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Using the Explicit User Profile to Predict User Engagement in Active Video Watching

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ABSTRACT

In this paper we leverage the explicit user profile (relating to experience, knowledge, and self-regulation) to predict user engagement in active video watching. Data from two user studies for informal learning of presentation skills in a Higher Education context is used to develop and validate the prediction models. Our results show that these user characteristics can reasonably predict the overall engagement (inactive, passive and constructive learners). Our approach can be used to inform adaptive interventions that prevent disengagement and enhance the learning experience.

CCS CONCEPTS

• **Applied computing** → **Interactive learning environments**;
• **Information systems** → *Personalization*;

1 INTRODUCTION

There is a growing area of adaptive learning systems that model learner engagement [1, 4, 5, 7, 11]. We address the engagement detection challenge in a new context: *using videos for informal learning of soft skills*. Videos enable independent self-regulated learning where students familiarise themselves with, or revisit key concepts in their own time [10]. We have developed an active video watching platform (AVW-Space) [6, 8], which taps into students' experiences with social video-sharing platforms (e.g. YouTube) and integrates interactive note-taking during video watching. Our focus is on the early prediction of user engagement in AVW-Space by using the explicit user profile relating to users' experience, knowledge, and self-regulation. We address the following research question: *Can we predict overall video engagement using only the user profile?*

2 FEATURES AND METHODS

We conducted two studies (referred to as Studies A and B) within two first-year UG courses at the University of Canterbury in 2017. AVW-Space was provided as an online training resource on presentation skills. **Study A** was conducted in a mandatory course for Engineering students. The participation in the study was worth 1% of the final grade. Of the 904 students enrolled in the course, 463 completed the user profile survey. There were 150 constructive, 153 passive, and 160 inactive students (categorised according to the ICAP framework [2]). **Study B** was conducted with Business students in their second semester of study. Of 400 students enrolled in the course, 204 completed the user profile. There were 62 constructive, 26 inactive, and 116 passive students.

Table 1: Feature values comparison (significant differences at $p < 0.01$ are indicated in bold; calculated using the Mann-Whitney test). In the range column, n indicates any number.

Feature	Range	Study A (463)	Study B (204)
Training	[1-5]	1.67	1.74
Experience	[1-5]	2.19	2.29
YouTube	[1-5]	4.11	4.01
YouTube for Learning	[1-5]	**3.15**	**2.66**
Conceptual Knowledge	[0-n]	12.49	11.79
MSLQ-I	[1-5]	3.68	3.61
MSLQ-E	[1-5]	4.07	4.01
MSLQ-TV	[1-5]	3.89	3.87
MSLQ-C	[1-5]	4.11	4.17
MSLQ-SE	[1-5]	3.59	3.63
MSLQ-MSR	[1-5]	3.22	3.28
MSLQ-R	[1-5]	**3.08**	**3.51**
MSLQ-E	[1-5]	3.59	3.64
MSLQ-O	[1-5]	**3.11**	**3.36**
MSLQ-ER	[1-5]	3.45	3.44

The user profile survey yielded 15 features. Four features capture previous **Training** on giving presentations, **Experience** in giving presentations, frequency in using **YouTube**, and the extent to which they use **YouTube for learning**. The total number of concepts relating to presentation the student could name is used as a proxy for the student's **Conceptual Knowledge**.

The remaining ten features are aggregations of scores on the MSLQ questions [9]: intrinsic motivation (**MSLQ-I**), representing the degree to which the student participates in academic tasks for reasons linked to challenge, curiosity and mastery; extrinsic motivation (**MSLQ-E**), the degree to which the student participates in academic tasks for reasons such as grades and rewards; Task Value (**MSLQ-TV**), which refers to the student's perceptions of

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Table 2: Classification results using user profile data. Metrics include: accuracy (Acc.), precision (Prec.), recall (Rec.). RFE selected features are presented in Table 1.

	Study A				Study B		
Three class classification							
Acc.	0.41			Acc.	0.63		
	In.	Pass.	Con.		In.	Pass.	Con.
Prec.	0.5	0.55	0.53	Prec.	0.88	0.87	0.81
Rec.	0.71	0.29	0.55	Rec.	0.98	0.69	0.88
Binary classification (one-class vs. others)							
	In.	Pass.	Con.		In.	Pass.	Con.
Acc.	0.66	0.62	0.62	Acc.	0.86	0.46	0.7
Prec.	0.77	0.77	0.77	Prec.	0.93	0.71	0.85
Rec.	0.79	0.82	0.79	Rec.	0.93	0.66	0.82

academic studies in terms of interest, importance and utility; Control (**MSLQ-C**) indicating whether the learner feels in control of his/her own performance; Self Efficacy (**MSLQ-SE**), the student's confidence in having skills to perform academic tasks; Metacognitive Self-Regulation (**MSLQ-MSR**); and several learning strategies: Rehearsal (**MSLQ-R**), Elaboration (**MSLQ-E**), Organisation (**MSLQ-O**) and Effort Regulation (**MSLQ-ER**).

In Table 1 we present an overview of values for the profile features and compare them across studies. Only three features had statistically significant differences between Study A and Study B: YouTube for Learning is higher for Study A, both MSLQ-Rehearsal and MSLQ-Organisation are higher for Study B. The remaining MSLQ features are similar in both studies.

Prediction models. Our task is to predict the overall engagement using just the explicit user profile. We consider two task settings. (1) Simply predict whether the student would be inactive, passive, or constructive. (2) Use binary classification, whereby for each category we build a binary classifier of the format One-class-vs-Others (e.g. Inactive vs. Passive + Constructive). We use all the explicit user profile features as predictors, and the categorisation relevant for each task setting as the target variable. The features are first preprocessed by removing near-zero variance predictors, and scaling the remaining ones between 0 and 1. We use upsampling to balance out the class distributions and prevent the classifier from always predicting the majority class.The classifiers are trained separately for each study. We use a Leave-One-Out cross-validation (LOOCV). From a range of classifiers we found support vector machines (SVM) with RBF kernel to yield best results.

Results. We evaluate using accuracy averaged over the LOOCV iterations, and precision and recall, calculated using the predictions from the final model. We report results in Table 2. In the three-class prediction setting, the results were noticeably higher for Study B (Acc.=.63), compared to Study A (Acc.=.41). That was also the case when looking at the precision and recall for each of the categories. Although better than a random choice (which would have an accuracy of approx. 33%), the results of the three-category prediction for Study A are not reliable enough to predict user engagement. The results for the binary classifiers are overall higher. The only binary classifier that suffers a drop in performance compared to the three-class prediction is the Passive classifier for Study B. In particular, the results for Study A show an improvement. Overall, the fairly high (at least 0.7) precision and recall values mean that the prediction model can be reliably used to predict user engagement.

3 DISCUSSION AND CONCLUSIONS

Key findings. We found that by using the explicit user profile we can predict whether a given user will be Inactive, Passive, or Constructive with a fair degree of accuracy, in particular when conducting binary classification. Our work gives supporting evidence that self-regulation abilities are important user characteristics to consider in adaptive video learning. Hence, surveys like MSLQ offer valuable insights for personalisation and adaptation.**Applications of the prediction models.** The models can be applied in several personalisation and adaptation contexts, such as planning interventions, e.g. implementing nudges is one of the primary goals for the AVW project [3]. The presented prediction models can help identify *whom* to target soon after the users start watching videos.

Conclusions. Our goal was to leverage the user profile to predict user engagement with the view of implementing early interventions to support beneficial video engagement. We found that experience, knowledge, and self-regulation from the user profile can be used for early prediction of user engagement with a reasonable degree of accuracy.

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