Is Students' Activity in LMS Persistent?

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Introduction. The most common method of blending the Internet in higher education today is by implementing Web-supported instruction, in which traditional face-to-face courses have auxiliary materials, usually using Learning Management Systems (LMS), e.g. WebCT, Moodle. Research of LMS in higher education has barely involved the examination of the individual's behavior over the learning period. Furthermore, although a large body of research exists regarding persistence in fully online learning configurations, only little was studied regarding the online persistence in Web-supported configurations. When empirically examining usage of Web learning environments, it has been noticed that two phenomenon are repeatedly occurring regarding volume and trends of activity: a) **Many are little active, while some are extensively active**; b) **Overall decrease in visiting** (usually with some spikes of access immediately before exams, assignment submission deadlines, or any other important events during the course) [1-4].

This study aims on identifying individuals' over-time patterns of online activity in Web-supported courses, both by volume and trends of activity. As our examination of patterns of persistence crosses courses, it might also promote the revealing of differences between courses regarding students' persistence within them.

Population. Log files of 58 Moodle one-semester-course websites offered by Tel Aviv University (TAU) in the academic year 2008/9 were analyzed (a full sample of the Moodle-supported courses; only logged activity from during the calendared term period were taken). Moodle's log files consist of actions taken within the course websites' modules, including: text pages, resources, forums, and users. Actions might be: viewing, adding, updating, or deleting. In total, 163,685 records of 1189 students were logged, and there were 1897 student enrollments which served as the basic analysis units (interdependence in the population was found to be insignificant).

Variables and Process. Five measures were calculated to describe students' activity in volume (*Cumulative Activity*, *Total Activity*) and trend (*First Tertile Proportion*, *Second Tertile Proportion*, *Activity per Day*). The main procedure involves the application of a Decision Tree algorithm on the trends-related variables, for finding patterns of persistence in students' behavior, and for defining rules of belonging to these patterns. We choose the variable *Activity per Day* as the independent variable the prediction of which should be given by the tree, and the two other variables – i.e., *First/Second Tertile Proportion* – as the variables according to which the tree will be constructed. CHAID method was used as an attribute selection measure based on the statistical chi-square test for independence, with a significance level of 0.05 for splitting nodes and merging categories, and a 10-fold cross validation.

Results and Discussion. Analyzing *Total Activity*, it was re-demonstrated that most of the students present low activity, while only a little are very active. Regarding the activity by tertiles, it was found that on average, *First Tertile Proportion* is 0.28 (STD=0.36), and *Second Tertile Proportion* is 0.62 (STD=0.34). For a consistent student, the activity of whom is equally distributed over the term, we would expect values of these two variables to be 1/3, 2/3, respectively. T-tests for comparing the means of the tertile-related variables with those of a consistent user's behavior confirmed that the differences are statistically significant, with $t(1896)=6.65$, $p<0.01$, for *First Tertile Proportion*, and $t(1896)=5.63$, $p<0.01$, for *Second Tertile Proportion*.

Running the Decision Tree algorithm, we got seven patterns of learners' activity: a) **Persistent Users**, active occasionally throughout the term; b) **High-extent Persistent Users**, active often throughout the term; c) **Mid-Late Users**, active during second, last thirds of the term; d) **High-extent Mid-Late Users**, active during second, last thirds of the term with high intensity; e) **Late Users**, active almost only during last third of the term; f) **Retain Users**, active almost only during first third of the term; and g) **Low-extent Users**, with overall low volume of activity. The largest groups were Late Users (with 23% of the students), Retain Users (20%) and High-extent Persistent Users (19.8%).

The three most prominent groups found are consistent with research about online learning: 1) Late Users behavior corresponds to the phenomena of students visit courses' websites towards the term-end exams (or other important dates during the semester) [3]; 2) Retain Users' rate of about twenty percents might be compared to studies which examined retain from online learning configurations. However, retention rate in online learning is largely varied between studies, and can get up to 84% [5]; 3) High-extent Persistent Users is a behavior which might be associated with high motivation (either internal, i.e., to learn as much as they can from this engagement, or external, e.g., to gain more points in the exam) or satisfaction, as was previously demonstrated regarding online courses [6].

Currently, as universities provide instructors and students with LMS for facilitating blended learning, it is important to understand how these systems are being used in practice. Instructors may use these results for making their teaching more efficient; education researchers might clarify the large interpersonal differences among students regarding online persistence; and university policy-makers may deepen their knowledge of the cost-effectiveness ratio of these systems.

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