Supporting Technology-enhanced Learning through Semi-automatic Detection and Management of Skill and Competence Structures

Alexander Nussbaumer, Christian Gütl, Dietrich Albert

Supporting Technology-enhanced Learning through Semi-automatic Detection and Management of Skill and Competence Structures

Alexander Nussbaumer[1], *Christian Gütl*[2], *Dietrich Albert*[1]

[1] Cognitive Science Section (CSS), Department of Psychology, University of Graz, Austria
[2] Institute for Information Systems and New Media (IICM), Graz University of Technology, Austria

Key words: *competence, skill, concept, knowledge, semantic, extraction, detection*

Abstract:

A paradigm shift from a knowledge to a competence society is going on, which also becomes increasingly important for educational and vocational training purposes. Skills and competences are employed to describe learning content, students' capabilities, learning processes, and the like. Creating descriptions of skills and competences and assigning them manually is usually an exhausting task. Thus technology-enhanced support is needed. This paper presents a solution approach which enables both the semi-automatic detection of skills and competences comprised in learning content, as well as their assignments to learning content, students, and learning processes, and the exploitation of these relational structures. The methodology is based on a skill model which incorporates both a conceptual and an action component.

1 Introduction

Dealing with knowledge and detecting semantic information about knowledge has been an active research and application field in computer science in the last years, since knowledge is widely accepted as an important resource in modern society. In particular knowledge representation and management have been extensively treated in scientific literature as well as used for commercial applications. However, a paradigm shift from a knowledge to a competence society is going on, which is characterised by not only focusing on the knowledge but also on the action component, and will be increasingly apply in various application domains including technology-enhanced learning and vocational training. Compared to knowledge, dealing with competences is even more complex on the semantic level and not well supported in technological solutions today. Especially, to our best knowledge, automatically detecting them in content corpora is not supported at all. This has motivated us to start research activities in this direction.

While knowledge is related to facts, concepts, and propositions, the terms *skill* and *competence* (or competency) refer to procedural cognitive constructs which are necessary for acting (Korossy, 1999). The need for skills and competences is derived from the fact, that it is often not sufficient to know something, but instead it is required to act on it. In the remainder of this paper, these terms are used synonymously, whereby competence is rather used to express the cognitive aspect and skill is rather used to refer to the technical and modelling aspect.

In cognitive science, competences have been researched for a long time and theoretical foundations have been made (Albert et al., 1999; Ley, 2006). Among others, a model has been proposed which consists of conceptual and action components (Heller et al., 2006). The conceptual component taken from knowledge representation models expresses knowledge in the widely applied way of concept structures. The action component describes how the concepts are used by humans on a cognitive level, for example, concepts can be remembered, understood, or applied. There are taxonomies which classify the action components, such as the Bloom taxonomy (Bloom, 1956) or the revised Bloom taxonomy (Anderson et al., 2001). The classified action components describe different cognitive processing modes and can be characterised with specific action verbs.

In order to use and process skills and competences in information technology, they have to be formally described and modelled. Currently much effort is done for proper competence definition and standardisation, which should allow machine processing and interoperability of skills. The IMS Global Learning Consortium released a specification for Reusable Definition of Competency or Educational Objective (RDCEO) which contains an information model, a best practices document and an XML binding. These results are the foundation document for the IEEE standardisation project of the Reusable Competency Definitions (RCD, 2007) standard, which is still on-going. However, this standard mainly describes the skills verbally and does not provide a granular skill model which is needed for the automatic detection of skills in learning objects.

Various skill models have been developed in research projects. For example, a skill model according to the cognitive approach described above has been developed in the iClass research project (Görgün et al., 2005) and a similar skill model relying on proficiency levels have been developed in the context of the TenCompetence research project (De Coi et al., 2006). While there are several research projects dealing with representing competences (such as TenCompetence (TenCompetence), iClass (iClass), or APOSDLE (APOSDLE)), none of them deals explicitly with acquiring a competence representation from text documents, but they rely on manually provided models and structures. Also, to our best knowledge, in the scientific literature no solutions have been published how to automatically detect skills in content corpora.

In this paper, a novel method is presented, how skills based on the iClass skill model can be semi-automatically detected in learning objects. Relations between learning objects and skills, especially the semantic information which learning objects teach which skills, can be uncovered with this method. Furthermore, a solution how to combine and manage these relations with relations between humans and skills, as well as relations between learning processes and skills will be presented. In this way, content authors are supported who usually create these relations manually.

