# Deliverable D3.2

# First Release of LA/EDM Services and Algorithms

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# EXECUTIVE SUMMARY

Workpackage 3 is mainly concerned with research and technical development of software components in the field of CbKST and FCA. These components include functions for (i) collecting, (ii) accumulating, (iii) analyzing, and (iv) interpreting educationally- relevant data ranging from conventional test results to broader activity data. Concrete functions cover

- evidence-based establishing and validating the teachers' domain models and teaching plans
- identifying individual learning paths and individual learning progress
- predicting individual learning trajectories
- adaptive assessments of competencies and competence states
- identifying individual learning styles
- evaluating the effectiveness of teaching methods and materials
- visualizing data and the results of analyses
- appropriate communication and reporting of teaching/learning activities
- appropriate communication and negotiation of individual learning achievements

In year one, our work primarily addressed to key aspects. The fundamental part was the conceptual research in the area of integrating elements of CbKST and FCA. In addition, we successfully developed and released the core components for the web platform, specifically the central control elements, interfaces, data storage, and basic analyses algorithms. Also me have release a first version of the theory-related Hasse diagram visualizations.

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# 1. Introduction to Competence-based Knowledge Space Theory

The LEA's BOX project aims at enriching learning analytics research and technologies by sound, and competence-centred approaches to learning analytics grounding on well-established psycho-pedagogical frameworks. The research on and implementation of such theory-grounded approach to learning analytics shall enable psycho-pedagogically meaningful learning analytics tailored to the needs of teachers and learners as main stakeholders and empowering their everyday teaching and learning practice. A perspective to learning analytics is taken that focuses on knowledge and competence. To be able to validly assess learning and learning progress and provide support and guidance in teaching and learning an appropriate and accurate representation of the knowledge domain (learning domain) in question is required. Knowledge Space Theory (KST), in particular its competence-based extensions, i.e. Competence-based Knowledge Space Theory (CbKST), form the main theoretical foundation for analytics in LEA's BOX. This theoretical framework provides a powerful basis for knowledge and competence modelling, structuring, assessment, and feedback. This section provides an introduction to the main concepts of KST and CbKST and their application.

## Overview and basic notions of CbKST

KST and CbKST constitute a powerful psychological framework for domain and learner knowledge representation that enables describing a learning domain and the knowledge or competence of individuals in a precise and formalized way (Albert & Lukas, 1999; Doignon & Falmagne, 1999; Falmagne & Doignon, 2011; Falmagne, Albert, Doble, Eppstein & Hu, 2013).

In the original formalisation of KST, the most basic assumption is that a knowledge domain can be represented by a set $Q$ of representative problems or items (e.g. Falmagne, Koppen, Villano, Doignon, & Johannesen, 1990). The knowledge state $K$ of a person is considered as the subset of problems of that domain that this person is capable to solve. The problems of a knowledge domain – although they might be of very different type – are dichotomous, i.e. can be coded as correctly or incorrectly solved (i.e. solved or not solved). The knowledge domain is described by establishing a structure on the item set. This means, the items of a domain are assumed to be not independent of each other; rather dependencies will exist among the problems of a domain, such that from the correct solution of a specific problem the mastery of certain other problems can be surmised. These dependencies are captured by the so-called prerequisite relation, which is a binary, reflexive, and transitive relation $R$ on the set $Q$ of all problems. If two problems $a$ and $b$ are in a prerequisite relation $aRb$, then the mastery of $a$ is a prerequisite for $b$. The prerequisite relation is also called surmise relation (as the mastery of a problem can be surmised from another one; see e.g. Doignon & Falmagne, 1999) or precedence relation (as the mastery of a problem and the knowledge associated with it precedes that of other problems; see Falmagne, Cosyn, Doignon, & Thiery, 2006). A prerequisite relation can be graphically depicted by a so-called Hasse diagram (e.g. Pemmaraju & Skiena, 1990), which is a directed graph with the nodes representing the problems of a domain and the arcs representing prerequisite relationships among those problems (see Figure 1(a) for an example). The prerequisite relation establishes a quasi order on the set of problems and thus puts restrictions on the subsets of problems that are expected to be observable knowledge states. The family of knowledge states corresponding to a prerequisite relation, including the empty set $\varnothing$ and the whole set $\mathcal{Q}$, make up the knowledge structure $\mathcal{K}$. For our item set represented in Figure 1(a) the knowledge structure is given by:

$$\mathcal{K} = \{\varnothing, \{a\}, \{b\}, \{a,b\}, \{b,c\}, \{a,b,c\}, \{a,b,d\}, \{a,b,c,d\}, \{a,b,d,e\}, \{a,b,c,d,e\}\}$$

A visualization of the knowledge structure through a Hasse diagram is presented in Figure 1(b). The so-called prerequisite function (also called surmise function or surmise system) is a generalization of the prerequisite relation and allows assigning multiple sets of prerequisites to a problem through clauses, each of which representing minimal states containing the respective problem. It has been introduced in order to care for the fact that there might be different ways of acquiring the mastery of a certain problem. A prerequisite function can be visualised by an And/Or graph; the induced knowledge structure is closed under union, but not necessarily under intersection.

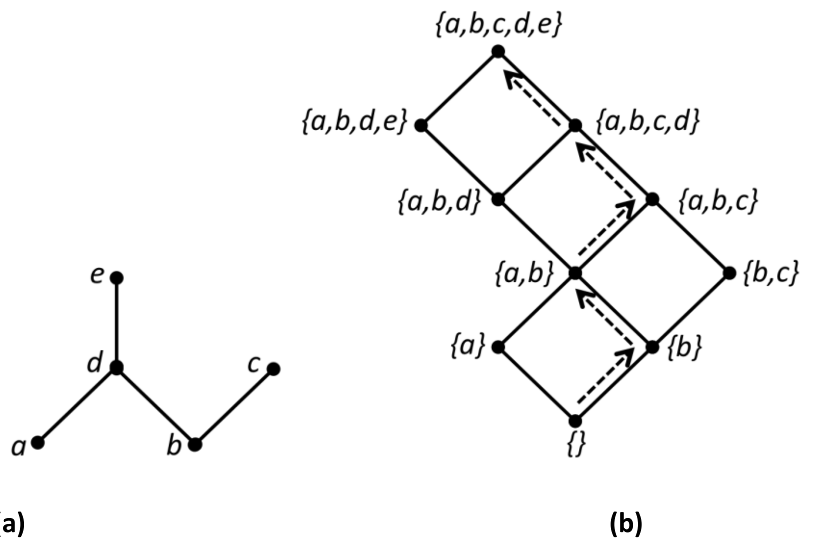


*Figure 1: (a) Example of a prerequisite relation on a knowledge domain $\mathcal{Q}$ = {a, b, c, d, e} and (b) the corresponding knowledge structure. Dashed arrows indicate a possible learning path.*

A knowledge structure as represented in Figure 1(b) collects the possible knowledge states, which are naturally ordered by set-inclusion and suggest meaningful learning paths relying on the prerequisite-wise organisation of the knowledge domain. In general, a knowledge structure will allow several learning paths starting from the naive knowledge state *{∅}* and leading to the knowledge state of full mastery *{Q }*. One possible learning path from our example is indicated in Figure 1(b), but there are also other meaningful sequences. In the teaching process, learning material related to and conveying knowledge required for the solution of the domain's problems should be presented in line with the learning paths through a knowledge structure (Falmagne et al., 2006). Furthermore, a knowledge structure can be used as a basis for efficient assessment algorithms that allow identifying the knowledge state of a learner by posing only a subset of problems. This is done by exploiting the prerequisite relation and drawing inferences from given answers, such that the next question to be presented can be adaptively selected, mimicking the examination procedure of a teacher in an oral testing (Dowling & Hockemeyer, 2001; Falmagne et al., 2006). The result of a CbKST assessment is richer and more meaningful than crude and abstract numerical indications in terms of marks or scores used in traditional assessment or standardised tests. Instead of a pure and singular numerical value describing a person's knowledge, the outcome of assessment is a knowledge state, i.e. essentially a list of problems that a person is able to solve at the time of the assessment. The knowledge state precisely characterises the current knowledge of a person. Given the knowledge state of an individual, advice for further progress in learning or for temporary retreat can be derived by making use of the so-called outer and inner fringes of a knowledge state (Falmagne et al., 2006).

The theoretical approach of KST, originally developed from a purely behaviouristic point of view, has been extended by taking into account and introducing psychological constructs in terms of cognitive abilities (competencies or skills) underlying the observable behaviour (e.g. Albert & Held, 1999; Doignon, 1994; Düntsch & Gediga, 1995; Falmagne et al., 1990; Hockemeyer, Conlan, Wade, & Albert, 2003; Heller et al., 2006; Kickmeier-Rust & Albert, 2010; Korossy, 1997; Ley, Albert, & Lindstaedt, 2007). Basic assumption of these competence-based approaches is the existence of a set of skills (or elementary competencies) that constitute latent cognitive constructs in terms of (cap)abilities required for solving the problems of a domain. Consequently, in CbKST a knowledge domain is identified with a set $Q$ of problems and a set $S$ of skills. The relationship between problems and skills is established through the assignment of skills to assessment problems, associating to each problem a family of subsets of skills sufficient for solving it (skill function) and associating to each subset of skills the set of problems that can be solved in it (problem function), which consequently induces a knowledge structure on the set of problems. The skill assignments induce dependencies and a structure on the set of skills, which however may only crop up in the respective problem set. When explicitly assuming that the skills of a domain are not independent from each other, a competence structure can be built in analogy to a knowledge structure, by identifying prerequisite relationships on the skill set (Korossy, 1997). A competence structure collects the possible competence states (subsets of skills) that correspond to the prerequisite relation established on the skills. In this case, the problem function (also called 'representation function') assigns to each competence state of the structure the problems solvable in it and conversely, the skill function (alternatively denoted as 'interpretation function') associates each problem with the minimal competence state sufficient for solving it. With competence-based extensions of Knowledge Space Theory, also an explicit reference to learning and teaching objects has been made, thus identifying a domain also with a set $L$ of learning objects (e.g. Heller et al., 2006). In this context, a differentiation between skills taught by a learning object and required to be able to understand it has been introduced and formalised by two mappings. Similarly, on the level of problems a distinction between skills tested by a problem and skills required to understand it has been introduced. This association of skills with objects representing learning content allows deciding which learning object should be presented next – in line with the selection of the next skills to be acquired based on the possible learning paths of the competence structure (Hockemeyer et al., 2003). More recent developments of CbKST integrate the competence approach with theory of human problem solving (Newell & Simon, 1972) in order to model and monitor learners' behaviour and skills in problems solving during learning and assessment situations (e.g. Augustin, Hockemeyer, Kickmeier-Rust, & Albert, 2011; Kickmeier-Rust & Albert, 2010).

