# An Approach for Knowledge Discovery in a Web Usability Context

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## ABSTRACT
Usability plays a key role in increasing user satisfaction and profits for Web sites. Successful and easy-to-use sites result from a human-centered design process with strong emphasis on evaluation. Usability evaluation can be an expensive and time consuming task. To tackle this situation we present a heuristic approach where data mining techniques help to determine relationships among different usability components and discover problems in their usage. We also describe some preliminary results.

### Author Keywords
Web usability; data mining; knowledge discovery; evaluation

### ACM Classification Keywords
H.5.2. Information interfaces and presentation (e.g., HCI): User Interfaces. H.2.8. Database applications: Data mining

## INTRODUCTION
The ultimate goal of any software application or Web site is providing a good service to users so that they are satisfied, their expectations are met, and they have a great user experience. Usability plays a key role in achieving these goals. The International Organization for Standardization (ISO) defines usability as the “extent to which a product can be used by specified users to achieve specified goals effectively, efficiently and with satisfaction in a specified context of use” (in ISO 9241-11). Today, there is still not a standard way to evaluate Web Usability quantitatively and qualitatively. Different approaches are used, such as analytical and empirical. However, it is still a challenge to define acceptable criteria for Web usability evaluation, and companies invest huge amounts of money to evaluate Web applications and Web sites, since keeping a user or client satisfied means maintaining a good reputation, increasing sales and revenues.

In this work, we describe a heuristic approach based on Nielsen’s usability components [8]. Our approach applies knowledge discovery techniques to determine relationships among different components, among attributes and components, and discover problems in the usage of usability patterns. The main goal is using this knowledge to suggest which components should be improved to increase Web usability. We carried out some preliminary experiments by applying two data mining techniques to a dataset containing evaluation reports of different Web sites. We used association rules and decision trees. The results obtained thus far, indicate that our proposal is viable to discover interesting relations from this type of data. The patterns and relations found can be helpful for Web site designers giving them clues about what to prioritize.

The rest of the article is organized as follows. First, we describe the main Web usability concepts related to our proposal. Then, we present our proposed approach and a case study describing the results obtained. Afterwards, we analyze some related work. Finally, we present our conclusions and future work.

## WEB USABILITY CONCEPTS
Problems for users and customers arise as a result of poorly designed Web sites with usability issues. Indeed, on the Web, usability is a necessary condition for being successful. In particular, Nielsen [8] points out that usability has five components:

- Learnability: How well the product supports both initial orientation and deeper learning?
- Efficiency: Once users have learned the design, how quickly can they perform tasks?
- Memorability: When users return to the design after a period of not using it, how easily can they reestablish proficiency?
- Errors tolerant: The ability to prevent errors or help users recover from those that occur.
- Satisfaction: How pleasant is it to use the design?

Nowadays, successful and easy-to-use sites are designed from the ground up to meet the needs of their users and customers. This focus is called human-centered design and means that you do the work up front to ensure that the Web site has the features that customers need with strong emphasis on Web site evaluation. There are several well-known methods for usability evaluation that can be classified in analytic or empirical. Analytic evaluation involves the analysis of the user interface to discover potential usability problems and guide modifications during the development of the system (i.e., expert reviews and cognitive walkthroughs). On the other hand, empirical evaluation methods collect usability data by observing or measuring activities of end users interacting with a prototype or an actual implementation of the system (i.e., controlled experiments, questionnaires, interviews, and focus groups).

However, usability evaluation can be an expensive and time consuming task, and data mining is therefore a promising way to simplify and improve current approaches.

## PROPOSED APPROACH

In this section we present an overview of our approach, and we describe the basic concepts of the two data mining techniques we use.

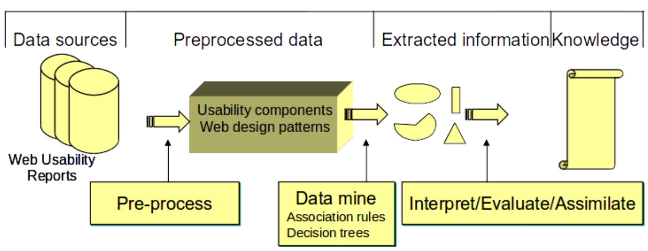


**Figure 1. Overview of our approach**

### Overview

We present in this article an approach (Figure 1) to discover knowledge from a dataset comprising evaluation reports of different Web site usability features. The first step in our approach is pre-processing, in which the information contained in Web usability reports is transformed into a dataset that can be used in a data mining tool. Then different data mining techniques can be applied. In this work we use association rules and decision trees. The process might iterate into a previous step, by selecting other parameters for the data mining techniques, for example, or some other pre-processing task. Once patterns are discovered, the next step is post-processing, in which patterns and relations found are filtered, ordered, visualized and analyzed. Finally, the knowledge discovered can be presented to users, i.e. web site designers and developers.

