

Towards the alignment of computer-based assessment outcome with learning goals: the LAERS architecture

Zacharoula K. Papamitsiou, Anastasios A. Economides

Information Systems Department

University of Macedonia

Thessaloniki, Greece

papamits@uom.edu.gr economid@uom.gr

Abstract—Computer-based assessment (CBA) measures learner’s progress in an automated manner. A challenge is to align the CBA outcomes with predefined learning goals. In this paper we propose an architecture that feeds the machine-readable results of learning analytics processes into an educational recommender system in order to produce personalized applicable feedback to guide learner during assessment. We describe the architecture, its inner structure, its separate modules, the data-flow between them and the basic mechanisms for data preparation and processing. Our goals are threefold: a) to meaningfully interpret learner’s interaction-generated data into goal-oriented feedback, b) to implicitly link task-level cognitive feedback to learning goals and performance, and c) to automate the delivery of personalized assessment tasks to examinee. Finally, we conclude with our planning on future work.

Keywords- computer-based assessment; formative feedback; learning analytics; educational recommender system

I. INTRODUCTION

Assessment of learners’ knowledge, skills and attitudes has always been a challenge in the educational settings. Many approaches have been proposed in order to improve assessment methodologies. The mediation of technology in education facilitates and simplifies assessment processes. Computer-based assessment (CBA) has therefore been recognized as a beneficial form of assessment that mechanizes these processes [1] [2] [3]. The issues of the alignment of the formative assessment outcomes with the predefined learning goals and students’ scaffolding during formative assessment are summarized under the common term of formative feedback [4] [5]. Its improvement remains an open research question.

Recently, exploitation of ‘Big Data’ in education has attracted increased interest and has led to new, more sophisticated proposals to support and measure learners’ performance that are synopsisized under the term Learning Analytics (LA). Processing large amounts of gathered educational data have potential to clearly determine what students already know and set the boundary between that and what they need to learn. LA focuses on the analysis and reporting of data for gaining insights to learners’ processes, targeting to predict behavior, act on predictions and inform and empower instructors and learners, applying both statistical methods and more sophisticated techniques (e.g. discourse

analysis, content analysis, sense-making modeling, social network analysis and more) [6] [7] [8] [9].

Furthermore, resources constitute a vital component of a LA system. That is because resources comprise the actual support services delivered to students. Educational Recommender Systems (ERS) have been proposed for providing personalized recommendation of resources [10] [11] [12] [13] [14] [15]. These systems can be used to refine suggestions to users through data gathering during an analytics cycle.

We propose an architecture that combines the LA assessment capabilities with the ERS potential for personalized recommendation of resources, in order to provide cognitive, task-level formative feedback to examinee during assessment.

II. ASSESSMENT AND RESOURCE HANDLING

A. Learning Analytics for Assessment and resources management

An extensive area of LA research deals with issues related to using LA for adaptive assessment of goal achievement during activities either within structured learning environments [16] [17] [18] or in open-ended learning environments (OELEs) [19] [20] [21] [22] [23]. In the case studies conducted in typical learning environments, the authors combined learner and learning data in order to generate the assessment results. Complementary, case studies conducted in OELEs showed that the automation and multidimensionality of the analysis of multimodal student activity data (e.g. gestures, facial expressions, eye-tracking, speech, emotions, etc.) during assessment could facilitate understanding of students’ behavior and thus, grant insight in students’ cognition mechanisms.

Another major issue in dataset-driven research concerns data resources and their management [24]. Research in this domain follows two approaches of handling resources: a) from a pedagogical aspect, researchers try to identify which is the attitude of participants towards resource usage [25] [26] [27] [28] [29], and b) from a technical aspect, the interest focuses on similarity calculation mechanisms deployment, aggregation of different datasets in the context of dataset-driven research, suggestion of infrastructures for storing and forwarding learning-resources metadata for learning resources discovery

and relevant data modeling [30] [31] [32] [33] for resource recommendation in larger scale and across different contexts.

