Exploring and Following Students’ Strategies When Completing Their Weekly Tasks

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**INTRODUCTION**

We wish to understand how students manage their learning when presented with tasks of varying difficulty by analysing the order in which students attempt such tasks. We investigate the following questions:

1. What strategies do students take in attempting the different tasks each week?
2. Are there differences between the strategies of the regular and advanced students?

We show how to represent and mine data from student tasks with different difficulty levels.

**THE DATA**

The data comes from a third year database course with a regular and advanced stream. Students completed weekly homework tasks with the following properties:

1. Different difficulty levels: easy, medium and hard
2. Marks awarded based on most difficult task completed
3. Automated feedback on student submissions given
4. Unlimited attempts allowed before deadline

The data extracted consisted of the marks for every student’s attempt on each task.

**STRATEGIES**

Figures 1 and 2 show the relative frequency of the different strategies taken by all students overall and each week respectively. Strategies are labelled based on the tasks completed, e.g. EH indicates a student completes that week’s Easy task first, followed by the Hard task. There are 16 possible strategies. The most common strategies observed are None (30%), E (31%), EM (11%) and EMH (15%).

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**CLUSTERING WITH MISSING INFORMATION**

Students were able to test their code at home, which meant we didn’t always have complete information about their strategies. For example, a student might have completed all three tasks but only submitted the hardest one!

The Solution

We clustered students based only on the highest difficulty task completed each week (using k-means, k=5, centroids: Fig 2). We then took the mode weekly strategy for each cluster (Table 1), which allowed us to compare student strategies despite the missing information.

**SLIDING WINDOW RULE MINING**

To find trends in changes of strategy we looked for association rules X → Y in which X occurred before Y in time and restricted our analysis to periods of three weeks. We used a sliding 3-week window over each student’s strategy vector, similar to rule mining in time-series subsequences [1], but with the time encoded into each item. From these item sets (n = 448) we searched for rules 1a,2b → 3c where a, b and c were the strategies used in consecutive weeks. The 5 highest confidence rules are shown in Table 2.

**CONCLUSION**

1. Clustering and rule mining can be applied to data from tasks in which students have choices between several activities
2. It is possible to handle missing information

**REFERENCES AND ACKNOWLEDGEMENTS**


Work was funded by the Human-Centred Technology Cluster of the University of Sydney. Poster template adapted from “Papert Landscape Poster”, originally created by Brian Amberg, accessed at http://www.latextemplates.com/template/papert-landscape-poster, 25 June 2016.