

Tianyong Hao · Wei Chen
Haoran Xie · Wanvimol Nadee
Rynson Lau (Eds.)

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Editors

Tianyong Hao
South China Normal University
Guangzhou, China

Wanvimol Nadee
Maejo University
Chiang Mai, Thailand

Wei Chen
Chinese Academy of Agricultural Sciences
Beijing, China

Rynson Lau
City University of Hong Kong
Hong Kong, Hong Kong SAR, China

Haoran Xie
Education University of Hong Kong
Hong Kong, Hong Kong SAR, China

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Preface

SETE 2018, the Third Annual International Symposium on Emerging Technologies for Education, was held in conjunction with ICWL 2018 organized by the Hong Kong Web Society. SETE was open to the public for organizing a workshop or track to achieve diversity in the symposium. Fueled by ICT technologies, the e-learning environment in the education sector has become more innovative than ever before. Diversified emerging technologies containing various software and hardware components provide the underlying infrastructure needed to create enormous potential educational applications incorporated by proper learning strategies. Moreover, these prevalent technologies might also lead to changes in the educational environment and thus in learning performance. Moreover, new paradigms are also emerging with the purpose of bringing these innovations to a certain level where they are widely accepted and sustainable. Therefore, this symposium aims at serving as a meeting point for researchers, educationalists, and practitioners to discuss state-of-the-art and in-progress research, exchange ideas, and share experiences about emerging technologies for education. This symposium provides opportunities for the cross-fertilization of knowledge and ideas from researchers in diverse fields that make up this interdisciplinary research area. We hope that the implications of the findings of each work presented at this symposium can be used to improve the development of educational environments.

This year's conference was located in Chiang Mai, the largest city in northern Thailand, which sits astride the Ping River, a major tributary of the Chao Phraya River.

This year we received 51 submissions from eight countries and regions worldwide. After a rigorous double-blind review process, 23 papers were selected as full papers, yielding an acceptance rate of 45%. In addition, three more short papers were selected. These contributions cover the latest findings in areas such as: emerging technologies of design, model and framework of learning systems, emerging technologies support for intelligent tutoring, emerging technologies support for game-based and joyful learning, and emerging technologies of pedagogical issues.

Moreover, SETE 2018 featured keynote presentations and two workshops, covering user modeling and language learning, and educational technology for language and translation learning.

We would like to thank the Organizing Committee and especially the organization co-chairs, Wanvimol Nadee, Tianyong Hao, and Wei Chen, for their efforts and time spent to ensure the success of the conference. We would also like to express our gratitude to the Program Committee members for their timely and helpful reviews. And last but not least, we would like to thank all the authors for their contribution in

maintaining a high-quality conference – We count on your continued support in playing a significant role in the Web-based learning community in the future.

August 2018

Tianyong Hao
Wei Chen
Haoran Xie
Wanvimol Nadee
Rynson Lau

Chiu-Lin Lai	National Taiwan University of Science and Technology, Taiwan
Guangliang Chen	TU Delft, The Netherlands
Yun Ma	City University of Hong Kong, Hong Kong SAR, China
Yunhui Zhuang	City University of Hong Kong, Hong Kong SAR, China
Zhenguo Yang	Guangdong University of Technology, China
Ke Niu	Beijing Information Science and Technology University, China
Peipei Gu	Zhengzhou University of Light Industry, China
Xiangyu Zhao	Beijing Research Center of Information Technology in Agriculture, China
Ruoyao Ding	Guangdong University of Foreign Studies, China

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A Service-Oriented Architecture for Student Modeling in Peer Assessment Environments

Gabriel Badea¹, Elvira Popescu¹, Andrea Sterbini²,
and Marco Temperini²(✉)

¹ Computers and Information Technology Department, University of Craiova,
Craiova, Romania

² Sapienza University, Rome, Italy
mar.te@diag.uniroma1.it

Abstract. Peer assessment functionalities are provided in several Learning Management Systems; data coming from the peer evaluation sessions could be used for automated or semi-automated grading, for the management of student modeling, and for providing the teacher with feedback about the learners. Various models for the representation of peer assessment data have been proposed in the literature. In this paper we build on the availability of such a model based on Bayesian Networks, and introduce: (1) a web service capable of representing data coming from peer evaluation sessions, in which student modeling is based on learners' *Competence* and *Assessment capability* features; (2) a protocol of communication, and the design of a related API, making the service available, i.e., allowing the exchange of data between the web service and the LMS supporting the peer assessment sessions; (3) a working example of using this API in the Moodle LMS, by means of enhancing the existing *Workshop* plugin.

