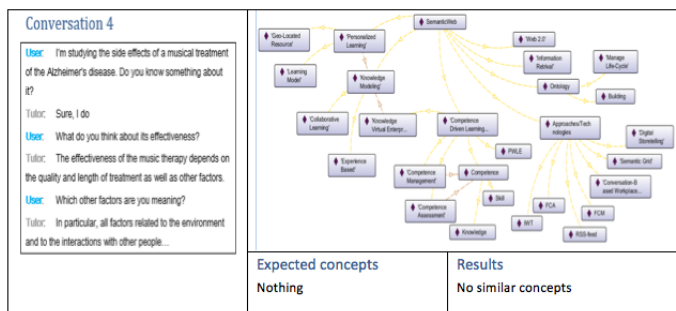
Fig. 8 - Experiment results (3/5).
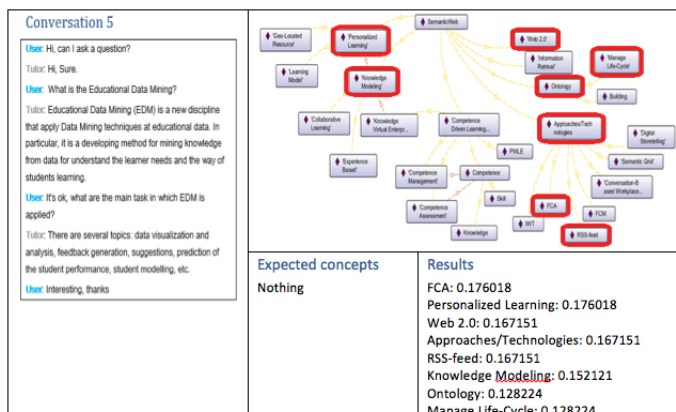

Fig. 9 - Experiment results (4/5).

Fig. 10 Experiment results (5/5).

In the first experiment showed in Fig.6, the prototype identified all treated concepts in the conversation chunk (the concepts are marked in green).

In the second experiment showed in Fig.7, the prototype identified both treated concepts in the conversation chunk (the concepts are marked in green) and some concepts more (the concepts are marked in orange).

In the third experiment showed in Fig.8, the prototype identified just one of the treated concepts in the conversation chunk (the concept is marked in green) and missed some concepts (the concepts are marked in red).

In the fourth experiment showed in Fig.9, as expected, the prototype did not identify any concepts.

In the fifth experiment showed in Fig.10, the prototype wrongly identified a set of concepts (the concepts are marked in red).

The results obtained from a first experimentation allow us to observe how the prototype, through the indexed documents, is able to identify the main concepts used in the conversation with a reasonable reliability. The third example, however, shows that the prototype give good results when the identified topics (the concepts in the conversation thread) are really related with the organizational knowledge and the available content. Although the concepts of the conversation are not modelled, the prototype still returns a set of concepts that do not meet the expected results. However the score associated to them is low.

These results are very important, because the extracted concepts may be utilized to select content for feedbacks. Considering a specific concept, a SPARQL query allows to select the content that can be used to increase and improve the educational experience.

The following Fig. 11 shows an example of a simple SPARQL query to retrieve information about tasks related to the concept "*Personalized Learning*" and useful to create a feedback for the user involved in a conversation.

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX skos: <http://www.w3.org/2004/02/skos/core#>
PREFIX unisa: <http://www.semanticweb.org/fraorc/ontologies/2013/11/unisa-jelks2013#>

SELECT DISTINCT ?s
WHERE
{
        ?s rdf:type unisa:Task.
        ?s skos:subject unisa:personalizedLearning
}
```

Fig. 11 - An example of Query SPARQL.

Final Remarks

In order to emphasize the rationale of the feedback generated by the ACLS

with respect to the objective of improving the meaningfulness of learning during tutorial dialogues, Table 3 provides the rules used to define the feedbacks.

In brief, according to (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 one.

The proposed approach has been implemented in the described prototype. It is able to automatically analyse the conversation chunks, identify treated topics and suggest all available material related to these topics and useful to enrich and get *learningful* the conversation itself.

Both the approach and the ACLS will be further experimented in the next months.

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