Visible Deadlines in Student Usage Patterns

September 11, 2013 Dr. Colm P. Howlin

Student activity logs can provide important insights into student behaviors. In this example we are going to look at some basic analysis of a 5 week course that had 5 objectives for the students to complete; one objective per week. Each objective had a deadline of Monday morning at 6am. Students could start an Objective early if the required prerequisite learning had already taken place and could continue to work on an objective once its deadline had passed to improve their score. The course was delivered online and students were free to use the system at any time. There was a total of 920 students taking this course.

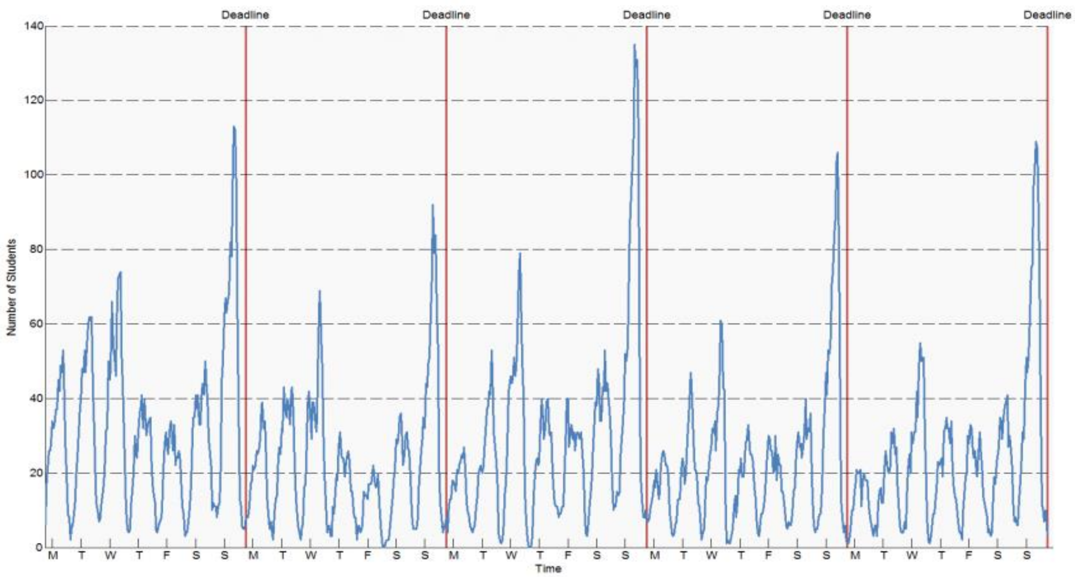

Figure 1 shows the number of students engaged with learning material per hour over the course of a 5 week course.

Figure 1 shows the number of students engaged with learning material per hour over the course of a 5 week course. The daily cycle of learning is clearly visible. The most noticeable feature of this graph is the peak in activity on the Sunday of each week; this is the last day before the objective was due.

Students are clearly being influenced by the presence of the deadlines. Deadlines are often used to encourage students and avoid procrastination, (Amabile, DeJong and Lepper 1976). It has been found that *"frequent deadlines enhanced distribution of practice and improved learning",* (Fulton, et al. 2013), and that deadlines can reduce student interest in the activity, (Ariely and Wertenbroch 2002). Given these finding, and the effect of the deadlines observed in this data, one interesting line of research would be to investigate if these deadlines have a positive or negative effect on different subpopulations of students.

Figure 2 highlights average weekly activity patterns. The peak before the deadline on Monday morning is again obvious, but there is also a second spike on Wednesday.