The remainder of this paper is structured as follows: The next section presents a framework for detecting and managing competence which enables applications to easily deal with competences. Section 3 outlines a method. how skills can be semi-automatically detected by using concept extraction and action verb recognition. Then, in Section 4, an on-going development is presented how to detect the action component. Finally concluding remarks and an outlook on further tasks are given.

2 A Framework for Skill Detection, Management, and Application

In this section a coherent framework for competence detection, management, and application is presented. The main goal of this framework is to create and management competence structures and to provide them to applications for further usage. In this paper, competence structures are the relations between skills on the one hand and learning objects, persons, and learning processes on the other hand (see Figure 1). This approach enables applications to exploit these structures for various purposes. Especially, indirect relations between learning objects, persons, and learning processes can be derived and utilised.

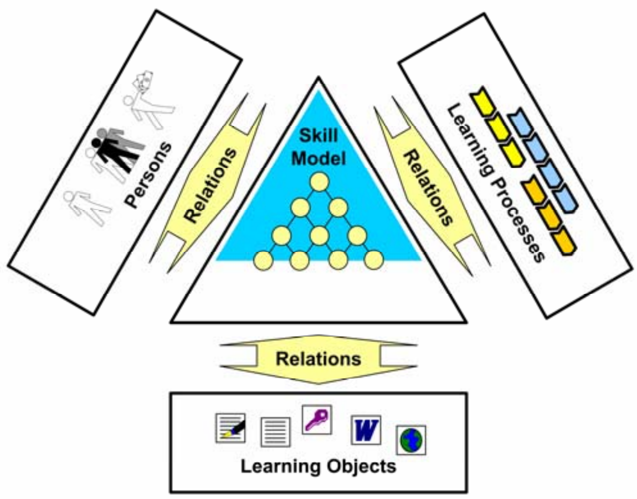

Figure 1: Competence structures. The relations between skills to learning objects, persons and learning processes.

An overview of the several conceptual units of the proposed framework is depicted in Figure 2. The framework consists of two parts, the competence detection and management part and the application part. The first one is the core element which is used by the second one. While the core part is supposed to be the same for different applications, the implementation of the application part depends on the concrete application. On the horizontal axis of this diagram, the life cycle of the skills and skill descriptions are depicted, which make up five processing layers of skills. Orthogonally to them, there are two further layers, the visualisation and user interface layer and the evaluation and benchmark layer. Both are applied on each of the horizontal layers respectively the several conceptual units.

The first horizontal layer comprises three different units which provide the infrastructure to create skill descriptions which are delivered to and further managed by the Skill Model unit. First, the unit for automatic skill discovery from digital objects is responsible for creating new skill descriptions by analysing sets of digital objects. Based on skill detection procedures algorithms are developed for the automatic extraction of the skill descriptions (see Section 3). Since it is unlikely that full automation can be reached out of the box, this component is designed that users can support this task. Second, the User Input unit provides an interface for domain authors to create skill description fully manually. Moreover, is can be used by authors to edit existing skill models or as feedback interface for the semi-automatic detection service.

Third, the Import unit is responsible for importing and converting already existing skill data sets maintained by external systems. Furthermore, skill models for specific domains to set up a skill management system could also be provided by a third party company.