The consideration of skills underlying performance, as implemented in CbKST, has several advantages: Given the observable knowledge state of a person it can be mapped to the corresponding competence state (i.e. subset of skills) this person has available. In this way, it is possible to better understand and predict observable behaviour, e.g. to explain why certain problems are not solvable by a person or to identify which other problems a person would be able to solve (e.g. Korossy, 1993). Furthermore, CbKST offers valuable information for teaching, providing guidance with respect to the skills a learner lacks or needs to acquire in order to master problems previously not solved. Since today curricula usually formulate learning objectives at the level of skills (Marte, Steiner, Heller, & Albert, 2008), competence-based approaches of Knowledge Space Theory facilitate the connection to the definition of learning goals and the specification of learning gaps. Besides, the modelling and assignment of skills facilitates the addition or deletion of learning objects and problems to and from a knowledge domain. This is not a straightforward process in a purely behavioural, problem-based approach, where modifying the set of problems or learning objects of the knowledge domain directly affects the prerequisite relation between those entities and has to be rebuilt. Skill assignments to problems are independent from each other, such that modifying the problem set does not require revising the prerequisite relation, but only calls for a re-computation of the knowledge structure. Furthermore, CbKST is also able to model and integrate skill assignments coming from distributed resources (Heller & Repitsch, 2008; Stefanutti, Albert, & Hockemeyer, 2005).

## Establishing Knowledge Representations in CbKST

To ensure meaningful application of CbKST the main goal is to validly identify the necessary pieces of information, that is, the prerequisite relationships among the items or skills representing a domain. A range of methods for uncovering prerequisites among problems or skills and for establishing knowledge and competence structures are available (for an overview see e.g. Held, Schrepp, & Fries, 1995). These methods differ with respect to the basic theoretical concepts, their implementation, and the conditions for their application.

Data analysis relies on the collection and investigation of answer patterns for a given item set in order to detect dependencies among the respective items and to establish a knowledge structure (e.g. Schrepp 1999; Ünlü & Sargin, 2010). All approaches of data analysis have in common that they require the availability of large data sets. Another way of building knowledge structures is to query experts in the knowledge domain in question on prerequisite relationships (e.g. Cosyn & Thiéry, 2000; Koppen & Doignon, 1990). For a given- item or skill set the relationships between these entities are determined by asking experts questions like 'Imagine a person is not able to master item Y. Is it then practically certain that this person will also fail problem X?' Further approaches for structure generation consider the demands that a problem imposes or the skills required for mastering it. These methods involve cognitive task analyses of the solution ways and underlying cognitive processes of representative problems of a knowledge domain. In systematic problem construction (e.g. Albert & Held, 1999) an analysis of the problem demands serves the organised formation of problems and thus, the systematic establishment of a knowledge structure for these problems. Another option is to identify and structure skills of a domain that can be associated with a given item set through solution way analysis, curriculum analysis, and/or content analysis of textbooks and learning objects (e.g. Korossy, 1997), or through analysis of work documentations and consultation of experts (Ley et al., 2010). Furthermore, the utilization of ontological information as represented in concept map has been proposed as an approach for establishing a structure among items or skills (Steiner & Albert, 2008).

## APPLICATIONS OF CBKST

Knowledge representations in terms of knowledge and competence structures provide a sound basis for the implementation and realisation of personalised learning experiences and has been implemented in different adaptive learning environments. For optimising adaptivity objectives and personalisation of learning, a learning system should tailor to the learner's prior knowledge, to the learning progress and growth in expertise, and to the desired learning outcome (e.g. Albert, Hockemeyer, & Mori, 2006). By presenting the learner with learning material that corresponds to his/her current knowledge level or competence without over- or underchallenging him/her, it can be ensured that the learner achieves the learning goal in a meaningful and supportive way. CbKST enables a theoretically founded and sound structuring of knowledge domains as a basis for this kind of intelligent educational adaptation of the learning process to a learner's current knowledge and competence (e.g. Albert, Hockemeyer, & Wesiak, 2002; Conlan et al., 2006).

Knowledge and competence structures are used for realising personalised learning paths, aiming at closing the gap between a learner's current knowledge and competence relative to a knowledge and competence state representing the learning goal. Given the knowledge or competence state of a learner, meaningful next learning steps can be identified, and previously learned material that is most suitable to be reviewed can be selected (e.g. Falmagne et al., 2006; Korossy, 1999b). Knowledge and competence structures in the tradition of CbKST can be used to assess the knowledge or competence of a learner through adaptive assessment procedures (e.g. Dowling & Hockemeyer, 2001). Such adaptive assessment is able to identify the current knowledge and competence of an individual by presenting him/her with only a subset of problems of a domain, by exploiting the prerequisites between them and taking into account a person's previous answers. The assessment result builds the starting point for deciding upon meaningful next steps of the learning process and for an according adaptive selection or recommendation of learning objects and content. More recent developments in the context of game-based learning consist in the elaboration of the concept of microadaptivity, which gives rise to the realisation of a non-invasive assessment of learners' available and lacking skills by monitoring and interpreting learner actions during problem solving situations (e.g. Augustin et al., 2011; Kickmeier-Rust & Albert, 2010). The assumptions on a learner's skill gathered through non-invasive assessment serve the provision of adaptive interventions and feedback tailored to the learner's available and lacking skills (e.g. Kickmeier-Rust, Steiner, & Albert, 2011).

To summarise, CbKST provides a framework to establish the theoretical structures and algorithms underlying adaptation. In this sense, the knowledge representations of CbKST have traditionally been used are usually not presented to the learner, but kept at the backend of a learning technology. More recently, the structures on skills and their association with learning objects and assessment problems have also been opened up to teachers and learners through a range of visual tools (see Figure 2 for an example) to support learning and teaching, as a basis for reflection, monitoring, and planning and Hasse diagrams have been identified as possible approach to visualize assessment results and learning paths (Kickmeier-Rust & Albert, 2013; Steiner, Nussbaumer, & Albert, 2009; Nakamura, Tsuji Seta, Hashimoto, & Albert, 2011). The theoretical structures of CbKST visualized through Hasse diagrams have also been used for direct presentation to learners, to make explicit the structure and prerequisites on the learning objects of a course and for use as navigation interface (Krauße & Körndle, 2005).

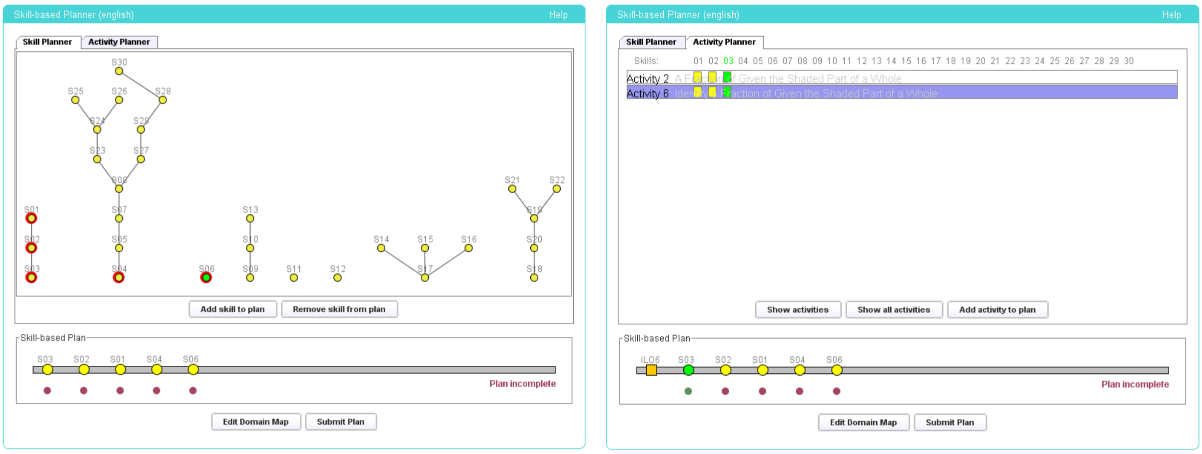


*Figure 2: Definition of a learning plan based on the visualisation of the prerequisite relation existing among skills and on the assignment of skills to learning objects.*

Formal Concept Analysis (FCA), established by Wille (1982), aims to describe concepts and concept hierarchies in mathematical terms. The starting point of the FCA is the specification of a “formal context” (also called *learning domain)*. The formal context *K* is defined as a triple (*G*, *M*, *I*) with *G* as a set of objects that belong to the learning domain, *M* as a set of attributes that describe the learning domain, and *I* as a binary relation between *G* and *M*. The relation *I* connects objects and attributes, i.e., (*g*, *m*) $\in$ *I* means the object *g* has the attribute *m*. A formal concept is a pair (*A*, *B*), with *A* as a subset of objects and *B* as a subset of attributes. *A* is termed the *extension* of the formal concept. It is the set of objects that belong to the formal concept. *B* is termed the *intension* and is the set of attributes that apply to all objects of the extension. The ordered set of all formal concepts is termed the concept lattice $\mathfrak{B}(K)$ (Wille, 2005). Every node of the Concept Lattice represents a single formal concept.

# 2. Conceptual Research Activities

The overarching goal of WP3 is to research and develop learning analytics on the basis of the theoretical foundations of Competence-based Knowledge Space Theory (CbKST) and Formal Concept Analysis (FCA). This work focuses on the collection, accumulation, analysis, and interpretation of educationally relevant data in terms of conceptual research and analysis, as well as technical implementation of learning analytics services on the basis of psycho-pedagogically meaningful knowledge and competence representations for domain and student modelling.

## Identification and Elaboration of Existing Methods and Algorithms and Potential Integration in LEA's Box

In a first step, the work focused on a comprehensive review of existing approaches in learning analytics and educational data mining, in order to establish an understanding of their benefits, but also drawbacks and current challenges in this field of research and development.