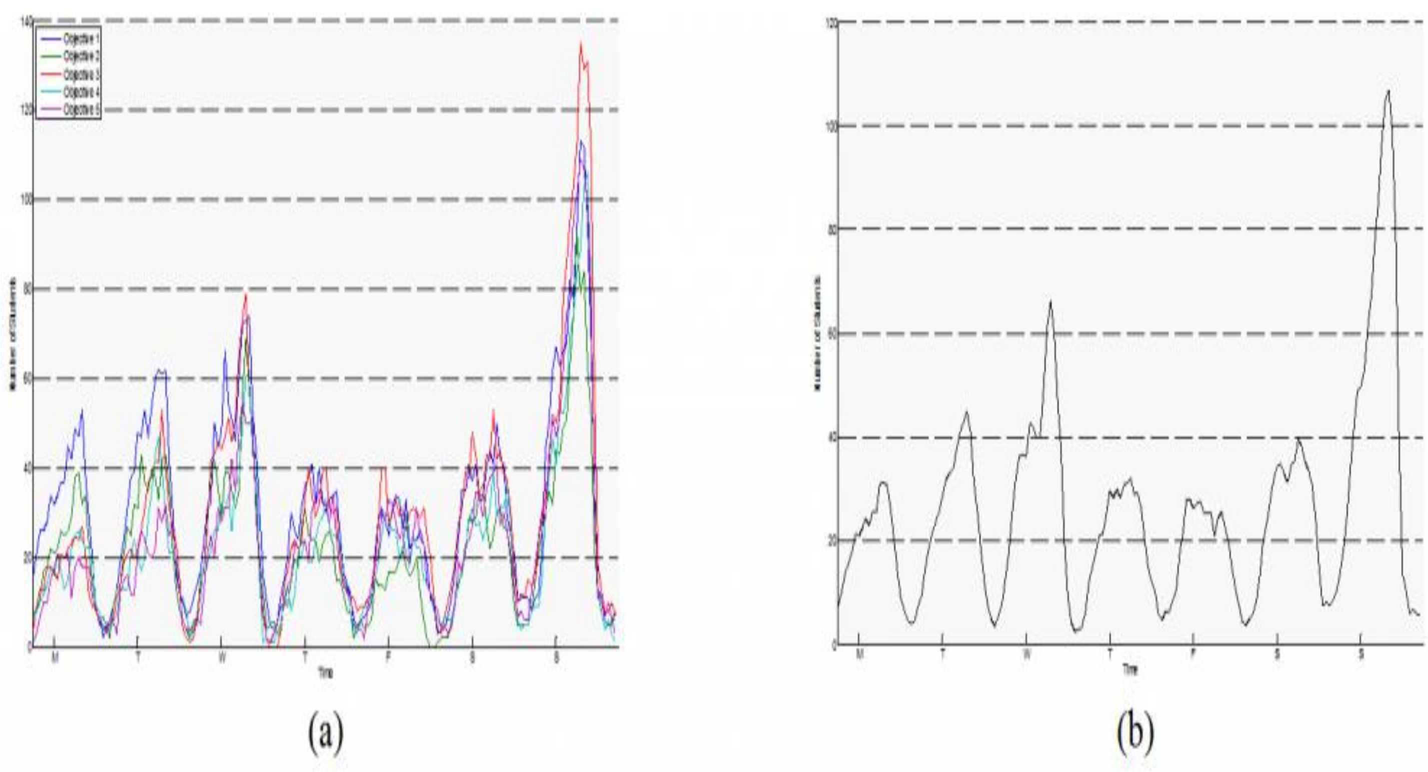

Figure 3: The number of students engaged with learning per hour. (a) shows the activity of all 5 objectives and (b) shows the average across the objectives

Figure 3 shows the average daily activity pattern. Here the peak working hours become apparent. We can see that activity grows over the course of the morning, and then slows in the afternoon, before peaking in the evening at around 8pm. This is consistent with the fact that most of these students are likely to be working during the day and can only study in the evening. It is also interesting to note that on the days with the least activity, Thursday and Friday, the pattern remains the same, except for the peak in the evening.

