EVALUATING THE PERFORMANCE OF ADAPTIVE LEARNING OBJECTS
SELECTION AND SEQUENCING IN ADAPTIVE EDUCATIONAL
HYPERMEDIA SYSTEMS

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Abstract

Adaptive learning objects selection and sequencing is recognized as among the most interesting research questions in adaptive educational hypermedia systems (AEHS). In order to adaptively select and sequence learning objects in AEHS, the definition of adaptation behavior, referred to as Adaptation Model, is required. Several efforts have been reported in literature aiming to support the Adaptation Model design by providing AEHS designers either guidance for the direct definition of adaptation rules, or semi-automatic mechanisms for making the design process less demanding via the implicit definition of such rules. The main drawback of the direct definition of adaptation rules is that there can be cases during the run-time execution of AEHS where no adaptation decision can be made, due to inconsistency, and/or insufficiency of the defined adaptation rule sets. The goal of the semi-automatic approaches is to generate a continuous decision function that estimates the desired AEHS response, overcoming the above mentioned problem. To achieve this, they use data from the implicit definition of sample adaptation rules and try to fit the response function on these data. Although such approaches bare the potential to provide efficient Adaptation Models, they still miss a commonly accepted framework for measuring their performance. In this paper, we present our performance evaluation methodology for validating the use of decision-based approaches for adaptive learning objects selection and sequencing in AEHS.

1. Introduction

Personalized Learning is a blended formal and informal educational model that is tailored to the needs and interests of each individual learner. Personalized Learning is a 21st century, “on the leading edge” approach to education that recognizes the unique skills, and competences of each learner.

Adaptive Educational Hypermedia Systems (AEHS) have been proposed as a useful tool in the context of personalized web-based learning, aiming to personalize the learning experience for a given learner [1, 2]. In order to adaptively select and sequence learning objects in AEHS, the definition of adaptation behavior, referred to as Adaptation Model, is required. The Adaptation Model (AM) contains the rules for describing the runtime behavior of the AEHS. These rules contain Concept Selection Rules which are used for selecting appropriate concepts from the Domain Model to be covered, as well as, Content Selection Rules which are used for selecting and sequencing appropriate resources from the Media Space. In order to define the runtime behavior of the AEHS, the definition of how learner’s characteristics influence the selection of concepts to be presented from the domain model (Concept Selection Rules), as well as the selection of appropriate resources (Content Selection Rules), is required.

In the literature, there exist several approaches aiming to support the Adaptation Model design by providing AEHS designers either guidance for the direct definition of adaptation rules, such as the Authoring Task Ontology (ATO) [3], and the Layered AHS Authoring-Model and Operators (LAOS) [4], or semi-automatic mechanisms for making the design process less demanding via the implicit definition of such rules [5].

The main drawback of the direct definition of adaptation rules is that there can be cases during the run-time execution of AEHS where no adaptation decision can be made, due to inconsistency, and/or insufficiency of the defined adaptation rule sets [6]. The goal of the semi-
automatic approaches is to generate a continuous decision function that estimates the desired AEHS response, overcoming the above mentioned problem [7]. To achieve this, they use data from the implicit definition of sample adaptation rules and try to fit the response function on these data. Although such approaches bare the potential to provide efficient Adaptation Models, they still miss a commonly accepted framework for measuring their performance. In this paper, we present our performance evaluation methodology for validating the use of decision-based approaches for adaptive learning objects selection and sequencing in AEHS, and demonstrate the use of this methodology in the case of our proposed statistical method for estimating the desired AEHS response [7].

The paper is structured as follows: Section 2 presents the proposed metrics for evaluating the performance of adaptive selection and sequencing in AEHS. Finally, we demonstrate the use of these metrics for evaluating our statistical semi-automatic approach for the definition of the Adaptation Model and discuss our findings and the conclusions that can be offered.

2. Proposed metrics for Performance Evaluation

As described in previous section, the proposed by the literature semi-automatic approaches use data from the implicit definition of sample adaptation rules. This definition of implicit adaptation rules, is given in the form of model adaptation decisions, over which the adaptation response function should be fit. These model decisions include both selection and sequencing rules. Thus, we have designed two performance evaluation metrics that indicate how well the response function fits the model selection and sequencing rules, respectively.

In order to evaluate the efficiency of a method for adaptively selecting learning objects, we have designed an evaluation criterion, as follows:

\[
\text{Selection Success} \% = 100 \times \left( \frac{\text{Correct Learning Objects Selected}}{n} \right),
\]

where \( n \) is the number of requested learning objects from the Media Space. Although this metric seems similar to the precision metric in information retrieval systems, its difference is critical. It evaluates the precision of selecting learning objects not on the entire space of the Media Space, but only on the desired sub-space which represent a set of \( n \) most preferred learning objects. This means that the proposed metric is harder, since it measures the precision over a smaller value space.

