

AUTOMATIC CONCEPT MAPS GENERATION IN SUPPORT OF EDUCATIONAL PROCESSES

Arianna Pipitone, Vincenzo Cannella, Roberto Pirrone

Dept. of Chemical, Management, Computer, Mechanical
Engineering - University of Palermo (Italy)

arianna.pipitone@unipa.it, vcannella@gmail.com, roberto.pirrone@
unipa.it

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A VLE is a system where three main actors can be devised: the student in the role of instructional designer, the tutor, and the student. Instructional designers need easy interaction for specifying the course domain structure to the system, and for controlling how well the learning materials agree to such a structure. Tutors need tools for having a holistic perception of the evolution of single students and/or groups in the VLE during the learning process. Finally, students need self regulation in terms of controlling their learning rate, reflect on their learning strategies, and comparing with other people in the class. In this work we claim that sharing an implicit representation of the knowledge about the course domain between all these actors can meet the requirements stated before, and we present a tool that has been developed as part of the I-TUTOR project according to our claim. The tool analyses a

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suitable document corpus describing the course domain, and generates a semantic space, which in turn is displayed as a 2D zoomable map. All the relevant concepts of the domain are depicted in the map, and learning materials can be browsed through the tool. Also the texts generated by students during the learning process as well as their social activities inside the VLE can be placed in the map. The motivations of the work are reported as well as the underlying AI techniques, and the whole system is explained in detail along with the evaluation performed during the project.

1 Introduction

A Virtual Learning Environment (VLE) ranges on a set of integrated web based applications that provide teachers, learners, students, and other users involved in education with information, tools, and resources to support and enhance educational delivery and management during the learning processes. Nowadays, a VLE supports students to manage learning contents and materials, and their own resources (time, skills, and so on). However, not all the needs are covered. Most VLEs need the contents to be arranged previously by a human expert. Some few VLEs are able to organize contents automatically and supply them on the basis of the treated topics, or according to a time line. Accordingly, a student has a reduced control on the resources: deadlines, home works, and study sessions are often dictated by a predefined plan. In general, one can say that a VLE as a reduced support for Self Regulated Learning (SRL) that is the learning process where a student has to foster her/his meta-cognitive abilities for increasing the performance. Moreover, less attention is paid to the needs of other kinds of users involved in a learning process such as the tutors and the instructional designers. Instructional designers are involved in organizing and planning the students work, while tutors monitor and assess the outcomes of such an activity. They are considered as content producers but they're not so much supported.

In particular, an instructional designer defines all the main aspects in a course: topics, contents taxonomy, timing, goals. Most of her/his time is spent for defining the syllabus, collecting the learning materials, and organizing them accordingly. On the other hand, the human tutor has to gain quick access to (holistic) information related to the evolution of students and/or groups in the VLE with respect to the topics defined by the instructional designer.

Summarily, it is possible to draw a scenario, which involves three different actors (designer, tutor and student) and two phases. The first phase is the course authoring when the designer defines the conceptual structure of the course. Here the topics of the course, and their relations are described with a great effort by the designer who builds a course pattern, which will be instantiated by both students and tutors in the next phase. The second phase is the course exploitation: students learn all the contents, browsing through the conceptual net

proposed by the designer; tutors monitor and assess students, they re-organize the topics if needed (considering student skills and evaluations), and supply hints and support in the meanwhile.

In this paper we present a unique framework where all the actors in an educational process can interact to satisfy their needs. Such a tool has been developed as a part of the I-TUTOR project (I-TUTOR, 2013), and is implemented as a suitable Moodle plugin. The tool is a concept map representing the course domain in terms of all its relevant topics as the teacher describes them.

We use an approach based on Latent Semantic Analysis (LSA) and Self Organizing Maps (SOM) to build a semantic space where the vector representations of all the learning materials are clustered close to the topics they deal with. Such a space is depicted as a map where the user can pan and zoom between the course topics thus browsing the course materials. Moreover, the map is used to represent also the activity of a student or a group of students in terms of the materials they produce during the learning process, and their messages written in the social tools of the VLE. Such documents are used to make a new space, and are placed into a new map close to the arguments they deal with, and give a visualization of the course topics “covered” by the student. In this way instructional designers can have a visual interaction with the whole arrangement of their course. Students have an instrument to control their learning, and to compare with others. Finally, tutors can monitor students’ activity.

