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Visualising Uncertainty for Open Learner Model Users

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Abstract. There is widening use of open learner models (OLM) to support learning and promote metacognitive behaviours, but learner model visualisations do not typically include information about uncertainty. We consider findings from the field of information visualisation and apply these to OLMs. Examples are given for how uncertainty visualisation might be usefully achieved.

Keywords: Open learner model, uncertainty, information visualisation.

1 Introduction

Open learner models (OLM) are learner models which are inspectable or can be directly interacted with in some way, by students or others [5]. There are now widening deployments of OLMs, especially at university level (e.g. [3,4,9,10,15,17]). The visualisations need to be understandable by users so that they can benefit from the purpose of the visualisations. These purposes are often to support or encourage metacognitive activities such as reflection, progress monitoring, planning and taking responsibility for learning [6], and studies have indicated improvements in learning with OLMs (e.g. [12,13,15]). Examples of OLM visualisations are given in Figure 1.

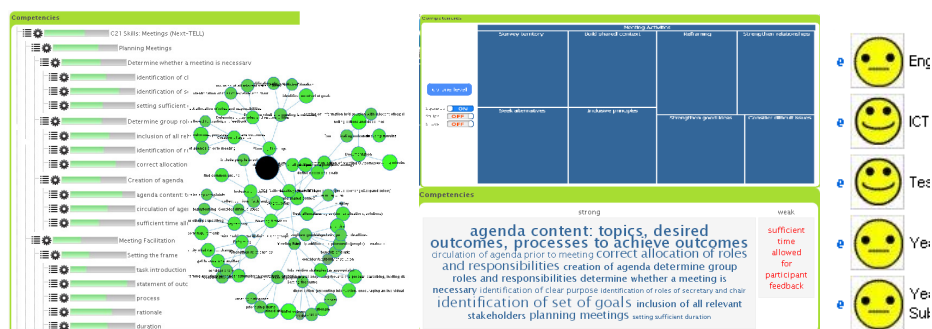


Fig. 1. OLM visualisations: skill meters, competency network, treemap, word cloud, smileies [4]

Uncertainty has long been a recognised problem in user and learner modelling (see [11]), with continuing interest in modelling techniques to overcome uncertainty in the modelling process (see examples in [8]), or methods to allow users to update or con-

tribute information to their models [5]. Nevertheless, some level of uncertainty may still be present. This has implications for personalisation in adaptive learning systems, but is also crucial in OLMs: if users access a visualisation of their knowledge, etc., to prompt metacognitive activities, how can uncertainty be incorporated into the visualisation to enable them to take appropriate decisions according to what is shown?

2 Uncertainty Visualisation

The field of information visualisation aims to communicate complex information in a way that enables people to more easily understand the data, and make appropriate inferences from it [7]. Ways of presenting information on the quality of data people reason over has received growing attention across a range of disciplines [2]. However, people can still have difficulty understanding visual representations of uncertainty even if trained in their use [16]. In education, learning analytics dashboards [18] and OLMs [5] are increasingly used, but instructors often have minimal training in how to interpret visualisations, and if uncertainty is involved, this can be even harder. Moreover, as one of the primary aims of OLMs is to encourage metacognitive behaviours in learners, failure to understand visualisations of their learner models and the uncertainty therein, can negatively impact users' metacognitive processes and, consequently, their learning. We therefore propose some generic methods to visualise uncertainty in OLMs, with visual variables that can be processed pre-attentively [19] or selectively [1], such as position, closure, opacity or grain, while avoiding visual complexity that may impede pre-attentive processing [14]. We illustrate with the Next-TELL OLM, as it has multiple visualisations which are all used by students [4].

As shown in Figure 1, one of the visualisations uses skill meters. However, while quite easy to interpret, skill meters typically provide no information about the uncertainty of data. To avoid learners taking this as indisputable data, we propose indicating uncertainty using, for example, the skill meter fill (grain or opacity); or more precise uncertainty information represented similarly to error bars, as in Figure 2. For discrete skill meter-like visualisations (used in the Next-TELL OLM for users to input self, peer and teacher assessments), opacity could be incorporated to reflect uncertainty. The Next-TELL competency network uses node size and shade to indicate level of competency of elements within a domain structure. To avoid difficulty processing the information if additional features were included within the nodes, we propose grain or dashed outlines (closure) to map uncertainty in the information indicated by a node. In systems where uncertainty in relationships between nodes are modelled, manipulating the style of the connector lines is an option. The treemap uses only size to indicate competency strength. Therefore change in shade, grain or opacity could be used to indicate uncertainty. However, in the Next-TELL context, care must be taken to ensure consistency between visualisations (the competency network uses shading to show strength of competencies). Smilies are also available in the Next-TELL OLM, but adding other 'face features' would increase the complexity of the visualisation. We therefore propose opacity. Unlike common uses of word clouds to show word frequency (e.g. in a document or discussion), the Next-TELL word cloud indicates

strength of competencies or understanding. In cases of uncertainty, the arrangement of (part of) a word cloud could be made ‘messier’, to reflect this.

Reasons for including uncertainty in OLM visualisations not only apply to supporting decision-making relating to the next stage of learning, but can also help focus user attention onto exploring their agreement with the learner model data (e.g. by viewing the evidence for the model which is also available in the Next-TELL OLM, or to suggest changes to the OLM to improve its accuracy, such as in [12]).

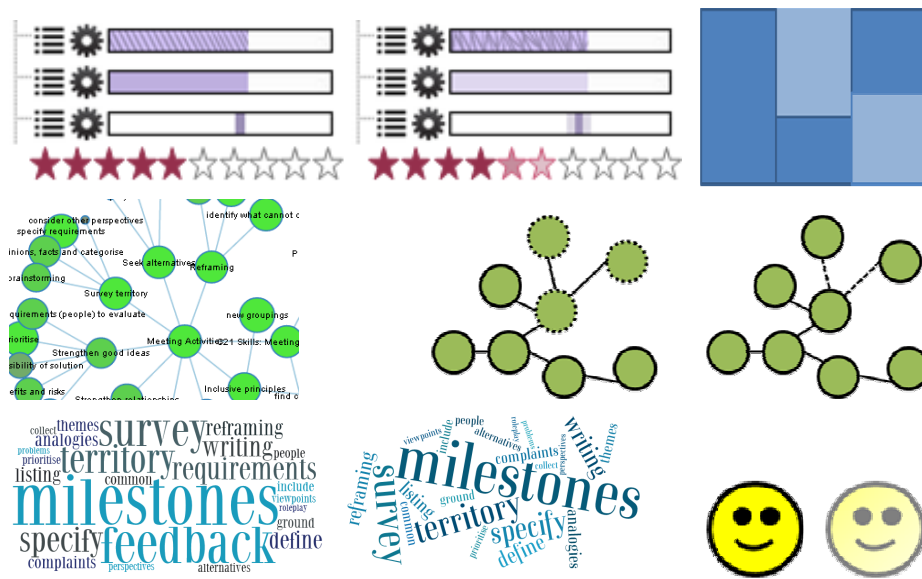


Fig. 2. Uncertainty visualisations (left: low uncertainty; right: high uncertainty; shade: treemap)

4 Summary

There is increasing use of OLMs, but few consider uncertainty in model data. This paper has highlighted potential methods to indicate uncertainty in various OLM visualisations, based on principles of uncertainty visualisation and the knowledge that OLM users are typically not trained in visualisation interpretation. In many cases opacity is a solution, as long as there are no other variables that may result in opacity making the visualisation over-complex for processing. Other solutions include grain and closure. We recommend such approaches be considered by OLM designers.

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