Moreover, when this metric is used in comparison with the amount of provided data for algorithm training, such as the number of requested combinations of learning objects which are mapped over learner profiles, it provides evidences about the trade-off that an instructional designer should make between the required effort and the improvement of the selection success rate.

In order to measure the sequencing performance of the method under evaluation, we compare the produced by the method learning object sequences with those produced by the model learning object decisions (defined directly by the instructional designer). To achieve this, we have defined an evaluation criterion, which measures the match between two learning object sequences, as follows:

\[
\text{Success} (\%) = 100 \times \left( \frac{1}{2} \left( \frac{N_{\text{concordant}} - N_{\text{discordant}}}{k(k-1)} \right) \right),
\]

where \( N_{\text{concordant}} \) stands for the concordant pairs of learning objects and \( N_{\text{discordant}} \) stands for the discordant pairs when comparing the resulting learning objects sequence with the reference one and \( n \) is the maximum requested number of learning objects per concept level in the Domain Concept Ontology of an AEHS.

3. Simulation Results and Discussion

Figure 1 presents average simulation results for learning objects selection.

![Fig. 1. Adaptive Selection of Learning Objects Training Results](image)

From these results we conclude that the success rate of adaptive learning objects selection is depending on the maximum requested resources from the Media Space \( n \), as well as the number of the learning objects and learner instances used for algorithmic training. The less number of resources from the Media Space are requested, the less probability of possible mismatches is. Additionally, for the same number of requested objects and the same number of learner profiles used, using more learning object metadata records produces higher selection success rates. Accordingly, for the same number of requested objects and the same number of learning object metadata records used, using more learner profiles produces higher selection success rates. More analysis on the results presented in Figure 1 shows that, when the desired number of learning objects \( n \) is relatively small (less than 20), the selected learning objects by the decision model are close to those the instructional designer would select (with success rate over 70%), when using an input set consisting of more than 500 combinations of learning objects mapped to learner profiles (calculated as the multiplication of the learning objects with the learner profiles used).

In order to investigate deeper the influence of the explicit combinations required from the instructional
designer (which is directly equivalent to the design effort required) we have executed additional experiments measuring the selection success rate per number of requested combinations. This metric provides evidences about the trade-off that an instructional designer should make between the required effort and the improvement of the selection success rate.

Fig. 2. Adaptive Selection Success per Requested Combinations

Figure 2 presents simulation results of the design trade-off for combinations of learning object metadata records with learner profiles that produce selection success over the threshold of 70% for different values of the desired number of learning objects (n). From these results it is evident that using a configuration of 500 combinations (which means classifying 50 learning object metadata records over 10 learner profiles or vice versa) the gain in the selection success rate is bigger than using configurations with more combinations. Furthermore, we can observe that using the combination of 10 learning object metadata records classified over 50 learner profiles produces higher gain in the generalization success rate, whereas, using the opposite combination, that is, 50 learning object metadata records classified over 10 learner profiles, produces better results during the algorithmic training. From the previous experiment, it is evident that in order to minimize the required design effort and in the same time to maximize the selection success rate, the combination of 10 learning object metadata records classified over 50 learner profiles is preferred.

The adaptive sequencing performance was evaluated by comparing the resulting learning object sequences with reference sequences for 50 different cases over the concept hierarchy of the Domain Ontology (10 randomly selected learner instances per concept level). Average evaluation results are shown in figure 3, presenting the success of the proposed sequencing method for different cases of maximum requested number of learning objects (n) per concept level. In figure 3 the different concept levels express the depth in the Domain Ontology of the root concept in the desired sequence. From these results we conclude that the success rate of the resulting learning object sequences is depending on the concept levels that the end sequence covers, as well as the maximum requested resources for each level.

Fig. 3. Average Simulation Results for Learning Path Selection

The less number of resources per level are requested, the smallest would be the resulted LO sequence, producing less probability of possible mismatches. Accordingly, for the same number of requested objects per concept level, the higher level the sequence root is, the longer would be the resulted sequence introducing more mismatches.

4. Conclusions

In this paper, we present our performance evaluation methodology for validating the use of decision-based approaches for adaptive learning objects selection and sequencing in AEHS, and demonstrate the use of this methodology in the case of our proposed statistical method for estimating the desired AEHS response. The application of such evaluation methodology has the potential to provide useful feedback for the design of AEHS.

References: