Using Hasse Diagrams for Competence-Oriented Learning Analytics

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Abstract. Learning analytics refers to the process of collecting, analyzing, and visualizing (large scale) data about learners for the purpose of understanding and pro-actively optimizing teaching strategies. A related concept is formative assessment – the idea of drawing information about a learner from a broad range of sources and on a competence-centered basis in order to go beyond mere grading to a constructive and tailored support of individual learners. In this paper we present an approach to competence-centered learning analytics on the basis of so-called Competence-based Knowledge Space Theory and a way to visualize learning paths, competency states, and to identify the most effective next learning steps using Hasse diagrams.

Keywords: Learning analytics, data visualization, Hasse diagram, Competence-based Knowledge Space Theory.

1 Introduction

Learning Analytics is a best practice and change on bringing together issues from human intelligence and computational intelligence, hence it fits perfectly in the HCI-KDD approach [1, 2]. In principle, the idea is to find theoretical frameworks, models, procedures, and smart tools to record, aggregate, analyze, and visualize large scale educational data. The principal goal is to make educational assessment and appraisal more goal-oriented, pro-active, and beneficial for students. In short, learning analytics is supposed to enable formative assessment of all kinds of information about a learner, on a large basis . Usually, the benefits are seen in the potential to reduce attrition through early risk identification, improve learning performance and achievement levels, enable a more effective use of teaching time, and improve learning design/instructional design [3]. Methods used for learning analytics and so-called "educational data mining" are extremely broad, for example, social network analyses, activity tracking, error tracking, keeping of e-Portfolios, semantic analyses, or log file analyses.

On the basis of this kind and amount of data, smart tools and systems are being developed to provide teachers with effective, intuitive, and easy to understand

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aggregations of data and the related visualizations. There is a substantial amount of work going on this particular field; visualization techniques and dashboards are broadly available (cf. [4, 5, 6]), ranging from simple meter/gauge-based techniques (e.g., in form of traffic lights, smiley, or bar charts) to more sophisticated activity and network illustrations (e.g., radar charts or hyperbolic network trees).

A special challenge for visualizations, however, is to illustrate learning progress (including learning paths) and - beyond the retrospective view - to display the next meaningful learning steps/topics. In this paper we introduce the method of *Hasse diagrams* for structuring learning domains and for visualizing the progress of a learner through this domain.

2 Displaying Learning: Past, Present, and Future

A Hasse diagram is a strict mathematical representation of a so-called *semi-order*. The technique was invented in the 60s of the last century by *Helmut Hasse*; entities (the knots) are connected by relationships (indicated by edges), establishing a *directed graph*. The properties of a semi-order are (i) reflexivity, (ii) anti symmetry, and (iii) transitivity. In principle, the direction of a graph is given by arrows of the edges; per convention however, the representation is simplified by avoiding the arrow heads, whereby the direction reads from bottom to top. In addition, the arrows from one element to itself (reflexivity property) as well as all arrows indicating transitivity are not shown. The following image (Figure 1) illustrates such a diagram. Hasse diagrams enable a complete view to (often huge) structures. Insofar, they appear to be ideal for capturing the large competence spaces occurring in the context of assessment and recommendations of learning.

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 but could also be the entire Semester). The beginning is shown as *{ }* (the empty set) at the bottom of the diagram. Now a learner might focus on three topics (K, P, or H); this, in essence, establishes three possible learning paths. After P, as an example, this learner might attend to topics K, A, or H next, which opens further three branches of the learning path until reaching the final state, within which all topics have been attended to (PKHTAZ).

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.* A common theoretical approach to do so is *Competence-based Knowledge Space Theory* (CbKST). The approach originates from Jean-Paul Doignon and Jean-Claude Falmagne [7, 8] and is a well-elaborated set-theoretic framework for addressing the relations among problems (e.g., test items). It provides a basis for structuring a domain of knowledge and for representing the knowledge based on *prerequisite relations*. While the original *Knowledge Space Theory* focuses only on performance (the behavior; for example, solving a test item), CbKST introduces a separation of observable performance and latent, unobservable competencies, which determine the performance (cf. [9]). In addition, the approach is based on a probabilistic view of having or lacking certain competencies.

