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A FCA STRATEGY FOR IMPROVING WEB-BASED LEARNING SITES

DIANA - FLORINA ŞOTROPA

Abstract. Nowadays, online educational systems show a rapid development due to the growth of the Internet, which offer unique opportunities to improve them based on users' experiences. This paper presents advances of a Formal Concept Analysis (FCA) based strategy for improving web-based learning sites. We have used together Web Usage Mining and Formal Concept Analysis techniques in order to create a visual overview of exploring web-logs and discover knowledge in web logs. We have focused on visualizing triadic data in order to emphasize user dynamics through the educational systems. Switching from a triadic to a polyadic perspective we have detected repetitive browsing habits. From all the revealed behaviors we distill then users life tracks by using Temporal Concept Analysis.

1. Introduction

The World Wide Web is a popular and interactive medium to propagate information today. There are different types of data that have to be managed and organized in such ways that they can be accessed by different users effectively and efficiently. Developing competitive activities in any web environment assumes keeping the paramount relationship with the users. Therefore, there is an increased interest and focus on the application of data mining techniques on the web for many researchers.

The purpose of using Web Mining techniques is to extract useful knowledge and implicit information from Web data. While many organizations rely on the Internet to conduct daily business, the study of Web mining techniques to discover useful knowledge has become increasingly important. Moreover, the requirement for adding value to e-services (such as e-learning, e-commerce,

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2010 *Mathematics Subject Classification.* 68T30, 68P20.

1998 *CR Categories and Descriptors.* H.3.5 [**Information Systems**]: Information Storage and Retrieval *Online Information Services*; I.2.6 [**Computing Methodologies**]: Learning *Knowledge acquisition.*

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e-banking) on the Web has become a necessity in order to satisfy users needs, preferences and offer them tailored and proper information. However, with the magnitude and diversity of available information on the Web, it is not insignificant to locate the relevant information in order to satisfy the requirements of people with different backgrounds. The purpose is to encourage visitors to access pages which are considered important, in exhibiting the links between relevant pages and in preventing disorientation. The majority of web surfers are non-expert users and they might find difficult to keep up with the rapid development of computer technologies. In order to assist Web surfers in browsing the Internet more efficiently, our interest is to model Web users' browsing patterns and use these patterns to make changes in our website according to user needs. Data mining is the appropriate methodology for systematically analyzing the behavior of past visitors and taking decisions on what has to be improved.

Online education is at least one activity that is having success when being developed through the web. There are provided easy to use tools for both students and teachers. However, it is very difficult and time consuming for educators to completely track and assess all the activities performed by all learners. Moreover, it is hard to evaluate the structure of the course content and its effectiveness on the learning process. Though, developing, maintaining, and improving a web based educational system comes with new challenges. Discovering users behavioral patterns is one of these challenges, since understanding these patterns may give valuable insights on how the system itself can be improved.

State of the art research in this field is focusing on detecting behavioral patterns and user profiles by using web-logs analysis, analyzing behavioral patterns and extracting information from them or studying the web user navigation dynamics. Many research papers in the field of Web Usage Mining are focusing on commercial websites [1]. We are focusing on web based e-learning platforms, since they are nowadays widespread in schools, colleges and universities. Considering the educational content, the usual web analytics instruments are not precise enough [2] and we have to use new instruments in order to extract knowledge from data.

This paper presents advances of a Formal Concept Analysis (FCA) based strategy for improving web-based learning sites. We describe how we used Web Usage Mining and Formal Concept Analysis (along with its varieties) to create a visual overview of our analysis published in the last years. Firstly we have focused on exploring web-logs and discover knowledge by the means of FCA and Triadic FCA (3FCA) [3]. Then we have focused on visualizing triadic data by using Circos, a graphic tool which show connections between data in a circular layout. Our next purpose was to emphasize user dynamics by means of FCA and 3FCA [4] which lead to studying behavior types while using educational systems. These analysis resulted in generating attractors, which are behavioral patterns to which users adhere while using the web based educational system [5]. After the behavioral patterns were classified our purpose was to evaluate student performances from both a quantitative and a qualitative perspective [6], [7]. In the next step we employ Tetradic FCA to compare web usage patterns with respect to the temporal development and occurrence [8]. Finally we emphasize how FCA and Answer set programming (ASP) can be used for detecting repetitive browsing habits. Our purpose was to determine trend-setters, i.e. users which firstly adhere to a specific behavior and the generate a bundle of users following them, followers, i.e. users who belong to a bundle and categories of bundles, i.e. different types of behavior revealed by users' access pattern in the electronic platform [9]. From all the revealed behaviors we distill then users life tracks by using Temporal Concept Analysis (TCA).