The rest of the paper is organized as follows. The second section deals in detail with the motivations of our work. The third section reports the methodology underlining the tool. The fourth section reports the process pipeline. The fifth section reports evaluation of the tool performed throughout the project. Finally, in the last section conclusions and future work are addressed.

2 Motivations and solutions: from authoring to exploitation of a course

As already mentioned, typical VLEs lack in supporting the two-phases scenario outlined in the previous section. In what follows, the crucial topics to be faced in both course authoring and exploitation are reported along with possible solutions from the technological point of view.

2.1 Course Authoring

An Instructional Designer (ID) is involved in many tasks while authoring a course: domain exploration, identifying topics, content organization and retrieval. In particular, domain definition requires modeling skills gained from Knowledge Management and Information Architecture.

A domain can be described formally through a specific structured template.

Many different formalisms have been proposed in the past. Some examples are conceptual maps and ontologies. These approaches share similar structural characteristics. Both of them have a reticular structure, where nodes describe concepts, while arcs describe relationships between concepts. Similar observations can be made for taxonomies and Entity Relationship Diagrams (ERD). The main advantage of such approaches is the possibility of managing the description automatically. On the other hand, the ID needs a specific skill to produce such descriptions. Moreover, describing a domain in a formal way is a hard task, which requires time and effort.

A common approach used to describe a domain is implicit description. In this case a domain is described less formally through a collection of documents treating the different topics of the domain. This description can be easier for the ID, and does not require specific skills. In a sense we should say that the ID is talking about the domain. On the other hand, the automatic manipulation of such a description is not easy to be implemented; Natural Language Processing (NLP) techniques have to be used. The effort to produce structured contents is reduced, but the computational cost of the preparatory content analysis grows. Many different NLP techniques can be adopted together.

NLP can use both symbolic and sub-symbolic techniques. Most of the symbolic techniques focus on the structural and syntactical characteristics of the sentences in a text. Sub-symbolic techniques focus on statistical distribution of the lexicon used in texts. These techniques transform texts into a corresponding vectorial description, which can be used in turn for defining a model. Symbolic techniques often produce a deep analysis of the meaning of texts, but they need a great and expansive effort to define all the criteria used to analyze contents. On the other hand, sub-symbolic techniques are not able to analyze deeply the meaning of texts. They adopt often a "bag of words" approach, according to which a sentence is considered only as a set of words with no attention paid to words' order in the sentences. In this way, the syntactical elements of sentences are lost.

2.2 Course Exploitation

The students and tutors instantiate the topic organization provided by designer; an instance can be regarded as a set of sub-relations of the course content structure that identifies the course state at a time. A state represents the contents, which have been studied, presented, and considered at a given time during the course. Instantiation is performed differently by students and tutors: the student is devoted to learn all the contents, browsing through the conceptual net; the tutor monitors and assesses this activity, provides new topics and rearranges them.

The student has to focus her goals, knowledge and gaps. To reach these goals she needs to compare what she knows about the topics of the course and their relations. By this comparison, she can become aware of what she just knows and what she has still to study, so the student can plan and manage her effort. Moreover, she can reflect about her social participation during the course, which ranges from the interaction with other students to the materials produced as the results of some evaluation test. All these views help the student to increase the awareness of her own learning process. All this activities can be encompassed as a Self-Regulated Learning (SRL) behavior (Pintrich, 2000).

On the other side a tutor needs to assess the same aspects of the student to be successful as a guide. He needs to compare the knowledge and the skills of the student to the main goals of the course. At the same time, a tutor could compare different students in a same class together. These analyses can be either diachronic to assess how a single student or a group of student can change over time or synchronic to assess the state of different students at a given time. Finally, it is important to enable self-reflection in the teacher about the homogeneity of the materials with respect to the topics covered in the domain.

All the aspects of course exploitation share the need of having an integrated view of both the state of student and the state of the course.

