The Effect of Predicting Expertise in Open Learner Modeling

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Abstract. Learner's self-awareness of the breadth and depth of their expertise is crucial for self-regulated learning. Further, of learners report self-knowledge assessments to teaching systems, this can be used to adapt teaching to them. These reasons make it valuable to enable learners to quickly and easily create such models and to improve them. Following the trend to open these models to learners, we present an interface for interactive open learner modeling using expertise predictions so that these assist learners in reflecting on their self-knowledge while building their models. We report study results showing that predictions (1) increase the size of learner models significantly, (2) lead to a larger spread in self-assessments and (3) influence learners' motivation positively.

Keywords: Prediction, Expertise, Open Learner Model, Self-assessment, Metacognition, Adaptive Educational Systems.

1 Introduction

Self-regulated learning is the ability to understand and control one's learning environments. Metacognition is an important part of self-regulated learning because it enables learners to scrutinize their current expertise levels and to plan and allocate scarce learning resources [15]. Being aware of one's own expertise is referred to as self-knowledge [8], which includes knowledge of one's strengths and weaknesses. In recent years, learner models have been increasingly opened to learners allowing them to scrutinize and update information stored in adaptive educational systems [6,14,5]. One of the potential benefits of this approach is to gain more accurate and extensive learner models allowing these systems to provide more effective personalization. Furthermore, the active involvement of learners in building and maintaining their models may contribute to learning [11,7].

To use open learner models to elicit learner's expertise, we need to find ways to support learners in estimating their expertise. In this paper, we hypothesize that expertise predictions have the potential to serve an important role in

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guiding learners in self-assessing their knowledge to quickly create rich learner models. While learner self-assessment may not necessarily be accurate, there is considerable evidence that bias may be systematic [13] and so it can be valuable.

We understand expertise predictions as representations of topics paired with score values ranging from 0 to 100 points such as *programming:75*. Predictions are calculated based on learners' self-assessments as they are reported to the system. While learners perform self-assessment, expertise predictions are promptly recalculated and displayed to the learners. Given these expertise predictions, we address the following questions: (1) *Will expertise predictions affect the size of learner models?* and (2) *Will expertise predictions motivate learners to focus on their strengths and weaknesses equally?* To answer these questions we propose a user interface featuring predictions and conduct an experimental study for evaluation.

Even though self-knowledge constitutes an important aspect of metacognitive behavior, it is important to emphasize that the validity of self-knowledge seems to be most crucial for learning per se. However, to determine the accuracy of learners' self-assessments goes beyond the scope of this paper.

2 Related Work

This work aims to *elicit a rich user model* as a basis for subsequent personalization in a learning environment. It builds on the growing body of work on *Open Learner Models* (OLMs). Open learner modeling research has shown that OLMs can play several roles, including improving the accuracy of the model, navigation within an information space and supporting metacognitive processes such as setting goals, planning, self-monitoring, self-reflection and self-assessment [5]. Our work builds on the last of these, so that we can quickly create a learner model. At the same time, the process of self-assessment support self-reflect, a valuable way to improve learning [2]. There are many forms of interfaces to open learner models [5] and the ways they can be part of an application or play a use independent role [10,4]. especially for supporting reflection [4]. Our work continues this trend, as we explore the creation of an interface to support self-assessment.

For large learner models, there are interface challenges for OLMs. The VlUM interface tackled this with a novel exploration interface tool [1] that could be incorporated into a system [11]. It showed an overview of the learner model. Each concept was color coded, green indicating a concept was known and red that it was not known. The colour intensity indicated the knowledge score, with learner control on setting the threshold for these colours. A later version, called SIV had ontological inference [12] so that data about fine-grained model concepts could be used to infer values for more general ones, and vice-versa. In this paper, our work explores a different approach to creation of the interface to a learner model because we aim to support learner self-assessment rather than reflection.