2. State of the art

Analyzing web educational content is paramount for improving the website in order to help the educational process. Web Mining constitues an important feedback for website optimization [10], for web personalization [11] and predictions [12].

Web mining can be categorized into three different classes based on which part of the Web is to be mined. These three categories are:

- Web Content Mining - the process of discovery of useful information from the web contents;
- Web Structure Mining - the process of discovery the model underlying the link structures of the web;
- Web Usage Mining - the process of analyzing web surfer's behaviors.

We are focusing on applying Web Usage Mining techniques in order to discover users interactions with the web. Surveys [13] and [14] present educational data mining works in order to show recent educational data mining advances. Liebowitz and Frank define in [15] blended learning as a hybrid of traditional and online learning, where the online component becomes a natural extension of the traditional one.

It has been shown in [12] that using only one algorithm with the best classification and accuracy in all cases is not possible, even if highly complicated data mining techniques are used. Thus, offline information, such as classroom attendance, punctuality, participation, attention and predisposition were suggested to increase the efficiency of such algorithms.

Due to the strength of its knowledge discovery capabilities and the subsequent efficient algorithms FCA seems to be particularly suitable for analyzing educational sites. For instance, papers [16] , [17] are devoted to the topic of improving discussion forums, while our own previous contributions are focusing on the user/student behavior [4], [5].

3. Problem Formulation

Analyzing user behavior has two aspects: one concerning the interests of the users and the information they access and the other concerning the way of accessing this information. First aspect is addressed by using techniques for the establishment of user profiles. The second aspect is addressed by using techniques for analyzing web server logs. These two aspects are complementary, since a web user is characterized by his/her interests and by her navigational behavior.

Web Usage Mining techniques involves analyzing data collected from web server access logs, proxy server logs, browser logs, user profiles, registration data, user sessions, cookies, user queries, bookmark data, mouse clicks and scrolls and any other data as the results of interactions. Web Usage Mining is a powerful tool to analyzing, designing and modifying a Web site structure as well as understanding and analyzing the site visitor's behavior in two aspects:

- the interest and information one access;
- the way one access this information.

Web Usage Mining activities emphasize two different aspects: how designers expect to be used the site by the visitors and the way visitors effectively using the site.

For demonstrative purposes we used an e-learning instrument called PULSE [18] . The data analyzed in this paper consists on two time periods, i.e., the second semesters of the academic years 2012-2013 and 2014-2015. It is helpful to have an informed learning management system that continually "educates" itself about the requirements of its users. We want to determine if:

- students are finding the essential web pages;
- students follow the optimal paths in reaching the sought information;
- how much time are students spending on specific web-pages;
- a web page is unnecessary;
- all pages are tailored for the used browsers or resolutions;
- there are changes in on-line traffic patterns and behavior over time.

Web Usage Mining can be divided in at least three different phases:

- data preparation;
- pattern discovering;
- pattern analysis and visualization.

An entry in a web server log contains the time stamp of the access, the IP address of the originating host, the type of access (GET or POST), the address of the requested document, referrer page URL, agent (browser and client operating system) and other data. In this phase the web log data must be cleaned, filtered, integrated and transformed in such a way that the irrelevant and redundant data can be removed and user session can identified [19] . We cleaned our data from accesses of robots and spider crawlers and we clustered it corresponding to actual student groups, academic week time intervals and classes of access files. The most important phases in Web Usage Mining are identification of sessions and users and also integration of data from other sources (such as performance or learning style of a student). The sessions are actual HTTP sessions, while the user is identified by his/her login ID. The logged data is integrated with the records about student performance (per laboratory work, tests and exams) and attendance, and with the correlation between the contents between different site sections regarding theoretical support (i.e., lectures, explained test papers, and theoretical support for labs) and laboratory work.

At the end of the preparation phase, grouping the log entries using the corresponding time stamp, the source and the target page we can obtain sequence of accessed pages, called chains. A set of visitor sessions produces a collection of chains, since multiple visitors may access the same pages in the same order. We group them into collections of similar chains based on common visited classes of files.