LA and EDM methods use different ideas and rationales for extracting meaningful information from learning related data, with the aim of understanding and optimising learning, learning environments, and instruction. The key dimensions involved in learning analytics and the individual stages of the learning analytics process have been analysed, to give an overview of the aspects and steps involved in analytics, including the stakeholders addressed (teachers, learners, educational institutions/administrators, researchers), the key objectives and applications from the perspectives of different target groups (e.g. feedback on learning progress, support educational decision making), and the types and sources of learning data (e.g. centralised vs. distributed data, indicators used). These, in turn influence the analytics methods employed in a concrete LA application depend on the target stakeholder group(s) and their objectives and the kind of data collected. Methods currently used to extract meaningful patterns from educational data have been identified; common approaches are prediction methods, structure discovery, relationship mining, discovery with models, distillation of data for human judgement, or multimodal approaches. An increasing number of tools exist that implement these methods and provide support in pre-processing, analysing, and visualising data. A systematic survey of analytics tools has been carried out for an overview on technologies available and used to support the learning analytics process. These may be tools providing comprehensive features for analytics and data mining purposes, in general, but may also be tools specifically targeting analytics in an educational context, and even a very specific learning analytics application and/or stakeholders. We have come up with ten categories to meaningfully group the functionality and application area of existing tools: tools for extraction, transformation, loading; web analytics tools; business intelligence tools; information visualisation tools; social network analysis tools; text analysis tools; general purpose analytics tools; data mining tools; special purpose learning analytics tools; and analytics in e-learning systems. Representative example tools have been identified for each category.

Although much progress has been achieved in learning analytics research in the last years, there are still a number of challenges to be addressed. The still existing research and practice gap is probably most important to mention, since it is related to a set of more specific challenges, including data integration from different sources and the implementation of meaningful and intuitive tools for teachers and learners. Beside, further empirical evidence on the positive impact and added value of analytics for learning and teaching is needed, to foster acceptance and uptake of learning analytics technologies in educational practice. In line with this, among the most recent trends on learning analytics, in particular efforts towards establishing more holistic portfolios of student performance and towards making achievement data more actionable have been identified, which also matches LEA's BOX objectives of researching and meaningfully advancing learning analytics based on psycho-pedagogically theoretical foundations.

The main outcome of this task were reported in D3.1 documenting the conducted review of the state of the art in learning analytics. This review has formed a solid starting point for the elaboration of the learning analytics approach of LEA's BOX, feeding into and inspiring the tasks engaged with the design and development of the general services and central executive (T3.2) and the conceptual research and technical implementation of competence-based learning analytics (T3.3), the results of which are integrated in the LEA's BOX platform (WP2).

# Design and Development of Formal Competence-Based LA/EDM Services

The work carried out in the context of T3.3 has been concentrated on researching, elaborating, and using CbKST and FCA as theoretical foundations for conducting psycho-pedagogically meaningful learning analytics. The actual work has been split into (i) a conceptual research part and (ii) a concrete development part.

The conceptual research part has started elaborating the psychological and mathematical foundations of CbKST and FCA for domain structuring and assessing learning performance and progress towards their application for learning analytics purposes. Approaches of analysing and interpreting learning data have been investigated and applied on simulated and available data sets from conventional tests and activity data from technology-enhanced learning.

CbKST can only be successfully applied for adaptive assessment, personalisation of learning, and visualisation of educationally relevant data if the structure of the knowledge domain is sufficiently known, i.e. the underlying knowledge and competence structures provide an appropriate representation of the domain in question. The use of data analysis algorithms, i.e. different variants of (inductive) item tree analysis, for establishing a structure on items of a knowledge domain in the tradition of CbKST and for the purpose of LEA's BOX has been investigated. Available methods for examining the quality of knowledge structure or for comparing different competing structures have been identified and applied to the established domain models, aiming at determining the most suitable and best-fitting knowledge representation for a given educational context/setting. These efforts shall serve as an approach for evidence-based establishing and validating existing teacher domain models and curricula, thus supporting refinement and optimisation of knowledge domain representations and teaching plans.

Approaches of using Hasse diagrams, i.e. directed graphs traditionally used in CbKST, for visualising learning data, assessment and analysis results have been examined. Hasse diagrams have furthermore been examined as a tool for uncovering and visualising learning progress and actual learning paths taken in a competence-oriented approach of structuring knowledge and learning domains. These efforts aim of establishing new ways of reporting and communicating of teaching and learning achievements as a basis for supporting teachers' and learners' reflection, monitoring, and decision making. Work has been initiated on approaches of adjusting and advancing these visualisations to be intuitively understood and providing an appropriate level of information.

Rusch and Wille (1996) proposed that knowledge spaces can be derived from knowledge contexts by applying the formal concept analysis (FCA). Their knowledge contexts consisted of a "learners X *not solved* items" matrix. This method would be an alternative data-driven approach to the (inductive) item tree analysis for establishing a structure on items. In order to provide intuitively understandable visualizations of concept lattices to teachers or even to the learners themselves, several configurations of the knowledge context have been compared to each other: for example, “learners X *solved* items”-, “items X *solved by* learners”-, and “items X *not solved by* learners”-matrices as well as the configuration initially suggested by Rusch and Wille (1996). The resulting concept lattice of the most promising configuration, “items X *solved by* learners”, is shown in Figure : This concept lattice encompasses items {a, b, c, d, e, f} as *objects* and learners {02 L, 03 L, 05 L, 08 L, 11 L, 13 L, 17 L, 20 L, 21 L, 22 L, 23 L} as *attributes*. The underlying knowledge context is based on the empirical data reported by Korossy (1999). The nodes of the concept lattice represent learners and the common set of items they were able to solve (i.e. the formal concept´s extension). The extension, i.e. the set of items solved by (a) particular learner(s) can be “read” by collecting all items which can be reached by descending paths. For example, the learner 11 L successfully solved items {a, b, c, e}, the learners 08 L and 22 L only solved items {a, c} and the learners 03 L and 17 L solved all items of the knowledge domain.

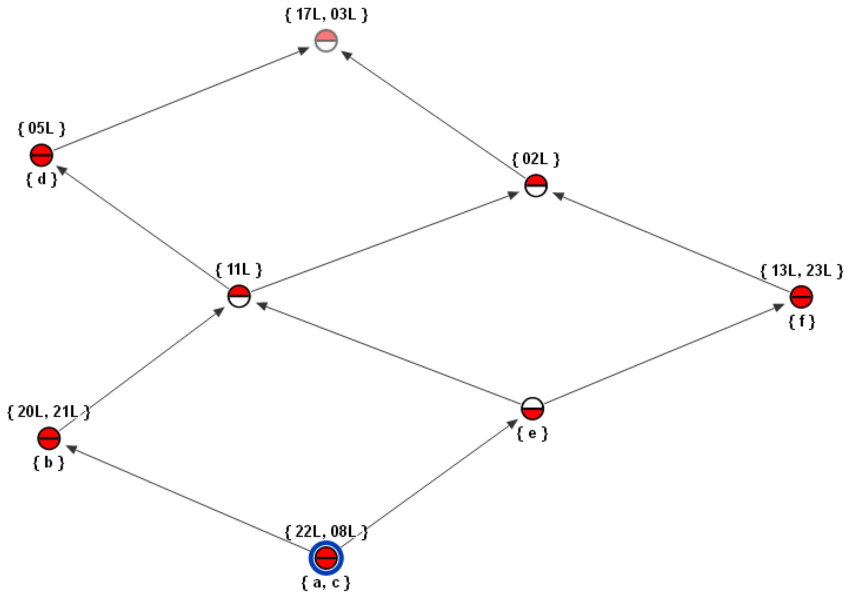


*Figure 3: A concept lattice as a visual representation of learners and the items {a, b, c, d, e, f} solved by them.*

By collecting the items which can be reached by ascending paths, the set of items which haven´t been solved by the learners can be inferred. In such a concept lattice the “better” students are located above weaker ones (which seems to be more intuitive). In addition to that, surmise relations between items can be directly inferred from the concept lattice: “harder” items are above the easier ones (i.e. above their prerequisites). An according Hasse diagram is shown in Figure  (left-hand side). For example, learners who have solved item {d} also solved the items {a, b, c, e}. The extensions of the formal concepts in Figure  lead to the knowledge space (see right-hand side of Figure ).

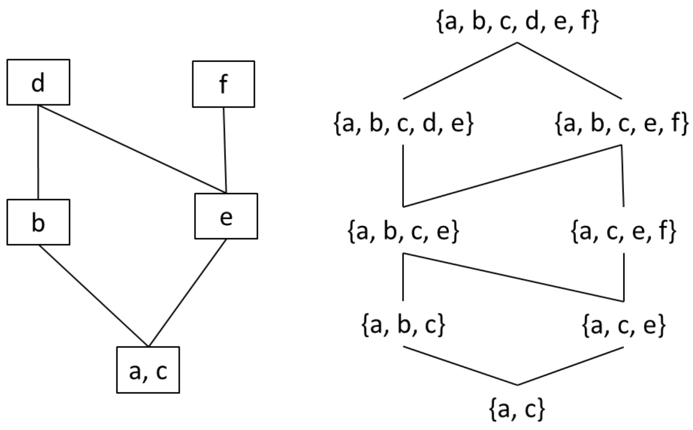


*Figure 4: The concept lattice enables to extract surmise relations between items (left-hand side) and the knowledge space (right-hand side).*

Besides all these advantages of applying the FCA, i.e. it enables to extract surmise relations between the items as well as the according knowledge space and it nicely visualizes learners and items (as well as their relations), unfortunately, the described FCA is vulnerable towards noisy data (i.e. *lucky guesses* and *careless errors*). Thus, at the moment it makes sense to use it for visualization purposes only. For an FCA-based data-driven extraction of surmise relations and knowledge spaces, further research is required to enrich the existing FCA with additional information (e.g. frequencies of solution patterns). Such an extended FCA approach should be stable enough to deal with noisy data. Different initial ideas are currently under investigation. However, in any case the already existing data-driven approach of the inductive item tree analysis as well as the more theory driven approach of expert-ratings on surmise relations between items can be applied for elaborating and validate knowledge spaces.

Establishing an extended FCA approach which is able to deal with lucky guesses and careless errors requires further investigations of the formal, i.e. mathematical, differences and similarities between the FCA, the KST and even competence-based extensions such as the CbKST. The underlying mathematical principles of all of these frameworks, such as set-, order-, and lattice theoretic properties are in fact very similar; however, researchers from the different research areas (FCA and KST) use different notations. Thus, work on identifying similarities and differences for unifying the approaches started with describing them in a unified notation.

# 3. TECHNICAL IMPLEMENTATION

As shown in the original architecture, the principle idea was to have the web platform (the box) that is equipped with an open interface to existing sources (i.e., tools, websites, apps, that are producing educationally relevant data). This data subsequently is processed within the platform and finally fed back to the user. The central component is a mechanism that controls the data flow and the deeper processing.