Keywords: Peer evaluation · Bayesian Network Model · Student model
Web service

1 Introduction

Analysis and evaluation are high level metacognitive skills, entailing knowledge well beyond the result granted by passive acquisition of notions [1]. While learning, a student can train such abilities through the participation in sessions of peer assessment [2], in addition to verifying and improving her own comprehension of a topic [3].

Moreover, peer assessment provides support for a wide range of assignments, including open-ended questions. Free text answers, short essays, programming code, discussion and motivation of the chosen solution to a problem, are examples of activities that can be proposed to students through open-ended questions, resulting as much more challenging and informative than multiple choice tests [4]. The feedback produced by a peer evaluation system can be useful in several ways: it can be directed to the teacher, in order to support monitoring the student's progress, or it can be aimed at the student, to provide assessment and suggestions for improvement. In such a system, student modeling can provide a powerful tool, supporting the production of meaningful feedback.

In particular, the use of Bayesian Network models to represent significant student traits has been investigated with success [5], also in the context of peer assessment systems [6]. In this paper we build on the availability of one of such models, and present: (1) a web service capable of representing data coming from peer evaluation sessions (described in Sect. 2); (2) a protocol of communication, and the design of a related API, making the service available, i.e., allowing the exchange of data between the web service and the LMS supporting the peer assessment sessions (described in Sect. 3); (3) a working example of using this API in Moodle LMS [7], by means of enhancing the dedicated *Workshop* plugin [8] (described in Sect. 4). Our plans for future development are summarized in Sect. 5.

2 Student Modeling Service Concept and Architecture

First we describe the model of Bayesian Network (BN) data representation, for a peer assessment session, as proposed in [9]. A student is rendered in the network as a set of discrete variables (probability distributions), representing: (1) his knowledge level on the question's topic (variable K); (2) his ability to evaluate (variable J); (3) his answer correctness/grade (variable C). In addition, a variable G is associated to the student's answer, for each grade given to it by peers. K, J and C are computed by evidence propagation, based on the peer assessments (G values), and possibly on the grades added in the network by the teacher, in relation to some of the answers. The final value of C is the estimated answer's grade. Dependencies are assumed among the above variables and are given by conditional probability tables: C and J depend probabilistically on K; G depends on J and C.

If the model is applied in a framework calling for teacher's grading work, then also the teacher's grades can be used as evidence (fixing the value of a C variable) and determine the network update by propagation, which has positive effects on the overall correctness of the grades inferred by the system [9]. On the other hand, also the bare use of the model, to just represent the data and make inferences on the final grades of the answers, with no grading work done by the teacher, has been shown effective [9].

Hence, the application of the model described above can enhance the management of data coming from a session of peer assessment, or from a sequence of sessions. We therefore believe it is worthwhile to implement the model in a web service, and make its functionalities available to teachers using peer evaluation on a web-based platform. In what follows, we describe the steps of use of such a service, in a realistic situation. The next section shows a more detailed description of the web service, and of its API.

Let us consider a typical peer assessment session, taking place in a web-based learning environment, which requires from each student the answer to an open-ended question and the evaluation (and grading) of a number of her peers' answers. After the session, the teacher can visualize the answers and the peer evaluations; this data can be analyzed in order to recognize the proficiency and difficulties of each student. In this context, the Bayesian Network modeling service can provide additional useful information regarding students' competence and assessment capability. In order to do that, the learning environment needs to provide an implementation of the API exposing the service. A schematic representation of the proposed architecture is included in Fig. 1.

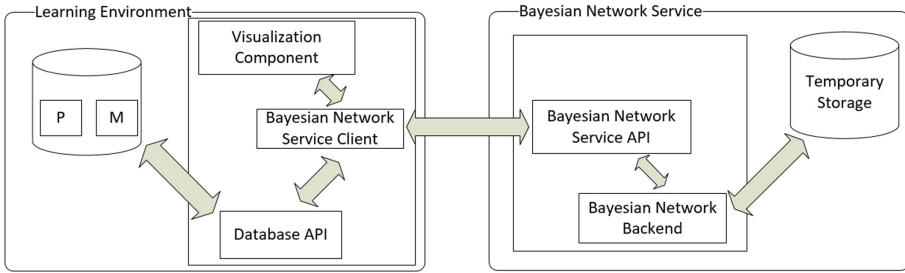


Fig. 1. Schematic system architecture (P represents the peer assessment data related to a given session, and M represents the student models, as computed by the BN service)

Based on the peer evaluation dataset sent by the educational platform, the service computes and returns the following data: (1) the students’ models (in terms of the K and J variables of each student); (2) the answers’ grades, as inferred by the service according to the available data; (3) a ranking of the answers, suggesting what is the most convenient answer to be graded by the teacher, in order to add the highest amount of information in the network and make the inferred grades more precise. At the first interaction, only the peer evaluation data would be sent to the service. In the following interactions, however, the current models can be sent as well, in order to allow the service to further enhance the modeling process.