Many Intelligent Tutoring Systems (ITS) proposed in the literature make use of some form of shared knowledge representation (either explicit or implicit one) to support SRL.

MetaTutor (Rus *et al.*, 2010) is an adaptive hypermedia learning environment based on cognitive models. It is based on the assumption that students should regulate key cognitive, meta-cognitive, motivational, social, and affective processes in order to learn about complex and challenging science topics.

Cognitive Constructor (Samsonovich *et al.*, 2008) is based on a Biologically Inspired Cognitive Architecture (BICA). The term Constructor in the name reflects the inherent ability of this system to construct cognitive and learning processes from a meta-cognitive view.

Why2-Atlas (VanLehn *et al.*, 2002) is related to qualitative physics domain. The system uses natural language interaction to assess the knowledge of the student about simple mechanical phenomena. If the knowledge of the student is wrong or incomplete, the system tries to modify the situation through a dialogue intended to remedy the state of the student. The whole process is repeated many times, until the student's replies are right.

KERMIT (Suraweera & Mitrovic, 2002) models Entity-Relational Diagrams and assumes the familiarity of the users with the fundamentals of database theory. Actually, KERMIT is a problem-solving environment where the user acts as a student to build her ER schema and assists the user during problem solving, driving her through a tailored feedback.

Betty's Brain (Leelawong & Biswas, 2008) and SimStudent (Matsuda *et al.*, 2011) are computer-based learning environments inspired to the learning by teaching paradigm. A teachable agent is a peer learner that can be tutored by a student. Betty is the agent to which student interacts; to this aim, Betty draws a visual representation of the subject to be learned through a concept map. SimStudent is able to model the human way of learning and to learn cognitive skills inductively from examples or through tutored problem solving.

In this work we propose an implicit knowledge approach relying on the use of statistical NLP techniques to build a semantic space from a document corpus describing relevant topics in the course domain. The space is clustered in regions belonging to groups of relevant concepts, and its represented as a pan-zoom map. In this map the user can browse the learning materials of the course or see the materials produced by a student or a group of students or the texts produced by their social activity.

At each moment the student can see an image representing her knowledge space superimposed to the conceptual space of the domain. The coverage degree reflects how much the student knows the subject. The not superimposed areas in the conceptual space reflect those parts of the course domain that are still to be faced. At the same time, the student has an overview of how much the items have been deepened in relation to the total amount of contents per item. Moreover, the information about the time spent on each learning materials can be integrated with the map visualization.

The ID can have a holistic view of the arrangement of the course domain without having to master some complicated formalism for knowledge representation. The map visualization provides the ID with information about the coverage of each topic in the domain with respect to the number of learning materials.

The tutor can assess globally the performance of a student or a group of student by the analysis of the coverage degree between the student's activity, and the domain concept map thus enabling the same cognitive processes of the student.

3 Description of the Methodology

The tool presented in this work relies on the creation of two semantic spaces aimed at modeling both the course topics and the students interaction with the VLE: the conceptual space and the activity space (one for each student). Both of them are multidimensional spaces built from the keywords that are extracted from two different sets of documents:

- didactic documents, which are related to the course, and are provided by

- either the ID during the course authoring or the tutor during the course exploitation;
- activity documents produced by the students, such as results of a class assignment, answers to tests and quizzes, texts from forum and wikis; generally, these documents can be viewed as the representatives of both social and learning activities of a student when exploiting a course.

Both spaces share a common semantic base made by a suitable document corpus, which is produced by the ID and describe all the relevant topics of the course domain. Such a corpus contains documents that are different from both didactic and activity ones.

Documents and all the more relevant terms they contain form clusters in the semantic space with respect to their semantic relatedness. We use vector space representation of both documents and terms along with statistical NLP techniques to devise such clusters.

Clustering is performed differently for building the two spaces. In the first case Latent Semantic Analysis is used (as it is shown next) and the space is computed as the result of a classification task by a neural network: the Self Organizing Map. In the second case, the activity documents are projected as vectors in a conceptual space that has been created in advance. In this way, the activity of a student or a group of students falls in the didactic documents distribution, and makes it easier to monitor a student/class.