B. Recommender Systems in the educational context

A traditional problem in the Technology Enhanced Learning (TEL) context has been the automated seeking and identification of suitable learning resources within a plethora of digital learning artifacts. These learning resources are produced in different and often diverse learning settings. As a result, the adoption of the recommender systems solution in the TEL context has attracted increased interest.

However, particularities of the TEL context (such as its inherent complexity) render inadequate the traditional two dimensional (user/item) approaches of RSs. Consequently, this statement shifts the information retrieval objectives of TEL recommenders towards additional parameter exploration (e.g. learner characteristics and contextual information). User model, domain model, recommendation strategy and algorithm have to be reconsidered.

In [12] the authors defined the TEL recommendation problem, identified the TEL recommendation goals and context variables, shortly presented datasets to support TEL recommendations and presented relevant TEL RSs reported in literature. Relevant work focuses on Adaptive Educational Hypermedia, Intelligent Tutoring Systems, Learning Networks, Educational Data Mining and Learning Analytics.

Examples of algorithmic approaches include recommendation of learning material based on similarity of content items and good learners' average rating strategy [34], recommendations according to the affective state of the learner [35], implementation of collaborative filtering to sequence learning activities [36], hybrid recommendations based on learner and content modeling [37] [38], context-aware recommendations for creativity process using topic map technology [39] and more.

III. THE LAERS ARCHITECTURE

Our suggested architecture is the engagement of an ERS with a LA engine. The LA engine will reveal what students already know and what they need to learn, and the ERS engine output will act as valuable scaffolding feedback to align assessment output with goal achievement. The integration of a LA engine with an ERS supports a CBA system for provision of formative prescriptive feedback to learners. The final output of the systems is the final assessment outcome (timely defined by the duration of the learning activity).

The whole mechanism is a 6-step iterative procedure that follows the 5-step categorization of the analytics cycle [40]:

- Gathering and storing of learners' data (capture),
- Assessment results generation (report),
- Interpretation of assessment results and comparison to learning goals (predict),
- Preparation of data to guide recommendation (predict),

- Generation of recommendations (act),
- Feeding recommendations back to learners (refine).

This approach attempts to add a complementary dimension in previous research towards the development and exploitation of ERSs for automated task-level recommendation during assessment. The involvement of LA concerns data extraction from initial task and their appropriate preparation to feed into the ERS.

A. The abstract architecture of LAERS

We assume a number of assessment assignments, a number of learners and their activities during assignments' tasks. Each of these modules is represented by a respective ontology. Table 1 synthesizes the attributes of each module.

TABLE I. MODULES AND ATTRIBUTES

| Module | Attributes | | |
|--------------------------------|---|--|---|
| | Name | Index | Description |
| $Q_j, j=1, \dots, J$ (task) | O_{bj} | $b=1, \dots, B$ | objectives |
| | M_{aj} | $a=1, \dots, A$ | resources (material) |
| | D_{kj} | $k=1, \dots, 5$ (1=easy, ..., 5=dif) | level of difficulty |
| | K_{yj} | $y=1, \dots, Y$ | related basic concepts (keywords) |
| | C_{cj} | $c=1, 2, 3$ (1=cognitive task, 2=critical task, 3=synthesis task) | category |
| A_j | learners' activity ^a during task j | | |
| $EXTD_i, i=1, \dots, n$ | U_i | $i=1, \dots, n$ | user |
| | LS_{fi} | $f=1, \dots, F$ | learning style |
| | P_{xi} | $x=1, \dots, X$ | preferences |
| | G_{ni} | $n=1, \dots, N$ | learning goals |
| | time-spent on the task j , frequency of requiring hints | | |
| $LAengine$ | A_{zj} | $z=1, \dots, Z$ | extracted keywords (from A_j) |
| | dA_{zj}, K_{yj} | | distance of A_{zj}, K_{yj} |
| | $T\ell$ | $\ell=1, \dots, L$ | tags |
| | $W\ell$ | $\ell=1, \dots, L$ | tags' weights |
| | $flag$ | | flag |
| ERS | I_p | $p=1, \dots, P$ | item={hint, worked example, instruction, study material, people, Q_j } |
| | IT_{sp} | $s=1, \dots, S$ | tags |
| | V_p | | rating frequency- vector |
| | Rec_{ij} | | resources |
| | Q_j | (same as the Q_j module) | |

a. user's activity may include for example an answer to a quiz question, a contribution in an argumentation dialogue, a proposed solution to a real-life problem, etc.