3 Bayesian Network Service and Corresponding API

We designed and implemented a Bayesian Network Service (BNS), as a Python-based library applied for modeling *Competence* and *Assessment capability* features of the learner, as mentioned in the previous section: K, the level of knowledge; J, the ability to assess peers’ work; and C, the correctness of the answer provided by the student. The BNS accepts as input the peer assessment session data, i.e.: (1) the peer evaluations, (2) those teacher’s grades that are available, and, optionally (3) the previous K values of the students. Then, it returns as output the computed student models and inferred grades.

In addition, we implemented a Python-based BNS API, which can be used to extend the functionality of any peer assessment platform. The main method provided by the API is *getStudentModels*, which accepts as input the peer evaluation session data, processes it and returns the corresponding student models. The exchanged data is represented in JSON format. In what follows we present some examples of input data:

- (1) *The list of grades assigned by each student to her peers*

```

"peer-assessments": {
  "S1" : { "S2": 0.83, "S3": 0.56 },           # grades given by student S1 to S2 and S3
  "S2" : { "S1": 0.70, "S3": 0.62 },
  ...   } # grades given by all other students participating in the peer assessment
    
```

Here the student with identifier S1 assigned a grade of 83 to student S2 and a grade of 56 to student S3 (on a 1 to 100 scale). Notice that all grades are normalized in the range 0-1 (e.g.: $83 \rightarrow 0.83$, $56 \rightarrow 0.56$).

(2) *The list of grades assigned by the teacher to each student*

```
"teacher-grades": {
  "S1": 0.6,           # grade given by the teacher to student S1
  "S2": 0.72,
  ... }              # grades given by the teacher to all other students
```

Notice that the teacher can assess the entire class of learners or only a subset of them.

(3) *The current student models, in terms of the K variables*

```
"student-models": {
  "S1" : { "K": [ 0.32, 0.31, 0.20, 0.10, 0.05, 0.02 ] },
  "S2" : { "K": [ 0.15, 0.20, 0.35, 0.17, 0.08, 0.05 ] },
  ...   }          # all other students' models
```

The students' knowledge level (K) is represented as a distribution of probabilities over the grades A-F; e.g., in case of student S1: $p(A) = 0.32$, $p(B) = 0.31$, $p(C) = 0.20$, $p(D) = 0.10$, $p(E) = 0.05$, $p(F) = 0.02$.

Starting from this input data, the BNS API computes the student models (K and J), and the answers' inferred grade (C). An example output, for the student S1, is as follows:

```
"S1" : {
  "C" : {
    "value" : 0.77,           # inferred grade (answer's Correctness)
    "probs" : [ 0.11, 0.15, 0.34, 0.21, 0.16, 0.03 ] # inferred probability distribution for C
  },
  "J" : {
    "value" : 0.82,           # inferred ability to Judge
    "probs" : [ 0.14, 0.35, 0.24, 0.21, 0.05, 0.01 ] # inferred probability distribution for J
  },
  "K" : {
    "value" : 0.85,           # inferred Knowledge about the topic
    "probs" : [ 0.25, 0.36, 0.21, 0.12, 0.05, 0.01 ] # inferred probability distribution for K
  }, ...
}
```

Moreover, the service orders the answers not yet graded by the teacher, to suggest which one should be given precedence, in case of further grading on teacher's part.

4 Proof of Concept - Integrating BNS in Moodle

We put our Bayesian Network Service to trial, by using it in Moodle LMS; more specifically, we extended the Moodle Workshop plugin with student modeling functionality. The *Workshop plugin* [8] is an effective peer assessment module based on sessions in which learners submit their own work and assess the work of peers according to the teacher's specifications. A session consists of several phases: (1) *setup phase* where the teacher sets the session description, provides instructions for the submission and assessment forms; (2) *submission phase* where the learners submit their work; (3) *assessment phase* where learners evaluate other peers' work; (4) *grading evaluation phase* where students are graded based on their competences; and (5) *closed phase* where the session ends and the teacher and learners can view the outcomes in a grades report.