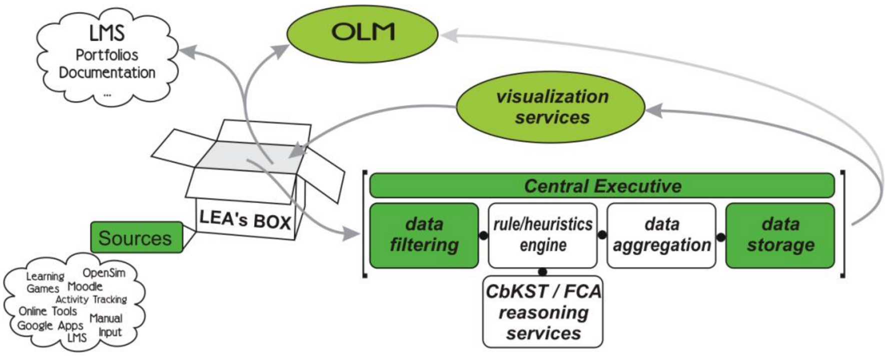


*Figure 5. Original system architecture; green areas indicate the achieved results in year 1.*

In year one, we released the components marked in green in the figure above. Further we extended this setup by additional components (marked in yellow in the following figure). First we integrated basic CbKST-based function to identify competence states on the basis of performance data. This gives the first system release a base functionality for analyses. Second, in addition to the main API of the system (LEA'S API), we integrated a Tincan based interface to enable a broader connectivity and interoperability. Third, we developed and released a major tool for competence and domain modelling, the so-called mind mapping tool. The tools is tailored to teacher's needs (based on the focus group and design studies of WP5).

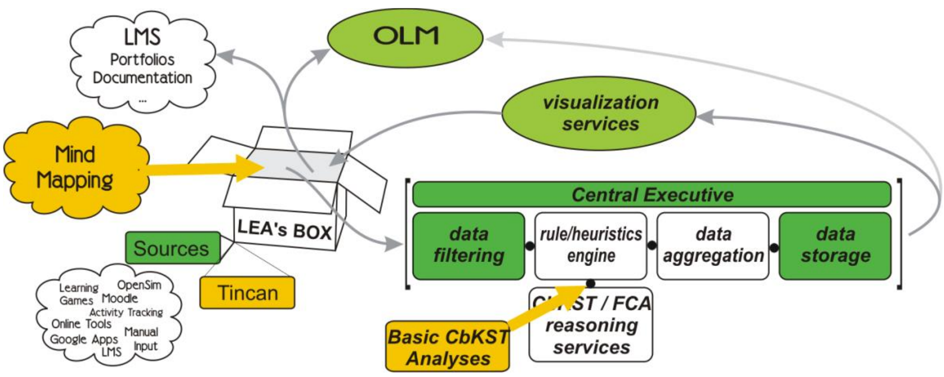


*Figure 6. Extended architecture; new elements are shown in yellow color.*

## 3.1. Data Storage

As reported in the system design document (D2.1), we devised a data structure that is able to cover a broad range of user needs. This was, again, a result of the focus group work. In conclusion, the data storage design was no trivial task since a variety of complex relationships arising from the user needs had to be considered. For example, the possibilities for grouping and subgrouping of students. Technically, the database is based on MySQL and hosted at TUGraz.

## 3.2. Central Executive and CbKST Function

In the centre of the platform is a control script based on php that is controlling the data flow (push/pull actions) and that is calling filtering services and the basic CbKST functions.
The basic CbKST analyses function receive performance data (e.g., the results of test items or activity data); on the basis of a so-called basis file, which holds the competence model in form of a binary matrix), as shown in the following figure. The left shows the prerequisite relation as graph, the middle in form of the binary matrix (the basis) and the left shows the competence space resulting from this basis. Based on the interpretation function (technically a set of rules), the incoming performance data are linked to competence states and the probability distribution of the states is updated. The result is the likelihood of the various states and the individual probabilities.

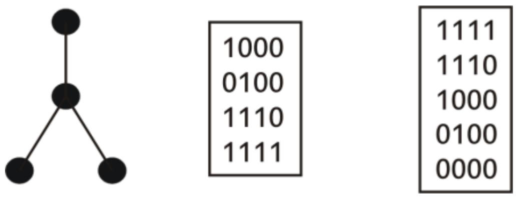


*Figure 7. Prerequisite relation – basis – space.*

## 3.3 Interfaces

A significant part of the work in year one was considering interoperability and connectivity. Therefore we are working on LEA's API which isn't to be released in year 1 in its final version. For this release, we installed a preliminary "run through" version which allows external tools to send performance data to the platform and the services.

id (INT; internal, not to be sent!)
source (INT, a unique identifier of the source)

student (TXT, any unique student token)

item (TXT, any unique identifier of a test item)

result (TXT, either the answer to the item or whether it's correct (1) or false (0), ideally use the latter)

timestamp (INT, the time)

For the seamless integration of platform, OLM, and visualizations, we defined and internal API (added as annex 1). In addition we established connectivity with the Tincan API. Tincan is a solid standard and successor of the well-know SCORM standard. A detailed overview is added as annex 2. The details about the data flow are given in the system design document (D2.1).

## 3.4 Domain Modelling – the mind mapping tool

A foundation of working with CbKST is to define domain models. These models can be evaluated, compared, used to identify misconceptions, or sued as plan for teaching. Inspired by existing applications for classroom management, such as ClassDojo (https://www.classdojo.com/), a mind mapping tool has been designed, whose aim is to implement some of the key ideas of Lea's Box in real classrooms. The mind mapping tool, its use in the classrooms and expected outcomes are described below.

The mind mapping tool (available as standalone version http://css-kmi.tugraz.at/mkrwww/leas-portal/lmm/client/ and integral part of the web platform) enables teachers to design their own mind maps or use existing ones and modify them. These maps can help teachers describe the competencies and skills connected to a particular field of interest. i.e. reading literacy, and the relationships between those skills. Furthermore, these mind maps also include descriptions of how a certain competency or skill can be demonstrated, so teachers can easily decide whether a particular student possesses the skill or not. There is also a full configuration tool where teachers can create virtual classrooms and add their students, so that later they can write down and monitor competencies of particular students and take appropriate action. The result of this approach is a visually structured description of the classroom sessions with the possibility of a follow-up assessment of students.

When using the mind mapping tool in real classrooms, teachers need to create a virtual classroom in the configuration tool, design a mind map related to a particular field of interest and write down details about the students' performance using the mind mapping tool. Doing this will enable teachers to better assess students' strengths and weaknesses related to a particular field, analyze the gaps in their knowledge and skills and choose appropriate activities to fill those gaps.

In the real classroom session, teachers can collect data based on students' performances. A big benefit of this approach is the possibility of gathering data in a structured framework.

Involving teachers in the process of making and using a mind map will help us define the learning paths, which are better suited to teachers' needs. The role of teachers is more active and it brings deeper understanding of the students' assessment. It will also enable us to explore particular fields and subjects in more depth and to better capture the relationships between different aspects and skills connected to these fields. In this context, teachers' point of view will offer us invaluable insight into certain areas of interest. In the next step of LEA´s box tools development, we will focus more on the students' point of view, their self-assessment and peer assessment. The mind-mapping tool will be used as a suitable tool for these purposes, for generating data and for gathering more data from their individual performances.

A more detailed psycho-pedagogical rational for concept map / mind map modelling approaches is attached in Annex 3.

A manual for the tool is attached as external document.

# 4. EXAMPLES

As proof of concept we established 2 examples for the data flow into the platform and the underlying analysis services. The first is based on a small learning app the 1x1 Ninja (developed in a prior project), an app for young children to practise multiplications. The tool can be accessed at http://css-kmi.tugraz.at/mkrwww/1x1ninja/. Although the app is in German language it is pretty self-explanatory and does not require any registration. Simply type any user name in to login field and enter the calculator-style app. The performance data of this app are passed to the Lea's Box platform, analysed, stored, and the results are visualized directly in through the platform, and the results are forwarded to the OLM system and contribute there to a student's general learner model (given that the student is registered in the OLM and the correct token is passed).

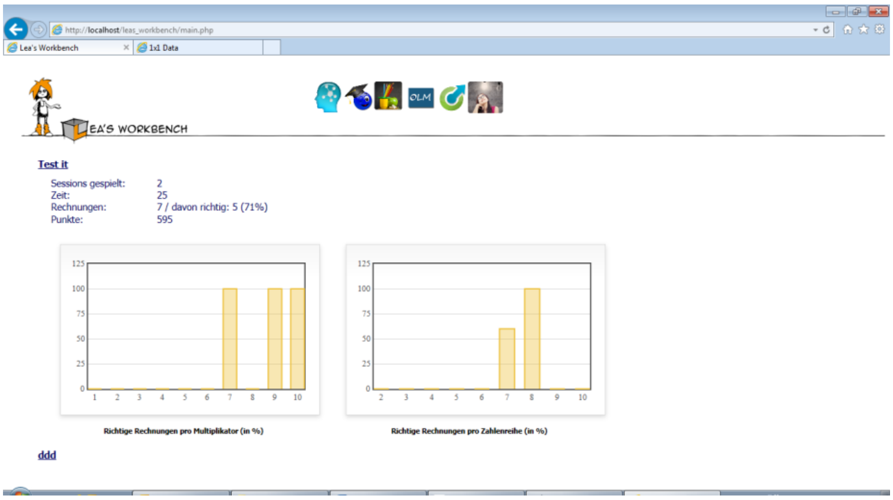


*Figure 8. 1x1 Ninja data displayed in Lea's Portal.*

The second example is realized with the myClass MTO tool. This is a standalone extension of myClass, design upon focus group and design studies and applied in German use cases (the tool is described in the context of D2.4). Briefly, the idea is to support planning, teaching, and controlling the development of competencies (in the use case meta-competencies such as planning skills or retentivity). In this case, the teacher is producing the performance information manually, using slider controls: The data are forwarded to Lea's platform and are analyzed there in terms of competence states.

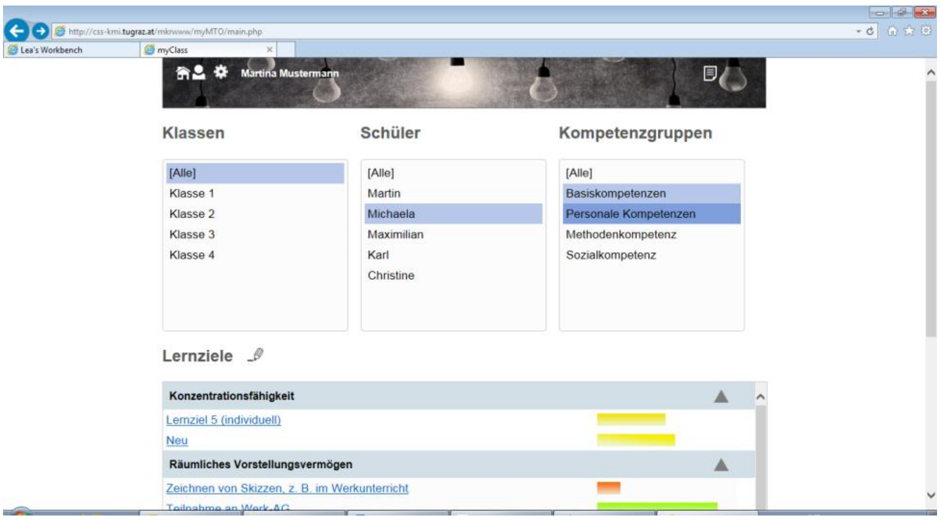


*Figure 9. Screenshot of myClass MTO.*

# 5. Hasse Diagram Visualization

Another part of the work in year one concerned the developed of web-based displays of learning paths and competence states on the basis of structured graphs, in particular Hasse diagrams.