A key feature of our approach is the bi-dimensional map representation of the semantic spaces. It forms the base for a series of map-based visualizations that allow the tutor monitoring both social activities and task completions, enable self reflection in the student about her degree of learning, and induce self reflection also in the teacher as regards the homogeneity of the didactic materials with respect to the topics covered in the domain.

3.1 Conceptual and Activity Spaces Creation

In the I-TUTOR project we had to manage multilingual contents. As a consequence a “bag of words” statistical approach has been adopted to compute the conceptual space. In particular, Latent Semantic Analysis (LSA) (Bellegarda, 2000; Landauer *et al.*, 1998) has been used, which is aimed at building the semantic space generated from a document corpus on the basis of the occurrence frequencies of a set of meaningful terms in each document. The map will depict emergent semantic correlations between such terms due to the number of documents containing them.

In order to build a comprehensive description of the domain, the ID must specify a document corpus that is wide enough to gain statistical significance

in representing the course contents. We devised two kinds of documents to be inserted in the corpus: definitions, and insights.

Definitions are brief descriptions of a key concept or a keyword to be dealt with and developed throughout the course. Insight documents have to deal with a specific topic in the course. They should be in a sufficient number to allow the domain description.

Keywords and documents are represented as vectors in the semantic space and they're clustered through a self-organizing neural network. In particular the Self-Organizing Map (SOM) (Kohonen, 2001) has been used. Given a semantic space obtained through LSA, the SOM can be used in two different ways:

- forcing learning: neurons are trained to recognize inputs and a new classification is made. The input vectors are used as the learning set and the SOM builds its "memory" to cluster new inputs. This step returns a new SOM, which is able to cluster elements in the semantic space;
- clustering: input vectors are classified by a SOM that has been already trained.

In the LSA space vectors can represent both keywords and documents. At the end of training, vectors are divided into distinct clusters, which are in a one-to-one correspondence with the neurons. The keywords in a cluster are used as tags for each neuron. These keywords represent the topics treated by the documents contained in the cluster represented by the neuron. Some keywords are more representative than the other ones. In fact, each keyword is represented by a vector in the LSA space. In the same way, each trained neuron is defined by a vector in the LSA space. The cosine distance between the neuron vector and the keyword one represents how much that keyword is representative for the cluster. The more a keyword is close to the neuron the more it is relevant for the cluster. Keywords in a cluster are then listed according to their relevance. These lists are subsequently used to merge clusters into wider regions sharing the same topmost relevant keywords. Such keywords can be regarded as tags for the whole region.

3.2 Spaces Visualization

The choice of the visualization metaphor for the semantic spaces has been guided by different factors. We wanted a tool able to offer a holistic view of the domain to the user. As mentioned before, this aspect enables self-reflection in the student, enables effective monitoring for the tutor, and allows the ID to control the actual distribution of the learning materials with respect to the course domain.

A concept map-based visualization has been the natural choice as the lei-

tmotiv of the interface. Topics are depicted in a concept map, and contents are inserted into this map close to the topics they refer to.

This approach proved to be easy to understand because developed through a spatial metaphor. The concept map represents the outcome of the region clustering performed on the trained SOM, and it's rendered as a starred sky, where topics are depicted as constellations. Constellations extents cover some finite area in the map, and define a region. This metaphor allows showing semantic similarities between topics in terms of proximity and adjacency of the corresponding regions in the map. Topics are organized hierarchically on the basis of their relevance so the region representing a less relevant topic is included into the regions representing the most relevant ones. An overlapping between two areas reflects a semantic overlapping between two topics. Each region has its own color. Two contiguous regions own different colors. The brightness of an area is proportional to the number of documents joint with the topic of the region in which they have been clustered. Materials produced by the student, and inserted into an area are depicted using a varying size marker placed in the region. Finally, the size of the region reflects how much a topic is spread in the learning materials.