A PHP-based client using BNS API was developed and integrated into the Workshop plugin. When an evaluation session moves to closed phase, the session data is encoded in JSON format and sent to the BNS. The service is responsible for creating the student models and sending them back to the client. The Workshop plugin decodes the response and stores the models in the database using the Moodle Database API; the Moodle database was also extended in order to accommodate the new functionality.

Furthermore, in order to provide better insights into the student *Competence* and *Assessment capability*, the Workshop plugin was modified to support the computation of two additional *inter-session* grades: *overall submission grade* and *overall assessment grade*. The *overall submission grade* reflects the student's abilities of solving tasks; it is computed as the average of the grades obtained for all his submitted answers, throughout the sessions. The *overall assessment grade* reflects the student's abilities of assessing other peers' work; it is computed as the average of the grades obtained for all the assessments provided by the student, throughout the sessions.

We are currently using Moodle Workshop in a class of around 60 students enrolled in a course on Programming Techniques (first year Bachelor course in Computer Engineering, at Sapienza University, Rome). Each peer assessment session consists of one programming task, whose solution entails the definition of an algorithm and its implementation in the C programming language. Three criteria are associated to each task, to provide the students with some guidelines regarding the evaluation process. In each session, a student is requested to solve her own task, and to evaluate three of her peers' solutions (randomly assigned). Each answer is assessed also by the teacher, in order to provide the students with expert evaluation, and to have a complete dataset that we plan to use in order to analyze the behavior of the BNS. We also aim to investigate the effectiveness and reliability of the enhanced Workshop plugin, compared to the base version. The results of our experimental study will be reported in a future paper.

5 Conclusion

This paper proposed a service-oriented approach for student modeling in peer assessment platforms. More specifically, we designed and implemented a web service based on a Bayesian Network model, which computes learners' *Competence* and *Assessment capability*, basing on data coming from peer assessment sessions, and on teacher's assessment of a subset of the answers. A corresponding Python-based API was also proposed for the Bayesian Network Service. As proof of concept, we used this API in Moodle, by enhancing the Workshop plugin with student modeling functionality.

As future work, we plan to further extend the Workshop module, by integrating open learner model visualization features (including ranking, comparison with peers, evolution over time). These could be used both by the teacher, for providing feedback and remedial interventions, and by the student, for spurring metacognitive awareness. We also plan to provide various metrics regarding students' activity (level of involvement, consistency etc.), as well as regarding the reliability of the computed student model.

Furthermore, our BNS API was conceived to be used by any platform offering peer assessment functionalities; we would therefore like to integrate it also with another system, in order to prove its flexibility and broad applicability. Finally, experimental studies need to be performed, in order to provide real world validation of our approach.

References

1. Bloom, B.S., Engelhart, M.D., Furst, E.J., Hill, W.H., Krathwohl, D.R.: Taxonomy of Educational Objectives: The Classification of Educational Goals. Handbook I: Cognitive Domain. McKay, New York (1956)
2. Sadler, P.M., Good, E.: The impact of self- and peer-grading on student learning. *Educ. Assess.* **11**(1), 1–31 (2006)
3. Li, L., Liu, X., Steckelberg, A.L.: Assessor or assessee: how student learning improves by giving and receiving peer feedback. *Br. J. Educ. Technol.* **41**(3), 525–536 (2010)
4. Palmer, K., Richardson, P.: On-line assessment and free-response input - a pedagogic and technical model for squaring the circle. In: Proceedings of 7th Computer Assisted Assessment Conference (CAA), pp. 289–300 (2003)
5. Conati, C., Gertner, A., VanLehn, K.: Using Bayesian networks to manage uncertainty in student modeling. *User Model. User-Adapt. Interact.* **12**(4), 371–417 (2002)
6. Sterbini, A., Temperini, M.: Analysis of open answers via mediated peer-assessment. In: Proceedings of 17th International Conference on System Theory, Control and Computing (ICSTCC) (2013)
7. Moodle learning management system. <https://moodle.org/>. Accessed 28 May 2018
8. Workshop plugin. https://docs.moodle.org/35/en/Using_Workshop. Accessed 28 May 2018
9. De Marsico, M., Sciarrone, F., Sterbini, A., Temperini, M.: Supporting mediated peer-evaluation to grade answers to open-ended questions. *EURASIA J. Math. Sci. Technol. Educ.* **13**(4), 1085–1106 (2017)