After data preparation phase, the pattern discovery method should be applied. This phase consists of different techniques derived from various fields applied to the available data. We propose a Formal Concept Analysis approach in order to be able to discover navigational patterns in the data.

4. Data mining by using Formal Concept Analysis

Formal Concept Analysis was introduced by Rudolf Wille the early 1980s in [20] as a mathematical theory. FCA is concerned with the formalization of concepts and conceptual thinking and has been applied in many disciplines such as software engineering, knowledge discovery and information retrieval. Ganter described the mathematical foundation of FCA in [21].

Formal Concept Analysis can be used as an unsupervised clustering technique. The starting point of the analysis is a database table consisting of rows G (i.e. objects), columns M (i.e. attributes) and crosses $I \in G \times M$ (i.e. relationships between objects and attributes). The mathematical structure used to reference such a cross table is called a formal context (G, M, I). Given a formal context, FCA then derives all concepts from this context and orders them according to a subconcept-superconcept relation. This results in a line diagram (called lattice).

The major advantage of using FCA w.r.t. other methods rely, besides the effectiveness of its algorithms, on the graphical expressiveness of conceptual hierarchies which can be used as a basis for further communication, knowledge acquisition and inference, as well as for further processing.

We have started our analysis motivated by the necessity of understanding "who is doing what" in an e-learning platform. In order to do this we have conceptually scaled the web log data, using the knowledge management suite ToscanaJ [22]. Therefore, we investigate which classes of files are accessed by students and which are the most used referrers.

In order to determine the Access File Classes we have divided all the accessed webpages into classes:

- LOGIN - in order to distinguish between users, PULSE has a login phase;
- HOME - class of pages which contains general information such as: lab attendances, links to laboratory support, links to assignments, marks, eval- uation remarks and current announcements;
- LECTURE - class of pages which contains the material concerning the lectures (e.g., teaching material used for courses, test paper result, technical solutions);
- LAB - class of pages which contains the laboratory material.

In order to determine the Referrer Classes we have divided all the referrer URLS (the site from which the current webpage was accessed) into classes. There are two disjoint subclasses of referrers, representing accesses from inside or outside of PULSE:

- inside PULSE - the Referrer Classes have similar values with their correspondent Access File Classes;
- outside PULSE - direct (bookmarks or direct accesses) or social (Facebook, Mail or Google).

Figure 1 depicts the referrer - access file pairs of classes, represented and visualized by ToscanaJ using a grid scale. This figure reveals on the left side of the grid the access file classes (i.e. HOME, LECTURE, LAB, LOGIN), on the right side the referrers (inside PULSE, social, direct) and inside the nodes the percentage of visitors which have landed on a page of PULSE. We emphasize the increased interest over HOME class. It is, as expected, the "command center" of PULSE [3]. It is worrying though that students access less the teaching and the laboratory support. However, the efficiency of learning is not expressed only through the online learning.

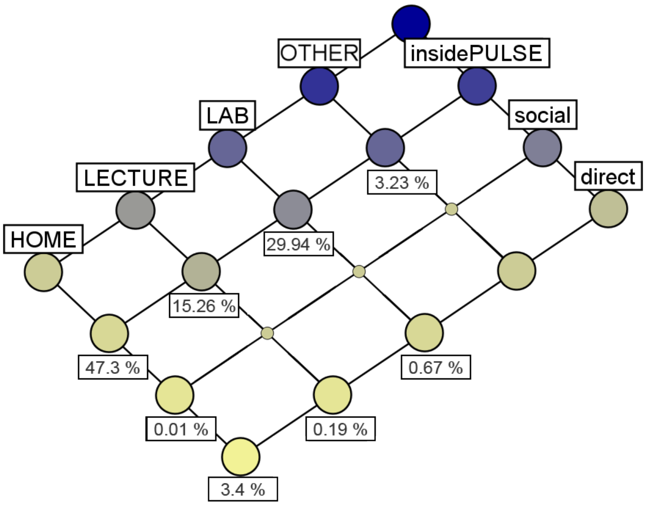


FIGURE 1. Pairs of Referrer Classes - Access File Classes visited in 2013

Considering students accesses, we switched our perspective to a triadic one, in order to observe their behavior.

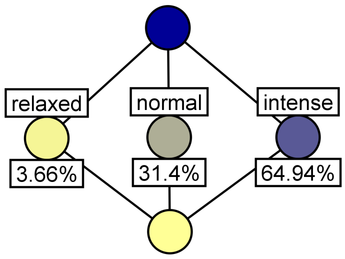
5. The polyadic approach

Rudolf Wille and Fritz Lehmann extended Formal Concept Analysis in 1995 [23] with Triadic Formal Concept Analysis (3FCA), considering objects, attributes and conditions.

Given a set of scales preprocessed with ToscanaJ suite, we have selected a triadic data set: the pairs Referrer - Access File Class as attribute set, timestamps as conditions and students Login as object set. Then, we have generated all triconcepts using Answer Set Programming techniques as described in [24], [25] .

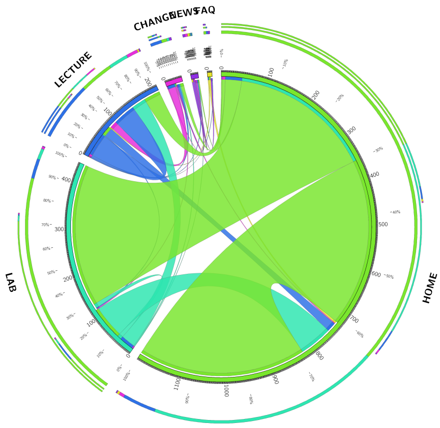
The problem of visualizing triadic data has not been yet satisfactory solved. Triadic conceptual structures have been visualized for instance using trilattices or graphs. The approach used in our paper is to define some dyadic projections and visualize the dyadic data obtained with a tool called Circos that uses a circular layout.

Circos as a visualizing tool has been developed to investigate structural patterns arising in bioinformatics and its circular layout emphasize connections between represented data [26] . The algorithm implementing the projection of the triadic structure over attributes, objects or conditions is described in [4].

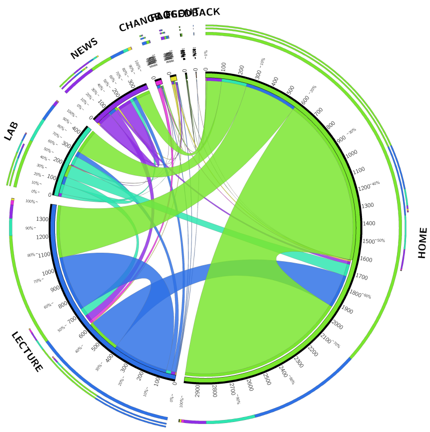


(a) Distribution of users over the three main classes of quantitative behavior

(b) The Relaxed Behavior



(c) The Normal Behavior

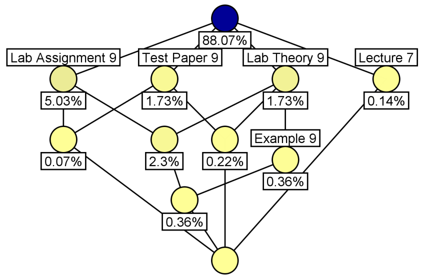


(d) The Intense Behavior

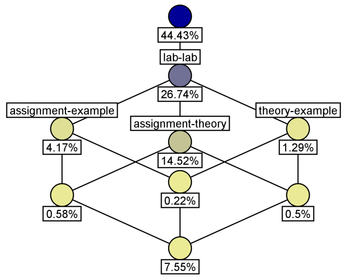
FIGURE 2. Users qualitative behavioral patterns

By switching to the triadic perspective we were able to detect three main quantitative behavioral patterns: *relaxed*, *normal* and *intense*.

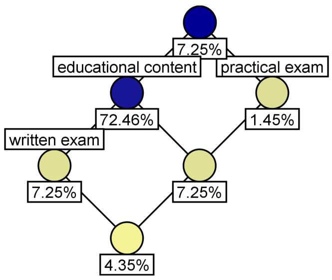
Figure 2(a) presents the distribution of users over these three main categories, while a circular view of triadic data expressing the correlation between educational performance and the relaxed, normal, and intense behavior of students is displayed in Figures 2(b), 2(c), 2(d). Using ToscanaJ suite we have managed to describe behaviors by using a nominal scale (see Figure 2(a)).