### Association rules

Association rules [1] imply an association relationship among a set of items in a given domain. Association rule mining is commonly stated as follows: Let I be a set of items and D be a set of transactions, each consisting of a subset X of items in I. An association rule is an implication of the form $X \rightarrow Y$, where $X \subseteq I$, $Y \subseteq I$ and $X \cap Y = \emptyset$. X is the antecedent of the rule and Y is the consequent. The rule has support s in D if s% of the transactions in D contains $X \cup Y$. The rule $X \rightarrow Y$ holds in D with confidence c if c% of transactions in D that contain X also contain Y. Given a transaction database D, the problem of mining association rules is to find all association rules that satisfy: minimum support (called minsup) and minimum confidence (called minconf).

In this work, the set of items is composed of the different components and/or features evaluated in a Web usability report and the overall evaluation indicated by the Web usability expert.

We used the Weka tool [4] and the Apriori algorithm to discover association rules using a value of minconf = 0.7 (70%) and a value of minsup = 0.1 (10%). The Apriori algorithm, although one of the most widely used for association mining, returns many rules that might be irrelevant for our purposes. To filter out rules, we use templates or constraints [6] that select those rules that are relevant to our goals. For example, we are interested in those association rules having as antecedent different components and features and as consequent the overall evaluation. Also we might be interested in rules combining usability features when the evaluation is good. To eliminate redundant rules, we use a subset of the pruning rules proposed in [7]. Basically, these pruning rules state that given the rules A, B $\rightarrow$ C and A $\rightarrow$C, the first rule is redundant because it gives little extra information. Thus, it can be deleted if the two rules have similar confidence values. Similarly, given the rules A $\rightarrow$B and A$\rightarrow$B, C, the first rule is redundant since the second consequent is more specific. Thus, the redundant rule can be deleted provided that both rules have similar confidence values.

### Decision Trees

A decision tree is a flowchart-like structure in which an internal node represents a test on an attribute, each branch represents an outcome of the test and each leaf node represents a class label, which is the decision taken after computing all attributes. A path from the root to a leaf represents a classification rule. In our work, the label corresponds to the evaluation of a Web site given by an expert and internal nodes represent the different Usability components and features evaluated.

There are various algorithms traditionally used to build decision trees. In this work we used the J48 algorithm, which is Weka implementation of the C45 algorithm proposed by [9].

## EXPERIMENTAL RESULTS

In this section we describe the dataset used and we present some examples of patterns discovered using association rules and decision trees.

### Dataset description

The experiments were carried out with 35 instances of evaluations of Web sites (in the areas of education, finances and e-commerce) carried out by Usability experts. The information for each instance consists of: the evaluation (achieved, not achieved, and partially achieved) for five different usability components (learnability, efficiency, memorability, error prevention, satisfaction), the values for six different features analyzed for each of these components, and the overall evaluation of the Web site. Examples of features for the learnability components are: visibility of system status, consistency with standards, user feedback. Examples of features considered for satisfaction are ease of navigation, pleasant layout, among others.

### Findings

As said in previous sections, we used the Weka tool to run the Apriori algorithm to discover association rules and the J48 algorithm to induce decision trees. We obtained different rule sets that showed interesting results. For example, when running the Apriori algorithm with a dataset containing the evaluation of usability components and the overall evaluation, some of the rules generated were the following.

R1: efficiency = achieved, memorability = achieved ==> evaluation = good, sup: (23/35), conf: (1)

R2: efficiency = achieved, satisfaction = achieved ==> evaluation = good, sup: (20/35), conf: (1)

R3: learnability = achieved, satisfaction = achieved 18 ==> efficiency = achieved 18, sup: (18/35), conf: (1)

Rule R1 means that in 23 out of 35 reports, when efficiency and memorability components are achieved, then the overall evaluation of the web site is good. On the other hand, R3 indicates that in 18 out of 35 of the reports, when learnability and satisfaction are achieved, the overall evaluation is good. This type of rules can give some clues to designers to which components they should focus on (efficiency and memorability in this case).

When running the Apriori algorithm with a dataset containing the evaluation of usability features and the overall evaluation, some of the rules generated were the following.

R4: p23=yes ==> p17=yes sup: (31/35) conf:(1)

R5: p23=yes ==> p24=yes sup: (31/35) conf:(1)

Rule R4 means that in 31 out of 35 of the reports, when "the site prevents users from making mistakes" then " the site contains actions such as do, undo and redo" with a confidence of 100%. Similarly, rule R5 means that in 31 out of 35 of the reports, when "the site prevents users from making mistakes" then "error messages are written in the user language", with a confidence of 100%. This type of rules can give some insight of different usability components, in this case about error tolerance.