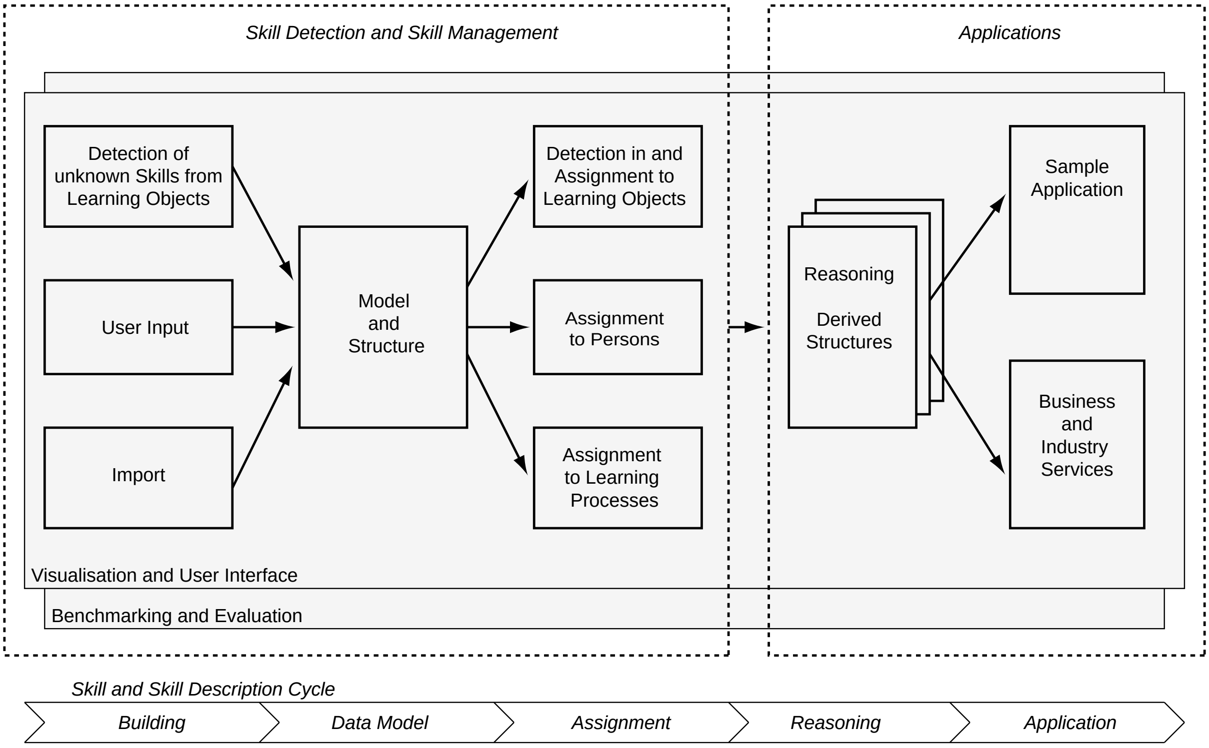

Figure 2: Conceptual units of the proposed competence-oriented framework

The second horizontal layer deals with the skill model management. The Skill Model unit is the central unit of this framework since it provides interface for all other units. It manages the information of all skill model which including the skill data model and patterns needed for the recognition.

The third layer deals with skill assignment to learning objects, persons, and learning processes. Therefore, there are three assignment units which are responsible for different operations. The first unit is responsible for detecting skills in learning objects. In this case, skills which are already described in the Skill Model unit are searched in the learning objects. Similar to detecting unknown skills, the method is described in Section 3. The second unit is responsible assigning skills to humans, which can done by skill assessment and which is often described in the literature. The third unit deals with assigning skills to learning processes, which has to be done manually in most cases. The three assignment units together form the competence structure as outlined in Figure 1.

In order to make use of the competence structures, skill reasoning units are responsible to derive further semantic structures. Essentially, indirect relations between the entities linked to the skills can be derived though semantic reasoning. For example, learning objects can be found which are appropriate for a specific person to close the skill gap of this person, or a learning process can be found which is appropriate for a specific student. Depending on the concrete application scenario, the specific expected reasoning results have to be determined. Therefore specific units are needed which are capable to retrieve respective results.

Applications can make use of the competence structures including the derived semantic information. For example, learning management systems (LMS) can calculate learning paths which meet the competence level of learners. Furthermore, learning processes for specific students can be defined which include particular learning objects

Orthogonal to the skill life cycle layers, there are two further layers: First, the Visualisation and User Interface layer indicates that for each conceptual unit user interface and perhaps visualisation techniques are important. Especially the domain author should be supported with an easily understandable visual interface while defining new skill description and assigning them to learning objects. Second, the Benchmarking and Evaluation layer acts as an interface to each conceptual unit in terms of benchmarking and evaluation. Especially, the validation of the achieved skill descriptions and structures are important tasks. Furthermore, benchmarking techniques have to be developed to measure the performance of the specific system activities, such as processing time and system behaviour with large sets of data (scalability).

The methods and implementation mentioned above focus on two parts of the framework, the semi-automatic creation of skills and the semi-automatic assignment of skills to learning objects. These are the crucial research parts, while the other units are either already sufficiently researched or they do not require research.