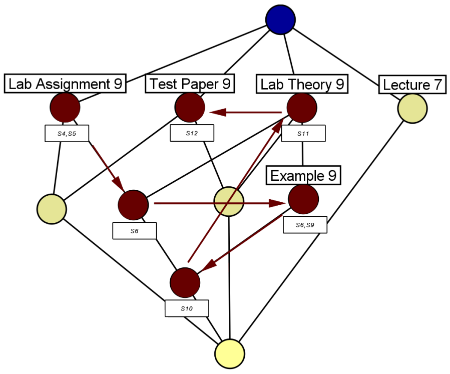
(a) Educational attractor for the 9th Laboratory



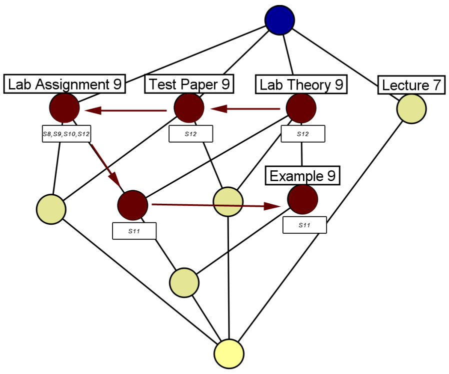
(b) Popular attractor - Sessions containing branches with laboratory related content



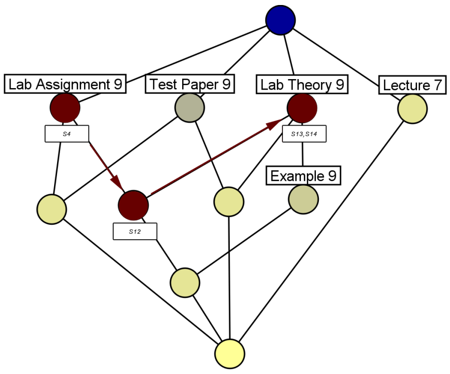
(c) Critical attractor - What are students visiting while preparing for exams?



(d) Early bird user behavior on an educational attractor



(e) Common user behavior on an educational attractor



(f) Late rise user behavior on an educational attractor

Figure 3. Users quantitative behavioral patterns

Nominal scales are used for scaling attributes whose values are mutually exclusive.

Considering a concept lattice, all the concepts can be read from the concept lattice in the following way. Each concept corresponds to exactly one node in the lattice. When looking at a node, the extent of the corresponding concept contains all the objects from the lattice reachable when going (only) downward. Analogously, the intent contains all the attributes reachable when going (only) upward.

Each node represented on the scale reveals a concept, which can be understood as a set of objects with a common set of attributes that satisfies the condition of maximality (i.e. no other object or attribute can be added to the extent, respectively to the intent of the concept without violating the first property).

After analyzing the results [4] we have observed that the relaxed behaviour occurs mainly during holiday (fewer accesses and the reduced number of Access File classes visited), the intense behavior occurs during examination periods (increased number of accesses) and the normal behavior occurs during the semester when there is no examination period or holiday (almost all Access File classes are visited). The dyadic representation presents only the quantitative aspect of the navigation meaning the number/percent of accesses. The circular visualization presented so far provides a more qualitative view on the navigational pattern, comprising more details about how and where students navigate.

Our next aim is to emphasize user dynamics through the site by studying users behavioral patterns. Behavioral patterns of user visits of an e-platform are characterized by some parameters (visited pages, frequency, time on page) and their study gives a valuable insight on how users are navigating and behaving in such a web based platform. On the other hand, one would like that users adhere to some specific patterns since these patterns might be either individual (sub)group patterns. Considering these insights we must evaluate the efficiency and the compliance of this adhesion to the scopes of the platform. There is also the possibility that one is interested in types of behavioral patterns which are to some degree unintended or independent to the design and the content of the web platform. All these types of behaviors are called attractors [5], and they represent behavioral patterns to which users adhere while using the educational system. Attractors are qualitative behavioral patterns, and they are distilled from frequently visited chain of pages where some deviation from the visit habit is allowed. Moreover, the entire design and scopes of some web based platform can be defined and modeled in terms of attractors: state what should users do and then evaluate if they adhered to these views or have found their own ways to use the system. For web based educational systems, we focus on three main types of attractors: educational, popular and critical attractors. Figure 3 presents some nominal scales regarding these types of attractors.