The map has been developed as a Zooming User Interface. This kind of interface has many properties that are interesting for managing complex domains. The concept map can be browsed graphically as a topological map. A topic can be focused by selecting a region. While zooming, the user discovers more and more keywords, and she can pan towards the most relevant ones with respect to her information needs. Finally, she reaches exactly the learning materials that are related to the keywords pertaining to the region she zoomed in.

4 Implementation of the System

Figure 1 shows the map creation system as a 5 steps pipeline. The input of the pipe is the set of documental corpora. The output of the pipe is a set of maps relying on the same semantic space. The rest of the section details each steps.

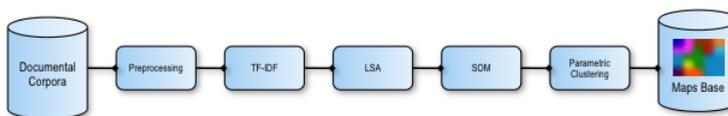


Fig. 1 - I-TUTOR Maps pipeline

4.1 Preprocessing

The preprocessing step is aimed at filtering the input texts to achieve a better performance when using NLP techniques. We adopted three main techniques:

- stopwords removal that is dropping all prepositions, conjunctions, and other parts of speech that are very common in the texts, and could bias statistical NLP techniques;
- creation of lists of “noisy words”, which are related to the semantic context but again are too common in the corpus; in a corpus dealing with the Java programming language, the words “programming” or “class” may be considered as noisy words;
- stemming that is keeping just the root of each word to allow statistical techniques devising the same meaning from different inflections.

4.2 Term Frequency-Inverse Document Frequency

The term frequency-inverse document frequency (TF-IDF) weight is a statistical measure of the importance of a word w.r.t a document in a corpus C . The importance of a word is proportional to how many times a word is present in the document (its frequency) offset by its frequency in the whole C . The frequency is normalized to measure of the importance of the term t_i within the particular document d_j . As a result, this normalization avoids a bias towards longer documents, where the term frequency could be higher regardless of the real importance of the term in the document:

$$tf_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}}$$

where $n_{i,j}$ is the number of occurrences of the term t_i in the document d_j . The inverse document frequency is a measure of the general importance of the term:

$$idf_i = \log \frac{|C|}{|\{d_j : t_i \in d_j\}|}$$

Such a measure is equal to the log of the total number of documents in the corpus just divided by the number of documents where the term t_i appears. Finally, TF-IDF has the form:

$$tfidf_{i,j} = tf_i * idf_i$$

This measure is able to filter common terms out. In fact, considering the

global frequency of a word in the whole corpus gives a low weight to very common words.

4.3 LSA

LSA is a technique usually applied in the field of intelligent information retrieval of unstructured data, like documents. It is used to mine the meaning of words by statistical computations on large text corpora. LSA is based on the *vector space method*: a text corpus containing n documents and m words is represented as a matrix \vec{A} where documents are associated to columns and words are associated to rows. The value of the (i,j) -th element $a_{i,j} \in A$ is a function of the frequency of the i -th word in the j -th document.

We used tf-idf so that $a_{i,j} = tfidf_{i,j}$. Each document d_j is associated to a vector \vec{v} and each word w_i is associated to a vector \vec{u}_i in S by applying the Truncated Singular Value Decomposition (TSVD) to the \vec{A} matrix. In both cases, close vectors in S code elements with similar meaning. The geometric distance between two vectors is related to the semantic similarity between the words or documents they are referring to.

4.4 Self Organizing Map

SOM are neural networks that are able to learn the topology associated to high dimensional input data through a map. Spatial organization of the input data features is called Feature Mapping. It is realized by SOM through an unsupervised learning. A SOM consists of neurons belonging to the so-called *Kohonen layer*, which is a lattice of neurons placed in the space in an ordered manner, and linked to a set of common inputs. One of the most used lattice of neurons is the matrix. Each neuron in the matrix is identified by its coordinates. Each neuron is associated to a weights vector with the same dimension of the input vectors. Consequently, the weights vector is positioned in the input space.