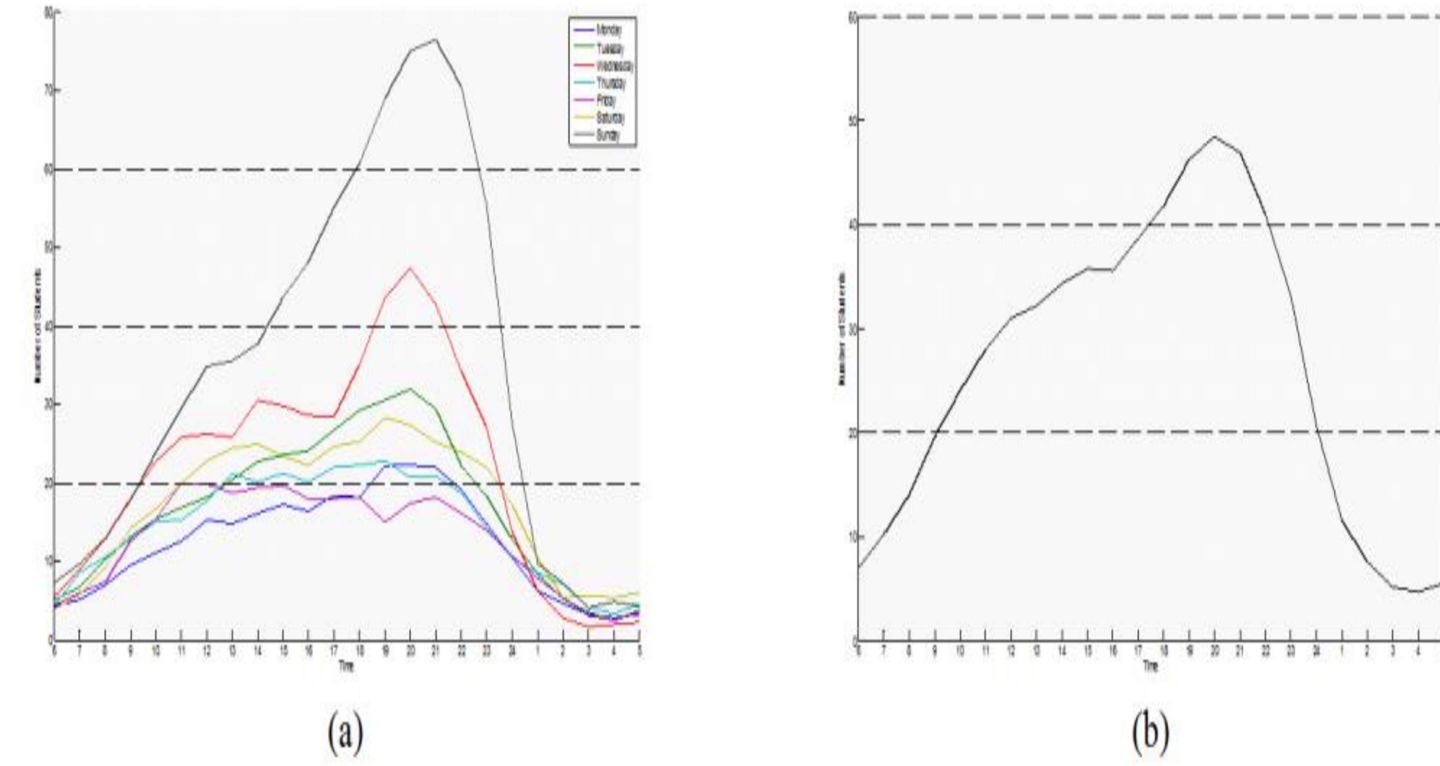

Figure 4: The number of students engaged with learning per hour. (a) shows the average activity per hour per day (b) shows the average across all days

Insights such as these, which are derived from the student activity logs, can provide valuable information to institutions, administrators and instructors so that they know when and how to provide targeted and effective support and resources.

This analysis hints at the wealth of information buried in the vast volumes of data collected on each student. Learning analytics and data mining techniques hold the key to extracting this information so that it can be used to form the basis of evidence based decision making in education.

Works Cited

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