Educational attractors reflect the educational purpose of the instructor and it should convince users to adhere to them. Figure 3(a) presents the educational attractor for the 9th Laboratory. It contains visits of the material provided for a laboratory, the related lecture, the test paper given during the lecture and their corresponding explanations. Popular attractors are those to which users adhere without being explicitly intended by the design or the content of the portal. This attractors might give important clues to what users consider to be interesting or the way they would like the website to be designed. For instance, we have observed that "branch-ing" behavior is a popular attractor. When the referrer is not the same as the last page accessed it means that the user opened a new browser tab or window, and we called that part of our page chain a new branch. Figure 3(b) shows that more than half of users' visits contain branches with lab related content. Critical attractors are behavioral patterns to which users adhere in stressful situations (deadlines, results posting). Critical attractors are a subclass of popular attractors, but we emphasized them since they reflect different habits. Figure 3(c) reveals that out of all pages which are flash-like visited (students stay only a few seconds and/or they refresh allot to see new content), the students visit the most the educational content.

Nevertheless it is interesting to investigate the evolution over time of one user or that of bundles of users adhering to a specific attractor using Temporal Concept Analysis. In order to do that, we have distilled from educational attractors users life tracks. Investigating all visits within the educational attractor (see Figure 3(a)) reflects a more structured navigation pattern inside PULSE and gives an understanding on how specific knowledge is gained by adhering to it. We have classified students according to their style of adopting this behavior: early birds, common and late rise users. Early birds users are students that usually access the provided information before it is expected. Common users are users that visit the provided material within the expected time interval. Late rise users are students that visit the provided material later then expected. Figures 3(d), 3(e) and 3(f) reveals the evolution of three different students during the entire semester. We emphasize the time evolution of PULSE accesses for the considered students by using Temporal Concept Analysis and we draw their life tracks, which are characterized by chains of states.

Life tracks are built by setting time at week level and marking the temporal trajectory of the student through the educational attractor. We have observed by studying students temporal trajectories through PULSE that early birds and common users adhere to the educational attractor, i.e., they follow the intended flow through PULSE. For each assignment students are expected to first read the assignment, then to consult the laboratory support (i.e., the theory and example) and then to check other related material (e.g., lecture notes and the explanations on the test papers). The late rise users often access only the assignment page. Moreover, it can be observed that each student preserves his/her access pattern (i.e., the order in which they access the provided material) on all educational attractors during the semester. Each student may fall in one of the above category but their specific behaviors are distinct. Grouping their specific behaviors have revealed their life tracks and their affiliation to one category.

After distilling users life tracks from specific educational attractors, we have switched from a dyadic and a triadic perspective to a polyadic one. We consider the problem of distilling relevant conceptual structures from web logs, i.e. investigate repetitive behavioral patterns. We have enlarged our set of data considering a tetradic approach. We have switched between quantitative methods for a bird-eyes view and then returned to qualitative techniques (such as FCA) to see the actual facts. Through this approach, we have managed to determine similar behavior that fit into classes of our interest [8]. Based on an analysis of users showing a common behavior, we determined bundle of users with similar behavior. We are very close to determine trend-setters (i.e., users which firstly adhere to an attractor and then generate a bundle of users following them), but we need to have another perspective on our data. For that we put together all our data and analyse it on a 5-adic perspective.

We have analyzed students that initiate a behavior that might be assimilated by other students, influencing them in the way they use the portal [9]. We emphasize different types of repetitive behavior:

- trend-setters, i.e., users which firstly adhere to a specific behavior and then generate a bundle of users following them;
- followers, i.e., users who copy the behavior of a trendsetter;
- patterns revealed by the occurrences of particular behaviors (in which weeks, for what trend-setter and what followers).

6. Conclusions and Future Work

Web is an excellent tool to deliver educational content in the context of an online educational system. Therefore the design of web pages is very important for the system administrator and web designers. These features have great impact on the number of visitors and on their experience. In this paper we tried to give a clear understanding of the data preparation process and pattern discovery process. We have presented a Formal Concept Analysis strategy for the analysis of the navigational behavior of web users in order to improve web-based learning sites. This analysis helps educators understand the users behavior and use the obtained knowledge for optimizing and personalizing the e-learning portal. We are currently working on formalizing all the concepts introduced in our papers by means of Formal Concept Analysis. In our future work, we intend to investigate trend-setters evolution over time. In order to deal with the temporal dimension of the data, we plan to apply temporal concept analysis on a conveniently chosen data set.

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Babeş-Bolyai University, Department of Computer Science, Cluj-Napoca, România

E-mail address: diana.halita@ubbcluj.ro