Fig.1 delineates the general scheme and data flow between the separate components of the system. The functionalities and roles of each of these modules are presented in the next sections.

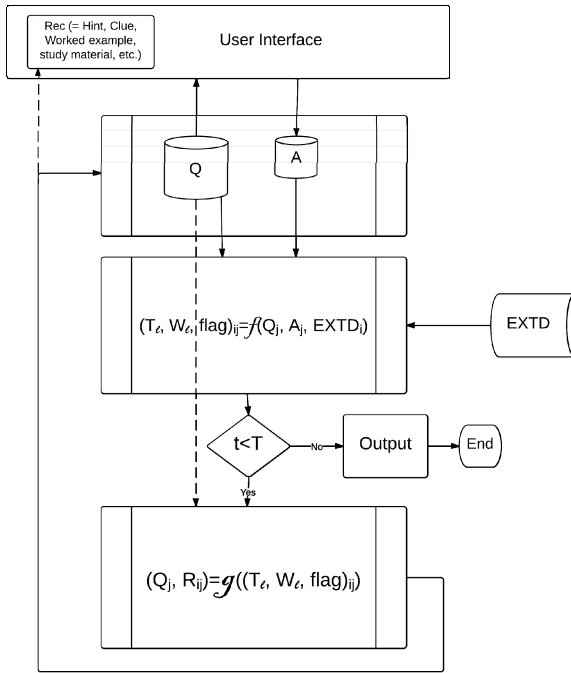


Figure 1. The general LAERS architecture

In general, the output $O(t)$ over time t is represented by a function f applied on previous data from the ERS, the LA and the Q and A modules:

$$O(t) = f(Q(t-1), A(t-1), ERS(t-1)), \quad (1)$$

$$\text{where } Q(t) = g(ERS(t-1)), \quad (2)$$

$$ERS(t) = h(LA(t)), \quad (3)$$

$$\text{and } LA(t) = k(QA(t), EXTD(t)) \quad (4)$$

($A(t-1)$ is the user's "answer").

B. The LA engine Module

The LA engine applies LA methods (interactive content analysis, latent semantic analysis, text mining, statistical analysis) on the data from the Q_j and A_j modules in order to mine data for tags generation, their weight calculation (based on word co-occurrence) and flag index generation (for guiding recommendation). First, Latent Semantic Analysis is applied on A_j data to extract the related keywords A_{zj} . Next, the conceptual similarity between K_{yj} and A_{zj} is calculated for concept mapping [41]. The interpretations of the concept maps can be used to guide evaluation by revealing the learner's needs [42]. Based on this concept mapping, the distance of these keywords is calculated [43] [44]. The result is considered for weight calculation. It is also used for flag generation. The flag indicates if the next task will be of different level or different category. Clustering algorithms are used to extract tags and compute their frequencies. Similarly, the initial task's objectives are assigned to the previous generated tags (creating

another concept map). This will be used in conjunction with $EXTD_i$ module attributes in order to construct the final assessment outcome.

So, if we assume a function f , which represents the data mining method, then a number of tags T_l , their weights W_l and a $flag$ are generated into triples $(T_l, W_l, flag)_{ij}$ accordingly, as in (5):

$$(T_l, W_l, flag)_{ij} = f(Q_j, A_j, EXTD_j). \quad (5)$$

This procedure is illustrated in Fig.2.