3 Skill Detection in Learning Content

Basis for the skill detection is a skill model which is appropriate for the detection procedure. As already described in Section 1, a skill model is proposed which consists of two components, concepts and action verb (see Figure 2). In more detail, a modelled skill consists of multiple concepts and one action verb. Hence, the task of detecting new skills in learning objects can be tackled by detecting concepts and action component in learning objects separately and by joining them to skill descriptions then. This skill model has been used in the iClass research project for knowledge structuring (Görgün et al, 2005).

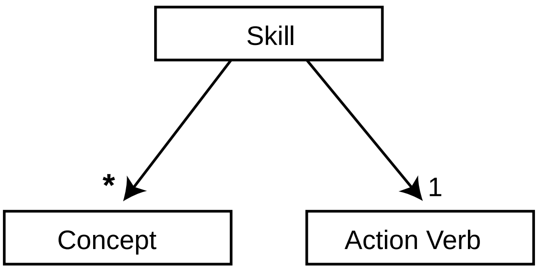

Figure 3: Skill Model.

Detecting concepts in digital objects has been researched well and can be seen as state of the art. A prominent approach to concept detection is the LSA and LSI family of algorithms (Landauer, 1998). Groups of terms are identify as concepts by dimension reduction of a highly dimensional vector space which represent a document corpus. A different approach to concept detection stems from the field of ontology learning. There a concept is an element in a model (an ontology) which is created by the domain author by inserting concepts. Therefore concept detection is a semi-automatic task in ontology learning (Maedche, 2002) and the domain author is being supported in creating elements of a model by an algorithm that suggests potential concepts based on text analysis.

Genre detection is an increasingly interesting research field in various application domains for diverse media (Bloehdorn, 2006). Unlike the thematic classification, genre identification discovers groups of media that share a common form of transmission, purpose, or discourse properties. To illustrate this, genre detection for web resources may distinguish research papers, personal experience reports, or commercial product information (see e.g. Stein & Meyer 2006). Though the strong interest in genre detection by the research community, to our best knowledge there is no genre detection solution available for detecting the action component applicable for skill detection.

To detect action verbs we propose an enhanced genre detection approache. Each action component category is assigned with specific patterns which are used to detect the respective component. There are several types of patterns which an algorithms tries to detect separately and assigns weights for their probability. Then the weights are summed up which results in a ranked list to be recommended to the domain author. Finally the domain author has to decide which action component is appropriate.

The next step of the skill detection process is joining concepts and action components to skills. There are two different steps in the skill detection process. First, detecting unknown skills from a set of learning objects (see Figure 4, Step 1), which is processed in the skill building life cycle. Second, detecting skills in learning objects which are already described in the Skill Model unit (see Figure 4, Step 2). While the first step has to be done primarily manually, for the second step an algorithm can be used which compares concepts and action component of current learning object with them already detected and stored in the system. The domain author is needed anyway to confirm or edit the suggested skill assignments. If no appropriate skill could be detected by the system, a fall back possibility to manually input the skill data is needed.

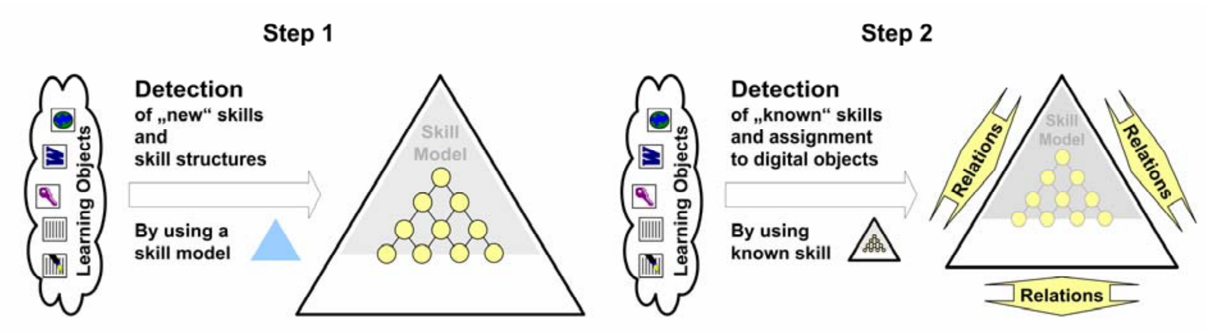

Figure 4: The two steps of skill detection.

4 Prototype Implementation

The implementation of a prototype for detecting the action component is still going on. According to the Bloom taxonomy (revised taxonomy by Anderson and Krathwohl), there are six different cognitive processing modes, how conceptual knowledge is treated by humans. In this approach it is intended to recognise automatically the first three categories.

The detection strategy is based on three different sources which are exploited. First, statistical analysis of the words contained in full text and description of digital object itself or of the contained multimedia objects (e.g. diagrams) might provide indications about the action component. Therefore, the action verbs which are assigned to the Bloom categories are exploited by comparing the action verbs with the words contained in learning objects. Table 1 gives an overview on these action verbs.

Second, all available meta-data are analysed with respect to hints in this directions. For example, Learning objects created in HTML or XHTML could comprise concrete hints in the used meta-data. Furthermore, if available, some fields in the learning object meta-data (LOM) contain explicit hints in this direction.

The third source is the structure of the layout of learning objects which might give information about the action component. Figure 5 gives three examples of different layouts which indicate the action component. The first example shows a list of short statements, which indicates that this learning object teaches a skill of the *remember* category, since these facts are supposed to be memorised. The second example gives a long text combined with an animated graphics. This is an indication that this learning object teaches a skill of the *understand* category, since textual description and graphics usually aim at explaining something. The third example consists of a step-by-step explanation. This may be an indication, that a skill of the *apply* category is taught by this learning object.

Category	Action Verbs
Remember (Knowledge)	list, define, tell, describe, identify, show, label, collect, examine, tabulate, arrange, define, duplicate, label, list, memorize, name, order, recognize, relate, recall, repeat, reproduce, state
Understand (Comprehension).	summarize, describe, interpret, contrast, predict, associate, distinguish, estimate, differentiate, discuss, extend, classify, describe, discuss, explain, express, identify, indicate, locate, recognize, report, restate, review, select, translate
Apply (Application)	apply, demonstrate, calculate, complete, illustrate, show, solve, examine, modify, relate, change, classify, experiment, discover, choose, dramatize, employ, interpret, operate, practice, schedule, sketch, solve, use, write

Table 1: The first three categories of the Anderson (Boom) taxonomy and the related action verbs.

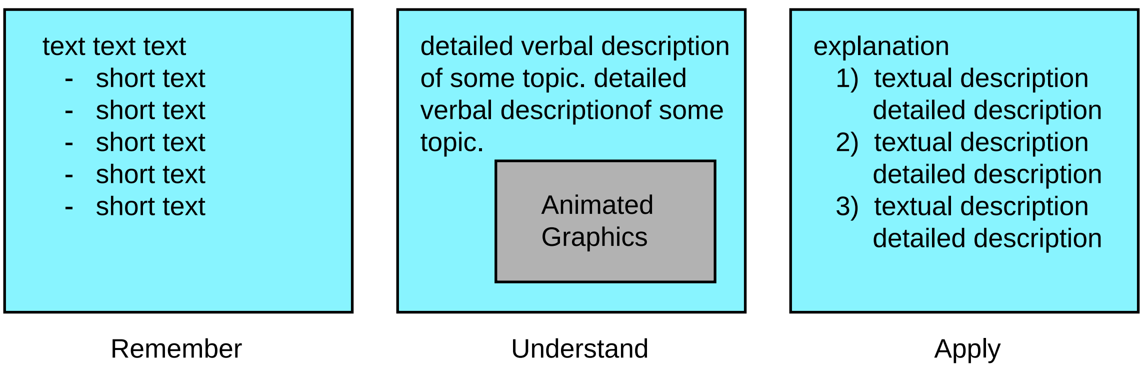

Figure 5: Examples for layout-based action component detection in learning objects.

5 Conclusion and Outlook

A framework for competence management and a method for detecting skills have been presented in this paper. Together they outline an approach for semi-automatic detecting skills in learning objects. Since manual assignments of skills to learning objects is an exhausting task for content authors, the solution approach described aims at supporting them in creating skill assignments. These assignments are valuable structural information which can be used in technology-enhanced learning for adaptive testing and learning-path creates, as well as user profiling in terms of knowledge and competences.