A Hasse diagram is a mathematical representation of a so-called semi-order which helps for structuring learning domains and for visualizing the progress of a learner through this domain. The properties of a semi-order are: (i) reflexivity, (ii) anti symmetry, and (iii) transitivity. The representation of this diagram is illustrated in the image below (see Figure 10)

The direction of a graph reads from bottom to top. The arrows from one element to itself (reflexivity property) as well as all arrows indicating transitivity are not shown, but they are included (used) so far.
In an educational context, a Hasse diagram can display the non-linear path through a learning domain starting from an origin at the beginning of an educational episode (which may be a single school, lesson or the entire semester). The beginning is shown as a {0} (empty set) at the bottom of the diagram. Now a learner might focus on three topics (X, Y, Z). In essence this establishes three possible learning paths, until reaching the final state (X, Y, Z).

In the context of formative learning analytics, a competence-oriented approach is necessary. Thus, a Hasse diagram can be used to display the competencies of a learner in the form of so-called competence states. The knots of this Hasse diagram indicate meaningful competence states of a student while the edges indicate admissible transitions from one competence state to another by acquiring another competency. In addition, the approach is based on a probabilistic view of having or lacking certain competencies.

Very briefly, a Hasse diagram shows all possible (admissible) competence or knowledge states
The visualization in the form of Hasse diagrams, finally, allows identifying the learning paths, the history of learning, the present state, and – most importantly, to find proper recommendations for the next and the very next learning steps.

We see the current status as a first provision of the technical basis. In the future we will look into modifications and redesigns to make the, in fact, complicated graphs more suitable and understand for teachers because we are convinced that such general approach bears significant advantages to convey relevant information.

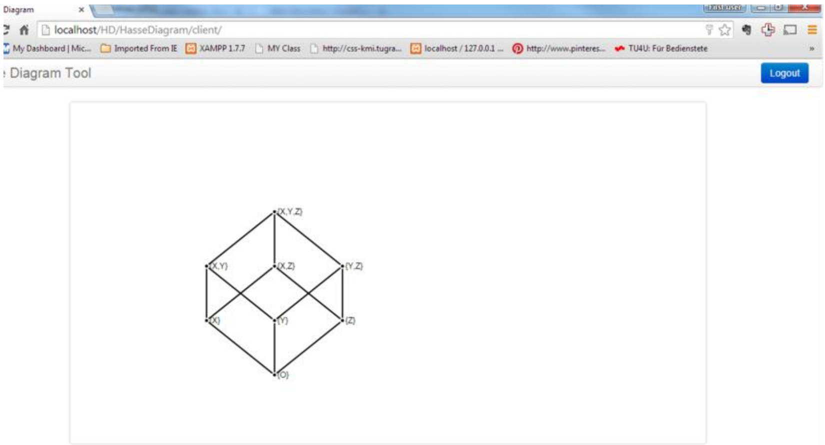


*Figure 10. First implementation of the Hasse visualization tool.*

# 6. OUTLOOK

In year 2, we will complete the CbKST/FCA services on the basis of year 1's research findings. In addition we will establish a "Learning Horizon" tool, that is working on the basis of a learning performance vector . The idea is to identify the current performance of a student to pass through a competence space in comparison to class mates and to estimate the possible target state for a student within a specific time frame (e.g., the remaining time in the semester). Also, we will integrate learning styles research and will use the mechanisms of FCA to identify and validate learning styles.

# 7. REFERENCES

Albert, D. & Held, T. (1999). Component based knowledge spaces in problem solving and inductive reasoning. In D. Albert & J. Lukas (Eds.), Knowledge spaces: Theories, empirical research, applications (pp. 15–40). Mahwah: Lawrence Erlbaum Associates.

Albert D. & Lukas J. (Eds.). (1999). Knowledge spaces: Theories, empirical research, applications. Mahwah: Lawrence Erlbaum Associates.

Albert, D., Hockemeyer, C., & Mori, T. (2006). Memory, knowledge, and e-learning. In L.G. Nilsson & N. Ohta (Eds.), Memory and society: Psychological perspectives (pp. 87-109). Hove: Psychology Press.

Augustin, T., Hockemeyer, C., Kickmeier-Rust, M., & Albert, D. (2011). Individualized skill assessment in digital learning games: Basic definitions and mathematical formalism. IEEE Transactions on Learning Technologies, 4, 138-148.

Cosyn, E. & Thiéry, N. (2000). A practical procedure to build a knowledge structure. Journal of Mathematical Psychology, 44, 383-407.

Doignon, J. (1994). Knowledge spaces and skill assignments. In G.H. Fischer & D. Laming (Eds.), Contributions to mathematical psychology, psychometrics and methodology (pp. 111–121). New York: Springer.

Doignon, J.P. & Falmagne, J.-C. (1999). Knowledge spaces. Berlin: Springer.

Dowling, C.E., & Hockemeyer, C. (2001). Automata for the assessment of knowledge. IEEE Transactions on Knowledge and Data Engineering, 13, 451–461.

Düntsch, I. & Gediga, G. (1995). Skills and knowledge structures. British Journal of Mathematical and Statistical Psychology, 48, 9–27.

Falmagne, J.-C. & J.-P. Doignon (2011). Learning Spaces. Heidelberg: Springer.

Falmagne, J.-C., Cosyn, E., Doignon, J.P., & Thiery, N. (2006). The assessment of knowledge, in theory and practice. In R. Missaou & J. Schmidt (Eds.), Formal Concept Analysis. 4th International Conference, ICFCA. Lecture Notes in Artificial Intelligence vol. 3874 (pp. 61-79). Berlin: Springer.

Falmagne, J.-C., Albert, D., Doble, C., Eppstein, D., & Hu, X. (eds.) (2013). Knowledge spaces. Applications in education. Berlin: Springer.

Falmagne, J.-C., Koppen, M., Villano, M., Doignon, J.P., & Johannesen, L. (1990). Introduction to knowledge spaces: How to build, test, and search them. Psychological Review, 97, 201-224.

Heller, J. & Repitsch, C. (2008). Distributed skill functions and the meshing of knowledge structures. Journal of Mathematical Psychology, 52, 147-157.

Heller, J., Steiner, C., Hockemeyer, C., & Albert, D. (2006). Competence-based knowledge structures for personalised learning. International Journal on E-Learning, 5, 75-88. [2]

Held, T., Schrepp, M., & Fries, S. (1995). Methoden zur Bestimmung von Wissensstrukturen – Eine Vergleichsstudie [Methods for determining knowledge structures – A comparative study]. Zeitschrift für Experimentelle Psychologie, 42, 205-236.

Hockemeyer, C., Conlan, O., Wade, V., & Albert, D. (2003). Applying competence prerequisite structures for eLearning and skill management. Journal of Universal Computer Science, 9, 1428-1436.

Kickmeier-Rust, M.D. & Albert, D. (2013). Using hasse diagrams for competence-oriented learning analytics. In: A. Holzinger & G. Pasi (eds.), HCI-KDD 2013. LNCS vol. 7947 (pp. 59-64). Berlin: Springer.

Kickmeier-Rust, M.D., Steiner, C.,M. & Albert, D. (2011). Apt to adapt: Micro- and macro-level adaptation in educational games. In T. Daradoumis, S. Caballé, A. Juan & F. Xhafa (Eds.), *Technology-Enhanced Systems and Tools for Collaborative Learning Scaffolding. Studies in Computational Intelligence* vol. 350 (pp. 221-238). Berlin: Springer.

Kickmeier-Rust, M.D., & Albert, D. (2010). Micro adaptivity: Protecting immersion in didactically adaptive digital educational games. *Journal of Computer Assisted Learning*, 26, 95-105.

Koppen, M. & Doignon, J.P. (1990). How to build a knowledge space by querying an expert. Journal of Mathematical Psychology, 34, 311-331.

Korossy, K. (1997). Extending the theory of knowledge spaces: a competence-performance approach. Zeitschrift für Psychologie, 205, 53-82.

Korossy, K. (1999). Modelling knowledge as competence and performance. In D. Albert and J. Lukas (Eds.), *Knowledge Spaces: Theories, Empirical Research, Applications* (pp. 103-132). Mahwah, NJ: Lawrence Erlbaum Associates.

Ley, T., Albert, D., & Lindstaedt, S.N. (2007). Competency management using the competence performance approach: Modeling, assessment, validation and use. In M.A. Sicilia (Ed.), Competencies in organizational e-learning: Concepts and tools (pp. 83-119). Hershey, PA: Idea Group Inc.

Marte, B., Steiner, C.M., Heller, J., & Albert, D. (2008). Activity- and taxonomy-based knowledge representation framework. International Journal of Knowledge and Learning, 4, 189-202. [3]

Newell A. & Simon H. (1972) Human problem solving. Englewood Cliffs, NJ: Prentice-Hall.

Nakamura, Y., Tsuji, H., Seta, K., Hashimoto, K., & Albert, D. (2011). Vilsualisation of learner's state and learning paths with knowledge structures. In: A. König et al. (eds.), KES 2011, Part IV. LNAI vol. 6884 (pp. 261-270). Berlin: Springer.

Rusch, A., & Wille, R. (1996). Knowledge spaces and formal concept analysis. In H. H. Bock and W. Polasek (Eds.), *Data analysis and information systems: Statistical and conceptual approaches* (pp. 427-436). Berlin: Springer.

Pemmaraju, S. & Skiena, S. (1990). Implementing discrete mathematics: Combinatorics and graph theory with mathematica. Reading, MA: Addison-Wesley.

Schrepp, M. (1999a). Extracting knowledge structures from observed data. British Journal of Mathematical and Statistical Psychology, 52, 213-224.

Stefanutti, L., Albert, D., & Hockemeyer, C. (2005). Structuring and merging distributed content. In P. Ritrovato, C. Allison, S. A. Cerri, T. Dimitrakos, M. Gaeta, & S. Salerno (Eds.), Towards the Learning Grid: Advances in Human Learning Services. Frontiers in Artificial Intelligence and Applications vol. 127 (pp. 113-118). IOS Press.

Steiner, C.M. & Albert, D. (2008). Personalising learning through prerequisite structures derived from concept maps. In H. Leung, F. Li, R. Lau, & Q. Li (eds.), Advances in web based learning – ICWL 2007. LNCS vol. 4823 (pp. 43-54). Berlin: Springer.

Steiner, C.M., Nussbaumer, A., & Albert, D. (2009). Supporting self-regulated personalised learning through competence-based knowledge space theory. Policy Futures in Education, 7, 645-661. [4]

Ünlü, A. & Sargin, A. (2010). DAKS: An R package for data analysis methods in knowledge space theory. Journal of Statistical Software, 37. Retrieved July 19, 2012 from www.jstatsoft.org/v37/i02/paper

Wille, R. (1982). Restructuring lattice theory: An approach based on hierarchies of concepts. In I. Rival (Ed.), *Ordered sets* (pp. 445–470). Dordrecht: Reidel.

Wille, R. (2005). Formal Concept Analysis as Mathematical Theory of Concepts and Concept Hierarchies, In B. Ganter , G. Stumme and R. Wille (Eds.), *Formal Concept Analysis* (pp. 1-34), Berlin: Springer.

# Annex 2: TinCan – a standard for multisource analytics

## 1.1 Process Mining and Structuring Data

Analytics is a decision support tool for interventions or for feedback. Assessment and evaluation generally reveals the knowledge state of a student, indicating if an intervention is needed. However, it would take more than just assessment results and evaluation metrics to decide which extra activity would best suit as an intervention. Multisource analytics harvest addition data sources such as course attendance, content use or even teacher's notes to support the decision for intervention. As for feedback, more than 500 meta-analyses of pedagogical research, representing approximately 20 to 30 million students undoubtedly prove that feedback is the most influential factor on learning and that feedback on how more effectively learning tasks can be done is more powerful than feedback on learning outcomes[1].

Feedback should be to the process rather than the outcomes of learning. To analyze a process, multisource data must be shaped into particular schemas that could represent cases of the process end-to-end. There may even be a set of schemas if subprocesses are needed to be identified. This prior stage of analytics is a challenge in that data from a variety of sources must be related and linked to the schemas to form each sample case.

## 1.2 From SCORM to Tin-Can

SCORM standard was developed as an ADL initiative with a final edition released in 2009. It defines a way to package learning objects to be ordered and presented by an LMS so that interoperability can be established between content and LMSs. However, not much of learning can be verified by SCORM – it only records browser sessions tracked on the LMS. The Tin Can API is also a standard developed by ADL which was finalized in April 2013. Tin Can sits next to SCORM, expected to replace SCORM eventually. Tin Can API is also known as the Experience API (xAPI), because it is a web service that allows software clients to read and write experiential data in the form of "statement" objects. The activity statements are written in a Learning Record Store (LRS), which can be accessed and analyzed by reporting or analytics software.

Any digital learning tool can create an activity stream to post in an Learning Record Store. While SCORM can only register start and end activities such as "John completed Course 1 with a score of 50%," using the xAPI, a learning tool can register any activity during the process of learning. The activities are reported in statements of the form "***Somebody Did Something*** with ***Outcome*** in ***Context***." Each argument in the activity statement is an XML object, as well as the statement itself. For example, the ***Context*** object has properties such as **platform**, **language** or **instructor** which can optionally be filled to describe the activity context better**.** While the Actor-Verb-Object structure is critical for a bare minimum of understanding, it is the context of the statement that may bring extra dimensionality to the analytics. Another opportunity for building a clearer picture of the learning

[1] J. Hattie and H. Timperley, "The Power of Feedback," Review of Educational Research, March 2007

experience as a whole is using the Activity Type property which categorize the Activity into a pre-defined type such as a course, a quiz or a game. Completing a course, completing a book or participating a discussion are different types of experience which the Activity Type can indicate, optionally in conjunction with the verb. The x API allows for several new capabilities that SCORM didn't, such as taking e-learning outside of the web browser, tracking learning plans and goals, ability to track real-world performance, games and simulations, as well as platform transition; e.g. start e-learning on a mobile device, finish it on a computer

## 1.3 The LMS – LRS Cooperation

xAPI calls need not go through an LMS, because LRS is a separate system which the xAPI uses directly. An LRS mechanism called "Statement forwarding" could be used to notify an LMS of incoming statements so that it can check out the present course and unlock the next course. Alternatively, a more loose coupling can be done by deploying software that uses the LRS like a memory storage and inform LMS(s) about course start or completion.

The learning tool needs not even be online all the time. The xAPI can be called asynchronously, because every statement object is saved with a timestamp and a unique ID. There may also be implementations where GPS, gyroscope or any kind of sensor information can as well be saved with the event. Whenever there is connection, all the recent events would be uploaded to the LRS.

It is only with such resolution of learning events, analytics tools can use schemas that are complex enough to represent the process of learning and support feedback.

Learning Management Systems are expected to adhere to the SCORM standard for many years ahead, and elearning courses will be published using SCORM to be uploaded to an LMS. However, it is also expected that the same courses as well as various learning tools (like gradebooks, digital performance tasks, complex assessment or collaborative learning platforms) will also use the Tin Can API to record events of learning in the form of activity statements and populate an LRS where the user is registered. Currently there are nearly 100 adopters.

## 1.4 Formative Feedback using an LRS

Reviews of the corpus of research on feedback, with a particular focus on formative feedback reveal that it has to be multidimensional, nonevaluative, supportive, timely, specific, credible, infrequent, and genuine[2]. It can be administered at various times during the learning process. There are a number of variables that have been shown to interact with formative feedback's success at promoting learning (e.g., individual characteristics of the learner and aspects of the task). Using learning analytics tools, formative feedback can even be on demand and support self-regulated learning. Such real-time analytics is possible with Tin Can compatibility ensuring interoperability throughout the data chain for all the activity (data) providers.

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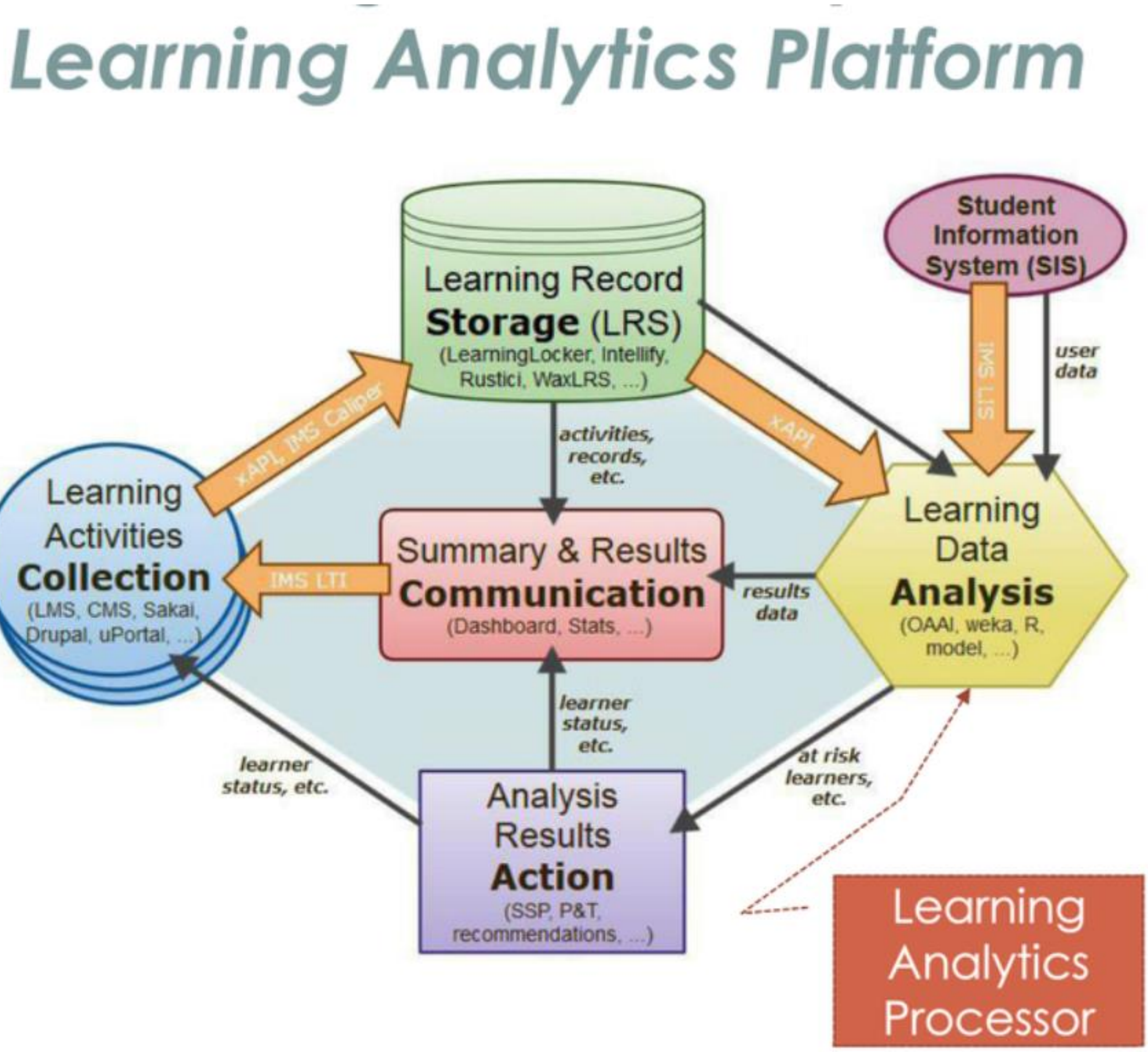
[2] V. J. Shute, "Focus on Formative Feedback," ETS Research Report, March 2007


Learning Analytics Platform
Learning Record
Storage (LRS)
(LearningLocker, Intellify, Rustici, WaxLRS, ...)
Student Information System (SIS)
IMS LIS
user data
xAPI, IMS Caliper
xAPI
activities, records, etc.
Learning Activities
Collection
(LMS, CMS, Sakai, Drupal, uPortal, ...)
IMS LTI
Summary & Results
Communication
(Dashboard, Stats, ...)
results data
Learning Data
Analysis
(OAAI, weka, R, model, ...)
learner status, etc.
learner status, etc.
at risk learners, etc.
Analysis Results
Action
(SSP, P&T, recommendations, ...)
Learning Analytics Processor

# Annex 3: Mapping Techniques in Education

## Introduction to Concept Mapping and Mind Mapping

Mind maps and concept maps constitute graphical node-link representations that specify the concepts of a knowledge domain and their interrelations (e.g. Coffey et al., 2003; Novak, 1998, 2001). Because of their multipurpose applicability, mapping strategies have become popular in the last decades, and this trend is still increasing. This goes in line with the growing amount of software tools and computer support available for mind and concept mapping for various purposes. Mapping techniques can be effectively applied to support instructional and learning processes in traditional and technology-enhanced education (e.g. Mandl & Fischer, 2000). Mind maps and concept maps provide useful and facilitative instruments in many stages of planning, developing and carrying out teaching and learning.

