# Comparing LMS usage behavior of mobile and web users

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Abstract—Mobile devices are gaining popularity due to their increasing functionality and usability, and their location and time independence. Consequently mobile technology has become important for both learners and educational institutions. In this paper, we examine usage behavior of mobile and web users within a learning management system (LMS). After motivating the topic and briefly sketching related work, the setup of a case study, the data-set and the findings are described. In short, it turns out that mobile users tend to quickly look up required or interesting information while web users have longer and deeper browsing sessions which include more course-specific functionality.

*Keywords*-LMS usage behavior; logfile analysis; web metrics; web mining; data-driven reseach; web analytics; case study

## I. INTRODUCTION

Mobile devices have become important and widely accepted for teaching and learning (cf. m-learning [1]). As learning management systems cover a lot of m-learning requirements, our research focuses on analyzing usage behavior in institutional platforms in order to draw conclusions about two target groups: (a) web users, i.e. users accessing the web-based entry point of the LMS and (b) mobile users, i.e. users browsing the mobile LMS site. Yet there is no more data on the environments of the LMS users available. For instance it is not possible to detect if mobile users browse the LMS via smart phone or tablet device, or if tablet users access the mobile site at all. Thus we characterize the two user groups according to Learning Analytics metrics to show similarities and differences in LMS usage behavior and indicate value-adding functionality.

Putting the focus on learners and educational institutions, Learning Analytics is defined as "the use of intelligent data, learner-produced data, and analysis models to discover information and social connections, and to predict and advise on learning" [2]. Such approaches are based on different data sources (logfiles, user interaction data with learning tools, eye-tracking, brain-computer interface etc) and range from traditional Web Analytics or the measurement of learning-related indicators to visualizations for providing reflection (e.g. SoLAR, GLASS etc) and recommender technology (e.g. APOSDLE, ReMashed etc).

The main objectives are to enable learners to monitor, reflect and improve their learning behavior with respect to activities, artifacts, actors and outcomes. In the scope of LMS technology, the logfile is the most important data source. In the following we describe a case study on an intensively used LMS platform and summarize the findings.

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## II. LEARN@WU CASE STUDY

Learn@WU is the LMS platform of the Vienna University of Economics and Business. After launching the platform in 2001, Learn@WU quickly became an essential component in the ICT infrastructure of the university, providing more than 120.000 learning resources for blended learning. Currently, this LMS is one of the most intensively used platforms world-wide, serving about 15.000 logins of registered users per day (up to about 2.500 concurrent users) with about 2,4 million page views per day. Students solve up to 600.000 interactive exercises per day. Special markup and navigation structures for mobile devices were added in May 2011. In the taken snapshot the number of mobile views were 1,3% of the overall views (see Table 1).

TABLE I. KEY FIGURES OF THE LEARN@WU LOGFILE FOR THE STUDY (TAKEN ON OCT 5, 2011; CSS AND IMAGES OMITTED; REQUESTS APPROXIMATELY IDENTICAL TO PAGE VIEWS; SESSIONS INCLUDING ALL REQUESTS BETWEEN LOGIN AND LOGOUT OR A 30-MINUTE TIMEOUT)

Indicator	Overall	Web	Mobile
No. requests	2.120.698	2.093.696	27.002
No. users	9.915	9.762	1.062
No. anonymous requests	679.930	675.784	4.146
No. authent. requests	1.440.768	1.417.912	22.856
No. sessions	34.342	32.158	2.184
No. sessions per user	3,17	3,29	2,06
No. requests per visit	41,95	44,09	10,47
No. devices per user	1,20	1,22	1,04

The (LMS) logfile was taken from one day (Oct 5, 2011) in an examination week. We analyzed this data-set according to a common method for Web Usage Mining [3] consisting of pre-processing, pattern discovery and pattern analysis/visualization. As patterns for characterizing the two user groups we calculated various indicators on the overall data (e.g. the usage frequency of LMS applications) and on local data-sets, i.e. similar LMS usage profiles (Cosine similarity, Pearson correlation).

### III. FINDINGS, DISCUSSIONS AND OUTLOOK

Table 1 gives an overview of key figures of the data-set used for our analysis. Most of the requests (page views) can be assigned to authenticated users (67,9%) and to web users (98,7%). Furthermore 909 users accessed the LMS by both computers and mobile devices. The high number of

anonymous requests results from logins and support pages, which are partially caused by bots and cannot be assigned to browsing sessions (visits) due to the masquerading of client IP addresses by a proxy. Thus the number of sessions has been calculated according to typical heuristics from Web Analytics (visits per user and device within a timeframe). The number of requests per user (3,29 vs. 2,06) and the number of requests per visit (44,09 vs. 10,47) are higher for web users. This indicates that mobile users use the LMS in a more efficient and targeted way. We analyzed the LMS usage with respect to browser versions and devices. It is observable that web users rather utilize different browsers (1,22) while mobile users normally use one device (1,04).



Figure 1. Usage frequency (logarithmic scale) of top-50 LMS applications by mobile users and web users

An analysis of the LMS usage reveals that the occurrences of the application URLs follow a power law distribution which however has a 'disturbance' at the beginning of the curve (see Figure 1). In particular, exercises (multiple-choice questions) and sample exams are the most frequently accessed tools, whereby web users used them significantly more often than the mobile users. The top-7 applications of web users are: 1) exercises (505.600 requests), 2) sample exams (240.110), 3) overview of exercises (43.263), 4) personal page on Learn@WU (42.222), 5) course overview (40.817), 6) viewing forum messages (20.827), and 7) LMS entry page (18.892). The top-7 tools of mobile users are: 1) exercises (2.892), 2) the personal page (2.600), 3) sample exams (1.664), 4) exam reviews (1.578), 5) overview of forums (980), 6) the LMS entry page (916), and 7) forum messages (659). Thus, the deviation from a power law distribution can be explained with seasonal effects such as an examination week.

Finally, we applied collaborative filtering techniques [4] in order to identify and analyze similar browsing sessions of users. Precisely we calculated the Cosine Similarity (each session is an n-dimensional vector of application usage frequency) and the Pearson Correlation (having application usage as user ratings for items). Figure 2 visualizes the clusters of mobile user-device sessions with a similarity higher than 0.5 (Cosine and Pearson). Both calculations result in a few large clusters with similar but unfortunately

trivial navigation sequences consisting of the actions "login", "entry page", "personal page", "exam review" and/or "logout", as indicated with three labels in Figure 2. However, course-related interactions are part of smaller session clusters and, to a large extent, of single sessions of mobile users. Analyzing the LMS usage of web users and of certain times of the day (e.g. afternoon or evening), we identified more meaningful session clusters containing learning-related applications, which is not addressed in detail in this paper.



Figure 2. Cluster of similar mobile sessions based on Cosine Similarity (left,  $cos(i,j) \ge 0.5$ ) and Pearson Correlation (right,  $r(x,y) \ge 0.5$ )

In short, it can be said that mobile users focus on accessing required or interesting information (e.g. exam review, calendar, lecture room etc). In comparison web users have more session clusters with course and learning-related interaction sequences (e.g. forum activities, downloads of materials, exercises and exams etc). This is backed up by the number of requests per session in Table 1. However, findings on mobile LMS usage are based on a data-set of one day in an examination week. As shown before, seasonal effects within an academic year have an influence on LMS usage behavior. Our analysis also shows that mobile users use course functionality if required (e.g. through pressure by examinations). Future work should focuses on the analysis of other data-sets (e.g. logfiles of other days or other kinds of learner interaction data) as well as the development of new performance indicator systems.

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