3 User Interface

Figure 1 depicts the proposed interface leveraging expertise predictions. In the upper part, learners select topics from a hierarchically structured domain ontology (giving 454 concepts), estimate their expertise scores and add the expertise to their model shown in the table below. To support learners' self-assessment, we provide expertise predictions by employing a score propagation algorithm [9]. Learner models are stored as ontology overlays [3]. The algorithm exploits models' structures to propagate expertise scores amongst ontology topics. The algorithm's scores are integrated with the learner model as shown in the bottom right part of Figure 1. The top left shows the selection of the topic (1). Learners can either enter a topic in the top text box (1a) or select one of the hierarchy of topics, such as Programming (1b). A selected topic then appears on the top right, where the learners assign their self-assessments (2) and Add/Update their scores to the model illustrated at the bottom. The prediction engine dynamically calculates scores based on the scores shown in column *self* and updates the model table. The learner can customize the model's display (3) by filtering the model according to a specific string and by setting a score threshold (ranging from 10 to 100 points in steps of 5) to restrict the display of predicted scores below the threshold value. Learners can now scrutinize (4) their model by inspecting its structure and scores. They can alter their self-assessments by clicking on a topic

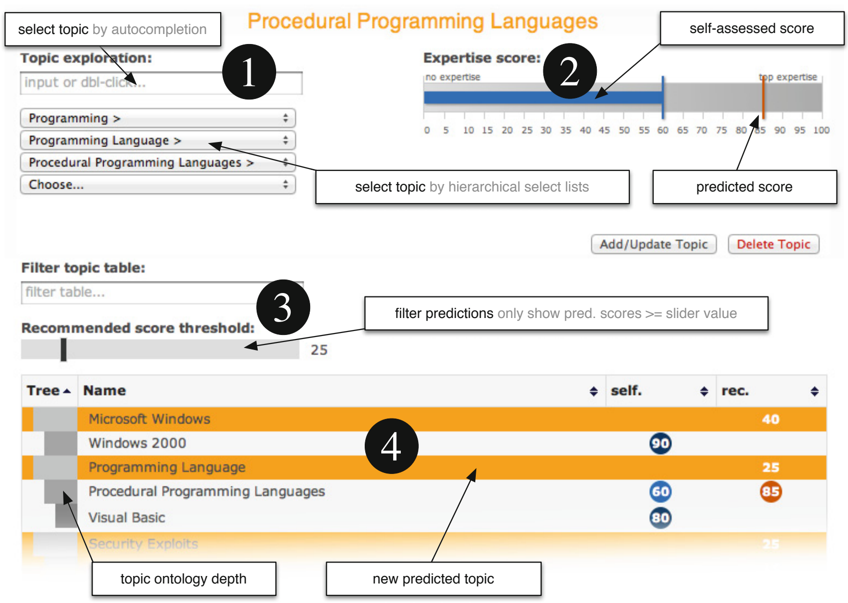

Fig. 1. Building the Learner Model Utilizing Expertise Predictions

in the model, which loads the topic in the top view as it is the case in Figure 1 for the topic *Procedural Programming Languages.*

4 Evaluation and Results

We conducted a user study with master students in a computer science program. Participants were randomly separated into two groups: The Control Group (using the proposed interface but without the prediction feature) and the Prediction Group (working with the same interface but with predictions). We put both interface variants online and notified the participants to start building their learner models from the scratch within two-weeks time. The prediction group was required to self-assess five topics in advance, then the prediction feature started to operate and adapted its results to the growing set of self-assessments. After both groups constructed their models, we asked them for feedback. Importantly, participants completed the given task as a one-off with no consequences (either benefits nor negative effects) for poor self-assessments. With 21 students in the Control Group and 29 students in the Prediction Group completing the task, we observed significant larger learner models in the Prediction Group (avg 38 topics vs. 20 topics).