The origins of concept maps can be traced back to the network theories of human memory, which have a long tradition in cognitive psychology (e.g. Collins & Quillian, 1969; Rumelhart, Lindsay, & Norman, 1972). These theories arose in the 1960's and 70's and are grounded in the notion that long-term memory can be seen as an internal semantic network structure. All these models on the mental representation of knowledge assume internal cognitive networks, postulating that there is a correspondence between the graphical network representation and memory. This nurtures the idea of representing an individual's personal knowledge by a network representation like a concept or mind map. Because of the claimed structural similarity between graphical network representations and the mental representation of long-term memory, it is assumed that the use of such network structures for presenting and communicating information is beneficial (Mandl & Fischer, 2000). In sum, the fact that concept maps and mind maps are assumed to be able to reflect semantic structures of human memory accounts for their widespread and effective use.

Mapping techniques provide instruments for structuring and representing knowledge, depicting the concepts of a content area and the relationships that exist between them (e.g. Novak, 2001). Therefore, they provide a natural way of creating and representing domain ontologies (Dicheva & Aroyo, 2002). A concept map is a directed graph (digraph) consisting of a finite, non-empty set C = {c1, ..., cn} of concepts (nodes) and a finite, non-empty set A of arcs, representing the relations between concepts (Albert & Steiner, 2005b). In traditional concept maps, the links between concepts are labeled and describe the relationship existing between the concepts. Links are directed, which is commonly depicted by using arrowheads. Two or more connected concepts constitute a meaningful unit of knowledge and are considered as a proposition (e.g. Anderson, 1974; Novak & Cañas, 2008). Concept map are usually represented in a more or less hierarchical fashion, depicting the most general concepts on top of the map and the more specific ones below (Novak, 2001). However, so-called 'cross-links' are possible and explicitly allowed and considered as a characteristic of concept maps. Cross-links are relationships between concepts in different regions or domains within a concept map. Therefore, the structure of a concept map is not strictly hierarchical, but rather semi-hierarchical (Coffey et al., 2003). Figure  presents an example of a concept map.

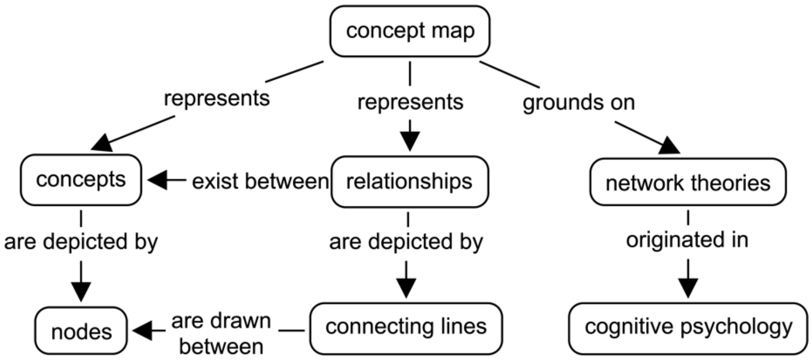



*Figure 1: Concept map describing what a concept map is.*

Mind maps (Buzan & Buzan, 1996) constitute a special case of concept maps. They are actually concept maps with only one kind of relationship, i.e. an unspecified relation, which can be understood as 'is connected to' or 'is associated with'. A mind map starts from a central word or concept; further concepts or ideas radiate out from this central point, similar to the association between thoughts. Mind maps can therefore also be called 'association networks'. The links between concepts are directed (i.e. from more central concepts to more peripheral ones) but unlabeled (Coffey et al., 2003). Mind maps traditionally feature a strict tree structure without any cross-links. Figure  presents an example mind map.

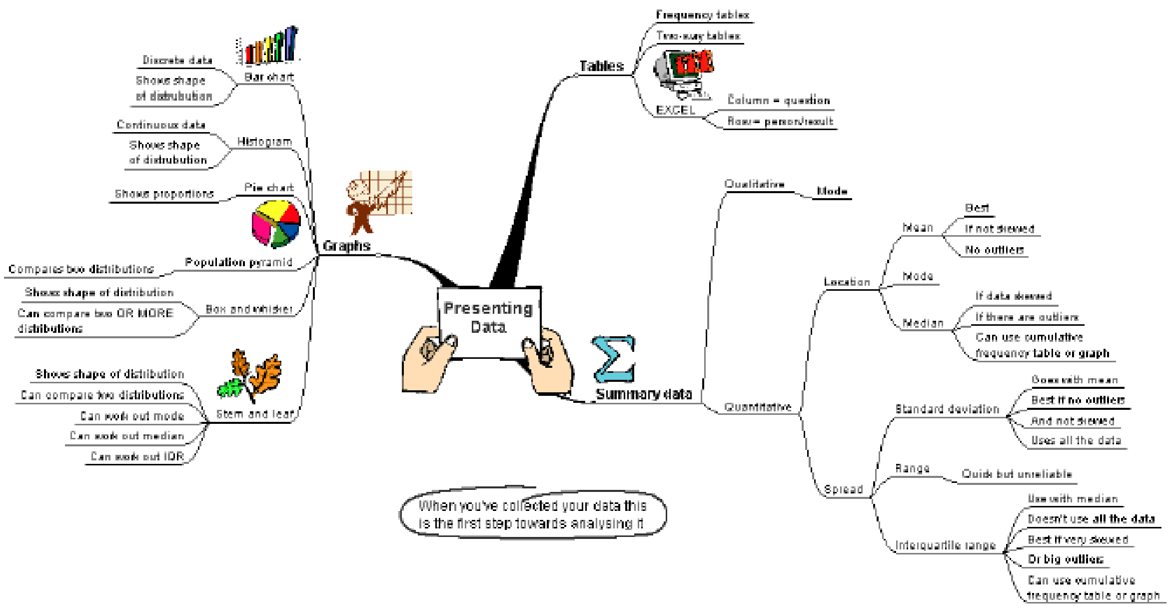



*Figure 2: Example mind map (adopted from Coffey et al., 2003, p. 90).*

Mapping techniques provide flexible approaches for knowledge structuring and representation and are usable by experts as well as by novices in a field. They serve versatile applications like learning, teaching, creativity tasks, knowledge assessment, instructional design etc. and primarily aim at capturing, depicting, and communicating information in a well-arranged, comprehensible, and (typically) visual way (for an overview of the use of concept mapping in education see Steiner, Albert and Heller (2007)).

## Using Mapping Techniques for Educational Planning

Curriculum development and instructional planning is of great importance at all levels of education. It involves the definition of learning goals, scope and sequence of instructional content, learners' interaction with content, and methods for the assessment of learning outcomes. Instruments applied in this context should effectively support knowledge elicitation and organization from a range of sources such as textbooks, reports, experts, lecture summaries etc. Curriculum planning instruments also need to support analyzing the relationships between curricular elements (Allen, Hoffmann, Kompella, & Sticht, 1993). Mapping techniques facilitate the representation of educational domains and can be applied for planning a curriculum or instruction on a particular topic (Coffey et al., 2003; Novak, 1998, 2001). In general, it may aid in developing and organizing a whole course, but also in preparing specific lessons (Zimmaro & Cawley, 1998).

With concept mapping, the structure of a knowledge domain is made explicit, by using the map as a tool for content and curriculum analysis. Concept maps generated in this context may contain both, content-based relations and instructional relations. Content-based relations describe semantic relationships among the concepts to be taught. Instructional relations are relations that provide information on the instructional sequence with respect to these concepts, by uncovering prerequisite relations among them. When utilizing concept maps in the initial instructional planning process, curriculum developer and educators gain a comprehensive understanding of what students need to learn (McDaniel, Roth, Miller, 2005). This may lead to identifying areas or subtopics as being trivial, so that they possibly can be dropped from a course, or as being worth to be emphasized during instruction. Concepts can be determined, that are fundamental for more than one topics or knowledge domains. Concept maps help educators to increase their potential of seeing multiple ways of constructing meaning. They help to explain why a particular concept is worth to know and how it is related to other concepts within and beyond the topic (Allen et al., 1993). Concept mapping used as a planning device for instruction may provide suggestions for an appropriate sequencing of the instructional material (Clark & James, 2004; Novak, 2001). The educator is supported in introducing and teaching concepts in an order that allows learners to better incorporate and integrate them with their existing knowledge. This is in line with the ideas of Ausubel's assimilation learning theory, which is often mentioned as the main theoretical basis for concept mapping applications (Novak & Cañas, 2008). Following the basic idea of cognitive network theories, assimilation theory assumes that memory and knowledge can be understood as a network of interrelated concepts and propositions – and emphasises the importance of existing knowledge for acquiring new knowledge elements. Meaningful learning consists in the assimilation and integration of new knowledge into an individual's existing cognitive structure (Ausubel, 1968).

Concept mapping can therefore help to design units of study that are relevant, meaningful, pedagogically sound, and interesting to learners (Martin, 1994). As a result, the use of mapping techniques for educational planning can help to improve curricular quality and clarity of teaching.

Different instructional planning strategies applying mapping techniques have been suggested. Allen et al. (1993) defined a six-step model for developing a so-called 'integrated curriculum knowledge map', starting from the collection of relevant concepts and/or skills of the knowledge domain, to establishing hierarchical and heterarchical links among them, creating course development nodes, assigning learning resources and/or activities, to finally selecting and sequencing course development nodes. Anderson-Inman and Ditson (1999) describe a curriculum-planning strategy that is comprised of three major steps: identifying the major concepts of a course and representing it in a concept map, with individual concepts representing individual lessons or units; extending the major concepts by adding key propositions and important examples, and finally expanding each major concept into a more detailed concept map. Such more detailed concept maps are useful for recording planned activities within a lesson. In this way, concept mapping serves for working out the subject matter content and how it will be translated into lessons. Clark and James (2004) suggested applying concept mapping for planning and organizing a course by creating a set of concept maps based on lecture summaries. From these maps an appropriate sequence for teaching the different course topics can be gained, ensuring that new concepts can be linked to already existing knowledge or concepts that have already been presented (again, in line with Ausubel's assimilation theory). Proceeding in this way, the resulting course is assumed to allow learners to better retain the knowledge acquired, to exit the course adequately competent, and with a solid foundation for further learning.