There are two main areas for further research and development activities lie in: first, the implementation of the prototype for action verb detection has to be finished and an evaluation has to made about quality and validity of detected action verbs from learning objects. Second, further research should be done in investigating other skill models and if they can be used instead of or in common with the one described above.

Acknowledgements:

The work presented in this paper is partially supported by European Community under the Information Society Technologies (IST) program of the 6th FP for RTD - project iClass contract IST-507922. The authors are solely responsible for the content of this paper. It does not represent the opinion of the European Community, and the European Community is not responsible for any use that might be made of data appearing therein.

References:

[1] Albert, D., & Lukas, J. (Eds.). (1999). Knowledge Spaces: Theories, Empirical Research, and Applications. Mahwah, NJ: Lawrence Erlbaum Associates.

[2] Anderson, L. W., Krathwohl D. R. (eds.) (2001). A Taxonomy for Learning, Teaching, and Assessing: A Revision of Bloom's Taxonomy of Educational Objectives. New York: Longman

[3] APOSDLE, http://www.aposdle.tugraz.at/

[4] Bloehdorn, S., Cimiano, P, Hotho, A. (2006). Learning Ontologies to Improve Text Clustering and Classification. In: From Data and Information Analysis to Knowledge Engineering. Springer Berlin Heidelberg

[5] Bloom, B. S. (ed.). (1956). Taxonomy of Educational Objectives, the classification of educational goals – Handbook I: Cognitive Domain New York: McKay

[6] Coffey, J. W., Hoffman R. R., Cañas A. J., Ford K. M. (2002). A Concept Map-Based Knowledge Modeling Approach to Expert Knowledge Sharing. *The IASTED International Conference on Information and Knowledge Sharing (IKS '02)*

[7] De Coi, J. L., Herder, E., Koesling, A., Lofi, C., Olmedilla, D., Papapetrou, O., Siberski, W. (2006). A Model for Competence Gap Analysis. *First European Conference on Technology Enhanced Learning (EC-TEL '06)*

[8] Görgün, I., Türker, A., Ozan, Y., & Heller, J. (2005). Learner Modeling to Facilitate Personalized E-Learning Experience. *Cognition and Exploratory Learning in Digital Age 2005 (CELDA'05), pp. 231-237.*

[9] Gütl, C., García-Barrios, V. M. (2006). Smart Multimedia Meeting Information Retrieval for Teaching and Learning Activities. *Society for Information Technology and Teacher Education (SITE '06)*

[10] Heller, J., Steiner, C., Hockemeyer, C., Albert, D. (2006). Competence-Based Knowledge Structures for Personalised Learning. *International Journal on E-Learning, 5(1), 75-88.*

[11] iClass, http://www.iclass.info

[12] Korossy, K. (1999). Extending the theory of knowledge spaces: A competence-performance approach. Zeitschrift für Psychologie, 2005, 53-82
[13] Ley, T. (2006). Organizational Competency Management – A Competence Performance Approach. Shaker Verlag, Graz.
[14] Landauer, T. K., Foltz, P. W., Laham, D. (1998). Introduction to Latent Semantic Analysis. Discourse Processes
[15] Maedche, A., Staab, S. (2001). Ontology Learning for the Semantic Web, IEEE Intelligent Systems, 16(2), 72-79
[16] Sowa, J.F. (1992). Conceptual graphs as a universal knowledge representation. *In Fritz Lehmann, editor, Semantic Networks in Articial Intelligence, pp 75-93, Pergamon Press*
[17] TenCompetence, http://www.tencompetence.org/

Authors

Alexander Nussbaumer, Dipl.-Ing.
Cognitive Science Section, Department of Psychology, University of Graz, Austria
Universitätsplatz 2 / III, A-8010 Graz, Austria
alexander.nussbaumer@uni-graz.at

Christian Gütl, Dipl.-Ing. Dr. techn.
Institute for Information Systems and New Media, Graz University of Technology, Austria
Inffeldgasse 16c, A-8010 Graz, Austria, Europe
cguetl@iicm.edu

Dietrich Albert, O.Univ.-Prof. Dr.rer.nat.
Cognitive Science Section, Department of Psychology, University of Graz, Austria
Universitätsplatz 2 / III, A-8010 Graz, Austria, Europe
dietrich.albert@uni-graz.at