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In our work, we examined a complex VLE dataset from a large Irish university in an attempt to characterize student behavior with respect to deadlines and grades. We demonstrate that, by clustering activity profiles represented as time series using Dynamic Time Warping, we can uncover meaningful clusters of students exhibiting similar behaviors even in a sparsely-populated system.

We use these clusters to identify distinct activity patterns among students, such as Procrastinators, Strugglers and Experts. These patterns can provide us with an insight into the behavior of students, and ultimately help institutions to exploit deployed learning platforms so as to better structure their courses.

**OBJECTIVES**

- Levels of activity in learning environments positively correlated with good grades
- Work submitted close to the deadline less likely to score well
- Evening activity a better predictor of good performance than daytime activity
- Loss of information when aggregating Moodle activity data into counts and looking for correlations with respect to these counts
- Sparsity of activity levels online
- Difference in activity levels from course to course, depending on the nature of the material
- Usage of only logs predictive for particular data set
- Methods incorporating multiple features needed to deal with the sparsity problem
- Concerns about privacy in intervention systems

**Solution:**

- Representing student’s efforts as a complete time-series of activity counts
- Mining student activity on sparse data via Time Series Clustering

**ABSTRACT**

Virtual Learning Environments (VLE), such as Moodle, are purpose-built platforms in which teachers and students interact to exchange, review and submit learning material and information.

In our work, we examined a complex VLE dataset from a large Irish university in an attempt to characterize student behavior with respect to deadlines and grades. We demonstrate that, by clustering activity profiles represented as time series using Dynamic Time Warping, we can uncover meaningful clusters of students exhibiting similar behaviors even in a sparsely-populated system.

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**TIME SERIES ANALYSIS**

**Fitness measure:**

1. Mean variance of the k-means clustering calculated using the weighted average of all the clusters’ variances, where the weight is based on the size of the cluster
   - Better scores awarded to the clusterings containing larger clusters with lower variances
2. Multiple random assignments of time series run to calculate the expected score which could be achieved by chance for a given number of clusters
   - The difference between a baseline clustering and actual results tested to define the significance of the clustering
3. Normalization of the weighted average variance score from Step 1 with respect to the random assignment score from Step 2
   - A good clustering characterized by a low resulting score

**Future Work**

- Behavior changes analysis
- External factors - Activity prediction
- Cross platform comparison

**CONTACT**

Ewa Młynarska
Email: ewa.mlynarska@insight-centre.org

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**ACKNOWLEDGEMENTS**

Table 1. The structure of two analyzed data sets, corresponding to two semesters of the same academic year.

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<th>Semester</th>
<th>Courses</th>
<th>Assign.</th>
<th>Students</th>
<th>Subm.</th>
<th>Activity logs</th>
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