Williams (2014, May 21) reports on the use of mind mapping in the instructional planning process as brainstorming method to identify topics to be covered. The mind map resulting from such process captures the key topics to be covered, e.g. structured according to different grade levels, and significant concepts to drive the instructional and inquiry process and unit questions. Besides, mind maps may be used to define and structure learning goals, e.g. competences and competence levels to be achieved (e.g. Aguado, Fernández, Garreta-Domingo, Griset & Valls, 2014). The hierarchical structure of a mind map seems to be well suited to mirror educational standards and competence models in education (e.g. BIFIE, 2012). Starting from a representation of the key competences and competence levels, for example, mind mapping appears a suitable instrument for teachers to these learning goals down into more fine-grained skills and learning objectives to be addressed their instruction, or to associate them with relevant educational resources.

Mapping techniques may be used as a technique for instructional planning and organizing not only in the context of traditional classroom instruction, but also in the context of designing e-learning courses or environments (Stoyanov, 1997), including the definition of characteristics of adaptive e-learning or cognitive systems (Stoyanov & Kirschner, 2004; McNeese & Ayoub, 2011). Creating concept maps can support the phases of problem definition, idea generation, and selection within the design process in the planning process of an e-learning environment.

## Other educational applications of mapping techniques

Concept maps that have been developed in the scope of educational planning offer a potential basis for communication with students (Anderson-Inman & Ditson, 1999). Maps depicting instructional content may help making instruction more conceptually transparent to learners. To this end, Novak (2001) suggested creating a global concept map, showing the basic concepts or ideas that are to be taught in a course, and a range of more detailed concept maps representing specific parts or topics of the instruction. This leads to a further application area of concept maps in education, which is their use as a teaching strategy.

Concept maps representing a knowledge domain can be used as teaching and communication instruments to present information and learning content, providing a visual overview and allowing a multitude of paths for working through or reading the presented information (e.g. Gurley, 2011; Novak, 1998). Especially in a computer-based learning environment concept maps serve as valuable tools for representing learning content and may be used as navigation interfaces (e.g. McDonald & Stevenson, 1999; Puntambekar, Stylianou, & Hübsher, 2003).

Concept mapping as a learning strategy involves the autonomous creation of map representations by students during learning, problem solving, or brainstorming, to foster active and meaningful learning and metacognition, and to enhance understanding and interconnection of knowledge elements (e.g. Daley & Torre, 2010; Nesbit & Adesope, 2006). When using mapping techniques in the context of a learning activity, individuals may be asked to create their own maps from scratch or, alternatively, to expand an 'expert skeleton map' that serves as an initial guide (Novak & Cañas, 2008). In collaborative learning, mapping techniques provide a means for visualising a common problem space and for assisting the establishment of a common understanding and the collection of ideas or solution approaches (e.g. De Simone, Schmid, & McEwen, 2001; Torres & Mariott, 2010).

Maps created by learners not only assist knowledge acquisition and interconnected understanding, but may also be exploited for the purpose of knowledge assessment (e.g. Daley & Torre, 2010; Ruiz-Primo, 2000). Concept maps allow evaluating and monitoring a person's knowledge of a domain and gaining a comprehensive picture about his/her understanding and misconceptions (e.g. Ruiz-Primo & Shavelson, 1996).

# REFERENCES


Aguado, G., Fernández, C., Garreta-Domingo, M., Griset, R., & Valls, A. (2014). Course Sprints: Combining teacher training, design thinking and hackathons. In: P. Zaphiris & A. Ioannou (eds.), LCT 2014. Part I. LNCS vol. 8523 (pp. 3-12). Springer International Publishing.

Albert, D. & Steiner, C.M. (2005). Representing domain knowledge by concept maps: How to validate them? In T. Okamoto, D. Albert, T. Honda, & F.W. Hesse (Eds.), The 2nd Joint Workshop of Cognition and Learning through Media-Communication for Advanced e-Learning (pp. 169-174). Tokyo: Sophia University.

Allen, B.S., Hoffman, R.P., Kompella, J., & Sticht, T.G. (1993). Computer-based mapping for curriculum development. In M.R. Simonson (Ed.), Proceedings of selected research and development presentations at the Annual Convention of the Association for Educational Communications and Technology. New Orleans, LA: Research and Theory Division.

Anderson, J.R. (1974). Retrieval of propositional information from long-term memory. Cognitive Psychology, 6, 451-474.

Anderson-Inman, L. & Ditson, L. (1999). Computer-based concept mapping. A tool for negotiating meaning. Learning & Leading with Technology, 26(8), 6-13.

Ausubel, D.P. (1968). Educational psychology: A cognitive view. New York: Holt, Rinehart and Winston.

BIFIE (Ed.) (2012). Bildungsstandards in Österreich. Überprüfung und Rückmeldung (3rd ed.) [Educational standards in Austria. Evaluation and reporting]. Salzburg: Bundesinstitut Bildungsforschung, Innovation & Entwicklung des österreichischen Schulwesens. Zentrum für Bildunsmonitoring und Bildungsstandards. Retrieved July 20, 2012 from https://www.bifie.at/system/files/dl/bist_ueberpruefung-und-rueckmeldung_201205_0.pdf

Buzan, T. & Buzan, B. (1996). The Mind Map book: How to use radiant thinking to maximize your brain's untapped potential. New York: Plume.

Clark, I.F. & James, P.R. (2004). Using concept maps to plan an introductory structural geology course. Journal of Geoscience Education, 52, 224-230.

Coffey, J.W., Carnot, M.J., Feltovich, P.J., Feltovich, J., Hoffman, R.R., Cañas, A.J., & Novak, J.D. (2003). A summary of literature pertaining to the use of concept mapping techniques and technologies for education and performance support. Retrieved June 6, 2005, from http://www.ihmc.us/ users/acanas/Publications/ ConceptMapLitReview/ IHMC%20Literature%20Review%20on%20Concept%20Mapping.pdf

Collins, A., & Quillian, M. (1969). Retrieval time from semantic memory. Journal of Verbal Learning and Verbal Behavior, 8, 240-248.

Daley, B.J. & Torre, D.M. (2010). Concept maps in medical education: an analytical literature review. Medical Education, 44, 440-448.

De Simone, C., Schmid, R.F., & McEwen, L.A. (2001). Supporting the learning process with collaborative concept mapping using computer-based communication tools and processes. Educational Research and Evaluation, 7, 263-283.

Dicheva, D. & Aroyo, L. (2002). Concept-based courseware authoring: An engineering perspective. In Proceedings of the International Conference on Advanced Learning Technologies (ICALT) (pp. 46-49). IEEE Computer Society.

Gurley, L. (2011). Concept mapping. Learning how to make them, use them, and teach them to others. Galatte Press.

Mandl, H. & Fischer, F. (2000). Mapping-Techniken und Begriffsnetze in Lern- und Kooperationsprozessen [Mapping techniques and concept maps in learning and cooperating processes]. In H. Mandl & F. Fischer (Eds.), Wissen sichtbar machen. Wissensmanagement mit Mapping-Techniken [Making Knowledge Visible. Knowledge Management with Mapping Techniques] (pp. 3-12). Göttingen: Hogrefe.

Martin, D. J. (1994). Concept mapping as an aid to lesson planning: A longitudinal study. Journal of Elementary Science Education, 6(2), 11-30.

McDaniel, E., Roth, B., & Miller, M. (2005). Concept mapping as a tool for curriculum design. Issues in Informing Science & Information Technology, 2, 505-514.

McNeese, M.D. & Ayoub, P.J. (2011). Concept mapping in the analysis and design of cognitive systems: A historical review. In B.M. Moon, R.R. Hoffman, J.D. Novak, & A.J. Cañas (Eds.), Applied concept mapping: Capturing, analyzing, and organizing knowledge (pp. 47-66). New York: CRC Press.

McDonald, S., & Stevenson, R. (1999). Spatial versus conceptual maps as learning tools in hypertext. Journal of Educational Multimedia and Hypermedia, 8, 43–64.

Nesbit, J.C. & Adesope, O.O. (2006). Learning with concept and knowledge maps: A meta-analysis. Review of Educational Research, 76, 413-448.

Novak, J.D. (1998). Learning, creating and using knowledge: Concept maps as facilitative tools in schools and corporations. Mahwah: Lawrence Erlbaum.

Novak, J.D. (2001). The theory underlying concept maps and how to construct them. Retrieved May 10, 2005, from http://cmap.coginst.uwf.edu/ info/printer.html

Novak, J.D. & Cañas, A.J. (2008). The theory underlying concept maps and how to construct and use them. Technical Report IHMC Cmap Tools 2006-01 Rev 01-2008. Florida: Institute for Human and Machine Cognition. Retrieved July 13, 2012 from http://cmap.ihmc.us/Publications/ResearchPapers/TheoryUnderlyingConceptMaps.pdf

Puntambekar, S., Stylianou, A., & Hübscher R. (2003). Improving navigation and learning in hypertext environments with navigable concept maps. Human-Computer Interaction, 18, 395-428.

Rumelhart, D.E., Lindsay, P.H. & Norman, D.A. (1972). A process-model for long-term-memory. In E. Tulving & W. Donaldson (Eds.). Organization of memory. New York: Academic Press.

Steiner, C.M., Albert, D., & Heller, J. (2007). Concept mapping as a means to build e-learning. In N.A. Buzzetto-More (Ed.), Advanced principles of effective e-learning (pp. 59-111). Santa Rosa: Informing Science Press.

Stoyanov, S. (1997). Cognitive mapping as a learning method in hypermedia design. Journal of Interactive Learning Research, 8, 309-323.

Stoyanov, S. & Kirschner, P. (2004). Expert concept mapping method for defining the characteristics of adaptive e-learning: ALFANET project case. Educational Technology Research and Development, 52, 41-56.

Torres, P.L. & Marriott, R.C.V. (Eds.) (2010). Handbook of research on collaborative learning using concept mapping. Hershey, PA: IGI Global.

Williams, M. (2014, May 21). Mind mapping for curriculum planning and beyond. [Web log post]. Retrieved from http://blog.thinkbuzan.com/imindmap/mind-mapping-for-curriculum-planning-and-beyond

Zimmaro, D.M. & Cawley, J.M. (1998). Concept map module. Retrieved February 6, 2006, from Pennsylvania State University, Schreyer Institute for Innovation in Learning Web site: http://www.ttuhsc. edu/SOM/success/DHPS/Concept%20Map%20Module.htm