4.1 Levels and Range of Self-assessments

We explored the levels and ranges of expertise scores learners used while building their models. The figures in Table 1 show that scores in the Control Group are skewed, meaning that participants tend to assign higher scores. The interquartile range ($iqr = Q_3 - Q_1$) amounts to $iqr = 30$ and median average deviation is $mad = 14.83$. Obviously, participants in the Control Group were reluctant to use scores up to the maximum value. Self-assessments in the Prediction Group are also skewed but to a smaller degree. Comparing the values for iqr and mad we see that scores used in the Prediction Group are closer to the perfect uniform distribution standard ($iqr = 50, mad = 25$). Additionally, the Prediction Group was willing to use high expertise scores. These results indicate that the Prediction Group focused their expertise scoring on a somewhat larger part of the model. Hence, this suggests that predictions help learners to explore their model more broadly, reflecting on both their strengths and weaknesses. However, we note that this may have been influenced by the novelty of the system. Figures from participants' feedback: 66% indicated it was fun to work with predictions and 62% that predictions shorten the time building their learner models. Furthermore, many of the participants were curious about how the prediction engine

Table 1. Distribution figures of learners' self-assessments

	n	min	Q_1	median	mean	sdev	Q_3	max	mad
Control group	411	5	40	60	52.94	21.31	70	90	14.83
Prediction group	1115	5	40	60	58.09	24.29	80	100	29.65

works. Together, this suggests that predictions may have led to a higher level of motivation to use the system. This could be very important for maintaining the model over a longer period.

4.2 Feedback

We asked the participants of the Prediction Group to complete an online questionnaire after building their models. For closed questions, 62% of participants liked the predicted scores although 38% rated them mostly useless. 83% found the slider element to be useful to limit the display of predicted scores. 62% believe that a prediction feature shortens the time to build a learner model. And finally, 66% said that it was fun to work with predictions.

From the open questions about likes, dislikes and improvements, it seems that participants found it challenging to decide what it means to be an expert. Selected quotes: *"When is someone an expert and when not?"*, *"I got a very good in Artificial Intelligence. But am I an expert in this topic?"*, *"Someone else might say that he has used Java for 10 years but he still feels that there are better people than him, so he gives himself 80%.", "Further I don't the reference point of the scores. (e.g. 'all people', students of informatics, ...?)"*. Even though we declared the expert level as having problem-solving capability in the respective topic, participants experienced difficulties. This is part of a broader challenge in defining what an expert level means.

Another finding concerns self-reflection. Selected quotes: *"It was interesting to think about questions i did not have in mind before (what is my expertise)."*, *"It helps to find mistakes and makes me rethink my self-assessment."*, *"Was interesting to see how the software thinks my expertise is."*. These statements suggest that predictions can trigger mechanisms to think about one's expertise in more detail as well as scrutinize one-selves believes.

Lastly, participants expressed the wish after a more transparent prediction process: *"I dislike the present interface because I don't understand how the predicted score is calculated."*, *"The system should reason (comment) its predictions."*, *"It would be nice to be able to get a short explanation from the system on how the score was derived."*, *"Scores were irritating, because I don't know how they are determined"*.

5 Conclusions and Future Work

We examined the effects of expertise predictions in supporting learners during self-assessment. Our study results indicate that predictions can have a positive influence on learners' motivation. This appears to be one reason that models for the Prediction Group were almost double the size of those for the Control Group. Furthermore, predictions appear to help learners to broaden their focus to include both their strengths and weaknesses. This may indicate that expertise predictions facilitate learners' reflection on their self-knowledge. The majority of participants appreciated the system's expertise predictions and also think that they shorten the time effort in building their models. Although we have not tested the validity of participants' self-assessments, our study represents a critical precursor before incorporating this class of interfaces into broader contexts, e.g., long term learner modeling. Moreover, tendencies to bias in self-assessments are likely to be consistent [13] and over the long term, changes in these self-assessment could be valuable for learners' reflection on their progress.

In future work, we will explore enhancing our predictions with a collaborative filtering approach, based on learners' similar expertise. This will introduce new topic areas to learners since they are not based on topics learners explicitly stated. We will explore if this helps learners explore more new areas over familiar ones.

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