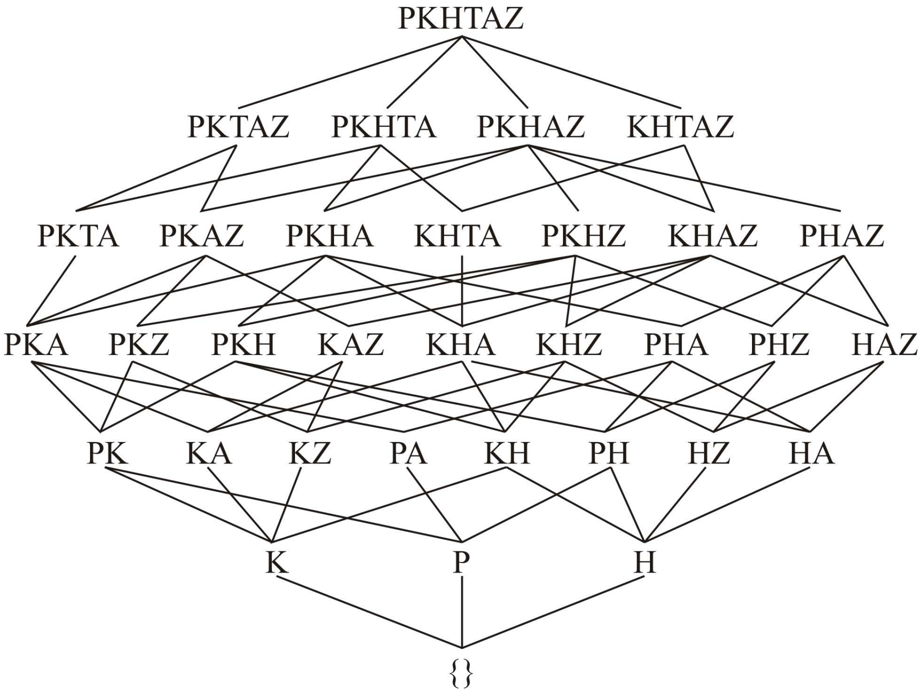

Fig. 1. An example for a directed graph, shown in form of a Hasse diagram

Very briefly, the idea is that usually one can find a natural structure, a natural course of learning in a given domain. For example, it is reasonable to start with the basics (e.g., the competency to add numbers) and increasingly advance in the learning domain (to subtraction, multiplication, division, etc.). As indicated above, this natural course is not necessary linear. On this basis, in a next step, we obtain a so-called competence space, the ordered set of all meaningful competence states a learner can be in. As an example, a learner might have none of the competencies, or might be able to add and subtract numbers; other states, in turn, are not included in the space, for example it is not reasonable to assume a learner has the competency to multiply numbers but not to add them. By the logic of CbKST, each learner is, with a certain likelihood, in one of the competence states. This allows displaying and coding of the state likelihoods for example by colors and thereby visualizing areas and set of states with high (or vice versa low) probabilities. An example is shown in Figure 3, where in the lower right part a color coded Hasse diagram is shown. The darker the colors, the higher the state probability. The simplest approach would be to highlight the competence state for a specific learner with the highest probability. The same coding principle can be used for multiple learners. This allows identification of various sub-groups in a class, outliers, the best learners, and so on (Figure 2).

A second aspect comes from the edges of the graph. Since the diagram reads from bottom to top, the edges indicate very clearly the "learning path" of a learner. Depending on the domain, we can monitor and represent each learning step from a first initial competence state to the current state. In the context of formative assessment, such information elucidates efforts of the learners, learning strategies, perhaps used learning materials, but also the efficacy of the teachers (Figure 2). By this means questions such as what was the initial knowledge of a learner before entering the educational progress, how effective and fast was the learning progress, what is the current state, etc., can also be answered.

Finally, a Hasse diagram offers the visualization of two very distinct concepts, the *inner* and *outer fringes*. The inner fringe indicates what a learner can do / knows at the moment. This is a clear hypothesis of which test/assessment items this learner can master with a certain probability. Such information may be used to generate effective and individualized tests. The concept of the outer fringe indicates what competency should or can be reasonably taught to a specific learner as a next step. This provides a teacher with clear recommendation about future teaching on an individualized basis.

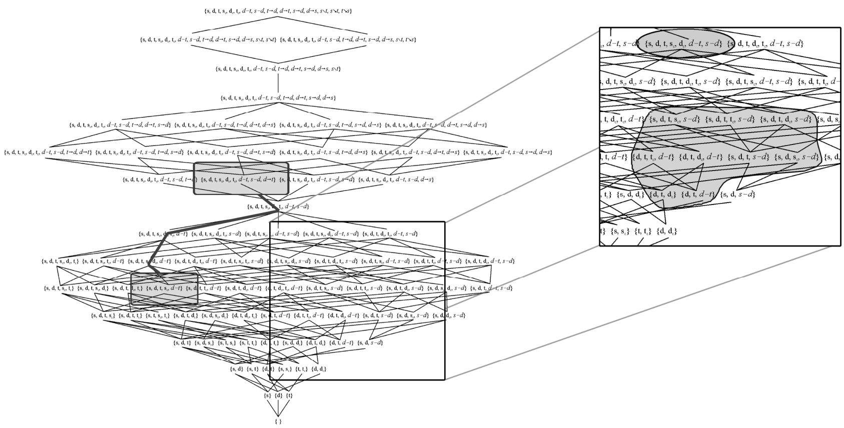

Fig. 2. Hasse diagram of a competence space; the left part illustrates an option to display a learning path from a starting state to the current competence state. The snapshot on the right illustrates a visualization of an individual (oval on the top) in comparison to the states 70 percent of the class are in.

The visualization in the form of Hasse diagrams was realized in the context of the European Next-Tell project (www.next-tell.eu) as part of the educational tool *ProNIFA*, which stands for probabilistic non-invasive formative assessment. The tool, in essence, establishes a handy user interface for services and functionalities related to learning analytics (in particular CBKST-based approaches). In principle the ProNIFA

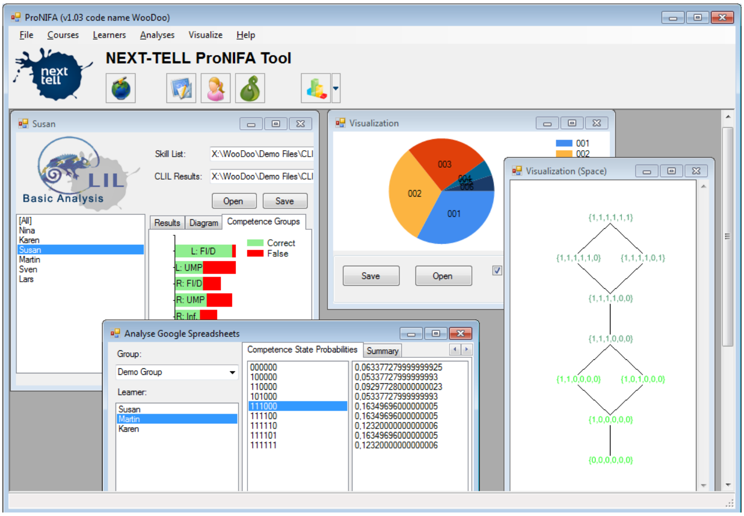

Fig. 3. Screen shots of the ProNIFA tool

tool is a front-end software for teachers and educators; the learning analytics services are running in the background on a server. ProNIFA provides several authoring, analysis, and visualization features. The tool is a Windows application that utilizes various interfaces and links to online-based contents. A distinct feature in the context of formative assessment is the multi-source approach. ProNIFA allows connection of the analysis features to a broad range of sources of evidence. This refers to direct interfaces (for example to *Google Docs*) and it refers to connecting, automatically or manually, to certain log files (cf. Figure 3).

3 Conclusion

There is no doubt that frameworks, techniques, and tools for learning analytics will increasingly be part of a teacher's work in the near future. The benefits are convincing – using the (partly massive) amount of available data from the students in a smart, automated, and effective way, supported by intelligent systems in order to have all the relevant information available just in time and at first sight. The ultimate goal is to formatively evaluate individual achievements and competencies and provide the learners with the best possible individual support and teaching.

The idea of formative assessment and educational data mining is not new but the hype over recent years resulted in scientific sound and robust approaches becoming available, and usable software products appeared.

The framework of CbKST offers a rigorously competence-based approach that accounts for the latent abilities of students. This is in line with the fact that educational policies in Europe are presently moving from a focus on knowledge to a focus on competency, which is reflected in revisions on curricula in the various countries. In addition, the probabilistic dimension allows teachers to have a more cautious view of individual achievements – it might well be that a learner has a competency but fails in a test; vice versa, a student might luckily guess an answer. The related ProNIFA software allows the collection of a broad range of information and with each bit of data that enters the model the picture of a learner becomes increasingly clearer and more credible. 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.

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References

1. Holzinger, A.: On Knowledge Discovery and interactive intelligent visualization of biomedical data - Challenges in Human–Computer Interaction & Biomedical Informatics. In: Helfert, M., Francalanci, C., Filipe, J. (eds.) Proceedings of the International Conference on Data Technologies and Application, DATA 2012, Rome, pp. 3–16. SciTec Press, Setubal (2012)
2. Holzinger, A., Yildirim, P., Geier, M., Simonic, K.-M.: Quality-based knowledge discovery from medical text on the Web Example of computational methods in Web intelligence. In: Pasi, G., Bordogna, G., Jain, L.C. (eds.) Qual. Issues in the Management of Web Information. ISRL, vol. 50, pp. 145–158. Springer, Heidelberg (2013)
3. Siemens, G., Gasevic, D., Haythornthwaite, C., Dawson, S., Buckingham Shum, S., Ferguson, R., Duval, E., Verbert, K., Baker, R.S.J.D.: Open Learning Analytics: an integrated & modularized platform: Proposal to design, implement and evaluate an open platform to integrate heterogeneous learning analytics techniques (2011), `http://solaresearch.org/OpenLearningAnalytics.pdf`
4. Ferguson, R., Buckingham Shum, S.: Social Learning Analytics: Five Approaches. In: Proceedings of the 2nd International Conference on Learning Analytics & Knowledge, Vancouver, British Columbia, Canada, April 29-May 02 (2012)
5. Duval, E.: Attention Please! Learning Analytics for Visualization and Re-commendation. In: Proceedings of the 1st International Conference on Learning Analytics & Knowledge, Banff, Alberta, Canada, February 27-March 1 (2011)
6. Dimitrova, V., McCalla, G., Bull, S.: Open Learner Models: Future Research Directions (Special Issue of IJAIED Part 2). International Journal of Artificial Intelligence in Education 17(3), 217–226 (2007)
7. Doignon, J., Falmagne, J.: Spaces for the assessment of knowledge. International Journal of Man-Machine Studies 23, 175–196 (1985)
8. Doignon, J., Falmagne, J.: Knowledge Spaces. Springer, Berlin (1999)
9. Albert, D., Lukas, J. (eds.): Knowledge Spaces: Theories, Empirical Research, and Applications. Lawrence Erlbaum Associates, Mahwah (1999)