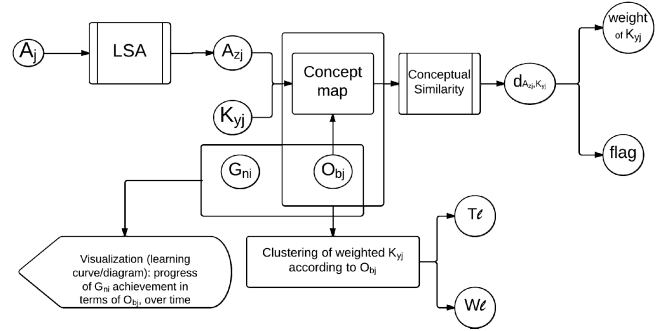


Figure 2. The LA Engine data flow and processing mechanism

For example, the LA engine computes the user's i "score" (distance of concepts used from concepts required) for every task j , based on Q_j and A_j module data, and stores this information on appropriate structures (ontologies), given the task's difficulty level, its category, and the answer given by the user. Then a set of triples $(T_l, W_l, flag)_{ij}$ is generated for the particular user.

C. The ERS module

The ERS module stores (in an ontology) a number of items I_p , that are assigned a set of tags IT_{sp} and a weighted vector V_p . These items will be used as feedback to the users: indexing the next task and a set of appropriate recommendations. The ERS module consumes the triples $(T_l, W_l, flag)_{ij}$ generated by the LA engine in order to produce personalized tag-based recommendations to the user i during the next task j according to his previously revealed needs. The recommendation is a couple (Q_j, Rec_{ij}) of the suggested task Q_j and its respective resources (Rec_{ij}) .

Defining a function g , which represents the recommendation algorithm (based on [45] and [46]), then a personalized recommendation R_{ij} for user i on the task j would be produced, as in (6):

$$\begin{cases} (Q_j, Rec_{ij}) = g((T_l, W_l, flag)_{ij}), \text{ for } j > 1. \\ Q_j, (Rec_{ij} = null), \text{ for } j = 1. \end{cases} \quad (6)$$

More specifically, the recommendation mechanism includes the following steps:

- Construction of item similarity model: items are considered similar when they share common tags.

Tags co-occurrence is calculated according to the Latent Dirichlet Allocation model [47] (as in (7)).

$$F=(P(IT_{1p}|I_p), P(IT_{2p}|I_p), \dots, P(IT_{sp}|I_p)). \quad (7)$$

where IT_{sp} are the tags for an item I_p .

- Determination of the candidate set of items (to reduce the number of items to rank): an item I_p belongs to the candidate set when its tags IT_{sp} include the previously generated tag T_l . So, the CandidateSet model is defined in (8).

$$CandidateSet = T_l \cup (\bigcup IT_{sp}) \quad (8)$$

- Ranking items: The cosine similarity is required to determine closeness between each item in the candidate list and the tag T_l . The weighted vector W_l for tag T_l has already been generated by the LA engine. The weighted tag vector for each item in the ERS module is calculated according to the $IT * IDF$ model [48].

The above data processing is depicted in Fig. 3.

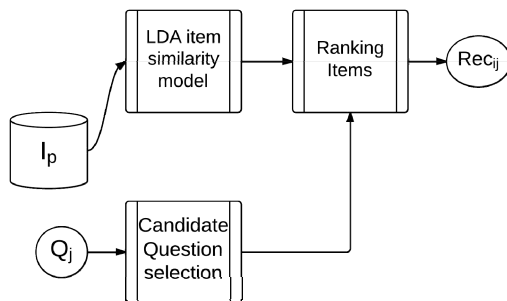


Figure 3. The ERS mechanism for selection of suitable next question Q_j and associate recommendations

IV. CONCLUSIONS AND FURTHER WORK

In this paper we presented an architecture that aims to meaningfully interpret learner's interaction-generated data into goal-oriented feedback. Our goal was to implicitly link task-level cognitive feedback to learning goals and performance and to automate the delivery of personalized assessment tasks to examinee. The proposed architecture is based on research on data-driven decision making in education [49]. The described system considers prior work both on the field of LA for assessment and dataset-driven approaches on educational recommenders systems. The contribution of this paper is a suggested architecture towards the automatic generation of adaptive assessment artifacts. The added value of our contribution is that it feeds valuable (machine readable) results from a LA system into another system (beyond the learners themselves) in order to guide recommendation of personalized assessment tasks (beyond resources or independent activities). We are planning to evaluate the system with real users during the next academic semester and measure its acceptance according to the Computer Based Assessment Acceptance Model (CBAAM) [50].

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