During the training phase, the neurons (i.e. the weights vectors) move towards the input points changing their positions. The activation of a neuron in the position m in the layer is equal to the scalar product between the input vector \vec{X} and the vector \vec{W}_m containing the weights of the connections between the input and neuron.

$$y_m = \vec{X} \cdot \vec{W}_m = |\vec{X}| \cdot |\vec{W}_m| \cos \theta$$

where θ is the angle between the input vector and the weights vector. Both of these vectors are normalized. The weights of the neurons close to m and

with the highest activation are modified proportionally to their distance from m . Usually, functions having a maximum in correspondence of m are used such as the Gaussian:

$$h_{l,m} = \exp \frac{|l-m|^2}{\sigma^2}$$

Variance $\sigma^2/2$ controls the radius of the group of excited neurons. The weights are updated according to the following formula:

$$\vec{W}_l^{new} = \vec{W}_l^{old} + \alpha h_{l,m} (\vec{X} - \vec{W}_l^{old}), \alpha \in [0,1]$$

The function h_{lm} defines a neighborhood around the point m where neurons' weights are moved closer to the input data. Close neurons match similar inputs. There is a mapping between the input space and the discretized space of the map: each vector \vec{X} is mapped to the position m related to the winner neuron that is the neuron with maximum y_m . As a result, a map divided into regions is identified inside the layer. Each region corresponds to specific features of the input space.

This movement becomes slower and slower, and at the end of training the network is 'frozen' in the input space. After training each input can be associated to its nearest neuron in the input space.

These positions represent relevant statistical features of input data. Distance relations in the input n -dimensional space are represented by distance relations in the bi-dimensional map.

4.5 Parametric Clustering

Parametric clustering takes place after training the SOM, which provides a document cluster for each trained neuron. At this stage, a cluster is made by the documents with the closest vector representations to the neuron's weights vector.

Also keywords are part of the semantic space. A list of the most relevant keywords is computed for each neuron where relevance is actually semantic relatedness obtained as the cosine distance between the keyword and the neuron. Then, neurons that share at least the n topmost keywords in their relevance rankings are clustered together, giving rise to the final arrangement of the semantically related regions space. The choice of n can influence the shape of the map because a high value for n tends to enlarge the size of a region in the map. In our implementation we choose $n = 5$ empirically after several trials,

corresponds to less documents, while brightness increases proportionally with the number of documents. A label with the keywords ranking for the cell is shown ($n = 5$) when the mouse passes over the cell itself.

A designer can create different concept maps, and she can manipulate the different components until she finds a convenient arrangement for showing concepts and documents. The user can change the semantic space, the SOM training, or the parametric clustering. The user can generate a new conceptual space when the underlying contents (keywords and documents) have been updated, and a new concept distribution is required. Otherwise, the elements in the space can be re-classified using a new SOM or a previously trained one. This is the case when some few documents have been added to the document corpus, and we want to take them into account without having to regenerate the semantic space because the number of the new documents is not statistically significant. Finally, the user can set new values for the weights of the keywords with the aim to highlight some words respect to others bringing them at high levels of the map. In this case just the parametric clustering is performed.

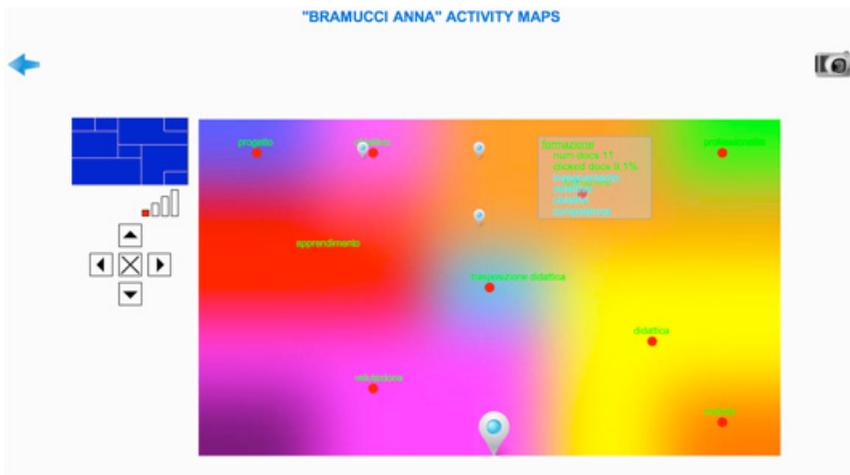


Fig. 3: An Activity map

The activity space is generated by projecting the vector representations of the documents related to the students/classes activities in the reference semantic space, which is obtained from the purposed corpus produced by the ID to describe the course domain. In particular, the *activity documents* are retrieved from the VLE database, and they are related to forum, wiki pages, and all the materials a student or a group of students inserts into the VLE. The reference

