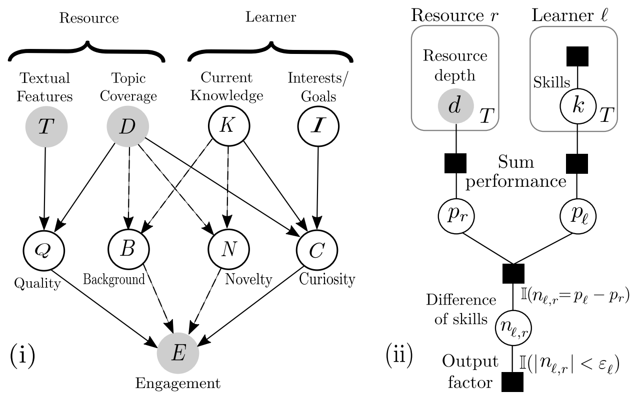

Figure 1: (i) Graphical model representing learner engagement (dashed arrows indicating the components tested) and (ii) TrueLearn factor graph (also, the part with dashed arrows in (i)), integrating resource topics (d), current knowledge (k) and novelty (n) to predict engagement (output factor). ε_ℓ is a dynamic factor of learner ℓ indicating the engagement margin with respect to the amount of novelty. Plates represent T top ranked Wikipedia topics.

plicit engagement (**?**).

Our Approach

We identify four factors that influence learners' engagement and develop a probabilistic graphical model that aims to recover those hidden variables using implicit engagement signals. Using a graphical model that learns from implicit engagement allows us to infer these hidden variables without compromising learner experience through excessive explicit user interventions. The identified factors are: i) baseline resource quality (Q), how engaging a resource is for the average learner; ii) background knowledge of the learner (B); iii) novelty of the learning material (N); and iv) curiosity or learning goals (C) of the learner as outlined in Figure 1. As a first step, we reformulate the IRT TrueSkill algorithm (**?**), to model learner knowledge and novelty as a function of engagement (dashed arrows in Figure 1 (i)).

TrueSkill has several features that make it an excellent starting point. It is a scalable and online algorithm that shares similarities with our problem and provides a good framework for embedding novelty and a dynamic learner factor (that accounts for knowledge changing over time). TrueSkill algorithm and its successor, TrueSkill 2 (**?**), have been deployed and time-tested with millions of users playing multiplayer video games in the Microsoft Xbox Live system giving substantial evidence of its scalability. The TrueSkill framework also provides a method to address dynamic factor involved in learning how the knowledge state of players changes over time (**?**). The Gaussian skill parameter in TrueSkill, when used with a humanly interpretable knowledge component space (e.g. the Wikipedia topics covered in a resource), provides an intuitive and transparent knowledge representation. We propose several reformulations of TrueSkill in (**?**), which we name *TrueLearn*. We also propose in (**?**) a reformulation of Knowledge Tracing to our problem, demonstrating however in a large dataset the superiority of TrueSkill inspired algorithms.

Data: We construct a dataset from the popular video lectures repository VideoLectures.Net (VLN). Since handcrafting the *Knowledge Components (KCs)* in a resource is not scalable, we use an automatic entity linking algorithm, known as Wikification (**?**). The English transcription of the lecture (or the English translation) is used to annotate the lecture with the 5 most relevant knowledge components using a Wikipedia text ontology through Wikifier (**?**). This allows us to work with multiple languages and modalities and automatise the extraction of KCs. We divide the lecture text into multiple fragments of approximately 5,000 characters (equivalent roughly to 5 minutes of lecture) before Wikification. The engagement label is computed by calculating the normalised watch time (**?**). The final dataset consists of 18,933 unique learners.

Models: We implement four baseline models to compare TrueLearn against: i) *Naïve persistence*, which assumes a static behaviour for all users, i.e. if the learner is engaged, they will remain engaged and vice versa; ii) *Naïve majority*, which predicts future engagement based solely on mean past engagement of users; iii) KT model (*Multi-Skill KT*) according to (**?**); and iv) *Vanilla TrueSkill* (**?**).

Table 1: Mean F1-Score with the full VLN dataset

Algorithm	F1-Score
Naïve persistence	0.629
Naïve majority	*0.640*
Vanilla TrueSkill	0.400
Multi skill KT	0.259
TrueLearn	**0.677**

Conclusions: The results in Table 1 show evidence that *TrueLearn* outperforms the baselines while retaining a transparent learner model. The model is run per learner and trained in an online fashion, thus being scalable. The next step is to model content quality and learner curiosity within the same framework. Exploration into future user interfaces for learning with lecture fragments and ways to planning learning trajectories and recommending material are also timely.

Acknowledgments

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