In Figure 2, we show the decision tree obtained with a dataset consisting only of the evaluation of usability components and the overall evaluation. In this tree, only two components are considered: efficiency and learnability. This means that these two components are the main ones for the usability reports considered. The precision for the classification is 83% (29 instances correctly classified).

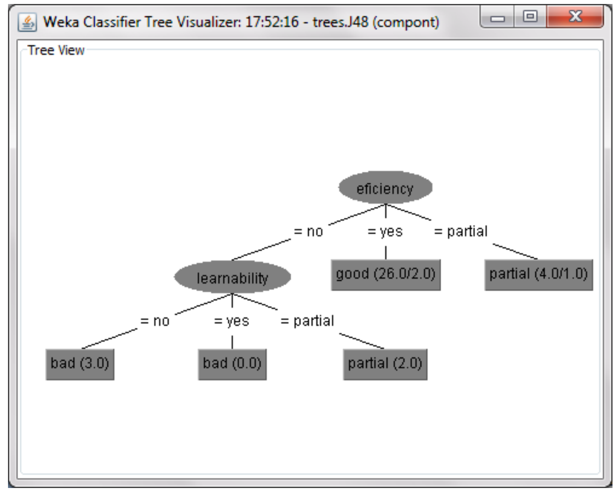


**Figure 2. Decision tree for usability components**

In Figure 3, we show the decision tree obtained with a dataset consisting only of the evaluation of usability components features and the overall evaluation. In this tree, the features that appear are the following: p16, p 21, p27, and p2. P6 stands for "titles and subtitles are short, meaningful, and simple". P21 stands for "mandatory fields in form are clearly distinguished from optional fields". P27 stands for "the user experience when using the site makes user tasks easier and faster than without the site". P2 means "menu instructions, navigation and error messages are consist over different pages".

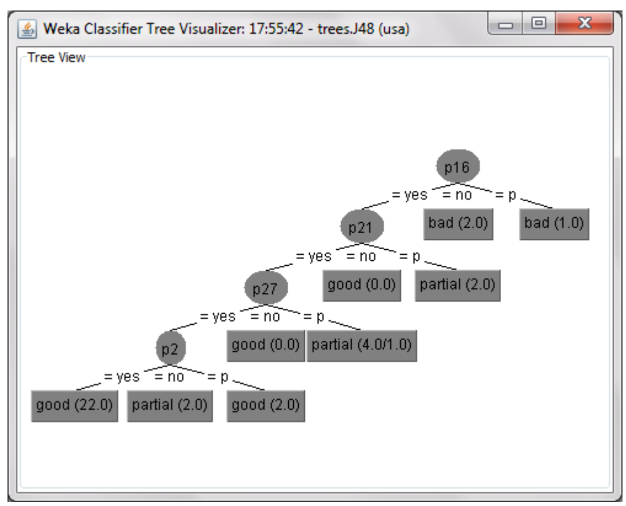


**Figure 3. Decision tree for usability features**

Analyzing the tree, we can form different classification rules, one for each leaf. For example, the first rule can be read as "if titles and subtitles are short, meaningful, and simple; and "mandatory fields in form are clearly distinguished from optional fields; and the user experience when using the site makes user tasks easier and faster than without the site; and menu instructions, navigation and error messages are consist over different pages then the overall evaluation of the Web site is good" with a precision of 22/28. This type of rules can give some insight of different usability features.

## RELATED WORK

There is a considerable amount of literature on automating usability Evaluation. For a complete review of the state of the art see [5], an extensive survey of usability evaluation methods organized according to a taxonomy that emphasizes the role of automation.

However, to the best of our knowledge, there are little approaches that applied data mining techniques to a dataset containing usability evaluation reports of different Web sites. Sikorski [10] proposed an approach based on AHP (Analytic Hierarchy Process) technique to supports user-centered decision making and product usability evaluation. Other work explored an approach based on learning models, using feedback from Web site managers, which helps to identify usability concerns of Web sites [2]. Finally, an approach called QUTC, which empowers the traditional QUT (Qualitative Usability Testing) process by extending it through data processing and data mining techniques [3].

## CONCLUSIONS AND FUTURE WORK

In this paper we have presented a knowledge discovery approach from data of Web site evaluations. The preliminary results obtained indicate that the approach is viable to discover interesting patterns and relations between different usability components and features. The knowledge discovered can be used by Web sites designers to prioritize certain usability components during the design of the site.

As a future work, we will carry out more experiments with a bigger dataset. Also, we will divide the evaluation considering the type of site evaluated, in order to find patterns for a certain type of site (e.g. educational, e-commerce, entertainment).

## ACKNOWLEDGMENTS

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