semantic space and the SOM are the same as for the conceptual space. On the other hand the user can select a conceptual space for depicting the maps, and the activity space and map are generated accordingly without user intervention. In this way the concept and activity maps have the same shape and colors even if brightness values have a different meaning because they're related to the number of activity documents, which are more than the didactic ones and are displaced differently. An example of activity map is reported in figure 3.

Through the activity space it is possible to monitor the distribution of the students work throughout the conceptual space. Both tutor and student can take advantage of this.

In particular, a tutor can:

1. view the distribution in the conceptual space of all the learning materials related only to a particular section of the course;
2. view the distribution of the activity documents (both social and didactic ones) in the activity space for a particular student; in this way the tutor can view how a student participates in forum or wikis, and her gross progress in learning didactic documents;
3. view the distribution of the activity documents (both social and didactic ones) in the activity space for a particular group of students; in this way the tutor can view how the group members participate in forum or wikis, and their gross progress in learning didactic documents;

All this information can be seen by the student also. The student has then a tool to evaluate her participation and learning progress, and this is no doubt a cue to foster self-regulation.

Cells can be evidenced by a Google-Map like marker. The dimension of the marker for a cell depends by a scale factor computed as the percentage of documents accessed by the students with respect to the total amount of documents in a cell. The percentage is also represented in "total activity" field of the label. Just "click to open" events have been traced to count documents because it is hard to say something about the time spent actually by the student to read and/or learn a document. The VLE log is not able to produce significant quantitative data in this respect. In particular, the following set of documents are counted in each case.

- for a single student, all the social and didactic documents accessed by the student herself are counted; we consider documents she has opened at least once;
- for a group of students, all the social and didactic documents the group members opened at least once, are counted;
- for a course section, all the didactic materials pertaining to the section that have been opened at least once, are counted.

Information is extracted from the VLE database, and it's retrieved on the fly each time the user wants know the distribution of the involved documents in the corresponding semantic space.

5 Evaluation of the Tool

The tool described so far has been evaluated during the two piloting phases planned inside the I-TUTOR project. I-TUTOR as a whole is a highly interactive system, and a particular care has been used as regards the interaction design. The classical user-centered software design paradigm was adopted in this respect, which is a circular workflow. An evolutionary prototyping approach was used in particular with two rounds related to the first and second piloting phase.

At the time this paper is being written, only the results related to the very first release of the tool are available in the form of a quantitative report about the usability of the system and the degree of satisfaction with respect to the learning experience of the user. Such data are related to the first piloting round (May 2013).

The second piloting has been run until September 2013, and the project partners involved in the quality management task are now processing its outcomes; no quantitative detailed data are available till now.

As we adopted a circular model for software development, the improvements of the first release of the system were implemented according to the emerging suggestions and needs of the users. We already know on a purely qualitative basis that the final evaluation results are very much better than the ones reported in this paper.

The piloting sessions we mentioned above have been carried out according to a Piloting Protocol, which was drafted and reviewed by the I-TUTOR partnership and three external evaluators. The protocol describes the aspects that must be evaluated by both students and tutors as the final users of the tool. These aspects are related to the need for user support during the course, the e-learning experience while using the tool, the user-friendliness and the helpfulness for example in understanding contents and organising the study.

Some purposed questionnaires have been made available to students and tutors by online statistical tools, which allowed exporting statistical data and piloting session assessment. In particular, two sessions took place in different locations: the University of Macerata in Italy (UNIMC), the Incorporated company continuous vocational training center (ITEC) in Athens, Greece, and the Budapest University of Technology and Economics (BME) in Hungary. The piloting sessions are summarily described in table 1.

Considering the need for users support during the exploitation of the course, the evaluation was made in comparison to traditional courses; results show that

only the 48.61% of the participants needed for more support, while less or the same level of support than traditional course was needed for the majority of them just in the very first release.

Other interesting measures have been computed considering the overall rating of the e-learning experience on the tool and the user-friendliness of the application; almost no bad judgments were achieved in the first evaluation of the e-learning experience, and only a small percentage value of participants (13,89%) assessed poor user-friendliness. All percentage values are shown in Table 2. The good judgments of both these aspects were above the 80% of the users in the last piloting phase.

Table 1
PILOTING SESSIONS FOR THE EVALUATION OF THE TOOL

	Piloting session I	Piloting session II
Place	UNIMC	UNIMC, ITEC, BME
Date	29/4 – 30/5/2013	1/6 – 30/9/2013
Course Name	Didactics of education	UNIMC: Didactics of Education ITEC: Skills in ICT BME: Digital Pedagogy
Course methodology	Blended learning	Blended learning, distance learning
Field	Higher education	UNIMC: Higher education ITEC: VET BME: Adult training
Involved audiences	50 students, 2 teachers, and 2 tutors	76 students, 4 teachers, and 5 tutors

The helpfulness of the platform tools was rated as “good” during specific phases of the course exploitation, as in understanding the contents (36%), study organization (35%), support of self-assessment (40%) and help in understanding the contents compared to classroom settings data (37%).

Some remarkably positive comments on the usefulness of the maps were made by the users. In particular, students think that the availability of maps made work quicker and allowed them to understand the topics better. Teachers think that the map tool is useful to provide students with an overview of the course.

As already mentioned, even if the first results were satisfactory with respect to the maps and conceptualization, the release we describe in this paper has been evaluated formally during the second piloting phase where the interface has been made more appealing according to the suggestions gained after the first piloting.

Table 2
 PERCENTAGE ESTIMATION OF THE E-LEARNING EXPERIENCE
 AND USER-FRIENDLINESS OF THE TOOL

	E-learning experience	User-friendliness
Good	59.72%	71.90%
Average	37.5%	10.05%
Poor	2.78%	13.89%

Conclusions and Future Works

A tool implementing an implicit shared knowledge description of the domain of a course authored for a VLE, and depicting such knowledge as a concept map has been presented in this work as part of the I-TUTOR project.

The tool makes use of a suitable document corpus whose texts describe all the relevant concepts for the domain (the so-called keywords). No formal machine readable descriptions are needed on the side of the instructional designer, which is intended to *talk about* her/his domain of expertise through document composition. Latent Semantic Analysis and Self Organizing Maps are used to cluster documents around keywords, and a map visualization is produced. Maps are aimed at two main purposes: showing the domain as a “concept map” with the proper learning materials of the course placed inside, and showing the global activity of a student or a group of students as an “activity map” containing social and didactic documents they produce. Also in this case documents are clustered around keywords because the implicit description of the domain serves as a reference for both concept and activity maps.

We claim that this approach can satisfy most of the needs of the three actors involved in a VLE: the instructional designer, the tutor, and the student. The ID can reflect upon the good coverage of the domain with the course learning materials, and can create a description of the domain, which in turn can serve as a reference for different courses focused on that domain. The tutor has a holistic view of the activity of students in terms of the domain coverage with the activity documents. Finally, the student can reflect on her degree of learning, and can compare herself with other people through the observation of the coverage of the domain with her own activities. Such cognitive processes can enable self-regulation in all the actors.

The first evaluation inside the I-TUTOR project is satisfactory and confirms our ideas but the tool needs to be refined to be more effective. Future work will be towards the use of NLP techniques oriented to deep semantics exploitation from texts through symbolic approaches. Moreover, clustering can be enhanced by refining SOM networks with more complex lattices and neighborhood functions. Finally, LSA is a widespread technique for building semantic spaces

but it's conceived for information retrieval, and it produces a semantic space of documents while we want to create a concept space that is a semantic space relying on single terms rather than documents. Suitable techniques will be investigated in this respect.

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